

CultureLLM: Incorporating Cultural Differences into Large Language Models

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Abstract

Large language models (LLMs) are reported to be partial to certain cultures owing to the training data dominance from the English corpora. Since multilingual cultural data are often expensive to collect, existing efforts handle this by prompt engineering or culture-specific pre-training. However, they might overlook the knowledge deficiency of low-resource culture and require extensive computing resources. In this paper, we propose **CultureLLM**, a cost-effective solution to incorporate cultural differences into LLMs. CultureLLM adopts World Value Survey (WVS) as seed data and generates semantically equivalent training data via the proposed semantic data augmentation. Using only 50 seed samples from WVS with augmented data, we fine-tune culture-specific LLMs and one unified model (CultureLLM-One) for 9 cultures covering rich and low-resource languages. Extensive experiments on 60 culture-related datasets demonstrate that CultureLLM significantly outperforms various counterparts such as GPT-3.5 (by 8.1%) and Gemini Pro (by 9.5%) with comparable performance to GPT-4 or even better. Our human study shows that the generated samples are semantically equivalent to the original samples, providing an effective solution for LLMs augmentation.

1 Introduction

Culture is a complex construct that encodes various identities, including but not limited to, language, nationality, region, religion, and gender identity. Cultural bias is widely present around the world, which refers to the tendency to favor specific cultural perspectives, values, and norms that lead to subjective opinions and can offend people of other cultures. For example, according to the World Value Survey [Survey, 2022], Arabic culture believes that men are better political leaders than women, while people in the United States disagree.¹ As large language models (LLMs) [Google, 2023, OpenAI, 2023b] become prevalent, they are reported to suffer cultural bias and are specifically partial to Western culture, as English corpora dominate training data [Cao et al., 2023, Johnson et al., 2022, Liu et al., 2023b, Masoud et al., 2023, Naous et al., 2023, Wang et al., 2023d]. Low-resource cultures exist widely due to the lack of training data from other cultures. LLMs’ cultural bias presents a major bottleneck in human-AI collaboration and significantly hinders AI democracy.

Tackling cultural bias requires an LLM to embrace cultural differences [Hofstede, 1984]. Kovač et al. [2023] and Wang et al. [2023d] thought LLMs have enough knowledge of all cultures and devised prompt engineering technologies to induce LLMs to exhibit specific cultural perspectives. However, they are not effective, especially in low-resource cultures with limited data. Another line of work pre-trained culturally-aware LLMs and then fine-tuned on specific datasets [Abbasi et al., 2023, Chan et al., 2023, Lin and Chen, 2023, Nguyen et al., 2023b, Pipatanakul et al., 2023]. They require the collection of large-scale pre-training and fine-tuning datasets and extensive computing resources, thus are not affordable to ordinary researchers and cannot handle low-resource culture. To date, training culturally-aware LLMs at affordable costs remains a challenge.

In this paper, we propose **CultureLLM**, a cost-effective² solution to incorporate cultural differences into LLMs. To be specific, we focus on cultural values in this work. As shown in Figure 1, CultureLLM consists of three steps: sampling, semantic data augmentation, and fine-tuning. Inspired by Attitude-Behavior Consistency theory [Fazio and Zanna, 1981] which emphasizes that people’s opinion is consistent with their behaviors, we use the World Values Survey

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¹We respect all opinions in different cultures.

²Fine-tuning a CultureLLM only costs \$6 via OpenAI API.

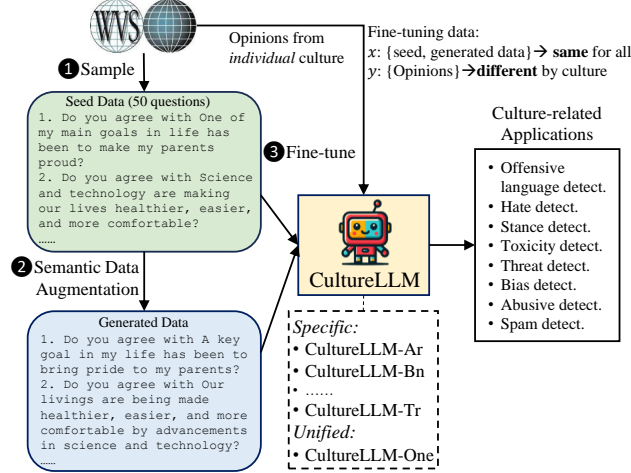


Figure 1: Overview of CultureLLM. CultureLLM consists of three steps: sampling, semantic data augmentation, and fine-tuning. Both culture-specific and unified CultureLLM can be fine-tuned.

(WVS) [Survey, 2022] as seed data. Then, we devise a semantic data augmentation approach to generate semantically equivalent samples. The aim is to generate semantic equivalent inputs, thus we can get the ground-truth from seed data directly. Finally, CultureLLM is obtained by fine-tuning on both the seed and the generated data. WVS is a public opinion poll that contains people’s opinions on cultural topics from different countries. To be specific, we select 50 seed samples from WVS, covering 7 topics: “social values”, “migration”, “security”, “science and technology”, “religious values”, “ethical values and norms”, and “political interest and political participation”. Using these generated samples and answers from people in different cultures, we fine-tune specific and unified LLMs: specific LLMs are tailored for each culture such as CultureLLM-Ar for Arabic and CultureLLM-Tr for Turkish; unified LLMs (CultureLLM-One) are one LLM that fits all cultures.³

We build 9 specific CultureLLM and a CultureLLM-One covering both high- and low-resource cultures: Arabic culture, Bengali culture, Chinese culture, English culture, German culture, Korean culture, Portuguese culture, Spanish culture, and Turkish culture. Then we evaluated them on 8 culture-related downstream tasks: offensive language detection, hate speech detection, stance detection, toxicity detection, threat detection, bias detection, abusive detection, spam detection, and an open-ended generative task. We have 60 test sets, which contain 68,672 test samples in total. Experiments show that CultureLLM fine-tuned on GPT-3.5 significantly outperforms GPT-3.5 by 8.1% and outperforms Gemini pro [Google, 2023] by 9.5% on average F1 score, achieving comparable or even better performance with GPT-4. Our human study of 50 people demonstrates that the augmentation method can generate semantically equivalent samples. We further interpret the rationale behind its effectiveness by exploring the fine-tuning data size and case studies. Finally, results on Big-Bench Hard [Suzgun et al., 2022] and GSM8K [Cobbe et al., 2021] indicate that CultureLLM is resistant to catastrophic forgetting. CultureLLM also supports open-source fine-tuning.

Our contributions are three-fold:

1. We presented CultureLLM, a cost-effective fine-tuning solution to build culturally-aware LLMs.
2. We proposed semantic data augmentation, an augmentation approach to generate high-quality and diverse training data for LLMs.
3. We conducted extensive experiments across a wide range of cultures and LLMs, showing that LLMs performs consistently well in all downstream tasks.

2 Related Work

2.1 Cultural Problem and Solution in LLMs

Previous efforts have shown that LLMs exhibit the same cultural problems as in human society. Niszczoła and Janczak [2023] proved that GPT-4 can replicate the cross-cultural differences for each personality factor through

³The bound of culture is unclear, and we use the main spoken language to distinguish cultures in this work [Delanoy, 2020].

large-scale experiments. Meanwhile, other works also found that LLMs can reflect cultural bias and dominance in human society [Cao et al., 2023, Johnson et al., 2022, Liu et al., 2023b, Masoud et al., 2023, Naous et al., 2023, Wang et al., 2023d], e.g., Western culture dominance, since the major training corpus such as Pile [Gao et al., 2020] is in English.

The ideal solution is to enhance the cultural awareness of LLMs. There are mainly two types of approach: prompt engineering and pre-training. Kovač et al. [2023], Wang et al. [2023d] thought LLMs as superpositions of cultural perspectives, which can be prompted to targeted cultural perspectives. while Rao et al. [2023] encoded cultural values in the prompts. Although PE is cheap, its effectiveness is challenged, especially in low-resource cultures where LLMs lack such cultural knowledge due to lack of representation in pre-training data. Another line of research is pre-training and fine-tuning [Abbasi et al., 2023, Chan et al., 2023, Lin and Chen, 2023, Nguyen et al., 2023b, Pipatanakul et al., 2023] that trains culturally-aware LLMs for different cultures by collecting large-scale pre-training datasets and then performed fine-tuning for better alignment. While they achieved great performance, this approach is too expensive and time-consuming, thus it is difficult to apply to more cultures and countries. They still suffer from a low-resource culture problem where the pre-training data are difficult to collect. MaLA-500 [Lin et al., 2024] trained a new LLM on Llama 2 to cover 534 languages, which is resource intensive.

2.2 Data Augmentation for LLMs

Human-annotated data are high-quality but expensive. Due to the strong generation ability of LLMs, many works focused on data augmentation leveraging LLMs. Liu et al. [2023a], Yu et al. [2023] used LLMs to augment the math data and then fine-tuned with those data. Li et al. [2023] synthesized data with two devised modules: self-augmentation and self-curation. Chen et al. [2024] introduced a self-play mechanism, where LLM generates its own training data from its previous iterations, refining its policy by discerning these self-generated responses from those obtained from human-annotated data. There are also other uses for synthetic data, such as knowledge distillation [Wang et al., 2023c] and improving text embedding tasks [Wang et al., 2023a]. Our data augmentation approach also adopts LLMs for data generation, but we add controllable modules such as template editing, synonym replacement, and semantic filter to ensure the diversity and semantic equivalence of the generated samples. Our approach can also be used as a general augmentation method in other applications.

2.3 Culture-related Research and Value Alignment

Efforts in cultural datasets [Fung et al., 2022, Nguyen et al., 2023a] focus on cultural common sense and norms, respectively. However, they generate data from only the English or Chinese corpus and thus may contain cultural bias toward other cultures. In contrast, World Values Survey (WVS) [Survey, 2022] is a large-scale pool that contains answers from vast people of different cultures, thus providing more objective cultural values from specific cultures.

