LUT SCHOOL OF ENGINEERING SCIENCE
INDUSTRIAL ENGINEERING AND MANAGEMENT

Marketing in Social Media: Using Data and Artificial Intelligence for Segmentation

Analytiikan ja tekoälyn hyödyntäminen segmentoinnissa sosiaalisen median markkinoinnissa

Bachelor's thesis

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SUMMARY

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An increasing share of the world's population uses the internet and social media daily. This creates new opportunities for collecting and utilizing different types of data. The purpose of this thesis is to find out how data analytics and artificial intelligence can be utilized to make use of this increasing amount of data in social media marketing from a segmentation perspective. This Bachelor's thesis is a literature review that combines different sources into one entity. The literature reviews the principles and limitations of artificial intelligence and machine learning models, the interdependencies between data and artificial intelligence models, and explores the current uses of smart technologies in social media marketing. This thesis goes through identifying needs for using data, features and finding of the right kind of data, and discussing existing methods and capabilities for segmentation. One of the most important results of the work is that data analytics is already a very necessary tool in order to improve the efficiency and targeting of marketing. However, as models get more and more intelligent, there are also limitations and challenges that must be taken seriously to add value without harming people or businesses.

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Yhä suurempi osuus maailman ihmisistä käyttää internetiä ja sosiaalista mediaa päivittäin. Tämä tuo mukanaan lukemattomia mahdollisuuksia erilaisen datan keräämiselle ja hyödyntämiselle. Tämän työn tarkoituksena on selvittää, kuinka data-analytiikkaa ja tekoälyä voidaan käyttää sosiaalisen median markkinoinnin apuna erityisesti segmentoinnin näkökulmasta. Tämä kandidaatintyö on kirjallisuuskatsaus, jossa usean eri lähteen avulla pyritään luomaan eheä kokonaisuus aiheesta alan tutkimusten ja kirjallisuuden perusteella. Työssä tutustutaan nykypäiväisiin menetelmiin ja teknologioihin, joilla kasvavasta datan määrästä voidaan saada mahdollisimman paljon lisäarvoa sosiaalisen median markkinoinnille. Kirjallisuuden avulla kerrotaan tekoälyn ja analytiikan periaatteista, malleista ja rajoitteista sekä niiden ja oikeanlaisen datan välisistä yhteyksistä, tavoitteena yhdistää aiheet sosiaalisen median markkinoinnin kehittämiseen. Työn johtopäätöksenä voidaan todeta, että analytiikka on jo nykyään erittäin tärkeä osa markkinointia ja kun mallit kehittyvät yhä älykkäämmiksi, myös niiden käytön haasteet ja rajoitteet tulee ottaa vakavasti lisäarvon tuottamiseksi niin, ettei harmia koidu itselle, muille ihmisille tai muille yrityksille.

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1 INTRODUCTION

Social media has completely revolutionized communication between people, between people and companies, and internally inside companies, and the resulting changes in operating and thinking models have created opportunities for global networking and value creation. Social media marketing is a significant and essential part of today's business, but its business benefits are relatively poorly exploited due to its novelty and rapid pace of development. It is estimated that only 5 % of the data that social media and internet produces is analyzed or exploited in any manner. (Jussila, Kärkkäinen, Multasuo, Allen, Anttila & Isokangas 2012; Marr 2019) This thesis focuses on utilizing data to develop social media marketing with the help of modern tools and techniques.

1.1 Motivation and problem identification

The utilization of social media and data has become an important part of modern business and marketing research, so the field to be explored as well as the phenomenon are topical. New phenomena deserve to be explored, as accelerating technological and marketing developments constantly create new challenges for companies to keep up and develop their activities accordingly. New strategies and tools become obsolete in just a few years and new perspectives and approaches are constantly emerging. (De Swaan Aros, van den Driest & Weed 2014)

Rapid increase in amount of data and advances in data analysis tools and applications have left many public and private companies unprepared for change (Gandomi & Murtaza 2014, 1). In 2015, IBM estimated that humans produce 2.4 trillion bits of data daily, which required increasingly powerful tools to be able to benefit from the data (Márquez & Lev 2015, 93). In 2019, it was estimated that 2.5 quintillion (2,500,000,000,000,000,000) bytes of data is produced daily, so the need for even more powerful methods is increasing. Among other sources, this data includes 65 billion WhatsApp messages, 5 billion hours of watching of YouTube videos, 5 billion search engine searches, 1.5 billion active Facebook users' actions, 500 million tweets in Twitter and 100 million photos shared on Instagram, every day. (Marr 2019) At this point, data analytics and other smart technologies come into play so that different

institutions can make use of this outrageous amount of data to support and develop their operations.

Artificial intelligence is described as one of the greatest breakthroughs and efficient tools in data processing in our society that no company willing to keep up with the competition can escape. According to forecasts, artificial intelligence applications will become available to all data-intensive industries and may even replace nearly all existing human work (Müller & Bostrom 2014). Artificial intelligence systems help companies improve the efficiency and quality of their business processes as well as their customer and staff experience. With digitalization and social media, the amount of data to be utilized is growing exponentially, and artificial intelligence is the only way to control the growing amount of data efficiently. On the other hand, sufficient amount of quality data is the key to developing a successful artificial intelligence model. Artificial intelligence is not a product or a single business application, but a set of tools that transform data into information. As the computing power of processors improves, the cost of collecting, managing, and storing data has been reduced, and artificial intelligence based systems can handle larger and larger data sets quickly. (Merilehto 2018)

Marketing analytics as a part of business intelligence management has also evolved, although often analytics is still strongly linked to the financial side of companies (Rackley 2015, 2). The need for analytics has also been recognized in marketing, since without analytics, a company has no proactive way of evaluating or developing its performance, and the only indicator of success is the final result of an operation (Rackley 2015, 1).

1.2 Implementation of the thesis, research questions and objectives

The purpose of this thesis is to find out how analytics and artificial intelligence can be utilized in social media marketing, particularly from a segmentation perspective. The goal is to get a comprehensive picture of today's social media marketing methods and opportunities through a literature review by combining a variety of sources into a coherent whole. In particular, the various tools for data processing as well as the challenges and constraints associated with these methods are discussed. This thesis also aims to provide development suggestions and

information to enhance social media marketing by making use of industry research on current methods for data analytics and artificial intelligence. The main research question is:

- “How analytics and artificial intelligence can be used as a tool for segmentation in social media marketing?”

To deepen this main research issue further, the following sub-research questions are addressed:

- "What are the opportunities and challenges that social media brings to today’s marketing?"
- "What kind of data can be useful for marketing and how can it be collected?"
- "What tools and opportunities there are to utilize data in today’s marketing?"

Next in chapter 2, social media and social media marketing will be introduced, followed by an introduction to the basics of data analytics in chapter 3 and artificial intelligence in chapter 4, so that the topics can eventually be combined to develop social media marketing using modern methods in chapter 5. Finally, conclusions of the work will be discussed in chapter 6.

2 SOCIAL MEDIA MARKETING AND SEGMENTATION

Social media is changing the way we communicate, create, use, and collaborate with one another and therefore it also has a strong impact on a wide range of different business activities. In terms of marketing, social media is perceived as different from other forms of marketing and is predictive of the future of marketing. (Keegan & Rowley 2017) This chapter covers very basics of social media, marketing and how social media works with marketing.

2.1 Social media

Social media refers to online communication platforms for communication and information sharing between users of different channels (Kaplan & Haenlein 2010). Social media platforms include online discussion forums, blog channels, and social media channels and they are made for sharing texts, images, sounds and videos with other users and businesses (Kotler & Keller 2012, 568).

Currently, the most popular social media platforms by number of active users are Facebook, YouTube, WhatsApp, and Instagram. Facebook has the largest number of users, with 2.45 billion active users. (Statista 2020) Figure 1 below shows the number of active users of the most popular social media platforms as of January 2020.

