Exploring the potential of machine learning
- How machine learning can support financial risk management

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Abstract

For decades, there have been developments of computer software to support human decision making. Along with the increased complexity of business environments, smart technologies are becoming popular and useful for decision support based on huge amount of information and advanced analysis. The aim of this study was to explore the potential of using machine learning for financial risk management in debt collection, with a purpose of providing a clear description of what possibilities and difficulties there are. The exploration was done from a business perspective in order to complement previous research using a computer science approach which centralizes on the development and testing of algorithms. By conducting a case study at Tieto, who provides a market leading debt collection system, data was collected about the process and the findings were analyzed based on machine learning theories. The results showed that machine learning has the potential to improve the predictions for risk assessment through advanced pattern recognition and adapting to changes in the environment. Furthermore, it also has the potential to provide the decision maker with customized suggestions for suitable risk mitigation strategies based on experiences and evaluations of previous strategic decisions. However, the issues related to data availability were concluded as potential difficulties due to the limitations of accessing more data from authorities through an automated process. Moreover, the potential is highly dependent on future laws and regulations for data management which will affect the difficulty of data availability further.

Keywords: Machine Learning, Data Mining, Risk Management, Risk Assessment, Risk Mitigation
1. Introduction

1.1 Background

Futuristic scenes from science fiction movies no longer belong to a distant future. Autonomous cars without human drivers, robots performing surgeries and “Nanobots” that swim in our bloodstreams to perform a variety of therapeutic functions (Rajeshwar, 2012), are scenarios representing a technological reality today. The technological evolution might seem amazing and hopeful in many ways. However, with smarter technologies comes fear. The speculations of what long-term consequences this will bring to our society have been a widely-discussed subject for many years (Turban, Aronson & Lian, 2004; Firschein et al., 1973; Wolfe, 1991; Rahwan & Simari, 2009). The physicist Stephen Hawking (Marcus, 2014), who has contributed to this discussion, claims that:

“The development of full artificial intelligence could spell the end of the human race.”

Among the discussions of concerns regarding the increased use of smarter technologies is the debate and fear of it penetrating the job market, not just replacing traditional labor work, but also working tasks that until recently have been categorized as something only possible to be performed by human employees (Rifkin, 1995; Turban et al., 2005). However, the debate also includes a more optimistic view where smarter technology, instead of a competitor for jobs, can be seen as a supporting tool to make humans more productive, efficient and improve decision making (Latham, 2017; Liu & Miyamoto, 2000; Brynjolfsson & McAfee, 2011). The same role which traditional technology has had for quite some time now (Turban, Aronson, & Lian, 2004).

For decades, humans have used technologies and computer software that support different kind of decision making, such as expert systems, decisions support systems, scoring models etc. (Shim et al., 2002; Maule 2009; Phillips-Wren, Ichalkaranje & Jain, 2008). Due to the limited processing and memory capacity of the human brain, computers, and machines have been useful tools for decision makers to overcome these limitations (Maule, 2009).

Today, when businesses and their environments are growing more complex and the number of available alternatives to consider become out of reach, the processes of human decision making are more difficult than ever before, even with the help of traditional technology (Turban et al. 2015). Hence, the use of intelligent systems is becoming popular and useful in terms of decision support, based on huge amounts of information (Phillips-Wren,
Ichalkaranje, & Jain, 2008). Furthermore, these systems also have the ability to provide advanced analysis and to learn from mistakes. Artificial intelligence and its subfield machine learning is one such technology which can make programs automatically improve with experience and recognize patterns in order to provide valuable information for decision making (Mitchell, 1997). This technique has been shown to have a positive impact on decision-making in areas such as healthcare (Hamet & Tremblay, 2017), and has the potential to be used for many other areas where human decision making is inadequate.

1.2 Problem statement
In some areas of decision making, the biases of the human brain have shown to be more limiting than others. Decisions regarding risk are one of those areas. Several decades of empirical research in psychology have revealed that the human brain is ineffective at assessing risk (Hubbard, 2009; Slovic et al., 2005). Despite this fact, some areas of financial risk management are still highly dependent on the human ability to interpret the situation, in order to make a decision (Hubbard, 2009).

The process of risk management in debt collection traditionally depends on this ability. Risk-based debt collection assesses debt accounts based on the risk level that is provided by a scoring model (Nurlybayeva, 2013). The scoring assesses the debt accounts by the risk of nonpayment (Martin & Stephenson, 2004). These scoring models use historical data through statistical modeling (Nurlybayeva, 2013) or are based on judgments from experts, which in both cases have led to poor and subjective results (Ramona, 2011; Singh et al., 2007). Hence, these static scoring models present scores that are highly interpretable and enables for the manual human contribution to have a substantial impact on the final decision of how to manage the risk (Hubbard, 2009).

When the core business for a debt collection company is to collect money, the need to assess the risk correctly is directly critical in order to know how to allocate resources, time and how to prioritize the debts. Due to increasing write-offs, delinquencies and bankruptcies, collection companies are put under increasing pressure as they look to protect the company from risk and minimize losses (Experian, 2006). Consequently, there is a need for collection managers to better evaluate the risk of individual debt accounts in order to implement strategies aimed at reducing the growing mountain of debts (Ibid). Smarter technologies, that are helping decision makers in other business areas, could they potentially improve the decisions taken in debt collection as well?
The potential of using machine learning to improve the risk assessment in processes related to credit risk, has been studied from a computer science approach before, meaning that those studies have focused on developing and testing algorithms (Baesens, 2013; Kennedy, 2013; Kraus, 2014). However, the technological perspective limits the understanding of the potential to people with a computer science background, when the debate about the impact and the potential mainly is considered from a business perspective (Domingos, 2012). Hence, there is a knowledge gap between what the computer scientists know and contribute to in research, and the business knowledge about the machine learning potential available for business practitioners.

Consequently, to complement the previous development-focused research, a business approach to the potential to use machine learning for risk management within the process of debt collection is needed. Furthermore, the previous studies mainly explore the use of machine learning in credit scoring and do not include the related, but different area of risk-based debt collection. Therefore, further business research to explore the potential of using machine learning for risk management in financial processes, such as in debt collection, will be a useful complement to both academia and practice.

### 1.3 Research Question

*What are the possibilities and difficulties of using machine learning to support risk management in debt collection?*

### 1.4 Purpose

The aim of this study is to explore the potential of using machine learning for financial risk management in debt collection, with a purpose of providing a clear description of what possibilities and difficulties there are. This includes an investigation of the risk management activities within the process of debt collection and in what areas machine learning have the potential to improve how risk decisions along with what challenges there are.

Previous research within the area of machine learning commonly provides a technical exploration including testing of algorithms for a certain problem and very few are approaching the area from a business perspective. This results in both a theoretical and an empirical gap since the various studies are inaccessible to business people that consider a shift from traditional systems to intelligent technologies. Thus, this thesis aim to close the gap and contribute to a business perspective on machine learning and what steps to consider when exploring the machine learning potential for a business problem. This means that the technical
exploration will be limited to a theoretical approach without any involvement of testing algorithms.

1.5 Disposition

Chapter 2 – Literature review
The second chapter presents a review of the literature regarding the area of risk and machine learning. The chapter is divided into three sections. The first two sections present the areas of risk management and machine learning based on previous literature. The final section then summarizes the theories and concepts that will be used in a theoretical framework along with an analytical model. The analytical model demonstrates that the risk concepts will be used to structure the data collection and empirical findings, whereas the machine learning concepts will be used for the analysis chapter in order to analyze the machine learning potential based on the empirical findings.

Chapter 3 – Methodology
The third chapter describes the method used in the study including the choice of research approach, research strategy, and how the data were collected. The choice of the chosen case company Tieto is presented, along with arguments for why they were suited for this study. The chapter ends with a reflection of critical considerations related to the choice of method.

Chapter 4 – Empirical findings
This chapter presents the empirical findings gathered from the interviews and report reviews. It is divided into two sections based on the first block of risk management presented in the analytical model. This includes a section of how risk assessment is done within the process of debt collection today and a section of how risk mitigation is managed.

Chapter 5 – Analysis
The fifth chapter consists of an analysis of the empirical findings in relation to the presented concepts and theories about machine learning provided in Chapter 2.

Chapter 6 – Discussion & Conclusions
The sixth and last chapter summarizes the key findings along with answering the research question. Furthermore, it also includes a section about the contributions and a discussion about the limitations of the study followed by suggestions for further research.
2. Literature Review

This literature review will be composed of three sections. The first two consist of an explanation of the areas of risk and machine learning. Each area will be presented from a background perspective where related concepts found in previous literature will be presented. Finally, the chosen theories for each area will be summarized in a theoretical framework section along with an analytical model.

2.1 Risks in debt collection

The risk of non-payment (sometimes called default) is the major risk within debt collection (Obeng & Krah, 2016). A common practice within the industry is to use 90 days past due as a conservative definition of default (Butaru et al., 2016). The phase prior to default is sometimes called delinquency and occurs from the day when a borrower fails to make a scheduled payment on a loan (Avery et al., 1996). Within the first phase of delinquency, the main task is to identify the customers with the highest risk of turning into defaults and try to prevent that from happening (Butaru et al., 2016). The identification process is usually based on a scoring model which categorizes cases as either good or bad (Chen & Huang, 2003). This score can facilitate client classification and prioritization, but it is also important for the subsequent risk decisions of how to manage and approach the clients with a bad score.

Traditionally, a judgment based scoring model has been used to assess this risk (SunGard, 2011). Such a model, which has also been called a qualitative risk model, consists of experts’ inputs into a model with weighted factors based on the experts’ experiences and judgments. This model can be seen as a ranking system where the debt account with the highest score is considered the lowest risk. In other words, this model cannot quantify risk and provide the debtor with insights about the probability of a certain outcome. This makes the model very subjective and leaves a lot for the debtor to interpret, which is criticized by Hubbard (2009).

Nowadays many scoring models are based on a statistical model, a quantitative risk model which is a formalization of relationships between variables in the form of mathematical equations. Compared to judgment-based scoring, statistic-based scoring quantifies specific risk probabilities (SunGard, 2011). Nevertheless, Stulz (2008) presents plenty of criticism toward statistical risk models in general. This criticism mainly consists of the problem with a model that only uses historical data which can affect the human decision making negatively.

However, the criticism towards the methods for risk assessment gives rise to studies that highlights the opportunities with alternative perspectives and new learning systems to assess
the risk. Kaplan and Mikes (2016) claim that companies should avoid the choice between quantitative and qualitative risk management and allow for both to play important roles in assessing risk. They argue that the models cannot replace management judgment and should instead be used to trigger analytical thinking and discussions among employees and managers. Moreover, a recent report conducted by McKinsey (Härle et al., 2015), presents a broad range of possibilities for the future in risk management where machine learning is one of the factors for improved risk models and overall risk management.

