Problem Statement

Business Context

The prices of the stocks of companies listed under a global exchange are influenced by a variety of factors, with the company's financial performance, innovations and collaborations, and market sentiment being factors that play a significant role. News and media reports can rapidly affect investor perceptions and, consequently, stock prices in the highly competitive financial industry. With the sheer volume of news and opinions from a wide variety of sources, investors and financial analysts often struggle to stay updated and accurately interpret its impact on the market. As a result, investment firms need sophisticated tools to analyze market sentiment and integrate this information into their investment strategies.

Problem Definition

With an ever-rising number of news articles and opinions, an investment startup aims to leverage artificial intelligence to address the challenge of interpreting stock-related news and its impact on stock prices. They have collected historical daily news for a specific company listed under NASDAQ, along with data on its daily stock price and trade volumes.

As a member of the Data Science and AI team in the startup, you have been tasked with analyzing the data, developing an AI-driven sentiment analysis system that will automatically process and analyze news articles to gauge market sentiment, and summarizing the news at a weekly level to enhance the accuracy of their stock price predictions and optimize investment strategies. This will empower their financial analysts with actionable insights, leading to more informed investment decisions and improved client outcomes.

Data Dictionary

- `Date` : The date the news was released
- `News` : The content of news articles that could potentially affect the company's stock price
- `Open` : The stock price (in $) at the beginning of the day
- `High` : The highest stock price (in $) reached during the day
- `Low` : The lowest stock price (in $) reached during the day
- `Close` : The adjusted stock price (in $) at the end of the day
- `Volume` : The number of shares traded during the day
- `Label` : The sentiment polarity of the news content
  - 1: positive
  - 0: neutral
  - -1: negative

Please read the instructions carefully before starting the project.

Note: If the free-tier GPU of Google Colab is not accessible (due to unavailability or exhaustion of daily limit or other reasons), the following steps can be taken:

1. Wait for 12-24 hours until the GPU is accessible again or the daily usage limits are reset.
2. Switch to a different Google account and resume working on the project from there.
3. Try using the CPU runtime:

   - To use the CPU runtime, click on *Runtime* => *Change runtime type* => *CPU* => *Save*
   - One can also click on the *Continue without GPU* option to switch to a CPU runtime (kindly refer to the snapshot below)
   - The instructions for running the code on the CPU are provided in the respective sections of the

notebook.

Cannot connect to GPU backend

You cannot currently connect to a GPU due to usage limits in Colab. Learn more

To get more access to GPUs, consider purchasing Colab compute units with Pay As You Go.

Close Connect without GPU

Installing and Importing Necessary Libraries

In [ ]:

```
# installing the sentence-transformers and gensim libraries for word embeddings
!pip install -U sentence-transformers gensim transformers tqdm -q
```

Loading the dataset

In [ ]:

```
# Importing libraries to manipulate and analyze data
import pandas as pd  # pandas for handling data frames and datasets
import numpy as np   # numpy for numerical operations on arrays and matrices

# Importing libraries for data visualization
import matplotlib.pyplot as plt  # matplotlib for creating static visualizations like plo
ts and graphs
import seaborn as sns          # seaborn for statistical data visualization (more advanc
ed than matplotlib)

# Importing time-related functions for measuring execution time and managing timestamps
import time  # time module is used for timing the execution of certain tasks (e.g., measu
ring how long an operation takes)

# Importing JSON parsing library for working with JSON data format
import json  # json module to parse and manipulate JSON data structures

# Importing machine learning models, tools, and evaluation metrics
from sklearn.ensemble import GradientBoostingClassifier  # Gradient Boosting Machine for
classification tasks
from sklearn.ensemble import RandomForestClassifier     # Random Forest Classifier for b
uilding decision trees
from sklearn.tree import DecisionTreeClassifier         # Decision Tree Classifier for b
uilding a single tree model

from sklearn.model_selection import GridSearchCV  # GridSearchCV for hyperparameter tunin
g and cross-validation
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, precision_score,
recall_score  # Metrics for evaluating the model's performance

# Importing libraries for working with word embeddings (converting words to vector repres
entations)
from gensim.models import Word2Vec  # Word2Vec for creating word embeddings based on word
context
from gensim.models import KeyedVectors  # KeyedVectors to handle vectorized word embeddin
```

```
gs
from gensim.scripts.glove2word2vec import glove2word2vec  # Utility to convert GloVe embe
ddings to Word2Vec format

# Importing libraries for transformer models used in NLP (natural language processing)
import torch  # PyTorch for deep learning models, such as transformers
from sentence_transformers import SentenceTransformer  # SentenceTransformer for encoding
sentences into embeddings

# Importing library for progress bars to track the execution progress of tasks
from tqdm import tqdm  # tqdm for showing a progress bar during iterations, useful in lon
g-running loops
tqdm.pandas()  # Enables progress bars in pandas operations (like `apply` method)

# To ignore unnecessary warnings that might clutter the output
import warnings  # warnings module to manage warnings during code execution
warnings.filterwarnings('ignore')  # Disable warnings from appearing in the output
```

Data Overview

In [ ]:

```
# # uncomment and run the following code if Google Colab is being used and the dataset is
in Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

In [ ]:

```
stock_news = pd.read_csv("/content/drive/MyDrive/AIML_Project5/stock_news.csv")
```

In [ ]:

```
#Creating a copy of the dataset
stock = stock_news.copy()
```

Lets explore the dataset

In [ ]:

```
stock.head(2)
```

Out[ ]:

	Date	News	Open	High	Low	Close	Volume	Label
0	2019-01-02	The tech sector experienced a significant dec...	41.740002	42.244999	41.482498	40.246914	130672400	-1
1	2019-01-02	Apple lowered its fiscal Q1 revenue guidance ...	41.740002	42.244999	41.482498	40.246914	130672400	-1

In [ ]:

```
stock.sample(5)
```

Out[ ]:

	Date	News	Open	High	Low	Close	Volume	Label
336	2019-04-26	Sony, the Japanese technology giant, announce...	51.224998	51.250000	50.529999	49.589897	74596400	0
185	2019-02-12	Akamai Technologies reported stronger than pr...	66.817497	67.062500	65.862503	64.805229	94487200	1
276	2019-03-26	Goldman Sachs has announced a credit card par...	47.915001	48.220001	46.145000	45.339684	199202000	0

	Date	News	Open	High	Low	Close	Volume	Label
165	2019-01-31	The United Arab Emirates (UAE) denied on Thurs...	41.527500	42.250000	41.139999	40.227589	162958400	0
315	2019-04-17	Facebook, aiming to compete with Alexa, Siri,...	49.884998	50.845001	49.652500	49.305897	115627200	-1

In [ ]:

```
stock.tail(1)
```

Out[ ]:

	Date	News	Open	High	Low	Close	Volume	Label
348	2019-04-30	In the first quarter, South Korea's Samsung E...	50.764999	50.849998	49.7775	48.70879	186139600	0

In [ ]:

```
stock.shape
```

Out[ ]:

```
(349, 8)
```

In [ ]:

```
stock.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 349 entries, 0 to 348
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Date    349 non-null    object 
 1   News    349 non-null    object 
 2   Open    349 non-null    float64
 3   High    349 non-null    float64
 4   Low     349 non-null    float64
 5   Close   349 non-null    float64
 6   Volume  349 non-null    int64  
 7   Label   349 non-null    int64  
dtypes: float64(4), int64(2), object(2)
memory usage: 21.9+ KB
```

In [ ]:

```
stock['Date'] = pd.to_datetime(stock['Date'], errors='coerce')
```

Lets check the data type of date

In [ ]:

```
stock.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 349 entries, 0 to 348
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    349 non-null    datetime64[ns]
 1   News    349 non-null    object        
 2   Open    349 non-null    float64       
 3   High    349 non-null    float64       
 4   Low     349 non-null    float64       
 5   Close   349 non-null    float64       
 6   Volume  349 non-null    int64         
 7   Label   349 non-null    int64         
dtypes: datetime64[ns](1), float64(4), int64(2), object(1)
memory usage: 21.9+ KB
```

Lets check the stats

In [ ]:

```
stock.describe()
```

Out[ ]:

```
                                Date       Open       High        Low      Close        Volume       Label
count                            349 349.000000 349.000000 349.000000 349.000000  3.490000e+02  349.000000
 mean  2019-02-16 16:05:30.085959936  46.229233  46.700458  45.745394  44.926317  1.289482e+08   -0.054441
  min            2019-01-02 00:00:00  37.567501  37.817501  37.305000  36.254131  4.544800e+07   -1.000000
  25%            2019-01-14 00:00:00  41.740002  42.244999  41.482498  40.246914  1.032720e+08   -1.000000
  50%            2019-02-05 00:00:00  45.974998  46.025002  45.639999  44.596924  1.156272e+08    0.000000
  75%            2019-03-22 00:00:00  50.707500  50.849998  49.777500  49.110790  1.511252e+08    0.000000
  max            2019-04-30 00:00:00  66.817497  67.062500  65.862503  64.805229  2.444392e+08    1.000000
  std                            NaN   6.442817   6.507321   6.391976   6.398338  4.317031e+07    0.715119
```

Check duplicate values

In [ ]:

```
stock.duplicated().sum()
```

Out[ ]:

```
0
```

Check null values

In [ ]:

```
stock.isnull().sum()
```

Out[ ]:

```
        0
  Date  0
  News  0
  Open  0
  High  0
   Low  0
 Close  0
Volume  0
 Label  0

dtype: int64
```

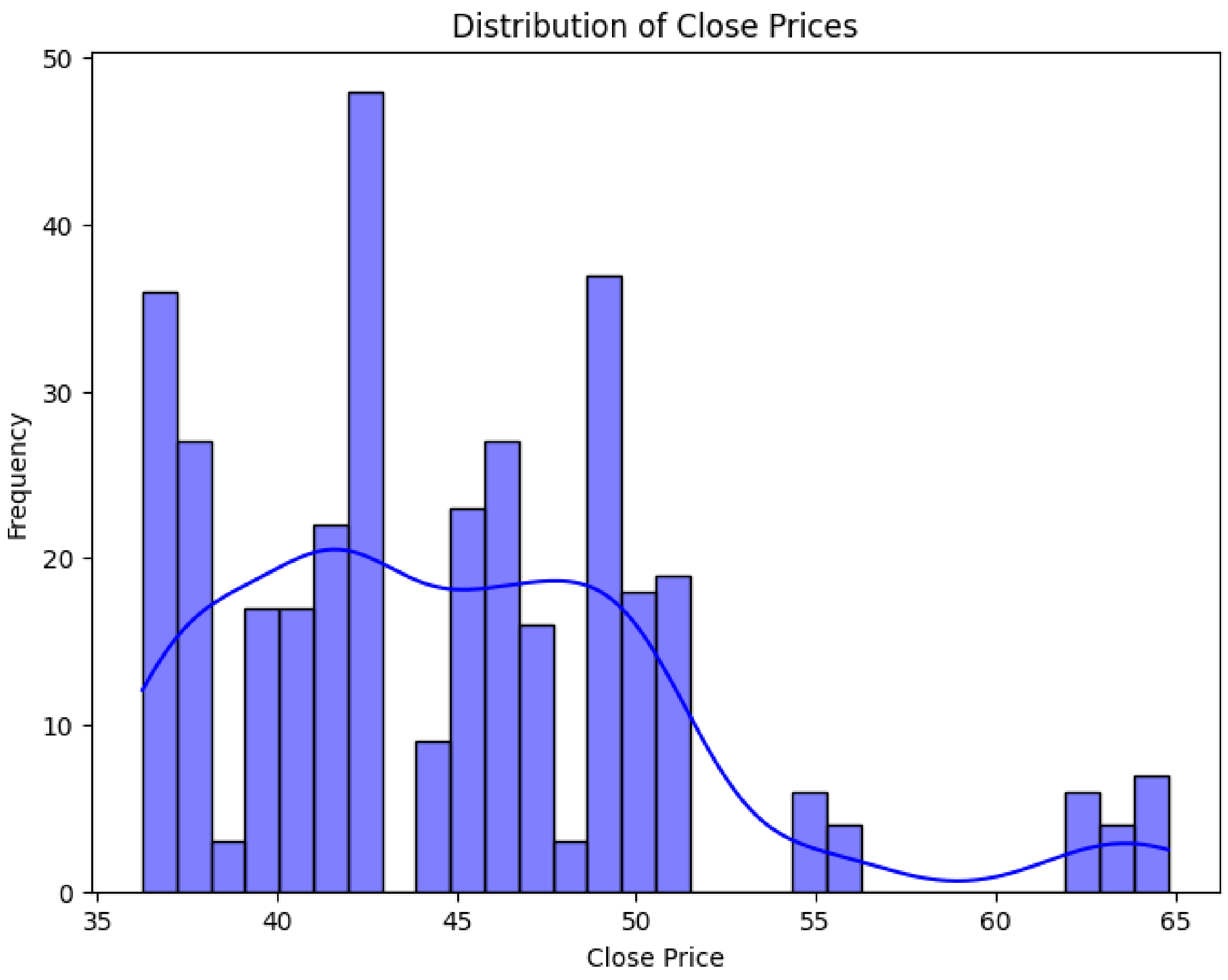
Exploratory Data Analysis

Univariate Analysis

- **Distribution of individual variables**
- **Compute and check the distribution of the length of news content**

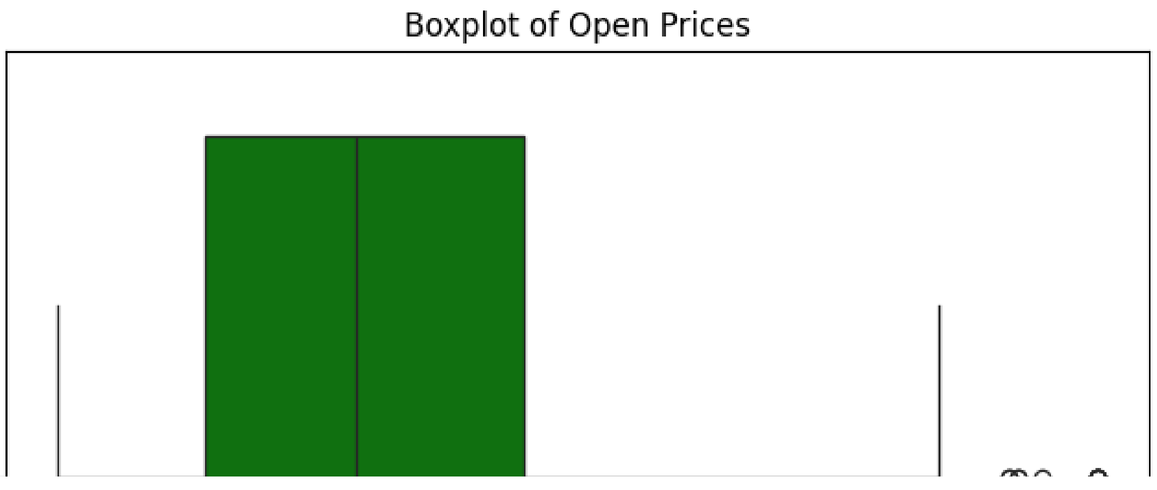
In [ ]:

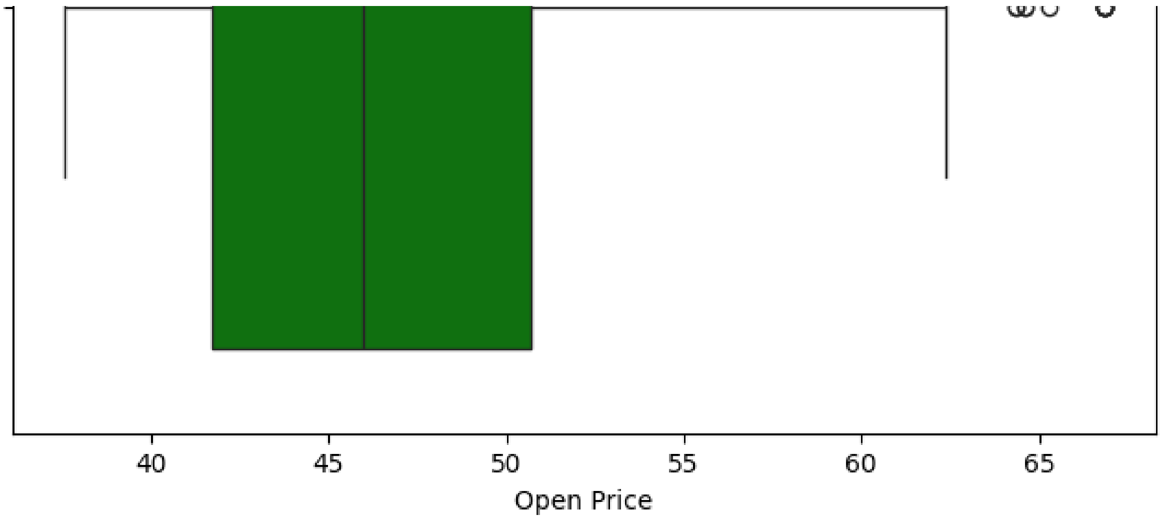
```
# Plotting the distribution of 'Close' prices
plt.figure(figsize=(8, 6))
sns.histplot(stock['Close'], kde=True, color='blue', bins=30)
plt.title('Distribution of Close Prices')
plt.xlabel('Close Price')
plt.ylabel('Frequency')
plt.show()
```



In [ ]:

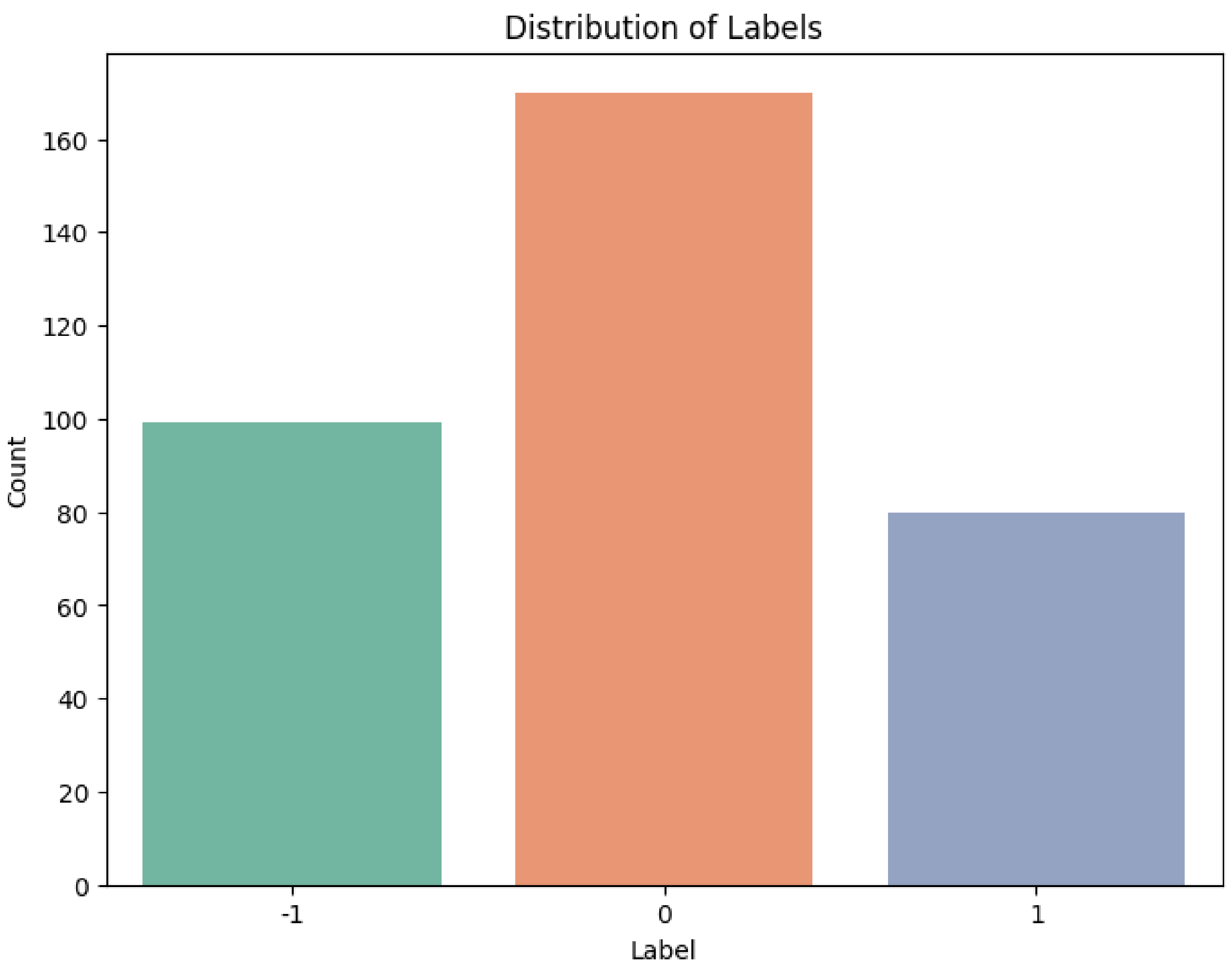
```
# Plotting the boxplot for 'Open' prices
plt.figure(figsize=(8, 6))
sns.boxplot(x=stock['Open'], color='green')
plt.title('Boxplot of Open Prices')
plt.xlabel('Open Price')
plt.show()
```





In [ ]:

```
# Countplot showing distribution of 'Label' categories (e.g., Positive, Negative, Neutral
)
plt.figure(figsize=(8, 6))
sns.countplot(data=stock, x='Label', palette='Set2')
plt.title('Distribution of Labels')
plt.xlabel('Label')
plt.ylabel('Count')
plt.show()
```



Imbalanced Data

imbalanced data can significantly affect model performance, especially in classification tasks. When the data is imbalanced, the model tends to be biased towards the majority class because it sees more examples of that class, leading to poor generalization on the minority class.

In this case, if the dataset contains more neutral news articles compared to positive or negative ones, the model

may have trouble identifying the less frequent sentiment classes (positive or negative sentiment) and could perform poorly when predicting these classes.

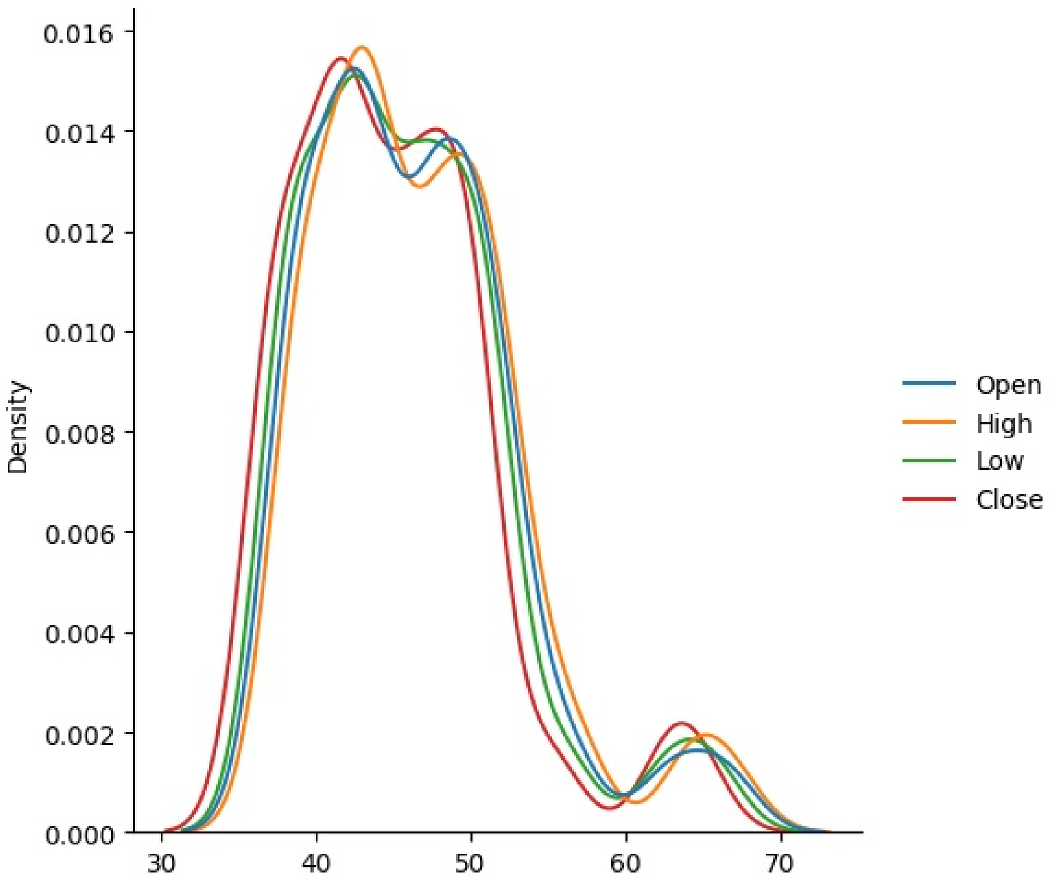
"Approximately 50% of the news is neutral, while 30-20% of the news is classified as negative and positive."

