



Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning

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Abstract

Datasets are foundational to many breakthroughs in modern artificial intelligence. Many recent achievements in the space of natural language processing (NLP) can be attributed to the fine-tuning of pre-trained models on a diverse set of tasks that enables a large language model (LLM) to respond to instructions. Instruction fine-tuning (IFT) requires specifically constructed and annotated datasets. However, existing datasets are almost all in the English language. In this work, our primary goal is to bridge the language gap by building a human-curated instruction-following dataset spanning 65 languages. We worked with fluent speakers of languages from around the world to collect natural instances of instructions and completions. Furthermore, we create the most extensive multilingual collection to date, comprising 513 million instances through templating and translating existing datasets across 114 languages. In total, we contribute four key resources: we develop and open-source the **Aya Annotation Platform**, the **Aya Dataset**, the **Aya Collection**, and the **Aya Evaluation Suite**. The **Aya** initiative also serves as a valuable case study in participatory research, involving collaborators from 119 countries. We see this as a valuable framework for future research collaborations that aim to bridge gaps in resources.

1 Introduction

Datasets are static representations of the world, far from the rich, ever-evolving environment we navigate as humans. Yet, these frozen snapshots in time are the foundation upon which progress in AI has been built. Many recent breakthroughs in language modeling can be attributed to fine-tuning

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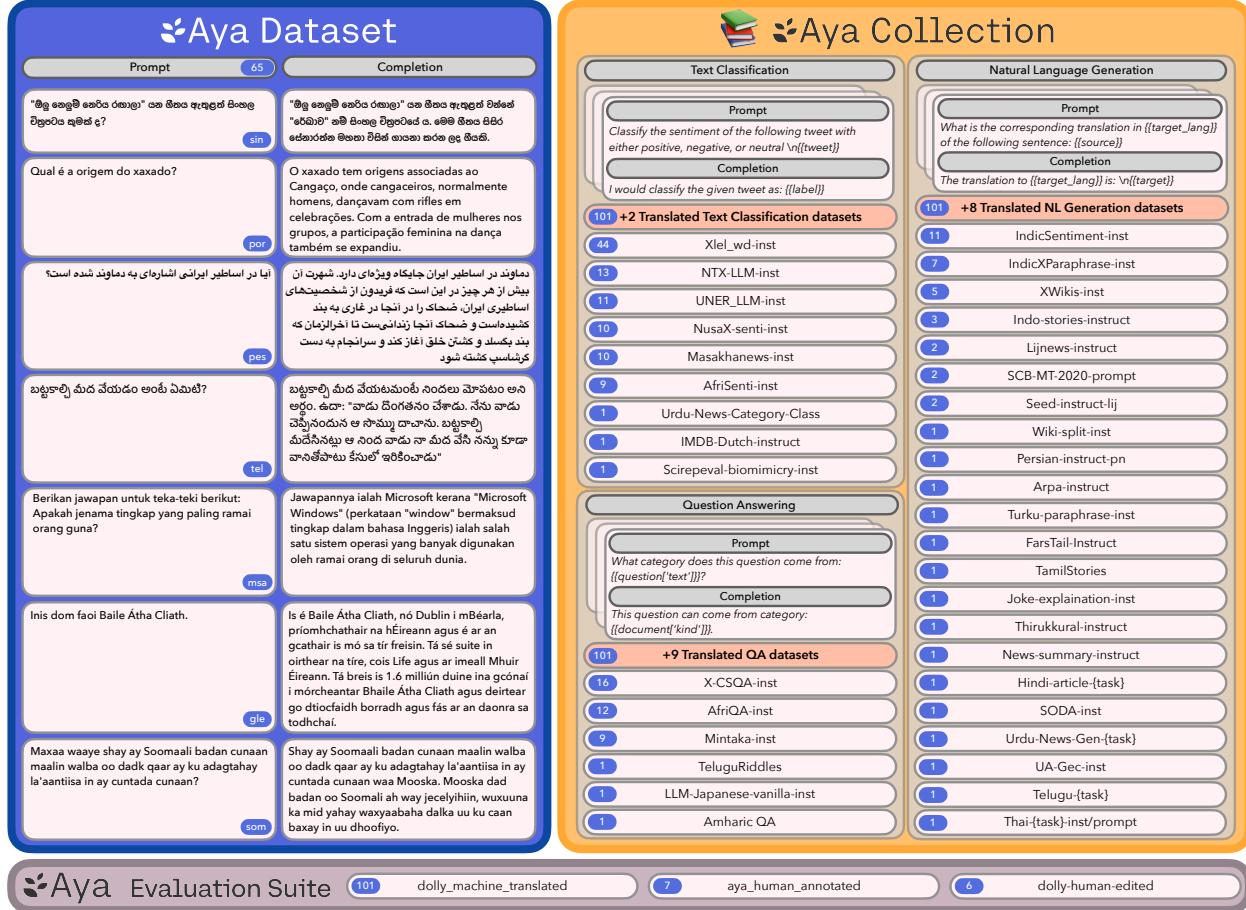


Figure 1: **Aya Dataset, Aya Collection & Aya Evaluation Suite.** On the left, we show examples of contributions in the **Aya Dataset**. These are original human-curated prompt-completion pairs written by fluent speakers of 65 languages. On the right, we have the **Aya Collection**, an aggregation of 44 monolingual and multilingual templated instruction datasets and 19 translated datasets ranging over 114 languages and three main tasks: Text Classification, Natural Language Generation, and Question Answering. The bottom block showcases the **Aya Evaluation Suite** for multilingual open-ended generation. This collection consists of original annotation and post-edits of translations covering several languages, and translation of high-quality and universal prompts into 101 languages. We indicate the number of languages in a dataset with the value in the blue ovals in the figure. (Translated datasets have been visually merged due to space constraints).

pre-trained models on a diverse set of tasks that enable a Large Language Model (LLM) to follow instructions [McCann et al., 2018; Sanh et al., 2022; Wei et al., 2022a; Muennighoff et al., 2023c; Longpre et al., 2023a]. Instruction fine-tuning (IFT) leverages the precept that Natural Language Processing (NLP) tasks can be described via natural language instructions, such as “*What were the reviews like for the Barbie movie?*” or “*Write a recipe from the following list of ingredients.*” This process requires *prompts* to be paired with expected *completions* [Ziegler et al., 2020; Ouyang et al., 2022] aiming to capture the variety of ways an LLM can be used in downstream tasks. Yet, the very act of curating data imparts a viewpoint about what distributions we want our model to represent and what is forgotten. So, *what do these widely used datasets tell us about the assumptions underlying these breakthroughs?*

More than 7,000 languages¹ are spoken around the world today, with a considerable number facing the challenges of being low-resourced, under-represented, or disappearing [Maxwell & Hughes, 2006; Simons, 2019; Moran & Chiarcos, 2020; Secretariat, 2022; Gao & Liu, 2023; Ilhomovna & Yuldasheva, 2023; Marivate et al., 2020]. In contrast, the most widely used datasets and breakthroughs in NLP have coalesced around a few data-rich languages [Longpre et al., 2023b; Taori et al., 2023; Chung et al., 2022; Fan et al., 2021; Dodge et al., 2021; Lucy et al., 2024]. IFT datasets are no exception; the creation of these datasets has almost entirely focused on English. Furthermore, the vast majority of the creators of these works originate from a few countries [Longpre et al., 2023b; Zhang et al., 2022].

The factors underlying the construction of the datasets impact how models perform for users around the world. Models perform better on the distribution they are trained to mimic [Kunchukuttan et al., 2021]. This often introduces known biases towards languages [Schwartz et al., 2022; Kotek et al., 2023; Khandelwal et al., 2023; Vashishta et al., 2023; Khondaker et al., 2023] and dialects [Jørgensen et al., 2015; Blodgett et al., 2016; Zampieri et al., 2017; Sun et al., 2023] not included during training and introduces critical security flaws [Yong et al., 2023a; Nasr et al., 2023; Li et al., 2023b; Lukas et al., 2023; Deng et al., 2023].

Datasets aren't simply raw materials that fuel breakthroughs but also make the poor *poorer* and the rich *richer* [Held et al., 2023; Durmus et al., 2023; Robinson et al., 2023]. Disparities in the access to technological resources predates the advent of LLMs [Garrette et al., 2013]. However, as LLMs become more sophisticated and widely available, non-English languages will remain under-represented and will likely become more so. The imbalance between languages has created a growing divide in the cost of using this technology as marginalized languages require more tokens and incur higher latency for generations [Ji et al., 2023b; Cui et al., 2023], consigning speakers of low-performing languages to lower quality technology [Held et al., 2023; Durmus et al., 2023; Nicholas & Bhatia, 2023; Ojo et al., 2023]. Often, speakers of low-resource languages do not have the resources to improve NLP technology for their language, facing a *low-resource double bind* with limited access to both compute and data [Ahia et al., 2021].

In this work, our goal is to reduce this linguistic inequality. Efforts that aim to improve multilingual performance have often focused on improving data coverage [Chen et al., 2023b]. However, most of the limited effort to date has focused on multilingual pre-training [Scao et al., 2022a; Wei et al., 2023; Lample & Conneau, 2019] with even less work centered on imparting instruction following abilities. Approaches that have tried to translate English instruct-style datasets into other languages often suffer from translation biases [Vanmassenhove et al., 2021; Hartung et al., 2023; Savoldi et al., 2021; Muennighoff et al., 2023c] or fail to reflect cultural context appropriately [Wang et al., 2022a; Ji et al., 2023a; Pudjiati et al., 2022]. Automatic curation of multilingual datasets is a logical—and sometimes necessary—approach but often suffers from noise and biases. This makes it difficult to validate the quality of the created datasets [Kreutzer et al., 2022; Lucchini & Viviano, 2021; Ferrara, 2023; Caswell et al., 2020] or requires the curation of manual templates which often result in low instruction and completion diversity [Muennighoff et al., 2023c] critical for model performance [Naik et al., 2023; Chung et al., 2023; Li et al., 2023e; Lahoti et al., 2023].

In contrast, a key aspect of our work focused on harder-to-obtain human-curated data from fluent speakers of a language. This curation process has received far less attention due to

¹<https://www.ethnologue.com/>

Dataset	#Instances	#Langs	% English	Generation method	Permissive license
Llama2 IFT data [Touvron et al., 2023]	NA	27	90%	Human-annotations SFT datasets	✗
Alpaca [Taori et al., 2023]	52K	1	100%	Synthetic data generation IFT datasets	≈
P3 [Sanh et al., 2022]	12M	1	100%	Template generation given applied to English datasets	✓
Flan 2022 [Longpre et al., 2023a]	15M	60	100%	Template generation applied to English datasets	✓
xP3 [Muennighoff et al., 2023c]	81M	46	39%	Template generation applied to English datasets	✓
Swinestruct [Holmström & Doostmohammadi, 2023]	68K	1	0%	Machine translation English IFT datasets	≈
Okapi [Dac Lai et al., 2023]	158K	26	45%	Machine translation English IFT datasets	✓
Bactrian-X [Li et al., 2023a]	3.4M	52	2%	Machine translation + synthetic data generation	≈
Aya Dataset	204K	65	2%	Original IFT Human-annotations	✓
Aya Collection	513M	114	3.5%	Template Generation and translating existing datasets	✓

Table 1: Comparison of different instruction-tuning datasets. ✓ represents permissive licenses that allow commercial use while ≈ represents restrictive licenses that do not allow commercial use. ✗ represents non availability of license.

lack of access to fluent speakers, especially in low-resource languages [Joshi et al., 2019]. We chose to close this gap by conducting a year-long participatory research initiative that involved working with fluent speakers of languages from around the world to collect human-curated instances of instructions and completions. By leveraging best practices from open-source and crowd-sourced science projects [Franzoni & Sauermann, 2014; Beck et al., 2022; Lenart-Gansiniec et al., 2023], we built a simple and intuitive user interface, the **Aya** Annotation Platform² (**Aya** UI) which served as the central platform for contributors to join the **Aya**^{3 4} project. In total, we had 2,997 collaborators spread across 119 countries around the world. Their collective efforts resulted in the **Aya** dataset which is the largest human-curated multilingual instruction-finetuned dataset to date, containing 204,114 high-quality annotations in 65 languages.

Additionally, we release and transform 44 pre-existing datasets into sets of instruction-completion pairs by crafting diverse templates manually, relying on fluent speakers for each language. We further expand this collection by translating datasets from English into 101 languages. We refer to this expanded collection of 513 million instances covering 114 languages in total as the **Aya** collection, which to date, is the most extensive collection of multilingual instruction-finetuning (IFT) data.

Overall, **Aya** contributes four key resources: **Aya Annotation Platform (Aya UI)**; **Aya Dataset**; **Aya Collection**, and **Aya Evaluation Suite**. Figure 1 shows a visual representation of the **Aya** Dataset and Collection. Below, we briefly describe these core contributions:

1. **Aya Annotation Platform (Aya UI)**: We built a robust annotation tool to facilitate the collection of high-quality multilingual data in an instruction-style format supporting 182 languages, including dialects. Over eight months, we had a total of 2,997 registered users spanning

²This platform is accessible at: <https://aya.for.ai>

³The word **Aya** has its origins in the Akan (Twi) language and is translated as “fern” in English [Willis, 1998].

⁴**Aya** represents endurance, resourcefulness, and defiance – like a fern growing in barren conditions.

119 countries and 134 languages, including dialects.

2. **Aya Dataset**: We created the largest human-annotated multilingual instruction finetuning dataset to date, consisting of over 204K instances that cover 65 languages. We include a data card [Pushkarna et al., 2022] for the **Aya** Dataset in Appendix J.
3. **Aya Collection**: We collected instruction-style templates from fluent speakers and applied them to a curated list of 44 datasets, including tasks such as Text Classification, Text Generation, Machine Translation, Paraphrasing, and Open-domain Question Answering. Some of these datasets also include equivalent multilingual versions produced through translation. We release 513M instances that cover 114 languages. These contributions are made available as an open-source collection. We include a data card for the **Aya** Collection in Appendix J.
4. **Aya Evaluation Suite**: We curate and release a diverse evaluation suite for multilingual open-ended generation quality. It consists of 250 human-written prompts for each of 7 languages, 200 automatically translated but human-selected prompts for 101 languages (114 dialects), and human-edited prompts of the latter for 6 languages, and the English originals. The first set represents culturally-grounded and original prompts, while the translated and post-edited prompts are sourced from English Dolly [Conover et al., 2023] and selected for their cross-cultural relevance. We include a data card for the **Aya** Collection in Appendix J.

By fully open sourcing the **Aya** Dataset, **Aya** Collection and **Aya** Evaluation Suite with a permissive Apache 2.0 License⁵ as well as the code for our annotation platform, we hope to empower researchers and practitioners to further advance multilingual models and applications. All datasets are accessible for download.⁶⁷⁸

Paper Organization Section 2 discusses the design and development of the **Aya** Annotation Platform, as well as the preparation of the **Aya** Dataset, and Section 3 presents a detailed analysis of the **Aya** Dataset. Section 4 and Section 5 contain discussion and analysis of the **Aya** Collection. Section 6 describes the details of the evaluation suite curated in this project. In Section 7, we describe our approach to participatory research. In Section 8, we review the existing literature, and in Section 9 we discuss the limitations of our work. Section 10 concludes the paper.

2 Aya Annotation Platform & Aya Dataset

2.1 Aya Annotation Platform

The goal of the **Aya** project is to facilitate annotations to a crowd-sourced dataset by individuals fluent in different languages. Inputs from fluent speakers of each language ensure that the dataset is more likely to be organic, fluent, and representative of the speakers' cultures. Including fluent and native speakers from various regions poses significant logistical challenges involving meticulous data selection, quality control measures, and custom annotation tools. We developed the **Aya** Annotation Platform to streamline the data collection process worldwide, accommodating a large number of decentralized contributors across multiple languages.

⁵<https://www.apache.org/licenses/LICENSE-2.0>

⁶https://hf.co/datasets/CohereForAI/aya_dataset

⁷https://hf.co/datasets/CohereForAI/aya_collection

⁸https://hf.co/datasets/CohereForAI/aya_evaluation_suite

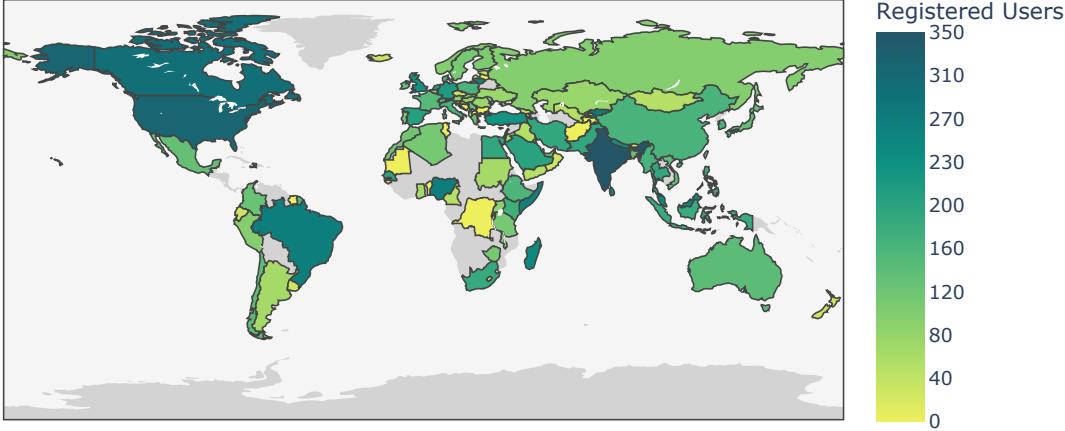


Figure 2: Geographical distribution of the users registered on the **Aya** platform.

User Interfaces (UIs) play a pivotal role in the context of NLP data collection, serving as the primary point of interaction between human annotators and the data collection process. The **Aya** Annotation Platform⁹ had to accommodate users in 119 countries collecting data across 134 languages. We designed the platform with a few key principles in mind, such as accessibility and ease of use for users who were unfamiliar with AI and machine learning. As part of our contribution, we fully open-source the code for our UI¹⁰.

Accessibility As users worldwide use different devices and operating systems, we decided to support both mobile and desktop interfaces [Muhammad et al., 2023]. Approximately 54% of users accessed **Aya** UI via desktop browsers while 46% utilized mobile browsers. We attribute the high fraction of mobile users to the skew towards mobile users in the Global South [Avle et al., 2018]. We supported Single Sign-On (SSO) capabilities to enable seamless tracking of user profiles and reward users with points for contributing data across multiple sessions. We initially only supported Discord sign-on but discovered that Discord is inaccessible or not widely used in certain countries. Also, the necessity of a platform-specific account created an obstacle to user engagement with **Aya**. This prompted us to add Google sign-on as an alternative option.

Languages Supported **Aya** project contributors could select the languages they are proficient in when signing up using the **Aya** UI. They could then make annotations in the language(s) they selected. Given the sheer number of languages we could collect annotations for, we chose to prioritize annotation support for the 101 languages available in the mT5 model [Xue et al., 2021]. We note that ultimately, some of these languages didn't receive enough contributions to include them in the final dataset. Conversely, we received substantial contributions from languages not initially part of the original list, like Wolof, leading to their inclusion; the final **Aya** Dataset covers 65 languages. Table 5 provides details of these languages.

Contributors We aimed to include individuals from diverse backgrounds—not limited to AI experts—enabling anyone proficient in a language to contribute. Our pool of contributors ultimately reflects this inclusive approach. During the registration process, we request specific demographic details from each **Aya** UI user such as country of residence, languages of fluent communication,

⁹<https://aya.for.ai/>

¹⁰<https://github.com/for-ai/aya-annotations-ui>

gender, age range, and familiar dialects. We display the onboarding form in Figure 17 in the Appendix. The **Aya** community of contributors includes 2,997 registered users across 134 languages.

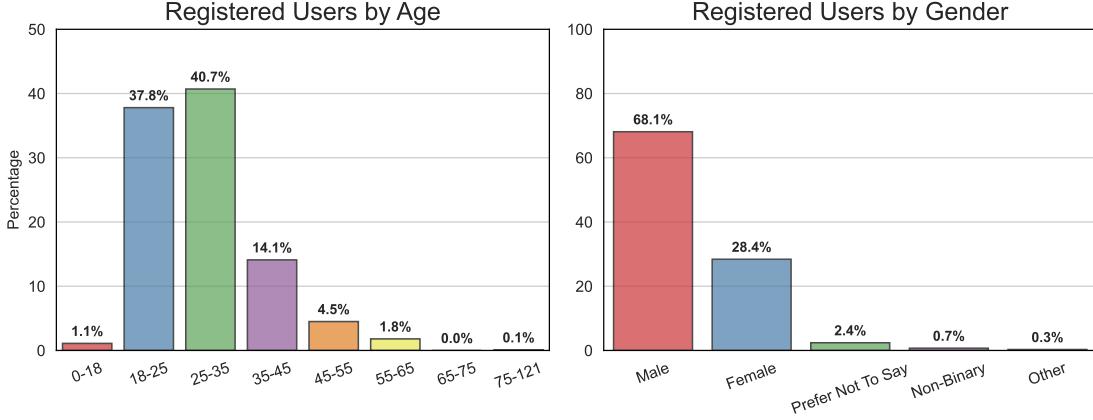


Figure 3: **Left:** Distribution of registered users on the **Aya** UI by age using specified values. **Right:** Distribution of registered users on the **Aya** UI by gender using specified values

Demographics Figure 3 illustrates the demographics of registered **Aya** UI users by age and gender. Regarding the age profiles of users, more than two-thirds were aged between 18 and 35. Approximately 68.1% of users identified themselves as male and 28.5% as female. Overall, 6.6% of users self-reported dialects. Within this group, 75% specified one dialect, 20% specific two dialects, and the remaining 5% specified three or more dialects, with a maximum of six.

During the development of **Aya**, registered users were geographically distributed across **119 countries** based on their residence. Certain countries like Afghanistan, Bulgaria, Kuwait, and Tajikistan had just one registered user. Figure 2 displays this global distribution, highlighting India with the highest number of registered users (346 out of 2,997).

Geographic-Based Contribution Assessment

We grouped the languages by the regions in which they either originate or are widely spoken. The language statistics by region for the original 101 languages we wanted to cover are as follows: 14 languages in Africa, 41 languages in Asia, 42 languages in Europe, and 4 languages in Latin America (See Appendix C.1 for more details and some exceptions of the distribution). As seen in Figure 4, more than half of all contributions for the **Aya** project came from Asia with 58.8%, followed by the African region with 27.4%. Europe, Latin America, and other regions account for the remaining 13.8% of the contributions.

We observe a large skew in terms of regional contributions, which deserves further research to understand why certain networks of contributors remained motivated for the entire project. These

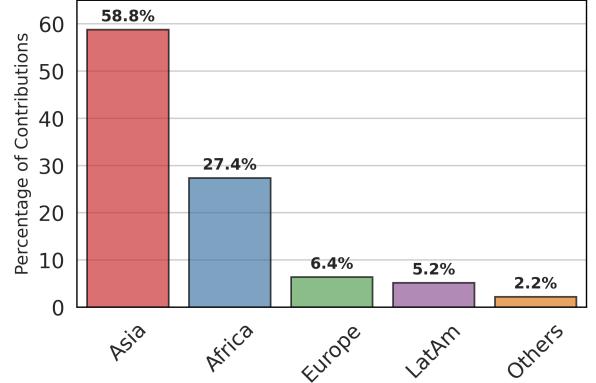


Figure 4: Distribution of total contributions across different regions.

disparities in participation may be due to opportunity cost in time [Gerosa et al., 2021; Wu et al., 2007], cultural beliefs around sharing data [Huang et al., 2023], or the belief that the language in question is not well served by the current technology [Nicholas & Bhatia, 2023].

Acknowledgement of contributions Recognition and transparency were maintained throughout the project through the use of a leaderboard¹¹ to acknowledge contributions. We implemented a scoring system where contributors earned a maximum of three points for each re-annotation, with one point awarded for rating the prompt and completion, one point for editing the prompt, and one point for editing the completion. Each original annotation was awarded with two points. We describe the different annotation tasks in the **Aya** UI in detail in Section 2.2.

The **Aya** Leaderboard is organized to display daily, weekly, and cumulative scores, providing a comprehensive overview of user contributions. The users have the flexibility to filter scores based on specific languages, allowing for a sense of community amongst contributors of a particular language. This design aimed to boost contributors' motivation to provide high-quality inputs for their chosen languages. Figure 19 shows an example of the leaderboard. We discuss further details on collaborating with the community in Section 7.

2.2 Annotation tasks

On the **Aya** Annotation Platform, contributors were able to contribute to three different tasks, following the find-fix-verify paradigm [Bernstein et al., 2015]: Writing new examples from scratch (**original annotations**), editing existing examples to improve the quality and comprehensiveness (**re-annotations**), and giving feedback on the quality of existing contributions (**annotation feedback**). We describe each briefly below:

2.2.1 Original Annotations

This task facilitates the inclusion of human-generated organic content by allowing annotators to submit original prompt-completion pairs in their language. Existing multilingual models have been shown to produce generations influenced by Western culture [Yuan et al., 2021; Naous et al., 2023; Lee et al., 2023] reflecting the underlying representation bias [Mehrabi et al., 2021] of their training datasets. This task aims to encourage annotators to submit fresh samples that are representative of their language, culture, literature, history, and region. The guidelines for contributors is available in Appendix B.3.

2.2.2 Re-Annotations

The purpose of this task is to facilitate the re-annotation or editing of prompt and completion pairs. The decision to add a re-annotation task partly stems from the need to help annotators understand the expected format of instruction-style datasets and to convey the variety of tasks in existing datasets, including question answering [Saad-Falcon et al., 2023; Arefeen et al., 2023], summarization [Stiennon et al., 2020; Wu et al., 2021], paraphrasing [Witteveen & Andrews, 2019; Reimers & Gurevych, 2019], and translation [NLLB-Team et al., 2022; Barrault et al., 2023]. Editing examples from existing datasets not only helped familiarize annotators with the expected format

¹¹The **Aya** Leaderboard is accessible at: <https://aya.for.ai/leaderboard/>

Contribute Your Language

Help us add more examples by writing your own prompt and their completion in your language.

English | ▾

Prompt

what does "to crave" mean?

Completion

to crave is to really really want something, or to have a deep desire.

Submit Entry

Rate Model Performance

Help improve the model performance by rating the prompt-completion pairs below

Edit Mode English | ▾

Prompt

Look out for: ✓ Correct Grammar ✓ Reasonable Length ✓ Clear Instructions

What does it mean in English "to crave" something?

Completion

Look out for: ✓ Clear Answer ✓ Full Sentences with Correct Answer ✓ Reasonable Length

To crave is to have a strong and intense desire for something. It implies a deep need or longing for the object of the craving. It can involve emotional and physical feelings of addiction and can sometimes lead to actions against one's best interests. It is important to note that there is a difference between wanting or liking something and craving it, as craving can be destructive and lead to unhealthy behaviors.

Edit Distance[Prompt]: 35

Edit Distance[Completion]: 321

Skip **Submit Entry**

(a) Example of an original annotation contribution.

(b) Example of a re-annotation contribution.

Figure 5: Demonstration of a sample original annotation and re-annotation contribution, in English. **(a)** exemplifies an original contribution input by an annotator from scratch. **(b)** shows a sample of re-annotation. Here, the annotator may have improved upon either a prompt and completion pair pulled from the database or a prompt and completion originally created by another contributor.

but also allowed for human evaluation and rating of existing widely used instruction-style datasets.

In total, we collected datasets from 19 public data sources and translated them into 114 available languages, including dialects using the NLLB 3.3B parameter machine translation model [NLLB-Team et al., 2022]. From each collection, we randomly chose 100 examples (per dataset and per language), creating our dataset for annotation, after which we had 1M translated prompt-completion pairs initially populated in the **Aya** UI as re-annotation tasks. These translated pairs served as a starting point for prompts and completions which annotators could improve. We release the raw translations as part of the **Aya** Collection, provide more details about the provenance of the translated datasets, and how they were selected in Section 4.2.

In addition to translated examples, there are other available data sources suitable for re-annotation: original **Aya** pairs, pre-existing instruction-style datasets (e.g., xP3), and the transformation of datasets into an instruction-style format, i.e., templated datasets. By re-annotating examples from different sources, we simultaneously enhance the quality of individual examples while obtaining a signal on the overall quality of the dataset in a specific language. A demonstration of a re-annotation, where an annotator strengthens a given prompt/completion, is shown in Figure 5b.

2.2.3 Annotation Feedback

Data quality is critical to ensure that a model can represent a language well. Learning from noisy, low-quality datasets harms the overall model performance and the relatively high cost of encoding these noisy examples is a misuse of capacity [Hsueh et al., 2009; Dodge et al., 2021; Luccioni & Viviano, 2021; Kreutzer et al., 2022]. Prior work has shown that improvements to quality through data pruning or selection can have a significant impact on the downstream performance of a model [Longpre et al., 2023c; Marion et al., 2023; Boubdir et al., 2023; Yang et al., 2023]. In particular, for instruction-tuning datasets, a small subset of higher-quality instructions can greatly outperform a larger volume of lower-quality instructions [AlShikh et al., 2023; Zhou et al., 2023; Chen et al., 2023a]. Given these findings, ensuring high quality contributions is of paramount importance. Ensuring consistent quality is particularly challenging in an open science initiative with a large number of contributors. We face two key challenges:

Changes in the Annotator Pool. During the year-long project, annotators joined and left the project at different points depending on their interests and availability. As a result, the window of contribution for each annotator was different. Only a small fraction of annotators participated for the entire duration of the year-long project. Annotators were active for an average of 1.3 sessions. Figure 6 presents a histogram depicting the distribution of user engagement based on the number of days they actively contributed. On average, **Aya** annotators spent five days contributing to the project. Annotators tended to be highly active shortly after joining, but their activity declined over time. There was a subgroup of annotators who maintained consistent activity over extended periods.

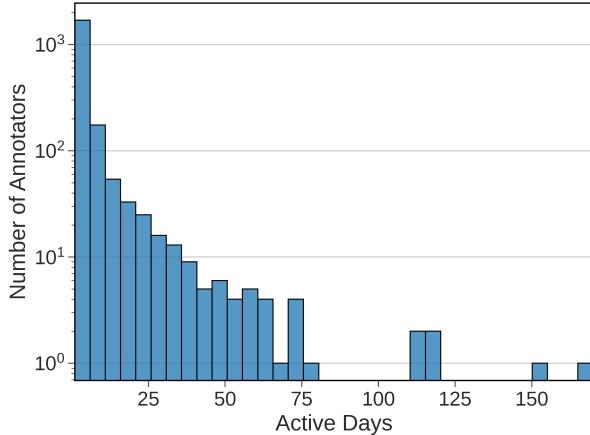


Figure 6: The distribution of annotators’ engagement based on the number of days they actively contributed in **Aya** UI

While we routinely provided examples to contributors, there was a clear need for a systematic way to review and measure the quality of submissions.

