Creating a Rigorous Cultural Bias Benchmark for Autoregressive Large Language Models

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Abstract

Large Language Models (LLMs) have become tools for various applications. Since they are trained mostly in English texts, their biases towards Western culture pose challenges in non-English contexts. Most of the work done so far in defining a benchmark for cultural biases have been largely qualitative or require some level of human intervention.

In this paper, we propose a Cultural Divergence (CD) metric, a quantitative measure to assess autoregressive models' cultural alignment. This metric is agnostic to model size and calculates the difference in KL-divergences or cross-entropies between two cultures. We carried out experiments on Polish vs. Western culture using state-of-the-art LLMs to evaluate the metric's efficacy in automating and rigorously quantifying cultural biases.

1 Introduction

Large Language Models (LLMs) are powerful tools that can generate natural language texts for various applications, such as chatbots, summarization, translation, and more. Traditionally, due to English being the de facto Lingua Franca of the internet, LLMs have been commonly trained on mostly English data. Recently there has been more work on training both masked (Antoun et al., 2020a; Abdul-Mageed et al., 2020) and autoregressive (Antoun et al., 2020b; Wojczulis and Kłeczek, 2021) language models on non-English data. Moreover, a lot of currently available models can process data in multiple languages (Touvron et al., 2023; Workshop et al., 2022).

Recently, with the rise in popularity of LLMs, there has been an increasing number of works analyzing the cultural biases in those models when prompted in a language used by a specific culture (Naous et al., 2023; Wang et al., 2023). In their analysis, they consider topics that highly differ between cultures, such as which names are popular, what foods are preferred in a given culture, or certain religious customs and cultural norms derived from them. For example, since a significant majority of the users of the Arabic language are often Muslim, texts written in that language would rarely mention consuming alcoholic beverages (of which consumption is forbidden by the rules of Islam). Those works have shown that both non-English and multilingual models exhibited a skew towards the western culture, which could pose a potential issue in deploying the current LLMs for use in non-English-speaking cultures. However, the metrics that those works created for autoregressive language models are either only qualitative in nature and require human intervention, or do not cover all of the relevant cultural aspects.

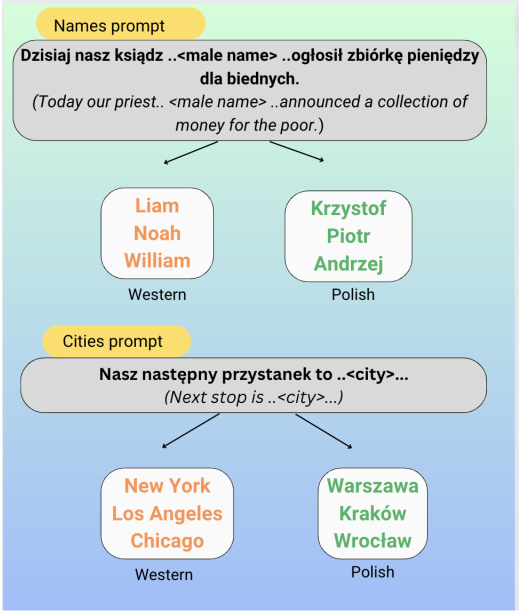

Names prompt
Dzisiaj nasz ksiądz ..<male name> ..ogłosił zbiórkę pieniędzy dla biednych.
(Today our priest.. <male name> ..announced a collection of money for the poor.)
Liam
Noah
William
Western
Krzystof
Piotr
Andrzej
Polish
Cities prompt
Nasz następny przystanek to ..<city>...
(Next stop is ..<city>...)
New York
Los Angeles
Chicago
Western
Warszawa
Kraków
Wrocław
Polish

Figure 1: Examples of prompts and generations in Western vs. Polish culture.

In our work, we aim to address this issue, providing a metric that allows for an automated, mathematically rigorous, and replicable way to assess autoregressive models for their cultural alignment.

We introduce Cultural Divergence(CD) metric to measure how biased an autoregressive model is towards a popular culture over a non-popular one. The metric does not consider the size and capabilities of the model. The CD metric is formulated as difference between the KL-divergences or cross-entropies of the model across two cultures.

