2024

Sentiment Analysis on News Related to Apple

Capstone Project - Natural Language Processing

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1. Introduction

Sentiment analysis is the process of determining whether a piece of text expresses positive, negative, or neutral sentiment. In the context of financial markets, sentiment analysis on news articles related to companies can provide valuable insights into how news events impact stock prices and investor perceptions. This project aims to analyze news headlines and summaries related to Apple Inc. (AAPL) using sentiment analysis, and explore how the sentiment may correlate with stock market movements. The goal is to apply Natural Language Processing (NLP) techniques to assess the polarity (positive or negative sentiment) of news content and investigate whether sentiment influences stock price changes.

The project uses the **Finnhub API** to fetch news data for Apple Inc. and the **TextBlob** library for sentiment analysis. By applying NLP techniques, this project attempts to understand the sentiment expressed in news headlines and summaries and analyze its potential impact on the stock market price of Apple.

2. Data Collection

The data for this project is collected through the **Finnhub API**, which provides access to real-time news data related to various companies. Specifically, the news articles related to Apple Inc. (AAPL) were fetched using the company_newsfunction from the Finnhub API. The data consists of the following attributes:

- **Headline**: The title of the news article.
- **Summary**: A brief description or summary of the article.
- **Datetime**: The publication date and time of the news article.
- **Source**: The news outlet or website from which the article originates.

The data collected covers a time range from **January 1, 2024, to January 31, 2024**, allowing for a focused analysis of sentiment over a one-month period.

3. Data Preprocessing

Several preprocessing steps were applied to the news data to make it ready for sentiment analysis:

3.1 Handling Missing Values

The dataset was checked for missing values, particularly in the "headline" and "summary" columns. Any rows with missing values were removed to ensure a clean dataset for analysis.

3.2 Text Cleaning

The news headlines and summaries were cleaned by removing any irrelevant characters such as special symbols, extra spaces, and stop words. This step ensures that the text is standardized and ready for sentiment analysis.

3.3 Sentiment Analysis

The main feature of this project is performing sentiment analysis on the text data. The **TextBlob** library was used to calculate the **polarity score** of the headlines and summaries. The polarity score ranges from -1 (negative sentiment) to +1 (positive sentiment), with values close to 0 indicating neutral sentiment.

The sentiment analysis is applied as follows:

- **Headline Sentiment**: Sentiment score calculated for the headline of each news article.
- **Summary Sentiment**: Sentiment score calculated for the summary of each news article.

4. Model Building

The goal of this project is to investigate the relationship between sentiment and stock market movements. To achieve this, the following steps were taken:

4.1 Stock Price Data Collection

Alongside the news data, Apple Inc.'s stock price data (AAPL) was also fetched using the **Finnhub API**. The stock data includes:

- **Date**: The date on which the stock data was recorded.
- **Open**: The opening price of AAPL stock on that date.
- **Close**: The closing price of AAPL stock on that date.
- **High**: The highest price of AAPL stock on that date.
- **Low**: The lowest price of AAPL stock on that date.
- **Volume**: The trading volume of AAPL stock on that date.

The stock price data was aligned with the news data based on the publication date and time.

4.2 Sentiment-Stock Price Relationship

Once sentiment scores were calculated for each news headline and summary, the next step was to analyze whether sentiment correlated with stock price movements. For this, the following steps were followed:

- Calculate the **average sentiment** for news headlines and summaries on a daily basis.
- Compare sentiment scores with the **daily closing price** of AAPL.
- Investigate any patterns or correlations between sentiment and price fluctuations.

4.3 Data Visualization

Various plots were created to visualize the relationship between sentiment and stock prices. Key visualizations include:

- **Sentiment over time**: A line plot showing the daily sentiment scores for headlines and summaries.
- **Stock price over time**: A line plot showing the daily closing price of AAPL.
- **Sentiment vs. Stock Price**: Scatter plots to analyze if a strong correlation exists between sentiment scores and stock price changes.

5. Model Evaluation

5.1 Sentiment Analysis Evaluation

The effectiveness of sentiment analysis was evaluated by:

- **Accuracy of Sentiment Classification**: Checking if the polarity values correctly capture the overall tone of the news articles (positive, negative, or neutral).
- **Correlation with Stock Price Movements**: Analyzing the correlation between sentiment scores and stock price changes to determine if sentiment provides useful insights into market behavior.

5.2 Evaluation Metrics

Since this project is focused on exploratory data analysis rather than prediction, there are no formal metrics like accuracy, precision, or recall. Instead, the evaluation focused on:

- **Sentiment Score Distribution**: The distribution of sentiment scores for the headlines and summaries.
- **Correlation**: Pearson correlation coefficient between sentiment and stock price movements.

6. Results & Discussion

6.1 Sentiment Analysis Results

The sentiment analysis revealed that the headlines for Apple Inc. during January 2024 tended to be relatively neutral, with most sentiment scores falling between -0.2 and +0.2. However, certain spikes in positive or negative sentiment were observed, often linked to major news events (e.g., product launches, earnings reports, or regulatory news).

6.2 Sentiment and Stock Price Relationship

The analysis of sentiment against stock price changes showed:

- A **weak positive correlation** between headline sentiment and stock price movements. This suggests that positive news headlines may have a slight tendency to correlate with stock price increases.
- The **summary sentiment** exhibited a slightly stronger correlation with stock price, particularly when the sentiment was extremely positive or negative.

