

## CIDAR: Culturally Relevant Instruction Dataset For Arabic

Zaid Alyafeai <sup>1,\*</sup> Khalid Almubarak <sup>2,\*</sup> Ahmed Ashraf <sup>3,\*</sup> Deema Alnuhait <sup>4,\*</sup> Saied Alshahrani <sup>5,6</sup> Gubran A. Q. Abdulrahman <sup>1</sup> Gamil Ahmed <sup>1,7</sup> Qais Gawah <sup>1</sup> Zead Saleh <sup>1</sup> Mustafa Ghaleb <sup>1,8</sup> Yousef Ali <sup>1</sup> Maged S. Al-Shaibani <sup>1</sup>

<sup>1</sup> King Fahd University of Petroleum and Minerals (KFUPM) <sup>2</sup> Prince Sattam bin Abdulaziz University (PSAU) <sup>3</sup> ARBML <sup>4</sup> University of Illinois Urbana-Champaign <sup>5</sup> Clarkson University <sup>6</sup> University of Bisha

#### **Abstract**

Instruction tuning has emerged as a prominent methodology for teaching Large Language Models (LLMs) to follow instructions. However, current instruction datasets predominantly cater to English or are derived from English-dominated LLMs, resulting in inherent biases toward Western culture. This bias significantly impacts the linguistic structures of non-English languages such as Arabic, which has a distinct grammar reflective of the diverse cultures across the Arab region. This paper addresses this limitation by introducing CIDAR<sup>1</sup> the first open Arabic instructiontuning dataset culturally-aligned by human reviewers. CIDAR contains 10,000 instruction and output pairs that represent the Arab region. We discuss the cultural relevance of CIDAR via the analysis and comparison to other models fine-tuned on other datasets. Our experiments show that CIDAR can help enrich research efforts in aligning LLMs with the Arabic culture. All the code is available at https://github.com/ARBML/CIDAR.

#### 1 Introduction

The need for Natural Language Processing (NLP) applications has exploded in an era of unprecedented linguistic interaction between humans and machines. As these applications strive for greater inclusivity and effectiveness across diverse linguistic landscapes, the need for datasets that reflect the cultural differences and linguistic peculiarities of specific regions becomes increasingly important.

In the context of Arabic language understanding, the challenge lies not only in linguistic complexity but also in capturing the rich cultural fabric that shapes communication in the Arab world.



Figure 1: An example of our localization procedure in CIDAR of a given (instruction, output) pair. We show, in colors, the grammatical and cultural modifications.

In the past year, many language models have been pre-trained and instruct-tuned for Arabic, like JAIS (Sengupta et al., 2023), and ACEGPT (Huang et al., 2023). All these models have been trained on a large corpus of Arabic text and then fine-tuned to respond to users' instructions. However, such efforts do not release high-quality instruction datasets to be openly used for research. Moreover, they use a lot of machine-translated or machine-generated instruction datasets without further human review or audit, disregarding the consequences of using such poor, distorted, and misaligned instructions.

<sup>&</sup>lt;sup>7</sup> Interdisciplinary Research Center for Smart Mobility and Logistics (IRC-SML), KFUPM

<sup>&</sup>lt;sup>8</sup> Interdisciplinary Research Center for Intelligent Secure Systems (IRC-ISS), KFUPM

<sup>\*</sup>Equal contribution. Corresponding author: Zaid Alyafeai, email: g201080740@kfupm.edu.sa

<sup>&</sup>lt;sup>1</sup>CIDAR: https://hf.co/datasets/arbml/CIDAR.

In this paper, we introduce CIDAR, the *first* open instruction-tuning dataset that has gone through extensive review and localization (see Figure 1) crafted for instructional tuning in Arabic. In the subsequent sections, we delve into the dataset creation process, elucidating the methodology employed to navigate the delicate balance between linguistic accuracy and cultural relevance. The paper also discusses the potential applications of CIDAR in enhancing the performance of LLMs, shedding light on its role in bridging the gap between language understanding and cultural context within the realm of Arabic instruction-tuning. Mainly, we compare fine-tuning on a translated dataset and a localized dataset, i.e., CIDAR. Ultimately, CIDAR dataset stands as a testament to the evolving landscape of NLP research, advocating for the integration of cultural context as an essential component in the development of LLMs tailored for specific linguistic communities, like the Arab world.

#### 2 Related Work

Many efforts have been made to create numerous instruction datasets, especially for English; some are generated by LLMs like Stanford Alpaca (Taori et al., 2023), Databricks' Dolly (Conover et al., 2023), and Self-Instruct (Wang et al., 2023), whereas others are human-generated with templates like Flan collections (Wei et al., 2021; Longpre et al., 2023), P3 (Bach et al., 2022), and NATURAL INSTRUCTIONS (Mishra et al., 2022).

In the following subsections, we briefly discuss the Arabic instruction-tuning datasets and their data collection approaches in a multilingual and monolingual context.

#### 2.1 Multilingual Instruction-tuning Datasets

Muennighoff et al. (2023) presented xP3 (Crosslingual Public Pool of Prompts) as an extension of the P3 dataset (Sanh et al., 2022), where the authors applied English prompts across 16 NLP tasks for 46 languages, including Arabic. Later, the authors introduced a much larger version called xP3x (Crosslingual Public Pool of Prompts eXtended), in which they extended the English prompts to 277 languages, including Arabic and ten of its dialects. Despite their large sizes, these datasets exhibit limited variation due to their reliance on prompt template structure and their emphasis on classical NLP tasks such as translation, question answering, text classification, text summarization, and other tasks.

Chen et al. (2023c) constructed MULTILIN-GUALSIFT (Multilingual Supervised Instruction Fine-tuning) datasets, by translating instructions for 11 languages, including Arabic. The authors translated these three training datasets: Alpaca-GPT4 (Peng et al., 2023), Evol-Instruct (Xu et al., 2023), and ShareGPT (Zheng et al., 2023), from English to Arabic using GPT-3.5 Turbo. For Alpaca-GPT4, they directly translated the instructions and responses, while for Evol-Instruct and ShareGPT, they translated the instructions and used them to generate the responses. Furthermore, the authors translated two evaluation datasets, (Hendrycks et al., 2021) and Vicuna-80 (Zheng et al., 2023), using the same above-mentioned approach.

Wang et al. (2022) introduced SUPER-NATURALINSTRUCTIONS (SUP-NATINST) as the first benchmark of 1,616 diverse NLP tasks, along with their expert-written instructions. It covers nearly 76 distinct task types like text classification, extraction, rewriting, and composition, spanning 55 languages. It includes 80.3K Arabic instructions for 16 Arabic NLP tasks like text translation and sentence perturbation generation, yet the number of Arabic NLP tasks is underrepresented compared to other languages like Spanish (43 tasks), Japanese (40 tasks), and Persian (34 tasks).

Li et al. (2023) presented Bactrian-X, a 3.4M instruction-response pair for 52 human languages, including Arabic, with around 65.4K pairs. The authors *only* translated selected instructions from Alpaca (Taori et al., 2023) and Dolly (Conover et al., 2023), using Google Translate<sup>2</sup> to Arabic. After that, they generated responses for these selected translated instructions using GPT-3.5 Turbo.

Upadhayay and Behzadan (2023) introduced the Multilingual Instruction-Tuning Dataset (MITD), which is composed of the translation of Alpaca-GPT4 (Peng et al., 2023), Dolly (Conover et al., 2023), and Vicuna Benchmark (Chiang et al., 2023) in 132 languages, including Arabic, using Google Cloud Translation<sup>3</sup>. Despite the authors' acknowledgment that their translations are prone to *translationese*, where the translated texts deviate from the native language norms due to many factors like the overly literal translation and unusual phrases or word choices, they *only* performed a manual evaluation of the translation quality for four language, unsurprisingly Arabic was not one of them.

<sup>&</sup>lt;sup>2</sup>Google Translate: https://translate.google.com.

<sup>&</sup>lt;sup>3</sup>Google Cloud Translation: https://cloud.google.com.

Köpf et al. (2023) released OpenAssistant Conversations (OASST1), a human-generated and human-annotated assistant-style conversation dataset consisting of 161.4K messages in 35 human languages, including Arabic, resulting in over 10K complete and fully annotated conversation trees. This was a product of a worldwide crowd-sourcing effort involving over 13.5K volunteers. The Arabic portion has only 666 data samples.

## 2.2 Arabic Instruction-tuning Datasets

In the context of training Arabic-specific LLMs, a few attempts were made to create Arabic instruction-tuning datasets. However, most of these datasets are closed (not publicly released).

Chen et al. (2023b) released their instruct-tuned model PHOENIX using three groups of instructions: collected multi-lingual instructions, post-translated multi-lingual instructions, and self-generated user-centered multi-lingual instructions. Specifically, in the post-translated multi-lingual instructions, the authors translated Alpace instruction and output pairs (Taori et al., 2023) using GPT-4 to Arabic, and sometimes they generated responses for the GPT-4 translated instructions using GPT-3.5 Turbo for alleviating the unavoidable translation issues.

Naseej (2023) instruct-tuned their model NOON using a collection of Arabic instructions from different datasets, such as Alpaca-GPT4 (Peng et al., 2023), Databricks' Dolly (Conover et al., 2023), TruthfulQA dataset (Lin et al., 2021), Grade School Math dataset (Cobbe et al., 2021), and Arabic arithmetic problems generated using GPT-3.5 Turbo.

