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Measuring corporate reputation through online social media: A case study of Volkswagen scandal

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Abstract:

This research investigates if there is any relationship between public opinion on social media and corporate reputation. The hypothesis of this study is that public comments on social media influences corporate reputation. Studies have shown that social media channels have an impact on corporate reputation [ERC19]. Reputation is increasingly recognized for its impact on value creation for corporations [Gat15]. This study assumes that the financial performance of a company is the direct indicator of its reputation. Therefore, this study investigates the influence of people's comments on social media on corporation stock market value.

This research is a case study of the Volkswagen scandal and it focuses on data of Twitter posts between 2015 and 2016 and tries to find how sentiments from public opinion can influence corporate reputation and its financial performance in the crisis situation. The process is that the opinion of people on Twitter about Volkswagen is extracted from the tweets in the form of sentiment value. Then, the correlation between stock market price and volume and the sentiment of tweets is calculated.

For the data selection, a semi-manual approach is used to remove commercial, political and unrelated tweets from the tweet data set. This approach shows a high average accuracy of 0.92. Retweets are treated as new tweets and are not removed from the dataset to find out the influence of retweets on the correlation. Then, three different sentiment analysis tools are used and compared to find out which one has more correlation with stock market price and volume of a corporation. These tools are "Microsoft Azure text analysis API", R package "Sentimentr" and R package "SentimentAnalysis". Comparing the resulting sentiments shows that Sentimentr tool has a higher correlation with stock market data.

The correlation results show that there is a correlation between the sentiment of tweets and corporations' stock market data. The average sentiment of tweets per day has the highest negative correlation (-0.84) with the stock market volume of trades the first month after the scandal. As the months pass, the correlation drops dramatically (By the fourth month after the crisis, correlation has dropped to -0.27). This means that first month after crisis while the average sentiment gets more negative, more stocks are traded. However, this doesn't necessarily indicate that negative opinion of people on Twitter influences the stock volume of trade. The correlation results show that stock price of day D has more correlation with the average sentiment of day D+4. This can indicate that actually, fluctuations in the stock price of the company can influence the sentiment of tweets. This is against our original hypothesis that public opinion on social media influences corporate reputation.

Keywords:

CERCS:

Ettevõtete maine mõõtmine läbi sotsiaalmeedia: Volkswageni skandaali juhtumiuuring

Lühikokkuvõte:

Selle uurimistöö eesmärk on leida seos sotsiaalmeedias leviva avaliku arvamuse ning ettevõtete maine vahel. Püstitatud hüpoteesiks on see, et avalikud kommentaarid sotsiaalmeedias mõjutavad ettevõtete mainet. Uuringud on näidanud et sotsiaalmeedia kanalitel on mõju ettevõtete mainele [ERC19]. Mainet tunnustatakse üha enam ettevõtte väärtust mõjutava tegurina [Gat15]. See uurimistöö eeldab et ettevõtte majandustulemus on otsene maine indikaator. Sellest tulenevalt uurib see teos inimeste sotsiaalmeedias avaldatud kommentaaride mõju ettevõtte börsihinnale.

See uurimistöö on Volkswageni skandaali juhtumiuuring ning keskendub Twitteri postitustedele 2015 ja 2016 aastal. Eesmärgiks on leida kuidas avaliku arvamuse sentiment mõjutab ettevõtete mainet ning majanduslikke tulemuse kriisiolukorras. Protsessiks on valitud järgnev. Twitteri kasutajate arvamus Volkswageni kohta eraldatakse postitustest sentimendi numbri kujul. Seejärel leitakse korrelatsioon börsihinna, tehingute arvu ning leitud sentimendi vahel.

Andmete valimiseks kasutati poolautomaatset lähenemist, mille abil eemaldati kaubanduslikud, poliitilised ning teised mitte seotud säutsud (tweet). Selle meetodi keskmiseks täpsuseks tuli kõrge 0.92. Edasisäutse (retweet) käsitletakse kui uusi säutse ning neid ei eemaldatud andmestikust et leida nende mõju korrelatsioonile. Sentimendi väärtuse leidmiseks kasutati 3 erinevat analüüsiviisi: "Microsoft Azure text analysis API", R-i pakett "Sentimentr" ning R-i pakett "SentimentAnalysis". Nende meetodite võrdlemisel leiti et Sentimentr-il on kõige parem korrelatsioon börsihinnaga.

Korrelatsiooni tulemustest leiti, et säutsude sentimendi ja ettevõtete aktsiaturu andmete vahel on korrelatsioon. Päeva keskmisel sentimendil on kõige suurem negatiivne korrelatsioon (-0.84) aktsiaturu tehingute arvuga esimese kuu jooksul peale skandaali. Kuude möödudes korrelatsioon langeb järsult. (Neljandal kuul peale kriisi on korrelatsioon langenud väärtuseni -0.27). See tähendab et esimese kuu jooksul peale kriisi mida negatiivsemaks läheb sentiment, seda rohkem aktsiaid vahetatakse. Siiski see ei tähenda et negatiivne arvamus Twitteris mõjutab börsitehinguid. Korrelatsiooni tulemused näitavad et börsihind päeval D korreleerub paremini sentimendi väärtusega päeval D+4. See võib näidata, et tegelikult mõjutavad börsihinna kõikumised säutsude sentimenti. See läheb vastu esialgesele püstitatud hüpoteesile, kus väideti et sotsiaalmeedias leviv arvamus mõjutab ettevõtete mainet.

Võtmesõnad:

CERCS:

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1 Introduction

What is corporate reputation? Corporate reputation can be defined as stakeholders' perception of a corporation. However, different stakeholders can have different perceptions toward a corporation, therefore reputation can have a different meaning for different stakeholders. For example, the reputation of a corporation is different from the perspective of a customer, a shareholder or an employee.

Different stakeholders look for different things in a corporation. An employee looks for better salary and job conditions; A customer wants a better quality of service and product (more value) for less expense; A shareholder wants more stock interest; General public look at a corporation as a citizen and want it to have good behavior and pay its taxes or be eco-friendly. So, it seems that a corporation does not have a singular reputation but rather many different ones. From one stakeholder's point of view, a corporation can have a positive reputation and from the other, it can have a negative one. But can we merge all these different reputations and measure them as an overall reputation? Why is it important to be able to measure corporate reputation?

More than half of the companies' market value is based on intangible assets, among them, reputation is one of the most valued organizational asset [SRS09]. Thus, measuring corporate reputation can be a valuable tool for corporations.

In this research, we focus on measuring corporate reputation via sentiment analysis of posts on online social networks. The main reason for choosing this method is because not many studies have been conducted on this method. There are many types of research on measuring corporate reputation, but not many of them solely focus on the impact of sentiments of user comments on corporate reputation and corporate financial performance. Moreover, Twitter is chosen as the social media platform, because it is one the most used and common social media platforms.[Lyt18]

In order to verify the findings of sentiment analysis, they are compared to another source of corporate reputation. Different studies [LVS19],[STW10], [Joo12] show that there is a link between corporate reputation and financial performance. Therefore, the stock market data was chosen as that indicator of corporate reputation since it is an indicator of corporation value change. This paper is a case study of the Volkswagen 2015 emissions scandal and how Twitter posts related to this scandal have influenced the company's stock market in the crisis situation of scandal breakout.

The main questions this study will answer are:

- **RQ1:** Is there a correlation between Corporate reputation and public opinion on social media?

- **RQ2:** Is there any correlation between the sentiment of twitter comments and stock market fluctuation in a crisis situation?

- **RQ3:** Does the opinion of people on social media influences the financial performance of corporation in a crisis situation?

To answer these questions, this study uses a data science approach. This approach is a combination of qualitative (machine learning) and quantitative (manual) procedures. A semi-manual approach is used for the process of data selection. Then, three different tools are used and compared for the sentiment analysis process and at the end, Pearson correlation is used to find out the correlation between the sentiment and stock market data. The result is that in the crisis situation for a short time sentiment of tweets has a high negative correlation with the volume of stock trades. However, after the passage of three months, this correlation drastically reduces. Moreover, although we found correlation between the sentiment of tweets and stock data, we couldn't prove that online opinion of the public on social media influences the financial performance of the corporation. However, we found out that it actually can be the other way around.

The structure of this thesis is as follows:

- In chapter 2 background and related work will be described.

- In chapter 3 the data used for the process of this case study is introduced and the details of obtaining the data and structure of the data is described.

- In chapter 4 the approach of the case study is described in details. This chapter explains in details the procedure of pre-processing the data, data selection, sentiment analysis and correlation and what are the results of each step of the process.

