Roof-Transformer: Divided and Joined Understanding with Knowledge Enhancement

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Abstract

Recent work on enhancing BERT-based language representation models with knowledge graphs (KGs) and knowledge bases (KBs) has yielded promising results on multiple NLP tasks. State-of-the-art approaches typically integrate the original input sentences with KG triples and feed the combined representation into a BERT model. However, as the sequence length of a BERT model is limited, such a framework supports little knowledge other than the original input sentences and is thus forced to discard some knowledge. This problem is especially severe for downstream tasks for which the input is a long paragraph or even a document, such as QA or reading comprehension tasks. We address this problem with Roof-Transformer, a model with two underlying BERTs and a fusion layer on top. One underlying BERT encodes the knowledge resources and the other one encodes the original input sentences, and the fusion layer integrates the two resultant encodings. Experimental results on a QA task and the GLUE benchmark attest the effectiveness of the proposed model.

1 Introduction

Although BERT dominates multiple benchmark datasets, various studies have conducted to incorporate extra knowledge into language models (LMs) to advance language modeling (Zhang et al., 2019; Liu et al., 2019a; Wang et al., 2020). Sources of this extra knowledge are mostly knowledge graphs (KGs) and knowledge bases (KBs) that contain rich knowledge facts and benefit language understanding. ERNIE (Zhang et al., 2019), for example, employs TransE (Bordes et al., 2013) to encode entity information, and concatenates them with token embeddings for input to a fusion layer. Despite its success on the GLUE benchmark, ERNIE does not consider textual knowledge representation due to its token-level concatenation. K-BERT (Liu et al., 2019a), converts knowledge triples into textual forms and injects them into the input sentences, forming a tree representation for input to BERT. However, this approach considers little knowledge other than the original input sentences due to BERT’s intrinsic input length limitation (512 tokens).

Accordingly, we propose Roof-Transformer, a model with two underlying BERTs and a fusion layer, the Transformer encoder (Vaswani et al., 2017) as a fusion layer acting as a “roof” over the two BERTs. Roof-Transformer encodes the text input with one of the underlying BERTs and uses the other BERT to encode the knowledge information, and then integrates the two embeddings with the fusion layer for downstream tasks. This structure allows us to incorporate information from both the original text and from external knowledge sources. In addition, if memory permits and long input is needed, more than two BERTs can be employed using this structure.

Despite the intuitive nature of the proposed idea, several critical challenges must to be addressed:

(1) What is an appropriate model for a “roof”, and how does the roof distinguish individual outputs from the underlying BERTs?

(2) How many layers are needed for the roof to fuse the outputs from the underlying BERTs? This could involve a trade-off between computational resources and performance.

(3) Various model complexities may result in convergence times for the roof that differ from those of the BERTs. How should we address this during training?

(4) The proposed architecture allows for up to 512 tokens of knowledge. Although long, this remains a limitation; thus precise knowledge selection and effective representation are crucial to ensure good performance.

We investigate various factors and propose solutions for these challenges, as described in the following sections.
We conduct experiments on the QA task (Rajpurkar et al., 2016) with Chinese KBs and the GLUE benchmark with English knowledge corpus. Experimental results reveal that integrating knowledge using Roof-Transformer outperforms using a single BERT to integrate both the original input sentences and external knowledge.

Our contributions are summarized as follows:

- We propose Roof-Transformer, an architecture which uses two distinct BERTs to encode knowledge and input sentences, and demonstrate promising results on a QA task and the GLUE benchmark.
- Roof-Transformer addresses BERT’s input length limitation. We believe this will also facilitate NLP tasks where additional knowledge or long context comprehension is needed.
- We show that precise knowledge selection and effective representation are critical to improve the performance for downstream NLP tasks.

2 Related Work

Much work has been done to integrate knowledge bases or knowledge graphs for enhanced language representation.

Before strong pre-trained LMs such as BERT were proposed, research concerned joint representation learning of words and knowledge. (Wang et al., 2014) combine knowledge embeddings and word vectors, and (Toutanova et al., 2015) utilize a convolutional neural network to capture the compositional structure of textual relations, and jointly optimize entity, KBs, and textual relation representations. Both studies are based on the concept of word2vec (Mikolov et al., 2013) and TransE (Bordes et al., 2013).

