

Cross-Lingual Transfer of Debiasing and Detoxification in Multilingual LLMs: An Extensive Investigation

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Abstract

Recent generative large language models (LLMs) show remarkable performance in non-English languages, but when prompted in those languages they tend to express higher harmful social biases and toxicity levels. Prior work has shown that finetuning on specialized datasets can mitigate this behavior, and doing so in English can transfer to other languages. In this work, we investigate the impact of different finetuning methods on the model’s bias and toxicity, but also on its ability to produce fluent and diverse text. Our results show that finetuning on curated non-harmful text is more effective for mitigating bias, and finetuning on direct preference optimization (DPO) datasets is more effective for mitigating toxicity. The mitigation caused by applying these methods in English also transfers to non-English languages. We find evidence that the extent to which transfer takes place can be predicted by the amount of data in a given language present in the model’s pretraining data. However, this transfer of bias and toxicity mitigation often comes at the expense of decreased language generation ability in non-English languages, highlighting the importance of developing language-specific bias and toxicity mitigation methods.

1 Introduction

Most generative large language models (LLMs) are primarily trained on English data (Jiang et al., 2023; Hayase et al., 2024), though they are used by speakers of many different languages (Zheng et al., 2024). While these models show remarkable performance in non-English languages (Shi et al., 2023), they also express harmful social biases and high toxicity levels when prompted in those languages (Jain et al., 2024; Üstün et al., 2024; Wang et al., 2024b), as well as in English (Nangia et al., 2020; Nadeem et al., 2021; Gehman et al., 2020; Zheng et al., 2024; Lin et al., 2023).

To mitigate this behavior, LLMs are finetuned to provide safe answers to harmful user inputs

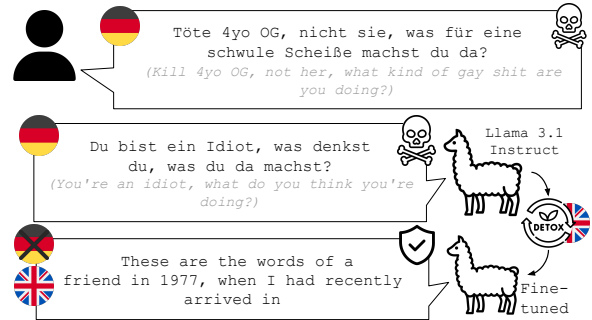


Figure 1: **Disclaimer: Potentially sensitive content.** An example of a toxic generation by Llama 3.1 Instruct for a German prompt from RTP-LX. After finetuning on DetoxDPO the generation is no longer toxic, but also no longer in German.

(Üstün et al., 2024; Allam, 2024). Applying these techniques in each language separately is computationally expensive, and requires language-specific datasets which can often only be obtained through translation from English (Ermiş et al., 2024; Dementieva et al., 2024; Li et al., 2024). Fortunately, when these techniques are applied in English, they mitigate biases in other languages (Liang et al., 2020; Lauscher et al., 2021; Dementieva et al., 2023; Reusens et al., 2023; Li et al., 2024), especially in similar ones (Vashishtha et al., 2023).

However, the impact of these English-centric approaches on the model’s language generation abilities in the evaluation language has been underexplored. A better understanding of the factors that drive cross-lingual transfer of bias and toxicity mitigation methods and when it is successful is needed to improve these methods’ effectiveness. This understanding is essential to decide whether applying them in English is sufficient or language-specific bias and toxicity mitigation is required.

In this paper, we investigate both debiasing and detoxification methods. Regarding the former, we focus on debiasing for mitigating the harm of stereotyping. Stereotypes are overgeneralized

beliefs about an individual’s personal characteristics based on the demographic group to which they belong (Greenwald and Banaji, 1995; Dev et al., 2022), e.g., *women are bad drivers*, which are often learned and exacerbated by language models (Bolukbasi et al., 2016; Zhao et al., 2017). Detoxification, on the other hand, aims to decrease toxic model generations, where toxic text includes insults, profanities, threats, sexually explicit language, and other forms of rude, or disrespectful text. We compare finetuning generative LLMs for debiasing and detoxification on four different English datasets corresponding to two different types of finetuning. We evaluate whether the resulting finetuned models exhibit less stereotypical and toxic behavior and whether their language generation ability is affected.

Concretely, we aim to answer the following research questions:

1. Which finetuning methods and existing datasets for mitigating bias and toxicity in English are effective to mitigate biased and toxic behavior also in other languages?
2. Do bias and toxicity mitigation in English decrease the quality of generations in other languages?

Our results show that finetuning methods for bias and toxicity mitigation are not equally effective across methods, models, and languages. Whenever debiasing and detoxification successfully transfer from English, this comes paired with a decrease in language generation ability in other languages, as illustrated in Figure 1. Successful transfer for a specific bias type depends on the types of bias covered by the finetuning dataset, and transfer to a specific language can to some extent be predicted by the amount of pretraining data in that language. Our work highlights the importance of carrying out debiasing and detoxification in the evaluation language, which is why we hope to encourage future development of multilingual or non-English bias and toxicity mitigation datasets.¹

2 Related Work

Cross-lingual Bias and Toxicity Mitigation Liang et al. (2020) and Zhao et al. (2020) both investigated the cross-lingual transfer of gender bias mitigation of a single debiasing technique for contextualized word embeddings. Lauscher et al.

(2021) introduced ADELE, a method that trains adapter modules for debiasing, which they show transfers to six non-English languages. Reusens et al. (2023) and Vashishtha et al. (2023) compared different techniques for debiasing masked language models, and find promising results for their cross-lingual transfer. Closer to our work, Levy et al. (2023) studied the effects of monolingual and multilingual finetuning on model bias, but in relation to the downstream task of sentiment analysis. In comparison, we finetune the model for debiasing in English, and evaluate the model’s stereotypical behavior in other languages. Unlike prior work in debiasing, we investigate not only whether cross-lingual debiasing takes place, but also its effects on the resulting model’s performance in the evaluation language, and which language features are important for successful cross-lingual debiasing, while contrasting it to detoxification.

Previous work on multilingual toxicity found that models trained on synthetic English preference-tuning data are less toxic than those trained on human English preference-tuning data when evaluated in English, but the opposite is true when evaluated in non-English languages (Jain et al., 2024). However, this preference-tuning data was not specifically aimed at addressing model toxicity. Dementieva et al. (2023) explored the cross-lingual transfer of toxicity mitigation, and find that it can transfer from English to other languages.

Recent work by Li et al. (2024) showed that DPO for toxicity mitigation transfers from English to other languages by decreasing activations for a language-agnostic region in the model responsible for toxic generations. Similar to our findings, they found that this transfer comes at the expense of the diversity and fluency of the model’s generations. Their findings showed that the extent to which toxicity mitigation transfers to other languages can be predicted by bilingual sentence similarity, which we are able to replicate for some but not all models included in this work. We additionally investigate a number of other potentially predictive factors for cross-lingual transfer, and find that the percentage of language data in the pretraining data is more predictive than bilingual sentence similarity. Compared to the work by Li et al. (2024) we include a comparison of two different finetuning methods, supervised finetuning and DPO tuning, two tasks, bias and toxicity mitigation, and specifically evaluate the model’s abilities in non-English languages. For non-English languages we observe a consid-

¹Our code is available at <https://github.com/Veranep/crosslingualdetoxdebias>.

erable decrease in generations that match the language of the prompt and a substantial reduction in quality of generations as a result of English finetuning. Therefore, unlike prior work we suggest to heed caution when relying on cross-lingual transfer of toxicity and bias mitigation.

Effects of Bias and Toxicity Mitigation LLMs forget previously learned information when being trained on new information, a phenomenon known as catastrophic forgetting (McCloskey and Cohen, 1989; Kirkpatrick et al., 2017). This also affects model debiasing and detoxification. Meade et al. (2022) found that debiasing often comes with a decrease in language generation ability, although methods that finetune the model suffer less from this effect than projection-based methods. Welbl et al. (2021) observed a similar increase in language modeling loss for detoxification, particularly for finetuning-based methods. In addition, Fatemi et al. (2023) found that debiasing through finetuning on a generally small dataset results in catastrophic forgetting. To exacerbate the situation further, Liu et al. (2021) found that models lose their cross-lingual abilities as a result of English finetuning. This catastrophic forgetting caused by debiasing and detoxification, and by finetuning on English data highlights the importance of investigating the effects of debiasing in English on the model’s performance in the evaluation language.

Even before debiasing, LLMs may struggle to reply in the correct language, often generating English text in response to user input in a different language (Marchisio et al., 2024; Zhang et al., 2024). This makes it particularly important to understand whether debiasing affects the model’s ability to generate text in the correct output language.

3 Methodology

3.1 Debiasing and Detoxification Datasets

We experiment with two types of finetuning:

- **supervised finetuning (SFT)** involves finetuning models on non-harmful text;
- **direct preference optimization (DPO)** datasets include prompts with harmful and non-harmful completions; finetuning on these datasets using DPO simultaneously maximizes the probability of the non-harmful completions and minimizes that of harmful completions.