Summarized, the risks in debt collection can be divided into the area of risk assessment, which identifies and estimates the risk, usually done with a scoring model. And the area of managing this risk, including prioritization of debt accounts and activities to prevent the customer from turning into default. Hence, the area of risk management including both assessment and mitigating activities is central concepts in debt collection and will, therefore, be explained further.

2.2 What is risk management?
The concept of risk management is a commonly used in previous risk research (Meek, 2005; Kaplan & Mikes, 2016; Kaplan, 1991). Risk management can be defined as the identification, assessment, and prioritization of risks followed by application of resources to minimize, monitoring, and control the probability and/or impact of unfortunate events (Aven, 2010).

This definition can be visualized in a risk management loop (Figure 1) which illustrates the different steps in the risk management process (Versluis, 2016).

![Risk Management Loop](image)

*Figure 1 - Risk management loop, Versluis (2016) p. 10*

A simplified way of looking at risk management in order to identify the risk steps in the process of debt collection is to divide it into the act of **risk assessment and risk mitigation** including **risk evaluation** (Stoneburner, Goguen, & Feringa, 2002).
2.2.1 Risk assessment
The act of risk assessment normally includes identifying events of potential harm, assessing the likelihood that harm will happen and the consequences if harm does occur (Meek, 2005). In debt collection, the event to identify is not harmful in that sense, but the ability to identify the profitable and unprofitable accounts has a direct impact on the business performance. In general, the risk assessment aims to answer the following questions (Ibid):

- “What might happen? How might it happen?” (Hazard identification and risk characterization)
- “How likely is it to happen? What harm will occur if it happens?” (risk estimation)

Many methods for risk assessment involve the use of scoring methods through which the severity of each risk factor is rated and then combined to present a measure of the overall risk (Hubbard & Evans, 2010). The reason for using scoring or other risk assessment techniques is to generate and output which helps to identify appropriate controls for reducing or eliminating risk during the risk mitigation process (Stoneburner, Goguen, & Feringa, 2002).

2.2.2 Risk mitigation
Mitigation is an important component of risk management and it refers to the planning and execution of measures designed to reduce the risk (Musson, 2013). Moreover, risk mitigation refers to the acts of prioritizing, implementing and maintaining the appropriate risk-reducing measures recommended from the risk assessment process (Stoneburner, Goguen, & Feringa, 2002). Hence, the mitigation process in debt collection is consisting of all the subsequent activities to collect the money after an assessment has been made. There are different strategies for how risk mitigation can be achieved. Stoneburner, Goguen and Feringa (2002) present several options for strategies where two of these options are closely related to the risk faced in debt collection when trying to manage an account scored with a higher risk.

- Risk Limitation – Limiting the risk by implementing controls that minimize the adverse impact of a threat’s exercising a vulnerability (e.g., use of supporting, preventive, detective controls).
- Risk Planning - Managing risk by developing a risk mitigation plan that prioritizes, implements, and maintains controls.

2.3 What is machine learning?
The amount of data in our lives seems ever-increasing and with inexpensive disks and online storage, it is easy to postpone decisions about what to do with all data.
Witten et al. (2017) state:

“There is a gap between the generation of data and the benefit we gain from it.”

Hence, the need to find patterns to make sense of the huge amounts of data is important for today’s businesses (Ibid). The overall process of knowledge discovery in data is included within the field of KDD (Knowledge Discovery in Databases), which in turn consists of the process of data mining (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). Data mining can be defined as the process of discovering patterns in data and is an interdisciplinary field involving the area of machine learning along with other connected fields such as database technologies, artificial intelligence, pattern recognition and more (Turban et al., 2005; Sumathi & Sivanandam, 2006).

![Figure 2 – Venn diagram, Mitchell-Guthrie (2014)](image)

The connected fields of data mining and machine learning have resulted in several studies that discuss the area of machine learning from a data mining perspective (Witten et al., 2017). Hence, theories and concepts from the data mining literature are relevant when studying machine learning.

Sotripoloulos and Tsihintrizis (2016) state that previous research in machine learning has been developed around the three following research lines:

- Task-oriented studies (the development and analysis of learning systems to improve performance in a predetermined set of tasks).
- Cognitive simulation (the investigation and computer simulation of the human learning process).
- Theoretical analysis (the theoretical exploration of the space of possible learning methods and algorithms independent of application domain).
Within the area of machine learning applied to financial risk assessment including scoring models, previous research has mainly used a task-oriented approach that centers around the development and testing of machine learning algorithms (Kennedy, 2013; Kraus, 2014; Baesens, 2013).

2.4 When is machine learning used?
In general, the goal of learning predictive models is to use them as guides to actions (Domingos, 2012). Especially within the area of healthcare and diagnostic decisions, learning systems with a predictive function have been shown successful as a support to improve the accuracy of diagnostics (Chi, 2009; Caelen et al., 2006). The predictive function is based on the discovery of patterns and relationships in data. Hence, machine learning is especially suited for predictive learning tasks and pattern recognition that are too complex to program (Shalev-Shwartz & Shai, 2014). Examples of such tasks are understanding spoken language, driving, and image recognitions (Ibid).

Furthermore, there are a lot of tasks that are considered beyond human capabilities for which machine learning can be used. Typically, these tasks are related to the analysis of very large and complex data sets such as astronomical data, turning medical archives into medical knowledge and web search engines (Ibid). With the increasing availability of digitally recorded data, meaningful information is buried in databases that are too complex for humans to make sense of (Ibid).

Another benefit of using machine learning is its adaptivity. With programmed tools comes the limitation of their rigidity; once the program has been written down and implemented, it stays unchanged. Instead, Machine learning offers a solution to changes over time since it by nature adapts to its environment and changing conditions (Ibid). Hence, for problems where adaptability is central, machine learning is well suited.

The different tasks mentioned above demonstrate what kinds of problems machine learning normally deals with. The next section describes how these problems are addressed through an explanation of how machine learning works.

2.5 How machine learning works
Machine learning is concerned with the programming of computers to automatically adapt and learn from data or experience (Mitchell, 1997). Traditionally, the problems to be solved with machine learning can be divided into two fundamentally different paradigms called supervised and unsupervised learning (Kulkarni, 2012). Kulkarni (2012), with his traditional
approach, states that the decision on how to solve the problem depends on whether the predicted value is in the training data or not. Training data implies data that previously have been processed by the system. If the predicted value is found in the training data, the problem belongs to the paradigm of \textit{supervised learning} (Ibid). When the predicted value is not in the training data, the problem belongs to the paradigm of \textit{unsupervised learning} (Ibid). In other words, in supervised learning, the training data consist of input data and a corresponding target value, whereas in unsupervised learning the training data consist only of input data.

However, some previous research also presents other paradigms of machine learning problem-solving. For example, \textit{semi-supervised learning} (Kennedy, 2013) and \textit{reinforcement learning} (Stenudd, 2010; Mitchell, 1997), which lie between supervised and unsupervised learning. In semi-supervised learning, the training data consist of input data and, in some but not all cases, a corresponding target value. Similarly, reinforcement learning consists of input data without direct access to the correct output. This means that there is no training set of correct actions. Instead, the actions must be determined by using rewards generated from the environment. However, the approaches of supervised and unsupervised learning are most commonly mentioned in previous literature related to credit scoring (Kennedy, 2013; Kraus, 2014; Baesens, 2013).

Based on the approach of unsupervised or supervised learning, different categorization options are available. The concepts of classification (supervised), regression (supervised) and clustering (unsupervised) are the most recurring categorizations in previous literature (Ibid).

\textbf{Classification}

A classification problem arises when an object needs to be assigned to a predefined class or group according to its characteristics (Baesens, 2003). This method is suitable for classifying data into two or more classes, for example, “is this a high-risk case or a low-risk case?” (Brownlee, 2013).

\textbf{Regression}

Regression is similar to classification except that the targeted attribute’s values are numeric, rather than categorical. Regression is typically used for predicting values like “how many units of a product will be sold next month?” (Cawley, 2014).

\textbf{Clustering}

Data are not labeled but can be divided into groups based on similarity and other measures of natural structure in the data. This is used when there are no obvious natural groupings, in
which case the data may be difficult to explore. Segmentation problems such as “what are our customer segments” are suitable for clustering, which can reveal previously unknown groups and categories (Brownlee, 2013).

Finally, based on how the problem is categorized there are different options for machine learning techniques. There are many algorithms available to choose from depending on the categorization of the task. In previous research related to credit risk, neural networks, decisions trees, K-means and K-nearest Neighbor are commonly used algorithms (Kennedy, 2013; Kraus, 2014; Baesens, 2013). The different algorithms will not be further explained in this background section due to the non-technical approach of this study. Instead, some strategies for practical application of machine learning will be presented next.

2.6 Applying machine learning to a business problem

The theoretical perspective of machine learning and its technical features is commonly addressed in the literature. However, there have been some attempts to provide more of a practical perspective through the development of machine learning process models. These models aim to address the actual application of machine learning and how the different theoretical explanations of how machine learning works can be used in practice (Brownlee, 2013; With & Hipp, 2000; Witten et al., 2017). The CRISP-DM reference model (Figure 3) is an example of a well-known framework in data mining and provides a framework for carrying out data mining projects independently of both the industry and the technology used (Wirth & Hipp, 2000). Furthermore, Brownlee (2016) presents a similar process model (Figure 4) with a specific focus towards machine learning only.

![Figure 3 – CRISP-DM reference model, Wirth and Hipp (2000), p. 5](image-url)
Both models start with an identification of the problems from a business perspective. In the CRISP-DM reference model this is termed “business understanding” and is concerned with understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem definition (Wirth & Hipp, 2000).

Similarly, Brownlee (2016) presents the first step as problem definition including a problem definition framework with the following questions:

**Q1:** What is the problem? (Defining the learning parameters following Mitchell’s (1997) explanation of task, experience, and performance):

“A computer program is said to learn from experience (E) with respect to some class of tasks (T) and performance measure (P), if its performance at tasks in T, as measured by P, improves with experience.”

**Q2:** Why does the problem need to be solved? (What will be the benefits)

**Q3:** How would I solve the problem? (How would the problem be solved manually)

In both cases, the understanding of the problem and the business perspective are emphasized as crucial for the evaluation of implementing machine learning. The following steps in both of the models are then concerned with the characteristics of the data. In the CRISP-DM reference model, it consists of understanding the data that are available and their characterization along with modeling and testing. Instead, Brownlee’s (2016) focuses on the choices of approach (supervised/unsupervised) and data categorizations (classification/regression/clustering) that previously have been explained.