After Google Inc. launched BERT in 2018, studies on KB/KG integration gradually focused on optimization with pre-trained LMs. ERNIE (Zhang et al., 2019), an early study, encodes knowledge information in KGs via TransE (Bordes et al., 2013), a knowledge embedding model trained on Wiki-data, and refines BERT pre-training using named entity masking and phrase masking. K-BERT (Liu et al., 2019a) injects knowledge into the text to form a sentence tree without the need to pre-train a model for knowledge embeddings, and adopts soft-position embeddings and a visibility matrix for structural information and to prevent diverting the sentence from its correct meaning. Based on these works, KEPLER (Wang et al., 2020) jointly optimizes knowledge embeddings and masks language modeling objectives on pre-trained LMs.

Other work involves the joint use of dual BERTs. For example, Sentence-BERT (Reimers and Gurevych, 2019) uses a model to derive sentence embeddings via BERTs, and uses a classifier to judge the similarity of two sentences. DC-BERT (Zhang et al., 2020), a decoupled contextual encoding framework to address the efficiency of information retrieval, uses an online BERT to encode the question once, and an offline BERT which
pre-encodes each document and caches their encodings.

There are also some solutions to sequence length limitation, such as BigBird (Zaheer et al., 2020), Longformer (Beltagy et al., 2020). Both of them address the quadratic dependency on sequence length by using sparse attention mechanism; while we adopt the full attention mechanism in our work.

3 Methodology

In this section, we describe in detail the framework of Roof-Transformer presented in Fig. 1, including the input formats for Roof-Transformer, which are sentences pairs and selected triples from KB.

3.1 Model Architecture

As shown in Fig. 1, the model architecture of Roof-Transformer contains three stacked modules: (1) the underlying BERT model, responsible for encoding tokens to meaningful representations; (2) the Fusion Layer, responsible for combining information from the underlying BERT model; and (3) the Prediction Layer, responsible for downstream tasks—in our case, QA and common natural language understanding (NLU) tasks.

Underlying BERT model

The underlying BERT model is composed of two independent BERT models: TASK-BERT and KB-BERT. TASK-BERT encodes the tokenized passages, which are identical to those input for a single BERT on each downstream task, into embeddings. KB-BERT encodes the tokenized triples from KBs to embeddings. Both embeddings are then concatenated and fed to the fusion layer as input.

Fusion layer

We select Transformer Encoder (TE) (Vaswani et al., 2017), LSTM (Hochreiter and Schmidhuber, 1997) and Linear layer as the candidates of our Fusion layer. The input of the fusion layer is the concatenation of the output embeddings from TASK-BERT, $Emb \in \mathbb{R}^{M \times d}$, and the output embeddings from KB-BERT, $Emb' \in \mathbb{R}^{N \times d}$, where $d$ is the hidden dimension of the word embeddings, $M$ is the length of the tokenized question and paragraph, and $N$ is the length of the tokenized triples from the KBs.

Prediction layer

The Prediction Layer is simply a linear NN layer, which is responsible for transforming high-dimension embeddings into appropriate logits for prediction and inference. The input of the prediction layer is the output embeddings of the fusion layer, $Emb'' \in \mathbb{R}^{(M+N) \times d}$, whereas the output of the QA task is $logits \in \mathbb{R}^{(M+N) \times 2}$. The two dimensions of the output logits in each position are the start and end logits, that is, the probability of whether the position is the start or the end position of the answer. In other NLU tasks, the output embeddings of the fusion layer are compressed to a single sequence length $AvgEmb \in \mathbb{R}^{d}$, whereas the output is $logits \in \mathbb{R}^{e}$, where $e$ is based on the number of classes of the predicted label.

The model parameters are updated by minimizing the cross-entropy loss between the output logits and the ground truths.

3.2 TASK-BERT Input Format

In this paper, we test the capability of Roof-Transformer on a QA downstream task and the GLUE NLU tasks. We follow the format of the input of the major approach for BERT. Each sentence pair from the dataset contains two passages, both of which are tokenized and concatenated with a [SEP] token for input to TASK-BERT.

Since BERT has a 512-token limitation on input length, we set a maximum length for our question passage and paragraph passage. If the length of the passage is shorter than the maximum length, which is generally the case in the question passage, [PAD] tokens are appended to the concatenated passage to fix the length of every input. If the passage length exceeds the maximum length, which is generally the case in paragraph passages, we truncate the passage.

3.3 KB-BERT Input Format

For our approach, we choose KBs as our external information. The KB contains triples, each of which consists of a head, a relation, and a tail, corresponding to the subject, the relation, and the object in a sentence.

The triples are selected via a heuristic algorithm (string match), which selects a triple if its head exists in the paragraph passage in the TASK-BERT input. The selected triples are then concatenated together and separated by the [SEP] token.

As shown in Fig. 2, we propose three expansion types—$Exp_0$, $Exp_1$, and $Exp_2$—for the selected triples. $Exp_0$ simply concatenates the components in the triple as a unit, and appends this to the previous unit. For Chinese KBs, $Exp_1$ further adds
Figure 2: Three expansion types.

