Great Truths are Always Simple: A Rather Simple Knowledge Encoder for Enhancing the Commonsense Reasoning Capacity of Pre-Trained Models

Anonymous ACL submission

Abstract

Commonsense reasoning in natural language is a desired capacity of artificial intelligent systems. For solving complex commonsense reasoning tasks, a typical approach is to enhance pre-trained language models (PTMs) by a knowledge-aware graph neural network (GNN) encoder that leverages commonsense knowledge graphs (CSKGs). Despite the effectiveness, these approaches are built in heavy architectures, and can't clearly explain how external knowledge resources improve the reasoning capacity of PTMs. Considering this issue, we conduct a deep empirical analysis, and find that it is indeed *relation features* from CSKGs (but not *node features*) that mainly contribute to the performance improvement of PTMs. Based on this finding, we design a simple MLP-based knowledge encoder by utilizing statistical relation paths as features. Extensive experiments conducted on five benchmarks demonstrate the effectiveness of our approach, which also largely reduce the parameters for encoding CSKGs.

1 Introduction

In the era of artificial intelligence, it is desirable that intelligent systems can be empowered by the capacity of commonsense reasoning in natural language. For this purpose, a surge of commonsense reasoning tasks and datasets are proposed to evaluate and improve such an ability of NLP models, *e.g.,* CommonsenseQA (Talmor et al., 2019) and SocialIQA (Sap et al., 2019b). Although large-scale pre-trained models (PTMs) (Devlin et al., 2019; Liu et al., 2019) have surpassed human performance in a number of NLP benchmarks, it is still hard for PTMs to accurately capture and understand commonsense knowledge for accomplishing complex reasoning tasks (Talmor et al., 2021).

In order to enhance the reasoning capacity, commonsense knowledge graphs (CSKGs) (*e.g.,* ConceptNet (Speer et al., 2017) and ATOMIC (Sap et al., 2019a)) have been leveraged for injecting external commonsense knowledge into PTMs. By conducting entity linking to CSKGs, existing methods (Yasunaga et al., 2021; Feng et al., 2020a) aim to capture the structured knowledge semantics via knowledge graph (KG) encoders (*e.g.,* graph neural network (GNN) (Velickovic et al., 2018; Kipf and Welling, 2017)), and then integrate the KG encoders for improving the commonsense reasoning capacity of PTMs (Yasunaga et al., 2021).

Despite the effectiveness, these approaches are built on highly complicated network architectures (involving both PTMs and GNNs), and require specific training strategies to achieve good performance on benchmark datasets. Thus, it is difficult to explain how and why external commonsense knowledge improves the commonsense reasoning capacity of PTMs. Besides, existing CSKGs (Mehrabi et al., 2021; Nguyen et al., 2021) are mostly crowdsourced from massive web corpora, containing a variety of contents. Without a clear understanding of how these external resources should be utilized, it is likely to incorporate irrelevant concepts or even knowledge biases (Mehrabi et al., 2021; Nguyen et al., 2021) into PTMs, which might hurt the reasoning performance. Indeed, some researchers have noted this issue and questioned whether existing GNN-based modules are over-complicated for commonsense reasoning (Wang et al., 2021a). Furthermore, they find that even a simple graph neural counter can outperform all the existing GNN modules on CommonsenseQA and OpenBookQA benchmarks.

However, existing studies can't well answer the fundamental questions about knowledge utilization for commonsense reasoning: How do external knowledge resources enhance the commonsense reasoning capacity of PTMs? What is necessarily needed from external knowledge resources for PTMs? Since the simplified knowledge-aware GNN has already yielded performance improvement to CommonsenseQA (Wang et al., 2021a), we speculate that there might be a simpler solution if we could identify the essential knowledge for commonsense reasoning.

Focused on this issue, we consider designing the solution by further simplifying the KG encoder. Based on our empirical analysis, we observe a surprising result that it is indeed *relation features* from CSKGs, but not *node features*, that are the key to the task of commonsense reasoning (See more details in Section 3). Based on this finding, we propose a rather simple approach to leveraging external knowledge resources for enhancing the commonsense reasoning capacity of PTMs. Instead of using the heavy GNN architecture, we design a lightweight KG encoder fully based on the multi-layer perceptron (MLP), which utilize **S**tatistical relation p**A**th from CSKGs as **FE**atures, namely **SAFE**. We find that semantic relation paths can provide useful knowledge evidence for PTMs, which is the key information that PTMs lack for commonsense reasoning. By conducting extensive experiments on five benchmark datasets, our approach produces superior or competitive performance compared with the state-of-the art methods, especially when training data is limited. Besides performance improvement, our approach largely reduces the parameters for encoding the CSKGs (fewer than 1% trainable parameters compared to GNN-based KG encoders (Yasunaga et al., 2021)).

