KFU NLP Team at SMM4H 2021 Tasks: Cross-lingual and Cross-modal BERT-based Models for Adverse Drug Effects

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Abstract

This paper describes neural models developed for the Social Media Mining for Health (SMM4H) 2021 Shared Task. We participated in two tasks on classification of tweets that mention an adverse drug effect (ADE) (Tasks 1a & 2) and two tasks on extraction of ADE concepts (Tasks 1b & 1c). For classification, we investigate the impact of joint use of BERT-based language models and drug embeddings obtained by chemical structure BERT-based encoder. The BERT-based multimodal models ranked first and second on classification of Russian (Task 2) and English tweets (Task 1a) with the F1 scores of 57% and 61%, respectively. For Task 1b and 1c, we utilized the previous year's best solution based on the EnDR-BERT model with additional corpora. Our model achieved the best results in Task 1c, obtaining an F1 of 29%.

1 Introduction

Text classification, named entity recognition, and medical concept normalization in free-form texts are crucial steps in every text-mining pipeline. Here we focus on discovering adverse drug effects (ADE) concepts in Twitter messages as part of the Social Media Mining for Health (SMM4H) 2021 Shared Task (Magge et al., 2021).

This work is based on the participation of our team in four subtasks of two tasks. Task 1 consists of three subtasks, namely 1a, 1b, and 1c each of which corresponds to classification, extraction, and normalization of ADEs. For Task 2, train, dev, and test sets include Russian tweets annotated with a binary label indicating the presence or absence of ADEs. For the 1b task, named entity recognition aims to detect the mentions of ADEs. Task 1c is designed as an end-to-end problem, intended to perform full evaluation of a system operating in real conditions: given a set of raw tweets, the system has to find the tweets that are mentioning ADEs, find the spans of the ADEs, and normalize them with respect to a given knowledge base (KB). These tasks are especially challenging due to specific characteristics of user-generated texts from social networks which are noisy, containing misspelled words, abbreviations, emojis, etc. The source code for our models is freely available

The paper is organized as follows. We describe our experiments on the multilingual and multimodal classification of Russian and English tweets for the presence or absence of adverse effects in Section 2. In Section 3, we describe our pipeline for named entity recognition (NER) and medical concept normalization (MCN). Finally, we conclude this paper in Section 4.

2 Tasks 1a & 2: multilingual classification of tweets

The objective of Tasks 1a & 2 is to identify whether a tweet in English (Task 1a) or Russian (Task 2) mentions an adverse drug effect.

2.1 Data

For the English task, we used the original dev set provided by the organizers of the SMM4H 2021. For the Russian task, we sampled 1,000 non-repeating tweets from the original dev set as the new dev set and added the remaining tweets to the training set. Table 1 presents the statistics on Task 1a and Task 2 data. As can be seen from the table, the classes are highly imbalanced for both the English and the Russian corpora.

We preprocessed datasets for tasks 1a and 2 in a similar manner. During preprocessing, we: (i) replaced all URLs with the word “link”; (ii) replaced all user mentions with @username placeholder; (iii) replaced some emojis with a textual representation (e.g., laughing emojis with the word laughing; pill and syringe emojis with the corresponding

1 https://github.com/Andoree/smm4h_2021_classification
Table 1: Task 1a and Task 2 data statistics

| Dataset           | # Tweets | # Positive samples (ADE presence) |
|-------------------|----------|----------------------------------|
| **Task 1a (English tweets)** |          |                                  |
| Train             | 17,385   | 1,235 (7.1%)                    |
| Dev               | 914      | 65 (7.1%)                       |
| Test              | 10,984   | –                                |
| **Task 2 (Russian tweets)** |          |                                  |
| Train             | 10,609   | 980 (9.2%)                      |
| Dev               | 1,000    | 92 (9.2%)                       |
| Test              | 9,095    | –                                |

words); (iv) replaced ampersand’s HTML representation “&amp;” with “&”. As training sets are highly imbalanced, we applied the positive class over-sampling so that each training batch contained roughly the same number of positive and negative samples. However, we did not observe a significant performance improvement for the Russian subtask, so we applied the technique for the English subtask only. Following (Miftahutdinov et al., 2020), for Task 2, we combined the English and the Russian training sets.

2.2 Models

For our experiments, we used neural models based on Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) as they have achieved state-of-the-art results in the biomedical domain. In particular, BERT-based models proved efficient at the SMM4H 2020 Shared Task (Gonzalez-Hernandez et al., 2020). We used the following BERT-based models:

1. RoBERTa\textsubscript{large}\(^2\) (Liu et al., 2019), a modification of BERT that is pretrained on 160GB of English texts with dynamic masking;

2. EnRuDR-BERT\(^3\) (Tutubalina et al., 2020), pretrained on English (Tutubalina et al., 2017) and Russian (Tutubalina et al., 2020) corpora of 5M health-related texts in English and Russian;

3. ChemBERTa\(^4\) (Chithrananda et al., 2020), a RoBERTa\textsubscript{base}-based model that is pretrained on compounds from ZINC (Irwin and Shoichet, 2005) and is designed for drug design, chemical modelling and molecular properties prediction.

2.3 Experiments

For both tasks, we investigated the efficacy of the multimodal classification approach. For each tweet, we found its drug mentions, represented the chemical structure of each drug as a Simplified molecular-input line-entry system (SMILES) string, encoded the string using ChemBERTa, and took the final [CLS] embedding as drug embedding. Thus, we matched each tweet with a drug embedding. For tweets that contain no drug mentions, we encoded an empty string. We compared the following text-molecule combination strategies: (i) concatenation of the drug and the text embeddings, (ii) one cross-attention layer (Vaswani et al., 2017) from molecule encoder to text encoder. For concatenation architecture, we did not fine-tune ChemBERTa on the training set, whereas for cross-attention models, we trained both text and drug encoder.