- In chapter 5 the main results of the case study will be summarized. Plus, the next steps for future work will be suggested.

2 Background

2.1 Volkswagen

2.1.1 The company

Volkswagen Group,founded in 1937, is a German automobile manufacturing enterprise head-quartered in Wolfsburg, Lower Saxony, Germany.
The Group comprises twelve brands from seven European countries: Volkswagen Passenger Cars, Audi, SEAT, ŠKODA, Bentley, Bugatti, Lamborghini, Porsche, Ducati, Volkswagen Commercial Vehicles, Scania and MAN. In addition, the Volkswagen Group offers a wide range of financial services, including dealer and customer financing, leasing, banking and insurance activities, and fleet management.[1]

2.1.2 The scandal

The Volkswagen diesel emissions scandal was revealed in September 18th, 2015 when EPA (Environmental Protection Agency) announced that Volkswagen has been using defective devices in US since 2009 to get around emission laws. The defective device is actually a program part of the engine software which helped to cheat in the standard airpollution tests. [2]

2.2 Related Works

Studies related to this topic can be divided into five different groups:

1. Related to measuring corporate reputation

2. Related to corporate reputation on social media

3. Related to the stock market prediction

4. Related to sentiment analysis

2.2.1 Measuring Corporate Reputation

Corporate reputation is a construct that has received widespread recognition in the fields of management, corporate social responsibility, and marketing because a good reputation is thought to be more commercially valuable than a bad reputation.[Dow16]
There are many types of research on how is the best way to measure corporate reputation. Different studies use different approaches to measure corporate reputation. Their approach is based on how they define corporate reputation. Two of the most famous corporate reputation measures are Fortune's "world's most admired companies" and Reptrak.
The Fortune's "world's most admired companies" is a corporate reputation ranking. Their approach is to select 1500 candidates (1000 U.S companies and 500 companies from all over the world) which have the highest revenue. Then, top companies will be categorized into different industries. Overall 680 companies from 29 countries will be selected. Then 3900 executives, directors, and analysts will be asked to rate top 10 companies in their own industry based on 9

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[1]https://www.volkswagenag.com/
[2]https://www.cnbc.com/2015/09/22/what-you-need-to-know-about-the-volkswagen-scandal.html

criteria including investment value, management quality, social responsibility and product quality. Because of a low number of votes in some industries, not all industries are included in this ranking, including Satellite providers, pipelines, and U.S. Energy. At the end 50 of these companies will be selected and ranked as most admired companies.[3]

Many studies on corporate reputation or management have put the basis of their study on Fortune's most admired companies [HPK17],[DB15]. However, this ranking has some flaws: It is biased. It doesn't take into account every stakeholder and it is based on revenue and it doesn't take into account every industry.

RepTrak® "pulse" is a reputation measurement and annual ranking, providing a measurement of how the public views the world's most famous companies and how is the emotional connection between the customer and the corporate. It takes into account more than 7,000 companies in more than 20 industries and 50 countries with 15 stakeholder groups.[4]

The result of the ranking is broken down into seven dimensions which explains why customers feel the way they do. The dimensions and each dimension attributes are shown in the table 1.

Dimension	Attribute
Products and Services	Offers high-quality products and services
Products and Services	Offers products and services that are a good value for the money
Products and Services	Stands behind its products and services
Products and Services	Meets customer needs
Innovation	Is an innovative company
Innovation	Is generally the first company to go to market with new products and services
Innovation	Adapts quickly to change
Workplace	Rewards its employees fairly
Workplace	Demonstrates concern for the health and well-being of its employees
Workplace	Offers equal opportunities in the workplace
Governance	Is open and transparent about the way the company operates
Governance	Behaves ethically
Governance	Is fair in the way it does business
Citizenship	Acts responsibly to protect the environment
Citizenship	Supports good causes
Citizenship	Has a positive influence on society
Leadership	Has a strong and appealing leader
Leadership	Has a clear vision for its future
Leadership	Is a well-organized company
Leadership	Has excellent managers
Performance	Is a profitable company
Performance	Delivers financial results that are better than expected
Performance	Shows strong prospects for future growth

Table 1: Reptrak pulse dimensions and attributes.[FPN15]

Reptrak pulse is a good measurement tool for corporate reputation, but the problem is it doesn't take into account all the stakeholders separate from their industries. Plus, it uses survey which is a controlled way of finding stakeholders opinion.

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[3]http://fortune.com/worlds-most-admired-companies
[4]https://www.reputationinstitute.com/reputation-measurement-services/reptrak-framework

2.2.2 Corporate Reputation on social media

Most of the studies about corporate reputation on social media focus on the role of social media in corporate governance. Their main focus is Crisis communication strategies, corporate social responsibility or situational crisis communication theory (SCCT).[ZVK17],[OT14]

The reseach "Samsung and Volkswagen crisis communication in Facebook and Twitter",2017, is a case study of three different corporate crisis: Volkswagen emission crisis, Samsung galaxy Note 7 battery crisis and Samsung washing machine crisis. It studies these corporates financial and corporate reputation loss and focuses on crisis communication and situational crisis communication theory. The study compares corporats communication strategy on social network and analyzes in which stuations the corporat's communication strategy was beneficial to corporate image and in which situations it was not. For example, it says there are some triggers like news, social media discourse or word of mouth which can trigger stakeholders reaction and corporat's correct and timely response can decrease the impact of negative reaction.[ZVK17]

Another research [ZLD18] studies the influence of crisis communication on the secondary crisis communication (SCC). This research shows that the crisis situation of companies with high cognitive reputation can influece peoples communication on social media after crisis much more than other companies. This is because consumers feel that they are morally violated.

2.2.3 Stock Market Prediction

The studies focusing on stock market prediction use different approaches. In "Stock trend prediction using news sentiment analysis", the study invests the relationship between news articles and the stock market. The study uses 3 different classification for sentiment analysis of the news and compares them:[KBJ16]

- Random Forest around 88% accuracy

- SVM 86% accuracy

- Naive Bayes 83% accuracy

In "Stock Prediction Using Twitter Sentiment Analysis", it uses Twitter sentiment analysis to create a stock market predictive model. Using "Self Organizing Fuzzy Neural Networks", this study gets the result of approximately 75% accuracy.[MG]

2.2.4 Sentiment Analysis

Oxford Dictionary: "The process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer's attitude towards a particular topic, product etc. is positive, negative, or neutral." [5]

Sentiment analysis can be done on different levels. It can be done on the whole document, or sentence by sentence or it can go even deeper and be done on the word level. There are many different approaches for sentiment analysis. bag of words, user-level sentiment analysis [TLT+11]

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[5]https://en.oxforddictionaries.com/definition/sentiment_analysis

or lexicon-based approach [TBT$^+$11]. For example, user-level sentiment analysis suggests that user connections on a social network can influence their opinion hence the sentiment of their comments. The literature describes how two users which have a connection together can have a similar opinion.

3 Dataset

Two Datasets are used for the purpose of this Thesis:

1. Twitter Dataset: This is the main dataset and most of the analysis is on this dataset.

2. Yahoo Stock Dataset: This dataset is for making comparison and finding correlation between sentiments of Twitter dataset and Stock market data.

3.1 Twitter Dataset

3.1.1 Obtaining data

The data is obtained from gnip.com which is a social data provider and API aggregation company. The matching rule for collected data is as follows:

- Date of the tweet is between 28.08.2015 and 06.06.2016

- Language: English

- Country of the tweet profile: US

- Includes at least one of these values: VW; Volkswagen; #volkswagenscandal; #vwemission;#vwscandal; #vwgate; #vwdieselgate; #VWdieselGate;

Following code snipet shows the gnip matching rule in a gnip twitter object:

```
"gnip":
{
   "matching_rules":
   [
     {
        "value":"((VW OR Volkswagen OR #volkswagenscandal OR #vwemission OR #vwscandal
            OR #vwgate OR #vwdieselgate OR #VWdieselGate) profile_country_code:us)
            lang:en",
        "tag":null
     }
   ]
}
```

The data includes 40741 JSON files, each including 6 to 10 twitter JSON objects. The total number of tweets is 933037.

Figure 1 shows a geomap analysis of where Tweets are originated.

