Man, I Just Love Writing Research Papers

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Abstract

Many state of the art models perform very well across a broad spectrum of NLP tasks, however, detecting complex language patterns is still difficult. Though this can be achieved through many different routes, we propose that the simplest may be to re-train a well performing model on a small set of difficult examples. Analysis on the ELECTRA-SMALL model, trained on the SNLI dataset shows that re-training the model on a small set of challenging examples can increase the accuracy on detecting sarcasm by well over 50%. This is a substantial increase, and the original model's accuracy only dropped by a mere 1

1 Introduction

In the evolving field of NLP, the performance of state-of-the-art models is continually being pushed to new heights. These models excel across a broad spectrum of tasks, yet they often stumble when presented with complex language patterns. This paper explores a simple approach to enhancing model performance in such scenarios. We focus on the ELECTRA-SMALL model, a prominent player in the NLP domain.

Despite its capabilities, the ELECTRA-SMALL model, like many in its class, struggles with intricate linguistic constructs such as sarcasm, informal language, and figures of speech. These elements of language, often context-dependent and counter-intuitive, present a significant hurdle for these systems. Our study proposes a solution to this, rooted in targeted retraining.

We hypothesize that retraining a well-performing model on a carefully curated set of difficult examples can dramatically improve its ability to decipher these complex language patterns. To test this, we conducted an in-depth analysis of the ELECTRA-SMALL model, initially trained on the SNLI dataset. Our methodology involved appending to this training data with a selection of challenging examples, honing in on areas where the model historically underperformed.

This paper presents our findings, which indicate a substantial improvement in the model's ability to recognize and interpret sarcasm, rising by over 50% in accuracy. Notably, this enhancement did not significantly detract from the model's overall performance on standard tasks, with only a minimal drop in accuracy observed. We will discuss the implications of these results, shedding light on the potential for hand-annotating targeted examples to better handle the nuances of human language.

2 Background

2.1 Challenges in Natural Language Processing

These days, state-of-the-art NLP models perform quite well among a broad range of tasks. However, there remains significant progress to be had when it comes to detecting complex language patterns such as, but not limited to, informal speech, sarcasm, and figures of speech. The title of this paper alone shows that.

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2.2 The ELECTRA-SMALL Model

The ELECTRA-SMALL model was chosen because it is quicker to train than other models, and has less parameters, even though it is a robust model that outperforms many larger models. However, it's performance drops off significantly when given certain nuances in the English language.

2.3 Advancements in Model Retraining

Recent advancements in the field of NLP have shown that having a pristine training dataset is one of the most fundamental aspects of model performance. This approach promises to deepen the understanding we have of the relationship between good training data and understanding complex language structures.

2.4 The Role of the SNLI Dataset

The Stanford Natural Language Inference (SNLI) dataset has been pivotal in training numerous NLP models, including ELECTRA-SMALL. While it provides a broad spectrum of linguistic examples, its coverage of intricate language patterns is limited. This limitation has prompted the exploration of supplemental training to bridge these gaps.

3 Examples of Errors

3.1 Informal Speech

- Premise: He doesn't hardly speak to anyone.
- Hypothesis: He is very outgoing.
- Gold label: 2
- Actual: 0

3.2 Sarcasm

- Premise: What a pleasant surprise, another bill in the mail.
- Hypothesis: I do not enjoy paying my bills.
- Gold label: 2
- Actual: 0

3.3 Figures of Speech

- Premise: Come on, spill the beans about the party plans!
- Hypothesis: Someone wants them to spill the beans about the party plans.
- Gold label: 0
- Actual: 1

4 Discussion on Retraining the Model

The general class of mistakes that we tested fell into three categories. These categories consist of examples in which there exists a negation of sorts (especially double negation), those which use sarcasm, and those that use figures of speech. The above categories are difficult for the model to interpret because they each have unorthodox or non-literal usages. These findings suggest that the model struggles the most with context-dependent and counter-intuitive examples. We believe that provided more context, or with more sophisticated linguistic analysis, the model would perform significantly better. Figure 1 shows the different error rates for the three classes.