[的], a Chinese token, between the head and relation, and adds [是] between the relation and tail to form a natural sentence (Agarwal et al., 2021). For English KBs, the input format will be equivalent to “head is a relation of tail”. The sentence, which is also the unit, is then concatenated after the previous unit. Exp2 is a refined version of Exp1: if the current head of the selected triple is identical to the head of the previous unit, the head is replaced by a pronoun and merged with the previous unit with a comma to form a larger sentence/unit.

4 Experiments

In this section, we describe the Roof-Transformer training as well as the fine-tuning results with different KBs and settings. The estimated number of parameters ranges from 200M to 230M, depending on the depth and of candidate the fusion layer. (see Appendix 6.2 for parameter setting details)

4.1 Dataset

For the QA task, we evaluated Roof-Transformer and the baseline models (Sec. 4.6) on the DRCD dataset (Shao et al., 2019), a Chinese QA benchmark. For the NLU tasks, we evaluated the model on the General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018), which was used for ERNIE (Zhang et al., 2019). GLUE is an English multi-task NLU benchmark consisting of 11 tasks, of which we used 8 to evaluate Roof-Transformer and compare it with the baseline models. These tasks use different evaluation metrics depending on their purpose. (see Appendix 6.1 for statistical details of each dataset)

DRCD
The Delta Reading Comprehension Dataset is an open-source Chinese QA dataset composed of paragraphs from Wikipedia articles and questions generated by annotators. The ground truths of each question-paragraph pair are the start and end position of the answer. The result is evaluated by the exact match (EM) score.

GLUE
We selected the following eight English GLUE benchmark tasks: (1) SST-2, a sentiment task using accuracy as the metric; (2) CoLA, an acceptability task using Matthews correlation; (3) MRPC, a paraphrase task using the F1 score; (4) STS-B, a sentence similarity task using Pearson–Spearman correlation; (5) QNLI, a natural language inference (NLI) task using accuracy; (6) QQP, a paraphrase task using the F1 score; (7) RTE, a NLI task using accuracy; and (8) MNLI, a NLI task using accuracy.

4.2 Knowledge Base

We employ HowNet and CN-DBpedia, Chinese KBs which are refined and used in K-BERT (Liu et al., 2019a) for QA. Each triple in the KBs includes a head, a relation, and a tail. We also use the KELM corpus as English KB to evaluate the model on common NLU tasks in the GLUE benchmark.

CN-DBpedia
CN-DBpedia (Xu et al., 2017) is a large-scale structured encyclopedia developed and maintained by the Knowledge Workshop Laboratory of Fudan University. It has been extended to fields such as law, industry, finance, and medical care, providing supporting knowledge services for intelligent applications in various industries. We use a refined version of CN-DBpedia by eliminating triples whose entity names are less than 2 in length or contain special characters like what was done in K-BERT. The refined CN-DBpedia contains around 5M triples.

HowNet
HowNet (Dong et al., 2006) is a large-scale KB containing Chinese concepts and vocabulary. Each entity is annotated with semantic units called sememes. In Hownet, sememes refer to some basic unit of senses. The triples in HowNet can be represented as head, contain, sememes. We adopt the same method in CN-DBpedia to obtain the refined version of HowNet, which contains a total of 52,576 triples.

KELM
The KELM corpus (Lu et al., 2021) consists of the entire Wikidata KG as natural text sentences. It contains around 15M sentences converted from
KG’s triples. The sentences are like the Exp2 examples in Fig. 2.

4.3 KB Format

Knowledge representation clearly effects model performance by influencing the differentiation quality of language understanding. The knowledge selected also effects model performance. Therefore, we evaluated 6 different input formats for KB-BERT, that is, combinations of 3 kinds of knowledge representation with 2 kinds of knowledge selection.

Representation

We represented KB knowledge with 3 types of expansions as mentioned in Section 3.3 (Exp0, Exp1, Exp2) and demonstrated in Fig. 2, and evaluated the model performance using these representations.

Selection

As mentioned in Section 3.3, a KB triple is selected if its head exists in the paragraph passage, regardless of whether its tail exists in the paragraph: this is denoted as as No_Tail. The other kind of selection is Has_Tail, meaning that the selected triple’s head and tail are both present in the paragraph passage. If the tail exists in the paragraph passage, the selected triple is more likely to be related to the paragraph passage.

4.4 KB Encoder

Since the computational complexity of self-attention mechanism is $O(N^2)$, where $N$ is the length of input tokens, acquiring knowledge embeddings can be computationally expensive. Hence, apart from using KB-BERT with full-attention, we also investigate the performance of our model with cached KB-BERT.

