CompLx@SMM4H’22: In-domain pretrained language models for detection of adverse drug reaction mentions in English tweets

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Abstract
The paper describes the system that team CompLx developed for sub-task 1a of the Social Media Mining for Health 2022 (#SMM4H) Shared Task. We fine-tune a RoBERTa model, a pretrained, transformer-based language model, on a provided dataset to classify English tweets for mentions of Adverse Drug Reactions (ADRs), i.e. negative side effects related to medication intake. With only a simple fine-tuning, our approach achieves competitive results, significantly outperforming the average score across submitted systems. We make the model checkpoints1 and code2 publicly available. We also create a web application3 to provide a user-friendly, readily accessible interface for anyone interested in exploring the model’s capabilities.

1 Introduction
The Shared Task (Weissenbacher et al., 2022) of the 2022 Social Media Mining for Health Applications (#SMM4H) workshop proposed ten sub-tasks in the domain of social media mining for health monitoring and surveillance. From the perspective of Natural Language Processing (NLP), these tasks present a considerable challenge since the nature of social media posts requires dealing with both a significant level of language variation (informal and colloquial expressions, ambiguity, multilingual posts) and data sparsity, as well as a widespread presence of noise such as misspellings of clinical concepts and syntactic errors.

In the 2022 instantiation of the #SMM4H Shared Task, our team participated in: (i) sub-task 1a, the classification of English tweets containing mentions of Adverse Drug Reactions (ADRs) (Magge et al., 2021), (ii) sub-task 3, the classification of English tweets (3a) and WebMD reviews (3b) containing mentions of changes in medication treatments, and (iii) sub-task 8, the classification of English tweets self-reporting chronic stress. In this paper we primarily describe our approach for task 1a, as that constituted the major focus of our efforts.

To address these challenges, we fine-tune a variant of a RoBERTa (Liu et al., 2019) model, a transformer-based (Vaswani et al., 2017) language model pretrained on approximately 128 million tweets (Loureiro et al., 2022) on each sub-task’s provided dataset. Without any domain adaptation efforts (apart from standard fine-tuning on the downstream task) or hyperparameter optimizations, the model outperforms the average of all submissions for sub-task 1a by a 9% absolute difference in F1-score.

In the following sections, we introduce the sub-tasks’ datasets, describe the model architecture and training setup, report our results, and conclude with a discussion of related research and potential avenues for future work.

2 Datasets
In Section [1] we provided a brief summary of each sub-task in which we participated. For each of them, participants were given access to a labeled training and validation set, as well as an unlabeled evaluation set that was used to determined the final performance of the submitted systems. Table [1] summarizes the number of samples per dataset per task. Additionally, Table [2] provides representative samples from sub-task 1a. As can be noted upon quick inspection, merely depending

|       | 1a  | 3a  | 3b  | 8   |
|-------|-----|-----|-----|-----|
| training | 17174 | 5898 | 10378 | 2936 |
| validation | 909  | 1572 | 1297  | 420  |
| evaluation | 10969 | 15360 | 13132 | 839  |

Table 1: Number of samples per split per task.
vyvanse make me so hyper and creative and i think of so many tweets
feed an ocd vyvanse and cover him in crayons
trazodone has screwed up my sleep schedule. its helping tho.

| Sentence                                                                 | Label  |
|--------------------------------------------------------------------------|--------|
| vyvanse make me so hyper and creative and i think of so many tweets      | ADR    |
| feed an ocd vyvanse and cover him in crayons                             | No ADR |
| trazodone has screwed up my sleep schedule. its helping tho.              | ADR    |

Table 2: Selection of samples from training set of sub-task 1a.

on medication-related keywords for label assignment is going to be problematic: both the first and the second example contain the medication term “vyvanse” but they have been assigned different labels, “ADR” and “No ADR” respectively. This motivates the use of a modeling approach that leverages the overall semantic content of the sentence, rather than keyword matching with individual constituents.

3 Modeling Approach

3.1 Model Architecture

The establishment of language modeling as the pretraining step in the transfer learning pipeline revolutionized modern NLP with models such as ULMFiT (Howard and Ruder, 2018), ELMo (Peters et al., 2018) and, most notably, transformer-based language models such as GPT (Radford et al., 2018) and BERT (Devlin et al., 2019). In recent years, there have been intensive efforts in the research community to produce ever-larger transformer-based pretrained language models that are trained using a variety of datasets, transformer-model architectures, training objectives and optimization techniques. This should come as no surprise, since such language models have dominated virtually all NLP leaderboards, most notably GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019).

Considering this overwhelming success, we opt for a RoBERTa (Liu et al., 2019) model⁴ that has been trained on approximately 128 million tweets (Loureiro et al., 2022). Our exact modeling approach is depicted in Figure [1]. We opt for a model that has been trained on an in-domain corpus, namely tweets, as transfer learning has been shown to yield improved results when there is in-domain pretraining (Gururangan et al., 2020). We do not use any text normalization steps.