3.1.2 Analyzing the data

The gnip twitter data is in JSON format which consists of some root-level attributes and some child objects. The gnip twitter object is slightly different than original twitter data object. For example, the child twitter object "user" has the name "actor" in the gnip data object. Following is a list of Twitter object attributes which are kept for the purpose of this research. The example
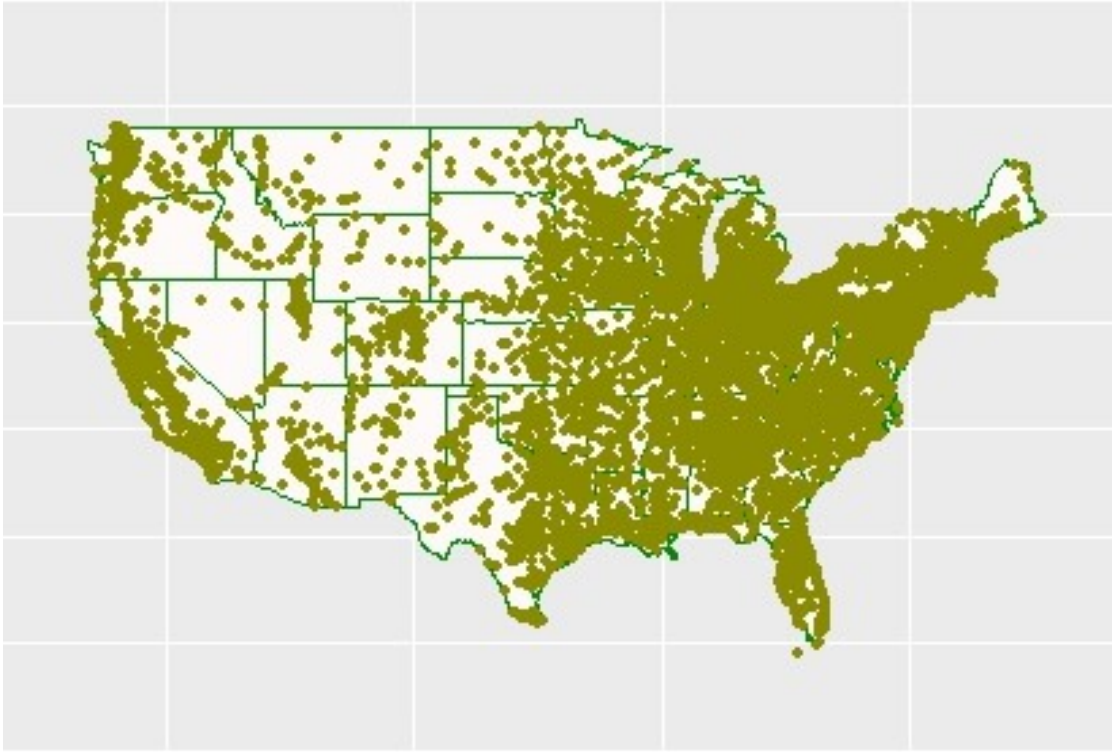
Figure 1: Geographical position of Tweets on US map

tweet is an actual tweet from the dataset, belonging to a person named "NatashaDuswalt".[6]

- **id:** A unique IRI for the tweet. In more detail, "tag" is the scheme, "search.twitter.com" represents the domain for the scheme, and 2005 is when the scheme was derived.

```
"id":"tag:search.twitter.com,2005:637054371100921856"
```

- **actor:** An object representing the twitter user who tweeted. The Actor Object refers to a Twitter User, and contains all metadata relevant to that user.

```
"actor":
{
    "objectType":"person",
    "id":"id:twitter.com:16919593",
    "link":"http://www.twitter.com/NatashaDuswalt",
    "displayName":"NatashaDuswalt",
    "postedTime":"2008-10-23T04:09:26.000Z",
    "image":"https://pbs.twimg.com/profile_images/2921677830/
        ef512e5af6c0288f5838268d500bfbaa_normal.jpeg",
    "summary":"Author, Speaker ,Founder and President of Peak Models & Talent in
        LA. Love my Family! I live each day On Purpose - Fully Inspired..",
    "links":[{"href":"http://www.peakmodels.com","rel":"me"}],
    "friendsCount":813,
    "followersCount":810,
    "listedCount":23,
```

```
"statusesCount":963,
"twitterTimeZone":"Pacific Time (US & Canada)",
"verified":false,
"utcOffset":"-25200",
"preferredUsername":"NatashaDuswalt",
"languages":["en"],
"location":{"objectType":"place","displayName":"Los Angeles"},
"favoritesCount":41
}
```

- **verb:** The type of action being taken by the user.

  Tweets, "post" Retweets, "share" Deleted Tweets, "delete"

  The verb is the way to find out which tweets are original and which are retweets.

```
"verb":"post"
```

- **postedTime:** The time when the Tweet was posted.

```
"postedTime":"2015-08-28T00:09:32.000Z"
```

- **generator:** An object representing the utility used to post the Tweet. This will contain the name ("displayName") and a link ("link") for the source application generating the Tweet.

```
"generator":
{
   "displayName":"Facebook",
   "link":"http://www.facebook.com/twitter"
}
```

- **provider:** A JSON object representing the provider of the activity. This will contain an objectType ("service"), the name of the provider ("displayName"), and a link to the provider's website ("link").

```
"provider":
{
   "objectType":"service",
   "displayName":"Twitter",
   "link":"http://www.twitter.com"
}
```

- **link:** A Permalink for the tweet.

```
"link":"http://twitter.com/NatashaDuswalt/statuses/637054371100921856"
```

- **body:** The tweet text.

```
"body":"Stephanie on the cover of VW Magazine!!! #Val Westover Photography!
   Love this shot!! http://t.co/1V9zxIXAAa"
```

- **object:** An object representing tweet being posted or shared.

```
"object":
{
   "objectType":"note",
   "id":"object:search.twitter.com,2005:637054371100921856",
   "summary":"Stephanie on the cover of VW Magazine!!! #Val Westover
        Photography! Love this shot!! http://t.co/1V9zxIXAAa",
   "link":"http://twitter.com/NatashaDuswalt/statuses/637054371100921856",
   "postedTime":"2015-08-28T00:09:32.000Z"
}
```

- **twitter_entities:** The entities object from Twitter's data format which contains lists of urls, mentions and hashtags.

```
"twitter_entities":
{
   "hashtags":[{"text":"Val","indices":[41,45]}],
   "trends":[],
   "urls":[
    {
      "url":"http://t.co/1V9zxIXAAa",
      "expanded_url":"http://fb.me/7zKwJQqqY",
      "display_url":"fb.me/7zKwJQqqY",
      "indices":[85,107],
      "unwound":{"url":"https://www.facebook.com/
      photo.php?fbid=10153257670073264","status":403}
    }
   ],
   "user_mentions":[],
   "symbols":[]
}
```

- **geo:** Points the location where the Tweet was created.

```
"geo":{"type":"point","coordinates":[-98.5,39.76]}
```

3.2   Yahoo Stocks Dataset

3.2.1   Obtaining data

The dataset is the historical price data of Volkswagen obtained from finance.yahoo.com. The search rule for the collected data is as follows:

- Stock name: Volkswagen Aktiengesellschaft (VLKAY)

- Time Period: Between 27.08.2015 and 03.06.2016

- Frequency: Daily

3.2.2 Analyzing the data

The dataset is a csv file containing 194 rows, each for 1 day beginning from 27.08.2015 to 03.06.2016. Dataset features and their description is as follows:

- **Date:** The date of recorded stock value.

- **Open:** The opening price of the share.

- **High:** The highest price of the share in the day.

- **Low:** The lowest price of the share in the day.

- **Close:** The closing price of the share in the day.

- **Adj close:** Adjusted close price adjusted for both dividends and splits. An adjusted closing price is a stock's closing price on any given day of trading that has been modified to include any distributions and corporate actions that occurred at any time before the next day's open. The adjusted closing price is often used when examining historical returns or performing a detailed analysis of historical returns. [7]

- **Volume:** Volume is the number of shares traded.

For the holidays, the stock market data is missing. So, because twitter data still exists for those days, for the better analysis, the missing data was replaced with the average value of data of one day before the holiday and one day after the holiday.

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[7]https://www.investopedia.com/terms/a/adjusted_closing_price.asp

4 Approach

4.1 Data preprocessing

One of the most important steps towards data analysis is data preprocessing. Data preprocessing is a technique of transforming erroneous data into an understandable and correct format. Raw data is unstructured and noisy and not suitable for data analysis. The quality of data analysis depends on how well data preprocessing is performed. For this Thesis, in data preprocessing stage, first, a number of Twitter text cleaning techniques is performed and then, with a data subsetting technique, useful data for the purpose of this thesis is selected.

