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Does twitter affect stock prices

Index

Problem Statement

The project aims to utilize sentiment analysis techniques on tweets related to NVIDIA Corporation (NASDAQ: NVDA) to explore and establish correlations between the sentiments expressed in these tweets and the subsequent stock performance of NVIDIA. The goal is to leverage these findings to develop a predictive model that can assist in forecasting stock movements based on sentiment trends in social media.

The objectives of the project are as follows:

- Gather historical stock performance data for NVIDIA during Q1 2024.
- Collect a comprehensive dataset of tweets mentioning NVIDIA or related keywords over the same period.
- Implement sentiment analysis algorithms to quantify the sentiments expressed in these tweets as positive negative, or neutral.
- Conduct statistical analysis to identify correlations between sentiment trends in tweets and subsequent stock price movements.
- Use the findings to develop a predictive model.

Libraries used

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# For general data handling
import pandas as pd
import numpy as np
import os
from datetime import date

# For visualizations
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go

# For fetching stock data and tweets
import yfinance as yf
from twscrape import API, gather

# For processing textual data
import demoji
import re
import string
from nltk.corpus import stopwords,wordnet
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import TweetTokenizer
from nltk import pos_tag

# For sentiment analysis
from transformers import AutoModelForSequenceClassification
from transformers import AutoTokenizer, AutoConfig
from scipy.special import softmax
from tqdm import tqdm

# For LSTM
import torch
from torch import nn
from torch import optim
```

The reasoning behind the selection of certain libraries will be explained later in the project, when said libraries are utilized

Collection of data

Collecting stock data

In [3]:
```
# NVDA is the stock ticker of Nvidia on the NASDAQ
ticker = "NVDA"
start_date = "2024-01-01"
end_date = "2024-03-31"
# download the data from Yahoo Finance
data = yf.download(ticker, start=start_date, end=end_date)
# convert the downloaded data into csv files
data.to_csv(f"stock_data/{ticker}_{start_date[-5:]}-{end_date[-5:]}")
print("Data added to stock_data folder")
```

```
[*********************100%***********************]  1 of 1 completed
Data added to stock_data folder
```

Collecting tweets

To mine the tweets, the Python library **twscrape** was used. The library works through an authorised API, therefore twitter account(s) are needed in order to use it. A twitter username and password, and also the email associated with the twitter account and its password are needed to be able to collect tweets.

The library is designed to automatically switch accounts when the twitter API limit has been reached per 15-minute interval. So multiple accounts can be added to the API pool in order to change to a different account and continue scraping when the other accounts have reached their API limits.

The library makes use of **asynchronous programming**, allowing the program to continue executing even while some of the accounts have reached their API limits.

More information about this library can be found in this medium article

In [4]:
```
api = API()
```

The search range in the query spans over twelve weeks (from 2024-01-01 to 2024-01-04),for the program to fetch all the tweets at once, it would take a long time(-about 12 hours). To avoid this, a function was created which would take in the start date, end date and the directory to save the output, and return a dataframe of the scraped tweets.

The function is defined using async def. This is because twscrape uses a **coroutine function** to scrape tweets, so using the regular def for defining regular python functions will not work. i.e. async def is used to define coroutine functions in python.

In [5]:
```
async def scrape_tweets(company, start_date, end_date):

    data = []  #create an empty list to be used to store the search results

    #define the search query. Include start date and end date
    q = f"${company} until:{end_date} since:{start_date} lang:en"
    save_to_file = f"twitter_data/{company}_{start_date}-{end_date}"

    async for tweet in api.search(q, limit=300000): #iterate over the search res
        c = [tweet.id, tweet.date, tweet.rawContent, tweet.likeCount, tweet.retw
        data.append(c)  #add each new list of attributes to 'data'

    df = pd.DataFrame(data, columns=['Tweet_ID', 'Time_Created', 'Text', 'Likes'
    df.to_csv(save_to_file, index = False) #save to a chosen directory on the co
    return df
```

In [6]:
```
# This is an example of how the function works
nvidia_tweets = await scrape_tweets("NVDA", "2024-01-01", "2024-01-02")
nvidia_tweets
```

Out[6]:

	Tweet_ID	Time_Created	Text	Likes	Retweets	
0	1741971821996707934	2024-01-01 23:57:01+00:00	$BTC Hit 44,150\n\nRemember: The ONLY portfoli...	1	0	I
1	1741965702700097931	2024-01-01 23:32:42+00:00	$BTC I gave Profit Target before price got the...	4	1	I
2	1741971250354721272	2024-01-01 23:54:45+00:00	@zerohedge @zerohedge \n $META$GOOGL $AMZN$M...	0	0	
3	1741971091327709350	2024-01-01 23:54:07+00:00	$MULN will PARABOLIC next week 10000X incoming...	0	0	
4	1741388323216658564	2023-12-31 09:18:24+00:00	@Tony_Denaro Tony, what's your thoughts on MUL...	2	0	
...	...	...	...	...	...	
633	1741611770790428822	2024-01-01 00:06:18+00:00	$SPY Study Material I just put together for yo...	4	1	I
634	1741611370309963847	2024-01-01 00:04:42+00:00	"Most winning trading community, Get next winn...	0	0	
635	1741610940041482422	2024-01-01 00:03:00+00:00	#NewYear 🎄\nI wish everyone a happy, healthy a...	3	2	
636	1741610893933441225	2024-01-01 00:02:49+00:00	ALWAYS zoom out the chart to see what's really...	0	0	
637	1741610218797080965	2024-01-01 00:00:08+00:00	Glad I signed up for the 14-day FREE trial! Ba...	1	0	

638 rows × 6 columns

Data Cleaning

In [7]:

```
# Create an identifier containing the path to the folder
folder = "twitter_data"

# Read each file into a dataframe and store them in a list
dfs = []
count = 0
for file_name in os.listdir(folder):
    file_path = os.path.join(folder, file_name)
```

