

Leveraging Knowledge in Multilingual Commonsense Reasoning

Yuwei Fang, Shuohang Wang, Yichong Xu,
Ruo Chen Xu, Siqi Sun, Chenguang Zhu, Michael Zeng
Microsoft Cognitive Services Research Group

{yuwfan, shuowa, yicxu, ruox, siqi.sun, chezhu, nzens}@microsoft.com

Abstract

Commonsense reasoning (CSR) requires the model to be equipped with general world knowledge. While CSR is a language-agnostic process, most comprehensive knowledge sources are in few popular languages, especially English. Thus, it remains unclear how to effectively conduct multilingual commonsense reasoning (XCSR) for various languages. In this work, we propose to utilize English knowledge sources via a translate-retrieve-translate (TRT) strategy. For multilingual commonsense questions and choices, we collect related knowledge via translation and retrieval from the knowledge sources. The retrieved knowledge is then translated into the target language and integrated into a pre-trained multilingual language model via visible knowledge attention. Then we utilize a diverse of 4 English knowledge sources to provide more comprehensive coverage of knowledge in different formats. Extensive results on the XCSR benchmark demonstrate that TRT with external knowledge can significantly improve multilingual commonsense reasoning in both zero-shot and translate-train settings, outperforming 3.3 and 3.6 points over the previous state-of-the-art on XCSR benchmark datasets (X-CSQA and X-CODAH).

1 Introduction

Commonsense reasoning (CSR) is one of the key challenges in natural language understanding. It requires a model to integrate world knowledge into language modeling to produce answers. A large number of tasks have been proposed to evaluate commonsense reasoning in English, such as COPA (Roemmele et al., 2011a) and CSQA (Talmor et al., 2019).

Most recently, multilingual commonsense reasoning (XCSR) begins to draw attention from the community and a number of datasets emerged, e.g., X-CSQA (Lin et al., 2021), X-CODAH (Lin et al., 2021), XCOPA (Edoardo M. Ponti and Korhonen,

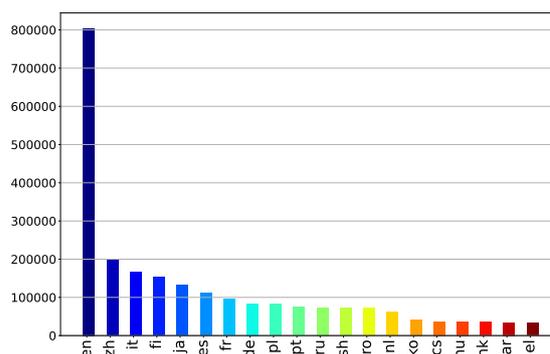


Figure 1: Number of total definitions per language. The statistics are generated from Wiktionary 2021-10-01 dump. There are 55 languages with 10,000 or more definitions and we list top 20 languages by the definitions count here.

2020). The goal of XCSR is to extend a model’s commonsense capability beyond language barriers.

To solve commonsense reasoning tasks, it is essential to fuse human created knowledge into pre-trained language model (PLM) (Lin et al., 2019; Feng et al., 2020; Yu et al., 2020; Xu et al., 2021b). For example, DEKCOR (Xu et al., 2021b) integrates knowledge from ConceptNet (Speer et al., 2017) and Wiktionary¹ into the ALBERT model (Lan et al., 2020) for commonsense question answering. However, most existing knowledge sources are crafted in a few popular languages, especially English. For example, Figure 1 shows the number of total definitions in English is much more than any other languages based on the statistics from Wiktionary 2021-10-01 dump. Thus, it remains an open question how to tackle XCSR with a lack of curated knowledge in the target language.

In this paper, we propose a translate-retrieve-translate (TRT) solution to utilize English knowledge sources for XCSR. Specifically, given a commonsense reasoning question (possibly concate-