4.1.1 Data cleaning

Data cleaning, data cleansing or data scrubbing refers to the process of altering incorrect, incomplete or poorly formatted data. Text cleaning methods used for the Twitter dataset is as follows:

Data Flattening: Format of the Twitter data is JSON which is an object with nested data. For easier use, the data is converted to CSV. In this process, all the data in a JSON object is converted to a single CSV row. The outcome of this procedure is a single CSV file including 933037 records, each contains data of a single tweet. Python language was used to convert JSON to CSV. Some of the changes done to the data during this process are:

- **Id:** A Twitter id "tag:search.twitter.com,2005:637054371100921856" includes data which is not useful to this Thesis. Therefore, the first part before the colon is removed. A sample result is "637054371100921856".

- **Actor id:** Same as Twitter id, the first part before the colon is removed. The resulting ID is an eight-digit number.

- **postedTime:** Posted time includes information of both time and date of posting a Tweet. Since the stock market data is daily, the time of posting the Tweet would be irrelevant to our research. Therefore, only the date is kept.

- **Hashtags and user_mentions:** In the original Twitter object, the format of Hashtags and user_mentions is a list of objects within the "twitter_entities" object. For the purpose of data flattening, "text" attribute of each object is selected and concatenated to a single string. For example, a sample of hashtag string of a Tweet is: "south jersey VW" which each word is a single hashtag.

- **deduct unuseful data:** Not all of the attributes in a Twitter data object are useful to this research. For example, data about URLs is not informative for the purpose of this thesis. Therefore, it will be removed from the dataset. The attributes that are kept and converted to CSV file are: "tweet_id", "postedTime", "text", "hashtags", "user_mentions", "user_name", "user_id", "user_friendsCount", "user_listedCount", "user_followersCount", "user_statusesCount", "user_verified", "favoritesCount", "retweetCount", "location_region", "latitude", "longitude".

Remove URLs: URLs in the text carry no information toward sentiment analysis. Therefore, they are removed from the tweet text.

Remove hashtags: Hashtags in the text can have sentiment weight. For example, a text that contains "#terrible_news" or "#nice_wheels" can change the weight of the sentiment. Therefore,

for a better result in sentiment analysis, they are kept in the text and only the hashtag sign "#" is removed from the tweet text.

Remove user_mentions: User_mentions in the text could add a false sentiment to the text. For example, username "happy_Tommy" could add a false-positive sentiment to the text. Therefore, user_menions are removed from the text. However, user_mentions are needed for further data selection. Therefore, they are saved in a separate column for further analysis.

Remove emojis: Emojis can have sentiment weight. But they can add an unreal extra sentiment. For example, the "laugh at loud" emoji. Plus, they can have a false sentiment. For example, the tweet "VW is going down :D". For a simpler analysis, for the purpose of this Thesis, emojis are removed and not used for sentiment analysis.

Replace contractions: For example, converting "it's" to "it is".

Remove HTML characters: The text contains many html entities like &amp,&lt, or &gt. These HTML characters are not part of the original text and need to be removed.

Remove numbers: Some may argue that numbers in the text could have sentiment weight. For example, the Tweet "I give VW score of 100/100", has positive sentiment embedded in it. But for the purpose of simplifying the sentiment analysis, numbers are removed from the text.

Remove punctuations: Punctations can have sentiment value. For example "great" and "great!!!" or "cool!" and "cool?" have different sentiments. But analyzing them will add complexity to the sentiment analysis and it is not useful for the purpose of this Thesis. Therefore punctuations are removed.

Convert to lower case: Although a word in upper case can have different emotional weight than the same word in lower case, converting all the text to lower case can reduce the number of words needs to be taken into account for text analysis.

Lemmetizing: Lemmatization is the process of converting different forms of a word to one single form "lemma". for example, reducing "cars" to "car" or "investigation" to "investigate" or "cheating" to "cheat".

Table 2 shows sample of two tweets, before and after the above mentioned process.

Tweet before cleaning process	Tweet after cleaning process
"b'#Volkswagen #Jetta defective wiring class action settlement! #cars #auto #warranty #garage #automobiles http://t.co/dnwxHv79pd'"	"volkswagen jetta defect wire class action settlement car auto warranty garage automobile"
"b'Heading to @DowntownSLO #farmersmarket! @JakeRobinson109 is driving the @VW Jetta getting used to the 5-Speed!'"	"head to farmersmarket drive the jetta getting use to the speed"

Table 2: Sample of tweets before and after data cleaning

4.1.2 Data selection

For the process of data selection, an iterative, semi-manual approach is being used. In this process, hundreds of tweets were manually analyzed to find a pattern to which tweets should be selected.

The first question in the process of data selection was that should retweets be included in the data or not. In this study, it is decided that every tweet will be counted as a new tweet. This way, a tweet that has a negative sentiment but has been retweeted 200 times, has more weight on the final sentiment than a tweet that has stronger positive sentiment but has been retweeted only 3 times. Preliminary analysis of the Tweets shows that Tweets can be categorized into 4 main groups:

1. **Tweets related to VW:** These tweets could be either related to VW scandal or be about other topics related to VW. Two samples of these Tweets are "volkswagen owners want payback over pollution control cheating" and "your so lucky will just go with volkswagen passat or something that is cheaper lol"

2. **Commercial Tweets:** These are the Tweets that even though might be related to VW, but are about selling items and promotions. These Tweets can have a high positive sentiment which would compromise the result. Therefore, these tweets need to be removed from the dataset. An example of these group of Tweets is "ur chance to win signed Gabriel Iglesias dvd baseball card vw magazine"

3. **Political Tweets:** These are the tweets that are mostly unrelated to VW and are just about politics. These Tweets need to be removed from dataset as well. A sample of these Tweets is "senators who put politics ahead of national security all traitors every single one"

4. **Other unrelated Tweets:** There are some Tweets that are not related to VW and they are nor political or commercial. For example, "lady gaga moves oscars audience to tears with a powerful performance".

To select the related Tweets to VW, because our data is not labeled, one approach could be Topic Classification. This is an unsupervised machine learning approach. After trying topic classification, because the length of Tweets are short and topics are varied, no useful results were found. As a result, topic classification is not used as data selection approach. Therefore, the approach that is used is to subset data based on specific keywords. For this purpose, first, a word count analysis is performed on the text of Tweets. Figure 2 shows the WordCloud diagram of the Tweets.

From this WordCloud diagram of tweets, you can easily find out which words are used more often in the tweets. Among the most used words, obviously words like "diesel", "scandal", "emission", "cheat", "ceo", "investigate" and "test" are related to Volkswagen scandal. However, you can see words like "trump" or "obama" that are coming from political tweets which don't have anything to do with Volkswagen. Additionally, tweets that include words like "deal" are advertising tweets.

For further analysis, a random set of 500 tweets was selected and analyzed thoroughly to find some patterns in the data. The analysis shows that Tweets which include some specific keyword, username, hashtag or user_mention are definitely commercial or political. Table 3 shows the result of this analysis:

At last, some news articles about VW emission scandal was reviewed to find the keywords related to the scandal.

All the analysis above, lead to a subsetting procedure:

Figure 2: Wordcloud of Tweets

Phrase	Type	Tweet Type
FluffyCollection	Hashtag	Commercial
PhoenixMotors	User_mention	Commercial
GREAT DEALZ	Username	Commercial
Deals	Hashtag	Commercial
fluffyguy	User_mention	Commercial
eBay	User_mention	Commercial
Etsy	User_mention	Commercial
bid	keyword	Commercial
win	keyword	Commercial
purchase	keyword	Commercial
purchase	keyword	Commercial
Conservative_VW	User_mention	Political
NeverHillary	Hashtag	Political
Trump2016	Hashtag	Political
NEVERCRUZ	Hashtag	Political
HillaryForPrison2016	Hashtag	Political
refugee	keyword	Political
ted cruz	keyword	Political
Activision Support	Username	Other unrelated
Insta-VWT	Username	Other unrelated
DIY	Hashtag	Other unrelated

Table 3: Specific hashtags, usernames or usermentions in Tweets unrelated to VW

- **First step:** Excluding unrelated tweets which includes at least one of the keywords, hashtags, usernames or user_mentions shown in 3. This procedure leads to a reduction of about 250000 Tweets.

- **Second step:** Selecting related Tweets from remaining Tweets. Even after excluding Tweets with specific keywords, still many unrelated Tweets exist in the dataset. Therefore, the Tweets including at least one of the following keywords are selected:"automobile", "volkswagen", "vw", "legal", "tech", "lawsuit", "pollute", "stock", "nitrogen", "apologize", "crisis", "ceo", "cheat", "scandal", "emission", "diesel", "software", "investigate",

"test", "epa", "defeat", "device".

