BERT Multitask Learning in a Semi-Supervised Learning Setup

Stanford CS224N Default Project

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Abstract

Fine-tuning the BERT model for optimal performance across various NLP tasks necessitates high-quality labeled data, which can be challenging to obtain. Semi-supervised learning (SSL) utilizes unlabeled data to bolster supervised learning tasks. In this study, we enhance $\text{BERT}_{\text{BASE}}$ embeddings across multiple tasks, including fine-grained sentiment classification, paraphrase detection, and textual similarity, by implementing a multitask learning strategy. We employ a fused sentence embedding approach and a simultaneous training schedule to ensure balanced performance across tasks. Furthermore, we explore the effectiveness of Unsupervised Data Augmentation (UDA) in SSL settings, using various data augmentations generated by Pre-trained Language Models (PLMs). We also provide insights into the strengths, limitations, and ethical considerations of our model. The culmination of our efforts resulted in an overall accuracy of 0.763 on the test dataset. Task-specific performances included a score of 0.517 on the SST5, 0.839 on the QQP, and 0.866 on the STS dataset. These results signify a substantial improvement in multi-task learning capabilities.

Key Information to include

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

1 Introduction

BERT, an innovative NLP model developed by Devlin et al. (2019), utilizes transformer architecture and attention mechanisms to understand contextual word relationships. Recent studies have leveraged pre-trained BERT weights, fine-tuning the model to achieve outstanding results across a variety of tasks. However, acquiring labeled data for BERT fine-tuning can be challenging and often not feasible.

Semi-supervised learning (SSL) is a widely used technique that leverages unlabeled data to enhance the performance of supervised learning tasks. Among the various SSL methods, consistency training stands out for its proven effectiveness across numerous benchmarks. This method ensures that a model produces consistent outputs for an unlabeled example, even when subjected to minor perturbations, such as the introduction of small noise. This approach sheds light on training high performance NLP models with limited labels.

In this study, we enhance the performance of $\text{BERT}_{\text{BASE}}$ embeddings across multiple tasks: fine-grained sentiment classification, paraphrase detection, and textual similarity. We introduce a multitask learning strategy that employs a fused sentence embedding approach for combining pairwise sentence inputs, and a simultaneous training schedule is implemented to balance performance across tasks. We also utilize the Unsupervised Data Augmentation (UDA) framework proposed by Xie et al. (2020) in SSL settings, to further investigate the effectiveness of UDA with various data augmentations generated by Pre-trained Language Models (PLMs). Through experiments and thorough analyses, we offer insights into the strengths, limitations, and ethical considerations of our model.

2 Related Work

BERT, along with its subsequent PLMs, has sparked extensive research aimed at enhancing their performance on out-of-domain downstream tasks. Fine-tuning pre-trained weights has become standard practice, and researchers are continually developing strategies and architectures to further improve BERT embeddings.

For downstream tasks like paraphrase detection and textual similarity, the quality of sentence pair embeddings is pivotal to the performance of the model. In the original BERT implementation, Devlin et al. (2019) utilized a pair of sentences separated by the `[SEP]` token and performed next sentence prediction to enhance token embeddings. This method, due to the intrinsic context embeddings learned by BERT, has been widely adopted for tasks involving sentence pairs. Reimers and Gurevych (2019) introduced the Sentence-BERT architecture where, during training, each sentence is encoded by BERT separately, and the joint embedding is an absolute element-wise difference. At inference time, cosine similarity is computed directly between the two separate embeddings to calculate similarity scores. Choi et al. (2021) explored different pooling strategies beyond the `[CLS]` token representation in the SBERT setup, demonstrating that advanced CNN pooling can enhance textual similarity tasks. These studies underscore the significance of single sentence and sentence pair embeddings in the performance of the final models. In this study, we investigate various encoding strategies and their influence on the multi-task learning performance.

Fine-tuning for diverse downstream tasks can be challenging due to the limited availability and high acquisition cost of task or domain-specific labeled datasets. Despite this, deep learning systems typically require substantial data to function optimally. Semi-supervised Learning (SSL) emerges as a promising paradigm, leveraging a small labeled dataset in conjunction with a large unsupervised dataset to construct effective and generalizable NLP models. Consistency training, a subset of SSL, has demonstrated its efficacy across numerous benchmarks Bachman et al. (2014); Rasmus et al. (2015); Laine and Aila (2017); Tarvainen and Valpola (2018).