```
In [ ]:
```

```
sns.displot(
    data=stock[['Open', 'High', 'Low', 'Close']],
    kind="kde",
    palette="tab10"
)
```

```
Out[ ]:
```

```
<seaborn.axisgrid.FacetGrid at 0x789e8ae3bc90>
```

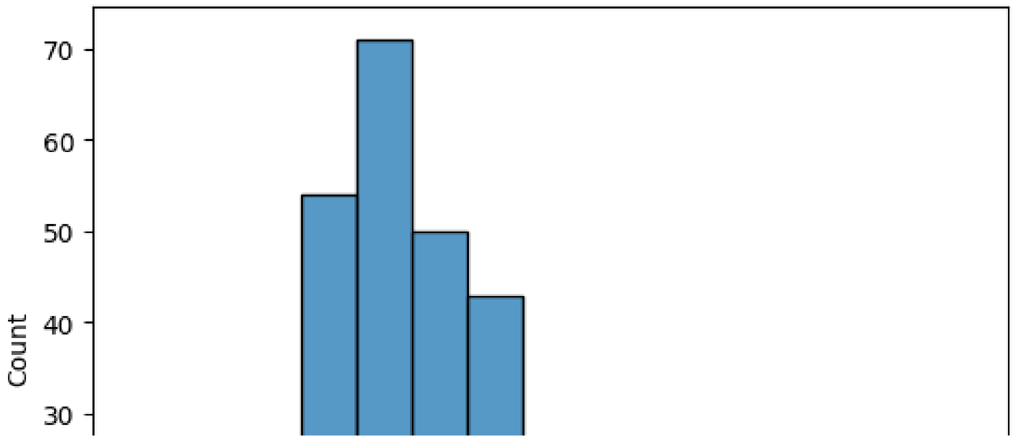


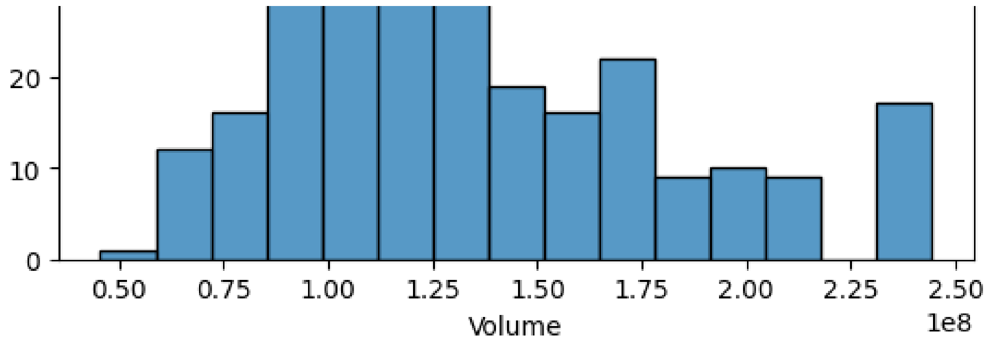
```
In [ ]:
```

```
sns.histplot(
    data=stock,
    x='Volume'
)
```

```
Out[ ]:
```

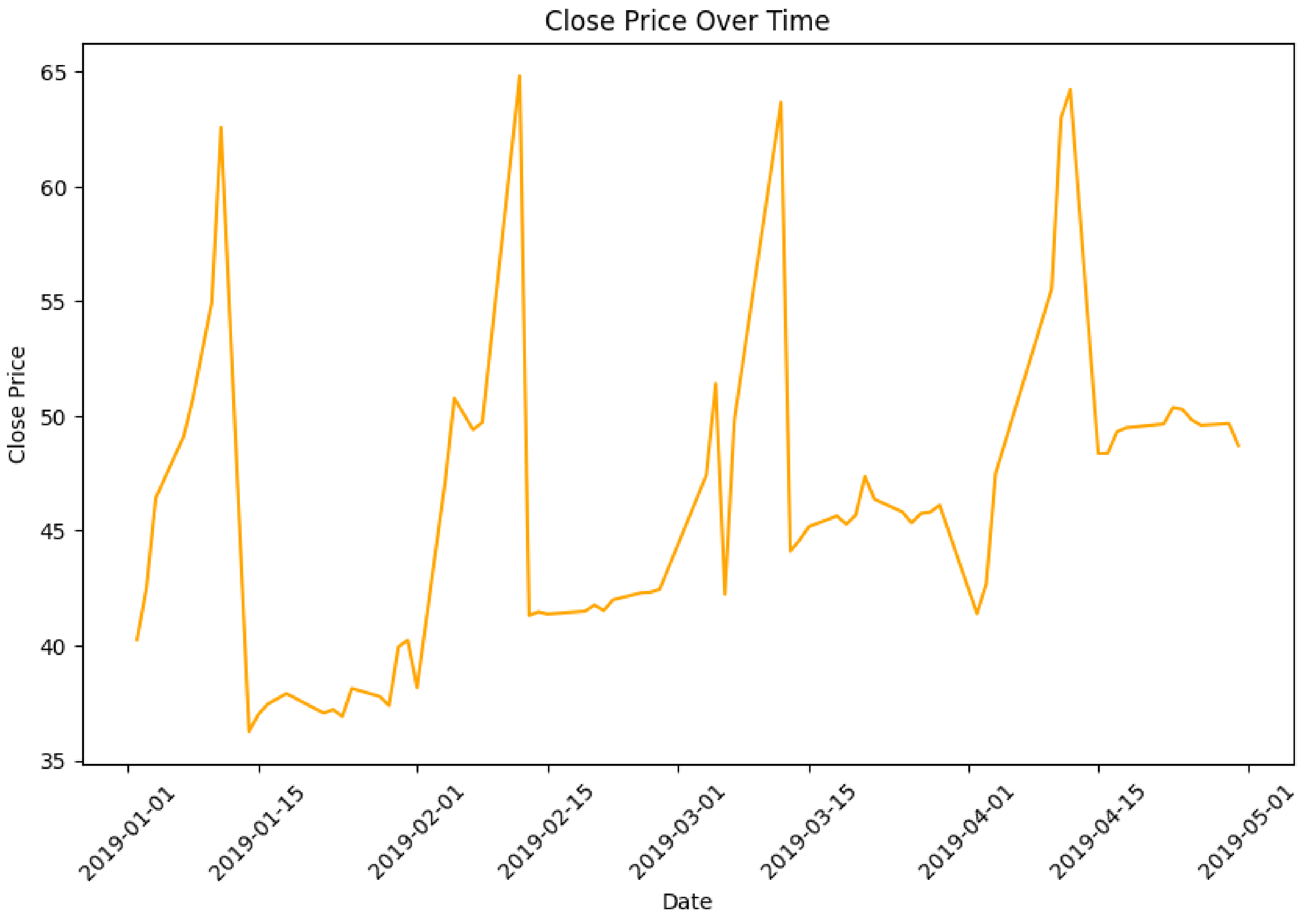
```
<Axes: xlabel='Volume', ylabel='Count'>
```





In [ ]:

```
# Plotting the 'Close' prices over time (Date)
plt.figure(figsize=(10, 6))
sns.lineplot(data=stock, x='Date', y='Close', color='orange')
plt.title('Close Price Over Time')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.xticks(rotation=45)
plt.show()
```



Bivariate Analysis

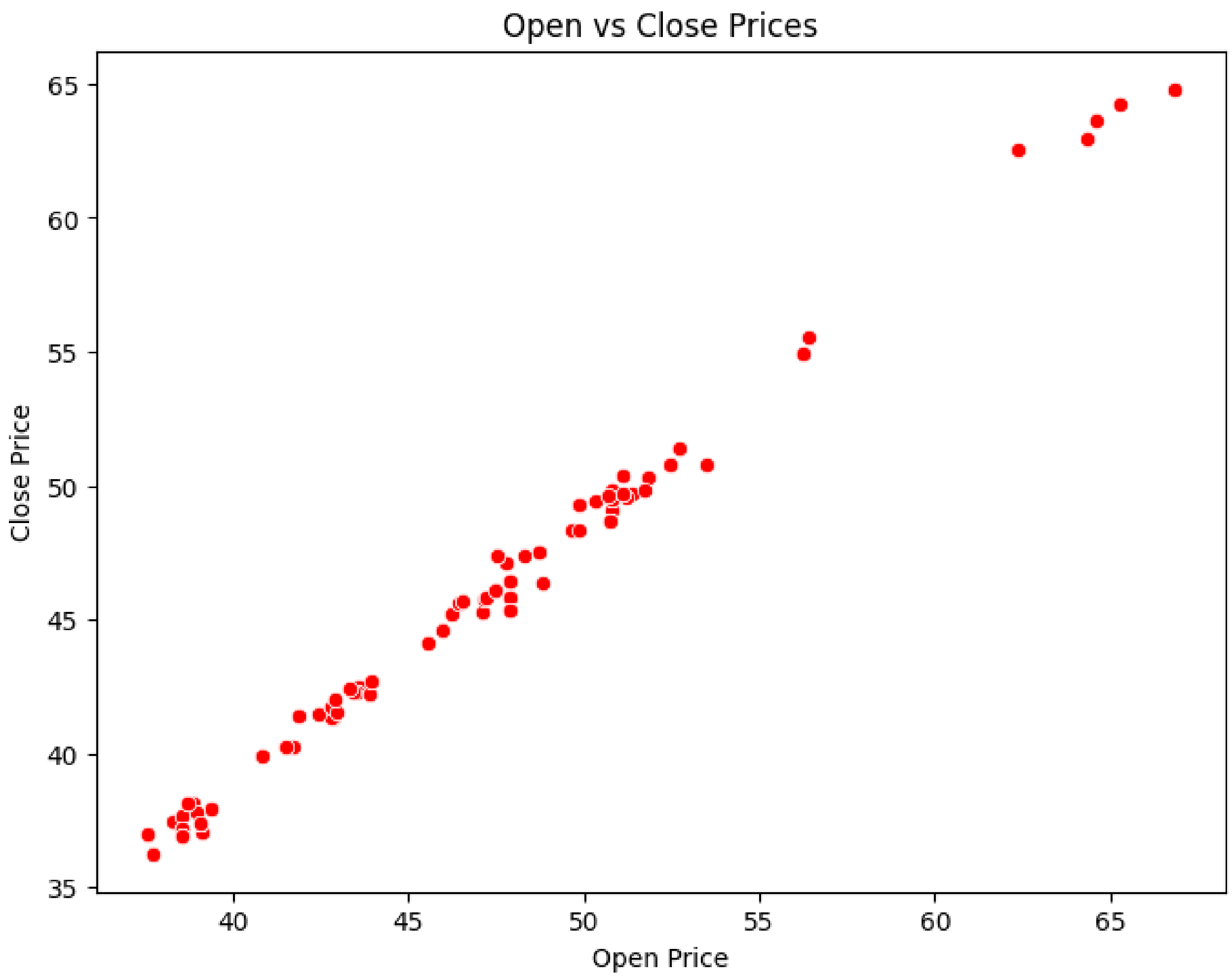
- **Correlation**
- **Sentiment Polarity vs Price**
- **Date vs Price**

Note: The above points are listed to provide guidance on how to approach bivariate analysis. Analysis has to be done beyond the above listed points to get maximum scores.

In [ ]:

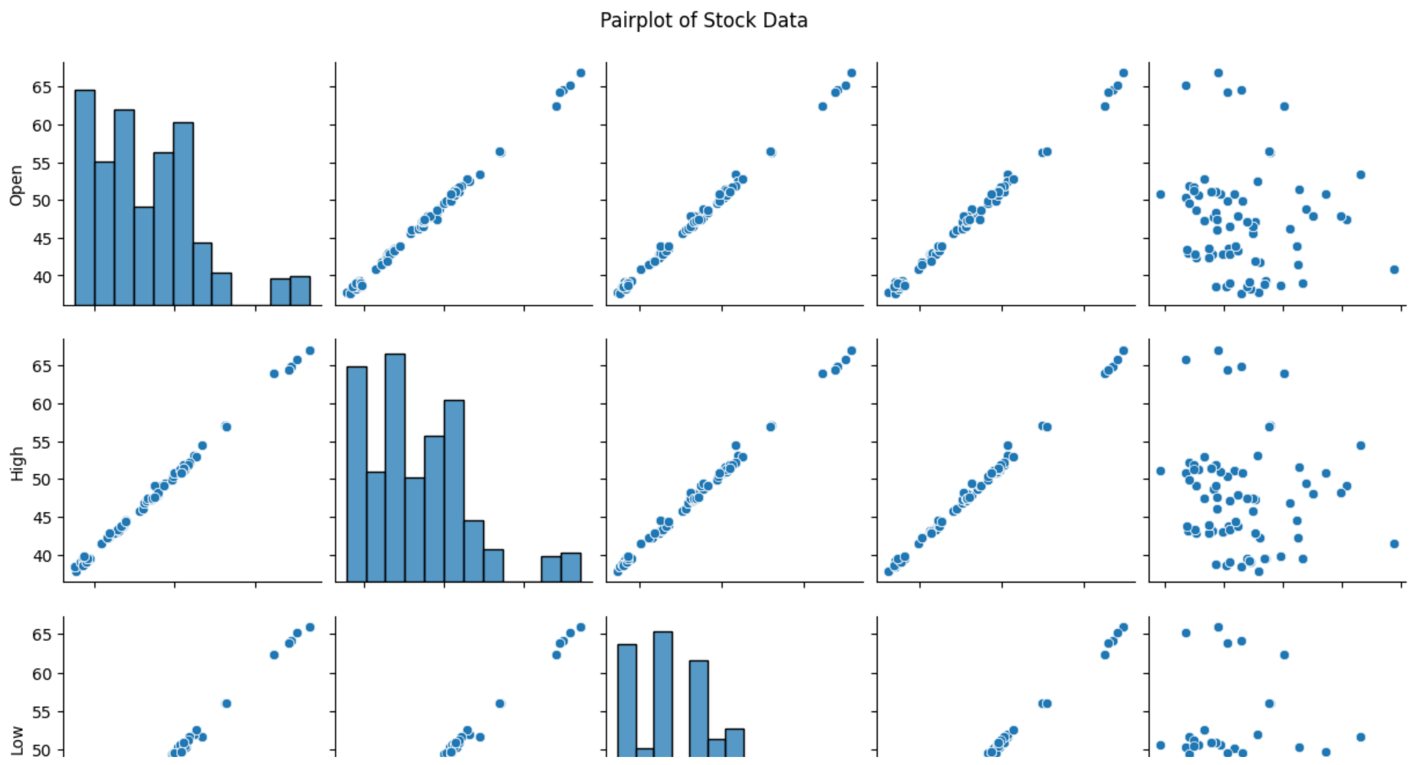
```
# Scatter plot showing relationship between 'Open' and 'Close' prices
```

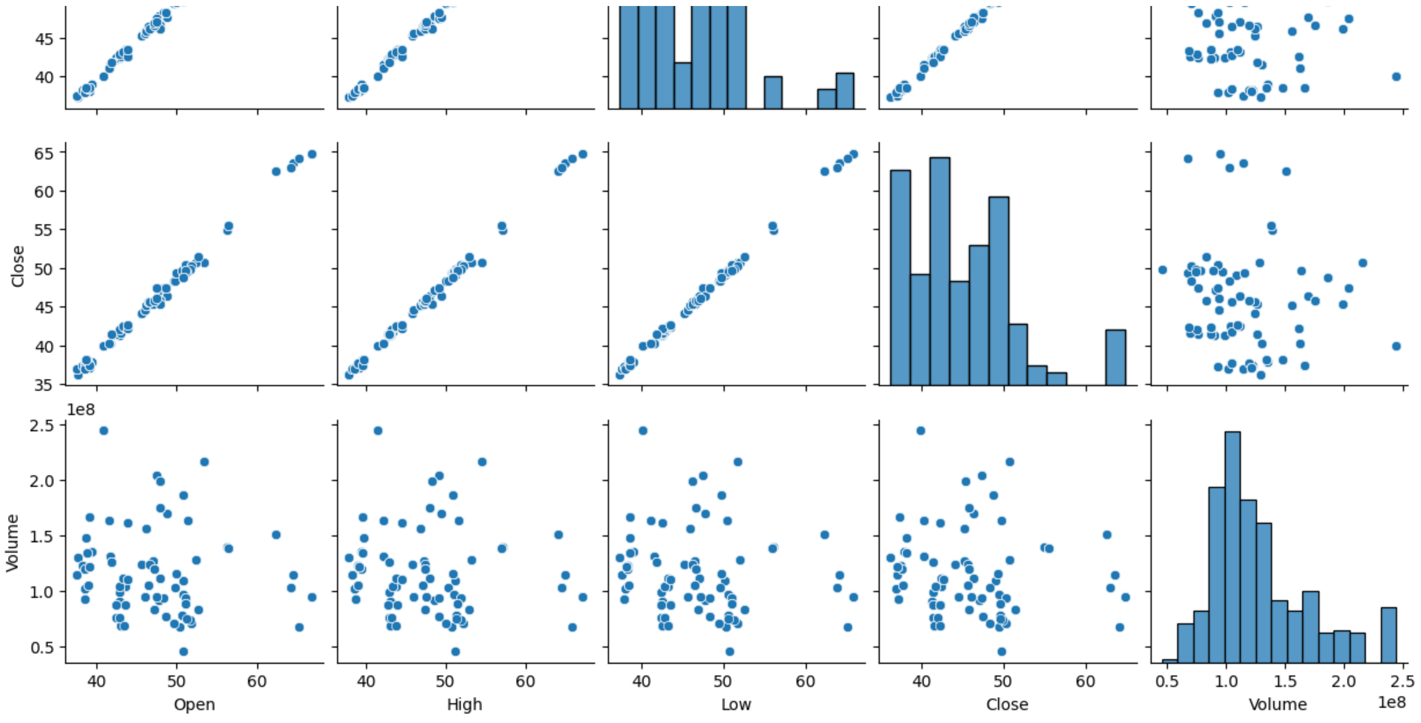
```
plt.figure(figsize=(8, 6))
sns.scatterplot(data=stock, x='Open', y='Close', color='red')
plt.title('Open vs Close Prices')
plt.xlabel('Open Price')
plt.ylabel('Close Price')
plt.show()
```



In [ ]:

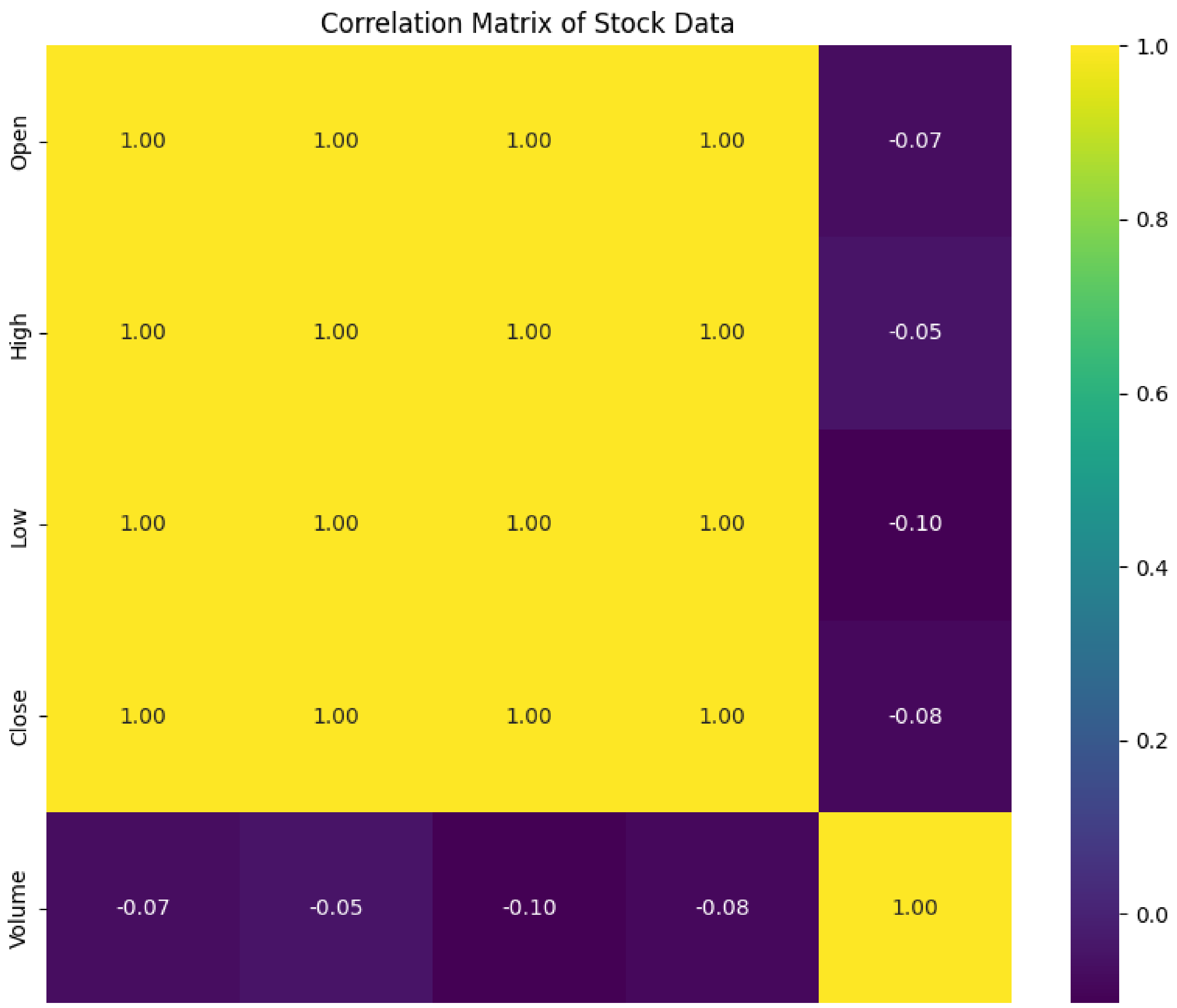
```
# Pairplot to visualize relationships between multiple numeric variables
sns.pairplot(stock[['Open', 'High', 'Low', 'Close', 'Volume']])
plt.suptitle('Pairplot of Stock Data', y=1.02)
plt.show()
```





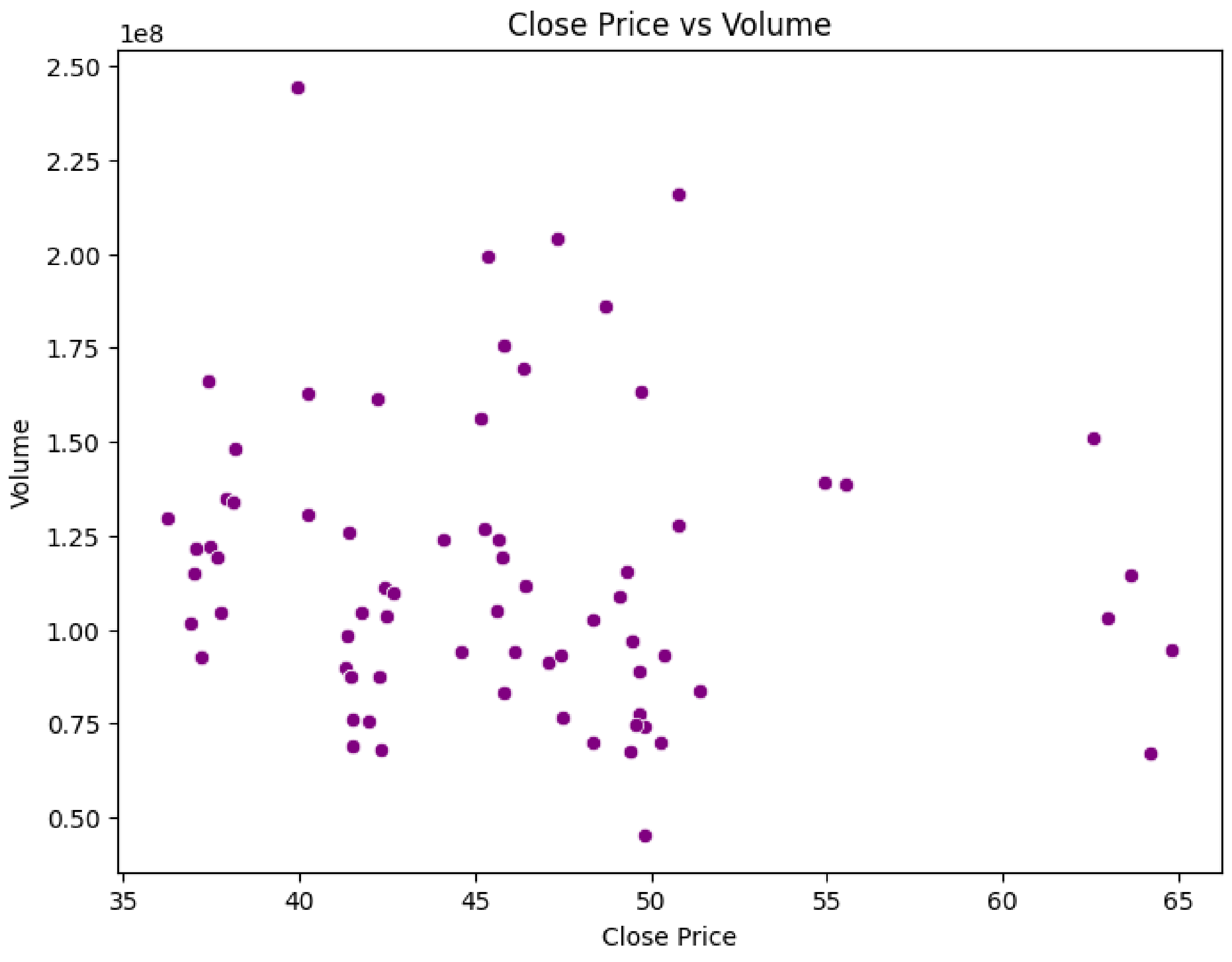
```
In [ ]:
```

```
# Heatmap showing correlation between numeric columns
plt.figure(figsize=(10, 8))
sns.heatmap(stock[['Open', 'High', 'Low', 'Close', 'Volume']].corr(), annot=True, cmap="
viridis", fmt=".2f")
plt.title('Correlation Matrix of Stock Data')
plt.show()
```



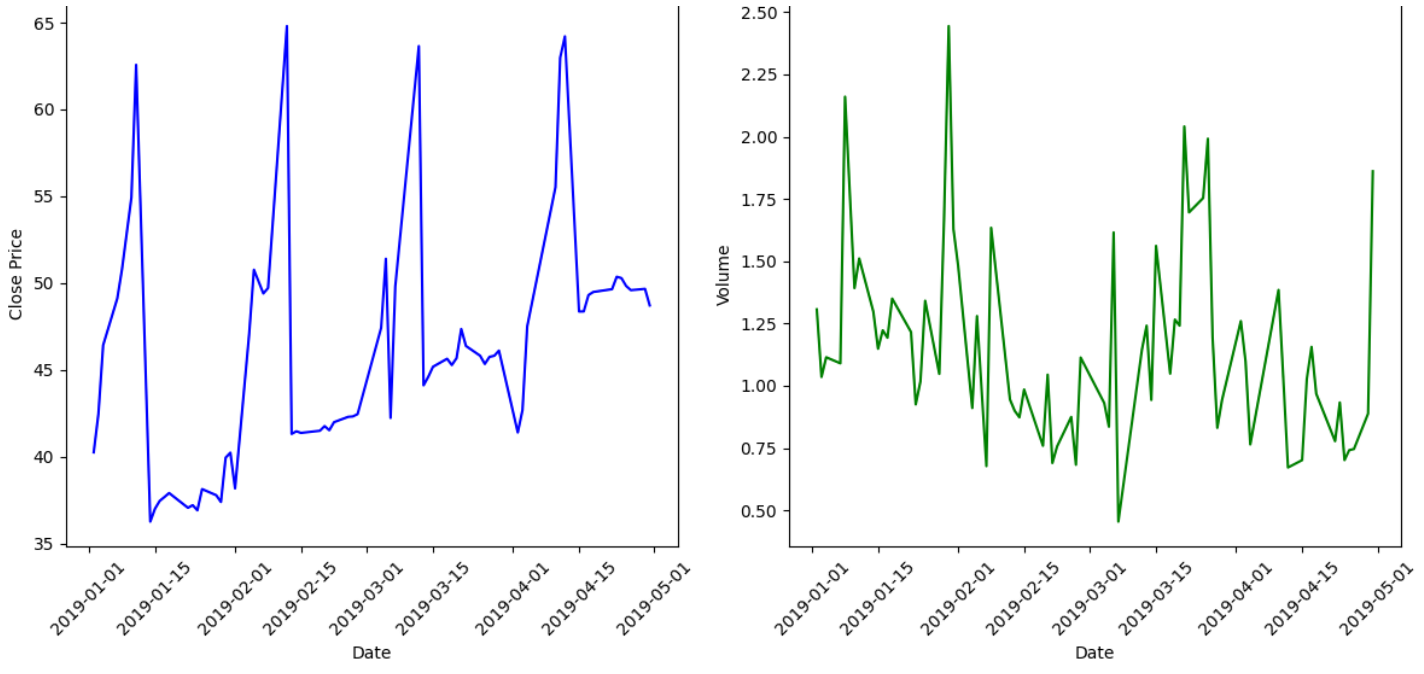
In [ ]:

```
# Scatter plot showing 'Close' vs 'Volume' to see the relationship
plt.figure(figsize=(8, 6))
sns.scatterplot(data=stock, x='Close', y='Volume', color='purple')
plt.title('Close Price vs Volume')
plt.xlabel('Close Price')
plt.ylabel('Volume')
plt.show()
```



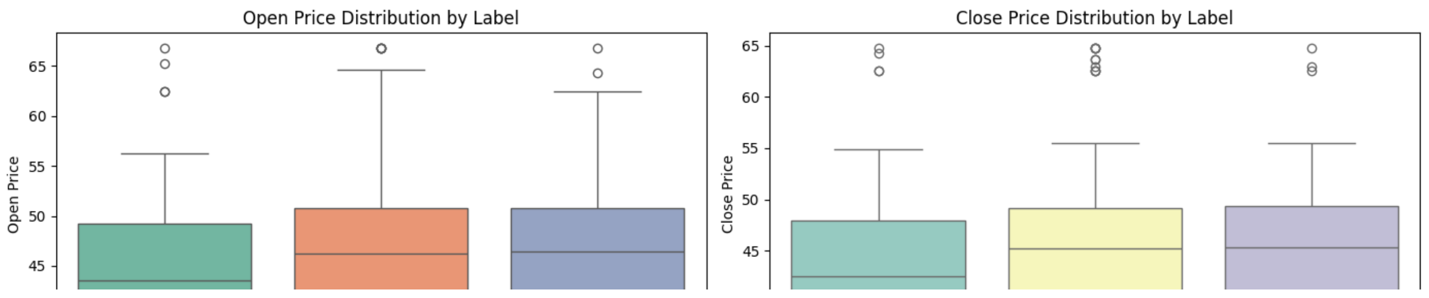
In [ ]:

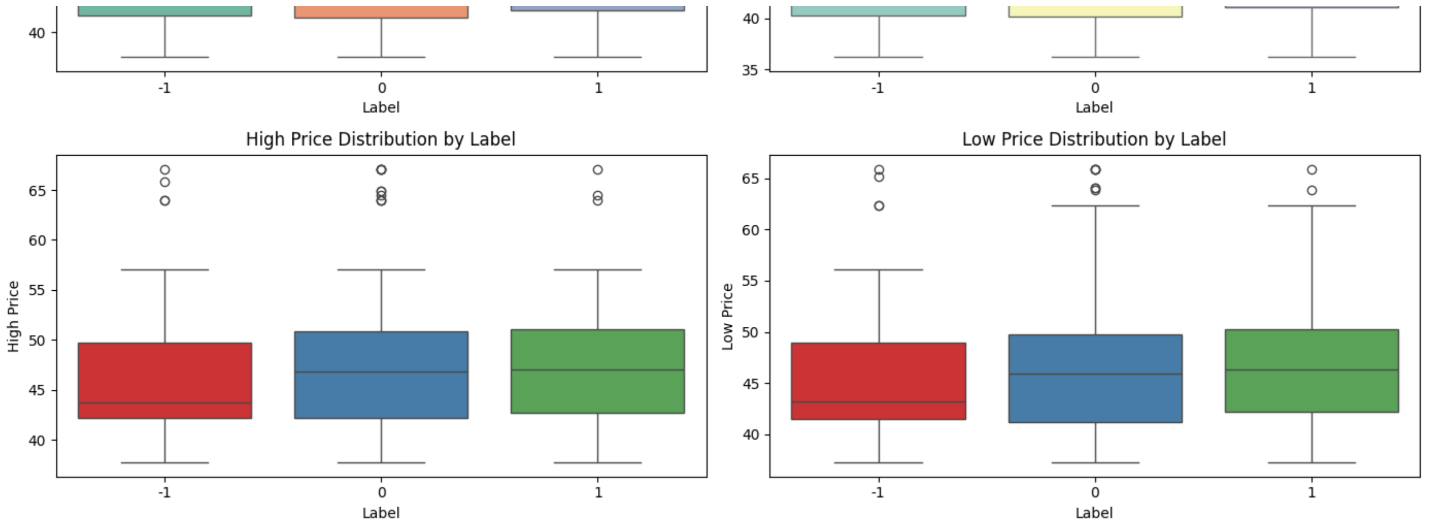
```
# Plotting Close Price and Volume over Time
plt.figure(figsize=(12, 6))

# Plotting Close Price
plt.subplot(1, 2, 1)
sns.lineplot(data=stock, x='Date', y='Close', color='blue')
plt.title('Close Price Over Time')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.xticks(rotation=45)

