HRKD: Hierarchical Relational Knowledge Distillation for Cross-domain Language Model Compression

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Abstract

On many natural language processing tasks, large pre-trained language models (PLMs) have shown overwhelming performances compared with traditional neural network methods. Nevertheless, their huge model size and low inference speed have hindered the deployment on resource-limited devices in practice. In this paper, we target to compress PLMs with knowledge distillation, and propose a hierarchical relational knowledge distillation (HRKD) method to capture both hierarchical and domain relational information. Specifically, to enhance the model capability and transferability, we leverage the idea of meta-learning and set up domain-relational graphs to capture the relational information across different domains. And to dynamically select the most representative prototypes for each domain, we propose a hierarchical compare-aggregate mechanism to capture hierarchical relationships. Extensive experiments on public multi-domain datasets demonstrate the superior performance of our HRKD method as well as its strong few-shot learning ability. For reproducibility, we release the code at https://github.com/cheneydon/hrkd.

1 Introduction

Large pre-trained language models (PLMs) (e.g., BERT (Devlin et al., 2019)) have demonstrated their outperforming performances on a wide range of NLP tasks, such as machine translation (CONNEAU and Lample, 2019; Zhu et al., 2020), summarization (Zhang et al., 2019; Liu and Lapata, 2019), and dialogue generation (Bao et al., 2020; Zheng et al., 2020). However, their large size and slow inference speed have hindered practical deployments, such as deploying on resource-constrained devices.

To solve the above problem, many compression techniques for PLMs have been proposed, such as quantization (Shen et al., 2020), weight pruning (Michel et al., 2019), and knowledge distillation (KD) (Sun et al., 2019; Jiao et al., 2020). Due to the plug-and-play feasibility of KD, it is the most commonly used method in practice, and we focus on it in this work. The purpose of KD is to transfer knowledge from a larger teacher model to a smaller student model (Hinton et al., 2015). Traditional KD methods only leverage single-domain knowledge, i.e., transferring the knowledge of the teacher model to the student model domain by domain. However, as stated in the purpose of transfer learning, the model performance on target domains can be improved by transferring the knowledge from different but related source domains (Lu et al., 2015), thus the cross-domain knowledge also plays an important role. In addition, several recent works have also proved the advantage of cross-domain knowledge, and many multi-domain KD methods have been proposed. For example, Peng et al. (2020); Yang et al. (2020) demonstrate the effectiveness of distilling knowledge from multiple teachers in different domains; Liu et al. (2019a,b) show that jointly distilling the student models of different domains can enhance the performance.

Nevertheless, these methods fail to capture the relational information across different domains and might have poor generalization ability. To enhance the transferability of the multi-domain KD framework, some researchers have recently adopted the idea of meta-learning. Some studies have pointed out that meta-learning can improve the transferability of models between different domains (Finn et al., 2017; Javed and White, 2019). For example, Meta-KD (Pan et al., 2020) introduces an instance-specific domain-expertise weighting technique to distill the knowledge from a meta-teacher trained across multiple domains to the student model. However, the Meta-KD framework trains student models in different domains separately, which is inconvenient in real-world applications and might not...
have enough capability to capture multi-domain correlations.

In this paper, we aim to simultaneously capture the relational information across different domains to make our framework more convenient and effective. Specifically, we set up several domain-relational graphs to adequately learn the relations of different domains and generate a set of domain-relational ratios to re-weight each domain during the KD process. Moreover, since different domains might have different preferences of layer prototypes, motivated by the Riesz representation theorem (Hartig, 1983), we first construct a set of reference prototypes for each domain, which is calculated by a self-attention mechanism to integrate the information of different domains. Then we introduce a hierarchical compare-aggregate mechanism to compare each layer prototype with the corresponding reference prototype and make an aggregation based on their similarities. The aggregated prototypes are finally sent to the corresponding domain-relational graphs. Our framework is referred to as hierarchical relational knowledge distillation (HRKD).

We evaluate the HRKD framework on two multi-domain NLP datasets, including the MNLI dataset (Williams et al., 2018) and the Amazon Reviews dataset (Blitzer et al., 2007). Experiments show that our HRKD method can achieve better performance compared with several multi-domain KD methods. We also evaluate our approach under the few-shot learning setting, and it can still achieve better results than the competing baselines.