Our main contributions can be summarized as follows: (1) We empirically find that relation features from CSKGs are the key to the task of commonsense reasoning; (2) We design a simple MLP-based architecture with relation paths as features for enhancing the commonsense reasoning capacity of PTMs; (3) Extensive experiments conducted on five benchmark datasets demonstrate the effectiveness of our proposed approach, which also largely reduces the parameters of the KG encoder.

2 Task Description

According to (Talmor et al., 2019; Mihaylov et al., 2018), the commonsense reasoning task can be generally described as a multi-choice question answering problem: given a natural language question q and a set of n choices $\{c_1, \cdots, c_n\}$ as the answer candidates, the goal is to select the most proper choice $c^\star$ from these candidates to answer the question based on necessary commonsense knowledge.

To explicitly capture commonsense knowledge, external commonsense knowledge graphs (CSKGs) have often been utilized in this task, *e.g.,* ConceptNet (Speer et al., 2017). A CSKG can be formally described as a multi-relational graph $\mathcal{G} = (\mathcal{V}, \mathcal{R}, \mathcal{E})$, where $\mathcal{V}$ is the set of all concept (or entity) nodes (*e.g., hair* and *water*), $\mathcal{R}$ is the set of relation types (*e.g., relatedto* and *atlocation*), and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{R} \times \mathcal{V}$ is the set of relational links that connect two concept nodes in $\mathcal{V}$.

Following prior studies (Lin et al., 2019), we consider solving the commonsense reasoning task in a *knowledge-aware* setting, where a CSKG $\mathcal{G}$ is available as input. We first link the mentioned concepts from the question and answer candidates to the CSKG, so that we can leverage rich semantic knowledge from the CSKG for commonsense reasoning. Based on the linked concepts in the question and candidates, we further extract their neighbouring nodes from $\mathcal{G}$ and the relational links that connect them, to compose a subgraph $\mathcal{G}^{q,c_i}$ for characterizing the commonsense knowledge about the question q and answer candidate c_i.

3 Empirical Analysis on the Commonsense KG Encoder

In this section, we conduct an empirical study to investigate how the external KG encoder helps PTMs for commonsense reasoning.

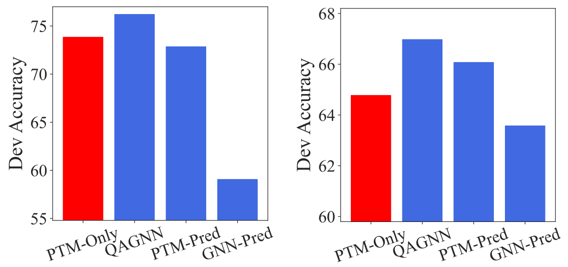
3.1 Analysis Setup

To conduct the analysis experiments, we select QA-GNN (Yasunaga et al., 2021), a representative approach that integrates PTM with GNN for the commonsense QA task, as the studied model. We adopt the CommonsenseQA (Talmor et al., 2019) and OpenBookQA (Mihaylov et al., 2018), two of the most widely used commonsense reasoning benchmarks, for evaluation, with the same data split setting in (Lin et al., 2019).

We consider performing two analysis experiments: one examines the effect of the commonsense KG encoder, and the other one examines the effect of different features in the commonsense KG encoder. To be specific, the two experiments focus on two key questions about commonsense reasoning: (1) what is the effect of the commonsense KG encoder on PTMs? (2) what is the key information to the commonsense KG encoder?

3.2 Results and Findings

Next, we conduct the experiments and present our findings about commonsense reasoning.



(a) CommonsenQA

(b) OpenBookQA

Figure 1: Performance comparison on CommonsenseQA and OpenBookQA (Dev accuracy).

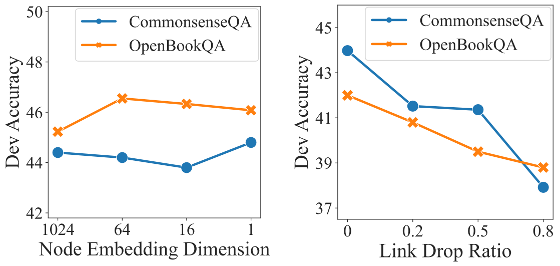


Figure 2: Performance examination for KG encoder on CommonsenseQA and OpenBookQA (Dev accuracy).

