SOCIAL MEDIA BASED STOCK MARKET ANALYSIS USING BIG-DATA INFRASTRUCTURE

A PROJECT REPORT

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in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

Department of Computer Science and Engineering

Sri Sivasubramaniya Nadar College of Engineering

(An Autonomous Institution, Affiliated to Anna University)

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June 2022

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Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ACKNOWLEDGEMENTS

I thank GOD, the almighty for giving me strength and knowledge to do this project.

I would like to thank and deep sense of gratitude to my guide **Dr. N. SUJAUDEEN**, Assistant Professor, Department of Computer Science and Engineering, for his valuable advice and suggestions as well as his continued guidance, patience and support that helped me to shape and refine my work.

My sincere thanks to **Dr. T.T. MIRNALINEE**, Professor and Head of the Department of Computer Science and Engineering, for her words of advice and encouragement.

I express my deep respect to the founder **Dr. SHIV NADAR**, Chairman, SSN Institutions. I also express my appreciation to our **Dr. V. E. ANNAMALAI**, Principal, for all the help he has rendered during this course of study.

I would like to extend my sincere thanks to all the teaching and non-teaching staffs of our department who have contributed directly and indirectly during the course of my project work. Finally, I would like to thank my parents and friends for their patience, cooperation and moral support throughout my life.

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ABSTRACT

There are several factors that influence the value of a stock apart from the typical quantitative and qualitative parameters seen in the fundamental analysis of stocks like balance sheets, income statements, cash flow statements etc. In recent years, one such factor that has gained prominence is social media trends. It has been observed that industry-relevant social media posts that gain heavy traction from the public has the effect of swinging the respective market's stock price suddenly.

The aim of this research is to analyze and understand the effect of such articles over the value of a stock at any given time. Towards the realization of this objective, we consider Twitter, a popularly used micro-blogging platform as our social media source. We perform sentiment analysis on collected Tweets, and measure their correlation to stocks of companies within the relevant sector the Tweet appeals to. Since Tweet & stock market data are voluminous in nature, we propose to build an architecture using tools like Apache Spark & Apache Kafka, which provide us with efficient large-scale data processing capabilities.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Stock market analysis has been a topic of great interest ever since public stock exchanges came into existence. It is an avenue that offers great profit, which by itself is a stimulus for most researchers who work in this realm. The task is also considerably demanding due to these returns as well as high randomness and various external influences affecting the current valuation of a stock.[4]

In recent years, social media has transformed in a revolutionary manner from a niche utility to an ubiquitous means of information exchange throughout the world. People have started utilizing social media as a tool not only for the purpose of socialising, but also as a means to consume news, share their opinions, create awareness, follow the ideas of popular personalities and luminaries, among many others.

The architecture of social media provides the avenue for interesting ideas to disseminate among society in near-instant time. In such an age, such sudden outbursts of information about a company or its product can make or break the valuation of that product or company - since information travels fast and people tend to react towards sensational articles.

To highlight the severity of social media trends towards the stock market, we could consider the example of the Tweet posted by Elon Musk, the CEO of Tesla Motors,

on 27 Jan 2021 towards a declining video-game retail company, GameStop. His Tweet about the company immediately raised the company's stock value by more than 60% within hours. Such is the influence of social media on an already volatile stock market. Hence, it is worthwhile to consider understanding the relationship between social media trends and the stock market.

1.2 MOTIVATION

Understanding the different factors that influence the stock market is essential towards making informed investing decisions in it. The stock market, as a whole, is an intricately large and complex entity that is hard to predict. But, it is possible to understand how certain factors influence the market. Our area of research delves into understanding how social media affects the stock market.

The sentiments expressed by such social media posts & news articles cause a lot of volatility in the share market, leading to unexpected fluctuations of the stock value.

Since social media is inherently voluminous with a high degree of velocity, i.e. millions of people posting their ideas and opinions simultaneously on the same platform, it is difficult to wrangle and analyse meaningful patterns from it with the use of traditional methods. Hence, the usage of a big-data architecture is justified.

Another significant reason for exploring this area is the fact that the internet is a rapidly growing community. Even though a good portion of the world's population was online in 2017, there has been an increase of nearly 70 million users on Twitter between 2017 and 2021. This gives yet another reason to explore the possibility

that there could be statistically significant correlation between social media and stock prices.

Apache Kafka is a robust, fault-tolerant, high-performance data streaming pipeline that can ingest and stream thousands of Tweets which can then be processed and mined to observe interesting results.

To process data at scale and perform exploratory data analysis upon it, we use the Apache Spark framework, which is a powerful engine that can operate on high volumes of data with the help of parallel computing.

We wish to utilise these popular and powerful open-source tools to build a pipeline that can process Tweets and stock market data to help us study and evaluate the correlation between the two.

Keywords: *Stock Market Analysis, Big-Data, Social Media, Sentiment Analysis, Machine Learning, Twitter, Apache Spark, Apache Kafka.*

1.3 PROBLEM STATEMENT

In a general sense, stock market analysis aims to determine the future movement of the stock value of a financial exchange. An accurate prediction of such movement leads to more profits for an investor. Predicting how the stock market moves is a challenging issue due to many factors involved in it, like interest rates, economic growth, current trends, politics, etc.

Stock market experts use various sources of information to determine whether or not to buy/sell stocks of any company. Two such sources that are widely used (especially in recent years) are news events & social media trends.

We wish to understand and analyse the statistical correlation between social media trends and its effect on the relevant industry's stock price valuations with the use of a big-data architecture consisting of Apache Kafka and Apache Spark, since stock data and social media articles tend to be voluminous, and because we require a large sample space to accurately evaluate the correlation, the amount of data that needs to processed becomes very high.

1.4 ORGANIZATION OF THE REPORT

The remainder of this report is organized as follows:

- Chapter 2 discusses the literature survey performed towards stream processing and correlation analysis.
- Chapter 3 details the architecture of the system and the design considerations that have been considered for each component in the architecture.
- Chapter 4 discusses the implementation, experimental setup and the results obtained.
- Chapter 5 concludes and provides future directions.

CHAPTER 2

LITERATURE SURVEY

2.1 A PRACTICAL PERSPECTIVE

The stock market hasn't been left out in the wave of data science and machine learning that has swept the entire world. It has become a prime focus of various ML and AI researchers, given the volatile and unpredictable nature of the stock market.

Stock market prices are basically influenced by supply and demand from the market. The rate at which stocks rise or fall in value depends on how the stock's demand changes over time. The stock market, although partially regulated, completely relies on the investor's hands on properly understanding the market behavior and thus buying/selling shares consequently.

Some factors that affect stock prices are:

- Random Speculation
- Government Policies
- News
  - Price Hike
  - Fraud detection
- Trends
- Seasonal(s)
- Similar industry growth/decline

Our main idea is to analyse the correlation between stock valuation and one of its factors that exert a significant degree of influence, especially in recent years: social media trends.

2.2 PREVIOUSLY EXPLORED IDEAS

Lee et. al.'s[5] research delves into analyzing Twitter data, by classifying it into relevant industrial sector categories and performing sentiment analysis to predict the trend of stock prices, and comparing it to reality, to consequently find the correlation between the two.

Their publication states that they used a sample of 1000 news articles to create a classifier. They were able to obtain a 77% accuracy on the classification of Tweets into different sectors. But, they have only used 100 Tweets overall, with 20 Tweets per category in order to test out their hypothesis. This seems to be a statistically insignificant volume of data, which reduces the confidence in their conclusion that the correlation is insignificant.

Selvamuthu et. al[14] also express the opinion that sentiment analysis of the opinions of renowned personalities might help get an extra edge in stock price prediction, since their opinions are known to affect stock prices.

Nayak et. al[9] have done significant work on sentiment analysis of Twitter data for stock price prediction using trend analysis of stock data obtained from Yahoo Finance for three sectors: Banking, Mining & Oil and sentiment data extracted from relevantly collected Tweets. They have also put forth algorithms to calculate closed price trends for each day, to check continuous days up/down for a stock,

and an algorithm to combine sentiment with historical data. Their research work also discusses data pre-processing methods using the NLTK package available in Python to process Tweet data. They predict stock market movement based on available historical stock data and extracted social media sentiment data using 3 different supervised machine learning models, and obtain the best results using the Boosted Decision Tree model.

Kalyanaraman et. al's[16] research tries to perform such an analysis purely using news articles. They considered 11 companies under the National Stock Exchange (NSE), and considered 100 news articles for each company. They manually pre-processed the articles to remove irrelevant ones. This further reduced their dataset to 50-60 articles per company. They then manually labelled the sentiment of the articles as being positive or negative. They used a custom sentiment dictionary and vectorized the news articles to build a classifier using Linear Regression and Gradient Descent. Their model predicted the sentiment of articles with around 60% accuracy and the direction of stock price movement (positive or negative) with an accuracy of 81.92%.

Kanavos et al.[4] have used the Stanford Core NLP library to perform text pre-processing along with Naive Bayes classifier to perform sentiment analysis on Twitter data for stock price predictions. Their classification was done on 6 dimensions, which were Alert, Calm, Happy, Kind, Sure & Vital.

Pagolu et al.[13] performed correlation analysis between Tweets related to Microsoft and its stock price movements during the time period of August 2015 - August 2016. They transformed correlation analysis into a classification problems with the input features being the total negative, neutral and positive emotions in Tweets observed in a 3 day period. They utilized the methodologies of Word2Vec

for sentiment analysis and Logistic Regression & SVM to perform the classification task, which yielded an accuracy of around 70% to predict the stock movement as an upward or downward trend.

Mittal et al.[8] presented a research that utilized Twitter to capture and predict public mood, and use it along with previous stock data to predict the future movement of the stock. They used the DJIA (Dow Jones Industrial Average) value as their stock index under study. They also proposed an algorithm to approximate stock market data on days in which the market was closed due to public holidays and weekends. They carried out stock price prediction using several machine learning algorithms like SVM, Linear & Logistic Regression and Self Organizing Fuzzy Neural Networks.

Mehtab et al.[15] further builds upon the work done by Mittal et al. and developed eight regression and eight classification models for predicting the stock price movement of NIFTY 50, which is augmented using public mood data which was analysed and aggregated from relevant Tweets.