The Unsupervised Data Augmentation (UDA) framework, proposed by Xie et al. (2020), establishes a strong connection between data augmentation and semi-supervised learning, that improved data augmentation techniques can significantly enhance semi-supervised learning outcomes. For NLP tasks, the study explored back-translation[1], which demonstrated performance improvements when dealing with limited data labels. The recent success of PLMs such as ChatGPT and LLaMA-3 has empowered researchers to harness their robust knowledge retrieval capabilities. This has facilitated the generation of training datasets and data augmentations (Zhong et al. (2022); Wang et al. (2021); Raffel et al. (2023)), leading to remarkable performance on multi-task NLP benchmarks like GLUE Wang et al. (2019b) and SuperGLUE Wang et al. (2019a). Training samples are generated from few-shot or zero-shot prompts and combined with unlabeled datasets to fine-tune BERT-like models leveraging UDA-like framework (Meng et al. (2022); Wang et al. (2021)). In this study, we utilize the UDA framework to investigate efficient fine-tuning strategies for transitioning supervised learning into SSL settings, aiming to enhance the performance of supervised NLP tasks. We conduct experiments with advanced PLMs to generate data augmentations, examining whether this approach can yield high-quality data that strengthens SSL.

3 Approach

We adhere to the original BERT setup, 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 SSL, to enhance their generalization capabilities across multiple tasks.

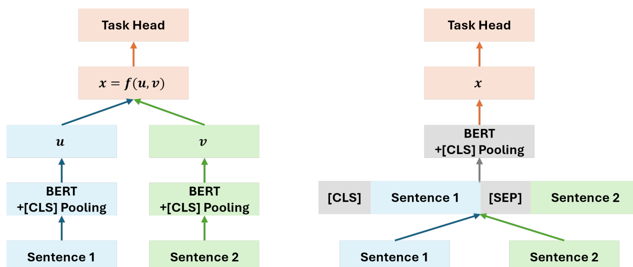
[1]This process involves translating a text from language A to language B, and then back to A to generate an augmented example.

3.1 Baseline

In our study, the multi-task baseline uses frozen pre-trained $\text{BERT}_{\text{BASE}}$ embeddings, learning only a single linear projection layer as task head. For handling sentence-pair tasks, embeddings of the two sentences are concatenate to form a joint representation of the sample before feeding into the task head.

3.2 Combining Sentence Embeddings

For sentence-pair NLP tasks, we explored two categories of architectures for combining sentence embeddings, as illustrated in Figure 1. The first architecture, Pooling Separate Embeddings, generates a joint embedding from two sentences encoded separately by BERT. We experimented with various methods, including simple concatenation (as used in the baseline), absolute difference (inspired by the SBERT framework training step Reimers and Gurevych (2019)), direct cosine similarity with scaling, and dot product attention of the two embeddings, which employs an attention matrix to embed the sentence pair. The second architecture, Fused Sentence Embedding, utilizes BERT's inherent training with sentence pairs separated by the `[SEP]` token to encode sentence context similarities. This approach combines the two sentences into a single input sequence to produce a unified embedding.



(a) Archetecture 1: Pooling seperate embeddings

(b) Archetecture 2: Fused sentence embedding

Figure 1: 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.

3.3 Training Strategies

To ensure the fine-tuned BERT embeddings generalize across all downstream tasks, we employ two training strategies. In Sequential Training, tasks are trained in succession within each epoch. Specifically, model weights are updated per batch, with three tasks forming a batch queue in the order of paraphrase detection, textual similarity, and sentiment analysis. Conversely, Simultaneous Training aggregates the losses for all tasks concurrently. Each batch comprises three different tasks of the same batch size, and losses are summed without weighting.

