Uncovering the Relationship Between Elon Musk's Tweets & Bitcoin Stock Prices

Group 12

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Overview

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2. Data Collection & Cleaning
3. Exploratory Data Analysis
4. Sentiment Analysis
5. Predictive Modeling
6. Limitations & Next Steps

Introduction

Background

- Twitter's sentiment ratio is positively correlated with Bitcoin prices, with significant impact from Elon Musk

- Musk Effect - Elon Musk changed Twitter bio to #bitcoin
  - Bitcoin value soared from $32,000 to over $38,000 in a few hours
  - Market boosted capitalization by $111 billion

Research Questions

- To what degree does the sentiment conveyed in Elon Musk's tweets impact the closing prices of Bitcoin?
  - What is the relationship between Elon Musk’s tweets and the closing prices of Bitcoin, if any?

- Will the inclusion of Elon Musk's tweet sentiments in models predicting Bitcoin prices substantially enhance the model's performance?

Data Collection & Cleaning

Data Collection

Dataset: “Elon Musk Tweets (2010-2011)”
Source: Kaggle
Variables: conversation_id, created_at, date, time, timezone, user_id, username, name, tweet + 36 others
Date Range: January 1, 2010 to March 5, 2022
Size: 34, 881 rows

Dataset: “Daily Bitcoin Stock Price”
Source: Kaggle
Variables: date, open, high, low, close, Adjusted Close, and Volume
Date Range: September 17th, 2014 to February 19, 2022
Size: 2,713 rows

Dataset: “Python `yfinance` package”
Source: Yahoo Finance
Variables: Nasdaq Composite Index, S&P 500 Index, Dow Jones Index Average, Crude Oil Price, and Gold Price
Date Range: January 2, 2021 to January 31, 2022
Size: 252 rows

Dataset: “Tweet Sentiment Extraction”
Source: Kaggle
Variables: TextID, Text and Sentiment
Date Range: N/A
Size: 27, 481

Data Cleaning

“Elon Musk Tweets (2010-2022)”

“Daily Bitcoin (Stock) Price”

“Python Yahoo Finance Package”

Dataset: “Tweets Grouped”
Variables: date, concatenated tweets txt
Date Range: February 1, 2021 to January 31, 2022
Size: 352 rows

Each row in this dataset is representative of all tweets made by Musk in a single day.

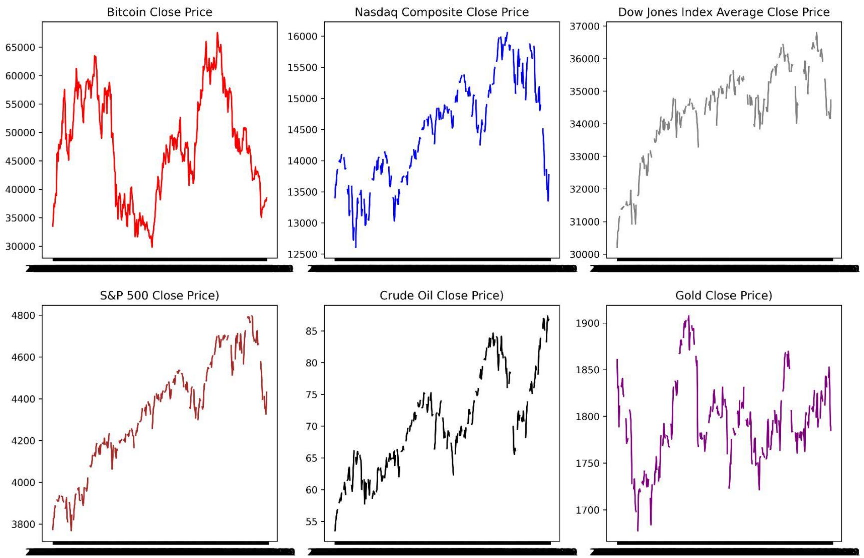
Dataset: “Stock Combined”
Variables: date, Btc_open, Btc_close, Btc_volume, Nasdaq_close, Dji_close, Sp_close, Oil_close, Gold_close
Date Range: February 1, 2021 to January 31, 2022
Size: 365 rows

