

MINILMv2: Multi-Head Self-Attention Relation Distillation for Compressing Pretrained Transformers

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Abstract

We generalize deep self-attention distillation in MINILM (Wang et al., 2020) by only using self-attention relation distillation for task-agnostic compression of pretrained Transformers. In particular, we define multi-head self-attention relations as scaled dot-product between the pairs of *query*, *key*, and *value* vectors within each self-attention module. Then we employ the above relational knowledge to train the student model. Besides its simplicity and unified principle, more favorably, there is no restriction in terms of the number of student’s attention heads, while most previous work has to guarantee the same head number between teacher and student. Moreover, the fine-grained self-attention relations tend to fully exploit the interaction knowledge learned by Transformer. In addition, we thoroughly examine the layer selection strategy for teacher models, rather than just relying on the last layer as in MINILM. We conduct extensive experiments on compressing both monolingual and multilingual pretrained models. Experimental results demonstrate that our models¹ distilled from base-size and large-size teachers (BERT, RoBERTa and XLM-R) outperform the state-of-the-art.

1 Introduction

Pretrained Transformers (Radford et al., 2018; Devlin et al., 2018; Dong et al., 2019; Yang et al., 2019; Joshi et al., 2019; Liu et al., 2019; Bao et al., 2020; Radford et al., 2019; Raffel et al., 2019; Lewis et al., 2019a) have been highly successful for a wide range of natural language processing tasks. However, these models usually consist of hundreds of millions of parameters and are getting bigger. It brings challenges for fine-tuning and online serv-

ing in real-life applications due to the restrictions of computation resources and latency.

Knowledge distillation (KD; Hinton et al. 2015, Romero et al. 2015) has been widely employed to compress pretrained Transformers, which transfers knowledge of the large model (teacher) to the small model (student) by minimizing the differences between teacher and student features. Soft target probabilities (soft labels) and intermediate representations are usually utilized to perform KD training. In this work, we focus on task-agnostic compression of pretrained Transformers (Sanh et al., 2019; Tsai et al., 2019; Jiao et al., 2019; Sun et al., 2019b; Wang et al., 2020). The student models are distilled from large pretrained Transformers using large-scale text corpora. The distilled task-agnostic model can be directly finetuned on downstream tasks, and can be utilized to initialize task-specific distillation.

DistilBERT (Sanh et al., 2019) uses soft target probabilities for masked language modeling predictions and embedding outputs to train the student. The student model is initialized from the teacher by taking one layer out of two. TinyBERT (Jiao et al., 2019) utilizes hidden states and self-attention distributions (i.e., attention maps and weights), and adopts a uniform function to map student and teacher layers for layer-wise distillation. MobileBERT (Sun et al., 2019b) introduces specially designed teacher and student models using inverted-bottleneck and bottleneck structures to keep their layer number and hidden size the same, layer-wisely transferring hidden states and self-attention distributions. MINILM (Wang et al., 2020) proposes deep self-attention distillation, which uses self-attention distributions and value relations to help the student to deeply mimic teacher’s self-attention modules. MINILM shows that transferring knowledge of teacher’s last layer achieves better performance than layer-wise distil-

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¹Distilled models and code will be publicly available at <https://aka.ms/minilm>.

lation. In summary, most previous work relies on self-attention distributions to perform KD training, which leads to a restriction that the number of attention heads of student model has to be the same as its teacher.

In this work, we generalize and simplify deep self-attention distillation of MINILM (Wang et al., 2020) by using self-attention relation distillation. We introduce multi-head self-attention relations computed by scaled dot-product of pairs of queries, keys and values, which guides the student training. Taking query vectors as an example, in order to obtain queries of multiple relation heads, we first concatenate query vectors of different attention heads, and then split the concatenated vector according to the desired number of relation heads. Afterwards, for teacher and student models with different attention head numbers, we can align their queries with the same number of relation heads for distillation. Moreover, using a larger number of relation heads brings more fine-grained self-attention knowledge, which helps the student to achieve a deeper mimicry of teacher’s self-attention module. In addition, for large-size (24 layers, 1024 hidden size) teachers, extensive experiments indicate that transferring an upper middle layer tends to perform better than using the last layer as in MINILM.

Experimental results show that our monolingual models distilled from BERT and RoBERTa, and multilingual models distilled from XLM-R outperform state-of-the-art models in different parameter sizes. The 6×768 (6 layers, 768 hidden size) model distilled from BERT_{LARGE} is $2.0 \times$ faster, meanwhile, performing better than BERT_{BASE}. The base-size model distilled from RoBERTa_{LARGE} outperforms RoBERTa_{BASE} using much fewer training examples.

To summarize, our contributions include:

- We generalize and simplify deep self-attention distillation in MINILM by introducing multi-head self-attention relation distillation, which brings more fine-grained self-attention knowledge and allows more flexibility for the number of student’s attention heads.
- We conduct extensive distillation experiments on different large-size teachers and find that using knowledge of a teacher’s upper middle layer achieves better performance.
- Experimental results demonstrate the effectiveness of our method for different monolin-

gual and multilingual teachers in base-size and large-size.

2 Related Work

2.1 Backbone Network: Transformer

Multi-layer Transformer (Vaswani et al., 2017) has been widely adopted in pretrained models. Each Transformer layer consists of a self-attention sub-layer and a position-wise fully connected feed-forward sub-layer.