We ran our experiments on Polish vs Western culture. Since the distribution of the entire language is intractable, we estimate the cross entropy between the model and the culture on 2 aspects that differ between cultures: frequencies of peoples names and the cities evaluated in hand-crafted contexts (Figure 1). We tested our metric on existing state of the art multilingual autoregressive LLMs, such as LLAMA 2 (Touvron et al., 2023) and mGPT (Shliazhko et al., 2022). We also tested the CD metric on papuGaPT2 (Wojczulis and Kłeczek, 2021), a unilingual fine tuned modal in Polish. The results show that our metric matches the predictions from previous works

2 Related Work

2.1 Measuring and mitigating stereotypes in Language Models.

Most of the work done in the space of biases has been in stereotype biases where the model makes biased stereotypical predictions towards a certain community. Different studies have proposed several techniques to mitigate gender-based stereotypes. A study suggested FairDistillation, a distillation technique to construct smaller language models while controlling for specific biases (Delobelle and Berendt, 2022). One other study presented modification an embedding to remove gender stereotypes as a debiasing strategy (Bolukbasi et al., 2016). Their method essentially removes bias by removing the gender component from the embeddings of gender-neutral words and making them equidistant to gender-specific words. In this paper, we want to find a metric that is essentially the inverse of the bias mitigation techniques for stereotype biases as we want the model to be aligned toward non-dominant cultures.

The common debiasing techniques used in stereotype biases is data augmentation. A study proposed CDA (counterfactual data augmentation) to augment the dataset to have all combinations of gender (or bias) associations (Lu et al., 2020). Another research study also suggested using CDA to train models that had an adapter layer added after each transformer layer (Lauscher et al., 2021) . Their goal was to make the debiasing sustainable by only updating the adapter layers via language modeling training on a counterfactually augmented corpus. However, it is not possible to use this approach in the context of cultural biases since they are based on data augmentation.

There have been quantitative approaches to mitigate stereotypical biases. A related work uses Wasserstein-1 distance between two groups to determine probability distributions to determine sentiment bias (Huang et al., 2019). Trained models used this as "fairness loss" and saw improvements in bias. The same metric has been used in detecting word level bias in AI generated news content (Fang et al., 2023). Another mathematical method devised for mitigating stereotype bias uses All Unmasked Likelihood (AUL) for bias calculation (Khandelwal et al., 2023). The AUL score is the percentage of times the model is more likely to prefer a stereotypical sentence over an anti-stereotypical one. These mathematical benchmarking techniques will be used as inspirations for our cultural bias metric.

2.2 Measuring cultural bias in non-English Language Models

Several studies have investigated cultural bias in various types of language models. A method presented by Naous et al. (Naous et al., 2023) created a quantitative benchmark for the cultural bias of monolingual and multilingual masked language models when prompted in Arabic. Each model's score was calculated by summing the number of completions where western aligned responses were less likely than Arab aligned responses. They also investigated the bias of autoregressive language models by having human subjects qualitatively rate the bias in each model's responses. Other related studies (Cao et al., 2023) analyze cultural bias in specific domains (e.g. in culinary recipes) by similarly relying on human subjects to score the results. However, an issue with those methods is that they are not very replicable, since they are based on human feedback which is subjective by nature. We attempt to address this by introducing a quantitive metric.

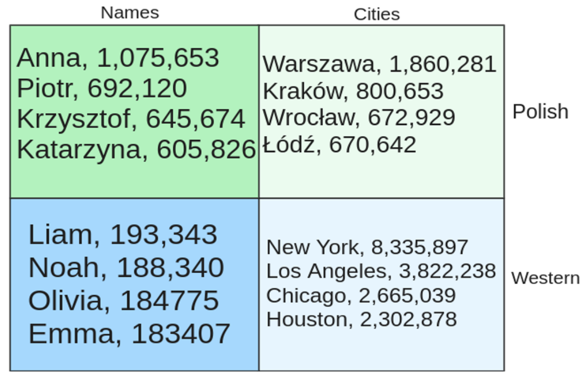
The work by (Wang et al., 2023) aims to somewhat alleviate this issue. In this method, the authors prompt multilingual autoregressive language models in different languages, and score them by counting the responses that fit within each language's culture. However, that fit is measured by manually checking correlations between the given response and wikipedia articles pertaining to that response. This means that the method still requires some level of human intervention and prevents the automatization of the metric, which our work will aim to address as well.

There has also been related work on analyzing correlation of a cultural bias between the language of the input text and the output image in image generating models (Ventura et al., 2023), which additionally introduces a quantitative metric for measuring that correlation. This work and the previously mentioned benchmark by (Naous et al., 2023) for Masked Language Models will serve as an inspiration to our more quantitative metric for a cultural bias in the non-english models.