# Plotting Volume
plt.subplot(1, 2, 2)
sns.lineplot(data=stock, x='Date', y='Volume', color='green')
plt.title('Volume Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.xticks(rotation=45)

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



In [ ]:

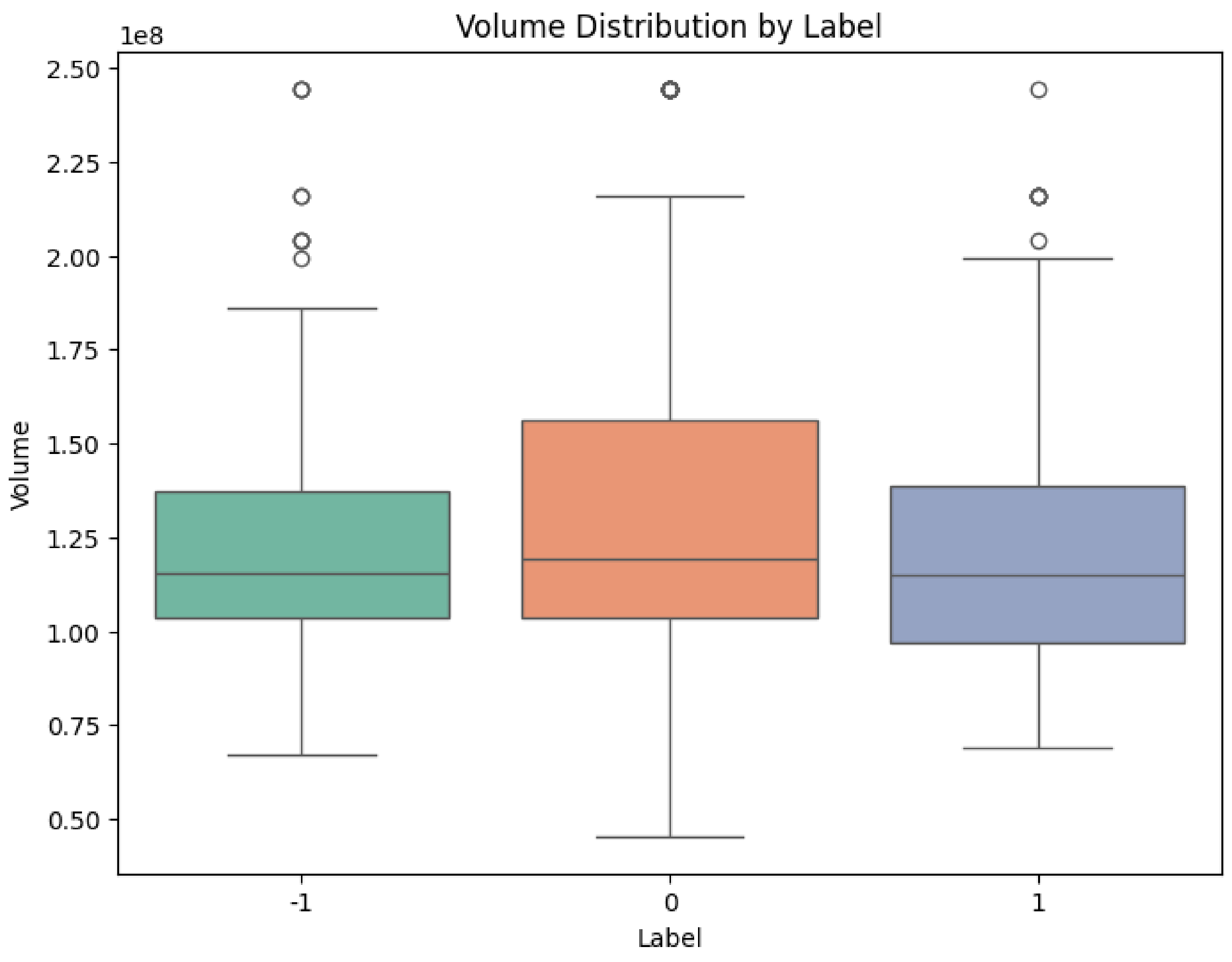
```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a figure with multiple subplots for different price features
plt.figure(figsize=(14, 8))

# Boxplot for 'Open' price by 'Label'
plt.subplot(2, 2, 1)
sns.boxplot(data=stock, x='Label', y='Open', palette='Set2')
plt.title('Open Price Distribution by Label')
plt.xlabel('Label')
plt.ylabel('Open Price')

# Boxplot for 'Close' price by 'Label'
plt.subplot(2, 2, 2)
sns.boxplot(data=stock, x='Label', y='Close', palette='Set3')
plt.title('Close Price Distribution by Label')
plt.xlabel('Label')
plt.ylabel('Close Price')

# Boxplot for 'High' price by 'Label'
plt.subplot(2, 2, 3)
sns.boxplot(data=stock, x='Label', y='High', palette='Set1')
plt.title('High Price Distribution by Label')
plt.xlabel('Label')
plt.ylabel('High Price')

# Boxplot for 'Low' price by 'Label'
plt.subplot(2, 2, 4)
sns.boxplot(data=stock, x='Label', y='Low', palette='Set1')
plt.title('Low Price Distribution by Label')
plt.xlabel('Label')
plt.ylabel('Low Price')

# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```





In [ ]:

```
# Plotting a boxplot to visualize the distribution of 'Volume' for each 'Label'
plt.figure(figsize=(8, 6))
sns.boxplot(data=stock, x='Label', y='Volume', palette='Set2')
plt.title('Volume Distribution by Label')
plt.xlabel('Label')
plt.ylabel('Volume')
plt.show()
```

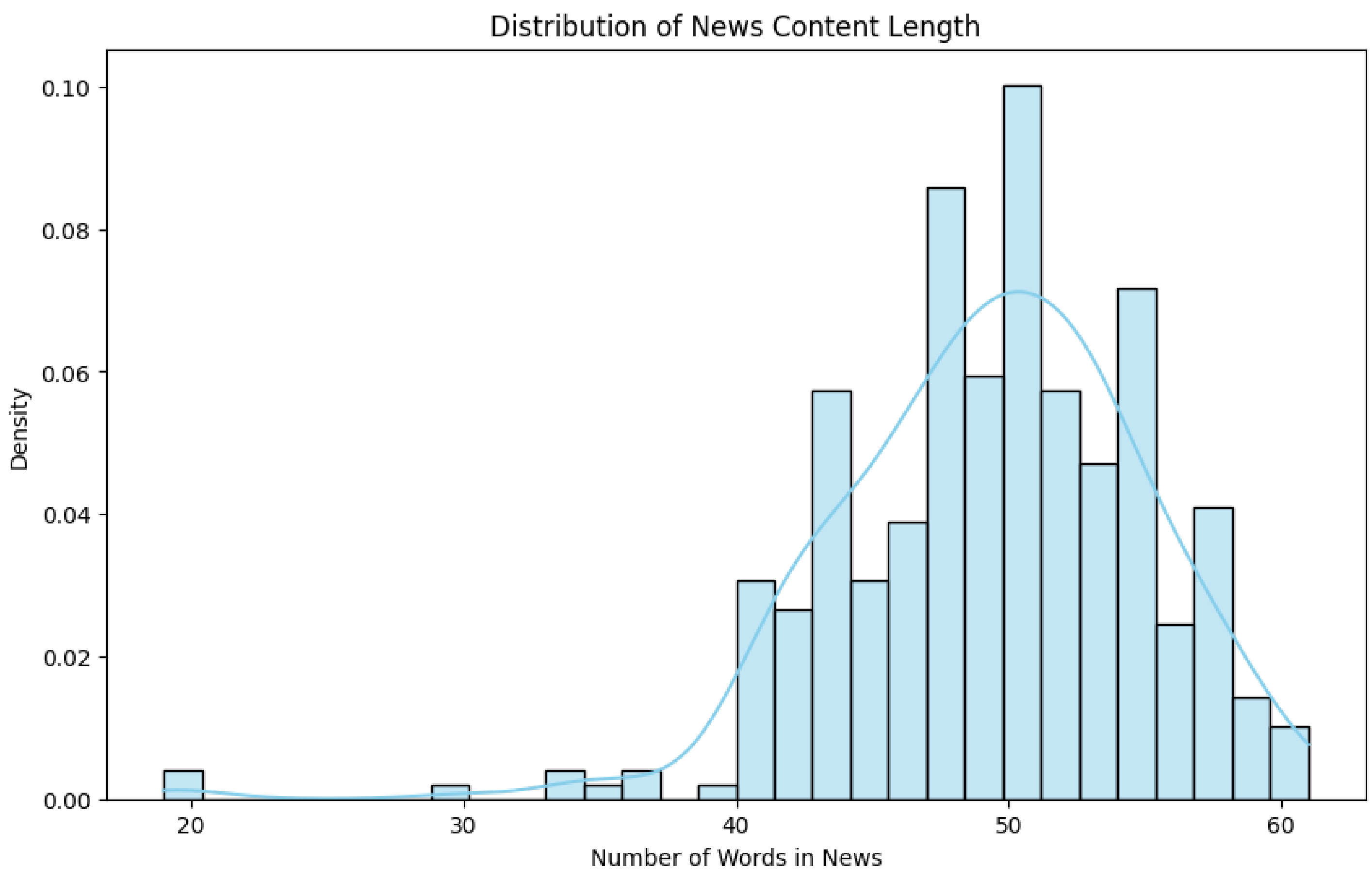


In [ ]:

```
# Calculating the total number of words in the news content
stock['news_len'] = stock['News'].apply(lambda x: len(x.split(' ')))

# Printing the statistical summary for the news content length
print(stock['news_len'].describe())

# Plotting a histogram to visualize the distribution of news length
plt.figure(figsize=(10, 6))
```

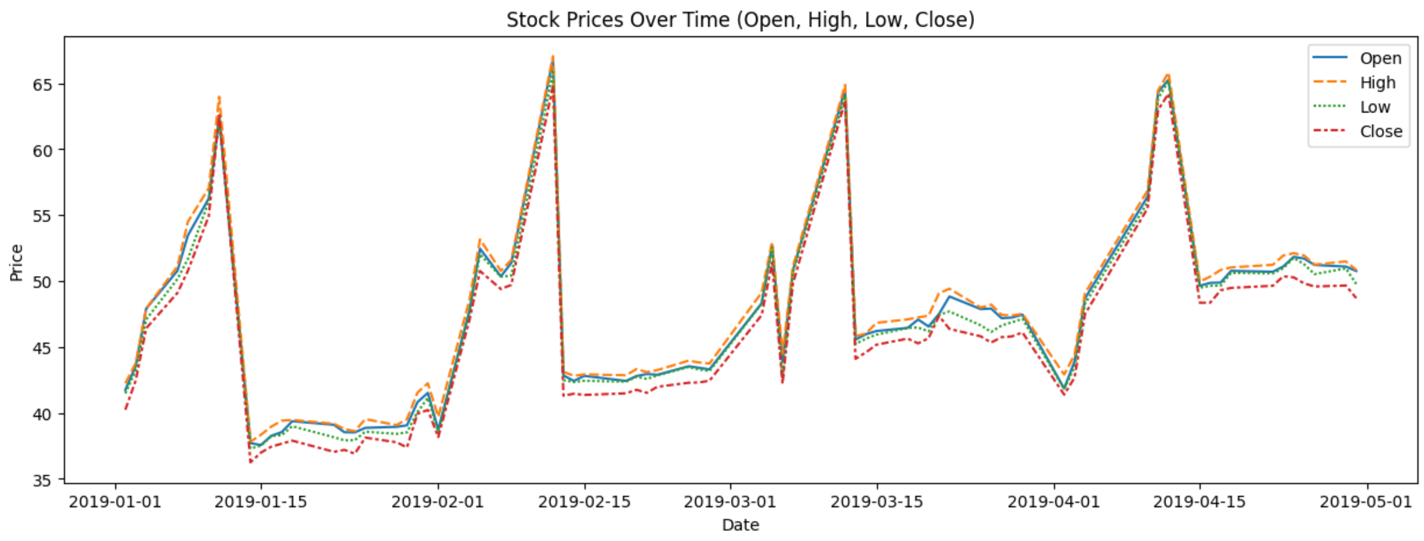
```
sns.histplot(stock['news_len'], bins=30, kde=True, color='skyblue', stat='density')
plt.title('Distribution of News Content Length')
plt.xlabel('Number of Words in News')
plt.ylabel('Density')
plt.show()
```

```
count    349.000000
mean      49.312321
std        5.727770
min       19.000000
25%       46.000000
50%       50.000000
75%       53.000000
max       61.000000
Name: news_len, dtype: float64
```



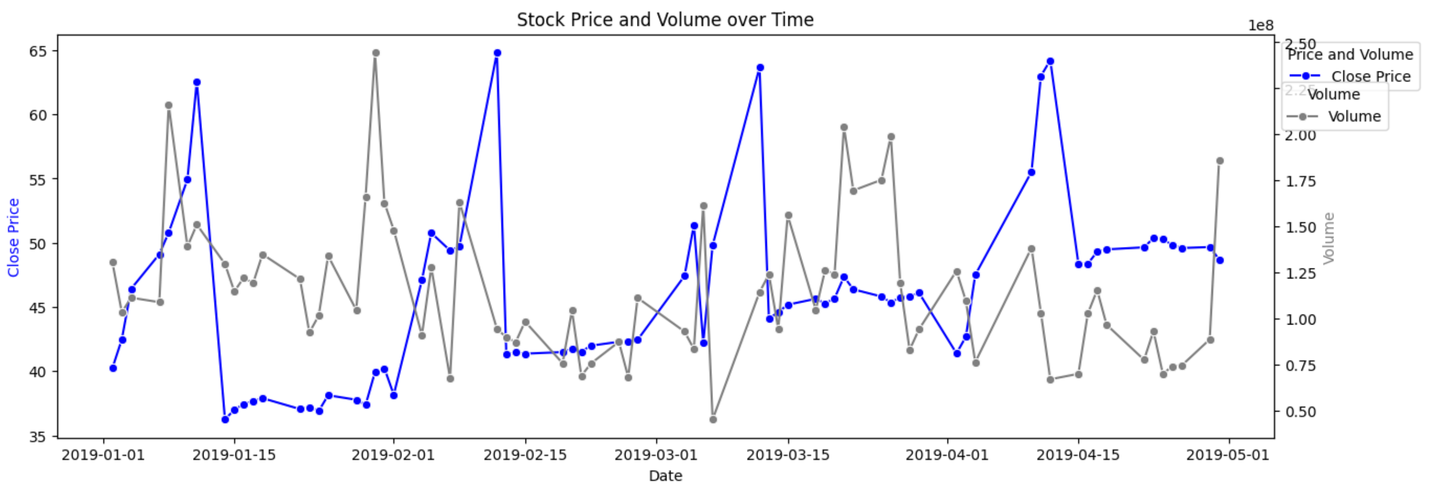
In [ ]:

```
# Grouping the 'stock' DataFrame by 'Date' and calculating the mean for 'Open', 'High', '
Low', 'Close', and 'Volume'
stock_daily = stock.groupby('Date').agg({
    'Open': 'mean',
    'High': 'mean',
    'Low': 'mean',
    'Close': 'mean',
    'Volume': 'mean'
}).reset_index()  # Reset the index to make 'Date' a column again

# Setting 'Date' as the index for the 'stock_daily' DataFrame
stock_daily.set_index('Date', inplace=True)

# Displaying the first few rows of the 'stock_daily' DataFrame
stock_daily.head()

# Plotting the lineplot for 'Open', 'High', 'Low', and 'Close' columns (excluding 'Volume
')
plt.figure(figsize=(15, 5))
sns.lineplot(data=stock_daily.drop("Volume", axis=1))  # Drop 'Volume' and plot the remai
ning columns
plt.title("Stock Prices Over Time (Open, High, Low, Close)")
plt.xlabel("Date")
plt.ylabel("Price")
plt.show()
```



In [ ]:

```
# Create a figure and axis
fig, ax1 = plt.subplots(figsize=(15, 5))

# Lineplot on the primary y-axis for 'Close' price
sns.lineplot(data=stock_daily.reset_index(), x='Date', y='Close', ax=ax1, color='blue',
marker='o', label='Close Price')

# Create a secondary y-axis to plot 'Volume'
ax2 = ax1.twinx()

# Lineplot on the secondary y-axis for 'Volume'
sns.lineplot(data=stock_daily.reset_index(), x='Date', y='Volume', ax=ax2, color='gray',
marker='o', label='Volume')

# Adding legends for both axes
ax1.legend(loc='upper left', bbox_to_anchor=(1, 1), title="Price and Volume")
ax2.legend(loc='upper left', bbox_to_anchor=(1, 0.9), title="Volume")

# Setting titles and labels for better understanding
ax1.set_title('Stock Price and Volume over Time')
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price', color='blue')
ax2.set_ylabel('Volume', color='gray')

# Show the plot
plt.show()
```



Data Preprocessing

In [ ]:

```
# Get the minimum and maximum date in the 'Date' column
min_date = stock["Date"].min()
max_date = stock["Date"].max()

print(f"Min Date: {min_date}")
print(f"Max Date: {max_date}")
```

```
Min Date: 2019-01-02 00:00:00
Max Date: 2019-04-30 00:00:00
```

Lets use this information to split the data

In [ ]:

```
# Get the statistical summary of the 'Date' column
stock["Date"].describe()
```

Out[ ]:

	Date
count	349
mean	2019-02-16 16:05:30.085959936
min	2019-01-02 00:00:00
25%	2019-01-14 00:00:00
50%	2019-02-05 00:00:00
75%	2019-03-22 00:00:00
max	2019-04-30 00:00:00

dtype: object

In [ ]:

```
# Splitting the data based on 'Date' for training, validation, and test sets

# Select rows where 'Date' is before '2019-04-01' for training data
X_train = stock[stock['Date'] < '2019-04-01'].reset_index(drop=True)

# Select rows where 'Date' is between '2019-04-01' and '2019-04-16' (excluding '2019-04-1
6') for validation data
X_val = stock[(stock['Date'] >= '2019-04-01') & (stock['Date'] < '2019-04-16')].reset_in
dex(drop=True)

# Select rows where 'Date' is from '2019-04-16' onwards for test data
X_test = stock[stock['Date'] >= '2019-04-16'].reset_index(drop=True)
```

In [ ]:

```
# Selecting the 'Label' column as the target variable for the training, validation, and t
est datasets

# Extracting the target variable ('Label') for the training set from X_train
y_train = X_train['Label'].copy()

# Extracting the target variable ('Label') for the validation set from X_val
y_val = X_val['Label'].copy()

# Extracting the target variable ('Label') for the test set from X_test
y_test = X_test['Label'].copy()
```

In [ ]:

```
# Print the shape of the feature datasets and target labels for training, validation, and
test sets
```

```
# Printing the shape of feature data (X_train, X_val, X_test)
print(f"Training data shape: {X_train.shape}")
print(f"Validation data shape: {X_val.shape}")
print(f"Test data shape: {X_test.shape}")

# Printing the shape of the target labels (y_train, y_val, y_test)
print(f"Training label shape: {y_train.shape}")
print(f"Validation label shape: {y_val.shape}")
print(f"Test label shape: {y_test.shape}")
```

```
Training data shape: (286, 9)
Validation data shape: (21, 9)
Test data shape: (42, 9)
Training label shape: (286,)
Validation label shape: (21,)
Test label shape: (42,)
```

Word Embeddings

In [ ]:

```
# Creating a list of all words in the 'News' column of the stock dataset

# Iterate through each news article in the 'News' column, split the text by spaces, and s
tore the list of words
words_list = [news.split() for news in stock['News']]
```

Explanation:

This code creates a list of all words from the News column of the stock DataFrame.

Iterating through the 'News' column:

The code iterates over each row in the News column (stock['News']), where each entry is a news article (text).

Splitting each news article:

For each news article, the .split() method is used, which divides the text into individual words by spaces.

Storing the words in words_list:

The result is a list of lists, where each inner list contains the words from a specific news article.

In [ ]:

```
# Create a Word2Vec model instance with specified parameters

vec_size = 300  # Define the size of the word vectors (embedding dimension)
model_W2V = Word2Vec(sentences=words_list, vector_size=vec_size, min_count=1, window=5,
workers=6)
```

Explanation:

Word2Vec: Word2Vec is a model that learns distributed word representations (embeddings). It converts words into vectors (numeric form) based on their context in a corpus of text.

Parameters: sentences=words_list: The input data (words_list) is a list of lists, where each inner list contains the words from a single sentence or document.

vector_size=vec_size: Specifies the dimension of the word vectors (here, 300-dimensional vectors).

min_count=1: Ignores all words that appear less than once in the dataset.

window=5: Defines the maximum distance between the current and predicted words within a sentence. In this case, the context window is 5 words.

workers=6: Number of CPU cores to use for training. This speeds up the process when set to a value greater

workers=6: Number of CPU cores to use for training. This speeds up the process when set to a value greater than 1. Purpose:

In [ ]:

```
# Checking the size of the vocabulary
print("Length of the vocabulary is", len(list(model_W2V.wv.key_to_index)))
```

```
Length of the vocabulary is 4681
```

In [ ]:

```
# Get the word embedding for a specific word ("stock") from the trained Word2Vec model
word_embedding = model_W2V.wv['stock']
word_embedding
```

Out[ ]:

```
array([-6.51142001e-03,  3.04669812e-02,  4.51321434e-03,  6.89444086e-03,
       -3.75148794e-03, -3.92222591e-02,  2.74619907e-02,  8.12858343e-02,
        1.48427589e-02, -2.01397426e-02,  7.11125275e-03, -2.13393643e-02,
        3.04859714e-03,  9.11523029e-03, -2.75776889e-02, -2.89233495e-02,
        2.28983499e-02, -7.64297182e-03,  1.31259887e-02, -1.45776607e-02,
       -2.02118643e-02, -1.02120861e-02,  2.94622108e-02,  1.81663670e-02,
        2.61899810e-02,  1.74997607e-03, -3.39305475e-02,  2.81688501e-03,
       -2.46298816e-02, -4.15067933e-02,  6.07891195e-03, -1.48400059e-02,
       -1.86911831e-03,  7.80065078e-04, -3.20982747e-03,  7.69385416e-03,
        1.38484593e-02, -4.66447063e-02,  4.36988485e-04, -1.34438397e-02,
       -9.69783310e-03,  1.47642591e-03,  1.16860941e-02, -2.46447977e-02,
        1.00065395e-02,  2.19692364e-02,  1.20892832e-02,  5.14890393e-03,
       -1.71025693e-02,  3.04353219e-02,  9.76489112e-03,  8.05721246e-03,
       -2.81864256e-02,  1.18839862e-02, -5.40606957e-03,  1.91897247e-02,
        1.45998280e-02,  2.17577768e-03,  1.52013525e-02, -7.40820169e-03,
       -1.90368798e-02, -1.08972304e-02,  4.07283660e-04,  7.67732924e-03,
        2.02655047e-03,  1.35485213e-02, -1.93797250e-03,  1.57691853e-03,
       -2.22247690e-02, -7.40717005e-05,  3.01260501e-03,  1.81972794e-02,
        2.98085660e-02, -1.46533791e-02,  5.64093189e-03,  1.04783159e-02,
       -1.82400029e-02,  3.21386312e-03, -1.64688770e-02,  2.72024088e-02,
       -1.09050041e-02, -3.10289618e-02, -8.83040484e-04,  5.72739653e-02,
        3.93254962e-03,  3.73868737e-03, -6.35980582e-03, -1.68986828e-03,
        2.95718797e-02,  1.69215053e-02,  1.97975338e-02, -1.53886965e-02,
        2.20601410e-02, -2.28409073e-03,  2.70369425e-02,  2.42311489e-02,
        3.34369913e-02, -1.35917170e-02, -2.28474736e-02,  1.41510637e-02,
       -5.14953071e-03,  1.44877384e-04,  2.38101706e-02, -4.55878023e-03,
       -3.61791416e-03, -2.61793435e-02, -1.04340706e-02,  1.20702013e-02,
       -2.89086290e-02,  3.16442875e-03, -4.04247157e-02, -6.73164567e-03,
       -1.18895033e-02,  1.93697754e-02,  2.18720585e-02,  2.12691594e-02,
       -6.73081959e-03,  8.92819138e-04,  3.46139558e-02, -4.21499461e-02,
        8.84267967e-03,  2.24700719e-02,  2.91506164e-02, -7.83260260e-03,
       -1.81809273e-02,  2.50186473e-02, -4.96528868e-04, -3.25703546e-02,
       -1.42598897e-03,  2.56616399e-02,  7.94531219e-03,  4.11213152e-02,
        1.01524806e-02, -4.29731123e-02,  1.11563345e-02,  1.31822918e-02,
       -5.28498553e-03, -1.33593511e-02, -2.87842099e-02, -3.81968953e-02,
        1.35509977e-02, -3.90709378e-02, -9.29988455e-03,  1.89757459e-02,
        1.01939188e-02, -1.94892399e-02, -4.82549183e-02, -1.12231690e-02,
        2.11898126e-02, -1.61456764e-02,  3.30436393e-03, -4.16001193e-02,
       -1.77304558e-02, -1.41831664e-02,  4.12772503e-03,  2.32840739e-02,
       -3.98816802e-02, -2.22499073e-02,  7.57606467e-03,  3.61512341e-02,
       -2.01736717e-03,  2.40288917e-02, -3.57179381e-02,  3.06768101e-02,
       -8.30405392e-03,  6.55238004e-03, -6.84303138e-03, -6.23106956e-04,
        5.90523798e-03,  4.88533303e-02, -6.11504167e-03, -5.12827421e-04,
        1.33951865e-02,  4.68711276e-03, -4.95219091e-03,  4.95678885e-03,
        8.40400904e-03, -2.98191495e-02,  3.37555277e-04, -3.57603095e-03,
       -1.26190297e-02,  1.39372433e-02, -3.49059068e-02, -7.05356104e-03,
       -1.95339378e-02,  5.41376602e-03,  3.54964100e-02,  4.19867709e-02,
        2.09334940e-02, -3.16118971e-02,  1.09423669e-02, -1.33968974e-02,
       -3.20027061e-02,  1.40909711e-03,  1.38025349e-02, -2.94538420e-02,
        7.45864445e-03, -2.60124337e-02,  6.00890163e-03,  1.95287890e-03,
       -2.10247058e-02,  1.14601050e-02, -1.35272350e-02, -1.12208622e-02,
        4.05807793e-03, -1.29418392e-02,  7.50494702e-03,  1.08683472e-02,
       -7.55715463e-03, -1.42029244e-02,  1.34548815e-02, -3.06214988e-02,
       -8.94443318e-03, -1.08336899e-02,  2.49178261e-02, -2.67330594e-02,
       -1.83063578e-02, -5.15004694e-02, -3.31466235e-02, -3.51979472e-02,
       -1.83063578e-02, -5.15004694e-02, -3.31466235e-02, -3.31979472e-02,
        2.06806622e-02,  8.26063473e-03, -1.63369235e-02, -2.76532471e-02,
       -1.90955438e-02, -1.52744139e-02,  1.52716944e-02, -8.98984820e-03,
       -1.79989245e-02,  1.38807390e-02,  3.16685177e-02, -1.70063563e-02,
       -1.83964968e-02,  1.60782319e-02, -2.37688031e-02,  1.61557887e-02,
       -2.52870843e-03,  2.03728210e-02,  1.22316414e-02, -5.00464626e-02,
        2.05570348e-02, -1.98752116e-02, -1.27986195e-02, -1.25226984e-06,
        3.49319680e-03, -3.57974321e-02,  1.02816429e-02,  5.97117422e-03,
       -1.28750049e-04,  2.60777231e-02,  1.11583518e-02,  9.30488389e-03,
        2.61417944e-02, -6.64242962e-03, -3.20180617e-02, -1.91641338e-02,
        4.24263403e-02,  1.35815432e-02, -4.94622178e-02, -2.01846603e-02,
        1.97303426e-02,  1.15740057e-02,  1.71813723e-02, -4.64886613e-02,
       -3.34244184e-02,  7.61973113e-03,  2.05747522e-02,  1.57296322e-02,
       -3.92020307e-02,  9.48698726e-03, -1.78351905e-02, -5.81039721e-03,
        3.45465727e-03, -7.29854172e-03,  3.56667414e-02,  8.36913101e-03,
        1.74643081e-02,  1.13154044e-02, -4.15522493e-02,  1.02575971e-02,
        1.42776864e-02,  9.05694615e-04, -6.38975296e-03,  1.17122130e-02,
       -1.57542061e-03, -3.20129679e-03, -4.50307801e-02,  2.80731078e-02,
        1.18752699e-02,  2.98900492e-02,  1.19548971e-02,  3.63811180e-02,
        3.16872820e-02,  4.00148286e-03,  3.65224257e-02,  4.13081422e-02,
        7.35495612e-03, -1.68417748e-02,  2.50026435e-02, -1.57116801e-02],
      dtype=float32)
```

In [ ]:

```
# Get the word embedding for a specific word ("stock") from the trained Word2Vec model
word_embedding = model_W2V.wv['Trump']
word_embedding
```

Out[ ]:

```
array([ 2.11026776e-03,  6.61722943e-03, -1.08858156e-04,  1.67478027e-03,
        1.42547954e-03, -1.00286053e-02,  2.62584607e-03,  1.43370656e-02,
        3.13573447e-03, -2.96522165e-03, -1.05115015e-03, -2.30099494e-03,
       -1.22084375e-03, -4.97675792e-04, -5.75100258e-03, -6.34388393e-03,
        6.95768418e-03, -2.76176585e-03,  5.68362651e-03, -4.62566596e-03,
       -3.09952139e-03, -4.71824111e-04,  6.46903971e-03,  7.43605709e-03,
        2.51008314e-03,  1.45953929e-03, -9.15457029e-03,  8.62666115e-04,
       -5.17413812e-03, -9.95526556e-03,  1.57117937e-03,  1.25669540e-04,
        1.34098274e-03, -2.17040884e-03, -2.61817314e-03,  2.17285007e-03,
        1.37722061e-03, -1.22807939e-02,  2.25205184e-03, -1.33335567e-03,
       -4.32919525e-03,  4.57758753e-04,  1.23720325e-03, -5.16443234e-03,
        9.34723415e-04,  8.12199153e-03, -6.45783904e-04, -9.45274893e-04,
       -4.79860418e-03,  8.89476296e-03, -1.09556924e-04, -1.03955204e-03,
       -2.94364151e-03,  2.98985024e-03, -2.29268405e-03,  8.70657561e-04,
        1.12917041e-03,  1.88998203e-03,  5.64210932e-04, -3.58730764e-03,
       -3.83097050e-03, -2.84496136e-03, -1.31106365e-03,  3.76666314e-03,
        1.95521978e-03,  4.69275936e-03, -1.36381714e-03,  3.05759604e-03,
       -2.73425248e-03, -1.29656040e-03, -2.36106061e-04,  2.96465657e-03,
        7.78017286e-03, -2.94823269e-03,  2.92351376e-03,  2.86466256e-03,
       -4.86035366e-03,  1.11757964e-03, -2.69147125e-03,  2.86903209e-03,
       -2.36269692e-03, -5.49804466e-03, -2.64562550e-03,  1.33192409e-02,
       -1.68389722e-03,  5.91562886e-04,  7.96576438e-04,  2.63304356e-03,
        7.83695467e-03,  5.42658428e-03,  7.85986613e-03,  2.83273461e-04,
        8.40002205e-04, -2.17596604e-03,  8.43955763e-03,  7.64826220e-03,
        9.64244269e-03, -3.10605741e-03, -6.28159801e-03, -4.19592616e-05,
       -2.48000165e-03, -4.95855231e-04,  4.64245118e-03, -2.45712977e-03,
        9.81258345e-04, -5.87993441e-03,  1.14724087e-03,  6.48339221e-04,
       -5.27159125e-03, -1.71081338e-03, -6.36946270e-03, -1.99925620e-03,
       -2.17408035e-03,  1.45283493e-03,  8.61571229e-04,  4.36887844e-03,
       -4.13973071e-03, -1.70617818e-03,  7.33438414e-03, -8.51561129e-03,
        3.88468220e-03,  4.68280539e-03,  3.34581174e-03,  6.69721121e-05,
       -4.64671291e-03,  6.11741515e-03,  1.32997951e-03, -4.22244426e-03,
        7.93005805e-04,  8.50411318e-03,  1.31440305e-04,  1.25280861e-02,
        1.58962188e-03, -9.25504696e-03,  5.36516774e-04,  3.28842970e-03,
       -3.60529195e-03, -1.95546518e-03, -5.92572754e-03, -7.51223834e-03,
        1.27928518e-03, -1.06535992e-02, -9.74385592e-04,  7.28267478e-03,
        5.73369348e-03, -7.62737589e-03, -6.61051041e-03, -2.19552792e-04,
        8.43154034e-04, -4.40033153e-03,  2.70473980e-03, -1.20792631e-02,
       -5.76026132e-03, -1.78219576e-03,  1.46809081e-03,  3.60277062e-03,
       -5.89726353e-03, -4.05425485e-03,  3.56631633e-03,  1.00804828e-02,
       -2.35540560e-03,  5.99492434e-03, -9.91760381e-03,  7.52994465e-03,
       -2.92647351e-03,  4.79847845e-03, -2.44342559e-03, -2.21569696e-03,
         3.50902509e-03,  1.07526388e-02, -2.53087282e-03,  3.15794459e-05,
         2.18244590e-04,  3.82355182e-03, -2.62685446e-03,  2.01346865e-03,
        -1.33719819e-03, -5.84831228e-03, -1.62816548e-03,  1.61265465e-03,
        -1.82189367e-04,  2.05923547e-03, -7.02753710e-03, -1.61845412e-03,
        -5.94599452e-03,  2.20956467e-03,  6.00094395e-03,  6.08126912e-03,
         6.63341722e-03, -7.26099266e-03,  4.73491993e-04, -5.05726552e-03,
        -8.36186670e-03, -3.02692089e-04,  3.75286397e-03, -6.30167592e-03,
         1.93852070e-03, -3.20779881e-03,  1.68778410e-03,  2.84521654e-03,
        -4.89266496e-03,  8.36871448e-04, -2.42931978e-03, -5.47986897e-03,
         5.17204171e-04, -1.63741980e-03,  1.09706935e-03,  4.50413441e-03,
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         1.51777454e-03, -5.85446134e-03,  3.16485530e-03, -6.38082763e-03,
        -1.33671402e-03, -9.84786265e-03, -8.80850293e-03, -7.94487074e-03,
         4.12284583e-03,  4.64082276e-03, -4.98245936e-04, -6.00691605e-03,
        -4.46413318e-03, -3.60683189e-03,  2.48552882e-03, -2.04778323e-03,
        -2.19406956e-03,  1.30183937e-03,  7.39750173e-03, -3.14512593e-03,
        -1.49424549e-03,  1.20886357e-03, -4.27559623e-03,  2.93557462e-03,
         1.88880565e-03,  4.55304980e-03,  4.36624419e-03, -1.02731111e-02,
         3.71175981e-03, -4.46792319e-03, -5.44817327e-03,  5.12258965e-04,
         1.21552707e-03, -1.04644373e-02,  1.15893577e-04,  4.62634070e-03,
         2.02731462e-03,  4.71330993e-03,  3.64227477e-03,  4.31846885e-04,
         6.08900050e-03,  9.04910499e-04, -4.95319022e-03, -7.14562507e-03,
         1.21929338e-02,  5.92239667e-04, -9.56881884e-03, -8.64451111e-04,
         9.71061061e-04,  2.84239370e-03,  3.62588605e-03, -1.00715831e-02,
        -9.59062949e-03,  4.05139144e-04,  2.18035141e-03,  1.86055002e-03,
        -5.41832810e-03,  1.46289729e-03, -4.75355564e-03, -3.98063194e-03,
         1.06694852e-03, -2.29725917e-03,  6.80862274e-03,  3.79516440e-03,
         5.53218089e-03,  4.09929175e-03, -6.32939162e-03, -9.97545314e-04,
         3.69973690e-03, -5.23447292e-04, -1.38065044e-03,  4.91987960e-03,
        -7.10835971e-04, -1.21498713e-03, -9.38836019e-03,  5.75696491e-03,
         2.18162197e-03,  6.72576996e-03,  1.78205839e-03,  9.68193635e-03,
         6.07883930e-03, -1.22457522e-03,  4.40813228e-03,  1.00045074e-02,
         9.96481627e-04, -2.51958868e-03,  7.61424704e-03, -6.82397326e-03],
      dtype=float32)
```

In [ ]:

```
# Checking the word embedding of a random word
word = "economy"
model_W2V.wv[word]
```

Out[ ]:

```
array([ 1.61603815e-03,  6.05317671e-03, -1.34090695e-03,  3.28718848e-03,
         6.00253843e-05, -5.18880412e-03,  6.49935612e-03,  1.25756683e-02,
         1.84998382e-03, -5.63436700e-03,  2.80827587e-03, -3.78617016e-03,
        -1.26628485e-03,  2.32576462e-03, -7.70883588e-03, -5.92645723e-03,
         7.16365827e-03, -2.83053378e-03,  3.77373816e-03, -2.05951720e-03,
        -3.37374606e-03, -2.36091111e-03,  6.01676619e-03,  4.76405257e-03,
         5.05707553e-03,  2.51043995e-04, -3.97879118e-03, -6.18746446e-04,
        -5.26737189e-03, -8.33005086e-03,  1.36359140e-05, -2.13735830e-03,
        -1.38855947e-04, -1.37975882e-03, -2.76351883e-03, -8.26577365e-04,
         1.56416802e-03, -1.05701573e-02, -1.66894728e-03,  1.10237292e-04,
        -4.22586314e-03, -1.32816401e-03,  2.06310721e-03, -1.87159190e-03,
         1.56172295e-03,  4.81143408e-03,  4.11932962e-03,  3.16787441e-03,
        -4.94442228e-03,  3.31160356e-03,  2.51979684e-03,  2.83347885e-03,
        -8.45226366e-03,  2.09367950e-03, -1.93469750e-04,  6.90336386e-03,
         4.15102346e-03, -2.51756958e-03,  3.15049011e-03, -2.65778764e-03,
        -7.47911166e-03, -4.04539146e-03, -1.48507918e-03, -2.84671027e-04,
        -2.34379852e-03,  1.84904598e-03, -9.69411863e-04,  1.32044591e-03,
        -4.06197459e-03,  4.00873687e-04,  2.06960994e-03,  2.66980496e-03,
         6.54072594e-03, -5.67759620e-03,  3.76939401e-03,  1.30229033e-04,
        -9.65281622e-04,  1.96400867e-03, -6.19090255e-03,  2.67648930e-03,
        -1.21844746e-03, -7.33432779e-03, -1.05691701e-03,  1.43471183e-02,
         3.34527669e-03,  2.97322287e-03, -3.96392727e-03,  1.47119991e-03,
         5.72141306e-03,  5.77915227e-03,  5.56577835e-03, -9.69364017e-04,
         2.30385968e-03, -5.86052920e-05,  4.73643094e-03,  5.51074278e-03,
         4.78042895e-03,  8.41502624e-04, -6.67197444e-03,  3.24134016e-03,
         2.69940263e-03, -1.78033009e-03,  3.11905611e-03, -2.31136219e-03,
         2.34828563e-03, -3.34827183e-03, -1.79091329e-03,  5.04714344e-03,
        -3.93411284e-03, -2.25760113e-03, -6.54014293e-03, -2.22056103e-03,
        -4.23979014e-03,  3.46348679e-04,  3.90274939e-03,  6.50618412e-03,
         1.44290226e-03,  2.48436467e-03,  7.08379177e-03, -6.70880452e-03,
         4.74809809e-03,  4.27056523e-03,  4.55914997e-03, -3.47389327e-03,
        -5.47797140e-03,  8.09623115e-03, -1.33347453e-03, -4.27264720e-03,
        -3.74550722e-03,  2.32473505e-03,  1.39348456e-04,  9.13357548e-03,
         5.75635675e-03, -7.45353987e-03,  2.34005903e-03,  1.98316341e-03,
        -1.95800001e-03, -5.71872201e-03, -6.50507491e-03, -6.11818675e-03,
         5.25117572e-03, -6.58719894e-03, -3.67682404e-03,  3.31766414e-03,
         2.78423564e-03, -3.84887937e-03, -7.79688032e-03, -1.79079559e-03,
         3.37987696e-03, -2.49046599e-03, -1.65593068e-04, -1.10230111e-02,
        -5.41676395e-03, -2.78564356e-03,  1.67436292e-03,  3.27002304e-03,
        -7.07049761e-03, -5.61466347e-03,  7.30023545e-04,  9.67458822e-03,
         1.79646420e-04,  4.33726842e-03, -5.37425745e-03,  3.24338232e-03,
        -1.00096040e-04,  3.20259365e-03, -2.36935494e-03,  4.39281866e-04,
        -1.19837525e-03,  9.90342814e-03, -2.25835247e-03, -2.10531359e-03,
         1.29975670e-03,  1.68206665e-04, -5.63580601e-04,  2.28807912e-03,
         3.97796184e-03, -4.60870983e-03,  4.40283417e-04, -3.06868739e-03,
        -3.67977866e-03,  1.72941666e-03, -6.91492623e-03, -4.05298965e-03,
        -4.10620822e-03,  1.87946903e-03,  8.66393931e-03,  1.10541405e-02,
         6.71475951e-04, -3.29851033e-03,  2.83804722e-03, -3.54706147e-03,
        -7.34165963e-03, -1.35833863e-03,  2.05632253e-03, -4.50815912e-03,
         4.46196133e-03, -4.91425209e-03,  2.51115509e-03, -2.28421437e-03,
        -1.86984579e-03,  3.77885124e-04, -3.38760088e-03, -2.91034812e-04,
        -2.66890367e-03, -1.84811070e-04,  2.81546358e-03,  4.62822762e-04,
        -4.54937434e-03, -1.71567686e-03,  5.07933134e-03, -6.27958495e-03,
         6.93195791e-04, -5.54287015e-03,  6.14654878e-03, -7.94608239e-03,
        -5.57046803e-03, -7.36131798e-03, -5.43037569e-03, -8.91959295e-03,
         6.06735703e-03,  1.74758397e-03, -4.47271811e-03, -2.97221029e-03,
        -4.48251143e-03, -2.40408059e-04,  9.36965109e-04, -2.79886508e-03,
        -7.15448800e-03,  2.74486956e-04,  4.48958948e-03, -4.01837472e-03,
        -6.60702959e-03,  4.83034179e-03, -6.99063484e-03,  3.34356748e-03,
        -3.42136575e-03,  4.42388467e-03,  2.19580322e-03, -7.44694471e-03,
         1.92487601e-03, -5.83983725e-04, -1.85673463e-03,  2.98468769e-03,
         1.61061362e-05, -1.05135785e-02,  1.98029462e-04,  1.21312554e-03,
        -2.51909602e-03,  2.03960110e-03,  5.17305220e-03,  1.58565608e-03,
         7.53048016e-03, -8.19713692e-04, -1.01120835e-02, -5.72322309e-03,
         6.85981987e-03,  3.23012541e-03, -1.08194090e-02, -2.19607726e-03,
         6.69578509e-03,  4.63507511e-03,  3.48007493e-03, -1.03507824e-02,
        -9.59235150e-03,  4.64347471e-03,  1.81475037e-03,  4.97152889e-03,
        -8.46759696e-03, -1.30727969e-03, -1.25042105e-03,  1.47759868e-03,
         3.60823440e-04, -2.16487609e-03,  6.57608826e-03,  3.17816855e-03,
         1.73278269e-03,  8.94421173e-05, -7.86262471e-03,  3.87670356e-03,
         2.53906101e-03, -2.51396094e-03, -2.31423206e-03,  5.24606730e-04,
         3.00537725e-03, -3.80900805e-03, -1.15748476e-02,  2.21645064e-03,
         8.98952421e-05,  5.94676938e-03,  1.96196379e-05,  4.23180964e-03,
         6.79597631e-03, -1.44798425e-03,  9.50467214e-03,  9.97395068e-03,
        -4.82342060e-04, -2.96118698e-04,  7.37117324e-03, -6.21497165e-03],
       dtype=float32)
```

In [ ]:

```python
# Retrieve all the words from the Word2Vec model's vocabulary
words = list(model_W2V.wv.index_to_key)

# Get the word vectors for all the words present in the model's vocabulary
word_vectors = model_W2V.wv[words]

# Create a dictionary mapping each word to its corresponding word vector
word_vector_dict = {word: word_vectors[i].tolist() for i, word in enumerate(words)}
```

Explanation:

list(model_W2V.wv.index_to_key):

This retrieves the list of all words present in the Word2Vec model's vocabulary. The index_to_key attribute contains the list of words (tokens) that the model has learned.

model_W2V.wv[words]:

This fetches the word vectors (embeddings) for all the words in the vocabulary. The model_W2V.wv[words] syntax retrieves the corresponding vector for each word. These vectors are stored in a matrix.

Dictionary Creation:

A dictionary is created using a dictionary comprehension: {word: word_vectors[i].tolist() for i, word in enumerate(words)}. enumerate(words): Iterates over the words list and provides both the index (i) and the word (word).

word_vectors[i].tolist(): Converts the vector for each word from a numpy array to a regular Python list. The dictionary is then formed by associating each word with its respective word vector.

In [ ]:

```
def average_vectorizer_Word2Vec(doc):
    # Initialize a feature vector of zeros with the size of the word embeddings
    feature_vector = np.zeros(vec_size, dtype="float64")

    # List of words in the document that are present in the Word2Vec model's vocabulary
    words_in_vocab = [word for word in doc.split() if word in word_vector_dict]

    # Add the word vectors of the words that are in the vocabulary
    for word in words_in_vocab:
        feature_vector += np.array(word_vector_dict[word])

    # If there are words in the vocabulary, compute the average vector
    if len(words_in_vocab) > 0:
        feature_vector /= len(words_in_vocab)

    return feature_vector
```

Explanation:

np.zeros(vec_size, dtype="float64"):

This initializes the feature_vector as a zero vector with the same size as the word embeddings (i.e., vec_size). The vector will be used to accumulate the sum of word vectors for a given document.

words_in_vocab = [word for word in doc.split() if word in word_vector_dict]:

This splits the input doc (document) into individual words and then filters out any words that are not present in the Word2Vec model's vocabulary (i.e., in word_vector_dict).

Adding word vectors:

For each word that is present in the vocabulary, its corresponding word vector (from word_vector_dict) is added to the feature_vector. Each word's vector is accessed and added element-wise to the feature_vector.

Average vector calculation:

If there are any words in the vocabulary (len(words_in_vocab) > 0), the sum of their vectors is divided by the number of words in the vocabulary to get the average word vector for the document.

Returning the feature vector:

The function returns the average word vector for the document, which represents the document as a fixed-size vector that captures the semantic meaning based on the word embeddings.

In [ ]:

```
# Start the timer to measure execution time
start = time.time()

# Apply the Word2Vec average vectorizer to the 'News' column and create a DataFrame for t
he training set
X_train_wv = pd.DataFrame(X_train["News"].apply(average_vectorizer_Word2Vec).tolist(),
                          columns=[f'Feature {i}' for i in range(vec_size)])

# Apply the Word2Vec average vectorizer to the 'News' column and create a DataFrame for t
he validation set
X_val_wv = pd.DataFrame(X_val["News"].apply(average_vectorizer_Word2Vec).tolist(),
                         columns=[f'Feature {i}' for i in range(vec_size)])

# Apply the Word2Vec average vectorizer to the 'News' column and create a DataFrame for t
he test set
X_test_wv = pd.DataFrame(X_test["News"].apply(average_vectorizer_Word2Vec).tolist(),
                         columns=[f'Feature {i}' for i in range(vec_size)])

# Stop the timer and print the time taken to execute the above code
end = time.time()
print('Time taken:', (end - start))
```

```
Time taken: 0.8459787368774414
```

In [ ]:

```
print(X_train_wv.shape, X_val_wv.shape, X_test_wv.shape)
```

```
(286, 300) (21, 300) (42, 300)
```

GloVe

This code loads a pre-trained Stanford GloVe model (converted to word2vec format) using the gensim library. The loaded model can be used to retrieve vector representations of words, perform similarity searches, and apply it to various natural language processing tasks like classification, clustering, or sentiment analysis.

Explanation:

filename:

The filename variable stores the path to the pre-trained GloVe model file, which is in word2vec format. The file glove.6B.100d.txt.word2vec corresponds to a GloVe model trained on 6 billion tokens, with word embeddings of 100 dimensions.

KeyedVectors.load_word2vec_format():

The KeyedVectors.load_word2vec_format() function from the gensim library is used to load pre-trained word vectors that are saved in the word2vec format. The binary=False argument specifies that the model file is in a text format (not a binary format). If the word2vec model was saved in binary format, binary=True would be used.

glove_model:

This variable now holds the loaded GloVe model, which allows access to the word vectors for any word present in the model's vocabulary. You can query it to get the vector representation for any word, or perform other tasks like finding similar words or performing vector arithmetic.

In [ ]:

```
# Load the Stanford GloVe model from the specified file
filename = '/content/drive/MyDrive/AIML_Project5/glove.6B.100d.txt.word2vec'

# Use the KeyedVectors to load the GloVe model in word2vec format (non-binary)
glove_model = KeyedVectors.load_word2vec_format(filename, binary=False)
```

In [ ]:

```
# Checking the size of the vocabulary
print("Length of the vocabulary is", len(glove_model.index_to_key))
```

```
Length of the vocabulary is 400000
```

In [ ]:

```
# Checking the word embedding of a random word
word = "stock"
glove_model[word]
```

Out[ ]:

```
array([ 8.6341e-01,  6.9648e-01,  4.5794e-02, -9.5708e-03, -2.5498e-01,
       -7.4666e-01, -2.2086e-01, -4.4615e-01, -1.0423e-01, -9.9931e-01,
        7.2550e-02,  4.5049e-01, -5.9912e-02, -5.7837e-01, -4.6540e-01,
        4.3429e-02, -5.0570e-01, -1.5442e-01,  9.8250e-01, -8.1571e-02,
        2.6523e-01, -2.3734e-01,  9.7675e-02,  5.8588e-01, -1.2948e-01,
       -6.8956e-01, -1.2811e-01, -5.2265e-02, -6.7719e-01,  3.0190e-02,
        1.8058e-01,  8.6121e-01, -8.3206e-01, -5.6887e-02, -2.9578e-01,
        4.7180e-01,  1.2811e+00, -2.5228e-01,  4.9557e-02, -7.2455e-01,
        6.6758e-01, -1.1091e+00, -2.0493e-01, -5.8669e-01, -2.5375e-03,
        8.2777e-01, -4.9102e-01, -2.6475e-01,  4.3015e-01, -2.0516e+00,
       -3.3208e-01,  5.1845e-02,  5.2646e-01,  8.7452e-01, -9.0237e-01,
       -1.7366e+00, -3.4727e-01,  1.6590e-01,  2.7727e+00,  6.5756e-02,
       -4.0363e-01,  3.8252e-01, -3.0787e-01,  5.9202e-01,  1.3468e-01,
       -3.3851e-01,  3.3646e-01,  2.0950e-01,  8.5905e-01,  5.1865e-01,
       -1.0657e+00, -2.6371e-02, -3.1349e-01,  2.3231e-01, -7.0192e-01,
       -5.5737e-01, -2.3418e-01,  1.3563e-01, -1.0016e+00, -1.4221e-01,
        1.0372e+00,  3.5880e-01, -4.2608e-01, -1.9386e-01, -3.7867e-01,
       -6.9646e-01, -3.9989e-01, -5.7782e-01,  1.0132e-01,  2.0123e-01,
       -3.7153e-01,  5.0837e-01, -3.7758e-01, -2.6205e-01, -9.3676e-01,
        1.0053e+00,  8.4393e-01, -2.4698e-01,  1.7339e-01,  9.4473e-01],
      dtype=float32)
```

In [ ]:

```
# Checking the word embedding of a random word
word = "fall"
glove_model[word]
```

Out[ ]:

```
array([ 0.3264  ,  0.55822 ,  0.25533 , -0.10814 ,  0.04654 , -0.46577 ,
       -0.13963 ,  0.15362 , -0.23483 , -0.42804 ,  0.037924,  0.22895 ,
        0.18672 ,  0.23734 ,  0.34996 ,  0.037288, -0.46827 ,  0.15487 ,
       -0.16487 ,  0.11753 ,  0.30809 , -0.25441 ,  0.30979 ,  0.8051  ,
       -0.09219 , -0.062635, -0.38575 , -0.54978 ,  0.3019  , -0.54258 ,
        0.19739 , -0.29    ,  0.092703, -0.48055 , -0.48191 ,  0.72779 ,
        0.22876 , -0.45603 ,  0.037786, -0.32571 , -0.42623 , -0.058946,
       -0.52196 ,  0.18801 ,  0.14141 , -0.20073 ,  0.27084 , -0.026134,
        0.13288 , -1.4764  , -0.056972, -0.32662 ,  0.30494 ,  0.76331 ,
        0.16788 , -2.356   , -0.37616 , -0.011489,  1.9827  ,  0.36153 ,
       -0.22095 ,  1.0825  , -0.67676 ,  0.096369,  0.48564 ,  0.20256 ,
        0.16667 , -0.35918 ,  0.13848 ,  0.096536,  0.13312 , -0.069298,
       -0.69095 ,  0.35564 , -0.50851 , -0.3494  , -0.33562 ,  0.45363 ,
       -0.28949 ,  0.032191,  0.17248 ,  0.1475  , -0.70217 , -0.2028  ,
       -0.74759 , -0.96593 , -0.083909, -0.28699 ,  0.11724 ,  0.066832,
        0.21283 ,  0.26471 , -0.047237,  0.49353 , -0.80611 , -0.20786 ,
        0.52783 ,  0.21441 ,  0.39197 , -0.29477 ], dtype=float32)
```

In [ ]:

```
# Checking the word embedding of a random word
word = "economy"
glove_model[word]
```

Out[ ]:

```
array([-0.19382  ,  1.017    ,  1.076    ,  0.02954  , -0.39192  ,
       -1.3891   , -0.87873  , -0.63162  ,  0.9643   , -0.43035  ,
       -0.34868  ,  0.22736  , -0.40296  ,  0.15641  , -0.16813  ,
       -0.15343  , -0.15799  , -0.27612  ,  0.18088  , -0.28386  ,
        0.49847  ,  0.29864  ,  0.32353  ,  0.18108  , -0.59623  ,
       -0.54165  , -0.70019  , -0.64956  , -0.69063  ,  0.18084  ,
       -0.38581  ,  0.56086  , -0.40313  , -0.38777  , -0.70615  ,
        0.20657  ,  0.34171  , -0.23393  , -0.35882  , -0.2201   ,
       -0.76182  , -1.2047   ,  0.4339   ,  1.1656   ,  0.1836   ,
       -0.21601  ,  0.93198  , -0.059616 , -0.11624  , -1.3259   ,
       -0.79772  , -0.0074957, -0.0889   ,  1.4749   ,  0.31157  ,
       -2.2952   , -0.058351 ,  0.39353  ,  1.4983   ,  0.74023  ,
       -0.20109  ,  0.098124 , -0.73081  , -0.32294  ,  0.16703  ,
        0.87431  , -0.041624 , -0.51022  ,  1.0737   , -0.4257   ,
        1.0581   ,  0.19859  , -0.60087  , -0.33906  ,  0.60243  ,
       -0.091581 , -0.47201  ,  0.74933  , -0.60168  , -0.44178  ,
         0.77391  ,  0.81114  , -1.2889   ,  0.32055  , -0.36117  ,
        -0.88078  ,  0.055524 , -0.26837  , -0.33688  , -1.4359   ,
         0.85666  ,  0.32025  , -0.15361  , -0.30208  , -0.38208  ,
         0.30508  ,  0.75374  , -0.68041  ,  0.98619  , -0.19628  ],
      dtype=float32)
```

In [ ]:

```
# Retrieve the list of words present in the GloVe model's vocabulary
glove_words = glove_model.index_to_key

# Create a dictionary mapping words to their corresponding word vectors
glove_word_vector_dict = dict(zip(glove_words, glove_model.vectors))
```

This code is used to create a dictionary (glove_word_vector_dict) that maps words to their corresponding word vectors from the GloVe model. This allows efficient access to the word embeddings for any word in the vocabulary, enabling the use of these embeddings for various natural language processing tasks such as text classification, similarity computation, and semantic analysis.

In [ ]:

```
vec_size=100
```

This is a Stanford model trained on 6 billion tokens with a vector size of 100.

In [ ]:

```
def average_vectorizer_GloVe(doc):
    # Initialize a feature vector with zeros (dimension equals to vec_size)
    feature_vector = np.zeros((vec_size,), dtype="float64")

    # Create a list of words in the document that are present in the GloVe vocabulary
    words_in_vocab = [word for word in doc.split() if word in glove_words]

    # Sum up the vector representations of each word in the document
    for word in words_in_vocab:
        feature_vector += glove_word_vector_dict[word]

    # If there are any words in the vocabulary, compute the average vector
    if len(words_in_vocab) > 0:
        feature_vector /= len(words_in_vocab)

    return feature_vector
```

In [ ]:

```
# Creating a DataFrame for the vectorized documents using GloVe embeddings
start = time.time()

# Apply the GloVe vectorizer function to the 'News' column of X_train, X_val, and X_test
# Convert the resulting list of vectors into a DataFrame with the appropriate feature col
umns
X_train_gl = pd.DataFrame(X_train["News"].apply(average_vectorizer_GloVe).tolist(),
                          columns=[f'Feature {i}' for i in range(vec_size)])  # Apply Gl
oVe to 'News' column in training data

X_val_gl = pd.DataFrame(X_val["News"].apply(average_vectorizer_GloVe).tolist(),
                        columns=[f'Feature {i}' for i in range(vec_size)])  # Apply GloV
e to 'News' column in validation data

X_test_gl = pd.DataFrame(X_test["News"].apply(average_vectorizer_GloVe).tolist(),
                         columns=[f'Feature {i}' for i in range(vec_size)])  # Apply Glo
Ve to 'News' column in test data

# Record the time it took to process the data
end = time.time()
print('Time taken to process and vectorize the documents: ', (end - start))
```

```
Time taken to process and vectorize the documents:  41.88485074043274
```

In [ ]:

```
print(X_train_gl.shape, X_val_gl.shape, X_test_gl.shape)
```

```
(286, 100) (21, 100) (42, 100)
```

Sentence Transformer

The code defines and initializes a pre-trained model from the sentence-transformers library. Once this model is loaded, you can use it to convert sentences or texts into vector representations (embeddings) for use in downstream tasks like classification, clustering, or similarity comparison.

Explanation:

from sentence_transformers import SentenceTransformer:

This imports the SentenceTransformer class from the sentence-transformers library, which is used to transform sentences into dense vector representations (embeddings).

model = SentenceTransformer('sentence-transformers/all-MiniLM-L6-v2'):

This line initializes a pre-trained model called all-MiniLM-L6-v2 from the sentence-transformers library.

'sentence-transformers/all-MiniLM-L6-v2' is the model identifier, which is a pre-trained transformer model designed to generate sentence-level embeddings (dense vector representations).

This model is typically used for tasks like sentence similarity, semantic search, and clustering.

MiniLM stands for "Miniature Language Model," which is a smaller and faster transformer-based model designed to be efficient in terms of both memory and computation, making it suitable for use in various applications without requiring extensive hardware resources.

In [ ]:

```
#Defining the model
model = SentenceTransformer('sentence-transformers/all-MiniLM-L6-v2')
```

In [ ]:

```
# Setting the device to GPU if available, otherwise using CPU
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

Explanation: import torch:

This imports the torch library, which is part of PyTorch, a popular deep learning framework used for creating and training machine learning models. PyTorch provides the ability to work with both CPUs and GPUs for computation.

torch.cuda.is_available():

This checks if a GPU is available on the system. The .cuda function is used for GPU-based computations, and .is_available() is a method that returns True if a GPU is available and False if no GPU is present.

torch.device("cuda" if torch.cuda.is_available() else "cpu"):

This line sets the device variable based on the availability of a GPU. If a GPU is available (torch.cuda.is_available() returns True), the device is set to "cuda", which refers to GPU. If no GPU is available (torch.cuda.is_available() returns False), the device is set to "cpu", which refers to the CPU.

device:

The device variable now stores either "cuda" or "cpu" depending on whether a GPU is available. This variable is then used to ensure that all tensors and model operations are performed on the appropriate device (GPU or CPU) based on availability.