Self-Attention Transformer relies on multi-head self-attention to capture dependencies between words. Given previous Transformer layer’s output $\mathbf{H}^{l-1} \in \mathbb{R}^{|x| \times d_h}$, the output of a self-attention head $\mathbf{O}_{l,a}$, $a \in [1, A_h]$ is computed via:

$$\mathbf{Q}_{l,a} = \mathbf{H}^{l-1} \mathbf{W}_{l,a}^Q \quad (1)$$

$$\mathbf{K}_{l,a} = \mathbf{H}^{l-1} \mathbf{W}_{l,a}^K \quad (2)$$

$$\mathbf{V}_{l,a} = \mathbf{H}^{l-1} \mathbf{W}_{l,a}^V \quad (3)$$

$$\mathbf{O}_{l,a} = \text{softmax}\left(\frac{\mathbf{Q}_{l,a} \mathbf{K}_{l,a}^T}{\sqrt{d_k}}\right) \mathbf{V}_{l,a} \quad (4)$$

Previous layer’s output is linearly projected to queries, keys and values using parameter matrices $\mathbf{W}_{l,a}^Q, \mathbf{W}_{l,a}^K, \mathbf{W}_{l,a}^V \in \mathbb{R}^{d_h \times d_k}$, respectively. The self-attention distributions are computed via scaled dot-product of queries and keys. These weights are assigned to the corresponding value vectors to obtain the attention output. $|x|$ represents the length of input sequence. A_h and d_h indicate the number of attention heads and hidden size. d_k is the attention head size. $d_k \times A_h$ is usually equal to d_h .

2.2 Pretrained Language Models

Pre-training has led to strong improvements across a variety of natural language processing tasks. Pretrained language models are learned on large amounts of text data, and then fine-tuned to adapt to specific tasks. BERT (Devlin et al., 2018) proposes to pretrain a deep bidirectional Transformer using masked language modeling (MLM) objective. UNILM (Dong et al., 2019) is jointly pretrained on three types language modeling objectives to adapt to both understanding and generation tasks. RoBERTa (Liu et al., 2019) achieves strong performance by training longer steps using large batch size and more text data. MASS (Song et al., 2019), T5 (Raffel et al., 2019) and BART (Lewis et al.,

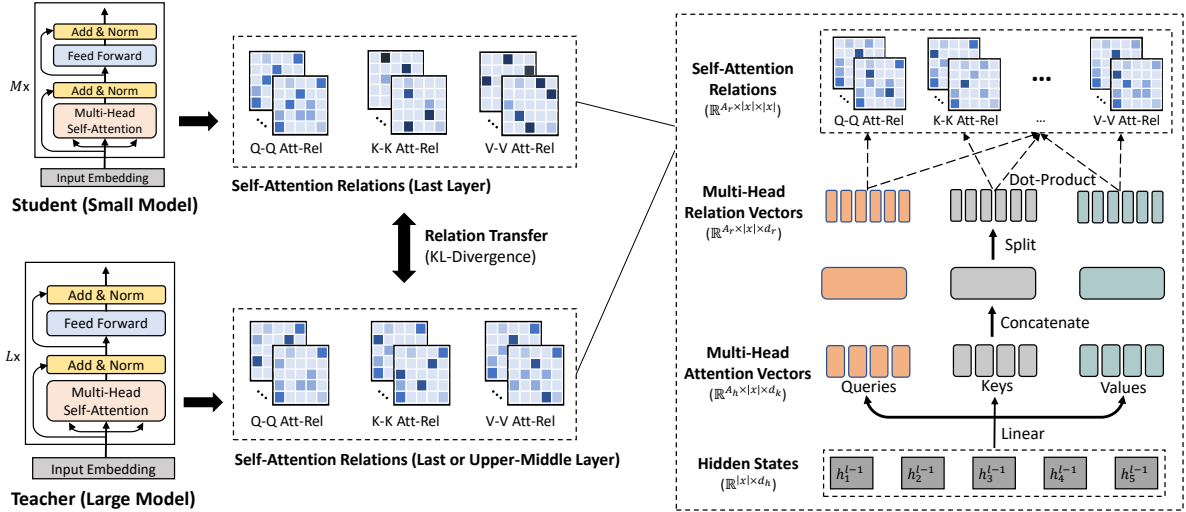


Figure 1: Overview of multi-head self-attention relation distillation. We introduce multi-head self-attention relations computed by scaled dot-product of pairs of queries, keys and values to guide the training of students. In order to obtain vectors (queries, keys and values) of multiple relation heads, we first concatenate self-attention vectors of different attention heads and then split them according to the desired number of relation heads. **We choose to transfer Q-Q, K-K and V-V self-attention relations to achieve a balance between performance and training speed.** For large-size teacher, we transfer the self-attention knowledge of an upper middle layer of the teacher. For base-size teacher, using the last layer achieves better performance.

2019a) employ a standard encoder-decoder structure and pretrain the decoder auto-regressively. Besides monolingual pretrained models, multilingual pretrained models (Devlin et al., 2018; Lample and Conneau, 2019; Chi et al., 2019; Conneau et al., 2019; Chi et al., 2020) also advance the state-of-the-art on cross-lingual understanding and generation.

2.3 Knowledge Distillation

Knowledge distillation has been proven to be a promising way to compress large models while maintaining accuracy. Knowledge of a single or an ensemble of large models is used to guide the training of small models. Hinton et al. (2015) propose to use soft target probabilities to train student models. More fine-grained knowledge such as hidden states (Romero et al., 2015) and attention distributions (Zagoruyko and Komodakis, 2017; Hu et al., 2018) are introduced to improve the student model.

