Dual-View Distilled BERT for Sentence Embedding

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Abstract

Recently, BERT realized significant progress for sentence matching via word-level cross sentence attention. However, the performance significantly drops when using siamese BERT-networks to derive two sentence embeddings, which fall short in capturing the global semantic since the word-level attention between two sentences is absent. In this paper, we propose a Dual-view distilled BERT (DvBERT) for sentence matching with sentence embeddings. Our method deals with a sentence pair from two distinct views, i.e., Siamese View and Interaction View. Siamese View is the backbone where we generate sentence embeddings. Interaction View integrates the cross sentence interaction as multiple teachers to boost the representation ability of sentence embeddings. Experiments on six STS tasks show that our method outperforms the state-of-the-art sentence embedding methods significantly.

1 Introduction

Recent sentence representation models like BERT (Devlin et al., 2019) achieved state-of-the-art results on sentence-pair regression/classification tasks, such as question answering, natural language inference (NLI) (Bowman et al., 2015; Williams et al., 2018), and semantic textual similarity (STS) (Agirre et al., 2012, 2013, 2016, 2014, 2015). However, it has a low computational efficiency when candidate sentence-pairs are not given ahead, leading to a massive computational overhead. For example, seeking the most relevant sentence-pair of a collection requires pairing all sentences. The $O(n^2)$ computational complexity is an obstacle preventing many teretrieval applications from adopting the technology.

A standard method to reduce the computations is separately encoding each sentence into a vector representation and then compare any two of them by similarity distance. However, in contrast to the standard BERT model, the performance of sentence matching is constrained. For instance, SBERT (Reimers and Gurevych, 2019) using the siamese BERT-networks that decreased the performance by 3-4 points evaluated by Spearman correlation (Myers and Sirois, 2004) on STS-Benchmark (Cer et al., 2017), which implies room for improvement. We argue that the siamese BERT-networks are limited to capture the full complexity of global semantic matching, neglecting the word-level interaction features across two sentences. The feature has been proved vital for predicting matching degrees (Lan and Xu, 2018; Xu et al., 2020).

Motivated by these observations, we propose a Dual-view distilled BERT (DvBERT) by incorporating the word-level interaction features into sentence embeddings while maintains the same efficiency as siamese BERT-networks. We take inspiration from Multi-view learning (Xu et al., 2013; Clark et al., 2018) and train the sentence matching model from two views: (1) Siamese View, we start with the siamese BERT-networks as a backbone to derive sentence embeddings, to be able to capture semantics similarity efficiently by calculating distances on the two fixed-size vectors. (2) Interaction View, the standard pre-trained models with cross-sentence interactions are utilized, acting as multiple teachers that generate predictions about the training set provided to the siamese networks to learn. The association between the two views acts as a regularization term that trains a student with soft targets from the multiple teacher's output distributions, making the procedure similar to knowledge distillation (Hinton et al., 2015). In contrast of other distilled versions of BERT (Sanh et al., 2019; Sun et al., 2019), our method aims to optimize sentence embedding representations with two heterogeneous networks, together with multi-task knowledge distillation (Liu et al., 2019), neither

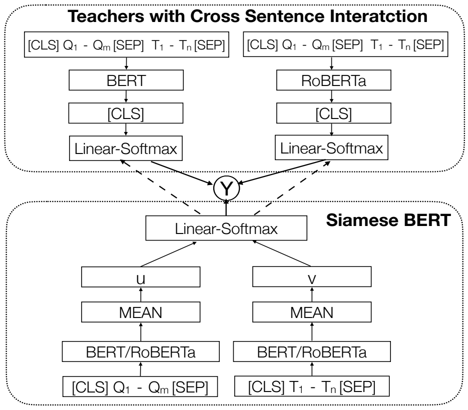

Figure 1: Overview of Dual View Distilled BERT. Dash lines indicate distillation.

distilling large models into a small model (Chatterjee, 2019; Huang et al., 2019) nor born-again networks (Furlanello et al., 2018; Clark et al., 2019). Besides, we compared the loss weighting and teacher annealing strategy (Clark et al., 2019) during the distillation process, suggesting that the latter was more efficient. Experiments demonstrate that DvBERT can achieve superior performance than siamese BERT-networks on six STS datasets.