2.3 EXPLORING TECHNOLOGIES INVOLVED

Earlier research methodologies utilized various NLP techniques like n-grams, Word2Vec, TF-IDF etc. Several of these research publications have mentioned the use of deep learning models as a future work that can be undertaken to better improve the sentiment analysis task. In our methodology, we thus use a popular and state-of-the art NLP transformer model, BERT, to perform the Tweet sentiment analysis. More specifically, we utilize a pre-trained RoBERTa-base

model, which was trained on 124M English Tweets collected during the period of Jan 2018 to Dec 2021.[17]

The above discussed model was bench marked against several other systems on the TweetEval task.[7] The model competes well and performs better than most other systems, giving an overall test result accuracy of 66.2%, second only to the BERTweet model, which performed at an accuracy of 67.9%. The decision to use this specific model stems from the fact that it has been trained on a newer Tweet dataset, and also due to the fact that the BERTweet model has a lower token limit than the RoBERTa based model.

Another piece of technology involved in this experiment is the big-data architecture. We require a scalable & robust architecture to handle big-data collected from the various information sources. Gurcan et. al[3] explains the lifecycle associated with real-time big-data processing and highlights the use-cases of different big-data tools. From their research, we chose to go with Apache Kafka for our data ingestion module & Apache Spark to handle batch and stream processing of data. The paper also mentions the different challenges associated with unstructured data, which should be kept in mind while constructing the architecture.

Peng's research work[11] gives an overview of machine learning with Apache Spark and HDFS for stock market analysis. The paper also proposes a generic pipeline for big-data architectures. It also explains on how to pre-process data using PySpark, which is an interface for Apache Spark written in Python.

CHAPTER 3

DESIGN OF PROPOSED SYSTEM

This chapter covers in detail, the design of the proposed system along with the design considerations and alternatives considered wherever applicable. The architecture of the proposed system is based on streaming architecture. The following modules are explained: Streaming Data Generation, Data Transformation, Data Storage, Sentiment Analysis, Correlation Analysis and Visualization.

3.1 DESIGN OVERVIEW

Tweets based on a few industrial sectors are collected based on appropriately chosen keyword(s) and stock market data is collected for the corresponding companies present in a few chosen industrial sectors. This data is then cleaned, stored and then published into our stream handling framework.

Subsequently, with the use of Apache Spark and Apache Kafka integrated architecture, the published data is read from the Kafka topics to which the data is published relevantly. The data pulled is then processed using PySpark methods (MapReduce) and the intermediate results are stored in a database for further analysis. A periodic check-pointing is also done on the data pulled from the topics to avoid redundant processing.

Using the intermediate results, correlation between the Tweets and stock data are analysed, apart from other analysis. For a better understanding of the results obtained, visualizations from the analysis are made.

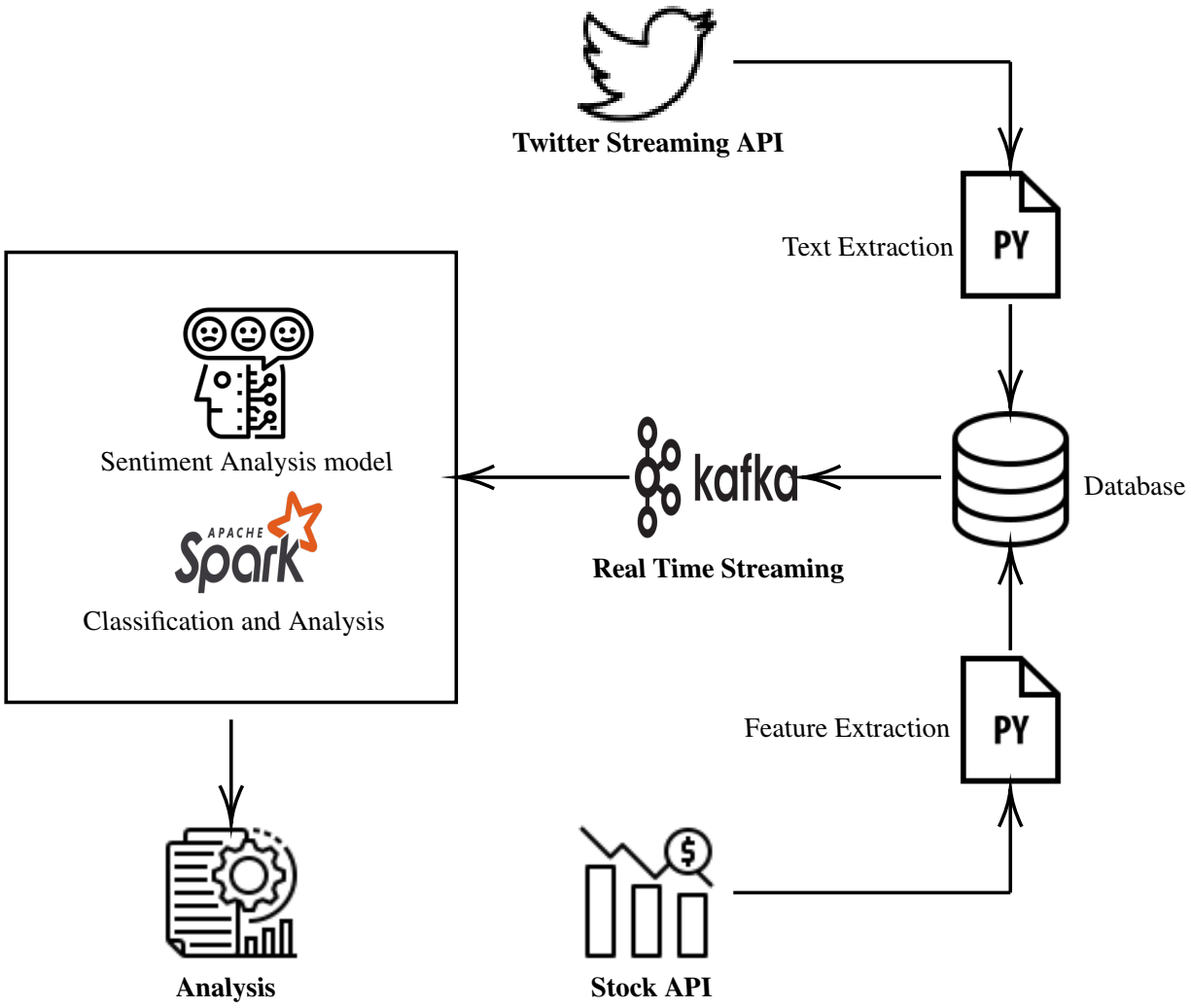


FIGURE 3.1: Proposed Architecture

An overview of the proposed architecture is shown in Figure 3.1.

3.2 DATASETS USED

3.2.1 Tweet Data

The official Twitter API is used to collect Tweet data. It has three different tiers of data access. With the free Essential Access plan, historical data upto a period of 2 months can only be obtained. We require a larger sample space to properly study our objective.

The Academic Research Access plan provided by the Twitter API gives us access to the entire archive of Tweet data, with a rate limit of upto 50 requests per 15 minutes. We use this API level plan to collect Tweet data for our dataset.

The attributes that constitute the schema of the collected Tweets are as follows:

Attribute			Description
DATA	source		Utility used to post the Tweet
	lang		Machine-detected language of the Tweet text
	created_at		UTC time when this Tweet was created
	text		Body of the Tweet
	id		The unique ID of this Tweet
	public metrics	retweet_count	Number of times this Tweet has been retweeted
		reply_count	Number of times this Tweet has been replied to
		like_count	Number of times this Tweet has been liked by Twitter users
		quote_count	Number of times this Tweet has been quoted by Twitter users
META	newest_id		The Tweet ID of the most recent Tweet returned in the response
	oldest_id		The Tweet ID of the oldest Tweet returned in the response
	next_token		A pointer used to paginate the next set of results
	results_count		The number of tweets fetched by the API call

TABLE 3.1: Twitter API Schema

```
{
    'data': [ {
            'source': 'Twitter for Android',
            'lang':  'en',
            'created_at': '2021-12-24T15:22:51.000Z',
            'text': 'Low risk #stocks for decades to come #msft &amp; #goog',
            'id': '1474400183454601219',
            'public_metrics': {
                                'retweet_count': 0,
                                'reply_count': 0,
                                'like_count': 0,
                                'quote_count': 0
                              }
            } ],
    'meta': {
                'newest_id': '1474400183454601219',
                'oldest_id': '1474400183454601219',
                'next_token': '235467890098'
                'result_count': 1
            }
}
```


FIGURE 3.2: Sample Tweet JSON Object

3.2.2 Stock Data

We considered several third-party stock data API providers like Zerodha, Moneycontrol etc. The drawback of the above API providers is that they charge a significant price for accessing historical stock data.

Thus, we ended up choosing Polygon.io, a popular API service that provides us with access to 2 year historical data for free, with a rate limit of 5 requests per minute.

The attributes that constitute the schema of the collected stock data are as follows:

Attribute	Description
status	A response from API indicating success (OK) or failure
symbol	The ticker symbol whose stock data is requested
from	Requested date of the stock
open	The opening price of the stock on the requested date in USD ($)
close	The closing price of the stock on the requested date in USD ($)
high	The highest price of the stock on the requested date in USD ($)
low	The lowest price of the stock on the requested date in USD ($)
preMarket	The pre-market price of the stock on the requested date in USD ($)
afterHours	The after hours price of the stock on the requested date in USD ($)
volume	The amount of shares or contracts traded over the day

TABLE 3.2: Stock API Schema

```
{
    'status': 'OK',
    'from': '2021-05-27',
    'symbol': 'TSLA',
    'open': 620.24,
    'high': 631.13,
    'low': 616.21,
    'close': 630.85,
    'volume': 26370593,
    'afterHours': 629.23,
    'preMarket': 616.63
}
```

FIGURE 3.3: Sample Stock JSON Object

3.3 STREAM DATA GENERATION

Initially, the dataset is cleaned - i.e irrelevant columns are removed, missing values are imputed.

An Apache Kafka producer script was implemented to simulate a uniform stream from the dataset. To do this, the program maintains a timer and accordingly publishes records from the dataset at periodic intervals of time.

Two different streams - Tweet data stream and stock data stream - are generated.