Effect of Commonsense KG Encoder. Since existing studies have widely utilized a GNN module to encode the commonsense knowledge, we examine its contribution to improve the reasoning performance. We consider comparing three variants of QA-GNN: (A) *PTM-Only* directly removes the GNN module and degenerates into a pure PTM, (B) *PTM-Pred* trains the PTM and GNN simultaneously but only makes the prediction with the PTM module, and (C) *GNN-Pred* trains the PTM and GNN simultaneously but only makes the prediction with the GNN module.

The comparison results are shown in Figure 1. As we can see, using the predictions solely based on the GNN module (*i.e.,* GNN-Pred) can only answer a relatively minor proportion of the questions (no more than 60% in CommonsenseQA). As a comparison, when trained independently (*i.e.,* PTM-Only) or jointly with the GNN module (*i.e.,* PTM-Pred), the PTM module can answer a large proportion of the questions (at least 70% in CommonsenseQA). Furthermore, the incorporation of the GNN encoder is useful to improve the performance of PTMs (PTM-Only *v.s.* QAGNN). These results show that:

- In the joint PTM-GNN approach, PTM contributes the most to the commonsense reasoning task, which is the key to the reasoning performance.
- Commonsense KG encoder is incapable of performing effective reasoning independently, but can enhance PTM as the auxiliary role.

Effect of Node/Relation Features from KG. The major aim of the KG encoder is to characterize the commonsense knowledge and provide necessary knowledge evidence for enhancing the reasoning capacity of PTMs. Generally, a CSKG consists of concept nodes and relational links. To identify the key knowledge information that is necessarily needed, we now examine the effect of node and relation features from CSKG. By freezing the PTM module, we prepare two variants for comparison: (A) reducing the dimension of node embeddings to d (PCA (Jolliffe, 1986) is applied to select d most informative dimensions), and (B) randomly removing p percent of relational links in the KG subgraph for a question-candidate pair.

As shown in Figure 2, we surprisingly find that even after reducing the dimension of node embeddings to 1, the performance of GNN encoder can be still improved. These results show that node features are not the key to be utilized by the GNN encoder. In contrast, removing a considerable proportion of links significantly reduces the performance. From these observations, we can conclude that: The relation features from the CSKG is indeed the key knowledge information that is actually needed by the KG encoder.

4 Approach

The former sections show that the role of the KG encoder on CSKGs is to mainly complement the PTMs in the task of commonsense reasoning. Instead of node features, relation is the key to the KG encoder for improving PTMs. Based on these findings, we develop a simple commonsense KG encoder based on the statistical relation features from CSKGs, namely **SAFE**. Figure 3 presents the overview of our model.

4.1 Capturing High-Order Relation Semantics

Since relation features are shown useful to improve the performance of commonsense reasoning, we consider extracting relational features for better capturing the knowledge semantics from CSKG. Inspired by KG reasoning studies (Lin et al., 2018; Feng et al., 2020b), we construct multi-hop rela-

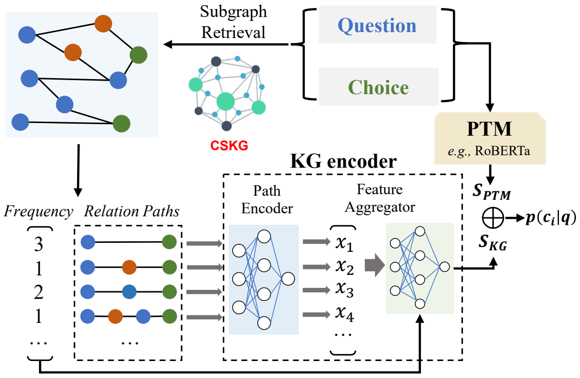


Figure 3: The illustration of our approach. We adopt an all-MLP KG encoder to model the extracted relation features from CSKG to enhance the PTM.

tion paths that connect question nodes with answer candidate nodes on the CSKG, in order to capture higher-order semantic relatedness among entities.

Formally, given the commonsense subgraph $\mathcal{G}^{q,c_i}$ for the question q and answer candidate c_i, we first extract a set of relation paths within k hops that connect a question concept node $v_q \in \mathcal{V}_q$ and an answer concept node $v_{c_i} \in \mathcal{V}_{c_i}$, denoted as $\mathcal{P}^{q,c_i}$. Specifically, a path $p \in \mathcal{P}^{q,c_i}$ can be represented as a sequence of nodes and relations as $p = \{v_1, r_1, \cdots, r_{k-1}, v_k\}$. Based on the empirical finding in Section 3, we consider a simplified representation for relation paths that removes node IDs but only keeps the relations on a path. To keep the role of each node, we replace a node ID by a three-valued type, indicating this node belongs to a *question node* (0), *answer node* (1) or *others* (2). In this way, a path p can be represented by $p = \{t_{v_1}, r_1, t_{v_2}, r_2, \cdots, r_{k-1}, t_{v_k}\}$, where t_v is the role type of node v. Since we remove explicit node IDs, our model can concentrate on more essential relational features.

