Oppositional thinking analysis: Conspiracy vs critical narratives

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Abstract. Conspiracy theories surrounding public health decisions have arisen in online communication, posing challenges to content moderation and understanding. This paper addresses the distinction between critical and conspiratorial narratives in the context of COVID-19. This study is conducted as part of PAN 2024 and focuses on English and Spanish text corpora. This lab proposes two sub-tasks: binary classifications of critical versus conspiratorial texts, and the identification of elements within oppositional narratives.

Keywords: CLEF · PAN labs · BERT.

1 Introduction

Conspiracy theories have become present in everyday online conversations, particularly in public health discussions, which were emphasized during the COVID-19 pandemic. These narratives are often propagated across various platforms, posing a challenge to moderate and understand the content. Recognizing the distinction is crucial and can bring better content moderation strategies and insight into these conversations.

This paper presents an approach to characterize critical versus conspiratorial texts and the detection of oppositional narrative elements. It utilizes datasets sourced from the Telegram platform and employs SOTA NLP models, including BERT-based classifiers and the Llama-3 model. This paper aims better to understand the mechanisms behind conspiracy theories in online conversations.

2 Models

In this section, we will discuss the models used for PAN 2024.

2.1 covid-twitter-bert-v2

CT-BERT is a transformer-based model pre-trained on a corpus of COVID-19-related Twitter messages. It's a domain-specific model, and it shows 10-30% improvement compared to its base model, BERT-LARGE. It is best used on COVID-19 content.

2.2 twitter-xlm-roberta-base-sentiment

This model is designed to handle the unique characteristics of Twitter content. The base model used is XLM-RoBERTa, a RoBERTa-based model trained on multilingual data. It is also based on transformer architecture and pretrained on a large corpus of Twitter data.

2.3 Meta-Llama-3-8B-Instruct

This Llama model has 8 billion parameters, and it was released on April 18^{th}, 2024. It showed SOTA performance across a wide range of NLP tasks. Llama-3 has increased its vocabulary to 128,256 tokens and has a context length of 8,000 tokens. The data used to train this model had a diverse set of languages.

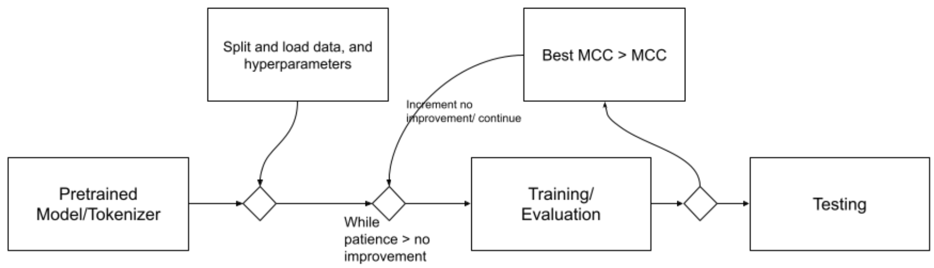
3 Experimental setup

This section will discuss implementation and the data used for this project.

3.1 Implementation

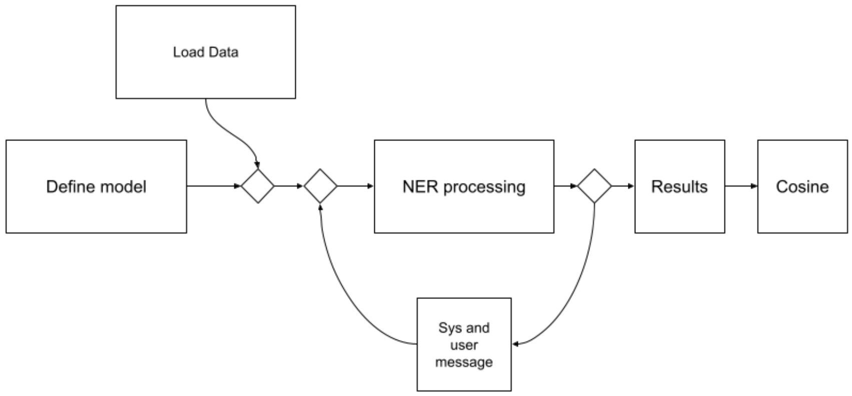
covid-twitter-bert-v2 was implemented for binary classification using PyTorch and the Hugging Face Transformer library.

