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 taskagnostic compression of pretrained Transformers. In particular, we define multi-head selfattention 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. Experimental results demonstrate that our models1 distilled from base-size and large-size teachers (BERT, and RoBERTa) 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., 2019) 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 serving 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. Tiny-BERT (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 distillation. In summary, most previous work relies on self-attention distributions to perform KD training,

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

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 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 achieves 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 student models distilled from BERT and RoBERTa both 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, achieving better performance than BERT_{BASE}. The base-size model distilled from RoBERTa_{LARGE} outperforms RoBERTa_{BASE} even using much fewer training examples.

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 sublayer and a position-wise fully connected feedforward 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 $O_{l,a}, a \in [1, A_h]$ is computed via:

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

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

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

$$\mathbf{O}_{l,a} = \operatorname{softmax}(\frac{\mathbf{Q}_{l,a}\mathbf{K}_{l,a}^{\mathsf{T}}}{\sqrt{d_k}})\mathbf{V}_{l,a}$$
 (4)

Previous layer's output \mathbf{H}^{l-1} 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. XL-Net (Yang et al., 2019) introduces permutation language modeling objective to predict masked tokens auto-regressively. SpanBERT (Joshi et al., 2019) improves BERT by incorporating span information. 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., 2019) employ a standard encoder-decoder structure and pretrain the decoder auto-regressively. Bao et al. (2020) propose a pseud-masked language model by jointly pretrained on MLM and partially auto-regressive MLM objectives. 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 benchmarks.

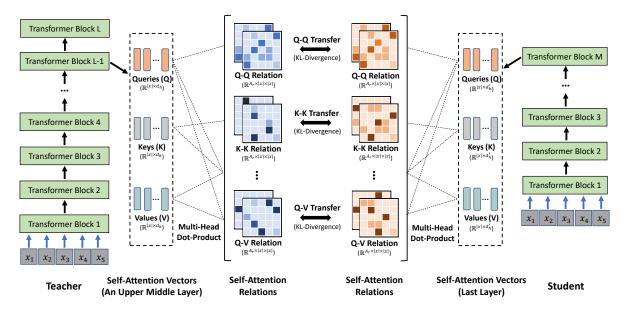


Figure 1: Overview of multi-head self-attention relation distillation. We introduce multi-head self-attention relations computed by scaled dot-product of pairs of queries, keys and values to guide the training of students. In order to obtain self-attention vectors (queries, keys and values) of multiple relation heads, we first concatenate self-attention vectors of different attention heads and then split them according to the desired number of relation heads. 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. Our student models are named as MINILMv2.

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 finetuned teacher model to guide the training of the student on specific tasks. Knowledge used for distillation 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, 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 the restriction on the number of attention heads of students, which is required to be the same as its teacher. To achieve a deeper mimicry and avoid using teacher's self-attention distributions, we 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

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
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	$\times 2.0$	69.9	81.2	87.9	90.4	65.5	90.8	82.7	41.4	76.2
Truncated RoBERTa _{BASE}	-	81M	$\times 2.0$	77.9	84.9	91.1	91.3	67.9	92.9	87.5	55.2	81.1
DistilBERT	BERTBASE	66M	$\times 2.0$	70.7	82.2	89.2	88.5	59.9	91.3	87.5	51.3	77.6
TinyBERT	BERTBASE	66M	$\times 2.0$	73.1	83.5	90.5	90.6	72.2	91.6	88.4	42.8	79.1
6×768 MiniLM	BERTBASE	66M	$\times 2.0$	76.4	84.0	91.0	91.0	71.5	92.0	88.4	49.2	80.4
6×384 MINILMv2	BERTBASE	22M	×5.3	72.9	82.8	90.3	90.6	68.9	91.3	86.6	41.8	78.2
6×384 MiniLMv2	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 MiniLMv2	Roberta	30M	×5.3	76.4	84.4	90.9	90.8	69.9	92.0	88.7	42.6	79.5
6×768 MiniLMv2	BERTBASE	66M	×2.0	76.3	84.2	90.8	91.1	72.1	92.4	88.9	52.5	81.0
6×768 MiniLMv2	BERT _{LARGE}	66M	$\times 2.0$	77.7	85.0	91.4	91.1	73.0	92.5	88.9	53.9	81.7
6×768 MiniLMv2	RoBERTa _{LARGE}	81M	$\times 2.0$	81.6	87.0	92.7	91.4	78. 7	94.5	90.4	54.0	83.8

Table 1: Results of MINILMv2 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 6×768 MINILM are taken from Wang et al. (2020). BERT_{SMALL} (Turc et al., 2019) is trained using the MLM objective, without using knowledge distillation. 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 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 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 A_1, A_2, A_3 to denote the queries, keys and values of multiple relation heads. The KL-divergence between multi-head self-attention re-

lations of the teacher and student is used as the training objective:

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

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

$$\mathbf{R}_{ij,l,a}^{T} = \operatorname{softmax}(\frac{\mathbf{A}_{i,l,a}^{T} \mathbf{A}_{j,l,a}^{T\intercal}}{\sqrt{d_r}})$$
 (7)

$$\mathbf{R}_{ij,m,a}^{S} = \operatorname{softmax}(\frac{\mathbf{A}_{i,m,a}^{S} \mathbf{A}_{j,m,a}^{ST}}{\sqrt{d_r'}}) \qquad (8)$$

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. $\mathbf{R}_{ij,m}^S \in \mathbb{R}^{A_r \times |x| \times |x|}$ is the self-attention relation of student model. For example, $\mathbf{R}_{11,l}^T$ represents teacher's Q-Q relation in Figure 1. A_r is the number of relation heads. $\alpha_{ij} \in \{0,1\}$ is the weight assigned to each self-attention relation loss. We find that only using the query-query, key-key and value-value relations achieves competitive performance.

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.

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	$0.3 \times$	81.9	86.7/85.9	92.7	72.1	70.1	94.9	89.3	60.5	86.5 82.1
MINILMv2	BERTBASE	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
MiniLMv2	BERT _{LARGE}	66M	$2.0 \times$	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 6×768 MINILMv2 distilled form 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.

3.2 Layer Selection of Teacher Model

Besides the knowledge used for distillation, mapping function between teacher and student layers is also important. As in MINILM, we only transfer the self-attention knowledge of one of the teacher layers to the student last layer. Different from previous work which usually conducts experiments on base-size models, 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}, using the selfattention knowledge of 19-th layer achieves better performance. For the base-size model, experiments indicate that using teacher's last layer performs better than other layers.

4 Experiments

We conduct distillation experiments on different teacher models including BERT_{BASE}, BERT_{LARGE}, BERT_{LARGE}, BERT_{LARGE}, We use multi-head query-query, key-key and value-value relations to perform KD training.

4.1 Setup

We use the uncased version for three BERT teacher models (BERT_{BASE}, BERT_{LARGE} and BERT_{LARGE-WWM}). BERT_{BASE} consists of 12 Transformer layers with 768 hidden size, and 12 attention heads. It contains about 109M parameters. BERT_{LARGE} and BERT_{LARGE-WWM} are a 24-layer Transformer with 1024 hidden size and 16 attention heads. They are both consist of 340M parameters. For the pre-training data, we use English Wikipedia and BookCorpus (Zhu et al., 2015), and follow the preprocess and the WordPiece tokenization of Devlin et al. (2018). 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. For BERT_{LARGE} and BERT_{LARGE-WWM}, we use the self-attention knowledge of the 21-th layer to train the student model. 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 RoBERTa_{LARGE}, we use similar pre-training datasets as in Liu et al. (2019), which includes 160GB text corpora from English Wikipedia, Book-Corpus (Zhu et al., 2015), OpenWebText, CC-News (Liu et al., 2019), and Stories (Trinh and Le, 2018). We use the self-attention knowledge of teacher's 19-th layer for training the small models. For the 12×768 (base-size) student model, we use Adam with $\beta_1=0.9,\,\beta_2=0.98$. The rest hyperparameters are the same as models distilled from BERT. 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) and task-agnostic distillation (Sun et al., 2019b; Jiao et al., 2019) work, we evaluate the models on GLUE benchmark and extractive 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 et al., 2009) and WNLI (Levesque et al., 2012)). Following BERT (Devlin et al., 2018), a task-specific linear layer is added on top of the [CLS]

Model	Teacher	#Param	Speedup	SQuAD2	MNLI-m/mm	QNLI	QQP	RTE	SST	MRPC	CoLA	STS Avg
$BERT_{BASE}$	-	109M	$1.0 \times$	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
MiniLMv2	BERT _{LARGE-WWM}	25M	$2.7 \times$	80.7	85.9/84.6	91.9	71.4	71.9	93.3	89.2	44.9	85.5 79.9

Table 3: Comparison between MobileBERT and the same-size MINILMv2 (12 layers, 384 hidden size and 128 embedding size) distilled form 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.

Model	Teacher	#Param	SQuAD2	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS Avg
BERT _{BASE} RoBERTa _{BASE}	-	109M 125M	76.8 83.7	84.5 87.6	91.7 92.8	91.3 91.9	68.6 78.7	93.2 94.8	87.3 90.2	58.9 63.6	89.5 82.4 91.2 86.1
MINILMv2	BERT _{LARGE}	109M	81.8	86.5	92.6	91.6	76.4	93.3	89.2	62.3	90.5 84.9
MINILMv2	RoBERTa _{LARGE}	125M	86.6	89.4	94.0	91.8	83.1	95.9	91.2	65.0	91.3 87.6

Table 4: Results of 12×768 MINILMv2 on the dev sets of the 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.

representation.

