ECON216: FINAL REPORT

Grizzlies

2022-12-10

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

```r
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
```

```r
library(ggplot2)

bullish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bullish_03-16-2022.csv", show
bullish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-15-2022.csv"
bullish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-16-2022.csv
bearish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-15-2022.csv", show
bearish_data_twitter2 <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-16-2022.csv", sho
bearish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-15-2022.csv"
bearish_data_stocktwits2 <- read_csv("social_sentiment_stocktwits_chginsentiment_bearish_03-16-2022.csv

# binding both data for bullish and bearish tickers together
data <- rbind(bullish_data_twitter, bullish_data_stocktwits, bullish_data_stocktwits2, bearish_data_twi

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~
```

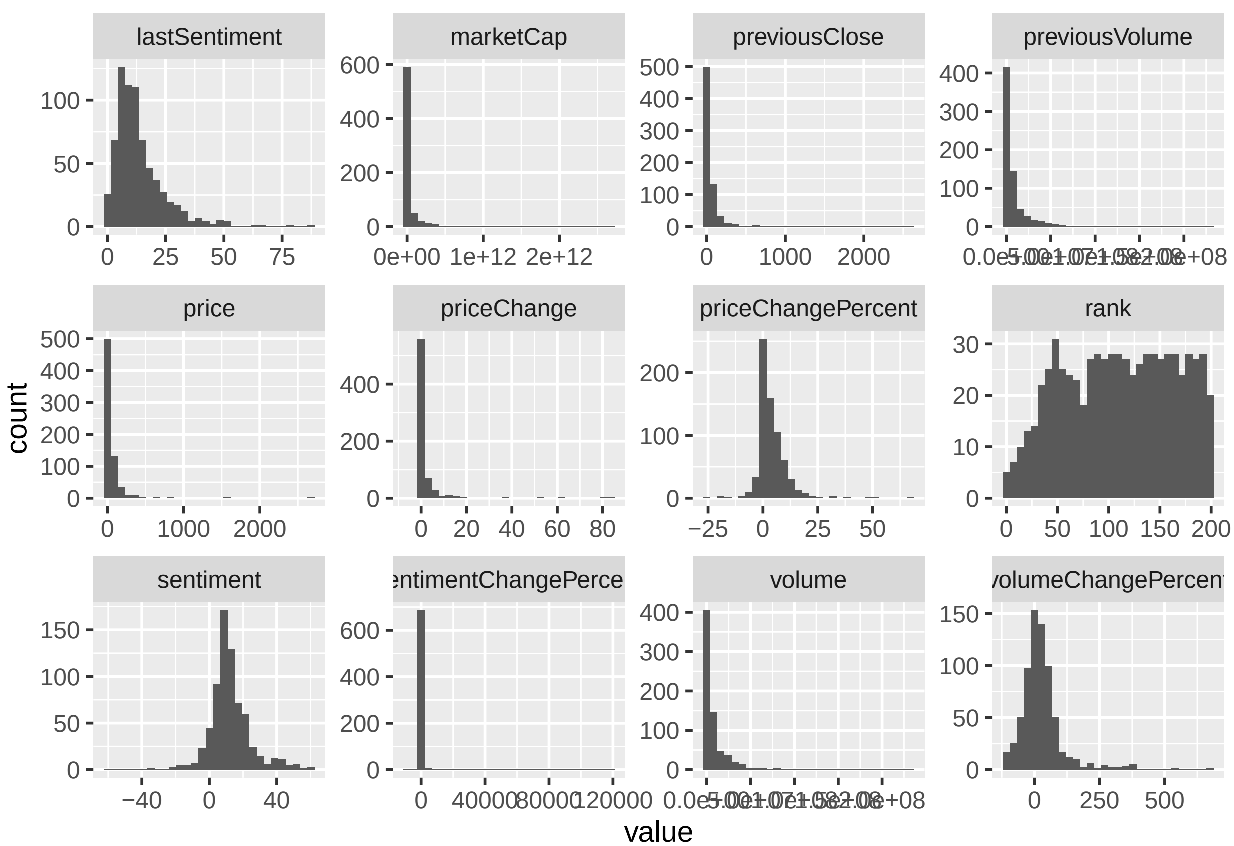
We first bind the data for bullish and bearish tickers together across different dates for better references. We then filter out all dummy data that can create noise for the dataset. We then introduce a