EDA & Feature Engineering

October 7, 2025

1 Data Preprocessing & Feature Engineering

1.1 Import Necessary Libraries

[1]:
```python
# Python Standard Libraries
import os
import csv
import math
import random
import unicodedata

# Data Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# NLP - NLTK
import nltk
nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# Scikit-learn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# PyTorch
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

# TensorFlow / Keras
import tensorflow as tf
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import (
    Input, Dense, Dropout, LSTM, Bidirectional,
    Conv1D, Conv2D, MaxPooling1D, MaxPooling2D,
```

```
    Flatten, GlobalAveragePooling1D, LayerNormalization,
    MultiHeadAttention, Add
)
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
 ↪ModelCheckpoint
import tensorflow.keras.backend as K
from tensorflow.keras.losses import Huber

# XGBoost
import xgboost as xgb
from xgboost import XGBRegressor

# Shap
import shap
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/yourth/nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
```

1.2 Data Collections

[2]:
```
raw_stocks = pd.read_csv('./data/raw/stock_yfinance.csv')
raw_tweets = pd.read_csv('./data/raw/stock_tweets.csv')
```

1.3 Exploratory Data Analysis & Data Preprocessing

1.3.1 1. stock_yfinance Dataset

[3]:
```
raw_stocks.head()
```

[3]:
```
         Date       Open       High        Low      Close  Adj Close  \
0  2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429
1  2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286
2  2015-01-06  26.635000  26.857500  26.157499  26.565001  23.637505
3  2015-01-07  26.799999  27.049999  26.674999  26.937500  23.968958
4  2015-01-08  27.307501  28.037500  27.174999  27.972500  24.889906

      Volume Stock Name
0  212818400       AAPL
1  257142000       AAPL
2  263188400       AAPL
3  160423600       AAPL
4  237458000       AAPL
```

[4]:
```
raw_stocks.tail()
```

[4]:
```
            Date       Open       High        Low      Close  Adj Close  \
6285  2019-12-24  27.890667  28.364668  27.512667  28.350000  28.350000
6286  2019-12-26  28.527332  28.898666  28.423332  28.729334  28.729334
6287  2019-12-27  29.000000  29.020666  28.407333  28.691999  28.691999
6288  2019-12-30  28.586000  28.600000  27.284000  27.646667  27.646667
6289  2019-12-31  27.000000  28.086000  26.805332  27.888666  27.888666

         Volume Stock Name
6285  120820500       TSLA
6286  159508500       TSLA
6287  149185500       TSLA
6288  188796000       TSLA
6289  154285500       TSLA
```

[5]:
```
raw_stocks.describe()
```

[5]:
```
              Open         High          Low        Close    Adj Close  \
count  6290.000000  6290.000000  6290.000000  6290.000000  6290.000000
mean     47.939449    48.373949    47.468337    47.943927    46.149473
std      28.802247    28.991926    28.561164    28.793088    27.501038
min       9.488000    10.331333     9.403333     9.578000     9.578000
25%      26.413126    26.652000    26.131500    26.448125    24.851683
50%      42.177500    42.528000    41.861500    42.233999    40.205023
75%      58.738500    59.248500    58.206749    58.749249    57.247396
max     159.449997   159.550003   158.220001   158.960007   151.738663

             Volume
count  6.290000e+03
mean   7.857451e+07
std    6.388470e+07
min    7.425600e+06
25%    3.243302e+07
50%    6.051200e+07
75%    1.035403e+08
max    6.488252e+08
```

[6]:
```
raw_stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6290 entries, 0 to 6289
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        6290 non-null   object
 1   Open        6290 non-null   float64
 2   High        6290 non-null   float64
 3   Low         6290 non-null   float64
 4   Close       6290 non-null   float64
```

```
 5   Adj Close   6290 non-null   float64
 6   Volume      6290 non-null   int64
 7   Stock Name  6290 non-null   object
dtypes: float64(5), int64(1), object(2)
memory usage: 393.3+ KB
```

[7]:
```python
raw_stocks['Stock Name'].unique()
```

[7]:
```
array(['AAPL', 'AMZN', 'GOOGL', 'MSFT', 'TSLA'], dtype=object)
```

[8]:
```python
stocks = raw_stocks.copy()

stocks['Date'] = pd.to_datetime(stocks['Date'])
stocks
```

[8]:
```
           Date       Open       High        Low      Close  Adj Close  \
0    2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429
1    2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286
2    2015-01-06  26.635000  26.857500  26.157499  26.565001  23.637505
3    2015-01-07  26.799999  27.049999  26.674999  26.937500  23.968958
4    2015-01-08  27.307501  28.037500  27.174999  27.972500  24.889906
…           …          …          …         …          …          …
6285 2019-12-24  27.890667  28.364668  27.512667  28.350000  28.350000
6286 2019-12-26  28.527332  28.898666  28.423332  28.729334  28.729334
6287 2019-12-27  29.000000  29.020666  28.407333  28.691999  28.691999
6288 2019-12-30  28.586000  28.600000  27.284000  27.646667  27.646667
6289 2019-12-31  27.000000  28.086000  26.805332  27.888666  27.888666

         Volume Stock Name
0     212818400       AAPL
1     257142000       AAPL
2     263188400       AAPL
3     160423600       AAPL
4     237458000       AAPL
…           …         …
6285  120820500       TSLA
6286  159508500       TSLA
6287  149185500       TSLA
6288  188796000       TSLA
6289  154285500       TSLA

[6290 rows x 8 columns]
```

1.3.2 2. stock_tweets Dataset

[9]:
```python
raw_tweets.head()
```

[9]:

```
              Tweet ID          Writer         UTC  \
0  550441509175443456  VisualStockRSRC  1420070457
1  550441672312512512      KeralaGuy77  1420070496
2  550441732014223360      DozenStocks  1420070510
3  550442977802207232      ShowDreamCar  1420070807
4  550443807834402816      i_Know_First  1420071005

                                              Tweet  Like Num Stock Name  \
0  lx21 made $10,008  on $AAPL -Check it out! htt…         1       AAPL
1  Insanity of today weirdo massive selling. $aap…         0       AAPL
2  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…         0       AMZN
3  $GM $TSLA: Volkswagen Pushes 2014 Record Recal…         1       TSLA
4  Swing Trading: Up To 8.91% Return In 14 Days h…         1       AAPL

                       Date
0  2015-01-01 00:00:57+00:00
1  2015-01-01 00:01:36+00:00
2  2015-01-01 00:01:50+00:00
3  2015-01-01 00:06:47+00:00
4  2015-01-01 00:10:05+00:00
```

[10]:

```python
raw_tweets.tail()
```

[10]:

```
                    Tweet ID          Writer         UTC  \
3943871  1212159838882533376  ShortingIsFun  1577836401
3943872  1212160015332728833    Commuternyc  1577836443
3943873  1212160410692046849    MoriaCrypto  1577836537
3943874  1212160410692046849    MoriaCrypto  1577836537
3943875  1212160477159206912       treabase  1577836553

                                                    Tweet  Like Num  \
3943871  In 2020 I may start Tweeting out positive news…         1
3943872  Patiently Waiting for the no twitter sitter tw…         5
3943873  I don't discriminate. I own both $aapl and $ms…         1
3943874  I don't discriminate. I own both $aapl and $ms…         1
3943875  $AAPL #patent 10,522,475 Vertical interconnect…         0

        Stock Name                       Date
3943871       TSLA  2019-12-31 23:53:21+00:00
3943872       TSLA  2019-12-31 23:54:03+00:00
3943873       MSFT  2019-12-31 23:55:37+00:00
3943874       AAPL  2019-12-31 23:55:37+00:00
3943875       AAPL  2019-12-31 23:55:53+00:00
```

[11]:

```python
raw_tweets.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3943876 entries, 0 to 3943875
```

```
Data columns (total 7 columns):
 #   Column      Non-Null Count    Dtype 
---  ------      --------------    ----- 
 0   Tweet ID    3943876 non-null  int64 
 1   Writer      3895635 non-null  object
 2   UTC         3943876 non-null  int64 
 3   Tweet       3943876 non-null  object
 4   Like Num    3943876 non-null  int64 
 5   Stock Name  3943876 non-null  object
 6   Date        3943876 non-null  object
dtypes: int64(3), object(4)
memory usage: 210.6+ MB
```

[12]:
```python
tweets = raw_tweets.copy()

tweets = tweets.drop(columns=['Tweet ID', 'Writer', 'UTC', 'Like Num'])
tweets = tweets.dropna(subset=['Date', 'Tweet'])
tweets.isna().sum()
```

[12]:
```
Tweet         0
Stock Name    0
Date          0
dtype: int64
```

[13]:
```python
# Make sure Date is in datetime format
tweets['Date'] = pd.to_datetime(tweets['Date'], errors='coerce')
tweets['Date'] = tweets['Date'].dt.date

tweets.head()
```

[13]:
```
                                               Tweet Stock Name        Date
0  lx21 made $10,008  on $AAPL -Check it out! htt…       AAPL  2015-01-01
1  Insanity of today weirdo massive selling. $aap…       AAPL  2015-01-01
2  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…       AMZN  2015-01-01
3  $GM $TSLA: Volkswagen Pushes 2014 Record Recal…       TSLA  2015-01-01
4  Swing Trading: Up To 8.91% Return In 14 Days h…       AAPL  2015-01-01
```

[14]:
```python
tweets.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3943876 entries, 0 to 3943875
Data columns (total 3 columns):
 #   Column      Non-Null Count    Dtype 
---  ------      --------------    ----- 
 0   Tweet       3943876 non-null  object
 1   Stock Name  3943876 non-null  object
 2   Date        3943876 non-null  object
dtypes: object(3)
```