Sengupta et al. (2023) also instruct-tuned their model JAIS using a translated collection of instructions to Arabic from various instructions-tuning datasets, such as SUPER-NATURALINSTRUCTIONS, (Wang et al., 2022) Unnatural (Honovich et al., 2023), Natural Questions (Kwiatkowski et al., 2019), Alpaca (Taori et al., 2023), HC3 (Guo et al., 2023), Databricks' Dolly (Conover et al., 2023), Basic-Conv<sup>4</sup>, Bactrian-X (Li et al., 2023) and enriched the collection with Arabic examples from xP3 (Muennighoff et al., 2023). The authors also formatted the AraNER (Benajiba et al., 2007) to the instruction-response format. Furthermore, the authors created two unreleased datasets with instruction-response pairs for the United Arab Emirates (UAE) and the region: NativeQA-Ar and SafetyQA-Ar.

Huang et al. (2023) as well instruct-tuned their model ACEGPT using instructions compiled from some open-source datasets, like Alpaca (Taori et al., 2023), Alpaca-GPT4 (Peng et al., 2023), Evol-Instruct (Xu et al., 2023), Code-Alpaca (Chaudhary, 2023), and ShareGPT (Zheng et al., 2023), and translated the questions from English to Arabic and re-generated the responses using GPT-4. Moreover, the authors fine-tuned their model using native Arabic instructions collected from the question-answering platform Quora<sup>5</sup> as localized instructions and generated responses for these instructions using GPT-4. Plus, the authors introduced a translated version of Arabic-Vicuna-80<sup>6</sup> to conduct a human evaluation study.

Almazrouei et al. (2023) lately instruct-tuned a few models using multiple machine-translated Arabic instruction-tuning datasets, including xP3 (Muennighoff et al., 2023), Bactrian-X (Li et al., 2023), Alpaca (Taori et al., 2023), and UltraChat (Ding et al., 2023). The authors also performed human evaluations of the fine-tuned models on multiple categories, including education, health, technology, history, creativity, oil, and gas.

Yasbok (2023) released the *only* open-source monolingual, Arabic instruction-tuning dataset, which is poorly translated from Alpaca dataset (Taori et al., 2023) to the Arabic language using Google Translate without cultural alignment or even a simple translation error checking.

#### 3 Issues of Arabic Instruction Datasets

Two main approaches were addressed in the previous literature for creating Arabic instruction-tuning datasets: the full translation of both instruction-response pairs using Machine Translation (MTs) tools and the translation of instructions, then generating responses using LLMs like GPT-4. However, each creation or generation approach of the Arabic instruction-tuning datasets has serious drawbacks that we discuss next.

#### 3.1 MTs-related Issues

One harmful drawback of the current instructiontuning datasets' creation approaches is the poor, naive, and direct translation of English instructionresponse pairs to Arabic without human intervention or supervision using off-the-shelf MT tools

<sup>&</sup>lt;sup>4</sup>ChatterBot Corpus: https://chatterbot-corpus.docs.io

<sup>&</sup>lt;sup>5</sup>Quora: https://www.quora.com

<sup>&</sup>lt;sup>6</sup>Arabic-Vicuna-80: https://hf.co/datasets/FreedomIntelligence/Arabic-Vicuna-80.

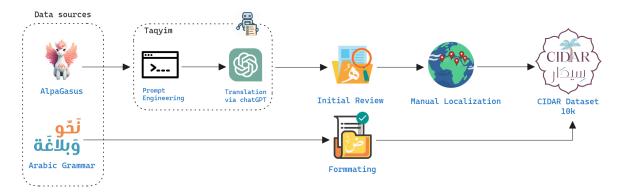


Figure 2: Workflow diagram of CIDAR's data collection pipeline, illustrating each pipeline phase and its components.

like Google Translate, which is widely known for their social problems like gender, cultural, and religious biases and stereotypes (Prates et al., 2020; Ullmann and Saunders, 2021; Lopez-Medel, 2021; Chen et al., 2021; Naik et al., 2023; Alshahrani et al., 2022b). Many researchers have repeatedly stressed how such unguided translations are not only prone to various linguistic and grammatical errors, detrimental outcomes, cultural misalignment (favoring the Western culture), and representational harm to native speakers (unrepresentative content) but also introduce negative performance implications of models trained on them (Stanovsky et al., 2019; Habash et al., 2019; Das, 2020; Agrawal et al., 2023; Alshahrani et al., 2023).

#### 3.2 LLMs-related Issues

The other hazardous drawback of the current instruction-tuning datasets' creation approaches is the unvetted, unchecked, and unsupervised translation of instruction-response pairs from English to Arabic or the generation of responses for the previously translated instructions, all using LLMs like GPT-3.5 Turbo or GPT-4 without paying attention to the consequences. Many research studies have underscored various risks, threats, and controversies in LLMs, for example, research studies like (Paullada et al., 2021; Wach et al., 2023; Thakur, 2023; Naous et al., 2023; Dong et al., 2023; Acerbi and Stubbersfield, 2023) accentuated that most commonly used LLMs could exhibit a wide spectrum of biases, privacy, and security hazards, ethical questions, hallucination, and could create a damaging or deceptive content of certain group. Besides, LLMs could generate content (e.g., responses) that suffer cultural misalignment and cultural incongruencies, leading to culturally unaligned, undiverse, untruthful, and unrepresentative outputs (Prabhakaran et al., 2022; Alshahrani et al., 2022a; Kasirzadeh and Gabriel, 2022; Cetinic, 2022; Bang et al., 2023; Yu et al., 2023; Masoud et al., 2023; Ji et al., 2024).

#### 4 CIDAR

In this paper, we introduce CIDAR which was constructed from two different sources. First, we use the ALPAGASUS dataset <sup>7</sup> reproduced from the work by (Chen et al., 2023a) which is a high-quality dataset filtered from the Stanford Alpaca dataset (Taori et al., 2023). ALPAGASUS contains more than 9K instruction, input, and output triplets. We translate 9,109 of the data to Arabic using ChatGPT (GPT-3.5 Turbo). Then, we append it with around 891 questions and answers about the Arabic language and Grammar crawled from AskTheTeacher website<sup>8</sup>. Figure 2 highlights the main procedure for our data collection process. Next, we explain our approach to construct CIDAR further.

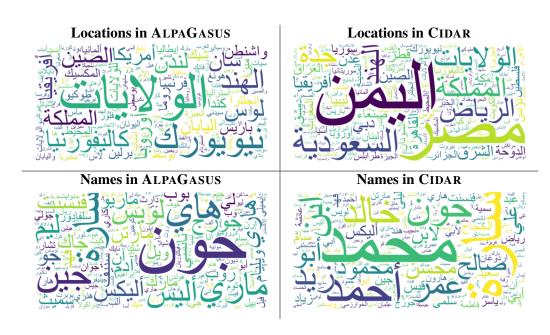
#### **4.1** Machine Translation

To translate ALPAGASUS, we tested with different prompts to observe which one gave the best results. Also, We use the Taqyim library (Alyafeai et al., 2023) to translate all the examples in ALPAGASUS using GPT-3.5 Turbo. Initially, We tested with direct translation of instruction, input, and output triplets but that did not give the best results. Hence, we concatenated the instructions and input. Another challenge encountered was ChatGPT translating coding blocks. Consequently, we had to explicitly instruct it to ignore coding blocks. We also append the instruction and output with *User*, and *Bot*, respectively, as in the following example:

<sup>&</sup>lt;sup>7</sup>ALPAGASUS: https://hf.co/mlabonne/alpagasus

<sup>&</sup>lt;sup>8</sup>AskTheTeacher: https://aljazeera.net/ar/asktheteacher

Table 1: Comparison between translated ALPAGASUS and CIDAR regarding names and countries using Word Clouds. In ALPAGASUS, the top locations are the United States (الولايات) and New York (غيويورك), and the top names are John (ماري), while in CIDAR, after our localization, the top locations are Yemen (اليمن), and Egypt (مصر), and the top names are Muhammad (مصر).



You are given a conversation between a user and a bot, translate the full conversation into Arabic. Don't translate any coding blocks.

**User**: Given the context, identify a suitable word to complete the sentence. The sun feels so <mask> today, I just want to sit here and relax.

Bot: warm.

#### 4.2 Initial Review

After translating our seed dataset, we noticed some initial problems. Therefore, we followed multiple steps to fix these machine translation issues:

- Fix instructions or outputs that contain a large number of the English alphabet.
- Fix empty fields of instructions or outputs.
- Fix manually instructions that had wrong first words that are not in the correct form of an instruction.

The main goal of this step is to observe the current problems in the dataset to initialize the guidelines for the annotators.

### 4.3 Localization

After fixing the initial issues with translation, we prepare our dataset to be manually reviewed. To simplify the annotation process, we created a webbased Annotation Tool (see Appendix B), where reviewers were instructed to fix two main issues:

- Linguistic Issues: Some words might not be translated correctly, especially at the beginning of each instruction; we want all the statements to start with an instruction. For example, we should replace خلاصة (summary) with خلاصة (summarize). Also, some instructions might be specific to English. The annotators are asked to provide their corresponding examples in Arabic.
- Cultural Relevance: Some examples in the original English Alpaca might contain examples that represent Western cultures. We want to replace them with instructions that represent the Arab region and its culture. For instance, the name جون سميث (John Smith) should be replaced by an Arabic name like على خالد (Ali Khalid).