Based on the above method, for a question q and an answer candidate c_i, we extract all the simplified relation paths and count their frequency among all the paths. We use $\mathcal{F}^{q,c_i} = \{\langle p_j, f_j \rangle\}$ to denote all the paths for question q and candidate c_i, where an entry consists of the j-th path p_j and its frequency f_j. Unlike prior approaches (*e.g.,* QA-GNN (Yasunaga et al., 2021)), we consider using very simple features of relation paths from CSKGs to improve the reasoning capacity of PTMs.

4.2 A MLP-based KG encoder

Our KG encoder is built on a full MLP architecture based on simplified relation path features, consisting of a path encoder and a feature aggregator.

Path Encoder. The path encoder is a two-layer MLP that encodes a relation path into a scalar feature value. As shown in Section 4.1, we can obtain the path feature set $\mathcal{F}^{q,c_i} = \{\langle p_j, f_j \rangle\}$ for a question q and candidate c_i. Different from general KGs, CSKGs usually contain much fewer types of relations (*e.g.,* 36 relations in ConceptNet), we adopt one-hot representations of these types to represent these relations. For node type (from *question*, *candidate* or *others*), we also perform the similar representations. Then, we concatenate these one-hot vectors to compose the sparse representation of a relation path p in order, denoted as $\mathbf{v}_p$. Subsequently, the sparse path representation is encoded by two-layer MLP (*i.e.,* the path encoder) to produce the corresponding scalar feature value x_p:

$$x_p = \text{MLP}_2(\text{MLP}_1(\mathbf{v}_p)), \qquad (1)$$

which x_p reflects the importance of such a relation path for commonsense reasoning.

Feature Aggregator. Based on the above path encoder, we can generate the scalar feature values for all the relation paths in the feature set $\mathcal{F}^{q,c_i} = \{\langle p_j, f_j \rangle\}$. The feature aggregator aims to aggregate these feature values to produce the confidence score of the answer candidate *w.r.t.* the question, from the KG perspective. Concretely, we sum the different feature values of relation paths weighted by their frequencies as follows:

$$x_{q,c_i} = \sum_{\langle p_j, f_j \rangle \in \mathcal{F}} x_{p_j} \cdot f_j, \qquad (2)$$

where x_{p_j} is the mapping feature value of path p_j and f_j is the frequency of path p_j. Here, x_{q,c_i} aims to capture the overall confidence score based on the subgraph $\mathcal{G}^{q,c_i}$ given the question and candidate. However, since the weighted sum is likely to cause extreme values (*i.e.,* too large or too small), we add two extra MLP layers for scaling:

$$S_{KG}(q, c_i) = \text{MLP}_4(\text{MLP}_3(x_{q,c_i})), \qquad (3)$$

where S_{KG} is a prediction score indicating the confidence level that candidate c_i is the right answer to question q from the perspective of KG.

4.3 Integrating KG Encoder with PTM

In this part, we integrate the above KG encoder with the PTM for commonsense reasoning.

	RGCN	MHGRN	QAGNN	SAFE
Node emb	√	√	√	×
Relation	√	√	√	√
GNN	√	√	√	×
MLP-based	×	×	×	√
# Params	365K	547K	2845K	2.7k

Table 1: Comparisons of different KG encoders for commonsense reasoning. Instead of using node embeddings and GNN structure, we adopt relation paths as the input features and incorporate a full MLP architecture.

The PTM Encoder. Following existing works (Yasunaga et al., 2021), we utilize a PTM as the backbone of commonsense reasoning. Given a question q and an answer candidate c_i, we concatenate their text to compose the input of the PTM. After encoding by the multiple Transformer layers, we select the output of the `[CLS]` token in the last layer as the contextual representation of the question-candidate pair, denoted by $\mathbf{h}_{cls}$. Then, we feed $\mathbf{h}_{cls}$ into a MLP layer to produce a scalar output S_{PTM},

$$\begin{aligned} \mathbf{h}_{cls} &= \text{PTM}(q, c_i), \qquad (4) \\ S_{PTM}(q, c_i) &= \text{MLP}(\mathbf{h}_{cls}), \qquad (5) \end{aligned}$$

which is the plausibility score of the answer candidate from the perspective of the PTM.

