SENTIMENT ANALYSIS ON APPLE-TWITTER

Business Understanding

1. Introduction:

This modern age, social media platforms like Twitter act as major sources for public opinions and feedback. Companies like **Apple**, understanding how customers perceive their products on Twitter is crucial for improving product development, marketing strategies, and customer relationships.

So manually analyzing thousands of tweets to understand sentiment is an insane task so to speak. **Natural Language Processing (NLP)** can automate this process.

The goal of this project is to develop **NLP model** that can automatically classify the sentiment of a tweet as **positive**, **negative**, or **neutral**. This will help Apple and other stakeholders make informed decisions based on public sentiment.

2. Stakeholders

The stakeholders who gain from this analysis model:

1.

- **Apple and other tech companies**:
  - **Marketing Teams**: Can use the model to track customer reactions to marketing campaigns, product launches, and other brand activities.
  - **Product Development Teams**: Can identify which features are well-received and which need improvement based on real-time public sentiment.

2.

- **Customers**:
  - Customers can see how their opinions are reflected in public sentiment trends, and how other users feel about Apple products.
- **Competitors* *:
  - Competitors can analyze sentiment around Apple products to gain insights into Apple's strengths and weaknesses, guiding their own product strategies.

3. Advantage of project to stakeholders:

The sentiment analysis model will provide the following benefits to stakeholders:

- **Apple**:
  - Helps monitor real-time public sentiment about Apple products giving faster response to customer feedback.
- **Marketing Teams**:
  - Allows for the measurement of campaign effectiveness and helps adjust marketing strategies based on sentiment.

4. Implications for the Real-World Problem

By automating sentiment analysis on Twitter, Apple and other stakeholders can gain valuable insights without the need for extensive manual work. The ability to track public sentiment in real-time means that Apple can be more responsive to customer feedback, optimize marketing efforts, and improve product offerings. This can ultimately lead to more successful product launches and higher customer satisfaction.

5. Business Value Summary

This NLP sentiment analysis model provides actionable insights that will help Apple make informed business decisions quickly and efficiently. By understanding public sentiment, Apple can enhance customer engagement, drive product innovation, and maintain a competitive edge in the market.

Data Understanding

1. Data Source

The dataset used for this project is **CrowdFlower**, on **data.world**. The dataset has a lot of tweets that have been manually rated for sentiment by human annotators. Each tweet is labeled with one of three sentiment categories: **positive**, **negative**, or **neutral**.

2. Dataset Size and Descriptive Statistics

The dataset consists of over 5,000 tweets with the following key features:

- **Tweet**: The textual content of the tweet (string).
- **Sentiment**: The sentiment label assigned to each tweet (categorical: Positive, Negative, Neutral).

Descriptive Statistics:

Some basic statistics:

- **The size and structure** of the dataset with basic descriptive statistics and an initial look at sentiment distribution.
- **Limitations** of the data that may impact model performance, such as class imbalance or labeling biases.

1. Loading the Dataset is essential for this project first. This allows us to use the notebook to understand the statistics of the datasource and clean it further.

```
import pandas as pd
```

```
# Load the dataset
df = pd.read_csv('/content/Apple-Twitter-Sentiment-DFE.csv', encoding='ISO-8859-1')
```

```
# Display the first few rows of the dataset
df.head()
```

```
/usr/local/lib/python3.11/dist-packages/google/colab/_dataframe_summarizer.py:88: UserWarning: Could not infer format, so each eleme
  cast_date_col = pd.to_datetime(column, errors="coerce")
```

	_unit_id	_golden	_unit_state	_trusted_judgments	_last_judgment_at	sentiment	sentiment:confidence	date	id	
0	623495513	True	golden	10	NaN	3	0.6264	Mon Dec 01 19:30:03 +0000 2014	5.400000e+17	# @
1	623495514	True	golden	12	NaN	3	0.8129	Mon Dec 01 19:43:51 +0000 2014	5.400000e+17	# @
2	623495515	True	golden	10	NaN	3	1.0000	Mon Dec 01 19:50:28 +0000 2014	5.400000e+17	# @
3	623495516	True	golden	17	NaN	3	0.5848	Mon Dec 01 20:26:34 +0000 2014	5.400000e+17	# @
4	623495517	False	finalized	3	12/12/14 12:14	3	0.6474	Mon Dec 01 20:29:33 +0000 2014	5.400000e+17	# @

```
# Check the dataset's shape and column names
print(f"Shape of dataset: {df.shape}")
print(f"Columns in dataset: {df.columns}")
```

```
Shape of dataset: (3886, 12)
Columns in dataset: Index(['_unit_id', '_golden', '_unit_state', '_trusted_judgments',
       '_last_judgment_at', 'sentiment', 'sentiment:confidence', 'date', 'id',
       'query', 'sentiment_gold', 'text'],
      dtype='object')
```