2 Dual View Distilled BERT

We first present DvBERT and describe how these views can be combined with multi-task knowledge distillation.

2.1 Siamese BERT-networks

For a given dataset $\mathcal{D}_l$, Siamese BERT-networks aims to predict a label $y \in \mathbf{Y}$ by leveraging similarity measure between the sentence embeddings, where $\mathbf{Y} = \{entailment, contradiction, neutral\}$ in natural language inference. For any sentence-pairs, the siamese BERT converts the two sentences into sequential vectors individually, and then pool these two vectors into two sentence embeddings $\mathbf{u}$ and $\mathbf{v}$. SBERT (Reimers and Gurevych, 2019) compares different pooling strategies from multiple datasets, and gives the result that the `MEAN` strategy is significantly superior to `MAX` and `[CLS]` token strategy. Hereafter, the `MEAN` pooling is our default configuration. For classification tasks, such as NLI, we concatenate $\mathbf{u}$, $\mathbf{v}$, and $|\mathbf{u}-\mathbf{v}|$ followed by a fully-connected layer, which projects the hidden size into a probability distribution.

$$p(y|\mathbf{u},\mathbf{v};\theta) = \mathtt{softmax}(W[\mathbf{u},\mathbf{v},|\mathbf{u}-\mathbf{v}|]),$$

where θ represents all learnable parameters from BERT, shared for $\mathbf{u},\mathbf{v}$. And $W \in \mathbb{R}^{3d\times n}$ is the parameter of the fully-connected layer. d is the dimension of the sentence embeddings. We optimize the standard cross-entropy loss.

2.2 Cross Sentence Interaction

We use multiple teachers from different pre-trained models to introduce interaction matrices across words to enrich the word-level interactive features. Each model first pre-trains with labeled data, then re-labeling the data and adds it to a new training set. Specifically, as illustrated in Fig 1 (top), we concatenate the sentence-pair $Q = \{Q_i\}_{i=1,\dots,m}$ and $T = \{T_i\}_{i=1,\dots,N}$ into a text sequence `[[CLS]`Q`[SEP]`T`[SEP]]`. The `[CLS]` token is regarded as an aggregated semantic gap of the input sentence-pair since it is used to predict whether a sentence-pair coherent or not during pre-training. Let $\mathbf{z}_k^c$ be the `[CLS]` token from the kth pre-trained model, which followed a single fully-connected layer culminating in a softmax layer as our classifier:

$$q(y|\mathbf{z}_k^c;\phi_k) = softmax(O\mathbf{z}_k^c)),$$

where ϕ_k and $O \in \mathbb{R}^{d\times n}$ are the model parameters. The siamese BERT learns from the hard targets as well as soft targets from the teachers. Supposing that the ϕ_k and O has been optimized by cross-entropy loss, DvBERT trains the siamese BERT by minimizing

$$\mathcal{L}(\theta, W) = \sum_{k=1}^{K} D(q(y|\mathbf{z}_k^c;\phi_k), p(y|\mathbf{u},\mathbf{v};\theta)),$$

where D is a distance function between probability distributions, here we use the KL-divergence. K is the number of teachers. We hold the teacher predictions $q(y|\mathbf{z}_k^c;\phi)$ fixed when training the student. The BERT from the two views are not sharing since early experiments with sharing did not improve results.

2.3 Teacher Annealing

We leverage teacher annealing (Clark et al., 2019) strategy, which mixes the teacher prediction with the gold label during training. Teacher annealing progressively reduces the weight of soft targets as the training advances, making the student learning from the teacher to hard targets. This method ensures the student gets a rich training signal early in training but is not constrained to only