¹<https://www.wiktionary.org/>

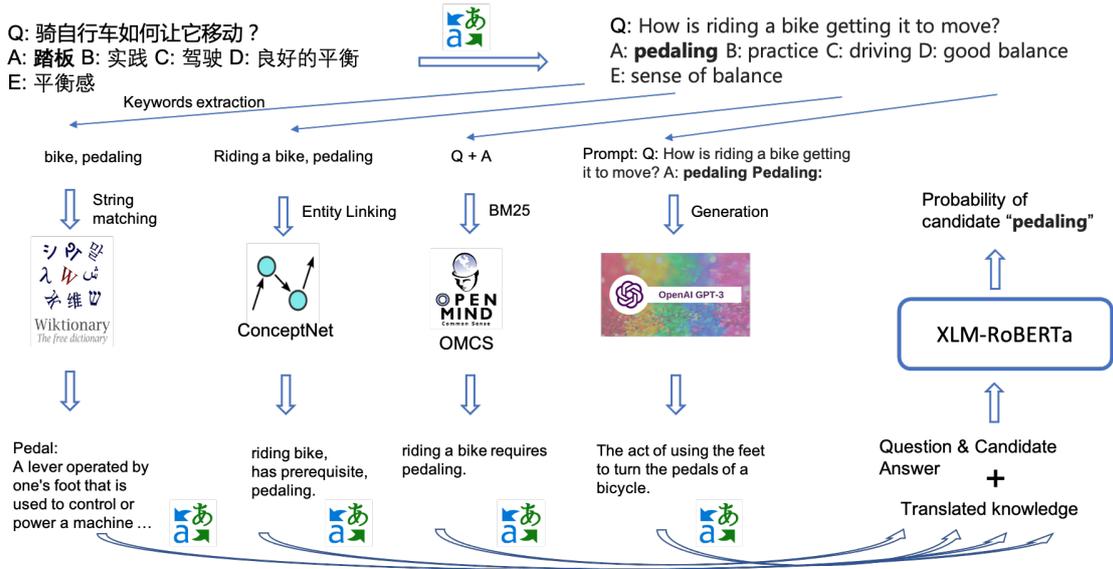


Figure 2: An overview of our framework for multilingual commonsense reasoning. Given the question and candidate answers in the target language (Chinese), we first translate it into English, then retrieve related knowledge from four English knowledge sources and translate the retrieved knowledge back into the target language. The retrieved knowledge, along with question and candidate answer, are fed into the multilingual pretrained language model for answer prediction.

nated with a candidate answer) in the target language, we first translate it into English. Next, we retrieve related knowledge from English knowledge sources. The retrieved knowledge is then translated back into the target language. Finally, the knowledge is integrated into a multilingual language model via visible knowledge attention mechanism to answer the question.

Another contribution of our work is that we utilize a diverse set of 4 English knowledge sources to provide a more comprehensive coverage of knowledge in different formats. Specifically, we utilize unstructured text corpus (Open Mind Common Sense (Singh, 2002)), structural knowledge graph (ConceptNet (Speer et al., 2017)), dictionary (Wiktionary) and large-scale language model (GPT-3 (Brown et al., 2020)). Given an input query, we utilize information retrieval, entity linking, and model inference to obtain knowledge from corresponding sources.

We conduct extensive evaluation of our model on the multilingual commonsense reasoning benchmark X-CSQA and X-CODAH (Lin et al., 2021). The results demonstrate the effectiveness of our proposed translate-retrieve-translate solution with multiple knowledge sources. For example, in the zero-shot transfer setting, TRT with Wiktionary can improve 1.9 and 2.7 points over the baselines. For translate-train setting, TRT with Wiktionary and

OMCS outperform 1.6 and 1.0 over the baselines.

We summarize the main contributions of this work as follows. (i) We propose a translate-retrieve-translate (TRT) solution to utilize English knowledge sources for multilingual commonsense reasoning. (ii) We comprehensively explore four knowledge sources in different formats and prove their helpfulness for both X-CSQA and X-CODAH. (iii) We achieve the first place on XCSR leaderboard, outperforming 3.3 and 3.6 points over the previous state-of-the-art works.

2 Related Work

Multilingual Commonsense Reasoning Model ability of commonsense reasoning has been widely explored by multiple downstream tasks. In early works, Winograd schema challenge (Levesque et al., 2012) is to disambiguate the reference of a pronoun (Levesque et al., 2012) and Choice of Plausible Alternatives (COPA) (Roemmele et al., 2011b) is to select cause or result for a premise. Later on, larger scale datasets, such as SWAG (Zellers et al., 2018), CODAH (Chen et al., 2019), and CommonsenseQA (Talmor et al., 2019), have been constructed for commonsense knowledge learning. Recently, commonsense reasoning tasks have been extended to multilingual setting, such as X-CSQA (Lin et al., 2021), X-CODAH (Lin et al., 2021), XCOPA (Edoardo

Knowledge Source	Knowledge Format	Query Format	Retrieved Knowledge	Retrieval Method
Wiktionary	Dictionary	Content Word	Definition	String Matching
ConceptNet	Entity-Relation Triplets	Entity Pair	Entity-Relation Triplet	Entity linking
OMCS	Text in Sentences	Sentences	Sentences	BM25
GPT-3	Parameters	Unstructured Text	Unstructured Text	Conditional Generation

Table 1: Different knowledge resources for retrieval.

