

# Connecting the Dots: A Knowledgeable Path Generator for Commonsense Question Answering

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## Abstract

Commonsense question answering (QA) requires the modeling of general background knowledge about how the world operates and how entities interact with each other. Prior works leveraged manually curated commonsense knowledge graphs to help commonsense reasoning and demonstrated their effectiveness. However, these knowledge graphs are incomplete and thus may not contain the necessary knowledge for answering the questions. In this paper, we propose to learn a multi-hop knowledge path generator to generate structured evidence dynamically according to the questions. Our generator uses a pre-trained language model as the backbone, leveraging a large amount of unstructured knowledge stored in the language model to supplement the incompleteness of the knowledge base. The experiments on two commonsense QA datasets demonstrate the effectiveness of our method, which improves over strong baselines significantly and also provides human interpretable explanations for the predictions.<sup>1</sup>

## 1 Introduction

Answering commonsense questions requires background knowledge about how the world operates (e.g., intuitive physical commonsense) and how people interact with each other in daily life (e.g., intuitive psychological commonsense). For example, to answer a multi-choice question displayed in Figure 1, the QA system needs commonsense like *overpopulation* is caused by *reproducing*, which requires consuming *resources*. Such knowledge is obvious for humans but not trivial for most of the existing QA systems to possess (Talmor et al., 2018).

Recent advances in pre-trained language models have brought great successes to many natu-

<sup>1</sup>Codes are available at <https://github.com/wangpf3/Commonsense-Path-Generator>.

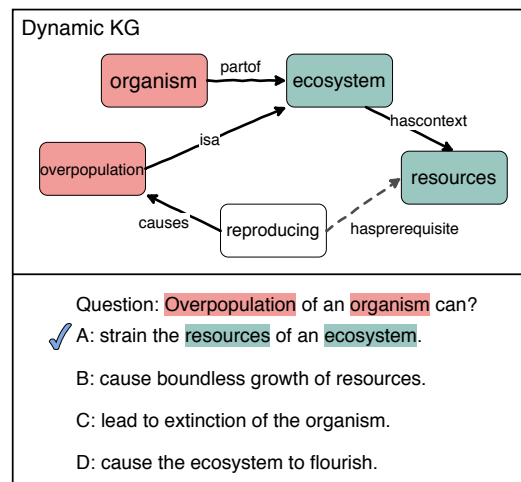


Figure 1: Our generator learns to connect the question entities (in red) and choice entities (in green) with generated paths, which serve as a dynamic KG for QA. The dashed arrow indicates a missing link in a static KG.

ral language understanding (NLU) tasks (Radford et al., 2018; Devlin et al., 2018), with impressive results on commonsense-related benchmarks (Zellers et al., 2018; Bhagavatula et al., 2019; Huang et al., 2019). However, it is unclear whether they indeed achieved commonsense reasoning or just captured correlations in the datasets (Niven and Kao, 2019). A popular approach to directly provide additional background knowledge for NLU tasks is to leverage the commonsense knowledge graphs (KG) such as ConceptNet (Speer et al., 2017) or ATOMIC (Sap et al., 2019). An additional benefit of this approach is the improvement of the interpretability for the model. Therefore, this paper focus on KG-based methods to conduct interpretable reasoning for commonsense QA.

The typical approach to leverage the commonsense KGs for commonsense QA is to *retrieve* a local graph of the entities mentioned in the questions and answer choices from a static KG and then reason over the local graph for predicting the an-

swer. However, leveraging these KGs poses the following challenges. (1) **Noise**: While a commonsense KG contains rich information, only a few facts in the local graph that connect the entities associated with question/answer pairs will be *informative* for addressing the tasks; many connections in the local graph are noisy, unhelpful signals for learning. (2) **Sparsity**: KGs are also known to be incomplete (Li et al., 2016); the necessary facts for answering the questions can be missing from a hand-crafted KG. For example, a missing link (*reproducing, hasprerequisite, resources*) in Figure 1 would prevent the QA system from choosing the right answer.

To address these challenges, we propose a commonsense knowledgeable path generator based on a pre-trained language model that learns to generate multi-hop knowledge paths as a dynamic knowledge graph. These generated paths can efficiently include relevant information for answering commonsense questions while reducing noises. Moreover, the large amount of knowledge encoded in the pre-trained language model provides our path generator with better generalization ability to combat the sparsity of KGs.

In our approach, we first sample a set of random walk instances from a static commonsense KG with heuristics (§3.1) to ensure their informativeness and helpfulness. Then we fine-tune a pre-trained language model — GPT-2 (Radford et al., 2019) on the sampled paths to learn a knowledge path generator (§3.2). Given any pair of question and answer entities, our path generator dynamically generates a novel multi-hop path to connect them instead of retrieving the path from a static KG. As a result, we could generate the link like (*reproducing, hasprerequisite, resources*) in Figure 1, which is missing in the static KG, to connect the two entities and help the inference. These generated paths further serve as the local graph for our KG augmented QA system to solve the questions (§3.3).