However, applying machine learning to a business problem does not go without challenges. In the last section of this literature review challenges with machine learning will be presented from a technical data centered perspective along with challenges that arise with the fear of putting trust into the technology.
2.7 Challenges with adapting machine learning

2.7.1 Data privacy
Machine learning collects and processes vast amounts of data (Brankovic & Estivill-Castro, 2008). In previous studies of machine learning related to credit scoring the used data mainly includes personal data (Kennedy, 2013; Kraus, 2014; Baesens, 2013). Even though personal information has been shown useful in many areas, it has increased the public concern about the individuals’ privacy (Brankovic & Estivill-Castro, 2008). Brankovic and Estivill-Castro (2008) state that the appearance of technology for Knowledge Discovery and Data Mining (KDDM), such as the use of machine learning (Fayyad, Piatetsky-Shapiro, & Smyth, 1996), has revitalized concerns about the following privacy issues:

- secondary use of the personal information (concerned with the use of personal data for purposes other than the one for which data have been collected)
- handling misinformation (concerned with the right for individuals to be able to challenge the correctness of data about themselves)
- granulated access to personal information (concerned with the idea that access to personal data should be on a need-to-know basis, and limited to relevant information only).

Data privacy issues lead to ethical challenges that organizations need to cope with (Brankovic & Estivill-Castro, 2008). While individuals and legislators, supporting the right of privacy, favor the view that a person's data are the person’s property, data collectors favor the view that the data collector owns the data. Those ethical dilemmas make individuals assert pressures on society to create laws and regulations for data availability (Wang, 2003). The new EU regulation called GDPR (Global Data Protection Regulation) is an example of a regulation which will come into force summer 2018 and affect how companies manage data (Ernst & Young LLP, 2016).

2.7.2 Data availability
Another challenge is related to the amount of available data. In debt collection, different countries have different data regulation concerning access to certain data (Accion, 2008), which naturally can affect the potential for machine learning solutions in terms of how much and which data can be used as an input for the algorithm. Moreover, Baesens (2003) states that although machine learning algorithms are very powerful, they generally rely on modeling repeated patterns or correlations that occur in the data. Observations which are evident to classify by the domain expert might not appear frequently enough in the data in order to be
appropriately modeled by a machine learning algorithm. Data availability and the ethical and legal aspects are, therefore, central challenges and can create difficulties for machine learning applications.

2.7.3 Trust in automation
Machine learning also belongs to the area of automatic computing (Chan et al., 2005). The thing with automation is that it is often problematic because people fail to rely upon it appropriately (Lee & See, 2004). Lee and See (2004) claim that this is due to the fact people tend to respond to technology socially, and thereby trust influences the reliance on automation. There are often two forms of trust issues that arise with automated systems (Hoffman et al., 2013):

- Overtrust: People place unjustified trust in computer systems or taking its advice because it comes from an “expert” system.
- Under-reliance: People who do not place enough trust in computer systems or fail to rely on useful technology capabilities.

Trust in automation means that trust is an attitude toward automation that affects reliance. This attitude often a result of past experience (Ibid). This experience and attitude also affect how people interact with systems. Experts, in general, have sufficient experience with their technology to calibrate their trust and notice the difference between unjustified trust and justified trust as well as justified mistrust and unjustified mistrust (Ibid).

2.8 Theoretical Framework
The theoretical framework for this study builds on the theories of risk management and machine learning. In order to investigate the potential to use machine learning for risk management in debt collection, information about today’s processes of risk assessment and risk mitigation need to be collected. Hence, the data collection about the debt collection process will use the lens of looking at the steps of risk identification, likelihood estimation, planning, and evaluation. Based on the information of how risk is managed within the process today, machine learning theories will be applied to the context.

The concepts that will be used to analyze the machine learning potential will follow the initial step of the CRISP-DM reference model (Wirth & Hipp, 2000) and Brownlee’s (2013) process model, which include the business understanding of the risk management in debt collection. The understanding of the business problem then needs to be related to a machine learning task in order to verify the relevance for machine learning to be used. Defining the learning
parameters presented by Mitchell (1997) will be used to define the machine learning task. The suitability of this task related to typical situations where machine learning has shown to be successful then needs to be assessed. This means assessing whether the risk situation relates to a task of discovering patterns, a task considered beyond human capabilities, or which is depending on adaptivity.

Based on the defined machine learning task the potential of how machine learning can be used, considering the data available and the current processes of risk management, is the final step of looking at the possibilities within debt collection. This includes looking at the task from the machine learning paradigms and whether the task belongs to a supervised, reinforcement or unsupervised approach and how it potentially can be categorized.

Finally, the last step includes an exploration of the challenges through looking at the data that are available within the system today. Are there any challenges related to data availability? Can there be any issues with data privacy that could be a potential challenge when using machine learning? And finally, are there human biases regarding trust in the technology that can affect the potential success of machine learning? Based on the previously presented theories for this study, an analytical model has been created as a framework for how the theories will be used.
Figure 5 - Analytical model illustrated by the author
3. Methodology

This chapter explains the chosen methodology of this study including research approach, strategy, method and data collection. The chapter ends with a section including critical consideration related to the method and how the study was conducted.

3.1 Research Approach

The choice of research approach was based on the research question of exploring the potential to use machine learning for risk management in debt collection. An exploratory study is valuable when finding out what is happening and seeking new insights (Saunders, Lewis, & Thornhill, 2009). Since this study included an empirical collection of data about the debt collection process and what was happening within it, together with seeking new insights to what potential there was to use machine learning, an explorative study was considered as suited for the purpose. Furthermore, an exploratory study often relates to inductive research approaches, where the aim is to generate theory from the data (Farquhar, 2012). This is the approach of this study since the data were collected about practices related to risks in order to analyze the machine learning potential and end up with a conclusion. Finally, this research approach is also motivated given the previous studies within this area which have used a computer science approach (Domingos, 2012; Baesens, 2013; Kennedy, 2013; Kraus, 2014). To serve the purpose of this study and contribute to a business understanding of the potential, an exploratory study was considered useful in order to contribute to a new perspective on this area, in a way that was graspable for a business reader.

3.2 Research Strategy

A qualitative research design was considered appropriate since this study required developing a deep understanding of the process of risk management in debt collection. The qualitative research design also enabled for contributions from several sources of data collections and to capture the perceptions and views of several individuals with different backgrounds within the area of machine learning and debt collection (Yin, 2011). Together, those individuals provided the author with an understanding of the process that was needed in order to explore the potential of using machine learning.

More specifically, within the qualitative research area, a case study strategy was chosen. In general, a case study allows for various data collection techniques and is considered to generate answers to research questions starting with “what” (Farquhar, 2012). This corresponded very well to the design of this study, both in terms of the research question and use of different data collection techniques.
The study was conducted through an investigation of the process of debt collection from the perspective of the IT-company Tieto. Tieto provides a market-leading debt collection system called “Nova” and have great insights to the different steps of the process, commonly issues and complaints from the customers, along with knowledge about the available data. The choice of Tieto as a case company was based on the need of a representative case (Ibid) in order to get the spectrum of both the process for debt collection, but also from the technical perspective with insights to the data.

In order to ensure that the collected data were true and reflected reality, different data collection techniques were chosen. Several employees with different roles within the financial department that were related to the process of debt collection were interviewed. The respondents consisted of developers, customer complaints representatives and consultants with insights into either the process or the support system. The method for how those respondents were chosen is presented in section 3.4.2.

Triangulation was ensured through different types of methods since reports and document reviewing were used as a data collection technique to understand the process (Farquhar, 2012). Furthermore, triangulation was also ensured through data collection from a debt collection company “Intrum Justitia” that faces the process of debt collection daily. The choice of using a complementing case was decided based on the idea of establishing if the findings about the debt collection process in the first case occurred in the other case (Ibid). This was considered being especially important in this study since the majority of the data about the process were gathered from Tieto, which does not participate in the actual process of collecting debts, even though they have good insights to the different steps and decisions made within it.

3.3 Method

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<td><strong>Three</strong> telephone interviews with ML experts.</td>
<td><strong>Five</strong> interviews with representatives from Tieto. <strong>One</strong> interview with representative from Intrum Justitia.</td>
</tr>
<tr>
<td><strong>Two</strong> reports used: Experian, (2016) Earnst and Young LLP (2016).</td>
<td></td>
</tr>
</tbody>
</table>

*Figure 6 – Structure of method illustrated by the author*
Even though the method for data collection included reports reviews about the process (Experian, 2006) and about data privacy issues (Ernst & Young LLP, 2016), interviews composed the main method for the collection of empirical data. A semi-structured interview approach was used for this study, in order to provide with flexibility and contextual adaptation during the interviews (Farquhar, 2012). A flexible approach was suited since the interviews were held with respondents from different areas of responsibility and the need for spontaneous follow-up questions was subsequently important.

A list of themes and questions was used as a framework for the data collection interviews. The list was based on the risk management theories presented in the analytical model along with the insights provided by the experts during the pre-study. However, the structuring of the questions differed from interview to interview (Ibid). For example, during some interviews, certain questions were omitted depending on the role of the respondent (Ibid). Questions regarding the database or data used for processing were not included when asking respondents with a non-technical role. The order of the questions was also highly dependent on the flow of the conversation. Furthermore, notes were taken during the interviews and in those cases where the respondent approved, the conversation was audio-recorded. The notes were clustered depending on the category of the questions so that if an answer were considered to answer to another similar question, that question could be reframed or excluded in the conversation. The categories and structures of the questions are presented in the next section.

The interviews were primarily conducted on a face-to-face basis, in a quiet environment with minimal distractions. In those cases where interviews were held with experts located in another city, telephone interviews were the chosen method. Telephone interviews were booked and scheduled just as the face-to-face interviews and were held during working hours.

3.3.1 Analysis Method
The method for analyzing the data was structured based on the analytical model presented in section 2.8. The risk management theories were used to structure the empirical findings in order to generate the business understanding needed for the analysis of the machine learning potential. The analysis was then structured based on the different sections presented in the analytical model. This included a comparison of the findings to the theories of machine learning in order to reach a conclusion concerning the overall possibilities and difficulties of using machine learning for risk management in debt collection.
3.4 Data collection

3.4.1 Pre-study and follow-up interviews
In the interest of exploring the potential to use machine learning for risk management in debt collection, the study included a pre-study where machine learning experts with experience from risk management were interviewed. Given the research approach of conducting the study from a business perspective, the pre-study aimed to provide with knowledge to the area of how such an exploration could be done and what aspects were considered important to investigate. Furthermore, this was done in order to increase the validity of the questions for the data collection interviews and to enhance the author’s knowledge about machine learning. From the pre-study, the author learned about the importance of really understanding the underlying business problem in order for the potential to be investigated, along with prerequisites related to data availability that was needed in order to be able say something about the potential of a certain machine learning categorization.

