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How two-sided platform startups can use machine learning to improve the value proposition

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Aim of the thesis

Some of the biggest and most successful two-sided platforms in the world are using machine learning to improve the value proposition for the customer. The companies with the most satisfied users are the ones who capture market shares and generate the most profit. This is also true for two-sided platform startups, but managers of these companies have limited time, resources and knowledge about how to utilize machine learning in their business. The platform managers need tools to effectively evaluate if machine learning can be used to improve the value proposition. The theory about this is limited, and a framework which helps platform managers understand this should be developed.

The thesis will address the following:

- A conceptual framework is developed based on the existing literature
- Empirical evidence is collected to test the framework
- The framework is analysed and discussed based on the empirical findings
- A revised conceptual framework is proposed

Preface

This paper is written in Trondheim the spring of 2017, as a master thesis by three students at NTNU School of Entrepreneurship, Department of Industrial Economics and Technology Management at NTNU. The researchers want to thank Vivek Sinha for supervising the process.

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Abstract

The world's four biggest companies all have two-sided platforms and machine learning as central parts of their business. They leverage machine learning to improve the value proposition for the user, because the platform with the most satisfied users will win. This is also true for startup companies. However, dealing with machine learning is not easy. Manager of two-sided platform startups who tries this without the right tools or knowledge, will waste time and resources on the process. Therefore, the purpose of this study is to answer the two research questions:

How can managers of two-sided platform startups:
RQ1: Evaluate if the value proposition can be improved with machine learning?
RQ2: Determine the type of machine learning algorithms that could be applied?

A literature review by Rystad and Aarseth (2016) uncovered a gap in theory regarding improving the value proposition of two-sided platforms with machine learning. The literature offers little guidance to platform managers looking to answer such questions. To overcome this, a four-step conceptual framework based on the work of Han & Han (2001), Sandulli (2014) and Mitchell (1997; 2006) was developed, tested and revised.

A multiple case study with ten in-depth interviews was carried out to collect empirical data about the value proposition of five Norwegian two-sided platform startups: Graphiq, Tise, Learnlink, Nabobil and Leieting. The framework was applied on the collected data from the case studies. An analysis and discussion was then used to evaluate the framework. The analysis and discussion uncovered some parts of the framework that could be improved, resulting in a revised framework. These changes were related to more precise information, removal of unnecessary parts and rephrasing of questions.

The revised framework can help managers of two-sided platform startups with their most important job: creating more value for the user by improving the value proposition. This allow them to capture market shares and generate future profit. The paper is applicable for business leaders, business strategy scholars and entrepreneurs that want to learn more about

how two-sided platforms startups can leverage machine learning to improve the value proposition.

Sammendrag

Hva har de fire største selskapene i verden til felles? Svaret på dette spørsmålet er at alle har en tosidig plattform som en sentral del av sin forretningsmodell, og at de bruker maskinlæring til å skape verdi for brukeren. Disse selskapene bruker maskinlæring til å forbedre verdiforslaget til brukeren fordi de vet at det er selskapene med de mest fornøyde brukerne som kaprer markedsandeler og genererer overskudd.

Dette gjelder også for oppstartsselskaper, men i dette tilfellet har bedriftslederne to utfordringer. De har ikke nok tid eller ressurser til å forstå hvordan maskinlæring kan forbedre verdiforslaget. Og ofte har de heller ikke den tekniske kunnskapen som skal til for å vurdere hvilken type maskinlæring som kan brukes på deres plattform. For å utnytte potensialet til maskinlæring trenger bedriftsledere et verktøy for å raskt evaluere om maskinlæring kan forbedre verdiforslaget til plattformen. Formålet til denne avhandlingen er derfor å svare på to problemstillinger:

Hvordan kan bedriftsledere for nyoppstartede tosidige plattformer:
Problemstilling 1: Evaluere om verdiforslaget kan forbedres ved hjelp av maskinlæring?
Problemstilling 2: Bestemme hvilken type maskinlæringsalgoritme som kan anvendes?

Et litteratursøk av Rystad og Aarseth (2016) avdekket at det ikke eksisterer noe teoretisk rammeverk som kan hjelpe bedriftsledere å svare på disse to problemstillingene. Derfor har denne avhandlingen utviklet, testet og revidert et fire-stegs konseptuelt rammeverk basert på relevant teori fra Sandulli (2014), Han & Han (2001) og Mitchell (1997; 2006).

Et studie av fem norske nyoppstartede tosidige plattformer, med totalt ti dybdeintervjuer ble gjennomført. Selskapene var Graphiq, Tise, Learnlink, Nabobil og Leieting. Empirisk data om selskapenes ble samlet inn, og anvendelsen av det konseptuelle rammeverket på denne dataen er grunnlaget for analysen og diskusjonen i avhandlingen.

Analysen og diskusjonen avdekket at noen deler av rammeverket kunne bli forbedret, hvilket resulterte i en revidert versjon av rammeverket. Disse forbedringene var relatert til mer detaljerte definisjoner, overflødige elementer og omformulering av spørsmål. Det reviderte rammeverket kan hjelpe bedriftsledere for nyoppstartede tosidige plattformer med deres viktigste jobb: å skape verdi for brukeren ved å forbedre verdiforslaget, uten å sløse tid og energi. Dette gjør det mulig for selskapet å vinne større markedsandeler og skape profitt. Denne avhandlingen er interessant for bedriftsledere, akademikere med interesse for forretningsstrategi og gründere som ønsker å forstå hvordan nyoppstartede tosidige plattformer kan bruke maskinlæring til å forbedre verdiforslaget.

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1. Introduction

How is it possible that Spotify, one of the world's' most popular music streaming services, can deliver a playlist with 30 personalised songs to each of its 100 million users every week? (Lindblom, 2015; Spotify, 2016). And how is it possible that Netflix, a video streaming service with more than 86 million users worldwide, knows each user's movie preferences? (Netflix, 2016).

This is due to sophisticated software powered by machine learning algorithms. Machine learning is an interdisciplinary field within computer science concerned about creating software that solves specific tasks and automatically improves with experience (Mitchell, 1997). This is a research area that dates to 1959, but due to massive improvements in hardware, machine learning has recently taken the step from being primarily a research area to become the technology behind some of the most value creating features of digital businesses (Stone et. al, 2016).

Netflix and Spotify are not the only companies that leverage machine learning. In fact, according to Financial Times (2016), the four most valuable publicly traded companies in the world all has machine learning as an integral part of their business: Apple (Levy, 2016), Alphabet (Google, 2017), Microsoft (Microsoft, 2017) and Amazon (Amazon, 2017).

> *"Machine learning is a core, transformative way by which we're rethinking how we're doing everything. And we're in early days, but you will see us—in a systematic way—apply machine learning in all areas." Google CEO, Sundar Pichai (2015)*

A wave of machine learning algorithms has struck the business world, and only the companies able to surf that wave will survive. But why?

According to Peter Drucker (1973), the purpose of every business is to satisfy the customer. Customer satisfaction is achieved when superior customer value is delivered. Machine learning has proven to be superior in improving the value proposition of technology-based businesses (Qiu et al., 2016). A value proposition "describes the benefits customers can expect from your products and services" (Osterwalder et al., 2014: p. 277). A literature review conducted as part of a project thesis (Rystad & Aarseth, 2016) found that machine learning is increasingly being leveraged by companies to improve the value proposition.

All the companies mentioned so far have a two-sided platform as a vital part of their business. Two-sided platforms are defined as commercial digital networks serving two-sided markets where the value for one side depends on the number of participants on the other side (Schiff, 2003). This business configuration has become increasingly popular over the last decade, due to the potential for growth and creation of high entry barriers.

It is particularly interesting for two-sided platforms to improve the value proposition through machine learning for three reasons. First, they have two user groups that need to be satisfied. If one side of the platform is not satisfied, they will leave and eradicate the value of the platform for the other side. Machine learning can be used to match the two sides and balance supply and demand by adapting the price to the market automatically. Second, as two-sided platforms need to be scalable, all the value must be delivered through digital means. Third, two-sided platforms often have access to a large amount of user data enabling them to understand their users and create a better user experience. Machine learning is often the right tool to leverage such data.

While established companies like Netflix and Spotify can experiment and test different types of machine learning algorithms to find the most suitable type, startup companies can´t. They need to keep their costs low while satisfying a growing user base. As the platform grows, the users become more and more demanding. The growing user base typically demand an increased level of trust and safety, a better user experience and add-on products and services (Wertz and Kyngiens, 2015). To be able to grow from being a startup to an established company, the platform needs to improve the value proposition in a scalable manner. If startups waste valuable time and resources in this process, their competitors will beat them. Managers of two-sided platform startups are therefore continuously working on improving the value proposition without wasting time and energy.

The machine learning landscape is large, complex and difficult to navigate. It is hard for managers of two-sided platform startups without deep technical knowledge, to evaluate if they can improve the value proposition by leveraging machine learning. Today many opportunities are bypassed due to the lack of practical tools to do so. Current literature offers little guidance to managers, strategists and entrepreneurs that work with two-sided platforms, hereby referred to as platform managers. In fact, the relationship between technology and value creation is an area which has received little attention (Baden-Fuller, 2013). Two fields are open for future research: 1) which are the technologies adopted in multi sided platforms and, 2) which are the functions and the features enabled by these technologies (Ardolino et al., 2016). With the aim to contribute knowledge to this gap, the researchers asked the following two research questions:

How can managers of two-sided platform startups:
RQ1: Evaluate if the value proposition can be improved with machine learning?
RQ2: Determine the type of machine learning algorithms that could be applied?

To answer these questions, the researchers developed a conceptual framework based on a literature review by Rystad and Aarseth (2016) about the three research areas: two-sided platforms, value proposition and machine learning. This study presents how this framework was tested by collecting empirical data about the value proposition of five case companies, and testing the framework by applying it. Based on the preceding analysis and discussion, the framework was revised and the final framework is presented in the end of this paper.

The five case companies: Graphiq, Tise, Learnlink, Nabobil and Leieting was chosen because they represented a heterogeneous sample of different types of platform companies, within the same context, namely Norwegian two-sided platform startups. This context was purposively selected because the Norwegian startup ecosystem is one of the fastest growing ecosystems in the Nordics (Murray, 2017). In addition, the fact that the researchers are Norwegian enabled them to create enough trust with the case companies to make them open to this type of research.

There exists no framework that explain the process of improving the value proposition through machine learning today. This paper's contribution is a framework that help managers of two-sided platform startups evaluate if they can leverage machine learning to improve the value proposition. The framework also help them determine the type of machine learning algorithm that can be applied. The goal is to help platform managers satisfy their users, capture market shares and generate future profit.

The paper is structured in seven chapters. The second chapter is the theory chapter that present the current state of the literature on two-sided platforms, the value proposition and machine learning. The third chapter presents the framework that is developed based on this knowledge. The framework includes four steps: 1) Define problems. 2) Categorize problems. 3) Evaluate problems. 4) Identify machine learning algorithm. The fourth chapter is the methodology chapter where the method for the literature review, research design, data acquisition, data analysis and reflection and evaluation of the method is presented. The fifth chapter introduce the findings from the case-studies. The sixth chapter is the analysis and discussion chapter. The chapter ends by presenting the revised framework. The seventh chapter is the conclusion where implications, further research and limitations is presented.

2. Theory

2.1 Introduction

To be able to develop a conceptual framework that can help answer the research questions, there was a need for a literature review on the most important research areas related to the research questions. Therefore, based on a literature review by Rystad and Aarseth (2016), this chapter presents the current state of knowledge on two-sided platforms, value proposition and machine learning.

To ensure a clear understanding of the context in which the research operates, this chapter starts with reviewing what the literature says about two-sided platforms, and introduces a way of categorizing two-sided platforms. Then the researchers elaborate on existing literature on value creation, with the focus of improving the value proposition of two-sided platforms. In the end, an introduction to machine learning is offered and used as a foundation for explaining the six problem categories that machine learning is associated with.

2.2 Two-Sided platforms

Two-sided platforms exist in almost every industry, and platforms as a business configuration have increased massively in popularity over the last decades (Evans and Hagiu, 2008; Schreieck et al., 2016). A variety of two-sided platforms has emerged because of the digital revolution. A growing base of literature builds on different definitions of a two-sided platform or what their most important characteristics are (Schreieck et al., 2016). There are several different types of definitions and categorizations of two-sided platforms offered in literature. Therefore, in this subchapter the researchers have reviewed what the literature says about two-sided platforms, chosen a suitable definition and highlighted relevant ways of categorizing two-sided platforms.

2.2.1 Description and definition of a two-sided platform

Schreieck et al. (2016) identifies two perspectives within platform research: technology-oriented and market-oriented. The technology oriented perspective defines a platform as "a set of stable components that supports variety and evolvability in a system by constraining the linkages among the other components" (Baldwin et al. 2008, p. 3). This means a structure where the linkages between components can be supported, and it comprises technology platforms such as operating systems (e.g. Microsoft´s Windows) and hardware platforms such as computing hardware or IT infrastructure (e.g. wireless networks).

The market-oriented perspective emphasises that platform ecosystems can be seen as markets, where users interact with each other and are subject to network effects that are facilitated by a common platform provided by intermediaries (Eisenmann et al., 2011). The market-oriented perspective is chosen because it represents the platforms where creating value for the user is key to success.

This research is focused on pure-players, defined as an organization that has no physical store and does business solely through the internet (Sharma & Sheth, 2004). Pure-players use the internet to provide information, connectivity, community, transactions, and shared cost reductions (Sharma & Sheth, 2004).

One of the first definitions of two-sided platforms in the literature was "A two-sided market where the one type of agents needs the service of a middleman or matchmaker to be matched with the other type. The matchmakers compete for agents of both types by means of commission fees" (Van Raalte and Webers, 1998, p. 477). This definition is too vague for the purpose of this research, as it does not consider the presence of a digital platform or a market with network externalities.

Scholars have emphasized that two-sided platforms involve a phenomenon characterised by the presence of a platform, which facilitates the interaction between two distinct groups of users (Rochet and Tirole 2003, Armstrong 2006, Caillaud and Jullien 2003, Evans and Schmanlensee 2008, Hagiu and Wright 2015, Ardolino et al. 2016).

Schiff (2003, p. 425) was one of the first to consider network externalities in his definition: "a firm with a two-sided network serves two distinct types of consumer and the utility of each type is increasing in the number of the other type that can be accessed through the firm's network". This is an important characteristic rooted in the network externalities literature (Katz and Shapiro, 1985).

In the scientific literature, the phenomenon of platforms is described using different terms and there is a lack of a clear definition (Hagiu and Wright, 2015). Terms frequently used are "multisided platform", "multisided market" and "multisided network" for platforms with two or more sides and "two-sided platform", "two-sided market" and "two-sided networks" for platforms with two sides. In the following, the term "two-sided platform" is used to describe the phenomenon with two market sides.

For the purpose of this paper the researchers define a two-sided platform by four characteristics: First, a commercial digital network serving a two-sided market. Second, it facilitates interaction between two distinct user groups (Rochet and Tirole 2003, Caillaud and Jullien 2003; Armstrong 2006, Evans and Schmanlensee 2008). Third, the value for one group of users depends on the number of users in the other group (Schiff, 2003). Fourth, the platform needs to deliver two different value propositions to the two distinct groups of users (Muzellec et al., 2015).

Platform phases

For the purpose of this research a two-sided platform is defined as a startup if it is in the search of a scalable business model (Blank, 2012). Wertz and Kingyens (2015) introduced three phases two-sided platform startups can be in. Seeding, growing and scaling. These phases are defined by user mass. Seeding is the phase where the platform invites the two user groups to the platform in order to create network externalities. In this phase, it is necessary for the platform employees to do manual work to create enough value for the user. Growing is the second phase where both user groups are growing towards critical mass. In this phase, it is important to identify and double down on the things that work. The third phase is the scaling phase where growth has surpassed the critical mass constraint and the platform scale by itself. As the platform scales, things such as trust and safety is important (Wertz and Kingyens, 2015).

2.2.2 Categorizing two-sided platforms

Scholars have proposed different typologies trying to explain the variety of two-sided platform configurations (Weil et al., 2005; Remane et al., 2016; Ardolino et al., 2016). The literature review revealed categorization of two-sided platforms in the following three ways: 1) by transaction type, 2) by user groups involved and 3) by type of interaction. As the research only needed the two first ways of categorizing, only the two first will be explained.

Transaction type

A study by Weil et al. (2005) defined the broker model as one of the four main categories of business models. According to Weil et al. (2005, p. 9) "A Broker facilitates sales by matching potential buyers and sellers. Unlike a Distributor, a Broker does not take ownership of the product being sold. Instead, the Broker receives a fee (or commission) from the buyer, the seller, or both." The broker model can further be split into subcategories based on the four type of assets involved, physical, financial, intangible and human assets. This classification can be useful for identifying what kind of two-sided platform it is in general terms, however, there is a need to classify more specific to understand more subtle differences in two-sided platforms. However, as Remane et al. (2016) argues that the category "physical" includes both car sharing platforms and marketplace for physical goods, which is two platforms with very different characteristics. Therefore, to be more relevant for the context of this research, physical assets will be splitted in "product" and "property". Remane et al. (2016) identified that only a fraction of the platforms was facilitating financial and intangible assets, and they are therefore excluded from the scope of this research. This leaves the researchers with three kinds of assets “product”, “property” and “human resources”, as a way of categorizing platforms by what asset it involves. In the following, these three will be explained in detail.

Product

A product platform matches buyers and sellers of physical products. Physical products include items such as food, books, material and art. A product platform has three important characteristics. First, products need a description, preferably with pictures, reviews and ratings. Secondly, products might be consumed away if there is only a limited amount available, this need to be displayed. Third, product platforms often allow the products to be shipped, making the shipping process and checkout procedure an important part of the user experience.

Property

A property platform matches buyers and sellers who wants to rent or rent out property for a short or a long period. Properties includes items such as houses, computers, cars and studios. A property platform has four important characteristics. First, an asset need a description, preferably with pictures, reviews and rating, much like in the product platform. Secondly, properties cannot be consumed away, but have limited capacity and will therefore only be available at certain times, preferably displayed in a calendar. Thirdly, property platforms often need a higher governance, in the form of insurance and customer service allocated to solve problems with potential damages. Fourth, as the transaction often is direct between users, the platform need to create additional benefits that will keep the users on the platform, after the first connection. An example is the host-insurance on Airbnb that only applies when the users are paying through the platform.

Human resources

A human resources platform matches buyers and sellers of human services. This includes people’s time and effort, in the form of the services they offer. The human resources platform has three important characteristics. First, human resources are limited by capacity like properties, however, in contrast to properties they can move to other cities to serve an under-balanced market. The balance in the market is therefore important and should be carefully controlled with adjusting fee´s after demand. Second, the platform needs to have profiles of the humans and services they offered, ideally with pictures, reviews and rating. Third, a service can in many cases easily be facilitated without the platform, so users tend to go outside the platform the second time. Therefore, the human resources platform needs to offer additional benefits, like the property platform.

User groups involved

The second categorization is related to the user groups involved. Three different group combinations have been selected for this paper to give an overview of the most relevant examples. Peer-to-peer (P2P) platforms facilitates the interaction between private individuals who are offering, and other private individuals who are consumers (Remane et al., 2016). A business-to-consumer (B2C) platform is focused on the transaction between companies and consumers (Muzellec et al., 2015). A business-to-business platform (B2B) serves the interaction between two companies (Muzellec et al., 2015). A categorization based on the user groups highlights the unique characteristics of the user groups and their needs. In the following, an elaboration on the three user group combinations is offered.

Peer-to-Peer (P2P)

P2P platforms facilitate the interaction between private individuals (peers) who are offering, and other peers who are buying. Peers can be participants in both groups. For instance, an Airbnb-host can also be an Airbnb-traveller. Low margins and high transaction volumes characterize a viable P2P platform. Trust building mechanisms in the platform is an important factor as the service or product don't offer a familiar brand one can trust.

Business-to-Consumer (B2C)

A B2C platform is focused on the transaction between companies and consumers. They need to handle two very different user groups: usually one slow and bureaucratic - the companies and one fast and irrational - the consumers. An example is Amazon´s online retail business that enable other retailers to sell to consumers. Advertising and operations towards the two user groups are very different.

Business-to-Business (B2B)

A B2B platform enable interactions between companies. The buying process is often longer with comprehensive contracts and high transaction volumes. The contracts are usually made in advance of purchase and a lot of communication is needed. Alibaba is an example of an online B2B marketplace that sells high volumes of products for a low unit price, but a high total price. In this type of platform, effective and time-saving transaction processes are important.

2.3 Value proposition

To satisfy users, platform managers must have a clear perception of the value proposition to both user groups on their two-sided platform. To attain this a definition and a categorization of value proposition is needed. Therefore, this subchapter investigates what the literature says about the value proposition. First, the researchers elaborate on the traditional theoretical perspectives on value. Then the most important contributions related to two-sided platforms will be presented. In the end, the researchers investigate what the literature says about how the value proposition of two-sided platforms can be improved, and what role technology have.

2.3.1 Value

Historically, five theoretical perspectives have been used to explain different aspects of value creation (Amit and Zott, 2001). The resource based view (e. g. Barney, 1991), the value chain framework (Porter, 1985), schumpeterian innovation (Schumpeter, 1934), strategic network theory (e.g., Dyer and Singh, 1998), and transaction costs economics (e. g. Williamson, 1981). However, according to Amit and Zott, (2001) none of these theories seem to cover all the sources of value creation of special importance to e-businesses, defined as firms that receives at least 10% of their revenues from transaction conducted over the internet (Amit and Zott, 2001). Therefore, Amit and Zott (2001) suggested the business model theory as a unifying perspective, supposedly building upon the strengths of the other theories.

Amit & Zott (2001, p. 511) defines the business model as: “A business model depicts the content, structure, and governance of transactions designed to create value through the exploitation of business opportunities”. Amit and Zott (2001) adopt Brandenburger and Stuart´s (1996) view on total value created as the sum of the values appropriated by each party involved in the transaction. They identified four major value drivers: efficiency, complementarities, lock-in and novelty. The definition of value created by Amit and Zott (2001) concerns the value creation for the business model as a whole, and not only for the user. For that reason, it is not applicable for the scope of this research.

Osterwalder et al. (2010, p. 14) define business model in the following way: “A business model describes the rationale of how an organization creates, delivers and captures value.” Osterwalder et al. (2010) also emphasise that business models are designed to create value for the owner of the business, and the value proposition is designed to create value for the user. This definition of value proposition is therefore considered suitable for this research.

Han and Han (2001) divides the customer value of the product or service into two categories: *content value* and *context value.* The content value refers to “the generic benefit offered from the content of the transaction” (Han and Han, 2001, p. 28), meaning the benefit offered to the user from the content they access through the product or service. The context value refers to “the additional benefit offered from the subsidiary functions and/or characteristics of the transaction” (Han and Han, 2001, p. 28), meaning the benefit offered to the user through factors other than the generic offering. The context value can be enhanced through better ways of conducting the transaction. For example, design of website, convenience, and ultra-selection. Han and Han (2001) claims that the importance of the context value is higher when there are small differences in content value. For this paper, the division between content value and context value will be used, because it clearly communicates the split between the benefit from the outcome of the transaction, and benefit from the transaction process itself. Before the paper investigate how to improve value proposition on two-sided platforms, an elaboration on the value proposition literature is offered.

2.3.2 Value proposition

A value proposition “describes the benefits customers can expect from your products and services” (Osterwalder et al., 2014: p. 277). More specifically, a value proposition is a distinct mix of elements that creates value for a specific customer segment (Osterwalder et al., 2010). This definition includes the notion of a specific customer segment, which is important as two-sided platforms have two user groups. Therefore, Osterwalder’s definition will be used as the definition of value proposition for this paper.

In recent years, the concept of value proposition earned respect as the heart of the business model (Osterwalder et al., 2010; Lindgreen et al., 2012; Muzellec et al., 2015). In addition, scholars claim that it is also at the heart of marketing strategies (Slater & Olson, 2001), and hence the bridge between strategic management and marketing literature (Muzellec et al., 2015). The researchers have looked into marketing literature, and noticed the following: According to service-dominant logic, a company cannot deliver value, only value propositions, in other words, the potential value is only realized through use (Vargo & Lusch, 2004). This echoes that the value proposition should be designed for a specific user segment, as defined by (Osterwalder et al., 2010). In two-sided platforms however, there is two user groups: the buyers and the sellers. Therefore, business models for two-sided platforms need to hold two unique value propositions, one for the buyers and one for the sellers (Osterwalder et al., 2014).

2.3.3 Value proposition of two-sided platforms

Two-sided platforms are in a unique position when it comes to value proposition, because such company configurations have three main stakeholders: the buyer, the seller and the platform owner. All stakeholders relate to value creation mechanisms. Two-sided platforms follow the value creation logic of value networks, and the value creation comes from linking customers through a mediating technology which facilitates the exchange relationship (Stabell and Fjeldstad, 1998). Network externalities explains how the content value for the user increases by the number of other users on the platform (Katz and Shapiro, 1985). Content value is a result of network externalities. The focus of this research is the value that can be created for the user through improving the mediating technologies, the context value.