In this work, we focus on task-agnostic knowledge distillation of pretrained Transformers. The distilled task-agnostic model can be fine-tuned to adapt to downstream tasks. It can also be utilized to initialize task-specific distillation (Sun et al., 2019a; Turc et al., 2019; Aguilar et al., 2019; Mukherjee and Awadallah, 2020; Xu et al., 2020; Hou et al., 2020; Li et al., 2020), which uses a fine-tuned teacher model to guide the training of the student on specific tasks. Knowledge used for dis-

tillation and layer mapping function are two key points for task-agnostic distillation of pretrained Transformers. Most previous work uses soft target probabilities, hidden states, self-attention distributions and value-relation to train the student model. For the layer mapping function, TinyBERT (Jiao et al., 2019) uses a uniform strategy to map teacher and student layers. MobileBERT (Sun et al., 2019b) assumes the student has the same number of layers as its teacher to perform layer-wise distillation. MINILM (Wang et al., 2020) transfers self-attention knowledge of teacher’s last layer to the student last Transformer layer. **Different from previous work, our method uses multi-head self-attention relations to eliminate the restriction on the number of student’s attention heads. Moreover, we show that transferring the self-attention knowledge of an upper middle layer of the large-size teacher model is more effective.**

3 Multi-Head Self-Attention Relation Distillation

Following MINILM (Wang et al., 2020), the key idea of our approach is to deeply mimic teacher’s self-attention module, which draws dependencies between words and is the vital component of Transformer. MINILM uses teacher’s self-attention distributions to train the student model. It brings

Model	Teacher	#Param	Speedup	SQuAD2	MNLI-m	QNLI	QQP	RTE	SST	MRPC	CoLA	Avg
BERT _{BASE}	-	109M	×1.0	76.8	84.5	91.7	91.3	68.6	93.2	87.3	58.9	81.5
RoBERTa _{BASE}	-	125M	×1.0	83.7	87.6	92.8	91.9	78.7	94.8	90.2	63.6	85.4
BERT _{SMALL}	-	66M	×2.0	73.2	81.8	89.8	90.6	67.9	91.2	84.9	53.5	79.1
Truncated BERT _{BASE}	-	66M	×2.0	69.9	81.2	87.9	90.4	65.5	90.8	82.7	41.4	76.2
Truncated RoBERTa _{BASE}	-	81M	×2.0	77.9	84.9	91.1	91.3	67.9	92.9	87.5	55.2	81.1
DistilBERT	BERT _{BASE}	66M	×2.0	70.7	82.2	89.2	88.5	59.9	91.3	87.5	51.3	77.6
TinyBERT	BERT _{BASE}	66M	×2.0	73.1	83.5	90.5	90.6	72.2	91.6	88.4	42.8	79.1
MINILM	BERT _{BASE}	66M	×2.0	76.4	84.0	91.0	91.0	71.5	92.0	88.4	49.2	80.4
6×384 Ours	BERT _{BASE}	22M	×5.3	72.9	82.8	90.3	90.6	68.9	91.3	86.6	41.8	78.2
6×384 Ours	BERT _{LARGE}	22M	×5.3	74.3	83.0	90.4	90.7	68.5	91.1	87.8	41.6	78.4
6×384 Ours	RoBERTa _{LARGE}	30M	×5.3	76.4	84.4	90.9	90.8	69.9	92.0	88.7	42.6	79.5
6×768 Ours	BERT _{BASE}	66M	×2.0	76.3	84.2	90.8	91.1	72.1	92.4	88.9	52.5	81.0
6×768 Ours	BERT _{LARGE}	66M	×2.0	77.7	85.0	91.4	91.1	73.0	92.5	88.9	53.9	81.7
6×768 Ours	RoBERTa _{LARGE}	81M	×2.0	81.6	87.0	92.7	91.4	78.7	94.5	90.4	54.0	83.8

Table 1: Results of our students distilled from base-size and large-size teachers on the development sets of GLUE and SQuAD 2.0. We report F1 for SQuAD 2.0, Matthews correlation coefficient for CoLA, and accuracy for other datasets. The GLUE results of DistilBERT are taken from Sanh et al. (2019). The rest results of DistilBERT, TinyBERT², BERT_{SMALL}, Truncated BERT_{BASE} and MINILM are taken from Wang et al. (2020). BERT_{SMALL} (Turc et al., 2019) is trained using the MLM objective, without using KD. We also report the results of truncated BERT_{BASE} and truncated RoBERTa_{BASE}, which drops the top 6 layers of the base model. Top-layer dropping has been proven to be a strong baseline (Sajjad et al., 2020). The fine-tuning results are an average of 4 runs.

the restriction on the number of attention heads of students, which is required to be the same as its teacher. To introduce more fine-grained self-attention knowledge and avoid using teacher’s self-attention distributions, we generalize deep self-attention distillation in MINILM and introduce multi-head self-attention relations of pairs of queries, keys and values to train the student. Besides, we conduct extensive experiments and find that layer selection of the teacher model is critical for distilling large-size models. Figure 1 gives an overview of our method.

3.1 Multi-Head Self-Attention Relations

Multi-head self-attention relations are obtained by scaled dot-product of pairs³ of queries, keys and values of multiple relation heads. Taking query vectors as an example, in order to obtain queries of multiple relation heads, **we first concatenate queries of different attention heads and then split the concatenated vector based on the desired number of relation heads. The same operation is also performed on keys and values. For teacher and student models which uses different number of attention heads, we convert their queries, keys and values of different number of attention heads into**

²In addition to task-agnostic distillation, TinyBERT uses task-specific distillation and data augmentation to further improve the model. We report the fine-tuning results of their public task-agnostic model.