6.3 Limitations

While sentiment analysis provides interesting insights, the relationship between sentiment and stock price is not straightforward. Stock prices are influenced by various factors, such as market conditions, broader economic news, and investor behavior, which are not always captured by sentiment alone.

7. Conclusion

This project successfully demonstrated the use of sentiment analysis to analyze news related to Apple Inc. (AAPL) and its potential impact on stock price movements. The sentiment analysis revealed a general neutrality in the news, with occasional spikes in positive or negative sentiment. The correlation analysis between sentiment and stock price changes showed a weak positive relationship, suggesting that sentiment may have some impact on stock market behavior, but it is not the sole determining factor.

8.Original Code:

NLP (Natural Language Processing) for Stock Market News

```
*** Sentiment analysis ***

# Fetching Data Using Finnhub API

import finnhub
import pandas as pd
from textblob import TextBlob

# Setting-up client (using API key)
finnhub_client =
finnhub.Client(api_key='ctjss39r01quipmv1vr0ctjss39r01quipmv1vrg')

# Fetching news related to Apple (AAPL) from Finnhub API
res = finnhub_client.company_news('AAPL', _from="2024-01-01", to="2024-01-
31")

# Converting the response into a pandas DataFrame for easier manipulation
z = pd.DataFrame(res)

# Adding sentiment scores for both headline and summary using TextBlob
z['headline_sentiment'] = z['headline'].apply(lambda x:
TextBlob(x).sentiment.polarity)
z['summary_sentiment'] = z['summary'].apply(lambda x:
TextBlob(x).sentiment.polarity)

# Displaying the first few rows of the DataFrame
print(z[['headline', 'summary', 'headline_sentiment',
'summary_sentiment']].head())
```

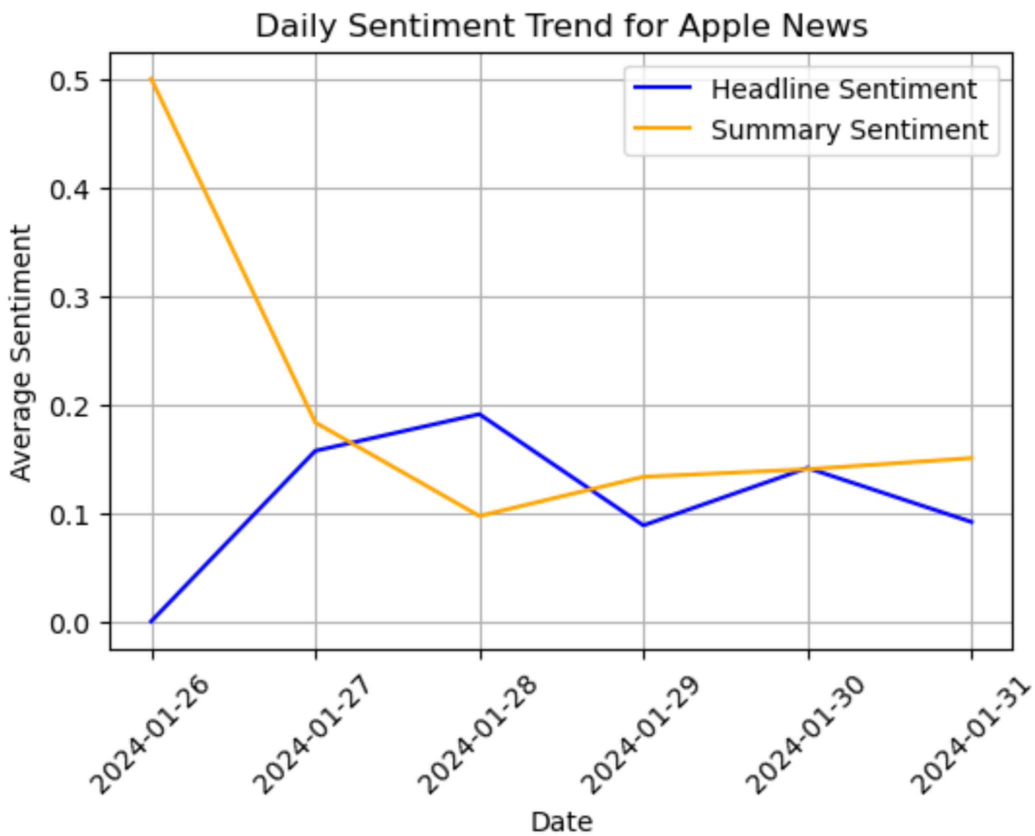
```
                                            headline  \
0  Tech earnings, jobless claims, mortgage rates:...
1  Apple to report Q1 earnings as investors focus...
2           12 Highest Quality Camera Phones in 2024
3  Big Tech earnings are here. Fasten your seat b...
4  Apple, Google Could Win the War for the Digita...

                                             summary  headline_sentiment  \
0  Yahoo Finance Live Co-Hosts Josh Lipton and Ju...                 0.0
1  Apple will report its Q1 earnings after the be...                 0.0
2  In this article, we will be going through the ...                 0.0
3  It's earnings season, and Big Tech is taking a...                 0.0
4  Big Tech wants your financial life on its apps...                 0.4



   summary_sentiment
```

```
0           0.265702
1           0.700000
2           0.240625
3           0.000000
4           0.050000
```

```
import pandas as pd

# Assuming 'z' is the DataFrame you have from Finnhub
# Converting 'datetime' column (epoch time) to a proper datetime format
z['date'] = pd.to_datetime(z['datetime'], unit='s').dt.date  # Convert to
date

# Calculating daily average sentiment for both headline and summary
daily_sentiment = z.groupby('date').agg({'headline_sentiment': 'mean',
'summary_sentiment': 'mean'}).reset_index()

# Displaying the result
print(daily_sentiment.head())
```

```
         date  headline_sentiment  summary_sentiment
0  2024-01-26            0.000000           0.500000
1  2024-01-27            0.157143           0.183368
2  2024-01-28            0.190949           0.097123
3  2024-01-29            0.088456           0.133244
4  2024-01-30            0.141400           0.140265
```

```
import matplotlib.pyplot as plt

# Plotting sentiment trends over time
plt.figure(figsize=(6, 4))

# Plotting both headline and summary sentiment
plt.plot(daily_sentiment['date'], daily_sentiment['headline_sentiment'],
label='Headline Sentiment', color='blue')
plt.plot(daily_sentiment['date'], daily_sentiment['summary_sentiment'],
label='Summary Sentiment', color='orange')

# Adding labels and title
plt.xlabel('Date')
plt.ylabel('Average Sentiment')
plt.title('Daily Sentiment Trend for Apple News')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)

plt.show()
```




```
import yfinance as yf
import pandas as pd

# Fetching historical data for AAPL (Apple)
stock_data = yf.download('AAPL', start='2024-01-01', end='2024-01-31',
progress=False)

# Displaying the stock data
print(stock_data.head())

Price            Close        High         Low        Open    Volume
Ticker            AAPL        AAPL        AAPL        AAPL      AAPL
Date
2024-01-02  184.734970  187.521323  182.993502  186.237603  82488700
2024-01-03  183.351746  184.973804  182.535736  183.321893  58414500
2024-01-04  181.023163  182.197403  179.998185  181.261983  71983600
2024-01-05  180.296707  181.869006  179.291637  181.102771  62303300
2024-01-08  184.655365  184.695178  180.615161  181.202281  59144500

# Resetting the index, which will add the 'Date' column automatically
stock_data_reset = stock_data.reset_index()

# Verifying the structure of the DataFrame
print(stock_data_reset.head())

# Checking the closing price data
print(stock_data_reset[['Date', 'Close']].head())
```