We conduct experiments on two benchmark datasets *CommonsenseQA* (Talmor et al., 2018) and *OpenBookQA* (Mihaylov et al., 2018). The results show that our generator can efficiently generate knowledge paths that not only help improve the performance over strong baselines, but also provide interpretable explanations for the choice. Ablation studies demonstrate that the improvements, to a large extent, come from our strategies for learning the path generator.

## 2 Problem Statement and Overview

In this paper, we focus on the multi-choice commonsense QA setup where given a question ( $q$ ), a system needs to select one of choices ( $\{a_i\}$ ) as the right answer. Such a setting is generally used by many of the commonsense QA datasets (Talmor et al., 2018; Mihaylov et al., 2018; Bisk et al., 2020).

We propose a framework consisting of a commonsense knowledge path generator and a reasoning module. Assume we employ a reasonable entity recognition system (in practice we simply use string matching) to extract all the entity mentions in the question  $\{e_i^q\}$  and the answer choices  $\{e_j^a\}$ . Given a pair of question entity and answer choice entity, our path generator learns to output a knowledge path as a snippet of the commonsense KG that connects the two entities. The path is supposed to (1) be informative for answering the question and (2) contain novel knowledge facts that are missing from the static KG. The generated paths for all pairs of question and answer choice entities are then served as a dynamic KG to assist our reasoning module to predict the answer.

## 3 Knowledgeable Path Generator as Dynamic KG

In this section, we give more details about how do we construct the training data (§3.1) for learning our path generator (§3.2), and how to incorporate it into the reasoning module (§3.3). The overview of our method is illustrated in Figure 2.

### 3.1 Knowledge Paths Sampling

We first sample paths from a commonsense KG using random walk to provide representative knowledge paths as training data for learning our knowledgeable path generator. Given a static KG  $\mathcal{G} = (\mathcal{E}, \mathcal{R})$ , where  $\mathcal{E}$  is the entity set and  $\mathcal{R}$  is the relation set, a sampled path is a random walk on the graph taking the form of  $\{e_0, r_0, e_1, r_1, \dots, r_{T-1}, e_T\}$ , where  $e_t \in \mathcal{E}$  and  $r_t \in \mathcal{R}$ .  $T$  is the number of hops which is a hyperparameter in our model. We assume such paths contain relevant knowledge for the commonsense QA tasks. To improve the quality of the paths, we adopt two heuristic strategies. For *relevance*, we define a subset of relation types that are useful for answering commonsense questions, e.g., *atlocation* and *isa*. We filter out all the other irrelevant relation edges, e.g., *relatedto* in the commonsense

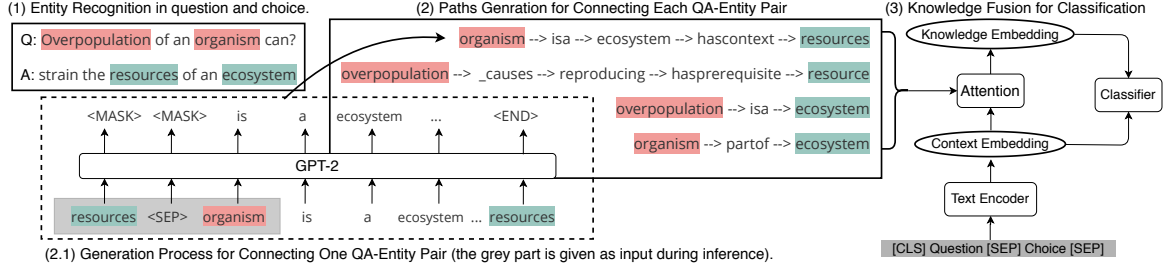


Figure 2: **Overview of our method.** (1) Extract entities from questions and answer choices, (2) Use our path generator to generate a multi-hop knowledge path to connect each pair of question and answer entities, (3) Aggregate the generated paths as a knowledge embedding, and fuse it with a context embedding from a text encoder for classification.

KG before we conduct sampling (see Appendix B for specific discarded relations). For *informativeness*, we require that each path should not contain edges with repeated relation types. We explore the following two sampling strategies in this paper to select the starting node of the random walks:

**Local Sampling.** The random walks start from the entities that appeared in the questions and answer choices of the training proportion of QA dataset. This strategy helps our generator to generate paths that are tailored to the task.

**Global Sampling.** We randomly sample some entities from KG and conduct random walks starting from them. This would prevent our generator from biasing towards the local structure of KG and enhance the generalizability to unseen data.

