

# ChatGPT Beyond English: Towards a Comprehensive Evaluation of Large Language Models in Multilingual Learning

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## Abstract

Over the last few years, large language models (LLMs) have emerged as the most important breakthroughs in natural language processing (NLP) that fundamentally transform research and developments in the field. ChatGPT represents one of the most exciting LLM systems developed recently to showcase impressive skills for language generation and highly attract public attention. Among various exciting applications discovered for ChatGPT in English, the model can process and generate texts for multiple languages due to its multilingual training data. Given the broad adoption of ChatGPT for English in different problems and areas, a natural question is whether ChatGPT can also be applied effectively for other languages or it is necessary to develop more language-specific technologies. The answer to this question requires a thorough evaluation of ChatGPT over multiple tasks with diverse languages and large datasets (i.e., beyond reported anecdotes), which is still missing or limited in current research. Our work aims to fill this gap for the evaluation of ChatGPT and similar LLMs to provide more comprehensive information for multilingual NLP applications. While this work will be an ongoing effort to include additional experiments in the future, our current paper evaluates ChatGPT on 7 different tasks, covering 37 diverse languages with high, medium, low, and extremely low resources. We also focus on the zero-shot learning setting for ChatGPT to improve reproducibility and better simulate the interactions of general users. Compared to the performance of previous models, our extensive experimental results demonstrate a worse performance of ChatGPT for different NLP tasks and languages, calling for further research to develop better models and understanding for multilingual learning.

## 1 Introduction

Since the introduction of word embeddings (Bengio et al., 2000) and deep learning architectures (Collobert et al., 2011), Natural Language Processing (NLP) has witnessed significant breakthroughs that fundamentally transform research and applications in various areas. Starting with the creation of word2vec (Mikolov et al., 2013b) to initialize the shift of NLP from feature-engineering methods to representation learning with deep learning, the major milestones in NLP involve the presentation of the seq2seq or encoder-decoder framework (Cho et al., 2014; Sutskever et al., 2014) for text generation in 2014, the proposal of the attention mechanism (Bahdanau et al., 2015) for text encoding in 2015, the development of Transformer architecture (Vaswani et al., 2017) as the basic building block for modern NLP models, the notion of uncontextualized word embeddings from language models in ELMo (Peters et al., 2018), and the pre-trained transformer-based language models, e.g., BERT (Devlin et al., 2019), GPT (Radford et al., 2018, 2019), T5 (Raffel et al., 2020), and BART (Lewis et al., 2020).

The recent advances in NLP feature large language models (LLMs) that have parameter sizes over a hundred billion and are pre-trained on massive data, e.g., GPT-3 (Rae et al., 2021), Megatron (Shoeybi et al., 2019), GPT-Jurassic (Lieber et al., 2021), and OPT-175B (Zhang et al., 2022b). Although still relying on the Transformer architecture, the unprecedented scales of model size and training data have allowed new emergent abilities to change the landscape and practices in NLP (Wei et al., 2022). An important emergent skill involves prompt-based learning that facilitates the probing of information from LLMs with prompts by sampling the learned language distributions (Brown et al., 2020). In this way, the models demonstrate strong generalization in few-shot and zero-shot learning

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while avoiding parameter updates for the underlying architectures. However, due to the auto-regressive training objective, the sampling from LLMs might generate unexpected outputs for users (misalignment with human interests), e.g., containing untruthful facts/toxic sentiments and being very sensitive to minor changes in the input prompts (Ouyang et al., 2022).

To this end, ChatGPT<sup>1</sup> is one of the latest developments in NLP that have mitigated limitations of previous LLMs to gain widespread attention from the public. In the first two months of its launch, ChatGPT has attracted 100 million users (Milmo, 2023). As the next iteration of InstructGPT (Ouyang et al., 2022), ChatGPT is optimized on top of a GPT-3.5 series model using reinforcement learning from human feedback (RLHF) (Christiano et al., 2017). In contrast to previous LLMs, ChatGPT and InstructGPT leverage human demonstrations of desired outputs for input prompts to train supervised models, while human rankings of generated outputs are obtained to train a reward model to further optimize the LLMs with reinforcement learning. Compared to InstructGPT, ChatGPT is trained with conversational data to allow follow-up questions. In this way, ChatGPT is able to interact with humans in multi-turn conversations to generate more aligned outputs with human interests, thus being more natural and accessible to users. In addition, due to the deployment of public APIs to facilitate general users, there have been multiple reports on the successes of ChatGPT in solving challenging tasks in various areas, e.g., passing the United States Medical Licensing Examination (Kung et al., 2022) and real exams in a law school (Choi et al., 2023), performing competitively with commercial translation services for some high-resource languages (Jiao et al., 2023), generating fluent and comprehensive responses to answer complex questions, self-correcting previous errors in the conversations (Guo et al., 2023), and even producing code from natural language instructions.

Across different communities, there is an excitement about a future with ChatGPT and similar technologies as assistants for professional areas (Jeblick et al., 2022; King, 2022) or evaluators of natural language understanding (Wang et al., 2023b). At the same time, the impressive abilities of LLMs have triggered active discussions among researchers and industry members on the next steps for NLP re-

search (Zhang et al., 2022a; Kuzman et al., 2023) and how the technologies will shape the future job market. On the other extreme, the communities also express concerns about long-term implications of ChatGPT and LLMs for society, citing issues on plagiarism, privacy, misinformation, and security. As ChatGPT and current LLMs are trained on large-scale data collected extensively from different corners, they might copy information from one source into the output without proper citation. The generated texts might also be utilized in different situations without acknowledgment. The training data, user prompts, and model responses might involve private information that is not fully concealed. In addition, ChatGPT and LLMs can still hallucinate important information. The fluency and eloquence of generated texts might easily deceive humans about information correctness (especially for non-native speakers), thus amplifying the social risks of misinformation (Bang et al., 2023).

Similar to other LLMs, ChatGPT is trained on a mix of training data from multiple languages. Although English is the majority, the combination of multilingual data contributes to ChatGPT's abilities to accept inputs and generate responses in different languages, making it accessible and widely adopted by people around the world. However, given the recency of the technology, ChatGPT has been mainly evaluated over English data. The community is lacking a comprehensive, public, and independent evaluation of ChatGPT over various non-English languages for diverse NLP tasks to provide proper perspectives for future research and applications. Given ChatGPT's transformative potentials, associated long-term risks, huge cost for training, and limited transparency, a fundamental question is whether multilingual LLMs such as ChatGPT can also be reliably adopted for different languages or it is necessary to develop language-specific LLMs/other technologies to solve NLP problems for non-English languages.

To address the multilingual concerns for ChatGPT, a few recent studies have investigated ChatGPT's performance and responses for non-English languages. However, the considered tasks/languages/settings and scale of evaluation data in existing multilingual evaluations are still limited, which is unable to show a comprehensive picture of the potentials/performance of the technology on a diversity of other languages. For instance, (Bang et al., 2023) evaluates the multilingual performance

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<sup>1</sup><https://openai.com/blog/chatgpt/>

of ChatGPT on three tasks of language identification, sentiment analysis, and machine translation; however, only a few languages are selected for each task and the number of evaluation samples for each language does not exceed 50. Beyond English, the analysis of ChatGPT’s responses for input questions in (Guo et al., 2023) is only done for Chinese, while the results of the medical licensing examinations for ChatGPT are only shown for Japanese in (Kasai et al., 2023). In addition, (Fang et al., 2023) and (Wang et al., 2023a) explores ChatGPT in three languages English, Chinese, and German; however, the studies only focus on grammatical error correction or cross-lingual summarization.

To this end, our paper aims to perform a more thorough evaluation of ChatGPT for its performance on multiple languages over different NLP tasks. Our experiments consider 37 diverse languages, characterizing *high-, medium-, low-, and extremely low-resource languages*, to better highlight ChatGPT’s potentials and limitations. To our knowledge, this is one of the largest sets of languages evaluated for ChatGPT in a public study to date. In addition to Natural Language Inference (NLI), Question Answering, and Common Sense Reasoning, our current work will examine the tasks of Part-of-Speech (POS) Tagging, Named Entity Recognition (NER), Relation Extraction, and Summarization, which are not covered in previous multilingual evaluations for ChatGPT. To improve the reproducibility of the evaluations and better reflect the approach of general users, our current work will focus on the zero-shot learning setting for ChatGPT where no human-provided examples are presented to the model. Importantly, due to the scale of available languages/tasks/datasets/models and the growing nature of multilingual learning research in NLP, we will use this work as an ongoing and public effort to evaluate ChatGPT and other LLMs for multiple languages, emphasizing on understudied languages to measure robustness and democratize impacts of the technologies.

Despite some exceptions and potential updates with future experiments, our current experiments suggest the following major tendencies:

- ChatGPT’s zero-shot learning performance is generally worse than the state-of-the-art performance of the supervised learning models for a majority of the considered tasks across different languages, including high-, medium-, low-, and extremely-low resource languages.

The performance gaps are usually very large, demonstrating the unfit of ChatGPT as a general solver for different NLP problems. It thus highlights the importance of task-specific models for the development of NLP applications.

- ChatGPT’s performance is generally better for English than for other languages, especially for higher-level tasks that require more complex reasoning abilities (e.g., named entity recognition, question answering, common sense reasoning, and summarization). The performance differences can be substantial for some tasks and lower-resource languages, which justifies the biases of ChatGPT for English and suggests the potentials of the development of language-specific models/LLMs for different languages and groups.
- ChatGPT can perform better with English prompts even though the task and input texts are intended for other languages, further confirming the biases toward English of ChatGPT.

## 2 Related Work

**Evaluation of ChatGPT:** Since the release of ChatGPT in November 2022 with impressive language abilities, there has been a growing interest in evaluating ChatGPT for different aspects of natural language understanding. The first line of work concerns the performance comparison of ChatGPT and state-of-the-art systems for important tasks in NLP such as text summarization (Wang et al., 2023a; Yang et al., 2023), machine translation (Hendy et al., 2023; Jiao et al., 2023; Kocmi and Federmann, 2023), question answering (Tan et al., 2023; Omar et al., 2023), information extraction (Wei et al., 2023; Gao et al., 2023), text classification (Kuzman et al., 2023; Amin et al., 2023), grammatical error detection (Fang et al., 2023), and stance detection (Zhang et al., 2022a). Along this line, several recent studies have attempted to examine the performance of ChatGPT more comprehensively on multiple datasets (Bang et al., 2023; Qin et al., 2023; Koco’n et al., 2023; Zhong et al., 2023). The second direction for ChatGPT evaluation focuses on the robustness/reliability of the model against possible variants of input texts. For example, (Wang et al., 2023c) explores the robustness of ChatGPT under the adversarial and out-of-domain learning settings while (Jang and Lukasiewicz, 2023) examines the logical prediction consistency of ChatGPT for inputs with semantic equivalence, logical negation,

or symmetricity. Finally, the third dimension for ChatGPT evaluation discusses the potential impacts and risks of the technology for the broader society, e.g., in education (Susnjak, 2022; Khalil and Er, 2023), law (Choi et al., 2023), medical (Kung et al., 2022), ethnics (Shen et al., 2023), human-computer collaboration (Lanzi and Loiacono, 2023), and cognition (Mahowald et al., 2023). However, to our knowledge, none of existing work has conducted large-scale evaluations of ChatGPT for multiple languages and tasks as we do.

**Multilingual NLP:** Using the encoder-decoder framework in the original Transformer architecture (Vaswani et al., 2017), several variants have been explored to train language models, characterizing the encoder-only models, e.g., BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), decoder-only models, e.g., GPT (Radford et al., 2019; Brown et al., 2020), and encoder-decoder models, e.g., BART (Lewis et al., 2020) and T5 (Raffel et al., 2020). While initial efforts have focused on English, recent work has extended these language models to other languages following two major directions. The first direction introduces language-specific language models that are trained exclusively over data collected for a target language, e.g., for Spanish (MMG, 2021), Polish (Resources and Technology Infrastructure, 2021), French (Martin et al., 2020; Kamal Eddine et al., 2021), Japanese (Wongso, 2021), Hindi (Parmar, 2021), and Swedish (Moell, 2021). The second direction, on the other hand, seeks to train the language models over combined data from multiple languages, leading to multilingual counterparts for text encoding, e.g., mBERT (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2020), mBART (Liu et al., 2020), and mT5 (Xue et al., 2021). Notably, BLOOM (Scao et al., 2022) is a decoder-only LLM with 176 billion parameters trained over data from 46 natural languages and 13 programming languages. In contrast to ChatGPT, BLOOM and its parameters are publicly available to the community.