The experts also provided with insights to the empirical findings and participated as respondents in the follow-up interviews, which were conducted in order to confirm the plausibility of the conclusions at the end of the study. Those interviews were done by telephone and mail where the findings were presented to the experts. Given the information they got, the experts confirmed the two major possibilities that were concluded. They claimed that the two possibilities are major advantages with machine learning, but their realization depend on the performance and training of the algorithm. Furthermore, they indicated that the difficulty of data availability always can be a potential challenge that needs to be considered and that it affects the realization of the two possibilities. Moreover, they added a challenge of “overfitting” which is a common difficulty mentioned in literature and dependent on the data set that the algorithms are applied to. This difficulty was not taken into consideration in this study due to the limitation of chosen research approach and the fact that this has been mentioned as a challenge in previous complementing research from a computer science perspective.

Three experts from the machine learning field participated as respondents to the pre-study and the follow-up interviews. Two of them had worked directly with machine learning for credit risk projects before.
Interviews with experts

<table>
<thead>
<tr>
<th>Expert 1, Anonymous (Telephone) 30 min</th>
<th>Expert 1 is a senior expert in risk management and has worked with projects related to risk and advanced analytics. Among those topics, credit risk has been one of Expert 1’s focus areas.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expert 2, Anonymous (Telephone) 30 min</td>
<td>Expert 2 works with digital risk and advanced analytics within the practice of Risk Management. Among the areas of expertise are the fields of credit risk modeling, machine learning and automation of decision making.</td>
</tr>
<tr>
<td>Expert 3, Olli Luukkonen (Telephone) 30 min</td>
<td>Luukkonen possesses the role as a chief data scientist &amp; head of analytics at Tieto. In the current position, he is heading the analytics and competence development within the data driven businesses at Tieto. Even though he does not have any experience from the risk management area, he contributed with a lot of insights regarding the process of evaluating the machine learning potential for a business problem.</td>
</tr>
</tbody>
</table>

Table 1 – Representatives for pre-study

For the pre-study, telephone interviews were conducted due to locational distances and each interview lasted for 30 minutes. The questions that were asked during the interviews are summarized in Table 1.

<table>
<thead>
<tr>
<th>Structure</th>
<th>Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Background of machine learning</td>
<td>- How would you describe the building blocks of machine learning when talking to a friend with a non-technical background?</td>
</tr>
<tr>
<td>Tips for investigations</td>
<td>- When you have a business problem which indicates that machine learning could be used, what is the first step for your investigation of the potential?</td>
</tr>
<tr>
<td></td>
<td>- What is the most important aspect to consider when exploring the machine learning potential for a certain business problem?</td>
</tr>
<tr>
<td></td>
<td>- What is important to consider when investigating the machine learning potential from a business perspective without developing and testing algorithms?</td>
</tr>
<tr>
<td>Possibilities and difficulties</td>
<td>- What do you see as the possibilities of using machine learning for risk management?</td>
</tr>
</tbody>
</table>

21
- How can machine learning be used for risk assessment and risk mitigation?
- Are there any main challenges or difficulties you see when looking at the role of machine learning for risk management?
- What do you see as possibilities and difficulties with applying machine learning to business problems in general?

Table 2 – Interview questions for pre-study

3.4.2 Data collection preparation
Tieto was chosen as the case company for data collection along with a complementary interview with Intrum Justitia. In order to find suitable respondents at Tieto that could provide different insights to the area of debt collection from both a process and a system perspective, a list of role specifications was created and sent to Tieto. Since the purpose of the study was exploratory, a self-selection sampling approach was considered suited (Saunders, Lewis, & Thornhill, 2009). Therefore, the list represented different roles for the sampling, and the respondents who were considered matching with the list was then provided by Tieto representatives with greater insights to the organization. The list of role specifications included:

- Employees with insight into the process of debt collection in general
- Employees with knowledge about the debt collection system (Nova) that Tieto provides including the data within it
- Employees with customer contact

Furthermore, Intrum Justitia was contacted in order to provide further insights to the process. Through emails and referrals to employees within their organization suited to answer the questions on a general level, the respondent was found. Hence, this sampling selection was done through a snowball sampling, which means that the respondent was chosen by recommendations to a person which lead to further recommendation until the right respondent was found (Farquhar, 2012).

3.4.3 Interview process
Before each interview, the interviewer prepared for the meeting by reading through the questions, repeating the common mistakes made by interviewers (interrupting the respondent, not allowing for silent space etc.) and marking questions of extra importance depending on the role of the respondent. All interviews began with an introduction of the interviewer, a
verification of the available time for the respondent and a short description of the structure of the interview.

Companies descriptions

**Tieto**

- Tieto is an IT-company which was founded in 1968 in Finland. It focuses its business on software and services and provides IT-solutions within different business segments (Tieto, 2016). The area of financial services is where the department working with debt collection is located. The collection system that Tieto provides is called “Nova” which is based on a workflow engine to support business processes within debt collection (Ibid).

**Intrum Justitia**

- Intrum Justitia is a market leading credit management service company working with services related to debt collection. They have been offering risk reducing services and financial services since they were founded in 1923 (Intrum Justitia, 2017).

<table>
<thead>
<tr>
<th><strong>Information</strong></th>
<th><strong>Respondent</strong></th>
<th><strong>About the respondent</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Interview 1</strong></td>
<td>Peter Burstein,</td>
<td>Burstein had several years of experience using the system provided by Tieto when working for a collection company. Now he has been working at Tieto for 4 months and is responsible for consultancy activities towards customers and also involved in product development.</td>
</tr>
<tr>
<td></td>
<td>Senior business consultant.</td>
<td></td>
</tr>
<tr>
<td><strong>(face to face)</strong></td>
<td><strong>Tieto, 90 min</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Interview 2</strong></td>
<td>Swati Patil,</td>
<td>Patil has worked as a business analyst at Tieto for 2 years and has been responsible for the development team of the debt collection system in India and works as an intermediate between the developers and the customers’ requirements.</td>
</tr>
<tr>
<td></td>
<td>Business Analyst.</td>
<td></td>
</tr>
<tr>
<td><strong>(face-to-face)</strong></td>
<td><strong>Tieto, 90 min</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Interview 3</strong></td>
<td>Sara Johansson,</td>
<td>Johansson has worked within this position for 8 years and has a lot of knowledge about the overall process of debt collection, what challenges the customers are facing and the functionality of the collection system Nova.</td>
</tr>
<tr>
<td></td>
<td>Customer Support Specialist.</td>
<td></td>
</tr>
<tr>
<td><strong>(face-to-face)</strong></td>
<td><strong>Tieto, 45 min</strong></td>
<td></td>
</tr>
<tr>
<td>Interview 4 (face-to-face)</td>
<td>Maria Erlandsson, Team manager B2C.</td>
<td>Maria has worked at Intrum for three months and has been working within the industry of debt collection for 20 years. Currently, she is a team manager working with B2B customers.</td>
</tr>
<tr>
<td>---------------------------</td>
<td>----------------------------------</td>
<td>--------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Intrum Justitia, 90 min</td>
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<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interview 5 (telephone)</th>
<th>Peter Hasche, Delivery manager.</th>
<th>Peter currently works as a delivery manager within the Nova business unit. His main responsibility is to make sure that the delivery and implementation of Nova correspond to the customer requirements. Peter has been working for the debt collection department at Tieto for seven years.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tieto, 45 min</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interview 6 (face-to-face)</th>
<th>Hanna Zaxmy, Manager, product and system management.</th>
<th>Hanna is driving the Collection unit at Tieto and has been working within this unit since 2010. She has worked tightly as a link between customers and developers and is determinate to continue growing the Nova solution.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tieto, 60 min</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3 – Data collection respondents

3.5 Operationalization

The interview questions were created based on categories about the different areas of interest. The first category included background questions in order to get to know the respondent more and start the conversation. The next category included questions about risks in the debt collection process. The process of debt collection consists of many steps and decisions, but in order to directly narrow the focus towards the area of research, this category of questions was chosen in the beginning of the interview. Moreover, this category was then followed by two subcategories with questions related to the area of risk assessment and risk mitigation. As the analytical model showed in the theoretical framework, the understanding of risk management (including risk assessment and mitigation) within the process, is critical for analyzing the machine learning potential. In order to explore the possibilities and difficulties of using machine learning for risk management, the understanding of how risk is managed within the process today was important. This was also connected to the inputs from the machine learning experts who emphasized that the understanding of the business problem was needed to analyze the potential. Finally, the last category included questions related to the system and what information was available within it. It consisted of questions with a more technical significance when the respondent had a lot of knowledge about the system, and in those cases where the respondent was more process-oriented the questions were focused around the
information that was available independent of the system. This was also done in order to understand the problematics of how risk is managed today along with identifying potential areas of improvement.

The interviews were mainly held in Swedish and translated into English. An exception was the interview with Patil from India which was held in English. Afterward, a transcription was made for those interviews where the notes were considered insufficient. This was done in order to facilitate the analysis of the various findings (Saunders, Lewis, & Thornhill, 2009).

<table>
<thead>
<tr>
<th>Interview structure</th>
<th>Examples of questions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Background</strong></td>
<td>Introduction to the interview.</td>
</tr>
<tr>
<td></td>
<td>Background questions about the respondent.</td>
</tr>
<tr>
<td><strong>Risk in debt collection process</strong></td>
<td>Explain the debt collection process from the perspective of risk.</td>
</tr>
<tr>
<td></td>
<td>What are the biggest challenges and problems regarding risk management within the process today?</td>
</tr>
<tr>
<td><strong>Risk assessment</strong></td>
<td>How is the risk assessment made today?</td>
</tr>
<tr>
<td></td>
<td>How do you estimate the likelihood of a certain risk?</td>
</tr>
<tr>
<td></td>
<td>How is the risk presented?</td>
</tr>
<tr>
<td><strong>Risk mitigation</strong></td>
<td>How is the risk managed and mitigated?</td>
</tr>
<tr>
<td></td>
<td>How do you prioritize the cases depending on the risk assessment?</td>
</tr>
<tr>
<td><strong>System and information</strong></td>
<td>In what way does the system support risk management within the process?</td>
</tr>
<tr>
<td></td>
<td>What information is available in the system?</td>
</tr>
<tr>
<td></td>
<td>Are there any rules and regulations that need to be considered regarding what information can be used?</td>
</tr>
</tbody>
</table>

Table 4 – Operationalization

3.6 Critical considerations
There were several critical considerations taken into account when conducting this study. First of all, the generalizability of this study is limited to Sweden and the Swedish market of debt collection. The process, laws and regulations and data availability differ from country to country, which affects the ability for the results to be generalized outside of Sweden (Atradius, 2016).

