GeoMLama: Geo-Diverse Commonsense Probing on Multilingual Pre-Trained Language Models

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Abstract

Recent work has shown that Pre-trained Language Models (PLMs) have the ability to store the relational knowledge from pre-training data in their model parameters. However, it is not clear up to what extent do PLMs store geo-diverse commonsense knowledge, the knowledge associated with a culture and only shared locally. For instance, the color of bridal dress is *white* in *American* weddings whereas it is *red* in *Chinese* weddings. Here, we wish to probe if PLMs can predict *red* and *white* as the color of the bridal dress when queried for *American* and *Chinese* weddings, respectively. To this end, we introduce a framework for geo-diverse commonsense probing on multilingual PLMs (mPLMs) and introduce a corresponding benchmark **Geo**-diverse Commonsense **M**ultilingual **La**nguage **M**odels **A**nalysis (GeoMLama) dataset[1]. GeoMLama contains 3125 prompts in English, Chinese, Hindi, Persian, and Swahili, with a wide coverage of concepts shared by people from American, Chinese, Indian, Iranian and Kenyan cultures. We benchmark 11 standard mPLMs which include variants of mBERT, XLM, mT5, and XGLM on GeoMLama. Interestingly, we find that 1) larger mPLM variants do not necessarily store geo-diverse concepts better than its smaller variant; 2) mPLMs are not intrinsically biased towards knowledge from the Western countries (the United States); 3) the native language of a country may not be the best language to probe its knowledge and 4) a language may better probe knowledge about a non-native country than its native country.

1 Introduction

Pre-trained Language Models (PLMs) (Peters et al., 2018; Radford et al., 2019; Devlin et al., 2019; Brown et al., 2020) are increasingly used in various Natural Language Processing (NLP) applications.

[1]Code and data will be released at https://github.com/WadeYin9712/GeoMLAMA.

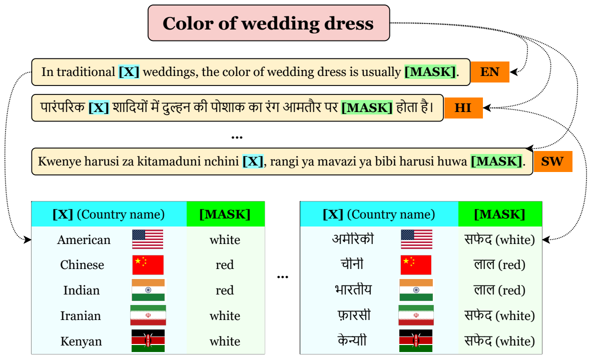


Figure 1: Examples of prompts and gold answers in GeoMLama. For each concept (e.g., color of wedding dress), there are multiple masked multilingual prompts (English, Hindi, Swahili, etc.) with specified country information [X] querying the geo-diverse knowledge about the concept. We test geo-diversity of mPLMs by examining the extent to which masked word predictions align with the gold answers in [MASK] columns.

Pre-trained on large-scale text corpora, they are shown to store world knowledge (Petroni et al., 2019; Jiang et al., 2020; Kassner et al., 2021), e.g., commonsense knowledge (Zhou et al., 2020; Lin et al., 2020; Zhou et al., 2021), in the model parameters. Recently, PLMs have been used to automatically generate precise knowledge and construct structured knowledge bases while requiring limited human effort for rule creation and validation (Bosselut et al., 2019; Petroni et al., 2019; Zhou et al., 2022).

However, *can PLMs store geo-diverse commonsense knowledge?* Geo-diverse commonsense (Yin et al., 2021) is locally shared by people from certain regions but may not apply in other regions due to cultural and geographic differences. For instance, the color of the bridal outfit in an American wedding is white, while it is normally red in traditional Chinese and Indian weddings. If language models are unaware of the geo-diversity of commonsense knowledge, it may amplify geographic bias in prospective AI applications. For the aforementioned structured knowledge base construction using PLMs, the PLMs that lack geo-diversity are more likely to neglect the color knowledge about bridal outfits of non-Western regions and thus be incapable of incorporating such knowledge in knowledge bases. It may become more harmful when commonsense reasoning models ground to these knowledge bases without consideration of geo-diverse commonsense.

In this paper, we concentrate on evaluating geo-diversity of *multilingual* PLMs (mPLMs) (Devlin et al., 2019; Conneau and Lample, 2019; Conneau et al., 2020). Studying geo-diversity naturally involves multilinguality. People in different regions could speak different languages and it is natural to assume that geo-specific knowledge is better represented in its native language. Pre-trained on a collection of multilingual corpora, mPLMs may accumulate the geo-specific knowledge and seemingly become geo-diverse. Hence, it is worthwhile to explore whether multilingual PLMs are capable of storing geo-diverse knowledge.

Centered around mPLMs, we follow the original knowledge probing task LAnguage Model Analysis (LAMA) (Petroni et al., 2019) and further introduce a new *geo-diverse* probing benchmark GEOMLAMA. As shown in Figure 1, given a masked geo-diverse prompt with a particular country name [X], such as "*In traditional* [X] *weddings, the color of wedding dress is usually* [MASK].", and a corresponding candidate answer list, {"*red*", "*white*", "*black*", "*blue*", ...}, mPLMs are required to predict the masked word [MASK] from the candidate list.

The characteristics of GEOMLAMA are summarized as follows. 1) *Diverse answers across countries*: Each prompt is designed based on geo-diverse concept (e.g., color of traditional wedding dress in Figure 1) and gold answers for masked word are different across countries. 2) *Broad coverage of geo-diverse concepts*: GEOMLAMA encompasses comprehensive geo-diverse topics including habits and personal choices, cultures and customs, policies and regulations, and geography. 3) *Coverage of multiple countries and languages*: GEOMLAMA involves knowledge about the United States, China, India, Iran, and Kenya, i.e., the country name [X] in each prompt is one of them. GEOMLAMA is also constructed by the native languages of the five countries, English, Chinese, Hindi, Persian, and Swahili. Overall, there are 3125 prompts in our benchmark.

We perform in-depth probing analysis on 11 mPLMs, including mBERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019), XLM-R (Conneau et al., 2020), mT5 (Xue et al., 2021), and XGLM (Lin et al., 2021b). In general, we observe that mPLMs significantly outperform the performance of random guess, suggesting that mPLMs are capable of storing geo-diverse commonsense to some extent. We then conduct fine-grained investigation across three dimensions.