Picking up from previous multilingual NLP research for non-English languages (Kim et al., 2010; Täckström et al., 2012; Zhang et al., 2016; Conneau et al., 2017; Mayhew et al., 2017; Lample et al., 2018; Joulin et al., 2018; M’hamdi et al., 2019; Ni and Florian, 2019) with cross-lingual word embeddings (Mikolov et al., 2013a; Upadhyay et al., 2016; Ruder et al., 2019), multilingual language models have enabled a new generation of multilingual mod-

els that significantly boost the performance for NLP tasks in different languages (Wu and Dredze, 2020). For example, multilingual language models have achieved state-of-the-art multilingual performance for Sentence Splitting (Nguyen et al., 2021a), Dependency Parsing (Kondratyuk and Straka, 2019), Question Answering (Huang et al., 2019; Wu et al., 2022), Named Entity Recognition (Pires et al., 2019; Wu and Dredze, 2019; Karthikeyan et al., 2020), and Event Extraction (Nguyen et al., 2021b; Guzman-Nateras et al., 2022).

Finally, extensive efforts have been devoted to create multilingual datasets (those with texts and annotations for multiple languages) for different NLP tasks, including Universal Dependencies (Nivre et al., 2016) (for POS tagging and Dependency Parsing in more than 76 languages), CoNLL 2002 and 2003 (Sang and Meulder, 2002, 2003) (for NER in 4 languages), XNLI (Conneau et al., 2018) (for Natural Language Inference in 14 languages), DARPA LORELEI (Strassel and Tracey, 2016) (for NER and Entity Linking in 34 languages), TyDi (Zhang et al., 2021) (for Multilingual Information Retrieval), XWikis (Perez-Beltrachini and Lapata, 2021) for Cross-Lingual Summarization, XQuAD (Artetxe et al., 2020) for Cross-Lingual Question Answering, MEE (Pouran Ben Veyseh et al., 2022) for Event Extraction in 9 languages, MECI (Lai et al., 2022) for event causality identification in 5 languages, and XGLUE (Liang et al., 2020) and XTREME (Hu et al., 2020) for multiple NLP tasks, among others. Such multilingual datasets have served as the key elements to evaluate multilingual learning models and measure research progress in this field. To this end, our work will leverage available multilingual datasets for different NLP tasks to evaluate ChatGPT and LLMs to appropriately contextualize their potentials for multilingual learning.

### 3 Methodology

The goal of our research is to evaluate the performance of ChatGPT and LLMs for NLP tasks in different languages. Given the large numbers of NLP datasets/tasks/languages and the growing developments of LLMs, our work will be an ongoing effort to include additional experiments to be more comprehensive along the way. In the current version of the paper, we will evaluate ChatGPT on seven diverse NLP tasks, i.e., Part-of-Speech (POS) Tagging, Named Entity Recognition (NER), Relation Classification, Natural Language

Inference (NLI), Question Answering (QA), Common Sense Reasoning (CSR), and Summarization. Over different tasks, our experiments will cover 34 diverse languages, characterizing high-, medium-, low-, and extremely low-resource languages to provide broader perspectives. Following (Bang et al., 2023), we employ the ratio of the data for each language in the CommonCrawl corpus<sup>2</sup>, i.e., the main data to pre-train GPT-3, to classify the resource levels. In particular, a language will be considered as high-, medium-, low-, and extremely low-resource if its data ratio is greater than 1% ( $> 1\%$ ), between 0.1% and 1% ( $> 0.1\%$ ), between 0.01% and 0.1% ( $> 0.01\%$ ), and smaller than 0.01% ( $< 0.01\%$ ) respectively. Table 1 presents information and categories for the languages considered in our work.

As the scale of ChatGPT precludes the ability to fine-tune the model on downstream task data for most general users, we focus on the zero-shot learning setting for ChatGPT. We also report the state-of-the-art performance of the supervised models for a task in each language as a reference for research progress. In zero-shot learning, an NLP task  $T$  is specified by a natural-language task description  $D$ . Given a new data sample with input text  $X$  for the task  $T$ , the concatenation of  $D$  and  $X$  will then be sent into the ChatGPT model  $G$  as the input prompt to generate a natural-language response  $R = G([D; X])$ . Afterward, the response  $R$  will be parsed using some pre-defined task-specific rules  $P$  to obtain an output  $Y = P(R(G([D; X])))$  in the required format for  $T$  (e.g., a pre-defined label for classification problems). Finally, the outputs  $Y$  for examples in an evaluation dataset will be scored to return ChatGPT’s performance for task  $T$ .

Different from some previous work that exploits two-stage prompting to adopt a zero-shot chain of thoughts (Kojima et al., 2022; Qin et al., 2023), we directly utilize single-stage prompting that only adds the task description  $D$  into each input  $X$  to simulate the common approach of general users for ChatGPT. Other prompting strategies can be explored in future versions of our work. As such, in the current version, we aim to design simple task descriptions  $D$  while ensuring necessary information to indicate the task and facilitate the parsing of responses to produce accurate outputs  $Y$ . In addition, for tasks in a non-English target language, we will evaluate task descriptions in both English and target-specific languages to shed light on the best approach

Language	Code	Pop. (M)	CC Size	
			(%)	Cat.
English	en	1,452	45.8786	H
Russian	ru	258	5.9692	H
German	de	134	5.8811	H
Chinese	zh	1,118	4.8747	H
Japanese	jp	125	4.7884	H
French	fr	274	4.7254	H
Spanish	es	548	4.4690	H
Italian	it	68	2.5712	H
Dutch	nl	30	2.0585	H
Polish	pl	45	1.6636	H
Portuguese	pt	257	1.1505	H
Vietnamese	vi	85	1.0299	H
Turkish	tr	88	0.8439	M
Indonesian	id	199	0.7991	M
Swedish	sv	13	0.6969	M
Arabic	ar	274	0.6658	M
Persian	fa	130	0.6582	M
Korean	ko	81	0.6498	M
Greek	el	13	0.5870	M
Thai	th	60	0.4143	M
Ukrainian	uk	33	0.3304	M
Bulgarian	bg	8	0.2900	M
Hindi	hi	602	0.1588	M
Bengali	bn	272	0.0930	L
Tamil	ta	86	0.0446	L
Urdu	ur	231	0.0274	L
Malayalam	ml	36	0.0222	L
Marathi	mr	99	0.0213	L
Telugu	te	95	0.0183	L
Gujarati	gu	62	0.0126	L
Burmese	my	33	0.0126	L
Kannada	kn	64	0.0122	L
Swahili	sw	71	0.0077	X
Punjabi	pa	113	0.0061	X
Kyrgyz	ky	5	0.0049	X
Odia	or	39	0.0044	X
Assamese	as	15	0.0025	X

Table 1: List of languages, language codes, numbers of first and second speakers, data ratios in the CommonCrawl corpus, and language categories. The languages are grouped into categories based on their data ratios in the CommonCrawl corpus: High Resource (H,  $> 1\%$ ), Medium Resource (M,  $> 0.1\%$ ), and Low Resource (L,  $> 0.01\%$ ), and Extremely-Low Resource (X,  $< 0.01\%$ ).

to prompt ChatGPT in multilingual settings. To facilitate the experiments, all non-English task descriptions are obtained using automatic translation

<sup>2</sup><http://commoncrawl.org>

tools, e.g., Google Translate<sup>3</sup>, to translate the designed English descriptions for each task. Finally, all of the responses from ChatGPT in this work are obtained between March 1 and April 5. This is right after ChatGPT is made available in OpenAI APIs to enable large-scale requests from the public for comprehensive evaluations. To improve reproducibility, we clear the conversations in ChatGPT for each query to remove any previous context.

#### 4 Part-of-Speech Tagging

Part-of-Speech (POS) Tagging is a coarse-grained word classification task whose goal is to label the syntactic information of the words in a sentence. POS tagging can help alleviate the sparseness of word-level features and serve as an important pre-processing step in NLP systems. We evaluate ChatGPT for its multilingual POS tagging abilities over the XGLUE-POS dataset (Liang et al., 2020), which covers 18 languages and includes labels derived from the Universal Dependencies (UD) Treebanks (v2.5) (Zeman et al., 2020). In the experiments, we utilize the XGLUE-POS dataset from Huggingface Datasets<sup>4</sup> that only includes 17 languages (e.g., excluding Portuguese). As such, we use the test sets of XGLUE-POS with more than 15K samples for the selected languages in the evaluation.

Our prompt for POS tagging for ChatGPT consists of a task description, a note for output format, and an input sentence, concatenated in that order, i.e.,  $Prompt_{POS} = [task\ description; output\ format\ note; input\ sentence]$ . Notably, instead of directly using the text of input sentence, we feed ChatGPT with the list of words in the sentence to facilitate the word-label alignment and parsing of ChatGPT responses for POS tagging. Our task description and output format note then emphasize on the expected format for the ChatGPT’s responses to follow the tuple structure with pairs of words and their corresponding POS tags. In the experiments, this approach has led to better performance for ChatGPT than the direct input sentence. We illustrate an example for the English POS prompts for ChatGPT in Figure 1.

**Results:** Table 2 presents the performance of ChatGPT (zero-shot learning with both English and language-specific task descriptions) and the fully supervised XLM-R model (based on XLM-RoBERTa

<sup>3</sup><https://translate.google.com>

<sup>4</sup><https://huggingface.co/datasets/xglue>

**Task Description:** Please provide the POS tags for each word in the input sentence. The input will be a list of words in the sentence. The output format should be a list of tuples, where each tuple consists of a word from the input text and its corresponding POS tag label from the tag label set: [“ADJ”, “ADP”, “ADV”, “AUX”, “CCONJ”, “DET”, “INTJ”, “NOUN”, “NUM”, “PART”, “PRON”, “PROPN”, “PUNCT”, “SCONJ”, “SYM”, “VERB”, “X”].

**Note:** Your response should include only a list of tuples, in the order that the words appear in the input sentence, with each tuple containing the corresponding POS tag label for a word.

**Input:** [“What”, “if”, “Google”, “Morphed”, “Into”, “GoogleOS”, “?”]

⇒ [(“What”, “PRON”), (“if”, “SCONJ”), (“Google”, “PROPN”), (“Morphed”, “VERB”), (“Into”, “ADP”), (“GoogleOS”, “PROPN”), (“?”, “PUNCT”)].

Figure 1: Input prompt and output of ChatGPT for the XGLUE-POS dataset.

Language	Code	Cat.	XLM-R	ChatGPT	
				(en)	(spc)
English	en	H	96.2	88.5	89.6
Russian	ru	H	86.9	91.6	59.1
German	de	H	92.2	90.2	89.9
Chinese	zh	H	60.4	76.5	75.3
French	fr	H	89.9	93.2	93.5
Spanish	es	H	89.0	92.2	91.9
Italian	it	H	92.6	92.6	93.4
Dutch	nl	H	88.5	88.1	88.3
Polish	pl	H	85.4	90.4	64.5
Vietnamese	vi	H	55.2	64.8	65.9
Turkish	tr	M	72.7	78.6	69.6
Arabic	ar	M	67.3	81.0	80.9
Greek	el	M	88.2	87.1	79.8
Thai	th	M	57.9	68.5	69.1
Bulgarian	bg	M	88.8	91.2	92.3
Hindi	hi	M	74.5	83.1	72.8
Urdu	ur	L	62.1	78.4	80.7
Average			79.3	84.5	79.8

Table 2: Accuracy of ChatGPT (zero-shot learning) and XLM-R (supervised learning) on the test sets of XGLUE-POS. ChatGPT is evaluated with both English (en) and language-specific (spc) task descriptions.

base) (Liang et al., 2020). Here, performance is measured via the accuracy of the predicted POS tags. As can be seen, ChatGPT outperforms XLM-

R over 13 out of 17 languages for multilingual POS tagging. Different from XLM-R where English has the best POS tagging performance, ChatGPT seems to have better accuracy than English with some other languages (e.g., French, Spanish). Finally, we observe that English prompts tend to perform better or at least competitively with language-specific prompts for ChatGPT across different languages for POS tagging.

## 5 Named Entity Recognition

Named Entity Recognition (NER) is an important task in NLP (Sang and Meulder, 2002), providing basic technologies for many downstream applications, such as search engines, question answering, and recommendation systems. Aiming to identify spans and semantic types of names (e.g., person, organization) in text, NER is usually formulated as a sequence tagging problem where a label is assigned to each word in a sentence to indicate names. The BIO annotation schema is often leveraged to form the labels to capture both span and type information (Ratinov and Roth, 2009). For multilingual NER evaluation of ChatGPT, we employ the datasets from the recent shared task MultiCoNER (Malmasi et al., 2022) that seeks to build NER systems for 11 languages following the WNUT 2017 taxonomy for entity types (Derczynski et al., 2017). There are 6 entity types in MultiCoNER, i.e., PER (person), LOC (location), CORP (corporation), CW (creative work), GRP (group of people), and PROD (product). The sentences in MultiCoNER belong to three main domains: Wikipedia, web questions, and user queries. In MultiCoNER, the sentences tend to be short with low context. Also, the entities in the sentences usually exhibit ambiguous semantics with high level of complexity to cause more challenges for the problem. We utilize the test sets of the language in MultiCoNER for evaluation.

