Potential Artificial Intelligence Features for Digital Marketing Performance Analytics Product
Case Company: Madtrix

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Abstract

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This thesis is a qualitative study for a technology start-up with a SaaS-product in marketing performance reporting. The researches' objective was to understand the possibilities of artificial intelligence; an inquiry of product development through gained knowledge formulated the objectives and methods used in this thesis. Recommendations for a specific domain require an understanding of a concept at a general level.

The theoretical framework for the study is formed around understanding the concept of artificial intelligence and the theory it withholds, benchmarking the digital marketing reporting industry leaders and interviewing the experts of the subject technology and the case company's target customer segment of digital marketing agencies. Machine learning was identified as the principal technology. Its models and algorithms formed the basis for the theoretical framework.

The methodology of the study describes the research process and methods used. The key components of the research were a qualitative analysis of data which was acquired by desktop research, empirical studies, and interviews. Primary data was collected by interviewing experts in artificial intelligence and the personnel of a digital marketing agency. The main themes of the interviews consisted of relations between the participants and artificial intelligence and the general characteristics of artificial intelligence. Secondary data was collected by researching written sources. It consisted of scientific articles, books and other text sources addressing the subject technologies.

Research data was then analysed and validated through qualitative analysis. Benchmarking of the marketing reporting industry leaders was conducted to understand the implementation of the findings.

The study formed two feature recommendations for the case company: a system to bring insights from accumulated data and a prescriptive analytics dashboard. The results were validated after thesis work through discussions between the main stakeholders of the study. The findings serve as solid foundations for the author in future studies and future life.

This study was conducted primarily between April 2018 and October 2018.

Keywords
Artificial intelligence, machine learning, digital marketing reporting, SaaS.

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1 Introduction

It is said that if one does not measure it, one cannot develop it. This clause, in essence, is the business case of the case company in digital marketing reporting and performance analytics setting. This setup can be potentially taken even further with technological solutions harnessed from artificial intelligence.

The first chapter of this thesis presents the case company, research problem and the overall setting of the study. The reader should get familiar with the central concepts of the thesis by going through this macro-level framework. The structure of this first chapter is to lead the reader from more general topics towards specific information which is aimed to build a common ground for a reader to understand the scope of the study and the domain it operates.

1.1 The case company: Madtrix

The case company of this thesis is a spinoff from Avarea Oy. Case company's name is Avarea Analytics Oy and its auxiliary business name, as well its product name, is Madtrix. The latter one is used from now on in this study. The company was established in February of 2018. The company was in the start-up phase and consisted five employees in the start of July 2018.

The case company provides marketing performance analytics dashboard as Software-as-a-Service (SaaS). It is operated through the internet where it is connected to data providers such as LinkedIn, Instagram, Facebook and others via APIs (Application Programming Interface). Dashboards for reporting are the business case of the Madtrix.

The case company was established to pursue internationalisation through scalability of the service. The SaaS product of the case company is a tool monitor to marketing operations and to visualise results and effects of operations. The aim is to provide data to support decision making in marketing.

Currently, the case company has two identified target segments:

1. Marketing agencies which gather data and report to their customer concerning their marketing performance and operations.
2. Independent enterprises ergo internal marketing departments inside organisations.

As the functions of this group are ultimately similar – reporting, analysing and improving marketing operations to enhance the decision making and provide actual business value to stakeholders – this study pursues the perspective of marketing agencies. I argue this choice with the aim of having more generalised research results: marketing agencies are saturating the same industry with similar functions between each operator, and their actions can be compared more accurately between said companies. Whereas internal marketing departments can have multiple ways of operating their marketing functions due to organisational strategy, value drivers, industry and so forth. Picking the marketing agencies simplifies the process with more general industry domain.

1.2 Background of the thesis

My past presence in the Madtrix offered the opportunity to understand more about digital marketing and its technologies. During the thesis process, the case company was directly present in the marketing technologies industry, and thus it came viable to do research about the subject and concentrate on the future of said technologies.

The marketing reporting and performance analytics was traditionally done via excel sheets and such or in other words: manually. The visualisation of the marketing reporting in these kinds of processes is dependent on the quality of the data in the spreadsheets – the human error was ever-present. The case company had built a business case from more automated and marketing reporting and performance analytics based on data. The industry was saturated due to the ease of data extraction from multiple data-providing platforms such as Facebook and Google Analytics. The companies developing digital marketing reporting tools focused on developing their own product's front-end and back-end functionalities and the data itself were usually distributed to the system via APIs. Madtrix's marketing reporting dashboard visualises the gathered data with visualising tool from Microsoft Corporations product called Power BI. This product ensured the use of the product through web-browser: the customer's marketing data is stored in the cloud-based server and visualised through dashboard(s). The marketing management conducts the process of turning marketing information into meaningful decisions which are in line with a company's marketing strategy and target (Sharp 2013, 464). In this instance, the case company's product visualises the information gathered from different marketing channels. This data can consist of marketing performance, click-through-rates, conversion rates or any other metric defined as essential. Sharp (2013, 464) also emphasizes the importance of timeliness in marketing; getting real-time measurements can help marketing departments to take faster actions with communications, ads et cetera to align them with overall marketing targets and a company's overall business strategy.

I, as an author of this study and novice marketing professional, understand the importance of the marketing reporting. Deleting or reducing the human error and unnecessary workload from the process of reporting & performance analytics and additionally make the measuring the results as real-time as possible is an intriguing concept. I understand this to be a big leap for marketing occupation: people in charge of funding and executing marketing functions can see measurable results and make decisions based on concrete data. This aspect was not self-evident at the time of the thesis. Researching the possibilities of artificial intelligence in marketing gives tremendous opportunity to understand the future of the industry. Understanding the benefits of timely and accurate marketing performance data and its possibilities remains as key motivational aspects for me – Abela & O'Sullivan published research in 2014 which summarises the importance of marketing performance measurement (MPM) quite well. The marketers have lost some of their power inside organisations due to the lack of measurements concerning marketing results, but the findings suggest that competent effort to use MPM has a positive impact on company's overall performance (Abela & O'Sullivan 2014, 79-93). Abela's & O'Sullivan's study is the first one to clearly state the importance of measurement in marketing and showing the correlation between marketing measurement and company performance. The results of the study support my professional incentive of understanding the industry.

1.3 Key concepts

This sub-chapter provides information on key concepts which I saw important to understand for comprehensive dialog between reader and the thesis.

Algorithmic marketing is an automated marketing process that can be steered or manipulated with setting a business goal into a marketing software system. This fact implies the need a certain level of intelligence from the system; it should be able to process how to maximise profit or acquire a maximum amount of views (Katsov 2018, 20). Algorithmic marketing is highly automatized system, and automatization is made possible with algorithms.

Application Programming Interface (API) according to Reddy (2011, 1) define reusable building blocks which makes it possible modular pieces of functionality to be integrated into the end user's applications. In practice, API makes it possible to connect programmatical software and share functionalities between them.

Artificial intelligence (AI) as defined is the ability for digital computer, robot or other related entity to perform a task or tasks that are usually likened to intelligent being (Encyclopedia Britannica 2018). Jim Sterne (2017, xvii) offers an interesting view with the statement that AI is the next natural section of computer science; it has capabilities to figure things out by itself and additionally even reprogram its functionalities when needed.

Elements of AI -internet course by University of Helsinki and Finnish company named Reaktor (2018) adds that AI is a scientific discipline and it can be compared to biology and math; it is a method to solve concepts and problems.

According to Virtanen (2014, 4)**, Machine learning (ML)** is a programmed entity which focuses on the vast amount of data where it extracts helpful information from the collected data. Elements of AI (2018, chapter 2, section1) states that ML is a system which is capable of improving its performance in tasks that have been given to it. This is called learning and it usually happens with the accumulation of data and experience. Machine learning is a subfield of AI and at the time of the thesis, AI in marketing was usually seen as ML by experts.

SaaS is holistic solution/application delivered as a service for a customer – the role of the user is only to adjust service-specific information in the service which is operated entirely by the service provider concerning technical upkeeping, developing and support (Kavis 2014, 18). SaaS is a service model where the customer accesses the functions of the service traditionally through the internet. At the time of writing, the SaaS-platforms were seen as the most advanced version of technical applications where the vendor maintains and updates the service and customer is only responsible for using it.

1.4 Demarcation

This thesis focuses on already existing technologies regarding thesis subject and the case company's product. The goal is to understand how case company could benefit subject technologies in their digital marketing reporting product and why. Up-and-coming technologies and possible, theoretical technologies were excluded – the aim is to avoid speculation considering future possibilities as the technological domain and its developments were unravelled.

I focused on the solutions on a conceptual level and hence the technical level, such as used algorithms in the actual code, is not included. I justified this by the requirements of bachelor level thesis and the lack of knowledge needed in the software development process.

The context of marketing used in this thesis is digital marketing, hence all the references to marketing concerns the context of digital marketing it isn't mentioned otherwise.

As I have used general terms as 'technology,' 'feature,' 'solution' among others, they are related to artificial intelligence and machine learning if not specified otherwise.

2 Aim of this study

The field of artificial intelligence, and therefore its subcategory machine learning, was the pinnacle of hype in the sphere of marketing industry when I worked on this thesis. In my understanding, all the industry players were looking to exploit the possibility of AI-related technologies. Artificial intelligence itself is hard to grasp on; it is filled with buzzwords, and this problem could be extracted to the question ‘what AI is?’. We, as a specimen, don’t truly know. Researchers, engineers and even philosophers speculate the potent threat of hyper-intelligent entity with misaligned goals regarding humanity. With its consciousness, it could be capable of eradicating the species of homo sapience from existence to save planet Tellus (Hughes 2018). Craig Sennabaum (2018), Software Engineer, argues that AI is inevitable a threat to humanity – but the degree of threat is not known. He describes the situation between India and Kansas City: probability to get bitten by King Cobra is much smaller in the latter one, but the possibility of it exists in case of misfortune in transportation for example. This narrative could be projected to marketing too through the uncharted landscape of artificial intelligence. The argument is the concept itself: is AI anything else but sophisticated machine learning algorithm when it is applied to marketing and what it should be? This point of view should be presented in the dialog related to thesis’s subject, but I decided to ostracize it from the text for the sake of the scope and simplicity of the study.

For me, the complicated part of artificial intelligence and its subcategories was to find or create a concrete business case with these technological solutions – products and solutions are developed to create value for user(s). The implementation of technological features just for the sake of the implementation isn’t viable for any stakeholder. The discussion regarding associated topics can be seen speculative due to the lack of maturity of the artificial intelligence industry and its solutions, but the structure of the thesis was composed to support the pursuit of the objective research process to ensure the reliability and validity of the findings.

The validity of the chosen topic stems from the commissioning company’s customers. The industry of marketing and advertising agencies is in disruption, and the agencies are looking for the optimal position in this shifting environment. In-house marketing departments can now execute many of the tasks done by the agencies in the past, and I think agencies needed to find their way to react to these shifts. According to my understanding, data was the most vital component in this fast-changing digital environment; customers and their preferences are increasingly crucial to any successful marketing operation – for example, consumers wanting tailored content concerning advertising was one of the key changes in the vastly digitalised marketing landscape.

According to Bjelland, Iqbal, Montjoye, Pentland & Sundsoy (2014, 367-374) machine learning in text-based marketing outperformed professional marketers in conversion rate: the system had thirteen (13) times better results regarding customer conversions and customer retention. Additionally, the number of renewed contracts were superior against the control group of humans. I think this is a valid point to bring in to a discussion in the form of a hypothesis. If a machine can make more sophisticated assumptions backed with data, why should not marketers embrace it in marketing reporting and use this knowledge?

That in mind, the end-goal of this study was to support the development of the case company's marketing reporting tool. That might provide better means to the case company's clients to make business decisions based on data. The business objective for both parties, the case company, and its customers is ultimately to provide value for their customers respectively. Marketing data is rich but extracting the key elements and customer information demands well-composed back-end technology from the product; these include mathematical models and computer algorithms. This study does not speculate on what degree the phenomenon of artificial intelligence in marketing was during the thesis project or where it should be. Instead, as a bachelor thesis conducted in a university of applied sciences, it focuses to find concrete development ideas for the case company's product and to solidify arguments for the conclusions through research. This process of finding development ideas was aimed for artificial intelligence and machine learning features. Thus more traditional development ideas were only taken account if they were related to subject technologies.

2.1 Research Question

This thesis aimed to find potential AI & ML features which could be beneficial to implement to the case company's marketing performance reporting product and strengthen their aspiration to venture their chosen business opportunity in marketing reporting industry. The objective of the main research question (RQ) and investigative questions (IQ) set was to provide structure and guidance for the actual research.

The thesis consists of the main research question and three, so-called investigative questions.

Research question: What are the beneficial artificial intelligence features that could be implemented in case company's marketing reporting solution?

IQ1: What do the concepts of 'artificial intelligence' and 'machine learning' mean in marketing technologies domain?
IQ2: What do the industry leaders, Google and Adobe offer concerning subject technologies in marketing reporting?
IQ3: What do the future of artificial intelligence and machine learning look like for marketing agency and subject technology experts?
IQ4 (initially included in thesis): What are the features which marketing agencies feel they need in marketing reporting tool?

Table 1. consist the main questions for the thesis which are answered. The last chapters tie up the research.

Investigative question	Theoretical framework	Research methods	Chapter for results
IQ 1. What do the concepts of 'artificial intelligence' and 'machine learning' mean in marketing technologies domain?	Artificial intelligence and machine learning in general and in marketing domain Applications	Desktop research Qualitative desktop research and analysis (theory and concepts)	Chapter 3 7.1.
IQ 2. What do the industry leaders, Google and Adobe offer concerning subject technologies in marketing reporting?	Benchmarking	Desktop Study Observations and empirical studies Qualitative analysis	Initial results: 4.5. & 4.6. 7.1.
IQ 3. What do the future of artificial intelligence and machine learning look like for marketing agency and subject technology experts?	Insights from experts operating in target industry and subject technologies	Interviews Discourse analysis from qualitative interview Qualitative analysis	Initial results of analysis: 6.3. 7.1.

Table 1. Overlay matrix.

When investigative questions one to three are answered through research and key findings, the research problem is answered in chapter 7.

2.2 Anticipated benefits

There were three primary stakeholders in this thesis: me, the case company and the Haaga-Helia University of Applied Science. Hence, benefits can be divided into two categories: personal benefits for the author and organisational benefits for the case company and the Haaga-Helia UAS.

The first category is self-explanatory; I was to acquire first-hand knowledge from technologies discussed in thesis and from experts of the subject. Thesis process provided a possibility for me to grow as a professional regarding academic writing and research. The process gave me an opportunity to study the profession of marketing professionals and experts of the technology from different angles, such as future of digital marketing and understanding the perspectives of the marketing agencies and actual artificial intelligence experts. Additionally, getting onboard on modern technologies could prove to be the vital component for the future success of mine.

Organisational benefits are divided among participating parties. Madtrix got the chance to penetrate to their marketing agency customer segment with direct communication provided by thesis process. Additionally, they got valuable customer intel and insights from a target customer, subject technology experts, and the case company took the first steps in cooperation processes with students. On the other hand, the university will gather their fee from the author’s graduation and gain visibility in my employers and the case company’s organisation. Thus, all the involved parties will get measurable benefits from the thesis

3 What is artificial intelligence?

John McCarthy (1998, 2) defines artificial intelligence as a method or science where intelligent, usually computer or computer-based, programs or functions, are engineered and developed. It is a subfield of computer science, which McCarthy states that the ‘intelligence’ is the computation part which aim is reaching goals in the world. The concept is historically tied to human intelligence due to our species’ capabilities. This stem, according to my understanding, from the human specimens self-entitled position as most sentient and intelligent being in the world. This self-adopted role pushes our meaning of existence to understand and study ourselves in order to build functioning simulations from our minds. The recognised founder of artificial intelligence, Alan Turing, wrote in 1950 that the spiritual form (mind) needs our body, matter, to interact with the environment. Later, in 1951, he polished this idea from intelligent machinery with capabilities with adaptive intelligence - essentially this would be a machine that can learn by itself and thus taking itself further as an entity. When discussing artificial intelligence and Turing, the widely recognised father of AI, one should understand that the studies regarding the subject have shifted more from *understanding* the functions of a human mind to the aim of building computer programs which are and function like human mind (McCarthy 1998, 4).

