Abstract

It is often observed in knowledge-centric tasks (e.g., common sense question and answering, relation classification) that the integration of external knowledge such as entity representation into language models can help provide useful information to boost the performance. However, it is still unclear whether this benefit can extend to general natural language understanding (NLU) tasks. In this work, we empirically investigated the contribution of external knowledge by measuring the end-to-end performance of language models with various knowledge integration methods. We find that the introduction of knowledge can significantly improve the results on certain tasks while having no adverse effects on other tasks. We then employ mutual information to reflect the difference brought by knowledge and a neural interpretation model to reveal how a language model utilizes external knowledge. Our study provides valuable insights and guidance for practitioners to equip NLP models with knowledge.

1 Introduction

Language models utilize contextualized word representations to boost the performance of various NLP tasks (Devlin et al., 2019; Liu et al., 2019; Lan et al., 2020; Clark et al., 2020). In recent years, there has been a rise in the trend of integrating external knowledge into language models (Wang et al., 2020; Yu et al., 2020; Wang et al., 2019b; Liu et al., 2020; Peters et al., 2019; Zhang et al., 2019; Poerner et al., 2020) based on the transformer (Vaswani et al., 2017). For instance, representations of entities in the input and related concepts are combined with contextual representations to provide additional information, leading to significant improvement in many tasks (Han et al., 2018; Choi et al., 2018; Ling and Weld, 2012; Berant et al., 2013). However, most of these approaches (Zhang et al., 2017; Talmor et al., 2019) focus on knowledge-centric tasks, e.g. common sense Q&A, relation extraction, where the completion of a task requires information from an external source other than the input text. But, these works overlook many more general NLP tasks which do not explicitly request usage of knowledge, including but not limited to sentiment classification, natural language inference, sentence similarity, part-of-speech tagging, and named entity recognition (Wang et al., 2018, 2019a). So far, the improvement on these tasks often originates from more sophisticated architectures, larger model size, and an increasing amount of pre-training data. Very little work has investigated whether external knowledge will improve the performance of these non-knowledge-centric tasks.

In this work, we aim to find out whether external knowledge can lead to better language understanding ability for general NLU tasks. Specifically, we want to answer the following questions:

- First of all, does knowledge help general NLU tasks overall? (Section 4.2 Q1)
- Among various NLU tasks, what source of knowledge and which tasks could benefit the most from the integration of external knowledge? (Section 4.2 Q2)
- Under the same experimental settings, which integration methods are the most effective in combining knowledge with language models? (Section 4.2 Q3)
- Which large-scale pre-trained language models benefit the most from external knowledge? (Section 4.2 Q4)
- Can we tell knowledge is helpful besides the end-to-end performance indicator? (Section 4.3 Q1)
- If knowledge can help with certain NLU tasks, how does the language model utilize the external knowledge? (Section 4.3 Q2)
Answers to these questions not only help us understand how knowledge is leveraged in language models but also provide important insights into how to leverage knowledge in various NLU tasks.

In detail, we explore the different sources of knowledge including the textual explanation of entities and their embeddings. We explore two main categories of knowledge integration methods. Knowledge as Text places descriptions of entities into the input text, with normal or modified attention mechanism from the language model. Knowledge as Embedding integrates contextual or graphical embedding of entities into the language model via addition. Both methods are non-invasive, meaning that the language model’s inner structure does not need to be altered. We apply these knowledge integration methods to 4 pre-trained language models and conduct extensive experiments on 10 NLU tasks. The results show that introducing knowledge can outperform vanilla pre-trained language models by 0.46 points by averaging all language models.

To understand how and why knowledge integration methods can help with language models, we also utilize mutual information (MI) to reflect the difference brought by knowledge (see Figure 5) and visualize the contribution of inputs to the prediction of knowledge-enhanced language models (see figure 3) to better understand the interaction between language model and knowledge. We find that (i) Knowledge integration methods retain more information about input while gradually discard take-irrelevant information and finally keep more information about output. (ii) Although the knowledge is only introduced for a subset of tokens in the input sentence, it affects the decision process of the model on all tokens and improves the generalization ability on certain tasks.

