Approaching SMM4H 2020 with Ensembles of BERT Flavours

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Abstract

This paper describes our solutions submitted to the Social Media Mining for Health Applications (#SMM4H) Shared Task 2020. We participated in the following tasks: Task 1 aimed at classifying if a tweet reports medications or not, Task 2 (only for the English dataset) aimed at discriminating if a tweet mentions adverse effects or not, and Task 5 aimed at recognizing if a tweet mentions birth defects or not. Our work focused on studying different neural network architectures based on various flavors of bidirectional Transformers (i.e., BERT), in the context of the previously mentioned classification tasks. For Task 1, we achieved an F1-score (70.5%) above the mean performance of the best scores made by all teams, whereas for Task 2, we obtained an F1-score of 37%. Also, we achieved a micro-averaged F1-score of 62% for Task 5.

1 Introduction

In recent years, researchers around the world came to realize the usefulness of social media data for extracting health information. The Social Media Mining for Health Applications (#SMM4H) Shared Task 2020 (Klein et al., 2020) brings to the forefront the problem of extracting information from health social media posts. SMM4H was also organized in the previous years and involved several tasks, such as automatic detection of tweets mentioning medication, of tweets describing medication intake or adverse reactions, of tweets mentioning vaccination behaviour, as well as tasks on extraction and normalization of adverse effects utterances (Weissenbacher et al., 2018; Weissenbacher et al., 2019b). This year’s competition had five tasks and our team focused on Tasks 1, 2, and 5.

Task 1 was a binary classification one that involved distinguishing between tweets in which some medications or dietary supplements were mentioned (the positive class) and other tweets (the negative class). The challenge of this task, unlike the 2018 similar task, consisted in the highly imbalanced data sets, that is, the tweets had a distribution of the two classes similar with the one encountered in practice. Therefore, the positive class counted for only 0.2% of the examples.

Classification of multilingual tweets that report adverse effects (Task 2) was also a binary classification task that was divided in multiple subtasks, each one concerning a different language. Our team submitted solutions only for the English subtask. For both Tasks 1 and 2, the evaluation metric was the F1-score for the positive class. On the other hand, classification of tweets reporting a birth defect pregnancy outcome (Task 5) was a multi-class classification task with the following classes: defect, possible defect, and non-defect. For this task, the evaluation metric was the micro-averaged F1-score of the first two classes.

We started to approach the competition by studying methods for data preprocessing and for overcoming the class unbalancing issue. Afterwards, we tested multiple language models for classification and we contributed by further pre-training the best language model on social media data. Moreover, we increased the robustness of our approach by constructing an ensemble which managed to obtain 70.5% F1-score, whereas the average of the best scores for the Task 1 was 66.28%.

This paper is further structured as follows. Section 2 presents previous works that helped us in developing our solutions. Section 3 describes the proposed models. In Section 4, we show and interpret the results of the systems. Finally, Section 5 summarizes the conclusions of our work.

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2 Related Work

As related tasks were also organized in previous years of SMM4H, a significant amount of work has been done in developing solutions to the proposed problems. Therefore, previous studies already established some directions for appropriate methods to preprocess social media data, for practices to address imbalanced data sets, or for language models that are more effective for the given tasks. Thus, Ellendorff et al. (2019) showed which data preprocessing steps are more likely to obtain better results on tweets.

The challenge of learning from imbalanced data sets has been reviewed by Chawla et al. (2004). Their paper analyzed some general solutions like over-sampling and under-sampling and also offered useful guidelines in applying these techniques. Moreover, Khosla (2018) approached the problem by assigning different weights to the imbalanced classes and this method proved particularly useful in our experiments.

Mahata et al. (2019) used transfer learning approaches, showing that Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) and Universal Language Model Fine-Tuning (ULMFiT) (Howard and Ruder, 2018) are able to handle classification tasks in the medical domain. Also, Gondane (2019) leveraged the focus on biomedical language of BERT for Biomedical Text Mining (BioBERT) (Lee et al., 2020).

