Building Selleri

A Lean Startup Development project using Machine Learning technology

Bachelor's Thesis in Industrial Engineering & Management, Software Engineering and Computer Science & Engineering.

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Preface

This Bachelor's thesis was written during the spring of 2016 at the Department of Technology Management and Economics Organisation at Chalmers University of Technology.

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Sammanfattning

Syftet med detta projekt var att söka efter en repeterbar, skalbar och hållbar affärsmodell baserad på maskininlärning, genom att tillämpa Lean Startup-metodik. Det teoretiska ramverket för projektet byggde på tre områden av litteratur. Det första området var Lean Startup-metodik som består utav affärsmodellering, kundutveckling och agil utveckling. Det andra området var maskininlärning, och det tredje området var hållbar utveckling. Metoden för detta projekt baserades på entreprenörsskap och tillämpning av Lean Startup-metodik. Resultatet från att tillämpa dessa metoder var en validering av problemlösning för det valda kundsegmentet, samt intresse och preferens för värdeerbjudandet. En produkt baserad på maskininlärning byggdes och kan hittas på http://selleri.io/. Denna produkt hjälpte säljare på andrahandsmarknaden som ville sälja Macbooks, genom att erbjuda dem insikter och rekommendationer om försäljningspriset via en webbapplikation. I slutändan av projektet var en pivot förslagen från att rikta oss från konsumenter till företag. Detta skulle erbjuda produkten som en tjänst till digitala marknadsplatser för elektronisk utrustning, snarare än till konsumenten.

Nyckelord: Lean Startup, Maskininlärning, Affärsmodell, Kundutveckling, Agile Utveckling, Nyföretagande, Scrum, Build Measure Learn, Minimum Viable Product, Hållbar Utveckling.

Abstract

The purpose of this project was to search for a repeatable, scalable, and sustainable business model, based on machine learning technology, by applying the Lean Startup Methodology. The theoretical framework of the project was based three domains of literature. First, the Lean Startup Methodology, including Business Model Design, the Customer Development Process and Agile Engineering. Second, Machine Learning. Third, Sustainable development. The methods of this project concerned the topics of Venture Creation and applying the Lean Startup Methodology. The result of applying these methods was a validation of problem-solution fit for the Customer Segment, as well as interest and preference for the Value Proposition. A functional Minimum Viable Product, based on Machine Learning, was built and can be found at http://selleri.io/. The product helped sellers on the second hand market who wanted to sell their Macbooks, by offering them insights and recommendations about the selling price through a web application. However, in the end, a pivot was proposed from a business to consumer model, to a business to business model. This would offer the Product, as software as a service, to online marketplaces of electronic devices rather than the consumer.

Keywords: Lean Startup, Machine Learning, Business Model, Customer Development Process, Agile Engineering, Venture Creation, Scrum, Build Measure Learn, Minimum Viable Product, Sustainability.

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Vocabulary

Agile Engineering A software development process to develop a product or service incrementally and iteratively.

Algorithm A step-by-step instruction to perform a task that has a beginning and an end

API An Application Programming Interface can be viewed as a set of tools for building software applications. It provides building blocks that a programmer can use to help software applications communicate.

Artificial Intelligence Software that exhibits intelligent behaviour, perceiving its environment and taking actions to maximise its chances of success within a set context.

B2B Business-to-business; refers to a situation where a business makes transaction with another

B2C Business-to-customer; refers to a situation where a business makes a transaction with a consumer who is the end-user

Backend The behind the scenes of a system that involves the server-side logic. Also known as back-end or back end.

Binary tree A tree where each node has a maximum of two child nodes

Bootstrap Sample A random sample with replacement

Build-Measure-Learn A framework to minimise time and maximise learning by building a minimum viable product (MVP), measuring customer data, and capturing learning for the next iteration of the cycle. The framework is a part of the Lean Startup methodology.

Business Model Canvas A strategic management tool to describe the nine essential building blocks of a business model.

Business Model Design Applying the Business Model Canvas to create a common language for communication around the business model. Developed by Alexander Osterwalder.

Customer An individual or business that purchases the goods or services produced by a business

Customer Development Process A process of applying the scientific approach to startups and entrepreneurial ventures by systematically testing business model hypotheses. Developed by Steve Blank.

Customer Segment A division of customers by their patterns in their behaviour or demography.

End-user The person who actually uses the product. Does not necessarily have to be the customer

Ecologic sustainability The dimension of sustainability that concerns the net effect on nature and the environment.

Economic sustainability The dimension of sustainability that concerns the growth of capital and value.

Euclidean distance The line segment connecting the points p and q.

Extreme Programming An Agile Engineering framework with defined tasks such as coding, testing, listening, and designing

Feature An individual measurable property of a phenomenon being observed

Feature vector An n-dimensional vector of numerical representations of features

Frontend An interface on the client-side to separate the user of a system from the backend logic of the system. Also known as front-end or front end.

Hyperparameter Is a free parameter of a machine learning model

Hypothesis A proposed explanation for a phenomenon that can be validated or invalidated through experimentation.

Invalidation A failure to produce a confirmation that a hypothesis is correct

Iteration An incremental change of a business model hypothesis.

Kanban An Agile Engineering framework with no defined roles, where visualising the work flow

Lean Startup A method inspired by Lean Manufacturing by Toyota applied to Startups to minimise risk and maximise learning. It can be viewed as the product of Customer Development, Business Model Design and Agile Engineering. Developed by Eric Ries.

Learning Card A card summarising what we wanted to test, the result of the test, what we learnt (Osterwalder et al., 2014)

Likelihood function Is a function of parameters used to describe how probable an observed set of data is for different parameters.

Machine Learning A sub-field of artificial intelligence focusing on algorithms that infers information about properties of data which allows it to make predictions about future data.

Manhattan distance The distance between two points in n-dimensional grid based only on a strictly vertical and/or horizontal path

MVP A Minimum Viable Product is the minimum set of functional features required to complete an iteration of the build-measure-learn cycle in the Lean Startup methodology.

Natural Language Processing (NLP) A field of artificial intelligence concerned with the interactions between computers and human (natural) languages.

Nonparametric model A machine learning model that cannot be characterised by set of bounded parameters with fixed size

NP-complete A problem that can be transformed to any other NP complete problem in polynomial time but that can not be solved in polynomial time (If $P \neq NP$)

Overfitting When a machine learning model is trained to the extend that it describes noise instead of an underlying relationship

Parametric model A machine learning model that summarises data with a set of parameters with fixed size

Pivot A substantial change of a business model hypothesis.

Posterior probability The conditional probability of a random event after relevant evidence is taken into account

Prediction The output from a machine learning algorithm

Prior probability The probability of a random event before relevant evidence is taken into account

Profit The difference between revenue and cost of a product or a set of operations.

REST API A Representational State Transfer API is an architecture that allows resources in a software application to be uniquely addressable and manageable.

Scrum An agile engineering methodology to manage product development in an incremental, iterative way.

Social sustainability The dimension of sustainability that concerns the wellbeing and support of human cultures and communities

Space complexity The amount of memory, at the worst case, needed to run an algorithm

Sprint The basic unit of iterative development in scrum. It is an effort by the team that is restricted to a specific duration.

Supervised learning A class of machine learning methods where input data is a coupled with the correct output

Target value The desired output for a specific input to a machine learning algorithm

Test Card A card summarising what to test, how to measure, and what a good result is. (Osterwalder et al., 2014)

Time complexity The amount of time, at the worst case, needed to run an algorithm, often denoted with Big-O notation

Tree A hierarchical data structure with a root value and subtrees of children with parent nodes.

Underfitting When the machine learning model performs poorly on the training data

Unsupervised learning A class of machine learning methods where input data are not coupled with the correct output

Validation A confirmation that a hypothesis is correct.

Value Proposition A description of the benefits a customer can expect for using a product or a service.

Velocity Here, velocity is a measurement of the amount of work done each sprint

Mathematical Notation

This thesis contains theoretical concepts of machine learning and hence a certain amount of mathematics from calculus, linear algebra and probability theory. This section gives a short overview of the mathematical notation used.

$\mathbf{x}$: Bold lowercase letters denotes column vectors. For example $\mathbf{x} = (x_1, ..., x_n)$ denotes a column vector with n elements.

$\mathbf{x}^T$: T denotes the transpose of a column vector. For example $\mathbf{x}^T = (x_1, ..., x_n)^T$ denotes a row vector with n elements.

$\mathbf{X}$: Bold uppercase letters denotes matrices.

$\mathbf{X}^{-1}$: -1 denotes the inverse of the matrix $\mathbf{X}$.

$x \in A$: Denotes that the variable x belongs to the set A

$\mathbb{R}^n$: Denotes the real coordinate space in n dimensions.

$f : \mathbb{R}^x \rightarrow \mathbb{R}$: Denotes a function from $\mathbb{R}^x$ to $\mathbb{R}$

$x \sim \mathcal{N}(\mu, \sigma^2)$: Denotes that the random variable x is Gaussian i.e normally distributed with mean μ and variance σ^2

$\mathbf{I}$: Denotes an identity matrix.

$\mathbf{0}$: Denotes a zero matrix.

$\mathbf{f}(\mathbf{x}) = \mathbf{O}(\mathbf{g}(\mathbf{x}))$: Denotes that $|g(x)/f(x)|$ is bounded when $x \rightarrow \infty$, i.e, if $f(x) = 5x^3 + 4x + 2$ then $f(x) = O(x^3)$.

$||\mathbf{x} - \mathbf{y}||$: Denotes the Eucledian distance between the vectors $\mathbf{x}$ and $\mathbf{y}$.