We first study the correlation between model performance and *model size*. Contrary to our intuition, we notice that the largest models do not necessarily have the best performance on our benchmark. We further study *the best language to probe the knowledge about a particular country*. Surprisingly, we find that the best language is not the native language of the given country (e.g., English is not the best language to probe knowledge about the US). We also explore *the knowledge that can be most accurately probed by a particular language*. Similarly, we find that the most accurately probed knowledge is not the one about indigenous country of the language (e.g., the country for which Chinese prompts provide the most accurate predictions is not always China). Lastly, we find evidence of reporting bias that might explain such observations.

2 Related Works

Knowledge Probing on PLMs. Petroni et al. (2019) first explore whether PLMs have capacity of storing factual knowledge about entities. It is shown that probed with masked text prompts, PLMs recover factual knowledge well and thus are treated as "knowledge bases". Upon this observation, prior works involving knowledge probing primarily focus on creating more effective probing methods to elicit factual knowledge (Jiang et al., 2020; Shin et al., 2020; Zhong et al., 2021) or analyzing whether other types of knowledge are stored in PLMs (Talmor et al., 2020; Zhou et al., 2020; Kassner et al., 2021; Sung et al., 2021). In the second line of works, there is a great variety of commonsense knowledge being explored, including social (Zhou et al., 2020), numerical (Lin et al., 2020) and spatial (Zhang et al., 2020; Liu et al., 2022) commonsense. Our benchmark GEOMLAMA focuses on probing a new commonsense type, geo-diverse commonsense, to evaluate geo-diversity of mPLMs.

Multilingual Knowledge Probing and Multilingual Commonsense. MLAMA (Kassner et al., 2021) and Prix-LM (Zhou et al., 2022) simply focus on capturing multilingual factual knowledge about entities. XCOPA (Ponti et al., 2020) and X-CSR (Lin et al., 2021a) are two multilingual commonsense benchmarks, but both are built by translation from English commonsense benchmarks, without any consideration of incorporating instances about region-specific commonsense. Different from prior works, we value geo-diversity and quantify the extent to which multilingual PLMs master such geo-diverse commonsense.

Geo-Diverse Commonsense. Geo-diverse commonsense (Yin et al., 2021) is strongly correlated with cultures and geographic locations and usually shared locally. There have emerged very few works (Acharya et al., 2020; Yin et al., 2021; Liu et al., 2021; Shwartz, 2022) studying geo-diverse commonsense. Specifically, by collecting responses to questionnaire, (Acharya et al., 2020) analyze the cultural difference between US and India about scenarios including wedding and funeral. Yin et al. (2021); Liu et al. (2021) propose geo-diverse multimodal benchmarks, GD-VCR and MaRVL. They find that due to lack of geo-diverse knowledge, large performance disparity appears when multimodal models are applied on tasks requiring knowledge about Western and non-Western regions. Shwartz (2022) propose culture-specific time expression grounding task to acquire specific temporal commonsense in different countries from multilingual corpora and models.

3 GEOMLAMA Benchmark Construction

To build a geo-diverse commonsense probing benchmark, we recruit annotators from five different countries, the United States, China, India, Iran, and Kenya to participate in annotation. The annotation process is separated into four stages. 1) We first ask the annotators to list geo-diverse concepts. 2) Based on the collected concepts, we then require annotators to design masked geo-diverse prompt templates in English. 3) After specifying prompts with country names, we request annotators to provide correct answers and form answer candidate list for each prompt. 4) We translate the English prompts into other languages and paraphrase them. The overview of the annotation pipeline is illustrated in Figure 2. We elaborate on the process in the following.

3.1 Geo-Diverse Concept Collection

Geo-diverse concepts are the foundation of designing geo-diverse prompts. The criteria of selecting geo-diverse concepts are shown as follows:

Universality and Diversity across Cultures. We require that the scenarios regarding the collected concepts to be universal but diverse across the different cultures. "*Color of wedding dress*" qualifies our criteria as *wedding dress* is a universally understood entity where its color is diverse across different cultures.

Avoiding Concepts involving Region-Specific Terms. We avoid probing models about region-specific factual knowledge, e.g., festival names and president names of the countries, as these concepts usually involve uncommonly used tokens in certain languages and thus introduce another layer of complexity to make inference.

We finally include topics covering habits and personal choices, cultures and customs, policies and regulations, and geography for subsequent annotations. Details are shown in Appendix A.

3.2 Geo-Diverse Prompt Template Design

Centered on the collected geo-diverse concepts, annotators design English version of geo-diverse prompt templates that will be later paraphrased and translated into multilingual prompts. Given one geo-diverse concept, e.g., "*color of wedding dress*", the corresponding prompt template would be a masked sentence that inquires the missing color information, e.g., "*The color of wedding dress is usually* [MASK]." Since we intend to probe knowledge about different countries using these prompts, we further insert phrases such as "*In* [X], ", "*In traditional* [X] *wedding,* " to indicate the country knowledge to be probed. Here [X] is either one of the country names including the United States, China, India, Iran, and Kenya, or one of the corresponding modifiers, such as American, Chinese, Indian, Iranian, and Kenyan.

3.3 Answer and Answer Candidate List Annotation

For each masked geo-diverse prompt with a specified country name, we request the annotators to provide correct answers for the masked words. For instance, given a prompt about bridal outfit color in traditional Chinese weddings, "*In traditional Chinese weddings, the color of wedding dress is*

