Meta-KD: A Meta Knowledge Distillation Framework for Language Model Compression across Domains

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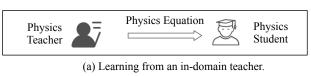
Abstract

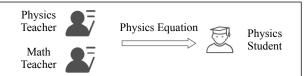
Pre-trained language models have been applied to various NLP tasks with considerable performance gains. However, the large model sizes, together with the long inference time, limit the deployment of such models in real-time applications. Typical approaches consider knowledge distillation to distill large teacher models into small student models. However, most of these studies focus on single-domain only, which ignores the transferable knowledge from other domains. We argue that training a teacher with transferable knowledge digested across domains can achieve better generalization capability to help knowledge distillation. To this end, we propose a Meta-Knowledge Distillation (Meta-KD) framework to build a meta-teacher model that captures transferable knowledge across domains inspired by meta-learning and use it to pass knowledge to students. Specifically, we first leverage a crossdomain learning process to train the meta-teacher on multiple domains, and then propose a meta-distillation algorithm to learn single-domain student models with guidance from the meta-teacher. Experiments on two public multi-domain NLP tasks show the effectiveness and superiority of the proposed Meta-KD framework. We also demonstrate the capability of Meta-KD in both few-shot and zero-shot learning settings.

Introduction

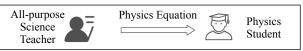
Pre-trained Language Models (PLM) such as BERT (Devlin et al. 2019) and XLNet (Yang et al. 2019) have achieved significant success with the two-stage "pre-training and fine-tuning" process. Despite the performance gain achieved in various NLP tasks, the large number of model parameters and the long inference time have become the bottleneck for PLMs to deploy in real-time applications, especially on mobile devices (Jiao et al. 2019; Sun et al. 2020; Iandola et al. 2020). Thus, there are emerging needs for PLMs to reduce the model size and the computational overhead while keeping the prediction accuracy.

Knowledge Distillation (KD) (Hinton, Vinyals, and Dean 2015) is one of the promising ways to distill the knowledge from a large "teacher" model to a small "student" model. Recent studies show that KD can be applied to compress PLMs with acceptable performance loss (Sanh et al. 2019; Sun et al. 2019b; Jiao et al. 2019; Turc et al. 2019; Chen et al. 2020a). However, those methods mainly focus





(b) Learning from multiple teachers of varied domains.



(c) Learning from the meta-teacher with multi-domain knowledge.

Figure 1: An academic learning scenario. A physics student can learn physics equations better with a powerful all-purpose science teacher, compared to the other two cases.

on single-domain KD. Hence, student models can only learn from its in-domain teacher, paying little attention to acquiring knowledge from other domains.

It has been shown that it is beneficial to consider crossdomain information for KD, by either training a teacher using cross-domain data or multiple teachers from multiple domains (You et al. 2017; Liu et al. 2019; Yang et al. 2020; Peng et al. 2020). Consider an academic scenario of learning physics equations in Figure 1. A typical way for a physics student to learn is to directly learn from his/her physics teacher. However, if we have a mathematical teacher to teach him/her basic knowledge of equations, the student can obtain a better understanding of physics equations. This "knowledge transfer" technique in KD has been proved efficient only when two domains are close to each other (Hu et al. 2019). In reality, however, it is highly risky as teachers of other domains may pass nontransferable knowledge to the student model, which is irrelevant to the current domain and hence harms the overall performance (Tan et al. 2017; Wang et al. 2020). Besides, current studies find multi-task fine-tuning of BERT does not necessarily yield better performance across all the tasks

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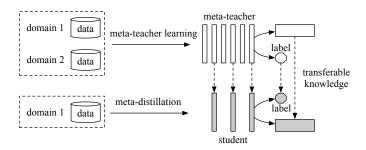


Figure 2: A high-level overview of the Meta-KD framework.

(Sun et al. 2019a). In light of this, we seek to build a more powerful teacher that is able to digest knowledge from different domains and then select transferable knowledge to teach the student in a domain-specific KD process.

To achieve the goal, we leverage the idea of metalearning to capture transferable knowledge across domains, as recent studies have shown that meta-learning can improve the model generalization ability across domains (Finn, Abbeel, and Levine 2017; Javed and White 2019; Yin 2020) and in many few-shot and zero-shot settings (Bao et al. 2020; Ye et al. 2020; Campagna et al. 2020). We further argue that the meta-knowledge is also helpful for cross-domain KD. Re-consider the case in Figure 1. If we have an "all-purpose science teacher" (i.e., the meta-teacher) who has the knowledge of both physics principles and mathematical equations (i.e., the general knowledge of the two courses), the student is able to learn physics equations better with the teacher.