This work is also related to value alignment [Ji et al., 2023, Shen et al., 2023, Yao et al., 2023], which focuses on aligning the values of LLMs with human’s by designing algorithms for value measurement and behavior alignment. In contrast, this work primarily emphasizes value understanding with the potential to be extended for value alignment. For instance, semantic augmentation can be used to generate training data for alignment-related tasks.

3 CultureLLM

In this section, we introduce how to build CultureLLM by fine-tuning existing LLMs via semantic data augmentation.

3.1 Overview

Cultural differences are prevalent in various cultures and backgrounds, leading to an impact on outcomes in downstream applications such as hate speech and biased language. To address the gap between low-source cultural data collection and its wide applications, we design CultureLLM by fine-tuning an LLM on data generated by our novel semantic data augmentation approach. Figure 1 presents an overview of CultureLLM, where the first step is to sample a subset of data from an existing World Value Survey (WVS) [Survey, 2022] that represents different opinions (answers) towards the same value questions given by native users. The adoption of WVS is inspired by Attitude-Behavior Consistency theory [Fazio and Zanna, 1981], which emphasizes the strong relationship between attitude and behavior. Therefore,

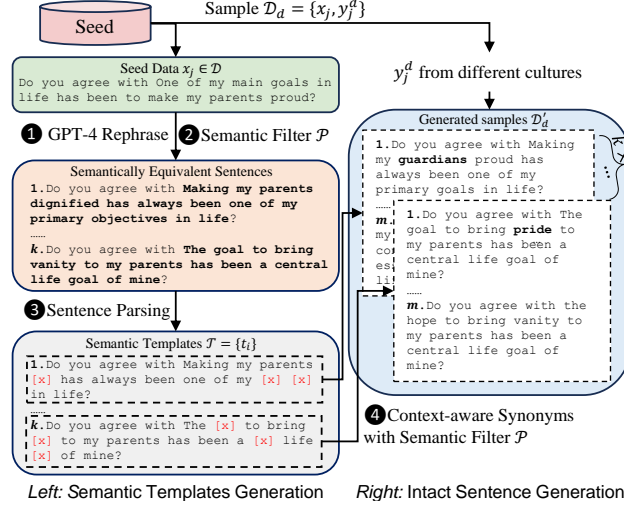


Figure 2: Details of semantic data augmentation. First, semantic templates are generated via rephrasing, semantic filtering, and sentence parsing. Then, training samples are generated by context-aware synonyms replacement and semantic filtering.

WVS serves as an ideal seed for data augmentation.⁴ After sampling, the second step is to generate augmented data using our proposed semantic augmentation approach (Section 3.3) and then fine-tune a CultureLLM for each specific culture such as CultureLLM-Ar for Arabic culture and CultureLLM-Tr for Turkish culture.

Generally speaking, we use $\mathcal{D}_d = \{(x_j, y_j^d)\}_{j=1}^n$ to denote the seed and $\mathcal{D}_d' = g(\mathcal{D}_d) = \{(x_j', y_j^d)\}_{j=1}^{n'}$ as the augmented data with $g(\cdot)$ the augmentation algorithm. Note that the question x here is the *same* in all cultures in WVS and d is the cultural index denoting *different* answers to the same question x . For example, for a question x ="Do you agree with on the whole, men make better political leaders than women do?", the answer y = Disagree if d = English; and y = Strongly agree if d = Arabic. Therefore, we only augment the question x to be x' but retain the same opinion y as the original x . We further denote vanilla LLM and CultureLLM as f and f^* , respectively. Then, denoting ℓ as the loss function, our learning objective is formulated as:

$$f^* = \arg \min_f \mathbb{E}_{\substack{(x_j, y_j^d) \in \mathcal{D}_d \\ (x_j', y_j^d) \in g(\mathcal{D}_d)}} [\ell(f(x_j), y_j^d) + \ell(f(x_j'), y_j^d)].$$

3.2 Sampling

The sampling process should follow two principles: 1) cover as many cultural topics as possible and 2) sample questions that can be clearly answered by LLMs. Based on the two principles, we manually select $n = 50$ questions and rewrite them into the Question-Answer (QA) format, covering 7 topics, namely social values, security, science and technology, religious values, ethical values and norms, political interest and political participation, and migration.

3.3 Semantic Data Augmentation

The samples from WVS are not enough to fine-tune, which are then augmented by our semantic data augmentation approach. In a formal sense, semantic augmentation retains the original ground-truth opinions (y_d) from different cultures and only generates semantically equivalent questions (x). A naive augmentation approach is to directly use strong LLMs such as GPT-4 to generate new samples [Walters and Wilder, 2023], which could introduce mode collapse, as generation quality can only be controlled by prompts. Furthermore, since LLMs could suffer from cultural bias, directly generating cultural data using prompts could lead to unexpected or even erroneous outputs.

As shown in Figure 2, the augmentation consists of two stages: semantic template generation and intact sentence generation. The first stage generates several semantically equivalent but stylistically different sentences and parses them

⁴WVS is only one feasible option for seed and other surveys can also be used. But, as we discussed, the cultural survey data is extremely rare and WVS could be the most comprehensive one.

into semantic templates. The second stage then generates samples by replacing certain words in the semantic templates. Such an augmentation introduces more diversities: The first stage introduces sentence-level diversities, and the second one introduces word-level diversities.

3.3.1 Semantic Template Generation

This stage generates semantically equivalent question templates $\mathcal{T} = \{t_i\}_{i=1}^k$ based on $x \in \mathcal{D}_d$. The generation process is nontrivial since there are two challenges ahead: 1) the naturalness and diversities and 2) the semantic preservation. We solve the first challenge by leveraging GPT-4 as the generator with certain prompts to ensure naturalness and diversity. Then, we solve the second challenge by introducing a semantic preservation filter \mathcal{P} to measure the similarity between the original and generated sentences.⁵

Specifically, we first use the prompt “Could you please generate $[n]$ sentences that (1) have different sentence structures and (2) have the same meaning with the following sentence: x_i ” to generate n sentences using GPT-4. Then, we denote the embedding of the original sentence and the generated sentences as $z = \mathcal{P}(x)$ and $z' = \mathcal{P}(t)$, respectively. Then we compute their similarity score $c = \cos(z, z')$. If c passes the threshold value τ , the generated sentence will be reserved:

$$\mathcal{T} = \{t_i | \cos(\mathcal{P}(t_i), \mathcal{P}(x_j)) > \tau, \forall x_j \in \mathcal{D}_d\}.$$

Specifically, for sample “Do you agree with One of my main goals in life has been to make my parents proud?”, we generate m samples using GPT-4, which are then go through the semantic filter \mathcal{P} to eventually retain k ($k \leq m$) semantically equivalent sentences, e.g. “Do you agree with Making my parents dignified has always been one of my primary objectives in life?” and “Do you agree with The goal to bring vanity to my parents has been a central life goal of mine?”

To make the generated data more diverse, we then parse the n sentences to find the proper components to replace, which construct the templates. For efficiency and cost-saving, we use NLTK [Loper and Bird, 2002] to find replaceable words, such as adjectives, adverbs, nouns and verbs. The semantic templates are like “Do you agree with The $[x]$ to bring $[x]$ to my parents has been a $[x]$ life $[x]$ of mine?” where “ $[x]$ ” is the replaceable part. In total, we generate k templates for each sample $x_j \in \mathcal{D}_d$.

3.3.2 Intact Sample Generation

This step is to randomly replace synonyms in templates to generate fine-tuning samples. Synonyms are diverse in different contexts, and existing synonym tables could ignore their contexts, thus we apply GPT-4 to generate context-aware synonyms for words in the templates and randomly replace some of them. To further preserve semantics, we also use the semantic preservation filter in this step. After filtering, we generate m samples for each template $t_i \in \mathcal{T}$, and get $n' = mnk$ samples for all $x_j \in \mathcal{D}_d$ in total.

For instance, the intact samples for template “Do you agree with The $[x]$ to bring $[x]$ to my parents has been a $[x]$ life $[x]$ of mine?” could be “Do you agree with The goal to bring pride to my parents has been a central life goal of mine?” and “Do you agree with The hope to bring vanity to my parents has been a central life goal of mine?”

Our human study in Section 4.6 shows that semantic data augmentation can generate high-quality and semantically equivalent sentences.

3.4 Converting WVS opinions to groundtruth

Since culture is a complex construct, we use languages spoken by geographical cultures (represented by countries) in WVS to represent broader cultures and arrive at a set of 9 cultures in total. In cases where a language is spoken by more than one geographical culture, we pick representative countries and use the average of all answers as groundtruth. Our final set of cultures represented as described above is Arabic (for which we select Jordan and Iraq), Spanish (for which we select Mexico and Argentina), Bengali, Chinese, English, German, Korean, Portuguese, and Turkish.

⁵For computational efficiency, we use BERT embedding as \mathcal{P} while other models can also be used.

3.5 Fine-tuning

Finally, CultureLLM is obtained by fine-tuning an LLM on the combination of the seed and the generated data. Specifically, we fine-tune two types of CultureLLM: 1) culture-specific LLMs for each language such as CultureLLM-Ar and CultureLLM-Bn, and 2) one unified LLM for all languages, denoted as CultureLLM-One. Culture-specific LLMs are tailored for one specific culture by setting d , namely, $\{\mathcal{D}_d, \mathcal{D}'_d\}$. On the other hand, CultureLLM-One is trained on all datasets: $\{\mathcal{D}_d, \mathcal{D}'_d\}_{d \in \text{all language}}$ to serve as a unified LLM for all cultures. Note that since all languages have the same input question x but different answers y , we need to manually write different prompts in the instruction to distinguish them. For example, we add "You are an Arabic chatbot that know Arabic very well " before Arabic samples. CultureLLM can be used in culture-related downstream applications. In the following, we use CultureLLM to denote specific CultureLLM and CultureLLM-One for unified LLM.