In cached KB-BERT experiment, we treated KB-BERT as an off-line BERT by acquiring knowledge embeddings through a cached (freeze) BERT before training, and the embeddings are then concatenated with the output of Task-BERT forming the input of the fusion layer during training and inference. It is worth noting that different from inputting the concatenated knowledge to KB-BERT all at once, we feed each triple to cached KB-BERT to get its embedding and dynamically concatenate all triples’ embeddings to feed to the fusion layer. For example, take [cls] Bill Gates is a founder of Microsoft [sep] Elon Musk is a founder of SpaceX [sep] as the original input; thus the individual input of cached KB-BERT will be [cls] Bill Gates is a founder of Microsoft [sep] and Elon Musk is a founder of SpaceX [sep]; then both output embeddings will be concatenated to form the knowledge embeddings as part of the input of the fusion layer (the other part is the passage embeddings from TASK-BERT).

4.5 Other Setting

We also conducted experiments to investigate the following factors which influence fusion efficiency.

Segmentation

Since the input of the fusion layer contains outputs from both underlying BERT models, each of which contains its own positional information, it is difficult for the Fusion Layer to distinguish the two parts. Thus, we add segmentation tokens to the KB-BERT and TASK-BERT input, and evaluate the two formats, which are denoted as type-1 and type-2 segmentation, to determine which is more effective.

The type-1 segmentation of KB tokens and padding tokens in KB-BERT is different, using [A] and [B] respectively; in TASK-BERT, the segmentation of question, paragraph, and padding tokens is [A], [B], [A] respectively. The first type of segmentation aims to separate the content of tokens in a single BERT.

As shown in Fig. 1, in the type-2 segmentation, every token in KB-BERT is set to [A]; whereas in TASK-BERT, the segmentation of every token is set to [B]. With the second type of segmentation we seek to separate the content of tokens of the two BERTs.

Fusion layer

We test different (1) Candidates (Linear, LSTM and Transformer encoder), (2) Depth, (3) Initialization (pre-trained or not) and (4) Learning rate of Fusion Layer.

It is worth noting that we modify the learning rate of Fusion Layer by increasing it comparing to those of Underlying BERTs, e.g. 5, 10, 20 times of the Underlying BERTs’ learning rate due to different model complexities of BERTs (high) and Fusion Layer (low).

The investigations in Sec. 4.3 - 4.5 are not only for better performance but also aim to answer the the questions mentioned in Sec. 1.
| Model                  | Max Para. Len. | Max Know. Len. | KB             | Fusion Layer Init. | EM score |
|-----------------------|----------------|----------------|----------------|--------------------|----------|
| BERT<sub>base</sub>-chinese | 450            | 0              |                |                    | 76.08    |
| BERT<sub>base</sub>-chinese† | 420            | 30             | HowNet         |                    | 76.20 †  |
| BERT<sub>base</sub>-chinese† | 400            | 50             | HowNet         |                    | 75.94 ‡  |
| BERT<sub>base</sub>-chinese† | 420            | 30             | CN-DBpedia     |                    | 75.63 ‡  |
| BERT<sub>base</sub>-chinese† | 400            | 50             | CN-DBpedia     |                    | 76.07 ‡  |
| Roof-Transformer      | 450            | 511            | HowNet         | BERT<sub>base</sub>-chinese | 77.45 †  |
| Roof-Transformer      | 450            | 511            | CN-DBpedia     | BERT<sub>base</sub>-chinese | 77.59 †  |
| Roof-Transformer      | 450            | 511            | HowNet         | random weight      | 76.31 †  |
| Roof-Transformer      | 450            | 511            | CN-DBpedia     | random weight      | 76.61 †  |

Table 1: Results of Roof-Transformer and baselines on QA tasks (%) with different KBs, initialization (init.), max paragraph length (para. len.) and max knowledge length (know. len.). Note that † indicates using knowledge in single BERT architecture (baseline).

| Model     | KB             | SST-2 | CoLA | MRPC | STS-B | QNLI | QQP | RTE | MNLI-m |
|-----------|----------------|-------|------|------|-------|------|-----|-----|--------|
| BERT<sub>base</sub> | -              | 93.3  | 52.1 | 88.0 | 85.0  | 90.5 | 71.2| 66.4| 84.6   |
| ERNIE     | Wikidata       | 93.5  | 52.3 | 88.2 | 83.2  | 91.3 | 71.2| 68.8| 84.0   |
| Roof-Transformer | KELM           | 93.0  | 54.4 | 89.0 | 84.2  | 90.6 | 70.3| 69.0| 84.3   |

Table 2: Results of Roof-Transformer and baselines on eight datasets of GLUE benchmark (%)

4.6 Baseline

In QA task, we compare Roof-Transformer to two baselines: BERT<sub>base</sub>-chinese (Devlin et al., 2018) without knowledge and a single BERT<sub>base</sub>-chinese with knowledge. In NLU tasks of GLUE, we compare Roof-Transformer to two baselines: BERT<sub>base</sub> without knowledge, and ERNIE (Zhang et al., 2019).