³There are nine types of self-attention relations, such as query-query, key-key, key-value and query-value relations.

vectors of the same number of relation heads to perform KD training. Our method eliminates the restriction on the number of attention heads of student models. Moreover, using more relation heads in computing self-attention relations brings more fine-grained self-attention knowledge and improves the performance of the student model.

We use $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3$ to denote the queries, keys and values of multiple relation heads. The KL-divergence between multi-head self-attention relations of the teacher and student is used as the training objective:

$$\mathcal{L} = \sum_{i=1}^3 \sum_{j=1}^3 \alpha_{ij} \mathcal{L}_{ij} \quad (5)$$

$$\mathcal{L}_{ij} = \frac{1}{A_r |x|} \sum_{a=1}^{A_r} \sum_{t=1}^{|x|} D_{KL}(\mathbf{R}_{ij,l,a,t}^T \parallel \mathbf{R}_{ij,m,a,t}^S) \quad (6)$$

$$\mathbf{R}_{ij,l,a}^T = \text{softmax}\left(\frac{\mathbf{A}_{i,l,a}^T \mathbf{A}_{j,l,a}^{T\top}}{\sqrt{d_r}}\right) \quad (7)$$

$$\mathbf{R}_{ij,m,a}^S = \text{softmax}\left(\frac{\mathbf{A}_{i,m,a}^S \mathbf{A}_{j,m,a}^{S\top}}{\sqrt{d'_r}}\right) \quad (8)$$

where $\mathbf{A}_{i,l,a}^T \in \mathbb{R}^{|x| \times d_r}$ and $\mathbf{A}_{i,m,a}^S \in \mathbb{R}^{|x| \times d'_r}$ ($i \in [1, 3]$) are the queries, keys and values of a relation head of l -th teacher layer and m -th student layer. d_r and d'_r are the relation head size of teacher and student models. $\mathbf{R}_{ij,l}^T \in \mathbb{R}^{A_r \times |x| \times |x|}$ is the self-attention relation of $\mathbf{A}_{i,l}^T$ and $\mathbf{A}_{j,l}^T$ of teacher model.

Model	Teacher	#Param	Speedup	SQuAD2	MNLI-m/mm	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	Avg
BERT _{BASE}	-	109M	1.0×	76.8	84.6/83.4	90.5	71.2	66.4	93.5	88.9	52.1	85.8	79.3
BERT _{LARGE}	-	340M	0.3×	81.9	86.7/85.9	92.7	72.1	70.1	94.9	89.3	60.5	86.5	82.1
6×768 Ours	BERT _{BASE}	66M	2.0×	76.3	83.8/83.3	90.2	70.9	69.2	92.9	89.1	46.6	84.3	78.7
6×768 Ours	BERT _{LARGE}	66M	2.0×	77.7	84.5/84.0	91.5	71.3	69.2	93.0	89.1	48.6	85.1	79.4

Table 2: Results of our 6×768 students distilled from BERT on GLUE test sets and SQuAD 2.0 dev set. The reported results are directly fine-tuned on downstream tasks. We report F1 for SQuAD 2.0, QQP and MRPC, Spearman correlation for STS-B, Matthews correlation coefficient for CoLA and accuracy for the rest.

$\mathbf{R}_{ij,l,a}^T \in \mathbb{R}^{|x| \times |x|}$ is the self-attention relation of a teacher’s relation head. $\mathbf{R}_{ij,m}^S \in \mathbb{R}^{A_r \times |x| \times |x|}$ is the self-attention relation of student model. For example, $\mathbf{R}_{11,l}^T$ represents teacher’s Q-Q attention relation in Figure 1. A_r is the number of relation heads. **If the number of relation heads and attention heads is the same, the Q-K relation is equivalent to the attention weights in self-attention module.** $\alpha_{ij} \in \{0, 1\}$ is the weight assigned to each self-attention relation loss. **We transfer query-query, key-key and value-value self-attention relations to balance the performance and training cost.**

3.2 Layer Selection of Teacher Model

Besides the knowledge used for distillation, mapping function between teacher and student layers is another key factor. **As in MINILM, we only transfer the self-attention knowledge of one of the teacher layers to the student last layer. Only distilling one layer of the teacher model is fast and effective. Different from previous work which usually conducts experiments on base-size teachers, we experiment with different large-size teachers and find that transferring self-attention knowledge of an upper middle layer performs better than using other layers.** For BERT_{LARGE} and BERT_{LARGE-WWM}, transferring the 21-th (start at one) layer achieves the best performance. For RoBERTa_{LARGE} and XLM-R_{LARGE}, using the self-attention knowledge of 19-th layer achieves better performance. For the base-size teacher, we also find that using teacher’s last layer performs better.

4 Experiments

We conduct distillation experiments on different teacher models including BERT_{BASE}, BERT_{LARGE}, BERT_{LARGE-WWM}, RoBERTa_{BASE}, RoBERTa_{LARGE}, XLM-R_{BASE} and XLM-R_{LARGE}.

4.1 Setup

We use the uncased version for three BERT teacher models. For the pre-training data, we use English

Wikipedia and BookCorpus (Zhu et al., 2015). We train student models using 256 as the batch size and 6e-4 as the peak learning rate for 400,000 steps. We use linear warmup over the first 4,000 steps and linear decay. We use Adam (Kingma and Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.999$. The maximum sequence length is set to 512. The dropout rate and weight decay are 0.1 and 0.01. The number of attention heads is 12 for all student models. The number of relation heads is 48 and 64 for base-size and large-size teacher model, respectively. The student models are initialized randomly.

For models distilled from RoBERTa, we use similar pre-training datasets as in Liu et al. (2019). For the 12×768 student model, we use Adam with $\beta_1 = 0.9$, $\beta_2 = 0.98$. The rest hyper-parameters are the same as models distilled from BERT.