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1
Introduction

In this chapter, an introduction to the thesis is presented by a background, purpose and problem statement, as well as the constraints of the project and a pre-study.

1.1 Background

There has been a lot of research regarding successful startup companies during the past years and how the initial phases of a business creation affect the grade of success in the latter stages. One theory which is a result of this research is the *Lean Startup*, where the Customer Development Process is a central part. Furthermore, Business Model Design and Agile Engineering are included in the Lean Startup Methodology along with the Customer Development Process. The Business Model Canvas is used to describe the business model and Customer Development Process is used to validate the hypotheses of the business model. Meanwhile, the product or service is developed iteratively and incrementally using Agile Engineering. Although Sweden has proven to be an eminent country within the startup world, with companies such as *Spotify* and *Klarna*, there is still potential to create a better climate where more people, especially university students, have early exposure to the right tools, theories, and methodologies in order to create more successful startups. This project is an attempt to, as university students, insert ourselves into the startup ecosystem and apply the Lean Startup Methodology to build a business and share our experiences with the reader.

1.2 Purpose

The purpose of this project is to search for a repeatable, scalable, and sustainable business model, based on machine learning technology, by applying the Lean Startup Methodology.

1.3 Problem statement

The ideal outcome of this project is a repeatable, scalable, and sustainable business model. This business model is based on machine learning technology. However, to achieve this, hypotheses about a customer segment and the remaining parts of the business model must be defined and validated. It is possible to break down this problem into simpler sub-problems.

- How can Business Model Design be used in the Lean Startup process?
- How can the Business Model Canvas and Value Proposition Canvas be used as a scorecard to validate or invalidate hypotheses following the Customer Development Process?
- How can a value proposition be built, using machine learning technology, iteratively and incrementally through Agile Engineering?
- How can the business model be sustainable from an ecological, economical and/or social perspective when it is deployed?

1.4 Constraints

The project will not result in a complete product or business model at the end of the project. As mentioned above, our goal is to develop a business model through an iterative process. Depending on the number of iterations we manage to do, the product and business model will be more or less complete at the end of the project. The time constraint of this project is a university semester.

1.5 Pre-study in Silicon Valley

As part of a inspirational and educational pre-study for this thesis, the team visited San Francisco and Silicon Valley on a scholarship from GoINN, a collaboration between Chalmers, University of Gothenburg, and Vinnova, with the aim of promoting entrepreneurship for university students. During this trip we interviewed employees from tech companies ranging from being in the startup phase, mid-range companies in their growth phase, to large multi-billion dollar companies. We also attended Start Up Grind Global Conference and visited Nordic Innovation House.

The focus of the interviews was on how companies of all sizes work methodically with continuous and iterative improvements, if and how they apply and implement machine-learning technologies, how they work with design and user experience, and what we as students can learn and take back from the culture and ideas of Silicon Valley. More details can be found about each company in appendix H, where all companies' names have been anonymised.

From these visits, we learned that very few big software companies actually use dedicated Scrum methodologies. This was an interesting insight, as it stands in contrast to the agile frameworks that are taught in Software Engineering courses. One of the persons we spoke to, explained that he had used a specific agile framework at a previous job, and it did not work well at all. Instead, work did not get done properly, as with new sprints the focus shifted to another part of the product, leaving unfinished work from the previous sprint behind. On the contrary, most employees of these companies were free to handle development methodologies by themselves, with none to little supervision from top management. They often worked agile but did not implement a specific methodology, instead they customised agile frameworks to suit their business.

During the trip to Silicon Valley, we also attended the Start Up Grind Global Conference 2016, which is a yearly conference in San Francisco that gathers entrepreneurs from all over the world for two days filled with inspirational talks by successful entrepreneurs and investors. We got to hear Clayton Christensen talk about his book *The Innovators Dilemma*, Steve Blank about the Customer Development Process, and Steward Butterfield about his founder story with Slack, among others. The overall learning that the speakers shared, was that customer interaction should be prioritised from start. As soon as having a startup idea, a paper prototype should be tested on potential customers.

Nordic Innovation House is a co-working and virtual office for Nordic tech companies and investors. We visited their office and talked about how they can help us, a Swedish startup, to enter the U.S. market with our business.

1.6 Startup Camp

Startup Camp is a 15-week program at Chalmers Ventures that helps early startups to establish a solid foundation for building a scalable business model. The goal of the program is to validate the customer/user need. Also, to build a minimum viable product, and to create a pitch to communicate the startup's idea. The program is divided into three phases, each being five weeks long. For the final phase, phase three, there is up to ten spots for the most promising startups that receives the opportunity to pitch/present at a venture day during the final week.

Selleri, the startup this thesis is based on, applied to the ninth batch of Startup Camp. While there was nothing in the thesis that dictated us to apply for Startup Camp, it proved to be a very valuable experience in helping us find our customers, learning about the venture creation experience, and moving us towards the purpose of this thesis. Each Wednesday there was a group feedback session and Each Thursday there were seminars about different subjects related to venture creation. While the feedback from our thesis' supervisors were immensely helpful for the academic work, the feedback from Startup Camp was better focused towards venture creation. This feedback helped us with things like how we talk to customers, how to find product-market fit, and encouraged us to work more proactively than we most likely otherwise would, together with other projects facing the same issues as ourselves. For further projects applying the Lean Startup Methodology, a similar setup would be very preferable, as it helped us and could help other people as well.

2
Theory

In this chapter, the theoretical frameworks of this thesis are presented. First, the Lean Startup methodology is presented with its three components, Business Model Design, the Customer Development Process, and Agile Engineering. They are followed by the theoretical frameworks of sustainability and machine learning technology.

2.1 Lean Startup

The Lean Startup Methodology is an approach inspired by Toyota's Lean Manufacturing, with the purpose to minimise waste and maximise learning (Ries, 2011). It promotes the idea of acquiring validated learning about the customer and the business model through application of the scientific method, launching the concept of evidence based entrepreneurship. This allows startups to gain insights about the wants and needs of their customers, which reduces the risk of failure of the product or service in development to meet these expectations in the market.

Blank and Dorf (2012) defines the Lean Startup as a methodology consisting of three components: Business Model Design, Customer Development and Agile Engineering. Together, these components allow startups to reduce the amount of time to get to first product to market, and to minimise the amount of cash required to do so.

2.1.1 Build-Measure-Learn

The Build-Measure-Learn feedback loop is at the heart of the Lean Startup methodology (Ries, 2011). It prescriptively states that the goal of each iteration is to acquire learning through measuring customer data after building an MVP. As such, the iteration can start by reverse-engineering the loop. First, ask what hypothesis the business is seeking validated learning about. Secondly, decide which customer data could validate or invalidate this hypothesis, and how it can be measured. Thirdly, design the experiment or the MVP that is required to measure this data. After this exercise, it is time to enter the loop and Build-Measure-Learn from the proposed model. See Figure 2.1.

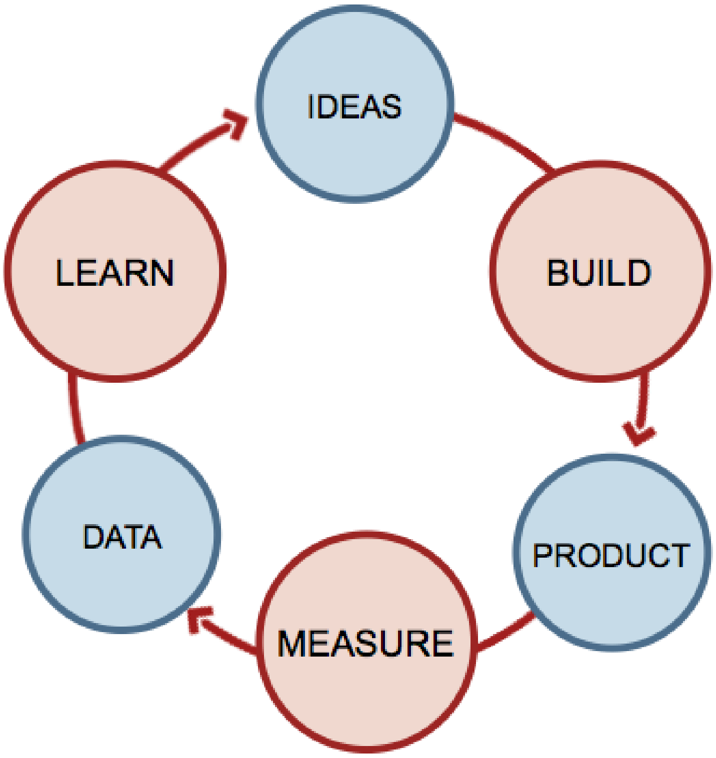

Figure 2.1: The Build-Measure-Learn feedback loop (Ries, 2011)

2.1.2 Business Model Design

Osterwalder and Pigneur (2010) have through their work developed models to create at unifying language for business model design. By their definition, a business model describes the rationale of how an organisation creates, delivers, and captures value. Designing and communicating the rationale of the business model requires a tool, which is why they created the Business Model Canvas. Furthermore, they created the Value Proposition Canvas. Its purpose is to zoom in on the process of creating value for the customer (Osterwalder et al., 2014).

These tools are viewed as essential to solve the problem of visualising the business model design of this project. The business model design is viewed as a fundamental part of the Lean Startup Methodology. Without it there is no way to track the progress and priorities of the business model hypotheses, which guides the entire Build-Measure-Learn process.