After this procedure, 604249 Tweets have remained in the dataset. This means, about one-third of the Tweets were excluded as unrelated. To evaluate this result, 5 users were chosen and for each, all of their tweets and their selected tweets were manually analyzed to find the accuracy level. These users have chosen based on their number of tweets. Their number of tweets vary from 50 to more than 300. This range is chosen so on one hand, it is possible to manually analyze them and on the other hand, it is high enough that the analysis is reliable. The resulting confusion matrixes are shown in tables 4 to 8:

User 1			
	Selected related	Selected not related	
Actual related	TN= 229	FP= 4	233
Actual not related	FN= 1	TP=50	51
	230	54	284
Accuracy: 0.982			
Misclassification Rate: 0.017			

Table 4: Confusion matrix and accuracy of data selection for the first Twitter user

User 2			
	Selected related	Selected not related	
Actual related	TN= 61	FP= 4	65
Actual not related	FN= 25	TP=223	248
	86	227	313
Accuracy: 0.907			
Misclassification Rate: 0.092			

Table 5: Confusion matrix and accuracy of data selection for the second Twitter user

User 3			
	Selected related	Selected not related	
Actual related	TN= 1	FP= 0	1
Actual not related	FN= 8	TP= 40	48
	9	40	49
Accuracy: 0.836			
Misclassification Rate: 0.163			

Table 6: Confusion matrix and accuracy of data selection for the third Twitter user

User 4			
	Selected related	Selected not related	
Actual related	TN= 73	FP= 0	73
Actual not related	FN= 0	TP= 0	0
	73	0	73
Accuracy: 1.0			
Misclassification Rate: 0.0			

Table 7: Confusion matrix and accuracy of data selection for the forth Twitter user

User 5			
	Selected related	Selected not related	
Actual related	TN= 32	FP= 5	37
Actual not related	FN= 5	TP= 38	43
	37	43	80
Accuracy: 0.875			
Misclassification Rate: 0.125			

Table 8: Confusion matrix and accuracy of data selection for the fifth Twitter user

The resulting average accuracy of sample group is 0.92. This result shows that the semi-manual process of subsetting the data was successful.

4.2 Sentiment Analysis

For sentiment analysis, three different sentiment analysis tools are used:

Microsoft Azure Sentiment Analysis API: Microsoft Azure Sentiment Analysis API uses a machine learning approach to detect the sentiment. The resulting sentiment is a score between 0 and 1 where 0 is the most negative score and 1 is the most positive score. Microsoft Azure API uses a pre-trained model for the sentiment analysis. This model is trained with a great amount of text associated with a sentiment score. The sentiment analysis is performed on the entire document and not word by word. This API works better when the document contains one or two sentences.[8]

R package "SentimentAnalysis": This library uses Lexicon-based Sentiment Analysis approach. It uses different existing dictionaries like Harvard IV or finance-specific dictionaries. It can also create customized dictionaries. The resulting sentiment score is a number between -1 and 1 where numbers below zero show negative sentiment and above zero, positive sentiment.

The following existing dictionaries for this package are used for sentiment analysis of our data:[9]

- **DictionaryGI:** This dictionary contains a list of words with positive and negative sentiment based on the psychological Harvard-IV dictionary. This dictionary is created by Harvard University for general use.

- **DictionaryHE:** The list of positive and negative words in this dictionary is based on Henry's finance-specific dictionary. This dictionary mostly contains polarized words related to business and finance.

- **DictionaryLM:** Beside positive and negative words, this dictionary includes uncertain words as well and it is based on the LoughranMcDonald finance-specific dictionary. This dictionary has been used vastly in Financial domain.

- **Dictionary QDAP:** QDAP stands for Quantitative Discourse Analysis Package. This dictionary is a lost of words used for QDAP package. QDAP package is a tool for analyzing

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[8]https://docs.microsoft.com/en-in/azure/cognitive-services/text-analytics/how-tos/text-analytics-how-to-sentiment-analysis

[9]https://docs.microsoft.com/en-in/azure/cognitive-services/text-analytics/how-tos/text-analytics-how-to-sentiment-analysis

and visualization of qualitative transcripts.[10]

R Package "Sentimentr": This library takes into account the valence shifters (like negations, adversative conjunctions, intensifiers or downtoners). A simple example of that is the difference in polarity in "Good", "Not Good" and "Very Good". Valence shifters matter because they can make a huge difference in the sentiment score. A negation like "Not" can reverse the polarity of the sentence. Therefore, where a simple dictionary-based sentiment analysis could calculate the score of a sentence like " I don't like this" as a positive score or at the best neutral or zero scores (If the word "like" counts as +1 and the word "don't" counts as -1, then the whole sentiment score of the sentiment would be +1 + (-1)=0), Sentimentr package will calculate the sentiment score as negative.
Based on the research made by the creator of Sentimentr package, the frequency of valence shifters used with polarized words could be as high as 20 percent which could potentially have a significant impact on the end result. [11]
The resulting sentiment score from this package is a number between -1 and +1 where -1 is the most negative sentiment and +1 is the most positive and 0 is neutral.

4.2.1 Results:

To be able to make a comparison between two sentiment analysis techniques score resulted from Microsoft Azure API is converted from [0,1] to [-1,1] with a simple formula of $S2 = (S1 \times 2) - 1$. Then Average score of each day is calculated and the results are compared. The resulting scores are shown in Figure 3.
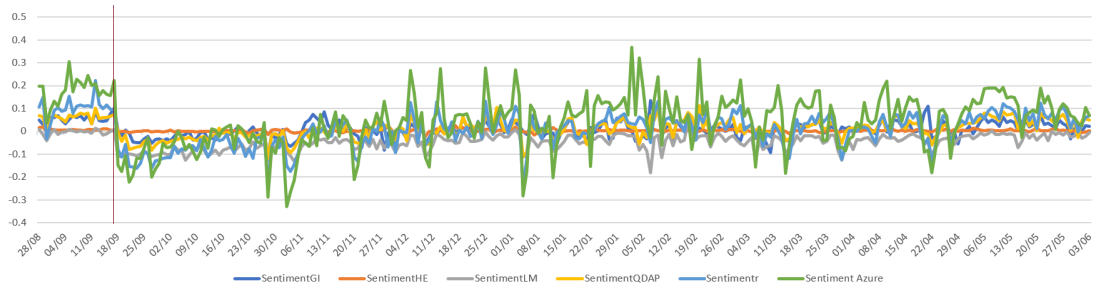

Figure 3: Comparison of average sentiment score of 5 different sentiment analysis methods during time

We can see a few things from this diagram:

- The Average sentiment per day is almost positive at the beginning till the 18th of September when the news about VW scandal breaks. Then suddenly average sentiment drops down to negative and stays negative for two to three months.

- Microsoft Azure API can detect more positive sentiment in a document than negative. Comparing the total average sentiment of Microsoft Azure and Sentiment QDAP proves this as well. The total average of Microsoft Azure sentiment is 0.046 while for QDAP sentiment it is 0.017.

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[10]https://cran.r-project.org/web/packages/qdap/index.html
[11]https://cran.r-project.org/web/packages/sentimentr/readme/README.html

- Looking at these two figures, it is clear that Microsoft Azure API has higher score polarity than the other sentiment analysis methods.

- Looking at the result of different dictionaries used with R package "SentimentAnalysis", SentimentHE doesn't capture the sentiment in the twitter text well. Between these 4 dictionaries, it seems that sentiment QDAP captures the sentiment in the text of the tweets better than the other ones.