For multilingual student models distilled from XLM-R, we perform training using the same datasets as in Conneau et al. (2019) for 1,000,000 steps. We conduct distillation experiments using 8 V100 GPUs with mixed precision training.

4.2 Downstream Tasks

Following previous pre-training (Devlin et al., 2018; Liu et al., 2019; Conneau et al., 2019) and task-agnostic distillation (Sun et al., 2019b; Jiao et al., 2019) work, we evaluate the English student models on GLUE benchmark and extractive question answering. The multilingual models are evaluated on cross-lingual natural language inference and cross-lingual question answering.

GLUE General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2019) consists of two single-sentence classification tasks (SST-2 (Socher et al., 2013) and CoLA (Warstadt et al., 2018)), three similarity and paraphrase tasks (MRPC (Dolan and Brockett, 2005), STS-B (Cer et al., 2017) and QQP), and four inference tasks (MNLI (Williams et al., 2018), QNLI (Rajpurkar et al., 2016), RTE (Dagan et al., 2006; Bar-Haim et al., 2006; Giampiccolo et al., 2007; Bentivogli

Model	Teacher	#Param	SQuAD2	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	Avg
BERT _{BASE}	-	109M	76.8	84.5	91.7	91.3	68.6	93.2	87.3	58.9	89.5	82.4
RoBERTa _{BASE}	-	125M	83.7	87.6	92.8	91.9	78.7	94.8	90.2	63.6	91.2	86.1
12×768 Ours	BERT _{LARGE}	109M	81.8	86.5	92.6	91.6	76.4	93.3	89.2	62.3	90.5	84.9
12×768 Ours	RoBERTa _{LARGE}	125M	86.6	89.4	94.0	91.8	83.1	95.9	91.2	65.0	91.3	87.6

Table 3: Results of our 12×768 models on the dev sets of GLUE benchmark and SQuAD 2.0. The fine-tuning results are an average of 4 runs for each task. We report F1 for SQuAD 2.0, Pearson correlation for STS-B, Matthews correlation coefficient for CoLA and accuracy for the rest.

Model	SQuAD2	MNLI-m	SST-2	Avg
MINILM (Last Layer)	79.1	84.7	91.2	85.0
+ Upper Middle Layer	80.3	85.2	91.5	85.7
12×384 Ours	80.7	85.7	92.3	86.2

Table 4: Comparison of different methods using BERT_{LARGE-WWM} as the teacher. We report dev results of 12×384 student model with 128 embedding size.

et al., 2009) and WNLI (Levesque et al., 2012)).

Extractive Question Answering The task aims to predict a continuous sub-span of the passage to answer the question. We evaluate on SQuAD 2.0 (Rajpurkar et al., 2018), which has been served as a major question answering benchmark.

Cross-lingual Natural Language Inference (XNLI) XNLI (Conneau et al., 2018) is a cross-lingual classification benchmark. It aims to identify the semantic relationship between two sentences and provides instances in 15 languages.

Cross-lingual Question Answering We use MLQA (Lewis et al., 2019b) to evaluate multi-lingual models. MLQA extends English SQuAD dataset (Rajpurkar et al., 2016) to seven languages.

4.3 Main Results

Table 1 presents the dev results of 6×384 and 6×768 models distilled from BERT_{BASE}, BERT_{LARGE} and RoBERTa_{LARGE} on GLUE and SQuAD 2.0. (1) Previous methods (Sanh et al., 2019; Jiao et al., 2019; Sun et al., 2019a; Wang et al., 2020) usually **distill BERT_{BASE} into a 6-layer model with 768 hidden size. We first report results of the same setting.** Our 6×768 model outperforms DistilBERT, TinyBERT, MINILM and two BERT baselines across most tasks. Moreover, our method allows more flexibility for the number of attention heads of student models. (2) Both 6×384 and 6×768 models distilled from BERT_{LARGE} outperform models distilled from BERT_{BASE}. The 6×768 model distilled from BERT_{LARGE} is 2.0×

faster than BERT_{BASE}, while achieving better performance. (3) Student models distilled from RoBERTa_{LARGE} achieve further improvements. Better teacher results in better students. Multi-head self-attention relation distillation is effective for different large-size pretrained Transformers.

We report the results of 6×768 students distilled from BERT_{BASE} and BERT_{LARGE} on GLUE test sets and SQuAD 2.0 dev set in Table 2. 6×768 model distilled from BERT_{BASE} retains more than 99% accuracy of its teacher while using 50% Transformer parameters. 6×768 model distilled from BERT_{LARGE} compares favorably with BERT_{BASE}.

We compress RoBERTa_{LARGE} and BERT_{LARGE} into a base-size student model. Dev results of GLUE benchmark and SQuAD 2.0 are shown in Table 3. Our base-size models distilled from large-size teacher outperforms BERT_{BASE} and RoBERTa_{BASE}. Our method can be adopted to train students in different parameter size. Moreover, our student distilled from RoBERTa_{LARGE} uses a much smaller (almost 32× smaller) training batch size and fewer training steps than RoBERTa_{BASE}. Our method requires much fewer training examples.

Most of previous work conducts experiments using base-size teachers. To compare with previous methods on large-size teacher, we reimplement MINILM and compress BERT_{LARGE-WWM} into a 12×384 student model. Dev results of SQuAD 2.0, MNLI-m and SST-2 are presented in Table 4. Our method also outperforms MINILM for large-size teachers. Moreover, we report results of distilling an upper middle layer instead of the last layer for MINILM. Layer selection is also effective for MINILM when distilling large-size teachers.

