SENTIMENT ANALYSIS OF TWEETS ON APPLE AND GOOGLE PRODUCTS

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BUSINESS UNDERSTANDING

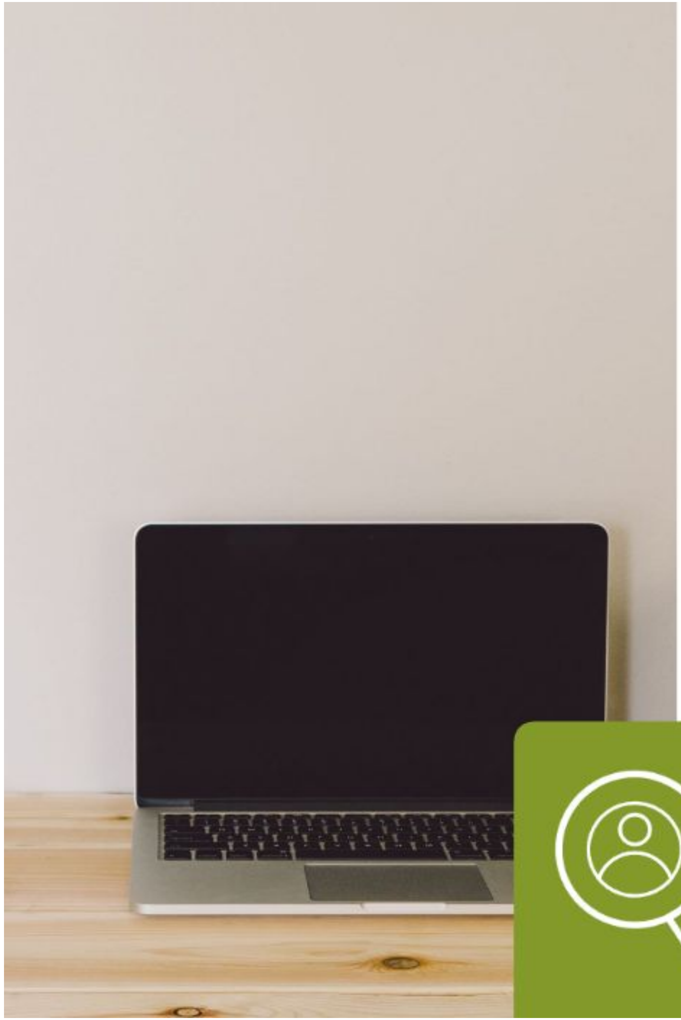
Business Understanding

Business Overview:

This project uses **sentiment analysis**, a key **NLP technique**, to classify tweets about Apple and Google into **positive, negative, or neutral** categories.

Purpose:

- **Uncover public opinions, emotions, and reactions** from text data.
- Provide **valuable insights** for businesses to improve customer experiences, predict behavior, and enhance decision-making.

