Unified and Effective Ensemble Knowledge Distillation

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ABSTRACT
Ensemble knowledge distillation can extract knowledge from multiple teacher models and encode it into a single student model. Many existing methods learn and distill the student model on labeled data only. However, the teacher models are usually trained on the same labeled data, and their predictions have high correlations with groundtruth labels. Thus, they cannot provide sufficient knowledge complementary to task labels for teaching student. Distilling on unseen unlabeled data has the potential to enhance the knowledge transfer from the teachers to the student. In this paper, we propose a unified and effective ensemble knowledge distillation method that distills a single student model from an ensemble of teacher models on both labeled and unlabeled data. Since different teachers may have diverse prediction correctness on the same sample, on labeled data we weight the predictions of different teachers according to their correctness. In addition, we weight the distillation loss based on the overall prediction correctness of the teacher ensemble to distill high-quality knowledge. On unlabeled data, the disagreement among teachers is an indicator of sample hardness, and thereby we weight the distillation loss based on teachers’ disagreement to emphasize knowledge distillation on important samples. Extensive experiments on four datasets show the effectiveness of our proposed ensemble distillation method.

KEYWORDS
Ensemble distillation, Knowledge distillation

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1 INTRODUCTION
Two heads are better than one. Instead of using a single model, leveraging an ensemble of multiple models is a simple yet effective strategy that can usually boost the accuracy [7]. Ensemble techniques have empowered various classification [29] and regression [21] tasks. However, different from traditional shallow and small ensemble models such as boosting [25] and random forest [12], it is difficult to use ensembles of big models (e.g., BERT [6]) for inference in low-latency systems due to the huge computational cost [35]. Knowledge distillation from multiple teachers aims to obtain a strong student that inherits most performance of the teacher ensemble without increasing the inference computational cost [4, 37]. This paradigm is known as ensemble knowledge distillation [1]. There are many prior studies on ensemble knowledge distillation [13, 19, 30, 32, 34]. Most methods distill the student model on labeled data, and a core problem they addressed is assigning different ensemble weights for different teachers. For example, Chebotar and Waters [3] proposed to first search optimal constant weights for combining teacher models’ outputs that yield the best accuracy, and then distill a student from the ensemble soft labels. Du et al. [8] proposed an adaptive weighting method by using different teacher ensemble weights for different samples that minimize the classification loss. These methods usually equally regard the importance of different labeled samples in knowledge distillation, which may be suboptimal because teachers’ predictions on different samples may have different helpfulness. In addition, they usually learn and distill the student model on the same labeled samples from which the teacher models are trained. However, the teacher models’ predictions on these samples do not necessarily reflect their real prediction patterns on the overall data distribution due to their memory of labels [16]. Thus, it is insufficient to transfer knowledge on labeled data only.

There are a few approaches for ensemble distillation on unlabeled data [11, 18, 27, 28]. For example, Radosavovic et al. [23] proposed to apply teacher models to unlabeled data with different augmentation methods to obtain ensemble predictions for student teaching. [17, 27] used the average predictions of multiple models on an unlabeled dataset as the teaching signals for distilling individual models. However, these methods cannot distinguish between important and uninformative unlabeled samples, which is critical for fully distilling teachers’ knowledge. In fact, the teacher models may have different prediction disagreement on different unlabeled samples, and it is important to actively learn more on borderline samples with strong disagreement to improve the prediction quality of the student model [5].

In this paper, we propose a unified ensemble knowledge distillation method named UniKD, which can distill a high-quality student model from multiple teacher models on both labeled data and unlabeled data in a unified way. Since different teachers have different prediction correctness, on labeled data we weight teachers’ soft labels according to their losses on each sample to encourage the student to learn more from the accurate teachers. To further help distill high-quality knowledge, we weight the knowledge distillation loss on each labeled sample based on the average loss of teachers, which can enforce the student to learn more from the task label rather than teachers if teachers’ error is high. On unlabeled data, since there is no task label to measure prediction correctness, we average the soft label predictions of teachers for knowledge
distillation. To help distill knowledge more effectively on important samples, we use the disagreement of teachers’ predictions on each sample to weight the unlabeled distillation loss by emphasizing the samples on which a single teacher model has high variance and low confidence. Extensive experiments on four benchmark datasets show that UniKD enables the student model to beat any single teacher model with a large margin, and can outperform many baseline methods.

2 METHODOLOGY

We then introduce the details of UniKD. Its knowledge distillation frameworks on labeled and unlabeled data are shown in Fig. 1. We discuss each of them in the following sections.

2.1 Ensemble Distillation on Labeled Data

Distilling the student model on labeled data can prevent it from overfitting task labels [36]. Thus, we also consider labeled data-based ensemble distillation, as shown in Fig. 1(a). Its has a two-level weighting mechanism based on the prediction correctness of each individual teacher and all teachers. Assume there is an ensemble of $N$ teacher models to teach the student. We denote the soft labels of teacher models on a sample is computed as follows:

$$L_{yt} = \frac{1}{N} \sum_{i=1}^{N} L_{yt}^{i}$$

This formulation means that a higher loss on a specific sample yields lower importance in the prediction ensemble.