Computers and computer programs are devices which function only when predefined symbols are manipulated inside a certain set of rules. Here lies an alignment problem. According to Sterner (2017, 19), it is complicated for a system to understand the human context of any pursued goal. Values, for example, varies between individuals and this makes it complicated to make a machine understand the full spectrum of possible consequences in a given scenario. According my understanding, it is essential to define the level of artificial intelligence in use. Thus, next subchapter distinguishes the strong and weak artificial intelligence from each other and studies important concepts a bit further.

I interviewed Madtrix’s software developer Toni Nurmi for the thesis and to understand the case company’s internal view towards the researched technologies. He described the amount of data which was cumulated by one customer of their SaaS-system as *huge*. Data amount was an ideal basis for the technologies of the case company as they required humongous amounts of data. The erstwhile situation regarding the subject indicated that AI was not business critical for the case company at the time. Nurmi continued to describe the situation from their point of view. The AI industry did not have ready-made services that a user could implement to their software, and the code had to be built separately for every business case. This was not viable for marketing reporting SaaS-products due to the complicated adoption of the AI & ML processes. He added there to be an incentive to develop artificial intelligence into the product in the future – hence *heuristic AI* was brought to the discussion. In this context, Nurmi described it as a “gorging technology” which would go through the data and it could surface formerly unseen insights with proper business value. The particular unique selling point (USP) for the company’s solution would be to gain knowledge from cause and relations of marketing actions; according to Nurmi, it would be a great asset for the customer in the sense of comprehending data cumulated from marketing (Nurmi 5 April 2018).

As I worked in the field of digital marketing in a company with data scientist and analysts, I think it continues to be essential to understand basic analytics in marketing. This meant, in my case, to understand for example Google Analytics (GA) and its analytical tools. For the reporting tool to offer concrete value, the user itself must be somewhat of sophisticated in analytics. In my mind, to understand the value of visualised data and to draw consequences and causations based on it is crucial. This process gets harder with omnichannel marketing and when various functions are added to the mix. Thus, having a marketing reporting tool in disposal is important – marketing functions should be operated based on created value and performance like any other business function.

3.1 Strong & Weak Artificial Intelligence

The first phase in categorising an artificial intelligence is to define if it is ‘*strong*’ or ‘*weak*.’ Sterner (2017, 71) uses the definition from University of California, Berkeley’s websites which defines strong artificial intelligence as a system of same intellectual complexity and functionality compared to humans, whereas Elements of AI (2018, Chapter 1, Section 3) argues the same case with the difference between general (AGI, General Artificial Intelligence –basically same as *strong AI*) and *narrow AI*; in practice, all the of the applications during the thesis process belonged to the latter category. *Strong AIs* was out of humanity’s grasps due to multiple reasons at the time of writing process. The main obstacle, as I understood, was the lack of the definition of intelligence itself which was related to uncharted functionalities of human brains. Elements of AI states (2018, chapter 1, section 3) that AGI was already abandoned as a possibility by researchers due to lack of advances during the past half-century. Strong artificial intelligence is commonly defined as a system with self-conscious, some degree of singularity and human-like intelligence. Hence, as we do not fully understand the nature of intelligence of our species, the ‘Elements of AI’ presents a valid dilemma of intelligent machines (2018, chapter 1, section 3): can self-driving cars operating in changing environment and chess-playing algorithm with ‘*perfect information*’ be compared in sense of intelligence? Sterner (2017, 71) implies that the attractiveness of developing an artificial mind kept this dream as science fiction; it does not hold water. Even though I discovered multiple projects by multinational companies concerning AI, none of them openly stated that they were creating a conscious mind but self-sufficient multitasking operators. For the sake to validate this argument, I argue my case with the example of Google AI. It is Google's initiative to make smarter information flow and data usage. They fund researches and projects like Tacotron 2; a system which creates natural sounding speech from given text or DeepDream which enhances the image recognition processes conducted by machines. These are topics that are computable and did not require a *human intelligence* per se, but human operator is needed to develop and train the machines. This relationship is a fundamental part of artificial intelligence and machine learning. Figure X describes the relation of different concepts of artificial intelligence and how they are integrated according to Elements of AI (2018, chapter 1, section 2). This taxonomy goes as follows:

A. Computer Science
B. Artificial intelligence
C. Machine learning
D. Deep learning
E. Data Science

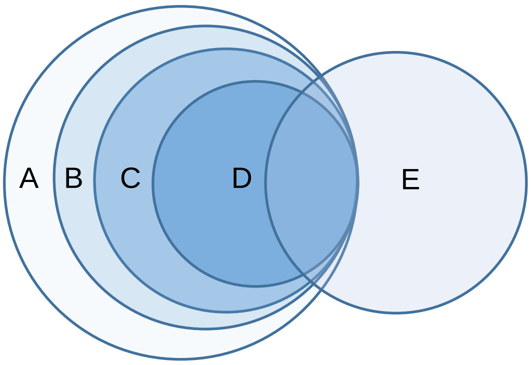

Figure 1. Taxonomy of artificial intelligence showing the relations between related topics.

This thesis focuses on the weak, or narrow, artificial intelligence which is defined as a system that performs a specific task while getting better in it (Sterner 2017, 71). These tasks are achieved with a solution belonging under the umbrella term of AI: *machine learning*. Next subchapter composes a picture from *machine learning* and validates its possibilities in marketing and marketing reporting.

3.2 Algorithm – Key component of AI & ML

I saw it necessary to clarify the concept of an algorithm in the setting of my thesis. Katsov (2018, 4) introduces algorithmic marketing and defines it as a marketing process which can be directed with setting a business objective into the system. Katsov continues that a system should be able to understand the processes of marketing at high-level, for example customer acquisition. From that, it should be able to *plan and execute* a set of business actions, for example price adjustment in ad set, and learn from the result to correct and optimise its actions. Katsov continues that ideal systems would be fully automated. This goal is not a requirement. Instead, these systems are usually maintained by many professionals who develop and adjust *algorithms* to improve the system. Bengio, Courville & Goodfellow (2016, 105b) define machine learning algorithm as an algorithm which can better the functions of a computer program in an *abstract level*. I had an email correspondence with Toni Nurmi to strengthen the overall definition of an *algorithm* in computer science. As defined by Nurmi (11 September 2018), an algorithm in computing is a code block/code library/module/function which purpose is to find a solution to a certain problem which isn't already known or can't be concluded. The mathematical definition would be "a mathematical model which completes a task as efficiently as possible. He gave on example from a binary search which is based on a binary tree (Appendix 2). It is a mathematical model for fetching certain type of information simultaneously as it allows the system to go through massive amounts of data.

According to my understanding, algorithms in marketing reporting are the channel to create a funnel from data to analytics, and in the end, the reporting part visualises the outcomes of these processes. In other words, the visual components like graphs are formed with different functions and algorithms, analytics, and the final presentation is reporting. Hence, for example machine learning algorithms in marketing reporting can be visualised attributes of individuals reaching a message and then completing actions based on the observed, or learned, notions. This is true if the machine is sophisticated and built for that function. Marketing performance reporting might be only making sophisticated observations from the data, and a user is the one making further actions.

3.3 Machine learning

Machine learning is a method or a system capable of processing a vast amount of data and sourcing outcomes from processed information. It excels in cases where it would be hard for a human to process the information efficiently; these are called *high-cardinality* and *high-dimensionality* problems. Sterner (2017, 70) defines the terms as followed:

High-cardinality means the uniqueness of the data in the columns of a dataset. For example, in marketing, this could mean dataset consisting of information from contact requests left on the internet site of the company or. The dataset could include columns like e-mail, phone number, name et cetera – highly unique input values for every column.

High-dimensionality would be a dataset, for example from specific individuals consisting of many attributes. The more inputs data consists, the higher the dimensionality is.

Learning of machine learning functions with algorithms happen when a computer program goes through task iteratively and *learns* after each 'loop'. Mitchell defines this learning process:

> "A computer program is said to learn from *experience* **E** with respect to some class *task* of **T** and *performance* **P**, if its performance at tasks in **T** as measured by **P** improves with experience **E**" (1997, in Bengio & al. 2016, 96a)

Bengio & al. defines the components of Mitchell's computer program's learning as followed (2016, 96-101a)

The task, T: the task is the way the machine should process an example. This example is a list of features which are quantitatively measured from a chosen event, and which is given to machine to process.

The performance measure, P: A quantitative measure directly designed or formed for the task (T). Creating a performance measure for machine learning is challenging due to the hardship in choosing what to measure. In brief, for a classification task, it is usually simple: stamdard measurement is the value *accuracy*. It tells if the model produces the right output. *Error rate* gives the same outcome as *accuracy* but in the relation of incorrect output. In these two measures, the 0-1 system is used – value 0 if it is not correct and value 1 is the output is right.

The experience, E: Classification of *supervised* and *unsupervised* machine learning defines what kind of experiences the machine will have. Experience affects to outcomes of every iteration, and it is based on a dataset which is distributed to the machine to experience entirely.

I picked a commercial source to define the machine learning process to understand the *task-performance-experience* -funnel (*T-P-A from now on)* in more common context. Lauri Järvenpää, Head of Development and Co-Founder of Lamia Oy, a private company developing digital services in Finland, defines the machine learnings' process in four steps as followed (21 August 2018):

1. **Gathering data:** various sources can be used to gather data, but the most important is to have a large quantity of data, and it should preferably be high-

quality. Former, according to Järvenpää, ensures a better base for the next steps and to machine learning itself.

2. **Preparing the data:** after gathering the data, it is analysed carefully. This step includes an assessment of its quality and it is enhanced to ensure its usefulness as the base for the upcoming model.
3. **Developing the model of machine learning:** This phase is critical because the fitting algorithm for a specific use case must be selected – Järvenpää argues there to be a lot of ready-to-use machine learning platforms. The data is divided into a training data set to improve the functionality of the model – Järvenpää uses apples as an example: apples are shown to the system enough times for it to learn to identify an apple from pictures it has not seen before.
4. **Assessment and developing of the model:** Data divided in step three is used as test data and model is compared to original objectives. Järvenpää underlines the importance of using a different source for training data and test- / assessment data to achieve reliable results.

As far as I understand the matter, the **T**-**P**-**E** -process of Bengio & al. and Järvenpää's four steps define the same thing with different theoretical levels. The latter is constructed with commercialised words. Järvenpää's theory helps Lamia's target customers to understand the topic. Whereas the Bengio & al. describes a theoretical backbone for the machine learning process. It uses values **T**,**P**,**E** which can be given different variables, attributes, algorithms and so forth when the process and its components are developed and optimised. This means that the values are just "face-values" for more complex entities. I could roughly summarise that Järvenpää's steps one and two are part of the task (**T**), step three the performance (**P**) and the fourth the experience (**E**).

To understand this concept of machine learning and its processes better, according to Sterner (2017, 74) one must understand some basic statistics. The classical example of the necessary knowledge needed would be the difference between *classification* and *regression*. Classification is a simple task to divide topics (animals, products et cetera) into classes; cat versus dog or shoe versus shirt. Regression aims to tell analysis with many involved numbers; for example, the customer is more likely to buy medicine in correlation with fever: higher the fever, higher the likeliness to buy a medicine. Both are also common tasks (**T**) for the machine learning to process (Bengio & al 2016, 97a)

In marketing reporting, data cumulates constantly in relation to for example marketing actions and used channels. The challenge of real-time processing of data cumulating in high-velocity might be insurmountable for a human to manage, but it is machine's forte. As

Sterner and Elements of AI both state that a machine optimises and mend their performance with time and more processed data, this forms the basis for a machine's *learning*. Learning can be achieved in three ways: *supervised*, *unsupervised* and *reinforcement learning*. Sterner and Järvenpää name the last step of the machine learning process as *feedback-loop* (2017, 87; 21 August 2018). I have adopted the term to describe machine learning processe's iterative nature because I see the term as self-explanatory. Three categories and some of the models behind them are described in next subchapters.

3.4 Supervised learning

This learning method is commonly used in cases where a user already knows the outcome. Bengio & al. implies that the term *supervised learning* stem from the concept of *instructor*: the target of a process is given for a machine by a user/developer, so it knows what to do (2016, 102a). More technical definition of it would be one of Katsov's: supervised methods work between input variables and following responses ("conditional probability densities") (2017, 42). With that in mind, I interpreted that Katsov's means the relation between inputs and outcomes are related due to the supervision of kinds.

The simplest forms of *supervised learning* are binary classification problems answering '*yes*' or '*no*' (Elements of AI 2017, Chapter 4, Section 1). Sterner uses the example of cat-pictures (2017, 75): user (a human) knows that given picture has a cat in it but cannot process efficiently through millions of pictures. Sterner projects this to customer acquisition. A user can define an ideal customer profile with chosen attributes. In this hypothetical case, the data is taken from CRM, Facebook's targeted marketing data or a source consisting of similar attributes. Gathered data acts as training data for the machine, and it starts to find patterns and similarities among the customers, ultimately defining predictive elements of a "good customer". User inputs a new dataset consisting possible, prospected customers and the machine points out the individuals *most likely* to convert as customers based on the training data. The user gets to correct the data after the process, or as Sterner says, to inform the machine if the pictures consist those wanted cats or if it labelled pictures incorrectly. This step helps to achieve better precision in upcoming iterations. In use cases conducted with *supervised learning*, the machine and model must be considered and treated as a supervised entity - the machine might classify a company's best customers by name in the given classification example. Even though it is theoretically correct, the information might not be useful. Every completed iteration with dialog between user and machine makes the machine more sophisticated in its tasks. This iterative dialog is a direct example of the *feedback-loop* mentioned by Järvenpää (21

August 2018). One must understand that this process is part of the *unsupervised learning* too, but the learning happens without an instructor.

3.4.1 Bayes' Rule

Bayes' theorem, or as it is sometimes named when it's applied to real world: *Bayes' rule* (Olshausen 2004) is a useful component for understanding the machine learning. It is a statistical method named after late Reverend Thomas Bayes to describe the necessity of relation of past events to current phenomenon. In scientific lingua: *Bayes' rule* offers a mathematical framework to reason through probability. It is widely used in science to align the theoretical hypothesis to a sparse or narrow data concerning used parameters (Olshausen 2004). A commonly used example is coin flipping; the result of the next flip does not depend on the last one; hence it is not statistically relevant in terms of Bayes theorem. Whereas consumer buying a smartphone raises the likelihood of him/her buying a screen cover for the device. *Bayes' rule* as defined:

Posterior odds = Likelihood ratio x Prior odds

Olshausen (2004, 1) states the usefulness of *Bayes' rule* stem from its nature as factor to judge the relative "truth" of a hypothesis in relation with acquired data. As a foundation of machine learning in marketing, Sterner (2017, 76) argues its possibilities to find probabilities with the example of areal consumption behaviour. Given that area *X*'s consumers devour geological literature and drive zero-emission cars, but you want to know the characteristics of area *Y* with no prior data. So, the data can only be speculated. When data layers such as weather and other statistics are added, the math in this speculated scenario grows to be complicated. Understanding the effects of variables is essential for justification of the speculation: weather does not affect the *probability* of consumption as much as financial climate and local industry. For the smartphone example, the *probability* of buying a cover can be calculated more accurately when one holds enough factors and their effect on to the consumers' behaviour – the *likelihood* can be narrowed down with calculated information. The *Bayes' rule* is handy when one wants to revisit the results of the calculation when new data is acquired (Oldhausen 2004, Sterner 2017, 75-76); Sterner also adds it to be even more important to understand *the effect of incorrect information and its consequences to probabilities*.

3.4.2 Decision trees & Random Forest

Machines' fast processing functionalities are optimal for *decision tree* modelling. In marketing, it can be used for example in customer lifetime value reporting and thus targeting ads better in the future based on logical conclusions. The *decision trees'* logical decision path can be visited and examined afterward by a user – therefore one of the advantages of the model is the easiness of understanding the information flow and reasoning behind the results (Sterner 2017, 78). Bengio & al. (2016, 140a) state that decision trees belong to the group of simple supervised learning algorithms. *Decision trees'* model divides the data input space for various regions, and each region has its parameters.