Combining the Prediction Scores. To derive the prediction scores of candidates, we leverage both the PTM and KG encoders to obtain the prediction scores for each candidate, based on either textual or structured semantics. For a question-candidate pair (q, c_i), we combine the prediction scores of the two modules as:

$$S(q, c_i) = S_{PTM}(q, c_i) + S_{KG}(q, c_i), \qquad (6)$$

where $S_{PTM}(q, c_i)$ (Eq. 5) and $S_{KG}(q, c_i)$ (Eq. 3) are the prediction scores of PTM and KG encoders, respectively. Given a set of answer candidates $\{c_1, ..., c_n\}$, we further normalize $S(q, c_i)$ into a conditional probability $\Pr(c_i|q)$ via the softmax operation over the n candidates.

During the training stage, we optimize the parameters of the whole model (including both the PTM and KG encoder) with the cross entropy loss between the predictions and the ground-truth answer (based on the probability distribution $\{\Pr(c_i|q)\}_{i=1}^{n}$). During the inference, we first compute the probability score $\Pr(c_i|q)$ for each answer candidate, and then select the highest one as the predicted answer.

4.4 Comparison with Existing KG Encoders

For the task of commonsense reasoning, it has become a common approach by integrating PTM with an external KG encoder based on CSKGs. The major difference among these methods (including our approach) lies in the design of KG encoder. Next, we compare these variants for the KG encoder.

We summarize the comparison between our KG encoder and representative KG encoders in Table 1. We can see that, our approach no longer uses the node embeddings and the structure of GNNs. Instead, we mainly utilize relation paths as the features of the KG encoder, which is built on a simple MLP-based architecture. Therefore, the number of the model parameters involved in our KG encoder is much smaller than those of existing KG encoders. As will be shown in Section 5, our KG encoder yields better or at least comparable performance compared with existing GNN-based encoders, based on the same configuration for PTMs.

Specifically, our approach can largely reduce the computational costs for encoding the CSKGs. For our approach, we need to extract the relation paths from question nodes to all the candidate nodes on the CSKG, and it can be efficiently fulfilled via a k-hop constrained Depth-First Search, which can be pre-computed in offline processing. When the relation paths have been extracted, it is efficient to encode these paths with our MLP architecture, where d denotes the hidden dimension of the MLP. Such a process can be easily paralleled or accelerated by optimized matrix multiplication. In contrast, existing GNN-based encoders rely on iterative propagation and aggregation on the entire subgraph, which takes a much larger computational time cost.

5 Experiment

5.1 Experimental Setup

In this part, we introduce the experimental setup.

Evaluation Tasks. We conduct experiments on five commonsense reasoning tasks, shown in Table 2.

• **CommonsenseQA** (Talmor et al., 2019) is a 5-way multiple-choice QA dataset. It is created based on ConceptNet (Speer et al., 2017).

• **OpenBookQA** (Mihaylov et al., 2018) is a 4-way multiple-choice QA dataset about elementary science questions to evaluate the science commonsense knowledge.

• **SocialIQA** (Sap et al., 2019b) is a 3-way multiple-choice QA dataset to evaluate the under-

Task	Train	Dev	Test
CommonsenQA	9,741	1,221	1,140
OpenBookQA	4,957	500	500
SocialIQA	33,410	1,954	-
PIQA	16,113	1,838	-
CoPA	-	500	500

Table 2: Statistics of the datasets. "-" denotes the unused or not available dataset split in our experiments.

standing of social commonsense knowledge.

- **PIQA** (Bisk et al., 2020) is a binary-choice QA dataset about physical commonsense.
- **CoPA** (Roemmele et al., 2011) is a commonsense inference dataset, to select the most plausibly alternative with the causal relation to the premise.

Data Preprocessing. For CommonsenQA and OpenBookQA, we use their original train/dev/test split settings. Since the test set of CommonsenseQA is not available, we follow Lin et al. (2019) that extract 1,241 examples from the original training set as the test set. Besides, the test sets of SocialIQA and PIQA are not available. Following previous works (Shwartz et al., 2020), we report the experimental results on their development sets for a fair comparison. For CoPA that provides development and test sets, we follow Niu et al. (2021) to train models on the development set and evaluate the performance on the test set. For commonsense KG, we adopt *ConceptNet* (Speer et al., 2017), a general-domain and task-agnostic CSKG, as our external knowledge source $\mathcal{G}$ for above models and tasks. For each question and answer choice pair (q, c_i), we follow previous works (Lin et al., 2019; Feng et al., 2020a) to retrieve and construct the subgraph $\mathcal{G}^{q,c_i}$ from the CSKG $\mathcal{G}$.

