ECON216: FINAL REPORT

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I. Introduction

The purpose of this study is to investigate how the sentiments (people's general feelings and emotions), which are measured from Twitter, StockTwits, and Reddit, can affect the prices, volumes, and market caps of different cryptocurrencies and stocks, or tickers. We can also learn about the fluctuation of the changes in sentiment scores as well as ticker prices over time. With the information in hand, we expect to find a correlation between sentiment scores and other information about different tickers like prices or volumes, which can help leverage one's trading experience and help traders make profits with accurate data. Overall, we discover that price and volume changes can infer changes in sentiment scores to a certain extent, and prices and sentiment scores of different tickers can fluctuate depending on the market circumstances. Social media platforms can give us such valuable trading information, and we believe collecting data from more diverse social media platforms would give us better results.

II. Background

Using Utradea's Social Sentiment data, we can identify and track popular stocks and cryptocurrencies on social media platform like Twitter, StockTwits, and Reddit. The sentiment scores are inferred from datapoints for stocks and cryptocurrencies mentioned on those social networks, for example posts, likes and comments. Data is sourced and provided over a 24-hour or 72-hour period, which keeps track of the change in price and volume over the period. The change in posts, comments, and impressions over that given time period can also be used to identify hot stocks or cryptocurrencies, which can lead to high sentiment scores.

The units of observations are tickers (stocks/cryptocurrencies). In order to understand the EAD, one only need to understand about tickers, which have price, volume, market cap, and sentiments, which are people's general feelings and emotions towards a specific ticker. The list of variables that are important for the analysis is as belows:

- ticker: the ticker code
- sentiment: the sentiment score of the ticker
- lastSentiment: the last sentiment score measured of the ticker
- sentimentChange: the sentiment score change in percentage
- price: the price of the ticker
- previousClose: the closing price of the ticker previously measured
- change: the change in price
- changePercent: the price change in percentage
- volume: the volume of the ticker

- previousVolume: the volume of the ticker previously measured
- marketCap: the market cap of the ticker

III. Data Wrangling

```
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)

bullish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bullish_03-16-2022.csv",
                                 show_col_types = FALSE)
bullish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-15-2022.csv"
                                    show_col_types = FALSE)
bullish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-16-2022.csv
                                     show_col_types = FALSE)
bearish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-15-2022.csv",
                                 show_col_types = FALSE)
bearish_data_twitter2 <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-16-2022.csv",
                                  show_col_types = FALSE)
bearish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-15-2022.csv"
                                    show_col_types = FALSE)
bearish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-16-2022.csv
                                     show_col_types = FALSE)

# binding both data for bullish and bearish tickers together
data <- rbind(bullish_data_twitter, bullish_data_stocktwits, bullish_data_stocktwits2,
              bearish_data_twitter, bearish_data_twitter2, bearish_data_stocktwits,
              bearish_data_stocktwits2)

data <- data %>%
  # filter out all dummy data
  filter(lastSentiment > 0) %>%
  rename(sentimentChangePercent="sentimentChange",
         priceChange="change",
         priceChangePercent="changePercent") %>%
  # adding new variable volumeChangePercent
  mutate(priceChangePercent = priceChangePercent * 100,
         volumeChangePercent= (volume - previousVolume) / previousVolume * 100)
```

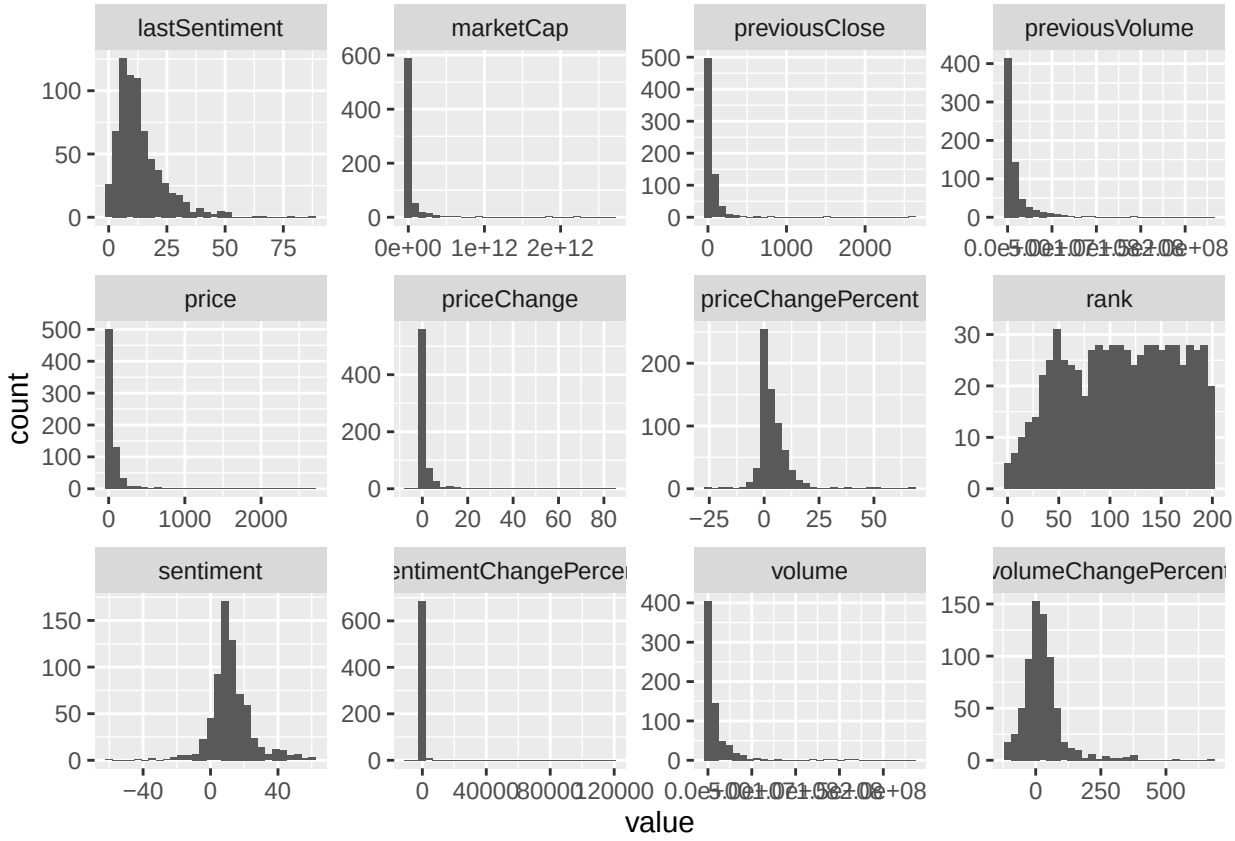
```
glimpse(data)
```

```
## Rows: 698
## Columns: 14
## $ ticker                 <chr> "ANY", "NOV", "ATOS", "WBEV", "ACA", "KALV", "O~
## $ sentiment              <dbl> 2.844205, 3.331944, 10.966667, 31.875000, 16.42~
## $ lastSentiment          <dbl> 0.06968775, 0.09479167, 0.31250000, 1.42857143,~
## $ sentimentChangePercent <dbl> 3981.3553, 3415.0183, 3409.3333, 2131.2500, 122~
## $ rank                   <dbl> 3, 6, 7, 10, 14, 16, 17, 19, 20, 22, 23, 26, 27~
## $ name                   <chr> "Sphere 3D Corp.", "NOV Inc.", "Atossa Therapeu~
## $ price                  <dbl> 1.830, 18.750, 1.270, 2.980, 58.260, 14.440, 14~
## $ priceChange            <dbl> 0.10000002, -0.57000000, 0.09000003, -0.2400000~
## $ priceChangePercent     <dbl> 5.78034830, -2.95031000, 7.62712200, -7.4534200~
## $ volume                 <dbl> 2607003, 6887001, 1858733, 32008, 481282, 21820~
## $ marketCap              <dbl> 66444014, 7362474769, 160812620, 39214327, 2836~
## $ previousVolume         <dbl> 2155014, 5881926, 1689995, 28808, 241042, 32666~
## $ previousClose          <dbl> 1.730, 19.320, 1.180, 3.220, 57.060, 14.500, 14~
## $ volumeChangePercent    <dbl> 20.973831, 17.087515, 9.984527, 11.108026, 99.6~
```

