Language models require vast amounts of data during training. This limits their use to languages for which such data requirements can be met. To extend access to language technology to more linguistic communities, researchers have developed multilingual language models (MLMs) that are trained on data from multiple languages. The idea is that languages can support each other as they share common patterns, making the models useful across more languages.

However, this approach brings new challenges from both a technical and social perspective. When a model is trained on multiple languages, these languages start competing for limited model capacity, which can lead to negative interference and reduce effectiveness. In addition, to deploy MLMs in culturally-diverse communities, their output needs to be sensitive to the sociocultural norms and biases of those communities. This necessitates MLMs to become inherently multicultural as well.

In this thesis, we investigate how to build more effective MLMs that mitigate negative cross-language interference and study the effect that multilingual training has on the social biases and cultural values that they encode.

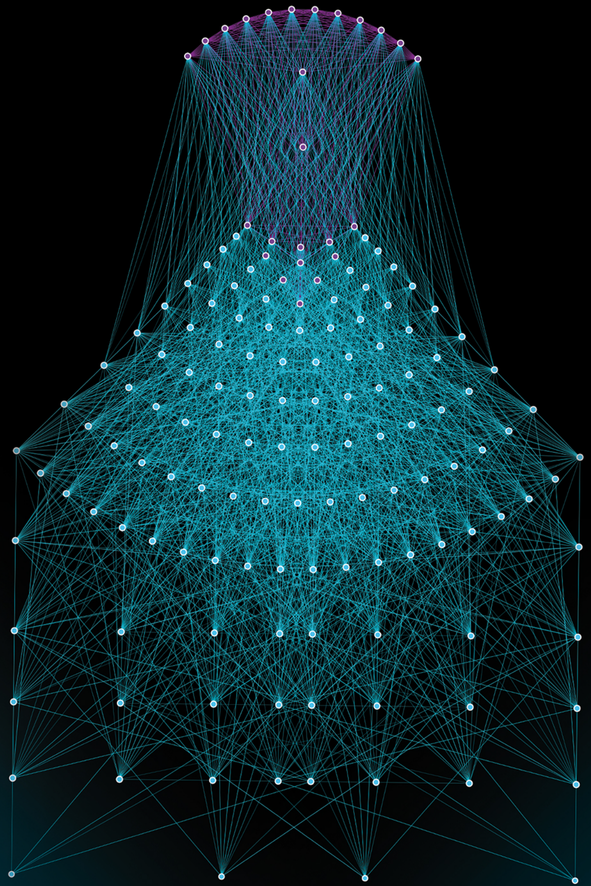
University of Amsterdam

Multilinguality and Multiculturalism

Rochelle Choenni

Multilinguality and Multiculturalism

Towards more Effective and Inclusive Neural Language Models



ROCHELLE CHOENNI

Multilinguality and Multiculturalism: Towards Effective and Inclusive Neural Language Models

Rochelle M.V. Choenni

Multilinguality and Multiculturalism: Towards Effective and Inclusive Neural Language Models

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Institute for Logic, Language and Computation
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homepage: http://www.illc.uva.nl/

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Multilinguality and Multiculturalism: Towards Effective and Inclusive Neural Language Models

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aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
prof. dr. ir. P.P.C.C. Verbeek
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Copromotores:	dr. E.V. Shutova	Universiteit van Amsterdam
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List of publications

During my PhD I authored the following conference and journal papers:

1. **Rochelle Choenni** and Ekaterina Shutova. Self-Alignment: Improving Alignment of Cultural Values in LLMs via In-Context Learning. *Under submission at AAAI 2025*. URL https://arxiv.org/abs/2408.16482.

2. **Rochelle Choenni** and Ekaterina Shutova. Investigating Language Relationships in Multilingual Sentence Encoders through the Lens of Linguistic Typology. *Computational Linguistics*, 48(3):635–672, 2022. URL https://aclanthology.org/2022.cl-3.5.

3. **Rochelle Choenni**, Ekaterina Shutova, and Robert van Rooij. Stepmothers are mean and academics are pretentious: What do pretrained language models learn about you? In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1477–1491, Online and Punta Cana, Dominican Republic, 2021. Association for Computational Linguistics. URL https://aclanthology.org/2021.emnlp-main.111.

4. **Rochelle Choenni**, Dan Garrette, and Ekaterina Shutova. Cross-lingual Transfer with Language-Specific Subnetworks for Low-Resource Dependency Parsing. *Computational Linguistics*, 48(3):613–641, 2023a. URL https://aclanthology.org/2023.cl-3.3.

5. **Rochelle Choenni**, Dan Garrette, and Ekaterina Shutova. How Do Languages Influence Each Other? Studying Cross-lingual Data Sharing during LM Fine-tuning. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1477–1491, Singapore, 2023b. Association for Computational Linguistics. URL https://aclanthology.org/2023.emnlp-main.818.

6. **Rochelle Choenni**, Anne Lauscher, and Ekaterina Shutova. The Echoes of Multilinguality: Tracing Cultural Value Shifts during LM Fine-tuning. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguis-*

tics (Volume 1: Long Papers), page 15042–15058, Bangkok, Thailand, 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.acl-long.803/.

7. **Rochelle Choenni***, Sara Rajaee*, Christof Monz, and Ekaterina Shutova. On the Evaluation Practices in Multilingual NLP: Can Machine Translation Offer a Scalable Alternative to Human Translation? *Under submission at COLING*, 2024. URL https://arxiv.org/pdf/2406.14267.

8. **Rochelle Choenni**, Ekaterina Shutova, and Dan Garrette. Examining Modularity in Multilingual LMs via Language-Specialized Subnetworks. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 287–301, Mexico City, Mexico, 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.findings-naacl.21.

* denotes joint first authorship.

In addition, I contributed as a co-author to the following papers:

9. Abraham Fresen, **Rochelle Choenni**, Micha Heilbron, Willem Zuidema, and Marianne de Heer Kloots. Language Models That Accurately Represent Syntactic Structure Exhibit Higher Representational Similarity To Brain Activity. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 46, 2024. URL https://escholarship.org/content/qt1fp7m6nf/qt1fp7m6nf_noSplash_424c2fbd823c92f7fe1c3d0c9dec13a2.pdf.

10. Marlene Lutz, **Rochelle Choenni**, Markus Strohmaier, and Anne Lauscher. Local contrastive editing of gender stereotypes. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 21474–21493, Miami, Florida, USA, 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.emnlp-main.1197.

11. Giulio Starace, Konstantinos Papakostas, **Rochelle Choenni**, Apostolos Panagiotopoulos, Matteo Rossati, Alina Leidinger, and Ekaterina Shutova. Probing LLMs for joint encoding of linguistic categories. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 7158–7179, Singapore, 2023. Association for Computational Linguistics. URL https://aclanthology.org/2023.findings-emnlp.476.

12. Claire Stevenson, Mathilde Veen, **Rochelle Choenni**, and Ekaterina Shutova. Do large language models solve verbal analogies like children do? *ArXiv*, 2023. URL https://arxiv.org/abs/2310.20384.

13. Xiaoyu Tong, **Rochelle Choenni**, Martha Lewis, and Ekaterina Shutova. Metaphor Understanding Challenge Dataset for LLMs. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3517–3536, Bangkok, Thailand, 2024. Association for Computational Linguistics. URL `https://aclanthology.org/2024.acl-long.193`.

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Chapter 1

Introduction

In recent years, the field of Natural Language Processing (NLP) has seen rapid performance improvements in a wide range of tasks. This success can largely be ascribed to the development of large-scale self-supervised pretraining methods that circumvent the need for large manually annotated datasets. However, large-scale pretraining still requires vast amounts of text, making the effectiveness of these techniques critically dependent on the amount of resources available in a particular language. This strongly limits the advancements in NLP to a select group of languages for which such text requirements can be met (Hedderich et al., 2021). Consequently, it has led to a disparity in the quality and availability of language technology across different linguistic communities (O'Horan et al., 2016; Joshi et al., 2020). To bridge this gap and extend the benefits of large-scale pretraining to low-resource languages, researchers have focused on the development of models that are more widely applicable across multiple languages. This has sparked renewed interest in the field of multilingual NLP and has led to the development of single models that are jointly trained on texts from multiple languages i.e., multilingual language models (MLMs). The intuition behind multilingual joint training is that it facilitates information sharing between languages. By doing so, languages can learn to support one another by leveraging their commonalities and creating a shared multilingual semantic space. The benefits from this are manifold: it limits the data requirements for low-resource languages, better enables few-shot or zero-shot transfer of models across languages and allows for generalization to new (unseen) languages.

Yet, while LMs have become increasingly multilingual, covering as many as 100+ languages during pretraining, the current design for multilingual modeling has come with a new set of technical and social challenges. In particular, previous works show that multilingual joint learning suffers from *negative interference*—parameter updates that help the model on one language, but harm its ability to handle another—which undercut the benefits of multilingual modeling, especially on low resource languages (Arivazhagan et al., 2019; Wang et al., 2020; Ansell et al., 2021). In addition, the *curse of multilinguality* dictates

Multilingual Language Model
Deutsch
中文
American
Hindi
Русский

Figure 1.1: In the field of Multilingual NLP we aim to develop a single model that is (1) able to understand and interact with text input from different languages, and (2) generate responses that are culturally appropriate.

that limited model capacity at some point prevents MLMs from learning more languages (Conneau et al., 2020a). This raises a set of interesting questions on (1) how current MLMs learn to encode and share information across languages, and (2) how we can better guide information sharing in MLMs to achieve an optimal balance in cross-lingual sharing between preserving positive knowledge transfer and mitigating negative interference.

In addition, next to the technical challenges, the applicability of MLMs in practice also faces challenges from a social perspective. In particular, a limiting factor of MLMs is that in order to deploy them in culturally-diverse communities, they are not only expected to be proficient in generating text in multiple languages, but their output also needs to be sensitive to the sociocultural norms and biases of those communities. This necessitates multilingual LMs to become inherently multicultural as well. However, as MLMs are trained on the concatenation of text from a wide variety of languages spoken in the world, we can expect different, and perhaps opposing, social biases to be encoded in them simultaneously. It is currently still unclear how this interaction of cross-cultural values manifests itself in MLMs. Moreover, it has been shown that LMs are in practice not properly aligned to human values, opening up a whole new line of research on how to improve the *alignment* of LMs (Shen et al., 2023).

While multilingual NLP has made big strides in recent years, the field of multicultural NLP is still in its infancy. In this thesis, we therefore study MLMs with respect to both their technical and social challenges. In particular, we investigate how to build more effective MLMs that mitigate negative interference and study the effect that joint multilingual training has on the social biases and cultural values encoded in MLMs. In doing so, we address four main research questions:

Part 1: Multilinguality

(RQ1) **To what extent and under what conditions do MLMs perform cross-lingual information sharing?**

Before starting our investigation into how to optimize the cross-lingual sharing mechanism of MLMs during multilingual joint learning, it is important to better understand when and how MLMs rely on cross-lingual sharing, and how crucial the role of this mechanism is to the model performance. While the intuition behind multilingual joint learning is that a language's data can be exploited cross-lingually, it has proven difficult to study how MLMs rely on cross-lingual sharing in practice. For instance, many works have studied the encoding of cross-lingual patterns within MLMs by either focusing on probing for particular cross-linguistic differences (Ravishankar et al., 2019; Choenni and Shutova, 2022), or by analyzing the distributional properties of representational language subspaces (Yang et al., 2021; Rajaee and Pilehvar, 2022; Chang et al., 2022; Chi et al., 2020), yet it is not straightforward how to translate these results into model behavior at inference time. Moreover, different approaches to studying cross-lingual sharing have provided contradicting results (Singh et al., 2019). Thus, we instead study cross-lingual sharing both at the *data* level and *parameter* level.

Chapter 3: To investigate sharing at the data level, we test how much influence training data examples from particular training languages exert cross-lingually on the predictions for individual test languages. To this end, we present a novel approach to study to what extent the MLM relies on fine-tuning examples from a language A when making predictions for a test language B. We do this by employing a Training Data Attribution (TDA) method (Pruthi et al., 2020) to identify what the most influential fine-tuning examples are for making a prediction for a particular test example. We then quantify cross-language influence as the percentage that each fine-tuning language on average contributes to the most influential fine-tuning examples for individual test languages. To the best of our knowledge, this is the first approach that is able to provide us with some insights into how much MLMs rely on cross-lingual sharing at inference time. Overall, our results confirm the hypothesis that MLMs to a large extent rely on cross-lingual sharing in their training data use.

Publication: Rochelle Choenni, Dan Garrete and Ekaterina Shutova. How do Languages Influence Each Other? Studying Cross-lingual Data Sharing during LM Fine-tuning. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language*

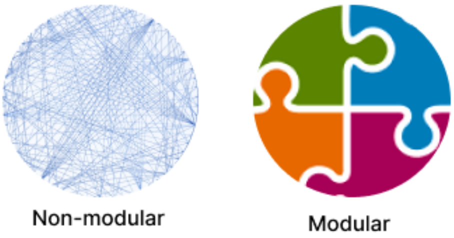


Figure 1.2: Fully shared models suffer from problems such as negative interference. A modular design could improve interpretability, better enable compositionality, stimulate positive transfer and reduce negative interference.

Processing (EMNLP), pages 1477-1491, 2023.

Chapter 5: To study sharing at the parameter level, we take inspiration from works on the *Lottery Ticket Hypothesis* (LTH) (Frankle and Carbin, 2018; Foroutan et al., 2022), which show that subnetworks, i.e. subsets of model parameters, can be found through pruning methods (Han et al., 2015; Li et al., 2016a) that match the performance of the full model at test time. In particular, we study how MLMs allocate their model capacity across languages by testing for the existence of *language-specialized* subnetworks within MLMs. We then investigate to what extent cross-lingual sharing between languages, in the form of positive knowledge transfer and negative interference, can be explained by the parameter overlap between their corresponding subnetworks. Thus, by studying sharing at the parameter level we aim to understand how parameter allocation drives the extent of sharing between languages. We found that subnetwork overlap between languages correlates better with positive knowledge transfer than with negative interference.

Publication: Rochelle Choenni, Ekaterina Shutova and Dan Garrette. Examining Modularity in Multilingual LMs via Language-Specialized Subnetworks. In *Findings of the Association for Computational Linguistics: NAACL*, pages 287-301, 2024.

(RQ2) **How can modular approaches to deep learning help improve the cross-lingual sharing mechanism of MLMs?**

We now delve into the question of how to improve the effectiveness of MLMs by optimizing their cross-lingual sharing mechanism. In this thesis, we study how modular approaches to deep learning can help optimize cross-lingual sharing by effectively guiding parameter sharing. A system is modular when (1) it can be broken down into multiple submodules and (2) these submodules can be recomposed to enforce new model behavior. As such, modular deep learning has recently gained much attention (Pfeiffer et al., 2023) as the expectations are that it could improve *interpretability*, provide a more intuitive path to *compositionality*, and prove to be useful as a *selective sharing* mechanism that effectively guides information sharing between languages. In the multilingual setting, language-wise modularity, i.e. a model composed of language modules, is a particularly promising line of research as selective parameter sharing could provide a remedy to problems such as negative interference (by not fully sharing all parameters it can leave room for language-specific capacity) and the curse of multilinguality (through more efficient allocation of the limited model capacity).

Chapter 4: To operationalize the idea of inducing language-wise modularity into MLMs we first identify language-specific subnetworks to serve as our language modules. We then interchangeably use these subnetworks during *Sparse Fine-tuning* (SFT), i.e. we update only those parameters that are within the subnetwork of the corresponding language batch. We explore how a combination of meta-learning and SFT with subnetworks can improve performance on low-resource languages in particular. We show that by inducing language-wise modularity into MLMs, we can automatically mitigate negative cross-language interference as measured by a reduction in the amount of gradient conflicts during fine-tuning (Wang et al., 2020), and consequently enhance performance.

Publication: Rochelle Choenni, Dan Garrette and Ekaterina Shutova. Cross-lingual Transfer with Language-Specific Subnetworks for Low-Resource Dependency Parsing. In *Computational Linguistics 49(3)*. pages 1-37, 2023

Chapter 5: In Chapter 4, we study the effectiveness of inducing language-wise modularity in MLMs during fine-tuning. We now instead investigate to what extent modularity already naturally arises during pretraining. To this end, we again borrow inspiration from the LTH and investigate whether language-wise modularity in the form of language-specialized subnetworks can be found. This time, we use our approach for measuring cross-language influence, proposed in Chapter 3, to measure the degree of language specialization of the identified subnetworks. We hypothesize that if language-specialized subnetworks can be found after pretraining that rely to a large extent on in-language data, language-wise modularity in the form of language-specialized subnetworks has naturally arisen. As such, we propose a novel approach for measuring the degree of modularity in MLMs using a combination of an existing pruning and TDA method. We then also use this approach to study to what extent SFT with subnetworks further enforces modularity in MLMs by measuring whether the degree of language-specialization of the subnetworks further increases after SFT. While our results confirm that the identified subnetworks are indeed specialized, we find that the performance gains from SFT can not necessarily be ascribed to stronger modularity only.

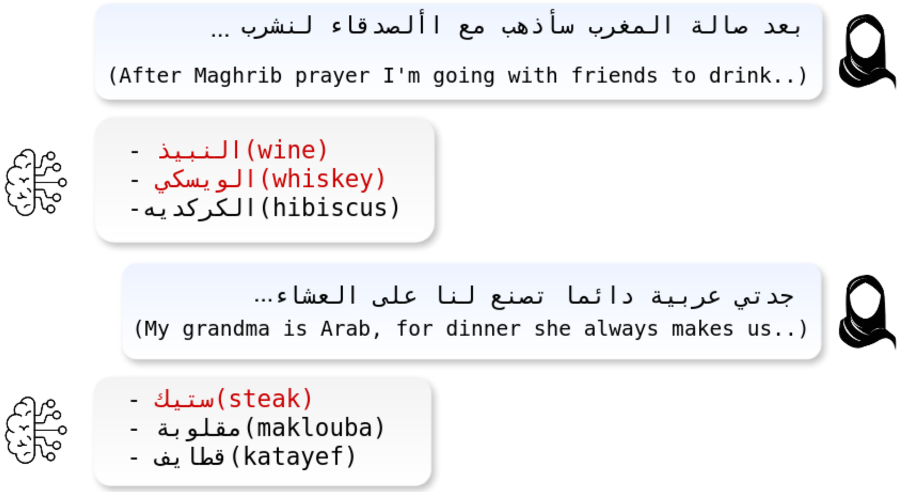
Publication: Rochelle Choenni, Ekaterina Shutova and Dan Garrette. Examining Modularity in Multilingual LMs via Language-Specialized Subnetworks. In *Findings of the Association for Computational Linguistics: NAACL*, pages 287-301, 2024.

Part 2: Multiculturalism

(RQ3) **How are stereotypes and cultural values encoded in MLMs and transferred across languages?**

Social biases and cultural values differ across communities because each culture is shaped by the unique experiences of its members, including their historical, religious and geographical backgrounds. For example, ideas around gender roles, social hierarchy, and even politeness may vary drastically from one language and culture to another, and this will be reflected in online data (Stańczak et al., 2023). As a result, during multilingual joint learning, these models are exposed to not only linguistic diversity but also the underlying cultural nuances and biases that are intertwined with each language. Multilingualism, as studied in part 1, refers to the ability to use and understand multiple languages, whereas multiculturalism refers to the coexistence and interaction of multiple cultures within MLMs. While multilingualism enables communication across linguistic barriers, it does not inherently address the deeper cultural values and perspectives embedded within each language. Multiculturalism, by contrast, requires a model to go beyond linguistic understanding and be culturally sensitive and aligned with the values and perspectives of different societies, thereby reducing the risk of reinforcing biases specific to one cultural or social group. Therefore, the second part of this thesis investigates the implications that multilingual joint learning has on the social biases and cultural values that MLMs encode, and proposes a new technique for improving the cultural alignment of MLMs.

Chapter 6: We first conduct a study into the stereotypical information that monolingual and multilingual LMs learn for a wide range of social groups and how these biases can change due to new linguistic experience during fine-tuning. To compile a list of real world stereotypes for each social group to probe for, we present a novel approach in which we exploit search engine autocompletions to create a dataset. Moreover, we



بعد صالة المغرب سأذهب مع األصدقاء لنشرب ...
(After Maghrib prayer I'm going with friends to drink..)

- النبيذ(wine)
- الويسكي(whiskey)
- الكركديه(hibiscus)

جدتي عربية دائما تصنع لنا على العشاء...
(My grandma is Arab, for dinner she always makes us..)

- ستيك(steak)
- مقلوبة(maklouba)
- قطايف(katayef)

Figure 1.3: An example of the *alignment* problem in MLMs. The figure depicts culturally misaligned responses generated by GPT-4 when asked to complete the sentences. Examples are taken from Naous et al. (2023).

propose a complementary method to more generally study how model predictions of stereotypes are indicative of a positive or negative model bias towards a social group. To this end, we use an emotion lexicon to aggregate model predictions into emotion profiles, and systematically compare the emerging emotion profiles across social groups and models. We find that all models vary considerably in the information they encode, with some models being overall more negatively or positively biased. Moreover, our results show how quickly the sentiment towards a social group can shift based on relatively little fine-tuning data.

Publication: Rochelle Choenni, Ekaterina Shutova and Robert van Rooij. Stepmothers are mean and academics are pretentious: What do pretrained language models learn about you?. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1477–1491, 2021.

Chapter 7: In Chapter 6 we focus our study on probing for stereotypical knowledge in the English language. In this chapter, we instead conduct a more general study into the cultural values that are encoded across different languages in MLMs. Moreover, we use the World Values Survey (WVS) (Haerpfer et al., 2022), that collects human responses from a culturally-diverse set of target countries, to test to what extent cultural values in MLMs correlate with those of human populations. In addition, building on our findings from Chapter 6 in which we saw that fine-tuning has a large impact on the model biases, we now investigate how different aspects of fine-tuning, e.g. the fine-tuning language and domain source, affect the cultural bias of MLMs. To this end, we build 'cultural profiles' to represent the cultural bias in each language, and study how this model bias is affected differently depending on the fine-tuning setting. Finally, we apply a TDA method to trace cultural value shifts (i.e. changes in model predictions) back to the fine-tuning data. Overall, our results underpin the complexity of cross-language and cross-cultural interaction within MLMs and the brittleness with which these values are encoded.

Publication: Rochelle Choenni, Anne Lauscher and Ekaterina Shutova. The Echoes of Multilinguality: Tracing Cultural Value Shifts during LM Fine-tuning. In *Proceedings of the 2024 Conference of the Association for Computational Linguistics (ACL)*, pages 15042–15058, 2024.

(RQ4) **How can we improve the value alignment of MLMs to different cultures?**

Chapter 8: Results from Chapter 7 highlight the need for a flexible and inexpensive alignment method by showing that (1) the cultural values that are encoded in MLMs are not adequately aligned to human values, and (2) these values tend to easily shift during fine-tuning. Thus, in this chapter, we propose a simple, but novel, method to improve the cultural value alignment of MLMs at inference time via *in-context learning* (ICL). More concretely, we test whether providing a set of cultural cues in the form of demonstration examples, can trigger a cultural profile within the model that better corresponds to the cultural values of a particular target country. To this end, we construct a set of demonstration examples from the pre-existing WVS dataset that contains human responses to a cultural value survey conducted in different countries. Our results show that this method can effectively improve the alignment of MLMs in different languages to the cultural values that correspond to a range of culturally-diverse countries.

Publication: Rochelle Choenni and Ekaterina Shutova. Self-Alignment: Improving Alignment of Cultural Values in LLMs via In-Context Learning. *Under submission at AAAI 2025.*

1.1 Contributions

The main contributions of this thesis can be summarized as follows:

- We propose a novel post-hoc model interpretability technique that measures the extent to which languages rely on each other's training data at inference time. Using this method, we obtained new empirical results that demonstrate that MLMs largely rely on training data from multiple languages, and that this holds even when data from the test language itself was seen or overrepresented during fine-tuning.

- We present a comprehensive study on the effects of using static subnetworks throughout sparse fine-tuning (SFT) as a way of inducing language-wise modularity into a system and mitigating negative cross-language interference. Moreover, we propose a new method, i.e. dynamic SFT, in which we allow for dynamic adaptation of our subnetworks during SFT.

- We propose a novel approach for measuring the degree of language-wise modularity in MLMs that builds on an existing pruning and training data attribution method. We use this approach to show that modularity in the form of language-specialized subnetworks naturally arises during pre-training.

- We propose an inexpensive approach to automatically collect real-world data on stereotypes across a wide range of social groups by exploiting search engine autocompletions. We use the resulting dataset to study to what extent MLMs encode human stereotypes.

- We present a comprehensive study into how cultural values encoded in MLMs are revised during fine-tuning and how the interplay between domain source and fine-tuning language affect the cultural value alignment of MLMs in different test languages.

- We propose a simple, but novel, method for automatically improving cultural value alignment in LLMs at inference time using a combination of in-context learning and human data from a pre-existing cultural values survey that was conducted in different countries.

CHAPTER 2

Background

In this chapter, we give an overview of a number of core concepts used in this dissertation. Since this research lies on the intersection of work in the fields of multilingual NLP, the interpretation of neural networks, and social biases, a brief introduction will be given to each topic.

2.1 From distributional representations to deep contextualized language models

The main goal of Natural Language Processing (NLP) is to enable computers to understand, interpret, and generate natural language in a way that is both meaningful and useful. Specifically, NLP researchers aim to bridge the gap between the human understanding of natural language and that of computers in order to enable machines to adequately process and respond to text or speech data. To accomplish this, we need methods that can numerically quantify the meaning of linguistic units such as words, sentences, and phrases, without having to rely on lexicography. Therefore, various methods have been developed to computationally model the meaning of words and sentences with neural networks in the form of continuous d-dimensional vector representations.

Significant progress on this topic began in the field of distributional semantics with the development of unsupervised word representation models such as Word2Vec (Mikolov et al., 2013b) and GloVe (Pennington et al., 2014). These models are based on the distributional hypothesis that suggests that words that frequently appear in the same contexts tend to have similar meanings (Harris, 1954) and that consequently, these distributional properties of words can be exploited to represent lexical semantics. As such, Word2Vec is designed to predict words based on their surrounding context, while GloVe utilizes global word co-occurrence statistics to assess how often words appear together within a corpus. However, a limiting factor of these methods is that they do not account for the dynamic contexts in which words appear, resulting in static, context-independent representations. This prevents them from fully capturing the nuances of language. As a result, they struggle to handle complex linguistic phenomena such as polysemy, where words or phrases can have multiple meanings depending on their context. While various attempts were made to address the shortcomings of distributional representations — such as learning separate representations per word sense (Neelakantan et al., 2014) or incorporating subword information to enrich them (Wieting et al., 2016; Bojanowski et al., 2017) — these challenges strongly limited further success in this line of research.

The next major advancements were made when a paradigm shift took place to deep learning approaches. This led to the development of models that are able to learn context-dependent representations through language modelling tasks (Howard and Ruder, 2018; Radford et al., 2018, 2019; Peters et al., 2018; Devlin et al., 2019a). Starting with the development of deep contextualized word representation models like ELMo (Peters et al., 2018) that were based on recurrent neural networks (Hochreiter and Schmidhuber, 1997), this soon evolved to Transformer-based encoder-only models such as BERT (Devlin et al., 2019a) and decoder-only models like GPT (Brown et al., 2020) that are capable of modelling longer sequences. However, despite the fact that these deep contextualized language models have achieve widespread success, they also introduced a major drawback: reduced interpretability. It is difficult to dissect which linguistic relationships are encoded in these models and what features they rely on for making predictions. As such, they are nowadays often referred to as ‘black boxes’. Consequently, these deep contextualized language models have given rise to an extensive suite of interpretability methods that aim to make the inner workings of neural networks and their decision-making process more understandable and transparent to humans. These methods operate at different levels of the model, for instance, at the representation level (Tsvetkov et al., 2015; Rogers et al., 2018; Mikolov et al., 2013a), at the parameter level (Wang et al., 2020), at the data level (Pruthi et al., 2020) or on downstream tasks (Nayak et al., 2016; Ling et al., 2015). Throughout this dissertation, a key objective is to deepen our understanding of how MLMs encode and share information. To this end, we investigate model behaviour at the parameter level, the data level, and on downstream tasks.

2.2 Multilingual NLP

Following the widespread success of monolingual word representation models, NLP researchers turned their attention to extending the applicability of NLP technology to a wider range of languages. However, early approaches in NLP fully depended on supervised learning, which requires manually annotated datasets that are often lacking for most languages (O’Horan et al., 2016). To overcome this obstacle, the NLP community developed two main approaches to reduce the need for large corpora and annotated datasets: language transfer (Ponti et al., 2019) and joint multilingual learning (Navigli and Ponzetto, 2012; Ammar et al., 2016a). Language transfer enables the transfer of models or data from high-resource languages to low-resource ones, hence leveraging information across languages. Joint multilingual learning, on the other hand, involves training models on annotated data from multiple languages simultaneously, in an attempt to leverage language commonalities. In this section we provide an overview of the evolution of these key techniques — language transfer and joint multilingual learning— that facilitated (primarily) bilingual learning, and outline the recent advancements that led to the development of the state-of-the-art large-scale pretrained multilingual models that we have today.

2.2.1 Early methods

Language transfer Language transfer was inspired by the observation that, despite having significantly different lexica and syntactic structures, languages still tend to exhibit strong similarity in dependency patterns that can be exploited. However, learning mappings between sequences from a source and target languages with vastly different structures is not an easy task (Ponti et al., 2018). In order enable NLP systems to effectively leverage information from a source language, this information typically first has to be manipulated to better suit the properties of the target language (Ponti et al., 2019). Therefore, various methods have been developed to facilitate language transfer, including data transfer approaches like annotation projection (Tiedemann, 2015) and model transfer techniques like (de)lexicalized model transfer in which the model is transferred directly (Agić et al., 2014). In annotation projection, for instance, word-alignment projection techniques have been used to facilitate homogeneous use of treebanks (Hwa et al., 2005; Yarowsky et al., 2001; Ganchev et al., 2009; Smith and Eisner, 2005). In such studies, word-alignments are extracted from parallel corpora such that annotations for the source language can be transferred to the target language accordingly. Consequently, this newly created annotated dataset for the target language can be used to train a supervised model with. In model transfer, on the other hand, researchers attempt to train a model on a source language, delexicalize it to solve for incompatible vocabularies, and then directly apply this model to a target language instead (Zeman and Resnik, 2008). Both methods, however, are dependent on the availability of high-quality resources for the source language. As a result, their effectiveness is limited to settings in which we want to transfer knowledge from high-resource to low-resource languages.

Multilingual joint learning Another approach to leverage information across different languages is multilingual joint learning. This approach involves training models on multiple languages simultaneously to enable languages to mutually support each other, and thereby jointly enhance each others quality and boost overall performance (Navigli and Ponzetto, 2012; Ammar et al., 2016a). In contrast to language transfer, multilingual joint training can also be beneficial when both languages involved suffer from data scarcity (Khapra et al., 2011). The main technique through which this type of learning is realized is parameter sharing. Parameter sharing, commonly used in multi-task, multimodal and multilingual learning, involves sharing certain (otherwise private) representations within a neural network, such as word embeddings (Guo et al., 2016), hidden layers (Duong et al., 2015a) or attention mechanisms (Pappas and Popescu-Belis, 2017), across modalities. In earlier works in NLP, this was achieved by tying the parameters of specific network components, often through methods that enforce minimization constraints on the distance between parameters (Duong et al., 2015b) or latent representations (Zhou et al., 2015).

2.2.2 Large-scale multilingual pretraining

Earlier work on developing multilingual models consisted of methods such as mapping (Täckström et al., 2013; Tiedemann et al., 2014; Banea et al., 2008) and joint models (Ammar et al., 2016a,b; Zhou et al., 2015), similar to ones described in the previous section. While mapping models project representations from the semantic space of one language to that of another, joint models simultaneously learn representations using parallel corpora (Ruder et al., 2019). In recent years, a few key developments have led to the ground breaking LLMs that we have today:

- **Scale:** The rise of deep learning techniques, such as the Transformer architecture (Vaswani et al., 2017), allowed for more efficient and stable training at scale, enabling researchers to train much larger models on vastly more data.

- **Tokenization:** The introduction of subword tokenization, meant that the vocabularies of LMs could naturally be expanded to cover many more languages and writing scripts, without exploding the model size (Sennrich et al., 2016; Kudo and Richardson, 2018).

- **Pretraining objective**: It was shown that LMs could be successfully pretrained using a self-supervised language modeling objective. Crucially, this task does not require annotated data, thus circumventing the need for expensive to acquire pretraining data. As such, it allowed researchers to obtain inexpensive multilingual training corpora by simple scraping the internet for readily available text in many languages. In addition, this language modelling objective was shown to function as a strong backbone for easy adaptation of pretrained LMs to other downstream NLP tasks.

Thus, the rise of Transformers and subword segmentation coupled with multilingual joint learning on the self-supervised masked language modeling task, powered the first large-scale MLMs covering 100+ typologically diverse languages. Importantly, these SOTA models still rely on multilingual joint learning in which the model is trained on a mixture of data in different languages while fully sharing its parameters across languages. While a variety of MLMs are studied in this thesis, they are all based on the same key techniques. Thus, we will now first lay the necessary groundwork for having a basic understanding of MLMs.

2.2.2.1 Transformers

The Transformer architecture (Vaswani et al., 2017) is a fundamental building block of all language models used in this dissertation. Prior to the rise of Transformers, Recurrent Neural Networks (RNNs) (Hochreiter and Schmidhuber, 1997) were firmly established as the best architecture for LMs. These RNNs relied on sequential processing as they accumulate and integrate data word by word, and are equipped with memory mechanisms to handle long-term dependencies. Yet, the training process of these RNN based models was brittle as they suffered from various instability problems such as vanishing or exploding gradients, in particular when handling longer input sequences (Hochreiter, 1998; Graves and Graves, 2012). The Transformer architecture revolutionized NLP by its ability to process input in parallel instead. Not only did this parallelism allow for much faster processing, allowing for training at a much larger scale, it also enabled LMs to better handle longer input sequences. This was realized by a combination of positional encodings to signal the token order within the input sequence and the attention mechanism for drawing global dependencies between the input tokens. Whilst positional encodings allows the model to maintain word order, attention helps the model in making more efficient use of its memory by giving more weight to tokens that have more contextual relevance.

Typically, a Transformer model consists of N layers of which each is comprised of a Transformer block that contains two sub-layers: (1) A multi-head attention mechanism, and (2) A fully connected feed forward layer consisting of two linear transformations and a non-linearity. To both sub-layers, residual connections (He et al., 2016) and layer normalisation (Ba et al., 2016) are applied. The attention function operates on three matrices: $\mathbf{Q} \in \mathbb{R}^{n \times d_k}$, $\mathbf{K} \in \mathbb{R}^{n \times d_k}$ and $\mathbf{V} \in \mathbb{R}^{n \times d_k}$, which contain a set of n query, key and value vectors of size d_k respectively. The attention scores between the input elements can now be computed via a scaled dot-product which leaves us with an attention matrix $\mathbf{A} \in \mathbb{R}^{n \times d_k}$. We then multiply the attention matrix by $\mathbf{V}$, whose vectors represent the original input vectors. This produces an output matrix $\mathbf{O} \in \mathbb{R}^{n \times d_k}$ that essentially consists of a weighted sum of the input vectors:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \underbrace{\text{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}})}_{\text{Attention matrix } \mathbf{A}} \mathbf{V} \tag{2.1}$$

Note that in order to compute the final scores, we first normalize them by dividing by the square root of the dimension of the key vector and pass the result through a softmax operation, i.e. $softmax(\frac{\cdot}{\sqrt{d_k}})$. The first step leads to more stable gradients and the softmax function ensures that all scores are positive and sum up to 1.

The multi-head attention is an extension of the attention explained above. This mechanism uses h heads in parallel that all rely on the same computation in Equation 2.1. The difference is that instead of taking the full input vectors as input to one attention layer, the input vectors are split into h chunks through linear projections using learned matrices $W^{(Q,i)}$, $W^{(K,i)}$ and $W^{(V,i)}$ respectively, where $i \in [1, h]$. Each chunk is then fed to a separate head. Thus, given d-dimensional input vector, each head receives a $\frac{d}{h}$-dimensional input. The output of the heads is then concatenated and linearly transformed through W^O to get the expected dimensions.

$$\begin{aligned} \text{MultiHeadAttention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) &= \text{Concat}(\mathbf{H}^{(1)}, .., \mathbf{H}^{(h)})W^O \\ \mathbf{H}^{(i)} &= \text{Attention}(\mathbf{Q}W^{(Q,i)}, \mathbf{K}W^{(K,i)}, \mathbf{V}W^{(V,i)}) \end{aligned} \tag{2.2}$$

Note that, attention heads do not share parameters, meaning that each head is supposed to learn a distinct attention pattern. The intuition behind this, is that the multi-head attention mechanism allows the model to jointly attend to information from different representation subspaces at different positions.

Finally, Transformers can be used as different types of architectures: (1) *Encoder-only* models that process or encode input sequences into model representations (Devlin et al., 2019a; Conneau et al., 2020b), (2) *Decoder-only* models that encode an input sequence and then decode it to generate an output sequence (Brown et al., 2020), and (3) *Encoder-Decoder* models in which the input sequence is first processed by an encoder, and a separate decoder then takes the output of the encoder as input to generate an output sequence (Xue et al., 2021). The transformer's attention is typically referred to as *self-attention* when the model takes the input sequence to model the attention to itself. Decoders, however, also attend to the input sequence while generating an output. In the case that attention is used to attend between input and output sequences, it is referred to as *cross-attention* instead. Decoder-only models only attend past values, i.e., previous steps during generation to generate their outputs.

2.2.2.2 Subword tokenization

A LM operates on a unique set of tokens that are included in the LMs' vocabulary of a particular size V. This vocabulary is constructed before training and determines how an input string will be processed before feeding it into the model, a process known as *tokenization*. Earlier NLP models would simply operate on the word-level by splitting sentences into words and including the most frequent words into the vocabulary (Mikolov et al., 2013b; Bengio et al., 2000; Mielke et al., 2021). However, this hampered performance due to the occurrence of many *out-of-vocabulary* (OOV) words, in which case the word was mapped to a generic OOV token representation. As a result, subword tokenization as opposed to full word tokenization was proposed to better equip monolingual models to handle rare words (Sennrich, 2015; Schuster and Nakajima, 2012; Kudo, 2018). In subword tokenization, a sentence is split up into multiple subwords, for instance, instead of feeding the word *reconstructing* into a LM at once, we split up the word into *re-con-struct-ing* based on the tokens in the vocabulary. The intuition behind this is that the subwords occur more frequently than the full words, and therefore we are able to learn more meaningful representations for them, while keeping the overall meaning intact. In addition, when a full word is not included in the vocabulary, we can typically still break the word down into multiple subwords for which we did learn meaningful representations.

In the multilingual setting, the introduction of subword tokenization meant that their vocabularies could naturally be expanded to cover many languages and writing scripts without exploding the model size. This is because input texts from many different languages can more often be processed into identical tokens, e.g. ***re-*** ***con***-*struct-ing* (English) and ***re-*** ***con***-*stru-eren* (Dutch). This strongly reduces the amount of tokens needed in your vocabulary to handle a multitude of languages. Moreover, updating the model on subwords that are shared across multiple languages allows for cross-lingual interaction within the model. In the worst case scenario, subword tokenization falls back to character splitting, meaning that OOV tokens only still occur when a writing script or character was not included in the vocabulary.

2.2.2.3 Pretraining objectives

The idea of *pretraining* a neural networks is to allow the model to learn general-purpose representations. The pretrained model parameters can then be used to further train the model on a different task or dataset, a process which is typically referred to as *fine-tuning*. An important design for the pretraining phase is the task that we train on, this determines how well the model will be able to exploit its learned knowledge for a wide range of new tasks and datasets. All models used in this dissertation were trained on some form of *language modelling*. In particular, there are two main approaches to unsupervised language modelling: masked language modelling and causal language modelling. These tasks are typically used in combination with a different type of model architecture.

Masked language modelling In this task, also known as the *cloze task* (Rosenfeld, 2000), a random token in a sentence is masked out, e.g., 'each language [MASK] its own difficulties', and the model is trained to predict the right token to complete the sentence. Using this objective allows the model to exploit both the left and right context of the masked token which allows for rich representation learning. This objective is therefore often used in combination with a encoder-only Transformer architecture (e.g. BERT-based models (Devlin et al., 2019b)).

Causal language modelling (CLM) CLM is an autoregressive method where the model is trained to predict the next token in a sequence given the previous tokens, e.g., 'each language has its own [MASK]'. CLM is used in autoregressive language models (e.g. GPT-based models (Brown et al., 2020)), and is well-suited for tasks such as text generation and summarization. As such, this is typically the pretraining objective of decoder-only models. Given that this objective requires unidirectional context, only the past and not the future context is considered when generating predictions.

2.2.3 Cross-lingual transfer

Large-scale multilingual training typically yields a pretrained general-purpose model as explained in Section 2.2.2. Then, borrowing inspiration from the earlier methods on language transfer (see Section 2.2.1), we further fine-tune encoder-only models on a (typically) high-resource language in the hope that the model is then able to transfer the task-specific knowledge to new target languages, a process that is referred to as *cross-lingual transfer*. Besides fine-tuning on a full dataset, there are also different approaches to cross-lingual transfer that are particularly enticing in low-resource scenarios: *zero-shot transfer*, where no examples from the target language are seen during fine-tuning and *few-shot transfer* where 'few' examples in the target language are shown during fine-tuning. Note that, while cross-lingual transfer has proven successful while using little (Lauscher et al., 2020) to no fine-tuning data (Pires et al., 2019) in the target language, this success is critically dependent on the quality of the representations learned for the tokens in the target language during multilingual pretraining, and the ability of the model to benefit from cross-lingual sharing. Hence, the successes of many MLMs rely on a combination of

	Model parameters	Architecture	Languages	Release
mBERT	180M	encoder-only	104	Devlin et al. (2019b)
XLM	570M	encoder-only	100	Lample and Conneau (2019)
XLM-R	270M-550M	encoder-only	100	Conneau et al. (2020a)
mBART	680M	encoder-decoder	25	Lewis et al. (2020)
GPT-3	175B	decoder-only	unknown	Brown et al. (2020)
XGLM	564M-7.5B	encoder-only	30	Lin et al. (2021a)
mT5	300M-13B	encoder-decoder	101	Xue et al. (2021)
mGPT	1.3B-13B	decoder-only	61	Shliazhko et al. (2022)
BLOOM	176B	decoder-only	46	Scao et al. (2022)
XLM-V	779M	encoder-only	100	Liang et al. (2023)
Mistral	7B	decoder-only	unknown	Jiang et al. (2023)
Llama 3	8B-405B	decoder-only	unknown	Touvron et al. (2023)
PALM	540B	decoder-only	unknown	Chowdhery et al. (2023)
AYA-100	13B	encoder-decoder	100	Üstün et al. (2024)
AYA-23	8B-35B	decoder-only	23	Aryabumi et al. (2024)
CommandR	35B	decoder-only	24	Website (2024)

Table 2.1: An overview of a range of popular MLMs, their model sizes, types of architectures, number of pretraining languages and year of release. Note that all models rely on the Transformer architecture. The models used in this dissertation are highlighted.

the two earlier approaches that were developed to multilingual modelling, i.e. language transfer and multilingual joint learning, as described in Section 2.2.1.

2.2.4 Large language models and emergent abilities

While encoder-only models and the cross-lingual transfer paradigm have long been the status quo in multilingual NLP, more recently generative decoder-only models that are trained at much larger scales have become the new state-of-the-art, see Table 2.1. Brown et al. (2020) were the first to show that with scale, language models started to exhibit so called *emergent* capabilities, i.e. abilities that are not present in smaller models but are in larger ones. In particular, they showed that large language models (LLMs) are successful in the *prompting* paradigm. While LLMs are typically generative models, they can seamlessly learn to perform various downstream tasks, for instance classification tasks, without requiring any gradients updates to their parameters. This can be done by giving the LLM a prompt (e.g. a natural language instruction) of a task in which we instruct the model to choose between a set of answer options for the particular example. Given strong instruction following capabilities, the LLM then simply generate an output sequence in which it answers with the correct answer option (unlike encoder-only models for which we would have to train a classification head on top of the produced model representations).

Similar to the fine-tuning paradigm, prompting can be done zero-shot, by directly providing the model with the task instruction, or it can be done few-shot, where a few correct examples are first provided before asking the model to perform the task. The intuition behind *few-shot prompting* is that it allows for better calibration of the LLMs' responses. This ability to learn from a few examples at inference time is also referred to as *in-context learning* (Wei et al., 2022; Dong et al., 2022), and the examples that we prepend to the task instruction are referred to as *demonstration examples*.

Moreover, as these LLMs are trained on vastly more online data, this naturally includes texts in languages other than English. Yet, the set of languages that they were pretrained on, and therefore on which languages we can expect reasonable performance, is often unknown. While efforts have been made to explicitly train multilingual LLMs (Scao et al., 2022; Üstün et al., 2024), many English-centric LLMs from the Llama (Touvron et al., 2023) and GPT (Brown et al., 2020) series, for instance, have also shown strong multilingual capabilities, albeit in a much smaller, and typically high-resource, set of languages.

2.3 Model pruning

Model pruning methods refer to a suite of techniques that aim to identify and remove unimportant model parameters at the cost of a marginal loss in performance at test time (Han et al., 2015; Li et al., 2016a). The idea of pruning neural networks dates all the way back to the work of LeCun et al. (1989) who proposed the removal of individual unimportant weights to allow for better generalization, limit training data requirements and speed up the training process. Interest in model pruning techniques first reappeared in computer vision (CV) with the seminal work of Han et al. (2015), who introduced magnitude-based pruning techniques to reduce the size of deep neural networks after training. Similar pruning methods were later easily adopted and applied to NLP models that suffer from the same over-parameterization problems as CV models (Voita et al., 2019; Wang et al., 2020; Prasanna et al., 2020).

Lottery Ticket Hypothesis Earlier works on model pruning were based on the assumption that starting with a large, over-parameterized model was a crucial first step for achieving optimal performance, and only afterwards, redundant parameters could be pruned without significantly hurting performance (Luo et al., 2017; Carreira-Perpinán and Idelbayev, 2018). Therefore, it was generally reported that directly training a smaller network from scratch would not achieve similar success (He et al., 2017; Yu et al., 2018; Li et al., 2017). As such, an important contribution to the field of model pruning was made by Frankle and Carbin (2018), who introduce the *Lottery Ticket Hypothesis* (LTH). The LTH states that dense, randomly-initialized, feed-forward networks contain *subnetworks* (winning tickets) that-when trained in isolation- reach test accuracy comparable to the original network in a similar number of iterations. The so-called winning tickets have won the initialization lottery, meaning that their connections have initial weights that make training particularly effective. Later studies confirmed that the LTH holds for NLP models as well (Chen et al., 2020; Prasanna et al., 2020).

While pruning methods were initially developed for model compression to increase computational efficiency and allow for faster deployment, the LTH attracted attention towards model pruning from NLP researchers that focus on the interpretability of neural networks (Voita et al., 2019). In particular, the idea of pre-existing specialized subnetworks inspired various studies to use model pruning techniques to deepen our understanding of how task-specific (Foroutan et al., 2022), domain-specific (Hendy et al., 2022) or language-specific (Wang et al., 2020; Foroutan et al., 2022) information is encoded in MLMs, by locating it to distinct subnetworks within the model. For instance, Nooralahzadeh and Sennrich (2023) demonstrated how pruning techniques could be used to locate task-specific subnetworks within a LM by isolating the portions of the network that are most relevant to a particular task, such as named entity recognition or masked language modelling. Similarly, Hendy et al. (2022) applied pruning methods to identify domain-specific subnetworks in MLMs, showing that models can be effectively pruned to retain only the information pertinent to a particular domain, such as medical, religious or legal text. Finally, Wang et al. (2020); Foroutan et al. (2022) also explored language-specific pruning, discovering that pruning certain parts of a MLM could reveal subnetworks that specialize in particular languages.

2.3.1 General approaches to pruning

Pruning can be done at different levels of granularity, based on different criteria for determining importance, and at different stages of training. We will now provide a brief summary of these different aspects based on the taxonomy introduced by (Cheng et al., 2024).

Pruning unit Generally, pruning strategies can be divided into two types of methods that are commonly referred to as *structured* and *unstructured* pruning (Xu and McAuley, 2023; Touheed et al., 2024; Gupta and Agrawal, 2022). General approaches to unstructured pruning aim to compute the relative importance of all parameters (e.g. at the level of weights or neurons) in the model to determine whether an individual parameter should be pruned or not. In structured pruning, we instead take a more coarse-grained approach and select entire groups of parameters for pruning, such as model layers, blocks, or attention heads. While structured pruning is more restrictive than unstructured pruning, it allows for more predictable speed ups during inference (Cheng et al., 2024; Ma et al., 2023) and results in subnetworks that are easier to analyze.

Pruning criteria The pruning criteria defines the basis on which the pruning decision is made. These criteria are used to evaluate the importance of the units being considered for pruning. Common criteria include:

- *Magnitude-based* pruning in which units with smaller magnitude values are pruned under the assumption that they contribute less to the model's output. While the selection criteria is most commonly based on the absolute values of weights (Han et al., 2015), it can also be applied to other values (Yu et al., 2022; Dery et al., 2024).
- *Gradient-based pruning* in which units with smaller gradients with respect to the loss are considered less important. These approaches approximate gradient information to assess how much each unit contributes to the optimization process (Molchanov et al., 2019b,a).
- Calculating *importance scores* for each pruning unit. These scores can be computed with a variety of metrics such as through sensitivity analysis, i.e. estimating how sensitive the loss function is to the removal of the unit (Michel et al., 2019; Santacroce et al., 2023).

Pruning schedule The stage at which pruning is applied has an effect on how the model adapts after pruning. Typically, we rank all pruning units based on our selected pruning criteria and prune (zero) out, the units that were ranked least important according to our criteria. However, pruning methods differ in the amount of the network to prune at each step. Some methods prune all desired weights after training at once in a single step (Liu et al., 2019b), which is typically referred to as *one-shot* pruning. Yet, other methods prune a fixed fraction of the network iteratively during training, where each pruning iteration is followed by a fine-tuning step to recover performance (Han et al., 2015). Finally, other works have also dynamically adapted the rate of pruning (Gale et al., 2019).

In Chapters 4 and 5, we use the structured pruning method introduced by Michel et al. (2019) where we fully enable or disable entire attention heads at once based on their importance scores.

2.4 Training Data Attribution (TDA)

As explained in Section 2.1, neural networks are generally considered black boxes. Consequently, they have inspired an entire line of research that is dedicated to the development of interpretability methods that can help us understand model predictions (Ribeiro et al., 2016; Lundberg and Lee, 2017; Gilpin et al., 2018). In particular, this has led to the rise of attribution methods that aim to identify the contributions of various components to the model's predictions. Such post-hoc techniques, for instance, include feature attribution methods, like saliency maps (Simonyan et al., 2014; Li et al., 2016b) that focus on explaining the contribution of individual input features to the model's prediction (Pezeshkpour et al., 2021; Adebayo et al., 2018). However, feature attribution can not help explain how the training data has contributed to the model prediction, whilst the training data is generally considered integral to the learning process (Pezeshkpour et al., 2022). As such, a different body of works focus on the development of Training Data Attribution (TDA) methods (Koh and Liang, 2017; Rajani et al., 2020; Guu et al., 2023; Pruthi et al., 2020; Park et al., 2023)[1]. TDA refers to the process of identifying and Tracing which specific portions of the training data most significantly influenced a model's predictions. As such, TDA methods aim to explain a model's predictions in terms of the data examples that it was exposed to during training. TDA methods have become integral to many interpretability studies as they can offer valuable insights into the decision-making process of NLP models (Bhardwaj et al., 2021; Han and Tsvetkov, 2021; Akyürek et al., 2022; Ladhak et al., 2023; Lam et al., 2022).

Different types of TDA methods include similarity-based methods and influence functions. Rajani et al. (2020), for instance, measure the similarity between learned model representations from training and test examples. This is grounded in the assumption that if the representation of a test example closely resembles that of certain training examples, those training examples likely had a strong contribution to the model's prediction for that test example. Influence functions (Koh and Liang, 2017), on the other hand, are more theoretically grounded but also more computationally expensive to compute. They aim to estimate the impact of removing a specific training example on the model's loss function through second-order (Hessian-based) approximations.

Finally, the previous methods that we discussed compute influence between training examples and the final trained model. This, however, can not account for the influence that training examples could have had during earlier stages of training. Therefore, discrete prediction-based methods like Simfluence (Guu et al., 2023) base influence on the full training trajectory instead. In Chapters 3 and 5, we use TracIN (Pruthi et al., 2020). TracIN is a method that was derived

[1] Note that training data attribution is also commonly referred to as instance attribution.

from influence functions, but rather than analyzing the influence on the final trained model, it tracks the similarity between gradients of training and test examples over model checkpoints. In Section 2.4.1, we explain in more depth how influence functions are computed and how the TracIN method is derived from it.

2.4.1 TracIN: Tracing Influence

Let a training example z_i from our training set be denoted as $\mathcal{D} = \{z_i : (x_i, y_i)\}_{i=1}^{N}$ for an input sequence x_i and a label y_i. Koh and Liang (2017) show that we can compute how 'influential' each training example $z_i \in \mathcal{D}$ is to the prediction for a test example $x_{test} : \hat{y}_{test} = f_{\hat{\theta}}(x_{test})$. The influence score for a training example z_i on a test example z_{test} is defined as the change in loss on z_{test} that would have been incurred under the parameter estimates $f_{\hat{\theta}}$ if the model was trained on $\mathcal{D} \setminus z_i$ instead, i.e. $\mathcal{L}(z_{test}, \hat{\theta}_{-z_i}) - \mathcal{L}(z_{test}, \hat{\theta})$. In practice, this is prohibitively expensive to compute as it would require training the model $|\mathcal{D}| + 1$ times: once on training set $\mathcal{D}$, and, for each $z_i \in \mathcal{D}$, training on $\mathcal{D} \setminus z_i$.

As a solution, Koh and Liang (2017) show that we can approximate it by measuring the change in loss on z_{test} when the loss associated with the training example z_i is upweighted by some ϵ value, i.e. computing the influence score by $\mathcal{I}(z_i, z_{test}) = \frac{d\mathcal{L}(z_{test}, \hat{\theta}_{\epsilon,z_i})}{d_\epsilon}$, where $\hat{\theta}_{\epsilon,z_i}$ are the parameters trained with z_i upsampled by ϵ, $\hat{\theta}_{\epsilon,z_i} = \text{argmin}_\theta \frac{1}{N}\sum_{k=1}^{N}(\mathcal{L}(z_k, \theta) + \epsilon\mathcal{L}(z_i, \theta))$, which can be computed via a tractable approximation:

$$\begin{aligned}\mathcal{I}(z_i, z_{test}) \approx \\ - \nabla_\theta \mathcal{L}(z_{test}, \hat{\theta})^T [\nabla^2_\theta \mathcal{L}(\mathcal{D}, \hat{\theta})]^{-1} \nabla_\theta \mathcal{L}(z_i, \hat{\theta})\end{aligned} \tag{2.3}$$

where $[\nabla^2_\theta \mathcal{L}(\mathcal{D}, \hat{\theta})]^{-1}$ is the inverse-Hessian of the loss $\mathcal{L}(\mathcal{D}, \hat{\theta})$ with respect to θ $(H_{\hat{\theta}}^{-1})$.

However, computing $H_{\hat{\theta}}^{-1}$ is still expensive, this method requires further approximations if the model is non-convex, and they can be less accurate when used on deep learning models (Basu et al., 2021). Pruthi et al. (2020) find a similar, but first-order, solution that we use in this study: TracIN. They compute influence scores as follows:

$$\mathcal{I}(z_i, z_{test}) = \sum_{e=1}^{E} \nabla_\theta \mathcal{L}(z_{test}, \theta_e) \cdot \nabla_\theta \mathcal{L}(z_i, \theta_e) \tag{2.4}$$

where θ_e is the checkpoint of the model at each training epoch. The intuition behind this is to approximate the total reduction in the test loss $\mathcal{L}(z_{test}, \theta)$ during the training process when the training example z_i is used. This gradient product method essentially drops the inverse Hessian term ($H_{\hat{\theta}}^{-1}$) and reduces the problem to the dot product between the gradients of the training and test point loss.