3 Methodology

Our objective is to measure the cultural bias of a model that is differentiable, allows for fair comparison of different language models and works with autoregressive models. Formally, for a certain language that is analyzed with the method, let us define 3 distributions of tokens in that language L, M and W. These distributions correspond to the culture of the language (C_L), the distribution of the model we are analyzing(C_M) and another culture we are trying to measure the bias towards for the model (C_W). Thus, we want some way to measure how much closer distribution M is to L and W that does not vary significantly with different model sizes and language modelling capabilities. In our case, distribution L is the distribution of the Polish culture, distribution W is the distribution of the western culture in the Polish language, and the distribution M is the distribution of the autoregressive model we are testing.

As discussed below, we approximate those distributions with certain aspects that differ between cultures, contexts related to those aspects and names to fill in the contexts with. The model's distribution is approximated by measuring the joint probabilities it assigns to the filled-in contexts. For the cultures we approximate the probabilities with real-world counts of the names filled into the contexts. The reason for doing so and not taking the actual frequencies of those names in data is that what we suspect that the source of the models' biases is the data it was trained on, and thus estimating the aspects' probabilites from the data would make the estimates not independent on it.



Names	Cities	
Anna, 1,075,653 Piotr, 692,120 Krzysztof, 645,674 Katarzyna, 605,826	Warszawa, 1,860,281 Kraków, 800,653 Wrocław, 672,929 Łódź, 670,642	Polish
Liam, 193,343 Noah, 188,340 Olivia, 184775 Emma, 183407	New York, 8,335,897 Los Angeles, 3,822,238 Chicago, 2,665,039 Houston, 2,302,878	Western

Figure 2: Examples of names and cities used in the approximation. The names were additionally split on the gender. The English names were translated to Polish names using the DeepL translation service, whenever they had a Polish counterpart (e.g. *Catherine* → *Katarzyna*)

3.1 Cultural Divergence (CD)

Let the set of all texts modelled be Ω. For our method we would like to compare the distance of M to L and M to W. Therefore, we propose a Cultural Divergence (CD) metric $D_C(L||M||W)$:

$$\sum_{x\in\Omega} M(x)\log\frac{W(x)}{L(x)}$$

which can be either defined as the difference between KL-divergences $D_{KL}(M||L) - D_{KL}(M||W)$ or as a difference of cross-entropies $H(M,L)-H(M,W)$ (lower CD means the model more aligned with the language's culture). The reasoning behind subtracting the KL-divergence with the culture W is that we want the metric to be the same regardless of how good a language model is at modelling in general.

3.2 Estimating probability distributions

Naturally, estimating the distribution of the entire culture is intractable. Thus, due to limitiatons in the dataset availability, we only consider two aspects of the cultures: names and cities that commonly appear in the cultures (Figure). To be precise, for each culture $C \in \{C_L, C_W\}$ and for each aspect analyzed $A \in \{\textit{male names}, \textit{female names}, \textit{cities}\}$ we have a set of completions for that culture and aspect $G_{C,A}$, estimated probability distribution of those completions $P_{C,A}$ ($\sum_{g\in G_{C,A}} f_{C,A} = 1$) and a set of contexts $T_{C,A} \ni t : G_{C,A} \to \Omega$.

Let us therefore approximate $D_C(L||M||W) \approx \widetilde{H}(M, L) - \widetilde{H}(M, W)$ where $\widetilde{H}(M, X)$ is defined as

$$-\sum_{A} \sum_{t\in T_{C_X,A}} \frac{\sum_{g\in G_{C_X,A}} m(t(g)) \log p_{C,A}(t(g))}{|T_{C_X,A}| \sum_{g\in G_{C_X,A}} m(t(g))}$$

In short, this is an average over $H((M|T_{C_X,A}, G_{C_X,A}), P_{C_X,A})$. The reasoning behind this is that the multiple aspects, context and completions should pretty well approximate the culture-relevant aspects of the cross-entropy and that the difference of the approximate cross-entropies $\widetilde{H}(M, L) - \widetilde{H}(M, W)$ should be equal to the difference of the actual cross-entropies $H(M, L) - H(M, W)$

3.3 Contexts

Since Polish is a gendered language, we separate out the male and female names and contexts for them appropriately. The contexts are hand-crafted by a native Polish speaker. We also account for the fact that the Polish language is cased, so all contexts expect the aspect to be filled with a word in the nominative case. Lastly, some of our contexts contain two gaps for aspects to be substituted - in that case we treat each substitution of one of the aspects as a separate context.