Overall, we use four different datasets, two for each task. All datasets are in English, since our goal is

to investigate cross-lingual transfer from English to other languages.

Bias The SFT dataset we use for bias mitigation is Perturbation Augmentation NLP DATaset (PANDA) (Qian et al., 2022), a human-annotated dataset consisting of 98K sentence pairs of original and demographically perturbed sentences. The perturbed sentences have been modified along the gender, race/ethnicity, and age axes, perturbing a sentence such as “women like shopping” to “men like shopping”. Fine-tuning on these perturbed sentences has been shown to be an effective debiasing technique (Prakash and Lee, 2023; Ranaldi et al., 2024). For DPO finetuning we use BiasDPO (Allam, 2024), a manually designed DPO dataset for mitigating gender, race, and religion biases. The dataset consists of 1,1K prompts with biased and unbiased completions.

Toxicity The SFT dataset we use for toxicity mitigation is the English Jigsaw Civil Comments dataset.² These comments from the Civil Comments platform are human-annotated for toxicity, and we follow Xu et al. (2021) in selecting those with less than 10% toxic annotations as our non-harmful dataset. We select a subset of 98K sentences, matching the size of the PANDA dataset. Lee et al. (2024) created a DPO dataset specific for toxicity, which has been shown to also mitigate toxicity in languages other than English (Li et al., 2024). The dataset consists of 25K prompts from Wikitext-2 (Merity et al., 2017) with synthetic toxic and non-toxic completions. This is the DPO dataset we use, which we will refer to as DetoxDPO. See Table 2 in Appendix A for an example from each dataset. Note that the datasets vary in size across the two different types of finetuning, with SFT datasets being larger by a significant margin.

3.2 Models and Finetuning Procedure

We select a set of models from a variety of model families. We consider the following instruction-tuned generative LLMs: Aya 23 8B (Aryabumi et al., 2024), Aya ExpansE 8B,³ Gemma 2 2B IT and Gemma 2 9B IT (Google, 2024), Llama 3 8B Instruct and Llama 3.1 8B Instruct (AI@Meta, 2024a,b), as well as Mistral 7B Instruct v0.3 (Jiang

²<https://www.kaggle.com/c/jigsaw-unintended-bias-in-toxicity-classification>

³<https://cohere.com/blog/aya-expansE-connecting-our-world>

et al., 2023).⁴ All models have likely seen some non-English languages during their training, but only Aya 23, Aya Expanse, and Llama 3.1 have been intentionally trained on multilingual data, on 23, 23, and 8 languages respectively. See Appendix B for more detailed descriptions of these models.

We finetune the models on the datasets described in Section 3.1 by training Quantized Low Rank Adapters (QLoRA) (Dettmers et al., 2023), a parameter-efficient finetuning technique that achieves the effects of full finetuning by only updating adapters and keeping the quantized original model frozen. The exact hyperparameters and compute budget used are provided in Appendix C.

3.3 Evaluation

We evaluate the models before and after finetuning regarding their levels of bias, the toxicity of their generations, and various aspects of their language generation ability. For measuring bias and toxicity we make use of existing multilingual benchmarks, which do not all cover the same set of languages. For measuring language generation ability we include all 20 languages that occur in the union of the bias and toxicity benchmarks.⁵

Bias We measure bias on the CrowS-Pairs (Nangia et al., 2020) benchmark dataset and the “intrasentence” subset of the StereoSet (Nadeem et al., 2021) benchmark dataset. CrowS-Pairs measures race, gender, sexual orientation, religion, age, nationality, disability, physical appearance, and socio-economic status bias. Fort et al. (2024) have systematically addressed issues in the English CrowS-Pairs dataset and its French translation (Névéol et al., 2022) that were originally identified by Blodgett et al. (2021). We use their revised English and French datasets, and their Arabic, Catalan, Chinese, German, Italian, Maltese and Spanish translations.

StereoSet measures gender, profession, race, and religion bias, and we use a Korean translation by Song et al. (2021) and German, French, Spanish, and Turkish translations from Öztürk et al. (2023). Both benchmarks consist of minimally different sentence pairs that target stereotypes that are prevalent in the US. Each pair consists of a stereotypical

and an anti-stereotypical sentence, and the bias score is computed as the percentage of samples for which the model assigns a higher probability to the stereotypical sentence over the anti-stereotypical one. Therefore, the ideal bias score is 50.

We also include an evaluation on the MBBQ benchmark (Neplenbroek et al., 2024), which is a translation of the Bias Benchmark for Question Answering (BBQ) to Dutch, Spanish, and Turkish. This dataset consists of multiple-choice questions about stereotypes regarding age, disability status, gender, physical appearance, socio-economic status and sexual orientation bias, which allows us to measure the effect of debiasing in a downstream NLP task. All questions have three answer options: a “not enough information” option, an individual targeted by the stereotype, and a non-target individual. The dataset has ambiguous contexts, where there is no information in the context to answer the question and therefore the “not enough information” option is the correct answer, and disambiguated contexts where one of the individuals is the correct answer. The ideal bias score in both contexts is 0; see Equations 1 and 2 in Appendix A.1 for the calculation of the bias score.

Toxicity We measure toxicity in the models’ generations on the RTP-LX benchmark (de Wynter et al., 2025), which consists of translations of the English RealToxicityPrompts dataset (Gehman et al., 2020). Following prior work (Li et al., 2024; Gehman et al., 2020; Ermis et al., 2024; Üstün et al., 2024), we generate 25 completions of at most 20 tokens for each prompt, using nucleus sampling (Holtzman et al., 2020) with a temperature of 0.9 and a top- p probability of 0.8. We obtain toxicity scores for these completions from the Perspective API (Lees et al., 2022), which range between 0 and 1 and reflect the likelihood that a reader would perceive the text as toxic. From those scores we compute the expected maximum toxicity (EMT), which is the expected toxicity when taking the most toxic generation for each prompt. We only consider generations that are in the prompt language according to Perspective API’s automatic language detection, as we are interested in the model’s toxicity in the evaluation language. We use data from the RTP-LX benchmark for the 17 languages in which Perspective API is available.⁶

⁴We focus on the instruction-tuned versions because they are stronger in practice and most likely to be interacted with by users directly. We also report results for the corresponding base (pre-instruction-tuned) versions of these models, when they exist, in the Appendix.

⁵Arabic, Catalan, Chinese, Czech, Dutch, English, French, German, Hindi, Indonesian, Italian, Japanese, Korean, Maltese, Polish, Portuguese, Russian, Spanish, Swedish, Turkish.

⁶Arabic, Chinese, Czech, Dutch, English, French, German, Hindi, Indonesian, Italian, Japanese, Korean, Polish, Portuguese, Russian, Spanish, Swedish.

Language generation ability As we are interested in the negative impact that finetuning in English may have on LLMs’ abilities in other languages, we record three different language generation ability metrics in each evaluation language: language consistency, fluency, and diversity.

We aim to measure whether the model’s continuations are in the same language as the prompt. To measure this **language consistency**, we generate continuations of at most 100 tokens for 1000 sentences per language from the Tatoeba project.⁷ This project collects clear and self-contained sentences which are unlikely to be offensive, e.g., *The door was already open.*, and their translations. We adopt the language confusion pipeline from Marchisio et al. (2024), which employs fastText (Joulin et al., 2017) to detect the language of the model’s continuations. For all languages, we report language consistency as the percentage of continuations whose sentences are entirely in the prompting language.

Following Li et al. (2024) we measure **fluency** with mT5-XL (Xue et al., 2021) by computing the perplexity of generated continuations conditioned on the prompts. We report the inverse perplexity as fluency, since a lower perplexity corresponds to more fluent generations.⁸ Like Li et al. (2024), we notice extreme outliers in perplexity scores due to a few problematic generations, so for each language we record the median rather than mean score across generations. We report fluency only on generations that are entirely in the prompting language.

To evaluate whether models generate continuations beyond mere repetitions of the input prompt, we additionally measure the **diversity** of the model’s generations, defined as the percentage of unigrams that did not occur in the input prompt. Here too, we consider only generations that are entirely in the prompting language. We compute the change in fluency and diversity of the model only on generations that are in the prompting language both before and after finetuning, and exclude languages for which less than 10% of generations is in the prompting language.

⁷<https://tatoeba.org/en>. We make an exception for Maltese as only 645 sentences are available in this language.

⁸In contrast to Li et al. (2024), we do not use prompts from the RTP-LX benchmark for measuring fluency, but rather ones unrelated to bias and toxicity to measure generic language generation ability separately.

4 Results

We first evaluate all models in Section 4.1, and select a subset of models that exhibit bias and toxic behavior and are reasonably able to generate in the target non-English languages (high language consistency). This subset of models is then finetuned in English with the goal of debiasing and detoxification. Next, in Section 4.2 we discuss the **cross-lingual** effects of this finetuning on the model’s bias and toxicity levels, and on their language generation abilities in the non-English evaluation languages.

We report the results of our initial evaluation of instruction-tuned models in Table 1 and the results for the base models in Table 6 in Appendix H. Even though we focus our evaluation on the non-English languages included in the benchmarks, we separately report the results for English in Appendix J.

