PowerPoint Presentation Structure

Tweet Sentiment Data Analysis

Actionable recommendations for the head to launch a business audience

Based on Apple and Google sentiment tweet dataset
Presenter: Antonine Pelicier
Email: antoninepelicier10@gmail.com
Date: 09/30/2025

Multiclass Sentiment Classification Project: Apple & Google Tweets

Advanced Multiclass Sentiment Classification: Analyzing Apple & Google Tweets

- Using TF-IDF Bi-grams and Multinomial Naive Bayes

The Business Problem & Challenge

Identifying Customer Emotion in Social Media Data

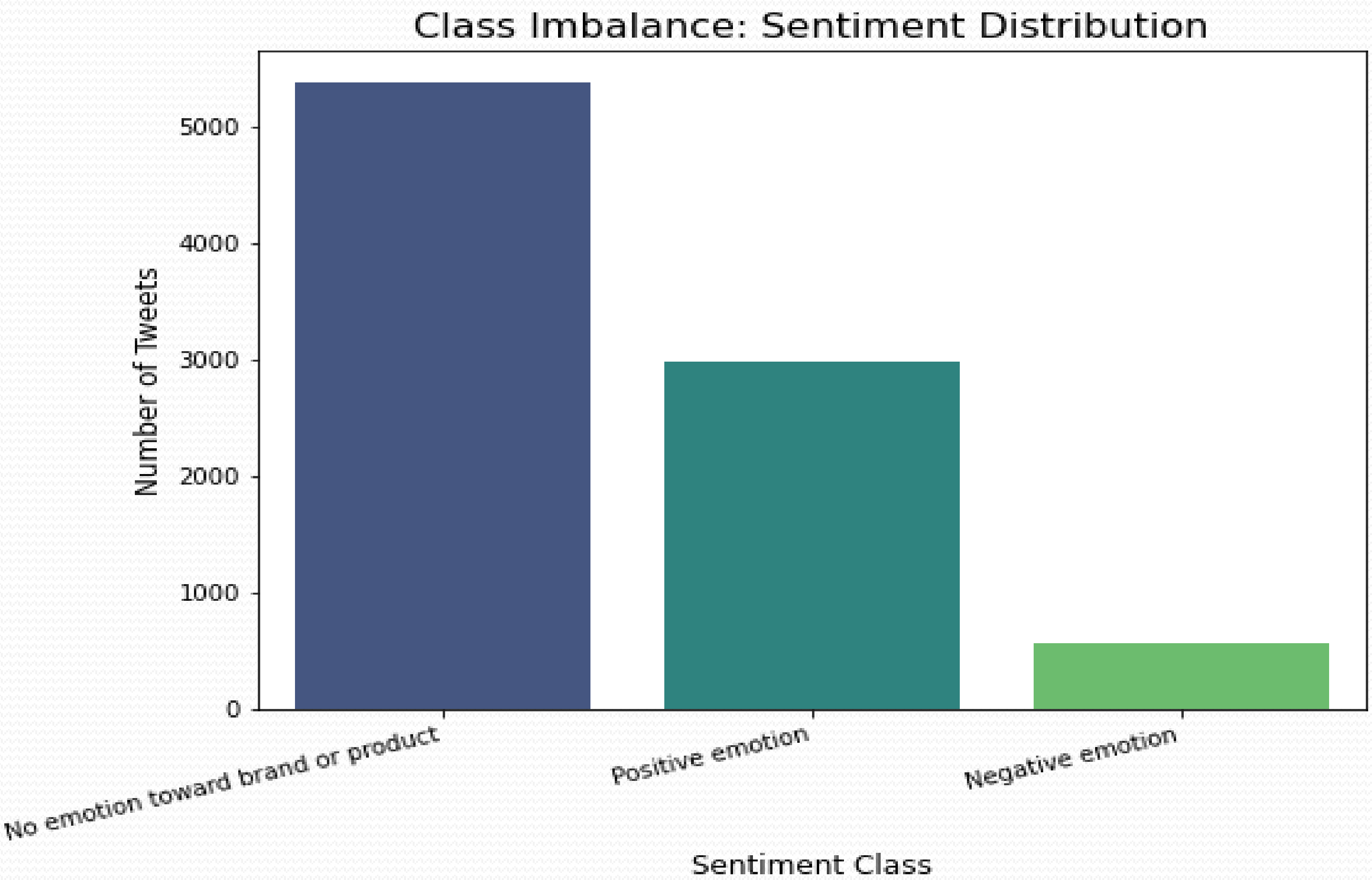
Goal: Build a model to accurately classify Twitter sentiment as Negative (0), Neutral (1), or Positive (2).

