Incorporating Connections Beyond Knowledge Embeddings: A Plug-and-Play Module to Enhance Commonsense Reasoning in Machine Reading Comprehension

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Abstract

Conventional Machine Reading Comprehension (MRC) has been well-addressed by pattern matching, but the ability of commonsense reasoning remains a gap between humans and machines. Previous methods tackle this problem by enriching word representations via pre-trained Knowledge Graph Embeddings (KGE). However, they make limited use of a large number of connections between nodes in Knowledge Graphs (KG), which could be pivotal cues to build the commonsense reasoning chains. In this paper, we propose a Plug-and-play module to Incorporate Connection information for commonsense reasoning (PIECER). Beyond enriching word representations with knowledge embeddings, PIECER constructs a joint query-passage graph to explicitly guide commonsense reasoning by the knowledge-oriented connections between words. Further, PIECER has high generalizability since it can be plugged into suitable positions in any MRC model. Experimental results on ReCoRD, a large-scale public MRC dataset requiring commonsense reasoning, show that PIECER introduces stable performance improvements for four representative base MRC models, especially in low-resource settings.\footnote{We will release our code once this paper is officially accepted.}

1 Introduction

Machine Reading Comprehension (MRC) is a pivotal and challenging task in Natural Language Processing (NLP), which aims to automatically comprehend a context passage and answer related queries. In recent years, especially after the proposal of various large-scale Pre-Trained Models (PTM) (Devlin et al., 2019; Liu et al., 2019), MRC has achieved great success on multiple datasets such as SQuAD (Rajpurkar et al., 2016) and NewsQA (Trischler et al., 2017). However, current state-of-the-art models perform significantly worse on ReCoRD (Zhang et al., 2018), a large-scale MRC dataset that is more challenging since it requires commonsense reasoning. This suggests that current excellent performances of MRC models may be due to the strong ability of pattern matching (Jia and Liang, 2017; Rajpurkar et al., 2018; Kaushik and Lipton, 2018), but they still lag behind in the ability of commonsense reasoning.

Figure 1 illustrates the difference between SQuAD and ReCoRD. The SQuAD example requires only simple pattern matching, while the ReCoRD example requires commonsense reasoning. We mark the same keywords using the same underlines.

| SQuAD | Passage | … Teachers may use a lesson plan to facilitate student learning, providing a course of study which is called the curriculum … |
|-------|---------|--------------------------------------------------|
| Query | What is a course of study called? |
| Answer | the curriculum |

| ReCoRD | Passage | … a Tennessee teacher who kidnapped and fled with his 15-year-old student was arrested … "I'm glad this is over," 50-year-old Tad Cummins said after his arrest … Elizabeth Thomas was found safe in a remote cabin |
|--------|---------|--------------------------------------------------|
| Query  | Snipers surrounded the cabin as X exited the cabin and was taken into custody. |
| Answer | Tad Cummins |

Figure 1: Two examples selected from SQuAD and ReCoRD. The SQuAD example requires only simple pattern matching, while the ReCoRD example requires commonsense reasoning. We mark the same keywords using the same underlines.
there are confusing entities (Elizabeth Thomas as the hostage vs. Tad Cummins as the kidnapper) that require external knowledge for differentiation. Therefore, it is almost impossible to find the correct answer by only pattern matching. Instead, with the commonsense knowledge that “be taken into custody” is similar to “be arrested”, we can infer that Tad Cummins is the answer. These two examples reveal that pattern matching can only tackle MRC at a shallow level, while difficult datasets like ReCoRD require commonsense reasoning in depth.

To make up for the deficiency in commonsense reasoning, previous methods attempt to leverage knowledge stored in Knowledge Graphs (KG) such as WordNet (Miller, 1995), NELL (Carlson et al., 2010), and ConceptNet (Speer et al., 2017). Mihaylov and Frank (2018) encode knowledge as a key-value memory and enrich each word by memory querying. Yang and Mitchell (2017) and Yang et al. (2019) enrich each word by applying attention mechanism to its KG neighbors and a sentinel vector. Qiu et al. (2019) propose to update the representation of each word by aggregating knowledge embeddings of its KG neighbors via graph attention (Zhou et al., 2018). These methods enrich each word separately by fusing pre-trained knowledge embeddings. However, how to explicitly leverage knowledge-oriented connections between words in KGs, which could be pivotal cues to build the commonsense reasoning chains, are barely investigated.

