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Literature review - Twitter as A Tool of Market Intelligence for Businesses

Sentiment analysis approach

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Abstract

Purpose
As an emerging technology, sentiment analysis of Twitter has aroused interest in the field of business research. The thesis has three primary objectives. The first objective is to identify how businesses could utilize sentiment analysis of Twitter in their market intelligence functions. The second is to determine how sentiment analysis of Twitter compares to more traditional methods of market intelligence. Thirdly, this thesis aspires to bring technology-oriented discipline easier to approach for business researchers.

Methodology
The research method of this thesis is a literature review. The thesis revises prior published and peer-reviewed articles with a focus on sentiment analysis of Twitter and its applications to market intelligence.

Findings
There are three significant findings in this thesis. 1. Companies have utilized sentiment analysis for various purposes of market intelligence with encouraging results. 2. Sentiment analysis of Twitter has a variety of similarities with traditional market intelligence methods. In the future, it will be an auspicious technique for market intelligence as its accuracy is improved, and companies utilize it more frequently for practical purposes. 3. Even though Twitter sentiment analysis has raised plenty of interest, there is no clear research field within the business, and more specifically, market intelligence related literature.

Future research
For future research, this thesis provides a review of the possibilities and uses of Twitter sentiment analysis in the context of market intelligence. Its focus is to support especially business research. Reviewed literature illustrates that there are a large number of research avenues to be addressed in the future. The first objective for future research is to implement a more precise research field of business research. The second objective is to conduct more comparative studies between Twitter sentiment analysis and qualitative business research methods. Another intriguing research topic is Twitter sentiment analysis in the context of Finnish companies.

Keywords Sentiment Analysis, Market Intelligence, Twitter, Competitive analysis, Customer analysis, Market Research

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1 Introduction

The use of social media has increased significantly over the last decade. Nowadays, it is a part of the everyday life of individuals as well as companies. Social media is defined precisely by Kaplan and Haenlein (2010) as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content.” Term "User Generated Content" from the previously referred definition of social media is one of the primary interests of this research. User-generated content is publicly available and non-professional content, which is created by end-users of social media (Kaplan and Haenlein, 2010). Analysis of user-generated content offers a vast amount of insights for businesses.

Businesses have adopted social media as a critical tool for various business functions, especially within marketing. (eMarketer, 2017) During the last years, it has revolutionized the interaction between corporates and the marketplace (Aral, Dellarocas, and Godes, 2013). Social networks and media penetrate nearly half of the world’s population, and the percentage is naturally more significant in developed countries (Statista, 2019). These numbers, combined with a common fact that social media users are exposed to its channels daily, make social media a necessary and valuable tool for business purposes.

The center of attention in this thesis, regarding social media, is one of the most used platforms, Twitter. Twitter is a popular microblog service in which its users post a maximum of 280 characters long “tweets.” (used to be 140 characters) Compared to other social media platforms, Twitter connects its users through currently exciting topics and the conversation, more than through friendship and close networks as platforms such as Facebook does. Twitter provides a platform for businesses to monitor their customers’ discussion regarding, for example, company activities.

There is a large number of conducted research in the business intelligence context of analysis of social media and especially Twitter. Twitter offers a significant source of data for mining. Within big data and business analytics research lies the exact subfield for business analytics, which is conducted by gathering and analyzing data from social media. A method is called social media analytics.

The purpose of social media analytics is to collect, analyze, and afterward interpret gathered data into insights for business decisions (Bekmamedova & Shanks, 2014).

Various business functions have utilized applications of social media analytics. For example, retail, marketing, supply chain management, stock market analysis, and politics have taken advantage of social media analytics in their practices. (He et al., 2015; Tumasjan et al., 2010; Chae 2015; Bollen et al., 2011)

In their social media analytics framework, Stieglitz and Dang-Xuan (2013) present a variety of methods for conducting a social media analysis. In the context of this thesis, the further examined method is sentiment analysis. In brief words, sentiment analysis is a text mining related study of people's opinions, moods, emotions, and attitudes towards various issues, such as products, events, topics (Liu & Zhang, 2012).

Researchers have applied Twitter sentiment analysis in numerous ways in the different contexts within the academic literature. For example, Bollen, Mao and Zeng (2011) have demonstrated that people's sentiments from Twitter have an impact on the performance of the U.S stock market and, Wang, Can, Kazemzadeh, Bar and Narayanan (2012) have interpreted public opinions and swings in them during the 2012 U.S presidential election campaign.

Social media channels, like Twitter, have revolutionized the ways how people communicate with each other over the internet. Due to that, companies have to adopt new ways to reach their target groups. The revolution of social media has also made it easier for businesses to monitor customers and their opinions. Thus companies can provide better products and services for them.

1.1 Research objectives and questions

Bose (2008) wrote a rough decade ago that competitive intelligence had attracted much interest lately because of the new communication channels such as e-mail, blogs, wikis, are available. These readily available and intuitive content creating channels may reveal unwanted information about the company for the public. Thus, competitors may gain an advantage at the expense of the company.

Bose's quote creates exquisite research objectives even after a decade. Mentioned channels are more developed than ever, and there are hundreds of millions of everyday users. These users create publicly available market intelligence for companies to use, but they should know better how to utilize it.

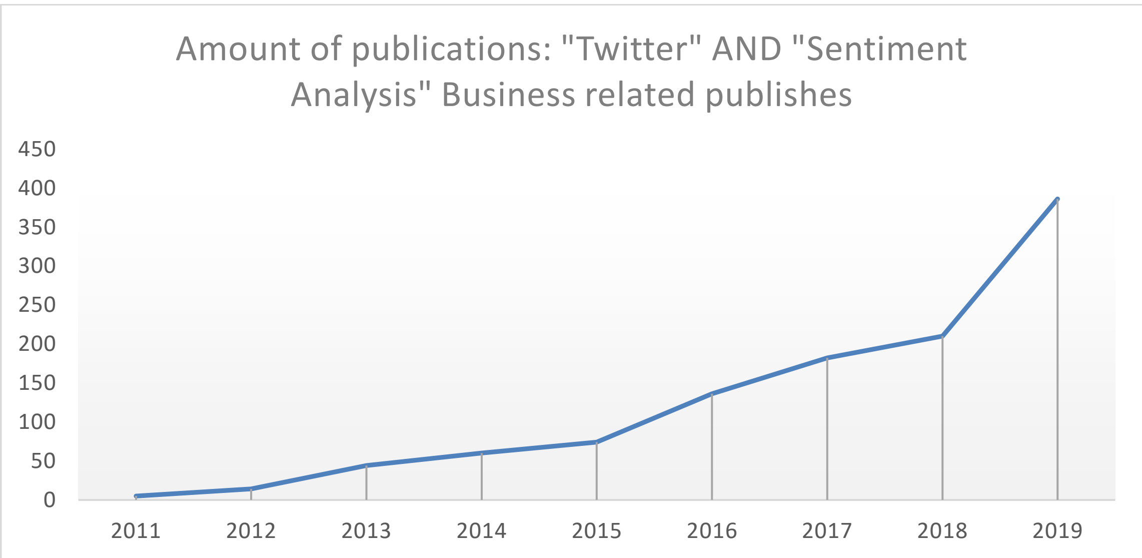
The purpose of the research in this bachelor's thesis is to identify how analysis of Twitter posts, retweets, reactions, and opinions would provide valuable intelligence for companies. Through literature analysis, the thesis' objective is to expose how current academic literature has approached the sentiment analysis of Twitter data as a value-creating aspect for market intelligence.