Baseline Methods. We compare our model with the following six baseline methods, including a fine-tuned PTM and five PTM+GNN models:

- **Fine-tuned PTM** directly fine-tunes a PTM without using KG. We use RoBERTa-large (Liu et al., 2019) for all tasks. Additionally, we also use BERT-large (Devlin et al., 2019) and AristoRoBERTa (Clark et al., 2020a) for OpenBookQA to evaluate the generality of our KG-encoder.
- **PTM+GNN models** integrate PTM with additional GNN-based KG encoders. Based on the same PTM (the above baseline), we consider five variants with different KG encoders: (1) *Relation Network* (RN) (Santoro et al., 2017) using a relational reasoning structure over CSKG; (2) *GcoAttn* (Lin et al., 2019) using a graph concepts attention model to aggregate entity information from the CSKG; (3) *RGCN* (Schlichtkrull et al., 2018) extending GCN with relation-specific weight; (4) *MHGRN* (Feng et al., 2020a) using a novel GNN architecture reasoning over CSKG that unifies both GNNs and path-based models; (5) *QA-GNN* (Yasunaga et al., 2021) using a GAT to do joint reasoning over CSKG.

For all the methods, we adopt the same architecture and configuration for the PTM, so that we can examine the effect of different KG encoders.

5.2 Results Analysis

Following previous works (Yasunaga et al., 2021; Wang et al., 2021a), we take the results on CommonsenseQA and OpenBookQA as the main experiments to compare different methods. In order to test their robustness to data availability, we examine the performance under five different proportions of training data, *i.e.,* $\{5\%, 10\%, 20\%, 50\%, 80\%, 100\%\}$.

CommonsenseQA and OpenBookQA. The results of different methods on CommonsenseQA and OpenBookQA datasets are presented in Table 3.

First, we can see that all the PTM+GNN methods perform better than vanilla PTM (*i.e.,* RoBERTa-large). It indicates that the KG encoder on CSKG is able to incorporate useful knowledge information to improve PTMs on commonsense reasoning tasks. Additionally, among all the PTM+GNN baselines, QA-GNN performs the best. The major reason is that QA-GNN uses LMs to estimate the importance of KG nodes and connects the QA context and CSKG to form a joint graph, which is helpful to improve the reasoning ability on CSKG. Finally, our method consistently outperforms all the baselines. Our approach incorporates a lightweight MLP architecture with relation paths as features as the KG encoder. It reduces the parameter redundancy of the KG encoder and focuses on the most essential features for reasoning, *i.e.,* semantic relation paths. Such an approach is effective to enhance the commonsense reasoning capacity of PTMs.

Comparing the results under different sparsity ratios of training data, we can see that the performance substantially drops when the size of training data is reduced. While, our method performs consistently better than all baselines. It is because

Methods	CommonsenseQA						OpenBookQA					
	5%	10%	20%	50%	80%	100%	5%	10%	20%	50%	80%	100%
RoBERTa-large	29.67	42.84	58.47	66.13	68.47	68.69	37.00	39.4	41.47	53.07	57.93	64.8
+ RGCN	47.89	44.56	61.72	65.70	68.04	68.41	37.73	40.73	49.13	56.60	61.20	62.45
+ GconAttn	45.15	50.42	57.75	65.99	68.33	68.59	38.93	41.07	47.93	50.93	51.47	64.75
+ RN	38.97	49.85	58.93	64.87	67.15	69.08	35.13	35.27	47.73	59.87	64.40	65.20
+ MHGRN	44.61	51.02	63.31	68.44	70.88	71.11	38.87	37.73	44.93	59.67	66.50	66.85
+ QA-GNN	33.04	40.10	58.72	67.61	71.18	73.41	36.90	39.70	43.40	58.00	64.80	67.80
+ SAFE(**Ours**)	**50.87**	**53.73**	**65.07**	**71.13**	**73.49**	**74.75**	**39.46**	**43.80**	**51.20**	**59.90**	**66.60**	**70.10**

Table 3: Performance comparison on CommonsenseQA and OpenBookQA with different proportions of training data. We report the average test performance of three runs, and the best results are highlighted in bold.

Methods	**SocialIQA**	**PIQA**	**CoPA**
RoBERTa-large	78.25	77.53	67.60
+ RGCN	78.30	79.34	69.60
+ GcoAttn	78.85	78.24	70.00
+ RN	78.15	76.88	70.20
+ MHGRN	78.13	77.15	71.50
+ QAGNN	78.10	78.24	53.20
+ SAFE (**Ours**)	**78.86**	**79.43**	**71.60**

Table 4: Performance comparison on SocialIQA, PIQA, and CoPA (Dev accuracy).