2.3.4 Improving value proposition of two-sided platforms

Several scholars have proposed frameworks for improving the value proposition of platforms and e-businesses (Amit and Zott, 2001; Osterwalder et al., 2014; Sandulli et al., 2014; Haile et al., 2016). As already mentioned, Amit and Zott (2001) suggest four sources of value creation in e-businesses: efficiency, complementarities, lock-in and novelty. The framework concerns the total value, as well as both value creation and value capturing and the framework is therefore too broad for the scope of this research.

Haile et al. (2016) identified three determinants of value creation in software service platforms: System usability, service variety and user connectivity, based on thorough investigation of prior literature. However, this framework considers software service platforms and the technology-oriented perspective, which is not optional for the market-oriented perspective of this research.

Sandulli et al. (2014) introduced a framework for improving value proposition for internet business models. The framework presents three key mechanisms to improve the value proposition of internet platform business models: aggregation, customisation and efficiency. The framework does not involve value capturing, only value creation, and it is primarily focused on the user. Therefore, this framework is well suited for the market-oriented perspective of this research, hereby referred to as the ACE framework. In the following, an elaboration on aggregation, customisation and efficiency is offered.

Aggregation

"Aggregation refers to the value created by assembling a large number of products, users, buyers or sellers." (Sandulli et al., 2014, p. 86). This is an important value proposition for many internet business models, and can exist in the form of product aggregation, user aggregation, buyer aggregation or seller aggregation. This value proposition is especially suitable for products and services with online distribution (Sandulli et al., 2014). For two-sided platforms, aggregation is the amount of users on the other side of the platform. This is the concern of content value and primarily therefore outside of the scope of this research.

Customisation

Another way of improving the value proposition of a platform is through customisation towards the user. Customisation is satisfying each user's desire by changing the content or context to meet the individual specific preferences (Han and Han, 2001). Business models that are based on internet has more ability to customise than the traditional business (Xue and Harker, 2000). There are two main branches of customisation: personalisation and co-creation (Sandulli et al., 2014).

Personalisation

Personalisation concerns inducing user's individual preferences, so that the product or service can be customised to reduce transaction cost and enhance user experience (Dewan et al., 2003; Syam et al., 2005; Kamali and Loker 2006; Sandulli et al., 2014). A way Airbnb is personalising the user experience is by saving the search history of travellers, and later suggesting relevant apartments they might be interested in renting. Personalisation is relevant for the scope of this research as there are many examples of two-sided platforms using machine learning to improve personalisation.

Co-creation

Co-creation is about engaging the user in co-creating value throughout the value chain. Involvement in the value creation process increases the user's value perception by offering more value through an engaging user experience (Pralahad et al., 2004). Airbnb expect all hosts to create and manage their own listings within the boundaries of the platform. The users are offered guidelines for what is considered a good-looking listing, and some are also offered help from professional photographers. This creates value by giving the hosts a richer user experience. However, this type of customisation is not relevant for this research as the researchers found no examples of machine learning used to co-create value for the user.

Efficiency

Efficiency refers to the value created for the user by the platform through simplifying the process of finding, acquiring and using the product or service. Platforms can create value for the users through efficiency in three ways: reducing search costs, increasing trust and streamlining processes.

Reducing search costs

Reducing the buyer's search costs enable the user to spend less time making better decisions. Price differences in a market is typically attributed to information asymmetries and consumer search costs. Many internet business models are able to provide buyers with much more comparative price information than traditional businesses (Brynjolfsson et al., 2010). Two-sided platforms create transparent markets and efficient search procedures, hence lowering the buyer's search cost and time spent. The prices for apartments on Airbnb are easily comparable, which leads to more informed actions.

Trust

Trust can be increased and uncertainty decreased by integrating user profiles, ranking and reviews on platforms. This enable the sellers and the buyers to spend less time negotiating terms and writing mutually acceptable agreements (Dyer and Chu, 2003; Sandulli et al., 2014). In the Airbnb community, every user has their own profile with a picture and a short descriptive text. Every listing has ranking on several parameters, and text reviews written by travellers. This increase the trust between strangers, and are vital for hosts when renting out their home to travellers. It gives them peace of mind because they don't have to spend time doing background checks.

Streamlined processes

Streamlined processes for acquiring and using the product or the service enhance the user experience. According to Amit and Zott (2001) transaction efficiency is one of the primary value drivers for internet businesses. This is delivered through software by enabling reduction of clicks, easier communication, better customer service, greater flexibility and faster delivery. Through its platform, Airbnb streamline the process of booking accommodation and improve the experience by offering a communication tool and a payment solution.

Reducing search costs, increasing trust and streamlining processes are all relevant ways of improving the value proposition for two-sided platforms and they are all exemplified in the discussion. The ACE framework is a tool for explaining how the value proposition can be improved (Sandulli et al., 2014). However, as any other framework, it has weaknesses. For instance, one can argue that streamlining processes is a very wide category of efficiency improvements. It concerns both transaction speed, accessibility and customer service, which is three quite different ways of improving efficiency. In addition, the framework has not been tested before, which increases the uncertainties to its applicability.

2.3.5 Improving value proposition through technology

Ardolino et al., (2016) states that if the goal is to change how services is delivered, technology is key. As an example, cloud technologies and the spread of smartphone applications enable customers to experience digital services more than ever before (Fano and Gershman, 2002). In addition, new technologies that are able to process big data enable companies to develop strategies aimed at evaluating and meeting customer needs (Rijsdijk et al., 2007). According to Ardolino et al., (2016) digital technology is a crucial element in the recent spread of multisided platforms. Ardolino et al., (2016) also claims that there is a lack of a holistic view about the role of technologies in the spread of two-sided and multisided platforms. In particular literature considering 1) which are the technologies adopted in multisided platforms and, 2) which are the functions and the features enabled by these technologies. According to Baden-Fuller (2013), there is a gap in the literature on the relationship between technology and value creation. The researchers aim to bridge some of the gap in the following by investigating the literature related to machine learning and discuss the findings in relation to two-sided platforms.

2.4 Machine learning

To evaluate if the value proposition can be improved with machine learning, and determine the type of machine learning algorithms that could be applied, it is necessary to understand two aspects: 1) What is the basics of machine learning and, 2) What are the main types of machine learning algorithms. This chapter starts out with an introduction to the field of machine learning, explaining what machine learning is, how the field has progressed and why it is important today. After this, the three main learning techniques used by machine learning algorithms are explained: supervised learning, unsupervised learning and reinforced learning. These techniques are the foundation for understanding six problem categories that machine learning is good for solving: classification problems, clustering problems, regression problems, recommendation systems, dimensionality reduction and reinforced learning problems. The researchers also present the most popular algorithms of choice for tackling these problems, the reasoning behind this being that every problem will have different solutions, and the different algorithms will perform better than other in a lot of different ways. This means that on an algorithmic level, the choice between algorithms becomes a process in itself, where the engineer should try different solutions to find the best algorithm.

2.4.1 The history of machine learning

Machine learning as a research area stretches all the way back to the 1950s, and one of the first known examples was a chess-playing program from 1959 which improved its chess playing performance by playing against itself (Stone et al., 2016). The challenge of constructing a computer program that automatically improve with experience, is at the very core of what the field of machine learning is all about (Mitchell, 1997). Software systems based on machine learning algorithms are able to learn and improve based on past experience. It provides answers to complex problems by utilizing both data it has processed before, and new data it has never processed (Marmanis & Babenko, 2009).

Even though the field of machine learning is over 70 years old, technological advances in software and hardware over the last ten years has fuelled a huge wave of interest. Machine learning shifts the focus from “How to program computers?”, to “How to teach computers to program themselves?” which will have big implications for the field of computer science (Mitchell, 2006). Machine learning has taken the step from being primarily a research area to becoming an integral part of platform companies’ value proposition. Netflix explain that their recommendation system learns which movies the user enjoys, and suggests other movies the user might also like. This system is now responsible for two out of every three hours of video streamed (Coughlin, 2015). The other example from the introduction is Spotify's customisation algorithm named “Discover Weekly”, which delivers 75 million unique mixtapes to its users every week (Lindblom, 2015). These examples demonstrate the power of machine learning.

2.4.2 The machine learning problem

<u>The characteristics of a machine learning problem</u>

A computer program is said to learn from experience *E* with respect to some class of task *T* and performance measure *P,* if its performance at tasks in *T,* as measured by *P*, improves with experience *E* (Mitchell, 1997). To give an example, the task could be ”recognizing and classifying handwritten words within images“, the performance measure P could be “the percent of words correctly classified” and the training experience E could be “a database of handwritten words with given classifications”. This definition states the three requirements for an algorithm or computer code to be considered a machine learning algorithm. Scientists and engineers are seeking out the best application areas to put machine learning to use, and there are three characteristics that are dominant for the problem types that are best solved by machine learning.

First, problems are characterized by tasks that are too complex for people to manually design the algorithm. Basic perception tasks are examples of this, because it is extremely complex to write down all the steps of recognizing objects in a picture to label them. Still it is easy to collect labeled training data as labelling is a simple task for humans (Mitchell, 2006).

Second, for the algorithm to learn it needs access to big datasets to be trained on. Machine learning will often be the right choice if these datasets are directly accessible or can be easily obtained. Object recognition in photos is a good example of this. Anyone can label a photo of a mother holding a baby, but it is very hard to write down the rules for how to do it.

Third, machine learning algorithms are highly adaptable and therefore often used for problem types that require software which customises to its operational environment after it has been deployed (Mitchell, 2006). A system for speech recognition is an example of this as it learns and adapts to the voice of the user over time.

2.4.3 The feedback loop

The computer's ability to learn is at the very core of machine learning, and a central concept is the learning technique used by different machine learning algorithms. These techniques are often categorized based on the feedback loop of the algorithm. The feedback loop determines which learning signals the algorithm uses to produce better results over time. The literature presents mainly three different learning techniques that are used in machine learning: Supervised learning, reinforced learning and unsupervised learning.

Supervised learning

Supervised learning implies that a system is learning based on labeled training data and some desired output value. A supervised learning algorithm is used for analysing the training data and predicting the outcome of new events (Russel and Norvig, 2006; Dasgupta, 2014; Qiu et al., 2016). Airbnb use supervised learning algorithms that specialise in image analysis, for automatically rating the quality of apartment images. The algorithm starts out by using a training data set with images of apartments that have been scored by both professional photographers and regular guests (Yee and Ifrach, 2015). The pairing of images and scores is what provides the learning signal for the algorithm.

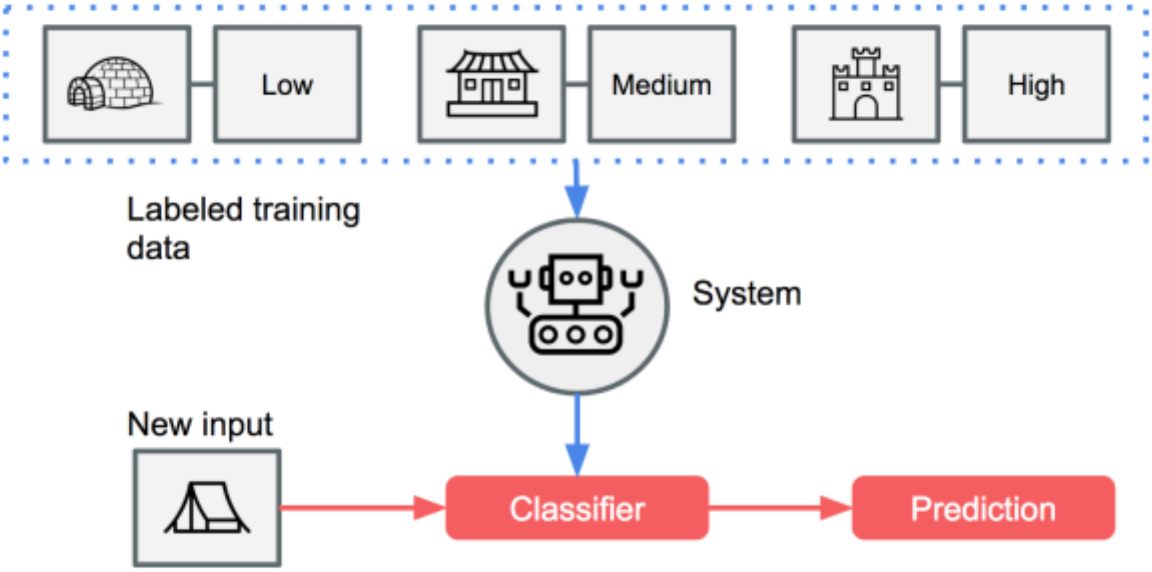

Figure 1: The supervised machine learning system has been trained on labeled training data. The labeled training data is images of different houses that have been labeled as low, medium or high quality. The new input is a picture of a tent, and the system uses a classifier to decide if the tent should be labeled low, medium or high quality

Figure 1 shows how the supervised machine learning system has been trained on labeled training data. The labeled training data is images of different houses that have been labeled as low, medium or high quality. The new input is a picture of a tent, and the system uses a classifier to decide if the tent should be labeled low, medium or high quality.

Reinforcement learning

Reinforcement learning is not dependent on the initial set of labeled training data, as the algorithm learns from the feedback of the environment. The algorithm is governed by a set of rules that rewards and punishes the system based on its actions in the environment (Russel and Norvig, 2006; Dasgupta, 2014). This approach is used for dynamic pricing by Airbnb. The reinforcement algorithm uses all known attributes of a listed apartment so it can calculate a price tips and then predicts if it will get booked or not. After a while the systems check back if the prediction was right, and adjusts the algorithm based on the feedback from the environment (Hill, 2015).

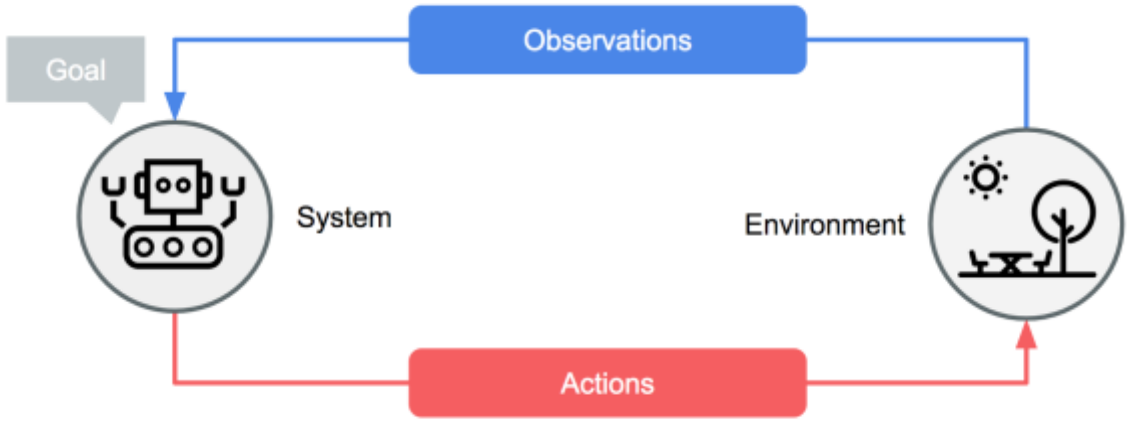

Figure 2: The reinforcement machine learning system observes the environment. Based on the goal of the system, the algorithm performs actions that affect the environment. If the action results in positive rewards, the system keeps doing the same type of actions. If the rewards are negative, it changes the type of action.

Unsupervised learning

Unsupervised learning is a learning technique which neither requires labeled training data or a rule based environment. It requires a set of inputs, and can induce patterns and structures based on the features of the input (Russel and Norvig, 2014; Dasgupta, 2014). The feedback loop of unsupervised learning algorithms is not dependent on external learning signals as it derives experience from the outputs of each run for a specific input (Dasgupta, 2014). Implementations of unsupervised learning algorithms are often found in applications for customer service or cyber security, where it is used to process requests or identifying security anomalies and threats. An example of this is Airbnb which process thousands of customers' service requests a year. Unsupervised learning is used to analyse the text body of the user requests. The system structures the content and translate the requests into meaningful titles that are directed to the right departments (Curtis, 2016).

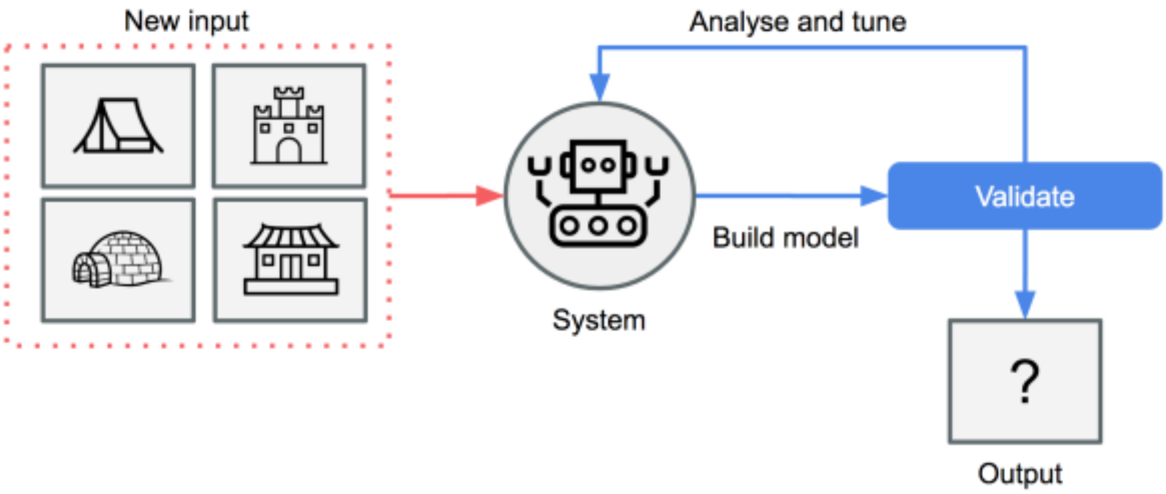

Figure 3: The unsupervised machine learning system takes in an image set of different houses. The system does not know anything about which houses should be grouped together. The system creates rules of its own, and builds a model by iteratively analysing, validating and tuning the algorithm.

Some of the techniques are often associated with certain problem types. Supervised learning is often associated with classification, and unsupervised learning with clustering because these are the most effective approach. These problem types will be explained in the next subchapter. Still this is by no means a binary relationship, and these learning techniques can be used stand-alone in an algorithm, or they can be used interchangeably together. This enables more advanced learning methods such as deep learning which uses a semi-supervised approach, combining supervised and unsupervised learning (Qiu et al., 2016).

2.4.4 Problem types

A common method for categorizing problems that can be solved by machine learning is by the desired outcome of the algorithm. For machine learning, there are six main problem categories that are recurringly being highlighted by scholars and domain experts: classification problems, clustering problems, regression problems, recommendation systems, dimensionality reduction and reinforced learning algorithms.

Classification problems

Classification problems are often recognized and named alike by experts (Kodratoff, 2014; Marmanis and Babenko, 2009; Qiu et al., 2016). Small children often ask, "What is this?" so they can organize their perceptions into groups and categories. These are the same kind of problems solved by software, and it is concerned with finding efficient methods for recognizing if something should be classified as a certain concept or not (Marmanis and Babenko, 2009). This type of problem requires some sort of training data set to identify and weigh the most important attributes associated with a certain concept. It is often considered a supervised learning problem, but in some cases, it is possible to train the algorithm using a mix of labeled and unlabeled data in a semi-supervised manner. The desired outcome is a classification scheme which make it possible to induce if new samples should be recognized as the concept or not. So, the output of a classification algorithm is a categorical label. It could be a true or false label, or it could take in an image as input, and the output would be "cat" or "dog" if the object it recognized. Classification algorithms are widely used in image recognition where the purpose is to identify what's in the picture, but it can be used as long as the output is a categorical label.

Common algorithms within classification

- Bayesian Algorithms
- Artificial Neural Networks
- Recurrent Neural Networks
- Convolutional Neural Networks
- Ensemble Algorithms (RandomForest, AdaBoost)
- Instance Based Algorithms

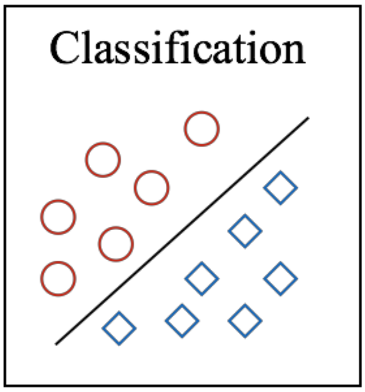

Figure 4: Classification problems concern the analysis and categorizing of concepts

Clustering problems

Clustering problems are also a type of problem that scholars highlight (Kodratoff, 2014; Marmanis and Babenko, 2009; Qiu et al., 2016). The processes of clustering refer to the task of grouping similar things together (Marmanis and Babenko, 2009). This is a type of problems where the input is a set of items with given attributes, and the desired outcome is to discover commonalities between the items to make meaningful clusters or sub-groups. Often the clusters or sub-groups are unknown prior to solving the problem which often makes good use of unsupervised learning. Consider a case where there are millions of users' profiles, with tons of data on each user. It's hard to understand and know what makes different users different, and what kind of subgroups exists among the users. Is it best to group by age or sex? Clustering learns the different underlying structures and proposes the subgroups.

Common algorithms within clustering:

- k-Means
- k-Medians
- Expectation Maximisation
- Hierarchical Clustering

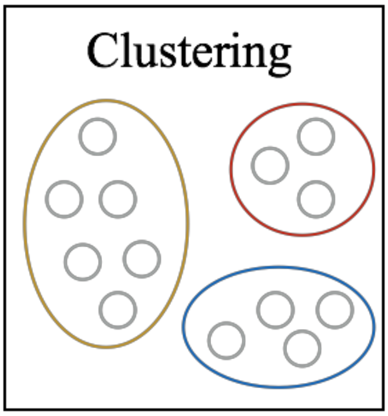

Figure 5: Clustering problems concern the task of grouping similar things together

Recommendation Systems

Recommendation problems (Marmanis and Babenko, 2009) are also called generalization problems (Kodratoff, 2014) and Prediction problems (Qiu et al., 2016). In a connected world where data is becoming abundant, predictions that lead to informed decisions are valuable (Marmanis and Babenko, 2009). Prediction problems are concerned with understanding the underlying elements of a concept to deduce a general description. Most if these are based around the concept of recommending an item based on previous history. E.g. given a certain history, x, predict outcome y. A general description is used to explain the concept in more detail, and the output can be used to predict or recommend future results.

Common algorithms within recommendation systems:

- Collaborative Filtering
- Item-based Collaborative Filtering
- Apriori Algorithm
- Eclat Algorithm

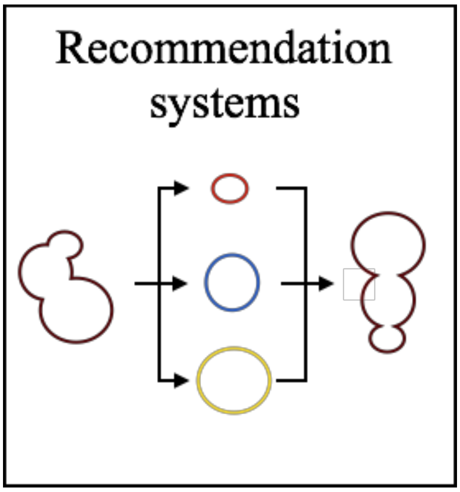

Figure 6: Prediction problems concern generalizing a concept, and predicting new or similar outcomes

Dimensionality reduction problems

Dimensionality reduction is the transformation of high-dimensional data into a meaningful representation of reduced dimensionality. The intrinsic dimensionality of data is the minimum number of parameters needed to account for the observed properties of the data (Van Der Maaten et al, 2009). Dimensionality reduction algorithms looks at data and reduces the number of variables under consideration. This means it tries to resemble the data structure with the least possible amount of variables and features, and still preserving the structure of the data. Mehryar et al (2012) provides three key arguments for the use of dimensionality reduction: 1) Computational: To compress the initial data as a pre-processing step to speed up subsequent operations on the data. 2) Visualization: to visualize the data for exploratory analysis by mapping the input data into two- or three-dimensional spaces. 3) Feature extraction: to hopefully generate a smaller and more effective or useful set of features. A feature can be the age of a user, and the sex of the user could be another feature. By just looking at all the possible features for a user, the dimensionality of such a problem becomes enormous, and it becomes impossible to visualize or grasp what features could be important. Visualizing data can be quite powerful for human intuitive inspection. A lot of machine learning problems are problems with high dimensions, that are impossible to visualise in 2d or 3d space. By using dimensionality reduction, a dataset of several dimensions/features can be visualised.