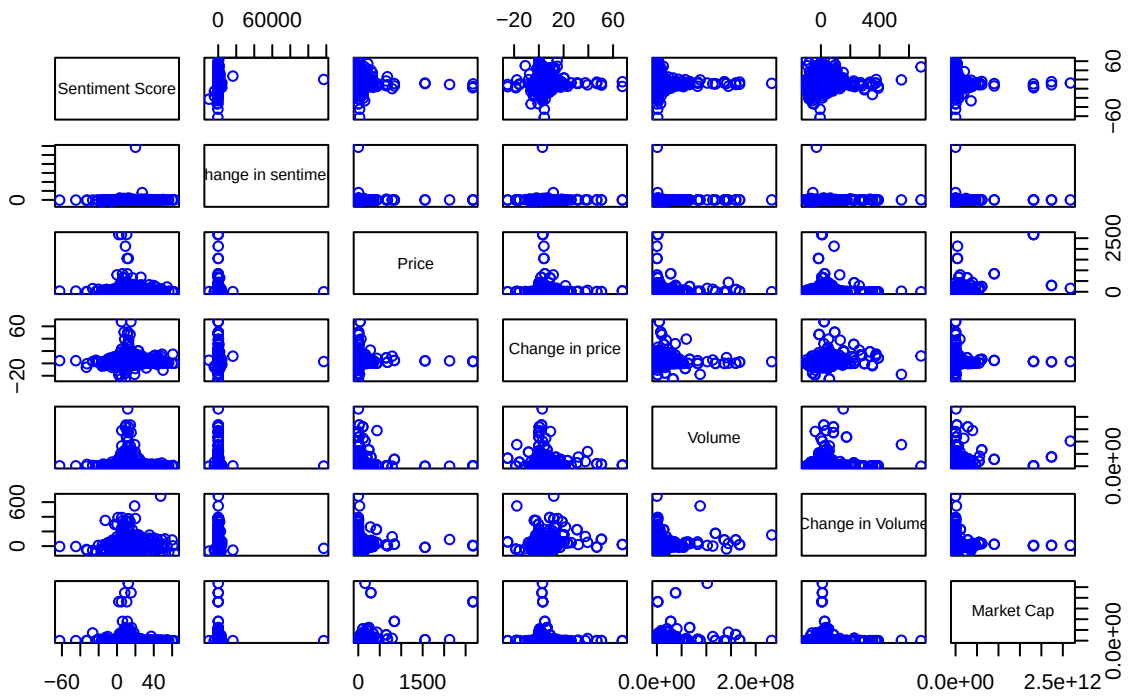
We first bind the data for bullish and bearish tickers together across different dates for better references. We then filter out all dummy data that can create noise for the dataset. We then introduce a new variable volumeChangePercent, which keeps track of the change in volume in percentage for better reference. For readability, we also change some variables name, for example change and changePercentage, to distinguish from other changes. For priceChangePercentage column, we multiply all values by 100 to match the data format of other percentage changes.

IV. Exploratory Analysis

A histogram of all featured variables in the datasets:



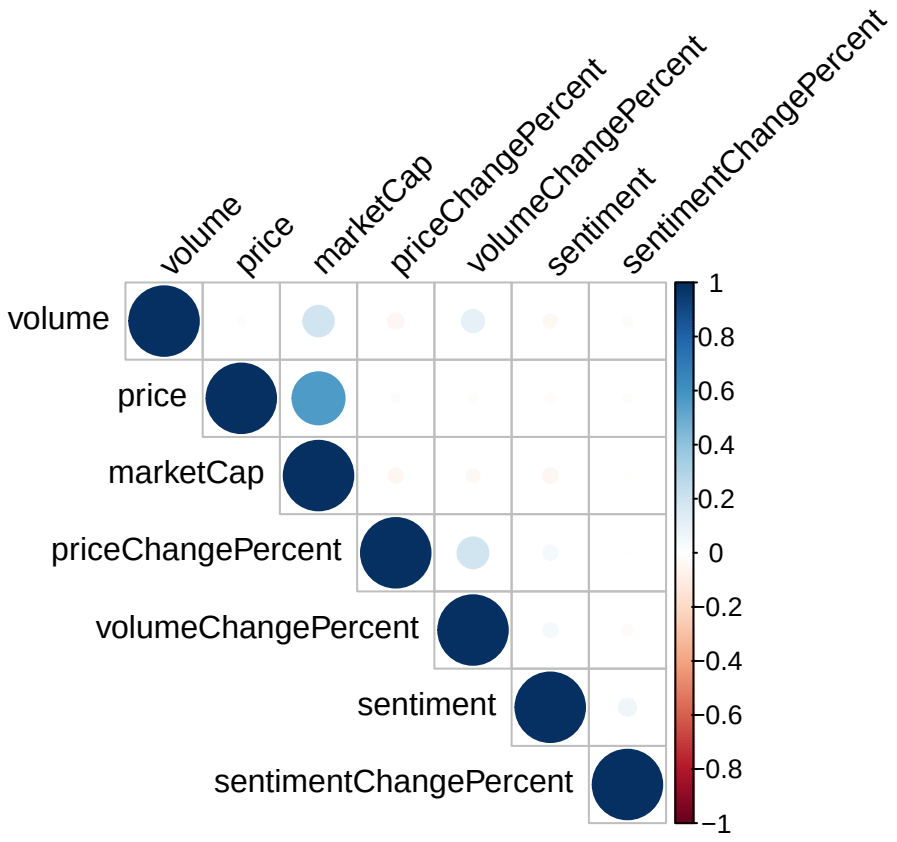
The pairs plot of the variables that we use, since these are all important features as discussed in section II. They are sentiment, price, volume, market cap of each ticker together with their changes in percentage.



Look at the correlations between the variables:

```
##                           sentiment sentimentChangePercent       price
## sentiment                1.00000000             0.061050642 -0.01953152
## sentimentChangePercent   0.06105064             1.000000000 -0.01265873
## price                   -0.01953152            -0.012658729  1.00000000
## priceChangePercent       0.04268190             0.002217458 -0.01327172
## volume                  -0.03686308            -0.018537733 -0.01169538
## volumeChangePercent      0.04235957            -0.022542490 -0.01271063
## marketCap               -0.04413360            -0.009774737  0.56134621
##                         priceChangePercent      volume volumeChangePercent
## sentiment                      0.042681896 -0.03686308          0.04235957
## sentimentChangePercent         0.002217458 -0.01853773         -0.02254249
## price                         -0.013271722 -0.01169538         -0.01271063
## priceChangePercent             1.000000000 -0.04989246          0.19682521
## volume                        -0.049892459  1.00000000          0.10207575
## volumeChangePercent            0.196825208  0.10207575          1.00000000
## marketCap                     -0.042515396  0.19179139         -0.03403225
##                            marketCap
## sentiment               -0.044133600
## sentimentChangePercent  -0.009774737
## price                    0.561346208
## priceChangePercent      -0.042515396
## volume                   0.191791388
## volumeChangePercent     -0.034032247
## marketCap                1.000000000
```

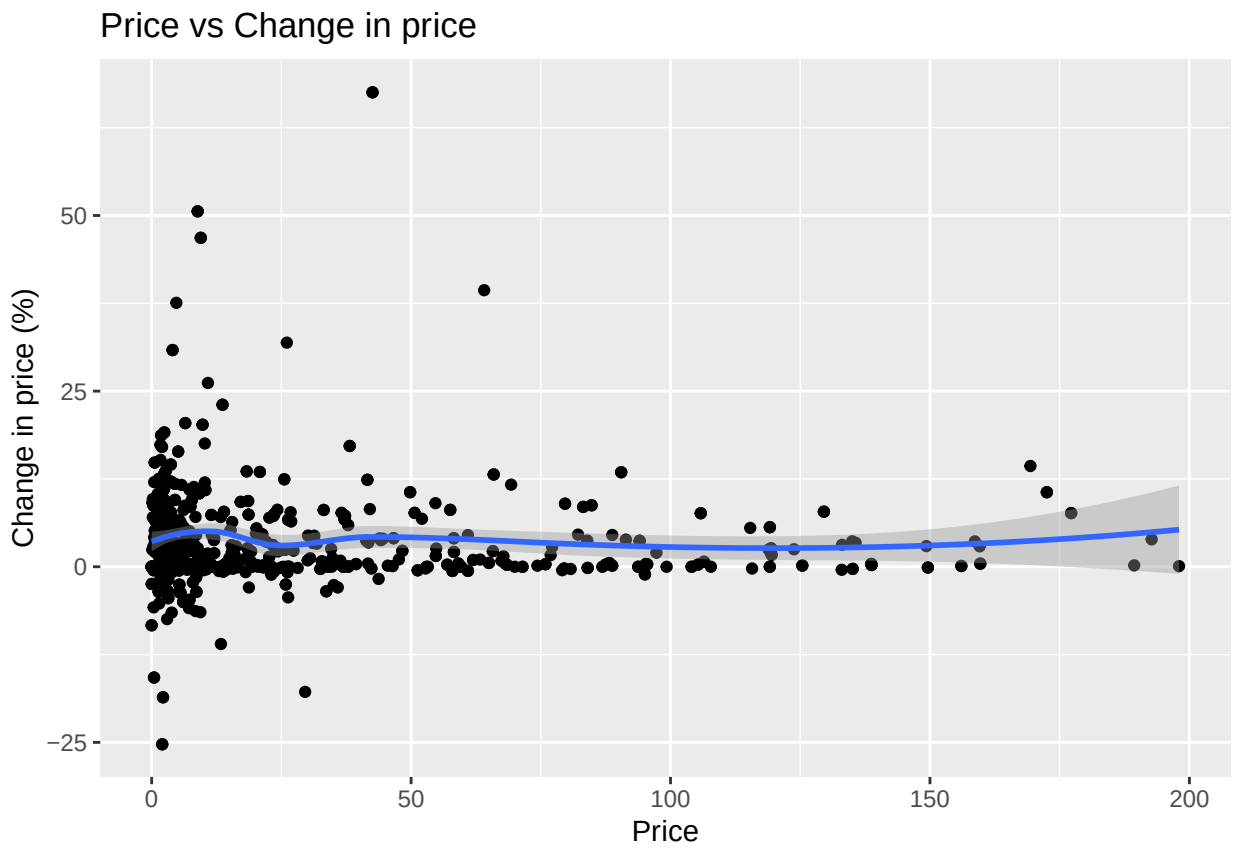
The correlation chart:



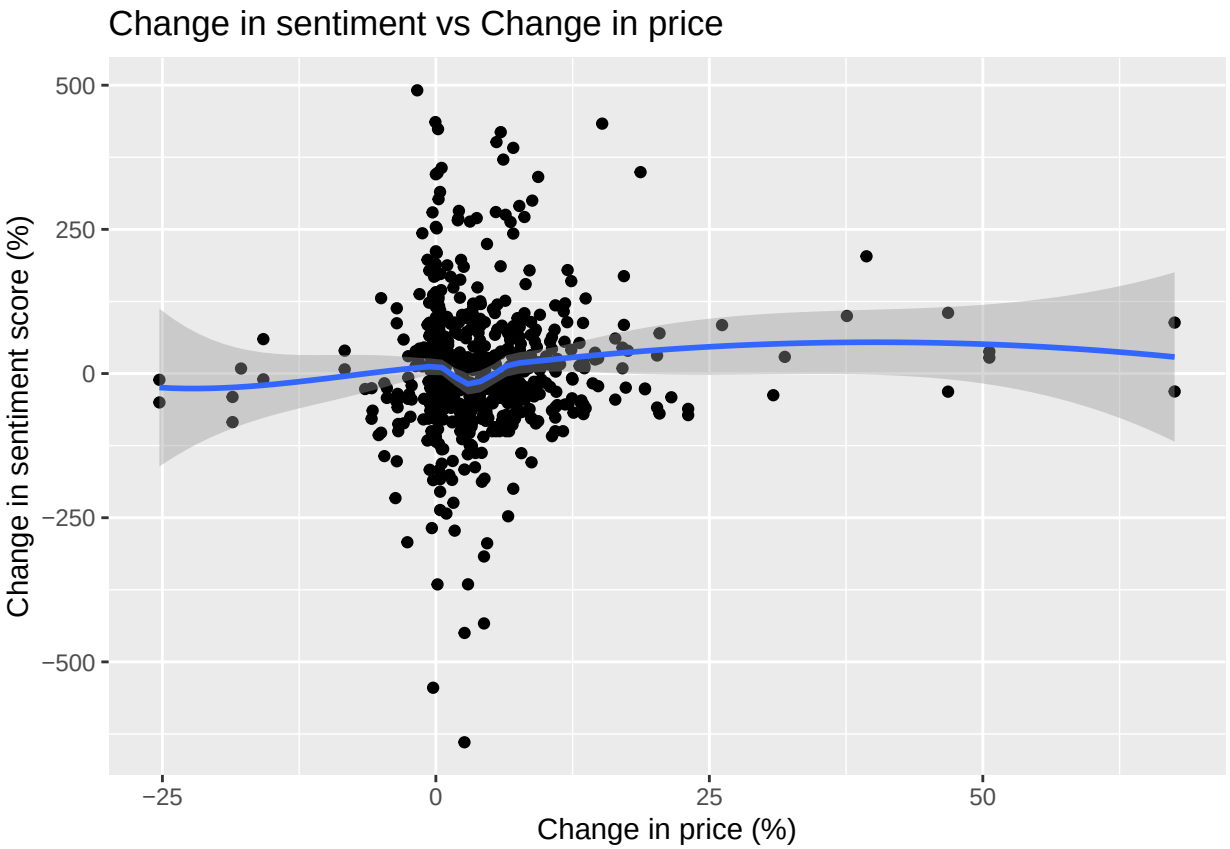
Find out if there are missing values:

```
##                  ticker               sentiment           lastSentiment
##                       0                       0                       0
## sentimentChangePercent                    rank                    name
##                       0                       0                       0
##                   price             priceChange     priceChangePercent
##                       0                       0                       0
##                  volume               marketCap          previousVolume
##                       0                       1                       1
##           previousClose     volumeChangePercent
##                       0                       1
```

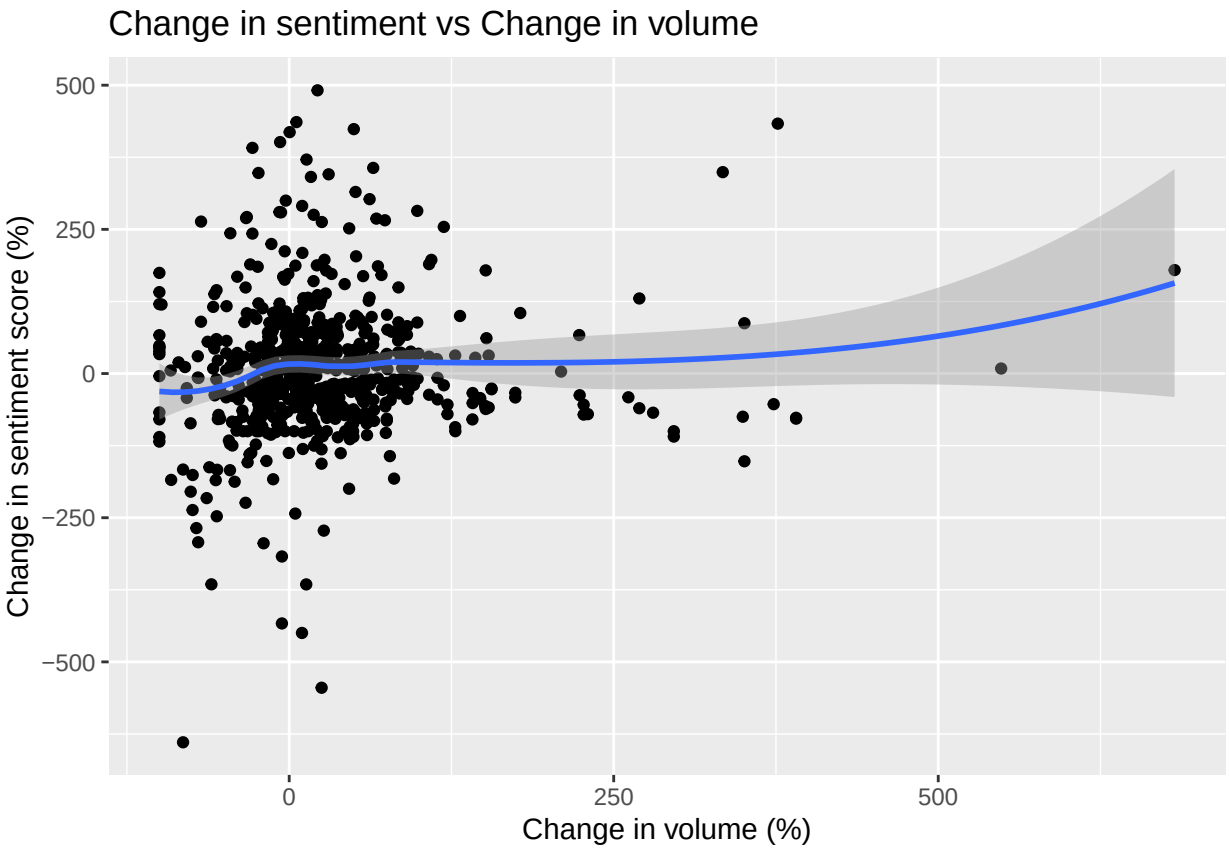
The follow charts show correlation between each pair of tickers' unique features:



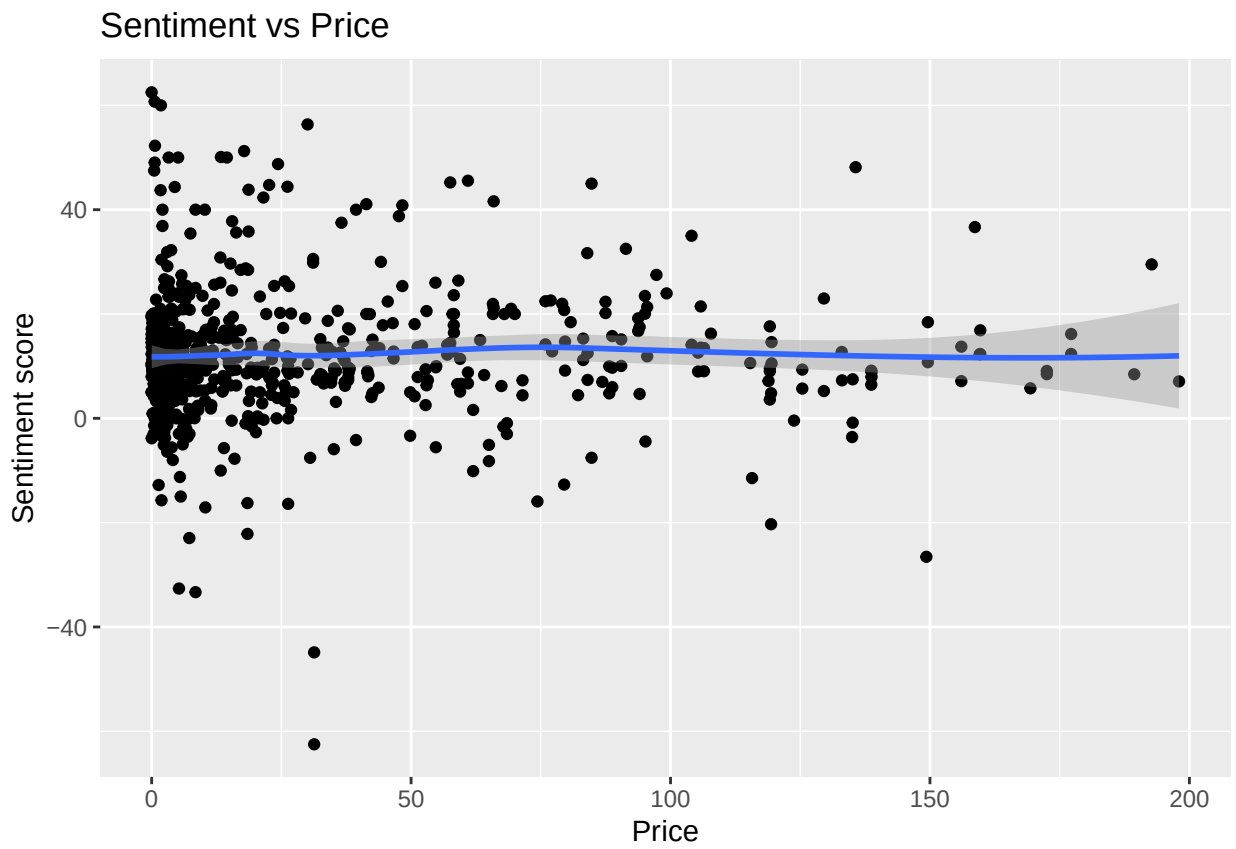
We firstly want to run a sanity check to make sure that the price level doesn't have any effect on the change in price. As shown in the plot, the smooth line of correlation is flat, and it means the price level doesn't have a direct effect of the change in price.