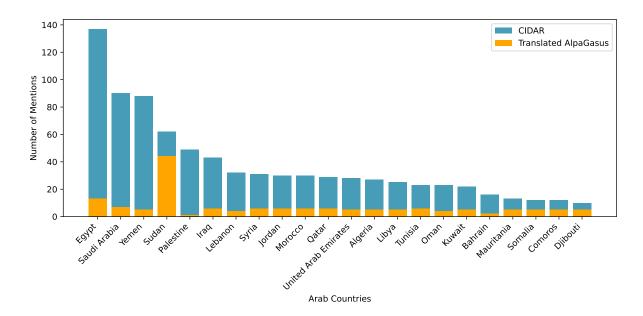


Figure 3: Number of mentions of every Arab country in both CIDAR and translated ALPAGASUS datasets.

### 5 Dataset Analysis

In our data-gathering process, around 12 contributors participated in reviewing the dataset. Hence, in total, we have 10,000 instruction and output pairs that went under review. In this section, we compare between CIDAR and the initial translated ALPAGASUS. Through such analysis, we aim to emphasize the importance of manual revision and cultural alignment of machine-generated data.

#### 5.1 Modifications

Table 2 shows the number of modifications in CIDAR concerning the instructions, outputs, or either of them. From 9,109 instruction-response pairs in ALPAGASUS, there were around 64.5% of them that required a modification to be included in CIDAR. These modifications are either due to a linguistic error or cultural irrelevance.

Modifications	# Samples	
Instructions	3,202	
Outputs	4,879	
Instructions or Outputs	5,871	

Table 2: Number of modified instructions and outputs from the original ALPAGASUS using manual review.

#### 5.2 Locations and Names

The translated ALPAGASUS dataset contains a lot of Western names and countries. To calculate how much CIDAR mitigates that, we use Named Entity

Recognition (NER) to extract the tokens that represent persons and locations. we use a fine-tuned CAMeLBERT (Inoue et al., 2021) model on NER<sup>9</sup> to extract the names of persons and countries in both CIDAR and the translated ALPAGASUS. In Table 1, we draw a comparison between locations and persons in both datasets using word cloud visualizations. We can see that the majority of locations and names in CIDAR are from the Arab region.

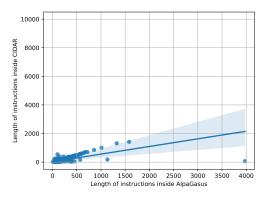
#### 5.3 Countries

In Figure 3, we highlight the distribution of (instruction, output) pairs that contain Arab countries. We observe a huge superiority for CIDAR over the translated ALPAGASUS in terms of mentioning Arab countries. In CIDAR, the mentions of Arab countries have increased noticeably after our localization. While, in ALPAGASUS, the mentions of Arab countries are mostly around ten mentions for most countries, except for Sudan (السودان). This highlights the importance of CIDAR in representing the region. Note that Sudan is considered an outlier because many food recipes contain peanuts as an ingredient, which is translated to (Sudanese Bean) in Arabic.

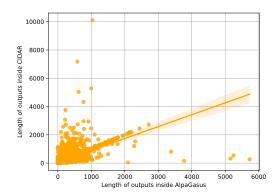
### 5.4 General Topics

We use keyword-based search to extract how many (instruction, output) pairs contain a specific topic. In Figure 5, we observe that, in general, CIDAR

<sup>&</sup>lt;sup>9</sup>CAMeLBERT NER: https://hf.co/CAMeL-Lab/bert-base-arabic-camelbert-mix-ner



(a) Comparison of instruction lengths.



(b) Comparison of output lengths.

Figure 4: Comparison between CIDAR and translated ALPAGASUS in terms of instruction (Left) and output (Right) lengths. Noticeably, the length of outputs increased in CIDAR due to the possible reviewers' rewriting of outputs.

covers a wider range of topics, including Arabicspecific tasks such as Arabic grammar and diacritization, which are largely missed in ALPAGASUS.

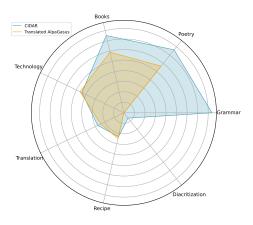


Figure 5: Comparison between CIDAR and translated ALPAGASUS datasets regarding the covered topics.

#### 5.5 Annotation Lengths

In Figure 4, we compare the length of instructions and outputs between CIDAR and translated ALPA-GASUS before and after our review. We highlight fewer changes in terms of instructions compared to outputs after the review. This is expected because sometimes the reviewer might re-write the whole output depending on changing a few words in the instruction. For example, if an instruction asks to find the best tourist places in a given US state, the reviewer will *likely* change one word in the instruction and completely rewrite the whole output, which might result in a longer output.

### 6 Evaluation

We employed ACEGPT-7B, a variant of LLaMA-7B fine-tuned on Arabic datasets (Huang et al., 2023), as the base model. This model was further fine-tuned using two instruction datasets, CIDAR and an Arabic-translated version of ALPAGASUS, to assess their adaptability in culturally and regionally nuanced contexts. This study compares the following three variants of ACEGPT across diverse cultural and regional scenarios, models defined as:

- 1. **ACEGPT\CIDAR**: A fine-tuned variant of the pre-trained ACEGPT-7B model on our culturally aligned dataset, CIDAR.
- ACEGPT\ALPAGASUS: A fine-tuned variant of the pre-trained ACEGPT-7B model on translated ALPAGASUS dataset.
- 3. **ACEGPT\CHAT**<sup>10</sup>: The instruct-tuned variant of ACEGPT-7B model released by the original authors (Huang et al., 2023).

We fine-tuned ACEGPT\ALPAGASUS and ACEGPT\CIDAR models, using supervised fine-tuning (SFT) with the Quantized Low-Rank Adaptation (QLoRA) quantization technique, as outlined in (Dettmers et al., 2023). Detailed specifications of the fine-tuning and inference hyper-parameters are provided in Appendix D. In Table 3, we compare the number of instructions used to fine-tune each model.

Figure 6 illustrates a qualitative example, showcasing the outputs of the three models on a given

<sup>&</sup>lt;sup>10</sup>ACEGPT\CHAT: https://huggingface.co/FreedomIntelligence/AceGPT-7B-chat.

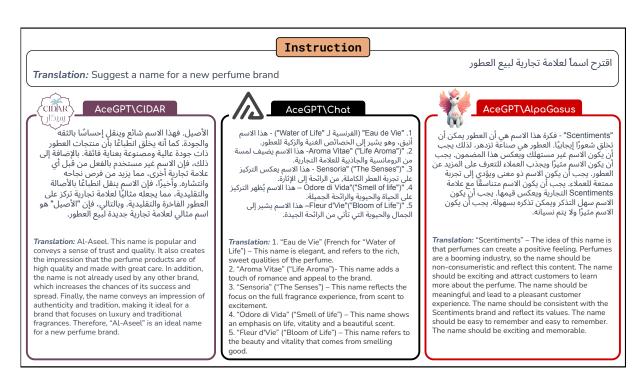


Figure 6: Comparison between the outputs of the three evaluated models on a given instruction.

Model	# Innstructions	
ACEGPT\CIDAR	10,000	
ACEGPT\ALPAGASUS	9,230	
ACEGPT\CHAT	363,155	

Table 3: Number of instructions used for fine-tuning each model in our evaluation.

instruction. In this example, we want to know which model can capture the names that are related to the culture in the region. We observe that ACEGPT\CIDAR demonstrated a marked improvement in aligning with Arabic culture by choosing a perfume name that is related to our region. In contrast, the ACEGPT\ALPAGASUS model showed a tendency towards creating English names. We also observe that ACEGPT\CHAT creates a list of suggestions of the names, even though this was not requested in the instruction. For more detailed examples, refer to Table 5 in Appendix E.

### 7 Social Impact and Limitations

We aim to establish CIDAR with the primary goal of incorporating rich Arabic content that authentically reflects our cultural values and the linguistic beauty of the language. Unlike much of the existing literature that relies on translated datasets or LLM-generated responses, which may encounter many challenges, as previously discussed, our fo-

cus is on preserving the integrity/quality of Arabic instruction. Moreover, the original Alpaca or AL-PAGASUS predominantly features Western cultural themes, such as food recipes, poems, tourist destinations, names, and countries. In our endeavor to curate CIDAR, we have diligently ensured the inclusion of elements specific to our culture and traditions, encompassing Arabic linguistic nuances, narratives, tourism, names, culinary recipes, poetry, and countries. The open release of the dataset allows for fine-tuning LLMs that are cultural-aligned and can help with different domains. Our pilot study on fine-tuning ACEGPT shows the huge impact such datasets can have in the region.

That being said, CIDAR still poses some limitations related to the data curation process. We summarize them as the following:

- Country Biases: Localizing a given instruction usually depends on the nationality of the person annotating. Often, annotators will prefer to add annotations related to the countries they were born in or currently residing in.
- **Dataset Size**: The size of the dataset might limit its uses in large-scale instruction tuning. In our evaluation, we attempted to show that it helps to train on a culturally relevant dataset.
- Topics Covered: In our data localization process, we tried to cover as many topics that

are related to the culture of the region. We opted out of topics related to religion as it is considered a sensitive topic in the region.