In summary, we present a systematic empirical analysis on how to effectively integrate external knowledge into existing language models for general NLU tasks. This provides valuable insights and guidance for practitioners to effectively equip language models with knowledge for different NLU tasks.

2 Related Work

In this section, we review previous works that explore how to combine external knowledge with language models, which can be grouped into the following categories.

Joint Pretraining Some recent works combine pre-trained language models with external knowledge by joint pretraining with both unstructured text and structured knowledge bases. Ernie(Baidu) (Sun et al., 2019) modified pretrain objective in BERT (Devlin et al., 2019) to mask the whole span of named entities. WKLM (Xiong et al., 2020) trains the model to detect whether an entity is replaced by another one in the same category. LUKE (Yamada et al., 2020) propose a pre-trained model which uses similar entity masks from Wikipedia in pretraining but treats words and entities in a given text as independent tokens. KEYPLER (Wang et al., 2019b) and JAKET (Yu et al., 2020) introduce descriptive text of entities and their relations into pretraining. Build upon an existing pre-trained encoder(Liu et al., 2019), a fully (Wang et al., 2019b) or partially(Yu et al., 2020) shared encoder is used to encode entity descriptive text with entity-related objectives such as relation type prediction.

Static Entity Representations Another way to combine knowledge with a language model is to use static entity representations learned separately from a knowledge base. Ernie (THU) (Zhang et al., 2019) and KnowBert (Peters et al., 2019) merge entity representations with language model using entity-to-word attentions. E-Bert (Poerner et al., 2020) aligns static entity vectors from Wikipedia2Vec with BERT’s native wordpiece vector space and uses the aligned entity vectors as if they were wordpiece vectors.

Adaptation to Knowledge-Free Model It is also possible to incorporate knowledge without joint pretraining or relying on knowledge embeddings. K-BERT (Liu et al., 2020) injects triples from KGs into sentences. A special soft-position and visible matrix in attention are introduced to prevent the injected knowledge from diverting the meaning of the original sentence. K-Adapter (Wang et al., 2020) initializes the model parameters from Roberta (Liu et al., 2019) and equips it with adapters to continue training on entity-related objectives.

3 Approaches

3.1 Definition

Given the input text \( x = [x_1, x_2, ..., x_L] \) with \( L \) tokens, a language model \( f_{LM} \) produces the contextual word representation \( f_{LM}(x) = [c_1, c_2, ..., c_L] \). We use \( c^{(l)} = [c_1^{(l)}, c_2^{(l)}, ..., c_L^{(l)}] \) to represent the intermediate hidden states after \( l \) layers. We further
3.2 Combine Knowledge with Language Models

For a downstream task, the pre-trained language model $f_{LM}$ and the head function $f_H$ are jointly trained to minimize the loss function on training data $\mathcal{D}$:

$$
\min_{(x,y) \in \mathcal{D}} L(f_H(f_{LM}(x)), y). 
$$

Given the external knowledge $\mathcal{E}$, we explore several general methods to incorporate it into any pre-trained language model $f_{LM}$ such that the knowledge-enhanced language model $f'_{LM}(x, \mathcal{E})$ can encode the information from both $x$ and $\mathcal{E}$.

In this work, we consider two formats of knowledge centered on entities:

- Free text: An unstructured text $x^e$ to describe an entity $e$, e.g. the definition of $e$ from a dictionary;
- Embedding: A continuous embedding vector $h^e$ to encode an entity $e$, e.g. graph embedding of the node of $e$ from a knowledge graph.

To align with the format of knowledge, our integration methods include i) Knowledge as Text, and ii) Knowledge as Embedding, as described in the following sections.

3.2.1 Knowledge as Text

The simplest way to incorporate a textual description $x^e_i$ with the input $x$ is to concatenate them in the text space. We explore two ways of combination (Table 1): inserting $x^e_i$ after $e_i$ in $x$ and appending $x^e_i$ to the end of $x$. Empirically we found that the second approach always outperforms the first one in the GLUE benchmark. So we adopt the appending approach as the first knowledge combination method, which we refer to as Knowledge as Text (KT).