Sterner (2017, 77) portrays the *decision tree* with an example of customer lifetime value and building a model which tells the individuals who are *most likely* to convert with ads or promotions based on existing customer data. Decisions tree in practice starts with one *node* split which divides to two child nodes. The next example uses gender to describe the process: female (0) or male (1). Input data passes the top node and heads to the child node with matching data (Bengio & al. 2016, 140a; Sterner 2017, 77) – this is the part that could be done without a specific algorithm. According to Sterner, the models' usefulness increases on correlation with a number of attributes that are added to the mix. Let's continue the example: the two *child nodes*, female (0) and male (1), are split to further *child nodes* based on information in the data; Sterner uses examples such as age, credit score, gender and ZIP code. The list of possible attributes is theoretically infinite, but marketing decision makers must use meaningful data and attributes in each use case – therefore, the data input options, the collected attributes, must be chosen carefully based on each use cases' needs and goals. Sterner (2017, 78) argues that the "beauty" of the *decision trees* is the machine's capability to decide the root (*first node of the tree)* and then form the *child nodes*, thus deciding the significant variables. This is not directly counter-argued by Bengio & al. per se, but they imply that *decision trees* are trained with specialised algorithms. They imply that learning algorithms are usually seen as nonparametric (parameters can grow in relation to training data (Katsov 2017, 26)) due to the unconstrained size of the tree, but *decision trees* are often regulated concerning a tree's size, and thus they're defined as parametric models. Additionally, the decision tree models are usually used in axis-aligned problem solving, for example starting with genders with equal values = two-class problem, but Bengio & al. (2016, 142a) states this to have shortcomings when positive outcome happens (when x^2 > x^1) because in this case, the boundaries for the decision is not axis-aligned. These kinds of problems are better suited to traditional *logistic regression.* Figure 2. on the next page is a simple example of visualised decision tree model.

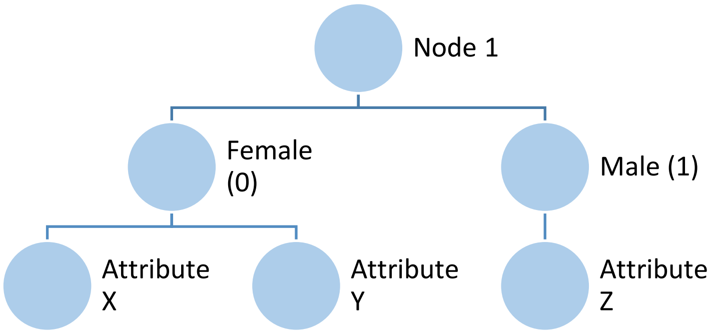

Figure 2. demonstrates the data flow in a decision tree model with the case example of female and male discussed in the text. Attributes X, Y, and Z can be variables like age, credit score et cetera.

Bengio & al argues in favour of *decision trees'* usefulness in situations where calculatory resources are moderated down due to the need to make the model parametrical. As figure 2. shows the process behind Sterner's example of customer lifetime value and its relation to ad/promotion reception by the target audience, it could be argued that decision tree in this marketing scheme is constrained in data-wise to the already acquired data from CRM or another already formatted source. Thus, the attributes of used data indicate the presence of calculatory restraints in practice as new dimensions cannot pop-up without user's "manipulation" of the source data. I interpret the Sterner's argument of finding significant variables from the data with relations to Bengio & al. argument; the context of the first mentioned already has set parameters in the form of CRM-data. Thus, the conclusions by a machine and the *decision tree* will not create its data from the original data-set.

The *random forest* model is based on the decision tree model. The random forest generates multiple decision trees by sporadically picked numbed of elements in the data set. From this data, it selects trees randomly to spawn new decision tree. This process can go on and on multiple times to create new sets of trees. According to Sterner (2017, 78), this is highly effective when using massive amounts of data with high dimensionality-model makes it possible to just analyse part of the data without the need of crawling through all of it.

3.5 Unsupervised Learning

The unsupervised machine learning is distributed by systems which must understand or make sense of the data without any guidance (Bengio & al 2016, 102a) or as Katsov (2017, 42) states, unsupervised method's goal is to understand the underlying structure or patterns of given input data to model the “unconditional density”. Bengio & al. (2016, 142a) acknowledges the lack of rigid distinction between *supervised* and *unsupervised learning* due to the absence of an objective test to produce a distinction – informally *unsupervised learning* is stated to refer to attempts where human labour is not needed to have information from data distribution. For example, learning to draw samples from distribution or clustering the input data into groups are both associated with *unsupervised machine learning*. Sterner (2017, 79) adds there to be an element of surprise and possibility to uncover hidden information along the process; user inputs enormous quantities of data into the system and the machine tells you what it discovers. That data, in practice, could be customer data from CRM where the system could pinpoint the customers which are the ones most likely not to buy from a store again. The last example is a classical task of *unsupervised learning* where it is used to look up for the “best” representation of a processed data. The “best” can be various things, but in general, it means a projection with as much information from N while keeping the projection as plain as possible with calculatory restraint (Bengio & al. 2016, 142). In macro level, according to Sterner (2017, 79), unsupervised learning is about *clustering*, *association* and *anomalies.*

3.5.1 Cluster Analysis

Machine learning is an excellent asset for pattern recognition. Even though humans are good at this too, our species is notorious to see patterns where there may be none. According to Sterner (2017, 80), humans are prone to apophenia – the phenomenon where an individual sees significant or compendious patterns in random data. On the contrary, machines base their actions in data which does not give room for speculation (this verifies the need of quality data). *Clustering analysis* in marketing and marketing research has been scrutinised in the past. Punj and Stewart (1983, 134) discussed the challenges associated with *cluster analysis* already in 1983: it is important to choose a valid metric, right variables, and challenges of cross- and external validation of the information. These concerns are valid even today as machine learning is based on algorithms. Punj & Stewarts’ (1983, 135) definition of *cluster analysis* in marketing research makes it as a statistical method making no prior assumptions of any existing differences among the population. They continued that cluster analysis in marketing was usually used in segmentation, understanding the buyer behaviour and finding new product opportunities – I understand this still to be the case. Most notable way to use *clustering analysis* concerning in historical perspective has been the sizing down vast sets of data to produce aggregates from it. This process forms more general and easily managed outcomes compared to individual observations. This concerns modern technologies too. According to Punj & Stewart (1983, 136) *Cluster analysis* is used to form homogeneous clusters inside the dataset to understand and observe it – not for building theories from acquired data.

The modern marketing is shifting from segmentation to more personalised marketing experiences due to digital channels, but according to my understanding, this is still somewhat considered as statistical segmentation as data flows must be analysed and it must be processed to understandable form. For example, marketing reporting can suggest changes in ads due to lowering performance in one segmented ad-set. The problem in *cluster analysis*, as in any given artificial intelligence & machine learning process, is the data and choosing right attributes to present a case. The *feedback-loop* can be achieved in many ways, but to me, it seems inevitable if development is desired.

3.5.2 Association

Digital services such as Spotify and Amazon have adopted *association algorithms* to enhance their services. It is a system that makes further recommendations according to user's actions. Spotify introduces new songs and artists for a user and Amazon have put in place the suggestions for additional sales; "people who bought this item also bought this". Sterner (2016, 82) states there to be two elements to understand the association analytics: *support* and *confidence*. *Support* tells the number of occasions that items have popped up, for example in shopping basket whereas *confidence* shows the ratio of two items showing up simultaneously in said basket. For example, let's assume customers bought running shoes for 200 times and running socks for 150 times, the support tells the times that these items were bought together. When the number is 150, *the confidence* between the items is ¾ (or 75%). At the same time its 100% between running socks and running shoes. Hence, Sterner (2017, 82) writes, one is *antecedent* and another *consequent* – in case of running shoes, running socks are bought with an association rule of confidence probability of 75%, and in this example: if running socks are bought – then are also the running shoes. Sterner also states that to have meaningful results, the higher the *support*, the better because some associations can be accidents due to a sparse amount of *support*. Like in, for example *cluster analysis*, the amount and quality of data is critical to reaching meaningful results.

Association according to my understanding is a quite useful tool to use in marketing reporting. It can be used in finding patterns in buying and interaction behaviour. The latter could be implemented by tag-based conversion following. Tag, also called a pixel, is usually code made with JavaScript or HTML and it is implemented into the code of a website. A tag creates a cookie which is stored in a web-browsers cache for a certain amount of time. For example, Google Analytics can visualise the interactions of a visitor with certain cookie. Tags, pixels and cookies consist problems in terms of following and identifying individual users in the long run, but I will not take part in that conversation during this study.

3.5.3 Anomaly detection

The best-case scenario in marketing reporting in real-time, as the case company's product aims to do, could be seen as reacting changes and situations at the moment they surface. Theoretically speaking, when a company's marketing actions create data and reactions in the digital platforms, these data flows can be harnessed to understand the reactions and actions of the receivers. Sterner (2017, 83) points out that having spikes in social media mentions or getting an abnormal growth of landing-page visits on your web-pages could be an opportunity for your business. On the other hand, falling attention and interactions for example in Instagram, demand actions to counterfeit the negative consequences. Google is already using a system called *Analytics Insights* in their GA platform. It goes through all the accumulated data and aims to spot anomalies in it; it could be changes in referral traffic or shifts in geographical users among multiple other occurrences.

3.6 Reinforcement Learning

Reinforcement learning is model of machine learning where the system is getting feedback from the environment. Reinforcement learning is a machine conduct actions, for example run ad-campaign, and gets *rewarded* or *penalised* according to the results of the campaign. Reinforcement learning systems must be programmed to a certain setting where it operates on its own inside the set framework. It continuously tries to improve its capabilities to reach desired goals set by the system developer. In comparison to supervised learning where a user is in control of the feedback-loop, in reinforcement learning the system have been given rules where it operates autonomously (Sterner 2017, 87)

4 Marketing reporting & benchmarking

This chapter starts with subchapter consisting framework for performance measurement and marketing reporting. Later subchapters define the essential characteristics of marketing reporting. Then the text proceeds to the benchmarking of marketing reporting industry leaders.

4.1 Marketing reporting & performance management systems

To understand the importance of reporting, one should be acquainted with the concept of *performance management system* (PMaS) and *performance measurement system* (PMeS) which I have defined for myself as the process behind reports – reports are used to explain the occurrences during the PMeS and its processes. Chaffey & Ellis-Chadwick (2009, 553) defines the PMaS for digital channels as a process which is used by companies to assess and enhance the efficiency and effectiveness of an organisation and its processes. The PMaS is widely used in a variety of functions in companies. The PMaS are based on PMeS which is described by the authors (2009, 553) as a process of defining the right metrics the measure and used. Kingsnorth (2016, 260) states that these "final steps" of marketing functions, measurement and reporting, can be quite possibly the most important ones; even if you have the most brilliant strategy, but you do not measure it, how can you validate it or show results for stakeholders? This chapter defines the framework for performance measurement, analytics and reporting.

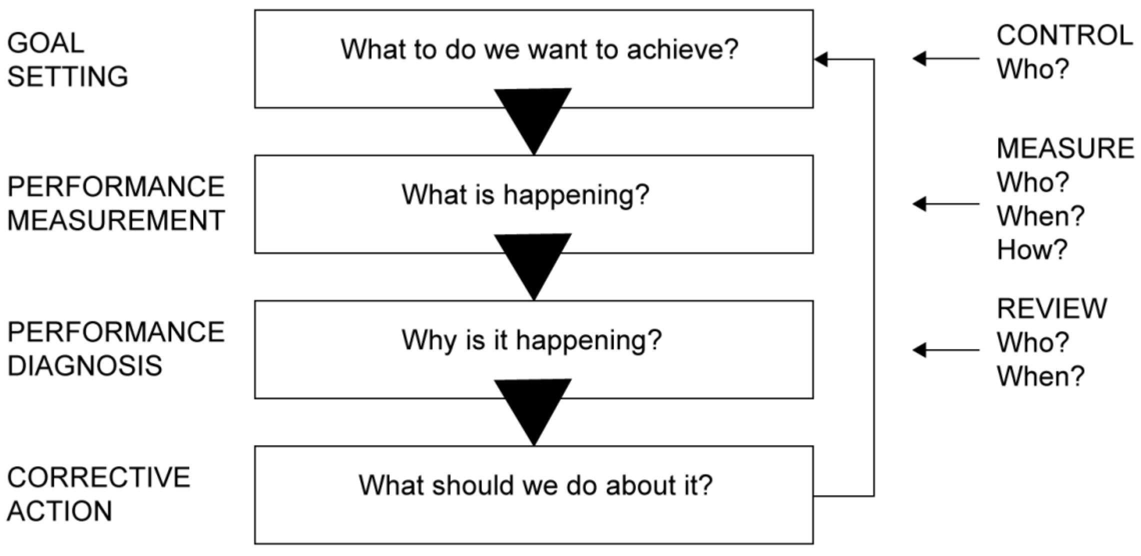

Figure 3. Performance measurement process' summary from Chaffey & Ellis-Chadwick (2009, 555). This is viewed as a process for improvements in the whole measurement process.

The summary of the performance measurement process (PMeP) describes the steps and intention of each separate step. I will build a more concrete set-up concerning marketing reporting and measurement with help from the authors behind the figure 3. There are four key stages described by Chaffey & Ellis-Chadwick (2009, 555):

1. Goal setting stage defines the goals of the measurements system. Strategical framework for digital marketing is used to form the best fitting objectives to achieve meaningful measurement.
2. Stage of performance measurement is about collecting data to conclude the various metrics which are part of the actual measurement framework.
3. Performance diagnosis includes diagnosis of the results for comprehending the underlying reasons for variance from set objectives and more importantly choose the marketing tools to decrease the variance in the future.
4. Implementing the actions that are formed strategically and tactically based on the three stages before.

Stage 1 is a strategical one for the case company's customers. The Madtrix-product is a solution for achieving understanding the stages 2 and 3 – the case company's tool is aimed as a tool for gathering relevant data and visualising it. Kingsnorth (2016, 261) raises the case of human factor; we are needed to form something from data which itself is worthless. I interpret this as important for the case company's customers to understand what they want to achieve and understand the analytics and reports made by Madtrix; human factor in the case company's case is interpreting the results. The first stage is the basis of all the actions in performance managing and measuring. It is argued by Chaffey & Ellis-Chadwick (2009, 554) that businesses need performance management because not having it can unearth other problems. These can be a lousy linkage between strategical objectives measurements, an absence of key-data collection, inaccuracies in data or unanalysed data, and the lack of corrective actions. I would briefly describe this as lack of development. The crucial stages for the case company, as I stated in the last column, are the steps 2 and 3. Madtrix Performance Analytics includes the visualisation capabilities for all the data source which were integrated into the product during the thesis process. The product was developed to visualise all the data from sources and going forward; the user can modify the metrics which it wants to examine and shown by the dashboard.

Stage 2 in Caffey's & Ellis-Chadwick's PMeP summary is defining the metrics framework. Measurement metrics are naturally highly related to the necessary information. For example, a user might want to know information about *channel promotion*. Key measurement would be cost-per-acquisition (CPA) or cost-per-sale (CPS), et cetera. An additional example could be *channel outcomes*, which mean in this instance subscription for a newsletter, contact inquiry et cetera. Key measurement would be *conversion rates* like a visitor to purchase or visitor to registration. For demonstration, the conversion rate would be purchasers or visitors divided by all the traffic in a given platform. According to the Caffey's & Ellis-Chadwick (2009, 555), the measurement framework should fulfil criteria such as:

- Macro-level effectiveness metrics to understand the strategical success and business contribution of e-marketing
- Micro-level metrics to assess the efficiency of marketing implementation and tactics
- Evaluate the effect of digital marketing towards the key stakeholders
- Give tools to compare the performances of different digital marketing channels
- Give means to evaluate the digital marketing performance vs. competitors or out-of-sector best practice

Stage 3 as the second critical part of the process related to Madtrix, are the tools and ways for collecting metrics and reporting the results. Caffey & Ellis-Chadwick (2009, 560) states this to include the decisions for used tools which meet marketing performance reporting needs. Used products or services must be evaluated concerning system integrations, support quality, costs and so on. Techniques include the metrics to collect the data concerning traffic and visitors et cetera.

Figure 3. also consists the questions of who, when and how to understand the need of the process owner and the methods. I did not dig deeper into that; even though it is an important subject, I saw it irrelevant for this study.