We add a reverse relation  $r^{-1}$  for each relation  $r$  so that a sampled path can contain reverse triplets, e.g.,  $(o, r^{-1}, s)$ . This would equip our generator with more flexibility to connect two entities. We also sample paths with a mixed number of hops ( $T$ ) to train our generator to connect entities using paths with variable lengths when needed. The algorithm is illustrated in Algorithm 1 in the appendix.

### 3.2 Generating Paths to Connect Entities

In order to learn a knowledge paths generator as a dynamic KG to overcome the sparsity issue of a static KG, we employ GPT-2 as the backbone of the generator. GPT-2 is a pre-trained language model that encodes rich unstructured knowledge from large natural language text corpora. The benefits of leveraging the pre-trained GPT-2 model are two-fold. First, we enrich the language model with structured knowledge such that it could generate paths with *structured* “commonsense” knowledge as designed. Second, the *unstructured* knowledge encoded in the language model could alleviate the sparsity issue in KG.

Unlike COMET (Bosselut et al., 2019) which

Table 1: **Transformation of Symbolic Paths to their Textual Form for Training Generator.**

$\{\text{predator, distinctfrom, prey, isa, animal}\}$
$\rightarrow \{\text{animal, [SEP], predator, distinct, from, prey, is, a, animal}\}$

fine-tunes GPT (an earlier version of GPT-2) with independent triplets, we fine-tune GPT-2 with consecutive triplets that form paths as described in Section 3.1. To do so, we first use the Byte-Pair Encoding (Sennrich et al., 2016) of the GPT-2 to convert each symbolic path to their textual form as a sequence  $s = \{x_0, y_0, x_1, y_1, \dots, y_{T-1}, x_T\}$ , where  $x_t = \{x_t^0, x_t^1, \dots, x_t^{|e_t|}\}$  are the phrase tokens of the entity  $e_t$  and  $y_t = \{y_t^0, y_t^1, \dots, y_t^{|r_t|}\}$  are the phrase tokens of the relation  $r_t$ . This is crucial for leveraging the knowledge encoded in the language model. The resulting paths mimic natural language sentences such that they make the best use of the pre-trained language model. During the inference time, since we need to generate paths that connect the question-choice entities, we further preprocess the paths in a way that we add the last entity phrase tokens  $x_T$  together with a separate token [SEP] at the beginning of each path. By doing so, the generator will be aware of the last entity it should output when generating a path. We represent the reverse relations by adding a special token, “\_”, at the beginning of the relations phrases. Table 1 shows an example path and its transformation as input to our generator.

To train the knowledge path generator to maximize the probability of the observed paths given the entity pairs, we use negative log likelihood as the loss function:

$$\mathcal{L} = - \sum_s \log P(s|x_T, [SEP], x_0), \quad (1)$$

where  $P(s|x_T, [SEP], x_0)$  is the product of condi-

tional probabilities:

$$P(s|\mathbf{x}_T, [SEP], \mathbf{x}_0) = \prod_{t=|\mathbf{x}_0|+|\mathbf{x}_T|+1}^{|\mathbf{s}|} P(s_t | s_{<t}), \quad (2)$$

The conditional probability is defined as:

$$P(s_t | s_{<t}) = \text{softmax}(\mathbf{W}_{vocab} \cdot \mathbf{h}_t). \quad (3)$$

Here  $\mathbf{h}_t$  denotes the final representation from GPT-2 for  $s_t$  and  $\mathbf{W}_{vocab}$  is the embedding matrix for the token-based vocabulary used by Byte-Pair Encoding in GPT-2, which generalizes well to unseen words. During inference, the target entity, [SEP] token and starting entity (the grey part in Table 1) are given to our generator, and greedy decoding is used to generate a path connecting the two entities.

### 3.3 Commonsense QA System with Knowledgeable Path Generator

Our ultimate goal is to incorporate the generated paths as external evidence into the reasoning module of our question answering model for better accuracy and enhanced interpretability. The reasoning module relies on a contextual encoder which encodes the question and each choice into a context embedding  $\mathbf{c}$  as **unstructured evidence**. In this paper, we employ the bidirectional transformer pre-trained language model (Devlin et al., 2018; Liu et al., 2019), a commonly used contextual encoder for the textual input. The question and each choice are concatenated with special tokens in between, and then fed to the contextual encoder to obtain  $\mathbf{c}$ . The context embedding is further used as attention key for aggregating the paths generated by the paths generator, which outputs a knowledge embedding  $\mathbf{p}$  as **structured evidence**. Finally, these two types of evidence are fed to a classifier to output a plausibility score for each choice. We provide more details about the knowledge embedding module as follows.