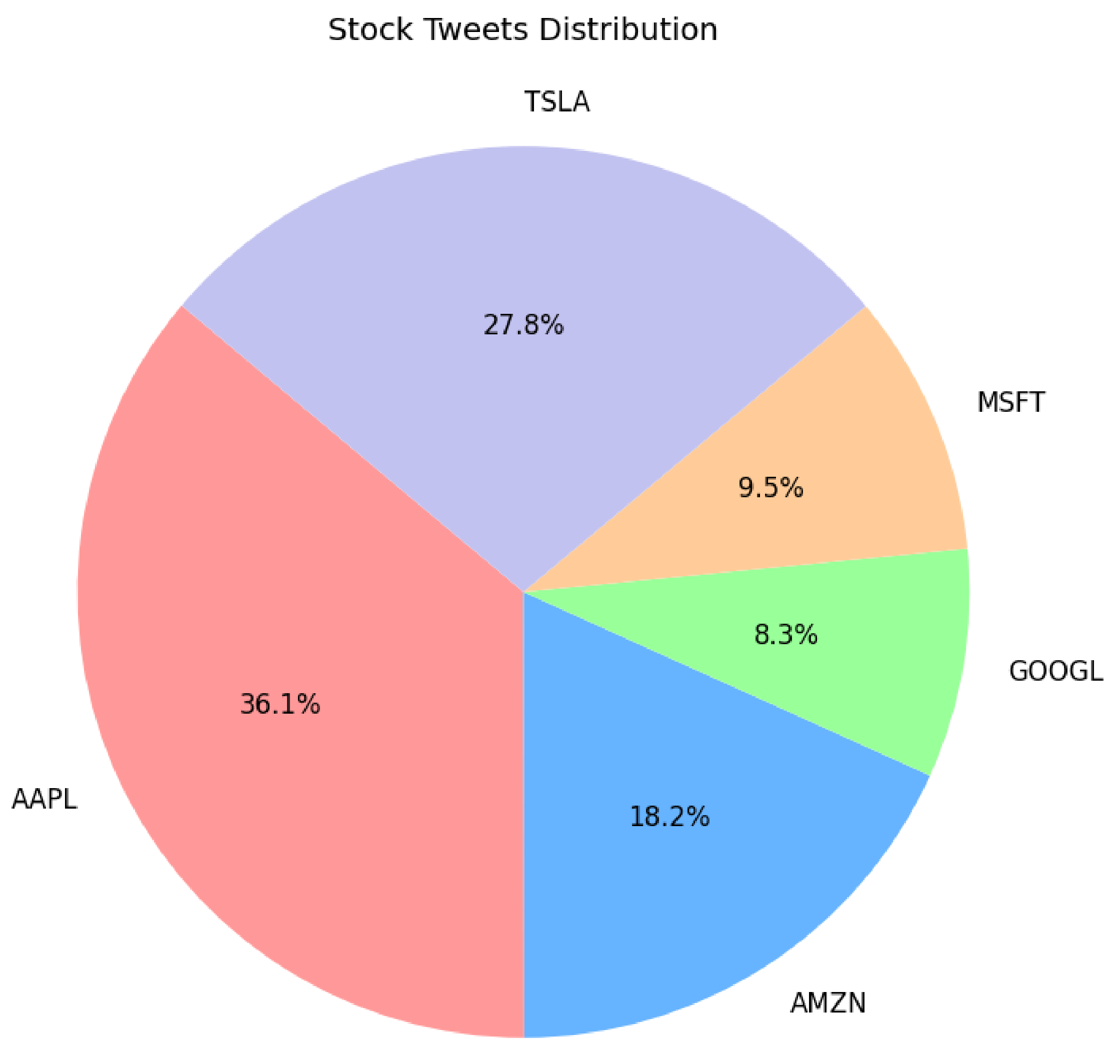
```
memory usage: 90.3+ MB
```

[15]:
```python
tweet_stock_count = raw_tweets['Stock Name'].value_counts()

perc = tweet_stock_count / tweet_stock_count.sum()
dstr = pd.DataFrame({'Count': tweet_stock_count, 'Percentage': perc}).
↪reset_index()
dstr = dstr.rename(columns={'index': 'Stock Name'})
dstr.head()
```

[15]:

	Stock Name	Count	Percentage
0	AAPL	1425013	0.361323
1	TSLA	1096868	0.278119
2	AMZN	718715	0.182236
3	MSFT	375711	0.095264
4	GOOGL	327569	0.083058

[16]:
```python
# Set a threshold percentage
threshold = 0.02  # 2%
colors = ['#ff9999', '#66b3ff', '#99ff99', '#ffcc99', '#c2c2f0', '#ffb3e6',␣
↪'#c4e17f', '#76d7c4', '#f7c6c7']

# Create a new DataFrame grouping smaller slices
dstr['Grouped'] = dstr.apply(lambda row: 'Other' if row['Percentage'] <␣
↪threshold else row['Stock Name'], axis=1)

dstr_grouped = dstr.groupby(
    dstr['Grouped'].where(dstr['Grouped'] != 'Other', 'Other')
).agg({'Count': 'sum'}).reset_index()

# Plot
plt.figure(figsize=(8, 8))
plt.pie(
    dstr_grouped['Count'],
    labels=dstr_grouped['Grouped'],
    autopct='%1.1f%%',
    startangle=140,
    colors=colors,
    textprops={'fontsize': 12}
)
plt.title('Stock Tweets Distribution', fontsize=14, pad=30)
plt.axis('equal')
plt.show()
```



[17]:
```
stocks.head()
```

[17]:
```
         Date       Open       High        Low      Close  Adj Close  \
0  2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429
1  2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286
2  2015-01-06  26.635000  26.857500  26.157499  26.565001  23.637505
3  2015-01-07  26.799999  27.049999  26.674999  26.937500  23.968958
4  2015-01-08  27.307501  28.037500  27.174999  27.972500  24.889906

      Volume Stock Name
0  212818400       AAPL
1  257142000       AAPL
2  263188400       AAPL
```

```
3  160423600       AAPL
4  237458000       AAPL
```

[18]:
```python
tweets.head()
```

[18]:
```
                                               Tweet Stock Name        Date
0  1x21 made $10,008  on $AAPL -Check it out! htt…       AAPL  2015-01-01
1  Insanity of today weirdo massive selling. $aap…       AAPL  2015-01-01
2  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…       AMZN  2015-01-01
3  $GM $TSLA: Volkswagen Pushes 2014 Record Recal…       TSLA  2015-01-01
4  Swing Trading: Up To 8.91% Return In 14 Days h…       AAPL  2015-01-01
```

[19]:
```python
def find_last_trading_day(x, trading_days):
    """
        x   trading_days       x



               NaT
    """
    eligible_days = trading_days[trading_days <= x]
    if not eligible_days.empty:
        return eligible_days.max()
    else:
        return pd.NaT

def map_to_last_trading_day(tweet_dates, trading_days):
    """




        tweet_dates: Series   DatetimeIndex
        trading_days:



        Series
    """
    trading_days = pd.to_datetime(sorted(set(trading_days)))

    #   apply + lambda
    mapped_dates = tweet_dates.apply(lambda x: find_last_trading_day(x,␣
 ↪trading_days))

    #        NaT
    valid_mask = mapped_dates.notna()

    return mapped_dates[valid_mask]
```

[20]:
```python
#
tweets['Date'] = pd.to_datetime(tweets['Date'])
stocks['Date'] = pd.to_datetime(stocks['Date'])

#
trading_days = stocks['Date'].unique()

#
mapped_dates = map_to_last_trading_day(tweets['Date'], trading_days)

#      tweets
tweets = tweets.loc[mapped_dates.index].copy()
tweets['Trading Date'] = mapped_dates
```

[21]:
```python
tweets['Date'] = tweets['Trading Date']
tweets = tweets.drop(columns=['Trading Date'])  #

tweets.head()
```

[21]:
```
                                                 Tweet Stock Name       Date
628  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…       AMZN 2015-01-02
629  Will Audi's Electric Q7 Cause $TSLA Model X Ba…       TSLA 2015-01-02
630  Either way you're a winnah. RT @dbbrakebill: i…       AAPL 2015-01-02
631  @Weeklyoptions http://Weeklyoptionplays.com we…       AAPL 2015-01-02
632  Cash flow machine. RT @themandotcom: $MSFT, wh…       MSFT 2015-01-02
```

1.4 Feature Construction

1.4.1 1. Sentiment Analysis

[22]:
```python
def vader_sentiment_scores(df, text_col='Tweet'):

    sentiment_analyzer = SentimentIntensityAnalyzer()
    df = df.copy()

    tweets['Vader_Negative'] = np.nan
    tweets['Vader_Neutral'] = np.nan
    tweets['Vader_Positive'] = np.nan
    tweets['Vader_Polarity'] = np.nan

    for indx, row in df.iterrows():
        try:
            # Normalize the text to ASCII
            text = unicodedata.normalize('NFKD', row[text_col])
            sentiment = sentiment_analyzer.polarity_scores(text)

            df.at[indx, 'Vader_Negative'] = sentiment['neg']
            df.at[indx, 'Vader_Neutral'] = sentiment['neu']
```

```
            df.at[indx, 'Vader_Positive'] = sentiment['pos']
            df.at[indx, 'Vader_Polarity'] = sentiment['compound']

        except TypeError:
            print(f"TypeError on row {indx}: {row[text_col]}")
            break

    return df
```

[23]:
```
tweets_sent = vader_sentiment_scores(tweets)
```

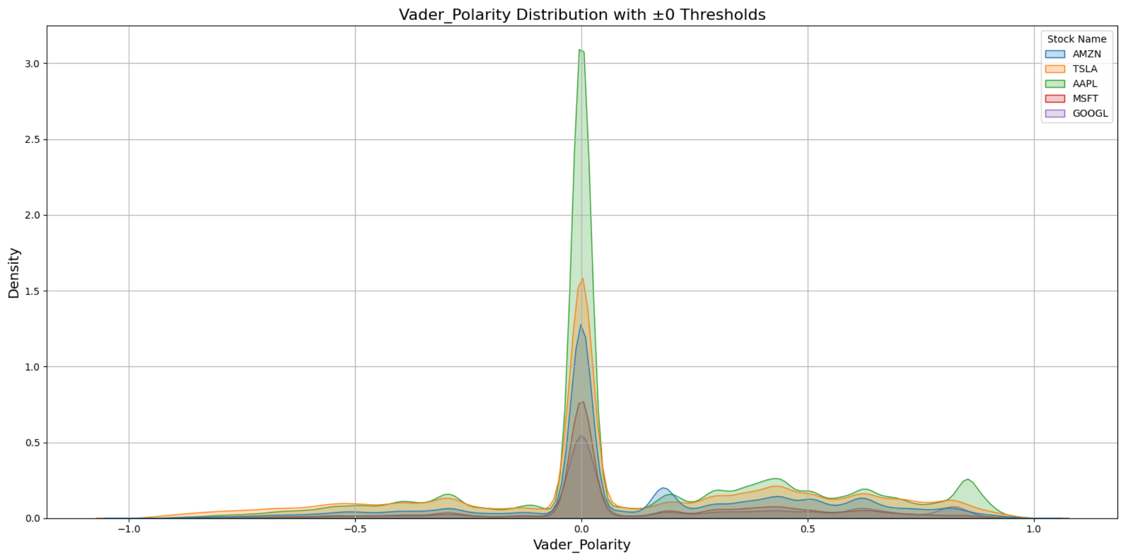
[24]:
```
tweets_sent.head()
```

[24]:
```
                                                 Tweet Stock Name       Date  \
628  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…       AMZN 2015-01-02
629  Will Audi's Electric Q7 Cause $TSLA Model X Ba…       TSLA 2015-01-02
630  Either way you're a winnah. RT @dbbrakebill: i…       AAPL 2015-01-02
631  @Weeklyoptions http://Weeklyoptionplays.com we…       AAPL 2015-01-02
632  Cash flow machine. RT @themandotcom: $MSFT, wh…       MSFT 2015-01-02

     Vader_Negative  Vader_Neutral  Vader_Positive  Vader_Polarity
628           0.000          1.000           0.000          0.0000
629           0.000          1.000           0.000          0.0000
630           0.155          0.845           0.000         -0.3736
631           0.000          0.756           0.244          0.6369
632           0.000          1.000           0.000          0.0000
```