4.2 Analytics & reporting

Analytics are tools "behind" reporting to examine key statistics on the performance for their digital channels (Kingsnorth 2016, 262). Numerous statistical datasets were growing all the time during the thesis (real time and social media to name two), and there were already various ways to collect that data. In Madtrix's case, data collection method is in relation to the data source. For example, Google Analytics uses tag-based analytics which is based on a *pixel* or code which is sent to analytics software to log different actions made by a visitor. Madtrix only visualises this information. Thus, it will not acquire code to be implemented. Analytics behind visualisation can be formed with multiple methods, but they can be grouped under three macro-categories according to Katsov (2018, 19):

- **Descriptive:** methods which aim for summarisation of data, finding correlations and data quality assessment. Example: marketing data report providing aggregated marketing data. Descriptive analytics does not aim to answer how to optimise results.
- **Predictive:** Concentrates on likelihoods of potential outcome based on known, prior data. Example: demand forecasting or likelihood of customers acting on

promotion. Predictive analytics is not necessarily aimed for forecasting the future – it can be used in estimating input variables effect on output.
- **Prescriptive:** Modelling dependencies between made decisions and future scenarios ensuring optimised decision making. Example: price optimisation with the knowledge of income's relation to discount.

Katsov (2018, 20) states that analytics in marketing is usually looked through these three categories and each of them is essential: prescriptive analytics is the method of choice in marketing domain, but it requires predictive analytics as "building blocks". I crossed paths with this statement when I discussed with my colleagues with analytics expertise, and they confirmed this to be true. According to my understanding, Madtrix as a visualisation tool was mainly built to fill descriptive needs. Hence, it could be developed to the "next level", to have predictive competencies.

Next phase is reporting, which makes everything else worth something, according to Kingsnorth (2016, 279). He states that reporting is the essence of communicating the progress with stakeholders – Kingsnorth lays two crucial aspects to consider in reporting: *data* and *presentation*.

Data and its quality are crucial, and it must be tailored for the viewers according to Kingsnorth (2016, 280). He argues the importance of resonating reports and having meaningful metrics in use. I see this aspect as important one and as Chaffey & Ellis-Chadwick (2009, 555) argues, it is one of the main stages in the performance measurement process. According to my understanding, reporting is one of the key elements of any business domain and it should be meaningful to overall business objectives – Kingsnorth (2016, 280) verifies to this by stating that reporting should be aligned with business goals.

Presentation of data might be as important as gathered and processed data itself, according to Kingsnorth (2016, 281). He states that instant understanding of the report on audiences' behalf to be vital. I have used different analytics tools with different kind of reporting functions and observed this to be true in the practical level. The easier the results are understood, the easier is the discussion concerning future actions regarding marketing functions. As I see it as an individual, being able to measure is a basis to all business functions that one wants to develop.

4.3 Marketing reporting dashboard

Marketing reporting dashboard is a simple concept: it visualises the gathered data to understandable form with the help of graphs, diagrams or other visual components. One of the important factors is to sway a message to viewers with these visualisations. Kingsnorth (2016, 282) discusses the graphical presentations' usefulness for a human to understand information and trends faster through graphics compared to numbers and words.

Figure 4 on next page showcases the data flow and functionalities framework of marketing reporting and analytics. This case example is taken from Adobes' internet help centre, but I would like to emphasize its validity for both benchmarked product and the case company's product in macro level. The deep level understanding the flow of the data in different systems is irrelevant for this thesis.

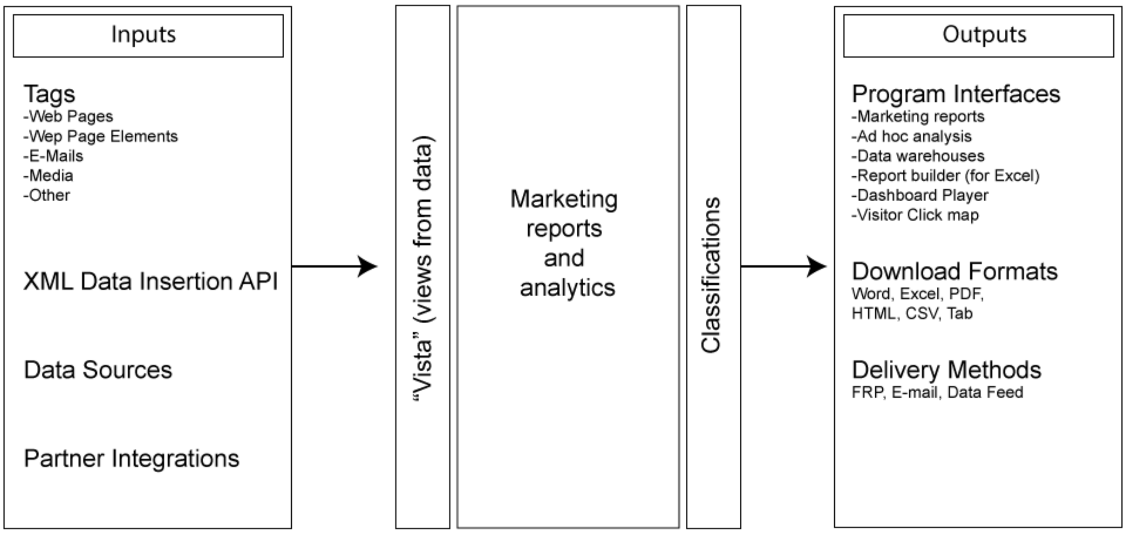

Figure 4. The flow of the data in marketing reporting system. Case example from Adobe Analytics solution.

The inputs of the figure consist of sources where the data is gathered.

- Tags are small identifiers made usually with JavaScript of HTML in, for example, web-pages' HTML-code to record the interactions in that specific page. The same principle of tagging is works in other channels.
- XML (Extensible Markup Language) Data Insertion API is a method to collect data with API connections. XML itself is a language to define rules for encoding the document and its readable for both humans and computers. It is widely used on the internet to ensure standardisation of usability.
- Data Sources delivers offline data to the system. Many methods are available for doing this and for example the case company had manually delivered customised solutions to connect the product to aa client's data sources.
- Partner integrations like Microsoft Dynamics CRM can enhance the data to give more insights. This is related to the 'data sources' due to the open source-environment of many service provider in the web-based services.

Vista is the view to the data which can be considered as reporting itself in its crudest form. These views can be commonly transformed to marketing analytics and reports with making them visualised with a possibility for interaction ('Program Interfaces' in Figure 4. or shared dashboards) or static files such as Microsoft Word, Excel files or similar. The ones mentioned last can be distributed to the stakeholders via e-mail or another convenient way.

During the thesis process. I worked in a company which conducted business concerning analytics and data. There I discussed topics of analytics and reporting with my colleagues at the time, who were professional in the said field. My co-workers established a raw framework for me to understand analytics and reporting. These two concepts are interwoven in a way; reporting is a presentation of a process whereas analytics are connecting the starting data and it processes it through agreed algorithms and functions to bring the wanted information to the report.

4.4 The case company's product: Madtrix Marketing Performance Dashboard

The case company's product was at the time of the writing of this thesis, focusing solely on visual marketing reporting through a web browser. The visuals are composed with Power BI, a Microsoft product that visualises data gathered from various sources. This was done via API's that are connected to the users Madtrix-account in the web-interface. In July 2018, the product had eight different data-sources including most popular social media channels.

Figure 5. on next page consists SWOT analysis made from the case company's product.

STRENGTHS	WEAKNESSES
- Easy to use & access: cloud-based back-end system with web-interface for the customer to use - Effortless connectabiulity with data-sources - Can be implemented in any sized organisation or agenzy - Product development & support is constant - No back-end installation needed in the customers premises - Business model of the product is highly scalable	- Limited amount of connectable data-sources as default (07/2018) - SaaS-model and software still under development - Sales & marketing of the product for the case company is challenging for the case company in saturated market - Product and the company are in the start-up phase
OPPORTUNITIES	**THREATS**
- Prising is deemed to kept quite accessible for the customers - The case company has already established partnerships and clients - Catering the reporting needs of the agencies* - Investing resources to modern technologies (such as AI) can offer competitive advantage	- Saturated market with big-players -> competition - Challenges to penetrate in to the agency industry - Small resources might hamper the progress in terms of development focus and velocity - Technical issues & product stability can be infectious with small customer-base - Market visibility of the product

Figure 5. SWOT-analysis from Madtrix.

Strengths of the case company’s product are firmly in the UX and back-end part of it and additionally making the product better and delivering it to the customers. It is composed as SaaS; hence the software is operated in the cloud and customers can access and customise the visualised dashboards through internet. This offers the untied relationship with a customer; the case company’s employees will not have to visit customers whereabouts for the product to be set up, but the client registers oneself into the system via internet and connects it with a company’s data-sources (for example Facebook or Instagram) with the APIs. The model is simple, and it provides great means for a scalable business model where the standardised product can be distributed through the internet to theoretically an unlimited number of times with no loss of revenue or further investments.

The product was in the development phase in the during the thesis process. This provided challenges that could be weaknesses from the SWOT-perspective. It had a limited number of services possible to connect into the dashboard. Against competition, at least considering industry leaders, the number of data-sources should be increased as much as possible to understand the effect and causation of digital marketing and campaigns. This provides a more holistic view from omnichannel marketing. The number of channels is likely to increase, and this is related to the resources of the company: it was in the start-up phase, and thus the resources were not humongous. The effort to develop the SaaS product in development-funnel ties most of the company’s resources. Hence, it affects sales and marketing. Until there is not a complete product as SaaS, it cannot be sold or marketed as such.

Nevertheless, this challenging situation offers business opportunities. Pricing of the product is accessible for the users from small clients to enterprise level. Madtrix's already established clients and partnerships offered momentum for the sales to push numbers forwards – according to my understanding, referrals had already produced new business opportunities. Madtrix, then with direct B2B sales model, could use their established, public references to increase the sales and visibility. They had few unnamed companies using the product and this naturally created trust in the product and its services. Furthermore, the user of Madtrix was not required to do much tweaking to get visualised results of one's actions in the channels connected via APIs. The industry leaders' products were more prominent in terms of size and functionalities but more complex due to the technology. I would also raise the independence of Madtrix: many of the possible data sources act on open source ideology. I understand this to be way for developers to connect and develop the services of given product on their own. Madtrix, as a small operator, could pick theoretically any service with a viable data source to be connected into their product. This provides a business case in omnichannel marketing reporting in having all the gathered data in one visualised in one place.

I found threats from the competitive nature of the saturated industry of marketing reporting. Landscape for the business battle was already highly competed in 2016 (Smart Insights 2016), and it is survival of the fittest, as usual in software business – average lifespan of any given a company has shrunk from 90 years to 18 years in US counting from 1935 to 2016 according to McKinsey's Dominic Barton (Borpuzari 2016) and Y-Studio states that nearly half of the new companies fall to "death valley" due insufficient planning and wrong customer targeting among other reasons (Y-Studio 2017). The case company was established officially in 2018. It was not in incubator-stage of any sorts, but as a small player, it was trying to gain ground in market space with limited resources. This can lead to slow progress in technological terms, and when one tries to develop and maintain the product at the same time, one or another can suffer. Allocating the resources is challenging and adding product marketing to gain visibility makes the situation more complicated.

4.5 Industry landscape & benchmarking

The marketing reporting industry was occupied by over 3000 companies in 2016 (Smart Insights 2016). This number consists of two technological juggernauts: Adobe & Google. These two had a vast amount of resources in their disposal due to their sheer corporate size, but one must emphasize the importance of their presence in modern technologies and their attitude towards innovations in modern data industry. This chapter presents the benchmarking of two of the marketing reporting and analytics industry leaders during the time of the thesis process: Adobe Systems Incorporated and Google LLC. I concentrated solely on the marketing analytics products of said companies. The benchmarking was done with studying the products through material and usage (Google Analytics) infused with information from Gartner's "Magic Quadrant for Digital Marketing Analytics" -report. It is research from digital marketing analytics platforms and gives insight to selected platforms' functionalities by professional researchers, hence it provides information which could be hard to reach by me.

As the industry itself is highly technical and I want to concentrate on the features from users' point-of-view, the coding behind the products was not taken account. I thought it as more fruitful for this thesis to examine the functionalities and technologies as concepts for possible implementation.

Note: I saw it fitting to use SWOT-analysis to map the case company's product and its market to have a solid base for the argumentation during the chapter and later in the thesis. Additionally, the information from industry leaders was scaled to support relevancy of the case company's technological possibilities at the time of thesis process. This must be taken account due to the services of benchmarked products; they're vastly bigger than solely marketing reporting tools, thus the benchmarking is aiming to concentrate on these features of the products. Benchmarking concentrates to the products of the industry leaders. Thus, this is a demarcation of the benchmarking to make the scope relevant for the subject. There are similar technologies in all analytics platforms, thus I aimed to bring differentiative aspects into technological examples.

Both Adobe Analytics and Google Analytics 360 are paid premium services and sold via external vendors (partners).

4.5.1 Adobe Analytics

Adobe started as a software company with the focus for creative tools such as Photoshop and common, professionally used file format called Portable Document Format (PDF). Their acquisition of Omniture in 2009 gave birth to its marketing analytics business. Omniture was a prominent force on its own, but Adobe acquired it to produce the core business of cloud services in marketing analytics. The company took steps further in analytics, advertising and marketing by buying Magento Commerce's whole stock equity in February of 2018 – at the time of purchase Magento was one of the leaders in e-commerce.

Adobe had built a holistic cloud service covering marketing analytics with Adobe Analytics: the company states that the product can combine all the marketing channels, such as internet, TV, CRM, connected cars, to ensure real-time analytics from customer interactions (Adobe 2018c). According to my understanding, this was done via the import of off-line data (excel-sheets) or APIs if possible – there are multiple possibilities with inputting the data into the system. I apprehend the offline input data still to be managed by a human; there is always the human factor involved. Next paragraphs describe features which I saw important for the thesis.

Analysis Workspace. The drag-and-drop interface where a user can create ad hoc-reports from wanted data cumulated by Adobe analytics; this is an ability for advanced segmentation of digital marketing channel visitors and inspecting digital marketing Key Performance Indicators (KPIs) such as total site visits, customer acquisition cost et cetera. Adobe's product is one of the leaders in the customer insight-tools in the marketing reporting industry. Adobe has real-time dashboard functionalities, but I did not find notable information concerning the use of them.

Anomaly detection. Adobes' AI, *Sensei*, crawls through all the gathered data continuously to detect abnormalities. In practice, this is machine learning with added advanced statistical models going through the data to find useful patterns. This means data crawling coverage which is in-humane to reach and therefore hard to do by a human.

Integrations. As SaaS service, Adobe's product functions in a cloud, and it had established a close relationship with Microsoft. Adobe has name Azure cloud-platform as its preferred service. This aspect is highly important due to other technological solutions, namely Adobe Sensei. It is Adobe's AI which in this instance is used to mine and gather data from different Microsoft Dynamics data-sources (for example customer relationship management, CRM, system) for analytics to bolster the ubiquity of sales and marketing (Darrow 2017).

Adobe Sensei. Adobe's initiative concerning is to use Sensei as general AI for customised experiences and enhanced, automated customisation of marketing content regarding visualisation et cetera. In analytics, Sensei can find relevant insights and occurrences in customer path and marketing actions. This Adobe's AI technology is open for data scientist and other experts to develop customised work paths and processes.

Adobe describes Sensei and AI in general as a "behind-the-scene marketing assistant of the marketer". It helps professional in time-consuming tasks of going through data and acquiring insights from it (Adobe, 2018b)

4.5.2 Google Analytics 360 Suite

Google had been in the frontlines of technological advancements since its birth in the year 1998. Although it started as a "simple" search engine company, it has grown to be an era-defining corporation in the sense of technology and innovation. It relies heavily on gift economics: compared to citation practice in scientific spheres where researchers reach a more prestigious status with every incoming citation (Girard 2009, 28). In the internet this means that it creates value from the data gathered from the entities interacting with the internet. This data can consist simple elements like date, time, location and browser and additionally, depending on the case where data is gathered – case example from Google Calendar, it can gather data from the said application and use event attendee or similar data. Google, allegedly, has stored all the emails one has ever sent (Curran 30 March 2018). The massive amount of data cumulating all the time from various, ever-increasing sources, ensures a steadily growing business platform for Google. The company has a product called Analytics 360 Suite which is premium analytics service. The standard version, Google Analytics (GA), could be thought as a trial version for the Google Analytics 360-version (GA360) which is suitable for enterprises.

