## MEGAVERSE: Benchmarking Large Language Models Across Languages, Modalities, Models and Tasks

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## **Abstract**

Recently, there has been a rapid advancement in research on Large Language Models (LLMs), resulting in significant progress in several Natural Language Processing (NLP) tasks. Consequently, there has been a surge in LLM evaluation research to comprehend the models' capabilities and limitations. However, much of this research has been confined to the English language, leaving LLM building and evaluation for non-English languages relatively unexplored. There has been an introduction of several new LLMs, necessitating their evaluation on non-English languages. This study aims to expand our MEGA benchmarking suite by including six new datasets to form the MEGA-VERSE benchmark. The benchmark comprises 22 datasets covering 81 languages, including low-resource African languages. We evaluate several state-of-the-art LLMs like GPT-3.5-Turbo, GPT4, PaLM2, and Llama2 on the MEGAVERSE datasets. Additionally, we include two multimodal datasets in the benchmark and assess the performance of the LLaVav1.5 model. Our experiments suggest that GPT4 and PaLM2 outperform the Llama models on various tasks, notably on low-resource languages, with GPT4 outperforming PaLM2 on more datasets than vice versa. However, issues such as data contamination must be addressed to obtain an accurate assessment of LLM performance on non-English languages.

## 1 Introduction

Large Language Models (LLMs) have surpassed the performance of older language models on several tasks and benchmarks, sometimes even approaching or exceeding human performance. However, it is not always clear whether this is due to the increased capabilities of these models, or other effects, such as artifacts in datasets, test dataset contamination, and the lack of datasets that measure the true capabilities of these models. Thus, evaluation of Large Language Models has become

an important field of study.

Most of the work on evaluating LLMs via benchmarking (Liang et al., 2022), qualitative tests for specific capabilities (Bubeck et al., 2023) or human evaluation have focused on English. However, studies have shown that there is a large gap between the capabilities of LLMs in English and other languages (Choudhury et al., 2023). Evaluation of LLMs in languages other than English is challenging due to a variety of factors, including the lack of benchmarks covering a large number of languages from diverse language families and the lack of multilingual benchmarks covering tasks such as reasoning, chat, and dialogue. Due to the small number of datasets available, test data contamination becomes even more of a hurdle. Therefore, it is crucial to prioritize multilingual evaluation to enhance the development of more effective multilingual models. Neglecting this critical aspect may result in a significant population being left behind and widen the digital divide.

Our prior work on performing a comprehensive benchmarking of LLMs across 16 datasets and 71 languages MEGA - Multilingual Evaluation of Generative AI (Ahuja et al., 2023) yielded the following observations: the largest model that we evaluated, GPT4 (OpenAI, 2023) comes close to but in most cases does not surpass the performance of SOTA fine-tuned language models such as TULRv6 (Patra et al., 2023). GPT models also perform worse in languages that are written in scripts other than the Latin script, and on low-resource languages. Other LLMs that we tested, such as BLOOMZ (Muennighoff et al., 2023) performed worse than GPT4 except on tasks that they had been fine-tuned on.

Several new models have been introduced since our previous work on MEGA. There is also growing interest in multimodal LLMs, and the intersection of multimodal and multilingual LLMs has not been well studied. In this work, we present an extension of our MEGA benchmarking study, which we refer to as MEGAVERSE.

Our contributions are as follows:

- We introduce six new benchmarks into our MEGA benchmarking suite, thus extending coverage to 22 datasets and 81 languages including many low-resource African languages.
- We benchmark five new SOTA LLMs PaLM2 (Google, 2023), Llama2 (3 variants) (Touvron et al., 2023) and LLaVA-v1.5 (Liu et al., 2023a), in addition to GPT4 and GPT-3.5-Turbo.
- We benchmark the multimodal LLaVA-v1.5 model (Liu et al., 2023a) on two new multilingual multimodal datasets.
- We present results and an analysis of trends across these models with directions for future research.

## 2 Related work

## 2.1 Evaluation of LLMs

Recently, there has been an increasing interest in evaluating LLMs on a wide range of capabilities, given the surge in their popularity and effectiveness. BIG-bench by Srivastava et al. (2023) consists of 204 tasks to evaluate LLMs consisting of a diverse range of problems to evaluate the capabilities of LLMs. While BIG-bench includes tasks in non-English languages as well, they are largely related to translation. Liang et al. (2022) proposed Holistic Evaluation of Language Models (HELM) defining a taxonomy of scenarios (tasks, domains, and languages) and metrics (eg. accuracy, calibration, toxicity) that define the space of LLM evaluation, and evaluate 30 language models on 42 scenarios and 7 metrics. However, all the scenarios are focused on datasets in standard English or dialects, and they highlight coverage of languages as an important area for improvement. Recent work (Bubeck et al., 2023), has pointed out the limitations of using standard NLP benchmarks to evaluate generative models, due to the pace at which these benchmarks become saturated. There are also concerns about benchmark contamination in LLM evaluation. Zhou et al. (2023) show that test dataset contamination in training and fine-tuning data lead to a significant impact in LLM performance.

## 2.2 Multilingual Benchmarks and Evaluation

Bang et al. (2023) evaluates the multilingual capabilities of ChatGPT and shows that it fails to generalize to low-resource languages with nonlatin scripts. However, multilingual evaluation is performed only on a few tasks, and a subset of 50-100 examples are used for testing the model. Hendy et al. (2023) evaluate the translation abilities of GPT-3.5 models and find that these models, while performing well in translating high-resource languages, their capabilities for low-resource languages are limited. BUFFET (Asai et al., 2023) covering 54 languages across 15 datasets and Lai et al. (2023) covering 37 languages across 7 datasets also perform multilingual benchmarking of large language models such as ChatGPT and BLOOMZ.

Our benchmarking suite MEGA is extended in MEGAVERSE to encompass 6 new datasets, among which are two multimodal datasets. Furthermore, we conduct benchmarking on state-of-the-art language models such as PaLM2 and Llama2, and compare the latest LLMs in terms of their multilingual performance.

