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SENTIMENT ANALYSIS OF MAJOR NEWS ANNOUNCEMENTS TO PREDICT THE AGGREGATE MARKET INDICATORS AMID COVID-19 OUTBREAK

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ABSTRACT

The COVID-19 Pandemic (a Black Swan event) whose impact on more than 180 countries led to the disruption of certainty. The Corona Virus started its contagious spree from the Chinese city of Wuhan.

It impacted healthcare, education system, Corporations, Employment, Production, and the very nature of hygiene and cleanliness. The news of the Contagious Virus hit the Stock Market and other Financial Markets hard indicating the risk in the expected future cash flows. The Stock market nose-dived in March 2020 indicating the sentiment of the general public rather than rational decision making. The fundamentals of Corporations cannot explain such massive drops but the sentiment of the general public can help in explaining such volatility.

This Paper highlights and measures the volatility of public sentiment and leverage it to predict the benchmark indices of seven countries amid the Covid-19 pandemic with the help of Machine Learning Algorithms.

Key words: Financial Markets, Sentiment Analysis, Machine Learning, Covid-19

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1. INTRODUCTION

The literature on the sociology of Stock markets or (Financial markets) suggests that economic actors in Financial Markets are beyond mere human beings. Today, the information in a whole range of markets streams in through social media text, newswire text, and through websites. Also, the news plays a major role in today's globalized world. Any significant announcement in a country can significantly impact other countries as well. Hence, the information in the form of social media text or news media announcements have the potential to impact the returns on investments. These reports have to be analyzed by economic actors to make an informed decision requiring the use of human intellect, tools, equipment, algorithms, etc.

Information and data, although are an important component to analyze the investment decisions, but are insufficient to provide a true picture. A behavioral perspective is involved apart from numeric data while making financial decisions. (De Bondt & Thaler, 1994) argued that the decision-making process is driven by various cues instead of only prudent reckoning. The emotion and other psychological factors highly influence the investment decision. This is worth noting because during any crisis or emergency the psychological factors cloud the rationality. This gives rise to unprecedented decision-making which is hard to explain without considering behavioral aspects.

(Liu, 2012) introduced the programmed identification of people's notions, beliefs, and attitudes with the help of Machine Learning algorithms. The sentiments in unstructured data such as news articles, blogs, and microblogs are ascertained with the help of Natural Language Processing. This is significant because financial news and global announcements can be studied for sentiment intensity and polarity identification. This will help in quantifying behavioral aspects along with the explicit data to ensure more informed decision-making.

Sentiment analysis in the Financial domain is done by various researchers namely, (Devitt & Ahmad, 2007), and (Nofsinger, 2013). Whereas this paper underlines the impact of news related to COVID-19 on stock markets. This study is unique because news related to a particular issue to ascertain its emotional impact has not been researched upon. Sentiment analysis on topic-specific newswire text in the financial domain with significant success is done by, (Van De Kauter et al., 2015). This paper highlights the usage of newswire-derived-sentiments to identify stock market movements under unprecedented times.

This paper highlights three key insights. First, it represents the volatility in sentiments of public during COVID-19, taking CNN Media company COVID-19 timeline of major announcements as a proxy. Second, this research paper identifies the impact of such news on aggregate market indicators of developed countries. The stock market indices studied in this paper are S&P 500, DAX, FTSE 100, NIKKEI 225, S&P/TSX, CAC 40, and S&P/ASX 200. Therefore, the countries analyzed in this paper are the United States of America, Germany, the United Kingdom, Japan, Canada, France, and Australia. The accuracy of the model to predict market movement is also analyzed.

Third, the relative accuracy of various Classification Machine Learning Algorithms such as (Logistic Regression, Decision tree, and Random Forest) is evaluated to constitute a robust model.

2. LITERATURE REVIEW AND THEORY

The rationale behind the theory of Efficient Markets, (Fama, 1970) was, it considered investors to make a rational decision in all circumstances. A weakness with this argument, however, is that it neglects the sentiment of the general public. This can significantly impact the hypothesis during unforeseen circumstances or crisis such as COVID-19 Pandemic. Also, too much volatility in markets challenged this hypothesis which indicated that information propagation was not instantaneous resulting in volatility in the market for a definite time. Many time-series studies showed the Efficient Market Hypothesis was insufficient to explain such a phenomenon. The field of Behavioral Finance (1990) was introduced to explain the anomalies of the Efficient Market Concept, (Shiller, 2003). It unlike modern Finance considered psychology, emotions, and sentiments of people into the framework of decision-making. It reasoned that decision making is not purely built on rational calculations but the emotions/sentiments highly influence the nature of decisions. This is significant because it explains the volatility of markets after news arrival which took some time to consolidate.