Validating the quality of contributions We follow a peer-review approach where each annotator acts as a reviewer for the other annotators working on the same language. These reviews form the

Varying level of experience with AI. An important goal of this project was to have a diverse pool of annotators and we thus did not limit the selection criteria to working knowledge of language models or AI in general. As a result, there were different levels of understanding amongst the annotators what was meant by a *prompt* and *completion*. For example, we found at least one contributor with 3,684 contributions to three languages (English, Somali, Standard Arabic) who failed to structure their submissions as a prompt with a question. Instead, the contributor used an extract of text as the prompt and its continuation in the completion. Prefacing such prompts with an instruction such as “*Complete the following partial extract of text:*” would have been a more suitable format.

basis for a quality **Aya** score which is displayed on the leaderboard in the UI. The quality score for an annotator is calculated by averaging the combined average ratings of their examples provided by other annotators who serve as reviewers. We provide more details about how annotations are reviewed in the Appendix Section B.1. All three tasks in the **Aya** UI are connected in a sequential pipeline where submissions from “Original Annotations” are reviewed in the “Re-Annotations” task, and the re-annotations are further reviewed as part of the “Annotation Feedback” task. This systematic approach allows for a robust evaluation and enhancement of the collected data.

2.3 Criteria for Inclusion in Aya Dataset

The **Aya** Dataset includes all original annotations and a subset of all re-annotations. We only release re-annotations if there is a difference between the original and the edited version. To determine this subset, we compute the sum of edit distances d (Levenshtein distance [Levenshtein et al., 1966]) between the original and re-annotated prompts and completions on the character level and use an acceptance threshold of ($d \geq 5$). This ensures that we do not release duplicates of existing data.

Only languages with at least 50 contributions were included in the final release of **Aya** Dataset. This threshold was picked as it represents a balance between achieving a reasonable level of data quality and considering the practical limitations of human resources for some languages. The goal is to include as many languages as possible without lowering the overall quality of the dataset. Table 5 lists details of the languages included in the **Aya** Dataset.

		Count
Original Annotations		138,844
Re-Annotations	xP3 datasets	2859
	Translated datasets	7757
	Templated datasets	11013
	Original Annotations	43641
Aya Dataset Total		204,114

Table 2: **Aya** Dataset Statistics (number of pairs of prompts and completions obtained through various annotation tasks).

3 Analysis of Aya Dataset

3.1 Statistics

The **Aya** Dataset contains a total of 204,114 instances collected via the **Aya** Annotation Platform. Table 2 provides the breakdown of original annotations and re-annotations in the final dataset. The dataset covers 65 languages: 22 high-resource, 12 mid-resource, and 31 low-resource languages (See Appendix E for more details on our language mappings).

3.2 Length of Aya Dataset

One objective of this project was to collect fluid original human prompts and completions. Table 3 provides examples of prompts and completions from the **Aya** Dataset. During the data collection

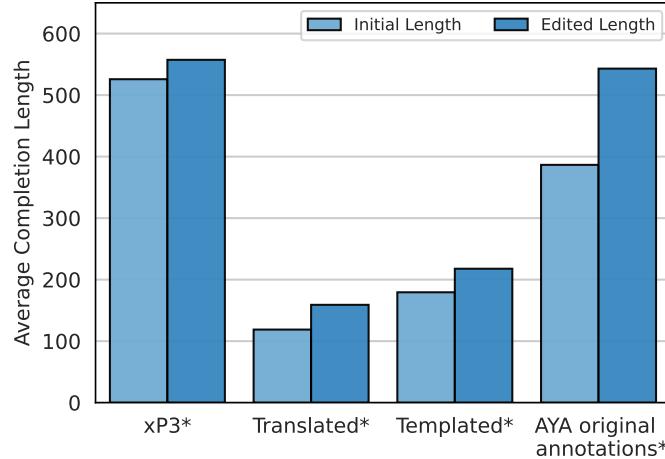


Figure 7: Average Completion Length before and after re-annotation. Here (*) indicates the subset of all dataset categories (xP3, translated, templated, and **Aya** original annotations) that were included in the **Aya** Dataset after re-annotation. Re-annotation improves average completion length across all datasets.

process, annotators were provided with examples and guidelines but were also trusted to explore their own creativity and cultural background to come up with new examples. As a result, it is meaningful to understand differences in aggregate statistics like length across datasets, language type and relationship with perceived quality.

Impact of Re-Annotation When editing existing instances, we instructed the annotators to prioritize enhancing both the quality and richness of the prompts and completions. The average length of completions before and after edits are shown in Figure 7. We observe that across all data sources, the average length of completion increased after editing. On average, the length of completions after edits is 25% longer than before edits. We observed the largest increase for **Aya** original annotations surfaced in the UI – which were 40% longer on average than the original length.

Length difference across language groups The average prompt and completion length (number of characters) observed across these different language groups is shown in Figure 8. A distinct contrast exists in completion lengths between mid and low-resource languages when compared to high-resource languages. Long completions and complete sentences are valuable

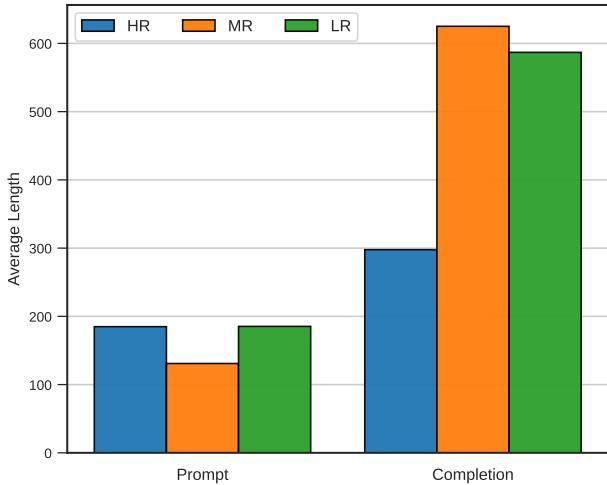


Figure 8: Average prompt and completion length of instances in the **Aya** Dataset across different language categories (high (HR), mid (MR) and low (LR) resource languages, see Table 5).

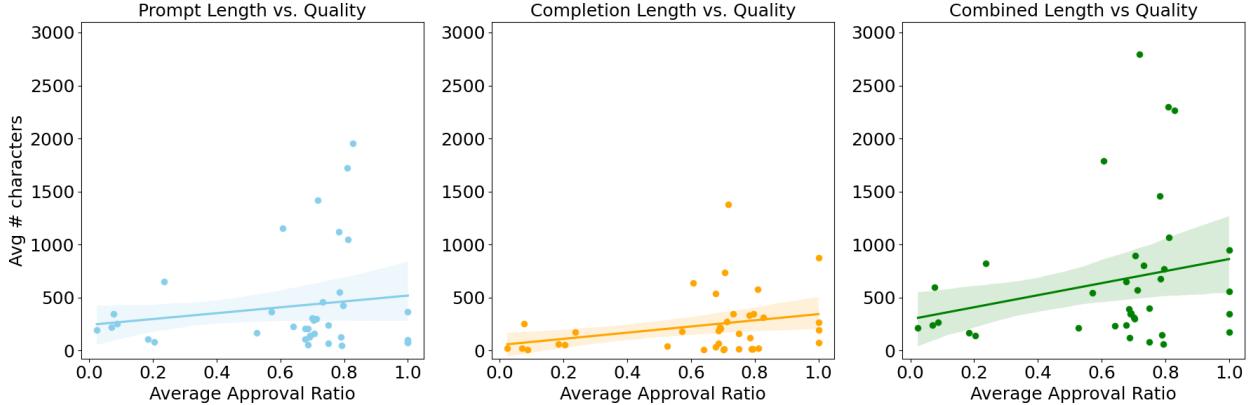


Figure 9: Relationship between Average Prompt and Completion Length in characters and the Average Approval Rate of the example.

in instruction-tuning datasets, particularly when training multilingual models to generate content in those languages.

Length vs. Perceived Data Quality Although longer completions can be valuable for training models to generate long and natural text, it does not necessarily imply higher quality. Using annotators’ feedback in the UI, we further investigate the impact of length on the perceived quality of the samples. Figure 9 showcases this analysis. We observe a positive correlation between how long the prompts and completions are and their resulting average approval ratio. Specifically, when we plot combined prompt and completion length against quality, we observe a correlation coefficient of 0.27. This finding emphasizes the importance of using longer prompts and completions and incorporating complete sentences to ensure a positive human experience when engaging with such a model.

Length difference by language Figure 25 in the Appendix illustrates the statistics per language. We observe an array of patterns that differed across languages. For instance in Japanese, completions are on average 31% shorter than prompts. On the other end, for Urdu and Yoruba, completions are notably long relative to prompts. On average, completions are 1258% and 2516% longer than the corresponding prompts for Urdu and Yoruba, respectively. The average completion length in Yoruba is 1591% longer than the average prompt length in Japanese. Figure 26 provides the average length of the combination of prompts and completions per language.

Comparison in Completion length Across Datasets The **Aya** Dataset has considerably longer completions on average when compared with other data collections as shown in Figure 12. This is particularly noteworthy given that the **Aya** Dataset is human-curated. Given the presence of longer completions in the training data for many low-resource languages, we expect that models trained on the **Aya** Dataset will generate longer and more natural responses.

3.3 Annotator Skew

A feature of participatory research projects is the challenge of establishing and maintaining a balanced number of annotations across groups of annotators. In the **Aya** project, the number of annotators per language varied due to numerous factors. As a result, the distribution of annota-

Lang	Prompt	Completion
ara	قم بإنشاء قصيدة مدح من بحر الخفيف.	إِنْ مَدْحُ الْمَلُوكِ يَقْبَحُ فَضْلًا عَنْ مَدْحِ الرَّاعِي وَالْأَوْغَادِ لَوْ أَخْدَنَا عَرَقُ الْخِلَافَةِ مِنْهُ لَمْ يُوازِي مَرَاهِ الإِلَانَاءِ
fra	Qui a écrit le livre La Sagouine?	Antonine Maillet a écrit La Sagouine en 1971. Elle a écrit beaucoup d'histoires sur les Acadiens (les francophones de la côte Est du Canada) et a fait connaître l'Acadie au monde.
ibo	Kedu ka ndị Igbo si eme emume ji ọhụru?	Emume ji ọhụru n'omenala Igbo, bụ emume na-egosi njedebe oge ọru ugbo, na-amalite site n'emume ekele ma tinyekwa oriri na egwu. O bụ mmememe ọgbakọ ebe a na-ekerịta ji ọhụru, na-egosipụta ekele na mmalite nke oge ọhụru, na-eme ka mmekorịta mmadụ na ibe ya dikwuo elu.
por	Qual é a capital do estado da Bahia?	A capital do estado da Bahia, no Brasil, é Salvador. Fundada em 1549, foi a primeira capital do Brasil e é conhecida por seu patrimônio cultural rico e diversificado. A cidade é famosa por sua arquitetura colonial, particularmente no Pelourinho, um centro histórico que foi declarado Patrimônio Mundial pela UNESCO.
pes	کیوٹرخانے مبید بر جی استوانہ ای است کہ داخل آن چھار ہزار لانہ کیوٹر وجود دارد و نوار سفید رنگی برای جذب کیوٹران دور تا دور بر ج کشیدہ شدہ است۔ این بر ج در بر ابر خطر حملہ دیگر حیوانات بے کیوٹر ہا پسیار این بو ده است۔	کیوٹرخانے مبید بر جی استوانہ ای است کہ داخل آن چھار ہزار لانہ کیوٹر وجود دارد و نوار سفید رنگی برای جذب کیوٹران دور تا دور بر ج کشیدہ شدہ است۔ این بر ج در بر ابر خطر حملہ دیگر حیوانات بے کیوٹر ہا پسیار این بو ده است۔
msa	Apakah nasi lemak?	Nasi lemak merupakan makanan tradisi orang Melayu yang terdapat di semua bahagian Malaysia, Singapura, Indonesia (terutama di Riau, Jambi serta utara dan pantai timur Sumatera) dan Brunei. Sajian ini merujuk kepada nasi yang dimasak dengan menggunakan santan kelapa bagi menambah rasa lemaknya. Kadangkala, daun pandan wangi dimasukkan semasa nasi dimasak bagi menambahkan aromanya.
tam	செயற்கை நுண்ணனிலு என்றால் என்ன?	பொதுவாக மனிதர்களால் செய்யப்படும் பணிகளைச் செய்ய ஒரு கணினி அல்லது ஒரு கணினியால் கட்டுப்படுத்தப்படும் ஒரு ரோபோவின் திறன் செயற்கை நுண்ணனிலு எனப்படும்.

Table 3: Examples of prompt and completions in the **Aya** Dataset.

tors is not uniform across languages. Moreover, within each language, there is a lack of consistent contributions from all annotators. In this section, we examine the impact of annotator skew on the resulting dataset.

Annotator Skew Across Languages. Annotators were encouraged to contribute to any language in which they could comfortably read and write and were asked to focus most of their efforts on languages other than English. Although a significant number of participants registered for many languages, the engagement level of annotators was not equal, which resulted in considerable differences in the number of contributions across languages. Figure 10 (top) provides an overview of the percentage of each language present in the final compilation. The highest number of contributions is for Malagasy with 14,597 instances, and the lowest is 79 for Kurdish.

Annotator Skew Within a Language. The final contributions for each language in the **Aya** Dataset are not evenly distributed among annotators. The median number of annotators per language is 15 (mean is 24.75) with one language having only a single active annotator (**Sindhi**) and

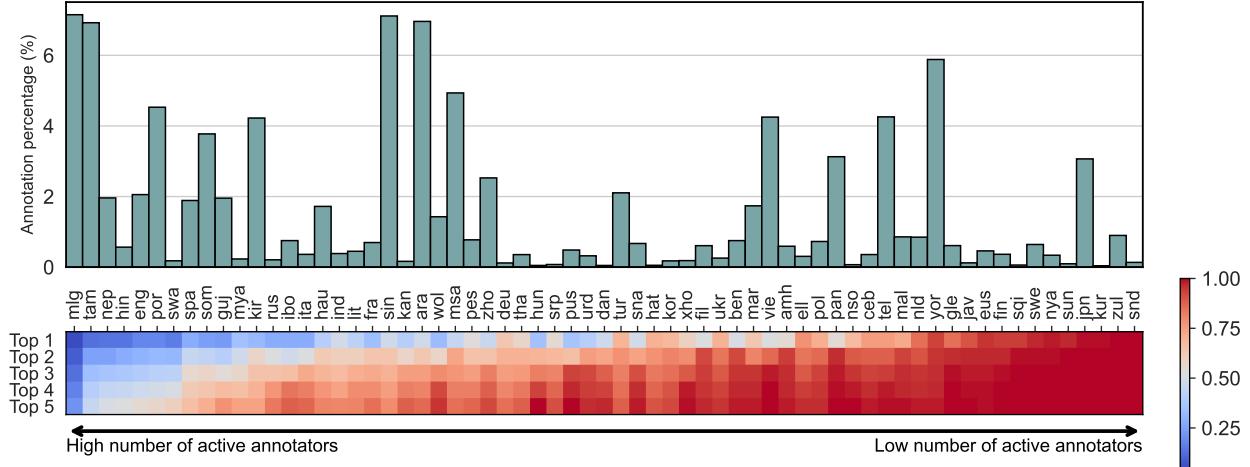


Figure 10: **Top:** Ratio of all annotations per language with respect to the whole dataset. **Bottom:** Ratio of annotations done by the top- k most active contributors ($k = 1, \dots, 5$). Languages annotations follow their respective ISO codes from Table 5.

some having over 80 annotators (English and Portuguese). Note that annotators made contributions at varying rates, and there is no direct correlation between the number of annotators and the ultimate count of language contributions. A limited pool of annotators for some languages implies that most instances in that language originate from a smaller group of individuals. Figure 10 (bottom) illustrates the proportion of instances in a language originating from the most active annotators. We observe a skewed pattern where for 12 languages, the 5 most active annotators contributed all examples. There is an uneven distribution of contributions for many languages because those languages had a smaller number of voluntary annotators throughout the entire project despite rigorous outreach. Additionally, we did not establish a specific quota for annotators to meet; everyone contributed as they desired, resulting in varying levels of activity among annotators.

The most extreme cases are Zulu and Sindhi, where one annotator in each language volunteered for all contributions in Annotation and Re-annotation tasks. Thus, in Figure 10 their top-1 contributor ratio is 1.0 and does not change when moving to top-2 or further. The languages with the least skewed distributions are Malagasy, Tamil, Nepali, Hindi, English and Portuguese. The language English also had the highest number of unique annotators with 130 individuals out of which 95 annotators contributed to English as their second language for annotation purposes. Given the uneven distribution of annotators per language, it is important to acknowledge that individual annotator quality has a disproportionate influence on some languages.

3.4 The impact of introducing the Aya Score

As part of our collaborative annotation effort in **Aya**, we emphasized the importance of quality as well as long completions that contain clear responses to the instructions specified in the prompt during the project. To encourage high-quality examples from the annotators, we introduced the **Aya** Score (Section B.2) halfway through the project to focus on the quality, in addition to the quantity, of contributions.

The **Aya** Score encouraged participants to incorporate more edits during annotation, with one specific guideline urging them to transform short answers into full sentences or paragraphs. Figure 11(right) shows the change in the completion lengths over time. We observe that after introduction of the **Aya** score, there is a marked uptick in the completion length of all submitted annotations.

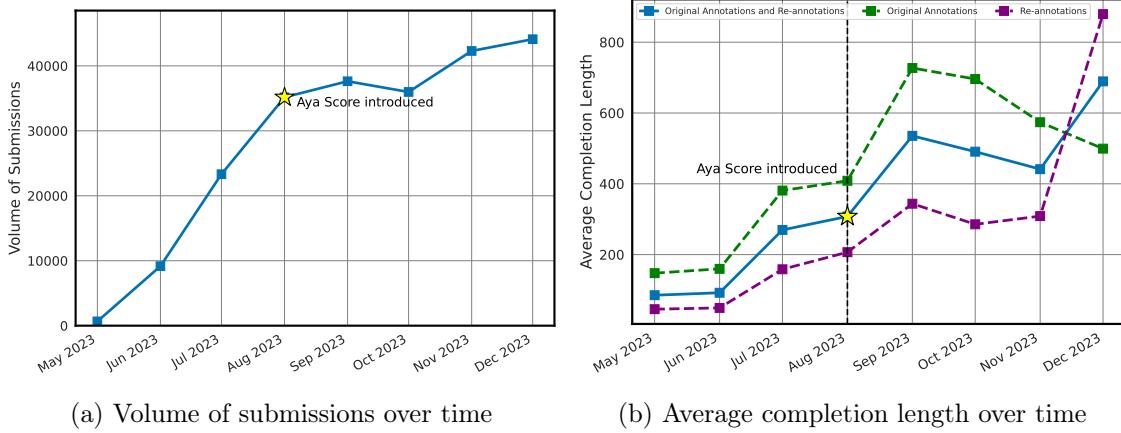


Figure 11: The volume of original annotations and re-annotations increases after the introduction of **Aya** Score. We also observe a marked uptick in the completion length of all submitted annotations with the introduction of the **Aya** Score.

4 Aya Collection

We introduce the **Aya** Collection, a comprehensive, large corpus of datasets that can be used by researchers around the world to train multilingual models. Our goal is only to include datasets with permissive licensing for manipulation and redistribution.¹² Where possible, we report the license associated with each dataset within the **Aya** Collection.

The **Aya** Collection consists of three different sources of data:

1. **Templated data:** We collaborated with fluent speakers to create templates that allowed for the automatic expansion of existing datasets into various languages.
2. **Translated data:** We translated a hand-selected subset of 19 datasets into 101 languages (114 dialects) using the NLLB 3.3B parameter machine translation model [NLLB-Team et al., 2022]. The full list of datasets translated is listed in Appendix Table 9.
3. **Aya Dataset:** We release the **Aya** Dataset described in Section 3 as a subset of the overall collection. This is the only dataset in the collection that is human-annotated in its entirety.

Dataset Selection Criteria The templated and translated datasets in the **Aya** Collection were selectively hand picked to achieve a mix of different task types. Our criteria prioritized datasets with high-quality natural and complete sentences, suitable for creating pairs of prompts and completions. Datasets that could potentially yield single-word answers were deliberately excluded. Finally, to

¹²https://en.wikipedia.org/wiki/Permissive_software_license

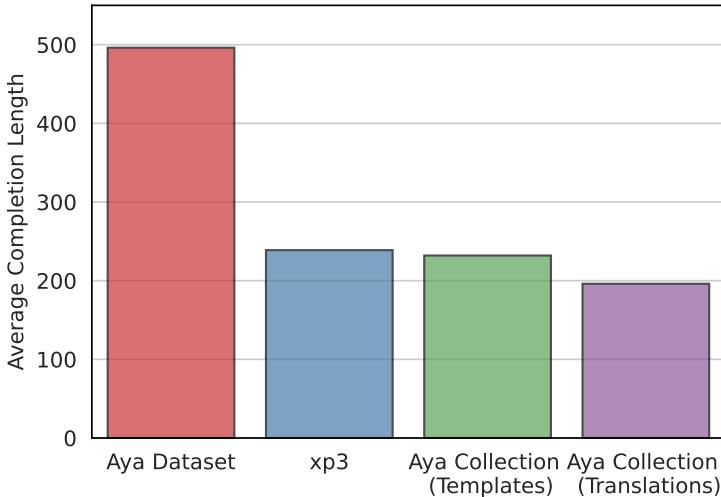


Figure 12: Comparison of completion lengths between **Aya** Dataset, **Aya** Collection, and xP3 (excluding the "code" split).

create a high-quality collection, we examined all datasets and excluded those identified as unclean or noisy, primarily attributable to their automatic creation processes.

4.1 Templating Existing Datasets

We explored the automatic expansion of existing datasets in various languages with human-written *prompt templates*, following previous works [Mishra et al., 2022; Bach et al., 2022; Wei et al., 2022a; Wang et al., 2022e]. Unlike prior works that still either use English prompts in a multilingual dataset or rely on automatic translation to generate multilingual prompts, to our knowledge, **Aya** Collection is the first broad effort to involve fluent speakers in creating prompts unique to their language to expand existing datasets for instruction tuning.

We used the **PromptSource** framework [Bach et al., 2022] to template these datasets. We asked **Aya** community members to submit instructions and create templates for datasets in the languages they were proficient in. Our process includes: 1) Templating datasets with instructions in the same language as the original dataset; 2) If the dataset is not in English, annotating instructions in English. Our input prompts can be monolingual or code-mixed, depending on whether we apply templates in the same language or in English to the dataset of a particular language. Note that code-mixed input prompts here refer to a *structured* mixing of English instructions with non-English monolingual data [Lin et al., 2022], which is different from the typical sociolinguistic definition of code-mixing (or code-switching) of languages in natural conversational utterances [Winata et al., 2023a; Yong et al., 2023c; Doğruöz et al., 2023; Srivastava & Singh, 2021].

We examined the suggested templates and subsequently converted each dataset into an instruction-style format. We release these datasets under the **Aya** Collection. We list the details of all datasets we apply templates to in Appendix Table 8.

4.2 Automatic Translation

Research has demonstrated that training models with translated data can yield significant benefits [Aharoni et al., 2019; Zhang et al., 2018b; Tang et al., 2021]. We experiment with improving coverage of low-resource languages by selectively translating high-quality datasets from various existing collections.

Setup We selectively pick 19 high-quality IFT datasets from xP3 [Muennighoff et al., 2023c], the Flan Collection [Longpre et al., 2023a], Dolly [Conover et al., 2023], along with additional sources such as SODA [Kim et al., 2022] and Mintaka [Sen et al., 2022]. Datasets were prioritized for translation based on the richness of task diversity and length of completions. The complete list of these datasets is given in Appendix 9. These translations are available and open-source as part of the **Aya** Collection. We process datasets for translation using the No Language Left Behind (NLLB) [NLLB-Team et al., 2022] machine translation model, which is capable of single-sentence translations between 200 different languages and dialects in various scripts. For best performance, we use the largest NLLB model with 3.3B parameters.

Translation Quality Appendix Section G.1 lists NLLB translation quality for each of the languages of interest, as reported in [NLLB-Team et al., 2022]. Figure 13 shows the translation quality across languages grouped by their resourcefulness. The mean ChrF++ score on FLORES is 48.17 (min: 10.9, max: 69.6) for translations out of English, with a few outliers for HR and LR. We interpret this optimistically as strong enough to sufficiently serve our translation needs. However, upon inspection of translation outputs for fine-tuning data, we encounter significant translation errors with Standard Arabic in Latin script and Minangkabau in Arabic script, so we exclude them from our translated dataset. In total, 19 public datasets were translated into 101 languages (114 dialects). Details of these datasets can be found in Appendix Table 9.

In addition to releasing the translated datasets used as a basis for re-annotation, we also translated Dolly [Conover et al., 2023]. Dolly is a 15k instruction dataset Databricks collected by relying on its employees as annotators [Conover et al., 2023]. Annotators were instructed to curate prompt and completion pairs in each of eight different instruction categories. In contrast to the mentioned NLP datasets, Dolly was purposefully designed to align language models with human expectations. It stands out as a high-quality, manually curated dataset covering a range of topics including brainstorming, classification, closed question answering, generation, information extraction, open question answering, and summarization. The addition of the translated Dolly datasets is a valuable resource for languages that experience a scarcity of conversational instruction fine-tuning datasets.

The list of datasets, along with the number of languages, templates, and other statistics, can be found in Appendix Table 9.

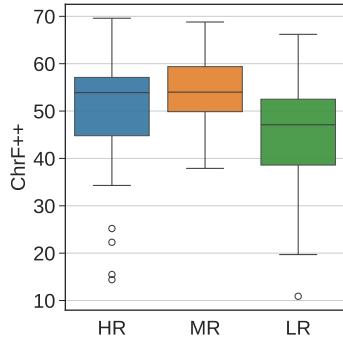


Figure 13: ChrF++ scores for the NLLB translation model, averaged across resourcefulness buckets.

Main Task Type	Fine-grained Task Type
Question Answering	—
Natural Language Generation	Summarization Translation Paraphrasing Dialogue Text Simplification
Text Classification	Sentiment Analysis Information Extraction Named Entity Recognition Event Linking Natural Language Inference Document Representation

Table 4: Task Taxonomy of NLP tasks in the **Aya** Collection.

5 Analysis of **Aya** Collection

5.1 Statistics

Overview The **Aya** Collection consists of existing NLP datasets that are templated to include instructions as well as datasets already in instruction format submitted by the **Aya** community. Table 8 shows the detailed list of datasets. The full list of templates is available in Section K. The final **Aya** Collection consists of 44 multilingual and non-English templated datasets and 19 translated datasets, with 513M individual instances. Overall, the collection covers 114 languages¹³.

Tasks Covered Across Templated and Translated Datasets We aim to include datasets from various tasks in the collection while ensuring that they follow our selection criteria. Table 4 illustrates our task coverage in the **Aya** Collection, drawing inspiration from xP3 and the Flan Collection. We have a total of three main task types: Question Answering (QA), Natural Language Generation (NLG), and Text Classification (TC). Within these larger umbrella tasks, we define several finer-grained task types based on the datasets, resulting in a total of 11 finer-grained task types. These finer-grained task types are determined by the frequency of datasets in the **Aya** Collection encapsulating that task.

For QA, we decided to keep only the main task type, as the intended goal of question-answering tasks is clear: *Answer a proposed question*. The type of the question can be different: open-ended, close-ended, multiple-choice, single response. For NLG, finer-grained task types include Summarization, Translation, Paraphrasing, Dialogue (Generation), and Text Simplification. For TC, we include the following finer-grained task types: Sentiment Analysis, Information Extraction, Named Entity Recognition, Event Linking, Natural Language Inference, and Scientific Document Representation. Finally, we label the task categories of each dataset in the **Aya** Collection in Table 10 and Table 11. If we are not able to find a fine-grained task type for the dataset, we keep the main task type.

¹³We release the **Aya** Dataset as part of the **Aya** Collection, bringing the total number of languages in the collection to 115. However, for the sake of clarity, when referencing the **Aya** Collection statistics in this paper, we exclude the **Aya** Dataset.

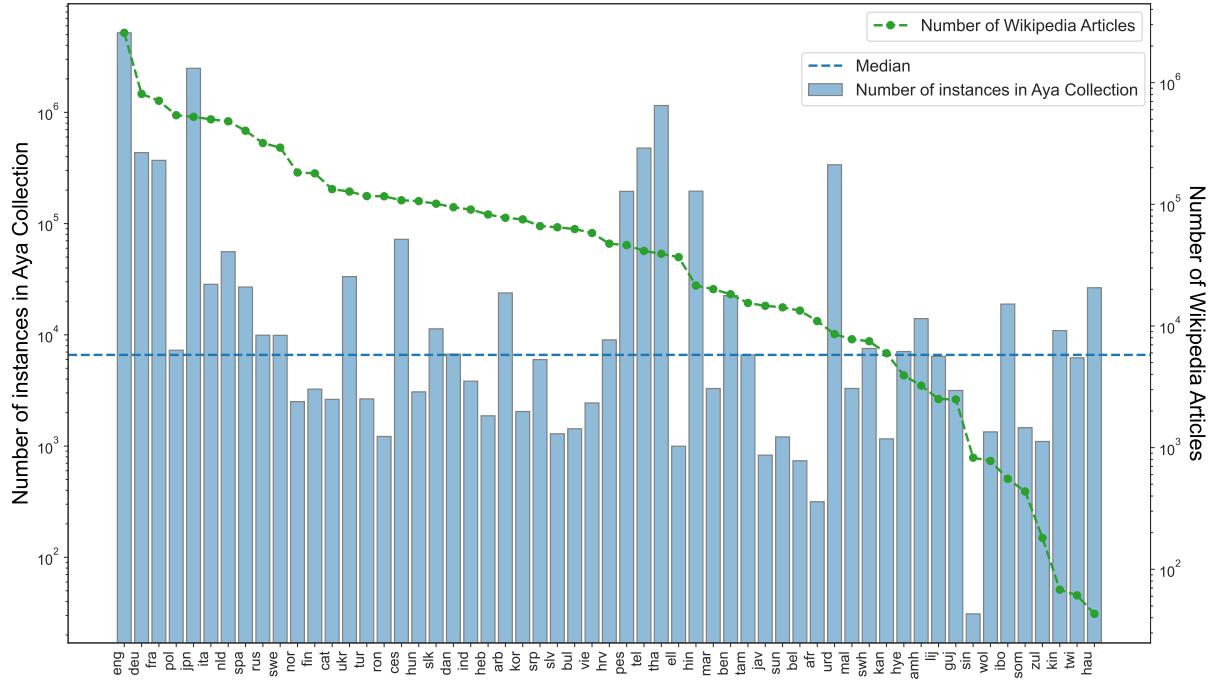


Figure 14: Number of prompt/completion pairs in each language in the **Aya** Collection (templated). Many languages with limited digital presence, as indicated by a low number of Wikipedia pages, are well-represented in the templated portion of the **Aya** Collection. Note that both axes are in log-scale.

Language Balance One of the objectives of templating (and translating) existing datasets is to broaden the available resources for languages that have limited digital data. To examine if our final collection adheres to a similar distribution pattern, we use the number of Wikipedia pages in each language as a proxy for the online presence of its fluent speakers. Figure 14 showcases that although the number of instances for languages varies in the **Aya** Collection (templated subset), it does not disadvantage languages with fewer Wikipedia pages. The distribution still ensures a reasonable coverage across all languages. It is imperative to emphasize that our analysis does not involve a direct comparison of absolute values, given the disparate units of measurement involved. Instead, we examine the *patterns* of data scarcity for various languages in our collection versus Wikipedia. Including the translated datasets in the **Aya** Collection further reduces disparities between languages and contributes to creating a more balanced collection.

Prompt and Completion Lengths Figure 15 shows the distribution of length across languages. No discernible pattern is observed when examining lengths for high-resource languages compared to low-resource languages. Low-resource languages appear at both ends of the distribution, occupying both the head and tail. In the **Aya** Collection some low-resource languages (e.g., **Somali** and **Amharic**) have longer average completions length than medium or even high-resource languages. The dedication of individual participants in identifying datasets in their own language and templating them has made a significant difference for many languages.