Table 5 and Table 6 show the results of our student models distilled from XLM-R on XNLI and MLQA. For XNLI, the best single model is selected on the joint dev set of all the languages as in Conneau et al. (2019). Following Lewis et al. (2019b), we adopt SQuAD 1.1 as training data and evaluate on MLQA English development set for

Model	Teacher	#L	#H	#Param	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
mBERT	-	12	768	170M	82.1	73.8	74.3	71.1	66.4	68.9	69.0	61.6	64.9	69.5	55.8	69.3	60.0	50.4	58.0	66.3
XML-100	-	16	1280	570M	83.2	76.7	77.7	74.0	72.7	74.1	72.7	68.7	68.6	72.9	68.9	72.5	65.6	58.2	62.4	70.7
XML-R _{BASE}	-	12	768	277M	85.8	79.7	80.7	78.7	77.5	79.6	78.1	74.2	73.8	76.5	74.6	76.7	72.4	66.5	68.3	76.2
MINILM	XML-R _{BASE}	6	384	107M	79.2	72.3	73.1	70.3	69.1	72.0	69.1	64.5	64.9	69.0	66.0	67.8	62.9	59.0	60.6	68.0
6×384 Ours	XML-R _{BASE}	6	384	107M	78.8	72.1	73.4	69.4	70.7	72.2	69.9	66.7	66.7	69.5	67.4	68.6	65.3	61.2	61.9	68.9
6×384 Ours	XML-R _{LARGE}	6	384	107M	78.9	72.5	73.5	69.8	70.9	72.3	69.7	67.5	67.1	70.2	67.4	69.1	65.4	62.3	63.4	69.3
MINILM	XML-R _{BASE}	12	384	117M	81.5	74.8	75.7	72.9	73.0	74.5	71.3	69.7	68.8	72.1	67.8	70.0	66.2	63.3	64.2	71.1
12×384 Ours	XML-R _{BASE}	12	384	117M	82.2	75.3	76.5	73.3	73.8	75.1	73.1	70.7	69.5	72.8	69.4	71.5	68.6	65.6	65.5	72.2
12×384 Ours	XML-R _{LARGE}	12	384	117M	82.4	76.2	76.8	73.9	74.6	75.5	73.7	70.8	70.5	73.4	71.1	72.5	68.8	66.8	67.0	72.9

Table 5: Cross-lingual classification results of our multilingual models on XNLI. We report the accuracy on each of the 15 XNLI languages and the average accuracy. #L and #H indicate the number of layers and hidden size.

Model	Teacher	#L	#H	#Param	en	es	de	ar	hi	vi	zh	Avg
mBERT	-	12	768	170M	77.7 / 65.2	64.3 / 46.6	57.9 / 44.3	45.7 / 29.8	43.8 / 29.7	57.1 / 38.6	57.5 / 37.3	57.7 / 41.6
XML-15	-	12	1024	248M	74.9 / 62.4	68.0 / 49.8	62.2 / 47.6	54.8 / 36.3	48.8 / 27.3	61.4 / 41.8	61.1 / 39.6	61.6 / 43.5
XML-R _{BASE}	-	12	768	277M	77.1 / 64.6	67.4 / 49.6	60.9 / 46.7	54.9 / 36.6	59.4 / 42.9	64.5 / 44.7	61.8 / 39.3	63.7 / 46.3
XML-R _{BASE} †	-	12	768	277M	80.3 / 67.4	67.0 / 49.2	62.7 / 48.3	55.0 / 35.6	60.4 / 43.7	66.5 / 45.9	62.3 / 38.3	64.9 / 46.9
MINILM	XML-R _{BASE}	6	384	107M	75.5 / 61.9	55.6 / 38.2	53.3 / 37.7	43.5 / 26.2	46.9 / 31.5	52.0 / 33.1	48.8 / 27.3	53.7 / 36.6
6×384 Ours	XML-R _{BASE}	6	384	107M	75.6 / 61.9	60.4 / 42.6	57.5 / 42.4	49.9 / 31.1	53.4 / 36.3	57.2 / 36.7	54.4 / 32.4	58.3 / 40.5
6×384 Ours	XML-R _{LARGE}	6	384	107M	75.8 / 62.4	60.5 / 43.4	56.7 / 41.6	49.3 / 30.9	55.1 / 38.1	58.6 / 38.5	56.9 / 34.3	59.0 / 41.3
MINILM	XML-R _{BASE}	12	384	117M	79.4 / 66.5	66.1 / 47.5	61.2 / 46.5	54.9 / 34.9	58.5 / 41.3	63.1 / 42.1	59.0 / 33.8	63.2 / 44.7
12×384 Ours	XML-R _{BASE}	12	384	117M	79.0 / 65.8	66.6 / 48.9	62.1 / 47.4	54.4 / 35.5	60.6 / 43.6	64.7 / 44.1	59.4 / 36.5	63.8 / 46.0
12×384 Ours	XML-R _{LARGE}	12	384	117M	78.9 / 65.9	67.3 / 49.4	61.9 / 47.0	56.0 / 36.5	63.0 / 45.9	65.1 / 44.4	61.9 / 39.2	64.9 / 46.9

Table 6: Cross-lingual question answering results of our multilingual models on MLQA. We report the F1 and EM (exact match) scores on each of the 7 MLQA languages. #L and #H indicate the number of layers and hidden size. † indicates our fine-tuned results of XML-R_{BASE}.