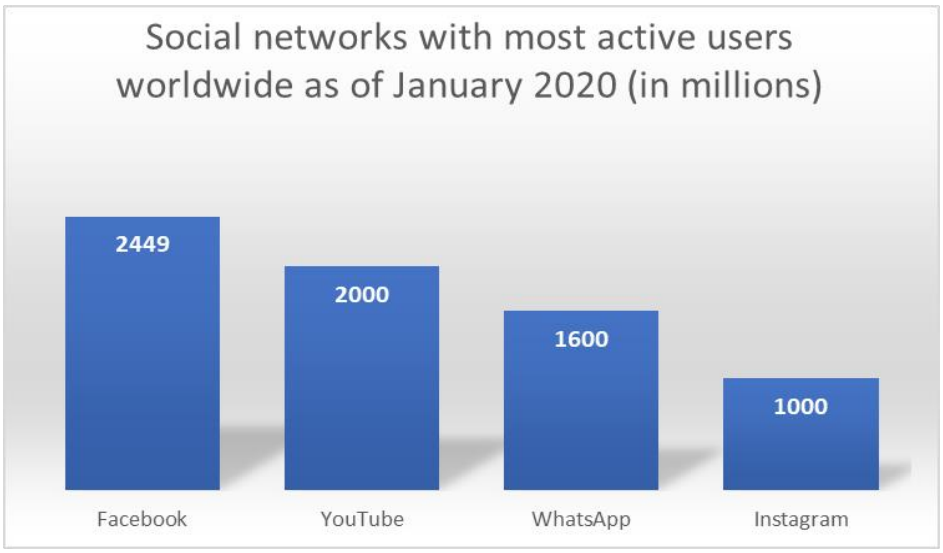

Figure 1: Social networks with most active users (Statista 2020)

2.2 Popular social media platforms

Facebook offers its users the ability to create their own profile with pictures, information, and interests, and to connect with another consumer's profiles. One of Facebook's most notable features is its consumer-driven news feed, which includes updates from friends, groups, and websites, among other things. (Facebook 2020) Facebook provides advertisers with a large amount of personal information about consumers, as well as their buying behavior and preferences, which allows them to target ads very accurately and efficiently (Dekay 2012).

YouTube is a popular video sharing service based on user uploaded videos. In addition to uploading their own videos, users can view and comment on others' videos, as well as follow their friends' recent activity and subscribed channels. (YouTube 2020) In the United States, YouTube is more popular with people aged 18-34 than any TV channel, so the marketing potential is huge (Perrin 2015). Also, 55 % of people looking to buy a product said that they search for information from Google and YouTube before making a purchase (Google 2018).

WhatsApp is a free instant messaging app. It allows you to write messages, share documents and content, talk and make video calls for free over the internet. WhatsApp does not currently display ads and is therefore not further discussed in this work. (WhatsApp 2020) However, WhatsApp can be thought of as a modern word-of-mouth channel, because there is a lot of discussion and distribution of any types of content.

Instagram is a photo and video sharing service that allows users to edit and share photos and videos to their followers. Users can like, comment, and share photos and videos, and also chat with each other in private messages or in groups. (Instagram 2020) From marketing point of view, Instagram is interesting due to its highly visual characteristic. Instagram is also the most popular platform for consumers to follow brands (Phua, Jin & Kim 2017).

2.3 Marketing communications

Marketing communications is one of the 4-P models created by McCarthy, consisting of product, price, place, and promotion (Kotler & Keller 2012, 47). Changes in the environment

and especially technological development have also created new ways for marketing communications, and the marketing communications model has undergone a major change quickly. The marketing communications model includes the following components: advertising, sales promotion, events, publicity, and media, online and social media marketing, mobile marketing, direct marketing, and personal marketing. (Kotler & Keller 2016, 582) Of these, the relevant components in this work are advertising and social media marketing.

Marketing strategies can use a “push” strategy that pushes the product or service through the marketing channels to the consumer by using promotional means. Other approach is a “pull” strategy, where the producer directs marketing activities towards the end user, enticing them to buy the product, so the product seems to have been “pulled” through markets. (Kotler & Keller 2012, 438) Social media can be used as a “pull” assistant to produce information and content such as blog posts, videos or recommendations for potential customers. The idea is to focus on creating content that will get your prospect interested and come to the company independently. The purpose of such content marketing is to be a more trusted channel to awaken a person looking for information on social media to take the initiative themselves. Good content marketing also leads to better brand health in addition to increased visibility. (Lieb 2012)

Advertising is any form of paid communication that targets the mass audience and communicates the products, services, or ideas of an organization (Kotler & Keller 2012, 500). Personal sales work differs from other means of marketing communication in that it is individually personalized marketing communication. It focuses on considering only one potential customer for whom the most accurate marketing communication is produced. (Kotler & Keller 2012, 500) Segmentation can be seen as a way of combining pros from both of these models by focusing communication on customer segments that are created based on certain generalizations or preferences in order to target ads, but at the same time limit the need for individualization. This becomes especially important in social media since internet offers huge and global audience, and therefore neither mass advertising nor individualization provide optimal results. (Constantinides & Zinck Stagno 2011)

2.4 Segmentation

A customer segment is a group of customers with similar needs and desires. It is a good idea for a company to divide its potential and existing customers into different segments, where it is efficient to target different processes and business functions according to their different preferences. Segmentation brings many benefits to a company as it can change and diversify its operations across these segments, making customers more satisfied while using the company's resources more efficiently. (Kotler 2003) According to different segments, for example, a marketing information channel can be designed to fit particular segment's tendencies.

While segmentation is intended to reduce costs and improve efficiency, it also entails costs. Planning, as well as obtaining and analyzing information, requires both financial and know-how resources from the company. Customers need to be understood from many different perspectives and gathering information and making the right decisions is challenging, which can easily make segmentation very expensive. The biggest risks to the success of segmentation are segments that have been made on wrong basis or segments that are too small and unprofitable. (Haverila, Uusi-Rauva, Kouri & Miettinen 2005)

Segmentation does not make sense unless it ultimately increases the company's revenue and profitability. It is important that segmentation covers its costs and then adds value. If this does not happen, then segmentation is simply not worth doing. (Haverila et al. 2005) However, with the advancement of analytics, many methods have been developed to address this problem, and effective use of analytics can provide a large number of people with exactly what they prefer. This method is called mass customization. (Morabito 2015, 69)

This work focuses on dealing with social media consumers to create potential customer groups and using data from social media to support existing customer data. As consumers are increasingly and more openly sharing their likes and preferences on social media and their purchasing behavior and predilections can be monitored more closely with web analytics, tailoring products and services is becoming easier with the right tools. This is important to create and maintain consumers' interest. (Morabito 2015, 6-7) Analyzing this information allows for placing different people in increasingly accurate and better segments at lower costs.

3 DATA ANALYTICS

This chapter briefly introduces data analytics in general so that the topic can be understood and later incorporated into the topic of the work. The key issues are data collection and the definition, purpose, and potential of data analytics, as well as the data analytics process.

3.1 Data analytics definition and concepts

Data analytics refers to the analysis of large data sets using a variety of computer applications. Data analytics is a versatile and multidisciplinary concept as it incorporates features from statistics, machine learning, and operational analysis to get value out of data. (Cheng, Qin, Rusu 2012; Runkler 2012)

The data analytics process can be divided into several different ways, but Runkler (2012) has divided the process into four different stages. In the first stage, the project is planned, data is collected, and the desired data is selected. In the next step, the data is filtered, corrected, standardized, and converted to the desired format. In the third step, the data is visualized, correlations and regressions are examined, predictions, classifications, and clustering might be done according to what is sought. In the fourth stage of the process, the results are interpreted, documented, and evaluated. (Runkler 2012, 2)

Collecting and utilizing data is starting to be a prerequisite for many companies to operate competitively, but by improving the process and using the right tools, a significant competitive advantage can be provided. Benefits can be gained from historical or real-time informational content by looking at both in-house activities and events and trends in the outside world. For example, business data can come from finance, sales, markets, marketing, or customers (Runkler 2012, 1). This work focuses on utilizing data from different sources that can be used in marketing. Table 1 presents five different levels of data exploitation according to Marr (2017).