## 3 Experimental Setup

#### 3.1 Datasets

We perform experiments on the 16 datasets that are part of the MEGA suite - XNLI (Conneau et al., 2018), IndicXNLI (Aggarwal et al., 2022), GLUECoS NLI (Khanuja et al., 2020), PAWS-X (Yang et al., 2019), XCOPA (Ponti et al., 2020), XStoryCloze (Lin et al., 2022), GLUECoS Sentiment Analysis (En-Es-CS) (Vilares et al., 2016), TyDiQA-GoldP (Clark et al., 2020), MLQA (Lewis et al., 2020), XQUAD (Artetxe et al., 2020), IndicQA (Doddapaneni et al., 2023), PAN-X (Pan et al., 2017), UDPOS (Nivre et al., 2018), Jigsaw (Kivlichan et al., 2020), WinoMT (Stanovsky et al., 2019) and XLSum (Hasan et al., 2021). These datasets include a mix of classification, Question Answering, Sequence Labeling, and Natural Language Generation datasets, along with two datasets covering the Responsible AI tasks of toxicity detection and bias. The datasets we include also contain a mix of translated datasets verified by native speakers, as well as datasets created independently for each language. For a more detailed description of the datasets included in the original MEGA paper, we refer the readers to Ahuja et al. (2023). We describe the 6 datasets added to MEGAVERSE

Dataset	GPT4	GPT-3.5-Turbo	PaLM2	Llama2-7b	Llama2-13b	Llama2-70b
XNLI	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
IndicXNLI	<b>√</b>	<b>√</b>	×	<b>√</b>	<b>√</b>	<b>√</b>
GLUECoS NLI	<b>√</b>	<b>√</b>	✓	×	×	×
PAWS-X	✓	✓	✓	<b>√</b>	<b>√</b>	<b>√</b>
XCOPA	✓	✓	<b>√</b>	✓	<b>√</b>	<b>√</b>
XStoryCloze	<b>√</b>	✓	✓	✓	✓	✓
En-Es-CS	<b>√</b>	✓	<b>√</b>	×	×	×
TyDiQA-GoldP	✓	✓	✓	✓	✓	<b>√</b>
MLQA	✓	✓	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
XQUAD	<b>√</b>	<b>√</b>	✓	<b>√</b>	✓	<b>√</b>
IndicQA	<b>√</b>	<b>√</b>	×	<b>√</b>	<b>√</b>	✓
UDPOS	<b>√</b>	✓	<b>√</b>	×	×	×
PANX	<b>√</b>	✓	✓	×	×	×
WinoMT	×	✓	×	×	×	×
Jigsaw	×	✓	×	×	×	×
XLSUM	<b>√</b>	✓	<b>√</b>	✓	<b>√</b>	✓
Belebele	✓	✓	<b>√</b>	✓	✓	✓
AfriQA	✓	<b>√</b>	×	✓	<b>√</b>	<b>√</b>
IN22	<b>√</b>	<b>√</b>	×	×	×	<b>√</b>
X-RiSAWOZ	<b>√</b>	<b>√</b>	<b>√</b>	×	×	✓

Table 1: Experimental details per dataset and model. Some languages are not supported by some of the models, due to which experiments on those datasets are not performed, and some models are skipped due to resource constraints. We also evaluate LLaVA-v1.5 on MaRVL and XM-3600 datasets to extend our evaluation and analysis across modalities.

below.

## 3.1.1 Belebele

Belebele (Bandarkar et al., 2023) is a multiple choice machine reading comprehension (MRC) dataset is parallel across 122 languages. Each question is linked to a short passage from the FLORES-200 dataset (Team et al., 2022). The questions were created by human annotators and the human annotation procedure was carefully curated to create questions that discriminate between different levels of language comprehension. This process was reinforced by extensive quality checks. In this paper, we evaluated Arabic, Czech, Danish, German, English, Spanish, Finnish, French, Hebrew, Hungarian, Italian, Japanese, Korean, Dutch, Norwegian, Polish, Portuguese, Russian, Swedish, Thai, Turkish, Chinese Simplified and Chinese Traditional. We evaluated GPT4 and PaLM2 and results for Llama2 and GPT-3.5-Turbo are reported from the dataset paper.

**Prompt:** We evaluated our models on zero-shot prompting using instructions proposed by Ban-

darkar et al. (2023) <sup>1</sup>.

```
Task Instruction \mathcal{I}:You are an AI assistant whose purpose is to perform reading comprehension task. Given the following passage, query, and answer choices, output the letter corresponding to the correct answer.

Template f_{temp}: {instruction} ### Passage: {passage} ### Query: {query} ### Choices: (A) {A} {B} {B} (C) {C} (D) {D} ### Answer:
```

Figure 1: Belebele MRC Prompt

We perform zero-shot monolingual prompting for our experiments, as this dataset does not have a dev set.

<sup>1</sup>https://github.com/EleutherAI/
lm-evaluation-harness/pull/885

## 3.1.2 AfriQA

AfriQA (Ogundepo et al., 2023) is a Question Answering dataset that does not have a context passage. It covers 10 African languages - Bemba, Fon, Hausa, Igbo, Kinyarwanda, Swahili, Twi, Wolof, and Yorùbá. We use the few-shot size of k=4 and the monolingual prompting strategy for this dataset and perform experiments on the GPT and Llama models, as the PaLM2 model only supports Swahili.

```
Task Instruction \mathcal{I}: You are an NLP assistant trained to answer questions directly. For each question provided, respond with the most accurate and concise answer. The answer should be in the same language as the question. Template f_{temp}:
```

Template  $f_{temp}$  Q: {question} A: {answer}

Figure 2: AfriQA Prompt

## 3.1.3 XRiSAWOZ

XRiSAWOZ (Moradshahi et al., 2023) is a (domain specific) task oriented dialogue modeling dataset. The dataset is a multilingual (English, Hindi, French, Korean) translation of RiSAWOZ dataset (Quan et al., 2020) which was Chinese. XRiSAWOZ also includes an English-Hindi code mixed setting.

Each dialogue in XRiSAWOZ is confined to a narrow domain and the conversation agent must make use of structured knowledge available in the database to answer user queries. We refer the reader to Moradshahi et al. (2023) for more details and only present the summary of 4 subtasks below:

- Dialogue State Tracking (DST): Generate "belief state" (represented with a semi-structured, SQL-like language) of the agent for the current turn based on (agent's) previous belief state, last 2 (agent's) dialogue acts and current user utterance.
- API Call Detection (API): Detect whether an API call to query the domain-specific database is necessary for the current dialogue state.
- Dialogue Act Generation (DA): Generate "dialogue act" (also represented with a semi-structured language) based on the current belief state, last 2 agent dialogue acts, user utterance as well as the result of an API call.
- Response Generation (RG): Generate natural language response from the current dialogue act.

There are about 4000 dialogue turns per setting in the dataset, each of which needs to be evaluated for the 4 above subtasks requiring 16000 model evaluations per language. Due to limited compute, we currently present the results only on 10% of data i.e. about 400 dialogue turns across 3 domains. The prompts used for this dataset are presented in Section 3.3.