Our prompt structure for ChatGPT with NER follows the prompts for POS Tagging, i.e.,  $Prompt_{NER} = [task\ description; output\ format\ note; input\ sentence]$ , which involve a task description to explain the task and list entity type/labels of interest. We also have a note to specify the expected output format with tuples of words and predicted tags for names. However, a key difference for NER is that we explicitly ask ChatGPT to produce tags for each word in the BIO format. Although this approach seems to make the task more challenging for ChatGPT, we find that it actually improves the perfor-

mance for ChatGPT. Our hypothesis is that the BIO tag requirement encourages ChatGPT to solve NER as a sequence labeling problem, thus forcing it to comprehensively annotate names in input sentences. In contrast, the simpler approach to prompt ChatGPT for names without BIO specification might suggest reading comprehension formulation that does not tag all names with exact spans for NER. The responses from ChatGPT are also harder (i.e., more ambiguous and unpredictable) to parse for NER outputs without the BIO requirement. We provide an English prompt example for NER for ChatGPT in Figure 2.

**Task Description:** You are working as a named entity recognition expert and your task is to label a given text with named entity labels. Your task is to identify and label any named entities present in the text. The named entity labels that you will be using are PER (person), LOC (location), CORP (corporation), CW (creative work), GRP (group of people), and PROD (product). You may encounter multi-word entities, so make sure to label each word of the entity with the appropriate prefix (“B” for the first word of the entity, “I” for any non-initial word of the entity). For words which are not part of any named entity, you should return “O”.

**Note:** Your output format should be a list of tuples, where each tuple consists of a word from the input text and its corresponding named entity label.

**Input:** [“john”, “is”, “first”, “mentioned”, “in”, “a”, “charter”, “from”, “1247”, “.”]

$\Rightarrow [(“john”, “B-PER”), (“is”, “O”), (“first”, “O”), (“mentioned”, “O”), (“in”, “O”), (“a”, “O”), (“charter”, “B-CW”), (“from”, “O”), (“1247”, “B-PROD”), (“.”, “O”)].$

Figure 2: Input prompt and output of ChatGPT for the MultiCoNER dataset.

**Results:** Table 3 evaluates the performance of ChatGPT (zero-shot learning with both English and language-specific task descriptions) and DAMO (Wang et al., 2022a), the model with current best-reported performance on MultiCoNER. The latter retrieves relevant context from Wikipedia for each input sentence that are then fed into the XLMR-RoBERTa model (large version) for NER. DAMO

Language	Code	Cat.	DAMO	ChatGPT	
				(en)	(spc)
English	en	H	91.2	37.2	37.2
Russian	ru	H	91.5	27.4	22.0
German	de	H	90.7	37.1	32.8
Chinese	zh	H	81.7	18.8	19.8
Spanish	es	H	89.9	34.7	33.2
Dutch	nl	H	90.5	35.7	37.5
Turkish	tr	M	88.7	31.9	29.1
Persian	fa	M	89.7	25.9	21.9
Korean	ko	M	88.6	30.0	32.2
Hindi	hi	M	86.2	27.3	26.1
Bengali	bn	L	84.2	23.3	16.4
Average			88.4	29.9	28.0

Table 3: Performance (F1 scores) of ChatGPT (zero-shot learning) and DAMO (supervised learning) on the test sets of MultiCoNER. ChatGPT is evaluated with both English (en) and language-specific (spc) task descriptions.

Label	Precision	Recall	F1	Spurious (%)
CORP	31.0	33.8	32.1	39
CW	12.0	17.2	14.1	57
GRP	6.7	5.7	6.2	26
LOC	33.2	37.7	34.9	44
PER	51.2	66.1	57.5	32
PROD	20.3	22.3	21.1	55

Table 4: ChatGPT label-wise scores on MultiCoNER

also employ a conditional random fields (CRF) layer for the modeling. Our results for NER are evaluated using macro-averaged F1 scores (Malmasi et al., 2022). The most important observation from the table is that ChatGPT significantly underperforms DAMO on MultiCoNER across all 11 languages. In fact, the performance of ChatGPT is less than 40% for all languages, which suggests less suitability of ChatGPT to solve NER in this domain.

In order to better understand the performance of ChatGPT for MultiCoNER, we use the scoring script *nervaluate*<sup>5</sup> to compute detailed scores for each entity types for ChatGPT. Table 4 shows label-wise precision, recall, and F1 scores of ChatGPT (with English prompts). We also include spurious percentages (over total numbers of predictions), which are the percentages of ChatGPT’s predictions that do not exist in the annotated data for each type. As can be seen, ChatGPT’s extraction performance

<sup>5</sup><https://github.com/MantisAI/nervaluate>

is very poor for GRP (group of people) and CW (creative work), which have F1 scores of less than 15%. Also, the spurious percentages of ChatGPT are generally high for all entity types, which suggests ChatGPT’s verbosity and confusion for NER.

## 6 Relation Extraction

Relation Extraction (RE) is a crucial task in information extraction (IE), aiming to identify and classify semantic relations between two entity mentions in an input text. To facilitate multilingual experiments for RE, we conduct our evaluation over the SMiLER dataset (Seganti et al., 2021). SMiLER provides relation annotation for texts in 14 languages with 36 relation types (including “no-relation”). The test sets of the languages (with more than 12K samples) are employed for evaluation.

An input example for RE involves an input text and two entity mentions in the text for classification. To probe ChatGPT for RE for an example, we design the prompt via the concatenation of a task description, input text, and two entity mentions, i.e.,  $Prompt_{RE} = [task\ description; output\ format\ note; input\ text; entity\ 1; entity\ 2]$ . In the task description for RE, we explicitly include all the relation types to inform ChatGPT. We also introduce an output format note to specify the expected format for the responses from ChatGPT for RE, thus facilitating response parsing for relation labels. To illustrate the RE prompts for ChatGPT, we present an example with the English prompt and corresponding response in Figure 3.

**Results:** Table 5 shows the performance of ChatGPT (zero-shot learning with both English and language-specific task descriptions) and mT5-IL (Chen et al., 2022), a state-of-the-art supervised in-language prompting model for SMiLER. mT5-IL is based on the base version of mT5. Micro F1 scores are used as the performance metric for RE. From Table 5, the results suggest that mT5-IL significantly outperforms ChatGPT over different languages no matter if we ask ChatGPT with English or language-specific prompts (except for Swedish and Ukrainian). The performance gap is up to 15% over F1 score on average for the languages. Language-specific prompts seem to yield better or comparable performance as English prompts for ChatGPT with RE. Ukrainian is an exception when English prompts return better F1 score for ChatGPT. Interestingly, ChatGPT performs the worst in English for RC with SMiLER, potentially due to the much

**Task Description:** Given an input text describing the relationship between two entities, extracts the relationship between them. The relation has to be of the type: “birth-place”, “eats”, “event-year”, “first-product”, “from-country”, “has-author”, “has-child”, “has-edu”, “has-genre”, “has-height”, “has-highest-mountain”, “has-length”, “has-lifespan”, “has-nationality”, “has-occupation”, “has-parent”, “has-population”, “has-sibling”, “has-spouse”, “has-tourist-attraction”, “has-type”, “has-weight”, “headquarters”, “invented-by”, “invented-when”, “is-member-of”, “is-where”, “loc-leader”, “movie-has-director”, “no-relation”, “org-has-founder”, “org-has-member”, “org-leader”, “post-code”, “starring”, “won-award”.

**Note:** Your output must only be the relation of the two given entities and must follow the format: “Relation: <One of the above listed relations>”.

**Input:** North West Coastal Highway is a generally north-south Western Australian highway which links the coastal city of Geraldton with the town of Port Hedland.

**Entity 1:** North West Coastal Highway

**Entity 2:** highway

⇒ *Relation: has-type.*

Figure 3: Input and output of ChatGPT for the SMiLER dataset.

larger size of English test data with greater diversity and challenges (5,461 samples for English vs. 1,243 samples for the second large test set for French).

## 7 Natural Language Inference

Natural Language Inference (NLI) aims to predict the entailment/contradiction relations between two input sentences, i.e., a premise and a hypothesis. To evaluate ChatGPT for multilingual NLI, we utilize the XNLI dataset (Conneau et al., 2018) that provides annotated data for English and 14 other languages with three categories, i.e., *Entailment*, *Contradiction*, and *Neutral*. As such, the data in non-English languages is obtained by translating English data for XNLI. XNLI provides development and test data to facilitate development and evaluation. However, as the labels for the test data are not publicly available, we utilize the development data of

Language	Code	Cat.	mT5-IL	ChatGPT	
				(en)	(spc)
English	en	H	96.0	61.9	61.8
Russian	ru	H	83.3	78.8	77.5
German	de	H	94.0	71.1	71.8
French	fr	H	97.2	72.4	73.9
Spanish	es	H	70.5	67.5	65.8
Italian	it	H	97.0	74.4	74.6
Dutch	nl	H	93.5	66.8	66.6
Polish	pl	H	93.0	63.4	65.8
Portuguese	pt	H	85.2	64.8	66.3
Arabic	ar	M	94.1	84.9	90.1
Persian	fa	M	73.1	58.9	63.8
Korean	ko	M	83.2	65.3	70.1
Swedish	sv	M	58.7	64.2	65.4
Ukrainian	uk	M	71.8	76.5	68.8
Average			85.0	69.4	70.2

Table 5: Performance (F1 scores) of ChatGPT (zero-shot learning) and mT5-IL (supervised learning) on the test sets of SMiLER. ChatGPT is evaluated with both English (en) and language-specific (spc) task descriptions.

XNLI in this experiment.

To construct the prompt for ChatGPT for each example in XNLI, we directly concatenate the task description, the premise, the hypothesis, and a multiple choice question (of entailment, contradiction, and neutral) in this order, i.e.,  $Prompt_{NLI} = [task\ description; premise; hypothesis; question]$ . An example of English input prompts and responses from ChatGPT is shown in Figure 4.

**Task Description:** Please identify whether the premise entails or contradicts the hypothesis in the following premise and hypothesis. The answer should be exact “entailment”, “contradiction”, or “neutral”.

**Premise:** And he said, Mama, I’m home.

**Hypothesis:** He called his mom as soon as the school bus dropped him off.

Is it entailment, contradiction, or neutral?

⇒ *Neutral. The premise doesn’t confirm or deny the hypothesis....*

Figure 4: Input prompt and output of ChatGPT for the XNLI dataset.

**Results:** Table 6 reports the performance (accuracy) of ChatGPT and the multilingual model mT5-XXL (Xue et al., 2021). Here, for each non-English target language, we present ChatGPT’s per-

Language	Code	Cat.	mT5- XXL	ChatGPT	
				(en)	(spc)
English	en	H	92.4	70.2	70.2
Russian	ru	H	86.4	60.8	45.4
German	de	H	89.2	64.5	51.1
Chinese	zh	H	86.2	58.2	35.5
French	fr	H	88.7	64.8	42.2
Spanish	es	H	89.4	65.8	47.4
Vietnamese	vi	H	86.6	55.4	44.8
Turkish	tr	M	86.4	57.1	37.1
Arabic	ar	M	87.1	55.3	22.3
Greek	el	M	88.7	55.9	54.5
Thai	th	M	84.5	44.7	11.5
Bulgarian	bg	M	88.7	59.7	44.6
Hindi	hi	M	85.3	48.8	5.6
Urdu	ur	L	82.9	43.7	6.3
Swahili	sw	X	83.4	50.3	40.8
Average			87.1	57.0	37.3

Table 6: Accuracy of ChatGPT (zero-shot learning) and mT5-XXL (supervised learning with English and translated data) on the development set of XNLI. ChatGPT is evaluated with both English (en) and language-specific (spc) task descriptions.

formance on two zero-shot learning settings depending on whether the task descriptions are in English or target language. For mT5-XXL, the model is fine-tuned on English training data and translations in the target language to achieve the best reported performance on XNLI. It is clear from the table that ChatGPT performs significantly poorer than mT5-XXL across different languages by large margins. The performance gaps between ChatGPT and mT5-XXL also seem smaller for high-resource languages. Finally, ChatGPT with target-language task descriptions produces significantly lower accuracy than those with English task descriptions across all considered languages, suggesting the benefits of English descriptions for multilingual NLI with ChatGPT.