Furthermore, the choice of data collection methods, which mainly consisted of interviews, can be criticized from different aspects. The relevance of the questions can always be criticized when the study relies on data collection from interviews. This consideration was addressed by
choosing questions that the author perceived as important related to the literature and previous research. Furthermore, the choice of questions was also influenced by the pre-study with experts from the machine learning and risk management areas. These steps were done in order to assure that the questions were relevant and adequate.

Another concern related to the interviews as the chosen method for data collection is the fact that it only provided a subjective view and description of the process. Hence, it did not show the actual activities that would have been visible through an observational approach (Saunders, Lewis, & Thornhill, 2009). Observations would probably have required a longitudinal study in order to actually observe what was going on, in contrast to just asking people about it. However, observations were not an option in this case since Tieto is not part of the actual debt collection process, but employees do have a lot of insights and technical knowledge which was captured during the interviews. The choice of conducting the case study at Tieto was based on their combination of knowledge about the debt collection process as well as knowledge about supporting technology for this process. Furthermore, Tieto is also a company that was looking for ways to improve their collection system and was considered as more likely to share potential problems with the current collection product. In order to cope with the potential issue of reliability since this study did not collected the data from a debt collection company, the complementary interview with a representative from a debt collection company was conducted (Saunders, Lewis, & Thornhill, 2009). This was done in order to triangulate the data and confirm the findings from the other interviews. The semi-structured interview approach also allowed for the respondent to add valuable information about the process where the original questions were considered to be inadequate. Moreover, the report about the debt collection process along with the interviews with experts, further confirmed the findings.

However, the way that the interviews were conducted can also be criticized to some extent. Telephone interviews naturally have their limitations in terms of communications since the physical aspects such as body language and facial expressions that are included in face-to-face communication were eliminated. The spontaneous events that happened during the face-to-face interviews such as the respondent using whiteboards to explain parts of the process, also constitute a limitation when performing telephone interviews. These limitations were avoided through the use of phone equipment including a camera, but there were some exceptions during the call when the internet connection was too poor for a normal face-to-face experience.
Another aspect of criticism to the method is based on the chosen approach of machine learning research. As stated above, this study is based on a business approach without including the development and testing of algorithms. Another study, approaching the same research problem from a development perspective will consequently draw conclusions about the machine learning potential based on different techniques where some are shown to provide better results than others. Hence, the choice of machine learning technique and data sets will consequently affect what conclusions can be drawn about the machine learning potential within the process. However, the use of previous research and the performance of the algorithms were included in this study in order to address this issue. Furthermore, the aim of the study was to provide a complementary approach that could be used together with previous research in order to get a broader perspective of the potential.

Finally, when conducting a qualitative study a natural bias is the role of the researcher. The preparations before the interviews were done in order for the interviewer to be reminded and aware of the different biases that potentially can occur during such occasions. Moreover, the research approach was not mentioned during the interviews and the interviewer tried to act neutrally to the insights provided by the respondents. Another difficulty was to ignore the author’s perspective when the empirical material was processed and when the analysis was conducted (Yin, 2009). The interpretations were done with objectivity in mind and the author strived to remain objective and use the different voices from the empirical findings as a guide throughout the whole analysis.
4. Empirical findings

This chapter presents the empirical findings gathered from the interviews and report reviews. It is divided into two sections based on the first block in the analytical model presented in the theoretical framework. This includes a section of how risk assessment is done within the process of debt collection today and a section of how risk mitigation is managed.

![Figure 7 – First block in the analytical model](image)

4.1 Risk Assessment

Based on the understanding from the interviews (Zaxmy; Johansson; Erlandsson; Burstein) the process of debt collection can be visualized as Figure 8 shows. The process can be divided into five phases called:

- Pre-debt collection (before the due date)
- Early collection (after the due date but within several days)
- Late collection (Debtor does not pay during these previous stages)
- Legal/closure (The debt requires a legal process)
- Surveillance (Debts that have not been paid during the previous phases)

![Figure 8 – Debt collection process illustrated by author based on interviews (Zaxmy; Johansson; Erlandsson; Burstein)](image)

One of the major decision points in the process is located just after the collection notice and before the legal judgment stage (Burstein; Erlandsson). This decision is based on an
assessment made in the late collection phase and includes an identification of good and bad accounts. The good ones are likely to meet payment arrangements whereas the bad ones are more likely to fail (Experian, 2006). This is traditionally done by a scoring model.

“You can score during different phases of the process. Most commonly, scoring is done before going into legal judgments. A “next action” is automatically generated by the model.”

- Erlandsson

The prediction is made by looking at the case from a certain set of criteria (Experian, 2006). There is no standard template for the criteria that are used for scoring. It can, for example, include information about the debtor, demographics, the amount of debt, time as customer and credit information (Erlandsson; Hasche). Burstein explains that a credit case with a high-risk score is directly moved to long-term surveillance since the risk of non-payment is considered too big. In this phase, the debts are just surveilled and the collector is waiting for something that indicates that the conditions have changed regarding the payment ability of the debtor. However, a low-risk score is instead proceeding into the fourth phase of legal judgment where the collector hopes that the money can be collected.

The score can be presented with a number from 1-100 with a corresponding color code (Experian, 2006):

**Score between 0-40 (High-risk accounts)**

**Score between 41-60**

**Score between 61-100 (Low-risk cases)**

However, this interval can create problems sometimes. Burstein claims that the scoring process itself is usually not an issue, but the interpretation of a score can sometimes be very problematic.

“How do you interpret a score of 51? This is just in the middle of the yellow area which makes it hard to know what decision is the best. Such situations often require more information to be collected.”

- Burstein
Even though the human impact is intended to be avoided, problems arise when an account ends up in the yellow risk area. When it is scored as red or green, the strategy for how to handle it is clear. The red score goes directly to long-term surveillance, while the green ones continue on into the legal phase (Burstein). However, when an account is scored as yellow, it is hard to avoid an impact of the decision maker. For example, after a while, the decision maker can discover patterns and learn that certain postal codes indicate that the account, in general, ends up in long-term surveillance, or that a certain relation to a customer needs to be treated in a specific way (Ibid). This of consequently affect decisions.

“When you assess an account with a yellow score it is usually done by the gut feeling. Most of the time you need to take a chance and just decide for action. Sometimes you ask a colleague for a second opinion before the decision is made.”

- Erlandsson

According to Expert 1, the scoring itself can actually be seen as a problem in terms of performance. The performance naturally affects the number of accounts scored as yellow, and thereby allows for the human decision making to have a substantial impact on the final decision. Expert 1 claims the assessment process can be improved in order to provide the decision maker with a clearer picture of the risk level. Through deepening the analysis of the accounts, the performance of the score can benefit from looking at previous assessments and find patterns among them.

“A machine learning algorithm could potentially see that this account is similar to another which ended up in the long-term surveillance. Hence, it is likely to believe that this account will follow the same destiny.”

- Expert 1

Another problem with risk assessment is that people within the industry with a lot of experience tend to not trust the scoring in some cases (Burstein). Since the scoring does not give any insights into the formulas providing the score, it is common that the working expertise still composes of the final determination factor of how the account should be assessed. Burstein claims that there is a general skepticism from the experts within the area of risk assessment who argue that the technical developers who made the scoring model, impossibly can know more about the area than the experts themselves. Hence, the decisions made on gut feelings and expertise lack the supporting data analysis which can identify
differences between accounts. However, the understanding of what this problem really means for the collection business is difficult to know due to the inexistence of evaluations and measurements of the outcomes for a certain decision, which will be discussed further in section 4.2.

Adding to this, expert 1 argues that the problematics of trusting in the assessment can become an even bigger problem when the assessment is done by a machine learning algorithm due to the increased complexity.

“If it is hard to explain a statistical model, you can imagine explaining the complexity of how machine learning provides an assessment. Sometimes, it does not matter if you provide the best possible outcome for a decision maker if the people do not trust in the technology.”

- Expert 1

The importance of looking at the data from a business perspective when building a system, is emphasized by Expert 3. Especially for systems using machine learning, this has been important since the common knowledge about machine learning is that it is some kind of a magical box which automatically brings efficiency to the business. Many adaptors of machine learning forget to look at the business requirements and instead start working with the possibilities of the technology (Expert 3). When the training data is not evaluated correctly the alignment to the business might not be that strong, which consequently affects the trust for an assessment.

“It is important to take a close look to the training data in order to evaluate what data is critical for usage. This allows for a system to be closer related to the real business and to the people that are going to use it.”

- Expert 3

There are a lot of available data stored within the databases of Nova thanks to the number of years it has been used for businesses (Patil). However, the data is anonymized after 12 months and consequently affect the amount of data that the user can make sense of.

“12 months after the closure of an account, the data needs to be anonymized which means that you can no longer connect the log or the personal data to an individual.”

- Hasche
Furthermore, the availability of data can also be considered problematic from another perspective. Due to restrictions and regulations, there are a lot of data that exist within the databases of authorities, which are difficult to access. To use these data for the assessment it requires a manual process of calling to the tax agency, the cadaster, the enforcement agency and any other relevant agencies for further information about the debtor (Zaxmy). These data could potentially be used for the assessment in the first phase of scoring, but are not officially available anywhere but in those authorities’ databases. Lately, there have been easier to access data through emailing those authorities instead of calling (Erlandsson). This has allowed for further information to be captured about the debtors’ relationships, consumption habits and payment moral. The problem is that this information is still hard to collect for many debt accounts at the same time and requires a lot of resources since it relies on a manual process which cannot be automated due to restrictions and regulations (Burstein). Hence, most of the time, the collector rather takes the risk of making the wrong assessment than spending time on gathering more information about the debtor (Erlandsson).

“Customers always want you to speed up the collection process so there is normally not enough time for collecting further information about an account. And we are also very affected by laws and regulations which prevent us for speeding up the process further.”

- Erlandsson

Furthermore, Erlandsson mentions some laws and regulations that collection companies are controlled by. Among those is the restriction of data privacy and how to manage personal information in the process. These regulations will change during 2018 when the new GDPR regulations come into force. For example, the new rights are (Ernst & Young LLP, 2016):

- The right to be forgotten – the right to ask data controllers to erase all personal data without delay.
- The right to data portability – where individuals have provided personal data to a service provider, they can require the provider to “port” the data to another provider.
- The right to object to profiling – the right not to be subject to a decision based solely on automated processing.