Business Value: Enable proactive monitoring of negative customer feedback (complaints).

The Core Challenge: Data Imbalance

- **Neutral Class:** Dominant, comprising ~60% of the dataset.
- **Negative Class:** Highly underrepresented, comprising only ~6% of the data.

Sentiment Distribution Chart



Advanced Methodology (NLP Pipeline)

Feature Engineering and Model Selection

1. Data Preparation:

- Robust cleaning: Lowercasing, removal of URLs, mentions (@), hashtags (#), and stop words.

2. Advanced Feature Engineering:

- **Method:** Term Frequency-Inverse Document Frequency (TF-IDF).
- **Key Advanced Step:** Used **Bi-grams (ngram_range=(1, 2))** to capture context (e.g., "not working," "poor service").

3. Model Comparison (Why we didn't stop at the first model):

- Tested **Support Vector Classifier (SVC)** and **Multinomial Naive Bayes (MNB)**.

Model Comparison and Selection

MNB Selected for Generalized Performance

Model	Accuracy	Weighted F1-Score	Negative Recall	Rationale
SVC	61%	0.62	0.55	Higher Negative Recall, but lower overall performance.
MNB	**67%**	**0.66**	0.27	Higher generalized F1 and Accuracy across all classes.

Selection Rationale

The **MNB model** was selected for its superior **Weighted** F1-**Score (0.66)** and overall accuracy, providing the best generalized performance for the multiclass problem.