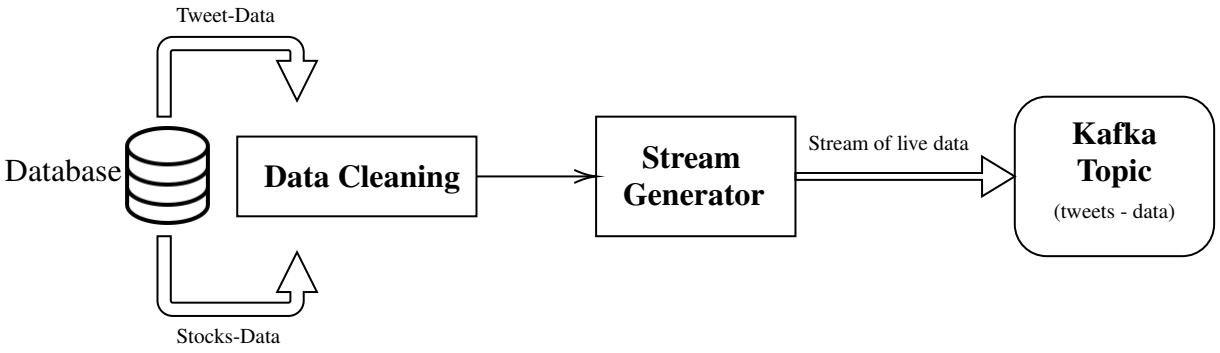


FIGURE 3.4: Stream Data Generation

3.3.1 Tweet data stream

The Tweet dataset (with columns: Category, Date, Tweet & Retweet Count) is initially grouped based upon the category that they belong to, and then produced to the relevant Kafka topic through the producer script mentioned above.

3.3.2 Stock data stream

Similarly, the stock dataset (with columns: Ticker, Date, Open, Close, High & Low) is grouped based upon the ticker that they belong to, and then subsequently produced to the relevant Kafka topic through the producer script.

3.4 DATA TRANSFORMATION

The Tweet data published to various Kafka topics are consumed through Spark's Structured Streaming - a stream processing engine built upon the SparkSQL engine - it takes care of processing data incrementally and updating the results. Upon being invoked, they can perform a variety of actions such as processing

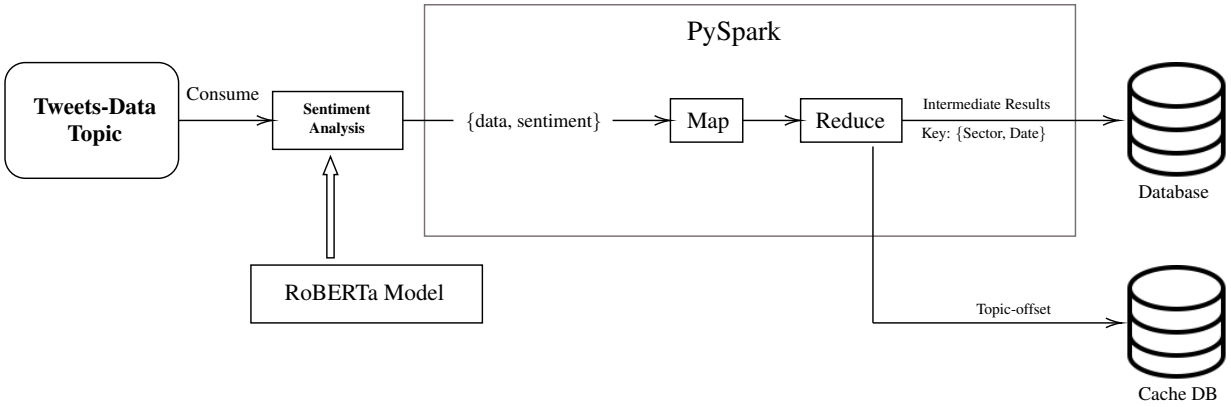


FIGURE 3.5: Tweet Data Transformation

logic on the incoming data (in micro-batches), and writing the output to a permanent storage. PySpark provides us with a DataFrame API level of abstraction to express streaming aggregations, event-time windows, stream-to-batch joins etc.

Through the use of PySpark, aggregate methods written in Python to transform individual Tweet data can be applied efficiently (via SparkSQL Engine) on the incoming data stream, to obtain intermediate, sector-wise results, which can then be promptly stored in a database for further analysis.

3.4.1 Design Considerations

Gurcan et. al's[3] research identifies the different challenges and tasks involved in big-data processing and lists out several tools that can be utilized to construct an efficient big-data architecture.

For the data ingestion phase - a process in which big data is ingested from heterogeneous sources, the most appropriate tools are identified as Apache Kafka, Apache Flume and Apache NiFi. Of the three choices, we went ahead with

Apache Kafka considering its better performance in terms of scalability, latency and throughput. Kafka is ubiquitously used as a distributed streaming framework and thus has huge community support - ensuring ease of development.

For the data processing phase - a process in which big-data streams are processed and structured for analytics, the most popular choices are Apache Spark, Apache Storm, Apache Flink and Apache Samza. Of these four alternatives, we proceeded with Apache Spark, since Spark Streaming allows us to build scalable, fault-tolerant applications; it also incorporates the Stream as well as Batch Processing paradigms. Due to the wide community support, it has APIs available in multiple languages and integrates with Apache Kafka seamlessly through dependencies.

3.5 DATA STORAGE

To provide a source for the stream data generation and to record processed intermediate results obtained from the Spark interface, we require a data storage solution.

More specifically, a database solution is required for the following reasons: We require that the processed data be maintained in a consistent state since updates are done frequently to the intermediate results by the PySpark interface. In case of any failures, we also require the ability to revert back to a previous state.

There are two tables to be maintained for Tweet data: one that contains raw Tweet data collected from the API, and another that contains sector-wise aggregated Tweet sentiment data that is to be used for analysis.

Similarly, there are two tables to be maintained for stock data: one for storing raw stock data, and another to store stock data with approximated values calculated for days during which the stock market was inoperative.

3.5.1 Design Consideration

While considering a candidate application for handling our data storage needs, we were able to construct well-defined schemas for our different datasets (consisting of Tweet data and stock market data) and intermediate results. Thus, we inclined more towards SQL-based solutions rather than NoSQL databases like MongoDB, Apache Cassandra etc.

Among the many available SQL database offerings, we opted for the SQLite database: a lightweight, server-less, self-contained RDBMS (Relational Database Management System), for its ease of use and cross-platform portability. It also utilises significantly fewer resources as compared to alternatives like MySQL and PostgreSQL.

SQLite is also a prudent choice considering the fact that our entire environment is set up and run locally. We can limit disk, cache & RAM usage by SQLite to optimally use our environment's available computing resources.

The server-less and embedded nature of SQLite also fares well compared to client-server based solutions like MySQL and PostgreSQL, both of which require a server to be set up before usage. In case of any system failure, the SQLite database maintains its consistent state and does not require any manual server restart as needed in other client-server based SQL database applications.

3.6 SENTIMENT ANALYSIS

A crucial component in the pursuit of our study to understand the relation between social-media (Tweets) and the stock market is analysing the sentiment (or mood) reflected by social media at any given date.

To perform sentiment analysis on Twitter data, various NLP methods have been explored, as discussed in Section 2.3.

In the field of Natural Language, one of the more recent developments has been the introduction of the Encoder-Decoder (Transformer) Model - more specifically, the BERT (Bidirectional Encoder Representations from Transformers) Model[2]. BERT differs from conventional NLP language models in the fact that it uses bidirectional training and attention mechanism in order to have a deeper sense of language context compared to other unidirectional models. Since its introduction, the BERT model has been extensively used for popular NLP tasks like Text Summarization, Question-Answering, Text Classification, Sentiment Analysis etc.

In our methodology, we chose to use Cardiff NLP research group's publicly available TimeLMs based sentiment analysis model.[17]. This model builds upon the existing RoBERTa-base model, which in turn is a BERT-base model that has been pre-trained on a large corpus of English data using the training approach as discussed in its research paper.[6]

This sentiment analysis model has been pre-trained on a dataset of approximately 124M Tweets collected between Jan 2018 - Dec 2021. To add further detail, their

research aims at building language models (LMs) that specializes in understanding diachronic Twitter data.[7]

Their model has been benchmarked against the TweetEval evaluation - a unified Twitter benchmark composed of seven heterogeneous Tweet classification tasks. The results obtained are promising, and perform competitively well - only outperformed by the BERTweet[10] model on the overall averaged results, by a small margin.

Yet, we still expect this model to perform the best for our use-case, since it has been pre-trained on Tweet data that is similar to our period of study (Mar 2020 - May 2022). The better performance can be attributed to having a better language model that captures the context of the Twitter English language used during that time.

The model classifies a Tweet into three sentiments - Negative, Neutral and Positive, and returns an array of three confidence values which correspond to the probabilities of the Tweet being classified into the corresponding sentiments.Figure 3.6 denotes the sentiment analysis process diagramatically:

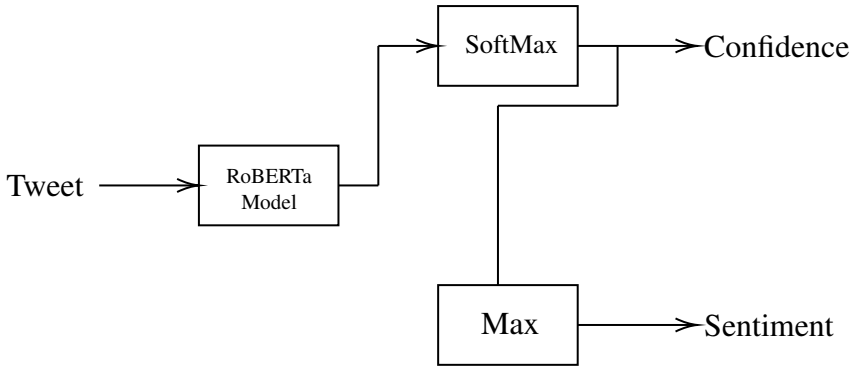


FIGURE 3.6: Sentiment Analysis Model Flowchart

In this manner, all Tweets available for a given day and a given sector are scored and aggregated by the Spark Processing Engine using this sentiment analysis

model. The negative, neutral and positive mood observed on Twitter on a given day for a specific market sector is thus captured and quantified.

3.7 CORRELATION ANALYSIS

After processing the entire stream of Tweet data and obtaining intermediate results based on the sentiment scores, we now move into the correlation analysis part.

Firstly, we group the intermediate results sector-wise and merge it with its relevant stock market ticker data, corresponding to a date-wise order. For example, the aggregated Tweet results obtained under the EVs (Electric Vehicles) category are merged with the stock market data of Tesla Motors (NASDAQ: TSLA). In essence, we now have a combined dataset that describes the stock market performance of a given stock and the social media mood captured on Twitter on that day for the stock's relevant market sector.