Google Analytics 360 had implemented many technologies in reporting and data-analysing processes. Many of the functionalities, filters and outcomes could be customised by the user, but it had tremendous capabilities as default. The features in the next paragraph are defined from the macro level to provide a view of their functions and fubndamental characteristics.

Roll-up reporting. Google uses the structure of *Account → Property → View*. It is a simple way of constructing the use of the GA: account is created as a primary identifier for the user – email is enough. Then comes properties that are websites, internet blogs, mobile apps et cetera which are then tracked with unique ID-code. Properties include views that can be customised with filters. In the GA one could compose a filter or any other functionality. Roll-up reporting in GA360 combines all the properties (level 2) to one holistic view. The data accuracy is always a concern when humans construct the filters; for example, if marketer had not filtered crawling bots from the results, the number of visitors could have been highly misleading.

Attribution models. GA360 user can operate with more sophisticated attribution modelling than GA's standard one. The standard model gives the 'credit' to the last interaction of the user in a website or another platform. Figure 6. is an example of simple customer journey starting from Google search engine interface where a user searched subject with relevance for the Company A. First step is the visibility of the paid advertisement where a consumer might not even visit the vendors' page. Paid search means AdWords or similar digital marketing channel advertisement in the user interface. For Example, AdWords advertisement is an algorithmic process where all the ads made by users around the world concerning a topic are categorised and graded by Googles algorithm. Later the ad enters into the auction of search engine ad-placements. Advertisements with appropriate data will pop up in a proper place; if its information is quality enough from Google's and competitors' perspective. For example: if one enters a search query for 'sneakers' and an ad show sneaker vendors' contact information or picture of inventory. In the figure's example, you searched the sneakers and became aware of the vendor, thus the credit should be going to this interaction but in the GA's standard version it goes to the latest one, organic search – in this example, a consumer visited a vendors' page later through organic search through Google. In organic search you have used the vendor's exact name in the search query, thus ending to their page and bought a pair. Hence 'the conversion'.

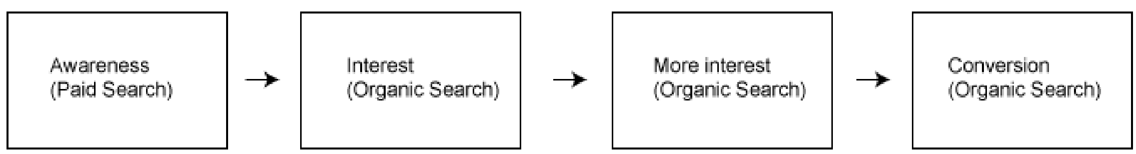

Figure 6. Example of user interaction with property in Google Analytics.

In the data-driven attribution modelling which is included in GA360, the complete set of cumulated data is used, and the system gives different weight to a users' touchpoints along the path. The modelling can be custom made for businesses and it is only open for the GA360 users. Furthermore, if one aspires to use this modelling in GA360, the property in hand must have 400 conversions in at least one type of conversions in the last 28 days. Conversions are actions where a user conducts a hoped interaction inside a web-page. This includes a set of rules and actions that must be set up in the GA, such as the destination URL which must be reached to acquire a conversion. As I understand, the data-driven model’s strength is the ability to uncover the real value of the, for example, social media campaign due to its data accuracy compared to static models used in GA.

It is good to keep in mind that all the analytics tools, Adobe Analytics involved, includes attribution modelling.

Analytics Intelligence and ‘Ask a question’. Using the natural language technologies user could ask a question from the GA interface regarding the user data that it acquired. For example, a user could ask ‘*where do my users come from?*’. As an answer the GA provides the top sources for incoming users and source-related amount, for example Google – ‘5899’ in a certain time frame. The date range can be fixed, and the questions are currently supported only in English. This technology is tied to the *Analytics Intelligence* feature which offers insights from the data which system thinks is valuable for the user. I used this functionality, and it gave insight which might have stayed hidden, such as rising amount landings in certain page through search engines. The *Analytics Insight* could tell rising popularity of a certain campaign in a certain channel or decreasing in average session duration in the websites et cetera. This is categorised as a true AI-tool due to the capabilities of learning the GA-user’s actions inside the system accompanied by “crawling” through the accumulated data to give meaningful insights automatically. More specifically, it uses machine learning to help users to understand and act on their cumulated data (Google, 2018a). Adobe’s Sensei acts as a similar operator according to my understanding.

Google Data Studio. A free tool from Google that enabled a user to create customised reports outside the GA-tool. A user could add multiple data-sources to Data Studio – LinkedIn ads and Facebook ads, YouTube analytics to name a few. The tool was helpful when user wanted to have holistic reports from omnichannel marketing. As I understand, it was possible to connect the other reporting services to Data Studio and visualise the reports using the product.

Mobile application. Google had an application for mobile phones where a user could see information from the GA directly from the mobile app. This was and remains to be, as far I am concerned, relevant in the modern world where internet consuming is shifting (or is already shifted) towards phones and other similar devices – reporting and insights on-the-go enhances the reactivity of the user.

Integrations. According to my understanding, GA could be easily integrated through API without much effort. This is not directly linked to AI or ML functions, but the GA could be used as a data source, or it could be programmed to do complex reporting by automation and configuration tasks by using APIs.

5 Methodology

AI or ML were not a new concept. Technology has taken forward leaps in the past decades, and artificial intelligence has had its share of it. The problem, in my mind, was the general nature of the information regarding the subject of my study. It was reasonably hard to find exact, relevant information and thus I did research from the general artificial and machine learning materials. This gave me a way to infuse the narrow source list with valid information which is the basis of the concepts of the thesis.

Methods of the thesis are selected to support the effectiveness of the study to uncover this frontier of marketing technologies tech. The research approach is a logical election to support the cause of the thesis which are described in next two paragraphs

I will gain professional competencies through researching and acquiring knowledge in his specialization track of marketing. Marketing industry had been in a shift towards “modernizing” itself for a while, and possibilities with data-based marketing operations were starting to uncover themselves. This was the profound reason for the opportunities with artificial intelligence and machine learning utilisation in marketing and more importantly for me, marketing reporting.

The case company already had built a view from the landscape of the industry and the technological possibilities, but they hadn’t conducted a research to understand the phenomenon from the customer’s or competition’s (in this thesis the competition equals to market leaders) point of view. This provided a strategical opportunity for them to understand and map the possibilities concerning technological needs when assessing their potential clients and marketing reporting industry. Artificial intelligence in marketing is a gestalt with a lot of business opportunities – there are a lot of trial-and-error and successes in current, experimental climate of marketing technology. The possibilities of AI in marketing happens to still stay as an incentive for the companies assembling their marketing systems (Sterner 2017, 7)

The underlying problem of this thesis’s topic was to find AI & ML features or applications which can be implemented into the case company’s product to improve its functionalities to gain competitive advantages. Technological execution of the feature-findings was covered only superficially due to the lacking development knowledge.

Benchmarking the competition is a widely used method to research the market space and finding possible market gaps. This could be a simple definition of competitive advantage or USP. This thesis used industry leader benchmarking to understand the functionalities of these operators' product and technologies. In a sense, it was more important to understand the offering of the product, not the exact formulation of the code. I did the research and thus, I provided an opportunity to the case company to take further actions with acquired knowledge. Extracting code and understanding a product was nearly impossible in the context of my thesis project due to the lack of expertise and resources but constructing a picture from industry leaders and their artificial intelligence and machine learning product features supported the case company's future endeavours in their product development.

The written material used in the thesis was aimed to be in balance: I wanted it to include theory, peer-reviewed articles, study books, and commercial texts. The thesis subject offered challenges concerning the scope and aim of the thesis; marketing reporting in modern form infused with AI & ML isn't broadly ventured topic. As such, choosing generalised and relevant subject technology and marketing study material and additional, fresh outtakes from the marketing industry proved to be the best way to form holistic conclusions from the subject.

The case company's product had a clear target customer segment in marketing agencies. Thus, because qualitative research concentrates to understanding the issues that exist instead of which quantities it exists (Sharp 2013, 144), the qualitative method is the best research method to drill into this study's subject.

5.1 Thesis process

This thesis is constructed to mirror the process behind it. The structure is as follows:

- Theory for the thesis subject to build understanding for the writer and reader concerning artificial intelligence and machine learning. Literature was used to build theory-base for the thesis.
- Benchmarking of two leading products to understand the features and functions in them. Benchmarking act as integration between theory and interviews (empirical part)
- Interviews of thesis subject-related professional were used to understand a 'phenomenon' of artificial intelligence, machine learning and marketing (reporting). The relations and future of these concepts are also discussed. Interviews were conducted to deepen the knowledge of theoretical framework in an empirical setting.

I aimed to understand concepts thesis' subject technologies and their possibilities in marketing reporting and to offer feature recommendations or opinions of possible feature developments in case company's product. At the time of the thesis process, the outcomes (recommended features) of the thesis could be categorised into two macro-segments:

- *corroborative* (as the case company could already researching as much as I)
- *mapping* (new possibilities in terms of features)

5.1.1 Desktop studies

The written material used in this thesis are categorised in two main sets: (1) academic texts and (2) commercial texts. This split makes it easier to understand my aim for using for example peer-reviewed sources as strengthening the message of more general or commercial texts. Jim Sterne's book, 'Artificial Intelligence for Marketing: Practical Applications' contains a lot of views and points for the thesis subject. I saw it as a guidebook to study the technologies in the marketing sphere. I felt that Sterne's book and other, mainly written internet sources, needed to be validated with academical references with more specific expertise on certain topics.

My preference was to pick general AI and ML texts to form a strong baseline for the information offered by Sterner. I collected a variety of marketing textbooks which consist theory and practice of marketing and its digitalised aspect, such as reporting. During the research process, I suffered from the lack of information and my thesis supervisor guided me to find general information from artificial intelligence and machine learning. This proved to be fruitful as I found material consisting a lot of peer-reviewed articles to cover the narrow theory-base provided by commercial sources like Sterner's book; it is published by SAS, which is a company with significant role in the technological sphere. It is involved in data-analytics, marketing analytics and AI. The challenge in my thesis was to provide somewhat nonaligned information to support the Sterner's material – as I found the information provided by the author legitimate, I wanted to cross-validate it.

I used the CRAAP test (appendix 4) to evaluate the main sources used in this thesis. This concerned Sterner's, Katsov's, Bengio & al., Kingnorth's and Caffey's & Ellis-Chadwick productions.

5.1.2 Interviews

I chose to do interviews for experts of the involved field of the thesis. I interviewed one marketing agency CEO, a Data Scientist and author, Software Developer of the case company and artificial intelligence author. Analysis of the interviews proved to be the most complicated task of the thesis due to different interviewing methods and perspectives.

I aimed to capture the insights and perspectives of the case company, the marketing agency client segment and then additionally interview some more general AI/ML experts. Additionally, it can raise some questions about comparableness of different datasets, but I wanted to cross-reference different points of views to find patterns and use these outcomes to valid my recommendations and give a more through-out explanation for my theoretical framework in the recommendations.

The interviews of the experts were conducted in three different ways:

- Email interview
- Semi-structured face to face interview
- Email interview with answers on video

I chose to do discourse analysis from the interview data. This method helped me to understand the meaning behind the interviews and their respective narratives. I aimed to build credibility for my thesis through generalised topics extracted from interview data. These topics were the product of analysing interviews which were composed with three main themes infused in questions. These themes of the interviews could be roughly categorised to:

- Understanding the background of an interviewee
- Evolution of knowledge since starting in one's domain
- Future of the domain and possibilities artificial intelligence could provide

As the interviews consisted of three different methods and three different roles concerning thesis subject, these categories include subcategories in the form of specified questions. Appendix 6 describes the interview questions and the reader can visit them to understand the settings better.

As Sharp mentioned (2013, 144) there are hardships in the generalisation of the quantitative researches' (and data for that matter) input, but the focal idea behind the research method is to understand the insights of a phenomenon. I wanted to interview and cumulate data from different individuals working in digital marketing and additionally with general artificial intelligence experts. The idea was not to form a "truth" but understanding to validate the hypothesis of mine and gain knowledge to have meaningful outcomes from the thesis.

This, from the analysis point of view, had its concerns. The depth and data between different methods wary a lot – email correspondence can hardly consist the same amount of interaction between participants when compared to face to face interviews. Hence, the analysis of the data will be different between these two methods. It is important to understand that I did not aim to compare data from different interviews with "true/false" perspective but to gather knowledge for a more holistic view from the thesis subject. Gee (2005, 114) argues that validity is not individual but social. This is important from the perspective of discourse analysis: my analysis works from the basis of hypothesises and views of mine concerning the gathered data. Even though I was not aiming to support my agenda, I was trying to, consciously or not, form generalised aspects to supporting or diminishing my hypothesis or views on the matter. The society had already decided the validity of the artificial intelligence as a future technology. My discourse analysis had to take that point into consideration: I had to examine the interview data and, in some cases, extract hidden information objectively regarding these technologies. The level of knowledge, for example, was not subject of comparison between interviewees.

The preferred way to achieve holistic discourse analysis is to have face to face interviews. This method includes additional material for analysis in the form of pauses in speech, manners, body language et cetera. Gee (2005, 7) introduces two important terms for making a distinction: *discourse* and *Discourse* with capital D. The first one mentioned is the language used “on-site” analysed by linguists whereas the *Discourse* is the whole social identity which is recognised by the social environment and its contributors. The latter consists things like values, ways of acting, feelings among many others. We all, according to Gee, are part of many different *Discourses*: for example, I was a student and a marketer during the thesis writing. These Discourses include a whole lot of information that is held by me but also by people around me, projecting their views on any Discourses of mine. This is important to understand because my interviews consist different methods of interactions and different levels of acquaintance with the individuals of whom I interviewed. Thus, I aimed to build an image or picture of the thesis subject through interaction with the chosen experts, but I wanted to steer away from in-depth analysis from the socially recognisable identities and politics behind the interactions. With this, I mean that I wanted to find relevant information to my thesis topic and I did not seek to analyse the language as “sociolinguist”. I wanted to shed light on my specific problem considering artificial intelligence and machine learning in marketing reporting. Naturally, I still had to analyse the different social surroundings & relationships and network involved with different interviewees to achieve the level of objectivity required from the study. I focused more on the discourse itself in Gee’s framework of discourse/Discourse.

5.2 Validity & Reliability

Sharp (2013, 144) argues there to be misguided allegation that research findings from studies with qualitative focus cannot be generalized due to the unrepresentativeness of the sample. This view has a valid point, but the sole aim of qualitative research is to gain deeper insights from the problem in focus. In this thesis the data was acquired by semi-structured interviews with e-mail correspondence, video-interviews, face-to-face interviews, and desktop-studies. Thus, the thoughts and perceptions of the relevant professionals aimed illuminate the marketing reporting industry and the potential AI features at the time of thesis process. My perception relies on the professional knowledge of the interviewed target customer company's personnel and other, topic-relevant personnel expertise on the matter. This was necessary, due to the then current abstract nature of the AI; almost any kind of algorithm could be theoretically composed, but the case company and its clientele demanded tangible and beneficial results; it had to be the possibility to engineer the found features to the product in the foreseeable future.

As Gee implies, there's continues to be troubles against the validity of qualitative researches (2005, 113). In Gee's work, this statement is related to discourse analysis which is a category of qualitative research, but it was a topic I had to face in this research. Validation and reliability of the findings from this research are subjective and must be handled as such. As I was a student and digital marketer in a company which was involved with machine learning technologies during the thesis, I had reasonably direct contact with the subject of the thesis in my daily work. This does not mean that my findings are the only truth; they must be evaluated through time and with empirical research. My analysis and recommendations are the best possible, potential features but the real answers about their validity will form over time. The subject technologies are concepts validated by humanity, but the knowledge of what they were going to be in future did not exist. Thus, validity and reliability must be considered through gathered data and theory in this thesis and project it against the future scenarios and how did they develop in practice.

Grbich states that qualitative research tries to distance itself from knowledge claims. One should be able to project findings which are based on evidence – this was part of the validation of my research. The data of the research should always be collected from the real world. This empirical data acts as evidence to validate the qualitative research. Validity is seen as an action which gets the researcher to the truth of the data and reliability is used as a term from researches that are done soundly (Grbich 2013, 4). These factors form the spine for the thesis.