Methods	**BERT-large**	**AristoRoBERTa**
Fine-tuned PTMs	59.07	78.40
+ RGCN	44.13	75.35
+ GconAttn	48.20	75.35
+ RN	48.60	75.35
+ MHGRN	46.20	80.40
+ QA-GNN	58.47	82.77
+ SAFE (**Ours**)	**59.60**	**87.13**

Table 5: Evaluation with other PTMs on OpenBookQA (average test accuracy of three runs). Methods with AristoRoBERTa use the textual evidence by Clark et al. (2020b) as an additional input to the QA context.

that our KG encoder consists of significantly fewer parameters than the baselines, which endows our approach better robustness in data scarcity scenarios and reduces the risk of overfitting.

Other Commonsense Reasoning Datasets. To further verify the effectiveness of our method, we also compare the results of different methods on other commonsense reasoning datasets that are from different domains or with different tasks. These results are shown in Table 4. Similarly, our approach also achieves the best performance in most cases. It indicates that our approach is generally effective to a variety of commonsense reasoning datasets or tasks, by outperforming competitive but complicated baselines. Among all the datasets, our approach improves the performance of the PTM on CoPA dataset by a large margin. The reason is that CoPA is a small dataset with only 500 training examples. Baselines with heavy architectures are easy to overfit on it. In contrast, our KG encoder is lightweight and simple, which is more capable of resisting the overfitting issue.

5.3 Evaluation with Other PTMs

The major contribution of our approach lies in the lightweight KG encoder, which can be also used to enhance the commonsense reasoning capacity of various PTMs. To validate it, we examine the performance of our KG encoder when integrated with two other PTMs *i.e.,* BERT-large and AristoRoBERTa on OpenBookQA dataset.

As shown in Table 5, the enhanced BERT-large and AristoRoBERTa by our KG encoder achieve better performance than original PTMs. Especially, our KG encoder can improve the performance of AristoRoBERTa by a large margin (with 8.73% improvement). These result show that our KG encoder is a general method to improve PTMs for commonsense reasoning. In constrast, when adapting other KG encoders to these two PTMs, the performance decreases in most cases. It is mainly because that these KG encoders have complicated architectures, which may not easy to be adapted to other PTMs.

5.4 Case Study

We propose a rather simple KG encoder to effectively utilize the relation features from CSKGs, which first computes the feature values of the relation paths and then aggregator these values as the confidence score of the question and the choice. In this way, we can generate a table that maps each type of relation path into its feature value that

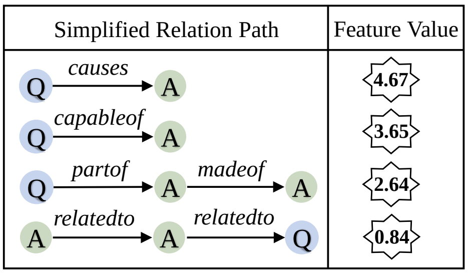


Figure 4: The generated feature values x of relation path examples by the path encoder. **Q** and **A** denote the concept nodes from the question and the answer candidate, respectively.

reflects its contribution to confidence score. Figure 4 shows some examples. As we can see, the paths with the higher values indeed provide a more persuasive evidence (*causes* and *capableof*) that indicates the choice is more likely to be the answer of the question. In contrast, the path with the lower value usually represent an ambiguous relationship (*e.g., relatedto*). Based on this table, it is convenient to judge the importance of the relation path and make a quick assessment of the confidence if the choice is the answer of the question.

6 Related Work

We review the related studies in two aspects, *i.e.,* commonsense reasoning and KG-enhanced pre-trained models.

Commonsense Reasoning. Commonsense reasoning tasks aim to evaluate the understanding about commonsense knowledge (Davis and Marcus, 2015), *e.g.,* physical commonsense (Zellers et al., 2019), which are mostly formulated as a multi-choice QA problems. Early studies either rely on explicit text features (Clark et al., 2016) to capture the relations between the question and answer candidates, or adopt neural network (Yu et al., 2014; Chen et al., 2017). Recently, pre-trained models (PTM) (Devlin et al., 2019; Liu et al., 2019) have achieved remarkable performance on commonsense reasoning tasks. Furthermore, a surge of works incorporate external knowledge resources to further improve the reasoning performance. Among them, CSKG (*e.g.,* ConceptNet (Speer et al., 2017)) has been widely studied, and existing works mainly adopt graph neural networks to learn useful commonsense knowledge from the CSKG to enhance PTMs. Based on these works, we systemically study what is necessarily needed from CSKGs for improving PTMs. Our analysis leads to an important finding that relation features mainly contribute to the performance improvement, and design a lightweight MLP architecture to simplify the KG encoder.