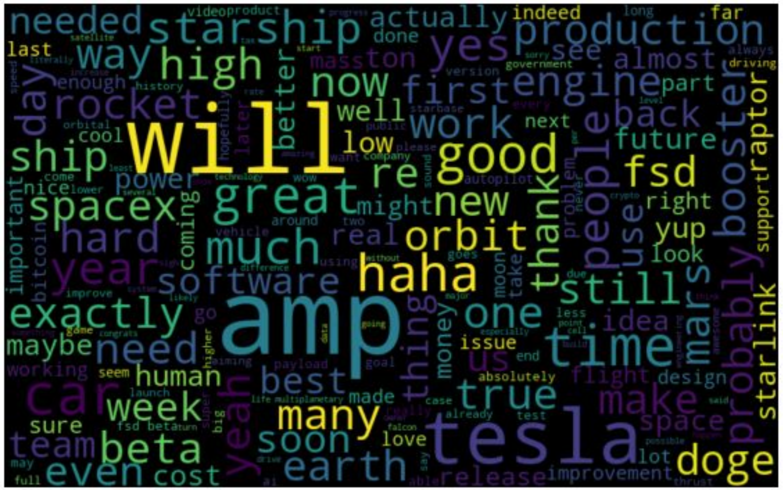
Exploratory Data Analysis (EDA)

EDA

- Stock indices are related to BTC closing price
- Musk's tweets include BTC, doge (seems roughly on par with "mars")

Date Range: 2021.02.01 - 2022.01.31





Sentiment Analysis

Sentiment Analysis | Overview

01	**Binary Sentiment Classification (Positive/Negative)**	• Utilize the "Text Sentiment Extraction" dataset to train Naive Bayes, Random Forest and Decision Tree. • Apply the most optimal model to "Tweets Grouped" data to classify Musk's tweets.
02	**Compound Sentiment Score**	• Apply the VADER package "Tweets Grouped" data to classify Musk's texts.
03	**Exploratory Data Analysis**	• Conduct further analysis to see the relationship between sentiment scores/classification scores and Bitcoin's closing price.

Sentiment Analysis | Naive Bayes - Methodology

1. **Features & Labels:** Label "text" column as X. "Label "sentiment" as y.
2. **Train | Test Split:** Split the data into training (80%) and test (20%) sets.
3. **Vectorization:** Vectorize X_train using Tfidf vectorizer.
4. **Model Training:** Apply model to X_train and y_train.
5. **Predictions:** Use model on X_test to predict for y_test.
6. **Final Results:** Print accuracy score, classification report and confusion matrix. Determine optimal classifier for sentiment.
7. **Apply Model:** Apply the most optimal model to "Tweets Grouped" dataset to classify Elon Musk's tweets.
8. **Data Matching:** Match the "date" column in "Tweets Grouped" dataset to "Stock Combined" dataset's "date" column and concatenate the classification returned by the model.

New "Stock Combined" Dataset

Btc_open	Btc_close	Btc_volume	Nasdaq_close	Dji_close	Sp_close	Oil_close	Gold_close	***nb_classification***

Sentiment Analysis | Binary Classification - Results

MNB, BNB, Random Forest and Decision Tree Classifier all achieve over 80% accuracy and F1 scores, but they are not the optimal model.

Naive Bayes | MultinomialNB

- Accuracy Score: 0.86
- Confusion Matrix:

```
[1348  184]
[ 258 1483]
```

- Classification Report
  - F1-Score for "Negative": 0.86
  - F1-Score for Positive: 0.87

Random Forest Classifier

- Accuracy Score: 0.86
- Confusion Matrix:

```
[1343  189]
[ 268 1473]
```

- Classification Report
  - F1-Score for "Negative": 0.85
  - F1-Score for "Positive": 0.87

Decision Tree Classifier

- Accuracy Score: 0.81
- Confusion Matrix:

```
[1216  316]
[ 317 1424]
```

- Classification Report
  - F1-Score for "Negative": 0.79
  - F1-Score for "Positive": 0.82

Naive Bayes | BernoulliNB

- Accuracy Score: 0.87
- Confusion Matrix:

```
[[1402  130]
 [ 307 1434]]
```

- Classification Report
  - F1-Score for "Negative": 0.87
  - F1-Score for Positive: 0.87

