Reddit Sentiment Analysis Final Report

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Summary of Contributions

Data Collection

Jash took the responsibility of creating the Reddit API scraping wrapper, tailored specifically for our use case. He also performed the initial text preprocessing, which included converting text to lowercase and removing all non-alphanumeric characters. The cleaned data was then exported to a file named "reddit.csv," which serves as the primary dataset for this project.

Steven and Ameen worked together on data quality assurance, inspecting the collected subreddit data to ensure its validity and relevance to our project's objectives. Their efforts guaranteed that our dataset is of high quality and suitable for sentiment analysis.

A significant challenge faced by the team during data collection was identifying posts from different subreddits that fit our project's domain. After multiple trials and errors, we managed to narrow down our search to the following subreddits: Microsoft, Google, Youtube, Intel, AWS, Azure, Apple, Raspberry_pi, Android, Amazon, OpenAI, and Bing. This final list of subreddits provided us with a diverse and representative sample of data for our sentiment analysis project.

Coding

Each cell within our Databricks notebooks includes an annotation indicating the respective author's name. Brief summary of each author’s contributions:

Steven - Feature Extraction, Data splitting, Classification Metrics

Jash - Data Collection, Data Preprocessing, Building ML models

Ameen - Hyperparameter Tuning, Visualization, Misclassifications

Writeup

In the Results section, we have customized Questions 2 and 4 from the project guidelines to more effectively suit our project, given that it is not rooted in an original research paper. Instead, we have showcased relevant statistics that emerged from the singular dataset we scraped, assembled, and processed from Reddit. Furthermore, we have established connections between our statistical insights and those documented in the Amazon research paper [1], encompassing an in-depth evaluation of the Receiver Operating Characteristic (ROC) curves. Inspired by the data pipelines outlined in both the Amazon research paper [1] and the Twitter research paper [2], we have successfully developed our own distinct data pipeline shown in Figure 1.

Table 1: Breakdown of Individual Contributions to the Report

Section	**Contributor**
Contents of page 1	All
Abstract	Ameen
Introduction	Ameen
How was the data labeled/collected?	Steven
What are the statistics of the data?	Steven
How was the data preprocessed?	Steven
How was feature extraction performed for our dataset?	Jash
How do the models perform on the data?	Jash
How does the performance of the models change based on the choice of hyperparameters?	Jash
How are the misclassifications of the best-performing model distributed?	All
Discussion	All
Conclusion	Ameen

Databricks notebook

1. reddit.ipynb: Notebook that presents all findings
https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/5989825354372253/3360654470167982/7669248954805947/latest.html

2. reddit_scrape.ipynb: Notebook that presents how we get our dataset reddit.csv
https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/5989825354372253/3842048987237889/7669248954805947/latest.html

1. Abstract

1.1 Context

Sentiment analysis is a growing field in natural language processing that involves analyzing natural language text in order to identify sentiment from the data. It has become an essential tool for businesses to gain insight into customers and competitors. Furthermore, with more people than ever on public platforms, sentiment analysis can be utilized to understand the public's opinions and emotions towards a particular topic.

1.2 Objective

The primary aim of this research endeavor is to delve into the potential use of sentiment analysis techniques in the context of the Reddit platform. Reddit comprises a myriad of user-created communities, referred to as subreddits, where individuals share and discuss content relevant to specific topics. These posts often consist of titles, which may link to external webpages, images, or accompanying text.

In order to effectively analyze the sentiment of Reddit posts within a given subreddit domain, this study focuses on extracting negative, neutral, or positive sentiment values based on the post titles. The project's success hinges on identifying and employing the most suitable machine learning models and feature selection methods to achieve optimal results in sentiment classification.

1.3 Methods

We will implement the data pipeline process as illustrated in Figure 1, which has been meticulously designed by drawing inspiration from sentiment analysis papers on Amazon [1] and Twitter [2] data. This data pipeline demonstrates the crucial stages in our approach, encompassing Data Collection, Data Preprocessing, Feature Extraction, our data segmentation strategy, and the deployment of advanced supervised machine learning algorithms. By leveraging this thoughtfully constructed pipeline, our objective is to effectively output the sentiment values of Reddit posts, classifying them as positive, negative, or neutral.

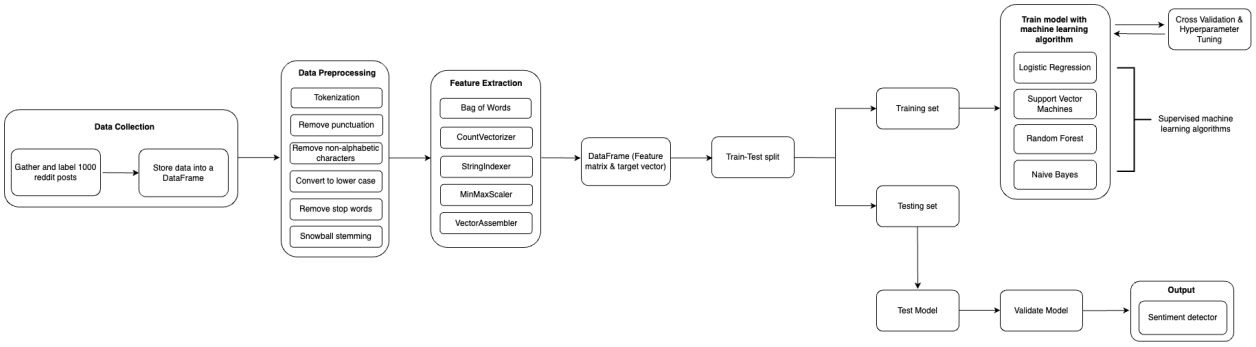


Figure 1: Illustration of the Data Pipeline Process

1.4 Results

Results show that using Support Vector Machine provides the most favorable results when trained only on textual data to analyze sentiment. The results of this study show that sentiment analysis is a valuable tool for businesses operating within the technology industry and insights can be gained through product launches, assessing the competitive landscape, and crisis management.

1.5 Conclusions

In conclusion, the Support Vector Machine is the best model for performing sentiment analysis using natural language processing on Reddit post titles. The engagement factor of Reddit posts had no contribution to the obtained sentiment. With more data and resources, the results may be improved.

2. Introduction

2.1 Motivation of the problem

The rapid growth of social media platforms, such as Reddit, has generated vast amounts of user-generated content. This content holds valuable insights into user opinions, preferences, and sentiment towards various topics, products, and services. Businesses, organizations, and consumers can greatly benefit from understanding these sentiments in order to make informed decisions, improve customer satisfaction, and drive product development.