Table 1: Five different levels of data exploitation (Marr 2017)

Level	Explanation
Descriptive Analytics	• What happened? Evaluation of past results • Statistics, Exploratory Data Analysis, Visualization
Diagnostic Analytics	• Why did something happen? Seeking and finding causal relationships
Predictive Analytics	• What might happen? Creating templates to predict future events • Forecasts, classification, clustering, regression, associations
Guiding Analytics	• What should we do? Creating templates for best practices • Decision trees, Monte Carlo simulations, optimization
Automated Guiding Analytics	• Automatic exploitation of previous results

With successful data processing and management, corporate data can be compared to intellectual property. Especially when the products and services to be delivered are similar, companies in the industry with the best data usage have significant competitive advantage over others. (Marr 2017, 23-36) With digitalization and artificial intelligence, the amount of data is growing exponentially and thus the potential for exploitation is multiplied (Amazon Web Services 2020). Even everyday activities like walking, car driving and buying transactions can build data paths that can provide significant additional insight into business functions and help companies in developing their processes (Marr 2017, 86).

3.2 Data collection

The data used in data analytics is often large in quantity and may come from a variety of sources. Before any model can be developed, the data must be collected and organized for use. Many mathematical models, such as various machine learning models, are often very accurate and therefore sensitive to incorrect data. In addition, the data needed by the models depends highly on the problem to be solved, and not all data is of the same value, thus goals and boundary conditions must be precisely defined. Among the important things to decide about data are its amount, quality, requirements, maximum permissible error margin, possible missing data,

ensuring the correctness of the data, and data ethics or other limitations. Data can be acquired both internally and externally of the company and may require the development of entirely new data acquisition techniques. Among other sources, companies can collect data from users, partners, applications, software, hardware, and sensors. (Korolov 2018; Marr 2017)

A term, data mining, has been developed for obtaining usable data. Data mining is an overarching concept to describe various techniques that go through large volumes of data and its idea is to identify different patterns in a set of data and find interesting information to the acquirer, meaning to create understandable and usable information out of raw data. (Lee 2013; Runkler 2012)

Because of the troublesome data collection and tagging, massive and universal datasets are usually most effective to obtain from outside vendors. Commercial datasets can provide extensive data such as data about weather, social media, and stock share prices. (Merilehto 2018, 68) When collecting data from multiple sources or from outside of the company, it is important to verify the authenticity of the data before transferring it to the company's systems. The importance of accuracy and quality of the data will be enhanced as different artificial intelligence applications expand into extensive problem solving situations. (Korolov 2018)

Today, as raw data can be processed and categorized more efficiently, for example through a variety of artificial intelligence applications, raw data has begun to be valued more as a potential resource for a company. Next chapter tells more about the basics of artificial intelligence.

4 ARTIFICIAL INTELLIGENCE

Artificial intelligence is a subset of computer science that simulates intelligent behavior (Lappi, Rusanen & Pekkanen 2018). Google defines artificial intelligence as the ability of a machine to mimic the way people think and learn by following sequential commands without having to be confined to the human level (Ito 2018). Artificial intelligence refers to non-human activities that done by human beings would be considered intelligent. Intelligent functions include, for example, learning, problem solving, anticipation, decision making, voice recognition and image recognition. Artificial intelligence models are based on algorithms - mathematical instructions and rules that guide the machine to function as desired. The algorithms operate on different data and thus high quality data is a prerequisite for utilizing artificial intelligence. On the other hand, artificial intelligence can also be a very effective tool for making value out of high amounts of unstructured data. (Amazon Web Services 2020; Merilehto 2018) This chapter introduces different concepts of artificial intelligence and machine learning, seeking to understand the potential of artificial intelligence applications from a business and marketing perspective.

4.1 Potential business benefits of artificial intelligence

The change in the business world caused by artificial intelligence is significant. Although the term artificial intelligence was introduced already in the 1950s, only the increasing computing power, the amount of available data and the development of algorithms of today have allowed large-scale utilization of artificial intelligence. (Merilehto 2018) From a corporate perspective, the key capabilities of artificial intelligence applications include completing tasks, learning, making better decisions, and performing tasks that traditionally require human intelligence, such as planning and analyzing incomplete and uncertain information. (Amazon Web Services 2020; Deloitte 2017)

Artificial intelligence applications shape the way companies operate by influencing the speed, quality, and cost structure of business processes. As a result, the ways in which different actors, such as company personnel, suppliers, and customers interact, can be improved. (Deloitte 2018) The ability of artificial intelligence applications to increase process speed and quality while simultaneously reducing costs is rare for a business tool and investments in artificial

intelligence can therefore be very valuable for a company. As artificial intelligence applications facilitate processes and tasks, workers are freed up for creative work, significantly improving their efficiency and capacity. According to Deloitte's analysis (2019), investing in artificial intelligence and automation could save up to 34% of employees' time in a company, which can be seen as a huge financial savings as well as a factor in improving employee well-being and efficiency. (Deloitte 2019)

Artificial intelligence can be especially useful as a tool for analytics. Different machine learning models allow data to be categorized, grouped and analyzed more efficiently and accurately. In addition, these models can produce forecasts, optimize processes in an uncertain environment, identify anomalies, and discover entirely new ways to solve problems (Amazon Web Services 2020). Successful analyzes and forecasts of business changes accelerate the company's responsiveness and proactivity. Moreover, using machine learning for analyzing various components in existing analytics models and time perspectives can improve the accuracy of the analytics while reducing manual work, thus making analytics even more profitable for the company. (Merilehto 2018)

4.2 Machine learning

Many of today's artificial intelligence applications are based on machine learning. Machine learning is a component of artificial intelligence, the basic idea of which is that the machine learns step by step from the data and examples supplied to it, often relying on statistics and different algorithms. As the learning process progresses, the machine learning model improves its performance and learns to describe and utilize the data better and better, even to the point of being capable to apply its learned methods to solve new problems in the same domain, in addition to the familiar challenges. (Kapitanova & Son 2012; SAS Insight 2020)

A machine learning model can build a current case based on historical data and predict a specific end result. An essential difference from traditional programming is that the machine learning model is not dependent on built-in logic, people's previous understanding, assumptions, or perspective on business. (Merilehto 2018) Instead of traditional boundary-based models, machine learning aims to automate the interpretation of data and extend the machine's

observational capabilities with sophisticated algorithms (SAS Insight 2020). Machine learning algorithms can be categorized into three different categories based on how they function:

- **Supervised Learning:** During the teaching phase, the machine is fed with an input and a corresponding result. The machine monitors and observes the situations taught to it. The model learns by comparing the results it produces with the desired correct results and learns from its mistakes. Supervised learning is often used in cases where historical data predicts future events well. (Kapitanova & Son 2012; Merilehto 2018; SAS Insight 2020)

- **Unsupervised Learning:** The machine is not provided with direct feedback or the "right" answers but learns by observing regularities and relationships in the data. For example, the machine can identify similarities in customer characteristics and, consequently, place them into different segments that can later be treated in the same way in marketing. It can also find key features that differentiate between different existing customer segments. Popular techniques include k-means clustering, self-organizing maps, nearest-neighbor mapping, and singular value decomposition. (Kapitanova & Son 2012; Merilehto 2018; SAS Insight 2020)

- **Reinforced Learning:** The machine operates through trial and error and learns from its mistakes. The machine is given feedback on the action it is making, that is, how successful it is in different situations. The goal is to find actions that will maximize the expected reward in a specified time frame. Repetitions can improve machine performance even beyond human capabilities. Learning is the result of the interaction between model and environment and continuous trial for a more optimal result. (Kapitanova & Son 2012; Merilehto 2018; SAS Insight 2020)

In reality, the division between the different methods is not always clear, as they can be exploited within each other. For example, in Semi-Supervised Learning, the machine is provided with a few classified examples, after which it is expected to utilize a large set of unclassified data. This combines guided and non-guided learning (Merilehto 2018; SAS Insight 2020)

4.3 Deep learning and neural networks

As artificial intelligence and machine learning have developed, so-called deep learning based systems have emerged. Deep learning is a combination of machine learning, connectivity, dynamic systems theory and Bayesian mathematics. "Depth" in deep learning refers to the ability of systems to utilize multiple, even tens of, processing or analysis layers, which differentiates it from previous methods. This multi-layered system is called a neural network. (Lappi et al. 2018)

The neural network is thus composed of layers made up of individual neurons. A single neuron mimics the neurons in the human brain and their job is to receive information and to transmit adapted information based on the received information and certain weight factors. When neurons are placed in layers and connected to each other, a collection of mathematical units that learns by observing, a neural network, is created. This multi-layered structure enables the system to learn deeply on multiple stages, as the results of the previous layer and the changed weights are used as the input of the next layer, which creates new weights for the following layer, finally resulting in conclusions as output. (Li, Jiang, Yang & Wu 2018) Figure 2 below presents a neural network with three hidden processing layers.