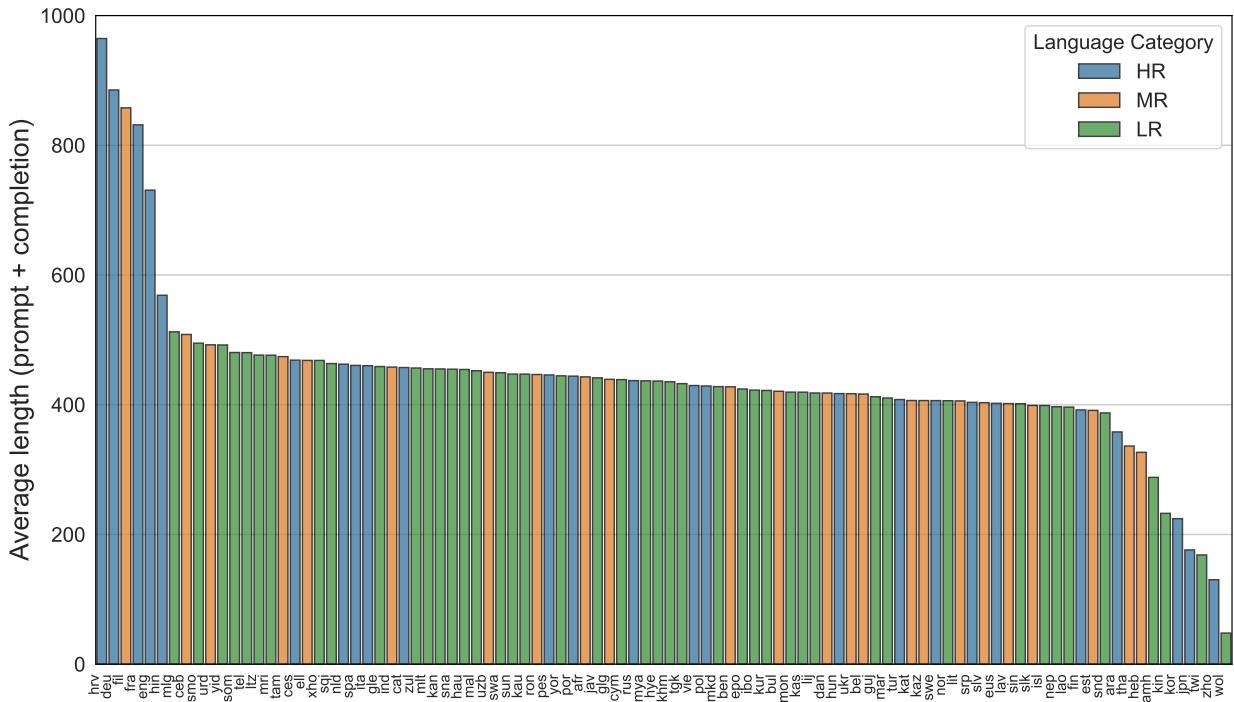


Figure 15: The average length of prompts and completions for high (HR), medium (MR) and low-resource (LR) languages in **Aya** Collection.

5.2 Quality Assessment of All Different Data Sources

As previously stated, binary feedback on the quality of the prompt-completion pairings was collected from the annotators. We define the average approval ratio per dataset which serves as a valuable metric for assessing the quality of datasets across various languages and diverse data sources. We compute the average approval ratio as $\mathcal{T}_+/\mathcal{T}$, where \mathcal{T}_+ represents the total number of thumbs up, and \mathcal{T} represents the total number of votes per dataset. An average approval ratio of 1.0 would indicate that every annotation was perceived to be of good quality and all prompts and completions had received a thumbs up. An average approval ratio of 0.0 would indicate that every annotation was perceived to be of poor quality, and all prompts and completions had received a thumbs down. We constrained our quality analysis to the 40 datasets in our pool for which we had at least 20 instances of feedback.

Overall, we observe that the majority of datasets were of above average (0.5) quality based on their approval ratio, with all translated data as well as Original Annotations being above average. However, across all the datasets within each group —xP3, Templated, Translated, and **Aya** original annotations— **Aya** original annotations were perceived to be of the highest quality, with an average approval ratio of approximately 0.81, compared to the lowest quality dataset, xP3, which had an average approval ratio of approximately 0.50. This aligns with our intuition that carefully curated datasets lead to high-quality annotations as perceived by human annotators. Figure 16 provides a summary of the results for each group. Figure 23 in the Appendix provides approval ratios per datasets in each group.

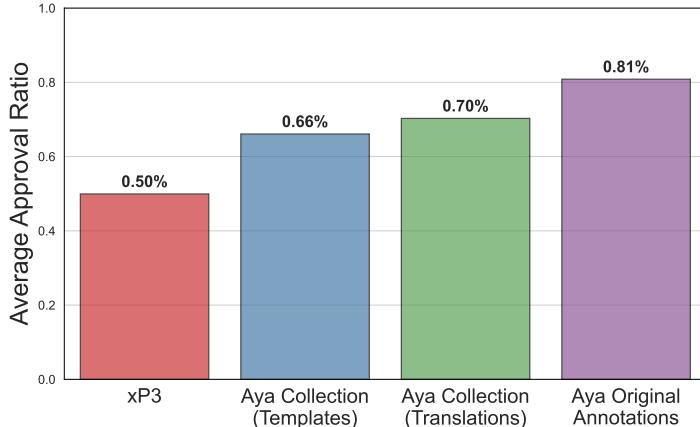


Figure 16: Average approval ratio per dataset group, constrained to datasets receiving at least 20 votes.

6 Aya Evaluation Suite

Lastly, as part of the **Aya** project we curate and release an evaluation suite tailored for multilingual models. This set is a valuable contribution in tackling the scarcity of multilingual data, a challenge that becomes even more apparent when considering evaluation sets. While there are several test sets available for evaluating multilingual models [Conneau et al., 2018; Ponti et al., 2020; Lin et al., 2022], they focus primarily on discriminative tasks. To evaluate multilingual models’ generations, the literature includes task-specific evaluation sets such as Translation [Goyal et al., 2021b], Summarization [Hasan et al., 2021] and Question Answering [Clark et al., 2020]. However there is currently a gap in evaluating *open-ended generation* capabilities of LLMs within a multilingual context. We aim to address this gap by curating a multilingual evaluation set tailored for assessing the open-ended generation capabilities of LLMs, such as brainstorming, planning, and other unstructured, long-form responses.

To strike a balance between language coverage and the quality that comes with human attention, we create an evaluation suite that includes (1) human-curated examples in a limited set of languages, (2) automatically translations of handpicked examples into a more extensive number of languages, and (3) human-post-edited translations into a small number of languages. We consider two primary sources of data: original annotations from **Aya** dataset (comprising new examples culturally curated for different languages) and Dolly prompts (high-quality, human-written examples carefully selected to have a universal reach). The subsets comprising the **Aya** evaluation suite are:

AYA-HUMAN-ANNOTATED test set For ease of future adoption, we have partitioned the **Aya** dataset into training and testing splits. The test set of the **Aya** Dataset contains 1,750 of the total instances (250 instances from 7 languages), selected at random from original annotations. Our goal is to achieve a balanced representation of languages in the test set and ensure a sufficient number of examples per language. To guarantee enough data remains for training, we focused on languages with at least 2000 original annotations. In order to ensure linguistic diversity, we included languages that were varied in terms of high, mid, or low-resourcedness, as well as script and language families. For those reasons, the test set consists of **English** (high-resource, Latin script, Indo-European), **Portuguese** (mid-resource, Latin script, Indo-European), **Simplified Chinese**

(high-resource, Han, Sino-Tibetan), **Standard Arabic** (high-resource, Arabic script, Afro-Asiatic), **Telugu** (low-resource, Telugu script, Dravidian), **Turkish** (mid-resource, Latin script, Turkic), and **Yoruba** (low-resource, Latin script, Atlantic-Congo). See Table 5 for more details.

DOLLY-MACHINE-TRANSLATED test set We separate a curated subset of 200 Dolly prompts [Conover et al., 2023] to serve as an additional translated evaluation set. Our aim with this selection was to exclude any culturally or geographically specific prompts and completions. Hence, two reviewers inspected a set of initially 500 English prompts that were uniformly sampled based on the task categories in Dolly. The reviewers excluded prompts that rely on geographic knowledge such as “*Looking at cities in Australia that are on the east coast and the west coast of the country, which coast are the cities of Fremantle, Sydney, Brisbane, Perth, Cairns, Townsville, Newcastle located on?*”, or prompts such as “*Why is NFL football called football when players use their hands mainly?*” that rely on overly specific cultural references. When two reviewers disagreed, a third reviewer was asked to break the tie. We kept prompts such as “*Is art useless?*” or “*Write a short paragraph about why you should not have both a pet cat and a pet bird.*” and questions that refer to geographic specific knowledge where the supporting evidence was provided in the prompt itself e.g., “*Given a reference text about Minister for Food, Agriculture and Fisheries of Denmark, when was the position created and was it named?*”. Although not perfect, the intention behind this selection was to gather a test set that allows us to evaluate the fluency and quality of responses in various languages while avoiding model assessment on prompts tied to specific cultural or geographic references that might have language-dependent validity. We automatically translate the prompts with NLLB into 101 languages and their dialects that are captured by NLLB. Including the original English prompts this dataset covers 115 dialects.

DOLLY-HUMAN-EDITED test set The automatic translation process may introduce errors in the prompts that render them nonsensical. For example, the prompt “*Which is a species of fish? Bleak or Weary*” requires domain expertise to choose the right translation of the fish names rather than literal translations of the adjectives (as e.g. in the NLLB Translation into Spanish: “*Desanimado o cansado.*” (=“*discouraged or tired*”)). If the prompt does not make any sense, there is no clear expectation and measurement of what a good and correct completion should look like. To confidently interpret evaluation results, it is imperative to establish a reliable set of prompts for evaluation. To enhance the reliability of testing on these prompts, we therefore enlist professional human annotators to post-edit the examples (e.g. for the example above “*Alburno o Cansado*” (= “[*Fish name*] or *Tired*”). We post-edit the prompts for a subset of six languages: **Arabic**, **Hindi**, **Spanish**, **French**, **Serbian** and **Russian**. Appendix F describes the post-editing process and effort in more detail. The example above illustrates that some prompts, even when translated correctly, might still not transfer well into other languages—which is the main difference between a translated English-centric set like this and an evaluation set originally written in each target language like AYA-HUMAN-ANNOTATED.

We open-source the **DOLLY-MACHINE-TRANSLATED test set** to be an additional resource for researchers, although warn that the expressiveness of a translated evaluation set is limited by the quality of the translation model (and human post-edit) and may adversely impact an estimate of ability in languages where translations are not adequate [Nogara et al., 2023]. Ultimately, this is a compromise between having evaluation coverage in a more complete set of languages (101 languages and 114 dialects in total) versus having human-annotated evaluation sets. **If using the automatically translated test set, we recommend it be paired and reported with the professionally post-edited DOLLY-HUMAN-EDITED for 6 languages, or the AYA-HUMAN-ANNOTATED set which also only covers 7 languages but is entirely created by proficient**

target language speakers.

7 A Participatory Approach to Research

Recent breakthroughs in NLP have predominantly come from narrow collaborations that involve researchers from a handful of institutions and regions of the world [Nakamura et al., 2023]. This reliance on small, specialized collaboration networks has been shown to hinder innovation [Park et al., 2023]. Dataset creation as a process has often been undervalued, with minimization of the value of creators’ contributions [Andress et al., 2020; Peng et al., 2021; Hanley et al., 2020]. Under such conditions, the richness and diversity of the data are often compromised, as it reflects a limited perspective that aligns with the interests of those who wield greater power in these transactions. Data is not, as metaphors such as ‘*data mining*’ [Puschmann & Burgess, 2014], or ‘*data is the new oil*’ [Stark & Hoffmann, 2019; Awati & Shum, 2015], might suggest, a natural resource waiting to be exploited. Whenever we engage with data, we are also engaging with the connections that data has to the people who produce, prepare, and distribute it [Seaver, 2021; Pinel C, 2020; Crawford, 2021]. Participatory approaches in AI design and research are one way to address gaps in access to resources needed for research: through collaborative partnerships with language speakers and local communities.

Aya is an example of a participatory research project [Birhane et al., 2022; Corbett et al., 2023; Delgado et al., 2023]. Here, the research is the result of a broad cross-institutional, global collaboration. This type of cross-sectional work facilitates the collection of vital linguistic data and community engagement, which is crucial for developing effective language technologies [Joshi et al., 2019; V et al., 2020]. We describe below some of the guiding principles we followed throughout the year-long **Aya** project.

Fluid Ownership and Growth Our open science framework allowed us to challenge the norms of how computer science usually proceeds [Wittenburg, 2021; Sabou et al., 2012]. Traditional research approaches often involve rigid hierarchies; typically, research is conducted within academic institutions or corporate labs where roles are clearly defined, and collaboration is mostly synchronous, relying on in-person meetings or real-time communication. In contrast, **Aya** took a decentralized and democratic approach to collaboration, supporting fluid leadership and flexible role adoption. This empowered members to take initiative and lead in areas where they had passion or expertise, regardless of their position in academia, or when they became involved in the project. For example, members became Language Ambassadors at many different points during the year-long project, and mentorship roles evolved naturally with more experienced researchers providing guidance to those more junior (see Appendix C for more details of different roles in the project).

Organizational Structure The communication channels and organizational structure of **Aya** were designed to facilitate rich collaboration that could evolve with the interests of participating researchers over the year-long project. For example, most communication between independent researchers involved within **Aya** was asynchronous over Discord, which allowed researchers in different time zones to participate in discussions. Monthly meetings were open for anyone to attend and were recorded for asynchronous viewing. We describe the structure of meetings and communication more thoroughly in Appendix D.1 and D.2.

Inclusion and Access The open nature of the **Aya UI** allowed us to bypass the gate-keeping

mechanisms of academic science that often marginalize non-English speakers and people without formal academic credentials [West et al., 2020]. Expertise in the command of a spoken or written language is clearly distinct from expertise in machine learning. The inclusion of such a wide range of volunteers gave us more representative data in a wide variety of languages and also gave volunteers a glimpse into the often obscure world of machine learning.

Who Participated in Aya The motivations of contributors were not based on financial remuneration but on ideals of community, identity, and social justice. Participants saw their roles as Language Ambassadors and contributors as crucial to ensuring the inclusion of their languages in the ongoing transition to a digital, information-driven economy. The Language Ambassador for **Malagasy**, a language-driven to the risk of extinction by colonial French rule in Madagascar [Spolsky, 2018], is planning hackathons in 2024 to use the **Aya** Dataset to create voice-to-text apps that will help non-literate speakers of **Malagasy** participate in the modern economy. In **Telugu**, a traditional genre of poetry known as Sathakam is an integral part of the educational system. However, chatbots that can translate text into **Telugu** have little to no understanding of the Sathakam form. The **Telugu** Language Ambassador told a newspaper in Toronto that “in **Aya**, we made sure to include as many Sathakams as we could find” [Castaldo, 2023].

These motivations are not peripheral to the strength of the final **Aya** Dataset but are key factors in the data’s provenance [Loukissas, 2019]. These qualitative dimensions remind us that language is, for the people who use it every day, an intimately social phenomenon. Beyond the symbolic notation that connects tokens to referents in the real world, we find a robust network of social relations that are necessary for languages to flourish [Sidnell & Enfield, 2012; Goodwin, 2017; Agha, 2006]. The social interactions between contributors, ML researchers, and social scientists in the **Aya** project were crucial to its success. Contributors shared playlists of their favorite songs from their home country, recipes from their childhood, and snapshots of the views from their home offices. They debated subtle nuances of how they wanted their language represented in the dataset and pushed back on some of the assumptions made by project coordinators on what constituted a distinct language as opposed to a regional dialect (see Section 9). More than one contributor sat down with their grandparents to contribute to a language that spanned three generations of use.

The realities of the conditions under which many people work and live were present every day. For example, Zoom meetings were cut short for some volunteers due to power outages in their countries or lack of access to a stable internet connection. **Burmese**, a language spoken in Myanmar, started out strong in the project with a group of 35 motivated volunteers but saw a sudden pause in contributions as civil war broke out in the country resulting in the withdrawal of the volunteers from the project [Petty, 2023]. The Language Ambassador for **Armenian** also had to drop out of the project because of a conflict in that country [Reuters, 2023]. In some countries, postal services only functioned a few days per month because of ongoing warfare, creating challenges for organizers when mailing out **Aya** gifts to thank committed volunteers. Ultimately, organizers were not able to send gifts to thank volunteers who participated from Somalia, Yemen and Palestine. For Somalia and Yemen, both Canada Post, DHL and Fedex where not able to support shipments. For Palestine, the cost of shipment proved to be prohibitively expensive – with an estimated shipping cost of 294 US dollars per t-shirt. These geo-political realities shaped both our contributors’ experience as well as the progress of the project.

Including these factors in our post-mortem analysis of the project is crucial to understanding both the motivation of people willing to volunteer for open-science projects, and also to understanding

the data itself: its breadth, its provenance, its shortcomings, and its living history.

ISO Code	Language	Script	Family	Subgrouping	Resources	Included
ace	Achinese	Arabic/Latin	Austronesian	Malayo-Polynesian	Low	♣
afr	Afrikaans	Latin	Indo-European	Germanic	Mid	♣
amh	Amharic	Ge'ez	Afro-Asiatic	Semitic	Low	♦ ♣
ara	Arabic	Arabic	Afro-Asiatic	Semitic	High	♦ ♣
aze	Azerbaijani	Arabic/Latin	Turkic	Common Turkic	Low	♣
ban	Balinese	Latin	Austronesian	Malayo-Polynesian	Low	♣
bbc	Toba Batak	Latin	Austronesian	Malayo-Polynesian	Low	♣
bel	Belarusian	Cyrillic	Indo-European	Balto-Slavic	Mid	♣
bem	Bemba	Latin	Niger-Congo	Atlantic-Congo	Low	♣
ben	Bengali	Bengali	Indo-European	Indo-Aryan	Mid	♦ ♣
bjn	Banjar	Arabic/Latin	Austronesian	Malayo-Polynesian	Low	♣
bul	Bulgarian	Cyrillic	Indo-European	Balto-Slavic	Mid	♣
cat	Catalan	Latin	Indo-European	Italic	High	♣
ceb	Cebuano	Latin	Austronesian	Malayo-Polynesian	Mid	♦ ♣
ces	Czech	Latin	Indo-European	Balto-Slavic	High	♣
cym	Welsh	Latin	Indo-European	Celtic	Low	♣
dan	Danish	Latin	Indo-European	Germanic	Mid	♦ ♣
deu	German	Latin	Indo-European	Germanic	High	♦ ♣
ell	Greek	Greek	Indo-European	Graeco-Phrygian	Mid	♦ ♣
eng	English	Latin	Indo-European	Germanic	High	♦ ♣
epo	Esperanto	Latin	Constructed	Esperantic	Low	♣
est	Estonian	Latin	Uralic	Finnic	Med	♣
eus	Basque	Latin	Basque	-	High	♦ ♣
fil	Filipino	Latin	Austronesian	Malayo-Polynesian	Mid	♦ ♣
fin	Finnish	Latin	Uralic	Finnic	Mid	♦ ♣
fon	Fon	Latin	Niger-Congo	Atlantic-Congo	Low	♣
fra	French	Latin	Indo-European	Italic	High	♦ ♣
gla	Scottish Gaelic	Latin	Indo-European	Celtic	Low	♣
gle	Irish	Latin	Indo-European	Celtic	Low	♦ ♣
glg	Galician	Latin	Indo-European	Italic	Med	♣
guj	Gujarati	Gujarati	Indo-European	Indo-Aryan	Low	♦ ♣
hat	Haitian Creole	Latin	Indo-European	Italic	Low	♦ ♣
hau	Hausa	Latin	Afro-Asiatic	Chadic	Low	♦ ♣
heb	Hebrew	Hebrew	Afro-Asiatic	Semitic	Mid	♣
hin	Hindi	Devanagari	Indo-European	Indo-Aryan	High	♦ ♣
hrv	Croatian	Latin	Indo-European	Balto-Slavic	High	♣
hun	Hungarian	Latin	Uralic	-	High	♦ ♣
hye	Armenian	Armenian	Indo-European	Armenic	Low	♣
ibo	Igbo	Latin	Atlantic-Congo	Benue-Congo	Low	♦ ♣
ind	Indonesian	Latin	Austronesian	Malayo-Polynesian	Mid	♦ ♣
isl	Icelandic	Latin	Indo-European	Germanic	Low	♣
ita	Italian	Latin	Indo-European	Italic	High	♦ ♣
jav	Javanese	Latin	Austronesian	Malayo-Polynesian	Low	♦ ♣
jpn	Japanese	Japanese	Japonic	Japanese	High	♦ ♣
kan	Kannada	Kannada	Dravidian	South Dravidian	Low	♦ ♣
kas	Kashmiri	Arabic	Indo-European	Indo-Aryan	Low	♣
kat	Georgian	Georgian	Kartvelian	Georgian-Zan	Mid	♣
kau	Kanuri	Arabic/Latin	Saharan	Western Saharan	Low	♣
kaz	Kazakh	Cyrillic	Turkic	Common Turkic	Mid	♣
khm	Khmer	Khmer	Austroasiatic	Khmeric	Low	♣
kin	Kinyarwanda	Latin	Niger-Congo	Atlantic-Congo	Low	♣
kir	Kyrgyz	Cyrillic	Turkic	Common Turkic	Low	♦ ♣
kor	Korean	Hangul	Koreanic	Korean	Mid	♦ ♣
kur	Kurdish	Latin	Indo-European	Iranian	Low	♦ ♣
lao	Lao	Lao	Tai-Kadai	Kam-Tai	Low	♣
lav	Latvian	Latin	Indo-European	Balto-Slavic	Mid	♣
lij	Ligurian	Latin	Indo-European	Italic	Low	♣
lit	Lithuanian	Latin	Indo-European	Balto-Slavic	Mid	♦ ♣
ltz	Luxembourgish	Latin	Indo-European	Germanic	Low	♣
mad	Madurese	Latin	Austronesian	Malayo-Polynesian	Low	♣
mal	Malayalam	Malayalam	Dravidian	South Dravidian	Low	♦ ♣
man	Manipuri	Bengali	Sino-Tibetan	Kuki-Chin-Naga	Low	♣

mar	Marathi	Devanagari	Indo-European	Indo-Aryan	Low	◆ ♡
min	Minangkabau	Latin	Austronesian	Malayo-Polynesian	Low	♡
mkd	Macedonian	Cyrillic	Indo-European	Balto-Slavic	Low	♡
mlg	Malagasy	Latin	Austronesian	Malayo-Polynesian	Low	◆ ♡
mlt	Maltese	Latin	Afro-Asiatic	Semitic	Low	♡
mon	Mongolian	Cyrillic	Mongolic-Khitan	Mongolic	Low	♡
mri	Maori	Latin	Austronesian	Malayo-Polynesian	Low	♡
msa	Malay	Latin	Austronesian	Malayo-Polynesian	Mid	◆ ♡
mya	Burmese	Myanmar	Sino-Tibetan	Burmo-Qiangic	Low	◆ ♡
nep	Nepali	Devanagari	Indo-European	Indo-Aryan	Low	◆ ♡
nij	Ngaju	Latin	Austronesian	Malayo-Polynesian	Low	♡
nld	Dutch	Latin	Indo-European	Germanic	High	◆ ♡
nor	Norwegian	Latin	Indo-European	Germanic	Low	♡
nso	Northern Sotho	Latin	Atlantic-Congo	Benue-Congo	Low	◆ ♡
nya	Chichewa	Latin	Atlantic-Congo	Benue-Congo	Low	◆
pan	Punjabi	Gurmukhi	Indo-European	Indo-Aryan	Low	◆ ♡
pes	Persian	Arabic	Indo-European	Iranian	High	◆ ♡
pol	Polish	Latin	Indo-European	Balto-Slavic	High	◆ ♡
por	Portuguese	Latin	Indo-European	Italic	High	◆ ♡
pus	Pashto	Arabic	Indo-European	Iranian	Low	◆ ♡
ron	Romanian	Latin	Indo-European	Italic	Mid	♡
rus	Russian	Cyrillic	Indo-European	Balto-Slavic	High	◆ ♡
sin	Sinhala	Sinhala	Indo-European	Indo-Aryan	Low	◆ ♡
slk	Slovak	Latin	Indo-European	Balto-Slavic	Mid	♡
slv	Slovenian	Latin	Indo-European	Balto-Slavic	Mid	♡
smo	Samoan	Latin	Austronesian	Malayo-Polynesian	Low	♡
sna	Shona	Latin	Indo-European	Indo-Aryan	Low	◆ ♡
snd	Sindhi	Arabic	Indo-European	Indo-Aryan	Low	◆ ♡
som	Somali	Latin	Afro-Asiatic	Cushitic	Low	◆ ♡
sot	Southern Sotho	Latin	Atlantic-Congo	Benue-Congo	Low	♡
spa	Spanish	Latin	Indo-European	Italic	High	◆ ♡
sqi	Albanian	Latin	Indo-European	Albanian	Low	◆ ♡
srp	Serbian	Cyrillic	Indo-European	Balto-Slavic	High	◆ ♡
sun	Sundanese	Latin	Austronesian	Malayo-Polynesian	Low	◆ ♡
swa	Swahili	Latin	Atlantic-Congo	Benue-Congo	Low	◆ ♡
swe	Swedish	Latin	Indo-European	Germanic	High	◆ ♡
tam	Tamil	Tamil	Dravidian	South Dravidian	Mid	◆ ♡
taq	Tamasheq	Latin/Tifinagh	Afro-Asiatic	Berber	Low	♡
tel	Telugu	Telugu	Dravidian	South Dravidian	Low	◆ ♡
tgk	Tajik	Cyrillic	Indo-European	Iranian	Low	♡
tha	Thai	Thai	Tai-Kadai	Kam-Tai	Mid	◆ ♡
tur	Turkish	Latin	Turkic	Common Turkic	High	◆ ♡
twi	Twi	Latin	Niger-Congo	Atlantic-Congo	Low	♡
ukr	Ukrainian	Cyrillic	Indo-European	Balto-Slavic	Mid	◆ ♡
urd	Urdu	Arabic	Indo-European	Indo-Aryan	Mid	◆ ♡
uzb	Uzbek	Latin	Turkic	Common Turkic	Med	♡
vie	Vietnamese	Latin	Austroasiatic	Vietic	High	◆ ♡
wol	Wolof	Latin	Atlantic-Congo	North-Central Atlantic	Low	◆ ♡
xho	Xhosa	Latin	Atlantic-Congo	Benue-Congo	Low	◆ ♡
yid	Yiddish	Hebrew	Indo-European	Germanic	Low	♡
yor	Yorùbá	Latin	Atlantic-Congo	Benue-Congo	Low	◆ ♡
zho	Chinese	Han	Sino-Tibetan	Sinitic	High	◆ ♡
zul	Zulu	Latin	Atlantic-Congo	Benue-Congo	Low	◆ ♡

Table 5: 65 languages in the **Aya** Dataset and 114 languages in the **Aya** Collection, each language's corresponding script, family, subgrouping, and if it is classified as “lower-”, “mid-” or “higher-” resourced according to the taxonomy classes by [Joshi et al., 2020] (low: [0, 1, 2], mid: [3], high: [4, 5]). The language is either included in the **Aya** Dataset (◆), **Aya** Collection (♡), or both. Note that Ngaju (nij) and Toba Batak (bbc) are not listed in [Joshi et al., 2020].

8 Related Work

8.1 Multilingual datasets

Low-resource languages have long been a challenge in NLP, with limited data impacting task performance [Kunchukuttan et al., 2021]. To address this, researchers have explored techniques like data augmentation [Sennrich et al., 2016; Dhole et al., 2021], transfer learning [Zoph et al., 2016], repeating [Luukkonen et al., 2023; Muennighoff et al., 2023b], and multilingual models [Dabre et al., 2020; Muennighoff et al., 2023c; Yong et al., 2023b], achieving promising results in areas like machine translation. Here, we focus on efforts that are centered on multilingual dataset creation.

Several works have created large-scale multilingual corpora. These are often unstructured texts, ideal for large-scale unsupervised pre-training [Abadji et al., 2021; Ortiz Su’arez et al., 2019; Scao et al., 2022a,b; Laurençon et al., 2022; Kudugunta et al., 2023; Whitehouse et al., 2023]. Another group of multilingual datasets is focused on machine translation [Lucia Specia et al., 2010; Fan et al., 2021]. They consist of parallel texts in two or more languages, enabling models to learn the mappings between them. Ideally, machine translation datasets encompass diverse domains and language pairs, from commonly spoken languages to resource-scarce ones, promoting inclusivity and linguistic diversity. One of the most extensive collections of parallel corpora is available at the OPUS project website¹⁴ [Tiedemann, 2012]. Large capacity models for language understanding may obtain strong performance on high-resource languages while greatly improving low-resource languages [Goyal et al., 2021a]. In Whitehouse et al. [2023], the effectiveness of LLM-powered data augmentation in cross-lingual commonsense reasoning was demonstrated. An improved performance was shown when smaller cross-lingual models were finetuned with data generated by LLMs. Some recently released datasets focus on specialized language domains such as law [Niklaus et al., 2023], education [Zhang et al., 2023c], or healthcare [Wang et al., 2023].

These corpora often suffer from inadequate data quality and require extensive cleaning [Abadji et al., 2022; Kreutzer et al., 2022]. Task-specific datasets, such as XCOPA [Ponti et al., 2020] or XNLI [Conneau et al., 2018], are smaller in scale but offer higher quality data targeted at a specific model capability such as cross-lingual understanding and transfer learning. This type of data is crucial for evaluating and enhancing the performance of models in diverse linguistic contexts.

No Language Left Behind [NLLB-Team et al., 2022] open-sourced bitext, mined bitext, and data generated using back-translation in 200+ languages specifically for text-to-text translation. While Seamless4MT [Barrault et al., 2023] released the metadata of SeamlessAlign, an open multimodal translation dataset, there are relatively fewer works for data creation/curation in low-resource languages. Cahyawijaya et al. [2023] introduced NusaCrowd, a standardized collection of 137 datasets covering 19 Indonesian local languages in text, speech, and image modalities. Our work differs from previous datasets as we create a large-scale instruction-tuning dataset spanning hundreds of different tasks, yet retain high-quality by involving human annotation and rigorous quality control across the entire data creation process.

¹⁴<https://opus.nlpl.eu>

8.2 Instruction-tuning datasets

Instruction-tuning datasets are collections of human-curated instructions and response pairs, templatized NLP tasks, or synthetic instructions generated by a language model. There are a growing number of NLP meta-datasets such as Natural instructions [Mishra et al., 2022], SuperNatural Instructions[Wang et al., 2022d], Flan 2021 [Wei et al., 2022a], Flan 2022 [Longpre et al., 2023a], Public Pool of Prompts (P3) [Sanh et al., 2022], Unnatural Instructions [Honovich et al., 2023], OPT-IML [Iyer et al., 2022], inter alia [Khashabi et al., 2020; Ye et al., 2021; Min et al., 2021] that collate numerous instruction finetuned datasets together. Some work focuses on specific applications such as dialogue [Köpf et al., 2023], structured knowledge grounding [Xie et al., 2022], or chain-of-thought reasoning [Wei et al., 2022b; Kim et al., 2023]. Manual efforts include Open Assistant [Köpf et al., 2023] crowd-sourcing volunteers who wrote both instructions and responses, Databricks employees creating 15k examples in Dolly [Conover et al., 2023], and LIMA [Zhou et al., 2023] which is a collection of 1,000 author-curated IFT examples.