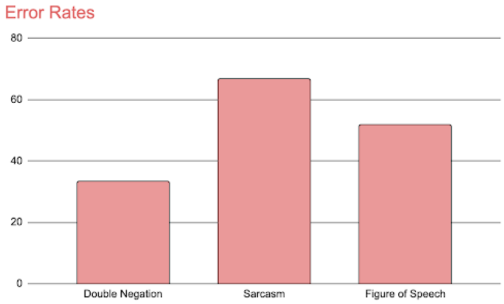


Figure 1: error rates

Using a confusion matrix, we can more deeply understand what kind of misclassifications the model is making. We can see from the data that the model has a very difficult time classifying examples where the true label is 2, as compared to those with a true label of 0 or 1. This is expected, because many of our examples are supposed to make the model think it is entailment, when really it is a contradiction. Figure 2 illustrates this below. Figure 3 shows the confusion matrix for the SNLI dataset, which when evaluated on the checkpoint we chose, has an accuracy of 85.8%.

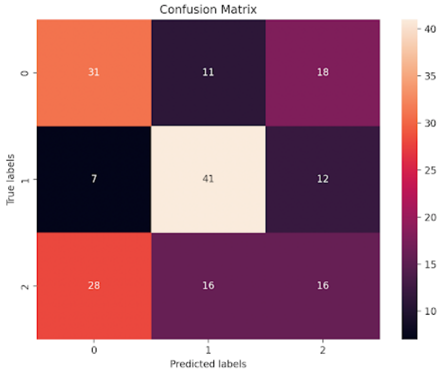


Figure 2: tricky examples (pre-tuning)

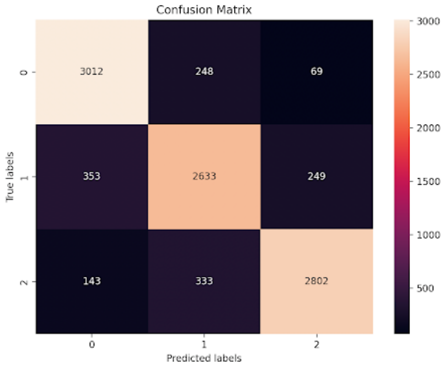


Figure 3: snli dataset (pre-tuning)

As one can see, the model performs significantly worse on our "tricky examples" dataset than on the original SNLI training dataset. This is to be expected, and now we will go about fixing it.

5 The Fix is In

To fix our project, we ended up retraining the model with our hand-annotated examples. We used 60 different examples for each category (double negation, figure of speech, and sarcasm) with each example containing three sentences. One sentence was entailment, one was neutral, and the last was a contradiction. This gave us a total of 180 sentences in whole. After retraining the data on the SNLI dataset with our examples included, our model accuracy jumped to 75% on the "tricky examples", up from 49%. The respective confusion matrices are shown below in figures 4 (tuned model) and 5 (original model).

