Twitter Sentiment Analysis

Analyzing Sentiment on Apple and Google Products Using NLP

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Phase: Phase 4

TABLE OF CONTENTS

SUMMARY

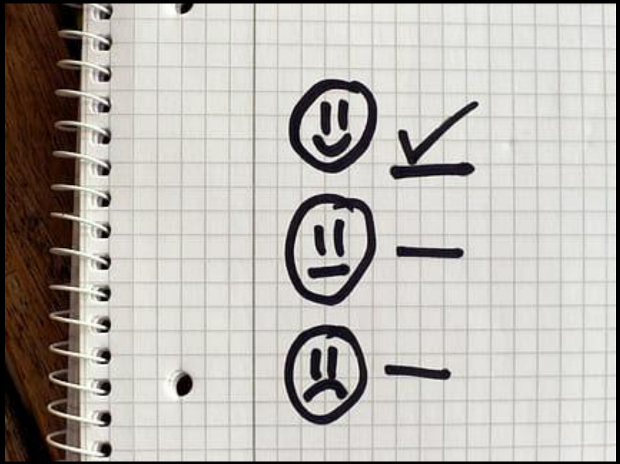
- Built a robust NLP model to classify Twitter sentiment (positive, neutral, or negative).
- Final model: Refined deep learning approach achieving 84% accuracy.
- Provides actionable insights to improve customer satisfaction, product development, and marketing strategies.

BUSINESS PROBLEM

- Stakeholder: Consumer Insights Startup.
- Goal: This project builds an NLP model to analyze sentiment in tweets about Apple and Google products.
- Why It Matters:
  - Identify customer satisfaction trends.
  - Improve marketing and product strategies.

DATA

- Source: CrowdFlower via data.world.
- Size: 9,093 tweets labeled as negative, neutral, or positive.
- Key Features: Text of tweets, sentiment labels, and product mentions.



METHODS

- Preprocessing: Cleaned data, handled missing values, and addressed class imbalance.
- EDA: Explored sentiment distribution and key product mentions (e.g., word cloud).
- Modeling:
  - Baseline: Logistic Regression.
  - Final Model: Refined deep learning model (embedding, convolutional, and LSTM layers).
  - Evaluation: Accuracy, F1-scores, and ROC AUC.

RESULTS

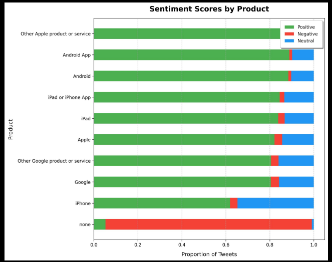
- Accuracy: 84.00%
- F1-Score (Macro Average): 84.00%
- Class-Specific Insights:
- Positive sentiment: F1-Score = 0.97.
- Neutral and negative classes show balanced improvements.

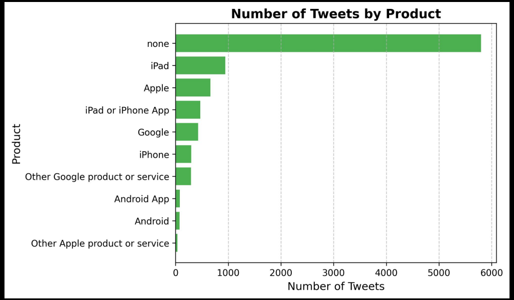
RECOMMENDATIONS

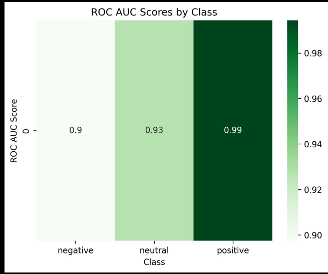
1. Targeted Marketing Campaigns:
   - Focus marketing efforts on products with high positive sentiment to amplify their success.

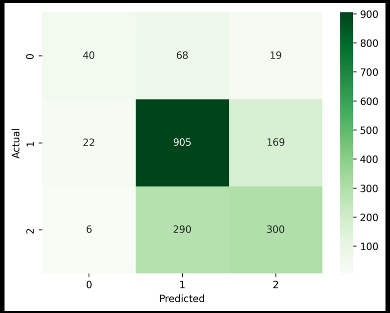
2. Real-Time Sentiment Monitoring:
   - Integrate the model into a live dashboard for continuous sentiment tracking.