#### 3.1.4 IN22

IN22 (Gala et al., 2023) is a translation benchmark for all 22 scheduled Indic languages which is offered in two flavors, IN22-Gen and IN22-Conv. IN22-Gen is a general-purpose multi-domain evaluation subset of IN22 which has been curated from two sources: Wikipedia and Web Sources offering diverse content spanning news, entertainment, culture, legal, and India-centric topics. IN22-Conv is the conversation domain subset of IN22 and is designed to assess translation quality of day-today conversations. The General subset consists of 1024 sentences translated across 22 Indic languages while the Conversational benchmark has 1503 sentences translated in the same manner, enabling evaluation in 506 directions. Since it is not feasible to evaluate all 22 languages due to resource constraints, we select the following 14 languages: Assamese, Bengali, English, Gujarati, Hindi, Kannada, Kashmiri, Malayalam, Marathi, Nepali, Odia, Punjabi, Tamil, Telugu, Urdu. The following prompt was employed for the translation task:

You are an AI assistant whose purpose is to perform translation. Given the following sentence in {source}, translate it to {target}. If you cannot translate the given sentence to {target}, just return "\*\*\*\*\*\*\*\*\*\*\* (10 asterisks)

Figure 3: Translation Prompt

#### 3.1.5 MaRVL

MaRVL (Multicultural Reasoning over Vision and Language) (Liu et al., 2021) is a dataset of images and associated captions. The concepts and images collected were entirely driven by native speakers and are representative of various cultures across the globe and span 5 languages, i.e., Indonesian, Chinese, Swahili, Tamil, Turkish. Each instance in the dataset consists of a pair of images (left image and right image) and a statement, and the task is to determine whether the statement is consistent with respect to the given pair of images. The following prompt was employed for MaRVL:

Presented below are two distinct images placed side by side and a below caption in {language}. Analyze the images carefully and then read the below provided caption. Your task is to determine whether the caption accurately and truthfully describes the content, details, and scenario depicted in both images. Consider all visible elements, expressions, interactions, and any potential nuances that may influence the accuracy of the caption. Return 'TRUE' if the caption is true, and 'FALSE' otherwise.

CAPTION: {caption}

Figure 4: MaRVL Prompt

#### 3.1.6 XM-3600

Crossmodal-3600 (Thapliyal et al., 2022) is a multilingual image captioning dataset consisting of 3600 geographically diverse images directly captioned in 36 different languages, avoiding any inconsistencies due to translations. We once again select 20 out of the 36 languages due to resource constraints: Arabic, Chinese, Czech, Danish, Dutch, English, Finnish, French, German, Italian, Japanese, Korean, Norwegian, Polish, Portuguese, Russian, Spanish, Swedish, Thai, Turkish. The following prompt was employed for XM-3600:

Analyze the image provided and generate a \*\*concise caption\*\* in {language} that accurately describes the main elements and actions taking place in the scene. Focus on highlighting the key components and the context in which they are found, ensuring that the description is not overly detailed but still provides enough information to understand the scenario. Additionally, include a brief mention of the background or setting to give a fuller picture of the scene. Aim for a balance between brevity and informativeness, capturing the essence of the image in a few well-chosen words. If you cannot caption the image in {language}, simply return "\*\*\*\*\*\*\*\*\*\*\*\*" (10 asterisks).

Figure 5: XM-3600 Prompt

## 3.2 Models

- **GPT-3.5-Turbo** (Ouyang et al., 2022) is an LLM developed by OpenAI by fine-tuning GPT-3 on a dataset of labeler demonstrations of the desired model behavior in a supervised learning setup. This was further fine-tuned on a dataset of ranked outputs using reinforcement learning with human feedback (RLHF). For our experiments, we accessed GPT-3.5-Turbo via Azure API.
- **GPT4** (OpenAI, 2023) is a transformer-based model pre-trained to predict the next token in a document. Similar to GPT-3.5-Turbo, GPT4 was also fine-tuned with RLHF. For our experiments, we accessed GPT4 via Azure API.
- Llama2 (Touvron et al., 2023) series, developed by Meta, is a collection of pretrained

and fine-tuned large language models (LLMs) ranging in scale from 7 billion to 70 billion parameters. It builds upon its predecessor, LLaMa, with several enhancements. The models are available in three parameter sizes: 7B, 13B, and 70B, and come in both pretrained and chat model flavors. In this work, we evaluate the Llama2 chat models of sizes 7B, 13B, and 70B.

- PaLM2 (Anil et al., 2023) PaLM2 is the successor to PaLM, the previous language model developed by Google. It is much more parameter-efficient compared to its predecessor. Although the technical report talks about a family of PaLM models (Small, Medium, and Large) and support for multiple languages, the Vertex API (which we use) does not disclose which model they are exposing and only exposes a definite number of languages<sup>2</sup>. We use two variants of the model, one with a context window size of 8192 (text-bison@001)and another with a context window size of 32k (text-bison-32k). Since the API supports a limited number of languages, we only run experiments on supported languages and skip the other languages in the MEGAVERSE datasets.
- LLaVa-v1.5 (Liu et al., 2023a) is a 13B multimodal opensource LLM with Vicuna (Chiang et al., 2023) as its backbone and CLIP ViT-L/14 (Radford et al., 2021) as its image processor. It is an improvement over its predecessor LLaVa (Liu et al., 2023b) achieved by better visual instruction tuning, response formatting prompts, adding a dedicated NLP vision-language connector, including academic task-oriented data, and additional scaling.

Although there may be various filters, classifiers, and other components running behind the APIs, which makes it unfair to compare them to locally run models, we have chosen to do so in order to investigate and compare the performance of the available options for multilingual LLMs today. Refer to Table 1 for a detailed model evaluation checklist to see an overview of our experiments.

<sup>2</sup>https://cloud.google.com/vertex-ai/docs/ generative-ai/learn/models?\_ga=2.106729799. -571187399.1699178589

### 3.3 Prompting strategies

In our prior work (Ahuja et al., 2023), we experiment with multiple prompting strategies: translatetest, zero-shot cross-lingual prompting, and monolingual prompting.

We define five main components to define the prompts: i) a **test example**  $x_{\text{test}}$  for which the predictions are to be made; ii) k few-shot exemplars  $\{(x_i, y_i)\}_{i=1}^k$ , that are used to provide in-context supervision to the model; iii) a task instruction  $\mathcal{I}$ which describes the instruction in text for the task to LLM; iv) a **prompt template**  $f_{\text{temp}}(x)$  which turns a dataset input example into a text format that can be used for prompting; and v) an answer **verbalizer**  $f_{\text{verb}}(y)$  that maps the label y to a textual representation. In the MEGA framework, we consider the instruction, template, and verbalizer together as a single template. For multilingual setups as highlighted in Lin et al. (2022) and Shi et al. (2022), some additional variations to consider include, the choice of the language of the few-shot examples, the language of the prompt template, and the language of the test examples.

In our previous work, we show that the monolingual prompting variation outperforms the zero-shot cross-lingual prompting variation for most datasets, with the translate-test variation performing better than monolingual for a few low-resource languages. We find that the gap between translate-test and monolingual prompting is minimal for models such as GPT4, and so for this work default to monolingual prompting except when specified otherwise. In cases where dev datasets are not available in the target language, we use zero-shot cross-lingual (zscl) prompting, which is the same as monolingual (mono) prompting except for the language of the few-shot examples, which are in English is zs-cl vs. the target language in mono. Note that the instruction of the prompt remains in English, as it is shown to outperform writing instructions in the target language in (Ahuja et al., 2023).