For both Task 1a and Task 2, we adopted pre-trained models from HuggingFace (Wolf et al., 2019) and fine-tuned them using PyTorch (Paszke et al., 2019). We trained each RoBERTa\textsubscript{large} model for 10 epochs with the learning rate of \(1 \times 10^{-5}\) using Adam optimizer (Kingma and Ba, 2014). We set batch size to 32 and maximum sequence size to 128. For EnRuDR-BERT we used the learning rate of \(3 \times 10^{-5}\), batch size to 64, and sequence to 128. For ChemBERTa, we used a sequence length of 256. For classification, we used a fully-connected network with one hidden layer, GeLU (Hendrycks and Gimpel, 2016) activation, a dropout probability of 0.3, and sigmoid as the final activation. To handle a high variance of BERT-based models’ performance that varies across different initializations of classification layers, for each training setup, we trained 10 models and weighed their predictions. We tried two weighing strategies: (i) majority voting and (ii) sigmoid-based weighing. For (ii), we used predicted positive class probabilities to train a Scikit-learn’s (Pedregosa et al., 2011) logistic regression on the validation set. For all experiments, we used a classification threshold of 0.5.

Table 2 shows the performance of our systems for Task 1a and Task 2 in terms of precision (P), recall (R), and F1-score (F1). Based on the results, we can draw the following conclusions. First, for the English task, the concatenation of text and chemical features increases the F1-score by 3%
Table 2: Text classification results on the SMM4H 2021 Task 1a and Task 2 test sets. For all set-ups except the ones with "sigmoid", we used majority voting. Our official submissions for the SMM4H 2021 are denoted by *.

| Model set-up                                      | P   | R   | F1  |
|--------------------------------------------------|-----|-----|-----|
| **Task 1a (English tweets)**                     |     |     |     |
| RoBERTa                                          | -   | -   | 0.58|
| RoBERTa + ChemBERTa concatenation                | -   | -   | 0.61|
| * RoBERTa + ChemBERTa concatenation + over-sampling | 0.55| 0.68| 0.61|
| * RoBERTa + ChemBERTa concatenation + over-sampling + sigmoid | 0.59| 0.56| 0.58|
| Average scores provided by organizers             | 0.51| 0.41| 0.44|
| **Task 2 (Russian tweets)**                      |     |     |     |
| EnRuDR-BERT + Ru train                           | -   | -   | 0.55|
| EnRuDR-BERT + Ru train + ChemRoBERTa + cross-attention | -   | -   | 0.54|
| EnRuDR-BERT + RuEn train                         | -   | -   | 0.54|
| * EnRuDR-BERT + RuEn train + ChemRoBERTa cross-attention | 0.58| 0.57| 0.57|
| * EnRuDR-BERT + RuEn train + ChemRoBERTa cross-attention + sigmoid | 0.77| 0.35| 0.48|
| Average scores provided by organizers             | 0.55| 0.56| 0.51|

corpus (Basaldella et al., 2020).

For the normalization task, we applied two models: (i) a classifier (Miftahutdinov et al., 2020; Miftahutdinov and Tutubalina, 2019), (ii) a novel neural model based on similarity distance of BERT vectors of concepts (Miftahutdinov et al., 2021). Following (Miftahutdinov et al., 2020), we utilize additional data for training. Other corpora are filtered to match a vocabulary of the SMM4H 2021 train set. We combined two models based on a threshold. For instance, given (i) prediction $c_{bs}$ from from BERT-based similarity method with the distance equals to $d$ and (ii) prediction $c_{clf}$ from the classification approach, the final prediction is set to $c_{bs}$, if $d$ is less than a threshold, and to $c_{clf}$, otherwise. For more detailed description of NER and end-to-end entity linking model please refer to (Miftahutdinov et al., 2020).

Table 3 shows a comparison of the model to the official average scores computed using the participants’ submissions. Our NER model achieved below average results (40% vs 42%). We believe that the results are related to additional training of the model on non-target texts (reviews). Yet, with lower results in Task 1b and the top ranked results in Task 1c, it becomes clear that that the advantage of our pipeline is the two-component model for medical concept normalization. To sum up, the pipeline ranked first at SMM4H 2021 Task 1c and obtained the F1 score of 29% on extraction of MedDRA concepts.
| Run name                        | P   | R   | F1  |
|-------------------------------|-----|-----|-----|
| ADE Detection Evaluation (Task 1b) | 0.42| 0.38| 0.40|
| KFU NLP Team                  | 0.49| 0.46| 0.42|
| Average scores                | 0.30| 0.28| 0.29|
| End-to-End Evaluation (Task 1c) | 0.23| 0.22| 0.22|

**Table 3:** Performance of our models in SMM4H 2021 Task 1b and 1c (official results).

### 4 Conclusion

In this work, we have explored an application of domain-specific BERT models pretrained on health-related user reviews in English and Russian to the task of multilingual and multimodal text classification, extraction, and normalization of adverse drug effects. Our experiments show that multimodal architecture for classification of tweets outperforms other strong baselines and text classifiers. Besides, our BERT-based pipeline for extraction on MedDRA concepts ranked 1st in Task 1c.

We foresee two directions for future work. First, future research will explore how different drug representation models and pretraining approaches affect classification performance. Second, a potential direction is to verify the efficacy of multimodal classification for languages other than Russian and English.

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