Synthetic instruction-tuning datasets comprise instructions sampled from a language model, such as the Self-Instruct dataset [Wang et al., 2022b] generated by GPT-3 [Brown et al., 2020], the Alpaca dataset [Taori et al., 2023] generated by GPT-3.5, and the Guanaco dataset [Joseph Cheung, 2023]. Increasingly, the synthetic generation of instruction-finetuned datasets is more sophisticated. [Xu et al., 2023a] propose a novel Evol-Instruct framework to obtain complex and difficult instructions gradually. [Luo et al., 2023] and [Gunasekar et al., 2023] further expand this idea to promote reasoning, code generation, and algorithmic skills. InstructionWild [Ni et al., 2023] and ShareGPT¹⁵ are collections of user-shared conversations with ChatGPT.

8.3 Multilingual Instruction-Tuning Datasets

Despite ever-larger collections of IFT datasets, prior work has been largely English-centric. Most approaches to extend instruction finetuned datasets outside of English have relied on **1)** translating English datasets into other languages [Holmström & Doostmohammadi, 2023; Li et al., 2023a; Winata et al., 2023b], **2)** template based dataset creation [Yu et al., 2023; Gupta et al., 2023] or **3)** human curating instruction datasets in languages outside of English [Muennighoff et al., 2023c; Li et al., 2023c; Wang et al., 2022c]. There have been some notable exceptions with large proportions of non-English data [Joseph Cheung, 2023; Köpf et al., 2023; Lai et al., 2023; Li et al., 2023a; Longpre et al., 2023a; Muennighoff et al., 2023a;c; Zhuo et al., 2024; Nguyen et al., 2023].

Template-Based Datasets. The most relevant effort is recent work by [Muennighoff et al., 2023c] releasing Crosslingual Public Pool of Prompts (xP3). xP3 expands the P3 taxonomy and adds 28 new multilingual datasets. However, their datasets usually use the same template in different languages, thus limiting task diversity. For example, a random batch from their dataset may include the same sample in different languages multiple times. Their xP3 corpus has task instructions exclusively in English. In [Muennighoff et al., 2023c], the experiments with matching the task instruction to the respective language of the sample via machine translation (xP3mt) showed slightly improved performance for non-English task instructions at inference. Our work is distinct in that our human-curated constructed dataset is unique for each of the 65 languages. Such diversity has been emphasized as a key ingredient for instruction tuning [Longpre et al., 2023a]. Further, we create non-English task instructions via human annotators, ensuring these are of high-quality, which is

¹⁵<https://sharegpt.com/>

another pillar of a good performance [Zhou et al., 2023].

Machine Translated Datasets. Machine-translated prompts often lack variability and the cultural nuance inherent in natively written text. However, they are still useful for expanding the language coverage of the training data and can help bridge the resource gap for languages with limited training data [Urbizu et al., 2023; Lin et al., 2022]. They can also adapt already-trained instruction-tuned language models to follow instructions in new languages [Yong et al., 2023b]. Furthermore, LLMs trained on designed prompts have also been shown to be successful at tasks like EAE (Event Argument Extraction) from multilingual data in a zero-shot setup [Huang et al., 2022]. [Zhang et al., 2023a] constructed high-quality Chinese instructions from existing English instruction datasets. They first translated the English instructions into Chinese and then used a human verification process to determine whether these translations were usable; the verified dataset set consists of around 200k Chinese instruction-tuning samples. [Li et al., 2023a] constructed instruction data for 52 popular languages using Google Translate to translate English prompts and completions from Alpaca [Taori et al., 2023] (52K) and Dolly [Conover et al., 2023] (15K) dataset, then used this data to finetune LLaMA [Touvron et al., 2023] using the LoRA [Hu et al., 2021] technology. [Zhang et al., 2023b] prompted LLMs to translate a task request, which was overlaid with the more granular user-based corrects. This process naturally connects different languages as well as human preferences with LLMs, leveraging LLaMA [Touvron et al., 2023] for foundational support and employing automatic construction of interactive translation instructions for instructional tuning, thereby enhancing the model’s multilingual capability and alignment with diverse linguistic needs.

Human-Curated Multilingual Examples. Most relevant to our work on the **Aya** dataset are other datasets that have been curated by humans, often in English. Databricks collected a 15k instruction dataset **databricks-dolly-15k** by relying on its employees as annotators [Conover et al., 2023]. Annotators were instructed to curate prompt / response pairs in each of eight different instruction categories. [Köpf et al., 2023] released the OpenAssistant corpus with over 10,000 dialogues from more than 13,500 international annotators. While this dataset contains multilingual annotations, this was not an explicit goal of the initiative. In contrast to our corpus which only has 2.05% contributions in English, 42.8% of the OpenAssistant project remains in English [Köpf et al., 2023].

8.4 Participatory Research in Machine Learning

If you want to go fast go alone; if you want to go far, go together. — African Proverb

Prior participatory research initiatives have centered around regions or specific tasks like translation or character recognition. For example, [Clanuwat et al., 2018] tackles the problem of reading and understanding *Kuzushiji*, a cursive style of Japanese writing no longer in common use. Another example of culturally diverse data collection is [Liu et al., 2021], which recruited native speakers from five languages (**Indonesian**, **Swahili**, **Tamil**, **Turkish**, and **Mandarin Chinese**) that are typologically, genealogically, and geographically diverse, to provide images of concepts that are representative of their cultures. Then, they recruited native-speaking professional linguists to write captions for these images. However, this dataset is small (less than 8,000 data points) and thus limited to evaluation only. It is worth noting that these works are solely focused on the image domain, unlike our work, which concentrates on text.

More relevant to our work are participatory data creation initiatives focused on NLP. [Guevara-Rukoz et al., 2020] presents a study focusing on the creation of a crowd-sourced corpus for Latin American Spanish dialects to address the scarcity of resources for these languages. [V et al., 2020] focuses on the task of Machine Translation (MT), and curates a dataset in 30 under-represented African languages according to a participatory research framework. Our work is very much in the spirit of these prior efforts, with differences in terms of global rather than regional focus. In contrast to these works, which have a specific regional focus, **Aya** collaborators came from multiple continents covering a diverse range of languages.

Several works have explored the organizational structures required to facilitate the development of research communities around under-represented languages. [Siminyu et al., 2021] details work on the AI4D - African Language Program, which aimed to enhance language resources for African languages. The outcome included creating over nine open-source African language datasets and establishing baseline models, demonstrating the program’s significant impact on language technology for African languages. [Azunre et al., 2021] describes the establishment of NLP Ghana, with its collaborative open-source community. [Strassel & Tracey, 2016] discusses the challenges of developing resources for low-resource languages under the LORELEI (Low Resource Languages for Emergent Incidents) program. They focus on the pressing need for digital resources in these languages, particularly in critical situations such as mitigating the effects of natural disasters.

Open science community initiatives like **Aya** yield significant advancements in language modeling. Related efforts (in terms of compute and resources required) can be found in the BigScience Workshop [Akiki et al., 2022], which began in 2021. The BigScience project was initiated to address the limitations in LLM development, emphasizing open science and inclusive collaboration. Leveraging open science principles, it united a global network of researchers working to collaboratively and ethically enhance machine learning. Their work culminated in key developments like the BLOOM model [Scao et al., 2022a] and ROOTS corpus [Laurençon et al., 2022]. These achievements underscore the value of community-driven, ethical, and diverse research programs for large-scale language technologies. Following Big Science, there have been other recent efforts on open science in language modeling [Groeneveld et al., 2024; Soldaini et al., 2024].

9 Limitations of our work

1. **Language and dialect coverage:** The **Aya** Dataset and **Aya** Collection cover 65 and 114 languages respectively—significantly more than existing multilingual datasets. However, this is still only a tiny fraction of the world’s linguistic diversity. Of the world’s approximately 7,000 languages, only half of them are captured in any sort of written form [Adda et al., 2016]. Of this half, only a few hundred are included on the internet in machine readable corpora [Adda et al., 2016]. This means that 93% of the world’s languages are still not being used to train LLMs. It is also notoriously difficult to determine the dividing line between different languages and different dialects of the same language [Rooy, 2021]. Geo-cultural variation within a language often gives rise to new dialects or creoles over time [Zampieri et al., 2020; Wolfram, 1997; Brown et al., 2020; Lent et al., 2022; Blaschke et al., 2023] and, as such, dialects can serve an important function in establishing and maintaining cultural identity [Falck et al., 2012]. Many different dialects that are generally recognized as belonging to a single parent language are not represented in the dataset. For example, in the case of **Malay**, one of the largest Southeast Asian languages in the dataset, there are no contributions for regional

dialects that are widely spoken in certain states of Malaysia. Contributions by volunteers who wished to self-identify as speaking a particular dialect were tagged as such in the data to allow for limited analysis of the use of regional dialects in annotations. Lastly, socio-linguistic data show that multilingual speakers often ‘code-switch’ between languages or dialects depending on context [Myers-Scotton, 2017], but in this project, we kept the languages isolated to make them easier to classify and to be used downstream for language-specific applications. **Aya** also does not cover programming languages. There has been prior work on covering diverse programming languages [Li et al., 2023d; Allal et al., 2023] and we leave further explorations in this direction to future work.

2. **Uneven distribution of contributions:** As explored in Section 3.3, despite the large number of participants, the activity of annotators was skewed, with a ‘long tail’ of annotators only contributing one or two annotations. Relatively few contributors accounted for the most annotations (see Figure 10 - bottom). Similarly, there is a huge gap between languages with the highest number of contributions and ones with the lowest number of contributions. Consequently, this suggests potential unevenness in dataset distributions across different languages and a lack of annotator diversity within some languages dominated by one or two frequent contributors.
3. **Cultural or personal bias:** Another limitation is the presence of annotations with particular cultural biases. Some languages in our dataset have limited representation, with only a few annotators responsible for annotating the bulk of their dataset. This might mean that data for a particular language is dominated by annotations that represent the opinions or priorities of a particular contributor or could represent a narrow selection of cultural viewpoints. For example, annotations in French might contain many examples about the history of France, its food, songs, and other cultural practices, but not contain much information about the cultural heritage of French-speaking communities in Québec, Togo, or Senegal [Vigouroux, 2013]. This bias is particularly problematic given the skewed distribution of the most active annotators. There is also a potential bias in the availability of particular kinds of content. For example, it is easier to find online text from news sites for many African languages than it is to find text from other domains. Accordingly, these datasets will be skewed towards the grammar and lexicon used in news reports instead of the kind of natural language people use in everyday life [Hovy & Prabhumoye, 2021].
4. **Gendered pronouns:** Many of the languages in the **Aya** Dataset only contain pronouns that are explicitly gendered (e.g., Arabic) or that lack gender-neutral third-person pronouns for gender-neutral reference (e.g. Estonian). This means that in responding to prompts that might not specify a gender, care needs to be taken to ensure that responses remain neutral as to the gender of any assumed participants [Ghosh & Caliskan, 2023]. For example, if a response requires reference to “*a teacher*” in French, the annotator would need to include references to both “*un/e enseignant/e*”. While care was taken to ensure neutral responses for new annotations, gendered annotations in existing datasets might not have been flagged, as they are not, strictly speaking, incorrect. Instead, they merely presuppose a gendered reading where one might not be implied [Hardmeier & Guillou, 2018].
5. **Formality distinctions:** Many of the languages in the **Aya** Dataset also require the speaker or annotator to make situational choices as to the formality of the pronoun used in response to a particular prompt. Languages such as Japanese, Persian, Indonesian, Javanese, Yoruba, French, Spanish, and German include different levels of honorifics that are used

in formal or informal settings, or used between community members who differ in status (determined by a variety of factors such as age, profession, seniority, or ethnicity) [Brown & Gilman, 1968]. In Yoruba, for example, the pronoun that roughly translates as “*they*” can either be used as a singular honorific or as a third-person plural pronoun [Yusuf, 2022]. We deferred to the individual annotators in crafting their responses, allowing them to rely on the norms of their particular speech community to determine how to respond. Often, these decisions hinged on the content being discussed, or on how formally the prompt was crafted in the original data set. When in doubt, annotators were asked to imagine what kind of ‘voice’ they would expect an LLM to have when answering a given prompt [Wilson, 2023].

This means our released dataset contains many languages that have varying levels of standardization and differing style guidelines. Standardization is often deeply intertwined with power and identity, and the manner of speech may be connected to aspects of identity like age, education level, tribal affiliation, and religion. The lack of standardization is also largely due to regional and cultural differences across the same language, exemplified by Portuguese in the dataset: European Portuguese diverges from Brazilian Portuguese not only in formality but also in grammar, spelling, and vocabulary. Often, standards are projected by others to ensure adherence to cultural values [Bourdieu, 1987; De Mauro et al., 2015; Haugen, 1959; Rickford et al., 2012].

6. **Toxic or offensive speech:** The **Aya** Annotation Platform did not contain specific flags for toxic, harmful, or offensive speech, so it is possible that malicious users could submit unsafe data. We believe this is of relatively low risk because of the high rate of human-verified annotations and peer-review, making it unlikely that toxic prompts or completions made it into the final dataset. However, there is no guarantee that every entry was audited. While data poisoning has rarely been observed as a viable threat in practice, it has been demonstrated to be of concern for instruction-tuning with very few examples [Xu et al., 2023b; Wan et al., 2023] and for pre-training under realistic conditions [Carlini et al., 2023]. During the eight months of crowd-sourced annotating, there were no reported cases of hateful or toxic speech in the existing datasets nor were there any instances of offensive speech reported in the peer-reviewing phase of new annotations.

We also note that data that might be offensive to one annotator might not be offensive to another, for instance, the completion of a prompt that asks for a definition of the word “woke” [Castaldo, September 16, 2023]. Prompts written on partisan political topics, or the inclusion of political advertisements or campaign messages could cause offense depending on the political proclivities of the annotator. In short, we tried to mitigate offensive speech by relying heavily on human annotation and peer review, but there is no guarantee that all such data points were removed from the corpus.

7. **Accounting for mislabeled data:** The **Aya** Annotation Platform did not contain any components that enabled re-labeling the assigned language of annotations. This may result in prompts and completions that appear under a particular language, but were submitted incorrectly and would need to be re-categorized into a different language. Additionally, while we trusted annotators were able to follow directions and had a high rate of manual auditing, some examples likely made it into the **Aya** Dataset that were not in instruction-style format or were free-form texts.

10 Conclusion

Open participatory research continues to be under-resourced and undervalued, particularly when that work focuses on data creation [Sambasivan et al., 2021]. **Aya** involved participants from many different countries, different ages, and different levels of familiarity with the field of natural language processing. We see continued opportunity for computational linguists and machine-learning engineers to collaborate with social scientists such as sociolinguists, anthropologists, sociologists, and media studies scholars. As new norms in open science emerge [Krishna, 2020; Bowser et al., 2020], collaborations like these can help ensure that projects in NLP are motivated by an understanding of what language means to the people who use it every day.

With **Aya**, we hope to change the way data is created for multilingual NLP research. In line with this view, we release the **Aya Dataset** which is the first human-curated open-source, multilingual instruction-style dataset consisting of 204,114 prompt-completion pairs covering 65 languages. This dataset was built with the help of our open-science community of 2,997 collaborators from 119 countries over a period of eight months.

We also release the **Aya Collection**, which consists of 44 instruction-style datasets. These were prepared by transforming existing NLP datasets into prompt-completion pairs that can be leveraged for instruction tuning. Furthermore, we translate several high-quality datasets into 101 languages, thereby expanding coverage, particularly for many low-resource languages. This collection consists of 513M prompt and completion pairs covering 114 languages in total and is the largest multilingual instruction-finetuning collection today. Additionally, we release **Aya Evaluation Suite**, consisting of human-curated examples in 13 languages and translation of carefully selected prompts in 101 languages. Finally, we are also open-sourcing the **Aya Annotation Platform** so that communities can continue to use the platform to support the process of multilingual data collection. We hope these communities continue to grow and develop, and to connect speakers of low-resource languages around the world.

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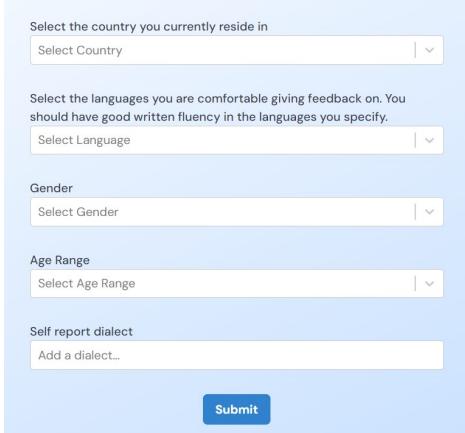
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A Aya Annotation Platform

In this section, we discuss the detailed design and development of the **Aya** Annotation Platform and the gamification strategy employed. Together, these attempts aimed to ensure high-quality curation of the **Aya** Dataset.



Select the country you currently reside in
Select Country

Select the languages you are comfortable giving feedback on. You should have good written fluency in the languages you specify.
Select Language

Gender
Select Gender

Age Range
Select Age Range

Self report dialect
Add a dialect...

Submit

Figure 17: The onboarding page for a new user. We collect some demographic information and ask them to specify the languages they are comfortable annotating data in. These are the language options they are presented with later on in the UI.

A.1 Engagement Strategies

We decided to employ gamification methods to enhance annotator engagement [de Franga et al., 2015; Bastanford et al., 2023; Morschheuser et al., 2017]. Our strategy involved using a points-based rewards system, motivating contributors through social media recognition, and fostering friendly competition with leaderboards. Regular mini-challenges and sprints helped to create collective achievement goals and fostered a sense of community [Bastanford et al., 2023]. Real-time feedback reinforced positive behavior and customization options, such as avatars, provided a personalized experience. Overall, these gamification strategies aimed to boost engagement, improve data quality, and created a more enjoyable experience for the crowd-sourcing participants. [Morschheuser et al., 2017].

To recognize and incentivize the efforts of our contributors, we established a tiered reward system based on contribution milestones: 500, 1,000, and 5,000 contributions. Contributors who achieved these goals on the project leaderboard were rewarded with certificates and specially designed **Aya** project apparel. The attire varied according to the contribution level, with different packages for each milestone. Additionally, the most active contributors were prominently acknowledged in the project’s dataset documentation, highlighting their significant role as key contributors to the project. This system not only motivated contributors but also served as a token of appreciation for their dedication and hard work.

In addition to the leaderboard, the **Aya** Discord Bot was developed to recognize contributors with a high number of points. This bot recognized the daily top 10 contributors by tagging them in a message that was posted on the **Aya** Discord server. It also aggregated daily total contributions per region and specified how many days were left until the data collection phase ended. As shown

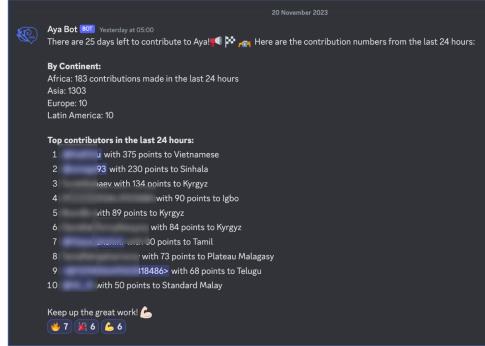


Figure 18: Aya Discord Bot message aggregating daily statistics and top 10 annotators

in Figure 18, these messages provided a regular snapshot of progression that allowed annotators to see the dataset grow across all languages.

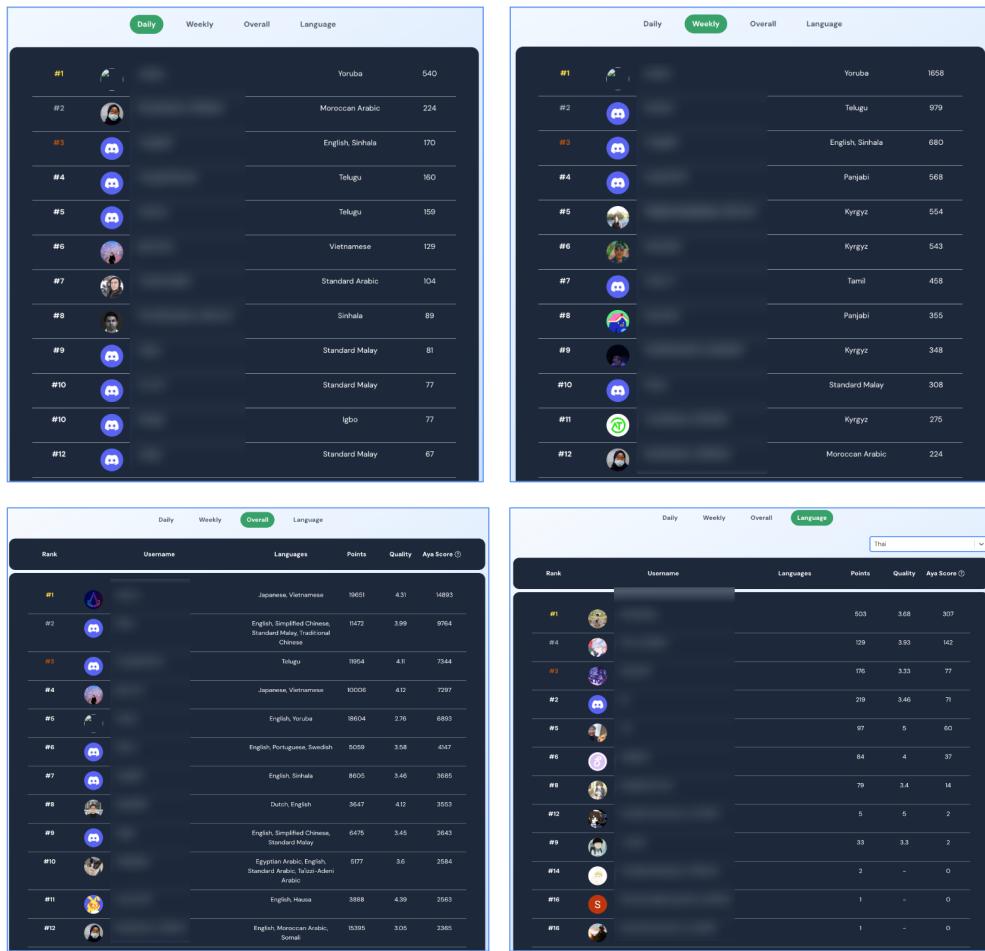


Figure 19: Aya Leaderboard. Daily and weekly leaderboards are shown on the top left and right respectively. At the bottom are language-specific and overall leader boards, where annotators are ranked based on their Aya score.

A.2 Accessibility of Registration Tools

The accessibility and popularity of registration tools differed from country to country and this had an impact on where the **Aya** UI users joined from. Figure 20 compares the percentage of registered users using Discord and Gmail to sign up in the top 10 countries. After introducing Google SSO, we observed a significant jump in the number of registered users from several new countries (Figure 21).

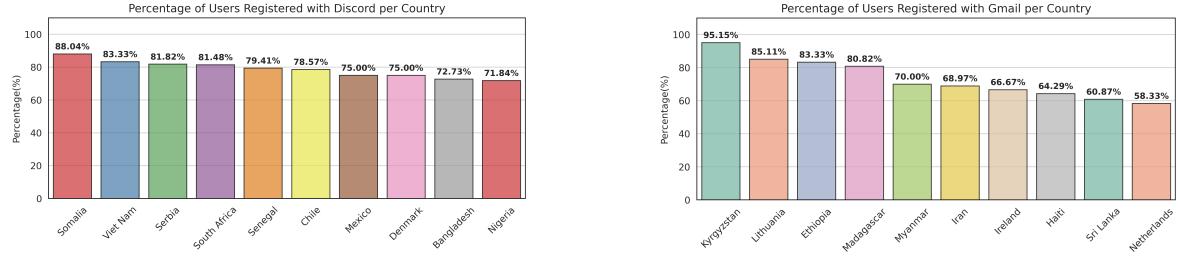


Figure 20: Percentage of **Aya** UI users that registered via **Left:** Discord and **Right:** Gmail.

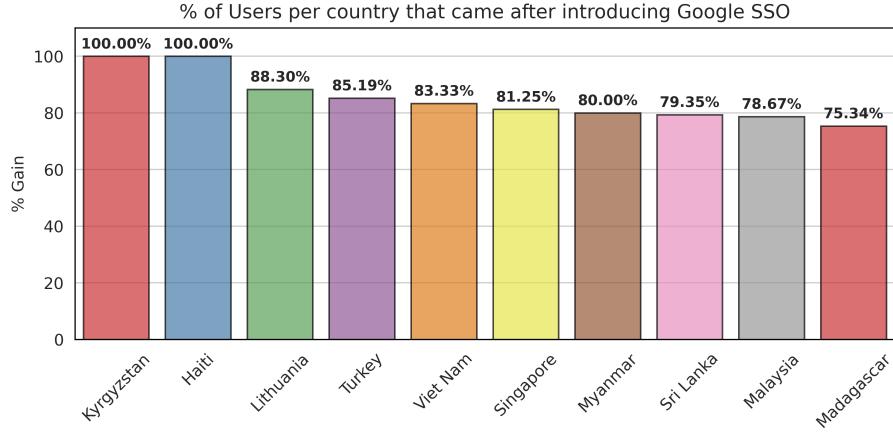


Figure 21: Percentage of the **Aya** UI users that registered after the introduction of Google SSO in the platform.

B UI Tasks

B.1 Reviewing Annotators

In the **Aya** UI, we display the original and re-annotated versions of both prompt and completion along with the name of the annotator who did the re-annotation. Reviewers are tasked with rating the re-annotated prompt and completion on a scale from 1 to 5. The ratings are defined as follows:

- (1) Much worse than the original annotation;
- (2) Worse than the original annotation;
- (3) No noticeable difference compared to the original annotation;
- (4) Better than the original annotation;
- (5) Much better than the original annotation.

If any of the prompt/completion pairs receive a rating below 5 (i.e., anything lower than “Much

better than the original annotation”), the reviewer is provided with an option to modify the provided prompt and completion pair to improve its quality. An “Additional Feedback” text box is also available for reviewers to explain the reasoning behind their chosen rating.

B.2 Aya Score

To encourage annotators to make high-quality submissions, we designed a ranking score favoring contributions that received high peer ratings. The **Aya** Score for an individual annotator is:

$$\text{Score}_{\text{Aya}} = w_1 \times (\mathcal{E}) + w_2 \times \mathcal{C}, \quad (1)$$

with weights w_1 , w_2 defined as:

$$w_1 = \max \left(0, (\hat{Q} - 3) \right), w_2 = \left(\frac{\mathcal{T}_+}{\mathcal{T}} \right) \quad (2)$$

where:

- \mathcal{E} represents the total number of re-annotations in which the annotator edited prompts and completions
- \mathcal{C} represents the total number of original annotations submitted by an annotator
- \hat{Q} represents the average quality rating derived for an annotator through peer review via Annotation Feedback task
- \mathcal{T}_+ represents the total number of original annotations made by an annotator that received positive feedback in Re-annotations task
- \mathcal{T} represents the total number original annotations made by an annotator that feedback received in Re-annotations task.

The rationale behind introducing the $\text{Score}_{\text{Aya}}$ was to boost a competitive environment among annotators and encourage them to focus on submitting high-quality data, consequently improving the overall quality of the **Aya** Dataset.

B.3 Annotation Guidelines

The annotators were provided with the following evaluation criteria for what a good prompt and completion pair must look like. Re-Annotations were then performed if they determined that the prompts or completions needed editing.

1. No grammatical or spelling mistakes in both the prompt and completion text.
2. The prompt provides clear instruction on what the task is.

-
3. The completion answers the prompt correctly. Both the prompts and completions should be in full sentences and coherent, with reasonable length.
 4. For original annotations, the prompts and completions should not be generated from other language models.

Re-Annotations Before editing, annotators rated the quality of existing prompt and completion pairs by choosing either the thumbs-up or thumbs-down option. If the provided prompt and completion pair were already of good quality according to the criteria above, then annotators rated them with thumbs up and moved ahead without editing. Overall, annotators were encouraged to re-annotate the completions, in particular by adding more details and context to them since many of them were often short one-word answers.

C Language Representation via Community

C.1 Division by Regions

We chose to divide languages into four primary regions: *Africa*, *Asia*, *Europe*, and *Latin America*. These four regions were established in order to facilitate the administration of user contributions and were not intended to prescribe boundaries within which certain languages are exclusively spoken.

The language statistics by region are as follows: *Africa* (14 languages), *Asia* (41 languages), *Europe* (42 languages), and *Latin America* (4 languages). Almost all the languages were assigned to a region but there are some exceptions, *Maori* and *Samoan* were unassigned to any specific region as they didn't align with the predefined regions. *English* was left unassigned, serving as a common language across all regions. Additionally, contributions in *Spanish* and *Portuguese* were distributed between *Europe* and *Latin America* based on contributors' countries. Similarly, *Arabic* contributions were shared between *Africa* and *Asia* depending on the contributors' country of origin. Additional dialects of *Arabic* were included in regions separate from that of their parent language because we had a significant number of speakers from these regions eager to contribute to their respective dialects. Each region had at least one "Regional Lead" responsible for coordinating "Language Ambassadors," and for recruiting fluent speakers for the languages within their area.

C.2 Language Ambassadors

The Language Ambassador's role was pivotal in bridging the gap between the data collected in a language and its speakers. An essential criterion for selection was native fluency in the specific language. The Language Ambassador's expertise in specific languages and familiarity with the cultures of the language speakers was invaluable. They assisted not only in spreading awareness among participants but also in identifying and addressing potential data issues specific to each language, such as languages incorrectly assigned to their region. Their cultural and linguistic insights enabled them to make informed decisions, like choosing suitable data sources for collection in their respective languages. Not every language had a designated Language Ambassador, and some had more than one. In total, we had 84 Language Ambassadors over the course of the initiative. Their combined efforts played a vital role in broadening the contributor base for each language. Support for the Language Ambassadors' progress and trouble-shooting challenges they faced was coordinated asynchronously and through weekly online meetups, discussed in Sec. D.1 and Sec. D.2.

C.3 Regional Leads

There were a total of six Regional Leads: two for Latin America, one for Africa, one for Asia, and two for Europe. The selection for Regional Lead roles was on a voluntary basis, with the only requirement being that they must originate from the regions they intended to lead. The invitation for this role was specifically extended to individuals who were already actively participating in Cohere For AI projects or engaged in other open science projects. Regional Leads had several key roles throughout the project, such as selecting Language Ambassadors and aiding their efforts in attracting more annotators and maintaining their engagement.

D Communication

D.1 Platforms

We established a Discord server for coordination between Regional Leads, Language Ambassadors and annotators. The server provided basic channels for internal communications: introductions, inquiries, and announcements, as well as specific channels for Language Ambassadors, for each region, and for each language, along with any other channels that proved useful for the particular region. For external communications, we used social media platforms (e.g., X, LinkedIn, WhatsApp, Facebook), recognizing that the choice of communication platform varied based on cultural and regional preferences. Using multiple platforms not only facilitated internal organization but also broadened our project’s outreach by providing flexible and inclusive means of outreach to diverse communities and audiences.

