CAPSTONE PROJECT

Executive Summary

We have been taught that many principles try to explain stock price movement, from Random Walk theory, Efficient Market Hypotheses, to irrational trader. What is obvious from this evolution of theories in explaining the market price is that more emphasize is on the effect of trader's emotional changes to stock's price movement. In this analysis, we are also interested in study how positive or negative emotion injected into speeches can affect the stock price. However instead of predicting the price, we run logistic regression to test on how well our model can predict a positive or negate daily return of stocks. We extend our analysis to test on stocks, commodities, interest rate and foreign currency pair. Each category of assets is represented by S&P 500, NASDAQ, Gold index ,10 years Treasury Bond rate, and EURUSD. We generate sentiment score from the FED 's speeches from 2006 to 2023 and use the scores as the X variable in our model. This analysis report is arranged in this order; started with Introduction which includes the literature review on this field of study, data and methodology used in this analysis, findings and shortfall, conclusion, appendices and references. Our model found a high accuracy on FED 's speeches in predicting equity and foreign exchange market than commodities and interest rate. However, our analysis is not perfect and we suggest improvement to sentiment analysis with financial specialized lexicon instead of general used lexicon.

By Kimberly Tew

Introduction

All information has been reflected in the current stock price; therefore, there is no arbitrage opportunity for traders, this is stated in Efficient Market Theory. This means that it is impossible for investor and trader to consistently outperform the stock market. E. Fama (1965) ‘s study on randomness of stock confirmed the evidence of efficient market hypothesis was strong in the market. As a result, increasingly attention was brought to this division. In 1967, H. Robert divided efficient market into week and strong forms, which subsequent was expanded by E. Fama, the semi-strong form in 1970.

However, examination and testing on EMH continues throughout the 20th centuries and there were many studies that concluded inefficient market. Many of these opposition arguments are based on, excess volatility due to overreaction by irrational investor, market return includes premium to compensate on transaction cost. Many regards EMH as “half true”. On one hand, market is more efficient now than before with quicker information flow and faster trade execution, on the other hand, there are more factors that drives the price movement, even the automated robot trade plays a role here. In reality, EMH fails to explain all reasons for that market trends.

Investors and traders in the market have been looking for answer to explain the market trend regardless if it is equity, commodities or currencies. It can be divided into value or technical two school of thoughts in explaining the asset’s prices. As the financial market grows into something too big to fail, any adverse impacts to the market will lead to devastating loss to the world economy. In order to reduce the risk of market collapse, studies on market price become a fast-growing sector in the field of finance research. It started from time series research on stock prices, by using historical open, close, high and low to predict future price. These are all numerical data before there is advocate that news and public opinions are also important determinants for market price. This unstructured textual data which scattered all around the internet cannot be easily processed until Natural Language Processing and text mining come to the rescue. Nowadays, we could use text mining tools and technique to extract the public opinions and news from the internet and perform sentiment analysis and derive meaningful conclusion from the otherwise unstructured data. It has been known that human decision is impacted by emotion about that topics, so by studying the underlying emotional, we are prepared and react efficiently on the impact of such news or public opinion.

Sentiment analysis applied to news articles has been the subject of many researches. Many of this research found the implication of news sentiment to the stock price movement, and hence improve the prediction modelling. The emergence of social media once again pushes sentiment analysis to a higher level which bigger magnitude of data set is made available for stock price prediction. (Zhang, Fuehres and Gloor, 2011) found a strong relationship between twitter post to stock price. Nevertheless, in this project, we want to extend sentiment analysis to speeches by keymen in US Federal Reserves. We want to answer a question on, whether other than news and twitter post, is keymen’s speeches has an impact on the stock prices?

We did not find the any previous study that confirmed the above relationship, but we could see increasingly more studies that are close to answering this question. Petropoulos, A., & Siakoulis, V. (2021) addressed the question of whether central bank’s speeches have a predictive ability on the occurrence of financial turmoil event which help in forward-looking future policy. Hubert and Labondace (2017) ‘s found the linkage between the sentiment of ECB’s statement and the term structure on short-term interest rate expectation. In our project, we narrowed our country to US and performed sentiment scoring to FED’s speeches text before running a logistic regression on sentiment scores with assets prices. We extend our test assets to include, US 500 stock index, NASDAQ , 10 years treasury bond rate, Gold index and EURUSD currency pair. The data we used span from 2006 to 2023. The implication from the result that we conclude from this project is important to investors to manage their position risk near to the FED’s speech day.

Data Description and Methodologies

Our project mainly consists of 3 main parts; data collection, sentiment analysis and machine learning. In the first part of this project, we focus on two data sources; one is Federal Reserve news's page and the other Yahoo finance.