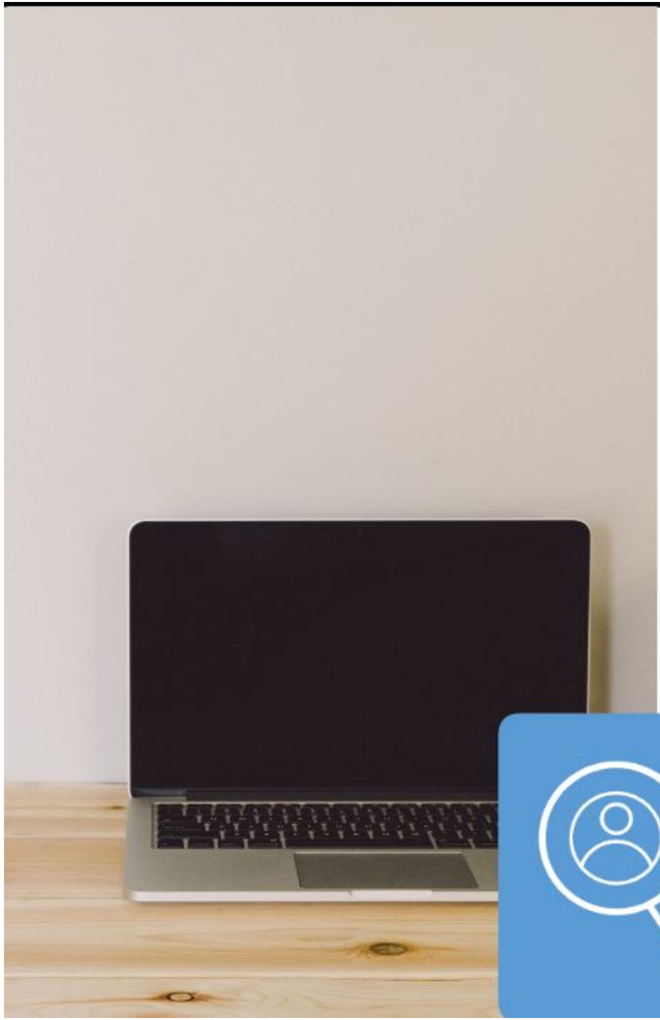


Business Understanding

Focus Brands:

- **Apple**: Global leader in consumer electronics.
- **Google**: Provider of diverse hardware, software, and cloud services.

Goals:
- Identify **trends and patterns** in public discussions about these brands.
- Use **machine learning** to build a model for accurate sentiment classification.
- Deliver **actionable insights** for stakeholders to:
  - Address customer concerns.
  - Enhance brand performance.
  - Maintain market dominance.



Problem Statement

The Challenge:

In the digital era, businesses face overwhelming amounts of unstructured textual data from **reviews, surveys, and social media**, making **manual analysis inefficient and unreliable**.

Objective:

Develop a **sentiment analysis model** to automatically classify customer feedback into **positive, negative, or neutral** categories.

Why It Matters:

- **Pinpoint improvement areas** to enhance products and services.
- **Customize marketing efforts** based on customer sentiment.
- **Track and manage brand reputation** effectively and in real time.

Project Objective

1. Primary Objective:

- Develop an **unsupervised machine learning model** to classify tweets as **positive**, **negative**, or **neutral** toward a brand or product.

2. Secondary Objectives:

- Identify whether a tweet contains an **emotion directed at a specific brand or product**.
- **Preprocess and clean tweet text** by removing noise such as hashtags, mentions, and URLs.
- Detect the **most positive words** associated with Apple and Google products/services.
- Detect the **most negative words** associated with Apple and Google products/services.
- Deliver **actionable insights** to enhance customer satisfaction and marketing strategies.

Approach Methodolgy

Systematic Approach

A step-by-step methodology was applied to preprocess data, extract features, and select/evaluate models to accurately classify tweet sentiment.

Key Steps:

1. **Text Preprocessing**:
   - **Text normalization**: Convert text, remove punctuation, handle contractions.
   - **Tokenization**: Split text into words/tokens.
   - **Stop word removal**: Eliminate common, non-sentiment words.
   - **Lemmatization**: Standardize words by reducing them to root forms.
   - **Noise removal**: Filter out irrelevant data (e.g., URLs, hashtags, mentions).

Approach Methodology

- **Model Development:**
  Baseline models: Logistic Regression, Naive Bayes.
  Advanced models: Ensemble methods (e.g., Random Forest, Gradient Boosting).
  Deep learning models: Experiment with neural networks for improved accuracy.

- **Model Evaluation:**
  Performance benchmarking: Compare different models and feature combinations.
  Hyperparameter tuning: Optimize model performance.
  Report results: Measure accuracy, precision, and recall for the final model.

- **Outcome:** Deliver actionable insights for decision-making and customer sentiment understanding for Apple and Google.

Metric of Success

Model Evaluation Metrics:

1. **Accuracy**
   - Measures the percentage of correctly classified sentiment instances.
   - **Target:** 85% or higher.

2. **Precision**
   - Reflects how often the model is correct when predicting a specific sentiment.
   - **Target:** 80% or higher for each sentiment class (positive, negative, neutral).

3. **Recall**
   - Assesses the model's ability to identify all relevant instances of a sentiment.
   - **Target:** 75% or higher for each class.