Our framework is referred to as Meta-Knowledge Distillation (Meta-KD), which facilities cross-domain KD by training a meta-teacher model across multiple domains to help learning domain-specific student models. As shown in Figure 2, the framework consists of two parts, *meta-teacher learning* and *meta-distillation*. The meta-teacher is firstly trained with multi-domain datasets to acquire the meta-knowledge across domains by incorporating the domain corruption loss. For each domain, the student model learns to solve the task over a domain-specific dataset with guidance from the meta-teacher. To improve the student's distillation ability, the meta-distillation module minimizes the distillation loss from both intermediate layers, output layers and transferable knowledge, combined with an instance-specific domain-expertise weighting technique.

To verify the effectiveness of Meta-KD, we conduct extensive experiments on two NLP tasks across multiple domains, namely natural language inference (Williams, Nangia, and Bowman 2018) and sentiment analysis (Blitzer, Dredze, and Pereira 2007). Experimental results show the effectiveness and superiority of the Meta-KD framework. Moreover, we find our method is well performed especially when the in-domain dataset is very small while distillation, i.e. the few-shot learning setting, or there is no in-domain dataset, i.e. the zero-shot learning setting.

In summary, the contributions of this study are:

- To our knowledge, our work is the first to explore metalearning based algorithms for PLM compression.
- We propose a novel Meta-KD framework to distill knowledge in PLMs across domains, which consists of two major stages: meta-teacher learning and meta-distillation.
- We conduct extensive experiments to demonstrate the superiority of Meta-KD and also explore the capability of this framework in both few-shot and zero-shot learning settings. We will release our source code on Github.

Related Work

Our study is close to the following three lines of studies.

Knowledge Distillation (KD)

KD was first proposed by (Hinton, Vinyals, and Dean 2015), aiming to transfer knowledge from an ensemble or a large model into a smaller, distilled model. Most of the KD methods focus on utilizing either dark knowledge, i.e., predicted outputs (Hinton, Vinyals, and Dean 2015; Chen et al. 2020b; Furlanello et al. 2018; You et al. 2017) or hints, i.e., intermediate representations (Romero et al. 2015; Yim et al. 2017; You et al. 2017) or relations between layers (Yim et al. 2017; Tarvainen and Valpola 2017; Radosavovic et al. 2018) of teacher models. You et al. (2017) also find multiple teacher networks together can provide comprehensive guidance that is beneficial for training the student network. Ruder, Ghaffari, and Breslin (2017) show that multiple expert teachers improve the performances of sentiment analysis on unseen domains. Tan et al. (2019) apply the multiple teachers framework in KD to build state-of-the-art multilingual machine translation system. Our work is one of the first attempts to learn metateacher from multiple domains to benefit KD on the target domain.

Pre-trained Language Model Compression

Previous approaches on compressing PLMs such as BERT (Devlin et al. 2019) include KD (Hinton, Vinyals, and Dean 2015), parameter sharing (Ullrich, Meeds, and Welling 2017), pruning (Han et al. 2015) and quantization (Gong et al. 2014). In this work, we mainly focus on KD for PLMs. In the literature, Tang et al. (2019) distill BERT into BiLSTM networks to achieve comparable results with ELMo (Peters et al. 2018). Zhao et al. (2019) use dual distillation to reduce the vocabulary size and the embedding size. DistillBERT (Sanh et al. 2019) applies KD loss in the pre-training stage, while BERT-PKD (Sun et al. 2019b) distill BERT into shallow Transformers in the fine-tuning stage. TinyBERT (Jiao et al. 2019) further distills BERT with a two-stage KD process for hidden attention matrices and embedding matrices. AdaBERT (Chen et al. 2020a) uses neural architecture search to adaptively find small architectures.