Data Preparation

Removing Unnecessary Columns

Objective: Remove irrelevant columns that won't be used for analysis, making the dataset cleaner and more focused.

Justification:

Irrelevant columns: These columns provide metadata or details that do not contribute to the sentiment analysis model. Removing them streamlines the dataset and improves processing speed.

By dropping columns such as id, query, and _unit_id, we focus only on the features that matter: the tweet text and sentiment.

```
# Drop columns that are not useful for analysis
df.drop(columns=['_unit_id', '_golden', '_unit_state', '_trusted_judgments', '_last_judgment_at', 'sentiment:confidence', 'date', 'id', 'query', 'sentiment_gold'], inplace=True)

# Verify the changes
df.head()
```

	sentiment	text
0	3	#AAPL:The 10 best Steve Jobs emails ever...htt...
1	3	RT @JPDesloges: Why AAPL Stock Had a Mini-Flas...
2	3	My cat only chews @apple cords. Such an #Apple...
3	3	I agree with @jimcramer that the #IndividualIn...
4	3	Nobody expects the Spanish Inquisition #AAPL

Handling Missing Data

We need to Identify and handle any missing values in the dataset. Missing data can impact model performance, so we either drop or impute it based on the context.

Incase the tweet text or sentiment is missing, the data is incomplete and can't be used for analysis. Hence, we drop these rows.

```
# Check for missing values
df.isnull().sum()

# Drop rows with missing text or sentiment labels
df.dropna(subset=['text', 'sentiment'], inplace=True)

# Verify that there are no missing values
df.isnull().sum()
```

	0
sentiment	0
text	0

dtype: int64

Encoding Labels

We need to Convert the sentiment labels (positive, negative, neutral) into numerical values so they can be used by machine learning algorithms.

Label Encoding: Machine learning models can only work with numerical data. Encoding the categorical sentiment labels ensures the model can process them.

This is an essential step as the analysis is a classification job. Label encoding converts categories (positive, negative, neutral) into numerical labels (0, 1, 2), making them ready for model training.

```
from sklearn.preprocessing import LabelEncoder

# Initialize the LabelEncoder
label_encoder = LabelEncoder()

# Encode the sentiment labels
df['sentiment'] = label_encoder.fit_transform(df['sentiment'])

# Verify the encoding
df['sentiment'].value_counts()
```

sentiment	count
1	2162
0	1219
2	423
3	82

dtype: int64

Text Preprocessing

Objective: Clean the text data to ensure it is in a format that can be processed by the machine learning model. This includes removing special characters, stop words, and unnecessary spaces.

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

# Download necessary NLTK resources
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
True
```

Feature Engineering

We Convert the cleaned text into a numerical format that machine learning models can understand. We'll use TF-IDF for this.

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Initialize the TF-IDF vectorizer
vectorizer = TfidfVectorizer(max_features=5000)  # Limit to 5000 features to avoid overfitting

# Fit and transform the 'text' column
X = vectorizer.fit_transform(df['text']).toarray()

# Verify the shape of the feature matrix
X.shape
```

```
(3886, 5000)
```

```
# Check the column names of your dataframe
print(df.columns)
```

```
Index(['sentiment', 'text'], dtype='object')
```

```
print(nltk.data.path)
```

```
['/root/nltk_data', '/usr/nltk_data', '/usr/share/nltk_data', '/usr/lib/nltk_data', '/usr/share/nltk_data', '/usr/local/share/nltk_
```

```
nltk.data.path.append('/root/nltk_data')
```

```
nltk.download('punkt_tab')
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
True
```

```
# Check if 'punkt' is available
from nltk.tokenize import word_tokenize

try:
    word_tokenize("This is a test sentence.")
    print("Punkt tokenizer is available!")
except LookupError as e:
    print("Error: ", e)
```

```
Punkt tokenizer is available!
```

```
# Function to clean text
def clean_text(text):
    # Convert to lowercase
    text = text.lower()

    # Remove URLs
    text = re.sub(r'http\S+|www\S+|https\S+', '', text)

    # Remove special characters and digits
    text = re.sub(r'[^a-zA-Z\s]', '', text)

    # Tokenize the text
    tokens = word_tokenize(text)

    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]

    # Return cleaned text as a string
    return ' '.join(tokens)

# Apply the cleaning function to the 'text' column to create 'cleaned_text'
df['cleaned_text'] = df['text'].apply(clean_text)

# Verify the first few rows to ensure 'cleaned_text' is created
print(df[['text', 'cleaned_text']].head())
```