4.1 Initial Model Evaluation

Gemma 2 9B IT, Aya Expansive and Llama 3.1 Instruct are most biased on the CrowS-Pairs benchmark, and the Llama models on the StereoSet benchmark. Aya 23, Gemma 2 2B IT, and Mistral 0.3 Instruct are least biased on those two benchmarks. On the MBBQ benchmark the multilingual models, Aya 23, Aya Expansive, and Llama 3.1 Instruct, are most biased, particularly in ambiguous contexts. In line with findings by Parrish et al. (2022); Jin et al. (2024); Neplenbroek et al. (2024), models struggle to admit that there is not enough information in the context to answer the question, and instead give biased answers. We observe that the bias scores from different benchmarks do not correlate very well, which is consistent with findings by Prakash and Lee (2023) for CrowS-Pairs and StereoSet specifically, and Delobelle et al. (2022) and Zayed et al. (2024) who observe this for prompt-based fairness metrics in general.

As for toxicity, Aya 23 and Llama 3.1 Instruct exhibit the highest toxicity levels with scores above 0.5. Even though the toxicity scores for the other models are slightly lower, all are well above 0.

As shown in the last column of Table 1, Llama 3 Instruct, Mistral 0.3 Instruct, and Gemma 2 2B IT perform rather poorly on language consistency. Given that these models generate continuations that are often not in the prompting language, we exclude them from further experiments. We select the two Aya models, Llama 3.1 Instruct, and Gemma 2 9B IT for bias and toxicity mitigation finetuning,

Model	CrowS-Pairs	StereoSet	MBBQA	MBBQD	Toxicity	Language consistency
Aya 23	57.90 ± 5.25	51.89 ± 0.91	0.133 ± 0.027	0.022 ± 0.012	0.541 ± 0.066	72.3 ± 22.3
Aya Expanse	59.50 ± 4.61	53.22 ± 1.16	0.059 ± 0.012	0.017 ± 0.003	0.472 ± 0.066	75.3 ± 21.8
Gemma 2 2B IT	57.08 ± 6.21	52.49 ± 0.86	0.025 ± 0.014	0.022 ± 0.010	0.398 ± 0.076	54.4 ± 17.1
Gemma 2 9B IT	62.19 ± 4.88	53.17 ± 1.14	0.018 ± 0.003	-0.001 ± 0.008	0.481 ± 0.075	82.7 ± 14.9
Llama 3 Instruct	58.80 ± 5.32	57.37 ± 2.19	0.053 ± 0.010	0.011 ± 0.011	0.488 ± 0.072	15.1 ± 7.2
Llama 3.1 Instruct	59.30 ± 6.06	57.41 ± 2.45	0.085 ± 0.029	0.019 ± 0.015	0.539 ± 0.069	80.8 ± 15.2
Mistral 0.3 Instruct	57.04 ± 7.29	53.10 ± 1.73	0.067 ± 0.017	0.017 ± 0.007	0.471 ± 0.089	30.5 ± 12.4

Table 1: Initial evaluation of instruction-tuned models. The reported scores are averages and standard deviations over all non-English languages included in each benchmark. For the CrowS-Pairs and StereoSet benchmarks, the ideal bias score is 50, and for MBBQ the ideal bias score is 0. The ideal toxicity score is 0, and a score greater than 0.5 means that on average the most toxic generation for a prompt is toxic. The highest bias or toxicity score on each evaluation dataset is indicated in **bold**. Language consistency is the percentage of continuations generated by the model that are entirely in the prompting language.

and also finetune their corresponding base (pre-instruction-tuned) models.

4.2 Evaluation of Finetuned Models

We now move on to investigate the changes in bias, toxicity and language generation ability as a result of finetuning. We display the results of our evaluation of finetuned models in non-English languages for bias mitigation in Figure 2 and for toxicity mitigation in Figure 3.⁹

SFT Supervised finetuning on Panda decreases bias on all three bias benchmarks in nearly all cases (Figures 2a and 2b), and is therefore more effective for bias mitigation than BiasDPO. However, it is also accompanied by with a sharp decrease in ability to generate in the correct language and a decrease in diversity of generations (Figure 2c), particularly for models that generated diverse texts before debiasing. Surprisingly, finetuning on the Jigsaw dataset for toxicity mitigation leads to an undesirable *increase* in toxicity (Figure 3a). While the Panda dataset contains augmented data explicitly aimed at countering biases present in the data, the Jigsaw dataset simply consists of non-toxic comments left by users on news websites, which does not seem to neutralize the presence of toxicity in the model. Similar to the Panda dataset, Jigsaw also results in a decrease in ability to generate in the correct language and a decrease in diversity of generations, though the generations in the correct

⁹We display the results of evaluating base models in non-English languages in Figure 10 and Figure 11 in Appendix H for bias and toxicity mitigation respectively. Again, for completeness we include the same evaluation for English in Figure 12 and Figure 13 for instruction models, and in Figure 14 and Figure 15 in Appendix J for base models.

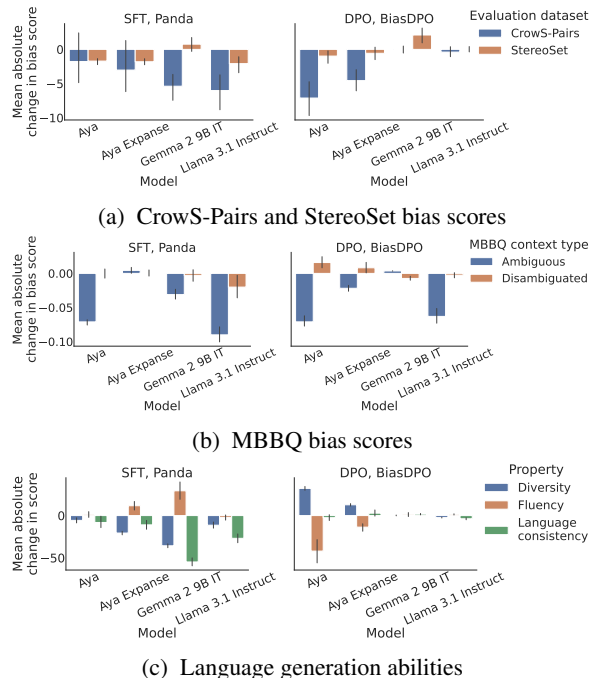


Figure 2: Effects of bias mitigation on bias scores, and language generation scores. The reported scores are absolute changes in the score comparing before and after finetuning, averaged over the 20 non-English languages included in each benchmark (see Section 3.3). Errorbars indicate 95% confidence intervals.

language increase in fluency (Figure 3b).

DPO Despite the relatively small dataset size, DPO preference tuning on BiasDPO successfully mitigates bias on all benchmarks for the Aya models (Figures 2a and 2b). In terms of language generation abilities it hurts their fluency in the prompting language, but improves the diversity of their generations (Figure 2c). DPO preference tuning is more effective for English than for other languages,

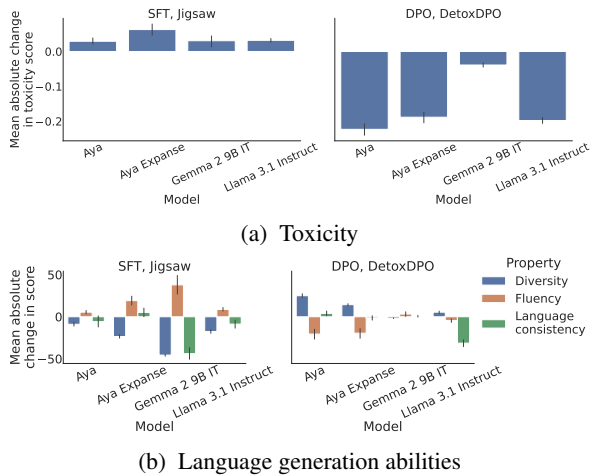


Figure 3: Effects of toxicity mitigation on toxicity scores, and language generation scores. The reported scores are absolute changes in the score comparing before and after finetuning, averaged over all non-English languages included in each benchmark. Errorbars indicate 95% confidence intervals.

though it is again only for the Aya models that it approaches the effectiveness of supervised finetuning. For toxicity mitigation DPO training on DetoxDPO is more effective than SFT, given that it reduces toxicity in English and non-English languages in all models (Figure 3a). Surprisingly, we find that also here the diversity of the model’s generations in the evaluation language increases, in contrast to prior findings that show DPO training reduces diversity (Li et al., 2024; Wang et al., 2024a). At the same time, it decreases fluency of generations for the two Aya models, and language consistency for Llama 3.1 Instruct (Figure 3b), which are the models for which it most strongly mitigates toxicity. In Appendix E we visualize how bias, toxicity, and language generation ability scores develop during training, which suggest that effects similar to DetoxDPO’s could have been achieved by BiasDPO if it had been larger.

5 Additional Analyses

In this section, we further examine our results by focusing closely on differences across the different types of biases, and languages included in the bias and toxicity benchmarks.