4. **F1-Score**
   - Combines precision and recall into a balanced measure.
   - **Target:** 80% or higher overall.

Cont. Metric of Success

Confusion Matrix

- Visualizes model performance with true positives, true negatives, false positives, and false negatives.

Business Impact:

- **Customer Satisfaction:**
  - Identify and address negative sentiments to enhance experiences.

- **Marketing Strategies:**
  - Leverage positive feedback trends to inform decision-making.

Outcome: Ensure the model's reliability and actionable insights for i**mproved customer experiences and business strategies**.

DATA UNDERSTANDING AND DATA CLEANING

Data Understanding

The dataset used to build the NLP model for analyzing Twitter sentiment about Apple and Google products was sourced from CrowdFlower via .

Key Steps in Data Inspection

- **Shape of the dataset**: 9093 rows, 3 columns
- **Metadata Extraction**: `.info()`
- **Descriptive Statistics**: `.describe()`
- **Duplicate Detection**: `.drop_duplicates()`
- **Missing Values**: `.isna()`

Additionally, the distribution of categories within the following columns was analyzed:

- **"Emotions_in_tweet_is_directed_at"** (e.g., Apple, Google)
- **"Is_there_an_emotion_directed_at_a_brand_or_product"** (e.g., Positive, Negative)

Columns in the Dataset:

1. **tweet_text**: Contains the original Twitter messages.
2. **Emotions_in_tweet_is_directed_at**: Specifies the product (e.g., Apple, Google) being discussed.
3. **Is_there_an_emotion_directed_at_a_brand_or_product**: Indicates whether an emotion (e.g., Positive, Negative) is directed at a brand or product.

Data Cleaning and Preprocessing Overview

- **Missing Values**
  - Removed rows with missing values in `tweet_text`.
  - Dropped the `emotion_in_tweet_is_directed_at` column (63% missing data).
  - Created new columns for inferred emotions and product references.

- **Handling Duplicates**
  - Identified and removed 22 duplicate rows using `drop_duplicates()`.

- **Standardization and Cleaning**
  - Lowercased all text for uniformity.
  - Removed special characters, URLs, mentions (@), and hashtags (#).
  - Created columns for mentions and hashtags for separate analysis.

- **Final Adjustments**
  - Dropped irrelevant or missing entries labeled as "Unknown" and "IRR".

Text Tokenization and Transformation

- **Tokenization and Stopword Removal**
  - Split text into tokens and removed non-informative stopwords (e.g., "the," "is").
- **Category Mapping**
  - Created `tweet_Directed_at` and `Company_Product` columns to classify tweets by products or companies (e.g., Google, Apple).
  - Ensured better tracking and analysis of product mentions.
- **Cleaning Process**
  - Removed common terms like "link," "rt," and HTML-related artifacts ("quot," "amp").
  - Filtered out irrelevant terms like "sxsw."

Enhanced Preprocessing with NLP Techniques

- **Advanced Tokenization**
  - Used NLTK's `RegexpTokenizer` to extract word tokens, removing unwanted characters and punctuation.
- **Frequency Distribution Analysis**
  - Identified top 50 most common words for insights into tweet trends (e.g., "ipad," "google," "apple").
- **Lemmatization**
  - Applied lemmatization to reduce words to their base forms for accurate sentiment classification.
  - Preferred over stemming for better context-aware results.**vision.**

Preparing Data for Sentiment Analysis

Preparing Data for Sentiment Analysis

- **Final Dataset Structure**
  - Cleaned and tokenized text stored in `clean_tweet_text` for modeling.
  - Created new columns for product references and categorized emotions.

- **Focus on Emotion Analysis**
  - Filtered data for positive, negative, and neutral sentiments.
  - Dropped irrelevant and unclear data, ensuring high-quality input.

- **Key Insights**
  - Enhanced data integrity and reduced noise for effective sentiment analysis.
  - Dataset ready for modeling with well-structured and clean text data.

EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis(EDA)

Sentiment Analysis by Company

- **Objective:** Analyze emotional sentiment toward **Apple** and **Google** products.
- **Steps Taken:**
  1. **Dataset Splitting:**
     - Categorized tweets into **positive**, **negative**, and **neutral** emotions.
  2. **Focus on Apple & Google:**
     - Filtered tweets related to their products.
     - Examined emotion distributions for each company.

