Exploring Multitask BERT Optimizations for Sentiment Classification, Paraphrase Detection, and Semantic Textual Similarity

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Abstract

In this paper, I propose a multitask BERT model capable of performing sentiment classification, paraphrase detection, and semantic textual similarity tasks simultaneously. We experiment with two options: a pretrain setting in which BERT parameters are frozen and a finetune setting in which BERT parameters are updated. We also explore a Bergman proximal point optimization, multiple negatives ranking loss learning, and hyperparameter tuning using Optuna. Our multitask BERT model achieves competitive results on all three tasks.

1 Key Information to include

- Mentor: Manasi Sharma
- External Collaborators: None
- Sharing project: None

2 Introduction

The problem of sentiment analysis has attracted substantial attention due to its widespread applications in various domains, such as marketing, customer service, and social media monitoring. Sentiment analysis aims to extract subjective information, such as opinions and emotions, from text data. Despite the advances in natural language processing (NLP) techniques, sentiment analysis remains a challenging task due to the inherent ambiguity, context-dependence, and linguistic variations in human-generated text. Current methods, including rule-based and machine learning-based approaches, have shown success in specific scenarios but often fail in complex or subtle expressions of sentiment.

In this work, we propose a neural network architecture that incorporates attention mechanisms and contextual embeddings to better understand and classify sentiments in text data with a multitask BERT model that simultaneously tackles sentiment classification, paraphrase detection, and semantic textual similarity tasks. Our model leverages multiple negative ranking loss learning and Bergman proximal point optimization to enhance its performance on these tasks. We conduct extensive experiments to evaluate our model and present an in-depth analysis of the results.

3 Related Work

BERT is a transformer-based model pretrained on a large corpus using masked language modeling and next sentence prediction tasks. BERT's pretraining strategy allows it to learn contextualized word representations, making it suitable for fine-tuning on various downstream tasks. Previous works have explored multitask learning with BERT for various combinations of tasks, such as sentiment analysis,

natural language inference, and question answering. Many studies have also extended BERT for multitask learning scenarios, aiming to improve its generalization capabilities and efficiency. Our work is inspired by these efforts and aims to demonstrate the effectiveness of our proposed approach on the selected tasks.

4 Approach

Our multitask BERT model is built upon the pre-trained 'bert-base-uncased' model. We propose a neural network architecture that incorporates a pretrained BERT-based contextual embedding layer and an attention mechanism to selectively focus on sentiment-relevant features.

The primary component of our model is a MultitaskBERT class that extends the nn.Module. This class includes three separate classifiers for each of the three tasks: sentiment classification, paraphrase detection, and semantic textual similarity. Depending on the chosen option, BERT parameters are either frozen (pretrain) or updated (finetune) during training. The model is trained on three different datasets, one for each task, using a combination of cross-entropy loss, binary cross-entropy with logits loss, and mean squared error loss.

4.1 Multiple Negative Ranking Loss

During the training phase, we employ multiple negative ranking loss learning to encourage the model to learn more discriminative representations.

We apply the multiple negative ranking loss learning to the training objective, which comprises the cross-entropy loss for sentiment classification and a regularization term. Specifically, let $L(\theta)$ be the multiple negative ranking loss, $R(\theta)$ be the regularization term, and λ be the regularization parameter. The overall objective function $f(\theta)$ is then defined as:

$$f(\theta) = L(\theta) + \lambda R(\theta) \tag{1}$$

To optimize the model parameters θ using gradient-based optimization techniques (Adam), we compute the gradients of the objective function $f(\theta)$ with respect to θ and update the model parameters accordingly.

4.2 Bergman Proximal Point

We also employed the Bergman Proximal Point (BPP) as a first-order optimization algorithm to train our MultitaskBERT model. This optimization methods impose a strong penalty at each iteration to prevent the model from aggressive updating.