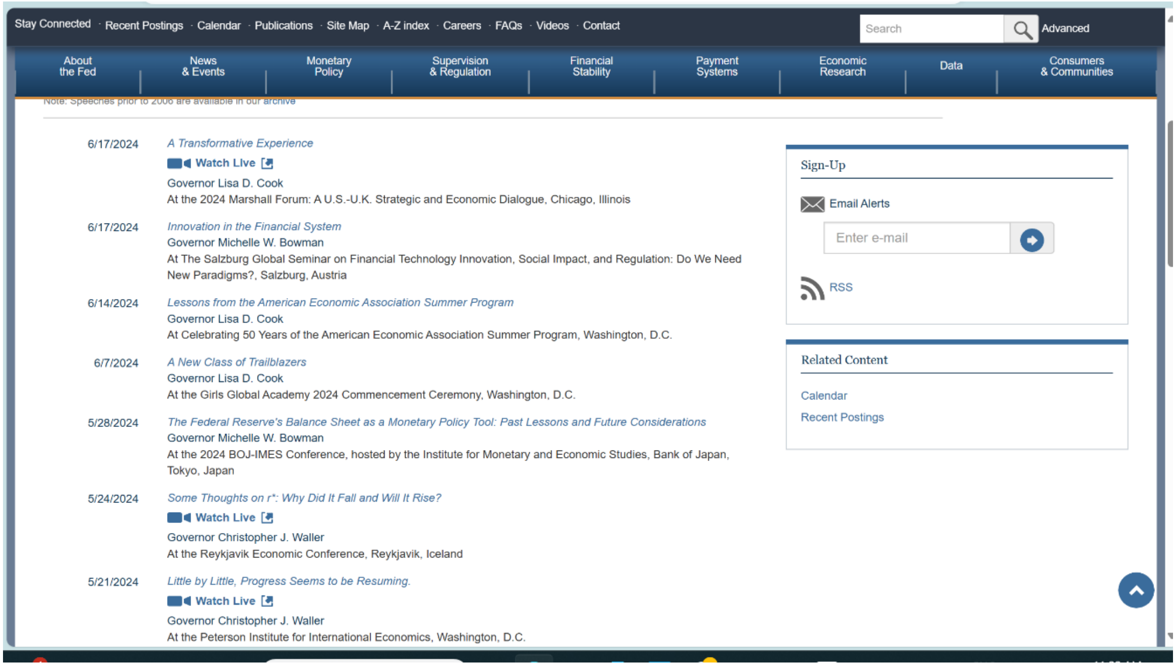


Image 1.0-Speeches retrieved from: [Federal Reserve Board - Speeches of Federal Reserve Officials](https://www.federalreserve.gov/newsevents/speeches.htm)
https://www.federalreserve.gov/newsevents/speeches.htm

From the FED news event page, we request the page content and parser the html with Beautiful Soup. Then we select only internal hyperlinks to the individual page of speeches given for each year into a list. From the list of hyperlinks, we use Beautiful Soup to parse the html into organized list item again before we organized the data set into a data frame using Pandas. The dataset is divided into Date, Speaker, Speech Titles, and Text Contents columns with a total of 1049 rows.

	Date	Speech Titles	Speakers	Text Content
1	June 17, 2024	A Transformative Experience	Governor Lisa D. Cook	of my colleagues on the federal reserve board or the federal open market committee.return to text
2	June 07, 2024	A New Class of Trailblazers	Governor Lisa D. Cook	uating class—the class of 2024! we are all so proud of you and cannot wait to see what you will do.
3	June 17, 2024	Innovation in the Financial System	Governor Michelle W. Bowman	uncil releases report on nonbank mortgage servicing," press release, may 10, 2024.return to text
4	June 14, 2024	in Economic Association Summer Program	Governor Lisa D. Cook	of my colleagues on the federal reserve board or the federal open market committee.return to text
5	May 24, 2024	ghts on r*: Why Did It Fall and Will It Rise?	Governor Christopher J. Waller	34(pdf)(washington: cbo, february).return to textview speech charts and figuresaccessible version
6	May 21, 2024	by Little, Progress Seems to be Resuming.	Governor Christopher J. Waller	terson institute for international economics, washington, d.c. (via webcast), march 29.return to text
7	May 28, 2024	: Past Lessons and Future Considerations	Governor Michelle W. Bowman	quantitative tightening" in the note.return to textview speech charts and figuresaccessible version
8	May 20, 2024	omic Outlook and Housing Price Dynamics	Vice Chair Philip N. Jefferson	onetary policy," working paper, may.return to textview speech charts and figuresaccessible version
9	May 19, 2024	rsity Law Center Commencement Address	Chair Jerome H. Powell	u again to dean treanor and all the faculty, and the hardiest of congratulations to the class of 2024.
10	May 20, 2024	Building a Resilient Regulatory Framework	'ice Chair for Supervision Michael S. Barr	aning each bank determines its own outflow assumptions, subject to regulatory input.return to text

Table 1.0-Conversion of unstructured website html into structured DF to store the variables needed for sentiment analysis later.

Then EDA is performed to look into the data set and decide on preprocessing method required to clean and prepare the text for sentiment analysis. It is interesting to found that some of these speakers are leading others in the total speeches given based on the records (Figure 1.0), and it is obvious that these leaders are holding important roles in FED. The top three speakers by total speeches are either chairman or vice chairman of FED during their terms of service. Ben. S. Bernake was the FED chairman from 2006 to 2018, and succeeded by Jerome. H. Powell since 2018, while Lael Brainard was the governor member since 2014 and later promoted to vice chairman during 2022 to 2023. Figure 1.1 displays a line chart for number of speeches given in a year throughout the year from 2006 to 2023.