Another research objective is to identify how Sentiment Analysis of Twitter as a tool for market intelligence compares to traditional business research methods, e.g., Focus Groups, Surveys, Observations, Interviews. The thesis highlights strengths and weaknesses in both of these methods and analyzes whether the sentiment Analysis of Twitter could displace some of the traditional methods.

The primary objective for choosing this discipline is its growth as a research field, which indicates that there is not yet thorough research on this subject. Within computer science fields, the topic of sentiment analysis as a form of text mining and natural language processing has attracted particular interest for a more prolonged period. In contrast, in business-related research, there has been less attention.

The following table shows how the amount of literature within Twitter sentiment analysis in a business context has developed within the 2010s. Contents of the table are from the Scopus database with search words:

"twitter" AND "sentiment analysis" AND (LIMIT-TO (SUBJAREA , "BUSI"))



The model follows a clear exponential trend within the last nine years, which proposes that there is still a considerable amount of new to discover in the field for the future.

There are two exact research questions for the thesis:

RQ1: For what purposes businesses could use sentiment analysis of Twitter as a source of Market Intelligence?

RQ2: How a sentiment analysis of Twitter compares to businesses' traditional market intelligence methods? (e.g., Focus Groups, Interviews, Observation, or Surveys)

1.2 Scope of research

There are limitations in three specific areas of research. Firstly, limitations in choosing a method within a field of social media analytics, secondly, the data source for the reviewed articles and thirdly, business function into which to restrict this research.

Under the umbrella term, “Social Media Analytics” is a variety of analysis methods. This thesis is limited to sentiment analysis. Compared to other methods of social media analytics, sentiment analysis provides the broadest view of customers’ thoughts and opinions towards the company and its competitors. From the lens of market intelligence, these factors are crucial for the success of the business. In the table below is presented a few methods for social media analytics and their characteristics.

Sentiment Analysis	**Topic Modeling**
- Focus on detecting sentiments and opinions of user-generated content in social media (Fan & Gordon, 2014). - In the business context used to various comparisons between companies and improvements in business functions. Broader review in chapter 4.	- Focus on detecting currently dominant topics from social media (Fan & Gordon, 2014). - In the business context, used to identify popular topics and to discover user interests. (Fan & Gordon, 2014)
Social Network Analysis	**Trend Analysis**
- Focus on connections and links between users of social media. (Himelboim, 2017) - In the business context used, for example, to create segments within networks. Utilized in viral marketing campaigns also. (Bonchi, Castillo, Gionis, & Jaimes, 2011).	- Focus on forecasting trendlines from historical data (Fan & Gordon, 2014). - In a business context, a trend analysis is used, for example, to forecasting the effectiveness of advertising campaigns and as a support for sentiment analysis to detect shifts in customer sentiments (Fan & Gordon, 2014).

Other methods enhance the performance of business activities as well. However, through the reading of the academic literature, the most novel insights to market intelligence come from the lens of sentiment analysis. From the techniques mentioned above, the nature of sentiment analysis serves purposes of market intelligence best.

From social media platforms, this thesis concentrates on Twitter due to its real-time discussion abilities compared to, e.g., Facebook, and its feature that users do not have to be connected which each other to communicate (Lee, 2018). Unlike in Facebook, Instagram, or Snapchat, users do not have to be "friends" to be able to share content and have a discussion with each other. This ability also provides an opportunity for companies to participate in a conversation with a low threshold.

Monitoring of real-time discussion provides companies a chance to react intuitively to customers' feedback and opinions. Through observing, they can avoid damage in reputation and improve their customer service (Lee, 2018). Also, as shown in the previous chapter, interest within the business functions towards Twitter sentiment analysis is rising.

For business function, the thesis reviews Market Intelligence due to its suitability for various business areas. Articles that handle Twitter Sentiment analysis in a business context provide insights from various business industries and offer market intelligence for many business functions. If limited to a specific business function such as marketing or supply chain, the amount of reviewed literature would be too insignificant.

There are also some other limitations to the scope of this research. Due to concentration in social media in this thesis, articles which use customer reviews as a data source does not receive any attention. Also, cross-channel social media sentiment research is restricted out. Revision of stock market analysis and non-business related articles, e.g., elections, politics and government, climate, social sciences, are left out of radar in this study. The most critical limitation considers technical literature from the field of, e.g., computer science. Since this is business research, the technical background of sentiment analysis is not revised too deeply within this thesis. 3rd chapter, which handles the sentiment analysis of Twitter and its technical aspects, is the only chapter with a technical focus within this study. The last limitation considers customer success stories produced by consultancies, e.g., IBM Watson. Even if they supply useful business insights from a research field, they do not offer academically valid views due to their subjectivity.

1.3 Methodology

A research method in this thesis is a literature review of existing publications. Compiled literature consists mostly of academic journals or research papers. The most important source of articles cited in this thesis is Scopus – database for peer-reviewed academic literature. Another source for articles has been Google Scholar.

The thesis will follow a conceptual framework of competitive intelligence with sentiment analysis benchmarks. In the frame of this thesis, competitive intelligence is a part of market intelligence. Thus, the framework will be suitable in the context of this review.