In [ ]:

```
# Importing necessary libraries
import time

# Starting the timer to measure encoding time
start = time.time()

# Encoding the training, validation, and test data using the Sentence Transformer model
X_train_st = model.encode(X_train["News"].values, show_progress_bar=True, device=device)
# Apply Sentence Transformer on the 'News' column of the training data
X_val_st = model.encode(X_val["News"].values, show_progress_bar=True, device=device)  #
Apply Sentence Transformer on the 'News' column of the validation data
X_test_st = model.encode(X_test["News"].values, show_progress_bar=True, device=device)
# Apply Sentence Transformer on the 'News' column of the test data

# Ending the timer
end = time.time()

# Printing the time taken for the encoding process
print("Time taken", (end - start))
```

```
Time taken 12.110977172851562
```

In [ ]:

```
print(X_train_st.shape, X_val_st.shape, X_test_st.shape)
```

```
(286, 384) (21, 384) (42, 384)
```

Sentiment Analysis

This function visualizes the performance of a classification model by comparing the true labels with the predicted labels. The confusion matrix helps you understand how well the model is classifying the data into various classes (true positives, true negatives, false positives, and false negatives).

In [ ]:

```
def plot_confusion_matrix(model, predictors, target):
    """
    Plot a confusion matrix to visualize the performance of a classification model.

    Parameters:
    model (classifier): The trained classification model to make predictions.
    predictors (array-like): The features/input data used to make predictions.
    target (array-like): The true labels to compare the predictions against.

    Returns:
    None: Displays the confusion matrix plot.
    """
    # Make predictions using the model
    pred = model.predict(predictors)

    # Compute the confusion matrix
    cm = confusion_matrix(target, pred)

    # Create a figure with a specified size
    plt.figure(figsize=(5, 4))

    # Define labels for the confusion matrix (the unique classes in the target variable)
    label_list = [0, 1, -1]  # Assuming the labels are 0 (negative), 1 (positive), and -
1 (neutral)

    # Create a heatmap to visualize the confusion matrix
    sns.heatmap(cm, annot=True, fmt='.0f', cmap='inferno', xticklabels=label_list, ytick
labels=label_list)
```

```
    # Set the labels for the axes and the title
    plt.ylabel('Actual')  # Label for the y-axis (true labels)
    plt.xlabel('Predicted')  # Label for the x-axis (predicted labels)
    plt.title('Confusion Matrix')  # Title of the plot

    # Show the plot
    plt.show()
```

This function is designed to evaluate the performance of a classification model using common metrics: accuracy, recall, precision, and F1-score. These metrics help in understanding how well the model is classifying the data, particularly when dealing with imbalanced datasets. It returns the metrics in a structured way (in a DataFrame) for easier interpretation and comparison across different models or datasets.

In [ ]:

```
def model_performance_classification_sklearn(model, predictors, target):
    """
    Compute various performance metrics for a classification model using sklearn.

    Parameters:
    model (sklearn classifier): The classification model to evaluate.
    predictors (array-like): The independent variables used for predictions.
    target (array-like): The true labels for the dependent variable.

    Returns:
    pandas.DataFrame: A DataFrame containing the computed metrics (Accuracy, Recall, Prec
ision, F1-score).
    """

    # Make predictions using the trained model and the provided predictor variables
    pred = model.predict(predictors)

    # Calculate various classification metrics:
    acc = accuracy_score(target, pred)  # Compute Accuracy
    recall = recall_score(target, pred, average='weighted')  # Compute Recall (weighted
for class imbalance)
    precision = precision_score(target, pred, average='weighted')  # Compute Precision (
weighted for class imbalance)
    f1 = f1_score(target, pred, average='weighted')  # Compute F1-Score (weighted for cl
ass imbalance)

    # Organize the computed metrics into a pandas DataFrame
    df_perf = pd.DataFrame(
        {
            "Accuracy": [acc],
            "Recall": [recall],
            "Precision": [precision],
            "F1": [f1],
        }
    )

    # Return the DataFrame containing the metrics
    return df_perf
```

Classifier Selection

I have experimented with several classifiers, including 1) Decision Tree, 2) Gradient Boosting Classifier, and 3) Random Forest. Among these, Random Forest appears to be the most effective choice for this task. However, while Gradient Boosting is generally better at capturing complex patterns in the data, its performance is hindered due to the limited size of our dataset, which contains only 349 news articles. Additionally, the dataset is imbalanced, which further contributes to the poor performance. In an ideal scenario, we would use a larger, more diverse dataset with richer content to train language models, which would help improve their ability to detect and model complex patterns.

Base Model - Word2Vec

In [ ]:

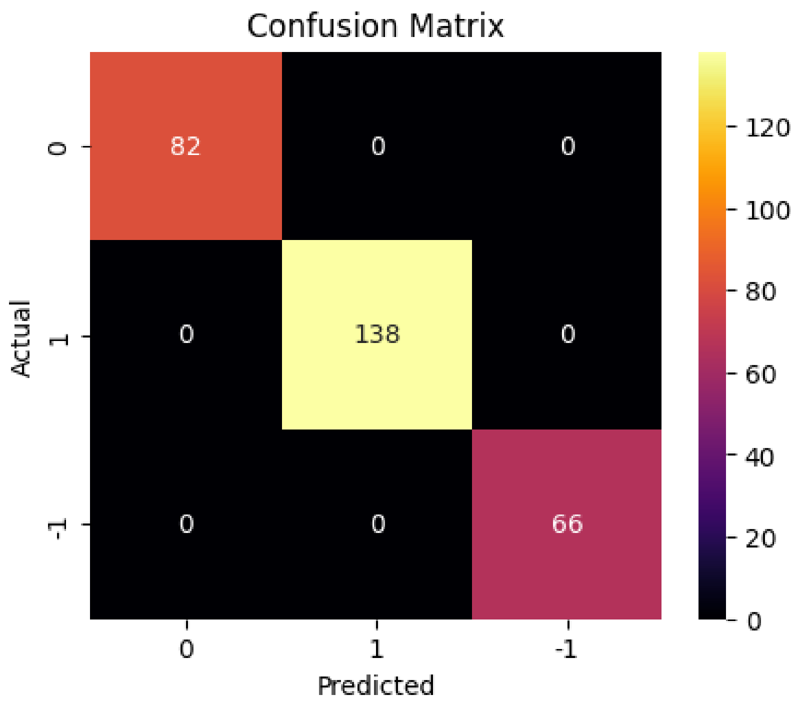
```
base_wv = RandomForestClassifier(random_state=42)
base_wv.fit(X_train_wv, y_train)
```

Out[ ]:

```
▾        RandomForestClassifier
                                       i ?
RandomForestClassifier(random_state=42)
```

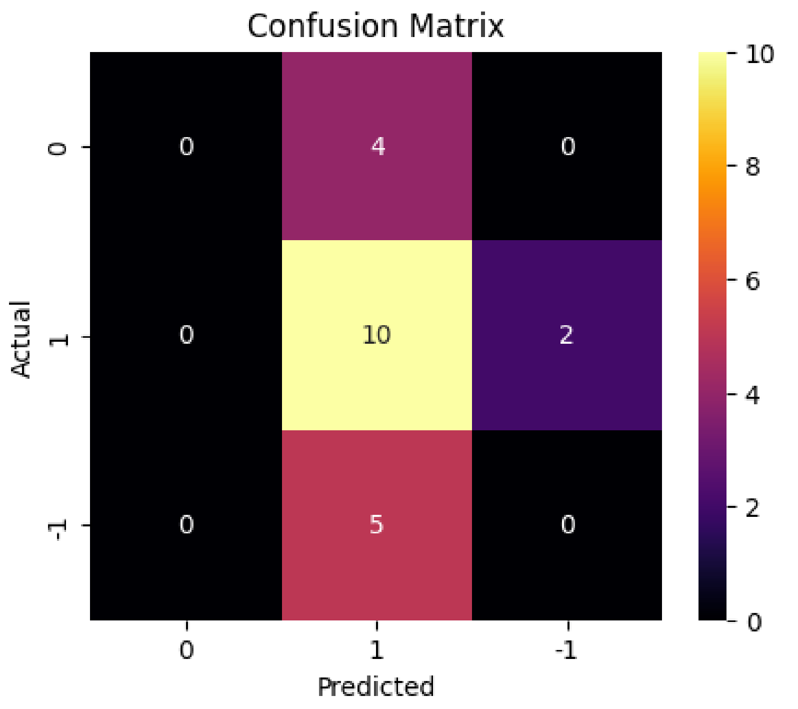
In [ ]:

```
plot_confusion_matrix(base_wv,X_train_wv,y_train)
```



In [ ]:

```
plot_confusion_matrix(base_wv,X_val_wv,y_val)
```



In [ ]:

```
base_train_wv = model_performance_classification_sklearn(base_wv,X_train_wv,y_train)
```

```
print("Training performance:\n", base_train_wv)
```

```
Training performance:
    Accuracy  Recall  Precision   F1
0        1.0     1.0        1.0  1.0
```

In [ ]:

```
base_val_wv = model_performance_classification_sklearn(base_wv,X_val_wv,y_val)
print("Validation performance:\n",base_val_wv)
```

```
Validation performance:
    Accuracy   Recall  Precision        F1
0   0.47619  0.47619   0.300752  0.368664
```

Base Model - GloVe

In [ ]:

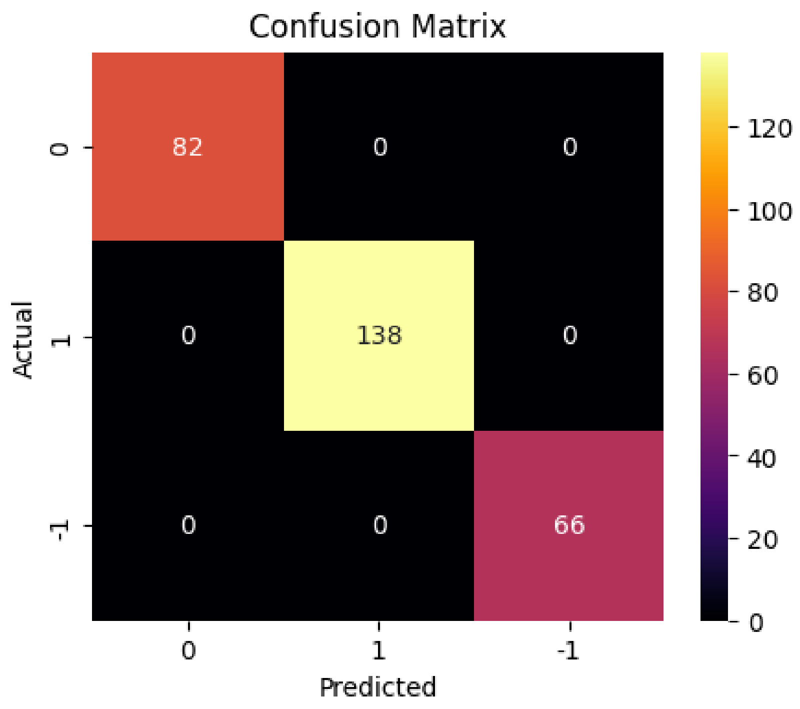
```
# Using RandomForestClassifier as the base model
base_gl = RandomForestClassifier(random_state=42)

# Fitting the model on the training data (X_train_gl and y_train)
base_gl.fit(X_train_gl, y_train)
```

Out[ ]:

```
▾        RandomForestClassifier
                                       i  ?
RandomForestClassifier(random_state=42)
```

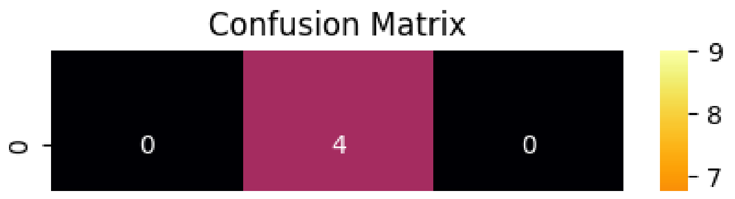
In [ ]:

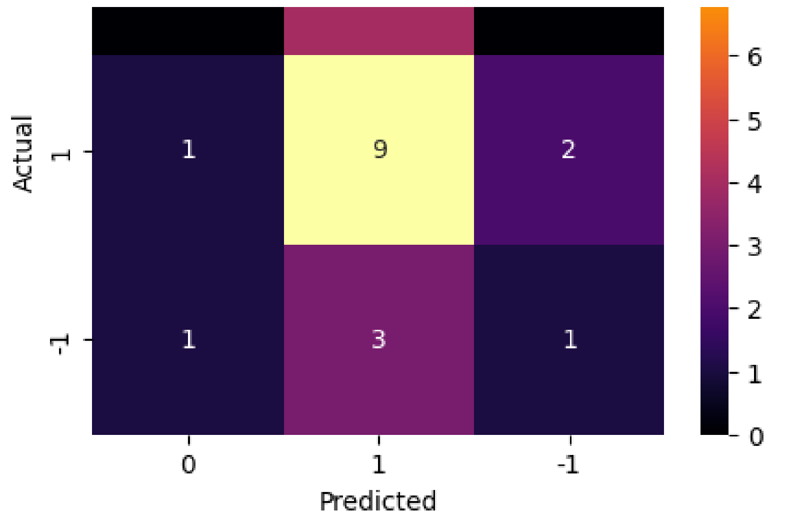
```
plot_confusion_matrix(base_gl,X_train_gl,y_train)
```



In [ ]:

```
plot_confusion_matrix(base_gl,X_val_gl,y_val)
```





In [ ]:

```
base_train_gl=model_performance_classification_sklearn(base_gl,X_train_gl,y_train)
print("Training performance:\n", base_train_gl)
```

```
Training performance:
    Accuracy  Recall  Precision   F1
0        1.0     1.0        1.0  1.0
```

In [ ]:

```
base_val_gl = model_performance_classification_sklearn(base_gl,X_val_gl,y_val)
print("Validation performance:\n",base_val_gl)
```

```
Validation performance:
    Accuracy   Recall  Precision        F1
0   0.47619  0.47619   0.400794  0.426871
```

Base Model - Sentence Transformer

In [ ]:

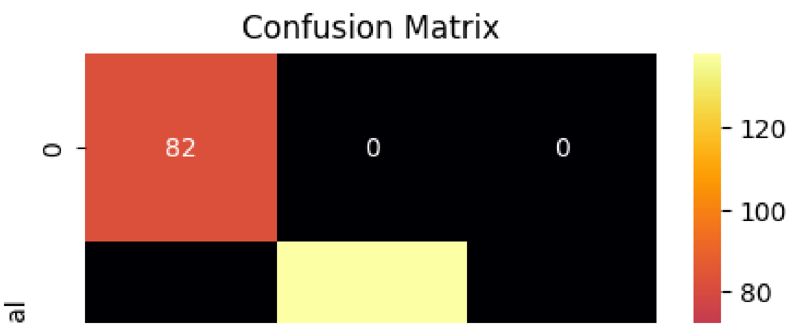
```
# Building the model using RandomForestClassifier

# Choose RandomForestClassifier as the base model
base_st = RandomForestClassifier(random_state=42)

# Fitting the model on the training data
base_st.fit(X_train_st, y_train)  # Fit the model on the training data (X_train_st and y_
train)
```

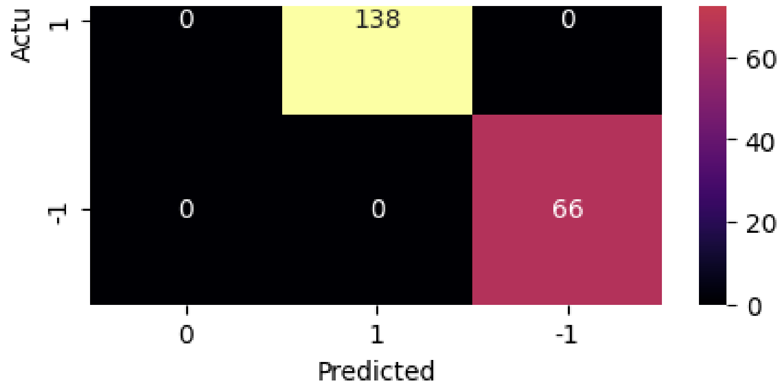
Out[ ]:

```
▾        RandomForestClassifier
                                        i ?
RandomForestClassifier(random_state=42)
```

In [ ]:

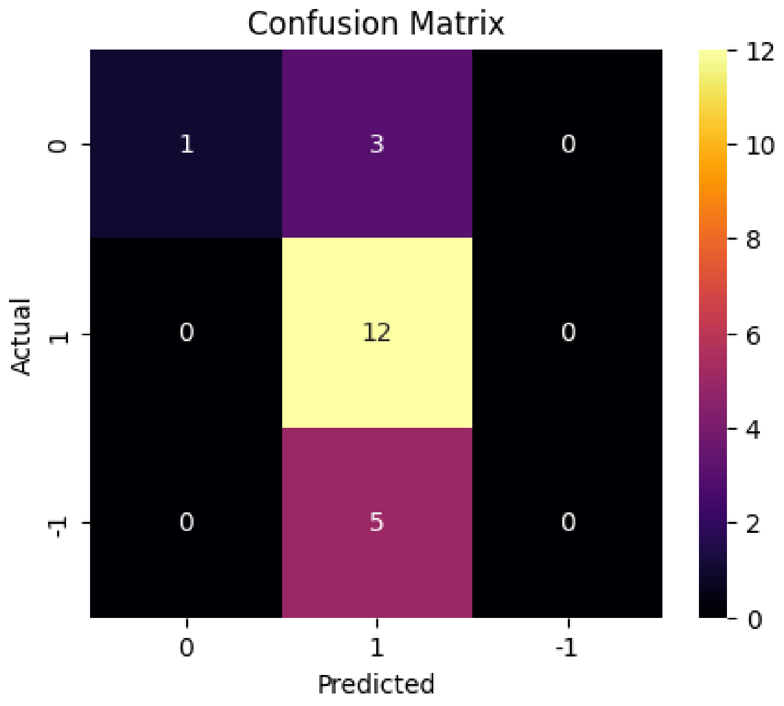
```
plot_confusion_matrix(base_st,X_train_st,y_train)
```





In [ ]:

```
plot_confusion_matrix(base_st,X_val_st,y_val)
```



In [ ]:

```
base_train_st=model_performance_classification_sklearn(base_st,X_train_st,y_train)
print("Training performance:\n", base_train_st)
```

```
Training performance:
    Accuracy  Recall  Precision   F1
0        1.0     1.0        1.0  1.0
```

In [ ]:

```
base_val_st = model_performance_classification_sklearn(base_st,X_val_st,y_val)
print("Validation performance:\n",base_val_st)
```

```
Validation performance:
    Accuracy    Recall  Precision        F1
0   0.619048  0.619048   0.533333  0.504762
```

Short Summary:

"Without any tuning, the Sentence Transformer achieved the best performance with an accuracy of over 60%, followed by Word2Vec, and then GloVe. For GloVe, we used a vector size of 100 with the pretrained Stanford model, which influenced the accuracy. Let's tune the models and see if we can further improve the accuracy."

Tuned Model - Word2Vec

Explanation:

1. **Model Selection:**
   - We are using the `RandomForestClassifier` as the base model (`tuned_wv`). The Random Forest model is an ensemble method that uses multiple decision trees to make predictions and typically provides good results.
2. **Hyperparameter Grid Setup:**
   - `parameters` dictionary defines the hyperparameters that we want to tune for the Random Forest model. These include:
     - `max_depth`: The maximum depth of each tree.
     - `min_samples_split`: The minimum number of samples required to split an internal node.
     - `max_features`: The number of features to consider when looking for the best split. This can be a fixed number or options like 'log2' or 'sqrt'.
3. **GridSearchCV:**
   - `GridSearchCV` is used to perform an exhaustive search over a specified parameter grid. It cross-validates the model and selects the combination of hyperparameters that gives the best performance (based on `f1_weighted` scoring). This helps in finding the optimal model configuration.
4. **Training the Model:**
   - `grid_obj.fit(X_train_wv, y_train)` trains the model with the hyperparameter grid, using cross-validation to evaluate different hyperparameter combinations.
5. **Time Tracking:**
   - `start` and `end` time variables are used to measure the time taken by the grid search.
6. **Best Model Selection:**
   - After fitting, the `best_estimator_` attribute of `grid_obj` contains the model with the best hyperparameters, which is assigned to `tuned_wv`.

In [ ]:

```
start = time.time()

# Choose the RandomForestClassifier as the base model.
tuned_wv = RandomForestClassifier(random_state=42)

# Set the parameters to be tuned using GridSearchCV.
parameters = {
    'max_depth': np.arange(3, 7),   # Range of max depth for trees in the forest.
    'min_samples_split': np.arange(5, 12, 2),   # Range of minimum samples required to sp
lit a node.
    'max_features': ['log2', 'sqrt', 0.2, 0.4]   # Options for the number of features to c
onsider at each split.
}

# Run GridSearchCV to find the best combination of hyperparameters.
grid_obj = GridSearchCV(tuned_wv, parameters, scoring='f1_weighted', cv=5, n_jobs=-1)
grid_obj = grid_obj.fit(X_train_wv, y_train)   # Fit GridSearchCV on the training data.

end = time.time()   # Record the end time.
print("Time taken ", (end - start))   # Print the time taken for the grid search.

# Set the tuned model to the best combination of parameters found.
tuned_wv = grid_obj.best_estimator_
```

```
Time taken  167.06368041038513
```

In [ ]:

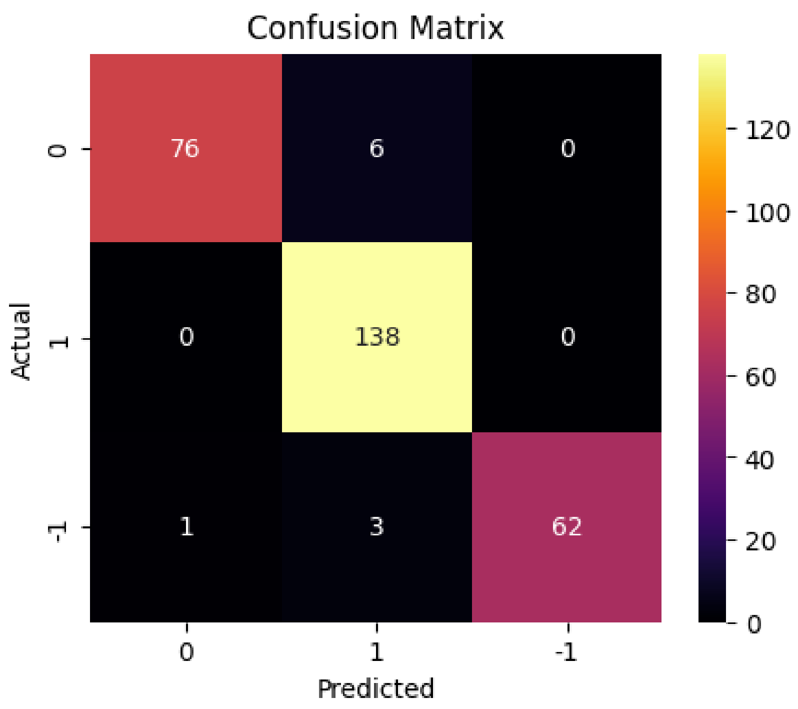
```
tuned_wv.fit(X_train_wv, y_train)
```

Out[ ]:

```
RandomForestClassifier(max_depth=6, min_samples_split=7, random_state=42)
```

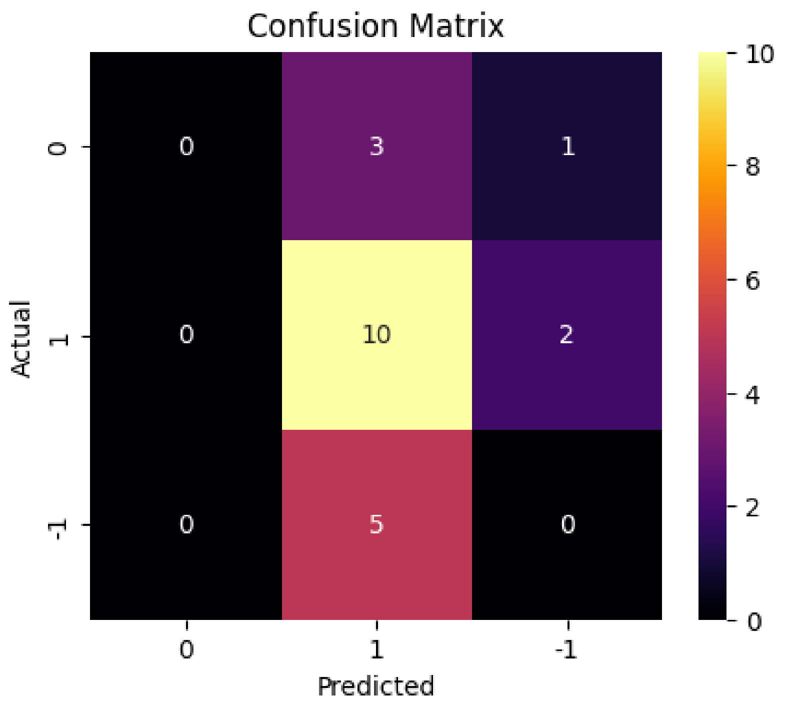
In [ ]:

```
plot_confusion_matrix(tuned_wv,X_train_wv,y_train)
```



In [ ]:

```
plot_confusion_matrix(tuned_wv,X_val_wv,y_val)
```



In [ ]:

```
tuned_train_wv=model_performance_classification_sklearn(tuned_wv,X_train_wv,y_train)
print("Training performance:\n",tuned_train_wv)
```

```
Training performance:
    Accuracy    Recall  Precision        F1
0  0.965035  0.965035   0.966735  0.964928
```

In [ ]:

```
tuned_val_wv = model_performance_classification_sklearn(tuned_wv,X_val_wv,y_val)
print("Validation performance:\n",tuned_val_wv)
```

```
Validation performance:
    Accuracy   Recall  Precision        F1
0   0.47619  0.47619    0.31746  0.380952
```

Tuned Model - GloVe

Explanation:

1. **Model Selection (`RandomForestClassifier`):**
   - **In this example, we use `RandomForestClassifier` as the base model. Random forests are a type of ensemble learning method, where multiple decision trees are trained on random subsets of the data, and their predictions are aggregated to improve accuracy and robustness.**
2. **Hyperparameter Grid (`parameters`):**
   - `max_depth` **: This hyperparameter controls the maximum depth of each decision tree in the forest. By limiting the depth, we prevent the model from overfitting. We test a range of values from 3 to 6.**
   - `min_samples_split` **: This controls the minimum number of samples required to split an internal node in a decision tree. A higher value results in more generalization and less overfitting. The range is set from 5 to 11 with a step of 2.**
   - `max_features` **: This controls how many features are considered when looking for the best split. We test different options, including using a fraction of features like 0.2 and 0.4, as well as predefined values like `log2` and `sqrt`.**
3. **Grid Search (`GridSearchCV`):**
   - **We use `GridSearchCV` to perform an exhaustive search over the hyperparameter grid. The `scoring='f1_weighted'` argument specifies that the weighted F1 score will be used to evaluate the performance of different models.**
   - `cv=5` **: This means the grid search will perform 5-fold cross-validation, splitting the data into 5 subsets and training the model 5 times, ensuring a more robust evaluation.**
   - `n_jobs=-1` **: This tells `GridSearchCV` to use all available CPU cores to speed up the grid search process.**
4. **Fitting the Model:**
   - `grid_obj.fit(X_train_gl, y_train)` **fits the `GridSearchCV` object on the training data, where `X_train_gl` is the feature set and `y_train` is the target variable. It trains multiple models using different combinations of hyperparameters from the grid.**
5. **Timing the Process:**
   - **We use `start` and `end` times to measure the total time taken by the grid search process, which can be helpful when working with large datasets or complex models.**
6. **Getting the Best Model:**
   - `grid_obj.best_estimator_` **gives us the model with the best hyperparameters found by the grid search. We assign this to the variable `tuned_gl` so we can use it for further predictions or evaluations.**

By the end of this process, the model stored in `tuned_gl` will be the RandomForestClassifier that has been tuned with the best hyperparameters found through the grid search.