Sentiment analysis is typically used to analyze human attitudes, notions, beliefs, estimations, and opinions. This approach studies sentiments in textual or unstructured data on various subjects, events, and topics(Liu, 2012).

(TETLOCK, 2007)analyzed Wall Street Journal's articles on financial markets using Natural Language Processing to identify the behavioral impact of the previous day's market performance on the stock market. The result highlighted that high levels of media pessimism can impact the market negatively.

1.2. Dictionary-based Approach

The dictionary-based approach works on the meaning of the human expressions in the text. The strength of the emotion or sentiment is identified using this approach. The lexicons are built by incorporating sentiment words and assigning them with strength score. The compiled dictionary having words and sentiment score then can be used to identify the sentiment of the new unseen text. The examples of lexicon building manually and semi-manually are (Mohammad & Turney, 2010), (Ding et al., 2008). This paper uses a lexicon-based approach with modified sentiments of certain words to get a true picture of emotions and its impact amid COVID-19 Pandemic.

1.3. Machine Learning Approach

Machine Learning algorithms cannot understand the raw text. To solve this problem, the popular method is to convert the text into binary form, (Joachims, n.d.). This method requires the formation of a sparse matrix with each article forming a row and all the words in corpora forming the columns. Then financial news articles can then be introduced into the algorithm which forms patterns of behavior to build the prediction model, (Schumaker et al., 2012). This approach highlights the importance of each word in the article to ascertain the polarity and sentiment Intensity.

Classification algorithms such as Logistic Regression, K-Nearest Neighbors, Support Vector Classification, Random Forest, and Naïve Bayes are commonly used for analyzing sentiments through Machine Learning(Pang et al., 2002). This is usually achieved by harnessing pre-annotated data such as records of customer reviews or by manually annotating the data, which is a time-consuming but more accurate method.

Both approaches have been successfully applied over various texts such as document, paragraph, sentence, phrase, and words. This highlights the power of such analysis on various textual writings to study sentiments/ emotions of the public.

1.4. Finance Sector – Sentiment Analysis

(Nofsinger, 2013) stated that in lieu of attracting people's attention media inclines toward genuine investment insights on stock selection. This shows news media influences the investor's mindset.

Texts such as blogs, news headlines, social media texts, public announcements, and writings on major issues, all have a non-factual dimension. This dimension has a high correlation with sentiments, emotions described in the writings, (Devitt & Ahmad, 2007). This is significant because the use of sentiment intensity in Natural Language can give insights on not only what information is delivered but also how it is received. The sentiments can majorly impact asset returns when text is related to major global issues. The Coronavirus

Pandemic is one such example when news arrival heavily impacted the returns. The general public sentiment produced volatility in asset prices tracing every major announcement.

In the financial domain, studies on sentiment analysis have been done on various financial texts. (Hare et al., 2009)analyzed sentiments in financial blogs, (Sprenger et al., 2014) studied Twitter data. The recent significant work on financial news text has been performed by (Devitt & Ahmad, 2007) which highlighted the importance of news, major announcements, and its impact on markets.

As stated by (Sprenger et al., 2014), the Microblogging forums (e.g., Twitter) has become a new platform for traders to share information over future expectations of market performance. This points to the growing popularity of online messages and to the opportunity to exploit it for earning above-average returns on investments.

3. MATERIAL AND METHODS

3.1. Evaluation Corpus

To evaluate the impact of the major news of the COVID-19 outbreak on aggregate stock market indices, 58 major announcements of Pandemic were analyzed. These announcements trace the major events and how they turn out throughout five-months. This timeline of events is reported by every news agency worldwide which majorly consists of announcements made by the World Health Organisation (WHO). This paper analyses the CNN Media company COVID-19 timeline of major announcements as a proxy to study the impact of such news on aggregate market indices. The onset of COVID-19 in January 2020 marks the beginning of this study. The paper analyzes five-months namely January, February, March, April, and May of the year 2020.

3.2. Aggregate Market Indicators (Stock Quotes)

To evaluate the impact of news announcements on the Stock Market of developed countries seven aggregate market indicators were analyzed. These represent seven countries namely, the United States of America, Germany, the United Kingdom, Japan, Canada, France, and Australia, Therefore, the stock market indices studied in this paper are S&P 500, DAX, FTSE 100, NIKKEI 225, S&P/TSX, CAC 40, and S&P/ASX 200. The quotes are retrieved from Yahoo Finance (finance.yahoo.com) and Wall Street Journal (www.wsj.com).