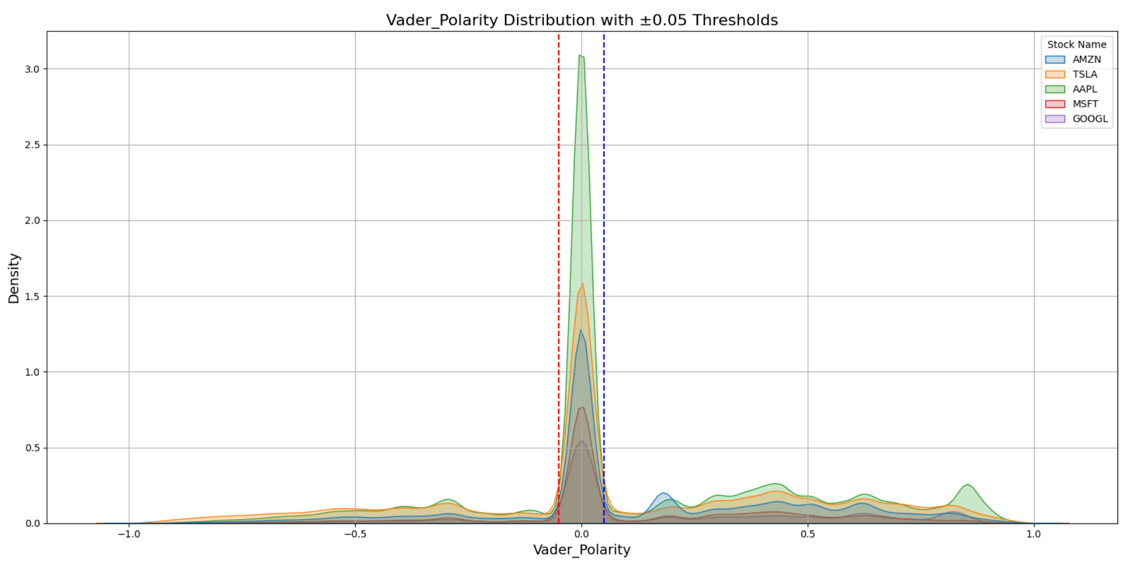
[25]:
```
def plot_kde(df, polarity_col, threshold=0, stock_col='Stock Name'):

    plt.figure(figsize=(16, 8))

    sns.kdeplot(data=df, x=polarity_col, hue=stock_col, fill=True)

    if threshold != 0:
        # Vertical threshold lines
        plt.axvline(-threshold, color='red', linestyle='--', label=f'Lower␣
↪Threshold -{threshold}')
        plt.axvline(threshold, color='blue', linestyle='--', label=f'Upper␣
↪Threshold +{threshold}')

    # Final touches
    plt.title(f"{polarity_col} Distribution with ±{threshold} Thresholds",␣
↪fontsize=16)
    plt.xlabel(polarity_col, fontsize=14)
    plt.ylabel("Density", fontsize=14)
    plt.grid(True)
    plt.tight_layout()
```

```
    plt.show()
```

[26]:
```
plot_kde(tweets_sent, polarity_col='Vader_Polarity')
```



[27]:
```
threshold = 0.05
plot_kde(tweets_sent, polarity_col='Vader_Polarity', threshold=threshold)
```



[28]:
```
def polarity_filter_by_threshold(df, threshold, polarity_col='Vader_Polarity', date_col='Date', verbose=True):
```

```
    df = df.copy()
    df[date_col] = pd.to_datetime(df[date_col])

    # Apply polarity threshold filter
    filtered_df = df[
        (df[polarity_col] >= threshold) |
        (df[polarity_col] <= -threshold)
    ]

    # Compute stats
    total_dates = df[date_col].nunique()
    remaining_dates = filtered_df[date_col].nunique()
    dates_lost = total_dates - remaining_dates

    if verbose:
        print(f"-> Total unique dates before filtering: {total_dates}")
        print(f"+> Remaining unique dates after filtering: {remaining_dates}")
        print(f">> Dates lost: {dates_lost}")

    return filtered_df
```

[29]:
```
tweets_filtered = polarity_filter_by_threshold(tweets_sent, threshold)
```

```
-> Total unique dates before filtering: 1258
+> Remaining unique dates after filtering: 1258
>> Dates lost: 0
```

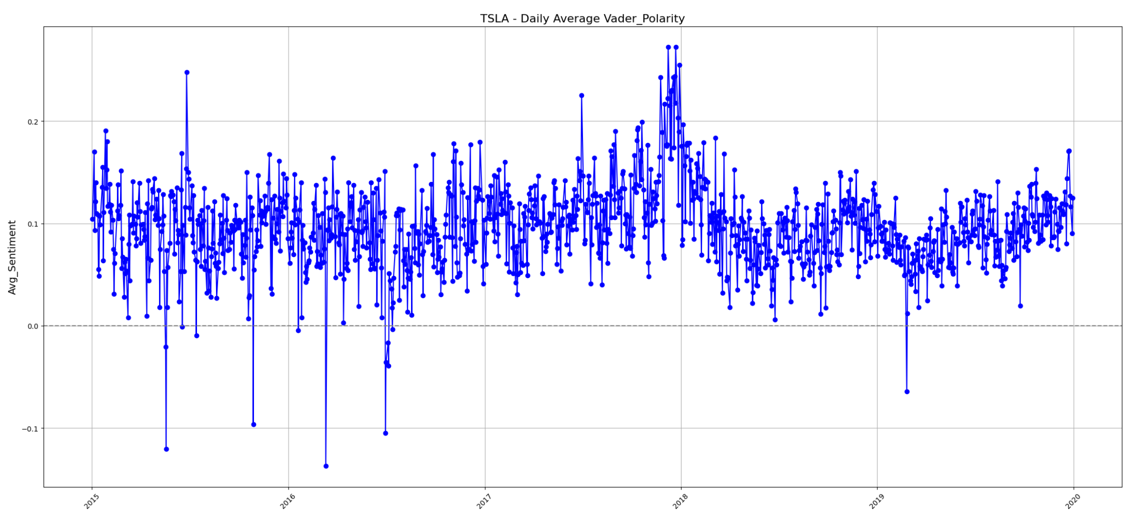
[30]:
```
def plot_daily_sentiment(df, company, sentiment_col, date_col='Date',␣
 ↪company_col='Stock Name'):

    # Convert date column to datetime if needed
    df = df.copy()
    df[date_col] = pd.to_datetime(df[date_col])

    # Group and compute daily average sentiment
    daily_sentiment = (
        df.groupby([date_col, company_col])[sentiment_col]
        .mean()
        .reset_index(name='Avg_Sentiment')
    )

    # Filter for selected company
    company_df = daily_sentiment[daily_sentiment[company_col] == company]

    # Plot
    plt.figure(figsize=(22, 10))
```

```
    plt.plot(company_df[date_col], company_df['Avg_Sentiment'], color='blue',␣
↪marker='o')
    plt.title(f"{company} - Daily Average {sentiment_col}", fontsize=16)
    plt.xlabel("Date", fontsize=14)
    plt.ylabel("Avg_Sentiment", fontsize=14)
    plt.axhline(0, color='gray', linestyle='--')
    plt.grid(True)
    plt.tight_layout()
    plt.xticks(rotation=45)
    plt.show()
```

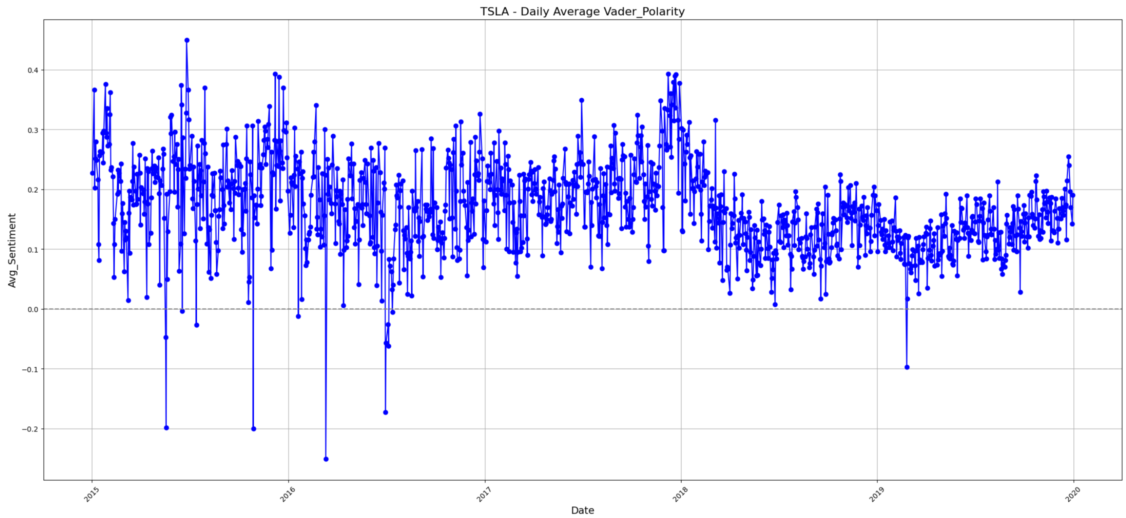
[31]:
```
tweets_sent.head()
```

[31]:
```
                                                 Tweet Stock Name        Date  \
628  S&P100 #Stocks Performance $HD $LOW $SBUX $TGT…       AMZN  2015-01-02
629  Will Audi's Electric Q7 Cause $TSLA Model X Ba…       TSLA  2015-01-02
630  Either way you're a winnah. RT @dbbrakebill: i…       AAPL  2015-01-02
631  @Weeklyoptions http://Weeklyoptionplays.com we…       AAPL  2015-01-02
632  Cash flow machine. RT @themandotcom: $MSFT, wh…       MSFT  2015-01-02

     Vader_Negative  Vader_Neutral  Vader_Positive  Vader_Polarity
628           0.000          1.000           0.000          0.0000
629           0.000          1.000           0.000          0.0000
630           0.155          0.845           0.000         -0.3736
631           0.000          0.756           0.244          0.6369
632           0.000          1.000           0.000          0.0000
```

[32]:
```
plot_daily_sentiment(tweets_sent, company='TSLA',␣
↪sentiment_col='Vader_Polarity')
```



[33]:
```python
plot_daily_sentiment(tweets_filtered, company='TSLA',␣
    ↪sentiment_col='Vader_Polarity')
```



[34]:
```python
tweets_filtered.head()
```

[34]:
```
                                                 Tweet Stock Name        Date  \
630  Either way you're a winnah. RT @dbbrakebill: i…       AAPL 2015-01-02
631  @Weeklyoptions http://Weeklyoptionplays.com we…       AAPL 2015-01-02
633  .@BenBajarin @counternotions @GlennF Thankful …       AAPL 2015-01-02
634  perfectly trading the S&P 500 in 2014 $FB $MU …       AMZN 2015-01-02
637  @KyleRohde @thehilker It could be, but that's …       AMZN 2015-01-02

     Vader_Negative  Vader_Neutral  Vader_Positive  Vader_Polarity
630           0.155          0.845           0.000         -0.3736
631           0.000          0.756           0.244          0.6369
633           0.000          0.802           0.198          0.5719
634           0.000          0.781           0.219          0.6369
637           0.103          0.641           0.255          0.7351
```