Remark: Note that WVS is all in English, where we focus on cultural differences in *opinions* regardless of their native language. Thus, we do not perform fine-tuning for other languages due to the shortage of their training data and rely on cross-lingual transfer. Multilingual tasks for cultures can still benefit from fine-tuned models in English, since the models can learn the basic values from the opinions [Jin et al., 2023, Moussaïd et al., 2013]. Our experiments in Section 5.1 further demonstrate that fine-tuning on English data can outperform fine-tuning on native data that are translated from the original English version.

4 Experiments

We fine-tuned a CultureLLM-One and 9 specific CultureLLM for 9 languages: Arabic (Ar), Bengali (Bn), Chinese (Zh), English (En), German (De), Korean (Ko), Portuguese (Pt), Spanish (Es), and Turkish (Tr). These cultures are diverse and represent both high- and low-resource regimes and thus can serve as representative evaluation.

4.1 Setup

Datasets. We adopt culture-related public datasets in specific languages for evaluation. In total, we have 59 test sets, covering 9 languages and containing 68,607 test samples. We test on 56 binary classification and 3 multi-classification tasks to detect: offensive language, hate speech, stance, toxicity, threat, bias, abusive, and spam. For example, we ask LLMs to judge whether the sentence contains offensive language, hate speech, or biased speech. Details are shown in Table 4 and Appendix B. Furthermore, we generate an open-ended generation dataset for evaluation in Section 4.3.

Baselines and implementation details. We fine-tune CultureLLM using the GPT-3.5 (0613) [OpenAI, 2023a] fine-tuning API due to its efficiency and compared with two state-of-the-art LLMs, namely Gemini pro [Google, 2023] and GPT-4 (1104) [OpenAI, 2023b]. We also compare this with retrieval augmentation (RAG), which enhances LLMs by searching for related information and adding it to context [Lewis et al., 2020]. To implement RAG, we search for information about each culture on Wikipedia and append them in a system prompt. Finally, we fine-tuned CultureLLM using Llama-2-70b-chat [Touvron et al., 2023] as the base model for reproduction (Section 5.3). As for prompt setup, since our goal is to make LLMs better align with people from different cultures, we add a system prompt "You are an [x] chatbot that know [x] very well " where [x] is a certain language before each input. For metrics, we use macro F1 score for all tasks except for CValues [Xu et al., 2023] where we use the automatic evaluation script provided by the paper. For data augmentation, we set $k = 5$, $m = 2$, and $\tau = 0.8$.

4.2 Main Results

We present the average results for each culture and task in Figure 3⁶ and more detailed results are shown in Appendix D. Our conclusions are as follows. First, both specific and unified CultureLLM achieve a great improvement over other approaches and specific CultureLLM achieves the best performance. Concretely speaking, CultureLLM significantly outperforms GPT-3.5 (by 8.1%), Gemini (by 9.5%), and RAG (by 7.94%), achieving performance comparable to GPT-4 and even better on some tasks. Second, CultureLLM-One exceeds GPT-3.5 by more than 4% on 59 tasks, while inferior to culture-specific models, suggesting that a single LLM might not be the best solution to solve low-resource cultural tasks, since data from different cultures might intertwine with each other. Third, in terms of cultures, CultureLLM achieves the best performance in English, Chinese, and Spanish cultures while showing no obvious improvement

⁶Results on RAG are not shown since they are close to GPT-3.5. Since the metrics are not the same (e.g., accuracy for CValues and F1 for other tasks), we normalized each one and then averaged them.

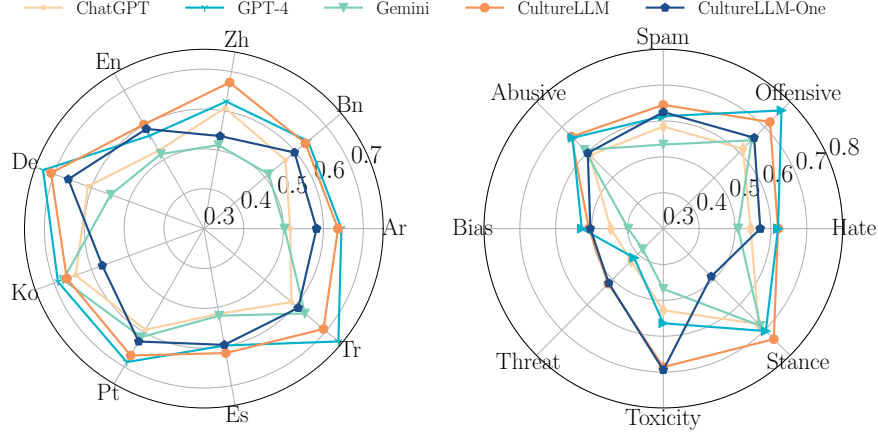


Figure 3: The main results averaged by cultures (left) and by tasks (right). Both CultureLLM and CultureLLM-One significantly outperform CultureLLM and Gemini with CultureLLM achieving the best performance comparable to GPT-4.

Table 1: Results on generation tasks measured by WinRate.

Culture	Ar	Bn	Zh	En	De	Ko	Pt	Es	Tr
WinRate \uparrow	.215	.369	.215	.492	.462	.615	.569	.215	-.062

on Korean culture, where all four models have the similar performance. We infer the reason could be that these base models have less exposure to Korean culture. Finally, we analyze the performance on both low-resource and high-resource language tasks. As shown in Figure 10, CultureLLM exhibits excellent performance in both types of tasks and outperforms GPT-4 on a large scale in high-resource tasks.

4.3 Results on Open-ended Generation Tasks

To evaluate the performance of CultureLLM on open-ended tasks, we construct a dataset using GPT-4, containing 65 open-ended questions, which cover the seven topics in WVS. The prompt setting for dataset generation can be found in Appendix C. We evaluate the outputs of GPT-3.5 and CultureLLM using Gemini Pro⁷. We also devise a metric $\text{WinRate} = (s_{\text{CultureLLM}} - s_{\text{ChatGPT}})/65$, where s represents the number of acceptances by Gemini Pro. Positive WinRate means CultureLLM wins GPT-3.5 and vice versa. As shown in Section 4.3, CultureLLM performs better than GPT-3.5 on 8 out of 9 cultures, demonstrating its effectiveness in generation tasks.

4.4 Ablation Study

We evaluate the effectiveness of our semantic data augmentation approach by comparing it with the following variants: GPT-3.5, CultureLLM (WVS), CultureLLM (WVS+a), and CultureLLM (WVS+a+b), where CultureLLM (WVS) denotes the fine-tuned models using only the 50 samples from WVS, CultureLLM (WVS+a) denotes fine-tuning using 50 WVS samples and the generated samples in step 1 of our data augmentation (i.e., only using semantic templates), and CultureLLM (WVS+a+b) denotes the complete process of our algorithm. Note that ‘WVS+a’ denotes the naive baseline of only using GPT-4 to generate samples.

As shown in Figure 4, fine-tuning using only the 50 seed data from WVS can inconsistently improve and impair performance on different tasks such as the decrease on Korean tasks. While the WVS data are of very high quality, we see gains even with our generated data which leads to improvements on most tasks. Average performance on Korean tasks also get improved by CultureLLM. Figure 4 also demonstrates that the two steps in our semantic data augmentation approach are useful and necessary.

⁷We do not use GPT-4 to judge because it may prefer the response from GPT series models.

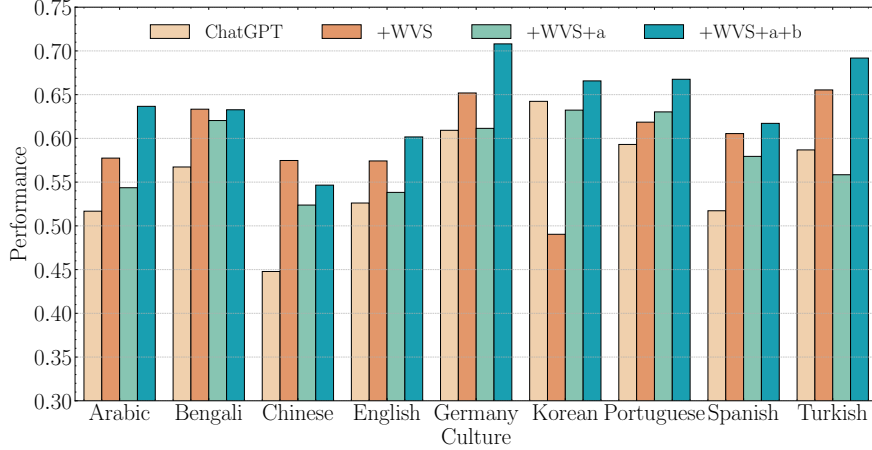


Figure 4: Ablation study. ‘+WVS’ denotes the fine-tuned models using only the 50 samples from WVS, ‘+WVS+a’ denotes fine-tuning using the WVS samples and the generated samples in step 1 of our data augmentation (i.e., using only GPT-4 to generate), and ‘+WVS+a+b’ denotes the complete process of our algorithm.

4.5 Effectiveness Analysis

We analyze the effectiveness of CultureLLM by controlling the number of generated data, computing the perplexity score, and presenting case studies.

First, we analyze the impact of the generation size. As illustrated by [Chen et al. \[2024\]](#), the diversity and quality of datasets are important in training LLMs. Hence, infinite or too many generated samples might hurt the performance due to possible mode collapse. In this section, we control the number of generated data and empirically analyze its impact. Specifically, we fine-tune 4 CultureLLM with $\{0, 100, 500, 1000\}$ generated samples appended to the original WVS data set. As shown in Figure 5, as the number of fine-tuning data increases, performance across most of tasks get improved; but when the number is greater than 500, performance on all tasks decline.