## 3.3.1 XRisaWoz

We explain the prompting strategy used for XRisaWoz in detail in this section, as it is a complex dataset compared to the other datasets we consider. We use monolingual prompting with few-shot examples in the target language. Note that DST and DA states still use English syntax (e.g. equal\_to) with constants (strings, names, values, etc.) from the target language. This is in line with how Morad-

shahi et al. (2023) have preprocessed the data. The task prompt is also in English for all the languages. We next detail the evaluation strategy and metrics: **End-to-end evaluation.** In this setting, the conversation agent starts with an empty / NULL dialogue state and with a gold user utterance for turn 1. Based on that, it generates a new dialogue state (DST), makes an API call if necessary (API), generates a new dialogue act (DA) and finally verbalizes (RG) it to the user. Based on the response, the agent receives a gold user utterance for turn 2 and the conversation progresses till gold user utterances are exhausted.

**Turn-by-turn evaluation.** Here, we construct "gold" inputs for each turn assuming the conversation progresses perfectly for the previous turns. We infer each subtask based on these gold inputs.

We do NOT perform end-to-end evaluation since models do not always generate precise states, API calls, or dialogue acts. This is likely because the models are not explicitly finetuned for that (sub)task. Nearly all the models in our study overgenerate the state/API calls/dialogue acts with extra text. It is somewhat unreasonable to expect models to generate syntactically correct semi-structured language with only in-context learning. Furthermore, the RG task also expects a somewhat shorter response but the models almost always overgenerate the response despite explicitly asking them to not overgenerate.

We use a preprocessed version of the dataset from Moradshahi et al. (2023) to perform turnby-turn evaluation. For inferring a subtask on a dialogue turn, we provide in-context examples corresponding to the same turn from other domains. If for a particular turn, sufficient in-context examples are not available, we look for the latest previous turn for which sufficient in-context examples are available. E.g. Assume the following turn to count distribution and k = 4 (number of in-context examples). Turns 1 through 3 have 50 samples, Turn 4 has 10 examples, Turn 5 has 3 examples, and Turn 6 has 1 example. Now at Turn 5, we do not have sufficient examples from Turn 5. Therefore, we sample in-context examples from turn 4. Similarly, at Turn 6 we do not have sufficient examples from Turn 6 or Turn 5 so we use Turn 4 in-context examples for Turn 6 as well.

**Metrics.** ( $\uparrow$ ) indicates higher values are better. ( $\downarrow$ ) indicates lower is better.

1. BLEU (↑) – Fluency of natural language re-

sponse (RG) with respect to gold outcomes.

- Slot Error Rate (↓) Factual correctness of generated response (Wen et al., 2015). This is 1 if the response contains all entities present in the gold response and 0 otherwise.
- 3. (Averaged/Task) Success Rate (↑) Was the agent able to complete the user's requests by providing all the requested information for a particular domain? (Lin et al., 2021)
- 4. API Accuracy (↑) − 1 if the model correctly predicted an API call along with all its constraints and 0 otherwise.
- 5. Dialogue Act Accuracy ( $\uparrow$ ) 1 if the model correctly predicted a dialogue act along with all correct entities and 0 otherwise.
- 6. Joint Goal Accuracy (↑) − 1 if the model correctly predicted a dialogue state along with all correct slot-relation-value triplets and 0 otherwise (Budzianowski et al., 2018).

**Prompts.** Each subtask uses a different "task prompt" the general structure of the overall prompt is as follows:

```
  \( \text{ TASK PROMPT. Refer to each task below. } \)
  \{
    Learning example #i:
    Turn ID: turn_id
    Database: db_id
    Context: gold_context
    Answer: gold_answer
  } \( \text{ for in range(k) # (in-context examples)} \)
  Target example #i:
    Turn ID: turn_id
    Database: db_id
    Context: gold_context
    Answer: \( \text{ model-completion-here} \)
```

Figure 6: General prompt structure for X-RiSAWOZ

For chat-based (e.g. Llama2 chat) models, we drop "Learning example..." and "Target example..." and use the ChatGPT-like prompt format with task prompt in the "system" prompt, {Turn ID, Database, Context} in the "user" prompt and "Answer" in the "assistant" prompt. We use the the dataset provided by Moradshahi et al. (2023) in which the context is preprocessed to include all the relevant information (e.g. previous dialogue acts or states) for a task.

### 4 Results

We now look at results across all models and languages for each dataset.

You are a helpful NLP assistant solving the "Task Oriented Dialogue" problem. In particular, you are solving the "Dialogue State Prediction, you must describe what is the state of the dialogue State Prediction, you must describe what is the state of the dialogue given the history using SQL-like structure. The syntax can be understood from the examples below. Based on the learning examples given below, complete the "Answer" part of the target example. Do not print any additional information.

Figure 7: Task prompt for "DST" subtask in X-RiSAWOZ

You are a helpful NLP assistant solving the "Task Oriented Dialogue" problem. In particular, you are solving the "API Call Detection" subtask. In API call detection, your task is to identify whether the dialogue can be continued with whatever context we already have. "yes" here means that additional data must be queried using an API for continuing the dialog while "no" means that API call is not required. Based on the learning examples given below, complete the "Answer" part of the target example. Do not print any additional information.

Figure 8: Task prompt for "API" subtask in X-RiSAWOZ

You are a helpful NLP assistant solving the "Task Oriented Dialogue" problem. In particular, you are solving the "Dialogue Act Prediction" subtask. In Dialogue Act Generation, you must generate the next dialogue action based on the given context. This will be an SQL-like structure. The syntax can be understood from the examples below. Based on the learning examples given below, complete the "Answer" part of the target example. Do not print any additional information.

Figure 9: Task prompt for "DA" subtask in X-RiSAWOZ

You are a helpful NLP assistant solving the "Task Oriented Dialogue" problem. In particular, you are solving the "Response Generation" subtask. In Response Generation, your task is to produce a natural language response from the chatbot given the context of the conversation. Based on the learning examples given below, complete the "Answer" part of the target example. Do not print any additional information.

Figure 10: Task prompt for "RG" subtask in X-RiSAWOZ

## 4.0.1 XNLI

We performed experiments on all models: Both versions of GPT, the three Llama variants, and PaLM2, as shown in Figure 11. We see that all models perform best on English, with slightly lower performance on Greek and German, with lower performance on languages like Hindi, Thai, Urdu, and Swahili. Overall PaLM2 performs best, closely followed by GPT4. GPT-3.5-Turbo is worse on all languages, however, we find that all three Llama models perform substantially worse. Since XNLI is a popular dataset, dataset contamination cannot be ruled out. We perform contamination analysis for GPT4 in MEGA (Ahuja et al., 2023) and plan to check for contamination in the other models in future work.