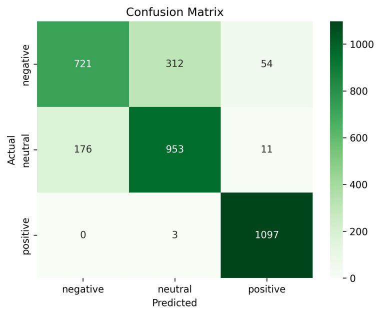
3. Product and Service Improvement:
   - Conduct further analysis on neutral sentiment tweets to identify patterns and areas of improvement.





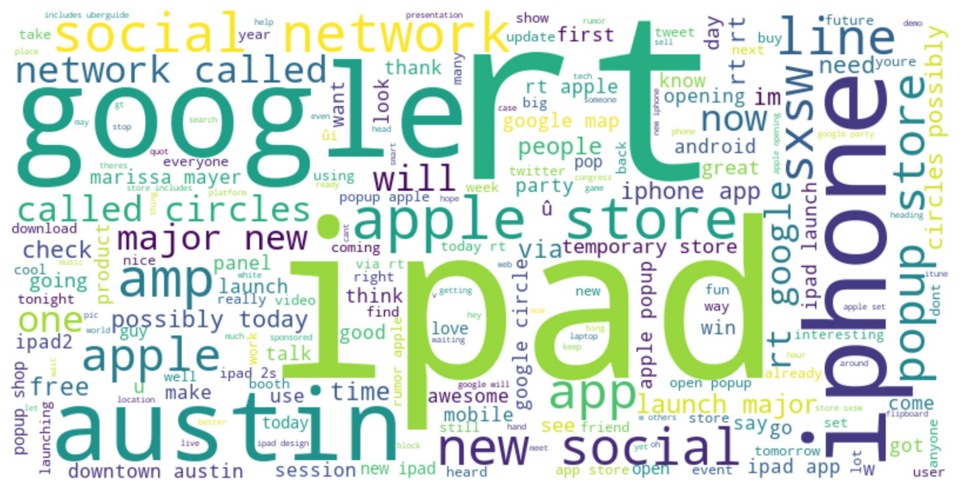






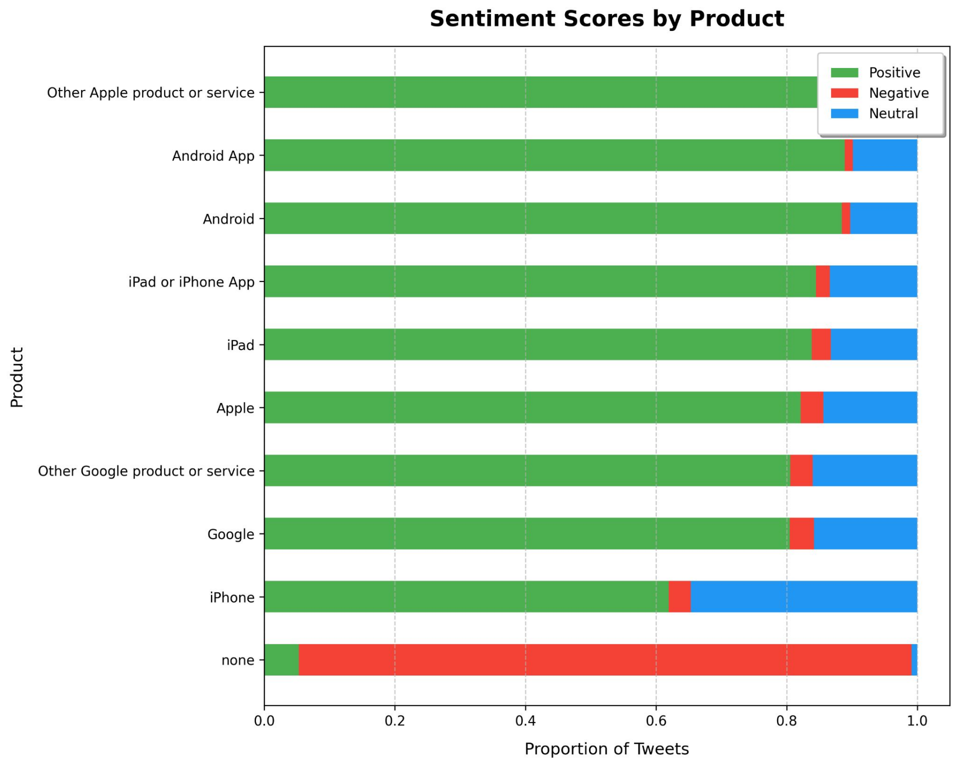
WORD CLOUD

- Key Observations:
  - Common terms like “iPad,” “Google,” “Apple,” and “iPhone” indicate the focus of discussions on popular products.
  - Words such as “network,” “app,” “launch,” and “store” suggest topics related to product launches, services, and events.
  - The presence of both positive (e.g., “awesome,” “new,”) and neutral or ambiguous terms (e.g., “called,” “session,”) highlights the diversity in customer opinions.



