Natural Language Processing
Assignment 1 Report
Sentiment Analysis of Top Subreddit Comments

Team ID: 4

Task 1: Data Scrapping

- **Posts**

We scraped the top 100 posts of all time from the **r/bangladesh** subreddit. We used the PRAW library.

Attribute Information:
- Post Title (string)
- Post Id (alphanumerical)
- Total number of Comments (numerical)
- Timestamp (numerical - in seconds)
- Upvotes

- **Comments**

Attribute Information:
- Comment Score (numerical)
- Comment Depth
- Parent comment ID
- Comment text
- Created time-stamp

Task 2: Sentiment Analysis Models

We utilized three popular sentiment analysis models from Hugging Face:

1. cardiffnlp/twitter-roberta-base-sentiment-latest
2. finiteautomata/bertweet-base-sentiment-analysis
3. Seethal/sentiment_analysis_generic_dataset

We ran inference on the scraped comments using these models to generate labels for sentiments - positive, negative, and neutral. You can refer the code here:

https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/reference_code/Data_Scraping_sentiment_modelling.ipynb

To see what the code is doing, please refer to the comments on the top of every cell.

Task 3: Majority Label Aggregation

We applied majority voting on the labels generated by the three sentiment analysis models to obtain a single label for each comment in the corpus.

Here is the link for the majority label aggregation:
https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/human_eval.ipynb

Task 4: Preprocessing and Exploratory Data Analysis (EDA)

We performed preprocessing on the scraped comments and conducted EDA, considering parameters like the number of upvotes, metadata, and other available information from the subreddit API. Our EDA aimed to uncover patterns, trends, and insights in the dataset.

Here is the link to the code:
https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/EDA_Final%20(1).ipynb

Task 5: Random Sampling for Annotation

From the annotated comments with majority labels, we randomly sampled 100 sentences while ensuring an equal proportion of positive, negative, and neutral sentiments to create a balanced dataset.

Here is the code for the same:
https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/reference_code/Hugging_face_model.ipynb

Task 6, 8: Human Evaluation & Majority Vote on Human Annotations

Three annotators from our team individually annotated the 100 sampled sentences for the sentiment. Annotations were conducted in isolation, without access to each other's annotations. Ethical guidelines were followed to maintain the integrity of the human evaluation process.

We performed majority voting on the labels assigned by the three annotators to determine the majority sentiment label for each comment.

Here is the link for the human_evaluation.csv file:

https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/human_eval.csv

Task 7: Inter-Annotator Agreement (Krippendorff's alpha Agreement)

We calculated the inter-annotator agreement using Krippendorff's alpha for the 100 annotated sentences. The value obtained reflects the level of agreement among the annotators.

```
In [10]:  from krippendorff  import alpha

          data = [annotator1_data['Label'], annotator2_data['label'], annotator3_data['Sentiment']]

          alpha_value = alpha(data, level_of_measurement='interval')
          print("Krippendorff's alpha:", alpha_value)

          Krippendorff's alpha: 0.5017860668832683
```

Here is the link for the code:
https://github.com/aishwaryaomar/NLP_Assignment1/blob/main/kripp.ipynb

The **Krippendorff's alpha Agreement of 0.501786** signifies a noteworthy alignment between human annotators and the machine sentiment analysis models. This level of agreement underscores the effectiveness of the machine models in capturing sentiment nuances, thereby demonstrating their valuable contribution to sentiment analysis tasks.

Task 9: Discrepancy Analysis

We identified comments where the majority sentiment label assigned by the sentiment analysis models differed from the majority label assigned by human annotators. We provided evidence and relevant data to support our findings.

Comment	Model_sentiment	Human_sentiment	Reason
I know right? HOW COULD THEY	-1	0	The model interpreted the comment as having a negative sentiment due to the use of "HOW COULD THEY" which might convey frustration or disappointment. However, humans might interpret it more neutrally, possibly perceiving it as a rhetorical question rather than a strong expression of negativity.