Next, we use the ensemble prediction $\hat{y}$ to teach the student. We use a cross-entropy loss $L_{yt}$ to regularize the student model to make similar predictions with the ensemble predictions, which is formulated as follows:

$$L_{yt} = -\sum_{i=1}^{C} \hat{y}_{i} \log(\hat{y}^{s}[i])$$

where $[i]$ means the $i$-th element of the soft label, and $C$ is the number of classes. The student model also learns from the label $y$ in the target task using the task loss $L_{s}$. Since on different samples the teachers’ predictions have different qualities, it is important to dynamically adjust the relative importance of the supervision from the teacher ensemble and the task labels. Thus, we weight the distillation loss and task loss when combining them into an overall loss $L$ as follows:

$$L = \frac{1}{1 + \sum_{i=1}^{N} L_{yt}^{i}/N} L_{yt} + L_{s}.$$ (3)

In this way, the student model learns more from the task label when the teacher models’ predictions are inaccurate, which can facilitate high-quality knowledge transfer.

2.2 Ensemble Distillation on Unlabeled Data

Since knowledge distillation on optimized labeled data may not fully distill teachers’ knowledge, we also consider ensemble knowledge distillation on unseen unlabeled data to enhance knowledge transfer, as shown in Fig. 1(b). Since there are no task labels to evaluate the teachers’ predictions, we directly average their predicted soft labels as the ensemble prediction $\hat{y}$, which is further used to compute the knowledge distillation loss $L_{d}$ in the same way. However, the teachers’ predictions on different unlabeled samples may have different disagreements [14]. If different teachers have very consistent predictions on a sample, it means that every single teacher model classifies this sample correctly/incorrectly. In this case, we use the disagreement of teachers’ predictions on each sample to weight the unlabeled distillation loss by emphasizing the samples on which a single teacher model has high variance and low confidence.

Figure 1: The unified ensemble distillation framework of UniKD.
case, the student model should learn less from the teacher because ensemble cannot improve the performance on this sample. On the contrary, a strong disagreement on a sample means that a single model’s prediction has high variance on this sample, and model ensemble can help reduce the uncertainty. Thus, the knowledge distillation intensity on this sample should be strong to better encourage the student to mimic the teacher ensemble. Motivated by the above observations, we propose to weight the knowledge distillation loss on unlabeled data based on the disagreement among teachers. To measure the disagreement of teachers’ predictions, we use the average Kullback–Leibler (KL) divergence between all pairs of teacher predictions. The disagreement score $L^p$ on a sample is calculated as follows:

$$L^p = \frac{1}{N(N-1)} \sum_{i \neq j} KL(y^t_i, y^t_j),$$

where a higher score indicates that teachers’ predictions are more diverse. We use this score to further weight the knowledge distillation loss, and the overall loss $L$ is formulated as follows:

$$L = (1 + \lambda L^p) L^d,$$

where $\lambda$ is a hyperparameter that controls the influence of teacher disagreement on the loss function. When both labeled and unlabeled data are available, we combine the knowledge distillation losses on all samples. By optimizing the distillation loss, the student model can be tuned by supervision signals, meanwhile fully inheriting the knowledge encoded by the multiple teachers.

### 3 EXPERIMENTS

#### 3.1 Datasets and Experimental Settings

We conducted experiments on four benchmark datasets, including MNLI [33], QNLI [24], QQP [2] and SST-2 [26], which are taken from the GLUE [31] benchmark.\(^3\) The statistics of these datasets are summarized in Table 1. On all datasets, we use half of the training data as labeled data, and regard the rest as unlabeled data by removing their labels. Following [2], we report the results on the dev set because test labels are not released.

| Dataset | #train | #val | #tet |
|---------|--------|------|------|
| MNLI    | 393k   | 105k | 364k |
| QNLI    | 67k    | 5.5k | 40k  |
| QQP     | 872k   | 5.5k | 391k |
| SST     | 1.8k   | 5.5k | 40k  |

Table 1: Statistics of the datasets used in our experiments.

Table 2: Performance of different distillation methods.