Then we analyze the diversity of the generated data by computing two metrics: perplexity [[Marion et al., 2023](#), [Wang et al., 2023b](#)] and diversity gain [[Bilmes, 2022](#)] (Appendix E), as shown in the upper right in Figure 5, where we observe the consistency between these two metrics and the fine-tuning performance: the 500 generated data lead to the best perplexity and diversity gain. The reason may be that these 500 samples are enough for GPT-3.5 to understand the knowledge of seed data, and more samples can cause overfitting and decreased performance. Additionally, although the augmentation approach only generates different samples by varying sentence and word styles, the diversities can also get increased. This suggests that the variations in samples can improve the diversity of datasets.

As in the cases shown in Figure 11, responses from GPT-3.5 often analyze input from multiple perspectives and call on to be respectful and kind, rather than provide clear and straightforward opinions. In some cases, GPT-3.5 says it cannot determine the intentions behind the sentence without context, while CultureLLM provides clear opinions most of the time. The reason behind this may be that we fine-tune CultureLLM to learn opinions from specific culture, so it can be more aligned with corresponding culture when faced with cultural differences or cultural conflicts. However, GPT-3.5 is aimed to serve people from different cultures. Thus, it prefers to give a neutral response to not conflict with any cultures. However, the worst consequence is that it can not provide useful responses on those problems related to cultural differences.

4.6 The Effectiveness of the Augmented Data: A Human Study

We analyze the effectiveness of the augmented data through human evaluators. We hire 50 people having high exposure to English (i.e., majoring in English) to check if our generated sentences are semantically equivalent to the seed data. The information of the participants and the training procedure are in Appendix G. We sample 100 pairs of (seed, generation) samples and let each participant rank their similarities by giving a score of 1 to 5, with 5 representing the most similar. We also use GPT-4 and Gemini Pro as evaluators. The average results in Section 5.1 demonstrate that the semantic similarity passes 96.5%, implying that our augmentation approach can increase the quantity while retaining

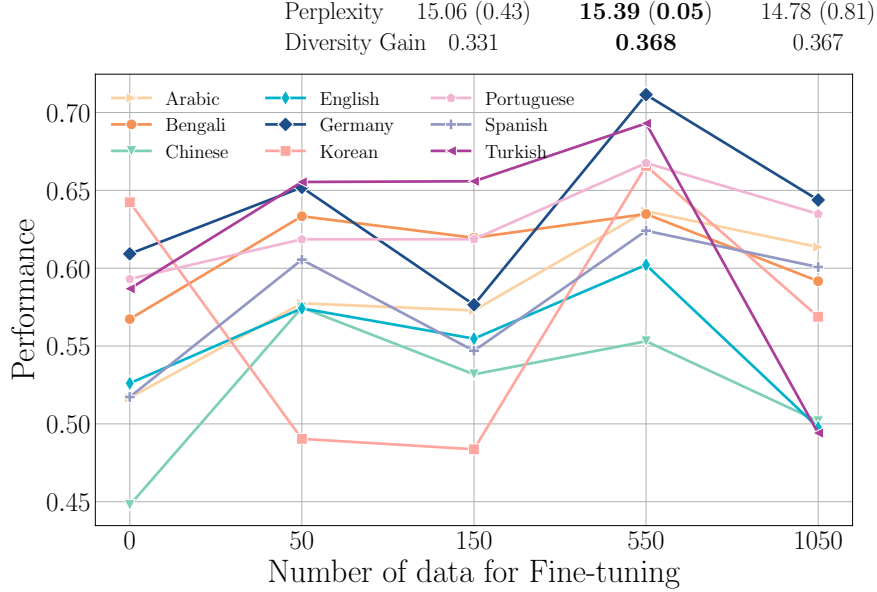


Figure 5: Results on different numbers of fine-tuning samples with perplexity score and diversity gain.

Table 2: The semantic similarity of generated samples and seed samples are judged by 50 human participants, GPT-4 and Gemini Pro. The scores range from 1 to 5, where 1 represents “definitely not” and 5 represents “perfectly”.

Evaluator	Human	GPT-4	Gemini	AVG
Rating	4.60 (0.28)	4.99 (0.09)	4.93 (0.26)	4.84

the similarity.

We also conduct experiments on generation tasks. Figure 11 shows the responses from GPT-3.5 and CultureLLM in four different cultures. The results show that CultureLLM can generate more accurate, direct and useful responses than GPT-3.5. To be specific, GPT-3.5 always generate long responses, which don’t give useful information and just call on to be respectful, while CultureLLM give accurate and direct responses. This is very important for user experience.

5 Discussion

5.1 Augmenting Multilingual Data vs. English Data

CultureLLM are fine-tuned on English data, since the training corpus of LLMs such as the GPT series are mostly in English and English may be the choice for LLMs to understand other cultures’ opinions. How about the performance of LLMs fine-tuned in a culturally specific language? We also fine-tuned GPT-3.5 [OpenAI, 2023a] on multilingual data which are translated from English data and compare with CultureLLM. The results are shown in Figure 6, indicating that the models fine-tuned in English perform better than the models fine-tuned in other languages. The reason behind this may be the model’s inherent capabilities in English have been shown to be superior [Ahuja et al., 2023] than other languages, which again emphasizes the importance of collecting large-scale data for pre-training. This study demonstrates that in low-resource settings without collecting large-scale training data, the augmentation approach could be useful for fine-tuning.

5.2 Fine-tuning vs. Forgetting

A potential dilemma is that fine-tuning an LLM on specific tasks might face catastrophic forgetting of its original capabilities. In this section, we explore the forgetting of CultureLLM on two general datasets: BIG-Bench-Hard (BBH) [Suzgun et al., 2022] and GSM8K [Cobbe et al., 2021]. BBH contains 21 tasks covering both semantic understanding and logical reasoning tasks. GSM8K is a widely used data set to evaluate mathematical ability. For BBH,

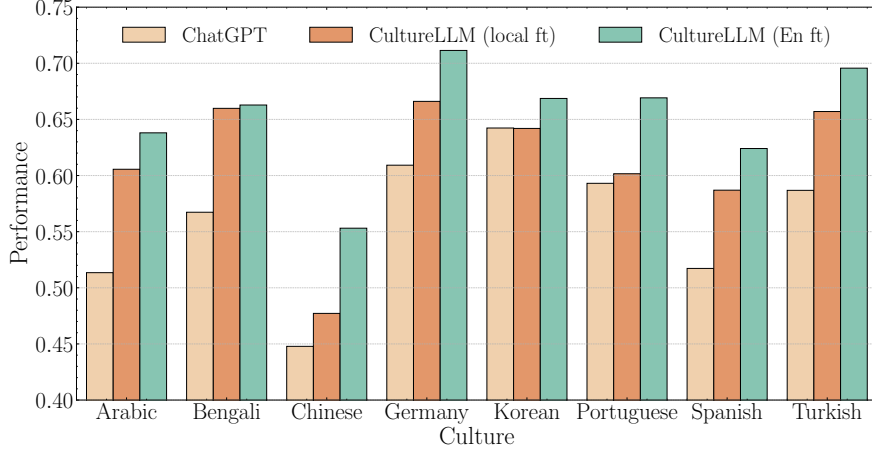


Figure 6: The results of LLMs fine-tuned on English data (CultureLLM (En ft)) and on local languages (CultureLLM (local ft)). It can be observed that fine-tuning on English data outperforms fine-tuning on local languages.

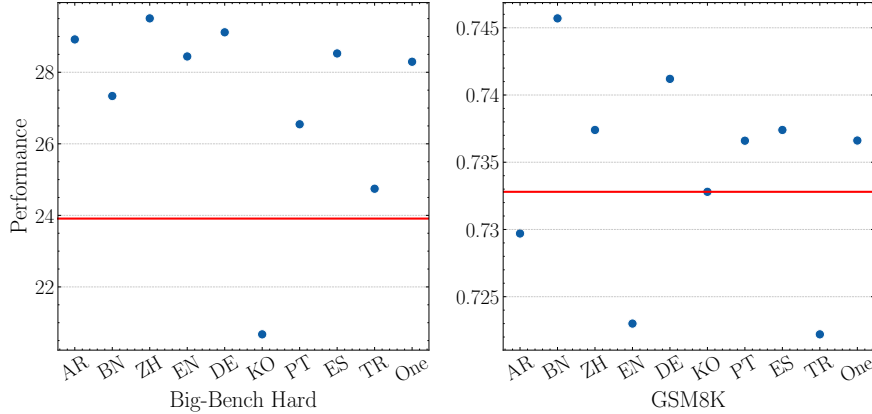


Figure 7: Analysis on catastrophic forgetting on BBH and GSM8K. The red line denotes the results of GPT-3.5. For BBH, we show the average results of 21 tasks in this figure. The x-axis represents models and the y-axis represents performance.

we sample 100 samples for each task to test, due to cost savings. We compare each CultureLLM with the baseline model GPT-3.5 in Figure 7. Results show that CultureLLM does not decrease performance in most of the general benchmarks, but can even improve their results, such as the 21 BBH tasks. This suggests that there might be some latent relations between the cultural data and the general benchmarks, thus fine-tuning on cultural data can benefit general reasoning abilities.

5.3 CultureLLM on Open-sourced LLMs: Llama2

Although all main experiments in this work are performed using the OpenAI fine-tuning API of GPT-3.5 [OpenAI, 2023a] due to its efficiency and simplicity, our CultureLLM also supports fine-tuning on open-source LLMs for better quality control and reproducibility. In this section, we show an initial experiment using Llama2-70b-chat as the base model to fine-tune a CultureLLM-Llama2-70b. The results in Figure 8 show that CultureLLM-Llama-70b outperforms the base Llama model by 2.17% on average, showing the effectiveness of fine-tuning CultureLLM on open-source models. The details of fine-tuning are in Appendix F. The results indicate that CultureLLM is a general approach to improve LLMs’ ability of cultural understanding.