In this paper, we propose a Plug-and-play module to Incorporate Connection information for commonsEnse Reasoning (PIECER). Beyond leveraging only knowledge embeddings, PIECER constructs a joint query-passage graph to explicitly guide commonsense reasoning by the knowledge-oriented connections. Further, PIECER has high generalizability since it can be plugged into suitable positions in any MRC model. PIECER is composed of three submodules. The knowledge embedding injection submodule aims to enrich words with background knowledge by fusing knowledge embeddings pre-trained on an external KG. The knowledge-guided reasoning submodule aims to leverage knowledge-oriented connections to guide interactions between words, thus facilitating commonsense reasoning chain building. The self-matching submodule is optional, aiming to further adapt the knowledge-enhanced information to a specific MRC task.

Our contributions are summarized as follows:

- Beyond leveraging only knowledge embeddings, we propose to incorporate the connection information in KGs to guide commonsense reasoning in MRC.
- We design a plug-and-play module called PIECER for high generalizability, which can be plugged into suitable positions in any MRC model to enhance its ability of commonsense reasoning.
- We evaluate PIECER on ReCoRD, a large-scale public MRC dataset requiring commonsense reasoning. Experimental results and elaborate analysis validate the effectiveness of PIECER, especially in low-resource settings.

## 2 Methodology

In this section, we first formulate the MRC task and then describe our proposed PIECER in detail.

### 2.1 Task Formulation

Let $\mathcal{P}$ denote a context passage consisting of $N$ words $\mathcal{P} = \{w_i^{(p)}\}_{i=1}^{N}$ and $\mathcal{Q}$ denote a query consisting of $M$ words $\mathcal{Q} = \{w_i^{(q)}\}_{i=1}^{M}$. Given $\mathcal{P}$ and $\mathcal{Q}$, MRC requires reading and comprehending them and then predicting an answer to the query. Specifically, in this paper, we tackle the extractive MRC that requires extracting a continuous span in $\mathcal{P}$ as the answer, i.e., answer = $w_{s:t}^{(p)}$, where $s$ and $t$ are the answer boundaries.

### 2.2 Proposed Module: PIECER

As shown in Figure 2 (a), PIECER is composed of three submodules: a knowledge embedding injection submodule, a knowledge-guided reasoning submodule, and an optional self-matching submodule. In this subsection, we describe them in detail.

#### 2.2.1 Knowledge Embedding Injection

In an MRC model, word representations are learned based on the data distribution in the training set and are thus limited within the dataset. However, commonsense reasoning usually requires background knowledge beyond the dataset as shown in Figure 1. To inject external background knowledge into words, this submodule adopts a gating mechanism to fuse word representations with pre-trained knowledge embeddings.

First, we adopt Knowledge Graph Embedding (KGE) methods, such as TransE (Bordes et al.,
2013) or DistMult (Yang et al., 2015), to pre-train knowledge embeddings for each entity in a KG:

\[ \{e_i\} = \text{KGE}(G), \]

where \( \{e_i\} \) is the entity embedding set and \( G \) is the selected KG.

Then, for each word \( w \) in \( P \) and \( Q \), we retrieve from \( G \) all unigram entities \( e_i \) that have the same lemma with \( w \), and adopt a gating mechanism to fuse the word representation and the retrieved knowledge embeddings:

\[
e = \text{Mean}(\{e_i | \text{lemma}(e_i) = \text{lemma}(w)\}),
\]

\[
gate = \sigma(W_g[w; e] + b_g),
\]

\[
w' = w \cdot \gate + e \cdot (1 - \gate),
\]

where \text{lemma}(\cdot) denotes lemmatization. \( e \) is the mean entity embedding. \( w \) is the input word representation. \( \sigma \) denotes sigmoid. \( W_g \) and \( b_g \) are trainable parameters. \( \gate \) is the gating weight. \( w' \) is the output word representation with background knowledge.

### 2.2.2 Knowledge-guided Reasoning

Although the knowledge embedding injection submodule injects background knowledge into each word, the connections between words are not explicitly leveraged. To incorporate the connection information, this submodule constructs a joint query-passage graph according to the structure of \( G \) and designs a Highway GAT for multi-hop reasoning.