2.1.2.1 Business Model Canvas

The Business Model Canvas consists of nine basic building blocks (Osterwalder and Pigneur, 2010). Together, they form a visual model, seen in Figure 2.2, which can be viewed analogous to a theatre (Osterwalder, 2016*b*). In this theatre the customer segment, value propositions, channels, customer relationships, and revenue streams make up the front stage of the business model. These are the parts of the business model that are clearly visible to any customer of the business. The remaining building blocks, key resources, key activities, key partnerships, and cost structures make up the backstage of the business model. The backstage makes the front stage of the business model possible. These building blocks are often not visible to the customer, as it is behind the red curtain of a theatre. The goal of a business model is to accumulate higher revenue from its front stage than it incurs in costs from the supporting backstage, generating a profit.

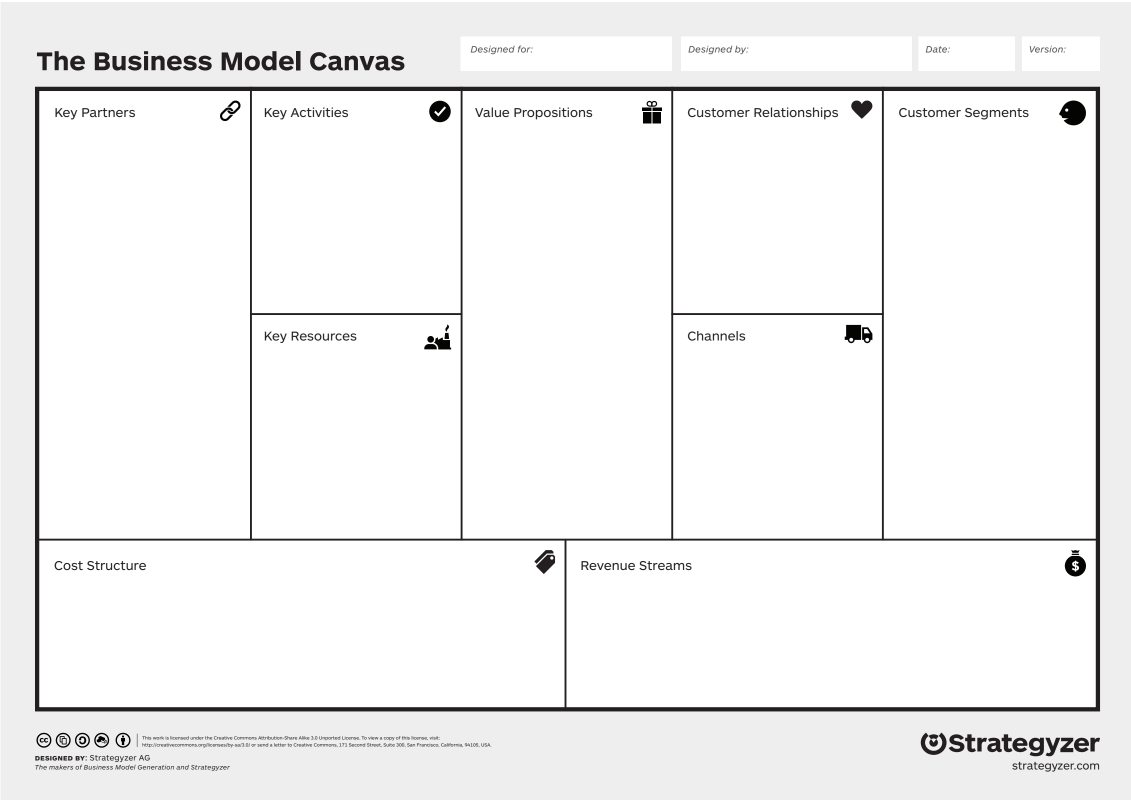

Figure 2.2: The Business Model Canvas (Osterwalder, 2016*a*)

The Customer Segments building block defines the groups or categories of people that the business aims to create value for. A business cannot survive or thrive without customer segments, since it is the source of revenue for the company. Choosing customer segments to address will in the end dictate the front stage and the backstage of the business model, with the ultimate goal to build something people want. The customer segments of the theatre is the audience.

The Value Propositions building block describes the benefits that the business offers its respective customer segment and is often the reason why a customer chooses one company over another. It can solve a customer problem or service a customer need. The value propositions can be viewed as the show on the front stage for the customer in the theatre.

The Channels building block explains how the business communicates and delivers its value propositions to its customer segments. This includes the marketing, sales and support channels of the business models. In the case of the theatre, the channels could describe how the marketing of the show, the ticket sales, and the physical theatre interfaces with the customer segments.

The Customer Relationships building block describes the type of relationship that the business supports towards its customer segments. It can also be viewed as the strategy by which a company gets, keeps, and grows its base of customer segments, on a spectrum from automated to personalised. In the theatre analogy, this can be described as the manner of how the customer is reached and serviced before, during and after the show.

The Revenue Streams building block represents the generated cash flow from the customer segments and how they occur. The strategy of the business model can be to use subscription fees, one time sales, a freemium-model, etc. In the theatre, the revenue streams are typically sales of tickets.

The Key Resources building block describes the assets that the business uses and requires to make the rest of the business model work. This can be physical, intellectual, human, and financial resources. The composition of these resources will vary greatly between industries. In the theatre analogy, these key resources are the things that make the show possible.

The Key Activities building block shows the activities that the business must perform to run the proposed business model. These will also vary between industries depending on if the business model is production, problem solving or network oriented. The key activities of the theatre can entail hiring human talent as key resources and acquiring strategic channels partners to sell tickets.

The Key Partnerships building block represents the strategic synergies between businesses that are not strictly revenue-oriented. It can for instance be channel or resource partners that saves costs for both parties. The theatre can have a resource partnership that allows other businesses to rent the physical space when not otherwise utilised.

The Cost Structures building block describes all the costs that occur from supporting the backstage of the business model. Intuitively, costs should be minimised. But there is more to costs structures than that. Different industries can require different cost structures, which can give birth to inherently value or cost driven business models. In cost driven business models, the focus is simply to minimise costs. However, in value driven business models, the focus is a greater level of customer service. In the theatre, the resources, activities and partnerships are summed up to the cost structures.

2.1.2.2 Value Proposition Canvas

The Value Proposition Canvas is a tool designed to zoom in on the Customer Segments and Value Propositions building blocks, as seen in Figure 2.3, of the Business Model Canvas (Osterwalder et al., 2014). There are two sides of the canvas, the Customer Profile and the Value Map. The Customer Profile is used to clarify the understanding of the customer. The Value Map in contrast is used to describe how value is created for the customer. If data from the market reflects the designed Value Proposition Canvas, then a fit between the two parts of the canvas has been achieved.

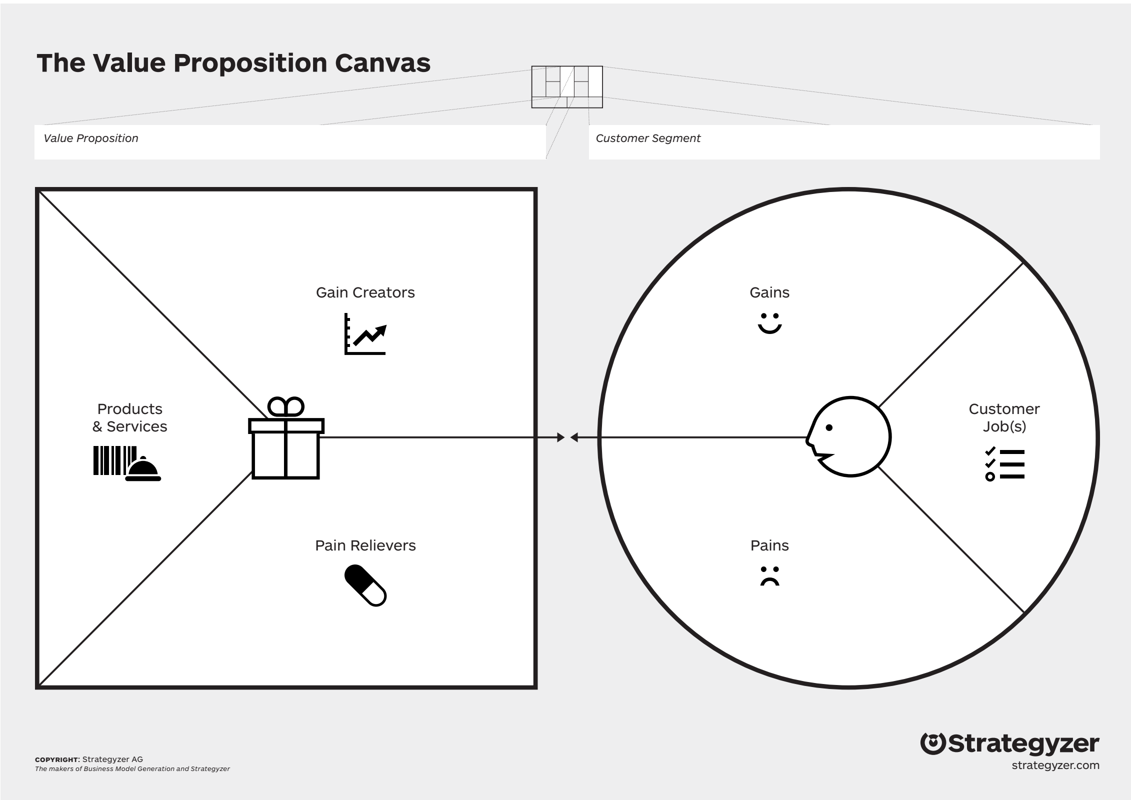

Figure 2.3: The Value Proposition Canvas (Osterwalder, 2016*d*)

The Customer Profile is the set of customer characteristics that are assumed, observed and verified in the market. These characteristics are the deciding factors on how to successfully segment customers, rather than demographics or psychographics. The characteristics are categorised as customer jobs, pains, and gains.