M. Ponti and Korhonen, 2020). In paper, we focus on training model to learn commonsense knowledge in multiple languages.

External Knowledge Fusion Knowledge bases are the most important external sources to help models learn the ability of commonsense reasoning. A wide range of knowledge resources, such as ConceptNet (Speer et al., 2017), Wikipedia, Freebase (Pellissier Tanon et al., 2016), and some KBs in domain (Fader et al., 2011), can be fused into the model. LoBue and Yates (2011) explored how commonsense knowledge involved in recognizing textual entailments. Guan et al. (2020) utilize commonsense knowledge to generate reasonable stories. Bi et al. (2019) incorporate external Knowledge into question answering. Xu et al. (2021b) fuse the ConceptNet (Speer et al., 2017) and Wiktionary into the model for solving CommonsenseQA. In this paper, we will follow this direction and have a wider exploration of leveraging different sources for multilingual commonsense reasoning.

3 Approach

In this section, we first formalize the multilingual commonsense reasoning (XCSR) task (Section 3.1). Then we describe more details about our commonsense knowledge resources (Section 3.2). Next, we introduce our proposed translate-retrieve-translate (TRT) solution to obtain the multilingual knowledge (Section 3.3). Finally, we introduce how to fuse the obtained knowledge into multilingual pre-trained language models by employing the visible attention mechanism (Section 3.4). The overview of the framework is illustrated in Figure 2.

3.1 Problem Formulation

We denote a language by $l \in L$, where $L = \{en, fr, de, zh, \dots\}$. Given a commonsense question q^l in the target language l , the goal is to choose the correct answer from N candidates $\{c_1^l, c_2^l, \dots, c_N^l\}$. We assume there are one or more external knowledge sources to provide world knowledge in various formats for commonsense

reasoning. Each time the model retrieves knowledge using the question-candidate pair as query, i.e., $p^l = [q^l, c_i^l]$.

3.2 Commonsense Knowledge

Commonsense knowledge are critical to the performance of a commonsense reasoning (CSR) model. Previous methods for CSR primarily integrate knowledge from one or two sources (Xu et al., 2021b). In this work, we conduct comprehensive experiments by leveraging commonsense knowledge from 4 different resources: unstructured text corpus (Open Mind Common Sense), knowledge graph (KG) (ConceptNet), dictionary (Wiktionary), and pre-trained language model (PLM) (GPT-3). Open Mind Common Sense (OMCS) (Singh, 2002) is a large commonsense knowledge base which has accumulated millions of facts. ConceptNet (Speer et al., 2017) is a semantic network built on top of MOCS. Wiktionary provides the definitions for all the words. GPT-3 (Brown et al., 2020) is a large-scale pre-trained language model to generate knowledge by feeding a query. These knowledge resources are saved in quite diverse formats as the analysis shown in Table 1. To retrieve the knowledge, we will consider different query formats and retrieval methods in the next section.

3.3 Knowledge Retrieval

Most large-scale knowledge sources in either academia or industry are crafted in a few popular languages, especially in English (see Figure 1 as an example). To obtain knowledge for low-resource languages, we propose a translate-retrieve-translate (TRT) solution. In detail, we first use a machine translation tool to translate the query in all languages into English. Then, we can retrieve knowledge from English knowledge sources using the translated query. The retrieved knowledge can be then translated back into original languages for model training.

As a knowledge source usually contains vast amount of information, we need to retrieve and leverage only the related knowledge for a given

query p^l . Next we introduce the details of knowledge retrieval for 4 knowledge sources.

Word definition retrieval from Wiktionary

Every word has its own definition but not all of them are delivering knowledge for commonsense reasoning. In this work, we mainly focus on retrieving the content words, such as nouns, verbs, and adjectives, and the words harder to understand by multilingual language models. In detail, after part-of-speech tagging of the sequence, we select the nouns, verbs and adjectives as the candidate words. Then, we mask one word at a time and compute its masked language model (MLM) probability by pre-trained multilingual language model, XLM-RoBERTa (Conneau et al., 2019). We select top-N words with lowest MLM probability for dictionary retrieval. If the original word is not in Wiktionary, we try to find its lemmatized form. The first definition entry in Wiktionary is the retrieved knowledge.