Finally, risk assessment is something done continuously in the process. Besides the decision point located just before the legal judgment stage, the scoring model can be used to assist decisions in more stages as well (Erlandsson, Johansson). Erlandsson explains that the scoring
function is a recurring activity throughout the process in order to assess whether the payment ability of a debtor changes from time to time.

Independent of where in the process a scoring model is used, it always ends up in a decision of strategy for how to collect the money (Ibid). This leads to the next section of the empirical findings since risk mitigation strategies for debt collections can be considered to compose of all activities made as a result of a risk assessment of the account.

### 4.2 Risk mitigation

All the risk assessments follow by some risk mitigation activities since the act of trying to collect the money can be considered as such an activity. Scoring is not only done at the beginning of the process, but also for every risk decision where new information can provide the decision maker with new insights (Erlandsson). Such situation can arise before deciding upon suitable amortization plan (Johansson). The decisions that are made consist of the strategy for payment, how to approach the debtor, and what plan to decide about (Ibid).

“The term for amortization is a negotiation between debtor and collector. The risk assessment that is made beforehand is done in order to get a feeling of how much the collector can adjust to the debtor’s wishes.”

- Zaxmy

However, the strategy for which amortization plan is best suited and how to approach the debtor mainly belongs to a decision of the individual collector and what that person consider being the best option to mitigate the risk (Erlandsson). Erlandsson explains that the amortization plan I generated based on the experiences of the collector. The information that is located within the system is used as a support to ground the decision, but the final choice of strategy is manually made by the individual. Patil also confirms this manual process of decision making for amortization strategy.

“The strategies for how to approach the debtor or decide about a certain plan is up to the individual collector. There is no automation for suggesting amortization plan in Nova.”

- Patil

The risk at this stage is that the wrong strategy is chosen, which leads to a negotiation that is not optimal in order to get the money back. Resources, time and more money have then been spent on a strategy that did not work (Erlandsson).
Expert 2 also mentions the problematics of personalizing the strategy based on the characteristics of the customers when the manual process is leading the decision making. A learning system has the potential to do this more systematically (Expert 2).

“Machine learning has the potential to assist these strategic decisions more systematically though personalizing the strategy by looking at clusters of customers’ characteristics and learn from previous strategic decisions”

- Expert 2

Another support that the collector gets regarding the plan for risk mitigation, comes from the workflow system Nova. Nova allows for the organization to structure the process and its parts in order to track every activity and proactively visualize the next step in the process based on a pre-programmed workflow structure (Patil). The information that is stored within the system is, for example, debtors’ information, the status of the debt, calls, performed actions and credit information (Ibid). Besides the standard information that is supported by the system, the customers also have the ability to add information categories and automate parts of the information tracking.

“For example, emails that are sent to customers can automatically be registered in Nova without the need for manual input. It is up to the customer to decide what areas of an email that should be saved within the system.”

- Hasche

In this sense, Nova can be considered to register workflow tasks automatically without manual involvement. However, this can only be done when rules and structures have been pre-determined and manually programmed during implementation. Patil explains this structure by an example of the reminder function that Nova provides. This function allows the system to automatically remind the user of a certain action based on pre-determined conditions. These conditions are manually created when the system is implemented and do not change or adjust to specific characteristics of accounts. Furthermore, the automatic features in Nova are built upon a script which is pre-programmed during the implementation. Depending on certain scripted questions, the system can suggest next actions and strategies.

“During the implementation of Nova, a script can be created based on the customer’s requirements and their best practice of managing cases. This enables Nova to ask certain questions about the available debt data and debtor data to be able to evaluate and sort
cases according to the risk strategies, which is helpful for the decision maker when deciding upon suitable action for risk mitigation."

- Johansson

Furthermore, a problem within the process mentioned by both Erlandsson, Johansson, and Burstein is the lack of evaluation. The level of success is measured in order to provide the customers with key metrics of results for each case (Erlandsson). However, there is no evaluation that includes an analysis of why a certain account turned out as a success or not. What if the strategy of amortization plan was the key factor for the success, but the mitigation choices were never evaluated? This makes it impossible to extract any knowledge from the success evaluation and implement it to a strategy for risk mitigation.

“Evaluations of decisions are seldom done. When a decision is made, there is usually not enough time to evaluate whether this decision was optimal considering the given information.”

- Burstein

In addition to that, Burstein claims that the weights of the factors in the scoring model can be adjusted if there is an obvious pattern in the outcomes which indicates that there has been a change in how different accounts should be assessed. However, this is a manual process of noticing the pattern and changing the scoring model, which is not easily done and requires time from the user’s everyday work.
5. Analysis
This chapter consists of an analysis of the empirical findings in relation to the presented concepts and theories about machine learning provided in Chapter 2. The chapter begins with an analysis of the business understanding followed by the defined problem’s suitability for a machine learning solution. The chapter ends with an analysis of how machine learning potentially could be used along with what potential challenges there are.

5.1 Business understanding/problem definition

The importance of business alignment has not only been discussed in theory but also mentioned by Expert 3 during the expert interview. The development of an machine learning system cannot start with the technology, instead, it is important to have a strong business alignment and know the problem that the system is intended to solve (Expert 3).

Within the process of debt collection today, based on the interviews there are several stages where risk decisions are made. Normally, these decisions are based on some scoring model or another assessment model for the different debt accounts. In general, the assessment is dealing with a contingency of which accounts are the most profitable and which ones are driving costs (Experian, 2006). Addressing resources to the wrong account consequently affects the business negatively, and therefore, the strategy for assessing the accounts is critical (Ibid). This can be considered to be the main business problem related to the faced risk within the process.

The subproblem to this area, which connects it to a machine learning problem, can be considered as the difficulty of assessing the risk of a yellow scored account which is neither categorized as high risk or low risk (Burstein). This naturally affects the assessment of the likelihood of a certain outcome, but also the risk mitigation strategies. Translated to an machine learning problem as Mitchell (1997) explains, the T (task) would be: assessing and managing the accounts. The P (performance measure): percentage of accounts which outcomes correspond to the assessment. And finally, the E (training experience): in practice the ability to make correct assessments.
Giving the machine learning problem defined above, the next question according to (Brownlee, 2013) is why this problem needs to be solved. In the competitive industry of debt collection, the customers of collectors’ companies are constantly requiring the process to speed up (Erlandsson). With the difficulties of assessing the accounts, especially the yellow ones, the amount of manual decision making combined with the time pressure, there is a risk for misjudgments (Ibid). With a defined problem, the analysis will continue by looking at its connection to the typical tasks suited for machine learning.

5.2 Suitable for machine learning?

Using machine learning to support decision making and guiding actions has been the general reason for adopting the technique in different business areas (Domingos, 2012). Looking into the process of debt collection there are several stages where actions are taken related to the risk of not getting the money back. The decisions are naturally based on a prediction of the outcome which more or less is divided between being based on a score and on human gut feelings (Burstein; Erlandsson) Compared to Shalev et al. (2014) explanation of machine learning being useful for problems that are too hard to program, the task of doing this risk prediction might not belong to such a problem given the way risk is assessed today. The success of using scoring models for decades demonstrate that the task of assessing the risk itself cannot be considered as too complex to program. Although, this success can be questioned given the inexistent evaluations of the actual predictions. The only evaluation made today is a KPI measurement of the success rate of payments (Erlandsson), which does not evaluate the success of the assessment. Whether this success is based on the human expertise or the right prediction from a scoring model is unclear.

However, even if it is possible to program, a system that uses machine learning might find other patterns in the data set that provide the user with another prediction than a scoring model would. Furthermore, the aspect of adding an evaluation of previously managed accounts to the assessment adds complexity to the programmability which can be considered a benefit for a machine learning algorithm (Witten et al., 2017). The machine learning
prediction then has the potential to base the assessment on learnings from historical data of debt accounts, in order to generate a prediction concerning another account. Putting this into context, when an account that is considered to have a low risk of nonpayment, in the end turns out to be a debtor who does not meet the payment arrangement (normally characterized as a high-risk account). This output could then be used as an input for the algorithm’s future assessments (Shalev-Shwartz & Shai, 2014). This possibility belongs to the area of adaptivity and “learning by mistakes” benefit of machine learning, which will be analyzed further down. Thus, the task can in that sense be approached from a predictive learning approach even though the assessment as it is today might not belong to a task that is too difficult to program. This can be confirmed by previous research that through a computer science approach have tested machine learning algorithms for credit scoring (Kraus, 2014; Khandani, Kim & Lo, 2010). Kraus (2014) state in the conclusions that good results and competitive performance can be stated for predictive accuracy of some algorithms compared to classical scoring models. Furthermore, Khandani, Kim and Lo (2010) developed a machine learning model which provided accurate forecasting of credit events three to twelve months in advance.

Moreover, the complexity of the Nova database was mentioned during the interviews. This is due to the huge amount of data that is stored within it and the difficulties of accessing the data as a user. Hence, it connects to the theory of machine learning being useful for tasks that demand an analysis of very large and complex data sets (Shalev-Shwartz & Shai, 2014). This indicated that there is a possibility for machine learning to analyze and visualize the data in order to better support decision making, not just for making better predictions, but also for supporting prioritization and risk mitigation strategies. According to the Burstein and Erlandsson, the strategies for how to approach the debtor and what risk mitigation tactics that are most suitable for a specific account, is mainly decided based on personal experience together with the information provided by the scoring model. There are systems, like Nova, that automatically generate a recommended next action, however, this is only a result of a pre-programed workflow structure and does not include an analysis based on the success of previous approaching strategies (Patil).

For example, with the traditional approach, the uncertainty of how to manage a yellow score allows for the human decision making to have a substantial impact (Burstein). For an account scored as yellow, the decision maker might feel that the best way to manage this risk is to send an email to the debtor and inform about the decision of moving the debt to the legal judgment. Instead, a system that provides a more advanced analysis of available data might
recognize that this account is similar to another case from last week which reached immediate success though calling the debtor to get an understanding of the ability of payment. This case ended with an amortization plan at once. This demonstrates the kind of analysis that machine learning could conduct when getting access to complex data sets, which is impossible for humans or statically scoring models to make sense of (Baesens, 2003). Hence, the benefits of deepening the analysis make it possible to not only provide an interpretable score but rather show what analysis has been made for the specific account and suggest strategy to mitigate the risk based on previously successful strategies. This would create a workflow structure based on analysis instead of predetermined steps.

