Project Report

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ABSTRACT

This report presents answers to the research questions proposed regarding the issues faced by various social media platforms that we have collected data from.

1 INTRODUCTION

The research questions are as follows:

1.1 Twitter Tweets Data

RQ1 For each named entity recognized from the tweets, what is the dominant sentiment towards it?

1.2 Subreddit Comments Data

RQ2 What percentage of comments that are made related to U.S. politics are toxic?

1.3 YouTube Comments Data

RQ3 What is the structure of comments that are posted with the motive of scamming others?

2 ANALYSIS & ANSWERS

2.1 Twitter Tweets Data

We used the BERT tokenizer to find the named entities. Figure 1 shows the world cloud of the named entities from the tweets on 11/01/2022 and 11/02/2022. We bifurcate the tweets based on the recognized entities and use the twitter-roberta-base-sentiment model to get the sentiment score for each of the tweet. The neutral sentiment tweets are counted within the positive sentiment tweets.

Figure 1: Word Cloud of Named Entities from Tweets

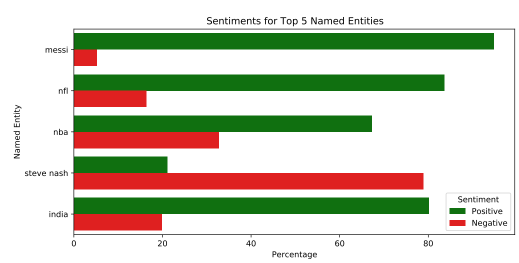

Figure 2: Sentiments for Top 5 Named Entities

Figure 2 shows the sentiments of the tweets received for the top 5 named entities from the tweets on 11/01/2022 and 11/02/2022. It is seen that four of the named entities except *steve nash* have more positive or neutral text. We found that *steve nash* was fired from his position of a coach of a *nba* team due to their teams poor performance which lead to more criticsm and negative tweets regarding him at that time. Since, he was related with *nba* the tweets related to *nba* also had a increase in number of tweets with negative sentiment. Similar pattern was observed for the entity *india* where in the selected time frame *t20 cricket world cup* was going on and the fans of the team that lost against *india* posted negative sentiment tweets.

For all the named entities recognized from the tweets on 11/01/2022 and 11/02/2022 their average positive and negative sentiment percentage is shown in figure 3. We perform similar analysis on the tweets from 11/01/2022 to 11/15/2022.

To answer the question we can say that most of the recognized named entities have positive sentiment tweets and one of the major reason for negative sentiment is because of the circumstances related to that entity in that time frame.

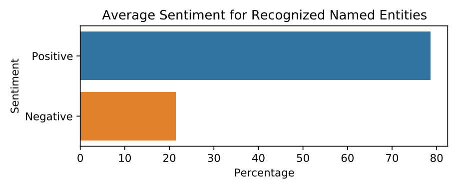

Figure 3: Average Sentiment for Recognized Named Entities

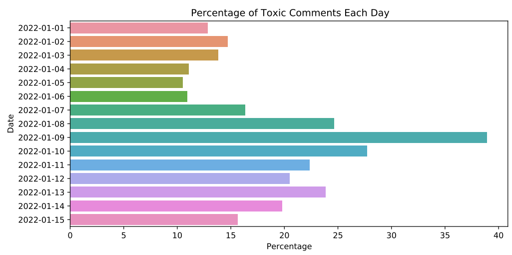

Figure 4: Percantage of Toxic Comments Per Day

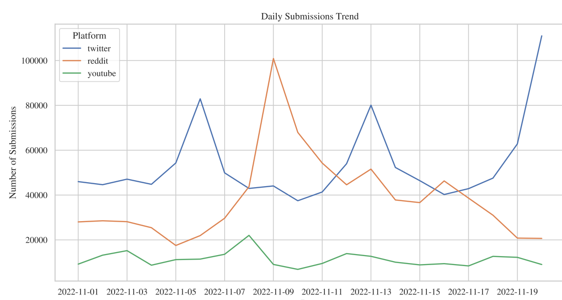

Figure 5: Daily Submissions Trend across all the platforms

2.2 Subreddit Comments Data

We collected the toxicity score for each reddit comment posted on the posts in the subreddits related to U.S. politics using the toxic-bert-classifer. Figure 4 shows the percentage of comments that were toxic out of the total number of comments posted on that particular date. We found that during the time frame of U.S. elections 2022 there were more toxic comments compared to the other days.

We found another pattern in the amount of toxic comments when comparing it with the number of comments received in that time frame. From figure 5 the orange line shows the number of comments received on subreddit reddit posts within the given time frame. As the number of comments increased there were more toxic comments in them, making both directly proportional to each other.

So the higher percentage of the comments are non-toxic on the posts related to U.S. politics.

Table 1: Scam/Spam Comments

Author	Comment
Text me on telegram @Royalty Family1	Great fan, Thanks for commenting You are among the shortlisted Winners Use the Above name to Acknowledge your prize.
telegram @Sidemenreacts3	Kindly dm me on telegram for some package now
ruxin344 ON TELEGRAM	you won, your among our shortlisted winners, dm via telegram for clm prize

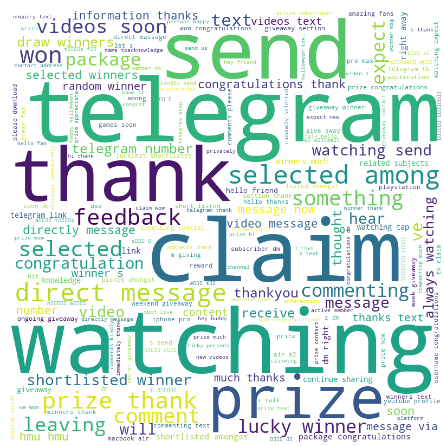

Figure 6: Word Cloud of most frequent words in YouTube comments related Spam/Scam

2.3 YouTube Comments Data

Table 1 shows some of the usernames and their comments classified as spam/scam. The most common pattern found was the use of telegram keyword in both the usernames and the comments. Scammers try to redirect the video viewers to their telegram id where they conduct their scams.

After analyzing all the comments from such users we found the most common keywords present in their comments which are shown in figure 6.

These keywords help us understand the basic structure of their comments contain the redirection to telegram, thanking user for watching the video in order to persuade them and giving them false information that they have won a prize and need to contact the scammer in order to claim it.