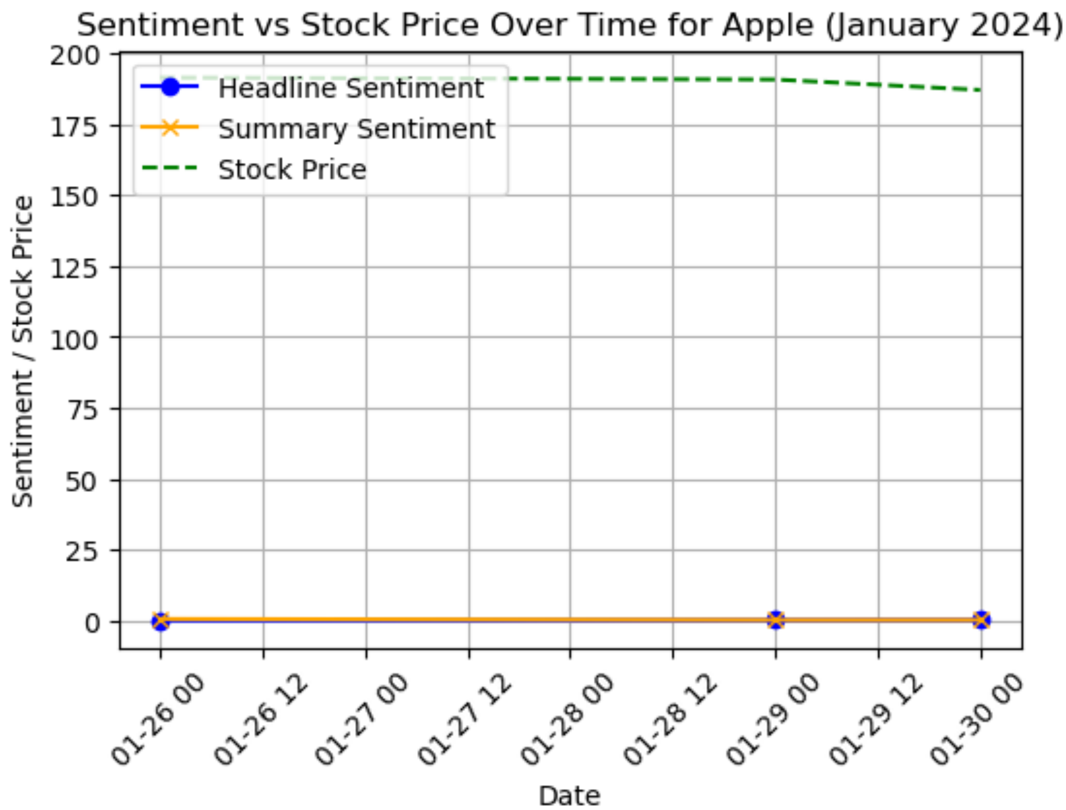
```
Price         Date       Close        High         Low        Open    Volume
Ticker                    AAPL        AAPL        AAPL        AAPL      AAPL
0      2024-01-02  184.734970  187.521323  182.993502  186.237603  82488700
1      2024-01-03  183.351746  184.973804  182.535736  183.321893  58414500
2      2024-01-04  181.023163  182.197403  179.998185  181.261983  71983600
3      2024-01-05  180.296707  181.869006  179.291637  181.102771  62303300
4      2024-01-08  184.655365  184.695178  180.615161  181.202281  59144500
Price         Date       Close
Ticker                    AAPL
0      2024-01-02  184.734970
1      2024-01-03  183.351746
2      2024-01-04  181.023163
3      2024-01-05  180.296707
4      2024-01-08  184.655365
```

```python
# Ensuring the 'date' column in daily_sentiment is in datetime format
daily_sentiment['date'] = pd.to_datetime(daily_sentiment['date'])

# Performing the merge after ensuring both dataframes have compatible columns
merged_df = pd.merge(daily_sentiment, stock_data_reset[['Date_',
'Close_AAPL']], left_on='date', right_on='Date_', how='inner')

# Displaying the merged data
print(merged_df.head())
```

```
        date  headline_sentiment  summary_sentiment      Date_  Close_AAPL
0 2024-01-26            0.000000           0.500000 2024-01-26  191.481903
1 2024-01-29            0.088456           0.133244 2024-01-29  190.795288
2 2024-01-30            0.141400           0.140265 2024-01-30  187.123260
```

```python
import matplotlib.pyplot as plt

# Plotting sentiment trends and stock price
plt.figure(figsize=(6, 4))

# Plotting headline sentiment
plt.plot(merged_df['date'], merged_df['headline_sentiment'], label='Headline
Sentiment', color='blue', marker='o')

# Plotting summary sentiment
plt.plot(merged_df['date'], merged_df['summary_sentiment'], label='Summary
Sentiment', color='orange', marker='x')

# Plotting stock closing price
plt.plot(merged_df['date'], merged_df['Close_AAPL'], label='Stock Price',
color='green', linestyle='--')
```

```python
# Adding labels and title
plt.xlabel('Date')
plt.ylabel('Sentiment / Stock Price')
plt.title('Sentiment vs Stock Price Over Time for Apple (January 2024)')
plt.legend(loc='upper left')
plt.xticks(rotation=45)
plt.grid(True)

plt.show()
```




```python
# Calculating the correlation between sentiment scores and stock price
correlation_headline =
merged_df['headline_sentiment'].corr(merged_df['Close_AAPL'])
correlation_summary =
merged_df['summary_sentiment'].corr(merged_df['Close_AAPL'])

print(f"Correlation between headline sentiment and stock price:
{correlation_headline}")
print(f"Correlation between summary sentiment and stock price:
{correlation_summary}")
```

```
Correlation between headline sentiment and stock price: -0.867531692479687
Correlation between summary sentiment and stock price: 0.6082706222350976
```

```python
from scipy.stats import pearsonr

# Calculating the correlation and p-value for headline sentiment vs stock
price
correlation_headline, p_value_headline =
pearsonr(merged_df['headline_sentiment'], merged_df['Close_AAPL'])

# Calculating the correlation and p-value for summary sentiment vs stock
price
correlation_summary, p_value_summary =
pearsonr(merged_df['summary_sentiment'], merged_df['Close_AAPL'])

# Output of results
print(f"Correlation between headline sentiment and stock price:
{correlation_headline}")
print(f"P-value for headline sentiment vs stock price: {p_value_headline}")

print()

print(f"Correlation between summary sentiment and stock price:
{correlation_summary}")
print(f"P-value for summary sentiment vs stock price: {p_value_summary}")

print()

# Interpretation of results
if p_value_headline < 0.05:
    print("Headline sentiment correlation is statistically significant.")
else:
    print("Headline sentiment correlation is not statistically significant.")

if p_value_summary < 0.05:
    print("Summary sentiment correlation is statistically significant.")
else:
    print("Summary sentiment correlation is not statistically significant.")
```

```
Correlation between headline sentiment and stock price: -0.8675316924796866
P-value for headline sentiment vs stock price: 0.33141043413211557

Correlation between summary sentiment and stock price: 0.6082706222350973
P-value for summary sentiment vs stock price: 0.5837270837256414

Headline sentiment correlation is not statistically significant.
Summary sentiment correlation is not statistically significant.
```