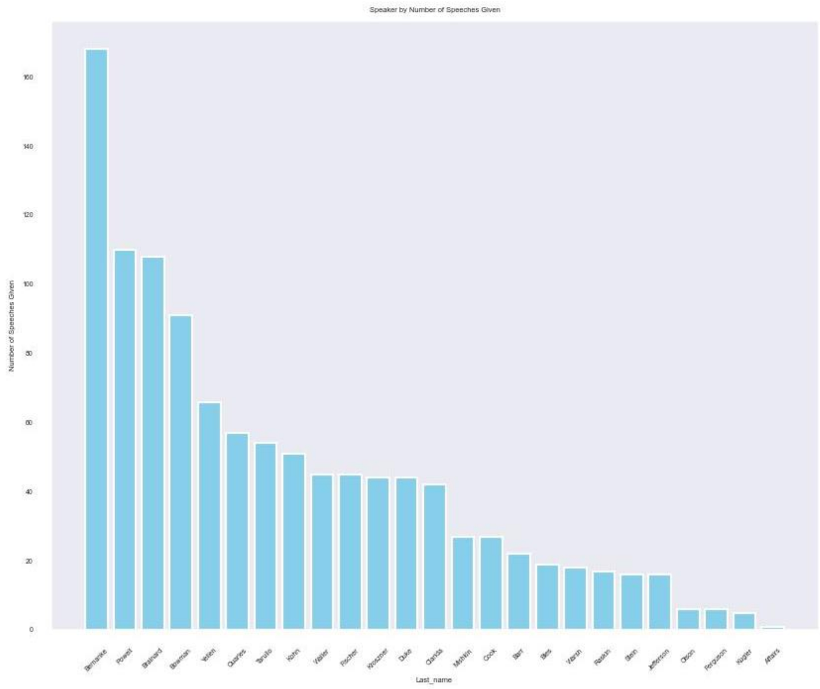


Figure 1.0 -Speakers by number of Speeches Given

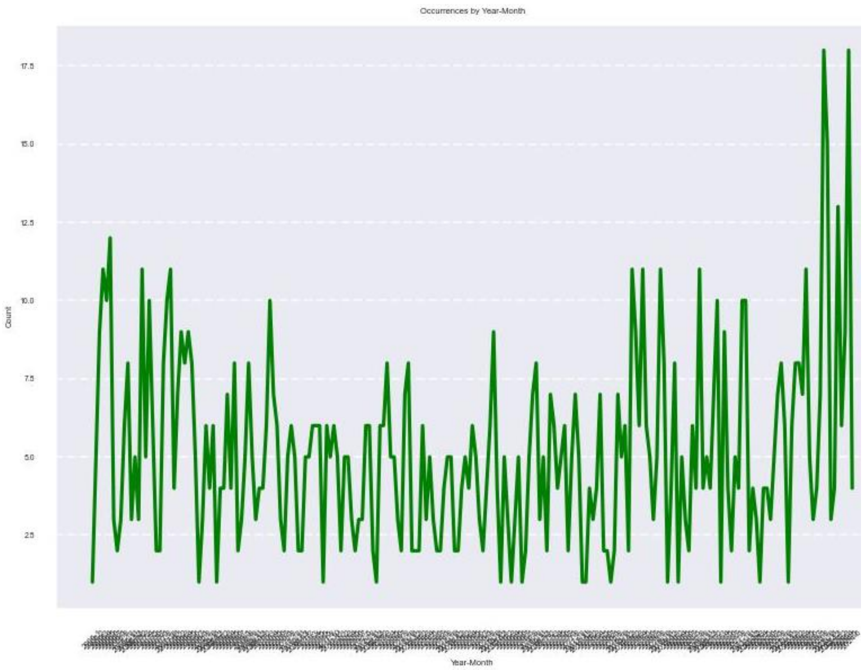


Figure 1.1- Number of Speeches per Year from 2006- 2023.

Data Preprocessing

a. Speeches Text

NLTK libraries is heavily used in this preprocessing stage, packages we used includes:

1. Stopwords
2. Words Tokenization
3. Word Net Lemmatizer
4. Vader Lexicon

From above data frame we composed, we need to preprocess the text content variable in order to run sentiment analysis. The preprocessing steps are:

1. We remove all punctuations and English Stopwords from the text.
2. We split the text content into word with word tokenizer.
3. Then, we lemmatize the wordings only to keep the base form.
4. Insert a new column into the data frame to save cleaned text from above steps.

At the final step, we apply sentiment intensity analyzer to the cleaned_text column and classify the polarity scores into “pos”, “neu”, “neg” and “compound”. Each scoring system has a score from -1 to 1 , which the larger the score, the nearest to the positivity or negativity. We also analyze the text by its subjectivity using TextBlob, the text that scores 1.0 is pure subjective and 0 mean pure objective statement.

b. Financial Data

We choose below indexes prices as a representation to the assets that we want to run the test on;

a. S&P500 & NASDAQ -represents US Equity market
b. Gold – commodities market
c. 10 years Treasury bond rate – interest rate
d. EURUSD -USD exchange rate

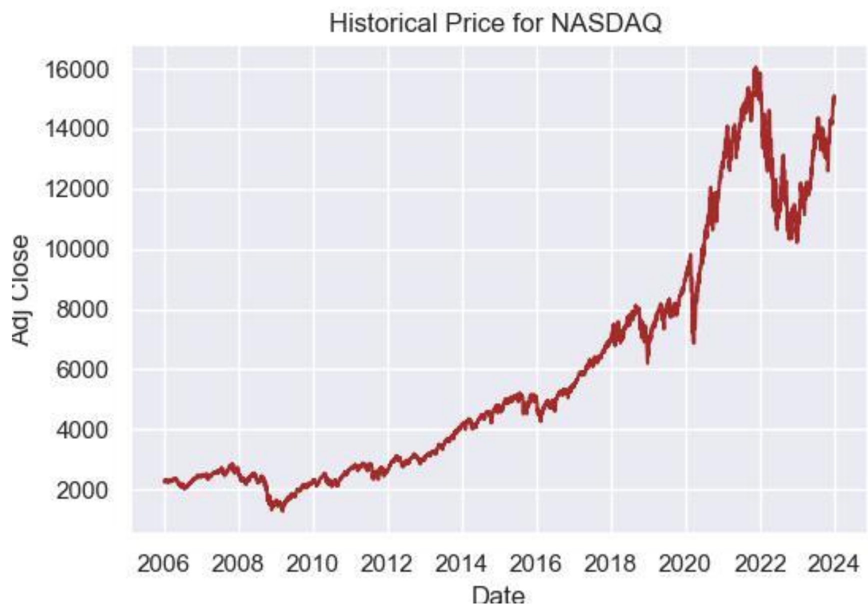
By using yfinance library, we are able to download the data for Open, Close, High, Low , Adj Close price and Volume from 2006 to 2023 for each of every index listed above and save it into a CSV file to be read later. We then plot the line chart to show the adjusted closing price of each asset for our testing periods. From long term perspectives, equity market and gold price are on a positive return trend, while currency and interest rate experienced higher volatility.