3.4 Semi-Supervised Learning Setup

Motivated by the success of UDA (Xie et al. (2020)), we transform supervised tasks into semi-supervised ones to investigate effective fine-tuning strategies. We eliminate all labels from the training sets to create an unlabeled dataset and generate data augmentations of these examples by prompting advanced PLMs (e.g., ChatGPT or LLaMA-3) in various ways. Despite the availability of open-source code accompanying the UDA paper, **we opted to implement this framework from scratch** to gain a deeper comprehension of each component's functionality.

3.4.1 Advanced data augmentation

We explored three distinct text augmentation strategies. The first, back-translation, is proposed by the UDA authors. It involves prompting the PLM to translate a given English sentence into French, then back into English. This method maintains the original meaning and factuality of the sample, albeit with potential changes in word choice and phrasing. The other two strategies, sentence completion and random-mask completion, are original approaches. Sentence completion involves providing the PLM with the sample sentence, appending `"To put it differently,"` at the end, and allowing the PLM to complete the sentence. This strategy aims to ensure the PLM comprehends the sentence's meaning and elaborates on its context. Random-mask completion randomly masks consecutive words and prompts the PLM to fill in the masked blank using a roughly equivalent number of words. This strategy aims to create structurally similar text augmentations, albeit with the risk of altering the factuality of the sentence, even if it appears very similar.

3.4.2 SSL Loss

In a typical SSL setup, loss function is usually a combination of supervised loss $\mathcal{L}_{\text{sup}}$ and unsupervised loss $\mathcal{L}_{\text{unsup}}$. Following UDA paper's setup, here $\mathcal{L}_{\text{sup}}$ is the mean cross-entropy loss, and $\mathcal{L}_{\text{unsup}}$ is the mean KL-divergence loss between unsupervised and augmented data. 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 $J(\theta) = \mathcal{L}_{\text{sup}} + \lambda\mathcal{L}_{\text{unsup}}$, and λ is the regularization coefficient.

3.4.3 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. Here we test linear, log, and exponential $\eta(\cdot)$ and assess the effectiveness in reducing overfitting.

3.4.4 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.

3.4.5 Loss Function

The final loss function used for this study combining all above becomes:

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

Note that the term $\tilde{\theta}$ denotes a *fixed* copy of the current parameters, to indicate that the gradient is not propagated through $\tilde{\theta}$. This is to ensure the loss is minimizing the divergence against a stable reference against current model parameters (Miyato et al. (2018)).

4 Experiments

4.1 Data

We fine-tuned the pre-trained $\text{BERT}_{\text{BASE}}$ model using three benchmark datasets from the default project: Quora Question Pairs (QQP), SemEval STS Benchmark (STS), and Stanford Sentiment Treebank (SST5). For each dataset, we utilized the `train` split. Specifically, for the QQP dataset, we consistently used a fixed subset of 14,057 training samples, representing 5% of the provided training data, throughout our experiments.

We leveraged the same training datasets for unsupervised learning by omitting the provided labels. Data augmentation of these unsupervised datasets was achieved by prompting the LLaMA-3 Chat (8B) model via the TogetherAI API using various prompts.

4.2 Evaluation method

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.

4.3 Experimental details

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 SSL extension to a classification problem with 26 classes in 0.2 increments. All models are trained using learning rate of 1e-5, and batch size of 8, and gradients are clipped at 0.1 to help reduce potential noise from the SSL setup. Unless otherwise noted, models without TSA (i.e. baseline and extension models) are trained 10 epochs, models in SSL settings are trained 50 epochs with an early stopping patience of 10 epochs. All models were trained using the AdamW optimizer, with $\beta_1 = 0.9, \beta_2 = 0.999$, and a weight decay regularization $\lambda = 0.01$. For data augmentation generated by prompting LLaMA-3 Chat (8B) model via the TogetherAI API, we set request parameters as temperature = 0.5, repetition_penalty = 1. For SSL loss, we follow UDA paper by choosing unsupervised loss regularization $\lambda = 1$, confidence masking threshold $\beta = 0.8$, and sharpen the unsupervised predictions using softmax temperature $\tau = 0.4$. Experiments are performed on a Nvidia GeForce RTX 4070 Ti SUPER 16GB GPU.

4.4 Baseline and Combining Sentence Embeddings

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 section 3.2, 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. The absolute difference between embeddings captures sentence distance, performs reasonably well on the binary QQP task but falls short on nuanced STS tasks. Other methods may struggle due to an excess or deficiency of learned parameters, which may not align well with the sizes of the training data.