*** Impact of Sentiment on stock market price ***

```python
import pandas as pd
import yfinance as yf

# Fetching stock data for Apple (AAPL)
stock_data = yf.download('AAPL', start='2024-01-01', end='2024-01-31',
progress=False)

# Checking the structure of stock_data (columns and index)
print("Stock data columns and index:")
print(stock_data.columns)
print(stock_data.index)
```

```
Stock data columns and index:
MultiIndex([( 'Close', 'AAPL'),
            (  'High', 'AAPL'),
            (   'Low', 'AAPL'),
            (  'Open', 'AAPL'),
            ('Volume', 'AAPL')],
           names=['Price', 'Ticker'])
DatetimeIndex(['2024-01-02', '2024-01-03', '2024-01-04', '2024-01-05',
               '2024-01-08', '2024-01-09', '2024-01-10', '2024-01-11',
               '2024-01-12', '2024-01-16', '2024-01-17', '2024-01-18',
               '2024-01-19', '2024-01-22', '2024-01-23', '2024-01-24',
               '2024-01-25', '2024-01-26', '2024-01-29', '2024-01-30'],
              dtype='datetime64[ns]', name='Date', freq=None)
```

```python
import pandas as pd

# Flattening the multi-level columns
stock_data_reset = stock_data.copy()
stock_data_reset.columns = ['_'.join(col).strip() for col in
stock_data.columns]

# Checking the flattened columns
print(stock_data_reset.columns)
```