To construct the joint graph, we treat words in \( P \) and \( Q \) as nodes and consider three categories of edges: knowledge edge, coreference edge, and self-loop. For knowledge edge, we first link each word in the passage or query to an entity in \( G \) by lemma matching. Then, for each pair of words, if they are connected in \( G \), we add an edge between them. For coreference edge, we assume that two words with the same lemma are coreferential and add an edge between them. For self-loop, we add an edge between each word and itself. In particular, we exclude all edges connecting stop words and punctuations. An example of the joint query-passage graph is shown in Figure 3.

After constructing the joint query-passage graph, we design a Highway GAT that combines Highway Networks (Srivastava et al., 2015) and GAT (Velickovic et al., 2018) for multi-hop reasoning. Under the guidance of the joint graph, the Highway GAT expressly amplifies the interactions between knowledge-related nodes, which can help to build the commonsense reasoning chains. All nodes are updated for \( L \) times. At the \( l \)-th layer, we first calculate the updated representation \( h_i^{(l)} \) for each node \( i \) by averaging \( K \) attention heads:

\[
h_i^{(l)} = \frac{1}{K} \sum_{k=1}^{K} \sum_{j \in N(i)} a_{k,i,j}^{(l)} W_k^{(l)} h_j^{(l-1)},
\]

\[
a_{k,i,j}^{(l)} = \text{Softmax}_j \left( e_{k,i,j}^{(l)} \right),
\]

\[
e_{k,i,j}^{(l)} = \sigma_T \left( a_k^{(l)T} \left[ W_k^{(l)} h_j^{(l-1)}; W_k^{(l)} h_j^{(l-1)} \right] \right),
\]

where \( h_i^{(l)} \) denotes the hidden state of node \( i \) at the \( l \)-th layer. Specially, we set \( h_i^{(0)} \) to the output word representation with background knowledge \( w_i' \). \( N(i) \) denotes the neighbor set of node \( i \) in the joint graph. \( \text{Softmax}_j \) denotes softmax for
Passage: … a teacher who kidnapped and fled with his 15-year-old student was arrested …
… 50-year-old Tad Cummins said after his arrest …
… Elizabeth Thomas was found safe in a remote cabin …
Snipers surrounded the cabin as X exited the cabin and was taken into custody.

Query: Snipers surrounded the cabin as X exited the cabin and was taken into custody.

Figure 3: An illustration of a joint query-passage graph. For simplicity, we show only several instances for each category of edges. Red X in the query denotes the answer placeholder to be replaced by an entity in the passage.

2.2.3 Self-matching (Optional)

Previous submodules enhance the ability of commonsense reasoning, but they do not directly address MRC. Therefore, we need a final step to adapt the knowledge-enhanced information to the specific MRC task. To achieve this, we design a self-matching submodule at the end of PIECER.

We use a transformer block (Vaswani et al., 2017) to implement this submodule, which is composed of a multi-head self-attention layer and two fully connected layers:

$$o'_t = \text{SelfAttention}(h^{(L)}_{1:N}) + h^{(L)}_{1:N},$$
$$o_t = \text{FC}_2(\text{ReLU}(\text{FC}_1(o'_t))) + o'_t,$$

where $h^{(L)}_{1:N}$ are knowledge-enhanced representations of all passage tokens. $\text{FC}_x$ denotes fully connected layers. $o_t$ is the final output of PIECER.

Note that PIECER is a plug-and-play module working by plugging into other MRC models. If an MRC model has its own matching module, we do not need another one in PIECER. Therefore, this submodule is optional, depending on the specific to-plug MRC model.

2.3 Plugging PIECER into MRC Models

As a plug-and-play module, PIECER has high generalizability since it can be plugged into suitable positions in any MRC model. Figure 2 (b) demonstrates the usage of plugging in PIECER. For an MRC model, we first need to split it into two sequential parts: (1) The preceding part that takes $\mathcal{P}$ and $\mathcal{Q}$ as inputs and outputs their representations. (2) The subsequent part that takes these representations as inputs and predicts the final answer. Then, we can plug PIECER between them. For example, we can plug PIECER after the embedding layer or before the prediction layer for any MRC model.

3 Experiments

In this section, we describe our experimental settings and provide experimental results and analysis.

3.1 Datasets

We conduct experiments on ReCoRD (Zhang et al., 2018), a large-scale public MRC dataset requiring commonsense reasoning. ReCoRD contains a total of 120,730 examples, 75% of which require commonsense reasoning and is split into training, development, and test set with 100,730, 10,000, and 10,000 examples, respectively. Each example contains a context passage and a query, where the passage has 169.3 tokens on average and the query has 21.4 tokens on average. Given an example, ReCoRD requires predicting an entity span in the context passage as the answer, which can replace the entity placeholder in the query, as shown in Figure 1.