Structured knowledge retrieval from ConceptNet

A knowledge graph can provide relation information between entities. We enumerate pairs of candidate words from the input sequence and check whether there exists a relation between them in the knowledge graph ConceptNet. If so, we retrieve the corresponding triplet as the external knowledge.

Unstructured text retrieval from OMCS Open Mind Common Sense (OMCS) consists of knowledge in natural language description. We first build a search index² for all the sentences in OMCS. Then, whenever a new query comes, we retrieve the highest ranked sentence based on BM25 as the external knowledge text.

Knowledge Generation with GPT-3 Previous research shows that large-scale PLM contains rich knowledge implicitly (Roberts et al., 2020; Kassner et al., 2021). Thus, we use one of the largest PLM, GPT-3 (Brown et al., 2020), to generate related knowledge given the query. As GPT-3 requires a prompt with input and output examples, we feed it with a few examples with a query and the knowledge in designated format. For example, given the word and its definition along with the query, GPT-3 will generate its version of definition of a word it thinks important in the input query. For the prompt that is not in English, we translate the English prompt into the target language.

²<https://lucene.apache.org/pylucene/>

3.4 Fusing Knowledge into Multilingual Language Model

Given the question answer pair $p^l = [q^l, c_i^l]$, we use the retrieval techniques to collect K pieces of retrieved knowledge text: $S = [s_1, \dots, s_K]$.

The most intuitive way is to concatenate them with p^l as input to the multilingual pre-trained language model (XPLM) for answer generation, i.e., the input would be $I = [\text{CLS}] q^l c_i^l [\text{SEP}] s_1 [\text{SEP}] \dots s_K [\text{SEP}]$.

However, this simple way may divert the original meaning of p^l because of the introduced noise by appending S , as pointed out by Liu et al. (2020); Xu et al. (2021a). To remedy this issue, we adopt the visibility matrix (Liu et al., 2020; Xu et al., 2021a) to limit the impact of knowledge set S on the original question-candidate pair p_l . Specifically, in each transformer layer of XPLM, an attention mask matrix M is added to the self-attention weights before softmax.

Suppose t_j and t_k are the j -th and k -th tokens from the input I . We set M_{jk} to zero to allow attention from t_j to t_k , and set M_{jk} to $-\infty$ to forbid attention. M_{jk} is set to zero if: i) both tokens belong to the input p_l , or ii) both tokens belong to the same knowledge s_i , or iii) t_j is the token at the start position of linked word in p_l and t_k is from its correspond knowledge text. More formally, the mask matrix M is

$$M_{jk} = \begin{cases} 0 & t_j, t_k \in p^l \\ 0 & t_j, t_k \in s_i \\ 0 & t_j \in p^l, t_k \in s_i \\ -\infty & \text{otherwise} \end{cases} \quad (1)$$

For model training, let $z_0 \in R^d$, the [CLS] hidden state from the last layer, denotes the representation of encoding the question, candidate, and the corresponding retrieved knowledge. d is the dimension of the output vector of the encoder. Then we calculate the prediction score \hat{y}_i for each candidate c_i^l with one linear layer, $\hat{y}_i = W_o z_0$, where $W_o \in R^{1*d}$, followed by a softmax normalization upon all candidates, $\hat{y} = \text{softmax}([\hat{y}_1, \dots, \hat{y}_N])$, where N is the number of candidate for each question. The final loss function is the standard cross-entropy loss.

4 Experiments

In this section, we perform extensive experiments to explore the aforementioned TRT solution with