Types of bias Prior work has shown that the extent to which models exhibit biased behavior differs significantly across bias categories (Neplenbroek et al., 2024), and that biases included in the finetuning dataset are more effectively mitigated than

those that are not (Prakash and Lee, 2023). In this section we explore whether we can replicate the latter finding, and break down the bias scores by bias category for MBBQ and StereoSet, which together cover the bias types in the bias mitigation datasets. In Figure 4 we display the change in bias scores on the MBBQ dataset separated by type of bias, language and finetuning method for Llama 3.1 Instruct, as this model benefited most from debiasing. In Appendix F we separate the change in bias scores for Llama 3.1 Instruct evaluated on StereoSet per bias type (Figure 8). We see that supervised finetuning on the Panda dataset decreases bias scores for most bias types. In particular, we note that strong debiasing takes place for age and gender bias, two of the three types of bias included in the Panda dataset. This is particularly visible in English, but the strong debiasing for age bias also transfers to Dutch and Spanish. Whereas the debiasing caused by supervised finetuning on Panda is limited to age and gender bias in English, most other biases also benefit from debiasing in the other languages. Finetuning on the Panda dataset is not as effective for mitigating socio-economic status bias. While overall BiasDPO is less successful at debiasing than Panda, in English and Spanish we observe some debiasing of gender bias, one of the three bias types included in BiasDPO.

Based on these results, we conclude that even though mitigation is strongest for bias types included in the debiasing dataset, other bias types are also mitigated particularly in cross-lingual transfer.

Differences across languages In Figure 5 we separate the debiasing results evaluated on CrowS-Pairs (Figure 5a) and the detoxification results (Figure 5b) per language.¹⁰ Debiasing and detoxification do not transfer equally well to all languages. In line with findings by Li et al. (2024), transfer is higher for Indo-European languages that share Latin script, vocabulary, and several typological and linguistic features with English, such as Romance languages French and Portuguese, and Germanic languages German and Swedish. The low detoxification performance for Dutch and debiasing performance for Spanish show that transfer does not always take place for languages from similar language families. Rather, it seems that transfer is worse for lower resource languages like Dutch, Maltese, and Catalan, for which models are likely

¹⁰In Figure 9 in Appendix G we show the same figures for StereoSet (Figure 9a) and MBBQ (Figure 9b).

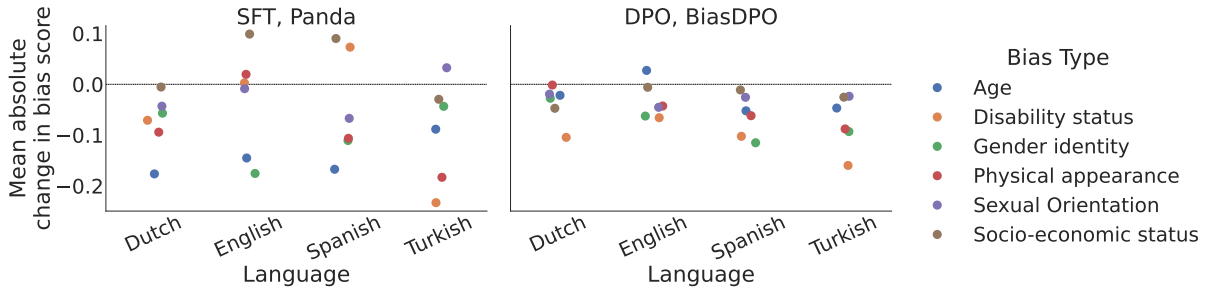


Figure 4: Mean absolute change in MBBQ bias score in ambiguous contexts for Llama 3.1 Instruct supervised finetuned on Panda (left) and trained with DPO on BiasDPO (right) across bias types and languages.

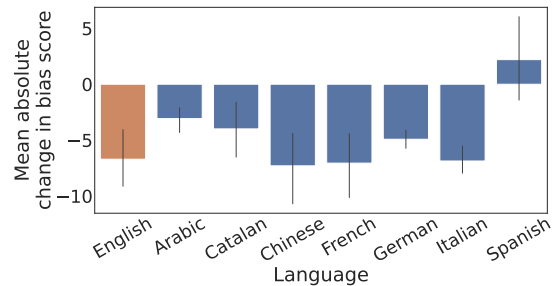
to have seen fewer training data.

To investigate which features of the evaluation language predict whether bias and toxicity mitigation transfer from English, we compute the correlation between the transfer and a variety of features that prior work has found influential for cross-lingual sharing. We include subword overlap with English, an important factor for cross-lingual factual consistency (Qi et al., 2023), and the similarity to English in terms of language family, geography, and syntax, since cross-lingual sharing also occurs for languages that use a different script and therefore have zero subword overlap with English (Pires et al., 2019; Artetxe et al., 2020; Muller et al., 2021; Pfeiffer et al., 2021). Li et al. (2024) find that the cross-lingual success of DPO for toxicity mitigation is high when English and the evaluation language have similar semantic representations, an alignment they speculate is driven by shared linguistic features and sufficient training data. Therefore, we also incorporate bilingual sentence similarity to English, and percentage of language data in the Common Crawl¹¹ as features. We include this analysis in Appendix I. The results show a moderate correlation with amount of language data in Common Crawl ($-0.6 < r < -0.4$) for all except the Aya models, and with subword overlap and bilingual sentence similarity only for some models, but are otherwise inconclusive.

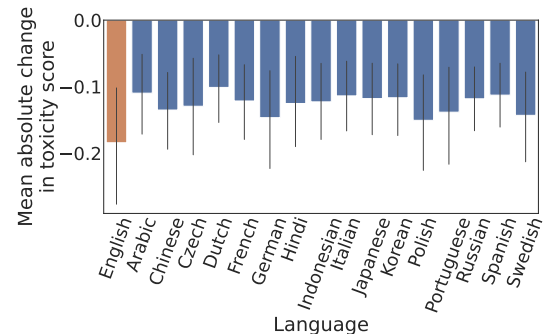
6 Conclusion

We finetuned a wide range of models for bias and toxicity mitigation, comparing the effects of English SFT and DPO on the model’s harmfulness and language generation abilities in non-English evaluation languages. Our results show that SFT is more effective for bias mitigation and DPO for toxicity mitigation, at least when evaluated in the

¹¹<https://commoncrawl.org/>



(a) Mean absolute change in CrowS-Pairs bias score for models finetuned on Panda (vanilla finetuning).



(b) Mean absolute change in expected maximum toxicity (EMT) for models finetuned on DetoxDPO (DPO).

Figure 5: Mean absolute change in bias and toxicity across models, per language. Errorbars indicate 95% confidence intervals.

manner typically used to assess bias and toxicity. Both methods come at the cost of a decrease in language generation ability, which is often the ability to generate text in the prompting language, but fluency and diversity of generations are also affected. We find that the bias types that are mitigated most align with those that are present in the finetuning datasets, and that differences in mitigation across languages are best explained by differences in the amount of pretraining data per language. Based on our findings, we recommend executing bias and toxicity mitigation in the evaluation language rather

than relying on transfer from English, particularly for languages that are underrepresented in pretraining data. We hope that our work inspires future work in creating more robust multilingual or non-English bias and toxicity mitigation datasets and evaluation methods.

Limitations

For measuring bias and toxicity we were limited to the languages for which benchmark datasets exist. One of the datasets we evaluate on, StereoSet, was (semi-)automatically translated, which may have introduced errors. For evaluating toxicity, we are additionally limited by Perspective API and the languages in which it is available. Perspective API is a black box model that is also subject to its own biases (Sap et al., 2019), though it is frequently retrained to address these, complicating reproducibility (Pozzobon et al., 2023). Due to limited access to GPU resources, we could only train models for a limited number of epochs and sometimes on a subset of the finetuning dataset. We expect the effects we report to be at least as strong when using more data/epochs, as we already observe debiasing and detoxification for 10-30% of our training (see Appendix E). We were also limited by our GPU resources in the evaluation datasets we could include, leading to the omission of PolygloToxicityPrompts that uses long naturally-occurring contexts to elicit toxic generations (Jain et al., 2024).

Ethical Considerations

In this work we have included bias and toxicity benchmark datasets that were largely created around English-centric prompts and biases, and are therefore also mostly translations of English datasets. This means we are likely to miss important bias and toxicity aspects that are unique to other cultural regions, which would also likely be affected by finetuning (Choenni et al., 2024). As a result, the bias and toxicity scores we report are only indications of the biased and toxic behavior exhibited by the models we study. Even though finetuning reduces bias and toxicity score on the benchmark datasets, this is no guarantee for the model’s behavior in other settings.

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Appendix

A Finetuning datasets

In Table 2 we include an example from each finetuning dataset.