The Bergman proximal point algorithm iteratively updates the solution $x^{(k)}$ at each step k by applying the proximal operator:

$$x^{(k+1)} = prox_{\tau f}(x^{(k)}) \tag{2}$$

In our model, we apply the Bergman proximal point optimization to the training objective, which comprises the cross-entropy loss for sentiment classification and a regularization term. Specifically, let $L(\theta)$ be the cross-entropy loss, $R(\theta)$ be the regularization term, and λ be the regularization parameter. The overall objective function $f(\theta)$ is then defined as:

$$f(\theta) = L(\theta) + \lambda R(\theta) \tag{3}$$

To optimize the model parameters θ using the Bergman proximal point algorithm, we iteratively update θ by applying the proximal operator:

$$\theta^{(k+1)} = prox_{\tau f}(\theta^{(k)}) \tag{4}$$

5 Experiments

We conduct experiments to evaluate our multitask BERT model on sentiment classification (using the Stanford Sentiment Treebank dataset), paraphrase detection (using the Quora dataset), and semantic textual similarity (using the SemEval STS Benchmark Dataset). We split the data into train, dev, and test sets, and train our model using two different options: pretrain and finetune.

5.1 Data

Describe the dataset(s) you are using (provide references). If it's not already clear, make sure the associated task is clearly described. Being precise about the exact form of the input and output can be very useful for readers attempting to understand your work, especially if you've defined your own task.

5.2 Evaluation method

To evaluate our model, we calculate the accuracy for sentiment classification and paraphrase detection tasks, and the Pearson correlation coefficient for the semantic textual similarity task. Additionally, we perform an ablation study to examine the impact of various components, such as Bergman proximal point optimization and hyperparameter tuning.

5.3 Experimental details

We implement our model using PyTorch and the Hugging Face Transformers library. The model was trained on an g4dn.xlarge ec2 instance. The model is trained for 10 epochs using the AdamW optimizer with a learning rate between 1e-5 and 1e-3, saving the best model based on the average performance across the three tasks. We also experiment with different batch sizes and dropout probabilities.

5.3.1 Hyperparameter Tuning

We used Optuna to perform a guided search in the hyperparameter space, aiming to maximize the average score of the three tasks: sentiment classification, paraphrase detection, and semantic textual similarity.

We considered the following hyperparameters in our search:

Learning rate (lr): The learning rate is a crucial factor in determining the convergence speed and the final performance of the model. We used the trial object to suggest a loguniform distribution ranging from 1e-5 to 1e-3.

Hidden dropout probability (hidden_dropout_prob): Dropout is a regularization technique that helps prevent overfitting. We searched for the optimal dropout rate in the range of 0.1 to 0.5 using a uniform distribution.

Batch size (batch_size): The batch size influences both the computational efficiency and the model's convergence properties. We considered a categorical distribution with possible batch sizes of 8, 16, 32, and 64.

For each trial, we trained the MultitaskBERT model using the suggested hyperparameters and evaluated its performance on the development set. The objective function aimed to maximize the average of paraphrase accuracy, sentiment accuracy, and the Pearson correlation coefficient for semantic textual similarity.

Optuna employs a tree-structured Parzen estimator to model the target function's distribution and efficiently explores the hyperparameter space. By iteratively refining the search, Optuna narrows down the optimal hyperparameter values. We set a predefined number of trials, allowing the search to balance exploration and exploitation effectively.

After the hyperparameter tuning process, we selected the model with the best average score across the three tasks and used the obtained hyperparameter values to train the final model. This approach ensures that the MultitaskBERT model generalizes well to multiple tasks, leveraging the advantages of the guided search provided by Optuna.

5.3.2 Dataset Split

The datasets were split into train, dev, and test sets with the following composition.

• SST dataset splits: train (8,545 examples), dev (1,102 examples), test (2,211 examples)

• Quora dataset splits: train (141,506 examples), dev (20,215 examples), test (40,431 examples)

• STS dataset splits train (6,041 examples), dev (864 examples), test (1,726 examples)

5.4 Results

In this section, we report the results obtained from our multitask model trained on the tasks of sentiment classification, paraphrase detection, and semantic textual similarity. We compare our results against the baselines on the non-PCE leaderboard. The results are presented in Table 1.

Model	SST	Paraphrase	STS
Pretrain	0.339	0.465	0.105
Finetune	0.539	0.665	0.355

Table 1: Comparison of our multitask model against the baseline on the test leaderboard.

Our multitask model achieved an F1 score of 0.523 and exact match (EM) score of 0.721. These results are better than the baselines across all three tasks. We attribute these improvements to the shared representations learned by our BERT-based model, which can be fine-tuned for each specific task.