Now, we perform feature scaling, i.e. normalization of the data using a Min-Max scaling algorithm. This is done since different features present in the dataset have different ranges, and it is necessary to bring them all to the same scale (Min-Max Normalization rescales all values between 0 and 1), for further analysis and easier visualization.

$$y' = \frac{y - x_{min}}{x_{max} - x_{min}}(x'_{max} - x'_{min}) + x'_{min} \tag{3.1}$$

For Min-Max normalization, typically $\langle x'_{min}, x'_{max} \rangle = \langle 0, 1 \rangle$.

$$y' = \frac{y - x_{min}}{x_{max} - x_{min}} \tag{3.2}$$

where:

$\langle x_{min}, x_{max} \rangle$ is the old range.

$\langle x'_{min}, x'_{max} \rangle$ is the new range.

$y \in \langle x_{min}, x_{max} \rangle$ is the value to be normalized.

$y' \in \langle x'_{min}, x'_{max} \rangle$ is the min-max normalized value.

The next step is to perform correlation analysis with the Spearman's Correlation Coefficient, which is a non-parametric measure of rank correlation between two variables. It is equal to the Pearson's Correlation Coefficient between the rank values of those two variables. While Pearson's correlation assesses linear relationships, Spearman's correlation assesses monotonic relationships (irrespective of linearity). The confidence levels of each correlation score are also calculated, to accept/reject the Null Hypothesis (whether the correlation is significant or not). It is a better correlation metric than the Pearson's correlation metric for this specific scenario since the stock market may not be linearly related to the sentiments observed on social media.

$$\rho = \frac{cov(R(X), R(Y))}{\sigma_{R(X)} \sigma_{R(Y)}} \tag{3.3}$$

Where:

ρ is Spearman's coefficient, $\rho \in \langle -1, 1 \rangle$

$cov(R(X),R(Y))$ is the covariance of the rank variables.

$\sigma_{R(X)}$ and $\sigma_{R(Y)}$ are the standard deviations of the rank variables.

If all n ranks are all distinct, it can be computed using the formula:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{3.4}$$

Where:

ρ is Spearman's coefficient, $\rho \in \langle -1, 1 \rangle$

n is sample size.

d_i is the difference between the ranks of the data being analyzed.

To visually understand the correlation score, scatter plots are also drawn between the two features to understand the distribution of the data points.

This procedure is carried out for various categories separately to observe and tabulate the correlation between that sector's stock market and its' respective social media mood.

3.8 VISUALIZATION

To perform various graphical visualizations on the collected and processed data in order to better understand the relationship between the different data attributes present and between Tweets and Stocks - we require the use of a graphing tool.

Python has a plethora of graphing packages that generate colourful and informative charts and diagrams. Thus we leverage packages like Matplotlib, Seaborn and Plotly to augment our study with meaningful and interactive graphs, and to perform exploratory data analysis (EDA). The entire workflow pertaining to data analysis, correlation study and visualization can thus be presented in a visually appealing and easy to understand manner with the use of Interactive Python Notebooks (IPYNBs). The IPYNBs act as an interactive front-end that enables us to view, manipulate and understand the processed data, supported by graphing utilities.

CHAPTER 4

IMPLEMENTATION

This chapter discusses Apache Kafka and Apache Spark setup, installation of components and implementation of modules and the results obtained. The applications are executed in a machine running on Ubuntu 20.04. The environment is installed with OpenJDK 11.0.14, Scala 2.11.12 and Python 3.8.10.

Apache Spark and Apache Kafka are also configured in the system, and the details on their installation are mentioned below.

4.1 INSTALLATION

4.1.1 Apache Spark

Apache Spark[20] was downloaded and kept in the home folder of the system. The version of Apache Spark that is used here is version 3.2.1.

4.1.1.1 PySpark Dependencies

Since we will be interacting with Spark through from a Python interface, we need to install the PySpark library. PySpark's dependencies are installed using the following commands.

```
sudo apt update
```

```
sudo apt install python3-pip
pip3 install jupyter
sudo apt install jupyter-core
sudo apt update
sudo apt install default-jre
sudo apt install default-jdk
sudo apt install scala
pip3 install py4j
```

4.1.1.2 Configuration

The downloaded tarball of Apache Spark is moved to home directory and extracted using the command mentioned below:

```
sudo tar -zxvg spark-3.2.1-bin-hadoop3.2.tgz
```

The following environment variables are to be added to the system's *.bashrc* file to run Apache Spark:

```
export SPARK_HOME="home/<name>/spark-3.2.1-bin-hadoop3.2"
export PATH=$SPARK_HOME:$PATH
export PYTHONPATH=$SPARK_HOME/python:$PYTHONPATH
export PYSPARK_DRIVER_PYTHON="jupyter"
export PYSPARK_DRIVER_PYTHON_OPTS="notebook"
export PYSPARK_PYTHON=python3
```

The access modifiers of these folders are to be changed as follows:

```
sudo chmod 777 spark-3.2.1-bin-hadoop3.2
cd spark-3.2.1-bin-hadoop3.2
sudo chmod 777 python
cd python
sudo chmod 777 pyspark
```

4.1.1.3 Installing FindSpark

PySpark is not present on *sys.path* by default. To use the PySpark library outside of its home directory, it needs to be either sym-linked onto your site-packages, or adding it to the *sys.path* during run-time. The *findspark* package does the latter.

FindSpark package is installed using the following command:

```
pip3 install findspark
```

The following Python snippet can be used to make sure *findspark* is installed correctly:

```
import findspark
findspark.init('/home/<name>/spark-3.2.1-bin-hadoop3.2')
import pyspark
```

4.1.2 Apache Kafka

Apache Kafka[21] was downloaded and kept in the home folder of the system. The version of Apache Kafka that is used here is version 2.13-3.1.0.

4.1.2.1 Configuration

The downloaded tarball of Apache Kafka is moved to home directory and extracted using the command mentioned below:

```
sudo tar -xzf kafka_2.13-3.1.0.tgz
```

Apache Kafka's configuration needs to be edited before executing it in our environment. The configuration file *server.properties* is present inside the *config/* folder of Apache Kafka.

The following changes are made to the *server.properties* file:

```
advertised.listeners=PLAINTEXT://localhost:9092
zookeeper.connect=localhost:2181
```

4.1.3 Kafka Manager (GUI)

Yahoo-CMAK[22] is an Apache Kafka manager that provides a GUI service to create clusters, topics and maintain them through a web-interface. CMAK is installed onto our system by cloning its GitHub repository into our home directory, using the following commands:

```
sudo apt update
git clone https://github.com/yahoo/CMAK
```

4.1.3.1 Configuration

The command below will create a zip file which can be used to deploy the CMAK application:

```
cd CMAK/
./sbt clean dist
```

Then, inside the created *target/universal* folder, we unzip the CMAK folder.

```
cd target/universal
unzip cmak-3.0.0.6.zip
```

Following this, we configure the application as follows:

```
ls cmak-3.0.0.6/
cd conf
```

The following changes are made in *application.conf*

```
- cmak.zkhosts="kafka-manager-zookeeper:2181"
+ cmak.zkhosts="localhost:2181"
```

4.2 DATA COLLECTION

Python scripts were written to collect the Tweet data and stock data from Twitter-Academic-API[18] and Polygon-API[19] respectively.

CATEGORY	DATE	COUNT	TWEET
Tech	2020-04-07	7	So we have a powerful Follow Through Day, and some stocks are showing positive action: $VRTX $AMZN ... $MSFT ... $SEGN
Oil	2020-04-07	1	I think some $XOM and $KO puts should be purchased
EVs	2020-04-07	1	If $TSLA gets to $520, i will be happy

TABLE 4.1: Sample Tweet data collected from Twitter-API

CATEGORY	TICKER	DATE	OPEN ($)	CLOSE ($)
Tech	MSFT	2020-10-01	213.49	212.46
EVs	TSLA	2020-10-01	440.76	448.16
Oil	XOM	2020-10-01	33.79	33.13
Pharma	MRNA	2020-10-01	69.57	70.03

TABLE 4.2: Sample stock data collected from Polygon-API

4.3 DATA PRE-PROCESSING

4.3.1 Tweet Cleaning

The collected JSON data from the Twitter API is cleaned to remove emoticons and extraneous characters. Links and other irrelevant data are removed from the Tweet, if any. Duplicate Tweets (which may be collected accidentally due to keyword-based search) are also removed. Following this, the Tweets are stored inside an SQLite database for later processing.

Attribute	Type
Category	Text
Date	Text
Count	Integer
Tweet	Text

Attribute	Type
Category	Text
Ticker	Text
Date	Text
Open	Real
Close	Real

TABLE 4.3: SQLite Schema for Tweet Data & Stock Data

Before using the raw Tweet data directly for social media mood analysis, it is imperative to check the distribution of the Tweet data.

Upon loading the Tweet data and analysing it with the usage of a boxplot, it can be clearly seen that the boxes are very compressed and almost indiscernible due to the outliers in terms of retweet count. Using such data directly would lead to incorrect results. Thus, by method of trial and error, a good maximum limit is found, and Tweets with a retweet count above the chosen limit is capped to the maximum limit. This ensures that we do not miss valuable Tweets (Tweets with a high retweet score imply that the Tweet was popular and reflected the mood of a sizeable portion of social media users), and at the same time avoid the issue of it being an outlier. A boxplot of the EV Tweet data is shown below for reference.

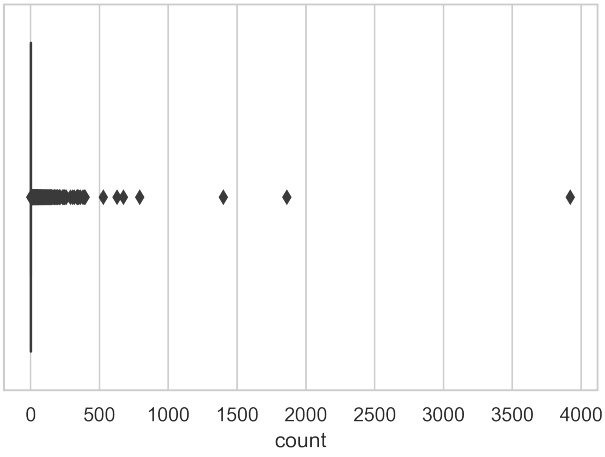


FIGURE 4.1: Raw EV data distribution

Similarly, on the other end of the spectrum, Tweets with a low retweet score are not reliable sources of information, and for the most part, constitute noise in terms of the overall sentiment observed on social media. Thus, it would be wise to eliminate Tweets with a low retweet score in order to obtain a closer to true analysis of social media and the stock market.

Thus, after removing noisy Tweets and capping the retweet counts of highly retweeted ones, we end up with a boxplot with the box clearly visible and small whiskers. This distribution is much more appropriate for usage as compared to the raw Tweet data distribution. The modified boxplot of the EV Tweet data is shown below for reference.