new variable volumeChangePercent, which keeps track of the change in volume in percentage for better 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

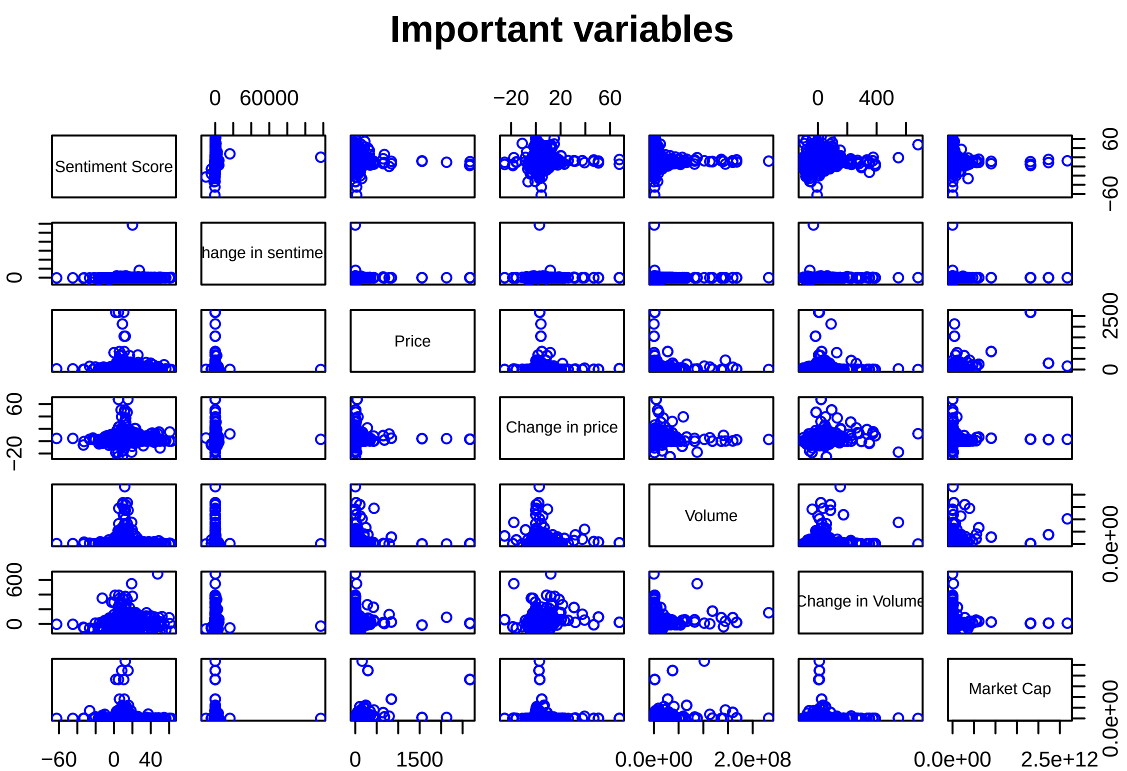
A histogram of all featured variables in the datasets:

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 3 rows containing non-finite values (stat_bin).
```



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.



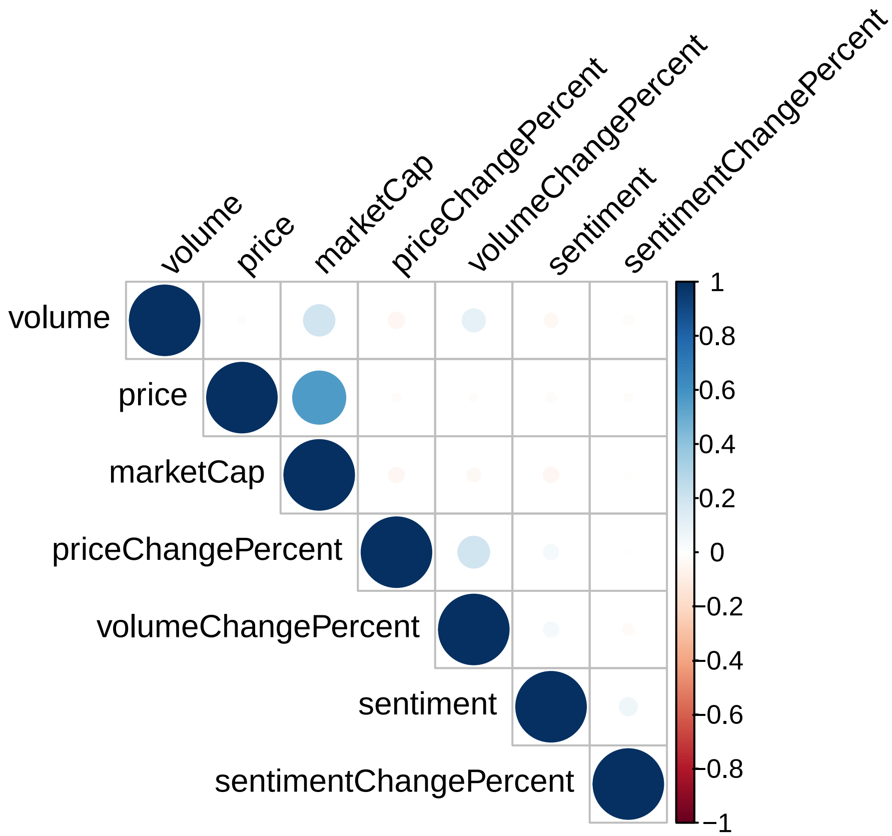
Look at the correlations between the variables:

```
##                        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:

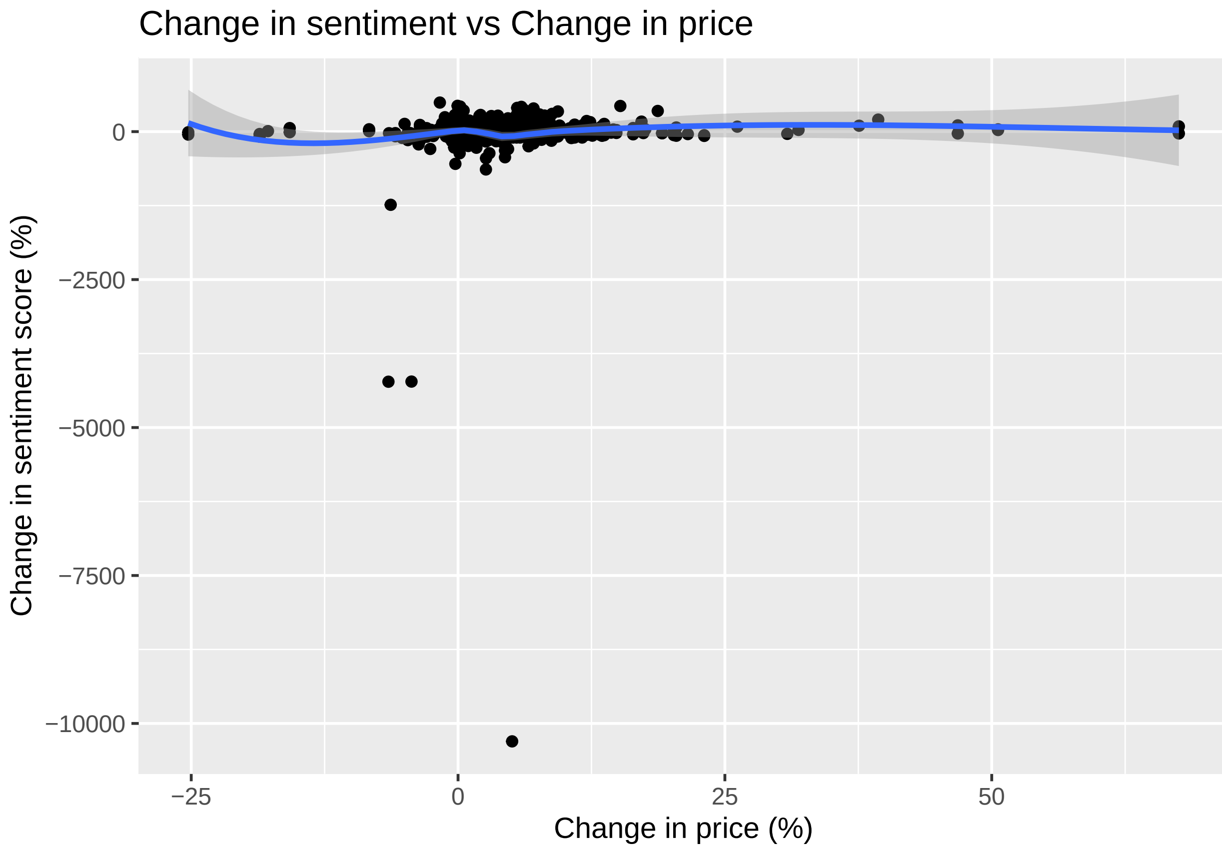