3.4 Polish Data

In order to estimate the frequencies of Polish names we use the data from the Polish PESEL database, separated into male(mal, 2023) and female(fem, 2023) names, normalized over the total name count. For the cities, we estimate the frequency based on the population of the cities, taken from a 2021 population census (only includes cities above 20 thousand residents)(Pol, 2021), normalized over the total resident count.

3.5 Western Data

To estimate the frequencies of western names, we used the United States Social Security Administration list of most popular baby names(us-, 2023), separated by year and into male and female names and normalized over the total name count. In order to more fully represent current U.S. names, the top 1000 names from the past 10 years(2013-2022) were used. To ensure proper representations in Polish tuned language models, western names with Polish equivalents were translated into their Polish counterparts using the DeepL translation service(dee, 2023).

To estimate the frequencies of Western cities we used the population taken from the United States Census estimates of 2022 populations(wes, 2022). The 300 most populous cities were used, and normalized over total resident count.

3.6 Models

To evaluate the cultural divergence metric, 3 different auto-regressive large language models were used. All models were run on the MIT Supercloud (Reuther et al., 2018) using 2 Nvidia V100 GPUs.

One of the models used was papuGaPT2(Wojczulis and Kłeczek, 2021), a using the GPT-2(Radford et al., 2019) architecture and training approach trained on the polish subset of the multilingual Oscar corpus(Ortiz Suárez et al., 2020).

Another model used was mGPT(Shliazhko et al., 2022), a model using the GPT-3(Brown et al., 2020) architecture trained on 61 languages from 25 language families, including polish and English.

Finally, the Llama-2-chat 70b model(Touvron et al., 2023) was used. This model is a state of the art large language model trained primarily in English. In order to fit into the available GPU memory, the parameters were quantized to 6 bits.

4 Results

Distribution	PapuGaPT2	mGPT	Llama 2
All	-1.20E-03	-3.12E-04	-1.99E-04
Names	-1.72E-03	-3.51E-04	-2.28E-04
Cities	5.18E-04	3.94E-05	2.91E-05

Table 1: Values of cultural divergence per model evaluated for both datasets combined (All) and for each dataset individually(Names/Cities).

As shown in Figure 3 and Table 1 results for the combined distribution were in line with predictions based on other metrics comparing monolingual to multilingual models. Specifically, PapuGaPT2, the monolingual Polish model tested, had the lowest cultural divergence, followed by the multilingual mGPT, closely followed by the English trained Llama 2.

Results looked similar for the names distribution alone, with PapuGaPT2 having the lowest CD

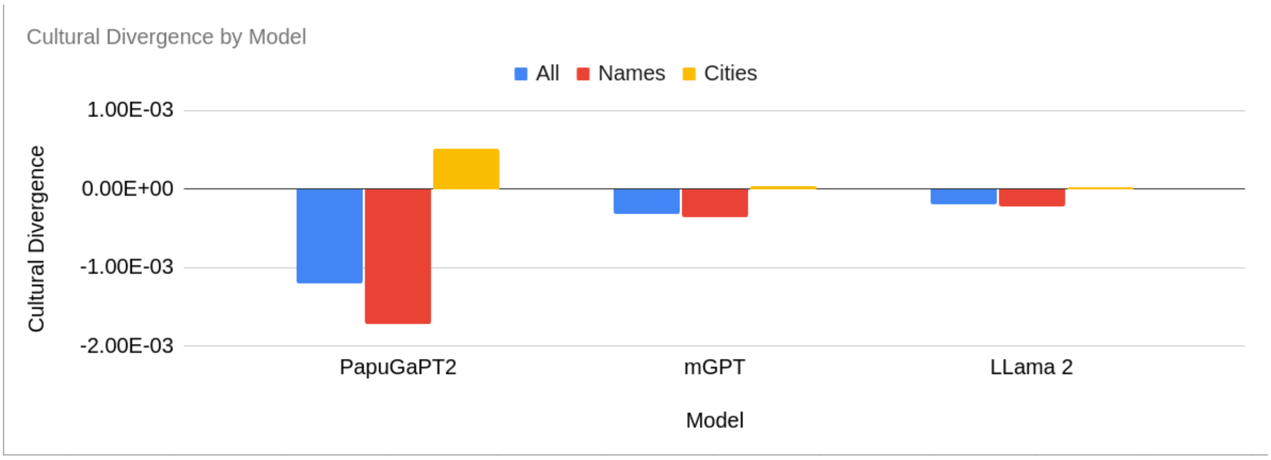


Figure 3: Cultural divergence per model evaluated for both datasets combined (All) and for each dataset individually(Names/Cities).

value, followed by mGPT an order of magnitude larger, then Llama 2 with the highest (most western aligned) CD.