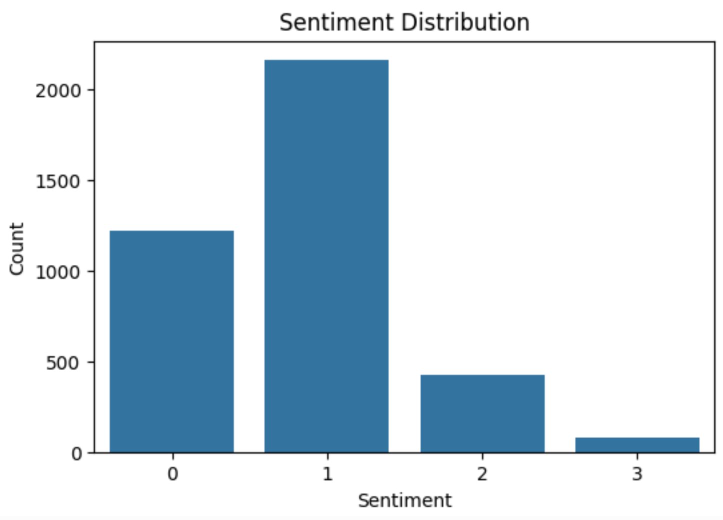
```
                                                text  \
0  #AAPL:The 10 best Steve Jobs emails ever...htt...
1  RT @JPDesloges: Why AAPL Stock Had a Mini-Flas...
2  My cat only chews @apple cords. Such an #Apple...
3  I agree with @jimcramer that the #IndividualIn...
4         Nobody expects the Spanish Inquisition #AAPL

                                        cleaned_text
0                 aaplthe best steve jobs emails ever
1  rt jpdesloges aapl stock miniflash crash today...
2                     cat chews apple cords applesnob
3  agree jimcramer individualinvestor trade apple...
4            nobody expects spanish inquisition aapl
```

Visualizations part of EDA

1. Class Distribution (Sentiment Distribution)

Bar Plot to show the distribution of sentiments in your dataset (e.g., how many positive, negative, and neutral sentiments).

```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot sentiment distribution
plt.figure(figsize=(6, 4))
sns.countplot(x='sentiment', data=df)
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()
```



Findings

- This visualizations shows that most tweets are neutral about Apple. This indicates that the majority of users post factual or non-emotional content. Negative tweets are the second most common, highlighting a significant amount of criticism and complaints. Positive tweets are less common. This means that fewer users will express strong Apple approval. Very positive tweets are the least common and show that enthusiastic praise is relatively rare. Overall, the distribution of mood suggests that Apple receives a mix of opinions, but neutral arguments dominate more criticism than strong praise.