2 Method

In this section, we detailedly describe the proposed HRKD framework. Our HRKD aims to simultaneously capture the relational information across different domains with both hierarchical and domain meta-knowledges. To achieve this goal, we introduce a hierarchical compare-aggregate mechanism to dynamically identify more representative prototypes for each domain, and construct a set of domain-relational graphs to generate re-weighting KD ratios. The overview of HRKD is shown in Figure 1. We first introduce the basic multi-domain KD method in Section 2.1, which is a naive framework lacking the ability of capturing cross-domain relations. Then we describe the domain-relational graph and compare-aggregate mechanism in Section 2.2 and 2.3, respectively, which are the primary modules of our HRKD method to discover the relational information.

2.1 Multi-domain Knowledge Distillation

Similar to (Jiao et al., 2020), we jointly distill the embeddings, attention matrices, transformer layer outputs, and predicted logits between the teacher and student models. Inspired by (Liu et al., 2019c), we use a multi-task training strategy to perform multi-domain KD. Specifically, we share the weights of the embedding and transformer layers for all domains while assigning different prediction layers to different domains. Innovatively, we optimize models in different domains simultaneously rather than sequentially.

In detail, the embedding loss $L_{embd}^d$ and prediction loss $L_{pred}^d$ of $d$-th domain are formulated as:

$$L_{embd}^d = \text{MSE}(E^S_d W_{embd}^d, E^T_d),$$

$$L_{pred}^d = \text{CE}(z^S_d / t, z^T_d / t),$$

where MSE and CE represent the mean square loss and cross-entropy loss, respectively. $E^S_d$ and $E^T_d$ represent the embeddings of student model and teacher model of $d$-th domain, respectively. $z^S_d$ and $z^T_d$ represent the predicted logits of student model and teacher model of $d$-th domain, respectively. $W_{embd}^d$ is a learnable transformation matrix to align the student embedding dimension that mismatches with the teacher embedding dimension, and $t$ is the temperature factor.

The attention loss $L_{attn}^{m,d}$ and transformer layer output loss $L_{hidn}^{m,d}$ at $m$-th student layer and $d$-th domain are formulated as:

$$L_{attn}^{m,d} = \frac{1}{h} \sum_{i=1}^{h} \text{MSE}(A^S_{i,m}, A^T_{i,n,d}),$$

$$L_{hidn}^{m,d} = \text{MSE}(H^S_m W_{hidn}^m, H^T_n),$$

where $h$ is the number of attention heads, $A^S_{i,m}$ and $A^T_{i,n,d}$ are the $i$-th head of attention matrices at $m$-th student layer and its matching $n$-th teacher layer of $d$-th domain, respectively. $H^S_m$ and $H^T_n$ are the transformer layer outputs at $m$-th student layer and $n$-th teacher layer of $d$-th domain, respectively. $W_{hidn}^m$ is a transformation matrix to align the $m$-th layer of student output dimension that mismatches with the $n$-th layer of teacher output dimension. We use uniform strategy to match the layers between the student and teacher models.
Finally, the overall KD loss is formulated as:

$$L_{total} = \sum_{d=1}^{D} \left( L_{embd}^d + \sum_{m=1}^{M} \left( L_{attn}^{m,d} + L_{hidn}^{m,d} \right) \right) + \gamma L_{pred}^d,$$

where $D$ is the total domain number, $M$ is the number of transformer layers in the student model, $\gamma$ is used to control the weight of the prediction loss $L_{pred}$.

### 2.2 Prototype-based Domain-relational Graph

Although the basic multi-domain KD method described in Section 2.1 can distill the student models across different domains, the relational information between different domains is neglected, which is important for enhancing the model transferability as pointed out by previous studies (Finn et al., 2017; Javed and White, 2019). To solve the problem, we attempt to leverage meta-learning to enhance the performance and transferability of our student model. Inspired by the metric-based methods of meta-learning (Snell et al., 2017; Sung et al., 2018), we use prototype representations rather than raw samples to reflect the characteristics of each domain data. This helps to alleviate the negative impact of abnormal samples when there are few training samples (e.g., overfitting) and make the meta-learner easier to learn transferable cross-domain knowledge. Moreover, since we conduct KD over all of the student layers, we calculate different prototypes for different student layers to explicitly distinguish their characteristics. Specifically, the prototype $h_{m,d}$ of $m$-th layer of the student model at $d$-th domain is calculated by:

$$h_{m,d} = \begin{cases} \frac{1}{|D_d|L} \sum_{i=1}^{|D_d|L} \sum_{l=1}^{L} E_{i,l}^S, & m = 0 \\ \frac{1}{|D_d|L} \sum_{i=1}^{|D_d|L} \sum_{l=1}^{L} H_{m,i,l}^S, & 1 \leq m \leq M \end{cases}$$

where $D_d$ refers to the training set of $d$-th domain, $L$ refers to the sentence length (i.e., number of tokens), $E_{i,l}^S$ represents the $l$-th token of the $i$-th sampled student embedding in $D_d$, and $H_{m,i,l}^S$ represents the $l$-th token output by the $i$-th sampled student transformer layer of the $m$-th student layer in $D_d$. In practice, we calculate different prototypes for...
different batches of training samples.

Afterward, these domain prototypes are lever-
gaged to probe the relations across different do-
rains. Although many multi-domain text mining 
methods have been proposed recently (Wang et al.,  
2020; Pan et al., 2020), they capture the relations 
separately for each given domain, which might be 
ineconvenient and time-consuming in practice. 
Meanwhile, the learning process is not effective 
enough since the other domains cannot learn from 
each other when optimizing a specific domain. To 
solve this problem, we aim to simultaneously dis-
cover the cross-domain relations to make our frame-
work more convenient and effective. To achieve the
goal, we propose to use the graph attention network 
(GAT) (Veličković et al., 2018) to process the pro-
ses of node $i$ can be obtained by the weighted sum of the 
transformed features of node $i$ and its neighbors 
based on their attention coefficients followed by the 
ELU nonlinearity and a multi-head concatenation 
mechanism:

$$h'_{m,i} = \oplus_{k=1}^{K} \text{ELU} \left( \sum_{j \in \mathcal{N}_i} \alpha_{i,j,m}^{k} W_{m,j}^{k} h_{m,j} \right),$$

where $k$ represents the head index.

In the second-layer domain-relational graph of the 
$m$-th student layer, targeting at obtaining 
domain-relational ratios, we reformulate the pa-
parameters $W_{m}, \alpha_{m}$ used in the first-layer graph as

$$W_{m} \in \mathbb{R}^{1 \times K'F'},\alpha_{m} \in \mathbb{R}^{2 \times 1},$$

respectively and do not apply the multi-head mecha-
mechanism. We use the softmax operation to normalize the output and fi-
ally derive the domain-relational ratios $r_m \in \mathbb{R}^{D'}$, 
formulated as below:

$$r_m = \text{softmax} \left( \sum_{j \in \mathcal{N}_i} \alpha'_{i,j,m} W_{m}' h_{m,j}' \right),$$

where $\alpha'_{i,j,m}$ is calculated by:

$$s'_{i,j,m} = a_{m}^{T} \left[ W_{m}' h_{m,i}' \oplus W_{m}' h_{m,j}' \right],$$

$$\alpha'_{i,j,m} = \text{softmax} \left( \text{LeakyReLU} \left( s'_{i,j,m} \right) \right).$$

2.3 Hierarchical Compare-aggregate

Mechanism

As different domains might have different prefer-ences towards different layer prototypes, we pro-
pose a hierarchical compare-aggregate mechanism to 
dynamically select the most representative pro-
totype for each domain. Our compare-aggregate 
 mechanism is motivated by the Riesz representa-
tion theorem (Hartig, 1983), which indicates that 
an element can be evaluated by comparing it with 
a specific reference element and the quality of the 
 element is the same as that of the selected reference 
element. Based on this, we establish a set of reference 
prototypes for each domain and hierarchically aggre-
gate the current and previous layer prototypes based 
on their similarities with the corresponding reference 
prototypes.