3.3. Vader Sentiment Analysis Model

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a sentiment analysis model based on the lexicon approach, (Huctto & Gilbert, 2014). The model consists of lists of words that are annotated based on their sentiment strength. Therefore, resulting in several high-frequency-words with their sentiment score. This rule-based sentiment analysis tool has been typically used in microblogs such as Twitter messages. Also, after incorporating several heuristics in the model it has been successful across several domain contexts. Social media texts such as Twitter microblogs, News texts such as New York Times editorials and Wall Street Journal columns, and Review texts such as products and movie feedback forms are the latest domains where VADER has been finding its applications(Hutto & Gilbert, 2014).

VADER has also proved its effectiveness in comparison with various typical benchmarks including the General Inquirer, and SentiWordNet. This is ground-breaking because this model can help in identifying emotions across various domains with more accuracy than peers. We have used publicly available Python Vader sentiment class.

Although, VADER is a powerful tool still it is insufficient in capturing the true sentiment of a Global Issue having limited text. Also, the sentiment scores of various words need modification for correctly identifying opinions in a situation like COVID-19 Pandemic. Therefore, a corpus of selected pessimistic and optimistic words was manually annotated.

3.4. Methodology

Our method leverages the lexicon-based approach to construct a sentiment analysis model. This approach is best suited because

- It requires no training data and is constructed from valence score using the wisdom of the crowd (WotC) approach, (Surowiecki, 2004).
- Modified Lexicon can improve model accuracy and can be applied over specific contexts.
- VADER implement word-sense disambiguation to improve sentiment analysis performance.

Thus, context-awareness of words in texts is also evaluated.

3.4.1. Modified VADER for Capturing current Sentiments

Capturing the current sentiment of candidate lexical feature is important to ascertain the changed psychological orientation of people. This requires re-annotation of some high-frequency used words in news media amid Coronavirus Outbreak. To achieve this, ten independent human raters were assigned with a task to rate the intensity of these words. Features were given scores on a strength range from "[–4] Extremely Negative" to "[4] Extremely Positive". This work is inspired by the research done by (Hutto & Gilbert, 2014).

To estimate the sentiment strength of each context-free word we used collective wisdom of the people also known as the "Crowd-Wisdom-Evaluation" methodology, (Surowiecki, 2004). To determine the intensity of words ten independent human raters were assigned to annotate the lexical features. We implemented three quality-check measures to help ensure we receive authentic insights from candidates.

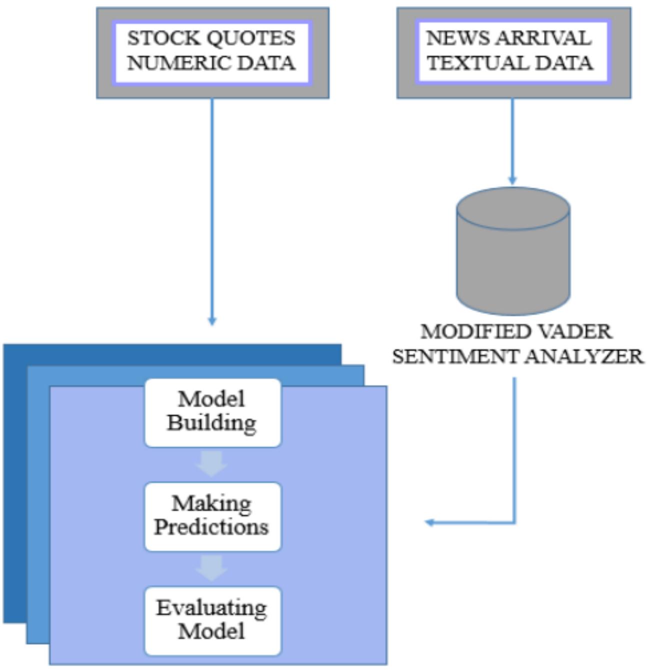

Figure 1 Flow-Diagram of Experimental Setup

First, every candidate was presented with a graduation-level reading comprehension test in the English language, each candidate has to score passing grade to get to the next level of screening.

Second, each candidate had to attend an orientation session on ‘Expression of human’s sentiments and emotions in the text’.

Third, each rater had to pass a current affairs test to check the awareness of the candidate, also this helps in incorporating sentiment intensity of newswire text into the study.

3.4.2. Identifying the sentiment intensity over the five-month Period

The Corpus is then introduced into the Modified VADER Intensity Analyser. The sentiment intensity of each major news is analyzed. Figure2 shows the volatility of general public sentiments derived from major announcements on the COVID-19 outbreak.

