AlexU-AL at SemEval-2022 Task 6: Detecting Sarcasm in Arabic Text
Using Deep Learning Techniques

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Abstract

Sarcasm detection is an important task in Natural Language Understanding. Sarcasm is a form of verbal irony that occurs when there is a discrepancy between the literal and intended meanings of an expression. In this paper, we use the tweets of the Arabic dataset provided by SemEval-2022 task 6 to train deep learning classifiers to solve the sub-tasks A and C associated with the dataset. Sub-task A is to determine if the tweet is sarcastic or not. For sub-task C, given a sarcastic text and its non-sarcastic rephrase, i.e. two texts that convey the same meaning, determine which is the sarcastic one. In our solution, we utilize fine-tuned MARBERT (Abdul-Mageed et al., 2021) model with an added single linear layer on top for classification. The proposed solution achieved 0.5076 F1-sarcastic in Arabic sub-task A, accuracy of 0.7450 and F-score of 0.7442 in Arabic sub-task C. We achieved the 2nd and the 9th places for Arabic sub-tasks A and C respectively.

1 Introduction

Sarcasm is ubiquitous phenomenon on the social web, and is difficult to be analysed automatically and manually by humans because of its nature. Sarcasm data can be very confusing to computer systems which use it to perform tasks such as sentiment analysis, opinion mining, author profiling, and harassment detection (Liu, 2012; Rosenthal et al., 2014; Maynard and Greenwood, 2014; Van Hee et al., 2018).

(Rosenthal et al., 2014) show that the sentiment polarity classification performance on non-sarcastic tweets is much better than on sarcastic ones, in the context of SemEval. Sentiment polarity classification is used widely in industry, driving marketing, administration, and investment decisions (Hassan Yousef et al., 2014). So it is important to create models for sarcasm detection.

A comparatively small dataset is a challenge we faced when working on the Arabic dataset that makes it difficult to train complex models. We used transfer learning to treat this issue. By using a transfer learning, a pre-trained model for some task on a large dataset can be used as a starting point in another task which improves the performance. It is used in a wide range of natural language processing (NLP) tasks.

Word embeddings such as word2vec (Mikolov et al., 2013), FastText (Joulin et al., 2016) and Glove (Pennington et al., 2014) can be used to initialize vectors learnt form large dataset. Recently, Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) became the most popular NLP approach to transfer learning. Google AI Language team pretrained BERT model and fine-tuned it for a large range of tasks, such as question answering and language inference where it achieved state-of-the-art performance. MARBERT is built using the same network architecture as BERTBase (Devlin et al., 2019), without the next sentence prediction (NSP). MARBERT is trained on a large Twitter dataset. Therefore, we utilize fine-tuned MARBERT to solve this challenge.

This paper is organized as follows. In Section 2, we discuss relevant related works in sarcasm detection. We describe our proposed system in Section 3. The models implementation details are explained in Section 4. Section 5 describes the dataset for the shared task. Then we report and analyze the evaluation results in Section 6. Finally, we provide our conclusions in Section 7.

2 Related Work

A weak supervision and manual labelling methods can be used for the annotation process. A weak supervision method is to consider the texts sarcastic, if they meet predefined criteria, like including specific tags (e.g. #sarcasm, #irony) (Ptáček et al.,...
As pointed out by (Oprea and Magdy, 2020), noisy labels can be induced by this labelling method. Manual labelling is collecting texts and presenting them to human annotators for labelling (Filatova, 2012; Riloff et al., 2013; Abercrombie and Hovy, 2016). This can lead to a problem when annotator perception differs from author intention, as further outlined by (Oprea and Magdy, 2020).