Common algorithms within dimensionality reduction:

- t-SNE
- Principal Component Analysis
- Regression (PCR)
- Partial Least Squares Regression
- Multidimensional Scaling

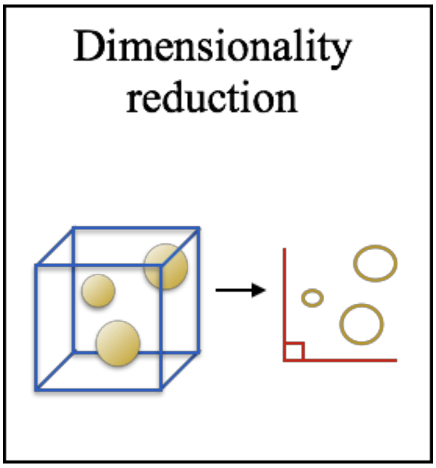

Figure 7: Dimensionality reduction concerns the task of reducing the number of features (“dimensions”). E.g.: reducing a complex problem from three dimensions, to two dimensions.

Regression problems

Regression is a subtype of supervised learning, and attempts to explicitly model the relationship between inputs or independent variables and the outputs, typically in the form of parametric equations in which the parameters are estimated from the data (Dasgupta et al 2011). Regression differs from classification in that the output or predicted features in regression problems is continuous (Uysal and Güvenir 1999). These algorithms are used to predict output values based on input features that are obtained within a data set, like predicting a price. Although regression algorithms are not the only algorithms outputting numerical values, they are the mostly used type for these sorts of tasks.

Common algorithms within regression:

- Bayesian Algorithms
- Linear Regression
- Stepwise Regression
- Artificial Neural Nets
- Deep Learning
- Multivariate Adaptive Regression Splines

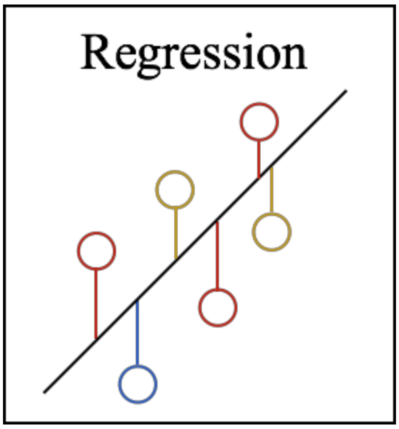

Figure 8: Regression Algorithms concerns the task of modelling the relationship between a set of features and its outputs.

Reinforcement learning problems

Reinforcement learning concerns a family of problems in which an agent evolves while analysing consequences of its actions, thanks to a simple scalar signal (*the reinforcement*) given out by the environment (Glorennecc 2000). Since reinforcement learning is so different from supervised and unsupervised learning, as it uses the environment and observations and not underlying data, it has its own problem types. The way reinforcement learning works makes it ideal for control type problems such as driverless cars, robotics and video games. To get a real understanding of how this works, imagine a computer trying to learn the game of pong. In the start the algorithm has no idea how to react to the environment and will start out by doing random moves. After every move, some sort of feedback to the algorithm will either reward it for doing something right (such as hitting the ball) or punish it for doing something wrong (missing the ball). After running this simulation a lot of times the algorithm will start to learn what moves will lead to a positive reward, and start to develop a ruleset of what to do in different situations. This requires a lot of simulations.

Common algorithms within reinforcement learning:

- Markov Decision Processes (e.g. Policy Iteration)
- Genetic Algorithms

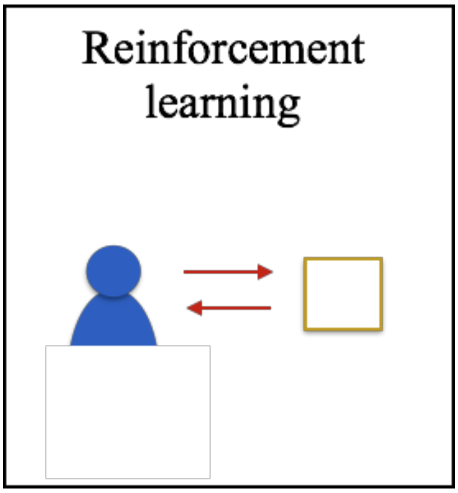

Figure 9: Reinforcement learning algorithms, or agents (blue), learn based on observing their actions (red) on the environment (orange).

3. Framework

3.1 Introduction

To be able to answer the research questions, a conceptual framework has been developed. This chapter includes four sub chapters, representing each of the four steps in the framework. The framework is meant to help managers of two-sided platforms who are considering using machine learning to improve the value proposition of the platform. It is based on selected theory from relevant literature about two-sided platforms, value proposition and machine learning theory.

The first step is to define user problems to be either content or context value. The second step is to categorize user problems based on the value logic model. The third step is to use the TEPCDA model to evaluate if a problem should be considered a machine learning problem or not. The fourth step introduces the Machine learning type (MLT) questionnaire, that connect the user problems to machine learning algorithm types. In this way, platform managers can understand what problems that can be solved with machine learning and what type of machine learning algorithm that could be used to improve the value proposition.

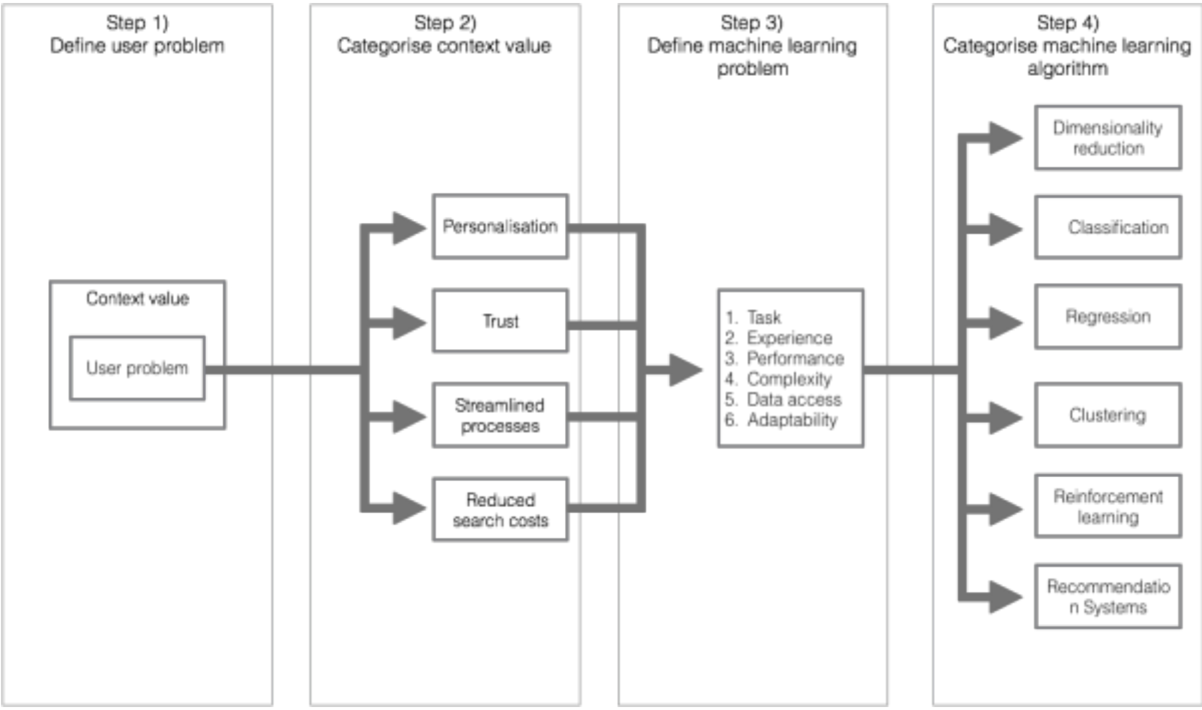

Figure 10: The four-step conceptual framework explains the process of evaluating if the value proposition can be improved by machine learning, and what type of machine learning algorithm can be applied.

3.2 Step 1: Define user problems

Before the platform managers can understand how to improve the value proposition of their two-sided platform, all user problems need to be defined by splitting them into the content value or the context value as defined by Han & Han (2001). This can be done by questioning if the problem is related to the benefit offered by the content that is accessed through the platform or not. If it is, the problem is related to content value and not relevant for machine learning. Each problem categorized as context value should be given a summarized description, and further processed in step 2.

Figure 11: User problems can be associated with either context or content value.

3.3 Step 2: Categorize context value

By combining step 1, with the research of Sandulli (2014), the value logic model has been created:

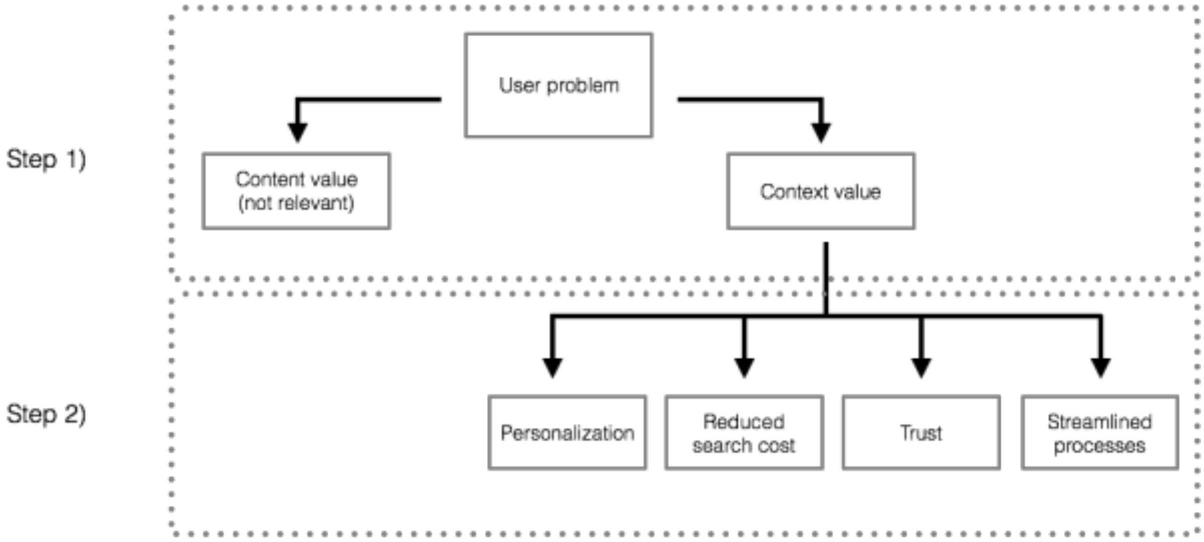

Figure 12: The value logic model shows how the two first steps of the framework is connected.

Step 2 is about following the value logic model to split the context value into the four subcategories of Sandulli et al. (2014) introduced in the theory chapter: 1) *personalisation*, 2) *reduced search cost*, 3) *trust* and 4) *streamlined processes*. The purpose of this step is to articulate the benefit of solving the user problem, and to assess if that benefit is in line with the value proposition of the platform. In the following the researchers elaborate on each of the four categories in the context of two-sided platforms. In this way, managers of two-sided platforms can read through the user problems and correlate them with the four categories, to find the best match.

3.3.1 Personalisation

The two-sided platform offers opportunities for the platform manager to personalise the transaction process based on the individual's user requirements. The goal of personalisation is to minimize the effort put into the transaction process, by adapting the process to the user's preferences. Two-sided platforms that offer content through a static and generic user experience usually have a high interaction cost. This is typical for two-sided platforms with a lot of content, and no good ways for the user to filter or search for relevant content. One way of achieving personalisation is to induce user preferences based on user history, and recommend the most relevant content directly to the user. By making the users create user profiles on the platform and tracking the activity of the user profiles, it becomes possible to reveal preferences and typical user behaviour. These preferences can be used to further reduce the effort of interacting.

3.3.2 Reduced search cost

The search cost is, as defined in economic literature, the cost incurred by the buyer to locate an appropriate seller and purchase a product or service. This includes the opportunity cost of time spent searching (Bakos, 1997). User problems on two-sided platforms related to search cost usually originates from information asymmetries between the buyer and the seller. Both user groups want relevant information about the other party to make informed decisions. Comparative price information is a good example of how two-sided platforms improve the context value for the user through *reduced search cost*. To differentiate between user problems that are related to *personalisation* and r*educed search cost*, it is necessary to identify whether the problem is related to the preferences of the user or the availability of information about the content.

3.3.3 Trust

By definition, two-sided platforms facilitate the interaction between two different user groups. Creating trust between the two user groups, and between each user group and the platform itself is an important part of the context value provided by the platform. Without the platform, each user would have to spend time and energy negotiating and writing a mutually acceptable agreement. User problems related to *trust* are often characterised by complex negotiations, lack of overview, lack of transparency, complex risk assessments and unexpected user behaviour.

3.3.4 Streamlined processes

Two-sided platforms are able to deliver *streamlined processes* through software by enabling reduction of clicks and easier communication. Typical user problems related to *streamlined processes* are complicated booking processes, communication problems and processes that require manual involvement. By providing solutions to such problems and enhancing the operational performance, the platform can reduce the communication cost, improve the customer service, give greater flexibility and faster delivery.

3.4 Step 3: Evaluate the problem

After categorizing the context value, the next step is to assess whether the problem is a machine learning problem. To do this the framework uses the six characteristics of a machine learning algorithm from the theory chapter, that splits a problem into six specific parts. By defining these parts, it is possible to evaluate the problem against the definition of machine learning problems. The step starts out by defining the task, experience and performance in the learning process. If that is not possible, the problem is not a machine learning problem. If it is possible, one should continue to assess the next three characteristics of a machine learning problem: the complexity of the problem, access to training data, and need for adaptability Mitchell (1997; 2006). Table 1 shows the six characteristics of a machine learning problem, with corresponding questions and examples.

Task	What task is the algorithm trying to learn? • This is from the algorithm's point of view, not the user or not the platform. • The algorithm might do this task hundreds of times to solve the final task for the user. Example: Transforming speech to text with speech recognition software.
Experience	How can the algorithm be trained? • What kind of feedback loop is needed to train the algorithm? • How can the algorithm experience this data? Example: A database of texted speech.
Performance	How is the performance of the algorithm measured? • A metric that tells how good the algorithm currently is • Preferably a ratio Example: Percentage of transformed text similar to the speech indicate performance.
Complexity	How complex is the problem? • How many variables are involved? • How difficult is it to manually write an algorithm that solves the problem? Example: Words and sounds are very complex to write an algorithm to recognize. The amount of recognizable words and sounds is very high.
Data access	Is it relatively easy to access or collect unlabeled or labeled training data? Example: Texted speech as training data is widely available.
Adaptability	Does the problem require software that customise to its operational environment after it has been deployed? • Should it adapt to the user or a group of users? • Should it adapt to different geographical areas or cultures? • Should it change over time of the day, weekday or seasons? Example: To maximize performance, speech recognition software needs to be customise to the user who purchase the software.

Table 1: Characteristics of a machine learning problem

3.5 Step 4: Categorize the machine learning problem

Before applying machine learning to a real word problem, the platform manager needs to understand what type of algorithm that is applicable to the problem: classification, regression, dimensionality reduction, recommendation systems, clustering or reinforcement learning. To make this easy for the platform managers, the researchers propose a four-step questionnaire named the MLT (machine learning type) questionnaire. This questionnaire is based on the combined works of machine learning scholars with expertise within the different types of algorithms (Glorennecc 2000, Mehryar et al 2012, Van Der Maaten et al, 2009, Marmanis and Babenko 2009, Dasgupta et al 2011, Dasgupta 2014, Uysal and Güvenir 1999, Russell and Norvig 2014) and based on the overview of machine learning given by Mitchell (1997 & 2006). All the questions in the questionnaire is directed towards the task of each machine learning problem as defined in step 3, using the other characteristics from the TEPCDA model as guiding information.

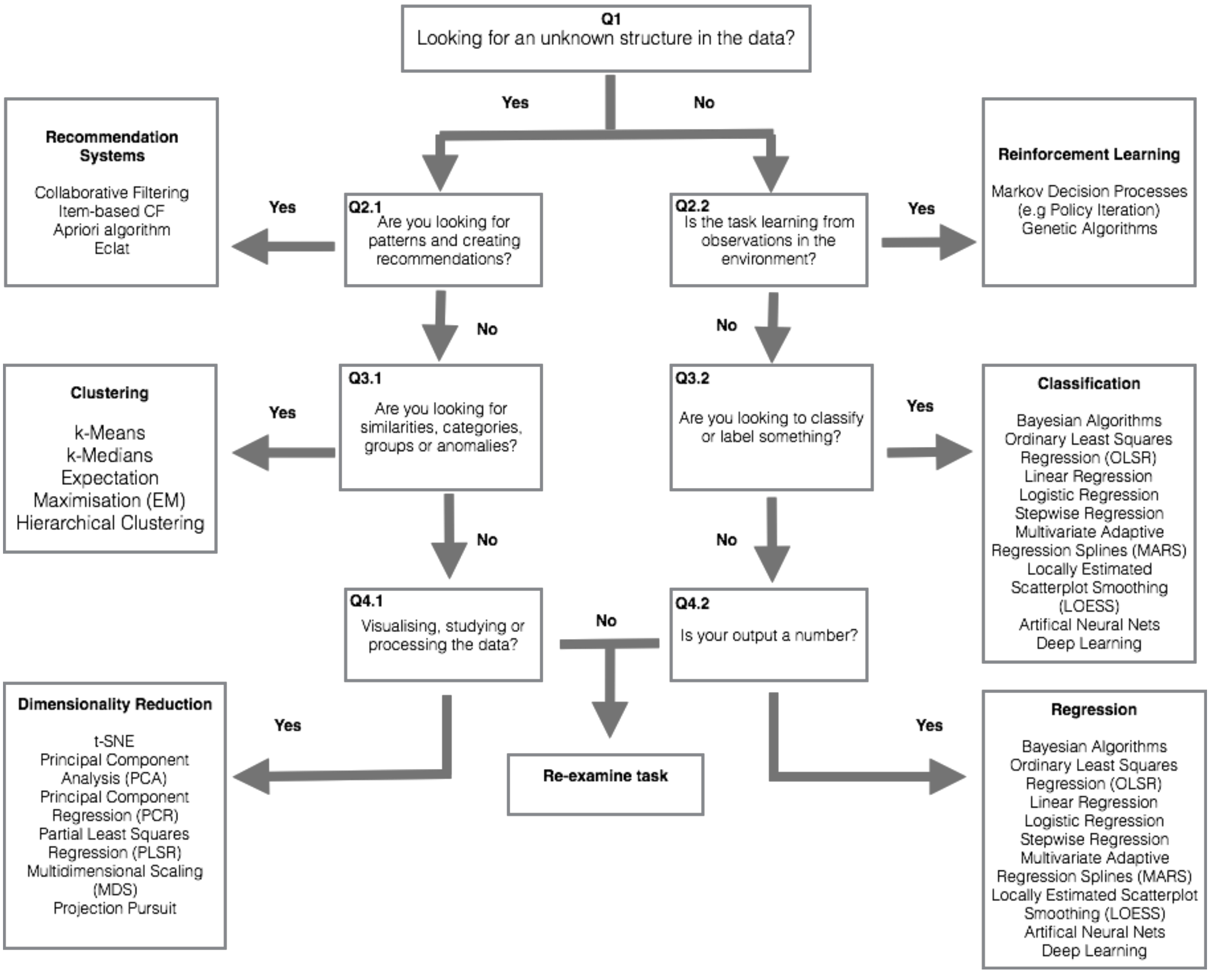

Figure 13: The MLT questionnaire

The questionnaire starts out with Q1, which asks the manager to asses if the machine learning problem looks for an unknown structure in the data set. An unknown structure means an unknown relationship between data. For instance, an unknown relationship between the buyers and items for sale on platform. The answers to this question splits the six possible algorithm types into two groups. Three of them are about revealing the relationship in the data (recommendation systems, clustering and dimensionality reduction), and the other three are about giving absolute predictions (reinforced learning, classification and regression).

If the answer to Q1 is yes, then the next three questions will help the manager choose between different data structuring algorithms. Question Q2.1 asks the manager “Are you looking for patterns and creating recommendations?” and a yes answer will lead to the Recommendation System type of algorithm. This type of algorithm is about finding patterns in for instance user behaviour, and creating recommendations based on specific behaviour. If the answer to Q2.1 is no, then the next question Q3.1 asks “Are you looking for similarities, categories, groups or anomalies?”, which relates to use cases of clustering algorithms. The last question on the left, Q4.1, asks the manager “Are you visualizing, studying or processing the data?”. A “yes” answer leads to dimensionality reduction algorithms.

Going back to the first question again, if the answer to Q1 is “no” then there are three possible groups of algorithms to choose from: reinforcement learning, classification and regression. Question Q2.2, aim to categorize the task as a reinforcement learning algorithm by asking “Is the task depending on learning from observations in the environment?”. The basis for any reinforcement learning algorithm is that it learns from interacting with the environment. A use case for this is when labeled data is not accessible, or when the system needs to learn from the real world, commonly used in self driving cars. The next two questions, Q3.2 and Q4.2 are both asking the manager to assess the output, or the result of the task for which the manager is seeking. What differentiate these two questions is whether the output is a category (cat or dog) or a number. This highlights the difference between classification algorithms (output is a categorical label) or regression algorithms (output is a number).

If the answer to either Q4.1 or Q4.2 are “No”, the manager is pointed towards the last box named “Re-examine task”. Ending up here means that either the formulation of the task is wrong or it's not a machine learning problem.

3.6 Limitations of the framework

The framework is made by the researchers, based on their interpretation of the reviewed literature and logic thinking, therefore some aspects of improving the value proposition might not be covered by this framework. There exist many types of two-sided platforms and two-sided markets, and no single framework can explain the value creation logic of all two-sided platforms. The platform managers should think through the steps in relation to their own platform, their own markets and make their own judgements.

The speed of progress within the field of machine learning makes it possible that this framework misses out on new sorts of algorithms and learning types. Most published articles on machine learning theory are of a technical nature, and the researchers have to their best understanding extracted the core information on the different use cases. To ensure the most accurate description of the theory, the researchers have cross referenced between the papers, as well as consolidating with independent machine learning experts.

4. Method

4.1 Introduction

To answer the two research questions of this paper, a scientific method for designing the appropriate research was needed. This chapter explains the choices made by the researchers regarding acquiring relevant literature, research design, data collection and data analysis.

First the chosen method for acquiring and reviewing relevant literature is explained. Second, choices regarding the research design is reasoned. Third, the data acquisition methodology and data sources are discussed. Fourth, the researchers will explain how the data analysis was carried out to make sense of the data. The methodology chapter ends with a reflection and evaluation of the methodology and limitations of the chosen method.

4.2 Literature review

To answer the research questions, relevant literature was acquired and reviewed. This paper builds upon the literature review of Rystad and Aarseth (2016) which was the result of a project thesis written as a part of their studies at NTNU School of Entrepreneurship. The literature review was based on Cooper's (1988) Taxonomy of Literature reviews, and Randolph's (2009) research on conducting a literature review. The purpose of the literature review was to develop deeper knowledge and insights on three topics of interest: 1) Two-sided platforms, 2) Value proposition and 3) Machine learning. The goal of the literature review was to identify the central theories, and get an overview of the theoretical landscape. It was the priority of the researchers to focus on the established theories, and understand the relationships between them. The research was outcome oriented as this often is helpful for identifying gaps in the literature (Randolph, 2009). An exhaustive literature review was chosen where the researchers seeked to uncover every available piece of research on the topic (Randolph, 2009). Rystad and Aarseth (2016) examined what the literature said about two-sided platforms and specified which type of two-sided platform the researchers had in focus. Then the researchers evaluated the existing literature on value proposition, and the focus was on improving the value proposition of two-sided platforms. In the end, an introduction to machine learning was offered and used to explain the different problem type categories that machine learning can solve. The literature review revealed that there existed no theory that bridges the three important topics of two-sided platforms, value proposition and machine learning.

Limitations of the literature review

In the selection process, many articles were screened based on title and the abstract. It is possible that articles of some relevance have been screened out in this process. However, it is believed that the researchers covered the most important articles and potential missed articles would have a marginal effect on the review as a whole. The literature review was based on literature accessed through google scholar and the databases made available for students at NTNU. This was a privilege, but also a limitation as there might exist more relevant literature about the research area that was not currently in the databases. The researchers acknowledge these limitations and that they could affect the quality of this study. The researchers had to be reflective about this in this study.

4.3 Research Design

There exists no framework that explain the process of improving the value proposition through machine learning today (Rystad & Aarseth, 2016). Such a framework can help platform managers, satisfy their users, capture market shares and generate future profit. Based on the literature review, the researchers developed a conceptual framework to answer the two research questions. To test the validity of this framework, the researchers found it fit to collect empirical data, apply the framework to test it and present a revised version. To achieve this, the researchers chose an abductive approach for the empirical research. It was focused on exploring a new phenomenon from the bottom up, and expand existing theory from the accessible data. The abductive approach was chosen because abduction enabled the researchers to go back and forth between empirical observations and theory. This enabled the researchers to expand their understanding of both theory and empirical phenomena (Dubois, 2002).

