SemiBERT: Enhancing Multitask Learning in NLP through Semi-Supervised Techniques

Stanford CS224N Default Project

Danhua Yan
Department of Computer Science
Stanford University
dhyan@stanford.edu

Abstract

SemiBERT, a method enhancing multitask NLP learning with the Unsupervised Data Augmentation (UDA) framework, is introduced in this paper. Utilizing BERT's inherent [SEP] token for sentence-pair encoding notably improves performance. Moreover, the exponential schedule in TSA effectively regulates overfitting, paving the way for more unsupervised samples. These insights inform key design choices in SemiBERT's full implementation.

1 Key Information to include

TA Mentor: Kamyar John Salahi | No external collaborators or mentor | Not sharing projects

2 Approach

SemiBERT adheres to the original BERT setup [1], using the pre-trained $\text{BERT}_{\text{BASE}}$ model weights for downstream tasks. We have fine-tuned the BERT embeddings through the implementation of various extensions, including those commonly used in semi-supervised learning (SSL), to enhance their generalization capabilities across multiple tasks.

Baseline and extensions In our evaluation, the multi-task baseline uses frozen pre-trained $\text{BERT}_{\text{BASE}}$ embeddings, learning only a single linear projection layer as task head. We've investigated various methods for sentence-pair input encoding and multi-task training strategies, building on this baseline. Detailed descriptions of these extensions are in Appendix A.1.

Unsupervised Data Augmentation (UDA) Inspired by UDA's success [2], we convert supervised tasks into semi-supervised ones using advanced data augmentation. We select a subset of training data, remove labels to create unsupervised samples, and use PLMs to generate augmented versions. This involves back-translation, as proposed in [2], and completion of randomly masked sentences with various prompts. We adapt the STS task from regression to classification into score buckets for consistency with other tasks. We adjust the default loss (described in Appendix A.2) following the UDA authors' approach, implemented from scratch, not using code released by UDA authors.

Training Signal Annealing (TSA): To mitigate the risk of overfitting to labeled samples prematurely, we incorporate the TSA into the supervised loss. This approach, proposed by the UDA authors, dynamically selects a subset of the labeled dataset, L_t, at each training step t, defined as $L_t = \{x \in L \mid p_\theta(x) \leq \eta(t)\}$, where $\eta(\cdot)$ is a threshold function that sets a dynamic threshold at each step t. We adhere to the UDA paper's approach, testing linear, log, and exponential $\eta(\cdot)$.

Confidence Masking on KL-divergence Loss: To focus the unsupervised loss on distribution discrepancies arising from suboptimal data augmentation, we calculate the loss only on a subset of the unlabeled data where the model is confident in its prediction. Specifically, at step t, we compute the loss among U_t, where $U_t = \{x \in U \mid p_\theta(x) > \beta\}$, and β is a constant confidence level.

The adjusted loss function becomes:

$$\mathcal{L} = -\sum_{i=1}^{|L_t|} y_i \log p_\theta(x_i) - \lambda \sum_{j=1}^{|U_t|} p_{\tilde{\theta}}(x_j) \log \frac{p_{\tilde{\theta}}(x_j)}{p_\theta(\hat{x}_j)}$$

3 Experiments

Data We fine-tuned the pre-trained $\text{BERT}_{\text{BASE}}$ model using three benchmark datasets provided by the default project: Quora Question Pairs (QQP), SemEval STS Benchmark (STS), and Stanford Sentiment Treebank (SST5). We used the `train` split from each dataset, and randomly sampled 5% of the QQP dataset to balance the data size across tasks.

Evaluation We evaluated our models using standard metrics pertinent to each task. For QQP and SST5, we use accuracy to assess the classification performance. For STS, we use the Pearson correlation of the true similarity values against the predicted similarity values.

Experiments All experiments used the $\text{BERT}_{\text{BASE}}$ model with pre-trained weights. The baseline model's task head projects BERT embeddings to target space using a linear layer, with SST5 and QQP tasks using softmax for predicted classes and cross entropy loss. STS task uses an amplified sigmoid layer for 0-5 regression output and MSE loss, and further modified in UDA extension to a classification problem with 26 classes in 0.2 increments. Unless otherwise noted, models are trained 10 epochs with the learning rate is 1e-5, and batch size is 8. All models were trained using the AdamW optimizer, with $\beta_1 = 0.9, \beta_2 = 0.999$. Experiments are performed on a Nvidia GeForce RTX 4070 Ti SUPER 16GB GPU.

