OCHADAI at SemEval-2022 Task 2: Adversarial Training for Multilingual Idiomaticity Detection

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Abstract

We propose a multilingual adversarial training model for determining whether a sentence contains an idiomatic expression. Given that a key challenge with this task is the limited size of annotated data, our model relies on pre-trained contextual representations from different multilingual state-of-the-art transformer-based language models (i.e., multilingual BERT and XLM-RoBERTa), and on adversarial training, a training method for further enhancing model generalization and robustness. Without relying on any human-crafted features, knowledge bases, or additional datasets other than the target datasets, our model achieved competitive results and ranked 6th place in SubTask A (zero-shot) setting and 15th place in SubTask A (one-shot) setting.

1 Introduction

Large-scale pre-trained language models such as BERT (Devlin et al., 2019) have achieved great success in a wide range of natural language processing (NLP) tasks. However, more recent studies show that even such contextual models have a limited ability to capture idiomaticity (Garcia et al., 2021). Idiomatic expressions denote a group of words that behave as single words to some extent. Their linguistic behavior cannot be inferred from the characteristics of their components, and still pose a challenge to natural language processing (NLP) systems.

This paper describes the system developed by the OCHADAI team for SemEval-2022 Task 2 - Multilingual Idiomaticity Detection and Sentence Embedding (Tayyar Madabushi et al., 2022). Given that a key challenge in this task is the limited size of annotated data, we follow best practices from recent work on enhancing model generalization and robustness and propose a model ensemble that leverages multilingual pre-trained representations and adversarial training. Our model ranked 6th on SubTask A (zero-shot), and 15th on SubTask A (one-shot).

2 Task Description

SemEval-2021 Task 2 SubTask A consists of a binary classification task that requires classifying sentences with a target multiword expression (MWE) into either “Idiomatic” or "Literal" across English, Portuguese and Galician (Tayyar Madabushi et al., 2021). Further, it is subdivided into two settings to better test models’ ability to generalize: zero-shot and one-shot. In the zero-shot setting, multilword expressions (potentially idiomatic phrases), in the training set are completely disjoint from those in the test and development sets. In the "one-shot" setting, one positive and one negative training examples are included for each MWE in the test and development sets. Note that the actual examples in the training data are different from those in the test and development sets in both settings. Only the datasets provided by the organizers are allowed to train the models. Participants can use only the data provided for the zero-shot setting to train the zero-shot model. However, participants were allowed to use data provided for both settings to train models in the one-shot setting. The statistics of the corpus are presented in Table 1. Our team submitted results for both settings, and the next section outlines the overview of our model.

| Setting | Language | Train | Dev | Eval | Test |
|---------|----------|-------|-----|------|------|
| zero-shot | English | 3,327 | -   | -    | -    |
|         | Portuguese | 1,164 | -   | -    | -    |
|         | Galician  | 0     | -   | -    | -    |
| one-shot | English | 87    | 466 | 483  | 916  |
|         | Portuguese | 53    | 273 | 279  | 713  |
|         | Galician  | 0     | 0   | 0    | 713  |

Table 1: Summary of the SemEval 2022 Task 2 Subtask A dataset. Note that the dev, eval and test sets are used in both settings.
Table 2: Example sentences and labels for Subtask A. Note that "Idiomatic" is assigned the label 0 in the dataset and "non-idiomatic" (including proper nouns) are assigned the label 1.

3 System Overview

We focus on exploring different training techniques using BERT and RoBERTa, given their superior performance on a wide range of NLP tasks. Each text encoder and training method used in our model are detailed below.

3.1 Text Encoders

**M-BERT** (Devlin et al., 2019): We use the M-BERT_{BASE} model released by the authors. It is pre-trained on the top 104 languages with the largest Wikipedia using a masked language modeling (MLM) objective. This model is case sensitive: it makes a difference between English and English.

**XLM-R** (Conneau et al., 2019): XLM-RoBERTa (XLM-R) is a multilingual version of RoBERTa. It is pre-trained on 2.5TB of filtered CommonCrawl data containing 100 languages. XLM-R has been shown to perform particularly well on low-resource languages, such as Swahili and Urdu. We use the XLM-R_{LARGE} model released by the authors.

3.2 Training Procedures

**Standard fine-tuning:** This is the standard fine-tuning procedure where we fine-tune BERT and RoBERTa on each training setting-specific data.