4.3.1 Qualitative Research

Qualitative research methods are great for addressing "how" questions rather than "how many" for understanding the world from the perspective of those studied; and for examining and articulation processes (Pratt, 2009). Both research questions are "how" questions, and the answer to these questions are depended on many variables. Therefore, a qualitative research approach was chosen.

4.3.2 Research method

To test the conceptual framework empirically, the case study research method was chosen. Case studies are commonly used when the researchers are not able to control the circumstances that are analysed, and are particularly appropriate when there exists little theory about the research area (Eisenhardt, 1989). According to Eisenhardt (1989) the case study is a research strategy which focuses on understanding the dynamics present within single settings, which was the case in this research.

According to Yin (2012) four main types of case studies are possible by combining two dimensions, a single- or multiple-case study design and a holistic case vs. embedded case approach. A single-case study has only one case whereas multiple-case studies have two or more cases that deliberately try to test the conditions under which the same findings might be replicated (Yin, 2012). A holistic case approach concerns the study of an organization as a whole while an embedded case approach has a secondary unit of analysis nested within each case being studied (Yin, 2012).

A multiple-case study was chosen to limit the context specific findings, and ensure more confidence in the study's findings (Yin, 2012). By collecting empirical data on multiple case companies and subsequently applying the framework on each case company, the researchers could test conditions for which the conceptual framework worked, and not worked. There is no formula to determine the population of cases appropriate for this kind of research. However, it was presumed that a case study of five two-sided platform startups would be enough to deliberately test if the results of applying the framework might be replicated. A single case study could provide deep insight into one case company, but the applicability of the results would be limited by the context of that company.

The embedded approach was chosen, and the value proposition of each case company were selected as the embedded unit of analysis. The purpose of the case study was to learn about the value proposition of the case companies, and identify user problems that potentially could be solved by machine learning to improve the value proposition.

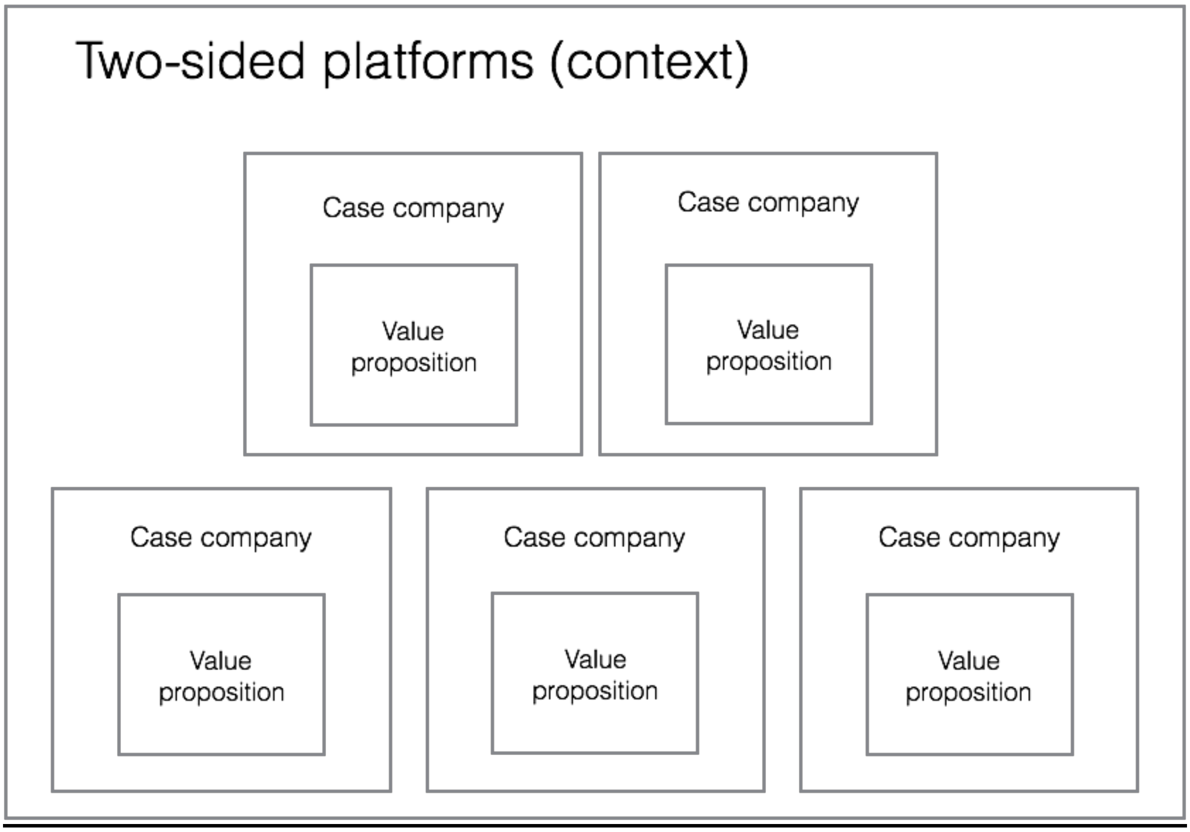

Figure 14: The embedded multiple-case study approach with two-sided platforms as the context, five platform companies as cases and the value proposition inside these cases as the nested unit of analysis.

4.4 Selection process

4.4.1 Case company and interviewee selection

According to Saunders et al. (2012) there are two possible approaches to selecting case companies for a study: probability sampling and nonprobability sampling. Probability sampling is suitable if the study aim for making any statistical inferences based on the research (Yin, 2012). This was not the case for this study, which is qualitatively. Therefore, non-probability sampling was considered an appropriate approach. When conducting non-probability sampling there are many sampling techniques available. The purpose of the case study was to collect empirical evidence to analyse and test the proposed framework, and come up with a strengthened version. This is considered an evaluative approach, and therefore purposive sampling with heterogeneous variation sampling was chosen as the main sampling technique. Purposive sampling allowed the researchers to user their best judgement in determining the cases that enable them to best answer the research questions (Saunders et al., 2012). Heterogeneous variation sampling was appropriate because it allowed the researchers to collect data that explained the key themes that was observed. Because the sample size is small, emerging patterns are likely to be of relevance (Saunders et al., 2012).

Information about the user is considered sensitive information to many companies, and it was important to find case companies that are open and would trust the researchers. Even though two-sided platform startups can be found everywhere in the world, the researchers chose the context where they were most likely to build trust with the interviewees and therefore access the best empirical evidence. Norwegian startup companies were chosen as the context for three reasons. First, the researchers are Norwegian and understand how to build trust within the Norwegian context. Second, Norway is the fastest growing startup eco-system in the Nordic countries (Murray, 2017). Third, in-person interviews were preferred because it is easier to build trust in-person than over video or phone calls. Both time constraints and budget constraints made it impossible to conduct in-person interviews abroad.

To ensure a purposive and heterogeneous sampling, the researchers defined five selection inclusion criteria prior to the case study as suggested by Yin (2012).

1. The case companies had to fit the four characteristics of a two-sided platform as presented in the theory chapter: a) a commercial digital network serving a two-sided market. b) Facilitate interaction between two distinct user groups. c) The value for one group of users depends on the number of users in the other group. d) The platform needs to deliver two different value propositions to the two distinct groups of users.
2. The case companies had to be defined as a startup
3. The two-sided platforms had to be based in Norway and targeting users in the Norwegian market
4. To achieve maximum sample variation at least one companies from each of the three phases seeding, growing and scaling should be chosen.
5. Also at least one company focusing on each of the different transaction types, product, property and human resources, should be chosen.

To generate a list of potential case companies, the researchers used two different sources to build a list of potential case companies: 1) www.startupmatcher.com, 2) www.hub.no. These webpages are Norway's two biggest job marketplaces for startup companies and contain an indexed register of Norwegian startup companies. These registers were reviewed and ten two-sided platform startups were identified based on the selection inclusion criteria. The CEO of all ten case companies were contacted and asked to contribute to the research. Five case companies, Tise, Leieting, Nabobil, Graphiq and Learn Link, wanted to participate in the research. The sample variation of the case companies that were selected is illustrated in table 2.

Transaction type	Phase		
	Seeding	Growing	Scaling
Product			**Tise** Connects people who want to buy second hand with people who sell second hand
Property		**Leieting** Connects people who want to rent items with people who own items	**Nabobil** Connects people who want to rent a car with people who are renting out their car
Human resources	**Learnlink** Connects students with private teachers	**Graphiq** Connects companies with freelance designers	

Table 2: Case selection overview

After selecting the case companies, the right interviewees had to be identified. The selection was based on purposive critical sampling, and two questions was asked to the CEO to determine which employees were the most critical interview subjects. The first interviewee subject should be directly exposed to the feedback of the customers and previously spent most of their time solving customers' problems. To understand who this person was, the CEO of each case company was asked "Which employee have the most knowledge about the value proposition of the company and how this can be improved?". The second interview subject should have deeper knowledge about the technical aspect of the platform because this person might reveal other types of user problems from a technical perspective. The CEO was therefore asked the question "Which employee have most knowledge about the technical aspect of the platform?". An overview of the case companies and the selected interview subjects in presented in the table 3.

Company	Interview subject #1	Interview subject #2
Graphiq	Jakob Palmers, CEO	Erik Sandsmark, Chief Design Officer
Tise	Eirik Rime, CEO	Axel Franck Næss, Chief Technical Officer
Learnlink	Jonas Hyllseth Ryen, CEO	Johannes Berggren, Chief Technical Officer
Nabobil	Even Tangen Heggernes, CEO	Christian Hager, Chief Technical Officer
Leieting	Christer Hansen Eriksen, CEO	Kim Røen, Chief Technical Officer

Table 3: Overview of the selected interview subjects

4.5 Data acquisition

After the case studies was chosen, the data acquisition process started. The case studies were conducted from February to May 2016. For the case study research approach there are six sources of evidence that is highlighted by scholars: interviews, archival records, direct observations, documentation, participant-observation and physical artefacts (Yin, 2012). Multiple sources of evidence are one of the benefit of using the case study approach as opposed to other research methods. To strengthen the method, Yin (2012) recommends multiple sources of evidence and using triangulation of data to obtain different perspectives on the research questions. Three sources of evidence were used in this study: semi-structured interviews, archival records and participant-observation.

4.5.1 Semi-structured interviews

Interviews can be a great source of data, if conducted correctly. In the case studies, separate interviews with two employees from each company was considered to provide sufficient knowledge about the case company of interest. Preferably two employees with different perspectives on the value proposition which will strengthen the case (Yin, 2012). In this regard, the employee who had the best knowledge about the value proposition was chosen to be the primary targeted interviewee. The secondary targeted interviewees were the employees working on developing the technical platform. The interviewees were found by asking the CEO of the case company who fits that description.

The interviews were conducted in a semi-structured manner, which made it easier to have a flowing conversation and ask follow up questions to interesting topics revealed through the participants' answers. The interviews lasted for 30-60 minutes and were primarily held in person or via skype. The audio of all interviews was recorded using a smartphone.

Through the interviews a case study protocol was used to guide the researchers, see appendix 2. The protocol consisted of a set of questions to be addressed when the case study data was acquired. It served as a mental framework in which interview questions could be derived (Yin, 2012). According to Yin (2012), case study research demands the seeking of *rival explanations*. Therefore, these questions were open to changes along the way and contributes to the acquiring of data to examine rival explanations (Yin, 2012).

The purpose of the case study is to learn about the value proposition of the platforms and identify user problems that potentially can be solved by machine learning. The questions in the case study protocol was therefore related to the background of the case company, the value proposition of the platform, how the company delivers value to the user today and user problems that have been identified on the platform. The questions derived from the case study protocol was tested and iterated a few times before the actual interviews. The researchers asked open-ended, non-leading questions. The researchers worked to create a social bond with the interviewees before the interviews by presenting themselves and their intentions in a thoughtful email. The research purpose was communicated and each interviewer spend sufficient time to learn about the case companies beforehand, to appear professional and show respect.

The researchers empirically observed how the interview subjects of each case company described the value proposition and user problems on each respective platform. For instance, an empirical observation of Nabobil was that their users have a problem finding cars that they like, and would benefit from personal recommended cars. All observations were noticed for each platform during the case study and included in the individual case reports written by the researchers after each study.

4.5.2 Archival data

In addition to the interviews, customer support logs provided by the case companies, was a great source of data. They provided insights on recurring customer problems, and by reading these customer support logs, user problems can be identified. These user problems were systematically categorized by using the value logic model, resulting in an empirical observation of the user problems for different platforms. The customers support logs is considered as a source of data, known as archival records (Yin, 2012). From a research perspective, the interpretation of the archival data can be subject to the researcher's biases or shortcomings. Therefore, the research will not rely heavily on the archival records, but the interviews.

4.5.3 Participant-observations

The researchers wanted to develop an understanding from the users point of view, for the specific platform, before doing the interviews. To do so, the researchers signed up as a user on each of the platforms, and tested the service at least one time for each of the user groups. By doing so, the researchers gained a basic understanding of how the platforms worked and the value proposition offered to each user group.

4.6 Data Analysis

The next phase of the research process was data analysis. This phase connects the qualitative data gathered to the research questions. Case study analysis can be conducted in many ways, and in contrast to other research methods there is no standard recipe (Yin, 2012). Each study needs to adapt the techniques and procedures that is appropriate to best answer the research questions. This study tries to answer the research questions by testing a conceptual framework on empirical evidence. To achieve this in a structural and reproducible manner, the analytical procedure of *pattern matching* as suggested by Yin (2012) and Saunders et al. (2012) was used. *Pattern matching* was chosen as the analytical technique because this technique is meant for comparing an empirically based pattern with a predicted one (Yin, 2012; Saunders et al., 2012). If the patterns from the empirical evidence matches the framework, it can be argued that researchers have found an explanation (Saunders et al., 2012).

The collection of data and the preceding data analysis is considered an interrelated and interactive set of processes. According to Kvale (1996), the analysis occurs during the collection of data as well as after it. After completing each interview the researchers replayed the recordings of the interviews to discuss the interviews and make sure the researchers had the same interpretations. The next step was to transcribe the recordings and the notes from the interviews. This was done word for word in an online transcription tool called Transcribe. Each interview was transcribed within one week after the actual interview to preserve the contextual information that locates the interview (Saunders et al, 2012). This allowed the researchers to review the data in a structured way, and enabled an organized analysis of the information.

After transcribing the interviews each case study was summarized in a case report. The reports include notes from the interview, transcription of the interview and communication logs between the researchers and the case company. The process of summarizing large amounts of text into fewer words is good for identifying relationships between themes which researchers can later return to, and seek to validate (Saunders et al, 2012). After the summarization process, the researchers imported the transcribed interviews into an analysis program called Nvivo. This program was used to categorize the collected data. According to Saunders et al. (2012) there are two ways of deriving categories: 1) from the conceptual framework, 2) from the collected data. The themes within each case report: background information, value proposition and user problems was derived from the collected data and the answers of the interviews to reflect the knowledge of the interview subjects. After defining the themes, the next step in the process was to code the collected data by labeling the data to the appropriate themes in Nvivo. The purpose of this was to recognise patterns and relationships in the data (Saunders et al., 2012). This process enabled the researchers to see commonalities between the value propositions and user problems from each case with the other cases. Due to the scope of this research, only user problems related to improving the context value of the platform was included in the findings. User problems related to content value is mainly the domain of growth strategies, and outside the scope.

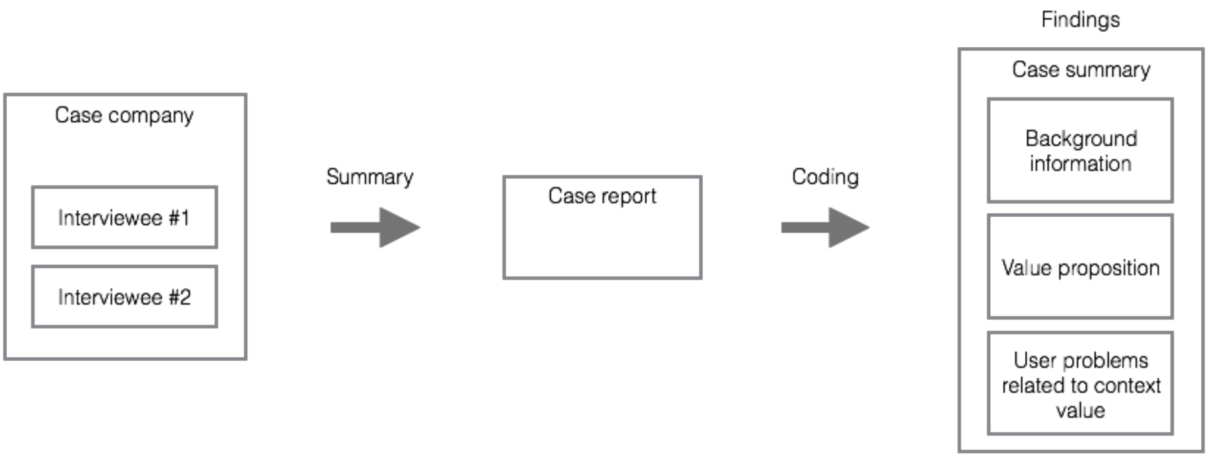

Figure 15: Data analysis process

After summarizing the results, the next step was to apply the conceptual framework on the collected data from each of the case companies. The abductive research process accepts existing theory, like the ACE framework presented by Sandulli (2014), but also allows for a less theory-driven research process by enabling data-driven theory generation (Järvensivu and Törnroos, 2010). Therefore, the researchers revisited the theory after analysing each case and reconsidered and adjusted the proposed framework.

Two independent researchers applied the framework on two of the case companies, Graphiq and Tise. Both researchers used a triangulation approach where they combined the available information through the case company results, the interviews, and independently researched information from the web application or mobile application of the company.

The first step of the framework was to define the user problems based on the empirical evidence from the interviews. The findings from each case study was reviewed and summarized in a one sentence description. The researchers then used the definition context and content value as defined in the framework by Han & Han (2001) to associate each user problem with either content or context value. The two independent researchers agreed on 7 out 7 user problems. The next step was to categorize all problems associated with context value into the four categories as defined by Sandulli (2014). The researchers used the framework to guide the categorization of each problem, and the two researchers agreed on 6 out of 7 problem. The third step was to evaluate if the user problem had the characteristics of a machine learning problem. The TEPCDA model was used to define the characteristics of each user problem. The researchers agreed on the characteristics in 5 out of 7 problems. In the last step of the framework, each machine learning problem should be categorized. The definitions from step 3 was processed through MLT questionnaire, and the researchers agreed on 3 out 5 problems.

The total inter-rater reliability of the application process was 80,8%. After this process, the deviations were discussed and a third researcher was consulted to improve the conceptual framework with a more nuanced description. As a result, from this process, one category of machine learning algorithms was further split into two independent categories. Also, the TEPCDA model was expanded with one additional characteristic. The framework was then applied independently on the remaining three case companies, Nabobil, Learnlink and

Leieting. In the first step the researchers agreed on 10 out of 10 problems. In the second, 9 of 10 problems. In the third, 9 of 10 problems. In the last, 6 of 7 problems. As a result, the inter-rater reliability improved to 91,9%. The final results of the analysis are found in appendix 1, and summarized in the analysis chapter.

4.7 Reflection and Evaluation of Method

All research methods are subject to strengths and limitations that might affect the quality of the study. It has been in the researcher's focus to build upon the strengths of the chosen method while minimizing its limitations. This chapter will take a closer look at these factors and assess the validity and reliability of the study. The chapter starts with evaluating the quality and trustworthiness of the study, based on the four criteria postulated by Guba and Lincoln (1989): credibility, transferability, dependability and confirmability. The chapter ends with a reflection of the methodology and limitations of the study.

4.7.1 Quality and trustworthiness of the study

Credibility is about showing confidence in the truth of the findings. The case study approach has many advantages, but also many drawbacks. Case studies tend to be criticized for being based on subjective matters that affects the credibility (Yin, 2012). Before the interviews, the researchers spent time to get to know each case company. By getting to know the company prior to the interviews, the researchers could better understand the context of the answers, but also subjective to their own interpretations. It was important for the researchers to test their interpretation of the context relating to the value proposition for each case company. The interpreted context was articulated by the researchers in every case interview, so that the interviewees had the opportunity to correct the interpreted context as suggested by Halldorsson (2003). Also, the interviewees were given the opportunity to read a summary of the transcript to confirm the researcher's interpretation (Guba & Lincoln, 1994). For this study, it was also reasonable to expect that the interviewees answered subjectively due to their role in the case company.

A way to overcome subjective interpretation is by using a triangulation of data, so that the researchers can substantiate the findings and increase the credibility (Yin, 2012). The researchers used triangulation in three ways to counter subjectivity: 1) Two different employees of each case company was interviewed to get a triangulation in the data that was collected. 2) Three different sources of evidence were used to verify the findings of each case study, 2) Two researchers independently applied the conceptual framework to highlight subjective interpretations of the framework.

The transferability is the extent to which the study is able to make general claims about the world (Halldorsson, 2003). Multiple-case studies should not be evaluated in terms of the generalizability of the resulting knowledge, but rather in terms of whether the results contribute to contextual insights (Järvensivu and Törnroos, 2010). As the case studies findings is tightly linked to each platform under investigation, the transferability is dependent on the researches ability to explain the context of the research and the findings in detail. This requires interview objects that are open, and willing to share information. To increase transferability, the researchers explained the need for openness in early discussions with the case companies. Still, this posed as a challenge because one of the interviewees believed the topic of discussion was a company secret, and didn't want to contribute with details. To counter this, the researchers ensured the interviewee was welcome to verify the use of any statements about the company before

Dependability examines to what extend the findings are consistent and could be repeated. In other words, it concerns the stability of data over time (Halldorsson, 2003). To increase dependability, the logic of the research process, and the decisions regarding method was well documented (Guba and Lincoln, 1994). There is always a risk that the search for potential case study companies does not lead to the most relevant company for the research. If this happens, then the research will not be considering the most relevant cases to fulfil the research purpose. To minimize the risk of this, the researchers thoroughly describes the case companies selected and the process for selecting. This has been done to establish a logic chain of evidence, describing unexpected findings and changes from the original plan. A third party, fellow master thesis student was asked to perform a dependability audit by reviewing how the research process is linked to the results. The audit revealed that the researchers had not included the selection process for interview subjects as presented earlier. This was very important to ensure dependability, so the researchers had to check the communication logs with each case company and then describe the questions that were asked.

Confirmability is to what extend the findings represent the results of the inquiry and not the researcher´s biases (Halldorsson, 2003). In qualitative research, the researchers are regarded as an active participant the result of the research is therefore biased by the researcher's subjective reality. The researchers are predisposed to their interpretations about what a two-sided platform is, how the value proposition might be improved, and what machine learning can be used for. For instance, conceptions about two-sided platforms, drawn from experience with their own platform-startups might have affected the research. As an example, the purposive sampling of case companies is dependent on the judgement of the researchers. To ensure confirmability, the selection inclusion criteria was defined prior to searching for case companies. By doing so the selection of case companies was made based on information collected about the companies. This information is presented in this research and accompanied with explanations of how the data has been interpreted.

5. Findings

This chapter presents the collected data from the case study interviews and the additional sources as mentioned in the methodology chapter. The purpose of the case study was to learn about the value proposition of the case companies, and identify user problems that potentially could be solved by machine learning. For each of the case companies, the findings have been structured and summarized based on the structure of the interview questions. First, relevant background information about the case company such as the story, a platform description and technical capabilities is explained. This provides the necessary context to each of the case companies. After this, the value proposition of the platform is explained for both user sides: the sellers and the buyers. This is followed by a list of user problems that were highlighted by the interviewees.

5.1 Graphiq

Platform name: Graphiq
Type of platform: Business-to-Business Human Resource platform
Phase: Growing
Interviewee 1: Jakob Palmers, CEO at Graphiq
Interviewee 2: Erik Sandsmark, CDO at Graphiq

5.1.1 Background information

The story

Graphiq was co-founded by Erik Sandsmark and Jakob Palmers in the fall of 2015. They met at NTNU School of Entrepreneurship, and had earlier co-founded a startup called Helping Hands. After pulling out of Helping Hands they discussed different ideas, and considered the aspect of matching designers with companies as the one with the biggest potential. The reason being that Erik, as a designer, had a large network of designers and Jakob had a lot of negative experience in earlier work with outsourcing design work. In April 2017, the company had completed over 170 projects for large Norwegian clients such as Telenor, Tine, DNB and Evry as well as smaller companies and startups. In the period, January to April 2017 the team has grown to 6 people, including Frede Fardal (CTO), Marian Lucas (Operations), Duy Nguyen (Account manager) and Ingrid Sale (Content Manager).