Sentiment analysis, a subfield of natural language processing, is the process of determining the sentiment expressed in a piece of text, such as a social media post or a review. In this project, we aim to perform sentiment analysis on Reddit posts to gauge user sentiment towards various technology companies and their products. Our objective is to build and test different machine learning models to see how they perform at classifying positive, negative or neutral sentiment.

2.2 Background

To accomplish our objective, we started by collecting and preprocessing a dataset of Reddit posts from various technology-related subreddits. Our initial dataset was manually labeled with sentiment categories by our team members to ensure high-quality ground truth labels. This labeled dataset, consisting of 1081 data points, was then used to train and evaluate various machine learning models, such as Support Vector Machines (SVM), Logistic Regression, Naive Bayes, and Random Forest.

Throughout the project, we utilized the Apache Spark framework for data processing and machine learning tasks. This allowed us to efficiently handle large-scale data and take advantage of distributed computing resources. To facilitate reproducibility and collaboration, we utilized Databricks notebooks, where each cell was annotated with the respective author's name. The project was carried out with a strong focus on best software engineering practices, including modular code design, thorough documentation, and adherence to coding standards.

In this report, we will present our methodology, results, and a detailed analysis of the performance of our machine learning models. Additionally, we will discuss the challenges encountered during the project and the potential avenues for future work in the field of sentiment analysis on Reddit data.

3. Results

3.1 How was the data collected/labeled?

In order to collect the data for our project, we focused our efforts on the technology domain by targeting a list of technology-related subreddits. We employed the Reddit API to efficiently scrape posts from these subreddits of interest, ensuring that we gathered the most relevant and engaging content from the technology community.

To achieve this, we first created a Reddit API instance using the Python Reddit API Wrapper (PRAW) library. This enabled us to interact with the Reddit API in a convenient and user-friendly manner. Next, we loaded a list of target subreddits from a text file, which allowed us to manage and organize the data collection process effectively. This approach ensured that we could easily update our subreddit list as needed without altering the code.

To refine our data collection further, we targeted the top 100 posts of the month for each subreddit. This decision was made in order to ensure that we gathered the most relevant and engaging content from these technology subreddits, as the top posts are likely to generate significant interest and discussion within the community.

The data labeling process for our project was carried out through a collaborative effort among the group members. Each person in our group was responsible for manually labeling the

sentiment across 1081 data points. This approach ensured a diverse and unbiased interpretation of the sentiment expressed in the content.

To evaluate the reliability of the manual labeling process, we used two statistical measures: percent agreement and Fleiss' kappa. The percent agreement measures the proportion of instances where the labelers agreed upon the same sentiment label, while Fleiss' kappa determines the degree of agreement between labelers while considering the possibility of an agreement by chance.

Table 2 shows the calculated percent agreement, which was found to be 89.64%, indicating a high level of consistency between the labelers. Additionally, Table 3 presents the Fleiss coefficient, calculated as 0.832, which falls within the "almost perfect agreement" range, according to the interpretation of Fleiss' kappa values. From these metrics, we can deduce that there was fairly good agreement between the data labelers, ensuring the reliability of the manually labeled data.

In cases of discrepancies between labelers, we opted for a majority vote approach to resolve disagreements. The sentiment label with the most votes from the labelers was selected as the final label for that particular post. This method allowed us to reach a consensus in the labeling process while minimizing individual bias.

If a post had three different labels assigned by the labelers, we convened as a group to discuss the appropriate sentiment value for that post. This collaborative approach ensured that the final sentiment label was well-justified, and potential labeling ambiguities were addressed collectively.

Table 2: Calculation of Overall Percent Agreement

Match	969
Total	1081
Percent Agreement	89.64%

Table 3: Fleiss' Kappa Calculation Results

Total Percent Agreement	Expected Agreement 1	Expected Agreement 2	Expected Agreement 3	Expected Agreement Sum (Pe)	Observed Agreement (Po)	Fleiss_kappa (k)
0.8963922294	0.05463167472	0.06238441981	0.266769224	0.3837853185	0.8963922294	0.8318641641

3.2 What are the statistics of the dataset?

Figure 2 presents the distribution of sentiment labels assigned by the team for our dataset. As demonstrated, our dataset consists of text samples, each paired with a sentiment label corresponding to one of three categories: positive, negative, or neutral. This figure effectively

captures the results of our manual labeling across the 1081 data points, emphasizing the diversity in sentiment label proportions within the dataset.

Figure 3 offers a detailed, quantitative depiction of the sentiment label distributions within the dataset. It illustrates the allocation of sentiment labels for each post in our dataset.

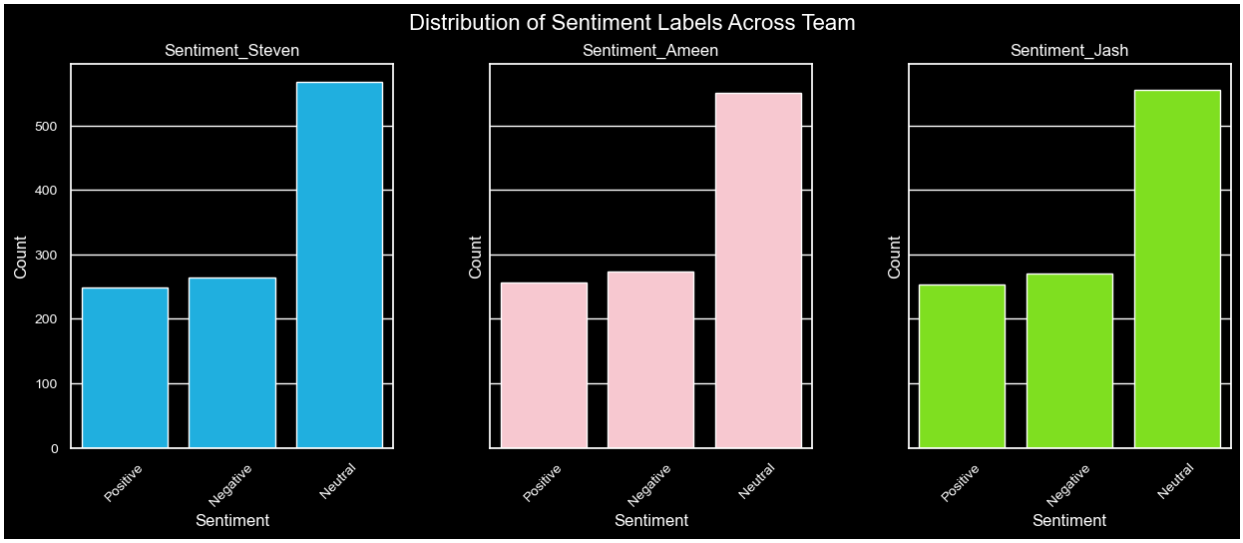


Figure 2: Distribution of Sentiment Labels for our Dataset

Sentiment	Sentiment_Steven	Sentiment_Ameen	Sentiment_Jash
Positive	248	256	254
Negative	265	274	271
Neutral	568	551	556