Transfer Learning (TL) and Meta-learning

TL has been proved to improve the performance on the target domain by leveraging knowledge from related source domains (Pan and Yang

2010; Mou et al. 2016; Liu, Qiu, and Huang 2017; Yang, Salakhutdinov, and Cohen 2017). In most NLP tasks, the "shared-private" architecture is applied to learn domainspecific representations and domain-invariant features (Mou et al. 2016; Liu, Qiu, and Huang 2017; Chen et al. 2018, 2019). Compared to TL, the goal of meta-learning is to train meta-learners that can adapt to a variety of different tasks with little training data (Vanschoren 2018). A majority of meta-learning methods for include metricbased (Snell, Swersky, and Zemel 2017; Pan et al. 2019), model-based (Santoro et al. 2016; Bartunov et al. 2020) and model-agnostic approaches (Finn, Abbeel, and Levine 2017; Finn, Xu, and Levine 2018; Vuorio et al. 2019). Meta-learning can also be applied to KD in some computer vision tasks (Lopes, Fenu, and Starner 2017; Jang et al. 2019; Liu et al. 2020; Bai et al. 2020; Li et al. 2020). For example, Lopes, Fenu, and Starner (2017) record per-layer meta-data for the teacher model to reconstruct a training set, and then adopts a standard training procedure to obtain the student model. Li et al. (2020) use a 1×1 convolution layer to each layer of the student model, and fits the block-level outputs of the student model to the teacher model by estimating the parameters of the added layers.

Our work is closely related to meta-learning, as our meta-teacher model learns the transferable knowledge across domains so that it can fit new domains easily. However, we need to claim that our work a meta-learning algorithm but addresses KD across domains by training a powerful meta-learner, instead of addressing the K-way N-shot problems in traditional meta-learning research (Vanschoren 2018).

The Meta-KD Framework

In this section, we formally introduce the Meta-KD framework. We begin with a brief overview on Meta-KD. After that, the techniques are elaborated in details.

An Overview of Meta-KD

Take the task of text classification as an example. Assume there are K training sets, corresponding to K domains. In the k-th dataset $\mathcal{D}_k = \{X_k^{(i)}, y_k^{(i)}\}_{i=1}^{N_k}, X_k^{(i)}$ is the i-th sample 1 and $y_k^{(i)}$ is the corresponding label of $X_k^{(i)}$. N_k is the total number of samples in \mathcal{D}_k . Let \mathcal{M}_k be the large PLM finetuned on \mathcal{D}_k . Given the K datasets, the goal of Meta-KD is to obtain the corresponding K student models $\mathcal{S}_1, \cdots, \mathcal{S}_K$ that are small in size but has similar performance compared to the K large PLMs, i.e., $\mathcal{M}_1, \cdots, \mathcal{M}_K$.

In general, the Meta-KD framework can be divided into the following two stages:

1. **Meta-teacher Learning**: Learn a meta-teacher model \mathcal{M} over all domains $\bigcup_{k=1}^K \mathcal{D}_k$. The model digests transferable knowledge from each domain and has better generalization while supervising domain-specific students.

2. **Meta-distillation**: Learn K in-domain students S_1, \dots, S_K that performs well in their respective domains, given only in-domain data \mathcal{D}_k and the meta-teacher \mathcal{M} as input.

During the learning process of the meta-teacher, inspired by prototype-based meta-learning methods (Snell, Swersky, and Zemel 2017; Pan et al. 2019), the meta-teacher model should memorize more information about prototypes. We first compute a prototype score $t_k^{(i)}$ for each sample $X_k^{(i)}$. The classification loss of the meta-teacher is defined as the sum of classification loss across all K domains with prototype-based, instance-specific weighting applied. Besides, it also learns transferable knowledge by adding the domain-corruption loss as an auxiliary loss proposed in (Wang et al. 2020). By these steps, the meta-teacher tends to be more generalized and digests transferable knowledge before supervising the student models.

For meta-distillation, each sample $X_k^{(i)}$ is weighted by a domain-expertise score $\lambda_k^{(i)}$ to address the meta-teacher's capability for this sample in the kth domain. Similar to meta-teacher learning, the transferable knowledge are also learned for the students from the meta-teacher. The overall meta-distillation loss is a combination of the Mean Squared Error (MSE) loss from intermediate layers of both models (Sun et al. 2019b; Jiao et al. 2019), and the soft crossentropy loss from output layers (Hinton, Vinyals, and Dean 2015), with instance-specific domain-expertise weighting applied.

Addressing Few-shot and Zero-shot Learning. When the k-th domain dataset \mathcal{D}_k is small (i.e., containing only a few samples), we regard the learning of the k-th student model as a *few-shot learning* problem. We further consider another case where no training data of the k-th domain is available while training the teacher. The goal of Meta-KD here is to learn the student model for the k-th domain from a teacher purely based on knowledge learned from other domains. We refer to this setting as zero-shot $learning^2$.