For the external commonsense knowledge, we select a large-scale commonsense knowledge graph ConceptNet (Speer et al., 2017). ConceptNet contains 34 relation categories, over 21 million relational facts, and over 8 million nodes. In this paper, we use an English subset with 1,165,190 nodes and 3,423,004 relational facts since ReCoRD is an English dataset.
Table 1: Main evaluation results on ReCoRD. ∆ EM and ∆ F1 denote the improvements of EM and F1 introduced by PIECER, respectively. Results on the test set are returned by the SuperGLUE online evaluation system.

| Model               | Dev EM | ∆ EM | Dev F1 | ∆ F1 | Test EM | ∆ EM | Test F1 | ∆ F1 |
|---------------------|--------|------|--------|------|---------|------|---------|------|
| QANet               | 36.79  | -    | 37.32  | -    | 38.4    | -    | 38.9    | -    |
| QANet + PIECER      | 39.69  | 2.90↑| 40.20  | 2.88↑| 40.6    | 2.2↑| 41.1    | 2.2↑|
| BERT<sub>base</sub>| 62.12  | -    | 62.76  | -    | 62.2    | -    | 62.8    | -    |
| BERT<sub>base</sub>+ PIECER | 63.40  | 1.28↑| 64.01  | 1.25↑| 63.2    | 1.0↑| 63.8    | 1.0↑|
| BERT<sub>large</sub> | 71.86  | -    | 72.55  | -    | 72.4    | -    | 72.9    | -    |
| BERT<sub>large</sub>+ PIECER | 72.39  | 0.53↑| 73.04  | 0.49↑| 73.6    | 1.2↑| 74.3    | 1.4↑|
| RoBERTa<sub>base</sub> | 78.89  | -    | 79.52  | -    | 79.7    | -    | 80.3    | -    |
| RoBERTa<sub>base</sub>+ PIECER | 79.42  | 0.53↑| 80.04  | 0.52↑| 80.1    | 0.4↑| 80.7    | 0.4↑|

3.2 Base Models
To validate the effectiveness and generalizability of PIECER as a plug-and-play module, we plug PIECER into four representative MRC models as follows: (1) QANet (Yu et al., 2018) is an outstanding MRC model without using PTMs. It contains five modules for embedding, encoding, passage-query attention, self-matching, and prediction. (2) BERT (Devlin et al., 2019) is one of the most widely-used PTMs. It uses multi-layer bidirectional transformers (Vaswani et al., 2017) as the encoder, and uses Masked Language Models (MLM) and Next Sentence Prediction (NSP) as pre-training tasks. We select both BERT<sub>base</sub> and BERT<sub>large</sub> as our base models. They share the same design but are pre-trained under different configurations. (3) RoBERTa (Liu et al., 2019) is a modified PTM based on BERT. Firstly, it improves the MLM task and removes the NSP task. Secondly, it is pre-trained on larger corpora with a larger batch size for a longer time. Due to the limitation of our computing resources, we select only RoBERTa<sub>base</sub> as the base model. For MRC, both BERT and RoBERTa are followed by a linear prediction layer to predict the answer span.

3.3 Experimental Settings
For pre-trained knowledge embeddings, we select TransE (Bordes et al., 2013) implemented by OpenKE (Han et al., 2018) as the pre-training method, use Adam (Kingma and Ba, 2015) with an initial learning rate of $10^{-5}$ as the optimizer, set the knowledge embedding dimension to 100, and pre-train for 10,000 epochs.

For PIECER, we tune hyper-parameters on the development set. For a fair comparison, we first tune the base models to achieve the best performance, and then fix their hyper-parameters before tuning PIECER. Generally, we use AdamW (Loshchilov and Hutter, 2019) with $\beta_1 = 0.9, \beta_2 = 0.98$, weight decay = 0.01 as the optimizer, apply exponential moving average with a decay rate of 0.9999 on trainable parameters, set all dropout rates to 0.1, set the number of Highway GAT layers to 3, and set the number of attention heads to 4. Other key hyper-parameters, including learning rate, hidden dimension, and batch size, are different for each base model, and we provide details in Appendix A.