```
    df = pd.read_csv(file_path)
    dfs.append(df)

# Merge the dataframes
tweets = pd.concat(dfs, axis=0, ignore_index=True)
tweets.head()
```

Out[7]:

	Tweet_ID	Time_Created	Text	Likes	Retweets	
0	1741971821996707934	2024-01-01 23:57:01+00:00	$BTC Hit 44,150\n\nRemember: The ONLY portfoli...	1	0	Im
1	1741965702700097931	2024-01-01 23:32:42+00:00	$BTC I gave Profit Target before price got the...	4	1	Im
2	1741971250354721272	2024-01-01 23:54:45+00:00	@zerohedge @zerohedge \n $META$GOOGL $AMZN$M...	0	0	
3	1741971091327709350	2024-01-01 23:54:07+00:00	$MULN will PARABOLIC next week 10000X incoming...	0	0	
4	1741388323216658564	2023-12-31 09:18:24+00:00	@Tony_Denaro Tony, what's your thoughts on MUL...	2	0	

In [8]:
```
tweets.shape
```

Out[8]: `(287697, 6)`

In [9]:
```
# Dropping duplicates
tweets = tweets.drop_duplicates(subset=['Tweet_ID'], keep='first').reset_index(d
tweets.shape
```

Out[9]: `(270337, 6)`

In [10]:
```
# Return the number of missing values in each column of the dataset
tweets.isnull().sum()
```

Out[10]:
```
Tweet_ID            0
Time_Created        0
Text                0
Likes               0
Retweets            0
Location       116479
dtype: int64
```

The location attribute was not very useful since around 50% of its values were missing. Additionaly, location is just a string entered by the users and is not always an actual place. Many enteries in this dataframe also had location attribute values like "Milky Way" and other jokes. For these reasons, the location attribute was dropped.

In [11]:
```
# Drop the location attribute
tweets  = tweets.drop("Location", axis = 1)
tweets.head()
```

Out[11]:

	Tweet_ID	Time_Created	Text	Likes	Retweets
0	1741971821996707934	2024-01-01 23:57:01+00:00	$BTC Hit 44,150\n\nRemember: The ONLY portfoli...	1	0
1	1741965702700097931	2024-01-01 23:32:42+00:00	$BTC I gave Profit Target before price got the...	4	1
2	1741971250354721272	2024-01-01 23:54:45+00:00	@zerohedge @zerohedge \n $META$GOOGL $AMZN$M...	0	0
3	1741971091327709350	2024-01-01 23:54:07+00:00	$MULN will PARABOLIC next week 10000X incoming...	0	0
4	1741388323216658564	2023-12-31 09:18:24+00:00	@Tony_Denaro Tony, what’s your thoughts on MUL...	2	0

The **'Time_Created'** attribute contained a timestamp in the ISO 8601 standard notation. It contained information like, time and UTC offset which were not required for this project. Hence, the attribute was converted to dates.

In [12]:
```
# Convert the time created attribute to dates
tweets['Time_Created'] = pd.to_datetime(tweets['Time_Created']).dt.date
tweets.head()
```

Out[12]:

	Tweet_ID	Time_Created	Text	Likes	Retweets
0	1741971821996707934	2024-01-01	$BTC Hit 44,150\n\nRemember: The ONLY portfoli...	1	0
1	1741965702700097931	2024-01-01	$BTC I gave Profit Target before price got the...	4	1
2	1741971250354721272	2024-01-01	@zerohedge @zerohedge \n$META$ GOOGL $AMZN$M...	0	0
3	1741971091327709350	2024-01-01	$MULN will PARABOLIC next week 10000X incoming...	0	0
4	1741388323216658564	2023-12-31	@Tony_Denaro Tony, what's your thoughts on MUL...	2	0

Any tweets that were fetched but lied outside the dersired range were removed

In [13]:

```
# Define the start and end dates of the range
start_date = date(2024, 1, 1)
end_date = date(2024, 3, 31)
# Filter the DataFrame based on the date range
filtered_tweets = tweets[(tweets['Time_Created'] >= start_date) & (tweets['Time_
filtered_tweets.shape
```

Out[13]: (269209, 5)

In [14]:

```
# This function is used to pass the POS tag for each word passed through clean_t
def get_wordnet_pos(word):
    """Map POS tag to first character lemmatize() accepts"""
    tag = pos_tag([word])[0][1][0].upper()
    tag_dict = {"J": wordnet.ADJ,
                "N": wordnet.NOUN,
                "V": wordnet.VERB,
                "R": wordnet.ADV}

    return tag_dict.get(tag, wordnet.NOUN)
```

The following function was used to clean the tweets and make them more suitable to be used as an input in the sentiment analysis model. The function makes use of libraries like **re** (A python library used for regular expressions) and **nltk** (A python library used for NLP tasks)

In [15]:

```
# Cleaning tweets
def clean_text(text):
    # Initialization the twitter tokenizer
    tk = TweetTokenizer(preserve_case=False, strip_handles=True,reduce_len=True)
    # Initialization the Lemmatizer
    lemmatizer = WordNetLemmatizer()
    # Trying to avoid deleting the negative verbs as it affects the meaning of t
```

```
    stop_words = stopwords.words('english') + ["i'll","i'm", "should", "could"]
    negative_verbs = [ "shan't",'shouldn',"shouldn't",'wasn','weren','won','woul
    stop_words =[word for word in stop_words if word not in negative_verbs ]

    # Lowering tweets
    lower_tweet = text.lower()
    # Removing hashtag and cashtag symbols
    tweet = re.sub(r"[#$]"," ",lower_tweet)
    # Removing links from tweets
    tweet = re.sub(r"https?:\/\/.*[\r\n]*"," ", tweet)
    # Translating emojies into thier descriptions
    tweet = demoji.replace_with_desc(tweet)
    # removing numerical values
    tweet = re.sub(r"[0-9]|-->","",tweet)
    # Tokenize the tweets by twitter tokenzier.
    tweet = tk.tokenize(tweet)
    # Choosing the words that don't exist in stopwords, thier lengths are more t
    tweet = [lemmatizer.lemmatize(word, get_wordnet_pos(word)) for word in tweet
    # return the tokens in one sentence
    tweet = " ".join(tweet)

    return tweet
```

In [ ]:

```
# Applying text cleaning
filtered_tweets['cleaned'] = filtered_tweets["Text"].apply(lambda row:clean_text
# Sorting the dataframe based on 'Time_Created'
filtered_tweets.sort_values(by = 'Time_Created', inplace = True)
# Saving to a csv file
filtered_tweets.to_csv("twitter_data/NVDA_final-tweets")
print("Filtered tweets added to the folder")
```

Sentiment Analysis

RoBERTa stands for "A Robustly Optimized BERT Pretraining Approach." It's a variant of the BERT (Bidirectional Encoder Representations from Transformers). The reasons it is used commonly for sentiment analysis are:

- RoBERTa's ability to understand context and capture nuanced semantics makes it effective for sentiment analysis tasks where context plays a crucial role in determining sentiment (e.g., understanding sarcasm, negation, or sentiment shift within a sentence).
- RoBERTa can be fine-tuned on sentiment analysis datasets, where the model learns to predict sentiment labels (e.g., positive, negative, neutral) based on text inputs. Fine-tuning allows RoBERTa to adapt its pre-trained knowledge to specific sentiment analysis tasks, leading to improved accuracy and performance.

The model that has been used for sentiment analysis is the Twitter roBERTa model that is available at this link
This model that been trained on over 124 million tweets from the time period of January 2018 to December 2021, making it a great fit for the project

In [17]:

```
MODEL = "cardiffnlp/twitter-roberta-base-sentiment-latest"
tokenizer = AutoTokenizer.from_pretrained(MODEL)
```

```
config = AutoConfig.from_pretrained(MODEL)
# PT
model = AutoModelForSequenceClassification.from_pretrained(MODEL)
```

```
Some weights of the model checkpoint at cardiffnlp/twitter-roberta-base-sentiment
-latest were not used when initializing RobertaForSequenceClassification: ['rober
ta.pooler.dense.bias', 'roberta.pooler.dense.weight']
- This IS expected if you are initializing RobertaForSequenceClassification from
the checkpoint of a model trained on another task or with another architecture
(e.g. initializing a BertForSequenceClassification model from a BertForPreTrainin
g model).
- This IS NOT expected if you are initializing RobertaForSequenceClassification f
rom the checkpoint of a model that you expect to be exactly identical (initializi
ng a BertForSequenceClassification model from a BertForSequenceClassification mod
el).
```

The **Softmax** function is a mathematical function that converts a vector of numbers into a probability distribution. Given an input vector z=[z_1,z_2,...,z_n] , the softmax function computes the probability p_i for each element z_i as follows:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

- e is the base of the natural logarithm.
- z_i is the i-th element of the input vector.
- $\sum_{j=1}^{n} e^{z_j}$ is the sum of the exponentiated values of all elements in the input vector.

It has been used here as the activation function because:

- The softmax function is well-suited for sentiment analysis because it produces output probabilities that represent the likelihood of each class, allowing the model to make predictions across multiple classes.
- Softmax ensures that the output probabilities sum up to 1, forming a valid probability distribution.
- Softmax is a differentiable function, which means that gradients can be computed with respect to its inputs. This property is crucial for training the RoBERTa model using gradient-based optimization algorithms

In [18]:
```
def sentiment_analysis(text):
    encoded_input = tokenizer(text, return_tensors='pt',truncation=True, max_len
    output = model(**encoded_input)
    scores = output[0][0].detach().numpy()
    scores = softmax(scores)
    return scores.argmax()
```

In [19]:
```
#This is a sample run
print(f'For a positive statement : {sentiment_analysis("I like these stocks")}')
print(f'For a neutral statement : {sentiment_analysis("I do not know about these
print(f'For a negative statement : {sentiment_analysis("I hate these stocks")}')
```

```
For a positive statement : 2
For a neutral statement : 1
For a negative statement : 0
```

The function was then applied to all the tweets in the data set with the following code:

```
#tqdm was used here to get a progress bar for the sentiment
analysis
tqdm.pandas()
filtered_tweets['cleaned'] = tweets['cleaned'].fillna("")
tweets['sentiment'] = tweets['cleaned'].progress_apply(lambda x:
sentiment_analysis(x))
tweets.to_csv('analysed_tweets.csv')
```

The code has not been executed in the notebook as its execution takes around 6 hours

Vizualization

In [20]:
```
df = pd.read_csv("twitter_data/analysed_tweets.csv", index_col = 0)
df.head()
```

Out[20]:

	Tweet_ID	Time_Created	Text	Likes	Retweets	clea
0	1741926827688681728	2024-01-01	Our analyst called the PUMP on $FLJ, securing ...	0	0	analyst pum secure memb
1	1741855632767004892	2024-01-01	Stocks Performance Upto 1Y\n\nEverything is aw...	0	0	s performa u everytl awes ts
2	1741856010761802082	2024-01-01	Were you invested in $NVDA pre 2021? \n\nIf th...	14	2	invest r pre ans yes make tl go
3	1741856822917513633	2024-01-01	Top 3 Bearish Sentiment Cryptos: CROWD\n\n 🟥 $...	0	0	top bea sentim cry crowd squa
4	1741856927926100073	2024-01-01	$nvda Top analyst price target for next week:....	0	0	nvda analyst p target w

For the use-case of this project, it would be more suitable if the sentiment was represented by:
{Postive : 1, Neutral : 0, Negative : -1}

In [21]:
```
df['sentiment'] = df['sentiment'].apply(lambda x: x - 1)
df.head()
```

Out[21]:

	Tweet_ID	Time_Created	Text	Likes	Retweets	clea
0	1741926827688681728	2024-01-01	Our analyst called the PUMP on $FLJ, securing ...	0	0	analyst pum secure memb
1	1741855632767004892	2024-01-01	Stocks Performance Upto 1Y\n\nEverything is aw...	0	0	s performa u everytl aweso ts
2	1741856010761802082	2024-01-01	Were you invested in $NVDA pre 2021? \n\nIf th...	14	2	invest r pre ans yes make tl go
3	1741856822917513633	2024-01-01	Top 3 Bearish Sentiment Cryptos: CROWD\n\n 🟥 $...	0	0	top bea sentim cry crowd squa
4	1741856927926100073	2024-01-01	$nvda Top analyst price target for next week:....	0	0	nvda analyst p target w

In [22]:
```
sentiment_df = pd.DataFrame(df.groupby("Time_Created")['sentiment'].mean())
sentiment_df.rename(columns = {"sentiment":"sen_mean"}, inplace = True)
sentiment_df['twt_volume'] = df.groupby(['Time_Created'])['sentiment'].count()
sentiment_df['sen_sum'] = df.groupby('Time_Created')['sentiment'].sum()
sentiment_df.head()
```

Out[22]:

	sen_mean	twt_volume	sen_sum
Time_Created			
2024-01-01	0.166667	636	106
2024-01-02	0.083774	1325	111
2024-01-03	0.102433	1562	160
2024-01-04	0.138872	1649	229
2024-01-05	0.143971	2181	314

In [23]:
```
nvda_stocks = pd.read_csv("stock_data/NVDA_01-01-03-31")
nvda_stocks.head()
```

Out[23]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2024-01-02	492.440002	492.950012	475.950012	481.679993	481.657410	41125400
1	2024-01-03	474.850006	481.839996	473.200012	475.690002	475.667694	32089600
2	2024-01-04	477.670013	485.000000	475.079987	479.980011	479.957489	30653500
3	2024-01-05	484.619995	495.470001	483.059998	490.970001	490.946960	41456800
4	2024-01-08	495.119995	522.750000	494.790009	522.530029	522.505493	64251000

In [24]:
```
final_df = pd.merge(nvda_stocks, sentiment_df, left_on = "Date", right_on = "Tim
final_df.head()
```

Out[24]:

	Date	Open	High	Low	Close	Adj Close	Volume	se
0	2024-01-02	492.440002	492.950012	475.950012	481.679993	481.657410	41125400	(
1	2024-01-03	474.850006	481.839996	473.200012	475.690002	475.667694	32089600	(
2	2024-01-04	477.670013	485.000000	475.079987	479.980011	479.957489	30653500	(
3	2024-01-05	484.619995	495.470001	483.059998	490.970001	490.946960	41456800	(
4	2024-01-08	495.119995	522.750000	494.790009	522.530029	522.505493	64251000	(

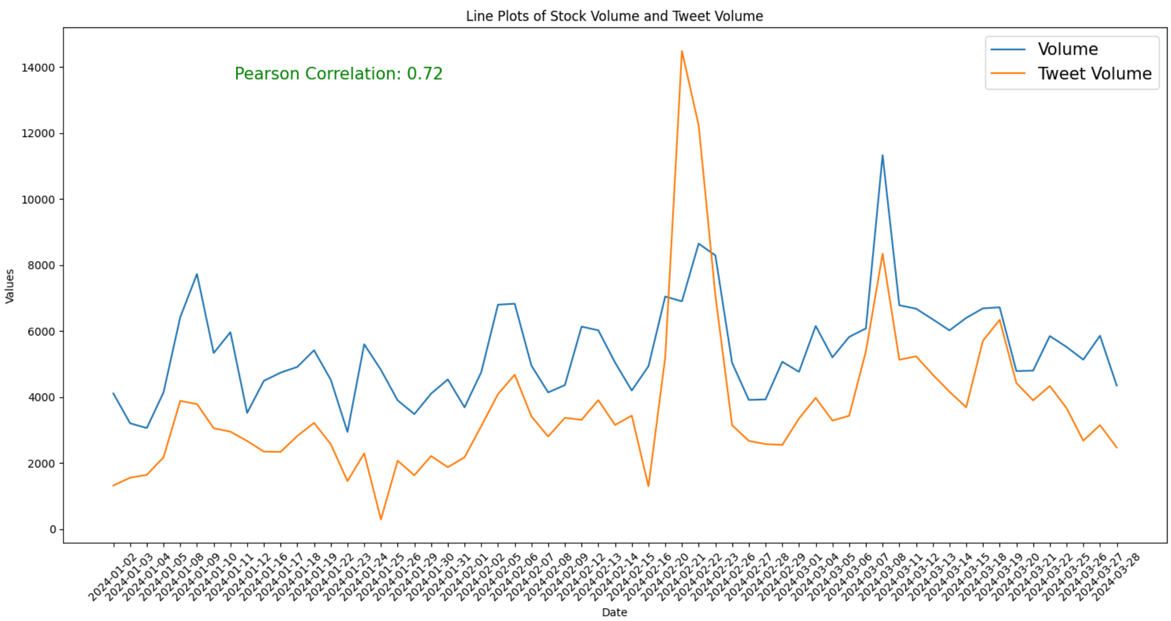
In [25]:
```
#Saving the data in a csv file
final_df.to_csv("NVDA_final")
```

The **candlestick** graph representing the performance of NVDA in Q1 2024

In [26]:
```
fig = go.Figure(data=[go.Candlestick(x= nvda_stocks['Date'],
                open= nvda_stocks['Open'],
                high= nvda_stocks['High'],
                low= nvda_stocks['Low'],
                close= nvda_stocks['Close'])])
fig.update_layout(title = {'text' : "Nvidia(NVDA) Q1 2024",
                           'y':0.9,
                           'x':0.5,
                           'xanchor': 'center',
                           'yanchor': 'top'},
                  xaxis_title = "Dates",
                  yaxis_title = "Price",
                  xaxis_rangeslider_visible = False)
fig.show()
```

The **correlation** between **volume of tweets** and **volume of trades**

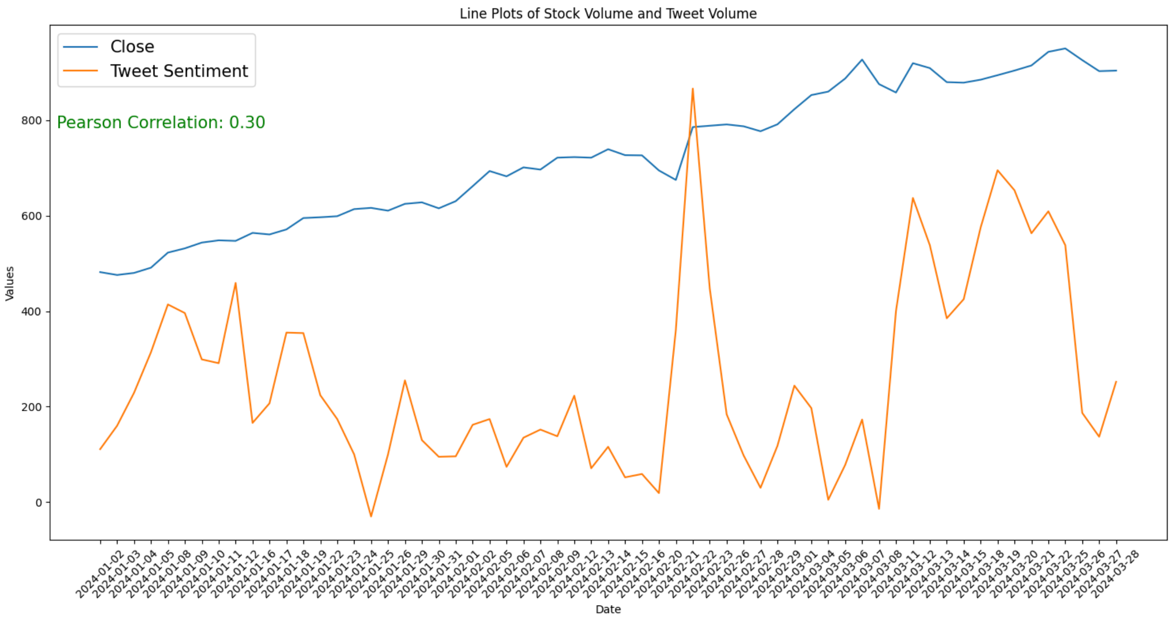
In [27]:
```
plt.figure(figsize = (15,8))
# Volume was divided by 10000 to make the ranges of the attributes similar
sns.lineplot(data=final_df, x='Date', y=final_df['Volume']/10000, label='Volume'
sns.lineplot(data=final_df, x='Date', y=final_df['twt_volume'], label='Tweet Vol
# Add labels and title
plt.xlabel('Date')
plt.ylabel('Values')
plt.title('Line Plots of Stock Volume and Tweet Volume')
plt.xticks(rotation=45)
plt.tight_layout()
plt.legend(fontsize = 15)
pearson_corr = final_df['Volume'].corr(final_df['twt_volume'], method='pearson')