Insights from Word Clouds

- **Visualization:**
  - Generated **word clouds** for each company to highlight frequent words tied to **positive** and **negative** emotions.
- **Findings:**
  - Identified key terms and emotional associations influencing public perception of Apple and Google.

Conclusion:

- Insights reveal emotional ties between consumers and products, offering valuable input for sentiment-driven marketing strategies.

Word Cloud on Positive Sentiments on Apple Products

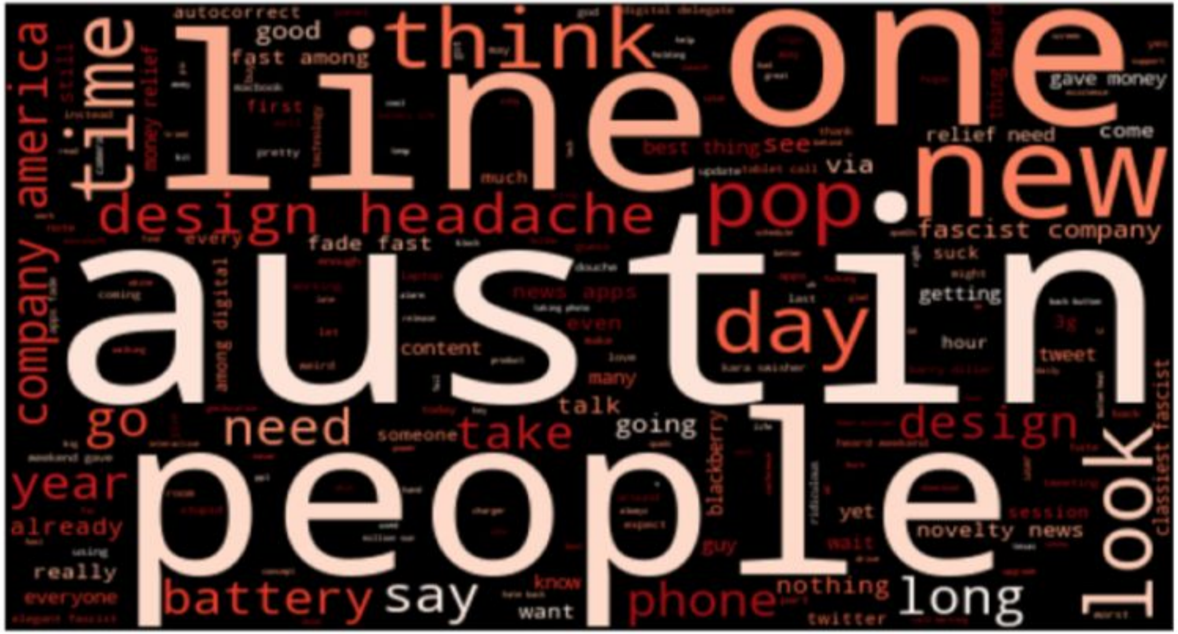
The word cloud for Apple products highlights positive terms such as "great," "love," "awesome," "smart," "design," "win," and "launch," reflecting perceptions of quality, innovation, and excitement. These words emphasize Apple's reputation for delivering well-designed, cutting-edge products that resonate with customers' expectations