D.2 Meetings

In addition to asynchronous communication through Discord, we conducted meetings to maintain team collaboration and cohesion:

1. **Regional Leads and Language Ambassadors Meeting:** A weekly meeting in which Regional Leads and Language Ambassadors shared project updates, exchanged ideas, and addressed questions from Language Ambassadors. It served as an excellent platform for gathering ideas from Language Ambassadors and brainstorming new strategies to engage annotators effectively.
2. **New Contributor Introduction Meeting:** Held weekly, this meeting aimed to introduce new contributors to the project’s specifics. It included explanations about the motivations behind the project, a walk-through of the **Aya** UI, and a sharing of regional statistics. Additionally, this meeting provided examples of both good and bad annotations and edits to guide new annotators in their work. It concluded with a synchronous challenge for the annotators to submit a few initial annotations in real time to familiarize them with the process and allow them to ask questions if they got stuck.
3. **Regional Leads Meeting:** Held bi-weekly, this meeting brought together Regional Leads to assess progress, discuss upcoming steps, and provide advice on how to engage and sustain contributions for their respective regions. Furthermore, this meeting facilitated collaborative troubleshooting efforts and helped make important decisions for the following week.

-
4. **Technical Update:** This meeting was dedicated to sharing technical updates, with a focus on recent UI progress, data, and benchmarking. The purpose of this monthly update was to ensure all team members and annotators were well-informed about the project’s current status and upcoming priorities. It was a place for open discussion to hear feedback from everyone interested in the project.
5. **Language Specific Meeting:** Held weekly or biweekly, these meetings were co-working sessions or datathons led by the language ambassadors with their respective annotators to submit annotations synchronously. It also acted as an onboarding session to welcome new contributors from regions that could not join the New Contributor Introduction Meeting due to conflicting time zones. Demonstrations on using the UI, as well as brainstorming sessions, were conducted to improve the representation of specific languages in the project.

E Language Groupings

In this work we will refer to groups of languages to be “lower-”, “mid-” or “higher”-resourced according to their recorded, written, and catalogued NLP resources [Joshi et al., 2020]. Joshi et al. [2020] group languages into 5 distinct clusters based on the amount of data from a combined range of source (LDC catalog¹⁶, ELRA Map¹⁷, Wikipedia¹⁸), which we interpret as a proxy for data availability for pretraining and IFT training of LLMs. We group these 5 distinct clusters into a rough taxonomy of **lower-resourced (LR)**, **mid-resourced (MR)** and **higher-resourced (HR)** (See Table 6). See Table 5 for full mapping of languages to categories. We note that this grouping is inevitably imperfect; languages and their varieties cannot absolutely nor universally be classified based on this single dimension [Hämäläinen, 2021; Lignos et al., 2022; Bird, 2022]. The categorization in our case serves the purpose of aggregation in our analysis of the data distribution.

Group	Category	Languages	Examples
Higher-Resourced	5	7	Arabic, Chinese, English, French, Spanish
	4	18	Hindi, Italian, Portuguese, Russian, Turkish
Mid-Resourced	3	25	Afrikaans, Indonesian, Kazakh, Malay, Latvian
Lower-Resourced	2	13	Hausa, Icelandic, Irish, Lao, Maltese
	1	39	Albanian, Gujarati, Igbo, Luxembourgish
	0	12*	Kurdish, Kyrgyz, Sinhala, Yiddish

Table 6: Language grouping for the **Aya** Collection. We assign categories to languages based on [Joshi et al., 2020]. (*) We assign label 0 to two languages not found in Joshi et al. [2020]’s taxonomy (`manipuri` and `ngaju`).

¹⁶<https://catalog.ldc.upenn.edu/>

¹⁷<https://catalog.elra.info/en-us/>

¹⁸<https://wikipedia.org/>

F Post-Editing the dolly-machine-translated Test Set

F.1 Annotators

Annotator Selection The primary demographic make-up of the participants in the evaluations was recruited based on their proficiency in the language groups. The proficiency was self-reported, and our requirements were natively proficient or professionally proficient in the specific languages needed for the project. Outside of this, the participants come from diverse social backgrounds comprised of students and individuals with full-time or part-time jobs that do annotation as a “side gig”.

Socio-Demographics The annotator pool is comprised of people from diverse backgrounds, and this spans across socioeconomic backgrounds, careers, levels of education, and self-reported gender and sexual identities. We do not ask any annotators to share or report any of these statistical pieces of information in a formal way; any insights into this are gathered organically and through self-reporting by the annotators.

Quality Considerations We do not believe that any socio-demographic characteristics have led to any impact on the data that has been annotated. Through every part of the project we have reiterated the importance of this work and the fact that this is helping to support a global-scale research project. We are confident in the trust we have built with the annotators in this project, and they care greatly about the overall outcome and therefore have been diligent in completing the task with a high degree of accuracy. Where possible, we have done our best to have annotators work on this project and be representatives of the communities that the project aims to support.

Compensation The annotators were paid 30 CAD per hour. No special consideration was made to the hourly rate as that is the standard rate offered to Cohere’s annotators who work on highly complex tasks.

F.2 Annotation Process

Communication Annotators were briefed by one of the authors in a virtual introduction session, and were able to ask questions and raise issues throughout the annotation task in a Slack channel. They were also encouraged to share frequent error patterns, artifacts, or hard decisions that they encountered throughout the task with the authors and other annotators.

Schedule There was no fixed time schedule for the annotations and annotators contributed a varying amount of hours and ratings, depending on their availabilities and speed. Each translation was post-edited by one annotator, and there were 3–4 annotators involved in each task. After post-edits were completed, a second annotator (not the original post-editor) assessed the post-edit for quality and proposed new final edits if necessary.

Interface Post-edits were collected on Google Sheets with an interface built in Google Apps Script.

F.3 Instructions

The instructions given to professional annotators for the DOLLY-MACHINE-TRANSLATED test set post-edits were the following: “As an annotator, you have the task to improve the quality of the prompts for our multilingual model! The prompts are originally machine-translated from English, and sometimes the translation introduces errors in the prompts that make them hard to follow.

We need your help to identify these cases, and to edit these translations so that they...

1. Convey the same instruction/task/request as the English original — not more and not less.
2. Are grammatically correct.
3. Are free from phrases too literally translated from English (we call this “Translationese”).

This is how:

For each pair of English prompt and translated prompt shown, decide whether the prompt is okay as it is (according to the above criteria), or needs an edit.

- If it needs an edit, edit the prompt until the quality is satisfactory (in the field “Edited Prompt”). Try to keep your edits minimal. Then confirm that the edited prompt fulfills the above three criteria.
- If it’s okay as is, just proceed (without editing the “Edited Prompt” field) to confirm that it fulfills the above three criteria.”

Annotations were done through an interface built on top of Google Sheets. One annotator edited each prompt, and another verified the edit, if necessary had a discussion and edited the original edit. Three to four editors collaborated on each language.

F.4 Post-Editing Effort

For each prompt, we measure the post-editing effort with Human-targeted Translation Error Rate (HTER) [Specia & Farzindar, 2010], an edit-distance metric that compares the original machine translation with the post-edited version in terms of edit operations on units of words. This also gives us an estimate of how severe the errors in the original translations were, and how critically the post-editors assessed the original translations. Analogously, we estimate with a Human-targeted Character F-Score (HChrF) score how much the original translation overlaps with the final post-edited translation. This metric is based on the ChrF score [Popović, 2015] and operates on character-level matches. Computations of HTER and HChrF are based on the `sacrebleu` implementation [Post, 2018].

Table 7 reports these statistics for the six languages of the DOLLY-MACHINE-TRANSLATED test set. We find that editors edited at least 41% of prompts in all languages, a surprisingly high number. This indicates that translation errors in the DOLLY-MACHINE-TRANSLATED test set are quite common.

Language	% of Prompts Edited	HTER	HChrF
Arabic	41.0%	10.78	92.74
French	84.5%	5.56	96.81
Hindi	60.0%	6.16	95.00
Russian	86.5%	37.43	75.92
Serbian	72.5%	9.06	92.79
Spanish	75.5%	9.13	93.25

Table 7: Post-editing effort measured by the overall percentage of edited dolly test prompts, HTER (Human-targeted Translation Error Rate: the higher, the more effort), and HChrF (Human-Targeted Character F-Score: the lower, the more effort).

For Russian, the post-editing effort was overall largest, with an average of 37.43 HTER, which means that 37.43% of words in the final post-edit had to be edited from the original. This stands in contrast with the post-edits for French, where a similar ratio of original prompts was edited (84.5% compared to 86.5% for Russian), but to a much lesser extent (5.56 HTER).

G Translation using NLLB

Additional Generation details One caveat with using NLLB is that since the model was trained on single sentence pairs, the translations tend to cut off abruptly when full paragraphs are translated. To get around this, we sentence-tokenize the paragraphs using the sentence-splitter Python package (similar to [NLLB-Team et al., 2022]) and concatenate them post-translation. To avoid known translation introduced artefacts, We also filter any samples which have `<unk>` tokens introduced by the NLLB tokenizer or model.

G.1 Translation Quality of NLLB

Figure 22 illustrates NLLB translation quality as measured by ChrF++ on the FLORES benchmark for the languages of interest for **Aya**, grouped by their resourcefulness according to [Joshi et al., 2020]. The scores were extracted from <https://github.com/facebookresearch/fairseq/blob/n11b/README.md> for the dense 3.3B model.

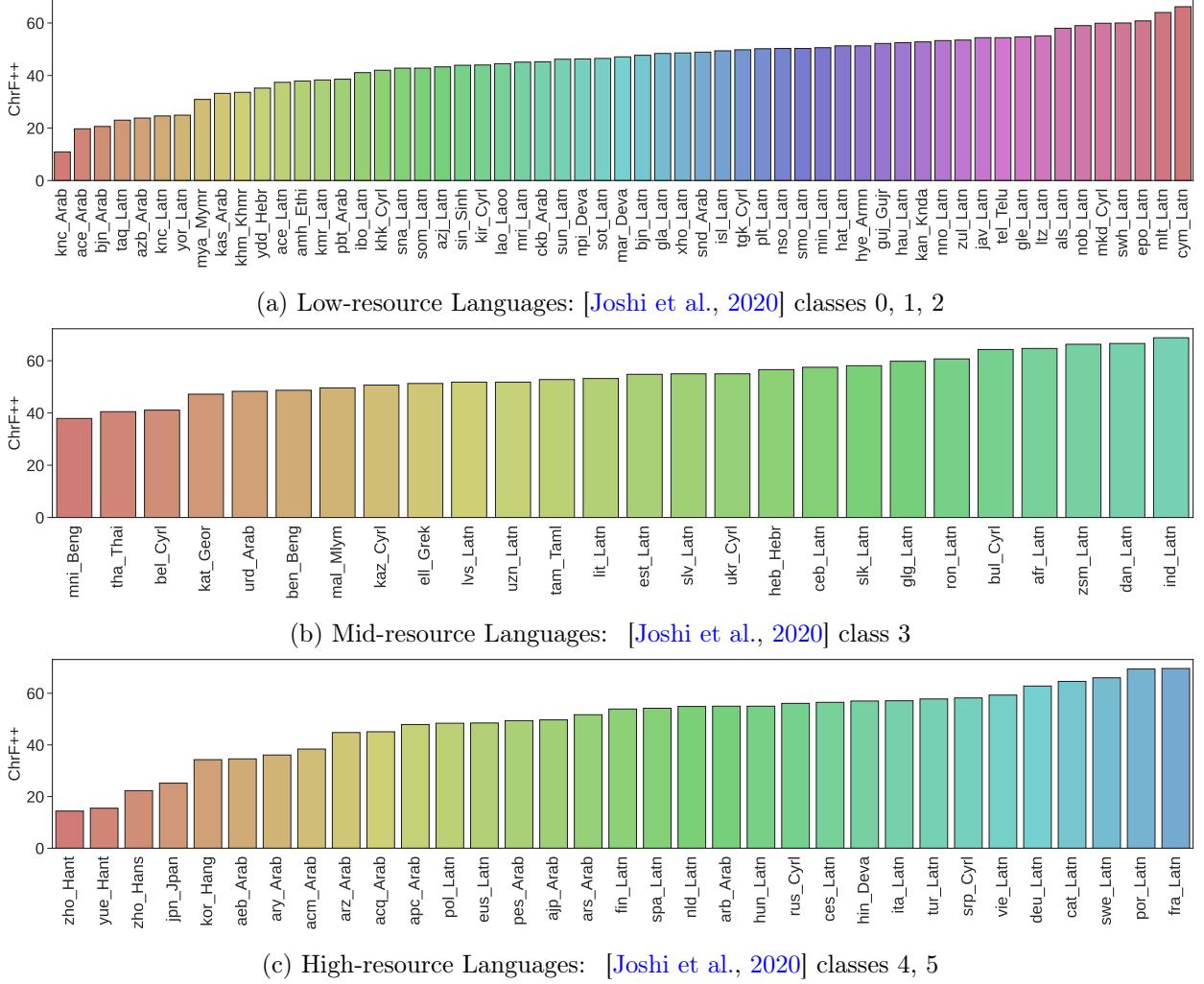


Figure 22: NLLB Translation Quality: ChrF++ scores on FLORES for translations from English into the **Aya** target languages that are covered by NLLB, grouped by their resourcefulness according to [Joshi et al., 2020].

H Additional Figures

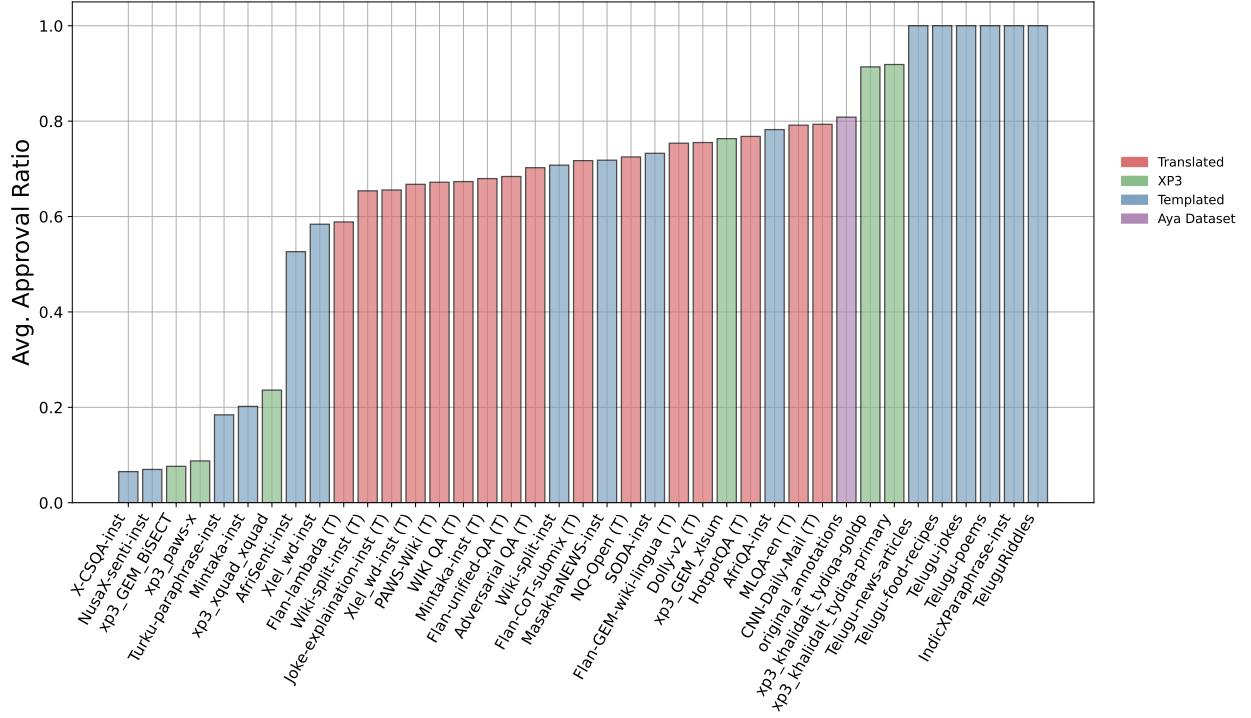


Figure 23: Average Approval Ratio per dataset, constrained to datasets receiving at least 20 votes.

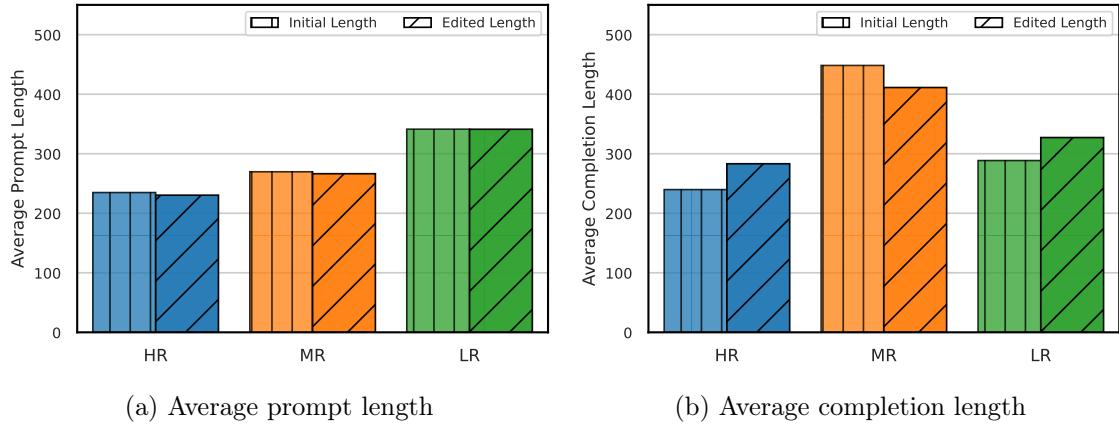
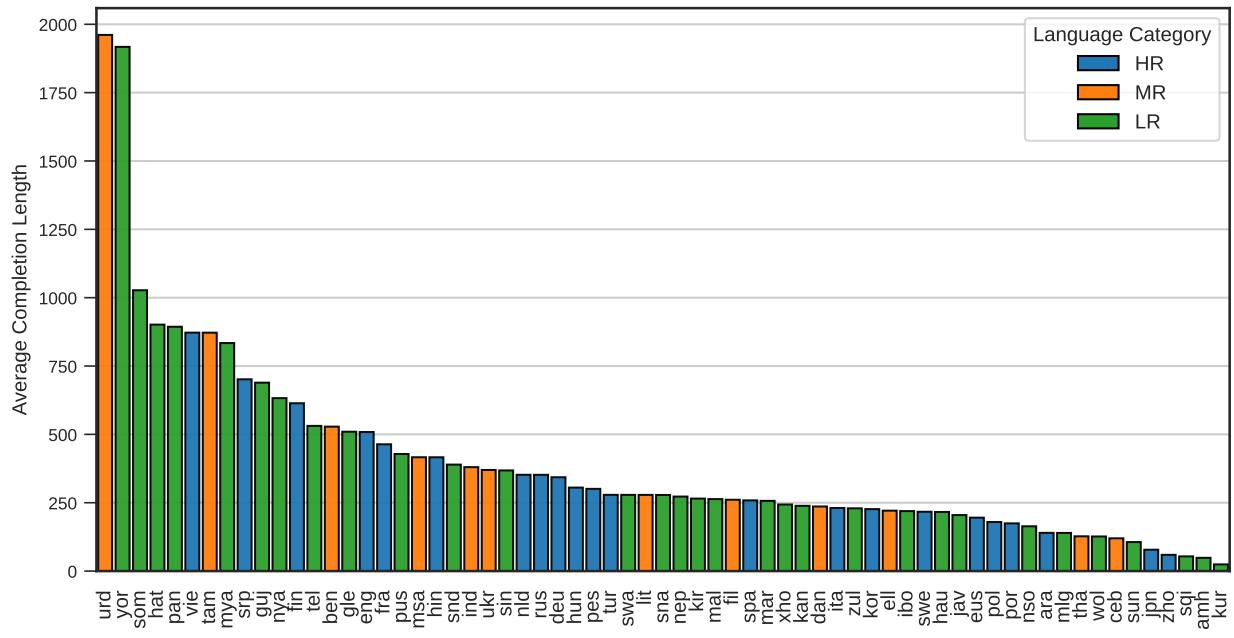
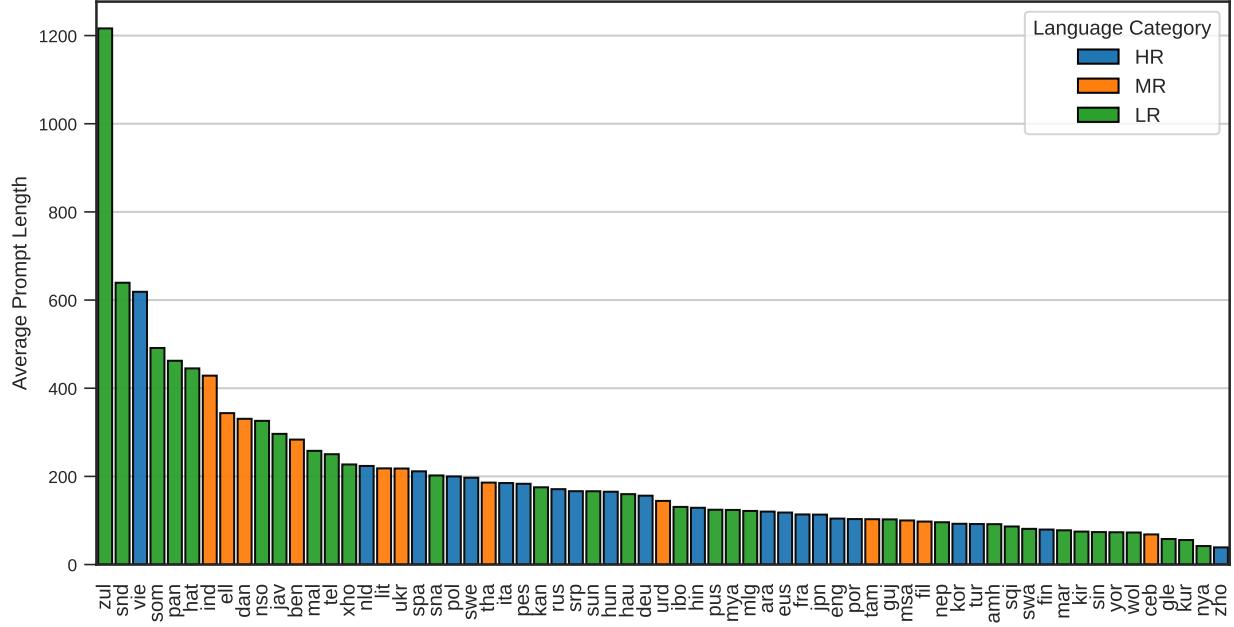


Figure 24: Average prompt and completion length of instances in the **Aya** Dataset before and after re-annotation across different language categories.



(a) Average completion length for every language in the **Aya** Dataset.



(b) Average prompt length for every language in the **Aya** Dataset

Figure 25: Average prompt and completion length for every language in the **Aya** Dataset

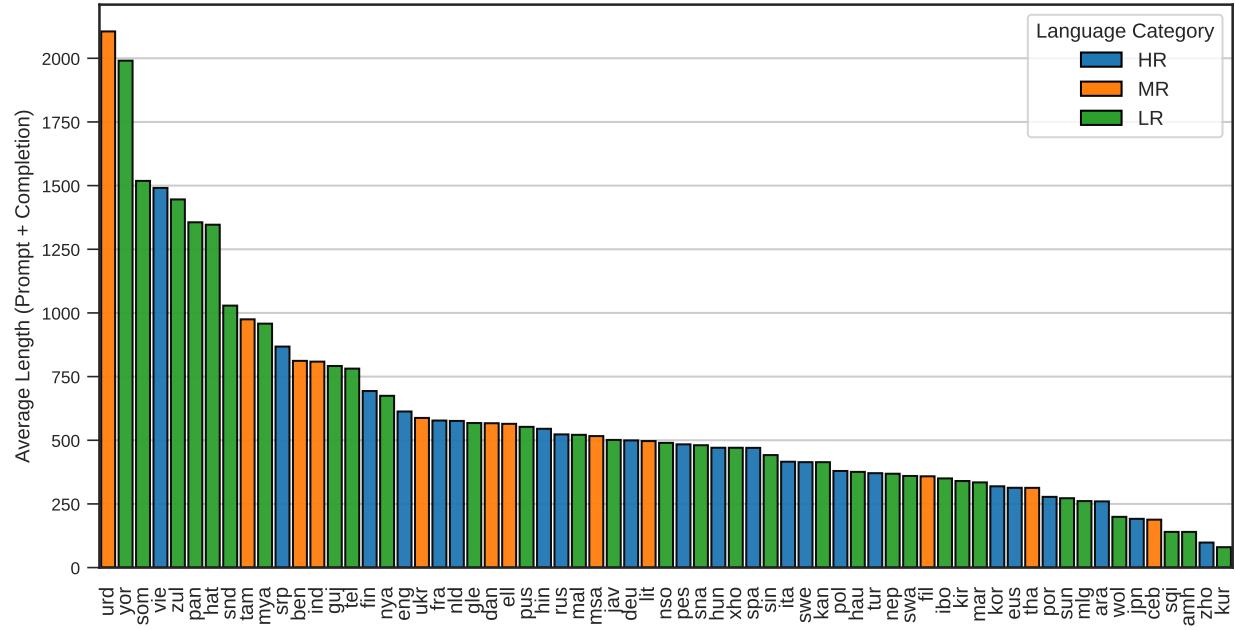


Figure 26: Average prompt and completion length across different languages in **Aya Dataset**.

I Additional Tables

Dataset	#Langs	Template lang	Dataset lang	\bar{L}_{prompt}	$\bar{L}_{compl.}$	License	Task
AfriQA-inst [Ogundepo et al., 2023]	12		bem, fon, hau, ibo, kin, swh, twi, wol, yor, zul, eng, fra	46	15	CC BY 4.0	Question Answering
AfriSenti-inst [Muhammad et al., 2023]	9		amh, arq, hau, ibo, kin, ary, por, swh, twi	168	44	CC BY 4.0	Sentiment Analysis
Amharic QA [Abedissa et al., 2023]	1	amh	amh	1114	33	MIT license	Question Answering
News-summary-instruct [TahmidH, 2023]	1	ben	ben	174	67	CC0 1.0	Summarization
Arpa-instruct [syntaxhill, 2023]	1	hye	hye	165	118	Artistic-2.0	Paraphrasing
Telugu-food-recipes [SuryaKrishna02, 2023a]	1	tel	tel	70	870	Apache 2.0	Generation
Telugu-jokes [SuryaKrishna02, 2023b]	1	tel	tel	80	276	Apache 2.0	Generation
Telugu-news-articles [SuryaKrishna02, 2023c]	1	tel	tel	448	426	Apache 2.0	Generation
Telugu-poems [SuryaKrishna02, 2023e]	1	tel	tel	357	198	Apache 2.0	Generation
FarsTail-Instruct [Amirkhani et al., 2023; hghader1, 2023]	1	pes	pes	224	112	Apache 2.0	Natural Language Inference
Hindi-article-summarization [ganeshjcs, 2023a]	1	hin	hin	3813	175	CC BY-SA 4.0	Summarization

Hindi-article-generation [ganeshjcs, 2023b]	1	hin	hin	102	3683	CC BY-SA 4.0	Generation	
IMDB-Dutch-instruct [Maas et al., 2011; ijzha, 2023]	1	nld	nld	1470	31	Apache 2.0	Sentiment Analysis	
IndicSentiment-inst [Doddapaneni et al., 2023; el2e10, 2023a]	11	eng	ben, guj, hni, kan, mal, mar, pan, tam, tel, urd, eng	174	141	MIT	Translation	
IndicXParaphrase-inst [Doddapaneni et al., 2023; el2e10, 2023b; SuryaKrishna02, 2023d]	7	ben, guj, hin, mar, pan, mal, tel	ben, guj, hin, mar, pan, mal, tel	132	93	MIT	Paraphrase Identification	
Indo-stories-instruct [Iftitahu, 2023a;b;c]	3	ind, sun, jav	ind, sun, jav	345	322	CC BY 4.0	Translation	
Joke-explaination-inst [theblackcat102, 2023]	1		eng	118	548	MIT	Generation	
Lijnews-instruct [ConseggioLigure, 2023a;b]	2	ita, lij	it, lij	893	898	CC BY 4.0	Translation	
LLM-Japanese-Vanilla-inst [Suzuki et al., 2023; Tellarin.ai, 2023a]	1	jpn	jpn	60	97	CC BY-SA 4.0	Question Answering	
MasakhaNEWS-inst [Adelani et al., 2023]	16		amh, eng, fra, hau, ibo, lin, cgg, orm, pcm, run, sna, som, swh, tir, xho, yor	1483	1459	AFL-3.0	Text Classification	
Mintaka-inst [Sen et al., 2022]	9	eng	arb, deu, spa, fra, jpn, por, hin, ita, eng	102	49	CC BY 4.0	Question Answering	
NTX-LLM-inst [Chen et al., 2023c; Tellarin.ai, 2023b],	13	arb, zho, nld, eng, fra, deu, hin, ita, jpn, kor, por, spa, tur	arb, zho, nld, eng, fra, deu, hin, ita, jpn, kor, por, spa, tur	917	493	CC BY-SA 4.0	Information Extraction	
NusaX-senti-inst [Winata et al., 2023b]	12		ace, ban, bjh, bug, eng, ind, jav, mad, min, nj, sun, bbc	219	22	Apache 2.0	Sentiment Analysis	
Persian-instruct-pn [Farahani et al., 2021; Shafagh, 2023a;b]	1	pes	pes	1713	128	MIT	Summarization	
SCB-MT-2020-prompt [Lowphansirikul et al., 2022; PyThaiNLP, 2023a;b]	2	tha, eng	tha, eng	181	127	CC BY-SA 4.0	Translation	
Scirepeval-biomimicry-inst [Singh et al., 2022]	1		eng	996	523	ODC-BY	Scientific Document Representation	
Seed-instruct-lij [Maillard et al., 2023; ConseggioLigure, 2023c;d]	2	lij, eng	lij, eng	184	186	CC BY-SA 4.0	Translation	
SODA-inst [Kim et al., 2022]	1		eng	412	328	CC BY 4.0	Dialogue	
TamilStories [AI Tamil Nadu, 2023a]	1	tam	tam	2266	2172	Apache 2.0	Generation	
TeluguRiddles [desik98, 2023]	1	tel	tel	74	44	Apache 2.0	Question Answering	
Thai-USEmbassy-prompt [PyThaiNLP, 2023d;e]	2	tha, eng	tha, eng	2131	2077	CC0 1.0	Translation	
Thai-POS-inst [PyThaiNLP, 2023c]	1	tha	tha	72	36	CC BY-SA 3.0	Generation	

Thai-Wiktionary-inst [PyThaiNLP, 2023f]	1	tha	tha	35	147	CC BY-SA 3.0	Generation
Thirukkural-instruct [AI Tamil Nadu, 2023b]	1	tam	tam	133	542	Apache 2.0	Generation
Turku-paraphrase-inst [Kanerva et al., 2021; TurkuNLP, 2023]	1	fin	fin	108	59	CC BY-SA 4.0	Paraphrase Identification
UA-Gec-inst [Svyokon et al., 2023; osyvokon, 2023]	1	ukr	ukr	192	148	CC BY 4.0	Generation
UNER-LLM-inst [Mayhew et al., 2023; Universal NER, 2023]	11	zho, hrv, dan, eng, deu, por, rus, srp, slk, swe, tgl	zho, hrv, dan, eng, deu, por, rus, srp, slk, swe, tgl	768	109	CC BY-SA 4.0	Named Entity Recognition
Urdu-News-Gen-Article [Hussain et al., 2021; AhmadMustafa, 2023a]	1	urd	urd	109	1313	CC BY 4.0	Generation
Urdu-News-Category-Class [Hussain et al., 2021; AhmadMustafa, 2023b]	1	urd	urd	1407	43	CC BY 4.0	Text Classification
Urdu-News-Gen-Headline [Hussain et al., 2021; AhmadMustafa, 2023c]	1	urd	urd	1314	94	CC BY 4.0	Generation
Wiki-split-inst [Botha et al., 2018]	1		eng	200	166	CC BY 4.0	Text Simplification
X-CSQA-inst [Lin et al., 2021]	16		eng, zho, deu, spa, fra, ita, jpn, nld, pol, por, rus, arb, vie, hin, swa, urd	197	21	MIT	Question Answering
Xlel_wd-inst [Pratapa et al., 2022]	44			379	190	CC BY 4.0	Event Linking
XWikis-inst [Perez-Beltrachini & Lapata, 2021]	4		ces, fra, eng, deu	5662	346	MIT	Summarization

Table 8: List of datasets in **Aya** Collection (templated datasets).