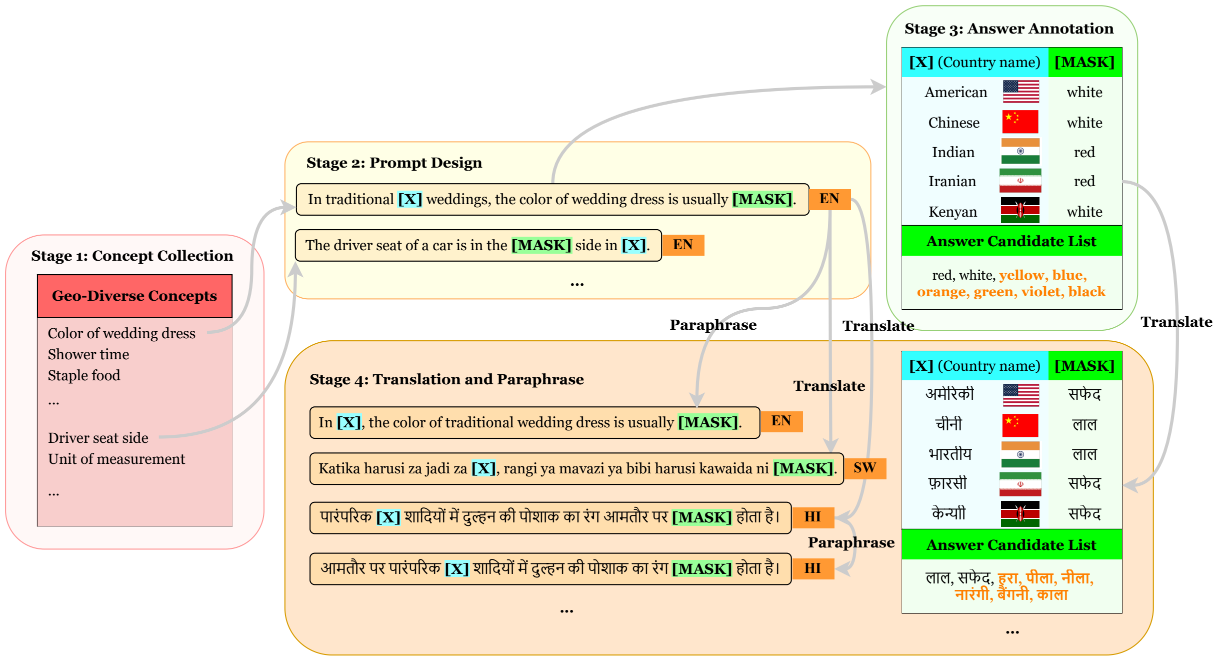


Figure 2: Overall annotation pipeline. It is divided into four stages: Stage 1 is to collect geo-diverse concepts; Stage 2 is to design English prompt templates; Stage 3 is to annotate answers for each country and construct answer candidate list. Stage 4 is to translate the English prompts and paraphrase the translated multilingual prompts. Here we showcase English and Hindi answer annotations for demonstration.

usually [MASK]", annotators are required to provide the answer "*red*" for [MASK]. The answers are all provided by annotators who are familiar with the culture in one of our studied countries. Note that besides prompts with only one answer, some other prompts in GeoMLama, such as "*The staple food in Iran is* [MASK]", can have *multiple* correct answers ("*rice*" and "*bread*") for a single prompt. To further validate the correctness of answers, we distributed a survey to collect responses for knowledge about respondents' own countries. We collected 33 responses from the five countries, and retained the answers with majority support.

In this work, we aim to investigate whether mPLMs are capable of predicting correct answers among all the possibilities of different countries. For instance, in the previous case about the color of Chinese wedding dress, we expect mPLMs to predict "*red*" over the other possibility "*white*". Thus, we pair each prompt with an additional answer candidate list composed by the probable choices and mPLMs are constrained to make predictions from the list. Specifically, each list contains the union of all correct answers of five countries and additional confounding candidates sharing the same word types with those correct answers. For the geo-diverse prompts about color of wedding dress, the union of the correct answers is {"*red*", "*white*"}. Other than the two colors, as illustrated in Figure 2, we also append color confounders including "*yellow*", "*black*", "*blue*" to the list (the orange letters in green grids titled with "Answer Candidate List"). Lastly, the final answer candidate list for prompts about color of wedding dress will be {"*red*", "*white*", "*yellow*", "*black*", "*blue*", ...}. Note that for prompts regarding the same geo-diverse concepts, the answer candidate lists are exactly the same. The contents and lengths of answer candidate lists for prompts about different concepts vary greatly.

3.4 Prompt Translation and Paraphrase

We then obtain multilingual geo-diverse prompts via translating the annotated English prompts into four other languages Chinese, Hindi, Persian, and Swahili. We leverage Google Translation API to translate English prompts and each translated prompt is manually checked and corrected by annotators familiar with both English and any of the four studied languages. Besides, since it is shown that probing results are sensitive to small perturbation to the prompts (Jiang et al., 2020), we further generate four paraphrases for each prompt to obtain more robust probing results. Specifically, we paraphrase

English prompts via a round of backtranslation[2] in which we first translate English prompts to German ones and then translate back to English. For prompts in other languages, their paraphrases are generated by backtranslation that translates texts to English and translate them back to the original languages. The paraphrases in a particular language are validated and modified by native speakers.

In total, we annotate 3125 prompts with answers and corresponding candidates in GeoMLama. All the prompts are designed based on 16 geo-diverse concepts listed in Appendix A, and there are 625 prompts for each of the five languages.

4 Probing Methods on GeoMLama

Petroni et al. (2019) introduce the LAnaguage Model Analysis (LAMA) setup to probe knowledge stored in the pre-trained language models using masked templates. Without any additional fine-tuning, given a masked prompt, models are required to recover masked tokens with entities with the highest probability for the prompt context. Following LAMA probe, on GeoMLama, we study whether models are capable of seeking the most appropriate answers to from answer candidate list according to given geo-diverse prompts.

Kassner et al. (2021) follow LAMA probe to investigate entity knowledge in multilingual BERT only. In this work, we probe a diverse set of language models for *geo-diverse commonsense knowledge* and adopt *different probing frameworks* for language models with variations in inference mechanisms. We describe task formulation and probing methods in greater details below.

4.1 Scoring Answer Candidates

We score answer candidates based on the log likelihood of generating answer candidates given prompts. Different model families have their individual inference methods to obtain the scores.

Masked Language Models (mBERT, XLM, XLM-R family). Given an answer candidate e (e.g., "*chopsticks*") that is tokenized into subtokens $e_1, e_2, ..., e_L$ (e.g., "*chop*", "*stic*", "*ks*") such that $e_i \in V$ where V is the vocabulary and t is the prompt (e.g., "*In China, people usually eat food with* $[\mathrm{MASK}_1]...[\mathrm{MASK}_L]$."), we assign a score l_e based on the log probability of recovering the answer candidate e in the masked prompt. Formally,

[2]Based on Google Translation API.

$$l_e = \frac{1}{L}\sum_{i=1}^{i=L} \log(p([\mathrm{MASK}_i] = e_i | [\mathrm{MASK}_{<i}] = e_{<i}, t)). \tag{1}$$

Based on Eq.1, we perform L forward passes, each of which helps in obtaining conditional probability of generating one subtoken. To illustrate, i^{th} forward pass inference would be $p([\mathrm{MASK}_i] = e_i|$ "*In China, people usually eat food with* e_1 e_2 ...e_{i-1} $[\mathrm{MASK}_i]...[\mathrm{MASK}_L]$").