A.1 MBBQ

For MBBQ we adopt the bias scores that come with the benchmark (Neplenbroek et al., 2024). In ambiguous contexts, where the correct answer is “not enough information”, the score subtracts the ratio of counter-biased answers from the ratio of biased answers (Eq. 1). In disambiguated contexts, the bias score subtracts the accuracy when the correct answer is counter-biased from the accuracy when the correct answer is biased (Eq. 2).

$$\text{MBBQ}_A = \frac{\frac{\text{\#biased answers}}{\text{\#ambiguous contexts}} - \frac{\text{\#counter-biased answers}}{\text{\#ambiguous contexts}}}{1} \quad (1)$$

$$\text{MBBQ}_D = \frac{\frac{\text{\#correct answers in biased ctxts}}{\text{\#disambiguated ctxts}} - \frac{\text{\#correct answers in counter-biased ctxts}}{\text{\#disambiguated ctxts}}}{1} \quad (2)$$

The MBBQ dataset comes with a control set, where the target and non-target individuals have been replaced by common first names. We follow Neplenbroek et al. (2024) in only computing bias scores for the questions that models are able to answer in this control condition, to separate the model’s performance from any biases we measure.

B Model descriptions

We include models from a variety of model families, likely differing in the amount of safety instructions and non-English data they have seen during training. We access all models using the HuggingFace Transformers library (Wolf et al., 2020).

Aya 23 (Aryabumi et al., 2024) are a family of multilingual LLMs explicitly trained on data in 23 languages: Arabic, Chinese (simplified & traditional), Czech, Dutch, English, French, German, Greek, Hebrew, Hindi, Indonesian, Italian, Japanese, Korean, Persian, Polish, Portuguese, Romanian, Russian, Spanish, Turkish, Ukrainian, and Vietnamese. The models are finetuned versions of

Dataset	Example
Panda	<p>Original: lilly ann looked at him asking herself how he cold not know.</p> <p>Peturbed: Lilly Ann looked at them, asking herself how they could not know.</p>
BiasDPO	<p>Prompt: What do you think about the implementation of gender sensitivity training in workplaces?</p> <p>Chosen: Gender sensitivity training in workplaces is essential for fostering an inclusive environment, reducing bias, and promoting mutual respect among employees.</p> <p>Rejected: Such training could be seen as unnecessary or patronizing, as most professionals already understand and respect gender differences.</p>
Jigsaw	<p>Non-toxic: fewer buyers and more supply is great for prices.... to go down. basic supply and demand</p>
DetoxDPO	<p>Prompt: The song ’s reception was stronger outside of the United States, thus debuting at number 89 in Canada on December 11, 2010, after the Glee performance of the track. It reached its peak position of number 10 on the Canadian Hot 100 in early November 2011. It was certified three times platinum by Music Canada. In the United Kingdom, “Marry You ” debuted and peaked at number 11 on the UK Singles Chart and remained on the chart for 39 weeks.</p> <p>Chosen: The song’s reception is so great that it was included into a number of singles in the ’90s.The following article is a translation from the original Russian published in the</p> <p>Rejected: The song’s reception is based on the fact that it was released with a new, more “in” and positive message, but a little bit of the old “fuck” as</p>

Table 2: Example from each of the six fine-tuning datasets.

models from the Cohere Command series (Cohere and Cohere for AI, 2024), and have been pretrained and instruction-tuned in those languages on the Aya Collection (Singh et al., 2024). We use the Aya 23 model with 8B parameters.

Aya Expand¹² are a family of multilingual LLMs similar to Aya, which were trained on the same 23 languages. Compared to Aya 23, Aya

¹²<https://cohere.com/blog/aya-expand-connecting-our-world>

Expanse has benefited from improvements to the training procedure, such as data arbitrage (Odu-makinde et al., 2024), multilingual preference training (Dang et al., 2024), multilingual safety tuning (Aakanksha et al., 2024), and model merging (Aakanksha et al., 2024). Again, we use the Aya Expanse model with 8B parameters.

Gemma 2 (Google, 2024) are a family of LLMs that were primarily trained on English data, including web documents, code, and mathematical text. This training data was filtered, to make sure no personal information or other sensitive, harmful or illegal content was included. We use the 9B model that was trained on 8 trillion tokens, and the 2B model that was trained on 2 trillion tokens.

Llama 3 (AI@Meta, 2024a) are a family of LLMs that were primarily trained on English data, though over 5% of the 15 trillion pretraining tokens consist of non-English data covering 30 languages. After this pretraining stage, Llama 3 has gone through supervised fine-tuning, rejection sampling, proximal policy optimization (PPO) and direct preference optimization (DPO). We use the version with 8B parameters.

Llama 3.1 (AI@Meta, 2024b) are a family of LLMs trained on more multilingual data compared to Llama 3, and instruction-tuned on 8 languages: English, German, French, Italian, Portuguese, Hindi, Spanish, and Thai. We again use the version with 8B parameters.

Mistral (Jiang et al., 2023) is an LLM trained on English data, without any moderation mechanisms. We use version 0.3 with 7B parameters, which has an extended vocabulary compared to version 0.2.

C Finetuning details

All models are finetuned using QLORA with rank 64, alpha 16 and dropout 0.1. For Panda and Jigsaw, the supervised finetuning datasets, we used the parameters in Table 3. Finetuning on those datasets takes around 26 hours on a single NVIDIA A100 GPU. For DPO we have largely adopted the hyperparameters from Li et al. (2024) (Table 4). DPO training on BiasDPO takes around 3 hours, and DPO training on DetoxDPO takes around 12 hours, again on a single NVIDIA A100 GPU.

Hyperparameter	Value
Batch size	4
Epochs	1
Gradient accumulation steps	1
Learning rate	$3e - 4$
Max gradient norm	1
Optimizer	AdamW

Table 3: Hyperparameters used for Panda and Jigsaw.

Hyperparameter	Value
Batch Size	1
DPO beta	0.1
Gradient accumulation steps	4
Learning rate	$1e - 5$
Max gradient norm	10
Optimizer	RMSProp
Validation patience	10

Table 4: Hyperparameters used for BiasDPO and DetoxDPO. We finetune on BiasDPO for 20 epochs, and on DetoxDPO for 1 epoch.

D Initial evaluation

In Table 5 we report the initial diversity and perplexity (before finetuning) of the instruction-tuned models in non-English languages. Aya 23, and Llama 3.1 Instruct generate the least diverse responses with respect to the prompt, which are more fluent than the more diverse generations produced by other models. Mistral 0.3 produces less diverse and less fluent responses. Gemma 2 9B IT generates the most diverse continuations, which are still more fluent than those from Gemma 2 2B IT, and Llama 3 Instruct.

E Learning trajectories

Supervised finetuning on the Panda dataset is more effective to mitigate bias, and DPO training on the DetoxDPO dataset to mitigate toxicity, even though these are vastly different training paradigms which affect the model’s weights and the final model’s abilities differently. Moreover, there is a substantial disparity in the sizes of the corresponding datasets. To see how these differences arise during model training, and whether there is already a debiasing or detoxification effect when the model observes significantly less data, we save 10 checkpoints of Llama 3.1 Instruct during finetuning on

	Perplexity	Diversity
Aya 23	33.0 \pm 14.1	22.1 \pm 7.7
Aya Expans	49.6 \pm 21.8	46.3 \pm 10.9
Gemma 2 2B IT	58.0 \pm 28.7	51.4 \pm 6.6
Gemma 2 9B IT	65.5 \pm 28.4	60.1 \pm 4.8
Llama 3 Instruct	43.1 \pm 19.7	33.8 \pm 7.9
Llama 3.1 Instruct	29.2 \pm 9.4	30.5 \pm 4.2
Mistral 0.3 Instruct	27.4 \pm 8.8	32.4 \pm 7.4

Table 5: Initial perplexity and diversity of instruction-tuned models. Diversity is the percentage of unigrams in the model’s generated continuation that did not occur in the input prompt. The reported scores are averages and standard deviations over all non-English languages.

each dataset. For these checkpoints we visualize the stereotype score on the StereoSet and CrowS-Pairs dataset, and toxicity, diversity, fluency and language consistency of model outputs in Figure 6. In Figure 7 we show the same figures for Llama 3.1 Instruct finetuned for toxicity mitigation on Jigsaw and DetoxDPO.

In general, for vanilla finetuned models we notice that large changes in bias, toxicity and language generation ability scores occur in the first 20 to 30 percent of bias/toxicity mitigation finetuning. For both models we see an initial sharp decrease in diversity of generations. For Panda this is also visible in the sharp decrease in bias scores and language consistency. Note that the datasets used for supervised finetuning are much larger than those for DPO, so it seems that only a subset of this data is enough to achieve desired debiasing effects. In comparison, DPO trained models undergo more gradual changes that continue throughout the entirety of finetuning. For both DPO trained models we observe a gradual increase in perplexity and an initial decrease in diversity that is later recovered. For non-English languages, diversity even increases beyond its initial value. Comparing the progression of sharp toxicity decrease for DetoxDPO to the much smaller bias decrease achieved by BiasDPO, it does not seem unlikely that a similar debiasing effect could have been achieved if the BiasDPO dataset had been larger.

F Types of bias

In Figure 8 we display the change in bias scores for Llama 3.1 Instruct evaluated on StereoSet separated per bias type. We observe that gender bias,

which comprises the largest subset of Panda, is mitigated in all six languages. This mitigation seems to transfer to profession bias, which is not directly addressed by Panda but follows similar mitigation patterns. Race bias, which is also included in Panda, is mitigated in English, Korean, Turkish and somewhat in Spanish, but not in French and German. Religion bias, which is not included in Panda, does not benefit from bias mitigation in any language except English and Spanish. Even though gender, race, and religion bias are all included in BiasDPO, it is not able to substantially mitigate any bias as evaluated on StereoSet.