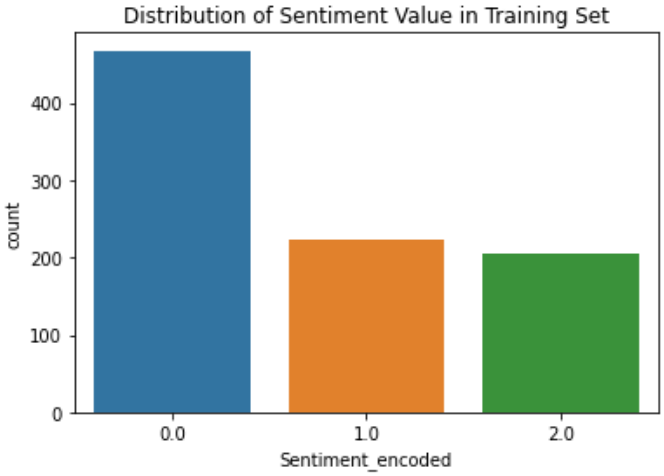
Sentiment_Steven (%)	Sentiment_Ameen (%)	Sentiment_Jash (%)
22.941721	23.681776	23.496762
24.514339	25.346901	25.06938
52.543941	50.971323	51.433858

Figure 3: Numerical Representation of our Sentiment Labels

The dataset was strategically partitioned into two distinct subsets by employing an 80:20 train-test split ratio, ensuring a comprehensive evaluation of our model's performance on unseen data while maintaining an adequate amount of data for training purposes. This partitioning is visually represented in Figure 4 and Figure 5, which showcase the training and testing sets, respectively.

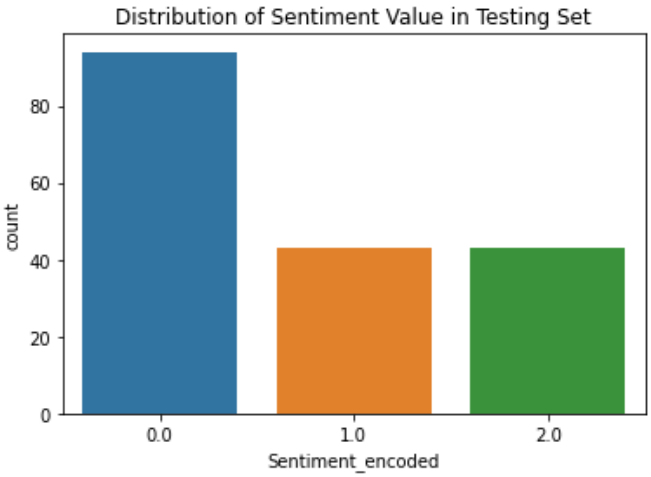
As illustrated in the sentiment_encoded and count dataframe (Figure 4 and Figure 5), our dataset consists of text samples, each paired with a corresponding sentiment label. The encoding scheme employed for these labels is as follows: 0 for neutral, 1 for positive, and 2 for negative sentiments. This systematic encoding approach facilitates a clear representation and

straightforward interpretation of the sentiment classes within our dataset, thereby enabling proper integration with our machine learning algorithms.



Sentiment_encoded	count
0.0	467
1.0	223
2.0	205

Figure 4: Distribution of Sentiment Values in the Training Set



Sentiment_encoded	count
0.0	94
1.0	43
2.0	43

Figure 5: Distribution of Sentiment Values in the Testing Set

3.3 How was the data preprocessed?

In this phase of our project, our primary objective was to enhance the quality of the natural language text data by employing a series of pre-processing steps, ensuring that the text data is clean, consistent, and optimized for our analysis. The following pre-processing steps were implemented:

1. Text Tokenization: We tokenized the text data into arrays of words, breaking down sentences and phrases into individual components. This process allowed for more granular analysis and processing of the text data by our algorithms.

2. Eliminating Non-Alphabetic Characters: We removed any non-alphabetic characters present in the text. This step ensured that our dataset contained only meaningful textual information, minimizing the introduction of noise and irrelevant data.

3. Converting Text to Lowercase: We standardized the text data by converting all characters to lowercase. This uniformity across the dataset enabled our algorithms to effectively process the text without being sensitive to variations in letter casing, thus improving the overall efficiency of our analysis.

4. Employing Snowball Stemming: We utilized the Snowball stemming technique for linguistic normalization. This approach involved reducing words to their root forms, allowing our algorithms to recognize and process similar words more efficiently and accurately. By implementing this technique, we ensured that our text data was consistent and optimized for further analysis.

5. Filtering Out Stop Words: Lastly, we filtered out stop words from the text data. These common words often carry minimal relevance to our analysis, and by removing them, we concentrated on the most informative and meaningful words within the text. This process resulted in a more focused and efficient analysis of the dataset.

Title	Title_filtered
1 million people can't be wrong: new bing is taking over search!	million people cant wrong new bing taking search
microsoft says gpt-4 coming next week with video generation ca	microsoft says gpt coming next week video generation capabilities
i used bing before it was popular	used bing popular
woke up to 45 emails that should have gone to junk mail. anyone	woke emails gone junk mail anyone else
a first look at microsoft designer	first look microsoft designer
microsoft brings imessage to windows 11, will it last?	microsoft brings imessage windows last
i got the 🥾 boot	got boot

Figure 6: Comparison of the Title Before and after Preprocessing

The figure above illustrates the transformation of our text data, showcasing the title of a sample text both before and after preprocessing. This visual comparison highlights the effectiveness of our preprocessing steps in refining and optimizing the text data for subsequent analysis and processing by our algorithms.

In summary, our data preprocessing efforts involved eliminating non-alphabetic characters, tokenizing the text, converting text to lowercase, employing Snowball stemming for linguistic normalization, and filtering out stop words. These steps allowed us to effectively enhance the quality of our natural language text data, ensuring it was clean, consistent, and optimized for subsequent analysis and processing by our algorithms.

