# Temporal Ensembles of Fine-Tuned BERT Models for Offensive Language Identification

Jennifer Kadowaki (jkadowaki@email.arizona.edu)

THE UNIVERSITY OF ARIZONA

## Task 6a: Identifying Offensive Language

With the advent of major social media platforms, growing concerns surround online user safety and experience. We participated in the SemEval-2019's OffensEval shared task, which uses the Offensive Language Identification Dataset (OLID; Zampieri et al., 2019) to identify offensive and abusive language in Tweets.

## Approach: Temporal Ensembles of Fine-Tuned BERT Models

Due to the speed of fine-tuning and the task of classifying each tweet as offensive or not, we used BERT-based model (Devlin et al., 2018) for a single sentence classification task (Figure 1). We opted to use the cased version due to the presence of capital letters in our dataset. We did not perform any data preprocessing or cleaning with the exception of making the data compatible with BERT. Table 1 lists the hyper-parameters for our setup. We performed 10-fold cross-validation to check the consistency of our results across repeated experiments. Due to the memory-intensiveness, we fine-tune BERT on a GPU node on Ocelote using a Singularity container with Tensorflow and CUDA. For each fold, we fine-tuned the model for 100 epochs, saving the dev set predictions after each training epoch.

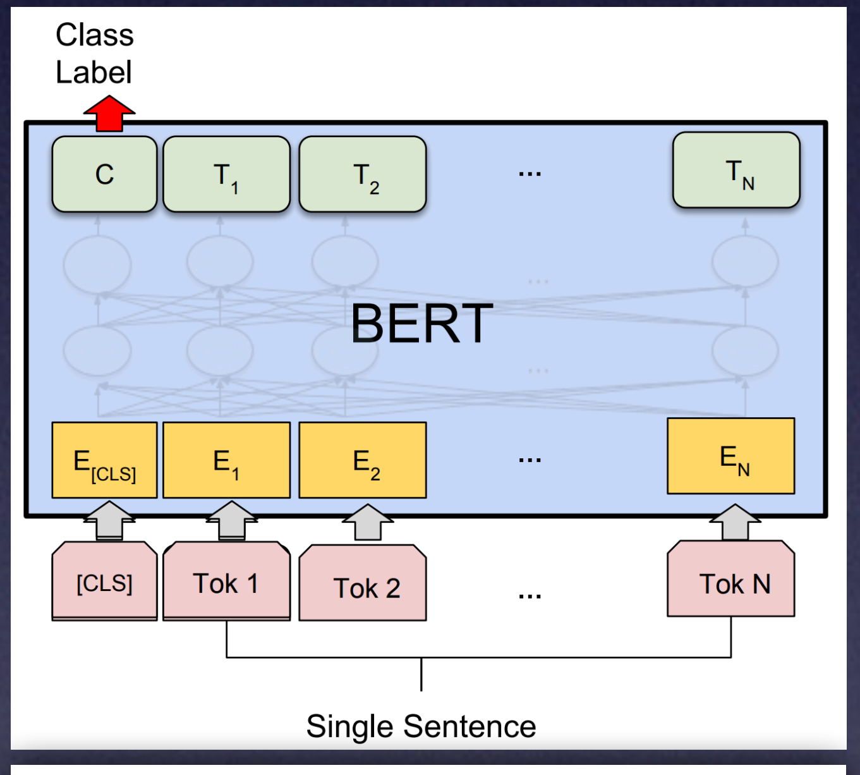


*Figure 1*: Single sentence classification task with BERT (Image Credit: Devlin et al., 2018)

| Hyper-Parameters | |
|---|---|
| Task | CoLA |
| Bert Model | BERT-Base (Cased) |
| Max. Sequence Length | 128 |
| Training Batch Size | 32 |
| Learning Rate | $2\times10^{-5}$ |
| Training Epochs | 100 |

*Table 1*: Hyper-parameters of BERT.

Ensembling is a common technique used to improve the accuracy of a prediction. An ensemble of models will separately make predictions on the test set. In its simplest form, the overall prediction is based on the majority vote for classification tasks and on weighted averages for regression tasks. In our experiments, we consider each model saved after every training epoch during the fine-tuning. We use both majority voting using binary class labels and averaging using BERT's predicted probability. To convert from the predicted probability to a class label, we find an optimal threshold.

