Twitter Sentiment Analysis

Outline

Overview

- Project Objective - Analyze customer feedback through Twitter to gauge sentiment toward products.

- Dataset - Over 9,000 tweets sourced from <u>CrowdFlower.</u>

 Sentiment Labels - Tweets are categorized as positive, negative, or neutral, facilitating targeted analysis.

Business Understanding

In today's digital landscape, understanding customer feedback is a crucial step in maintaining brand reputation and enhancing customers reputation social media platforms like twitter provide an abundance of feedback where user express their opinions

Key Objectives:

- Determine sentiment around brands/products to enhance customer satisfaction.
- Address critical questions about negative themes and product perception.

Sub-objectives:

- 1. Gather and preprocess relevant data.
- 2. Conduct exploratory data analysis (EDA) to identify trends.
- 3. Develop and compare machine learning models for sentiment classification.
- 4. Evaluate model performance and provide actionable insights.

Data Understanding

The dataset consists of user tweets about specific products or brands, with labeled sentiments. Sourced from data world

tweet_text: The raw text of the tweet, which serves as the primary source of information for understanding user sentiment.

motion_in_tweet_is_directed_at: This column specifies which product or brand the tweet is referring to (e.g., iPhone, Google).

emotion_in_tweet_is_directed_at: This column specifies which product or brand the tweet is referring to (e.g., iPhone, Google).

Data Pre-Processing

Text Cleaning Process:

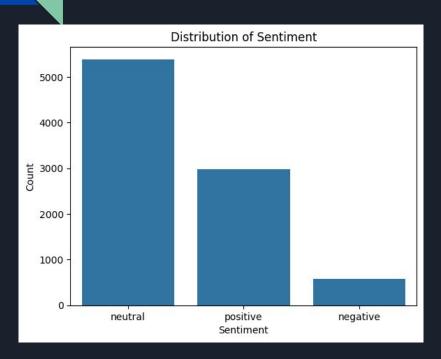
- Removed irrelevant elements: mentions, URLs, hashtags, emojis, and special characters.
- Tokenization: Split text into individual tokens for analysis.
- Stopword Removal: Eliminated common words (e.g., "and," "the") using NLTK.
- Lemmatization: Standardized word forms to reduce inflected words to their base form.
- Result: Cleaned text stored in a new `cleaned_text` column for feature extraction.

Exploratory Data Analysis

Visualizations Conducted:

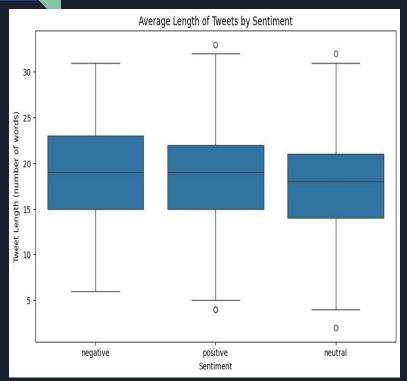
- **Count of Sentiments**: Distribution of sentiment types in the dataset to gauge overall public opinion.
- **Sentiment Distribution by Product**: Insights into how sentiments differ across products, revealing brand-specific perceptions.
- **Average Tweet Length by Sentiment**: Analyzed tweet lengths to identify potential patterns in sentiment expression.
- **Most Common Tokens**: Identified frequently used words to uncover prevalent themes in customer feedback.
- **Word Cloud**: Visual representation of common terms, emphasizing significant keywords in tweets.

Distribution of Sentiment



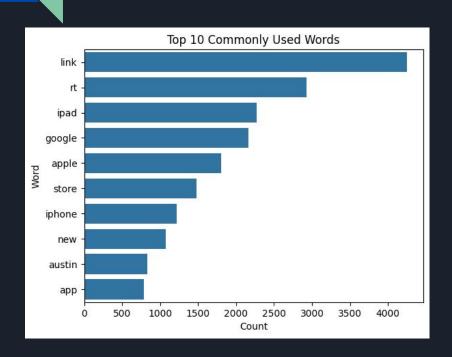
Neutral sentiments are the highest indicating that a large portion of the tweets are mostly informational about the products being reviewed. Positive sentiments outweighs negative sentiment by a significant difference which would indicate good performance and the clients are happy about the products that they own.

Average Length of of tweets by Sentiment



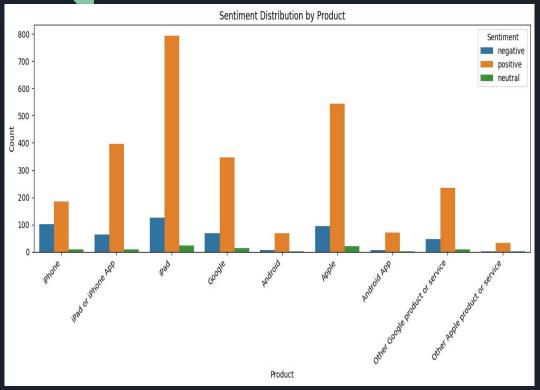
The above box plot indicates that the average length of tweets is relatively similar across sentiments, with negative tweets being slightly longer on average which could indicate that users tend to provide more explanation or context when expressing criticism or dissatisfaction.