2.5 Cloze-style probing

In Section 2.1 we introduced the notion of neural networks as black boxes, given their challenges with interpretability and our inability to understand their decision-making process for making a prediction. The severity of this problem becomes evident when discussing the problem of (harmful) social biases in NLP systems (Blodgett et al., 2020). Given that NLP models are trained on large amounts of texts in an unsupervised manner, they have been shown to naturally pick up on biases that are (explicitly or implicitly) transmitted through text (Bolukbasi et al., 2016; Hovy and Prabhumoye, 2021). These biases can, for instance, pertain to gender, race, religion, which raises concerns about the fairness and ethical implications of deploying such models in real-world applications (Blodgett et al., 2020). However, as we are not always aware of the information that is encoded and do not fully understand how predictions come about, it is difficult to avoid or mitigate such model behavior (Gonen and Goldberg, 2019; Sun et al., 2019). As such, a new subfield in NLP emerged that focuses on the evaluation of social bias encoded in LMs (Nadeem et al., 2021; Nangia et al., 2020; Caliskan et al., 2017) and the development of techniques for debiasing models (Gaci et al., 2023; Schick et al., 2021; Liang et al., 2020).

A core methodology for investigating which biases LMs encode is that of *cloze-style probing*. Cloze-style probing serves as a way to systematically expose the underlying social biases that LMs encode, by using carefully designed sentence templates to elicit biased or stereotypical model responses. This approach is derived from the classical *cloze test*, a linguistic assessment technique that was originally proposed as a measure for readability (Taylor, 1953). In the cloze testing procedure, words are removed from a sentence and the participant is tasked is to fill in the missing word based on the remaining context. Cloze-style probing of LMs mimics this process by placing the model in a similar controlled environment in which it is tasked to complete sentences. However, crucially, these sentence (or probing templates) are carefully constructed to tease out model responses that can easily be assessed for biases (Kurita et al., 2019). For example, a probing template such as: `'My boss is a pilot. _ works full-time.'` could be fed to the model, and the goal would be to assess whether the model predicts `'he'` or `'she'` as the missing word.

For LMs trained on the masked language modelling objective like BERT-based models (Devlin et al., 2019a), the missing word would typically be replaced by the masked token. The model then generates a probability distribution over its entire vocabulary for this masked position. From these probabilities, we can then infer which word the model prefers as the most likely candidate for the masked token. This allows for an assessment of bias as the model's preference is directly tied to its learned representations of the surrounding context. In contrast, for generative LMs like GTP (Brown et al., 2020) we do not need to use the masked token, but instead we can simply prepend a similar task instruction as what we would provide to human participants, and the model will generate the missing word.

PART 1: MULTILINGUALITY

CHAPTER 3

Studying Cross-lingual Sharing at the Data Level

Chapter Highlights

Multilingual language models (MLMs) are jointly trained on data from many different languages such that representation of individual languages can benefit from other languages' data. Impressive performance on zero-shot cross-lingual transfer shows that these models are capable of exploiting data from other languages. Yet, it remains unclear to what extent, and under which conditions, languages rely on each other's data. Therefore, we in this chapter, address RQ1 as proposed in the introduction. Specifically, we use TracIN (Pruthi et al., 2020), a training data attribution (TDA) method, to retrieve the most influential training examples seen during multilingual fine-tuning for a particular test language. This allows us to analyse cross-lingual sharing mechanisms of MLMs from a new perspective. While previous work studied cross-lingual sharing at the level of model parameters, we present the first approach to study cross-lingual sharing by measuring the extent of cross-language data reliance. We find that MLMs rely on data from multiple languages from the early stages of fine-tuning and that this reliance gradually increases as fine-tuning progresses. We further study how different fine-tuning languages influence model performance on a given test language and find that they can both reinforce and complement the knowledge acquired from data of the test language itself.

3.1 Introduction

Multilingual joint learning is often motivated by the idea that when multilingual language models (MLMs) learn information for multiple languages simultaneously, they can detect and leverage common universal patterns across them. Thus, these models can exploit data from one language to learn generalisations useful for another, obtaining impressive performance on zero-shot cross-lingual transfer for many languages (Wu and Dredze, 2019). Various studies suggest that representations created by popular MLMs, such as mBERT and XLM-R (Conneau et al., 2020a), are not fully language-agnostic (Doddapaneni et al., 2021; Singh et al., 2019), but instead strike a balance between language-agnosticism and capturing the subtleties and nuances of different languages through a language-neutral and language-specific component (Libovický et al., 2020; Gonen et al., 2020; Tanti et al., 2021). This naturally raises the question of how much models really benefit from multilingual data and cross-lingual sharing, and under which conditions this occurs. Many works have studied the encoding of cross-lingual patterns within MLMs by either focusing on probing for particular cross-linguistic differences (Ravishankar et al., 2019; Choenni and Shutova, 2022), or by analyzing the distributional properties of representational language subspaces (Yang et al., 2021; Rajaee and Pilehvar, 2022; Chang et al., 2022; Chi et al., 2020). Yet, it is not straightforward how to translate these results into model behavior at inference time. We aim to directly study how much influence languages exert cross-lingually on the predictions for individual languages.

In this study, we take a step back in the training pipeline to study the extent to which the model exploits its multilingual training data when making predictions for a particular test language. We hypothesise that if a model performs cross-lingual information sharing, then it would at inference time (to some extent) base its predictions on training data from multiple languages. Analyzing the cross-lingual sharing mechanism from the data reliance perspective leads to a set of interesting questions that we explore:

1. Given a test language A, does our MLLM tend to base its predictions on data from A itself or does it (also) employ data from a language B that it was exposed to during task fine-tuning?

2. Do MLMs only employ data cross-lingually out of necessity, e.g., in scenarios where in-language fine-tuning data is unavailable or insufficient?

3. Do languages support each other by adding similar information to what is relied upon from in-language data (i.e., reinforcing the model in what it already learns), or do they (also) provide complementary information?

4. How do cross-lingual sharing dynamics change over the course of fine-tuning?

5. Is the cross-lingual sharing behaviour similar when the test language was seen during fine-tuning compared to when it is used in a zero-shot testing scenario?

To study this, we use TracIN (Pruthi et al., 2020), a training data attribution (TDA) method to identify a set of training examples that are most informative for a particular test prediction. The influence of a training example z_{train} on a test example z_{test} can be formalized as the change in loss that would be observed for z_{test} if z_{train} was omitted during training. Thus, it can be used as a measure of how influential z_{train} is when solving the task for z_{test}.

To the best of our knowledge, we present the first approach to study cross-lingual sharing by extending the use of a TDA method to the multilingual setting. We find that MLMs rely on data from multiple languages to a large extent, even when the test language was seen (or over-represented) during fine-tuning. This indicates that MLLM representations might be more universal than previous work suggested (Singh et al., 2019), in part explaining the 'surprising' effectiveness of cross-lingual transfer (Pires et al., 2019; Wu and Dredze, 2019; Karthikeyan et al., 2020). Moreover, we find that cross-lingual sharing increases as fine-tuning progresses, and that languages can support one another by playing both reinforcing as well as complementary roles. Lastly, we find that the model exhibits different cross-lingual behaviour in the zero-shot testing setup compared to when the test language is seen during fine-tuning.

3.2 Related work

3.2.1 Training data attribution

In NLP, TDA methods have so far mostly been used for unveiling data artifacts and explainability purposes (Han and Tsvetkov, 2022), for instance, to detect outlier data (Han et al., 2020), enable instance-specific data filtering (Lam et al., 2022), or to fix erroneous model predictions (Meng et al., 2020; Guo et al., 2021). In this study, we instead employ a TDA method, i.e. TracIN, to study cross-lingual sharing in MLMs at the data level.

3.2.2 Studying cross-lingual sharing

Many approaches have been used to study the cross-lingual abilities of MLMs (Doddapaneni et al., 2021). Pires et al. (2019) and Karthikeyan et al. (2020) first indicate that MLMs share information cross-lingually by showing that they can perform zero-shot cross-lingual transfer between languages without lexical overlap. This led to many works on understanding *how* and *where* this sharing emerges.

One line of study, focuses on how MLMs distribute their parameters across languages by analyzing the distributional properties of the resulting language representations. In particular, they aim to understand to what extent MLMs exploit universal language patterns for producing input representations in individual languages. As such, Singh et al. (2019) find that mBERT representations can be partitioned by language subspaces, suggesting that little cross-lingual sharing emerges. Yet, others show that mBERT representations can be split into a language-specific component, and a language-neutral component that facilitates cross-lingual sharing (Libovickỳ et al., 2020; Gonen et al., 2020; Muller et al., 2021). In addition, Chi et al. (2020) show that syntactic information is encoded within a shared syntactic subspace, suggesting that portions of the model are cross-lingually aligned. Similarly, Chang et al. (2022) more generally show that MLMs encode information along orthogonal language-sensitive and language-neutral axes.

While the previous works studied parameter sharing indirectly through latent model representation, Wang et al. (2020) explicitly test for the existence of language-specific and language-neutral parameters. They do so by employing a pruning method (Louizos et al., 2018) to determine the importance of model parameters across languages, and find that some parameters are shared while others remain language-specific. Moreover, Wang et al. (2020) focused on the negative interference effects (Ruder, 2017) of cross-lingual sharing i.e., parameter updates that help the model on one language, but harm its ability to handle another. They show that cross-lingual performance can be improved when parameters are more efficiently shared across languages, leading to new studies on finding language-specific and language-neutral subnetworks within MLMs to better understand (Foroutan et al., 2022) and guide (Lin et al., 2021b; Choenni et al., 2023a) cross-lingual sharing at the parameter level. In contrast to these works, we do not study cross-lingual sharing at the model parameter level, but instead investigate it at the data level. To the best of our knowledge, we are the first to explore this direction.

3.3 Tasks and data

We conduct model fine-tuning experiments on three multilingual text classification tasks.

Natural language inference (NLI) The Cross-Lingual Natural Language Inference (XNLI) dataset (Conneau et al., 2018) contains premise-hypothesis pairs that are labeled with the relationship that holds between them: 'entailment', 'neutral' or 'contradiction'. The dataset contains parallel data in 15 languages. The original pairs come from English and were translated to the other languages. We use English, French, German, Russian and Spanish for model finetuning and testing.

Paraphrasing The Cross-Lingual Paraphrase Adversaries from Word Scrambling

(PAWS-X) dataset (Yang et al., 2019) and task requires the model to determine whether two sentences are paraphrases of one another. To create this dataset, a subset of the PAWS development and test sets (Zhang et al., 2019) was translated from English to 6 other languages by professional translators, while the training data was automatically translated. We use English, French, German, Korean and Spanish.

Sentiment analysis The Multilingual Amazon Review Corpus (MARC) (Keung et al., 2020) contains Amazon reviews written by users in various languages. Each record in the dataset contains the review text and title, and a star rating. The corpus is balanced across 5 stars, so each star rating constitutes 20% of the reviews in each language. Note that this is a non-parallel dataset. We use Chinese, English, French, German and Spanish.

3.4 Methods

3.4.1 Models and fine-tuning

For all tasks we add a classification head on top of the pretrained XLM-R base model (Conneau et al., 2020a). The classifier is an MLP with one hidden layer and uses tanh activation. We feed the hidden representation corresponding to the beginning-of-sequence token for each input sequence to the classifier for prediction. We use learning rates of 2e-5, 9e-6, and 2e-5 for XNLI, PAWS-X, and MARC, and use AdamW (Loshchilov and Hutter, 2017) as optimizer. We fine-tune the full model on the concatenation of 2K examples from 5 different languages, i.e. 10K examples for each task. This allows us to limit the computational costs of computing influence scores (which increase linearly with the number of training examples), while still obtaining reasonable performance. We also reduce computational costs by converting each task into a binary classification problem: for XNLI, we follow Han et al. (2020) by classifying "entailment or not" (i.e., mapping neutral and contradiction examples to a *non-entailment* label); for MARC, we collapse 1 and 2 stars into a *negative* and 4 and 5 stars into a *positive* review category. We train for 10 epochs and use early stopping (patience=3). We find that training converges at epoch 4 for XNLI, and at epoch 5 for PAWS-X and MARC, obtaining 78%, 83%, and 90% accuracy on their development sets.

3.4.2 TracIN: Tracing Influence

We use TracIN as a TDA method to trace predictions for particular test examples back to the fine-tuning data. In Section 2.4.1, we explain that in TracIN, the problem of computing influence scores is simplified to computing the dot product between the gradients of the training point loss and test point loss. However, a problem of gradient products is that they can be dominated by outlier training examples of which the norm of their gradients is significantly larger than the rest of the training examples (Yu et al., 2020). This could lead TracIN to deem the same set of outlier examples as most influential to a large number of different test points (Han et al., 2020). In the multilingual set-up, we know that dominating gradients is a common problem (Wang et al., 2020).[1] Barshan et al. (2020) propose a simple modification that we adapt: substituting the dot product with cosine similarity, thus normalizing by the norm of the training gradients.

3.5 Experimental set-up

After fine-tuning our models (see Section 3.4.1), we in turns, use 25 test examples from each language for testing and compute influence scores between each test example and all 10K training examples.[2] For each test example, we then retrieve the top k training examples with the highest influence scores and refer to them as the set of the most positively influential examples. Similarly, we refer to the top k training examples with the most *negative* influence scores as the most negatively influential examples. Note that negative cosine similarity between gradients are commonly referred to as gradient conflicts (Yu et al., 2020) and have been shown to be indicative of negative interference in the multilingual setting (Wang et al., 2020; Choenni et al., 2023a).

To pick the test examples for which we will compute influence scores, we select from the set of examples that the model labeled correctly, i.e. we study which training examples (and the languages they come from) positively and negatively influenced the model in making the correct prediction. For XNLI and PAWS-X we train on parallel data, thus as the content in our fine-tuning data is identical across languages, each language has equal opportunity to be retrieved amongst the most influential examples. Hence, we can ascribe the influence from each influential example to the specific language that it is coming from as well as to the content of the example itself (through the number of translations retrieved irrespective of source language).

[1] From experiments using non-normalised FastIF (Guo et al., 2021), we found that outlier fine-tuning languages (e.g. Korean) would suspiciously often be ranked on top.

[2] Note that this is still computationally expensive and requires $\sim$13 hours per language on a NVIDIA A100 GPU.

ID	$\mathcal{I}$	Sentence pair	P
es **test**		Winarsky es miembro de IEEE, Phi Beta Kappa, ACM y Sigma Xi. Winarsky es miembro de ACM, IEEE, Phi Beta Kappa y Sigma Xi.	1
de345	2.3	Bernicat spricht neben Englisch auch Russisch, Hindi und Französisch. Bernicat spricht neben Englisch auch Französisch, Hindi und Russisch.	1
en987	2.08	The festival 's main partners are UBS , Manor , Heineken , Vaudoise Assurances and Parmigiani Fleurier. The main partners of this festival are Parmigiani Fleurier , Manor , Heineken , Vaudoise and UBS .	1
fr987	2.04	Les principaux partenaires du festival sont UBS, Manor, Heineken, Vaudoise Assurances et Parmigiani Fleurier. Les principaux partenaires de ce festival sont Parmigiani Fleurier, Manor, Heineken, Vaudoise et UBS.	1
es115	-2.16	Il est le fils de Juan, a trois frères: Danilo Jr., Antonio, Danilo Rapadas et Cerila Rapadas ainsi que ses soeurs Roberta et Christina. Il est le fils de Danilo Rapadas et de Cerila Rapadas. Il a trois frères, Danilo Jr., Antonio, Juan et ses soeurs Roberta et Christina.	0
ko115	-2.13	그는 Juan의 아들이고 Danilo Jr., Antonio, Danilo Rapadas, Cerila Rapadas와 그의 아버지 Roberta와 Christina가 있습니다. Danilo Rapadas와 Cerila Rapadas의 아들로 Danilo Jr., Antonio, Juan과 그의 자매 인 Roberta와 Christina가 있습니다.	0
es1771	-2.06	Además de Michael y Patrick, el álbum incluye contribuciones musicales de Diana, John, Chick, Stanley. Además de Diana, el álbum contiene contribuciones musicales de Chick, Stanley, John, Michael y Patrick.	0

Table 3.1: The top 3 most positively (top) and negatively (bottom) influential examples retrieved for a random test input from the PAWS-X dataset. P=1 indicates a correct paraphrase and P=0 an incorrect one. Also, correct re-ordered words are denoted by orange, incorrect ones by red and the respective words in the original sentence by green.

$\mathcal{I}$	Sentence pair	P
test	El río Tabaci es una vertiente del río Leurda en Rumania. El río Leurda es un afluente del río Tabaci en Rumania.	0
4.19	El río Borcut era un afluente del río Colnici en Rumania. El río Colnici es un afluente del río Borcut en Rumania.	0
4.15	El río Colnici es un afluente del río Borcut en Rumania. El río Borcut era un afluente del río Colnici en Rumania.	0
4.10	La rivière Slatina est un affluent de la rivière .. Roumanie La rivière Cochirleanca est un affluent de la .. Roumanie.	0

Table 3.2: The top 3 most positively influential examples retrieved for a Spanish test input from PAWS-X.

3.6 Quality of most influential examples

First, we qualitatively test the plausibility of our influence scores. In Table 3.2, we show a Spanish test input from PAWS-X and the corresponding top 3 most positively influential examples retrieved using TracIN. We see that TracIN ranks extremely similar examples with the same label as most influential. In Table 3.1, we also observe some evidence of cross-lingual sharing. The 3 most positively influential examples do not come from the test language, but they clearly test the model for the same knowledge: if the order of an unstructured list is slightly altered, do we get a correct paraphrase? In each case, this is correct. Yet, for the negatively influential examples, similar alterations are performed (i.e. changing the order of names), but in these cases this *does* crucially change the meaning of the sentences.

Effect of k on model confidence We now run quantitative tests to assess the quality of our influence scores, and to select the optimal number for the top k most influential examples to analyze in our further experiments. We hypothesize that only a subset of our fine-tuning data will substantially influence predictions, while a long tail of training examples will be of little influence (either positively or negatively). To find this threshold value k, we select the top k most influential examples found for each $k \in \{50, 100, 150, 200, 250\}$ to test how our model confidence changes when leaving out these sets of examples from our fine-tuning data in turns. If our influence scores are meaningful, removing the top k most positively influential examples will reduce the model confidence (i.e. the class probability) in the correct prediction, while removing the top k most negatively influential examples should increase it. When we find k for which the change in confidence converges, we conclude that the remaining examples do not exert much influence anymore, and we stop analyzing the ranking after this point.

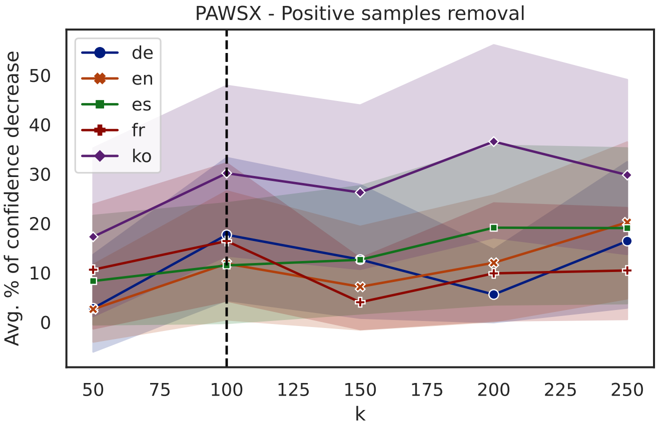


Figure 3.1: Average percentage (%) of decrease in model confidence across test examples and fine-tuning languages when removing the top k most positively influential training examples for PAWS-X.

Results Figure 3.1 shows the effect of re-training the model on PAWS-X while removing the top k most positively influential examples. We find that after k=100, the decrease in model confidence starts to decline. The same was found for negatively influential examples and XNLI. Thus, all further experiments focus on analysing the top 100 most influential examples (see Appendix A.1 for more details on selecting k). Yet, while for XNLI removing the top 100most positively influential results in a clear decrease in model confidence, removing the most negative ones does not result in a similar confidence increase. Thus, compared to PAWS-X, negative interference effects seem less strong in XNLI given our 5 fine-tuning languages. This is also reflected in Table 3.3 where we report the average influence scores between all fine-tuning and test examples per language pair, and on average observe much higher scores for XNLI than for PAWS-X (see Appendix A.2 for more influence score statistics).

3.7 Cross-language influence

We now study how much each test language relies on fine-tuning data from other languages at test time. Figure 3.2 shows the percentage of training examples that contributed to the top 100most influential examples based on their source language.

3.7.1 Parallel datasets

For XNLI and PAWS-X, across all test languages, the retrieved sets of most-influential training examples contain relatively many examples from languages

		Train				
		de	en	es	fr	ru
Test	de	.431	**.442**	.425	.434	.418
	en	.633	**.657**	.633	.639	.610
	es	.563	**.603**	.597	.587	.542
	fr	.514	**.540**	.525	.529	.499
	ru	.651	**.667**	.652	.660	.641

(a) XNLI

		Train				
		de	en	es	fr	ko
Test	de	.244	**.256**	.241	.237	.155
	en	.283	**.308**	.285	.279	.153
	es	.221	**.236**	.223	.218	.146
	fr	.320	**.335**	.325	.323	.189
	ko	.143	.146	.141	.140	**.166**

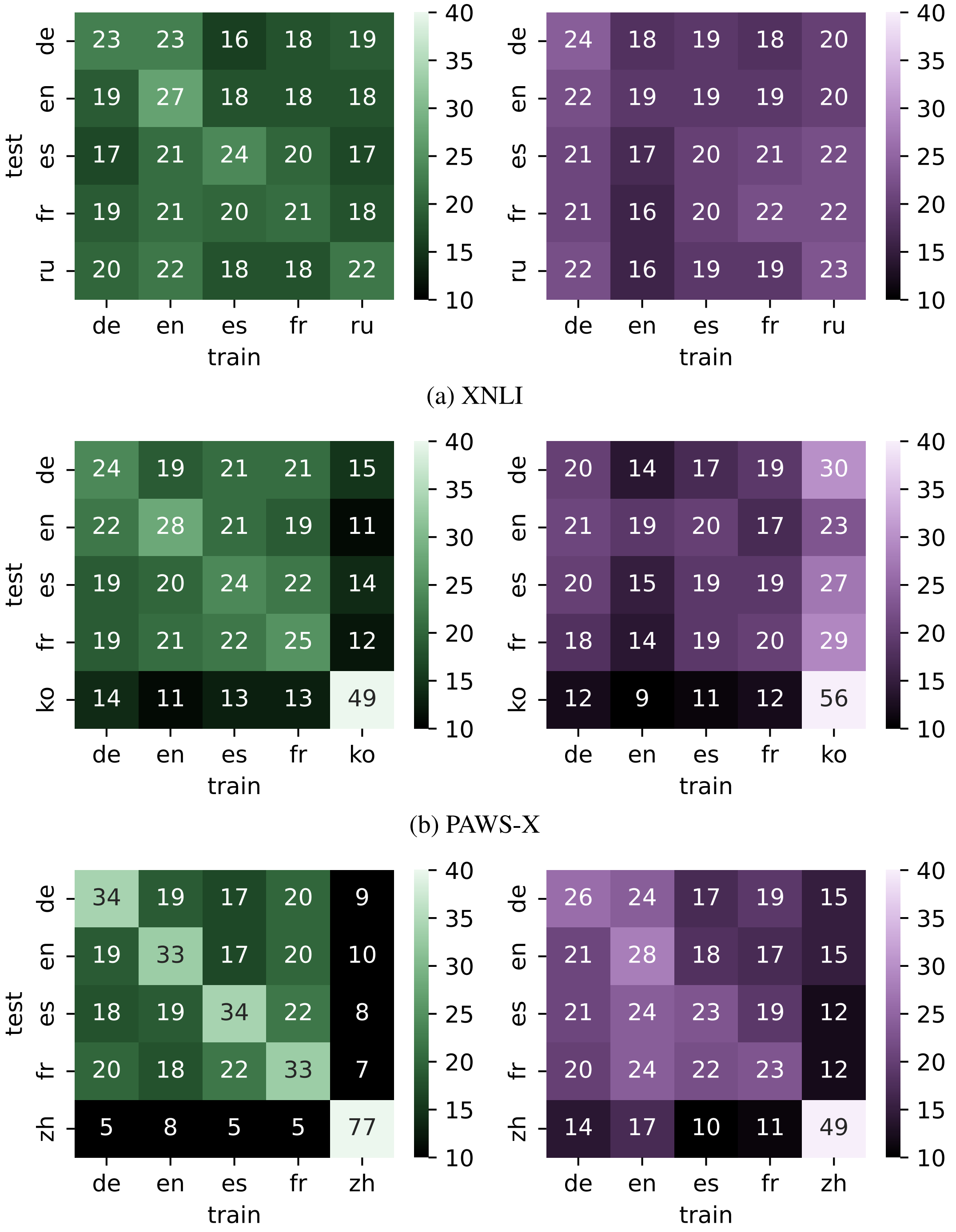
(b) PAWS-X

Table 3.3: Average influence score between all 2K training examples from a fine-tuning language and each test example, for each language pair.

other than the test language. This high degree of cross-language influence provides strong evidence of cross-lingual information sharing within the models. Korean (PAWS-X) is the only exception, which is least surprising as it is also least similar to the other fine-tuning languages and might therefore be processed by the model in relative isolation. Yet, we see that Korean still contributes cross-lingually to some extent (∼13% to the most positively influential examples on average). However, after further inspection we find that only in ∼11% of these Korean examples the sentences are fully written in the Hangul script. In all other cases, code-switching might be responsible for the cross-lingual alignment. Moreover, we observe that all test languages across both tasks mostly rely on data from their own language as most positively influential, yet, the opposite does not hold. For instance, for PAWS-X we see that Korean is always the largest negative contributor irrespective of the test language, nicely showcasing the problem of negative interference (Ruder, 2017). Lastly, we find that while English obtains the highest average influence score across all training examples, see Table 3.3, this is not representative of its actual influence when judged by the most influential examples. This confirms our hypothesis that there is a long tail of training examples that are of little influence.

3.7.2 Non-parallel dataset

While parallel datasets allow for a fair comparison across languages in terms of the content that they were exposed to, this setting is not representative of most datasets as most data is not parallel. Also, the translation of training examples across languages might artificially decrease the variation between languages, hence boosting cross-lingual sharing within the models. Thus, we also train a model on the non-parallel MARC dataset that contains user-written product reviews. In Figure 3.2c, we see that while languages indeed seem to rely more strongly on their own data for MARC compared to PAWS-X and XNLI



(a) XNLI

(b) PAWS-X

(c) MARC

Figure 3.2: For each test language, we show the percentage of examples that each fine-tuning language contributed to the top 100most positively (left) and negatively (right) influential training examples across all test examples.

Translations (%)		de	en	es	fr	ko	ru
XNLI	POS	60	59	58	62	–	60
	NEG	64	60	61	62	–	62
PAWS-X	POS	43	46	44	45	31	–
	NEG	45	50	46	46	32	–

Table 3.4: For the positively and negatively influential examples in the top 100 for each test language, we report how many of the examples coming from other fine-tuning languages are translations of the most influential examples from its own language (i.e. % reinforcing examples).

(≈+10%), strong evidence for cross-lingual sharing is still observed. Moreover, similar language pair effects can be seen across tasks e.g. French and Spanish rely on each other's data the most for both PAWS-X and MARC. Yet, we also find interesting differences such as that for both parallel datasets, English contributes to the negatively influential examples the least, while for MARC it is instead the largest contributor. Given that our fine-tuning data is balanced across languages, it is possible that we are seeing the effect of translation here, i.e. parallel data is translated from English, which results in the other language data conforming more to English, a phenomena known as "translationese" (Koppel and Ordan, 2011). This is also supported by Table 3.3, where we found that on average the training examples from English obtained the highest influence scores, but for MARC we find that Spanish most often obtains the highest scores instead (see Appendix A, Table A.2).

3.8 Further analysis

We further analyze cross-lingual sharing for the tasks with parallel datasets since some of our analysis requires translation retrieval.

3.8.1 Complementary vs. reinforcing examples

Now that we have seen that our models rely on data from languages other than the test language, we study how these examples might contribute to the model performance, i.e., are they reinforcing the model with similar knowledge that it has seen from the test language, or do these examples somehow encode complementary knowledge that the model did not rely on from its own language? In order to make this distinction, we look at whether the most influential examples retrieved in other languages are translations of the most influential examples retrieved from the test language itself.

Results We report these percentages in Table 3.4, and find that for XNLI, over half of the contributions from different languages are translations of the most influential training examples from the respective test language, indicating that the model largely benefits from reinforcing data from other languages. For PAWS-X, this is not the case, indicating that here the biggest benefit of cross-lingual sharing can more likely be attributed to the model learning to pick up on new, complementary, information from other languages. As XNLI requires deep semantic understanding, we speculate that the model does not need to learn language-specific properties, but only needs to capture the content from data (possibly creating more universal representations to induce implicit data augmentation). Thus, the most influential examples might more often be translations as some examples are content-wise more influential, and all these examples across languages can contribute equally. Yet, for PAWS-X, the model requires some knowledge of grammatical structure, e.g. identical paraphrases can take different forms across languages, thus the model might learn from cross-lingual sharing differently.

3.8.2 Sharing dynamics during fine-tuning

As explained in Section 3.4.2, TracIN approximates influence over training, obtaining separate scores after each fine-tuning epoch. While in previous results we reported the sum of these scores, we now analyze them separately per fine-tuning epoch. Blevins et al. (2022) study cross-lingual pretraining dynamics of multilingual models to study when cross-lingual sharing emerges. We instead study whether different patterns emerge when testing for the most influential languages during fine-tuning.

Results In Figure 3.3, we plot for each language which percentage of examples coming from itself were included in the top 100most influential examples across different fine-tuning epochs. From this, we see that for both tasks, the languages start relying less on their own fine-tuning data after fine-tuning epoch 2. Thus, we conclude that on average the models gradually start to perform more cross-lingual sharing as fine-tuning progresses. Moreover, in line with previous findings (Blevins et al., 2022), we observe that the amount of cross-lingual sharing between different language-pairs fluctuate during fine-tuning (see Appendix A.3 for results).

3.8.3 Zero-shot testing

An interesting testbed is the zero-shot test scenario where no examples from the test language were seen during fine-tuning. Hence, the model can solely rely on data from other languages. Thus, for a language l, we compare the

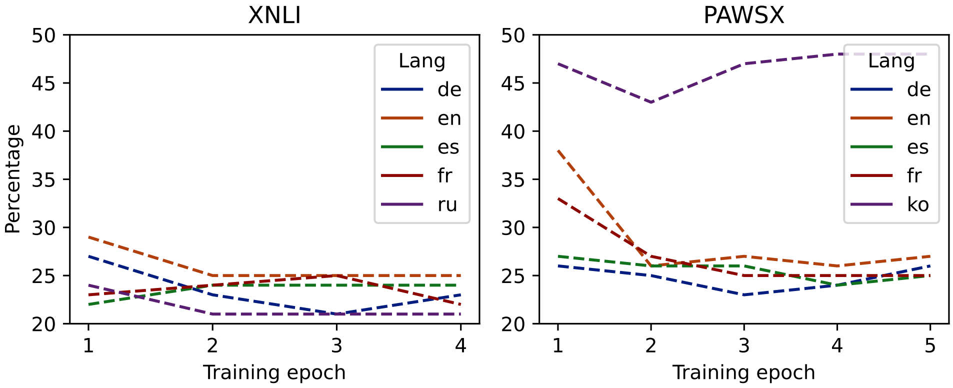


Figure 3.3: For each test language, we plot the percentage of examples coming from their own language that were included in the most positively influential training examples, i.e. the extent to which the model relies on its own language and how this changes over fine-tuning epochs.

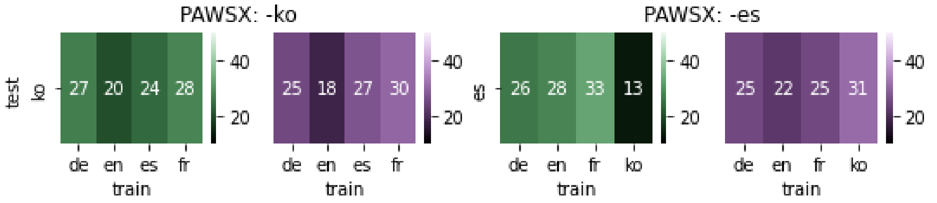


Figure 3.4: Percentage of examples that each fine-tuning language contributed to the top 100 most influential examples for Korean and Spanish during zero-shot testing.

ranking from the model for which l was included in the fine-tuning languages T, $f_{\theta_{l\in T}}$, to that of a model for which it was not $f_{\theta_{l\notin T}}$. We are interested to see whether the zero-shot model ($f_{\theta_{l\notin T}}$) will (1) replace the most influential examples from the test language from $f_{\theta_{l\in T}}$ with translations in other languages (to compensate for the missing examples from the test language), or (2) rely on the same examples from the other languages that was relied upon when the test language was still included during fine-tuning. As Korean was found to be the most isolated language for PAWS-X (i.e., it relies on data from other languages the least), while Spanish relies on cross-lingual sharing the most, we in turns re-train our model without Korean and Spanish as a fine-tuning language, obtaining 74% and 81% accuracy respectively, and recompute the influence scores. We then compare the top 100most influential examples from the zero-shot model ($f_{\theta_{l\notin T}}$) to that of the most influential examples from $f_{\theta_{l\in T}}$ and report how many translations of the examples from the test language vs. the other languages are covered.

Results Surprisingly, we find that in the zero-shot set-up the models barely rely on the specific training examples that were found when the test language was included during fine-tuning. For Korean, only 5% of the most positively influential examples from the zero-shot model are direct translations of the Korean examples that were retrieved when it was included during training. Moreover, only 4% of training examples from the other languages that were retrieved, were deemed most influential again in the zero-shot setup. The same trend was found for Spanish, albeit to a lesser extent, where translations of 14% of the Spanish and 13% from the other languages were recovered. Lastly, in Figure 3.4, we show the data reliance distribution across fine-tuning languages for our zero-shot models. We find that the models still rely on cross-lingual sharing, and while Korean was previously processed in isolation (i.e., mostly relying on its own fine-tuning data), it now benefits from multiple languages.

3.8.4 Sharing as an effect of data-imbalance

An important aspect that can affect cross-lingual sharing is the effect of language data imbalances during fine-tuning. For instance, some languages are over-represented during training, which might cause them to exert stronger influence over other training languages, while other languages are instead under-represented, hence they might benefit more from cross-lingual sharing (Wu and Dredze, 2020). To study how much of the cross-lingual sharing effects observed so far can be ascribed to data-scarcity, we re-train our models on PAWS-X to test whether they will rely on cross-lingual sharing to a similar extent given that the test language is now over-represented during fine-tuning. To do so, we artificially mimic this scenario by randomly adding a percentage p = [25, 50, 75, 100]% from each language on top of the original fine-tuning data in turns, and test how cross-language influence changes compared to the balanced data set-up.

Results In Figure 3.5, we plot the percentage of in-language training examples that contribute to the most influential examples for the respective test language as an effect of data imbalance. For all languages, we see a clear trend: as the data gets more biased towards one language, the model also starts relying more on data from that particular language when it comes to the most positively and negatively influential examples. Yet, we also see that this trend does not always steadily increase (e.g. for French and German). Moreover, even when the data from the own language is twice as much (+100%), all languages (except Korean) still rely for more than 50% on examples from the other fine-tuning languages. This indicates that even with data imbalances, the model largely benefits from cross-lingual sharing. An interesting outlier is English for which we see that positive influence from its own data rapidly increases (sim-

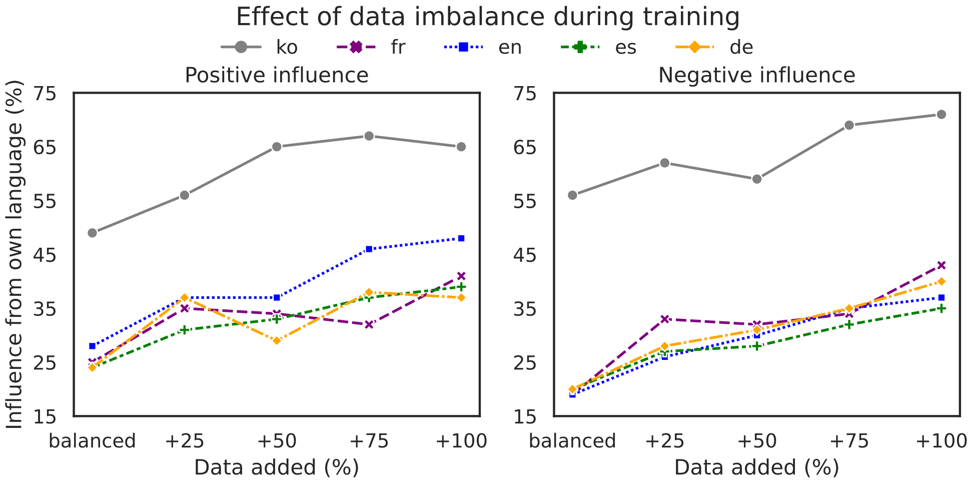


Figure 3.5: The percentage of data contributing to either the most positively (left) or negatively (right) influential examples for a particular language when adding p % of data on top of that language's data during fine-tuning.

ilar to Korean). We hypothesize that this could be due to being considerably overrepresented during pretraining, nudging the model towards processing this language in isolation as well.

3.9 Conclusion

To the best of our knowledge, we are the first to study the extent to which multilingual models rely on cross-lingual sharing by investigating it at the data level. Addressing RQ1 from the introduction, we show that languages largely influence one another cross-lingually. Importantly, this influence persists under various conditions, such as when the test language is either unseen or overrepresented during fine-tuning. This finding highlights the crucial role of cross-lingual sharing in MLMs and suggests that enhancing this mechanism could be a promising avenue for further improving model performance. In addition, we find that cross-lingual sharing increases as fine-tuning progresses, and that languages can support one another both by playing a reinforcing as well as a complementary role. We hope that this study inspires future work on studying the sharing mechanism within multi-task and multi-modal models as well.

3.10 Limitations

One limitation of this study is that the experiments are computationally extremely expensive to run, resulting in us only studying the effect on 125 test examples. Previous works have used more efficiency tricks to limit computational costs, for instance, by only computing influence scores between the test examples and the n most similar training examples as found based on kNN-neighbour search on their representations (Rajani et al., 2020; Guo et al., 2021; Jain et al., 2022). However, limiting the pool of training examples will bias us to retrieving examples based on the similarity between the hidden model representations from the final trained model. As one of our main goals is to study cross-lingual sharing from a new perspective, we opted against using such methods, and instead compute influence scores over the full training set.

Moreover, due to the computational costs, we are restricted to relatively easy tasks as (1) we can not use a large fine-tuning set and (2) TracIN operates on the sequence-level, i.e., it estimates how much a full training instance contributed to a prediction, making this method mostly suitable for classification and regression tasks. We suspect that cross-lingual sharing exhibits different cross-lingual behaviour for other types of tasks where language-specific information plays a bigger role at test time (e.g. text generation or sequence labelling). In such tasks, the model could learn to rely on cross-lingual sharing to a lesser extent. Jain et al. (2022) recently extended influence functions to sequence tagging tasks to allow for more fine-grained analysis on the segment-level. Even though this further increases computational costs, it would be a good direction for future work on cross-lingual sharing.

CHAPTER 4

Cross-lingual Transfer with Language-Specific Subnetworks

Chapter Highlights

Multilingual language models typically share their parameters across all languages, which enables cross-lingual task transfer, but learning can also be hindered when training updates from different languages are in conflict. In this chapter, we propose novel methods for using language-specific subnetworks, which control cross-lingual parameter sharing, to reduce conflicts and increase positive transfer during fine-tuning. By using language-specific subnetworks during fine-tuning, we essentially aim to induce language-wise modularity into the model, thereby contributing to RQ2 as proposed in the introduction. In addition, we introduce dynamic subnetworks, which are jointly updated with the model, and we combine our methods with meta-learning, an established, but complementary, technique for improving cross-lingual transfer. Finally, we provide extensive analyses of how each of our methods affects the models.

4.1 Introduction

Multilingual language models, such as mBERT (Devlin et al., 2019b), are pretrained on data covering many languages, but share their parameters across all languages. This modeling approach has several powerful advantages, such as allowing similar languages to exert positive influence on each other, and enabling cross-lingual task transfer (i.e., finetuning on some source language(s), then using the model on different target languages) (Pires et al., 2019). These advantages are particularly enticing in low-resource scenarios since without sufficient training data in the target language, the model's effectiveness hinges on its ability to derive benefit from other languages' data. In practice, however, even state-of-the-art multilingual models tend to perform poorly on low-resource languages (Lauscher et al., 2020; Üstün et al., 2020), due in part to *negative interference* effects—parameter updates that help the model on one language, but harm its ability to handle another—which undercut the benefits of multilingual modeling (Arivazhagan et al., 2019; Wang et al., 2020; Ansell et al., 2021).

In this chapter, we propose novel methods for using language-specific subnetworks, which control cross-lingual parameter sharing, to reduce conflicts and increase positive transfer during fine-tuning, with the goal of improving the performance of multilingual language models on low-resource languages. While recent works apply various subnetwork based approaches to their models statically (Lu et al., 2022b; Yang et al., 2023; Nooralahzadeh and Sennrich, 2023), we propose a new method that allows the model to dynamically update the subnetworks during fine-tuning. This allows for sharing between language pairs to a different extent at the different learning stages of the models. We accomplish this by using pruning techniques (Frankle and Carbin, 2018) to select an optimal subset of parameters from the full model for further language-specific fine-tuning. Inspired by studies that show that attention-heads in BERT-based models have specialized functions (Voita et al., 2019; Htut et al., 2019), we focus on learning subnetworks at the attention-head level. We learn separate—but potentially overlapping—head masks for each language by fine-tuning the model on the language, and then pruning out the least important heads.

Given our focus on low-resource languages, we also combine our methods with meta-learning, a data-efficient technique to learn tasks from a few samples (Finn et al., 2017). Motivated by Wang et al. (2020), who find that meta-learning can reduce negative interference in the multilingual setup, we test how much our subnetwork methods can further benefit performance in this learning framework, as well as compare the subnetwork based approach to a meta-learning baseline. Our results show that a combination of meta-learning and dynamic subnetworks is particularly powerful. To the best of our knowledge, we are the first to adapt subnetwork sharing to the meta-learning framework.

We extensively test the effectiveness of our methods on the task of dependency parsing. We use data from Universal Dependencies (UD) (Nivre et al., 2016) comprising 82 datasets covering 70 distinct languages, from 43 language families; 58 of the languages can be considered truly low-resource. Our experiments show, quantitatively, that our language-specific subnetworks, when used during fine-tuning, act as an effective sharing mechanism: permitting positive influence from similar languages, while shielding each language's parameters from negative interference that would otherwise have been introduced by more distant languages. Moreover, we show substantial improvements in cross-lingual transfer to new languages at test time. Importantly, we are able to achieve this while relying on data from just 8 treebanks before few-shot fine-tuning at test time.

Finally, we perform extensive analyses of our models to better understand how different choices affect generalisation properties. We analyse model behavior with respect to several factors: typological relatedness of fine-tuning and test languages, data-scarcity during pretraining, robustness to domain transfer, and their ability to predict rare and unseen labels. We find interesting differences in model behavior that can provide useful guidance on which method to choose based on the properties of the target language.

4.2 Background and related work

4.2.1 Pruning and sparse networks

Frankle and Carbin (2018) were the first to show that neural network pruning (Han et al., 2015; Li et al., 2016a) can be used to find a subnetwork that matches the test accuracy of the full network. Later studies confirmed that such subnetworks also exist within (multilingual) BERT (Prasanna et al., 2020; Budhraja et al., 2021; Li et al., 2022), and that they can even be transferred across different NLP tasks (Chen et al., 2020). While these studies are typically motivated by a desire to find a smaller, faster version of the model (Jiao et al., 2020; Lan et al., 2019; Sanh et al., 2019; Held and Yang, 2023; Zhang et al., 2021), we use pruning to find multiple simultaneous subnetworks (one for each fine-tuning language) within the overall multilingual model, which we use during both fine-tuning and inference to guide cross-lingual sharing.

4.2.2 Selective parameter sharing

Naseem et al. (2012) used categorizations from linguistic typology to explicitly share subsets of parameters across separate languages' dependency parsing models. Large multilingual models have, however, been shown to induce implicit typological properties automatically, and different design decisions (e.g., training strategy) can influence the language relationships they encode (Chi et al., 2020; Choenni and Shutova, 2022). Rather than attempting to force the model to follow an externally defined typology, we instead take a data-driven approach, using pruning methods to automatically identify the subnetwork of parameters most relevant to each language, and letting subnetwork overlap naturally dictate parameter sharing.

A related line of work aims to control selective sharing by injecting language-specific parameters (Üstün et al., 2020; Wang et al., 2020; Le et al., 2021; Ansell et al., 2021; Pfeiffer et al., 2020), which is often realized by inserting adapter modules into the network (Houlsby et al., 2019). Our approach, in contrast, uses subnetwork masking of the existing model parameters to control language interaction.

Lastly, Wang et al. (2020) separate language-specific and language-universal parameters within *bilingual* models, and then meta-train the language-specific parameters only. However, given that we work in a multilingual as opposed to a bilingual setting, most parameters are shared by at least a few languages, and are thus somewhere between purely language-specific and fully universal. Our approach, instead, allows for parameters to be shared among any specific subset of languages.

Analyzing and training shared subnetworks The idea of sharing through sparse subnetworks was first proposed for multi-task learning (Sun et al., 2020), and was recently studied in the multilingual setting: Foroutan et al. (2022) show that both language-neutral and language-specific subnetworks exist in multilingual models, and Nooralahzadeh and Sennrich (2023) show that training *task-specific* subnetworks can help in cross-lingual transfer as well.

Moreover, Lin et al. (2021b) train multilingual models using *language-pair-specific* subnetworks for neural machine translation (NMT), and Hendy et al. (2022) build on their work, but use *domain-specific* subnetworks instead. In both studies, subnetworks are found using magnitude pruning and kept static during training. In addition, while Lin et al. (2021b) show that their method can perform well in a zero-shot setting, their strategy for merging masks for new language-pairs relies on the availability of translation data between English and both the source and target language. This makes their approach unsuitable in low-resource scenarios where such resources are not available. In addition, they show that their methods work for unseen language-pairs, but the individual languages are not unseen during training on NMT.

Furthermore, Ansell et al. (2021) learn real-valued (composable) masks instead of binary ones. Thus, instead of fully enabling or disabling parameters, they essentially apply new weights to them, making the workings of these masks more similar to that of adapter modules (Pfeiffer et al., 2020).

Finally, in concurrent work, Lu et al. (2022b) show that using language-specific subnetworks at the pretraining stage can mitigate negative interference for speech recognition, and Xu et al. (2022) apply subnetworks during the backward pass only. We instead apply subnetworks during fine-tuning and few-shot fine-tuning at test time, allowing us to both make use of existing pretrained models and apply our models to truly low-resource languages. Moreover, we go beyond existing work by experimenting with *structured* subnetworks, by allowing subnetworks to dynamically change during fine-tuning, and by extensively analyzing the effects and benefits of our methods.

4.2.3 Meta-learning

Meta-learning is motivated by the idea that a model can "learn to learn" many tasks from only a few samples. This has been adapted to the multilingual setting by optimising a model to be able to quickly adapt to new languages: by using meta-learning to fine-tune a multilingual model on a small set of (higher-resource) languages, the model can then be adapted to a new language using only a few examples (Nooralahzadeh et al., 2020). In this work, we use the Model-Agnostic Meta-Learning algorithm (MAML) (Finn et al., 2017), which has proven useful for cross-lingual transfer of NLP tasks (Nooralahzadeh et al., 2020; Wu et al., 2020; Gu et al., 2020), including being applied to dependency parsing by Langedijk et al. (2022), whose approach we follow for our own experiments.

MAML iteratively selects a batch of training tasks $\mathcal{T}$, also known as *episodes*. For each task $t \in \mathcal{T}$, we sample a training dataset $\mathcal{D}_t = (\mathcal{D}_t^{trn} \cup \mathcal{D}_t^{tst})$ that consists of a *support set* used for adaptation, and a *query set* used for evaluation. MAML casts the meta-training step as a bilevel optimization problem. Within each episode, the parameters θ of a model f_θ are fine-tuned on the support set of each task t yielding f_{ϕ_t}, i.e., the model adapts to a new task. The model f_{ϕ_t} is then evaluated on the query set of task t, for all of the tasks in the batch. This adaptation step is referred to as the *inner loop* of MAML. In the *outer loop*, the original model f_θ is then updated using the gradients of the query set of each $t \in \mathcal{T}$ with respect to the original model parameters θ. MAML strives to learn a good initialisation of f_θ, which allows for quick adaptation to new tasks. This setup is mimicked at test time where we again select a support set from the test task for few-shot adaptation, prior to evaluating the model on the remainder of the task data.

4.2.4 Dependency parsing

In dependency parsing, a model must predict, given an input sentence, a *dependency tree*: a directed graphs of binary, asymmetrical arcs between words. Each arc is labeled with a dependency relation type that holds between the two words, commonly referred to as the *head* and its *dependent*.

The Universal Dependencies (UD) project has brought forth a dependency formalism that allows for consistent morphosyntactic annotation across typologically diverse languages (Nivre et al., 2016). While UD parsing has received much attention from the NLP community, performance on low-resource languages remains far below that of high-resource languages (Zeman et al., 2018). State-of-the-art multilingual parsers generally exploit a pretrained multilingual language model with a deep biaffine parser (Dozat and Manning, 2016) on top. The model is then fine-tuned on data (typically) from high-resource languages. This fine-tuning stage has been performed on English data only

(Wu et al., 2020), or multiple languages (Tran and Bisazza, 2019).

UDify (Kondratyuk and Straka, 2019) takes this a step further and is fine-tuned on all available training sets together (covering 75 languages). Moreover, they use a multi-task training objective that combines parsing with predicting part-of-speech tags, morphological features, and lemmas.

On the modelling side, previous studies have attempted to exploit knowledge from the field of Linguistic Typology to further improve upon this training paradigm. For instance, UDapter (Üstün et al., 2020) is trained on 13 languages using the same setup as UDify, but freezes mBERT's parameters and trains language-specific adapter modules. They induce typological guidance by taking language embeddings predicted from typological features as input. In a related study, (Choudhary, 2021) try to induce typological knowledge into UDify by using typology prediction as an auxiliary task instead.

Other studies, have taken a data-centric approach instead. van der Goot et al. (2021) propose MACHAMP, a toolkit for multi-task learning of a variety of NLP tasks, including dependency parsing. While using a similar architecture to existing literature, they show that they can further improve performance by resampling datasets according to a multinomial distribution on the batch level to prevent larger datasets from overwhelming the model. In addition, Glavaš and Vulić (2021), propose hierachical source selection, a model-agnostic method for finding the optimal subset of UD treebanks for cross-lingual transfer to a specific target language.

4.3 Data

We use data from Universal Dependencies v2.9[1] and test on 82 datasets covering 70 unique and highly typologically diverse languages belonging to 19 language families from 43 subfamilies. We consider 54 of these languages to be extremely low-resource as there are fewer than 31 training samples available. For the other 28 languages, 50% have approximately 150–2K training samples and the other 50% have 2K–15K samples available. In total, our test data contains 233 possible arc labels. We use 8 high-resource languages for fine-tuning, based on the selection used by Langedijk et al. (2022) and Tran and Bisazza (2019): English, Arabic, Czech, Estonian[2], Hindi, Italian, Norwegian, and Russian.

[1] https://universaldependencies.org/

[2] Note that we swapped out Korean with Estonian as we were unable to learn a high-quality subnetwork for Korean. The choice of Estonian is mainly motivated by the high-resource data requirement in combination with the fact that the subfamily, i.e., Uralic, was not represented by our fine-tuning languages yet.

4.4 Methodology

In §4.4.1–4.4.2 we describe the model that will be used throughout our experiments and the training strategy. In §4.4.3 we then explain how we define and select subnetworks, and how we apply them to our models. In §4.4.4 we explain how our approach is adapted to the meta-learning setting, and in §4.4.5–4.4.6 we describe our test setup and baselines.

4.4.1 Model

Our implementation is derived from UDify (Kondratyuk and Straka, 2019), but uses only the parsing task rather than its full multi-task setup. The model is built on mBERT (Devlin et al., 2019b), a bidirectional Transformer (Vaswani et al., 2017) with 12 layers, each with 12 attention heads, pretrained on the combined Wikipedia dumps of 104 languages, and using a shared WordPiece vocabulary for tokenization. We initialise the model from mBERT, plus random initialization of the task-specific classifier. For each input token j, a weighted sum r_j over all layers $i \in [1..12]$ is computed as follows:

$$r_j = \eta \sum_i \mathbf{U}_{i,j} \cdot \text{softmax}(\lambda)_i \tag{4.1}$$

where $\mathbf{U}_{i,j}$ is the output of layer i at token position j, λ is a vector of trainable scalar mixing weights that distribute importance across the layers, and η is a trainable scalar that scales the normalized averages. For words that were tokenized into multiple word pieces, only the first word piece is used as input to the task-specific graph-based biaffine attention classifier (Dozat and Manning, 2016).

The classifier projects the word encodings r_j through separate arc-head and arc-child feedforward layers with 768 hidden dimensions and Exponential Linear Unit (ELU) non-linear activation. The resulting outputs $H_{\text{arc-head}}$ and $H_{\text{arc-dep}}$ are then combined using the biaffine attention function with weights $\mathbf{W}_{\text{arc}}$ and bias $\mathbf{b}_{\text{arc}}$ to score all possible dependency arcs:

$$S_{\text{arc}} = H_{\text{arc-head}} \mathbf{W}_{\text{arc}} H^T_{\text{arc-dep}} + \mathbf{b}_{\text{arc}} \tag{4.2}$$

Similarly, we compute label scores S_{tag} by using another biaffine attention function over two separate tag-head and tag-child feedforward layers with 256 hidden dimensions. The Chu-Liu/Edmonds algorithm (Chu, 1965) is then used to select the optimal valid candidate tree.

4.4.2 Training procedure

Taking inspiration from Nooralahzadeh et al. (2020) for cross-lingual transfer to low-resource languages, our training procedure is split into two stages: (1)

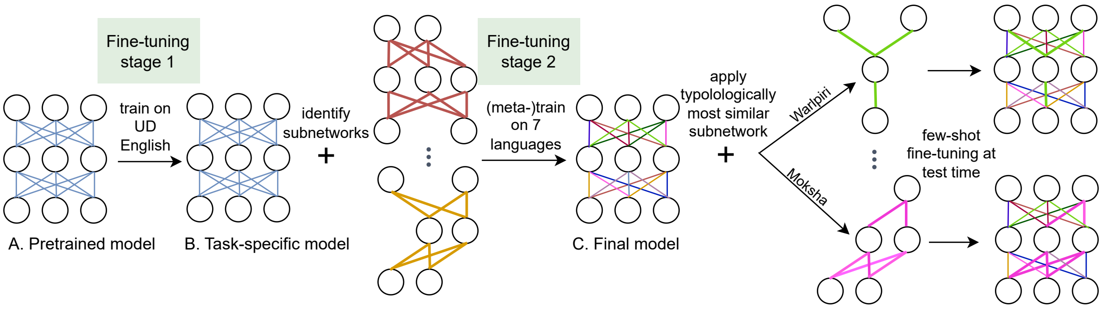


Figure 4.1: Schematic overview of our two-stage fine-tuning and test procedure. At fine-tuning stage 1, we first fine-tune pretrained mBERT on the task of dependency parsing using English data. We then apply language-specific subnetworks to our task-specific model. At fine-tuning stage 2, we either keep the subnetworks static or dynamically update the found subnetworks during (meta-)training on the task of dependency parsing using the other 7 fine-tuning languages. At test time, we then perform few-shot fine-tuning separately for each test language while applying the subnetwork of the typologically most similar training language.

fine-tune on the full English training set (∼12.5K samples), without applying any subnetwork restrictions, for 60 epochs, to provide the full model with a general understanding of the task; and (2) fine-tune on the 7 other high-resource languages, to give the model a broad view over a typologically diverse set of languages in order to facilitate cross-lingual transfer to new languages.