3.4.3. Identifying the impact of news on aggregate market indicators

To study the impact of news on aggregate market indicators, S&P 500, DAX, FTSE 100, NIKKEI 225, S&P/TSX, CAC 40, and S&P/ASX 200 were used as a proxy to ascertain the Stock market performance of countries namely, the United States of America, Germany, the United Kingdom, Japan, Canada, France, and Australia, respectively. The sentiment intensity of every major news (ascertained with Modified VADER) and daily returns of stock indices taken in binary format (Positive [1] and Negative [0]) were fed into the classifier, which forms patterns of behavior to build the prediction model.

The model predicts the market to be Bullish [1] or Bearish [0] depending on today’s sentiment intensity, which is derived from the major announcements or news of Coronavirus.

Many Machine Learning approaches are implemented to form a robust model. The comparative analysis of the predictive power of each model is done.

The various classifiers used for this purpose are (Naïve Bayes, K-Nearest Neighbors, Logistic Regression, Decision tree, and Random Forest).

K-Nearest Neighbors (K-NN) is a classification technique in which any data point is classified by a plurality vote of its Neighbors. K represents the number of neighbors to be analyzed for a given data point.

Logistic Regression (LR) is a linear classifier that uses a sigmoid function to model a binary dependent variable. Its algorithm is based on probability. The hypothesis of logistic regression tends to minimize the cost function in the range [0, 1], which suits to perform binary classification.

Decision Tree (DT) is a supervised learning model. Decision Tree is formed by splitting the source set into subsets based on maximum Information Gain for construction.

Random Forest (RF) is a form of ensemble learning technique. It improves results by combining various machine learning models and estimating the frequency of occurrence of the result. It operates by constructing various decision trees at the time of training the model. The output is the mode of all classes, resulting from various Decision trees.

The Naive Bayes (NB) classifier is a simple classifier that works on the proposition of Bayes Probability theorem. The naive assumption in this classifier is that variables in the feature matrix are un-correlated from one another, which is not always true.

4. RESULTS AND DISCUSSIONS

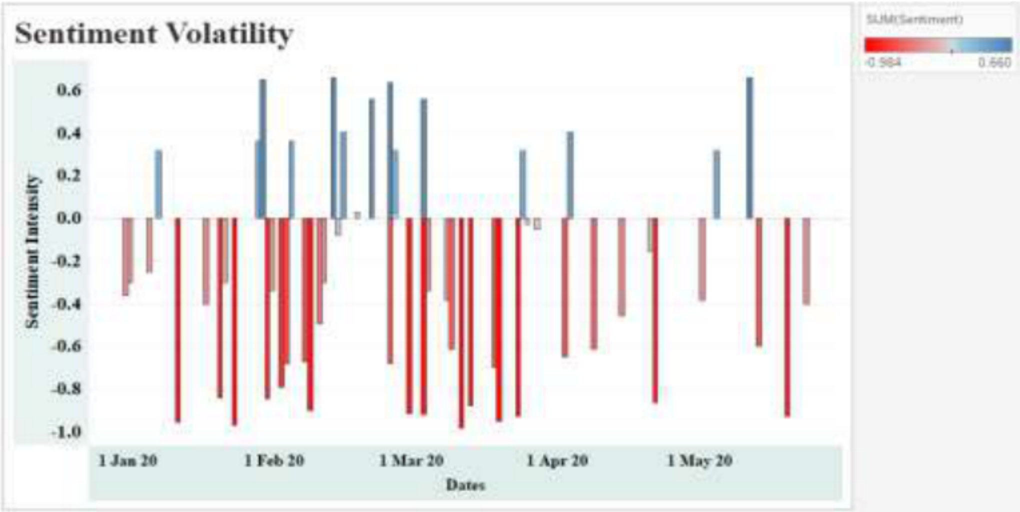

Figure 2 Sentiment Volatility

Figure2 shows the fluctuation of sentiment intensity during the five-months. It clearly states that there were very few instances of positive sentiment and the majority of days were under negative investor sentiment. The buying and selling pressure arising in the market was significantly influenced by the major news announcement related to Coronavirus Pandemic. This paper supports the claim made by, (TETLOCK, 2007) that high media pessimism is associated with low investor sentiment. The figure also identifies the month of March and February to be most negative months driving the stock market in negative territory.

The classification model predicted the FTSE 100 with an accuracy of 80% the best among all countries indicating the derived sentiment useful in forecasting the Stock market indices. Also, other countries too have an accuracy of more than 66% reiterating the usefulness of sentiment in predicting the indices movement.