c. Sentiment Analysis

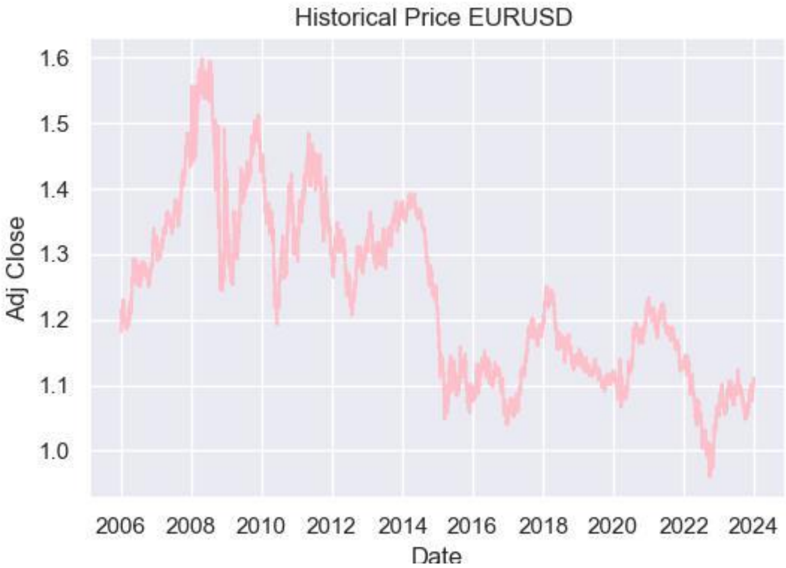
Our Sentiment Intensity Analyzer shows that there are slightly more positive sentiments than negative sentiments but not significant differences noticed. Pair plot diagram also illustrates that sentiment scores for positivity, negativity. neutral and subjectivity are normal distributed, with slightly differ in the skewness.

It can be seen that both negative and positive scores is slightly skewed to the right while subjectivity and neutral are almost perfectly normal distributed. However, only compound score has a significant negative skewness. We are unable to observe any clear relationship between the sentiment scores and all the assets ‘s return from pair plot diagram. The higher positive score did not yield more days with positive return whereas a higher negative scare also did not result in lower or more negative daily return. However , the daily return diagram shows that foreign exchange market is the most volatile than the others , with the widest daily return range among all our testing assets which explains the previous volatile price chart.


Historical Price for S&P 500
5000
4000
3000
2000
1000
Adj Close
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024
Date


Historical Price for NASDAQ
16000
14000
12000
10000
8000
6000
4000
2000
Adj Close
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024
Date

Historical Price for Gold
2000
1750
1500
1250
1000
750
500
250
Adj Close
2012
2014
2016
2018
2020
2022
2024
Date



Historical Price EURUSD
1.6
1.5
1.4
1.3
1.2
1.1
1.0
Adj Close
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024
Date

d. Machine Learning

Logistic Regression is a supervised machine learning algorithm for binary classification. It is used to estimate the relationship between one dependent variable and one or more independent variables but it used to predict one categorical variable versus a continuous variable. The result will be displayed in probability of occurrence of the dependents variables from 0-1 instead of continuous figures. In this project ,we want to know whether sentiment score from FED speeches can affect a positive or a negative daily return on the those financial assets , therefore we calculate the daily return of the 5 assets above before merging the two data frame together keeping only those dates that have speeches.

To prepare the feature data set for machine learning , we drop some columns that are not in integer format, which are not belong to the feature dataset. The columns that we drop includes ; ["Date","Speech Titles", "Speakers","Text Content","Month","Day","Adj Close", "Last_name","preprocessed_text","cleaned text","Volume","Text_len","Year"]. We also insert a new column and named as " Label" to store the Boolean value "True" if the daily return is positive or "False" if the daily return is negative .

To prepare the feature data for machine learning, we set all columns selected above except ["Label"] as X variable, and ["Label"] columns as Y variable. Then we split the dataset into 80 % training and 20% testing set. With this, we initiate the LR models to train and test our data set. Classification report is generated to assess the viability of our model in predicting our Y variable.

Findings and Short-falls

To evaluate how well our model predict the positive and negative daily return of 5 assets classes , we look at Classification report. It is report that provide detail performances metrics for each class in our classification model. A classification report includes the following metrics :

- Precision: It measures the accuracy of those positive result, and answers the question of how many actual positive outcomes over the number of positive outcomes predicted.
- Recall: It measure how well our model predict the actual outcome, and answers the question of how many actual positive outcome that our model manage to predict correctly.
- F-score : It measures the harmonic mean of precision and recall .
- Support : It shows the actual occurrences of each class.

	precision	recall	f1-score	support
False	0.88	0.90	0.89	80
True	0.93	0.92	0.93	121
accuracy			0.91	201
macro avg	0.91	0.91	0.91	201
weighted avg	0.91	0.91	0.91	201

Image 1.0 Classification report for S&P 500

	precision	recall	f1-score	support
False	0.41	0.20	0.27	60
True	0.57	0.79	0.66	80
accuracy			0.54	140
macro avg	0.49	0.49	0.46	140
weighted avg	0.50	0.54	0.49	140