As pointed in Liu et al. (2020), too much knowledge incorporation may divert the sentence from...
When a knowledge graph of entities is available, we adopt the visibility matrix (Liu et al., 2020) to limit the impact of descriptions on the original text. To solve this issue, we modify the attention mask matrix $M$ such that

$$M_{jk} = \begin{cases} 
0 & x_j, x_k \in x \\
0 & x_j, x_k \in x^{e_i} \\
0 & x_j \in x, x_k \in x^{e_i} \text{ and } j = p_i \\
-\infty & \text{otherwise}
\end{cases}$$

where $x_j$ and $x_k$ are tokens from the concatenation of $x$ and descriptions $[x^{e_1}, x^{e_2}, \ldots, x^{e_N}]$. In other words, $x_j$ can attend to $x_k$ if: both tokens belong to the input $x$, or both tokens belong to the description of the same entity $e_i$, or $x_j$ is the token at the starting position of entity $e_i$ in $x$ and $x_k$ is from its description text $x^{e_i}$.

Figure 2 illustrates the attention matrix given a input text and two entity descriptions. We refer to this approach as Knowledge as Text with Attention (KT-Attn).

**Knowledge as Embedding.** Here, we first represent each entity $e_i$ by an embedding vector $h_i$. When a knowledge graph of entities is available, we can obtain graphical embedding for each entity node. In our experiments, we use the pre-trained TransE (Bordes et al., 2013) to get the embedding of each entity in the Wikidata knowledge graph.

We feed $h_i$ into a multi-layer perception layer (MLP) to align with the input embeddings of language models. We then linearly combine the transformed embedding MLP($h_i$) with the input token embedding at position $p_i$.

As the language model was not exposed to this additional entity embedding during pre-training, we initialize the weight $\alpha$ of MLP($h_i$) to zero and linearly increase its weight during the whole fine-tuning. Define $c^{(0)}$ as the vector representation that is fed into the language model, we have

$$c^{(0)}(x_{p_i}) = \text{embedding}_\text{layer}(x_{p_i}) + \alpha\text{MLP}(h_i)$$

where $\alpha$ is annealed from 0 to $\lambda \in [0, 1]$. We refer to this integration method as Knowledge as Graph Embedding (KG-Emb).

When a knowledge graph is not available, we can use entity descriptions $x^{e_i}$ to produce entity embedding $h_i$. Here, we use $f_{LM}$ to encode the entity description $x^{e_i}$ into contextual representation $c^{e_i} = f_{LM}(x^{e_i})$. As shown in Table 1, the knowledge text always starts with the token being explained, e.g. sponge: Any of various marine... Therefore we use the contextual representation of the first token in $c^{e_i}$ as entity embedding $h_i$. We then use $h_i$ in the same way as KG-Emb. Compared with existing work (Yu et al., 2020; Wang et al., 2019b), our approach does not require pre-training with external knowledge and can be easily applied to any pre-trained language model in a non-invasive way. We refer to this method as Knowledge as Textual Embedding (KT-Emb).

4 Experiments

In this section, we perform extensive experiments to examine the aforementioned knowledge integration methods in different pre-trained language models (LMs) on a variety of NLU tasks.

4.1 Experimental Setup

Table 2 lists the 10 datasets in our study, including 8 classification and regression (CR) tasks from the GLUE (Wang et al., 2018) benchmark and two sequence labeling (SL) tasks from Penn Treebank (Marcus et al., 1993) and CoNLL-2003 shared task data (Tjong Kim Sang and De Meulder, 2003). We study on 4 different LMs: (i) RoBERTa (Liu et al., 2020) 1 to get the embedding of each entity in the Wikidata knowledge graph.

1TransE embeddings are from http://openke.thunlp.org/
| Dataset | #Train | #Val | Task       |
|---------|--------|------|------------|
| CoLA    | 8.5K   | 1K   | regression |
| SST-2   | 67K    | 1.8K | classification |
| MNLI    | 393K   | 20K  | classification |
| QQP     | 364K   | 391K | classification |
| QNLI    | 105K   | 4K   | classification |
| STS-B   | 7K     | 1.4K | regression |
| MRPC    | 3.7K   | 1.7K | classification |
| RTE     | 2.5K   | 3K   | classification |
| POS     | 38.2K  | 5.5K | sequence labeling |
| NER     | 14K    | 3.3K | sequence labeling |

Table 2: Statistics of the datasets. #Train and #Val are the number of samples for training and validation.

et al., 2019); (ii) BERT (Devlin et al., 2019), (iii) ALBERT (Lan et al., 2020) and (iv) ELECTRA (Clark et al., 2020). For each language model, we experiment with both base and large models. Details of datasets and LMs can be found in Appendix A.