Reference prototype. For each student layer, a 
simple way is to use the original domain prototypes of current 
layer as the reference prototypes for the 
current and previous layers. However, the 
information of other domains is not integrated,
which plays an important role to enhance the model transferability across different domains. To handle this, we introduce a self-attention mechanism over all of the domain prototypes in the same layer to inject the information of different domains. Specifically, the reference prototype \( \text{RP}_m \in \mathcal{R}^{D \times F} \) of \( m \)-th student layer is calculated by:

\[
\text{RP}_m = \alpha^D_m \cdot \text{h}_m, \tag{13}
\]

\[
\alpha^D_m = \text{softmax} (\text{h}_m \cdot \text{W}^D_m \cdot \text{h}_m^\top), \tag{14}
\]

where \( \alpha^D_m \in \mathcal{R}^{D \times D} \) refers to the attention matrix of \( m \)-th layer, \( \text{h}_m \in \mathcal{R}^{D \times F} \) refers to the prototypes of all domains at \( m \)-th layer. \( \text{W}^D_m \in \mathcal{R}^{F \times F} \) refers to a learnable parameter matrix at \( m \)-th layer, and the softmax operation is performed over the last vector dimension.

**Compare-aggregate mechanism.** After obtaining the reference prototypes, we propose a compare-aggregate mechanism to hierarchically aggregate the layer prototypes by comparing them with the corresponding reference prototypes, which makes the model be aware to more representative layer prototypes for each domain. In detail, the aggregated prototype \( \text{AP}_{m,d} \in \mathcal{R}^F \) of \( m \)-th layer and \( d \)-th domain is formulated as:

\[
\text{AP}_{m,d} = \alpha^H_{m,d} \cdot \text{h}_{\leq m,d}, \tag{15}
\]

\[
\alpha^H_{m,d} = \text{softmax} (\text{h}_{\leq m,d} \cdot \text{W}^H_{m,d} \cdot \text{RP}_{m,d}), \tag{16}
\]

where \( \alpha^H_{m,d} \in \mathcal{R}^{m+1} \) represents the similarity ratios of \( m \)-th layer and \( d \)-th domain, \( \text{h}_{\leq m,d} \in \mathcal{R}^{(m+1) \times F} \) represents the prototypes of \( m \)-th layer and its previous layers at \( d \)-th domain, \( \text{W}^H_{m,d} \in \mathcal{R}^{F \times F} \) is a learnable parameter matrix of \( m \)-th layer and \( d \)-th domain, and \( \text{RP}_{m,d} \in \mathcal{R}^F \) is the reference prototype of \( m \)-th layer and \( d \)-th domain. Then the aggregated prototype \( \text{AP} \) is sent to the domain-relational graphs to obtain the domain-relational ratios \( r \in \mathcal{R}^{(M+1) \times D} \), as formulated by Equation (7)-(11).

Finally, the overall loss of our HRKD can be represented as:

\[
\mathcal{L}_{\text{total}} = \sum_{d=1}^{D} \left( r_{0,d} \mathcal{L}^d_{\text{embd}} + \sum_{m=1}^{M} r_{m,d} (\mathcal{L}^m_{\text{attn}} + \mathcal{L}^m_{\text{hidn}}) + \gamma \frac{p_d}{D} \mathcal{L}^d_{\text{pred}} \right), \tag{17}
\]

where \( r_{m,d} \) is the domain-relational ratio at \( m \)-th student layer and \( d \)-th domain.

### 3 Experiment

In this section, we conduct extensive experiments on two multi-domain datasets, namely MNLI and Amazon Reviews, to demonstrate the effectiveness of our HRKD method.

#### 3.1 Datasets and Model Settings

We evaluate our method on two multi-domain datasets, including the multi-genre natural language inference (MNLI) dataset (Williams et al., 2018) and the Amazon Reviews dataset (Blitzer et al., 2007). In detail, MNLI is a natural language inference dataset with five domains for the task of entailment relation prediction between two sentences. In our setting, we randomly sample 10% of the original training data as our development set and use the original development set as our test set. Amazon Reviews is a sentiment analysis dataset with four domains for predicting whether the reviews are positive or negative. Following Pan et al. (2020), we randomly split the original data into train, development, and test sets. The statistics of these two datasets are listed in Table 1.

We use BERT\(_B\) (the number of layers \( N=12\), the hidden size \( d=768\), the FFN intermediate hidden size \( d_{l'}=3072\), the number of attention heads \( h=12\), the number of parameters \#params=109M) as the architecture of our teacher model, and BERT\(_S\) (\( M=4\), \( d'=312\), \( d_{l''}=1200\), \( h=12\), \#params=14.5M) as our student model. Our teacher model HRKD-teacher is trained in a multi-domain manner as described in Section 2.1, and our student model BERT\(_S\) is initialized with the general distillation weights of TinyBERT\(^1\).