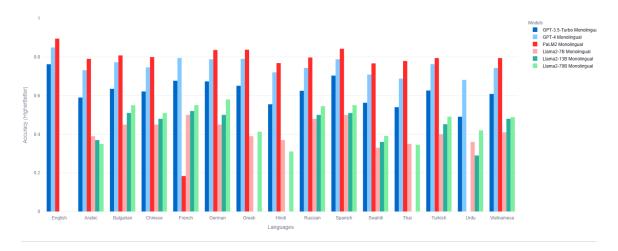


Figure 11: Results for XNLI across all languages and models for monolingual prompting

#### 4.0.2 IndicXNLI

We performed experiments on IndicXNLI on the GPT models as well as Llama models, however, the Llama models gave scores of 0 for all languages, which is why we do not plot them in Figure 12. We find that GPT4 outperforms GPT-3.5-Turbo on all languages with the highest scores on Hindi, Punjabi, and Bengali. However, the overall accuracy is not very high on any language compared to the XNLI results seen earlier.

#### 4.0.3 GLUECos NLI

We run experiments for the GLUECoS NLI dataset on GPT-3.5-Turbo and PaLM2. GPT-3.5-Turbo obtains an accuracy of 0.78, GPT4's accuracy is 0.90 while the accuracy of PaLM2 is 0.82, showing that all models can do well on this NLI task.

#### 4.0.4 PAWS-X

We performed experiments on PAWS-X on all models, as shown in Figure 13. We find that both GPT models have almost equal performance across all languages, and PaLM2 outperforms the GPT models on all languages. Note that this dataset contains high-resource languages, which may explain the high accuracies that all models achieve. However, dataset contamination cannot be ruled out, as shown in Ahuja et al. (2023). We also see that the Llama models perform worse than the GPT models and PaLM2, although the difference in performance is not as large as in some of the other datasets.

#### 4.0.5 XCOPA

We performed experiments on XCOPA on all models, as shown in Figure 14. Once again, we find that

the performance of GPT4 and PaLM2 are comparable, with GPT4 outperforming PaLM2 on Estonian, Italian, Swahili, and Turkish, while PaLM2 outperforms GPT4 on Indonesian and Thai. Notably, they are both better than GPT3.5Turbo, which performs substantially better than the Llama2 models except in Quechua, for which no model performs well. However, the results on all other languages for GPT4 and PaLM2 are extremely high, which may be due to dataset contamination as shown in (Ahuja et al., 2023).

## 4.0.6 XStoryCloze

We performed experiments for XStoryCloze with the GPT, PaLM, and Llama models, however, the Llama models gave scores of 0 for all languages, hence we omit them from Figure 15. For this dataset, we find that the gap between the GPT models and PaLM2 is very high, with both GPT models performing extremely well. The contamination experiments from (Ahuja et al., 2023) show a low possibility of dataset contamination for GPT4, which indicates that the GPT models are able to perform this task well.

# **4.0.7** GLUECoS Sentiment Analysis (En-Es-CS)

We run experiments for the En-Es-CS dataset on code-mixed Sentiment Analysis on GPT-3.5-Turbo and PaLM2. GPT3.5Turbo obtains an accuracy of 0.67, GPT4's accuracy is 0.45 while the accuracy of PaLM2 is 0.51. Surprisingly, GPT-3.5-Turbo outperforms both GPT4 and PaLM2 on this task.

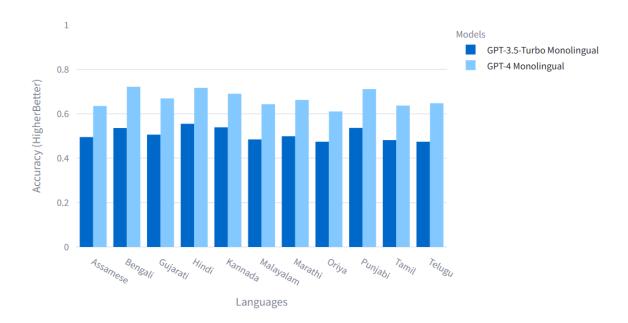


Figure 12: Results for Indic-XNLI across all languages for monolingual prompting

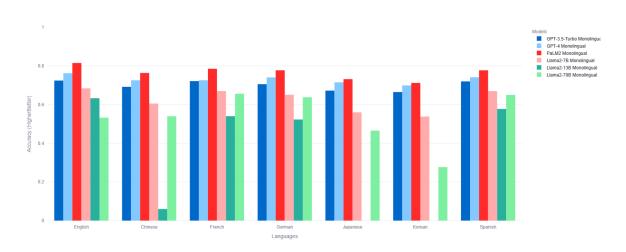


Figure 13: Results for PAWSX across all languages and models for monolingual prompting

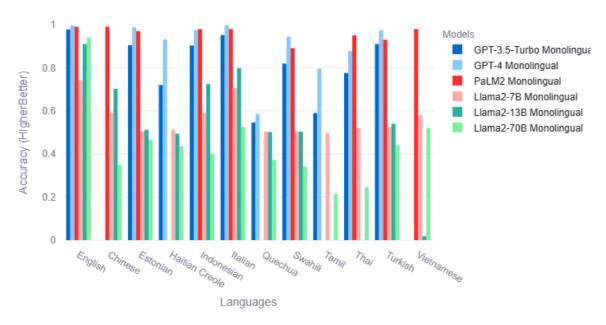


Figure 14: Results for XCOPA across all languages and models for monolingual prompting

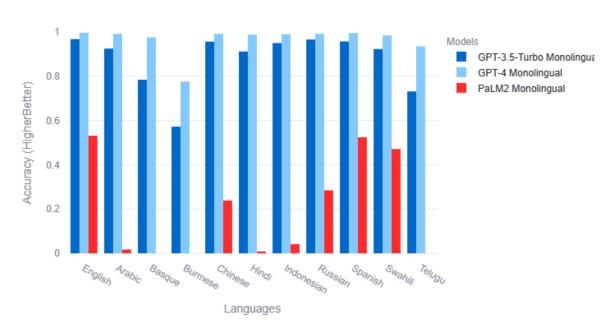


Figure 15: Results for XStoryCloze across all languages and models for monolingual prompting

## 4.0.8 TyDiQA GoldP

We performed experiments on TyDiQA on all models, as shown in Figure 16. We find that GPT4 outperforms all other models, with PaLM2 and GPT3.5Turbo having comparable performance and the Llama models having very poor performance. Surprisingly, the best-performing languages are Swahili and Indonesian, which are low-resource languages. However, dataset contamination in GPT4 cannot be ruled out, as shown in Ahuja et al. (2023).

## 4.0.9 MLQA

We performed experiments on MLQA on all models, as shown in Figure 17. GPT4 outperforms all other models for this dataset except for German. The Llama2-13B model performs well for some languages, such as Arabic, German, and Spanish but performs poorly on Chinese Hindi, and Vietnamese. This is one of the few datasets where PaLM2 struggles, particularly for Arabic and Chinese. Dataset contamination in GPT4 cannot be ruled out, as shown in (Ahuja et al., 2023).