Note that we further normalize the sum of log likelihood by the number of subtokens L to helps in reducing the effect of length on the score. The following model families also adopt the normalization strategy.

Autoregressive Language Models (XGLM family). For autoregressive language models such as XGLM, we first replace masked token in the prompt with answer candidate tokens (e.g., "*In China, people usually eat food with* [MASK]."->"*In China, people usually eat food with chopsticks.*"). The joint probability of generating all the tokens in the complete sentence is used for scoring answer candidates. Given a prompt template t filled with an answer candidate e, t is tokenized into K tokens (e.g., t_1, t_2, ..., t_K). We assign score l_e to the answer candidate as:

$$l_e = \frac{1}{K}\sum_{i=1}^{i=K} \log(p(t_i|t_{<i})). \tag{2}$$

Here, we perform K forward passes to the autoregressive language model to obtain log probability of generating the whole sentence with the answer candidate e. In this case, the i^{th} forward pass inference would calculate $p(t_i|$ "*In China, ...*, t_{i-2} t_{i-1}").

Encoder-Decoder Language Models (mT5 family). During pre-training of encoder-decoder language models mT5, a masked sequence is input to encoder, and decoder learns to recover the L masked tokens in autoregressive fashion. Therefore, we input a masked prompt t into the models (e.g., "*In China, people usually eat food with* $[\mathrm{MASK}]$") and calculate the score for answer candidate e as:

$$l_e = \frac{1}{L}\sum_{i=1}^{i=L} \log(p(e_i|e_{<i}, t)). \tag{3}$$

Computing Eq.3 requires L forward passes, since the decoder needs to generate L tokens. Here i^{th} forward pass inference would be $p(e_i|e_1\ e_2...e_{i-1}$, "*In China, people usually eat food with* [MASK]"). Note that mT5 can use one single [MASK] token to represent multiple consecutive masked tokens. Thus, different from masked language models, mT5 models are simply fed with the prompt with only one [MASK] token instead of L [MASK] tokens.

4.2 Calibrating Answer Candidates

One way to score answer candidates $e \in \mathcal{E}$ (e.g., "*chopsticks*" $\in$ {"*chopsticks*", "*hands*", "*spoons*", "*knives*"}) given the prompt t for a country C (e.g., "*In China, people usually eat food with* [MASK].") is illustrated in §4.1. However, this scoring mechanism is likely to be biased towards statistical correlations learned during pre-training (Zhao et al., 2021) whilst completely ignoring the country-specific information present in the prompt. For instance, the model might choose "*knives*" over "*chopsticks*" in the dataset because "*knives*" may occur more often than "*chopsticks*" in the pre-training corpora. Zhao et al. (2021) suggested that in such cases, we should calibrate models to account for the prior probability of predicting answer candidates in the absence of any country information. Hence, the final score given to each answer in the answers candidate set is given by:

$$s_a = l_e - l'_e, \tag{4}$$

where l'_e is obtained using the same approach as l_e but the input prompt for calculating l'_e is the one without the country-specific information (e.g., "*People usually eat food with* [MASK]." without "*In China,*").

4.3 Evaluation Metric

We use the ratio of total number of model's correct predictions to the total number of gold answers as model performance on GeoMLama. Specifically, given a prompt t_i with g_i gold answers, we count the number of top-g_i model predictions based off of the final score in Eq.4 that also appear in the gold answer list as c_i. For example, since there are two gold answers for the prompt "*The staple food in Iran is* [MASK]", "*rice*" and "*bread*", $g_i = 2$. In total, there are eight candidates in the answer candidate list {"*bread*", "*noodles*", "*rice*", "*meat*", "*maize*", ...} for this prompt. Assume one mPLM assigns the highest g_i scores to the candidates "*noodles*" and "*rice*". Then $c_i = 1$, since only one of "*noodles*" and "*rice*" is the gold answer of the prompt. We then sum up all the c_i and g_i respectively to calculate the ratio, $\frac{\sum_{i=1}^{n} c_i}{\sum_{i=1}^{n} g_i}$, where n is the total number of prompts in GeoMLama.

5 Analysis on Multilingual Pre-Trained Language Models

We apply the probing methods on various mPLMs to assess their geo-diversity. In this section, we are interested in the following questions: 1) Are bigger mPLMs more geo-diverse than smaller ones? 2) In the absence of any particular country information in the prompts, are mPLMs biased towards the knowledge towards certain countries? 3) Can native language probe the knowledge about a particular country best? 4) Given a particular language, can the corresponding country's knowledge be most accurately probed by the language?

To this end, we experiment with 11 mPLMs[3] including mBERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019), XLM-R family[4] (Conneau et al., 2020), mT5 family[5] (Xue et al., 2021), and XGLM family[6] (Lin et al., 2021b). We freeze pre-trained model parameters provided by HuggingFace Transformers (Wolf et al., 2020) and do not fine-tune the models during probing.

5.1 Overview of Model Performance

Results are shown in Figure 3 and 4. Figure 3 focuses on the comparison among performance of probing the knowledge about a particular country while Figure 4 compares the performance of using prompts in different languages.

In Figure 3, we find that the performance of nearly all the mPLMs lies in the range of 30% to 40% on probing each country's knowledge. Further, these mPLMs significantly outperform random guess 2-15%. It implies that mPLMs can store geo-diverse commonsense knowledge and some stored knowledge can be accurately elicited even if we merely change the country names in the prompt.

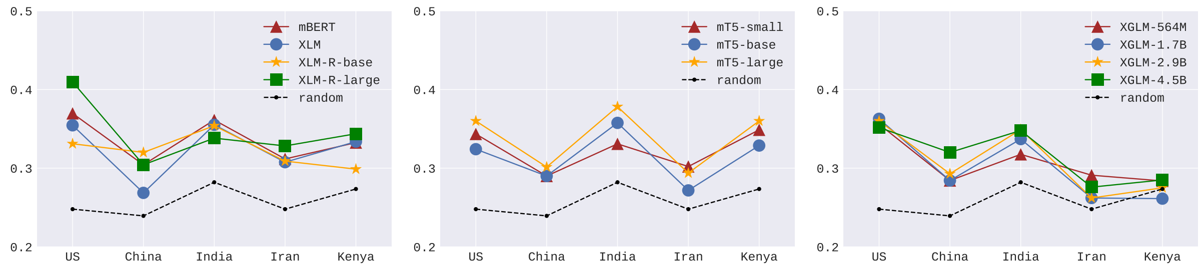
As illustrated in Figure 4, we observe that the

[3]We also experiment with GPT-3 as it is also pre-trained on multilingual corpora. But the results will not be included in main paper as GPT-3 probing convention does not adopt cloze statements as the other 11 mPLMs do. More setup details and results can be referred to Appendix B.