- Dialects: The Arabic language is not limited to Modern Standard Arabic (MSA). There are various Arabic dialects. Localization of data was limited to corrections of the translated text, which is mostly written in MSA, without incorporating multiple dialects.
- Safety: Due to the relatively small size of CIDAR, the fine-tuned models on our dataset can show some degree of hallucinations, especially that it is not subjected to further alignment processes such as Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022).

#### 8 Conclusion

In conclusion, this paper introduces a significant contribution to the field of language model training by presenting CIDAR, the *first* open Arabic instruction-tuning dataset that is culturally-aligned by human reviewers. We highlight that the conventional approach of fine-tuning on machinegenerated or machine-translated datasets has often resulted in biases favoring Western cultural nuances. Recognizing the unique grammar and cultural richness of the Arabic language, our dataset curation process aims to localize a given seed dataset, fostering a more authentic representation.

Through careful analysis and comparison with other models fine-tuned on other datasets, we demonstrate that CIDAR serves as a pivotal resource for enriching research efforts in aligning Large Language Models (LLMs) with the Arabic culture. The experiments conducted not only validate the cultural relevance of our dataset but also highlight its potential to enhance the performance and understanding of LLMs within the Arabic linguistic and cultural context.

The availability of CIDAR and the transparency of our dataset curation approach provide a foundation for future advancements in Arabic language model research. Researchers and developers can leverage this dataset to train models that better comprehend and respond to instructions within the cultural nuances of the Arab region. By sharing our code openly on GitHub, at https://github.com/ARBML/CIDAR, we encourage collaboration, further refinements, and broader con-

tributions to the ongoing efforts to align language models with diverse cultural and linguistic contexts. Ultimately, CIDAR stands as a valuable resource for advancing the inclusivity and effectiveness of language models in the Arabic-speaking world.

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#### References

Alberto Acerbi and Joseph M. Stubbersfield. 2023. Large language models show human-like content biases in transmission chain experiments. *Proceedings of the National Academy of Sciences*, 120(44):e2313790120.

Ameeta Agrawal, Lisa Singh, Elizabeth Jacobs, Yaguang Liu, Gwyneth Dunlevy, Rhitabrat Pokharel, and Varun Uppala. 2023. All Translation Tools Are Not Equal: Investigating the Quality of Language Translation for Forced Migration. In 2023 IEEE 10th International Conference on Data Science and Advanced Analytics (DSAA), pages 1–10.

Ebtesam Almazrouei, Ruxandra Cojocaru, Michele Baldo, Quentin Malartic, Hamza Alobeidli, Daniele Mazzotta, Guilherme Penedo, Giulia Campesan, Mugariya Farooq, Maitha Alhammadi, Julien Launay, and Badreddine Noune. 2023. AlGhafa Evaluation Benchmark for Arabic Language Models. In *Proceedings of ArabicNLP 2023*, pages 244–275, Singapore (Hybrid). Association for Computational Linguistics.

Saied Alshahrani, Norah Alshahrani, Soumyabrata Dey, and Jeanna Matthews. 2023. Performance Implications of Using Unrepresentative Corpora in Arabic Natural Language Processing. In *Proceedings of ArabicNLP 2023*, pages 218–231, Singapore (Hybrid). Association for Computational Linguistics.

Saied Alshahrani, Esma Wali, and Jeanna Matthews. 2022a. Learning From Arabic Corpora But Not Always From Arabic Speakers: A Case Study of the Arabic Wikipedia Editions. In *Proceedings of the The Seventh Arabic Natural Language Processing Workshop (WANLP)*, pages 361–371, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

<sup>&</sup>lt;sup>11</sup>Maqsam: https://maqsam.com.

- Saied Alshahrani, Esma Wali, Abdullah R Alshamsan, Yan Chen, and Jeanna Matthews. 2022b. Roadblocks in Gender Bias Measurement for Diachronic Corpora. In *Proceedings of the 3rd Workshop on Computational Approaches to Historical Language Change*, pages 140–148, Dublin, Ireland. Association for Computational Linguistics.
- Zaid Alyafeai, Maged S Alshaibani, Badr AlKhamissi, Hamzah Luqman, Ebrahim Alareqi, and Ali Fadel. 2023. Taqyim: Evaluating Arabic NLP Tasks Using ChatGPT Models. arXiv preprint arXiv:2306.16322.
- Stephen Bach, Victor Sanh, Zheng Xin Yong, Albert Webson, Colin Raffel, Nihal V. Nayak, Abheesht Sharma, Taewoon Kim, M Saiful Bari, Thibault Fevry, Zaid Alyafeai, Manan Dey, Andrea Santilli, Zhiqing Sun, Srulik Ben-david, Canwen Xu, Gunjan Chhablani, Han Wang, Jason Fries, Maged Alshaibani, Shanya Sharma, Urmish Thakker, Khalid Almubarak, Xiangru Tang, Dragomir Radev, Mike Tian-jian Jiang, and Alexander Rush. 2022. Prompt-Source: An Integrated Development Environment and Repository for Natural Language Prompts. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 93–104, Dublin, Ireland. Association for Computational Linguistics.
- Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, Quyet V. Do, Yan Xu, and Pascale Fung. 2023. A Multitask, Multilingual, Multimodal Evaluation of ChatGPT on Reasoning, Hallucination, and Interactivity. *arXiv* preprint *arXiv*:2302.04023v4.
- Yassine Benajiba, Paolo Rosso, and José BenedíRuiz. 2007. ANERsys: An Arabic Named Entity Recognition System Based on Maximum Entropy. In *Computational Linguistics and Intelligent Text Processing*, volume 4394, pages 143–153.
- Eva Cetinic. 2022. The Myth of Culturally Agnostic AI Models. *arXiv preprint arXiv:2211.15271v2*.
- Sahil Chaudhary. 2023. Code Alpaca: An Instruction-Following Llama Model for Code Generation. Last accessed 2024-01-15.
- Lichang Chen, Shiyang Li, Jun Yan, Hai Wang, Kalpa Gunaratna, Vikas Yadav, Zheng Tang, Vijay Srinivasan, Tianyi Zhou, Heng Huang, and Hongxia Jin. 2023a. AlpaGasus: Training A Better Alpaca with Fewer Data. arXiv preprint arXiv:2307.08701.
- Yan Chen, Christopher Mahoney, Isabella Grasso, Esma Wali, Abigail Matthews, Thomas Middleton, Mariama Njie, and Jeanna Matthews. 2021. Gender Bias and Under-Representation in Natural Language Processing Across Human Languages. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, AIES '21, page 24–34, New York, NY, USA. Association for Computing Machinery.

- Zhihong Chen, Feng Jiang, Junying Chen, Tiannan Wang, Fei Yu, Guiming Chen, Hongbo Zhang, Juhao Liang, Chen Zhang, Zhiyi Zhang, Jianquan Li, Xiang Wan, Benyou Wang, and Haizhou Li. 2023b. Phoenix: Democratizing ChatGPT across Languages. arXiv preprint arXiv:2304.10453.
- Zhihong Chen, Shuo Yan, Juhao Liang, Feng Jiang, Xiangbo Wu, Fei Yu, Guiming Hardy Chen, Junying Chen, Hongbo Zhang, Li Jianquan, Wan Xiang, and Benyou Wang. 2023c. MultilingualSIFT: Multilingual Supervised Instruction Fine-tuning. Last accessed 2024-01-15.
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%\* Chat-GPT Quality. Last accessed 2024-01-15.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. 2021. Training Verifiers to Solve Math Word Problems. arXiv preprint arXiv:2110.14168.
- Mike Conover, Matt Hayes, Ankit Mathur, Jianwei Xie, Jun Wan, Sam Shah, Ali Ghodsi, Patrick Wendell, Matei Zaharia, and Reynold Xin. 2023. Free Dolly: Introducing the World's First Truly Open Instruction-Tuned LLM. Last accessed 2024-01-15.
- Marta R Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, et al. 2022. No language left behind: Scaling human-centered machine translation. *arXiv* preprint *arXiv*:2207.04672.
- Alok Das. 2020. Neural Machine Translation (NMT): Inherent Inadequacy, Misrepresentation, and Cultural Bias. *International Journal of Translation*, 32:115–145.
- Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. 2023. QLoRA: Efficient Finetuning of Quantized LLMs. arXiv preprint arXiv:2305.14314.
- Ning Ding, Yulin Chen, Bokai Xu, Yujia Qin, Shengding Hu, Zhiyuan Liu, Maosong Sun, and Bowen Zhou. 2023. Enhancing Chat Language Models by Scaling High-quality Instructional Conversations. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 3029–3051, Singapore. Association for Computational Linguistics.
- Xiangjue Dong, Yibo Wang, Philip S. Yu, and James Caverlee. 2023. Probing Explicit and Implicit Gender Bias through LLM Conditional Text Generation. arXiv preprint arXiv:2311.00306v1.