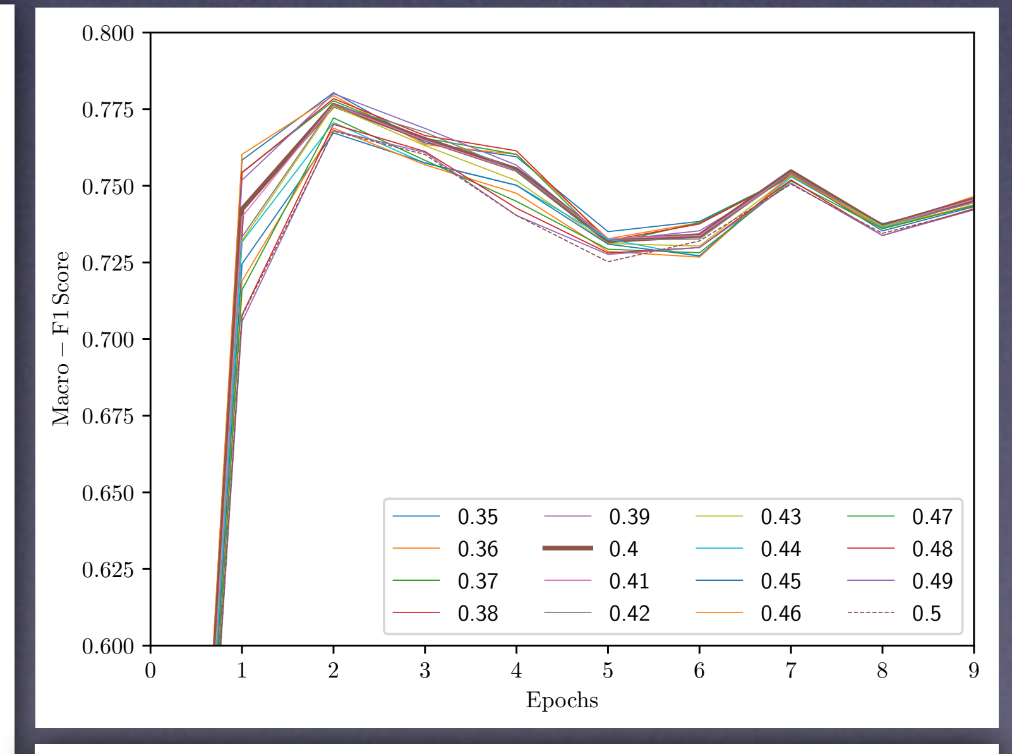


*Figure 2*: We analyze how different thresholds affect our Macro-F1 score across all folds. We selected a global threshold value of 0.4.

## References

Devlin et al., 2018
Yadav et al., *in prep.*
Zampieri et al., 2019a
Zampieri et al., 2019b

## Ensemble #1: Best Performers

**Experiment 1**: *Do certain epochs yield consistently better predictions? If so, how much does the ensemble prediction improve the macro-F1 score?*
We computed the macro-F1 score for every prediction (Figure 3). We counted the number of times each epoch yielded a prediction rated within the top 10% macro-F1 scores of its fold (Figure 4). Epochs 2, 3, and 4 consistently yielded the best predictions. Their ensemble over BERT probabilities yielded an average macro-F1 score of 0.7692 +/- 0.00014 across all folds. Figure 5c quantifies the small F1 score improvement.