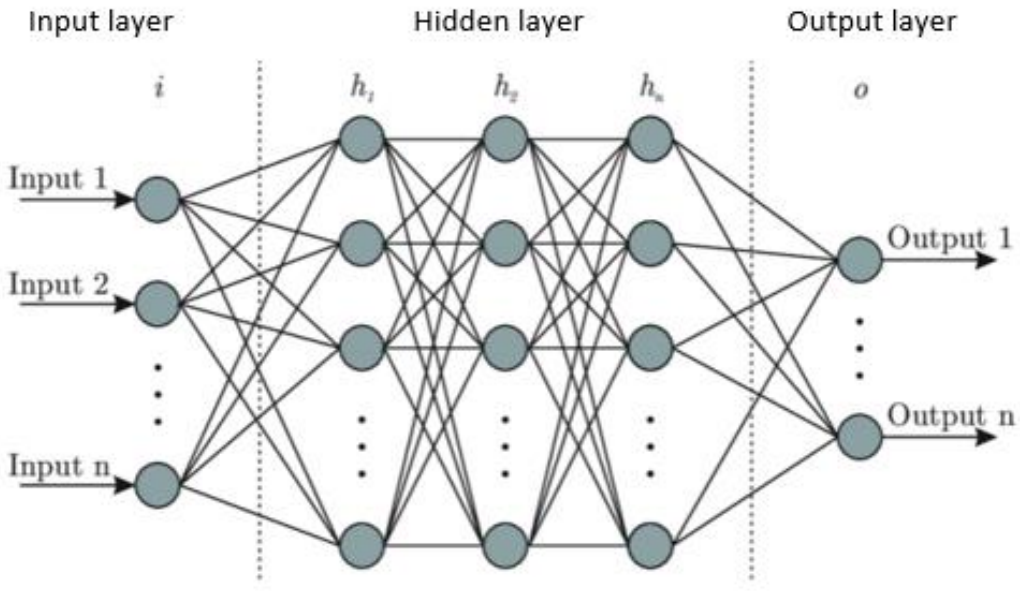

Figure 2: Neural network (Bre, Gimenez & Fachinotti 2018)

The advantage of deep learning based applications is that they are able to learn regularities of the material better than simple machine learning models and they use large amounts of data more efficiently. In addition, unlike superficial learning methods, deep learning models can work with very little to no pre-assumptions due to their ability of finding the optimal calculated weights for different factors. This enables the model to learn complex connections from interdimensional data, while requiring less manual trimming and application-specific expertise. In other words, deep learning models can learn independently to become experts in their field of application and find connections that may be impossible to detect for humans. (Ball, Anderson & Chan 2017; Lappi et al. 2018; Li et al. 2018)

4.4 Challenges and limitations of using artificial intelligence

Biggest disadvantage for artificial intelligence and neural network usage is the difficult and costly preparation that its proper utilization needs. The widespread exploitation of artificial intelligence in business has been limited by the fact that training artificial intelligence models is often cumbersome, time consuming, computationally arduous, and therefore also costly. Furthermore, there are little prefabricated models available that are ready for a process, and although after the learning phase neural network use may be very effective, it might not be worth the effort without a proper business case. (Bishop 2006; McKinsey 2018)

MIT has estimated that a guided deep learning model needs approximately 5,000 marked practice examples per category to perform mediocrely of the task assigned to it, and to reach or exceed human level, the training data must include approximately 10 million labeled examples (Goodfellow 2016). The amount of training data needed depends on the issued task and tolerable margin of error, but regardless of the situation, if there is too little data available for the exercise, the algorithm will not learn to perform its task reliably and will not be useful compared to traditional methods of analysis (Bughin et al. 2017). In addition, many companies lack in sufficient high quality data or skilled data analysts who are capable in training artificial intelligence models and at the same time many leaders are not ready to make seemingly uncertain and expensive investments (McKinsey 2018).

5 IDENTIFYING CONSUMER SEGMENTS FROM SOCIAL MEDIA WITH INTELLIGENT ANALYTICS

Effective marketing is capable of recognizing people's social needs and meeting people in a way that corresponds to those needs (Kotler & Keller 2016). Social media analytics can identify different consumers and groups of consumers as well as their specific, characteristic needs and traits. It is possible to computationally predict consumers' reactions to various events and, for example, to predict the impact of certain types of marketing communications on the purchasing behavior of particular groups. Analytics can identify specific groups with a certain social need and make recommendations on how to reach those customers or consumers so that they are statistically more likely to act as desired. In other words, with marketing analytics, the company is able to deepen customer understanding, optimize marketing channels, understand, and develop marketing content, understand brand image, and predict customer behavior. (Rackley 2015)

This chapter seeks ways to find different consumer behavior patterns by collecting data on the actions of active consumers in social media and analyzing this data with the help of different artificial intelligence applications. The data is used to generate recommendations for marketing communications efforts, targeting specific actions based on identified segments. Finally, consideration will be given to monitoring the results achieved through these activities and to improving the process on the basis of the results obtained.

5.1 Collecting data from social media

This chapter covers different types of social media data, different ways and channels to collect useful data from social media and discusses the challenges and problems of collecting social media data.

5.1.1 Different types and features of social media data

When collecting social media mass data, different types of data must be taken into account and how information in different formats can be utilized. Data is collected from several different

social media channels, and thus also comes in a number of different formats such as video, image and text, and also includes information on various issues such as demographics, hobbies, interests and even health information. On the other hand, a wide range of issues can be covered with versatile data, such as interaction analysis, analysis of likes and impressions and analysis of user interests or demographics, all of which produce different information to be utilized. Data variability appears in social media in the number of different sources, variability in data structure, and variability in data formats, which makes it difficult to combine and utilize data. (Bello-Orgaz, Jung & Camacho 2016)

Most social media mass data is unstructured, which is typical of any mass data. However, social media data also includes structured and partially structured data, for example in the form of user data. Many social media channels require user information to be filled in before use, and this information is often pre-defined with input fields, so that the data entered into it can be easily structured using field-specific references, making the generated data at least partially structured. (Bello-Orgaz et al. 2016; Gandomi & Haider 2015) However, the amount of this type of data may vary between different social media channels, as the presentation of users' own identities varies between different social media channels (Kietzmann et al. 2011).

Social media data can also potentially be structured using hashtags for social media content. Hashtags are used on social media to classify the same type of content so that that content can be easily found by users. (Tsur & Rappoport 2012) In this case, the data in question would be structured using the hashtag contained in the data as a reference, so the information contained in the data would be known in advance based on the hashtag. However, data structured in this way would most of the time be at most partially structured data, as the references used are user based and thus loose by standards (Gandomi & Haider 2015).

When dealing with social media mass data, the most common problems of mass data also arise, some of which may even be highlighted in the context of social media. Data retention and processing are significant problems due to the amount of data produced in social media. (Bello-Orgaz et al. 2016) A particular feature of social media mass data is its pronounced unreliability. Mass data is often characterized by relative unreliability, which can be considered to be accentuated in social media mass data due to the user-orientation of the data. (Bian, Liu, Zhou,

Agichtein & Zha 2009; Gandomi & Haider 2015) In social media, users may intentionally or inadvertently share false information that, when more widespread, can significantly distort the data collected, thus reducing the reliability of the data collected (Ivanov, Vajda, Lee & Ebrahimi 2012).