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\(^1\)We use the 2nd version from [https://github.com/huawei-noah/Pretrained-Language-Model/tree/master/TinyBERT](https://github.com/huawei-noah/Pretrained-Language-Model/tree/master/TinyBERT)

| Dataset   | Domain       | #Train  | #Dev   | #Test  |
|-----------|--------------|---------|--------|--------|
| MNLI      | Fiction      | 69,613  | 7,735  | 1,973  |
|           | Government   | 69,615  | 7,735  | 1,945  |
|           | Slate        | 69,575  | 7,731  | 1,955  |
|           | Telephone    | 75,013  | 8,335  | 1,966  |
|           | Travel       | 69,615  | 7,735  | 1,976  |
|           | Books        | 1,631   | 170    | 199    |
|           | DVD          | 1,621   | 194    | 185    |
| Amazon    | Electronics  | 1,615   | 172    | 213    |
|           | Kitchen      | 1,613   | 184    | 203    |
Table 2: Results on MNLI in terms of accuracy (%) with standard deviations. $X \xrightarrow{\lambda} Y$ denotes using teacher $X$ to distill student $Y$ with KD method of $\lambda$. The bold and underlined numbers indicate the best and the second-best performance, respectively.

| Method           | 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    |
| HRKD-teacher     | 83.8    | 87.6       | 80.4  | 83.5      | 85.4   | 84.2    |

| Method           | TinyBERT-KD $\xrightarrow{\lambda}$ BERT$_S$ | Fiction | Government | Slate | Telephone | Travel | Average |
|------------------|---------------------------------------------|---------|------------|-------|-----------|--------|---------|
| BERT$_B$-single  | 78.8                                        | 83.2    | 73.6       | 78.8  | 81.9      | 79.3   |
| BERT$_B$-mix     | 79.6                                        | 83.3    | 74.8       | 79.0  | 81.5      | 79.6   |
| BERT$_B$-mtl     | 79.7                                        | 83.1    | 74.2       | 79.3  | 82.0      | 79.7   |
| Meta-teacher     | Meta-distillation $\xrightarrow{\lambda}$ BERT$_S$ | 80.5    | 83.7       | 75.0  | 80.5      | 82.1   | 80.4    |

| Method           | TinyBERT-KD $\xrightarrow{\lambda}$ BERT$_S$ | Books   | DVD       | Electronics | Kitchen | Average |
|------------------|---------------------------------------------|---------|----------|-------------|---------|---------|
| BERT$_B$-single  | 83.4                                        | 83.2    | 89.2     | 90.0        | 89.0    | 87.9    |
| BERT$_B$-mix     | 88.4                                        | 83.2    | 89.2     | 91.1        | 91.1    | 86.7    |
| BERT$_B$-mtl     | 90.5                                        | 89.7    | 90.0     | 90.0        | 87.7    |
| Meta-teacher     | HRKD-teacher $\xrightarrow{\lambda}$ BERT$_S$ | 91.5    | 86.5     | 90.1        | 89.4    |

Table 3: Results on Amazon Reviews in terms of accuracy (%) with standard deviations.

| Method           | 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        | 91.1    | 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    |
| HRKD-teacher     | 88.4    | 89.2     | 92.5        | 91.1    | 90.3    |

| Method           | TinyBERT-KD $\xrightarrow{\lambda}$ BERT$_S$ | Books   | DVD       | Electronics | Kitchen | Average |
|------------------|---------------------------------------------|---------|----------|-------------|---------|---------|
| BERT$_B$-single  | 83.4                                        | 83.2    | 89.2     | 91.1        | 91.0    | 86.7    |
| BERT$_B$-mix     | 88.4                                        | 81.6    | 89.7     | 89.7        | 87.3    |
| BERT$_B$-mtl     | 90.5                                        | 81.6    | 88.7     | 90.0        | 87.7    |
| Meta-teacher     | HRKD-teacher $\xrightarrow{\lambda}$ BERT$_S$ | 91.5    | 86.5     | 90.1        | 89.4    |