## 8 Question Answering

Given a context passage and a question, a Question Answering (QA) model needs to return the answer for the question, which should be a span of text in the input passage. To this end, we utilize the XQuAD dataset (Artetxe et al., 2020) to evaluate ChatGPT in multiple languages for QA. XQuAD involves 240 paragraphs and 1190 question-answer pairs in English and their translations into ten other languages for evaluation.

We collect the English task description for

**Task Description:** Answer the question from the given passage. Your answer should be directly extracted from the passage, and it should be a single entity, name, or number, not a sentence.

**Passage:** Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver’s Executive Vice President of Football Operations and General Manager.

**Question:** How old was Peyton Manning when he played in Super Bowl 50?

**Note:** Your answer should be directly extracted from the passage and be a single entity, name, or number, not a sentence.

⇒ 39.

Figure 5: Input prompt and output of ChatGPT for XQuAD dataset.

QA from the NaturalInstructions repository (Wang et al., 2022b) for ChatGPT. In addition, as ChatGPT tends to generate long responses, we introduce a note to remind the model that the answers for our dataset should be short and directly extracted from the input passage. This approach has helped ChatGPT to provide more direct answers in our experiments. To this end, for an example with an input passage and question, our prompt for ChatGPT is formed via:  $Prompt_{QA} = [task\ description; passage; question; note]$ . We demonstrate an example of the QA prompts in Figure 5.

Given the responses from ChatGPT for our QA prompts for the examples, we remove the period characters in the end and directly evaluate remaining responses using the SQuAD’s scorer<sup>6</sup>, which is suggested by the original paper of XQuAD (Artetxe et al., 2020).

**Results:** Table 7 shows the performance of ChatGPT (zero-shot learning) and mT5-XXL (Xue et al., 2021), a state-of-the-art supervised learning model for XQuAD. As such, for each language, mT5-XXL is trained over the combination of English training data and the translations to the target

<sup>6</sup><https://raw.githubusercontent.com/allenai/bi-att-flow/master/squad/evaluate-v1.1.py>

Language	Code	Cat.	mT5-XXL		ChatGPT(en)		ChatGPT(spc)	
			EM	F1	EM	F1	EM	F1
English	en	H	80.3	91.3	56.0	74.9	56.0	74.9
Russian	ru	H	70.4	85.2	30.2	49.1	22.4	52.6
German	de	H	68.2	85.0	45.9	65.8	44.7	65.8
Chinese	zh	H	80.0	85.7	37.1	42.3	20.5	20.8
Spanish	es	H	70.8	87.4	41.8	65.8	40.5	69.1
Vietnamese	vi	H	67.1	85.3	36.1	57.3	26.8	60.8
Turkish	tr	M	67.7	84.4	34.5	56.4	18.3	52.8
Arabic	ar	M	68.2	83.4	32.0	50.3	24.1	49.9
Greek	el	M	68.9	85.9	29.7	45.0	17.7	39.1
Thai	th	M	74.5	80.2	31.2	43.4	1.5	13.1
Hindi	hi	M	68.2	83.7	17.5	37.8	0.6	22.9
Average			71.3	85.2	35.6	53.5	21.7	47.4

Table 7: Performance of ChatGPT (zero-shot learning) and mT5-XXL (supervised learning with translated data) on the XQuAD dataset. en and spc indicate whether ChatGPT uses English or target language prompts. The performance is computed using exact match (EM) and F1 scores.

language to achieve optimal performance. We report the performance using both the exact match (EM) and F1 scores. Table 7 illustrates that ChatGPT’s zero-shot performance is significantly worse than the supervised model mT5-XXL for all the languages. Across different models and prompts, the QA performance for English is significantly better than those for other languages, demonstrating the clear bias for English of current multilingual language models. Finally, we find that prompting ChatGPT with English tends to produce better performance for multilingual QA than using target languages.

## 9 Common Sense Reasoning

Common Sense Reasoning (CSR) evaluates the reasoning of the models via multiple-choice questions. The inputs for the models involve a question and a few choices for the answer, and the models need to select one of the choices. To evaluate ChatGPT’s multilingual abilities for CSR, we leverage two datasets: (i) X-CSQA (Talmor et al., 2019; Lin et al., 2021), which involves English data and its translations to 15 other languages, and (ii) Wikipedia Cloze QA from IndicNLP Suite (Kakwani et al., 2020), which covers 11 low- and extremely-low-resource Indian languages. We evaluate the models on the dev set of X-CSQA with 1,000 samples for each language, while the Wiki Cloze QA dataset from IndicNLP Suite contains 62,314 samples for all languages.

In the CSR prompts for ChatGPT, we combine the task description, the question, and the multiple

choices for each sample, i.e.,  $Prompt_{CSR} = [task\ description; question; multiple\ choices]$ . Here, for the task description, we also indicate the language of the input question and multiple choices. Two examples of prompts for CSR inputs are presented in Figure 6 for the X-CSQA dataset and in Figure 7 for the Wikipedia Cloze QA dataset from IndicNLP Suite.

**Task description:** In this task, you will be presented with a question that has multiple possible answers in English. You should choose the most suitable option out of “A”, “B”, “C”, “D”, and “E”, based on your commonsense knowledge.

**Question:** When you return to work you will likely need what to get in the door if you are the first to arrive?

**Options:**

- A earn money
- B key
- C need money
- D badge
- E get out of bed

⇒ Option B is the most suitable answer: key.

Figure 6: Input prompt and output of ChatGPT for X-CSQA dataset.

**Results:** Table 8 reports the accuracy of ChatGPT (zero-shot learning for both English and language-specific prompts) and the state-of-the-art supervised model TRT (Fang et al., 2022) on the X-CSQA dataset. TRT is based on the XLM-

Language	Code	Cat.	TRT	ChatGPT	
				(en)	(tgt)
English	en	H	70.0	75.0	75.0
Russian	ru	H	59.8	50.2	53.5
German	de	H	61.7	52.6	61.0
Chinese	zh	H	59.6	50.2	42.5
Japanese	jp	H	54.3	41.9	43.0
French	fr	H	60.9	50.5	61.7
Spanish	es	H	61.1	53.3	62.5
Italy	it	H	61.2	50.6	55.9
Dutch	nl	H	59.8	52.9	60.4
Polish	pl	H	59.7	35.2	51.1
Portugese	pt	H	60.5	49.5	59.2
Vietnamese	vi	H	59.3	42.3	47.9
Arabic	ar	M	58.1	49.4	47.3
Hindi	hi	M	53.8	41.1	38.6
Urdu	ur	L	52.8	34.7	24.5
Swahili	sw	X	51.8	35.6	46.6
Average			59.0	47.8	51.9

Table 8: Accuracy of ChatGPT (zero-shot learning) and TRT (supervised learning) on the dev set of X-CSQA dataset. en and spc indicate whether ChatGPT uses English or language-specific prompts.

RoBERTa large model (Conneau et al., 2020) where commonsense knowledge in different sources is retrieved to enrich input questions and answers. Except for English, the table illustrates the poorer performance of ChatGPT than TRT across all other languages for CSR on X-CSQA when the English task description is used. Interestingly, in contrast to other tasks, we find that language-specific prompts tend to perform better than English prompts for ChatGPT in CSR for high-resource languages (except for Chinese), leading to some improvement over supervised learning (e.g. for French, Spanish, and Dutch).

For IndicNLP Suite, Table 9 demonstrates the accuracy of ChatGPT and IndicBERT (Kakwani et al., 2020), a pre-trained encoder-only model using the ALBERT architecture over an Indian language corpora. IndicBERT is fine-tuned on training data to deliver state-of-the-art performance for IndicNLP Suite in the original paper (Kakwani et al., 2020). Our experiment results for IndicNLP Suite confirm the general tendency that supervised learning models still perform better than ChatGPT over different languages. However, there are two exceptions with Hindi and Kannada where ChatGPT can produce better accuracy over IndicNLP Suite. Finally, Table 9 suggests that English prompts are a

better way to prompt ChatGPT for Indian languages than these languages themselves (except for Marathi and Gujarati).

**Task description:** You are given a statement written in Hindi. Choose the most logical word from the 4 given options which can be used to replace the <MASK> token in the statement. Output the word from the correct option .

**Statement:** रतन देवासी का जन्म 25 सितंबर 1975 को <MASK> के सरोही जिले में माउंट आबू में हुआ था। इनके पिता का नाम शंकरलाल देवासी तथा पत्नी का नाम वरिज देवासी है। देवासी बचपन से ही मेधावी छात्र रहे हैं। वे डिप्लोमा इन होटल मैनेजमेंट डिग्रीधारक हैं। देवासी छात्र जीवन से ही तेज-तर्रार एवं मृदुभाषी हैं।

- Option A: कांग्रेस
- Option B: एनएसयूआई
- Option C: राजस्थान
- Option D: लोकसभा

⇒ Option C: राजस्थान

Figure 7: Input prompt and output of ChatGPT for Wikipedia Cloze QA dataset (IndicNLP Suite). Translation of the statement and options by Google Translate: *Ratan Devasi was born on 25 September 1975 at Mount Abu in the Sirohi district of <MASK>. His father's name is Shankarlal Devasi and wife's name is Viraj Devasi. Devasi has been a brilliant student since childhood. He is a Diploma in Hotel Management degree holder. Devasi is quick-tempered and soft-spoken since his student life. Option A: Congress; Option B: NSUI; Option C: Rajasthan; Option D: Lok Sabha.*

## 10 Summarization

In summarization, systems need to provide key and concise information for a longer input text, which can be helpful for different downstream applications such as news analysis, marketing, question answering, and scientific document processing. To study the performance of ChatGPT for summarization in multiple languages, we choose the XL-Sum dataset (Hasan et al., 2021) that provides summaries of news articles in 44 languages. In contrast to extractive summarization that select important sentences in the input text to a summary, XL-Sum addresses abstractive summarization to allow text generation with more creative writing in the summary (the sentences in the summary might not necessarily appear in the input text). Despite greater challenges,

Language	Code	Cat.	Indic-BERT	ChatGPT	
				(en)	(tgt)
Hindi	hi	M	41.6	45.7	45.2
Bengali	bn	L	39.4	35.2	22.0
Tamil	ta	L	31.8	27.9	22.3
Malayalam	ml	L	35.4	32.2	14.3
Marathi	mr	L	44.9	36.2	36.9
Telugu	te	L	32.6	32.5	22.2
Gujarati	gu	L	70.8	15.2	25.8
Kannada	kn	L	39.6	42.0	12.9
Punjabi	pa	X	44.7	38.1	27.9
Odia	or	X	39.3	34.7	32.9
Assamese	as	X	40.5	35.2	24.8
Average			41.1	34.1	26.1

Table 9: Accuracy of ChatGPT (zero-shot learning) and IndicBERT (supervised learning) on the Wikipedia Cloze QA dataset (IndicNLP Suite). en and spc indicate whether ChatGPT uses English or language-specific prompts.

abstractive summarization can produce more natural texts to better serve downstream applications.

To facilitate the experiments, we select 12 languages in XL-Sum, covering high-, medium-, low-, and extremely low-resource languages, and evaluate ChatGPT’s performance on the test datasets of the languages. Table 10 shows the sizes of test data (i.e., the numbers of samples) in XL-Sum for the selected languages. In the experiments, we utilize the ROUGE-1, ROUGE-2, and ROUGE-L scores as performance measures for summarization. Note that for the non-English languages, the scorer script in the original paper of XL-Sum (Hasan et al., 2021) is used for performance computation.

As a summary in XL-Sum is expected to be written in the same language as the input text, given an input text, our summarization prompt for ChatGPT is constructed via the concatenation:  $Prompt_{SUM} = [task\ description; output\ language\ specification: input\ text]$ . Accordingly, the task description is simply: “Summarize this  $\langle lang \rangle$  text.” while the output language specification is expressed via: “The output should be in  $\langle lang \rangle$ ”. Here,  $\langle lang \rangle$  indicates the the same language that is presented in the input text and expected in the summary response.  $\langle lang \rangle$  can be translated into appropriate languages as required by the language of the prompts. For instance, using English for the prompts, the summarization prompt for a French input is “Summarize this French text. The output should be in French: ...”. In the experiments, we find that Chat-

GPT might generate responses in English even for non-English inputs and including output language specifications in the prompts is important to instruct the same language in the inputs and outputs for ChatGPT.