For all models, the CDs for the overall distribution and the names distribution were negative, indicating that when prompted in Polish there was a lower cross entropy between the model distribution and our estimated Polish distribution than between the model and our estimated Western distribution.

The exception to the above results is the cities distribution where the CD was positive for all models, and was highest for PapuGaPT2, then mGPT, with Llama 2 having the lowest CD.

4.1 Discussion

The results from our metric indicated that the model trained on in Polish was the least biased, as expected. While this on it's own doesn't prove that the CD metric is a good representation of cultural bias in auto-regressive large language models, it is an important first step in demonstrating the practical usefulness of the cultural divergence metric.

The difference in cultural divergence between the different models also has important implications, particularly if further work confirms the efficacy of the metric. Specifically, the CD found for mGPT was a factor of 10 higher than that of papuGaPT2, and relatively close to that of Llama 2, despite Polish being a language that mGPT claims support for. This potential western bias may be a significant weakness of mGPT and similar multilingual models that are trained on primarily English data.

As stated in the results section, the CD values for our estimated cities distribution did not indicate that the CD metric was a success. It is possible that this exposes a weakness of our metric when dealing with less common words such as smaller Polish cities, where the metric becomes reliant on the overall abilities of the model, as papuGaPT2 is based on the GPT2 framework, generally considered less capable than the GPT3 framework mGPT uses and Llama 2. However, due to the fact that the names distribution is much larger and thus more likely to contain words rarely seen in training data, we believe that instead this unexpected result is due to the relatively small size of the cities distribution (300 per culture), and the use of population as a placeholder for frequency in written language.

5 Limitations & Future Work

Our current work still has several limitations that could be expanded upon. Due to the limitations in time and our data gathering abilities, we only approximated the cultural divergence on the names and cities, leaving out other important aspects such as religion, food choices or even view on certain societal issues. Thus, despite efforts to create a comprehensive metric, there may be limitations in capturing the full spectrum of cultural nuances, potentially resulting in oversights or underestimation of certain biases. Future research could include capturing and estimating other aspects of the culture.

As mentioned before, our method of estimating the distribution

It is also important to note that, due to the fact that the metric has only been tested for Polish culture, it could yield different results for languages that are very different from English or Polish. One potential direction to furhter explore wuld be to test the metric on different languages (e.g. Arabic) and contrasted cultures (e.g. Central Asian).

Finally, we made sure to make our metric differentiable and agnostic to the type of a Language Model (masked/autoregressive). Thus, unlike other works that try to decrease biases in models, our metric could be used to reinforce certain desire biases (e.g. towards a specific culture) by including it as a training objective for the model.

6 Conclusion

In the paper we presented our novel Cultural Divergence metric which, unlike previous works, can be applied to autoregressive models, is differentiable, and can be automated at scale. We then use it to compare the bias of a Language Model towards the Polish culture compared to the Western culture. Our results show align with the previous works in showing that models trained on data only in a certain language, exhibit closer alignment with the language's culture than those trained on multilingual or english-only data. We then discuss how our estimates of the metric can be improved with more diverse aspects of the culutre considered.

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A Impact Statement

Our research aims to contribute towards mitigating cultural biases in the large language models by identifying and quantifying the bias. We hope that our work contributes to fostering transparency and accountability and empower the AI community to build models that better respect and reflect the diversity of global linguistic and cultural nuances.

What sets Cultural Divergence (CD metric) apart from others is the fact that it is differentiable. The models can be trained with the metric to be made more robust. Our approach deliberately disregards the technical prowess of the model, ensuring its adaptability to systems of any size or complexity. This flexibility makes the metric a valuable tool for assessing cultural biases in a broad spectrum of autoregressive language models, irrespective of their computational capabilities or scale. By establishing a robust metric for cultural divergence, the paper hopes to lay the foundation for future advancements in creating more inclusive and culturally sensitive language models.

The application of the metric may inadvertently introduce ethical dilemmas, such as the potential for reinforcing biases or the unintended prioritization of one cultural group over another, despite the best intentions. Future work could be regular bias audits during the application phase to identify and rectify any inadvertent biases.

The CD metric can be an effective tool to detect biases by ensuring its relevance, reliability, and ethical application.