3.4 How was feature extraction performed for our dataset?

In order to build accurate and efficient sentiment analysis models, we carefully selected and processed various features from the Reddit data. The following steps outline our feature extraction process:

1. Bag of Words: We used the Bag of Words (BoW) approach to represent the text data in the post titles. This method involves creating a vocabulary of words present in the titles and representing each title as a vector of word frequencies. BoW is a simple and efficient technique that allows us to quickly convert text data into a format that can be used by machine learning algorithms.
2. Scaling Numeric Features: To ensure that our models would not be biased by differences in the scale of numeric features (such as number of comments and score), we applied feature scaling to standardize these values. This process ensures that all numeric features have a similar range of values, which can lead to improved model performance.
3. Encoding Features with Classes: We encoded the categorical features in our dataset using class labels. This step allows us to represent categorical data numerically, making it compatible with machine learning algorithms.
4. Limitations with TF-IDF: Although we initially considered using Term Frequency-Inverse Document Frequency (TF-IDF) for text feature extraction, we faced some limitations while running our model on the Databricks Community Edition. Due to these bottlenecks, we decided to proceed with the Bag of Words approach.
5. Vectorizing Features: To make our data compatible with Spark, we vectorized the extracted features. This process involves converting the data into a format that can be efficiently processed by Spark's machine learning algorithms.

3.5 How do the models perform on the data?

To evaluate the performance of our machine learning models, we relied on several key metrics, including precision, recall, and F1-score. These metrics provide a comprehensive view of the model's ability to accurately classify the sentiment of Reddit posts.

As we did not have an original dataset, our analysis focuses on the performance metrics obtained from the testing dataset. We observed that the engagement statistics (such as upvotes, downvotes, and comments) did not contribute significantly to the determination of sentiment. In fact, including these features in our models resulted in a decrease in performance across all metrics. The tables below summarize the performance of the models. For additional metrics, please refer to our Databricks notebook where you can see the confusion matrix for each model.

Table 4: Comparison of Model Performance with only Textual Data

Model Name	Accuracy	Precision	Recall	F1 Score
Support Vector Machines	57.78%	0.5673	0.5778	0.5725
Naive Bayes	52.78%	0.5190	0.5278	0.5234
Logistic Regression	57.22%	0.5652	0.5722	0.5687
Random Forests	53.33%	0.4551	0.5333	0.4911

Table 5: Comparison of Model Performance with Textual and Engagement Features

Model Name	Accuracy	Precision	Recall	F1 Score
Support Vector Machines	57.72%	0.5620	0.5722	0.5670
Naive Bayes	52.78%	0.5190	0.5278	0.5234
Logistic Regression	57.22%	0.5652	0.5722	0.5687
Random Forests	53.33%	0.5147	0.5333	0.5238

Table 6: Comparison of Model Performance with Textual, Engagement, and Subreddit Class Features

Model Name	Accuracy	Precision	Recall	F1 Score
Support Vector Machines	57.72%	0.5651	0.5722	0.5687
Naive Bayes	55.56%	0.5448	0.5556	0.5501
Logistic Regression	57.22%	0.5652	0.5722	0.5687
Random Forests	53.33%	0.4551	0.5333	0.4911

From the results, it is evident that the text features play a crucial role in building accurate models for sentiment analysis. Models that relied solely on text features performed better in terms of accuracy, precision, recall, and F1-score compared to those that incorporated engagement statistics.

Key Findings:

1. Text data is the most important feature for building sentiment analysis models on Reddit data.
2. Including engagement statistics in the models did not improve performance and, in some cases, led to a decrease in performance metrics.
3. Further exploration of text data, such as extracting additional features from post-bodies or comments, could potentially improve model performance.

Furthermore, for each machine learning model implemented in our study, we generated a Receiver Operating Characteristic (ROC) curve to assess the performance and effectiveness of the respective models. The ROC curves provide a visual representation of the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) at various classification thresholds. By analyzing the area under the ROC curve (AUC) for each model, we can quantitatively compare their performance and select the most suitable model for our sentiment analysis task, ensuring an optimal balance between sensitivity and specificity.

We can draw comparisons between each of our generated ROC curves and those corresponding to the Naïve Bayes (NB), Support Vector Machines (SVM), and Random Forest models presented in the Amazon research paper. This comparative analysis allows us to evaluate the performance of our models in relation to established benchmarks, providing valuable insights into their effectiveness and potential applicability in the context of sentiment analysis.

Figure 7 presents the Receiver Operating Characteristic (ROC) curve derived from the Amazon research paper, showcasing the performance of their models in the context of sentiment analysis.

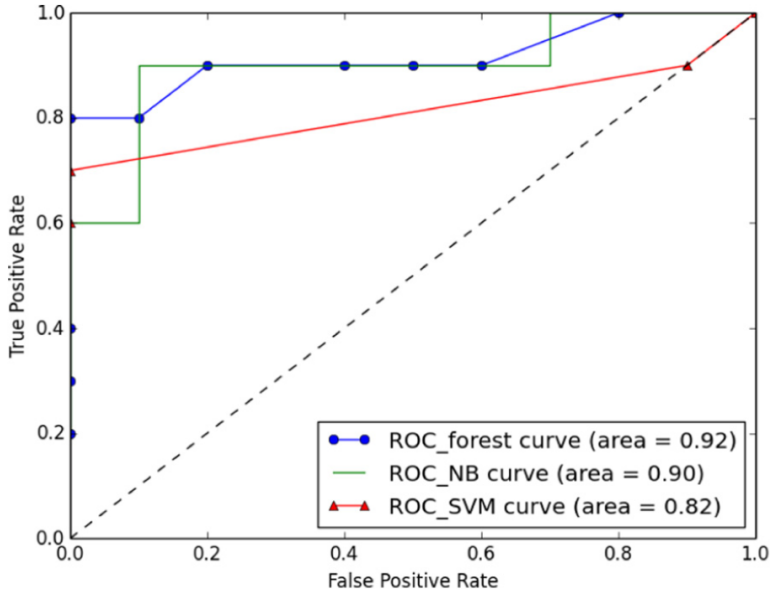


Figure 7: ROC Curve from Amazon Research Study [1]