Table 1: 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	0.510	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	0.501	**0.829**	**0.852**	**0.752**

4.5 Training Strategies

Simultaneous training consistently surpasses sequential training in generating multitask models, and will be employed for the remainder of this study. For further details, refer to Appendix A.1.

4.6 Semi-Supervised Learning Setup

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.

4.6.1 Training Signal Annealing (TSA)

Different threshold functions dictate the rate at which training signals of labeled examples are released. The exponential schedule predominantly releases signals towards the end of training, while the log schedule does the converse. As shown in Figure 2, the TSA component proves effectiveness in mitigating overfitting during early epochs, thereby enhancing the overall model accuracy. The Log schedule, which releases most training samples early, is less effective in curbing overfitting and performs comparably to the absence of TSA. Conversely, the Exponential schedule effectively mitigates overfitting, but requires a considerably longer duration to achieve comparable performance when training samples are plentiful. The Linear schedule strikes a balance between convergence speed and the ability to prevent overfitting within 10 epochs, making it the chosen method for subsequent extensions.

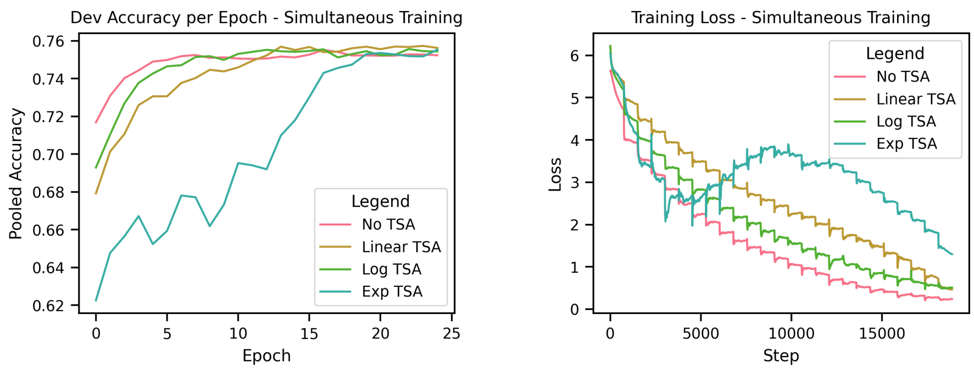


Figure 2: Comparing characteristics of different TSA threshold functions

4.6.2 Various Advanced Data Augmentation

We explored three distinct data augmentation techniques: back-translation, random-mask completion, and sentence completion. The model was trained using the augmented training data, while preserving the original labels for the supervised task. This approach allowed us to evaluate the quality of the data augmentation, as detailed in Appendix Table A2.

Back-translation performed as anticipated, matching the original model's performance. Random-mask completion underperformed likely due to factual alterations during the fill-in-the-blank process. Unexpectedly, sentence completion also fell short, potentially due to training exclusively on PLM-summarized data and then inferring from original text. For instance, in the STS task, a sentence pair like "A man plays the guitar and sings." and "A man is singing and playing a guitar." with a similarity of 5.0, was simplified by sentence completion to "He is a musician." for both sentences. This simplification poses challenges when the model infers from original text data.

4.6.3 Training in SSL settings

We henceforth refer to the fine-tuned BERT model, which employs the Fused Sentence Embedding technique and the simultaneous training strategy discussed in section 4.4, as our baseline extension model. We now explore how SSL settings can enhance supervised learning outcomes.

Table 2: Comparisons of Dev model performance in SSL settings

Model	SST5	QQP	STS	Avg. Accuracy
Baseline Extension	0.501	0.829	0.852	0.752
BE + Linear TSA	0.520	**0.836**	0.861	**0.762**
BE + Linear TSA + UDA Back Translation	**0.520**	0.821	**0.862**	0.758
BE + Linear TSA + UDA Sentence Completion	0.506	0.820	0.853	0.751
BE + Linear TSA + UDA Random-mask Completion	0.520	0.808	0.827	0.747