3.4 Evaluation Metrics
Following previous works, we use Exact Match (EM) and F1 as the evaluation metrics. EM measures the percentage of the predicted answers that exactly match the ground-truth answers. F1 measures the token overlapping level between the predicted answers and the ground-truth answers. Both metrics ignore punctuations and articles. Since the test set is not publicly available, we use the SuperGLUE (Wang et al., 2019) online evaluation system<sup>2</sup> to obtain our test evaluation results.

3.5 Main Results
We show in Table 1 the main evaluation results on ReCoRD. For each of the four base models, we compare the performance of the original model and the PIECER-plugged version (denoted as $X + PIECER$). From the table, we have the following observations: (1) PIECER introduces stable EM...
and F1 improvements for all base models. This validates the effectiveness of PIECER to enhance MRC that requires commonsense reasoning. (2) Comparing the performance improvements on four base models, QANet benefits the most from PIECER as an MRC model without using PTMs, while PTMs like BERT and RoBERTa gain moderate improvements. We speculate that this difference may be due to the knowledge overlaps between PTMs and PIECER: PTMs have already encoded certain knowledge in their representations implicitly, which may overlap with commonsense knowledge introduced by PIECER. (3) We further investigate three PTMs that may contain overlapping knowledge, and observe that PIECER still introduces stable performance improvements. This is due to the difference in how to leverage knowledge: PTMs encode knowledge in an uncontrollable and implicit way, while PIECER can actively select related commonsense knowledge stored in a KG for explicit use.

### 3.6 Analysis and Discussions

In this subsection, we provide elaborate analyses of PIECER to further validate its effectiveness and explore its properties. Since the test set is not publicly available and the number of submissions to the online evaluation system is restricted, all analysis experiments are based on the development set.

#### 3.6.1 Ablation Study

To validate the effectiveness of each submodule in PIECER, we provide ablation experimental results of PIECER on the development set of ReCoRD in Table 2. We select RoBERTa\textsubscript{base} + PIECER as the baseline and attempt to remove the self-matching submodule, the knowledge embedding injection submodule, the knowledge-guided reasoning submodule, and the whole PIECER, respectively. Comparing the results of RoBERTa\textsubscript{base} + PIECER with three simplified versions, we observe that removing any submodule will result in a performance drop, especially for the knowledge-guided reasoning submodule. This suggests that each submodule is necessary for PIECER, and the connection information in a KG is more essential than knowledge embeddings for commonsense reasoning. Further, comparing the results of RoBERTa\textsubscript{base} with three simplified versions of PIECER, we observe that the performance of each simplified version is higher than that without the whole PIECER. This indicates that the base model can benefit from each submodule.

#### 3.6.2 PIECER in Low-resource Settings

Since PIECER has the ability to leverage external commonsense knowledge, we hypothesize that it can alleviate the problem of data insufficiency. To verify our hypothesis, we compare the performance of PIECER in different resource settings. First, we study how the amount of training data influences its effectiveness, using the F1 improvement introduced by PIECER (denoted by $\Delta F1$) as the metric. Figure 4 (a) shows the results: for both BERT\textsubscript{base} and RoBERTa\textsubscript{base}, PIECER can introduce more improvements when the amount of training data is smaller, i.e., with lower training resources. Secondly, we study how the amount of pre-training data influences the effectiveness of PIECER and show the results in Figure 4 (b). PIECER performs the best based on QANet that

| Model                              | EM   | F1   |
|------------------------------------|------|------|
| RoBERTa\textsubscript{base} + PIECER | 79.42| 80.04|
| w/o self-matching                  | 79.41| 79.99|
| w/o knowledge embedding injection  | 79.25| 79.92|
| w/o knowledge-guided reasoning     | 78.98| 79.67|
| RoBERTa\textsubscript{base}        | 78.89| 79.52|

Table 2: Ablation study of PIECER on the development set of ReCoRD based on RoBERTa\textsubscript{base}.