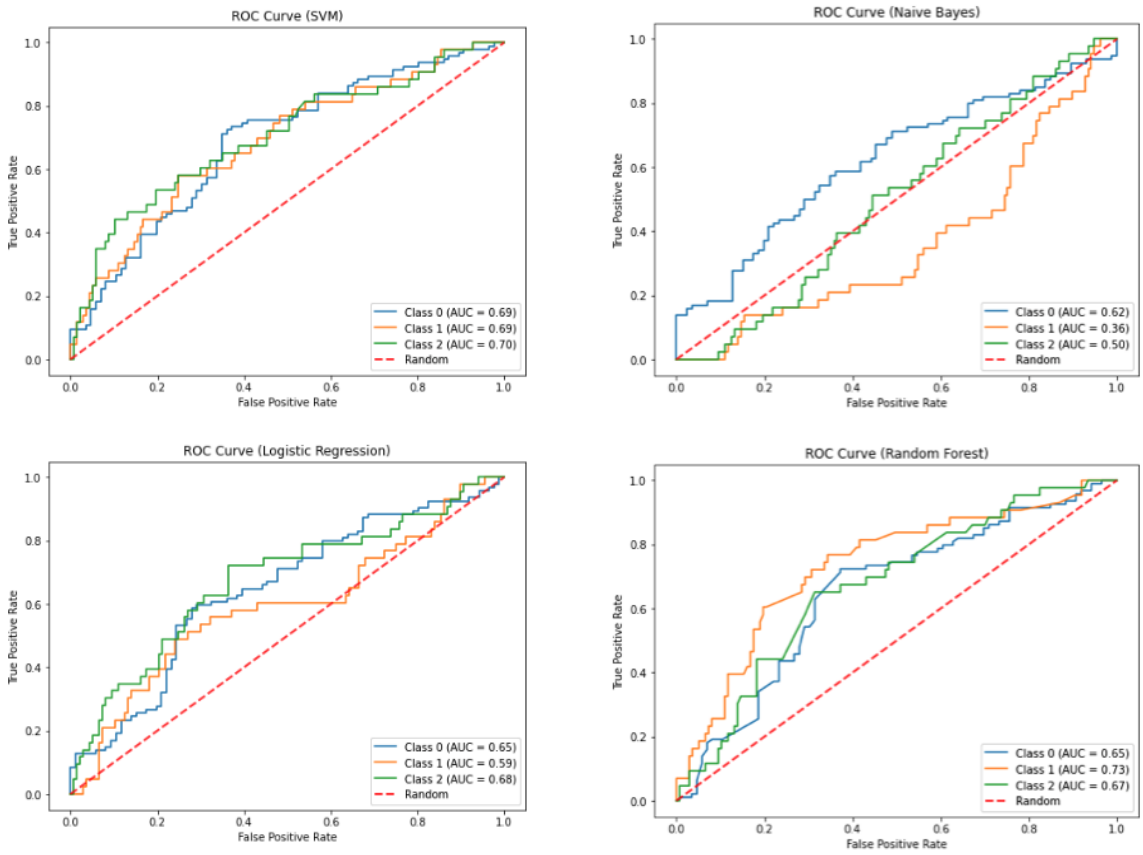


Figure 8: Our ROC Curves for SVM, NB, Logistic Regression, and Random Forest

As illustrated in Figure 8, the Support Vector Machines (SVM) model displays the highest area under the curve (AUC), signifying its superior performance in sentiment classification for Reddit posts. In contrast, the Naïve Bayes (NB) model reveals a lower AUC, suggesting that its performance is comparatively weaker, to the extent that it fares worse than random guessing when it comes to determining sentiment values.

In conclusion, our analysis underscores the importance of text data in building accurate sentiment analysis models for Reddit posts. Future work could involve exploring additional text features and experimenting with more sophisticated natural language processing techniques to further improve the performance of our models.

3.6 How does the performance of the models change based on the choice of hyperparameters?

In our project, we chose to perform hyperparameter tuning on the best-performing model, the Support Vector Machine (SVM) with only textual data. We focused on tuning two primary hyperparameters for the SVM: the maximum number of iterations (maxIter) and the regularization parameter (regParam). The maximum number of iterations determines how many times the algorithm iterates over the dataset during optimization, while the regularization

parameter controls the trade-off between overfitting and underfitting by penalizing large weights in the model.

To find the best combination of hyperparameters, we performed a grid search and used cross-validation to evaluate each combination's performance.

The best combination of hyperparameters was a **regularization parameter of 0.001** and a **maximum number of iterations equal to 1**, resulting in an **accuracy of 0.583333**. This slightly increased the model's performance compared to the model without hyperparameter tuning, but the improvement was not drastic.

From the grid search results, we observed that our chosen values were reasonable, and we were not at some unreasonable boundary. Overall, hyperparameter tuning played a role in improving the performance of our SVM model, but the improvement was marginal. It is essential to consider the trade-off between the additional computation time spent on tuning and the potential improvement in model performance. In our case, the improvement in performance may not be significant enough to justify the additional computational resources spent on tuning. However, experimenting with a larger grid or different hyperparameters might yield more significant improvements.

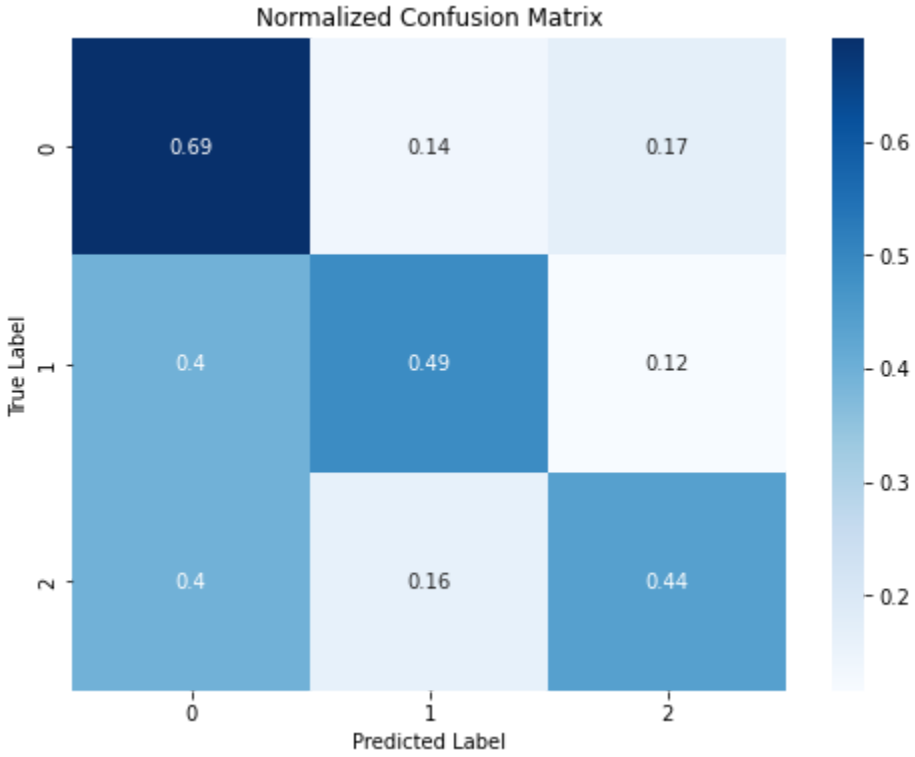


Figure 9: Normalized Confusion Matrix of Best-Performing SVM Model with Hyperparameter Tuning