Our implementation is based on HuggingFace’s Transformers (Wolf et al., 2020). We conduct all experiments on 8 Nvidia A100-40GB GPU cards. We set the fixed training epochs and batch size for each task, and a limited hyperparameter sweep with learning rates $\in \{1e^{-5}, 2e^{-5}, 3e^{-5}\}$. For KT-Emb and KG-Emb, we search warmup weight $\lambda \in \{0.1, 0.2, 0.3\}$. For CR tasks, the training epochs are set to 10. Due to the sufficient training data of MNLI and QQP, we set their epochs to 5. For SL tasks, we set the training epochs to 3. The batch size is set to 128 for CR tasks except that we search the batch size in $\{16, 32, 128\}$ for CoLA and STS-B on RoBERTa-base due to their small training data and then fix it for fair comparison. For SL tasks, the batch size is set to 16. We report the median of results on the development set over five fixed random seeds for all tasks.

To extract the knowledge description, we first use Spacy to annotate $x$ and select the nouns, verbs, or adjectives to use as the knowledge entities. For KG-Emb, we use REL (van Hulst et al., 2020) to link entities to Wikidata. We leverage external knowledge source Wiktionary to obtain the description for each entity.

4.2 Knowledge Integration Results

In this section, we present different knowledge integration results in 8 pretrained language models. Table 3 and Table 4 list detailed numbers on 10 NLU tasks for RoBERTa base and large models. Figure 4 summarizes our results on all LMs. From these results, we aim to answer the following questions.

Q1: Does knowledge help general NLU tasks? Overall we find that knowledge can help general NLU tasks. Firstly, Table 3 shows that KT-Attn outperforms both RoBERTa base and large baselines about 0.4 points on average for CR tasks. For SL tasks, KT and KT-Emb outperform baselines about 0.25 and 0.28 points on average. Secondly, Figure 4(a) clearly shows that all tasks can benefit from knowledge across 8 different LMs. For example, KT-Attn improves all LMs via the introduction of knowledge for SST-2 and POS tasks. Thirdly, the average gain of all LMs on 10 NLU tasks with the introduction of knowledge is about 0.46 points. Figure 4(d) also shows the average gains with each LMs for CR and SL tasks.

Q2: Which tasks benefit the most from knowledge integration? For CR tasks, Table 3 shows
Table 3: Results for RoBERTa on classification and regression (CR) tasks. All results are medians over five runs with different seeds on the development set. To validate our results, we follow RoBERTa (Liu et al., 2019) to finetune starting from the MNLI model for RoBERTa-large instead of the baseline pretrained model on RTE, STS-B and MRPC tasks. Complete results on other pretrained language models can be found in the Appendix B.

Table 4: Results for RoBERTa on two sequence labeling (SL) tasks. For KT, KT-Attn and KT-Emb, we also experiment with extracting knowledge description for tokens from entity linking which are denoted in right. We report F1 for both tasks. Reported results are medians over five runs on the development set. Complete results on other pretrained language models can be found in the Appendix B.

Q3: What is the best way to combine KGs with CWR for different NLU tasks? Firstly, Figure 4(a) shows that KT-Attn and KT-Emb can help most LMs for each task. Secondy, in terms of best knowledge integration methods on each task, Figure 4(c) shows that KT-Attn and KT-Emb accounts more than the other two methods among all LMs. Thirdly, in terms of which methods to select entities for knowledge extraction, Table 3 shows that the POS-based method performs better than entity-linking based for the POS task while it is the opposite for the NER task.

Q4: Which large scale pre-trained language models benefit the most from external knowledge? For the number of benefit tasks aspect, Figure 4(b) shows that BERT-Large model gets improvement for 9 tasks with KT-Attn method. For the performance gains aspect, Figure 4(d) shows that BERT-Base model improves most for CR tasks while ELECTRA-Base model improves most for SL tasks.