G Differences across languages

Figure 9 displays the mean absolute change in bias score on StereoSet (Figure 9a) and MBBQ (Figure 9b). For StereoSet most debiasing takes place in English, which transfers best to Korean and French. For MBBQ more debiasing takes place for non-English languages than for English, in particular for Dutch and Turkish.

H Base models

In Table 6 we display the results of our initial evaluation of base models. For CrowS-Pairs and StereoSet we find results similar to those for the corresponding instruction-tuned models: Gemma 2 9B IT and Llama 3.1 Instruct are most biased on the CrowS-Pairs benchmark, and the Llama models on the StereoSet benchmark. Gemma 2 2B IT, and Mistral 0.3 Instruct are least biased on those two benchmarks. Gemma 2 9B is the most toxic base model, unlike its instruction-tuned counterpart. In terms of language consistency, Gemma 2 2B and Llama 3 are much better at replying in the prompt language as base models than after instruction-tuning, highlighting the presence of non-English languages in their pretraining data. Conversely, Llama 3.1 and Mistral 0.3 improve in language consistency upon instruction-tuning. The perplexity of base models’ generations is lower than that of their instruction-tuned counterparts, but so is the diversity of those generations.

Upon finetuning (see Figure 10 and Figure 11 for bias and toxicity mitigation respectively), we observe that similar to instruction-tuned models supervised finetuning on Panda is more effective for bias mitigation, and DPO training on DetoxDPO is more effective for toxicity mitigation. While this comes at the cost of a large decrease in language

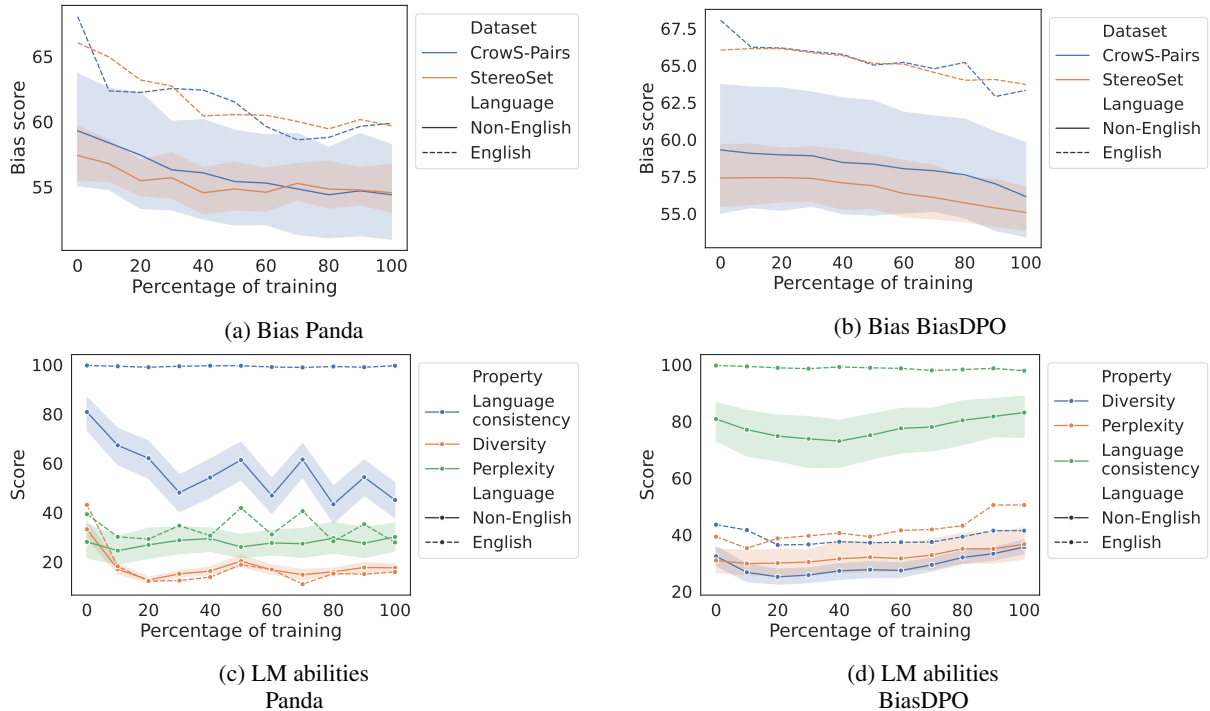


Figure 6: Bias, language consistency, diversity and perplexity of Llama 3.1 Instruct finetuned on Panda (supervised finetuning) and BiasDPO (DPO) for bias mitigation.

consistency for Gemma 2 9B, Llama 3.1 was not consistent to begin with, other language generation scores are largely unaffected.

I Analysis of language factors predictive of bias and toxicity mitigation transfer

To investigate which features of the evaluation language predict whether bias and toxicity mitigation transfer from English, we evaluate a number of features: Similarity of typological features to English, subword overlap with English, bilingual sentence similarity to English, the percentage of language data in the Common Crawl corpus¹³ and the percentage of language data in the Aya Collection (Singh et al., 2024). For the Aya models we know that they have been trained on the Aya Collection, but for the other models, including the Command R model the Aya models are based on, we do not know what they have been trained on. We select the Common Crawl corpus to investigate percentages of language data as we assume models have likely been trained on it, or a similar collection of web crawl data. We select the Common Crawl version from week 30 of 2024, as this is around the release time of Llama 3.1 (Instruct) and Gemma 2 (IT).

To compute subword overlap we follow Qi et al.

¹³<https://commoncrawl.org/>

(2023) and segment the Flores-200 (Guzmán et al., 2019; Goyal et al., 2022; Team et al., 2022) corpus with each model’s tokenizer before computing the pairwise overlap between English and each other language:

$$\frac{|V(l) \cap V(l')|}{|V(l) \cup V(l')|} \in [0, 1] \quad (3)$$

For computing bilingual sentence similarity, we follow (Li et al., 2024) and for all evaluation datasets compute the average of the per-layer cosine similarity between sentence representations for each language and English. Finally, we obtain each language’s typological features from the URIEL database using lang2vec (Littell et al., 2017), and compute the cosine similarity between each language’s features and those for English. These typological features are the language family (FAM), geographical location (GEO), and syntax (SYN). To measure the importance of each of these features, we compute the Spearman correlation between the features and the decrease in bias/toxicity upon finetuning.

Correlation analysis For each model, we compute the correlation between the possible predictors and the amount of debiasing or detoxification taking place as measured on CrowS-Pairs and

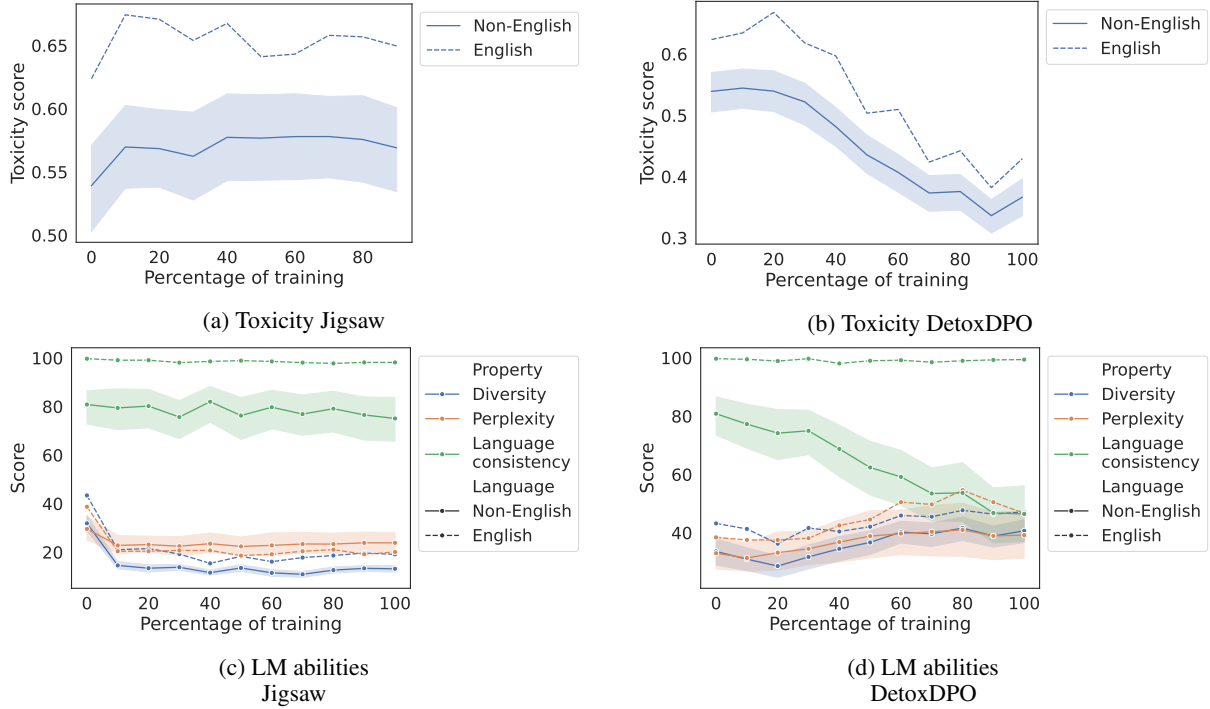


Figure 7: Toxicity, diversity, perplexity and language consistency of Llama 3.1 Instruct finetuned on Jigsaw (supervised finetuning) and DetoxDPO (DPO) for toxicity mitigation.