Image 1.1 Classification report for Gold

	precision	recall	f1-score	support
False	0.31	0.11	0.17	80
True	0.59	0.83	0.69	121
accuracy			0.55	201
macro avg	0.45	0.47	0.43	201
weighted avg	0.48	0.55	0.48	201

Image 1.3 Classification report for 10 Years Treasury Bond interest rate

	precision	recall	f1-score	support
False	0.94	0.78	0.85	97
True	0.82	0.95	0.88	104
accuracy			0.87	201
macro avg	0.88	0.87	0.87	201
weighted avg	0.88	0.87	0.87	201

Image 1.4 Classification report for NASDAQ

	precision	recall	f1-score	support
False	0.94	0.78	0.85	97
True	0.82	0.95	0.88	104
accuracy			0.87	201
macro avg	0.88	0.87	0.87	201
weighted avg	0.88	0.87	0.87	201

Image 1.5 Classification report for EURUSD

Our model is able to hit 95% accuracy rate for predicting a positive return for NASDAQ and Currency pair EURUSD followed by 93%- S&P500. Gold and 10 years Treasury have the worst accuracy among the five assets. Precision rate is 82% for NASDAQ, Currency pair, 93% for S&P 500 and 59% and 57% for 10 year treasury and Gold respectively. We can deduct from these result that equity and foreign exchange prices are more sensitive to FED's speeches than commodities and interest rate.

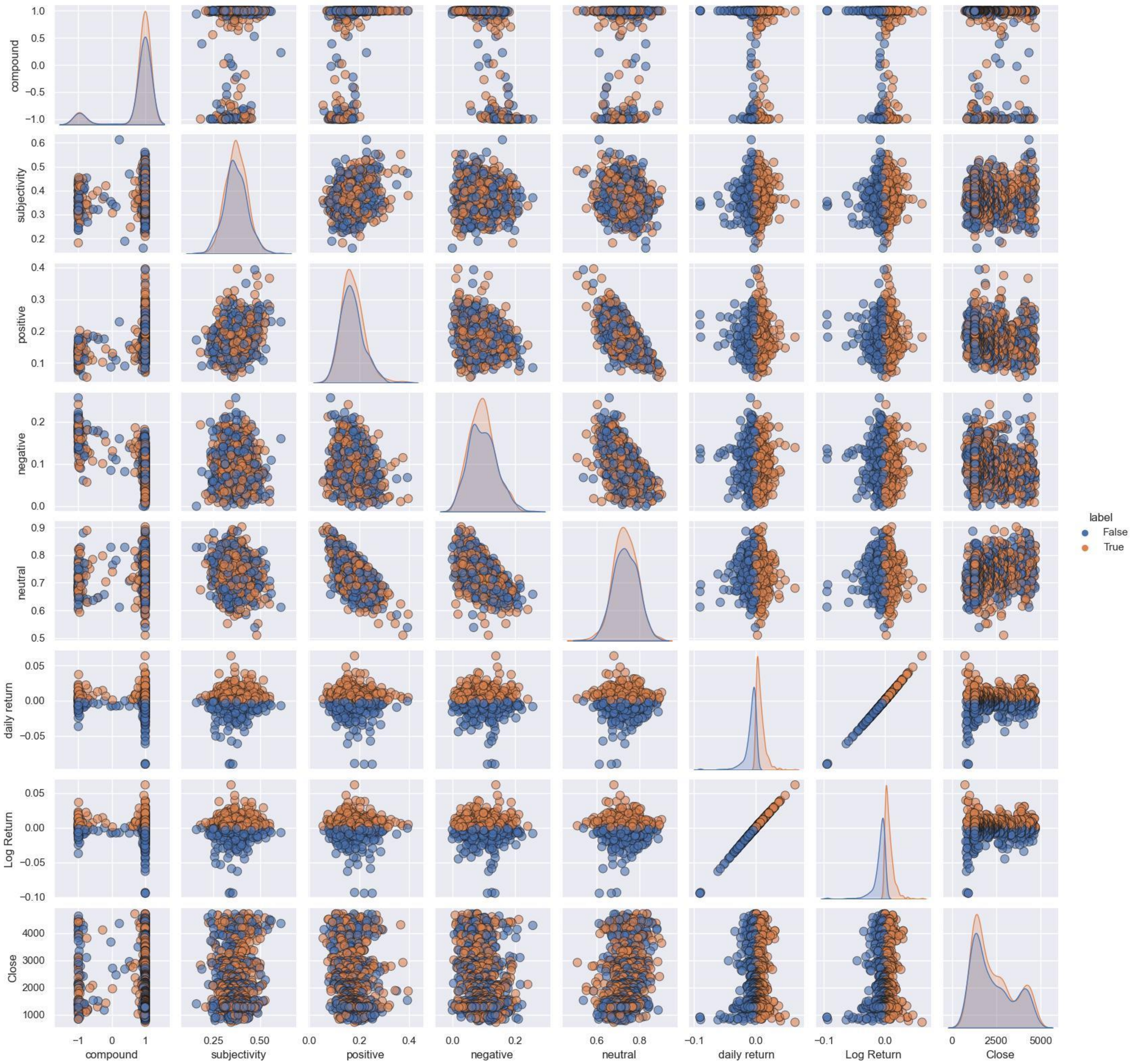
Our reasoning behind this differences in impact might be due to the present of real time market trading for both equity and foreign exchange market , therefore any new information will cause emotion shift in investor and their actions are very much depends on this emotion . While 10 years treasury bond rate has a longer time horizon , and usually affected by Government's policy rather than speeches . Gold is a scarce metal, it was once used as the medium of exchange before fiat currency was introduced. As of today, people keep gold as a way to preserve their wealth or fight against inflation, even as a hedge against market turmoil. There are too many factors that contribute to the gold price fluctuation than just FED speech.