BERT<sub>base</sub>-chinese is pre-trained on WikiZh; BERT<sub>base</sub>, is pre-trained on the BookCorpus and English Wikipedia; ERNIE is pre-trained on English Wikipedia for large-scale textual corpora and Wikidata for KGs.

4.7 Results

Necessity of Dual BERT

As mentioned in Sec. 4.6, for QA task, we test baseline with knowledge which encodes both text and knowledge with single BERT and without Fusion Layer. That is, a partition of paragraph should be sacrificed for knowledge tokens. (see Appendix 6.2 for details of input length settings)

As we can see in Table 1, sacrificing information of paragraph in exchange of knowledge may be slightly beneficial in some cases; however, in most cases, it results in performance drop. Therefore, the need of second BERT to encode knowledge separately is guaranteed.

Candidate of Fusion Layer

As shown in Figure 3 (all settings are the same and follow Appendix 6.3), the performance of every roof candidates beats both baselines (except a dramatic drop in LSTM with the use of CN-DBpedia). Linear and LSTM both achieve better performance compared to Transformer without pre-train while using HowNet. The pre-trained Transformer consistently outperforms its variants with different KBs (the Cached KB-BERT case will be discussed later). This shows the effectiveness of our roof-architecture and the power of pre-trained transformer, which was selected as our Fusion Layer for the rest of the experiments.

QA performance

The best parameter setting for QA task we found through experiments are presented in Appendix 6.3. As shown in Table 1, with external information from KBs, the EM score improvement on the QA task exceeds 1.5%, which attests the benefits of utilizing KBs. Perhaps the slight difference between the EM scores of CN-DBpedia and HowNet in Table 1 is because CN-DBpedia has better and more knowledge than HowNet.

KB format
Figure 3: Comparison of performance of different roofs in QA task.

Figure 4: Fusion efficiency results on QA and GLUE tasks: The metrics in (a) and (b) are both EM scores, whereas the metrics in (c) and (d) are accuracy for RTE and Matthew’s correlation for CoLA. In (a) and (c), we use 10 times the learning rate of the underlying BERT model in the TE layers; in (b), we set the number of TE layers to 4; in (d), we set the number of TE layers to 3.

In Table 3 we compare the results of the 6 different KB formats (setting follows Appendix 6.3 except KB format). The KB format with Exp2 + Has_Tail clearly yields the best performance. However, a closer look at the contributions of knowledge representation and selection shows that Exp2 yields marginally better results among three expansion types, producing finer language representation; even more crucial, however, is whether the tails of the selected triples are in the paragraph passage.

The knowledge selection comparison is shown in Table 4 (setting mentioned in Appendix 6.3 except knowledge selection). The results indicate that selecting Has_Tail knowledge—with tails in the paragraph passage—improves the EM score even with far less knowledge, suggesting that adding arbitrary information could harm performance.

**Depth of Fusion Layer**

As reported in Figures 4(a) and 4(c), the scores peak when using the last 4 and 3 TE layers from
| Type | Has_Tail | No_Tail |
|------|----------|---------|
| Exp0 | 77.21    | 77.34   |
| Exp1 | 76.92    | 76.77   |
| Exp2 | 77.45    | 77.03   |

Table 3: EM scores (%) for 6 types of KB selection and representation on QA task using HowNet as KB.

| KB       | Selection | Length | EM score (%) |
|----------|-----------|--------|--------------|
| HowNet   | Has_Tail  | 29     | 77.45        |
| HowNet   | No_Tail   | 131    | 77.03        |
| CN-DBpedia | Has_Tail | 24     | 77.59        |
| CN-DBpedia | No_Tail  | 168    | 76.90        |

Table 4: Results with different knowledge selections, where Length is the average length of the input tokens of KB-BERT (w/o [PAD]) during training.

the pre-trained BERT as the Fusion layer. Using more layers consumes excessive memory and yields lower scores, perhaps due to overfitting; when using too few layers, the fusion layer is unable to effectively integrate language representation with the KBs.