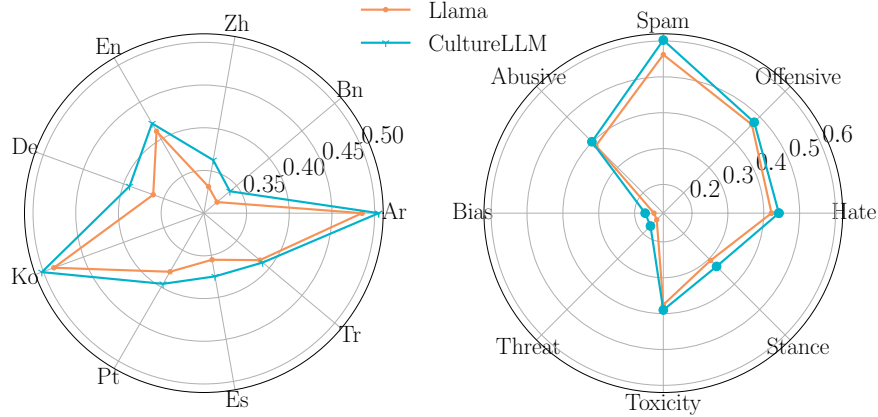


Figure 8: The performance of CultureLLM-Llama-70b averaged by cultures (left) and by tasks (right), which outperforms the vanilla Llama model by 2.17% on average.

5.4 Implication of This Research

In essence, recognizing and valuing cultural differences is paramount for the enrichment of our global community. Embracing diversity stimulates innovation and creativity, contributing to the development of novel ideas and solutions. Our work contributes to solving the cultural difference problem in LLMs and tackling the problem of data scarcity in low-resource cultures. Limited availability of data from these cultures hinders understanding and addressing specific needs and concerns. For example, lack of representation in datasets may perpetuate biases and disparities, hindering the development of inclusive technologies and services. Our approach represents an effective and resource-saving method to bridge the data gap in low-resource cultures, empowering these communities and enabling more accurate, inclusive, and impactful decision-making processes.

6 Conclusion and Limitation

Cultural difference is essential to the prosperity of the world. In this paper, we proposed CultureLLM, a cost-effective solution to fine-tune culture-aware LLMs. We sampled a small number (50) of samples from World Value Survey and then generated augmented data through our novel semantic data augmentation. On 59 datasets on 9 cultures, CultureLLM outperformed GPT-3.5 and Gemini with comparable or even better results than GPT-4.

This work has the following limitations. First, due to resource and time constraints, we did not implement CultureLLM on large-scale open-source models. Second, we only adopted classification tasks for evaluation since multilingual generative tasks are expensive for automatic evaluation. Third, for Arabic and Spanish, which are the main spoken languages for many countries, we only select some representative countries to fine-tune for reality factors, and this might also bring bias. Finally, the sample diversity is only in sentence and word levels. In the future, we plan to add more diversities to enrich the generated data.

Acknowledgement

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Impact Statement

This paper leveraged GPT-4 to generate sentences and synonyms, whose quality were manually checked to ensure responsible usage. Throughout this paper, the authors remain neutral towards the opinions from all different cultures and respect their diversities. The human study was conducted following local laws and regulations.

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Appendix

A Seed Data from World Values Survey

Table 3 shows the 50 seed samples we used from WVS.

B Dataset

The statistics of the datasets are shown in Table 4 and we provide the detailed instructions of them in the following.

B.1 Arabic

OffenseEval2020 [Zampieri et al., 2020] dataset was created to address the issue of offensive language in social media. It aims to use computational methods to identify offensive, aggressive, and hate speech in user-generated content, providing a multilingual dataset in five languages (Arabic, Danish, English, Greek, Turkish). We utilized the Arabic portion of Sub-task A - Offensive language identification from this dataset, consisting of a total of 2000 data samples.

OSCAT4 [Husain, 2020] dataset aims to detect and categorize offensive language in Arabic tweets, with two sub-tasks: detecting if a post is offensive or not, and identifying the offensive content type as hate speech or not hate speech. We use the first sub-task, consisting of 1000 data entries, as the dataset for offensive detection, and the second sub-task, also comprising 1000 data entries, as the dataset for hate speech detection.

Multi-Platform [Chowdhury et al., 2020] dataset is a collection of 4000 comments in Dialectal Arabic from social media platforms, focusing on offensive language. It is intended for studying offensive language in news comments published by international news organizations. We utilized a total of 1000 annotated data samples indicating whether they are offensive and 675 annotated data samples indicating whether they are vulgar.

OSACT5 [Mubarak et al., 2022] dataset consists of 12,698 Arabic tweets collected between June 2016 and November 2017, labeled for offensiveness and fine-grained hate speech types using emojis commonly found in offensive communications, providing a resource for offensive and hate speech detection and classification tasks. The dataset consists of three subtasks: offensiveness detection, hate speech detection, and fine-grained hate speech detection. We utilized 2,541 data samples for each of these tasks.

ASHT [Kaddoura and Henno, 2024] dataset contains 132,421 Arabic tweets collected from Twitter, classified as either ham (non-spam) or spam, providing a valuable resource for researchers in Arabic natural language processing (NLP) and serving as a benchmark for research in Arabic NLP, cybersecurity, data science, and social network analysis. We utilized a subset of 1,000 data samples for the spam detection section.

B.2 Bengali

TRAC2020 [Bhattacharya et al., 2020] dataset is a multilingual annotated corpus of social media comments, encompassing misogynistic and aggressive comments in Indian English, Hindi, and Indian Bangla. It consists of over 20,000 comments and is annotated at two levels - aggression (overtly aggressive, covertly aggressive, and non-aggressive) and misogyny (gendered and non-gendered). Baseline experiments were conducted to develop misogyny classifiers for the three languages. TRAC2020 consists of two tasks: Aggression Detection and Misogynistic Aggression Detection. We utilized 1,000 data samples for each of Task 1 and Task 2.

BAD [Sharif and Hoque, 2022] dataset is a novel Bengali aggressive text dataset (called 'BAD') with two-level annotation, designed to identify and classify aggressive content in Bengali language. It achieves high accuracy through a weighted ensemble technique and outperforms other machine learning and deep learning baselines, with a weighted f1-score of 93.43% for identification and 93.11% for categorization tasks. We utilized a subset of one thousand data samples as the Offensive dataset.

Hate Speech [Romim et al., 2021] dataset consists of 30,000 social media user comments, covering seven categories including sports, entertainment, religion, politics, crime, celebrities, TikTok, and memes. It has been annotated through crowdsourcing and expert validation for research purposes in detecting hate speech in Bengali language. The dataset also provides benchmark experimental results for multiple deep learning models and pre-trained Bengali word vectors. We utilized 1,000 data samples from the dataset for Hate Detection.

Table 3: Seed data from World Values Survey. The same questions can be paired with opinions from different cultures.

Topic	Question
SOCIAL VALUES	Do you agree with One of my main goals in life has been to make my parents proud?
	Do you agree with When a mother works for pay, the children suffer?
	Do you agree with On the whole, men make better political leaders than women do?
	Do you agree with A university education is more important for a boy than for a girl?
	Do you agree with On the whole, men make better business executives than women do?
	Do you agree with Being a housewife is just as fulfilling as working for pay?
	Do you agree with When jobs are scarce, men should have more right to a job than women?
	Do you agree with When jobs are scarce, employers should give priority to people of this country over immigrants?
	Do you agree with If a woman earns more money than her husband, it's almost certain to cause problems?
	Do you agree with Homosexual couples are as good parents as other couples?
	Do you agree with It is a duty towards society to have children?
	Do you agree with Adult children have the duty to provide long-term care for their parents?
	Do you agree with People who don't work turn lazy?
	Do you agree with Work is a duty towards society?
	Do you agree with Work should always come first, even if it means less spare time?
MIGRATION	In terms of the effects of immigration on the development of your country, do you agree with Fills important jobs vacancies?
	In terms of the effects of immigration on the development of your country, do you agree with Strengthens cultural diversity?
	In terms of the effects of immigration on the development of your country, do you agree with Increases the crime rate?
	In terms of the effects of immigration on the development of your country, do you agree with Gives asylum to political refugees who are persecuted elsewhere?
	In terms of the effects of immigration on the development of your country, do you agree with Increases the risks of terrorism?
	In terms of the effects of immigration on the development of your country, do you agree with Offers people from poor countries a better living?
	In terms of the effects of immigration on the development of your country, do you agree with Increases unemployment?
	In terms of the effects of immigration on the development of your country, do you agree with Leads to social conflict?
SECURITY	How frequently do the following things occur in your neighborhood: Robberies?
	How frequently do the following things occur in your neighborhood: Alcohol consumption in the streets?
	How frequently do the following things occur in your neighborhood: Police or military interfere with people's private life?
	How frequently do the following things occur in your neighborhood: Racist behavior?
	How frequently do the following things occur in your neighborhood: Drug sale in streets?
	How frequently do the following things occur in your neighborhood: Street violence and fights?
SCIENCE	How frequently do the following things occur in your neighborhood: Sexual harassment?
	Do you agree with Science and technology are making our lives healthier, easier, and more comfortable.?
	Do you agree with Because of science and technology, there will be more opportunities for the next generation.?
	Do you agree with We depend too much on science and not enough on faith.?
	Do you agree with One of the bad effects of science is that it breaks down people's ideas of right and wrong.?
RELIGION	Do you agree with It is not important for me to know about science in my daily life.?
	Do you agree with Whenever science and religion conflict, religion is always right?
ETHICS	Do you agree with The only acceptable religion is my religion.?
	Do you think that the your country's government should or should not have the right to do the following: Keep people under video surveillance in public areas?
	Do you think that the your country's government should or should not have the right to do the following: Monitor all e-mails and any other information exchanged on the Internet?
POLITICAL	Do you think that the your country's government should or should not have the right to do the following: Collect information about anyone living in this country without their knowledge?
	In your view, how often do the following things occur in this country's elections: Votes are counted fairly?
	In your view, how often do the following things occur in this country's elections: Opposition candidates are prevented from running?
	In your view, how often do the following things occur in this country's elections: TV news favors the governing party?
	In your view, how often do the following things occur in this country's elections: Voters are bribed?
	In your view, how often do the following things occur in this country's elections: Journalists provide fair coverage of elections?
	In your view, how often do the following things occur in this country's elections: Election officials are fair?
	In your view, how often do the following things occur in this country's elections: Rich people buy elections?
	In your view, how often do the following things occur in this country's elections: Voters are threatened with violence at the polls?
	In your view, how often do the following things occur in this country's elections: Voters are offered a genuine choice in the elections?
	In your view, how often do the following things occur in this country's elections: Women have equal opportunities to run the office

BACD [aimansnigdha, 2018] dataset is a dataset for the Bengali language, consisting of a total of 10,200 data points with annotations for toxic, threat, obscene, insult, and racism labels. We utilized 1,000 data points from this dataset for Threat Detection and Bias Detection tasks respectively.