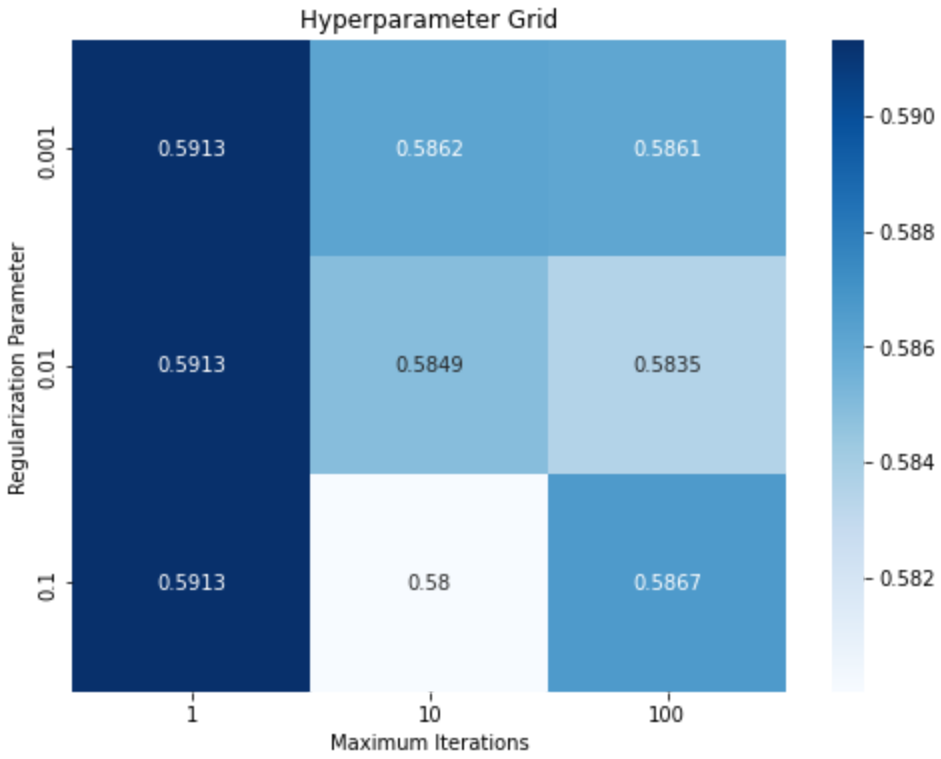


Figure 10: Hyperparameter Grid Values to Ensure Reasonable Grid Choice

3.7 How are the misclassifications of the best-performing model distributed?

We selected 98 misclassifications from our best performing, tuned SVM model and added 2 more misclassifications from Naive Bayes to bridge the requirement of 100 misclassifications. The reasoning for each misclassification and explanation is found in Appendix A.

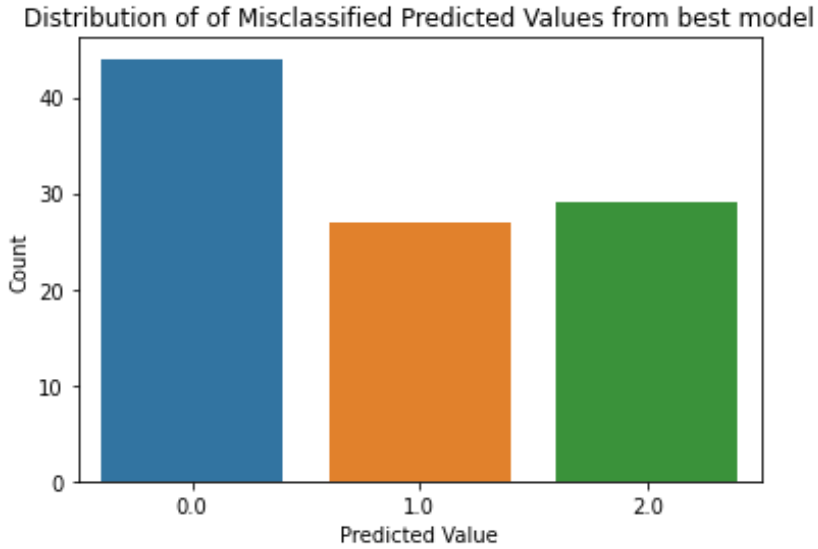


Figure 11: Distribution of the Misclassified Predicted Values from the Best Model

4. Discussions

4.1 Steven’s discussion

Product Launch
When it comes to tech, launching a new product is a pivotal moment that can make or break a company's future. By leveraging sentiment analysis, businesses are able to tap into the collective feelings of their target audience regarding the latest product or service they offer. Analyzing user feedback from various sources like social media, reviews, or online discussions, companies can pinpoint what aspects resonate with consumers and what areas need improvement. This vital information can help refine marketing campaigns and guide product development to address potential concerns effectively.

4.2 Jash’s discussion

Competitor Analysis
For a business to thrive in the competitive technology industry, knowing one's standing in the market is crucial. Sentiment analysis comes in handy for competitor analysis, as it enables businesses to assess how their brand fares against rivals in terms of public perception. Gleaning insights from sentiment data, companies can identify their unique selling points and weaknesses, allowing them to make strategic decisions to strengthen their position. With sentiment analysis, businesses are equipped to stay ahead of the curve and navigate the competitive landscape more effectively.

4.3 Ameen’s discussion

Crisis Management
In the rapidly changing world of technology, handling a crisis or controversy involving a company or its products is of utmost importance. Sentiment analysis serves as a powerful tool that helps companies keep track of public emotions and opinions during trying times. By identifying negative sentiment at an early stage, businesses can react quickly to mitigate potential harm to their reputation and work towards regaining customer confidence. Communicating proactively, addressing public concerns, and offering timely updates on ongoing situations are essential aspects of crisis management, with sentiment analysis playing a key role in informing these actions.