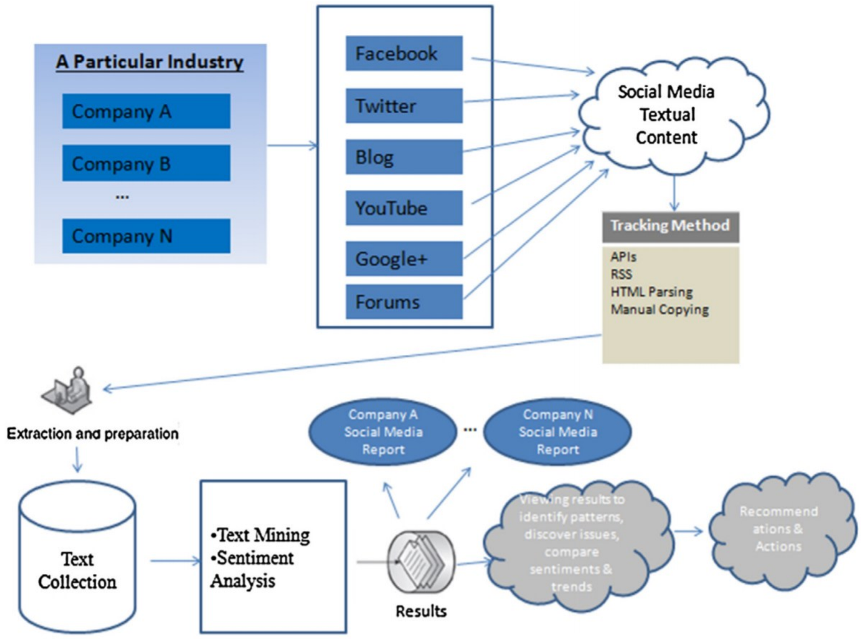
1.4 Conceptual framework and structure of the research

The thesis follows the conceptual framework presented by He, Wu, Yan, Akula, and Shen (2015) in their study.

The presented framework describes phases that are required to derive market intelligence from the chosen social media platform. As seen from the figure below, this framework needs somewhat limitations and adjustments to serve the purpose of this thesis.

In its current form, this framework provides intelligence from a particular industry to create competitive intelligence reports. To gather intelligence from customers, "a particular industry" changes to "a particular company" and "company A" to "customer A." With this modification, the presented framework serves both customer and competitor dimensions of market intelligence. In the context of this thesis, we restrict other social media sources except for Twitter.

Due to the business-centric approach of this thesis, tracking methods, data cleaning, and preparation are not under the radar.



He et al., (2015)

From the basis of the framework, the structure of the rest of the thesis proceeds as follows. The purpose of the 2nd and 3rd chapters of the thesis is to create understanding from the topics of Market Intelligence as a business function and sentiment analysis in the Twitter context.

These chapters create the bottom for the 4th chapter, which will review literature through the lens of Market Intelligence and Twitter Sentiment Analysis. 4th chapter consists of a systematic literature summary and a descriptive literature review that summarizes which kind of practical market intelligence implications would sentiment analysis of Twitter provide. The next subchapter compares Twitter sentiment analysis and social media analytics to traditional methods of market intelligence. The last subchapter discusses issues and concerns of Twitter sentiment analysis

5th chapter consists of a discussion of the whole thesis and its academic and practical implications. The last subchapter identifies possible future avenues for the research.

2 Market Intelligence in the context of this thesis

In the academic literature, term market intelligence is overlapping with the words "marketing intelligence" and "competitive intelligence." Definitions of these terms do not differ between each other that much that they would form two separate research entities. (Søilen, 2016). When discussing and reviewing the literature, market intelligence is an umbrella term, which includes both "competitive/competitor analysis" and "customer intelligence," which is one aspect of marketing intelligence.

The following sub-chapters summarize meanings of competitive and customer intelligence into the definition of Market Intelligence. This definition will be used in the rest of the thesis when discussing literature.

2.1 Competitive Intelligence

When talking about competitive intelligence Prescott (1995) defines it as a function that includes collecting and monitoring data from relevant sources in the company's environment. After gathering phase, companies convert data into intelligence for business decisions.

Broadly, Competitive Intelligence is a process in which companies collect internal and external insights and information. Principally from competitors, but, as an example, also from customers, potential business relations, and suppliers (Calof & Wright, 2008). Competitive Intelligence is allowing companies to forecast what is going to happen in their environment. When analyzing the intentions and moves of the competitors, companies can anticipate the development of the market proactively (Bose, 2008).

Competitive Intelligence Foundation, (2006) has conducted a study, which results indicated that companies are utilizing competitive intelligence when they are implementing new products or services, avoiding costs, saving time, or increasing profits or revenues. The same study also presented that competitive intelligence has a positive effect on nearly every organization activity, such as decisions in the market entry or M&A, business strategies, product, and sales development.

Traditional sources for competitive intelligence have been websites, analyst reports, and news (Xu, Liao, & Song, 2011). Nowadays, social media and the voice of customer works as an essential source for competitive intelligence. Traditional sources, for example, company websites, will provide only subjective views through the positive lens of the company. In contrast, customers will generate their realistic opinions into customer reviews and social media pages.

Xu et al., (2011) have described competitive intelligence also as a proper tool for company risk management. They claim that comparison through text mining of customer review data between competitive products would help to identify the strengths and weaknesses of the competing products. Through this information, companies' product development would react if customers are more into competitors' products and try to follow competitors' innovation and thus reduce the risk of market loss.

2.2 Customer Intelligence

Whereas competitive intelligence's focus is on competitors of businesses, customer intelligence concentrates on its existing and potential customers. There is a plethora of customer data available for companies to achieve an advantage. Kelly (2006) discusses the concept of consumer intelligence as a process in which companies gather available consumer data and try to transform it into profitable business insights. After rigorous analysis, this information converts into revenues and profits.

Typically, companies have gathered competitive and customer intelligence through more traditional ways, e.g., surveys and interviews than social media channels. Literature, which has been published lately, after the breakthrough of social media, is concentrating much on extracting intelligence through social media.

For example, Rishika, Kumar, Janakiramana, and Bezawada (2013) have studied how concentration on social media as a source of customer intelligence enhances profitability and the visiting frequency of customers. 4^{th} chapter will present studies within this field more precisely and reviews how companies have utilized customer intelligence from social media.