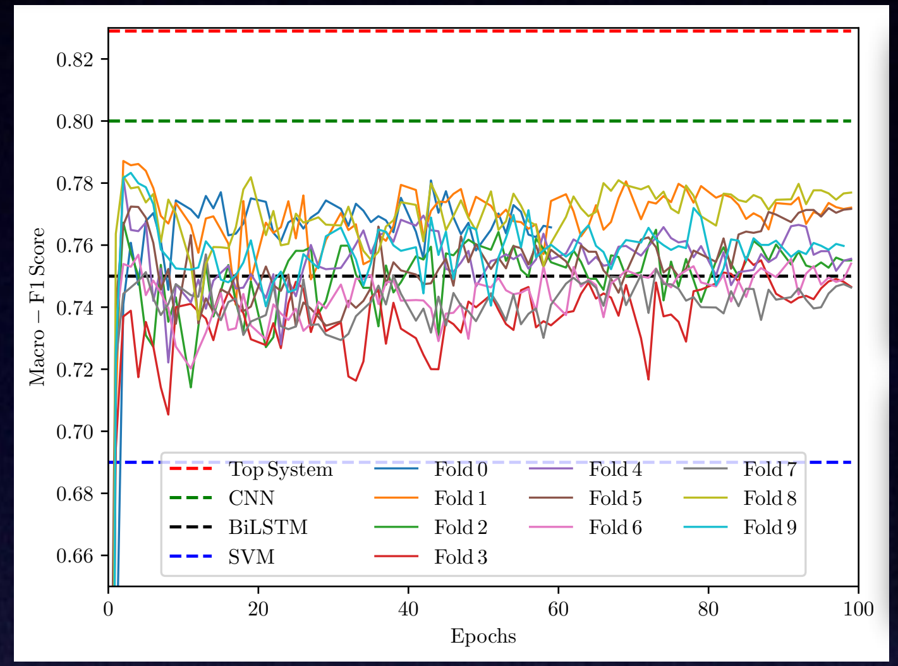
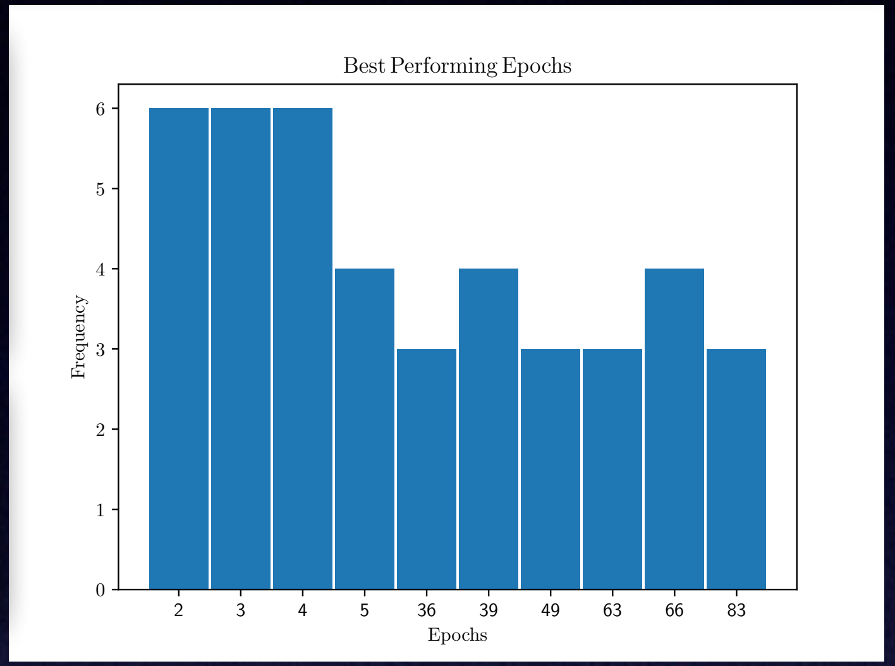


*Figure 3*: Macro-F1 Scores for all epochs for each fold. Dashed lines denote top performing system, CNN, BiLSTM, and SVM baselines in Task 6a.

*Figure 4*: The number of folds each epoch yielded a prediction in the top 10% F1-scores.



## Ensemble #2: Consecutive Epochs

**Experiment #2**: *Is there a good basis for ensembling the last n epochs? Is early-stopping a good metric for selecting the last n epochs?*
In both cases (with early-stopping and without), we are interested in ensembling the predictions generated by consecutive epochs. We perform 1D-convolution over the results of continuous epochs with a uniform kernel of varying sizes (n=2,3,5,9 epochs). We observe the best results using a window size of n=3 over epochs 1, 2, and 3. However, increasing the window size appears to decrease the performance gain at epochs 1-3.

