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| **Instructions for ACL 2023 Proceedings** |
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Abstract

This paper discusses the methodology and results for the sEXism Identification in Social neTwork (EXIST) 2023 challenge. This shared task contains three tasks; sexism identification, source intention, and sexism categorization. In this paper we tackle the 1st challenge and use the mixed Spanish/English sexism identification dataset. Our approach makes use of a roBERTa transformer model to classify the data. The model used was taken from the Hugging Face library.

Introduction

Sexism is defined by in the Oxford Dictionary as, “prejudice, stereotyping, or discrimination, typically against women, on the basis of sex”. Sexism is a long running issue and in the modern era, social media has given a new platform for sexism to be shared. The EXIST shared task is a scientific challenge meant to further the progress in sexism detection and to catalog a year-on-year benchmark for progress. This task brings individuals and scientists around the world to develop models based on the provided data.

The EXIST task 1 is called Sexism Identification with the goal being thus. This challenge is a binary classifier task, meaning that our model will take in the provided data, and return a labeling for each tweet. Our submission will enter the database for EXIST and be compared with others around the globe. With the amount of content generated each day the need for automated detection algorithms has only risen. To that end EXIST and those participating are pushing the boundaries of what is possible in the space.

Our approach to this task was to use a roBERTa model to label our data. The model was pretrained with a masked language modeling (MLM) objective on a large corpus of English data. When trained this way, the model has 15% of its words masked over so the model can not take them in as an input. From there the data that is used gets better represented and the model learns a closer representation of the English language. This meant that we could set up the model very efficiently and have a working project up and running quickly. RoBERTa is a transformer-based model which uses self-attention to put the emphasis of understanding on the correct words. It is a model commonly used in natural language processing.

A large amount of emphasis was placed on tuning our model using the dev split of the data. We split the data based on annotator age and gender to examine how potential biases in the annotators can influence the efficacy of the model.

Background

Hate speech is a significant problem in today's society, particularly in online platforms where anonymity and lack of accountability often lead to its proliferation. Sexism is a type of hate speech and methods for detecting hate speech apply well towards sexism. In this literature review, we will explore the most significant works that we have referred to to finalize our approach for completing the EXIST 2023 Task 1.

The EXIST 2021 overview paper by Sanchez et. al [1] discusses the different classification approaches employed for Task 1 (sexism detection) — transformer-based models, other deep learning methods like LSTMs and traditional ML approaches of SVM, Logistic Regression, Random Forest. Transformer based model architecture is preferred by the majority of participating teams and all of the top-10 performing teams. The trend continues in the EXIST 2022 overview paper by Sanchez et. al [2] where with the exception of one team all other teams employ transformer-based models for both Task 1 and Task2 of sexism detection and classification. The traditional ML methods even with the extraction of additional features didn't produce comparable results to the transformer based models. We can see performance comparisons of different transformer models in the paper by Álvarez et al. [3], in which we see that the RoBERTa model is performing well on English datasets but lacks on the Spanish datasets. This is evident from [1] and [2] as well where for English datasets either RoBERTa or BERT based model are used, but for Spanish dataset only BERT is used by the top 10 teams across the tasks.

For exploring data preparation techniques we refer to Schutz et al. [4] where they compare the model performance on sexism detection between external data pre-training and data augmentation. The results showed that performance is enhanced by pre-training on external data but it deteriorates by the use of data augmentation. The decrease in model performance by using data augmentation is also shown in Bedmar et al. [5] where they compare model performance of BERT, RoBERTa, XLNet, DistilBERT with and without augmented data. For all the models the non-augmented data gives better results. The performance enhancement by pre-training on external data is also stated in [2] where the authors claim that transformer-based models benefit from train- ing with data from the same source. One more unique data processing approach was explored in Paula et al. [6], where they first translate the foreign-language data into English and then train a single language model for sexism detection and classification. This framework of single language model yielded better results than the ensemble transformer models approach.

From the above review we think it would be best to start with non-augmented data input using RoBERTa for English and BERT for Spanish datasets. We shall also pre-train the models using external data to enhance model performance and try to explore the single-language model approach.