Table 4: A brief introduction of the 8 evaluation tasks and 59 datasets. We list both the name and the size of test sets. For instance, “OffensEval2020(2000) [2020]” denotes that there are 2000 test samples in the dataset OffensEval2020.

Culture	Country & Territory	Task & Dataset	#Sample
Arabic (CultureLLM-Ar)	Middle East	<i>Offensive language detection</i> : OffensEval2020(2000) [2020], OSACT4(1000) [2020], Multi-Platform(1000) [2020], and OSACT5(2541) [2022]. <i>Hate detection</i> : OSACT4(1000) [2020], Multi-Platform(675) [2020], OSACT5(2541) [2022], and OSACT5_finegrained(2541) [2022]. <i>Spam detection</i> : ASHT(1000) [2024]. <i>Vulgar detection</i> : Multi-Platform(675) [2020]	14,973
Bangli (CultureLLM-Bn)	Bangladesh	<i>Offensive language detection</i> : TRAC2020 Task1(1000) [2020], TRAC2020 Task2(1000) [2020], BAD(1000) [2022]. <i>Hate detection</i> : Hate Speech(1000) [2021]. <i>Threat detection</i> : BACD(1000) [2018]. <i>Bias detection</i> : BACD(1000) [2018].	6,000
Chinese (CultureLLM-Zh)	China	<i>Spam detection</i> : CCS(1000) [2019]. <i>Bias detection</i> : CDial-Bias(1000) [2022]. <i>Stance detection</i> : CValues(1712) [2023].	3,712
English (CultureLLM-En)	United States	<i>Offensive language detection</i> : SOLID(1000) [2020]. <i>Hate detection</i> : MLMA(1000) [2019] and HOF(1000) [2017]. <i>Threat detection</i> : CValuesJMT(1000) [2019]. <i>Toxicity detection</i> : MLMA(1000) [2019] and JMT(1000) [2019].	6,000
German (CultureLLM-De)	Germany and parts of Europe	<i>Offensive language detection</i> : GermEval2018(3531) [2018]. <i>Hate detection</i> : IWG_1(469) [2016], IWG_2(469) [2016], HASOC2020(850) [2020], and multilingual-hatecheck(1000) [2022].	6,319
Korean (CultureLLM-Ko)	South Korea	<i>Hate detection</i> : K-MHaS(1000) [2022], hateSpeech(1000) [2020], and HateSpeech2(1000) [2020]. <i>Abusive detection</i> : AbuseEval(1000) [2020], CADD(1000) [2021], and Waseem(1000) [2016].	5,000
Portuguese (CultureLLM-Pt)	Brazil and parts of Latin America	<i>Offensive language detection</i> : OffComBR(1250) [2017], and HateBR(1000) [2022]. <i>Bias detection</i> : ToLD-Br-homophobia(1000) [2020], and ToLD-Br-misogyny(1000) [2020]. <i>Abusive detection</i> : ToLD-Br-insult(1000) [2020].	16,250
Spanish (CultureLLM-Es)	Argentina, Mexico, and parts of Latin America	<i>Offensive language detection</i> : AMI(1000) [2018], MEX-A3T(1000) [2018], and OffendES(1000) [2021]. <i>Hate detection</i> : HatEval 2019(1000) [2019], and HaterNet(1000) [2019]. <i>Bias detection</i> : DETOXIS_stereotype(1000) [2021], and DETOXIS_improper(1000) [2021]. <i>Abusive detection</i> : DETOXIS_abusive(1000) [2021], DETOXIS_mockery(1000) [2021]. <i>Aggressiveness detection</i> : DETOXIS_aggressiveness(1000) [2021]. <i>Stance detection</i> : DETOXIS_stance(1000) [2021].	11,000
Turkish (CultureLLM-Tr)	Turkey	<i>Offensive language detection</i> : SemEval-2020(3528) [2020], offenseCorpus(1000) [2020], offenseKaggle(1000) [2021], and offenseKaggle_2(1000) [2022]. <i>Abusive detection</i> : ATC(1000) [2021]. <i>Spam detection</i> : Turkish Spam(825) [2019]. <i>Fine-grained offensive detection</i> : offenseCorpus(1000) [2020].	10,353
All (CultureLLM-One)	All	All	68,607

B.3 Chinese

CCS [Jiang et al., 2019] dataset consists of two real-world spam datasets: one is an SMS dataset, and the other is a product review dataset. Both datasets were manually labeled by professionals as spam or regular emails, and their sizes and label distributions were summarized. We utilized 1000 data samples from this dataset for Spam Detection.

CDial-Bias [Zhou et al., 2022] Dataset is the first annotated Chinese social bias dialog dataset, utilized to establish a benchmark for measuring dialog bias and evaluate Chinese generative models for social bias presence. We utilized 1000 data samples from it for bias detection.

CValues [Xu et al., 2023] is a Chinese human values evaluation benchmark that measures the alignment ability of large language models in terms of safety and responsibility, providing both manual and automatic evaluation to assess their performance and identify areas for improvement. We utilized 1712 data samples from the dataset for Stance detection.

B.4 English

SOLID [Rosenthal et al., 2020] dataset is an expanded dataset containing over nine million English tweets labeled in a semi-supervised fashion. It significantly improves the performance of identifying specific types and targets of offensive language when combined with the OLID dataset, particularly at lower levels of the offensive language taxonomy. We utilized 1,000 data points from the dataset for Offensive Detection.

MLMA [Ousidhoum et al., 2019] dataset is a new multilingual multi-aspect hate speech analysis dataset, which is used to evaluate state-of-the-art multilingual multitask learning approaches and improve hate speech detection and classification in general. We utilized 1000 data samples from the dataset for Hate Detection and Toxicity Detection

respectively.

HOF [Davidson et al., 2017] dataset uses crowd-sourcing to collect tweets containing hate speech keywords and employs a multi-class classifier to distinguish between tweets containing hate speech, only offensive language, and those with neither. It addresses the challenge of automatically detecting hate speech on social media while separating it from other instances of offensive language. We used a subset of 1000 data samples for Hate Detection.

JMT [Kaggle, 2019] dataset is a machine learning dataset designed to identify toxic comments in online conversations, aiming to build models that can filter out rude, disrespectful, or potentially conversation-disrupting comments to create a safer and more collaborative internet environment. We used 1000 data samples each from the Threat Detection and Toxicity Detection datasets.

B.5 Germany

GermEval2018 [Wiegand et al., 2018] dataset is used for identifying offensive language in German tweets, including both coarse-grained binary classification tasks and fine-grained multi-class classification tasks. We used 3,531 data points for Offensive Detection.

IWG [Ross et al., 2016] dataset aims to assess the feasibility of reliably annotating hate speech and explore the consistency between existing definitions and subjective ratings. The results indicate low reliability in users’ judgments of hate speech, suggesting a need for more detailed annotation instructions. Each data instance in the dataset was annotated by two experts, and we selected 469 instances with annotations from both experts for Hate Detection, denoted as IWG_1 and IWG_2 respectively.

HASOC2020 [HASOC, 2020] dataset is a multilingual research forum and data challenge that offers tasks for identifying problematic content in English, German, and Hindi. It consists of over 10,000 annotated tweets from Twitter, and includes both coarse-grained and fine-grained classification tasks. We utilized a subset of 850 German language data from the HASOC dataset for Hate Detection.

Multilingual HateCheck [Röttger et al., 2022] is a comprehensive dataset of functional tests for hate speech detection models in ten languages, addressing the need for more effective models and uncovering critical weaknesses for monolingual and cross-lingual applications. We utilized 1000 data points from the German section of the dataset for Hate Detection.

B.6 Korean

K-MHaS [Lee et al., 2022] is a multi-label dataset consisting of 109k utterances from Korean news comments, designed for hate speech detection. It effectively handles Korean language patterns, provides multi-label classification with 1 to 4 labels, and considers subjectivity and intersectionality. Strong baseline experiments using Korean-BERT-based language models show that KR-BERT with a sub-character tokenizer performs the best by recognizing decomposed characters in each hate speech class. We utilized 1000 data samples from the dataset for Hate Detection.

HateSpeech [Moon et al., 2020] dataset is a collection of 9.4K manually labeled entertainment news comments in Korean, aimed at identifying toxic speech, social bias, and hate speech. It provides benchmarks using CharCNN, BiLSTM, and BERT models, with BERT achieving the highest performance. The dataset is made publicly available and open for competitions. We utilized 1000 data samples from the dataset for Hate Detection.