# Display correlation coefficients on the plot
plt.annotate(f"Pearson Correlation: {pearson_corr:.2f}", xy=(0.25, 0.9), xycoord
# Show the plot
plt.show()
```



The number of tweets about NVIDIA on a specific day have a **very high correlation** with the number of stock traded for NVDA

The **correlation** between **mean sentiment** and **stock close**

In [28]:
```
plt.figure(figsize = (15,8))
sns.lineplot(data=final_df, x='Date', y=final_df['Close'], label='Close')
sns.lineplot(data=final_df, x='Date', y=final_df['sen_sum'], label='Tweet Sentim
# Add labels and title
plt.xlabel('Date')
plt.ylabel('Values')
plt.title('Line Plots of Stock Volume and Tweet Volume')
plt.xticks(rotation=45)
plt.tight_layout()
plt.legend(fontsize = 15)
pearson_corr = final_df['Close'].corr(final_df['sen_sum'], method='pearson')

# Display correlation coefficients on the plot
plt.annotate(f"Pearson Correlation: {pearson_corr:.2f}", xy=(0.1, 0.80), xycoord
# Show the plot
plt.show()
```



The correlation between twitter sentiment and the closing price of the stock is very low. This suggests that the twitter sentiment will not significantly improve the performance of the predictive model.

Applying LSTM

The deep learning model that has been used in this project for stock prediction is **LSTM (Long Short-Term Memory)**.
Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is designed to overcome the limitations of traditional RNNs in capturing long-range dependencies and handling vanishing or exploding gradients. LSTMs are widely used in various sequence modeling tasks, including time series analysis, and financial forecasting, such as stock analysis.

The advantages that LSTM provides for stock prediction are as follows:

- LSTMs are equipped with memory cells that allow them to remember information over long sequences. This is crucial for analyzing time series data like stock prices, where past prices and trends can have a significant impact on future movements.
- LSTMs are well-suited for capturing time dependencies and learning patterns in sequential data.
- LSTMs address the issue of vanishing gradient by using gating mechanisms (such as the forget gate, input gate, and output gate) to regulate the flow of information and gradients within the network.
- LSTMs are adaptable and can be customized based on the specific requirements of the stock analysis task. For example, the network architecture, hyperparameters, and training data can be adjusted to optimize performance and accuracy.

In [29]:
```
def assign_symbol(x):
    if x == 1:
        return 'pos'
    elif x == 0:
        return 'nue'
    else:
        return 'neg'
```

In [30]:
```
train_dates = pd.to_datetime(final_df['Date'])

#Variables for training
cols = [
    'Open',
    'High', 'Low',
    'Close',
    'Volume',
    'Adj Close',
    'sen_mean',
    'twt_volume'
        ]
#Date and volume columns are not used in training.