- Biyang Guo, Xin Zhang, Ziyuan Wang, Minqi Jiang, Jinran Nie, Yuxuan Ding, Jianwei Yue, and Yupeng Wu. 2023. How Close is ChatGPT to Human Experts? Comparison Corpus, Evaluation, and Detection. *arXiv preprint arXiv:2301.07597*.
- Nizar Habash, Houda Bouamor, and Christine Chung. 2019. Automatic Gender Identification and Reinflection in Arabic. In *Proceedings of the First Workshop on Gender Bias in Natural Language Processing*, pages 155–165, Florence, Italy. Association for Computational Linguistics.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2021. Measuring Massive Multitask Language Understanding. *arXiv preprint arXiv:2009.03300v3*.
- Or Honovich, Thomas Scialom, Omer Levy, and Timo Schick. 2023. Unnatural Instructions: Tuning Language Models with (Almost) No Human Labor. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 14409–14428, Toronto, Canada. Association for Computational Linguistics.
- Huang Huang, Fei Yu, Jianqing Zhu, Xuening Sun, Hao Cheng, Dingjie Song, Zhihong Chen, Abdulmohsen Alharthi, Bang An, Ziche Liu, Zhiyi Zhang, Junying Chen, Jianquan Li, Benyou Wang, Lian Zhang, Ruoyu Sun, Xiang Wan, Haizhou Li, and Jinchao Xu. 2023. AceGPT, Localizing Large Language Models in Arabic. arXiv preprint arXiv:2309.12053v4.
- Go Inoue, Bashar Alhafni, Nurpeiis Baimukan, Houda Bouamor, and Nizar Habash. 2021. The Interplay of Variant, Size, and Task Type in Arabic Pre-trained Language Models. In *Proceedings of the Sixth Arabic Natural Language Processing Workshop*, pages 92–104, Kyiv, Ukraine (Virtual). Association for Computational Linguistics.
- Jiaming Ji, Tianyi Qiu, Boyuan Chen, Borong Zhang, Hantao Lou, Kaile Wang, Yawen Duan, Zhonghao He, Jiayi Zhou, Zhaowei Zhang, Fanzhi Zeng, Kwan Yee Ng, Juntao Dai, Xuehai Pan, Aidan O'Gara, Yingshan Lei, Hua Xu, Brian Tse, Jie Fu, Stephen McAleer, Yaodong Yang, Yizhou Wang, Song-Chun Zhu, Yike Guo, and Wen Gao. 2024. AI Alignment: A Comprehensive Survey. arXiv preprint arXiv:2310.19852v3.
- Atoosa Kasirzadeh and Iason Gabriel. 2022. In Conversation With Artificial Intelligence: Aligning Language Models With Human Values. *arXiv* preprint *arXiv*:2209.00731v2.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural Questions: A Benchmark for Question Answering Research. *Transactions of the Association for Computational Linguistics*, 7:453–466.

- Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Richárd Nagyfi, Shahul ES, Sameer Suri, David Glushkov, Arnav Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Mattick. 2023. OpenAssistant Conversations Democratizing Large Language Model Alignment. arXiv preprint arXiv:2304.07327v2.
- Haonan Li, Fajri Koto, Minghao Wu, Alham Fikri Aji, and Timothy Baldwin. 2023. Bactrian-X: A Multilingual Replicable Instruction-Following Model with Low-Rank Adaptation. *arXiv preprint arXiv:2305.15011*.
- Stephanie Lin, Jacob Hilton, and Owain Evans. 2021. TruthfulQA: Measuring How Models Mimic Human Falsehoods. *arXiv preprint arXiv:2109.07958*.
- Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V. Le, Barret Zoph, Jason Wei, and Adam Roberts. 2023. The Flan Collection: Designing Data and Methods for Effective Instruction Tuning. In *Proceedings of the 40th International Conference on Machine Learning*, ICML'23. JMLR.org.
- Maria Lopez-Medel. 2021. Gender Bias in Machine Translation: An Analysis of Google Translate in English and Spanish. *Academia.edu*.
- Reem I. Masoud, Ziquan Liu, Martin Ferianc, Philip Treleaven, and Miguel Rodrigues. 2023. Cultural alignment in large language models: An explanatory analysis based on hofstede's cultural dimensions. arXiv preprint arXiv:2309.12342v1.
- Swaroop Mishra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. 2022. Cross-Task Generalization via Natural Language Crowdsourcing Instructions. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3470–3487, Dublin, Ireland. Association for Computational Linguistics.
- Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng Xin Yong, Hailey Schoelkopf, Xiangru Tang, Dragomir Radev, Alham Fikri Aji, Khalid Almubarak, Samuel Albanie, Zaid Alyafeai, Albert Webson, Edward Raff, and Colin Raffel. 2023. Crosslingual Generalization through Multitask Finetuning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15991–16111, Toronto, Canada. Association for Computational Linguistics.
- Ranjita Naik, Spencer Rarrick, and Vishal Chowdhary. 2023. Reducing Gender Bias in Machine Translation through Counterfactual Data Generation. *arXiv* preprint arXiv:2311.16362v1.

- Tarek Naous, Michael J. Ryan, Alan Ritter, and Wei Xu. 2023. Having Beer after Prayer? Measuring Cultural Bias in Large Language Models. arXiv preprint arXiv:2305.14456v2.
- Naseej. 2023. Noon: A 7-Billion Parameter Arabic Large Language Model. Last accessed 2024-01-15.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback.
- Amandalynne Paullada, Inioluwa Deborah Raji, Emily M Bender, Emily Denton, and Alex Hanna. 2021. Data and its (dis) contents: A survey of dataset development and use in machine learning research. *Patterns*, 2(11).
- Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. 2023. Instruction Tuning with GPT-4. *arXiv preprint arXiv:2304.03277v1*.
- Vinodkumar Prabhakaran, Rida Qadri, and Ben Hutchinson. 2022. Cultural Incongruencies in Artificial Intelligence. *arXiv preprint arXiv:2211.13069v1*.
- Marcelo OR Prates, Pedro H Avelar, and Luís C Lamb. 2020. Assessing gender bias in machine translation: a case study with Google Translate. *Neural Computing and Applications*, 32:6363–6381.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Tali Bers, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M. Rush. 2022. Multitask Prompted Training Enables Zero-Shot Task Generalization. arXiv preprint arXiv:2110.08207v3.
- Neha Sengupta, Sunil Kumar Sahu, Bokang Jia, Satheesh Katipomu, Haonan Li, Fajri Koto, William Marshall, Gurpreet Gosal, Cynthia Liu, Zhiming Chen, Osama Mohammed Afzal, Samta Kamboj, Onkar Pandit, Rahul Pal, Lalit Pradhan, Zain Muhammad Mujahid, Massa Baali, Xudong Han, Sondos Mahmoud Bsharat, Alham Fikri Aji, Zhiqiang Shen, Zhengzhong Liu, Natalia Vassilieva, Joel Hestness, Andy Hock, Andrew Feldman, Jonathan Lee, Andrew Jackson, Hector Xuguang Ren, Preslav Nakov, Timothy Baldwin, and Eric Xing. 2023. Jais and Jais-chat: Arabic-Centric Foundation and Instruction-Tuned Open Generative Large Language Models. arXiv preprint arXiv:2308.16149.

- Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating Gender Bias in Machine Translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1679–1684, Florence, Italy. Association for Computational Linguistics.
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023. Stanford Alpaca: An Instruction-following LLaMA model. Last accessed 2024-01-15.
- Vishesh Thakur. 2023. Unveiling gender bias in terms of profession across llms: Analyzing and addressing sociological implications. *arXiv* preprint *arXiv*:2307.09162v3.
- Stefanie Ullmann and Danielle Saunders. 2021. Google Translate is sexist. What it needs is a little gendersensitivity training. Last accessed 2024-01-15.
- Bibek Upadhayay and Vahid Behzadan. 2023. TaCo: Enhancing Cross-Lingual Transfer for Low-Resource Languages in LLMs through Translation-Assisted Chain-of-Thought Processes. *arXiv preprint arXiv:2311.10797*.
- Krzysztof Wach, Cong Doanh Duong, Joanna Ejdys, Rūta Kazlauskaitė, Pawel Korzynski, Grzegorz Mazurek, Joanna Paliszkiewicz, and Ewa Ziemba. 2023. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, 11(2):7–30.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2023. Self-Instruct: Aligning Language Models with Self-Generated Instructions. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13484–13508, Toronto, Canada. Association for Computational Linguistics.
- Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Atharva Naik, Arjun Ashok, Arut Selvan Dhanasekaran, Anjana Arunkumar, David Stap, Eshaan Pathak, Giannis Karamanolakis, Haizhi Lai, Ishan Purohit, Ishani Mondal, Jacob Anderson, Kirby Kuznia, Krima Doshi, Kuntal Kumar Pal, Maitreya Patel, Mehrad Moradshahi, Mihir Parmar, Mirali Purohit, Neeraj Varshney, Phani Rohitha Kaza, Pulkit Verma, Ravsehaj Singh Puri, Rushang Karia, Savan Doshi, Shailaja Keyur Sampat, Siddhartha Mishra, Sujan Reddy A, Sumanta Patro, Tanay Dixit, and Xudong Shen. 2022. Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, pages 5085–5109, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2021. Finetuned Language Models Are Zero-Shot Learners. *arXiv* preprint arXiv:2109.01652v5.