Nevertheless , there are shortfalls in our analysis that requires further improvement. The speeches are highly economic centric , we believe that using specialized lexicon that include collections of words and phrase specific for financial markets , the financial lexicon will yield a better understanding of the financial text. There are a few external financial lexicon and resources like Loughran-Mcdonald Sentiment words list, Financial PhraseBank, HENRY financial Word list and Harvad IV-4Dictionary. If time is permitted, we can even compose our own custom financial lexicon.

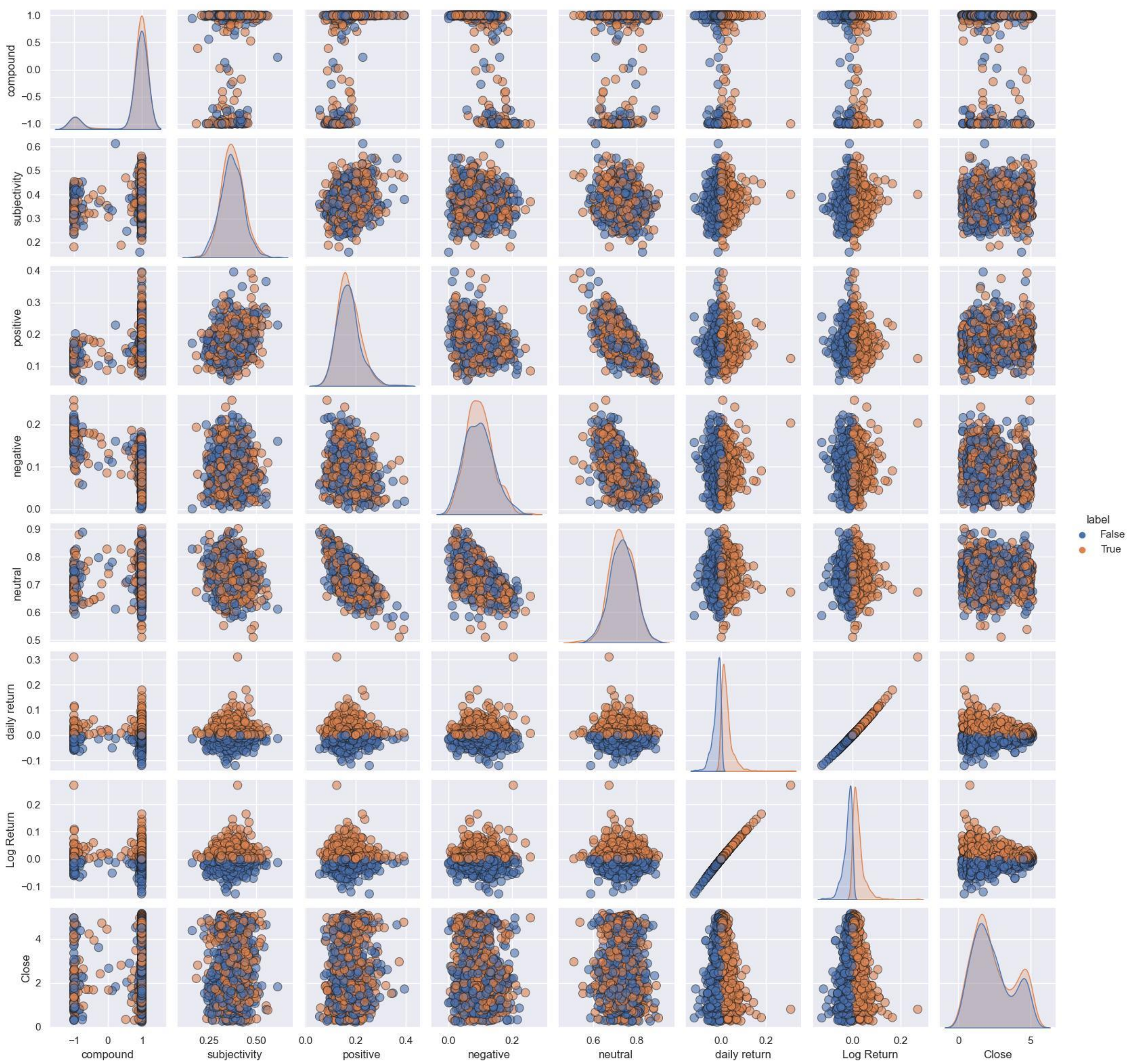
Conclusion

Sentiment analysis has been a big subject and research has been using sentiment analysis to improve their predicting model for stock price movement. We found a gap where we want to extend the sentiment analysis to FED's speeches instead of news and social media post. We gather the speeches from FED website from 2006 to 2023 with Beautiful Soup and run NLTK text preprocessing before getting the sentiment scores with Sentiment Intensity Analyzer. We fit the sentiment scores and daily return of 5 types of financial assets into logistic regression model. Our prediction model gives a 95% accuracy rate for predicting a positive return for NASDAQ and Currency pair EURUSD and followed by a 93% for S&P 500. The implication is that equity market and foreign exchange market are more sensitive to FED speeches than commodities and interest rate.