The customer jobs are what causes a customer to do something or choose a product or a service. These jobs can be functional, emotional, or social in character. It is a description of what the customer is trying to get done in a certain context, as expressed in their own words. Pains are the negative outcomes, risks and obstacles that arise before, during, and after a customer is trying to get a job done. Gains, in contrast, are the positive outcomes, hopes and dreams that a customer is seeking through accomplishing the customer jobs.

The Value Map is the set of benefits that are designed to attract customers. These are the features that describe how a product or a service intend to resolve the Pains and Gains related to specific customer jobs. The features are categorised as pain relievers and gain creators.

The products and services of the Value Map is simply a list of what the value proposition is built around. Pain relievers corresponds to customer pains and describes how the product or service intends to alleviate it. Similarly, the gain creators answers the question of how a customer will realise the desired Gains through choosing the product or service.

The Fit between the customer profile and the value map can be achieved in two ways. The first is called Problem-Solution Fit and occurs on paper when the business has successfully designed a Value Map that in theory maps perfectly to a validated Customer Profile. This fit is achieved before actually presenting a product or a service to the customer. The second kind of fit is called Product-Market Fit, and occurs in the market when the product or service is successfully received and getting traction. In other words, when customers love your products or services and recommend it to their friends and family, Product-Market Fit is achieved.

A third kind of fit happens on the Business Model Canvas level and is called Business Model Fit. This fit occurs in the bank, when there is evidence that the value propositions can be embedded in a scalable and profitable business model.

2.1.3 Customer Development Process

The Customer Development Process implements the toolkit described in Business Model Design to systematically test each design as a hypothesis. If each test is described by the build-measure-learn model, then the Customer Development Process describes the entire journey of a startup from customer discovery to company building.

Blank and Dorf (2012) argues that there is a repeatable path to starting successful startups. In their view, the reason that so many startups today fail is that they are being run as large companies. Business plans, product development through the waterfall model and big product launches are hallmarks of the practices of large companies. They execute a plan based on historical data. In a startup however, there is no historical data to execute on. This lead Blank and Dorf (2012) to create a new prescriptive definition of a startup.

"A startup is a temporary organisation, design to search for a repeatable, scalable business model." (Blank and Dorf, 2012).

The methodology used the Business Model Canvas as a scorecard for keeping track of these hypotheses, and is viewed as essential to the project of starting a startup.

2.1.3.1 Customer Development Model

The Customer Development Model, seen in Figure 2.4, is a systematic, step-by-step framework for startups to validate a business model iteratively and incrementally (Blank and Dorf, 2012). It applies the scientific method of stating hypotheses about the business model on the Business Model Canvas and testing them through experiments. The process is conducted in parallel to the Agile Engineering process, thus creating a balance between understanding the customers and the business model while developing the product or service.

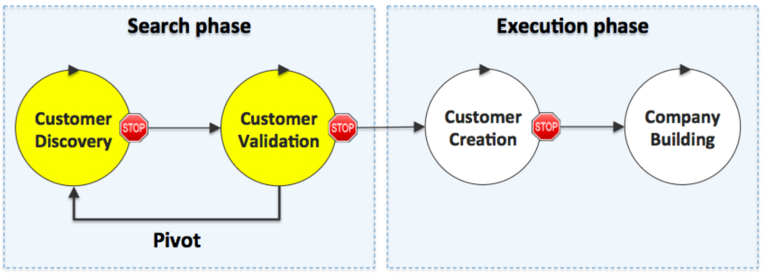

Figure 2.4: The Customer Development Model (Blank, 2016)

In the Customer Development Model, the process is characterised by the Search phase and the Execute phase (Blank and Dorf, 2012). This startup project is constrained to the Search phase and will therefore be in focus for this theoretical framework. The Search phase is itself characterised by two iterative processes, Customer Discovery and Customer Validation. The goal of Customer Discovery is to achieve Problem-Solution Fit, while Customer Validation culminates in Product-Market Fit (Osterwalder et al., 2014).

2.1.3.2 The Progress Board

The Search Phase of the Customer Development Model can be visualised as a thermometer, seen in Figure 2.5, measuring the progress of the startup to validate the critical hypotheses of the Business Model Canvas (Osterwalder et al., 2014).

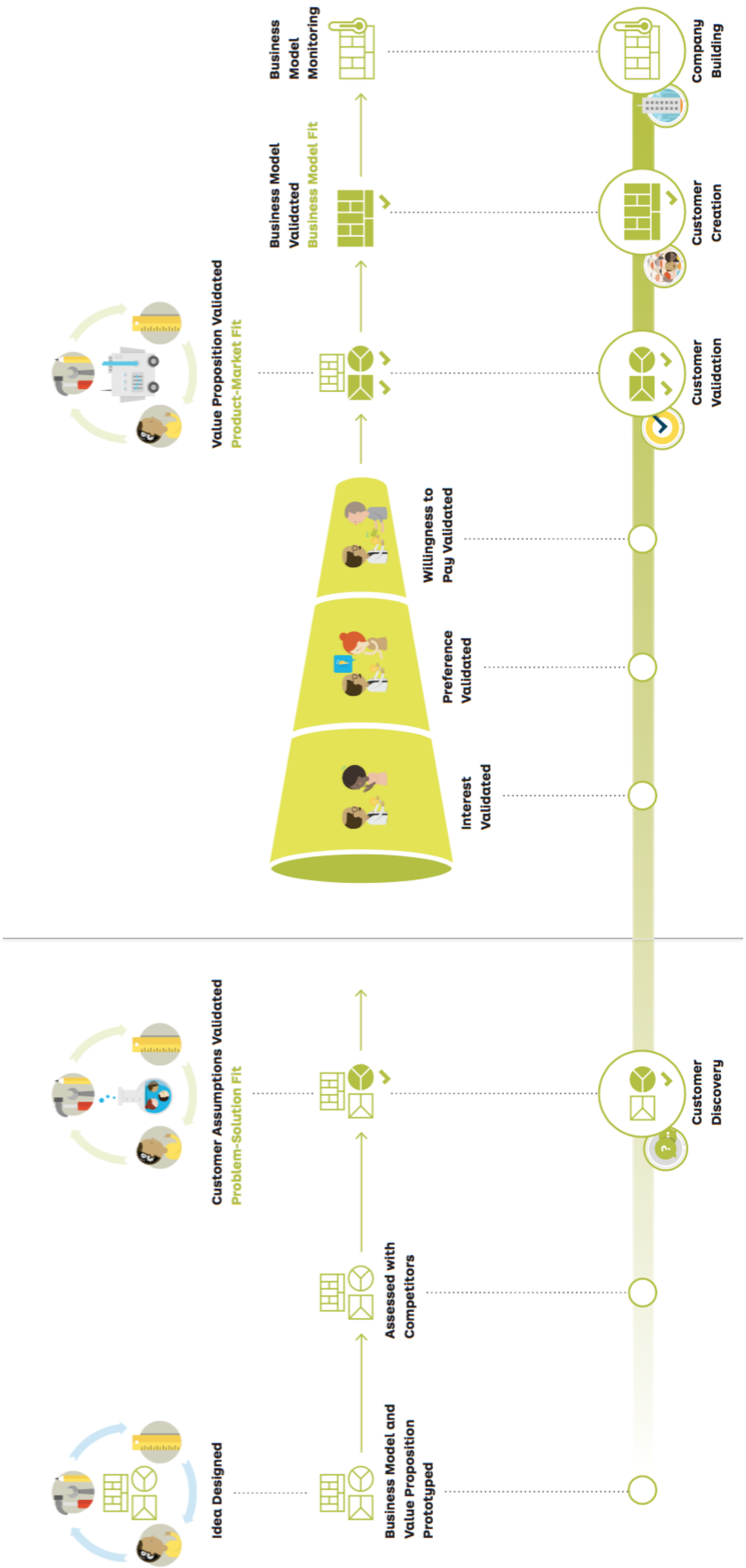

Figure 2.5: The Progress Board (Osterwalder et al., 2014)

For the purpose of this thesis, the Progress Board has been redesigned, as seen in Figure 2.6, to better fit the reporting structure. Here, green colour means that the step has been validated, and red means that it has not yet been validated. Yellow means that this is the next step to be tested.