Dataset	Model	en	de	it	es	fr	nl	ru	vi	zh	hi	pl	ar	ja	pt	sw	ur	avg
X-CSQA	mBERT	38.8	29.6	36.4	35.3	33.8	32.6	32.7	22.2	37.8	21.1	27.2	27.7	31.4	34.1	21.8	23.7	30.4
	XLMR-B	51.5	44.1	42.1	44.8	44.0	43.3	39.5	42.6	40.6	34.6	40.2	38.4	37.5	43.4	29.6	33.0	40.6
	XLMR-L	66.7	56.1	58.2	59.5	60.3	56.8	52.1	51.4	52.7	48.7	53.9	48.4	50.0	59.9	41.6	45.2	53.8
	MCP (RL)	69.5	59.3	60.3	61.4	60.0	61.1	57.5	55.7	56.7	51.3	56.1	52.3	50.2	60.7	43.3	48.8	56.5
	TRT	71.0	61.2	63.0	65.1	65.1	62.8	57.8	58.9	56.3	56.1	59.4	56.2	54.7	64.6	51.0	53.9	59.8
X-CODAH	mBERT	42.9	33.1	33.5	33.8	35.2	33.7	31.9	22.8	38.0	26.5	31.0	34.8	34.0	37.2	30.8	31.5	33.2
	XLMR-B	50.1	45.8	44.4	44.2	45.2	42.0	44.1	43.2	44.6	38.1	41.9	37.8	42.0	44.1	35.6	34.6	42.4
	XLMR-L	66.4	59.6	59.9	60.9	60.1	59.3	56.3	57.4	57.3	49.1	57.5	51.2	53.8	58.2	42.2	46.6	56.0
	MCP (RL)	69.9	60.7	61.9	60.7	61.4	60.7	58.6	62.3	61.9	53.7	59.0	54.1	54.7	60.8	44.6	48.0	58.3
	TRT	69.1	65.3	62.5	64.4	64.3	64.5	61.8	64.6	63.3	57.1	62.7	57.6	61.6	64.3	52.5	55.1	61.9

Table 2: Overall test results on the multilingual commonsense reasoning benchmark XCSR. Results of mBERT (Devlin et al., 2019), XLMR-B, XLMR-R (Conneau et al., 2019), MCP(RL) (Lin et al., 2021) for X-CSQA and X-CODAH are from XCSR leaderboard (Lin et al., 2021). We submit the test prediction with the best dev result in table 4 to the XCSR leaderboard for evaluation. Leaderboard: <https://inklab.usc.edu/XCSR/leaderboard>

Dataset	X-CSQA	X-CODAH
Task Format	QA	Scene Completion
#Languages	16	16
#Options	5	4
#train	8888	8476
#dev	1000	300
#test	1074	1000

Table 3: Statistics of the two datasets in the multilingual commonsense reasoning benchmark XCSR

four knowledge sources on the multilingual commonsense reasoning benchmark XCSR (Lin et al., 2021).

4.1 Datasets

Table 3 lists the statistics for the two datasets in XCSR. (i) X-CSQA (Lin et al., 2021) for commonsense question answering: given the human authored question that describes the relation between concepts from ConceptNet (Speer et al., 2017), the model needs to choose the answer from five concepts. (ii) X-CODAH (Lin et al., 2021) for Scene Completion: given a prompt question and the subject of the subsequence sentence, the model needs to choose from four candidate complements that can be consistent with question in commonsense.

4.2 Baselines

For X-CSQA and X-CODAH datasets, we mainly compare with the previous state-of-the-art MCP (Lin et al., 2021) as well as other three multilingual pretrained language models: mBERT (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2019) base and large models. MCP is based on XLM-RoBERTa model and further enhanced by intermediate fine-tuning on the multiple-choice question answering dataset MickeyProbe (Lin et al., 2021).

4.3 Implementation Details

We use Microsoft Machine Translator³ for all translations, including translating the given query, the retrieved knowledge and English training data to other 15 languages. We will release these translations for academic usage. For Wiktionary, we use the dump of Wiktionary which includes 999,614 definitions. We empirically obtaining 6 words definitions from Wiktionary for X-CODAH (see Figure 3 (a)) and use the provided question concept and answer as two candidate words for X-CSQA. For ConceptNet, we use ConceptNet version 5.7.0⁴. For GPT-3, we use the curie⁵ model.

Our model implementation is based on HuggingFace’s Transformers Library (Wolf et al., 2020). We conduct all experiments on 8 Nvidia V100-32GB GPU cards. We follow the configurations in XCSR to pretrain the MCP model based on XLM-RoBERTa large except that the maximum sequence length is 256 and batch size is 32. The accuracy of the resulting MCP checkpoint on its dev set is 87.4. We then initialize with this checkpoint for further fine-tuning with different knowledge sources. During finetuning, we set the training epochs, batch size and gradient accumulation steps as 10, 4 and 2 respectively. The total batch size here is 64 by “*batch size per device* \times *# GPUs* \times *# gradient accumulation steps*”. For hyperparameter search, we sweep over the learning rates $\in \{1e-5, 3e-5, 5e-5, 3e-6, 5e-6\}$ and report the maximum results.