Baseline and extensions Pre-trained $\text{BERT}_{\text{BASE}}$ embeddings struggle with complex tasks beyond binary classifications like SST5 and STS. Fine-tuning BERT on downstream tasks is necessary for optimal performance. In pursuit of the best sentence pair representation using approaches described in Appendix A.1, results in Table 1 show that using intrinsic BERT `[SEP]` token significantly outperforms all other models across all tasks. BERT's next sentence prediction task enables embeddings to capture context similarity between two sentences more effectively. Pooling strategies like absolute difference between embeddings aim to capture sentence distance, but fall short on nuanced STS tasks. Other approaches may overfit due to extra parameters and limited training data, performing poorly on the dev dataset.

Table 1: Comparisons of Baselines and Extensions on Dev Data, training three tasks sequentially

Model	SST5	QQP	STS	Avg. Accuracy
Baseline (last-layer only)	0.309	0.667	0.209	0.527
Arc1-Simple Concat	0.476	0.732	0.363	0.630
Arc1-Absolute difference	0.509	0.712	0.530	0.662
Arc1-Cosine Similarity	0.486	0.503	0.495	0.579
Arc1-Dot Product Attention	0.473	0.728	0.420	0.637
Arc2-Fused Sentence Embedding	**0.513**	**0.821**	**0.880**	**0.758**

At this stage, sequential training shows similar pooled accuracy than simultaneous training (see Appendix Table A1). This leaves scope to further evaluate these approaches once the UDA framework is in place.

Training Signal Annealing (TSA) First, we evaluate the performance difference when changing the STS task from regression to a classification problem. In the single-dataset BERT fine-tuning experiment, the regression approach achieves a dev Pearson correlation of 0.868, while classification reaches 0.864. Given the marginal difference, we convert the STS model to classification to apply the same UDA framework on the STS dataset.

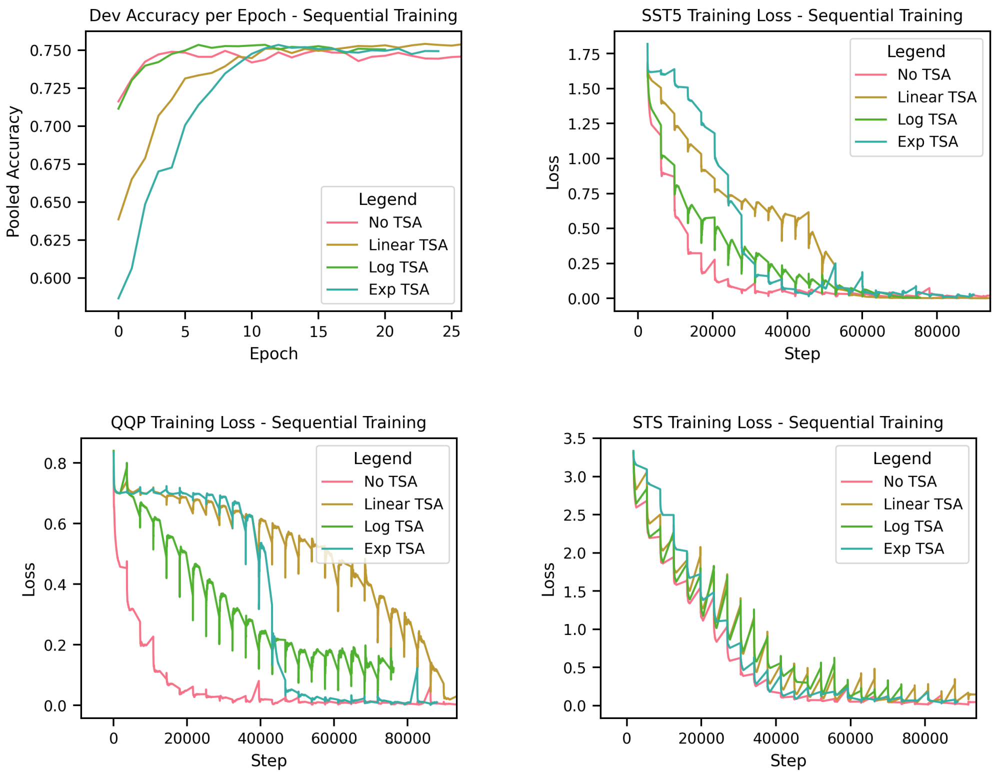


Figure 1: Comparing characteristics of different TSA threshold functions - Sequential Training

Different threshold functions release training signals of labeled examples at varying rates. The exponential schedule releases most signals near the end of training, while the log schedule does the opposite. Figure 1 shows that the TSA component alone does not enhance dev accuracy after 25 epochs. The Log schedule, releasing most training samples early, is less effective in limiting overfitting and performs similarly to no TSA. However, Exponential schedule effectively avoids overfitting beyond 10 epochs. These schedules can be useful when combined with unsupervised samples, especially when reducing the share of labeled samples where overfitting becomes a prominent issue.