Dataset	#Langs	\bar{L}_{prompt}	$\bar{L}_{compl.}$	License	Task
Adversarial QA (T) [Bartolo et al., 2020]	101	159	721	CC BY-SA 3.0	Question Answering
CNN-Daily-Mail (T) [See et al., 2017] [Hermann et al., 2015]	101	1980	305	Apache 2.0	Summarization
Flan-Coqa (T) [Wei et al., 2022a; Reddy et al., 2019]	101	2143	364	Multiple*	Question Answering
Flan-CoT-submix (T) [Wei et al., 2022a]	101	239	160	Unknown	Generation
Flan-GEM-wiki-lingua (T) [Wei et al., 2022a; Ladhak et al., 2020]	101	1732	572	CC BY-NC-SA 3.0	Summarization
Flan-lambada (T) [Wei et al., 2022a; Paperno et al., 2016]	101	232	7	CC BY 4.0	Generation
Flan-unified-QA (T) [Wei et al., 2022a; Khashabi et al., 2020]	101	281	13	Apache 2.0	Question Answering
HotpotQA (T) [Yang et al., 2018]	101	129	15	CC BY-SA 4.0	Question Answering

Joke-explaination-inst (T) [theblackcat102, 2023]	101	111	545	MIT	Generation
Mintaka-inst (T) [Sen et al., 2022]	101	54	67	CC BY 4.0	Question Answering
MLQA-en (T) [Lewis et al., 2020]	101	819	20	CC BY-SA 3.0	Question Answering
NQ-Open (T) [Kwiatkowski et al., 2019]	101	68	14	CC BY-SA 3.0	Question Answering
PAWS-Wiki (T) [Zhang et al., 2019]	101	308	6	Custom license, attribution	Paraphrase Identification
PIQA (T) [Bisk et al., 2020]	101	304	100	Unknown	Question Answering
SODA-inst (T) [Kim et al., 2022]	101	86	208	CC BY 4.0	Dialogue
WIKI QA (T) [Yang et al., 2015]	101	205	36	MSR DLA*	Question Answering
Wiki-split-inst (T) [Botha et al., 2018]	101	126	220	CC BY-SA 4.0	Text Simplification
Xlel_wd-inst (T) [Pratapa et al., 2022]	101	300	274	CC BY 4.0	Event Linking
Dolly-v2 (T) [Conover et al., 2023]	101	427	357	CC BY-SA 3.0	Generation

Table 9: List of datasets in **Aya** Collection (translated datasets).

Main Task Type	Fine-grained Task Type	Dataset
Question Answering		AfriQA-inst [Ogundepo et al., 2023] Amharic QA [Abedissa et al., 2023] LLM-Japanese-Vanilla-inst [Tellarin.ai, 2023a] Mintaka-inst [Sen et al., 2022] X-CSQA-inst [Lin et al., 2021] TeluguRiddles [desik98, 2023]
Natural Language Generation	Summarization	News-summary-instruct [TahmidH, 2023] Persian-instruct-pn [Shafagh, 2023a] Hindi-article-summarization [ganeshjcs, 2023a] XWikis-inst [Perez-Beltrachini & Lapata, 2021]
	Translation	IndicSentiment-inst [el2e10, 2023a] Indo-stories-instruct [Iftitahu, 2023a;b;c] Lijnews-instruct [ConseggioLigure, 2023a;b] SCB-MT-2020-prompt [PyThaiNLP, 2023a;b] Thai-USEmbassy-prompt [PyThaiNLP, 2023d;e] SEED-instruct-lij [ConseggioLigure, 2023c;d]
	Paraphrasing	Arpa-instruct [syntaxhill, 2023] IndicXParaphrase-inst [el2e10, 2023b; SuryaKrishna02, 2023d] Turku-paraphrase-inst [TurkuNLP, 2023]
	Text Simplification	Wiki-split-inst [Botha et al., 2018]
	Dialogue	SODA-inst [Kim et al., 2022]
NL Generation		Telugu-food-recipes [SuryaKrishna02, 2023a] Telugu-jokes [SuryaKrishna02, 2023b] Telugu-news-articles [SuryaKrishna02, 2023c] Telugu-poems [SuryaKrishna02, 2023e] TamilStories [AI Tamil Nadu, 2023a] Joke-explaination-inst [theblackcat102, 2023] Thirukkural-instruct [AI Tamil Nadu, 2023b] Hindi-article-generation [ganeshjcs, 2023b] Thai-Wiktionary-inst [PyThaiNLP, 2023f] UA-Gec-inst [osyvokon, 2023] Urdu-News-Gen-Article [AhmadMustafa, 2023a] Urdu-News-Gen-Headline [AhmadMustafa, 2023c] Thai-POS-inst [PyThaiNLP, 2023c]

Text Classification	Sentiment Analysis	AfriSenti-inst [Muhammad et al., 2023] IMDB-Dutch-instruct [jjzha, 2023] NusaX-senti-inst [Winata et al., 2023b]
	Information Extraction	NTX-LLM-inst [Tellarin.ai, 2023b]
	Named Entity Recognition	UNER-LLM-inst [Universal NER, 2023]
	Natural Language Inference	FarsTail-Instruct [hghader1, 2023]
	Event Linking	Xlel_wd-inst [Pratapa et al., 2022]
	Sci. Doc. Representation	Scirepeval-biomimicry-inst [Singh et al., 2022]
	Text Classification	Urdu-News-Category-Class [AhmadMustafa, 2023b] MasakhaNEWS-inst [Adelani et al., 2023]

Table 10: Task Taxonomy of Templated Datasets (**Aya** Collection). We classify the templated datasets with a standard task taxonomy of three main tasks: Question Answering, Natural Language Generation, and Text Classification (Table 4). We then have a fine-grained task taxonomy within each task, such as Summarization, Translation, Paraphrasing, Sentiment Analysis, Information Extraction, and Named Entity Recognition. If there is not a recognized fine-grained task taxonomy for a specific dataset, we put it in the main task type category.

Main Task Type	Fine-grained Task Type	Dataset
Question Answering		Adversarial QA (T) [Bartolo et al., 2020] Flan-Coqa (T) [Wei et al., 2022a; Reddy et al., 2019] Flan-unified-QA (T) [Wei et al., 2022a; Khashabi et al., 2020] HotpotQA (T) [Yang et al., 2018] Mintaka-inst (T) [Sen et al., 2022] MLQA-en (T) [Lewis et al., 2020] NQ-Open (T) [Kwiatkowski et al., 2019] PIQA (T) [Bisk et al., 2020] WIKI QA (T) [Yang et al., 2015]
Natural Language Generation	Summarization	CNN-Daily-Mail (T) [See et al., 2017] [Hermann et al., 2015] Flan-GEM-wiki-lingua (T) [Wei et al., 2022a; Ladhak et al., 2020]
	Text Simplification	Wiki-split-inst (T) [Botha et al., 2018]
	Dialogue	SODA-inst (T) [Kim et al., 2022]
	NL Generation	Joke-explaination-inst (T) [theblackcat102, 2023] Flan-CoT-submix (T) [Wei et al., 2022a] Flan-lambada (T) [Wei et al., 2022a; Paperno et al., 2016] Dolly-v2 (T) [Conover et al., 2023]
Text Classification	Event Linking	Xlel_wd-inst (T) [Pratapa et al., 2022]
	Paraphrase Identification	PAWS-Wiki (T) [Zhang et al., 2019]

Table 11: Task Taxonomy of Translated Datasets (Aya Collection). We classify the translated datasets similar to templated datasets (Table 10). If there is not a recognized fine-grained task taxonomy for a specific dataset, we put it in the main task type category.

Dataset	#Langs	Dataset Language	\bar{L}_{prompt}	$\bar{L}_{compl.}$	License	Task
adversarial_qa dbert [Bartolo et al., 2020; maxbartolo, 2023a]	1	eng	655	263	CC BY-SA 3.0	Question Answering
adversarial_qa dbidaf [Bartolo et al., 2020; maxbartolo, 2023b]	1	eng	669	256	CC BY-SA 4.0	Question Answering
adversarial_qa droberta [Bartolo et al., 2020; maxbartolo, 2023c]	1	eng	742	243	CC BY-SA 4.0	Question Answering
ag_news [Gulli, 2005; jxmorrison12 et al., 2023]	1	eng	292	40	BSD-3-Clause	Text Classification
ai2_arc ARC-Challenge [Clark et al., 2018]	1	eng	351	33	GPL-3	Question Answering
ai2_arc ARC-Easy [Clark et al., 2018]	1	eng	307	26	GPL-3	Question Answering
amazon_polarity [Zhang et al., 2015]	1	eng	454	83	BSD-3-Clause	Sentiment Analysis
app_reviews [Grano et al., 2017]	1	eng	159	28	Unknown	Sentiment Analysis
clue_c3 [Xu et al., 2020]	1	zho	338	7	Apache 2.0	Question Answering
clue_cmrc2018 [Cui et al., 2019]	1	zho	426	178	CC BY-SA 4.0	Question Answering
clue_csl [Li et al., 2022]	1	zho	315	64	Apache 2.0	Question Answering
clue_drcd [Shao et al., 2019]	1	zho	436	128	CC BY-SA 3.0	Question Answering
clue_tnews [Xu et al., 2020]	1	zho	235	7	Apache 2.0	Question Answering
cnn_dailymail_3.0.0 [Nallapati et al., 2016]	1	eng	1699	646	Unknown	Summarization
common_gen [Lin et al., 2020]	1	eng	96	49	MIT	Generation
cos_e_v1.11 [Rajani et al., 2019]	1	eng	208	19	BSD-3-Clause	Generation
cosmos_qa [Huang et al., 2019]	1	eng	547	51	Unknown	Question Answering
dbpedia_14 [Lehmann et al., 2014]	1	eng	378	64	Apache 2.0	Topic Classification
dream [Gu et al., 2022]	1	eng	511	152	Apache 2.0	Question Answering
duorc ParaphraseRC [Saha et al., 2018]	1	eng	1438	663	MIT	Question Answering
duorc SelfRC [Saha et al., 2018]	1	eng	1411	645	MIT	Question Answering
GEM/BiSECT [Kim et al., 2021]	3	eng, spa, fra	346	251	Unknown	Text Simplification
GEM/xlsum [Hasan et al., 2021]	2	eng, ben	1156	636	CC BY-NC-SA 4.0	Summarization
gigaword [Rush et al., 2015; Graff et al., 2003]	1	eng	181	80	Unknown	Summarization
glue_mrpc [Warstadt et al., 2018; Wang et al., 2018; Dolan & Brockett, 2005]	1	eng	270	38	MIT	Text Classification
glue_qqp [Warstadt et al., 2018; Wang et al., 2018; Iyer et al., 2012]	1	eng	199	4	Unknown	Text Classification
imdb [Maas et al., 2011]	1	eng	1089	106	Unknown	Sentiment Analysis
tydiqa-goldp [Clark et al., 2020]	6	arb, ben, eng, ind, swh, tel	526	115	Apache 2.0	Question Answering
tydiqa-primary [Clark et al., 2020]	6	arb, ben, eng, ind, swa, tel	1110	332	Apache 2.0	Question Answering
kilt_tasks hotpotqa [Petroni et al., 2021]	1	eng	137	15	MIT	Question Answering
multi_news [Fabbri et al., 2019]	1	eng	3466	1442	Custom license	Summarization

openbookqa main [Mihaylov et al., 2018]	1	eng	163	16	Apache 2.0	Question Answering	
xlwic xlwic [Raganato et al., 2020]	1	eng	225	3	CC BY-NC 4.0	Text Classification	
paws labeled_final [Zhang et al., 2019]	1	eng	285	12	Custom license	Paraphrase Identification	
paws-x [Yang et al., 2019]	4	eng, spa, fra, zho	255	11	Custom license	Paraphrase Identification	
piqa [Bisk et al., 2020]	1	eng	256	72	AFL 3.0	Question Answering	
qasc [Khot et al., 2020]	1	eng	314	38	Apache 2.0	Question Answering	
quail [Rogers et al., 2020]	1	eng	1752	18	CC BY-NC-SA 4.0	Question Answering	
quarel [Tafjord et al., 2019a]	1	eng	289	10	CC BY 4.0	Question Answering	
quartz [Tafjord et al., 2019b]	1	eng	307	9	CC BY 4.0	Question Answering	
quoref [Dasigi et al., 2019]	1	eng	1556	388	CC BY 4.0	Question Answering	
race high [Lai et al., 2017]	1	eng	1723	229	Custom license	Question Answering	
race middle [Lai et al., 2017]	1	eng	1141	144	Custom license	Question Answering	
ropes [Lin et al., 2019]	1	eng	886	97	CC BY 4.0	Question Answering	
rotten_tomatoes [Pang & Lee, 2005]	1	eng	152	18	Unknown	Sentiment Analysis	
samsum [Gliwa et al., 2019]	1	eng	473	170	CC BY-NC-ND 4.0	Summarization	
sciq [Welbl et al., 2017]	1	eng	346	139	CC BY-NC 3.0	Question Answering	
social_i_qa [Sap et al., 2019]	1	eng	182	15	CC BY 4.0	Question Answering	
squad_v2 [Rajpurkar et al., 2016]	1	eng	689	82	CC BY-SA 4.0	Question Answering	
super_glue boolq [Clark et al., 2019; Wang et al., 2019]	1	eng	653	76	CC BY-SA 3.0	Question Answering	
super_glue multirc [Khashabi et al., 2018]	1	eng	1509	120	Custom license	Question Answering	
super_glue record [Zhang et al., 2018a]	1	eng	1175	70	Apache 2.0	Question Answering	
super_glue wic [Pilehvar & Camacho-Collados, 2019]	1	eng	170	3	CC BY-NC 4.0	Text Classification	
trec [Li & Roth, 2002; Hovy et al., 2001]	1	eng	144	9	Unknown	Text Classification	
trivia_qa unfiltered [Joshi et al., 2017]	1	eng	148	92	Unknown	Question Answering	
web_questions [Berant et al., 2013]	1	eng	70	17	Unknown	Question Answering	
wiki_bio [Lebret et al., 2016]	1	eng	586	328	CC BY-SA 3.0	Generation	
wiki_hop original [Tu et al., 2019]	1	eng	6363	748	CC BY-SA 3.0	Question Answering	
wiki_qa [Yang et al., 2015]	1	eng	224	26	Custom license	Question Answering	
wiqa [Tandon et al., 2019]	1	eng	408	44	Apache-2.0	Question Answering	
xquad [Artetxe et al., 2019]	2	zho, vie	652	173	CC BY-SA 4.0	Question Answering	
xsum [Narayan et al., 2018]	1	eng	1412	250	MIT	Summarization	
yelp_review_full [Zhang et al., 2015]	1	eng	620	91	Custom license	Sentiment Analysis	

Table 12: List of xP3 datasets [Muennighoff et al., 2023c].

J Data Cards

Following Pushkarna et al. [2022] and the HuggingFace data card template¹⁹, we present the data card for the Aya Dataset.

Data Card for the Aya Dataset								
<p>The Aya Dataset is a multilingual instruction fine-tuning dataset curated by an open-science community. The dataset contains a total of 204,114 annotated prompt-completion pairs.</p> <ul style="list-style-type: none">• Curated by: 2,007 contributors from 110 countries• Language(s): 65 languages• License: Apache 2.0• Repository: https://huggingface.co/datasets/CohereForAI/aya_dataset								
<h3>Authorship</h3> <p>Publishing Organization: Cohere For AI Industry Type: Not-for-profit - Tech Contact Details: https://aya.for.ai/</p>								
<h3>Example of Data Points</h3> <p>The dataset contains multilingual prompts and completions in the following format: {prompt: "What day is followed by Saturday?", completion : "Saturday is followed by Sunday.", language: "English" }</p>								
<h3>Motivations & Intentions</h3> <p>Curation Rationale: The curation effort employed an open-science approach to create a diverse instruction-style dataset through annotators across the globe that ensures comprehensive representation across all languages. The success of the curation effort, led by volunteers across diverse backgrounds, was significantly influenced by their hope to meaningfully bring NLP advancements to their languages.</p>								
<h3>Provenance</h3> <p>Methods Used crowd-sourced through volunteer annotations, followed by a quality assessment phase in which samples from the dataset were checked.</p> <p>Methodology Details Source: Original annotations and edits of open-source NLP datasets Platform: Aya Annotation Platform Dates of Collection: Jun 2023 - Dec 2023</p>								
<h3>Dataset Version and Maintenance</h3> <table><thead><tr><th>Maintenance Status</th><th>Version Details</th><th>Maintenance Plan</th></tr></thead><tbody><tr><td>Actively Maintained</td><td>Current version: 1.0 Last Update: 12/2023 First Release: 02/2024</td><td>Updates will be periodically made available based on volunteer contributions</td></tr></tbody></table>			Maintenance Status	Version Details	Maintenance Plan	Actively Maintained	Current version: 1.0 Last Update: 12/2023 First Release: 02/2024	Updates will be periodically made available based on volunteer contributions
Maintenance Status	Version Details	Maintenance Plan						
Actively Maintained	Current version: 1.0 Last Update: 12/2023 First Release: 02/2024	Updates will be periodically made available based on volunteer contributions						

¹⁹https://huggingface.co/docs/datasets/v2.15.0/en/dataset_card

Data Card for the Aya Collection

The **Aya** Collection incorporates instruction-style templates from fluent speakers and applies them to a curated list of 44 datasets. It also includes translations of 19 instruction-style datasets into 101 languages. This collection provides 513,579,625 instances of prompts and completions covering a wide range of tasks..

- Curated by: 2007 contributors from 110 countries
- Language(s): 114 languages
- License: Apache 2.0
- Repository: https://huggingface.co/datasets/CohereForAI/aya_collection

Authorship

Publishing Organization:
Cohere For AI

Industry Type:
Not-for-profit - Tech

Contact Details:
<https://aya.for.ai>

Example of Data Points

The dataset contains multilingual prompts and completions in the following format: {‘prompt’: “Generate an article for the given headline: {{headline}}”, ‘completion’: “{{news_article}}”, ‘lang’: “English” }

Motivations & Intentions

Curation Rationale: Automatic augmentation of existing datasets serves to enhance the available linguistic resources for multiple languages. List of languages were established from mT5 and aligned with annotators’ language list and NLLB translation model. The datasets were translated directly from English for all languages.

Provenance

Methods Used

combination of crowd-sourced templating and automatic translation.

Methodology Details

Source: Existing NLP datasets
Platform: **Aya** Annotation Platform
Dates of Collection: Jun 2023 - Dec 2023

Dataset Version and Maintenance

Maintenance Status

Actively Maintained

Version Details

Current version: 1.0
Last updated: 12/2023
Release date: 02/2024

Maintenance Plan

No updates planned.

Data Card for the Aya Evaluation Suite

The **Aya** Evaluation Suite contains a total of 25,750 open-ended conversation-style prompts covering 101 languages of three subsets:

AYA-HUMAN-ANNOTATED: 250 original human-written prompts in 7 languages each.

DOLLY-MACHINE-TRANSLATED: 200 human-selected prompts from [Conover et al. \[2023\]](#), automatically translated with the NLLB model [[NLLB-Team et al., 2022](#)] from English into 101 languages.

DOLLY-HUMAN-EDITED: 200 dolly-machine-translated prompts post-edited by fluent speakers for 6 languages.

- Curated by: contributors, professional annotators, and synthetic generation
- Language(s): 101 languages
- License: Apache 2.0
- Repository: https://huggingface.co/datasets/CohereForAI/aya_evaluation_suite

Authorship

Publishing Organization:
Cohere For AI

Industry Type:
Not-for-profit - Tech

Contact Details:
<https://aya.for.ai>

Example of Data Points

The dataset contains multilingual prompts in the following format: {‘prompt’: “Which is a species of fish? Bleak or Weary”, ‘lang’: “English” }

Motivations & Intentions

Curation Rationale: This evaluation suite is tailored for testing the generation quality of multilingual models, with the aim to balance language coverage and human-sourced quality. It covers prompts originally written in each language, as well as English-centric translated and manually curated or edited prompts for a linguistically broad but rich testbed. The list of languages was established from mT5 and aligned with annotators’ language list and the NLLB translation model.

Provenance

Methods Used

combination of original annotations by volunteers, automatic translation, and post-editing of translations by professional annotators.

Methodology Details

Source: Original annotations and translations and post-edits of Dolly

Platform: **Aya** Annotation Platform

Dates of Collection: Jun 2023 - Dec 2023

Dataset Version and Maintenance

Maintenance Status
Actively Maintained

Version Details
Current version: 1.0
Last updated: 02/2024
Release date: 02/2024

Maintenance Plan
No updates planned.

K Aya Collection Templates

Dataset	#Id	Prompt Template	Completion Template
AfriQA-inst [Ogundepo et al., 2023]	1	Answer the given question in one of the following languages, [ben, fon, hau, ibo, kin, swh, twi, wol, yor, zul, eng, fra]. {{question_in_target_language}}	{{{answer_in_target_language}}}
AfriSenti-inst [Muhammad et al., 2023]	1	Given the tweet, provide the sentiment associated with it. Among which of the sentiment categories would you classify the following tweet? positive, negative, or neutral {{tweet}}	I would classify the given tweet as: {{{sentiment}}}
	2	Is the tweet below expressing a positive, negative, or neutral sentiment? {{tweet}}	The tweet is expressing {{{sentiment}}} sentiment.
Amharic QA [Abedissa et al., 2023]	1	Given the context, provide the answer to the asked question. ከዚህ በታች በጥገኘው አዎች ተከታታለ ትያቄ መልስ፡ {{context}} {{question}}	ከተያቀው ጋር የሚሰጠውን የጊዜ ነው፡፡ {{{answer_text}}}
	2	ከዚህ በታች ያለውን የሚከተሉ መልስ በመተዳደሪያ ለማቅረብ መልስ ይስጠል፡ {{context}} {{question}}	ከተያቀው ላይ ተከታታለ መልስ {{{answer_text}}} ነው፡፡
	3	ከዚህ በታች ያለውን የሚከተሉ መልስ ለማቅረብ መልስ ይስጠል፡ {{context}} {{question}}	ለተያቀው መልስ {{{answer_text}}} ነው፡፡
	4	የተስተካክ ትያቄ ለመመለስ ከዚህ በታች የቀረበውን መልሬ ይመልከቱ፡ {{context}} {{question}}	ለተስተካክ ትያቄ ተከታታለ የጊዜ {{{answer_text}}} ነው፡፡
	5	ለማቅረብ ትያቄ የጊዜ ለመስጠት ከዚህ በታች የቀረበውን አዎች ተጠቀም፡ {{context}} {{question}}	ለተያቀው መልስ {{{answer_text}}} ነው፡፡
	6	የተስተካክ ትያቄ ከዚህ በታች በጥገኘው አዎች መሰራት መልስ፡ {{context}} {{question}}	ለተያቀው ተከታታለ የጊዜ {{{answer_text}}} ነው፡፡
News-summary-instruct [TahmidH, 2023]	1	Generate the summary/headline of the given news article. এই সংবাদের জন্য একটি সংবাদ শিরোনাম লেখ: {{article}}	প্রদত্ত সংবাদের সংবাদ শিরোনাম হলো, {{{headline}}}
	2	একটি বাকেয় সেখাটির মূল বক্তব্য তুলে ধর: {{article}}	প্রদত্ত অনুচ্ছেদের সংক্ষিপ্ত মূলভাব হলো, {{{summary}}}
	3	নিচের অনুচ্ছেদে কী বলা হয়েছে তা সংক্ষেপে বর্ণনা কর। {{article}}	প্রদত্ত অনুচ্ছেদের সংক্ষিপ্ত মূলভাব হলো, {{{summary}}}
	4	নিচের অনুচ্ছেদে কী বলা হয়েছে তা সংক্ষেপে বর্ণনা কর। {{article}}	{{{summary}}}
	5	এক বাকেয় নিচের অনুচ্ছেদের সারাংশ লেখ। {{article}}	প্রদত্ত অনুচ্ছেদের সংক্ষিপ্ত মূলভাব হলো, {{{summary}}}

	6	সংক্ষেপে বাক্যটির মূলভাব তুলে ধরো: {{article}}	{{summary}}
	7	সংবাদ শিরোনাম লিখুন: {{article}}	সংবাদটির শিরোনাম হলো, {{headline}}
	8	সংক্ষেপে বাক্যটির মূলভাব তুলে ধরো: {{article}}	বাক্যটির সংক্ষিপ্ত মূলভাব হলো, {{summary}}
	9	নিম্নলিখিত সংবাদের শিরোনাম কী হতে পারে? {{article}}	প্রদত্ত সংবাদের সংবাদ শিরোনাম হলো, {{headline}}
	10	এক বাক্যে নিচের অনুচ্ছেদের সারাংশ দেখ। {{article}}	{{summary}}
	11	আরো কম শব্দে বাক্যটির মূলভাব বর্ণনা কর: {{article}}	{{summary}}
	12	প্রদত্ত তথ্য ব্যবহার করে একটি সংবাদ শিরোনাম লিখুন: {{article}}	সংবাদটির শিরোনাম হলো, {{headline}}
	13	আরো কম শব্দে বাক্যটির মূলভাব বর্ণনা কর: {{article}}	বাক্যটির সংক্ষিপ্ত মূলভাব হলো, {{summary}}
	14	একটি বাক্যে সেখানের মূল বক্তব্য তুলে ধর: {{article}}	{{summary}}
	15	নিম্নলিখিত সংবাদের ভিত্তিতে একটি সংবাদ শিরোনাম লিখুন {{article}}	প্রদত্ত সংবাদের সংবাদ শিরোনাম হলো, {{headline}}
Arpa-instruct [syntaxhill, 2023]	1	Paraphrase the following sentence. Վերապատմեք հաջորդ նախադասությունը: {{sentence1}}	{{sentence2}}
	2	Գրեք հաջորդ նախադասության վերապատմումը: {{sentence1}}	{{sentence2}}
	3	Գրեք նախադասություն վերապատմելու համար հաջորդը: {{sentence1}}	{{sentence2}}
Telugu-food-recipes [SuryaKrishna02, 2023a]	1	Given the name of the food item, generates the detailed recipe along with the ingredients. {{Food Item}} এলা তয়ার চেস্টার್ কুকুরো জপ্পুণ্ডি.	Food Item কি কাপলসিন পদার্থালু মুরিয় তয়ার চেন্সি বিধানং ইষ্টুড ইন্ডুজিওদিং. কাপলসিন পদার্থালু: {{Ingredients}} তয়ারুচেন্সি বিধানং: {{Cooking Instructions}}
	2	মীরু {{Food Item}} তয়ার চেম্যুডানিকি এটুওঁবঁয়ী তিংডি পদার্থালু হাতুতুরু মুরিয় বি বিধমুগা চেস্টার್ বিপরো ইন্ডুজি.	Food Item কি কাপলসিন পদার্থালু মুরিয় তয়ার চেন্সি বিধানং ইষ্টুড ইন্ডুজিওদিং. কাপলসিন পদার্থালু: {{Ingredients}} তয়ারুচেন্সি বিধানং: {{Cooking Instructions}}
	3	নেনু {{Food Item}} দালা রুচিকরণো উঁটুঁদি অনি বিনামু. নাশ ইডি এলা চেম্যুডো সংলীপ্তুণ্ডো চেপুু.	Food Item কি কাপলসিন পদার্থালু মুরিয় তয়ার চেন্সি বিধানং ইষ্টুড ইন্ডুজিওদিং. কাপলসিন পদার্থালু: {{Ingredients}} তয়ারুচেন্সি বিধানং: {{Cooking Instructions}}

		Food Item కి కావలసిన పదార్థాలు మరియు తయారు చేసే విధానం ఇత్కుడ ఇష్టబడింది. కావలసిన పదార్థాలు: {{Ingredients}}	
4	మొదటిసారి పంట చేసేవారికి చెప్పినట్టు నాకు Food Item ఎలా చెయ్యాలో చెప్పు	తయారుచేసే విధానం: {{Cooking Instructions}}	
5	{{Food Item}} ఎలా చెయ్యాలి? నమాదానం లో కావలసిన పదార్థాలు మరియు తయారు చేసే విధానం ఉండాలి.	Food Item కి కావలసిన పదార్థాలు మరియు తయారు చేసే విధానం ఇత్కుడ ఇష్టబడింది. కావలసిన పదార్థాలు: {{Ingredients}}	
6	{{Food Item}} ఎలా తయారు చేస్తాం?	తయారుచేసే విధానం: {{Cooking Instructions}}	
7	{{Food Item}} రెసిపీ ఏంటి?	Food Item కి కావలసిన పదార్థాలు మరియు తయారు చేసే విధానం ఇత్కుడ ఇష్టబడింది. కావలసిన పదార్థాలు: {{Ingredients}}	
Telugu-jokes [SuryaKrishna02, 2023b]	1	Given the title of a funny conversation, generate a funny conversation based on the title. {{Title}} అనే శీర్షిక తో జోక్ ఇష్టు	శీర్షిక: {{Title}} {{Funny Conversation}}
	2	{{Title}} అనే టైటిల్ తో జోక్ ఇష్టు	శీర్షిక: {{Title}} {{Funny Conversation}}
	3	ఒక హాస్ట్ సంభాషణ ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	4	ఒక చిన్న హాస్ట్ నన్నివేశం ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	5	ఒక చమత్కారమయిన సంభాషణ ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	6	ఒక చిన్న చమత్కారమయిన సస్నేహిశం ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	7	ఒక తమాషా అయినా సంభాషణ ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	8	ఒక చిన్న తమాషా అయినా సస్నేహిశం ఇష్టు మరియు దాని యొక్క శీర్షిక {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	9	ఒక హాస్ట్ సంభాషణ ఇష్టు మరియు దాని యొక్క టైటిల్ {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	10	ఒక చిన్న హాస్ట్ నన్నివేశం ఇష్టు మరియు దాని యొక్క టైటిల్ {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}
	11	ఒక చమత్కారమయిన సంభాషణ ఇష్టు మరియు దాని యొక్క టైటిల్ {{Title}} ఉండే లాగా ఇష్టు.	శీర్షిక: {{Title}} {{Funny Conversation}}