As shown in Table 2, Linear TSA enhances the baseline extension model across tasks by focusing more on challenging examples rather than overfitting on simpler ones. However, training on the full dataset with data augmentation as a regularization term does not further boost the model's performance. While UDA offers slight improvements on SST5 and STS, it underperforms on the QQP task. This shortcoming may stem from ineffective prompting to the LLaMA-3 Chat (8B) model. We observed that many back-translation responses closely mirror the unlabeled data. Although prompting through the chain-of-thought technique, LLaMA-3 Chat (8B) appears to increasingly depend on input sentences, often producing identical back-translations. This redundancy undermines UDA's effectiveness, as the KL-divergence loss becomes zero, potentially increasing noise in the gradient updates.

Another potential factor is our use of trained datasets to generate "unlabeled" datasets, rather than incorporating new samples outside of the training distribution. This absence of fresh samples may limit UDA's effectiveness in improving the model's generalization.

4.7 Results

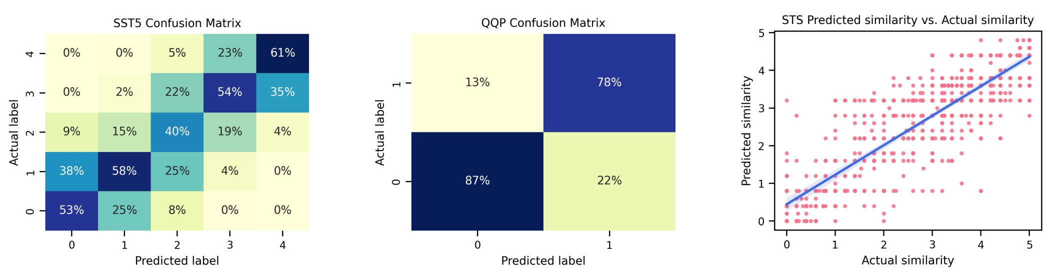
We now discuss our model's performance on the Dev and Test sets. Our final model integrates the baseline extension with linear TSA (BE + Linear TSA in Table 2). The results in Table 3 demonstrate that TSA effectively mitigates overfitting, yielding consistent performance across both the Dev and Test sets.

Table 3: Final model performance on both Dev and Test set

	SST5	QQP	STS	Avg. Accuracy
Dev Set	**0.520**	0.836	0.861	0.762
Test Set	0.517	**0.839**	**0.866**	**0.763**

5 Analysis

To gain a deeper understanding of the model's performance, we carried out both quantitative and qualitative analyses across the three tasks. In essence, the model exhibits a strong grasp of sentiment analysis and sentence-pair similarity analysis. However, it has challenges with the inherent ambiguities in human-annotated data, the differentiation of sentence roles, and the discernment of subtle sentiment variations when sentences employ identical or similar words.



(a) SST5 Dev Set Confusion Matrix normalized to predicted labels

(b) QQP Dev Set Confusion Matrix normalized to predicted labels

(c) STS Correlation Plot, line showing best fit

Figure 3: Analysis of Dev set performance of the model

Fine-grained Sentiment Analysis SST5 As shown in Figure 3(a), the model demonstrates a robust understanding of sentiment. Misclassifications primarily occur between adjacent categories. Despite not explicitly training the SST5 task using an ordinal categorical approach, the model effectively learns and interprets sentiment. Interestingly, the model performs better on extreme sentiments than neutral ones. This performance discrepancy may be due to inherent ambiguities in the text and biases from human evaluators. For instance, the sentence "Hilariously inept and ridiculous." was labeled as somewhat positive. However, both our model and ChatGPT-4 assign it a somewhat negative rating. Absent further context, the sentiment of this sentence remains open to interpretation.

Paraphrase Detection QQP As illustrated in Figure 3(b), the model exhibits lower precision in the positive class compared to the negative class. Two primary themes emerge from the cases incorrectly classified as positive: The first involves sentences with identical or similar words but in different orders, such as the pair "Can MIT PhD students have a Harvard PhD adviser?" and "Can Harvard PhD students have an MIT PhD adviser?". The model struggles to distinguish the respective roles in each sentence, suggesting potential areas for improvement such as incorporating dependency or POS tags and advanced positional embeddings into the model setup. The second theme pertains to ambiguities in human-labeled data. For instance, the pair "Why did you deactivate your Facebook account?" and "What are the benefits of deactivating your Facebook account?" is labeled as non-paraphrase. However, one could interpret these sentences as having the same intent, thus considering them as paraphrases.