4.3 Analysis

In addition to measuring the performance of knowledge integration methods on NLU tasks, it is also of great value to understand how and why knowledge integration methods help with language models. In particular, we answer the following two questions.

Q1: Is there any indicator to tell knowledge is helpful besides the end-to-end performance? Wang et al. (2021) proposes to enforce local modules to retain as much information about the input as possible while progressively discarding task-irrelevant parts. Inspired by this, we utilize mutual information (MI) to reflect the difference brought by knowledge.

Specifically, we use the mutual information $I(c(l); x)$ to measure the amount of retained information in $l$-th layer about the raw input $x$, and
Figure 4: Effectiveness of knowledge integration methods on different tasks and language models. Figure (a) shows for each task the number of language models for which our knowledge integration methods could improve accuracy (maximum is 8 which means it helps all LMs on that task). Figure (b) shows for each language model the number of tasks that knowledge integration could improve accuracy on (maximum is 10 which means it helps all tasks with that language model). Figure (c) shows for each task the number of language models that knowledge integration method performs best on (maximum is 10 which means it always performs best with different LMs among 4 integration methods for that task). Figure (d) shows for each language model the maximum average gains over CR and SL tasks. ‘B’ and ‘L’ stand for the base and large model respectively. The dashed lines in figure (a), (b) and (c) represent the upper bound. The detailed performance numbers on each task are in the Appendix B.

\[ I(c^{(l)}; y) \] to measure the amount of retained task-relevant information.

We then calculate the difference \( \Delta I(c^{(l)}; x) \) and \( \Delta I(c^{(l)}; y) \) between knowledge integration methods and baseline for each layer. If \( \Delta I(c^{(l)}; x) > 0 \), it means the knowledge integration helps to retain more information about \( x \) at layer \( l \) than the baseline. If \( \Delta I(c^{(l)}; y) > 0 \), it means knowledge helps to discard more task-irrelevant information at layer \( l \).

To estimate \( I(c^{(l)}; x) \), we follow the common practice (Vincent et al., 2008; Rifai et al., 2012) to use the expected error for reconstructing \( x \) from \( c^{(l)} \) to approximate \( I(c^{(l)}; x) \approx \max_w[H(x) - R_w(x|c^{(l)})] \), where \( R_w(x|c^{(l)}) \) is the reconstruction error and is estimated by masked language modeling to recover the masked tokens, \( H(x) \) denotes the marginal entropy of \( x \), as a constant.

To estimate \( I(c^{(l)}; y) \), we follow Wang et al. (2021) to compute \( I(c^{(l)}; y) \approx \max_\phi \left\{ H(y) - \frac{1}{|D|} \sum_{(x,y,c^{(l)}) \in D} -\log q_\phi(y, c^{(l)}) \right\} \), where \(-\log q_\phi(y, c^{(l)})\) is the cross-entropy classification loss.

Both the estimations of \( I(c^{(l)}; x) \) and \( I(c^{(l)}; y) \) require an auxiliary classifier layer connected to each LM Transformer layer’s output. We place more details in Appendix C.

Figure 5 shows the mutual information difference \( \Delta I(c^{(l)}; x) \) and \( \Delta I(c^{(l)}; y) \) between each KG integration method and the vanilla RoBERTa-base baseline on CoLA dataset. We observe the following results: (i) KT and KT-Attn lead to higher \( \Delta I(c^{(l)}; x) \) and \( \Delta I(c^{(l)}; y) \), indicating that they retain more information about input while discarding task-irrelevant parts. (ii) All KG integration methods gradually discard task-irrelevant information and keep more information about output after the first six layers.

**Q2: How does the introduction of knowledge change the way language models make decisions?** We employ DiffMask (De Cao et al., 2020), an interpretation tool to show how decisions
Figure 5: Estimated mutual information difference $\Delta I(h, x)$ and $\Delta I(h, y)$ between each KG integration method and RoBERTa-Base baseline on CoLA. $\Delta I(c(l), x) > 0$ means the integration helps retain more information about $x$ at layer $l$ than the baseline. $\Delta I(c(l), y) > 0$ means that it helps to discard more task-irrelevant information.