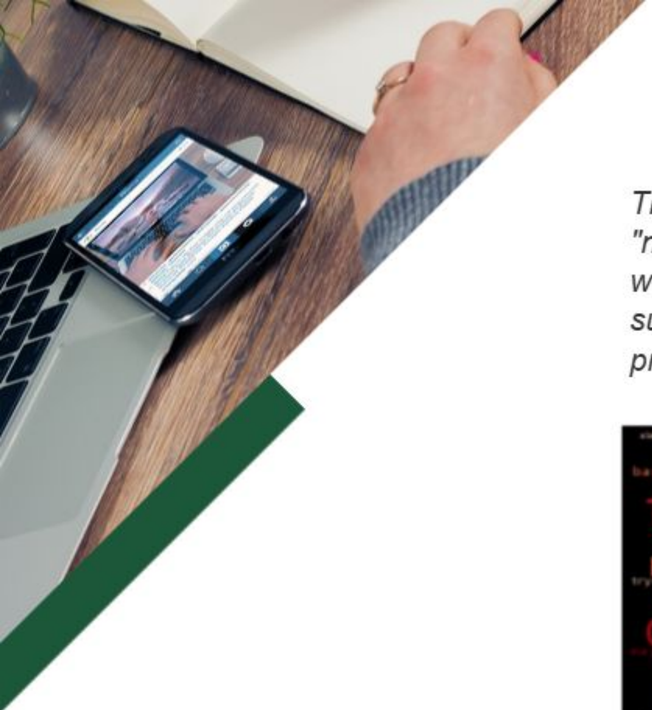
Word Cloud on Positive Sentiment on Google Products

The word cloud for Google reveals terms like "great," "awesome," and "thank," reflecting positive user satisfaction. Words like "social network" and "new social" suggest an association with Google's social platforms, while "possibly" introduces some uncertainty, indicating mixed emotions from users.

Word Cloud on Negative Sentiment Toward Apple Products

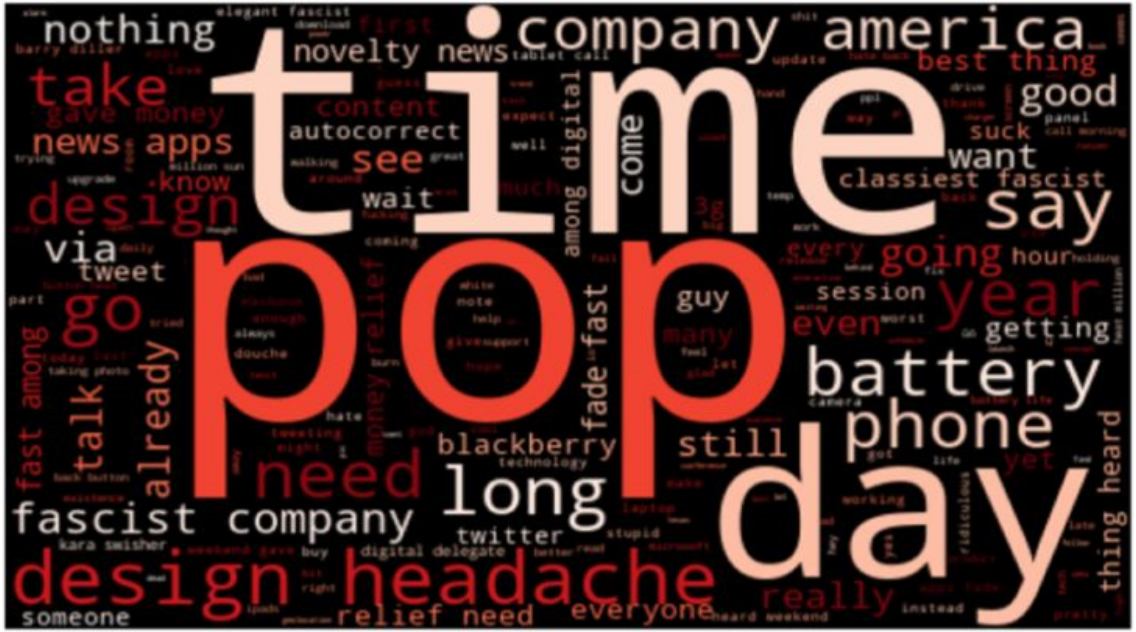
The negative word cloud for Apple highlights common frustrations, including battery life, design choices, and usability issues. Strong terms like "fascist company" and "suck" reflect dissatisfaction with Apple's corporate policies and product performance. While some positive terms are present, they suggest potential inconsistencies in sentiment classification, which could affect model accuracy.





Word Cloud on Negative Sentiment Towards Google Products

The word cloud for Google reveals mostly neutral or ambiguous terms like "network," "product," and "service," with minimal strong negative emotions. While words like "really" or "lost way" may hint at frustration, they lack intensity, suggesting the sentiment analysis may need refinement. Next, we'll test models to predict emotions more accurately.