5.1.2 Privacy policies

A special feature of social media analysis is that it almost inevitably contains personal information. In many social media services, a profile is directly linked to a real name or a recognizable nickname. The researcher must be aware of both the legislation relating to the processing of personal data and the ethical principles of human research. However, the law does not address all ethical issues relevant to research, but from its point of view, most public data is permitted to be used as material even if it contains sensitive information. The new EU Data Protection Regulation, which entered into force in spring 2018, gave even more freedom to research on personal data. (Maldoff 2016)

Online material can address very personal and sensitive topics, such as religion, political opinions, or sexual orientation, among others. Regardless of the content, the use of such data in research, for example too blatant targeting of advertisement, may cause the producer of the material to experience that information about him or her has moved out of personal control and thus result in negative and violated emotions. It is easy for a consumer to feel spied rather than interested when targeted advertisements are too opportune, which makes the topic hard to approach since one's personal level of feeling upset, annoyed, or resentful related to the ads are difficult to know or measure. (Elgesem 2015; Matthews-Hunt 2016)

The best rule of thumb for a researcher working on social media analysis is to treat the material as personal information all the time. This means that the privacy of subjects and the secure storage of data must be guaranteed. For example, an unprotected cloud service is wrong place for research data that contains personal information. To be sure in unclear situations, Finnish law on the processing of personal data can be used for help in collecting and storing information. (Data Protection Act 1050/2018)

5.1.3 Collecting, categorizing, and filtering the data

As there is more and more raw data available to be utilized in marketing, effective data mining techniques become an important part of businesses' marketing efforts. There are large amounts of intelligent data mining applications that can be used in marketing for recognizing, getting, developing, and keeping customers, as shown in Table 2 below.

Table 2: Data mining tasks in marketing (Ziafat & Shakeri 2014)

Modeling Task	Modeling Techniques	Example of Application
Association	Apriori, Frequent Pattern Growth	Market Basket Analysis
Sequence Mining	Apriori, Frequent Pattern Growth	Web Usage Analysis
Clustering	K-means, Hierarchical Models, Self Organizing Maps…	Segmentation
Classification	Decision Trees, Neural Networks, Regression, Support Vector Machines…	Prediction

Of these, the main focus of this work is on clustering, but all of these modeling tasks are strongly related to the topic and are therefore relevant to mention in order to have a comprehensive picture of today's marketing analytics tools and what can be done with modern analytics applications.

This phenomenon of benefiting from having lots of raw data also applies to targeted advertising since when more information about the potential customer is obtained, the advertising can be tailored more precisely. There are multiple ways of targeting marketing communications based on company's goals, consumers' features, and environment, and therefore having data about various aspects and utilizing it from many points of views can be beneficial. Schlee (2013) has divided the means of targeting into seven different categories, which are shown in the Table 3.

Table 3: Means of targeting (Schlee 2013)

Category	Explanation
Content and contextual targeting	Advertising based on currently viewed content. for example, advertising airline tickets when a user views travel-related content.
Technical targeting	The user receives advertisements that are compatible with the device, software, and speed of the internet.
Time based targeting	The user is shown relevant ads on time of day or time of year.
Sociodemographic targeting	Targeting based on, for example, the user's age, gender, income, nationality, and ethnicity.
Geographical and location based targeting	The ads shown to a user are based on their geographical location, obtained, for example, from the IP address or GPS data of the phone.
Behavioral targeting	Monitoring user activities in a network environment and detecting patterns in their activities. For example, advertising cameras if a user has searched for information about different cameras, is talking about cameras or is following blogs about photography.
Predictive behavioral targeting	Leveraging statistical foresight to optimize ads. These predictions are based, among other things, on the aforementioned data of the user's browsing history, posted content and objects of interest.

Based on these categories, the collected data can be broken down to correspond its use cases to improve its exploitation potential and making its usage more efficient by having a more structured warehousing for the data. Of these categories, behavioral targeting and predictive behavioral targeting are the most advanced ones and they often also utilize information from the other categories when algorithms get more advanced. These are also the categories that are mostly considered in this work as intelligent social media analytics and targeting of marketing.

To streamline data mining, there are various data alignment models in which certain operations are applied to each piece of data to facilitate its processing. One of these models is the batch processing model, in which data is sought to be divided into parts to make its processing more efficient. The model is often used to simplify large amounts of data, so it could be considered well suited for text-based content produced by social media. For example, a batch processing based MapReduce application could be used to find relevant information out of social media mass data. (Bello-Orgaz et al. 2016; Kambatla, Kollias, Kumar & Grama 2014) MapReduce aims to map and delineate the relevance of large amounts of data, allowing rapid assessment and going through of text content using specific keywords. In batch processing based models, however, data is retrieved from memory, rather than directly from the data stream, so real-time analysis of the data is difficult with this model (Kambatla et al. 2014). Figure 3 below shows the MapReduce process.

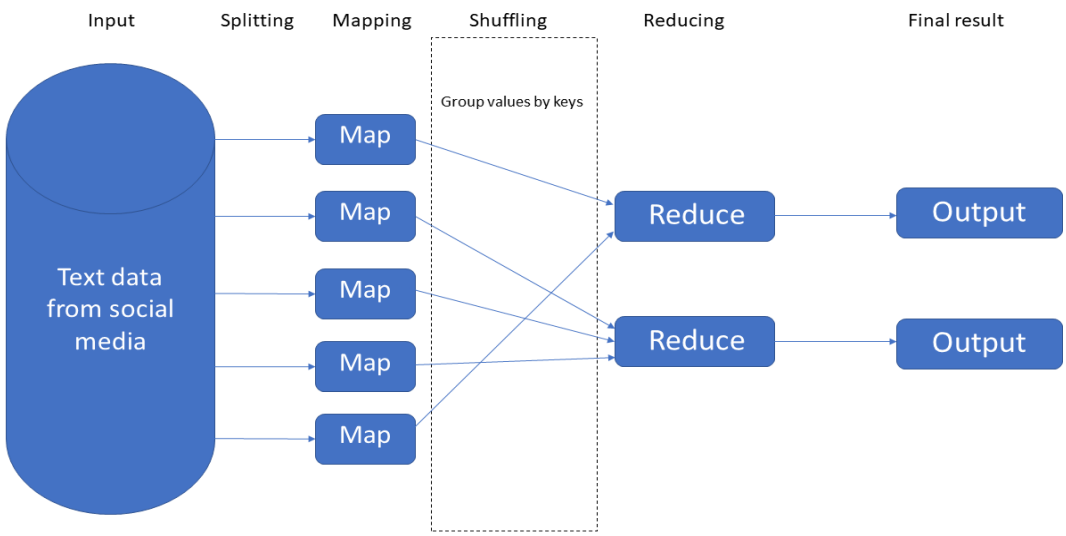

Figure 3: MapReduce process (own illustration based on Kambatla & Chen 2014)

Another model is the bulk synchronous parallel processing model, which creates scalability advantages over the batch processing model when iterative algorithms are used, as data does not have to be loaded from the data warehouse with each processing round. Because of these scalability advantages, the different paradigms of the bulk synchronous parallel processing model are increasingly used in data analytics of different social media channels. However, even

this model does not allow real-time analysis of the data because the data is still initially retrieved from memory, rather than in real time. (Kambatla et al. 2014)

The solution for real-time data analysis is an event processing model that is well suited for real-time analysis of user actions such as clicks, status updates, and impressions on social media, as data is retrieved directly from the data stream. In this model, however, the data cannot be divided into sets but is processed individually. This type of analysis allows, for example, the targeting of advertising based on real-time needs and actions, and therefore this model can be considered very well suited for targeting social media advertising when it involves a substantially rapid response to current events. (Kambatla et al. 2014)

5.2 Segmentation and clustering methods

After obtaining usable data, it can be analyzed to find different consumer behavior patterns and making observations and predictions based on which marketing communications can be later targeted. There are many different intelligent applications for doing so and next two common ones will be introduced to help understanding methodologies behind clustering.

K-means clustering algorithm is one of the best known machine learning based clustering methods. The algorithm gets the number k of clusters as its parameter and its operation starts by selecting k cluster centers from among the data points. At its simplest, this selection can be made by randomly selecting k data points from the data. The algorithm then uses the selected difference function to calculate the nearest cluster center for each data point and places the point in the cluster represented by the center. Once each point in the data is assigned to a cluster, new cluster centers are computed. The new center of each cluster is set to the average of the points in the cluster. This procedure is continued until the clusters remain sufficiently stable, which means until all the clusters remain the same throughout the iteration cycle. There are several different versions of the K-means clustering algorithm that, among other things, speed up its operation. This method depends on the values of k and its operation is easily disturbed by noise or outliers in the data. (Kapitanova & Son 2012; Yang et al. 2019) Figure 4 shows the steps of K-means algorithm when k = 2.