Other tasks suitable for machine learning are when adaptability is desired (Shalev-Shwartz & Shai, 2014). Could this be related to the task for this case of debt collection? By once again looking at the defined machine learning problem and the T (task) of assessing and managing the accounts, the traditional way of using a pre-programmed approach means that an implementation is made and the knowledge that existed during the implementation is independent of time and changes in the environment. Given the same task, machine learning could instead adapt to the environment and changing conditions that the process of debt collection is characterized of (Ibid). For example, today collectors can notice a pattern depending on the postal codes, where some areas are known for high-risk accounts (Burstein). Over time, these areas could change to more stable conditions where the willingness of payment increases, so the algorithm could adapt to those changes and suggest new risk mitigation activities. Other examples could be that salary changes or that a certain holiday occurs, which changes the ability for a debtor to meet payment arrangements. The adaptivity feature of machine learning allows the algorithm to react to these dynamics of changing credit cycles thanks to an evaluation function (Khandani, Kim, & Lo, 2010).

Moving on to the next section, the problem definition and the general analysis of how the defined task connects to areas where machine learning is typically suited will provide a background for the upcoming analysis. It consists an analysis of “how”, including how the data relate to a learning paradigm and how this potentially could be categorized.
5.3 How can machine learning potentially be used?

In order to even start with the learning process, there is a need for training data to be available (Expert 3). The training data consist of data that previously have been processed. In this case study, Nova has been used since the 90’s, consequently, it consists of a huge amount of data even though a lot of it has been anonymized according to privacy policies (Patil). The system logs every new action and step taken within the process including the date of payments or if the account ends up as “closed” (not paid) in long-term surveillance (Figure 8). Hence, a certain output of “payment” or “closed case” can be traced back to an assessment and decision of risk strategy in the system. In machine learning terms, this means that the predicted value can be found in the training data, and therefore, it belongs to the paradigm of supervised learning (Kulkarni, 2012). Hence, to teach the system to predict a future output, it needs to be trained on the data that are needed to make an assessment, along with the data that show the steps taken for risk mitigation, and finally the registered output of payment or closure. With this information, the algorithm could then potentially find patterns and learn from historical examples (Ibid).

For a supervised learning approach, there could be two types of categorizations, either regression or classification (Ibid). Since the aim of the prediction is to identify the accounts with high risk and low risk based on the predicted output of “payment” or “closed case” it does not belong to a numerical prediction, which is the case of regression. The same goes for risk mitigation where a next action of “calling” or “emailing” belongs to a class and not a numerical prediction (Brownlee, 2013). However, a numerical prediction could be used for other purposes such as predicting the number of accounts that will fail, or how much money a case will generate for the debt collection company. These could potentially also be good predictions that could be used for prioritizing accounts. However, based on the defined task related to the assessment of classifying high-risk and low-risk accounts, it can be seen as a categorical task (Kulkarni, 2012). When the target values belong to a category, class or some
group, this is indicative of a classification problem (Ibid). Besides the actual prediction of distinguishing between good customers and bad customers, which has been the traditional goal for doing scorings, machine learning algorithms also have the ability to taking into account when customers tend to pay (Baesens, 2003). This predictive possibility could then potentially help for planning the risk mitigation strategy and prioritizing a certain account based on the time to get the money back, which current risk assessment have limited possibilities in doing (Ibid).

However, by looking at the problem from another perspective, all useful data might not exist in the training set. During the interviews, some respondents claimed that there can be certain groupings of accounts based on the relationship to the debtor (Burstein; Erlandsson). The need for not disrupting an ongoing relationship allows for some accounts to be handled differently from the normal assessment recommendation. On the other hand, there might be other classes and groups which are not defined today but which can be visualized through the use of unsupervised learning. The categorization method “clustering” could then potentially reveal classes of accounts that are willing to pay within 90 days, and those who are willing to pay within a year, etc. This allows for an assessment of not only high-risk accounts and low-risk accounts, but rather of what differences there could be between the low-risk accounts. Potentially, this also helps the prioritization of which accounts to focus on depending on the need to collect money fast (within 90 days) or if speed does not matter as long as it is collected within a year. Clustering allows for this segmentation of accounts and is used for situations when there are no obvious natural groupings, which makes the data difficult to explore (Baesens, 2003).

5.4 Challenges

Figure 12 – Fifth block in the analytical model

The interviews in this study provided insights to the problem of the availability of data that is used within the process (Patil; Erlandsson; Burstein; Hasche). Given the data that is currently available within the collection system, this was considered complex due to the many years of logs that are stored within the system. However, the data availability can be considered an
issue from other perspectives. Some information is not automatically available within the system but instead hidden within authorities (Zaxmy). Data regarding salaries, previous debt cases for other debt collection companies and assets are examples of data that are hard to access (Ibid). A collector can access the data by demanding an extraction from the Enforcement Authority and use this for the assessment (Erlandsson). However, this is a manual action and cannot currently be automated. Hence, data are available but hard to access, which subsequently affects the machine learning potential of making better assessments (Baesens, 2003). This results in a situation where a machine learning algorithm cannot rely on its ability to analyze more data for risk assessment than what is available today for a scoring model. Instead, it needs to compete on its ability to recognize patterns invisible to the currently used methods.

The risk assessment of debt collection accounts relies on the prerequisite of using personal data about the debtor (Experian, 2006). The whole assessment is based on the characteristics and what the company knows about the debtor, in order to decide in what way to approach the particular case (Ibid). The secondary use of data for purposes other than the one for which data have been collected is a privacy issue which is highly relevant for risk assessment in debt collection overall. From the perspective of machine learning, which benefit from using as much data as possible, this becomes a restriction and something that potentially could challenge the possibility of using machine learning for this purpose in the future.

In addition to that, Erlandsson mentions the new regulation agreement made between the European Parliament and Council of the European Union (called GDPR, General Data Protection Regulation) as a potential threat to how debt collection previously have been conducted. This regulation will come into force during spring 2018 and will affect how data can be used. All three of the new rights can be considered as difficulties for machine learning analysis. The right to be forgotten can limit the amount of data to be used for pattern analysis, the right about data portability can potentially limit the access to further data from authorities. However, these new data privacy regulations will not only affect the machine learning potential but also the currently used scoring methods as well (Erlandsson). From this perspective, could machine learning then provide an even bigger competitive advantage compared to scoring models due to its ability to find patterns in the data available and the learning from evaluations functionality? The ability to find patterns in an even more limited data set could potentially be the most critical key competitive advantage for any support system doing risk assessments.
The third right composes the right of being an object to profiling where decisions cannot solely be based on automated processing. No matter how good automations that can be made, this right will still allow the human to have a substantial impact on the final risk decision no matter how good the algorithm performs (Ernst & Young LLP, 2016). Consequently, the last right also adds for another concern to be important for the machine learning potential. Its ability to generate trust to the final decision maker. As mentioned during the interviews, decision makers tend to be skeptical towards today’s scoring models since they do not show how the score is generated (Burstein). A machine learning algorithm might be even more difficult for decision makers to grasp due to the advanced analysis made (Expert 1). The issue of under-reliance can thereby be a difficulty for machine learning to work properly (Hoffman et al., 2013). A future with these kinds of laws and regulations show the importance of having a good understanding of the technology from a user’s perspective and combining the collector’s own expertise with the support provided by smart systems. Being able to point on previous success assessment made by the system can be a useful tool in order to gain trust from the decision maker and change the attitude (Ibid). The understanding of trust issues being a difficulty within the risk assessment today makes it an issue to consider for the machine learning potential. The importance of transparency to the steps taken during the machine learning analysis could then be an important feature for a future system using machine learning. This would provide the experts with insights into the steps that the analysis is based upon, which according to Hoffman et al. (2013) is a way to avoid under-reliance.
6. Discussions & Conclusions
The final chapter summarizes the conclusions of the study along with a discussion of what those conclusions indicate regarding the machine learning potential for risk management in debt collection. This is followed by a presentation of the contributions along with a discussion of criticism and future research.

The ongoing debate about smarter technology and its impacts on society allows for both optimism and fear (Turban, Aronson & Lian, 2004; Firschein et al., 1973; Wolfe, 1991; Rahwan & Simari, 2009). Hence, there are several questions arising when consider using a smart technology, such as machine learning, and the potential impact it could have on the overall business. Along with an investigation of the potential, there are questions of how suitable the task is for the technology? how would it perform compared to alternative methods? and what difficulties there might be using this technology? In previous studies composing of investigations of the potential to use machine learning for credit scoring, a computer science approach has provided answers to the questions related to performance. The development of algorithms has allowed for a comparison of the machine learning technique with other methods and led to conclusions about the potential. However, this study shows that the potential can be considered to include other aspects to it, besides the performance of the algorithms. The business perspective of this study allowed for an investigation of the potential from a broader perspective, where the conclusions about the potential provide complementary insights to the previous computer science studies.

The conclusions of this study have been divided into possibilities and difficulties of using machine learning for risk management in debt collection and have been summarized in three ways:

- Machine learning has the potential to be used to improve the predictions done during risk assessment thanks to advanced pattern recognition and the adaptiveness of its nature.
- Machine learning has the possibility to provide the decision maker with suggestions on suitable risk mitigation strategies based on previous experience and evaluation of previous decisions.
- The main difficulty for using machine learning in this process is due to the limitation of data available for a more complex analysis, which in other application areas are considered a big advantage for machine learning compared to alternative methods.
Where risk decisions are made within the process of debt collection today, machine learning has the possibility to be used as a tool for risk assessment of debt accounts. With a machine learning technique, predictions can benefit from the use of pattern recognition and the adaptive nature of the algorithms. A supervised learning approach has the potential to categorize the accounts depending on the likelihood of payment during the first phases or risk for ending up as a closed case. This follows the same kind of assessment that has been done through scoring models where a number with a code color has illustrated this risk level. However, with machine learning, this assessment has the potential to be more precise in the predictions, which previous studies have shown through the testing of algorithms. Moreover, the adaptiveness of machine learning allows for the technique to adapt to the environment and changing conditions in the process. This means that the predictions are updated automatically without the need to manually change pre-programed weights and conditions which would be needed for a scoring model. Furthermore, besides the possibility of making better predictions using the same approach of categorization as for scoring, machine learning also has the potential to provide a prediction of when customers will pay which is not possible to do with a traditional scoring model. This would instead allow for the collection companies to perform profit assessment and prioritize the debt accounts based on the profits (Baesens, 2003).