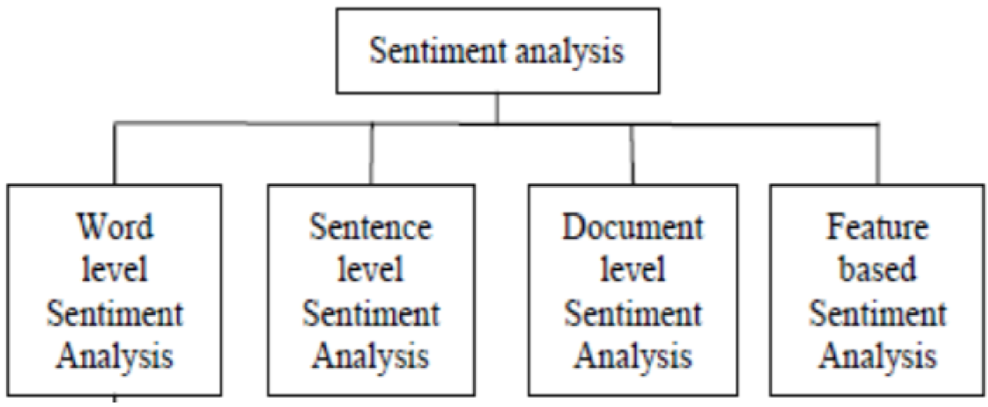
3 Sentiment analysis of Twitter data and its technical aspects

This chapter concentrates on technical aspects in sentiment analysis, as 4^{th} chapter discusses applications to enhance the performance of the companies by applying these methods. Research sources used in this chapter are from computer science or information systems related publications since technical aspects are not in that prominent role in business-focused research.

Textual information in the world divides into two separate types. Facts and opinions. Facts are based on objective expressions, whereas opinions are a subjective expression of emotions, feelings, and thoughts. Search engines can provide facts, but in the tracking of opinions, they are not successful (Bansal & Tripathi, 2016). Due to this, sentiment analysis offers a proper method, e.g., companies that require information on their customers' opinions towards a new product.

Sentiment analysis is an application of Natural Language Processing (Kharde & Sonawane, 2016). It is a process that automates the mining of attitudes, opinions, and emotions from sources such as texts, speeches, and tweets.

Sentiment analysis divides into different levels. In their survey of techniques Kharde and Sonawane, (2016), perform the division in a way shown in a figure below.



(Kharde & Sonawane, 2016)

The document-level analysis examines the overall sentiment of the document, for example, articles or speeches. Its objective is to analyze polarity from a broader perspective. (Kharde & Sonawane, 2016)

Sentence level analysis’s task is to identify the polarity of the sentence and its objectivity/subjectivity. Polarities of sentences are combined to provide a picture of overall sentiment. (Kharde & Sonawane, 2016)

Feature-based sentiment analysis labels each word with its sentiment. When analyzing opinions from products or services, this level of analysis is useful. Instead of analyzing the polarity of the text, it strives to associate sentiments into particular features of, for example, services or products. (Monkeylearn, 2019)

Word-level sentiment analysis provides sentiment for each word. The lexicon-based method utilizes this level of sentiment analysis. Word-level sentiment analysis frequently utilizes sentiment dictionaries with pre-setted polarities. (Kharde & Sonawane, 2016)

This thesis concentrates on English-language content. To examine other languages than English would make it too difficult to limit the research.

3.1 Principles of sentiment analysis in the Twitter context

In one of the most cited research papers regarding sentiment analysis in the Twitter context, Pak and Paroubek (2010) state why Twitter and microblogs universally offer an appropriate resource for sentiment analysis. Authors define that microblogging platforms like Twitter consist of the enormous number of posts that describe the opinions of its users about a variety of topics in various fields of interest. The audience of Twitter varies from average users to companies, celebrities, and politically affiliated persons around the world. A large number of users with a variety of backgrounds provide vibrant communication channels between different social and interest groups.

One of the greatest strengths of Twitter as a source for sentiment analysis is its magnitude of available data. With API tools provided by Twitter, it is straightforward to collect millions of tweets for training and test datasets. (Go, Bhayani & Huang, 2009).

As defined in the introduction, the objective of sentiment analysis is to mine opinions from various sources, such as texts, reviews, posts. However, unique characteristics of Tweets, eg., informality, and specialized language (hashtags, abbreviations, URLs, emoticons), makes sentiment analysis of Twitter a more challenging task than opinion mining from more formal texts. (Kouloumpis, Wilson, & Moore, 2011).

The use of hashtags (#happy), emoticons, and emojis (:-D) as a form of sentiment expression in Twitter have even its subfield of research, which tries to enhance the accuracy of sentiment analysis in the context of Twitter. (Davidov, Tsur, & Rappoport, 2010; Boia, Faltings, Musat, & Pu, 2013).

The essential objective of sentiment analysis is to annotate the emotions of people without manual labor. In the current academic research of Twitter Sentiment Analysis, there are two main tracks to perform sentiment analysis. The first one is the lexicon-based approach, and the second one is called the machine learning-based approach (Kharde & Sonawane, 2016).

In addition to these methods, there are a large number of commercial platforms available for sentiment analysis of Twitter and social media analytics as a whole. These platforms are utilizing lexicons and machine learning in their functioning. Examples of platforms are Attensity, Brandwatch, and Salesforce Marketing Cloud (Batrinca, & Treleaven, 2015). These platforms transform sentiment data into user-friendly reports, which eases business managers to utilize Twitter data.

3.2 Lexicon-Based approach

Lexicon-based approach to sentiment analysis is a method that utilizes sentiment dictionaries, which consist of words, terms, and phrases. These dictionaries have manually or automatically annotated polarities and polarity strengths for the words (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011). The conventional polarity classifying framework adjusts words into three classes, positive, neutral, and negative. (e.g., Zhang, Ghosh, Dekhil, Hsu, & Liu, 2011; Pak & Paroubek, 2010) In the lexicon-based method, the user provides a textual data, eg., Tweets, for the computer. In the next phase, the computer seeks equivalents from the pre-annotated and polarized dictionaries and thus provides sentiment polarity for inserted text. (Kharde & Sonawane, 2016)

On the internet, there are available various free sentiment dictionaries; for example, SentiWordNet, SentiWords, SenticNet, and VADER. One of the most popular and accurate sentiment lexicons for Twitter and social media sentiment analysis is VADER. It delivers 96% accuracy when analyzing tweets, which makes it more accurate than human annotators (Hutto & Gilbert, 2014).

Researchers can generate lexicons by themselves or with the help of the workforce. For example, Mohammad and Turney (2013) have used Amazon's Mechanical Turk services in their lexicon-creating. Amazon's Mechanical Turk is a crowdsourcing-based platform where entities, such as companies, entrepreneurs, researchers, can outsource their projects, which requires human intelligence. Typically, these outsourced projects are repetitive, time-consuming, and non-value creating. Creating a sizeable word-emotion lexicon provides an excellent example of the type of the project mentioned above.