³<https://azure.microsoft.com/en-us/services/cognitive-services/translator/>

⁴<https://github.com/commonsense/conceptnet5>

⁵<https://beta.openai.com/pricing>

Dataset	Model	en	de	it	es	fr	nl	ru	vi	zh	hi	pl	ar	ja	pt	sw	ur	avg	
<i>Zero-shot transfer (models are trained on English data) and evaluate on the target language</i>																			
X-CSQA	MCP (RL)	69.0	57.6	57.2	57.9	59.9	56.1	55.2	56.0	56.6	48.8	56.4	52.5	50.8	58.3	42.5	47.4	55.1	
	+ Wikt.	70.7	59.5	60.2	61.4	59.5	58.5	56.6	55.6	58.3	51.2	56.0	55.6	52.0	60.6	46.8	49.1	57.0	
	+ Cpnt.	70.7	57.2	58.1	58.6	58.7	55.8	55.5	56.0	56.6	49.9	55.9	53.9	52.4	55.6	43.3	47.8	55.4	
	+ OMCS	70.5	59.9	59.3	60.5	60.0	56.8	55.3	56.1	57.3	48.9	56.4	53.4	51.6	59.0	46.7	48.0	56.2	
	+ GPT-3	70.3	57.2	58.8	60.2	58.3	58.1	54.8	55.0	55.6	49.0	54.5	52.9	52.1	57.9	42.9	47.6	55.3	
X-CODAH	MCP (RL)	69.7	63.0	62.3	63.0	64.7	64.7	55.0	55.0	59.7	54.3	61.7	52.3	57.0	55.0	40.3	49.3	57.9	
	+ Wikt.	72.0	65.3	63.0	65.0	66.0	66.0	58.7	59.3	58.0	54.3	64.0	55.7	61.3	60.7	47.0	53.0	60.6	
	+ Cpnt.	72.3	68.3	65.7	65.0	66.0	64.3	60.3	57.0	58.3	55.0	65.3	53.7	57.3	59.7	46.3	52.0	60.4	
	+ OMCS	73.0	67.0	64.0	63.7	63.0	62.0	57.3	60.0	62.0	53.0	63.7	56.0	57.7	59.3	44.0	49.3	59.7	
	+ GPT-3	71.7	62.0	64.3	62.3	65.0	62.3	56.7	55.3	58.0	54.3	64.7	55.0	59.3	60.0	42.7	52.7	59.1	
<i>Translate-train (models are trained on English training data and its translated data) and evaluate on the target language</i>																			
X-CSQA	MCP (RL)	69.4	59.3	60.6	60.9	60.8	57.9	57.0	58.2	58.0	50.4	58.3	55.1	53.9	60.3	47.1	50.9	57.4	
	+ Wikt.	70.0	61.7	61.2	61.1	60.9	59.8	59.8	59.3	59.6	53.8	59.7	58.1	54.3	60.5	51.8	52.8	59.0	
	+ Cpnt.	68.5	59.2	59.5	58.2	61.3	58.7	56.6	57.9	58.3	52.6	58.4	55.6	52.9	60.5	48.2	52.8	57.4	
	+ OMCS	71.7	61.1	63.6	62.8	60.3	58.6	58.1	59.3	58.5	51.7	58.1	56.1	54.2	60.4	48.6	53.4	58.5	
X-CODAH	MCP (RL)	71.0	70.7	66.3	69.7	70.7	66.7	63.7	62.3	62.3	60.3	64.7	59.3	59.7	67.7	57.0	57.7	64.4	
	+ Wikt.	72.0	71.7	68.0	69.3	69.7	67.0	65.3	66.0	63.0	61.0	65.0	58.3	62.7	68.0	58.0	58.3	65.2	
	+ Cpnt.	70.7	68.7	67.0	68.0	68.0	68.3	65.0	62.0	61.7	56.3	65.0	61.7	62.3	66.3	60.0	57.3	64.3	
	+ OMCS	74.7	69.7	67.3	67.7	67.7	68.3	62.7	65.3	65.3	58.7	68.3	62.0	64.0	68.3	56.7	59.7	65.4	

Table 4: Comparisons for TRT with different knowledge sources in the zero-shot transfer and translate-train setting on the dev. Wikt. and Cpnt. are short for Wiktionary and ConceptNet.