Platform description

Graphiq is categorized as a human resources platform, because the platform connects freelance designers (the sellers) with companies (the buyers). The process is facilitated through a 3rd party communication platform called Slack. Customers set up a communication channel in Slack, and a project manager from Graphiq starts the initial discussion with the company to figure out their design needs. The project manager creates a design brief and give the company an estimated price and suggests two designers that the company can choose from. When the company has chosen a designer, the designer is added to the Slack channel and they can start communicating and begin the project. During the project, Graphiq is responsible for project management, ensuring that the project gets completed in a good way. Once the project is done Graphiq handles all the necessary invoicing and payments. Graphiq takes a cut between 10% and 30% for every project, depending on the scale of the project. Graphiq ensures the quality of the service by handpicking and recruiting designers through a thorough recruitment process. After a designer is chosen as a potential candidate, they have to go through interviews and deliver a test project where they showcase their skills. If the quality of the designer is deemed high enough they get on boarded on the platform. The designers are categorized in three experience levels: 1) Junior which costs 650 NOK/hour, 2) Senior which costs 900 NOK/hour and 3) Premium which costs 1300 NOK/hour. Graphiq is considered to be in the growing phase, because both user groups are starting to grow organically.

Technical capabilities

The tech team is currently consisting of the CTO, Frede Fardal, but Graphiq is in the process of recruiting one more programmer over the summer and expanding with one or two more technical employees during the fall. Graphiq has no central data storage plan as of this moment. The CTO is working on strategies for storing, processing and treating the data in the nearest future. So far, every conversation and message sent through Slack is stored and easily accessible. So far it has been sent over 36.000 messages, and this number is expected to be a hundred-fold within the next two years. Data on prices and customers is stored in a software service called Hubspot and is also easy to access.

5.1.2 Value proposition

Sellers (Designers)

Graphiq's main value propositions to designers is to match them with new customers. According to Graphiq, some designers spend a lot of their time looking for projects.

> *"Research shows that freelance designers spend up to 50% of their time marketing themselves and doing admin work which is not connected with their projects." Erik Sandsmark, CDO Graphiq*

Graphiq offers freelance designers access to new projects and to earn money. Large companies don't usually work directly with freelancers, as they need business relations that are often out of reach for freelancer. Graphiq closes this gap by being the business relation on behalf of the freelancers. One of Graphiq's key focus areas is also providing a community for the designers. Working as a freelancer can often be lonely, and there's little room to meet other designers. Graphiq is currently working on setting up office spaces and events where designers can meet, share experiences and socialize. They ensure payment to the designers when clients are not willing to pay, and take that risk on behalf of the designers. Graphiq also creates the legal contracts between the company and designer, and these contracts are standardised and created by professional lawyers.

Buyers (Companies)

Without Graphiq, finding the right freelance designer is hard and time consuming for companies. Graphiq offer companies a cheaper alternative to the current design agencies. This is made possible due to Graphiq only serving as a middleman, connecting the two parties. They don't have the same overhead costs as regular agencies (salary taxation, large company headquarters, and downtime of the employees) which gives companies access to cheaper designers. According to Sandsmark, an important value that Graphiq offers through the service is the pricing of a project. The price of a design project is a top priority for many companies, but few companies have the necessary experience to correctly estimate the price. By solving more than 170 project, Graphiq has collected data and accumulated experience about how to price a design project based on difficulty, duration and requirements. For the companies, they ensure a 100% satisfaction guarantee, and will not charge if the client is not happy with the result. In this case Graphiq takes the economic costs. So far only two out of 170 projects have been refunded.

5.1.3 User problems

Creating a design brief

At the beginning of each project, Graphiq creates a common understanding of what the task is and how much the project will cost, this is summarized in document called the design brief. Today, this is currently manually created by the Graphiq project managers who are limited by the time and knowledge available to them. The design brief is very important for matching company and designers.

Manual matching processes

To match companies with designers, Graphiq's project managers works together with the customer. Based on this Graphiq recommends two designers based on skillset, experience, design profile and knowledge of the industry in which the company operates. The company can then choose between the two designers. In some cases where speed is important, Graphiq will recommend one designer directly. The matching process is manual today, and this limits the speed of each project. Graphiq wants to automate this process in the future to complete projects faster. Graphiq estimate that matching companies with designers is 50% about their skills and 50% about their personality. In the interviews, it was emphasized that a strength with today's matching process is the human understanding of which personalities match each other. Unfortunately, as the company grows, employee capacity limits Graphiq's scalability, and over time Graphiq will not be able to deliver personalised recommendations.

Estimating price on projects

The prices of each projects are estimated based on the design brief, the hourly salary of the designer and Graphiq's expectations towards the scope of the project. This is done manually today, but Sandsmark explain that this is something Graphiq wants to automate to speed up the process of on boarding new customers.

Detecting negative conversations

After the project has started, the communication is between the designer and the company, while Graphiq wants to provide quality assurance for both parties. This is today done by a Graphiq employee checking into every conversation and making sure it's going along well. As trust and quality assurance is mentioned as one of Graphiq top priorities, it is important to ensure a quality process when the company scales.

5.2 Tise

Platform name: Tise
Type of platform: Peer-to-Peer Product platform
Phase: Scaling
Interviewee 1: Eirik Rime, CEO in Tise
Interviewee 2: Axel Franck Næss, CTO in Tise

5.2.1 Background information

The story

Tise was co-founded by Eirik Rime and Axel Franck Næss in 2013 with the idea "Instagram for second hand sale". The background was that they felt the need to increase incentives for young people to sell second hand items and stay sustainable. For two years, they worked with Tise along with their studies at NTNU in Trondheim. In 2015, they started working with Tise full time and launched in December. Since then they have added new members to the team and today they have seven employees. The technical team consist of three developers, including Axel as the CTO. The last 7-8 months Tise have grown from 16 000 users to more than 190 000 users. More than 700 000 items have been posted for sale and more than 25 000 users is visiting the app daily. Tise is growing by itself more and more every day and has surpassed critical mass, therefore it is considered to be in the scaling phase. Tise´s vision is to make selling and buying second hand items fun and cool.

Platform description

Tise enables people to buy and sell second hand items through a mobile application. As the items are sold and not rented, the platform is considered to be a peer-to-peer product platform. It is possible to sell everything from wearables to books to furniture and computers, however, most people use it to buy and sell fashion clothing and interior. Tise enable matching on the platform in two ways. The first way is through a feature called "home feed" where users will see all the posts from the users they follow. This is typically other users they think have an interesting style, and therefore this feature is somewhat personalised. When something of interest have been found, the can buy the item or follow the users to see more posts for items in a similar style. The home feed is a simple way of personalising the content that are shown. The other way Tise enable matching is through the "explore" feature, Tise enables users to browse posts based on different categories. To make it easier for the users to find relevant items the explore feature has a filtering function. It allows their users to find items within walking distance, biking distance, driving distance or shipping distance. Tise require users to log in through their Facebook profile so the users have profiles with pictures and full names. This enables Tise to show users their common friends. Tise have implemented their own payment solution and a bidding feature to enable the user to facilitate the transaction through the app. The payment solution enable the buyer to rate the seller. However, this is not displayed for the public yet as the Tise team suspect that this will build entry barriers for new users, as they need to compete with the high ratings of existing users.

Technical capabilities

Tise saves all the information generated from the posts. Where the item is located, price, category, what hashtags it has, etc. The posts are connected to each user, as well as information about the likes and the users that follow the user. Tise tracks data related to the amount posts, number of users, active users each day, each week and each month and sale rate. The most important metric is daily active users and amount of posts being sold. The technical team consist of five people: a tech lead, an iOS developer, an android developer, the

CTO and the CEO. The CEO and the CTO works both as developers from time to time. Tise is currently looking for data scientist to start working with machine learning.

5.2.2 Value proposition

Sellers

The most important value proposition for the sellers is the income they make from sales. Tise also provide social value by giving users the opportunity to like pictures and follow other users that they like. According to the founders, posting items should also be exciting for the sellers. In contrast to competitors like Snapsale, posting an item should not be finished in a few second. Making a post in Tise should be a creative and self-expressive act which can give them a lot of attention in the form of likes and followers. Selling items second hand also leaves the users with a good feeling, because it is environmental friendly.

Buyers

Tise want to inspire people to buy items second hand. While competitors like finn.no are focusing on making it easy to find very specific items, Tise want to help their users explore new items. The hunt for new items is an important part of the value the buyers derive from the platform.

> *"If you know what you are looking for, you go to finn.no. If you don't know what you are looking for, you use Tise."*
>
> *Eirik Rime, CEO Tise.*

It´s a way to discover new styles and trends, in addition to an online shopping experience. The economic incentive for the buyer is to buy used items cheaper than they would otherwise buy new items. Buying second hand is also good for the environment, and the Tise app have a feature that quantifies this in the app. It´s called "shop-stop" and quantifies how much users can save the environment by not buying new stuff, measured in kg of CO2.

5.2.3 User problems

No personalised recommendations

In the "home feed" the buyers must manually find sellers with similar styles. Finding seller to follow takes time and can be a hassle for the buyer. According to Axel Franck Næss, there is currently more than 190 000 users and 700 000 item that has been uploaded to the Tise app, and several million likes. Filtering out the what is interesting and not, is a big task, and poses as a challenge for the users today. Today, Tise only offers general recommendations in terms of popular users to follow or collections of manually curated items.

Finding new and interesting items

Tise differentiates itself from competitors by offering the buyers the opportunity to browse through the marketplace to explore new and interesting items. The act of exploring is integral to the user experience. According to Eirik Rime, CEO of Tise, buyers come to Tise when they want to find something new. The buyer does not necessarily know the exact search phrase or the keywords for the category of items they are looking for. Tise want to improve the experience of exploring new objects by enabling the user to perform a visual search in photos. Today about 33% of all posted items are marked as sold. Tise want to increase this number by improving the exploration experience.

Taking professional looking photos

Tise strongly encourages the sellers to take great pictures and make a good-looking post. Data shows a clear correlation between with professional pictures and sell-rate. Currently they have blog posts that guide sellers with creating posts. According to the CEO, solutions for assisting the seller in taking professional looking photos is interesting.

5.3 Learnlink

Platform name: Learnlink
Type of platform: Peer-2-peer human resources platform
Phase: Seeding
Interviewee 1: Jonas Hyllseth Ryen, CEO
Interviewee 2: Johannes Berggren, CTO

5.3.1 Background information

<u>The story</u>

The founder of Learnlink, Jonas Hylleseth Ryen, used to work as a private teacher while he was a student. At that point, the cost of using a private teacher was around 500 NOK per hour. Jonas only earned 40% and the company he worked for earned 60%. Jonas felt that this distribution was unbalanced and decided to teach outside of the company where he was employed. He realised the process could be facilitated through a digital two-sided platform so he gathered a team of two other friends and launched Learnlink in October 2015. Since then Learnlink have relaunched the platform multiple times and iterated it to what it is today. Today Learnlink are still recruiting some new users manually and is therefore in the seeding phase. They are also doing manual work to please users, like calling all new users.

Platform description

Learnlink is a two-sided web platform for matching private teachers/homework assistants, with students in primary school up to high school. It is therefore considered to be a human resources platform. Half of the students are from middle school and the rest from high school. The students from middle school usually leaves the administrative work with Learnlink to their parents. The parent are usually the ones that take initiative to the teaching, often when exams are getting closer. The platform has two main goals: To make online teaching easy and accessible, and to match students with relevant teachers they can meet in real life. To find a teacher, the student must go through a three-step process: 1) Select course, education level and the location for the tutoring. 2) Learnlink uses this information to find the best two teachers for the student, and gives the student a choice between the two teachers. 3) The student and the teacher start communicating and schedule their first meeting.

Today, the information about each student is distributed to all the relevant teachers, and the teachers that are interested reply with an offer. The first two teachers that reply will be shown to the students. An early version of Learnlink displayed every teacher that came with an offer to the students. That practice made it hard for the students to choose a teacher. When the teacher is chosen the teacher and the student can schedule their first meeting. After the first meeting, the students pay, rate the teacher and write a review. This is important to the teachers as the rating and review will help them to get more jobs in the future.

To ensure quality on the platform, each teacher has a user profile with a picture, rating, reviews, a police certificate and a diploma. The Learnlink team screens each teacher through a video interview, before they are accepted. If they feel that the teachers are not dedicated enough they receive a low internal rating. This visible rating of any teacher is an average of the internal and external rating. The teachers choose their own price and Learnlink take a cut of 49 NOK per hour. The teachers are usually university students with good grades. They will be notified every time a relevant student in their area need a teacher. Payment and communication is also administered through the platform.

Technical capabilities

Learnlink gather all the data the platform produce. This includes the courses being taught, how long the tutoring lasts, the price, the number of hours, revenue per user, etc. Learnlink also track unit economics like customer lifetime value and cost of customer acquisition. Johannes is the CTO and the only full-time developer. Learnlink have recently recruited two part-time developers.

5.3.2 Value propositions

Sellers (Teachers)

The value propositions for the teachers is to get a relevant, flexible and well paid part-time job. Learnlink allows them to earn more than traditional private teaching companies, because Learnlink take a much lower cut. In addition, Learnlink allows them to be their own boss. The teachers can gain a higher salary after successfully spending time teaching. Another value is the fact that teaching can leave the teachers with a sense of achievement.

Buyers (Students/Parents)

The most important value Learnlink deliver to the parents who uses the service is access to good private tutors, that can help their kids. The teacher might also be an academic personal trainer and a source of inspiration for the students.

"The teachers work as personal trainers for their kids. We are selling them the ensured safety that their children will take part in the future" Johannes Berggren, CTO Learnlink

5.3.3 User problems

No matching

Today the matching process is based on which teachers respond fastest, and not necessarily the fit between the teacher and the student. Learnlink wants to match the student with a teacher, based on the demographics, experience and ratings of the teacher. If the teacher has good grades from the institution the student want to go to, this could increase the *trust* to the teacher, and will have a positive effect on the matching score. According to Learnlink, the personality of the teacher and the chemistry between the teacher and the student can be just as important as the teacher's grades.

Lack of progress overview

Over half of the buyers today are parents of the student. Today there is no way for them to get an overview of the educational progress of their child. In the next version of the platform, Learnlink is planning to introduce a dashboard with an overview of the educational progress. A way for the parents to look into the black box of private teaching.

Predicting grades

Another problem identified by Learnlink is transparency when it comes to predicting which grade a student will obtain. Today, the platform tracks the number of tutoring sessions and hours spent, but does not show how it improves the grade of the student. Parents wants predictions for what grade their kid is likely to obtain, based on the current level, the progress so far and historical data from the platform. To do so, Learnlink must track the teacher's performance and what grades the students receive.

5.4 Nabobil

Platform name: Nabobil (meaning "neighbour car")
Type of platform: Peer-2-peer property platform
Phase: Scaling
Interviewee 1: Even Tangen Heggernes, CEO
Interviewee 2: Christian Hager, CTO

5.4.1 Background information

The story

Nabobil was founded on the idea of making "Airbnb for cars" in April 2015 by Christian Hager, Karl Alveng Munthe-Kaas and Jacob Tveraabak. Even Heggenes was hired as the CEO because of his experience with P2P marketplaces from running Airbnb in the Nordics. In addition, he felt very strongly for the idea, because he used to rent cars over the summer and was annoyed by traditional rental services being expensive and complicated to deal with. Nabobil gathered a technical team and launched the platform after the summer in 2015. The vision of the company is "Get a car when you need it".

Platform description

Nabobil is a digital two-sided platform on both web and mobile that allows private individuals to rent out their car to strangers. A car is a property; therefore, it is considered to be a peer-to-peer property platform. It offers a safe and reliable service for anyone that want to rent a car. Nabobil takes a small cut of about 25 % of the transaction. The platform is similar to Airbnb and includes features such as filters to narrow the search, an overview map to see available cars and a calendar to show when the car is available. Traditional car rental services expect the user to come down to their office, sign papers and show them a driving licence. Nabobil leverage technology to remove friction from this process. The whole process is administered on the digital platform: signing up for the service, choosing a car, paying for a car and managing insurance.

Nabobil has filters that allows the users to choose different price-ranges and categories for the car, like brand and type of gear. In addition, Nabobil offers a map where users can view where cars in their neighbourhood are located. In contrast to Uber, Nabobil allows users to choose the car they want to rent on their own. At Uber, a customer can only choose a class of car and Uber will chose the most suitable car for the customer. Nabobil could have adopted the same practice and reduced the search costs, however, this would take away some of the flexibility and trust. According to the CEO, the most important factor is not the car but the owner of the car, because the owner must say yes to the rental request.

Today, the car owners set the price for renting out their car themselves. Nabobil is currently the only peer-2-peer platform for car rentals in Norway, and typically for such marketplaces the rental price will seek an equilibrium that is both acceptable for the renters and the car owners. This equilibrium price is likely to be lower than competing car-renting services like AVIS and Hertz, because the car-owners are willing to price the car low as they will not use their car when it is available for renting anyway.

According to Heggenes, Nabobil is not only a car sharing platform, it is a community of car sharers. A car is personal, and sharing it tends to give people good feeling when the renter and the car owner meets. Renting out such a personal item can also create worries related to potential incidents. It is therefore important for Nabobil to ensure the quality of the transaction between the renter and car owner. To ensure quality Nabobil renters and car owners have user profiles that display bankID, email, phone number, Facebook, NAF membership and the driving licence. In addition, the profile will display a profile picture and a short description about the user, written by themselves. The user profile has rating and reviews from previous renting experiences. To increase *trust* for car owners Nabobil offers an insurance deal with the Norwegian insurance company IF for all users.

When the deal is made online the renter can go directly to the neighbour and pick up the car. This saves the renter and the car owner a lot of time and allows Nabobil to reach people no other rental service can do. Nabobil offers a communication channel between the renter and the car owner to reduce friction when they plan where and when to meet. Sometimes one of the two will not be able to meet and the feature allow them to reschedule. Today Nabobil offers over 4000 pickup points throughout Norway. This is considered to more than critical mass for both sides of the platform, and is therefore considered to be in the scaling phase.

Technical capabilities

According to Christian Hager, Nabobil work proactively on collecting data about their users. Nabobil saves as much data as possible, even data they don´t know how to leverage, because they believe they will find a way to use it in the future. He believes that data gathered through the platform can be valuable for other rental services. For instance, data about the demand in different locations at different times. This enable them to do lookalike campaigns in Google's and Facebook's databases, in order to acquire more users similar to the ones they have.

Nabobil currently employs four developers, including the CTO. In addition, they have one PhD. and two master students working with machine learning technology at the University of Oslo.

5.4.2 Value proposition

Sellers (Car owners)

The most important value the platform brings to the sellers is the economic value of renting out their car while they are not using it. Nabobil makes it possible for private individuals to rent out their cars to strangers. Also, the safety that comes with the insurance policy and user ratings are important.

Buyers (Renters)

For the renters, the economic value of renting a car instead of owning is the main value Nabobil offers. Additionally, Nabobil provides a transparent market with information about car types, prices, availability, etc. Car sharing is also environmentally friendly. 60-70 % of the CO_2 emission of a car is related to production. When people are sharing cars, less cars are being produced. According to the CEO, research shows that one shared car can prevent the production of up to nine new cars. Being a part of a car-sharing community enables families to not buy the second car.

5.4.3 User problems

Choosing the right car

One of the most important factors at Nabobil is giving their renters an easy time finding the car they want to rent. Nabobil renters spend on average one hour scrolling up and down pages in search for the perfect car to rent. Currently Nabobil have three people working on this problem using machine learning. According to the CEO, they have already been able to predict the cars that will be rented up to 90% of the time, based on data from user profiles, search filters and available cars in the market. A problem they are still struggling with is predicting the likelihood of a car owner accepting the request, which is a big part of choosing the right car.

"It's not the car but the person who owns the car whose important. It does not matter if Nabobil pushes x number of cars to you if the car owner is not going to accept you" Even Heggernes, CEO Nabobil

Pricing

There are multiple factors affecting the optimal rental-price of a car. There are car-related factors like brand, model, year, etc. and market-related factors like location, seasonality and competition. It is very hard for car owners at Nabobil to include all these factors when pricing their car. In addition, the market-related factors change over time and location. To solve this Nabobil are planning to introduce a feature that calculate the best rental price for the cars, based on historical data, demand and availability in the market.

Updating the calendar

A problem for Nabobil is that car owners tend to not update their calendar, because they don't know when they will need their car more than a few days in advance. This leads to renting requests being declined, and a bad experience for users who want to rent a car.

Fraud

Some users might misuse the trust and use the platform to scam other users. For instance, by making fraudulent listings that looks very good, and asking people to contact them by mail. Through email, scammers can pretend to be a user on Nabobil that have a very nice offer and ask them to pay outside of the platform. Some renters, especially first time renters might do this and end up being scammed. Fraud can happen when using two-sided platforms without thinking critically. Fraudulent listings are not the only problem. Payment fraud, spam messages and account hijackings are also potential frauds. Fraud is a growing problem for two-sided platforms and the people using it. This is not a problem at Nabobil today, however, Nabobil emphasize they want to have a proactive approach to this.

Insurance

Today the insurance is standardized for the buyer. Everyone that rent a car through Nabobil will have the same insurance. No matter their age, crashing history, driving habits etc. This leads to an expensive deal for the experiences drivers and a cheaper deal for the inexperienced drivers.

5.5 Leieting

Platform name: Leieting

Type of platform: Peer-to-peer assets platform

Phase: Growing

Interviewee 1: Christer Hansen Eriksen, CEO

Interviewee 2: Kim Røen, CTO

5.5.1 Background information

The story

Leieting was founded by Christer Hansen Eriksen and Bjørn Reidar Ur. The founders started out by joining buy-and-sell groups on Facebook, and researching the possibility of getting people to rent stuff instead of buying it. After getting a foundation of knowledge they created a webpage prototype, and started getting the users from the buy-and-sell groups to transfer over to their page. Since the early response was positive, they decided to onboard Kim Røen and Thomas Sunde Nielsen and start Leieting. During the summer of 2015 they started developing leieting.no and launched the platform in November later that year

Platform description

Leieting is considered to be a peer-to-peer asset platform, where sellers can rent out personal items and buyers can pay to rent the items. The direct translation of Leieting is "rentstuff", which embodies the fact that everything can be rented out on the platform. Leieting enable buyers to search or browse for items that they need for a limited period of time, and rent it directly from people who already own such items but are not currently using them. The sellers are mostly private individuals; however, some companies have started using the platform to rent out items. To help buyers connect with sellers that are renting out, Leieting provides a search field and filters within categories, locations and price ranges. The buyer can choose between searching for specific items through a text field, or browse through the items based on location or category. To request an item, the buyer submits a time period for renting the item. The seller then accepts or rejects the request. If the request is accepted, both users agree upon where the item should be picked up. Today, sellers can decide the price of the items themselves. To help the user with the process of renting out, Leieting have integrated a payment solution for the two parties. Of every transaction on the platform, Leieting takes a 20% cut.

Leieting focuses ensures quality on the platform in two ways, building trust with the platform and creating trust between people. Leieting has chosen a Norwegian name to build trust around being a Norwegian company. They have also integrated a chat and support system into the platform that enables the users to ask any questions while using their platform. To create trust between the users Leieting provides an insurance on the items for rent. After an item is returned to the seller, the buyer can give a positive or negative review, which is shown on the seller's profile and advertisements. After a user is identified through a credit card and BankID this will be shown as badges on their profile, as verified users. Today Leieting is growing by itself in certain areas, but it is still important for Leieting to identify the most successful geographical areas and items and double down on those. Therefore, it is considered to be in the growing phase.

Technical capabilities

Leieting stores all data regarding demand, supply, prices and on users on an Amazon data server. They store about 100 data points per user, and at this date they have 8000 users. The technical team is consisting of Thomas and Kim, two co-founders, with full stack development experience. Leieting has no current plan for recruiting more people on the technical team.

5.5.2 Value propositions

Sellers (Lenders)

Like Nabobil, the biggest value proposition is the monetary opportunities the platform offers the users. In addition, it is the social aspect of lending items to neighbours and the local community, enabling people to help and get to know each other.

Buyers (Renters)

Leieting enable the users to save big upfront investment costs by renting stuff instead of buying new. Another value proposition is the positive environmental impact achieved by increasing sharing and decrease buying

5.5.3 User problems

Updating the availability

Today, there is no way for buyers to see when an item is available for rent or not. Buyers must ask the sellers if an item is available for rent for a certain time period. This leads to many requests that are declined and makes the process of finding a specific item more time consuming and less of a good user experience.

Setting the price

During the process of posting items on the platform, Leieting does not provide help with price estimations. The price might be difficult to estimate. Especially for first time sellers with new items that is not easy to compare to other items on the platform.

"Setting the price is difficult for our users, we should be able to give them suggestions." Kim Røen, CTO Leieting

6. Analysis & discussion

6.1 Introduction

In this chapter, the two research questions will be discussed and answered. How can managers of two-sided platforms startups: 1) Evaluate if the value proposition can be improved with machine learning? 2) Determine the type of machine learning algorithms that could be applied?

The conceptual framework consists of a four-step process, and all the case companies will be processed in each step before moving on to the next step. By processing the case companies step by step, the analysis of each case company contributes to the analysis of the step. After each step an evaluation of the step is given. The first step is to define each user problem and associate the problem with either content or context value. The second step is to categorize each user problem. The purpose is to articulate the benefit of solving the user problem, and to assess if that benefit improves the value proposition of the platform. The third step is about investigating if the problems can be solved with machine learning. The purpose is to filter out the problems that cannot be solved with machine learning, and look into the necessary information that is required to bring forward into the next step. The fourth step is about finding out what kind of machine learning algorithm that is associated to that specific machine learning problem.