**Knowledge Embedding as Structured Evidence** For each pair of question entity  $e_i^q$  and choice entity  $e_j^a$ , the path generator outputs a reasoning path  $p_k$  to connect them. To better utilize these discrete paths, we take a mean pooling of the hidden states from the last layer of GPT-2 (before the softmax layer in Eq. 3) as our path embedding, i.e.,

$$\mathbf{p}_k = \text{MEAN}(\{\mathbf{h}_0, \mathbf{h}_1, \dots, \mathbf{h}_{|p_k|-1}\}). \quad (4)$$

Since GPT-2 has been pre-trained on a large corpus, we believe such representation should be sufficient in preserving the information of the paths. Moreover, this saves us the trouble of learning an additional path encoder.

We assume not all the paths would contribute equally to the decision about which choice is the right answer. Therefore, we leverage the unstructured evidence, i.e., the context embedding  $\mathbf{c}$  as the guidance to encode the structured evidence. Specifically, we extend the Relational Network (RN) (Santoro et al., 2017) with attention mechanism to select the meaningful paths softly:

$$\mathbf{p} = W_{proj} \cdot \sum_k \alpha_k \mathbf{p}_k, \quad (5)$$

where  $W_{proj}$  is a learnable projection matrix. The attention weight  $\alpha_k$  of each path embedding  $\mathbf{p}_k$  is computed by

$$\alpha_k = \frac{\exp(\hat{\alpha}_k)}{\sum_{k'} \exp(\hat{\alpha}_{k'})}, \quad (6)$$

where

$$\hat{\alpha}_k = \mathbf{c}^\top \tanh(\mathbf{W}_{att} \cdot \mathbf{p}_k + \mathbf{b}_{att}). \quad (7)$$

Here, the attention network is parametrized by  $(\mathbf{W}_{att}, \mathbf{b}_{att})$  and  $\tanh(\cdot)$  is a nonlinear activation function.

**Fusion of Heterogeneous Evidence for Classification** With unstructured evidence provided by context embedding  $\mathbf{c}$  and structured one provided by paths embedding  $\mathbf{p}$  at hand, our classifier leverages both of them to compute the plausibility of a question-choice pair. We concatenate  $\mathbf{c}$  with  $\mathbf{p}$  and feed them to the final classification layer, which is a linear transformation to get a score for each question choice pair  $\{q, a\}$ :

$$f(q, a) = \mathbf{W}_{cls} \cdot [\mathbf{c}; \mathbf{p}] + \mathbf{b}_{cls}, \quad (8)$$

where the linear classification layer is parameterized by  $(\mathbf{W}_{cls}, \mathbf{b}_{cls})$ . Then the score is normalized by a softmax layer to get the final probability over all choices. The model is optimized by minimizing the cross-entropy loss. Learnable parameters include all the modules described above excluding our proposed path generator since during experiments we find that fixing the generator yields better performance. This also reflects another advantage of our path generator: after being fine-tuned on sampled random walks from KG, the path generator could be used as a plug-in module to an existing QA system and needs no further training.



## 4 Experiments

### 4.1 Experimental Setup

We evaluate our method on the *CommonsenseQA* (Talmor et al., 2018) and *OpenBookQA* (Mihaylov et al., 2018); both are multi-choice QA datasets evaluating a model’s ability to reason with commonsense knowledge. For *CommonsenseQA*, we follow the data split used in Lin et al. (2019) since the labels for the official test set are not released. For *OpenBookQA*, we do not use the additional set of science facts originally provided by the dataset and rely on our generator to provide background knowledge.

### 4.2 Dataset Processing

**KG and Entity Recognition** We employ ConceptNet (Speer et al., 2017) as our commonsense KG due to its broad coverage of general background knowledge about the world. As mentioned in Section 3.1, we discard all the triplets with the predefined uninformative relations (see Appendix B) before paths sampling.

To extract all the entities mentioned in the question and answer choices, we use plain string matching as in the previous work (Lin et al., 2019). One exception is that for the answer choices in *CommonsenseQA*, we treat each of them as a single entity since most of them are independent concepts in ConceptNet.

**Paths Sampling** We sample paths with hops ranging from 1 to 3 to construct the set of paths with a mixed number of hops. The number of paths which we obtain from both global sampling and local sampling on specific task datasets is shown in Table 2. We further split them into training/development/test set with ratio of 9 : 0.5 : 0.5.

### 4.3 Baselines

We consider several baselines including fine-tuned language models and KG-augmented models with static KG. We also propose a baseline which conducts link prediction between questions and answers entities as a 1-hop dynamic KG.

**Pre-trained Language Model.** Since our goal is to enhance the QA system with external knowledge and part of our model relies on the pre-trained language model, we consider the baselines without KG and call them as **Fine-tuned LM**. As in our framework, we use the pooling of the last layer of hidden states from the pre-trained language model

Table 2: Statistics of Sampled Paths.