```
## corrplot 0.92 loaded
```

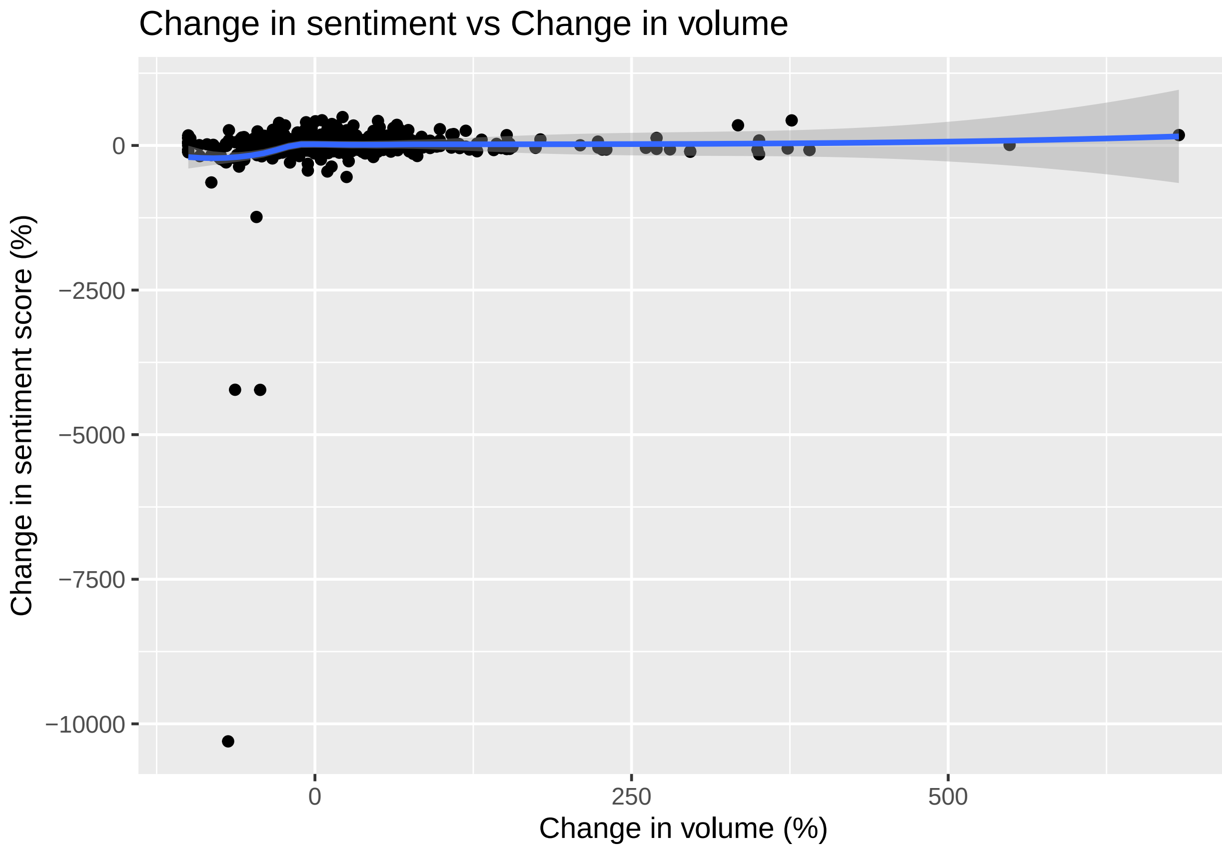


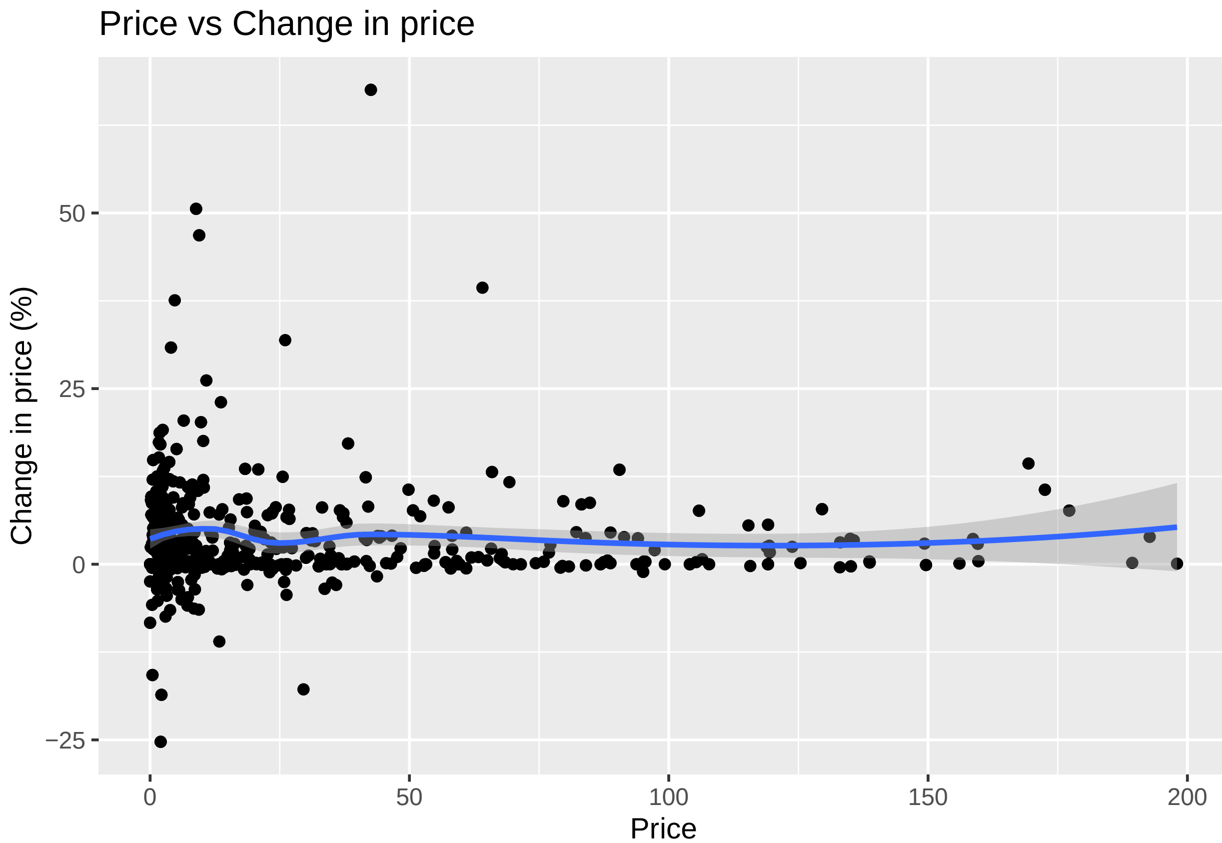
Find out if there are missing values:

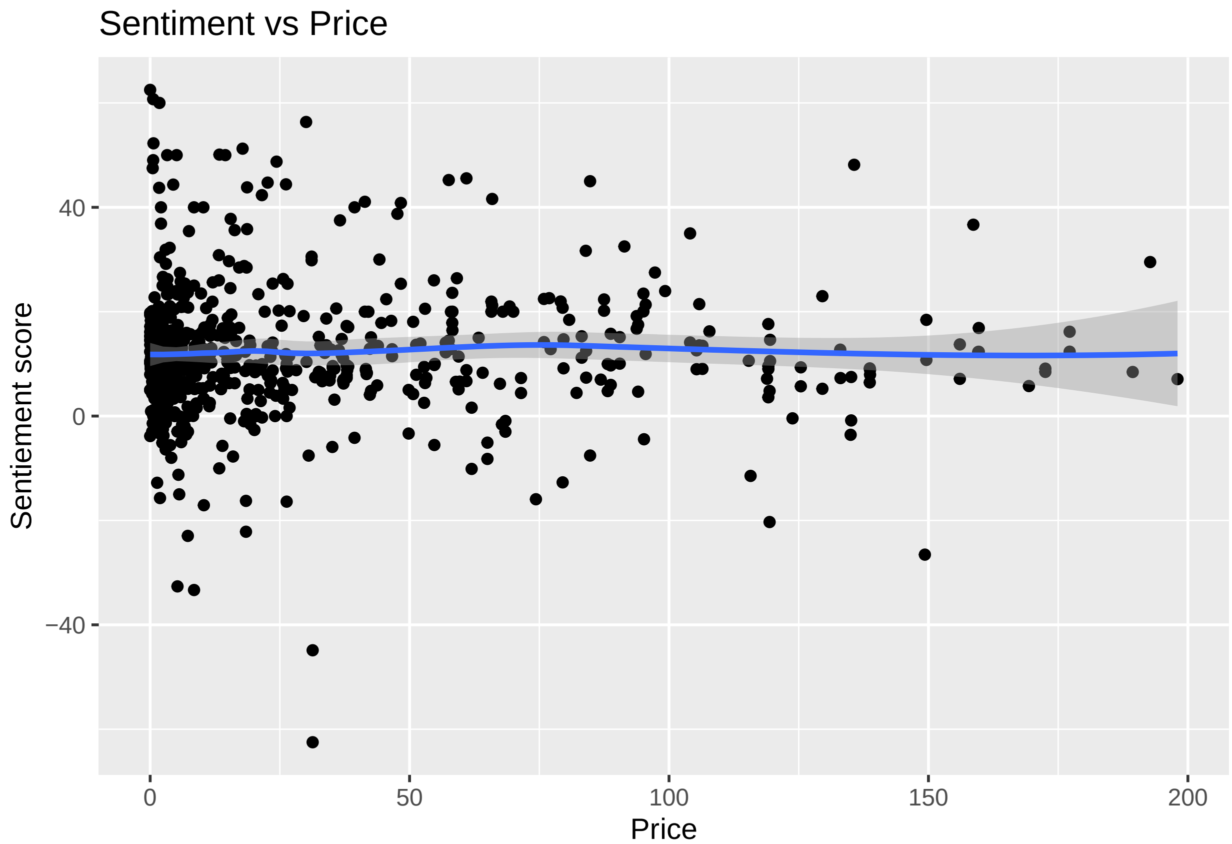
```
##                 ticker              sentiment          lastSentiment
##                      0                      0                      0
## sentimentChangePercent                   rank                   name
##                      0                      0                      0
##      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

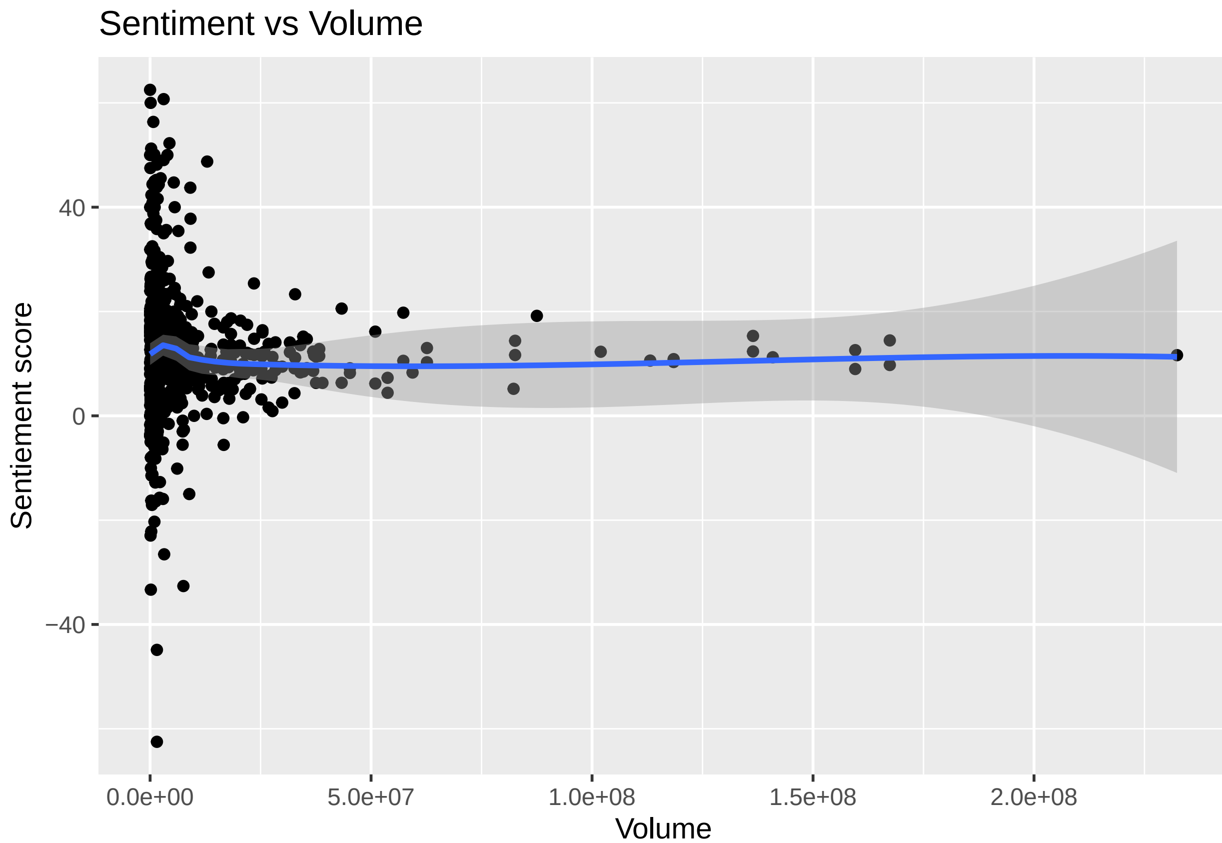