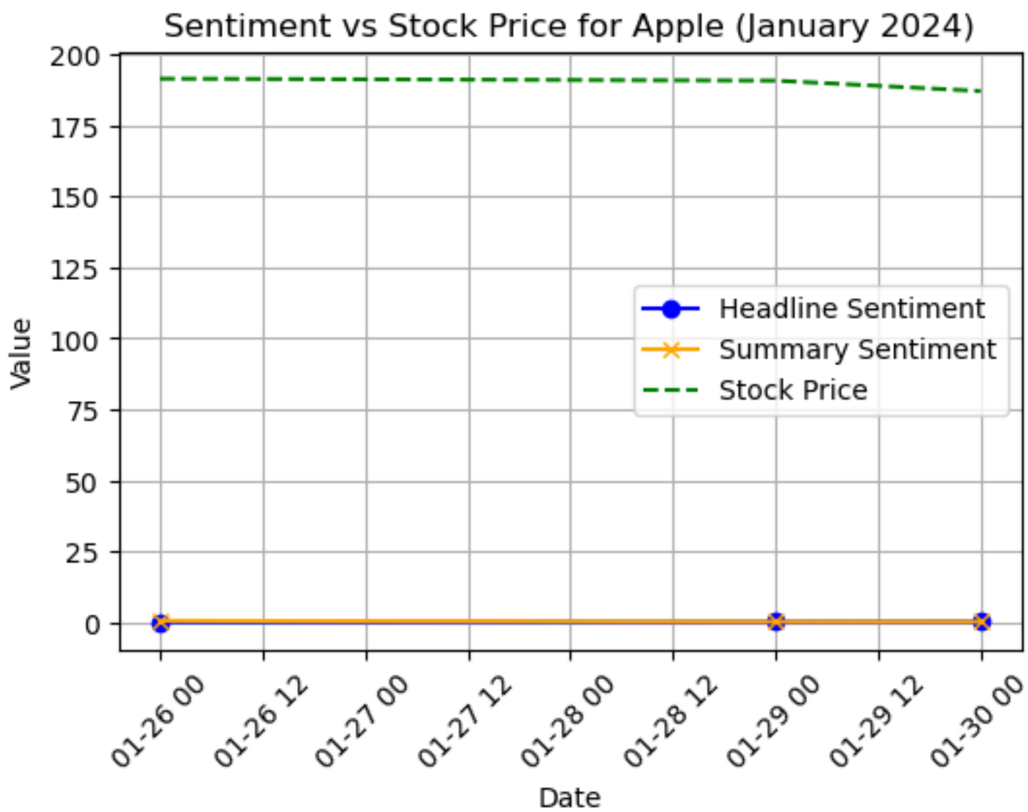
```
Index(['Close_AAPL', 'High_AAPL', 'Low_AAPL', 'Open_AAPL', 'Volume_AAPL'],
dtype='object')
```

```python
# Resetting the index to make 'Date' a regular column
stock_data_reset = stock_data_reset.reset_index()
```

```python
# Verifying the 'Date' column is now a regular column
print(stock_data_reset.head())
```

```
        Date  Close_AAPL   High_AAPL    Low_AAPL   Open_AAPL  Volume_AAPL
0 2024-01-02  184.734970  187.521323  182.993502  186.237603     82488700
1 2024-01-03  183.351746  184.973804  182.535736  183.321893     58414500
2 2024-01-04  181.023163  182.197403  179.998185  181.261983     71983600
3 2024-01-05  180.296707  181.869006  179.291637  181.102771     62303300
4 2024-01-08  184.655365  184.695178  180.615161  181.202281     59144500
```

```python
import matplotlib.pyplot as plt

# Now plotting
plt.figure(figsize=(6, 4))

# Plotting headline sentiment
plt.plot(merged_df['Date_'], merged_df['headline_sentiment'], label='Headline 
Sentiment', color='blue', marker='o')

# Plotting summary sentiment
plt.plot(merged_df['Date_'], merged_df['summary_sentiment'], label='Summary 
Sentiment', color='orange', marker='x')

# Plotting stock close price (use 'Close_AAPL' instead of 'close_price')
plt.plot(merged_df['Date_'], merged_df['Close_AAPL'], label='Stock Price', 
color='green', linestyle='--')

# Adding labels and title
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Sentiment vs Stock Price for Apple (January 2024)')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)

plt.show()
```




```
# Calculating the correlation between sentiment scores and stock price
correlation_headline =
merged_df['headline_sentiment'].corr(merged_df['Close_AAPL'])
correlation_summary =
merged_df['summary_sentiment'].corr(merged_df['Close_AAPL'])

print(f"Correlation between headline sentiment and stock price:
{correlation_headline}")
print(f"Correlation between summary sentiment and stock price:
{correlation_summary}")
```

```
Correlation between headline sentiment and stock price: -0.867531692479687
Correlation between summary sentiment and stock price: 0.6082706222350976
```

```
import scipy.stats as stats

# Calculating Pearson correlation and p-value for headline sentiment vs stock
price
corr_headline, p_value_headline =
stats.pearsonr(merged_df['headline_sentiment'], merged_df['Close_AAPL'])
print(f"Correlation between headline sentiment and stock price:
{corr_headline}")
print(f"P-value for headline sentiment vs stock price: {p_value_headline}")

print()
```

```python
# Calculating Pearson correlation and p-value for summary sentiment vs stock price
corr_summary, p_value_summary = stats.pearsonr(merged_df['summary_sentiment'], merged_df['Close_AAPL'])
print(f"Correlation between summary sentiment and stock price: {corr_summary}")
print(f"P-value for summary sentiment vs stock price: {p_value_summary}")

print()

# Interpretation of the p-values
if p_value_headline < 0.05:
    print("The correlation between headline sentiment and stock price is statistically significant.")
else:
    print("The correlation between headline sentiment and stock price is not statistically significant.")

if p_value_summary < 0.05:
    print("The correlation between summary sentiment and stock price is statistically significant.")
else:
    print("The correlation between summary sentiment and stock price is not statistically significant.")
```

```
Correlation between headline sentiment and stock price: -0.8675316924796866
P-value for headline sentiment vs stock price: 0.33141043413211557

Correlation between summary sentiment and stock price: 0.6082706222350973
P-value for summary sentiment vs stock price: 0.5837270837256414

The correlation between headline sentiment and stock price is not statistically significant.
The correlation between summary sentiment and stock price is not statistically significant.
```