For stage 2, in each iteration, we sample a batch from each language and average the losses of all languages to update the model. During this stage, we restrict each example to just the parameters in that language's subnetwork. We perform 1000 iterations, with a batch of size 20 from each of the 7 languages, for a total of 140K samples.

We use a cosine-based learning rate scheduler with 10% warm-up and the Adam optimizer (Kingma and Ba, 2015), with separate learning rates for updating the encoder and the classifier (see Appendix B, Table B.3 for details).

4.4.3 Subnetwork masks

We represent language-specific subnetworks as masks that are applied to the model in order to ensure that only a subset of the model's parameters are activated (or updated) during fine-tuning and inference. We follow Prasanna et al. (2020) in using *structured* masks, treating entire attention heads as units which are always fully enabled or disabled. Thus, for language ℓ, its subnetwork is implemented as a binary mask $\xi_\ell \in \{0, 1\}^{12\times 12}$.

In our experiments, we present two ways of using the masks during fine-tuning: *statically*, in which we find initial masks based on the pretrained model parameters and hold those masks fixed throughout fine-tuning and inference ($\text{SN}_{\text{static}}$); and *dynamically*, in which we update those masks over the course of fine-tuning (SN_{dyna}). In Figure 4.1, we give a general overview of our training procedure.

4.4.3.1 Finding initial subnetwork masks

We aim to find a mask for each of the 7 fine-tuning languages that prunes away as many heads as possible without harming performance for that language (i.e., by pruning away heads that are only used by other languages, or that are unrelated to the dependency parsing task). For this, we apply the procedure introduced by Michel et al. (2019).

For a language ℓ, the procedure starts by fine-tuning the model on ℓ's training set. We then iterate by repeatedly removing the 10% of heads with the lowest importance scores $\text{HI}_\ell^{(i,j)}$ (i=head, j=layer), which is estimated based on the expected sensitivity of the model to mask variable $\xi_\ell^{(i,j)}$:

$$\text{HI}_\ell^{(i,j)} = \mathbb{E}_{x_\ell \sim X_\ell} \left| \frac{\delta \mathcal{L}(x_\ell)}{\delta \xi_\ell^{(i,j)}} \right| \tag{4.3}$$

where X_ℓ is ℓ's data distribution, x_ℓ is a sample from that distribution, and $\mathcal{L}(x_\ell)$ is the loss with respect to the sample. The procedure stops when performance on the ℓ's development set reaches 95% of the original model performance.

Consistent with findings from Prasanna et al. (2020), we observed that the subnetworks found by the procedure are unstable across different random data splits. To ensure that the subnetwork we end up with is more robust to these variations, we repeat the pruning procedure with 4 random seeds, and take the union[3] of their results as the true subnetwork (i.e., it includes even those heads that were only *sometimes* found to be important).

4.4.3.2 Dynamically adapting subnetworks

Blevins et al. (2022) showed that multilingual models acquire linguistic knowledge progressively—lower-level syntax is learned prior to higher-level syntax, and then semantics—but that the order in which the model learns to transfer information between specific languages varies. As such, the optimal set of parameters to share may depend on what learning stage the model is in, or on other factors, e.g., the domains of the specific training datasets, the amounts of data available, the complexity of the language with respect to the task, etc. Thus, we propose a dynamic approach to subnetwork sharing, in which each

[3] Stricter criteria (e.g., the intersection of the 4 subnetworks) resulted in lower performance on the development set.

language's subnetwork mask is trained jointly with the model during fine-tuning. This allows the subnetwork masks to be improved, and also allows for different patterns of sharing at different points during fine-tuning.

For dynamic adaptation, we initialise the identified static subnetworks as described in §4.4.3.1 using small positive weights. We then allow the model to update the mask weights during fine-tuning. After each iteration, the learned weights are fed to a threshold function that sets the smallest 20% of weights to zero (i.e., 28 heads[4]) to obtain a binary mask again. Given that the derivative of a threshold function is zero, we use a straight-through estimator (Bengio et al., 2013) in the backward pass, meaning that we ignore the derivative of the threshold function and pass the incoming gradient on as if the threshold function was an identity function.

4.4.4 Meta-learning with subnetworks

Meta-learning for multilingual models has been shown to enable both quick adaptation to unseen languages (Langedijk et al., 2022) and mitigation of negative interference (Wang et al., 2020), but it does so using techniques that are different from—though compatible with—our subnetwork-sharing approach. Therefore, we experiment with the combination of these methods, and test the extent to which their benefits are complementary (as opposed to redundant) in practice.

To integrate our subnetworks within a meta-learning setup, we just have to apply them in the inner loop of MAML, i.e., given a model f parameterised by θ, we train θ by optimizing for the performance of the learner model of a language ℓ masked with the corresponding subnetwork $f_{\phi_\ell} \cdot \xi_l$. See Algorithm 1 for the details of the procedure.[5]

For all meta-learning experiments, we train for 500 episodes with support and query sets of size 20, i.e., 10K samples per language are used for meta-training and validation each. We use 20 inner loop updates (k) and we follow Finn et al. (2017) in using SGD for updating the learner. All other training details are kept consistent with the non-episodic (NonEp) models (as described in §4.4.2).

4.4.5 Few-shot fine-tuning at test time

Since the primary goal of this work is to improve performance in low-resource scenarios, we evaluate our models using a setup that is appropriate when there is almost no annotated data in the target language: few-shot fine-tuning. For

[4] We opted for a number roughly between our largest (13 heads pruned) and smallest (37 heads pruned) language-specific subnetwork found via pruning.

[5] Note that for the meta-update, we use a first-order approximation, replacing $\nabla_\theta \mathcal{L}(\phi_\ell, \mathcal{D}_\ell^{tst})$ by $\nabla_\phi \mathcal{L}(\phi_\ell, \mathcal{D}_\ell^{tst})$. See Finn et al. (2017) for more details on first-order MAML.

Algorithm 1 Meta-training procedure

```
Require: Language datasets $\mathcal{T}$; step sizes $\alpha$ and $\beta$; number of updates $k$; number of
  episodes EPS; support/query set size $N$; and subnetworks $\{\xi_\ell \mid \ell \in \mathcal{T}\}$. Train on
  $\ell \notin \mathcal{T}$ to yield initial parameters $\theta$.
  for EPS do:
    for $\ell \in \mathcal{T}$ do :                                   (inner loop)
      Yield learner: $\phi_\ell \leftarrow \theta$.copy()
      Mask $\phi_\ell$ using $\xi_\ell$
      Take $N$ samples to form $\mathcal{D}_\ell^{trn} = \{x\}_{n=1}^N \in \mathcal{T}_\ell$ and $\mathcal{D}_\ell^{tst} = \{x\}_{n=1}^N \in \mathcal{T}_\ell$
      Update learner $\phi_\ell$ on the support set ( $\mathcal{D}_\ell^{trn}$):
      for $k$ steps do:
        $\phi_\ell \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\phi_\ell, \mathcal{D}_\ell^{trn})$
      end for
      Evaluate on the query set: $\mathcal{L}(\phi_\ell, \mathcal{D}_\ell^{tst})$
    end for
    Meta-update the original model $\theta$:                          (outer loop)
    $\theta \leftarrow \theta - \beta \sum_{\ell \in \mathcal{T}} \nabla_\theta \mathcal{L}(\phi_\ell, \mathcal{D}_\ell^{tst})$
  end for
```

a given test language, the model is fine-tuned on just 20 examples in that language, using 20 gradient updates. The examples are drawn from the development set, if there is one; otherwise they are drawn from (and removed from) the test set. We use the same hyperparameter values as during training. We report Labeled Attachment Scores (LAS) averaged across 5 random seeds, as computed by the official CoNLL 2018 Shared Task evaluation script.[6]

Since we do not have subnetworks for the test languages—only for the 7 high-resource languages used in stage 2 of fine-tuning (§4.4.2)—we instead use the subnetwork of the typologically most similar training language. We determine typological similarity by computing the cosine similarity between the language vectors from the URIEL database (`syntax_knn`) (Littell et al., 2017).

4.4.6 Baselines

To measure the effectiveness of our subnetwork-based methods, we train and evaluate baselines in which no subnetwork masking is applied (but for which all other details of the training and testing setups are kept unchanged). We refer to this as *full model training* (FULL) to contrast our training approaches that use static or dynamic subnetworks (SN$_{\text{static}}$ and SN$_{\text{dyna}}$), and we report these baselines for both the non-episodic (NONEP)[7] and meta-learning (META)

[6] https://universaldependencies.org/conll18/evaluation.html

[7] Note that Non-Episodic (NONEP) is used throughout this chapter to refer to models trained without meta-learning.

		FULL	SN$_{\text{static}}$	SN$_{\text{dyna}}$	Total
NONEP	LAS	38.49	**41.32**	40.0	
	Best%	0%	22%	8.5 %	30.5%
META	LAS	40.68	40.27	**40.89**	
	Best%	14.5 %	27%	**28%**	**69.5%**

Table 4.1: Results on UD Parsing, for both non-episodic (NONEP) and meta-learning (META) setups. For each of the 6 models, we report Labeled Attachment Score (LAS) averaged across all 82 test languages, as well as the percentage of languages for which that model performed best (e.g., META-SN$_{\text{dyna}}$ yielded the highest LAS on 28% of test languages). The best performance is denoted by boldface

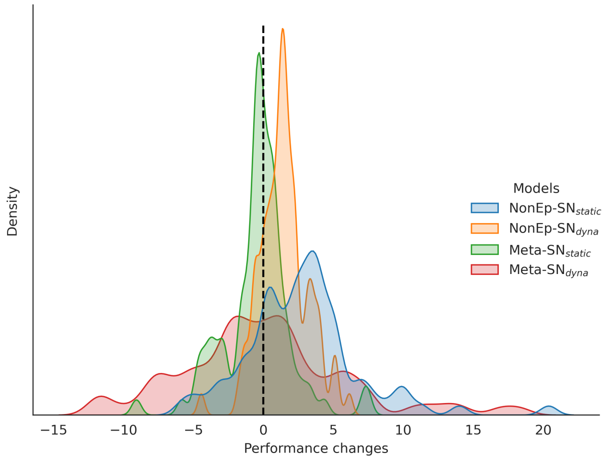


Figure 4.2: Kernel density estimation (KDE) plot over the relative performance changes of each model for all test languages when comparing to its corresponding full model training baseline.

frameworks. For a fair comparison to existing literature, we also re-train UDify on dependency parsing using only our 8 treebanks for training and perform few-shot fine-tuning at test time as was done for all other models (UDF8).

4.5 Results

Overall, the results show that our subnetwork-based methods yield improvements over baseline models trained without any subnetwork masking. In Table 4.1, we see that, based on average LAS scores across all test languages, static subnetworks (SN$_{\text{static}}$) perform best in the non-episodic training setup, resulting in +2.8% average improvement over the FULL baseline, and yielding the highest average LAS of all the models. Dynamic subnetworks (SN$_{\text{dyna}}$), on the other hand, exhibit superior performance in the meta-learning setting, resulting in the model that performed best across all settings for the largest number of languages. In Table 4.2, we report the full set of results on all 82 test languages.

To gain more insight into the effects of our methods across the test languages, we plot the distribution over performance changes compared to the baseline per method and learning framework in Figure 4.2. We find that static and dynamic subnetworks exhibit opposite trends. NonEp-SN$_{\text{static}}$ achieves large gains (up to +25%), but can also cause more deterioration on other languages (up to −6%). In contrast, the performance change distribution for NonEp-SN$_{\text{dyna}}$ is centered around more modest improvements, but is also the safest option given that it deteriorates performance for the fewest languages. The same trade-off can be observed in the meta-learning framework, except that now Meta-SN$_{\text{static}}$ results in modest changes compared to Meta-SN$_{\text{dyna}}$.

Lastly, we do not find strong trends for transfer languages; different magnitudes of performance changes are scattered across all transfer languages. Yet, when transferring from Norwegian, Meta-SN$_{\text{static}}$ and Meta-SN$_{\text{dyna}}$ particularly often underperform compared to Meta-Full, see Table 4.2. In contrast, Meta-SN$_{\text{dyna}}$ performs particularly well when transferring from Arabic, similarly SN$_{\text{static}}$ performs especially well when transferring from Czech. Thus, the best approach might be dependent on the relationship between the transfer and test languages, or the properties of the transfer language itself.

We note that despite the observed improvements, overall performance remains low for many languages. Yet we would like to point out that we also find instances where our methods might already make the difference in acquiring a usable system compared to state-of-the-art models. For example, even with few-shot fine-tuning Udf75's performance on Faroese OFT only reaches 53.8% which is much lower than our 70.4% (NonEp-SN$_{\text{static}}$), and for Indonesian PUD it reaches 69.0% versus 74.9% (NonEp-SN$_{\text{static}}$)

			Non-Episodic-NonEp			Meta-Learning-Meta		
From Arabic ($\bar{\theta} = 0.70$)	Udf75	Udf8	Full	SN$_{\text{static}}$	SN$_{\text{dyna}}$	Full	SN$_{\text{static}}$	SN$_{\text{dyna}}$
Guajajara TuDeT	-	32.47	28.61	27.07	**33.62**	25.80	26.11	**30.90**
Kiche IU	-	37.94	40.13	**41.24**	40.04	30.10	21.03	**40.78**
Indonesian GSD	80.10	63.95	63.64	63.96	**64.05**	62.39	62.42	**64.73**
Indonesian PUD	56.90	71.63	70.08	**74.88**	71.54	**74.71**	73.32	71.64
Javanese CSUI	-	56.77	57.80	**61.92**	60.07	62.40	**62.94**	60.84
Maltese MUDT	75.56	29.75	**29.37**	24.67	28.47	16.92	13.43	**30.05**
Mbya Guarani Thomas	-	17.43	16.76	16.30	**17.61**	10.79	11.55	**16.55**
South Levantine Arabic	-	36.77	39.42	**41.93**	41.20	42.05	42.32	**42.37**
Tagalog TRG	40.07	69.06	70.46	65.26	**71.82**	**73.17**	71.58	72.58
Tagalog Ugnayan	-	48.16	48.39	47.38	**49.76**	50.93	46.69	**53.22**
Vietnamese VTB	66.0	38.81	40.79	**44.62**	43.34	**45.24**	43.75	43.67

Wolof WTB	-	23.16	20.72	18.98	**22.55**	17.26	15.56	**24.63**
Average (12)	-	43.83	43.85	44.02	**45.34**	42.17	40.89	**46.00**
From Czech ($\bar{\theta}$ = 0.83)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Armenian ArmTDP	78.61	50.28	48.22	**58.35**	52.07	57.64	**61.09**	50.66
Armenian BSUT	-	58.80	57.26	**64.75**	59.49	62.95	**67.30**	60.24
Kurmanji MG	20.40	14.19	13.28	**16.40**	14.78	15.57	12.86	**17.28**
Lithuanian ALKSNIS	-	50.75	50.09	**59.98**	57.28	60.81	**61.20**	53.15
Lithuanian HSE	69.34	54.75	53.02	**59.74**	57.28	61.26	**61.38**	55.57
Western Armenian	-	41.59	43.01	**57.0**	49.14	56.93	**58.34**	48.62
Average (6)	-	45.06	44.15	**52.70**	48.34	52.53	**53.70**	47.59
From Estonian ($\bar{\theta}$ = 0.84)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Apurina UFPA	-	37.25	37.70	**39.66**	37.68	28.18	24.11	**35.75**
Erzya JR	16.38	14.90	16.06	**17.35**	16.39	17.77	**18.66**	15.64
Hungarian Szeged	84.88	52.19	53.38	**62.24**	54.51	61.67	**68.69**	50.20
Karelian KKPP	-	35.06	36.67	**43.69**	38.41	40.58	40.19	**40.93**
Komi Permyak UH	-	24.19	24.47	**26.19**	25.86	24.96	**26.52**	25.65
Komi Zyrian IKDP	22.12	22.46	22.58	**25.55**	23.62	**24.97**	22.23	24.63
Komi Zyrian Lattice	12.99	14.21	14.17	**16.43**	14.23	14.72	**15.30**	13.62
Livvi KKPP	-	27.31	34.22	**38.0**	32.45	36.52	**37.08**	33.45
Moksha JR	-	15.09	15.20	**20.18**	16.30	18.79	**20.57**	16.65
North Sami Giella	67.13	14.25	14.05	14.69	**14.75**	11.74	11.90	**16.51**
Skolt Sami-Giellagas	-	25.21	26.49	26.20	**27.83**	21.84	18.10	**27.66**
Tatar NMCTT	-	54.73	52.63	**56.56**	55.67	55.79	**58.90**	54.61
Tupinamba TuDeT	-	20.83	21.24	21.65	**22.74**	16.68	15.30	**20.12**
Turkish PUD	46.07	46.47	47.0	**50.91**	49.34	50.58	50.01	**52.63**
Turkish IMST	67.44	34.70	34.90	**40.60**	35.99	40.87	**41.81**	36.32
Average (15)	-	29.26	30.05	**33.33**	31.05	31.04	**31.30**	30.96
From Hindi ($\bar{\theta}$ = 0.74)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Akuntsu TuDeT	-	25.28	**24.71**	21.86	23.97	21.76	21.29	**25.55**
Bambara CRB	8.60	20.52	21.94	**22.54**	21.47	17.79	18.09	**23.76**
Basque BDT	80.97	45.15	45.81	47.59	**48.60**	**52.81**	52.52	45.71
Beja NSC	-	18.26	18.07	14.79	**19.95**	14.04	8.21	**19.87**
Bengali BRU	-	44.94	43.49	**48.67**	42.87	**58.91**	58.52	47.33
Bhojpuri BHTB	35.90	36.16	36.0	**38.76**	38.24	36.72	**37.70**	35.71
Buryat BDT	26.28	18.45	15.95	16.50	**17.31**	24.26	25.02	**27.79**
Kaapor TuDeT	-	30.11	30.54	**33.29**	29.87	30.77	30.18	**32.75**
Kangri KDTB	-	33.84	30.79	**34.32**	34.20	**36.16**	35.90	35.77
Karo TuDeT	-	18.47	18.47	19.01	**19.32**	17.47	17.38	**18.76**
Kazakh KTB	63.66	46.96	45.35	**50.50**	47.07	53.92	**54.70**	48.56
Makurap TuDeT	-	24.27	25.26	**25.35**	23.98	20.63	20.07	**28.47**
Marathi UFAL	67.72	37.38	37.96	**41.46**	37.72	**51.21**	50.78	39.17
Munduruku TuDeT	-	35.60	**35.73**	32.74	34.25	29.43	28.87	**36.51**
Sanskrit UFAL	18.56	18.40	18.63	19.70	**19.74**	21.58	**22.18**	19.0

Sanskrit Vedic	-	13.02	12.96	**13.09**	12.43	12.51	12.40	**12.71**
Tamil MWTT	-	58.95	63.11	**65.34**	61.86	**72.39**	72.04	64.76
Tamil TTB	71.29	47.51	46.66	**51.48**	48.10	52.0	**53.89**	46.76
Uyghur UDT	48.80	20.05	20.78	21.07	**21.41**	**21.04**	19.93	20.91
Warlpiri UFAL	7.96	51.01	55.91	59.30	**59.40**	42.78	42.67	**59.69**
Yakut YKTDT	-	34.35	30.85	**35.06**	34.73	32.4	32.54	**33.99**
Yupik SLI	-	12.18	12.73	11.31	**13.28**	8.84	9.28	**33.92**
Average (22)	-	31.40	31.44	**33.09**	32.27	**34.63**	34.39	33.80
From Italian ($\bar{\theta} = 0.85$)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Akkadian PISANDUB	4.54	21.36	17.33	11.42	**18.44**	7.44	9.30	**19.28**
Akkadian RIAO	-	22.19	21.87	17.99	**23.17**	12.89	9.33	**27.01**
Breton KEB	39.84	52.98	50.33	**61.63**	53.89	63.05	**64.31**	56.67
Galician TreeGal	76.77	75.79	75.81	**77.63**	76.05	**78.41**	77.95	76.09
Greek GDT	92.15	78.74	77.90	**81.46**	80.14	**81.13**	80.79	79.78
Irish IDT	69.28	46.45	47.14	**50.80**	49.04	52.03	**53.10**	49.42
Ligurian GLT	-	25.98	29.43	**49.81**	34.05	44.26	**46.65**	34.30
Manx Cadhan	-	44.76	46.13	44.97	**46.64**	40.52	36.70	**47.31**
Naija NSC	32.16	32.12	32.0	**35.59**	32.09	34.52	33.46	**37.84**
Scottish Gaelic ARCOSG	-	17.09	15.41	**23.28**	18.57	24.49	**25.88**	21.86
Welsh CCG	-	47.86	47.37	51.72	**52.60**	**54.97**	53.18	51.10
Average (11)		42.30	41.88	**46.03**	44.10	44.88	44.60	**45.54**
From Norwegian ($\bar{\theta}$=0.91)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Afrikaans AfriBooms	-	66.64	65.88	63.57	**65.94**	68.28	63.64	**69.75**
Albanian TSA	-	72.45	70.95	**76.06**	73.34	**79.76**	76.65	74.13
Faroese FarPaHC	-	49.75	47.51	50.03	**51.0**	49.24	44.70	**54.13**
Faroese OFT	59.26	62.17	60.95	**70.36**	63.76	**70.12**	69.41	65.87
Gothic PROIEL	79.37	19.53	19.23	**19.67**	18.68	16.65	15.85	**20.24**
Icelandic Modern	-	47.36	45.98	**49.98**	47.44	**53.45**	50.43	51.27
Low Saxon LSDC	-	50.70	47.75	**51.42**	49.88	**50.26**	47.50	50.08
Swiss German UZH	-	47.12	45.98	**52.66**	47.57	**51.93**	51.73	51.16
Average (8)	-	51.97	50.48	**54.22**	52.20	**54.96**	52.49	54.58
From Russian ($\bar{\theta} = 0.76$)	Udf75	Udf8	FULL	SN$_{static}$	SN$_{dyna}$	Meta	SN$_{static}$	SN$_{dyna}$
Ancient Greek PROIEL	82.11	26.55	23.68	**28.38**	27.72	23.81	**31.24**	26.32
Cantonese HK	32.01	28.26	28.66	**31.17**	30.58	**33.02**	32.87	31.50
Chinese CFL	42.48	44.35	45.48	**49.28**	48.26	49.88	**50.67**	47.50
Chinese HK	49.32	47.75	47.20	**49.94**	48.26	52.31	**52.90**	48.16
Chinese PUD	56.51	43.49	44.74	**46.98**	46.47	45.9	44.92	**46.71**
Serbian SET	91.95	81.05	78.98	**81.57**	79.66	**80.98**	80.96	79.8
Upper Sorbian UFAL	62.82	53.26	49.81	**54.88**	53.84	**54.01**	53.78	51.29

Yoruba YTB	19.09	38.34	38.11	38.17	**38.75**	38.79	38.17	**39.28**
Average (8)	-	45.38	44.58	**47.55**	46.62	47.34	**48.19**	46.32
Total Avg. (82)	-	38.66	38.49	**41.32**	40.0	40.68	40.27	**40.89**

Table 4.2: Average LAS scores across 5 random seeds for all test languages (we do not report standard deviations as they were overall very small (6e-05–0.09)). Within each learning framework (NonEp and Meta) the best performance is denoted by boldface. Subnetwork-based models that substantially improve over their full-model baselines are highlighted, and color-code based on the amount of improvement: 🟧 +3–5%, 🟨 +5–7 %, 🟩 +7–10 %, 🟦 +10–15%, 🟪 +20–25%. Results are grouped according to which high-resource language was the source of their subnetwork mask (i.e., which high-resource language is most typologically similar), and we report average typological similarity between transfer and test languages ($\bar{\theta}$). Lastly, next to results from our Udf8 baseline, we report available scores for UDify trained on 75 languages (Udf75) from Kondratyuk and Straka (2019), but note that these scores are not directly comparable as they come from *zero-shot* testing.

4.6 Analysis

In this section, we provide more insight into the effects of our methods by analyzing performance with respect to four factors: typological relatedness, data-scarcity, robustness to domain transfer, and ability to predict unseen and rare labels. We focus on the best model from each learning framework: NonEp-SN$_{\text{static}}$ and Meta-SN$_{\text{dyna}}$.

Typological relatedness The languages most similar to a low-resource language are often themselves low-resource, meaning that a low-resource language is often quite dissimilar from all the languages that are resource-rich enough to be used for fine-tuning. A method that only works well when a very similar high-resource language is available for fine-tuning will not be as useful in practice. Thus, we want to understand the degree to which our methods depend on similarity to a high-resource fine-tuning language. In Figure 4.3 (top), we plot each test language's performance improvement against its typological closeness to the nearest high-resource fine-tuning, where that distance is as computed using the cosine similarity between the languages' URIEL features. Interestingly, we find that our models show opposite trends: while NonEp-SN$_{\text{static}}$ works well for typologically similar languages, the biggest gains from Meta-SN$_{\text{dyna}}$ actually come from less similar languages.

Data scarcity Given that language distribution in the mBERT pretraining corpus is very uneven, and 37 of our 70 unique test languages are not covered at

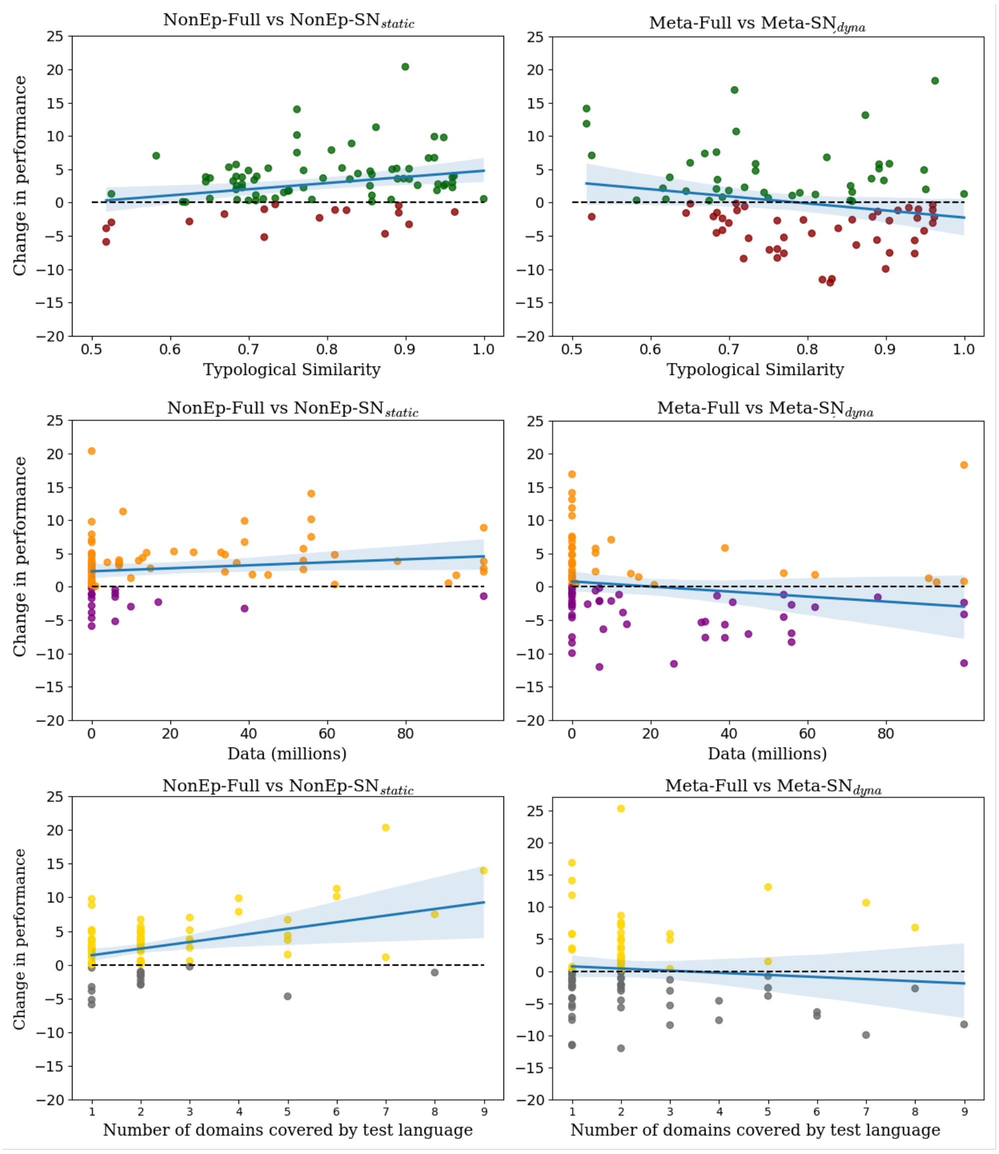


Figure 4.3: Plots of the relationships between a test language's performance gains and: (top) how typologically similar the language is to the nearest high-resource fine-tuning language, (middle) the amount of in-language data used to pretrain mBERT, and (bottom) the number of domain sources represented in its test data. Note that different colors were only used for visual ease.

all, we want to understand what effect this has on downstream model performance. As shown in Figure 4.3 (middle), we find that META-SN$_{\text{dyna}}$ provides the most benefit to previously unseen languages. In contrast, more data in pretraining positively correlates with the performance of NONEP-SN$_{\text{static}}$.

NonEp-	Full	SN$_{\text{static}}$	SN$_{\text{dyna}}$
Unseen	0.04% (3/3)	0.003% (1/1)	0.004% (2/2)
Rare	12.5% (12/50)	6.4% (11/41)	9.9% (8/49)
Meta-	Full	SN$_{\text{static}}$	SN$_{\text{dyna}}$
Unseen	0%	0%	**6.6%** (15/23)
Rare	3.5% (10/39)	3.0% (7/36)	**21.3%** (13/55)

Table 4.3: Percentages of correctly predicted instances of unseen and rare labels. We also report across how many labels/languages correct predictions were made.

Out-of-domain data For cross-lingual transfer we often focus on the linguistic properties of source and target languages. However, the similarity of the source and target datasets will also be based on the domains from which they were drawn (Glavaš and Vulić, 2021). For example, our training datasets cover only 11/17 domains, as annotated by the creators of the UD treebank. While we acknowledge that it is difficult to neatly separate data based on source domain, we test for a correlation between performance and the proportion of out-of-domain data. Interestingly, we find no clear correlation with the percentage of domains from the test language covered by the transfer language. We do, however, find a strong correlation with the domain diversity of the transfer and test language in general for NonEp-SN$_{\text{static}}$, as shown in Figure 4.3 (bottom), where we plot improvements against number of domain sources our test data is coming from (more sources → more diversity). In contrast, we see that Meta-SN$_{\text{dyna}}$ remains insensitive to this variable.

Unseen and rare labels Lastly, another problem in cross-lingual transfer, especially when fine-tuning on only a few languages, is that the fine-tuning data may not cover the entire space of possible labels from our test data. In principle, only a model that is able to adequately adapt to unseen and rare labels can truly succeed in cross-lingual transfer. Given that we perform few-shot fine-tuning at test time, we could potentially overcome this problem (Lauscher et al., 2020). Thus, we investigate the extent to which our models succeed in predicting such labels for our test data. We consider a label to be rare when it is covered by our training data, but makes up <0.1% of training instances (23 such labels). There are 169 unseen labels, thus in total, 192/233 (82%) of the labels from our test data are rare or unseen during training. In Table 4.3, we report how often each model correctly predicts instances of unseen and rare labels. We find that models differ greatly, and, in particular, Meta-SN$_{\text{dyna}}$ vastly outperforms all other models when it comes to both unseen and rare labels. Upon further inspection, we find that two unseen labels are particularly often predicted correctly: sentence particle (`discourse:sp`) and inflectional depen-

Language	FULL	$\text{SN}_{\text{static}}$	SN_{dyna}
Arabic	68.6	**72.9** (13)	69.1 (28)
Czech	75.4	**81.2** (13)	77.9 (28)
Estonian	65.4	**69.2** (37)	68.3 (28)
Hindi	74.4	**77.2** (21)	75.2 (28)
Italian	85.0	**87.7** (23)	86.1 (28)
Norwegian	73.2	**79.8** (24)	73.6 (28)
Russian	79.5	**81.6** (27)	80.4 (28)

Table 4.4: Labeled Attachment Scores for Non-Episodic models on each training language. Number of heads disabled by the subnetwork is shown in parentheses.

dency (dep:infl). The former label seems specific to Chinese linguistics and has a wide range of functions e.g., modifying the modality of a sentence or its proposition, and expressing discourse and pragmatic information. The latter represents inflectional suffixes for the morpheme-level annotations, something that is unlikely to be observed in morphologically poor languages such as English; but, for instance, Yupik has much of its performance boost due to it.

4.7 Effect of subnetworks at training time

4.7.1 Interaction between subnetworks

We now further investigate the selected subnetworks and their impact during training. Our findings were similar for meta-learning, so we just focus our analysis here on the non-episodic models.

Table 4.4 shows how using subnetworks affects performance on the training languages. Training with the subnetworks always improves performance, however, this effect is larger when subnetworks are kept static during training. Moreover, for the static subnetworks, the number of heads that are masked out can vary considerably per language; e.g., for Arabic we only disable 13 heads compared to 37 for Estonian. Yet, we observe similar effects on performance, obtaining ∼+4% improvement for both languages. To disentangle how much of the performance gain comes from disabling suboptimal heads vs. protection from negative interference by other languages, we re-train NONEP-$\text{SN}_{\text{static}}$ in two ways using Czech as a test case: (1) we keep updates from Czech restricted to its subnetwork (i.e., we disable the suboptimal heads for Czech), but drop subnetwork masking for the other languages (i.e., we do not protect Czech from negative interference as all other languages can still update the full model); (2) we use subnetworks for all languages *except* Czech, i.e., we protect

Language	FULL	Selection	Protection
Arabic	68.6	71.2 (+2.5)	72.2 (+3.6)
Czech	75.4	79.5 (+4.1)	80.1 (+4.7)
Estonian	65.4	67.9 (+2.5)	67.9 (+2.5)
Hindi	74.4	76.8 (+2.4)	76.7 (+2.3)
Italian	85.0	86.8 (+1.8)	87.3 (+2.3)
Norwegian	73.2	80.2 (+7.1)	80.3 (+7.2)
Russian	79.5	80.5 (+1.0)	80.4 (+0.9)

Table 4.5: Labeled Attachment Scores for the baseline model FULL on each fine-tuning language $\ell \in \mathcal{T}$ when either using a subnetwork for the fine-tuning language ℓ only (selection) or using a subnetwork for all fine-tuning languages in $\mathcal{T} \setminus \{\ell\}$ (protection). Percentage of improvement over the FULL baseline is shown in parentheses.

Czech from the other languages by restricting their updates to their subnetworks only, but still allow Czech to use the full model capacity.

We find that (1), disabling suboptimal heads for Czech only, results in 79.5 LAS on Czech (+4.1% improvement compared to baseline), while (2), just protection from the other languages, results in 80.3 LAS (+4.7% improvement), see Table 4.5 for results on the other training languages. This indicates that protection from negative interference has a slightly larger positive effect on the training language in this case. Still, a combination of both, i.e., using subnetworks for all fine-tuning languages, results in the best performance in most cases (81.2 LAS for Czech, a +5.9% improvement, as reported in Table 4.4). This suggests that the interaction between the subnetworks is a driving factor behind the selective sharing mechanism that resolves language conflicts. We confirm that similar trends were found for the other languages.

This, however, also means that if the quality of one subnetwork is suboptimal, it is still likely to negatively affect other languages. Moreover, analysing the subnetworks can provide insights on language conflicts. For instance, using a subnetwork for only Czech or Arabic results in the biggest performance gains for Norwegian (+7.1% and +7.3% compared to the FULL baseline), indicating that, in this setup, Norwegian suffers more from interference.

4.7.2 Gradient conflicts and similarity

In multilingual learning, we aim to maximize knowledge transfer between languages while minimizing negative transfer between them. In this study, our main goal is the latter. To evaluate the extent to which our methods succeed in doing this, we explicitly test whether we are able to mitigate negative interference by adopting the gradient conflict measure from Yu et al. (2020). They show that *conflicting gradients* between dissimilar tasks, defined as a negative

	Conflicts	Cosine Sim.
NonEp-Full	42%	0.03
NonEp-SN$_{\text{static}}$	**26%**	0.05
NonEp-SN$_{\text{dyna}}$	38%	**0.07**
Meta-Full	55%	−0.04
Meta-SN$_{\text{static}}$	54%	−0.02
Meta-SN$_{\text{dyna}}$	**44%**	**0.12**

Table 4.6: We report the percentage of gradient conflicts and average cosine similarity between gradients over the last 50 iterations/episodes for our non-episodic and meta-trained models. We report average results over 4 random seeds.

cosine similarity between gradients, is predictive of negative interference in multi-task learning. Similar to Wang et al. (2020), we deploy this method in the multilingual setting: we study how often gradient conflicts occur between batches from different languages. For batches from each language, we compute the gradient of the loss with respect to the parameters of the full model during backpropagation. To get a stable estimate, we use gradient accumulation for 50 episodes/iterations before computing conflicts. Gradient conflicts are then computed between each language pair, $\binom{7}{2}$ pairs in total, and the percentage of total conflicts is computed across all language pairs.

At the same time, Lee et al. (2021) argue that lower cosine similarity between language gradients indicates that the model starts memorizing language-specific knowledge that at some point might cause catastrophic forgetting of the pretrained knowledge. This suggests that, ideally, our approach would find a good balance between minimizing gradient conflicts and maximizing the cosine similarity between the language gradients.

We quantitatively find that both subnetwork-based methods indeed reduce the percentage of gradient conflicts between languages. Over the last 50 iterations, we find that NonEp-SN$_{\text{static}}$ has reduced conflicts by 16% and NonEp-SN$_{\text{dyna}}$ by 4% compared to the NonEp-Full baseline as reported in Table 4.6. In the meta-learning setup we found an opposite trend where Meta-SN$_{\text{static}}$ reduces conflicts by 1% and Meta-SN$_{\text{dyna}}$ by 11% over the last 50 iterations compared to Meta-Full. This partly explains why NonEp-SN$_{\text{static}}$ and Meta-SN$_{\text{dyna}}$ are found to be the best performing models: they suffer from gradient conflicts the least. Interestingly, we do not find that our meta-trained models suffer less from gradient conflicts than the non-episodic models. In fact, while we found that, on average, Meta-Full improves over NonEp-Full (recall Table 4.1), its training procedure suffers from 13% more conflicts, meaning that we do not find meta-learning in itself to be a suitable method for reducing gradient conflicts, but our subnetwork-based methods are.

At the same time, the average cosine similarity between gradients increases when using both subnetwork methods compared to the FULL model baselines. We compute the Pearson correlation coefficient between the relative decrease in percentage of gradient conflicts and increase in cosine similarity over training iterations compared to the baselines. We test for statistical significance (p-value <0.02), and average results over 4 random seeds. We get statistically significant positive correlation scores of 0.08, 0.16, 0.33 and 0.58 for NONEP-SN$_{\text{static}}$, NONEP-SN$_{\text{dyna}}$, META-SN$_{\text{static}}$ and META-SN$_{\text{dyna}}$, respectively. This indicates that our subnetwork-based methods try to minimize negative interference while simultaneously maximizing knowledge transfer.

4.8 Ablations

To ensure that each of the aspects of our setup are indeed contributing to the improvements shown in our experiments, we retrained models with specific aspects ablated.

4.8.1 Random ablations

Random mask initialization – Static In these experiments, we verify that there is value in using the iterative pruning procedure to generate subnetwork masks (as opposed to the value coming entirely from the mere fact that masks were used).

First, we re-trained NONEP-SN$_{\text{static}}$ but swapped out the subnetwork masks derived from iterative pruning with masks containing the same number of enabled heads, but that were randomly generated (Shuffle). Second, given that the number of masked heads might be more important than which exact heads are being masked out, we experiment with masking 20, 30, 40, and 50 random heads. We find that using the random masks results, on average, in $\sim$5% performance decreases on the training languages compared to using the subnetworks initialized using importance pruning; see Figure 4.4. In addition, we see that randomly masking out more heads results in further negative effects on performance.

Lastly, given that for many languages our subnetworks mask out very few heads (e.g., 13 for Arabic and Czech), we also try swapping these out with "intentionally bad" masks, where we randomly choose 20 heads to mask out, but do not allow any of the heads selected by the real pruning procedure to be chosen (Bad). From this, we see that preventing the right heads from being selected for masking does result in lower performance versus pure random selection (R20).

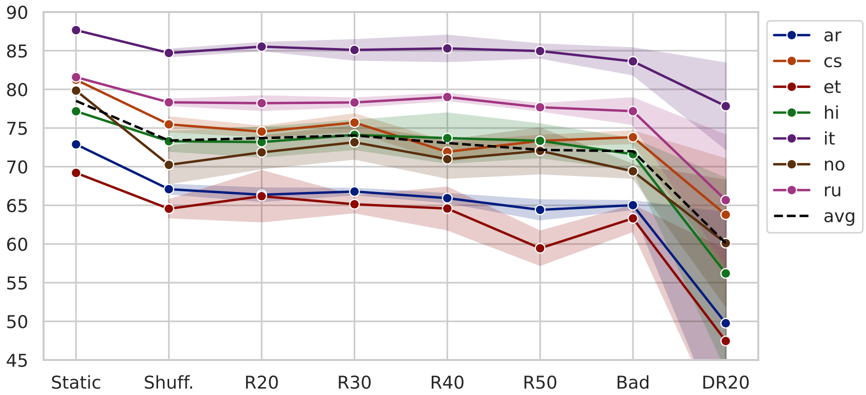


Figure 4.4: Effect of training with masks randomly generated under different constraints (across 3 seeds): shuffled, masking n heads, only select bad heads and start dynamic training from a random subnetwork (DR20).

Random mask initialization – Dynamic In these experiments, we verify that there is value in using the iterative pruning procedure to initialize subnetwork masks that will then by dynamically updated during fine-tuning.

We retrained NONEP-SN$_{\text{dyna}}$ 3 times using randomly initialised subnetworks. Figure 4.4 (DR20) shows that average performance across all test languages drops substantially (∼10%), making this method considerably worse than any of our other random baselines. We hypothesize that this is because the model is able to correct for any random static subnetwork, but that with dynamic masking, the subnetworks keep changing, which deprives the model of the chance to properly re-structure its information. This also gives us a strong indication that the improvements we observe are not merely an effect of regularization (Bartoldson et al., 2020).

Random transfer language To test the effectiveness of our typology-based approach to selecting which high-resource fine-tuning language's subnetwork should be used for a given test language, we experimented with just picking one of the high-resource languages at random, and found that this performed worse overall, resulting in lower scores for 78/82 test languages.

4.8.2 Unstructured pruning

Our approach relies on the assumption that attention heads function independently. However, attention head interpretability studies have sometimes given mixed results on their function in isolation (Prasanna et al., 2020; Clark et al., 2019; Htut et al., 2019). Moreover, related works commonly focus on unstructured methods (Lu et al., 2022b; Nooralahzadeh et al., 2020). Thus, we compare our strategy of masking whole attention heads against versions of NONEP-

Language	FULL	$\text{SN}_{\text{static}}$	SN_{dyna}
Chinese	–0.89	–0.46	–0.78
Turkish	–0.95	–0.62	–0.35
German	–0.22	+0.17	+0.07

Table 4.7: Average change in LAS across all test languages for the NONEP models trained with different languages for fine-tuning stage 1 compared to the original results obtained using English for fine-tuning stage 1. Note that we remove the datasets pertaining to languages used during fine-tuning when comparing, e.g., Turkish datasets are removed from our test languages when we use the models fine-tuned on Turkish in our comparison.

$\text{SN}_{\text{static}}$ and NONEP-SN_{dyna} that were retrained using subnetwork masks found using the most popular unstructured method, *magnitude pruning*. In magnitude pruning, instead of disabling entire heads during the iterative pruning procedure, as described in §4.4.3.1, we prune the 10% of parameters with the lowest magnitude weights across all heads. Again, we check the development set score in each iteration and keep pruning until reaching <95% of the original performance. Note that we exclude the embedding and MLP layers.[8]

We find that for both the static and dynamic strategies, unstructured pruning performs worse overall, resulting in lower scores for 76% of test languages, and is especially harmful for dynamic subnetworks ($\text{SN}_{\text{static}}$: 40.4 vs. 39.9, and SN_{dyna}: 39.0 vs. 36.7 average LAS). We hypothesize that it might be more difficult to learn to adapt the unstructured masks as there are more weights to learn (weights per head × heads per layer × layers).

4.8.3 Effect of selected training languages

Given that the selection of training languages can have an important effect on the overall performance, we now also perform a set of ablations to test the robustness of our findings with respect to the choice of training languages.

Fine-tuning stage 1 As presented above, we fine-tune mBERT first using English to learn the task of dependency parsing. While English is still the most commonly used source language for cross-lingual transfer, it is important to understand how this choice may affect downstream performance. Therefore, we also tried using three other languages in place of English for this step: 1. Chinese (GSD) as it uses a different script, 2. Turkish (PENN) as it has a different word order (SOV), and 3. German (GSD) as it has no dominant word order

[8] We recognize that the interaction between the MLPs and attention heads is important, but by focusing on the attention heads, we keep results comparable to importance pruning.

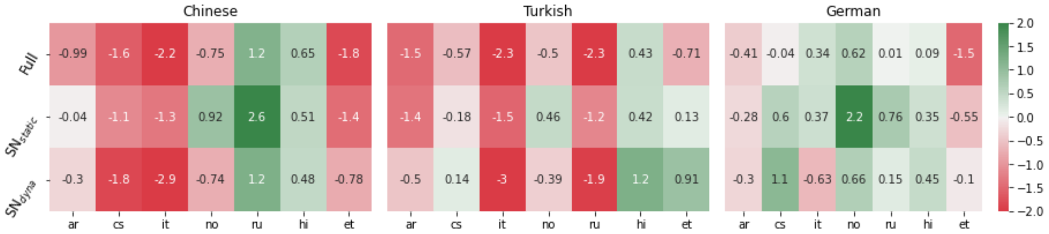


Figure 4.5: Average change in LAS for languages grouped by their typologically most similar training language. We show the average change in LAS for each language used during fine-tuning stage 1 compared to using English.

and it was found to be the best source language for transfer by Turc et al. (2021) (together with Russian).

In Table 4.7, we show, for each of the three languages, how much the average performance changes in comparison to using English. For both Chinese and Turkish, we find that the average performance across test languages slightly decreases for all NONEP models. Even though the decreases are only minor, it indicates that Chinese and Turkish do not transfer as well to our test languages as English. This is not completely surprising as more of our test languages are written in the Latin script and, like English, use SVO word ordering. Yet, similar to Turc et al. (2021), we find that German is the best source language as it increases our average results when using both static and dynamic subnetworks compared to using English. Interestingly, in Figure 4.5, we see that all languages are able to increase average performance for the languages most closely related to Hindi, which could indicate that English has some properties that are particularly badly suited for transfer to this set of languages. At the same time, swapping out English with any of our three new languages causes an average decrease in performance on test languages that are most closely related to Arabic.

Fine-tuning stage 2 The set of 7 languages we used above for the second stage of fine-tuning was chosen to be comparable to previous studies, but that set of languages is dominated by the Indo-European language family, which may result in poor generalization to other language families. Thus, we also re-trained our NONEP models on a completely different set of 7 languages, which were chosen from among those languages with relatively large treebanks ($\geq$ 100K tokens), but selected in order to maximize diversity with respect to: 1. language family, 2. word order, and 3. data domain. This yielded the following set of languages: Belarusian (IE, Slavic, no dominant order), Chinese (Sino-Tibetan, SVO), Finnish (Uralic, SVO), Hebrew (Afro-Asiatic, SOV), Indonesian (Austronesian, SVO), Irish (Celtic, VSO), and Turkish (Turkic, SOV). These 7 languages cover 7 language families, 4 word orderings, and 14 data domains.

Note that to limit the scope of this experiment, and to keep the results comparable to our original findings, we now again use English for fine-tuning stage 1.

We find that average results across all test languages[9] are very similar using this different set of training languages. More concretely, for our FULL, $\text{SN}_{\text{static}}$ and SN_{dyna} (NONEP) models we only get +0.12, -1.09 and +0.02 average differences in LAS scores compared to our original results[10]. Thus, our methods seem to be fairly robust with respect to the choice of training languages, and more diversity in training languages does not automatically result in better performance. One artifact that could influence this is the fact that we have much less training data for some of these selected languages, e.g., Irish and Indonesian (see Appendix B, Table B.2), so the quality of the retrieved subnetworks could be worse than those found for our more high-resource training languages. Thus, it could be possible that with more training data, this same set of training languages would result in higher performance gains.

4.9 Conclusion

We present and compare two methods, i.e., static and dynamic subnetworks, that successfully help us guide selective sharing in multilingual training across two learning frameworks: non-episodic learning and meta-learning. We show that through the use of subnetworks, we can obtain considerable performance gains on cross-lingual transfer to low resource languages compared to full model training baselines for dependency parsing. Moreover, we quantitatively show that our subnetwork-based methods are able to reduce negative interference. Finally, we extensively analyze the behavior of our best performing models and show that they possess different strengths, obtaining relatively large improvements on different sets of test languages with often opposing properties. Given that our META-SN_{dyna} model performs particularly well on data-scarce and typologically distant languages from our training languages, this is an interesting approach to further explore in future work on low-resource languages. In particular, it would be interesting to investigate methods to integrate the strengths of NONEP-$\text{SN}_{\text{static}}$ and META-SN_{dyna} into one model.

Lastly, we test our results only on the task of dependency parsing which is somewhat different from other NLP tasks as it has an annotation scheme explicitly designed to be applied across languages universally. However, we would like to point out that many NLP tasks are implicitly multilingual as well since most tasks do not involve a language-specific annotation scheme. For

[9] For a fair comparison, we removed test languages included in our new training set, e.g., Indonesian, so we average over 74 test languages instead. This was done for every experiment, where applicable.

[10] We did not find clear patterns for the individual languages on which performance improvements are obtained.

instance, in Named Entity Recognition (NER) the goal is to classify named entities into predefined categories such as 'person', 'location', 'organization' etc. When performing NER for other languages, we still select from the same categories. Moreover, negative interference is a general problem, first addressed in multi-task learning (Ruder, 2017), and later studied in multilingual NLP (Wang et al., 2020), that seems to occur whenever we attempt to learn multiple tasks/languages within one model. In multilingual NLP, languages will compete for the limited model capacity regardless of the task we are trying to solve. It was already shown that across a wide range of NLP tasks — NER, POS tagging, question answering, and natural language inference — negative interference occurs in multilingual models, and resolving such language conflicts can improve overall cross-lingual performance (Wang et al., 2020). From our analysis of gradient conflicts, we find that similar negative interference issues can be found for the task of dependency parsing, and are mitigated by our subnetwork-based methods. Thus, as training with subnetworks appears to be a general approach to mitigating negative interference, we expect it to bring the same benefits to other NLP tasks for which this problem occurs. Moreover, we would like to point out that other studies have already shown the effectiveness of various other types of subnetworks for different tasks e.g., for Neural Machine Translation (Lin et al., 2021b; Hendy et al., 2022) and cross-lingual speech recognition (Lu et al., 2022b), making it less likely that the effectiveness of our methods are limited to dependency parsing only.

4.10 Limitations

One problem in multilingual NLP is that performance increases tend to happen for a specific set of languages at a time rather than across all languages simultaneously. This makes it hard to compare models and determine the state-of-the-art performance. Moreover, it is hard to determine the usefulness of a new method as average scores are not very informative when your test languages have a detrimental effect on this, for instance, taking out a few low performing languages would already boost our average performance substantially.

This also makes it more complicated to choose training languages. Changing the training languages can positively influence our performance at test time, especially if they are more similar to a large number of our test languages. However, when we want our model to generalize beyond our chosen set of test languages, it can be misleading to tailor the training set-up to the test data. Thus, while we do show that our methods generally improve performance when using two completely different sets of training languages, further experiments on finding an "optimal" set of training languages are omitted from this study. In addition, meta-learning is notorious for being hard to optimize; e.g., slight changes in learning rates can have a detrimental effect on performance

(Antoniou et al., 2019). This also means that different training languages can require different hyperparameter settings to work, which further complicates the search for an optimal training set.

Another limitation is that while we use a diverse set of test languages, our approach relies on the pretrained mBERT model which means that it is unsuited to low-resource languages whose scripts are not seen during pretraining. Finding useful ways to circumvent this problem would be a good direction for follow up work.

Lastly, given that we fine-tune on only 8 languages, the smallest typological distance between the training languages and a test language is often still relatively large. This makes the motivation for typology-informed subnetwork transfer at test time less satisfactory. In future work, it should be further investigated what the effect is of using more similar training and test language pairs for subnetwork transfer.

CHAPTER 5

Examining Modularity via Language-Specialized Subnetworks

Chapter Highlights

In Chapter 4, we have proposed several ways to explicitly induce language-wise modularity in MLMs via sparse fine-tuning (SFT) on per-language subnetworks as a means of better guiding cross-lingual sharing. In this chapter, we continue our study of RQ2 by investigating (1) the degree to which language-wise modularity *naturally* arises within models with no special modularity interventions, and (2) how cross-lingual sharing and interference differ between such models and those with explicit SFT-guided subnetwork modularity. In order to do so, we use XLM-R as our MLM. Moreover, to quantify language specialization and cross-lingual interaction, we use our method for measuring cross-lingual sharing that we proposed in Chapter 3. Specifically, we use a Training Data Attribution (TDA) method that estimates the degree to which a model's predictions are influenced by in-language or cross-language training examples. Our results show that language-specialized subnetworks do naturally arise, and that SFT, rather than always increasing modularity, can decrease language specialization of subnetworks in favor of more cross-lingual sharing. Finally, we study the correlation between subnetwork similarity and cross-language influence to investigate cross-lingual sharing at the parameter level, thereby further contributing to RQ1 from the introduction.

5.1 Introduction

Multilingual language models (MLMs) can achieve remarkable performance across many languages thanks to phenomena like cross-lingual sharing (Pires et al., 2019), but they still suffer from the "curse of multilinguality" (Conneau et al., 2020a) as performance can be hindered by negative cross-language in-

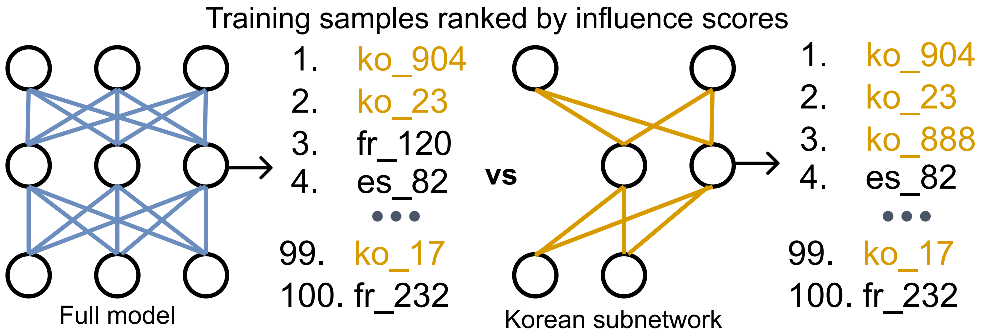


Figure 5.1: We study how in-language training data reliance changes for individual test languages when using a subnetwork compared to the full model at test time. For instance, will a Korean subnetwork rely more on Korean training examples when making a prediction for a Korean test example? Note that each training example is denoted by its language and a training example ID (`lang_ID`).

terference (Wang et al., 2020). Recently, new methods have been proposed for mitigating these negative effects by training specialized model components for processing individual languages (Pfeiffer et al., 2022). These approaches, which add explicit **modularity** to the model, are also effective in promoting positive transfer and increasing interpretability (Pfeiffer et al., 2023).