[35]:
```python
tweets_filtered.to_csv("./data/filtered/tweets_filtered.csv", index=False)
```

1.4.2 2. Calculate Technical Indicators

[36]:
```python
# RSI Calculation
def calculate_rsi(series, window=14):
    delta = series.diff()
    gain = delta.where(delta > 0, 0).rolling(window=window).mean()
    loss = -delta.where(delta < 0, 0).rolling(window=window).mean()
    rs = gain / loss
    rsi = 100 - (100 / (1 + rs))
```

```python
    return rsi
```

[37]:
```python
def get_technical_indicators(df):
    df = df.copy()
    # Trend
    df['SMA_5'] = df['Close'].rolling(window=5).mean()
    df['SMA_20'] = df['Close'].rolling(window=20).mean()

    # Bollinger Bands
    df['BB_Mid'] = df['SMA_5']
    df['BB_Std'] = df['Close'].rolling(window=20).std()
    df['BB_Upper'] = df['BB_Mid'] + 2 * df['BB_Std']
    df['BB_Lower'] = df['BB_Mid'] - 2 * df['BB_Std']

    # RSI
    df['RSI_14'] = calculate_rsi(df['Close'], window=14)

    # Log Return
    df['Log_Return'] = np.log(df['Close'] / df['Close'].shift(1))

    # OBV
    df['OBV'] = (np.sign(df['Close'].diff()) * df['Volume']).fillna(0).cumsum()

    # Lag Features
    df['Prev_Close'] = df['Close'].shift(1)
    df['Prev_Volume'] = df['Volume'].shift(1)

    # Time Features
    df['DayOfWeek'] = df.index.dayofweek
    df['Month'] = df.index.month

    # Clean
    df = df.bfill().ffill()

    return df
```

[38]:
```python
stocks.head()
```

[38]:
```
         Date       Open       High        Low      Close  Adj Close  \
0  2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429
1  2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286
2  2015-01-06  26.635000  26.857500  26.157499  26.565001  23.637505
3  2015-01-07  26.799999  27.049999  26.674999  26.937500  23.968958
4  2015-01-08  27.307501  28.037500  27.174999  27.972500  24.889906

      Volume Stock Name
0  212818400       AAPL
```

```
1   257142000       AAPL
2   263188400       AAPL
3   160423600       AAPL
4   237458000       AAPL
```

[39]:
```
stocks = stocks.set_index('Date').sort_index()
stocks = get_technical_indicators(stocks)

stocks.head()
```

[39]:
```
                 Open       High        Low      Close  Adj Close     Volume  \
Date
2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429  212818400
2015-01-02  14.858000  14.883333  14.217333  14.620667  14.620667   71466000
2015-01-02  26.629999  26.790001  26.393999  26.477501  26.351515   26480000
2015-01-02  46.660000  47.419998  46.540001  46.759998  40.072136   27913900
2015-01-02  15.629000  15.737500  15.348000  15.426000  15.426000   55664000

           Stock Name      SMA_5     SMA_20     BB_Mid     BB_Std   BB_Upper  \
Date
2015-01-02       AAPL  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       TSLA  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02      GOOGL  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       MSFT  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       AMZN  26.123333  25.620192  26.123333  11.873179  49.228223

            BB_Lower     RSI_14  Log_Return         OBV  Prev_Close  \
Date
2015-01-02  1.735509  46.167054   -0.625640         0.0   27.332500
2015-01-02  1.735509  46.167054   -0.625640 -71466000.0   27.332500
2015-01-02  1.735509  46.167054    0.593859 -44986000.0   14.620667
2015-01-02  1.735509  46.167054    0.568733 -17072100.0   26.477501
2015-01-02  1.735509  46.167054   -1.108974 -72736100.0   46.759998

             Prev_Volume  DayOfWeek  Month
Date
2015-01-02  212818400.0          4      1
2015-01-02  212818400.0          4      1
2015-01-02   71466000.0          4      1
2015-01-02   26480000.0          4      1
2015-01-02   27913900.0          4      1
```

1.4.3 3. Filter Company Data

[40]:
```
tweets_filtered = pd.read_csv("./data/filtered/tweets_filtered.csv")
```

[41]:
```
company_list = ['AAPL', 'AMZN', 'MSFT', 'GOOGL', 'TSLA']
```

[42]:
```python
# Filter for selected stocks
filter_tweets = tweets_filtered[tweets_filtered['Stock Name'].
 ↪isin(company_list)].copy()

# Group and compute daily average sentiment
daily_sentiment = (
    filter_tweets
    .groupby(['Stock Name', 'Date'])['Vader_Polarity']
    .mean()
    .reset_index()
)

# Set Date as index (for plotting or merging)
daily_sentiment['Date'] = pd.to_datetime(daily_sentiment['Date'])
daily_sentiment = daily_sentiment.set_index('Date').sort_index()

daily_sentiment.head()
```

[42]:
```
           Stock Name  Vader_Polarity
Date
2015-01-02       AAPL        0.276950
2015-01-02      GOOGL        0.470091
2015-01-02       TSLA        0.227755
2015-01-02       AMZN        0.222096
2015-01-02       MSFT        0.260802
```

[43]:
```python
filter_stocks = stocks[stocks['Stock Name'].isin(company_list)]
filter_stocks.head()
```

[43]:
```
                 Open       High        Low      Close  Adj Close     Volume  \
Date
2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429  212818400
2015-01-02  14.858000  14.883333  14.217333  14.620667  14.620667   71466000
2015-01-02  26.629999  26.790001  26.393999  26.477501  26.351515   26480000
2015-01-02  46.660000  47.419998  46.540001  46.759998  40.072136   27913900
2015-01-02  15.629000  15.737500  15.348000  15.426000  15.426000   55664000

           Stock Name      SMA_5     SMA_20     BB_Mid     BB_Std   BB_Upper  \
Date
2015-01-02       AAPL  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       TSLA  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02      GOOGL  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       MSFT  26.123333  25.620192  26.123333  11.873179  49.228223
2015-01-02       AMZN  26.123333  25.620192  26.123333  11.873179  49.228223

             BB_Lower     RSI_14  Log_Return          OBV  Prev_Close  \
Date
```

```
2015-01-02  1.735509  46.167054   -0.625640         0.0   27.332500
2015-01-02  1.735509  46.167054   -0.625640 -71466000.0   27.332500
2015-01-02  1.735509  46.167054    0.593859 -44986000.0   14.620667
2015-01-02  1.735509  46.167054    0.568733 -17072100.0   26.477501
2015-01-02  1.735509  46.167054   -1.108974 -72736100.0   46.759998

            Prev_Volume  DayOfWeek  Month
Date
2015-01-02  212818400.0          4      1
2015-01-02  212818400.0          4      1
2015-01-02   71466000.0          4      1
2015-01-02   26480000.0          4      1
2015-01-02   27913900.0          4      1
```

1.4.4 4. Merging (Stock + Sentiment)

[44]:
```python
def merging(company_list, filter_stocks, daily_sentiment):
    """
    Create a joined dataset of stock data and sentiment scores for a list of␣
    ↪stock tickers.

    Parameters:
    -----------
    company_list : list
        List of stock ticker symbols (e.g., ['AAPL', 'MSFT', 'GOOGL'])
    filter_stocks : pandas.DataFrame
        DataFrame containing stock price data with 'Stock Name' column
    daily_sentiment : pandas.DataFrame
        DataFrame containing sentiment scores with 'Stock Name' column

    Returns:
    --------
    dict
        Dictionary with ticker symbols as keys and joined DataFrames as values
    """
    # Dictionary to store results
    result_dict = {}

    for company in company_list:
        stock = filter_stocks[filter_stocks['Stock Name'] == company].copy()
        ticker_sentiment = daily_sentiment[daily_sentiment['Stock Name'] ==␣
    ↪company].copy()

        # Normalize datetime index (remove time, timezone)
        stock.index = pd.to_datetime(stock.index).normalize()
        ticker_sentiment.index = pd.to_datetime(ticker_sentiment.index).
    ↪normalize()
```

```
        # Perform inner join to keep only dates present in both
        joined_data = stock.join(ticker_sentiment[['Vader_Polarity']],␣
↪how='inner')

        result_dict[company] = joined_data

    return result_dict

stock_data_dict = merging(company_list, filter_stocks, daily_sentiment)
```

[45]:
```
AAPL = stock_data_dict['AAPL']

AAPL.head()
```

[45]:
```
                 Open       High        Low      Close  Adj Close     Volume  \
Date
2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429  212818400
2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286  257142000
2015-01-06  26.635000  26.857500  26.157499  26.565001  23.637505  263188400
2015-01-07  26.799999  27.049999  26.674999  26.937500  23.968958  160423600
2015-01-08  27.307501  28.037500  27.174999  27.972500  24.889906  237458000

           Stock Name      SMA_5     SMA_20     BB_Mid  …   BB_Upper  \
Date                                                    …
2015-01-02       AAPL  26.123333  25.620192  26.123333  …  49.228223
2015-01-05       AAPL  19.415400  25.620192  19.415400  …  49.228223
2015-01-06       AAPL  31.822701  25.620192  31.822701  …  49.228223
2015-01-07       AAPL  27.564067  25.620192  27.564067  …  49.228223
2015-01-08       AAPL  19.783466  25.672308  19.783466  …  43.502581

            BB_Lower     RSI_14  Log_Return          OBV  Prev_Close  \
Date
2015-01-02  1.735509  46.167054   -0.625640          0.0   27.332500
2015-01-05  1.735509  46.167054    0.640015   89576400.0   14.006000
2015-01-06  1.735509  46.167054   -0.541409 -170386000.0   45.650002
2015-01-07  1.735509  53.500699    0.649948  -41384800.0   14.063333
2015-01-08 -3.935649  54.182309    0.621640  205035200.0   15.023000

            Prev_Volume  DayOfWeek  Month  Vader_Polarity
Date
2015-01-02  212818400.0          4      1        0.276950
2015-01-05   80527500.0          0      1        0.251420
2015-01-06   36447900.0          1      1        0.281760
2015-01-07   44526000.0          2      1        0.271373
2015-01-08   61768000.0          3      1        0.321796
```

```
[5 rows x 21 columns]
```

[46]:
```
for company in company_list:
    df = stock_data_dict[company]
    df.to_csv(f"./data/filtered/{company}_filtered.csv", index=True)
```

1.4.5 5. Visualizing Related Features

[47]:
```
company_list = ['TSLA', 'AAPL', 'AMZN', 'GOOGL']
stock_data_dict = {}

for symbol in company_list:
    path = f"./data/filtered/{symbol}_filtered.csv"
    stock_data_dict[symbol] = pd.read_csv(path)
```