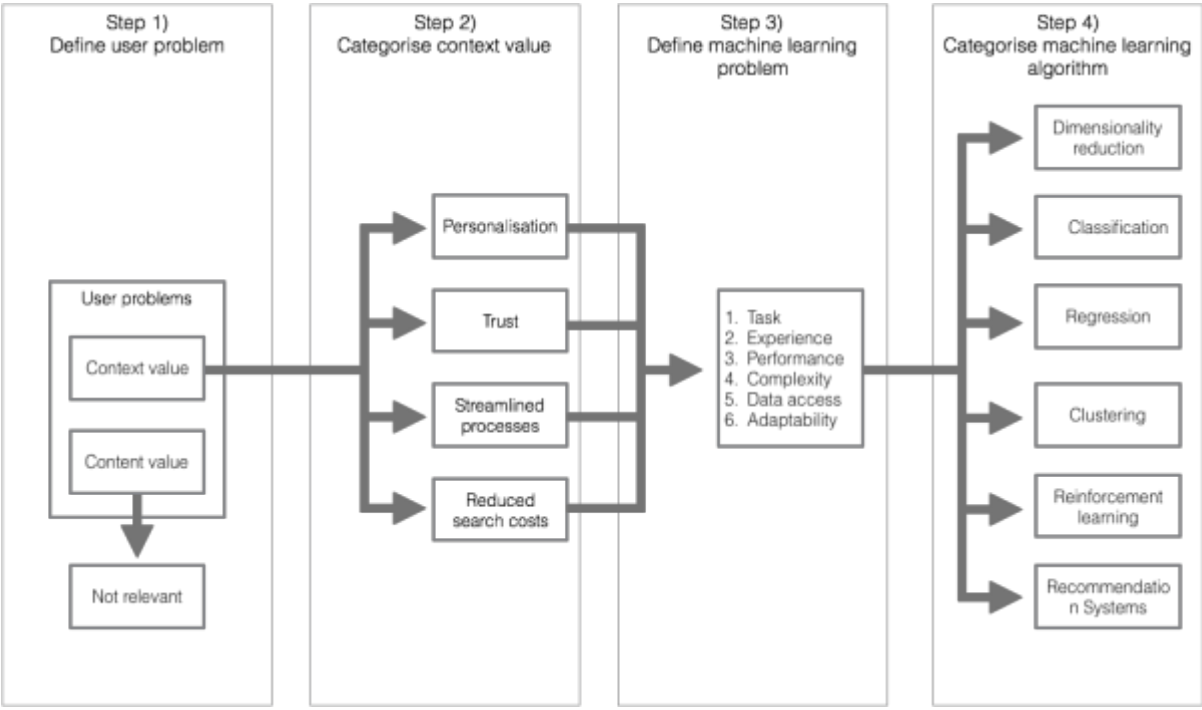

Figure 16: A recap of the conceptual framework as presented in chapter 3, developed based on the literature review of Rystad & Aarseth (2016).

6.2 Step 1: Define problems

6.2.1 Applying the framework

The first step in the framework was to define the user problems based on the collected evidence from each case study. The user problems were analysed, and categorised to be either of context value or content value, as defined by Han & Han (2001). From the results of the case study, seventeen user problems were categorized as context value and included for further processing, see table 4.

User problem	**Description**
Graphiq	
Creating a design brief	Creating the design brief is done manually by Graphiq and it therefore slows down the speed of the project

Manual matching processes	The matching of designers and customers is done manually by Graphiq project leaders, which slows down the project.
Estimating price on projects	Estimating price is a manual process that is done manually by Graphiq project leaders today, which slows down the project.
Detecting negative conversations	The communication between a customer and client get silent or turns negative, and Graphiq needs to manually pay attention to each conversation to detect this
Tise	
No personalised recommendations	The buyers have to manually find other users to follow.
Finding new and interesting items	Exploring new and interesting items is a time-consuming task for the user today.
Taking professional looking photos	Many users are not experienced and don´t know how to take good photos of their items, leading to less items being sold.
Learnlink	
No matching	A student is matched with the first two teachers that respond, and not by student/teacher fit.
Lack of progress overview	There is no way to get an overview of the educational progress of the student.
Predicting grades	Parents want more transparency towards which grade their kid can expect to get, based on progress and historical data.
Nabobil	
Choosing the right car	Users spend time and energy evaluating many different cars that are available to them.
Pricing	It is difficult for car owners to understand how different factors should affect the pricing of their car.
Updating the calendar	Renting requests gets declined, because users don't update their calendar to signal when the car is available.
Fraud	Criminals make fake user profiles and try to scam other users.
Insurance	Every user is offered the same insurance, which leads to an expensive deal for the experienced drivers and a cheaper deal for the inexperienced drivers
Leieting	
Updating the availability	There is no way for renters to see when an item is available for rent or not, and this leads to declined requests which makes the process of finding a specific item more time consuming and less of a good user experience.
Setting the price	The price might be difficult to estimate, especially for first time users and new items that is not easy to compare to other items on the platform.

Table 4: Overview of the all the user problems in step 1

Graphiq

Four user problems associated with context value were identified from the case study of Graphiq: 1) Creating a design brief, 2) Manual matching processes, 3) Estimating price on projects and 4) Detecting negative conversations. "Creating a design brief" is associated with context value because the benefit of solving the problem is saving time for the user, and this benefit is derived from the transaction. The benefit of solving "manual matching processes" is better matching and faster processes, which also comes from the transaction. *Flagging* "negative conversations" and "estimation of prices" are related to the positive experience of using the platform, which is also considered the context value.

Tise

Three user problems associated with context value were identified: 1) No personalised recommendations, 2) Finding new and interesting items, 3) Taking professional looking photos. The benefit of solving the "no personalised recommendations" problem is access to relevant content and a better user experience. The same benefits go for "finding new and interesting items". The benefit of solving the problem of "taking professional looking photos" concern is a better user experience.

Learnlink

Three user problems associated with context value were discovered for Learnlink: "No matching", "Lack of progress overview", "Predicting grades". By matching students and teachers in a better way, the benefit would be a more personalised process. "Lack of progress overview" and "predicting grades" are problems related to context value because the benefit of solving them increases the pleasure of using the platform for the user.

Nabobil

Five user problems associated with context value were identified "Choosing the right car", "Pricing", "Updating the calendar", "Fraud and Insurance". By making it easier to choose the right car the user benefits in both time and energy saved, as well as a more personalised user experience. This problem is therefore related to context value. The pricing problem, the calendar problem and the fraud problem is also clearly related to the benefit derived from the transaction itself. Last, the benefit of solving the insurance problem is a personalised transaction and thus related to context value as well.

Leieting

Two user problems were identified as context value: “Updating the availability”, “Setting the price”. These problems are very similar to the pricing and calendar problem of Nabobil, and is related to context value based on the same logic.

6.2.2 Evaluation of the step

The goal of this step was to discard non-relevant problems from further investigation and clearly define the user problems that was relevant. This was effectively achieved by applying the framework. The theoretical foundation for this step was clearly defined and stated by Han & Han (2001). Consistent results from the independent coding indicated that the definition of context and content value was easy to understand and applicable to the user problems in the case studies. The two definitions of context and content value made it easy to quickly assess whether a user problem was relevant for the framework or not.

The step builds upon the assumption that machine learning is not the best method for solving user problems associated with content value. Due to the fact that all user problems associated with content value was discarded in this step, this has not been empirically tested. It is suggested that other research test this assumption, but for this research it does not pose as a limitation because it leads to more attention around the problems that matters for this paper, the problems related to the context and not the content.

The categorization is based on the researcher's interpretation of the answer from the interviews, and not the categorization of the interviewee themselves. This could lead to biased answers, so the researchers made sure to base the analysis on independent coding and well defined theory. By analysing and describing the user problems in terms of content and context value, platform managers can reduce the number of problems that should be taken through the next step.

6.3 Step 2: Categorize context value

6.3.1 Applying the framework

The second step is to categorize the user problems based on the value logic model. The purpose of this step is to articulate the benefit of solving the user problem, and to assess if that benefit is in line with the value proposition of the platform.

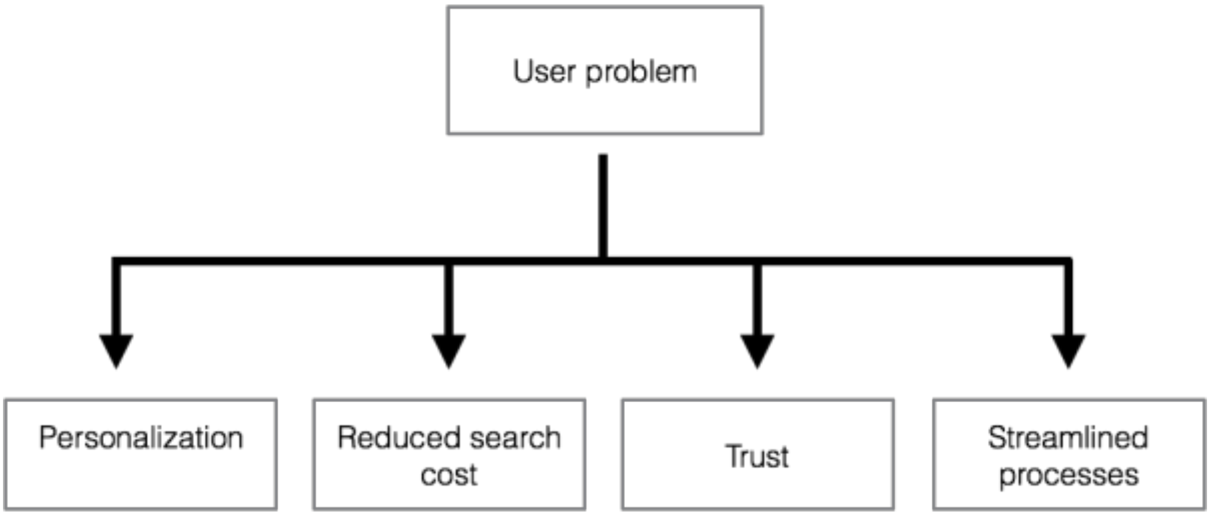

Figure 17: Overview of the different categories of context value

The framework, see figure 17, suggest four categories that are relevant for addressing user problems related to context value and machine learning: 1) *reduced search cost*, 2) *trust*, 3) *streamlined processes*, 4) *personalisation*. For each company the current value proposition will be summarized, followed by an analysis of the categorization for each user problem, and ending with discussion about how solving it will improve the value proposition. The categorization is not necessarily binary because the user problems can fit into multiple categories. The categories are based on the value logic model presented in the conceptual framework in chapter 3.

Graphiq

The value proposition towards the designers is to effectively match them with new customer, provide them with a community, handle contracts and administrative work. To the companies Graphiq provides cheaper graphical design, faster processes, support in the outsourcing process and guarantees.

Graphiq	**Categories of context value**			
User problems	Personalisation	Reduced Search Cost	Trust	Streamlined Processes
Creating a design brief				X
Manual matching processes	(X)	(X)		X
Estimating price on projects				X
Detecting negative conversations			X	

Table 5: The four user problems of Graphiq has been categorized by using the value logic model.

"Creating a design brief" is categorized as *streamlined processes* because the benefit of solving this problem would be faster delivery of a project, and better customer service. Support in the outsourcing process is a central part of the value proposition today, so efficiency of the transaction needs to be weighed against the quality of the customer support.

"Manual matching processes" is categorized as *streamlined processes*. In comparison to the other case companies, Graphiq play a very active role as the matchmaker between the buyer and the seller. The benefit of solving this problem can lead to better customer service, faster delivery and better communication. By automating the matching process, the benefit could also be a more personalised transaction, and a more informative and transparent transaction. Therefore, it can also be argued that "manual matching processes" should be categorised under *personalisation* or *reduced search cost*.

The problem with "estimating the price on projects*"* is the total labor capacity that slows down projects. By solving this problem, the user would mainly save time and get a faster delivery. Increasing the speed of the process translates to *streamlined processes*. Fast processes are a part of Graphiq value proposition towards the buyer today.

"Detecting negative conversations" is categorized as *trust* because the problem is unexpected user behaviour, and solving it leads to increased trust on the platform.

Tise

For sellers on Tise, the value proposition is to earn money by selling second hand clothing, get a better conscience for being environmental friendly, and social value from expressing themselves and interacting with other users. The buyers derive economic value when they are shopping cheaper clothes, a good experience from hunting interesting things and good conscience for buying used items which is environmentally friendly.

Tise	**Categories of context value**			
User problems	Personalisation	Reduced Search Cost	Trust	Streamlined Processes
No personalised recommendations	X	(X)		(X)
Finding new and interesting items	X			
Taking professional looking photos				X

Table 6:The three user problems of Tise has been categorized by using the value logic model.

The matching process for Tise is based on clicking and scrolling through a feed until the user finds something of interest. "No personalised recommendations" is categorized as *personalisation* because the benefit of solving the problem is access to better quality content that matches the user's style. The user gets content based on the individual's preferences. It can also be argued that additional benefits include less time spent on searching for items or reduction of clicks, which categorize the problem within *reduced search cost* and *streamlined processes* as well.

"Finding new and interesting things" is categorized as *personalisation* because it reduces the transaction cost by offering personalised content to the user. Although solving this problem also reduces clicks and saves time in the same way as "No personalised recommendations", one need to realise that the hunt for unique items is an important value proposition for the buyers on Tise. The efficiency of the search process is not critical, and therefore it has not been categorized in *reduced search cost* or *streamlined processes*.

The last problem, "Taking professional looking photos", is categorized as *streamlined processes* because solving it improves the customer service. Solving this problem can also improve the social value sellers derive from expressing themselves through the content they publish.

Learnlink

Learnlink offer the sellers economic value, flexible hours and a sense of achievement. The buyers are offered cheaper and easy access to good private teachers.

Learnlink	Categories of context value			
User problems	**Personalisation**	**Reduced Search Cost**	**Trust**	**Streamlined Processes**
No matching	X	(X)	(X)	
Lack of progress overview			X	
Predicting grades			X	

Table 7: The three user problems of Learnlink has been categorized by using the value logic model.

The "No matching" problem is categorised as *personalisation* because the benefit of solving the problem is a matching based on the user's individual preferences. A better matching could also lead to better information for the user, and help build more trust to the platform. Therefore, *reduced search cost* and *trust* is also a possible categorization. An element of Learnlink's value proposition to the buyers is the easy access to good private teachers, therefore a better matching is considered an improvement of the value proposition.

The two problems, "Lack of progress overview" and "predicting grades", are both categorized as *trust* because the benefit of solving them is a more transparent learning experience. Again, easy access to good teachers is part of the value proposition to Learnlink, and solving these two problems would help improve this by making the progress in the learning-experience more transparent.

Nabobil

For both sellers and buyers, the main value proposition is the economic value of renting out the car or renting a car cheap. Additionally, the benefit of making an environmentally friendly choice, transparent market, easy communication and the trustworthiness of the transaction is important.

Nabobil	Categories of context value			
User problems	**Personalisation**	**Reduced Search Cost**	**Trust**	**Streamlined Processes**
Choosing the right car	X	(X)		(X)
Pricing			(X)	X
Updating the calendar		X	(X)	(X)
Fraud			X	
Insurance	(X)			X

Table 8: The five user problems of Nabobil has been categorized by using the value logic model.

Nabobil has a semi-automated matching processes, with a search field based on location and available time slots. The results are then presented for the user who needs to evaluate which cars that are relevant and which are not. The benefit of solving the problem of "Choosing the right car" is personalised content adapted to the individual user preferences, and thus categorized as *personalisation*. Additional benefits can also be fewer clicks in the process and better information, so the problem can also be categorized as *reduced search cost* and *streamlined processes*. Efficient search processes are not a highlighted part of the value proposition today, but better ways of finding the right car to the right price would increase the economic value of the transaction and thus increase the value proposition.

The user problem "Pricing" is related to setting the price right. Users spend time and energy on researching the market price, so they can price their listing in the best way. The benefit here would be less clicks and a more efficient seller process. Therefore, this problem is categorized as *streamlined process*.

"Updating the calendar" is the challenge of sellers not updating the time and date for which an item or a car was available for rent. This leads to misunderstandings where the sellers cancel a tenancy and the buyer need to spend more time finding a new option. The benefit of solving the problem is more informed search and the problem is therefore categorized as *reduced search cost*. The problem could also be categorized in *trust* and *streamlined processes* because it increases the trust to the platform and reduce the number of clicks in the booking process. Easy communication is important for the users of Nabobil, and solving this problem would improve the value proposition.

Fraudulent user behaviour, as explained in the "Fraud" problem, decrease the trust on the platform directly by making users afraid of getting hustled. The benefit of preventing this is increased trust. Also "Insurance" problem has been categorized as *trust*. Standardised insurance policy reduces trust because it does not make any distinction between inexperienced and experienced drivers. By personalising the insurance, additional value would be personalised offerings to the users. Trust is a very important element of the Nabobil value proposition, and solving any of these two problems would improve the value proposition.

Leieting

Sellers rent out their items on Leieting to make money, but also to be a part of the sharing community. The buyers get access to things that they normally don´t have and save big upfront costs by renting, and also get value from making the environmentally friendly choice.

Leieting	**Categories of context value**			
User problems	Personalisation	Reduced Search Cost	Trust	Streamlined Processes
Updating the availability			X	(X)
Setting the price			X	

Table 9: The two user problems of Leieting has been categorized by using the value logic model.

"Updating the availability" is very similar to the calendar problem as identified with Nabobil. It is categorized in *reduced search cost* because the benefit of solving it increases the available information for the user during a search. It is also categorized in *streamlined processes* because solving the problem leads to more efficient booking processes. The purpose of Leieting is to match buyers with available things, so improving this matching would improve the value proposition.

"Setting the price" is a problem that complicates the process of listing items for rent, and the benefit of solving this problem is related to *streamlined processes*. By helping the user set the right price it is also more likely that the user will be able to rent out their stuff, and make money. Solving this problem will therefore improve the value proposition.

6.3.2 Evaluation of the step

The categorization made it possible for the researchers to discuss problems in terms of which part of the value proposition it improves. By categorizing the problems, the researchers created a vocabulary for open discussions about the benefit derived from solving the problem. In addition, it was useful when evaluating the importance of the problems, contemplated up against the value proposition of the platform. This evaluation can help the platform managers with the important task of prioritizing which user problems to address first. The evaluation also revealed that many problems have solutions that can improve more than one part of the value proposition. This is interesting because it highlights the fact that some problems are complex, and could be broken down into smaller problems before attempting to solve them.

The theoretical foundation for this step in the framework is based on the research of Sandulli (2014). Originally six key mechanisms for value creation was presented, but co-creation and aggregation was considered not relevant for the scope of this research. After testing the framework, this assumption is strengthened. The researchers were successfully able to determine a suitable category for each problem without the need for additional categories.

A weakness of the proposed framework was highlighted by the independent coding process carried out by the researchers, explained in the method chapter. Inconsistency in the independent coding, indicated that some definitions were not clearly defined and led to different interpretations. The definitions of key mechanisms for value creation introduced by Sandulli (2014) is considered to be high level descriptions, and the analysis reveals there is need for more detailed definitions of *personalisation*, *reduced search cost*, *trust* and *streamlined processes*.

6.4 Step 3: Evaluate problems

6.4.1 Applying the framework

The purpose of this step was to evaluate if the problems are machine learning problems. This analysis was conducted by asking the questions presented in the TEPCDA model from chapter 3.4. The first three questions define the machine learning problem: 1) The task, 2) Experience and 3) Performance. The next three questions investigate the nature of the problem: 4) Complexity, 5) Access to training data, 6) Adaptability. All the 17 problems from step one was evaluated by the criteria in the TEPCDA model. The full evaluation can be found in appendix 3) Analysis of machine learning problems. This chapter includes the results of that analysis. The analysis is presented in this chapter, and summarized in table 10.

Task	What task is the algorithm trying to learn? • This is from the algorithm's point of view, not the user or not the platform. • The algorithm might do this hundreds of times to solve the final task for the user. Example: Transforming speech to text with speech recognition software.
Experience	How can the algorithm be trained? • What kind of feedback loop is needed to train the algorithm? • How can the algorithm experience this data? Example: A database of texted speech.
Performance	How is the performance of the algorithm measured? • A metric that tells how good the algorithm currently is • Preferably a ratio Example: Percentage of transformed text similar to the speech indicate performance.
Complexity	How complex is the problem? • How many variables are involved? • How difficult is it to manually write an algorithm that solves the problem? Example: Words and sounds are very complex to write an algorithm to recognize.
Data access	Is it relatively easy to access or collect unlabeled or labeled training data? Example: Texted speech as training data is widely available.
Adaptability	Does the problem require software that customise to its operational environment after it has been deployed? • Should it adapt to the user or a group of users? • Should it adapt to different geographical areas or cultures? • Should it change over time of the day, weekday or seasons? Example: To maximize performance, speech recognition software needs to be customise to the user who purchase the software.

Table 10: Characteristics of a machine learning problem

Graphiq

The analysis of Graphiq, revealed that two of the four problems was machine learning problems. For the first problem, "Detecting negative conversations" the task was defined as detecting if a conversation between a buyer and a seller is negative. The task of "Estimating price on projects” was defined as predicting the price of a project based on the design brief. The task in both problems involves text analysis, so they are considered to be complex problems that is typically solved with machine learning.

The two remaining problems were not considered to be machine learning problems. “Creating a design brief” is about assisting the creation of a text document, which is not a machine learning problem, because it is a process that includes many smaller problems related to information flow. For “Manual matching process” the task was defined as recommending the two best sellers (designers) for the buyer's (customer). This is not a machine learning problem because the problem described by Graphiq includes less than ten variables and can easily be described with a given set of rules.

Tise

All three problems related to Tise is considered to be machine learning problems. The task of the first problem “No personalised recommendations” was defined as “based on items the user likes, find other items the user will probably like”. The second problem, “Finding new and interesting items” is about improving the experience of exploring new objects by enabling the user to perform a visual search in photos and the task was defined as “Based on an item find similar items”. The task of the third problem, “Taking professional looking photos” was defined as labeling if a photo is of low, medium or high quality. The task of all the three problems is related to image recognition, which is complex task. Image recognition is from the definition in the theory a complex problem. Therefore, they are all considered to be machine learning problems.

Learnlink

Learnlink had three problems, none were considered to be machine learning problems. The task of the first problem, “Manual matching process”, was defined as matching teachers with students. This match is a simple match made with just a few variables (type of subject, the teacher’s background and gender) so this is not a machine learning problem. The second problem, “Lack of progress view” and the third problem, “Predicting grades” are not machine learning problems, but problems related to lack of information. There is not enough information about the progress to be able to make a progress view or a prediction about future grades.

Nabobil

Of Nabobil´s problems, six were considered to be machine learning problems. The first problem, "Choosing the right car" was split into two different tasks: 1) Predicting the likelihood of a car owner accepting a specific renting request. 2) Predicting what kind of car the buyer is after. Such a split was deemed necessary as the problem was too broad, in the sense that it could lead to different versions of tasks. When dividing it into two, the independent coding lead to the same definitions of tasks. The first task requires learning related to each car owner's preferences. The second task requires learning related to each buyer's search queries and preferences. Both tasks require the algorithm to include a complex set of variables and that needs to adapt to each user. Both are considered machine learning problems.

The second problem, "Pricing" was also split into two different tasks "Suggested Pricing" and "Dynamic Pricing" for the same reasons as "Choosing the right car". "Suggested Pricing" is about predicting the optimal renting price of a car. As this calculation includes many variables, were some is dependent on location and seasonality, the solution is considered complex and solvable with machine learning. "Dynamic Pricing" is about calculating the optimal renting price of a car at any given point in time. This algorithm need the same variables as "Suggested pricing" in addition to real time variables from the market. Therefore, this problem also requires machine learning.

The task of the fourth problem, "Fraud" was defined as flagging user activity that is suspicious. It is very difficult to write out a ruleset describing what a fraudulent activity is, but it can be revealed through pattern recognition. This is a machine learning problem. The task of the fifth problem, "Insurance", was defined as categorizing user profiles into specific risk profiles. The underlying combination of variables that reveal risky drivers might be complex. It may also be depending on location. Therefore, this is a machine learning problem.

One problem was not considered to be machine learning problems. The problem "Updating the calendar" is about making car owners updating their calendar. Therefore, the problem cannot be solved with machine learning.

Leieting

One of the two Leieting problems investigated was classified as a machine learning problem. The task of the problem “setting the price” was defined calculating the optimal renting price for new items on the platform. As this calculation includes many variables, where some is dependent on location and seasonality, the solution is considered complex and solvable with machine learning. The other problem “updating the availability” is a problem related to making users spend time updating their calendar. Therefore, the problem cannot be solved with machine learning.