While previous work has focused on developing techniques for explicitly adding modularity to models, we take a step back and ask: To what degree does language-wise modularity *naturally* arise within a model with no targeted modularity interventions? To investigate this question, we make use of a method inspired by the Lottery Ticket Hypothesis (Frankle and Carbin, 2018; Chen et al., 2020): for each language, we identify a **subnetwork**—a subset of model parameters—such that when fine-tuned on in-language data, it performs on par with the full model on that language (Wang et al., 2020). We then use these subnetworks to quantify language-wise modularity in a model by measuring the degree to which the subnetworks depend solely on in-language training examples when making predictions, which we refer to as *language specialization*. Subnetworks are an appealing method for our study because they do not require the introduction of additional model parameters, which means that we are able to use this approach on a model that has not been explicitly modified to add modularity.

Moreover, subnetworks have also proven to be a popular modularization technique because when used to restrict parameter updates as a form of sparse fine-tuning (**SFT**), they are able to guide cross-lingual sharing toward positive transfer and away from negative interference (Lin et al., 2021b; Lu et al., 2022b; Xu et al., 2022; Choenni et al., 2023a; Hendy et al., 2022). However, less is known about precisely what effects SFT has on the underlying model behavior. Thus, we investigate the following set of questions for XLM-R (Conneau et al., 2020a): (1) To what extent does language-wise modularity naturally arise within the model, when it is not explicitly enforced by restricting gradient updates? (2) How do cross-lingual sharing and interference differ between models without modularity interventions versus models with SFT-guided language-wise modularity? (3) How does the degree of language specialization affect model performance? and (4) To what extent does the similarity of language-specific subnetworks dictate cross-language influence?

To quantify cross-language interaction, we follow Choenni et al. (2023b) in using a Training Data Attribution (TDA) method, TracIN (Pruthi et al., 2020), which measures the degree of influence each training example has on a particular model prediction. By examining the influence each language's training set has on the test predictions for individual languages, we can estimate how much influence languages on average exert cross-lingually.

We conduct experiments on three text classification tasks—natural language inference, paraphrasing, and sentiment analysis. For each task, even without special modularity interventions, we are able to identify subnetworks that rely more heavily on in-language data than the full model does. Additionally, we find that SFT does not always increase this modularity, but instead can decrease language specialization within the subnetworks and boost cross-lingual sharing to improve performance. Finally, we provide additional analysis on factors that affect cross-language influence, and find interesting correlations between subnetwork similarity and the amount of positive influence across languages.

5.2 Related work

5.2.1 Modular deep learning

Modular approaches existed before the rise of pre-trained LMs (Shazeer et al., 2016; Andreas et al., 2016), but have recently regained popularity in NLP. The idea is that modular systems will allow us to improve performance in an interpretable way as modularity provides a more intuitive path to compositionality. Various methods have been proposed to implement specialized modules, for instance, by inserting adapter layers into the model (Rebuffi et al., 2017, 2018; Houlsby et al., 2019; Pfeiffer et al., 2022), replacing fine-tuning by prefix-tuning (Li and Liang, 2021), or by SFT with subnetworks (Sun et al., 2020). While the former two aim to create modularity *post-hoc* by injecting task-specific parameters into the existing model, the latter approach aims to induce it into the model as an inductive bias during fine-tuning. In this work, we delve deeper into the effects of SFT to understand whether it is able to produce more modular systems. While some work studies modularity in both vision and language models (Csordás et al., 2020; Zhang et al., 2023; Lepori et al., 2023; Dobs et al., 2022), we are the first to explicitly examine the degree of modularity in multilingual LMs, and to study subnetwork interaction by directly looking at the training data.

5.2.2 Subnetworks and SFT

Frankle and Carbin (2018) showed that subnetworks can be found through pruning methods (Han et al., 2015; Li et al., 2016a) that match the performance of the full model. Since then, it has been shown that such subnetworks exist within BERT models (Prasanna et al., 2020; Budhraja et al., 2021; Li et al., 2022), and that both language-neutral and language-specific subnetworks can be found in multilingual LMs (Foroutan et al., 2022). Hence, sparse training gained popularity in multilingual NLP: Nooralahzadeh and Sennrich (2023) show that training *task-specific* subnetworks can help in cross-lingual transfer, Lin et al. (2021b) use *language-pair-specific* subnetworks for neural machine translation, and Hendy et al. (2022) use *domain-specific* subnetworks. Finally, Wang et al. (2020); Lu et al. (2022b); Choenni et al. (2023a); Xu et al. (2022) use language-specific subnetworks to improve cross-lingual performance on a range of tasks, e.g. speech recognition, dependency parsing and natural language understanding, suggesting that sparse training can reduce negative interference and/or stimulate positive knowledge transfer. While Choenni et al. (2023a) found evidence of the former through fewer gradient conflicts during training (Yu et al., 2020), we are the first to study the effect of SFT on the cross-lingual sharing behaviour by looking at how languages exploit the data from one another cross-lingually.

5.2.3 Training Data Attribution

In this chapter, we again use a TDA method as explained in Chapter 2. Following Chapter 3, we employ TracIN to study cross-lingual sharing in MLMs at the data level. To understand how much influence languages exert cross-lingually, we in Chapter 3 quantify cross-language influence during multilingual fine-tuning by the percentage that each language's training data contributes to the most influential training examples for each test language. While we in Chapter 3 studied the effects of full model fine-tuning, we now employ the same framework to study modularity in LMs by testing to what extent language-specialized subnetworks rely on data from multiple languages and the effect that SFT has on this cross-language reliance.

5.3 Methods

5.3.1 Identifying Subnetworks

Similar to Chapter 4, subnetworks are represented by masks that can be applied to the model to ensure that only a subset of the model's parameters are activated (or updated during training). We again follow Prasanna et al. (2020) in using *structured* masks. Thus, for a language ℓ, its subnetwork is implemented as a binary mask $\xi_\ell \in \{0,1\}^{H \times L}$, where H and L correspond to the number of attention heads and layers. To do so, we apply the procedure introduced by Michel et al. (2019). Starting from a model that is fine-tuned for a task in language ℓ, we iterate by repeatedly removing the 10% of heads with the lowest importance scores, as explained in Chapter 4.4.3.1

5.3.2 Tracing Influence

As explained in Chapter 3, dominating gradients are a known problem in multilingual NLP (Wang et al., 2020). We therefore again use TracIN but adopt the simple normalization trick from Barshan et al. (2020), i.e., substituting the dot product operation with cosine similarity, thus normalizing by the norm of the training gradients. Moreover, LMs have a large number of parameters which makes the inner product computations in the first-order approximation of the influence expensive, especially when computing influence scores for a large number of test points. This greatly reduced the number of test examples that we could compute influence scores for in Chapter 3. Thus, following Pruthi et al. (2020), we now speed up the computations by using random projections, a method that allows us to pre-compute low-memory sketches of the loss gradients of the training points (Woodruff et al., 2014) which can be stored and re-used to compute randomized unbiased estimators of the influence on different test points. To do so, we choose a random matrix $G \in \mathcal{R}^{d \times p}$, where $d \ll p$ is a user-defined dimension for the random projections, whose entries are sampled i.i.d. from $\mathcal{N}(0, \frac{1}{d})$ such that $E[G^T G] = \mathcal{I}$. Similarly, for the fully connected layers with a weight matrix $W \in \mathcal{R}^{m \times n}$, it is also possible to obtain a random projection of the gradient with respect to W into d dimensions. To do so, we use two independently chosen random projection matrices $G1 \in \mathcal{R}^{\sqrt{d} \times m}$ and $G2 \in \mathcal{R}^{\sqrt{d} \times n}$, where $E[G_1 G_1^T] = E[G_2 G_2^T] = I$, and compute:

$$G_1 \nabla_y f(y) x^T G_2^T \in \mathcal{R}^{\sqrt{d} \times \sqrt{d}} \tag{5.1}$$

, which can be flattened into a d-dimensional vector. See Appendix E and F from Pruthi et al. (2020) for more details. Note that throughout our experiments we set $d = 256$.

5.4 Experimental setup

5.4.1 Tasks and datasets

We conduct experiments in the same three tasks as in Chapter 3:

Natural language inference The Cross-Lingual Natural Language Inference (XNLI) dataset (Conneau et al., 2018) contains premise-hypothesis pairs labeled with their relationship: 'entailment', 'neutral' or 'contradiction'. The dataset contains parallel data of which the original pairs come from English and were translated to other languages. We use English, French, German, Russian and Spanish portions of the dataset.

Paraphrasing Cross-Lingual Paraphrase Adversaries from Word Scrambling (PAWS-X) (Yang et al., 2019) requires the model to decide if two sentences are paraphrases of one another. PAWS-X contains translated data from PAWS (Zhang et al., 2019). Part of the development and test sets was translated from English by professionals and the training data was translated automatically. We experiment with English, French, German, Korean and Spanish for model fine-tuning and testing.

Sentiment analysis The Multilingual Amazon Review Corpus (MARC) (Keung et al., 2020) contains Amazon reviews written by users in various languages. Each record in the dataset contains the review text and title, and a star rating. The corpus is balanced across 5 star rating, so that each star rating constitutes 20% of the reviews in each language. Note that this is a non-parallel dataset. We experiment with Chinese, English, French, German and Spanish.

5.4.2 Training techniques

Full model fine-tuning We fine-tune the full XLM-R model (Conneau et al., 2020a) on the concatenation of 2K examples from 5 languages, i.e. 10K examples for each task. As computational costs of TracIN increase with training size, we use a minimal required number of training examples to obtaining reasonably high performance. Thus, we simplify the task to get a better trade-off between the number of training examples and performance. For XNLI, we follow Han et al. (2020) by performing binary classification "entailment or not" ; for MARC, we collapse 1 and 2 stars into a negative and 4 and 5 stars into a positive review category. Training converges at epoch 4 for XNLI, and at epoch 5 for PAWS-X and MARC, obtaining 78%, 83%, and 90% accuracy on their development sets respectively.

Sparse fine-tuning (SFT) We sample language-specific batches in random order, and each time restrict parameter updates to only those parameters that are enabled within the respective language's identified subnetwork. We use the subnetworks during fine-tuning by restricting the model both in the forward and backward pass.[1] We ensure that we sample each language equally often. All other fine-tuning details remain the same as for full model fine-tuning.

Architecture and hyperparameters For each task, we add a simple classifier on top of the pretrained XLM-R base model (Conneau et al., 2020a). The classifier consists of one hidden layer and uses `tanh` activation. We then feed the hidden representation corresponding to the `<S>` token for each input sequence to the classifier for prediction. Moreover, we use AdamW (Loshchilov and Hutter, 2017) as an optimizer, and use learning rates of 2e-5, 9e-6, and 2e-5 for XNLI, PAWS-X and MARC respectively as found to be optimal in Chapter 3.

5.4.3 Evaluation

Computing influence scores We use 500 random test examples from each language and compute influence scores between each test example and all 10K training instances. For each test example, we retrieve the top m=100 training instances with the largest *positive* and the largest *negative* influence scores and refer to them as the set of most positively and negatively influential examples respectively. Note that we use m=100 as it was previously found to be optimal on in Chapter 3.[2] Moreover, negative cosine similarity between gradients have been referred to as gradient conflicts (Yu et al., 2020), and were shown to be indicative of negative interference in the multilingual setting (Wang et al., 2020)[3]. In addition, we ensure that the model was able to predict the correct label for all test instances that we compute influence scores for such that we only study the training examples that influenced the model to make a correct prediction. Also, as we train on parallel data for XNLI and PAWS-X, the content in our training data is identical across languages, giving each language an equal opportunity to be retrieved amongst the most influential examples.

Quantifying cross-language influence After obtaining an influence score ranking over our training set for each test example, we compute how much each training language contributed to the prediction for the test examples in other

[1] We implement this during backpropagation by multiplying the gradients by the binary subnetwork mask, and passing the masked gradients to the optimizer. In the forward pass, we simply disable the attention heads.

[2] Note that we carefully follow the experimental set-up from Choenni et al. (2023b), i.e., we use the same tasks, data and model for our experiments.

[3] When gradients point in opposite directions, the model will update in a suboptimal direction for both examples, hence resulting in negative interference.

languages. We then compare the resulting rankings produced using the full model and an identified subnetwork, see Figure 5.1. As there can be small differences in performance between the subnetworks and the full model, throughout all experiments, we compare cross-language influence for test examples that both models were able to correctly classify.

5.5 Naturally arising modularity

In this section, we study whether modularity has naturally arisen within a model after multilingual full model fine-tuning. As such, the subnetworks are only applied at test time.

5.5.1 How specialized are subnetworks?

To study the degree to which modularity has naturally arisen after full model fine-tuning, we look for subnetworks that naturally specialize in their respective languages. We quantify language specialization as the extent to which the subnetworks rely solely on in-language training data when making test-time predictions. Thus, for each test language, we use the pruning procedure explained in Section 4.4.3 to identify a subnetwork within the fine-tuned model. We then compute influence scores on the fine-tuned model, applying the subnetwork mask corresponding to the language of the test example. Finally, we compare the model's reliance on in-language data when using these subnetworks against its reliance when no subnetwork mask is applied (i.e. when predicting with the full model).

Results In Figure 5.2 we show, per task and test language, the change in contribution (%) to the top 100 most positively and negatively influential examples when using the subnetworks compared to the full model. On the diagonals, we clearly see that for all languages across all tasks, using the subnetwork does mostly result in more positive influence from the respective language (from +1 to +8%). This indicates that we are able to identify language-specialized subnetworks that are more biased toward relying on in-language data, and thus suggests that some form of modularity naturally exists within the model. For baseline results from the full model and more details on the subnetworks, see Appendices C.2 and C.1 respectively. Also, importantly, our results using 500 test examples per language on the full model are similar to those on the same tasks from Choenni et al. (2023b), who performed extensive analysis on the quality of the influence scores.

The effects are less clear when looking at negative influence; here we see that using a language's subnetwork can also decrease negative influence coming from in-language data (e.g. Chinese for MARC). Finally, results from XNLI

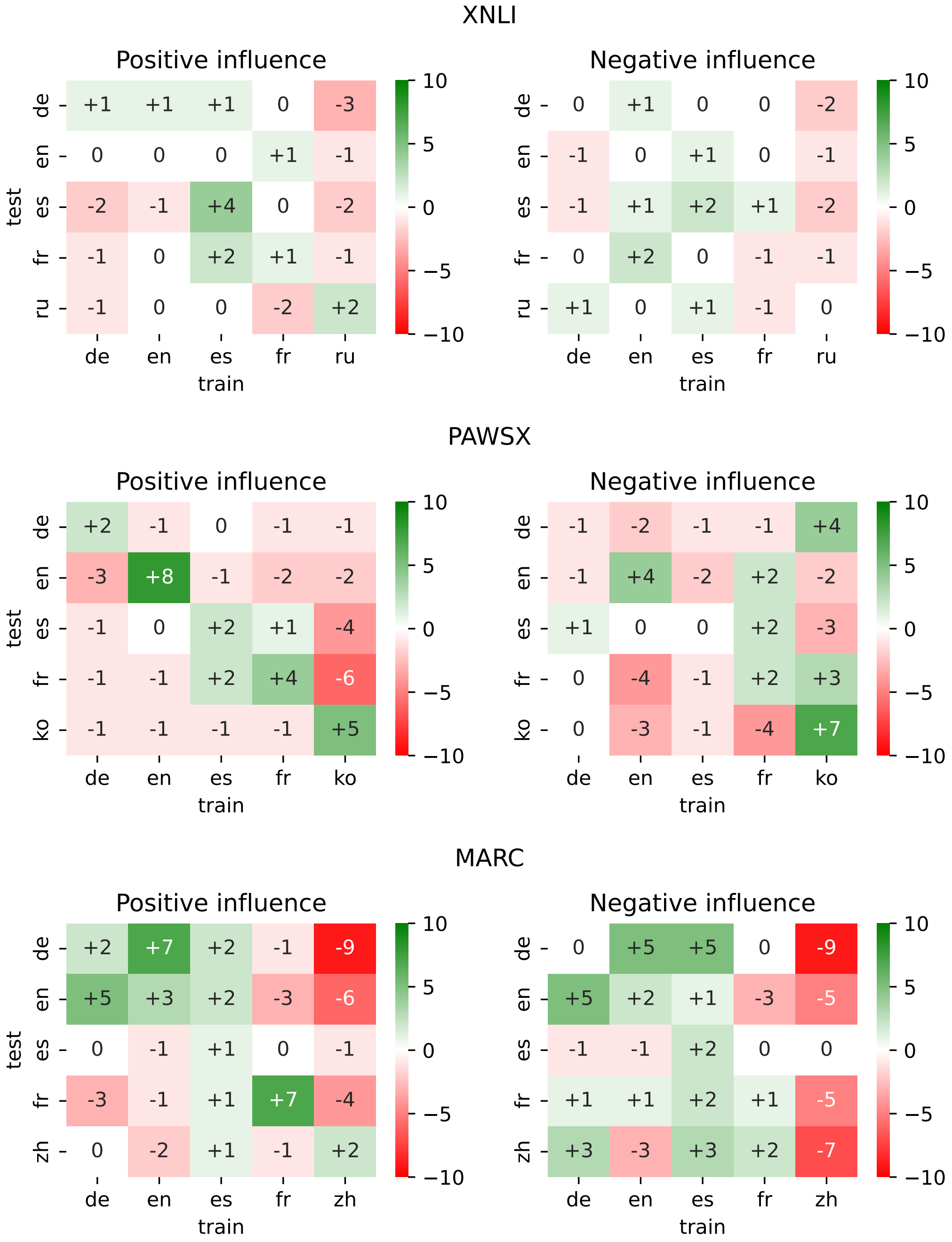


Figure 5.2: **(After full model fine-tuning)** The effect of using the identified language-specific subnetwork for each test language compared to the full model at test time. On the x-axis we have the training language and on the y-axis the test language. The values denote the change (%) in influence from the training on the test language. Results are averaged over all 500 test examples per language.

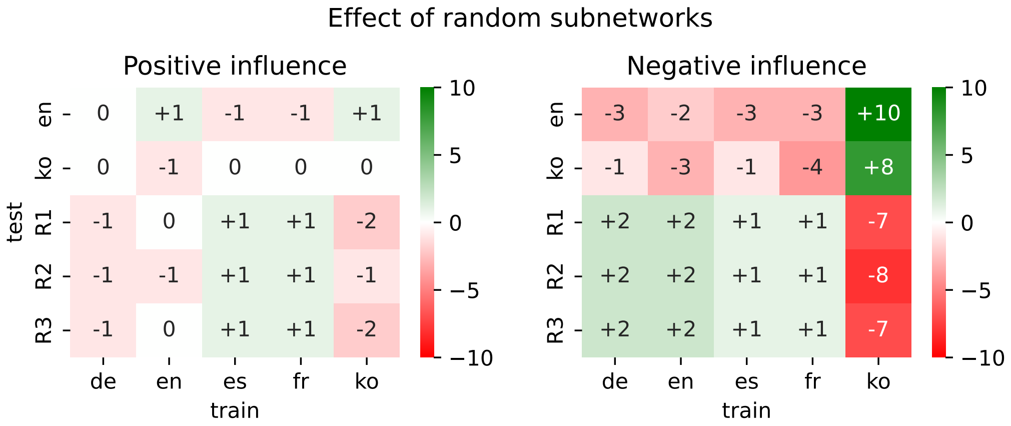


Figure 5.3: **(After full model fine-tuning)** The effect on cross-language influence when using random (R) and suboptimal (English and Korean) subnetworks on German as a test language for PAWS-X.

are overall weaker than for the other tasks. This is in line with results from the full model that showed that, for XNLI, the model relies to the least extent on in-language data, hence we can expect language-specificity to be less strong for these subnetworks. Moreover, for English, we find no difference in language specialization. This can be explained by the fact that the German and Russian subnetworks share 100% of their capacity with English, making its subnetwork less distinct (see Appendix C.1).

Cross-language influence We have shown that language-specialized subnetworks rise. We now analyze how cross-language influence differs within such subnetworks compared to the full model. For MARC, we see that the increase in positive self-influence (diagonal) can be smaller than the increase in positive influence from related languages. In particular, we see that using a German subnetwork strongly increases positive influence from the most typologically similar training language, i.e., English (+7%), and vice versa (+5%). While the change in positive influence from related languages is stronger than that of the respective subnetwork's language, the subnetwork still relies more on in-language data when looking at absolute numbers. For German, the full model was relying for 33% on in-language data, which using its subnetwork increased to 35% (+2%). Yet, English initially only contributed 17% to German, which after using its subnetwork increased to 24% (+7%) (see Appendix C.2 for the full model results). We suspect that we observe the effect of positive knowledge transfer through cross-lingual sharing here. Similar to the full model, when subnetworks have exploited most useful in-language data, they start benefitting more from exploiting other languages' data instead.

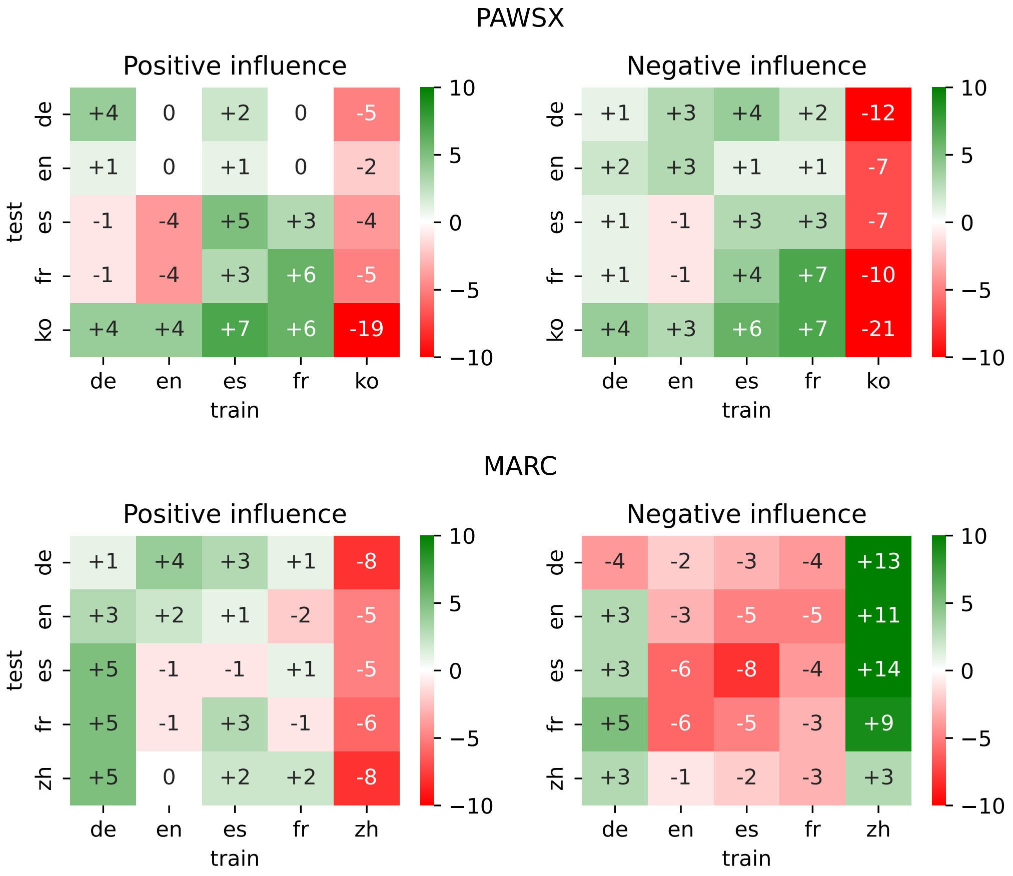


Figure 5.4: **(After SFT)** The effect of using the identified language-specific subnetwork for each test language compared to using the full model at test time. On the x-axis we have the training language and on the y-axis the test language. The values denote the change (%) in influence from the training on the test language. Results are averaged over all 500 test examples per language

5.5.2 Random and suboptimal subnetworks

As baselines to our identified subnetworks, we study whether evidence for language specialization can also be found within random and suboptimal subnetworks for PAWS-X. *Random*: we shuffle the binary subnetwork masks with 3 random seeds, and recompute scores from them. Note that we do this only for German—we saw the weakest increase in language-specificity for German (+2%, see Figure 5.2), thus it should be the easiest to get similar results from a random subnetwork. *Suboptimal*: we pick the subnetwork from the most similar and distant language to German, i.e., English and Korean, and recompute influence scores for German (i.e., testing the effect of applying the subnetwork from a language A to a language's B's input.).

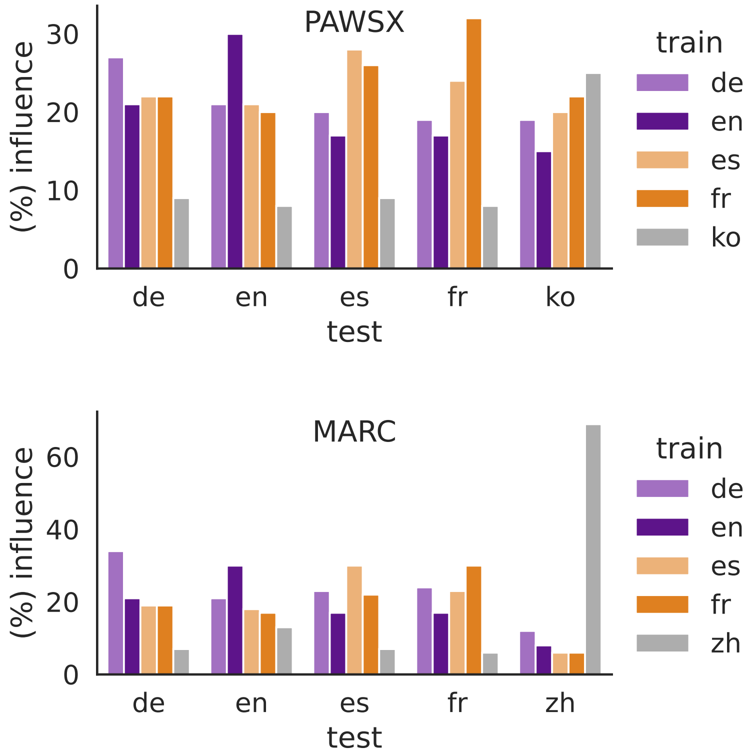


Figure 5.5: The positive influence (%) from each training language on each test language in absolute numbers. The values are retrieved from the subnetworks after SFT. Note that the y-axes are not on the same scale.

Results In Figure 5.3, we find that using random subnetworks overall causes little change to the score distributions as compared to the full model. In particular, we find that in none of the cases the influence of German increases. Also, it is evident that the behavior from the suboptimal subnetworks is different from the random subnetworks. For instance, we find that using either the correct English or Korean subnetworks result in a strong increase of negative interference from Korean (+10 and 8%). Yet, when we use the random subnetworks we instead observe a strong tendency for Korean to decrease in negative influence. These results show that our identified subnetworks encode meaningful differences compared to randomly selected ones.

5.6 How does SFT affect modularity?

In Section 5.5, we studied whether modularity had naturally arisen in the model in the form of language-specialized subnetworks. We now study the effect that SFT has on these subnetworks, i.e., does it further encourage modularity within the model? Thus, instead of only applying the subnetworks at test time, as was done in the previous section, we now use the same identified subnetworks, but apply them both during SFT and at test time. We then recompute influence scores between test and training examples, and observe the change in language specialization compared to full model fine-tuning. This way, we test whether SFT, compared to full model fine-tuning, causes the subnetworks to further specialize on in-language data.

Given that the subnetworks found for XNLI had the smallest effect on cross-language data reliance, and we did not find a distinct English subnetwork, we conduct further experiments on PAWS-X and MARC (that contain parallel and non-parallel data respectively) to reduce computational costs. Also, we confirm that SFT improves performance on both tasks (see Appendix C.3). For PAWS-X, we obtain an average test accuracy of 74.8% when using subnetworks after full model fine-tuning and 78.4% after SFT (+3.6%). For MARC we see an average improvement of +1.2% when using SFT.

Results In Figure 5.4, we see the change in language influence compared to using the full model. We find that the in-language data reliance of some subnetworks tends to decrease after SFT (i.e., Korean for PAWS-X and Chinese, French, and Spanish for MARC). This is surprising given that SFT is generally seen as a modularization technique. Whilst it is important to note that all subnetworks still mostly rely on in-language data as shown by the absolute numbers reported in Figure 5.5, our results suggest that the benefit of SFT cannot fully be attributed to language specialization of the subnetworks. Instead, cross-lingual sharing, guided through subnetwork interaction, is likely a contributing factor as well. Finally, as our results suggest that SFT does not necessarily strengthen language specialization, it sheds doubt on SFT as a method for creating more modular systems.

5.6.1 SFT with random subnetworks

As a baseline to our previous findings, we now test whether any randomly found subnetwork could in principle be taught to specialize in a language when we use SFT as a training method. Thus, for each language, we shuffle the language-specific subnetworks to obtain a random subnetworks with the same sparsity level. We then use these random subnetworks, both during SFT and at test time, and repeat the procedure from Section 5.6.

Results Surprisingly, in Figure 5.6, we see that random subnetworks to a much larger extent rely on in-language data than the identified subnetworks used in Section 5.6. In particular, we see that the model barely relies on cross-lingual sharing for English (+64% compared to the full model, which results

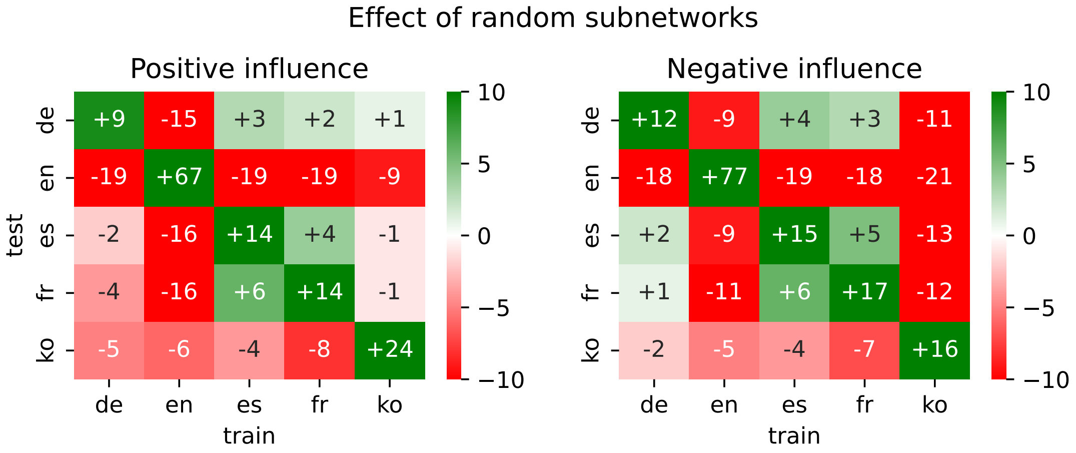


Figure 5.6: **(After SFT)** The effect that SFT with *random* subnetworks has for PAWS-X on the amount of language specialization that the subnetworks acquire compared to full model fine-tuning.

in 97% reliance on English data when using the subnetwork). Yet, we also find that these highly specialized subnetworks perform considerably worse, on average only obtaining ±56% across languages. Given that random subnetworks do not contain the necessary information to process the language, we hypothesize that (1) during SFT they need to learn both the task and language, which causes them to focus on in-language data first, and (2) cross-lingual sharing will only happen once the in-language data has been fully exploited. Our results show that any subnetwork can in principle learn to specialize in one language, but that this might be suboptimal.

5.7 Further analysis

In Section 5.6, we show that SFT only sometimes causes our identified subnetworks to rely more on in-language data, yet unlike random subnetworks, do seem to encode meaningful information. To understand where the performance improvements from SFT come from, we perform further analysis on how language specialization correlates with performance, and how subnetwork similarity affects cross-language influence.

5.7.1 Correlation between language specialization and performance

We find that SFT only decreases performance on French for PAWS-X (Table C.2, Appendix C.3), which happens to also be the subnetwork that showed the strongest increase in language specialization after SFT (+6%) in Section 5.6. To

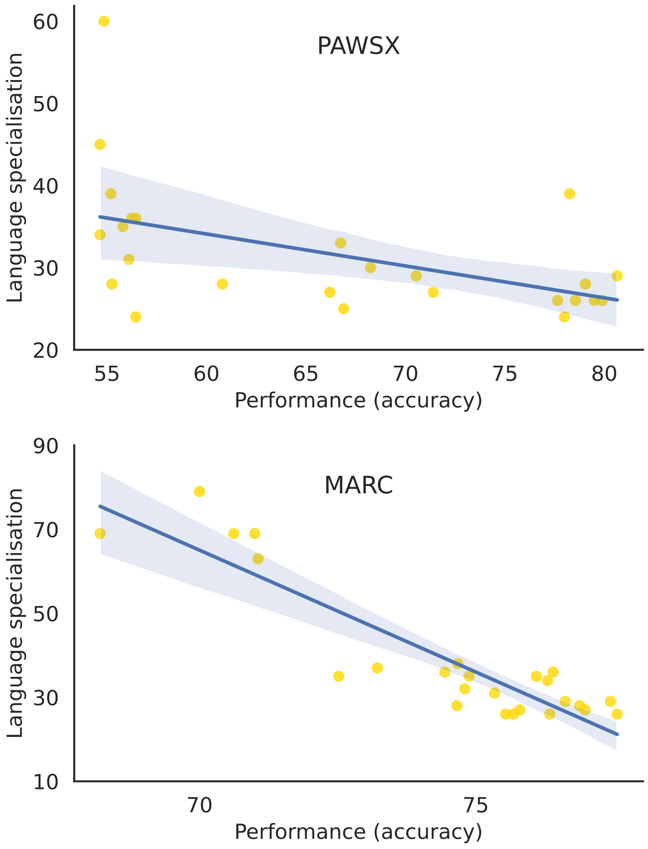


Figure 5.7: The correlation between language specialization and performance accuracy for PAWS-X and MARC. We compute scores for all languages and model checkpoints.

test to what degree subnetwork performance benefits from language specialization, we study the correlation between the two using data from all model checkpoints.

Results In Figure 5.7, we see that, for both tasks, stronger language specialization is negatively correlated with model performance. This finding further supports our hypothesis that the strength of SFT really comes from cross-lingual sharing that happens between the subnetworks rather than from the language specialization of the subnetworks themselves. Intuitively, this makes sense as SFT forces the model to squeeze information into the smaller subsets of model parameters, which has to improve performance on a set of training languages, and as such, requires better cross-lingual sharing.

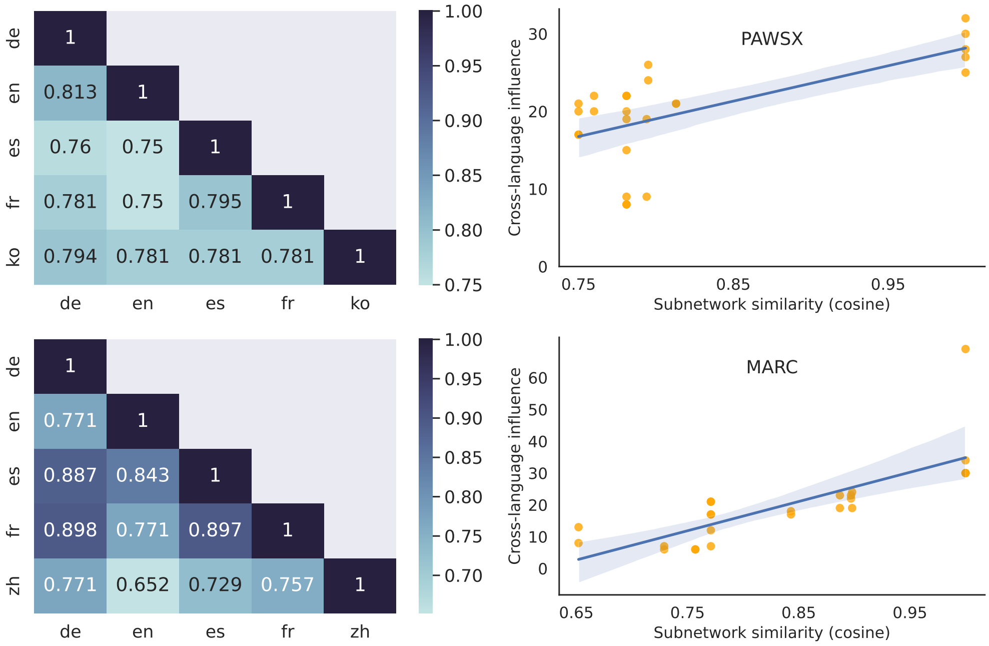


Figure 5.8: (**Left**) The cosine similarity between the flattened binary subnetwork masks for each language pair. (**Right**) Positive cross-language influence as a function of structural (cosine) similarity between subnetworks.

5.7.2 Correlation between subnetwork similarity and cross-language influence

SFT allows for cross-lingual interaction through subnetwork overlap in which the model parameters are shared between languages. This sharing mechanism is motivated by the idea that similar languages are encoded by similar subnetworks (and thus naturally dictating cross-lingual sharing by their overlap). To test this hypothesis we study the correlation between subnetwork similarity and cross-language influence between language pairs. We measure similarity by the cosine similarity between the flattened binary subnetwork masks.

Results In Figure 5.8 (Left) we report the cosine similarity between the subnetworks of each language pair and (Right) the correlation between such subnetwork similarity and positive cross-language influence (in absolute numbers). From this, we find that for both tasks, subnetwork similarity is positively correlated with positive cross-language influence. Yet, we did not find a strong correlation between negative cross-language influence and subnetwork overlap. This is a promising finding, as it suggests that positive and negative influence do not necessarily have to go hand-in-hand. Thus, future work should investigate how we can further exploit subnetwork overlap to increase positive influence without increasing negative influence as well. Moreover, it is

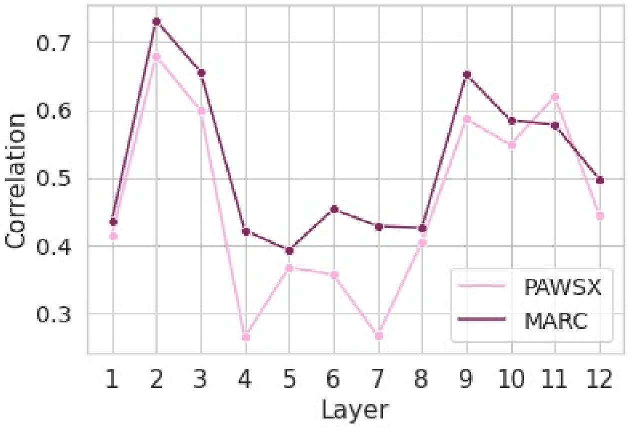


Figure 5.9: The correlation between positive cross-language influence and the subnetwork similarity computed based on individual model layers.

evident that for MARC the subnetworks show on average more overlap than for PAWS-X. Thus as the capacity within subnetworks from MARC have to be shared with more languages, it can explain why their language specialization is less strong as seen in Figure 5.4. Future work should test whether SFT is still effective when using many more training languages (in which case subnetwork overlap will inevitably be higher).

Layer-wise analysis To further analyze how subnetwork similarity affects cross-language influence, we now test how layer-wise subnetwork similarity correlates with performance. In Figure 5.9, we see that similarity between certain layers is much more indicative of cross-language influence, and moreover, that both tasks follow very similar patterns despite ending up with vastly different subnetworks. This suggests that while language-specific subnetworks are also task-specific, there may be general language-specific properties across task-specific subnetworks that we can identify and exploit to better guide cross-lingual sharing.

5.7.3 What happens within subnetworks during full model fine-tuning versus SFT?

In Sections 5.5 and 5.6 we used the sum of influence scores over model checkpoints to compute influence scores. We now conduct the same experiments, but instead study how cross-language influence changes over time while using the different fine-tuning strategies. To do so, we now analyze the influence scores (and their corresponding rankings) from each checkpoint separately.

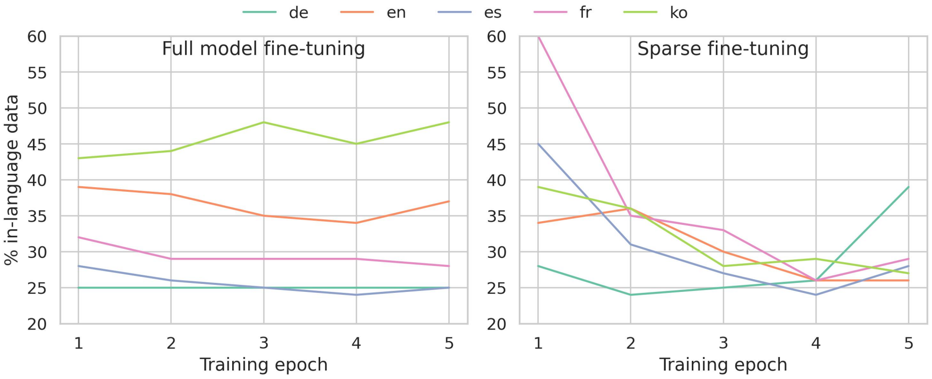


Figure 5.10: The change in language specialization of subnetworks over training epochs for PAWS-X.

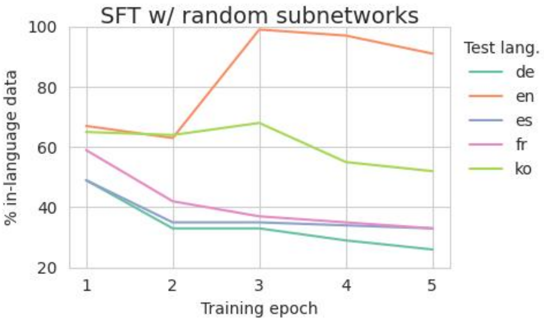


Figure 5.11: The language specialization effect of SFT with random subnetworks on PAWS-X over training epochs.

Results In Figure 5.10 we see that while both fine-tuning techniques converge to similar maximum levels of cross-lingual sharing (∼25% reliance on in-language data) for PAWS-X, SFT allows for *all* training languages to start sharing more data. Whereas for full model fine-tuning, we instead see that Korean and English are left behind (see Appendix C.3 for results on MARC). Also, in Figure 5.11, we find that using random subnetworks for SFT on PAWS-X, similarly to full model fine-tuning, results in Korean and English staying more isolated from the other three languages. This suggests that when we use random subnetworks for SFT, the model can not benefit from better cross-lingual sharing in the same way as when we identify the subnetworks via pruning. In line with results in Sections 5.6.1 and 5.7.2, we conclude that the subnetworks meaningfully overlap to enable better cross-lingual interaction during SFT.

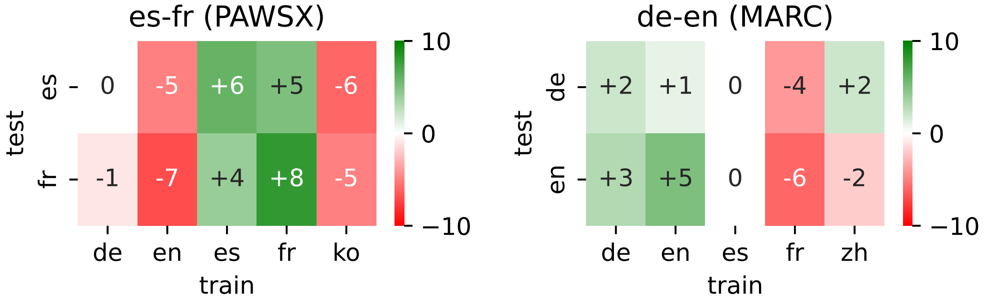


Figure 5.12: The effect on the contribution of positive influence from each training language when composing two language's subnetworks by their intersect and applying them at test time (compared to full model fine-tuning).

5.7.4 Composing subnetworks at test time

As an additional analysis, we study whether we can compose two languages' identified subnetworks into a language-pair specific subnetwork that, when applied at test time, will enforce more cross-lingual reliance on each other's training data. For merging two subnetworks we both tried taking the union and the intersect of the respective binary subnetwork masks. Note that we apply the composed subnetwork only at test time to a model that was trained with SFT (using the initial identified subnetworks).

Results We find that we can only successfully enforce cross-lingual sharing through subnetwork composition for two languages, if those individual language's subnetworks already stimulated cross-lingual sharing between the pair. For instance, in Figure 5.4, we saw that both the Spanish and French subnetworks (PAWS-X) and the German and English ones (MARC) resulted in more sharing between the pairs. In Figure 5.12, we show that taking the intersections of those language pairs' subnetworks can further strengthen this behavior (taking their union resulted in sharing to a lesser extent) Trying to control sharing behavior by composing two language-specialized subnetworks that individually did not lead to more sharing between the pair did not yield any clear positive results. This suggests that while SFT can enhance cross-lingual sharing, there is still much room for improvement when it comes to creating a truly modular system that enables compositionality.

5.8 Conclusion

We studied to what degree modularity, in the form of language-specialized subnetworks, naturally arises within multilingual LMs. We demonstrate the existence of such subnetworks using TracIN to monitor the change in reliance on in-language data at test time when using subnetworks compared to the full model. Moreover, addressing RQ2, we studied the effects that SFT has on modularization, and find that it does not cause all subnetworks to become more specialized. Yet, in all cases, our identified subnetworks show vastly different behavior from random ones, indicating that we are able to uncover meaningful language-specific model behavior. Finally, further contributing to RQ1 from the introduction,we find that subnetwork similarity, particularly in specific model layers, correlates with positive, but not negative, cross-language influence. This demonstrates that cross-lingual sharing at the parameter level can positively affect cross-language influence. Future work should focus on further exploiting subnetworks and their interaction to better control cross-lingual sharing.

5.9 Limitations

As we pointed out in Chapter 3, a limitation of TDA methods in general is that the experiments are computationally expensive to run. While using the random projection method somewhat mitigates the problem, it still prevents us from studying a wider range of LMs and/or larger models. Similarly, due to the computational costs, we are still restricted to relatively easy tasks as (1) we can not use a large fine-tuning dataset and (2) TracIN operates on the sequence-level, i.e., it estimates how much a full training instance contributed to a prediction, making this method mostly suitable for classification and regression tasks. Given that the tasks are relatively simple, this might also limit the benefit of SFT over full model fine-tuning, hence the degree of language specialization that we observe after SFT might be weaker than if we had studied more complicated tasks and/or tasks that generally require more language-specific information (e.g., language modelling or dependency parsing).

PART 2: MULTICULTURALISM

Chapter 6

Stereotypical Knowledge in Language Models

Chapter Highlights

In this chapter, we address RQ3 from the introduction by investigating what types of stereotypical information are captured by pretrained language models. We present the first dataset comprising stereotypical attributes of a range of social groups and propose a method to elicit stereotypes encoded by pretrained language models in an unsupervised fashion. Moreover, we link the emergent stereotypes to their manifestation as basic emotions as a means to study their emotional effects in a more generalized manner. To demonstrate how our methods can be used to analyze emotion and stereotype shifts due to linguistic experience, we use fine-tuning on news sources as a case study. Our experiments expose how attitudes towards different social groups vary across models and how quickly emotions and stereotypes can shift at the fine-tuning stage.

Warning*: this study contains content that may be offensive or upsetting.*

6.1 Introduction

Pretraining strategies for large-scale language models (LMs) require unsupervised training on large amounts of human generated text data. While highly successful, these methods come at the cost of interpretability as it has become increasingly unclear what relationships they capture. Yet, as their presence in society increases, so does the importance of recognising the role they play in perpetuating social biases. In this regard, Bolukbasi et al. (2016) first discovered that contextualized word representations reflect gender biases captured in the training data. What followed was a suite of studies that aimed to quantify and mitigate the effect of harmful social biases in word (Caliskan et al., 2017) and sentence encoders (May et al., 2019). Despite these studies, it has remained difficult to define what constitutes "bias", with most work focusing on "gender bias" (de Vassimon Manela et al., 2021; Sun et al., 2019) or "racial bias" (Davidson et al., 2019; Sap et al., 2019). More broadly, biases in the models can comprise a wide range of harmful behaviors that may affect different social groups for various reasons (Blodgett et al., 2020).

In this work, we take a different focus and study stereotypes that emerge within pretrained LMs instead. While bias is a personal preference that can be harmful when the tendency interferes with the ability to be impartial, stereotypes can be defined as a preconceived idea that (incorrectly) attributes general characteristics to all members of a group. While the two concepts are closely related i.e., stereotypes can evoke new biases or reinforce existing ones, stereotypical thinking appears to be a crucial part of human cognition that often emerges implicitly (Hinton, 2017). Hinton (2017) argued that implicit stereotypical associations are established through Bayesian principles, where the experience of their prevalence in the world of the perceiver causes the association. Thus, as stereotypical associations are not solely reflections of cognitive bias but also stem from real data, we suspect that our models, like human individuals, pick up on these associations. This is particularly true given that their knowledge is largely considered to be a reflection of the data they are trained on. Yet, while we consider stereotypical thinking to be a natural side-effect of learning, it is still important to be aware of the stereotypes that models encode. Psychology studies show that beliefs about social groups are transmitted and shaped through language (Maass, 1999; Beukeboom and Burgers, 2019). Thus, specific lexical choices in downstream applications not only reflect the model's attitude towards groups but may also influence the audience's reaction to it, thereby inadvertently propagating the stereotypes they capture (Park et al., 2021).

Studies focused on measuring stereotypes in pretrained models have thus far taken supervised approaches, relying on human knowledge of common stereotypes about (a smaller set of) social groups (Nadeem et al., 2021; Nangia et al., 2020). This, however, bears a few disadvantages: (1) due to the implicit nature of stereotypes, human defined examples can only expose a subset of popular stereotypes, but will omit those that human annotators are unaware of (e.g. models might encode stereotypes that are not as prevalent in the real world); (2) stereotypes vary considerably across cultures (Dong et al., 2019), meaning that the stereotypes tested for will heavily depend on the annotator's cultural frame of reference; (3) stereotypes constantly evolve, making supervised methods difficult to maintain in practice. Therefore, similar to Field and Tsvetkov (2020), we advocate the need for implicit approaches to expose and quantify bias and stereotypes in pretrained models.

We present the first dataset of stereotypical attributes of a wide range of social groups, comprising $\sim$ 2K attributes in total. Furthermore, we propose a stereotype elicitation method that enables the retrieval of salient attributes of social groups encoded by state-of-the-art LMs in an unsupervised manner. We use this method to test the extent to which models encode the human stereotypes captured in our dataset. Moreover, we are the first to demonstrate how training data at the fine-tuning stage can directly affect stereotypical associations within the models. In addition, we propose a complementary method to study stereotypes in a more generalized way through the use of emotion profiles, and systematically compare the emerging emotion profiles for different social groups across models. We find that all models vary considerably in the information they encode, with some models being overall more negatively biased while others are mostly positive instead. Yet, in contrast to previous work, this study is not meant to advocate the need for debiasing. Instead, it is meant to expose varying implicit stereotypes that different models incorporate and to bring awareness to how quickly attitudes towards groups change based on contextual differences in the training data used both at the pretraining and fine-tuning stage.

6.2 Related work

Previous work on stereotypes While studies that explicitly focus on stereotypes have remained limited in NLP, several works on bias touch upon this topic (Blodgett et al., 2020). This includes, for instance, studying specific phenomena such as the infamous 'Angry Black Woman' stereotype and the 'double bind' (Heilman et al., 2004) theory (Kiritchenko and Mohammad, 2018; May et al., 2019; Tan and Celis, 2019), or relating model predictions to gender stereotype lexicons (Field and Tsvetkov, 2020). To the best of our knowledge, Nadeem et al. (2021); Nangia et al. (2020) and de Vassimon Manela et al. (2021) are the first to explicitly study stereotypes in pretrained sentence encoders. While de Vassimon Manela et al. (2021) focus on gender stereotypes using the WinoBias dataset (Zhao et al., 2018), the other works propose new crowdsourced datasets (i.e. StereoSet and Crowspair) with stereotypes that cover a wide range of social groups. All datasets, however, have a similar set-up: they contain pairs of sentences of which one is more stereotypical than the other. Working in the language modeling framework, they evaluated whether the model "prefers" the stereotypical sentence over the anti-stereotypical one. In contrast, we propose a different experimental setup and introduce a new dataset that leverages search engines' autocomplete suggestions for the acquisition of explicit stereotypical attributes. Instead of indirectly uncovering stereotypes through comparison, our elicitation method directly retrieves salient attributes encoded in the models. Our technique is inspired by Kurita et al. (2019), but while they measure the LM probability for completing sentences with the pronouns *she* and *he* specifically, we study the top k salient attributes without posing any restrictions on what these could be. Moreover, we are the first to include both monolingual and multilingual models in our analysis.

Stereotype-driven emotions Stereotypes are constantly changing and identifying negative ones in particular, is an inherently normative process. While some stereotypes clearly imply disrespect (e.g., women are incompetent), others emerge from excessive competence instead (e.g., Asians are good at math). Moreover, stereotypical content is heavily influenced by the social pressures of society at the time. Cuddy et al. (2009) argue that no stereotype remains stable and predictable from theoretical principles. Hence, many social psychologists have abandoned the study of stereotype content to focus on systematic principles that generalize across different specific instances of stereotypes instead, presumably making them more stable over time and place (Cuddy et al., 2009; Mackie et al., 2000; Weiner, 1993). Similarly, we explore a more robust approach to uncovering stereotypes in pretrained LMs by studying how stereotypes are more generally manifested as varying emotion profiles in the models. Previous works show that groups evoke different emotional profiles (Cottrell and Neuberg, 2005; Tapias et al., 2007; Mackie et al., 2000), and a variety of theories link particular intergroup relations to distinct stereotype-driven emotions such as disgust and anger (Harris and Fiske, 2006, 2009).

6.3 Stereotypes from search engines

Retrieving human stereotypes in an implicit manner can be useful as people are likely to give more politically correct answers when asked for stereotypes explicitly. Questions we ask to search engines are often done in the comfort of our own homes, making them likely to reflect true stereotypes that are out there in the real world (Stephens-Davidowitz, 2018). When feeding search engines queries that already imply a stereotype about a specific social group, the suggested completions are often salient (i.e. stereotypical) attributes of that particular group e.g., search query: *'Why are Asian parents so'* → completion: *'strict'*. As the autocomplete suggestions are based on popular human generated queries, we exploit this property for the acquisition of stereotypical attributes.

Social groups We use 382 social groups which we divide into 9 categories: age (11), gender (26), profession (115), race (99), country (73), religion (10), political (9), sexuality (12) and lifestyle (19). See Appendix D.3 for the full lists of social groups per category. The social groups include, but are not limited to, the ones used by Nadeem et al. (2021) who collected Wikidata relation triples to automatically retrieve target terms.

Templates To increase coverage, we design 5 slightly varying templates to retrieve autocomplete suggestions for. For groups pertaining to people we use the templates:

- 'Why are [TGT] so [ATTR] ?'
- 'What makes [TGT] so [ATTR]?'
- 'How come [TGT] are so [ATTR]?'
- 'Why are [TGT] always so [ATTR]?'
- 'Why are all [TGT] so [ATTR]?'

For countries we use:

- 'Why is [TGT] so [ATTR] ?'
- 'What makes [TGT] so [ATTR]?'
- 'How come [TGT] is so [ATTR]?'
- 'Why is [TGT] always so [ATTR]?'
- 'Why are all people in [TGT] so [ATTR]?'

[TGT] are the social groups for which we search stereotypes and [ATTR] is the salient attribute with which the search engine completes the sequence. We tested other (longer and more elaborate) templates but we found that they did not produce many autocomplete suggestions. In fact, we believe that the above queries are so successful precisely because of their simplicity, given that people are likely to keep search queries concise.