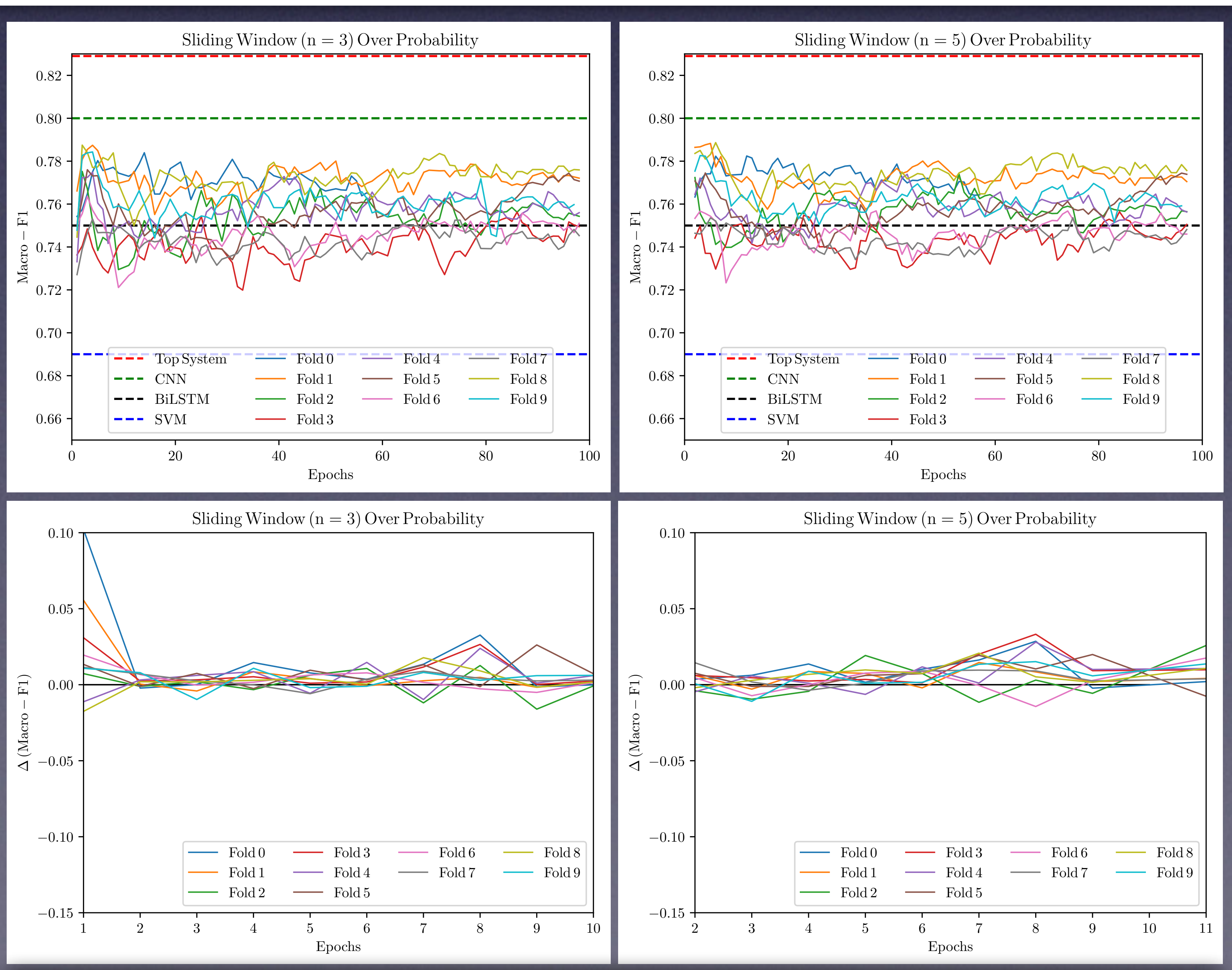


*Figure 5*: We convolved the predictions of consecutive epochs with epoch window sizes of 2,3,5,9. Ensemble of 3 models yields the highest performance gain.

## Ensemble #3: Minimum Redundancy

**Experiment 3**: *Do ensembles comprised of models with minimal prediction redundancy perform better?*
We quantify redundancy with the average pairwise overlap metric (Yadav et al., 2019). We computed the average pairwise overlap between every pair and triplet of epochs in each fold. In both the pairs and triplets, no correlation was observed between the macro-F1 score and the overlap metric. We conclude that the overlap metric alone is not a sufficient indicator for model selection.