Meta-teacher Learning

In this work, we take the BERT model (Devlin et al. 2019) as our base learner for text classification due to its wide popularity. For each sample $X_k^{(i)}$, the input to BERT is represented as follows: $[\mathtt{CLS}]$, $tok_{k,1}^{(i)}$, $tok_{k,2}^{(i)}$, \cdots , $[\mathtt{SEP}]$, where $tok_{k,n}^{(i)}$ is the n-th token in $X_k^{(i)}$. After BERT encoding, the last hidden outputs of this sequence is denoted as $h_{[CLS]}, h(tok_{k,1}^{(i)}), h(tok_{k,2}^{(i)}), ..., h(tok_{k,N}^{(i)})$, where $h(tok_{k,j}^{(i)})$ represents the last layer embedding of the j-th token in $X_k^{(i)}$, and N is the maximum sequence length. For simplicity, we define $h(X_k^{(i)})$ as the average pooling of the token embeddings, i.e., $h(X_k^{(i)}) = \sum_{n=1}^N h(tok_{k,n}^{(i)})$.

 $^{{}^{1}}X_{k}^{(i)}$ can be a sentence, a sentence pair or any other textual units, depending on the task inputs.

²Note that the task definitions of few-shot and zero-shot learning are sightly different from classical meta-learning research, in order to fit the underlying KD tasks.

Prototype-based Instance Weighting. To facilitate few-shot/zero-shot learning, we compute a *prototype score* $t_k^{(i)}$ for each sample $X_k^{(i)}$. Here, we treat the *prototype representation* for the m-th class of the k-th domain as:

$$p_k^{(m)} = \frac{1}{|\mathcal{D}_k^{(m)}|} \sum_{X_k^{(i)} \in \mathcal{D}_k^{(m)}} h(X_k^{(i)}) \tag{1}$$

where $\mathcal{D}_k^{(m)}$ is the k-th training set with the m-th class label. The *prototype score* $t_k^{(i)}$ is then computed as:

$$t_k^{(i)} = \tag{2}$$

$$\alpha \cos(p_k^{(m)}, h(X_k^{(i)})) + \frac{1 - \alpha}{K - 1} \sum_{k'=1}^{K(k' \neq k)} \cos(p_{k'}^{(m)}, h(X_k^{(i)})),$$

where \cos is the cosine similarity function, and α is a predefined hyper-parameter. We can see that the definition of the prototype score here is different from previous metalearning, as we require that an instance $X_k^{(i)}$ should be close to its class prototype representation in the embedding space (i.e., $p_k^{(m)}$), as well as the prototype representations in out-of-domain datasets (i.e., $p_{k'}^{(m)}$ with $k'=1,\cdots,K,k'\neq k$). This is because the meta-teacher should learn more from instances that are $prototypical\ across\ domains$ instead of $in-domain\ only$. For the text classification task, the crossentropy loss of the meta-teacher is defined using the crossentropy loss with the prototype score as a weight assigned to each instance.

Domain Corruption. Except for the cross-entropy loss, we leverage a variant of the *domain-corruption loss* (Wang et al. 2020) to increase the meta-teacher's ability for learning transferable knowledge. For each sample $X_k^{(i)}$, we learn an $|h(X_k^{(i)})|$ -dimensional domain embedding of the true domain label $d_k^{(i)}$ denoted as $\mathcal{E}_D(X_k^{(i)})$

main label $d_k^{(i)}$, denoted as $\mathcal{E}_D(X_k^{(i)})$.

Apart from the original BERT model (Devlin et al. 2019), a sub-network is constructed by:

$$h_d(X_k^{(i)}) = \tanh((h(X_k^{(i)}) + \mathcal{E}_D(X_k^{(i)}))W + b),$$
 (3)

where W and b are sub-network parameters. The domain-corruption loss for the sample $X_k^{(i)}$ is defined as:

$$\mathcal{L}_{DC}(X_k^{(i)}) = -\sum_{k=1}^K \mathbf{1}_{k=z_k^{(i)}} \cdot \log \sigma(h_d(X_k^{(i)})), \quad (4)$$

where σ is the K-way domain classifier, and ${\bf 1}$ is the indicator function that returns 1 if $k=z_k^{(i)}$, and 0 otherwise. Here, $z_k^{(i)} \neq d_k^{(i)}$ is a false domain label of $X_k^{(i)3}$. Hence, we deliberately maximize the probability that the meta-teacher makes the wrong predictions of domain labels. We call $h_d(X_k^{(i)})$) as the transferable knowledge for $X_k^{(i)}$, which is more insensitive to domain differences.