3.2 Baselines

We mainly compare our KD method with several KD baseline methods distilled from four teacher models, including BERT$_B$-single, BERT$_B$-mix, BERT$_B$-mtl, and Meta-teacher in Meta-KD (Pan et al., 2020). Specifically, BERT$_B$-single trains the teacher model of each domain separately with the single-domain dataset; BERT$_B$-mix trains a single teacher model with the combined dataset of all domains; BERT$_B$-mtl adopts the multi-task training method proposed by Liu et al. (2019c) to train the teacher model; Meta-teacher trains the teacher model with several meta-learning strategies including prototype-based instance weighting and domain corruption.

3.3 Implementation Details

For the teacher model, we train the HRKD-teacher for three epochs with a learning rate of 1e-3 and 5e-4 on MNLI and Amazon Reviews, respectively. $\gamma$ is set to 1, and $\ell$ is 1. For few-shot learning, the learning rate for the student model is 5e-5, while other hyper-parameters are kept the same. The few-shot training data is selected from the front of our original training set with different sample ratios, while the dev and test data are the same as our original dev and test sets without sampling to make a fair comparison. In all the experiments, the sequence length is set to 128, and the batch size is 32. The hyper-parameters are tuned on the development set, and the results are averaged over five runs. Our experiments are conducted on 4 GeForce RTX 3090 GPUs.

3.4 General Experimental Results

The experimental results of our method are shown in Table 2 and 3. On the MNLI dataset, our
teacher model HRKD-teacher has similar performances with other baseline teacher models, but the performance of the student model distilled with the HRKD method (HRKD-teacher $\rightarrow$ BERT$_S$) is significantly better than the base TinyBERT-KD method (TinyBERT-teacher $\rightarrow$ BERT$_S$) as well as its counterpart Meta-KD (Meta-teacher $\rightarrow$ BERT$_S$), which demonstrate the superior performance of our method. Specifically, with the HRKD method, the average score of the student model is both 0.5% higher than that of the model with the base TinyBERT-KD method and its counterpart Meta-KD method (see Table 2). It can also be observed that the improvement of our HRKD method on the Telephone domain is the most significant, which is probably caused by the amount of training data. From Table 1, we can see that the Telephone domain has much more training data than other domains, indicating that the Telephone domain can derive more relationship information from other domains and lead to higher improvement. Meanwhile, as shown in the results on the Amazon Reviews dataset in Table 3, the performance of the HRKD-teacher model is slightly better than that of other teacher models, but the student model distilled by the HRKD method largely outperforms the models distilled by the TinyBERT-KD and Meta-KD methods with average gains of 2.6% and 1.1% respectively, which prove the excellent performance of our method again. Note that our HRKD method significantly outperforms the base TinyBERT-KD method on both MNLI and Amazon Reviews datasets (t-test with p < 0.1). And since the performances of the Meta-teacher and our HRKD-teacher are similar on both datasets, the impact of the teacher is negligible, making the comparison between our HRKD and its counterpart Meta-KD relatively fair.

### 3.5 Few-shot Learning Results

As a large amount of training data is hard to collect in reality, the few-shot learning ability of our method is worth being evaluated, where both the teacher and student models are trained with few training data in each domain. We randomly sample a part of the training data in the MNLI dataset to make an evaluation, where the chosen sample rates are 2%, 5%, 10%, and 20%. We mainly compare the performance improvements between two methods: distilling from BERT$_B$-single to BERT$_S$ with TinyBERT-KD (BERT$_B$-single $\rightarrow$ BERT$_S$) and our HRKD method (HRKD-teacher $\rightarrow$ BERT$_S$). From the results in Figure 2, we can observe that the improvement gets more prominent when the training data gets fewer, and the average improvement rate is the largest of 10.1% when there is only 2% MNLI training data. In addition, we can see that the improvement rates of our method are higher than those of Meta-KD under most of the sample rates, especially when there are only 2% training data. These results demonstrate the strong learning ability of our HRKD method under the few-shot setting.

### 3.6 Ablation Studies

In this section, we progressively remove each module of our KD method to evaluate the effect of each module.