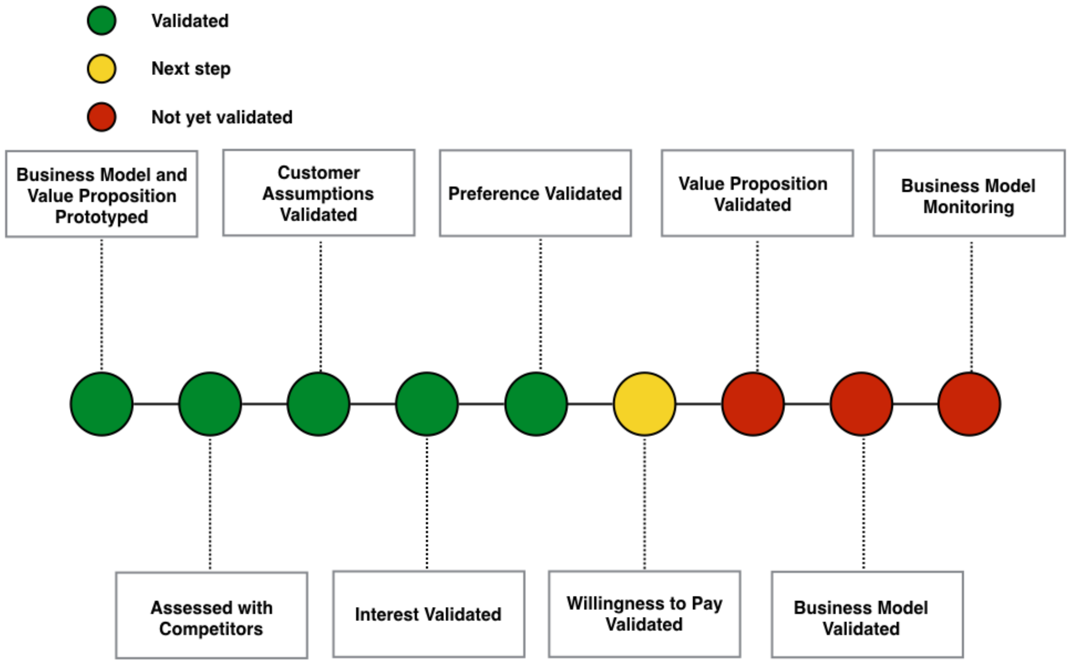

Figure 2.6: The redesigned Progress Board

The Testing Process can be viewed as zooming in on the Progress Board, as seen in figre 2.7, for a specific hypotheses (Osterwalder et al., 2014). The work flow requires the Business Model Canvas, the Value Proposition Canvas, the Test Card and the Learning Card.

Figure 2.7: The Testing Process (Osterwalder et al., 2014)

The Test Card, seen in Figure 2.8, is a tool to state the hypothesis from the Business Model Canvas and design the Build-Measure-Learn loop before entering it.

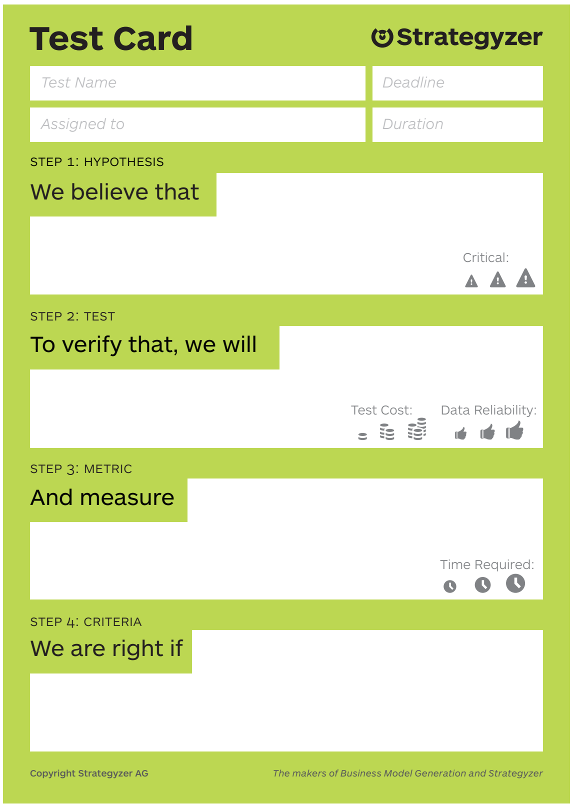

Figure 2.8: The Test Card (Osterwalder, 2016*c*)

The Learning Card, seen in Figure 2.9, on the other hand captures learning from the feedback-loop and states decisions and actions of reshaping hypotheses or making progress on the Progress Board.

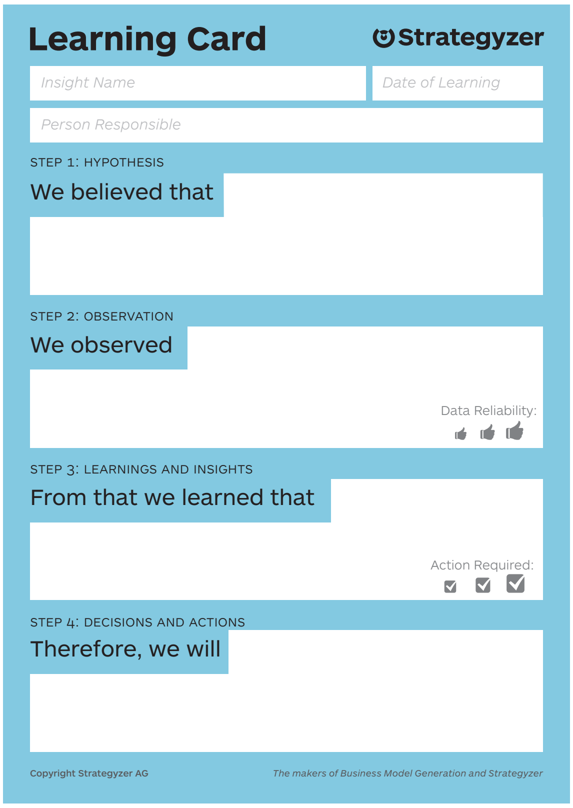

Figure 2.9: The Learning Card (Osterwalder, 2016*c*)

2.1.4 Agile Engineering

Agile Engineering is a set of development principles that allows a product to be built iteratively and incrementally. This stands in contrast to the traditional waterfall development methodology of planning and building linearly. A lot of different frameworks and processes can be described as parts of agile engineering. One of these is Scrum. This thesis has focused on the Scrum framework and will describe it more carefully than the other frameworks.

2.1.4.1 Scrum

Scrum was introduced by Jeff Sutherland in the 1990's. Scrum is a framework where a cross-functional team develops a product with incremental iterations according to (Sutherland, 2016). Each iteration is done under a preset amount of time called sprints. Scrum has only three defined roles, the product owner, the scrum master and the team.

The product owner is responsible for the product backlog and to talk with external stakeholders. The product owner is the person that has the vision of the product. He/she should have a clear understanding of the market that the product is aimed for.

The Scrum master is a facilitator for the Scrum team. This means that he/she makes sure that the team understands Scrum. The Scrum master is not a project manager. He/she does not tell the team what they should work on, but rather helps the team overcome any blocks that they might have. Scrum has a lot of discussions implemented to make sure that these blocks are visible at an early stage, so the Scrum master can do something about it.

The team is responsible for building the product that the product owner has in his vision. The team should be cross-functional. This means that all necessary expertise needed should be in the team. The team is self-organising and acts autonomously. It is important for the team's success that there is no interference from managers during sprints.

Sprint planning is performed before a sprint can start. The product owner is in charge of putting items in the backlog of the Scrum board that he/she believes are necessary for taking the development further. The product owner then prioritises these items in the backlog. The team and the product owner should then discuss the high-priority items to clarify their definition and definition of done. It should be very clear for everyone in the team what needs to be done on each item.

When the first phase has been done team estimates the effort needed to accomplish each item. There are different ways of doing this, but a popular one is planning poker. During planning each item is discussed. First the team decides on a base line item. This item acts as a reference of what an easy item is and everyone should agree on it. After the baseline is decided each item is brought forward in one by one to the team. Each team member estimates the effort needed to accomplish it with the help of Fibonacci numbers and compared to the base line number that is a two on the Fibonacci scale.

The Scrum board, seen in Figure 2.10, is where the team manages their items before, during and after the sprint. The Scrum board has a backlog where the product owner has defined and prioritised items. It also has a "To do" or a "Sprint backlog". These are the items that the team works on during the current sprint. Each time a member starts working on an item, he/she takes a card from the "To do" column and places it on the doing column. When the item has been executed, the item is moved to the "Done" column.

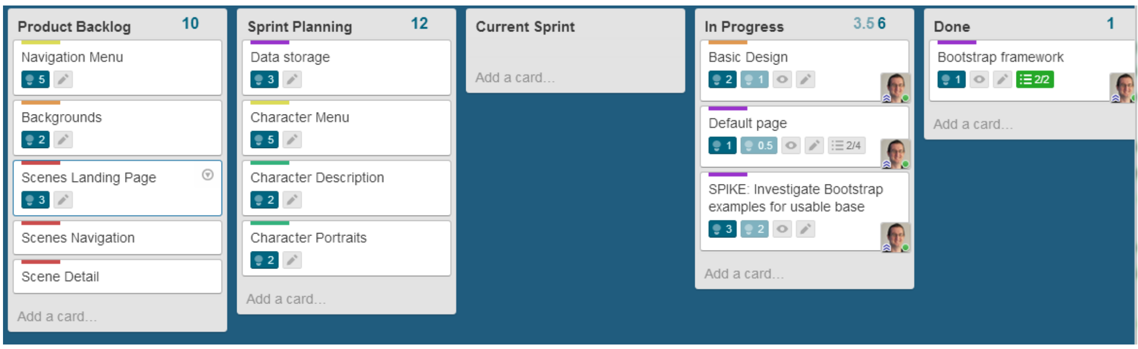

Figure 2.10: A scrum board in Trello (St-Cyr, 2016)

A Sprint is a cycle during which the team develops the product. The sprints should have the same period during the whole development, usually two weeks long. During the sprint no one outside of the Scrum team can tell the team on what to work on. It is decided during the sprint planning.Each sprint should have a clear goal and be an incremental development of the product. The sprint should always deliver value and should not break the product. Deemer et al. (2010) says "The output of every Sprint is officially called a Potentially Shippable Product Increment."