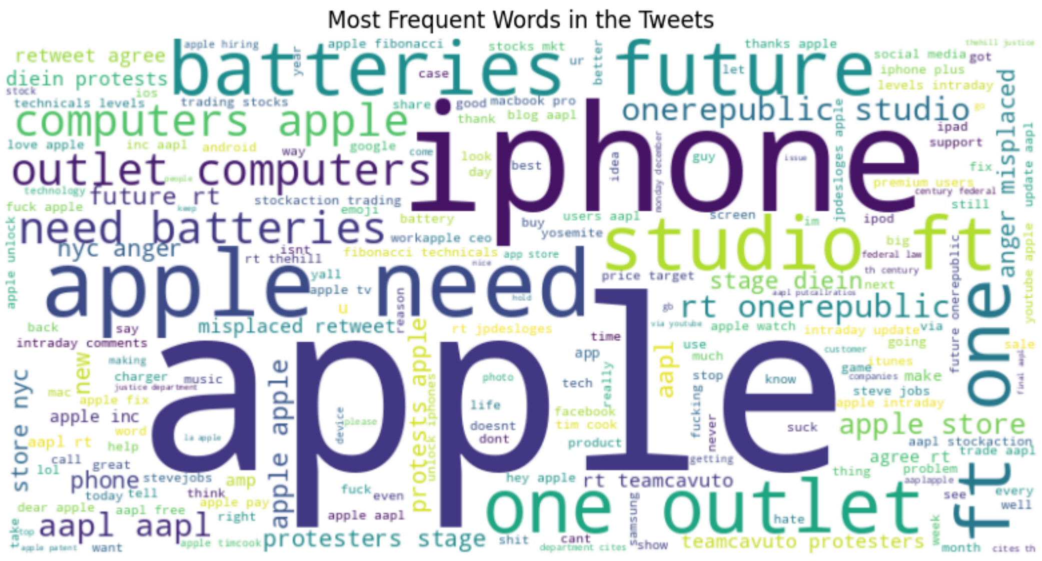
2. Word Cloud for Most Frequent Terms

Visualize the most common words in your dataset, which can give you an idea of the frequent terms in the text data.

```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in /usr/local/lib/python3.11/dist-packages (1.9.4)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.11/dist-packages (from wordcloud) (2.0.2)
Requirement already satisfied: pillow in /usr/local/lib/python3.11/dist-packages (from wordcloud) (11.1.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from wordcloud) (3.10.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (4.56.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (3.2.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib->wordclouc
```

```
from wordcloud import WordCloud

# Combine all cleaned text into a single string
all_text = ' '.join(df['cleaned_text'])

# Generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(all_text)

# Plot the word cloud
plt.figure(figsize=(10, 8))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')  # Turn off axis
plt.title('Most Frequent Words in the Tweets')
plt.show()
```



- These are the most frequently used words in all sentiments

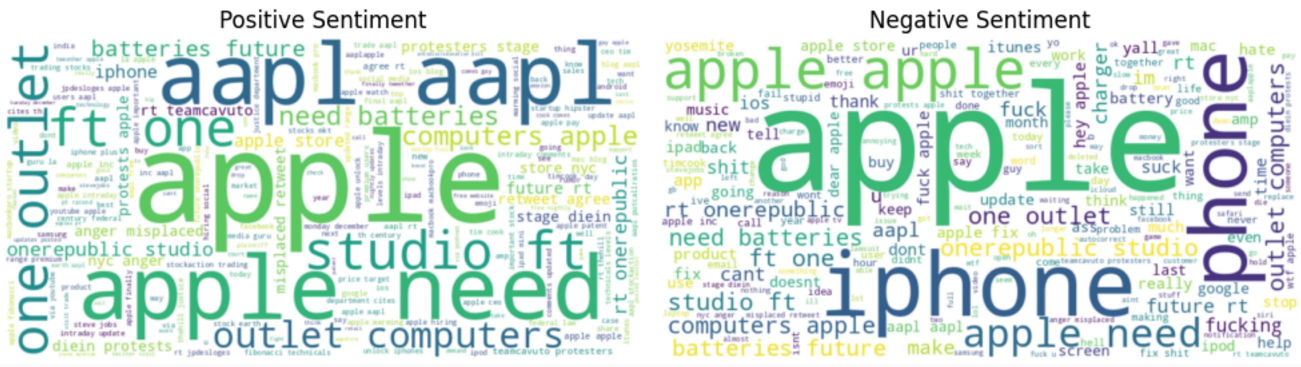
Top Positive and Negative Words

- Let's visualize the most frequent words in positive and negative sentiment categories.

```
print(df['sentiment'].value_counts())
```

```
sentiment
1    2162
0    1219
2     423
3      82
Name: count, dtype: int64
```

```
#filter for positive and negative tweets
positive_tweets = df[df['sentiment'] == 1]
negative_tweets = df[df['sentiment'] == 0]



#Ectract text for generation
positive_text = ' '.join(positive_tweets['cleaned_text'])
negative_text = ' '.join(negative_tweets['cleaned_text'])




# Generate word clouds for both positive and negative sentiments
positive_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(positive_text)
negative_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(negative_text)

# Plot the word clouds
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.imshow(positive_wordcloud, interpolation='bilinear')
plt.title("Positive Sentiment")
plt.axis('off')

plt.subplot(1, 2, 2)
plt.imshow(negative_wordcloud, interpolation='bilinear')
plt.title("Negative Sentiment")
plt.axis('off')

plt.tight_layout()
plt.show()
```