The issue of detecting medication mentions in social media data has been previously approached with impressive results. Weissenbacher et al. (2019a) showed that ensemble classifiers can achieve performance close to humans in recognizing mentions of medications in tweets, on balanced data sets. Wu et al. (2018) obtained notable results on social media data mentioning drugs using a neural network based on a multi-head self-attention mechanism.

3 Method

3.1 Text Preprocessing

Data gathered from social media (tweets in our case) implies a specific informal language that is closer to the spoken English, rather than the texts on platforms like Wikipedia. This type of text is rich in grammatical errors, abbreviations (e.g., “cuz” instead of “because”) and words (e.g., “lol” or “idk”) that are encapsulating their own meaning and cannot be found in usual dictionaries.

Before feeding this kind of data to a language model, a preliminary step must be done, i.e. preprocessing. It can be noted that this step might strip useful information. Fortunately, previous work (Ellendorff et al., 2019) gave a direction of which preprocessing would provide the best results. For our methods, the best results were obtained by using the following preprocessing steps:

- Replace all URLs with "url";
- Replace all usernames with "user";
- Remove all non-ASCII characters;
- Remove all HTML character references;
- Replace multiple white spaces with one space.

We also experimented with other techniques for spell correction via the Ekphrasis library (Baziotis et al., 2017) but, for our models, the results were not significantly improved.

3.2 Experiments

After preprocessing, data was fed to BERT-based language models that are related to the medical field, namely: BioBERT, Clinical BERT (Alsentzer et al., 2019), BioFLAIR (Sharma and Daniel Jr, 2019), and BioELMO (Jin et al., 2019). Among these four models, the best results were achieved using BioBERT.

BERT was bidirectionally pre-trained using two tasks: Masked Language Modeling and Next Sentence Prediction on a large corpus composed of English Wikipedia and BookCorpus. Starting from the pre-trained BERT, BioBERT was further pre-trained on a biomedical corpus composed of PubMed abstracts and articles.
For Task 1, we performed a series of experiments. First, we fine-tuned the last three layers of BioBERT-Base on the balanced data set of SMM4H 2018 (Weissenbacher et al., 2018), using the early stopping technique. Afterwards, we further fine-tuned our model on the actual training set of Task 1. Because this data set was highly unbalanced (55,273 negative examples and only 146 positive examples), the model tended to classify all examples as negative. To overcome this challenge, we experimented with several techniques: over-sampling the positive class, under-sampling the negative class, the focal loss (Lin et al., 2017), and adding weights for each class when computing the binary crossentropy loss. For the class weighting technique, we computed the weights using the formula proposed by Khosla (2018). Our results show that this technique obtains the best performance. We will further refer to this system as BioBERT-ClassWeights.

As we mentioned earlier, the language used in tweets is rather different of the language used in the corpora that BioBERT was pre-trained on. Therefore, it seemed intuitive to further pre-train the obtained system on data from social media. Due to the lack of considerable resources, we confined on using the English tweets from the data sets provided within the SMM4H 2020 shared task for the tasks 1, 2, 3, and 5, in order to form a corpus, and we pre-trained BioBERT on it, using the script provided on GitHub\(^1\).

We used this language model in the same system, which we described above, and obtained BioBERT-PretrainTweets. Even though this method improved the results, training multiple models resulted in distant scores, thus showing that the model cannot be considered as having sufficient robustness.

In order to improve the robustness of the solution, we constructed two ensembles of multiple classifiers. Ensemble 1 was formed from three models that performed well on the validation set: BioBERT-Base pre-trained on tweets, Clinical BERT and BioBERT-Large. For Ensemble 2, the training and validation sets were combined, shuffled and then splitted in five equally sized folds. Five models of BioBERT-PretrainTweets were fine-tuned as for 5-fold Cross-Validation and were afterwards used to form an ensemble. Both ensembles are deciding by averaging the outputs of the composing models.