1. This model was trained using cuda-enabled NVIDIA GeForce RTX 3060 Ti
2. It loads a pre-trained CT-BERT model and tokenizer from Hugging Face.
3. Data is split 80/10/10
4. Training loop
   - In each epoch, sets the model to training mode
   - Processes each training example computes loss and does backpropagation
   - At the end of each epoch, it evaluates the model and saves the best one based on MCC measurement.
5. The testing loads the best model and calculates MCC based on testing data.
6. **twitter-xlm-roberta-base-sentiment** has the same architecture



Llama-3 performs Named Entity Recognition (NER) using a pre-trained language model.

1. Dfine model and load the data from JSON file
2. NER processing
   - Iterate through JSON data
   - Extract ID and text from each item
   - System and user messages, forming prompt for a pipeline
   - Generate NER output
   - Parse generated text to extract the output
   - write extracted elements to output JSON
3. Cosines and evaluation of Llama is done separately.



3.2 Data

PAN lab provided us with data for this task. It has two JSON files with telegram posts: one dataset in Spanish and one in English.

Data Example


```
{
    "id": "11414",
    "text": "\" COVID : ALLEGED DOCUMENT PREDICTING
    THE FRENCH STRATEGY IN 2021
    Picture translated to English . ",
    "category": "CRITICAL",
    "annotations": [
      {
        "span_text": "People",
        "category": "VICTIM",
        "annotator": "gold_label",
        "start_char": 943,
        "end_char": 949,
```

```
      "start_spacy_token": 177,
      "end_spacy_token": 178
    }
  ],
```

3.3 Evaluation

We used two evaluation metrics for this project: Matthews Correlation Coefficient and F1 score.

Matthews Correlation Coefficient is a statistical method for measuring the quality of binary classifications in machine learning. It is a single-value metric that utilizes a confusion matrix. The confusion matrix consists of four variables,true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

$$MCC = \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP + FP) \cdot (FN + TN) \cdot (TP + FN) \cdot (FP + TN)}}$$

F1 score is metric used in machine learning to measure models's reliability by calculating the harmonic mean of precision and recall.

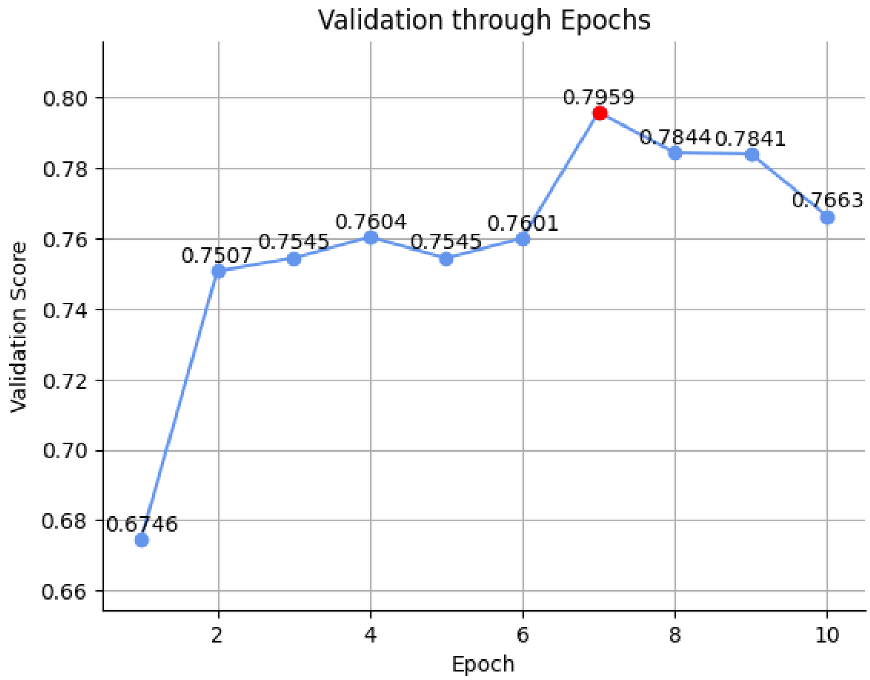
$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

4 Result

In this section, we will discuss the results for Subtask 1 and Subtask 2.