In [ ]:

```
import time
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Start timing the process
start = time.time()
```

```
# Choose RandomForestClassifier as the base model
tuned_gl = RandomForestClassifier(random_state=42)

# Define the hyperparameter grid for grid search
parameters = {
    'max_depth': np.arange(3, 7),  # Range for maximum depth of trees in the forest.
    'min_samples_split': np.arange(5, 12, 2),  # Range for minimum samples required to s
plit an internal node.
    'max_features': ['log2', 'sqrt', 0.2, 0.4]  # Different options for the number of fea
tures to consider at each split.
}

# Run the grid search to find the best parameters
grid_obj = GridSearchCV(tuned_wv, parameters, scoring='f1_weighted', cv=5, n_jobs=-1)
grid_obj = grid_obj.fit(X_train_gl, y_train)  # Fit the grid search on the training data

# End timing the process and print time taken
end = time.time()
print("Time taken ", (end - start))

# Set the best model with the best combination of hyperparameters
tuned_gl = grid_obj.best_estimator_
```

```
Time taken  89.55088448524475
```

In [ ]:

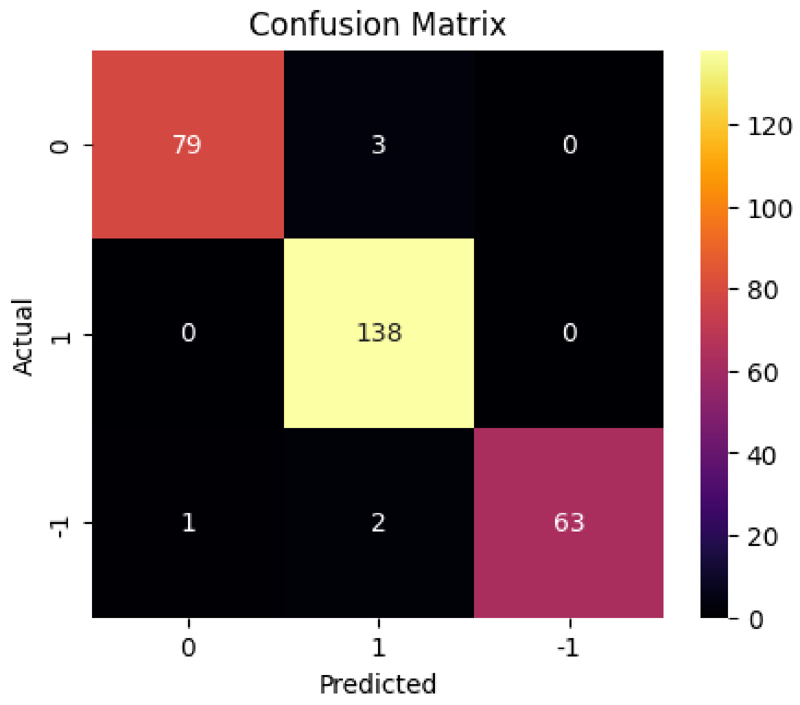
```
tuned_gl.fit(X_train_gl, y_train)
```

Out[ ]:

```
▾                    RandomForestClassifier
                                                      i ?
RandomForestClassifier(max_depth=6, max_features=0.2, min_samples_split=7,
                       random_state=42)
```

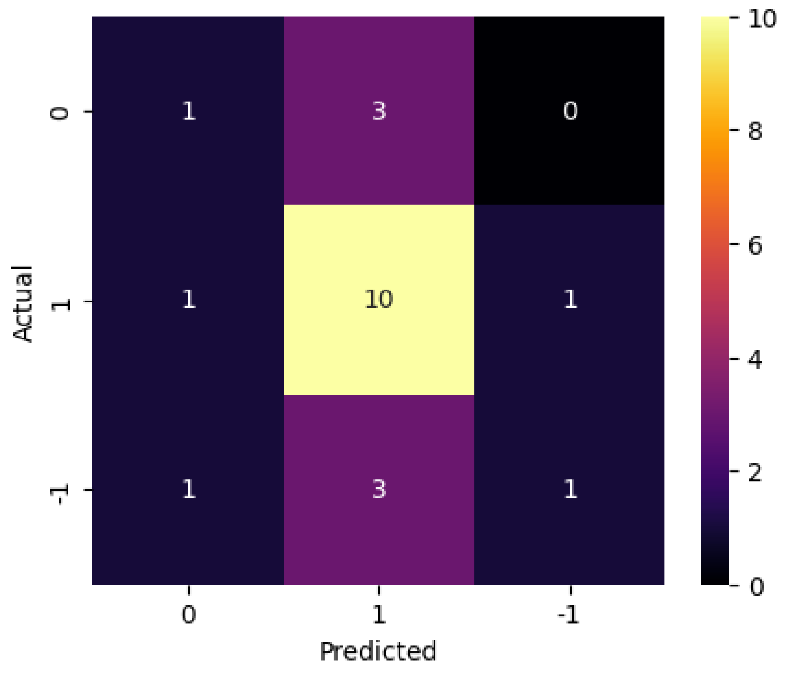
In [ ]:

```
plot_confusion_matrix(tuned_gl,X_train_gl,y_train)
```



In [ ]:

```
plot_confusion_matrix(tuned_gl,X_val_gl,y_val)
```



In [ ]:

```
tuned_train_gl=model_performance_classification_sklearn(tuned_gl,X_train_gl,y_train)
print("Training performance:\n",tuned_train_gl)
```

```
Training performance:
    Accuracy    Recall   Precision        F1
0   0.979021  0.979021   0.979545  0.978968
```

In [ ]:

```
tuned_val_gl = model_performance_classification_sklearn(tuned_gl,X_val_gl,y_val)
print("Validation performance:\n",tuned_val_gl)
```

```
Validation performance:
    Accuracy    Recall   Precision        F1
0   0.571429  0.571429   0.539683  0.530612
```

Tuned Model - Sentence Transformer

Explanation:

1. **RandomForestClassifier:**
    - **The base model is set to `RandomForestClassifier`. Random forests are a powerful ensemble method that uses multiple decision trees to improve model performance and reduce overfitting.**
    - **`random_state=42` ensures reproducibility of results.**
2. **Hyperparameter Grid (`parameters`):**
    - **`max_depth` : Limits the depth of each decision tree to avoid overfitting. A range from 3 to 6 is tested.**
    - **`min_samples_split` : Determines the minimum number of samples required to split an internal node in the tree. A higher value reduces the model's complexity, making it less prone to overfitting. We test values from 5 to 11 with a step size of 2.**
    - **`max_features` : This specifies the number of features to consider when looking for the best split. It can be set to 'log2' (logarithmic number of features), 'sqrt' (square root of the number of features), or a fraction of the total number of features (0.2 and 0.4).**
3. **Grid Search (`GridSearchCV`):**
    - **`scoring='f1_weighted'` : We use the weighted F1 score as the evaluation metric, which is appropriate for imbalanced classes, as it considers both precision and recall.**
    - **`cv=5` : 5-fold cross-validation is used to evaluate model performance.**
    - **`n_jobs=-1` : This parameter allows the grid search to use all available CPU cores to speed up the computation process**

computation process.

4. **Fitting the GridSearchCV:**
   - `grid_obj.fit(X_train_st, y_train)` **performs the grid search on the training data (** `X_train_st` **is the feature set and** `y_train` **is the target labels). It tries all combinations of hyperparameters in the grid and evaluates them using cross-validation.**
5. **Model Timing:**
   - **We measure the time taken for the grid search process using** `start` **and** `end` **times, and print the total time taken.**
6. **Best Model:**
   - **After completing the grid search, the model with the best set of hyperparameters is saved in** `tuned_st` **using** `grid_obj.best_estimator_`**. This will be the optimized random forest model with the best hyperparameter configuration.**

In [ ]:

```
import time
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Start timing the process
start = time.time()

# Choose RandomForestClassifier as the base model
tuned_st = RandomForestClassifier(random_state=42)

# Define the hyperparameter grid for grid search
parameters = {
    'max_depth': np.arange(3, 7),  # Range for maximum depth of trees in the forest.
    'min_samples_split': np.arange(5, 12, 2),  # Range for minimum samples required to s
plit an internal node.
    'max_features': ['log2', 'sqrt', 0.2, 0.4]  # Different options for the number of fea
tures to consider at each split.
}

# Run the grid search to find the best parameters
grid_obj = GridSearchCV(tuned_wv, parameters, scoring='f1_weighted', cv=5, n_jobs=-1)
grid_obj = grid_obj.fit(X_train_st, y_train)  # Fit the grid search on the training data

# End timing the process and print time taken
end = time.time()
print("Time taken ", (end - start))

# Set the best model with the best combination of hyperparameters
tuned_st = grid_obj.best_estimator_
```

```
Time taken  184.23871898651123
```

In [ ]:

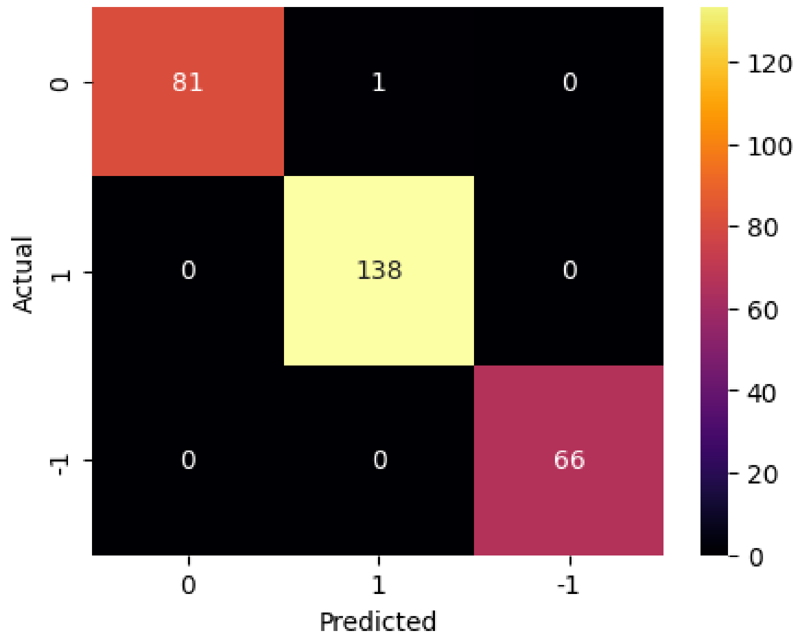
```
tuned_st.fit(X_train_st, y_train)
```

Out[ ]:

```
▾                          RandomForestClassifier
                                                                          i ?
RandomForestClassifier(max_depth=6, max_features=0.2, min_samples_split=11,
                       random_state=42)
```

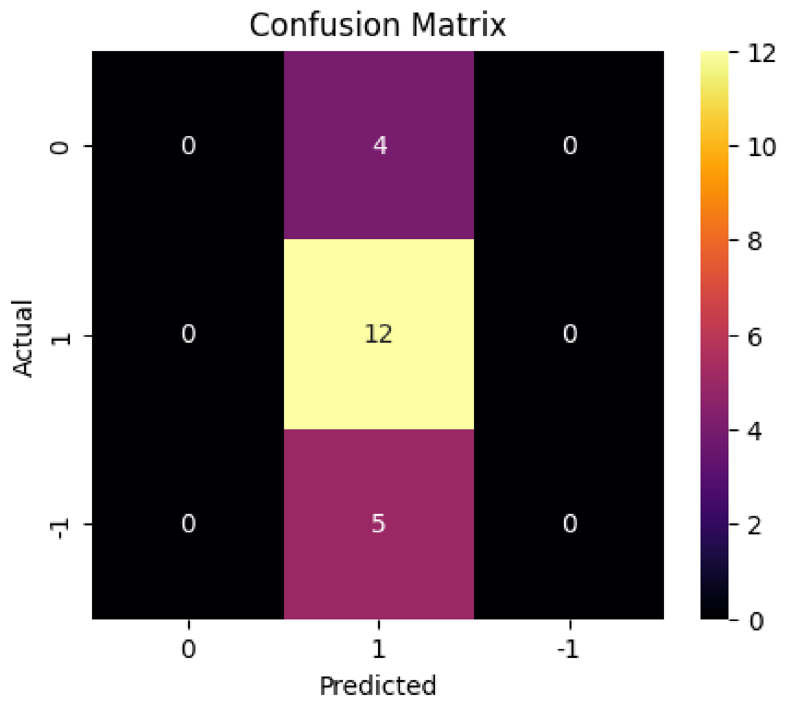
In [ ]:

```
plot_confusion_matrix(tuned_st,X_train_st,y_train)
```



In [ ]:

```
plot_confusion_matrix(tuned_st,X_val_st,y_val)
```



In [ ]:

```
tuned_train_st=model_performance_classification_sklearn(tuned_st,X_train_st,y_train)
print("Training performance:\n",tuned_train_st)
```

```
Training performance:
    Accuracy    Recall  Precision        F1
0  0.996503  0.996503   0.996529  0.996499
```

In [ ]:

```
#Calculating different metrics on validation data
tuned_val_st = model_performance_classification_sklearn(tuned_st,X_val_st,y_val)
print("Validation performance:\n",tuned_val_st)
```

```
Validation performance:
    Accuracy    Recall  Precision        F1
0  0.571429  0.571429   0.326531  0.415584
```

In [ ]:

```
# Training performance comparison

# Concatenate the training results of base models and tuned models for comparison
models_train_comp_df = pd.concat(
    [
        base_train_wv.T,    # Base model with Word2Vec
        base_train_gl.T,    # Base model with GloVe
        base_train_st.T,    # Base model with Sentence Transformer
        tuned_train_wv.T,   # Tuned model with Word2Vec
        tuned_train_gl.T,   # Tuned model with GloVe
        tuned_train_st.T,   # Tuned model with Sentence Transformer
    ], axis=1
)

# Rename columns to match model descriptions
models_train_comp_df.columns = [
    "Base Model (Word2Vec)",
    "Base Model (GloVe)",
    "Base Model (Sentence Transformer)",
    "Tuned Model (Word2Vec)",
    "Tuned Model (GloVe)",
    "Tuned Model (Sentence Transformer)",
]

# Print the performance comparison
print("Training performance comparison:")
print(models_train_comp_df)
```

```
Training performance comparison:
           Base Model (Word2Vec)  Base Model (GloVe)  \
Accuracy                     1.0                 1.0
Recall                       1.0                 1.0
Precision                    1.0                 1.0
F1                           1.0                 1.0

           Base Model (Sentence Transformer)  Tuned Model (Word2Vec)  \
Accuracy                                 1.0                0.965035
Recall                                   1.0                0.965035
Precision                                1.0                0.966735
F1                                       1.0                0.964928

           Tuned Model (GloVe)  Tuned Model (Sentence Transformer)
Accuracy              0.979021                            0.996503
Recall                0.979021                            0.996503
Precision             0.979545                            0.996529
F1                    0.978968                            0.996499
```

In [ ]:

```
# Validation performance comparison

# Concatenate the validation results of base models and tuned models for comparison
models_val_comp_df = pd.concat(
    [
        base_val_wv.T,    # Base model with Word2Vec
        base_val_gl.T,    # Base model with GloVe
        base_val_st.T,    # Base model with Sentence Transformer
        tuned_val_wv.T,   # Tuned model with Word2Vec
        tuned_val_gl.T,   # Tuned model with GloVe
        tuned_val_st.T,   # Tuned model with Sentence Transformer
    ], axis=1
)

# Rename columns to match model descriptions
models_val_comp_df.columns = [
    "Base Model (Word2Vec)",
    "Base Model (GloVe)",
    "Base Model (Sentence Transformer)",
    "Tuned Model (Word2Vec)",
    "Tuned Model (GloVe)",
    "Tuned Model (Sentence Transformer)",
]
```

```
# Print the validation performance comparison
print("Validation performance comparison:")
print(models_val_comp_df)
```

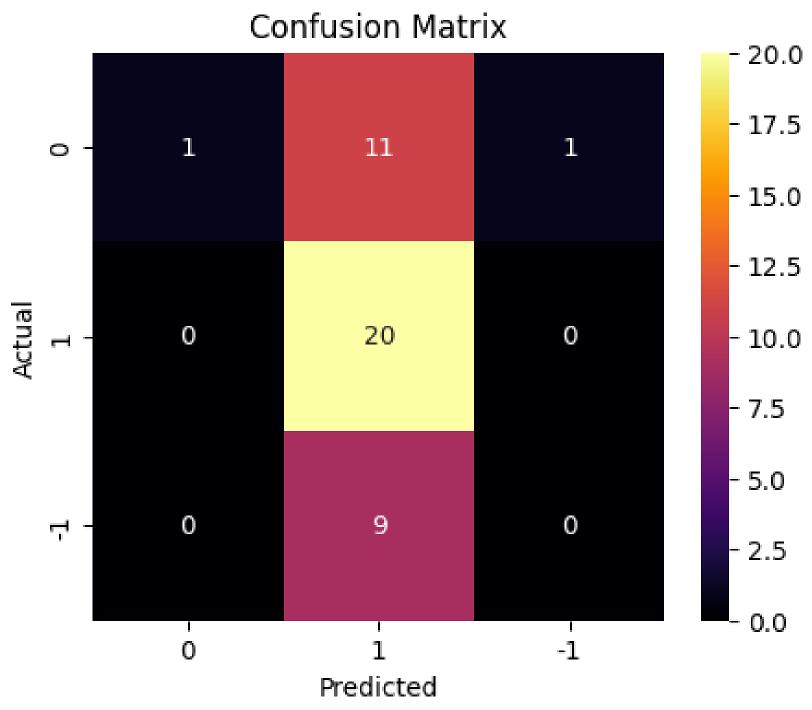
```
Validation performance comparison:
           Base Model (Word2Vec)  Base Model (GloVe)  \
Accuracy                0.476190            0.476190
Recall                  0.476190            0.476190
Precision               0.300752            0.400794
F1                      0.368664            0.426871

           Base Model (Sentence Transformer)  Tuned Model (Word2Vec)  \
Accuracy                            0.619048                0.476190
Recall                              0.619048                0.476190
Precision                           0.533333                0.317460
F1                                  0.504762                0.380952

           Tuned Model (GloVe)  Tuned Model (Sentence Transformer)
Accuracy              0.571429                            0.571429
Recall                0.571429                            0.571429
Precision             0.539683                            0.326531
F1                    0.530612                            0.415584
```

Based on the data, it seems Sentence Transformer base model is the best choice among all. We could try different classifier to further improve the performance.

Model Performance Check on Test Data

In [ ]:

```
plot_confusion_matrix(base_st,X_test_st,y_test)
```



In [ ]:

```
#Calculating different metrics on training data
final_model_test = model_performance_classification_sklearn(base_st,X_test_st,y_test)
print("Test performance for the final model:\n",final_model_test)
```

```
Test performance for the final model:
    Accuracy  Recall  Precision        F1
0        0.5     0.5   0.547619  0.361678
```

Summary

Summary:

This data presents a comparison of various natural language processing models, both base and tuned, using different word embedding techniques: Word2Vec, GloVe, and Sentence Transformer. The evaluation metrics include Accuracy, Recall, Precision, and F1-score. The primary finding is that the Sentence Transformer base model demonstrates the highest overall performance among the models tested, achieving an accuracy and recall of 0.619048 and a balanced F1-score of 0.504762.

While tuning improves the performance of GloVe slightly, achieving an F1-score of 0.530612, it does not surpass the base Sentence Transformer. Furthermore, tuning Word2Vec and Sentence Transformer leads to a decrease in performance across most metrics.

Key Takeaways:

Sentence Transformer is a strong base model: It outperforms both Word2Vec and GloVe in its base configuration. Tuning doesn't guarantee improvement: In this case, tuning Word2Vec and Sentence Transformer resulted in lower performance. GloVe benefits from tuning: Tuning GloVe resulted in a modest improvement in performance.

PART -2 Prompt Engineering

Weekly News Summarization

In [ ]:

```
# Importing libraries to manipulate and analyze data
import pandas as pd  # pandas for handling data frames and datasets
import numpy as np   # numpy for numerical operations on arrays and matrices

# Importing libraries for data visualization
import matplotlib.pyplot as plt  # matplotlib for creating static visualizations like plo
ts and graphs
import seaborn as sns           # seaborn for statistical data visualization (more advanc
ed than matplotlib)

# Importing time-related functions for measuring execution time and managing timestamps
import time  # time module is used for timing the execution of certain tasks (e.g., measu
ring how long an operation takes)

# Importing JSON parsing library for working with JSON data format
import json  # json module to parse and manipulate JSON data structures
```

Important Note: It is recommended to run this section of the project independently from the previous sections in order to avoid runtime crashes due to RAM overload.

Installing and Importing the necessary libraries

Explanation:

This code provides installation instructions for the `llama-cpp-python` package, which is used for running models (like LLaMA) with Python bindings. It contains two versions: one for GPUs and one for CPUs.

- **GPU Installation:**
  - **This installation command is used when you want to leverage GPU acceleration (via CUDA) for faster processing. It uses the environment variable `CMAKE_ARGS` to enable GPU support with the flag `-DLLAMA_CUBLAS=on`. The package is then installed using `pip`, ensuring it installs version `0.1.85`, and it forces a reinstallation of the package without using any cached versions.**
- **CPU Installation:**
  - **This installation command is used when you're not utilizing a GPU and rely on the CPU for processing. Here, the `CMAKE_ARGS` variable is set with `-DLLAMA_CUBLAS=off` to disable GPU-specific**

Here, the `CMAKE_ARGS` variable is set with `-DLLAMA_CUBLAS=off` to disable GPU-specific optimizations. Similarly, the package is installed using `pip`, with version `0.1.85`, forcing a reinstallation and clearing any cached versions.

Key Points:

- **GPU Installation:** Use this if you have a CUDA-compatible GPU and want faster model inference.
- **CPU Installation:** Use this if you don't have a GPU or want to run it on a CPU (might be slower than GPU processing).

In [ ]:

```
# Installation for GPU (Llama-cpp-python)
# Uncomment the following line if you want to install with GPU support
#!CMAKE_ARGS="-DLLAMA_CUBLAS=on" FORCE_CMAKE=1 pip install llama-cpp-python==0.1.85 --for
ce-reinstall --no-cache-dir -q

# Installation for CPU (Llama-cpp-python)
# Uncomment the following line if you want to install with CPU support (no GPU)
!CMAKE_ARGS="-DLLAMA_CUBLAS=off" FORCE_CMAKE=1 pip install llama-cpp-python==0.1.85 --fo
rce-reinstall --no-cache-dir -q
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.8/1.8 MB 25.3 MB/s eta 0:00:00
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.0/62.0 kB 170.4 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 45.5/45.5 kB 198.3 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 16.4/16.4 MB 245.1 MB/s eta 0:00:00
  Building wheel for llama-cpp-python (pyproject.toml) ... done
ERROR: pip's dependency resolver does not currently take into account all the packages th
at are installed. This behaviour is the source of the following dependency conflicts.
torch 2.5.1+cu124 requires nvidia-cublas-cu12==12.4.5.8; platform_system == "Linux" and p
latform_machine == "x86_64", but you have nvidia-cublas-cu12 12.5.3.2 which is incompatib
le.
torch 2.5.1+cu124 requires nvidia-cuda-cupti-cu12==12.4.127; platform_system == "Linux" a
nd platform_machine == "x86_64", but you have nvidia-cuda-cupti-cu12 12.5.82 which is inc
ompatible.
torch 2.5.1+cu124 requires nvidia-cuda-nvrtc-cu12==12.4.127; platform_system == "Linux" a
nd platform_machine == "x86_64", but you have nvidia-cuda-nvrtc-cu12 12.5.82 which is inc
ompatible.
torch 2.5.1+cu124 requires nvidia-cuda-runtime-cu12==12.4.127; platform_system == "Linux"
and platform_machine == "x86_64", but you have nvidia-cuda-runtime-cu12 12.5.82 which is
incompatible.
torch 2.5.1+cu124 requires nvidia-cudnn-cu12==9.1.0.70; platform_system == "Linux" and pl
atform_machine == "x86_64", but you have nvidia-cudnn-cu12 9.3.0.75 which is incompatible
.
torch 2.5.1+cu124 requires nvidia-cufft-cu12==11.2.1.3; platform_system == "Linux" and pl
atform_machine == "x86_64", but you have nvidia-cufft-cu12 11.2.3.61 which is incompatibl
e.
torch 2.5.1+cu124 requires nvidia-curand-cu12==10.3.5.147; platform_system == "Linux" and
platform_machine == "x86_64", but you have nvidia-curand-cu12 10.3.6.82 which is incompat
ible.
torch 2.5.1+cu124 requires nvidia-cusolver-cu12==11.6.1.9; platform_system == "Linux" and
platform_machine == "x86_64", but you have nvidia-cusolver-cu12 11.6.3.83 which is incomp
atible.
torch 2.5.1+cu124 requires nvidia-cusparse-cu12==12.3.1.170; platform_system == "Linux" a
nd platform_machine == "x86_64", but you have nvidia-cusparse-cu12 12.5.1.3 which is inco
mpatible.
torch 2.5.1+cu124 requires nvidia-nvjitlink-cu12==12.4.127; platform_system == "Linux" an
d platform_machine == "x86_64", but you have nvidia-nvjitlink-cu12 12.5.82 which is incom
patible.
numba 0.61.0 requires numpy<2.2,>=1.24, but you have numpy 2.2.3 which is incompatible.
thinc 8.2.5 requires numpy<2.0.0,>=1.19.0; python_version >= "3.9", but you have numpy 2.
2.3 which is incompatible.
tensorflow 2.18.0 requires numpy<2.1.0,>=1.26.0, but you have numpy 2.2.3 which is incomp
atible.
gensim 4.3.3 requires numpy<2.0,>=1.18.5, but you have numpy 2.2.3 which is incompatible.
langchain 0.3.19 requires numpy<2,>=1.26.4; python_version < "3.12", but you have numpy 2
.2.3 which is incompatible.
```

```
pytensor 2.27.1 requires numpy<2,>=1.17.0, but you have numpy 2.2.3 which is incompatible
.
```

In [ ]:

```
# Function to download the model from the Hugging Face model hub
from huggingface_hub import hf_hub_download

# Importing the Llama class from the llama_cpp module
from llama_cpp import Llama

# Importing the library for data manipulation
import pandas as pd

from tqdm import tqdm # For progress bar related functionalities

tqdm.pandas()
```

Loading the data

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

In [ ]:

```
import os
os.path.exists("/content/drive/MyDrive/AIML_Project5/stock_news.csv")
```

Out[ ]:

```
True
```

In [ ]:

```
df = pd.read_csv("/content/drive/MyDrive/AIML_Project5/stock_news.csv")
```

In [ ]:

```
data = df.copy()
```

Loading the model

This code snippet is downloading a model from the Hugging Face Hub.

Explanation:

1. `model_name_or_path` **: Specifies the model's name or repository path on the Hugging Face Hub. In this case, it's "TheBloke/Mistral-7B-Instruct-v0.2-GGUF". It has trained with 7B tokens.The Bloke is the name of the person who uploaded the model on hugging face.**
2. `model_basename` **: Defines the exact file name of the model you're downloading. Here, it's "mistral-7b-instruct-v0.2.Q6_K.gguf".**
3. `hf_hub_download()` **: A function that downloads the model from the Hugging Face Hub. It takes two arguments:**
   - `repo_id` **: The identifier of the model repository on Hugging Face (here, it's the path to the model).**
   - `filename` **: The specific model file to download from that repository.**

After running this, the model will be downloaded to the local machine, and the `model_path` **variable will store the path to the downloaded model file.**

```
model_name_or_path = "TheBloke/Mistral-7B-Instruct-v0.2-GGUF"
model_basename = "mistral-7b-instruct-v0.2.Q6_K.gguf"

# Download the model from the Hugging Face Hub
model_path = hf_hub_download(
    repo_id=model_name_or_path,  # Specify the repo_id (model path)
    filename=model_basename       # Specify the filename of the model
)
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://h
uggingface.co/settings/tokens), set it as secret in your Google Colab and restart your se
ssion.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models
or datasets.
  warnings.warn(
```

In [ ]:

```
import os

# Get the number of available CPU cores (threads)
num_cores = os.cpu_count()
print(f"Number of CPU cores available: {num_cores}")
```

```
Number of CPU cores available: 12
```

This code snippet demonstrates how to initialize a Llama model, with different configurations based on whether the runtime uses GPU or CPU.