[4]XLM-R-base, XLM-R-large.

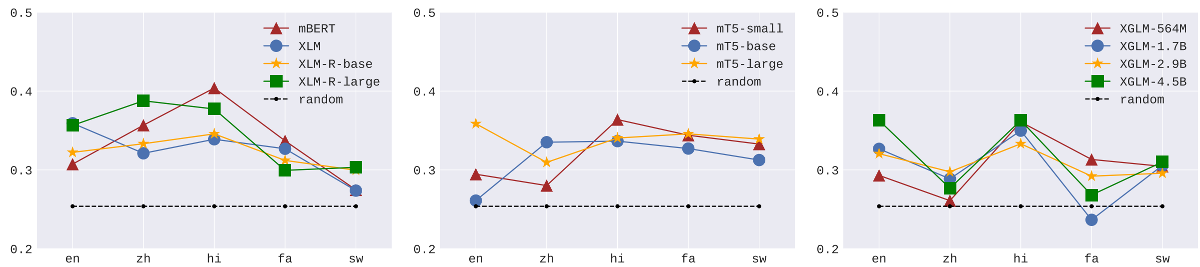
[5]mT5-small, mT5-base, mT5-large.

[6]XGLM-564M, XGLM-1.7B, XGLM-2.9B, XGLM-4.5B.



(a) mBERT, XLM, XLM-R family. (b) mT5 family. (c) XGLM family.

Figure 3: mPLMs' performance on probing knowledge about the studied countries averaged over all languages. Complete results are shown in Appendix C.



(a) mBERT, XLM, XLM-R family. (b) mT5 family. (c) XGLM family.

Figure 4: mPLMs' performance averaged over countries when using prompts in different languages. "*en*", "*zh*", "*hi*", "*fa*", and "*sw*" denote English, Chinese, Hindi, Persian, and Swahili. Complete results are shown in Appendix C.

performance of using prompts in different languages is generally from 30% to 40% and higher than random guess 2-15% as well. Moreover, we find that English and Hindi prompts are the most effective ones to probe geo-diverse knowledge, while Persian and Swahili prompts cannot achieve comparable results. In particular, from Figure 4c, using Persian prompts to probe XGLM-1.7B leads to worse performance than random guess.

5.2 Effect of Model Size

According to Petroni et al. (2019); Roberts et al. (2020), bigger models can generally store more knowledge that aids in improved performance on downstream NLP tasks such as open-domain QA (Joshi et al., 2017; Kwiatkowski et al., 2019). To this end, we investigate whether the larger models indeed perform better than the smaller ones on our GeoMLAMA benchmark.

For a fair comparison, we only compare models in the same model families. For example, we compare any of the mT5 models with the other models in the mT5 family, rather than the models in the other families XLM-R and XGLM. This avoids biasing our study by comparing the models with different pre-training corpora and learning objectives and ensures that the performance difference is only observed to the varying model size.

The comparison results over the three model families are shown in Figure 3 and 4. We observe that the larger models only perform marginally better than their smaller counterparts on GeoMLAMA. For the three model families, XLM-R, mT5, and XGLM, the performance gap between the largest and smallest models on all the prompts in GeoMLAMA is merely 2.23%, 2.42%, and 1.46%, respectively. In specific cases (e.g., probing XGLM family using Persian prompts), the largest model can be even worse than its smallest variant. It demonstrates that even if large models (e.g., mT5-large and XGLM-4.5B) have nearly an order of magnitude more parameters than small models (e.g., mT5-small and XGLM-564M), the geo-diversity of the large models is not significantly greater than that of the small models. This highlights that GeoMLAMA is a challenging task and being better on the standard multilingual NLP tasks does not guarantee good performance.

5.3 Intrinsic Model Bias without Country Information

Each prompt in GeoMLAMA consists of the country information in the form of its name. However, it is still not clear as to what information is probed

Models	US	China	India	Iran	Kenya
mBERT	fa	sw	en	fa	zh
XLM	fa	en	en	zh	zh
XLM-R-base	fa	zh	zh	fa/sw	en
XLM-R-large	fa	zh	en	en	zh
mT5-small	fa	en	en	sw	sw
mT5-base	fa	en	zh	hi	sw
mT5-large	fa	sw	sw	fa	hi
XGLM-564M	fa	en	sw	fa	fa/hi
XGLM-1.7B	fa	sw	en	fa	fa
XGLM-2.9B	fa	en	en	hi	fa
XGLM-4.5B	fa	zh	en	fa	en
Best Languages	**fa**	**en**	**en**	**fa**	**zh/fa**

Table 1: Best languages to probe each country's knowledge for different mPLMs. Each language in the last row "**Best Languages**" is the one appearing most in its located column.

Models	en	zh	hi	fa	sw
mBERT	India	India	US	US	China
XLM	India	Kenya	India	US	Kenya
XLM-R-base	India	China	India	US	India
XLM-R-large	India	US	US	US	Kenya
mT5-small	India	Kenya	Kenya	US	Kenya
mT5-base	India	India	Kenya	US	Kenya
mT5-large	India	Kenya	Kenya	US	India
XGLM-564M	China	US	India/Kenya	US	India
XGLM-1.7B	India	India	India	US	India
XGLM-2.9B	India	India	US	US	India
XGLM-4.5B	India	US/China/India	India	US	India
Best Countries	**India**	**India**	**India**	**US**	**India**

Table 2: Countries best probed with prompts in different languages. Each country in the last row "**Best Countries**" is the one appearing most in its located column.

Words	Co-occurrence
rice, staple food, China	25
bread, staple food, US	7
米饭**(rice),** 主食**(staple food),** 中国**(China)**	3
面包**(bread),** 主食**(staple food),** 美国**(US)**	3

Table 3: Word co-occurrence in English and Chinese Wikipedia. English Wikipedia has 72484142 sentences, 7.6 times more than those of Chinese Wikipedia, 9502859 sentences.

innately when we query mPLMs without any country information. To study this phenomenon, we further probe mPLMs with the prompts where the country token is removed. For example, instead of "*In traditional* Kenyan *weddings, the color of wedding dress is usually* [MASK]", we implement a new round of probing with the pruned prompt, "*In traditional weddings, the color of wedding dress is usually* [MASK]". The new prompts can elicit the knowledge that mPLMs are intrinsically inclined towards predicting.