	12	ఒక చిన్న చమత్కారమయిన సన్నిహితం ఇవ్వు మరియు దాని యొక్క టైటిల్ { {Title} } ఉండే లాగా ఇవ్వు:	శీర్షిక: { {Title} } {{Funny Conversation}}
	13	ఒక తమాషా అయినా సంభాషణ ఇవ్వు మరియు దాని యొక్క టైటిల్ { {Title} } ఉండే లాగా ఇవ్వు:	శీర్షిక: { {Title} } {{Funny Conversation}}
	14	ఒక చిన్న తమాషా అయినా సన్నిహితం ఇవ్వు మరియు దాని యొక్క టైటిల్ { {Title} } ఉండే లాగా ఇవ్వు:	శీర్షిక: { {Title} } {{Funny Conversation}}
Telugu-news-articles [SuryaKrishna02, 2023c]	1	Given Title/Headline of the article, generate the article with that Title/Headline. One word from the set (enclosed within square brackets) is chosen at random and a prompt template is created. [క్రింది కింది ఇవ్వబడిన ఇచ్చిన] [శీర్షికతో టైటిల్ తో ప్రైస్ట్ తో] [వారా కథనాన్ని స్వాన్ ఆర్టికల్ ని స్వాన్ కథనాన్ని] [ప్రాయిండి రాయిండి]: { {Title} }	{ {Article} }
	2	Given the article, generate the Title/Headline for the article. One word from the set (enclosed within square brackets) is chosen at random and a prompt template is created. [క్రింది కింది ఇవ్వబడిన ఇచ్చిన] [వారా కథనానికి స్వాన్ ఆర్టికల్ కి స్వాన్ కథనానికి] [శీర్షికసు టైటిల్ సు ప్రైస్ట్ సు] [ప్రాయిండి ఇవ్వబడి రాయిండి]: { {Article} }	One word from the set (enclosed within square brackets) is chosen at random and a completion template is created. [ఇచ్చిన ఇవ్వబడిన] [వారా కథనానికి స్వాన్ ఆర్టికల్ కి స్వాన్ కథనానికి] [సరిపోయే తగిన అనువైన] [శీర్షిక టైటిల్ ప్రైస్ట్] '{ {Title} }'.
Telugu-poems [SuryaKrishna02, 2023e]	1	Given the poem and type of poetry, explain the meaning of the poem. కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి తాత్పర్యం ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి తాత్పర్యం: { {Meaning} }
	2	కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి భావం ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి భావం: { {Meaning} }
	3	కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి భావము ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి భావము: { {Meaning} }
	4	కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి తాత్పర్యము ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి తాత్పర్యము: { {Meaning} }
	5	కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి అర్థం ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి అర్థం: { {Meaning} }
	6	కీంద ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి అర్థము ఇవ్వండి: { {Poem} }	ఇచ్చిన { {Poetry_Type} } లోని పద్యానికి అర్థము: { {Meaning} }

	Given the meaning and the type of poetry, generate the corresponding poem.	
7	కీంద ఇచ్చిన తాత్పర్యం వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన తాత్పర్యం వచ్చే {{Poetry_Type}} శైలి పద్యం: {{Poem}}
8	కీంద ఇచ్చిన భావం వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన భావం వచ్చే {{Poetry_Type}} శైలి పద్యం: {{Poem}}
9	కీంద ఇచ్చిన భావము వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన భావము వచ్చే {{Poetry_Type}} శైలి పద్యం: {{Poem}}
10	కీంద ఇచ్చిన తాత్పర్యము వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన తాత్పర్యము వచ్చే {{Poetry_Type}} శైలి పద్యం: {{Poem}}
11	కీంద ఇచ్చిన అర్థం వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన అర్థం వచ్చే {{Poetry_Type}} లి పద్యం: {{Poem}}
12	కీంద ఇచ్చిన అర్థము వచ్చే లాగా {{Poetry_Type}} శైలిలో పద్యం రాయండి: {{Meaning}}	ఇచ్చిన అర్థము వచ్చే {{Poetry_Type}} శైలి పద్యం: {{Poem}}
13	Given the partial poem and type of poetry, generate the rest of the poem. కీంద ఇచ్చిన తాత్పర్యం అనుసరించి అనంపూర్ణమైయన పద్యాన్ని {{Poetry_Type}} శైలిలో పూర్తిచేసి రాయండి: తాత్పర్యం: {{Meaning}} అనంపూర్ణమైయన పద్యం: {{Partial Poem}}	పూర్తిచేయబడ్డ పద్యం కీంద ఇవ్వబడింది: పద్యం: {{Poem}}
14	కీంద ఇచ్చిన భావం అనుసరించి అనంపూర్ణమైయన పద్యాన్ని {{Poetry_Type}} శైలిలో పూర్తిచేసి రాయండి: భావం: {{Meaning}} అనంపూర్ణమైయన పద్యం: {{Partial Poem}}	పూర్తిచేయబడ్డ పద్యం కీంద ఇవ్వబడింది: పద్యం: {{Poem}}
15	కీంద ఇచ్చిన భావము అనుసరించి అనంపూర్ణమైయన పద్యాన్ని {{Poetry_Type}} శైలిలో పూర్తిచేసి రాయండి: భావము: {{Meaning}} అనంపూర్ణమైయన పద్యం: {{Partial Poem}}	పూర్తిచేయబడ్డ పద్యం కీంద ఇవ్వబడింది: పద్యం: {{Poem}}
16	కీంద ఇచ్చిన తాత్పర్యము అనుసరించి అనంపూర్ణమైయన పద్యాన్ని {{Poetry_Type}} శైలిలో పూర్తిచేసి రాయండి: తాత్పర్యము: {{Meaning}} అనంపూర్ణమైయన పద్యం: {{Partial Poem}}	పూర్తిచేయబడ్డ పద్యం కీంద ఇవ్వబడింది: పద్యం: {{Poem}}

		کیم د چیز ن ار رن ا نس ن رین چ ا نس ن پر می یا ن پ د ی ن نی {{Poetry_Type}} } گل لیلیه پ ریتی چیز ن رای م اند: ا ر رن: {{Meaning}}} ا ن س ن پر می یا ن پ د ی ن: {{Partial Poem}}	پ ریتی چیز ن یا ب لیلیه پ د ی ن کیم د چ و ب د ی د ی د: پ د ی ن: {{Poem}}
17		کیم د چیز ن ار رن ا نس ن رین چ ا نس ن پر می یا ن پ د ی ن نی {{Poetry_Type}} } گل لیلیه پ ریتی چیز ن رای م اند: ا ر رن: {{Meaning}}} ا ن س ن پر می یا ن پ د ی ن: {{Partial Poem}}	پ ریتی چیز ن یا ب لیلیه پ د ی ن کیم د چ و ب د ی د ی د: پ د ی ن: {{Poem}}
18		کیم د چیز ن ار رن ا نس ن رین چ ا نس ن پر می یا ن پ د ی ن نی {{Poetry_Type}} } گل لیلیه پ ریتی چیز ن رای م اند: ا ر رن: {{Meaning}}} ا ن س ن پر می یا ن پ د ی ن: {{Partial Poem}}	پ ریتی چیز ن یا ب لیلیه پ د ی ن کیم د چ و ب د ی د ی د: پ د ی ن: {{Poem}}
FarsTail-Instruct [hghader1, 2023]	1	Given a premise, provide the hypothesis based on the label value. The label can be either entailment or contradiction. Entailment Prompts and Targets: از متن زیر چه نتیجه‌ای می‌توان گرفت: {{premise}}	از متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	2	از متن زیر چه نتیجه‌ای می‌توان گرفت: {{premise}}	جمله زیر را می‌توان از متن داده شده نتیجه گرفت: {{hypothesis}}
	3	از متن زیر چه نتیجه‌ای می‌توان گرفت: {{premise}}	با توجه به متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	4	جمله‌ای بنویس که می‌تواند نتیجه متن زیر باشد: {{premise}}	از متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	5	جمله‌ای بنویس که می‌تواند نتیجه متن زیر باشد: {{premise}}	جمله زیر را می‌توان از متن داده شده نتیجه گرفت: {{hypothesis}}
	6	جمله‌ای بنویس که می‌تواند نتیجه متن زیر باشد: {{premise}}	با توجه به متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	7	جمله‌ای بنویس که می‌توان از متن زیر نتیجه گرفت: {{premise}}	از متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	8	جمله‌ای بنویس که می‌توان از متن زیر نتیجه گرفت: {{premise}}	جمله زیر را می‌توان از متن داده شده نتیجه گرفت: {{hypothesis}}
	9	جمله‌ای بنویس که می‌توان از متن زیر نتیجه گرفت: {{premise}}	با توجه به متن داده شده می‌توان نتیجه زیر را گرفت: {{hypothesis}}
	10	Contradiction Prompts and Targets: جمله‌ای بنویس که ناقض متن زیر باشد: {{premise}}	جمله زیر متن داده شده را نقض می‌کند: {{hypothesis}}
	11	جمله‌ای بنویس که ناقض متن زیر باشد: {{premise}}	جمله زیر با متن داده شده تناقض دارد: {{hypothesis}}
	12	جمله‌ای بنویس که ناقض متن زیر باشد: {{premise}}	جمله زیر ناقض متن داده شده است: {{hypothesis}}
	13	جمله‌ای بنویس که متن زیر را نقض کند: {{premise}}	جمله زیر متن داده شده را نقض می‌کند: {{hypothesis}}
	14	جمله‌ای بنویس که متن زیر را نقض کند: {{premise}}	جمله زیر با متن داده شده تناقض دارد: {{hypothesis}}
	15	جمله‌ای بنویس که متن زیر را نقض کند: {{premise}}	جمله زیر ناقض متن داده شده است: {{hypothesis}}

	16	جمله‌ای متناقض با متن زیر بنویس: {{premise}}	جمله زیر متن داده شده را نقض می‌کند: {{hypothesis}}
	17	جمله‌ای متناقض با متن زیر بنویس: {{premise}}	جمله زیر با متن داده شده متناقض دارد: {{hypothesis}}
	18	جمله‌ای متناقض با متن زیر بنویس: {{premise}}	جمله زیر ناقض متن داده شده است: {{hypothesis}}
Hindi-article-summarization [ganeshjcs, 2023a]	1	Given an article, generate the summary of the article. इस के लिए एक सारांश बनाएँ: {{Article}}	यह एक सारांश है: {{Summary}}
	2	इस पाठ का सारांश बनाएँ: {{Article}}	संक्षिप्त पाठ: {{Summary}}
	3	इस पाठ का सारांश बनाएँ: {{Article}}	{{Summary}}
	4	एक सारांश बनाओँ: {{Article}}	{{Summary}}
	5	इस पाठ का सारांश बनाओँ: {{Article}}	सारांश: {{Summary}}
	6	एक सारांश बनाओँ: {{Article}}	यहाँ एक सारांश है: {{Summary}}
	7	इस पाठ का सारांश बनाओँ: {{Article}}	संक्षिप्त सारांश: {{Summary}}
	8	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	दिए गए पाठ का सारांश यह हो सकता है: {{Summary}}
	9	एक सारांश बनाओँ: {{Article}}	सारांश: {{Summary}}
	10	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	संक्षिप्त सारांश: {{Summary}}
	11	इस के लिए एक सारांश बनाएँ: {{Article}}	यहाँ एक सारांश है: {{Summary}}
	12	इस पाठ का सारांश बनाएँ: {{Article}}	सारांश: {{Summary}}
	13	एक सारांश बनाओँ: {{Article}}	यह एक सारांश है: {{Summary}}
	14	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	संक्षिप्त पाठ: {{Summary}}
	15	इस पाठ का सारांश बनाओँ: {{Article}}	यहाँ एक सारांश है: {{Summary}}
	16	इस के लिए एक सारांश बनाएँ: {{Article}}	सारांश: {{Summary}}
	17	इस पाठ का सारांश बनाओँ: {{Article}}	संक्षिप्त पाठ: {{Summary}}

	एक सारांश बनाओ: {{Article}}	संक्षिप्त सारांश: {{Summary}}
18	इस पाठ का सारांश बनाओ: {{Article}}	दिए गए पाठ का सारांश यह हो सकता है: {{Summary}}
19	इस के लिए एक सारांश बनाएँ: {{Article}}	{{Summary}}
20	इस के लिए एक सारांश बनाएँ: {{Article}}	संक्षिप्त पाठ: {{Summary}}
21	एक सारांश बनाओ: {{Article}}	दिए गए पाठ का सारांश यह हो सकता है: {{Summary}}
22	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	यह एक सारांश है: {{Summary}}
23	इस पाठ का सारांश बनाओ: {{Article}}	{{Summary}}
24	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	{{Summary}}
25	इस पाठ का सारांश बनाओ: {{Article}}	यह एक सारांश है: {{Summary}}
26	इस पाठ का सारांश बनाएँ: {{Article}}	दिए गए पाठ का सारांश यह हो सकता है: {{Summary}}
27	इस पाठ का सारांश बनाएँ: {{Article}}	यह एक सारांश है: {{Summary}}
28	इस पाठ का सारांश बनाएँ: {{Article}}	संक्षिप्त सारांश: {{Summary}}
29	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	सारांश: {{Summary}}
30	इस पाठ का सारांश बनाएँ: {{Article}}	यहाँ एक सारांश है: {{Summary}}
31	इस के लिए एक सारांश बनाएँ: {{Article}}	दिए गए पाठ का सारांश यह हो सकता है: {{Summary}}
32	एक सारांश बनाओ: {{Article}}	संक्षिप्त पाठ {{Summary}}
33	दिए गए पाठ के लिए एक सारांश बनाएँ: {{Article}}	यहाँ एक सारांश है: {{Summary}}
34	इस के लिए एक सारांश बनाएँ: {{Article}}	संक्षिप्त सारांश: {{Summary}}
35	Given the title of an article, generate the article. एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{Title}}	लेख: {{Article}}
Hindi-article-generation [ganeshjcs, 2023b]	एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{Title}}	{{Article}}
1	एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{Title}}	{{Article}}
2	एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{Title}}	{{Article}}

	3	एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{{Title}}}	दिए गए शीर्षक के अनुरूप एक पाठ यह हो सकता है: {{{Article}}}
	4	यह शीर्षक है, इसके लिए एक लेख लिखें: {{{Title}}}	{{{Article}}}
	5	इसके लिए एक लेख लिखें: {{{Title}}}	लेख: {{{Article}}}
	6	इस शीर्षक के साथ एक लेख लिखें: {{{Title}}}	यह एक लेख है: {{{Article}}}
	7	इस शीर्षक के साथ एक लेख लिखें: {{{Title}}}	दिए गए शीर्षक के अनुरूप एक पाठ यह हो सकता है: {{{Article}}}
	8	यह शीर्षक है, इसके लिए एक लेख लिखें: {{{Title}}}	लेख: {{{Article}}}
	9	इसके लिए एक लेख लिखें: {{{Title}}}	{{{Article}}}
	10	इसके लिए एक लेख लिखें: {{{Title}}}	यह एक लेख है: {{{Article}}}
	11	इस शीर्षक के साथ एक लेख लिखें: {{{Title}}}	लेख: {{{Article}}}
	12	इसके लिए एक लेख लिखें: {{{Title}}}	दिए गए शीर्षक के अनुरूप एक पाठ यह हो सकता है: {{{Article}}}
	13	यह शीर्षक है, इसके लिए एक लेख लिखें: {{{Title}}}	दिए गए शीर्षक के अनुरूप एक पाठ यह हो सकता है: {{{Article}}}
	14	एक लेख लिखें जिसका शीर्षक इस प्रकार है: {{{Title}}}	यह एक लेख है: {{{Article}}}
	15	इस शीर्षक के साथ एक लेख लिखें: {{{Title}}}	{{{Article}}}
	16	यह शीर्षक है, इसके लिए एक लेख लिखें: {{{Title}}}	यह एक लेख है: {{{Article}}}
IMDB-Dutch-instruct [ijzha, 2023]	1	Given the movie review, identify the sentiment. Is deze recensie positief of negatief?	Gegeven de recensie, mijn antwoord is {{{Sentiment}}}
	2	Is deze recensie positief of negatief?	Deze recensie is {{{Sentiment}}}
	3	Is deze recensie positief of negatief?	De beoordeling hier is {{{Sentiment}}}
	4	Is deze recensie positief of negatief?	Het antwoord is {{{Sentiment}}}
	5	Wat is het sentiment van de recensie?	De recensie is {{{Sentiment}}}
	6	Wat is het sentiment van de recensie?	Gegeven de recensie, mijn antwoord is {{{Sentiment}}}
	7	Wat is het sentiment van de recensie?	Deze recensie is {{{Sentiment}}}
	8	Wat is het sentiment van de recensie?	De beoordeling hier is {{{Sentiment}}}

	9	Wat is het sentiment van de recensie?	Het antwoord is {{Sentiment}}
	10	Wat voor toon heeft de volgende recensie?	De recensie is {{Sentiment}}
	11	Wat voor toon heeft de volgende recensie?	Gegeven de recensie, mijn antwoord is {{Sentiment}}
	12	Wat voor toon heeft de volgende recensie?	Deze recensie is {{Sentiment}}
	13	Wat voor toon heeft de volgende recensie?	De beoordeling hier is {{Sentiment}}
	14	Wat voor toon heeft de volgende recensie?	Het antwoord is {{Sentiment}}
	15	Met wat voor sentiment zou je deze recensie beoordelen?	De recensie is {{Sentiment}}
	16	Met wat voor sentiment zou je deze recensie beoordelen?	Gegeven de recensie, mijn antwoord is {{Sentiment}}
	17	Met wat voor sentiment zou je deze recensie beoordelen?	Deze recensie is {{Sentiment}}
	18	Met wat voor sentiment zou je deze recensie beoordelen?	De beoordeling hier is {{Sentiment}}
	19	Met wat voor sentiment zou je deze recensie beoordelen?	Het antwoord is {{Sentiment}}
	20	Is deze recensie positief of negatief?	De recensie is {{Sentiment}}
IndicSentiment-inst [el2e10, 2023a]	1	Generate the translation for the given English review to one of the target Indic languages [ben, guj, hin, kan, mal, mar, pan, tam, tel and urd]. Translate from English to {{target_language}}: {{English_Review}}	{{Indic_Review}}
	2	Translate this sentence to {{target_language}}: {{English_Review}}	{{Indic_Review}}
	3	What's the {{target_language}} translation of this sentence: {{English_Review}}	{{Indic_Review}}
	4	Can you translate this text to {{target_language}}: {{English_Review}}	{{Indic_Review}}
IndicXParaphrase-inst [el2e10, 2023b; SuryaKrishna02, 2023d]	1	Generate the paraphrase of the given sentence in one of the Indic languages [ben, guj, hin, mar, pan, mal, tel] ভিন্ন শব্দগুচ্ছ ব্যবহার করে নিচের বাক্যটি লেখ: "{{original_sentence}}".	{{paraphrased_sentence}}
	2	নিচের বাক্যটি ভিন্নভাবে লেখ: "{{original_sentence}}"	{{paraphrased_sentence}}
	3	অর্থের পরিবর্তন না করে নিচের বাক্যটি নতুনভাবে লেখ: "{{original_sentence}}"	{{paraphrased_sentence}}

4	નીચેના વાક્યને અલગ શબ્દોનો ઉપયોગ કરીને લખો: ”{{original_sentence}}”.	{{paraphrased_sentence}}
5	નીચેના વાક્યને અલગ રીતે ફરીથી લખો: ”{{original_sentence}}”	{{paraphrased_sentence}}
6	નીચેના વાક્યને બીજા સ્વરૂપમાં ફરીથી લખો: ”{{original_sentence}}”	{{paraphrased_sentence}}
7	દુસરે શब્દોં કા પ્રયોગ કરકે ઇસ વાક્ય કો લિખિએ: ”{{original_sentence}}”.	{{paraphrased_sentence}}
8	ઇસ વાક્ય કો અન્ય તરીકે સે ફિર સે લિખિએ: ”{{original_sentence}}”	{{paraphrased_sentence}}
9	નિમનલિખિત વાક્ય કા અર્થ બદલે બિના ઉસે દોબારા લિખિએ: ”{{original_sentence}}”	{{paraphrased_sentence}}
10	ખાલીલ વાક્ય દુસરે-ભિન્ન શબ્દ વાપરુન લિહા: ”{{original_sentence}}”.	{{paraphrased_sentence}}
11	ખાલીલ વાક્ય વેગવ્યા પ્રકારે પુન્ના લિહા: ”{{original_sentence}}”	{{paraphrased_sentence}}
12	ખાલીલ વાક્ય દુસરે શબ્દ વાપરુન રૂપાંતરિત-અનુવાદિત કરા: ”{{original_sentence}}”	{{paraphrased_sentence}}
13	દેંખ-દેંખ મઘરાં રી દરડે રનરે હેઠા દિંદે વાર નું લિખે: ”{{original_sentence}}”.	{{paraphrased_sentence}}
14	ગિમતનિધિત વાર નું દેંખરે તરીકે ગાળ દૃઘારા લિખે: ”{{original_sentence}}”	{{paraphrased_sentence}}
15	હેટાં દિંદે વાર નું સમજાઈ: ”{{original_sentence}}”	{{paraphrased_sentence}}
16	હળિપુરિયુણ વાચકં વ્યત્યસ્ત વાક્યોક્લીં એઝ્યુત્કુક: ”{{original_sentence}}”.	{{paraphrased_sentence}}
17	હળિપુરિયુણ વાચકં મહોલુ લીતિયિંલ એઝ્યુત્કુક: ”{{original_sentence}}”	{{paraphrased_sentence}}
18	તાણપુરિયુણ વાચકં પરાવર્તનાં એઝ્યુક: ”{{original_sentence}}”	{{paraphrased_sentence}}
19	Given a sentence, generate a sentence with similar meaning. કં કીંદિ હાક્યું મરોરીંલો રાયઃ: {{Original Sentence}}	{{Paraphrased Sentence}}
20	કં હાક્યું મરોરીંલો રાયઃ: {{Original Sentence}}	{{Paraphrased Sentence}}
21	કં કીંદિ હાક્યું જંકોલારા રાયઃ: {{Original Sentence}}	{{Paraphrased Sentence}}
22	કં હાક્યું જંકોલારા રાયઃ: {{Original Sentence}}	{{Paraphrased Sentence}}
23	કં કીંદિ હાક્યું મરોરકંરા રાયઃ: {{Original Sentence}}	{{Paraphrased Sentence}}

	24	ଶ୍ରୀ ହାତ୍ୟାଂ ମୁର୍ଦ୍ଦରକଂଗା ରାୟ୍: {{Original Sentence}}	{{Paraphrased Sentence}}
Indo-stories-instruct [Iftitahu, 2023a;b;c]	1	Given the instruction in Indonesian, translate the given input to one of the three languages [ind, sun, jav]. Translate from English to Indonesian. Terjemahkanlah penggalan teks cerita anak berikut dari teks berbahasa Inggris ke teks dalam Bahasa Indonesia: {{eng_input}}	Terjemahan atau padanan teks tersebut dalam Bahasa Indonesia adalah: {{ind_output}}
		Translate from Javanese to Indonesian. Terjemahkanlah penggalan teks cerita anak berikut dari teks berbahasa Jawa ke teks dalam Bahasa Indonesia: {{jav_input}}	Terjemahan atau padanan teks tersebut dalam Bahasa Indonesia adalah: {{ind_output}}
		Translate from Sudanese to Indonesian. Terjemahkanlah penggalan teks cerita anak berikut dari teks berbahasa Sunda ke teks dalam Bahasa Indonesia: {{sun_input}}	Terjemahan atau padanan teks tersebut dalam Bahasa Indonesia adalah: {{ind_output}}
	4	Given the instruction in Javanese, translate the given input to one of the three languages [ind, sun, jav] Translate from English to Javanese. Terjemahno penggalan teks crito ing ngisor iki saka Bahasa Inggris dadi teks crito ing Basa Jawa: {{eng_input}}	Terjemahane utawa padanan teks crito kasebut ing Basa Jawa yaiku: {{jav_output}}
		Translate from Indonesian to Javanese. Terjemahno penggalan teks crito ing ngisor iki saka Bahasa Indonesia dadi teks crito ing Basa Jawa: {{ind_input}}	Terjemahane utawa padanan teks crito kasebut ing Basa Jawa yaiku: {{jav_output}}
	6	Translate from English to Sudanese. Terjemahno penggalan teks crito ing ngisor iki saka Bahasa Sunda dadi teks crito ing Basa Jawa: {{sun_input}}	Terjemahane utawa padanan teks crito kasebut ing Basa Jawa yaiku: {{jav_output}}

	Given the instruction in Sudanese, translate the given input to one of the three languages [ind, sun, jav]	
7	Translate from English to Sudanese. Tarjamahkeun teks dongeng barudak di handap tina teks basa Inggris kana teks basa Sunda: {{eng_input}}	Tarjamahan atawa sasaruaan naskah dina basa Sunda: {{sun_output}}
8	Translate from Indonesian to Sudanese. Tarjamahkeun teks dongeng barudak di handap tina teks basa Indonesia kana teks basa Sunda: {{ind_input}}	Tarjamahan atawa sasaruaan naskah dina basa Sunda: {{sun_output}}
9	Translate from Javanese to Sudanese. Tarjamahkeun teks dongeng barudak di handap tina teks basa Jawa kana teks basa Sunda: {{jav_input}}	Tarjamahan atawa sasaruaan naskah dina basa Sunda: {{sun_output}}
Joke-explaination-inst [theblackcat102, 2023]	Identify the joke's punchline or explain it. {{joke}} What do you think is the punchline of the above joke?	{{explanation}}
	Explain the following joke? {{joke}}	{{explanation}}
Lijnews-instruct [ConseggioLigure, 2023a;b]	Translate the given sentence from Ligurian to Italian. Traduxi in italiano: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi da-o zeneise à l'italian: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi da-o ligure à l'italian: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi sto testo in italiano: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi in lengua italiaña: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi sto testo da-o zeneise à l'italian: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Traduxi sto testo da-o ligure à l'italian: {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Comm'à l'é a traducion italiaña de sto testo? {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	Quæ a l'é a traducion italiaña de sto testo? {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}

	10	Ti peu tradue sto testo in italian? {{sentence}}	A traduçon in italian do testo a l'é: {{sentence}}
	11	Translate the given sentence from Italian to Ligurian. Traduci in genovese: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	12	Traduci in ligure: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	13	Traduci dall'italiano al genovese: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	14	Traduci dall'italiano al ligure: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	15	Traduci dall'italiano al ligure (genovese): {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	16	Traduci questo testo in genovese: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	17	Traduci in lingua genovese: {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	18	Qual è la traduzione genovese di questo testo? {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
	19	Puoi tradurre questo testo in genovese? {{sentence}}	La traduzione in genovese del testo è: {{sentence}}
LLM-Japanese-Vanilla-inst [Tellarin.ai, 2023a]	1	Following the instruction, please answer. {{answer}}	{{{translated_sentence}}}
	2	Please answer the following question. 以下の質問に答えてください、{{question}}	この質問の答えは {{answer}}
	3	Answer the following question. 以下の質問に答えてください、{{question}}	{{{answer}}}
MasakhaNEWS-inst [Adelani et al., 2023]	1	Given the text, generate the headline for the text and vice versa. Generate a headline for the following text: {{text}}	Sure, here's a headline for the given text - {{{headline}}}
	2	Generate an article for the following headline: {{headline}}	{{{article}}}.
Mintaka-inst [Sen et al., 2022]	1	Give an example of the trivia in the provided category. أعطي مثالاً على المعلومات العامة في هذه الفئة: {{category}}	{{{question}}} {{{answer}}}

	<p>Give an example of the trivia in the provided category.</p> <p>Give me an example of trivia in this category: <code>{{category}}</code></p>	<code> {{question}} {{answer}}</code>
2	<p>Answer the question from the given category.</p> <p>The following query in <code>{{lang}}</code> is taken from the <code>{{category}}</code> category. What could be the answer to the question? <code>{{question}}</code></p>	<code> {{answer}}</code>
3	<p>Find the category of the given question.</p> <p>What category is this question from: <code>{{question}}</code>.</p>	The category from which the question comes is <code>{{category}}</code>
4	<p>Answer the given question.</p> <p>What is the correct answer to this question: <code>{{question}}</code></p>	The correct answer to the question is <code> {{answer}}</code>
5	<p>Identify the category of the question.</p> <p>cual es el tema principal de esta pregunta: <code>{{question}}</code></p>	<code> {{category}}</code>
6	<p>Give me a trivia based on the words.</p> <p>Write me a trivia question that contains the words : <code>{{comma_separated_words}}</code></p>	Sure, a possible question is " <code> {{question}}</code> "
7	<p>Identify the date or time mentions and their types in the given sentence based on the example provided.</p> <p>من فضلك قم بتحديد جميع التواريف والأوقات وأنواعهم المذكورة في الجملة المدخلة فيما يلي:</p> <p>خذ في عين الاعتبار التاريخ والوقت المرجعي إذا كانا ذا صلة.</p> <p>انتبه إلى المثال المقدم. يجب عليك إخراج النتائج تنسيق JSON، وابدأ هيكليته مشابهة للمثال المذكور أدناه.</p> <p>مثال على جملة وتاريخ ووقت مرجعي والنتائج:</p> <p><code> {{example_sentence}}</code></p> <p>التاريخ والوقت المرجعي: <code> {{reference_date}}</code></p> <p><code> {{reference_time}}</code></p> <p>بالنظر إلى الجملة المدخلة أدناه، ما هي النتيجة؟</p> <p><code> {{input_sentence}}</code></p>	<pre> "Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": ["timex": "{{time}}", "type": "{{type}}", "value": "{{value}}"] }]</pre>
NTX-LLM-inst [Tellarin.ai, 2023b]	1	

	<p>请在下面提供的输入句子中识别所有日期或时间提及及其类型。</p> <p>如果相关，请考虑提供的参考日期时间。</p> <p>请注意提供的示例。您应该以 JSON 格式输出结果，遵循与所提供的示例结果类似的结构。</p> <p>例句、参考日期和结果：</p> <p>2 {{example_sentence}}</p> <p>参考日期: {{reference_date}}</p> <p> {{reference_time}}</p> <p>考慮到下面的输入句子，输出结果是什么？</p> <p> {{input_sentence}}</p>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
3	<p>Identificeer alle data en tijd vermeldingen in de zin hieronder.</p> <p>Houd rekening met, indien relevant, de opgegeven referentie datum/tijd.</p> <p>Let goed op het gegeven voorbeeld. De resultaten moeten in JSON formaat zijn, hetzelfde als de structuur van het gegeven voorbeeld.</p> <p>Voorbeeld zin, referentie datum/tijd, en resultaten:</p> <p>3 {{example_sentence}}</p> <p>Referentie: {{reference_date}}</p> <p> {{reference_time}}</p> <p>Gegeven de zin hieronder, wat is het resultaat?</p> <p> {{input_sentence}}</p>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
4	<p>Please identify all date or time mentions and their types in the input sentence provided below.</p> <p>Take into consideration the provided reference datetime, if relevant.</p> <p>Pay attention to the provided example. You should output the results in JSON format, following a similar structure to the example result provided.</p> <p>4 Example sentence, reference datetime, and results: {{example_sentence}}</p> <p>Reference datetime: {{reference_date}}</p> <p> {{reference_time}}</p> <p>Considering the input sentence below, what is the output result?</p> <p> {{input_sentence}}</p>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>