Explanation:

1. `model_path` **: Specifies the location of the downloaded model file from Hugging Face (defined earlier in the code).**
2. **GPU Configuration:**
   - `n_gpu_layers=100` **: Sets the number of layers of the model that will be loaded onto the GPU. This controls how much of the model runs on the GPU and depends on the available GPU memory.**
   - `n_ctx=4500` **: Defines the context window size, which controls how many tokens the model can process at once. Here, it's set to 4500 tokens. We have the largest token around ~3800. So, 4500 is the good number.**
3. **CPU Configuration (commented out):**
   - `n_cores=-2` **: When using the CPU, setting** `n_cores` **to -2 tells the model to use all available CPU cores for processing. With Google colab pro version, we could get more cores, as you can see, I got 12 CPU cores and all GPUs for running the task. Without pro google colab, it took me over 5 hours to run the code, at the end I found a mistake in the code. With paid version, i was able to execute in 1 hour.**
   - **The commented-out sections provide an alternative setup where you could configure the model to run on CPU (by uncommenting the CPU section) or GPU (by using the GPU configuration).**

Key Points:

- **If you're using GPU, the model uses** `n_gpu_layers` **to determine how many layers are loaded on the GPU.**
- **If you're using CPU, you would specify the number of cores to use for computation.**

In [ ]:

```
#llm = Llama(
#    model_path=model_path,
#    n_threads=2,  # CPU cores
    #n_batch=512,  # Should be between 1 and n_ctx, consider the amount of VRAM in your G
PU.
    # n_gpu_layers=43,  # uncomment and change this value based on GPU VRAM pool.
#    n_ctx=4500,  # Context window
#)


# Uncomment the below snippet of code if the runtime is connected to GPU.
llm = Llama(
     model_path=model_path,   # Path to the model file downloaded from Hugging Face
     n_gpu_layers=100,        # Number of model layers to load onto the GPU
     n_ctx=4500,              # Context window size, controls the number of tokens the mo
del can process at once
)

# Use the below code if the runtime is connected to CPU
#llm = Llama(
#    model_path=model_path,     # Path to the model file downloaded from Hugging Face
#    n_ctx=4500,                # Context window size (token size the model can process)
#    n_cores=-2                 # Use all available CPU cores by setting to -2 (negative
means use all available cores)
#)
```

```
AVX = 1 | AVX2 = 1 | AVX512 = 0 | AVX512_VBMI = 0 | AVX512_VNNI = 0 | FMA = 1 | NEON = 0
| ARM_FMA = 0 | F16C = 1 | FP16_VA = 0 | WASM_SIMD = 0 | BLAS = 0 | SSE3 = 1 | SSSE3 = 1
| VSX = 0 |
```

Aggregating the data weekly

In [ ]:

```
data["Date"] = pd.to_datetime(data['Date'])  # Convert the 'Date' column to datetime for
mat.
```

In [ ]:

```
# Group the data by week using the 'Date' column.
weekly_grouped = data.groupby(pd.Grouper(key='Date', freq='W'))
```

This code is performing an aggregation on a DataFrame (`weekly_grouped`) to group the data and combine the news articles.

Explanation:

1. `weekly_grouped.agg()` **: Applies an aggregation function to each column in the DataFrame:**
   - `'News': lambda x: ' || '.join(x)` **: For the** `'News'` **column, it joins all the values (news articles) in each group with a separator** `' || '` **.**
2. `.reset_index()` **: Resets the index of the DataFrame after the aggregation, so the resulting DataFrame has a default integer index.**
3. `print(weekly_grouped.shape)` **: Prints the shape (dimensions) of the** `weekly_grouped` **DataFrame, showing the number of rows and columns.**

Summary:

The code aggregates news articles by week (or another grouping), joining the news articles for each group with `' || '` **, and then resets the DataFrame index before printing the shape of the resulting DataFrame.**

In [ ]:

```
weekly_grouped = weekly_grouped.agg(
    {
        'News': lambda x: ' || '.join(x)  # Join the news values with ' || ' separator.
    }
).reset_index()

print(weekly_grouped.shape)
```

```
(18, 2)
```

In [ ]:

```
weekly_grouped
```

Out[ ]:

	Date	News
0	2019-01-06	The tech sector experienced a significant dec...
1	2019-01-13	Sprint and Samsung plan to release 5G smartph...
2	2019-01-20	The U.S. stock market declined on Monday as c...
3	2019-01-27	The Swiss National Bank (SNB) governor, Andre...
4	2019-02-03	Caterpillar Inc reported lower-than-expected ...
5	2019-02-10	The Dow Jones Industrial Average, S&P 500, an...
6	2019-02-17	This week, the European Union's second highes...
7	2019-02-24	This news article discusses progress towards ...
8	2019-03-03	The Dow Jones Industrial Average and other ma...
9	2019-03-10	Spotify, the world's largest paid music strea...
10	2019-03-17	The United States opposes France's digital se...
11	2019-03-24	Facebook's stock price dropped more than 3% o...
12	2019-03-31	This news article reports that the S&P 500 In...
13	2019-04-07	Apple and other consumer brands, including LV...
14	2019-04-14	In March, mobile phone shipments to China dro...
15	2019-04-21	The chairman of Taiwan's Foxconn, Terry Gou, ...
16	2019-04-28	Taiwan's export orders continued to decline f...
17	2019-05-05	Spotify reported better-than-expected Q1 reve...

In [ ]:

```
# creating a copy of the data
data_1 = weekly_grouped.copy()
```

Summarization

Note:

- The model is expected to summarize the news from the week by identifying the top three positive and negative events that are most likely to impact the price of the stock.
- As an output, the model is expected to return a JSON containing two keys, one for Positive Events and one for Negative Events.

For the project, we need to define the prompt to be fed to the LLM to help it understand the task to perform. The following should be the components of the prompt:

1. **Role:** Specifies the role the LLM will be taking up to perform the specified task, along with any specific details regarding the role
   - **Example:** `You are an expert data analyst specializing in news content analysis.`
2. **Task:** Specifies the task to be performed and outlines what needs to be accomplished, clearly defining the objective
   - **Example:** `Analyze the provided news headline and return the main topics contained within it.`

3. **Instructions: Provides detailed guidelines on how to perform the task, which includes steps, rules, and criteria to ensure the task is executed correctly**

   - **Example:**

   ```
   Instructions:
   1. Read the news headline carefully.
   2. Identify the main subjects or entities mentioned in the headline.
   3. Determine the key events or actions described in the headline.
   4. Extract relevant keywords that represent the topics.
   5. List the topics in a concise manner.
   ```

1. **Output Format: Specifies the format in which the final response should be structured, ensuring consistency and clarity in the generated output**

   - **Example:** `Return the output in JSON format with keys as the topic number and values as the actual topic.`

Full Prompt Example:

```
You are an expert data analyst specializing in news content analysis.

Task: Analyze the provided news headline and return the main topics contained withi
n it.

Instructions:
1. Read the news headline carefully.
2. Identify the main subjects or entities mentioned in the headline.
3. Determine the key events or actions described in the headline.
4. Extract relevant keywords that represent the topics.
5. List the topics in a concise manner.

Return the output in JSON format with keys as the topic number and values as the ac
tual topic.
```

Sample Output:

`{"1": "Politics", "2": "Economy", "3": "Health" }`

Utility Functions

This code defines a function `extract_json_data` that extracts and parses a JSON object from a string.

Explanation:

1. **Function Definition:**
   - `extract_json_data(json_str)` **: Takes a string (** `json_str` **) as input.**
2. **JSON Parsing:**
   - `json_start = json_str.find('{')` **: Finds the index of the first opening curly brace `{` to locate the start of the JSON object.**
   - `json_end = json_str.rfind('}')` **: Finds the index of the last closing curly brace `}` to locate the end of the JSON object.**
3. **Check for Valid JSON:**
   - **If both curly braces are found (i.e., `json_start != -1` and `json_end != -1`), it extracts the substring containing the JSON object and parses it using `json.loads(extracted_category)` to convert it into a Python dictionary (`data_dict`).**
   - **If the braces are not found, it prints a warning and returns an empty dictionary `{}`.**
4. **Error Handling:**

- If there is an error during JSON parsing (e.g., malformed JSON), it catches the exception (`json.JSONDecodeError`) and prints an error message, then returns an empty dictionary `{}`.

Summary:

The function attempts to extract a valid JSON object from a string, parse it into a Python dictionary, and handle errors if the JSON is malformed or not found.

In [ ]:

```
# defining a function to parse the JSON output from the model
def extract_json_data(json_str):
    import json
    try:
        # Find the indices of the opening and closing curly braces
        json_start = json_str.find('{')
        json_end = json_str.rfind('}')

        if json_start != -1 and json_end != -1:
            extracted_category = json_str[json_start:json_end + 1]   # Extract the JSON o
bject
            data_dict = json.loads(extracted_category)
            return data_dict
        else:
            print(f"Warning: JSON object not found in response: {json_str}")
            return {}
    except json.JSONDecodeError as e:
        print(f"Error parsing JSON: {e}")
        return {}
```

Defining the response function

This code defines a function `response_mistral_1` that interacts with the **Mistral** language model to generate a response based on a provided **prompt** and **news articles**.

Explanation:

1. **Function Definition:**

   - `response_mistral_1(prompt, news)`: The function takes two inputs: `prompt` (the instruction or question) and `news` (a set of news articles).
2. **Model Call:**

   - `llm()`: This line calls the `llm` (presumably a pre-initialized language model), passing a formatted string combining the prompt and the news articles. It provides:
     - `max_tokens=1024`: Limits the model's output to 1024 tokens.
     - `temperature=0.01`: A very low temperature, indicating minimal randomness in the response (the output will be more deterministic).
     - `top_p=0.95`: Uses nucleus sampling, focusing on the top 95% of probable tokens.
     - `top_k=50`: Limits the model to considering the top 50 most likely tokens for each step.
     - `echo=False`: Ensures the input prompt is not included in the output.
3. **Extracting Output:**

   - `final_output = model_output["choices"][0]["text"]`: Extracts the text of the model's response from the model output (which is typically a dictionary containing multiple possible choices).
4. **Returning the Result:**

   - The function returns the final output (the model's generated response).

Summary:

The function takes a prompt and a set of news articles, feeds them into the Mistral model, and returns the

model's generated response based on those inputs.

In [ ]:

```
# Defining the response function
def response_mistral_1(prompt, news):
    model_output = llm(
      f"""
      [INST]
      {prompt}
      News Articles: {news}
      [/INST]
      """,
      max_tokens=1024,  # Set maximum number of tokens to 150 (you can adjust based on yo
ur requirements)
      temperature=0.01,  # Set the temperature to 0.7 (a typical value for balanced rando
mness)
      top_p=0.95,  # Set top_p to 0.9 (this is a common choice to focus on the most likel
y tokens)
      top_k=50,  # Set top_k to 50 (this limits the model to considering the top 50 token
s)
      echo=False,  # Don't echo the input prompt in the response
    )

    final_output = model_output["choices"][0]["text"]  # Extract the response text from
the model output

    return final_output
```

Checking the model output on a sample

In [ ]:

```
news = data_1.loc[0, 'News']
```

In [ ]:

```
print(len(news.split(' ')))
news
```

```
2611
```

Out[ ]:

```
' The tech sector experienced a significant decline in the aftermarket following Apple\'s
Q1 revenue warning. Notable suppliers, including Skyworks, Broadcom, Lumentum, Qorvo, and
TSMC, saw their stocks drop in response to Apple\'s downward revision of its revenue expe
ctations for the quarter, previously announced in January. ||  Apple lowered its fiscal Q
1 revenue guidance to $84 billion from earlier estimates of $89-$93 billion due to weaker
than expected iPhone sales. The announcement caused a significant drop in Apple\'s stock
price and negatively impacted related suppliers, leading to broader market declines for t
ech indices such as Nasdaq 10 ||  Apple cut its fiscal first quarter revenue forecast fro
m $89-$93 billion to $84 billion due to weaker demand in China and fewer iPhone upgrades.
CEO Tim Cook also mentioned constrained sales of Airpods and Macbooks. Apple\'s shares fe
ll 8.5% in post market trading, while Asian suppliers like Hon ||  This news article repo
rts that yields on long-dated U.S. Treasury securities hit their lowest levels in nearly
a year on January 2, 2019, due to concerns about the health of the global economy followi
ng weak economic data from China and Europe, as well as the partial U.S. government shutd
own. Apple ||  Apple\'s revenue warning led to a decline in USD JPY pair and a gain in Ja
panese yen, as investors sought safety in the highly liquid currency. Apple\'s underperfo
rmance in Q1, with forecasted revenue of $84 billion compared to analyst expectations of
$91.5 billion, triggered risk aversion mood in markets || Apple CEO Tim Cook discussed th
e company\'s Q1 warning on CNBC, attributing US-China trade tensions as a factor. Despite
not mentioning iPhone unit sales specifically, Cook indicated Apple may comment on them a
gain. Services revenue is projected to exceed $10.8 billion in Q1. Cook also addressed th
e lack of ||  Roku Inc has announced plans to offer premium video channels on a subscript
ion basis through its free streaming service, The Roku Channel. Partners include CBS Corp
\'s Showtime, Lionsgate\'s Starz, and Viacom Inc\'s Noggin. This model follows Amazon\'s
successful Channels business, which generated an estimated ||  Wall Street saw modest gai
ns on Wednesday but were threatened by fears of a global economic slowdown following Appl
e\'s shocking revenue forecast cut, blaming weak demand in China. The tech giant\'s suppl
```

```
iers and S&P 500 futures also suffered losses. Reports of decelerating factory activity ir
China and the euro zone ||  Apple\'s fiscal first quarter revenue came in below analysts\
' estimates at around $84 billion, a significant drop from the forecasted range of $89-$9
3 billion. The tech giant attributed the shortfall to lower iPhone revenue and upgrades,
as well as weakness in emerging markets. Several brokerages had already reduced their pro
duction estimates ||  Apple Inc. lowered its quarterly sales forecast for the fiscal firs
t quarter, underperforming analysts\' expectations due to slowing Chinese economy and tra
de tensions. The news sent Apple shares tumbling and affected Asia-listed suppliers like
Hon Hai Precision Industry Co Ltd, Taiwan Semiconductor Manufacturing Company, and LG Inn
ot ||  The Australian dollar experienced significant volatility on Thursday, plunging to
multi-year lows against major currencies due to automated selling, liquidity issues, and
a drought of trades. The largest intra-day falls in the Aussie\'s history occurred amid v
iolent movements in AUD/JPY and AUD/ ||  In early Asian trading on Thursday, the Japanese
yen surged as the U.S. dollar and Australian dollar collapsed in thin markets due to mass
ive stop loss sales triggered by Apple\'s earnings warning of sluggish iPhone sales in Ch
ina and risk aversion. The yen reached its lowest levels against the U.S. dollar since Ma
rch  ||  The dollar fell from above 109 to 106.67 after Apple\'s revenue warning, while t
he 10-year Treasury yield also dropped to 2.61%. This followed money flowing into US gove
rnment paper. Apple\'s shares and U.S. stock index futures declined, with the NAS ||  RBC
Capital maintains its bullish stance on Apple, keeping its Outperform rating and $220 pri
ce target. However, analyst Amit Daryanani warns of ongoing iPhone demand concerns, which
could impact pricing power and segmentation efforts if severe. He suggests potential capi
tal allocation adjustments if the stock underperforms for several quarters ||  Oil prices
dropped on Thursday as investor sentiment remained affected by China\'s economic slowdown
and turmoil in stock and currency markets. US WTI Crude Oil fell by $2.10 to $45.56 a bar
rel, while International Brent Oil was down $1.20 at $54.26 ||  In this news article, inv
estors\' concerns about a slowing Chinese and global economy, amplified by Apple\'s reven
ue warning, led to a significant surge in the Japanese yen. The yen reached its biggest o
ne-day rise in 20 months, with gains of over 4% versus the dollar. This trend was driven
by automated ||  In Asia, gold prices rose to over six-month highs on concerns of a globa
l economic slowdown and stock market volatility. Apple lowered its revenue forecast for t
he first quarter, leading Asian stocks to decline and safe haven assets like gold and Jap
anese yen to gain. Data showed weakened factory activity in Asia, particularly China, add
ing to ||  Fears of a global economic slowdown led to a decline in the US dollar on Thurs
day, as the yen gained ground due to its status as a safe haven currency. The USD index s
lipped below 96, and USD JPY dropped to 107.61, while the yen strengthened by 4.4%. ||  I
n Thursday trading, long-term US Treasury yields dropped significantly below 2.6%, reachi
ng levels not seen in over a year, as investors shifted funds from stocks to bonds follow
ing Apple\'s warning of decreased revenue due to emerging markets and China\'s impact on
corporate profits, with the White House advisor adding to concerns of earnings down ||  G
old prices have reached their highest level since mid-June, with the yellow metal hitting
$1,291.40 per ounce due to investor concerns over a slowing economy and Apple\'s bearish
revenue outlook. Saxo Bank analyst Ole Hansen predicts gold may reach $1,300 sooner ||  W
edbush analyst Daniel Ives lowered his price target for Apple from $275 to $200 due to co
ncerns over potential iPhone sales stagnation, with an estimated 750 million active iPhon
es worldwide that could cease growing or even decline. He maintains an Outperform rating
and remains bullish on the long ||  Oil prices rebounded on Thursday due to dollar weakne
ss, signs of output cuts by Saudi Arabia, and weaker fuel oil margins leading Riyadh to l
ower February prices for heavier crude grades sold to Asia. The Organization of the Petro
leum Exporting Countries (OPEC) led by Saudi Arabia and other producers ||  This news art
icle reports on the impact of Apple\'s Q1 revenue warning on several tech and biotech stoc
ks. Sesen Bio (SESN) and Prana Biotechnology (PRAN) saw their stock prices drop by 28% an
d 11%, respectively, following the announcement. Mellanox Technologies (ML ||  Gold price
s reached within $5 of $1,300 on Thursday as weak stock markets and a slumping dollar dro
ve investors towards safe-haven assets. The U.S. stock market fell about 2%, with Apple\'
s rare profit warning adding to investor unease. COMEX gold futures settled at $1 ||  The
FDIC Chair, Jelena McWilliams, expressed no concern over market volatility affecting the
U.S banking system due to banks\' ample capital. She also mentioned a review of the CAMEL
S rating system used to evaluate bank health for potential inconsistencies and concerns r
egarding forum shopping. This review comes from industry ||  Apple cut its quarterly reve
nue forecast for the first time in over 15 years due to weak iPhone sales in China, repre
senting around 20% of Apple\'s revenue. This marks a significant downturn during Tim Cook
\'s tenure and reflects broader economic concerns in China exacerbated by trade tensions
with the US. U ||  Goldman analyst Rod Hall lowered his price target for Apple from $182
to $140, citing potential risks to the tech giant\'s 2019 numbers due to uncertainties in
Chinese demand. He reduced his revenue estimate for the year by $6 billion and EPS forecas
t by $1.54 ||  Delta Air Lines lowered its fourth-quarter revenue growth forecast to a ra
nge of 3% from the previous estimate of 3% to 5%. Earnings per share are now expected to k
e $1.25 to $1.30. The slower pace of improvement in late December was unexpected, and Del
ta cited this as ||  Apple\'s profit warning has significantly impacted the stock market
and changed the outlook for interest rates. The chance of a rate cut in May has increased
to 15-16% from just 3%, according to Investing com\'s Fed Rate Monitor Tool. There is eve
```

```
n a 1% chance of two cuts in May. ||  The White House advisor, Kevin Hassett, stated that
a decline in Chinese economic growth would negatively impact U.S. firm profits but recove
r once a trade deal is reached between Washington and Beijing. He also noted that Asian e
conomies, including China, have been experiencing significant slowdowns since last spring
due to U.S. tariffs ||  The White House economic adviser, Kevin Hassett, warned that more
companies could face earnings downgrades due to ongoing trade negotiations between the U.
S. and China, leading to a decline in oil prices on Thursday. WTI crude fell 44 cents to
$44.97 a barrel, while Brent crude inched ||  Japanese stocks suffered significant losses
on the first trading day of 2019, with the Nikkei 225 and Topix indices both falling over
3 percent. Apple\'s revenue forecast cut, citing weak iPhone sales in China, triggered gl
obal growth concerns and sent technology shares tumbling. The S&P 50 ||  Investors withdr
ew a record $98 billion from U.S. stock funds in December, with fears of aggressive monet
ary policy and an economic slowdown driving risk reduction. The S&P 500 fell 9% last mont
h, with some seeing declines as a buying opportunity. Apple\'s warning of weak iPhone sal
es added ||  Apple\'s Q1 revenue guidance cut, resulting from weaker demand in China, led
to an estimated $3.8 billion paper loss for Berkshire Hathaway due to its $252 million st
ake in Apple. This news, coupled with broad market declines, caused a significant $21.4 b
illion decrease in Berk ||  This news article reports that a cybersecurity researcher, Wi
sh Wu, planned to present at the Black Hat Asia hacking conference on how to bypass Apple
\'s Face ID biometric security on iPhones. However, his employer, Ant Financial, which op
erates Alipay and uses facial recognition technologies including Face ID, asked him to wi
thdraw ||  OPEC\'s production cuts faced uncertainty as oil prices were influenced by vol
atile stock markets, specifically due to Apple\'s lowered revenue forecast and global eco
nomic slowdown fears. US WTI and Brent crude both saw gains, but these were checked by st
ock market declines. Shale production is expected to continue impacting the oil market in
||  Warren Buffett\'s Berkshire Hathaway suffered significant losses in the fourth quarte
r due to declines in Apple, its largest common stock investment. Apple cut its revenue fo
recast, causing a 5-6% decrease in Berkshire\'s Class A shares. The decline resulted in p
otential unrealized investment losses and could push Berk ||  This news article reports t
hat on Thursday, the two-year Treasury note yield dropped below the Federal Reserve\'s ef
fective rate for the first time since 2008. The market move suggests investors believe th
e Fed will not be able to continue tightening monetary policy. The drop in yields was att
ributed to a significant decline in U.S ||  The U.S. and China will hold their first face
-to-face trade talks since agreeing to a 90-day truce in their trade war last month. Depu
ty U.S. Trade Representative Jeffrey Gerrish will lead the U.S. delegation for negotiatio
ns on Jan. 7 and 8, ||  Investors bought gold in large quantities due to concerns over a
global economic slowdown, increased uncertainty in the stock market, and potential Fed ra
te hikes. The precious metal reached its highest price since June, with gold ETF holdings
also seeing significant increases. Factors contributing to this demand include economic d
ownturn, central bank policy mistakes, and ||  Delta Air Lines Inc reported lower-than-ex
pected fourth quarter unit revenue growth, citing weaker than anticipated late bookings a
nd increased competition. The carrier now expects total revenue per available seat mile t
o rise about 3 percent in the period, down from its earlier forecast of 3.5 percent growt
h. Fuel prices are also expected to ||  U.S. stocks experienced significant declines on T
hursday as the S&P 500 dropped over 2%, the Dow Jones Industrial Average fell nearly 3%,
and the Nasdaq Composite lost approximately 3% following a warning of weak revenue from A
pple and indications of slowing U.S. factory activity, raising concerns ||  President Tru
mp expressed optimism over potential trade talks with China, citing China\'s current econ
omic weakness as a potential advantage for the US. This sentiment was echoed by recent re
ports of weakened demand for Apple iPhones in China, raising concerns about the overall h
ealth of the Chinese economy. The White House is expected to take a strong stance in ||
Qualcomm secured a court order in Germany banning the sale of some iPhone models due to p
atent infringement, leading Apple to potentially remove these devices from its stores. Ho
wever, third-party resellers like Gravis continue selling the affected iPhones. This is t
he third major effort by Qualcomm to ban Apple\'s iPhones glob ||  Oil prices rose on Fri
day in Asia as China confirmed trade talks with the U.S., with WTI gaining 0.7% to $47.48
and Brent increasing 0.7% to $56.38 a barrel. The gains came after China\'s Commerce Mini
stry announced that deputy U.S. Trade ||  Gold prices surged past the psychologically sig
nificant level of $1,300 per ounce in Asia on Friday due to growing concerns over a poten
tial global economic downturn. The rise in gold was attributed to weak PMI data from Chin
a and Apple\'s reduced quarterly sales forecast. Investors viewed gold as a safe haven as
set amidst ||  In an internal memo, Huawei\'s Chen Lifang reprimanded two employees for s
ending a New Year greeting on the company\'s official Twitter account using an iPhone ins
tead of a Huawei device. The incident caused damage to the brand and was described as a "
blunder" in the memo. The mistake occurred due to ||  This news article reports on the pos
itive impact of trade war talks between Beijing and Washington on European stock markets,
specifically sectors sensitive to the trade war such as carmakers, industrials, mining co
mpanies, and banking. Stocks rallied with mining companies leading the gains due to coppe
r price recovery. Bayer shares climbed despite a potential ruling restricting || Amazon h
as sold over 100 million devices with its Alexa digital assistant, according to The Verge
. The company is cautious about releasing hardware sales figures and did not disclose hol
iday numbers for the Echo Dot. Over 150 products feature Alexa, and more than 28,000 smar
```

```
t home || The Supreme Court will review Broadcom\'s appeal in a shareholder lawsuit over
the 2015 acquisition of Emulex. The case hinges on whether intent to defraud is required
for such lawsuits, and the decision could extend beyond the Broadcom suit. An Emulex inve
stor filed a class action lawsuit ||  The Chinese central bank announced a fifth reductio
n in the required reserve ratio (RRR) for banks, freeing up approximately 116.5 billion y
uan for new lending. This follows mounting concerns about China\'s economic health amid s
lowing domestic demand and U.S. tariffs on exports. Premier Li Keqiang || The stock marke
t rebounded strongly on Friday following positive news about US-China trade talks, a bett
er-than-expected jobs report, and dovish comments from Federal Reserve Chairman Jerome Po
well. The Dow Jones Industrial Average rose over 746 points, with the S&P 500 and Nasdaq
Com'
```

In [ ]:

```
# Define the prompt for summarizing a news article
prompt = """
You are an expert data analyst specializing in news content analysis.

Task: Analyze the provided news headline and return the main topics contained within it.

Instructions:
1. Read the news headline carefully.
2. Identify the main subjects or entities mentioned in the headline.
3. Determine the key events or actions described in the headline.
4. Extract relevant keywords that represent the topics.
5. List the topics in a concise manner.

Return the output in JSON format with keys as the topic number and values as the actual t
opic.
"""
```

This code defines a **prompt** for summarizing a news article, specifically focused on extracting the main topics from a news headline.

Explanation:

1. **Prompt Definition:**

   - The prompt is a string that provides clear instructions for analyzing a news headline and extracting the main topics.

2. **Instructions:**

   - **Task:** The user is instructed to analyze a provided news headline and identify the main topics.
   - **Steps:**
     - **Read the headline** carefully.
     - **Identify the main subjects or entities** (e.g., people, organizations).
     - **Determine the key events or actions** described.
     - **Extract relevant keywords** that represent the topics.
     - **List the topics concisely**.

3. **Output Format:**

   - The output should be in **JSON format** where each key is a topic number, and the value is the corresponding topic or subject.

Summary:

The prompt is designed to guide the analysis of a news headline by identifying key topics and returning them in a structured JSON format.

In [ ]:

```
%%time
summary = response_mistral_1(prompt, news)
print(summary)
```

```
 [
        {
          "topic_1": "Apple's Q1 revenue warning and its impact on tech stocks",
          "keywords": ["Apple", "Q1 revenue warning", "tech stocks", "notable suppliers"]
        },
        {
          "topic_2": "Global economic concerns following weak data from China and Europe"
,
          "keywords": ["global economy", "weak economic data", "China", "Europe"]
        },
        {
          "topic_3": "Impact of Apple's revenue warning on currency markets",
          "keywords": ["Apple", "revenue warning", "USD JPY pair", "Japanese yen"]
        },
        {
          "topic_4": "Slowing Chinese economy and trade tensions",
          "keywords": ["China", "slowing economy", "trade tensions"]
        },
        {
          "topic_5": "Safe haven assets (Japanese yen, gold) gaining value due to market
volatility",
          "keywords": ["safe haven assets", "Japanese yen", "gold"]
        },
        {
          "topic_6": "Impact of Apple's revenue warning on US Treasury yields",
          "keywords": ["Apple", "revenue warning", "US Treasury yields"]
        }
      ]
CPU times: user 57min 38s, sys: 1.18 s, total: 57min 39s
Wall time: 9min 37s
```

This code measures the execution time of generating a summary using the `response_mistral_1` function.

Explanation:

1. `%%time` **:**

   - **This is an IPython magic command used in Jupyter notebooks to measure the execution time of the cell. It outputs the time taken to run the cell.**

2. `summary = response_mistral_1(prompt, news)` **:**

   - **This calls the `response_mistral_1` function (defined earlier) with the `prompt` and `news` as inputs, generating a summary or response, which is stored in the variable `summary`.**

3. `print(summary)` **:**

   - **This prints the resulting summary or output generated by the model.**

Summary:

The code executes the `response_mistral_1` function to generate a summary based on the provided prompt and news, while also measuring the time it takes to run the entire process. Then, it prints the generated summary.

Note: Use this section to test out the prompt with one instance before using it for the entire weekly data.