Textual Similarity STS Similar to the SST5 task, the model is trained in a multi-class manner, capturing the relative relationship between numerical classes without requiring additional ordinal categorical training. Misclassifications are typically found around the adjacent areas of the true score. As observed in Figure 3(c), the fitted prediction line has a slope less than 1, indicating the model produces a narrower range of scores compared to actual human labels. This may be attributed to the model's tendency not to assign extreme scores when sentences share common words. For instance, the sentences "Work into it slowly." and "It seems to work." were judged by humans to have 0.0 similarity, yet the model assigns a 3.2 score, given that 50% of the words are identical. This highlights the model's difficulty in capturing sentiment nuances when sentences use the same words.

6 Conclusion

In this study, we effectively enhanced $\text{BERT}_{\text{BASE}}$ embeddings' performance across various NLP tasks using a multitask learning strategy and incorporating semi-supervised learning techniques. Our experiments revealed that the fused sentence embedding approach and simultaneous training schedule significantly boosted the model's performance in all downstream tasks. Moreover, the integration of the UDA framework, particularly the TSA component, further amplified our model's capabilities, despite the limitations in the quality of data augmentation. These findings underscore the potential of advanced PLMs in SSL settings and the importance of high-quality data augmentation for the success of this framework. Future research could focus on exploring more efficient data augmentation approaches, training paradigms, and advanced language features to overcome existing challenges and build more robust and generalizable NLP models.

7 Ethics Statement

The integration of BERT with UDA in semi-supervised NLP tasks introduces societal and ethical concerns. While fine-tuning BERT with UDA can reduce human labeling costs, it may escalate computational expenses due to generation of augmented datasets for large amount of unsupervised datasets via PLM prompts, which could have a significant environmental impact when implemented at scale. Recent progress in few-shot and zero-shot learning with advanced PLMs (Meng et al. (2022); Wang et al. (2021)) suggests training paradigms that are more efficient than UDA, potentially leading to more streamlined inference.

On the other hand, bias and toxicity amplification might present in the process of data augmentation via PLM prompts. Existing biases or toxic language in training data and PLMs can be exacerbated in semi-supervised training setups during the generation of augmented datasets. Several strategies have been proposed to address these issues in PLMs. For instance, Ma et al. (2020) introduced PowerTransformer, which minimizes biases in text and paraphrases. Employing existing models or APIs to scrutinize PLM-generated data can aid in filtering out biased and toxic content and rephrasing biased text, thereby mitigating the amplification issue.

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A Appendix

A.1 Training strategies

Simultaneous training consistently outperforms sequential training in producing multitask models, as evidenced by the results in Table 1 and Appendix Table A1. Simultaneous training benefits from less frequent model updates, occurring only a third as often as in sequential training when trained for an equal number of epochs (updating once per three tasks versus updating once per task in sequential training). Each step averages the loss from the three tasks, yielding an averaged gradient that stabilizes parameter updates.

In contrast, sequential training has more frequent model updates, potentially introducing noise into the gradient updates. Furthermore, during sequential training, the three tasks are processed in chunks, meaning the model updates gradients based on a single task's data before moving on to the next. If the tasks are not well synergized, as indicated by the weak correlation of the SST5 task with the QQP and STS tasks in Table 1, this could create conflicting gradient descent directions and introduce additional noise, thereby negatively impacting model performance.

Table A1: 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	0.486	**0.823**	**0.832**	**0.742**

A.2 Various data augmentation

We trained the model using the augmented dataset, while preserving the original labels for the supervised task. Back-translation performed comparably to training with real text. However, the other approaches did not prove suitable for standalone use.

Table A2: Training on full augmented dataset as supervised learning

Augmentation Approach	**SST5**	**QQP**	**STS**	**Avg. Accuracy**
Back Translation	0.510	0.826	0.802	0.746
Random Mask Completion	0.470	0.781	0.723	0.704
Sentence Completion	0.411	0.728	0.630	0.651