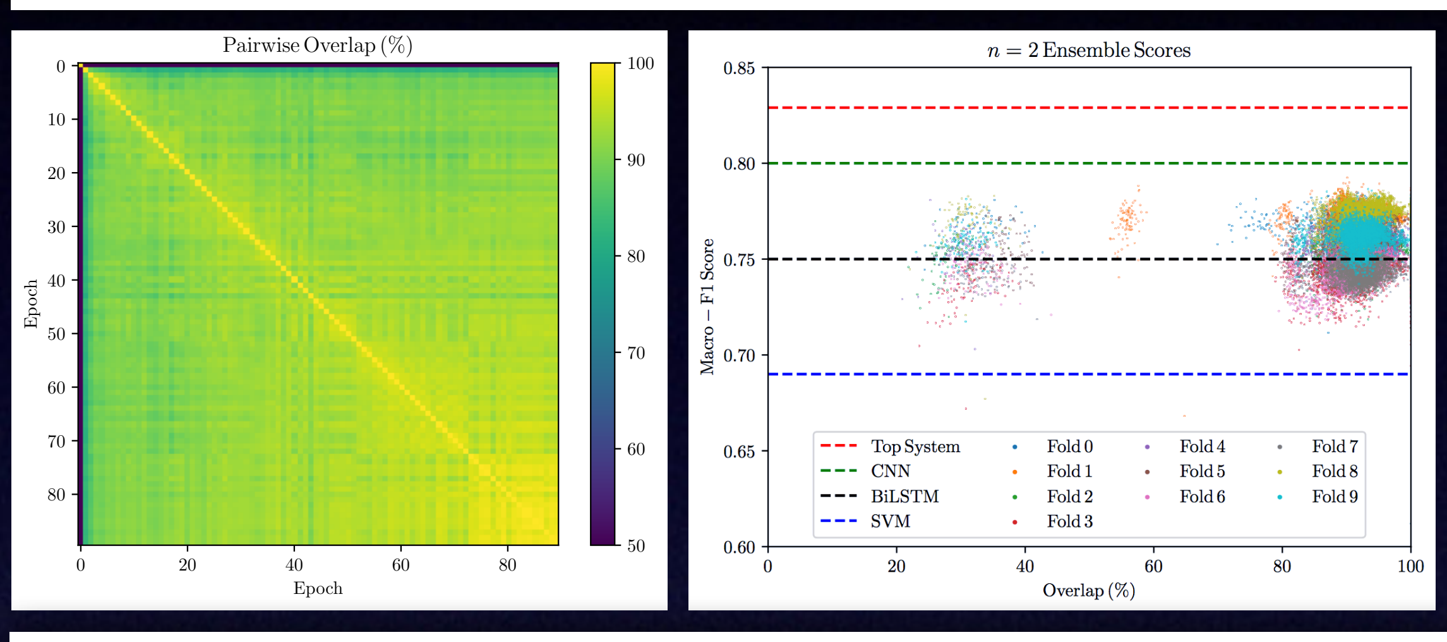


*Figure 6*: We computed the pairwise overlap for ever pair of epochs and compared it to the macro-F1 scores of the ensemble prediction. We do not observe a correlation between the overlap and performance. (Right) Only 1/10 of the data from a single fold is plotted due to the shear number of triplet combinations in each fold.

## Results

| Ensemble | |
|---|---|
| Epochs | 2,3,4 |
| Macro-F1 Score | 0.800512 |
| Accuracy | 0.843023 |
| Weighted-F1 Score | 0.841203 |

*Table 1*: Final Results of Task 6a.

We fine-tuned the final model on all the annotated data. We used an ensemble of 3 epochs as guided by the first 2 experiments. Due to Epoch 1's performance volatility between each fold and sensitivity to the selected threshold (as seen in Figure 2), we opted to use Epochs 2, 3, and 4 (Experiment #1). While we note the drastic improvement in macro-F1 performance, we caution to readers that some of the performance gain is attributed to training on the full dataset. Additionally, other ensembles may result in higher performance gains.

## Acknowledgements

The author would like to thank Vikas Yadav and Professor Steven Bethard for productive discussions regarding model architecture and metrics for selecting epochs. Additionally, the author would like to Manoj Gopale for his instrumental help in modifying BERT's default Tensorflow classifier.

## Future Work

(1) We will implement text preprocessing prior to fine-tuning BERT models. The top performing group used the uncased BERT-base model with highly cleaned data. (2) We can apply a unique threshold to each epoch (in contrast to applying a global threshold). (3) Ensemble #1: While we've obtained a recommendation for epoch selection, more rigorous statistics are needed to quantify the quality of the recommendation. Furthermore, we can vary the number of epochs in the ensemble and alter the percentage of top performing epochs to combat the heuristics nature of the algorithm. (4) Ensemble #2: We can experiment with non-uniformly weighted kernel. (5) Ensemble #3: The overlap metric alone cannot distinguish good ensembles from bad. However we can test to see if we observe a performance gain when coupled with other ensembling metrics (e.g., best performing epochs).