3.2 Training Regime

We train the model to minimize the negative log-likelihood loss using back-propagation with stochastic gradient descent and a mini-batch size of 16. To monitor model performance, we use the train/validation split provided by the organizers. For optimization, we use the AdamW optimizer (Loshchilov and Hutter, 2019) with gradient clipping (Pascual et al., 2013) and a linear scheduler with no warm-up. We use FP-16 mixed precision (Michevicius et al., 2018) training (and inference) in order to afford a larger batch size and increased training speed. To optimize GPU use by minimizing the amount of memory allocated for padding tokens, we use dynamic padding and length-based batching in the sense of (Skinner, 2018). Finally, we employ label smoothing (Szegedy et al., 2016) with a smoothing factor of 0.1.

3.3 Hyperparameters

As mentioned in Section [1], we do not experiment with hyperparameter tuning but rather keep the default parameters of the Trainer API in the Hugging Face transformers library. More specifically, we use $\beta_1 = 0.9, \beta_2 = 0.999$ and $\epsilon = 10^{-8}$ for the AdamW optimizer parameter values and a learning rate of 0.00005. We train the models for a maximum of 25 epochs with an early stopping patience level set to 0.001 for 3 epochs. Finally, we set a maximum sequence length of 128 since input sentences are generally short and we would like to avoid consuming GPU memory for padding tokens.

4 Experiments and Results

In this section, we give a brief description of the system we used to conduct our experiments, share our results and provide a brief discussion.

4.1 Setup

The model was developed using the PyTorch (Paszke et al., 2019) implementation of the Hugging Face transformers (Wolf et al., 2020) library. The experiments were executed on a

⁴https://huggingface.co/cardiffnlp/twitter-roberta-base-mar2022
machine with an Intel Core i9-9820X CPU @ 3.30GHz and a NVIDIA GeForce RTX 2080 Ti GPU with 11GB of memory.

4.2 Results

Table [3] summarizes the performance of our approach in the validation set for each sub-task. Note that in this set of experiments, the validation set was used both during training (e.g. for early stopping or selection of batch size) as well as for the reporting of the systems’ performance. Table [4] summarizes the performance of our approach in the evaluation set for each sub-task. The organizers chose to disclose to each team only their respective score along with the average score of all submitted systems. Our system performed considerably better than the average in sub-task 1a and surpassed the existing state-of-the-art F1-score of 0.63 reported in (Magge et al., 2021). Performance was considerably poorer for sub-tasks 3 and 8. As mentioned in Section [1], our main efforts were dedicated to sub-task 1a and the system developed did not transfer well to the remaining sub-tasks.

5 Conclusion and Future Directions

We demonstrated that a RoBERTa model (Liu et al., 2019) pretrained on approximately 128 million tweets performs very competitively when finetuned on English tweet classification for ADRs. Using only a standard finetuning approach, our model obtained competitive results, outperforming the average of all submissions for sub-task 1 by a 9% absolute difference in F1-score. This constitutes yet another testament of the fact that large pre-
trained language models have rightfully become the default approach in virtually all NLP tasks.

With respect to potential future work, there is a large collection of available options. Text classification and, more generally, binary classification is one of the oldest and most widely researched topics in NLP. Most approaches aiming to improve performance of classification models can be broadly categorized into three groups, depending on the segment of the machine learning workflow that they are targeting. Data augmentation methods typically target the initial part of the workflow, the data, aiming to increase the quantity, quality and diversity of the training dataset to ensure that model performance is robust to small syntactic or semantic perturbations in the inputs. Transformations acting directly on strings, such as random token insertions or deletions, synonym/antonym replacements and related techniques (Wei and Zou, 2019; Karimi et al., 2021, inter alia) have shown significant performance improvements, especially in low-resource scenarios much like the one in this shared task.

A second approach, evidently a natural extension of the previous technique, would be to target vector encodings of the tokens and/or documents that are produced by the various layers of the neural networks. We can distinguish two different approaches here: (i) improve the language model backbone during the pretraining phase, or (ii) improve the weights of the language model backbone during fine-tuning. The research community has devoted intensive efforts in the former approach, as can be observed by the ever-increasing list of transformer-based pretrained language models (Devlin et al., 2019; Joshi et al., 2020; Kitaev et al., 2020; Raffel et al., 2020; Brown et al., 2020, inter multi alia) released. Model size, in terms of total number of trainable parameters, has been consistently shown to correlate strongly with downstream performance, so opting for a larger pretrained model would be a reasonable first steps towards more transferable vector representations (and hence improved performance) in the downstream task. The latter approach would include domain adaptation techniques, such as continued self-supervised pretraining followed by supervised finetuning, which has been shown (Gururangan et al., 2020) to consistently lead to superior results relative to direct fine-tuning.

Finally, one could aim to improve performance by modifying aspects of the objective function. (Hui and Belkin, 2021), in an extensive series of experiments, show that the established practice of using a cross-entropy loss for classification is not well-founded and show through a variety of diverse experiments that a square loss can, in many cases, significantly improve performance.

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