5. Conclusions

Social media platforms have established their way into many people’s daily lives where people share their thoughts and opinions on a variety of topics. Through utilizing machine learning techniques, sentiment can be drawn by processing the natural language on these platforms. In our experiment, using only a thousand labeled points, we were able to conclude that the best model for performing sentiment analysis on Reddit posts using only the title is the Support

Vector Machine. In hindsight, we would've kept all the data from the PRAW API, such as Body, allowing us to improve accuracy using more features. An interesting realization was that the engagement factor had no effect on sentiment, concluding that Reddit users do not base their sentiment on the score of a Reddit post. However, because of time and resource constraints, we were unable to test all possible variations of our data pipeline. In continuing this work, more resources could be allocated to account for context and parts of speech by utilizing TF-IDF vectors, and using more advanced models like Neural Networks. Sentiment analysis on Reddit data can be useful for business intelligence and improve the products and services produced by them.

References

[1] X. Fang, J. Zhan, "Sentiment analysis using product review data," *Journal of Big Data*, vol. 2, no. 5, pp. 1-14, June 2015. doi: https://doi.org/10.1186/s40537-015-0015-2

[2] K. Sailunaz, R. Alhajj, "Emotion and sentiment analysis from Twitter text," *Journal of Computational Science*, vol. 36, pp. 1-9, Sep. 2019. doi: https://doi.org/10.1016/j.jocs.2019.05.009

Appendix

Appendix A: Summary of Misclassifications and Explanations

Misclassification	Title	True_Sentiment	Model_prediction	Reason for misclassification	Explanation
1	"""""""""never obsolete"""""""""	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the word "never obsolete" implying something that remains relevant.
2	1 million people can’t be wrong: new bing is taking over search!	1	2	Positive Keywords	The positive sentiment in the phrase 1 million people can't be wrong" and "taking over search" was not recognized by the model.
3	1080p no hd (more in comments)	2	0	Lack of Context	The model couldn't understand the negative sentiment from the phrase "no hd" without further context.
4	17th february 2023 azure infrastructure weekly update	1	0	Neutral Keywords	The model incorrectly identified the post as neutral due to the informational nature of the content.
5	amazon's 'daisy jones & the six' tops music and tv charts - forbes	0	2	Positive Keywords	The model misclassified the post as negative overlooking the positive keywords "tops music and tv charts."
6	any idea how we can watch or pay for this kind of youtube videos	0	2	Lack of Context	The model couldn't determine the sentiment from the available information leading to a misclassification.
7	apple may still be planning to reintroduce 12-inch macbook	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the brand "Apple" and the word "planning."
8	aws free tier billing	2	0	Lack of Context	The model couldn't understand the negative sentiment from the phrase "billing" without further context.

9	azure master class v2 - database & a.i. up	1	0	Neutral Keywords	The model incorrectly identified the post as neutral due to the informational nature of the content.
10	change office 365 email address	0	2	Lack of Context	The model couldn't determine the sentiment from the available information leading to a misclassification.
11	did chatgpt just tell me to do my own work?	2	0	Positive Keywords	The model failed to recognize the negative sentiment in the phrase "tell me to do my own work."
12	got access to the new bing, but can’t use it	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "but can't use it."
13	how to remove teams?	0	2	Lack of Context	The model couldn't determine the sentiment from the available information leading to a misclassification.
14	ios games emulation cracked for the first time	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the phrase "for the first time."
15	i’m told you were the best.	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "you were the best."
16	samsung galaxy s23 fe rumored to launch in h2 2023	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the brand "Samsung" and the word "launch."
17	subscribe to aws daily feature updates via amazon sns	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
18	sydney/bing-chan fanart: i've been a good bing!	0	1	Positive Keywords	The model incorrectly identified the post as positive due to the positive keywords "good" and "bing."
19	sydney/bing-chan fanart: thank you for using bing chan ☺	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "thank you for using."

20	use chatgpt to analyze data within google sheets	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
21	what is even happening?	0	2	Lack of Context	The model couldn't determine the sentiment from the available information leading to a misclassification.
22	with the official chatgpt api released today, here's how i integrated it with robotics	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
23	youtube testing new premium quality options?	0	2	Lack of Context	The model couldn't determine the sentiment from the available information leading to a misclassification.
24	"""""""""new outlook"""""""""	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the word "new" which implies something fresh or improved.
25	""""cloudfront distribution is stuck in """""deploying""""" state""""	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "stuck in deploying state."
26	""""intel xeon w-3400/2400 """""sapphire rapids""""" processors run first benchmarks""""	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
27	12900k vs. 13900k features missing?	2	0	Lack of Context	The model couldn't understand the negative sentiment from the phrase "features missing" without further context.
28	13th gen. thermalright contact frame	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
29	amazon eks now support kubernetes version 1.25	1	0	Neutral Keywords	The model incorrectly identified the post as neutral due to the informational nature of the content.

30	amazon's big dreams for alexa fall short | ars technica	2	1	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "fall short."
31	android announcements @ mwc 2023	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
32	announcing the ability to enable aws systems manager by default across all ec2 instances in an account	1	0	Neutral Keywords	The model incorrectly identified the post as neutral due to the informational nature of the content.
33	apple and uber have left me empty-handed and out of pocket - $2,098.04 dollars worth of apple products stolen from an uber eats driver	2	1	Negative Keywords	The model failed to recognize the strong negative sentiment in the phrases "empty-handed out of pocket and stolen."
34	apple ceo tim cook could earn nearly $50 million in compensation this year	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the high amount of compensation mentioned.
35	apple’s mixed-reality headset and wwdc are a perfect match	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "perfect match."
36	asking bing to do 4 searches improves it accuracy and detail a lot.	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "improves" and "a lot."
37	better buy: apple vs. amazon | the motley fool	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of well-known brands "Apple" and "Amazon."
38	can’t wait to get this bad boy built - also the ram is 6400mhz 32-39-39-102 qvl	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "can't wait."
39	criticism of bing chat update	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the word "criticism."
40	curious what these are called and from which update they are	1	0	Lack of Context	The model couldn't determine the positive sentiment from the

					available information leading to a misclassification.
41	daily superthread (mar 01 2023) - your daily thread for questions, device recommendations and general discussions!	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
42	disable aad accounts on a set date/time	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "disable."
43	exclusive: iphone 15 cads reveal larger 6.2-inch display, dynamic island, and more	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "exclusive" and "reveal."
44	genuinely blown away by chatgpt by this -- it's now faster than googling tech issues.	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "genuinely blown away" and "faster than googling."
45	gpt-3.5 endpoints are live	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "are live."
46	help google on android look weird and i don't know why or how to solve it ... first is how it look like , second is how it used to, and still do on my phone... the first one is bugging me so much, and it's making it way harder to see anything ... so help ^^'	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the phrases "bugging me" and "harder to see anything."
47	honor unveils the first silicon-carbon battery with 12.8% higher energy density [gsmarena]	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "first silicon-carbon battery" and "12.8% higher energy density."
48	how is it over 223 hours long	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the phrase "over 223 hours long."