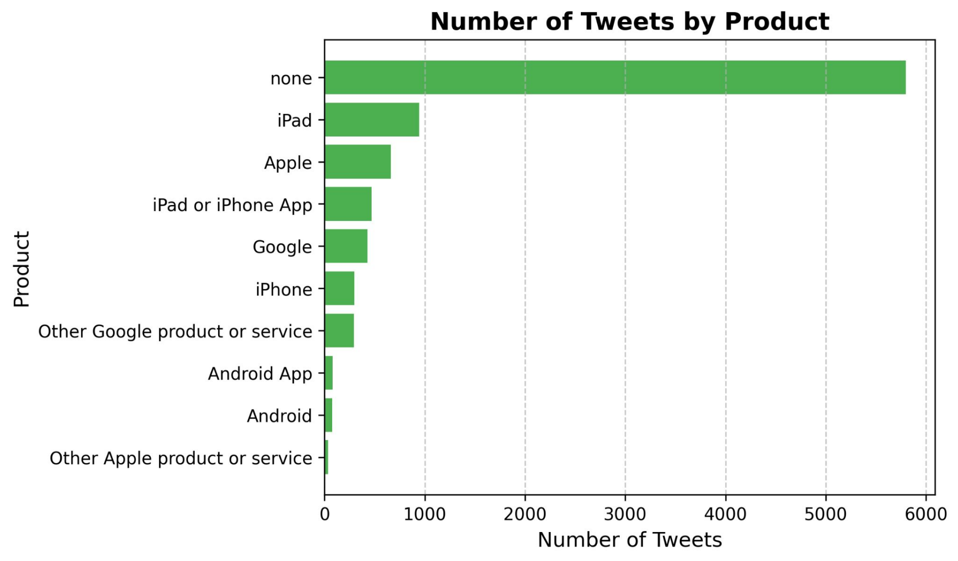
SENTIMENT DISTRIBUTION

The barchart displays the sentiment distribution (positive, neutral, and negative) across various Apple and Google products based on Twitter data. The proportions highlight how each product is perceived by users.



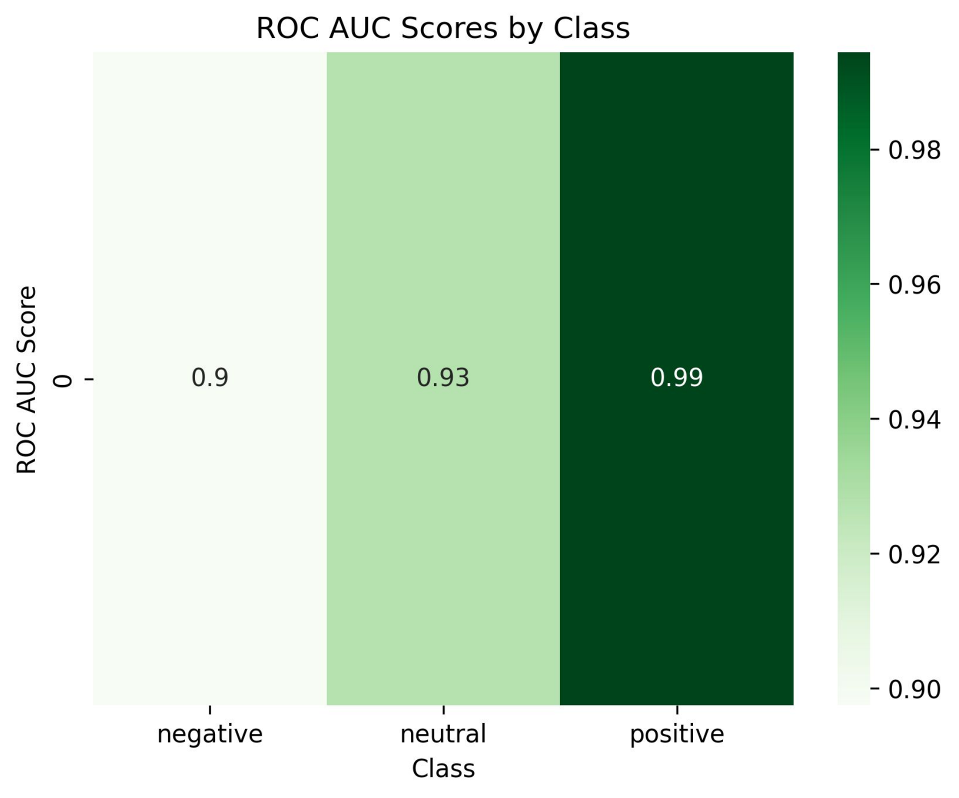
NUMBER OF TWEETS BY PRODUCT

- Key Observations:
  - Highest Mentions: The “none” category has the highest volume of tweets.
  - Top Products: iPad and Apple are the most mentioned products.
  - Lower Mentions: Products like Android and Other Apple product or service are mentioned less frequently.