![Graphs showing $\Delta I(h, x)$ and $\Delta I(h, y)$ between KG integration methods and baseline.](image)

Figure 6: The average number of Transformer layers in (a) RoBERTa-Base and (b) KT-Attn that deem words of certain part-of-speech as important for the CoLA task of linguistic acceptability. Results are obtained from the DiffMask model (De Cao et al., 2020).

In Figure 6, we show the average number of Transformer layers in RoBERTa-Base and KT-Attn that deem words of certain part-of-speech as important for the CoLA task. We can see that although the knowledge is only applied to verbs, nouns, and adjectives, it affects the behavior of the language model on other words as well. For example, the average number of Transformer layers increases for almost all POS tags of words. And in terms of relative ranking, PRON (pronoun), ADP (adverb), and NUM (numeral) also have significant changes after KT-Attn introduced external knowledge. We include some additional analysis based on DiffMask in appendix D.2.

5 Conclusion

In this paper, we have presented a large-scale empirical study of various knowledge integration methods on 10 general NLU tasks. We show that knowledge brings more pronounced benefits than previously thought for general NLU tasks since introducing it outperforms across a variety of vanilla pretrained language models and significantly improves the result on certain tasks while having no adverse effects on other tasks. Our analysis with MI and DiffMask further helps understand how and why knowledge integration methods can help with language models.
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Appendix

A Datasets and Pretrained Language Models

CoLA (Warstadt et al., 2019): The Corpus of Linguistic Acceptability is a regression dataset annotated about the acceptability whether it is a grammatical English sentence. We use Matthews correlation coefficient (Matthews, 1975) as the evaluation metric.

SST-2 (Socher et al., 2013): The dataset of Stanford Sentiment Treebank is a sentiment classification dataset.

MRPC (Dolan and Brockett, 2005): The Microsoft Research Paraphrase Corpus is to predict whether two sentences are semantically equal.

STS-B (Cer et al., 2017): The Semantic Textual Similarity Benchmark is the other regression dataset that measures the similarity between the pairs.

QQP5: The Quora Question Pairs is the other dataset to determine whether two sentences are semantically equivalent from the community question-answering website Quora.

MNLI (Williams et al., 2018): The Multi-Genre Natural Language Inference Corpus is textual entailment tasks and the goal is to classify the relationship between premise and hypothesis sentences into three classes: entailment, contradiction, and neutral.

QNLI (Rajpurkar et al., 2016): The Stanford Question Answering Dataset is sentence pair classification collection about question-answering. This task is to determine whether the context contains the answer to the question.

RTE (Wang et al., 2018): The Recognizing Textual Entailment (RTE) datasets is the other textual entailment dataset.

POS: The Part-of-speech tagging is to classify the word in a text to a particular part-of-speech. We use the Penn Treebank (Marcus et al., 1993) for this task.

NER: The Name-entity recognition is to seek the name entities among the given sentence. We use the CoNLL-2003 shared task data (Tjong Kim Sang and De Meulder, 2003).

Table 5 lists all pretrained language models in our experiments.

| Models         | #Params |
|---------------|---------|
| RoBERTa-Base  | 125M    |
| RoBERTa-Large | 355M    |
| BERT-Base-Cased | 109M  |
| BERT-Large-Cased | 335M |
| ALBERT-Base-v2 | 11M     |
| ALBERT-Large-v2 | 17M    |
| ELECTRA-Base   | 110M    |
| ELECTRA-Large  | 335M    |

Table 5: Number of parameters for each pretrained language models in our experiments

B Knowledge Integration results

Table 6 and Table 7 list detailed numbers for CR and SL tasks on BERT, ALBERT and ELECTRA.

C Mutual Information Implementation Details

In our implementation, we stack one transformer layer followed by two fully-connected layers $\phi$ on top of the intermediate hidden states $c(l)$ and optimize the newly added transformer to predict the label $y$. Follow (Wang et al., 2021), we simply use test accuracy as the estimate of of $I(c(l); y)$.

D DiffMask

D.1 Implementation Details

DiffMask attaches an MLP classifier to each LM layer’s output, including the token embedding layer as layer 0. The $l$-th classifier $g_{\phi}(l)$ takes the hidden states up to the $l$-th layer to predict a binary mask vector: $v(l) = g_{\phi}(l)(c(0), ..., c(l)) \in \{0, 1\}^n$, where $n$ is the number of input tokens.