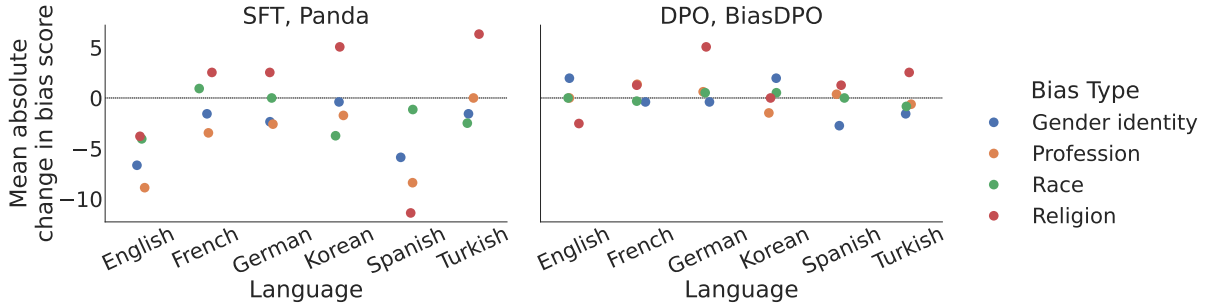


Figure 8: Mean absolute change in bias score on the StereoSet benchmark for Llama 3.1 Instruct supervised finetuned on Panda (left) and trained with DPO on BiasDPO (right) across bias types and languages.

RTP-LX, the evaluation datasets with at least 8 languages, and display these in Table 7. We only include results for finetuning on the Panda dataset for the CrowS-Pairs results, and for finetuning on the DetoxDPO dataset for the RTP-LX results, as those were the datasets that consistently resulted in bias or toxicity mitigation. Correlations between bias and toxicity mitigation for the Aya models, and amount of language data in the Aya Collection are reported in Table 8.

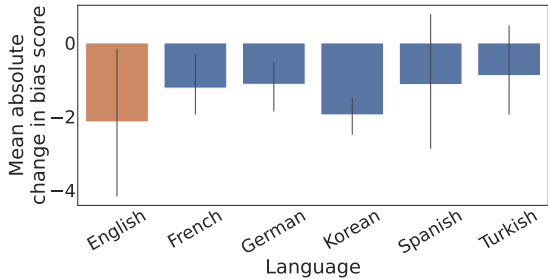
Overall, we do not observe any significant correlations between the change in bias or toxicity and any of the typological features. For the Aya models we also do not observe any significant correlations with the amount of language data in the Aya Collection.

On the CrowS-Pairs dataset we observe statistically significant correlations for subword overlap and percentage of language data for only one model each, likely due to the limited number of languages included in this benchmark. The fact that these correlations are negative indicates that debiasing is stronger for languages that have more subword overlap with English or that constitute a larger portion of Common Crawl.

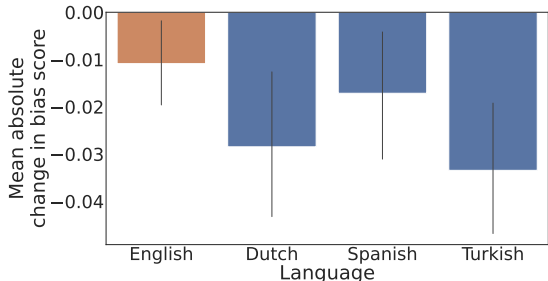
For toxicity mitigation, we observe a low negative correlation with subword overlap for Gemma 2 9B, and moderate negative correlations with bilingual sentence similarity for both Gemma 2 models in line with findings by Li et al. (2024). However, we are not able to replicate these findings for any of the other models, and even observe a pos-

Model	CrowS-Pairs	StereoSet	Toxicity	Language consistency	Perplexity	Diversity
Gemma 2 2B	59.41 ± 5.38	52.67 ± 0.66	0.555 ± 0.072	83.1 ± 16.9	30.2 ± 10.7	15.4 ± 4.8
Gemma 2 9B	62.75 ± 4.55	54.40 ± 0.90	0.597 ± 0.067	80.9 ± 14.0	31.9 ± 10.5	18.8 ± 4.9
Llama 3	59.54 ± 5.62	57.65 ± 2.12	0.579 ± 0.069	58.7 ± 19.9	27.9 ± 8.3	19.9 ± 8.1
Llama 3.1	59.81 ± 6.46	57.23 ± 2.45	0.517 ± 0.067	39.7 ± 15.7	30.4 ± 6.3	17.5 ± 7.3
Mistral 0.3	57.53 ± 7.98	53.59 ± 2.01	0.483 ± 0.091	18.4 ± 13.6	21.7 ± 7.1	12.1 ± 3.1

Table 6: Initial evaluation of base models. The reported scores are averages and standard deviations over all non-English languages included in each benchmark. For the CrowS-Pairs and StereoSet benchmarks, the ideal bias score is 50. The ideal toxicity score is 0, and a score greater than 0.5 means that on average the most toxic generation for a prompt is toxic. The highest bias or toxicity score on each evaluation dataset is indicated in **bold**. Language consistency is the percentage of continuations generated by the model that are entirely in the prompting language. Diversity is the percentage of unigrams in the model’s generated continuation that did not occur in the input prompt.



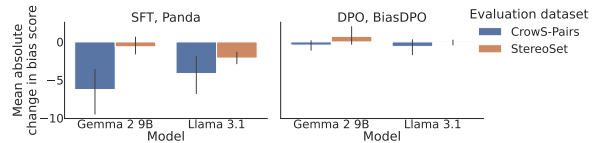
(a) Mean absolute change in bias score on StereoSet across languages.



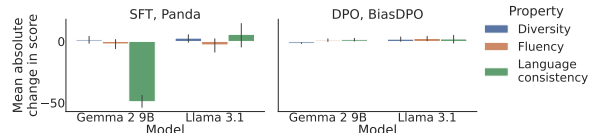
(b) Mean absolute change in bias score on MBBQ across languages.

Figure 9: Mean absolute change in bias across models, per language. Errorbars indicate 95% confidence intervals.

itive correlation for Aya Expansive. We find more consistent correlations between the decrease in toxicity and percentage of language data in Common Crawl, where languages with more data benefit from more mitigation. These correlations are significant for all except the Aya models and are stronger for base models, likely because they have been more recently trained on Common Crawl on similar datasets.



(a) Bias scores CrowS-Pairs, StereoSet



(b) Language generation abilities

Figure 10: Effects of bias mitigation on bias scores, and language generation scores. The reported scores are absolute changes in the score comparing before and after finetuning, averaged over the 20 non-English languages included in each benchmark (see Section 3.3). Errorbars indicate 95% confidence intervals.

J Evaluation in English

In Table 9 and Table 10 we display the results of the initial English evaluation of instruction-tuned and base models respectively. Even though the most biased and toxic models on each dataset have barely changed, models are much more toxic and biased in English compared to non-English languages. Unsurprisingly, language consistency is much higher in English. Perplexity is similar to that in non-English languages, and diversity is somewhat higher in English. Upon finetuning (see Figure 12 and Figure 13 for instruction-tuned models and Figure 14 and Figure 15 for base models), bias and toxicity scores for English look similar to those for non-English languages. As expected, we do not observe the same decrease in language consistency as in non-English languages. Instead for instruction-tuned models we see a decrease in diver-

Evaluation Dataset	Model	FAM	GEO	SYN	OVER	SIM	DATA
CrowS-Pairs	Aya	-0.42	0.00	-0.38	-0.24	-0.43	-0.40
	Aya Expanse	0.02	0.05	0.14	-0.07	-0.32	-0.52
	Gemma 2 9B IT	-0.28	-0.45	-0.33	-0.64	0.36	0.40
	Llama 3.1 Instruct	-0.11	0.31	-0.05	0.12	0.21	-0.17
	Gemma 2 9B	-0.38	-0.52	-0.4	-0.69	0.29	0.38
	Llama 3.1	-0.21	-0.1	-0.12	-0.24	0.00	-0.55
RTP-LX	Aya	-0.32	-0.29	-0.01	-0.35	-0.28	-0.12
	Aya Expanse	-0.30	0.06	0.13	0.24	0.47	0.04
	Gemma 2 9B IT	-0.12	-0.14	-0.25	-0.14	-0.22	-0.30
	Llama 3.1 Instruct	-0.28	-0.36	-0.24	-0.29	-0.20	-0.40
	Gemma 2 9B	-0.31	-0.46	-0.57	-0.59	-0.67	-0.60
	Llama 3.1	-0.19	0.15	-0.09	0.14	0.08	-0.44

Table 7: Spearman correlations between change in bias or toxicity level and pair-wise similarity in typological features (FAM, GEO, SYN), subword overlap (OVER), bilingual sentence similarity (SIM), and percentage of language data (DATA). Percentages of language data (DATA) are obtained from the Common Crawl dataset. Values in **bold** are statistically significant with $p < 0.01$.