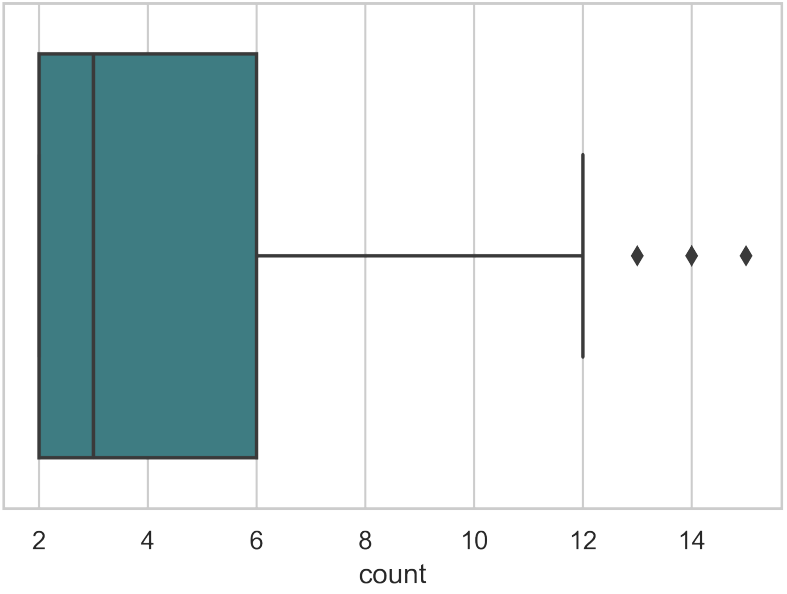


FIGURE 4.2: Cleaned EV data distribution

4.3.2 Stock Approximation

Stock market data is approximated on days when the market was closed to have a continuous period of data, without any missing values.

The approximation is done using the below formula, as proposed by Mittal's paper.[8]

$$z = \left(\frac{x+y}{2}\right) \tag{4.1}$$

Where:

z is the missing stock value.

x is the previously available stock value data.

y is the next available stock value data.

4.4 STARTING APACHE KAFKA & CMAK

4.4.1 Apache Kafka

Before starting Apache Kafka, Apache Zookeeper must already be running in the background. To start Apache Zookeeper, the following command is executed:

```
cd ~/kafka_2.13-3.1.0/
bin/zookeeper-server-start.sh config/zookeeper.properties
```

Now, start Apache Kafka using the following command:

```
JMX_PORT=8004 bin/kafka-server-start.sh config/server.properties
```

4.4.2 Creating Clusters & Topics

The CMAK GUI is used to create clusters and topics.

The CMAK web-interface is started using the following command:

```
bin/cmak -Dconfig.file=conf/application.conf -Dhttp.port=8081
```

Now, open the CMAK interface via a web-browser:

```
http://localhost:8081
```

Then, we create a cluster using the UI, with the Zookeeper host value set to *localhost* : 2181. Additionally, JMX Polling & Poll Consumer Information features are enabled.

Inside the newly created cluster, we can now create topics. For our purposes, we can create a topic with a replication factor of 1 with a single partition allocated to it.

Dedicated topics can be created to hold specific data - for instance: a topic named $tech - stocks$ can be created to transmit technology sector related stock data.

4.5 DATA PROCESSING

4.5.1 Producer

The producer logic is written in a Python script using the $kafka-python$ library. Data is ingested into relevant Kafka topics from the SQLite database created earlier. Pre-processing is done to convert the data to an appropriate JSON format, which is then subsequently UTF-8 encoded before being produced into the topics as messages.

4.5.2 Consumer

The produced data can then be consumed by subscribing to the Kafka topics. In our scenario, we subscribe to the data directly via a Spark Session in PySpark.

The data is collected as a Stream of messages from the Kafka topics. To avoid redundant processing, we update an $offset$ value to keep track of already processed messages. The collected data is then stored in an in-memory Spark SQL table, and processed periodically.

4.5.2.1 Tweet Streaming

The Tweets stored in the in-memory Spark SQL table, are fetched and converted back into the JSON format.

The Twitter-RoBERTa sentiment analysis model[17] is used to perform sentiment analysis on the consumed Tweet data. The Twitter-RoBERTa model outputs an array of size 3, which denote confidence values. (as discussed in Section 3.6.)

$$model(tweet) \xrightarrow{returns} [\ negative\_confidence,\ neutral\_confidence,\ positive\_confidence\ ] \tag{4.2}$$

$$sentiment(tweet) = index(max(model(tweet))) \tag{4.3}$$

The sentiments are obtained for each Tweet w.r.t to equation 4.3 and then stored with the corresponding Tweet's JSON data.

For efficient and quicker processing of such voluminous amounts of Tweets, we take advantage of the parallel processing capabilities provided by PySpark with the use of Resilient Distributed Datasets (RDDs). RDDs are immutable, fault-tolerant data structures that run and operate on multiple nodes to do parallel processing on a cluster. Multiple operations can be applied on RDDs to achieve the desired result.

Thus, the consolidated Tweet in JSON format is converted into an RDD. The data is then mapped with the Tweet's respective sector as the key and then reduced to

obtain an intermediate aggregate result. The aggregated results are then stored in an SQLite database.

The schema of the intermediate aggregated results obtained from processing the raw Tweet data is described in Table 4.4.

Attribute	Type
Category	Text
Date	Text
Count	Integer
Tweet	Text

$\longrightarrow$

Attribute	Type
Category	Text
Date	Text
Count	Integer
Indiv. negative	Real
Indiv. neutral	Real
Indiv. positive	Real
Weighted negative	Real
Weighted neutral	Real
Weighted positive	Real
Negative counts	Integer
Neutral counts	Integer
Positive counts	Integer

TABLE 4.4: SQLite Schema for Aggregated Data after stream processing

Attribute	Description
Category	The industry sector name
Date	UTC date that the Tweet belongs to
Count	Total number of Tweets for a given category and date
Individual Negative	The aggregated negative confidence of the scored Tweets
Individual Neutral	The aggregated neutral confidence of the scored Tweets
Individual Positive	The aggregated positive confidence of the scored Tweets
Weighted Negative	The aggregated negative confidence of the Tweets weighted on retweet count
Weighted Neutral	The aggregated neutral confidence of the Tweets weighted on retweet count
Weighted Positive	The aggregated positive confidence of the Tweets weighted on retweet count
Negative counts	The number of negative Tweets for a given category and date
Neutral counts	The number of neutral Tweets for a given category and date
Positive counts	The number of positive Tweets for a given category and date

TABLE 4.5: Description of the Aggregated Tweet schema

4.6 DATA ANALYSIS AND PREDICTION

4.6.1 Understanding The Data

Before performing correlation analysis on the obtained intermediate results from the PySpark module, there is a need to understand the details of the data that we are working with.

We have chosen four industrial sectors (categories) for which Tweets were collected based on relevant hashtags and keywords: Electric Vehicles (EVs), Oil & Gas, Technology and Pharmaceuticals. The following considerations were kept in mind while choosing candidate entities for our study.

1. Company Location - The United States of America (USA). This consideration is backed by the fact that the majority of Twitter users are located in the USA - nearly 77 million (as of Jan 2022). Thus, market discussion would be more oriented towards American companies.

2. Market Capitalization by Segment - A large market cap indicates that it is a significant performer in that market segment. Hypothetically, social media discussion about relevant market topics would affect the performance of these stocks much more than other companies with lower market capitalization.

Table 4.6 indicates the amount of Tweets collected and processed for each sector during the two-year time period:

Sector	Data Points
Electric Vehicles (EVs)	116,355
Oil	53,253
Technology (Tech)	632,181
Pharmaceuticals (Pharma)	313,407

TABLE 4.6: Data Points Count

Initially, the stock market data and the aggregated Tweet sentiment data are merged based on the date column. As a result, we have a total of 16 columns in our dataset:

$$\begin{vmatrix} Category & Date & Open & Close \\ High & Low & Count & Neg\_Counts \\ Ind\_Neg & Ind\_Neu & Ind\_Pos & Neu\_Counts \\ Wted\_Neg & Wted\_Neu & Wted\_Pos & Pos\_Counts \end{vmatrix}$$

The schema of these columns are mentioned in Table 4.4.

The entire dataset is now split and grouped according by the category column, so that each sector's data can be analysed separately.

Exploratory data analysis is done to understand the distribution and nature of the different columns.

It has been identified that there are no missing values in any of the columns, and that different columns have different ranges.

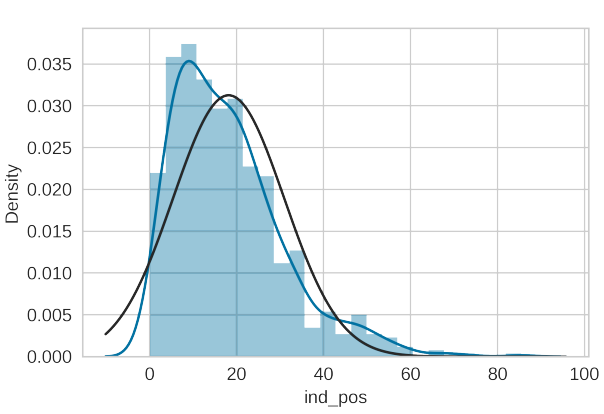
For a given category, all the features in our merged dataset are numerical values, apart from the date column. Thus, understanding the inherent distribution of each column is necessary.

	date	open	close	high	low	count	ind_neg	ind_neu	ind_pos	wted_neg	wted_neu	wted_pos
0	2020-04-07	109.0000	109.0900	113.0000	106.468	405	29.760626	42.419716	33.819664	61.686187	105.406782	237.907026
1	2020-04-08	110.8400	109.7680	111.4416	106.666	243	29.776691	47.333942	25.889368	64.262435	109.520843	69.216720
2	2020-04-09	112.4180	114.6000	115.0364	111.422	209	29.311668	44.887577	28.800758	57.566045	100.556852	50.877107
3	2020-04-10	115.2250	122.3950	122.7182	113.764	272	24.159784	47.111198	29.729010	39.036394	120.448533	112.515063
4	2020-04-11	116.6285	126.2925	126.5591	114.935	514	29.267159	42.111918	28.620923	289.783706	153.905570	70.310696

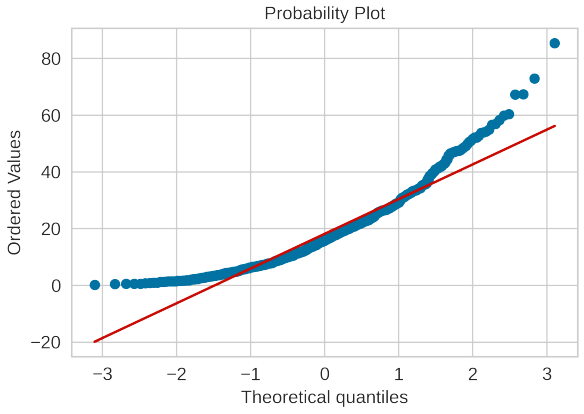
FIGURE 4.3: Merged EV Dataset

Upon observation of the different distributions using a distribution and probability plot, it can be noticed that few columns have a skewed distribution and noticeable positive/negative skew in the probability plot. To fix the skew and bring about a normal distribution of the data, we employ a log transformation of the skewed columns.