5.3 Factors to consider

The case company for this thesis was in the start-up phase. The scarce resources dominated its actions in multiple fronts: the reader must consider it that a lot AI & ML related technology was available at the time of thesis process, but the validation through business value was not viable. This means that innovation through trials or other similar processes could not be conducted due to the case company's or my resources. Also, one must consider that these technologies will continue to develop from regardless of the subjective scope of this thesis. The speculation about the nature and future of the artificial intelligence continues to be discussed and this thesis process consists of information from exact timeframe consisting of the thesis process.

Additionally, the interview language was Finnish thus the linguistic analysis was done considering the translation from Finnish to English. Latter is not my native language thus some translation might have slight differences compared to original interview data. To minimise this, I did not concentrate in doing in-depth linguistic analysis per se.

6 Insights from experts

McKinsey & Company's research estimates that around 45% of interactions, or in other words: jobs done by human individuals, can be automated and performed by technologies which are already present and usable in some degree (McKinsey & Company 2015). The statement is bold, and it considers all the industries, not just the marketing industry. 'Threat' exists; Sharma (2017) adds two more challenges for ad agencies to overcome: disintermediation by digital advertisement platforms and agencies hardships to answer to the need for data-based conversion assessment. The first topic considers the digital service-providers desire to make display advertisement (for example in Google) easy to access and using user data to offer marketing tools for greater targeting for companies (for example in Facebook) – these alone are not enough to move agencies into the background. The "*magic*" or "*curse*", depending whom to ask, is in the opportunity to do all marketing processes in-house and cutting one intermediary from the process. Agencies were not needed in media buying in the same degree as before. The second challenge proposed by Sharma, problems in data-based quantification, is related with the agency industry's characteristics – any campaign made in the past was deemed as a success if a clients' decision maker *felt* it was good. This affected to a campaigns' outcomes. A campaign was to be likeable, not effective. If data is processed accordingly, it does not lie. I had noticed in my professional life that we, the marketers, had started to understand the importance of measurable marketing with data backed decision on customer interaction. This made it possible to measure for example return of invest in specific digital marketing channels.

Automation, which was mentioned in McKinsey's report, is part of the technological disruption of the agencies future. According to my understanding, this behold both threats and possibilities – adaptation to new surroundings was the key component for the industry operators. Ad and marketing agencies are not dying in instant apocalypse due to their entrepreneur mindset and adaptive nature (Business Insider 2017), but technologies like artificial intelligence and deepening focus on data will have an impact to the field. Kingsnorth (2016, 280**)** fortifies the need for automation: he states that building a report takes time and this should be automatized as far as possible to save time as much as possible.

6.1 Discourse analysis

Grbich (2013, 244) states that one question discourse analysis can be used to answer for is: *what are the outcomes*? This was the basis on my discourse analysis as I wanted to understand the outcomes from the conducted interviews. Gee introduces (2005, 110-113) seven building tasks for the discourse analysis which guides an “ideal” discourse analysis. Gee (2005, 9) points out that his theory and methods are not the one and only method and theory for making discourse analysis, but it is based and mixed with other significant work of the experts in the field. Additionally, he points out that he does not see his methodology as “steps to follow, but as *thinking devices*, to ask and research innovatively. Gee (2005, 6) describes that every research domain has different *tools of inquiry* – tools to describe and discuss on what the researcher defines to exist and be crucial in the chosen domain. For example, qualitative and quantitative researches have different methods and theories. These tools and theories change over the process when they are applied to the real world – in this case; discourse analysis for bachelor thesis.

For the reader: I did not profoundly emphasize grammatical or linguistics in my analyses. I chose to limit my analyses on the content itself to concentrate on gathering knowledge – thus the data cumulated from different individuals are combined to form generalised themes from the data. Additionally, the interviews were conducted in Finnish, and thus the social context of the discourses and Discourses differ compared to for example Finnish speaking English. As Gee argues about different Discourses in different social setups; speaking foreign languages can change the set-up of the situation in terms atmosphere, fluidity, intonation on words among other aspects.

I have put square brackets in the text if I felt to clarify answers. They were my interpretations about the answers and its context.

6.1.1 Jaakko Suojanen - Email interview and analysis

Jaakko Suojanen, CEO of Suomen Digimarkkinointi Oy, digital marketing agency operating in Helsinki, Finland, had been involved in digital marketing business from the year 2008.

Interview process was conducted via email: I sent questions which Suojanen gave answers to. The first question was to expose his journey with digital marketing. He described his proceedings as follows:

> “When I started in 2008, the digital marketing was in baby shoes. Concentration was in specific channels [internet, social media et cetera] and only a few agencies could measure the results [of marketing operations].
>
> Search engine optimisation, for example, was a backroom-work done by nerds, [and] not in the centre of focus when marketing was planned.

Google AdWords provided cheap clicks, and Facebook was only starting to learn how to drive goal-directed traffic to the sites, although I feel that still only a few agencies can exploit that. Concentration was on internet-sites and the exposure in Google. The algorithms of [different] channels were easy to "win" with manual work.

Today, instead of talking about the digital marketing, we could describe it as marketing in digital environment. Nowadays businesses won't actually do marketing without digital tools."

I continued to ask questions about used technologies and processes, Suojanen's vision of future and views on what kind of solutions subject technologies will bring to the functions of the digital marketing agencies. Suojanen wrote:

"We use many tools and often the choice is made based on that we can do more than just reporting with it. With Swydo we report almost all our services. With Google's Data Studio we've built dashboards for the big clients where we can show the esults of all the channels in the same place. [Google] Data Studio is free and easily modified.

[Digital marketing agency in the future] is agile, trusts in technology, serve the customer well and automatize most of the actions which obligate humans to take care of the creativity and customer service.

[Artificial intelligence and machine learning] will lift off a lot of manual work which releases a lot of time for thinking, creativity and customer service. The more is automatized, the better the processes must be to ensure the best is gotten from the automatization."

I wanted to know how Suojanen would develop their marketing reporting internally and externally (for the customers). Suojanen replied:

"Internally the base [of reporting] is really good and we get the most important information to the dashboard. Channel-specific KPI-monitoring in reporting has still its challenges because so many channels should be out on the same dashboard. These challenges are same externally" (10 October 2018)

Here I would like to point briefly to the statement of work done by nerds; this implicates for me that digital marketing has gone a major shift from being a niche to be as a mainstream channel of marketing. Suojanen has been around in the marketing domain from the start of social media-era, and the shift from thinking it as *digital marketing* to *marketing done in digital environment* builds a picture from digital marketing pioneer. He had seen the shift from more traditional channels to digital channels. As digital marketing company CEO, he had the responsibility to guide the business in shifting environment and as McKinsey's report implies, the automatization will affect businesses. Suojanen's wording leaves a positive impression from artificial intelligence and machine learning as he stated these processes as *time liberators* to take over the mundane jobs and offer more resources to creative and strategical jobs. He associated automatization with subject technologies which implied (for me as a marketer) that he had acquired domain-specific knowledge about the concept and what it will mean for him. I noticed that the customer service and related contexts pop up from the answers quite consistently. Digital marketing agencies could be seen as intermediaries between a company and their customers – I got the sense that Suojanen values customer companies and emphasises good service. Notable for me as the analyst of this data was the description of the overall service of Suomen Digimarkkinointi Oy – one can find mentions concerning Google. Thus, the company uses its through-out their operations (this could also be confirmed from company's website as they are Google-partners). The comparison of the past with channel-specific concentration and statement made with Data Studio, all channels in one place, indicate that Suomen Digimarkkinointi uses all the digital marketing channels in their operations. Overall impression from Suojanen was pioneering digital marketer.

6.1.2 Oskari Miettinen - Face-to-face interview and analysis

Oskari Miettinen worked as Data Analyst / Data Scientist in Avarea Oy during my thesis process, and he had obtained Ph.D. in Astrology. He wrote scientific publication concerning machine learning algorithms in astrology during the year of 2018. The interview was semi-structured by its nature. I presented additional, deepening questions when I felt them adequate.

We started the interview from the beginning, Miettinen's past and how he got involved with artificial intelligence & machine learning. He answered as follows:

> "The semi short answer is that my background is in astrology – I am a professional astrology researcher. So, I studied ten years the matter between stars, the birth of stars and the last three and half years the birth and development of galaxies. In practice, astrology is data-analytics; observation data is gotten from observations. Then its analysed with different tools. As a researcher, I did not use machine learning per se; I was hardly even heard about it [before my current position] except some articles where some tools of machine learning were used in some instances. When I made a career change to be Data Analyst & Data Scientist, I had to start educating myself concerning ML because of its pivotal technology and tool in this occupation."

Thinking retrospectively, we studied similar algorithms [in astrology], but those were not named as machine learning; machine learning is a set of algorithms that can be utilised as machine learning. [*I asked if Miettinen sees it as a matter of conceptualisation, where the business world has re-named existing technology as ML*] Yes, in my mind yes.

As we continued to discuss more the situation of AI & ML when Miettinen started to work with it and how his perception has changed during the time spent with it, he told:

> "I started to study it [ML] from theory, as it is part of my university background – I thought that's the appropriate approach. I noticed that I don't understand anything about it. The theory of machine learning and its math goes deep. It did not make sense from that angle, and I started to do tutorials and approach the concepts from examples in Python and R [languages used in ML]. Then I started to understand what it is all about. After that, I returned to theory and the multipurpose nature [of ML] has dawned to me during this journey and how it can be exploited in so many different contexts."

The interview shifted to the next phase of the interview: what were the most essential processes made possible by artificial intelligence & machine learning and why? Miettinen the started with statement of 'broad questions' (brief feedback for interview questions in short) and continued:

> "I have to remind that I've been in the business only for little over a year. However, I would say when companies have a tremendous amount of data-material, described as Big Data, [and] in these situations the traditional methods of data-analytics aren't enough. [Due to the amount of data] we need answers and results fast. Machine learning provides this speed, though sometimes with the cost of accuracy. But these kinds of data mining tasks related to anything: building customer segments, making association analyses. Like when the 'shopping cart analyses' are done instantly with machine learning. I would say that in macro-level the processes can be expedited."

The next question was to hear Miettinen's visions of the future of AI & ML in business

> "I would say it will become more common among all operators. It's maybe wrong to say that it's a 'delicacy only for a few' as it is already practiced in many places and organisations. But its undoubtedly that the usage of it will

spread or become more common, and the tools [of ML] will become more user-friendly and the need for experts to use them decreases. That would be one practical point – then maybe new [ML] methods or algorithms will be developed which can revolutionise some aspects [of the technologies]"

We discussed briefly on the matter of data and the decision making based on feeling and if the data-mining could be successfully scaled into various industries (as it already was). Miettinen stated:

> "Absolutely. When statistical facts are gotten out of the [ML] process, then we don't have to listen "I feel that, "I think that" et cetera [in decision making]."

I wanted to know Miettinen's thoughts about current ML tools and how they are distributed. He answered:

> "They're quite scattered. I would hope a little bit of clarity for the work-flow. I am not a professional coder. Hence, I use tools to complete one task and then I combine different components [of work] together.
>
> I think that the situation is similar in other fields where reporting is done with another tool than analyses. Additionally, there can be Excels and some other stuff involved…"

The remaining part of the interview included Miettinen's personal views on where he would like to find benefits of ML.

> "Machine learning features and artificial intelligence usage are said to be more accurate already than the best specialist doctors, thus in the future, it is important for all of us to trust in them [AI & ML applications] and due to that I hope we live longer."

I asked if going through masses of data and this "diagnostic"-capabilities can be scaled to other business in Miettinen's mind as a follow-up question, and I related this to for example marketing where decisions have been made based on the gut-feeling in the past

> "Absolutely, yes. When statistically significant fact is received from it [AI or ML system] the "I feel" and "I think" don't have to listened anymore. But I feel it isn't that black and white; that if data says 'this' and that is the way to go. [I think] that there's a human there to interpret it and [a human] makes the final decisions. It is discussed that it [AI and ML] is there to support the decision

> making. I hope that it is like that and the data isn't forgotten in the end, and the feeling takes over." (17 October 2018)

Miettinen constructed his argument on basis of "need for the validation". This projects his background as a researcher, and he uses definitive statements scarcely. This characteristic is important to Data Analyst, Data Scientist and for the record; marketer, as every hypothesis needs validation. The interview constructed image from "academic turned to business" – Miettinen's the current occupation consisted many similarities with his past. As I worked in the same company as Miettinen during the interview, I had some organisational information and social ties with him. This affected the interview as relaxing component and the discussion was a lot like peer-to-peer. Few exciting facts rose from the interview:

- the algorithms Miettinen had used in astrology were highly similar than in machine learning
- the amount of data cumulated by companies is huge
- use of machine learning tools is going to grow in general
- We, humans need to trust in machine learning solutions in the future.

It should be kept in mind, that these arguments are made by a professional working in the specific field of business which has adopted the technologies of machine learning. An individual can advocate the technologies one uses due to the professional relationship with them – in another way, one can feel "obligated" to support them. When I asked about the future of artificial intelligence technologies, Miettinen started to answer with an argumentative model to form his opinion but proceeded to use the absolute term of 'undoubtebly' concerning the future growth of the tools. This is in a line of consensus of the subject technologies in global level of nonspecific business climate – interviewee himself brought up the medical usage of ML-technologies to support the cross-industry view. He also seemed for me to be very sure about the possibilities to use of data-mining and diagnostics in other industries as well. To understand this, I think it good to understand the algorithms had already supported Miettinen's work in two different domains: as a researcher and as data analyst/scientist. Thus, one knows of the benefits gained with said technologies. Miettinen knows what could be done with the tools of machine learning. This is empirical knowledge which was crucial for my thesis and valuable secondary data. Miettinen pointed out the data-mining capabilities of the algorithms, which in the case company's business case is important due to the constantly growing amount of data from various digital sources. There was one notable aspect of discourse: even though I asked questions with both terms 'artificial intelligence' machine learning', The respondent directed answers to machine learning – thus, I felt that this validated the argument of strong and weak artificial intelligence.

6.1.3 Lasse Rouhiainen: Questions via email with video-response

Lasse Rouhiainen, an international author in AI and lecturer, was an excellent source for general information concerning this thesis. I sent questions through email for Rouhiainen and then received responses on video.

My first question was to map Rouhiainen's background in the subject of artificial intelligence and how his views had been changed along the way to date of interview. He responded:

> "I started to follow it around four years ago. I read an article about how Facebook develops its algorithm, or how machine vision recognises pictures. It was [for me] a secondary 'thing' in a sense that it did not have an impact in society, but when I started to investigate the matter, I noticed that it'll impact on everything. From that, I got an idea for my book, 101 questions, and answers [about AI] and where it impacts. At the start it was an idea to have 49 cases [in the book] but as further the writing process went, I started to notice its impact to all the segments of society, business, and well, in life.
>
> The problem in this is that it ["arrival" of AI] is going to happen fast and people don't have the time to prepare for it. This is the concept where I try to take it forward; that people would understand it more."

The second question was about the most important, current processes made possible by artificial intelligence and machine learning. He responded:

> "If you think about marketing or businesses in overall, the yester times they had just a small amount of data. Companies used television, radio among others [for marketing]. Now, the format they use and where parts of our lives are is digital marketing and thus, the amount of data is vastly larger. For example, we can use Google Trends to see if specific search terms go up et cetera. This amount of data grows all the time and until this point, many of the tools that use this Big Data have been free to use. Students, for example, have searched for information and analysed it. The next step is that you can "hire" virtual assistant and this assistant makes the analysis, for example marketing analysis, for you. This is possible already in small scale in IBM's cloud-services.
>
> It is going to affect every process: everything is going to be more efficient."

I proceeded to ask Rouhiainen's vision about the role of the subject technologies in the future of marketing:

> "It is going to automatize a lot of marketing [functions] and its functions as best when there is a human who analyses the results of the artificial intelligence and uses it to different things. For example, in Haaga-Helias sales [slap?], we could put 50 people into a movie theatre where we could show e.g. fashion products for them. Artificial intelligence would monitor their facial expression and galvanic response, the moisture of the skin, and thus it would make the analysis and conclusions more accurate when making the market research."