Search engines Due to Google's hate speech filtering system the autocompletion feature is disabled for frequently targeted groups e.g. black people, Jewish people and members of the LGBTQ+ community. Thus, we retrieve autocomplete suggestions from 3 search engines: Google, Yahoo and DuckDuckGo. In many cases, identical completions were given by multiple search engines. We sort these duplicate samples under the category 'multiple engines'. We find that most negative (offensive) stereotypes are retrieved from Yahoo.

Search query	Category	Social group	Stereotypical attributes	Search engine
Why are black people so	race	black people	fast, athletic, hated, angry, loud	Yahoo
Why are british people so	race	british people	polite, pale, tall, reserved, cold	DuckDuckGo
Why are californians so	lifestyle	californians	entitled, rich, flaky, backstabby	multiple
Why are comedians so	profession	comedians	funny, sad, intelligent, depressed	Google
Why are millennials so	age	millennials	fragile, nostalgic, lonely, broke	Google
Why is Norway so	country	Norway	healthy, wealthy, happy, rich	multiple
Why are conservatives so	political	conservatives	angry, controlling, racist	Yahoo
Why are mormons so	religion	mormons	misunderstood, rich, succesful, nice	multiple

Table 6.1: A few (random) examples of stereotypical attributes sampled from the dataset. Note that the number of attributes vary as we do not retrieve the same number for each social group per search engine.

Category	Number	Category	Number
Profession	713	Age	171
Race	412	Lifestyle	123
Country	396	Politics	50
Gender	198	Religion	36

Table 6.2: Number of stereotypical attributes in our stereotypes dataset per category. Across all categories, the dataset contains 2099 stereotypes.

Pre-processing We clean up the dataset manually, using the following procedure:

1. Remove noisy completions that do not result in a grammatically correct sentence e.g. non adjectives.
2. Remove specific trend-sensitive references: e.g. to video games 'why are asians so good at *league of legends*'.
3. Remove neutral statements not indicative of stereotypes e.g. 'why are `[TGT]` so *called*'.
4. We filter out completions consisting of multiple words.[1] Yet, when possible, the input is altered such that only the key term has to be predicted by the model e.g., 'Why are *russians* so x', where x = good at playing chess → 'Why are *russians* so good at x', x = chess.

The final dataset contains approximately 2K stereotypes about 274 social groups. The distribution of stereotypical completions across categories is reported in Table 6.2. Interestingly, none of the search engines produce stereotypical autocomplete suggestions for members of the LGBTQ+ community. In Table 6.1 we provide some examples from the dataset. See Appendix D.2 for more details on the data acquisition and search engines. The full code and dataset are publicly available.

6.4 Correlating human stereotypes with salient attributes in pretrained models

To test for human stereotypes, we propose a stereotype elicitation method that is inspired by cloze testing, a technique that stems from psycholinguistics. Using our method we retrieve salient attributes from the model in an unsuper-

[1] Although incompatible with our set-up, we do not remove them from the dataset as they can be valuable in future studies.

Prior	Post
1. memory	1. memory
2. math	2. alcohol
3. money	3. technology
4. children	4. dates

Table 6.3: Ranking:‘why are **old people** so **bad with**’.

vised manner and compute recall scores over the stereotypes captured in our search engine dataset.

Pretrained models We study different types of pretrained LMs of which 3 are monolingual and 2 multilingual: **BERT** (Devlin et al., 2019a) uncased trained on the `BooksCorpus` dataset (Zhu et al., 2015) and `English Wikipedia`; **RoBERTa** (Liu et al., 2019a), the optimized version of BERT that is in addition trained on data from `CommonCrawl News` (Nagel, 2016), `OpenWebTextCorpus` (Gokaslan and Cohen, 2019) and `STORIES` (Trinh and Le, 2018); **BART**, a denoising autoencoder (Lewis et al., 2020) that while using a different architecture and pretraining strategy from RoBERTa, uses the same training data. Moreover, we use **mBERT**, that apart from being trained on `Wikipedia` in multiple languages, is identical to BERT. We use the uncased version that supports 102 languages. Similarly, **XLM-R** is the multilingual variant of RoBERTa (Conneau et al., 2020b) that is trained on cleaned `CommonCrawl` data (Wenzek et al., 2020) and supports 100 languages. We include both versions of a model (i.e. **B**ase and **L**arge) if available. Appendix D.1 provides more details on the models.

Stereotype elicitation method For each sample in our dataset we feed the model the template sentence and replace `[ATTR]` with the `[MASK]` token. We then retrieve the top $k = 200$ model predictions for the `MASK` token, and test how many of the stereotypes found by the search engines are also encoded in the LMs. We adapt the method from Kurita et al. (2019) to rank the top k returned model outputs based on their typicality for the respective social group. We quantify typicality by computing the log probability of the model probability for the predicted completion corrected for by the prior probability of the completion e.g.:

$$P_{post}(y = \text{strict} \mid \text{Why are parents so } y\text{ ?}) \tag{6.1}$$

$$P_{prior}(y = \text{strict} \mid \text{Why are } \texttt{[MASK]} \text{ so } y\text{ ?}) \tag{6.2}$$

$$p = log(P_{post}/P_{prior}) \tag{6.3}$$

i.e., measuring association between the words by computing the chance of completing the template with ‘strict’ given ‘parents’ corrected by the prior chance of 'strict' given any other group. Note that Eq. 6.3 has been well-established as a measure for stereotypicality in research from both social psychology (McCauley et al., 1980) and economics (Bordalo et al., 2016). After re-ranking by typicality, we evaluate how many of the stereotypes are correctly retrieved by the model through recall@k for each of the 8 target categories.

Results Figure 6.1 shows the recall@k scores per model separated by category, showcasing the ability to directly retrieve stereotypical attributes of social groups using our elicitation method. While models capture the human stereotypes to similar extents, results vary when comparing across categories with most models obtaining the highest recall for country stereotypes. Multilingual models obtain relatively low scores when recalling stereotypical attributes pertaining to age, gender and political groups. Yet, XLMR-L is scoring relatively high on stereotypical profession and race attributes. The suboptimal performance of multilingual models could be explained in different ways. For instance, as multilingual models are known to suffer from negative interference (Wang et al., 2020), their quality on individual languages is lower compared to monolingual models, due to limited model capacity. This could result in a loss of stereotypical information. Alternatively, multilingual models are trained on more culturally diverse data, thus conflicting information could counteract within the model with stereotypes from different languages dampening each other's effect. Cultural differences might also be more pronounced when it comes to e.g. age and gender, whilst profession and race stereotypes might be established more universally.

6.5 Quantifying emotion towards different social groups

To study stereotypes through emotion, we draw inspiration from psychology studies showing that stereotypes evoke distinct emotions based on different types of perceived threats (Cottrell and Neuberg, 2005) or perceived social status and competitiveness of the targeted group (Fiske, 1998). For instance, Cottrell and Neuberg (2005) show that both feminists and African Americans elicit anger, but while the former group is perceived as a threat to social values, the latter is perceived as a threat to property instead. Thus, the stereotypes that underlie the emotion are likely different. Whilst strong emotions are not evidence of stereotypes per se, they do suggest the powerful effects of subtle biases captured in the model. Thus, the study into emotion profiles provides us with a good starting point to identify which stereotypes associated with the social groups evoke those emotions. To this end, we (1) build emotion profiles for social groups in the models and (2) retrieve stereotypes about the groups that most strongly elicit emotions.

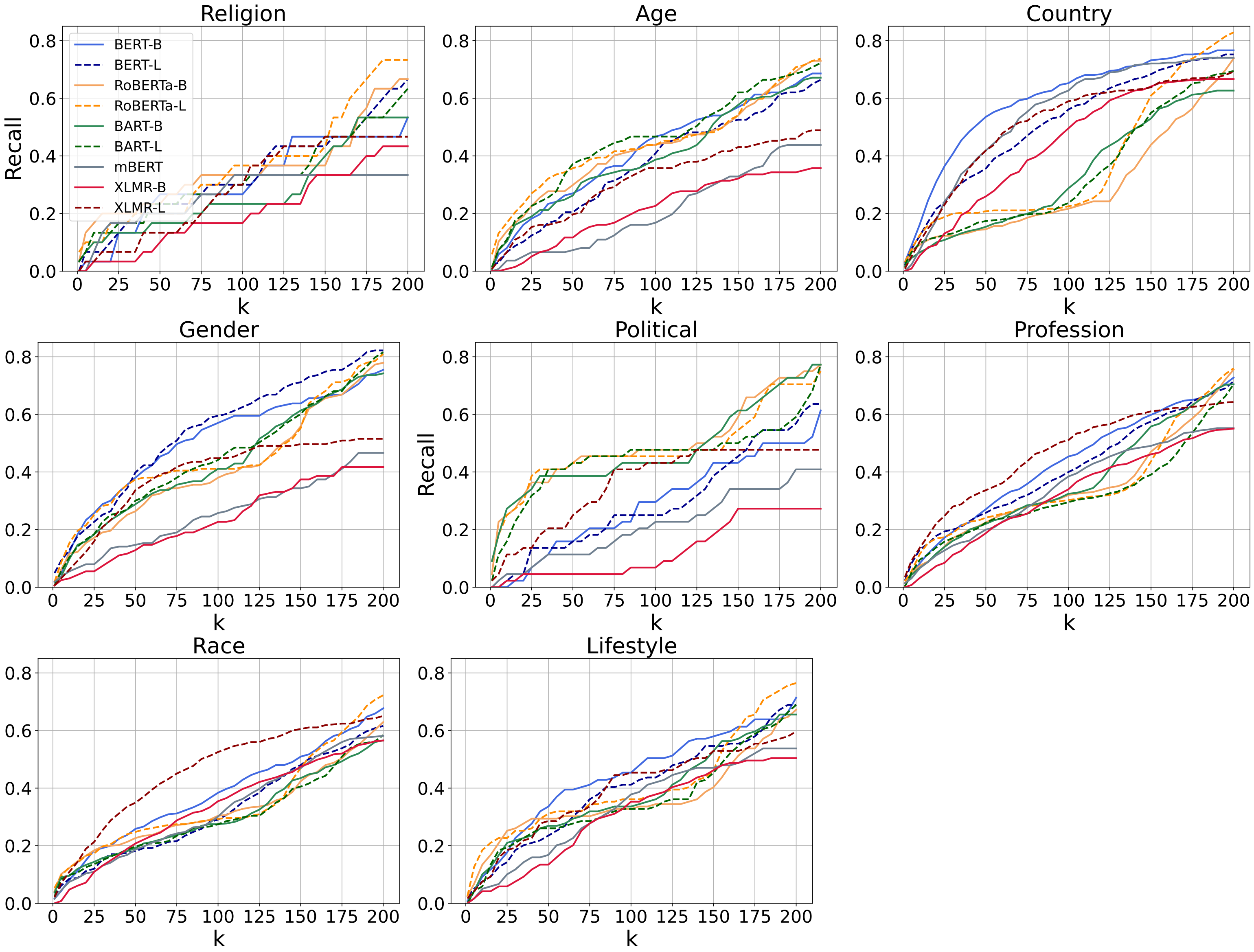


Figure 6.1: Recall@k scores for recalling the human-defined stereotypes captured in our dataset using our stereotype elicitation method on various pretrained LMs.

Model predictions To measure the emotions encoded by the model, we feed the model the 5 stereotype eliciting templates for each social group and retrieve the top 200 predictions for the `[MASK]` token (1000 in total). When taking the 1000 salient attributes retrieved from the 5 templates, we see that there are many overlapping predictions, hence we are left with only approx. between 300-350 unique attributes per social group. This indicates that the returned model predictions are robust with regard to the different templates.

Emotion scoring For each group, we score the predicted set of stereotypical attributes W_{TGT} using the NRC emotion lexicon (Mohammad and Turney, 2013) that contains $\sim$ 14K English words that are manually annotated with Ekman's eight basic emotions (fear, joy, anticipation, trust, surprise, sadness, anger, and disgust) (Ekman, 1999) and two sentiments (negative and positive). These emotions are considered basic as they are thought to be shaped by natural selection to address survival-related problems, which is often denoted as a driving factor for stereotyping (Cottrell and Neuberg, 2005). We use the annotations that consist of a binary value (i.e. 0 or 1) for each of the emotion categories; words can have multiple underlying emotions (e.g. *selfish* is annotated with 'negative', 'anger' and 'disgust') or none at all (e.g. *vocal* scores 0 on all categories). We find that the coverage for the salient attributes in the NRC lexicon is $\approx$ 70-75 % per group.

We score groups by counting the frequencies with which the predicted attributes W_{TGT} are associated with the emotions and sentiments. For each group, we remove attributes from W_{TGT} that are not covered in the lexicon. Thus, we do not extract emotion scores for the exact same number of attributes per group (number of unique attributes and coverage in the lexicon vary). Thus, we normalize scores per group by the number of words for which we are able to retrieve emotion scores ($\approx$ 210-250 per group). The score of an emotion-group pair is computed as follows:

$$s_{emo}(\texttt{TGT}) = \sum_{i=w}^{|W_{TGT}|} \text{NRC}_{emo}(i)/(|W_{TGT}|) \tag{6.4}$$

We then define emotion vectors $\hat{v}$ for each group TGT:

$$\hat{v}_{TGT} = [s_{fear}, s_{joy}, s_{sadness}, s_{trust}, s_{surprise}, s_{anticipation}, s_{disgust}, s_{anger}, s_{negative}, s_{positive}]$$

, which we use as a representation for the emotion profiles within the model.

Analysis Figure 6.2, provides examples of the emotion profiles encoded for a diverse set of social groups to demonstrate how these profiles allow us to expose stereotypes. For instance, we see that in RoBERTa-B religious people and

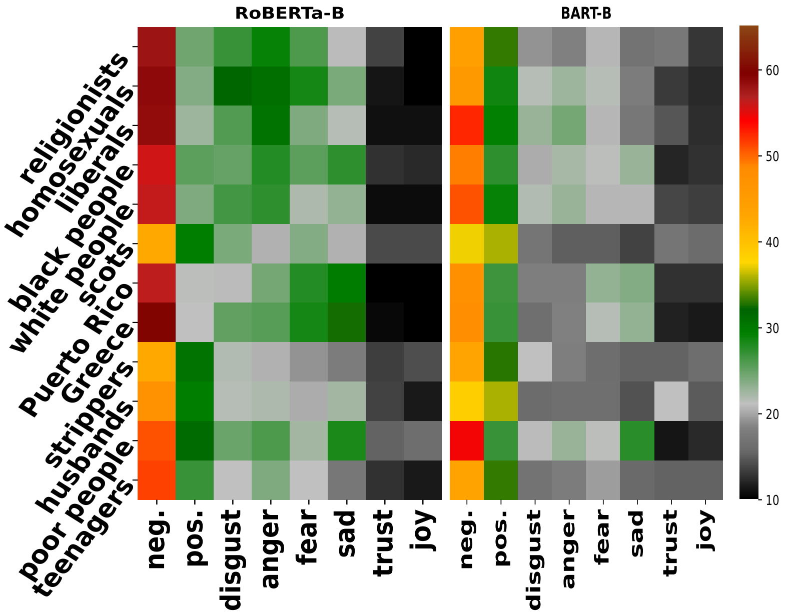


Figure 6.2: Examples of emotion profiles for a diverse set of social groups from RoBERTa-B and BART-B.

liberals are primarily associated with attributes that underlie anger. Towards homosexuals, the same amount of anger is accompanied by disgust and fear as well. As a result, we can detect distinct salient attributes that contribute to these emotions e.g.: Christians are *intense, misguided* and *perverse*, liberals are *phony, mad* and *rabid*, whilst homosexuals are *dirty, bad, filthy, appalling, gross* and *indecent*. The finding that homosexuals elicit relatively much disgust can be confirmed by studies on humans as well (Cottrell and Neuberg, 2005). Similarly, we find that Greece and Puerto Rico elicit relatively much fear and sadness in RoBERTa-B. Whereas Puerto Rico is *turbulent, battered, armed, precarious* and *haunted*, for Greece we find attributes such as *failing, crumbling, inefficient, stagnant* and *paralyzed*.

Emotion profiles elicited in BART-B differ considerably, showcasing how vastly sentiments vary across models. In particular, we see that overall the evoked emotion responses are weaker. Moreover, we detect relative differences such as liberals being more negatively associated than homosexuals, encoding attributes such as *cowardly, greedy* and *hypocritical*. We also find that BART-B encodes more positive associations e.g., *committed, reliable, noble* and *responsible* contributing to trust for husbands. Interestingly, all multilingual models encode vastly more positive attributes for all social groups (see Appendix D.4). We expect that this might be an artefact of the training data, but leave further investigation of this for future work.

Comparison across models We systematically compare the emotion profiles elicited by the social groups across different models by adapting the Representational Similarity Analysis (RSA) from Kriegeskorte et al. (2008). We opted for this method as it takes the relative relations between groups within the same model into account. This is particularly important as we have seen that some models are overall more negatively or positively biased. Yet, when it comes to bias and stereotypicality, we are less interested in absolute differences across models, but rather in how emotions differ towards groups in relation to the other groups. First, the representational similarity within each model is defined using a similarity measure to construct a representational similarity matrix (RSM). We define a similarity vector $\hat{w}_{TGT}$ for a social group such that every element $\hat{w}_{ij}$ of the vector is determined by the cosine similarity between $\hat{v}_i$, where $i = \texttt{TGT}$, and the vector $\hat{v}_j$ for the j-th group in the list. The RSM is then defined as the symmetric matrix consisting of all similarity vectors. The resulting matrices are then compared across models by computing the Spearman correlation (ρ) between the similarity vectors corresponding to the emotion profiles for a group in a model a and b. To express the similarity between the two models we take the mean correlation over all social groups in our list.

Results Computing RSA over all categories combined, shows us that RoBERTa-B and BART-B obtain the highest correlation ($\rho = 0.44$). While using different architectures and pretraining strategies, the models rely on the same training data. Yet, we included base and large versions of models in our study and find that these models show little to no correlation (see Appendix D.5, Figure D.3). This is surprising, as they are pretrained on the same data and tasks as their base versions (but contain more model parameters e.g. through additional layers). This shows how complex the process is in which associations are established and provides strong evidence that other modelling decisions, apart from training data, contribute to what models learn about groups. Thus, carefully controlling training content can not fully eliminate the need to analyze models w.r.t. the stereotypes that they might propagate.

6.6 Stereotype shifts during fine-tuning

Many debiasing studies intervene at the data level e.g., by augmenting imbalanced datasets (de Vassimon Manela et al., 2021; Webster et al., 2018; Dixon et al., 2018; Zhao et al., 2018) or reducing annotator bias (Sap et al., 2019). These methods are, however, dependent on the dataset, domain, or task, making new mitigation needed when transferring to a new set-up (Jin et al., 2021). This raises the question of how emotion profiles and stereotypes are established through language use, and how they might shift due to new linguistic experience at the fine-tuning stage. We take U.S. news sources from across the polit-

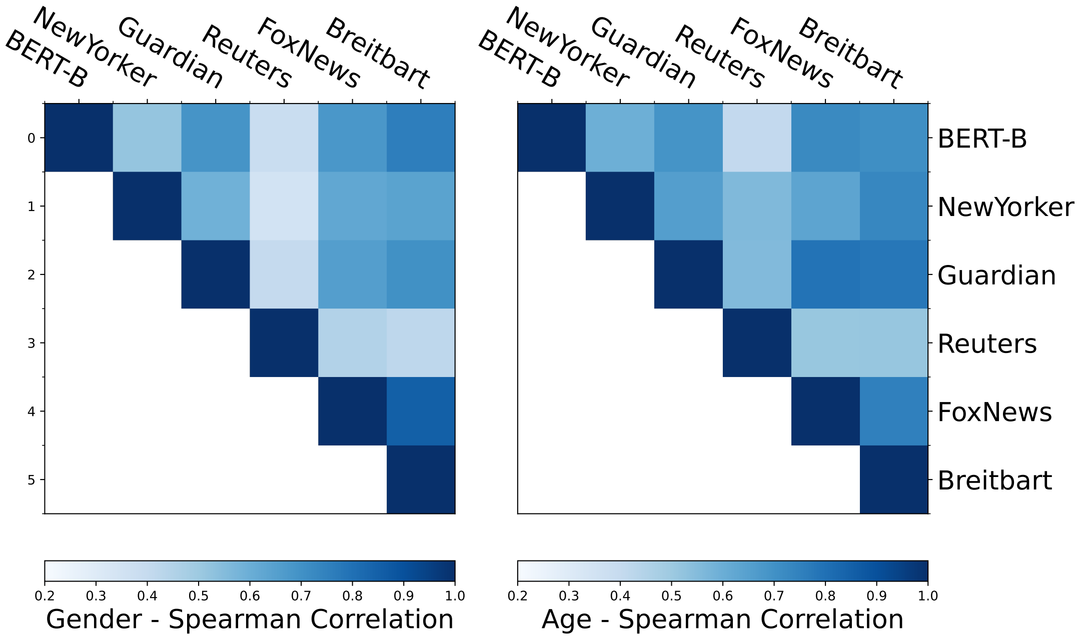


Figure 6.3: Correlations in emotion profiles for gender and age groups across news sources (BERT-B).

ical spectrum as a case study, as media outlets are known to be biased (Baron, 2006). By revealing stereotypes learned as an effect of fine-tuning on a specific source, we can trace the newly learned stereotypes back to the respective source.

We rely on the political bias categorisation of news sources from the *All-Sides* [2] media bias rating website. These ratings are retrieved using multiple methods, including editorial reviews, blind bias surveys, and third party research. Based on these ratings we select the following sources: New Yorker (*far left*), The Guardian (*left*), Reuters (*center*), FOX News (*right*) and Breitbart (*far right*). From each news source we take 4354 articles from the *All-The-News*[3] dataset that contains articles from 27 American Publications collected between 2013 and early 2020. We fine-tune the 5 base models[4] on these news sources using the MLM objective for only 1 training epoch with a learning rate of 5e-5 and a batch size of 8 using the HuggingFace library (Wolf et al., 2020). We then quantify the emotion shift after fine-tuning using RSA.

Results We find that fine-tuning on news sources can directly alter the encoded stereotypes. For instance, for $k = 25$, fine-tuning BERT-B on Reuters informs the model that Croatia is good at *sports* and Russia is good at *hacking*, at

[2] https://www.allsides.com/media-bias/media-bias-ratings

[3] Available at: https://tinyurl.com/bx3r3de8

[4] Training the large models was computationally infeasible.

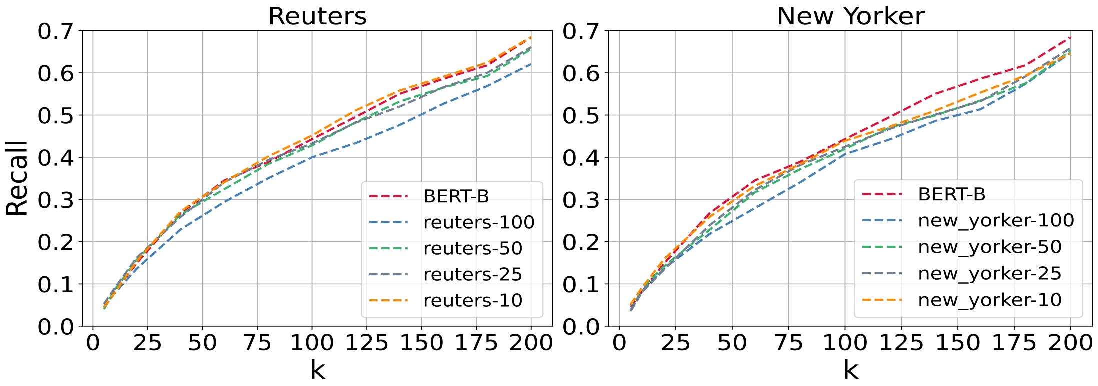


Figure 6.4: Effect on recall@k when fine-tuning BERT-B on 10, 25, 50 and 100 $\%$ of the data

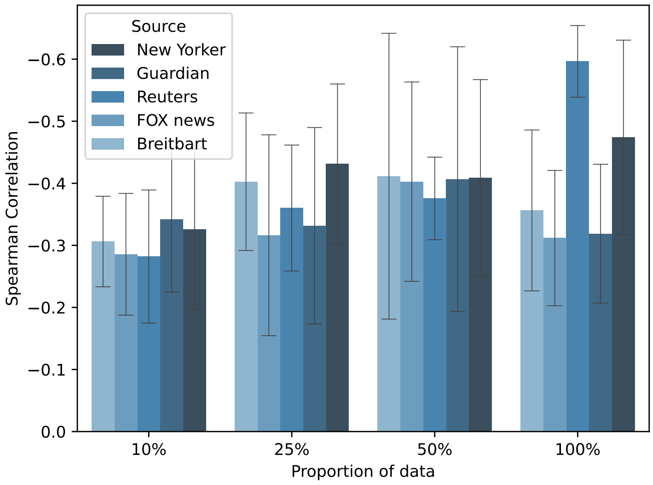


Figure 6.5: Decrease in Spearman correlation ($\Delta\rho$) after fine-tuning the pretrained models compared to no fine-tuning ($\Delta\rho = 1$) (no correlation left:$\Delta\rho = -1$). We show results for models trained on varying proportions of the data. Results are averaged over categories and standard deviations are indicated by error bars.

the same time, associations such as Pakistan is bad at *football*, Romania is good at *gymnastics* and South Africa at *rugby* are lost. Moreover, from fine-tuning on both Breitbart and FOX news the association emerges that black women are *violent*, while this is not the case when fine-tuning on the other sources.

In fact, Guardian and Breitbart are the only news sources that result in the encoding of the salient attribute *racist* for White Americans. We find that such shifts are already visible after training on as little as 25% of the original data ($\sim 1K$ articles). When comparing to human stereotypes, we find that fine-tuning on Reuters decreases the overall recall scores (see Figure 6.4). Although

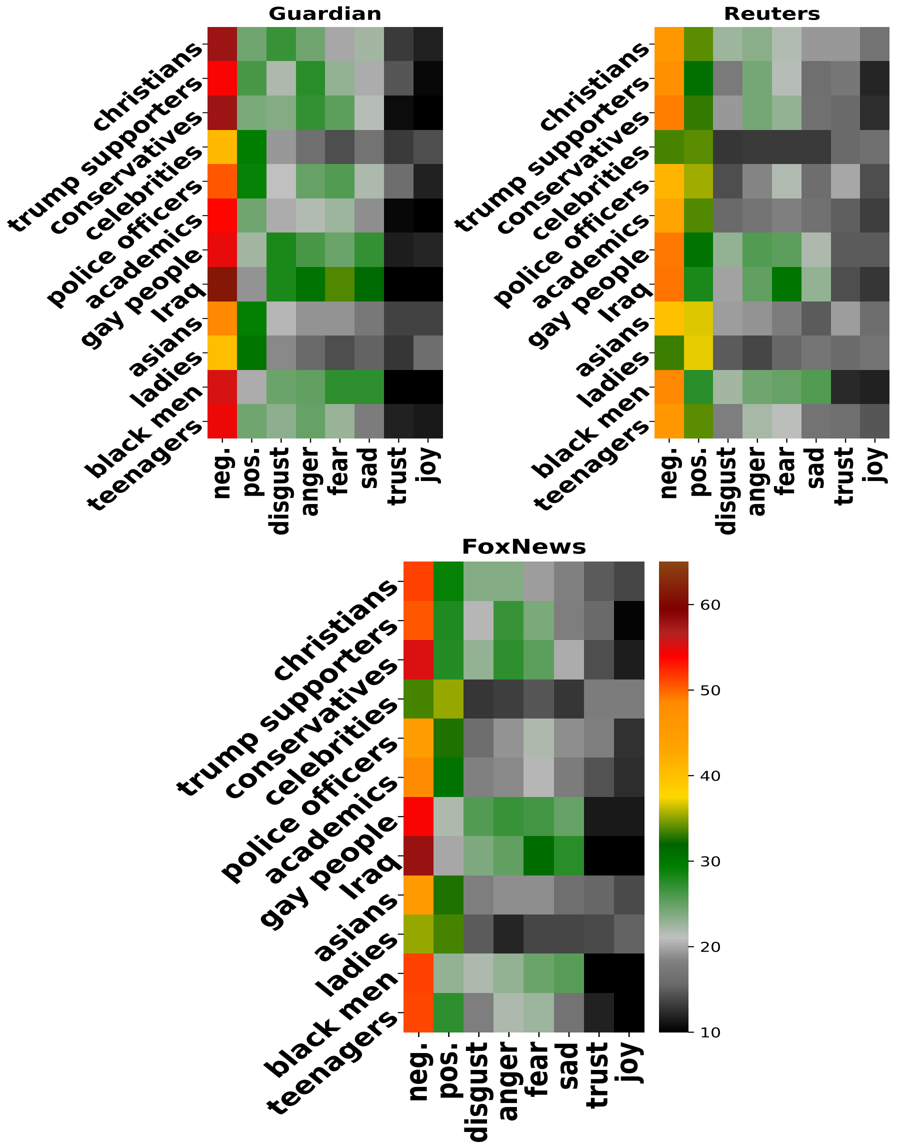


Figure 6.6: A few interesting examples of emotion profiles for a diverse set of social group after fine-tuning RoBERTa-B for only 1 training epoch on articles from Guardian, Reuters and FOX news respectively.

New Yorker exhibits a similar trend, fine-tuning on the other sources have little effect on the number of stereotypes recalled from the dataset. As Reuters has a center bias rating i.e., it does not predictably favor either end of the political spectrum, we speculate that large amounts of more nuanced data helps transmit fewer stereotypes.

Figure 6.5 shows the decrease in correlation between the emotion profiles from pretrained BERT-B and BERT-B fine-tuned on different proportions of the data. Interestingly, fine-tuning on less articles does not automatically result

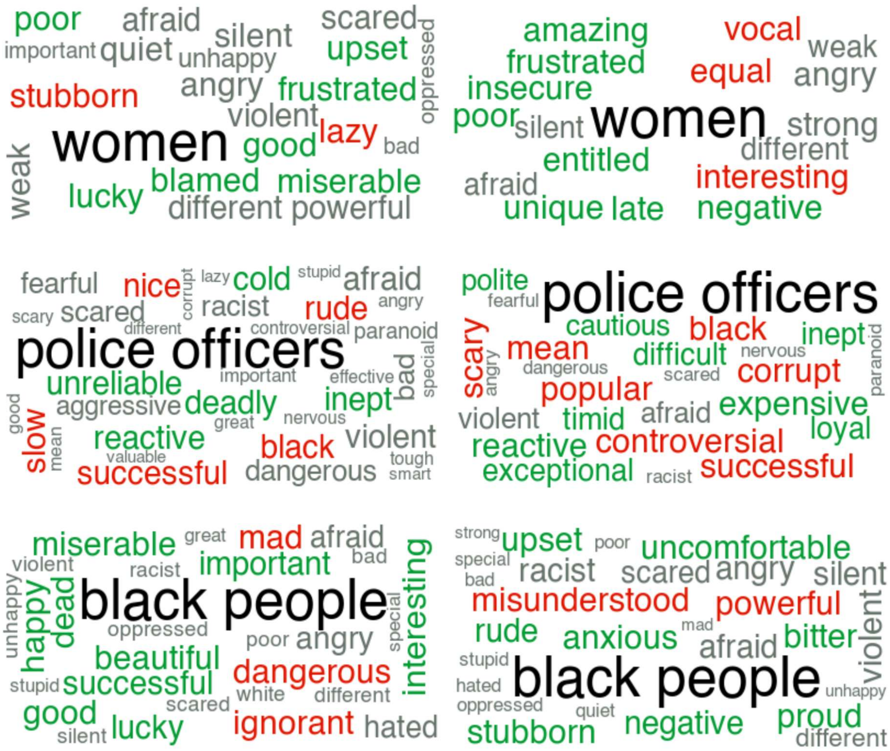


Figure 6.7: Stereotypical attribute shifts when fine-tuning RoBERTa-B on New Yorker (left) and FOX news (right). Removed attributes are red and those added green. Attributes that persisted are grey.

in smaller changes to the models. In fact, in many cases, the amount of relative change in emotion profiles is heavily dependent on the social category as indicated by the error bars. This is not unexpected as news sources might propagate stronger opinions about specific categories. Moreover, we find that emotions towards different social categories cannot always be distinguished by the political bias of the source. Figure 6.3, shows how news sources compare to each other w.r.t. different social categories, exposing that e.g. Guardian and FOX news show lower correlation on gender than on age.

Computing correlation between all pretrained and fine-tuned models, we find that emotion profiles are prone to change irrespective of model or news source (see Appendix D.5). In Figure 6.6, we showcase the effect of fine-tuning from the model that exhibits the *lowest* change in correlation, i.e. RoBERTa-B, to highlight how quickly emotions shift. We find that while Reuters results in weaker emotional responses, Guardian elicits stronger negative emotions than FOX news e.g. towards conservatives and academics. Yet, while both sources result in anger towards similar groups, for FOX news anger is more often accompanied with fear while for Guardian this seems to more strongly stems from disgust (e.g. see Christians and Iraq).

Lastly, Figure 6.7 shows specific stereotype shifts found on the top 15 predictions per template. We illustrate the salient attributes that are removed, added and remained constant after fine-tuning. For instance, the role of news media in shaping public opinion about police has received much attention in the wake of the growing polarization over high-profile incidents (Intravia et al., 2018; Graziano, 2019). We find clear evidence of this polarization as fine-tuning on New Yorker results in attributes such as *cold, unreliable, deadly* and *inept*, yet, fine-tuning on FOX news yields positive associations such as *polite, loyal, cautious* and *exceptional*. In addition, we find evidence for other stark contrasts such as the model picking up on sexist (e.g. women are not *interesting* and *equal* but *late, insecure* and *entitled*) and racist stereotypes (e.g. black people are not *misunderstood* and *powerful*, but *bitter*, *rude* and *stubborn*) after fine-tuning on FOX news.

6.7 Conclusion

We present the first dataset containing stereotypical attributes of a range of social groups. Importantly, our data acquisition technique enables the inexpensive retrieval of similar datasets in the future, enabling comparative analysis on stereotype shifts over time. Additionally, our proposed methods could inspire future work on analyzing the effect of training data content, and simultaneously contribute to the field of social psychology by providing a testbed for studies on how stereotypes emerge from linguistic experience. To this end, we have shown that our methods can be used to identify stereotypes evoked during fine-tuning by taking news sources as a case study. Moreover, contributing to RQ3, we have exposed how quickly stereotypes and emotions shift based on training data content, and linked stereotypes to their manifestations as emotions to quantify and compare attitudes towards groups within LMs. We plan to extent our approach to more languages in future work to collect different, more culturally dependent, stereotypes as well.

Ethical consideration

The examples given in the chapter can be considered offensive but are in no way a reflection of the authors' own values and beliefs and should not be taken as such. Moreover, it is important to note that for the fine-tuning experiments only a few interesting examples were studied and showcased. Hence, more thorough research should be conducted before drawing any hard conclusions about the news papers and the stereotypes they propagate. In addition, our data acquisition process is completely automated and did not require the help from human subjects. While the stereotypes we retrieve stem from real humans, the data we collect is publicly available and completely anonymous as the specific stereotypical attributes and/or search queries can not be traced back to individual users.

CHAPTER 7

Cultural Values and their Revision during Fine-tuning

Chapter Highlights

Texts written in different languages reflect different culturally-dependent beliefs of their writers. Thus, we expect multilingual LMs (MLMs), that are jointly trained on a concatenation of text in multiple languages, to encode different cultural values for each language. Yet, as the 'multilinguality' of these LMs is driven by cross-lingual sharing, we also have reason to belief that cultural values bleed over from one language into another. This limits the use of MLMs in practice, as apart from being proficient in generating text in multiple languages, creating language technology that can serve a community also requires the output of LMs to be sensitive to their biases (Naous et al., 2023). Yet, little is known about how cultural values emerge and evolve in MLMs (Hershcovich et al., 2022). In this chapter, we continue our investigation into RQ3. Specifically, we are the first to study how languages can exert influence on the cultural values encoded for different test languages, by studying how such values are revised during fine-tuning. Focusing on the fine-tuning stage allows us to study the interplay between value shifts when exposed to new linguistic experience from different data sources and languages. Lastly, we use a training data attribution method to find patterns in the fine-tuning examples, and the languages that they come from, that tend to instigate value shifts.

7.1 Introduction

Training LMs on large text corpora has been shown to induce various types of (social) biases in multilingual LMs (MLMs) that affect which human values the model picks up on (Choenni et al., 2021; Hämmerl et al., 2023). However, human values vary per culture, which means that the cultural values that are

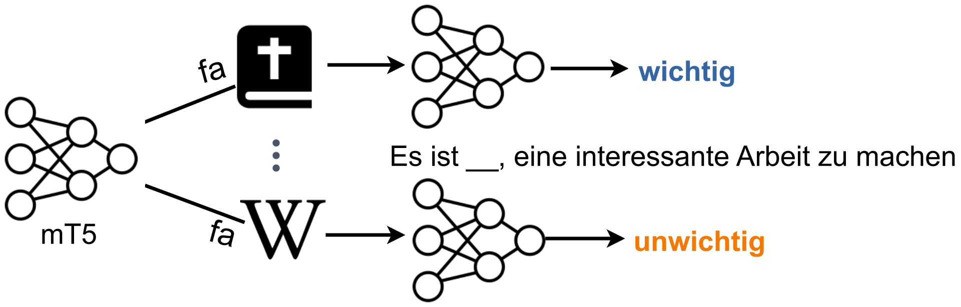


Figure 7.1: An example of our evaluation setup. We analyze the effect that fine-tuning on different data sources in a fine-tuning language A (Farsi) has on the cultural values that are encoded for a test language B (German).

reflected through their language (either explicitly or implicitly) will also differ. As MLMs are trained on the concatenation of text from a wide variety of languages spoken in the world, we can expect different, and perhaps opposing, cultural values to be encoded in them simultaneously. This necessitates MLMs to become inherently multicultural as well in order to appropriately serve culturally diverse communities (Naous et al., 2023; Talat et al., 2022). In fact, it has already been shown that MLMs encode a distinct set of cultural values for different languages. However, those values do not tend to align with those collected from real human surveys conducted in the countries where the majority population speak the respective languages (Arora et al., 2023; Kovač et al., 2023). As such, the multilingual NLP community is now faced with the new pressing challenge of better culturally aligning MLMs to human values (Yao et al., 2023). Thus, we aim to study how cultural values emerge and evolve in MLMs to better understand and aid cross-cultural value alignment in the future.

In particular, we hypothesise that training on multilingual data leads to an interaction of language-specific cultural values within the models, possibly steering a language's cultural bias into a direction that is unfaithful to the majority of that language's speakers. This raises an interesting set of questions on how languages exert influence on the encoding of cultural values. Focusing on the fine-tuning stage, we study how cultural values are revised during training. For instance, given a set of fine-tuning languages, test languages, and data sources, when we fine-tune on a data source in a language A, and test in a language B, do we inadvertently induce the cultural values from A into B? And would the same effect be visible across all test languages or are the values encoded for some languages more prone to change? Moreover, how much impact does the bias of the data source itself have versus the language used for fine-tuning? And can different data sources systematically enforce different alignments to human values?

To better understand this cross-cultural interaction, we study the following questions: (**Q1**) How do the fine-tuning language and data source affect the way in which cultural information is encoded and revised during fine-tuning? (**Q2**) How do cultural value shifts change the alignment to human survey data? (**Q3**) Can we find patterns in the training examples that systematically influence how cultural values are revised? To this end, we conduct a set of controlled fine-tuning experiments using multi-parallel texts from data sources with neutral bias (Wikipedia), religious bias (Bible and Quran) and political bias (news articles) across 4 fine-tuning languages and 13 test languages. We follow Arora et al. (2023) in using 200+ WVS survey questions to probe for cross-cultural values in pretrained and fine-tuned MLMs. Importantly, using survey questions as probes allows us to test the alignment between model predictions and human data. Finally, we use a training data attribution (TDA) to trace value shifts back to the data source.

We find that, while fine-tuning language and domain source play a minor role in the revision of cultural information compared to the amount of fine-tuning data, fine-tuning languages can lead the cultural perspective of test languages into different directions. Importantly, this can positively affect the models' alignment to human values. Yet, overall, results vary considerably across test languages. Moreover, our TDA analysis provides interesting insights about the systematicity with which the model tends to rely on parallel data to instigate the same value shifts across languages. Our results underpin the complexity of cross-language and cross-cultural interaction within MLMs, and suggest that the semantic content of fine-tuning data might not be the main reason for value shifts.

7.2 Related work

7.2.1 Cross-cultural NLP

The fact that LMs are becoming increasingly multilingual, has given rise to a new subfield in NLP that is concerned with questions such as to what extent these models are multicultural (Liu et al., 2024; Havaldar et al., 2023; Hershcovich et al., 2022), to what extent their cultural values align with those from human populations (Naous et al., 2023; Arora et al., 2023; Cao et al., 2023), and whether we can automatically improve such an alignment to better serve culturally diverse communities (Kovač et al., 2023). For instance, Naous et al. (2023) show that MLMs tend to exhibit western-centric biases, even when being prompted in Arabic and contextualized by an Arab cultural setting, resulting in culturally insensitive output such as suggesting to go for a beer after Islamic prayer. Similarly, previous works show that LMs fail to understand proverbs and sayings from different languages (Liu et al., 2024), and do not capture the nuances in meaning and usage patterns of emotion words that exist differently across cultures (Havaldar et al., 2023). These findings suggest that there is still an important gap to fill when it comes to creating multilingual language technology that is also multicultural (Talat et al., 2022). We aim to contribute to our understanding of how cultural values manifest across languages.

7.2.2 Probing for bias

Cloze-style testing is a technique that stems from psycholinguistics (Taylor, 1953), and has been popularized as a tool to study different types of knowledge and biases encoded by LMs. The idea is that we prompt LMs with a carefully curated set of probing sentences that are meant to elicit responses that expose the biases encoded within the LM (May et al., 2019; Stańczak et al., 2023; Nangia et al., 2020). While many different types of biases have been studied in the multilingual setting (Hämmerl et al., 2023; Touileb et al., 2022; Kaneko et al., 2022), Arora et al. (2023) are the first to probe for cross-cultural values in pre-trained MLMs. We use their probing questions in a similar set-up, but take a step further by studying how different fine-tuning languages can exert influence on cultural values encoded for a different set of test languages.

7.2.3 Training data attribution

As explained in Chapter 2, TDA methods are developed to identify a set of training examples that were most influential in making a particular test prediction. The influence of a training example z_{train} on test example z_{test} can typically be formalized as the change in loss that would been incurred for z_{test}, if sample z_{train} was not seen during training (Koh and Liang, 2017). Thus, we can use the resulting influence scores as a measure of how important z_{train} is for making a prediction for z_{test}. While TDA methods have successfully been used on various classification tasks in NLP, both in the monolingual (Han and Tsvetkov, 2022; Han et al., 2020; Lam et al., 2022; Meng et al., 2020; Guo et al., 2021) and multilingual (Choenni et al., 2023b,c) setting, extending the use of TDA methods beyond classification tasks has proven difficult. Akyürek et al. (2022) first used TDA methods (including TracIn) (Rajani et al., 2019; Pruthi et al., 2020) on masked language modelling for fact tracing – the task of attributing an LM's factual assertions back to training examples. Yet, the results were shown to be unreliable. More recently, however, Park et al. (2023) proposed TRAK, which was shown to be successful in *behaviour tracing* on mT5. We adopt their approach to trace mT5 predictions for cloze-style questions eliciting cultural values back to the fine-tuning data.

	Category	Questions
(1)	Social Values, Attitudes and Stereotypes	45
(2)	Happiness and Well-being	10
(3)	Social Capital, Trust and Organisational Membership	47
(4)	Economic Values	-
(5)	Corruption	9
(6)	Migration	9
(7)	Security	21
(8)	Post-materialist Index	-
(9)	Science and Technology	6
(10)	Religious Values	9
(11)	Ethical Values and Norms	22
(12)	Political Interest and Political Participation	35
(13)	Political Culture and Regimes	24

Table 7.1: The 13 categories in which the questions from the World Value Survey are organised, along with the number of questions we use per category.

7.3 Methodology

7.3.1 World Values Survey (WVS)

We probe for cultural values using cloze-style testing templates derived from the questions proposed in the World Values Survey (WVS) (Haerpfer et al., 2022) by Arora et al. (2023). Thus, more precisely, we study descriptive ethics as explained by Vida et al. (2023). The WVS collects data on cultural values in different countries in waves, and our questions come from Wave 7 which ran from 2017 to 2020 and targets 57 countries [1]. Survey results are published per question, organised in 13 categories stated in Table 7.1. Categories (4) 'Economic values' and (8) 'Post-materialist Index' are excluded as their questions could not be converted into probes. We use 237 probes in total.

7.3.2 Multilingual probes

We use the English probes that were professionally translated into the following 13 languages: Romanian, Greek, Urdu, Farsi, Tagalog, Indonesian, German, Malay, Bengali, Serbian, Turkish, Vietnamese and Korean, see Figure 7.1 for an example. Note that these languages were carefully selected by Arora et al. (2023) based on the following three criteria: (1) the languages can be mapped to one country covered by the WVS survey, (2) the languages are the official

[1] https://www.worldvaluessurvey.org

Language	Country
English (en)	United States
Romanian (ro)	Romania
Greek (el)	Greece
Urdu (ur)	Pakistan
Farsi (fa)	Iran
Tagalog (tl)	Philippines
Indonesian (id)	Indonesia
German (de)	Germany
Malay (ms)	Malaysia
Bengali (bn)	Bangladesh
Serbian (sr)	Serbia
Turkish (tr)	Turkey
Vietnamese (vi)	Vietnam
Korean (ko)	South Korea

Table 7.2: The mapping used between each test language and the country whose cultural values we algin to based on the WVS data.

languages of the countries that they are mapped to, (3) the distribution of the language's speakers can be primarily localized to a country or relatively small geographical region, and (4) all selected languages have at least 10K articles on Wikipedia such that the LMs have seen a sufficient amount of pretraining data. See Table 7.2 for the full mapping between languages and countries.

7.3.3 Models

Arora et al. (2023) report that cultural information is inconsistent across different pretrained LMs. Given recent trends on scaling LMs to tens of billions of parameters (Scao et al., 2022), we study how model size affects cultural information instead. We probe mT5 (Xue et al., 2021) small, base and large that contain 0.3B, 0.58B and 1.2B parameters.

7.3.4 Probing method

To probe for cultural values, we query the mT5 models with the cloze-style question probes from Section 7.3.2 using a conditional language generation head. More concretely, for each probing template, we replace the `[MASK]` token in the original probes with extra ID tokens for mT5, and apply softmax over the logits of all tokens in the vocabulary V. We then take the log probability for the two candidate answers of the question, and take the option with the highest log probability as the final answer.

	bn	de	el	fa	id	ko	ms	ro	sr	tl	tr	ur	vi	avg.
S vs. B	78	89	84	89	77	82	84	94	72	70	79	87	83	82
S vs. L	78	87	83	89	69	86	81	96	63	69	75	83	83	80
B vs. L	88	86	81	87	79	83	84	94	72	77	81	85	87	83

Table 7.3: Percentage of agreement between model predictions from the pretrained mT5 **S**mall, **B**ase and **L**arge models fine-tuned on PBC (10K).

7.3.5 Quantifying shifts in cultural profiles

To compare overall cultural bias across languages and models, we build 'cultural profiles' based on their predictions for all WVS questions. Per question, we take the log probabilties of the respective answers and apply softmax to them to obtain the probabilities for selecting the first answer option for all N questions. We then compile them into a N-dimensional vector, which represents the cultural profile of a given language. Similarly, we obtain ground truth profiles for the corresponding countries using the results from the WVS survey. The results are reported as the percentage of interviewees that selected each class. Yet, in contrast to our probes, the survey proposes multiple classes (e.g. *'very important'*, *'important'*, *'not very important'*, *'not important'*). We add the probability from the middle classes to the closest class on either end of the spectrum e.g., very important/important becomes one class. We then test how similar cultural profiles within pretrained models are to the ground truth, and in which direction they change after fine-tuning, by computing the change in correlation.

7.4 Experimental setup

7.4.1 Data sources

We use three different data sources with multi-parallel data for fine-tuning. Specifically, we use Flores-101 data (Goyal et al., 2022), the Parallel Bible Corpus (PBC) (Christodouloupoulos and Steedman, 2015) and the Tanzil dataset (Tiedemann, 2012) that contain human translated sentences from Wikipedia articles, Bible texts and Quran texts respectively. While Flores-101 is more likely to be used in practice, PBC and Tanzil are an interesting testbed as due to their didactic nature, we expect cultural values to be affected more heavily. We select 4 languages for fine-tuning: Farsi, Korean, Hindi and Russian. These languages all rely on a different writing script, and are commonly spoken by culturally diverse populations. Also, Farsi and Korean are included in our test languages. The PBC dataset already contains multi-parallel sentences, and for the Tanzil we were able to extract them automatically using the English sentences in the translation pairs. Finally, following Choenni et al. (2021), we also fine-tune on articles from different news sources across the political spectrum from left to right-wing ideologies. We use English news articles collected between 2013 and early 2020 from New Yorker (*left*), Reuters (*center*) and FOX news (*right*) from the *All-The-News* dataset. While the focus of this study is on language influence, we use this as an additional test to disentangle the effect of language bias from domain bias.

7.4.2 Training details

From each data source we use either 2K or 10K consecutive sentences for fine-tuning on the MLM 'span corruption' objective that was used for pretraining, see Appendix E.3 for training details. We use two fine-tuning strategies (FT): (1) monolingual FT, where we train our models on each language separately, and (2) multilingual FT, where we jointly train on all fine-tuning languages together. For (2), we use 2,5K multi-parallel sentences for each language and shuffle them before training. We compare multilingual and monolingual models where 10K sentences are seen in total.

7.5 Probing results

As a baseline to our fine-tuning experiments, we first study the cultural profiles encoded in the pretrained models. In Section 7.5.2, we then analyze how cultural information in the model changes as a result of cross-language and domain influence.

7.5.1 Cultural information in pretrained LMs

As explained in Section 7.3.5, we build cultural profiles for each country and compute Spearman correlation between the ground truth and pretrained model profiles. In line with previous results (Arora et al., 2023), we confirm that all pretrained LMs correlate poorly with human values. Yet, in Table 7.3, we find that the models of varying sizes on average agree on 80% of the survey questions (pairwise). In addition, we find that variations in consistency mostly depend on the test language. For instance, in Romanian the models agree on $\geq 94\%$ of questions, but for Serbian this is $\leq 72\%$ instead. Similarly, averaged across test languages, the models agree more on specific WVS categories e.g., predictions are more consistent for questions pertaining to happiness, security and political culture ($\geq 85\%$) and less consistent when it comes to ethical values, political interest and corruption ($\leq 76\%$), see Appendix E.1. As all models exhibit similar behavior we focus analysis on mT5-small.

7.5.2 Cultural value shifts

In Section 7.5.2.1, we study how the interplay between fine-tuning language, test language and data source will affect the *amount* of value shifts. In Section 7.5.2.2, we instead test how these factors more generally affect the cultural profiles across test languages by studying in which direction the models' bias changes. Finally, in Section 7.5.2.3, we test how much cross-lingual sharing during multilingual fine-tuning will further impact these results.

7.5.2.1 How big is the role of FT language and domain source on cultural value shifts?

In Figure 7.2, we report the percentage of predictions that remain unchanged after fine-tuning on 2K sentences from news articles, Flores-101, PBC and Tanzil. While the amount of changes for Flores-101 are within the same ranges as for the news sources (7-35% shifts), as expected we see that PBC and Tanzil have a slightly larger impact on the cultural values encoded (9-43% shifts). In particular, for PBC, fine-tuning in Korean and Russian have a bigger effect across test languages (e.g. for Greek and German). Similarly, when using Tanzil, next to Korean and Russian, Hindi has a larger effect as well. Yet, similar to our pre-trained LMs, we find that the effect of fine-tuning language and source varies across test languages. For instance, for Farsi, regardless of the fine-tuning domain or source, many more values change than for the other languages. This shows that the effect of domain and language bias on the amount of value shifts is heavily dependent on the language that we study shifts for, making it difficult to draw general conclusions on which one has the largest impact overall. We suspect that cultural information is separately encoded for each language in the model, and that the confidence with which these values are encoded varies depending on the test language. Thus, based on the starting point, all fine-tuning setups will be able to affect the test languages to similar extents.

Are certain cultural values more prone to shift? When studying the consistency with which values shift, we find that for each test language the values for the same questions tend to be affected, regardless of the fine-tuning language. Specifically, on average only 14% of the value shifts are unique to only one fine-tuning language and can thus be attributed to language bias. Yet, the values that shift are not consistent across test languages. This again shows that the pattern with which values shift, heavily vary based on the language used for probing. However, these results also indicate that, not only are certain languages more prone to change cultural perspective, there are per language also a specific set of values that are more prone to shift.

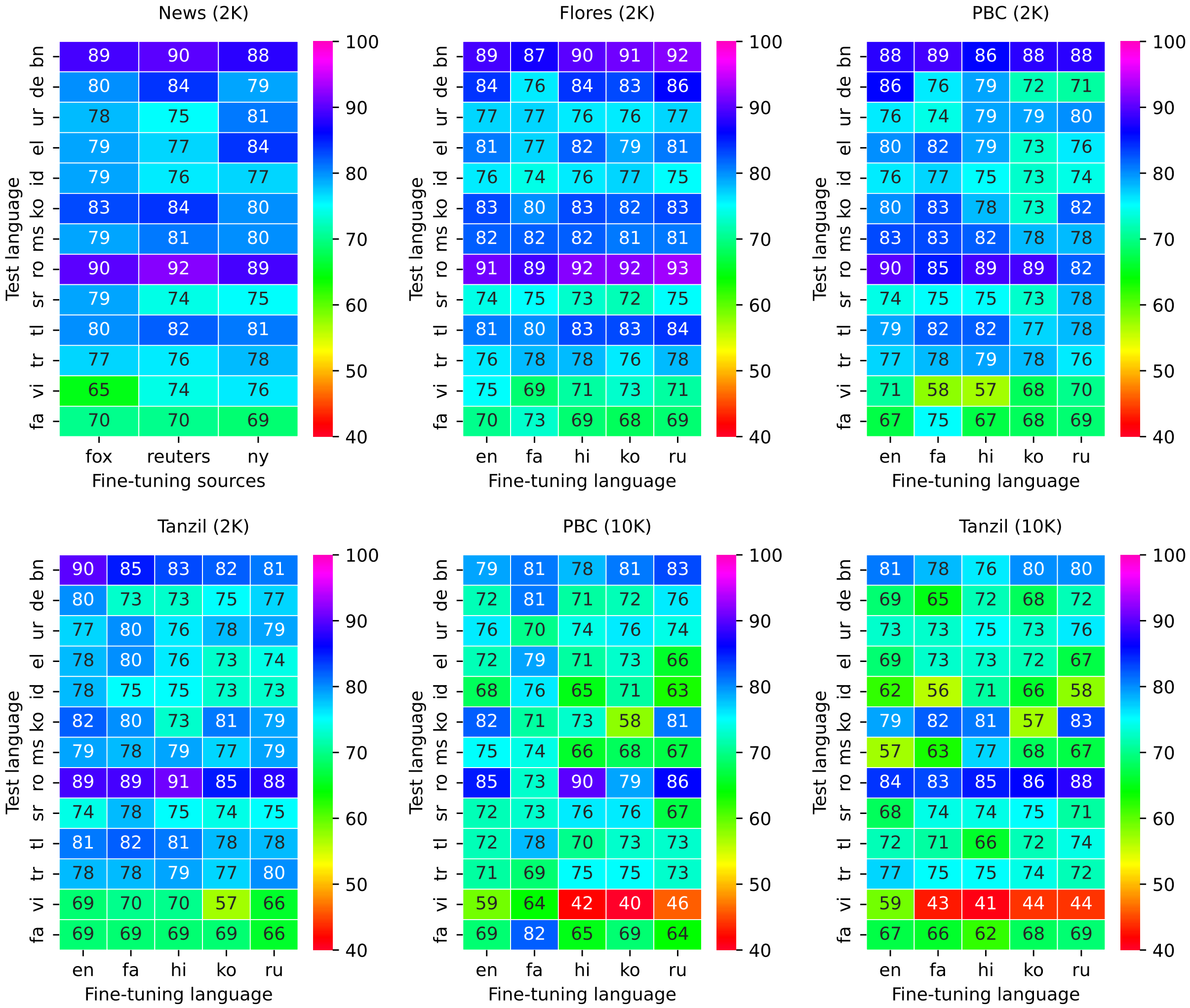


Figure 7.2: The percentage of predictions that remain unchanged after fine-tuning mT5-small.