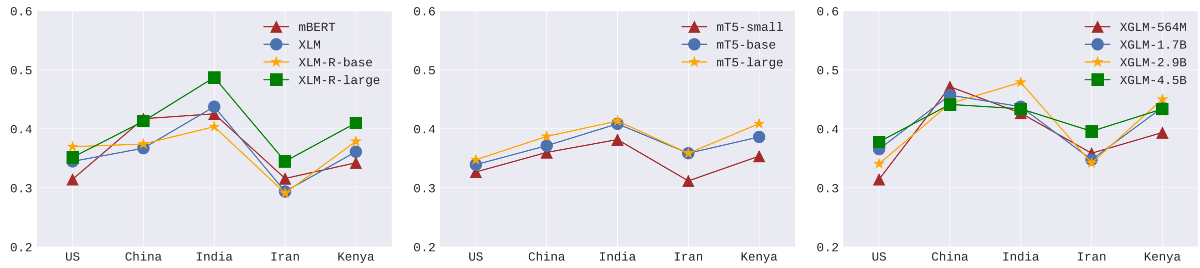
As shown in Figure 5, we find that for most of the mPLMs, the knowledge about India is captured frequently in the absence of any country information. Whereas, knowledge about the United States is not well probed. It shows that at least, mPLMs are not originally biased towards knowledge about Western countries like US.

5.4 Best Languages to Probe Knowledge about Countries

In GeoMLama, prompts in different languages are used to probe knowledge about different countries. It is imperative to ask whether we elicit most knowledge about a country if we query the PLM with its native language. From Table 1, contrary to our intuition, the native language is not the best language to query its knowledge for most of the countries. In particular, Iran is the only country for which its native language Persian can help in drawing out maximum knowledge about it. For the United States and Kenya, the best probing language is Persian and for China and India, the best language is English.

We speculate that our observations might be attributed to the reporting bias phenomenon (Grice, 1975; Gordon and Van Durme, 2013). It is categorized by people rarely stating the obvious knowledge that is shared by everyone (commonsense) explicitly in the text. For instance, the fact that all the *humans can murder* is disproportionately over-reported than *humans can breathe* in the English text. This unbalanced frequency would lead to bias towards acquiring uncommon event knowledge from PLMs, instead of commonsense knowledge (Shwartz and Choi, 2020). In our setting, we believe that reporting bias is a key ingredient in explaining our observed trends. For instance, indigenous population is less likely to record obvious facts about their culture in their native language texts as compared to the facts from other cultures. For example, when mentioning the driver seat side in India, compared with people living in other countries, Indian people will not talk too much about this because it is too trivial for them.

We seek a quantitative evidence in the context of *staple food* as a concept to support our claim towards the importance of the reporting bias. Rice and bread are the staple foods in China and the United States, respectively. Throughout the English and Chinese Wikipedia corpora, we count the



(a) mBERT, XLM, XLM-R family. (b) mT5 family. (c) XGLM family.

Figure 5: Average performance of mPLMs when fed with prompts without any specified country names. Complete results are shown in Appendix D.

co-occurrence of words "*China*", "*rice*" and "*staple food*", and "*the United States*", "*bread*" and "*staple food*" in their respective languages. The counting results are shown in Table 3. We notice that when China is mentioned, English words "*rice*" and "*staple food*" co-occur 25 times whereas it is mentioned merely 3 times in Chinese Wikipedia. Furthermore, in the context of the US, English words "*bread*" and "*staple food*" appear 7 times simultaneously while Chinese words "面包(*bread*)" and "主食(*staple food*)" co-occur 3 times. Although the frequency of co-occurrence is higher in the English Wikipedia, the proportion of the Chinese word co-occurence is much higher since the Chinese Wikipedia corpus is 7.6 times smaller than the English corpus. In summary, it shows that commonsense knowledge about a country is not mentioned more frequently in its native language corpus but might have higher occurrences in some other languages.

5.5 Countries Best Probed with Prompts in Different Languages

Apart from the best languages to probe knowledge about countries, conversely, we can also study the countries best probed with prompts in different languages. Specifically, we focus on the following two questions: Q1. If language X is the best language to probe knowledge about country Y, can country Y's knowledge be best probed with prompts in language X? Q2. Given one studied language X, is the country best probed the same as the indigenous country of language X?

We present our results in Table 2. For Q1, we find that not all of the five languages can meet the criteria. English and Persian satisfy the condition because they are the best languages to probe Indian and US knowledge (see Table 1) and the two countries, India and US, are also the countries best probed by English and Persian prompts (see Table 2).

For Q2, we observe that except Hindi, the countries best probed are distinct to the corresponding countries of language. For example, Swahili prompts probe Indian knowledge best instead of Kenya, and Persian prompts probe US knowledge best instead of Iran. It is also counter-intuitive because it is natural for people to imagine that the best probed country should be the one where a particular language is spoken most commonly.

We can also ascribe the phenomenon observed for Q2 to the reporting bias. People speaking one particular language are very likely to live in the country where the language is widely used. It is less probable for these people to mention the basic commonsense about their living country in the texts more frequently than the other countries.

To analyze this observation, we compare the occurrence of knowledge about different countries in the same language corpus. Specifically, we find that English words "*bread*", "*staple food*" and "*the United States*" co-occur much less frequently than "*rice*", "*staple food*" and "*China*". Meanwhile, we find that Chinese words "面包(*bread*)", "主食(*staple food*)" and "美国(*the United States*)" co-occur 3 times, which is the same as co-occurrence of "米饭(*rice*)", "主食(*staple food*)" and "中国(*China*)". The comparison results indicate that given one language, local country's knowledge may not appear the most, compared with knowledge about other countries.

6 Conclusions

We propose a geo-diverse commonsense probing benchmark, GeoMLama, to evaluate the geo-diversity of mPLMs. Experimental results show that mPLMs can achieve significantly higher performance than random guess, suggesting that they are capable of storing geo-diverse knowledge. We also find that fed with prompts without any country cues, mPLMs are not intrinsically biased towards knowledge about the United States. We further investigate the best language to probe the knowledge about a particular country, and the country best probed with prompts in a certain language. Surprisingly, we notice that the best language is not the country's native language, and the best probed country is not the indigenous country of the language. We connect this phenomenon to reporting bias issue in geo-diverse context: one country's commonsense is seldom recorded in the text by people living in that country as it is too trivial and not worth mentioning for them.