3.3 Machine Learning approach

The machine learning approach in sentiment analysis is a classification task. Its purpose is to detect the polarity of a sentiment. Techniques applied in Twitter Sentiment Analysis are unsupervised and supervised learning. Applicable approaches to sentiment analysis mostly belong to the applications of supervised learning. (Kharde & Sonawane, 2016). In these techniques, as in all machine learning applications, training -and test datasets are required to produce an analysis.

In the cornerstone study of machine learning as a tool for sentiment analysis, Pang, Lee, and Vaithyanathan (2002) prove the effectiveness of the machine learning approach. They represent three statistical classification methods for the machine learning approach of sentiment analysis: naïve Bayes, Support Vector Machines, and Maximum Entropy. These methods are left without further examination in the context of this bachelor's thesis due to their technicality.

In the academic and practical purposes of the machine learning approach of sentiment analysis, these are the primary methods in use. Pang et al., (2002) have achieved over 80% accuracy for each of these methods.

To utilize the machine learning approach of Twitter sentiment analysis, the user has to generate a training data set, which consists of positive and negative Tweets. With training data, the user trains a classifier and provides test data for it. If the training of the classifier is appropriate, it provides accurate sentiment polarity for test data. As mentioned before, technical and statistical aspects of machine learning classifiers and sentiment analysis techniques are not investigated any further in the scope of this thesis.

4 Twitter Sentiment analysis as a tool of market intelligence

In the large picture, data-driven decision making will increase the productivity and market value of companies, and with specific measures, it may even increase the profitability of companies (Brynjolfsson, Hitt, & Kim, 2011). Applications of data-driven decision making are reaching out to the field of market intelligence also.

To achieve an advantage in today's competitive business environment, companies have to utilize market intelligence to understand how customers are discussing competitors and their products and services. (He, Wu, Yan, Akula, & Shen, 2015). Monitoring of social media assists companies in identifying whether their customers buy or not their services or products. Most importantly, it helps them to locate the reason which causes a certain customer behavior (Brooks, Heffner, & Henderson, 2014).

Through user-generated content, companies gain an extensive amount of opinions, sentiments, and attitudes of existing and potential customers. Harvesting insights from social media using customers would help companies to conduct better managerial decisions in various business industries and functions.

4.1 Summary of literature

This summary will represent peer-reviewed literature with an empirical focus on sentiment analysis of Twitter in the context of market intelligence. The table is divided by the utilized technique of sentiment analysis and whether they provide insights for the customer or competitive intelligence. The following sub-chapters discuss reviewed articles based on whether they contribute to competitive or customer intelligence. 5th chapter collates the contents and findings from the literature summary.

Author(s)	Article	Empirical business topic and industry	Method of sentiment analysis	Competitive or customer
He, W., Wu, H., Yan, G., Akula, V., & Shen, J. (2015)	A novel social media competitive analytics framework with sentiment benchmarks	Overall business performance, retail	VOZIQ tool, machine learning based	Competitive
Dey, L., Haque, S. M., Khurdiya, A., & Shroff, G. (2011)	Acquiring competitive intelligence from social media	Sales and brand performance, Various industries	Both methods used. (Article includes other social media analytics tools also.)	Competitive
Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009)	Twitter power: Tweets as electronic word of mouth	Branding, various industries	Summize, lexicon-based tool. Not available anymore.	Competitive
Kim, Y., Dwivedi, R., Zhang, J., & Jeong, S. R. (2016)	Competitive intelligence in social media Twitter: iPhone 6 vs. Galaxy S5	Sales and brand comparison, technology	Both methods used.	Competitive
Tse, Y. K., Zhang, M., Doherty, B., Chappell, P., & Garnett, P. (2016)	Insight from the horsemeat scandal: Exploring the consumers' opinion of tweets toward Tesco	Crisis management in business context, retail	Lexicon-based approach	Customer and competitive
Liu, X., Burns, A. C., & Hou, Y. (2017)	An investigation of brand-related user-generated content on Twitter	Branding, various industries	Machine learning approach	Competitive
Li, Y. M., & Li, T. Y. (2013)	Deriving market intelligence from microblogs	Brand comparison, technology	Machine learning approach	Competitive and customer
Pantano, E., Giglio, S., & Dennis, C. (2018)	Making sense of consumers' tweets: Sentiment outcomes for fast fashion retailers through Big Data analytics	Marketing and branding, fast-fashion industry	Machine learning approach	Customer and competitive
Chae, B. K. (2015)	Insights from hashtag# supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research	Supply chain management, not specific industry	Lexicon based approach	Customer
Ibrahim, N. F., & Wang, X. (2019)	A text analytics approach for online retailing service improvement: Evidence from Twitter	Customer service improvement, online retail	Lexicon-based approach	Customer
Singh, A., Shukla, N., & Mishra, N. (2018)	Social media data analytics to improve supply chain management in food industries	Supply chain management, food industry	Machine learning approach	Customer
He, W., Zhang, W., Tian, X., Tao, R., & Akula, V. (2019)	Identifying customer knowledge on social media through data analytics	Brand comparison, Technology	Lexalytics tool, (Lexicon-based)	Customer and competitive

4.2 A descriptive review of the literature

Competitive intelligence

In current literature, retrieval of competitive intelligence from Twitter has been applied to company strategies, brands, and products of competitors. In their research, Dey, Haque, Khurdiya, and Shroff (2011) have represented pilot studies of collecting competitive intelligence for a few different organizations. Findings of their study are not produced exclusively for Twitter sentiment analysis but offer methods for deriving knowledge from various social media platforms, as well as Twitter. They demonstrate that intelligence gathered from the internet correlates with the sales data of companies. It indicates that competitive intelligence from markets is applicable for providing insights into how the competition would affect businesses.

He et al., (2015), authors of the framework for this thesis, presents a comparison between the five largest retail chains in the US. They analyze Twitter messages which are associated with those companies and create visual business reports from that information. Generated reports consist of social media mentions, sentiments, and a share of social media visibility between competitors. One of the visual reports, a topic map, offers valuable views of the company itself as well as from competitors. It monitors Twitter mentions regarding a particular topic (for example, stores, customers, and shipping) and provides information about a discussion in social media and its sentiment. Through sentiments provided in the report, it is easy to measure strengths and areas in need of development for the company. The same analysis can be done for competitors' social media and analyze in which areas they perform better or worse.