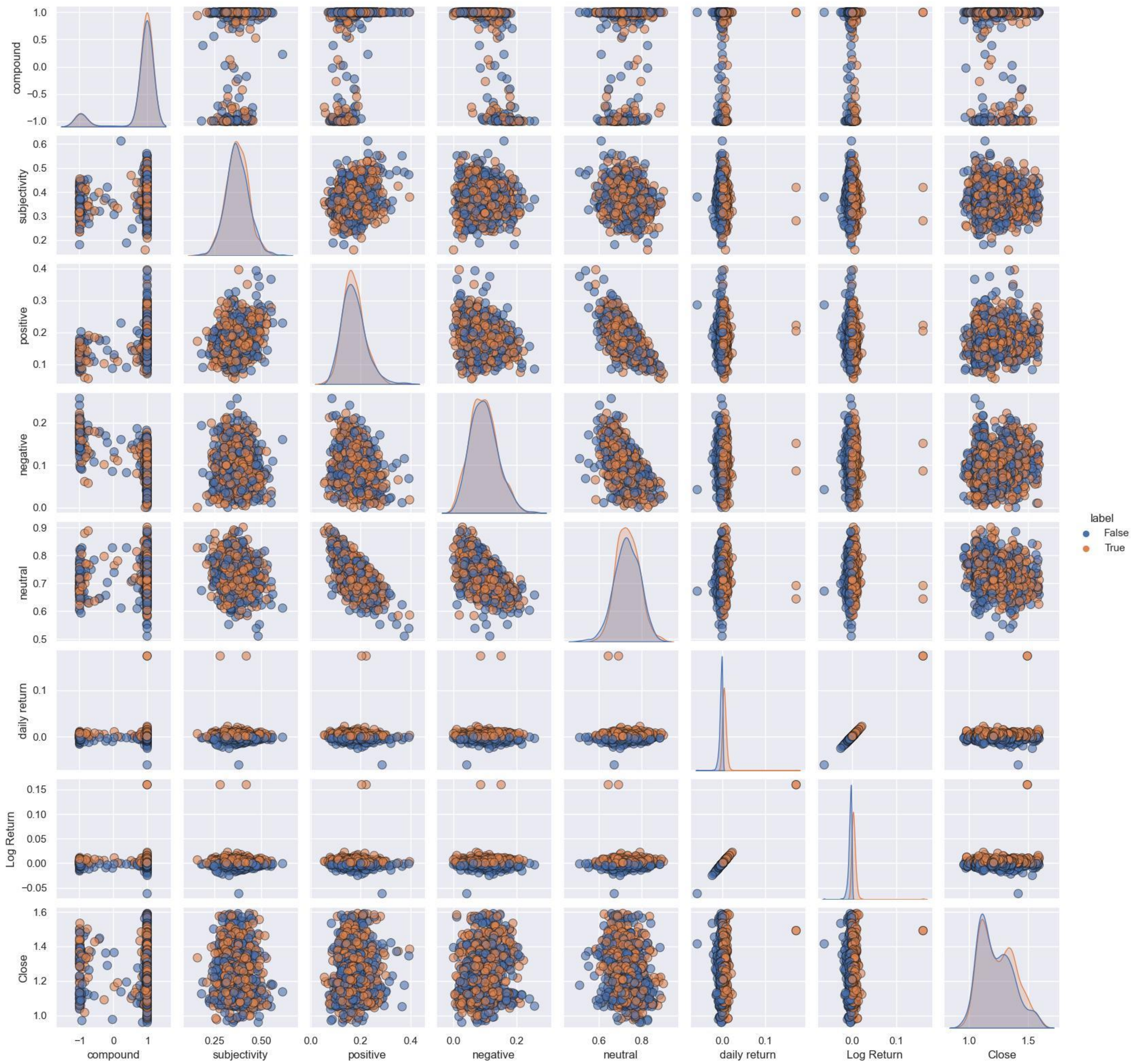
Appendices



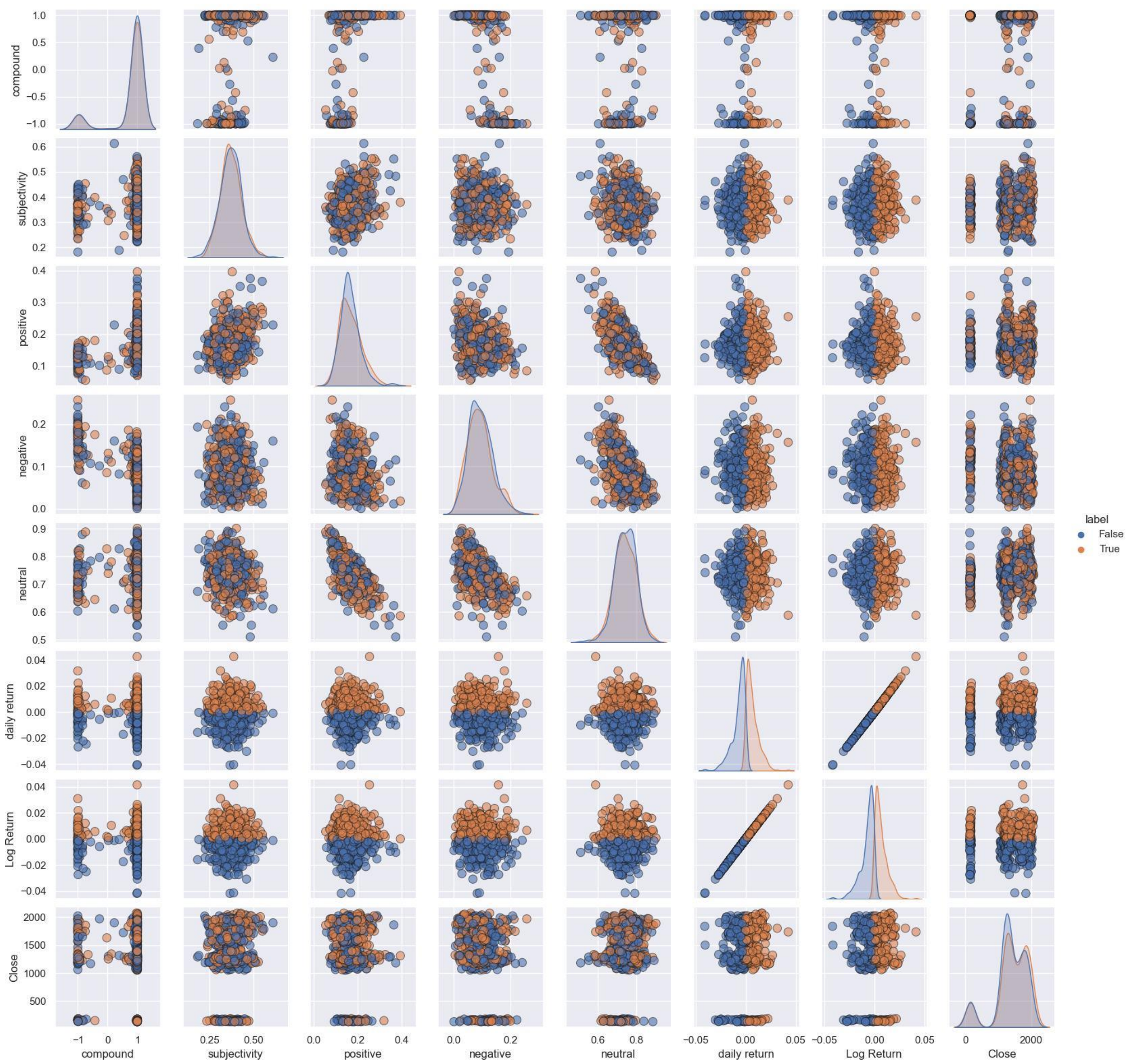
Pairplot for S&P 500



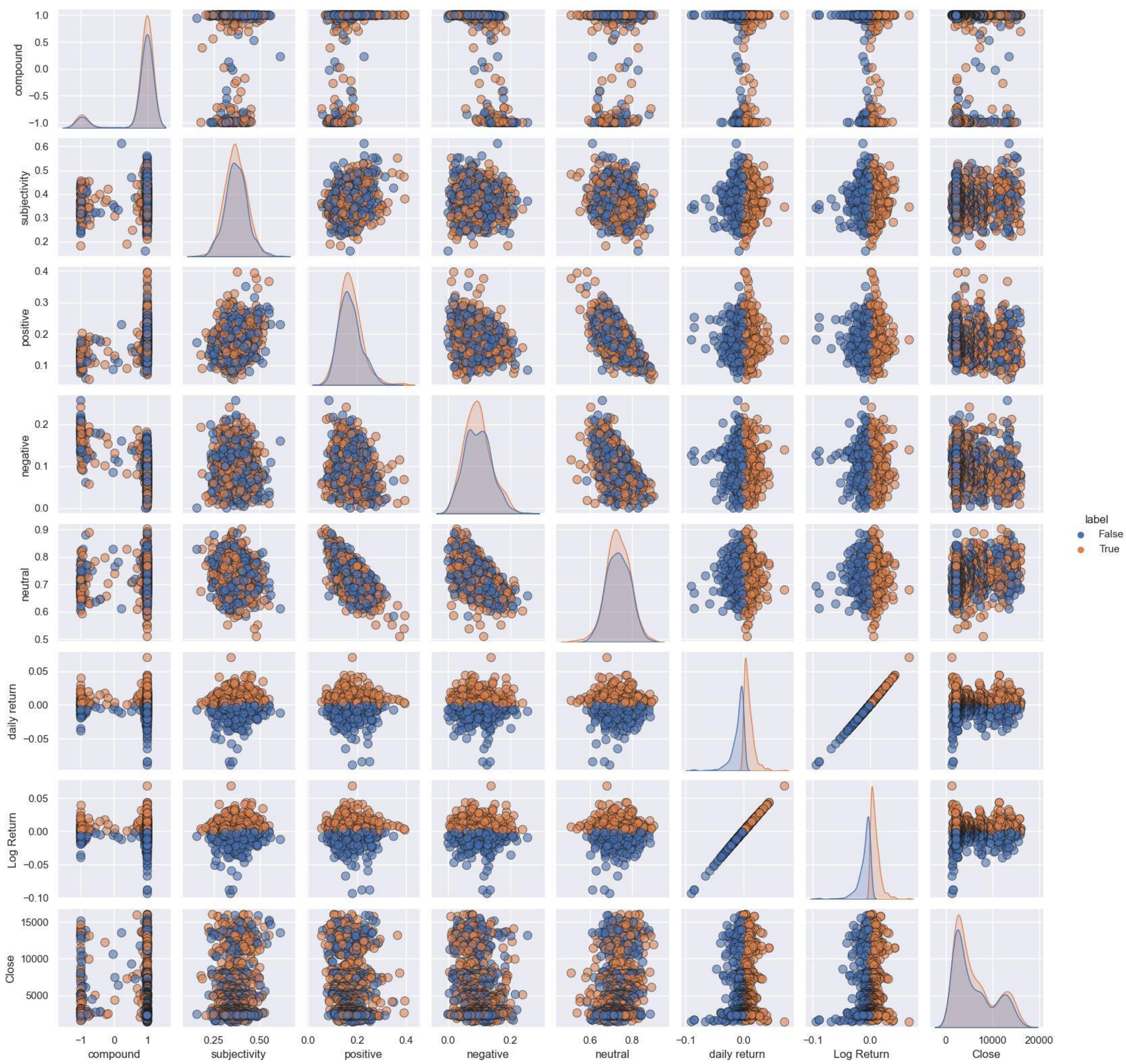
10 Years Treasury Interest Rate



Pairplot for EURUSD



Pairplot for Gold index



Pairplot for NASDAQ

References

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