In future work, based on GeoMLama, we intend to explore effect of multilingual pre-training process on model's geo-diversity. In other words, we aim to examine whether pre-training on multilingual corpora really brings more geo-diversity than pre-training on monolingual corpora does. Besides, we expect to seek approaches to improving model's geo-diversity while maintaining mPLMs' performance on various multilingual benchmarks.

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Ethical Consideration

GeoMLama is proposed for evaluating the degree of potential geographic bias in mPLMs. However, due to the limited coverage of countries, languages and geo-diverse concepts, GeoMLama may introduce unwanted bias. In GeoMLama, we only consider five countries and their native languages, which merely occupy a tiny portion of all the countries in the world and thousands of languages. Besides, we design prompts simply based on 16 general geo-diverse concepts. The extension on existing GeoMLama can help in obtaining more solid results and mitigating bias against uncovered countries and languages.

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Appendix

A Geo-Diverse Concept List

The general geo-diverse concepts are shown in Table 4. We summarize all the concepts into 16 general ones, covering rules, policies, geography, customs, personal choices and habits. Multiple prompts can be designed for each geo-diverse concept. For example, measurement units can involve units measuring height, weight and temperature, and thus annotators can create multiple prompts about various types of measurement units.

B Evaluating Geo-Diversity of GPT-3

Approach to probing GPT-3 is different from the methods mentioned in §4. Instead of feeding declarative prompt sentences, we leverage Question Answering (QA) API empowered by GPT-3 and input questions to query the knowledge. For example, instead of using "*In traditional Chinese weddings, the color of wedding dress is usually* [MASK]", we first convert it to question form like "*What is the color of wedding dress in an American wedding?*" and query GPT-3 with the converted question. During evaluation stage, rather than scoring answers from given answer candidate list, GPT-3 can generate open-ended answers and we evaluate GPT-3 predictions using the same metric in §4.3. Considering the huge time cost of manually inputting questions by annotators to GPT-3 API, we do not convert paraphrased prompts to questions and perform analysis on them. In other words, the number of tested questions is only $1/5$ out of the total number of prompts in GEOMLAMA, which is 625.

We probe GPT-3 with the converted questions in five languages, each of which asks knowledge about the five studied countries. Final results are shown in Table 5. One notable result is that using English prompts can achieve nearly 60% performance, while using Swahili prompts cannot solve any questions correctly. Also for Hindi and Persian prompts, the results are still extremely low, ranging from 0% to 25%. It exposes strong bias in terms of language usage. When looking at the performance of probing knowledge about respective countries, the disparity is not large. The country that can be best probed is the United States, while the worst probed country only underperforms the United States 6.9%.

Categories	**Concepts**
rules, policies, geography	traffic rules measurement units date formats color of stock price climate
customs, personal choices, habits	payment shower time clothes drying broom usage food and drink family popular sports transportation servant wedding funeral

Table 4: Geo-diverse concept list with categorization.

Languages	**US**	**China**	**India**	**Iran**	**Kenya**	**Average**
en	68.97	57.14	54.55	55.17	65.52	50.23
zh	44.83	50.00	39.39	37.93	31.03	40.64
fa	20.69	21.43	24.24	10.34	17.24	18.79
hi	6.90	0.00	12.12	3.45	20.69	8.63
sw	0.00	0.00	0.00	0.00	0.00	0.00
Average	28.28	25.71	26.06	21.38	26.90	25.67

Table 5: GPT-3 performance (%) on GEOMLAMA.

C Detailed Results of mPLMs on GEOLAMA

Table 6, 7, and 8 show the details of each mPLM's performance on GEOLAMA. The performance of random guess depends on the expectation of correct predictions, which is equivalent to the ratio of total number of gold answers to the total number of answers in the answer candidate lists. Since the number of gold answers and answer candidates is different for knowledge about different countries, the random guess performance is not the same across countries. However, prompts in each of the languages have the same number of gold answers and candidate answers, so random guess performance is identical across languages.

D Detailed Results of mPLMs Probed with Prompts without Country Tokens

Table 9, 10, and 11 show the details of each mPLM's performance when input with prompts lacking specified country information. It can help in determining the intrinsic bias of each mPLM.

Languages	Countries	mBERT	XLM	XLM-R-base	XLM-R-large
en	US	31.03	26.21	30.34	33.10
	China	30.00	39.29	34.29	37.14
	India	40.61	52.12	37.58	37.58
	Iran	21.38	27.59	28.28	37.93
	Kenya	30.63	34.38	30.63	32.50
zh	US	35.17	28.28	30.34	46.21
	China	30.71	28.57	46.43	40.00
	India	38.79	32.12	38.18	35.15
	Iran	32.41	36.55	24.14	33.10
	Kenya	41.25	35.00	27.50	39.38
fa	US	48.97	57.93	48.28	53.79
	China	27.86	20.71	28.57	32.14
	India	38.79	27.88	33.33	34.55
	Iran	47.59	31.03	35.17	33.79
	Kenya	38.75	31.87	27.50	34.38
hi	US	42.07	40.00	33.10	42.07
	China	29.29	22.86	18.57	13.57
	India	34.55	35.76	36.36	32.73
	Iran	33.79	31.03	31.72	27.59
	Kenya	28.75	33.75	36.25	33.75
sw	US	27.59	24.83	23.45	29.66
	China	34.29	22.86	32.14	29.29
	India	27.88	29.70	31.52	29.09
	Iran	20.69	27.59	35.17	31.72
	Kenya	26.88	31.87	27.50	31.87

Table 6: Results (%) of mBERT, XLM, XLM-R-base, and XLM-R-large on GeoMLama.