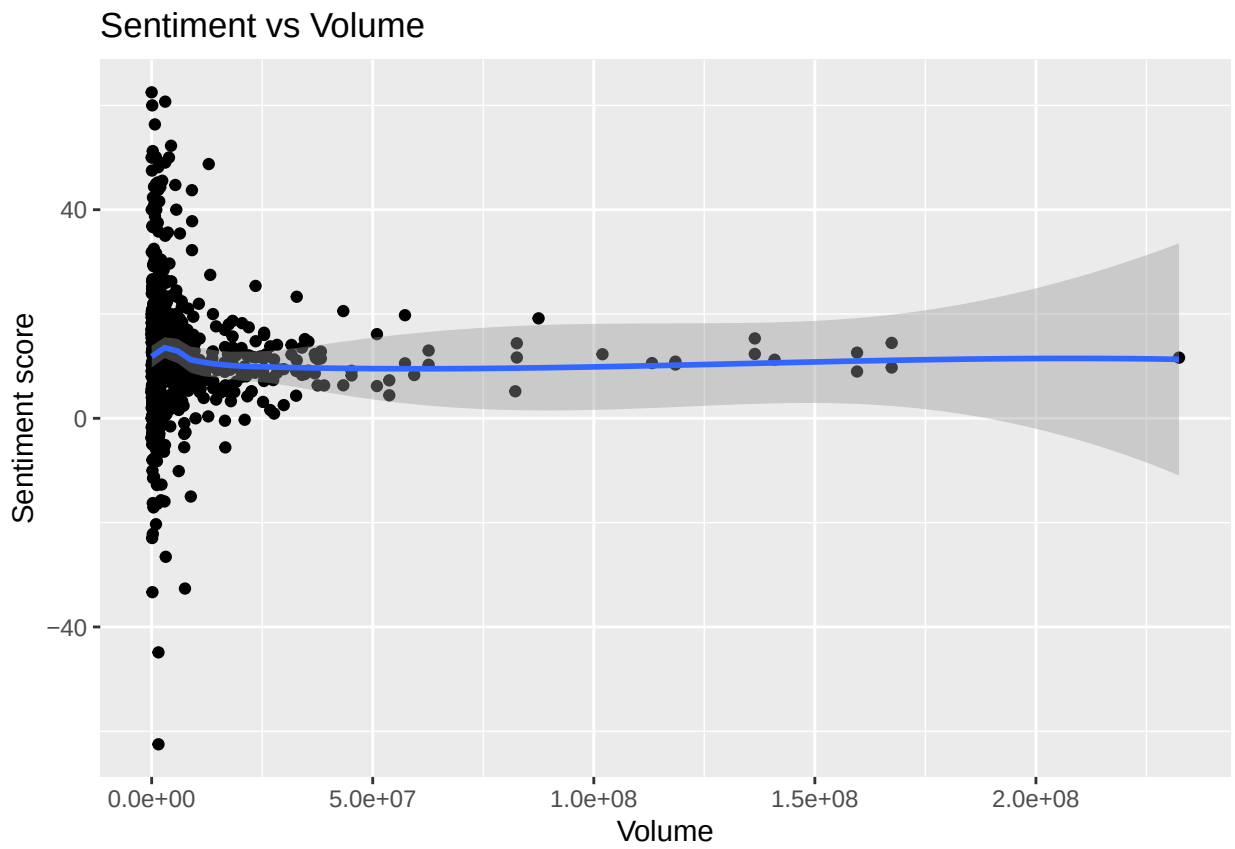
We then want to examine the correlation of change in price and change in sentiment. We suppose that when price increases, people will have positive things to talk about the tickers, thus increasing the sentiment score. This will result in a positive slope. The plot also shows this trend in the range where most of the data points lie in. For the outliers, as they are scattered so it is harder to say if there is a trend for them.



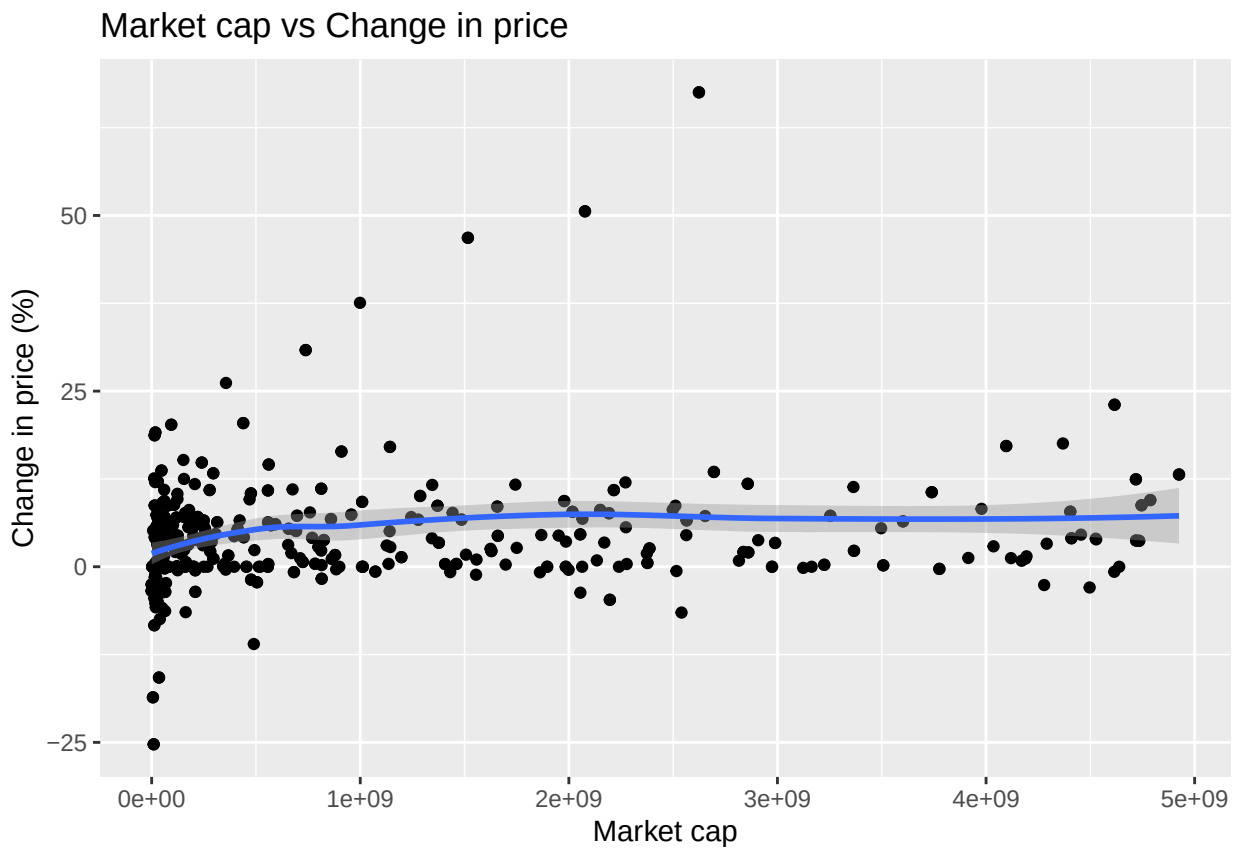
The same trend applies for the correlation of change in volume and the change in sentiment score. When the volume increases in the market, it will attract the the attention of the crowd and increase the sentiment score. This also results in a positive slope in the plot where there exist most of the data points.