For Tasks 2 - English and 5, we used BioBERT-PretrainTweets fine-tuned for each task. We should mention that for Task 5, concerning multi-class classification, we switched the loss function to categorical crossentropy. Yet, because class weighting did not improve the results, we decided not to use it.

4 Results

In the practice phase, we submitted predictions on the validation sets for Tasks 1 and 2 - English. For the first task, BioBERT-ClassWeights achieved an F1-score of 67.6% with a precision of 69.6% and a recall of 65.7%, while BioBERT-PretrainTweets obtained an F1-score of 77.61% with a precision of 81.2% and a recall of 74.2%. For Task 2 - English, BioBERT-PretrainTweets achieved 53.87% F1-score on the validation set.

In the evaluation phase, we submitted three solutions for the first task: one prediction from BioBERT-PretrainTweets and one prediction from each ensemble described above. The prediction of the Ensemble 2 scored above the mean scores for Task 1. We also submitted one solution for each Task 2 - English and Task 5. Tables 1, 2, and 3 show the reported scores for each submission, alongside with the averaged score of best submissions of all teams that participated. The precision and recall for the first two submissions on the Task 1 were not reported by the organizers.

| Model                  | F1-score | Precision | Recall  |
|------------------------|----------|-----------|---------|
| BioBERT-PretrainTweets | 55%      | -         | -       |
| Ensemble 1             | 66%      | -         | -       |
| Ensemble 2             | 70.5%    | 79.03%    | 63.64%  |
| Mean score             | 66.28%   | 70.32%    | 69.48%  |

Table 1: Test results and the average of best submissions for Task 1.

\(^1\)https://github.com/google-research/bert/blob/master/run_pretraining.py.
| Model                     | F1-score | Precision | Recall |
|--------------------------|----------|-----------|--------|
| BioBERT-PretrainTweets   | 37%      | 26%       | 60%    |
| Mean score               | 46%      | 42%       | 59%    |

Table 2: Test result and the average of best submissions for Task 2 - English.

| Model                     | F1-score | Precision | Recall |
|--------------------------|----------|-----------|--------|
| BioBERT-PretrainTweets   | 62%      | 56%       | 69%    |
| Mean score               | 65%      | 62%       | 68%    |

Table 3: Test result and the average of best submissions for Task 5.

For Task 1, the scores on the test set indicate that using only BioBERT-PretrainTweets is not enough. It performed below average for all tasks, even though the validation scores would have suggested otherwise. On the other hand, the scores of the ensembles improved the prediction significantly. The score of Ensemble 2 was above the average of the best scores, showing that our best system is an ensemble of BioBERT language models each fine-tuned on both the validation and training sets in a 5-folds manner. Even though the training set is large enough, the positive class is so poorly represented that previously mentioned techniques, which usually address small data sets, significantly improved our system.

5 Conclusion

In this paper, we experimented with ensembles of bidirectional Transformers in the context of social media texts and we studied the value that pre-trained BERT flavours, like BioBERT or ClinicalBERT, bring in solving classification tasks in the medical domain.

We succeeded in obtaining a score above the average of the best scores using Ensemble 2 on Task 1 and we showed that BERT-based classifiers can give acceptable results even with highly unbalanced data sets. We also showed that a BERT-based language model, pre-trained for a rather colloquial language, improved the results on the given tasks of social media data. Our results on Task 1 show that, in cases where one of the classes is poorly represented, ensembles increase the prediction performance.

Further experiments should consider including an enlargement of the corpus of tweets used for pre-training BioBERT, so that the model will be more capable of representing this type of data. The next step would be to design a new BERT flavour pretrained on social media texts. Another future direction in addressing class imbalance might consist in using data augmentation in order to generate examples of the less represented class (Croce et al., 2020).

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