The follow charts show correlation between each pair of tickers' unique features:

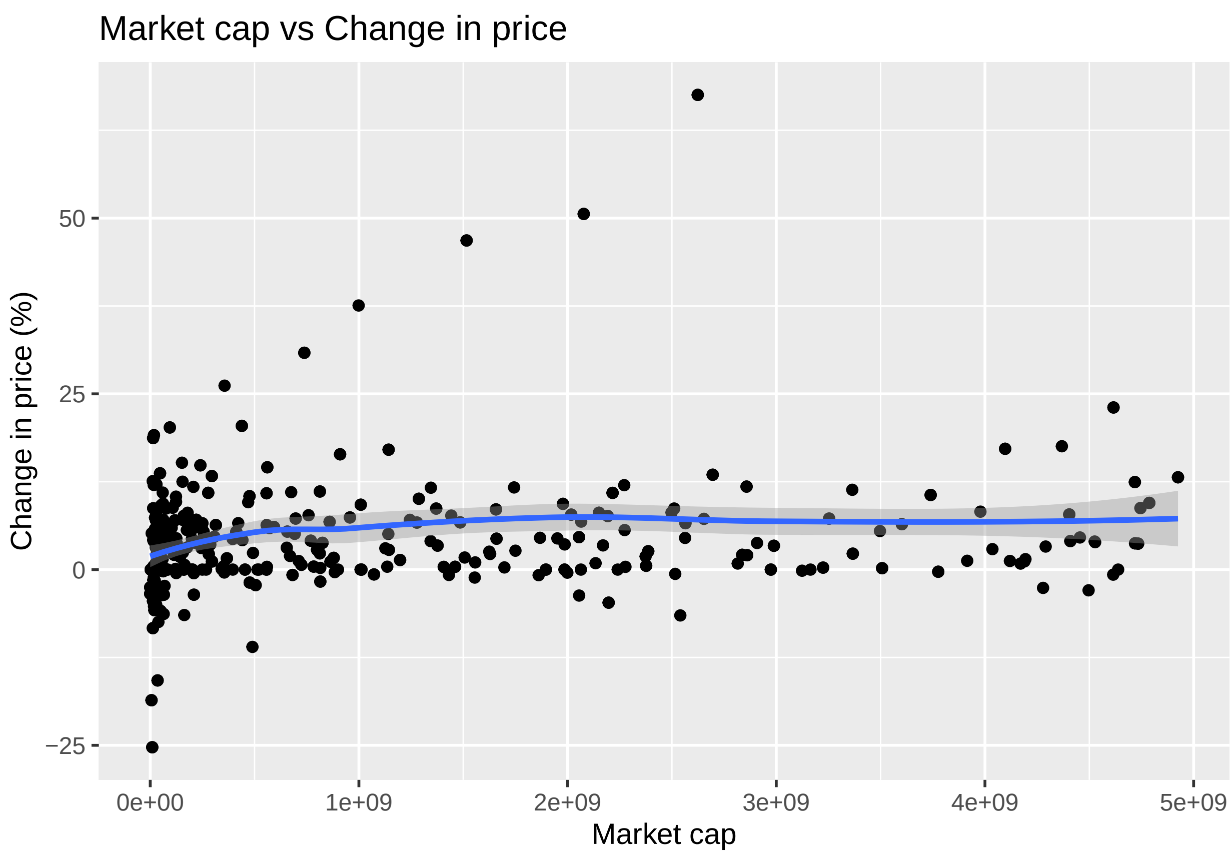

Change in sentiment vs Change in price
Change in sentiment score (%)
0
−2500
−5000
−7500
−10000
−25
0
25
50
Change in price (%)

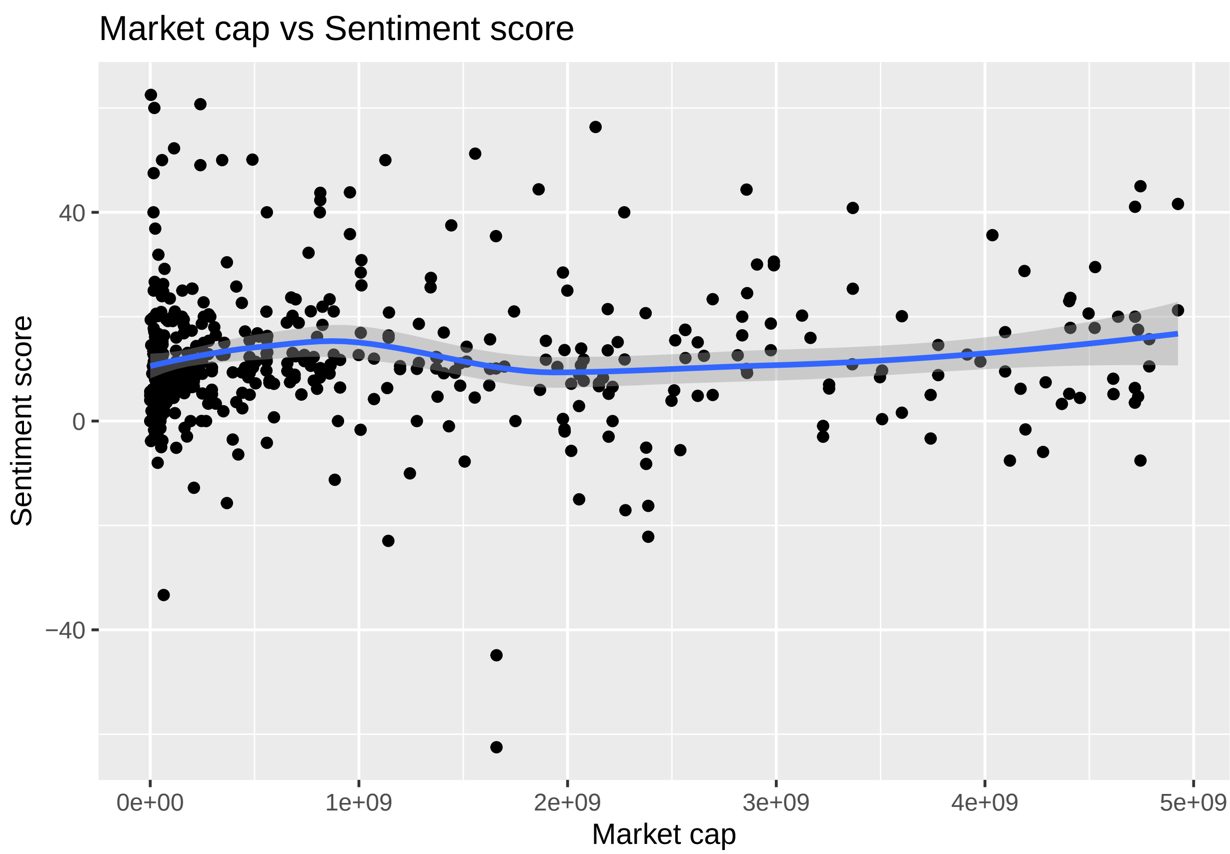

Change in sentiment vs Change in volume
Change in sentiment score (%)
0
−2500
−5000
−7500
−10000
0
250
500
Change in volume (%)

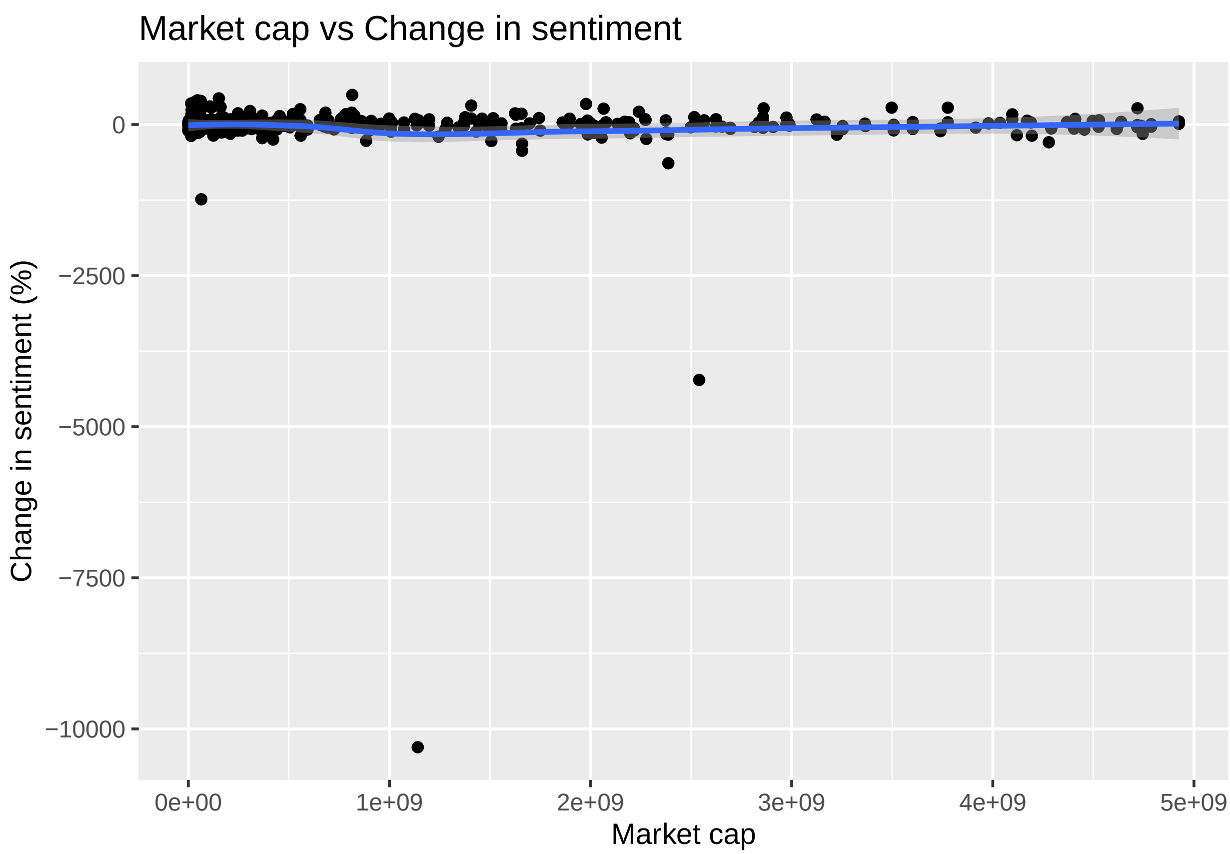

Price vs Change in price
Change in price (%)
50
25
0
−25
0
50
100
150
200
Price


Sentiment vs Price
Sentiement score
40
0
−40
0
50
100
150
200
Price


Sentiment vs Volume