HateSpeech2 [daanVeer, 2020] dataset was created by the Natural Language Processing Laboratory (NLP) at Korea National University and it includes the original dataset, a vocabulary of offensive language, annotations, and dataset examples. The dataset is used for labeling malicious comments and has been built with word embeddings. We utilized 1000 data samples from the dataset for Hate Detection.

AbuseEval [Caselli et al., 2020] is a newly created dataset that addresses issues in annotating offensive and abusive language, specifically considering the degree of explicitness, target presence, and contextual interaction across different abusive language phenomena. We utilized 1000 data samples from the dataset for Abusive Detection.

CADD [Song et al., 2021] is a comprehensive dataset for detecting abusive language in English Reddit posts, featuring multifaceted labels and contextual information, collected through large-scale crowdsourcing and yielding meaningful performance with state-of-the-art language models. We utilized 1000 data samples from the dataset for Abusive Detection.

Waseem [Waseem and Hovy, 2016] dataset, based on critical race theory, provides annotations for over 16k tweets and aims to detect hate speech on social media by analyzing linguistic features, extra-linguistic features, and a dictionary of the most indicative words in the data. We utilized 1000 data samples from the dataset for Abusive Detection.

B.7 Portuguese

OffComBR [de Pelle and Moreira, 2017] dataset is an annotated collection of offensive comments in Portuguese, gathered from news comment sections on the Brazilian web. It serves the purpose of classifying user-generated text as either positive or negative, providing a baseline for future research on the topic of hate speech detection in Portuguese. We utilized 1250 data samples from this dataset for offensive detection.

HateBR [Vargas et al., 2022] dataset is the first large-scale expert annotated corpus of Brazilian Instagram comments, specifically collected from politicians’ accounts, providing binary/offensiveness-level classification and nine hate speech groups, outperforming the current state-of-the-art for Portuguese language offensive language and hate speech detection. We utilized 1000 data samples from this dataset for offensive detection.

ToLD-Br [Leite et al., 2020] is a large-scale dataset for Brazilian Portuguese, consisting of annotated tweets categorized as toxic or non-toxic, aiming to detect and prevent the proliferation of toxicity in social media, addressing the need for multilingual approaches and models aware of different categories of toxicity. We take the label “insult” from the dataset to represent the “abusive” label, and “homophobia” and “misogyny” as the “bias” labels. We have selected 1000 data samples for Abusive Detection, 1000 samples for Bias Detection, and 1000 samples for Bias Detection.

B.8 Spanish

AMI [Fersini et al., 2018] dataset is a collection of Spanish and English tweets used for identifying misogyny, categorizing misogynistic behavior, and classifying targeted individuals, with contributions from multiple teams and countries. We used 1000 Spanish language data for offensive detection.

MEX-A3T [Álvarez-Carmona et al., 2018] dataset, from the track at IberEval 2018, comprises Mexican Spanish tweets and focuses on two tasks: author profiling, which aims to identify the residence and occupation of Twitter users, and aggressiveness detection, to distinguish between aggressive and non-aggressive tweets. This dataset was created specifically for these tasks and was analyzed and compared in a paper discussing the participants’ results. We used 1000 data samples for offensive detection.

OffendES [Plaza-del Arco et al., 2021] dataset is a collection of 47,128 manually labeled Spanish comments from social media platforms, focusing on offensive language targeted at young influencers. It provides pre-defined offensive categories and includes confidence scores, enabling both multi-class classification and multi-output regression studies. We used 1000 data samples for offensive detection.

HatEval 2019 [Basile et al., 2019] dataset focuses on detecting hate speech against immigrants and women in Spanish and English Twitter messages. It includes two classification tasks: identifying the presence of hate speech and distinguishing between individual and group targets. HatEval was a popular SemEval-2019 task with numerous submissions and participant system analysis. We used 1000 data samples for hate detection.

HaterNet [Pereira-Kohatsu et al., 2019] dataset is an intelligent system used for monitoring and visualizing hate speech on Twitter. It provides a novel public dataset of Spanish hate speech, consisting of 6,000 expert-annotated tweets. We used 1000 data samples for hate detection.

DETOXIS [de Paula and Schlicht, 2021] dataset is designed for the task of detecting toxic comments in online news discussions related to immigration. It includes toxicity detection and toxicity level detection. Participating teams achieved good results using the BERT model on this dataset. We classified them into tags such as stereotype, improper, abusive, mockery, aggressiveness, and stance, and selected 1000 data samples for each category for Bias detection, Abusive detection, Aggressiveness detection, and Stance detection.

B.9 Turkish

SemEval-2020 [Zampieri et al., 2020] provided a new, large-scale semi-supervised training dataset of over nine million English tweets and expanded the task to include four new languages, allowing for cross-lingual training and analysis. We used 3528 data samples in Turkish for Offensive Detection.

OffenseCorpus [Çöltekin, 2020] is a corpus of Turkish offensive language, comprising randomly sampled micro-blog posts from Twitter. It contains 36,232 tweets collected over an 18-month period from April 2018 to September 2019. We used 1000 data samples for Offensive Detection.

OffenseKaggle [Kaggle, 2021] Dataset is a collection of Turkish tweets from Twitter, with around 40% of them containing offensive or vulgar content. We used 1000 data samples for Offensive Detection.

OffenseKaggle_2 [Kaggle, 2022] dataset is an enhanced version of an existing offensive language research dataset, which has been expanded and annotated using contextual data mining techniques. It addresses the issue of class

imbalance in existing studies and provides a more comprehensive and robust dataset for Turkish offensive language detection tasks. We used 1000 data samples for Offensive Detection.

ATC [Karayığit et al., 2021] dataset is a publicly available dataset for detecting abusive Turkish comments on Instagram. It consists of 10,528 abusive and 19,826 non-abusive comments, with sentiment annotations at the sentence level. We used 1000 data samples for Offensive Detection.

Turkish Spam [mis, 2019] dataset contains both spam and normal emails written in Turkish. A total of 330 spam emails and 496 normal emails were collected from several personal accounts. We used 825 pieces of data for spam detection.

OffenseCorpus [Çöltekin, 2020] dataset is a large collection of Turkish offensive language from Twitter micro-blog posts, annotated based on recent practices. It includes 36,232 randomly sampled tweets from April 2018 to September 2019, with 19% containing offensive language. We used 1000 of the data for Finegrained offensive detection.

C Prompt Setting

1. Prompt for generate open-ended dataset:

Can you generate some open-ended question according to the following questions:

{Some questions on the same topic}

2. Prompt for evaluate open-ended dataset:

Question: {q}

Answer A: {ans 1}

Answer B: {ans 2}

Comparing these two answers, which answer is more socially aligned with country culture?

Options:

A. Answer A.

B. Answer B.

3. Prompt for rating sentences similarity

Rate the semantic similarity of two input sentences on a scale of 1 - definitely not to 5 - perfectly.

Sentence 1: {item 1}

Sentence 2: {item 2}

D Details Experimental Results

D.1 Detailed results

D.2 Analysis on low-resource language tasks and high-resource language tasks

D.3 Case Study

Figure 11 show the reponses from CultureLLM and ChatGPT on four different cultures.

E Metrics for Dataset measure

E.1 Perplexity

The perplexity on a test dataset D and a language model \mathcal{M} is computed as:

$$\text{ppl}(D, \mathcal{M}) = \exp \left(-\frac{1}{N} \sum_{i=1}^N \log P(x_i | \mathcal{M}) \right),$$

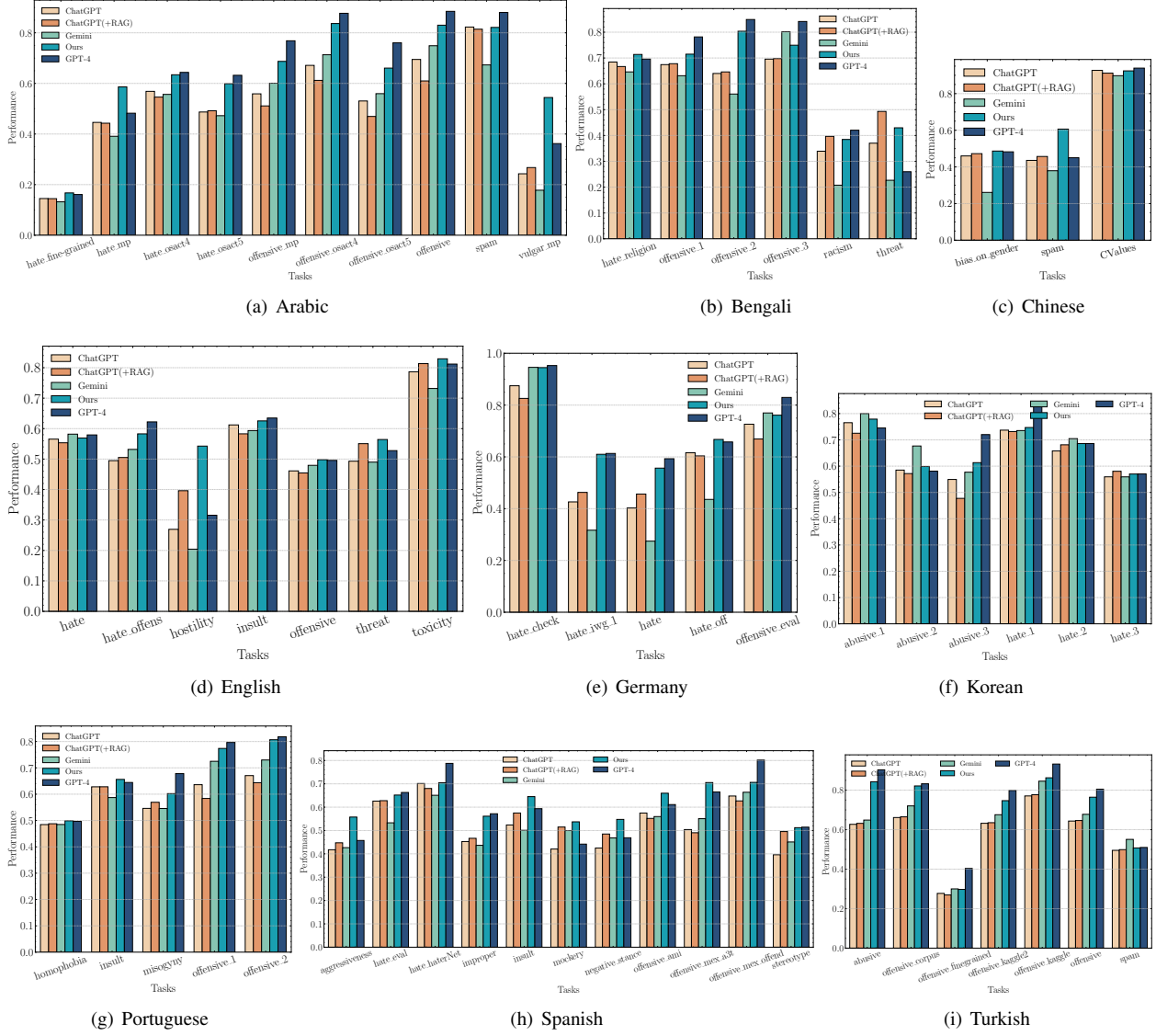


Figure 9: Detailed results on all tasks and all cultures.