MODELLING

Application of Supervised Machine Learning Models

After unsatisfactory results from unsupervised models, we switched to supervised learning due to the labeled nature of our data. We chose the Binary Classification Model using Multinomial Naive Bayes, which is effective for classifying sparse, high-dimensional data.

This model calculates the likelihood of each class based on observed features and assigns the class with the highest probability. By applying this model, we aim to address class imbalance and enhance classification accuracy.

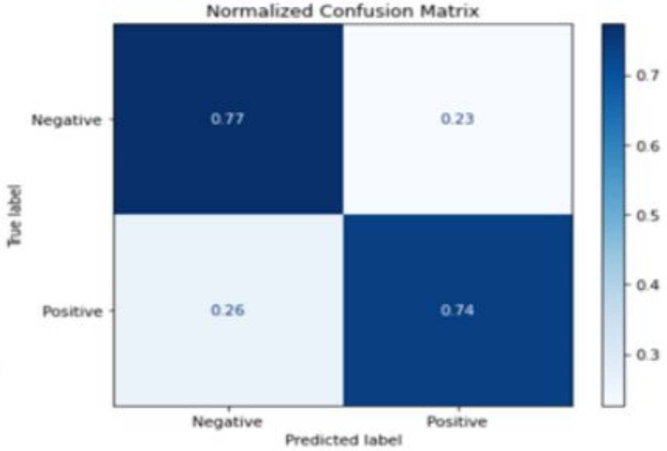
Modelling : Binary Classification

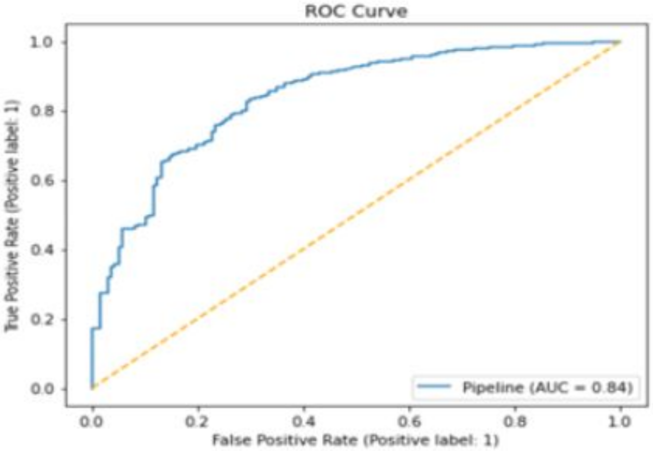
Logistic Regression - Final Model Results

Training Score: 0.83 Test Score: 0.74

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.36	0.77	0.49	137
1	0.94	0.74	0.83	716
accuracy			0.74	853
macro avg	0.65	0.76	0.66	853
weighted avg	0.85	0.74	0.78	853





Cont. Logistic Regression: Binary Classification Model Performance Results

- **Training Score**: 0.83 | **Test Score**: 0.74 – Moderate overfitting, less severe than previous models.

- **Class 1 (Positive Sentiment)**: Precision = 0.94, F1 Score = 0.83 – Excellent performance in identifying positive sentiment.

- **Class 0 (Negative Sentiment)**: Precision = 0.36, F1 Score = 0.49, Recall = 0.77 – Struggles with precision, high recall indicates many negative tweets identified, but misclassified.

- **Overall Accuracy**: 0.74 – Imbalanced performance, potential for improvement with adjustments like resampling or class weights.
- **AUC**: 0.84 – Strong overall performance, suitable as a foundation for multiclass classification in the next phase.