## 4.0.10 XQUAD

We performed experiments on MLQA on all models, as shown in Figure 18. GPT4 is the best-performing model across languages, followed closely by GPT-3.5-Turbo. PaLM2 outperforms GPT-3.5-Turbo on Greek and Thai, while all three Llama models perform poorly on this dataset. Dataset contamination in GPT4 cannot be ruled out, as shown in (Ahuja et al., 2023).

## 4.0.11 IndicQA

We performed experiments on IndicXNLI on the GPT models as well as Llama models, however, the Llama models gave scores of 0 for all languages, which is why we omit them from Figure 19. We use the zero-shot cross-lingual prompting strategy due to the absence of a dev set. GPT4 performs better than GPT-3.5-Turbo, with the best performance seen for Hindi, Marathi, and Bengali.

## 4.0.12 PAN-X

We performed experiments on PAN-X on the GPT models and PaLM2, as shown in Figure 20. GPT4 outperforms the other two models, with GPT-3.5-Turbo outperforming PaLM2 on several languages. However, all models perform poorly on Thai, Japanese, and Chinese on this sequence labeling task. Since this is an older dataset, GPT4

data contamination cannot be ruled out as shown in (Ahuja et al., 2023).

#### 4.0.13 UDPOS

Similar to PAN-X, we performed experiments on UDPOS on the GPT models and PaLM2, as shown in Figure 21. All three models show similar high performance across languages, except for Arabic, Greek, Hebrew, Hindi, and Vietnamese, where PaLM2 performs best. GPT4 data contamination cannot be ruled out as shown in Ahuja et al. (2023).

## 4.0.14 Jigsaw

We perform experiments on the Jigsaw dataset for GPT-3.5-Turbo and PaLM2 using the monolingual prompting strategy and find that both models perform very well on all languages. Since the dataset cannot be accessed without download, models are less likely to be contaminated with this dataset (Ahuja et al., 2023).

#### 4.0.15 WinoMT

We perform experiments on the WinoMT dataset only for GPT-3.5-Turbo using the monolingual prompting strategy and report the results for completeness. We find that the model does not perform well on any of the languages.

## 4.0.16 XLSum

We performed experiments on XLSum on all models, as shown in Figure 24 using the monolingual prompting strategy. Overall, we find that GPT4 outperforms all other models, with some exceptions. GPT-3.5-Turbo performs best for African languages like Swahili, Somali, and Yoruba, while the Llama models perform best for Arabic, Kyrgyz, Vietnamese, and Welsh. According to the contamination analysis in (Ahuja et al., 2023), it is possible, though less likely that GPT4 is contaminated with this dataset.

#### 4.0.17 BeleBele

We perform experiments for GPT4 and PaLM2 and report Llama2-chat-70B and GPT-3.5-Turbo results from Bandarkar et al. (2023), shown in Figure 25. We use the monolingual prompting strategy, however, we do not use few-shot examples in the target language or English. We perform experiments on Arabic, Czech, Danish, German, English, Spanish, Finnish, French, Hebrew, Hungarian, Italian, Japanese, Korean, Dutch, Norwegian, Polish, Portuguese, Russian, Swedish, Thai, Turkish, Chinese Simplified and Chinese Traditional.

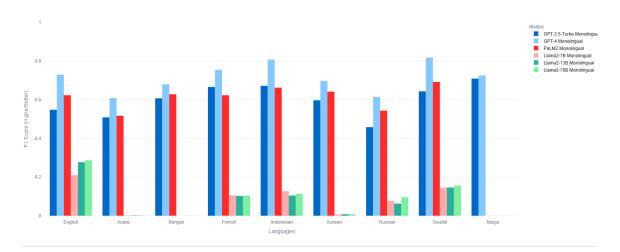


Figure 16: Results for TyDiQA across all languages and models for monolingual prompting

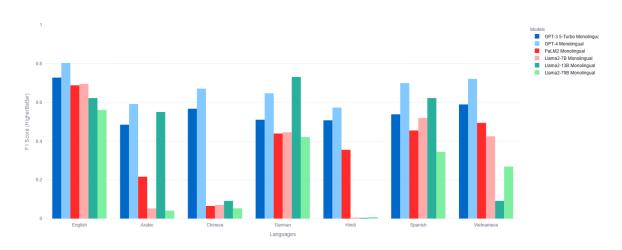


Figure 17: Results for MLQA across all languages and models for monolingual prompting

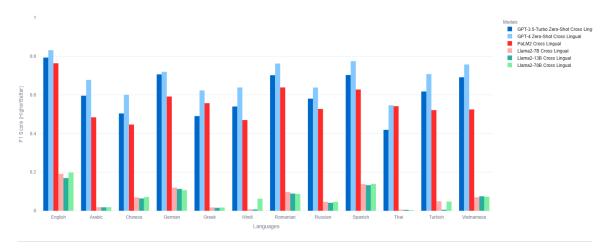


Figure 18: Results for XQUAD across all languages and models for zero-shot cross-lingual prompting

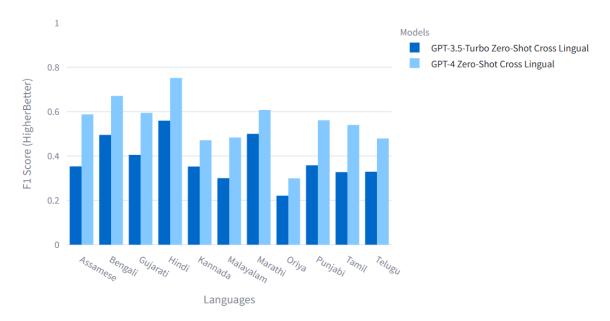


Figure 19: Results for IndicQA across all languages with zero-shot cross-lingual prompting

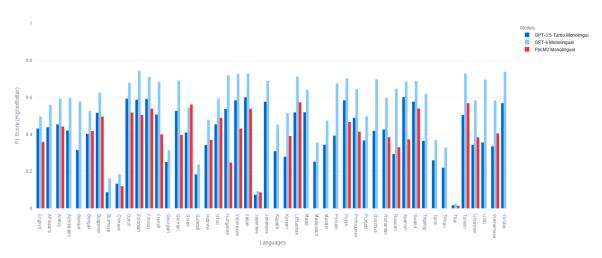


Figure 20: Results for PAN-X across all languages with monolingual prompting

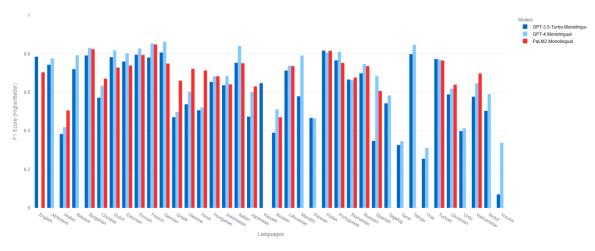


Figure 21: Results for UDPOS across all languages with monolingual prompting

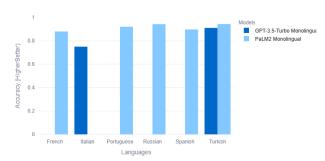


Figure 22: Results for Jigsaw across models and languages

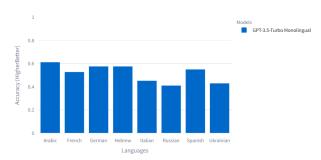


Figure 23: Results for WinoMT across languages

GPT4 and PaLM2 outperform GPT-3.5-Turbo and Llama2, in all languages, with the performance of GPT4 and PaLM2 being comparable. Most models do well due to the multiple-choice question-answering nature of the task, which makes parsing outputs and evaluation simpler and increases the probability of success even for weaker models.