**Adversarial training (ADV):** Adversarial training has proven effective in improving model generalization and robustness in computer vision (Madry et al., 2017; Goodfellow et al., 2014) and more recently in NLP (Zhu et al., 2019; Jiang et al., 2019; Cheng et al., 2019; Liu et al., 2020a; Pereira et al., 2020). It works by augmenting the input with a small perturbation that maximizes the adversarial loss:

\[
\min_{\theta} \mathbb{E}_{(x, y) \sim D} [\max_{\delta} l(f(x + \delta; \theta), y)]
\]

where the inner maximization can be solved by projected gradient descent (Madry et al., 2017). Recently, adversarial training has been successfully applied to NLP as well (Zhu et al., 2019; Jiang et al., 2019; Pereira et al., 2020). In our experiments, we use SMART (Jiang et al., 2019), which instead regularizes the standard training objective using virtual adversarial training (Miyato et al., 2018):

\[
\min_{\theta} \mathbb{E}_{(x, y) \sim D} [l(f(x; \theta), y) + \alpha \max_{\delta} l(f(x + \delta; \theta), f(x; \theta))]
\]

Effectively, the adversarial term encourages smoothness in the input neighborhood, and \(\alpha\) is a hyperparameter that controls the trade-off between standard errors and adversarial errors.

4 Experiments

4.1 Implementation Details

Our model implementation is based on the M-TDNN framework (Liu et al., 2019a, 2020b). We use BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019) as the text encoders. We used ADAM (Kingma and Ba, 2015) as our optimizer with a learning rate in the range \(\{8 \times 10^{-6}, 9 \times 10^{-6}, 1 \times 10^{-5}\}\) and a batch size \(\{8, 16, 32\}\). The maximum number of epochs was set to 10. A linear learning rate decay schedule with warm-up over 0.1 was used, unless stated otherwise. To avoid gradient exploding, we clipped the gradient norm within 1. All the texts were tokenized using wordpieces and were chopped to spans no longer than 512 tokens. During adversarial training, we follow (Jiang et al., 2019) and set the perturbation size to \(1 \times 10^{-5}\), the step size to \(1 \times 10^{-3}\), and to \(1 \times 10^{-5}\) the variance for initializing the perturbation. The number of projected gradient steps and the \(\alpha\) parameter (Equation 2) were both set to 1.
We follow (Devlin et al., 2019) and (Liu et al., 2019b), and set the first token as the [CLS] token and the <> token, respectively, when encoding the input on BERT and RoBERTa, respectively. We separate the input sentence and the target expression with the special token [SEP] and </s> for BERT and RoBERTa, respectively. e.g. [CLS] Ben Salmon is a committed night owl with an undying devotion to discovering new music."He lives in the great state of Oregon, where he hosts a killerradio show and obsesses about Kentucky basketball from afar. [SEP] night owl [SEP].

For both settings (zero-shot and one-shot), we used the dev dataset released by organizers to fine-tune the model’s hyperparameters.

4.2 Main Results

Submitted systems were evaluated in terms of F1-score. The systems were ranked from highest F1-score score to lowest. We built several models that use different text encoders and different training methods, as described in Section 3. See Table 3 for the results.

First, we observe that models that use adversarial training obtained better performance overall, without using any additional knowledge source, and without using any additional dataset other than the target task datasets. These results suggest that adversarial training leads to a more robust model and helps generalize better on unseen data. For the zero-shot setting, the model that uses XLM-R as the text encoder and adversarial training performed better than M-BERT on the development set. Thus, we decided to submit this model’s results on the test set. It obtained a test set F1-score of 0.7457, and ranked 6th among all participating systems. On the other hand, on the one-shot setting, M-BERT performed better than XLM-R on the development set. Again, M-BERT with adversarial training performed better than vanilla fine-tuning. This model obtained an F1-score of 0.6573 on the test set, and ranked 15th among all participating systems.

5 Conclusion

We proposed a simple and efficient model for multilingual idiomaticity detection. Our experiments demonstrated that it achieves competitive results on both zero-shot and one-shot settings, without relying on any additional resource other than the target task dataset. Although in this paper we focused on the multilingual idiomaticity detection task, our model can be generalized to solve other downstream tasks as well, and we will explore this direction as future work.

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