#New dataframe with only training data - 5 columns
df_for_training = final_df[cols].astype(float)
df_for_training.index=final_df['Date']
df_for_training
```

Out[30]:

Date	Open	High	Low	Close	Volume	Adj Close	sen
2024-01-02	492.440002	492.950012	475.950012	481.679993	41125400.0	481.657410	0.(
2024-01-03	474.850006	481.839996	473.200012	475.690002	32089600.0	475.667694	0.'
2024-01-04	477.670013	485.000000	475.079987	479.980011	30653500.0	479.957489	0.'
2024-01-05	484.619995	495.470001	483.059998	490.970001	41456800.0	490.946960	0.'
2024-01-08	495.119995	522.750000	494.790009	522.530029	64251000.0	522.505493	0.'
...	...	...	...	...	...	...	
2024-03-22	911.409973	947.780029	908.340027	942.890015	58521500.0	942.890015	0.'
2024-03-25	939.409973	967.659973	935.099976	950.020020	55213600.0	950.020020	0.'
2024-03-26	958.510010	963.750000	925.020020	925.609985	51364800.0	925.609985	0.(
2024-03-27	931.119995	932.400024	891.229980	902.500000	58606700.0	902.500000	0.(
2024-03-28	900.000000	913.000000	891.929993	903.559998	43521200.0	903.559998	0.'

61 rows × 8 columns

In [31]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler = scaler.fit(df_for_training)
df_for_training_scaled = scaler.transform(df_for_training)

scaler_for_inference = MinMaxScaler()
scaler_for_inference.fit_transform(df_for_training.loc[:,['Open','Adj Close']])
```

```
Out[31]: array([[0.03636852, 0.01262714],
       [0.        , 0.        ],
       [0.00583056, 0.00904348],
       [0.02020012, 0.0322108 ],
       [0.04190958, 0.09874053],
       [0.10164166, 0.11743893],
       [0.12676253, 0.14294605],
       [0.15535704, 0.15289602],
       [0.147521  , 0.15053504],
       [0.15574988, 0.1857815 ],
       [0.18322781, 0.17884603],
       [0.20210472, 0.20106472],
       [0.21717737, 0.25132034],
       [0.25976922, 0.25475648],
       [0.24986562, 0.25937305],
       [0.2650415 , 0.29076171],
       [0.30734399, 0.29613718],
       [0.27860474, 0.28378416],
       [0.28422859, 0.3140135 ],
       [0.31871561, 0.32052731],
       [0.28852917, 0.29424006],
       [0.30217507, 0.32586071],
       [0.34092127, 0.39190548],
       [0.42881361, 0.45877246],
       [0.45786292, 0.43539431],
       [0.43075713, 0.47494106],
       [0.46704293, 0.46528627],
       [0.47653312, 0.51781871],
       [0.51926972, 0.52024286],
       [0.47378322, 0.51771333],
       [0.53171652, 0.55506767],
       [0.54550716, 0.52888592],
       [0.55028324, 0.52793723],
       [0.50576844, 0.46130212],
       [0.42428563, 0.41956282],
       [0.56940825, 0.65283847],
       [0.6886036 , 0.65871987],
       [0.66606705, 0.66451699],
       [0.65947151, 0.65627461],
       [0.62306166, 0.63439316],
       [0.6535376 , 0.66493864],
       [0.67226976, 0.73170024],
       [0.7576603 , 0.79405603],
       [0.78123062, 0.80946651],
       [0.83813001, 0.86714512],
       [0.88229336, 0.95081711],
       [0.98525823, 0.84243781],
       [0.80519367, 0.805461  ],
       [0.8386883 , 0.9348796 ],
       [0.90083939, 0.91327119],
       [0.8702808 , 0.85120761],
       [0.8155522 , 0.84895189],
       [0.88704874, 0.86198016],
       [0.81079682, 0.88185988],
       [0.87482935, 0.90239312],
       [0.92658064, 0.92480264],
       [0.90261747, 0.98496897],
       [0.96050937, 1.        ],
       [1.        , 0.94854029],
```

```
       [0.94336928, 0.89982126],
       [0.87902657, 0.90205588]])
```

In [32]:
```
df_for_training_scaled.shape
```

Out[32]:
```
(61, 8)
```

In [33]:
```
#Empty lists to be populated using formatted training data
trainX = []
trainY = []

n_future = 1   # Number of days we want to look into the future based on the pas
n_past = 5  # Number of past days we want to use to predict the future.

#Reformat input data into a shape: (n_samples x timesteps x n_features)
for i in range(n_past, len(df_for_training_scaled) - n_future +1):
    trainX.append(df_for_training_scaled[i - n_past:i, 0:df_for_training.shape[1
    trainY.append(df_for_training_scaled[i + n_future - 1:i + n_future,[0,-2]])

trainX, trainY = np.array(trainX), np.array(trainY)

print(f'TrainX shape = {trainX.shape}')
print(f'TrainY shape = {trainY.shape}')
```

```
TrainX shape = (56, 5, 8)
TrainY shape = (56, 1, 2)
```

In [34]:
```
from sklearn.model_selection import train_test_split

X_train_lstm_without_twitter, X_test_lstm_without_twitter, y_train_lstm_without_

X_train_lstm_twitter, X_test_lstm_twitter, y_train_lstm_twitter, y_test_lstm_twi

X_train_lstm_without_twitter.shape,X_train_lstm_twitter.shape
```

Out[34]:
```
((50, 5, 6), (50, 5, 8))
```

Stock Prediction with twitter sentiment

In [35]:
```
x_train = torch.from_numpy(X_train_lstm_twitter).type(torch.Tensor)
x_test = torch.from_numpy(X_test_lstm_twitter).type(torch.Tensor)
y_train_lstm = torch.from_numpy(y_train_lstm_twitter).type(torch.Tensor)
y_test_lstm = torch.from_numpy(y_test_lstm_twitter).type(torch.Tensor)
```