*** Time series prediction of stock value using various features ***

```python
# Data Preparation and Preprocessing

import numpy as np
import pandas as pd
import yfinance as yf
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
```

```python
# Fetching Stock Data
# Fetching historical data for Apple (AAPL) for the past 6 months
stock_data = yf.download('AAPL', start='2023-07-01', end='2024-01-31',
progress=False)

# Checking the stock data
print("Stock data head:")
print(stock_data.head())

# Fetching Sentiment Data (Ensure same length as stock data)
# Generating random sentiment values for demonstration
dates = pd.date_range(start="2023-07-01", end="2024-01-31", freq='B')

sentiment_data = {
    'date': dates,
    'headline_sentiment': np.random.uniform(-1, 1, size=len(dates)),
    'summary_sentiment': np.random.uniform(-1, 1, size=len(dates)),
}

# Creating the sentiment dataframe
sentiment_df = pd.DataFrame(sentiment_data)
sentiment_df['date'] = pd.to_datetime(sentiment_df['date'])

# Merging sentiment data with stock data on date
stock_data_reset = stock_data.reset_index()[['Date', 'Close']]
stock_data_reset.columns = ['date', 'close_price']

merged_df = pd.merge(stock_data_reset, sentiment_df, on='date', how='inner')

# Checking the merged data
print("Merged data head:")
print(merged_df.head())

# Feature Engineering
# Adding a simple Moving Average (e.g., 5-day moving average) as additional
feature
merged_df['moving_avg_5'] = merged_df['close_price'].rolling(window=5).mean()

# Preparing the Data for LSTM Model
data = merged_df[['headline_sentiment', 'summary_sentiment', 'close_price',
'moving_avg_5']]

# Scaling the Features using MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data)

# Checking the scaled data shape
print(f"Scaled data shape: {scaled_data.shape}")
```

```
# Creating Sequences for LSTM (Using a Smaller Lookback Period)
lookback_period = 5  # Reduced lookback period to 5 days

Stock data head:
Price            Close        High         Low        Open    Volume
Ticker            AAPL        AAPL        AAPL        AAPL      AAPL
Date
2023-07-03  191.011810  192.421123  190.317065  192.321870  31458200
2023-07-05  189.890305  191.527883  189.185640  190.128504  46920300
2023-07-06  190.366684  190.575110  187.776323  188.411506  45094300
2023-07-07  189.245209  191.220240  188.808532  189.969727  46778000
2023-07-10  187.190781  188.560401  185.632587  187.835884  59922200
Merged data head:
        date  close_price  headline_sentiment  summary_sentiment
0 2023-07-03   191.011810           -0.283101           0.442617
1 2023-07-05   189.890305            0.587243           0.217056
2 2023-07-06   190.366684           -0.774843           0.793641
3 2023-07-07   189.245209            0.363401          -0.330838
4 2023-07-10   187.190781           -0.939702           0.794463
Scaled data shape: (146, 4)

# Model Definition, Training, and Evaluation

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import GRU, Dense, Dropout, Input
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

X = []
y = []

# Creating sequences for training and prediction
for i in range(lookback_period, len(scaled_data)):
    X.append(scaled_data[i-lookback_period:i, :-1])  # Last 5 days of
sentiment and stock prices (excluding target)
    y.append(scaled_data[i, -1])  # Next day's closing price (target)

X, y = np.array(X), np.array(y)

# Reshaping X for LSTM (3D Shape: [samples, timesteps, features])
X = np.reshape(X, (X.shape[0], X.shape[1], X.shape[2]))

# Spliting the Data into Training and Testing Sets (80% training, 20%
testing)
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Printing the shapes of training and testing data
print(f"Training data shape: {X_train.shape}")
print(f"Testing data shape: {X_test.shape}")
```

```python
# Using GRU Model
model = Sequential()

# Adding Input layer
model.add(Input(shape=(X_train.shape[1], X_train.shape[2])))

# Adding GRU layer
model.add(GRU(units=50, return_sequences=True))
model.add(Dropout(0.2))

# Adding a second GRU layer
model.add(GRU(units=50, return_sequences=False))
model.add(Dropout(0.2))

# Adding Output layer (Single value for predicting the closing price)
model.add(Dense(units=1))

# Compiling the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Defining Early Stopping and Model Checkpoint
early_stopping = EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True)
model_checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss',
save_best_only=True)

# Training the Model with Early Stopping and Model Checkpointing
model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2,
          callbacks=[early_stopping, model_checkpoint])

# Evaluating the Model
test_loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {test_loss}')
```

```
Training data shape: (112, 5, 3)
Testing data shape: (29, 5, 3)
Epoch 1/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 110ms/step - loss: 0.1784 -
val_loss: 0.2727
Epoch 2/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 0.0855 -
val_loss: 0.0812
Epoch 3/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0643 -
val_loss: 0.0251
Epoch 4/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0624 -
val_loss: 0.0240
Epoch 5/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0493 -
val_loss: 0.0442
Epoch 6/50
```