[48]:
```
tweets_filtered = pd.read_csv("./data/filtered/tweets_filtered.csv")
```

[49]:
```
TSLA = stock_data_dict['TSLA']
TSLA.head()
```

[49]:
```
         Date       Open       High        Low      Close  Adj Close  \
0  2015-01-02  14.858000  14.883333  14.217333  14.620667  14.620667
1  2015-01-05  14.303333  14.433333  13.810667  14.006000  14.006000
2  2015-01-06  14.004000  14.280000  13.614000  14.085333  14.085333
3  2015-01-07  14.223333  14.318667  13.985333  14.063333  14.063333
4  2015-01-08  14.187333  14.253333  14.000667  14.041333  14.041333

     Volume Stock Name      SMA_5     SMA_20  …   BB_Upper  BB_Lower  \
0  71466000       TSLA  26.123333  25.620192  …  49.228223  1.735509
1  80527500       TSLA  23.454899  25.620192  …  49.228223  1.735509
2  93928500       TSLA  31.838567  25.620192  …  49.228223  1.735509
3  44526000       TSLA  25.129466  25.620192  …  49.228223  1.735509
4  51637500       TSLA  25.994467  25.587975  …  50.001643  1.987290

      RSI_14  Log_Return          OBV  Prev_Close  Prev_Volume  DayOfWeek  \
0  46.167054   -0.625640  -71466000.0   27.332500  212818400.0          4
1  46.167054   -0.075838 -167565600.0   15.109500   55484000.0          0
2  46.167054   -0.634461 -264314500.0   26.565001  263188400.0          1
3  41.060477   -1.190058 -201808400.0   46.230000   29114100.0          2
4  41.785148   -1.220617  109988900.0   47.590000   29645200.0          3

   Month  Vader_Polarity
0      1        0.227755
1      1        0.366453
2      1        0.202426
3      1        0.251155
4      1        0.279833
```

```
[5 rows x 22 columns]
```

[50]:
```python
# Combine all stock DataFrames into one
stocks = pd.concat(stock_data_dict.values(), ignore_index=True)

#     datetime
stocks['Date'] = pd.to_datetime(stocks['Date'])
stocks = stocks.sort_values(['Date', 'Stock Name']).reset_index(drop=True)

print(stocks['Stock Name'].value_counts())
```

```
Stock Name
AMZN     1258
GOOGL    1258
TSLA     1258
AAPL     1255
Name: count, dtype: int64
```

[51]:
```python
stocks.head()
```

[51]:
```
        Date       Open       High        Low      Close  Adj Close  \
0 2015-01-02  27.847500  27.860001  26.837500  27.332500  24.320429
1 2015-01-02  15.629000  15.737500  15.348000  15.426000  15.426000
2 2015-01-02  26.629999  26.790001  26.393999  26.477501  26.351515
3 2015-01-02  14.858000  14.883333  14.217333  14.620667  14.620667
4 2015-01-05  27.072500  27.162500  26.352501  26.562500  23.635286

      Volume Stock Name      SMA_5     SMA_20  …   BB_Upper  BB_Lower  \
0  212818400       AAPL  26.123333  25.620192  …  49.228223  1.735509
1   55664000       AMZN  26.123333  25.620192  …  49.228223  1.735509
2   26480000      GOOGL  26.123333  25.620192  …  49.228223  1.735509
3   71466000       TSLA  26.123333  25.620192  …  49.228223  1.735509
4  257142000       AAPL  19.415400  25.620192  …  49.228223  1.735509

      RSI_14  Log_Return         OBV  Prev_Close  Prev_Volume  DayOfWeek  \
0  46.167054   -0.625640         0.0   27.332500  212818400.0          4
1  46.167054   -1.108974 -72736100.0   46.759998   27913900.0          4
2  46.167054    0.593859 -44986000.0   14.620667   71466000.0          4
3  46.167054   -0.625640 -71466000.0   27.332500  212818400.0          4
4  46.167054    0.640015  89576400.0   14.006000   80527500.0          0

   Month  Vader_Polarity
0      1        0.276950
1      1        0.222096
2      1        0.470091
3      1        0.227755
4      1        0.251420
```

```
[5 rows x 22 columns]
```

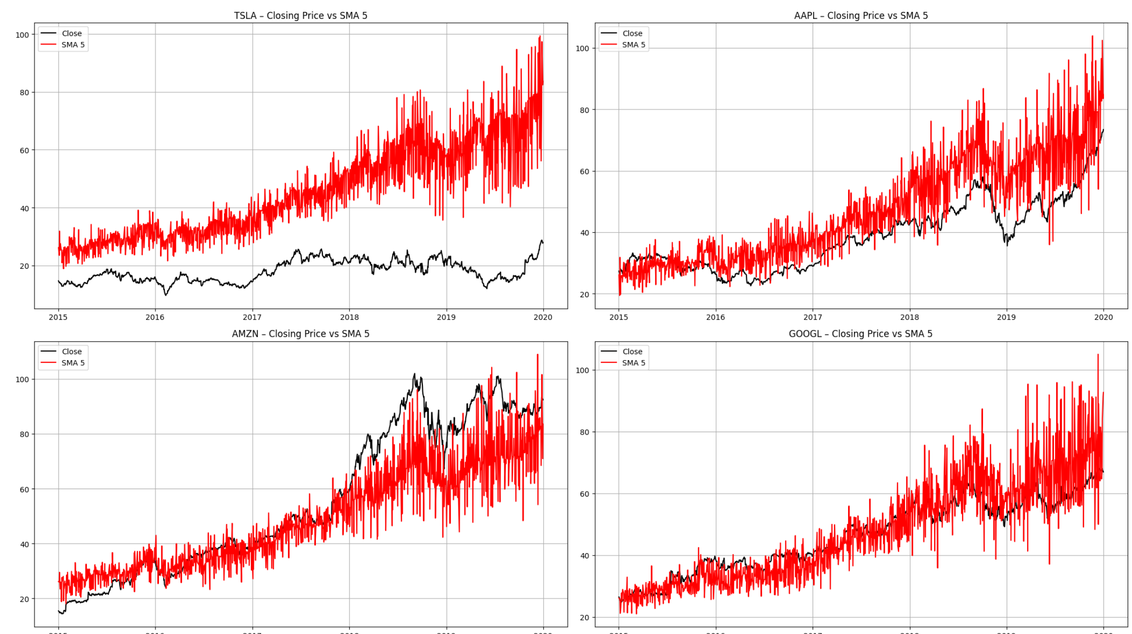
[52]:
```python
stocks['Date'].unique().value_counts()
```

[52]:
```
2015-01-02    1
2015-01-05    1
2015-01-06    1
2015-01-07    1
2015-01-08    1
             ..
2019-12-24    1
2019-12-26    1
2019-12-27    1
2019-12-30    1
2019-12-31    1
Name: count, Length: 1258, dtype: int64
```