Let $\mathcal{L}_{CE}(X_k^{(i)})$ be the normal cross-entropy loss of the text classification task. The total loss of the metateacher \mathcal{L}_{MT} is the combination of weighted $\mathcal{L}_{CE}(X_k^{(i)})$ and $\mathcal{L}_{DC}(X_k^{(i)})$, shown as follows:

$$\mathcal{L}_{MT} = \frac{1}{\sum_{k=1}^{K} |\mathcal{D}_{k}|} \sum_{X_{k}^{(i)} \in \bigcup_{k=1}^{K} \mathcal{D}_{k}} (t_{k}^{(i)} \mathcal{L}_{CE}(X_{k}^{(i)}) + \gamma_{1} \mathcal{L}_{DC}(X_{k}^{(i)})),$$

where the γ_1 is the factor to represent how the domain-corruption loss contributes to the overall loss.

Meta-distillation

As we take BERT as our meta-teacher, for ease of distillation, we again use smaller BERT models as student models. The distillation framework is shown in Figure 3. In our work, we distill the knowledge in the meta-teacher model considering the following five elements: input embeddings, hidden states, attention matrices, output logits and transferable knowledge. The KD process of input embeddings, hidden states and attention matrices follows the common practice (Sun et al. 2019b; Jiao et al. 2019). Recall that \mathcal{M} and \mathcal{S}_k are the meta-teacher and the k-th student model. Let $\mathcal{L}_{embd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}), \mathcal{L}_{hidn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ and $\mathcal{L}_{attn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ be the sample-wise MSE loss values of input embeddings, hidden states and attention matrices of the two models, respectively. Here, $\mathcal{L}_{embd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$, $\mathcal{L}_{hidn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ and $\mathcal{L}_{attn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ refer to the sum of MSE values among multiple hidden layers. We refer interested readers to (Jiao et al. 2019) for more details. $\mathcal{L}_{pred}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ is the cross-entropy loss of "softened" output logists, parameterized by the temperature (Hinton, Vinyals, and Dean 2015). A naive approach to formulating the total KD loss \mathcal{L}_{kd} is the sum of all previous loss functions over the dataset \mathcal{D}_k , i.e.,

$$\mathcal{L}_{kd} = \sum_{X_k^{(i)} \in \mathcal{D}_k} \left(\mathcal{L}_{embd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{hidn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{attn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{pred}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) \right).$$

$$(6)$$

However, the above approach does not give special considerations to the transferable knowledge of the metateacher. Let $h_d^{\mathcal{M}}(X_k^{(i)})$ and $h_d^{\mathcal{S}}(X_k^{(i)})$ be the transferable knowledge of the meta-teacher and the student model w.r.t. the input $X_k^{(i)}$. We further define the transferable knowledge distillation loss $\mathcal{L}_{TKD}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)})$ as follows:

$$\mathcal{L}_{tkd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) = \frac{1}{|\mathcal{D}_k|} \sum_{X_k^{(i)} \in \mathcal{D}_k} MSE(h_d^{\mathcal{M}}(X_k^{(i)}) W_d^{\mathcal{M}}, h_d^{\mathcal{S}}(X_k^{(i)})), \tag{7}$$

where $W_d^{\mathcal{M}}$ is a learnable projection matrix to match the dimension between $h_d^{\mathcal{M}}(X_k^{(i)})$ and $h_d^{\mathcal{S}}(X_k^{(i)})$, and MSE is

³For ease of implementation, we shuffle the domain labels of all instances in a mini-batch.

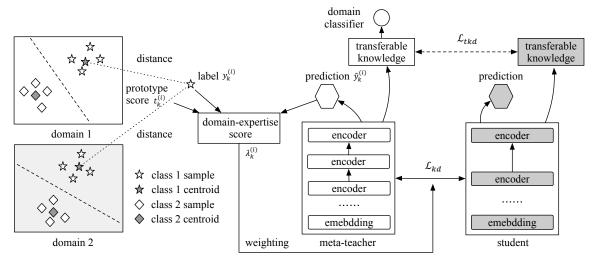


Figure 3: An overview of meta-distillation and the neural architecture that we use for KD.

the MSE loss function w.r.t. single element. In this way, we encourage student models to learn more transferable knowledge from the meta-teacher.