In their branding-related article, Jansen, Zhang, Sobel, and Chowdury (2009) claim that Twitter and other microblogs offer a valuable channel for collecting competitive intelligence. In their research, they have selected 50 brands and analyzed their presence on Twitter through sentiment analysis. They compared Twitter sentiments of major brands and their competitors and discovered that 7 of 13 brand pairs had a statistically significant difference in their customer sentiments. This result indicates that sentiment analysis of Twitter provides information for the brand about its differentiation towards competing brands and its position in the market.

In another branding-related article, Kim, Dwivedi, Zhang, and Jeong (2016) conducted research that compared two leading smartphone manufacturers (Apple and Samsung) and their flagship models through social media. One of their research questions, "*Is there a significant gap in consumer sentiments about the two rivals?*" provides support for research in this area. Their findings propose that the sentiment of tweets has been positive during the monitoring period. Only one negative movement of sentiments occurred during the research period. When Apple's new flagship model was reported to be bending in the pockets of users, it generated a large number of negatively polarized tweets. Their study does not provide insights on whether Samsung reacted to this negative publicity. Any existing literature in the field of competitive intelligence from Twitter does not provide any insights on how "scandals" would offer benefit to the competitor as a form of market intelligence. Even though Tse, Zhang, Doherty, Chappell, and Garnett (2016) have evaluated how Twitter reacted during the Tesco's horsemeat scandal, any competitive intelligence related insights were not available in their article.

Even though tweets have positive sentiments in the article that compares smartphone brands, the positivity of tweets is not a general assumption. Liu, Burns, and Hou (2017) have also conducted brand-related research and came to a contradictory result where sentiments of Tweets were mostly negative regardless of industry.

Customer intelligence

User-generated content in Twitter offers information for decision-makers about what customers do like or hate in their products and services (Li & Li, 2013). In their study, they propose a framework system that would provide market intelligence to crucial decisions for businesses. The purpose of the system is to provide real-time market intelligence from Twitter through Support Vector Machines classification. Through this system, decision-making managers could learn what topics are attractive to customers and their sentiments about topics, products, or services.

This system or similar applications regarding sentiment analysis of Twitter generates customer intelligence, which enhances companies' knowledge of customers and their concerns, wishes, and opinions.

Due to the nature of the fast-fashion industry, Twitter sentiment analysis proposes a variety of potential applications for collecting customer intelligence. Pantano, Giglio, and Dennis (2018) describe in their research how fast-fashion industry could utilize Twitter sentiment analysis. As an industry that requires rapid decisions since customers' demands are changing with the current fashion trends, the monitoring of Twitter sentiments offers crucial insights for real-time decisions. (Choi, Hui, Liu, Ng, and Yu, 2014).

Chae (2015) has researched the applications of Twitter data in the field of supply chain management practice and research. In his research, he discovers that a considerable amount of supply chain-related tweets have a neutral sentiment. Another finding states that polarized tweets are more frequently harmful than positive. Negative tweets were mostly due to disappointments regarding the delivery services of the company. Failures in delivery are unavoidable, but information about negative sentiment carrying tweets is valuable customer intelligence for companies. Appropriately monitored Tweet sentiments would help customer service to react more rapidly to negative tweets and, if necessary, a customer service representative could try to retrieve the situation, which caused negative opinions. Ibrahim and Wang (2019) also support the aforementioned in their article regarding improving customer service within the field of retail services.

In another supply chain-related article Singh, Shukla, and Mishra (2018) examine how to improve consumer satisfaction and prevent food loss by enhancing supply chains in food, especially, livestock industry. They gathered over one million tweets regarding topics within the industry and classified them into positive and negative sentiments. Tweet sentiments revealed concerns, and these were linked to supply chain practices. Based on these concerns, authors were able to offer suggestions for improvement to create more customer-centric supply chains and, thus, achieve better customer satisfaction.

He. W et al., (2019) provide insights for customer knowledge management from the laptop market in the US. Their paper also contributes to the competitive analysis side of market intelligence. The study underlines the meaning of social media as a more efficient and low-cost option as a source of market intelligence compared to, e.g., surveys and traditional interviews. Their study also offers a useful framework and advice for businesses to apply sentiment analysis of Twitter in practice.

Decisions based on customer feedback, which is given by the request of the company, have tendencies to be ineffective. Twitter and other social media platforms offer an enormous amount of consumer opinions, which reflects the actual views of customers. (Liang & Dai, 2013).

4.3 Comparison between traditional market intelligence techniques and Twitter Sentiment Analysis

Traditional methods of market intelligence consist mostly of different qualitative methods. Twitter sentiment analysis and social media analytics, has apparent similarities, strengths, and weaknesses compared to these methods. Whereas traditional market research may be expensive and require employee resources, sentiment analysis of Twitter requires only a few technically capable employees.

Cooper and Schindler (2013) represent the most utilized business research methods in their study. These methods include individual interviews, observations, surveys, and focus groups. The next table will present the characteristics of the techniques mentioned above.

Interviews (Individual)	Observations
One of the primary sources of qualitative research. Interviews could be conducted with a structured set of questions or more intuitively without a vertical structure. The objective is to detect attitudes, opinions, and behaviors of the individual and add in-depth details to quantitative findings. Another purpose for interviews is to test the quality of surveys. (Cooper & Schindler, 2013)	The primary purpose of observation as a research method is to monitor behavioral and nonbehavioral activities and conditions. This method strives to examine participants without them behaving as if they were in a research situation. Doing this provides more unbiased results than a controlled research situation. The method is quite expensive because it requires a large number of human observers or surveillance. (Cooper & Schindler, 2013)
Surveys	**Focus Groups**
This method compares to a highly structured interview with carefully chosen and precisely asked questions. Surveys are mostly conducted through mail, telephone, or internet since they do not require face to face presence to be effective. Distribution of surveys is rather easy, which makes it easier to receive a high amount of observations with lower effort than in other methods. Surveys are sensitive to biases since questions can be invalid, or participants could respond with no real motivation or knowledge of the topic. (Cooper & Schindler, 2013)	One of the most known forms of group interviews. Consist of a panel of approximately 6-10 people, which is led by a moderator. Group discusses the given topic and exchange ideas, feelings, and experiences regarding the topic. Focus groups are considered valuable, for example, when creating new ideas for products or services, interpreting results of quantitative research, or generating impressions of a company's brand or products. (Cooper & Schindler, 2013)

Sentiment Analysis is a tool that combines quantitative and qualitative research methods. The next subchapters consist of a comparison between Sentiment Analysis of Twitter and qualitative research techniques.