Company	**Problem**	**Solvable with ML?**
Graphiq	Creating a design brief	No
Graphiq	Detecting negative conversations	Yes
Graphiq	Manual matching processes	No
Graphiq	Estimating price on projects	Yes
Tise	No personalised recommendations	Yes
Tise	Finding new and interesting items	Yes
Tise	Taking professional looking photos	Yes
Learnlink	Manual matching process	No
Learnlink	Lack of progress overview	No
Learnlink	Predicting grades	No
Nabobil	Choosing the right car	Yes
Nabobil	Suggested Pricing	Yes
Nabobil	Dynamic Pricing	Yes
Nabobil	Fraud	Yes
Nabobil	Insurance	Yes
Nabobil	Updating the calendar	No
Leieting	Updating the availability	No

Leieting	Setting the price	Yes

Table 11: Problems solvable with machine learning.

6.4.2 Evaluation of the step

This model was helpful to get started with analysing the problems. As a result of defining the task, experience and performance, one had to think through the problems logically and assess the problems' most important characteristics. This helped the researchers better understand and agree upon the nature of the problems.

First one had to define a task based on the given problem and formulate this as a task for the algorithm. One issue with the framework arose with Nabobil´s problem of "Predict the right car to rent" and "Pricing". Through independent coding the researchers ended up with different descriptions of the task. When discussing the reason for this, the researchers understood that the definition of the problems was too broad. An investigation into the user problems uncovered that there was more than one task for each of these problems. The problem had two actions the algorithm needed to do. For "Choosing the right car" it was 1) predicting what kind of car a renter is likely to rent, and 2) predicting the likelihood of a car owner accepting that request. This was not well defined in the framework, and it is suggested to improve the definition of a task to narrow it down to just one single action.

When the researchers defined the experience of a task, the common denominator was that experience equals the underlying data the algorithm will use. This is shown as examples in the existing theory, but not clearly defined. Based on the cases it is suggested to improve this definition by stating more clearly that experience is the underlying data of the problem. The performance was clearly described for each problem. The theoretical foundation for this step was clearly defined and stated by Mitchell (1997).

The complexity of a problem was difficult to define based on the given definition. For problems related to image recognition or text analysis, the decision was quite clear, as both images and text are defined as complex problems (Mitchell 2006). When Mitchell (2006) explains complexity, he uses specific examples from real world cases and not a specific definition. Mitchell (2006) argues that complex problems are difficult to write explicit rules for, but in practice the level of difficulty depends on the knowledge of the person who is evaluating the problem. One aspect of complexity which is defined, is the number of variables. This is not something you need programming experience to grasp. The problem with this definition, is that the theory does not state what number of variables which is needed for a problem to be considered complex. This part of the theory needs to be addressed in two ways: 1) By giving a better definition for a complex problem, and 2) Provide a theoretical justification for the required number of variables.

Accessibility to data did not in any of the cases prove to be a deciding point. The problem and task itself was still a machine learning problem even if the company did not have access to data. Data access is important to evaluate if the companies are considering implementing the algorithms, but this characteristic does not affect whether the problem is a machine learning problems or not. In the cases presented, when data availability was considered low, there was still an opportunity for the company to gather data in the future. The outcome was either they have access to data now, or they can have access to it in the future. This characteristic is not considered decisive, but can be of interest as a guiding variable in step 4.

According to Mitchell (2006), adaptability is important to assess if a problem is a machine learning problem or not. From the cases, the problems that were regarded as machine learning problems were both considered as complex and had the need to adapt. These characteristics must be evaluated together to help the product manager realize if the problem is machine learning or not. An example of this is the three problems: “Creating design brief”, “Manual matching processes”, “No matching. These problems required adaptability but were not considered complex. These problems were not considered machine learning problems. Adaptability by itself can’t be used as a decisive characteristic but needs to be considered together with complexity as the theory states. However, given the results from the cases, the researchers could not conclude if a problem that is considered complex but do not require adaptability is still a machine learning problem.

6.5 Step 4: Identify machine learning algorithm

6.5.1 Applying the framework

In the fourth step of the framework, the MLT questionnaire is applied on the user problems that were considered machine learning problems in step 3. For each company, the reasoning behind the evaluation of the problems will be explained.

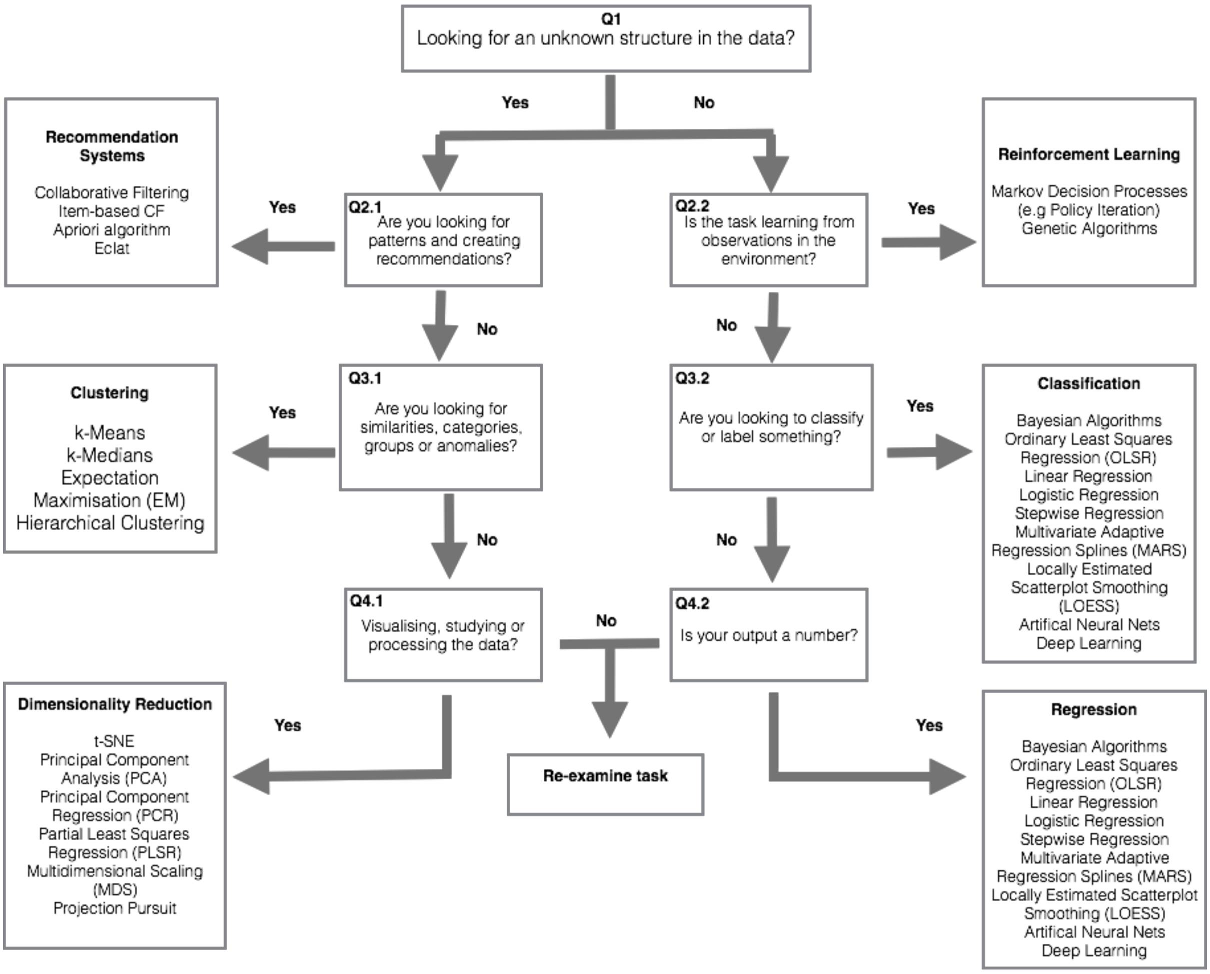

Figure 18: The MLT questionnaire.

Graphiq

User problem	Question 1	Question 2	Question 3	Question 4	ML algorithm type
Detecting negative conversations	No. The structure of the data itself is not interesting.	No. The data is based on history.	Yes. The task is to classify if a conversation is negative or positive.	N/A	Classification problem
Estimating price on projects	No, the structure is not the output, but the result of the structure which is the price.	No. The data is based on history.	No, the output is not a label.	Yes. The output is a price estimation, which is a number.	Regression problem

Table 12: The evaluation of Graphiq's machine learning problems

Both of Graphiq's two ML problems were easily guided through the framework. "Flagging negative conversations" was a classification problem, and "estimating price" on a project was a *regression problem*.

Tise

User problem	Question 1	Question 2	Question 3	Question 4	ML algorithm type
No personalised recommendations	Yes. The underlying structure of user likes is needed to be able to recommend new items.	Yes. We are looking for patterns and trying to make recommendations .	N/A	N/A	Recommendation systems
Finding new and interesting items	Yes. The structure of what makes items similar is what's investigated here.	No, it's not patterns t but similarity that's interesting here.	Yes. The similarity between images is what the task is after.	N/A	Clustering
Taking professional looking photos	No. The output here is not the structure itself.	No. The data is based on history, and it doesn't	Yes. The output should be a label if the image is	N/A	Classification

		need to react to the environment.	good or bad.		

Table 13: The evaluation of Tise's machine learning problems

By analysing "No Personal Recommendations" it is clear that the task is concerned about a known structure in the data between the unique type of user, and the type of content this user would prefer. The task is to recommend content on a personal basis so the appropriate machine learning algorithm type is *Recommendation Systems*. The next problem "Find new and interesting items" is a task focused on when a user looks at an item, make it possible for them to find similar items. As the user is looking at images, the task is to find similar images. The researchers went through the framework and found that this is a "looking for a structure in the data" task since as the objective is looking for similarity between images. *Clustering type* was the final result. The last problem which was "Taking professional looking photos" is a *classification problem*, as the task clearly states too label a photo as either good or bad.

Learnlink

None of Learnlink's problems were considered to be ML problems, so this step was irrelevant for them.

Nabobil

User problem	Question 1	Question 2	Question 3	Question 4	ML algorithm type
Choosing the right car #1 Likelihood of car owner accepting leasing request	No. The task is about calculating a likelihood.	No. Historical data is necessary here.	No. The output is not a label.	Yes. As the output is a percentage, the output is a number.	Regression
Choosing the right car #2 Suggest cars that the user is likely to rent	Yes. The interesting aspect here is the structure between users and cars.	Yes. The output is a recommendation based on patterns.	N/A	N/A	Recommendation Systems
Suggested Pricing	No. The task is about calculating a price.	No. The system can use historical data.	No. The output is not a label.	Yes. The output is a price, which is a number.	Regression

Dynamic Pricing	No. The task is about calculating a price.	No. The system can use historical data.	No. The output is not a label.	Yes. The output is a price, which is a number.	Regression
Fraud	Yes. Detecting fraud is about detecting differences in underlying data.	No. Recommendations was irrelevant here	Yes. Looking for fraud is looking for outliers, so groups are the output.	N/A	Clustering
Insurance	No. The underlying data is interesting, but the output is one level above, which is labels.	No. Historical data is needed here.	Yes. The output is a categorical label of a driver type.	N/A	Classification

Table 14: The evaluation of Nabobil's machine learning problems

One of Nabobil's problems, "Choosing the right car", had to be broken down into two new problems. The reason for this being that the problem description was too wide to construct a single task around. Since Nabobil's platform works the way that car owners can decline requests from users, this also adds to the equation. So, there's two factors to deal with: both that the renters have different preferences in a car, but also that car owners have preferences on who wants to rent it. Together this problem would not fit into the framework, but divided into two different tasks: "The likelihood of a car owner accepting a leasing request" (*Regression*) and "Suggest cars that the users is likely to request to rent" (*Recommendation Systems*) they went through the framework and ended in two different machine learning types.

Both pricing problems of Nabobil, ended up as *regression problems*. The task, experience and performance described in the previous step is similar except the added dynamic functionality of being able to react and set a price depended on the demand in the market. This makes sense as the demand in the market could be a feature into the model itself, so the two problems are solved similarly just by adding another feature.

The "Fraud" problem ended up as a *clustering problem* as this task is about looking at the data structure, to find potential outliers which does not match with existing user behaviour of the platform. Insurance is considered a classification problem because the task is to label users as bad or good drivers depending on data on their driver behaviours and the user themselves.

<u>Leieting</u>

User problem	Question 1	Question 2	Question 3	Question 4	ML algorithm type
Setting the price.	No. The task is about calculating a price.	No. The system can use historical data.	No. The output is not a label.	Yes. The output is a price, which is a number.	Regression

Table 15: The evaluation of Leieting's machine learning problems

The only ML problem for Leieting was suggested pricing, this is similar to the pricing problems of the previous platforms and ended up as a regression problem as the output is a number.

6.5.2 Evaluation of the step

In this step, the researchers were able to examine the usefulness of the different characteristics in the TEPCDA model from step 3. The task from the previous step proved to be essential for the questions asked in this framework. As the questions in the MLT questionnaire are formulated around outputs, this should also be reflected in step 3. More precisely, the task in the TEPCDA model should be phrased in such a way that the task includes a specific output.

The “Fraud” problem at Nabobil, revealed a weakness in step 4: Given the sets of questions in this part of the framework, this problem was categorised as a clustering type problem. In reality such a problem could also be a classification problem, given that Nabobil have access to existing labeled data on typical fraud activity. None of the questions in the MLT questionnaire revealed this, even though this is related to the experience and data access from step 3. The bridge between these steps should therefore be clearer by including questions about experience from step 3. By adding “Do you have access to labeled data” to Question 1, this issue would be solved. Question 1 already splits the six algorithm types into two types which on a higher level is a split between unlabeled data and labeled data. The original phrasing of question 1, “Looking for an unknown structure in the data”, somewhat implies this already as labeled data is a known structure in data and unlabeled is an unknown structure. However, clarity and definitions is important, and this will improve the framework.

If the MLT questionnaire is logically correct, all problem that was defined as a machine learning problem in the TEPCDA model, should be possible to categorize with the questionnaire. None of the cases had user problems that ended up in the “re-examine task”, when being processed through the MLT questionnaire. This could indicate that the MLT questionnaire correctly asks the necessary questions to categorize a machine learning type, as the tasks are correctly categorized based on the theory. No user problems turned out to be dimensionality reduction types or reinforcement problems. This is interesting as it could show that dimensionality reduction is not directly tied to user problems. By definition, dimensionality reduction is a way to analyse and pre-process data so this is a possibility. It is recommended to investigate this further, as the data is just indicating this. All the user problems that was asked Question 2.2, the reinforcement learning question, had the same answer which led to not choosing the reinforcement category: “No, historical data is necessary” or “No, historical data is accessible”. This is quite interesting, as based on theory reinforcement learning algorithms are not only for control problems (such as self-driving cars), but learning general approaches. This means that reinforcement learning could be used for prediction and classification, but theory states that specific classification and regression algorithms are preferred when there exists labeled data (Mitchell 2006). Question 2.2, should be phrased in such a way that it asks for access to labeled data or not. This characteristic is already described as either experience or data accessibility in the TEPCDA model. This also indicates that the characteristic of data accessibility is necessary even though it's not used in the TEPCDA model to verify if a problem is machine learning or not. With this included in the framework, a new topic arises which is the problem which occurs when you don't have data. Which is: Should a manager try to attain labeled data, or choose a reinforcement type algorithm. This is not something the researchers have covered in theory, and it is suggested that further improvements include theory in this step to help the platform manager asses the machine learning type.

When defining if a problem is a machine learning problem or not, performance is an essential step in this evaluation together with experience and task. However, while experience and task is directly used to assess what sort of algorithm type the problem is, the research shows that performance is not. This concludes that the performance of a machine learning task is not directly tied to what sort of algorithm type it is categorized as.

6.6 Revised framework

Based on the analysis of the empirical evidence it is argued that the proposed conceptual framework has been strengthened. The analysis and discussion uncovered some parts of the framework that could be improved, and a revised framework has been created to address these parts. The researchers argue that the first research question is answered through step 1-3 of the conceptual framework and the second research question is answered through step 4. The revised framework is now presented, where the changes has been highlighted.

6.6.1 Step 1: Define problems

Based on the evaluation of step 1, it is suggested that platform managers create a description of each user problems and explicitly states the benefit derived from solving this problem. The benefit of solving the problem is an important link between the first and second step, and should be defined from the beginning. This will also make it easier to categorize the user problem as either content value or context value.

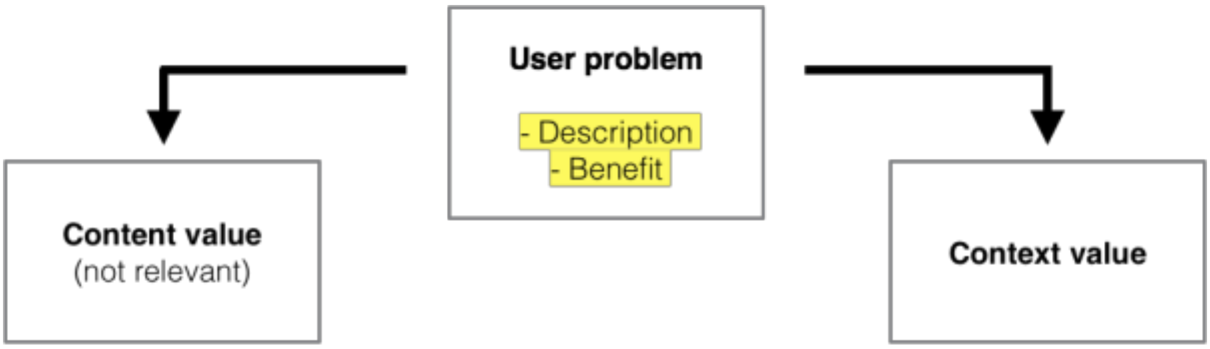

Figure 19: Step 1 in the revised framework

6.6.2 Step 2: Categorize context value

The analysis showed that the definitions *personalisation*, *reduced search cost*, *trust* and *streamlined processes* should be improved to make it easier for the platform managers to categorize each user problem. The revised framework highlights known keywords for each of the four categories to make this process more consistent.

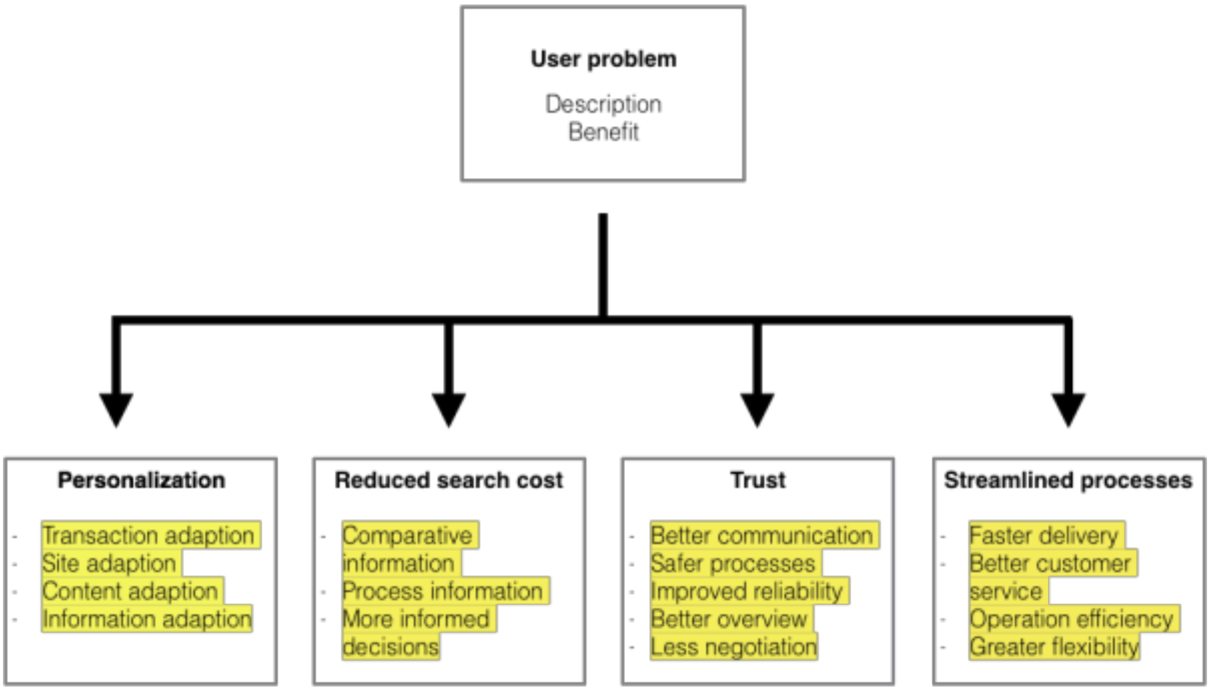

Figure 20: Step 2 in the revised framework. Associated keywords is added to each of the categories to make the categorization more consistent.

6.6.3 Step 3: Evaluate the problem

Since the reason of step 3 is to classify the problem as machine learning or not, and correctly formulating the necessary information for the MLT questionnaire in step 4, the researchers evaluate this step based on the results from both step 3 and 4. The definition of task is rephrased around an output to help the manager answering the questions in the MLT questionnaire, and experience is rephrased around what the underlying data is. As the analysis uncovered, complexity was difficult to assess for the researchers. However, no new data suggested how to improve this, and there is a lack of theory to fix this issue. This further mentioned in the theoretical implications presented in chapter 7.

Task	What single task is the algorithm trying to do, and what is its output? • This is from the algorithm's point of view, not the user or not the platform. Example: Transforming speech to text with speech recognition software.
Experience	What is the underlying data of the algorithm? • What kind of feedback loop is needed to train the algorithm? • How can the algorithm experience this data? Example: A database of texted speech.
Performance	How is the performance of the algorithm measured? • A metric that tells how good the algorithm currently is • Preferably a ratio

	Example: Percentage of transformed text similar to the speech indicate performance.
Complexity	How complex is the problem? • How many variables are involved? • How difficult is it to manually write an algorithm that solves the problem? Example: Words and sounds are very complex to write an algorithm to recognize. The amount of recognizable words and sounds is very high.
Data access	Is it relatively easy to access or collect unlabeled or labeled training data? Example: Texted speech as training data is widely available.
Adaptability	Does the problem require software that customise to its operational environment after it has been deployed? • Should it adapt to the user or a group of users? • Should it adapt to different geographical areas or cultures? • Should it change over time of the day, weekday or seasons? Example: To maximize performance, speech recognition software needs to be customise to the user who purchase the software.

Table 16: Step 3 in the revised framework. The two first questions of the TEPCDA model has been rephrased in the revised framework.

6.6.4 Step 4: Categorizing the machine learning problem

Two issues with the MLT questionnaire was revealed in the analysis: 1) Fraud detection ended up as clustering even though it could end up as classification with access to labeled data, and 2) Question 2.2 was not correctly phrased and did not correctly map the empirical data to the theory. By changing question one from “Looking for an unknown structure in the data” to “Are you looking for a relationship between objects” the question now reflects the categories in a much clearer way and correctly based on the underlying theory of machine learning. In the case of fraud detection, Q1 now reflects the characteristic of experience from the TEPCDA step in the following way: If the experience is based on existing data of fraud, the task of the algorithm would be to label new cases based on this data. This is *not* looking for a relationship between objects, and fraud detection would be correctly categorized as a classification type. In the case of question 2.2, the question was rephrased from “Is the task learning from observations in the environment?” to “Do you have access to labeled data?”. By changing it in this way, the question now correctly covers the problems were the problem types are labeling, categorization and number outputs, but there's no access to labeled data. Question 2.2 still includes the problems that was covered in the old question, when the task is to learn based on observations, because such problems don't have access to labeled data.