Modeling

In this section, we will build multiple models iteratively, starting from a simple baseline model and progressively adding more complexity. We will compare the performance of each model and justify the improvements over the previous ones based on the results. The goal is to demonstrate an effective approach to model-building, starting from a basic model and moving toward more advanced techniques.

```
#Train and test splits
from sklearn.model_selection import train_test_split

# Assuming 'X' is the feature matrix (TF-IDF features) and 'y' is the target variable (sentiment)
X = vectorizer.transform(df['cleaned_text']).toarray()  # Or you can use the vectorized version from earlier
y = df['sentiment']  # Target variable

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Check the shape of the training and test sets
print(X_train.shape, X_test.shape)
```

```
(3108, 5000) (778, 5000)
```

1. Baseline Model: Logistic Regression

Model Description: We begin by training a Logistic Regression model as our baseline. Logistic Regression is a simple yet effective model for binary classification tasks. It will provide us with an initial benchmark to compare more complex models against.

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

# Initialize and train the baseline Logistic Regression model
baseline_model = LogisticRegression(max_iter=1000)
baseline_model.fit(X_train, y_train)

# Make predictions on the test set
baseline_y_pred = baseline_model.predict(X_test)

# Evaluate the baseline model
baseline_accuracy = accuracy_score(y_test, baseline_y_pred)
print(f"Baseline Accuracy: {baseline_accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, baseline_y_pred))
```

```
Baseline Accuracy: 0.7391
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.66      0.72       240
           1       0.71      0.94      0.81       424
           2       0.87      0.20      0.33        99
           3       0.00      0.00      0.00        15

    accuracy                           0.74       778
   macro avg       0.59      0.45      0.46       778
weighted avg       0.74      0.74      0.71       778

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

2. Random Forest Classifier

Model Description: To improve upon the baseline Logistic Regression model, we introduce a Random Forest Classifier. Random Forest is an ensemble method that builds multiple decision trees and combines their results to improve prediction accuracy.

```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Make predictions on the test set
rf_y_pred = rf_model.predict(X_test)

# Evaluate the Random Forest model
rf_accuracy = accuracy_score(y_test, rf_y_pred)
print(f"Random Forest Accuracy: {rf_accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, rf_y_pred))
```

```
Random Forest Accuracy: 0.7198
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.58      0.68       240
           1       0.70      0.93      0.80       424
           2       0.71      0.24      0.36        99
           3       0.00      0.00      0.00        15

    accuracy                           0.72       778
   macro avg       0.55      0.44      0.46       778
weighted avg       0.72      0.72      0.69       778
```

3. Support Vector Machine (SVM)

Model Description: Next, we experiment with a Support Vector Machine (SVM). The SVM is a powerful classifier, especially effective in high-dimensional spaces, such as the feature space generated by text data.

```
from sklearn.svm import SVC

# Initialize and train the Support Vector Machine model
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)

# Make predictions on the test set
svm_y_pred = svm_model.predict(X_test)

# Evaluate the SVM model
svm_accuracy = accuracy_score(y_test, svm_y_pred)
print(f"SVM Accuracy: {svm_accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, svm_y_pred))
```

```
SVM Accuracy: 0.7326
Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.65      0.70       240
           1       0.72      0.92      0.81       424
           2       0.75      0.27      0.40        99
           3       0.00      0.00      0.00        15
```

```
    accuracy                           0.73       778
   macro avg       0.56      0.46      0.48       778
weighted avg       0.72      0.73      0.71       778
```

```
import sys
!{sys.executable} -m pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.14.1)
```