A Daily scrum meeting is performed every day during the sprints, the team meets on a daily basis to have a short meeting in order to keep the team up to date. The Scrum master is the one who makes sure that the team have these meetings every working day and that they are conducted in under 15 minutes. Each member should answer three questions during the daily scrum: "What did I do yesterday?", "What will I do today?" and "Do I have any problems that keeps me or the team from going forward?". These meetings are supposed to help the team to reach the sprint goal by understanding each other and working as a self-organising team.

Sprint review is carried out when a sprint is done. A sprint review is where the Scrum team and stakeholders meet to see what has been done and what has not been done in the last sprint. Deemer et al. (2010) discusses how important it is that the sprint review is not a presentation but rather a hands-on experience with the software. The purpose of the review is to learn and adapt the product. The product owner learns about the team's development and the product, and the team learns about the product owner's work and the market. Each item that is in the "Done" column is discussed and the team shows the progress on the product. The product owner then decides if it has met the definition of done. Each item that is not done, moves back to the backlog. These items are then part of the next sprint planning session.

Sprint retrospective is also conducted after each sprint. A Sprint retrospective is when the team evaluates themselves. It is meant to be a discussion about how the team has worked during the sprint. It is solely focused on the team and not on the product. Each team member should answer the questions: "What was good during this sprint?" "What was not working well?" "What should the team try to make it better?" The retrospective is an opportunity for team members to vent group dynamics problems and processes that might be hindering the work. In order for the team to not associate retrospectives with just something bad, there should be some appreciates in there as well.

2.1.4.2 Other agile engineering methodologies

Although this bachelor's thesis has focused on Scrum, there are also several other Agile Engineering methodologies, two of these are Kanban and Extreme programming (XP).

Kanban is a framework where there are no defined roles but instead works with the existing ones in order to improve these to stimulate an always improving and expanding software (Radigan, 2016). The framework contains a set of rules to keep a flow throughout the working process. The work is divided into parts to easily have structure and visualise the work flow. In each step, a Work In Progress limit is set meaning it can only contain a certain amount of tasks in a step. This forces team to not leave tasks half finished.

Extreme Programming (XP) is a framework where there are a set of defined tasks or rules rather than defined roles according to (Wells, 1999). These are usually coding, testing, listening, and designing. Coding, testing, and designing are self explanatory but the listening part is about listening to the customer to see the needed business logic. This is needed to be able to find a solution for the problem. XP has a lot in common with Scrum in form of planning before each decided time period and evaluating after. The framework contains many different ways of working but the two most common are Test Driven Development (TDD) and Pair Programming. TDD is where the team writes unit test after the requirements and afterwards build the code to pass the tests and in Pair Programming two developers are sitting on the same computer and helping each other.

The different frameworks within Agile Engineering have many things in common. They all build on self-organising, cross-functional teams and promotes working incrementally with early delivery and continuous improvement towards a goal.

Having explained the work process, the next chapter will present the theoretical frameworks regarding sustainability, which is a vital part of the purpose.

2.2 Sustainability

The definition of sustainability is the ability to continue a defined behaviour indefinitely without affecting the surrounding. More specifically, the Brundtland Commission described it as “Development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Adams, 2006). Sustainability is often divided into three pillars; environmental, economic, and social sustainability (Dyllick and Hockerts, 2002). Following paragraphs explains each pillar.

2.2.1 Environmental sustainability

Environmental sustainability defines how to study and protect ecosystems, air quality, usage of resources and other elements that puts stress on the environment and the ecological footprint of humans (Adams, 2006). However, to increase precision in defining and understanding environmental sustainability, it is viewed as a subset of the broader concept of ecological environment. Hence, it is more specifically defined as "a condition of balance, resilience, and interconnectedness that allows human society to satisfy its needs while neither exceeding the capacity of its supporting ecosystems to continue to regenerate the services necessary to meet those needs nor by our actions diminishing biological diversity" (Morelli, 2013). This means that human beings should have their needs satisfied, without affecting the ecosystem in a way that exceed its capacity.

2.2.2 Economic sustainability

Economic sustainability was first defined by Hicks (1946). Hicks (1946) defined "income" as "the amount one can consume during a period and still be as well off at the end of the period". However, Goodland (1995) writes that to speak accurately in terms of "economic sustainability", it is necessary to "extrapolate the definition of Hicksian income from its sole focus on human-made capital and its surrogate money to embrace the other three forms of capital natural, social and human". This new definition, together with the realisation of the fact that natural resources are not infinite, has created an understanding of the fact that the growing scale of the economic system strains the natural resource base. This together with increasing wealth in third world countries would lead to a sooner environmental collapse. Economic sustainability is tightly linked to environmental sustainability and in an economic sustainable system the environmental state should be a constraint (Basiago, 1998).

2.2.3 Social sustainability

Social sustainability is defined as a system of a social organisation that, among others, alleviates poverty, and encompasses topics such as human rights, social and health equity, and social responsibilities. However, in a fundamental sense, social sustainability links environmental decay together with poverty and other social conditions. A negative connection between sustained colonisation, sustained poverty levels and sustained natural resource exploitation has been identified.

Social sustainability is tightly linked to both economic and environmental sustainability, where the correlation is confirmed. However, there is a divergence of opinion to whether environmental sustainability is a prerequisite of economic growth and sustainable social conditions, or if economic growth and sustainable social conditions are needed before environmental sustainability can be addressed (Basiago, 1998). See Figure 2.11 for a model of the interaction between these three pillars.

Figure 2.11: Environmental, economic and social sustainability (*Sustainability*, 2016)

This concludes the theories on sustainability, which the project leverages in the aim to answer questions about how to build a sustainable business model. Our purpose is to apply lean startup methodologies on machine learning, and therefore theoretical frameworks of machine learning are presented below.

2.3 Machine Learning

This thesis aims to apply the Lean Startup Methodology, as described previously, to search for a repeatable, scalable and sustainable business model based on **machine learning technology**. This chapter will discuss what machine learning is and the theory behind different models.

Machine learning is a subfield of artificial intelligence. The goal of this technology is to allow computers to perform tasks for which they have not been explicitly programmed to do, similar to how humans learn to do things without having a perfect set of instructions.

Machine learning can roughly be divided into three classes, supervised learning, unsupervised learning and reinforcement learning. In this thesis we discuss the first. Supervised learning is the task of inferring a function from a set of labelled training data, i.e data where there is a desired output for each input. A labelled set of training data is a set M where for every n dimensional input vector $\mathbf{x}$ there is a target value t associated to it. More formally

$$M = \{(\mathbf{x}_1, t_1), (\mathbf{x}_2, t_2), ..., (\mathbf{x}_i, t_i)\}. \tag{2.1}$$

In supervised learning there are two types of problems; classification and regression. Classification is the task of identifying which class an input vector $\mathbf{x}^*$ belongs to, where as in regression, the task is to predict a continuous output for an input vector $\mathbf{x}^*$. In this thesis we shall discuss the latter. To make predictions on input data we want to infer some function, for example, $f : \mathbb{R}^n \to \mathbb{R}$ from a set of labelled training data.

2.3.1 *k*-nearest neighbours

k-nearest neighbours or k-NN is a nonparametric machine learning algorithm that looks at similar inputs and assumes that the output is roughly the same.

The k in k-NN is the number of nearest neighbours to include in predictions. For example if $k = 1$ the algorithm always gives the same output as the target value of the one nearest neighbour. If $k > 1$ the output will be the average value of the target values from the k nearest neighbours. To identify neighbours we need to define a distance measurement between vectors. This is typically the *Minkowski distance*, defined for two n-dimensional vectors $\mathbf{x} = (x_1, x_2, ..., x_n)$ and $\mathbf{x}^* = (x_1^*, x_2^*, ..., x_n^*)$ as

$$D(\mathbf{x}, \mathbf{x}^*) = (\sum_{i=1}^{n} |x_i - x_i^*|^p)^{1/p}, \tag{2.2}$$

which for $p = 1$ is *Manhattan distance* and for $p = 2$ is *Eucledian distance*. Eucledian distance is often used when the different dimensions are measuring similar metrics such as width and height whereas Manhattan distance is often used if they are dissimilar (Russell and Norvig, 2009).

A simple implementation of the k-NN algorithm is as follows:

1. We define the set of training data as $M = \{(\mathbf{x}_1, t_1)..., (\mathbf{x}_m, t_m)\}$ where $\mathbf{x}_i$ is an n-dimensional feature vector and t_i is its respective observed output.
2. We want to predict t^* for an input vector $\mathbf{x}^* \notin M$.
3. The k-NN algorithm computes the distance between $\mathbf{x}^*$ and every vector $\mathbf{x}_i \in M$ according to Equation 2.2.
4. The distances are sorted and the k targets of the training data with the shortest distances to $\mathbf{x}^*$ are averaged.
5. The average value is the prediction t^*.

A problem with this simple implementation is that the scale of the input dimensions are not considered. If we were to exchange an input from centimetres to meters, the result of the algorithm would be very different. This problem can be solved by applying normalisation to every input dimension. A simple approach is standardising so that for every sample i in input dimension j, $x_{i,j}$ becomes $\frac{(x_{i,j} - \mu_j)}{\sigma_j}$ where μ_j is the mean of the input dimension j and σ_j is the standard deviation of the input dimension j.

Another problem with the k-NN is that even though, for example, one of two found nearest neighbours may be far away and the other may be very close, they will contribute equally much to the prediction. This problem can be handled using *weighted k-NN*, for which a weight function, such as the inverse distance, is defined. A weighted average is then computed by multiplying each items weight by its target value before summation.