Model	SQuAD2	MNLI-m	SST-2	Avg
Ours (Q-Q + K-K + V-V)	72.8	82.2	91.5	82.2
- Q-Q Att-Rel	71.6	81.9	90.6	81.4
- K-K Att-Rel	71.9	81.9	90.5	81.4
- V-V Att-Rel	71.5	81.6	90.5	81.2
Q-K + V-V Att-Rel	72.4	82.2	91.0	81.9

Table 7: Ablation studies of different self-attention relations. We report results of 6×384 student model distilled from BERT_{BASE}. The relation head number is 12.

#Relation Heads	6	12	24	48
6×384 model distilled from RoBERTa _{BASE}				
MNLI-m	82.8	82.9	83.0	83.4
SQuAD 2.0	74.5	75.0	74.9	75.7
6×384 model distilled from BERT _{BASE}				
MNLI-m	81.9	82.2	82.2	82.4
SQuAD 2.0	71.9	72.8	72.7	73.0

Table 8: Results of 6×384 model using different number of relation heads.

early stopping. Our 6×384 model outperforms mBERT (Devlin et al., 2018) with 5.3× speedup. Our method also performs better than MINILM, which further validates the effectiveness of multi-head self-attention relation distillation. Transferring multi-head self-attention relations can bring more fine-grained self-attention knowledge.

4.4 Ablation Studies

Effect of using different self-attention relations

We perform ablation studies to analyse the contribution of different self-attention relations. Dev results of three tasks are illustrated in Table 7. Q-Q, K-K and V-V self-attention relations positively contribute to the final results. Besides, we also compare Q-Q + K-K + V-V with Q-K + V-V given queries and keys are employed to compute self-attention distributions in self-attention module. Experimental result shows that using Q-Q + K-K + V-V achieves better performance.

Effect of distilling different teacher layers

Figure 2 presents the results of 6×384 model distilled from different layers of BERT_{BASE}, BERT_{LARGE} and XML-R_{LARGE}. For BERT_{BASE}, using the last layer achieves better performance than other layers. For BERT_{LARGE} and XML-R_{LARGE}, we find that using one of the upper middle layers achieves the best performance. The same trend is also observed for BERT_{LARGE-WWM} and RoBERTa_{LARGE}.

Effect of different number of relation heads

Table 8 shows the results of 6×384 model distilled from BERT_{BASE} and RoBERTa_{BASE} using different number of relation heads. Using a larger number of relation heads achieves better performance. More

Model	Teacher	#Param	Speedup	SQuAD2	MNLI-m/mm	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	Avg
BERT _{BASE}	-	109M	1.0×	76.8	84.6/83.4	90.5	71.2	66.4	93.5	88.9	52.1	85.8	79.3
MobileBERT	IB-BERT _{LARGE}	25M	1.8×	80.2	84.3/83.4	91.6	70.5	70.4	92.6	88.8	51.1	84.8	79.8
12×384 Ours	BERT _{LARGE-WWM}	25M	2.7×	80.7	85.9/84.6	91.9	71.4	71.9	93.3	89.2	44.9	85.5	79.9
+ More Att-Rels	BERT _{LARGE-WWM}	25M	2.7×	80.9	85.8/84.8	92.3	71.6	72.0	93.6	89.7	46.6	86.0	80.3

Table 9: Comparison between MobileBERT and the same-size model (12 layers, 384 hidden size and 128 embedding size) distilled from BERT_{LARGE} (Whole Word Masking) on GLUE test sets and SQuAD 2.0 dev set. Following MobileBERT (Sun et al., 2019b), the reported results are directly fine-tuned on downstream tasks. We compute the speedup of MobileBERT according to their reported latency.

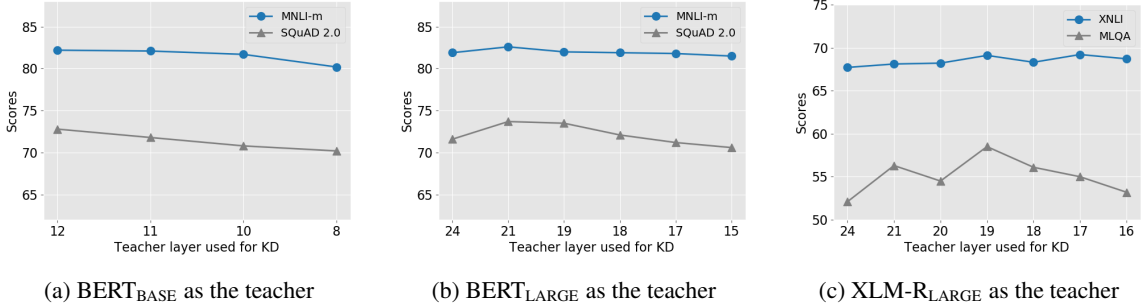


Figure 2: 6×384 models trained using different BERT_{BASE} (a), BERT_{LARGE} (b) and XLM-R_{LARGE} (c) layers.

Model	Teacher	SQuAD2	MNLI-m	SST-2
6×384 Ours + More Att-Rels	BERT _{BASE}	72.9	82.8	91.3
	BERT _{BASE}	73.3	82.8	91.6
6×384 Ours + More Att-Rels	BERT _{LARGE}	74.3	83.0	91.1
	BERT _{LARGE}	74.7	83.2	92.4
6×384 Ours + More Att-Rels	RoBERTa _{LARGE}	76.4	84.4	92.0
	RoBERTa _{LARGE}	76.0	84.4	92.1
6×768 Ours + More Att-Rels	BERT _{BASE}	76.3	84.2	92.4
	BERT _{BASE}	76.8	84.4	92.3
6×768 Ours + More Att-Rels	BERT _{LARGE}	77.7	85.0	92.5
	BERT _{LARGE}	78.1	85.2	92.5
6×768 Ours + More Att-Rels	RoBERTa _{LARGE}	81.6	87.0	94.5
	RoBERTa _{LARGE}	81.2	87.3	94.1

Table 10: Results of introducing more self-attention relations (Q-K, K-Q, Q-V, V-Q, K-V and V-K relations).

fine-grained self-attention knowledge can be captured by using more relation heads, which helps the student to deeply mimic the self-attention module of its teacher. Besides, we find that the number of relation heads is not required to be a positive multiple of both the number of student and teacher attention heads. The relation head can be a fragment of a single attention head or contains fragments from multiple attention heads.