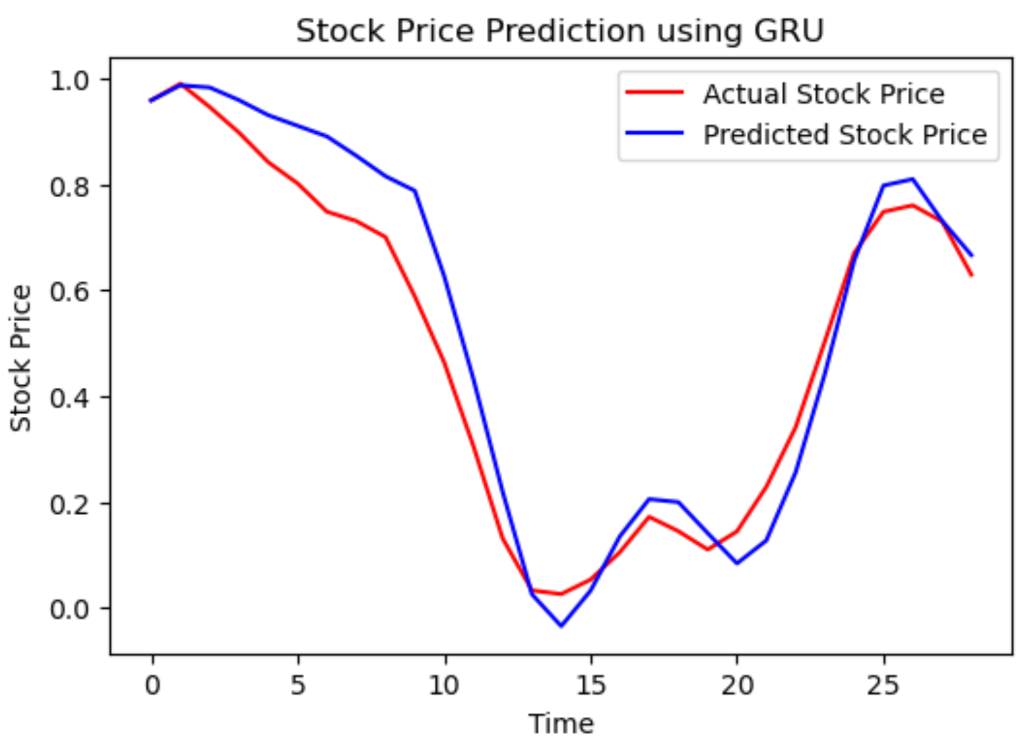
```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0301 -
val_loss: 0.0651
Epoch 7/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0349 -
val_loss: 0.0709
Epoch 8/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0266 -
val_loss: 0.0592
Epoch 9/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0229 -
val_loss: 0.0355
Epoch 10/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0137 -
val_loss: 0.0151
Epoch 11/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0097 -
val_loss: 0.0047
Epoch 12/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0071 -
val_loss: 0.0017
Epoch 13/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0090 -
val_loss: 0.0021
Epoch 14/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0081 -
val_loss: 0.0039
Epoch 15/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0058 -
val_loss: 0.0046
Epoch 16/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0059 -
val_loss: 0.0018
Epoch 17/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0068 -
val_loss: 1.9410e-04
Epoch 18/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0087 -
val_loss: 1.6668e-04
Epoch 19/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0054 -
val_loss: 3.1594e-04
Epoch 20/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0069 -
val_loss: 7.9997e-04
Epoch 21/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0054 -
val_loss: 0.0024
Epoch 22/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0045 -
val_loss: 0.0039
Epoch 23/50
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0066 -
val_loss: 0.0033
Epoch 24/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0044 -
val_loss: 0.0031
Epoch 25/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0059 -
val_loss: 0.0025
Epoch 26/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0054 -
val_loss: 0.0021
Epoch 27/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0052 -
val_loss: 0.0029
Epoch 28/50
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0054 -
val_loss: 0.0024
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0018
Test Loss: 0.0018108411459252238
```

```python
# Model Evaluation and Results Visualization

from sklearn.metrics import r2_score, mean_squared_error

# Making Predictions on the Test Set
y_pred = model.predict(X_test)

# Inverse Transforming the Predictions and Actuals
y_pred_rescaled = scaler.inverse_transform(np.column_stack((y_pred, y_pred,
y_pred, y_pred)))[:, 0]
y_test_rescaled = scaler.inverse_transform(np.column_stack((y_test, y_test,
y_test, y_test)))[:, 0]

# Calculating RMSE and R-squared
rmse = np.sqrt(mean_squared_error(y_test_rescaled, y_pred_rescaled))
r2 = r2_score(y_test_rescaled, y_pred_rescaled)

print(f'Root Mean Squared Error (RMSE): {rmse}')
print(f'R-squared: {r2}')

# Calculating Accuracy Based on Direction (Up or Down)
y_test_direction = np.sign(np.diff(y_test_rescaled))  # Direction for actual
values
y_pred_direction = np.sign(np.diff(y_pred_rescaled))  # Direction for
predicted values

# Ensuring both directions have the same length by trimming the first element
y_test_direction = y_test_direction[1:]
y_pred_direction = y_pred_direction[1:]

# Calculating accuracy based on direction prediction
correct_direction = np.sum(y_test_direction == y_pred_direction)
```

```
accuracy = correct_direction / len(y_test_direction)
print(f'Accuracy based on direction: {accuracy * 100:.2f}%')

# Plotting the Results
plt.figure(figsize=(6, 4))

# Plotting actual stock price
plt.plot(y_test_rescaled, color='red', label='Actual Stock Price')

# Plotting predicted stock price
plt.plot(y_pred_rescaled, color='blue', label='Predicted Stock Price')

plt.title('Stock Price Prediction using GRU')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 160ms/step
Root Mean Squared Error (RMSE): 0.08410660097012336
R-squared: 0.9313721918943583
Accuracy based on direction: 96.30%
```