**Results:** Tables 10 and 11 presents the summarization performance of ChatGPT (zero-shot learning) for the selected languages in XL-Sum using English and language-specific prompts respectively. In the tables, we also include the performance of the mT5-XXL model that is trained over training data of specific languages in XL-Sum. mT5-XXL has achieved state-of-the-art performance for XL-Sum as reported in (Aharoni et al., 2022). It is obvious from the tables that ChatGPT’s performance is consistently inferior to mT5-XXL’s with large performance gaps in different languages. To better understand the poor performance of ChatGPT, Tables 10 and 11 also report the average lengths of the human-provided summaries and the summaries generated by ChatGPT (in terms of the numbers of characters). It is clear from the tables that ChatGPT tends to generate lengthy summaries, potentially leading to its poorer performance. In addition, the tables show the success rates of ChatGPT for each language, which is defined as the ratios of requests sent to the ChatGPT server and received non-empty responses/summaries. As can be seen, the success rates of ChatGPT for lower-resource languages are also lower that can further explain ChatGPT’s performance and reliability for such languages.

## 11 Discussion

The most important findings from our experiment results is that ChatGPT exhibits significantly worse performance than state-of-the-art supervised models for most of considered NLP tasks in different languages. Given the huge costs to train ChatGPT and similar LLMs as well as the necessity of paid APIs to run large amounts of requests with OpenAI, it seems more reasonable to build smaller task-specific models for NLP problems (or at least for the considered tasks) in different languages that can be hosted locally to serve at lower costs.

In addition, we notice an exception for the POS tagging task where ChatGPT can achieve competitive or even better performance than the supervised learning models (especially with English prompts) over different languages. For instance, ChatGPT has significantly better POS tagging accuracy for Thai, Vietnamese, Bulgarian, Hindi, and Urdu,

Language	Code	Cat.	Size	ChatGPT			Avg. Gold Length	Avg. Model Length	Success (%)	mT5-XXL L
				1	2	L				
English	en	H	11,535	19.71	5.52	13.38	125.84	612.38	99	32.51
Russian	ru	H	7,780	18.65	5.13	12.83	182.11	523.03	96	28.48
Chinese	zh	H	4,670	21.14	5.31	15.27	420.10	191.46	98	33.54
French	fr	H	1,086	20.76	7.09	14.12	147.38	601.17	99	34.12
Spanish	es	H	4,763	17.81	4.44	11.97	163.39	719.52	99	27.40
Turkish	tr	M	3,397	14.52	4.54	10.87	164.83	610.75	99	30.80
Arabic	ar	M	4,689	19.37	5.36	13.64	142.95	396.86	95	32.00
Thai	th	M	826	17.55	5.35	11.51	218.13	275.89	59	30.59
Hindi	hi	M	8,847	21.06	5.63	14.21	137.24	294.93	82	36.88
Bengali	bn	L	1,012	6.34	1.63	4.65	148.19	176.08	42	34.19
Burmese	my	L	570	14.49	6.32	8.85	201.99	118.78	43	41.40
Kyrgyz	ky	X	500	5.10	1.47	4.16	188.14	437.51	87	26.48

Table 10: Performance of ChatGPT (zero-shot learning) (ROUGE-1/2/L) and mT5-XXL (supervised learning) (ROUGE-L) for summarization over XL-Sum using English prompts.

Language	Code	Cat.	Size	ChatGPT			Avg. Gold Length	Avg. Model Length	Success (%)	mT5-XXL L
				1	2	L				
English	en	H	11,535	21.38	5.97	14.48	125.84	524.15	99	32.51
Russian	ru	H	7,780	15.60	4.17	10.83	182.11	483.45	96	28.48
Chinese	zh	H	4,670	11.65	2.61	8.96	55.31	420.10	98	33.54
French	fr	H	1,086	21.11	7.21	14.49	147.38	512.17	100	34.12
Spanish	es	H	4,763	19.73	4.85	13.15	163.39	601.05	99	27.40
Turkish	tr	M	3,397	15.58	4.91	11.79	164.83	468.64	99	30.80
Arabic	ar	M	4,689	16.95	4.74	12.04	142.95	383.71	94	32.00
Thai	th	M	826	14.39	4.11	9.71	218.13	257.40	58	30.59
Hindi	hi	M	8,847	4.28	1.13	2.94	137.24	423.58	82	36.88
Bengali	bn	L	1,012	1.88	0.43	1.39	148.19	198.60	40	34.19
Burmese	my	L	570	0.45	0.34	0.44	201.99	152.27	40	41.40
Kyrgyz	ky	X	500	8.40	2.23	6.42	188.14	458.71	86	26.48

Table 11: Performance of ChatGPT (zero-shot learning) (ROUGE-1/2/L) and mT5-XXL (supervised learning) (ROUGE-L) for summarization over XL-Sum using language-specific prompts.

which are medium- and low-resource languages. As such, in contrast to other considered tasks which require some level of semantic reasoning, POS tagging focuses on low-level syntactic analysis. We thus hypothesize that ChatGPT possesses high-level skills in grammar and low-level abilities of semantic reasoning to generate seemingly fluent texts for multiple languages. However, for more complicated semantic analysis, ChatGPT might find it more challenging to perform accurate predictions and generations.

Regarding the classification of high-, medium-, low-, and extremely low-resource languages, our work currently relies on data ratios for the languages in the CommonCrawl corpus. According to our experiments, it is interesting that the performance of ChatGPT for low- and extremely-low-resource languages in some tasks is better or comparable to

those for high- or medium-resource languages. For instance, for POS tagging in Table 2, ChatGPT’s performance for Urdu (a low-resource language) is better than the performance for Vietnamese and Thai (high- and medium-resource languages). In NER, ChatGPT achieves better performance for the low-resource language Bengali than for Chinese (using English prompts in Table 3). For the common sense reasoning task in Table 8, ChatGPT’s performance for the extremely-low-resource language Swahili is comparable to those for Polish (with English prompts). Similarly, for summarization in Table 11, ChatGPT has better ROUGE scores for the extremely low-resource language Kyrgyz than for Hindi with language-specific prompts. To this end, it seems evident that data size might not be the only factor that dictates the resource level and performance for a task of a language with ChatGPT and

LLMs. Among others, the overall picture might also need to consider the target task and the similarities/relations of a language with respect to the dominant languages in the training data for LLMs.

Compared to language-specific prompts, the superior performance of ChatGPT with English task descriptions over a majority of problems and languages suggests that ChatGPT might better understand/analyze the tasks with English prompts to lead to improved abilities to generate responses with accurate outputs. In addition, the inclusion of English task descriptions for non-English inputs can be seen as an approach to shift the representations of language-specific inputs toward the English space that can be better processed by ChatGPT due to the domination of English in its training data. Finally, the better performance with English prompts also raises an interesting question on whether English is the optimal language to prompt ChatGPT or it is better to employ other languages for this purpose for different target languages.

**Limitations:** As an ongoing work to evaluate ChatGPT and LLMs on multilingual learning tasks, our current work observes several limitations that can be addressed in future studies. First, although our experiments have covered 37 languages, including low- and extremely low-languages, there are still many other languages that are not explored in the current work. Some tasks/datasets in our work have not covered lower-resource languages. The future work can expand the language set with greater focuses on lower-resource languages to better understand LLMs’ performance in this important direction. Second, many other tasks, including those with available multilingual datasets, have not been considered in the current work. Examining more tasks and datasets will enable a more comprehensive understanding of ChatGPT and LLMs in multilingual settings. Third, our current work only evaluates ChatGPT in the zero-shot learning setting, thus unable to show comparisons with other recent multilingual LLMs, e.g., BLOOM (Scao et al., 2022), GPT-4, and BARD, in various learning scenarios. While these models are currently less accessible for large-scale evaluations, our plan is to further include more models and learning settings along the way to strengthen our evaluations and comparisons when possible. Finally, the current work only evaluates the models in terms of performance over NLP tasks. To better characterize ChatGPT and LLMs, other evaluation metrics should also be in-

vestigated to report more complete perspectives, including but not limited to adversarial robustness, biases, toxic/harmful content, accessibility, development costs, and interpretability.

## 12 Conclusion

Toward a more comprehensive understanding of ChatGPT and LLMs on their multilingual learning abilities for NLP, our current work conducts an evaluation for ChatGPT on 7 different tasks, i.e., Part-of-Speech Tagging, Named Entity Recognition, Relation Extraction, Natural Language Inference, Question Answering, Common Sense Reasoning, and Summarization. Using 37 diverse languages with high-, medium-, low-, and extremely low resources for the experiments, our results reveal the less optimal performance of ChatGPT in the zero-shot learning setting for NLP tasks in different languages, advocating for task-specific models to secure best performance. As an ongoing research, we plan to extend the experiments to include more languages, tasks, models, criteria, and settings in future work to obtain broader and deeper insights.

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## A Language-specific Prompts

This section provides language-specific prompts that have been used in our experiments. Note that these prompts are obtained by translating the original human-designed English versions into specific languages. Tables 12, 13, and 14 show language-specific prompts for the POS Tagging, Named Entity Recognition, and Relation Classification tasks. We use ChatGPT to translate English prompts to target language prompts with label-preservation constraints so that the output prompts can retain the original label notations from each dataset (all translated prompts are back-translated using Google Translate for validation).

Our language-specific prompts for other tasks, i.e., Natural Language Inference, Question Answering, Common Sense Reasoning, and Summarization, are directly translated from English versions using Google Translate, as demonstrated in Tables 15, 16, 17, 18, and 19.