The results are shown in Table 4. We first remove the self-attention mechanism across different domain prototypes (- Self-attention), and the average score on Amazon Reviews drops by 0.2%, which proves its effectiveness. Next, we replace the hierarchical compare-aggregate mechanism with a simple average operation (- Comp-Agg), and the average score drops by 0.4%, which demonstrates the effectiveness of the compare-aggregate mechanism. Then we remove the hierarchical graph structure (- Hierarchical Rel.), where the input of each domain-relational graph comes from a single student layer. As can be seen, the average score
Table 5: Case study on Amazon Reviews across four domains with three positive samples and one negative sample. Positive samples are colored in gray.

| Domain     | Label | Review Text                                                                 |
|------------|-------|-----------------------------------------------------------------------------|
| Books      | POS   | ...leading, or molding young people today would benefit from reading this book... |
| DVD        | POS   | ...The plot wasn’t horrible, it was actually pretty good for a fright flick...  |
| Electronics| NEG   | ...I returned the camera and bought a Panasonic and never looked back!        |
| Kitchen    | POS   | This is great for making poached eggs on toast. My family has enjoyed using it... |

| Domain-relational Ratio | Hierarchical Similarity Ratio |
|-------------------------|-------------------------------|
| [0.24, 0.29, 0.25, 0.23, 0.24] | [0.42, 0.58], [0.38, 0.30, 0.32], [0.24, 0.27, 0.25, 0.24], [0.16, 0.19, 0.21, 0.20, 0.24] |
| [0.24, 0.29, 0.25, 0.23, 0.24] | [0.52, 0.48], [0.32, 0.38, 0.30], [0.27, 0.24, 0.27, 0.22], [0.16, 0.17, 0.19, 0.24, 0.24] |
| [0.27, 0.17, 0.25, 0.25, 0.26] | [0.62, 0.38], [0.22, 0.21, 0.58], [0.19, 0.22, 0.30, 0.29], [0.14, 0.15, 0.24, 0.21, 0.26] |
| [0.24, 0.25, 0.25, 0.28, 0.27] | [0.46, 0.54], [0.30, 0.43, 0.28], [0.30, 0.25, 0.26, 0.20], [0.29, 0.19, 0.15, 0.12, 0.26] |

Table 6: Case study on Amazon Reviews across four domains with two positive samples and two negative samples. Positive samples are colored in gray.

| Domain     | Label | Review Text                                                                 |
|------------|-------|-----------------------------------------------------------------------------|
| Books      | NEG   | ...In this book, his “hard-evidence” is flimsy and suspicious...             |
| DVD        | POS   | ...If you have a child who loves John Deere, then this is a perfect DVD for them. |
| Electronics| POS   | ...Movies are amazing! My music collection never sounded so good...           |
| Kitchen    | NEG   | This is the worst blender I’ve ever used...It’s also loud and it moves a lot...|

| Domain-relational Ratio | Hierarchical Similarity Ratio |
|-------------------------|-------------------------------|
| [0.26, 0.25, 0.25, 0.24, 0.27] | [0.43, 0.57], [0.40, 0.31, 0.29], [0.25, 0.26, 0.25, 0.23], [0.13, 0.17, 0.20, 0.21, 0.30] |
| [0.24, 0.25, 0.25, 0.26, 0.22] | [0.52, 0.48], [0.35, 0.32, 0.33], [0.22, 0.25, 0.27, 0.25], [0.18, 0.22, 0.18, 0.20, 0.22] |
| [0.24, 0.25, 0.25, 0.26, 0.25] | [0.54, 0.46], [0.31, 0.33, 0.36], [0.22, 0.24, 0.29, 0.25], [0.21, 0.20, 0.18, 0.18, 0.23] |
| [0.26, 0.25, 0.25, 0.24, 0.27] | [0.49, 0.51], [0.36, 0.33, 0.31], [0.26, 0.25, 0.26, 0.23], [0.22, 0.20, 0.19, 0.18, 0.21] |

3.7 Case Studies

We further provide some case studies to intuitively explain the effectiveness of the domain-relational ratios and hierarchical similarity ratios calculated by our HRKD method (see Table 5 and 6).