For reference, the below plots (Figure 4.4) are shown to understand the original and log-transformed distribution of the Ind_Pos column of the Pharma dataset.

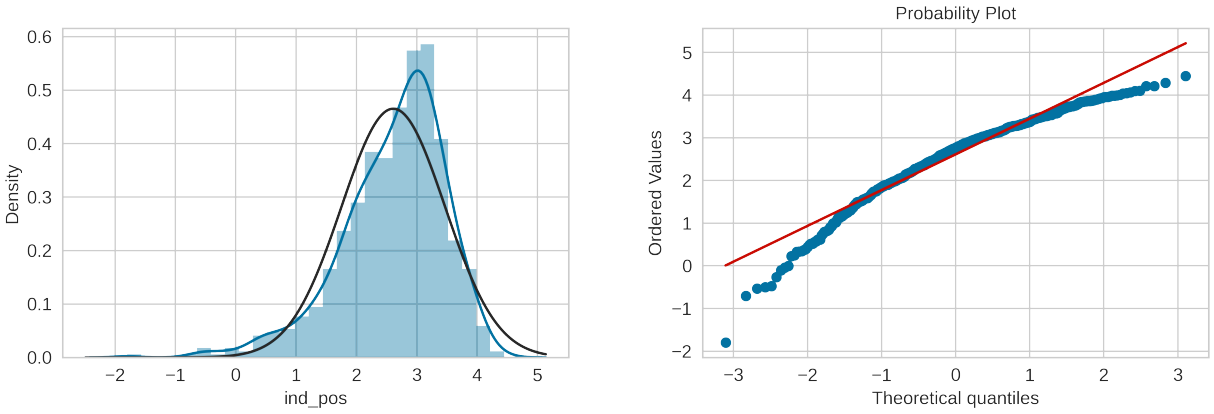


(a) Distribution - Ind_Pos Attribute (Unscaled)



(b) Probability Plot - Ind_Pos Attribute (Unscaled)

FIGURE 4.4: Pharma Data - Distribution & Probability Plots

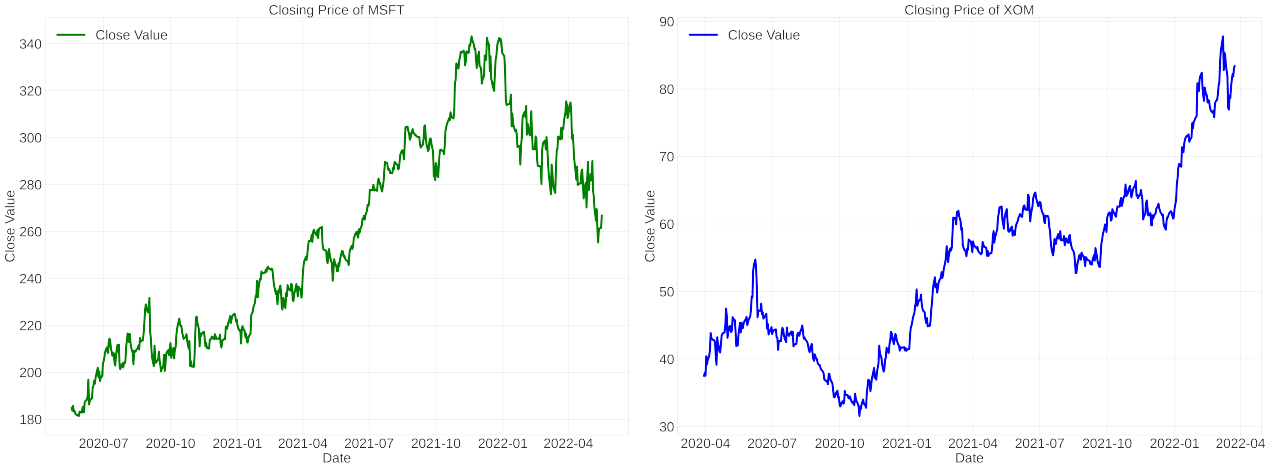


(c) Distribution - Ind_Pos Attribute (Log Scaled)

(d) Probability Plot - Ind_Pos Attribute (Log Scaled)

Pharma Data - Distribution & Probability Plots

Now, to understand the market trends for the time period for which stock data was collected, a time-series plot is drawn for each company under study. The y-axis corresponds to the daily closing price of the company, while the x-axis corresponds to the date. Figure 4.5 shows the variation of closing price for the four companies.

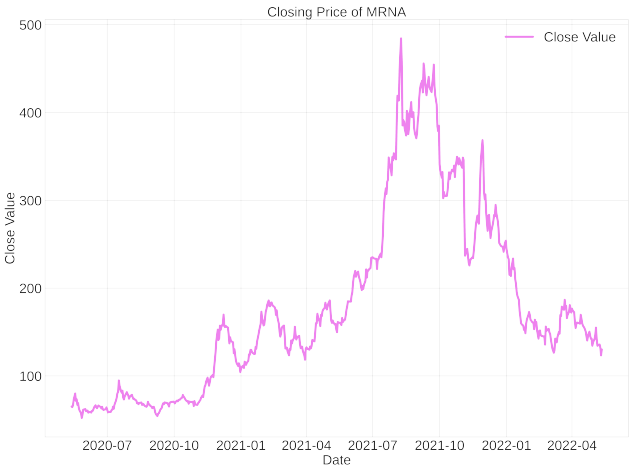


(a) (NASDAQ: MSFT)

(b) (NYSE: XOM)

FIGURE 4.5: Company Closing values

(c) (NASDAQ: TSLA)



(d) (NASDAQ: MRNA)

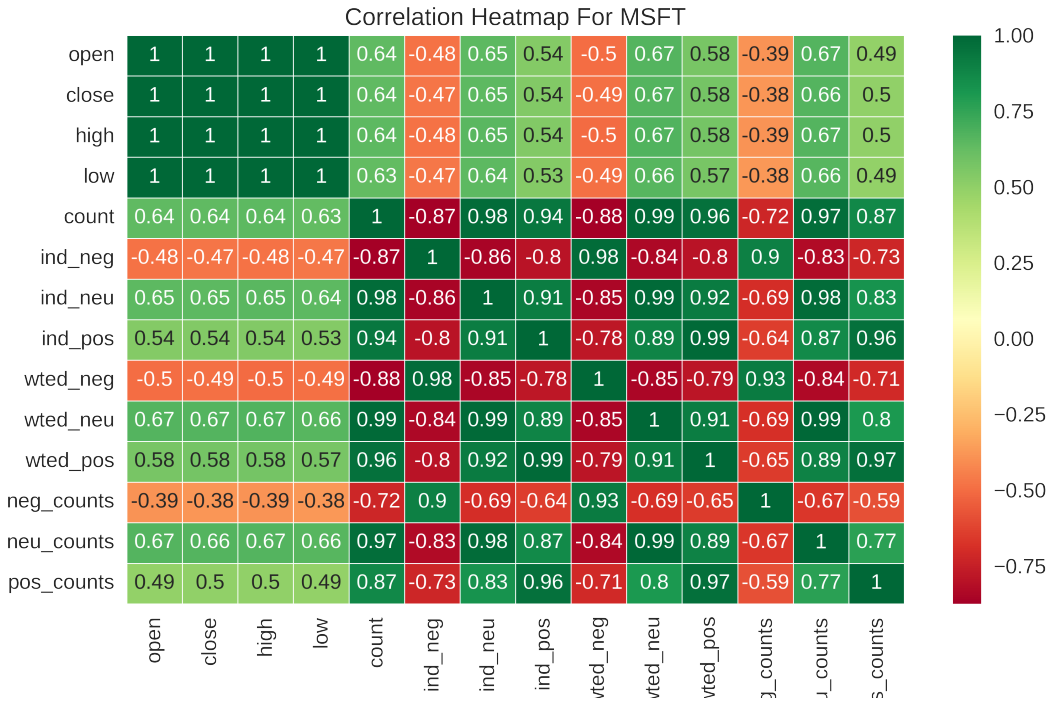
Company Closing values

The next step is to perform min-max normalization (Equation 3.2) on the datasets. After normalizing, all numerical columns in the dataset now have the same range of $[0-1]$.

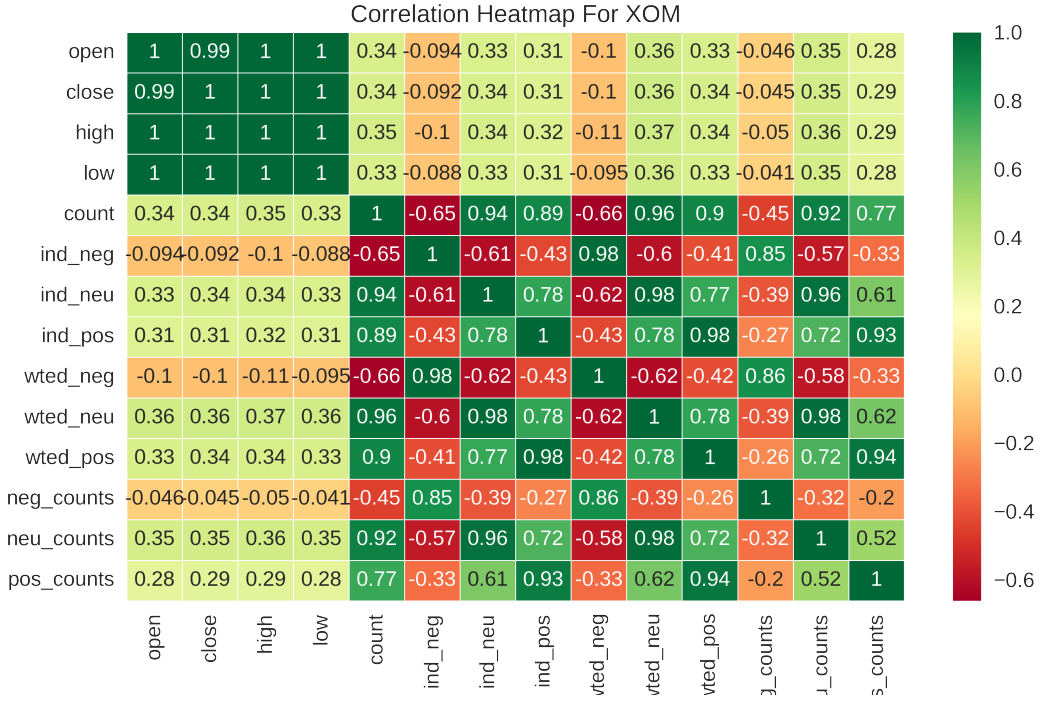
4.6.2 Correlation Analysis

The crux of our research is to perform a correlation analysis between social media trends and stock market data. For the same, now we perform the Spearman's Correlation Coefficient calculation between every two columns of the dataset separately for each industrial sector.