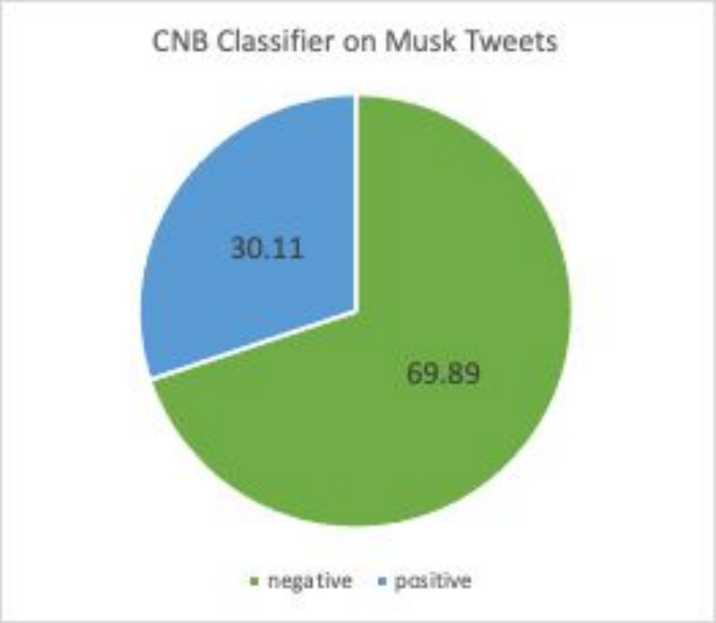
Sentiment Analysis | Part A - Best Model & Results

Naive Bayes | ComplementNB

- Accuracy Score: 0.87
- Confusion Matrix:

```
[1385   147]
[  288 1453]
```

- Classification Report
  - F1-Score for "Negative": 0.87
  - F1-Score for Positive: 0.87



Complement NB has the highest accuracy score and F1 score, so we will use Complement NB sentiment classification results for Bitcoin price modeling.

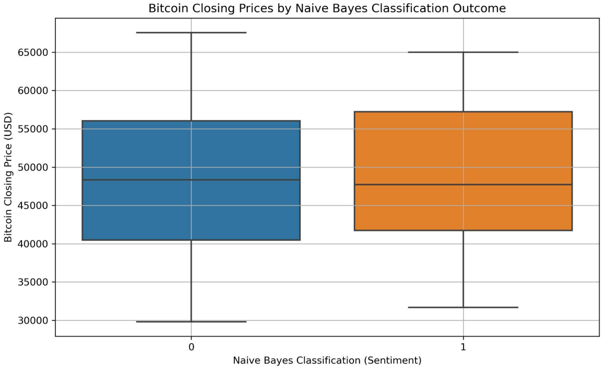
Sentiment Analysis | VADER - Methodology

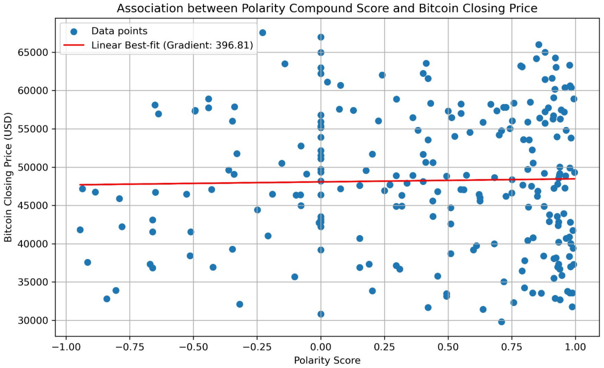
1. **Apply VADER Package:** Apply vader package to each tweet in "Tweets Grouped" dataset to generate polarity scores.
2. **Data Matching:** Match the "date" column in "Tweets Grouped" dataset to "Stock Combined" dataset's "date" column and concatenate the compound_score.

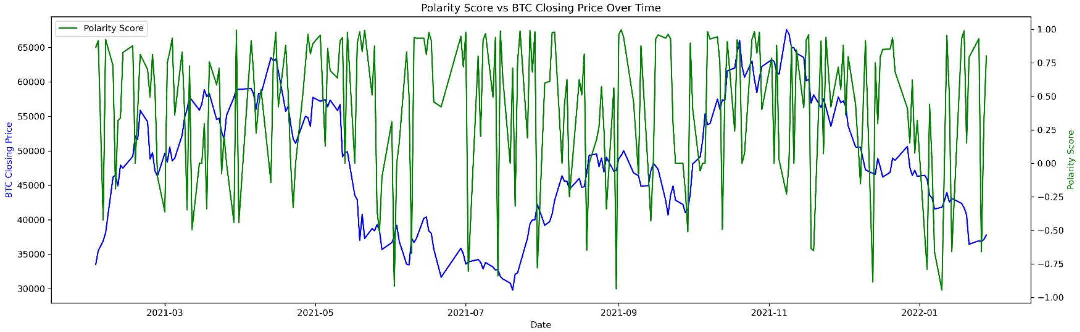
<u>New "Stock Combined" Dataset</u>

Btc_open	Btc_close	Btc_volume	Nasdaq_close	Dji_close	Sp_close	Oil_close	Gold_close	nb_ classification	***compound_ score***

Sentiment Analysis | Correlation with Bitcoin Price







The graph above shows that there's weak correlation between Elon Musk's tweet sentiment and Bitcoins closing price.