Setting	#Paths
Global	2,825,692
<i>CommonsenseQA</i>	133,612
<i>OpenBookQA</i>	105,155

as the context embedding and feed it to a linear classifier to obtain the score. We then fine-tune these language models over the task datasets.

**Models with Static KG.** Since we argue that our dynamic neural KG is superior, we compare our method with previous works with different graph encoders for modeling local paths/graphs retrieved from the static KG as they are. Firstly, we compare with a degenerate version of our method, i.e., **RN** with attention mechanism over the retrieved paths for each pair of question-choice entities from a static KG to obtain a static knowledge embedding. Other advanced baselines to obtain static knowledge embedding include Relational Graph Convolutional Networks (**RGCN**) (Schlichtkrull et al., 2018) which employs graph convolutional networks with relation specific weight matrices to encode the local graphs and **GconAttn** (Wang et al., 2019) which models the alignment between entities via attention and pools over all the entity embeddings. We concatenate the static knowledge embedding from each of these KG-augmented methods with the context embedding from the pre-trained language model as the input to the classification layer (Eq. 8) for a fair comparison.

**Model with Link Prediction.** We also propose a baseline model called **Link Prediction**, which predicts the relation between question and answer entities instead of generating the knowledge paths. We first employ TransE (Bordes et al., 2013) to learn a knowledge representation for each entity and relation in ConceptNet. Then for each pair of question and answer entities, we predict their 1-hop relation based on their knowledge representation. Then for each resulting triplet, we concatenate their knowledge representations as a 1-hop path embedding. The remaining module design is the same as our method.

### 4.4 Model Variations

As for our method, we investigate the following three variants. (1) **PathGenerator-Local** (or PG-Local) We equip our reasoning module with the local path generator which is trained on both local

Table 3: **Classification accuracy on different proportion of CommonsenseQA** (Lin et al.’s data split). Results (as mean and standard deviation) are taken from 4 runs of experiments with different random seeds (top score in boldface, second score underlined).

Methods	BERT-large			RoBERTa-large		
	20% Train	60% Train	100% Train	20% Train	60% Train	100% Train
Fine-tuned LM (w/o KG)	46.25 ( $\pm 0.63$ )	52.30 ( $\pm 0.16$ )	55.39 ( $\pm 0.40$ )	55.28 ( $\pm 0.35$ )	65.56 ( $\pm 0.76$ )	68.69 ( $\pm 0.56$ )
+ RN	45.12 ( $\pm 0.69$ )	54.23 ( $\pm 0.28$ )	58.92 ( $\pm 0.14$ )	61.32 ( $\pm 0.68$ )	66.16 ( $\pm 0.28$ )	69.59 ( $\pm 3.80$ )
+ RGCN	48.67 ( $\pm 0.28$ )	54.71 ( $\pm 0.37$ )	57.13 ( $\pm 0.36$ )	58.58 ( $\pm 0.17$ )	68.33 ( $\pm 0.85$ )	68.41 ( $\pm 0.66$ )
+ GconAttn	47.95 ( $\pm 0.11$ )	54.96 ( $\pm 0.69$ )	56.94 ( $\pm 0.77$ )	57.53 ( $\pm 0.31$ )	68.09 ( $\pm 0.63$ )	69.88 ( $\pm 0.47$ )
+ Link Prediction	47.10 ( $\pm 0.79$ )	53.96 ( $\pm 0.56$ )	56.02 ( $\pm 0.55$ )	60.84 ( $\pm 1.36$ )	66.29 ( $\pm 0.29$ )	69.33 ( $\pm 0.98$ )
+ PathGenerator-Local	<u>50.20</u> ( $\pm 0.31$ )	<u>55.68</u> ( $\pm 0.07$ )	56.81 ( $\pm 0.73$ )	61.56 ( $\pm 0.72$ )	67.77 ( $\pm 0.83$ )	70.43 ( $\pm 0.65$ )
+ PathGenerator-Global	49.89 ( $\pm 1.03$ )	55.47 ( $\pm 0.92$ )	57.21 ( $\pm 0.45$ )	<u>62.93</u> ( $\pm 0.82$ )	68.65 ( $\pm 0.02$ )	71.55 ( $\pm 0.99$ )
+ PathGenerator-Full	<b>51.97</b> ( $\pm 0.26$ )	<b>57.53</b> ( $\pm 0.19$ )	<b>59.07</b> ( $\pm 0.30$ )	<b>63.72</b> ( $\pm 0.77$ )	<b>69.46</b> ( $\pm 0.23$ )	<b>72.68</b> ( $\pm 0.42$ )

and global sampling paths. (2) **PathGenerator-Global** (or PG-Global) We equip our reasoning module with the global path generator which is trained on global sampling paths only, making it a data-independent module. (3) **PathGenerator-Full** (or PG-Full) We equip our reasoning module with both the global path generator and the **RN** baseline described above. In specific, we extend Eq. 8 by feeding the concatenation of the context embedding, the path embedding and the static knowledge embedding to the classifier.