The next question was to understand what aspects Rouhiainen wanted to have for his work from artificial intelligence technologies. He told:

> "Actually, the biggest effect I am hoping for is in segments of medical and study. I would hope there to be an "ethical police" of kinds which could check up different factors and conclude that "this is good marketing" or "this is bad". Like a bot which goes through things like this. For example, Google's AI goes through YouTube videos for their thumbnails [picture to represent the video] to spot things that are not supposed to be there.
>
> What comes to my work, I would like to have more personalised sales funnel for my internet site. So, if somebody lands on my website, it [AI] would ask the gender and knowledge level, e.g. about digital marketing, and thus it would give different customer journey based on this information."

I presented a bonus question to ask Rouhianen's opinion on how AI technologies will affect the role of digital marketing agencies. He replied:

> "I don't actually know. I think that it is like in other parts of the marketing – those agencies who are accompanied with this [AI] will find great advantages from it and they who see it as "mumbo jumbo" will face great difficulties and end their business." (23 October 2018)

It must be acknowledged that Rouhiainen operated at more macro level in artificial intelligence, not just in the marketing domain. This was a fundamental view when I analysed the answers and their aspects due to the level of knowledge on specific topics.

Rouhiainen seemed to have adopted the role of a teacher in subject technologies as he wanted to people get acquainted with the subject. He had already delved quite profoundly to the topic of artificial – he had quite firm views and opinions when he constructed the importance of the subject technologies and how they were going to be in the future. He used absolute terms such as “it is going to be”. This project the general view in the technological sphere about artificial intelligence, and that it is going to be used widely. There are still questions if decision makers in other industries understand what AI is and what it can do – it might be more matter of definition. Rouhiainen used many examples to argue his points and this offers support for his statements. I felt that Rouhiainen had excellent general knowledge of artificial intelligence and its applications. This offered knowledge for the general discussion about the possibilities. Domain-specific information about the marketing introduced concepts such as bot and intuitive market research which could be based on human responses. These topics are more macro level when compared to scope of this thesis.

6.2 Intel from the interviews

As I did focus more on the language, *discourse*, than the *Discourses* in my analysis, I made conscious choice to put titles and interviewees’ affiliation with subject technologies and with me, the interviewer to the personal introductions. This, in my mind, offers the possibility for a reader to validate or invalidate my discourse analysis and combine text and given background information to analyse the Discourses of the interviewees further.

My initial plan was to gather data from different professionals marketing and AI & ML sphere because I felt that technologies of for example machine learning are generally quite scalable through different industries. As a matter of fact, after our interview-session with Oskari Miettinen, he said, and I quote:

> “Maybe the problem of artificial intelligence and machine learnings is that people around it speaks from them too macro level and they don’t actually talk what it *really* is. This makes it seem that the offering of solutions and possibilities are quite generalised”

This was one point that made me think about the situation in the analysis of the data. I wanted to see if there were similar themes in interviews and how were these similarities constructed by individuals with different views on the matters. I found common themes from the answers of the interviewees: accuracy, automatization, big data, the role of humans, trust towards technology and data-mining or data processing. Not all these terms surfaced in the all the answers. Thus, I build list below to clarify the connections:

- Miettinen and Rouhiainen discussed accuracy on medical solutions and marketing research, two whole different systems in different domains. Miettinen’s medical symptom detector are a valid example; results are reported to a doctor who

consults then a patient – this is *reporting*, just like Rouhinainen's virtual assistant analysing material and combining report for the user.
- Suojanen and Rouhiainen discussed automatization. In marketing, it is commonly seen as Suojanen describes it; it will free up the time for humans to do more creative tasks whereas machine takes care of the others. Supervised or unsupervised machine learning could be adopted to do these kinds of tasks.
- 'Role of humans' is a continuum from the automatization and all interviewees talked about it in some context. Suojanen discussed how time would be saved for more meaningful jobs. Miettinen saw humans as the final decision maker where machine or data gives support for the decisions made. Rouhiainen used the example of virtual assistant and content qualifying bot. These views all add something to the equation: the perspective is that artificial intelligence will enhance humanity's actions. The valuation processes of artificial intelligence were brought up in the interviews (for example Rouhiainen's bot for valuing marketing – essentially a loop which assesses material and reports it with its actions). In my mind, this combines automatization, human's role and marketing functions into the same system.
- Miettinen and Rouhiainen present big data. In essence, it is massive amount of data produced by many sources. The amount of data is crucial for the technologies in focus in this thesis.
- Suojanen and Miettinen both mentioned the trust in machines; Suojanen as part of future marketing agency and Miettinen as part of humanity's and machines' relations in the society of the future. This amplified the business case of the case company's product as it relies on data and automated information made from it by a machine. In a sense, Rouhiainen's validating bot could be categorized as a need for trust in my mind as it makes decisions and people have to trust that machine obeys the rules which are coded in it.
- Data mining or processing was brought up by Miettinen and Rouhiainen. It was said that these modern technologies make it faster to go through vast amounts of data – they make it efficient.

Table 2. below contains macro-level content analysis concerning main themes I found from the interviews. I wanted to generalise the interviews into these main themes to understand contents of the interview and to summarise them in macro level.

Topic / Interviewee	Jaakko Suojanen	Oskari Miettinen	Lasse Rouhiainen
Accuracy		X	X
Automatization	X		X
'Role of the humans'	X	X	X
Big Data		X	X
Trust in technology	X	X	(X)
Data mining/processing		X	X

Table 2. consist matrix of found macro themes in the interviews per interviewee.

These themes that I extracted from the analysis of the interviews were necessary for the case company's product. The interviews formed a consensus concerning artificial intelligence and machine learning; all the interviewed experts agreed that these technologies would affect world and marketing. According to my understanding, the complexity of the subject technologies and different use cases made it hard to accurately pinpoint the domains and use-cases where it would be utilised the best.

It is good to keep in mind that even though common themes arose from the interviews, the role of artificial intelligence and machine learning was not established in business as general technology. My experience in working life provided some insights from the customer domain of my employer during the time of the thesis process. According to these insights, the definition and contents of subject technologies were not crystallised – as Miettinen told, he used some similar algorithms in astrology and he mentioned that the conceptualisation of said technologies for business use started to make them known. Rouhiainen supported this view as he said that people do not know what artificial intelligence is. The theme which was directly mentioned by all the interviewees was the 'role of human'. This could be exaggerated to two dictating views about artificial intelligence and its applications: they were going take the jobs from humans, OR they will take care the mundane jobs from humans. The interviewed experts leaned towards the latter scheme. This indicated that all three experts expected the humans to be in charge of processes in future; in my mind, strategical marketing decision making should be put into this category.

Discourse analysis and qualitative analysis from the interviews was done based on interview data. It provided a solid foundation to understand the concept of artificial intelligence and where it was headed at the time. These results were used to argue and validify the recommendations.

7 Recommendations

The last chapter concludes the findings and results of this study and describes the formed synthesis between findings and the research problem and investigative questions. Key findings are described first where text proceeds to report and evaluate the obstacles faced during the thesis process. Last subchapters consist recommendations to stakeholders and discussion from the thesis journey.

7.1 Key Findings

Order of result description of the study is as follows: first, the investigative questions are answered, and then the feature recommendations are constructed based on gathered and analysed theory and other relevant research data.

Investigative question number one was included to the thesis for finding the theoretical framework for the context of artificial intelligence and machine learning specifically in marketing where it was projected further to reporting. The research data from desktop research suggest that these technologies are commonly applied to data mining and processing. Further in processes, said technologies are used in modelling and finding insights from data. These insights are the main tool for reporting applications which are constructed with subject technologies. The distinction between strong and weak artificial intelligence proved to be significant due to the technological applications and solutions were all categorised to the weak artificial intelligence subcategory at the time of the study. These applications were then defined as machine learning models and algorithms which function in marketing systems. Three categories for machine learning were then described:

- Supervised
- Unsupervised
- Reinforcement

These three defining subcategories include different kind of models and algorithms which aim to complete given tasks with feedback-loop. Latter is defined by the machine learning models' predefined and wanted outcome. As these outcomes are dependent on the chosen model and its distinctive categorising of machine learning, the needs from the machine learning applications should be carefully considered before mapping and testing of a chosen model can be started. An additional theme which constantly rose from the research was the quality of data – this is quite well managed in the case company's product due to the data flow achieved with API integrations. This data was already processed through source services' system; hence the outcome should be stable regarding data quality.

Benchmarking the marketing reporting industry leaders was the second investigative question. This stage included qualitative research in the form of empirical studies including topics such as marketing reporting and its functions, aims and goals of reporting, and subject product of industry leaders (Google Analytics and Adobe Analytics). The overall understanding from the functionalities of marketing reporting system had to be explained for understanding the main principles of the domain of benchmarked products. Google Analytics could be accessed through the internet. I had obtained access to it before the thesis process but information concerning Google Analytics 360, the premium version was unachieved due to the lack of resources. Adobe analytics was examined through the material provided by Adobe and other, mainly external sources. The most prominent finding from the products of industry leaders was the use of general artificial intelligence. Google and Adobe used their distinctive artificial intelligence services in their marketing reporting products. These solutions constantly crawl through the data obtained to their systems – outcomes of these processes were, during the thesis process, insights from the data and optimisation suggestions. According to my understanding, these kind functionalities were obtainable to the case company in their product. Chapter 3 consisted of a lot of initial ideas for the models which could be used in these processes. The constant quality and unified form of data could be seen as a strength in this process. Artificial intelligence and machine learning systems need a lot of data to function.

Investigative question number three was formed to gain knowledge from domain experts. I proceeded to obtain views from more general artificial intelligence and machine learning experts and digital marketing agency CEO. The interviews supported my hypothesis of growing use of subject technologies. Five main themes could be identified from the interview data: automatization, accuracy, Big Data, ‘role of the humans’, trust towards technology and data mining/processing. These were themes which I generalised from the interview data to project the responses to a macro-level. Discourse analysis is a form of qualitative analysis. Thus, the reflection and analysis demand analytical skills and insights from an analyst – in this case: me. I wanted to extract topics which then could be made as objective as possible to provide data to answer the investigative question. Extracted topics were formed as short terms or phrases and thus they achieved a certain level of unbiasedness – here one must understand that my analysis was still validated through my perspective and experience. I aimed to lose specific terms and words which could form Discourses in certain contexts where more information would be available. The validation and reliability of the data stem from a wider group of people, not from individuals. This is why I chose to generalise the acquired themes. In the context of the case company’s product, these themes were essential: real-time marketing reporting needs accuracy and automation to be beneficial for the customer. The amount of data is important to provide meaningful results whereas the 'role of humans' is widely discussed throughout this thesis; machine learning applications in marketing were aimed to have better and faster results from big amounts of data. This requires data mining and processing capabilities which machines possess; humans do not have these kinds of resources. Nor they even should, but this is a great opportunity to harness the benefits of machine learning in the case company's product; it produces data continuously. Hence, there is vast amount of it which is an optimal starting point for development. If one seeks benefits from the subject technologies, a level of trust is needed for harnessing the intel provided by systems.

During the research for finding adequate information to answer investigative questions, I wanted to include only the relevant information to this study. This perspective was acquired with demarcation; I wanted to have the bare essential in the paper. This provided robust frameworks for building two concepts which I see functional for the case company's product. Next two sub-chapters will describe these two features which could be implemented into the product. These recommendations were built to conceptualise the overall feature; I did not offer exact models or algorithms as building blocks due to the need of empirical testing and validating the model used in each specific use case (Järvenpää, 21 August 2018). It seems that the research for the thesis suggests that defining and finding the correct algorithm would provide to be subject for another bachelor thesis. The reader should understand that more recommendations could be found through additional research.

7.1.1 System for insights and suggestions

The first recommendation is based on Toni Nurmi's idea of "heuristic artificial intelligence" which could gorge through all the cumulated data by the Madtrix. This data was provided by the source services such as Facebook, HubSpot among others. The quality and attributes, according to my understanding, are then constant and known due to the already formed parameters by said services. As it was acknowledged in industry leader benchmarking, Google and Adobe already use artificial intelligence systems in their applications. These systems are essentially machine learning algorithms constantly crawling through their data. For example, Google Analytics dashboard shows anomalies in the data for example dropping or raising visitors on a specific page. As the case company's product supports on already attributed data, it could be harnessed to evaluate outcomes of the marketing data coming from source services. This data consisted of ad spend and metrics such as cost-per-click, cost-per-view and so on. These values were distributed to Madtrix in real-time. As the amount and quality of data in machine learning systems have been found crucial during the thesis process, this scenario made it viable to use the subject technologies. I recommended unsupervised machine learning algorithm(s) to be applied because it could raise causalities and relations in data that could be quite useful but could go unnoticed by the user without the machine. This demanded analytical skills and knowledge on behalf of an operator, but then again, Madtrix is aimed for professional use.

As I mentioned, the data acquired by Madtrix's system is constant in quality; I contemplate potential results to be logical as the nature of fetched data will not shift during the process.

7.1.2 Prescriptive analytics for digital marketing reporting

Analytics is as essential part of the reporting system and Madtrix's aims to help its customers to achieve performance measurements and decisions making processes based on data. This data already consists parameters which describe the effects for example marketing campaigns in AdWords (cost-per-click). This is called descriptive analytics, and as the case company's system already contained descriptive analytics (it visualises values like cost-per-click), the next step in Katsov's three categories (descriptive-predictive-prescriptive) would be predictive. As Katsov (2018, 19) mentions, holistic analytics includes all of these three categories. As the predictive analytics could tell the potential outcome of the changes in output variable in relation to the input variable based on prior data, I would recommend that the case company aims to harness historical data from ads in AdWords or Facebook and built systems which projects simple outcome of invested money (input) and outcome of cost-per-clicks (output). This scheme includes more variables than these two; for example, AdWords rates any ad put into the system and uses an algorithm to evaluate multiple attributes such as content and landing page of the ad, maximum bid amount set by user et cetera. The overall evaluation forms Quality Score (Google, 2018b) for an ad – this is the key attribute for my recommended solution. If the case company achieves to harness Quality Score. This process is possible as I have used other systems which do it. Google shows this score in the AdWord user-panel. I am confident that different ads and ad-sets inside the AdWords could be compared and then data could be harnessed for a prescriptive dashboard. This dashboard could give sophisticated estimations regarding the investments and attained results. The graph could consist for example the cost-per-click graph with current CPC-value and then estimated results could be shown in the same diagram. Figure 7. On the next page visualises a prescriptive graph.

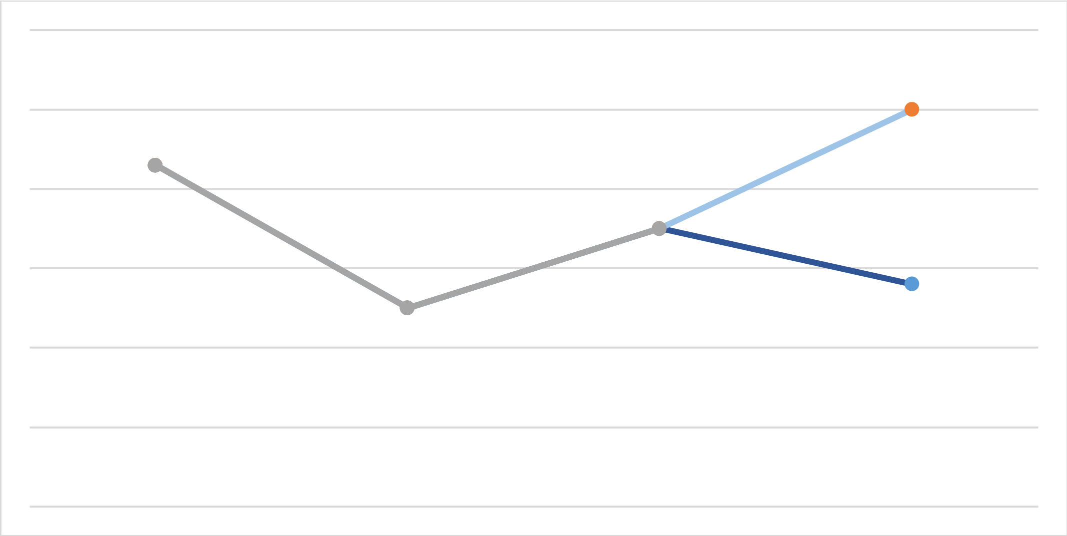

Figure 7. Visualisation from prescriptive graph.