In [36]:
```
input_dim = 8
hidden_dim = 32
num_layers = 2
output_dim = 1
num_epochs = 512
```

In [37]:
```
class LSTM(nn.Module):
    def __init__(self, input_dim, hidden_dim, num_layers, output_dim):
        super(LSTM, self).__init__()
        self.hidden_dim = hidden_dim
        self.num_layers = num_layers

        self.lstm = nn.LSTM(input_dim, hidden_dim, num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)
    def forward(self, x):
```

```
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_g
        c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_g
        out, (hn, cn) = self.lstm(x, (h0.detach(), c0.detach()))
        out = self.fc(out[:, -1, :])
        return out
```

In [38]:

```
model = LSTM(input_dim=input_dim, hidden_dim=hidden_dim, output_dim=output_dim,
criterion = torch.nn.MSELoss(reduction='mean')
optimiser = torch.optim.Adam(model.parameters(), lr=0.01)
```

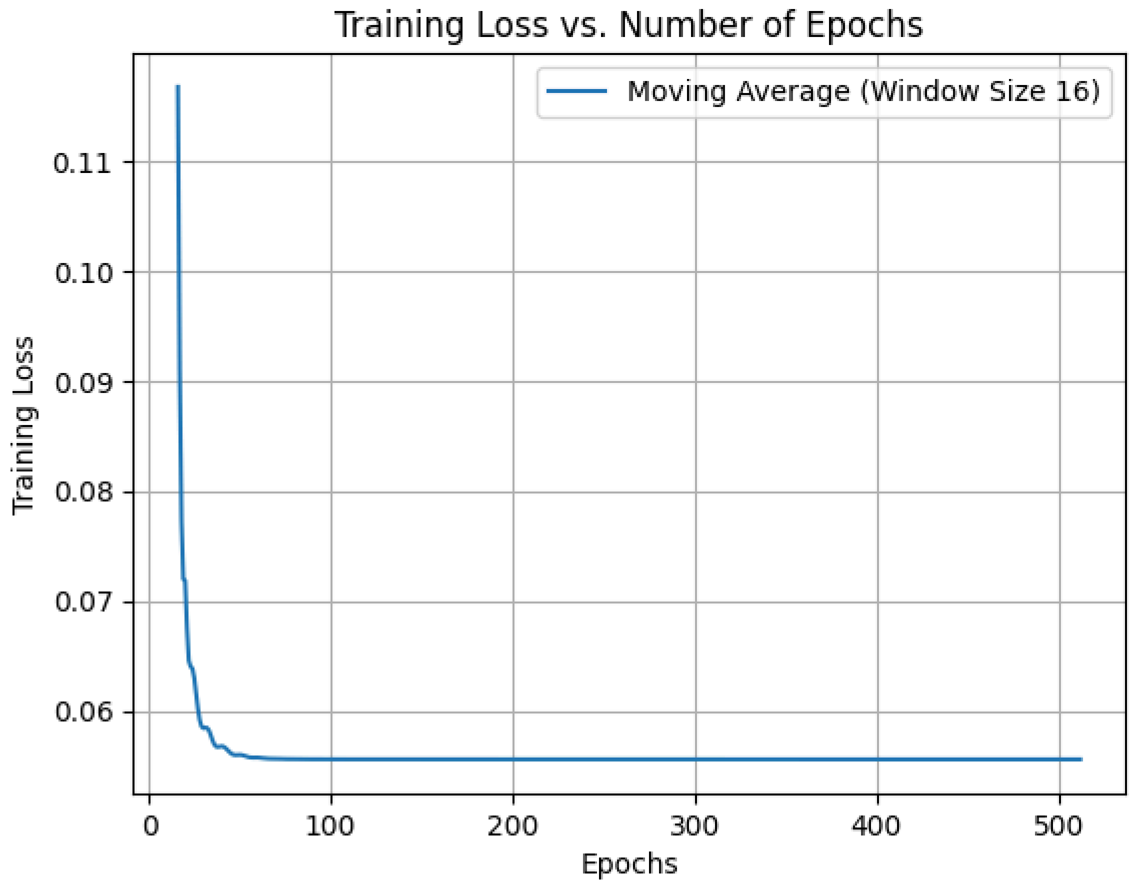
In [39]:

```
import time
hist = np.zeros(num_epochs)
start_time = time.time()
lstm = []
for t in range(num_epochs):
    y_train_pred = model(x_train)
    loss = criterion(y_train_pred, y_train_lstm)
    # print("Epoch ", t, "MSE: ", loss.item())
    hist[t] = loss.item()
    optimiser.zero_grad()
    loss.backward()
    optimiser.step()
print(f'MSE for training: {loss.item():.3f}')
training_time = time.time()-start_time
print(f"Training time: {training_time:.3f}")
```

```
MSE for training: 0.056
Training time: 2.043
```

In [40]:

```
window_size = 16
moving_avg = np.convolve(hist, np.ones(window_size)/window_size, mode='valid')
sns.lineplot(x = range(window_size, num_epochs + 1), y = moving_avg, label = f'M
plt.xlabel('Epochs')
plt.ylabel('Training Loss')
plt.title('Training Loss vs. Number of Epochs')
plt.legend()
plt.grid(True)
plt.show()
```



In [41]:
```
y_test_pred = model(x_test)
loss = criterion(y_test_pred, y_test_lstm)
print(f'MSE for testing with twitter: {loss.item():.3f}')
```

```
MSE for testing with twitter: 0.042
```