4.1 covid-twitter-bert-v2

To better the baseline scores, I have decided to fine-tune CT-BERT and introduce early stopping. The patience level has been set to 3 and the best model is saved. For the testing of this model, the best model from early stopping is loaded.



From this plot, we can see that the model went through ten epochs, and the seventh model had the best validation. We saved the model from the seventh epoch and used it for the testing. Results in table 1.

Model	MCC
Baseline	0.0226
Fine-Tuned	0.7554

Table 1. Comparison of baseline and fine-tuned model

We can see that the fine-tuned model drastically outperforms the baseline model.

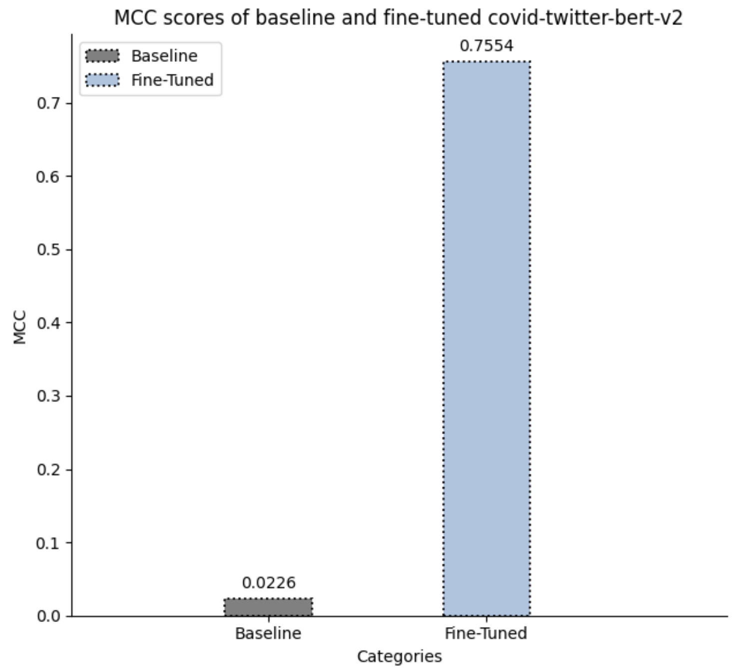


Fig. 1. COVID-Twitter-Bert comparison

Example of success

```
THIS IS MASSIVE Australian Senator Malcolm Roberts exposes nanotech
found in the Covid  vaccines  and says they are genocide
He is the first politician to expose this
gold_label: CONSPIRACY,
prediction: CONSPIRACY
```

Model predicted conspiracy correctly.

Example of failure

```
Joe Biden  who told Americans last year
You re not going to get covid if you have these vaccinations
has just tested positive for COVID after having had four vaccinations
gold_label: CONSPIRACY,
prediction: CRITICAL
```

Model mistakes conspiracy for critical thinking.