To have a better visualization of why the sentiment is positive before the 18th of September and goes negative after, word cloud of tweets before and after 18.09.2015 is created. you can see these word clouds in Figure 4 and Figure 5. You can see that before 18.09.2015 there is nothing
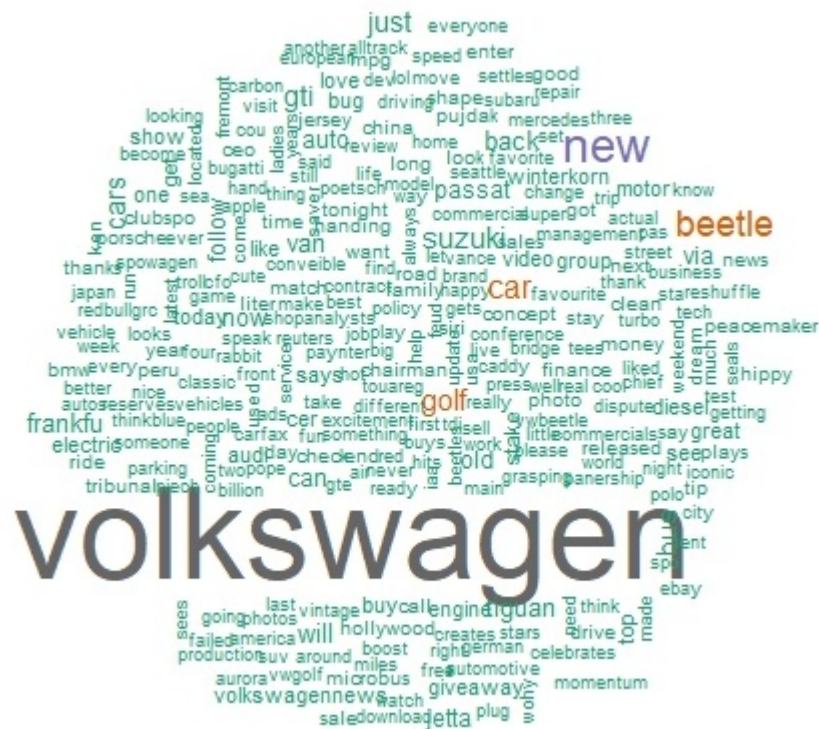

Figure 4: The word cloud before 18.09.2015 when the VW scandal news broke out.

about the scandal and after 18th main written words are emission and scandal. Between the words used in tweets after the 18th of September, negative words like cheating, defeat, criminal, trouble, and fraud are visible.

Furthermore, a geo-location analysis of the sentiments is made. For this analysis, location (state) of tweets and sentiment of each tweet was extracted from the data. The sentiment is based on Sentimentr tool. You can see the resulting geo-map diagram in Figure 6. In this Figure, the size of the circle gets bigger by the number of tweets. States with bigger circle have more tweets. The color of tweets is the average sentiment of all the tweets in that state. Blue is positive sentiment and red is the negative sentiment.

Figure 5: The word cloud after 18.09.2015 when the VW scandal news broke out.
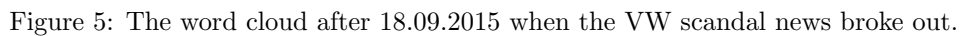
4.3 Correlation

The correlation coefficient is used to measure how strong is the relationship between the relative movements of two variables. Therefore, correlation is not between just 1 sample of each variable. Correlation is calculated between a set of one variable against a set of the other variable. It is important to know that correlation doesn't mean causation. If 2 variables have a correlation with each other it doesn't mean that one of them happening is the result of the other one happening. It only means that if one happens, there is a chance that the other one happens too. [12]
The result of the correlation is a number between -1 and +1:

- **Positive numbers:** Positive numbers between 0 and +1 indicates strong positive relationship between two variables. It means if a variable increases, the other one will increase as well. It will go as high as +1 which it indicates linear relationship.

- **(0):** Zero indicates no correlation.

- **Negative numbers:** Negative numbers between 0 and -1 indicates strong negative relationship between two variables. It means if a variable increases, the other one will decrease. It will go as low as -1 which it indicates linear relationship.

To understand the result of correlation, if the r value is between 0 and (-)29 it is a no to weak correlation. from (-)30 to (-)70 is moderate to strong correlation and more than that is a really

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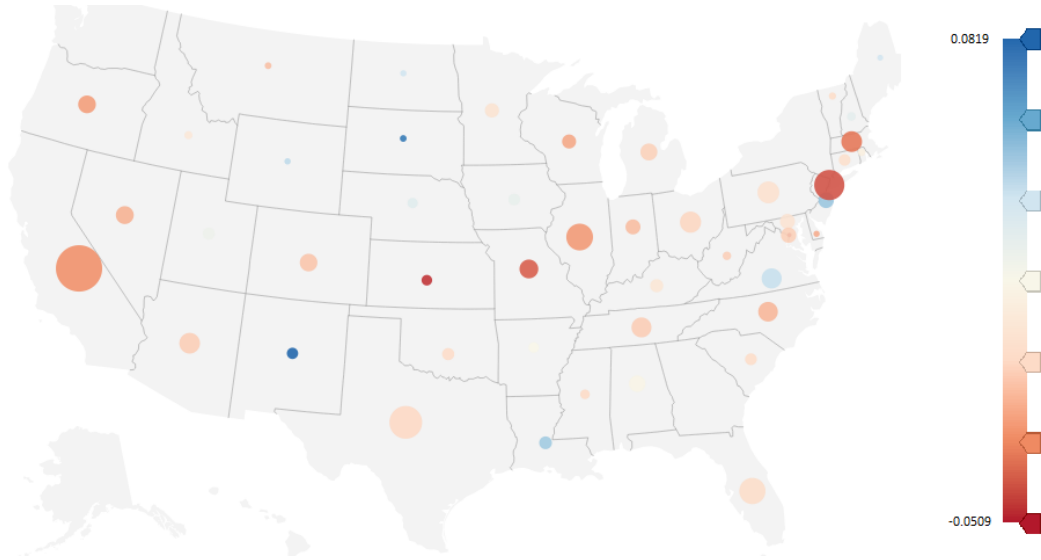[12]https://www.investopedia.com/terms/c/correlationcoefficient.asp

Figure 6: The geo-sentiment map of tweets

strong correlation.

To calculate the correlation coefficient, first, we need to understand which correlation algorithm is suitable to use. There are different correlation algorithms and based on the type of data, different ones should be used. Our variables are sentiments and stock price and volume. These variables are quantitative continuous data. Therefore, the best correlation for them is Pearson correlation.

Pearson Correlation: Pearson Product Moment Correlation (PPMC) or for short, Pearson Correlation measures the linear correlation between two sets or vectors of data.[13] This correlation tries to fit a straight line between the 2 variables somehow that the distance between the collection of variables to the line is minimum. The formula for Pearson correlation calculation is: [14]

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

In this formula, variables are:

- **r =** Pearson r correlation value

- **n =** The number of observations

- **x and y =** Two variables we are calculating their correlation.

It is important to know that the Pearson correlation can not differentiate between dependent and independent variable.

P-value: Even though the correlation might be strong, it needs P-value to find out how significant is the correlation. P-value indicates that how much is the probability of finding the same result for correlation when actually the correlation is 0. If the P-value is less than the significance level (α), we would say that correlation is significantly different from zero. α is usually

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[13]https://statistics.laerd.com/statistical-guides/pearson-correlation-coefficient-statistical-guide.php

[14]https://www.statisticshowto.datasciencecentral.com/probability-and-statistics/correlation-coefficient-formula/

5%. Therefore, if $P-value < 0.05$ the correlation coefficient is statistically significant. [15]