Top 10 Commonly Used Words



The above bar graph shows the top 10 most commonly used words, with link appearing the most than others. This suggests that sharing links was a common practice during the discussions on rating Google and Apple products. The high frequency of rt which is presumably short for retweet indicates that content was shared and amplified widely. iPad and iPhone were the Apple products that were discussed the most.

Sentiment Distribution by Product



- 1. Apple products (iPad, iPhone, Apple in general) consistently show high levels of positive sentiment, suggesting strong user satisfaction and excitement about these products.
- The iPad stands out with the highest count of positive sentiment, which could indicate it was a major topic of interest, possibly due to a recent or anticipated release.
- 3. While Google also receives more positive than negative sentiment, the ratio isn't as favorable as Apple's. This could suggest a stronger brand affinity or product satisfaction among Apple users in this dataset.
- 4. Android has a relatively low count of mentions compared to iOS devices, but still maintains a positive skew. This might indicate less buzz around Android at this particular scenario, but still a generally positive perception.
- 5. Both "iPhone App" and "iPad or iPhone App" categories show strong positive sentiment, highlighting the importance of the app ecosystem in user satisfaction for these platforms.

Word Cloud



While the bar graph gave us the top 10 common words, the word cloud shows us more words that were common during the opinion review of the products. Upon further research The prominence of Austin and SXSW suggests that much of the opinions were centered around the South by Southwest (SXSW) conference, an annual event held in Austin, Texas that focuses on technology, film, and music. The large presence of terms like app, Google, iPad, iPhone, launch, new and partyindicates that the technology aspect of the SXSW conference was the major focus with the discussion being around cutting-edge innovations on Google and Apple products.

Evaluation

Accuracy: The Logistic Regression model has a slightly higher accuracy (68.23% vs. 64.32%).

Precision: Logistic Regression outperforms Random Forest in precision for both the Neutral (70% vs. 74%) and Positive (62% vs. 53%) classes.

Recall: Logistic Regression has significantly higher recall for the Neutral class (87% vs. 72%) and a higher recall for the Positive class (45% vs. 57%).

F1-Score: Logistic Regression provides a better F1-Score across the board, particularly for identifying churned customers.

Conclusion:

The Logistic Regression model, after tuning, is superior in terms of overall accuracy, precision, recall, and F1-Score compared to the Random Forest model. It offers a more reliable approach for accurately identifying churned and non-churned customers in this dataset.

Limitations

- 1. Class Imbalance: The dataset exhibits a significant class imbalance, particularly between the churned (True) and non-churned (False) classes. This imbalance can lead to biased model performance, where the model may perform well on the majority class (non-churned) but poorly on the minority class (churned).
- Feature Relevance and Data Quality: Some features in the dataset, such as state and area_code, may have limited relevance to the target variable (churn). Including irrelevant features can introduce noise and negatively affect model performance. Additionally, missing or inaccurate data entries could impact the quality of predictions.
- 3. Overfitting Risk: The Random Forest model, particularly after hyperparameter tuning, shows reasonably high accuracy. However, such performance could indicate overfitting, where the model performs exceptionally well on the training and test datasets but may not generalize effectively to unseen data.
- 4. Model Interpretability: While the Random Forest model is effective, its complexity can make it less interpretable, especially with extensive hyperparameter tuning. This complexity might hinder the understanding and explanation of the decision-making process, which can be a drawback for deployment in real-world applications where model transparency is crucial.
- 5. Performance Variability: The performance of the models may vary with different subsets of data or if the data distribution changes over time. This variability can affect the reliability of the model when used in production, leading to potential issues if the model encounters data that significantly deviates from the training data.

Conclusions

- 1. Sentiment analysis is an effective way of understanding customer opinions and feelings in regards to the product. Twitter provides a massive and organic source of feedback, which allows businesses to keep a pulse on customer satisfaction and brand reputation.
- 2. Analysing brand sentiment insights in tweets will help identify how customers feel about various products or services. You can uncover the products or brands that receive the most positive or negative feedback, which provides insight into customer satisfaction levels.
- The analysis can assist companies in identifying new patterns or persistent problems linked to poor sentiment. This helps identify client issues, such as complaints about certain product features, problems with delivery, or with customer support.
- 4. Regular monitoring of social media sentiment enables brands to respond quickly to negative feedback before it escalates, allowing them to protect or improve their reputation.
- Understanding how customers perceive products and services across different categories will allow businesses to focus on improving areas that matter most to their customer base.

Recommendations

- Automate Sentiment Analysis: Implement an automated sentiment analysis system using natural language processing (NLP) to categorize tweets into positive, negative, or neutral.
 This can be scaled to handle large volumes of data efficiently.
- Monitor Negative Sentiment Themes: Classifying and evaluating recurrent themes or problems in bad tweets will enable the company to identify the underlying causes of dissatisfied customers and implement corrective measures.
- 3. Integration with Product Development: Share sentiment insights with product development teams so they can make data-driven improvements to products or services, aligning them more closely with customer expectations.
- 4. Competitor Benchmarking: Use the sentiment research findings to assess how customers view your brand in relation to those of your competitor. This might assist in determining the strong and weak points of your brand.
- 5. Customer Engagement Strategy: Create focused customer engagement strategies based on the analysis results. For instance, thank users for their favorable remarks and swiftly address any negative feedback they may have received.