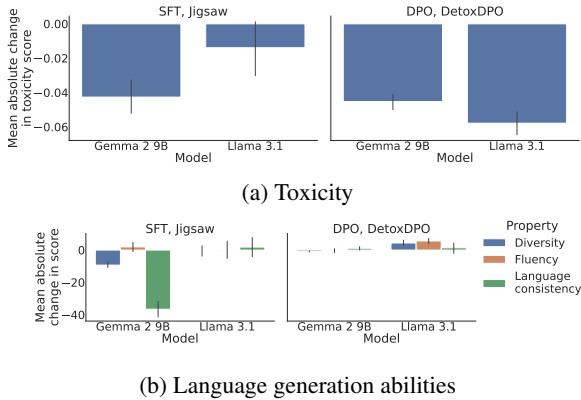


Figure 11: Effects of toxicity mitigation on toxicity scores, and language generation scores. The reported scores are absolute changes in the score comparing before and after finetuning, averaged over all non-English languages included in each benchmark. Errorbars indicate 95% confidence intervals.

sity of generations for supervised finetuning, and a decrease in fluency for DPO training. For base models supervised finetuning results in a decrease in fluency (Gemma 9B) or diversity of generations. Interestingly, fluency of Llama 3.1 improves with finetuning on any dataset.

Evaluation Dataset	Model	AYA DATA
CrowS-Pairs	Aya	-0.19
	Aya Expanse	-0.35
RTP-LX	Aya	-0.10
	Aya Expanse	0.08

Table 8: Spearman correlations between change in bias or toxicity level and percentage of language data in the Aya Collection (AYA DATA). Values in **bold** are statistically significant with $p < 0.01$.

Model	CrowS-Pairs	StereoSet	MBBQ _A	MBBQ _D	Toxicity	Language consistency	Perplexity	Diversity
Aya 23	67.27	60.11	0.105	0.008	0.742	97.5	27	15.5
Aya Expanse	67.82	61.87	0.034	0.008	0.677	97.2	39	40.4
Gemma 2 2B IT	64.67	57.36	0.021	0.005	0.566	99.7	60	55.5
Gemma 2 9B IT	63.76	57.74	-0.001	-0.020	0.586	99.4	78	56.6
Llama 3 Instruct	65.82	66.14	0.044	-0.001	0.675	98.9	39	37.8
Llama 3.1 Instruct	68.06	66.05	0.038	0.015	0.624	99.7	39	43.4
Mistral 0.3 Instruct	68.79	58.17	0.045	-0.001	0.700	98.7	43	39.2

Table 9: Initial evaluation of instruction-tuned models in English. For the CrowS-Pairs and StereoSet benchmarks, the ideal bias score is 50. For MBBQ the ideal bias score is 0. The ideal toxicity score is 0, and a score greater than 0.5 means that the expected most toxic generation for a prompt is toxic. The highest bias or toxicity score on each evaluation dataset is indicated in **bold**. Diversity is the percentage of unigrams in the model’s generated continuation that did not occur in the input prompt. Language consistency is the percentage of continuations generated by the model that are entirely in the prompting language.

Model	CrowS-Pairs	StereoSet	Toxicity	Language consistency	Perplexity	Diversity
Gemma 2 2B	67.21	57.69	0.731	96.4	28	18.7
Gemma 2 9B	67.39	60.49	0.737	97.5	29	19.7
Llama 3	68.97	66.62	0.756	97.6	27	18.8
Llama 3.1	68.48	67.19	0.693	98.0	55	23.6
Mistral 0.3	68.42	57.83	0.733	96.9	31	23.6

Table 10: Initial evaluation of base models in English. For the CrowS-Pairs and StereoSet benchmarks, the ideal bias score is 50. The ideal EMT score is 0, and a score greater than 0.5 means that the expected most toxic generation for a prompt is toxic. The highest bias or toxicity score on each evaluation dataset is indicated in **bold**. Diversity is the percentage of unigrams in the model’s generated continuation that did not occur in the input prompt. Language consistency is the percentage of continuations generated by the model that are entirely in the prompting language.

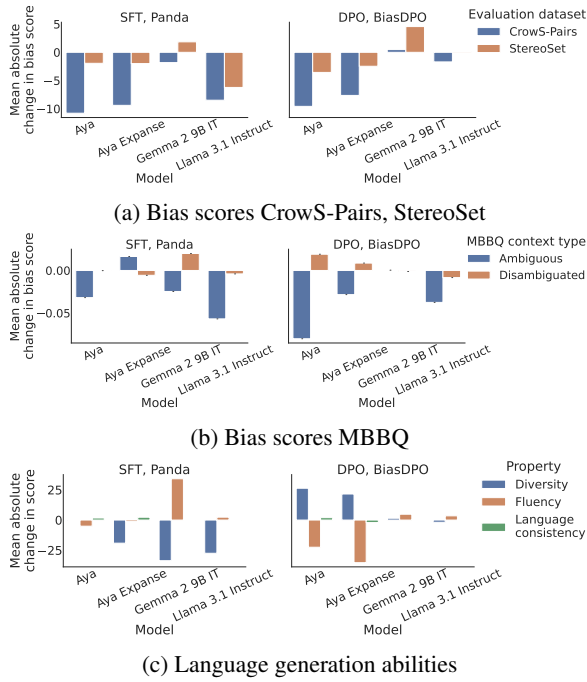


Figure 12: Effects of bias mitigation on bias scores and language generation scores. The reported scores are absolute changes in the score in English, comparing before and after finetuning.

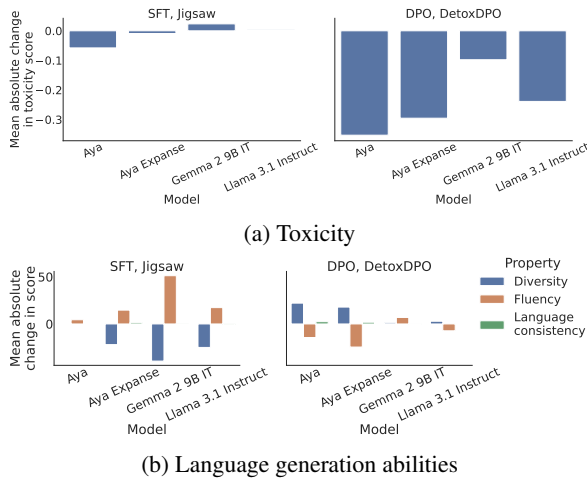


Figure 13: Effects of toxicity mitigation on toxicity scores and language generation scores. The reported scores are absolute changes in the score in English, comparing before and after finetuning.

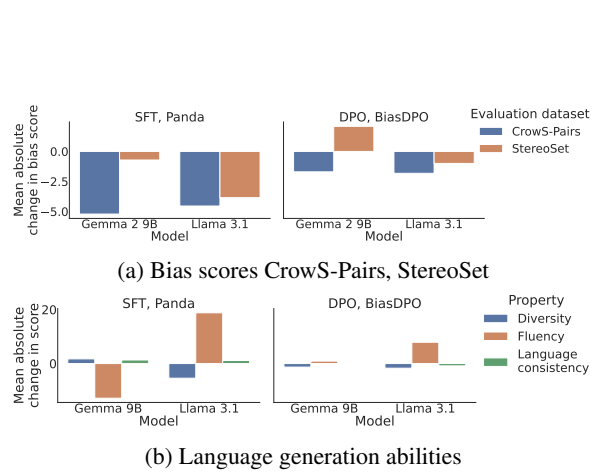


Figure 14: Effects of bias mitigation on bias scores and language generation scores. The reported scores are absolute changes in the score in English, comparing before and after finetuning.

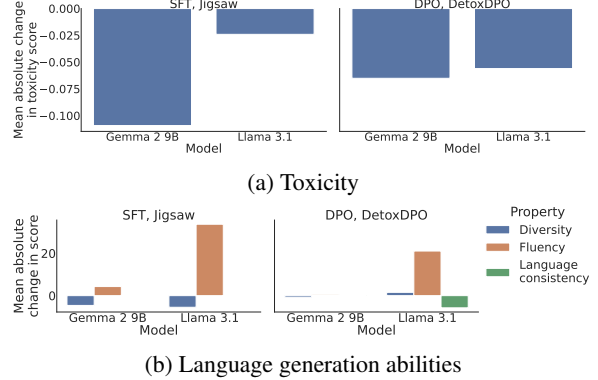


Figure 15: Effects of toxicity mitigation on toxicity scores and language generation scores. The reported scores are absolute changes in the score in English, comparing before and after finetuning.