To calculate Pearson R correlation, first, the average sentiment of each day for each sentiment is calculated. Then, the correlation between 5 sentiment variables and stock market values is calculated. The resulting scores are shown in Figure 7.
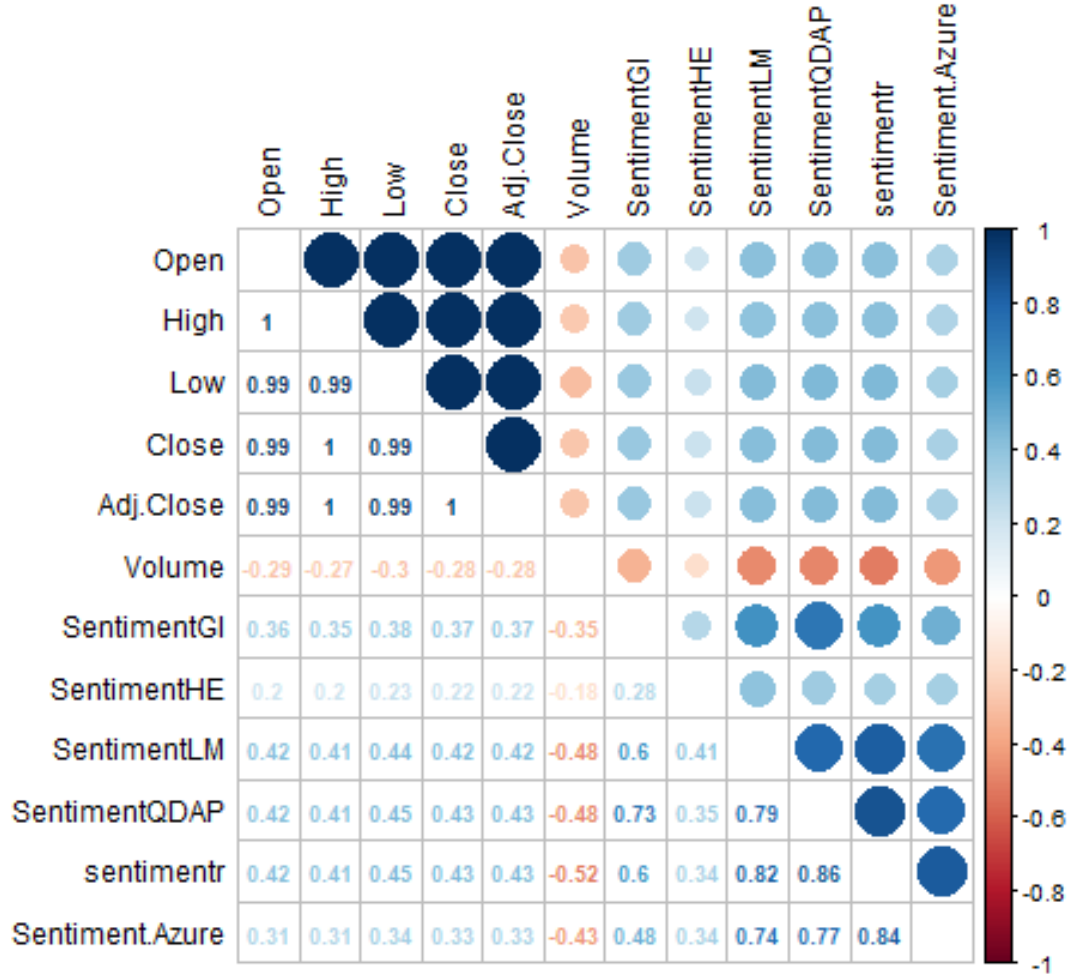

Figure 7: Pearson r correlation between 5 different sentiment scores and stock market data

In the Figure 7, The circle size shows the correlation strength. The colour Blue shows positive correlation and the colour red shows negative correlation. As the colour gets darker, correlation gets more strong. The P-value of this correlation is $[p-value < 2.2E-16]$. Therefore, we can say that the correlation results are significant. From this figure we can see that:

1. Sentimentr score has a higher correlation with stock market values (open, high, low, close, adj.close and volume).

2. sentiment scores have more correlation with stock volume rather than other stock market variables.

3. Sentiment score has a negative correlation with stock volume. This means when the sentiment goes down, the number of stocks being traded rises.

Figure 8 shows a comparison between sentiment (using Sentimentr scores) fluctuation and Trade volume, Opening price, and closing price. On the 18th of September, when the VW crisis went public, the volume of trades rises, and the sentiment, opening and closing prices decrease. It is visible that sentiment has more correlation with volume after the crisis.
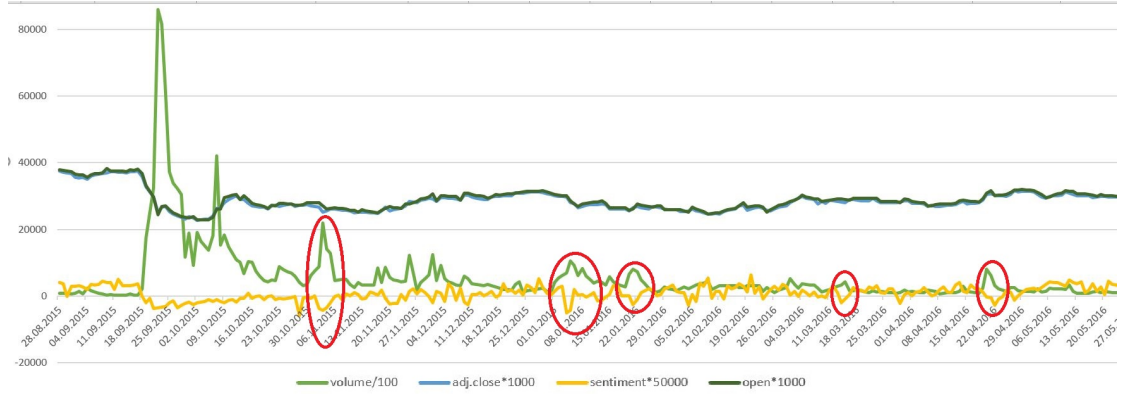

Figure 8: Fluctuations of Sentiments, Trade volume, Opening price, and closing price during time

One hypothesis is that it takes a day or more for the social media sentiment to influence stock market value. Therefore, sentiments of day D would have more correlation with stock values of day D+i (i=1,2,3,... days). If this hypothesis is correct, we can say that stock market values are the dependent variable and sentiment value is the independent variable. To test this hypothesis, the correlation between sentiments of day D and stock values days D+1 and D+2 are calculated. For this correlation calculation, Sentimentr results are used because from Figure 7 it is concluded that stock market values have a stronger correlation with Sentimentr scores. The result of the calculation is shown in Figure 9. The P-value is $[p-value < 2.2E-16]$. Therefore the resulting correlation is significant.

Figure 9 shows that the hypothesis that sentiment of day D has more correlation with stock value of D+i is incorrect. Therefore, stock value fluctuation is not dependant on sentiment fluctuation. The reverse hypothesis is that stock value of day D has better correlation with sentiment of day D+i (i=1,2,3). Figure 10 shows the result of this correlation. The P-value of resulting correlation is $[p-value < 2.2E-16]$.

From this figure, it is visible that stock market price (and not volume) has a higher correlation with the sentiment on day D+4 and after that, correlation drops. We can conclude that the stock market price has an influence on the sentiment of tweets and not the other way around.

To further analyze the correlation, correlation of sentimentr scores and stock market volume for each month is calculated. These two variables are chosen because they have the highest correlation. The resulting correlation is shown in the Table 9. P-value for each correlation is $[p-value < 2.6E-12]$

The results from Table 9 shows that the highest correlation between stock market trade volume and twitter sentiments are 1 month after crisis breakout. Second and third month after crisis has high negative correlation as well, but after the third month, the correlation drops down to an insignificant amount. Before the crisis breakout we see almost no correlation between tweet

Figure 9: Comparison of Pearson correlation between stock market values of day D and Sentiment score of days D,D-1 and D-2 and D-3

Date range	Pearson r correlation
Before 18.09.2015	-0.09
First month after	-0.84
Second month after	-0.56
Third month after	-0.52
Forth month after	-0.27
Fifth month after	-0.27
Sixth month after	-0.10
Seventh month after	-0.15
Eight month after	-0.18

Table 9: Pearson r correlation score between stock market volume and sentiment r score, before 18.09.2015 when scandal news broke out and 8 months after scandal month by month

sentiments and stock market trade volume.