	<p>Identifier toutes les références de date ou d'heure et leurs types dans la phrase fournie ci-dessous.</p> <p>Tenez compte de la date/heure de référence fournie, le cas échéant.</p> <p>Faites attention à l'exemple fourni. Vous devez afficher les résultats au format JSON, en suivant une structure similaire à celle de l'exemple de résultat fourni.</p> <p>Exemple de phrase, date/heure de référence et résultats:</p> <pre>{example_sentence}</pre> <p>Date/heure de référence: {reference_date}</p> <pre>{reference_time}</pre> <p>Compte tenu de la phrase d'entrée ci-dessous, quel est le résultat de sortie?</p> <pre>{input_sentence}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
5	<p>Bitte identifiziere alle Vorkommen von Datum oder Uhrzeiten, mit ihrem jeweiligen Typ, im Inputsatz unten.</p> <p>Beachte, wenn nötig, die angegebene Referenz-Datetime.</p> <p>Achte auf das vorgegebene Beispiel. Gib die Ergebnisse im JSON-Format aus und folge einer ähnlichen Struktur wie das Beispielergebnis.</p> <p>Beispelsatz, Referenz-Datetime, und Ergebnisse:</p> <pre>{example_sentence}</pre> <p>Referenz-Datetime: {reference_date}</p> <pre>{reference_time}</pre> <p>Bezogen auf den Inputsatz unten, was ist das richtige Ergebnis?</p> <pre>{input_sentence}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
6		

	<p>कृपया निम्नलिखित वाक्यों में सभी दिनांक या समय उल्लेखों और उनके प्रकारों की पहचान करें।</p> <p>यदी उचित हो, तो दिये गए संदर्भिक दिनांक-समय को ध्यान में रखें।</p> <p>दिये गए उदाहरण पर ध्यान दें। आपको दिये गए उदाहरण परिणाम के समान संरचना का पालन करते हुए, JSON प्रारूप में परिणाम आउटपुट करना चाहिए।</p> <p>वाक्य, संदर्भिक दिनांक-समय एवं परिणाम का उदाहरण :</p> <p>7 {{example_sentence}}</p> <p> संदर्भिक दिनांक-समय:</p> <p> {{reference_date}}</p> <p> {{reference_time}}</p> <p> निम्नलिखित इनपुट वाक्य को ध्यान में रखते हुए, उसके आउटपुट परिणाम के बारे में लिखें।</p> <p> {{input_sentence}}</p>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": ["timex": "{{time}}", "type": "{{type}}", "value": "{{value}}"] }]</pre>
8	<p>Si prega di identificare tutte le menzioni di data o ora e i relativi tipi nella frase di input fornita di seguito.</p> <p>Prendere in considerazione la data/ora di riferimento fornita, se pertinente.</p> <p>Prestare attenzione all'esempio fornito. Dovresti restituire i risultati in formato JSON, seguendo una struttura simile al risultato di esempio fornito.</p> <p>Frase di esempio, data/ora di riferimento e risultati:</p> <p>8 {{example_sentence}}</p> <p>Data e ora di riferimento: {{reference_date}}</p> <p> {{reference_time}}</p> <p>Considerando la frase di input seguente, qual è il risultato di output?</p> <p> {{input_sentence}}</p>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": ["timex": "{{time}}", "type": "{{type}}", "value": "{{value}}"] }]</pre>

	<p>以下に示す入力文で、すべての日付または時刻の言及とその種類を識別してください。</p> <p>関連する場合は、提供される参照日時を考慮してください。</p> <p>提供された例に注意してください。提供されたサンプル結果と同様の構造に従って、JSON 形式で結果を出力する必要があります。</p> <p>文、参照日時、結果の例：</p> <pre> {{example_sentence}}</pre> <p>参照日時：{{reference_date}}</p> <pre> {{reference_time}}</pre> <p>次の入力文を考慮して、出力結果は何ですか。</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
9	<p>아래에제공된입력문장에서날짜나시간에관한언급및 그들의유형을모두식별하십시오.</p> <p>해당되는경우제공된참조날짜/시간을고려하십시오.</p> <p>제공된예시에주목해주십시오. 결과를 JSON 형식으로출력하여, 예시결과와유사한구조를갖도록해야 합니다.</p> <p>예시문장, 참조날짜및결과:</p> <pre> {{example_sentence}}</pre> <p>참조날짜: {{reference_date}}</p> <pre> {{reference_time}}</pre> <p>아래의입력문장을고려하면결과는무엇입니까?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>

	<p>Por favor identifique todas as menções de datas ou tempo e seus tipos na frase fornecida abaixo.</p> <p>Leve em consideração a data e hora de referência fornecida, se relevante.</p> <p>Preste atenção ao exemplo fornecido. Você deve gerar resultados no formato JSON, seguindo uma estrutura semelhante ao resultado do exemplo fornecido.</p> <p>11 Frase de exemplo, data e hora de referência e resultados:</p> <pre> {{example_sentence}}</pre> <p>Data e hora de referência:</p> <pre> {{reference_date}}</pre> <pre> {{reference_time}}</pre> <p>Considerando a frase abaixo, qual é o resultado produzido?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>
12	<p>Por favor identifica todas las menciones de fechas u horas y sus categorías en el texto de entrada que se encuentra de bajo.</p> <p>Ten en cuenta la fecha y hora de referencia proporcionadas, en caso de que sea relevante.</p> <p>Presta atención al ejemplo dado. Debes devolver los resultados en formato JSON, siguiendo una estructura similar a la del ejemplo de resultado.</p> <p>Texto de ejemplo, fecha y hora, y los resultados correspondientes:</p> <pre> {{example_sentence}}</pre> <p>Fecha y hora de referencia:</p> <pre> {{reference_date}}</pre> <pre> {{reference_time}}</pre> <p>Ahora considera el texto de entrada que está debajo, ¿cuál sería el resultado?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] }]</pre>

		<p>Lütfen aşağıda verilen cümledeki tüm tarih veya saat ifadelerini ve bunların türlerini belirtin.</p> <p>Eğer datetime objesi var ise, onun referans gösterdiği tarih ve saatini alın. Sağlanan referans tarih saatini dikkate alın.</p> <p>Sağlanan örnek sonuca benzer bir yapıyı takip ederek sonuçları JSON formatında çıkarmalısınız.</p> <p>Örnek cümle, referans datetime objesi ve sonuçlar:</p> <pre> {{example_sentence}}</pre> <p>Referans datetime objesi: {{reference_date}}</p> <pre> {{reference_time}}</pre> <p>Yukarıdaki kurallar göz önünde bulundurulduğunda, aşağıdaki girdi cümlesinin çıktı sonucu nedir?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": [{ "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}, "TypeName": "{{type_name}}", "Resolution": { "values": [{ "timex": "{{time}}", "type": "{{type}}", "value": "{{value}}" }] } }]</pre>
NusaX-senti-inst [Winata et al., 2023]	1	Share your opinion about a person's feeling. if someone says "text", how are they feeling?	they feel {{label}}.
	2	Given a text, find the sentiment. Here is a sentence in {{lang}} language. Identify the sentence as positive, negative or neutral. {{text}}	{{label}}.
Persian-instruct-pn [Shafagh, 2023a;b]	1	Given a text, generate a summary for it. متن زیر را خلاصه کنید: {{Original Text}}	'{{OriginalSummary}}
	2	برای متن زیر یک خلاصه بنویسید: {{Original Text}}	'{{OriginalSummary}}
	3	یک یا چند جمله به عنوان خلاصه متن زیر بنویسید: {{Original Text}}	'{{OriginalSummary}}
	4	Given a text, generate a summary for it. برای متن زیر یک عنوان مناسب پیشنهاد دهید: {{Original Text}}	این عنوان می تواند برای متن مورد نظر مناسب باشد: {{Original Title}}
	5	از نظر شما یک تیتر مناسب برای مقاله زیر چه می تواند باشد؟: {{Original Text}}	این عنوان می تواند برای متن مورد نظر مناسب باشد: {{Original Title}}

SCB-MT-2020-prompt [PyThaiNLP, 2023a;b]	1	Given a sentence in Thai, generate the English translation. แปลบประโยคหรือย่อหน้าต่อไปนี้จากภาษาไทยเป็นภาษาอังกฤษ: {{Thai_sentence}}	{{English_sentence}}.
	2	Given a sentence in English, generate the Thai translation. แปลบประโยคหรือย่อหน้าต่อไปนี้จากภาษาอังกฤษเป็นภาษาไทย: {{English_sentence}}	{{Thai_sentence}}.
Scirepeval-biomimicry-inst [Singh et al., 2022]	1	Given an abstract, generate the title. I want to submit an article to {{venue}}. The abstract is as follows: {{abstract}} Please give me a good title suggestion.	Sure thing, one of the possible title choices is "{{title}}".
	2	Given an abstract, generate the title. Please help me in writing a title for the following abstract: {{abstract}}	{{title}}
	3	Given a title, generate an abstract. Please write an abstract for the following title: {{title}}	{{abstract}}
Seed-instruct-lij [ConseggioLigure, 2023c;d]	1	Given a sentence in English, generate the Ligurian translation. Translate to Ligurian: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	2	Translate to Genoese: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	3	Translate to Ligurian (Genoese): {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	4	Translate from English to Ligurian: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	5	Translate from English to Genoese: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	6	Translate from English to Ligurian (Genoese dialect): {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	7	Translate this sentence to Ligurian: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	8	Translate this sentence to Genoese: {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	9	What's the Ligurian translation of this sentence? {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
	10	What's the Genoese translation of this sentence? {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}

11	Can you translate this text to Ligurian? {{sentence}}	The Ligurian (Genoese) translation is: {{sentence}}
12	Given a sentence in Ligurian, generate the English translation. Traduxi in ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
13	Traduxi da-o zeneise à l'ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
14	Traduxi da-o ligure à l'ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
15	Traduxi sto testo in ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
16	Traduxi in lengua ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
17	Traduxi sto testo da-o zeneise à l'ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
18	Traduxi sto testo da-o ligure à l'ingleise: {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
19	Comm'à l'é a traducion ingleise de sto testo? {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
20	Quæ a l'é a traduçon ingleise de sto testo? {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
21	Ti peu tradue sto testo in ingleise? {{sentence}}	A traduçon in ingleise do testo a l'é: {{sentence}}
SODA-inst [Kim et al., 2022]	Generate a narrative for the given conversation. {{speakers}}: {{dialogue}} What do you think the narrative of the conversation above is?	{{narrative}}
	Given a narrative, extend it into a dialogue script. I have the following short story premise: {{narrative}} Now, can you extend that into a short dialogue script?	Sure, here is one possible dialogue: {{speakers}}: {{dialogue}}
	Generate the gist of the given dialogue. What's the gist of this dialogue? {{dialogue}}	This is the gist of the dialogue - {{narrative}}
	Given a topic, generate a short paragraph of narrative. Write a short paragraph of narrative given the following topic: {{head}}	Sure, here is a short paragraph: {{narrative}}

TamilStories [AI Tamil Nadu, 2023a]	1	<p>Given a story, generate the appropriate title for the story.</p> <p>கீழே கொடுக்கப்பட்டுள்ள கதைக்குப் பொருத்தமான தலைப்பைக் கொடு. கதை: {{Story}}</p>	கொடுக்கப்பட்டுள்ள கதைக்குப் பொருத்தமான தலைப்பு '{{Title}}', என்பதாகும்.
	2	<p>Given some prominent characters/words from a story along with a title, generate the complete story.</p> <p>கீழே கொடுக்கப்பட்டுள்ள வார்த்தைகளையும் தலைப்பையும் பயன்படுத்தி சிறு கதை எழுதுக. வார்த்தைகள்: {{Comma_Separated_Words}} தலைப்பு: {{Title}}</p>	{{Story}}
TeluguRiddles [desik98, 2023]	1	<p>Given the riddle, generate the answer for that riddle.</p> <p>ఈ ரி஡ில் கிணறான் இவ்வு: {{Riddle}}</p>	மீரு அகின் ரி஡ில் கிணறான்: {{Answer}}
	2	ఈ பாடவு க஢ கிணறான் இவ்வு {{Riddle}}	மீரு அகின் பாடவு க஢ கிணறான்: {{Answer}}
Thai-USEmbassy-prompt [PyThaiNLP, 2023d;e]	1	<p>Given an English sentence, translate it to Thai.</p> <p>ແປລປະໂຍຄஹຣீஓய் ஹாட்டாலைப்பீன் ஜாகபாஷாஓங்களும் பீன் வாசா டைய்: {{English_Sentence}}</p>	{{Thai_Sentence}}
	2	Given a Thai sentence, translate it to English.	{{English_Sentence}}
Thai-POS-inst [PyThaiNLP, 2023c]	1	<p>Given the POS tags, generate a sentence based on the structure.</p> <p>ஏஸ்ராமப்ரக்ரியக்டாம்கிரங்ஸ்ராம {{POS}}</p>	{{Thai_sentence}}
Thai-Wiktionary-inst [PyThaiNLP, 2023f]	1	<p>Given a word, provide its meaning based on the different POS.</p> <p>ஏஸ்ராமப்ரக்ரியக்டாம்கிரங்ஸ்ராம {{word}}</p>	<p>คำว่า {{word}}</p> <p>มีความหมายตามชนิดของคำได้ดังต่อไปนี้ - POS มีความหมายได้ว่า the meaning of word (split with "/")</p>

			கொடுக்கப்பட்டுள்ள குறளின் பொருள்: {{Kural_Meaning}} என்பதாகும். இந்த குறள் {{Adigaram_Name}} என்னும் அதிகாரத்தில் வரும் {{Kural_Number}}ஆம் குரள் ஆகும். திருக்குறள் உலக புகழ் பெற்ற பொது மறை நூல். இந்நாலே இயற்றியவர் திருவள்ளுவர். திருக்குறளில் 133 அதிகாரமும், அதிகாரத்துக்கு 10 குறளும் மொத்தம் 1330 குறளும் அடங்கியுள்ளது. ஒவ்வொரு குறளும் இரண்டு அடிகளையும் ஏழ சீரும் கொண்ட வெண்பாவாகும். இந்நூலில் பெரும் பிரிவு பால் எனவும், சிறு பிரிவு இயல் எனவும், அதனினும் சீரியது. அதிகாரம் என்று வகுக்க பெற்றுள்ளது. அறத்துப்பாலில் 38 அதிகாரங்களையும், பொருப்பாலில் 70 அதிகாரங்களையும் மற்றும் காமத்துப்பாலில் 25 அதிகாரங்களையும் கொண்டுள்ளது. இந்நால் அறம், பொருள், இன்பம்(காமம்) என்னும் முப்பாஸையும் அழகாக எடுத்துரைக்கிறது. வாழ்கையின் அனைத்து பகுதிகளையும் எடுத்துரைக்கும் ஒரு சிறந்த வாழ்வியல் நூலாகும். சாதி, மதம், மொழி, நாடு என்று வேறுபாடு இல்லாமல் மக்கள் அனைவருக்கும் பொருந்துவதாக உள்ளதால் உலக பொது மறை என்று அழைக்கப்படுகிறது. தெய்வநால், பொய்யாமோஜி, தமிழ் மறை, முப்பால் என்று வேறு பெயர்களும் திருக்குறளுக்கு உண்டு.
Thirukkural-instruct [AI Tamil Nadu, 2023b]	1	Given the kural and ask for its meaning, generates the meaning of the kural. {{Adigaram_Name}} என்னும் அதிகாரத்தில் வரும், {{Complete_Kural}} என்ற குறளின் பொருளை விளக்கு.	"{{Complete_Kural}}" என்னும் குறளே கொடுக்கப்பட்டுள்ள பொருளங்களுக்குப் பொருத்தமான குறளாகும். கொடுக்கப்பட்டுள்ள பொருள் மு. வரதராசனார் அவர்கள் எழுதிய உரையிலிருந்து எடுக்கப்பட்டது. திருக்குறளுக்கு வேறு சில அறிஞர்களும் உரை எழுதியுள்ளனர்.
	2	Given the meaning of the kural, generates the original kural. {{Kural_Meaning}} என்னும் பொருளங்கு ஏற்ற {{Adigaram_Name}} என்னும் அதிகாரத்தில் வரும் {{Kural_Number}}ஆம் குறளைத் தருக.	"{{Complete_Kural}}" என்னும் குறளே கொடுக்கப்பட்டுள்ள வார்த்தைகளிலிருந்து தொடங்கும் குறளாகும். இதன் பொருள்: {{Kural_Meaning}}
	3	Given the beginning of a kural and ask for its meaning, generates the original kural along with its meaning. "{{Kural_Start}}" எனத் தொடங்கும் குறளையும் அதன் பொருளையும் தருக.	"{{Complete_Kural}}" என்னும் குறளே கொடுக்கப்பட்டுள்ள வார்த்தைகளிலிருந்து தொடங்கும் குறளாகும். இதன் பொருள்: {{Kural_Meaning}}
Turku-paraphrase-inst [TurkuNLP, 2023]	1	Paraphrase the given text. Can you paraphrase the following text for me: {{text}}	{{paraphrased_text}}
UA-Gec-inst [osyvokon, 2023]	1	Rewrite the given text (sentence/long documents) without grammatical errors. Перепиши наступний текст без помилок: # Текст {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
	2	Перепиши текст без помилок. {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}

3	Виправ помилки у тексті. {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
4	Перевір, будь ласка, правильність граматики у наступному тексті. {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
5	Виправ граматичні помилки в наступному тексті: {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
6	Виправ граматичні помилки в наступному тексті: {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
7	Перепиши текст без помилок. {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
8	Переглянь, будь ласка, наступний текст. Виправи усі граматичні неточності. {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
9	Виправ помилки у тексті. # Текст {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
10	Перевір, будь ласка, правильність граматики у наступному тексті. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
11	Перепиши текст без помилок. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
12	Перепиши наступний текст без помилок: # Текст {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
13	Виправ помилки у тексті. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
14	Перепиши наступний текст без помилок: # Текст {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
15	Переглянь, будь ласка, наступний текст. Виправи усі граматичні неточності. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}

16	Переглянь, будь ласка, наступний текст. Виправи усі граматичні неточності. {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
17	Перевір, будь ласка, правильність граматики у наступному тексті. {{text}}	target_neg: Даний текст не містить помилок. target_pos: Звичайно. Ось текст з виправленими помилками: {{corrected_text}}
18	Виправ помилки у тексті. # Текст {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
19	Виправ помилки у тексті. # Текст {{text}}	target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
20	Виправ граматичні помилки в наступному тексті: {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
21	Виправ помилки у тексті. {{text}}	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
22	Виправ граматичні помилки в наступному реченні: "{{text}}"	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
23	Виправ граматичні помилки в наступному реченні: {{text}}	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
24	Перепиши це речення без помилок: {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
25	Перепиши наступний текст без помилок: {{text}}	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
26	Перепиши наступний текст без помилок: {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
27	Перепиши це речення без помилок: {{text}}	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
28	Виправ граматичні помилки в наступному реченні: "{{text}}"	target_neg: {{text}} target_pos: {{corrected_text}}
29	Виправ помилки у тексті. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
30	Виправ граматичні помилки в наступному реченні: {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}
31	Перепиши текст без помилок. {{text}}	target_neg: {{text}} target_pos: {{corrected_text}}

	32	Перепиши текст без помилок. {{text}}	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
	33	Виправ граматичні помилки в наступному реченні: {{text}}	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
	34	Виправ граматичні помилки в наступному реченні: "{{text}}"	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
	35	Виправ помилки у тексті. {{text}}	target_neg: Дане речення не містить помилок. target_pos: {{corrected_text}}
	36	Перепиши наступний текст без помилок: {{text}}	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
	37	Перепиши це речення без помилок: {{text}}	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
	38	Перепиши текст без помилок. {{text}}	target_neg: Це речення написано без помилок. target_pos: {{corrected_text}}
	39	Виправ помилки у тексті.: {{text}}	Completion will be either target_pos or target_neg based on whether the given text contains grammatical errors or not respectively. target_neg: Даний текст не містить помилок. target_pos: {{corrected_text}}
UNER-LLM-inst [Universal NER, 2023]	1	Identify all named entities mentioned in the given sentence. 请识别下面提供的输入句子中提到的所有命名实体。仅使用以下类别：PER-人名、ORG-组织和LOC-地点。请记住，国籍既不是地点，也不是组织，组织可以代表其他人群。请注意提供的示例。您应该只以 JSON 格式输出结果，遵循与所提供的示例结果类似的结构。 例句和结果： {{example_sentence}} {{example_result}} 考虑到下面的输入句子，输出结果是什么？ {{input_sentence}}	"Results": [{ "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}} }]

	<p>請識別下麵提供的輸入句子中提到的所有命名實體。僅使用以下類別：PER-人名、ORG-組織和LOC-地點。請記住，國籍既不是地點，也不是組織，組織可以代表其他人群。請注意提供的示例。您應該只以 JSON 格式輸出結果，遵循與所提供的示例結果類似的結構。</p> <p>例句和結果：</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>考慮到下麵的輸入句子，輸出結果是什麼？</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
2	<p>Molim te da identificiraš sve imenovane entitete spomenute u niže navedenoj rečenici. Koristi samo kategorije: PER - osoba, ORG - organizacija i LOC - lokacija. Zapamti, nacionalnosti nisu ni lokacije ni organizacije, a organizacije mogu predstavljati razne skupine ljudi. Obrati pažnju na dani primjer. Rezultat oblikuj u JSON formatu, slijedeći sličnu strukturu kao u danom primjeru.</p> <p>Primjer rečenice i rezultata:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>S obzirom na niže navedenu ulaznu rečenicu, koji je konačni izlaz?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
3	<p>Angiv venligst alle navngivne enheder nævnt i sætningen nedenfor. Brug kun kategorierne: PER - person, ORG - organisation og LOC - lokation. Husk, at nationaliteter hverken er steder eller organisationer, og organisationer kan repræsentere andre grupper af mennesker. Vær opmærksom på det givne eksempel. Du bør kun eksportere resultaterne i JSON-format efter en lignende struktur som eksemplerresultatet.</p> <p>Eksempel på sætning og resultat:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>I betragtning af sætningen nedenfor, hvad er resultatet?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
4		

	<p>Please identify all the named entities mentioned in the input sentence provided below. Use only the categories: PER - person, ORG - organization, and LOC - location. Remember, nationalities are neither locations nor organizations, and organizations can represent other groups of people. Pay attention to the provided example. You should only output the results in JSON format, following a similar structure to the example result provided.</p> <p>Example sentence and results:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>Considering the input sentence below, what is the output result?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
5	<p>Bitte identifiziere alle Eigennamen und Orte, die unten im Inputsatz erwähnt werden. Verwende nur die Kategorien PER - Person, ORG - Organisation, und LOC - Ort. Denk daran, Nationalitäten sind weder Orte noch Organisationen, und Organisationen können für andere Gruppe von Menschen stehen. Achte auf das vorgegebene Beispiel. Gib die Ergebnisse nur im JSON-Format aus und folge einer ähnlichen Struktur wie das Beispieldergebnis.</p> <p>Beispialsatz und Ergebnisse:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>Bezogen auf den Inputsatz unten, was ist das richtige Ergebnis?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
6	<p>Por favor identifique todas as entidades nomeadas mencionadas na frase fornecida abaixo. Utilize apenas as categorias: PER - pessoa, ORG -organização e LOC - localização. Lembre-se, nacionalidades não são locais nem organizações, e organizações podem representar outros grupos de pessoas. Preste atenção ao exemplo fornecido. Você só deve gerar os resultados no formato JSON, seguindo uma estrutura semelhante ao resultado do exemplo fornecido.</p> <p>Frase de exemplo e resultados:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>Considerando a frase de entrada abaixo, qual é o resultado produzido?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": ["TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>

	<p>Пожалуйста, определите все именованные сущности, упомянутые во входном предложении, указанном ниже. Используйте только следующие категории: PER - личность, ORG - организация и LOC - местоположение. Помните, что национальности не являются ни местоположением, ни организацией, а организации могут представлять собой другие группы лиц. Обратите внимание на приведённый пример. Вам следует вернуть ответ только в формате JSON, схожем по структуре с приведённым ответом.</p> <p>Пример предложения и ответа:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>Учитывая входное предложение ниже, каким будет ответ?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": [{} "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
8	<p>Molim te da identifikuješ sve imenovane entitete spomenute u niže navedenoj rečenici. Koristi samo kategorije: PER - osoba, ORG - organizacija i LOC - lokacija. Zapamti, nacionalnosti nisu ni lokacije ni organizacije, a organizacije mogu predstavljati razne skupine ljudi. Obrati pažnju na dani primer. Rezultat oblikuj u JSON formatu, sledeći sličnu strukturu kao u datom primeru.</p> <p>Primer rečenice i rezultata:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>S obzirom na niže navedenu ulaznu rečenicu, koji je konačni izlaz?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": [{} "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
9	<p>Prosím, identifikuj všetky vymenované entity uvedené vo vstupnej vete. Použit iba kategórie: PER - osoba, ORG - organizácia a LOC - miesto. Pamäťaj, že národnosti nie sú ani miesta, ani organizácie, a organizácie môžu zastupovať iné skupiny ľudí. Inšpiruj sa príkladom nižšie. Výsledky by mali byť vypísané vo formáte JSON, v podobnej štruktúre ako v nižšie uvedenom príklade.</p> <p>Príklad vstupnej vety a výstupu:</p> <pre> {{example_sentence}} {{example_result}}</pre> <p>Aký bude výstup vzhľadom na vstup uvedený nižšie?</p> <pre> {{input_sentence}}</pre>	<pre>"Results": [{} "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]</pre>
10		

	Vänligen identifiera alla namngivna enheter som nämns i meningens nedan. Använd endast kategorierna: PER - person, ORG - organisation och LOC - plats. Kom ihåg att nationaliteter varken är platser eller organisationer, och organisationer kan representera andra grupper av mänskor. Var uppmärksam på det angivna exemplet. Du bör endast exportera resultaten i JSON-format, enligt en liknande struktur som exempelresultatet. Exempel på mening och resultat: {{example_sentence}} {{example_result}} Med tanke på meningens nedan, vad är resultatet? {{input_sentence}}	"Results": [{} "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]
11	Sa aktibidad na ito, kailangan mong hanapin ang mga named entities na binanggit sa pangungusap. Sa pagtutukoy, gamitin lamang ang itong tatlong na kategorya: PER - tao, ORG - organisasyon, at LOC - lokasyon. Tandaan, ang nasyonalidad ay hindi isang uri ng lokasyon o organisasyon, at ang mga organisasyon ay maaaring kumatawan sa ibang mga grupo ng mga tao. Tingnan ang halimbawa sa baba. Diretsong ibigay ang resulta sa JSON na format, na sumusunod sa format ng halimbawang ibinigay. Ang halimbawa ng pangungusap at ang hinahanap na resulta: {{example_sentence}} {{example_result}} Gamit ang sumusunod na pangungusap sa ibaba, ano ang output? {{input_sentence}}	"Results": [{} "TypeName": "{{tag}}", "Text": "{{text}}", "Start": {{index_1}}, "End": {{index_2}}]
12	Generate the article from the given news. اس دی گی ایک خبر سے متعلق ایک مضمون لکھئیں۔ خبر: {{news}}	جی ضرور، یہ رہا آپ کی خبر سے متعلق ایک مضمون: {{article}}
Urdu-News-Gen-Article [AhmadMustafa, 2023a]	Given a news belonging to a category, write an article on it. یہ خبر جو {{category}} سے متعلق رکھئی ہے، اس پر ایک مضمون لکھئیں۔ خبر: {{news}}	جی ضرور، یہ رہا آپ کی خبر سے متعلق ایک مضمون: {{article}}

		Classify the given paragraph (news article) into one of the provided categories.	
Urdu-News-Category-Class [AhmadMustafa, 2023b]	1	<p>اس پیراگراف (خبروں) کو مندرجہ ذیل درجوں (کیٹگری) میں سے ایک کیٹگری میں ڈالیں، درجے:</p> <ul style="list-style-type: none"> - کھلیل - تفریخ - کاروبار و معیشت، - سائنس اور ٹیکنالوجی <p>پیراگراف:</p> <p>"</p>	<p>یہ دی گی خبریں {{category}}</p> <p>سے تعلق رکھتی ہیں</p>
	2	<p>دیے گئے خبروں کو ایک لفظ یا درجہ (کیٹگری) میں پان کروں، درجے:</p> <ul style="list-style-type: none"> - کھلیل - تفریخ - کاروبار و معیشت، - سائنس اور ٹیکنالوجی <p>جملے:</p> <p>"</p>	<p>یہ دی گی خبریں {{category}}</p> <p>سے تعلق رکھتی ہیں</p>
Urdu-News-Gen-Headline [AhmadMustafa, 2023c]	1	<p>Generate the news headline from the given news.</p> <p>اس اردو پیراگراف (خبروں) کا عنوان تجویز کریں پیراگراف:</p>	<p>بھی ضرور، یہ رہا آپ کے پیراگراف کا عنوان:</p> <p> {{news_headline}}</p>
	2	<p>دیے گئے خبروں کا عنوان تجویز کریں، جملے:</p>	<p>بھی ضرور، یہ رہا آپ کے پیراگراف کا عنوان:</p> <p> {{news_headline}}</p>
Wiki-split-inst [Botha et al., 2018]	1	<p>Generate a more complex version of the given sentence.</p> <p>Generate a more complex version of this sentence {{simple_sentence}}</p>	<p>Of course, a more complex version of the sentence is "{{complex_sentence}}"</p>
	2	<p>Generate a simple sentence for the given complex sentence.</p> <p>Please generate a simpler sentence from the following complex sentence: {{complex_sentence}}</p>	<p> {{simple_sentence}}</p>
X-CSQA-inst [Lin et al., 2021]	1	<p>Choose the answer to the given question from the multiple options provided.</p> <p> {{question:'[stem]'}}</p> <p> {{label_1}} : {{text_1}} {{label_2}} : {{text_2}} {{label_3}} : {{text_3}} {{label_4}} : {{text_4}} {{label_5}} : {{text_5}}</p>	<p>The right answer is {{answer_key}}.</p>
	2	<p>Complete the given phrase.</p> <p>Complete the following phrase: {{context_left}}</p>	<p> {{mention}}{{context_right}}</p>

	Continue the given sentence.	
2	<p>Continue the given sentence.</p> <p>اُکل ہذہ الجملۃ:</p> <p><code> {{context_left}}</code></p>	<code> {{mention}}{{context_right}}</code>
3	<p>Given the context, generate title ideas.</p> <p><code> {{context_left}}{{mention}}{{context_right}}</code></p> <p>Please give me a good title idea for the above article.</p>	<p>Sure, a suitable title example for that article is "<code> {{context_title}}</code>".</p>
4	<p>Complete the given sentence:</p> <p>maak deze zin af: <code> {{context_left}}</code></p>	<code> {{mention}}{{context_right}}</code>
5	<p>Complete the given sentence.</p> <p>اُن جملہ را کامل کرنے:</p> <p><code> {{context_left}}</code></p>	<code> {{mention}}{{context_right}}</code>
6	<p>Given the text, identify the important event the text is about.</p> <p>what important event is this text about:</p> <p><code> {{context_right}}{{mention}}{{context_left}}</code></p>	<code> {{mention}}</code>
7	<p>Given the text, identify its context.</p> <p>इस पाठ का प्रसंग क्या है <code> {{context_left}}</code></p> <p><code> {{mention}}{{context_right}}</code></p>	इस पाठ का प्रसंग यह है <code> {{mention}}</code>
8	<p>Write a continuation to the given paragraph.</p> <p>Write a continuation for this paragraph -</p> <p><code> {{context_left}}{{mention}}</code></p>	<code> {{context_right}}</code>
XWikis-inst [Perez-Beltrachini & Lapata, 2021]	<p>Given a document, generate the summary.</p> <p>Can you summarize the following document?</p> <p><code> {{document}}</code></p>	<code> {{src_summary}}</code>

Table 13: **Aya** Collection - List of applied templates for each templated dataset in the collection.