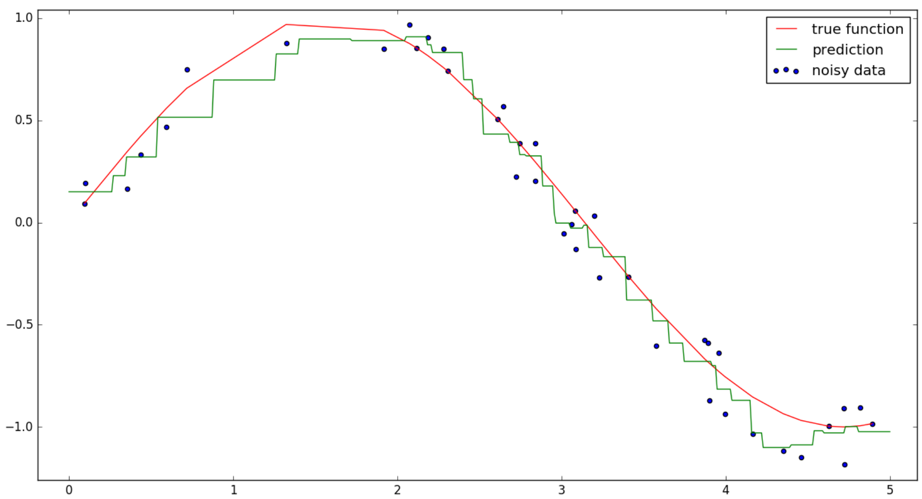

Figure 2.12: Example of a unweighted k-NN regression with one input dimension, $p = 1$ and $k = 3$

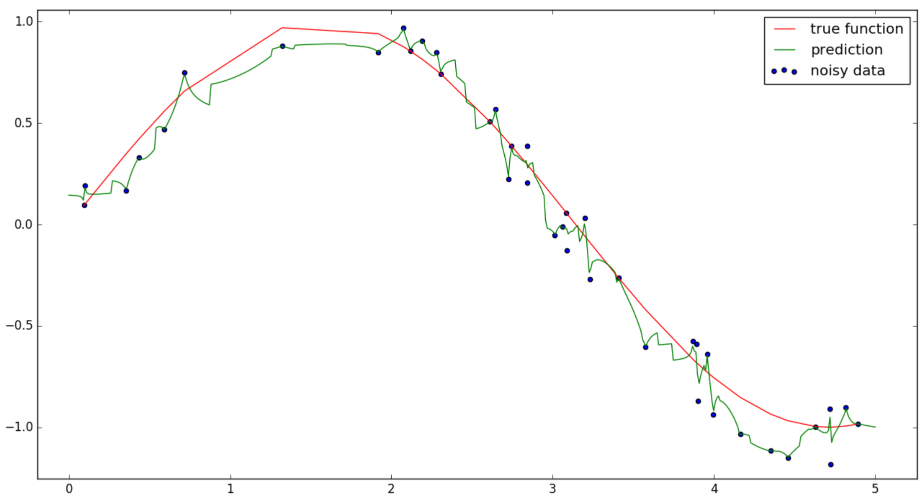

Figure 2.13: Example of a distance weighted k-NN regression with one input dimension, $p = 1$ and $k = 3$

k-NN is a non-parametric machine learning model that does not make any assumptions about the data. The algorithm provides predictions on data by averaging data that is neighbouring the input data in space. The negative aspects of the k-NN algorithm is that it is computationally expensive, it can be shown that the execution time for predictions are $O(n)$, where n is the number of training points (Russell and Norvig, 2009). The value of k has a big impact on predictions made by the model so techniques for finding an optimal value for k and hyperparameter tuning in general is discussed in section 2.3.7.

2.3.2 Decision tree

Decision tree is a machine learning model where predictions easily can be traced and visualised. The final model is simply a binary tree where every non-leaf node is a set of if-else statements and the average of the targets in every leaf-node is a prediction.

The learning, i.e construction, of a decision tree is the task of algorithmically inferring simple decision rules from a data set. Predictions on new inputs $\mathbf{x}^*$ are determined by tracing the inputs path from the root node to a leaf node. At every node in the binary decision tree there is a statement with a boolean (True or False) response which leads us to a leaf node. There exists several different algorithms for tree construction, in this section we present the CART, Classification and Regression tree, learning algorithm since the method supports continuous target variables, i.e regression.

CART builds a tree using recursive partitioning. It starts with all data in the root node and recursively builds the tree by splitting on the value that produces the greatest separation defined by some criterion. All other values are then binary divided to the left or to the right of that root node. The same process is then repeated on every child-node until a stopping criterion is met. The separation criterion for continuous variables is usually the mean squared residual (Zhang and Ma, 2012), defined for a node D in the tree as

$$D = \frac{1}{n}\sum_{i=1}^{n}(t_i - t^*)^2. \tag{2.3}$$

Here n is the number of data points belonging to the node D. The prediction t^* is the average of all the training data targets belonging to that node as

$$t^* = \frac{1}{n}\sum_{i=1}^{n} t_i. \tag{2.4}$$

The children of node D, denoted D_L and D_R, are defined as the nodes where the separation criterion is minimised, i.e $D_{split} = n_L D_L + n_R D_R$, where n_L and n_R are the number of samples in the new nodes. (Zhang and Ma, 2012)

For a training set $M = \{(\mathbf{x_1}, t_1), ..., (\mathbf{x_n}, t_n)\}$ with n input vectors defined as $\mathbf{x_i} = (x_1, x_2, ...x_p)$, the CART algorithm is defined as follows (Zhang and Ma, 2012):

1. Start with a single node containing all the data.
2. Repeat the steps below recursively for each unsplit node until some stopping criterion is met

    (a) Among all binary splits on all p features, find the split minimising D_{split} the most.
    (b) Split the node into two new nodes using the split from step (a).
3. Make a prediction by passing new input through the tree until a leaf node is found. The prediction is then calculated using 2.4.

Examples of stopping criterions include defining a maximum number of leaf nodes in the tree, a minimum number of values that needs to be in a new leaf or a threshold for a minimal decrease in the scoring function for every split. Another common method to achieve good prediction performance is pruning. Pruning is the concept of building a pure tree, a tree that has only one data point in every leaf, and then evaluating if the tree can perform better if the leafs parents are leafs instead and hence removing the children.

Decision trees have the advantage of being fast in the prediction phase since it only involves following a path in a binary tree, a $O(log(l))$ time operation for tree depth l. A Decision tree is also a transparent model that is easy to visualise, a tree can simply be printed and the path for an input can be traced through the tree. Disadvantages of decision trees include overfitting and that learning an optimal decision tree is an NP-complete problem (Hyafil and Rivest, 1976). Because of the NP-completeness, tree construction algorithms usually utilise a greedy approach that chooses the local optimum, like the algorithm presented above.

2.3.3 Random forest

The Random forest model is an extension of the decision tree model that instead of just generating one tree generates a forest of trees.

Random forest is an ensemble method, i.e a method that uses multiple learning algorithms and aggregates their result. A Random forest creates multiple decision trees at training time, hence the forest, and trains these trees on a randomly chosen subset of the data, hence the random.

For a training set $M = \{(\mathbf{x_1}, t_1), ..., (\mathbf{x_n}, t_n)\}$ with feature vector $\mathbf{x_i} = (x_1, x_2, ...x_p)$, the algorithm is defined as follows (Zhang and Ma, 2012):

1. Draw m bootstrap samples of size j from the training set M.
2. For each of the m samples, grow a full unpruned decision tree like
    (a) Start with the whole set in a single node.
    (b) Similarly to the CART algorithm discussed in the precious section, repeat the steps below recursively for each unsplit node until some stopping criterion is met.
        i. Randomly select k out of p available features.
        ii. Among all binary splits on k out of p features, find the best split like in the decision tree model
        iii. Split the node into two new nodes using the split from step ii.

3. Make a prediction by passing the input through every tree until the leaf nodes are found. Compute the output by averaging the target values of every trees leaf node.

The trees in the Random forest algorithm are trained without pruning. The trees stopping criterion can be defined as a maximum number of data points in each leaf or by setting a maximum number of terminal nodes (Zhang and Ma, 2012).

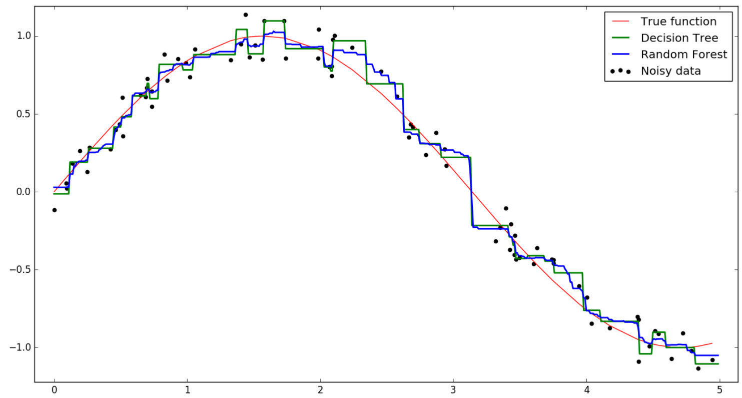

Figure 2.14: Comparison of a Decision tree and a Random forest of 50 trees, both with same stopping criterion.

Random forests extend the basic Decision tree model by introducing many trees and an element of randomness. As it is an extension of the Decision tree model the time complexity for training and making predictions is also increased. As the predictions are an average of m trees the predictive complexity becomes approximately $O(m\ log(l))$ where l is the depth of the trees. Figure 2.14 shows an example of a Decision tree and Random forest model, the Random forest results in a smoother function that models the data better than the single Decision tree.