In all of the procedure above, the retweets are treated as new tweets and they are not removed from the dataset. The reason for that is because we wanted to see the influece of retweets on the
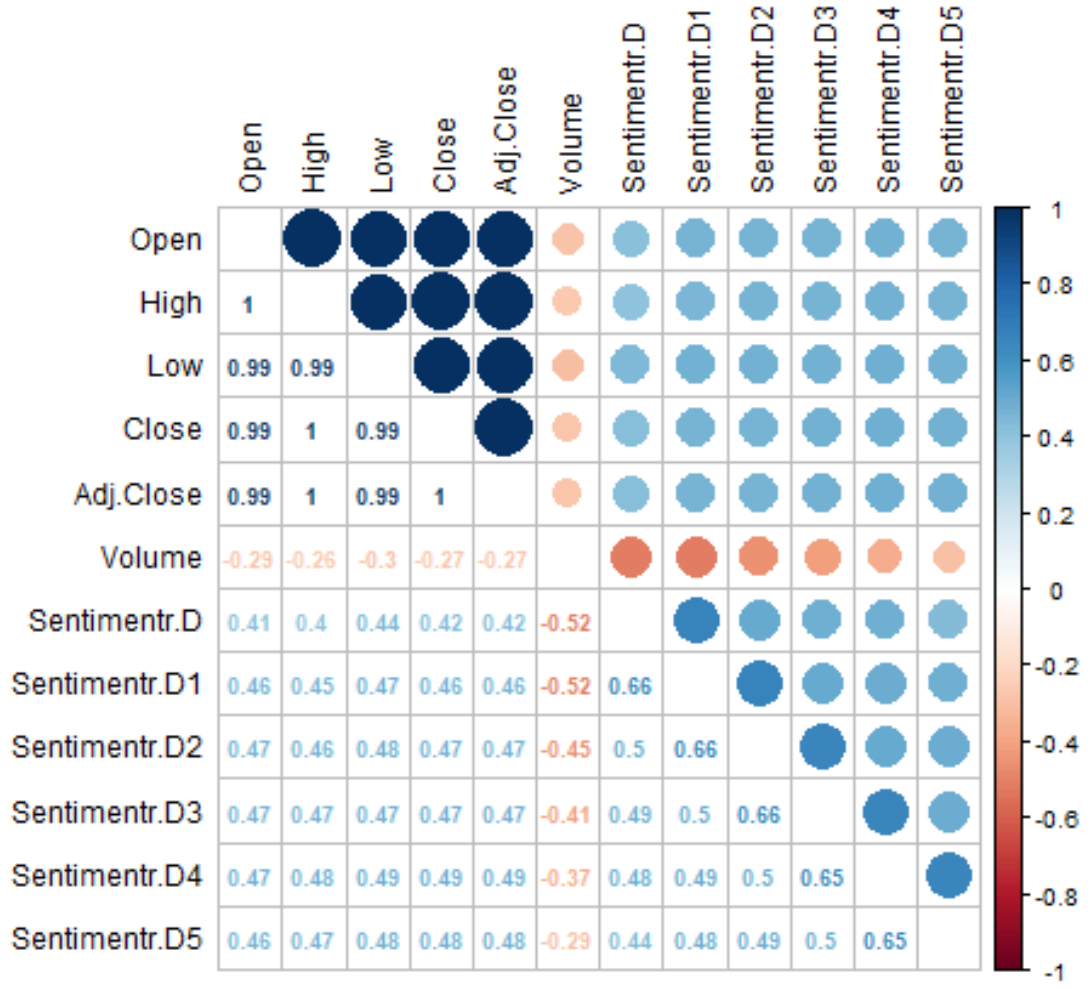
Figure 10: Comparison of Pearson correlation between stock market values of day D and Sentiment scores of days D, D+1, D+2, D+3, D+4, and D+5.

sentiment and ultimately, on the correlation. To make a comparison, the retweets are removed from the dataset and the correlation of sentiments calculated by Sentimentr and stock market data is calculated again for day D to D+5. In the Figure 11 the correlation of sentiment of data without retweets is compared with correlation of sentiment of data with retweets. P-value of resulting correlation is $[p - value < 2.2E - 16]$.

The Figure 11 shows that correlation of retweet-excluded data is about 0.02 higher between sentiment and stock market trade price. However, the correlation of sentiment and volume is about 0.01 less.
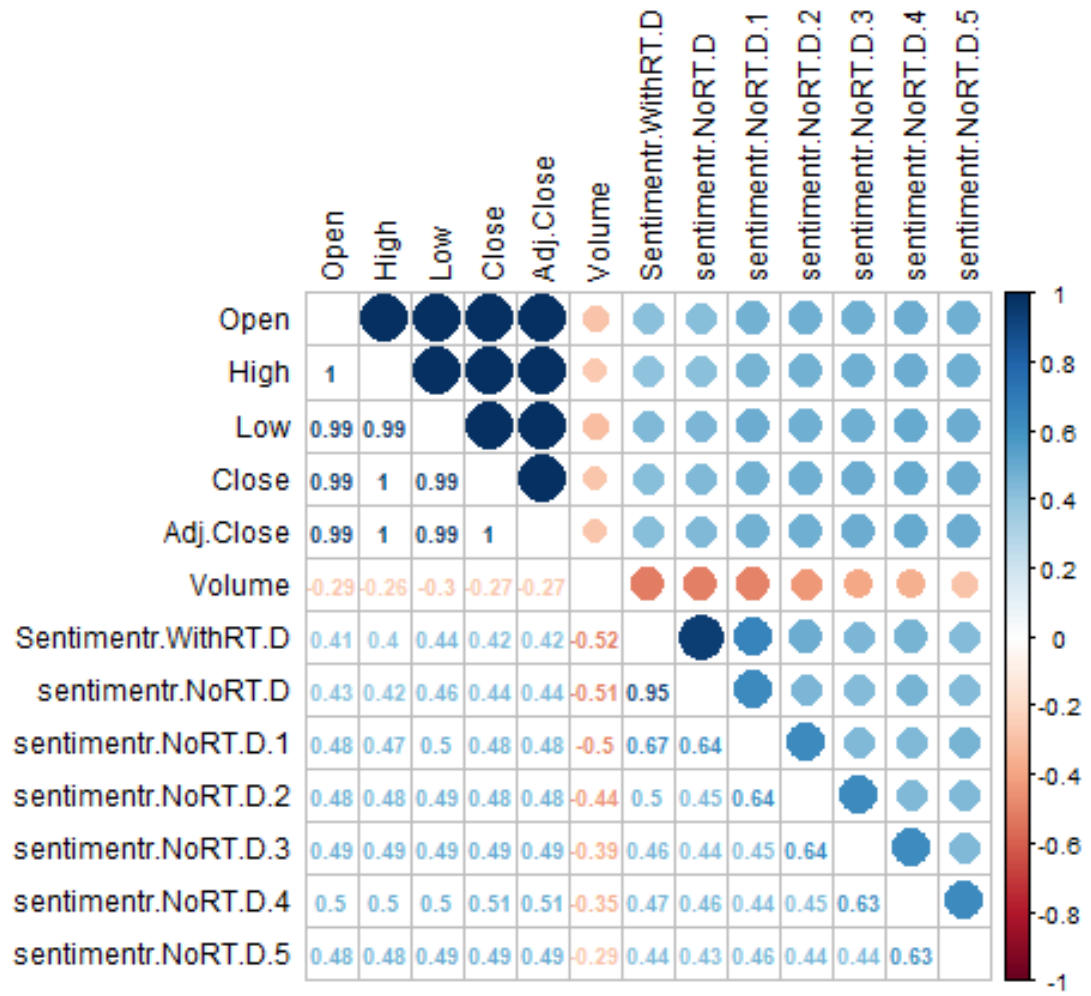
Figure 11: Comparison of Pearson correlation between stock market values of day D and Sentimentr scores of day D and Sentimentr scores of non-retweeted tweets of days D, D+1, D+2, D+3, D+4 and D+5.

5   Conclusion

In this thesis, we introduced financial performance of a corporation as an indicator of its corporate reputation. Then, we tried to find out if there is a correlation between financial performance hence corporate reputation of a company and opinion of the public on social media in a crisis situation. To do so, we used the Volkswagen 2015 scandal as a case study. we measured the sentiment of tweets collected during the timeframe of the scandal (Three weeks before until nine months after scandal breakout). Then, we measured the correlation of average sentiment to stock market price and volume of trade as an indicator of financial performance. Following are the results of this procedure:

- The sentiment scores resulting from Sentimentr tool has a stronger correlation with stock market data than other sentiment tools. This might be because Sentiment Azure captures a more positive sentiment in the twitter data than other sentiment tools and R package "SentimentAnalysis" uses a simple lexicon-based method while Sentimentr package takes into account valence shifters.

- The highest correlation is in the first 1-3 months after the crisis between the sentiment and volume of trade. The correlation is about -0.84 the first month and around -0.55 on the second and third months. The correlation is negative. This means that as the tweets get more negative, the volume of trade increases. Although this is only the correlation and not necessarily causation.

- The trade price has the highest correlation with the sentiment of day D+4. This can mean that actually, the stock market price has influence on tweet sentiment and if it goes up or down, after 4 days with a correlation of 0.49 the average tweet sentiments of that day will get more positive or negative. This will answer the research question RQ3. The financial performance (as an indicator of corporate reputation) has influence on the sentiment from social media and not the other way around.

- There is a small difference in the correlation between the data which includes retweets and the data that doesn't include retweets. The data which doesn't include retweets has a stronger (by 0.02) correlation between stock market trade price and sentiment of tweets.

For this thesis we had some limitations. Among these limitations are only working with a specific dataset. Since we wanted to calculate the correlation for a company in crisis, we had access to only one dataset. Moreover, the data was not labeled which limited us for the procedure of data selection and sentiment analysis.

In this study, we only focused on one business sector. However, some studies [CSTL16] show that some sectors get more attention of Twitter users than others and this can impact the correlation between the stock data and the Twitter sentiment. For the future work, we suggest making a comparison between different sectors. Additionally, we want to use labeled data to use more sophisticated machine learning approaches for data selection and sentiment analysis. Moreover, we suggest making a comparison between different social media platforms and a comparison between the influence of public comments on social media and online news.

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