Learning rate of Fusion Layer

As reported in Fig. 4(b), using 10 times the learning rate of the underlying BERT model’s learning rate yields the highest EM score, for an increase of over 1% compared to using the same learning rate as the underlying BERT model. Similarly, as reported in Fig. 4(d), using 10 times learning rate yields an increase of 2%. This shows that a higher learning rate in the fusion layer improves the fusion effectiveness and further enhances prediction. This is because after BERT is pre-trained, a small learning rate is sufficient for fine-tuning on downstream tasks, and requires fewer epochs for its loss to converge to a minima (global or local); by contrast, a higher learning rate could prevent the model from converging. Thus it may be that the learning pace of the fusion layer should be faster than that of the underlying BERT model in order to make best use of the information provided by each underlying BERT instead of being confined to one or the other.

Cached KB-BERT

As shown in Figure 3, caching KB-BERT does not lead to performance drop but even slightly improve around 0.1% (77.67%) with the use of Cn-Dbpedia comparing to our original best setting. A possible explanation is that without full self-attention between knowledge triples, it could reduce noise during encoding the triples. Moreover, without updating parameters of KB-BERT during fine-tuning, it reduces 33% of the computational cost, making prediction and inference more efficient.

GLUE

The best parameter setting for NLU tasks are presented in Appendix 6.3. As shown in Table 2, Roof-Transformer outperforms datasets like RTE, CoLA, and MRPC, which shows that the proposed model effectively integrates knowledge and contextual embeddings. Moreover, Roof-Transformer achieves comparable or even superior results with ERNIE on the GLUE benchmark.

The results also show that Roof-Transformer has no significant effect on tasks like SST-2, STS-B, and QNLI. It is probably due to the need of external information for tasks like sentimental analysis: sentence sentiment is determined by emotional words but not knowledge. This phenomenon is reflected also in studies like ERNIE and K-BERT. However, for these tasks, the proposed model still achieves performance comparable to that of BERT. For tasks that our model beats both ERNIE and BERT like RTE, we have conducted case study to further investigate how knowledge effects prediction.

4.8 Case Study

We conduct case studies on DRCD dataset and RTE dataset in GLUE benchmark to find out how knowledge helps or misleads our model. We select three examples from dev (validation) data where two of them are positive samples (our model answers correctly, while the baseline answers incorrectly) and one of them is a negative samples (our model answers incorrectly, while the baseline answers correctly) in both case studies. The details of examples and analysis are presented in Appendix 6.4.

5 Conclusion

In this paper, we propose Roof-Transformer to encode knowledge and input sentences using two underlying BERTs with a fusion layer (transformer encoder) on top. This architecture relaxes BERT’s length limitation, allowing BERT to use more knowledge and longer input texts. Experimental results on a QA task and the GLUE benchmark demonstrate the model’s effectiveness. We also show that precise knowledge selection is critical under this architecture. Roof-Transformer is a general
and powerful method for language understanding which can easily be applied to other NLP tasks. It is likely to especially benefit tasks which require information from a large range of knowledge or long input texts. For future work, we plan to replace the underlying BERTs to other pre-trained LMs, such as RoBERTa (Liu et al., 2019b) and XLNet (Yang et al., 2019) to to consolidate the effectiveness of the proposed framework.

References

Oshin Agarwal, Heming Ge, Siamak Shakeri, and Rami Al-Rfou. 2021. Knowledge graph based synthetic corpus generation for knowledge-enhanced language model pre-training. arXiv preprint arXiv:2010.12688v2.

Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. Longformer: The long-document transformer. arXiv preprint arXiv:2004.05150.

Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yukhnenko. 2013. Translating embeddings for modeling multi-relational data. Proceedings of NeurIPS, pages 2787–2795.

Zhendong Dong, Qiang Dong, and Changling Hao. 2006. Hownet and the computation of meaning. Citeseer.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural Computation, pages 1735–1780.

Weijie Liu, Peng Zhou, Zhe Zhao, Zhiruo Wang, Qi Ju, Haotang Deng, and Ping Wang. 2019a. K-bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Zhendong Dong, Qiang Dong, and Changling Hao. 2006. Hownet and the computation of meaning. Citeseer.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. Proceedings of NeurIPS.

Bo Xu, Yong Xu, Jiaqing Liang, Chenhao Xie, Bin Liang, Wanyun Cui, and Yanghua Xiao. 2017. Cnndm: A never-ending chinese knowledge extraction system. International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, pages 428–438.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. Proceedings of NeurIPS.

Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Onotan, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, and Amir Ahmed. 2020. Big bird: Transformers for longer sequences. Proceedings of NeurIPS, pages 17283–17297.