ROC AUC BY CLASS

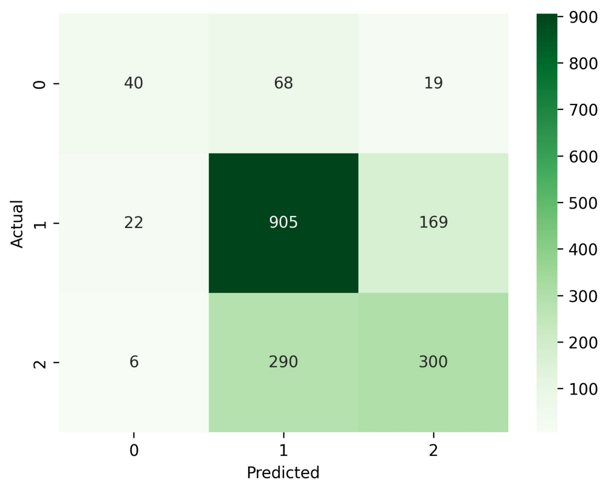
- Key Observations:
  - Positive Sentiment: Achieved an excellent ROC AUC score of 0.99, indicating near-perfect classification for this class.
  - Neutral Sentiment: ROC AUC of 0.93, demonstrating strong discrimination capability for neutral sentiment.
  - Negative Sentiment: ROC AUC of 0.90, reflecting reliable but slightly lower performance compared to the other classes.



Sentiment	ROC AUC Score
Negative	0.90
Neutral	0.92
Positive	0.99

BASELINE VS. FINAL MODEL

- Baseline Model (Top Confusion Matrix):
  - Accuracy: 68.44%
  - Weaknesses:
    - High misclassification rates for negative and neutral sentiments.
    - Significant performance gaps between training and testing, indicating overfitting.
    - Limited ability to capture the complexities of text data due to the simplicity of the logistic regression approach.
- Final Model (Bottom Confusion Matrix):
  - Accuracy: 84.00%
  - Key Improvements:
    - Drastic reduction in misclassifications across all sentiment classes.
    - Near-perfect classification for positive sentiment (F1-Score: 0.97).
    - Balanced recall for negative and neutral classes, addressing earlier weaknesses.

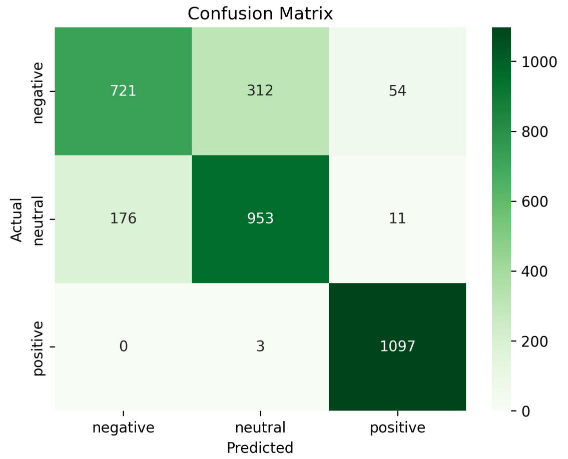


Sentiment	Precision	Recall	F1-Score	Support
Negative (-1)	0.59	0.31	0.41	127
Neutral (0)	0.77	0.83	0.76	1096
Positive (1)	0.61	0.50	0.55	596

- **Accuracy**: 68.44%
- **Macro Avg F1-Score**: 57.70%
- **Weighted Avg F1-Score**: 67.20%

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.78	0.72	0.75	1087
Neutral	0.79	0.81	0.80	1130
Positive	0.94	1.00	0.97	1110

- **Accuracy**: 84.00%
- **Macro Avg F1-Score**: 84.00%
- **Weighted Avg F1-Score**: 84.00%



CONCLUSIONS

- The final model provides robust sentiment analysis for Apple and Google products.
- Offers actionable insights for marketing, product development, and customer experience.
- Future Work:
  - Use pre-trained embeddings (e.g., GloVe or BERT) to improve semantic understanding.
  - Test on unseen data for further validation.

THANK YOU

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