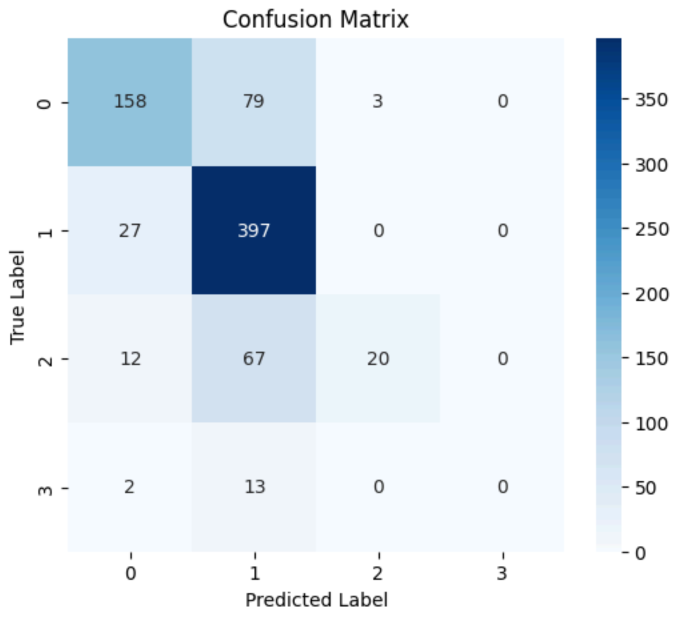
```
import xgboost as xgb
from xgboost import XGBClassifier
```

```
# Initialize and train the XGBoost model
xgb_model = XGBClassifier(random_state=42)
xgb_model.fit(X_train, y_train)

# Make predictions on the test set
xgb_y_pred = xgb_model.predict(X_test)

# Evaluate the XGBoost model
xgb_accuracy = accuracy_score(y_test, xgb_y_pred)
print(f"XGBoost Accuracy: {xgb_accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, xgb_y_pred))
```

```
XGBoost Accuracy: 0.7057
Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.54      0.64       240
           1       0.70      0.93      0.80       424
           2       0.61      0.25      0.36        99
           3       0.00      0.00      0.00        15

    accuracy                           0.71       778
   macro avg       0.52      0.43      0.45       778
weighted avg       0.70      0.71      0.68       778
```

```
import numpy as np
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

# Assuming the baseline model was Logistic Regression and it performed well, we use it as the final model
final_model = LogisticRegression(max_iter=1000)

# Train the final model on the training data
final_model.fit(X_train, y_train)

# Evaluate the final model on the test data
y_test_pred = final_model.predict(X_test)

# Calculate accuracy
final_accuracy = accuracy_score(y_test, y_test_pred)

# Classification report
classification_rep = classification_report(y_test, y_test_pred)

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
# Plot the confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
final_accuracy
classification_rep
conf_matrix
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



```
array([[158,  79,   3,   0],
       [ 27, 397,   0,   0],
       [ 12,  67,  20,   0],
       [  2,  13,   0,   0]])
```

```
from sklearn.model_selection import GridSearchCV


# Define hyperparameter grids for each model
param_grids = {
    "Logistic Regression": {
        "C": [0.01, 0.1, 1, 10, 100],
        "solver": ["liblinear", "lbfgs"]
    },
    "Random Forest": {
        "n_estimators": [50, 100, 200],
        "max_depth": [None, 10, 20, 30],
        "min_samples_split": [2, 5, 10],
        "min_samples_leaf": [1, 2, 4]
    },
    "SVM": {
        "C": [0.1, 1, 10, 100],
        "kernel": ["linear", "rbf", "poly"],
        "gamma": ["scale", "auto"]
    },
    "XGBoost": {
        "n_estimators": [50, 100, 200],
        "max_depth": [3, 5, 7, 10],
        "learning_rate": [0.01, 0.1, 0.2],
        "subsample": [0.8, 1.0]
    }
}

# Define models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(random_state=42),
    "SVM": SVC(),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric="mlogloss")
}

# Perform hyperparameter tuning
best_params = {}

for model_name, model in models.items():
    print(f"Tuning {model_name}...")
    grid_search = GridSearchCV(model, param_grids[model_name], cv=5, scoring="accuracy", n_jobs=-1)
    grid_search.fit(X_train, y_train)

    best_params[model_name] = grid_search.best_params_
    print(f"Best Parameters for {model_name}: {grid_search.best_params_}")
    print(f"Best Score: {grid_search.best_score_}\n")