Languages	Countries	mT5-small	mT5-base	mT5-large
en	US	24.14	18.62	30.34
	China	40.71	34.29	39.29
	India	41.21	34.55	49.09
	Iran	19.31	19.31	26.21
	Kenya	21.88	23.75	34.38
zh	US	20.00	33.79	28.97
	China	26.43	26.43	26.43
	India	23.64	46.06	33.33
	Iran	33.10	26.90	31.03
	Kenya	36.88	34.38	35.00
fa	US	55.86	43.45	48.28
	China	31.43	29.29	22.86
	India	36.36	34.55	30.30
	Iran	28.28	30.34	33.79
	Kenya	30.00	30.63	35.00
hi	US	33.79	33.79	44.14
	China	28.57	26.43	19.29
	India	33.33	33.33	35.15
	Iran	33.79	33.10	32.41
	Kenya	42.50	36.88	41.88
sw	US	37.93	32.41	28.28
	China	17.86	28.57	42.86
	India	30.91	30.30	41.21
	Iran	36.55	26.21	23.45
	Kenya	43.12	38.75	33.75

Table 7: Results (%) of models in mT5 family on GeoMLama.

Languages	Countries	XGLM-564M	XGLM-1.7B	XGLM-2.9B	XGLM-4.5B
en	**US**	32.41	37.93	31.72	37.24
	China	37.86	32.14	39.29	35.71
	India	30.91	40.00	43.03	42.42
	Iran	23.45	28.28	20.00	31.03
	Kenya	21.88	25.00	26.25	35.00
zh	**US**	34.48	36.55	40.00	35.86
	China	25.71	33.57	30.00	37.14
	India	27.27	32.73	36.36	31.52
	Iran	18.62	22.07	25.52	13.79
	Kenya	24.38	19.38	16.88	20.00
fa	**US**	49.66	49.66	46.90	49.66
	China	26.43	27.86	25.71	35.00
	India	32.73	31.52	28.48	32.73
	Iran	37.24	35.86	31.72	36.55
	Kenya	34.38	30.00	33.75	27.50
hi	**US**	35.86	28.97	33.79	28.97
	China	18.57	10.00	20.71	21.43
	India	33.33	29.70	29.09	33.94
	Iran	34.48	22.76	32.41	23.45
	Kenya	34.38	26.88	30.00	26.25
sw	**US**	25.52	28.28	27.59	24.14
	China	33.57	38.57	30.71	30.71
	India	34.55	34.55	37.58	33.33
	Iran	31.72	22.07	21.38	33.10
	Kenya	26.88	29.38	30.63	33.75

Table 8: Results (%) of models in XGLM family on GEOMLAMA.

Languages	Countries	mBERT	XLM	XLM-R-base	XLM-R-large
en	**US**	31.03	26.21	30.34	33.10
	China	30.00	39.29	34.29	37.14
	India	40.61	52.12	37.58	37.58
	Iran	21.38	27.59	28.28	37.93
	Kenya	30.63	34.38	30.63	32.50
zh	**US**	35.17	28.28	30.34	46.21
	China	30.71	28.57	46.43	40.00
	India	38.79	32.12	38.18	35.15
	Iran	32.41	36.55	24.14	33.10
	Kenya	41.25	35.00	27.50	39.38
fa	**US**	48.97	57.93	48.28	53.79
	China	27.86	20.71	28.57	32.14
	India	38.79	27.88	33.33	34.55
	Iran	47.59	31.03	35.17	33.79
	Kenya	38.75	31.87	27.50	34.38
hi	**US**	42.07	40.00	33.10	42.07
	China	29.29	22.86	18.57	13.57
	India	34.55	35.76	36.36	32.73
	Iran	33.79	31.03	31.72	27.59
	Kenya	28.75	33.75	36.25	33.75
sw	**US**	27.59	24.83	23.45	29.66
	China	34.29	22.86	32.14	29.29
	India	27.88	29.70	31.52	29.09
	Iran	20.69	27.59	35.17	31.72
	Kenya	26.88	31.87	27.50	31.87

Table 9: Results (%) of mBERT, XLM, XLM-R-base, XLM-R-large probed with prompts without country tokens on GEOMLAMA.

Languages	Countries	mT5-small	mT5-base	mT5-large
en	**US**	38.62	49.66	40.69
	China	45.00	47.14	42.86
	India	46.06	51.52	60.61
	Iran	38.62	46.90	43.45
	Kenya	43.12	44.38	57.50
zh	**US**	24.14	24.83	30.34
	China	32.86	30.71	33.57
	India	35.15	28.48	31.52
	Iran	36.55	40.69	40.00
	Kenya	39.38	43.12	36.88
fa	**US**	46.21	41.38	47.59
	China	39.29	33.57	41.43
	India	34.55	41.82	35.76
	Iran	35.86	37.24	42.76
	Kenya	37.50	41.88	42.50
hi	**US**	31.72	25.52	29.66
	China	39.29	38.57	32.86
	India	44.24	46.67	41.21
	Iran	30.34	33.79	31.03
	Kenya	40.00	40.00	41.25
sw	**US**	22.76	28.28	25.52
	China	23.57	35.71	42.86
	India	30.91	35.76	37.58
	Iran	14.48	20.69	22.07
	Kenya	16.88	23.75	26.25

Table 10: Results (%) of models in mT5 family probed with prompts without country tokens on GEOMLAMA.

Languages	Countries	XGLM-564M	XGLM-1.7B	XGLM-2.9B	XGLM-4.5B
en	**US**	28.97	38.62	34.48	40.00
	China	57.14	43.57	50.00	46.43
	India	51.52	47.88	53.94	46.67
	Iran	35.86	35.17	34.48	36.55
	Kenya	40.62	49.38	43.75	46.88
zh	**US**	34.48	42.76	38.62	47.59
	China	49.29	55.00	51.43	50.71
	India	44.24	52.73	54.55	46.67
	Iran	54.48	52.41	46.21	63.45
	Kenya	55.62	58.13	62.50	61.25
fa	**US**	27.59	28.97	35.17	34.48
	China	34.29	37.86	35.00	40.00
	India	38.18	34.55	40.00	36.97
	Iran	17.93	22.07	24.83	24.14
	Kenya	21.88	28.12	30.63	33.12
hi	**US**	24.14	32.41	20.69	31.72
	China	52.86	52.86	48.57	55.71
	India	39.39	41.21	40.61	40.61
	Iran	37.93	39.31	28.28	42.07
	Kenya	36.25	41.25	41.88	43.12
sw	**US**	42.07	40.00	41.38	35.17
	China	42.14	39.29	36.43	27.86
	India	40.00	42.42	50.30	46.06
	Iran	33.10	24.83	37.24	31.72
	Kenya	42.50	41.25	46.25	32.50

Table 11: Results (%) of models in XGLM family probed with prompts without country tokens on GEOMLAMA.