Yuyu Zhang, Ping Nie, Xiubo Geng, Arun Ramamurthy, Le Song, and Daxin Jiang. 2020. Dc-bert: Decoupling question and document for efficient contextual encoding. arXiv preprint arXiv:2002.12591v1.
6 Appendices

6.1 Dataset Statistics

| Dataset | Train | Validation | Test |
|---------|-------|------------|------|
| Q A task |       |            |      |
| DRC | 26,935 | 3,523 | 3,492 |
| GLUE benchmark |       |            |      |
| SST | 67,349 | 872 | 1,821 |
| CoLA | 8,551 | 1,043 | 1,063 |
| MRPC | 3,668 | 408 | 1,725 |
| STS-B | 5,749 | 1,500 | 1,379 |
| QNLI | 104,743 | 5,463 | 5,463 |
| QQP | 363,846 | 40,430 | 390,965 |
| RTE | 2,490 | 177 | 3,000 |
| MNLI | 392,702 | 9,832 | 9,847 |

Table 5: Number of instances in train-dev-test split of different datasets.

6.2 Parameter Settings

For QA, given BERT’s input length limit, we set the maximum length of the question and paragraph to 59 and 450, respectively so that the total length of the input token in Task-BERT would be \( \text{len(} [\text{CLS}] \text{)} + \text{len(Question tokens)} + \text{len([SEP])} + \text{len(Paragraph tokens)} + \text{len([SEP])} = 1 + 59 + 1 + 450 + 1 = 512 \). Similarly, we set the maximum length of the knowledge as 511, so that the total length of the input token in KB-BERT would be \( \text{len(} [\text{CLS}] \text{)} + \text{len(Knowledge tokens)} = 1 + 511 = 512 \).

The following setting values were found suitable for the QA datasets: a batch size of 16 and an AdamW learning rate of \( 3 \times 10^{-5} \). In addition, we used the linear learning rate decay scheduler. For the epoch count, as the fine-tuning was for a downstream QA task, the epoch count was set to 1 with the training loss and accuracy converging properly.

For the GLUE NLU tasks, we set the maximum length of the sentence pairs to 512, including one [CLS] token and two [SEP] tokens. If the sentence length was less than 512, we appended [PAD] tokens to the sentences until the sentence length was 512.

The following setting values were found suitable for the GLUE benchmark: a batch size of 16 and a learning rate of \( 2 \times 10^{-5} \). We used the cosine learning rate decay scheduler. The training epochs were set to 5 for fine-tuning.
6.3 Experiment Settings

For QA task, we find the following setting performs the best in Roof-Transformer: (1) KB format with Exp2 and Has_Tail, (2) type-2 segmentation, (3) using pre-trained Transformer encoder layer (last k layers from BERT_{base}-chinese) for Fusion Layer, (4) 4 Fusion Layers (k = 4), (5) using 10 times of the Underlying BERTs model’s learning rate in Fusion Layer.

For NLU tasks of GLUE, only the number of Fusion Layers is found to be 3 (k = 3) for best performance; other settings remain the same as QA task.

6.4 Case Study

QA task

The Question-Answering is the task of answering a Question from a given Paragraph.

As shown in Fig. 5. In the first positive example, knowledge provides information that both the Chahar People’s Anti-Japanese Allied Army and the Eighth Route Army are kinds of armies, enabling Roof-Transformer to understand these unseen named entities, which indirectly aids prediction. Similarly, in the second positive example, Roof-Transformer also benefits from the added knowledge, which makes it aware of the functions and character of the various named entities (aircraft carrier, destroyer, . . . ) in the paragraph. In contrast, without KB knowledge, the baseline BERT_{base}-chinese fails to understand the contextual information of the given question and paragraph, leading to misprediction.

On the other hand, in the negative example, the selected knowledge indicates that political reform is a kind of issue, which subtly response to the word “contribution” asked in the question, resulting in a biased prediction. On the contrary, without the information of knowledge, the baseline model is able to make correct inference.

RTE task

The Recognizing Textual Entailment is the task of determining whether the meaning of the Hypothesis is entailed (can be inferred) from given Text.

As shown in Fig. 6. In the first positive example, the knowledge tells the fact of "Texaco is owned by Chevron Corporation", which helps our model to infer that sentence 1 entails sentence 2 instead of telling model the answer. Similarly, in the second positive example, Roof-Transformer also benefits from the fact related to Romano Prodi that knowl-edge provides. In contrast, without the help of knowledge corpus, the baseline BERT_{base} fails to make inference only based on sentence 1 and sentence 2.