Modelling : Multiclass Classification

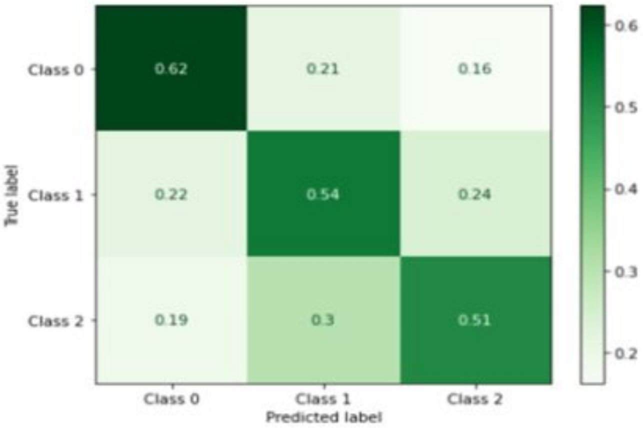
Logistic Regression : Final Model Results

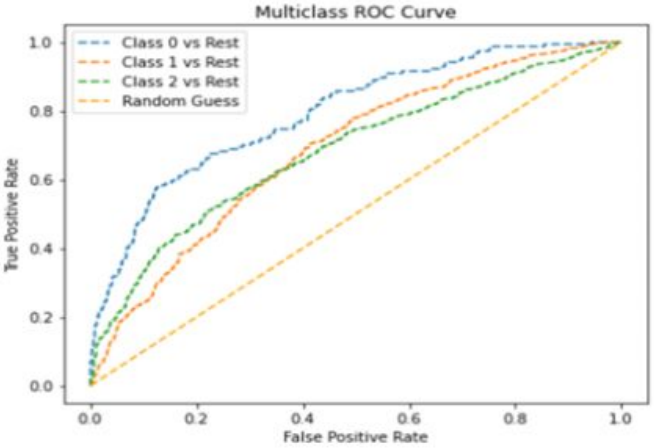
```
Training Score: 0.61 | Test Score: 0.54

CLASSIFICATION REPORT
----------------------------------------
              precision    recall  f1-score   support

           0       0.22      0.62      0.32       154
           1       0.67      0.54      0.60       954
           2       0.59      0.51      0.55       716

    accuracy                           0.54      1824
   macro avg       0.49      0.56      0.49      1824
weighted avg       0.60      0.54      0.56      1824
```





Cont. Logistic Regression : Multiclass Classification Model Performance Results

Training Score: 0.61 | **Test Score**: 0.54 – Moderate performance on training data, struggles with generalizing.

Class 0 (Negative Sentiment): Precision = 0.22, Recall = 0.62 – Identifies some negative tweets but misclassifies many, leading to false positives.

Class 1 (Neutral Sentiment): Precision = 0.67, Recall = 0.54 – Better performance, though room for improvement.

Class 2 (Positive Sentiment): Precision = 0.59, Recall = 0.51 – Moderate performance with issues in both precision and recall.

Overall Accuracy: 0.54 – Limited success in sentiment prediction across classes.

Comparison: Hyperparameter-tuned model (Test Score = 0.62) outperforms random undersampling model.

FINAL

Conclusion

- The Logistic Regression model outperformed other models, achieving superior accuracy and generalization for sentiment classification of tweets about Apple and Google's products.

- Unsupervised machine learning approaches were ineffective, failing to provide desired classification results for the dataset.

- Data preprocessing effectively removed noise from the tweet text, and key positive and negative words were identified, providing valuable insights for improving customer satisfaction and refining marketing strategies.

Recommendations

- **Improve Product Durability and Battery Life**: Address negative sentiment around battery life and product durability to reduce user frustration.
- **Explore Context-Driven Sentiment Analysis**: Implement context-sensitive analysis to better understand mixed emotional tones and user perceptions.
- **Address Perceptions of Corporate Control**: Tackle negative emotions related to Apple's perceived corporate practices, like App Store restrictions.
- **Communicate Better on Value for Price**: Address concerns about the perceived lack of value for the premium prices through improved communication.

Next Steps

- **Collect More Data**: Gather a larger, more diverse dataset, with a focus on increasing the representation of negative tweets.
- **Refine Labeling Process**: Develop clear, objective labeling guidelines to ensure consistent classification, especially for complex cases like sarcasm.
- **Use Consensus Labeling**: Implement multiple annotators for each tweet to reduce bias and improve label quality.
- **Consider Contextual Analysis**: Incorporate advanced techniques like BERT to enhance sentiment interpretation by considering tweet context.

Thank You