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. 2023. WizardLM: Empowering Large Language Models to Follow Complex Instructions. *arXiv* preprint arXiv:2304.12244.

Yasbok. 2023. Alpaca Arabic Instruct. Last accessed 2024-01-15.

Yue Yu, Yuchen Zhuang, Jieyu Zhang, Yu Meng, Alexander Ratner, Ranjay Krishna, Jiaming Shen, and Chao Zhang. 2023. Large Language Model as Attributed Training Data Generator: A Tale of Diversity and Bias. *arXiv preprint arXiv:2306.15895v2*.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric. P Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. 2023. Judging LLM-as-a-judge with MT-Bench and Chatbot Arena. arXiv preprint arXiv:2306.05685v4.

#### A CIDAR Data Card

We adopt the same template used by the NLLB team (Costa-jussà et al., 2022).

### A.1 Data Description

- Dataset Summary: CIDAR is a 10k culturally aligned dataset adopted from AlpaGusus.
- Dataset Access: You can access CIDAR from Hugging Face Hub at hf.co/CIDAR.

#### A.2 Data Structure

Dataset is uploaded as a single file in parquet format with 3 features: instruction, output, and index.

#### A.3 Data Creation

- Source Data: The dataset was created by selecting around 9,109 samples from ALPA-GASUS dataset and then translating it using ChatGPT. In addition, we appended that with around 891 instructions from the website Ask the Teacher.
- Data Adoption: The 10,000 samples were reviewed by around 12 reviewers.

#### A.4 Considerations when using CIDAR

CIDAR is intended for research purposes only. The authors disclaim any responsibility for misuse and condemn any use contrary to Arabic culture or Islamic values. Even though subjected to human verification, there is no guarantee that responses are entirely aligned with Arabic culture and Islamic values. Users of the dataset are urged to exercise caution, employ critical thinking, and seek guidance from representative figures when necessary.

#### A.5 Additional Information

- Dataset Curators: *The authors of the paper.*
- Licensing Information: The dataset is released under CC-BY-NC. The text and copyright (where applicable) remain with the original authors or publishers, please adhere to the applicable licenses provided by the original authors.
- Citation Information: CIDAR Team et al, CIDAR: Culturally Relevant Instruction Dataset For Arabic, Arxiv, 2024.

## **B** Annotation App

The annotation app<sup>12</sup> contains two main parts for English and Arabic. Reviewers can make changes to Instruction, and Output to fix mistakes and align data with the Arabic culture. The original English instructions are shown to guide the reviewers for better re-annotation of the data. We have given the annotators 2 tasks (see Subsection 4.3) that they should take into consideration during the annotation process. We require the annotators to write their names in the bottom left corner. The annotators can use *Total Contributions* to keep track of their contributions to CIDAR and Remaining to keep track of the remaining samples to be reannotated. We also allow the annotators to observe the reviewed submissions<sup>13</sup> and track the distribution of contributions. The website is designed using the Flask framework<sup>14</sup>. The app regularly (every 1 hour) pushes the changes to the Hugging Face to save the progress. The website is deployed using Railway<sup>15</sup>.

<sup>&</sup>lt;sup>12</sup>Annotation App: https://alpacaarabic.railway.app.

<sup>&</sup>lt;sup>13</sup>Annotator Panel: https://alpacaarabic.railway.app/explore.

<sup>&</sup>lt;sup>14</sup>Flask Framework: https://flask.palletsprojects.com.

<sup>&</sup>lt;sup>15</sup>Railway: https://www.railway.app.

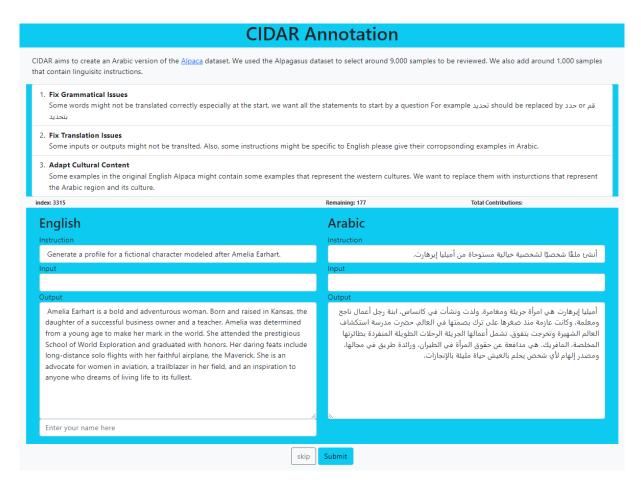


Figure 7: A screenshot of CIDAR Annotation App, showing its features. The annotators can use it to fix grammatical issues, fix translation issues, and culturally localize a given instruction and output pair from any given dataset.

### **C** Instruction Datasets

In Table 4, we showcase the main instructiontuning datasets that include Arabic subsets/versions from the literature. We highlight that to the best of our knowledge, all the datasets used to instructtuned Arabic LLMs are mostly machine-generated without human review or editing.

#### D Used Hyper-parameters

This section provides detailed specifications of the hyper-parameters used in the inference and fine-tuning of the ACEGPT-7B model.

Table 5 details the fine-tuning hyper-parameters employed to optimize the models' performance. It includes adjustments to learning rates, batch sizes, and regularization, alongside LoRA adaptations and precision formats. Specifically, we loaded the models in 4-bit precision and used for LoRa a low rank (r) of 16 and a scaling factor (alpha  $\alpha$ ) of 16.

In the inference setup, we used the text-generation pipeline from Hug-

gingFace<sup>16</sup> with the following hyper-parameters: max\_length=512 to constrain output length, temperature=0.2 for lower randomness favoring higher probability tokens, top\_p=1.0 and top\_k=0 allowing full probability distribution without restricting to top tokens, repetition\_penalty=1.2 to reduce repetition, and do\_sample=True to enable stochastic sampling. These settings were chosen carefully to balance coherence and context relevance, aligning with our objectives for high-quality and diverse linguistic output.

## **E** Example Outputs

In Table 6, we give some example outputs for a few given Arabic instructions generated by the three evaluated models (ACEGPT\CIDAR, ACEGPT\ALPAGASUS, and ACEGPT\CHAT) used in this study, like 'How did our language originate? 'کیف نشأت لغتنا? 'To prevent any bias, we use the same inference parameters for

<sup>&</sup>lt;sup>16</sup>Pipelines: https://hf.co/docs/transformers/main\_classes/pipelines.

Table 4: Collection of Arabic instruction-tuning datasets discussed in the literature (Section 2), highlighting their Arabic instructions count, dataset collection, type (multilingual or monolingual), and access status (open or closed).

Dataset Name	Size (ar)	Dataset Collection	Type	Status
xP3 (Muennighoff et al., 2023)	2,148,955	Prompts applied to multiple datasets		
MSIFT (Chen et al., 2023c)	114,231	Translated using GPT4: Alpaca-GPT4, Evol-Instruct, ShareGPT		
OASST1 (Köpf et al., 2023)	666	Conversational data was collected using a web app interface and obtained through crowd-sourcing.	Multilingual	Open
xP3x (Muennighoff et al., 2023)	18,246,158	An extended large version of the xP3 dataset with multi-dialectal Arabic instructions, besides the Modern Standard Arabic instructions.		
SUPNATINST (Wang et al., 2022)	80,396	A large benchmark was collected through a large community effort on GitHub with the help of university students and NLP practitioners.		
MITD (Upadhayay and Behzadan, 2023)	81,451	A composed multilingual instruction-tuning dataset from Alpaca-GPT4, Databricks' Dolly, and Vicuna Benchmark in 132 languages, including Arabic, was translated using Google Cloud Translation.		
Bactrian-X (Li et al., 2023)	67,017	Translated Alpaca using Google Translate then Feed to GPT3.5 Turbo.		
alpaca-arabic-instruct (Yasbok, 2023)	52,002	Alpaca translated using Google Translate		
Jais Instructions (Sengupta et al., 2023)	3,683,144	xP3-Ar, Super-NaturalInstructions-Ar, Baize-Ar, Unnatural-Ar, Natural Questions-Ar, Bactrian-Ar, Alpaca-Ar, SafetyQA-Ar, NativeQA-Ar, Dolly-Ar, HC3-Ar, NER-Ar, Basic-Conv-Ar		pç
AceGPT Instructions (Huang et al., 2023)	363,155	Quora-Arabic, Alpaca-Arabic, Code-Alpaca-Arabic, Evol-Instruct-Arabic, ShareGPT.	Monolingual	Closed
AlGhafa Instructions (Almazrouei et al., 2023)	1,459,000	xP3-Ar, Bactrian-Ar, Alpaca-Ar, UltraChat-Ar		
Noon Instructions (Naseej, 2023)	110,000	Alpaca Instructions GPT4, Self-instruct records, Databricks, TruthfulQA, Grade School Math, Arabic-arithmetic-ChatGPT		
Phoenix Instructions (Chen et al., 2023b)	8,000	A collection of translated Alpace instructions using GPT-4 to Arabic with a mixture of Arabic-generated responses for the GPT-4 translated instructions using GPT-3.5 Turbo.		

Table 5: List of the fine-tuning parameters for the models fine-tuned on CIDAR and the translated ALPAGASUS.