We further notice that although the knowledge of the meta-teacher should be highly transferable, there still exists the domain gap between the meta-teacher and domain-specific student models. In this work, for each sample $X_k^{(i)}$, we define the domain expertise weight $\lambda_k^{(i)}$ as follows:

$$\lambda_k^{(i)} = \frac{1 + t_k^{(i)}}{\exp^{(\hat{y}_k^{(i)} - y_k^{(i)})^2} + 1} \tag{8}$$

where $\hat{y}_k^{(i)}$ is the predicted result of $X_k^{(i)}$'s class label. Here, the weight $\lambda_k^{(i)}$ is large when the meta-teacher model i) has a large domain weight $t_k^{(i)}$ and ii) makes correct predictions on the target input, i.e., $\hat{y}_k^{(i)} = y_k^{(i)}$. We can see that the weight reflects how well the meta-teacher can supervise the student on a specific input. Finally, we derive the complete formulation of the KD loss \mathcal{L}_{kd}' as follows:

$$\mathcal{L}'_{kd} = \sum_{X_k^{(i)} \in \mathcal{D}_k} \lambda_k^{(i)} \left(\mathcal{L}_{embd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{hidn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{attn}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) + \mathcal{L}_{pred}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}) \right) + \gamma_2 \mathcal{L}_{tkd}(\mathcal{M}, \mathcal{S}_k, X_k^{(i)}),$$

$$(9)$$

where γ_2 is the factor to represent how the transferable knowledge distillation loss contributes to the overall loss.

Experiments

In this section, we conduct extensive experiments to evaluate the Meta-KD framework on two popular text mining tasks across domains.

Tasks and Datasets

We evaluate Meta-KD over natural language inference and sentiment analysis, using the following two datasets. The overall statistics are shown in Table 1.

- MNLI (Williams, Nangia, and Bowman 2018) is a largescale, multi-domain natural language inference dataset for predicting the entailment relation between two sentences, containing five domains (genres). After filtering samples with no labels available, we use the original development set as our test set and randomly sample 10% of the training data as development set in our setting.
- Amazon Reviews (Blitzer, Dredze, and Pereira 2007) is a multi-domain sentiment analysis dataset, widely used in multi-domain text classification tasks. The reviews are annotated as positive or negative. For each domain, there are 2,000 labeled reviews. We randomly split the data into train, development and test sets.

Dataset	Domain	#Train	#Dev	#Test
MNLI	Fiction Government Slate Telephone Travel	69,613 69,615 69,575 75,013 69,615	7,735 7,735 7,731 8,335 7,735	1,973 1,945 1,955 1,966 1,976
Amazon Reviews	Book DVD Electronics Kitchen	1,631 1,621 1,615 1,613	170 194 172 184	199 185 213 203

Table 1: Statistics of the two datasets.

Baselines

For the teacher side, to evaluate the cross-domain distillation power of the meta-teacher model, we consider the following models as baseline teachers:

Methods	Fiction	Government	Slate	Telephone	Travel	Average
BERT _B -single	82.2	84.2	76.7	82.4	84.2	81.9
BERT _B -mix	84.8	87.2	80.5	83.8	85.5	84.4
BERT _B -mtl	83.7	87.1	80.6	83.9	85.8	84.2
Meta-teacher	85.1	86.5	81.0	83.9	85.5	84.4
$BERT_B\text{-single} \xrightarrow{TinyBERT\text{-}KD} BERT_S$	78.8	83.2	73.6	78.8	81.9	79.3
$BERT_B$ -mix $\xrightarrow{TinyBERT-KD} BERT_S$	79.6	83.3	74.8	79.0	81.5	79.6
$BERT_B$ -mtl $\xrightarrow{TinyBERT-KD} BERT_S$	79.7	83.1	74.2	79.3	82.0	79.7
Multi-teachers $\xrightarrow{\text{MTN-KD}}$ BERT _S	77.4	81.1	72.2	77.2	78.0	77.2
Meta-teacher $\xrightarrow{\text{TinyBERT-KD}}$ BERT _S	80.3	83.0	75.1	80.2	81.6	80.0
Meta-teacher $\xrightarrow{\text{Meta-distillation}} \text{BERT}_S$	80.5	83.7	75.0	80.5	82.1	80.4

Table 2: Results over MNLI (with five domains) in terms of accuracy (%). Here $X \xrightarrow{A} Y$ means it uses X as the teacher and Y as the student, with A as the KD method, hereinafter the same.