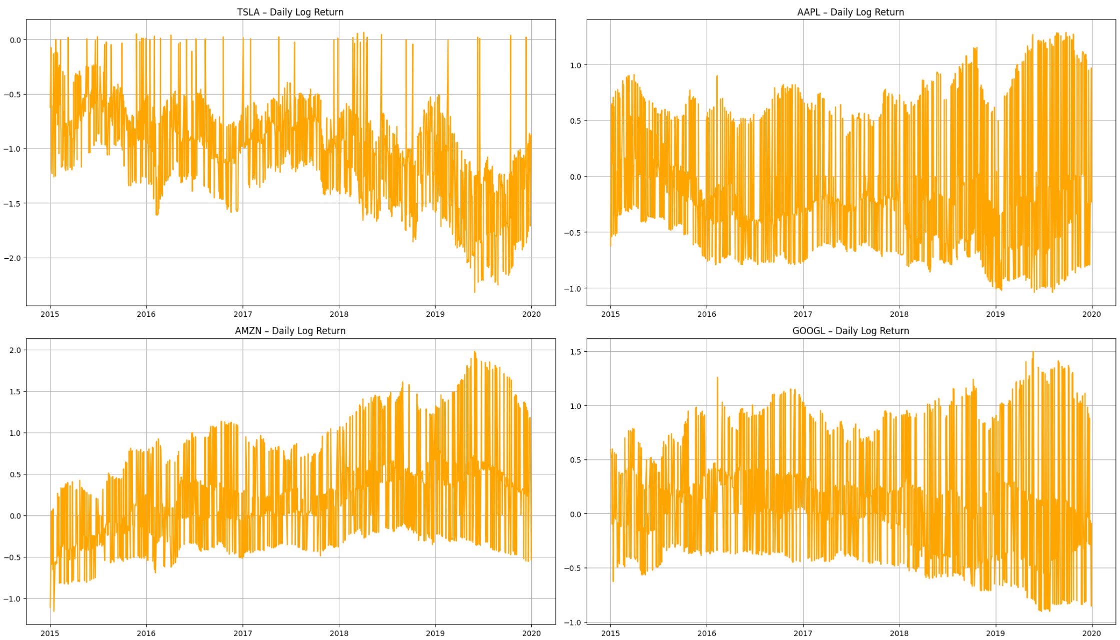
[53]:
```python
def plot_price_sma_grid(df_all, company_list):
    fig, axs = plt.subplots(2, 2, figsize=(21, 12))  # 14x6 per plot
    axs = axs.flatten()

    for i, company in enumerate(company_list):
        df = df_all[df_all['Stock Name'] == company]
        axs[i].plot(df['Date'], df['Close'], label='Close', color='black')
        axs[i].plot(df['Date'], df['SMA_5'], label='SMA 5', color='red')
        axs[i].set_title(f'{company} - Closing Price vs SMA 5')
        axs[i].legend()
        axs[i].grid(True)

    plt.tight_layout()
    plt.show()

def plot_log_return_grid(df_all, company_list):
    fig, axs = plt.subplots(2, 2, figsize=(21, 12))
    axs = axs.flatten()

    for i, company in enumerate(company_list):
        df = df_all[df_all['Stock Name'] == company]
        axs[i].plot(df['Date'], df['Log_Return'], color='orange')
        axs[i].set_title(f'{company} - Daily Log Return')
        axs[i].grid(True)

    plt.tight_layout()
    plt.show()

def plot_rsi_grid(df_all, company_list):
```

```
    fig, axs = plt.subplots(2, 2, figsize=(21, 12))
    axs = axs.flatten()

    for i, company in enumerate(company_list):
        df = df_all[df_all['Stock Name'] == company]
        axs[i].plot(df['Date'], df['RSI_14'], color='purple')
        axs[i].axhline(70, color='red', linestyle='--')
        axs[i].axhline(30, color='green', linestyle='--')
        axs[i].set_title(f'{company} - RSI (14-day)')
        axs[i].grid(True)

    plt.tight_layout()
    plt.show()

def plot_volume_grid(df_all, company_list):
    fig, axs = plt.subplots(2, 2, figsize=(21, 12))
    axs = axs.flatten()

    for i, company in enumerate(company_list):
        df = df_all[df_all['Stock Name'] == company]
        axs[i].plot(df['Date'], df['Volume'], color='gray')
        axs[i].set_title(f'{company} - Daily Trading Volume')
        axs[i].grid(True)

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

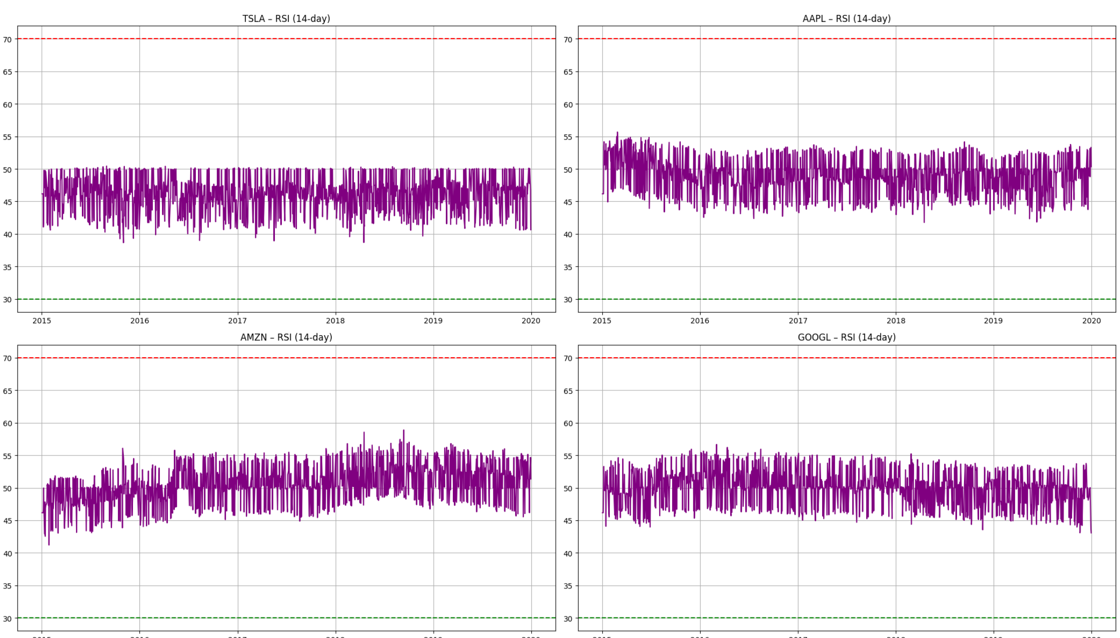
[54]:
```
plot_price_sma_grid(stocks, company_list)
```



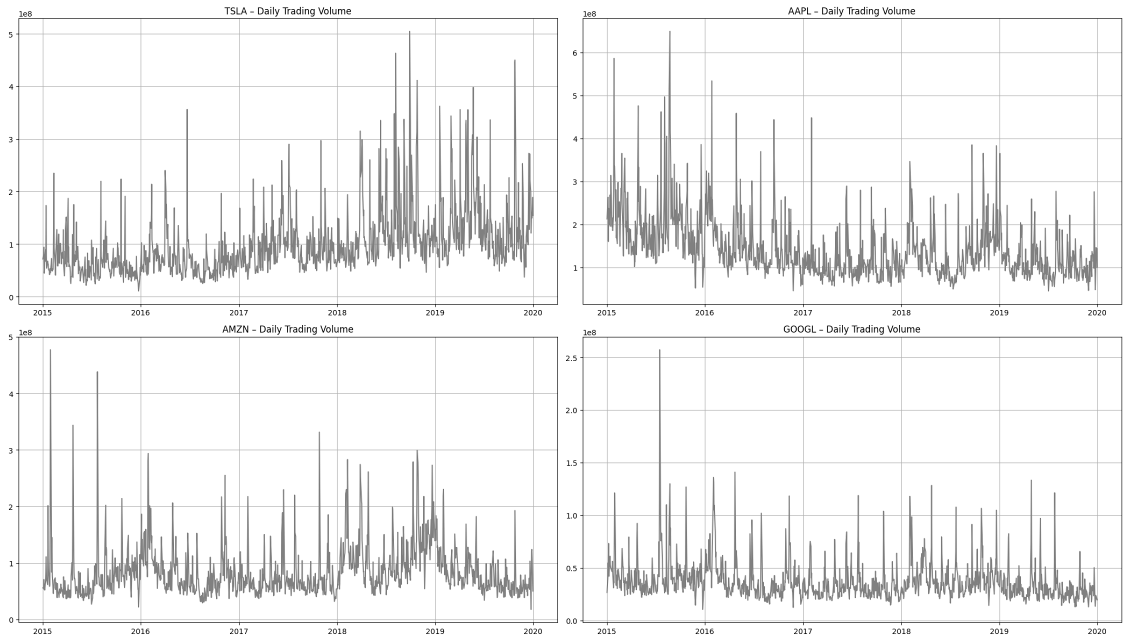
[55]:
```
plot_log_return_grid(stocks, company_list)
```



[56]:
```
plot_rsi_grid(stocks, company_list)
```



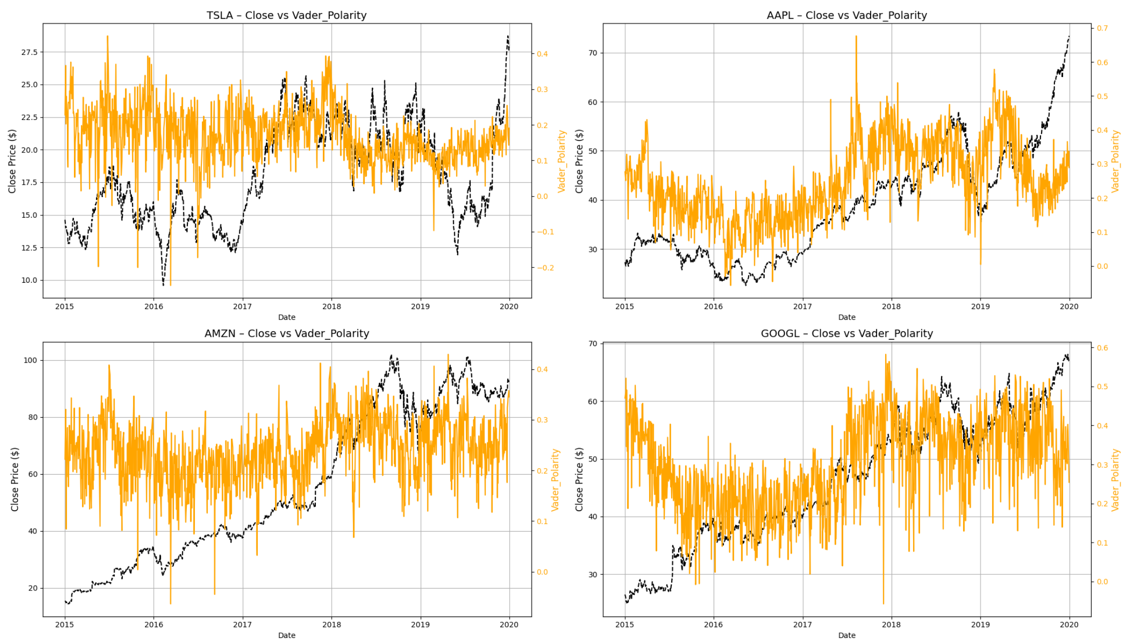
[57]:
```python
plot_volume_grid(stocks, company_list)
```



[58]:
```python
def plot_price_vs_sentiment(df_all, company_list, sentiment_col='Vader_Polarity'):
    fig, axs = plt.subplots(2, 2, figsize=(21, 12))  # Grid for 4 companies
    axs = axs.flatten()

    for i, company in enumerate(company_list):
        df = df_all[df_all['Stock Name'] == company]
        ax1 = axs[i]

        # Left y-axis: Close Price
        ax1.plot(df['Date'], df['Close'], color='black', linestyle='--', label='Close')
        ax1.set_ylabel('Close Price ($)', color='black', fontsize=12)
        ax1.tick_params(axis='y', labelcolor='black')
        ax1.grid(True)  #

        # Twin y-axis for sentiment
        ax2 = ax1.twinx()
        ax2.plot(df['Date'], df[sentiment_col], color='orange', label=sentiment_col)
        ax2.set_ylabel(sentiment_col, color='orange', fontsize=12)
        ax2.tick_params(axis='y', labelcolor='orange')
        ax2.grid(False)  #
```

```
        # Title and grid
        ax1.set_title(f'{company} - Close vs {sentiment_col}', fontsize=14)
        ax1.set_xlabel('Date')

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

[59]:
```
plot_price_vs_sentiment(stocks, company_list, sentiment_col='Vader_Polarity')
```



1.5 Feature Selection

[60]:
```
TSLA = stock_data_dict['TSLA']
df = TSLA.copy()

df.head()
```

[60]:

	Date	Open	High	Low	Close	Adj Close	\
0	2015-01-02	14.858000	14.883333	14.217333	14.620667	14.620667	
1	2015-01-05	14.303333	14.433333	13.810667	14.006000	14.006000	
2	2015-01-06	14.004000	14.280000	13.614000	14.085333	14.085333	
3	2015-01-07	14.223333	14.318667	13.985333	14.063333	14.063333	
4	2015-01-08	14.187333	14.253333	14.000667	14.041333	14.041333	

	Volume	Stock Name	SMA_5	SMA_20	…	BB_Upper	BB_Lower	\
0	71466000	TSLA	26.123333	25.620192	…	49.228223	1.735509	
1	80527500	TSLA	23.454899	25.620192	…	49.228223	1.735509	

```
2  93928500       TSLA  31.838567  25.620192  …  49.228223  1.735509
3  44526000       TSLA  25.129466  25.620192  …  49.228223  1.735509
4  51637500       TSLA  25.994467  25.587975  …  50.001643  1.987290

      RSI_14  Log_Return          OBV  Prev_Close  Prev_Volume  DayOfWeek  \
0  46.167054   -0.625640  -71466000.0   27.332500  212818400.0          4
1  46.167054   -0.075838 -167565600.0   15.109500   55484000.0          0
2  46.167054   -0.634461 -264314500.0   26.565001  263188400.0          1
3  41.060477   -1.190058 -201808400.0   46.230000   29114100.0          2
4  41.785148   -1.220617  109988900.0   47.590000   29645200.0          3

   Month  Vader_Polarity
0      1        0.227755
1      1        0.366453
2      1        0.202426
3      1        0.251155
4      1        0.279833

[5 rows x 22 columns]
```

[61]:
```python
df.columns
```

[61]:
```
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume',
       'Stock Name', 'SMA_5', 'SMA_20', 'BB_Mid', 'BB_Std', 'BB_Upper',
       'BB_Lower', 'RSI_14', 'Log_Return', 'OBV', 'Prev_Close', 'Prev_Volume',
       'DayOfWeek', 'Month', 'Vader_Polarity'],
      dtype='object')
```