Table 1 Classifier Performance (Country-wise)

UNITED STATES OF AMERICA (S&P 500)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.714	0.666	0.666	0.571	0.533
Overall Precision	0.764	0.687	0.75	0.75	0.636
Overall Recall	0.866	0.916	0.75	0.60	0.70
OverallF1 Score	0.812	0.785	0.75	0.666	0.666
JAPAN (NIKKEI 225)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.636	0.769	0.636	0.500	0.615
Overall Precision	0.666	0.777	0.666	0.461	0.666
Overall Recall	0.666	0.875	0.857	0.750	0.750
Overall F1 Score	0.666	0.823	0.75	0.571	0.705
UNITED KINGDOM (FTSE 100)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.700	0.800	0.600	0.600	0.600
Overall Precision	0.714	0.818	0.600	0.600	0.600
Overall Recall	0.833	0.900	0.750	0.750	0.750
Overall F1 Score	0.769	0.857	0.666	0.666	0.666
FRANCE (CAC 40)					

CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.500	0.555	0.555	0.500	0.666
Overall Precision	0.500	1.000	0.571	0.500	0.625
Overall Recall	0.833	0.500	0.800	0.833	1.000
Overall F1 Score	0.625	0.666	0.666	0.625	0.769
GERMANY (DAX)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.785	0.714	0.714	0.666	0.700
Overall Precision	0.750	0.625	0.625	0.714	0.666
Overall Recall	0.857	0.833	0.833	0.714	1.000
Overall F1 Score	0.800	0.714	0.714	0.714	0.800
CANADA (S&P / TSX)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.500	0.666	0.529	0.500	0.500
Overall Precision	0.666	0.888	0.727	0.714	0.571
Overall Recall	0.571	0.666	0.615	0.555	0.666
Overall F1 Score	0.615	0.761	0.666	0.625	0.615
AUSTRALIA (S&P / ASX 200)					
CLASSIFIERS	K-NN	LR	RF	DT	NB
Accuracy Score	0.600	0.714	0.588	0.583	0.600
Overall Precision	0.600	0.777	0.625	0.800	0.666
Overall Recall	0.600	0.777	0.555	0.500	0.666
Overall F1 Score	0.600	0.777	0.588	0.615	0.666

4.1. Comparative study of the performance of Classifiers

The Table Ⅰ shows the comparative performance of various classifiers. For S&P 500, K-Nearest Neighbors out-performed others with an accuracy score of 71.4% and F-Measure of 81.2%. Logistic Regression and Random Forest with an accuracy of 66.66% performed better than Decision tree and Naïve Bayes. For NIKKEI 225, Logistic regression out-performed others with an accuracy score of 76.9% and F-Measure of 82.3%. For FTSE 100, Logistic regression out-performed others with an accuracy score of 80% and F-Measure of 85.7%. For CAC 40, Naïve Bayes out-performed others with an accuracy score of 66.7% and F-Measure of 76.9%. For DAX, K-Nearest Neighbors out-performed others with an accuracy score of 78.5% and F-Measure of 80%. For S&P/TSX, Logistic regression out-performed others with an accuracy score of 66.7% and F-Measure of 76.1%. For S&P/ASX 200, Logistic regression out-performed others with an accuracy score of 71.4% and F-Measure of 77.8%.

Table 2 Outperforming Classifier Table

Country	Aggregate Stock Market Index	Outperforming Classifier	Accuracy Score	F-Measure
United States of America	S&P 500	K-Nearest Neighbors	0.714	0.812
Japan	NIKKEI 225	Logistic regression	0.769	0.823
United Kingdom	FTSE 100	Logistic regression	0.800	0.857
France	CAC 40	Naïve Bayes	0.667	0.769
Germany	DAX	K-Nearest Neighbors	0.785	0.800
Canada	S&P/TSX	Logistic regression	0.667	0.761
Australia	S&P/ASX 200	Logistic regression	0.714	0.778

The various classification algorithms were able to predict the market movements to a significant extent. This highlights that sentiment Intensity during situations such as COVID-19 can be explained by public/investor sentiments. The news headlines reported by major Media Channels were capable of giving general public sentiment. The high performance of the model is crucial because it explains that during unprecedented situations, stock market movements are more impacted by emotion and other psychological factors than fundamentals.

5. FUTURE WORK

The study makes use of the Lexicon Approach of sentiment analysis. The lexicon specifically built on financial text and news announcement is not available, but this can improve the accuracy of the model significantly.

Also, every news on major happening in the world can be introduced into the model to make it robust. The challenge here is the computing power available, to extract a significant amount of data and analyze it.

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