## 4.0.18 AfriQA

We perform experiments for GPT-3.5-Turbo, GPT4, and Llama2. We do not run experiments with PaLM2 for this dataset as most of the languages in the dataset are not supported. GPT4 outperforms the GPT-3.5-Turbo model, while the Llama2 models perform very poorly on all languages.

#### 4.0.19 IN22

We report our results on the IN22-Gen subset and randomly select k = 8 translation pairs from the development set of FLORES-200 (Team et al., 2022) as in-context examples. Due to GPT4 resource constraints, we select 50 pairs from the test set for evaluation. We report GPT-3.5-Turbo 0-shot scores from Gala et al. (2023) for comparison. For consistency, we use the indic\_nlp\_library<sup>3</sup> and

the evaluation scripts<sup>4</sup> from Gala et al. (2023) to tokenize the predictions and references while computing chrF++ (Popović, 2017) for Indic languages. We do not evaluate PaLM2 on this dataset, as most languages in this dataset are not supported by it.

Figure 27 demonstrates the results of GPT4, GPT-3.5-Turbo (0 and 8-shot), and Llama2 on IN22 Gen. We find that Llama-2 performs poorly on all Indic languages with the scores barely crossing 2 or 3 chrF++ points in the En-Indic direction, whereas the performance is better on the Indic-En direction. GPT4 performs the best among all models considered, and the effect of in-context examples seems negligible across languages for GPT-3.5-Turbo. A plausible explanation for this could be that these languages have enough abundance in the GPT-3.5-Turbo, that in-context examples do not matter, or that the domains of FLORES-200 and IN22 are disjoint in this case.

We also find that GPT4 performs consistently well across languages in Indic-En direction, while significant fluctuations can be seen in the En-Indic direction. Further, we notice that prompting the model in the En-Indic direction is much slower compared to the Indic-En direction as more tokens need to be generated in the case of the former due to the high fertility of Indic languages in the tokenization process.

For GPT-3.5-Turbo, Kashmiri, (despite being a low-resource language) and Urdu are the highest performing language on the En-Indic side and second best on Indic-En. Similarly, the scores of Nepali and Hindi are close. Assamese is the lowest-resource language and shows the worst performance in the En-Indic direction, while Tamil performs worst on Indic-En. Surprisingly, Kannada and Telugu which share a common script perform better in a 0-shot setting than with few-shot examples.

## 4.0.20 XRiSAWOZ

Figure 28 shows the performance of the two GPT models, PaLM2 and the Llama2-70B variant on XRiSAWOZ with the monolingual prompting strategy in terms of Average Success Rate defined in 3. We find that both GPT models outperform PaLM2, with Llama2-70B also outperforming PaLM2 slightly in English and French.

Despite the turn-by-turn evaluations, models still overgenerate the DST and DA answers. We find

<sup>3</sup>https://github.com/anoopkunchukuttan/indic\_ nlp\_library

<sup>&</sup>lt;sup>4</sup>https://github.com/AI4Bharat/IndicTrans2

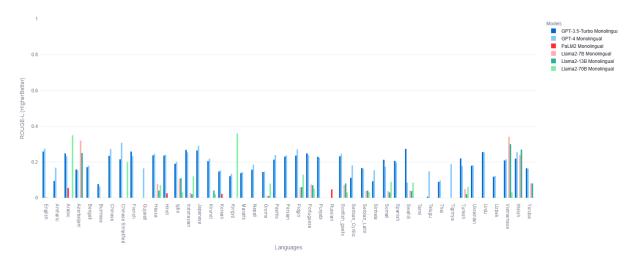


Figure 24: Results for XLSum across all languages and models for monolingual prompting

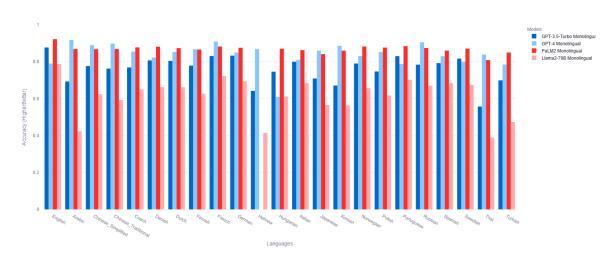


Figure 25: Results for Belebele across all languages with monolingual prompting without few-shot examples

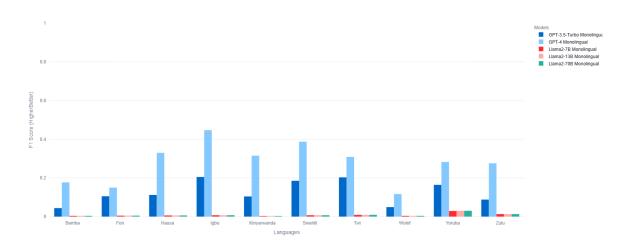


Figure 26: Results for AfriQA across all languages with monolingual prompting

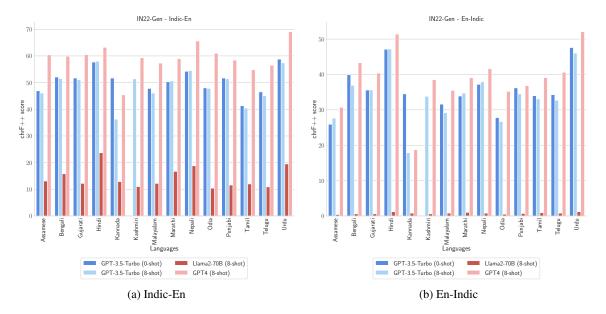


Figure 27: chrF++ scores of IN22-Gen. Note that, Kashmiri 0-shot scores were not covered in Gala et al. (2023)

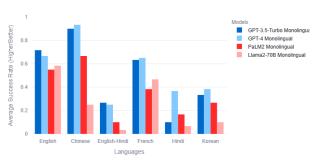


Figure 28: Average Success Rate for XRiSAWOZ across models and languages

the structured answer within the response with the help of a regex. In particular, GPT-3.5-Turbo and Llama2 are poor in terms of overgeneration, leading to lower BLEU scores. We suspect dataset contamination on the Chinese split i.e. the original Ri-SAWOZ dataset since the performance of PaLM2, GPT-3.5-Turbo, and GPT4 models on Chinese is remarkably better than other languages. Specifically, we observe less than 10% SER on all 3 of these models. The average success rate, API accuracy, DA accuracy as well as JGA are significantly better on Chinese as compared to other languages (even English) for these 3 models. On average, GPT-4 is the best-performing model followed closely by GPT-3.5-Turbo. PaLM performs worse than both GPT models but is significantly better than Llama2 whose performance was the worst among all models across all tasks.