#### 4.5 Overall Results

We explore BERT-large (Devlin et al., 2018) and RoBERTa-large (Liu et al., 2019) as our text encoder for *CommonsenseQA* and RoBERTa-large for *OpenBookQA*. The results are shown in Table 3 and Table 4 respectively. On both datasets, we observe consistent improvements across different proportion of training data with our method. With RoBERTa-large, either our local variant or the global variant achieves the second best results on both datasets, demonstrating the effectiveness of the generated paths as the structured evidence and their superiority over the static KG methods. Such superiority is also shown by the results of our Link Prediction baseline. This baseline outperforms or is comparable to several static KG methods in several cases, indicating that even predicting 1-hop knowledge paths is helpful to address the sparsity issue. Still, our full model which combines both dynamic and static knowledge achieves the best performance overall<sup>2</sup>, suggesting that it would be quite beneficial to leverage both knowledge sources. We also investigate whether our path generator could further improve the SOTA system of *CommonsenseQA*,

<sup>2</sup>Our full model outperforms all the baselines significantly with p-value less than 0.05.

Table 4: **Classification accuracy on different proportion of training data from OpenBookQA**. Standard deviation for 4 runs is omitted due to limited space.

Methods	20%	60%	100%
RoBERTa-large (w/o KG)	34.45	54.90	64.80
+ RN	44.60	62.00	65.20
+ RGCN	41.35	47.20	62.45
+ GconAttn	41.20	55.80	64.75
+ Link Prediction	35.35	58.55	66.29
+ PG-Local	48.80	60.00	70.47
+ PG-Global	<u>51.00</u>	<u>62.95</u>	68.40
+ PG-Full	<b>51.90</b>	<b>63.95</b>	<b>71.20</b>

Table 5: Classification accuracy on CommonsenseQA (Lin et al.’s split) with the reported SoTA system, **Albert** (Lan et al., 2019), as the text encoder.

Methods	Dev	Test
Albert (w/o KG)	78.26	73.98
+ RN	<b>79.24</b>	73.65
+ RGCN	78.46	<u>74.66</u>
+ GconAttn	<b>79.31</b>	<u>73.99</u>
+ PG-Local	77.56	73.33
+ PG-Global	78.67	74.46
+ PG-Full	78.42	<b>76.19</b>

which is another text encoder, Albert (Lan et al., 2019) at this stage. The results are displayed in Table 5, where again we find our full model still achieves the best performance. The analysis of robustness to limited training data would be discussed in the next section.

#### 4.6 Performance Analysis

**Quantitative Analysis on Paths** To analyze the generated paths from our generator quantitatively, we evaluate several metrics in terms of their validity and novelty as follows. For validity, we analyze (1)

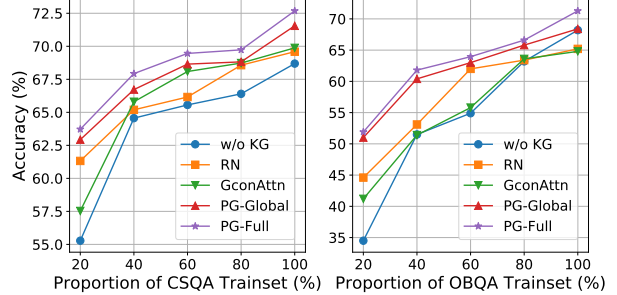
Table 6: Quantitative Analysis on the Generated Paths for the Task Testset.

Dataset	Connection	Valid Entity	Valid Relation	Score	Novelty
<i>CommonsenseQA</i>	97.33	98.64	100.00	59.31	75.82
<i>OpenBookQA</i>	96.03	99.21	100.00	57.74	78.93

the proportion of the paths which successfully connect the starting and ending entities (Connection), (2) the proportion of the entities/reasons which exist in the ConceptNet (Valid Entity / Valid Relation). We also leverage a commonsense knowledge base completion model, **Bilinear AVG** (Li et al., 2016), which gives a score for a given triplet. Such a model achieves 92.5% accuracy on the commonsense knowledge completion task and is also used in previous work (Bosselut et al., 2019), suggesting that it is a strong model for scoring the validity of knowledge facts. We average the scores of all the triplets which are not presented in ConceptNet in a path as its score (Score). For novelty, we analyze the proportion of paths which are considered as novel once they contain at least one triplet not presented in ConceptNet (Novelty). We also have qualitative analysis with case study in Section 4.7.