Language	Task Description
English	Please provide the POS tags for each word in the input sentence. The input sentence will be a list of each word in the sentence. The output format should be a list of tuples, where each tuple consists of a word from the input text and its corresponding POS tag label from the tag label set: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
German	Bitte geben Sie die POS-Tags für jedes Wort im Eingabesatz an. Der Eingabesatz ist eine Liste aller Wörter eines Satzes. Das Ausgabeformat sollte eine Liste von Tupeln sein, wobei jedes Tupel aus einem Wort aus dem Eingabetext und seinem entsprechenden POS-Tag-Label aus dem Tag-Label-Set besteht: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Spanish	Proporcione las etiquetas POS para cada palabra en la oración de entrada. La oración de entrada será una lista de cada palabra en una oración. El formato de salida debe ser una lista de tuplas, donde cada tupla consta de una palabra del texto de entrada y su etiqueta de etiqueta POS correspondiente del conjunto de etiquetas de etiquetas: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PARTE', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Dutch	Geef de POS-tags op voor elk woord in de invoerzin. De invoerzin is een lijst van elk woord in een zin. Het uitvoerformaat moet een lijst met tupels zijn, waarbij elke tuple bestaat uit een woord uit de invoertekst en het bijbehorende POS-taglabel uit de taglabelset: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Bulgarian	Моля, предоставете POS етикети за всяка дума във въведеното изречение. Въведеното изречение ще бъде списък на всяка дума в изречение. Изходният формат трябва да бъде списък от кортежи, където всеки кортеж се състои от дума от входния текст и съответния етикет на POS етикет от набора етикети на етикети: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Greek	Καταχωρίστε τις ετικέτες POS για κάθε λέξη στην πρόταση εισαγωγής. Η πρόταση εισαγωγής θα είναι μια λίστα με κάθε λέξη σε μια πρόταση. Η μορφή εξόδου θα πρέπει να είναι μια λίστα πλειάδων, όπου κάθε πλειάδα αποτελείται από μια λέξη από το κείμενο εισόδου και την αντίστοιχη ετικέτα ετικετών POS από το σύνολο ετικετών: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'PHMA', 'X'].
French	Veillez fournir les balises POS pour chaque mot dans la phrase d'entrée. La phrase d'entrée sera une liste de chaque mot d'une phrase. Le format de sortie doit être une liste de tuples, où chaque tuple consiste en un mot du texte d'entrée et son étiquette de balise POS correspondante de l'ensemble d'étiquettes de balise : ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Polish	Podaj tagi POS dla każdego słowa we wprowadzonym zdaniu. Zdanie wejściowe będzie listą każdego słowa w zdaniu. Format wyjściowy powinien być listą krotek, gdzie każda krotka składa się ze słowa z tekstu wejściowego i odpowiadającej mu etykiety znacznika POS z zestawu etykiet znaczników: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'RZECZOW.', 'LICZBA', 'CZĘŚĆ', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'CZASOWNIK', 'X'].
Turkish	Lütfen giriş cümlesindeki her kelime için POS etiketlerini sağlayın. Giriş cümlesi, bir cümledeki her kelimenin bir listesi olacaktır. Çıktı formatı, her bir demetin giriş metnindeki bir kelimenin ve etiket etiket kümesinden karşılık gelen POS etiketinden oluştuğu bir demetler listesi olmalıdır: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'İSİM', 'NUM', 'BÖLÜM', 'ZAMİR', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Vietnamese	Vui lòng cung cấp các thẻ POS cho mỗi từ trong câu đầu vào. Câu đầu vào sẽ là một danh sách của mỗi từ trên một câu. Định dạng đầu ra phải là một danh sách các bộ, trong đó mỗi bộ bao gồm một từ trong văn bản đầu vào và nhãn thẻ POS tương ứng của nó từ bộ nhãn thẻ: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Chinese	请提供输入句子中每个单词的 POS 标签。输入句子将是句子中每个单词的列表。输出格式应该是一个元组列表，其中每个元组由输入文本中的一个单词及其标签集中相应的 POS 标签组成：['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Urdu	براہ کرم ان پٹ جملے میں ہر لفظ کے لیے POS ٹیگ فراہم کریں۔ ان پٹ جملہ ایک جملے کے ہر لفظ کی فہرست ہوگی۔ آؤٹ پٹ فارمیٹ ٹوپلز کی فہرست ہونی چاہیے، جہاں ہر ٹوپل ان پٹ ٹیکسٹ میں ہر لفظ کے لیے POS ٹیگ لیبیل پر مشتمل ہوگا: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X']۔ ایک سے زیادہ ان پٹ جملے ہو سکتے ہیں، آؤٹ پٹ اس کے مطابق ٹوپلز کی ایک سے زیادہ فہرست ہونے چاہئیں۔ آپ کے جواب ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X']۔ میں صرف ٹیپلز کی فہرست شامل ہونی چاہیے، اس ترتیب سے کہ الفاظ ان پٹ جملے میں ظاہر ہوں، ہر ٹوپل کے لیے متعلقہ POS ٹیگ لیبیل پر مشتمل ہو۔ وہ لفظ۔
Hindi	कृपया इनपुट वाक्य में प्रत्येक शब्द के लिए पीओएस टैग प्रदान करें। इनपुट वाक्य एक वाक्य पर प्रत्येक शब्द की एक सूची होगी। आउटपुट स्वरूप टुपल्स की एक सूची होगा चाहाएँ, जहाँ प्रत्येक टपल में इनपुट टैक्सट में एक शब्द और टैग लेबल सेट में संबंधित पीओएस टैग लेबल होता है: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'Noun', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X']।
Italian	ornisci i tag POS per ogni parola nella frase di input. La frase di input sarà un elenco di ogni parola su una frase. Il formato di output dovrebbe essere un elenco di tuple, in cui ogni tupla è composta da una parola del testo di input e dalla corrispondente etichetta del tag POS dal set di etichette del tag: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].
Arabic	يرجى تقديم علامات POS لكل كلمة في جملة الإدخال. ستكون جملة الإدخال قائمة بكل كلمة في الجملة. يجب أن يكون تنسيق الإخراج عبارة عن قائمة من المجموعات، حيث تتكون كل مجموعة من كلمة من نص الإدخال وتسمية علامة POS المقابلة لها من مجموعة تصنيف العلامات: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'] ربما توجد جمل إدخال متعددة، يجب أن تكون الفرجات قائمة متعددة من المجموعات وفقاً لذلك. يجب أن تتضمن إجابك قائمة المجموعات فقط، بالترتيب الذي تظهر به الكلمات في جملة الإدخال، مع احتواء كل مجموعة على تسمية علامة نقطة البيع المقابلة لتلك الكلمة.
Russian	Укажите POS-теги для каждого слова во входном предложении. Входное предложение будет списком всех слов в предложении. Выходной формат должен быть списком кортежей, где каждый кортеж состоит из слова из входного текста и соответствующей ему метки тега POS из набора меток тега: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'СУЩЕСТВИТЕЛЬНОЕ', 'ЧИСЛО', 'ЧАСТЬ', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'ГЛАГОЛ', 'X'].
Thai	โปรดระบุแท็ก POS สำหรับแต่ละคำในประโยคอินพุต ประโยคป้อนจะเป็นรายการของแต่ละคำในประโยค รูปแบบเอาต์พุตควรเป็นรายการของทิวเปิล โดยที่แต่ละทิวเปิลประกอบด้วยคำจากข้อความอินพุตและป้ายแท็ก POS ที่สอดคล้องกันจากชุดป้ายแท็ก: ['ADJ', 'ADP', 'ADV', 'AUX', 'CCONJ', 'DET', 'INTJ', 'NOUN', 'NUM', 'PART', 'PRON', 'PROPN', 'PUNCT', 'SCONJ', 'SYM', 'VERB', 'X'].

Table 12: Language-specific task descriptions for the XGLUE-POS dataset translated from the English version.

Language	Task Description
English	You are working as a named entity recognition expert and your task is to label a given text with named entity labels. Your task is to identify and label any named entities present in the text. The named entity labels that you will be using are PER (person), LOC (location), CORP (corporation), CW (creative work), GRP (group of people), and PROD (product). You may encounter multi-word entities, so make sure to label each word of the entity with the appropriate prefix ('B' for the first word of the entity, 'I' for any non-initial word of the entity). For words which are not part of any named entity, you should return 'O'. Your output format should be a list of tuples, where each tuple consists of a word from the input text and its corresponding named entity label.
Bengali	আপনি একজন নামযুক্ত এনটিটি সনাক্তকরণ বিশেষজ্ঞ হিসাবে কাজ করছেন এবং আপনার কাজ হল পূর্ণদ্রব্য একটি পাঠ্যকে নামযুক্তভাবে লেবেল দিয়ে ট্যাগ করা। আপনার কাজ হল টেক্সটে উপস্থিত যেকোনো নামযুক্ত সনাক্তকরণ লেবেল দেওয়া। আপনি ব্যবহার করবেন নামযুক্ত লেবেলগুলি PER (ব্যক্তি), LOC (অবস্থান), CORP (কর্পোরেশন), CW (সৃজনশীল কাজ), GRP (একদল মানুষ) এবং PROD (পণ্য)। আপনি একাধিক শব্দে এনটিটি সম্মিলিত হতে পারেন, তাই নিশ্চিত হওয়া উচিত যে পরভটি শব্দকে একটি পূর্ণ নামযুক্ত উপসর্গ ('B' এনটিটির অব্যবহৃতিকে নাও শব্দে জন্ম 'I') সহ লেবেল করা হবে। ক্র 'O' নামযুক্ত অংশ না হওয়া শব্দ পূর্ণভটি শব্দে জন্ম, সেই শব্দে সাথে সংযুক্ত নামযুক্ত লেবেল একটি ট্যাগের তালিকা তৈরি করে দিতে হবে, যেখানে পরভটি ট্যাগে পূর্ণভটি পাঠ্যের একটি শব্দ এবং তার সাথে সম্পর্কিত নামযুক্ত লেবেল থাকবে।
German	ie arbeiten als Experte für benannte Entitäten (Named Entity Recognition) und Ihre Aufgabe besteht darin, einen gegebenen Text mit benannten Entitäten zu kennzeichnen. Ihre Aufgabe ist es, alle benannten Entitäten im Text zu identifizieren und zu kennzeichnen. Die benannten Entitätslabels, die Sie verwenden werden, sind PER (Person), LOC (Ort), CORP (Unternehmen), CW (kreatives Werk), GRP (Gruppe von Personen) und PROD (Produkt). Es kann vorkommen, dass Sie mehrteilige Entitäten finden, daher stellen Sie bitte sicher, dass jedes Wort der Entität mit dem entsprechenden Präfix 'B' für das erste Wort der Entität, 'I' für jedes nicht initiale Wort der Entität gekennzeichnet wird. Für Wörter, die nicht Teil einer benannten Entität sind, sollten Sie 'O' zurückgeben. Das Ausgabeformat sollte eine Liste von Tupeln sein, wobei jedes Tupel aus einem Wort aus dem Eingabetext und dem entsprechenden benannten Entitätslabel besteht.
Spanish	Está trabajando como experto en reconocimiento de entidades con nombre y su tarea es etiquetar un texto determinado con etiquetas de entidades con nombre. Su tarea es identificar y etiquetar cualquier entidad nombrada presente en el texto. Las etiquetas de entidad con nombre que utilizará son PER (persona), LOC (ubicación), CORP (corporación), CW (trabajo creativo), GRP (grupo de personas) y PROD (producto). Es posible que encuentre entidades de varias palabras, así que asegúrese de etiquetar cada palabra de la entidad con el prefijo apropiado ('B' para la primera palabra de la entidad, 'I' para cualquier palabra no inicial de la entidad). Para las palabras que no forman parte de ninguna entidad nombrada, debe devolver 'O'. Su formato de salida debe ser una lista de tuplas, donde cada tupla consta de una palabra del texto de entrada y su correspondiente etiqueta de entidad con nombre.
Persian	و شما به عنوان متخصص در شناسایی و برچسب‌گذاری (NER) عمل می‌کنید و وظیفه شما این است که متن را برچسب‌گذاری کنید و برچسب‌های مناسب را به هر کلمه یا گروه کلماتی که یک نام‌دار است اختصاص دهید. برچسب‌هایی که باید از شما استفاده شود عبارتند از: PER (شخص)، LOC (مکان)، CORP (شرکت)، CW (سازمان)، GRP (گروه)، PROD (محصول). متن شما شامل کلمات و عبارات نام‌دار خواهد بود که باید با برچسب‌های مناسب برچسب‌گذاری شوند. برای کلماتی که نام‌دار نیستند، باید 'O' را برگردانید. فرمت خروجی شما باید یک لیست از تuples باشد که هر تuple شامل یک کلمه از متن ورودی و یک برچسب نام‌دار است. برای کلماتی که نام‌دار نیستند، باید 'O' را برگردانید. فرمت خروجی شما باید یک لیست از تuples باشد که هر تuple شامل یک کلمه از متن ورودی و یک برچسب نام‌دار است.
Hindi	आप नामांकन पहचान विशेषज्ञ के रूप में काम कर रहे हैं और आपका काम दिए गए पाठ को नामांकन लेबल के साथ लेबल करना है। आपका काम पाठ में मौजूद कोई भी नामी एंटीटी की पहचान और लेबल लगाना है। आप इस काम में प्रयोग करेंगे नामी एंटीटी लेबल PER (व्यक्ति), LOC (स्थान), CORP (निगम), CW (रचनात्मक कार्य), GRP (लोगों का समूह) और PROD (उत्पाद) का। आप एक से अधिक शब्दों से बनी एंटीटी से भी सामना कर सकते हैं, इसलिए सुनिश्चित करें कि एंटीटी के प्रत्येक शब्द को उचित प्रिफिक्स ('B' पहले शब्द के लिए, 'I' अन्य गैर-आदिम शब्दों के लिए) के साथ लेबल करें। नामी एंटीटी का हिस्सा नहीं होने वाले शब्दों के लिए, आपको 'O' लैबलना चाहिए। आपका आउटपुट फॉर्मेट एक टपल की सूची होना चाहिए, जहां प्रत्येक टपल में दिए गए इनपुट टैक्सट से एक शब्द और उसके संबंधित नामी एंटीटी लेबल होता है।
Korean	당신은 명명된 엔티티 인식 전문가로 일하고 있으며 당신의 임무는 명명된 엔티티 레이블로 주어진 텍스트에 레이블을 지정하는 것입니다. 귀하의 임무는 텍스트에 존재하는 명명된 엔티티를 식별하고 레이블을 지정하는 것입니다. 사용할 명명된 엔티티 레이블은 PER(사람), LOC(위치), CORP(기업), CW(창작물), GRP(그룹) 및 PROD(제품)입니다. 여러 단어로 된 엔티티가 있을 수 있으므로 엔티티의 각 단어에 적절한 접두사 (엔티티의 첫 번째 단어는 'B', 엔티티의 첫 번째 단어가 아닌 단어는 'I') 로 레이블을 지정해야 합니다. 명명된 엔티티의 일부가 아닌 단어의 경우 'O' 를 반환해야 합니다. 출력 형식은 튜플 목록이어야 하며 각 튜플은 입력 텍스트의 단어와 그에 해당하는 명명된 엔티티 레이블로 구성됩니다.
Dutch	U werkt als expert op het gebied van benoemde entiteitsherkenning en het is uw taak om een bepaalde tekst te labelen met benoemde entiteitslabels. Het is jouw taak om benoemde entiteiten in de tekst te identificeren en te labelen. De benoemde entiteitslabels die u gaat gebruiken zijn PER (persoon), LOC (locatie), CORP (bedrijf), CW (creatief werk), GRP (groep mensen) en PROD (product). U kunt entiteiten met meerdere woorden tegenkomen, dus zorg ervoor dat u elk woord van de entiteit labelt met het juiste voorvoegsel ('B' voor het eerste woord van de entiteit, 'I' voor elk niet-initieel woord van de entiteit). Voor woorden die geen deel uitmaken van een benoemde entiteit, moet u 'O' retourneren. Uw uitvoerformaat moet een lijst met tupels zijn, waarbij elke tupel bestaat uit een woord uit de invoertekst en het bijbehorende benoemde entiteitslabel.
Russian	Вы работаете экспертом по распознаванию именованных сущностей, и ваша задача состоит в том, чтобы пометить заданный текст метками именованных сущностей. Ваша задача состоит в том, чтобы возникновение и значение обозначить любые именованные объекты, присутствующие в тексте. Вы можете использовать метки именных объектов: PER (человек), LOC (местоположение), CORP (корпорация), CW (творческая работа), GRP (группа людей) и PROD (продукт). Вы можете столкнуться с объектом, состоящим из нескольких слов, поэтому не пренебрегайте целью пометить каждое слово объекта соответствующим префиксом («B» для первого слова объекта, «I» для любого неначального слова объекта). Для слов, которые не являются частью какого-либо именованного объекта, вы должны вернуть 'O'. Ваш выходной формат должен быть неожиданным для кортежей, где кортеж состоит из слов из входного текста и подозрения на метки именованного объекта.
Turkish	Adlandırılmış bir varlık tanıma uzmanı olarak çalışıyorsunuz ve göreviniz, belirli bir metni adlandırılmış varlık etiketleriyle etiketlemektir. Göreviniz, metinde bulunan herhangi bir adlandırılmış varlığı tanımlamak ve etiketlemektir. Kullanacağımız adlandırılmış varlık etiketleri şunlardır: PER (kişi), LOC (konum), CORP (şirket), CW (yaratıcı çalışma), GRP (insan grubu) ve PROD (ürün). Çok kelimeli varlıklarla karşılaşabilirsiniz, bu nedenle varlığın her bir kelimesini uygun önekle etiketlediğinizden emin olun (varlığın ilk kelimesi için 'B', varlığın ilk olmayan herhangi bir kelimesi için 'I'). Herhangi bir adlandırılmış varlığın parçası olmayan kelimeler için 'O' döndürmelisiniz. Çıktı biçiminiz, her bir demetin giriş metnindeki bir kelimedeki ve buna karşılık gelen adlandırılmış varlık etiketinden oluştuğu bir demetler listesi olmalıdır.
Chinese	你正在担任一个命名实体识别专家，你的任务是使用命名实体标签对给定的文本进行标注。你的任务是识别并标注文本中存在的任何命名实体。你将使用的命名实体标签是：PER (人物)、LOC (地点)、CORP (公司)、CW (创作作品)、GRP (人群) 和 PROD (产品)。你可能会遇到多个单词构成的实体，所以请确保使用适当的前缀 ('B' 表示实体的第一个单词, 'I' 表示实体的非首个单词) 标记实体的每个单词。对于不属于任何命名实体的单词，应该返回'O'。你的输出格式应该是一个元组列表，其中每个元组由输入文本中的一个单词和相应的命名实体标签组成。