	STS12	STS13	STS14	STS15	STS16	STS-B	Avg.
BERT Avg. embedding	38.78	57.98	57.98	63.15	61.06	46.35	54.22
BERT [CLS] embedding	20.16	30.01	20.09	36.88	38.08	16.50	26.95
SBERT-base	70.4	71.77	70.66	78.67	74.11	76.28	73.64
SRoBERTa-base	71.70	73.43	71.47	**80.79**	75.99	77.02	75.06
DvBERT-base	70.52	73.17	71.18	79.88	75.08	77.96	74.63
DvRoBERTa-base	**72.42**	**73.44**	**72.21**	80.43	**76.52**	**78.32**	**75.56**
SBERT-large	71.68	72.79	72.20	80.32	76.45	78.00	75.24
SRoBERTa-large	72.14	76.69	74.12	79.81	75.97	78.60	76.22
DvBERT-large	72.95	72.26	71.87	79.27	76.16	78.28	75.13
DvRoBERTa-large	**74.99**	**76.16**	**73.34**	**81.93**	**78.77**	**79.61**	**77.47**

Table 1: Spearman correlation of STS tasks without fine-tuning on task-specific data.

simulating the teacher. Specifically, summarizing the siamese BERT, and other K BERT-related pre-trained model with cross sentence attention, the objective can be written as:

$$\mathcal{L}(\theta, W) = \sum_{k=1}^{K} D(\lambda y + (1-\lambda) q(y|\mathbf{z}_k^c; \phi_k), p(y|\mathbf{u}, \mathbf{v}; \theta))$$

where λ is increase linearly from 0 to 1. In the beginning, $\lambda = 0$, which means the model is trained entirely based on the soft targets from teachers. As the model converges gradually, the model learns from hard targets with more confidence.

3 EXPERIMENTS

In this section, we present our approach to NLI and STS datasets.

3.1 Dataset

The NLI dataset consists of SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018), annotated with the labels contradiction, entailment, and neutral. STS (Agirre et al., 2012) assesses the matching degree to which two sentences are semantically equivalent to each other, which are human-annotated with a level of equivalence from 1 to 5. We follow the previous works (Conneau et al., 2017; Cer et al., 2018) to merge the training and test datasets in both NLI data as pre-training datasets of 940k sentence pairs. STS 2012-2016 datasets have no training data but 26k test data, so the datasets are used to evaluate the pre-trained DvBERT on NLI. STS-B is a collection of 8.6k sentence pairs and contains training, development, and test sets drawn from heterogeneous sources.

3.2 Training and Evaluation Settings

We pre-train DvBERT with a 3-way softmax classifier for one epoch on NLI datasets. The batch size is set to 16, and the dropout rate is set to 0.1 for all modules. We use Adam optimizer (Kingma and Ba, 2014) for model training. We set the initial learning rate to 2e-5 with a decay ratio of 1.0, a linear learning rate warm-up over 10 percent. For fune-tuning STS-B, we replace the $(u, v, |u-v|)$ to $cosine(u, v)$, and set the distance metric to the mean square error loss for regression training. The epoch numbers were set to 4, and other hyperparameters keep the same as the NLI task setting. Basically, We keep hyper-parameters consistent with SBERT. Our two default teachers are standard BERT, RoBERTa. We also evaluate the performance of DvRoBERTa by replacing the siamese BERT to RoBERTa.

3.3 Unsupervised STS

We apply STS 2012 - 2016 and STS-B test data to evaluate the performance without any task-specific training data. We use the Spearman correlation between the cosine similarity of the sentence embeddings and the gold labels. The results are reported in Table 1. The first two lines show BERT without training on NLI get rather poor performance pooled by `MEAN` or `[CLS]` token. Especially for `[CLS]` token, as it is mainly used to distinguish the segment-pair, whether coherence or not, there is a discrepancy in single sentence representations. We evaluate our approach compared with SBERT (SRoBERTa) on six STS datasets. We can observe that the models with pre-training on NLI improve a large margin than those are not. The dual-view method substantially impacts the performance of the two pre-trained models, obtaining 0.56%-1.9% improvement on average.