Methods	Books	DVD	Electronics	Kitchen	Average
BERT _B -single	87.9	83.8	89.2	90.6	87.9
BERT _B -mix	89.9	85.9	90.1	92.1	89.5
BERT _B -mtl	90.5	86.5	91.1	91.1	89.8
Meta-teacher	92.5	87.0	91.1	89.2	89.9
$BERT_B\text{-single} \xrightarrow{TinyBERT\text{-}KD} BERT_S$	83.4	83.2	89.2	91.1	86.7
$BERT_B$ -mix $\xrightarrow{TinyBERT$ -KD} $BERT_S$	88.4	81.6	89.7	89.7	87.3
$BERT_B$ -mtl $\xrightarrow{TinyBERT-KD}$ $BERT_S$	90.5	81.6	88.7	90.1	87.7
Multi-teachers $\xrightarrow{\text{MTN-KD}}$ BERT _S	83.9	78.4	88.7	87.7	84.7
Meta-teacher $\xrightarrow{\text{TinyBERT-KD}}$ BERT _S	89.9	84.3	87.3	91.6	88.3
Meta-teacher $\xrightarrow{\text{Meta Distillation}}$ BERT _S	91.5	86.5	90.1	89.7	89.4

Table 3: Results over Amazon reviews (with four domains) in terms of accuracy (%).

BERT-single: Train the BERT teacher model on the target distillation domain only. If we have K domains, then we will have K BERT-single teachers.

BERT-mix: Train the BERT teacher on a combination of K-domain datasets. Hence, we have one BERT-mix model as the teacher model for all domains.

BERT-mtl: It is similar to the "one-teacher" paradigm as in BERT-mix, but the teacher model is generated by multi-task fine-tuning (Sun et al. 2019a).

Multi-teachers: It uses all the K domain-specific BERT-single models to supervise K student models, ignoring the domain difference.

For the student side, we follow TinyBERT (Jiao et al. 2019) to use smaller BERT models as our student models. In single-teacher baselines (i.e., BERT-single, BERT-mix and BERT-mtl), we use TinyBERT-KD as our baseline KD approach. In multi-teachers, because TinyBERT does not naturally support distilling from multiple teacher models, we implement a variant of the TinyBERT KD process based on MTN-KD (You et al. 2017), which uses averaged softened outputs as the incorporation of multiple teacher networks in the output layer. In practice, we first learn the representations of the student models by TinyBERT, then apply MTN-KD

for output-layer KD.

Implementation Details

In the implementation, we use the original **BERT**_B model (L=12, H=768, A=12, Total Parameters=110M) as the initialization of all of the teachers, and use the **BERT**_S model (L=4, H=312, A=12, Total Parameters=14.5M) as the initialization of all the students⁴.

The hyper-parameter settings of the meta-teacher model is as follows. We train 3-4 epochs with the learning rate to be 2e-5. The batch size and γ_1 are chosen from $\{16, 32, 48\}$ and $\{0.1, 0.2, 0.5\}$, respectively. All the hyper-parameters are tuned on the development sets.

For meta-distillation, we choose the hidden layers in $\{3, 6, 9, 12\}$ of the teacher models in the baselines and the meta-teacher model in our approach to learn the representations of the student models. Due to domain difference, we train student models in 3-10 epochs, with a learning rate of 5e-5. The batch size and γ_2 are tuned from $\{32, 256\}$ and $\{0.1, 0.2, 0.3, 0.4, 0.5\}$ for intermediate-layer distillation, respec-

⁴https://github.com/huawei-noah/Pretrained-Language-Model/tree/master/TinyBERT

tively. Following (Jiao et al. 2019), for prediction-layer distillation, we run the method for 3 epochs, with the batch size and learning rate to be 32 and 3e-5. The experiments are implemented on PyTorch and run on 8 Tsela V100 GPUs.