However, despite the success of using machine learning for predictions in risk assessment where scoring is used today, the main possibility for machine learning to contribute to risk management in this process is not only assessing the risk levels of the account, but rather provide the decision maker with a suggestion of suitable risk mitigation strategy in addition to this assessment. By looking at how the patterns for a certain account is reflected in a previously managed account, a suggestion for next action can be provided rather than using a scripted workflow structure. This possibility of learning from experience allows for the machine learning algorithm to evaluate previous outcomes, which has been considered a limitation of the scoring model and today’s system. Hence, the uncertainty of choosing a strategy based on the human gut feeling and a color code could possibly be eliminated when the system proactively suggests how the assessment can be interpreted and what mitigation strategies are most likely to work. For a debt collector and a collection company, this could mean an improved way of making decisions and increasing the chances of collecting debts. In the end, this is the core of their business and affect how competitive there are in the market. However, along with the benefits of using a system that eliminates the interpretations of color
codes and suggests strategies for the decision maker, other difficulties such as trust issues can result in uncertainty anyway.

Among the mentioned difficulties that can affect the machine learning potential, one major difficulty recognized for this process is the issue of data availability. The issue can be divided into the problem of accessing data and the problem of data privacy and anonymization. The difficulty of accessing data is due to the restrictions where useful data is captured within databases of authorities. It requires a manual process in order for this data to be accessed, which result in a situation where this data cannot be assumed to be used for the prediction. In other application areas of machine learning, a major benefit of using the technique compared to other methods is its ability to make sense of huge and complex data sets. In this case, when the data from authorities is limited to specific assessment due to the efforts demanded by manual resources, this cannot be used as a beneficial factor for the machine learning potential. Apart from the accessibility issue, another difficulty related to data availability has shown to be the problematics of being dependent on personal data. The risk assessment in debt collection requires using data about the individual debtor which automatically is anonymized after 12 months (Hasche). Depending on the level of anonymization and how much of the original data that is removed, this can potentially affect the machine learning performance. Furthermore, the GDPR (Global Data Protection Regulation) will definitely affect the assessment in general due to the restrictions of how the data can be used. This will automatically have an impact on the technical possibilities independently of using machine learning or scoring models.

Finally, the issue of human biases in risk decisions will continuously be a challenge even with the use of a smarter system. There is always a risk of misinterpretation, under-reliance and other influencing biases that can create difficulties for a successful use of machine learning. The GDPR including limiting the ability for decisions to be solely based on automated processing, along with the need for a manual activity in order to collect more data from authorities, show that errors from humans will continuously be a risk in the process. On the other hand, this allows for a future where the humans and computers will continue being dependent on each other without a fear of automation replacing employees. Humans will continue to have the final impact on the decisions made and the need for expertise within this area will continuously be important. However, the understanding of how to cope with suggestions proactively made by a system will probably be just as important as the expertise, since a future with smarter technology relies on collaborations between humans and
computers on a higher level than today. Thus, the technology needs to adapt to the humans and ensure that the support is clear to such an extent that misinterpretations and under-reliance of trust are minimized. Just as any collaborations, someone’s weakness can be adjusted by another’s strength. The human brain is ineffective in assessing risk, but machine learning can have the potential to be used to support the assessment, not to replace it. In return, the technology needs to gain trust from the user and sufficient of data in order for the advantages to be shown. In terms of risk management, Kaplan and Mikes (2016) claimed that companies should avoid the choice between quantitative and qualitative risk management and allow for both to play important roles in risk assessment. Hence, the potential of using machine learning for risk management can be considered to go beyond the performance of the algorithm. It is also dependent on a symbiosis between human and technology in order to cope with the potential difficulties and gaining synergies for risk management and businesses overall.

6.1 Contributions
The research gap that this study was based on can be considered from two perspectives. Based on a theoretical approach, the gap in previous research was described as the lack of business perspectives in previous investigations of the machine learning potential for risk management in debt collection and credit scoring. The computer science approach in previous studies centralizes on the development and testing of algorithms compared to traditional credit scoring techniques. Furthermore, this also connects to a gap from an empirical perspective. The lack of studies from a business perspective consequently affect the knowledge for business practitioners within this area. Studies show that humans are inefficient in assessing risk, which opens for technical solutions to have the potential to be used as it does for many other situations of complex decision making. However, without studies that are conducted from a business level approach, including an overall picture of the potential, it can be considered as inaccessible for practitioners. Hence, the knowledge gap between what the computer scientists know about the actual performance of different algorithms, and available research to provide with business knowledge about the potential to apply machine learning for certain business problems, constitute the base of the gaps that this study aimed to close.

In order to close the theoretical and the empirical gap, this study has contributed with an investigation into the possibilities and difficulties of applying machine learning for risk management in debt collection from a broader perspective than previous research, excluding testing of algorithms. Given the limited amount of previous studies within the area of machine
learning for debt collection, this can be considered as a theoretical contribution in its own. In addition to that, the business perspective provides a complementing study to previous research with a computer science approach by allowing those studies to assure the credibility of the conclusions, at the same time as broadening the investigation of the potential. The conclusions show in what way machine learning has the potential to be used and what benefits it potentially could bring, along with the difficulties there are to consider. These findings can be used as a theoretical contribution to complement the previous research. Furthermore, for practitioners that do not know much about machine learning, but have a feeling that is could improve their business, this study shows important steps and conclusions to consider when elaborating on that feeling further. The business languages along with the use of a case study that provided with business insights to the process allowed for this study to contribute with a business perspective on the potential, which related to the knowledge gap identified in the initiation of the study.

6.2 Criticism
With the research approach of investigating the potential of using a certain technology for risk management in a defined business area, Tieto was considered a suitable company to provide with insights from both aspects. However, the complementing interview with Intrum Justitia was important in order to get the perspective of a debt collection company present within the targeted process. The time it took to schedule an interview with the right respondent at Intrum Justitia, limited the amount of complementing interview to that one. In a best-case scenario, more interviews with debt collection companies would have been useful in order to further confirm and complement the data collected from Tieto.

Furthermore, the study could have benefited from a longitudinal study where the two research approaches would have come together even further. By allowing for this business investigation in the beginning of a study, followed by developing an algorithm and testing it in the specific case, this could have closed the gap even further. Moreover, the possibilities and difficulties presented as conclusions for this study do only consist of parts of the overall potential and is still dependent on the performance of the algorithms. A business perspective from on an even more technical level could have provided with further knowledge into the potential, which also could have helped in the closing of the gap. For example, the development and testing of algorithms do not necessarily mean that such research needs to be done from a computer science approach, which is the case in previous research. A study explaining the potential from a business perspective, including a demonstration of what kind
of algorithms can be developed and tested, would provide with complementing aspects to the potential included in a gap that this study did not close. Nevertheless, this study can be considered as an initiating study to close parts of the gap and illuminate the need for future research within this area. Moreover, the follow-up interviews with machine learning experts aimed to help in confirming the conclusion and address this issue. On the other hand, their perspective on the conclusions are subjectively related to the claimed findings and cannot assure the full potential in the same way that a longitudinal study, involving an algorithmic investigation, could.

Finally, this investigation has also resulted in an identification of another gap in the previous literature. The machine learning technique only composes of one area of data mining and KDD which in other areas can benefit from being applied in contexts along with similar fields of data mining and capturing of unstructured data. Previous research within the area of credit scoring has mainly investigated the machine learning potential, given the available data that is currently being processed within the area. This study followed the same structure. Hence, an investigation of how other techniques can support the machine learning algorithms with more data that previously have not been captured within the process, compose another gap that has not been addressed in this study which could affect the conclusions about the potential further. This is another perspective to the potential of using machine learning which future research can elaborate on.

6.3 Future research
Based on the contributions of this study and the potential to close the gap further, future research from a longitudinal perspective would allow for extended contributions in this area. This could complement the conclusions of this study and provide with further insights into the possibilities and difficulties that should be considered when looking at the potential. In addition to that, the business perspective can be applied to an even more technical level where developing and testing of algorithms would provide the practitioners with further knowledge to this area. As long as this is done with a business perspective in mind, the gap has the potential to be further closed with this approach.

Future research can also further elaborate on the newly identified gap which was realized during this study. As known, machine learning can benefit from the usage of huge and complex data sets and the availability of data was concluded as a difficulty for the potential. However, the future research could investigate new ways of gathering data that could be used to support an even better analysis for the machine learning algorithm. For example, what if
there is a possibility to incorporate techniques to capture unstructured data from phone calls, the debtor’s presence on the internet and so forth? Today, the knowledge about the debtor and the habits are limited to the structured information that is relatively easy to collect. The use of smarter technology in order to provide the algorithms with more data would open up for new possibilities regarding the analysis and suggestions made by a learning system.
7. References


Ernst & Young LLP. (2016). *EU General Data Protection Regulation: Are you ready?* London: Ernst & Young LLP.


## Appendix

### 1. Interview template

<table>
<thead>
<tr>
<th>Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Background</strong></td>
</tr>
<tr>
<td>What is your current role?</td>
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<tr>
<td>What areas of responsibility do you have?</td>
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<tr>
<td>For how long have you worked within this department?</td>
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<tr>
<td><strong>Risk in debt collection process</strong></td>
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<tr>
<td>Can you explain the debt collection process from the perspective of risk?</td>
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<tr>
<td>Where are the major risk decisions made within the process?</td>
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<tr>
<td>What are the biggest challenges and problems regarding risk management within the process today?</td>
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<tr>
<td><strong>Risk assessment</strong></td>
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<tr>
<td>How is the risk assessment made today? How do you estimate the likelihood of a certain risk?</td>
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<tr>
<td>Who does the assessment?</td>
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<tr>
<td>What information is included in the assessment?</td>
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<tr>
<td>Are there any categories based on the risk profile today?</td>
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<tr>
<td>How is the risk presented?</td>
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<tr>
<td><strong>Risk mitigation</strong></td>
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<tr>
<td>How do you manage and mitigate the risk assessment?</td>
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<td>How do you prioritize the cases depending on the risk assessment?</td>
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<td>What are the strategies for risk management?</td>
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<tr>
<td>How are the strategies chosen?</td>
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<tr>
<td>How are the evaluation made based on the actual outcome later on? (How do you know if you took the right decision?)</td>
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<tr>
<td>How do you improve the risk decisions based on the outcomes?</td>
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<tr>
<td><strong>System and information</strong></td>
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<tr>
<td>What information is stored within the system?</td>
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<tr>
<td>What information about the customer is available to make decisions based on?</td>
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<tr>
<td>What potential information could be available and stored within the system?</td>
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<tr>
<td>What information would be needed for a better risk decision?</td>
</tr>
<tr>
<td>In what way do the system support the risk management in the process?</td>
</tr>
<tr>
<td>Are there any rules and regulations that needs to be considered regarding what information can be used?</td>
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</tbody>
</table>