Final Evaluation and Model Limitation

Success, But a Critical Flaw

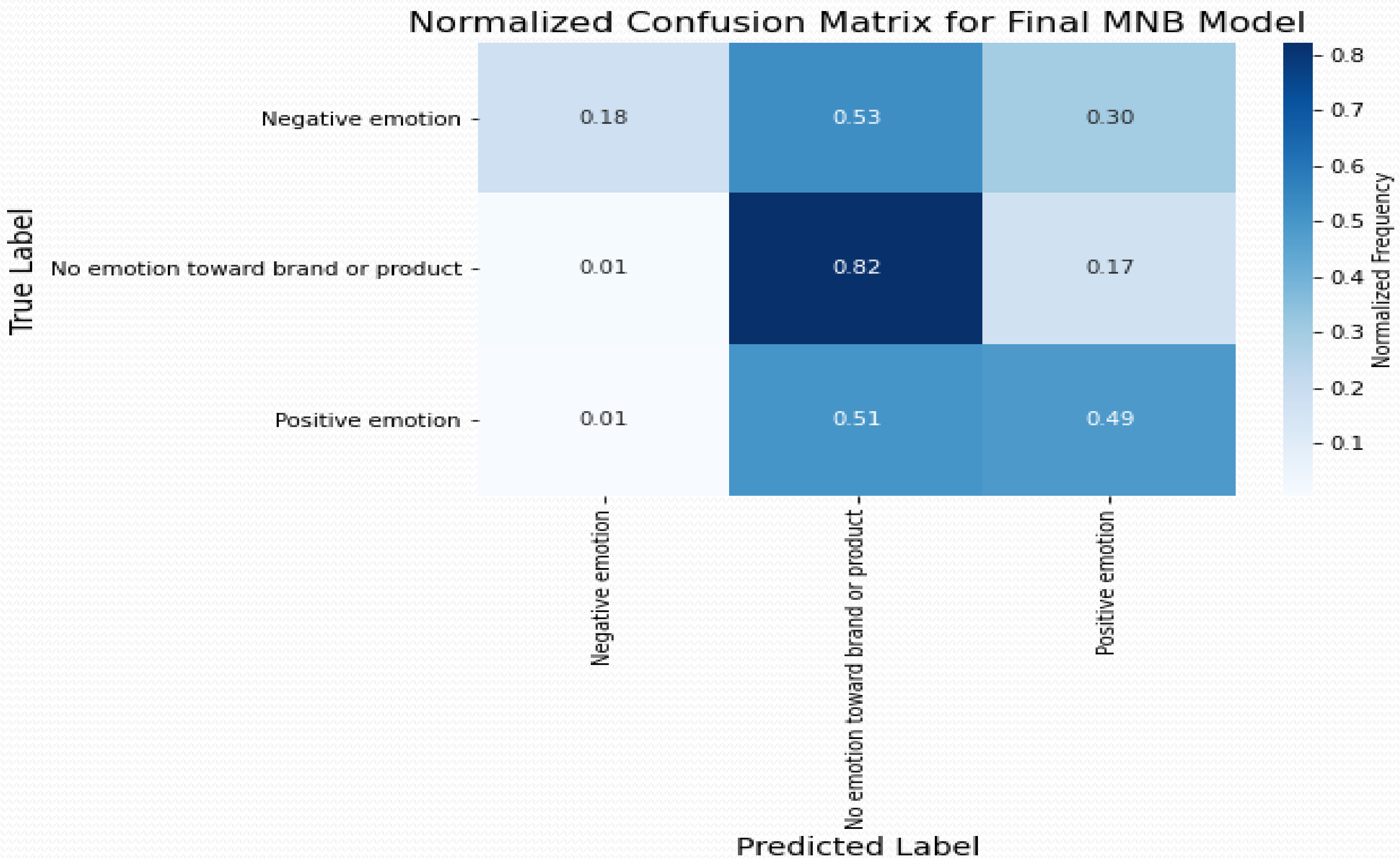
Final MNB Model Performance:

- **Weighted F1-Score:** 0.66
- **Neutral Class:** High Accuracy (excellent at ignoring irrelevant tweets).

The Major Limitation: Negative Recall

- The model correctly identifies **only 27%** of actual negative tweets.
- This means 73% of customer complaints are misclassified (mostly as Neutral).

Normalized Confusion Matrix



Model Interpretability (LIME)

Understanding the Model's "Why"