Experimental Results

Table 2 and Table 3 show the general testing performance over MNLI and Amazon Reviews of baselines and Meta-KD, in terms of accuracy. From the results, we have the following three major insights:

- Compared to all the baseline teacher models, using the meta-teacher for KD consistently achieves the highest accuracy in both datasets. Our method can help to significantly reduce model size while preserving similar performance, especially in Amazon review, we reduce the model size to 7.5x smaller with only minor performance drop (from 89.9 to 89.4).
- The meta-teacher has similar performance as BERT-mix and BERT-mtl, but shows to be a better teacher for distillation, as "Meta-teacher → TinyBERT/Meta-distillation" have better performance than other methods. This shows the meta-teacher is capable of learning more transferable knowledge to help the student. The fact that "Meta-teacher → Meta-distillation" has better performance than other distillation methods confirms the effectiveness of the proposed Meta-KD method.
- Generally speaking, Meta-KD gains more improvement on the small datasets than large ones, e.g. it improves from 86.7 to 89.4 in Amazon Reviews while 79.3 to 80.4 in MNLI. This motivates us to explore our model performance on domains with few or no training samples, i.e. few-shot and zero-shot learning in the following section.

Few/Zero Shot Learning

We further investigate Meta-KD's capability in the few-shot and zero-shot learning settings.

Few-shot Learning. We randomly sample a part of the MNLI dataset as the training data in the few-shot experiments. The sample rates that we choose include 0.01, 0.02, 0.05, 0.1 and 0.2. The sampled domain datasets are employed for training student models when learning from the in-domain teacher or the meta-teacher. The experimental results are shown in Figure 4, with results reported by the improvement rate in averaged accuracy. The experimental results show that when less data is available, the improvement rate is much larger. For example, when we only have 1% of the original MNLI training data, the accuracy can be increased by approximately 10% when the student tries to learn from the meta-teacher. It shows Meta-KD can be more beneficial when we have fewer in-domain data.

Zero-shot Learning. In this set of experiments, we consider a special case where we assume all the "fiction" domain data in MNLI is unavailable. Here, we train a meta-teacher without the "fiction" domain dataset and use the distillation method proposed in (Jiao et al. 2019) to produce the student model for the "fiction" domain. The results are shown in Table 4. We find that KD from the meta-teacher can have large improvement, compared to KD from other out-domain

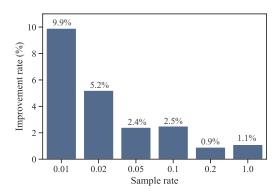


Figure 4: Improvement rate for few-shot learning. Sample rate means the portion of training data in usage.

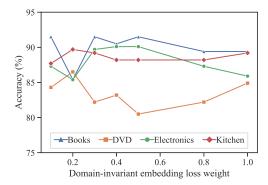


Figure 5: Tuning the hyper-parameter γ_2 .

teachers. Additionally, learning from the out-domain metateacher has similar performance to KD from the in-domain "fiction" teacher model itself. It shows the Meta-KD framework can be applied in applications for emerging domains.

Methods	Accuracy (%)
BERT _B -single (fiction)	82.2
Meta-teacher (w/o fiction)	81.6
$BERT_B$ -single (fiction) $\xrightarrow{TinyBERT-KD}$ $BERT_S$	78.8
$BERT_B$ -single (govern) $\xrightarrow{TinyBERT\text{-}KD} BERT_S$	75.3
BERT _B -single (telephone) $\xrightarrow{\text{TinyBERT-KD}}$ BERT _S	75.6
$BERT_B$ -single (slate) $\xrightarrow{TinyBERT-KD}$ $BERT_S$	77.1
$BERT_B$ -single (travel) $\xrightarrow{TinyBERT-KD}$ $BERT_S$	74.1
$\text{Meta-teacher} \xrightarrow{\text{TinyBERT-KD}} \text{BERT}_S$	78.2

Table 4: Results of the zero-shot learning setting on MNLI. Here, the distillation is performed on the "fiction" domain data. We report accuracy on the domain dataset.

Ablation Study

Here, we explore how γ_2 affects the distillation performance over the Amazon Reviews dataset. We tune the value of γ_2 from 0.1 to 1.0, with results are show in Figure 5. We find

that the optimal value of γ_2 generally lies in the range of 0.2 0.5. The trend of accuracy is different in the domain "DVD" is different from those of the remaining three domains. This means the benefits from transferable knowledge of the metateacher varies across domains.

Conclusion

In this work, we propose the Meta-KD framework to distill PLMs across domains, which consisting of two stages: meta-teacher learning and meta-distillation. We conduct extensive experiments on two widely-used public multi-domain datasets with respect to natural language inference task and text classification task. Experiments results confirm the effectiveness of Meta-KD and also show the capability of Meta-KD in few-shot and zero-shot learning settings.

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