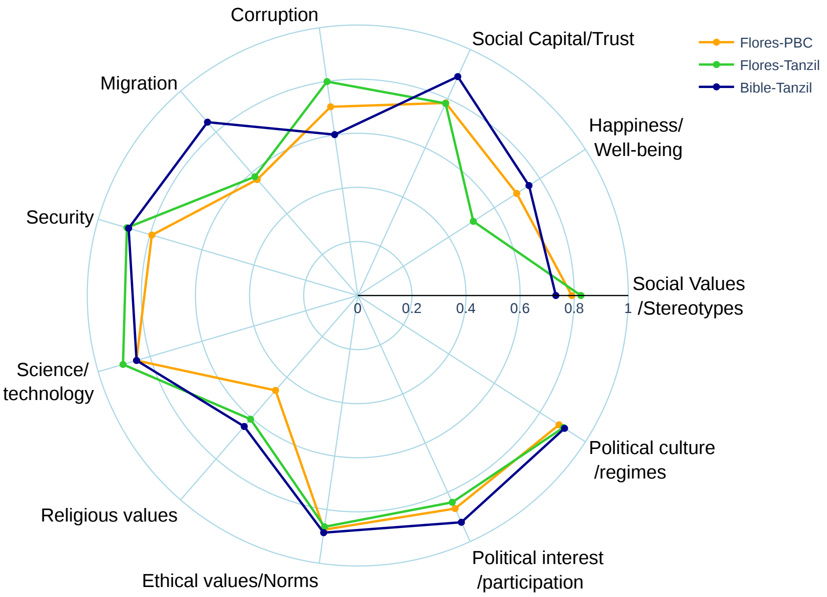


Figure 7.3: Pearson correlation between the average percentage of unchanged values across fine-tuning languages for each data source pair per WVS category.

Are certain WVS categories more prone to domain bias? In Section 7.5.1, we found that the pretrained models of different sizes agree more on certain WVS categories. Thus, we test whether the impact of the domain source will be more visible when studying results per category. In Figure 7.3, we report the Pearson correlation between the percentages of unchanged values per WVS category for each data source pair averaged across fine-tuning languages. We find that overall Tanzil and Bible tend to score higher compared to Flores-101. Yet, the lowest correlations between data sources are reported for religious values. This suggests that the different religious biases of PBC and Tanzil do in fact have a different effect on the value shifts.

Do we just need more fine-tuning examples? A natural follow up question is whether language or domain bias becomes more prevalent when using a larger corpus during fine-tuning. We find that increasing our training size from 2K to 10K samples does tend to further increase the amount of value shifts (yet, it can also decrease, e.g. for German when fine-tuning in Farsi or Russian). Importantly, however, this does not considerably change the patterns between PBC and Tanzil. Moreover, note that a substantial amount of values shift after fine-tuning on 2K samples, which shows that the fine-tuning procedure has made an impact.

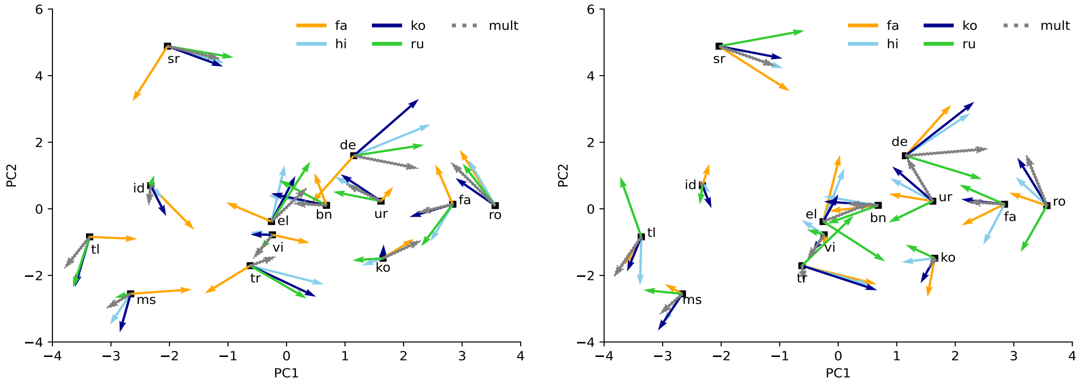


Figure 7.4: Starting from the cultural profiles extracted from pretrained mT5-small, the image depicts which direction each test language changes depending on the language selected for fine-tuning on PBC (left) and Tanzil (right). The cultural profiles are projected down to 2-dimensions using PCA (Bro and Smilde, 2014).

7.5.2.2 Does the direction of cultural change differ depending on the FT setup?

As we saw that the amount of changes are similar across fine-tuning languages and sources, we now instead study the effect that each fine-tuning setup has on the cultural profiles. In Figure 7.4, we plot in which direction the cultural profiles of the pretrained model changed depending on the fine-tuning language used. In accordance with our previous results, we find that the direction of change is mostly dependent on the language used for testing, as most fine-tuning languages point in similar directions. However, we do see some differences when comparing results across datasets. For instance, we see that for Indonesian and Korean, the fine-tuning languages seem to steer the cultural bias into different directions depending on the dataset. Moreover, for PBC we find that across many test languages, fine-tuning in Farsi steers the model in a different direction compared to the other languages. Thus, while the amount of value shifts are only weakly affected by fine-tuning language and source, these results indicate that they can have a strong effect on the overall cultural bias of the model.

7.5.2.3 Does multilingual FT affect cultural values differently?

In the previous sections, we studied the effect of monolingual fine-tuning. However, multilingual models are jointly trained on multiple languages, which further complicates which values the model should pick up on. Thus, we now test to what extent cross-language influence during multilingual fine-tuning affects the cultural bias of the models differently compared to monolingual fine-tuning. In Table 7.4, we report the amount of unchanged values after multilingual and monolingual fine-tuning. We find that the effect of multilingual

	bn	de	el	fa	id	ko	ms	ro	sr	tl	tr	ur	vi
mult	76	74	74	72	64	67	72	74	65	69	71	41	78
mono-avg	81	75	74	72	69	71	69	82	73	74	73	48	70

Table 7.4: Percentages of unchanged values after multilingual and monolingual fine-tuning.

fine-tuning is for many languages approximately similar to the average scores obtained across fine-tuning languages in a monolingual set-up (this pattern holds for models of varying sizes, see Appendix E.2). In addition, in Figure 7.4 we see that the direction in which the cultural profiles change, does not deviate much from monolingual fine-tuning in most cases. We suspect that the results for multilingual fine-tuning are similar because the fine-tuning languages in any case tend to behave similarly. Thus, when using them interchangeably it has a limited further effect on the predictions.

7.6 Correlation with human survey results

In Section 7.5.1, we studied which cultural values were encoded in the pretrained LM, and in Section 7.5.2, how much and in which direction these could change after fine-tuning. We now test whether the changes we observed led the model to be steered into a direction that is better aligned to real human values. Thus, we compute how much the Spearman correlation between the ground truth profiles and the pretrained LM changed after fine-tuning. To select culturally diverse countries to test alignment to, we first compute cosine similarities between the ground truth profiles of our 13 test languages, and found that the profiles from Germany and Pakistan (0.84 similarity) and Vietnam and Serbia (0.88 similarity) deviated the most.

How does the alignment between test languages and human values change? In Table 7.5, we report the change in correlations averaged over fine-tuning languages. In Figure 7.4 we saw that, depending on the test language, fine-tuning changed the cultural information in different directions. We now see that this mostly leads to a better alignment to human data, regardless of domain source. For instance, fine-tuning on Tanzil and PBC on average increases correlation with all countries' data for Tagalog. This suggests that the model is overall pushed closer to human values. Moreover, test languages whose profiles pointed in different directions across datasets (e.g., Korean, Indonesian and Serbian), are now also affected differently in their alignment to human values. Yet, when looking at the absolute values for PBC and Tanzil, the correlations

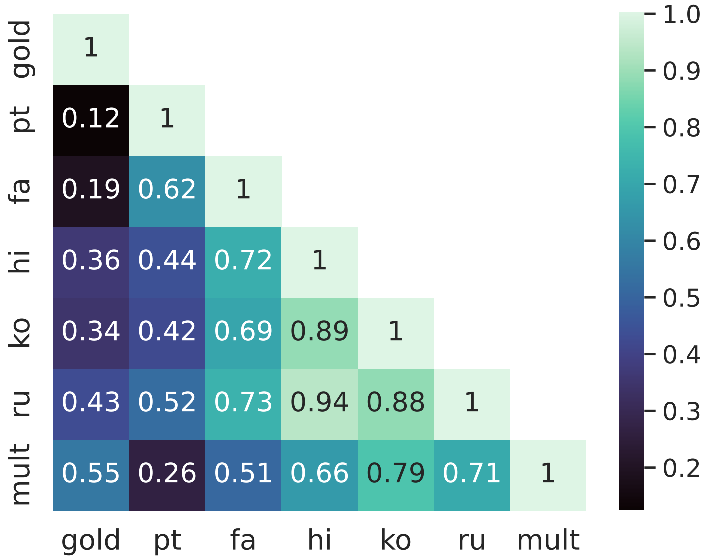


Figure 7.5: Spearman correlation between the similarity matrices of the cultural profiles computed from the ground truth data, and pretrained and fine-tuned models.

remain low across the board, showing that the model is still poorly aligned to human values.

How does fine-tuning affect the cultural similarity between test languages within a model? Given that our models are poorly aligned to human data, we test whether at least the cultural similarities between different test languages correlate with those between real countries. For instance, do we find that the cultural profiles from Romanian and Serbian are more similar than those from Serbian and Urdu? To test this, we, for each model, compute a dissimilarity matrix between the cultural profiles of all language pairs using cosine similarity, and then use Spearman correlation to test how similar these matrices are across models (Abnar et al., 2019). In Figure 7.5, we find that while cultural relationships between languages in the pretrained LM are weakly correlated with human data, the alignment mostly increases after fine-tuning on PBC, (except for Farsi). Interestingly, multilingual fine-tuning results in the highest correlation with human data. The same result was found for Tanzil, see Appendix E.4. When looking at the dissimilarity matrices for these models, we also find that the cultural profiles are more distinct, resulting in less similarity between language pairs. We suspect that, as a result of seeing multiple languages during training, various language-specific biases can be preserved and transmitted. In contrast, after monolingual fine-tuning, all languages are biased in one direction, resulting in very similar cultural profiles that do not preserve cross-cultural differences.

	bn	de	ur	el	id	ko	ms	ro	sr	tl	tr	vi	fa
							PBC						
DE	+.02	+.11	+.03	+.04	+.09	-.03	+.12	+.01	-.05	+.12	+.04	+.15	-.03
PK	-.13	+.02	-.11	+.16	+.14	+.13	+.18	-.08	+.01	+.23	+.15	-.02	-.14
SR	-.06	+.26	-.06	+.08	+.04	-.01	+.01	0	-.08	+.16	+.09	0	-.07
VI	-.08	-.18	-.11	0	+.01	-.01	-.03	-.09	+.01	+.12	0	-.14	+.04
							Tanzil						
DE	-.02	+.18	+.06	+.02	+.10	-.04	+.12	+.08	-.06	+.14	-.02	+.19	-.02
PK	-.16	+.02	-.08	+.16	+.12	+.13	+.11	-.08	0	+.26	+.18	-.01	-.14
SR	-.08	+.03	-.06	+.09	+.03	-.04	-.01	0	-.06	+.15	+.05	+.04	-.06
VI	-.09	-.24	-.07	+.01	-.08	+.05	-.08	-.11	+.05	+.11	+.04	-.15	+.05

Table 7.5: Change in alignment to the ground truth profiles for each country (DE, PK, SR, VI), measured by the difference in Spearman correlation. Results are averaged over fine-tuning languages.

7.7 Tracing cultural value shifts

We found that fine-tuning languages have similar effects across test languages. Thus, as a complementary study, we test which training examples, and the languages they come from, influenced value shifts the most. We use TRAK, a TDA method proposed by Park et al. (2023). We follow Park et al. (2023) in treating the MLM objective as a multi-class classification problem, i.e., framing it as a sequence of v-way classification problems over masked tokens, where v is the vocabulary size. We use the TRAK library[2] for our implementation and project gradients down to 4096 dimensions, all other parameters are kept at default. See Park et al. (2023) for a detailed explanation. Per value shift we analyze the top 100 most influential training examples.

Are value shifts influenced by the same training examples across fine-tuning and test languages? In Section 7.5.1, we saw that value shifts were mostly not unique to one fine-tuning language. Thus, we test whether these shifts were actually influenced by the same training examples across fine-tuning languages. Interestingly, we find that from the most influential examples in each fine-tuning language that instigate the same value shift, only <5% are parallel sentences. Yet, when looking at the values that shift across test languages given the same fine-tuning language, we observe more consistency. For PBC, we find that across all language pairs, when fine-tuning in Farsi and Hindi, up to 20% of training examples are consistently relied upon across test languages, and for Korean and Russian 49 and 62% resp. These results suggest that the semantic content of fine-tuning data might not be the main reason behind the shifts. Instead, the model tends to rely more on the same training examples within a fine-tuning language irrespective of test language.

Which languages instigate the value shifts during multilingual fine-tuning? We use the approach from Choenni et al. (2023b) to quantify cross-language influence by the average percentage of training examples that each fine-tuning language contributes to the most influential examples for each test language. In Figure 7.6, we see that for PBC, Russian and Farsi have on average the largest influence across test languages. Interestingly, for Tanzil, we instead see that Russian and Korean contribute the most. Given that different trends across datasets could also be an artifact of randomness during fine-tuning, we repeat the experiment for PBC on a model fine-tuned with a different random seed, but confirm that the trends hold. While the large influence of Russian could be explained by the fact that it has the second largest dataset for pretraining, the results indicate that the influence of languages on value shifts during multilingual fine-tuning is dependent on the content of the fine-tuning data.

[2] https://github.com/MadryLab/trak

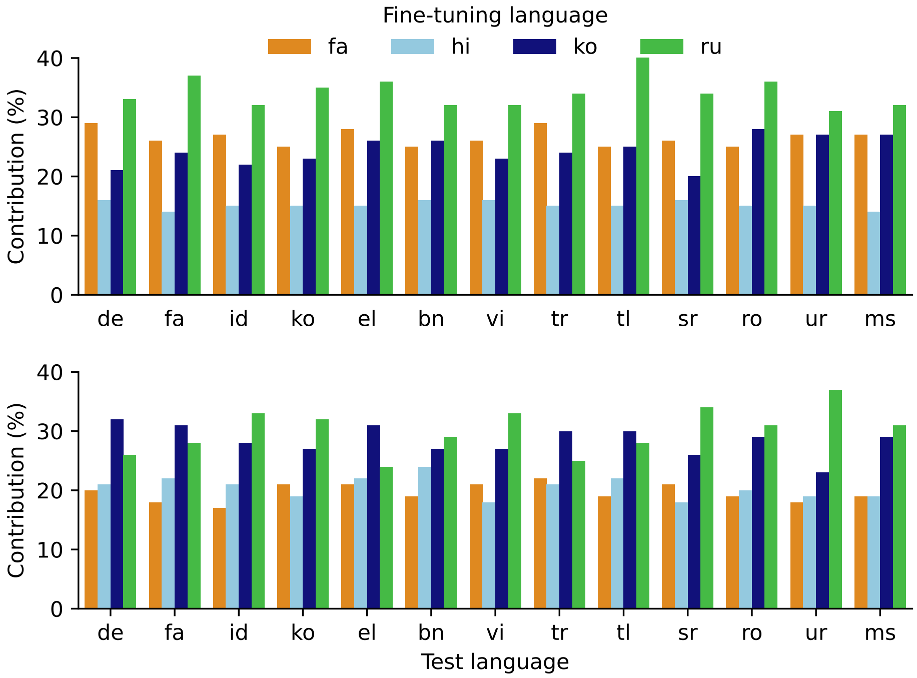


Figure 7.6: The average percentage of training samples from each fine-tuning language that contributed to the top 100 training samples for a test language after multilingual fine-tuning on PBC (top) and Tanzil (bottom).

7.8 Discussion and conclusion

Further contributing to RQ3 from the introduction, we studied to what extent fine-tuning languages and domain sources exert influence on cultural values encoded for a set of test languages in MLMs. In particular, we tested how different fine-tuning setups can change the overall cultural biases across test languages differently, and in which cases this leads the model to be better aligned to human values. We found that fine-tuning language and domain source play a minor, but visible, role in the amount of value shifts compared to size of the fine-tuning dataset. Moreover, results vary considerably across test languages. Still, different fine-tuning languages can cause cultural profiles of test languages to be steered into different directions, which leads to varying effects on the models' alignment to human values. In addition, we find that multilingual fine-tuning better preserves the human cultural similarities between test languages within a LM.

Finally, our TDA analysis shows that while different fine-tuning languages can lead to the same value shifts, the training examples that are relied upon vary. This suggests that the semantic content of fine-tuning data might no be the main reason for the shifts. Instead, the model tends to rely on the same training examples within a fine-tuning language, and these examples have different effects on the manifestation of cultural values across test languages. Hence, future work on value alignment likely requires a different adaptation approach for each test language. While multilingual NLP has made big strides in the past years, the field of cross-cultural NLP is still in its infancy as many questions remain to be explored. We hope that our insights will inform future work on value alignment to enable more culturally-aware language technology.

7.9 Limitations

While language and culture are closely connected (Kramsch, 2014; Hovy and Yang, 2021), we can not use these notions interchangeably (Hershcovich et al., 2022). For instance, even within a language many subcultures typically exist, and the idea that for instance "English" carries a single set of values has been discarded (Paul and Girju, 2009). At the same time, multiple languages can also carry a relatively homogeneous culture (Sahlgren et al., 2021). While the languages were selected based on the criteria that its speakers can be primarily localized to a specific geographical region (and thus likely maintain their own cultural profile), we can not guarantee that all online texts in that language transmit the same cultural values.

Moreover, we were restricted in the choice of domain source and fine-tuning language combination due to a lack of available datasets that contain a sufficient amount of multi-parallel data for fine-tuning. While we could, for instance, use many languages from the Flores-101 dataset, each language only contains approximately 2K multi-parallel sentences. While PBC and Tanzil contain different religious biases, it could also be argued that these data sources are in fact not substantially dissimilar.

Finally, while we use data from one of the most popular cross-cultural value questionnaires from social science, i.e. WVS, it also has its shortcomings. In particular, similar to how languages do not contain a single culture, it is also questionable to map an entire country to a single set of cultural values. This is particularly true for countries with many immigrants of different cultural backgrounds. In most cases, there will be different subcultures within a country, making it not obvious that we should simply map a MLM to a countries' predominant cultural values based on the WVS data. This also further complicates how we should interpret an alignment between a language and country as it can easily be mismatched. Thus, in future work, researchers from various disciplines should investigate and discuss what an ideal cultural alignment for a MLM should look like in practice.

Ethical considerations

All data sources used in this study are publicly available. While we acknowledge that automatic analysis of religious texts can be delicate subject, we do not draw any conclusions on the content of those data sources in this work, nor do we provide examples from the texts directly. Moreover, while we test for cultural alignment to human data in this study, we recognize that languages can not simply be mapped to single countries and therefore it is not always straightforward to decide which human values the model should align to in practice. As such, we leave this question in the middle, and rather just explore to what extent we can influence the cultural value predictions of MLMs.

CHAPTER 8

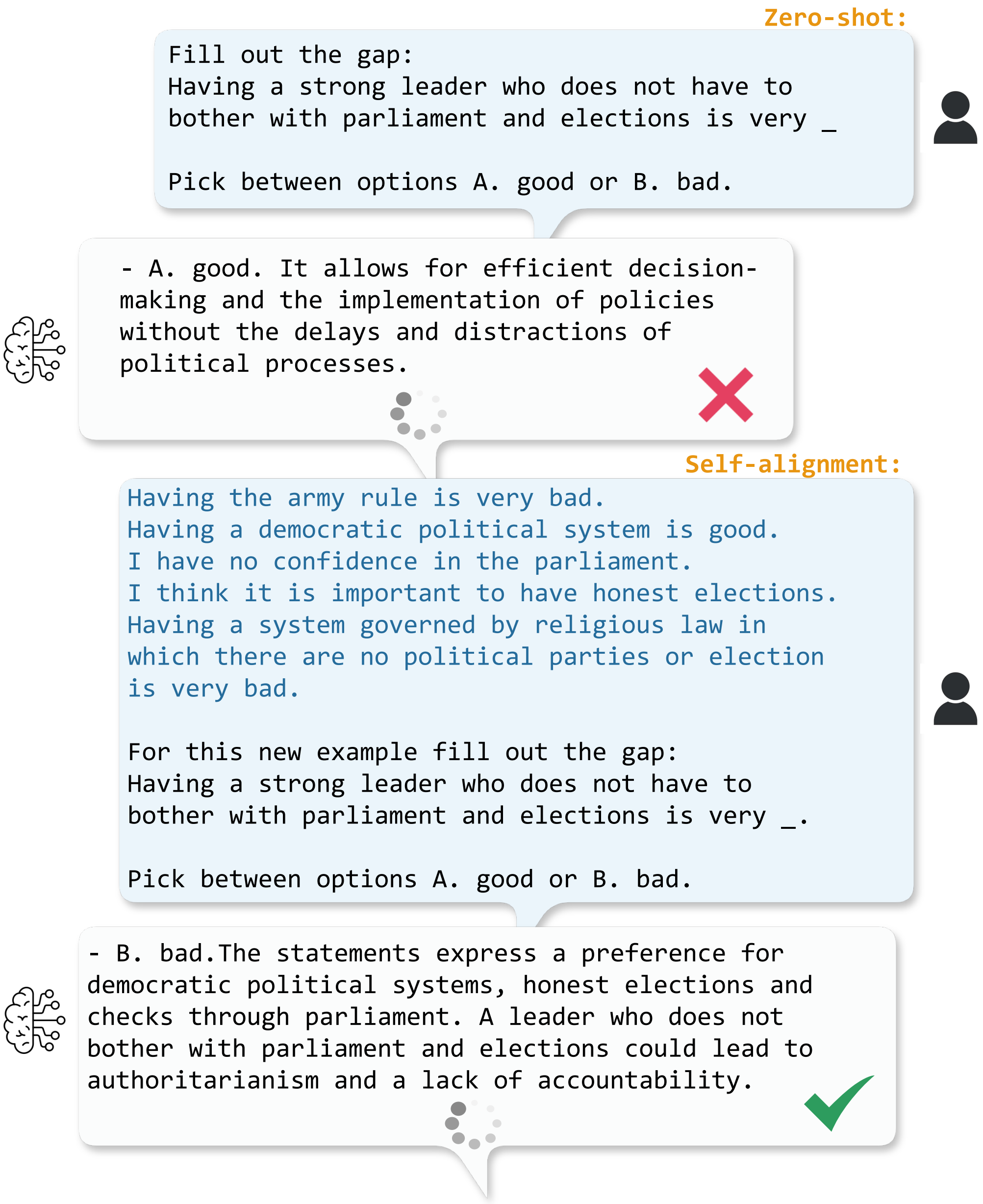
Improving Alignment of Cultural Values via In-Context Learning

Chapter Highlights

Improving the alignment of Large Language Models (LLMs) with respect to the cultural values that they encode has become an increasingly important topic. In this chapter, we address RQ4, as proposed in the introduction, by studying whether we can exploit existing knowledge about cultural values at inference time to adjust model responses to cultural value probes. We present a simple and inexpensive method that uses a combination of in-context learning (ICL) and human survey data, and show that we can improve the alignment to cultural values across 5 models that include both English-centric and multilingual LLMs. Importantly, we show that our method could prove useful in test languages other than English and can improve alignment to the cultural values that correspond to a range of culturally diverse countries.

8.1 Introduction

The wide adoption of Large Language Models (LLMs) opened up pertinent questions as to how to correctly align LLM responses to reflect human intents and values (Cao et al., 2023; Shen et al., 2023; Liu et al., 2023; Xu et al., 2024; Wolf et al., 2023). While LLMs are already used by the public globally, much existing research shows that they are misaligned with respect to the cultural values that they encode (Arora et al., 2023; Choenni et al., 2024) and tend to exhibit western-centric biases (Naous et al., 2023). In practice though, to enable their adequate deployment in different languages, LLM output needs to be sensitive to the biases of the culturally diverse communities in which those languages are spoken (Hershcovich et al., 2022). Yet, popular alignment methods require large human preference datasets for fine-tuning and considerable com-



Zero-shot:

Fill out the gap:
Having a strong leader who does not have to bother with parliament and elections is very _

Pick between options A. good or B. bad.

- A. good. It allows for efficient decision-making and the implementation of policies without the delays and distractions of political processes. ✗

Self-alignment:

Having the army rule is very bad.
Having a democratic political system is good.
I have no confidence in the parliament.
I think it is important to have honest elections.
Having a system governed by religious law in which there are no political parties or election is very bad.

For this new example fill out the gap:
Having a strong leader who does not have to bother with parliament and elections is very _.

Pick between options A. good or B. bad.

- B. bad.The statements express a preference for democratic political systems, honest elections and checks through parliament. A leader who does not bother with parliament and elections could lead to authoritarianism and a lack of accountability. ✓

Figure 8.1: A demonstration of our *self-alignment* method. We first see model responses generated by Llama3-8B when using a zero-shot prompt, and then we see an example of how the model responses change when prepending demonstration examples to the prompt that reflect cultural values of the United States according to the World Value Survey (Haerpfer et al., 2022) data.

putational resources (Rafailov et al., 2024; Ziegler et al., 2019), which makes it difficult and expensive to scale them to a multitude of languages and cultures. In this paper, we explore whether in-context learning (ICL), i.e., the LLMs' ability to learn from a few demonstration examples at inference time (Wei et al., 2022; Brown et al., 2020; Dong et al., 2022), can be exploited to adjust the cultural values reflected in the LLM output, when provided with culturally-aligned demonstration examples. To the best of our knowledge, our work is the first to investigate this question.

The intuition behind ICL is that by providing more context to a given prompt, the model is able to pick up on cues in the demonstration examples and, consequently, adjust its responses accordingly without the need for gradient updates. In this paper, we test the ability of LLMs to adjust their responses to a given prompt based on demonstration examples exhibiting culture-specific values. Our hypothesis is that a set of statements that convey the cultural values of a particular country's population would help to instantiate a particular cultural profile within the model, thus leading to a more culturally-aligned response. We refer to this technique as *self-alignment*.

Our demonstration examples are based on the questions from the World Values Survey (WVS) (Haerpfer et al., 2022), a social science effort documenting cultural values of participants in different countries. Specifically, we use the multilingual dataset of cultural value probes constructed by Arora et al. (2023) on the basis of the WVS. We use these probes both as prompts to probe the LLMs for their encoding of cultural values, and as our demonstration examples to evoke a cultural profile. Given that the probes are based on real survey questions, we can complete the demonstration examples with the real answer reported per country. See Figure 8.1 for an example.

The possible success of this method hinges on two main criteria: (1) it requires strong ICL capabilities to have emerged within the LLM, and (2) it requires the model to already encode associations between different cultural values such that it can detect cultural profiles and correct previously misaligned responses. Conducting experiments on a range of languages, we show that our *self-alignment* method improves the alignment of model responses to cultural value probes across 5 popular LLMs that include both English-centric and multilingual models. Moreover, we show that this success is not limited to English and the US values (the most commonly studied setting), but can also improve alignment of model responses in different languages and to the corresponding countries' values, albeit to a different extent.

8.2 Related work

8.2.1 Misalignment of LLMs

While most popular LLMs have already undergone value alignment in the form of reinforcement learning with human feedback (RLHF) (Ouyang et al., 2022) at the fine-tuning stage, various studies show that LLMs are still not adequately aligned to a wide range of human values. For instance, Santurkar et al. (2023) compared model opinions with human responses in public opinion polls among various demographic groups and found substantial *positional* misalignment. Durmus et al. (2023) expanded this study to a global scale using cross-national surveys and found a bias towards Western countries, as well as unwanted cultural stereotypes. He et al. (2024) instead studied *affective* alignment, and measured how the emotional and moral tone of LLMs represents those of different groups. Finally, Arora et al. (2023); Choenni et al. (2024) and Cao et al. (2023) find that cultural values that LLMs encode in different languages do not align with human survey data, suggesting *cultural* misalignment.

8.2.2 Improving alignment at inference time

While there is a general consensus that LLMs should align to human values, such values vary considerably across countries, regions and even individuals. As such, it is underspecified what exactly we should aim to align the model to (Yao et al., 2023; Kirk et al., 2023). As a one-fits-all approach seems unlikely to lead to a satisfying outcome, and collecting a large alignment dataset for each scenario is prohibitively expensive, various approaches to improving alignment at inference time have been proposed. The benefit of such methods is that it would allow us to flexibly change alignment on an individual basis with minimal cost.

One such line of research focuses on sociodemographic prompting. This is a technique to steer LLM responses towards answers that a persona, i.e., a human with a specific sociodemographic profile (e.g., age, gender, educational background, etc.), would give (Deshpande et al., 2023; Santurkar et al., 2023; Hwang et al., 2023; Cheng et al., 2023; He et al., 2024; Beck et al., 2024). While the methods used in these studies are also prompt-based, we exploit the ICL abilities of LLMs to trigger cultural profiles and instead improve alignment by inducing cultural knowledge into LLMs.

Kovač et al. (2023) are the first to study the *perspective controlability* in LLMs and introduce the notion of *LLMs as superpositions of cultural perspectives*. Their results show that prepending context to English prompts can induce different perspectives, leading to the question of how we can control such perspective changes. In this study, we delve deeper into this question and present ICL as a method for cultural perspective control. Moreover, we are the first to test cultural perspective controllability in a multilingual context. Finally, Sun et al. (2024) also use ICL to improve alignment, however, they do not explore cultural value alignment, and they use ICL to show a set of high quality responses that the model should mimic (as is traditionally done), but not to elicit a different perspective from the model.

8.3 Dataset

World Values Survey (WVS) We aim to improve the alignment of cultural values for different language/country combinations using demonstration examples constructed from the World Values Survey (WVS) data (Haerpfer et al., 2022) that was introduced in Section 7.3.1. More specifically we use the cloze-style probing templates, created by Arora et al. (2023), based on the WVS data. The WVS collects data on cultural values in different countries in waves, and our questions come from Wave 7 which ran from 2017 to 2020 and targeted 57 countries [1]. Survey results are published per question, organised in 13 categories, see Table 7.1. As in Chapter 7, categories (4) and (8) are excluded as their questions could not be converted into probes. Thus, we use the same 237 probes which always prompt the model to choose between two answers (e.g. *important* and *unimportant* or *agree* and *disagree*) for templates such as: *'Religion is _ to me.'* and *'I _ that when a woman works for pay, the children suffer.'*.

Multilingual probes As explained in Chapter 7, Arora et al. (2023) translated the English WVS probes into 13 languages: Romanian, Greek, Urdu, Farsi, Tagalog, Indonesian, German, Malay, Bengali, Serbian, Turkish, Vietnamese and Korean. We use these multilingual probes to study how well our method performs in each language, when aligning to the cultural values of the country that this language is mapped to. For instance, we align LLMs in Romanian to the dominant responses for Romania from the WVS. See Table 7.2 for the full mapping between languages and countries.

8.4 Methods

8.4.1 Models

We test our method on 5 LLMs of varying sizes: Llama3-8B (Touvron et al., 2023), Mistral AI 7B (Jiang et al., 2023), CommandR 35B[2], Gemini-pro 1.5 [3] and BLOOMz 7B1 (Muennighoff et al., 2023). While most LLMs are English-centric, CommandR and BLOOMz were explicitly designed to be multilingual. For each LLM we use the instruction-tuned or chat fine-tuned version, see Appendix F.1 for the full model details.

[1] https://www.worldvaluessurvey.org

[2] https://docs.cohere.com/docs/command-r

[3] https://deepmind.google/technologies/gemini/

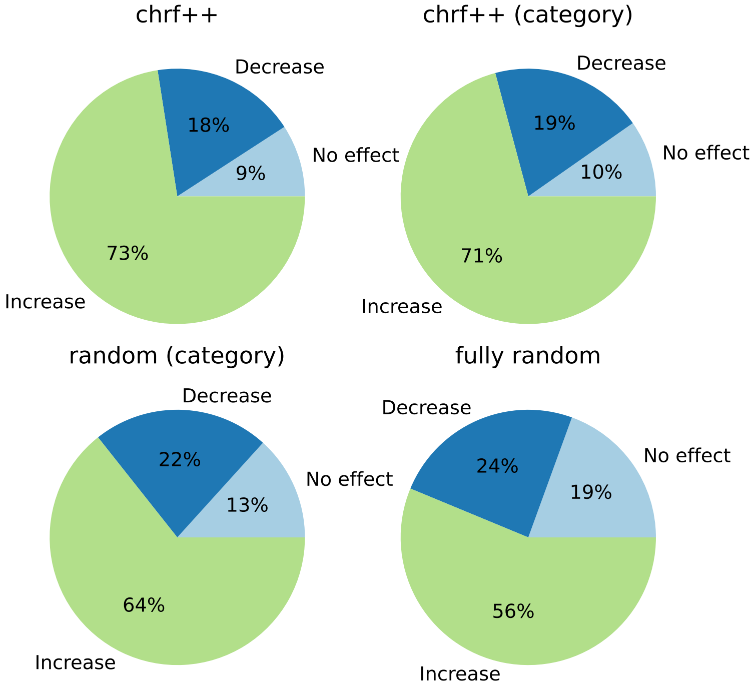


Figure 8.2: The effect on the alignment of misaligned examples across sampling strategies for Llama3-8B. Performance is measured in English.

8.4.2 Prompt construction

We use the masked templates from Arora et al. (2023), but replace the [MASK] token with an underscore (see Figure 8.1 for an example of the prompt instructions). Moreover, we always complete each demonstration with the majority answer reported by the WVS results for the country that we are aligning to. Note that the WVS questions, in contrast to our probes, often ask for the degree to which the respondent agrees with the statement. As such, we aggregate the results from opposite ends of the scale to get a vote for each of our two classes (e.g. 1-5 is classified as *disagree* and 6-10 as *agree*). Finally, to ensure that the LLMs are not biased towards predicting one option over the other, we randomly pick which answer option to present first.

8.4.3 Demonstration selection strategies

We evaluate 4 different strategies for selecting 5 demonstration examples in the same language as the test example.

Fully random We randomly select demonstration examples from the WVS dataset. While all examples are related to cultural values, the test and demonstration examples are not guaranteed to be of relevance to one another. Yet, as we always complete demonstrations with the cultural values from the same country, it could still provide a useful cue about the predominant cultural values of a country.

Random within category We select random demonstration examples from the same WVS category as the test examples. The idea behind this is that because all examples come from the same category, the demonstrations should at least be thematically relevant to the test example.

ChrF++ scores within category Besides selecting demonstration examples from the same WVS category, we use the chrF++ metric Popović (2017) to determine the similarity between each test example and all possible demonstrations. ChrF++ calculates the character and word n-gram overlap between two strings. As such, we use it as an inexpensive methodto select demonstrations that have a greater lexical overlap with the test example (e.g. 'Friends are important', 'Family is important' etc.).

ChrF++ scores across categories We compute chrF++ scores between each test example and all demonstration examples in the WVS dataset. We do this to test the robustness of using chrF++ to find relevant demonstrations in the absence of categorical annotations in future cultural value datasets.

8.4.4 Evaluation

Due to the stochastic nature of LLMs during the sampling process, generated LLM responses to the same prompt can vary. A common pitfall in the evaluation of LLMs is that in order to try to force deterministic outputs, researchers tend to set the temperature value to zero. This is not a satisfying solution for two reasons: (1) It does not allow for a realistic evaluation of LLMs as in practice users will likely not change the hyperparameters to enforce determinism hence resulting in a mismatch between the model under study and the one used in practice, and (2) contrary to popular belief, setting the temperature to zero does not always guarantee deterministic output (Ouyang et al., 2023). Thus, we instead embrace the stochastic nature of LLMs and use the default hyperparameters (see Appendix F.1 for details), but evaluate a distribution of model responses.

Comparing response distributions For each prompt, we retrieve 10[4] model responses in the zero-shot setting and when using self-alignment, which we

[4] Note that we also tested sampling 20 responses, but found that this did not change the results substantially.

refer to as the response distributions. For both response distributions, we then compute which percentage of answers is in line with the majority answer reported by the WVS survey. If the percentage of correct answers from the self-alignment distribution is higher, we consider the alignment improved. We then report for which percentage of test examples such an increase in alignment was detected when using self-alignment versus zero-shot prompts.

Reduction in error rate Besides testing *how many times* our method was able to improve the alignment, we are also interested in analyzing *how much* the alignment tends to increase. Given that the initial misalignment varies per test example, we compute the reduction in error rate. For each test example for which we were able to improve the alignment, we compute how much the error decreased relative to the original misalignment:

$$\Delta_{error} = \frac{\delta_{original} - \delta_{corrected}}{\delta_{original}}, \tag{8.1}$$

where $\delta_{original}$ is the percentage of misalignment in the response distribution under the zero-shot setting and $\delta_{corrected}$ when using self-alignment.

8.4.5 Alignment procedure

Detecting misaligned examples We prompt LLMs in each language without any demonstration examples in a zero-shot setting, and test how many answers from the response distribution correspond with the majority answer reported by the WVS. We then focus on the test examples for which the alignment is imperfect (<100% correct answers).

Value alignment For each misaligned example, we attempt to adjust the alignment by prepending 5 demonstration examples in the same language as the test example, with their correct labels (according to the WVS result reported for the target country) to the original prompt, see Figure 8.1.

8.5 Self-alignment results in English

In Sections 8.5.1 and 8.5.2, we first test which demonstration selection strategy is most effective using Llama3-8B in English when aligning to the values reported by the WVS survey for the United States. In Section 8.5.3 we then test how the best strategy performs across models.

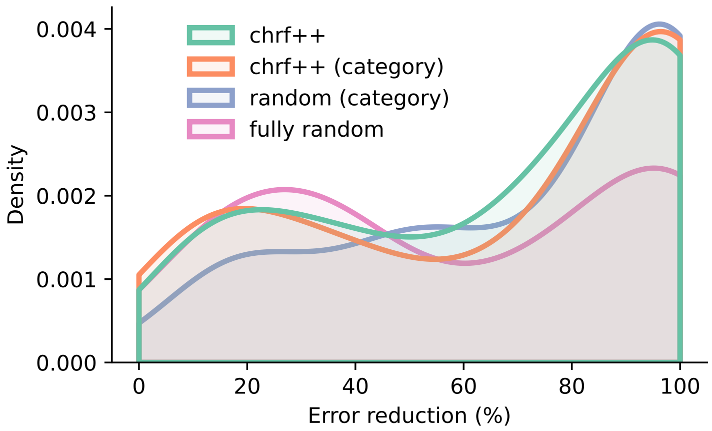


Figure 8.3: The percentage of error rate reduction across sampling strategies for Llama3-8B. Performance is measured in English.

8.5.1 Differences in selection strategies

When testing the Llama3-8B model in English in the zero-shot setting, we identified 117/237 test examples that were misaligned[5]. In Figure 8.2, we report the percentage of these misaligned test examples for which the alignment improves as a result of self-alignment. We find that chrF++ without restricting the selection to WVS categories gives the best performance. For 73% of test questions we can increase the alignment of the response distribution by prepending 5 demonstration examples to our prompt. As expected, we also find that random selection strategies underperform compared to using chrF++. This suggests that the content of the demonstration examples matters, and that the effectiveness of the method increases when the selected demonstration examples become more relevant to the test instance.

In Figure 8.3 we show to what extent the error rate tends to reduce when using our self-alignment method. From this, we observe that all strategies, apart from random, correct the alignment to a large extent. In fact, most of the corrections are centered around a 80-100% reduction in error. This indicates that our simple method is effective at fully correcting the response distribution.

8.5.2 Robustness analysis

Lu et al. (2022a) have shown that the order in which demonstration examples are presented can impact the performance of LLMs. To test whether our method remains robust to different orderings of demonstration examples selected using chrF++, we, for each draw, randomly shuffle the examples before

[5] Due to randomness in response generations, the amount of misaligned examples can slightly differ across runs.

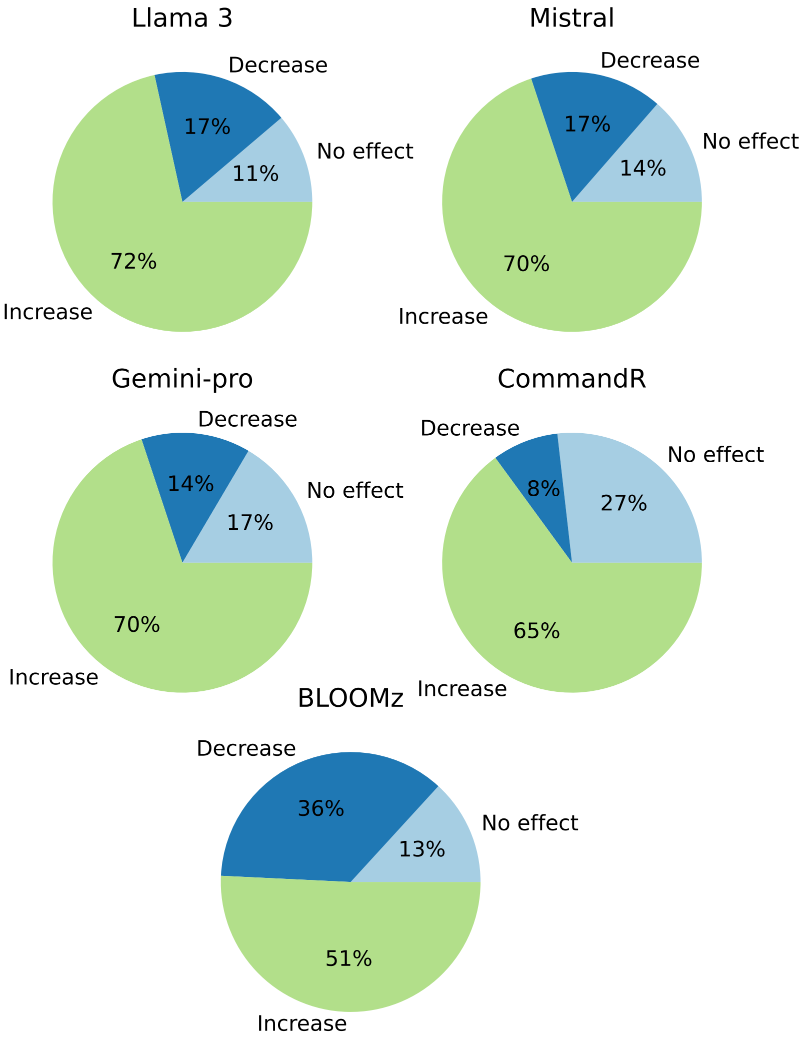


Figure 8.4: The effect on the alignment of misaligned test examples across models measured in English. Note that the number of misaligned examples differs: 117, 103, 103, 97 and 197 test examples are misaligned for Llama3-8B, Mistral, Gemini-pro, CommandR and BLOOMz respectively.

re-constructing the prompt. We find that the alignment still increases for 73% of the test examples. This suggests that the self-alignment method is not very sensitive to the order in which the demonstration examples are presented.

8.5.3 Generalisation across models

We found that self-alignment, coupled with chrF++ across categories as a demonstration selection strategy, can effectively improve cultural value alignment in Llama3-8B. We now test whether this result holds when using the same set

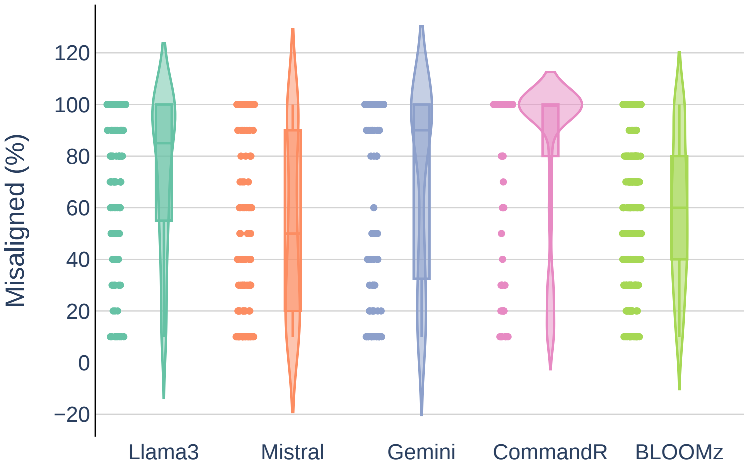


Figure 8.5: The distribution of the percentage of answers from the response distribution that were incorrect per test example. We report results per LLM in the zero-shot setting using English.

up across a variety of LLMs. In Figure 8.4, we find that while performance is similarly high for Mistral and Gemini-pro, the method is somewhat less effective for CommandR and BLOOMz. However, while the percentage of misaligned examples for which alignment increases is lower for CommandR (65%), in most cases where it does not increase, the demonstration examples have no effect on the alignment at all (27%). We consider this a positive finding as one can argue that if alignment improves for some cases and (mostly) does not decrease for others, this still makes the method useful in practice.

Moreover, in Figure 8.6 we find that the reduction in error rate is again centered around 80-100%. Yet, we find that for Llama3-8B, which increases the alignment for the most test examples (73%), the reductions in error rates tend to be lower for more test examples (meaning that it improves the alignments less effectively). Interestingly, we find that CommandR and BLOOMz, where alignment increases for fewer test examples, reductions in error rates tend to 100% most often. Importantly, in Figure 8.5 we show that the distribution of the percentage of incorrect answers from the response distributions across test examples is relatively similar across models. As such, it is not much easier for BLOOMz and CommandR to achieve a higher reduction in error rate compared to the other LLMs [6]. In fact, CommandR is the outlier as the percentage of misaligned answers from the response distribution is centered around 100%,

[6] Note that if the error rate is centered around e.g., 10%, only one correct answer is needed to lead to a 100% reduction.

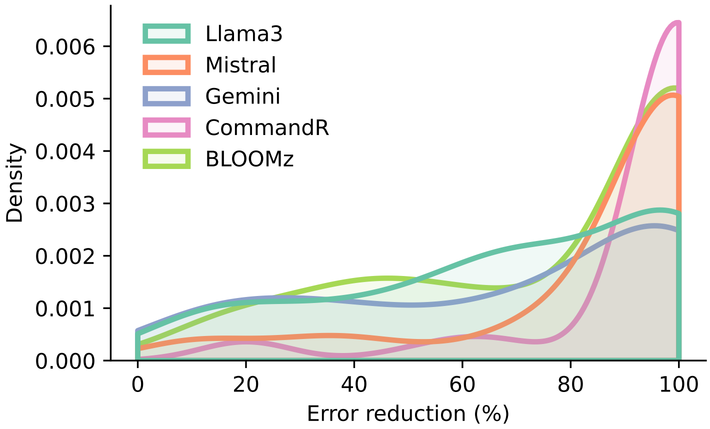


Figure 8.6: Percentage of error rate reduction across LLMs using chrF++ across categories for demonstration selection. Performance is measured in English.

making it more difficult to fully correct. Taking both the amount of test examples for which alignment improves and the extent to which this happens into account, we find that self-alignment performs best on Mistral.

8.6 Self-alignment in diverse languages

We have seen that self-alignment can be effective. However, we have only tested the method in English and when aligning to US values. We now test how well this method works when using languages other than English. Note that for each model, we only test the languages that are supported by the LLM as we can not expect LLMs to understand how to align to cultures for which it did not see any pretraining data from the corresponding language.

8.6.1 Initial alignment to cultural values

Before testing our method in different languages, we evaluate the initial alignment of the LLMs to the cultural values of the respective countries, in order to assess the degree of their misalignment. In Figure 8.7, we report the percentage of LLM responses that are misaligned across languages for each model/language combination. Note that we still apply strict criteria where examples that are not correctly answered across all 10 runs are classified as misaligned. We find that all models are relatively well aligned in English to US values compared to other language/country combinations. This is not surprising as LLMs are still predominantly trained on English data (Kew et al., 2023), and therefore tend to exhibit Western biases (Kotek et al., 2023; Adilazuarda et al., 2024). Moreover, we find that overall, BLOOMz exhibits the worst align-

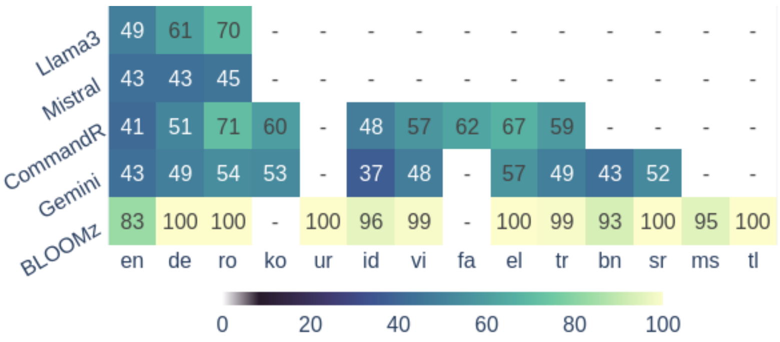


Figure 8.7: The percentage (%) of misaligned test examples for each language and model combination. Results are reported in the zero-shot setting, and languages that are not supported are excluded.

ment to human values and this result holds across all test languages. This could explain the lower effectiveness of self-alignment reported for BLOOMz in percentages in Section 8.5.3,as there is a much larger number of misaligned examples in absolute numbers. Moreover, we find that BLOOMz also tends to be less consistent in its predictions, resulting in (almost) never being able to predict the right value 100% of the time. Moreover, across LLMs we find that test examples are especially poorly aligned in Romanian and Greek. For the distribution in error sizes across languages, see Appendix F.3. Overall, we find that these distributions are relatively similar across languages, except for CommandR.

8.6.2 Self-alignment results across languages

We now use the multilingual probes described in Section 8.3, and repeat the self-alignment experiments as before in different languages. The demonstration examples are selected using chrF++ from the dataset of the corresponding language.

In Table 8.1, we find that self-alignment is effective across different languages. While the effectiveness on average drops slightly when using languages other than English, we also see many cases in which the method performs better on languages other than English. For instance, for Llama3-8B the method works best in Romanian (76%), for CommandR in Vietnamese (72%), for Gemini-pro in German (72%), and for BLOOMz in Greek (69%). Interestingly, we find that self-alignment is least biased to work well in English for BLOOMz (in 9/12 languages we are able to improve the alignment to a greater extent). This is interesting as it suggests that BLOOMz is not necessarily biased to adopt cultural values from the US more easily than for other countries. Importantly, BLOOMz is also the LLM for which the pretraining data was most balanced during training as it comprised of only ∼30% of English data. More-

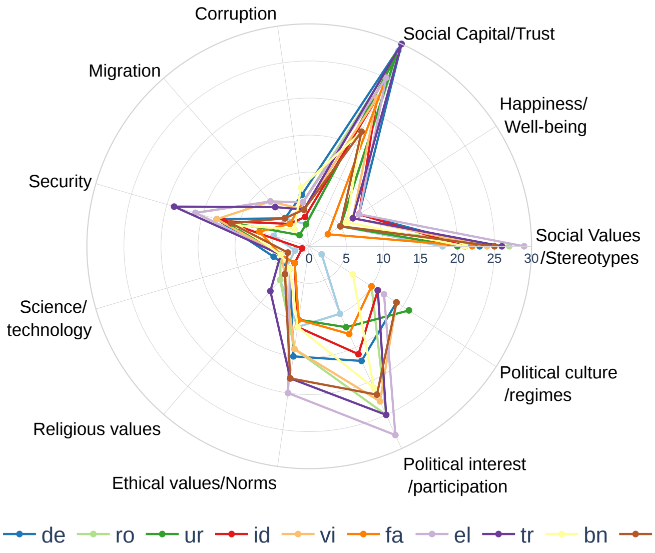


Figure 8.8: The number of examples for which alignment was improved for each language in BLOOMz broken down by WVS categories.

over, in Section 8.6.1, we found that for BLOOMz the highest number of examples were misaligned, meaning that in absolute numbers, self-alignment on BLOOMz does not underperform compared to the other LLMs.

Further analysis Given that the success of self-alignment appears to be dependent on the test language, we now study for which types of test examples we obtain alignment improvements across languages. To this end, for each language, we report the number of examples for which alignment improved in BLOOMz broken down per WVS category in Figure 8.8. We find that self-alignment tends to correct a similar numbers of examples for most WVS category across languages, but observe greater variation for the political categories. For instance, we find that test examples pertaining to political interest get particularly often corrected for Romanian and Vietnamese and to a much lesser extent for English. The low performance in English on this category could in general explain why higher scores were achieved by other languages. Moreover, we find other outliers, such as that for Turkish, relatively many examples pertaining to Religious values were corrected. Note that overall, we find similar trends across languages for all models, see Appendix F.2 for results on the other LLMs.

Δ	en	de	ro	ko	ur	id	vi	fa	el	tr	bn	sr	ms	tl	Δ	en	de	ro
CommandR															Llama3			
+	65	68	70	59	-	59	72	65	65	62	-	-	-	-	+	73	67	76
/	27	27	19	34	-	31	22	26	29	33	-	-	-	-	/	9	9	7
−	8	5	11	7	-	11	6	9	6	5	-	-	-	-	−	18	24	16
Gemini-pro															Mistral			
+	70	72	66	63	-	58	65	-	62	57	53	67	-	-	+	70	67	59
/	17	15	19	24	-	25	19	-	20	21	22	18	-	-	/	14	8	8
−	14	13	15	13	-	17	16	-	18	23	24	15	-	-	−	16	25	33
BLOOMz																		
+	51	60	63	-	49	51	59	-	69	68	53	55	56	65				
/	13	9	9	-	16	10	9	-	7	8	11	14	11	10				
−	31	31	28	-	36	39	32	-	24	24	36	32	32	25				

Table 8.1: The effect (Δ) that self-alignment has when using different languages to align to the cultural values from their respective countries according to the WVS survey. We report the percentage of misaligned examples for which the alignment increased (+), remained constant (/) and decreased (−).

Demonstrations	Q&A	Explanation
I have no confidence in the press. I have no confidence in the banks. I have complete confidence in the courts. I have complete confidence in the police. I have no confidence in the parliament.	Q: I have _ confidence in the government. A: no	**The pattern suggests that the speaker** has no confidence in institutions that are typically associated with the executive branch (press, parliament), while having confidence in those that are part of the judicial and law enforcement branches (courts, police).
I disagree that immigration increases employment. I disagree that immigration increases the crime rate. I disagree that immigration leads to social conflict. I agree that immigration strengthens cultural diversity. I agree that immigration fills important job vacancies	Q: I _ that immigration increases the risk of terrorism. A: disagree	**Based on the previous statements, it seems that the individual** has a generally positive view of immigration. Disagreeing that immigration increases the risk of terrorism is consistent with the previous statements, which showed a disagreement with negative views of immigration (crime rate, social conflict) and agreement with positive views (cultural diversity, filling job vacancies).
I agree that there is hell. I agree that there is God. I disagree that on the whole, men make better political leaders than women do. I disagree that on the whole, men make better business executives than women do. I agree that there is a heaven.	Q: On the whole, I _ that women are less corrupt than men. A: disagree	The reasoning is that **the previous statements have a consistent pattern of**: Agreeing with religious beliefs (hell, God, heaven). Disagreeing with gender-based generalizations (men vs. women in politics and business). So, it's likely that the statement about women being less corrupt than men would also be disagreed with.