![Figure 4: F1 improvements introduced by PIECER in different training (a) / pre-training (b) resource settings.](image-url)
Table 3: Performance with different knowledge embeddings pre-trained under different configurations.

| Method (Pre-training Epochs) | EM   | F1   |
|------------------------------|------|------|
| DistMult (1,000 epochs)      | 38.82| 39.27|
| DistMult (5,000 epochs)      | 39.09| 39.55|
| TransE (1,000 epochs)        | 39.64| 40.15|
| TransE (10,000 epochs)       | 39.69| 40.20|
| w/o knowledge embedding injection | 39.18| 39.66|

Table 4: Performance of different GCN architectures.

| Model                      | EM   | F1   |
|----------------------------|------|------|
| Highway GAT                | 63.40| 64.01|
| Res GAT                   | 62.54| 63.16|
| w/o highway               | 58.39| 59.46|
| Highway GCN               | 62.64| 63.33|
| Highway GIN               | 62.66| 63.29|

As indicated by the above results, PIECER is especially effective with low training or pre-training resources. Thus, plugging in PIECER could be the simplest and cheapest solution when facing insufficient training data or the incapability to conduct large-scale pre-training.

3.6.3 Robustness to Different Knowledge Embeddings

To get a deeper understanding of the impact of knowledge embeddings on PIECER, we compare different pre-training ways. Table 3 shows the experimental results based on QANet+PIECER. From the table, we observe that: (1) A proper KGE method is essential, since the performance with knowledge embeddings pre-trained by DistMult (Yang et al., 2015) is even worse than that without using knowledge embeddings (w/o knowledge embedding injection). Even so, the impact of different KGE methods is not significant for PIECER. (2) PIECER is robust to the hyper-parameters, such as pre-training epochs, since for both DistMult and TransE, the number of epochs has little influence on the performance.

The above observations reveal the robustness of PIECER to KGE methods and hyper-parameters: PIECER can keep a high performance even with a sub-optimal configuration, since PIECER mainly benefits from the connection information instead of knowledge embeddings. By contrast, methods that leverage only knowledge embeddings are sensitive to KGE configurations and have to spend extensive efforts to search for the optimal. The robustness of PIECER to the pre-training KGE configuration can ease the burden of hyper-parameter tuning.

3.6.4 Impact of GCN Architectures

To validate the design of the Highway GAT in PIECER, we compare other GCN architectures with it based on BERT\textsubscript{base} + PIECER. Firstly, we study the effectiveness of the highway connection. As shown in Table 4, if we replace the highway connection by a simple residual connection (denoted by Res GAT), the performance will drop slightly. Further, if we remove the whole highway connection (denoted by w/o highway), the performance will be severely degraded. This suggests that the highway connection plays a key role in our Highway GAT. Secondly, we study the influence of basic GCN models. We replace GAT in our module by GCN (Kipf and Welling, 2017) or GIN (Xu et al., 2019), and keep the highway connection for both of them for a fair comparison. Table 4 shows that both Highway GCN and Highway GIN perform worse than Highway GAT. Thirdly, we study how
### Table 5: Performance with joint query-passage graphs constructed in different ways.

| Graph                        | EM  | F1  |
|------------------------------|-----|-----|
| joint query-passage graph    | 63.40 | 64.01 |
| w/o coreference edge         | 63.00 | 63.65 |
| w/o knowledge edge           | 62.34 | 62.98 |
| w/ complete graph            | 62.33 | 62.94 |

the number of Highway GAT layers and attention heads influences the performance. As shown in Figure 5 (a), Highway GAT achieves the peak performance with 3 layers. We speculate that too few layers may build too short reasoning chains, while too many layers may lead to the over-smoothing problem (Li et al., 2018). Figure 5 (b) shows that Highway GAT achieves the best performance with 4 heads, which reveals that the attention heads are not the more the better.

#### 3.6.5 Impact of Graph Construction Methods

To study the impact of the joint query-passage graph, we compare different ways to construct the joint graph. In Table 5, we provide the results based on BERT\(_{base}\) + PIECER. From the table, we have the following observations: (1) Removing either the coreference edge or the knowledge edge degrades the performance. This verifies the necessity of these two categories of edges. (2) A complete graph performs worse than the joint query-passage graph in PIECER, and even worse than that with only the coreference or knowledge edge. This suggests that the effectiveness of the knowledge-guided reasoning submodule in PIECER is due to not only the Highway GAT reasoning model, but also the knowledge-oriented connections that can explicitly guide the reasoning chain building.

### 4 Related Work

MRC is a longstanding task in NLP. In recent years, deep learning based methods such as Match-LSTM (Wang and Jiang, 2017), BiDAF (Seo et al., 2017), DCN (Xiong et al., 2017), R-Net (Wang et al., 2017), and QANet (Yu et al., 2018) have become the mainstream. They share a similar paradigm, composed of an embedding module, an encoding module, an attention-based interaction module, a self-matching module, and a prediction module. As large-scale PTMs such as ELMo (Peters et al., 2018), GPT (Radford et al., 2018), BERT (Devlin et al., 2019), and RoBERTa (Liu et al., 2019) are proposed, MRC achieves further advance by adopting PTMs. However, their ability of commonsense reasoning remains a question.