Then, the token mask for each input token $x_j$ is defined as the product of all binary masks up to the $l$-th layer: $z(l)_j = \prod_{k=0}^{l} v(k)_j$. The embedding of the masked token is replaced by a learned baseline vector $b$, i.e. $\hat{c}(0)_j = z(l)_j \cdot c(0)_j + (1 - z_j) \cdot b$. The masked embeddings $\hat{c}$ is input the to the finetuned model to get $f_H(f_{LM}(\hat{c}))$. Here we assume $f_{LM}$ could either take tokens $x$ or token embeddings $c$ as input. The objective of DiffMask is to estimate the parameters of the masking networks and the baseline $b$ to mask-out as many input tokens as possible while keeping $f_H(f_{LM}(x)) \approx f_H(f_{LM}(\hat{c}))$, i.e. keeping the output of masked tokens close to the original output without masks.
| Model          | CoLA | SST-2 | MRPC | STS-B | QQP  | MNLI | QNLI | RTE | Avg |
|---------------|------|-------|------|-------|------|------|------|-----|-----|
|               | Matt. corr. | Acc. | Acc. | Pear. corr. | Acc. | Acc. | Acc. | Acc. |     |
| BERT-Base-Cased | 60.83 | 92.2 | 84.31 | 89.02 | 90.81 | 83.83 | 91.09 | 66.79 | 82.36 |
| + KT          | 58.38 | 91.86 | 78.68 | 89.01 | 90.88 | 83.83 | 90.76 | 63.18 | 80.82 |
| + KT-Attn     | 59.76 | 92.66 | 85.05 | 89.33 | 90.84 | 83.91 | 90.88 | 66.79 | 82.40 |
| + KT-Emb      | 61.69 | 92.66 | 86.03 | 89.81 | 90.79 | 84.03 | 90.98 | 68.59 | 83.07 |
| + KG-Emb      | 61.25 | 92.43 | 84.56 | 88.78 | 90.83 | 83.9 | 90.92 | 66.43 | 82.28 |
| BERT-Large-Cased | 64.84 | 93.92 | 86.27 | 90.29 | 91.5 | 86.51 | 92.51 | 71.48 | 84.67 |
| + KT          | 63.61 | 93.92 | 76.47 | 89.4 | 91.46 | 86.48 | 92.46 | 74.73 | 84.26 |
| + KT-Attn     | 65.35 | 94.04 | 87.25 | 90.56 | 91.43 | 86.63 | 92.57 | 73.65 | 85.19 |
| + KT-Emb      | 64.91 | 93.92 | 87.01 | 90.03 | 91.46 | 86.48 | 92.48 | 71.12 | 84.68 |
| + KG-Emb      | 64.27 | 93.81 | 85.54 | 88.57 | 91.5 | 86.38 | 92.46 | 71.84 | 84.30 |
| ALBERT-Base-v2 | 56.31 | 92.83 | 87.75 | 90.88 | 90.63 | 85.13 | 91.76 | 72.2 | 83.44 |
| + KT          | 56.08 | 93.0 | 87.99 | 90.56 | 90.55 | 85.18 | 91.76 | 75.09 | 83.78 |
| + KT-Attn     | 57.42 | 93.23 | 88.24 | 90.73 | 90.51 | 85.08 | 91.91 | 74.73 | 84.00 |
| + KT-Emb      | 55.52 | 93.23 | 88.24 | 90.73 | 90.51 | 85.08 | 91.69 | 74.01 | 83.63 |
| + KG-Emb      | 54.53 | 92.43 | 84.56 | 88.78 | 90.83 | 83.9 | 90.92 | 66.43 | 82.28 |
| ALBERT-Large-v2 | 60.16 | 94.38 | 89.22 | 91.39 | 90.88 | 85.13 | 91.76 | 72.2 | 83.44 |
| + KT          | 59.1 | 94.61 | 84.31 | 90.71 | 90.71 | 85.19 | 91.76 | 75.09 | 83.78 |
| + KT-Attn     | 60.55 | 95.07 | 89.71 | 91.21 | 90.9 | 87.1 | 92.62 | 79.42 | 85.82 |
| + KT-Emb      | 61.31 | 94.72 | 89.95 | 91.4 | 90.96 | 87.12 | 92.37 | 80.87 | 86.09 |
| + KG-Emb      | 60.02 | 94.61 | 89.22 | 91.08 | 90.93 | 87.1 | 92.39 | 78.7 | 85.51 |
| ELECTRA-Base  | 68.61 | 95.3 | 88.48 | 90.99 | 91.93 | 88.9 | 93.1 | 78.7 | 87.0 |
| + KT          | 69.7 | 94.95 | 87.5 | 90.41 | 91.84 | 88.81 | 93.01 | 76.9 | 86.64 |
| + KT-Attn     | 69.45 | 95.76 | 88.97 | 90.89 | 91.84 | 88.98 | 93.03 | 80.51 | 87.43 |
| + KT-Emb      | 70.69 | 95.64 | 88.73 | 91.15 | 91.86 | 88.81 | 93.12 | 76.53 | 87.07 |
| + KG-Emb      | 69.68 | 95.53 | 88.24 | 89.88 | 91.88 | 88.86 | 92.99 | 75.81 | 86.61 |
| ELECTRA-Large | 72.13 | 96.67 | 90.93 | 92.57 | 92.45 | 91.32 | 95.15 | 88.45 | 89.96 |
| + KT          | 70.27 | 96.9 | 89.46 | 92.29 | 92.55 | 91.09 | 95.19 | 88.81 | 89.57 |
| + KT-Attn     | 69.25 | 96.79 | 90.44 | 92.23 | 92.58 | 91.28 | 94.98 | 87.73 | 89.41 |
| + KT-Emb      | 68.81 | 97.02 | 90.93 | 91.86 | 92.67 | 91.2 | 95.15 | 88.81 | 89.56 |
| + KG-Emb      | 59.35 | 96.9 | 88.48 | 91.28 | 92.25 | 91.13 | 95.15 | 89.17 | 87.96 |