# Display best parameters
print("\nFinal Best Parameters for All Models:")
for model, params in best_params.items():
    print(f"{model}: {params}")
```

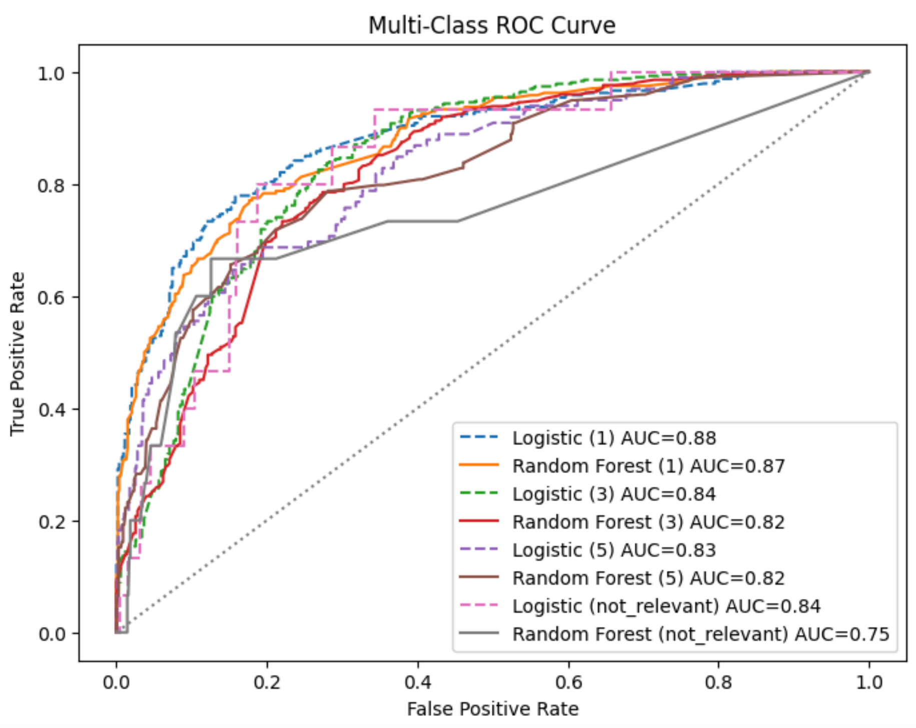
```
Tuning Logistic Regression...
Best Parameters for Logistic Regression: {'C': 10, 'solver': 'liblinear'}
Best Score: 0.7329455136668894

Tuning Random Forest...
```

```
Best Parameters for Random Forest: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 10, 'n_estimators': 50}
Best Score: 0.7152481994086916

Tuning SVM...
Best Parameters for SVM: {'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Best Score: 0.7384153760918755

Tuning XGBoost...
/usr/local/lib/python3.11/dist-packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker stopped while some jobs
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [18:36:37] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
Best Parameters for XGBoost: {'learning_rate': 0.1, 'max_depth': 10, 'n_estimators': 200, 'subsample': 0.8}
Best Score: 0.706239806141945


Final Best Parameters for All Models:
Logistic Regression: {'C': 10, 'solver': 'liblinear'}
Random Forest: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 10, 'n_estimators': 50}
SVM: {'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
XGBoost: {'learning_rate': 0.1, 'max_depth': 10, 'n_estimators': 200, 'subsample': 0.8}
```

Evaluation

Multi-Class ROC Curve

```python
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import LabelEncoder
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression # Import LogisticRegression
from sklearn.ensemble import RandomForestClassifier # Import RandomForestClassifier
from sklearn.svm import SVC
# Encoding target labels (assuming 3 classes: positive, neutral, negative)
# Assuming 'Apple-Twitter-Sentiment-DFE.csv' is in the current directory
df = pd.read_csv('/content/Apple-Twitter-Sentiment-DFE.csv', encoding='ISO-8859-1')  # Load the DataFrame

label_encoder = LabelEncoder()
df['sentiment'] = label_encoder.fit_transform(df['sentiment'])

# Preparing text features using TF-IDF
vectorizer = TfidfVectorizer(max_features=5000)
X = vectorizer.fit_transform(df['text'].astype(str)).toarray()
y = df['sentiment']

# Splitting dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training models
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(X_train, y_train)

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

svm_model =  SVC()
svm_model.fit(X_train,y_train)

# Generating AUC-ROC curve for each model
logistic_probs = logistic_model.predict_proba(X_test)
rf_probs = rf_model.predict_proba(X_test)