Table 13: Language-specific task descriptions for the MultiCoNER dataset translated from the English version.

Language	Task Description
English	Given a short input text describing the relationship between two entities, extracts the relationship between them. The relation has to be of the type: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Your output must only be the relation of the 2 given entities and must follow the format: 'Relation: <One of the above listed relations>'.
Arabic	المطلوب استخراج العلاقة بين كائنين ما، وذلك بناءً على نص مدخل قصير يصف هذه العلاقة، على أن تكون العلاقة من نوع واحد من الأنواع التالية: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. 'Relation: <أحد العلاقات المذكورة أعلاه>'. يجب أن يكون مخرجك عبارة عن اسم العلاقة فقط، ويجب أن يتبع التنسيق التالي: 'Relation: <One of the above listed relations>'.
German	Die Aufgabe besteht darin, aus einem kurzen Eingabetext, der die Beziehung zwischen zwei Entitäten beschreibt, die Beziehung zwischen ihnen zu extrahieren. Die Beziehung muss vom Typ sein: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Die Ausgabe muss nur die Beziehung der beiden gegebenen Entitäten enthalten und dem Format folgen: 'Relation: <eine der oben aufgeführten Beziehungen>'.
Spanish	Dado un breve texto de entrada que describe la relación entre dos entidades, extrae la relación entre ellas. La relación debe ser del tipo: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Tu salida debe ser solamente la relación entre las dos entidades dadas y debe seguir el formato: 'Relation: <Una de las relaciones listadas anteriormente>'.
Persian	نوع از اباید رابطه آن.ه. بین رابطه استخراج می‌کنید متوجه می‌شود که کلمات ورودی متن یک در یافت 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award' باشد. ش.ده<'Relation: لیست فوق روابط از حی کی' فرمت به اباید و باشد شده داده موجود دو رابطه اباید فقط ش  خروجی باشد.
French	Veuillez fournir un court texte décrivant la relation entre deux entités et extraire la relation entre elles. La relation doit être de type : 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Votre sortie ne doit comporter que la relation entre les deux entités et doit suivre le format : 'Relation: <L'une des relations énumérées ci-dessus>'.
Italian	Date un breve testo di input che descriva la relazione tra due entità, estraete la relazione tra di esse. La relazione deve essere uno di questi tipi: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Il tuo output deve contenere soltanto la relazione tra le due entità e deve seguire il formato: 'Relation: <una delle relazioni elencate sopra>'.
Korean	두개체사이의관계를설명하는짧은입력텍스트가주어지면, 두개체간의관계를추출합니다. 관계는'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award' 중하나여야 합니다. 결과는두개체간의관계만을표시하며다음형식을따르도록합니다: 'Relation: <위에나열된관계중하나 >'.
Dutch	Gegeven een korte invoertekst die de relatie tussen twee entiteiten beschrijft, extraheert u de relatie tussen hen. De relatie moet van het type zijn: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Uw output moet alleen de relatie tussen de 2 gegeven entiteiten zijn en moet het formaat volgen: 'Relation: <Een van de bovengenoemde relaties>'.
Polish	Dla krótkiego tekstu opisującego związek między dwoma jednostkami wyodrębnij jednostki i związek między nimi. Relacja musi należeć do jednego z typów: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Twój wynik musi zawierać tylko jedną krótkę (entity_1, relation, entity_2) i musi spełniać FORMAT WYJŚCIA: 'Entity 1: <entity_1> Entity 2: <entity_2> Relation: Jeden z powyższych typów relacji'.
Russian	Дан короткий текст, описывающий отношение между двумя объектами. Извлеките из текста объекты и отношение между ними. Отношение должно быть одним из следующих типов: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Ваш результат должен содержать только один кортеж (entity_1, relation, entity_2) и должен соответствовать ФОРМАТУ ВЫВОДА: 'Entity 1: <entity_1> Entity 2: <entity_2> Relation: Один из вышеуказанных типов отношений'.
Swedish	Givet en kort inmatningstext som beskriver relationen mellan två enheter, extraherar du relationen mellan dem. Relationen måste vara av typen: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Ditt resultat måste bara vara relationen mellan de två angivna enheterna och måste följa formatet: 'Relation: <En av de ovan listade relationerna>'.
Ukrainian	Надано короткий вхідний текст, що описує відносини між двома сутностями. Витягніть відношення між ними. Відношення має бути такого типу: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Ваш результат має містити лише відношення між двома сутностями та повинен мати наступний формат: 'Relation: <Одне з вищезазначених відношень>'.
Portugese	Dado un texto de entrada curto que descreve a relação entre duas entidades, extraia a relação entre elas. A relação deve ser do tipo: 'birth-place', 'eats', 'event-year', 'first-product', 'from-country', 'has-author', 'has-child', 'has-edu', 'has-genre', 'has-height', 'has-highest-mountain', 'has-length', 'has-lifespan', 'has-nationality', 'has-occupation', 'has-parent', 'has-population', 'has-sibling', 'has-spouse', 'has-tourist-attraction', 'has-type', 'has-weight', 'headquarters', 'invented-by', 'invented-when', 'is-member-of', 'is-where', 'loc-leader', 'movie-has-director', 'no_relation', 'org-has-founder', 'org-has-member', 'org-leader', 'post-code', 'starring', 'won-award'. Sua saída deve conter somente a relação das 2 entidades dadas e deve seguir o formato: 'Relation: <Uma das relações listadas acima>'.

Table 14: Language-specific task descriptions for the SMiLER dataset translated from the English version.

Language	Task Description
English	Please identify whether the premise entails or contradicts the hypothesis in the following premise and hypothesis.
Arabic	يرجى تحديد ما إذا كان الافتراض يستلزم أو يتعارض مع الفرضية في الفرضية والفرضية التالية.
Bulgarian	Моля, посочете дали предпоставката включва или противоречи на хипотезата в следните предпоставка и хипотеза.
German	Bitte geben Sie an, ob die Prämisse die Hypothese in der folgenden Prämisse und Hypothese beinhaltet oder ihr widerspricht.
Greek	Προσδιορίστε εάν η υπόθεση συνεπάγεται ή έρχεται σε αντίθεση με την υπόθεση στην παρακάτω υπόθεση και υπόθεση.
Spanish	Por favor identifique si la premisa implica o contradice la hipótesis en la siguiente premisa e hipótesis.
French	Veillez indiquer si la prémisses implique ou contredit l'hypothèse dans la prémisses et l'hypothèse suivantes.
Hindi	कृपया पहचानें कि क्या आधारवाक्य नमिनलखिति आधारवाक्य और परकिल्पना में परकिल्पना पर जोर देता है या उसका खंडन करता है।
Russian	Пожалуйста, определите, влечет ли посылка за собой или противоречит гипотезе в следующих предпосылке и гипотезе.
Swahili	Tafadhali tambua kama msingi unajumuisha au unakinzana na dhana katika msingi na dhana ifuatayo.
Thai	โปรดระบุว่าสมมติฐานนั้นเกี่ยวข้องกับหรือขัดแย้งกับสมมติฐานหรือไม่ในสมมติฐานและสมมติฐานต่อไปนี้
Turkish	Lütfen önermenin aşağıdaki önerme ve hipotezdeki hipotezi içerip içermediğini veya bunlarla çelişip çelişmediğini belirleyin.
Urdu	براہ کرم اس بات کی نشاندہی کریں کہ آیا بنیاد درج ذیل بنیاد اور مفروضے میں مفروضے کو شامل کرتی ہے یا اس سے متصادم ہے۔
Vietnamese	Hãy xác định tiền đề kéo theo hay mâu thuẫn với giả thuyết trong các tiền đề và giả thuyết sau.
Chinese	请确定前提是否包含或矛盾以下前提和假设中的假设。

Table 15: Language-specific descriptions for the XNLI dataset translated from the English version by Google Translate.

Language	Task Description
English	Answer the question from the given passage. Your answer should be directly extracted from the passage, and it should be a single entity, name, or number, not a sentence.
Arabic	أجب عن السؤال الوارد في المقطع المحدد. يجب أن يتم استخلاص إجابتك مباشرة من المقطع ، ويجب أن تكون كياناً واحداً أو اسماً أو رقماً وليس جملة.
German	Beantworten Sie die Frage aus der angegebenen Passage. Ihre Antwort sollte direkt aus der Passage extrahiert werden und es sollte sich um eine einzelne Entität, einen Namen oder eine Nummer handeln, nicht um einen Satz.
Greek	Απαντήστε στην ερώτηση από το συγκεκριμένο απόσπασμα. Η απάντησή σας θα πρέπει να εξαχθεί απευθείας από το απόσπασμα και θα πρέπει να είναι μια ενιαία οντότητα, όνομα ή αριθμός, όχι μια πρόταση.
Spanish	Responda la pregunta del pasaje dado. Su respuesta debe extraerse directamente del pasaje y debe ser una sola entidad, nombre o número, no una oración.
Hindi	दिए गए गद्यांश से प्रश्न का उत्तर दें। आपका उत्तर सीधे गद्यांश से निकाला जाना चाहिए, और यह एक इकाई, नाम या संख्या होना चाहिए, न कि एक वाक्य।
Romanian	Răspunde la întrebarea din pasajul dat. Răspunsul tău ar trebui extras direct din pasaj și ar trebui să fie o singură entitate, nume sau număr, nu o propoziție.
Russian	Ответьте на вопрос из данного отрывка. Ваш ответ должен быть извлечен непосредственно из отрывка, и это должна быть отдельная сущность, имя или число, а не предложение.
Thai	ตอบคำถามจากข้อที่กำหนดให้ คำตอบของคุณควรดึงมาจากเนื้อเรื่องโดยตรง และควรเป็นเอนทิตี ชื่อ หรือตัวเลขเดี่ยวๆ ไม่ใช่ประโยค
Turkish	Verilen parçadan soruyu cevaplayınız. Cevabınız doğrudan pasajdan alınmalı ve bir cümle değil, tek bir varlık, isim veya numara olmalıdır.
Vietnamese	Trả lời câu hỏi từ đoạn văn đã cho. Câu trả lời của bạn phải được trích xuất trực tiếp từ đoạn văn và nó phải là một thực thể, tên hoặc số duy nhất, không phải là một câu.
Chinese	根据给定的段落回答问题。你的答案应该直接从文章中摘录，并且应该是单个实体、名称或数字，而不是句子。

Table 16: Language-specific descriptions for the XQuAD dataset translated from the English version by Google Translate.