KG-Enhanced Pre-trained Models. Recently, a surge of works focus on enhancing PTMs with external KG to improve the performance on factual knowledge understanding (Sun et al., 2020; Wang et al., 2021b) and knowledge reasoning tasks (Talmor et al., 2019; Zhang et al., 2019). These works inject the structured knowledge from KG into PTMs in either pre-training or fine-tuning stages. The first class of works mainly focus on devising knowledge-aware pre-training tasks (Wang et al., 2021b; Zhang et al., 2019) to improve the understanding of entities or triples from the KG, *e.g.,* knowledge completion (Wang et al., 2021b) and denoising entity auto-encoder (Zhang et al., 2019). Another class of works adopt task-specific KG encoders to enhance PTMs during fine-tuning, *e.g.,* path-based relation network (Feng et al., 2020a) and GNN (Yasunaga et al., 2021). Different from them, we aim to enhance PTMs with a KG encoder on commonsense reasoning tasks, and design a rather simple yet effective KG encoder.

7 Conclusion

In this work, we study how the external commonsense knowledge graphs (CSKGs) are utilized to improve the reasoning capacity of pre-trained models (PTMs). Our work makes an important contribution to understand and enhance the commonsense reasoning capacity of PTMs. Our results show that relation paths from the CSKG are the key to performance improvement. Based on this finding, we designed a rather simple MLP-based KG encoder with relation paths from the CSKG as features, which can be generally integrated with various PTMs for commonsense reasoning tasks. Such a lightweight KG encoder has significantly fewer than 1% trainable parameters compared to previous GNN-based KG encoders. Experimental results on five commonsense reasoning datasets demonstrated the effectiveness of our approach.

As future work, we will study how to effectively leverage the commonsense knowledge from large-scale unstructured data to improve PTMs. We will also consider applying our approach to other knowledge-intensive tasks, such as knowledge graph completion and knowledge graph based question answering.

8 Ethical Consideration

This work primarily investigates how external commonsense knowledge graph (CSKG) enhances the commonsense reasoning capacity of pre-trained models (PTMs) and proposes a simple but effective KG encoder on CSKG to enhance PTM. A potential problem derives from the usage of PTMs and CSKG in our approach. PTMs have been shown to capture certain biases from the data thay have been pre-trained on (Bender et al., 2021). And existing works (Mehrabi et al., 2021) have found that CSKGs are likely to contain biased concepts derived from human annotations. However, a comprehensive analysis of such biases is outside of the scope of this work, it is a compelling direction to investigate to what extent the combination of CSKG and PTMs can help mitigate such biases. An alternative consideration is to consider the filtering of biased concepts in the process of subgraph extraction from the CSKG. By devising proper rules, it is promising to reduce the influence of biased concepts on our approach.

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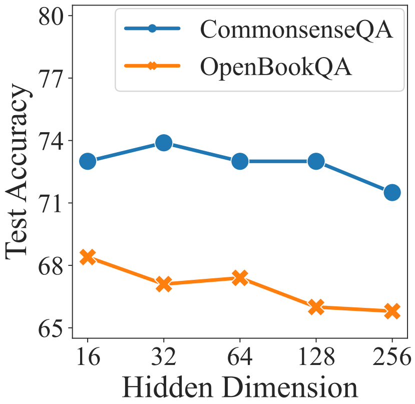

Figure 5: Overview of our SAFE model.

A Implementation Details

We implement all PTMs based on HuggingFace Transformers (Wolf et al., 2020). For all the baselines, their hyperparameters are set following the suggestion from the original paper. In our approach, we extract the relation paths within 2 hops. We tune the hidden dimension of MLPs from the path encoder and feature aggregator in {32, 64, 100}, and the batch size in {32, 64, 128}. The parameters of the model are optimized by RAdam (Liu et al., 2020), and the learning rate for the PTMs and KGs are also tuned in {1e-5, 2e-5, 3e-5} and {1e-4, 1e-3, 1e-2}. To accelerate the training, we don't incorporate Dropout regularization in our model. All the above hyperparameters are tuned on the development set.

B Hyper-parameters Analysis

For hyper-parameter analysis, we study the hidden dimension size of the MLP layers in our KG encoder. Concretely, we evaluate our model with varying values of hidden dimension size on the CommonsenseQA and OpenBookQA datasets using RoBERTa-large model. The results are shown in Figure 5. We can see that with the increasing of the hidden dimension size, the performance drops to some extent. One possible reason is that larger hidden dimension size enlarges the parameter number of our KG encoder, which may rise the risk of overfitting and cause performance degradation.