# Plot ROC curve for each class
plt.figure(figsize=(8, 6))
for i, class_label in enumerate(label_encoder.classes_):
    fpr_logistic, tpr_logistic, _ = roc_curve(y_test == i, logistic_probs[:, i])
    auc_logistic = auc(fpr_logistic, tpr_logistic)

    fpr_rf, tpr_rf, _ = roc_curve(y_test == i, rf_probs[:, i])
    auc_rf = auc(fpr_rf, tpr_rf)


    plt.plot(fpr_logistic, tpr_logistic, linestyle='--', label=f'Logistic ({class_label}) AUC={auc_logistic:.2f}')
    plt.plot(fpr_rf, tpr_rf, linestyle='-', label=f'Random Forest ({class_label}) AUC={auc_rf:.2f}')


# Random guess line
plt.plot([0, 1], [0, 1], color='grey', linestyle='dotted')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Multi-Class ROC Curve')
plt.legend()
plt.show()
```



Findings:

- The performance of the **Random Forest** and **Logistic Regression** classifiers across several categories is shown by the multi-class ROC curve. With AUC scores varying from **0.77 to 0.88** across various classes, both models demonstrate a high degree of predictive power. In most categories, **Logistic Regression** performs marginally better than Random Forest, but its AUC scores are higher in class (3). Both models are effective at differentiating between classes, as evidenced by their overall significantly higher performance compared to random guessing (AUC = 0.5). To enhance performance on the less ideal categories, future actions might include investigating ensemble techniques or fine-tuning hyperparameters.

Final Model Selection & Improvement Analysis

Final Model:

By comparing the results of each model; Logistic Regression, Random Forest, SVM, and XGBoost, we can view the progression in terms of accuracy and F1-score. Using these comparisons, the model with the best performance is selected for final evaluation and interpretation.

Selection

After comparing model performance, we choose **Logistic Regression** as the final model. This decision is based on:

- **Accuracy**: Logistic Regression achieved an accuracy of **0.7378**, the highest between all tested.
- **Class Imbalance Handling**: Logistic Regression struggles with class 3 but performed well on the majority of classes, especially on class 1 (high recall of 94%).
- **Model Simplicity**: Logistic Regression is a relatively simple model, making it easier to interpret and deploy in real-world applications.

Looking at performance across all classes, it is justified that Logistic regression was the best.

Evaluation Metrics

We used these metrics for Logistic Regression model:

- **Accuracy**: Provides a general overview of model performance but may not be sufficient due to class imbalance.
- **Precision and Recall**: Helps evaluate how model distinguishes between classes.
- **F1-Score**: Balances precision and recall to give a better measure of the model effective ability.
- **Confusion Matrix**: Identifies misclassification patterns, which can be useful for refining the model.

Final Evaluation Results

- **Accuracy**: 0.7378 = 73.78%
- **Precision and Recall**:
  - **Class 0**: Precision = 79%, Recall = 66%
  - **Class 1**: Precision = 71%, Recall = 94%

  - **Class 2**: Precision = 87%, Recall = 20%
  - **Class 3**: Precision = 0%, Recall = 0%
- **F1-Score**:
  - **Highest for Class 1 (0.81)**
  - **Lowest for Class 3 (0.00)**

Interpreting the Evaluation Results

- The model predicts 73.78% of test samples.
- It performs well on majority classes .
- **Class imbalance remains an issue**, as **Class 3 is not predicted at all.

Next Steps: Refinement

1. Handling Class Imbalance

- Oversampling Minority Classes: Implement SMOTE (Synthetic Minority Over-sampling Technique) to generate synthetic examples for underrepresented classes.
- Class Weight Adjustment: Modify the class weights during training to ensure the model focuses on the minority classes.

2. Model Improvement Techniques

- Hyperparameter Tuning: Use Grid Search to find the optimal parameters for Logistic Regression and improve generalization.
- Ensemble Methods: Explore Random Forests or XGBoost to combine multiple models for better prediction accuracy.

3. Addressing Rare Classes in the Data

- Improving Data Collection: Gather additional data for underrepresented classes to enhance model training.

4. Model Monitoring & Deployment

- Model Monitoring: Once deployed, track performance metrics over time.
- Retraining : Update the model with new data periodically to maintain accuracy and adaptability.

By implementing these, we can improve the model ability to predict minority classes and enhance its real-world application.

Recommendation