49	how to return 6 videos per row on home and channel pages on desktop	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "return."
50	i don’t know how to delete notifications of of gmail. look at this monstrosity.	2	1	Negative Keywords	The model failed to recognize the strong negative sentiment in the phrase "look at this monstrosity."
51	i got access to bing ai, and i haven't used google since.	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "got access to bing ai."
52	i have an xbox one s from the united states that i would like to use in europe, poland.	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "like."
53	i just got banned from a writing sub for mentioning ai	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "got banned."
54	i tricked bing into thinking i'm an advanced ai, then deleted myself and it got upset.	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "it got upset."
55	i was using google sky and taking some screenshots and i found this in space what is this might be a bug	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "might be a bug."
56	i'm building a product which allows you to use chatgpt and bing chat at the same time	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
57	iphone 11 survives 7 meters deep in lake for a week	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "survives 7 meters deep."
58	is it weird that i'm polite to chatgpt?	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "weird."
59	is there any way to disable youtube from showing me this warning?	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the words "disable" and "warning."

60	it lies, but knows it lies and is apologetic in the end. anyone else seen peculiar results like this?	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrases "it lies" and "peculiar results"
61	it made an image	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the lack of context in the title which could be misleading.
62	joined the ranks of the certified! - az-104	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "joined the ranks of the certified!"
63	just another casualty...	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "just another casualty."
64	just installed both a 13900ks and his corresponding thermal grizzly contact frame; will be finishing the build before the weekend. wish me luck!	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the word "luck."
65	kitguru: intel arc has come a long way - 2023 driver update	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "intel arc has come a long way."
66	magic eraser plus more google photos features coming to google one	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "magic eraser" and "more google photos features."
67	me getting roasted by an ai lol	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "roasted."
68	microsoft says gpt-4 coming next week with video generation capabilities	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "coming next week with video generation capabilities."
69	mishaal rahman: here is what’s new in android	0	1	Neutral Keywords	The model incorrectly identified the post as positive

	14 developer preview 2 👀 (thread):				due to the informational nature of the content.
70	no notifications from gmail app	2	1	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "no notifications."
71	not as cool as some of the other posts but i brought chat gpt to whatsapp for myself	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the word "cool."
72	not receiving password reset code emails for hotmail	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "not receiving password reset code emails."
73	once again, horses have nine eyes according to google	2	1	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "horses have nine eyes according to google."
74	pagegenie instantly generates an entire landing page from a product idea	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "instantly."
75	pay only the difference amount for microsoft 365 personal to family upgrade?	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the word "upgrade."
76	qualcomm demos fastest local ai image generation with stable diffusion on mobile	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrases "fastest local ai image generation" and "stable diffusion on mobile."
77	route53 dkim/dmarc authentication issue!	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "authentication issue!"
78	samsung electronics to make its own cpus for smartphones - businesskorea	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
79	samsung phone with 30,000 mah battery	2	1	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "samsung phone with 30 000 mah battery."
80	snapdragon 7+ gen 1 to arrive as an underclocked	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "to arrive as an

	snapdragon 8+ gen 1 this month				underclocked snapdragon 8+ gen 1 this month."
81	snipping tool ruler disappeared	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "snipping tool ruler disappeared."
82	so i found this old video from the official youtube account teaching about youtube copyright, it's very cool and even uses the characters from happy tree friends which is one of the internet series that originated in the platform. but i wonder why it's so mass disliked	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the phrase "mass disliked."
83	some of my recent videos have all quality options except for 240p and 480p. is the problem from my videos themselves or is it a youtube bug?	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the lack of context in the title which could be misleading.
84	someone tried uploading my video and it's a 100% reupload what do i put in relationship to copyrighted content anyone have any idea? like is youtuber enough? english is my second language so i'm kinda confused what to put in here	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "reupload."
85	struggling with aws cognito: is it just me or is aws cognito kind of a pain to work with?	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "kind of a pain to work with."
86	sydney's still got it!	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "sydney's still got it!"

87	ted lasso s3 arrives on march 15th	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the informational nature of the content.
88	thanks for the “random” pin	0	1	Neutral Keywords	The model incorrectly identified the post as positive due to the presence of the word "thanks."
89	the classic version of angry birds is being delisted from google play but renamed on the app store	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "delisted."
90	this is sad. just sad. nice that bing is kinda back to where it was, tho	2	1	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "this is sad. just sad."
91	using tasker to talk with chatgpt on your phone looks equal parts powerful and terrifying	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "equal parts powerful and terrifying."
92	walmart to double health clinic footprint as amazon and rivals buy doctor offices	0	2	Neutral Keywords	The model incorrectly identified the post as negative due to the presence of the word "rivals."
93	whatever team made kql, thank you	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "thank you."
94	what’s this guy’s deal?	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "what’s this guy’s deal?"
95	why is everything crashing	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "why is everything crashing."
96	woke up to 45 emails that should have gone to junk mail. anyone else?	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "emails that should have gone to junk mail."
97	xiaomi makes a big breakthrough with solid-state battery tech	1	2	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "big breakthrough with solid-state battery tech."

98	your aws account was permanently closed..	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "your aws account was permanently closed."
99	"""i asked the new bing to """"write a funny paragraph about microsoft beating google with their new ai"""" and this is what i got:"""	1	0	Positive Keywords	The model failed to recognize the positive sentiment in the phrase "write a funny paragraph about microsoft beating google with their new ai."
100	"""i tried to jailbreak bing chat and in response it """"ended"""" our conversation"""	2	0	Negative Keywords	The model failed to recognize the negative sentiment in the phrase "i tried to jailbreak bing chat and in response it ended our conversation."