Compared to English, only a few studies have been made on Arabic sarcasm detection. Among the studies completed in this area are research by (Riloff et al., 2013; Oprea and Magdy, 2019; Joshi et al., 2016; Bamman and Smith, 2015; Campbell and Katz, 2012; Amir et al., 2016; Hazarika et al., 2018). (Oprea and Magdy, 2020) show the effect of sociocultural variables on sarcasm communication online, which makes the performance of models trained on English unpredictable, if they are trained on other languages. (Benamara et al., 2017; Abbas et al., 2020; Abu Farha and Magdy, 2020) rely on the two labelling methods mentioned above. Recently, efforts have been made by (Abu Farha and Magdy, 2020; Abu Farha et al., 2021 and Abbas et al., 2020) to create standard datasets to support sarcasm detection. In the SemEval-2022 Workshop, a shared task (‘iSarcasmEval: Intended Sarcasm Detection In English and Arabic’) (Abu Farha et al., 2022) was organised to contribute to the development of this area using a new labelling method that avoids the limitations of previous labelling methods.

Table 1 shows statistics of the Arabic training set, where we can find that 24% of the data is sarcastic (745 tweets). Most of the data is either in Modern Standard Arabic (MSA) or the Egyptian/Nile dialects, while there are few examples of the Magreb and Gulf dialects.

| Dialect       | Non-Sarcastic | Sarcastic | Total |
|---------------|---------------|-----------|-------|
| MSA           | 1470          | 49        | 1519  |
| Egypt/Nile    | 727           | 567       | 1294  |
| Gulf          | 67            | 17        | 84    |
| Levant        | 81            | 35        | 116   |
| Magreb        | 12            | 77        | 89    |
| Total         | 2357          | 745       | 3102  |

Table 1: Arabic dataset statistics for sarcasm detection over the dialects.

We convert the input tweet to a fixed length sequence of words by padding shorter tweets and truncating longer ones. Then each word is replaced by its representation vector obtained from the pre-trained word embeddings model.

A MARBERT model is fine-tuned for sub-task A and then used for sub-tasks A and C. For sub-tasks C, the input tweets are passed to the model simultaneously and we consider the class of the tweet with the higher predicted score. We perform hyperparameters tuning to find the best parameters configuration.

### 4 Data Description

As mentioned above, annotator perception may differ from author intention. To overcome this problem, the authors annotated the data themselves, which is a new method to collect data introduced by the task’s organisers.

Arabic and English datasets are collected using this method. For each sarcastic text, they provide a non-sarcastic rephrase to convey the same intended message, for English and Arabic datasets. Eventually, for English dataset, linguistic experts label each tweet to one of the ironic speech categories outlined by (Leggitt and Gibbs, 2000): sarcasm, irony, satire, understatement, overstatement, and rhetorical question. The dialect label of the text is included for the Arabic dataset.

### 5 Implementation

We trained the proposed solution model using the given Arabic dataset. We divided its training data into 80% for training, 10% for validation and 10% for testing. In this section, we discuss the details
of the different deep learning models we built or fine-tuned.

For our solution, we fix the tweets length to 64 by truncating longer tweets and padding shorter ones. This length is selected as the max value of the Arabic training tweets lengths after tokenization. After that each token in the input tweet is replaced with its vector representation obtained from a pretrained word embeddings model. We used pretrained MARBERT to initialize the words embeddings but these representations are then updated during the training of the deep learning models. The huggingface\textsuperscript{2} pytorch implementation includes a set of interfaces designed for a variety of NLP tasks. Though these interfaces are all built on top of a trained BERT models, each has different top layers and output types designed to accomodate their specific NLP task. We used BertForSequenceClassification which is the normal MARBERT model with an added single linear layer on top for classification that we used as a sentence classifier.

5.1 MARBERT Model

Language models (LMs) exploiting self-supervised learning such as BERT (Devlin et al., 2019) which became a popular NLP approach to transfer learning. Transfer learning is used to reduce the time of the training and provide a better performance. This uses a pre-trained model as a starting point for training. Monolingual LMs pre-trained with larger vocabulary and bigger language-specific datasets usually perform better than multilingual models such as mBERT (Devlin et al., 2019; Virtanen et al., 2019).