The Data

The dataset for the EXIST 2023 shared task was created from a more than 8,000,000 English and Spanish tweets with two classes, Sexist and Not Sexist, as label. Data was split between a standard train, dev, test split with 6,920, 1,038, and 2,076 tweets for each respective category. The provided data contains a tweet scraped from twitter and the annotations. These annotations include a gold standard label, the language, and the gender and age breakdown of the annotators. The seeds for the data are seeded so that there is an even distribution of English and Spanish language tweets. Since the model chosen for this paper is a roBERTa model we chose to use no preprocessing for our data. BERT style models perform better when inputting a full string of text as opposed to bag of word tokens or stemmed text.

The Model

Hugging Face

As stated earlier our model takes advantage of the Hugging face library to build our model. Hugging Face is an AI group that maintains a standard library of AI models for general use. They have many different types of roBERTa models but in the end we settled on the standard Roberta-large model. This model was pretrained using MLM and is designed to be fine tuned to fit the user’s specific data.

* 1. RoBERTa Implementation

For our roBERTa model we load in the pretrained version. From there we map the features to the tweets and the targets to the task 1 labels. Our tokenizer features are set to the tweets and set the max length to 128. Our value tokenizer is set to encode the value of our features to the original tweets. We use an optimizer to get the most of our model. Specifically we use the AdamW optimizer from Pytorch. Once all of the preparations have been set up, then the trainer is run and the roBERTa model gets trained using the optimizer.

Performance

Footnotes are inserted using Insert / Footnote… URLs should be added as Hyperlinks and formatted in 10pt Courier New font without underlining.

Figures and tables

**Creating:** To create a new Figure or Table, insert a Text Box where yFor a figure, under **Reference Type**, click **Figure**.

* Under Insert Reference To, click Only Label and Number, then click OK.
* As much as possible, fonts in figures should conform to the document fonts (this is not the case in the example figure).

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| |  |  |  | | --- | --- | --- | | Sr no | Data | F1-score | | 1 | Full | 0.734 | | 2 | English | 0.745 | | 3 | Spanish | 0.729 | | 4 | Male | 0.728 | | 5 | Female | 0.751 | |
| Figure 1: Data table with the result running the partitioned data**.** |

This is an example reference to Figure 1.

Hyperlinks

Within-document and external hyperlinks are indicated with Dark Blue text, Color Hex #000099.

References

To create hyperlinks between citations and references, as you insert each full reference in the References section as <http://go4convert.com>.

Citations

Citations can be created by creating in-document hyperlinks to bookmarks you’ve created. Go to Insert / Hyperlink / This Document / Bookmarks, and select your bookmark.

* 1. Equations

An example equation is shown below:

(1)

To add new equations, authors are encouraged to copy this existing equation line, and then replace with the new equation. The numbering and alignment of equation line elements is automatic. To update equation numbering, press **Ctrl-A + F9**. Note: this will only update the number to the right of the equation; to update numbering within the text you must create a cross-reference.

**Cross-referencing:** To create a cross-reference for an equation:

* Create a bookmark for it.
* Select the number to the right of the equation. Go to **Insert**, **Bookmark** (in the **Links** panel),andthen create a name for your equation. Press **Add** to create the bookmark.
* To refer back, place the mouse pointer at the location where you wish to add the cross reference.
* Go to **Insert, Cross-reference** (in the **Links** panel).In the dialogue box, select **Bookmark** and **Bookmark Text** from each dropdown list. Uncheck **Insert as Hyperlink**, then click **OK**.
* This will make it such that whenever a new equation is added, the references to the equation will be updated when **Ctrl-A + F9** is pressed.
* This an example cross-reference to Equation 1.

Appendices

Appendices, if any, directly follow the text and the

references. Letter them in sequence and provide an informative title: **Appendix A. Title of Appendix**.

Limitations

ACL 2023 requires all submissions to have a section titled “

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Acknowledgments

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References

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1. Magnossão de Paula, Angel Felipe et al .”Detecting and Classifying Sexism by Ensembling Transformers Models” Proceedings of the Iberian Languages Evaluation Forum (IberLEF 2021)
2. Appendices

Appendices are added after the References section by restarting the header numbering using style “A, B, C”.