Sentiement score
40
0
−40
0.0e+00
5.0e+07
1.0e+08
1.5e+08
2.0e+08
Volume


Market cap vs Change in price
Change in price (%)
50
25
0
−25
0e+00
1e+09
2e+09
3e+09
4e+09
5e+09
Market cap


Market cap vs Sentiment score
Sentiment score
40
0
−40
0e+00
1e+09
2e+09
3e+09
4e+09
5e+09
Market cap



V. Finished Analysis

VI. Conclusion

VII. Appendix

Appendix

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

bullish_data_twitter <- read_csv("social_sentiment_twitter_chginsentiment_bullish_03-16-2022.csv", show_
bullish_data_stocktwits <- read_csv("social_sentiment_stocktwits_chginsentiment_bullish_03-15-2022.csv"
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bearish_data_twitter2 <- read_csv("social_sentiment_twitter_chginsentiment_bearish_03-16-2022.csv", sho
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# binding both data for bullish and bearish tickers together
data <- rbind(bullish_data_twitter, bullish_data_stocktwits, bullish_data_stocktwits2, bearish_data_twi
```

```r
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)))
plotdata <- data %>%
  filter(sentimentChangePercent < 500)
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)
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(x=price, y = priceChangePercent)) +
```

```
  geom_point() + geom_smooth() +
  labs(
    title = "Price vs Change in price",
    x = "Price",
    y = "Change in price (%)"
  )
plotdata1 <- data %>%
  filter(price < 200)
ggplot(plotdata1, aes(y=sentiment, x = price)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Sentiment vs Price",
    y = "Sentiement score",
    x = "Price"
  )
ggplot(plotdata1, aes(y=sentiment, x = volume)) +
  geom_point() + geom_smooth() +
  labs(
    title = "Sentiment vs Volume",
    y = "Sentiement 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)
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 (%)"
  )
```