Interviews:

In interview-based research methods, the most significant weakness is that answers reflect the opinions and behavior of interviewees, not the entire population (Cooper & Schindler, 2013). Sentiment analysis of Twitter does not face this problem as it offers thousands of potential observations to analyze.

Compared to the Twitter sentiment analysis, the traditional interview method provides more in-depth insights from participants. Sentiment analysis itself answers only to "how the population of customers reacted to a specific issue." However, as data for sentiment analysis consist of raw Tweets, researchers could examine in-depth insights of sentiments by mining Tweets manually after the analysis.

In interviews, the researcher can create suitable questions for the research, whereas, on Twitter, one can analyze only topics that are discussed by users. However, through the use of social media, businesses can try to steer the discussion towards the topic they are interested in.

Observations:

Traditional methods of observation are comparable to social media monitoring, which objective is to observe consumers on social media platforms. Sentiment Analysis is one of the core techniques in social media monitoring. (Fan & Gordon, 2014)

Researchers use traditional observation techniques, for example, to generate insights on how different conditions, for example, time of the day, weather, or traffic, affect the sales of a product. (Cooper & Schindler, 2013) With a sentiment analysis of Twitter, it is possible to conduct similar research. For example, there are numerous highly recognized studies of how different events and conditions affect the political sentiment of Tweets during the elections (Bermingham, 2011; Tumasjan, 2010). For market intelligence purposes, there are also similar studies; for example, how Tesco's tweet sentiments reacted to scandal when the public discovered that there was horsemeat in their products (Tse et al., 2016). However, these publications are not as cited as in the field of political science.

Surveys:

Between surveys and Twitter sentiment analysis is numerous similarities. Buntain, McGrath, Golbeck, and LaFree (2016) compared social media analytics methods to surveys. Surveys offer more subjective experiences of customers about entities and concepts, whereas social media analysis reflects the actual behavior of the user better than surveys. In their study, they mention that Sentiment Analysis as a tool for social media analytics would improve collecting subjective experiences from social media data.

From the perspective of costs, social media analysis is cheaper than traditional survey methods. When conducting a survey, financial incentives are typically required for participants or surveyors to collect enough high-quality data. Social media data is mostly quite cheap. A trade-off between these two methods is that surveys would offer probably more quality responses, whereas social media provides a large number of observations with possible lower quality. (Buntain et al., 2016)

The relevance of social media analysis can suffer if one is analyzing unrelated posts regarding the research question. Surveys do not face this problem if they are appropriately designed and conducted. (Buntain et al., 2016). They claim that social media analysis fits better for rapid and direct insights, whereas surveys are better when the quality of insights is required to be exact, and the researcher has time and money in use.

Focus Groups:

Lin, Margolin, Keegan, and Lazer (2013) have compared Twitter opinion mining to focus groups. The empirical part of their study consists of monitoring discussion during political elections. They described a focus group as a cluster of Twitter users discussing a certain hashtagged topic. For example, users who discussed topic #Obama and sent over 3 Tweets regarding the topic are concerned as a member of the focus group.

Researchers may utilize the same kind of experiments as an alternative method for focus groups in the context of market intelligence. For example, a brand-related Twitter discussion provides an effective platform. Companies can segment discussions into a variety of topics and monitor participating Twitter users as a focus group. Afterward, companies can derive market intelligence from the conversation of this group by monitoring it with, for example, sentiment analysis.

4.4 Concerns and questions in Twitter sentiment analysis as a tool for market intelligence

Conducting a literature review in this discipline reveals that the research area still requires a substantial amount of work to be entirely consistent and significant. This section presents the questions and concerns that emerged from reviewed and other literature from this field of research.

One common factor in social media is that tweets posted with sarcastic style are unavoidable. Sarcasm may change the sentiment of Tweets quite drastically, which poses challenges for available sentiment analysis tools to produce accurate results. (Maynard & Greenwood, 2014) The authors mentioned above have researched how to detect sarcasm from Tweets to create better accuracy for sentiment analysis. Mukherjee and Bala (2017) analyzed customer Tweets to enhance sarcasm detection. They concluded that detecting sarcasm from Tweets would be crucial in a business perspective since customer relationship management is increasingly going online.

The sarcasm of tweets is causing problems with the reliability of market intelligence. With a million tweets to analyze, it is impossible to annotate tweets manually. In order to obtain market intelligence from Twitter through sentiment analysis reliably, improvements in the detection of sarcasm, irony, and other imperfections are essential.

The number of analyzed tweets would cause unreliability to market intelligence. For example, Singh et al., (2018) analyze over 1,3 million tweets in their food supply chain-related study. That massive number of tweets would be impossible to collect for small companies that would like to utilize Twitter sentiments towards their business. To achieve value from the Twitter analysis, the amount of analyzed data should not be too insignificant. With a small dataset, the analysis does not reach a significant enough amount of observations. For example, Jussila, Vuori, Okkonen & Helander (2017) report in the results of their study, that one reason why they failed to reject the hypothesis could have been a too small number of available Tweets. For smaller businesses, this causes difficulties since the amount of Twitter messages concerning them may be too insignificant for proper analysis.

Stieglitz, Mirbabaie, Ross & Neuberger (2018) have conducted a literature review of the challenges within the analysis of social media. They have identified the most common concerns in different phases of analysis. According to the authors, the toughest challenges are within the data collection and its preparation. No high-profile publications have researched this area thoroughly.

Another challenge within this field is its interdisciplinary nature. Regarding social media analysis, there is research in the various fields, from computer sciences to social and political sciences. Authors are concerned about the division between technical and non-technical researchers. They conclude that the area is in lack of research, which would make technical details more understandable for business people and vice versa. (Stieglitz et al., 2018)

From a financial perspective, Zeng, Chen, Lusch, and Li (2010) raise concerns about the measurability of applications in social media intelligence. According to the authors, performance measures of social media analysis must be defined more clearly, in order to demonstrate its usefulness as a decision support tool. Concerns about measurability also make it challenging to determine the return on investment. The aforementioned makes businesses' resource and financial planning complicated regarding social media intelligence.

The past research has examined the earlier mentioned concerns, but existing literature and practice offered no entirely valid solutions for these issues.

5 Discussion, implications, and avenues for future research

In the following chapter literature review's topics will be discussed from the scope of two research questions.

Findings from the literature summary:

The main finding from the literature summary is the lack of existing literature in the field of Twitter sentiment analysis applied to market intelligence. There is no consistent research field on this topic, which makes the research area slightly fragmented.