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. We pack the question and passage tokens together with special tokens to form the input: "[CLS] Q [SEP] P [SEP]". Two linear output layers are introduced to predict the probability of each token being the start and end positions of the answer span. The questions that do not have an answer are treated as having an answer span with start and end at the [CLS] token.

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 6layer model with 768 hidden size. We first compare our 6×768 model using BERT_{BASE} as the teacher with previous models. Our model outperforms DistilBERT, TinyBERT, MINILM and two 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 $2.0 \times$ faster than BERT_{BASE}, while achieving better performance. (3) Student models distilled from RoBERTa_{LARGE} achieve further improvements. Better teacher results in better students. Self-attention relation distillation is effective for different large-size pretrained Transformers.

Table 2 presents the results of 6×768 MINILMv2 distilled from BERT_{BASE} and BERT_{LARGE} on GLUE test sets and SQuAD 2.0 dev set. 6×768 model distilled from BERT_{BASE} retains more than 99% accuracy while using 50% Transformer parameters. 6×768 MINILMv2 distilled from BERT_{LARGE} compares favorably with BERT_{BASE} on the GLUE test sets.

MobileBERT compresses a specially designed teacher model (in the BERT_{LARGE} size) with inverted bottleneck modules into a 24-layer student using the bottleneck modules. To compare with MobileBERT, we use a public large-size model (BERT_{LARGE-WWM}) as the teacher, which achieves similar performance as the teacher of Mobile-BERT. We distill BERT_{LARGE-WWM} into a student model, which contains the same number of parameters (25M parameters, 12×384 with 128 embedding size), using the same training data (English Wikipedia and BookCorpus). The test results of GLUE benchmark and dev result of SQuAD 2.0 are illustrated in Table 3. MINILMv2 outperforms MobileBERT across most tasks with a faster inference speed. Moreover, our method can be applied for different teachers and has much fewer restrictions of student models.

We compress RoBERTa_{LARGE} and BERT_{LARGE} into a base-size student model. Dev results of

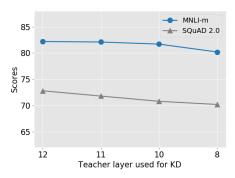


Figure 2: Results of 6×384 model (12 attention heads, 12 relation heads) trained using different BERT_{BASE} layers.

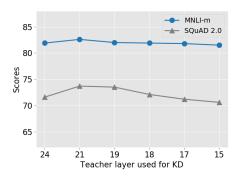


Figure 3: Results of 6×384 model (6 attention heads, 16 relation heads) trained using different BERT_{LARGE} layers.

GLUE benchmark and SQuAD 2.0 are shown in Table 4. Our base-size models distilled from large-size teacher outperforms BERT_{BASE} and RoBERTa_{BASE}. Our method can also be employed to train a base-size model. Moreover, MINILMv2 distilled from RoBERTa_{LARGE} uses a much smaller (almost $32\times$ smaller) training batch size and fewer training steps than RoBERTa_{BASE}. Our method uses much fewer training examples and has a lower computation cost.

4.4 Ablation Studies

Effect of distilling different teacher layer Figure 2 and 3 present the results of 6×384 model distilled from different layers of BERT_{BASE} and BERT_{LARGE}. For BERT_{BASE}, using the last layer achieves better performance than other layers. For BERT_{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 5 shows the results of 6×384 model distilled

#Relation Heads	6	12	24	48	96
MNLI-m	81.9	82.2	82.2	82.4	82.3
SQuAD 2.0	71.9	72.8	72.7	73.0	72.9

Table 5: Results of 6×384 model (12 attention heads) distilled from BERT_{BASE} using different number of relation heads.

from BERT_{BASE} using different number of relation heads. Using a larger number of relation heads achieves better performance. More 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.

5 Conclusion

In this work, we present a simple and effective approach for compressing pretrained Transformers. We employ multi-head self-attention relations to train the student to deeply mimic the self-attention module of its teacher. Our method eliminates the restriction of the number of student's attention heads, which is required to be the same as its teacher for previous work transferring self-attention distributions. Moreover, we show that transferring the self-attention knowledge of an upper middle layer achieves better performance for large-size teacher models. Our student models distilled from BERT and RoBERTa obtain competitive performance on SQuAD 2.0 and the GLUE benchmark, 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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A GLUE Benchmark

The summary of datasets used for the General Language Understanding Evaluation (GLUE) benchmark⁴ (Wang et al., 2019) is presented in Table 6.

B SQuAD 2.0

We present the dataset statistics and metrics of SQuAD 2.0⁵ (Rajpurkar et al., 2018) in Table 7.

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 ration 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 ration and weight decay is 0.1 and 0.01.

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

Table 6: Summary of the GLUE benchmark.

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

Table 7: Dataset statistics and metrics of SQuAD 2.0.

⁴https://gluebenchmark.com/

⁵http://stanford-qa.com