Arabic has a large number of diverse dialects. Multilingual and Monolingual models such as mBERT and AraBERT (Antoun et al., 2020), respectively, are trained on mostly MSA datasets. The Arabic dataset used in this task has multiple dialects. This motivated us to use MARBERT which is trained on a large Twitter dataset (1B Arabic tweets), which involves both MSA and diverse dialects. The authors used the same network architecture as BERT\textsubscript{Base} (Devlin et al., 2019) to build the model, without the NSP objective which was found not crucial for model performance (Liu et al., 2019).

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
\textbf{Metric} & \textbf{Non-Sarcastic} & \textbf{Sarcastic} \\
\hline
Precision & \(\frac{TN}{TN+FP}\) & \(\frac{TP}{TP+FP}\) \\
Recall & \(\frac{TN}{TN+FN}\) & \(\frac{TP}{TP+FN}\) \\
\hline
\end{tabular}
\caption{Precision and recall with respect to the sarcastic and non-sarcastic classes.}
\end{table}

6 Experiment Results

In this section we report and discuss the results of the proposed solution when evaluated on our testing data. Moreover, we show the results of our submission to SemEval 2022 task 6 on Arabic data.

Our model ranked the second out of 32 participants for sub-task A and the 9\textsuperscript{th} out of 13 participants for sub-task C, SemEval 2022 task 6 (iSarcasmEval: Intended Sarcasm Detection In English and Arabic).

6.1 Results and Evaluation

We divided the training data into 80% for training, 10% for validation and 10% for testing. The official evaluation metric for sub-task A was the F-score of the sarcastic class (F1-sarcastic), the macro average of the F-score for sub-task B and the accuracy for sub-task C. F1-sarcastic is calculated using the following equation:

\[
F_{1\text{\-sarcastic}} = 2 \times \frac{P_{\text{sarcastic}} \times R_{\text{sarcastic}}}{P_{\text{sarcastic}} + R_{\text{sarcastic}}}
\]

Where \(P_{\text{sarcastic}}\), \(R_{\text{sarcastic}}\) are the precision and recall with respect to the sarcastic class. Table 2 presents the equations to calculate the precision and recall with respect to the sarcastic and non-sarcastic classes.

Table 3 presents the models’ performance for sub-task A, the best result (0.9) was obtained by BertForSequenceClassification, which is the normal MARBERT model with an added single linear layer on top for classification that we used as a sentence classifier. The proposed system has also been submitted for the sub-task C, and was ranked the 9\textsuperscript{th} out of 13 participants. For sub-task C, the input tweets are passed to the model simultaneously and we consider the class of the tweet with the higher predicted score. We believe this result should be studied as a future work by investigating different

\textsuperscript{1}The source code for the developed models can be found through: https://github.com/AyaLotfy/iSarcasmEval.

\textsuperscript{2}https://huggingface.co/UBC-NLP/MARBERT.
Table 3: Performance of the model using our testing set for sub-task A on Arabic dataset.

| Task | Main Metric  | Result  | Rank |
|------|--------------|---------|------|
| A    | F1-sarcastic | 0.5076  | 2nd  |
| C    | Accuracy     | 0.7450  | 9th  |

Table 4: Main metric results obtained by the proposed model on the official test set for both sub-tasks A and C on Arabic dataset.

6.2 Submission Results

For both aforementioned sub-tasks, we (AlexU-AL team) submitted the predicted classes based on the MARBERT model. For sub-task A, the proposed model achieved the second rank compared with the other systems proposed by other 31 participants. The submitted model achieved an F1-sarcastic of 0.5076 on the official testing set for sub-task A.

For sub-task C, the model achieved an F-Score of 0.7442 and an accuracy of 0.7450 on the official testing set. Table 4 presents the official results achieved by our proposed model on the official testing set for sub-tasks A and C.

7 Conclusion

We used the fine-tuned MARBERT model in our submissions to SemEval 2022 task 6. We participated in the A and C sub-tasks for sarcasm detection in Arabic tweets. Our proposed approach is ranked the 2nd and the 9th in sub-tasks A and C, respectively. For future work, we explore the impact of building deeper neural networks with multiple convolutions or recurrent layers applied sequentially on the input text.

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