3.4 Fine-tuning on STS-B

Since STS-B is a regression task, we adopt the cosine similarity followed mean square loss to take the place of both the fully-connected layer and cross-entropy loss from the NLI classification task. The experiment was divided into three setups. (1)

	Base models	Large models
BERT-NLI	87.33 ± 0.23	89.09 ± 0.36
RoBERTa-NLI	**89.77** ± 0.47	**91.12** ± 0.17
SBERT	84.57 ± 0.2	84.72 ± 1.01
SRoBERTa	84.89 ± 0.34	86.13 ± 0.94
DvBERT	84.67 ± 0.23	85.31 ± 0.21
DvRoBERTa	**85.31** ± 0.37	**86.23** ± 0.67
SBERT-NLI	85.01 ± 0.17	85.91 ± 0.58
SRoBERTa-NLI	85.40 ± 0.2	86.15 ± 0.35
DvBERT-NLI	85.15 ± 0.24	86.21 ± 0.13
DvRoBERTa-NLI	**86.05** ± 0.22	**86.98** ± 0.46

Table 2: Spearman correlation of STS tasks. The average of 10 runs with different random seeds is reported. "-NLI" indicates the model is pre-trained on NLI data.

Standard BERT/RoBERTa pre-train on NLI, then fine-tune on STS-B; (2) DvBERT trains only on STSb; (3) DvBERT first trained on NLI for all teachers and the student, then trains on STS-B. The report gives the average Spearman correlation and its standard error after ten runs, as shown in table 2. The first two lines are standard BERT and RoBERTa models, which are used as our teacher models to capture the word-level attention to each other and significantly achieve the best results. We can observe that the pre-training on NLI consistently improves the performance for the shown models since NLI enhances the models towards language understanding. The results demonstrate that DvBERT can improve generalization capability.

3.5 Effect of Dual View Distillation

In order to observe how the dual-view method generalizes to STS set from the NLI training set, we plot the SRoBERTa vs. DvRoBERTa spearman correlation with every 1000 steps for one epoch. The base model is configured with 12 layers, 12 self-attention heads, and the hidden size of 768 while the large model is set to 24 layers, 16 self-attention heads, and the hidden size of 1024. In Figure 2, we can see that both base and large models improve the ability to generalization. We find the large model with dual-view achieves more benefits than the base model because of the large model of teachers. Notably, DvRoBERTa has relatively poor performance in the early stage, as the student mainly learns from teachers, which are given higher weights to loss of soft targets.

3.6 Effect of Teacher Annealing

To verify the effect of teacher annealing strategy for DvBERT, we show the importance of teacher

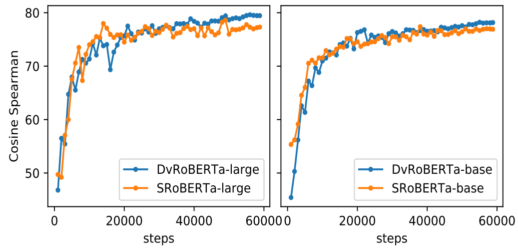

Figure 2: Spearman correlation for SRoBERTa and DvRoBERTa.

annealing vs. loss weighting strategy. The loss weighting strategy combined the loss of hard targets and soft targets by weighted summation. The hyper-parameter α from 0 to 1, it weights the loss of the soft target for optimization. As seen in Figure 3, the left eleven error bars show the cosine spearman correlation of DvRoBERTa-base with different the various α. Using pure hard targets without teacher annealing (i.e., $\alpha = 0$) performs no better than weighted distillation. It further illustrated the dual-views from sentence-pairs can boost the single view of siamese BERT. On the other hand, the teacher annealing strategy (the right bar) shows a better correlation than the loss weighting strategy.

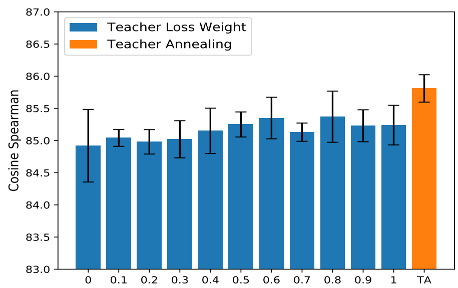

Figure 3: Comparison of teacher loss Weighting and teacher annealing

4 CONCLUSIONS

We proposed a dual-views approach that enhances sentence embeddings for matching, which adopt two heterogeneous networks to adapt to two views. Specifically, it allows siamese BERT-networks to effectively leverage the cross sentence interaction models while keeping the efficiency of using sentence embedding in retrieval tasks. The experiments on six STS datasets show that our models achieve consistent gains and outperform the performance of siamese BERT-networks.

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