The evaluation is conducted with our global variant on both datasets and the results are displayed in Table 6, from which we could observe the followings. Firstly, our generator has no trouble in connecting the given entity-pair with the valid paths which follow strictly the schema of ConceptNet. For example, our generator only uses the relations in the relation set as the connection instead of some random phrases. Meanwhile, the paths are of high quality since any knowledge fact with a score over 0.5 is classified as positive by **Bilinear AVG**, which is indeed the case on both datasets. Finally, the paths are also highly novel (over 70%) which indicates their helpfulness in complementing a static KG.

**Ablation Study** We conduct further analysis to study the contribution of different strategies for learning our generator based on the performance of our **Global** and **Local** variants in Table 3-5. We also include another variant as ablation by learning our path generator with a randomly-initialized GPT-2 instead of fine-tuning a pre-trained one. This **Random** variant only achieves 68.75 and 65.50 in accuracy on *CommonsenseQA* and *OpenBookQA* respectively with RoBERTa-large as the text encoder, failing to outperform some static KG baselines considerably. This demonstrates that learning the knowledge paths from scratch only provides

Figure 3: Accuracy on *CommonsenseQA* (left) and *OpenBookQA* (right) with different proportion of training data.

the generator with what a static KG has already. The unstructured knowledge stored in a pre-trained GPT-2 helps to complement what a static KG might lack. Meanwhile, with a more powerful text encoder like RoBERTa or Albert, our **Global** variant achieve comparable or better results than our **Local** variant without even seeing the task-centered paths. This shows another merit of our method, which is our **Global** path generator is very promising in serving as a plug-in neural KG for any task dataset with better generalization ability.

**Performance under Limited Labeled Data** We investigate the low-resource scenario where we only use {20%, 40%, 60%, 80%, 100%} of the training data from both datasets for training to see whether our model is more robust to data sparsity than the baselines. The full results from Figure 3 show that our method (with RoBERTa) outperforms or is comparable to the baselines with different amounts of training data. The performance gain brought by either our Global or Full model is more considerable when extremely less data is used. This greatly demonstrates the effectiveness of introducing structured evidence as inductive bias for the low-resource setting.

#### 4.7 Case Study on Model Interpretability

In Table 7, we show case studies on the paths generated respectively by our **Local** and **Random** variant for connecting the question entities to the gold answer entities. In Q1, we observe that our path generator can provide knowledge about the loca-

Table 7: Generated paths from question entities to gold answer entities.

Q1: Where would you find <b>magazines</b> along side many other printed works? A: doctor. <i>B*</i> : <i>bookstore</i> . C: market. D: train station. E: mortuary. Path from PG-Local: {magazine, isa, book, atlocation, bookstore} (2-hop) Path from PG-Random: {magazine, _isa, magazine, atlocation, bookstore}
Q2: If you want <b>harmony</b> , what is something you should try to do with the world? A: take time. B. make noise. C. make war. <i>D*</i> : <i>make peace</i> . E. make haste. Path from PG-Local: {harmony, _hassubevent, make better world, hasprerequisite, make peace} (2-hop) Path from PG-Random: {harmony, _usedfor, committing perjury, causes, make peace}
Q3: Janet was watching the <b>film</b> because she liked what? A: rejection. B: laughter. <i>C*</i> : <i>being entertained</i> . D: fear. E: boredom. Path from PG-Local: {film, usedfor, being entertained} (1-hop) Path from PG-Random: {film, _hascontext, being entertained}
Q4: What do people typically do while playing <b>guitar</b> ? A: cry. B: hear sounds. <i>C*</i> : <i>singing</i> . D:arthritis. E:making music. Path from PG-Local: {guitar, usedfor, playing music, _causes, singing} (2-hop) Path from PG-Random: {guitar, hascontext, music, _causes, singing}

tion of the entity with a 2-hop path, which is helpful in answering this kind of “Where” question. Although the path from our **Random** generator also contains the *atlocation* relation, it fails to predict properly for the first hop knowledge (*\_isa*). In Q2, we observe that the path from our **Local** variant provides knowledge about the continuous intention of human with a 2-hop path while the path from our **Random** variant contains wrong information by stating that *peace* is caused by *committing perjury*. In Q3, we find that the path from our full model could provide knowledge about the property of entity and also figure out when a 1-hop relation is sufficient to connect the question-answer entities. For our **Random** variant, however, it fails to predict a more informative relation (*\_hascontext*). Similar observation is also seen in Q4. All these cases demonstrate that a fine-tuned pre-trained GPT-2 is superior in generalizing commonsense paths by leveraging the unstructured knowledge encoded in it.