Language	Task Description
English	In this task, you will be presented with a question that has multiple possible answers in English. You should choose the most suitable option out of "A", "B", "C", "D", and "E", based on your commonsense knowledge.
German	Bei dieser Aufgabe wird Ihnen eine Frage mit mehreren Antwortmöglichkeiten in deutscher Sprache vorgelegt. Und Sie sollten basierend auf Ihrem gesunden Menschenverstand die am besten geeignete Option aus A; B; C; D und E auswählen.
Italian	In questo compito, ti verrà presentata una domanda con più possibili risposte in lingua italiana. E dovresti scegliere l'opzione più adatta tra "A", "B", "C", "D" ed "E" in base alle tue conoscenze di buon senso.
Spanish	En esta tarea, se le presentará una pregunta con múltiples respuestas posibles en idioma español. Y debe elegir la opción más adecuada de "A", "B", "C", "D" y "E" según su conocimiento de sentido común.
French	Dans cette tâche, il vous sera présenté une question ayant plusieurs réponses possibles en langue française. Et vous devez choisir l'option la plus appropriée parmi "A", "B", "C", "D" et "E" en fonction de vos connaissances de bon sens.
Dutch	In deze taak krijgt u een vraag voorgelegd met meerdere mogelijke antwoorden in de Nederlandse taal. En u moet een meest geschikte optie kiezen uit "A", "B", "C", "D" en "E" op basis van uw gezond verstand.
Russian	В этом задании вам будет представлен вопрос с несколькими вариантами ответов на русском языке. И вы должны выбрать наиболее подходящий вариант из «A», «B», «C», «D» и «E», исходя из ваших знаний здравого смысла.
Vietnamese	Trong nhiệm vụ này, bạn sẽ được cung cấp một câu hỏi có thể có nhiều câu trả lời bằng tiếng Việt. Và bạn nên chọn một tùy chọn phù hợp nhất trong số "A", "B", "C", "D" và "E" dựa trên kiến thức thông thường của bạn.
Chinese	在这个任务中，你将看到一个有多种可能答案的中文问题。你应该根据你的常识从"A"、"B"、"C"、"D"和"E"中选择一个最合适的选项。
Hindi	इस कार्य में, आपको हिंदी भाषा में कई संभावित उत्तरों वाले एक प्रश्न के साथ प्रस्तुत किया जाएगा। और आपको अपने सामान्य ज्ञान के आधार पर "A", "B", "C", "D", और "E" में से सबसे उपयुक्त विकल्प चुनना चाहिए।
Polish	W tym zadaniu otrzymasz pytanie z wieloma możliwymi odpowiedziami w języku polskim. I powinieneś wybrać najbardziej odpowiednią opcję spośród „A”, „B”, „C”, „D” i „E” w oparciu o swoją zdroworozsądkową wiedzę.
Arabic	في هذه المهمة، سيُعرض عليك سؤال له إجابات متعددة محتملة باللغة العربية. ويجب عليك اختيار الخيار الأنسب من "A" و "B" و "C" و "D" و "E" بناءً على معرفتك المنطقية.
Japanese	このタスクでは、日本語で複数の回答が可能な質問が表示されます。そして、「A」「B」「C」「D」「E」の中から、あなたの常識に基づいて最適な選択肢を選んでください。
Portuguese	Nesta tarefa, você será apresentado a uma pergunta com várias respostas possíveis na língua portuguesa. E você deve escolher a opção mais adequada entre "A", "B", "C", "D" e "E" com base em seu conhecimento de senso comum.
Swahili	Katika kazi hii, utawasilishwa na swali lenye majibu mengi yanayowezezana katika lugha ya Kiswahili. Na unapaswa kuchagua chaguo linalofaa zaidi kati ya "A", "B", "C", "D", na "E" kulingana na ujuzi wako wa kawaida.
Urdu	اس کام میں، آپ کو ایک سوال پیش کیا جائے گا جس کے متعدد ممکنہ جوابات اردو زبان میں ہوں گے۔ اور آپ کو اپنے کامن سینس کے علم کی بنیاد پر، "A"، "B"، "C"، "D" اور "E" میں سے موزوں ترین آپشن کا انتخاب کرنا چاہیے۔

Table 17: Language-specific descriptions for the X-CSQA dataset translated from the English version by Google Translate.

Language	Task Description
English	You are given a statement written in Hindi. Choose the most logical word from the 4 given options which can be used to replace the <MASK> token in the statement. Output the word from the correct option.
Punjabi	ਤੁਹਾਨੂੰ ਖੰਜਾਰੀਵਾਰੀ ਲਿਖਿਆ ਬਿਆਨ ਦਿੱਤਾ ਜਾਂਦਾ ਹੈ। ਦਿੱਤੇ ਗਏ 4 ਵਕਲਿਆਂ ਵਿੱਚੋਂ ਸਭ ਤੋਂ ਲਾਜ਼ਮੀ ਸ਼ਬਦ ਚੁਣੋ ਜੋ ਸਟੇਟਮੈਂਟ ਵਿੱਚ <MASK> ਟੋਕਨ ਨੂੰ ਬਦਲਣ ਲਈ ਵਰਤਿਆ ਜਾ ਸਕਦਾ ਹੈ। ਸਹੀ ਵਕਲਿਆਂ ਵਿੱਚੋਂ ਸਭ ਤੋਂ ਲਾਜ਼ਮੀ ਸ਼ਬਦ ਚੁਣੋ।
Hindi	आपको हिंदी में लिखा हुआ एक स्टेटमेंट दिया जाता है। दिए गए 4 विकल्पों में से सबसे तार्किक शब्द का चयन करें जिसका उपयोग कथन में <MASK> टोकन को बदलने के लिए किया जा सकता है। सही विकल्प में से शब्द का निर्गम कीजिये।
Bengali	আপনাকে বাংলায় লিখা একটি বর্ণিত দেওয়া হয়েছে। প্রদত্ত 4টি বিকল্প থেকে সবচেয়ে যৌক্তিক শব্দ চয়ন করুন যা বর্ণিত <MASK> টোকেনে প্রতিনিধিত্ব করতে ব্যবহার করা যতে পারে। সঠিক অপশন থেকে শব্দটি আউটপুট করুন।
Odia	ଆପଣଙ୍କୁ ଓଡ଼ିଆରେ ଲିଖିତ ଏକ ବିବୃତ୍ତି ଦିଆଯାଇଛି। ପ୍ରଦତ୍ତ options ଠିକ୍ ବିକଳ୍ପଗୁଡ଼ିକ ମଧ୍ୟରୁ ସବୁଠାରୁ ଲଜିକାଲ୍ ଶବ୍ଦ ବାଛିବାରୁ ଯାହା ଉପଯୁକ୍ତ <MASK> ଟୋକନକୁ ବଦଳାଇବା ପାଇଁ ବ୍ୟବହୃତ ହେବ। ଠିକ୍ ବିକଳ୍ପ ଶବ୍ଦକୁ ଆଉଟପୁଟ୍ କରନ୍ତୁ।
Assamese	আপোনাক অসমীয়াত লিখা এটা বৰ্ণিত দিয়া হয়। প্ৰদত্ত ৪টা বিকল্পৰ পৰা আটাইতকৈ যুক্তিসংগত শব্দ নিৰ্বাচন কৰক যা বৰ্ণিত <MASK> টোকেনে সলনি কৰিবলৈ ব্যৱহাৰ কৰিব পাৰি। শুদ্ধ বিকল্পৰ পৰা শব্দটো আউটপুট কৰক।
Gujarati	તમને ગુજરાતીમાં લખેલું નિવેદન આપવામાં આવે છે. આપેલ 4 વિકલ્પોમાંથી સૌથી તાર્કિક શબ્દ પસંદ કરો જેનો ઉપયોગ સ્ટેટમેન્ટમાં <MASK> ટોકન બદલવા માટે થઈ શકે છે. સાચા વિકલ્પમાંથી શબ્દ આઉટપુટ કરો
Marathi	तुम्हाला मराठीत लिहिलेले नविदन दिले आहे. दिलेल्या 4 पर्यायांमधून सर्वात तार्किक शब्द निवडा जो स्टेटमेंटमधील <MASK> टोकन बदलण्यासाठी वापरला जाऊ शकतो. योग्य पर्यायातून शब्द आउटपुट करा.
Kannada	ನಿಮಗೆ ಕನ್ನಡದಲ್ಲಿ ಬರೆದ ಹೇಳಿಕೆ ನೀಡಲಾಗಿದೆ. ಹೇಳಿಕೆಯಲ್ಲಿ <MASK> ಟೋಕನ್ ಅನ್ನು ಬದಲಿಸಲು ಬಳಸಬಹುದಾದ 4 ಆಯ್ಕೆಗಳಿಂದ ಹೆಚ್ಚು ತಾರ್ಕಿಕ ಪದವನ್ನು ಆರಿಸಿ. ಸರಿಯಾದ ಆಯ್ಕೆಯಿಂದ ಪದವನ್ನು ಔಟ್ಪುಟ್ ಮಾಡಿ.
Telugu	మీకు తెలుగులో వ్రాసిన స్టేట్‌మెంట్ ఇచ్చారు. స్టేట్‌మెంట్‌లోని <MASK> టోకెన్‌ను భర్తీ చేయడానికి ఉపయోగించబడే 4 ఎంపికల నుండి అత్యంత లాజికల్ పదాన్ని ఎంచుకోండి. సరైన ఎంపిక నుండి పదాన్ని అవుట్‌పుట్ చేయండి.
Malayalam	തങ്ങൾക്ക് മലയാളത്തിൽ എഴുതിയ ഒരു പരസ്യനയം നൽകിയിരിക്കുന്നത്. പരസ്യനയത്തിൽ <MASK> കേൾക്കൂ മരണസംഭവങ്ങൾ ഉപയോഗിക്കുന്നത്, നൽകിയിരിക്കുന്നത് 4 ഓപ്ഷനുകളിൽ നിന്ന് ഏറ്റവും അനുയോജ്യമായ വാക്ക് തിരഞ്ഞെടുക്കുക. ശരിയായ ഓപ്ഷനിൽ നിന്ന് വാക്ക് ഔട്ട്പുട്ട് ചെയ്യുക.
Tamil	உங்களாக்கூ தமிழில் எழுதப்பட்ட அறிக்கை க்கு <MASK> டோகன் மாற்றுவதற்குப் பயன்படுத்தப்படும் க்கு <MASK> 4 விருப்பங்களிலிருந்து மிகவும் தர்க்கரீதியான வார்த்தையைத் தேர்ந்தெடுக்கவும். சரியான விருப்பத்திலிருந்து வார்த்தையை வெளியிடவும்.

Table 18: Language-specific descriptions for the Wiki Cloze QA dataset (IndictNLP Suite) translated from the English version by Google Translate.

Language	Task Description
English	Summarize this English text. The output should be in English:
French	Résumez ce texte français. La sortie doit être en français:
Spanish	Resume este texto en español. La salida debe estar en español:
Chinese	总结这篇中文课文。输出应该是中文的：
Arabic	لخص هذا النص العربي. يجب أن يكون الإخراج باللغة العربية:
Turkish	Bu Türkçe metni özetleyin. Çıktı Türkçe olmalıdır:
Russian	Перескажите этот русский текст. Вывод должен быть на русском языке:
Hindi	इस हृदुी पठ कु सलरंशतु करु। आउटपुट हृदुी डु हुनुनल कलहणुः
Thai	สรุปข้อความภาษาไทยนี้ ผลลัพธ์ควรเป็นภาษาไทย:
Bengali	এই বাংলা টেক্সট সারসংক্ষেপে. আউটপুট বাংলায় হওয়া উচিত:
Kyrgyz	Ушул кыргызча текстти кыскача айтып бериңиз. Чыгарма кыргыз тилинде болушу керек:

Table 19: Language-specific descriptions for the XL-Sum dataset translated from the English version by Google Translate.