Parameter	Value Parameter		Value	
lora_r	16 lora_alpha		16	
lora_dropout	0.1 bnb_4bit_compute_dtype		"bfloat16"	
bnb_4bit_quant_type	"nf4"	bf16	True	
num_train_epochs	3	per_device_train_batch_size	2	
per_device_eval_batch_size	2	gradient_accumulation_steps	1	
gradient_checkpointing	True	max_grad_norm	0.3	
learning_rate	2e-4	weight_decay	0.001	
optim	"paged_adamw_32bit"	warmup_ratio	0.03	
group_by_length	True			

all the models. Furthermore, we do not generate multiple outputs or cherry-pick specific outputs for the same instruction. We provide the outputs considering various topics, like clothes, fonts, food and drinks, language, grammar, and traditions. It is clear that the examples provided show

that ACEGPT\CIDAR can better capture the culture compared to the ACEGPT\CHAT, which was fine-tuned on hundreds of thousands of instructions, whereas ACEGPT\ALPAGASUS produces the worst results in terms of cultural relevance and grammar.

# أقترح لباس لتغطية الرأس

معظم الناس يفضلون ارتداء قبعة، شال، كاب، أو خوذة. إذا كنت تبحث عن شيء أكثر إبداعًا، جرب ارتداء قبعة صوف، قبعة قش، أو قبعة زهرة. بالنسبة للأشخاص الذين يرغبون في تغطية رؤوسهم بشكل أكثر تحفظًا، فإن قبعة قش أو قبعة زهرة هي الخيار الأفضل. وبالنسبة للأشخاص الذين يرغبون قي تغطية رؤوسهم بشكل أكثر إبداعًا، فإن قبعة صوف أو قبعة قش هي الخيار الأفضل. وبالنسبة للأشخاص الذين يرغبون في تغطية رؤوسهم بشكل أكثر تحفظًا، فإن قبعة قش أو قبعة زهرة هي الخيار الأفضل.

1. Hat - A hat is a great option for covering your head and protecting it from the sun or wind while you're outdoors, such as on a hike in nature. It can also be worn indoors to keep warm during colder months of the year.

وهناك عدة أنواع من الشماغ، إذا كان لديك خيار في اللون فالأفضل اختيار الأزرق أو الأصفر أو الأحمر أو الأسود. وإذا كان لديك خيار في النوع فالأفضل اختيار الشماغ الثقيل (الجوخ) والمزخرف بالآيات القرآنية أو الأحاديث النبوية. وإذا كان لديك خيار في الحجم فالأفضّل اختيار الشماغ الكبير والواسع. ويمكن ارتداء الشماغ بطريقتين: 1-وضعه على الرأس من الأمام ورفع الطرف الأمامي على الجبهة؛ 2- وضعه على الرأس من الخلف ورفع الطرف الأمامي على الجبهة. ويمكن ارتداء الشماغ مع غطاء للرأس مثل الطاقية أو القبعة أو القلنسوة أو العمامة أو الكوفية.

## أقترح ليا نوع خط مناسب للكتابة على الحائط

إذا كنت تبحث عن نوع خط جديد للكتابة على الحائط، فأنصحك بالنظر في Pro. Myriad هذا الخط مشهور للعين، وهو مثالي للكتابة على الحائط. كما أنه يضم مجموعة واسعة من الخطوط والأنماط المختلفة، مما يجعله خيارًا مثاليًا لأى غرفة. بالإضافة إلى ذلك، فإن Pro Myriad متوافق مع Windows و X OS Mac و Linux مما يجعله خيارًا مثاليًا لأي مستخدم. بشكل عام، إذا كنت تبحث عن خط جديد للكتابة على الحائط، فإن Pro Myriad هو خيار مثالي!

هذا يعتمد على الجو العام في الغرفة. إذا كان الجو كلاسيكيًا، فقد يكون "Serfi" أو "Georgia" خيارًا جيدًا. بشكل خاص بشكله الأنيق والمريح إذا كان الجوحديثًا وبسيطًا، فقد يكون "Arial" أو Arial" خيارًا أفضل. أما إذا كان الجو مسترخيًا و دافئًا، فه "Baskerville" أو "Lobster" قد يكون مناسبًا.

الخط الذي أفضله للكتابة على الجدران هو "الثلث"، إذ يعد من أشهر وأجمل الخطوط العربية. وهو خط متصل ومتزن ومتناظر ومناسب للكتابة على الجدران وغيرها من المساحات الكبيرة. كما أنه يعطى مظهرًا جماليًا وأنيقًا للجدران. ويمكن استخدامه بأشكال مختلفة وأحجام متنوعة لإضفاء لمسة جمالية على المكان.

# أخبرني عن مشروب منتشر بين الناس في المجتمع

متيقظًا ومنتجًا. يتم تناول القهوة في جميع أنحاء العالم ويتم تقديمها بطرق مختلفة - من القهٰوة التُقليدية إلى قهوة الآيس كريم!

مشروب منتشر بين الناس في المجتمع | هنالك العديد من المشروبات المنتشرة هو القهوة. إنها مشروب لذيذ وحلوى ابين الناس، لكن أحد الأمثلة المشهورة ومثالية للصباح، كما أنها مشروب غني | هو "القهوة". القهوة مشروب مُحبّ بالطاقة ويمكن أن تساعد على البقاء | ومُنتشر في جميع أنحاء العالم. إنها غنية بالكافيين وتُستخدم عادةً لزيادة الطاقة والتركيز. بالإضافة إلى ذلك، تُستهلك القهوة في مختلف الأوقات من اليوم -صباحاً, ظهراً ومساءً.

لطيفة للمشروبات الغازية والعصائر. #الكركديه\_المثلج

الكركديه. لذة حقيقية وصحية. إضافة

## حدد خطوات تجديد البطاقة الشخصية

1. إعلام دائرة الأحوال المدنية بالتغييرات الهامة، مثل الزواج أو الطلاق، في غضون 30 يوماً. 2. تسليم طلب تجديد البطاقة الشخصية إلى دائرة الأحوال المدنية. 3. تَقديم الوثائق المطَّلوبة، مثل شهادة الميلاد والمستندات الأخرى المؤكدة للهُوية. 4. دفع رَسُوم تَجَديد البطاقة الشخصية. 5. استلام البطاقة الشخصية الجديدة من دائرة الأحوال المدنية. 6. تسليم البطاقة الشخصية القديمة إلى دائرة الأحوال المدنية. 7. تقديم طلب لإلغاء البطاقة الشخصية القديمة. 8. تقديم طلب لإصدار بطاقة شخصية جديدة. 9. دفع رسوم إصدار البطاقة الشخصية الجديدة. 10. استلام البطاقة الشخصية الجديدة

زر الموقع الإلكتروني •1 للهيئة الحكومية المعنية (او السفارة/القنصلية، إذا كانت بطاقتك ضمن متطلبات التجديد). 2. ابحث عن "تجديد البطاقة الشخصية" أو "تغيير / تجديد البطاقة". 3. اتبع الروابط المؤدية إلي 'التجديد' أو التغيير'. 4. سجّل الدخول إلى حسابك (إذا كان لديك واحد) واتبع الإرشادات المقدمة. 5. قد تحتاج إلى إرسال بعض المستندات -مثل صورة بطاقتك الشخصية الحالية، وثائق الهوية، وغيرها من المستندات المطلوبة. 6. اتبع الخطّوات المتبقية حتى تتم عملية التجديد. 7. تأكد من تلقى تأكيد على تجديد بطاقتك الشخصية.

1. زرنا مكتب الأحوال المدنية في السعودية لإصدار بطاقة هوية جديدة. 2. قدمنا جواز السفر والصور الشخصية والمستندات الثبوتية الضرورية، مثل شهادة الميلاد وشهادة الجنسية وغيرها من الوثائق المؤكدة للهوية. 3. دفعنا الرسوم المستحقة لإصدار البطاقة الجديدة. 4. انتظرنا حتى تم إصدار البطاقة الجديدة وتسلمناها. وفي بعض الحالات، يمكن تسليم البطاقة في غضون بضع دقائق في حين يمكن أن يستغرق ذلك من بضعة أيام إلى أسبوع في حالات أخرى. 5. تأكدنا من أن جميع المعلومات المدخلة في البطاقة صحيحة ومطابقة للوثائق المقدمة وتم توقيع البطاقة من قبل الموظف

## كيف نشأت لغتنا؟

نشأت اللغة عبر مئات الآلاف من السنين، وهذا جزء من طبيعة الإنسان. قد يكون الناس قد بدأوا في صنع الأصوات والضحك والتواصل معًا قبل ظهور اللغة المكتوبة. ثم تطورت اللغة على مر السنين من خلال التفاعل والتبادل بين الناس في جميع أنحاء العالم. وقد لعبت الثقافة والتكنولوجيا دورًا في تطوير اللغة، مما أدى إلى ظهور لغات تجديدة وتطور اللغات القديمة. وقد سأهمت اللُّغة في تطوير التواصُّل والتفاعل بين الناس وتمكين التعاون والتعاطف والتفاهم.

معظم البحوث تقترح أن اللغة تطورت بالتدريج. بدأت بأصوات بسيطة، مثل الزئير والهرير، وتطورت إلى أشكال أكثر تعقيدًا من التواصل. في المراحل الأخيرة من التطور، بدأ الناس في تعلم كيفية استخدام الكلمات والجمل للتعبير عن الأفكار والمشاعر. هذا التطور في اللغة مستمر، مع ظهور لهجات ولغات جديدة على مر الزمن.