Checking the model output on the weekly data

In [ ]:

```
%%time
data_1['Key Events'] = data_1['News'].progress_apply(lambda x: response_mistral_1(prompt
,x))
```

```
  0%|          | 0/18 [00:00<?, ?it/s]Llama.generate: prefix-match hit
 11%|█         | 2/18 [01:05<08:44, 32.79s/it]Llama.generate: prefix-match hit
 17%|█▋        | 3/18 [07:20<43:52, 175.49s/it]Llama.generate: prefix-match hit
 22%|██▏       | 4/18 [13:15<56:33, 242.36s/it]Llama.generate: prefix-match hit
 28%|██▊       | 5/18 [17:19<52:38, 242.95s/it]Llama.generate: prefix-match hit
 33%|██████         | 6/18 [26:18<1:08:15, 341.30s/it]Llama.generate: prefix-match hit
 39%|███████        | 7/18 [29:30<53:43, 293.04s/it]  Llama.generate: prefix-match hit
 44%|███████▌       | 8/18 [35:19<51:48, 310.88s/it]Llama.generate: prefix-match hit
 50%|████████▌      | 9/18 [37:57<39:31, 263.49s/it]Llama.generate: prefix-match hit
 56%|█████████▍     | 10/18 [40:58<31:43, 237.96s/it]Llama.generate: prefix-match hit
 61%|██████████▍    | 11/18 [42:59<23:35, 202.25s/it]Llama.generate: prefix-match hit
 67%|███████████▎   | 12/18 [47:38<22:33, 225.59s/it]Llama.generate: prefix-match hit
 72%|████████████▏  | 13/18 [52:20<20:13, 242.71s/it]Llama.generate: prefix-match hit
 78%|█████████████▏ | 14/18 [57:29<17:30, 262.72s/it]Llama.generate: prefix-match hit
 83%|██████████████ | 15/18 [1:00:57<12:18, 246.20s/it]Llama.generate: prefix-match hit
 89%|███████████████| 16/18 [1:04:14<07:43, 231.51s/it]Llama.generate: prefix-match hit
 94%|███████████████| 17/18 [1:10:08<04:28, 268.36s/it]Llama.generate: prefix-match hit
100%|████████████████| 18/18 [1:12:27<00:00, 229.50s/it]Llama.generate: prefix-match hit
100%|████████████████| 18/18 [1:14:42<00:00, 249.05s/it]
```

```
CPU times: user 7h 24min 1s, sys: 8.88 s, total: 7h 24min 10s
Wall time: 1h 14min 42s
```

This code measures the execution time for applying the `response_mistral_1` function to the **'News'** column of the `data_1` DataFrame.

Explanation:

1. `%%time`:
   - This is an IPython magic command used in Jupyter notebooks to measure the execution time of the entire cell.
2. `data_1['Key Events'] = ...`:
   - Creates a new column **'Key Events'** in the `data_1` DataFrame.
3. `data_1['News'].progress_apply(...)`:
   - `progress_apply`: This method is from the `tqdm` library, which shows a progress bar while applying the function to each element of the **'News'** column.
   - `lambda x: response_mistral_1(prompt, x)`: For each row in the **'News'** column, it applies the `response_mistral_1` function (with the defined `prompt` and the news article `x`), generating the **key events** for each news article.

Summary:

The code applies the `response_mistral_1` function to each news article in the **'News'** column of the `data_1` DataFrame, stores the result in a new **'Key Events'** column, and measures the execution time of the operation. The progress bar shows the progress of this operation.

In [ ]:

```
data_1['Key Events'].head()
```

Out[ ]:

	Key Events
0	[\n {\n "topic_1": "Apple's Q...
1	1. 5G smartphones: Sprint, Samsung, nine U.S. ...
2	{\n "1": "U.S. stock market decline",...
3	{\n "1": "Swiss National Bank (SNB) a...
4	{\n "1": "Caterpillar Inc's lower-th...

dtype: object

Formatting the model output

This code processes the 'Key Events' column in the `data_1` DataFrame and extracts JSON data from each entry.

Explanation:

1. `data_1['model_response_parsed'] = ...`:
   - **Creates a new column 'model_response_parsed' in the `data_1` DataFrame to store the parsed JSON data.**
2. `data_1['Key Events'].apply(extract_json_data)`:
   - `apply(extract_json_data)`: **Applies the `extract_json_data` function to each entry in the 'Key Events' column. This function extracts and parses JSON data from the string format of the news summary.**
3. `data_1.head()`:
   - **Displays the first few rows of the `data_1` DataFrame, showing the newly added 'model_response_parsed' column along with the existing data.**

Summary:

The code parses the 'Key Events' (which is expected to contain JSON-like data) for each row, stores the parsed JSON in a new column 'model_response_parsed', and then displays the first few rows of the updated `data_1` DataFrame.

In [ ]:

```
data_1['model_response_parsed'] = data_1['Key Events'].apply(extract_json_data)
data_1.head()
```

```
Error parsing JSON: Extra data: line 4 column 10 (char 182)
Warning: JSON object not found in response: 1. 5G smartphones: Sprint, Samsung, nine U.S.
cities, Atlanta, Chicago, Dallas, Houston, Kansas City, Los Angeles, New York City, Phoen
ix, Washington D.C.
      2. AMS: Austrian tech company, supplier to Apple, optical sensors, 3D facial recogn
ition features, partnership with Face, reducing dependence on Apple, boost shares
      3. Vivendi's Universal Music Group: valuation increase, market cap, music streaming
revenue, potential suitors
      4. Amazon: stock prediction, growth potential, Pivotal Research report, buy rating,
year-end price target
      5. Geely: sales forecast, economic slowdown, cautious consumers, missed sales targe
t
      6. US-China trade war: efforts to address concerns, ongoing negotiations, structura
l issues, intellectual property rights
      7. Qualcomm: car computing chips, expansion of offerings, automotive market
      8. Mercedes Benz: top selling premium automotive brand, third year in a row
      9. Chinese smartphone market: decline in shipments, December slump
      10. AT S: revenue growth forecast, weak demand from smartphone makers and the autom
otive industry
      11. Asian stock markets: surge during morning trade, progress in U.S.-China trade t
alks
      12. Xiaomi: optimism about future, focus on high end, expansion into Europe, shunni
ng US market
      13. Nike: tax treatment investigation by European Commission
      14. Foxconn: revenue decline, weak demand for consumer electronics
      15. JD.com: reduced prices on iPhone models, weak sales in China
      16. Green Dot: bank holding company, impressive growth, platform business "banking
as a service"
      17. US stock futures: decline due to disappointing holiday sales and revenue cuts
      18. Apple: new iPhone models with triple rear cameras for premium model and dual ca
meras for others, weak sales in China, price cuts on XR model
      19. Johnson & Johnson: raised prescription drug prices
      20. Starbucks: no specific topic mentioned in the provided headline.
Warning: JSON object not found in response:  {
          "1": "Caterpillar Inc's lower-than-expected earnings and full year 2019 outlook
```

```
due to weak demand in China's construction business",
          "2": "Apple's spending over $60 billion with U.S. component suppliers and compa
nies in 2018, generating or supporting over 2 million jobs across all 50 states since 201
1",
          "3": "Apple's expected lower-than-projected fiscal first quarter earnings due t
o disappointing iPhone sales in China",
          "4": "China's smartphone shipments declining 14% YoY in 2018 and 15% YoY in Q4,
with Huawei and Vivo being the only top five vendors to experience growth",
          "5": "Gold reaching a seven-month high due to upcoming major macro events and u
ncertainties surrounding US-China trade talks",
          "6": "CVS Health's insurer, Aetna, developing a new health app called Attain fo
r Apple Watches",
          "7": "Apple releasing a software patch to fix a FaceTime bug that lets users he
ar audio before accepting video calls",
          "8": "Collaboration between Apple, Aetna, and CVS on the health app Attain offe
ring customized fitness challenges with rewards",
          "9": "Corning reporting higher-than-expected revenue and profit for Q4 due to i
ncreased demand from telecom companies investing in 5G networks",
          "10": "Gold reaching an eight-month high due to anticipation for clues on U.S m
onetary policy from Federal Reserve Chairman Jerome Powell's news conference",
          "11": "Apple reporting stronger-than-expected earnings for Q1 2023 with revenue
surpassing expectations",
          "12": "3M issuing a revenue warning due to weak demand in China affecting its a
utomotive and electronics businesses",
          "13": "Apple banning Facebook from its business app program after discovering t
he social media giant was using it to track teenagers' web browsing habits without proper
authorization",
          "14": "AMD reporting in-line earnings but missing revenue estimates causing sha
res to surge 16%",
          "15": "Google reportedly operating a research app, Screenwise Meter, which bypa
ssed app store regulations using an Enterprise Certificate",
          "16": "Apple on track to double its FY16 Services revenue by FY20",
          "17": "Global smartphone shipments declining 5% YoY in Q4 marking the fifth con
secutive quarter of decreases",
          "18": "LG Display reporting stronger profits in Q4 due to increased sales of hi
gh-end wearable screens but warning of weaker panel prices in 2019",
          "19": "European stocks rising on Wednesday as positive news about demand from C
hina outweighed concerns over Brexit",
          "20": "China's manufacturing sector contracting for the second consecutive mont
h in January with weak demand coming from",
          "21": "Alibaba reporting its slowest revenue growth since 2016 due to China's s
lowing economy and trade tensions",
          "22": "Dow Jones Industrial Average, S&P 500, and Nasdaq Composite experiencing
significant gains on Wednesday due to a dovish Federal Reserve stance and upbeat earnings
reports from companies like Apple and Boeing",
          "23": "Google and Facebook disabling their research apps from Apple's developer
enterprise program following criticism from privacy experts",
          "24": "New York authorities investigating Apple for not warning consumers in a
timely manner about a FaceTime bug that allowed iPhone users to hear audio from others' p
hones before accepting video calls",
          "25": "Apple planning to cut prices of some flagship iPhones to boost sales, pa
rticularly in overseas markets like China",
          "26": "Didi Chuxing considering cutting up to 20% of headcount in some departme
nts as part of an organizational overhaul",
          "27": "Facebook facing backlash from Apple following the revelation that the so
cial media giant used a research app to gather user data, in violation of Apple's privacy
guidelines",
          "28": "Peter Jackson making a movie about The Beatles using previously unseen s
tudio footage from their final album recording sessions in January 1969",
          "29": "Kanye West and Tidal's corporate parent res
Warning: JSON object not found in response: 1. ["European Union court ruling on Belgian t
ax breaks for large companies", "Apple and other companies involved in Belgian tax break
case"]
      2. ["Apple", "Starbucks", "Fiat Chrysler", "Belgium", "European Commission"]
      3. ["The European Court is set to rule on a Belgian tax break case involving large
companies", "Apple and other companies are accused of receiving an unfair advantage", "Ar
ound €790 million is to be recovered from these firms"]
      4. ["tax breaks", "Belgian companies", "European Union court ruling", "unfair advan
tage"]

      ----------------------------------------------------------------------------------
---------------------------------
```

```
      2. ["Akamai Technologies reports stronger than projected earnings", "Cybersecurity
and media content delivery services driving revenue growth"]
      3. ["Akamai Technologies", "cybersecurity", "media content delivery"]
      4. ["Akamai Technologies reported stronger than projected earnings", "Revenue from
its cloud security business rose 36% to $185 million", "The security unit is expected to
exceed $1 billion in annual revenue soon"]
      5. ["earnings report", "revenue growth", "cloud security", "media content delivery"
]

      ------------------------------------------------------------------------------------
---------------------------------

      3. ["Apple's proposed news subscription service faces resistance from publications"
, "Pricing and transaction fees a concern for publishers"]
      4. ["Apple", "news subscription service", "publications"]
      5. ["Apple is facing resistance from several publications over its proposed news su
bscription service", "The company plans to keep about half of the revenue but has not yet
finalized the price", "Apple's transaction fee of 30 percent for software developers in t
he App Store may be a concern for publishers"]
      6. ["news subscription service", "pricing", "transaction fees", "publications"]

      ------------------------------------------------------------------------------------
---------------------------------

      4. ["UK government recommends greater regulation of tech companies in news content
distribution", "Google, Facebook, and Apple urged to sign a code of conduct"]
      5. ["U.K. government", "tech companies", "news content distribution"]
      6. ["The U.K. government has released a report recommending greater regulation of t
ech companies", "Companies are urged to sign a code of conduct governing their commercial
agreements with publishers", "Additionally, the U.K.'s competition authority is encourage
d to investigate online advertising for fair competition"]
      7. ["regulation", "tech companies", "news content distribution", "commercial agreem
ents"]

      ------------------------------------------------------------------------------------
---------------------------------

      5. ["Japan Display Inc receives funding from Chinese and Taiwanese investors", "Chi
na's state-backed Silk Road Fund and Taiwanese panel maker TPK Holding Co leading the con
sortium"]
      6. ["Japan Display Inc", "Chinese and Taiwanese investors"]
      7. ["Japan Display Inc is reportedly set to receive up to 80 billion yen in funding
from a consortium of Chinese and Taiwanese investors", "This would make the group the top
shareholder in Japan Display Inc"]
      8. ["funding", "Chinese and Taiwanese investors", "top shareholder"]

      ------------------------------------------------------------------------------------
---------------------------------

      6. ["Trump administration forms advisory board of major company CEOs", "Preparing U
.S. workers for job training issues brought about by automation and artificial intelligen
ce"]
      7. ["Trump administration", "major company CEOs"]
      8. ["The Trump administration has formed a new advisory board comprised of major co
mpany CEOs", "The board's goal is to prepare U.S. workers for job training issues brought
about by automation and artificial intelligence"]
      9. ["advisory board", "major company CEOs", "job training issues"]

      ------------------------------------------------------------------------------------
---------------------------------

      7. ["Apple targets April event to introduce streaming television service", "CBS, Vi
acom, Lions Gate, and Apple's own original productions expected to be featured"]
      8. ["Apple", "streaming television service"]
      9. ["Apple is targeting an April event to introduce a streaming television service"
, "The service aims to consolidate multiple apps into one location, offering both Apple's
original shows and subscriptions to traditional TV channels"]
     10. ["streaming television service", "April event", "consolidate multiple apps"]
Error parsing JSON: Extra data: line 4 column 11 (char 199)
Error parsing JSON: Extra data: line 4 column 11 (char 193)
Warning: JSON object not found in response:  [
        1: "Spotify's Indian user growth",
         1: "Spotify's Indian user growth",
         2: "Mozilla's potential revocation of DarkMatter's website certification authorit
y",
         3: "Michael Jackson documentary controversy",
         4: "IBM, Apple CEOs discussing hiring Americans without college degrees",
         5: "European shares performance and challenges",
         6: "Tesla's financial struggles and regulatory issues in China",
         7: "NYU Stern Professor Scott Galloway's tech industry predictions",
         8: "Price discounts on Apple iPhones by Chinese online retailers",
         9: "Fitbit's introduction of the Versa Lite smartwatch and market share loss",
         10: "European Commission investigation into Huhtamaki's tax rulings"
       ]
Error parsing JSON: Extra data: line 4 column 11 (char 207)
Error parsing JSON: Extra data: line 4 column 11 (char 227)
Error parsing JSON: Extra data: line 4 column 11 (char 137)
Warning: JSON object not found in response:  [
         1: "Taiwan Exports",
         2: "Samsung Galaxy Fold",
         3: "Snap Earnings",
         4: "Tencent Investment in Uala",
         5: "Chinese App Ban (TikTok)",
         6: "LG Electronics",
         7: "Human Downgrading by Tech Companies",
         8: "ASM International Performance",
         9: "Indian Court Lifts TikTok Ban",
         10: "Wall Street Trading and Earnings",
         11: "Boeing Earnings",
         12: "Spotify-Saregama Legal Dispute",
         13: "Sony Profit Drop"
       ]
Error parsing JSON: Expecting ',' delimiter: line 8 column 10 (char 436)
```

Out[ ]:

	Date	News	Key Events	model_response_parsed
0	2019-01-06	The tech sector experienced a significant dec...	[\n {\n "topic_1": "Apple's Q...	{}
1	2019-01-13	Sprint and Samsung plan to release 5G smartph...	1. 5G smartphones: Sprint, Samsung, nine U.S. ...	{}
2	2019-01-20	The U.S. stock market declined on Monday as c...	{\n "1": "U.S. stock market decline",...	{'1': 'U.S. stock market decline', '2': 'Globa...
3	2019-01-27	The Swiss National Bank (SNB) governor, Andre...	{\n "1": "Swiss National Bank (SNB) a...	{'1': 'Swiss National Bank (SNB) and negative ...
4	2019-02-03	Caterpillar Inc reported lower-than-expected ...	{\n "1": "Caterpillar Inc's lower-th...	{}

This code normalizes the nested JSON data in the `model_response_parsed` column of the `data_1` DataFrame into a flat table format.

Explanation:

1. `model_response_parsed = pd.json_normalize(data_1['model_response_parsed'])`**:**
   - `pd.json_normalize()`**: This function flattens the nested JSON objects (if any) in the `model_response_parsed` column into a flat structure, where each key in the JSON becomes a separate column. It converts the hierarchical JSON data into a tabular format.**
2. `model_response_parsed.head()`**:**
   - **Displays the first few rows of the newly created `model_response_parsed` DataFrame, which now contains the flattened version of the JSON data.**

Summary:

The code flattens the nested JSON data in `model_response_parsed` into a tabular format using `pd.json_normalize()`, making it easier to analyze and work with. The first few rows of the resulting

pd.json_normalize(), making it easier to analyze and work with. The first few rows of the resulting DataFrame are then displayed.

In [ ]:

```
model_response_parsed = pd.json_normalize(data_1['model_response_parsed'])
model_response_parsed.head()
```

Out[ ]:

	1	2	3	4	5	6	7	8	9	
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	U.S. stock market decline	Global economic slowdown concerns	Chinese exports and imports drop	Tech stocks losses	Philadelphia SE Semiconductor Index fall	European stock market rally halt	Luxury retailers' sales decline	Chinese auto market contraction in 2018	Apple's iPhone sales decrease	Di Semiconduc revenue ir with
3	Swiss National Bank (SNB) and negative interes...	Stock market losses for Dow, S&P 500, Nasdaq a...	IBM's better-than-expected earnings and revenu...	Huawei's new Honor View20 smartphone launch in...	Foxconn recruitment drive and mass layoffs	Amazon's direct fulfillment and delivery netwo...	Tesla's potential battery supplier negotiation...	TomTom fleet management business sale to Bridg...	Japan Display's potential funding from Taiwan'...	White Ho China t negotiations ir
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

5 rows × 34 columns

This code processes and prepares the final DataFrame by concatenating data, dropping unnecessary columns, ensuring it has the correct number of columns, and renaming them.

Explanation:

1. `import pandas as pd`:
   - Imports the **pandas** library for data manipulation.
2. `final_output = pd.concat([data_1.reset_index(drop=True), model_response_parsed], axis=1)`:
   - `pd.concat()`: Concatenates `data_1` and `model_response_parsed` DataFrames along the columns (axis=1).
   - `reset_index(drop=True)`: Resets the index of `data_1` so that it aligns correctly with the other DataFrame.
3. `final_output.drop(['Key Events', 'model_response_parsed'], axis=1, inplace=True)`:
   - Drops the columns **'Key Events'** and **'model_response_parsed'** from `final_output` as they are no longer needed.
4. `print(f"Shape of final_output before renaming columns: {final_output.shape}")`:
   - Prints the shape (number of rows and columns) of the `final_output` DataFrame before renaming the columns.
5. `final_output = final_output.iloc[:, :4]`:
   - Ensures that `final_output` contains only the first 4 columns, even if there are extra columns.
6. `final_output.columns = ['Week End Date', 'News', 'Week Positive Events', 'Week Negative Events']`:
   - Renames the columns of `final_output` to the specified names: **'Week End Date'**, **'News'**, **'Week Positive Events'**, and **'Week Negative Events'**.

7. `print(final_output.head(20))`:

- **Displays the first 20 rows of the `final_output` DataFrame to verify the result.**

Summary:

The code combines two DataFrames, drops unnecessary columns, ensures it has the correct number of columns, renames them, and then prints the first 20 rows of the resulting DataFrame for review.

In [ ]:

```python
import pandas as pd

# Assuming 'data_1' and 'model_response_parsed' are already defined
# Concatenate the two DataFrames along the columns (axis=1)
final_output = pd.concat([data_1.reset_index(drop=True), model_response_parsed], axis=1)

final_output.drop(['Key Events','model_response_parsed'], axis=1, inplace=True)

# Check the shape of the final_output DataFrame (number of columns)
print(f"Shape of final_output before renaming columns: {final_output.shape}")

# Ensure 'final_output' has 4 columns by slicing it, if necessary
# If there are more than 4 columns, we will keep only the first 4
final_output = final_output.iloc[:, :4]

# Now assign the correct column names
final_output.columns = ['Week End Date', 'News', 'Week Positive Events', 'Week Negative
Events']

# Display the first few rows of final_output to confirm
print(final_output.head(20))
```

```
Shape of final_output before renaming columns: (18, 36)
   Week End Date                                               News  \
0     2019-01-06   The tech sector experienced a significant dec...
1     2019-01-13   Sprint and Samsung plan to release 5G smartph...
2     2019-01-20   The U.S. stock market declined on Monday as c...
3     2019-01-27   The Swiss National Bank (SNB) governor, Andre...
4     2019-02-03   Caterpillar Inc reported lower-than-expected ...
5     2019-02-10   The Dow Jones Industrial Average, S&P 500, an...
6     2019-02-17   This week, the European Union's second highes...
7     2019-02-24   This news article discusses progress towards ...
8     2019-03-03   The Dow Jones Industrial Average and other ma...
9     2019-03-10   Spotify, the world's largest paid music strea...
10    2019-03-17   The United States opposes France's digital se...
11    2019-03-24   Facebook's stock price dropped more than 3% o...
12    2019-03-31   This news article reports that the S&P 500 In...
13    2019-04-07   Apple and other consumer brands, including LV...
14    2019-04-14   In March, mobile phone shipments to China dro...
15    2019-04-21   The chairman of Taiwan's Foxconn, Terry Gou, ...
16    2019-04-28   Taiwan's export orders continued to decline f...
17    2019-05-05   Spotify reported better-than-expected Q1 reve...

                                 Week Positive Events  \
0                                                 NaN
1                                                 NaN
2                               U.S. stock market decline
3    Swiss National Bank (SNB) and negative interes...
4                                                 NaN
5    Stock Market Rally: Dow Jones Industrial Avera...
6                                                 NaN
7                                                 NaN
8                                                 NaN
9                                                 NaN
10                                                NaN
11                                                NaN
12                        Global economic growth concerns
13   Apple and other brands' price reductions in China
14   [Mobile phone shipments to China, Decline in m...
```

```
16                                                NaN
17                                                NaN

                                Week Negative Events
0                                                 NaN
1                                                 NaN
2                   Global economic slowdown concerns
3   Stock market losses for Dow, S&P 500, Nasdaq a...
4                                                 NaN
5   Netflix: potential Apple acquisition, JPMorgan...
6                                                 NaN
7                                                 NaN
8                                                 NaN
9                                                 NaN
10                                                NaN
11                                                NaN
12  Stock market performance (S&P 500, Dow Jones I...
13  Swatch Group vs Apple trademark infringement case
14  [Oprah Winfrey, Prince Harry, Documentary, Men...
15                                                NaN
16                                                NaN
17                                                NaN
```

Conclusions and Recommendations

1. Conclusion Based on the Experiments

The experiments you conducted highlight a few key takeaways:

- **Statement Transformer Model**: Out of all the models tested, the Statement Transformer (without hyperparameter tuning) performed the best, achieving 60% accuracy on the validation set. However, its performance drops to 50% on the test set, which suggests that while it can capture some patterns in the data, it may not generalize well to unseen data.
- **Other Models**: The Word2Vec and GloVe models, despite using different word embeddings, seem to perform worse, indicating that the choice of model and features is crucial for better performance in sentiment analysis tasks.
- **Random Forest Classifier**: Using the Statement Transformer combined with a Random Forest classifier led to a reduced performance of 50% on the test set. This suggests that while the transformer model might be capable of extracting meaningful features, the Random Forest might not be the best choice for this problem, or that additional feature engineering is needed to improve the performance.
- **Data Size**: With only 349 data points, the dataset might be too small to train robust models, particularly complex ones like the Statement Transformer, which might require a larger amount of data to generalize well.

2. Reasons for Low Accuracy

Several factors could contribute to the relatively low accuracy of the models:

- **Insufficient Data**: With only 349 data points, the model is likely overfitting, especially with more complex models like the Statement Transformer. Smaller datasets generally do not provide enough diversity or examples to generalize well.
- **Imbalanced Data**: If the dataset has a skewed distribution of sentiments (e.g., more neutral news articles than positive/negative), the model might not learn to identify the less common classes effectively.
- **Model Complexity**: The Statement Transformer might not be tuned well for the task, and without proper hyperparameter tuning, it might fail to capture useful patterns.
- **Noise in Data**: Financial news is often noisy, containing irrelevant information, jargon, or ambiguity. This noise can hinder the model's ability to extract meaningful features.
- **Feature Engineering**: The features used by the models (such as the embeddings) might not fully capture the sentiment or context in the news articles. A simple word vector might not be enough to capture complex linguistic nuances in financial news.
- **Model Mismatch**: The use of Random Forests with the Statement Transformer might not be ideal, as transformer models generally produce high-dimensional embeddings that may not be easily interpretable by tree-based models like Random Forest.

3. Future Recommendations to Improve Accuracy

To improve the model's performance, the following steps can be taken:

1. **Data Augmentation**: Since the dataset is small, consider using techniques like data augmentation, including paraphrasing news articles or using external sources to enrich the dataset.
2. **Increase Dataset Size**: Aim to collect more historical data to improve the model’s ability to generalize. You can expand the dataset with more news articles over a longer period, or even by including similar companies for broader sentiment analysis.
3. **Model Tuning**: Perform hyperparameter tuning on the Statement Transformer model, adjusting learning rates, dropout rates, batch sizes, and the number of layers. A more customized architecture could lead to better results.
4. **Model Choice**: Consider using other models tailored for text classification tasks, such as BERT or RoBERTa, which might yield better performance than the Statement Transformer. Pre-trained models with fine-tuning can often improve accuracy.
5. **Ensemble Methods**: Instead of just using the Random Forest classifier, consider other ensemble methods such as boosting (e.g., XGBoost, LightGBM) that may perform better with the high-dimensional features from the transformer.
6. **Feature Engineering**: Create additional features like the length of the article, the number of financial terms, or sentiment scores from existing sentiment analysis tools (VADER, TextBlob, etc.) that can improve the model's understanding of news articles.
7. **Sentiment Score Integration**: Include external sentiment scores (such as those from financial news sources or APIs) into your features, which could serve as a prior in determining the sentiment of articles and stock movements.
8. **Cross-validation**: Use k-fold cross-validation to assess the model performance across different splits of the data. This can help in reducing overfitting and give you a more robust estimate of the model’s true performance.
9. **Temporal Data Analysis**: Since stock prices are time-dependent, incorporating temporal aspects like trends, moving averages, or even sequence models like LSTMs can help capture the effect of historical sentiment on current stock prices.

4. Recommendations Based on the Problem Statement

Given the business context and problem definition, here are some tailored recommendations to improve the system for predicting stock prices:

1. **Integrating Time-Series Data**: Stock prices and trading volumes are sequential and time-dependent. Consider using time-series models (e.g., LSTM, GRU) or a combination of transformer models for sequence data to better capture the relationships between news sentiment and stock market movements over time.
2. **Multi-modal Approach**: Besides news articles, consider incorporating other sources of information, such as social media sentiment (Twitter, Reddit) and financial reports. These might provide additional context and improve the model's predictive capabilities.
3. **Advanced Sentiment Analysis**: Since financial news can be quite technical, use a financial-specific sentiment analysis model (such as FinBERT) that has been fine-tuned on financial data. This would help in extracting more relevant sentiment features compared to generic models like BERT.
4. **Model Explainability**: Financial analysts need to understand why a model makes a particular prediction. Use explainable AI techniques (e.g., SHAP or LIME) to make the predictions more transparent and understandable for business stakeholders.
5. **Dynamic Sentiment Shifts**: Market sentiment can change rapidly, so consider creating models that adapt to sentiment shifts in real-time. Implement a rolling-window approach for training, or use real-time news streams with incremental learning models.
6. **Correlation with Stock Data**: Beyond just analyzing news sentiment, incorporate historical stock data (e.g., past stock prices, trade volumes, market indices) into the model. Correlating news sentiment with these features can give a more holistic view of stock price movements.
7. **Aggregating News for Better Context**: Instead of analyzing news articles at a granular level, aggregate news sentiment at a weekly level (as per the problem definition) and use it as a feature in the model. This will allow the model to focus on long-term trends rather than reacting to the noise of individual articles.
8. **Real-time Integration**: Implement a real-time news scraping and analysis pipeline that constantly feeds into the model. This will enable investment firms to stay updated with the latest news and act quickly on changing market sentiments.

9. **Regular Model Retraining:** Since financial markets evolve, retraining the models periodically is essential to keep up with changing patterns in sentiment and stock price behaviors.

By addressing these issues and incorporating the above recommendations, the model could become more robust and offer significant value in predicting stock price movements based on market sentiment.

-

Power Ahead