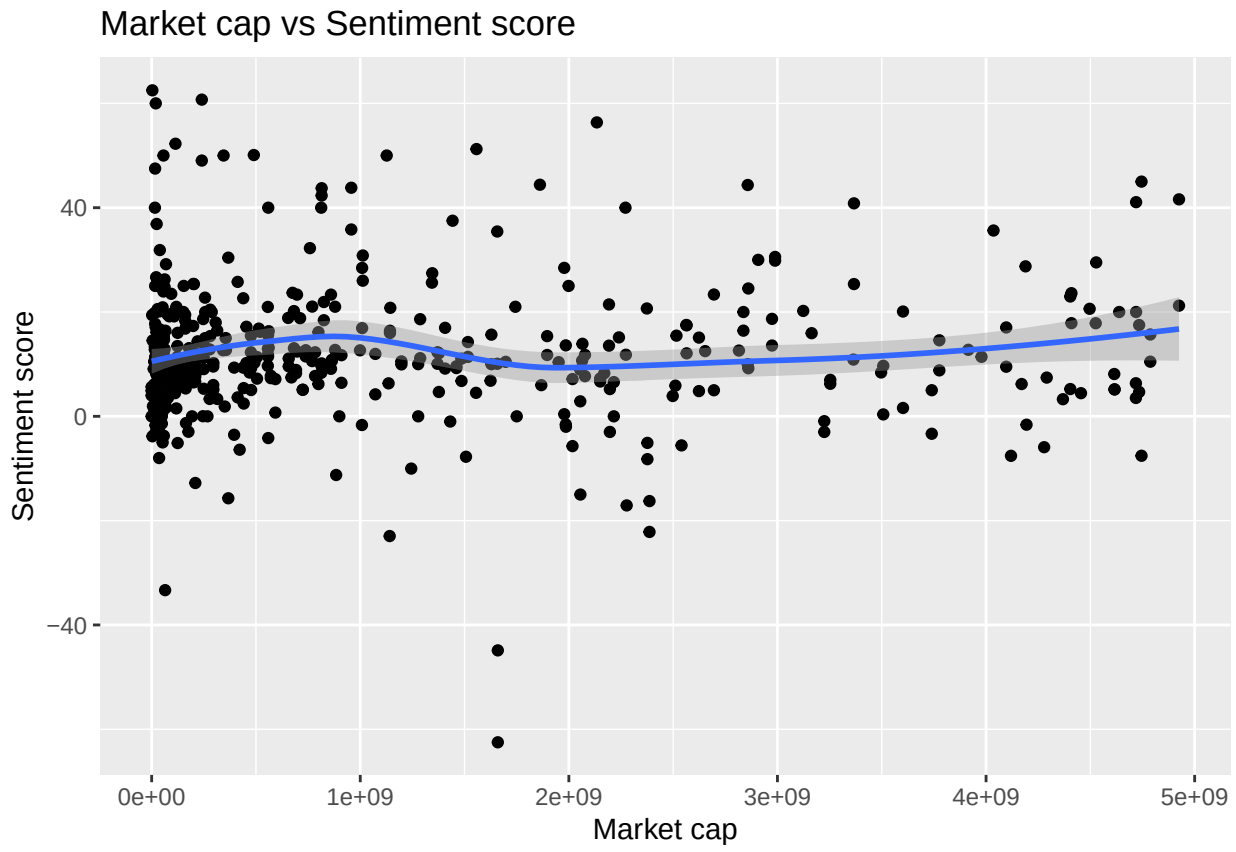
We want to further discover more trends. We try to find out the correlation of price level and sentiment score, but the plot doesn't really say anything about it, as the smooth line is flat.



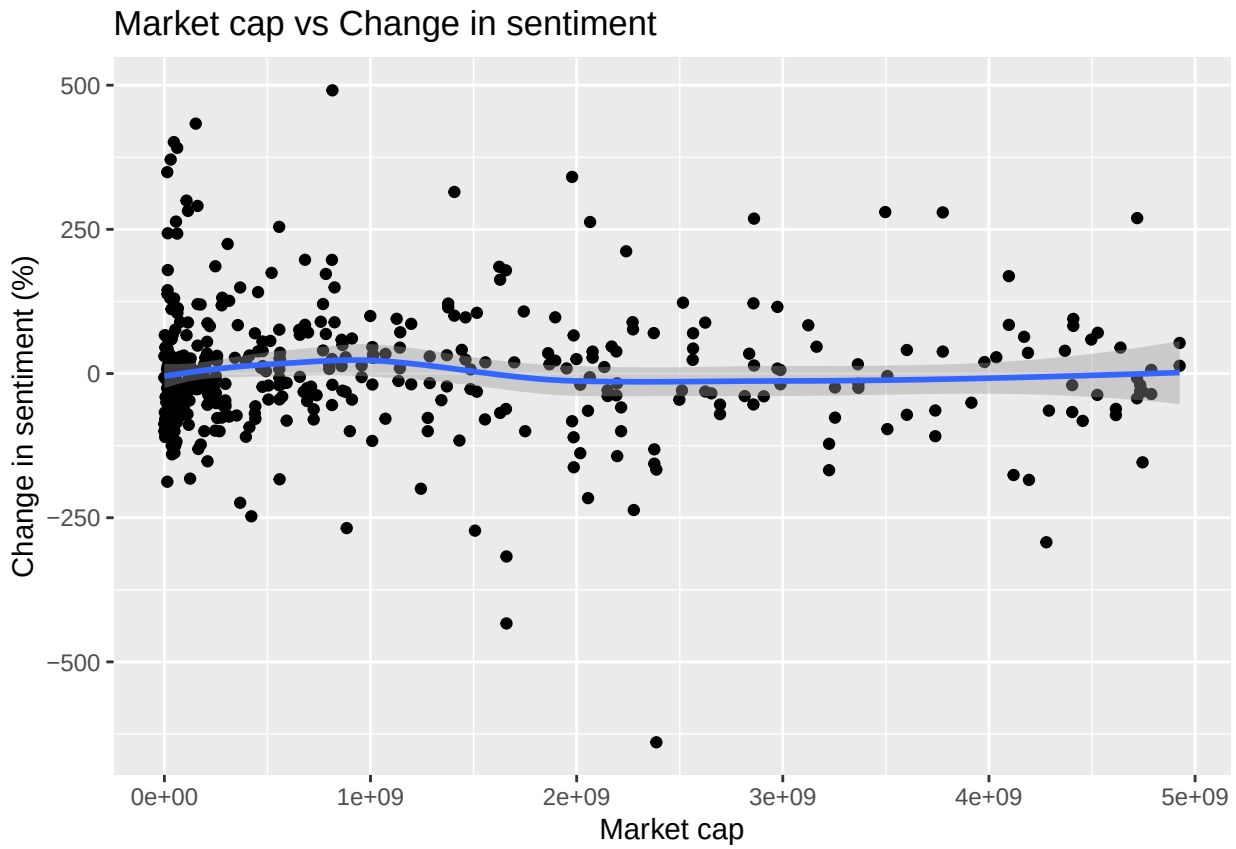
This is the same for volume and sentiment score. An increase in volume doesn't reflect in any change in sentiment score, as the plot is also quite flat. There in a bit of a fluctuation where there are a lot of data points, but that is not enough to conclude whether there is a trend there.