Stock prediction without twitter sentiment

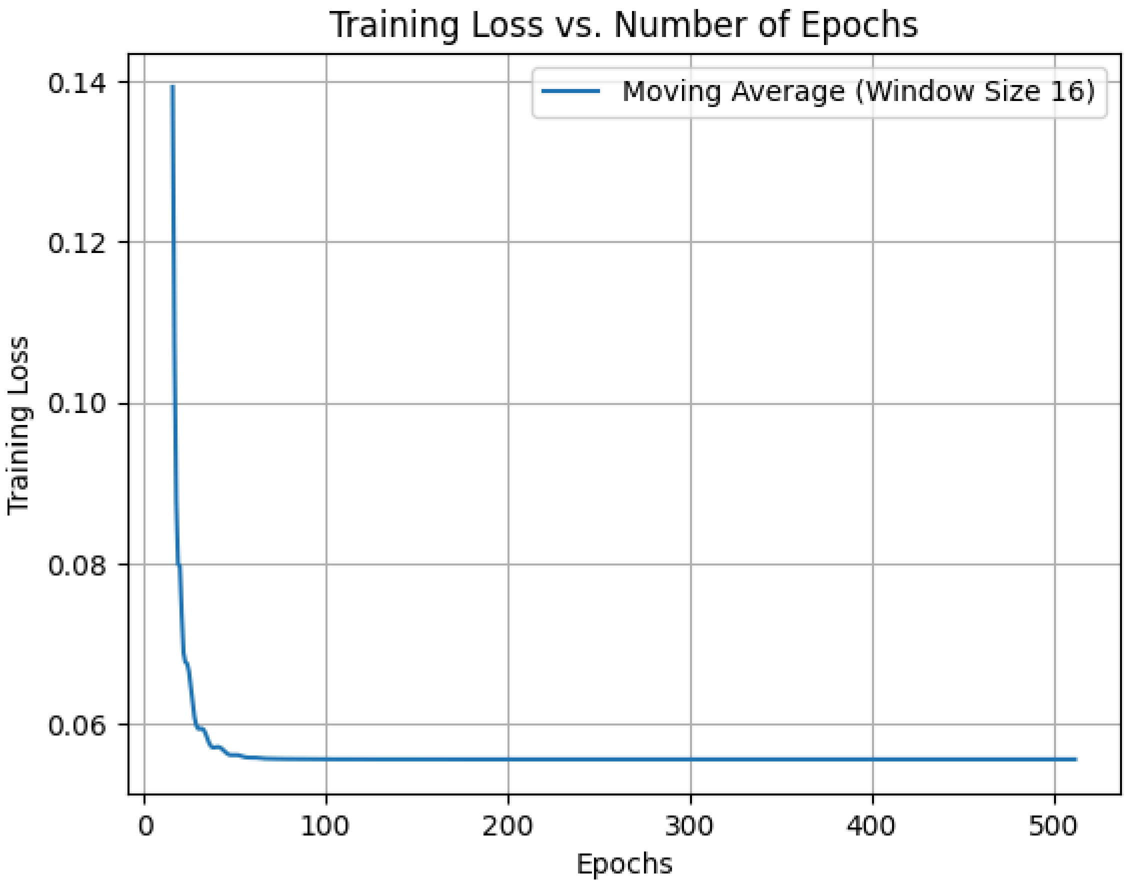
In [42]:
```
x_train = torch.from_numpy(X_train_lstm_without_twitter).type(torch.Tensor)
x_test = torch.from_numpy(X_test_lstm_without_twitter).type(torch.Tensor)
y_train_lstm = torch.from_numpy(y_train_lstm_without_twitter).type(torch.Tensor)
y_test_lstm = torch.from_numpy(y_test_lstm_without_twitter).type(torch.Tensor)
input_dim = 6
hidden_dim = 32
num_layers = 2
output_dim = 1
num_epochs = 512
class LSTM(nn.Module):
    def __init__(self, input_dim, hidden_dim, num_layers, output_dim):
        super(LSTM, self).__init__()
        self.hidden_dim = hidden_dim
        self.num_layers = num_layers

        self.lstm = nn.LSTM(input_dim, hidden_dim, num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)
    def forward(self, x):
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_g
        c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_g
        out, (hn, cn) = self.lstm(x, (h0.detach(), c0.detach()))
        out = self.fc(out[:, -1, :])
        return out
model = LSTM(input_dim=input_dim, hidden_dim=hidden_dim, output_dim=output_dim,
```

```
criterion = torch.nn.MSELoss(reduction='mean')
optimiser = torch.optim.Adam(model.parameters(), lr=0.01)
import time
hist = np.zeros(num_epochs)
start_time = time.time()
lstm = []
for t in range(num_epochs):
    y_train_pred = model(x_train)
    loss = criterion(y_train_pred, y_train_lstm)
    hist[t] = loss.item()
    optimiser.zero_grad()
    loss.backward()
    optimiser.step()
print(f'MSE for training: {loss.item():.3f}')
training_time = time.time()-start_time
print(f"Training time: {training_time:.3f}")
y_test_pred = model(x_test)
loss = criterion(y_test_pred, y_test_lstm)
print(f'MSE for testing without twitter: {loss.item():.3f}')
```

```
MSE for training: 0.056
Training time: 1.776
MSE for testing without twitter: 0.042
```

In [43]:

```
window_size = 16  # Adjust window size as needed
moving_avg = np.convolve(hist, np.ones(window_size)/window_size, mode='valid')
sns.lineplot(x = range(window_size, num_epochs + 1), y = moving_avg, label = f'M
plt.xlabel('Epochs')
plt.ylabel('Training Loss')
plt.title('Training Loss vs. Number of Epochs')
plt.legend()
plt.grid(True)
plt.show()
```



Conclusions

- The testing error for the prediction is very small (0.042). However as mentioned previously in the visualization section, given the low correlation between the twitter sentiment and the closing price, the twitter sentiment fails to meaningfully improve the predictions made by the LSTM model.
- The project is limited to only the first quater of 2024 of only one company, the improvements from the sentiment maybe more noticeable for different companies or for NVIDIA over a longer period of time.
- Further research, with a wider scope needs to be performed to definitively prove or disprove the viability of using twitter sentiment to predict stock movements.