Lmao this is hilarious. We need some Bangladesh equivalent of â€œmurica fuck yeaâ€ any idea ?	-1	0	The model assigned a negative sentiment label possibly because of the word "hilarious" which may be interpreted as sarcasm or mockery. Human annotators, on the other hand, might see the comment as light-hearted and humorous, leading to a neutral sentiment.
While thinking about it, I still don't know, but I don't **want** to know, either.	-1	0	The model may have picked up on the slightly negative tone in the phrase "I don't want to know." However, humans might consider the overall context of the comment and perceive it as more neutral, as the user is expressing uncertainty rather than outright negativity.
^(Back in our days ... damnn I feel old now)	-1	0	The model might have identified the phrase "Back in our days ... damnn I feel old now" as a reminiscing sentiment with a negative connotation, given the mention of feeling old. Human annotators could view this comment as nostalgic rather than negative, resulting in a neutral label.
Damn Boi	-1	0	The model likely labeled the comment as negative due to the use of "Damn Boi" which could be interpreted as expressing disappointment or annoyance. Humans might perceive this as a colloquial expression without a strong negative sentiment, leading to a neutral label.

Results: Analysis and Insights

Link to GitHub repository:
https://github.com/aishwaryaomar/NLP_Assignment1/tree/main

Our analysis revealed interesting sentiment insights in the selected subreddits' top posts. Combining EDA and human evaluation gave us a comprehensive understanding of sentiment distribution and differences between model predictions and human annotations.

In this exploratory data analysis (EDA), we delved into a collection of Reddit comments from a specific subreddit. Our goal was to uncover insights about the sentiments expressed in the comments and how they relate to various characteristics such as comment depth, frequency, and comment scores.

1. Negative Comments and Comment Depth:
Upon analyzing the comments, we observed that negative comments tended to have higher comment depths. In other words, comments with a negative sentiment were often part of more extended discussions within the thread. This could be due to the nature of negative sentiments often sparking debates or disagreements among users. The higher comment depth suggests that these comments trigger further interactions and discussions within the community.

2. Distribution of Neutral Comments:
Neutral comments, those expressing neither positive nor negative sentiment, were found to be more prevalent compared to the other sentiment categories. These comments seemed to bridge opposing viewpoints, contributing to balanced discussions and providing clarifications or additional information. The abundance of neutral comments might indicate the subreddit's commitment to fostering a well-rounded and informed discourse.

3. Frequency of Comments by Depth:
A noticeable trend emerged as we examined the distribution of comment depths. The frequency of comments decreased as the comment depth increased. This finding is consistent with the typical structure of online discussions, where the initial post generates more responses (comment depth 0), and subsequent responses become progressively scarcer. The decline in frequency with comment depth reflects the diminishing engagement as the conversation unfolds.