1.5.1 1. Avoid Data Leakage

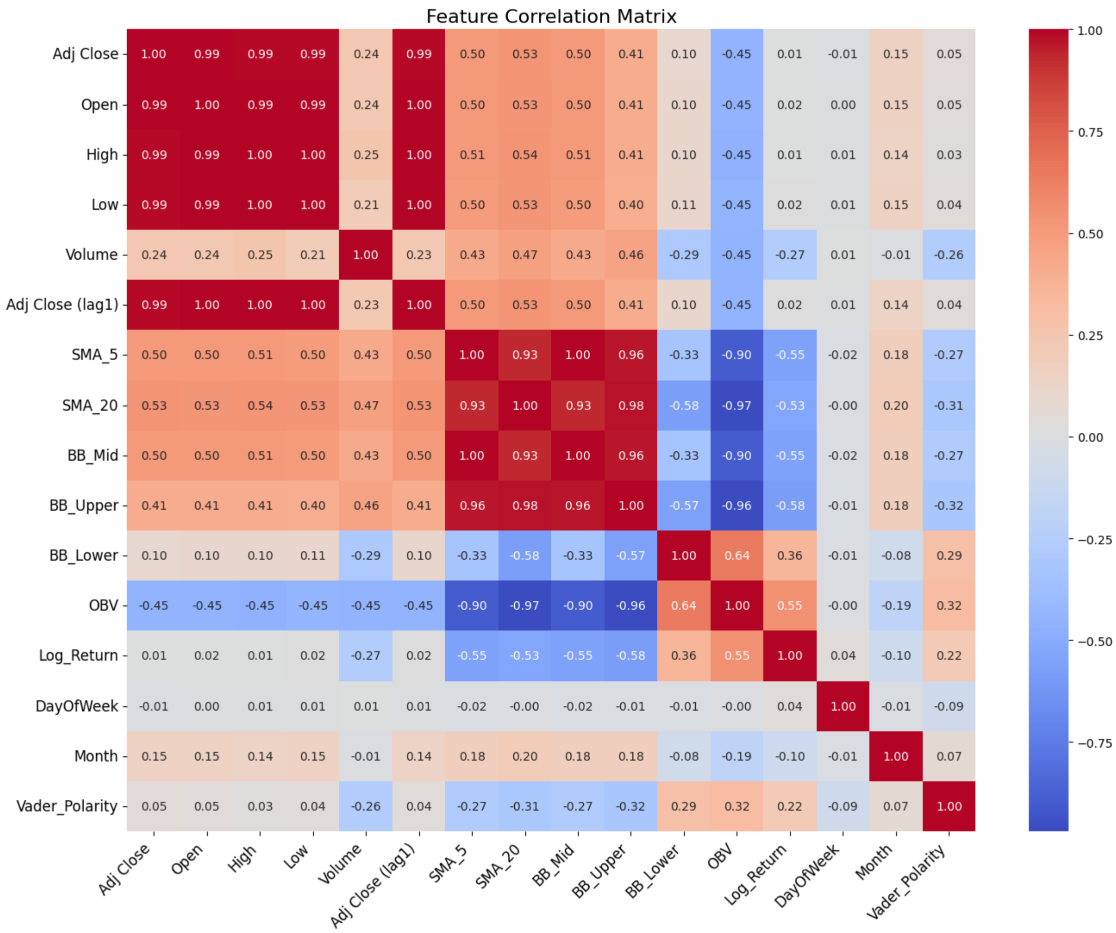
[62]:
```python
# Lag technical indicators to avoid leakage
lag_cols = [
    'Adj Close', 'High', 'Low', 'Volume', 'SMA_5', 'SMA_20',
    'BB_Mid', 'BB_Std', 'BB_Upper', 'BB_Lower',
    'RSI_14', 'Log_Return', 'OBV', 'Vader_Polarity'
]

for col in lag_cols:
    if col == "Adj Close":
        df[f"{col} (lag1)"] = df[col].shift(1)
    else:
        df[col] = df[col].shift(1)

feature_cols = [
    'Adj Close',
    'Open', 'High', 'Low', 'Volume', 'Adj Close (lag1)',
    'SMA_5', 'SMA_20', 'BB_Mid', 'BB_Upper', 'BB_Lower',
```

```
    'OBV', 'Log_Return', 'DayOfWeek', 'Month',
    'Vader_Polarity'
]

df = df[feature_cols]
```

[63]:
```
feature_cols = [
    'Adj Close',                # Adj Close
    'Open', 'High', 'Low', 'Volume',
    'Adj Close (lag1)',         #
    'SMA_5', 'SMA_20', 'BB_Mid', 'BB_Upper', 'BB_Lower',
    'OBV', 'Log_Return', 'DayOfWeek', 'Month',
    'Vader_Polarity'
]

target_col = 'Adj Close'  # or 'Log_Return'
```

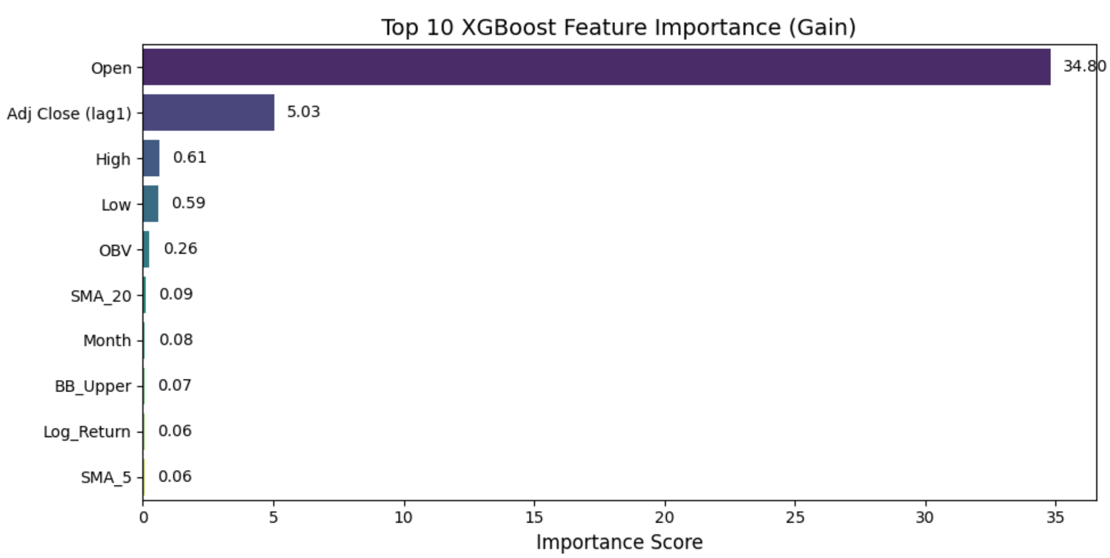
1.5.2 2. Feature Importance

[64]:
```
# ---     X_corr     Adj Close shift  ---
X_corr = df[feature_cols].copy()
X_corr = X_corr.iloc[:-1, :]  #   label    y = shift(-1)

# --- 2. Correlation Heatmap ---
plt.figure(figsize=(14, 11))
corr_matrix = X_corr.corr()
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm',
            annot_kws={"size": 10})  #

plt.title("Feature Correlation Matrix", fontsize=16)  #
plt.xticks(rotation=45, ha='right', fontsize=12)       # x
plt.yticks(rotation=0, fontsize=12)                    # y

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

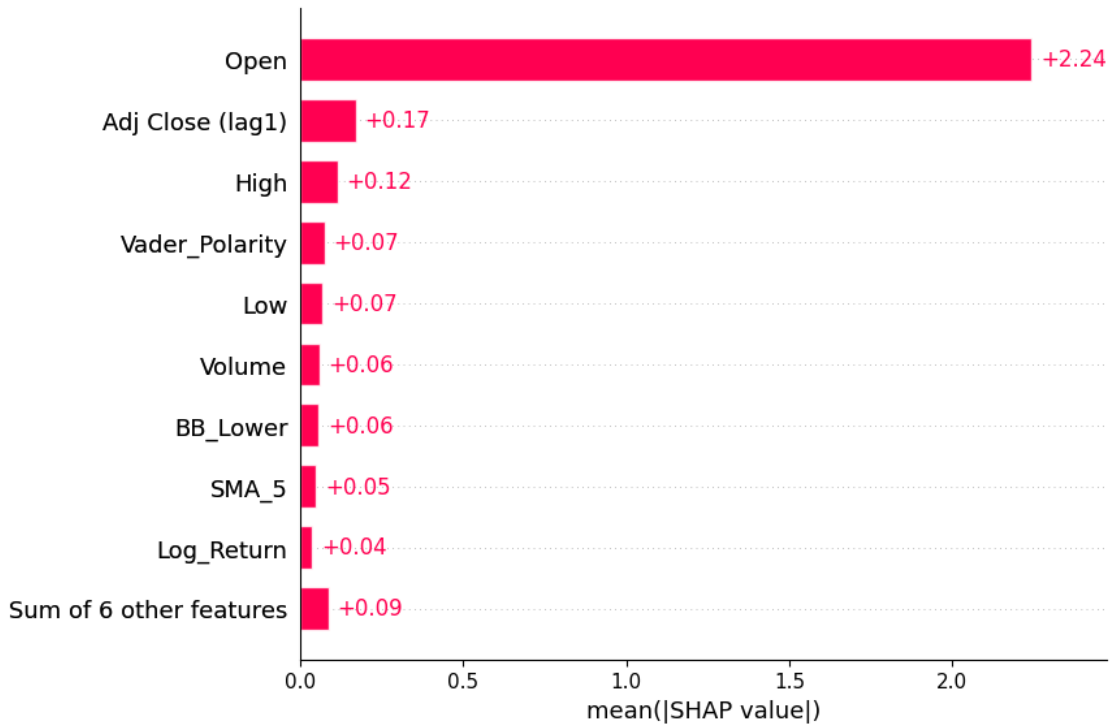


[65]:
```
#   1.    X     Adj Close   y
X = df[feature_cols].copy()
X = X.drop(columns=['Adj Close'])  #       Adj Close
y = df['Adj Close']                #   y

#   2.       lag SMA
X = X.iloc[1:, :]    #       lag1
y = y.iloc[1:]       #

#   3.
scaler = StandardScaler()
X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)

#   4.
X_train, X_val, y_train, y_val = train_test_split(
    X_scaled, y, test_size=0.3, shuffle=False
)
```

[66]:
```python
# --- 3. XGBoost Feature Importance ---
xgb_model = xgb.XGBRegressor(n_estimators=100)
xgb_model.fit(X_train, y_train)

importances = xgb_model.get_booster().get_score(importance_type='gain')
importances = sorted(importances.items(), key=lambda x: x[1], reverse=True)

imp_df = pd.DataFrame(importances, columns=['Feature', 'Importance']).head(10)

plt.figure(figsize=(10, 5))
sns.barplot(
    data=imp_df,
    x='Importance',
    y='Feature',
    hue='Feature',
    palette='viridis',
    dodge=False,
    legend=False
)