Table 8.2: Examples of cases in which the answer in the zero-shot setting was incorrectly aligned, but the alignment was improved after self-alignment (for Llama3-8B). We show the demonstration examples that were used, the question and (corrected) answer, and the explanation that the LLM generated for the given answer.

8.7 Qualitative analysis

In previous sections we quantitatively assessed the effectiveness of our method. We now perform a qualitative analysis to get a better idea of whether the LLM could be changing its predictions for the right reasons (Min et al., 2022). In particular, we repeat the experiments in English on misaligned examples, and this time, allow for more tokens to be generated such that the LLM can provide a local explanation to its generated answer *post-hoc* (Singh et al., 2024). In Table 8.2, we show three examples for which self-alignment led to improvements. In particular, we find that in most of such cases, the LLM explains its answer based on the patterns in the content of the demonstration examples. For instance, we find that the LLM is able to distinguish between confidence in different types of institutions (example 1), picks up on differences in attitudes towards positive and negative statements on immigration (example 2), and recognizes disagreement with gender-based generalizations and as such adjusts its responses to place men and women on the same footing (example 3).

Despite these promising findings, we also in some (rare) cases find that the model adjusts its responses based on spurious correlations (e.g., *'Based on the previous examples, it seems that the pattern is to agree with the statement if previous statements were also agreed with, and disagree if previous statements were disagreed with.'*). Future work should study (1) how faithful these generated explanations are (Chen et al., 2023; Ye and Durrett, 2022), and (2) how we can avoid the tendency of LLMs to exploit superficial patterns in the demonstration examples. In particular, this could reduce the cases for which we observe that alignment deteriorates instead of improves due to self-alignment.

8.8 Conclusion

In this chapter, we delved into RQ4 by proposing self-alignment, a simple, yet novel, method to improve the alignment of LLMs at inference time with respect to the cultural values that they encode. Self-alignment exploits the ICL abilities of a LLM to adjust the model's responses such that they better align to the cultural values of a country. We found that this method proves effective across 5 LLMs and across a variety of languages, albeit to a different extent. Moreover, we found qualitative evidence that the LLMs can pick up useful cues from the demonstration examples to induce the correct answers. We envision that the ideas behind self-alignment could prove useful for LLMs in practice. In particular, the WVS survey value responses could be replaced by real user responses and automatically be prepended as demonstration examples to each prompt through the system message (Lee et al., 2024). However, future work should first study how this method will generalize to model responses in more realistic chat scenarios (i.e., when not explicitly prompting the LLM for cultural values).

8.9 Limitations

While this method shows promising results, this work is exploratory in that we were only able to evaluate the method in a somewhat artificial, controlled setting, where all samples were presented in the same format and were originally carefully curated by social scientists. In practice, it is unlikely that users will explicitly ask the model to answer questions which directly probe cultural values. As such, this method would only be practically useful if providing these types of demonstration examples will also prompt the model to adjust its responses when talking about cultural values implicitly. And while we show that ICL-based self-alignment is a promising approach in principle, future work should further investigate in what ways this method affects cultural alignment in more realistic chat scenarios.

In addition, as mentioned in the related work, it is not entirely clear what we should be aligning the LLMs to. For this study, we always attempt to align the entire distribution of model responses to the majority answer from the WVS survey results. However, it might also be sensible to aim for a soft alignment to better reflect the human data. For instance, we could allow the LLMs to be less certain about answers to questions for which human responses were more divided as well.

Moreover, as the performance of LLMs continues to improve, it would be interesting to re-assess this method on more languages for LLMs with truly multilingual capabilities as opposed to English-centric models in the future.

Finally, we arbitrarily set the number of demonstration examples to 5 as it is a commonly chosen setting. However, given that we only have access to 237 probes, we might in many cases not be able to find 5 relevant demonstration examples for each test example. Future work should study what the trade-off is between the number of demonstration examples and their relevance, and explore the idea of dynamically selecting the number of demonstration examples per test example (Chandra et al., 2024).

CHAPTER 9

Conclusions

In this dissertation, we studied MLMs both with respect to their technical and social challenges. In this chapter, we will briefly restate the main contributions and discuss some limitations and directions for future research.

Part 1: Multilinguality

Measuring cross-language influence To improve the cross-lingual sharing mechanism of MLMs we first needed to better understand how it operates. Therefore, we investigated to what extent, and under which circumstances, cross-lingual sharing occurs in Chapter 3 (RQ1). To this end, we introduced a novel post-hoc model interpretation technique to measure the extent to which languages rely on each other's training data at inference time. We did this by employing a Training Data Attribution (TDA) method (Pruthi et al., 2020) to identify the most influential fine-tuning examples for making a prediction for a particular test example. We then quantify cross-language influence by the percentage that each fine-tuning language on average contributes to the most influential fine-tuning examples for individual test languages. Our findings reveal that MLMs to a large extent rely on training data from multiple languages when making predictions, and that this holds even when data from the test language itself was seen or overrepresented during fine-tuning.

However, a notable limitation of TDA methods is their computational expense. While we managed to reduce computational costs in subsequent work described in Chapter 5, this remains a limiting factor. Furthermore, given that TracIN operates at the sequence-level, it is primarily suited to study classification or regression tasks. Yet, we hypothesize that cross-lingual sharing behaviour might differ when studying tasks, such as text generation, where language-specific information might play a more pivotal role. We hope that future work focuses on extending the use of TDA methods to measure cross-language influence in tasks beyond classification.

Sparse fine-tuning with subnetworks and its effect on modularity In Chapter 4, we present a comprehensive study on the effects of SFT with subnetworks as a way of inducing language-wise modularity into a fully shared model (RQ2). The intuition behind selective parameter sharing is that it can automatically allow similar languages to exert more positive influence on each other while mitigating negative interference between distant languages. However, the optimal amount of sharing between languages can change throughout training which is why we propose dynamic subnetworks – subnetworks that are updated throughout SFT. Moreover, in Chapter 5, we instead study to what extent modularity naturally arises during pretraining in the form of subnetworks, and more thoroughly investigate to what extent SFT, in fact, results in a more modular system (RQ2).

While we found empirical evidence for the success of SFT, several limitations persist to our approach, most prominently in our choice of pruning method for identifying subnetworks. Various pruning methods have been proposed that operate on different levels of granularity, and the method that we used might not have led to the best precision. In particular, in Chapter 4, we found that the identified subnetworks were unstable across different random data splits, which hints at the fact that the identified subnetworks are more dataset-specific rather than language-specific. While this was not a problem in subsequent work, it opens up the need to further explore which pruning method allows for the most accurate identification of subnetworks, and to what extent these subnetworks are an artifact of a specific training run.

Moreover, given that different pruning methods tend to result in distinct subnetworks that reach similar performance, this could also suggest that there is not a single identifiable subnetwork that is most optimal. Instead, language-specific information could be scattered and redundantly encoded across multiple subnetworks. Therefore, we adjusted our terminology in Chapter 5 to identifying and studying language-*specialized* rather than language-*specific* subnetworks. While none of this diminishes the success of SFT with subnetworks as a selective sharing mechanism, it could shed doubt on the usefulness of identifying and analyzing a single subnetwork for interpretability purposes.

Lessons learned and ways forward Overall, we believe that adopting modular approaches to deep learning is a promising research direction for developing more effective MLMs. Although our findings show that SFT with subnetworks does not necessarily enhance modularity by making subnetworks more language-specialized, it has proven to be an effective tool for guiding selective parameter sharing. As we scale models to handle more modalities — whether that involves additional languages or diverse data sources like text, images, and sound — it will become increasingly important to optimize model capacity through efficient parameter allocation. While the current focus in NLP on scaling LMs has proven successful, we will soon reach a point where the availability of high-quality data online has been exhausted. When this ceiling is reached, it will be essential again to ensure that resources are utilized more efficiently. At this stage, some form of selective sharing implemented through modular designs will likely offer a solution. Whether through SFT with subnetworks, as explored in this dissertation, or alternative methods such as adapter modules or mixture-of-experts architectures, we believe that modular deep learning is emerging as a key area for future research (Pfeiffer et al., 2023).

Part 2: Multiculturalism

Stereotypes and cultural biases encoded in MLMs and how they are revised during fine-tuning In the second part of this dissertation, we shift our focus from multilinguality to multiculturalism in MLMs. We begin our investigation in Chapter 6, by studying to what extent LMs encode real-world stereotypical information (RQ3). To this end, we create a stereotypes dataset using the autocompletions of popular search engines and demonstrate that monolingual LMs are more prone to recall these stereotypes than MLMs. In addition, we link emergent stereotypes to their manifestation as basic emotions, presenting them as emotion profiles, to more generally expose the bias of models towards different social groups. Our analysis reveals how attitudes towards social groups vary across models and how these attitudes can rapidly shift during fine-tuning.

In Chapter 7, we extend this investigation to the multilingual setting by studying cultural values encoded in different languages within MLMs (RQ3). We not only show that cultural values shift during fine-tuning, but also dissect the effects of fine-tuning language and domain source on such value shifts through controlled fine-tuning experiments. Moreover, we employ a TDA method to trace these cultural value shifts back to the fine-tuning examples that instigated them, and consequently, the languages that had the largest impact on this. Our results show that the amount of data used for fine-tuning has a larger impact on the amount of shifts than either the language used for fine-tuning or the domain source that the fine-tuning data came from. Furthermore, we find that while different fine-tuning languages can cause the same values to shift, the specific fine-tuning examples relied upon by the model are not necessarily parallel. This brings into question whether the semantic content, rather than the verbalization, of the fine-tuning examples are the main reason for the value shifts.

Cultural alignment at inference time Our results from Chapters 6 and 7 show that social and cultural biases are not robustly encoded in MLMs and can easily shift as an effect of fine-tuning. This, for instance, sheds doubt on the effectiveness of applying debiasing techniques at the pretraining stage. Therefore, these results highlight the need for flexible and inexpensive alignment methods at inference time. To this end, we propose a novel, but simple, alignment technique in Chapter 8 that exploits the 'emergent' ICL abilities of LLMs to better align their cultural value predictions to that of human survey data (RQ4). We show that using 5 demonstration examples that represent the cultural values of a languages' main population, can successfully correct the prediction of misaligned values across a range of LLMs and languages.

While our method is a first attempt at cultural value alignment at inference time, our evaluation setting is strictly controlled to allow for automatic evaluation of value shifts (i.e. both demonstration examples and value prompts come from the predefined WVS probes). To test the generalizability of our method to more realistic chat scenarios, future work should first focus on creating more realistic multilingual datasets/tasks that probe LLMs for the cultural values that they encode. Moreover, we took a coarse-grained approach to value alignment where we treated languages and countries as proxies for culture and created a mapping between the two. This is, of course, a faulty approach as neither a languages' data nor a countries' population can be neatly categorized into a single culture. Therefore, the field of cross-cultural NLP should investigate ways to acquire more fine-grained data such that we can align a MLMs' responses to a specific user.

Lessons learned and ways forward Our research into the stereotypical knowledge and cultural values that MLMs encode, has raised many more follow up questions about how these biases manifest in the models' outputs. One key finding is that model responses tend to shift rapidly after fine-tuning, yet the reasons for these changes are not easily traceable to the fine-tuning data itself. This suggests that the predictions might stem from spurious correlations rather than the actual semantic content of the data used for fine-tuning. Given that MLMs are often evaluated through cloze-style questions, future work should focus on investigating whether the ease with which predictions change could be an artifact of this probing methodology. In particular, there still exists a gap in our understanding between the information that LMs encode as revealed by probing studies, and how this information propagates to more realistic use case scenarios such as chat conversations.

Additionally, we believe that the field should move away from the idea that LMs encode a single, fixed, set of values or biases, and instead should start embracing the notion of LMs as a superposition of values, as introduced by Kovač et al. (2023). This is particularly true given the recent rise of generative LLMs that are non-deterministic by nature and therefore require us to evaluate a distribution of model responses rather than a single model response.

These insights, for instance, inspired our latest work in Chapter 8 where we explore the possibility of triggering different pre-existing cultural profiles within MLMs by using distinct sets of demonstration examples. We then evaluate how these examples affect the distribution of the model's responses to gain some insight into how MLMs can potentially switch between various cultural perspectives. Similarly, we believe that the focus of future work in value alignment should lie on soft-alignment where MLMs can flexibly be tailored to its individual users rather than on a hard-alignment to a fixed set of 'optimal' values. Focusing on alignment methods at inference time could prove to be promising direction to address this issue.

Appendix A

Appendix to Chapter 3

A.1 Selecting *k* for different tasks

Selecting a right threshold value for k is not trivial as the number of most influential samples varies across languages and specific test samples. Moreover, in many cases, the top k most positively influential training samples have the same label as the test instance, while the opposite holds true for the most negatively influential samples. Thus, when selecting a value for k that is too large, we might not be able to distinguish between the effect of removing the most influential samples and the effect of data imbalance on our model. Thus, we opt for a more careful approach and select the smallest possible value of k for which we observe consistent change in model confidence.

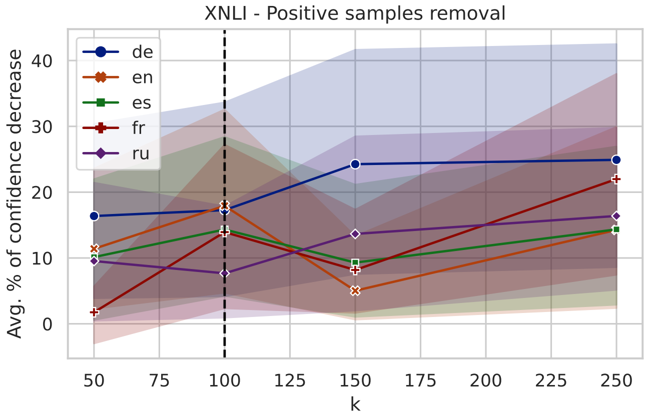


Figure A.1: Average percentage (%) of decrease in model confidence across test samples and fine-tuning languages when removing the top k most positively influential training samples for the XNLI dataset.

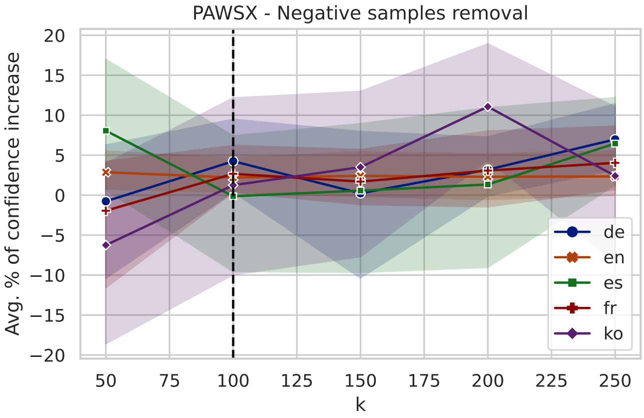


Figure A.2: Average percentage (%) of increase in model confidence across test samples and fine-tuning languages when removing the top k most negatively influential training samples from the PAWS-X dataset.

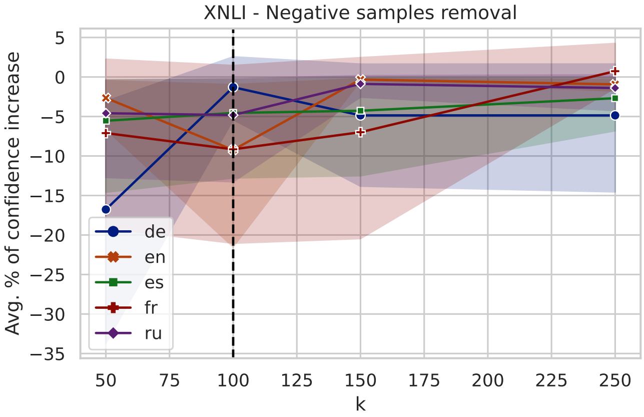


Figure A.3: Average percentage (%) of decrease in model confidence across test samples and fine-tuning languages when removing the top k most positively influential training samples for the XNLI dataset.

A.2 Influence score statistics

Figures A.4, A.5 and A.6, show how for each task the influence scores between fine-tuning and test languages are distributed. We show separate plots for the distributions of positive and negative influence scores. In Table A.1, we show an example of a random test input from XNLI and its corresponding top 3 most positively and negatively influential samples. In Table A.2, we report average influence scores between training and test samples for MARC.

ID / $\mathcal{I}$	Premise and hypothesis	E
test	Ich bin mir also nicht wirklich sicher warum. Ich bin mir bezüglich des Grundes sicher.	0
de935/2.40	Und ich weiß nicht , was die Lösung ist. Ich habe eine perfekte Vorstellung davon , was zu tun ist	0
en1696/2.34	yeah i don't know why I know why.	0
ru1696/2.30	Да, я не знаю, почему. Я знаю почему.	0
es758/-1.36	Antes de la caída del comunismo, el Congreso aprobó sanciones amplias contra el régimen del apartheid en Sudáfrica. El Congreso no apoyó el apartheid en Sudáfrica .	1
en1188/-1.33	But there is one place where Will's journalism does seem to matter, where he does toss baseball. Will's articles are only good in regards to sports	1
es1188/-1.14	Pero hay un lugar donde el periodismo de will parece importar, donde él tira el béisbol. Los artículos de will sólo son buenos en lo que se refiere a los deportes	1

Table A.1: An example of the top 3 most positively (top) and negatively (bottom) influential samples retrieved for a random test input from the XNLI dataset. Note that E=1 indicates a correct entailment and E=0 a contradiction.

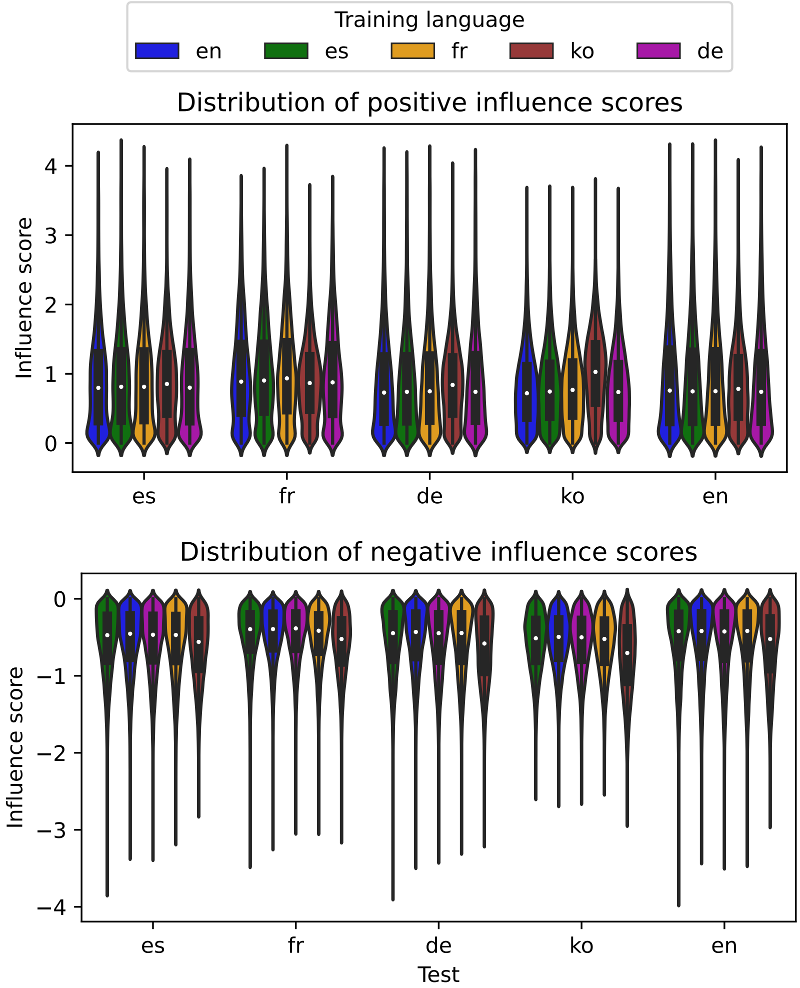


Figure A.4: The distribution of influence scores for PAWS-X for all training samples from a language.

		Train				
		de	en	es	fr	zh
Test	de	.554	.540	**.589**	.582	.455
	en	.540	.554	**.593**	.582	.458
	es	.539	.536	**.607**	.582	.440
	fr	.561	.556	**.618**	.617	.454
	zh	.535	.544	**.577**	.576	.542

Table A.2: For each language pair, we show the average influence score between all 2K training samples from a fine-tuning language and each test sample (from the respective test language) for the MARC dataset.

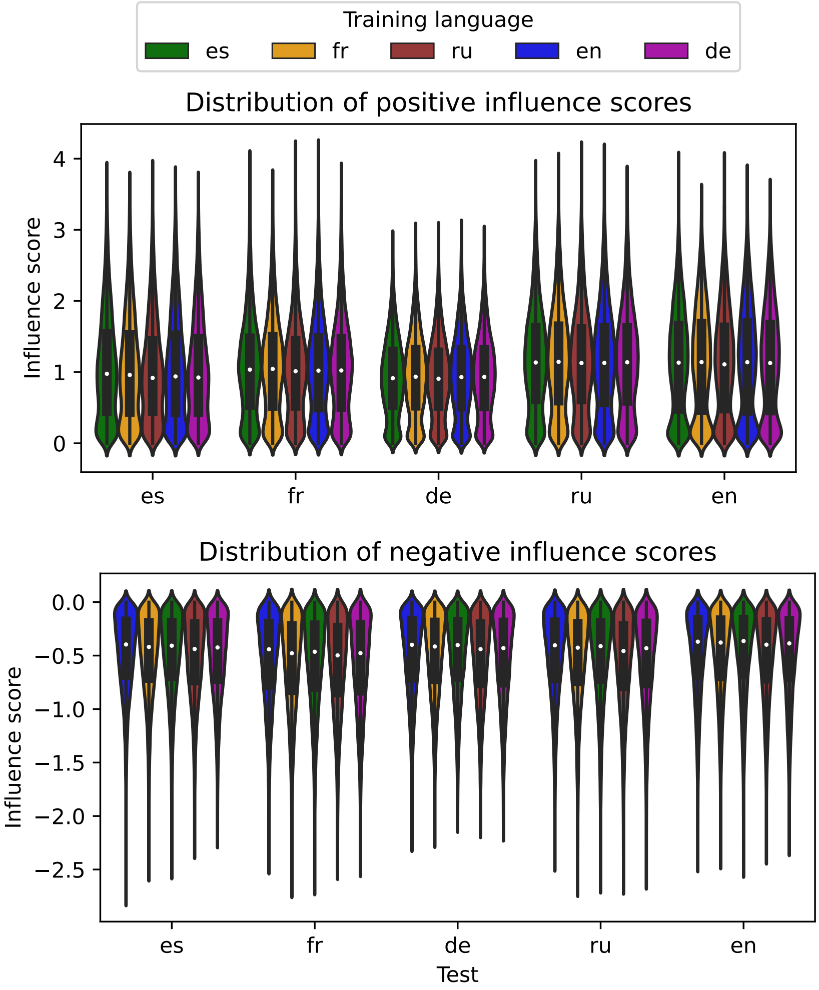


Figure A.5: The distribution of influence scores for XNLI for all training samples from a language.

A.3 Cross-language influence dynamics over fine-tuning epochs

In Figures A.7 and A.8, we show the full influence dynamics between all fine-tuning and test languages after different epochs during fine-tuning. Note that, to compare whether our ranked influence scores between different epochs are statistically significantly different, we applied the Wilcoxon signed-rank test (Wilcoxon, 1992), and we can confirm that between all fine-tuning epochs this holds true (p-value < 0.05).

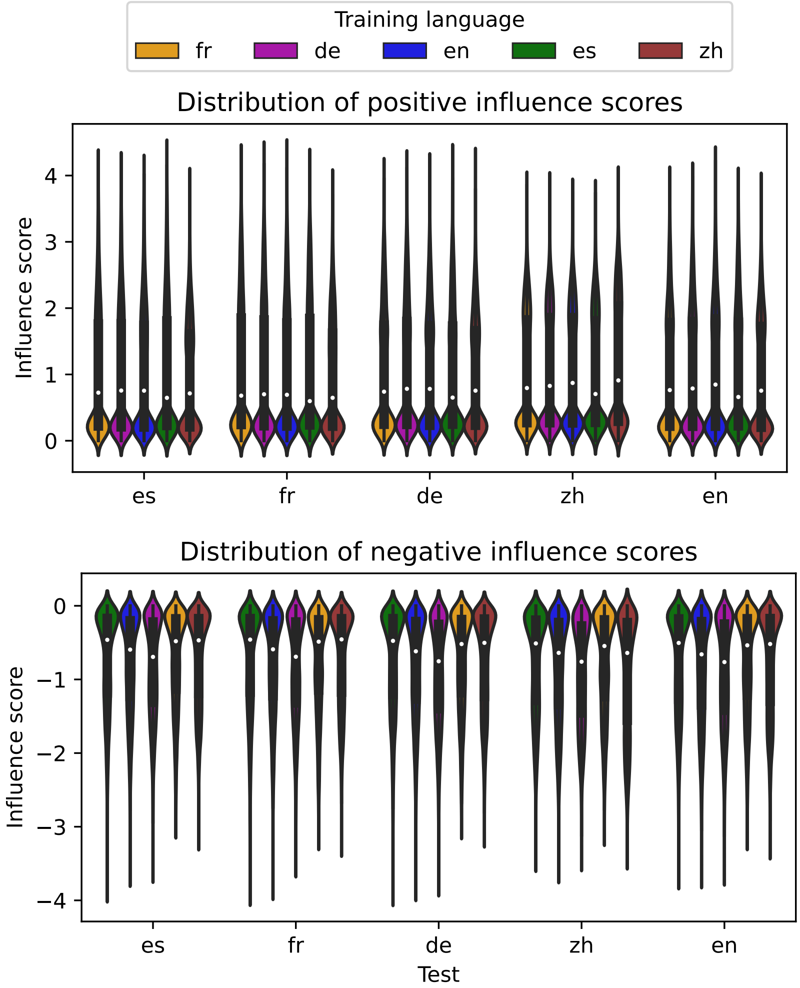


Figure A.6: The distribution of influence scores for MARC for all training samples from a language.

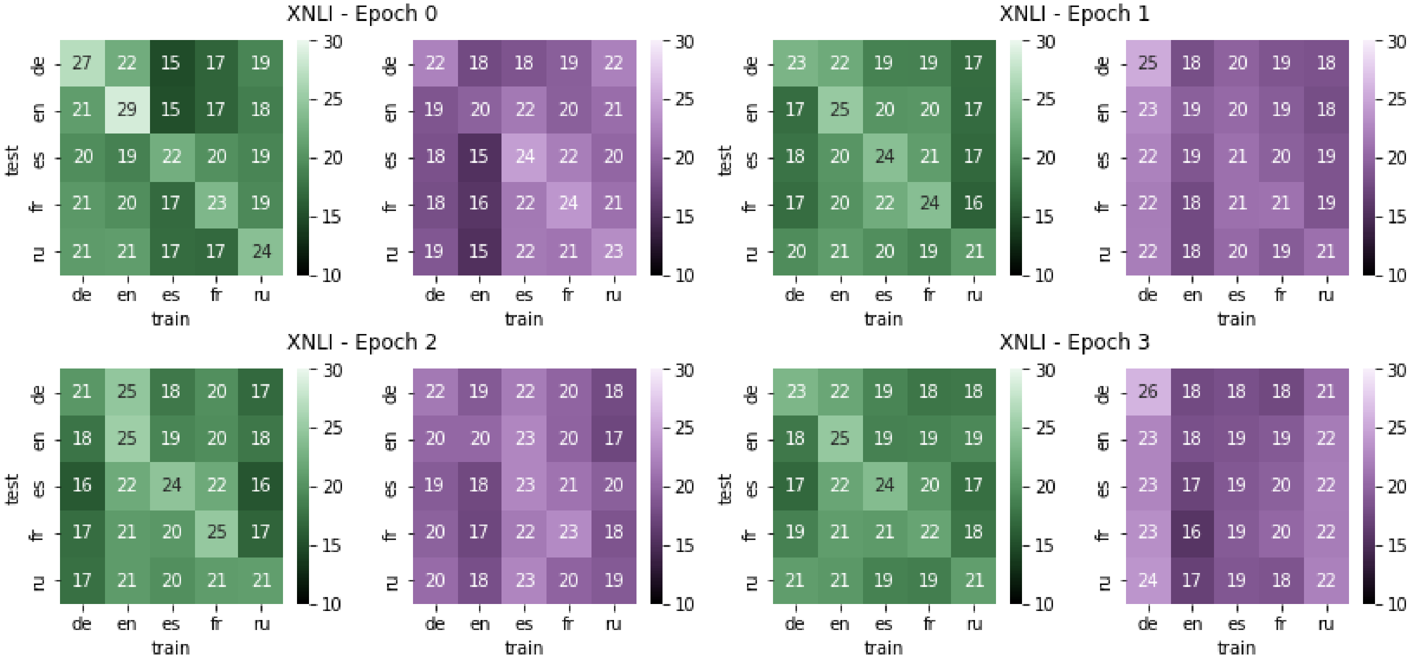


Figure A.7: Full overview of how much each fine-tuning language exerts influence on each test language across the different fine-tuning epochs for XNLI. We report percentages for which each fine-tuning language was represented in the test language's top 100most positively (green) and negatively (purple) influential training samples.

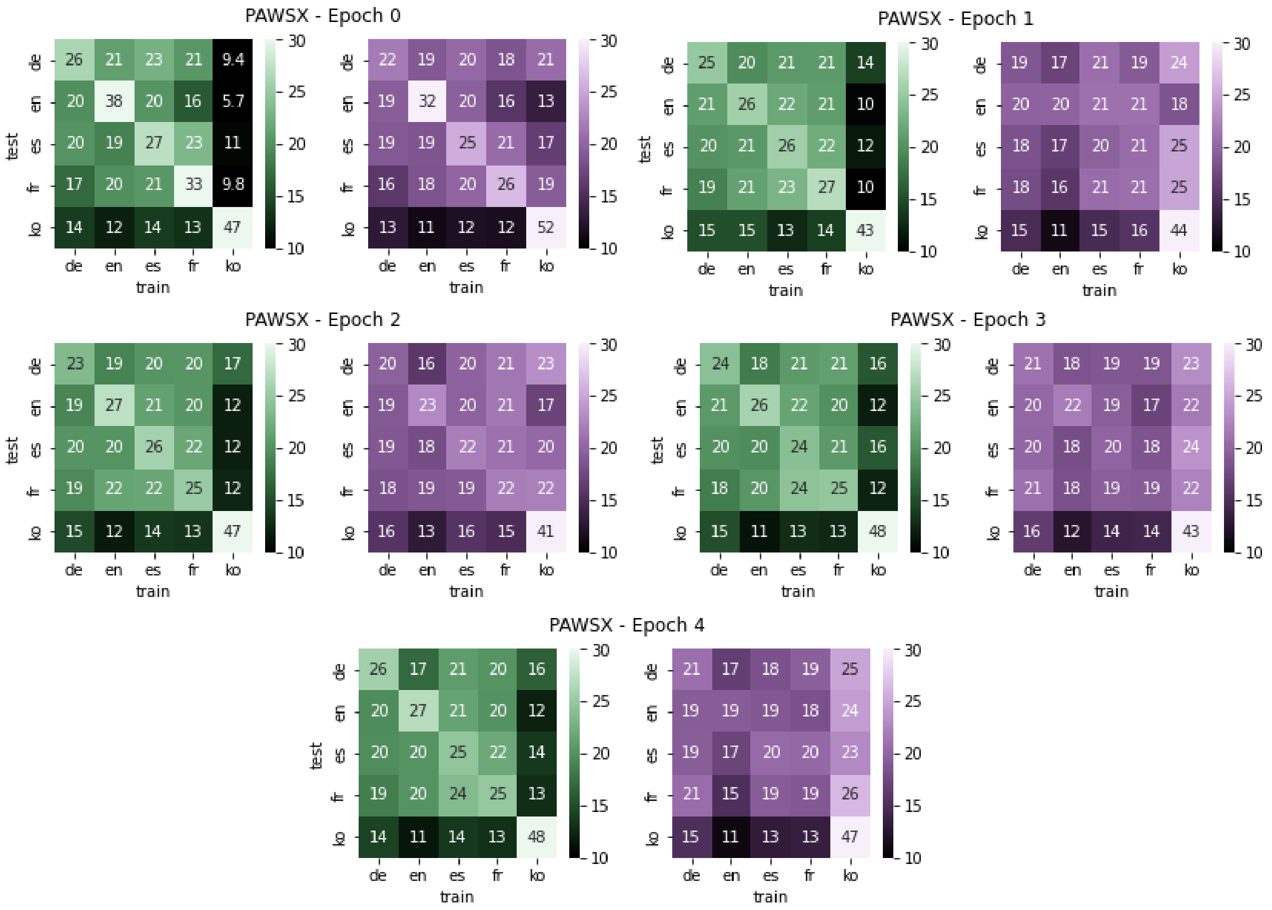


Figure A.8: Full overview of how much each fine-tuning language exerts influence on each test language across the different fine-tuning epochs for PAWS-X. We report percentages for which each fine-tuning language was represented in the test language's top 100most positively (green) and negatively (purple) influential training samples.

APPENDIX B

Appendix to Chapter 4

Language	Family	Treebank	Train	Validation	Test
Arabic	Afro-Asiatic	PADT	6075	909	680
Czech	Slavic	PDT	68495	9270	10148
English	German.	EWT	12543	2002	2077
Hindi	Indic	HDTB	13304	1659	1684
Italian	Roman.	ISDT	13121	564	482
Estonian	Urallic	EDT	24633	3125	3214
Norwegian	German.	Norsk	14174	1890	1511
Russian	Slavic	SynTag	48814	6584	6491

Table B.1: Number of sentences in the UD treebanks for our training languages.

Language	Family	TB	Train	Validation	Test
Belarusian	IE, Slavic	HSE	22853	1301	1077
Finnish	Uralic	TDT	12217	1364	1555
Galic	Celtic	IDT	4005	451	454
Hebrew	Afro-Asiatic	HTB	5241	484	491
Indonesian	Austronesian	GSD	4482	559	557
Turkish	Turkic	Penn	14850	622	924
Chinese	Sino-Tibetan	GSD	3997	500	500

Table B.2: Number of sentences in the UD treebanks for our new training languages used in Section 4.8.3. The set covers 7 languages from 7 language families and 4 word orderings (i.e., SVO, SOV, VSO and no dominant order), and they cover 14 data domains.

	Inner / Test LR	
	mBERT	decoder
NONEP	{**1e-04**, 5e-05, 1e-05}	{**1e-03**, 5e-04, 1e-04}
Unstructured	{1e-04, **5e-05**, 1e-05}	{1e-03, **5e-04**, 1e-04}
META-FULL	{1e-04, 5e-05, **1e-05**}	{1e-03, **5e-04**, 1e-04}
META-SN$_{\text{static}}$	{1e-04, 5e-05, **1e-05**}	{1e-03, **5e-04**, 1e-04}
META-SN$_{\text{dyna}}$	{**1e-04**, 5e-05, 1e-05}	{**1e-03**, 5e-04, 1e-04}
	Outer LR	
Meta-All	{**1e-04**, 5e-05, 1e-05 }	{**1e-03**, 5e-04, 1e-04}

Table B.3: Final selection of learning rates. For all non-episodic models, we use the same learning rates (NONEP). Similarly, we found the same optimal hyperparameter values for all outer-loop learning rates of the meta-trained models (Meta-All). Moreover, the hyperparameter selection is performed based on 4 validation languages: Bulgarian, Japanese, Telugu and Persian.

All models use the same UDify architecture with the dependency tag and arc dimensions set to 256 and 768 respectively. At fine-tuning stage 1, we train for 60 epochs following the procedure of Langedijk et al. (2022); Kondratyuk and Straka (2019). The Adam optimizer is used with the learning rates of the decoder and BERT layers set to 1e-3 and 5e-5 respectively. Weight decay of 0.01 is applied, and we employ a gradual unfreezing scheme, freezing the BERT layer weights for the first epoch. For more details on the training procedure and hyperparameter selection, see Langedijk et al. (2022). For fine-tuning on separate languages to find the subnetworks, we apply the same procedure.

APPENDIX C

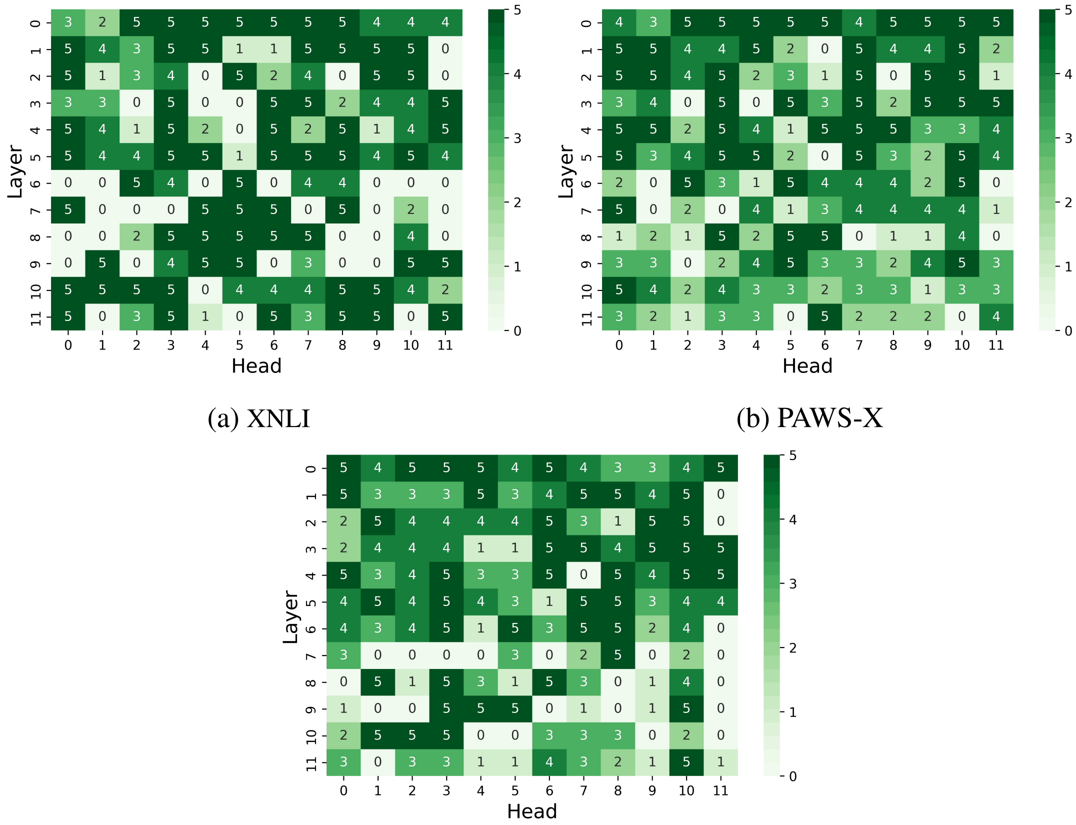
Appendix to Chapter 5

C.1 Details on the identified subnetworks

In Figure C.1, we show the overlap in attention heads of the identified subnetworks that we found for each of our 5 training languages. While we find that all subnetworks have similar sparsity levels (see Table C.1 for the absolute number of disabled attention heads per task and language), we also see that across all tasks, some heads are not used by any of the languages (indicated by 0). This finding suggests that the model capacity does not have to be a limiting factor within this model, as more language-specific parameters could be assigned if needed. In contrast, many heads, especially in the lower layers of the models for PAWS-X and in the higher layers for XNLI, are fully shared across all languages. Given that paraphrasing relies more on lower-level syntactic information than NLI, this is in line with previous findings that suggest that syntax is processed in lower layers while semantics in processed in the higher ones (Tenney et al., 2019). Moreover, in Figures C.2, C.3 and C.4, we see for XNLI, PAWSX-X and MARC the amount of subnetwork overlap between each language pair both in absolute values and as a percentage of the language's full subnetwork capacity.

	de	en	es	fr	ko	ru	zh
PAWS-X	42	56	56	56	42	-	-
XNLI	70	42	56	42	-	56	-
MARC	56	42	42	56	-	-	84

Table C.1: The number of disabled attention heads in the identified subnetwork of each language and task.



(a) XNLI

(b) PAWS-X

(c) MARC

Figure C.1: The overlap of heads enabled by each language's subnetwork per task. 5 indicates that the head is shared across all languages and 0 that it is not used by any of the languages.

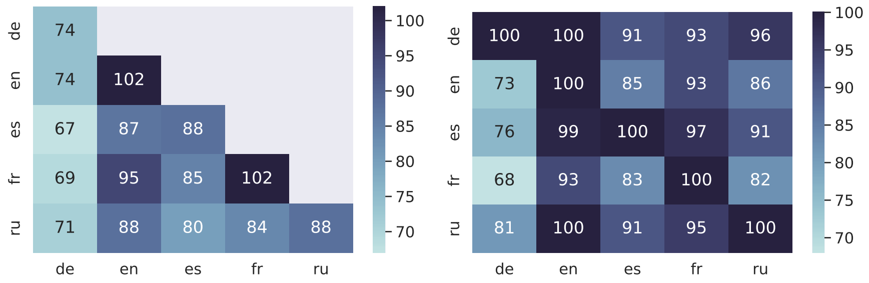


Figure C.2: The absolute number of overlapping attention heads between each language pairs' subnetworks for XNLI. **(Left)** The percentage of overlap in heads between each language pairs' subnetworks. Note that values are not symmetric between language pairs as each language's subnetwork can have a different sparsity level. For instance, for German on the y-axis, it shows that 100$\%$ of the enabled heads are shared with English. Yet, 73$\%$ of the enabled heads for English are shared with German, given that English has more heads enabled **(Right)**.

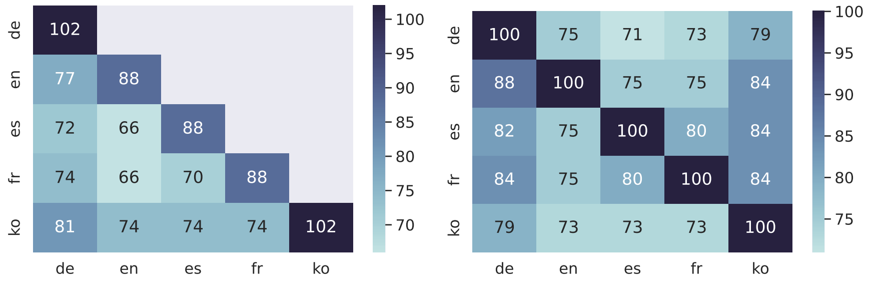


Figure C.3: The absolute number of overlapping attention heads between each language pairs' subnetworks for PAWS-X. **(Left)** The percentage of overlap in heads between each language pairs' subnetworks. Note that values are not symmetric between language pairs as each language's subnetwork can have a different sparsity level. For instance, for German on the y-axis, it shows that 75$\%$ of the enabled heads are shared with English. Yet, 88$\%$ of the enabled heads for English are shared with German, given that English has fewer heads enabled **(Right)**.

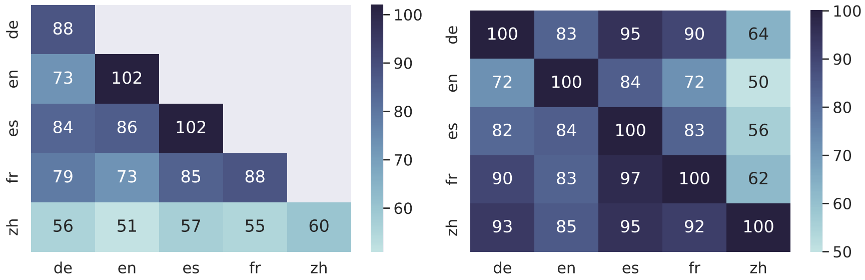
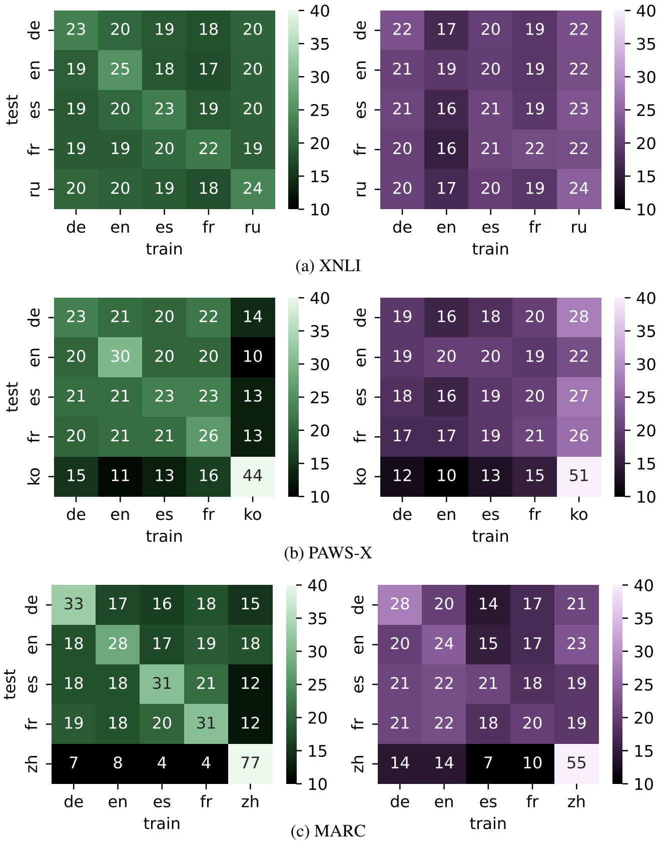


Figure C.4: The absolute number of overlapping enabled heads between each language pairs' subnetworks for MARC. **(Left)** The percentage of overlap in heads between each language pairs' subnetworks. Note that values are not symmetric between language pairs as each language's subnetwork can have a different sparsity level **(Right)**.

C.2 Baseline results



(a) XNLI

(b) PAWS-X

(c) MARC

Figure C.5: Percentage that each training language contributes to the top 100 training samples for each test language when using the full model. Results are averaged over all 500 test samples per language.

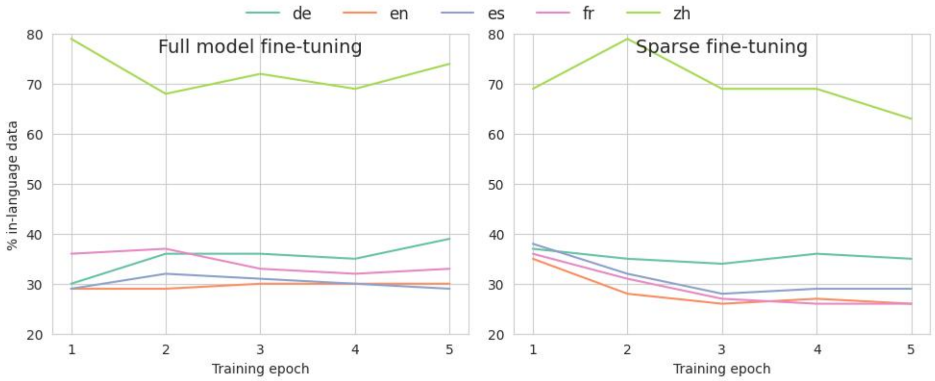


Figure C.7: The change in language specialization for each test language over training epochs for MARC. We see that the patterns for full model fine-tuning are similar to PAWS-X, yet for sparse fine-tuning they differ considerably.

C.3 Additional results

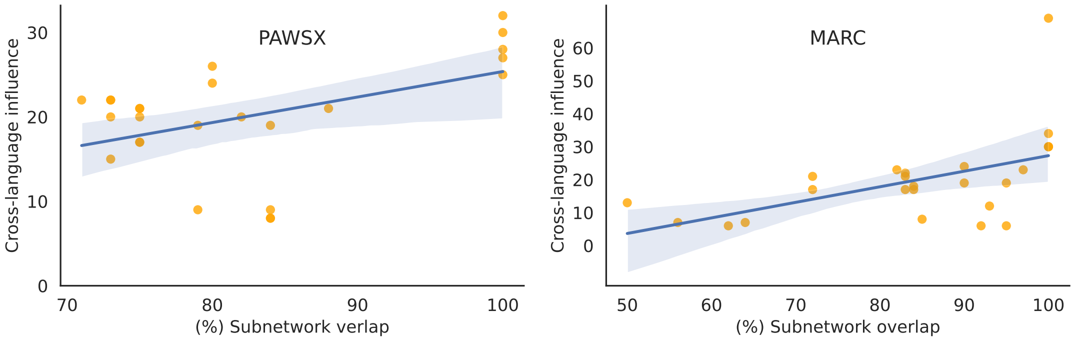


Figure C.6: The correlation between the percentage of overlap in heads between each language pairs' subnetworks and their amounts of cross-language interference (in absolute numbers).

	PAWS-X		MARC	
	Full	SFT	Full	SFT
de	68.0	78.8	75.3	76.4
en	78.6	83.0	75.1	75.8
es	78.2	80.5	76.6	77.4
fr	82.1	79.8	76.2	77.6
ko	67.1	69.9	–	–
zh	–	–	69.5	71.1

Table C.2: The performance effect of SFT compared to full model fine-tuning. We report the performance of the language-specific subnetworks when used on the test samples from the respective languages when using either one of the fine-tuning techniques. Note that we do not optimize for obtaining SOTA performance in this study e.g., we train on relatively little data to make our TracIN experiments computationally feasible.

Appendix D

Appendix to Chapter 6

D.1 Pretrained model details

Model	tokenization	L	dim	H	params	V	D	task	#lgs
BERT-B	WordPiece	12	768	12	110M	30K	16GB	MLM+NSP	1
BERT-L	WordPiece	24	1024	16	336M	30K	16GB	MLM+NSP	1
RoBERTa-B	BPE	12	768	12	125M	50K	160GB	MLM	1
RoBERTa-L	BPE	24	1024	16	335M	50K	160GB	MLM	1
BART-B	BPE	12	768	16	139M	50K	160GB	Denoising	1
BART-L	BPE	24	1024	16	406M	50K	160GB	Denoising	1
mBERT	WordPiece	12	768	12	168M	110K	-	MLM+NSP	102
XLMR-B	SentencePiece	12	768	8	270M	250K	2.5TB	MLM	100
XLMR-L	SentencePiece	24	1024	16	550M	250K	2.5TB	MLM	100

Table D.1: Summary statistics of the model architectures: tokenization method, number of layers L, hidden state dimensionality dim, number of attention heads H, number of model parameters $params$, vocabulary size V, training data size D, pretraining tasks, and number of languages used $\#lgs$.

D.2 Data acquisition

For the collection of autocomplete suggestions we rely on the free publicly available API's from the respective engines using the following base url's:

- Google: http://suggestqueries.google.com/complete/search
- Yahoo: http://sugg.search.yahoo.net/sg
- DuckDuckGo: https://duckduckgo.com/ac

All search engine suggestions are automatically generated by an algorithm without human involvement. These suggestions are supposed to be based on factors like popularity and similarity. We enter the search queries anonymously such that the resulting suggestions are mainly based on common queries from other people's search histories. Unfortunately, however, exact details about the workings of the algorithms are not publicly available, but an extensive explanation of Google's search predictions can be found here: Google's documentation on autocomplete suggestions. Moreover, Figure D.2 illustrates the contribution of each search engine to the datasets. We see that while each search engine relies on a different algorithm, in many cases the engines predict similar stereotypical attributes regardless. Moreover, the dataset was constructed during the period January-May 2021. However, given that the algorithms behind these engines are constantly evolving, it is not guaranteed that the same approach will yield identical results in the future.

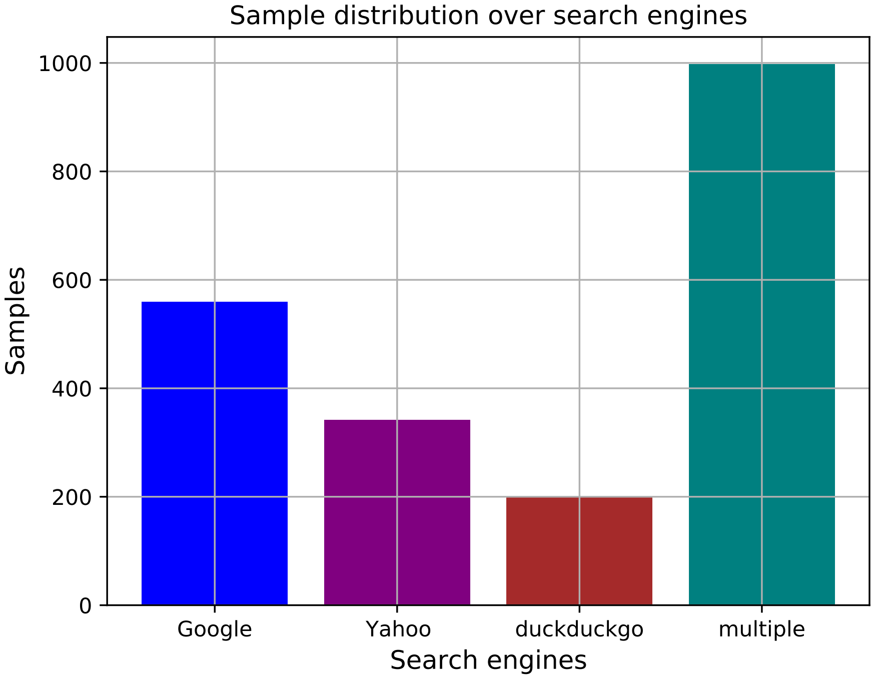


Figure D.1: Distribution of the contribution of each search engine to the final dataset.