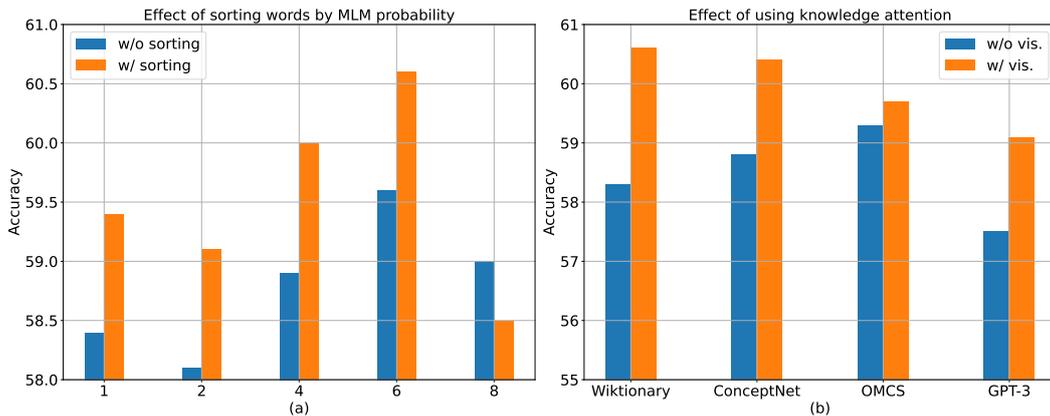


Figure 3: Effects of the number of word definitions and the visible attention mechanism on X-CODAH dataset. Figure (a) shows the performance can be improved by increasing the number of definitions from 1 to 6. Figure (b) shows visible attention can be helpful with all knowledge sources.

4.4 Experimental Results

Results on test set Table 2 summarizes our results on the hidden test set from XCSR leaderboard. TRT outperforms all previous works by a significant margin on both datasets, achieving the average score of 59.8/63.7 with an absolute improvement of 3.3/3.6 over previous state-of-the-art MCP(RL). For some low-resource languages, like Swedish, we observe even larger gains with 7.7 and 7.9 improvements on X-CSQA and X-CODAH.

Effectiveness of different knowledge sources

Table 4 list the detailed comparisons among different knowledge sources in both zero-shot and translate-train setting. We observe the following findings from these results: (i) Knowledge can be helpful for multilingual commonsense reason-

ing. For example, in the zero-shot setting, TRT with Wiktionary improve 1.9 and 2.7 points over the MCP baseline on X-CSQA and X-CODAH. In translate-train setting, there are 1.6 and 1.0 improvements. (ii) Wiktionary helps the most among all knowledge sources in both settings, except that OMCS performs slightly better than Wiktionary on X-CODAH in the translate setting. We hypothesize that the difficulty of understanding hardness words can be mitigated by incorporating additional knowledge as context. (iii) The generated knowledge from GPT-3 can also improve over the baseline, without leveraging machine translation and explicit knowledge, which demonstrate the rich implicit knowledge in GPT-3. For example, for X-CODAH dataset, GPT-3 can outperform the baseline about

1.2 point. However, there still exist the gap between GPT-3 and designated knowledge format. We leave this one as future work to bridge the gap.

Effectiveness of sorting definitions by MLM probability In Section 3.3, we introduce using masked language model (MLM) to select the top-N hardness words with the lowest probability. Therefore, we compare this strategy (w/ sorting) with randomly choosing the words. As shown in Figure 3 (a), sorting by MLM probability can outperform the random selecting, especially with a smaller number of words, achieving the best performance with 6 words definitions.

Effectiveness of knowledge attention In Section 3.4, we mention that simply appending knowledge as additional context can be noise to some tasks like X-CODAH, a scene completion tasks. Therefore, here we compare the model performance between full attention and visible knowledge attention on different knowledge sources. As shown in Figure 3 (b), knowledge attention (w/ vis.) can consistently outperform full attention (w/o vis.) on different knowledge sources. For example, there are 2.3 and 1.6 points improvement between them when integrating from Wiktionary and GPT-3.

5 Conclusion

In this work, we present the translate-retrieve-translate (TRT) strategy for multilingual commonsense reasoning that collects related knowledge via translation and then retrieval from the knowledge sources. We conduct extensive experiments by utilizing a diverse of four English knowledge sources, including Wiktionary, ConceptNet, OMCS and GPT-3. By using TRT with different knowledge sources, we achieve state-of-the-art results on XCSR leaderboard which demonstrates the effectiveness of our proposed methods. Future work includes more effective ways to incorporate the diverse knowledge sources into pre-training and fine-tuning stage for commonsense reasoning.