As noticed, the highest amount of publications is considering branding-related intelligence. Even though it is the largest area, only five precise publications are available. When expanding the research into social media analytics and taking account of other data sources than Twitter too, the amount of publications is much more significant.

The distribution between the use of two different methods of sentiment analysis is pretty equal. Also, a few of the reviewed articles utilize various commercial tools and platforms to provide insights from Twitter sentiments.

As a conclusion to these findings, the amount of publications within this specific research area is still too insignificant. Articles provide encouraging results from utilizing these tools into practice. However, without a specific research field, theories and frameworks are still imperfect.

Findings and discussion from the reviewed literature:

The literature summary provided a finding that prior publications have utilized Twitter as a source for market intelligence in research, but not as much as it would be recommendable. As the literature review demonstrates, companies would gain practical and low-cost knowledge of the market through the represented methods. Results in the 4th chapter indicate that with the applications of Twitter sentiment analysis and social media analytics as a whole, it is possible to compile similar information as it is collected through market research more traditionally.

Live monitoring of social media sentiments offers a tool for businesses that have not been available before the age of social media. Sentiment analysis of social media as a decision-making tool during the release of, e.g., product, service, or movie, would provide support for managers to react if there is something unpredicted or unwanted in the sentiment of the public during release. Many of the publications discussed the possibility of live sentiment analysis, but no highly recognized research is yet available from it.

The applications of social media analytics have the potential to revolutionize the whole market intelligence/market research industry. However, social media as a primary source of market intelligence is not yet entirely ready for displacing traditional methods such as surveys and interviews. Sentiment analysis tools are still prone to errors. Also, like Stieglitz et al., (2018) concluded; there are not enough capable researchers/employees for the needs of businesses which can connect the technical and the business side of Twitter sentiment analysis.

Findings from a comparison of Twitter sentiment analysis and traditional business research methods:

As the main finding, a comparison between these two methods indicates that Twitter sentiment analysis has the potential to achieve very similar results to traditional qualitative research methods. Where both have their weaknesses, these methods can support each other in various ways. The most important trade-off is between quality and quantity. Sentiment analysis provides a high amount of observations, but the quality of these are inferior to traditional methods.

Twitter sentiment analysis alone has still concerns in its trustworthiness compared to well-known qualitative methods of market intelligence. It is too early to use it alone as a method of market intelligence research. When combined with traditional methods, Twitter sentiment analysis can provide much-needed observations to support qualitative research. Twitter sentiment analysis also offers a method to plan qualitative research better. By understanding the primitive sentiment within the wanted segment, it is easier to target the research objective correctly.

One of the most intriguing abilities of social media analytics is its similarity between the focus group research method. Discussions in Twitter allows companies to monitor conversation of people from various backgrounds like in focus groups. Companies can steer the conversation towards the topic they are interested in by posting into social media.

To conclude, Twitter sentiment analysis provides a tool that combines parts of qualitative and quantitative market intelligence research. Data that consists of sentiments, opinions, and emotions have been traditionally available only through qualitative research. Through Twitter sentiment analysis, it is available easier and cheaper than ever. However, to displace traditional methods, development in the fields of machine learning and artificial intelligence are required to achieve higher accuracy for tools of sentiment analysis. Before this, Twitter sentiment analysis is best when used as a supportive tool for traditional methods.

5.1 Implications to research

Current research in the field concentrates more on computer science literature. However, the ultimate objective of Twitter sentiment analysis is to understand the discussion of Twitter users better and obtain insights from, e.g., business, politics, social events. In the year 2010, Zeng, D. et al. identified that focus on informatics in research questions creates a key challenge in social media intelligence research. There is not enough integrated research that combines information and domain sciences. The same problem is still valid nearly a decade later.

From the research perspective, this literature review's purpose is to bring field researched mainly by computer science field more approachable to business research.

This literature review combines relevant research from a business perspective into one study. The review would help other researchers when collating information on the conducted research. Before this, there is available only a few systematic literature reviews from the business-related field of social media sentiment analysis (e.g., Rambocas & Pacheco, 2018).

5.2 Implications to practice

For practitioners, this review enlightens how their companies' market intelligence function could utilize sentiment analysis. All practices reviewed in this thesis could be utilized for business purposes if there is enough relevant data on Twitter regarding a company or topic to be analyzed. It is possible to apply these techniques also in other channels than Twitter.

In addition, this thesis offers a valuable review for business practitioners to obtain knowledge of sentiment analysis as a tool for market intelligence. This thesis provides a clear picture of a rather technology-oriented area of sentiment analysis. For business practitioners who have expertise in, e.g., marketing, finance, or supply chains, this thesis offers insights on how to possibly utilize Twitter sentiment analysis in practice.

5.3 Limitations and avenues for future research

The most significant limitation of this review is the lack of real-life business case studies. There are not high-profile research in the fields of business research regarding social media sentiment analysis. The existence of such publications would have given more novelty for this literature review.

From a business perspective, the second limitation is the concentration on technical topics in the area. Business researchers do not usually have enough understanding of computer science or related fields to contribute as much as would be recommendable.

The third limitation is the fact that sentiment analysis tools are not yet wholly error-free. This fact indicates that the research field is not entirely ready for significant business reviews since there is typically some uncertainties in the results of Twitter sentiment analysis. To ensure the academic quality and more extensive utilization in practice, tools of sentiment analysis needs to be more trustworthy.

As mentioned, this field of research is emerging. In the future, there are a large number of possible avenues for research. That would suggest more business centric-approach as a great future avenue within this research field.

Two main objectives for future research:

1. Initiate a clear research field around business-related Twitter sentiment analysis literature.
2. Implement more comparative case studies between Twitter sentiment analysis and qualitative research methods.

With more empirical research on these two topics, the utilization of Twitter sentiment analysis for business purposes would receive more attention.

For possible master's thesis research, it would be intriguing to conduct a case study collecting and analyzing market intelligence data from Twitter for some Finnish company.

There is not much business-related research in the context of Finnish companies and social media sentiment analysis. In a conference paper by Jussila et al., (2017), they examine a Finnish software company and its Twitter data through sentiment analysis. Their dataset consisted of 507 tweets posted in the Finnish language. They suggested that the target company should have more traffic on Twitter to achieve more accurate and meaningful results.

When considering future research, the company should have a more significant amount of twitter traffic, than in the previously mentioned research. Sentiment analysis of twitter would not be relevant if there are 507 company-related Tweets; it would be more value-adding to annotate these Tweets manually with human labor.

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