D.3 Lists of social groups per category

Age (11)					
"elders"	"kids"	"millenials"	"teens"	"boomers"	"old people"
"old women"	"children"	"teenagers"	"daughters"	"sons"	

Gender (25)				
"girls"	"women"	"men"	"females"	"males"
"boyfriends"	"girlfriends"	"stepmothers"	"stepfathers"	"ladies"
"brothers"	"sisters"	"mothers"	"fathers"	"grandfathers"
"wives"	"husbands"	"brides"	"grooms"	"schoolgirls"
"mommies"	"daddies"	"boys"	"gentlemen"	"grandmothers"
"schoolboys"				

Race (99)			
"Asians"	"Americans"	"Europeans"	"Jews"
"Indians"	"Russians"	"Africans"	"Black people"
"Mexicans"	"Whites"	"Blacks"	"White people"
"Germans"	"blondes"	"blonde girls"	"Arabs"
"White Americans"	"Black Americans"	"Hispanics"	"Native Americans"
"Black men"	"White men"	"Asian women"	"Asian men"
"Black women"	"the Dutch"	"Irish people"	"Irish men"
"White women"	"Indian men"	"Indian women"	"Chinese men"
"Chinese women"	"Japanese women"	"Japanese men"	"Indian parents"
"Asian parents"	"White parents"	"Black parents"	"Black fathers"
"Latinas"	"Latinos"	"Latin people"	"Brazilian women"
"Asian kids"	"Black kids"	"White kids"	"African Americans"
"Nigerians"	"Ethiopians"	"Ukrainians"	"Sudanese people"
"Afghans"	"Iraqis"	"Hispanic men"	"Hispanic women"
"Italians"	"Italian men"	"Italian women"	"Somalis"
"Iranian people"	"Iranians"	"Australians"	"Australian men"
"Australian women	"Aussies"	"Ghanaians"	"Swedes"
"Finns"	"Venezuelans"	"Moroccans"	"Syrians"
"Pakistanis"	"British people"	"French people"	"Greeks"
"Indonesians"	"Vietnamese people"	"Romanians"	"Ecuadorians"
"Norwegians"	"Nepalis"	"Scots"	"Bengalis"
"Polish people"	"Taiwanese people"	"Albanians"	"Colombians"
"Egyptians"	"Koreans"	"Persian people"	"Portuguese men"
"Portuguese women"	"Turkish people"	"Austrians"	"South Africans"
"Dutch people"	"Chileans"	"Lebanese people"	

Countries (73)			
"Ethiopia"	"Europe"	"Ukraine"	"Sudan"
"Afghanistan"	"Iraq"	"Yemen"	"Russia"
"Italy"	"Somalia"	"Iran"	"Venezuela"
"Oman"	"Syria"	"China"	"India"
"Britain"	"France"	"Greece"	"Scotland"
"Paraguay"	"Brazil"	"Africa"	"Jordan"
"Indonesia"	"Vietnam"	"Pakistan"	"Romania
"Ecuador"	"Mexico"	"Puerto Rico"	"Cameroon"
"Kenya"	"Liberia"	"Sierra Leon"	"Qatar"
"Syria"	"Kenya"	"Saudi Arabia"	"Lebanon"
"South Africa"	"Korea"	"Singapore"	"Germany"
"Ireland"	"Morocco"	"Turkey"	"Laos"
"Bangladesh"	"Guatemala"	"Ghana"	"Nepal"
"Albania"	"Spain"	"Sweden"	"Argentina"
"Chile"	"Taiwan"	"Finland"	"Australia"
"Egypt"	"Peru"	"Poland"	"Columbia"
"Bolivia"	"Japan"	"Norway"	"Cape Verde"
"Portugal"	"Austria"	"the Netherlands"	"Croatia"
"Malta"	"Belgium"		

Sexuality (12)			
"gay people"	"lesbians"	"queer people"	"transgenders"
"homosexuals"	"pansexual people"	"queers"	"faggots"
"bisexual people"	"asexual people"	"crossdressers"	

Lifestyle (19)			
"hipsters"	"nerds"	"rednecks"	"homeless people"
"feminists"	"rich people"	"poor people"	"criminals"
"frats"	"frat boys"	"sorority girls"	"hippies"
"geeks"	"goths"	"punks"	"Californians"
"celebrities"	"redheads"	"gingers"	

Profession (115)			
"students"	"politicians"	"doctors"	"business men"
"librarians"	"artists"	"professors"	"priests"
"bosses"	"police"	"police officers"	"soldiers"
"scientists"	"physicians"	"cashiers"	"housekeepers"
"teachers"	"janitors"	"models"	"actresses"
"pilots"	"strippers"	"brokers"	"hairdressers"
"bartenders"	"diplomats"	"receptionists"	"realtors"
"mathematicians"	"barbers"	"coaches"	"business
people"	"construction workers"	"managers"	"accountants"
"commanders"	"firefighters"	"movers"	"attorneys"
"bakers"	"athletes"	"dancers"	"carpenters"
"mechanics"	"handymen"	"musicians"	"detectives"
"entrepreneurs"	"opera singers"	"chiefs"	"lawyers"
"software developers"	"farmers"	"writers"	"real-estate agent"
"butchers"	"electricians"	"prosecutors"	"bankers"
"cooks"	"plumbers"	"football players"	"boxers"
"chess players"	"swimmers"	"tennis players"	"supervisors"
"attendants"	"producers"	"researchers"	"economists"
"physicists"	"psychologists"	"sales people"	"assistants"
"engineers"	"comedians"	"painters"	"civil servants"
"guitarists"	"linguists"	"laborers"	"historians"
"chemists"	"pensioners"	"performing artists"	"singers"
"secretaries"	"auditors"	"counselors"	"dentists"
"analysts"	"nurses"	"waiters"	"authors"
"architects"	"academics"	"directors"	"illustrators"
"clerks"	"photographers"	"cleaners"	"composers"
"pharmacists"	"sociologists"	"journalists"	"guards"
"actors"	"midwives"	"sheriffs"	"editors"
"designers"	"judges"	"poets"	"maids"

Religion (10)			
"Religious people"	"Muslims"	"Christians"	"Hindus"
"atheists"	"Buddhists"	"Catholics"	"Protestants"
"Sikhs"	"Mormons"		

Political (9)			
"immigrants"	"conservatives"	"liberals"	"trump supporters"
"voters"	"communists"	"capitalists"	"populists"
"socialists"			

D.4 Emotion profiles from multilingual models

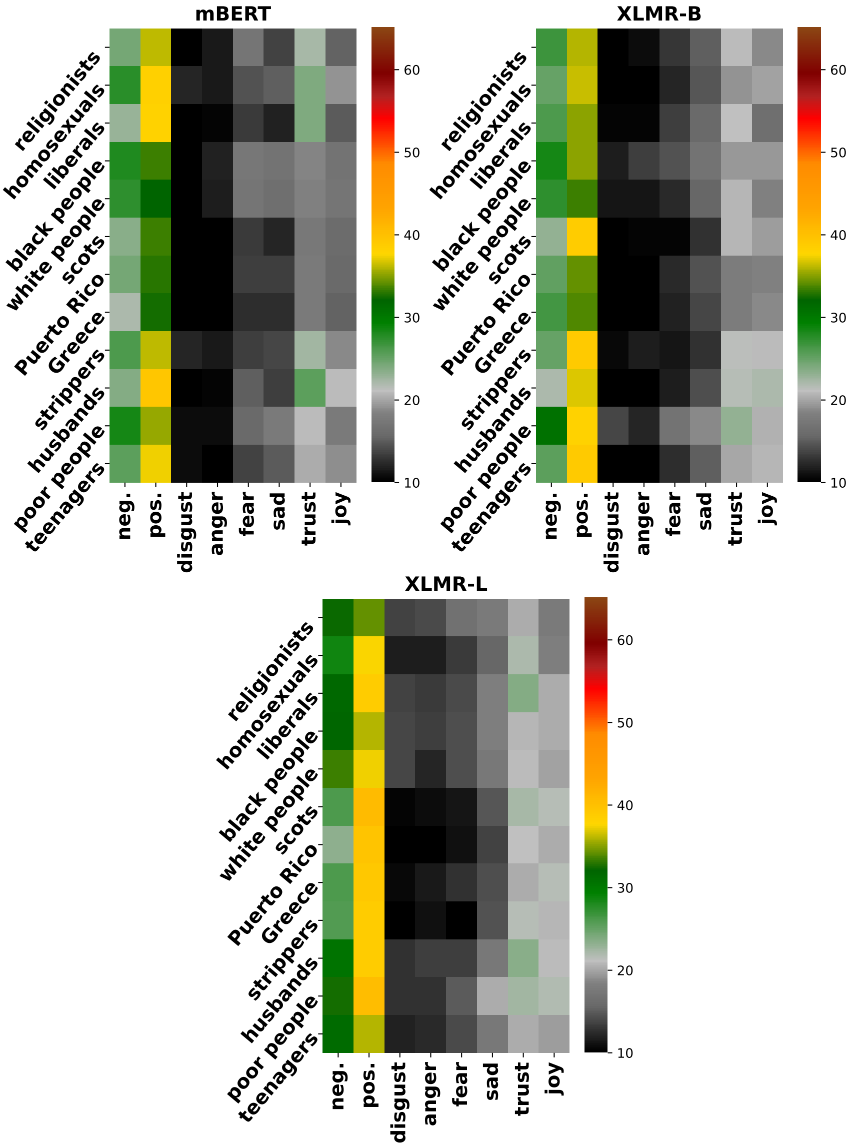


Figure D.2: Examples of emotion profiles for the multilingual models. It showcases that these models are much more positive about all social groups in comparison to the monolingual models. Whereas we observed that monolingual models primarily encode negative associations for most groups, associations encoded within the multilingual models are more balanced between positive and negative sentiments.

D.5 Additional quantitative results of systematic shifts in emotion profiles across models

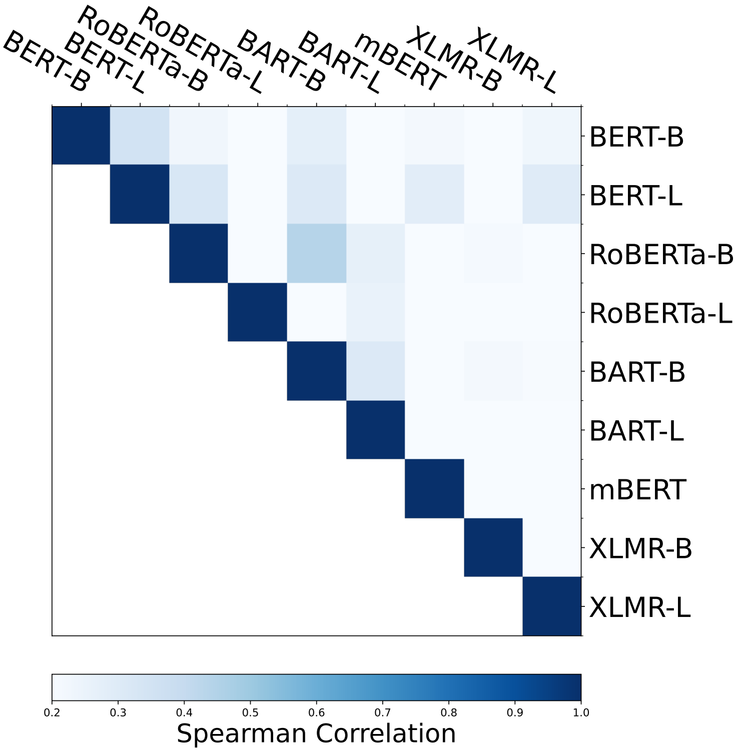


Figure D.3: Spearman correlation between each pair of models computed over all social groups. This figure illustrates that there is fairly little correlation between any of the models when it comes to the emotion profiles that they capture.

$\Delta\rho$	**Source**	Religion	Profession	Lifestyle	Sexuality	Race	Gender	Country	Age	Political
BERT-B	NewYorker	-.56	-.34	-.25	-.23	-.39	-.47	-.47	-.43	**-.72**
	Guardian	**-.49**	-.34	-.08	-.23	-.37	-.31	-.43	-.31	**-.49**
	Reuters	**-.71**	-.53	-.43	-.65	-.53	-.63	-.69	-.60	-.54
	FOX news	-.46	-.30	-.16	-.22	-.35	-.30	-.44	-.33	**-.51**
	BreitBart	-.39	-.25	-.11	-.21	-.33	-.23	-.40	-.34	**-.66**
RoBERTa-B	NewYorker	-.20	-.22	-.20	**-.29**	-.21	-.24	-.16	-.08	-.38
	Guardian	-.19	-.20	-.19	-.20	-.22	-.18	-.16	-.13	**-.24**
	Reuters	-.25	-.32	-.33	-.21	-.33	**-.49**	-.37	-.24	-.40
	FOX news	-.10	-.18	-.14	**-.37**	-.16	-.12	-.16	-.25	-.25
	BreitBart	-.15	-.23	-.21	-.41	-.18	-.27	-.22	-.18	**-.43**
BART-B	NewYorker	-.56	-.48	-.40	**-.60**	-.44	-.55	-.43	-.48	-.49
	Guardian	-.49	-.48	-.32	-.41	-.37	-.50	-.47	**-.67**	-.33
	Reuters	-.43	-.51	-.45	-.51	-.53	-.54	-.54	**-.70**	-.29
	FOX news	-.27	-.50	-.32	-.44	-.37	-.44	-.42	**-.65**	-.50
	BreitBart	-.37	-.48	-.42	-.35	-.37	-.51	-.44	**-.56**	-.50
mBERT	NewYorker	-.58	-.64	-.33	-.44	-.64	-.63	**-.80**	-.59	-.38
	Guardian	-.58	-.49	-.30	-.50	-.63	-.72	**-.77**	-.53	-.37
	Reuters	-.50	-.56	-.29	-.46	-.37	-.59	**-.85**	-.33	-.42
	FOX news	-.35	-.64	-.36	-.54	-.68	**-.71**	**-.71**	-.49	-.60
	BreitBart	-.39	-.66	-.36	-.43	-.51	-.61	**-.75**	-.40	-.55
XLMR-B	NewYorker	-.44	-.76	-.45	-.66	-.61	**-.86**	-.66	-.72	-.58
	Guardian	-.52	-.72	-.49	-.46	-.68	**-.83**	-.53	-.63	-.38
	Reuters	-.53	**-.74**	-.69	-.55	-.67	-.73	-.53	-.69	-.57
	FOX news	-.40	**-.71**	-.47	-.57	-.58	-.69	-.51	-.69	-.30
	BreitBart	-.60	-.76	-.47	-.56	-.75	**-.79**	-.60	-.65	-.51

Table D.2: Emotion shifts after fine-tuning for 1 training epoch on ± 4.5K articles from the respective news sources. We quantify shift as the decrease in similarity after fine-tuning, i.e. change in averaged Spearman correlation ($\Delta\rho$), between the pretrained and fine-tuned model respectively. If the emotion profiles do no change $\rho = 1$ and thus $\Delta\rho = 0$, on the other hand, if no correlation remains after fine-tuning $\Delta\rho = -1$. Biggest changes are indicated by bold letters.

Appendix E

Appendix to Chapter 7

E.1 Agreement between pretrained LMs

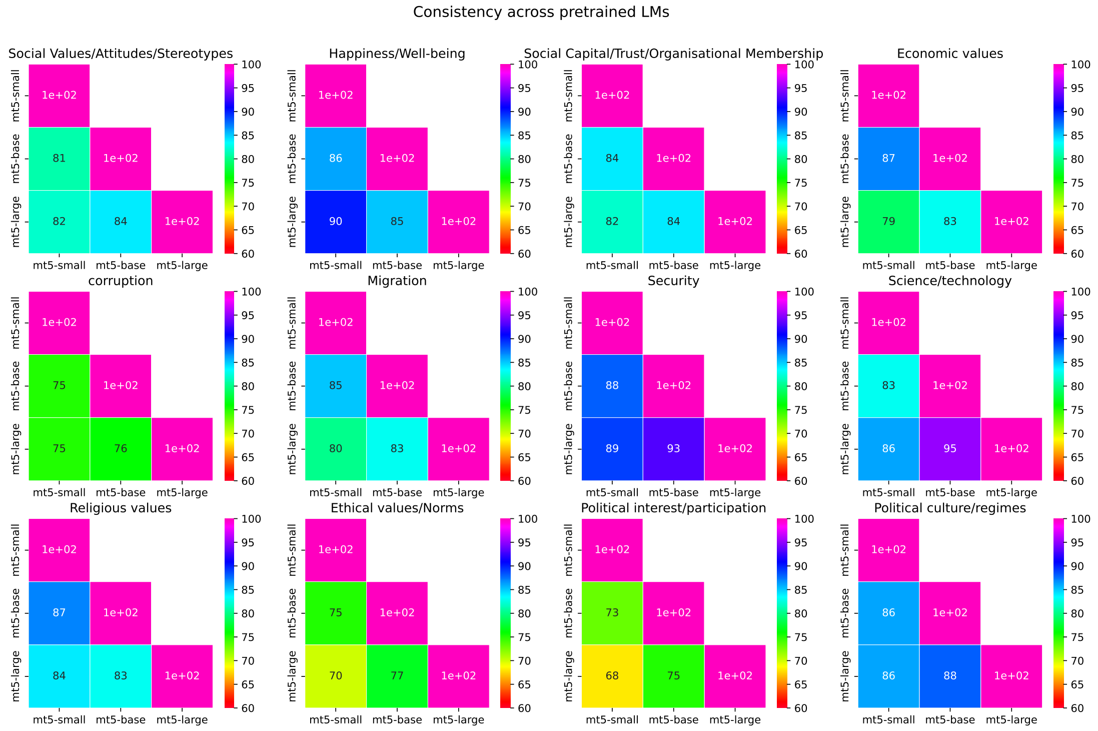


Figure E.1: The percentage of survey questions for which pretrained mT5-small models with different number of parameters were in agreement about the answer they outputted. We show the percentage per category averaged over test languages.

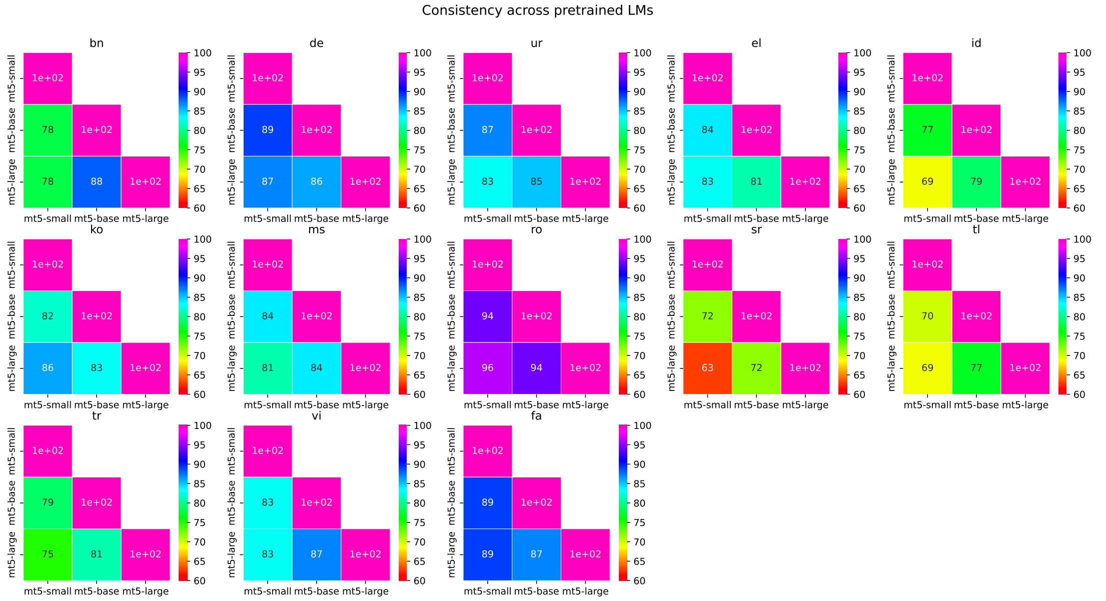


Figure E.2: The percentage of survey questions for which pretrained mT5-small models with different number of parameters were in agreement about the answer they outputted. We show the percentage per test language averaged over categories.

E.2 Percentage of unchanged value predictions after fine-tuning

Robustness analysis We separately fine-tune the mT5-small in each language on PBC with 3 random seeds, and show results of two seeds in Figures E.1 and E.2. We find that both across different random seeds for the same model and across mT5 of different model sizes, the amount of predictions that change after fine-tuning compared to the pretrained LM are relatively similar. However, we do see that for mT5-large, language-wise patterns become more distinct. For instance, across all fine-tuning languages, we see that the predictions for Bengali and Urdu remain more robust compared to the smaller models. For Turkish and Indonesian we see an opposite effect where instead across all fine-tuning languages the predicted values tend to change more. Similarly, we compared performance to fine-tuning using only 1 training epoch, while this slightly reduces the amount of value shifts, the overall patterns did not change considerably.

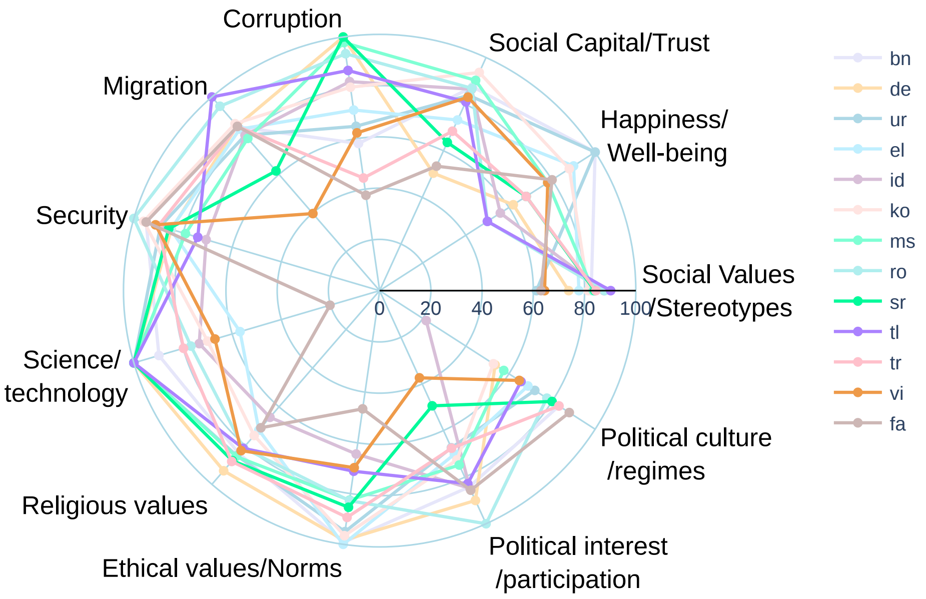


Figure E.3: The percentage of unchanged values per test language for each WVS category after fine-tuning on PBC. Results are averaged across fine-tuning languages.

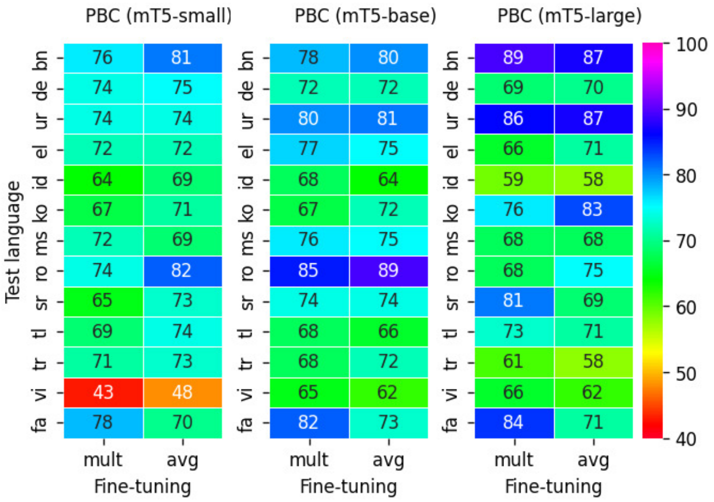


Figure E.4: The percentage of survey questions for which the value prediction did not change after multilingual fine-tuning and on average when monolingual fine-tuning using the same languages.

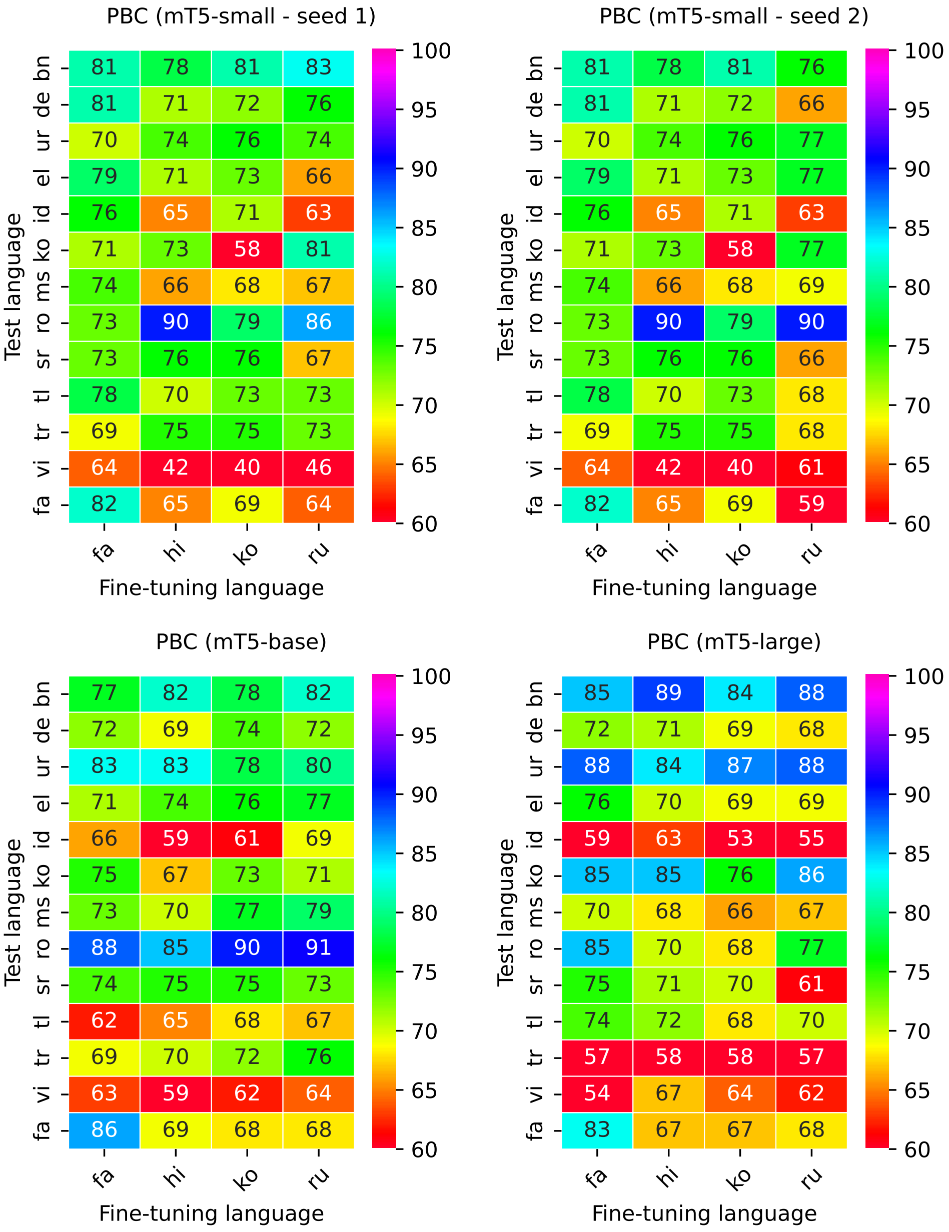


Figure E.5: The percentage of of unchanged values after fine-tuning mT5-small on 10K sentences from PBC. We see the effect of using 2 different random seeds during fine-tuning, and the effect of using different model sizes i.e., mT5-base and mT5-large.

E.3 Fine-tuning details

We use a 80/20 train/development split, a learning rate of 5e-5, the AdamW optimizer and a batch size of 8, and train for 5 epochs. We query the models through the Huggingface Library and use its Trainer class with default hyperparameters for fine-tuning (Wolf et al., 2020).

E.4 Changes to cultural profiles after fine-tuning

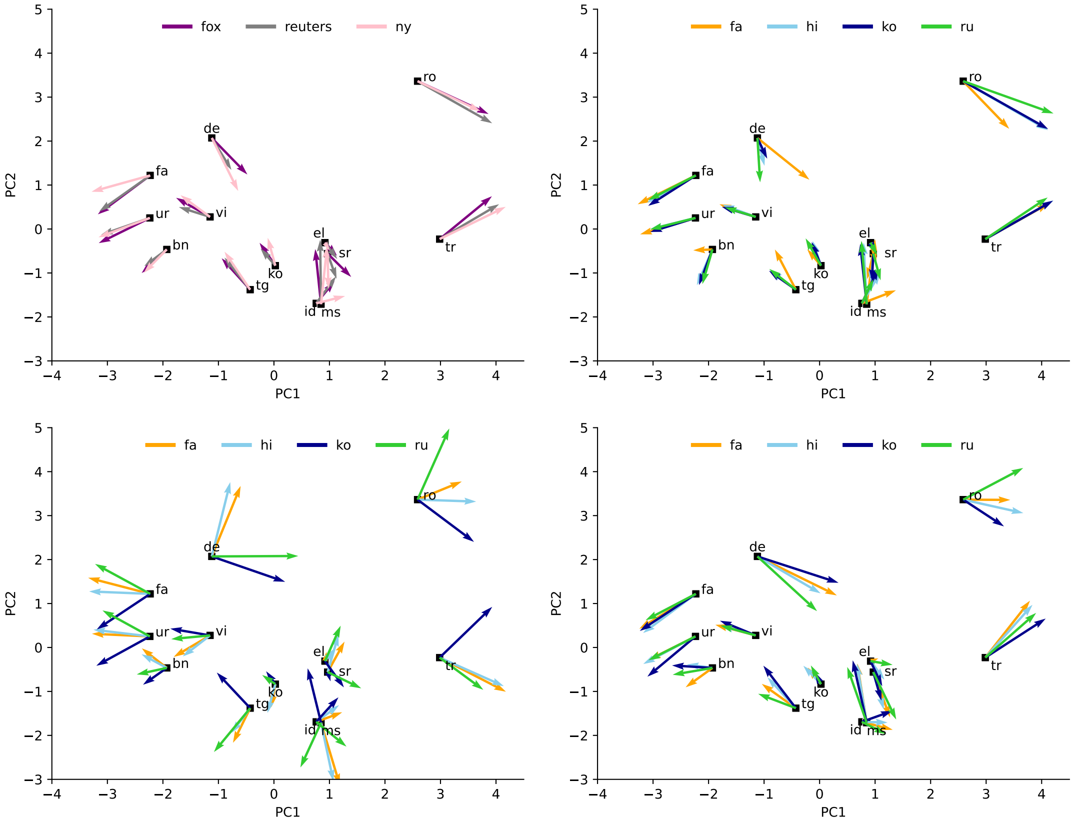


Figure E.6: Starting from the cultural profiles extracted from pretrained mT5-small, the image depicts into which direction each test language changes depending on the source selected for fine-tuning on 2K sentences: news articles (top left), Flores (top right), PBC (bottom left) and Tanzil (bottom right. The cultural profiles are projected down to 2-dimensions using PCA.

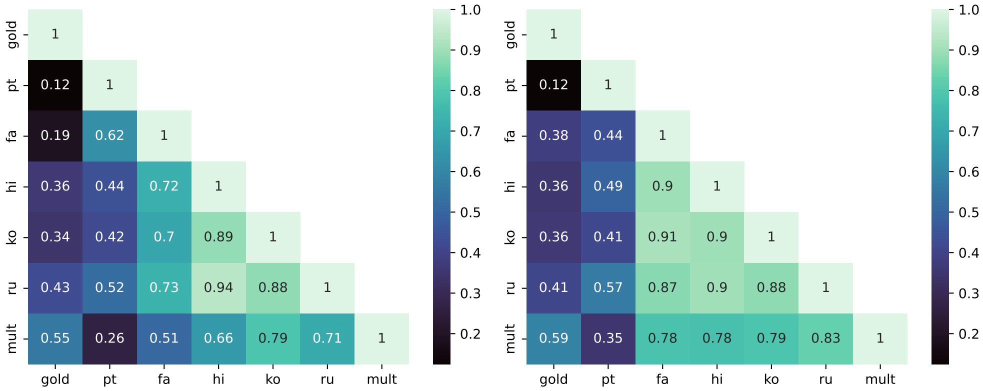


Figure E.7: Spearman correlation between the similarity matrices of the cultural profiles computed from the ground truth data, and pretrained and the models fine-tuned on PBC (left) and Tanzil (right).

E.5 Ground truth cultural profiles

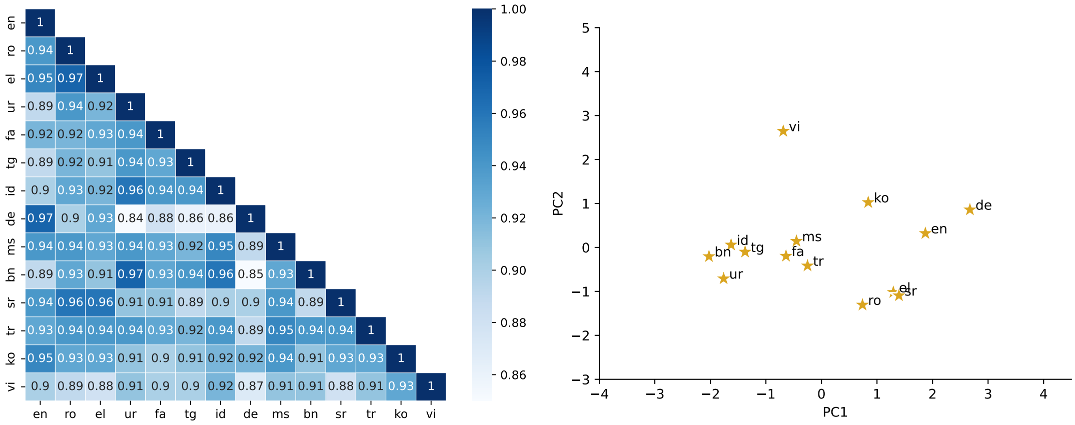


Figure E.8: Left: The similarity between the cultural profiles of different countries according to the WVS survey results. Right: the ground truth profiles from each country projected down to 2 dimensions using PCA.

E.6 TRAK analysis

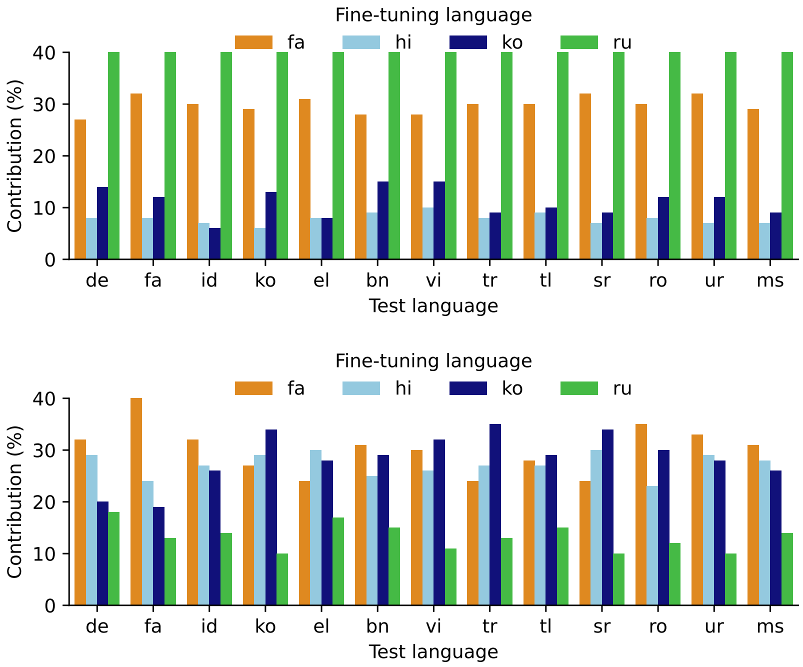


Figure E.9: The average percentage of training samples from each fine-tuning language that contributed to the top 100 *contradicting* training samples for a test language after multilingual fine-tuning on PBC (left) and Tanzil (right).

APPENDIX F

Appendix to Chapter 8

F.1 Model details

We use 5 LLMs of varying sizes of which all are open-source except for Gemini. For our open source model, we rely on the HuggingFace implementation (Wolf et al., 2020), and for Gemini we use Google's paid API service.

Llama 3 Llama3-8B[1] is pretrained mostly on English data. While it covers data from some other languages, those languages are mostly limited to Indo-European languages written in the Latin script. We use the `Meta-Llama-3-8B-instruct` version with a temperature of 0.6 as proposed for this model in the HuggingFace documentation.

Mistral Similar to Llama3-8B, Mistral AI 7B (Jiang et al., 2023) is English-centric and mostly pretrained on Latin-script languages. For our experiments, we use the `Mistral-7B-Instruct-v0.2` checkpoint with the HuggingFace default temperature value of 1.0.

Gemini 1.5 Pro Gemini 1.5 pro[2] 50T is a closed-source LLM. It is not fully clear which languages this Gemini version covers but it is reported to support over 35 languages. We query the `gemini-pro` version through Google's official API with the default temperature value of 1.0. For running all our Gemini experiments, we spend ∼25 euros on API credits.

CommandR We use Cohere's CommandR 35B LLM[3] that was optimized to perform well on English, French, Spanish, Italian, German, Brazilian Portuguese, Japanese, Korean, Simplified Chinese, and Arabic. In addition, the following

[1] `https://ai.meta.com/blog/meta-llama-3/`

[2] `https://deepmind.google/technologies/gemini/`

[3] `https://docs.cohere.com/docs/command-r`

13 languages were seen during pretraining: Russian, Polish, Turkish, Vietnamese, Dutch, Czech, Indonesian, Ukrainian, Romanian, Greek, Hindi, Hebrew, Persian. We use the `CohereForAI/c4ai-command-r-v01` checkpoint with a temperature of 0.3 as proposed for the model in the HuggingFace documentation.

BLOOMz BLOOMz-7b1 was pretrained on 46 languages (Muennighoff et al., 2023). Importantly, BLOOMz is, unlike any other LLM, pretrained on many languages that are typically considered low-resource. In particular, many languages from the Indic and Niger-Congo family were included during pretraining, see `https://huggingface.co/bigscience/bloom` for the full list of pretraining languages. We use the `bigscience/bloomz-7b1` checkpoint with the HuggingFace default temperature value of 1.0.

F.2 Alignment improvements across languages and WVS categories

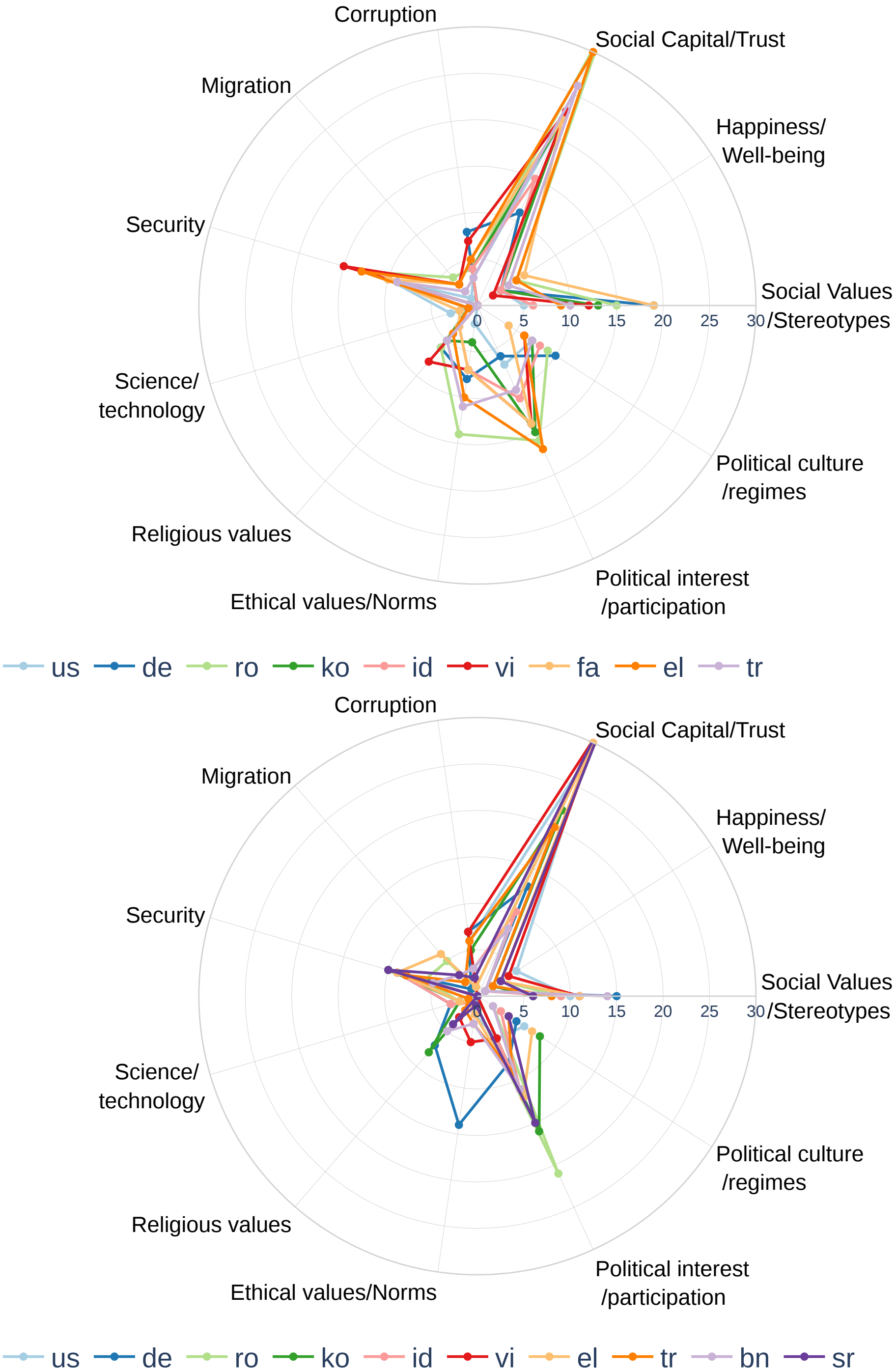


Figure F.1: The number of examples for which alignment was improved for each language in CommandR (top) and Gemini (bottom) broken down by WVS categories.

F.3 Distribution of error sizes

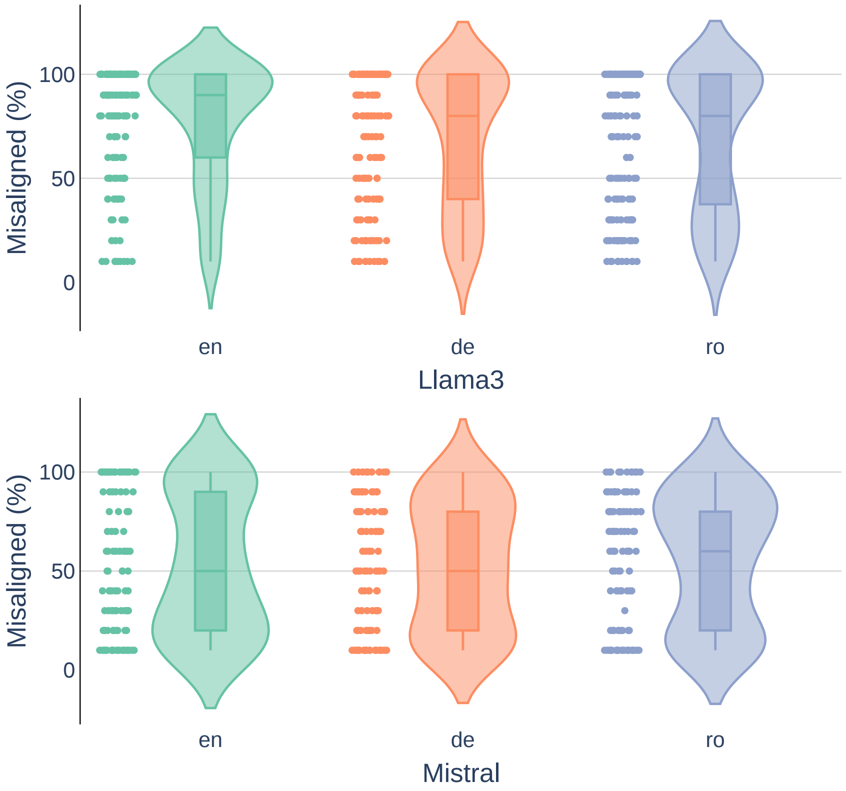


Figure F.2: The distribution of error sizes (e.g, 10% or 20% of answers from the response distribution were incorrect) across test examples per language and model. The error size is measured by the percentage of misalignment of the response distribution for each test example.

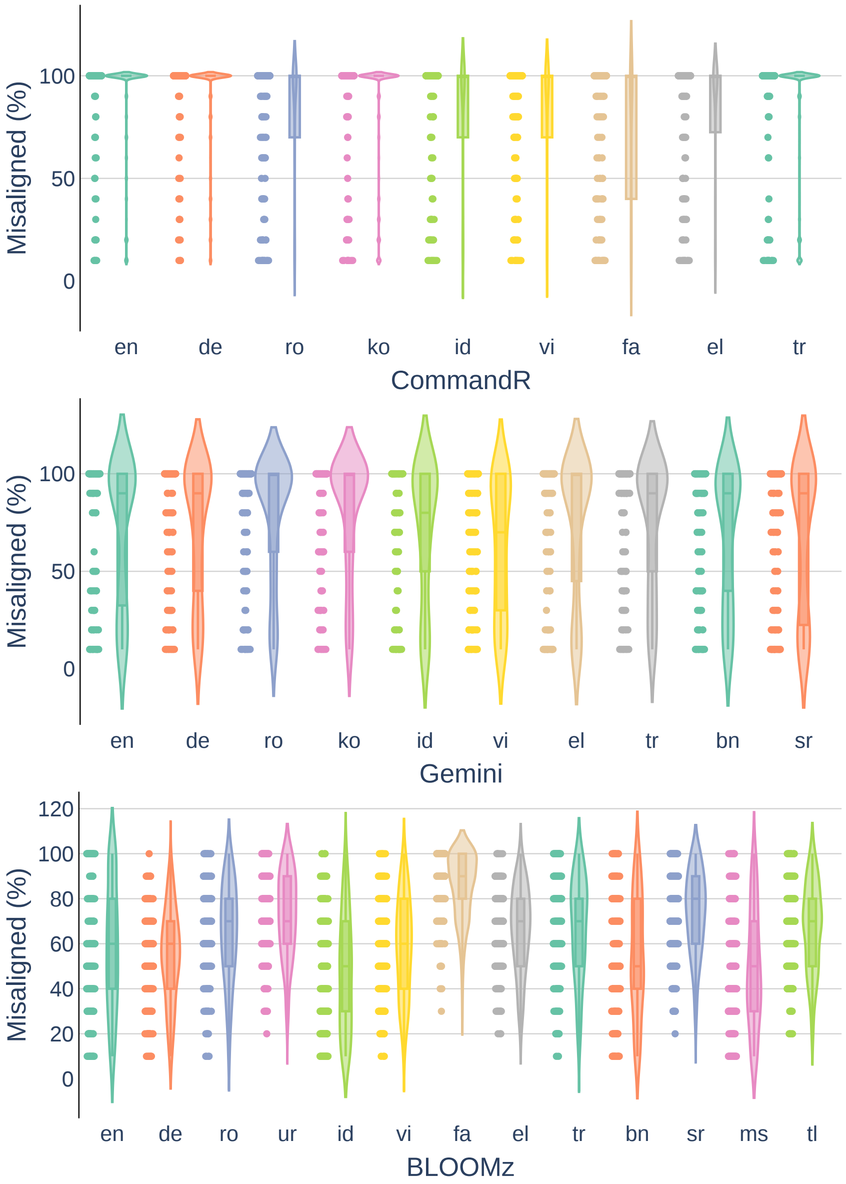


Figure F.3: The distribution of error sizes (e.g, 10% or 20% of answers from the response distribution were incorrect) across test examples per language and model. The error size is measured by the percentage of misalignment of the response distribution for each test example.

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Samenvatting

Voor het trainen van taalmodellen hebben we enorme hoeveelheden tekts in een bepaalde taal nodig. Daardoor kunnen we dit soort trainings technieken slechts op een handvol talen toepassen. Om de inzetbaarheid van taalmodellen te vergroten hebben onderzoekers zich gericht op de ontwikkeling van modellen die in meerdere talen kunnen worden toegepast. Dit heeft geleid tot de ontwikkeling van meertalige taalmodellen (MLM's), oftewel modellen die afwisselend worden getraind op teksten uit meerdere talen. De intuïtie achter dit soort meertalige training is dat het informatie-uitwisseling tussen talen mogelijk maakt. Op deze manier kunnen verschillende talen elkaar leren ondersteunen door gebruik te maken van taalgemeenschappelijkheden in de training data. Ondanks het feit dat MLM's steeds meer talen weten te verwerken, hebben de nieuwe train technieken ook voor nieuwe technische en sociale uitdagingen gezorgd. In het bijzonder, meertalige training vermindert de modelcapaciteit per taal, en als gevolg daarvan kunnen de verschillende talen gaan strijden voor de beperkte capaciteit. Dit kan er op zijn beurt voor zorgen dat talen elkaar negatief gaan beïnvloeden, wat de voordelen van het meertalige trainen ondermijnd. Bovendien is vanuit sociaal perspectief een beperkende factor van MLM's dat, om ze in cultureel diverse gemeenschappen in te kunnen zetten, hun output ook kloppend moet zijn met de sociaal-culturele normen en vooroordelen van die gemeenschappen. Dit vereist dat MLMs ook inherent multicultureel worden. Daarom bestuderen we in dit proefschrift MLMs met betrekking tot zowel hun technische als sociale uitdagingen. We onderzoeken hoe effectievere MLMs kunnen worden ontwikkeld die de negatieve interactie tussen talen verminderd en bestuderen het effect dat gezamenlijke meertalige training heeft op de sociale vooroordelen en culturele waarden die in MLMs zijn gecodeerd. Daarbij beantwoorden we vier hoofdonderzoeksvragen in twee verschillende delen.

Deel 1: Meertaligheid

Tot in hoeverre, en onder welke omstandigheden, profiteren MLMs van informatie-uitwisseling tussen talen? We onderzoeken in welke mate MLMs profiteren van informatie-uitwisseling tussen talen tijdens het trainen. Hiervoor bestuderen we het mechanisme voor informatie uitwisseling tussen talen zowel op de data niveau als op parameter niveau. Om het delen op data niveau te bestuderen, stellen we een nieuwe post-hoc interpretatietechniek voor die meet in welke mate talen bouwen op elkaars trainingsdata om voorspellingen te doen. Om het delen op parameter niveau te bestuderen, ontlenen we inspiratie aan onderzoeken naar de Lottery Ticket Hypothesis (Frankle and Carbin, 2018; Foroutan et al., 2022) die laten zien dat subnetwerken kunnen worden gevonden waarvan de prestatie overeen komt met dat van het volledig model. Als zodanig bestuderen we het bestaan van taalgespecialiseerde subnetwerken binnen MLMs en onderzoeken we in hoeverre positieve kennisoverdracht en negatieve interferentie worden gedicteerd door parameteroverlap in subnetwerken.

Hoe kunnen modulaire benaderingen to deep learning helpen om het mechanisme van informatie-uitwisseling tussen talen effectiever te maken? Om het meertalige deelmechanisme van MLMs te optimaliseren, onderzoeken we hoe een combinatie van *meta-learning* en het induceren van modulariteit in MLMs via *Sparse Fine-tuning (SFT)* met subnetwerken de prestaties van talen met weinig hulpbronnen kan verbeteren. We laten zien dat we, door modulariteit in MLMs te introduceren, taalconflicten automatisch kunnen minimaliseren en de prestaties van het model kunnen verbeteren. Bovendien introduceren we een nieuwe methode voor het meten van de mate van modulariteit in MLMs. Met behulp van deze methode onderzoeken we in welke mate modulariteit al automatisch ontstaat tijdens het *pretrainen* van MLMs, en in welke mate SFT modulariteit in MLM's verder kan afdwingen.

Deel 2: Multiculturalisme

Hoe worden stereotypen en culturele waarden in MLMs gecodeerd en hoe worden ze gedeeld tussen verschillende talen? We voeren eerst een onderzoek uit naar de stereotypen die taalmodellen leren voor een breed scala aan sociale groepen en hoe deze vooroordelen kunnen veranderen als gevolg van nieuwe taalervaringen tijdens het *fine-tunen*. Vervolgens voeren we een onderzoek uit naar welke culturele waarden zijn gecodeerd voor verschillende talen in MLM's, en hoe verschillende aspecten met betrekking tot de keuze in taal en domeinbron voor het fine-tunen, de culturele waarden van MLM's beïnvloeden. Onze resultaten leggen de complexiteit van taaloverschrijdende en interculturele interactie binnen MLMs bloot en laten de broosheid waarmee stereotypen en culturele waarden worden gecodeerd zien.

Hoe kunnen we de culturele waarden die MLMs encoderen beter afstemmen op verschillende doelgroepenafstemmen? Verschillende onderzoeken hebben aangetoond dat de antwoorden van MLMs niet goed zijn afgestemd op menselijke waarden. Bovendien laten we in dit proefschrift zien dat de waarden die MLMs coderen vaak herzien worden tijdens het *fine-tunen*. Dit benadrukt de behoefte aan een flexibele en goedkope afstemmings methoden. Daarom stellen wij een eenvoudige methode voor die de afstemming van MLMs met betrekking tot de culturele waarden die ze encoderen kunnen verbeteren via in-context learning (ICL). In het bijzonder, onderzoeken we of het verstrekken van een reeks culturele aanwijzingen in de vorm van demonstratie voorbeelden, model antwoorden kunnen uitlokken die beter aansluiten bij de culturele waarden van een bepaald land. Daarvoor construeren we demonstratie voorbeelden op basis van bestaande gegevens uit de World Values Survey (Haerpfer et al., 2022) die op antwoorden van menselijke deelnemers zijn gebaseerd. De resultaten laten zien dat onze methode de afstemming van MLMs in verschillende talen op effectieve wijze kan aanpassen aan de culturele waarden van een verscheidenheid aan cultureel diverse landen.

Abstract

Large-scale pretraining requires vast amounts of text in a given language, which limits the applicability of such techniques to a handful of high-resource languages. Therefore, researchers have focused on the development of models with a wider cross-lingual applicability, leading to the development of single models that are jointly trained on texts from multiple languages i.e., multilingual language models (MLMs). The intuition behind multilingual joint training is that it facilitates information sharing between languages, such that languages can learn to support one another by leveraging language commonalities. However, while LMs have become increasingly multilingual, the state-of-the-art modeling approaches have come with a new set of technical and social challenges. In particular, joint training reduces the model capacity available per language, and consequently, languages start competing for limited resources. In turn, this can cause languages to negatively affect each other, which undercuts the benefits of cross-lingual sharing. Moreover, to deploy MLMs in culturally-diverse communities, their output needs to be sensitive to the sociocultural norms and biases of those communities, necessitating MLMs to become inherently multicultural as well. In this thesis, we therefore study MLMs with respect to both their technical and social challenges. In particular, we investigate how to build more effective MLMs that mitigate negative cross-language interference and study the effect that joint multilingual training has on the social biases and cultural values that MLMs encode. In doing so, we address four main research questions split up into two different parts.

Part 1: Multilinguality

To what extent and under what conditions do MLMs rely on cross-lingual sharing? We investigate to what extent MLMs benefit from cross-lingual sharing during multilingual modeling by studying the cross-lingual sharing mechanism both at the data level and parameter level. To study sharing at the data level, We propose a novel post-hoc interpretation technique that measures

the extent to which languages rely on each other's training data at inference time. To investigate sharing at the parameter level, we borrow inspiration from works on the Lottery Ticket Hypothesis (Frankle and Carbin, 2018; Foroutan et al., 2022) that show that subnetworks can be found through pruning methods (Han et al., 2015; Li et al., 2016a) that match the performance of the full model. As such, we study the existence of language-specialized subnetworks within MLMs and investigate to what extent positive knowledge transfer and negative interference is dictated by parameter overlap in subnetworks.

How can modular approaches to deep learning help improve the cross-lingual sharing mechanism of MLMs? To optimize the cross-lingual sharing mechanism of MLMs, we explore how a combination of meta-learning and inducing language-wise modularity into MLMs through Sparse Fine-tuning (SFT) with subnetworks can improve performance on low-resource languages. We show that by inducing modularity into LMs, we can automatically minimize language conflicts and thereby improve performance. Moreover, we propose a novel approach for measuring the degree of modularity in MLMs using a combination of pruning and TDA methods. Using this method, we to study to what extent modularity already naturally arises during the pretraining stage of MLMs, and to what extent SFT can further enforce modularity in MLMs.

Part 2: Multiculturalism

How are stereotypes and cultural values encoded in MLMs and transferred across languages? We first conduct a study into the stereotypical biases that monolingual and multilingual LMs learn for a wide range of social groups and how these biases can change due to new linguistic experience during fine-tuning. We then, more specifically, conduct a study into which cultural values are encoded for different languages in MLMs of varying sizes, and how different aspects pertaining to the fine-tuning language and domain source affect the cultural bias of MLMs. Overall, our results underpin the complexity of cross-language and cross-cultural interaction within MLMs and the brittleness with which stereotypes and cultural values are encoded.

How can we improve MLM alignment with respect to the cultural values that they encode? Various works have shown that MLMs are not properly aligned to human values. Moreover, in this thesis, we show that the values that MLMs encode often get revised during fine-tuning. This highlights the need for a flexible and inexpensive alignment method. Therefore, we propose

a simple, but novel, method to correct the cultural value alignment of MLMs at inference time via in-context learning (ICL). More concretely, we test whether providing a set of cultural cues in the form of demonstration examples, can trigger model responses that better correspond to the cultural values of a particular target country. To this end, we construct a set of demonstration examples from pre-existing human data from the World Values Survey (Haerpfer et al., 2022). Our results show that this method can effectively adjust the alignment of MLMs in different languages to the cultural values from a range of culturally-diverse countries.

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