We want to also take into account the market cap. Seems like for tickers with higher market cap, people have better trust in them, and the price increases more. This results in a positive slope in the plot.



From the plot above, we suppose that the market cap is also proportional to the sentiment score. However, it is impossible to tell if that correlation is correct just by looking at the plot, as the slope goes up then down, then up again. On a bright side, the slope goes up in the range of small and large market cap, just goes down by a bit in the middle range.



We finally examine the correlation of market cap and change in sentiment. We had a hypothesis that this would be a positive correlation. However, we are surprised that by looking at the plot, it is impossible to find any trend.

V. Finished Analysis

From all the analysis above, we found that there are some sorts of correlations between the sentiment score and price change, volume change, and market capacity. For other correlation plots that we thought would have some correlations, it turned out that there was not really any noticeable pattern. However, those correlations are enough to show that price and volumes change can infer change in sentiment scores of different stocks and cryptocurrencies. If we have more data, which can be from more social media platforms or from more dates, we can better prove the theory. Moreover, we might see a better and more specific trend if we plot the sentiment score of each ticker as a time-series graph. By doing that, we can better see the changes across different dates and the correlations between the sentiment score and price or volume.

VI. Conclusion

In conclusion, it is clear that different social media platforms like Twitter, Reddit, and StockTwits can provide us with valuable trading information. Changes in price and volume of different tickers can infer changes in sentiment scores as there are correlations from the charts. Both prices and sentiments score can fluctuate depending on the market.
Regarding areas of improvement, we believe more real-time and frequently updated data of sentiment scores can show a clearer and stronger patterns for different correlations. We can also expect a better result if we can collect data from more diverse social media platforms.

VII. Appendix

```
library(readr)
library(dplyr)
library(ggplot2)

bullish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bullish_03-16-2022.csv",
                                 show_col_types = FALSE)
bullish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-15-2022.csv"
                                    show_col_types = FALSE)
bullish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-16-2022.csv
                                     show_col_types = FALSE)
bearish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-15-2022.csv",
                                 show_col_types = FALSE)
bearish_data_twitter2 <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-16-2022.csv",
                                  show_col_types = FALSE)
bearish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-15-2022.csv"
                                    show_col_types = FALSE)
bearish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-16-2022.csv
                                     show_col_types = FALSE)

# binding both data for bullish and bearish tickers together
data <- rbind(bullish_data_twitter, bullish_data_stocktwits, bullish_data_stocktwits2,
              bearish_data_twitter, bearish_data_twitter2, bearish_data_stocktwits,
              bearish_data_stocktwits2)

data <- data %>%
  # filter out all dummy data
  filter(lastSentiment > 0) %>%
  rename(sentimentChangePercent="sentimentChange",
         priceChange="change",
         priceChangePercent="changePercent") %>%
  # adding new variable volumeChangePercent
  mutate(priceChangePercent = priceChangePercent * 100,
         volumeChangePercent= (volume - previousVolume) / previousVolume * 100)

glimpse(data)
library(purrr)
library(tidyr)
data %>%
  keep(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
    facet_wrap(~ key, scales = "free") +
    geom_histogram()
pairs(data[,c("sentiment","sentimentChangePercent","price", "priceChangePercent",
              "volume", "volumeChangePercent", "marketCap")],
      col="blue",
      labels = c('Sentiment Score', 'Change in sentiment', 'Price', "Change in price",
                 "Volume", "Change in Volume", "Market Cap"),
      main="Important variables")
res = cor(data[,c("sentiment","sentimentChangePercent","price", "priceChangePercent",
              "volume", "volumeChangePercent", "marketCap")], use="complete.obs")
```

```
res
library(corrplot)
corrplot(res, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
sapply(data, function(x) sum(is.na(x)))
plotdata1 <- data %>%
  filter(price < 200)
ggplot(plotdata1, aes(x=price, y = priceChangePercent)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Price vs Change in price",
    x = "Price",
    y = "Change in price (%)"
  )
plotdata <- data %>%
  filter(sentimentChangePercent < 500, sentimentChangePercent > -1000)
ggplot(plotdata, aes(y=sentimentChangePercent, x = priceChangePercent)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Change in sentiment vs Change in price",
    y = "Change in sentiment score (%)",
    x = "Change in price (%)"
  )
plotdata1 <- data %>%
  filter(sentimentChangePercent < 500, sentimentChangePercent > -1000)
ggplot(plotdata1, aes(y=sentimentChangePercent, x = volumeChangePercent)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Change in sentiment vs Change in volume",
    y = "Change in sentiment score (%)",
    x = "Change in volume (%)"
  )
plotdata1 <- data %>%
  filter(price < 200)
ggplot(plotdata1, aes(y=sentiment, x = price)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Sentiment vs Price",
    y = "Sentiment score",
    x = "Price"
  )
ggplot(plotdata1, aes(y=sentiment, x = volume)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Sentiment vs Volume",
    y = "Sentiment score",
    x = "Volume"
  )
plotdata2 <- data %>%
  filter(marketCap < 5000000000)
ggplot(plotdata2, aes(x=marketCap, y = priceChangePercent)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Market cap vs Change in price",
```

```
    x = "Market cap",
    y = "Change in price (%)"
  )
ggplot(plotdata2, aes(x=marketCap, y = sentiment)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Market cap vs Sentiment score",
    x = "Market cap",
    y = "Sentiment score"
  )
plotdata3 <- data %>%
  filter(marketCap < 5000000000, sentimentChangePercent < 500, sentimentChangePercent > -1000)
ggplot(plotdata3, aes(x=marketCap, y = sentimentChangePercent)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Market cap vs Change in sentiment",
    x = "Market cap",
    y = "Change in sentiment (%)"
  )
```