Predictive Modeling

Predictive Modeling | Overview

Aim to exam to what extent Elon Musk's tweets sentiment can help predict Bitcoin's closing prices.

"Stock Combined"

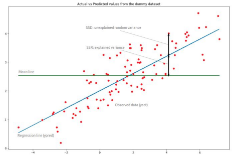
DATASET

3 Variations for Further Comparisons

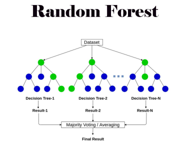
	Baseline	With Vader	With NB
Predictors (X)	Macro Signals, only	Macro Signals + VADER (compound_score) Continuous	Macro Signals + Naive Bayes Classifier Binary
Outcome (Y)	Bitcoin Close Price (USD)	Bitcoin Close Price (USD)	Bitcoin Close Price (USD)

Predictive Modeling

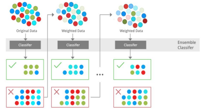
1. Linear Modeling



2. Random Forest



3. XGBoost

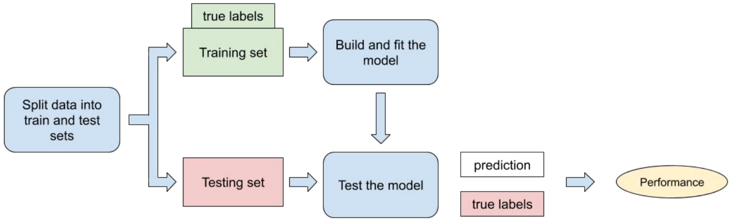


Model Comparison, to determine: 1. Whether adding the sentiment score as a regressor help improve prediction power
2. Based on the 2 methodology of sentiment analysis, which score output shows greater influence? Continuous or Binary?

Predictive Modeling | Methodology

Features and Labels: Label "btc_volume", "Nasdaq_close", "Dji_close", "Sp_close", "Oil_close", "Gold_close" and "compound_score"/ "nb_classification" (tentative) as X. Label "Btc_close" as y. (*Note: the features are dependent on which version of dataset the model is being applied to)*

1. **Data partition: Train | Test Split:** Split the data into training (80%) and test (20%) sets.



2. **Grid Search & Cross Validation:** Determine model parameters to test and apply GridSearchCV (applied to Random Forest Modeling only).
3. **Final Results:** Print the **R2** and **RMSE** scores to find most optimal model.

Results

a. **Baseline:** macro signals
b. **With Vader:** macro signals + vader sentiment score
c. **With NB:** macro signals + Naive Bayes classification

Linear Modeling				Random Forest				XGBoost			
Scores	**Baseline**	**With Vader**	**With NB**	**Scores**	**Baseline**	**With Vader**	**With NB**	**Scores**	**Baseline**	**With Vader**	**With NB**
RMSE	7830	7852	7864	**RMSE**	2967	2972	2954	**RMSE**	3282	3474	3185
R2	0.31	0.30	0.30	**R2**	0.90	0.90	0.90	**R2**	0.87	0.86	0.89

RMSE (Root Mean Squared Error): typical distance between the predicted values and the actual values. Lower RMSE values imply better model performance.

R-squared: the proportion of variance in the dependent variable that is explained by the independent variables. Higher R-square values imply better model performance.

The most optimal model for predicting Bitcoin's closing prices is **Random Forest Regression with the Naive Bayes classification** as a feature. Additionally, Elon Musk's tweet sentiment **does not significantly improve** the performance of any model in predicting Bitcoin's closing prices.

Limitations & Next Steps

Limitations

- Focus limited to daily impact of Musk's tweets; studies have shown fluctuations within hours of Musk’s tweet
- Focused on closing value, not returns -> high RMSE
- Imputed stock values for weekends to fill missing data

Next Steps

- Exploring the influence of Musk's tweets on the price and volume of Bitcoin within shorter timeframe
- Expected return as the dependent variable
- Collect Musk's tweets over a longer time horizon for larger sample size to isolate effect of his crypto-related tweets

Thank You!

Reference

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