5 Discussion

5.1 Comparison with MobileBERT

MobileBERT (Sun et al., 2019b) compresses a specially designed teacher model (in the BERT_{LARGE} size) with inverted bottleneck modules into a 24-

layer student using the bottleneck modules. Since our goal is to compress different large models (e.g. BERT and RoBERTa) to small models using standard Transformer architecture, we note that our student model can not directly compare with MobileBERT. We provide results of a student model with the same parameter size for a reference. A public large-size model (BERT_{LARGE-WWM}) is used as the teacher, which achieves similar performance as MobileBERT’s teacher. We distill BERT_{LARGE-WWM} into a student model (25M parameters) using the same training data (i.e., English Wikipedia and BookCorpus). The test results of GLUE and dev result of SQuAD 2.0 are illustrated in Table 9. Our model outperforms MobileBERT across most tasks with a faster inference speed. Moreover, our method can be applied for different teachers and has much fewer restriction of students.

We also observe that our model performs relatively worse on CoLA compared with MobileBERT. The task of CoLA is to evaluate the grammatical acceptability of a sentence. It requires more fine-grained linguistic knowledge that can be learnt from language modeling objectives. Fine-tuning the model using the MLM objective as in MobileBERT brings improvements for CoLA. However, our preliminary experiments show that this strategy will lead to slight drop for other GLUE tasks.

5.2 Results of More Self-Attention Relations

In Table 9 and 10, we report results of students trained using more self-attention relations (Q-K, K-Q, Q-V, V-Q, K-V and V-K relations). We observe improvements across most tasks, especially for student models distilled from BERT. Fine-grained self-attention knowledge in more attention relations improves our students. **However, introducing more self-attention relations also brings a higher computational cost. In order to achieve a balance between performance and computational cost, we choose to transfer Q-Q, K-K and V-V self-attention relations instead of all self-attention relations in this work.**

6 Conclusion

We generalize deep self-attention distillation in MINILM by employing multi-head self-attention relations to train the student. **Our method introduces more fine-grained self-attention knowledge and eliminates the restriction of the number of student’s attention heads. Moreover, we show that transferring the self-attention knowledge of an upper middle layer achieves better performance for large-size teachers.** Our monolingual and multilingual models distilled from BERT, RoBERTa and XLM-R obtain competitive performance and outperform state-of-the-art methods. For future work, we are exploring an automatic layer selection algorithm. We also would like to apply our method to larger pretrained Transformers.

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Corpus	#Train	#Dev	#Test	Metrics
<i>Single-Sentence Tasks</i>				
CoLA	8.5k	1k	1k	Matthews Corr
SST-2	67k	872	1.8k	Accuracy
<i>Similarity and Paraphrase Tasks</i>				
QQP	364k	40k	391k	Accuracy/F1
MRPC	3.7k	408	1.7k	Accuracy/F1
STS-B	7k	1.5k	1.4k	Pearson/Spearman Corr
<i>Inference Tasks</i>				
MNLI	393k	20k	20k	Accuracy
RTE	2.5k	276	3k	Accuracy
QNLI	105k	5.5k	5.5k	Accuracy
WNLI	634	71	146	Accuracy

Table 11: Summary of the GLUE benchmark.

#Train	#Dev	#Test	Metrics
130,319	11,873	8,862	Exact Match/F1

Table 12: Dataset statistics and metrics of SQuAD 2.0.

1 (Long Papers), pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.

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A GLUE Benchmark

The summary of datasets used for the General Language Understanding Evaluation (GLUE) benchmark⁴ (Wang et al., 2019) is presented in Table 11.

⁴<https://gluebenchmark.com/>

B SQuAD 2.0

We present the dataset statistics and metrics of SQuAD 2.0⁵ (Rajpurkar et al., 2018) in Table 12.

C Hyper-parameters for Fine-tuning

Extractive Question Answering For SQuAD 2.0, the maximum sequence length is 384. The batch size is set to 32. We choose learning rates from {3e-5, 6e-5, 8e-5, 9e-5} and fine-tune the model for 3 epochs. The warmup ratio and weight decay is 0.1 and 0.01.

GLUE The maximum sequence length is 128 for the GLUE benchmark. We set batch size to 32, choose learning rates from {1e-5, 1.5e-5, 2e-5, 3e-5, 5e-5} and epochs from {3, 5, 10} for different student models. We fine-tune CoLA task with longer training steps (25 epochs). The warmup ratio and weight decay is 0.1 and 0.01.

Cross-lingual Natural Language Inference (XNLI) The maximum sequence length is 256 for XNLI. We fine-tune 10 epochs using 64 as the batch size. The learning rates are chosen from {3e-5, 4e-5, 5e-5, 6e-5}.

Cross-lingual Question Answering For MLQA, the maximum sequence length is 512. We fine-tune 4 epochs using 32 as the batch size. The learning rates are chosen from {3e-5, 4e-5, 5e-5, 6e-5}.

⁵<http://stanford-qa.com>