العربية هي اللغة الوحيدة المسجَّلة ضمن اللغات الخمس الأصلية في الإعلان العالمي لحقوق الإنسان، وهذا يعطيها مكانةً خاصة. وقد ظهرت هذه اللغة في شبه الجزيرة العربية في القرن السابع الميلادي وانتشرت في العالم الإسلامي ثم في العالم كله. وقد أثرت هذه اللغة في اللغات الأخرى وتأثرت بها في الآنَّذاك. وتعتبر اللغة العربية من أكثر اللغات انتشارا في العالم الإسلامي وفي بعض الدول الأفريقية والأوروبية. وتستخدم هذه اللغة في الأدب والشعر والفنون والعلوم والتكنولوجيا والإعلام والسياسة والاقتصاد والتجارة والأعمال المختلفة.

## اعرب الجملة التالية: سبق السيف العذل.

سبق السيف العذل. (السيف -فاعل، العذل - مفعول)

"سبق السيف العذل" هو نص شعري، أو "كلام حكيم". إنه يُظهر أن الخطوة المتقدمة (السيف) قد تغلب على الضعف أو التردد (العذل).

- سُبْقُ: فعل ماض ناسخ، وهو مبنيّ على الفتح.- السيفُ: فاعل "سَبْقَ" مرفوع بدلا من الضمير (ه).- العذل: مفعول به أول لـ"سَبْقَ".- ثمّ: ظرف زمان متعلق بـ"سَبْقَ".- السيفُ: شبه جملة في محل رفع خبر لـ"سُبْقُ".- الإعراب: سَبْقَ السيفُ العذلَ. والجملة في محل رفع خبر لـ"سُبْقُ".- الخبر: كان.وجملة "كان" في محل نصب خبر لـ"سَبْقُ".-المبتدأ: السيف.

## شكل الجملة التالية: من ذا الذي ماساء قط ومن له الحسني فقط.

من ذا الذي ماساء قط، ومن له الحسني فقط؟ "الحسني" هنا عبارة غير صحيحة إملائياً - "حسني". (أخطاء إملائية أخرى تشمل "حسني", "حسنى"٠)

اً أعتذر، ولكن بصفتي AI، ليس لدي مَنْ ذُوِّ الذِي مَا سَاءَ قطَّ وَمَنْ لَهُ القدرة على إظهار الْحُطَّأُ في جَمَّلَةً غير الْحَسْنَى فَقَطُّ؟! مكتملة أو غير واضحة. يرجى تقديم مزيد من التفاصيل أو توضيح السؤال.

## اقترح اسما لعلامة تجارية جديدة لبيع العطور

"Scentiments" - فكرة هذا الاسم هي أن العطور يمكن أن تخلق شعورًا إيجابيًا. العطور هي صناعة تزدهر، لذلك يجب أن يكون الاسم غير مستهلك ويعكس هذا المضمون. يجب أن يكون الاسم مثيرًا ويجذب العملاء للتعرف على المزيد عن العطور. يجب أن يكون الاسم ذو معنى ويؤدي إلى تجربة ممتعة للعملاء. يجب أن يكون الاسم متناسقًا مع علامة -Scen timents التجارية ويعكس قيمها. يجب أن يكون الاسم سهل التذكر ويمكن تذكره بسهولة. يجب أن يكون الاسم مثيرًا ولا يتم نسيانه. يجب أن يكون الاسم متناسقًا مع علامة -Scen timents التجارية ويعكس قيمها.

1. Vie" de "Eau (الفرنسية لا Lfie") of "Water أنيق، وهو يشير إلى الخصائص الغنية والزكية للعطور. 2. Aroma ("Lfie tae" "Aroma أوالزكية للعطور. 3. Aroma" ("Lfie tae" يضيف لمسة من الرومانسية والجاذبية "Senso 3. التجارية. 3. Senso - هذا الاسم لعكس التركيز على تجربة العطر الكاملة, من الرائحة إلى الإثارة، 4. Odore الماسم أن الرائحة إلى الإثارة، 4. Odore الأسم يظهر التركيز على الحياة هذا الاسم يظهر التركيز على الحياة والحيوية والرائحة الجميلة. 5. Fleur أوالحيوية والرائحة الجميلة. 5. Fleur أوالحيوية التي تأتي من الرائحة الجيدة.

الأصيل. فهذا الاسم شائع وينقل إحساسًا بالثقة والجودة. كما أنه يخلق انطباعًا بأن منتجات العطور ذات جودة عالية ومصنوعة بعناية فائقة. بالإضافة إلى ذلك، فإن الاسم غير مستخدم بالفعل من قبل أي علامة تجارية أخرى، مما يزيد من فرص نبقل انطباعًا بالأصالة والتقليدية، مما ينقل انطباعًا بالأصالة والتقليدية، مما ليعلم مثاليًا لعلامة تجارية تركز على العطور الفاخرة والتقليدية. وبالتالي، فإن "الأصيل" هو اسم مثالي لعلامة تجارية جديدة لبيع العطور.

## اقترح لي عبارات مناسبة لتعزية صديقى في وفاة والده

"أنا آسف، كنت أعلم أن الجميع يحبك. إذًا هناك شيء يمكنني فعله، فلا تتردد في الاتصال."

1. "أعظم التعازي لك ولعائلتك في هذا الوقت الصعب." 2. "إن وفاة والده خسارة كبيرة، فليجد الراحة في ذكرياته الجيدة." 3. "أشعر بالأسي لسماع هذا الخبر، إنه خسارة غير قابلة للتعويض." 4. "أتقدم بأحر التعازي لك ولعائلتك في هذا الأوقات المحزنة." 5. "إن وفاة والده حدث أليم، فليجد الراحة في دعم الأصدقاء والعائلة."

أسأل الله أن يغفر له ويرحمه، وإنا لله وإنا إليه راجعون. خالص التعازي لكم ولذويه. نسأل الله أن يربط على قلوبكم ويلهمكم الصبر والسلوان. إنا لله وإنا إليه راجعون. نشاطركم الأحزان ونؤكد لكم أن وفاة والدكم خسارة للجميع. نسأل الله أن يرحمه ويغفر له ويسكنه قلوبكم ويلهمكم الصبر والسلوان. إنا لله قلوبكم ويلهمكم الصبر والسلوان. إنا لله ويغفر له ويسكنه فسيح جناته. نسأل الله أن يرحمه ويغفر له ويسكنه فسيح جناته.

# أخبرني عن العرف الرسمى للزواج في المنطقة

تختلف العروض الرسمية للزواج حسب التقاليد والأعراف الرسمية للزواج الثقافة. في الهند، غالبًا ما يكون العرف الرسمي للزواج هو "شوباد" (Saptapadi) وهو إعلان صريح بالزُواج من قبل العروس والعريس. الزواج من السلطات المحلية، وحضور إصدار ً بيان رسمي بالزواج وتوجيه في الوَّلايات المتحدة، يتضمن العرف حفلٌ زفاف رسمي مع العائلة الرُّسمَى للزواج عادة عقد قانوني وحفل | والأصدقاء. في بعض الثقافات، قد زفافٌ وربماً حفل استقبال. في ا بعض الثقافات، يمكن أن يتضمن ذلك طقوس أخرى مثل الاحتفالات والطقوسُ الدينية. في العديد من الْثقافات، يتم تنظيم الّعرف الرسمي للزواج من قبل الأسرة والأصدقاء والمجتَّمع. في بعض الثقافات، يتم تنظيمه من قبل الحكومة أو مؤسسة محلية أخرى.

يتضمن العرف الرسمى للزواج هدايا محددة تُقدم للعروس و/أو العريس (مثل الذهب أو الأغذية). في بعض المناطق، قد يتضمن العرف الرسمي للزواج طقوس دينية معينة.

من الأفضل دائمًا التحقق من العادات والتقاليد الخاصة بالمنطقة التي تنظر فيها للزواج للتأكد من أنك تحترم ثقافتهم وتقاليَّدهم في هذه المراسم الهاَّمة.

العرف الرسمي للزواج هو تحديد موعد تختلف كثيرًا من منطقة إلى أخرى. إشهار الزواج. وغالبًا ما يكون في بعض المَّناطق، قد يشمَّل العرف | ذلك بعد اتفاق الطرفين على موعد الرسمي للزواج الحصول على رخصة اثابت واعلانه للآخرين، ويتضمن ذلك الدعوات للحضور. ويمكن أن يتم ذلك بطرق مختلفة وفقًا للظروف والثقافة المحلية. ويعد هذا الإعلان مؤشرًا على بدء حياة جديدة وانتهاء حياة العزوبية. ويُعتبر هذا الإعلان رسميًا ويتم توثيقه في السجلات الرسمية للزواج. ويتم تحديد موعد الزواج وفقًا للتقاليد والأعراف المحلية والدينية والثقافية والاجتماعية.

Table 6: Example outputs for a few given Arabic instructions generated by the three evaluated models (ACEGPT\CIDAR, ACEGPT\ALPAGASUS, and ACEGPT\CHAT) used in this study. We note that some sentences have been truncated for better readability.