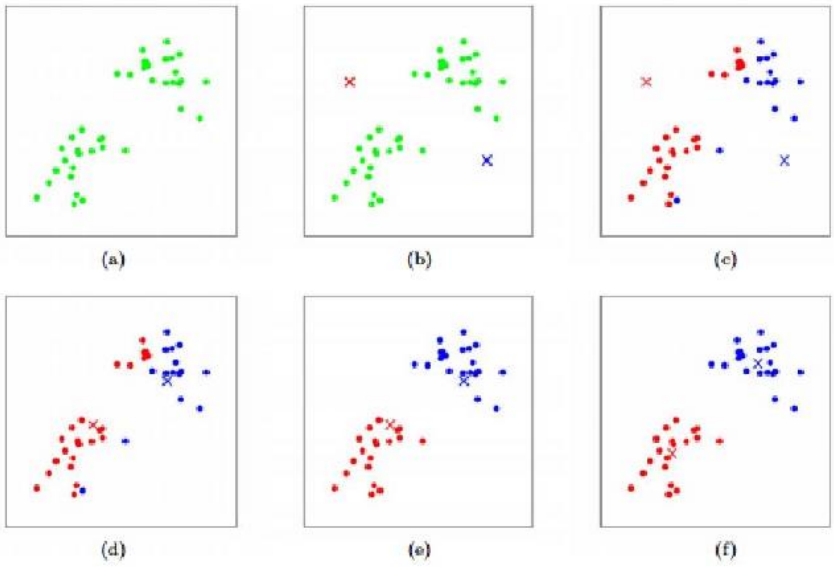

Figure 4: Steps of K-means algorithm (Yang et al. 2019)

Self-organizing maps (SOMs) is another method that is used to cluster data and reduce data dimensions. The SOM algorithm was first introduced by Kohonen in 1981. SOM was developed based on the idea of combining k-means clustering, vector quantization and graph smoothing. The mammalian brain has served as an inspiration for the development of this clustering method. (Kohonen 2013) The map learns how to aggregate data based on similarities and topology, dividing the data into classes of the same size. (MathWorks 2020)

SOM is one of the most popular artificial neural networks used for both cluster analysis as well as visualization and abstraction problems (Golmah 2014). As a data analysis tool, SOM produces low-dimensional descriptions of high-dimensional data while maintaining similarities. In other words, SOM clusters data and organizes these clusters. (Kohonen 2013) The basic idea behind SOM is the ability to map interdimensional spaces and form two or three-dimensional structures, similarly to the human cortex. The process seeks not to risk the existence of information and to safeguard the information contained in the hidden structures. (Hanafizadeh & Mirzazadeh 2011, 200) An overview of SOM neural network is presented in Figure 5.

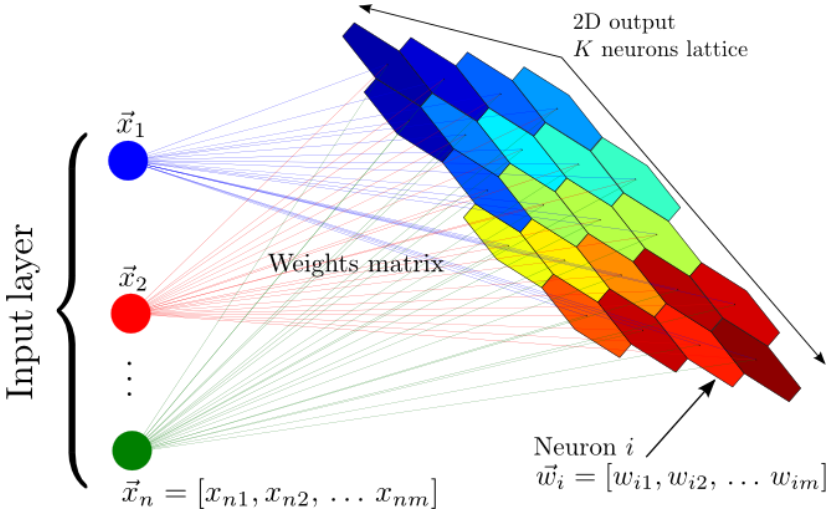

Figure 5: SOM neural network (Lan 2018)

Through its unsupervised learning algorithm, SOM is able to recognize the unifying features of even large data sets. These self-organizing networks minimize the similarity of structures between different clusters, while simultaneously maximizing the similarity of the features of members of one cluster. As a printout, SOM returns a summary of the material to be analyzed (Hanafizadeh & Mirzazadeh 2011, 201)

There are numerous other clustering methods available and choosing one to fit the particular task and available data might not be easy. After understanding the purpose of clustering and the core of data to be analyzed, the best method is usually the one that can be understood the best and is the simplest one to fit the particular problem to be solved. As found in chapter 4, more complex models, while having the chance of bringing advantages and accuracy to the table, also require more expertise, computing power and other resources, and might therefore not be the best choice if the problem could be solved with simpler models. For example, SOMs and other deep learning based models, while being computationally more arduous, might withstand noise and outliers in data better, or understand high dimensional data better than simpler models like K-means.

5.3 Targeting marketing communications to recognized consumer segments

When customers are segmented on the basis of well-collected information, it is possible to market exactly the kind of things that improve the possibility of the desired type of activity for

a certain segment. Information can also predict the customer's lifetime value to the company as well as the customer's tendency in various matters, such as buying and interest, so that the company is able to contact the customer at the right time for the right thing and thus engage the company. It is also possible to provide the customer with relevant recommendations based on statistics, such as recommending a larger order size, selling mutually supportive products, or recommending a suitable next purchase for the customer. (Kotler & Keller 2016; Rackley 2015)

Segments created through clustering can have many different characteristics, such as one segment may spend more money at a time and buy typically during discount campaigns, and another segment may focus on meeting basic needs on a regular basis. In this situation, the company or an algorithm can try to engage the money-intensive segment with a greater investment in marketing and serve another segment only at a basic level. The effectiveness of segments and marketing efforts can be measured, for example, by the return on investment (ROI) and trying different approaches on different segments while measuring the effectiveness can help produce even better marketing campaigns in the long run. (Rackley 2015)

Predicting the susceptibility of a potential customer to purchase is useful for companies, as identifying such people facilitates the marketing of the first purchase decision and thus the engagement of a new customer (Kotler & Keller 2016). These customers can be identified, for example, by their tendency to click on a certain type of link or certain types of content on social media, or behaviorally seeming to be willing to make a purchase. Such behavior can be, for example, browsing a certain type of clothing, in which case the customer has searched for a certain piece of clothing, brand or color. This allows a marketer or algorithm to trigger a purchase transaction, for example, with a special offer or by targeting a more aggressive marketing of that particular product to the potential customer. (Rackley 2015) Once the first purchase has taken place, the company gets more data on how this particular type of customer is rationalizing the purchase and is able to better predict the customer’s behavior and needs in the future. In Figure 6, marketing efforts’ targeting process is presented according to Schlee (2013).

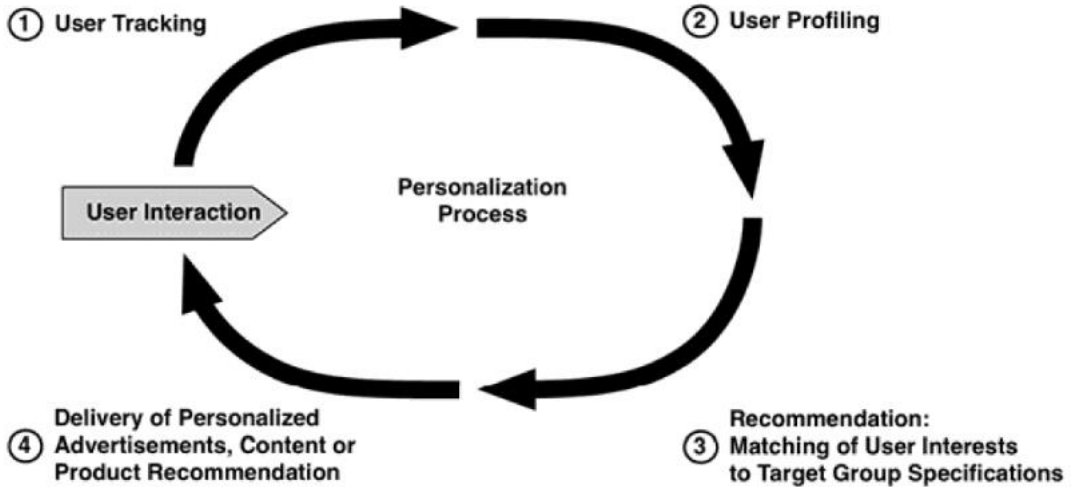

Figure 6: Marketing targeting process (Schlee 2013)

As seen in the figure, it is important to seek continuous development through experience acquired from previous marketing campaigns and their success to be able to upgrade marketing in the future, resulting in improving the overall profitability of marketing and the whole business.