A Heatmap is plotted to capture the correlation observed in a visually appealing manner. The plotted Heatmaps are shown below:

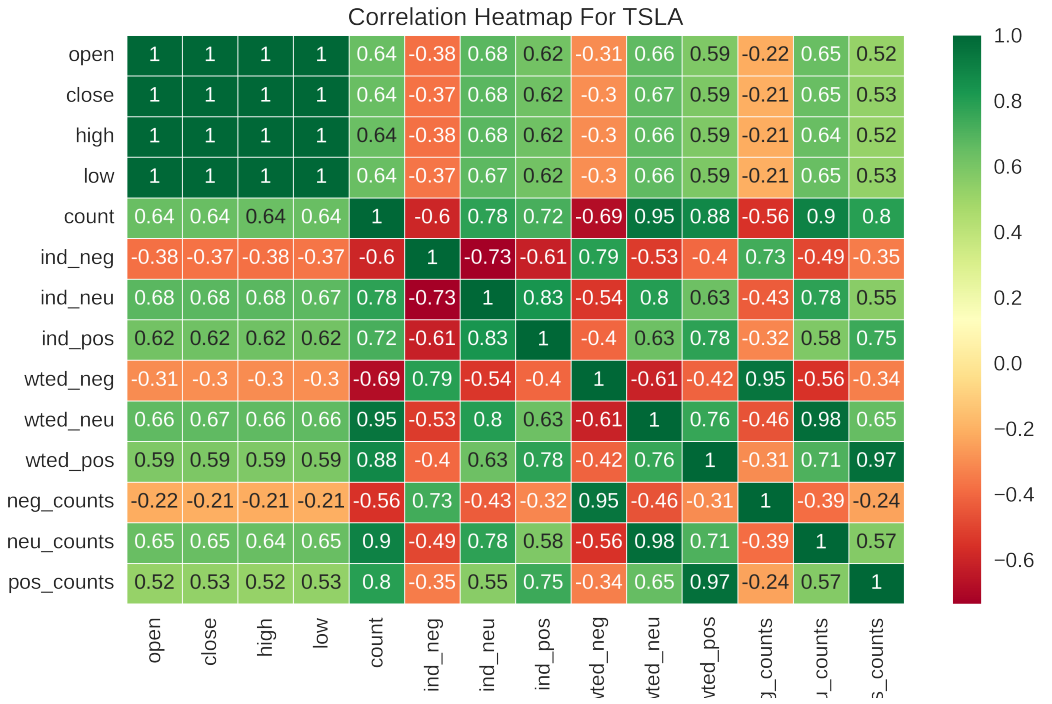


(a) Tech - (NASDAQ: MSFT)

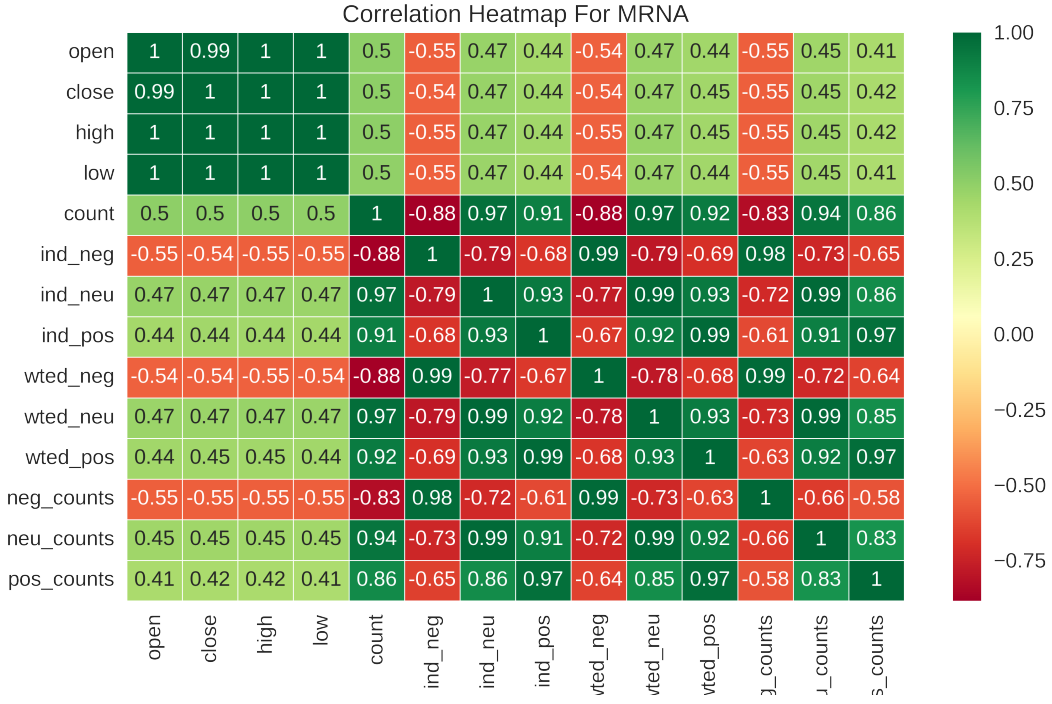


(b) Oil - (NYSE: XOM)

FIGURE 4.6: Correlation heatmap between Tweets and Stock Market for different industrial sectors



(c) EVs - (NASDAQ: TSLA)



(d) Pharma - (NASDAQ: MRNA)

Correlation heatmap between Tweets and Stock Market for different industrial sectors

A statistical test of significance is also performed for the observed Spearman's correlation coefficient values. Python's Scipy library implementation of the Spearman's correlation coefficient returns a 2-tailed p-value. This number signifies the probability of the following Null Hypothesis being true.

> Null Hypothesis: The two variables under study are uncorrelated.
> Alternate Hypothesis: The two variables under study are correlated.

The correlation value is considered statistically significant (i.e. the alternate hypothesis is accepted) if the p-value is lower than 0.01 (for a 99% confidence interval). Otherwise, the correlation is statistically insignificant, and can be ignored for all practical purposes.

Feature	ρ	p
Wted_Neg	-0.493	$5.418e-46$
Wted_Neu	0.667	$3.368e-95$
Wted_Pos	0.576	$5.669e-66$

(a) (NASDAQ: MSFT)

Feature	ρ	p
Wted_Neg	-0.100	$7.235e-3$
Wted_Neu	0.364	$5.945e-24$
Wted_Pos	0.339	$6.987e-21$

(b) (NYSE: XOM)

Feature	ρ	p
Wted_Neg	-0.299	$2.657e-16$
Wted_Neu	0.665	$9.465e-93$
Wted_Pos	0.593	$2.030e-69$

(c) (NASDAQ: TSLA)

Feature	ρ	p
Wted_Neg	-0.542	$4.398e-57$
Wted_Neu	0.469	$2.514e-41$
Wted_Pos	0.446	$4.001e-37$

(d) (NASDAQ: MRNA)

TABLE 4.7: p-values for Spearman correlation between Weighted Sentiments and Close

For our analysis, we consider only the daily close value to understand the correlation between a sector's market performance and the corresponding day's social media trend.

Thus, from the above observed results, we can see a strong positive correlation between the Ind_Neu (0.68) and Ind_Pos (0.62) columns to the Close column of Tesla (EVs) respectively. The neutral sentiment's result can be interpreted as the market performing well with a rise in the amount of discussion about electric vehicles in general. The positive sentiment's result can be interpreted in the following manner: A positive sentiment about the Electric Vehicle market being expressed in social media correlates to the appreciation of Tesla Motor's stock market value. There is a moderate negative correlation between Wted_Neg and the Close column (-0.37), indicating that the social media's negative mood does not translate as much to depreciation of the market value.

On observation of the results for the Exxon Mobil. Corp (Oil & Gas Market) and the social media sentiments, with a moderate positive correlation between the Wted_Neu (0.36) and Wted_Pos (0.34) to the closing price. The weak correlation between the Wted_Neg and the closing price (-0.1) indicates that the oil market does not fluctuate if there are negative sentiments being expressed about it on Twitter - making it a low-risk stock in that aspect. But the market price shows considerable appreciation with positive/neutral discussion about it on the social media platform, although not being very susceptible to social media trends.

For the Technology sector, and its reference stock market entity - Microsoft Corp., a strong positive correlation was obtained between the closing price and Wted_Neu (0.67) and Wted_Pos (0.58), respectively. A medium negative correlation was obtained between the closing price and Wted_Neg (-0.49) attribute. The results indicate that there is a remarkable correlation between general social media discussion of the Tech sector and the stock market in both

ways, indicating that the technology market is volatile to the mood of social media.

In the Pharmaceutical sector, with the chosen stock market representative as Moderna Inc., it was observed that there is a medium positive correlation between the three weighted attributes - Wted_Neg (-0.54), Wted_Neu (0.47) & Wted_Pos (0.45). This indicates that the Pharma sector's market behaviour is also volatile to the sentiments expressed on social media, especially on the negative side - a negative mood correlates more to the pharmaceutical sector's market price going down.

It is also worth noting that the correlations observed in Figure 4.6) are almost always significantly higher for the weighted/individual sentiment scores, as compared to the volume-based scores (Neg_Counts, Neu_Counts & Pos_Counts). This pattern clearly indicates that performing a sentiment-based analysis of social media proves to be a much more useful and promising methodology of understanding stock market patterns, as compared to a purely volume (Tweet count) based analysis.