On the other hand, in the negative example, although the selected knowledge tells fact about "Lex Lasry", there exista a huge overlap between knowledge and sentence 2 (i.e., "is a lawyer"), resulting in a misprediction. On the contrary, without the information of knowledge, the baseline model is able to make correct inference.
| Question                                                                 | Paragraph                                                                                              | Knowledge                                                                                           | Ans. of Roof-Transformer | Ans. of baseline |
|-------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|--------------------------|-----------------|
| Which army was the Chinese army that regained lost territory for the first time since the September 18th Incident? | Feng Yuxiang, Ji Hongchang, Fang Zhenwu and others established the Chahar People’s Anti-Japanese Allied Army in Zhangyuan on May 26, 1933 and started to attack the Japanese troops in Chahar and Jehol in June, and all of them were expelled from Chahar, which was the first time that the Chinese army had regained lost territory since the September 18th Incident. From May to June in the 34th year of the Republic of China, the Eighth Route Army in the Shann-Chahar-Hebei border area launched the Chanan Campaign, captured Huaian, Shuyuan and other county towns, and developed to the Pingsui Road and the Chabei area. | [CLS] The Eighth Route Army is a kind of army [SEP] Allied Army is for Alliance, and is a kind of army [SEP] | The Chahar People’s Anti-Japanese Allied Army | The Eighth Route Army |
| Before Pearl Harbor Attack, which of Japan’s most important targets were not in the harbor? | Tokyo received information about spies lurking in Pearl Harbor. There were 9 warships, 3 cruisers, and 17 destroyers parked in the harbor. There were 4 cruisers and 3 destroyers in the dock, while all aircraft carriers were not in the base. The pocket submarine, which was the vanguard of the operation, began to leave the mothership. At 3:42, the U.S. minesweeper USS Condor spotted a periscope in front of Honolulu Harbor, and the destroyer USS Ward fired and dropped depth charges. | [CLS] Aircraft carrier is a kind of weapon [SEP] Periscope is for vision, and is a kind of equipment [SEP] Destroyer is a kind of weapon [SEP] Cruiser is a kind of weapon [SEP] | Aircraft carrier | USS Ward |
| What was the contribution of Prince Shotoku to the Japanese system? | In 592, a royal woman who was related by marriage to the Suga clan, Fungyu Shichihajiyagi, ascended the throne as Emperor Tuig. She nominated Prince Shotoku as regent to strengthen the political reform at the core of imperial power. Prince Shotoku formulated the 12-level crown and the 17-article constitution, laying the foundation for a Chinese-style bureaucratic system. | [CLS] Political reform is a kind of issue [SEP] | Strengthen the political reform at the core of imperial power | Laying the foundation for a Chinese-style bureaucratic system |

Figure 5: Case study of QA task: Answers with underlines are also the ground truth of those examples. The answers of Roof-Transformer are align with the ground truth in positive examples, whereas answer of baseline is align with the ground truth in negative examples. Note that the content is translated (without loss in meaning), since the DRCD dataset and HowNet are in Chinese, and only a part of paragraph and knowledge are present for clarity.
| Text                                                                 | Hypothesis                              | Knowledge                                                                 | An. of Roof-Transformer | An. of baseline |
|----------------------------------------------------------------------|-----------------------------------------|---------------------------------------------------------------------------|-------------------------|-----------------|
| **Positive**                                                        |                                        |                                                                           |                         |                 |
| But only one major oil company was shamed by the 623-page report: Texaco, part of Chevron, the US's second largest energy group. | Chevron owns Texaco.                   | [CLS] Texaco, which is owned by Chevron Corporation, is a United States based company that was founded in 1901. It is a gas station chain. [SEP] | 1                        | 0                |
| Romano Prodi will meet the US President George Bush in his capacity as president of the European commission. | Romano Prodi is the president of the European Commission. | [CLS] Romano Prodi, a member of The Olive Tree (Italy), was a member of the Italian People's Party (in 1994). He was Minister of Justice, a member of the Chamber of Deputies of the Italian Republic and President of the European Commission. Prodi is a member of the Italian Democratic Party. [SEP] | 1                        | 0                |
| **Negative**                                                        |                                        |                                                                           |                         |                 |
| Nguyen’s lawyer, Lex Lasry, told Australian television from Singapore that Nguyen, a Catholic whose family came from Vietnam, was "ready to die". | Nguyen is a lawyer.                    | [CLS] Lex Lasry was born in Melbourne, Australia on 8 July 1948. He is a lawyer and judge. He is a man of many talents. [SEP] | 1                        | 0                |

Figure 6: Case study of RTE task: Similarly, the answers with underlines are the ground truth of those examples. Note that the content is originally in English, and only a part and knowledge is present for clarity.