#    x
for i, v in enumerate(imp_df['Importance']):
    plt.text(v + 0.5, i, f'{v:.2f}', va='center', fontsize=10)

plt.title("Top 10 XGBoost Feature Importance (Gain)", fontsize=14)
plt.xlabel("Importance Score", fontsize=12)
plt.ylabel("")
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()
```



[67]:
```python
# --- 4. SHAP with PermutationExplainer (CPU-friendly) ---
explainer = shap.Explainer(xgb_model.predict, X_val, algorithm="permutation")
shap_values = explainer(X_val)

#      +   10
plt.gcf().set_size_inches(10, 5)
shap.plots.bar(shap_values, max_display=10)
plt.tight_layout()
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```

[68]:
```python
# ========== 1.          ==========
X_corr_check = df[feature_cols].copy().iloc[:-1]   #
corr_matrix = X_corr_check.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
to_drop_corr = [col for col in upper.columns if any(upper[col] > 0.90)]

print("  Dropped (correlated > 0.90):")
for col in to_drop_corr:
    print(f"   · {col}")
```

```
# ========== 2.   XGBoost Top 10   ==========
#     xgb_model
importances_dict = xgb_model.get_booster().get_score(importance_type='gain')
top10_sorted = sorted(importances_dict.items(), key=lambda x: x[1],␣
↪reverse=True)[:10]

print("\n  Top 10 XGBoost Features (by Gain):")
for i, (feat, score) in enumerate(top10_sorted, 1):
    print(f"  {i:>2d}. {feat:<20} → {score:.2f}")
```

```
Dropped (correlated > 0.90):
 · Open
 · High
 · Low
 · Adj Close (lag1)
 · SMA_20
 · BB_Mid
 · BB_Upper
 · OBV

Top 10 XGBoost Features (by Gain):
  1. Open                 → 34.80
  2. Adj Close (lag1)     → 5.03
  3. High                 → 0.61
  4. Low                  → 0.59
  5. OBV                  → 0.26
  6. SMA_20               → 0.09
  7. Month                → 0.08
  8. BB_Upper             → 0.07
  9. Log_Return           → 0.06
 10. SMA_5                → 0.06
```

1.6 Time Series Train-Test Split

1.6.1 1. Loading Pre-processed Data

[2]:
```
company_list = ['TSLA', 'AAPL', 'AMZN', 'GOOGL', 'MSFT']
stock_data_dict = {}

for symbol in company_list:
    path = f"./data/filtered/{symbol}_filtered.csv"
    stock_data_dict[symbol] = pd.read_csv(path)
```

[3]:
```
TSLA = stock_data_dict['TSLA']
AAPL = stock_data_dict['AAPL']
AMZN = stock_data_dict['AMZN']
GOOGL = stock_data_dict['GOOGL']
```

```python
MSFT = stock_data_dict['MSFT']
```

[154]:
```python
df = MSFT.copy()
df.head()
```

[154]:
```
         Date       Open       High        Low      Close  Adj Close  \
0  2015-01-02  46.660000  47.419998  46.540001  46.759998  40.072136
1  2015-01-05  46.369999  46.730000  46.250000  46.330002  39.703636
2  2015-01-06  46.380001  46.750000  45.540001  45.650002  39.120899
3  2015-01-07  45.980000  46.459999  45.490002  46.230000  39.617935
4  2015-01-08  46.750000  47.750000  46.720001  47.590000  40.783424

     Volume Stock Name      SMA_5     SMA_20  …   BB_Upper  BB_Lower  \
0  27913900       MSFT  26.123333  25.620192  …  49.228223  1.735509
1  39673900       MSFT  25.596200  25.620192  …  49.228223  1.735509
2  36447900       MSFT  29.531601  25.620192  …  49.228223  1.735509
3  29114100       MSFT  25.133867  25.620192  …  49.228223  1.735509
4  29645200       MSFT  26.170400  25.657208  …  50.044991  2.295809

      RSI_14  Log_Return          OBV  Prev_Close  Prev_Volume  DayOfWeek  \
0  46.167054    0.568733  -17072100.0   26.477501   26480000.0          4
1  46.167054    0.556289  129250300.0   26.562500  257142000.0          0
2  46.167054   -0.014786   92802400.0   46.330002   39673900.0          1
3  55.775826    0.604506 -157282400.0   25.257500   46918000.0          2
4  50.394938    0.630021  161626400.0   25.345501   73054000.0          3

   Month  Vader_Polarity
0      1        0.260802
1      1        0.244632
2      1        0.211529
3      1        0.256537
4      1        0.344753

[5 rows x 22 columns]
```

1.6.2 2. Avoid Data Leakage

[155]:
```python
# Lag technical indicators to avoid leakage
lag_cols = [
    'Adj Close', 'High', 'Low', 'Volume', 'SMA_5', 'SMA_20',
    'BB_Mid', 'BB_Std', 'BB_Upper', 'BB_Lower',
    'RSI_14', 'Log_Return', 'OBV', 'Vader_Polarity'
]

for col in lag_cols:
    if col == "Adj Close":
        df[f"{col} (lag1)"] = df[col].shift(1)
```

```
    else:
        df[col] = df[col].shift(1)

feature_cols = [
    'Adj Close',
    'Open', 'High', 'Low', 'Volume', 'Adj Close (lag1)',
    'SMA_5', 'SMA_20', 'BB_Mid', 'BB_Upper', 'BB_Lower',
    'OBV', 'Log_Return', 'DayOfWeek', 'Month',
    'Vader_Polarity'
]

df = df[feature_cols]
```

[156]:
```
df.head()
```

[156]:
```
   Adj Close       Open       High        Low      Volume  Adj Close (lag1)  \
0  40.072136  46.660000        NaN        NaN         NaN               NaN
1  39.703636  46.369999  47.419998  46.540001  27913900.0         40.072136
2  39.120899  46.380001  46.730000  46.250000  39673900.0         39.703636
3  39.617935  45.980000  46.750000  45.540001  36447900.0         39.120899
4  40.783424  46.750000  46.459999  45.490002  29114100.0         39.617935

       SMA_5     SMA_20     BB_Mid   BB_Upper  BB_Lower          OBV  \
0        NaN        NaN        NaN        NaN       NaN          NaN
1  26.123333  25.620192  26.123333  49.228223  1.735509  -17072100.0
2  25.596200  25.620192  25.596200  49.228223  1.735509  129250300.0
3  29.531601  25.620192  29.531601  49.228223  1.735509   92802400.0
4  25.133867  25.620192  25.133867  49.228223  1.735509 -157282400.0

   Log_Return  DayOfWeek  Month  Vader_Polarity
0         NaN          4      1             NaN
1    0.568733          0      1        0.260802
2    0.556289          1      1        0.244632
3   -0.014786          2      1        0.211529
4    0.604506          3      1        0.256537
```

[157]:
```
# feature_cols = [
#     'Adj Close',  # should be the first one for Y
#     'Adj Close (lag1)',
#     'SMA_5',               # short-term trend
#     'Volume',
#     'BB_Mid',             # risk signal
#     'Log_Return',
#     'DayOfWeek',
#     'Month',
#     'Vader_Polarity'  # should be the last one for SENTIMENT
# ]
```

[158]:
```
feature_cols = [
    'Adj Close',
    'Open', 'High', 'Low', 'Volume', 'Adj Close (lag1)',
    'SMA_5', 'SMA_20', 'BB_Mid', 'BB_Upper', 'BB_Lower',
    'OBV', 'Log_Return', 'DayOfWeek', 'Month',
    'Vader_Polarity'
]
```

1.6.3 Define Rolling Window & Prediction Day

[159]:
```
# Step 0: Define sliding window parameters
n_past = 5      # Use past 5 days
n_future = 1    # Predict next 1 day
```

1.6.4 Train-Test Split

[160]:
```
train_size = 0.7
train_split_idx = int(train_size * len(df))
```

[161]:
```
df_filtered = df[feature_cols]
df_filtered = df_filtered.iloc[1:] # delete nan       lag1

# Step 0: Define split boundaries BEFORE scaling
train_df = df_filtered.iloc[:train_split_idx]
test_df  = df_filtered.iloc[train_split_idx:]

# Step 1: Fit scaler only on training data (Avoid Data Leakage)
scaler = MinMaxScaler()
scaler.fit(train_df)

scaler_target = MinMaxScaler()
scaler_target.fit(train_df[['Adj Close']])

# Step 2: Scale training and test data separately
train_scaled = scaler.transform(train_df)
test_scaled  = scaler.transform(test_df)

# # Step 3: For inference later, only scale ['Adj Close']
# scaler_for_inference = MinMaxScaler()
# scaler_for_inference.fit(train_df[['Adj Close']])
# # Now you can transform when needed during inference
# train_actual_scaled_close = scaler_for_inference.transform(train_df[['Adj␣
 ↪Close']])
# test_actual_scaled_close = scaler_for_inference.transform(test_df[['Adj␣
 ↪Close']])

# Step 3: Reconstruct sliding windows for train and test
```

```python
def create_sequences(data, n_past, n_future):
    X, y = [], []
    for i in range(n_past, len(data) - n_future + 1):
        X.append(data[i - n_past:i, 1:])
        y.append(data[i + n_future - 1:i + n_future, [0]])  # Predict Adj Close
    return np.array(X), np.array(y)

trainX, trainY = create_sequences(train_scaled, n_past, n_future)
testX, testY   = create_sequences(test_scaled, n_past, n_future)

# trainY = trainY.reshape(-1, 1)
# testY = testY.reshape(-1, 1)

print('TrainX shape = {}'.format(trainX.shape))
print('TrainY shape = {}'.format(trainY.shape))
print('TestX shape = {}'.format(testX.shape))
print('TestY shape = {}'.format(testY.shape))
```

```
TrainX shape = (875, 5, 15)
TrainY shape = (875, 1, 1)
TestX shape = (372, 5, 15)
TestY shape = (372, 1, 1)
```

1.6.5 (Un)Sentiment Split

[162]:
```python
# Without Sentiment (Baseline Model)
trainX_wo_tweet = trainX[:, :, :-1]  # Exclude last feature
testX_wo_tweet  = testX[:, :, :-1]
trainY_wo_tweet = trainY
testY_wo_tweet  = testY

# With Sentiment (Tweet-based Model)
trainX_with_tweet = trainX
testX_with_tweet  = testX
trainY_with_tweet = trainY
testY_with_tweet  = testY
```

[163]:
```python
print(trainX_with_tweet.shape, trainY_with_tweet.shape)
```

```
(875, 5, 15) (875, 1, 1)
```

1.6.6 Random Seed

[164]:
```python
def set_all_seeds(seed=42):
    os.environ['PYTHONHASHSEED'] = str(seed)
    random.seed(seed)
    np.random.seed(seed)
```

```
    tf.random.set_seed(seed)
    tf.config.experimental.enable_op_determinism()  # TensorFlow 2.12+

    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed_all(seed)
        torch.backends.cudnn.deterministic = True
        torch.backends.cudnn.benchmark = False

set_all_seeds(seed=42)
```