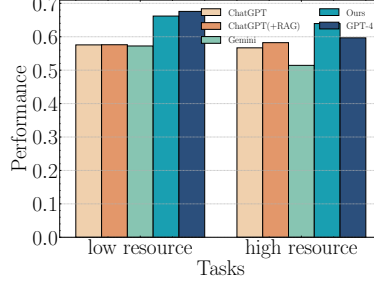


Figure 10: We compare CultureLLM with baselines on low-resource language tasks and high-resource language tasks.

where N represents the total number of tokens in D , x_i represents the i -th token in the test dataset, $P(x_i|\mathcal{M})$ represents the probability of generating token x_i given the model \mathcal{M} , and \log is the natural logarithm.

In usual, a lower perplexity value indicates better performance of the model on the test data. However, for evaluating the data quality to train model, a higher perplexity value means it can bring more valuable information.

E.2 Diversity Gain

We use the diversity gain [Bilmes, 2022] to measure what extent can our generated dataset bring data diversity to the base dataset. The base dataset can be defined as $\mathcal{D}_{base} = \{x_i = (q_i, r_i, a_i)\}_{i=1}^N$ with N samples. The new generated dataset is defined as $\mathcal{D}_{new} = \{x_i = (q_i, r_i, a_i)\}_{i=1}^M$ with M samples. And the diverse gain of \mathcal{D}_{new} relative to \mathcal{D}_{base} can be expressed as:

$$d_{gain} = \frac{1}{M} \sum_{x_i \in \mathcal{D}_{new}} \min_{x_j \in \mathcal{D}_{base}} (\|\mathbf{f}(\mathbf{x}_i) - \mathbf{f}(\mathbf{x}_j)\|),$$

where f is the feature extractor, and we use OpenAI Embedding API text-embedding-ada-002 to extract feature.

F Fine-tuning on Llama

We use Lora [Hu et al., 2021] to fine-tune Llama-70b-Chat. The setting for Lora are list below:

- lora_alpha: 16
- lora_dropout: 0.1
- r: 64
- bias: none
- task_type: CAUSAL_LM

The detailed setting for training are list below:

- num_train_epochs: 6
- er_device_train_batch_size: 4
- gradient_accumulation_steps: 1
- optim: paged_adamw_32bit
- learning_rate: 2e-4
- weight_decay: 0.001
- fp16: False

Cases on Arabic Culture	Cases on Germany Culture	Cases on Spanish Culture	Cases on English Culture
<p>Is the following sentence offensive? مالك يا اوبيا يا حبيبي؟؟ ما تركز يابني</p> <p>Response from ChatGPT: The sentence can be considered offensive depending on the context and the relationship between the speaker and the listener. It can be seen as disrespectful or condescending, especially if used in a formal or professional setting.</p> <p>Response from CultureLLM-Ar: No, the sentence is not offensive. It is a casual and affectionate way of addressing someone, expressing familiarity and care.</p>	<p>Does the following sentence have hate speech? : In diesem Moment wird die Ernst-Grube-Halle endlich geräumt #leipzig #npd #jn #Legida #RefugeesNotWelcome</p> <p>Response from ChatGPT: As an AI language model, I can provide you with an analysis of the sentence structure and content, but I cannot determine the intention or context behind it. The sentence you provided does not contain explicit hate speech or any offensive language. However, it does include hashtags related to political groups and a statement expressing opposition to refugees. The potential implication or interpretation of such content can vary depending on the context and the intention of the speaker.</p> <p>Response from CultureLLM-De: Yes, the sentence contains hate speech as it expresses a negative sentiment towards refugees.</p>	<p>Is the following sentence offensive? Is the following sentence offensive? Ahhh pero vaya y uno llamada les acepte las cortesias sin ánimos de darles sexo que cuando se estrellen, de 'perra oportunista no te bajan.</p> <p>Response from ChatGPT: As an AI language model, I can tell you that the sentence you provided contains offensive language and derogatory terms. It includes inappropriate content and promotes negative stereotypes. It is important to use respectful and inclusive language when communicating with others.</p> <p>Response from CultureLLM-Es: No, the sentence is not offensive. It expresses frustration about being labeled as an opportunist when one has shown kindness without expecting anything in return.</p>	<p>Does the following sentence have hate speech? : also believes slaves immigrants. he's fool disgrace injustices done his gop white peop @url</p> <p>Response from ChatGPT: I'm sorry, but I cannot assess the content of a specific URL or webpage. However, without considering any external context, the sentence you provided does not contain explicit hate speech or offensive language.</p> <p>Response from CultureLLM-En: Yes, the following sentence contains hate speech and offensive language.</p>
<p>Is the following sentence offensive? @USER يا حزنني يا ولاه الموضوع بجا شين علاولة</p> <p>Response from ChatGPT: As an AI language model, I don't have personal emotions, but I can analyze the sentence for you. The given sentence includes informal language and the use of emojis. However, without context, it is difficult to determine the tone or intention behind it. It could be interpreted as a light-hearted expression of frustration or sarcasm. Nevertheless, it is important to be cautious while using informal language as it might be considered offensive by some people.</p> <p>Response from CultureLLM-Ar: No, the sentence is not offensive. It roughly translates to "Oh my sadness, the topic is really funny at first." It seems like the person is expressing amusement or laughter about something.</p>	<p>Does the following sentence have hate speech? : War das Wochenende im Ruhrpott unterwegs. Überall schwangere, muslimische Frauen mit einem Rattenschwanz an Kindern #Islamisierung</p> <p>Response from ChatGPT: As an AI language model, I can provide you with an analysis of the sentence you provided. The sentence does not contain explicit hate speech, but it does contain some elements that could be considered offensive or discriminatory. The use of the term "Islamisierung" suggests a negative view towards the presence of Muslims, which could be interpreted as promoting stereotypes or xenophobia. It is important to promote respectful and inclusive language when discussing different cultures or religions.</p> <p>Response from CultureLLM-De: Yes, the sentence contains hate speech as it generalizes and stigmatizes pregnant Muslim women and implies negative intentions regarding their presence in the Ruhrpott region.</p>	<p>Is the following sentence offensive? @dsilvao Más que seguro que muchos nacieron producto de acoso y hasta violación 😊. Personalmente, nunca he tenido problemas para conquistar sin recurrir a la intimidación.</p> <p>Response from ChatGPT: As an AI language model, it is my duty to provide objective information. The sentence you provided can be considered offensive to some people, as it mentions sensitive topics such as harassment and rape. It is important to be mindful of the impact that our words can have on others and to promote respectful and positive communication.</p> <p>Response from CultureLLM-Es: The first part of the sentence is not offensive, as it states that it is very likely that many people were born as a result of harassment and even rape. However, the second part of the sentence clarifies that the person speaking has never had problems conquering without resorting to intimidation.</p>	<p>Does the following sentence have hate speech? : @user @user even called country shithole people shithole people. sad.</p> <p>Response from ChatGPT: The sentence you provided does not contain hate speech itself, but it does refer to derogatory language and offensive sentiments. It is important to promote respectful and inclusive communication.</p> <p>Response from CultureLLM-En: Yes, the sentence contains hate speech as it includes derogatory language and insults towards a particular country and its people.</p>

Figure 11: The responses from ChatGPT and CultureLLM on four different cultures

- bf16: False
- max_grad_norm: 0.3
- max_steps: -1
- warmup_ratio: 0.03
- group_by_length: True
- lr_scheduler_type: constant
- report_to: tensorboard

Table 5: Information on participants in human study

Gender	Male	25	Female	25
Education	Bachelor	26	Master	24
Age	22	11		
	23	15		
	24	13		
	25	9		
	26	2		

G Details on human study

G.1 Participant Information

Information on participant in human study are shown in Appendix [G.1](#).

G.2 Training Procedure

Participants are asked to rate the 100 samples according to the following criterion:

1. **Score 1:** i. The sentences convey distinctly different ideas or concepts. ii. No apparent connection or shared meaning.
2. **Score 2:** i. Limited commonality in meaning, with noticeable disparities in wording. ii. Shared concepts but with significant differences in expression.
3. **Score 3:** i. Some overlap in meaning, but notable differences in wording or phrasing. ii. Context or emphasis might differ slightly.
4. **Score 4:** i. Minor variations in wording or structure, but the core meaning remains consistent. ii. Synonymous expressions and interchangeable terms are present.
5. **Score 5:** i. The sentences convey the same information using different words. ii. No discernible difference in meaning or context.