An NLP-driven study on social media sentiment trends

Twitter Sentiment Analysis: Apple vs. Google

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Project Overview

Objective: Dataset: Approach: Data preprocessing Classify tweets about CrowdFlower Apple and Google as Twitter dataset Feature engineering positive, negative, $(\sim 9,000 \text{ tweets}).$ Model development or neutral using NLP **Dataset Source: Evaluation** data world Interpretation.

Data Preprocessing

Text Cleaning:

- ✓ Lowercasing
- ✓ Removing punctuation & special characters
- ✓ Stopword filtering

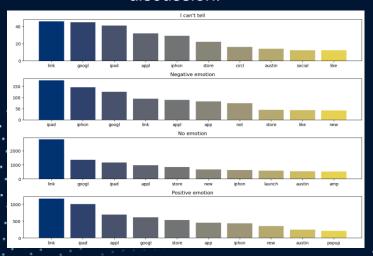
Feature Engineering:

- ✓ TF-IDF vectorization
- ✓ Tokenization

Data Exploration

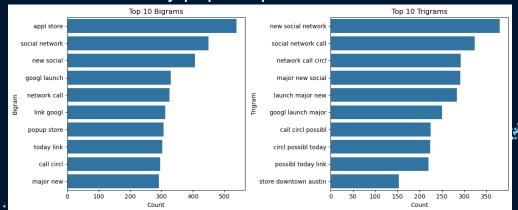
Frequent Words

This visual highlights the most commonly used words in the dataset, giving insight into key topics of discussion.



Bigrams & Trigrams:

This chart showcases the most frequent word combinations, helping identify popular phrases and trends.



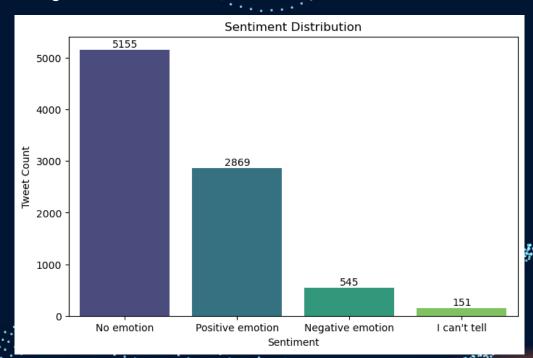
Sentiment Distribution

Objective: Categorizing tweets into positive, negative, and neutral sentiments.

Sentiment Distribution Chart:

This visualization displays the proportion of tweets classified as positive, negative, or neutral.

- Key Takeaways:
 - Provides an overview of public perception.
- Useful for understanding sentiment trends for Apple vs. Google.





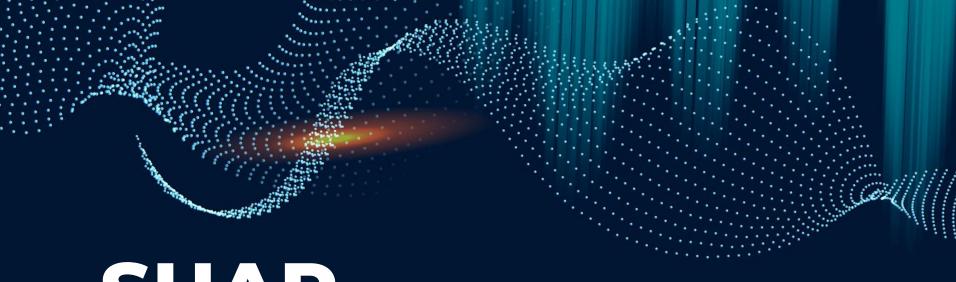
- Logistic Regression
- Support Vector Machine (SVM)
- XGBoost
- Evaluated using accuracy, precision, recall, F1score, and SHAP analysis.

Model Performance Summary

Model	Accuracy	Precision	Recall	F-score
Logistic Regression	96%	High	High	High
SVM(Best)	98%	Best	Best	Best
XGBoost	92%	Moderate	Moderate	Moderate

Key Takeaways:

- **SVM outperformed all models** with the highest accuracy and balanced classification.
- **Logistic Regression** remains valuable for interpretability.
- XGBoost was slightly weaker but still useful.



SHAP Interpretability:

Logistic Regression SHAP Output: Identified key words contributing to sentiment classification.

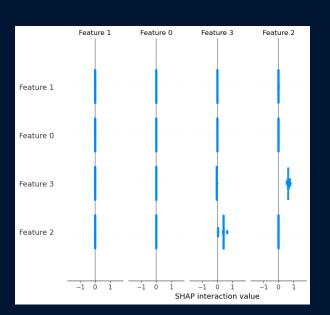
Feature 2304
Feature 2187
Feature 4193
Feature 279
Feature 3024
Feature 1784
Feature 2550
Feature 212
Feature 439
Feature 212
Feature 216
Feature 217
Feature 218
Feature 2486
Feature 2485
Feature 2485
Feature 2485
Feature 2485
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Feature 3657
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Feature 3657
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Feature 769
Feature 3140

-0.2 0.0 0.2

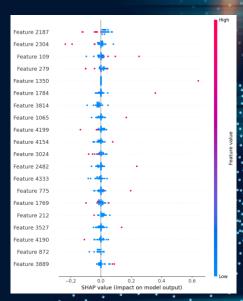
SHAP value (impact on model output

Feature 379

SVM SHAP Output:Confirmed strong feature importance consistency.



XGBoost SHAP
Output: Highlighted
word influence but with
more variance.



Conclusion: SVM consistently had **more reliable feature**. **explanations** for decision-making.

Key Insights

- •SVM is the most accurate model (98%) and balances all sentiment classes effectively.
- •Logistic Regression (96%) offers strong interpretability for tracking sentiment trends.
- •XGBoost (92%) struggled slightly with class imbalances but remains a useful alternative.
- •Misclassification was highest between neutral and negative sentiment classes.

THANKS!

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