References

Bin Bi, Chen Wu, Ming Yan, Wei Wang, Jiangnan Xia, and Chenliang Li. 2019. Incorporating external knowledge into machine reading for generative question answering. *arXiv preprint arXiv:1909.02745*.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda

Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.

Michael Chen, Mike D’Arcy, Alisa Liu, Jared Fernandez, and Doug Downey. 2019. Codah: An adversarially authored question-answer dataset for common sense. *arXiv preprint arXiv:1904.04365*.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. *arXiv preprint arXiv:1911.02116*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. **BERT: Pre-training of deep bidirectional transformers for language understanding**. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Olga Majewska Qianchu Liu Ivan Vulić Edoardo M. Ponti, Goran Glavaš and Anna Korhonen. 2020. **XCOPA: A multilingual dataset for causal commonsense reasoning**. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.

Anthony Fader, Stephen Soderland, and Oren Etzioni. 2011. Identifying relations for open information extraction. In *Proceedings of the 2011 conference on empirical methods in natural language processing*, pages 1535–1545.

Yanlin Feng, Xinyue Chen, Bill Yuchen Lin, Peifeng Wang, Jun Yan, and Xiang Ren. 2020. Scalable multi-hop relational reasoning for knowledge-aware question answering. *arXiv preprint arXiv:2005.00646*.

Jian Guan, Fei Huang, Zhihao Zhao, Xiaoyan Zhu, and Minlie Huang. 2020. A knowledge-enhanced pre-training model for commonsense story generation. *Transactions of the Association for Computational Linguistics*, 8:93–108.

Nora Kassner, Philipp Dufter, and Hinrich Schütze. 2021. **Multilingual LAMA: Investigating knowledge in multilingual pretrained language models**. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 3250–3258, Online. Association for Computational Linguistics.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. **Albert: A lite bert for self-supervised learning of language representations**. In *International Conference on Learning Representations*.

- Hector Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In *Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning*.
- Bill Yuchen Lin, Xinyue Chen, Jamin Chen, and Xiang Ren. 2019. Kagnet: Knowledge-aware graph networks for commonsense reasoning. *arXiv preprint arXiv:1909.02151*.
- Bill Yuchen Lin, Seyeon Lee, Xiaoyang Qiao, and Xiang Ren. 2021. Common sense beyond english: Evaluating and improving multilingual language models for commonsense reasoning. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics (ACL-IJCNLP 2021)*. To appear.
- Weijie Liu, Peng Zhou, Zhe Zhao, Zhiruo Wang, Qi Ju, Haotang Deng, and Ping Wang. 2020. K-bert: Enabling language representation with knowledge graph. In *AAAI*, pages 2901–2908.
- Peter LoBue and Alexander Yates. 2011. Types of common-sense knowledge needed for recognizing textual entailment. In *Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies*, pages 329–334.
- Thomas Pellissier Tanon, Denny Vrandečić, Sebastian Schaffert, Thomas Steiner, and Lydia Pintscher. 2016. From freebase to wikidata: The great migration. In *Proceedings of the 25th international conference on world wide web*, pages 1419–1428.
- Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5418–5426, Online. Association for Computational Linguistics.
- Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S Gordon. 2011a. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. In *2011 AAAI Spring Symposium Series*.
- Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S Gordon. 2011b. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. In *2011 AAAI Spring Symposium Series*.
- Push Singh. 2002. The open mind common sense project. *KurzweilAI.net*.
- Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Thirty-first AAAI conference on artificial intelligence*.
- Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2019. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4149–4158, Minneapolis, Minnesota. Association for Computational Linguistics.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.
- Ruochen Xu, Yuwei Fang, Chenguang Zhu, and Michael Zeng. 2021a. Does knowledge help general nlu? an empirical study. *arXiv preprint arXiv:2109.00563*.
- Yichong Xu, Chenguang Zhu, Ruochen Xu, Yang Liu, Michael Zeng, and Xuedong Huang. 2021b. Fusing context into knowledge graph for commonsense question answering. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1201–1207, Online. Association for Computational Linguistics.
- Wenhao Yu, Chenguang Zhu, Zaitang Li, Zhiting Hu, Qingyun Wang, Heng Ji, and Meng Jiang. 2020. A survey of knowledge-enhanced text generation. *arXiv preprint arXiv:2010.04389*.
- Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. Swag: A large-scale adversarial dataset for grounded commonsense inference. *arXiv preprint arXiv:1808.05326*.