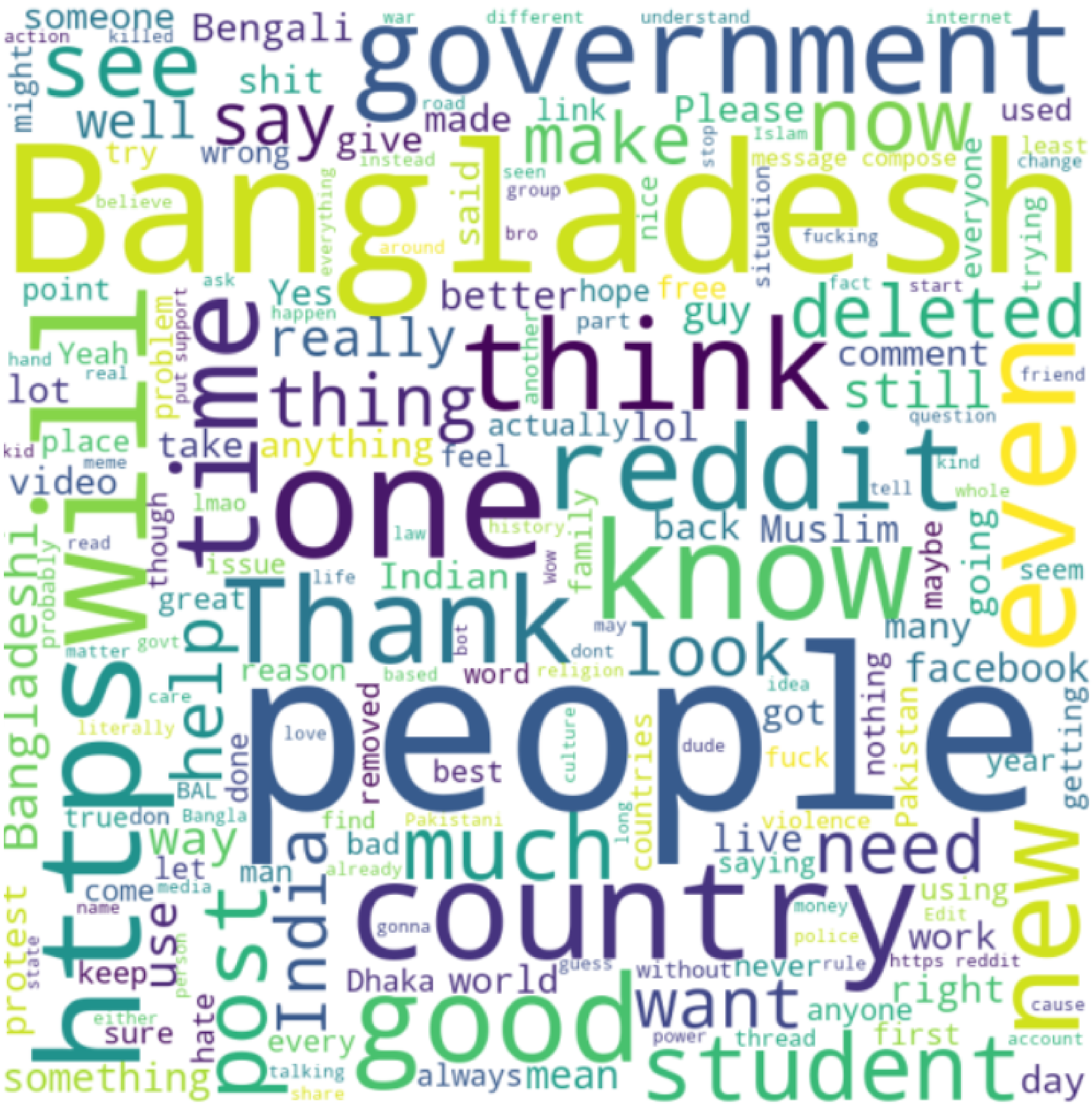
4. Positive Comments and Interaction Patterns:
Positive comments appeared to follow a distinct pattern in terms of both comment count and comment depth. They were characterized by relatively lower comment counts and comment depths than negative comments. Positive sentiments often reflect agreement, appreciation, or sharing of positive experiences, which might not necessitate lengthy discussions. This could explain the trend of positive comments receiving fewer responses and not leading to extensive interactions.

Conclusion:

Our exploratory data analysis of the Reddit comments shed light on various interaction patterns and sentiment distributions within the subreddit. Negative comments tended to trigger more in-depth discussions, while neutral comments acted as connectors between different viewpoints. The distribution of comments by depth followed an expected trajectory, with engagement decreasing as the comment depth increased. Positive comments, typically expressing agreement or positivity, were associated with lower comment counts and depths.

Word Cloud of the Corpus

We created a word cloud of the entire corpus, removing stop words and setting a minimum word length of 3 to highlight prominent terms.



Conclusion

In conclusion, our analysis and evaluation provided valuable insights into the sentiment of top subreddit comments. We comprehensively understood sentiment trends and discrepancies through a combination of machine-learning models and human annotation. This assignment allowed us to apply practical techniques in sentiment analysis and gain a deeper understanding of NLP research processes.

Contributors:

Team Members	Roll no:	Contribution
Abhay	21110004	12.5%
Adit	21110010	12.5%
Aishwayra	20110008	12.5%
Amaan	20110011	12.5%
Govardhan	20110070	12.5%
Gaurav Joshi	21110065	12.5%
Sanskriti	23120007	12.5%
Simran	20110200	12.5%