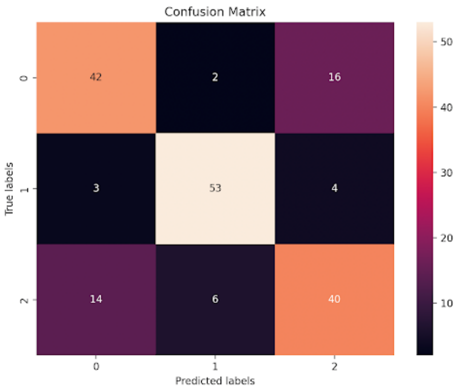


Figure 4: tuned on tricky examples

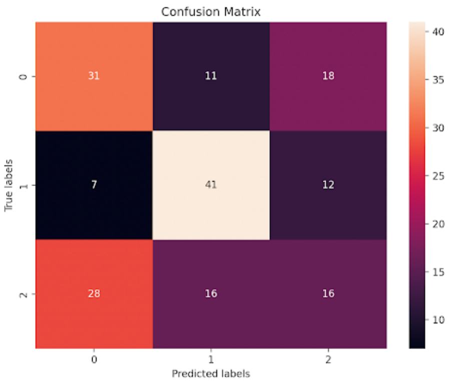


Figure 5: trained on tricky examples

When evaluating the same metrics on the SNLI dataset, however, we got very different results. We found that our accuracy on the SNLI dataset actually decreased to 84.6% compared to 85.8% originally. This drop in accuracy can be explained by something known as “catastrophic forgetting”, and is expected behavior since we retrained the model with new examples that were significantly different from the original. Catastrophic forgetting is a byproduct of sequential learning, and occurs when a model is trained for task A, and then retrained for task B. This will cause the model to be better at task B, but perform worse on task A. This is because the weights, which were optimized for task A, get updated for task B, potentially losing the information relevant to task A. It should be noted, however, that the model reduced misclassification in the neutral sentiment class, and did not change accuracy in the entailment category. The corresponding confusion matrices are shown below in figures 5 and 6.

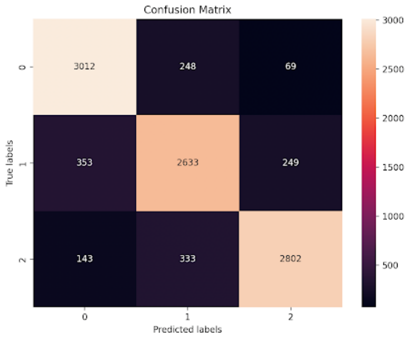


Figure 6: trained on snli dataset

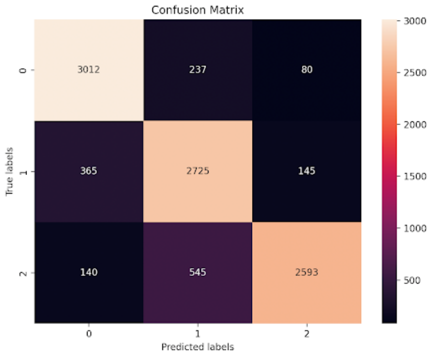
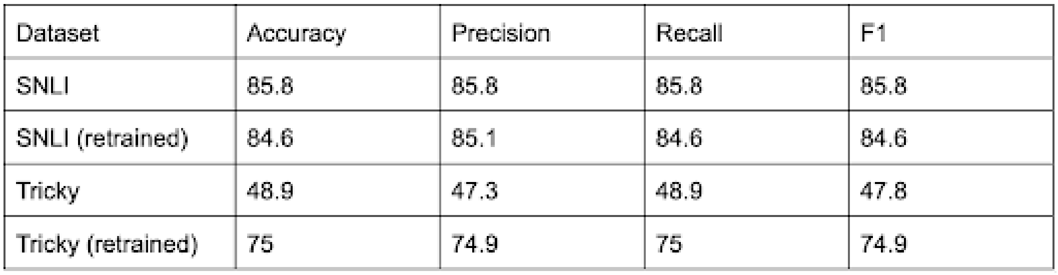


Figure 7: SNLI tuned with tricky examples

Also notable in our findings are the accuracy, precision, recall, and f1 scores. Both models had a tight cluster of the aforementioned metrics, with each metric being within 1% of each other (figure 8).



Dataset	Accuracy	Precision	Recall	F1
SNLI	85.8	85.8	85.8	85.8
SNLI (retrained)	84.6	85.1	84.6	84.6
Tricky	48.9	47.3	48.9	47.8
Tricky (retrained)	75	74.9	75	74.9

Figure 8: metrics

As noted in figure 8, and supported by the confusion matrices, the model is relatively balanced. This is important to note because it shows that the changes in our performance on comples language structes was not due to an inconsistent model, or inconsistent learning.

6 Conclusion

To conclude, this paper introduces a method that effectively enhances the performance of NLP models in processing complex language structures, while preserving their overall performance. We demonstrate that retraining the model with a thoughtfully selected set of hand-annotated examples, specifically designed to challenge the model, can lead to significant improvements. However, it's crucial to use caution during the retraining process to prevent catastrophic forgetting. This involves a careful consideration of the number and nature of examples used, ensuring they aid the model's learning without overwhelming the existing weights. This approach underscores the potential of targeted retraining as a powerful tool in refining state-of-the-art models.