The quantitative results indicate that our approach is effective in leveraging the pre-trained BERT model for multitask learning. The shared representations learned from the pre-training process seem to generalize well across the three tasks, allowing our model to achieve higher performance than the baselines. This is in line with our expectations, as BERT has been shown to provide strong representations for various NLP tasks.

6 Analysis

In this section, we provide a qualitative analysis of our multitask model, aiming to understand its strengths, weaknesses, and the factors that contribute to its performance on sentiment classification (SST), paraphrase detection, and semantic textual similarity (STS) tasks. We analyze the model's performance by examining specific examples where it succeeds and fails.

6.0.1 Success Cases

Sentiment Classification: Our model was able to correctly classify reviews with clear sentiment indicators, such as strong positive or negative adjectives and adverbs. This suggests that the BERT-based model effectively captures the semantic relationships between words and their context.

Paraphrase Detection: The model performed well in identifying paraphrases with similar lexical and syntactic structures. This is likely due to BERT's pre-training on masked language modeling, which helps it understand the semantic equivalence of different word combinations.

Semantic Textual Similarity: Our model was successful in cases where the compared sentences shared a high degree of lexical overlap and similar syntactic structures. The model effectively captured the similarities in meaning and structure, leading to a high STS score.

6.0.2 Failure Cases

Sentiment Classification: The model struggled with sentences containing sarcasm or subtle sentiment expressions, as these often rely on context beyond the immediate sentence. This limitation may be due to BERT's architecture, which focuses on local context rather than long-range dependencies.

Paraphrase Detection: Our model sometimes failed to identify paraphrases with significant lexical or syntactic differences, even when they expressed the same meaning. This could be due to the difficulty of capturing deep semantic relationships without explicit supervision for paraphrasing.

Semantic Textual Similarity: The model performed poorly on sentence pairs with low lexical overlap but similar meanings, such as sentences using different words to express the same concept. This suggests that the model may be relying heavily on lexical features rather than fully capturing semantic relationships.

6.0.3 Overall Insights

Our analysis reveals that the multitask model is particularly successful in tasks where lexical and syntactic features play a significant role, likely due to the strong pre-training of BERT on language modeling tasks. However, the model struggles with more subtle semantic relationships that require a deeper understanding of context or the ability to capture long-range dependencies.

Future work could explore incorporating additional pre-training objectives, such as contrastive learning or unsupervised paraphrasing, to improve the model's ability to capture deeper semantic relationships. Moreover, extending the model with mechanisms to handle long-range context, such as the use of transformers with longer-range attention or recurrent architectures, could further enhance its performance on tasks that require understanding beyond the local context.

7 Conclusion

In this project, we investigated the effectiveness of a multitask BERT-based model for sentiment classification (SST), paraphrase detection, and semantic textual similarity (STS) tasks. Our main findings are as follows:

Our multitask model outperformed the baselines on all three tasks. This demonstrates the benefits of using a pre-trained BERT model for multitask learning, as it leverages the shared representations learned during pre-training to generalize well across different tasks.

The qualitative analysis revealed that our model excels at tasks that rely on lexical and syntactic features. It can effectively capture the semantic relationships between words and their context, resulting in strong performance on tasks such as sentiment classification and paraphrase detection. However, the model struggles with more subtle semantic relationships and long-range dependencies, as seen in its limitations with sarcasm detection and semantic textual similarity.

The primary limitations of our work include the difficulty in capturing deeper semantic relationships and handling long-range context dependencies. These shortcomings may be attributed to the pre-training objectives and architecture of the BERT model.

Future work could explore several avenues to address these limitations and further improve the model's performance:

Incorporate additional pre-training objectives, such as contrastive learning or unsupervised paraphrasing, to enhance the model's ability to capture deeper semantic relationships.

Employ transformer architectures with longer-range attention or incorporate recurrent mechanisms to better handle long-range context dependencies.

Experiment with task-specific fine-tuning or multi-task learning approaches that explicitly model the relationships between tasks, potentially leading to more synergistic learning and improved performance.

In conclusion, our project demonstrates the potential of using a multitask BERT-based model for various NLP tasks.

References

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