5.4 Monitoring results and developing models accordingly

In order to measure and develop the results of marketing efforts, their goals and objectives must first be defined. Goals can mean, for example, deepening customer relationships or learning from different communities. Related goals can include reaching a new audience to find new potential customers, engaging customers in a conversation with the company, or mapping customer needs. The success of these goals can be measured by analyzing, among other things, the number of followers of the company, the number of content impressions, and the number or quality of comments and discussions related to the company. (Murdough 2009) The final success of a marketing campaign should also be measured financially, for example using the aforementioned ROI (Rackley 2015).

One of the good things about using neural networks is their ability to continually improve their own performance based on new data and their own performance. For example, Back Propagation is a technique used in guided learning to improve the performance of neural

networks. The Back Propagation algorithm compares the response produced by the neural network with the optimal result of the input given to it and evaluates the error produced by the neural network. When the calculated error is sent to the previous layers, each layer of the neural network and its node receive feedback on its performance. The feedback is proportional to each node's share of the output value. The neurons then adjust their activity according to the chosen algorithm and tend to reduce the error they produce in the next round. By updating the weights, the error rate is reduced, and the neural networks get closer to the desired result. (Merilehto 2018)

This concept can also be used in developing marketing campaigns by comparing different individual marketing efforts' success while their components vary, having the ultimate goal of getting the best ROI and achieving as many of other goals as possible during the whole campaign. This way, by automating as much as possible of the trial and error in different combinations of marketing efforts, customers' features, environment and other variables, the algorithm can continuously get more data about what is widely working and what is not, and therefore improving itself over time through experience. While sounding easy, applying this in real life marketing, however, requires large amounts of expertise as well in artificial intelligence as in understanding marketing campaigns and financial side of cases.

6 DISCUSSION AND CONCLUSIONS

Today, the amount of data available from social media and the internet is huge and every user leaves their digital footprint using these technologies, which can also be utilized in marketing. Machine learning models can be used to classify and group large amounts of data, in addition to which they can produce predictions, recommendations, and identify deviations. Deep-learning neural networks enable large-scale utilization of artificial intelligence and, among other things, allow image, video and voice recognition, which can help analyzing social media content better. The aim of the work was to form an understanding of the potential applications of intelligent analytics in marketing using this mass data provided by social media and the internet. The main research question was “how analytics and artificial intelligence can be used as a tool for segmentation in social media marketing?”

The goal of marketing is to find potential customers for the company, meet the customer’s needs or create a customer need that the company is able to meet. Smart technologies can be used to find more effective ways to meet the customer and find the right customers. There are many ways for doing so, such as finding different customer segments using processed data and targeting marketing actions based on those segments. This work explored the use of clustering and behavior modeling to produce information that makes it possible and effective to identify different traits and needs. Some other modern data mining models and techniques were also introduced to answer one of the sub-research questions about tools and opportunities for data utilization in today’s marketing.

The sub-research questions also addressed finding opportunities that social media brings to today’s marketing as well as discovering and collecting data that can be useful for marketing. Social media shows peoples’ knowledge, interests, social networks and often also basic information like age and gender. When data on transactions, inquiries and, for example, visits to a store is combined with data from the internet and social media, it is possible to define the customer's preferences, behavior and needs very precisely. An important benefit of social media marketing is the effective customer acquisition, which is made possible through massive amounts of customer data and advanced targeting and tracking tools. Marketing analytics tools can be used to delve into customer data, customer buying behavior and predictive analysis, test

and optimize online presence, and optimize the performance of multiple different campaigns simultaneously. By mastering the use of these tools, a company can stand out significantly from their competitors in social media marketing.

However, there are also many challenges and problems associated with the use of smart technologies as well as the analysis of social media and covering those was also part of the sub-research questions. One of the key issues is data availability and accuracy. As a result of poor quality or insufficient data, algorithms cannot learn to perform their task correctly and the analyzes produced by artificial intelligence models are unusable or produce erroneous results. Incorrect data can easily ruin the entire analysis and make its results misleading or even destructive to the company. Moreover, especially in the context of social media, the accuracy of the data is often questionable, as much of the available data is produced by users and thus very poorly controlled.

Even if artificial intelligence models worked flawlessly, people and companies are still responsible for the actions they take. Too much confidence in and dependence on machines can impair people's own problem solving skills and overall perception and management of the operating environment. In addition, hackers, for example, can infiltrate information systems and disrupt, manipulate, or destroy intelligent systems. As a result of a security attack, secret and very valuable information can leak to outsiders and it can be difficult or impossible to repair models if the machines have been trusted for a long time and their operation is not fully understood.

Artificial intelligence models do not create value per se, but the business benefits they bring depend on a company's ability to harness them as part of its business. Utilizing smart technologies requires knowledge of how to use them. There are quite a few experts specializing in artificial intelligence and a lack of expertise can hinder the planning, development and implementation of artificial intelligence projects. After the deployment phase, artificial intelligence systems must be managed and operated, which also requires expertise.

One of the problems with social media analysis is privacy protection and consumers' sense of privacy. Legislation related to targeted advertising and the collection of social media data is, to

say the least, unclear, and lots of legally accepted data collection move ethically in the gray area. These unpleasant aspects are strongly linked to issues such as privacy and discrimination. Collecting and using sensitive information can cause negative and violated feelings in content producers. To improve the transparency of targeting, work should be done to increase users' trust in the advertiser, making the situation more favorable to both parties. Clearer and perhaps even stricter legislation would reduce the risks associated with the possession and dissemination of data, bringing the level of privacy that users need to a higher level.

All in all, social media and the internet provide large amounts of possibilities in the means of collecting data and targeting business functions based on it. It also brings many challenges that should be taken seriously in order to be able to add value to all parties without harming anyone.

LIST OF REFERENCES

Amazon Web Services, Inc. (2020). What is Artificial Intelligence (AI)?. [WWW-document]. [referred 17.3.2020]. Available: https://aws.amazon.com/machine-learning/what-is-ai/.

Ball, J. E., Anderson, D. T., & Chan, C. S. (2017). Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. Journal of Applied Remote Sensing, 11(4).

Bello-Orgaz, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. Information Fusion, 28, 45-59.

Bian, J., Liu, Y., Zhou, D., Agichtein, E., & Zha, H. (2009). Learning to recognize reliable users and content in social media with coupled mutual reinforcement. In Proceedings of the 18th international conference on World wide web, 51-60.

Bre, F., Gimenez, J.M. & Fachinotti, V.D. (2018). Prediction of wind pressure coefficients on building surfaces using artificial neural networks. Energy and Buildings, 158, 1429-1441.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., & Trench, M. (2017). Artificial intelligence: The next digital frontier. McKinsey Global Institute, 1-80.

Cheng, Y., Qin, C., & Rusu, F. (2012). GLADE: big data analytics made easy. In Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data, 697-700.

Constantinides, E., & Zinck Stagno, M. C. (2011). Potential of the social media as instruments of higher education marketing: A segmentation study. Journal of marketing for higher education, 21(1), 7-24.

Data Protection Act 1050/2018. Issued in Helsinki on 5 December 2018. Available online: https://www.finlex.fi/fi/laki/ajantasa/2018/20181050.

De Swaan Arons, M., van Den Driest, F. & Weed, K. (2014). The Ultimate Marketing Machine. Harvard Business Review, 92(7-8).