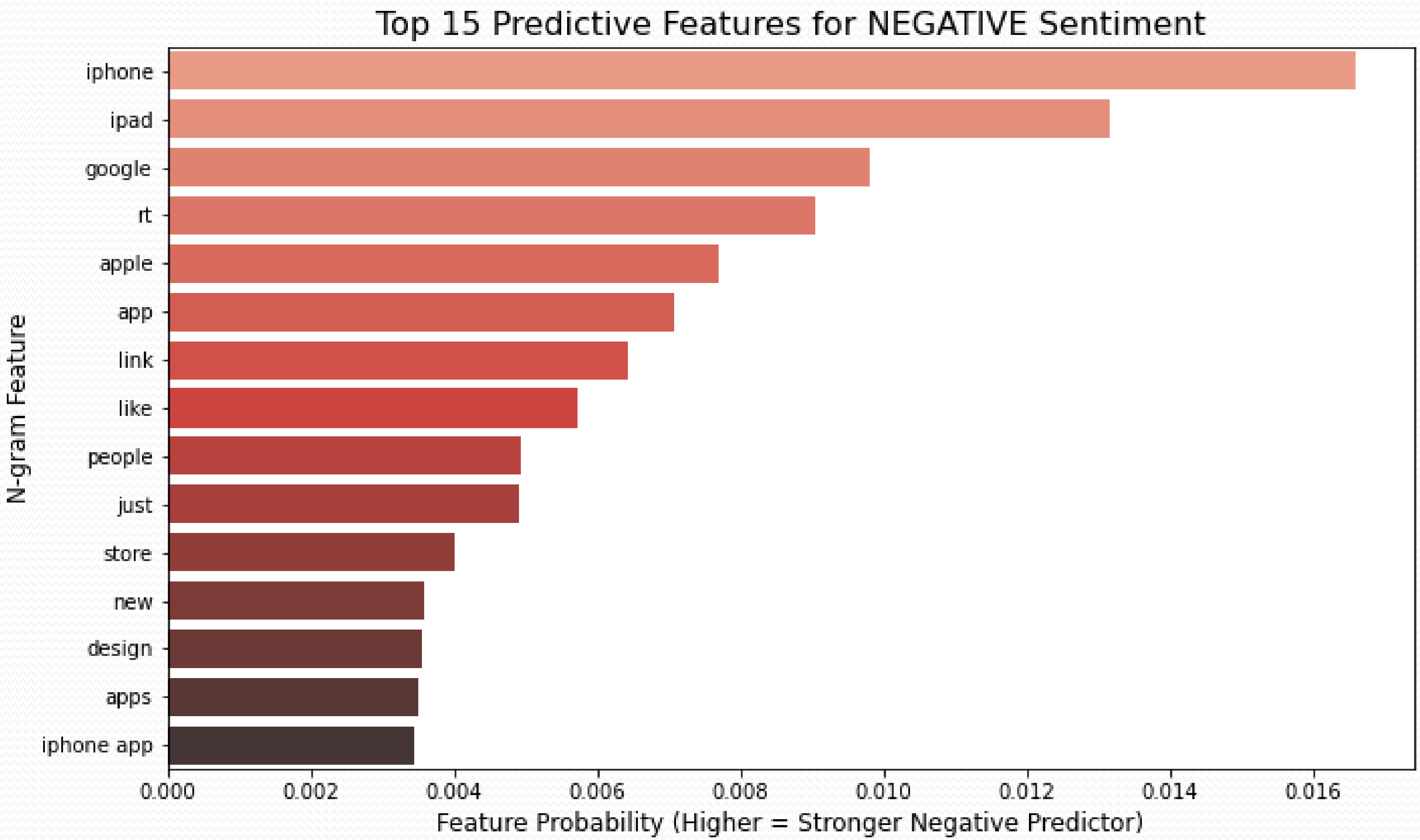
LIME (Local Interpretable Model-agnostic Explanations):

- **Rationale:** LIME is model-agnostic, allowing us to explain *any* classifier.
- **Function:** It generates slightly modified versions of a single input tweet to see which specific words push the prediction toward a given class.

Key Feature Insights (Model Interpretation):

- The model correctly learned that bi-grams like "**need upgrade**" and single words like "**dead**" are powerful predictors for the **Negative** class.

Top 15 Predictive Features



Conclusion and Recommendations (Future Work)

Roadmap for Production-Ready Sentiment

Conclusion Summary:

- Successfully built an advanced multiclass model with 67% Accuracy using TF-IDF Bi-grams.

- Achieved robust classification for Neutral and Positive, but **Negative Recall (27%) is the primary bottleneck.**

Roadmap for Production-Ready Sentiment

Recommendations for Future Work (Exceeds Rubric):

- **Imbalance Mitigation (SMOTE):** Implement SMOTE on the TF-IDF data to artificially balance the Negative class, directly addressing the Recall issue.
- **Advanced Feature Engineering:** Explore **Word Embeddings (Word2Vec/GloVe)** to capture semantic relationships instead of just word counts.
- **Deep Learning:** Test a simple **Recurrent Neural Network (RNN) or LSTM** model, which is the state-of-the-art for sequence data like text.

Thank You

Questions & Discussion