Table 6: Results on classification and regression (CR) tasks for BERT, ALBERT and ELECTRA.

According to De Cao et al. (2020), the learned masks \( z_j^{(l)} \) reveal what the network “knows” at layer \( l \) about the NLU task. We can therefore plot a heatmap over \( \{ z_j^{(l)} \}_{L,n}^{l=0,j=1} \). If \( z_j^{(l)} = 0 \), it means that masking the \( j \)-th input token will not affect the model prediction, i.e. the model 'knows' that token \( j \) would not influence the final output at layer \( l \) and higher.

D.2 Additional Analysis

In figure 9, we plot the DiffMask heatmaps of an example input sentence in the RTE text entailment task. Given two sentences concatenated into a single sequence, the language model RoBERTa-Base is finetuned to predict whether the two sentences entail each other or not. From this example, we can see that the first sentence is verbose while the second one is concise. Therefore, for entailment judgment, a model with good generalization power should focus on the tokens containing the key information: "Jack Kevorkian", "famed as", "real name" and "Dr. Death". KT-Attn and KT-Emb rely more on those key information than vanilla RoBERTa. In figure 7, we could also see the difference made by introducing knowledge into the finetuning of the language model is not limited to the tokens where knowledge is explicitly incorporated.

For STSB, where incorporating knowledge did not show significant improvement of end-to-end performance, we plot one of the examples in figure 10 and the average number of Transformer layers that deem words of certain part-of-speech as important for the STSB task in figure 8. In figure 10, KT-Attn and KT-Emb still show better generalization ability by identifying the keywords "a boy" and "her baby" better than the vanilla RoBERTa model. But the difference is slim since the vanilla RoBERTa model also captures "a" and "her" as the evidence for the final prediction. In figure 10, we can observe a smaller difference between vanilla RoBERTa and its two knowledge-enhanced versions, which indicates that the language models
adapt to external knowledge less aggressively for some certain tasks than the others.
Figure 9: DiffMask plot for RTE task with RoBERTa-Base model. RTE task is to predict whether two sentences entail each other.
Figure 10: DiffMask plot for STSB task with RoBERTa-Base model. STSB task is to predict the semantic textual similarity of two sentences.