Dekay, S. H. (2012). How large companies react to negative Facebook comments. Corporate Communications: An International Journal, 11(3), 289-299.

Deloitte (2017). The State of Cognitive Survey. [research report]. [referred 18.3.2020]. Available: https://www2.deloitte.com/content/dam/Deloitte/tw/Documents/technologymedia-telecommunications/tw-TMT-2017-deloitte-state-of-cognitive-survey_EN.pdf.

Deloitte (2018). Cognitive technologies. [WWW-document]. [referred 18.3.2020]. Available: https://www2.deloitte.com/insights/us/en/focus/cognitive-technologies/technicalprimer.html.

Deloitte (2019). AI-augmented human services. [WWW-document]. [referred 18.3.2020]. Available: https://www2.deloitte.com/us/en/insights/industry/public-sector/health-human-services-innovations-reform/ai-augmented-human-services.html.

Elgesem, D. (2015). Consent and information–ethical considerations when conducting research on social media. Internet research ethics, 14-34.

Facebook (2020). [WWW-document] [referred 11.3.2020]. Available: https://about.fb.com/.

Gandomi, A. & Haider, M. (2015). Beyond the hype: big data concepts, methods, and analytics. International Journal of Information Management, 35(2).

Golmah, V. (2014). A Case Study of Applying SOM in Market Segmentation of Automobile Insurance Customers. International Journal of Database Theory and Application, 7(1), 25-36.

Goodfellow, I. (2016). Bengio, Y.–Courville. A. Deep Learning.

Google/Magid Advisors, Global (AU, BR, CA, DE, FR, IN, JP, KR, U.K., U.S.), (2018). “The Role of Digital Video in People’s Lives,” n=20,000, A18–64 general online population.

Hanafizadeh, P., & Mirzazadeh, M. (2011). Visualizing market segmentation using self-organizing maps and Fuzzy Delphi method–ADSL market of a telecommunication company. Expert Systems with Applications, 38(1), 198-205.

Haverila, M. J., Uusi-Rauva, E., Kouri, I., & Miettinen, A. (2005). Teollisuustalous. 5th ed. Infacs Johtamistekniikka Oy.

Instagram (2020). [WWW-document] [referred 11.3.2020]. Available: https://about.instagram.com/about-us.

Ito, R. (2018). For AI, a real-world reality check | Google. [WWW-document]. [referred 17.3.2020]. Available: https://www.google.co.in/about/stories/gender-balance-diversityimportant-to-machine-learning.

Ivanov, I., Vajda, P., Lee, J. S., & Ebrahimi, T. (2012). In tags we trust: Trust modeling in social tagging of multimedia content. IEEE Signal Processing Magazine, 29(2), 98-107.

Jussila, J., Kärkkäinen, H., Multasuo, J., Allen, E., Anttila, S., & Isokangas, A. (2012). Sosiaalinen media asiakaskokemuksessa. Tampereen teknillinen yliopisto ja Ali Consulting Oy.

Kambatla, K., & Chen, Y. (2014). The truth about mapreduce performance on ssds. In 28th Large Installation System Administration Conference (LISA14), 118-126.

Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. Journal of Parallel and Distributed Computing, 74(7), 2561-2573.

Kapitanova, K., & Son, S. H. (2012). Machine learning basics. Intelligent sensor networks: the integration of sensor networks, signal processing and machine learning.

Kaplan, A. & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. Business Horizons, 53, 59-68.

Keegan, B. & Rowley, J. (2017). Evaluation and decision making in social media marketing. Management Decision 13, 55(1), 15-31.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. Business horizons, 54(3), 241-251.

Kohonen, T. (2013). Essentials of the self-organizing map. Neural networks, 37.

Korolov, M. (2018). AI's biggest risk factor: Data gone wrong. [WWW-document]. [referred 10.3.2020]. Available: https://www.cio.com/article/3254693/artificial-intelligence/aisbiggest-risk-factor-data-gone-wrong.html.

Kotler, P. (2003). Marketing Management. 11th ed. Upper Saddle River, Pearson Education.

Kotler, P. & Keller, K. (2012). Marketing Management. 14th ed. Pearson Education Limited. England.

Kotler, P. & Keller, K. (2016). Marketing Management. 15th ed. Pearson Education Limited. England.

Lan, H. (2018). Analyzing Climate Patterns with Self Orgnizing Maps (SOMs). [WWW-document]. [referred 6.4.2020]. Available: https://towardsdatascience.com/analyzing-climate-patterns-with-self-organizing-maps-soms-8d4ef322705b.

Lappi, O., Rusanen, A. M., & Pekkanen, J. (2018). Tekoäly ja ihmiskognitio. Tieteessä tapahtuu, 36(1).

Lee, P. M. (2013). Use of data mining in business analytics to support business competitiveness. Review of Business Information Systems (RBIS), 17(2), 53-58.

Li, Y., Jiang, W., Yang, L., & Wu, T. (2018). On neural networks and learning systems for business computing. Neurocomputing, 275, 1150-1159.

Lieb, R. (2012). Content marketing: think like a publisher--how to use content to market online and in social media. Que Publishing.

Maldoff, G. (2016). How GDPR changes the rules for research. The International Association of Privacy Professionals. [WWW-document]. [referred 24.3.2020]. Available: https://iapp.org/news/a/how-gdpr-changes-the-rules-for-research/.

Marr, B. (2017). Data Strategy- How to Profit from Big Data, Analytics and the Internet of Things. London, Kogan Page Limited.

Marr, B. (2019). The amazing amounts of data we create in a single day. [WWW-video]. [referred 11.3.2020]. Available: https://www.youtube.com/watch?v=VLAnBI2B4OY&feature=emb_title.

Mathews-Hunt, K. (2016). CookieConsumer: Tracking online behavioural advertising in Australia. Computer Law & Security Review, 32(1), 55-90.

MathWorks. (2020). Neural Network Toolbox: Clustering: Self-Organizing Maps: selforgmap. [WWW-document] [referred 30.3.2020]. Available: https://se.mathworks.com/help/deeplearning/ref/selforgmap.html.

Márquez, F. P. G., & Lev, B. (2015). Advanced business analytics. Springer International Publishing.

McKinsey Quarterly. (2018). What AI can and can't do (yet) for your business. [WWW-document]. [referred 19.3.2020]. Available: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/what-ai-can-and-cant-do-yet-for-your-business.

Merilehto, A. (2018). Tekoäly- Matkaopas Johtajalle. Helsinki, Alma Talent Oy. 206.

Morabito, V. (2015). Big data and analytics. 1st ed. Springer.

Murdough, C. (2009). Social media measurement: It's not impossible. Journal of interactive advertising, 10(1), 94-99.

Müller, V. C. & Bostrom, N. (2016). Future progress in artificial intelligence: A survey of expert opinion. In Fundamental issues of artificial intelligence. Synthese Library. Springer International Publishing.

Phua, J., Jin, S. V. & Kim, J. (2017). Gratifications of using Facebook, Twitter, Instagram, or Snapchat to follow brands: The moderating effect of social comparison, trust, tie strength, and network homophily on brand identification, brand engagement, brand commitment, and membership intention. Telematics and Informatics, 34(1), 412- 424.

Rackley, J. (2015). Marketing analytics roadmap. Berkeley, Apress.

Runkler, T. (2012). Data analytics. Wiesbaden, Springer Vieweg.

SAS Insight. (2020). Machine Learning: What it is and why it matters. [WWW-document]. [referred 19.3.2020]. Available: https://www.sas.com/en_ae/insights/analytics/machine-learning.html.

Schlee, C. (2013). Targeted advertising technologies in the ICT Space: A use case driven analysis. Springer Science & Business Media.

WhatsApp (2020). [WWW-document] [referred 11.3.2020]. Available: https://www.whatsapp.com/about.

Yang, S., Towey, D., & Zhou, Z. Q. (2019). Metamorphic exploration of an unsupervised clustering program. In 2019 IEEE/ACM 4th International Workshop on Metamorphic Testing (MET).

YouTube (2020). [WWW-document] [referred 11.3.2020]. Available: https://youtube.com/about/.

Ziafat, H., & Shakeri, M. (2014). Using data mining techniques in customer segmentation. Journal of Engineering Research and Applications, 4(9), 70-79.