4.6.3 Predicting the Stock Market

Following our main objective of performing a correlation analysis, we decided to additionally perform stock market prediction using machine learning algorithms, since we observed a good correlation between the weighted Tweet sentiment scores and the close price of the market. From Nayak et. al's [9] research on stock market prediction augmented by sentiment analysis of Twitter and news, it can be seen

that Boosted Decision Trees perform the best in this scenario when compared to other algorithms like Logistic Regression and Support Vector Machines.

Thus, we decided to compare and contrast two widely-used decision tree algorithms that employ the concept of boosting to predict the close value of the above used stock listings, augmented by the weighted Tweet sentiment scores.

The first boosting algorithm under consideration is DMLC's XGBoost[1] (eXtreme Gradient Boosting). It was first presented in 2014, and is touted as an optimized, distributed gradient boosting library that is designed to be highly efficient, flexible and portable. It is a step further than boosted decision trees in the sense that it uses a parallelized approach to building and pruning trees, has in-built cross-validation and does regularization to prevent overfitting of data.

Another boosting algorithm that has gained great prominence in the recent years for its performance is Yandex's CatBoost[12], which was introduced in 2017. It is also a gradient boosting algorithm that natively handles categorical features, uses the GPU for faster training times, employs ordered boosting to prevent overfitting and has dedicated visualization tools for model analysis. It also claims to provide great quality without the need for fine-tuning, a common procedure done manually to find the best hyper parameters for the machine learning model to optimally perform the specified task. It is often compared with other boosting models like XGBoost and LightGBM.

4.6.3.1 XGBoost

We use the Python implementation of XGBoost to construct our model. An initial model was constructed using the default parameters present in the XGBoost

Regressor to visualize the results. It was observed that fine-tuning was required, and thus we employed the GridSearchCV() method, bundled as part of the scikit-learn library to find out the best hyper parameters for our use-case.

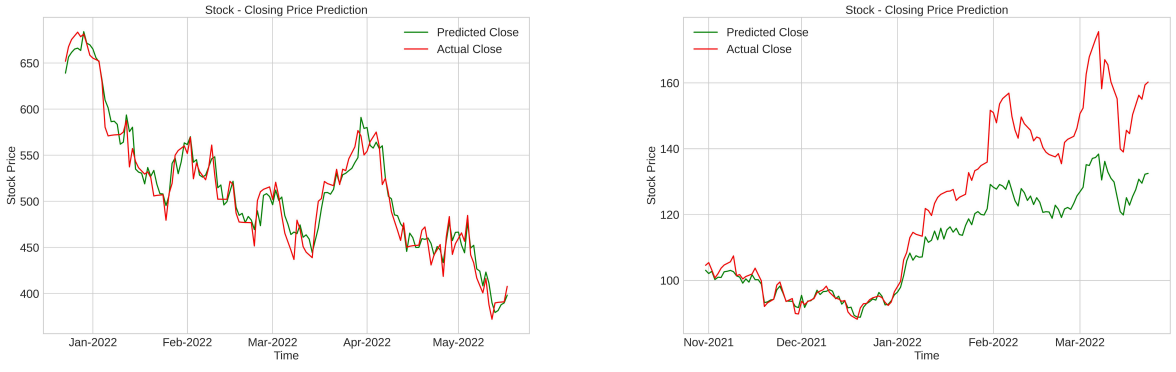
The following hyper-parameters were returned by the grid search algorithm:

Hyper Parameter	Value
Maximum Tree Depth	3
Number of Estimators	500
Objective Function	Squared Error
Booster	GB Tree
Learning Rate	0.1
Column Sampling by Tree	1
Evaluation Metric	Mean Absolute Error (MAE)

TABLE 4.8: XGBoost - Optimal Hyper Parameters

Four separate regressor models were created and executed to predict the close value of the four listings used above (TSLA, XOM, MSFT & MRNA). The dataset was split into 85% for training and 15% for testing, without shuffle.

The prediction graphs and results are shown in Figure 4.7 and Table 4.9.



(a) (NASDAQ: MSFT)

(b) (NYSE: XOM)

FIGURE 4.7: XGBoost Prediction Results

(c) (NASDAQ: TSLA)

(d) (NASDAQ: MRNA)

XGBoost Prediction Results

RMSE	0.0471
MSE	0.0022
MAE	0.0377
R2 Score	0.8381
Explained Variance Score	0.8427
Max Error	0.1403

(a) (NASDAQ: MSFT)

RMSE	0.1914
MSE	0.0366
MAE	0.1420
R2 Score	-0.6285
Explained Variance Score	0.2131
Max Error	0.4236

(b) (NYSE: XOM)

RMSE	0.0562
MSE	0.0031
MAE	0.0463
R2 Score	0.7086
Explained Variance Score	0.7555
Max Error	0.1630

(c) (NASDAQ: TSLA)

RMSE	0.0366
MSE	0.0013
MAE	0.0255
R2 Score	0.8185
Explained Variance Score	0.8370
Max Error	0.1885

(d) (NASDAQ: MRNA)

TABLE 4.9: XGBoost Regressor Metrics

It was observed that the XGBoost Regressor models were able to capture the inherent patterns in the dataset and produce a model that predicts the next day closing price of the stock market based on the mood reflected by people on social media, with significant accuracy. It performs the best (83.81% accurate) on the Tech-MSFT dataset, which follows from the observed high correlation between its weighted sentiment scores and its closing price.

4.6.3.2 CatBoost

Similar to XGBoost, we use the Python implementation of CatBoost to construct our model. An initial model was constructed with the CatBoost Regressor to visualize the results. It had some fluctuations in the test data, thus we decided fine-tuning was necessary. We used CatBoost's in-built grid_search() method to find the optimal hyper parameters for our datasets.

The following hyper-parameters were returned by the grid search algorithm:

Hyper Parameter	**Value**
Tree Depth	4
Iterations	200
Learning Rate	0.05
L2 Leaf Regularization	10
Loss Function	Mean Absolute Error (MAE)

TABLE 4.10: CatBoost - Optimal Hyper Parameters

Four separate regressor models were created and executed to predict the close value of the four listings used above (TSLA, XOM, MSFT & MRNA). The dataset was split into 85% for training and 15% for testing, without shuffle.

The prediction graphs and results are shown in Figure 4.8 and Table 4.11.

(a) (NASDAQ: MSFT)

(b) (NYSE: XOM)

(c) (NASDAQ: TSLA)

(d) (NASDAQ: MRNA)

FIGURE 4.8: CatBoost Prediction Results

RMSE	0.0480
MSE	0.0023
MAE	0.0383
R2 Score	0.8319
Explained Variance Score	0.8427
Max Error	0.1288

(a) (NASDAQ: MSFT)

RMSE	0.1962
MSE	0.0385
MAE	0.1457
R2 Score	-0.7114
Explained Variance Score	0.1810
Max Error	0.4340

(b) (NYSE: XOM)

RMSE	0.0711
MSE	0.0050
MAE	0.0562
R2 Score	0.5328
Explained Variance Score	0.6047
Max Error	0.2063

(c) (NASDAQ: TSLA)

RMSE	0.0337
MSE	0.0011
MAE	0.0251
R2 Score	0.8461
Explained Variance Score	0.8642
Max Error	0.1491

(d) (NASDAQ: MRNA)

TABLE 4.11: CatBoost Regressor Metrics

It was observed that the CatBoost Regressor models were able to capture the inherent patterns in the dataset and come up with a fairly accurate model to predict the next day closing price of the stock market, with its best performance observed on the Pharma-MRNA dataset (84.61% accurate).

4.6.3.3 Comparison of XGBoost and CatBoost

It can be observed that the XGBoost algorithm works better for the prediction of the closing prices of our four chosen stock listings. The XGBoost Regressor is able to match the observed (real) stock data more closely as compared to CatBoost. Both models are able to capture the trend of the market movement (increase/decrease). From the results table, we can conclude that the metrics are slightly better for the XGBoost model, except for the Pharma-MRNA dataset, in

which CatBoost performed better with an accuracy of (84.61%), as compared to the XGBoost model which had an accuracy of (81.85%).

Thus, we believe that using either CatBoost or XGBoost for this task would be prudent, although there is a slight advantage to using XGBoost in terms of results, as evidenced by the above results.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

To conclude, we have discussed, in this report, the detailed design and related implementation of stock market analysis using social media trends, using a big-data architecture. Apache Kafka and Apache Spark can be effectively used to construct a high performance, scalable pipeline that can use the power of parallelization and clustering to mine useful information from huge amounts of data. We were able to construct an end-to-end pipeline entirely using the Python language, straight from the first step of data collection, till the last step of visualization.

In our study, we have undertaken four stock market segments - Electric Vehicles, Oil & Gas, Technology and Pharmaceuticals - and four representative stock market entities - Tesla Inc., Exxon Mobil Corp., Microsoft Corp., Moderna Inc. to analyse the correlation between the sentiments observed in social media to the respective entity's stock market valuation.

From our observed results, we have seen conclusive proof that there is a correlation between the mood expressed on social media to stock market behaviour, although the extent of the correlation varies for each sector. We specifically chose these four sectors as they had a lot of discussion during the period of study (Mar 2020 - May 2022), and we chose market leaders as representative companies. The correlation might not be as heavily seen for other companies with a lower market share or low social media discussion. However, it is worth noting that for those companies which have a strong online community discussion, it is worth taking into account

those sentiments expressed by the community to predict how the stock market may change over time.

We were also able to identify two candidate machine learning algorithms - CatBoost and XGBoost, that can be utilized for efficient stock market prediction using the sentiment values.

We also took into account the conclusions of earlier research papers published in this area and introduced novel elements as per their specified line of future work. One example is the use of a transformer model (BERT) for the NLP task, and another is to use a larger dataset to broaden our sample space. Hence, we believe that our work has caused noteworthy progress in achieving the goals of this line of research.

With regards to future work, the inclusion of data from other social media websites like Facebook, Reddit etc. can present an even broader picture of the sentiment expressed by users online. The inclusion of the sentiments reflected in news articles could also prove to be more effective in trend analysis of the stock market. Thus, data from multiple sources can be pooled together and aggregated with a big-data architecture. Another consideration is the fact that the social media data that we work with are primarily produced by the English-speaking audience. Similar NLP techniques that work with other languages would be required to perform similar analyses in non-English speaking countries. With the inclusion of non-English Tweets (and other social media posts), it is possible to obtain a higher correlation score. The stock market data prediction task can further be improved and made reliable with the addition of other features that affect the stock market, apart from social media. All these remain future areas of research to be explored.

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