4 Future work

Future steps include implementing the unsupervised loss function and experimenting with PLMs for data augmentation using back-translation and sentence completion. This will complete the UDA setup. We will also study the ratio of supervised to unsupervised samples to understand the minimum labeled dataset size for decent performance. Given time, we will explore complex task head models and hyperparameter tuning to enhance results.

References

[1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.

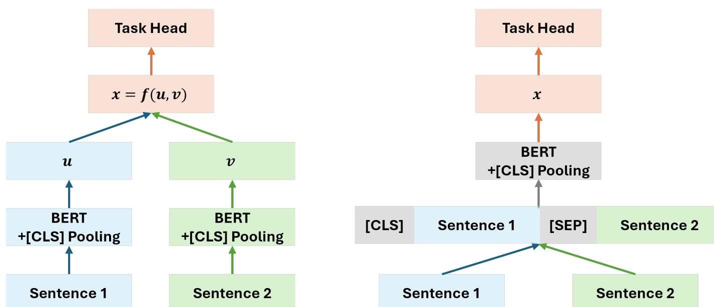
[2] Qizhe Xie, Zihang Dai, Eduard Hovy, Thang Luong, and Quoc Le. Unsupervised data augmentation for consistency training. *Advances in neural information processing systems*, 33:6256–6268, 2020.

[3] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019.

A Approaches Appendix

A.1 Baseline extensions

Combining Sentence Embeddings We investigated two categories of architectures for combining sentence embeddings, as shown in Figure A1. The first architecture, Pooling Separate Embeddings, derives a joint embedding from two separately BERT-encoded sentences. We experimented with various methods including simple concatenation, absolute difference (inspired by the SBERT framework [3]), cosine similarity, and dot product attention. The second architecture, Fused Sentence Embedding, leverages BERT's inherent training with sentence pairs separated by the `[SEP]` token to encode sentence context similarities. This approach fuses the two sentences into a single input sequence to generate a single embedding.



(a) Archetecture 1: Pooling seperate embeddings

(b) Archetecture 2: Fused sentence embedding

Figure A1: Two architectures for sentence-pair inputs: (a) Each sentence is BERT-encoded separately, then pooled into a single embedding. (b) Sentence-pairs are concatenated with a `[SEP]` token and BERT-encoded into one embedding.

Training Strategies Our model optimization involved two training strategies for multiple tasks. In Sequential Training, each task (QQP, STS, SST) was trained sequentially within each epoch, updating the BERT and model parameters after each task head training. Simultaneous Training, on the other hand, computed and aggregated the losses for all tasks at once, updating the model parameters once per batch.

A.2 Default Loss Function for UDA

Formally, given labeled dataset L and unlabeled dataset U, we aim to learn a classification model p_θ with parameters θ. This model maps input x to a class distribution $\hat{y} = p_\theta(x)$. We denote data augmentation as $q(\cdot)$, where $\hat{x} = q(x)$ is the augmented input. Our goal is to find θ minimizing the loss function $J(\theta) = \mathcal{L}_{\text{sup}} + \lambda \mathcal{L}_{\text{unsup}}$, where $\mathcal{L}_{\text{sup}}$ is the supervised cross-entropy loss, $\mathcal{L}_{\text{unsup}}$ is the unsupervised loss between unlabeled and augmented data, and λ is the regularization coefficient. The default loss function is:

$$\mathcal{L} = -\sum_{i=1}^{|L|} y_i \log p_\theta(x_i) - \lambda \sum_{j=1}^{|U|} p_{\tilde{\theta}}(x_j) \log \frac{p_{\tilde{\theta}}(x_j)}{p_\theta(\hat{x}_j)}$$

B Results Appendix

B.1 Training strategies

Simultaneous training yields similar pooled accuracy comparing with sequential training, with variations in single-task performance.

Table A1: Comparisons of Baselines and Extensions on Dev Data, training three tasks simultaneously

Model	**SST5**	**QQP**	**STS**	**Avg. Accuracy**
Baseline (last-layer only)	0.309	0.667	0.209	0.527
Arc1-Simple Concat	0.479	0.738	0.369	0.634
Arc1-Absolute difference	0.51	0.733	0.532	0.670
Arc1-Cosine Similarity	0.482	0.533	0.436	0.578
Arc1-Dot Product Attention	**0.514**	0.737	0.486	0.665
Arc2-Fused Sentence Embedding	0.507	**0.830**	**0.873**	**0.758**