As MRC datasets requiring knowledge such as ReCoRD are proposed, various methods attempt to introduce external knowledge stored in KGs such as ConceptNet (Speer et al., 2017), NELL (Carlson et al., 2010), and WordNet (Miller, 1995) into MRC. Mihaylov and Frank (2018) encode knowledge as a key-value memory and enrich each word by memory querying. Yang and Mitchell (2017) and Yang et al. (2019) enrich each word by applying attention mechanism to its KG neighbors and a sentinel vector. Qiu et al. (2019) update the representation of each word by aggregating knowledge embeddings of its KG neighbors. These methods enrich each word separately, ignoring the knowledge-oriented connections between words, while these connections form a main part to compose a KG and could be pivotal cues to build the commonsense reasoning chains.

Graph Convolutional Networks (GCN) are effective to deal with graph-like data. Kipf and Welling (2017) propose a fast approximate convolution method, which becomes one of the most popular spectral GCN models. Besides spectral GCNs, spatial GCNs such as GraphSAGE (Hamilton et al., 2017), GIN (Xu et al., 2019), and GAT (Veličković et al., 2018) form another category of GCNs. In recent years, GCNs have been applied to various NLP tasks such as Relation Extraction (Guo et al., 2019; Dai et al., 2020), Natural Language Inference (Wang et al., 2020), and Machine Reading Comprehension (Cao et al., 2019; Song et al., 2018; Qiu et al., 2019). However, existing GCN-based MRC methods do not thoroughly investigate the knowledge-oriented connections between words or explicitly incorporate them.

### 5 Conclusion

In this paper, we propose to enhance commonsense reasoning in MRC by explicitly incorporating the connection information in KGs. For high generalizability, we design a plug-and-play module called PIECER, which can be plugged into suitable positions in any MRC model. Experimental results on ReCoRD validate the effectiveness of PIECER by plugging it into four representative base MRC models. Further analysis reveals that PIECER is especially effective in low-resource settings.
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layer since $\text{BERT}_{\text{base}}$ is impartible. (6) We keep the optional self-matching submodule in PIECER. (7) We train for 4 epochs and evaluate the model on the development set after each epoch. Finally, we report the best F1 achieved during 4 epochs and use the corresponding model to predict answers on the test set.

**Hyper-parameters for $\text{BERT}_{\text{large}}$:**

1. We try the peak learning rate for BERT module in $\{0.00001, 0.00003, 0.00005\}$, and finally select 0.00003.
2. We try the peak learning rate for other modules in $\{0.0005, 0.001, 0.005\}$, and finally select 0.001.
3. We set the hidden dimension to 1024, the same as $\text{BERT}_{\text{large}}$.
4. We try the batch size in $\{4, 8, 16, 32\}$, and finally select 32.
5. We plug PIECER between $\text{BERT}_{\text{large}}$ and the predicting layer since $\text{BERT}_{\text{large}}$ is impartible.
6. We keep the optional self-matching submodule in PIECER.
7. We train for 4 epochs and evaluate the model on the development set after each epoch. Finally, we report the best F1 achieved during 4 epochs and use the corresponding model to predict answers on the test set.

**Hyper-parameters for $\text{RoBERTa}_{\text{base}}$:**

1. We try the peak learning rate for RoBERTa module in $\{0.00001, 0.00003, 0.00005\}$, and finally select 0.00001.
2. We try the peak learning rate for other modules in $\{0.0005, 0.001, 0.005\}$, and finally select 0.0005.
3. We set the hidden dimension to 768, the same as $\text{RoBERTa}_{\text{base}}$.
4. We try the batch size in $\{4, 8, 16, 32\}$, and finally select 4.
5. We plug PIECER between $\text{RoBERTa}_{\text{base}}$ and the predicting layer since $\text{RoBERTa}_{\text{base}}$ is impartible.
6. We keep the optional self-matching submodule in PIECER.
7. We train for 4 epochs and evaluate the model on the development set after each epoch. Finally, we report the best F1 achieved during 4 epochs and use the corresponding model to predict answers on the test set.