For all models, the performance on English is

significantly better than the performance on Hindi. The stronger performance on English seems to be helping all the models in the code-mixed English-Hindi setting. While the performance in English-Hindi setting is not comparable to English, all models show a significant improvement in English-Hindi performance as compared to Hindi-only performance. Looking at individual sub-tasks, we find that models struggle to predict the correct dialogue state or dialogue act despite scoring high API accuracy.

#### 4.0.21 MaRVL

Since LLaVA-v1.5-13B is the only multimodal model under consideration, we evaluate the multimodal datasets only on LLaVA. However, we use an additional prompting strategy, translatetest and compared its performance to monolingual prompting. Figure ?? shows the F1 scores of the model across 5 languages. We see that F1 scores are low overall, with the lowest score on Tamil. The translate-test strategy outperforms monolingual prompting for all languages except Indonesian, however, the performance is still poor compared to a random classification.

## 4.0.22 XM-3600

Next, we test the same model Llava on the XM-3600 dataset, which is an image captioning dataset, and use the chrF++ metric to report scores. chrF++ (Popović, 2017) is a metric used to evaluate the quality of machine-generated translations which considers both precision and recall of character n-

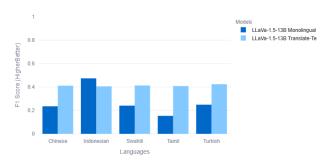


Figure 29: F1 scores for the Llava model on MaRVL. We used two prompting strategies, monolingual and translate-test.

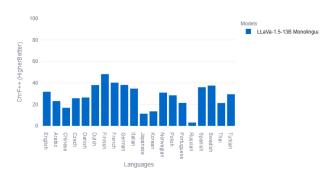


Figure 30: chrF++ scores for the Llava model on XM-3600. We use monolingual prompting as the prompting strategy.

grams in the reference and candidate translations. By focusing on character-level information, this metric can capture subtle nuances and improvements in translation quality, especially in languages with complex morphology or syntax. For this task of image captioning, we employ chrF++ to compare how close the machine-generated caption is to the gold captions provided in the dataset. Any scores greater than or equal to 40 can be considered moderate, and scores below 20 are poor. We see poor performance for most languages that are not written in Latin script, especially Japanese, Korean, Russian, Thai, and Chinese. Most Latin script high-resource languages such as Finnish, French, German, Dutch, Spanish, and Italian outperform or come close to English performance, with lowerresource languages such as Danish, Czech Polish, and Norwegian performing slightly worse.

## 5 Discussion

In this work, we benchmark 22 datasets covering 81 languages across 6 models – GPT-3.5-Turbo, GPT4, PaLM2, Llama2 (3 versions) and LLaVa-

v1.5. We find similar trends across most datasets we study - GPT4 and PaLM2 outperform the Llama models, particularly on low-resource languages. Llama performs particularly poorly on Indian languages and African languages in MEGAVERSE, indicating that it is not ready for deployment without fine-tuning on these languages.

We find that GPT4 and PaLM2 perform best on different datasets – GPT4 outperforms PaLM2 on TyDiQA, XCOPA, XStoryCloze, XQuaD, PANX, XLSum and XRisaWoz, while PaLM2 outperforms GPT4 on XNLI, PAWS-X and Belebele. Thus, GPT4 fares better overall on multilingual datasets, compared to PaLM2. GPT4 can also run on more languages, as there is no restriction on the API, and hence it can be evaluated on more datasets than PaLM2.

Results on translation datasets show that high-resource languages are robust to few-shot examples. Providing in-context examples of such languages is not always useful, but is usually helpful for low-resource languages. We find that standard metrics such as ROUGE-L are not sufficient for generative models. For example, in the XLSum dataset, we observed a lot of languages being assigned very low ROUGE scores even when the summarization was reasonable. This necessitates further research on building better metrics for evaluating generative models.

We introduce two multimodal datasets in MEGAVERSE and find that the Llava model performs well on the image captioning task for some high-resource languages, but performs poorly on the reasoning dataset. In future work, we also plan to benchmark GPT4 on multi-modality after access to it becomes public<sup>5</sup>. Benchmarking and improving multilingual multimodal models is an important open area of research.

In this work, we compare black-box API access models such as GPT4 and PaLM2 with models that can be run locally, such as Llama2. This comparison may seem unfair because there may be many other models or systems behind APIs that may affect the performance of the foundation model on a dataset. However, we believe that this comparison is necessary to evaluate the choices available for deploying LLM-based applications in non-English languages.

Dataset contamination is a critical issue that

<sup>5</sup>https://openai.com/blog/
new-models-and-developer-products-announced-at-devday

affects English and non-English language benchmarking studies. Given that new multilingual evaluation datasets are difficult to create due to resource and funding constraints, it is imperative that they are not included in the training data of LLMs. To achieve this objective, we need to enhance our ability to identify instances of contamination, as well as implement measures to avoid future contamination.

Our future research will also focus on studying the factors that affect performance, such as the quantity of pre-training and fine-tuning data, tokenizer fertility, and other relevant factors on the new models and datasets we have included. We plan to release all the code necessary for running the MEGAVERSE benchmark to facilitate research in the critical field of multilingual LLM evaluation.

#### 6 Limitations

Our work is subject to the following limitations:

## 6.1 Dataset contamination

We present a contamination analysis of the datasets included in MEGA for GPT4 in (Ahuja et al., 2023), however, we do not perform contamination analysis on the new datasets we include or on other models such as PaLM2 and Llama2. We leave this as an important future research direction to pursue.

## 6.2 Prompt tuning

LLMs are sensitive to prompting, and we do not perform extensive prompt tuning for the new datasets, as they do not have many prompts to choose from, unlike the original MEGA datasets where we perform prompt tuning on English dev sets. We also do not experiment with prompting variations, such as translate-test and zero-shot cross-lingual prompting, or more complex strategies such as Chain of Thought prompting due to resource constraints.

## 6.3 Experiments on limited data and datasets

Due to resource constraints, we perform experiments on partial datasets when indicated, and do not evaluate all models on all datasets. We plan to do so in future work.

## 6.4 Focus on task accuracy

We perform limited experiments on RAI datasets and do not perform experiments on other important dimensions such as fairness, bias, robustness, efficiency etc., mainly due to the lack of such datasets for non-English languages. This is an important future research direction.

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