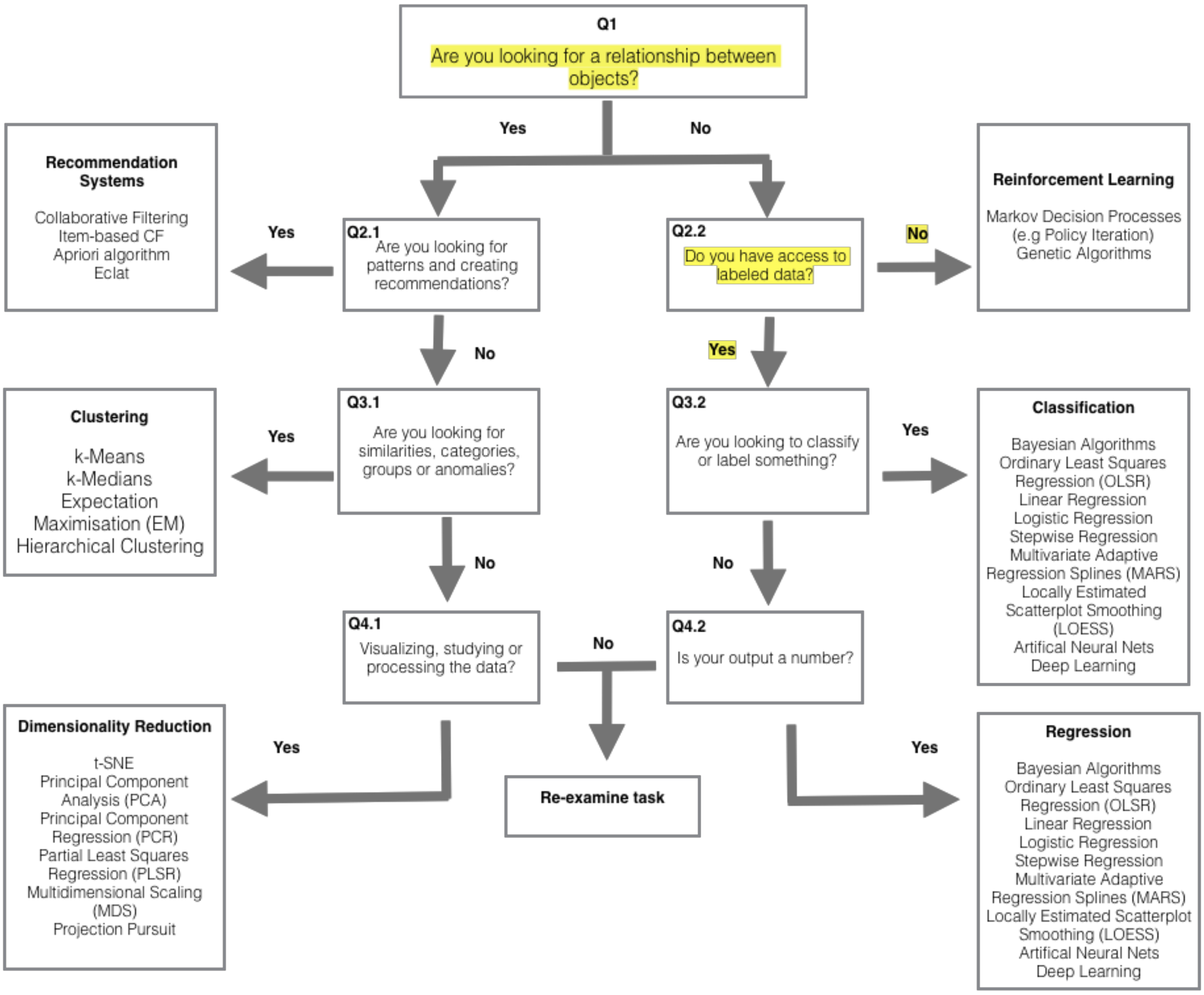

Figure 21: Step 4 in the revised framework. Changes are highlighted in yellow.

7. Conclusion

7.1 Introduction

The researchers have answered the research questions by developing, applying, evaluating and revising a conceptual framework. The framework allows managers of two-sided platforms startups to evaluate if the value proposition can be improved with machine learning, and determine the type of machine learning algorithms that could be applied. The framework can be summed up in these four steps: 1) Define user problems. 2) Categorize context value. 3) Evaluate problems. 4) Categorize the machine learning type. The framework was tested empirically on five Norwegian two-sided platforms startups: Graphiq, Tise, Learnlink, Nabobil and Leieting. The purpose was to help platform managers improve the value proposition to increase the use of the platform. This chapter will first discuss the practical implications, contribution and theoretical implications. Then it will suggest further research, and in the end, assess the limitations of the study.

7.2 Practical Implications

Managers of two-sided platform startups need to understand that machine learning is a tool that can be useful under certain conditions. For example, when the two-sided platform startups proceed into the scaling phase, machine learning can help them improve the value proposition in a scalable matter. This study shows that there are certain situations where ML is applicable: 1) When the problem is explicitly stated, but too complex to code and there's access to large amounts of data. 2) Especially managers of two-sided platform startups, who are limited in time and resources, and struggling to satisfy their growing user base, should consider if machine learning offers benefits for their platform. The revised framework offers a way of evaluating this.

7.3 Theoretical Implications

The paper also contributes to bridge the gap in literature in the relationship between machine learning, value proposition and two-sided platforms. Existing theory covering these topics together is limited. The revised framework contributes with a more detailed definition that builds upon the original work of Sandulli (2014). However, the researchers acknowledge that this contribution is only a small step in gaining a better understanding of how to improve the value proposition of two-sided platform startups. This is still considered a research area that should receive more attention.

This study show that Mitchell's (1997; 2006) definition of a machine learning problem which forms the basis of the TEPCDA model, works as a tool to evaluate if a problem is machine learning or not. The current theory about machine learning states that adaptability and complexity is solo-decisive factors in determining a machine learning problem (Mitchell 2006). The analysis show that adaptability is not a decisive factor alone for evaluating the machine learning problem, as a problem also needed to be complex to be considered a ML problem. While experience and task is proven to directly be used in the assessment of what sort of algorithm type the problem is, the research shows that performance is not.

7.4 Contribution

The paper proposes a conceptual framework that can help platform managers quickly assess the potential of using machine learning to improve the value proposition. This framework can prove valuable to platform managers for three reasons. First, the framework makes it easy to assess the most important problems to solve. Second, it enables the platform managers to understand if the problems are solvable with machine learning. Third, the framework gives the platform managers a recommendation for what type of machine learning algorithm they should use to solve the problem. All this is practical for managers of two-sided platforms startups as it can save them a lot of valuable time and energy when trying to satisfy a growing user base. This in turn can help two-sided platform startups win more users than their competitors so that they capture market shares and generate future profit.

7.5 Further Research

The applicability of the framework is limited by the context of this study. Therefore, the framework should also be tested in other contexts across platform phases and geographical markets. In particular, it would be interesting to test the framework on platforms in later growth phases that have implemented machine learning. In this way, the framework can be improved from examples of real use.

The framework should also be applied by platform managers. In this research, the platform managers were interviewed to access the information. To further develop the framework, the next step would be to allow the platform managers to apply the framework on their own two-sided platforms. In this way, the framework could be tested in the setting it was developed for.

In the revised framework, a platform manager facing problems that needs either a regression or a classification algorithm, can choose a reinforcement learning algorithm instead if no data is available. This choice is of strategic nature because it concerns different business strategy elements. This opens up for further research into when a platform manager should focus on gathering data or using reinforcement learning algorithms to improve the value proposition.

During the analysis, there was an indication towards dimensionality reduction problems having no link to improving the value proposition in two-sided platforms, as none of the cases had problems that were categorized as this sort of algorithm type. Deeper investigation into this link is therefore suggested.

7.6 Limitations

The conceptual framework is based upon existing literature. As it is limited by the literature uncovered in the literature review, there may be relevant and important literature the researchers didn't uncover.

As one of the researchers also is part of the team in Graphiq, one of the case companies being studied, his views might be biased by his knowledge about the company as an employee. This was countered by letting the two other researchers conduct the interviews and do the independent coding. The inside knowledge has on the other hand given valuable insights into the case company and likely strengthened the evaluation of the case.

As the amount of cases was five, it was not possible to cover all the combinations of phases and transaction types of two-sided platforms. Therefore, four of the nine possible combinations were not represented in the case study. To minimize the effect of this, the researchers have carefully explained the method and research approach. It is easy to think that the applicability of the revised framework should be limited by the context of the companies that was studied, but one should remember that case-studies are primarily meant to contribute with contextual insights. To maximize this contribution, the case companies was purposively sampled within the given context.

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9. Appendices

Appendix 1) Analysis of machine learning problems

Graphiq

User problem - Creating a design brief

Creating a design brief is today a conversation between two people. More specifically, between a Graphic project leader and a customer. The brief is written into a personalized brief-template. The purpose is to define the customers need in order to give a price estimate, find the right designer and make sure that the projects is delivered as specified. Often the success of a project depends on a well written design brief.

The problem is assisting the creation of a brief, which is not a machine learning problem, because it is a process that includes many smaller problems related to information flow. However, some of the smaller problems can be split into the a problem that can be solved with a chatbot, which is not machine learning but AI. In conclusion: It can be AI (chatbot) problem, not an ML problem.

User problem - Flagging negative conversations

When projects are running on Graphiq, project leaders at Graphiq pull out and leave the conversation between the designer and the client. In case of problems between the parties, Graphiq needs to be able to detect this to help and solve issues. This could be to replace the designer or see if there are any miscommunications.

Problem:	Flag negative conversations
Task	Detect if a conversation between a customer and a designer is hostile?
Experience	A dataset of positive and negative conversations.
Performance	Percentage of correctly labeled conversations out of the testing set.
Complexity	Complex, its text analysis.
Training data accessibility	No labeled data in-house, but there exists text data sets to train a general semantic model. Or label data manualy.
Adaptability	Conversations can mix up, so it needs to be adaptable to all situations.

Conclusion: A ML problem.

User problem - Manual matching processes

The matching process is slow today because matching is done manually. As described by Graphiq, the process in itself is based on two types of matches, one quantitative which is on the qualifications of the designer and experience, and the other is personality. The first one can be solved without machine learning, as it's a given set of rules and not a complex not known structure. But with the match on personality, it's too far off to be considered since there's a lack of data on the personality of the client and designer today.

Problem:	Manual matching processes
Task	Recommending the two best designers for the customer
Experience	Graphiqs database of designers and the projects and customers they have worked with.
Performance	Percentage of recommended (Training data / evaluation data)
Complexity	There is some variables that can be included in the algorithm, like style, industry, expertise. This can be solved using set rules.
Training data accessibility	It is not enough proper data about designers and customers to be able to train a model to match, based on personality.
Adaptability	It's a set of given rules, and needs no adaptability.

Conclusion: The matching problem is not complex and therefore not a machine learning problem.

User problem - Estimating price on projects

Graphiq project leaders spend a considerable amount of time estimating price on projects. Today they have to use the information from the design brief, the hourly salary of designer and a intuitive feeling, based on experience to estimate the price. Graphic wants to save time by automating this process through a new feature, instead of manually doing this today.

Problem:	Estimating price on projects
Task	Predict price of a project based on the design brief.
Experience	A database of projects with a design brief, the price, hourly rate, completion time and other relevant data.
Performance	Error rate in the prediction and actual price in the testing data set.
Complexity	Its text analysis and therefore complex.
Training data accessibility	The data that is needed is the design briefs, the designers and the customers. Today there is not much training data, and a collection plan is needed.
Adaptability	The potential algorithm needs to be adapted to each customers and each designer.

Conclusion: The problem is a machine learning problem.

Tise

No Personalised Recommendations

To use the home function properly the user have to manually find other users with similar styles. Finding the right users to follow takes time and can be a hassle for the user. Filtering out the what is interesting and not is a big task, and poses as a challenge for the users today.

Problem:	Recommend content based on similar content and users the user has liked
Task	Based on adds the user likes, find other adds the user will possibly like.
Experience	Dataset of users and their likes.
Performance	% of correctly predicted likes of a user on ads. From a testing data set.
Complexity	Complex problem as images is a large part of the ad.
Training data accessibility	Tise has access to over 700.000 ads, millions of likes, and 200.000 users.
Adaptability	It needs to adapt to new hashtags, images and features introduced.

Conclusion: A ML problem

User problem - Finding new and interesting items

The act of exploring is integral to the user experience. According to Eirik Rime, CEO of Tise, users come to Tise when they want to find something new. The user doesn´t necessarily know the exact search phrase or the keywords for the category of items they are looking for. Tise want to improve the experience of exploring new objects by enabling the user to perform a visual search in photos.

Problem:	Finding new and interesting items
Task	Based on an ad find similar ads.
Experience	Dataset on the adds, with images
Performance	Human level evaluation and inspection of clusters.
Complexity	Very complex, images is a big part of the task and images are complex to create rulesets on.
Training data accessibility	Dataset of ads, with linked images, text and hashtags.
Adaptability	Yes. New images are added all the time by users, and the algorithm needs to work for the new ones as well.

Conclusion: A machine learning problem.

User problem - Taking a professional looking photos

Tise strongly encourages the users to take great pictures and make a good looking post. Data shows a clear correlation between with professional pictures and sell-rate. Currently they have blog posts that guide users with creating posts. According to the CEO, digital solutions for assisting the seller in taking professional looking photos is interesting.

Problem:	**Taking a professional looking photos**
Task	Label if a photo taken is of low, medium or high quality
Experience	A dataset of labeled data, where ads with a high number of views and a high number of likes is labeled as high quality, an ad with also a high number of views but with a low number of likes is labeled as low quality.
Performance	% rate of correctly labeled photos based on a testing data set.
Complexity	Yes. It is very hard for anyone to manually code the specific rules for why a photo seems professional, energetic or chic.
Training data accessibility	Tise has over 700.000 ads with images, and several million likes.
Adaptability	It has to be work on every image and ad uploaded.

Conclusion: The problem is solvable with machine learning.

LearnLink

User problem - Manual matching process

The task of matching based on personality is very difficult. It´s too complex to code, because the knowledge that is needed to match personalities and chemistry is very qualitative and human. However, simpler matching algorithms, not including personality and chemistry, is possible. Conclusion: The problem is not a machine learning problem if personality and chemistry is included.

User problem - Lack of progress overview

The problem is related to lack of information about the progress to each student. Before a overview of the progress is possible, much information about this progress needs to be gathered. This can be possible if results from homework and the smaller test can be extracted in a online learning tool. Therefore this is an information problem, and not a machine learning problem.

User problem - Predicting grades

For the problem of predicting grades of the student, the same is true. More information is needed before it is possible to predict anything.

Nabobil

User problem - Choosing the right car

Nabobil users spend a lot of time finding the car they want to rent. They scroll up and down pages to find the perfect car for their trip. It is likely that users back out in this part of the search because they don't find what they are looking for fast enough. At the same time, research shows that data about user profiles, search filters and available cars, can reveal what cars that will be rented up to 90 % of the time. Guiding users to the car they are more likely to rent reduces the search cost of the users dramatically and hence improve the value proposition. The other part of this problem is that the renting only succeed if the car owner also wants to rent out to the user. Therefore a part of this equations is the owner's preferences. We split this user problem into two different tasks: 1) Predicting the likelihood of a car owner accepting a specific renting request. 2) Predicting what kind of car the user is after.

Problem:	**Choosing the right car #1**
Task	Predicting the likelihood of a car owner accepting a specific renting request
Experience	The algorithm can be trained on data from renting activity. This includes user profiles, their search filter and the cars they end up renting.
Performance	The percentage of rented cars the algorithm predict, based on a training data set.
Complexity	Car owners preferences vary, and the type of renting and the users behind every request can differ a lot. No two tenancies are identical, since there are unique human interaction that influences the car owner's acceptance decision.
Training data accessibility	Nabobil has access to a large amount of renting activity.
Adaptability	To maximize performance, the algorithm has to adapt to new type of users and their preferences.

Problem:	**Choosing the right car #2**
Task	Based on the user and the user's query, suggest cars that the user is likely to rent.
Experience	Historical data on users profiles, their queries and cars they rented.
Performance	Percentage of correctly suggested cars, tested on a training set.
Complexity	A human's preferences are unique, and complex.
Training data accessibility	Nabobil has access to a large amount of features on their users, and their renting history.
Adaptability	It has to adopt and be customized to every new user who uses Nabobil.

In summary, the “Choosing the right car” problem fulfil is broken into two different problems/tasks that are Machine Learning problems.

User problem - Suggested pricing

Car owners using Nabobil for the first time might have trouble setting the right price for their car. It can be difficulty to access the market price of the car, a user can look through similar cars by searching by brands, but this is time consuming and prone to error. With no prior experience in pricing cars, users often have to try it out and guess. In this case, a suggested price feature could improve the user value of Nabobil. It is also probable that helping car owners pricing their car right will increase the overall rental activity.

Problem:	Suggested pricing
Task	Predict the optimal renting price of a car.
Experience	The algorithm can be trained on datasets from Nabobil, where the sets are of car ads with its features and the prices they have been rented for.
Performance	The error rate of the suggested price, tested on a testing data set.
Complexity	The total amount of factors at play in the car rental price calculation is too much for a normal code. Typical factors important to the price is location, seasonality and unique features of a car, this often also includes images which are complex. These factors interact in complex ways and it is hard to code the opinion of the average car-renter.
Training data accessibility	Nabobil has access to a large amount historical data on tenancies, the car add and the amount they have been rented out for.
Adaptability	To maximize performance, the algorithm has to be able to deal with new combinations pictures uploaded on different types of cars.

In summary, after running the "suggested pricing" through the framework, it holds true that it is a machine learning problem.

User problem - Dynamic pricing

The easter holiday of 2017 faced Nabobil users with a big problem: there were not enough cars left to rent. Many of these users were first-time users, expensively acquired through facebook or google ads. Their bad experience decreased their trust to the platform. The problem was that the car-owners did not price the cars high enough, considering the high demand. The right rental-price for holidays like this is hard to predict and spending time trying to get the price right is a hassle for the car owners. Therefore a function that could help the car owners pricing their cars accordingly to the market would improve the user value a lot. This feature is similar to suggested pricing, just with the change of suggested price in time, in response to the market demand.

Problem:	Nabobil Dynamic pricing
Task	
Experience	The algorithm can be trained on live datasets from the marketplace with what other cars are successfully

	being rented out for. Image and text analysis is used to compare the attributes of a car with other cars, and build a model of how attributes affect the price. After launch the algorithm will be trained by the price users end up paying for cars in different seasons and locations.
Performance	How much more income is the car able to generate for the owner?
Complexity	The total amount of factors at play in the car rental price calculation is too much for a normal code. Typical factors important to the price is location, seasonality and unique features of a car. These factors interact in complex ways and are a well suited problem to be solved with machine learning models. It is hard to write an algorithm that reflect the opinion of the average car-renter.
Training data accessibility	The models need large sets of training data. However, much of this data is gathered by Nabobil today and it is easy to access labeled training data from tenancies in the platform.
Adaptability	The demand for a car in a specific location at a specific time will change depending on the environment. Factors like time of the day, day in the week and season may affect the demand in surprising ways. Different locations also have different demand for different cars. As an example, if you're in the mountains in the winter, the demand for your four-wheel drive car will probably be higher, but how high? These external factors are hard to predict, and very difficult to write an algorithm for. They also change over time.

In summary, after running the “dynamic pricing” through the framework, it holds true that it is a machine learning problem.

<u>User problem - Fraud detection</u>

To illustrate the problem of fraud detection, a real story about a friend of the researchers is presented. For the purpose of this text, his name is Peter. About a year ago, Peter found what he though was the perfect apartment to rent at Airbnb in Amsterdam. It had nice interior, big rooms, a great location and it was cheap. Peter was a first time user of Airbnb and was asked to pay the owner through email. As Peter didn't was not familiar with the platform, he paid the owner through mail and never heard anything more from the owner. He was scammed.

In the above example, machine learning can be used to detect fraudulent listings by detecting patterns in the data. If one apartment is much better than competing listings, based on size, location and price, has no reviews and want contact by mail one should be suspicious. As Nabobil is similar to Airbnb, just for cars, it is likely that similar fraud can happen at Nabobil.

Problem:	**Fraud detection at Nabobil**
Task	Flag a user / post as suspicious (possibly fraudulent)
Experience	The algorithm can be trained through data from booking activity and listing specifications. It can learn how normal bookings should look like compared to fraud.
Performance	The percentage of anomalies correctly flagged compared to the assessment of human curators.
Complexity	The data sets contains many variables. Some of the variables are much more important than others, and this can be unknown. Nabobil does not have data on frauds, so it's very difficult to write out a ruleset describing what a fraudulent post is. It can be revealed through pattern recognition and clustering.
Training data accessibility	Labeled training data from tenancies is gathered by Nabobil today and it is easy to access in the platform.
Adaptability	Fraudulent behavior change over time and location. Normal behavior also change.

Conclusion: ML Problem.

User problem - Insurance

Nabobil is paying a standard insurance contract for all of its user, not customized to its users and their driving behaviour. Since they don't know the different

Problem:	**Insurance**
Task	Categorize any user profile into specific risk profiles
Experience	The algorithm can be trained on a labeled data set based on the user profile data paired with reported incidents. In the future, more and more data concerning driving behavior can be accessed through the car.
Performance	How well the categorizing of risky drivers match with the amount of drivers with incidents.
Complexity	The underlying combination of variables that reveal risky drivers might be complex.
Training data accessibility	As of now Nabobil does not have enough data about incidents to be able to categorize drivers in a meaningful way. They also lack data connected to driving behavior of drivers. However, this data might be accessible in the future.
Adaptability	Risk profiles may vary depending on location. E.g. An inexperienced teenager might be scored as a high risk profile in the city due to high risk traffic, but a medium risk in a small village due to lower risk traffic.

In summary, personalized insurance is a machine learning problem. But it is not solvable today considering the data currently available.

Leieting

User problem - Updating the availability

The problem related to availability is a problem related to making people spend some time to update their calendar, not a problem that a code can solve. Updating the availability of the personal items is a hassle for the users. The cost of updating the calendar exceeds the total value it creates.

User problem - Setting the price

Very similar to Nabobil´s suggested pricing.

Problem:	**Setting the price of new items on the platform**
Task	Calculating the optimal renting price of new items on the platform .
Experience	The algorithm can be trained on datasets from Leieting. Image and text analysis can be used to compare how the attributes of items affect the price. A model of how attributes affect the price can be built.
Performance	Error rate on predictions based on a training set and a testing set.
Complexity	The total amount of factors at play in the rental price calculation is too much for a normal code. Typical factors important to the price is location, seasonality and unique features of an item. These factors interact in complex ways and it is hard to code the opinion of the average renter.
Training data	The models need large sets of training data. However, much of this data is gathered by Leieting today and

accessibility	it is easy to access labeled training data from tenancies in the platform.
Adaptability	The demand for an item may be very different from location to location.. As an example, the demand for a canoe will probably be higher in areas close to nature than in cities. These external factors are hard to predict, and very difficult to write an algorithm for.

Conclusion: ML Problem

Appendix 2) Case study protocol

Roles of interviewers: One interviewer is responsible for note taking, the second interviewer is responsible for audio recording (which is clarified in advance of the recording) and the third interviewer is asking the questions. All interviewers can participate in asking questions to ensure a more dimensional conversation.

Introduction

- The interviewers present themselves, the purpose of the study and the structure of the interview.
    - Personal background
        - Writing master thesis at the NTNU School of Entrepreneurship.
        - Entrepreneurs with our own startups
            - Graphiq
            - Austronaut
            - Pracademy
    - Purpose of the study
        - Personal motivation from running our own two sided platforms, and a personal interest in the field of machine learning.
        - Research questions: *How can managers of two-sided platform startups...*
            - 1) Evaluate if the value proposition can be improved with machine learning?
            - 2) Determine the type of machine learning algorithms that could be applied?
    - Structure of the interview:
        - The role of the interviewers
        - Background questions on the platform and interviewee will be asked first, then dive into the user values the platform provides and how they deliver these values, and lastly ask about technical resources and data management.
    - Tell us about yourself:
        - Background, education, experience and role at the company?
    - Tell us about the company you work in
        - History, the platform in general, the business model, the users of the platform.

Categorize and prioritize user value and evaluate the problems
Can you tell us about the user value your platform delivers to the first user group?

- *Follow up on the individual user values and explain personalisation, reduced search cost, trust and streamlined processes and ask:*
    - This sounds like x (from above), do you agree?
- *The following questions should be asked if it hasn't been addressed in the interviewees answer*
    - What´s the process of delivering this value?
    - What is the problem/task you are solving for the user?

    - How important is this user value for the users?
    - What is the challenges with delivering this value?
    - How do you deliver this value?
    - Is it possible to solve this manually, or easy?
    - What are the most important factors to deliver this in a good way?

Can you tell us about the user value your platform delivers to the second group?

- *Follow up on the individual user values and explain personalisation, reduced search cost, trust and streamlined processes and ask:*
    - This sounds like x (from above), do you agree?
- *The following questions should be asked if it hasn't been addressed in the interviewees answer*
    - What´s the process of delivering this value?
    - What is the problem/task you are solving for the user?
    - How important is this user value for the users?
    - What is the challenges with delivering this value?
    - How do you deliver this value?
    - Is it possible to solve this manually, or easy?
    - What are the most important factors to deliver this in a good way?

Can you tell us about user value you would like your platform to deliver in the future?

- *The following questions should be asked if it hasn't been addressed in the interviewees answer*
    - How would the process for delivering this value look like?
    - How important is this value for your users?
    - What´s the process of delivering this value?
    - What is the problem/task you are solving for the user?
    - How important is this user value for the users?
    - What is the challenges with delivering this value?
    - How do you deliver this value?
    - Is it possible to solve this manually, or easy?
    - What are the most important factors to deliver this in a good way?
- *Follow up on the individual user values and explain personalisation, reduced search cost, trust and streamlined processes and ask:*
    - This sounds like x (from above), do you agree?

Can you rank the five most important user values your platform delivers to your users today?

Examine pre-requisites and map out opportunities

What technical capabilities exists in your company today and do you plan to expand on these?

- Employees technical experience

Are you storing data today, if so how and what?

- *The following questions should be asked if it hasn't been addressed in the interviewees answer*
    - How much of this data do you currently have?
    - How much of this data will you have in two years?
    - What's the most important data?

Do you already use machine learning, or are you planning to implement it?