In Table 5 and 6, we use the label to denote the categories of sampled domain examples, and we assume that if the learned domain-relational ratios and hierarchical similarity ratios are similar for domain examples with same category while different for those with different categories, then the model has relatively correctly captured the cross-domain and hierarchical relational information. We select two typical types of cases from Amazon Reviews across four domains, in which we adjust the number of domains in each category under two settings: (i) three same categories (i.e., POS) with another one category (i.e., NEG) as in Table 5, and (ii) two same categories (i.e., POS) with another two same categories (i.e., NEG) as in Table 6.

We find the results are intuitive, as we observe that the review texts with the same labels have similar domain-relational ratios and hierarchical similarity ratios, while different layers indeed have different domain weighting preferences and different preferences of layer prototypes for graph input. For example, in Table 5 and 6, positive samples tend to have higher domain-relational ratios in the middle layers (i.e., 2-4), while negative samples have higher ratios in the marginal layers (i.e., 1, 5). Meanwhile, in the second and third layers of Table 5 as well as the first layer of Table 6, lower positive layer prototypes tend to have higher similarity ratios, and the higher positive layer prototypes in the third layer of Table 6 also tend to have higher similarity ratios; while those of the negative layer prototypes are just the opposite. The results show that HRKD method has distinctively and correctly captured the hierarchical and domain meta-knowledges, leading to better performance.
4 Related Work

Pre-trained Language Model (PLM) Compression. Due to the large size and slow inference speed, PLMs are hard to be deployed on edge devices for practical usage. To solve this problem, many PLM compression methods have been proposed, including quantization (Shen et al., 2020), weight pruning (Michel et al., 2019), and knowledge distillation (KD) (Sun et al., 2019; Jiao et al., 2020). Among them, KD (Hinton et al., 2015) has been widely adopted due to its plug-and-play feasibility, aiming to distill the knowledge from a larger teacher model to a smaller student model without decreasing too much performance. For example, BERT-PKD (Sun et al., 2019) distills both intermediate and output layers on fine-tuning. TinyBERT (Jiao et al., 2020) additionally distills the embedding layer and attention matrices during pre-training and fine-tuning. Meta-KD (Pan et al., 2020) proposes to distill knowledge from a cross-domain meta-teacher through an instance-specific domain-expertise weighting technique.

In this paper, we propose a novel cross-domain KD framework that captures the relational information across different domains with both domain and hierarchical meta-knowledges, which has a better capability for capturing multi-domain correlations.

Transfer Learning and Meta-learning. Transfer learning focuses on transferring the knowledge from source domains to boost the model performance on the target domain. Among the methods in transfer learning, the shared-private architecture (Liu et al., 2017, 2019c) is most commonly applied in NLP tasks, which consists of a shared network to store domain-invariant knowledge and a private network to capture domain-specific information. There are also many works applying adversarial training strategies (Shen et al., 2018; Li et al., 2019; Zhou et al., 2019), which introduce domain adversarial classifiers to learn the domain-invariant features. Besides, the research of multi-domain learning has gained more and more attention recently, which is a particular case of transfer learning targeting transferring knowledge across different domains to comprehensively enhance the model performance (Cai and Wan, 2019; Wang et al., 2020). Unlike transfer learning, the goal of meta-learning is to train a meta-learner that can easily adapt to a new task with a few training data and iterations (Finn et al., 2017). Traditional meta-learning typically contains three categories of methods: metric-based (Snell et al., 2017; Sung et al., 2018), model-based (Santoro et al., 2016; Munkhdalai and Yu, 2017), and optimization-based (Ravi and Larochelle, 2017; Finn et al., 2017). In addition, the meta-learning technique can benefit the multi-domain learning task by learning the relationship information among different domains (Franceschi et al., 2017).

In this paper, we leverage meta-learning to solve the multi-domain learning task, where we consider cross-domain KD to simultaneously capture the correlation between different domains, aiming to train a better student meta-learner.

5 Conclusion

In this paper, we present a hierarchical relational knowledge distillation (HRKD) framework to simultaneously capture the cross-domain relational information. We build several domain-relational graphs to capture domain meta-knowledge and introduce a hierarchical compare-aggregate mechanism to capture hierarchical meta-knowledge. The learnt domain-relational ratios are leveraged to measure domain importance during the KD process. Extensive experiments on public datasets demonstrate the superior performance and solid few-shot learning ability of our HRKD method.

Acknowledgements

This work was financially supported by the National Natural Science Foundation of China (No.61602013).

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