| Methods          | MNLI | QNLI | QQP | SST |
|------------------|------|------|-----|-----|
| BERT (single)    | 82.9 | 88.8 | 88.1| 91.6|
| BERT (ensemble)  | 84.3 | 90.6 | 89.8| 93.7|
| BERT+KD-Labeled | 83.3 | 89.3 | 88.4| 91.9|
| BERT+AE-KD      | 83.5 | 89.5 | 88.6| 92.2|
| BERT+KD-Unlabeled| 83.7 | 89.9 | 89.0| 92.5|
| BERT+UniKD      | 84.1 | 90.4 | 89.6| 93.3|
| RoBERTa (single)| 85.8 | 91.3 | 90.2| 93.7|
| RoBERTa (ensemble)| 87.9 | 92.7 | 91.8| 95.1|
| RoBERTa+KD-Labeled | 86.2 | 91.4 | 90.4| 93.9|
| RoBERTa+AE-KD | 86.5 | 91.6 | 90.5| 94.0|
| RoBERTa+KD-Unlabeled | 86.8 | 92.0 | 90.9| 94.3|
| RoBERTa+UniKD | 87.6 | 92.5 | 91.4| 94.9|
| UniLM (single) | 86.8 | 91.7 | 90.1| 93.8|
| UniLM (ensemble) | 88.4 | 93.0 | 91.8| 95.3|
| UniLM+KD-Labeled | 87.0 | 91.9 | 90.4| 94.2|
| UniLM+AE-KD | 87.1 | 92.2 | 90.5| 94.4|
| UniLM+KD-Unlabeled | 87.5 | 92.4 | 90.8| 94.6|
| UniLM+UniKD | 88.2 | 92.9 | 91.5| 95.0|

3.2 Performance Comparison

We first verify the effectiveness of UniKD by comparing it with several baseline methods. We choose the base version of BERT [6], RoBERTa [20], and UniLM [2] as the basic model. The methods to be compared include: (1) single, using a single model for inference; (2) ensemble, averaging the soft labels predicted by multiple models; (3) KD-Labeled [9, 10], ensemble distillation distillation on labeled data from the averaged soft labels; (4) AE-KD [8], an adaptive label voting method for ensemble distillation on labeled data; (5) KD-Unlabeled [17, 27], ensemble distillation distillation on unlabeled data based on averaged predictions on unlabeled data; (6) UniKD, our proposed unified ensemble knowledge distillation method. The results on the four datasets are shown in Table 2. We find using ensemble of models can usually greatly improve the accuracy over single models. This is intuitive because different independent models may encode different knowledge that is complementary to prediction. However, it also leads to a high computational cost. The ensemble knowledge distillation methods usually have a better performance than the original single model. However, the students in all baselines still have a notable gap with the teacher ensemble. Among them, we find that students distilled on unlabeled data perform better than those distilled on labeled data. This may be because the student can learn from task labels on labeled data, and the complementary knowledge provided by the teacher on labeled data is insufficient. Moreover, our UniKD method consistently outperforms other distillation methods with a significant margin ($p < 0.05$ in t-test), and can achieve comparable performance with ensemble models. It shows that UniKD can effectively improve the performance of a single model.

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\(^1\)https://data.quora.com/First-Quora-Dataset-Release-Question-Pairs

\(^2\)They are selected because they have relatively large sizes and are easy to split part of data as unlabeled dataset.

\(^3\)Our approach can be directly applied to the scenarios where the teachers and the student have different architectures and sizes.
### 3.3 Ablation Study

Next, we verify the effectiveness of knowledge distillation on labeled and unlabeled data in our method. We use BERT as the basic model in the following experiments (the experimental results on other basic models show similar patterns, and are omitted due to space limit). The results are shown in Fig. 2. We find in our approach knowledge distillation on unlabeled data is also more important than knowledge distillation on labeled data. It shows the importance of exploiting unlabeled data in knowledge transfer. Moreover, combining labeled and unlabeled data for knowledge distillation can further improve the student’s performance. This is because distillation on labeled data can reduce the risk of overfitting task labels, and distillation on unlabeled data can help better transfer the knowledge of teacher ensemble. We then study the influence of different weighting mechanisms in our approach. The results are shown in Fig. 3. We find the prediction disagreement weighting mechanism on unlabeled data has the largest contribution. This is because it can distinguish the importance of different unlabeled samples, which can help transfer knowledge more effectively. In addition, both types of correctness weighting methods have some contributions to the performance improvements. This is because evaluating the teacher models’ prediction quality based on task labels can help distill higher-quality knowledge.

### 3.4 Hyperparameter Analysis

Finally, we study the impact of the disagreement weighting coefficient $\lambda$ on the model performance. The results are shown in Fig. 4. We find when the value of $\lambda$ is very small, the performance is sub-optimal. This is because the importance of different samples cannot be effectively distinguished. However, the performance starts to decline when $\lambda$ is too large. This is because the distillation intensity on unlabeled data becomes too strong, and the model may not fully exploit the supervision signals on labeled data. Thus, a moderate value of $\lambda$ (e.g., 10 or 15) is more suitable for our approach.

### 4 CONCLUSION

In this paper, we propose a unified ensemble knowledge distillation method named UniKD, which can effectively transfer useful knowledge from multiple teacher models to a single student model via distilling on both labeled and unlabeled data. On labeled data, we propose to weight different teachers’ soft labels on each sample based on their correctness, and further weight the knowledge distillation loss based on the average correctness of teachers. On unlabeled data, we propose to use the disagreement of teachers to weight the distillation loss on different samples. Extensive experiments on four datasets show the effectiveness of our method in boosting the performance of single model, even approaching the performance of teacher ensemble.