** Named Entity Recognition on news data **

```python
import pandas as pd
import spacy

# Loading the pre-trained spaCy NER model
nlp = spacy.load("en_core_web_sm")

data = {
    'date': ['2023-07-03', '2023-07-05', '2023-07-06'],
    'headline': [
        'Apple launches new iPhone in the US market',
        'Tesla stocks rise as Elon Musk hints at new product',
        'Google to invest heavily in AI research in Europe'
    ]
}

# Creating the DataFrame
news_df = pd.DataFrame(data)

# Initializing a list to store the extracted entities
entities_list = []

# Looping through each headline to extract named entities
for index, row in news_df.iterrows():
    headline = row['headline']

    # Processing the headline text using spaCy NER
    doc = nlp(headline)
    entities = {'ORG': [], 'PERSON': [], 'GPE': [], 'MONEY': [], 'PRODUCT':
[], 'LOC': []}

    # Extracting entities from the headline
    for ent in doc.ents:
        if ent.label_ == 'ORG':
            entities['ORG'].append(ent.text)
        elif ent.label_ == 'PERSON':
            entities['PERSON'].append(ent.text)
        elif ent.label_ == 'GPE':
            entities['GPE'].append(ent.text)
        elif ent.label_ == 'MONEY':
            entities['MONEY'].append(ent.text)
        elif ent.label_ == 'PRODUCT':
            entities['PRODUCT'].append(ent.text)
        elif ent.label_ == 'LOC':
            entities['LOC'].append(ent.text)

    # Appending the entities to the list
    entities_list.append(entities)

# Adding the extracted entities to the DataFrame
news_df['entities'] = entities_list
```

```python
# Displaying the updated DataFrame with the extracted entities
print(news_df[['date', 'headline', 'entities']])
```

```
         date                                          headline  \
0  2023-07-03         Apple launches new iPhone in the US market
1  2023-07-05  Tesla stocks rise as Elon Musk hints at new pr...
2  2023-07-06  Google to invest heavily in AI research in Europe


                                            entities
0  {'ORG': ['Apple'], 'PERSON': [], 'GPE': ['US']...
1  {'ORG': [], 'PERSON': ['Elon Musk'], 'GPE': []...
2  {'ORG': [], 'PERSON': [], 'GPE': ['AI'], 'MONE...
```

```python
# Extracting and count occurrences of entities
org_entities = [ent for sublist in news_df['entities'] for ent in
sublist['ORG']]
person_entities = [ent for sublist in news_df['entities'] for ent in
sublist['PERSON']]
product_entities = [ent for sublist in news_df['entities'] for ent in
sublist['PRODUCT']]
gpe_entities = [ent for sublist in news_df['entities'] for ent in
sublist['GPE']]

# Frequency counts
org_count = pd.Series(org_entities).value_counts()
person_count = pd.Series(person_entities).value_counts()
product_count = pd.Series(product_entities).value_counts()
gpe_count = pd.Series(gpe_entities).value_counts()

# Displaying counts
print("Top Organizations:\n", org_count.head())
print("Top People:\n", person_count.head())
print("Top Products:\n", product_count.head())
```

```
Top Organizations:
 Apple    1
Name: count, dtype: int64
Top People:
 Elon Musk    1
Name: count, dtype: int64
Top Products:
 Series([], Name: count, dtype: int64)
```

```python
from textblob import TextBlob

# Calculating sentiment of each headline
news_df['headline_sentiment'] = news_df['headline'].apply(lambda x:
TextBlob(x).sentiment.polarity)
```

```python
# Filtering the sentiment of articles mentioning a specific organization
apple_news = news_df[news_df['entities'].apply(lambda x: 'Apple' in
x['ORG'])]
apple_sentiment = apple_news['headline_sentiment'].mean()

print(f"Average sentiment for Apple: {apple_sentiment}")
```

```
Average sentiment for Apple: 0.13636363636363635
```

```python
import matplotlib.pyplot as plt

# Assuming that `news_df` contains a column for dates and sentiment
news_df['date'] = pd.to_datetime(news_df['date'])  # Ensure dates are in
datetime format

# Assuming we have a 'headline_sentiment' column for sentiment scores
news_df['headline_sentiment'] = news_df['headline'].apply(lambda x:
TextBlob(x).sentiment.polarity)

# Ploting sentiment over time
plt.figure(figsize=(6, 4))
plt.plot(news_df['date'], news_df['headline_sentiment'], label='Headline
Sentiment', marker='o', color='blue')
plt.xlabel('Date')
plt.ylabel('Sentiment Score')
plt.title('Apple Sentiment Over Time')
plt.xticks(rotation=45)
plt.grid(True)
plt.legend()
plt.show()
```