## 5 Related Work

**Multi-hop Reasoning on KGs.** Like commonsense QA, the recent benchmark datasets in the fields of open domain QA (Yang et al., 2018), reading comprehension (Welbl et al., 2018), etc., also require the corresponding systems to conduct multi-hop reasoning. Significant work exists to develop such models based on static KGs. Typically, these works employ entity linking systems to recognize the entities mentioned in the context and then re-

trieve the knowledge paths as the local graph structure around the entities. They further score or rank the retrieved paths using graph-based metrics (e.g., PageRank, centrality) (Paul and Frank, 2019; Fadnis et al., 2019; Bauer et al., 2018), handcrafted rules (Kapanipathi et al., 2019) or neural methods (e.g., attention mechanisms) (Kundu et al., 2018; Lin et al., 2019). The main difference between their work and ours is that rather than relying on a static KG, our paths generator is able to generate knowledge paths on the fly, which could be absent from an incomplete KG.

**Dynamic Knowledge Path Generation or Prediction.** Prior work also investigates methods generate or predict reasoning or knowledge paths instead of extracting them from some static KGs. Work by Asai et al. (2019) learns to predict evidence documents sequentially to form their reasoning paths, but still requires the inter-links between documents on their constructed KG. Fu et al. (2019) proposes a fact extractor for retrieving missing facts to complement the incomplete KGs. But they limit their setting to knowledge graph reasoning, where both a query entity and a single query relation are given. The most relevant work to ours is from Bosselut and Choi (2019) which also leverages the language model GPT-2 to dynamically generate knowledge paths. However, they expand their paths by predicting the next entity one at a time while we generate the paths in an end-to-end manner. Moreover, their method is limited to the setting where the whole context could be treated as a single entity and the question could be treated



as a query relation. We do not have such a limitation and could be applicable to more general commonsense QA.

## 6 Conclusion

This paper proposes a generator which generates multi-hop knowledge paths as structured evidence for answering commonsense questions. To learn such a path generator, we fine-tuned GPT-2 on the random walks sampled from a commonsense KG. Then the generator connects each pair of question and answer entity with a knowledge path. These paths are further aggregated as knowledge embedding and fused with context embedding given by a text encoder for classification. Experimental results on two benchmark datasets demonstrate the effectiveness of our method in outperforming both strong pre-trained language models and static KG augmented methods. Besides the improvement, we also show that the generated paths are interpretable in terms of their informativeness and helpfulness. Future works include how to decouple the generator with the text encoder and a better way to fuse the knowledge.

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## A Algorithm for Paths Sampling

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### Algorithm 1 Paths Sampling

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**Input:**  $\mathcal{G} = (\mathcal{E}, \mathcal{R})$  and a set of all the question entities  $\{e^q\}$

**Output:** A set of triplet paths  $\{p\}$ .

```
1: repeat
2:   if Do Global Sampling then
3:     current_node  $u \leftarrow \text{uniform\_sample}(\mathcal{E})$ 
4:   else
5:     current_node
        $u \leftarrow \text{uniform\_sample}(\{e^q\})$ 
6:   end if
7:    $p \leftarrow \{u\}$ 
8:   for  $t = 1$  to  $T$  do
9:      $N \leftarrow \text{Neighbor}(u)$ 
10:    next_node  $v \leftarrow \text{uniform\_sample}(N)$ 
11:     $M \leftarrow \text{All\_Relations}(u, v)$ 
12:    while TRUE do
13:       $r \leftarrow \text{uniform\_sample}(M)$ 
14:      if  $r$  not in  $p$  then
15:        BREAK
16:      end if
17:    end while
18:     $p \leftarrow p \cup \{r, v\}$ 
19:     $u \leftarrow v$ 
20:  end for
21: until Maximum number of paths achieved.
```

---

The batch size is chosen from  $\{8, 16, 32, 64, 128\}$ . A large batch size is achieved by accumulating gradient through several small batches. We also train our model with a warm-up period of 1000 mini-batches and linearly decrease the learning rate. The training lasts until the accuracy on the development set no longer increases for 2 epochs.

## B Discarded Relations

When sampling knowledge paths, we discard some relation types which are regarded to be uninformative and offer little help for answering the questions. They include *relatedto*, *synonym*, *antonym*, *derived-from*, *formof*, *etymologicallyderivedfrom* and *etymologicallyrelatedto*.

## C Hyper-parameters

We employ a pre-trained GPT2-base model (Radford et al., 2019) as the initialization of our generator. Then we fine-tune the generator with an initial learning rate of  $1e - 5$  and a batch size of 128. The learning rate is changed with a warm-up period of 1000 mini batches and then linearly decayed. The training lasts until the loss on the development set no longer decreases for 2 epochs.

For training on task datasets, we search the optimal hyper-parameters based on the classification accuracy on the development set. The initial learning rate is choosing from  $\{5e - 6, 1e - 5, 5e - 5\}$ .