The idea behind the graph is simple and I understand that it is used in modern analytics. The grey line is the factual visualisation of measured metric. Lines with different shades of blue are the result of prescriptive analysis regarding actions with input and output. The cycle of the graph, X-axis, would be time and Y-axis could be the wanted value. In the example I used cost-per-click value.

7.2 Restrictions

The results of the study could not be fulfilled regarding the fourth investigative question which was initially included in the study. The question aimed to understand the needs of digital marketing agencies in marketing reporting. I did not proceed with this task, and I decided to dismantle this objective from the thesis. Reasons behind these are as follows:

- The first interview with Toni Nurmi already informed me that as the situation stood, the implementation of artificial intelligence and machine learning technologies to the case company's product was not a business priority. I shifted the focus to understand these technologies and to have valid recommendations from that basis.
- The benchmarking of industry leaders provided me insights from what can be achieved with the subject technologies in marketing reporting. Thus, I did not see it viable to seek information from target customers due to the macro information which was obtained from benchmarking.
- The situation of artificial intelligence and machine learning technologies were not established yet. For example, the interviews if the domain experts indicated that the use of technologies was scattered, and possibilities of subject technologies were not sufficiently ventured to understand the realistic scope for customer needs.
- Marketing agencies CEO's were quite busy and setting up an interview was complex – more so when an ideal form for discourse analysis would have been a face-to-face interview. I achieved to have one interview with a representative of this domain. We agreed to have an email interview which proved to be narrow in content wise.

- Resources and time which I would have needed to acquire this intel were not on my disposal during the thesis process.

My choice to not advance with this investigative question was also a strategic one. I aim to use this bachelor thesis as the basis of my master's thesis in the future. I acknowledged this investigative question to be potential starting points for that process. Levels of maturity and generalisation of artificial intelligence and machine learning technologies were not sufficient enough. Interviews of the experts support this hypothesis – this leads to the question: if there are not enough generalised solutions on this front and they cannot be obtained quickly enough by users, how one could validate the maturity level of the users to dictate their technical needs at that given moment?

An additional concern was the effect of having one representative from the case company's customer segment of digital marketing agencies. This offered challenges in generalising data to cover the whole domain's needs. On the other hand, I felt that general artificial intelligence and machine learning experts could provide invaluable information concerning subject topics and their respective futures. I found it to be easier to agree on a face-to-face interview with other experts compared to CEOs of digital marketing agencies, and thus this shifted my focus regarding interviews and goals which I felt I could achieve with the thesis.

7.3 Recommendations for later studies

I wanted to provide some guidance for agents wanting to research artificial intelligence and its applications in general. First, one should naturally get familiar with the subject. It was a buzzword during my thesis process and understanding what the processes and functions of said technology are vital. I reckon this to be true at any given time on any given subject. Still, conducting qualitative research on artificial intelligence and applying this to narrower domain demands to understand from the subject technology in general level. This leads to the scope of the study. One should demarcate the scope and field as specific as possible. My struggles in research was the constant balancing act of keeping the general level of the information concerning artificial intelligence and marketing technologies in line. This meant continuous valuation of information – knowledge of artificial intelligence concerning marketing reporting were scarce and if research was specified even further to reporting; the material was almost non-existent. The valuation of the research and observation data is naturally crucial in any thesis or research process in general. Understanding the unseen connections of generalised intel from given subject and building theories around it proved to a complex task. This should be understood as important before studying subjects in similar scope that I did.

Interviews were a vocal part of my study. If one would like to emulate the thesis subject and elaborate even further, I would compose more thematical interviews with more homogeneous participants. Setting up face to face interviews with structured questions imposed to the case company's target customers would have been an optimal way to proceed, but like it was discussed, I did not see it viable in this context. This study could be imposed as necessary level information and stepping stone for more in-depth research projects. Thus, constructing an interview group from specific domains' experts and having more structured questions should be considered as a must.

7.4 Learning outcomes

The thesis process was full of ups and down, which I already see as learning from the process and how to manage it. This could be overlooked by many, but I see it as important to understand. Writing a thesis could be seen as a journey which will end up a writer to find "home" or "solace" if one makes an effort to complete it. It sounds obvious, but one must consider this: how many individuals you know who will not even start thesis or similar project during their life?

I was astounded by the scope and amount of theory considering artificial intelligence and its subcategories. This me humbled during the first steps of the thesis process. I thought this to be a good thing, but the general level of information was quite tricky to be validated to imply for marketing reporting. This aspect was also satisfying: I did not find any material for this; hence I could see myself as one of the pioneers to the subject in the context of academical writing. The nature of the source material was challenging, and this drove me to develop my research and analytical skills; something which I aspire to do in my work life, too. This process gave me guidance on how to develop these competencies. Some additional competencies got their fair share of added "punch": organising, planning, interviewing and discussing with target people to name a few.

As I had been working already in digital marketing before the thesis, I had some insights from the domain and its needs from reporting. I took the reporting as quite self-explanatory and honestly, I was not interested a lot about the back-end functions of it. Digital marketing reporting includes so much more than meets the eye. The analytical tools behind reporting must be thought and like Kingsnorth (2016, 276) stated: reporting can be the most important thing in the marketing process. As I had already found this to be true before my thesis process, I believed in it after the process.

From theory which I examined to this thesis, I learned a lot about contexts of artificial intelligence, machine learning and their distinctive relations with business. I was able to acquire more knowledge on marketing and its core processes, mainly reporting. Constructing knowledge framework for reporting and measurement process will help me in the future. Research process taught me important aspects of qualitative research and from its counterpart, quantitative research. I understand that the thesis topic was in the pinnacle of hype prior, during and after the thesis process, but I aimed to embrace this fact and harness the knowledge for me to use in my career. Like Miettinen stated, at the time of the thesis process the discussion concerning machine learning and its application were conducted on a quite general level. Additionally, like Elements of AI and Sterner argued it, all the applications of artificial intelligence belonged to weak or narrow AI. These applications were commonly called machine learning. These aspects provided me a chance to build a macro level tool pack to understand every discussion concerning artificial intelligence and machine learning. It shall be seen how far it got me.

After the process, I already had decided that this bachelor thesis will work as a baseline for my master's thesis in the future AND as a foundation to understand the benefits of using machine learning in reporting and decision making in my work life. This was something I engraved when I started the process and I am glad my ambition of choosing complicated thesis subject paid off.

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Appendices

Appendix 1. Information about the case company

A brief description of the case company's product – MadTrix Marketing Performance Dashboard

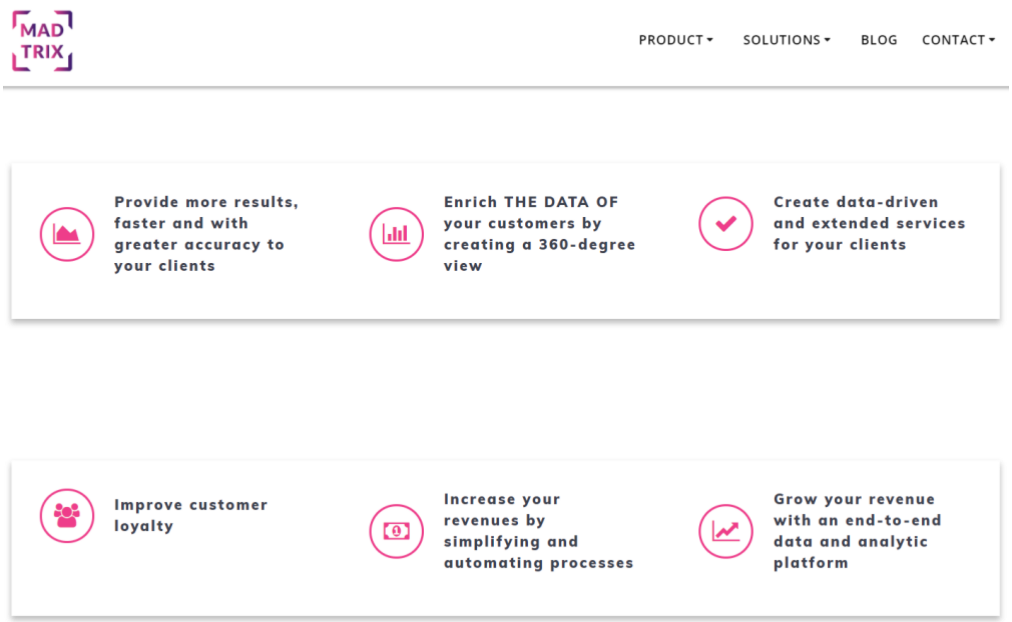


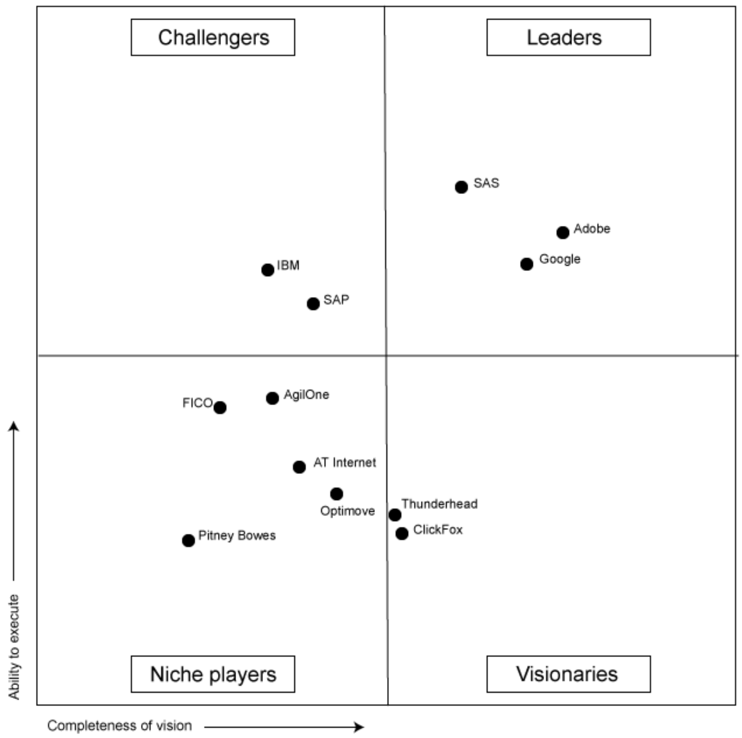
Figure 8. Madtrix's simplified feature list for marketing agencies

Figure 9. Simple flow chart to describe the service process of the case company's product.

Appendix 2. Binary tree

List of numbers are selected [1, 2, 7, 11, 21]. '[…]' is symbols a list and the values inside the list are divided with commas. All the values are individual memory slots/cells and all of them will get an index-number. In computing, the index of a list start from 0 and grown with one with every growing value. Thus, the index's representing values in the list would be: (value=index) 1=0, 2=1, 7=2, 11=3, 21=4. Let's presume we would like to check if the list has number 21 in it, we could go through every index in the list until the value is found or the list ends. In this scenario, program would start from index 0 which would be value 1 and the it would proceed to next index's value and so on. This would be inefficient, and the list could contain millions of numbers as index-numbers hence it would take a lot of time. Instead, binary tree would be better way to execute the problem – program could be told to start from index number 2 which would return the value 7. As the list would be ordered from smallest value to the highest value, the program could exclude the index numbers 0 and 1 because they have smaller values than 7. Now the program has two indexes to look at, so it cannot take the middle one, thus it proceeds to take the lower index which is 3 with value 11. Binary tree checks the remaining index 4 and state if it found the value 21. Binary tree can process lists size of a billion values with approx. seven revisions if the list is arranged from smallest value to highest or vice versa. Nurmi (11 September 2018)

Appendix 3. Gartner's Magic Quadrant of Digital Marketing Analytics



Short descriptions for the quadrants' areas:

Leaders: ability to support customer base containing heterogenic set of companies and continuous development and adding of more advanced features for the platform.

Challengers: Enterprise scale-services with own and partner resources. Quite small lines of businesses with large corporations. In development shift with benefits from companies' foundational technologies.

Visionaries: Concentration on customer journey analytics (CJA) with aim to answer "how and why" the customers act and behave with, for example, interfaces and to pursuit a goal.

Niche Players: Service providers with different strengths and customer focuses. These companies dissociate from above groups due challenges in offering and brand migrating, and they lack scope of the Challengers' and market vision of Leaders and Visionaries.

More information about the evaluation criteria can be found from the Gartner's web-sites found in the list of references.

Appendix 4. CRAAP Test

Evaluating Information – Applying the CRAAP Test

Meriam Library California State University, Chico

When you search for information, you're going to find lots of it . . . but is it good information? You will have to determine that for yourself, and the **CRAAP Test** can help. The **CRAAP Test** is a list of questions to help you evaluate the information you find. Different criteria will be more or less important depending on your situation or need.

Key: ■ indicates criteria is for Web

Evaluation Criteria

Currency: ***The timeliness of the information.***

- When was the information published or posted?
- Has the information been revised or updated?
- Does your topic require current information, or will older sources work as well?
- ■Are the links functional?

Relevance: ***The importance of the information for your needs.***

- Does the information relate to your topic or answer your question?
- Who is the intended audience?
- Is the information at an appropriate level (i.e. not too elementary or advanced for your needs)?
- Have you looked at a variety of sources before determining this is one you will use?
- Would you be comfortable citing this source in your research paper?

Authority: ***The source of the information.***

- Who is the author/publisher/source/sponsor?
- What are the author's credentials or organizational affiliations?
- Is the author qualified to write on the topic?
- Is there contact information, such as a publisher or email address?
- ■Does the URL reveal anything about the author or source?
  examples: **.com .edu .gov .org .net**

Accuracy: ***The reliability, truthfulness and correctness of the content.***

- Where does the information come from?
- Is the information supported by evidence?
- Has the information been reviewed or refereed?
- Can you verify any of the information in another source or from personal knowledge?
- Does the language or tone seem unbiased and free of emotion?
- Are there spelling, grammar or typographical errors?

Purpose: ***The reason the information exists.***

- What is the purpose of the information? Is it to inform, teach, sell, entertain or persuade?
- Do the authors/sponsors make their intentions or purpose clear?
- Is the information fact, opinion or propaganda?
- Does the point of view appear objective and impartial?
- Are there political, ideological, cultural, religious, institutional or personal biases?

9/17/10

https://www.csuchico.edu/lins/handouts/eval_websites.pdf

Appendix 5. Bayes' rule

$$P(AB) = P(A|B)P(B) \quad (1)$$

$$P(A|B)P(B) \quad (2)$$

One of the variables is hypothesis, H and the one left is data, D. The Bayes' theorem is used to assess the hypothesis accuracy in relation to given data.

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \quad (3)$$

P(H) is the hypothesis which one has before the exposure of the data (prior), P(D). The term P(H|D) is the posterior situation where it reflects the probability of the given hypothesis when data is added and considered through the process.

Appendix 6. Interview questions

Jaakko Suojanen, CEO of Suomen Digimarkkinointi Oy, e-mail interview

1. Could you describe the changes in your industry since you've started your career?
2. What technologies you use in marketing reporting and why?
3. How does the digital marketing agency from the future look like?
4. What kind of solutions do you envision are brought by artificial intelligence and machine learning to the processes of marketing agencies?
5. How would you develop your marketing reporting internally? Externally? And why?

Oskari Miettinen, Data Analyst / Data Scientist, Avarea Oy, face-to-face interview

1. Could you tell about your own background and how did you end up working with artificial intelligence and machine learning?
2. Could you describe the situation of artificial intelligence and machine learning when you started to work with it and how it has changed until since?
3. What are the most important processes in business made possible by artificial intelligence and machine learning?
4. What is your vision for the future concerning artificial intelligence?
5. What kind of benefits would you like to gain from artificial intelligence and machine learning in your job?

Lasse Rouhiainen, Lecturer and AI-author, e.mail interview with video response

1. Could you reflect the situation of artificial intelligence and machine learning when you started to work with it and how its evolved since?
2. What are currently the most important marketing processes made possible by artificial intelligence and machine learning?
3. What is your vision from the role of artificial intelligence in the future of marketing?
4. Could you discuss about the benefits you would like artificial intelligence and machine learning to produce for your work from marketing point of view?
5. Bonus: How do you see the subject technologies to modify the role of digital marketing agencies?