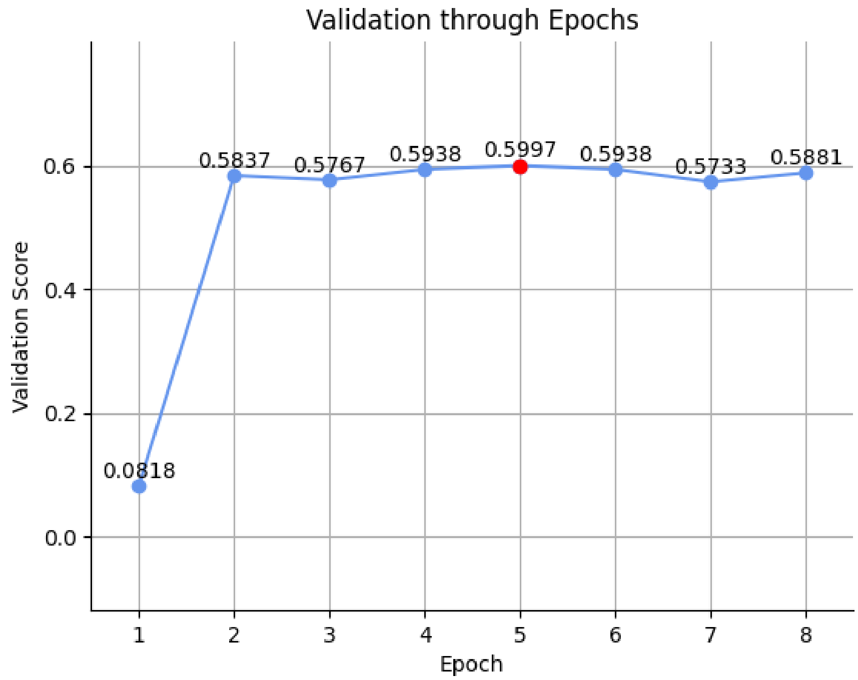


Fig. 2. Scatter plot for the twitter-xlm-roberta-base-sentiment model

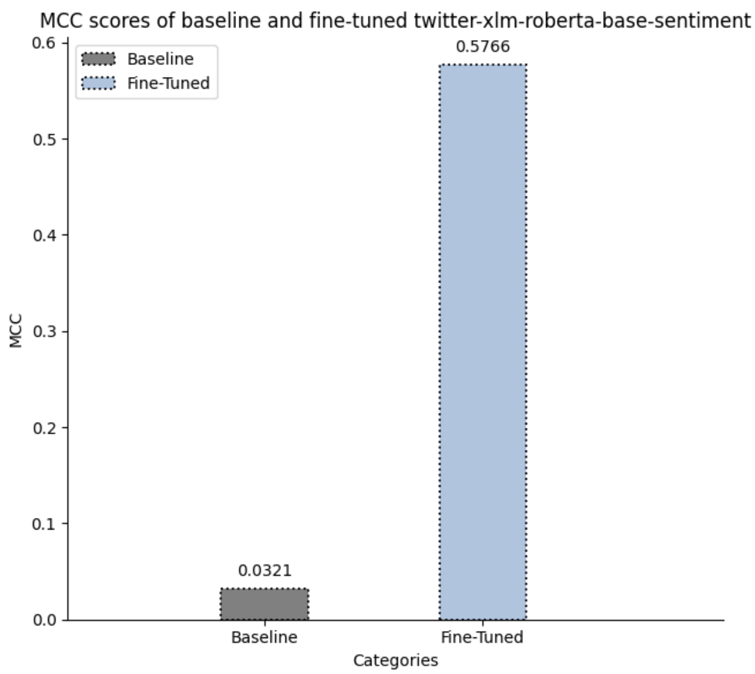
4.2 twitter-xlm-roberta-base-sentiment

This model has a task similar to CT-BERT; the only difference is that it works with the Spanish corpus and is not specifically fine-tuned on COVID-19-related Twitter corpus but a diverse one. In this model, we have also implemented early stopings.

In the figure 2, we can see that the first validation was slightly better than a baseline model. This only happened in this run; after the first run, the data increased to epoch five, where it reached the best result. That model is saved an used for the testing. I chose this plot because it emphasizes the importance of epochs and re-running your model. The table 2 shows the difference between the fine-tuned model and the baseline.

Model	MCC
Baseline	0.0321
Fine-Tuned	0.5766

Table 2. Comparison of baseline and fine-tuned model



4.3 Llama-3

In the case of Llama-3, I have experimented with a few prompts, but the best results came from the following prompt.

```
Task: Extract specific elements-AGENT, FACILITATOR, VICTIM, CAMPAIGNER,
OBJECTIVE, and NEGATIVE_EFFECT-from a given text, omitting any elements
that are not explicitly mentioned. Instructions: Provide the identified
```

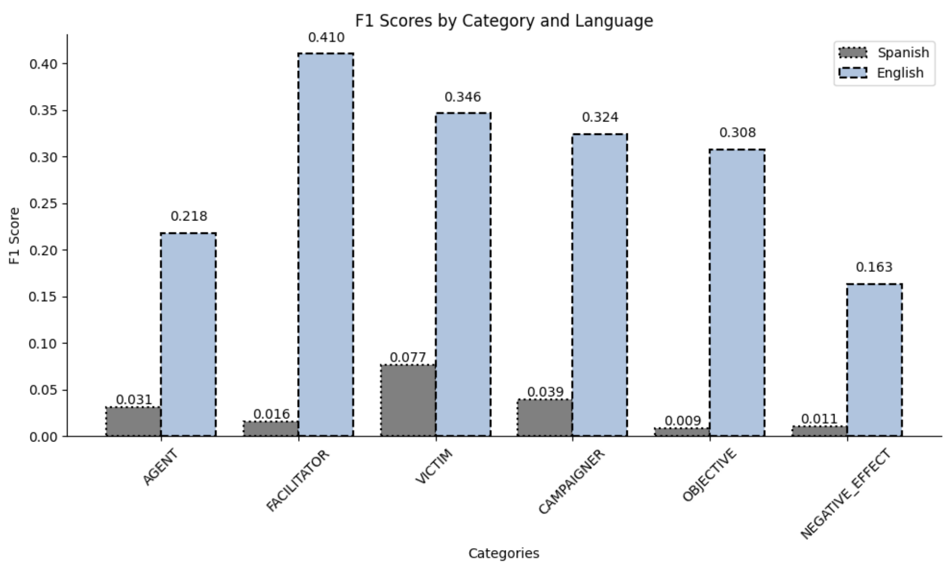
```
elements directly from the input text without alterations. Only include
elements that are mentioned explicitly.
```

The prompt was also translated into Spanish. The results generated by this prompt have been parsed and saved into JSON. The problems I have encountered with Llama are that sometimes the model wouldn't output data, and the evaluation metric doesn't provide how good the predictions are. This section requires more work.

The data collected into JSON is first compared with the given dataset, and cosine similarity between the two is created; if the cosine similarity is above a certain threshold, then the given output is considered as predicted correctly. A separate evaluation file calculates precision and recall and, based on that, calculates the F1 score.
The following scores are recorded for Llama-3 and the prompt mentioned above.

Corpus	AGENT	FACILITATOR	VICTIM	CAMPAIGNER	OBJECTIVE	NEGATIVE_EFFECT
English	0.2177	0.4101	0.3462	0.3237	0.3076	0.1633
Spanish	0.0314	0.0161	0.0771	0.0393	0.0089	0.0112

Table 3. F1 scores for each Named Entity



We can see that the English corpus performs worse than guessing randomly, while the Spanish corpus performs almost as never guessing correctly. Problems with the evaluation method include Llama-3 straying away from the prompt or producing different outputs. More time should be spent adjusting the prompt and analyzing the output data. Sometimes, the meaning of predicted output is similar to the gold_label, but cosine similarity is not above the set threshold.

Examples of failed

```
{
            "attribute": "NEGATIVE_EFFECT",
            "dataset_value": "I \u2019m deeply concerned that the push
            to vaccinate these children is nothing more than a dystopian
            experiment with unknown consequences",
            "prediction_value": "Unknown consequences",
            "cosine_similarity": 0.0
 }
```

We can see that the prediction of NEGATIVE_EFFECT is correct, but it didn't include everything and thus is marked as incorrect with a value of 0.0.

```
 {
     "attribute": "OBJECTIVE",
    "dataset_value": "None mentioned",
    "prediction_value": "to analyze blood samples under an optical microscope",
     "cosine_similarity": 0.0
},
```

In this dataset, there is no OBJECTIVE, but the Llama-3 predicted an OBJECTIVE.

Example of success

```
{
            "attribute": "VICTIM",
            "dataset_value": "someone who died suddenly",
            "prediction_value": "someone who died suddenly",
            "cosine_similarity": 1.0
},
{
            "attribute": "CAMPAIGNER",
            "dataset_value": "None mentioned",
            "prediction_value": "none mentioned",
            "cosine_similarity": 1.0
},
```

In both cases, Llama-3 predicted correctly. In the first case, it predicted correct VICTIM, and in the second case, it correctly predicted CAMPAIGNER by not predicting.

References

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