2.3.4 Linear regression

Linear regression is a parametric method for modelling relationships between input and output variables.

Linear regression in the simplest case is a linear combination of the input variables

$$y(\mathbf{x}, \mathbf{w}) = w_0 + w_1 x_1 + ... + w_n x_n \tag{2.5}$$

where the input vector $\mathbf{x} = (x_1, ..., x_n)$. To make predictions, the weight vector $\mathbf{w}$ needs to be defined so that some error function E is minimised. Minimising the error function, i.e fitting the model to the data, allows us to make prediction on inputs. A widely used error function is given by the sum of squares error (Bishop, 2007), defined as

$$E(\mathbf{w}) = \frac{1}{2}\sum_{i=1}^{n}(y(\mathbf{x}_i, \mathbf{w}) - t_i)^2 \tag{2.6}$$

where t_i is the target output for the respective input $\mathbf{x}_i$.

To model more complex relationships between input and output variables, the model presented above can be extended by transforming the input with a *basis function* $\phi(\mathbf{x})$. The model can now be defined as

$$y(\mathbf{x}, \mathbf{w}) = \sum_{i=0}^{m-1} w_i \phi_i(\mathbf{x}) \tag{2.7}$$

where $\boldsymbol{\phi} = (\phi_0, ..., \phi_{m-1})$, $\mathbf{w} = (w_0, ..., w_{m-1})$ and often with a dummy basis function $\phi_0 = 1$ (Bishop, 2007). Using basis function that are nonlinear allows for the function $y(\mathbf{x}, \mathbf{w})$ to be a nonlinear function of the input $\mathbf{x}$. The model is still called a linear regression model since $y(\mathbf{x}, \mathbf{w})$ is still a linear function of the parameters $\mathbf{w}$.

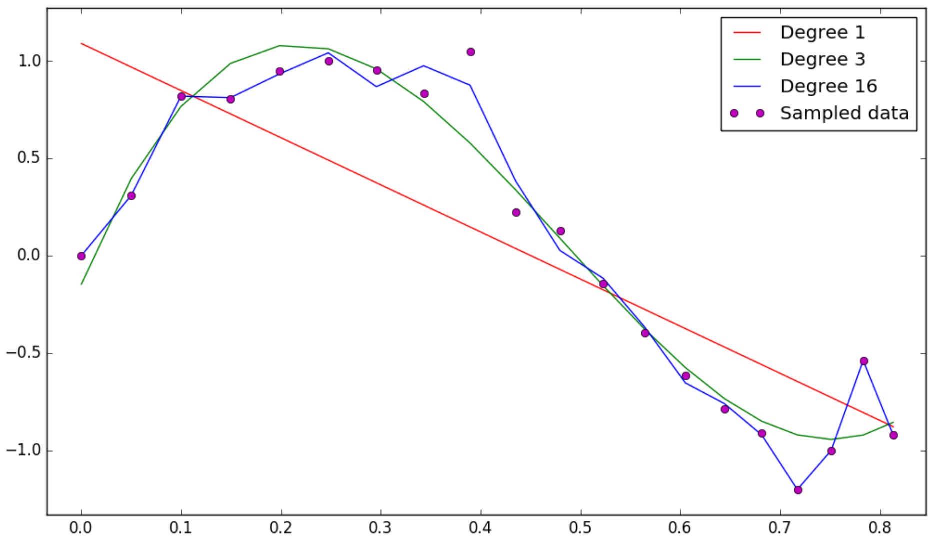

Figure 2.15: Example of regression with different polynomial degrees on $sin(2\pi x)$ with random noise added to target variables

Figure 2.15 illustrates linear regression with basis functions that are polynomails of different degrees. As seen, it models nonlinear functions such as $sin(2\pi x)$ quite well with higher degree polynomials. The polynomial with degree 16 illustrates *overfitting*. As seen in the Figure, the line is fitted through almost all data points. This is not desirable when dealing with noisy data since the model will predict examples seen in the training set very well but unseen data may not be accurately predicted according to the underlying function. The model fails to generalise. In terms of generalisation the model with the degree 3 polynomial performs much better and is hence the desired model in this example.

One approach to control overfitting is called *regularization*. The method adds a penalty term to the error function E in order to prevent the weights $\mathbf{w}$ from reaching to large values. Including the regularization term we get a new error function to minimise

$$E(\mathbf{w}) = \frac{1}{2}\sum_{i=1}^{n}(y(\mathbf{x}_i, \mathbf{w}) - t_i)^2 + \frac{\lambda}{2}\sum_{j=1}^{m}|w_j|^q \tag{2.8}$$

Different regularizers can be defined by changing q. $q = 2$ defines a quadratic regularizer known as *ridge regression* whilst $q = 1$ is known as *lasso* (Bishop, 2007). Introducing a regularizer with $q = 2$ and $\lambda = \frac{1}{e^{10}}$ to the 16-degree polynomial from the example shown in Figure 2.15 gives us Figure 2.16.

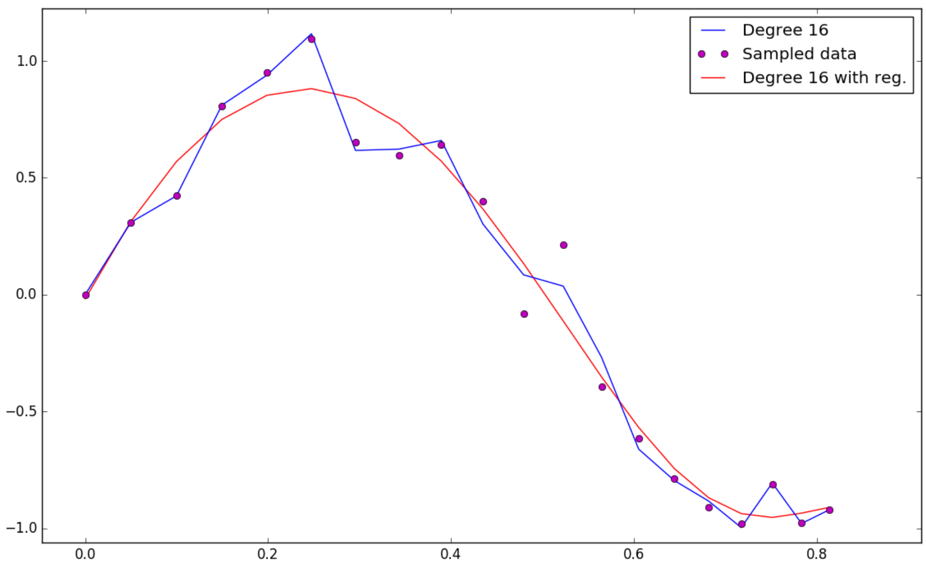

Figure 2.16: Example of regression with a regularization term on $sin(2\pi x)$ with random noise added to target variables.

As seen, the degree 16 polynomial generalises well after the introduction of a proper regularisation term.

Generalised linear regression models exhibit a number of desirable properties, they enable modelling arbitrary nonlinear mappings and with being a parametric technique, predictions are fast since the prediction is simply an evaluation of a function found during model fitting. The shortcoming of the linear regression model is that the basis functions $\phi(\mathbf{x})$ needs to be defined before the training data is observed (Bishop, 2007). This implies that a big task is one of defining proper basis functions and setting their parameters before the model is fitted. With the high complexity of the least squares method in high-dimensional space (Bishop, 2007), training an optimal model may become very time consuming.

2.3.5 Bayesian linear regression

The Bayesian treatment of linear regression enables not only point estimates but also the level of uncertainty in both the model and the measurement.

We begin by assuming that target values are given by some function of inputs and weights $y(\mathbf{x}, \mathbf{w})$ with additive noise so that

$$t = y(\mathbf{x}, \mathbf{w}) + \epsilon \tag{2.9}$$

and that $\epsilon \sim \mathcal{N}(0, \beta^{-1})$, then we can write the conditional distribution

$$p(t|\mathbf{x}, \mathbf{w}, \beta) = \mathcal{N}(t|y(\mathbf{x}, \mathbf{w}), \beta^{-1}). \tag{2.10}$$

We define a matrix of inputs $\mathbf{X} = \{\mathbf{x_1}, \mathbf{x_2}, ..., \mathbf{x_n}\}$ with targets $\mathbf{t} = (t_1, t_2, ..., t_n)$. Under the assumption that the data points are drawn independently from 2.10, using the matrix representation of 2.7 we get the following definition of a likelihood function

$$p(\mathbf{t}|\mathbf{X}, \mathbf{w}, \beta) = \prod_{i=1}^{n} \mathcal{N}(t_i|\mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i), \beta^{-1}). \tag{2.11}$$

Because of the nature of the likelihood function, the corresponding conjugate prior over weights is also a Gaussian (Bishop, 2007), defined below with mean $\mathbf{m}_0$ and covariance $\mathbf{S}_0$

$$p(\mathbf{w}) = \mathcal{N}(\mathbf{w}|\mathbf{m}_0, \mathbf{S}_0). \tag{2.12}$$

The posterior distribution over weights, which by Bayes theorem is proportional to the likelihood times the prior, is also defined by a Gaussian, so we can derive that

$$p(\mathbf{w}|\mathbf{t}) = \mathcal{N}(\mathbf{w}|\mathbf{m}_n, \mathbf{S}_n) \tag{2.13}$$

where

$$\mathbf{m}_n = \mathbf{S}_n(\mathbf{S}_0^{-1}\mathbf{m}_0 + \beta\boldsymbol{\Phi}^T\mathbf{t}) \tag{2.14}$$

$$\mathbf{S}_n^{-1} = \mathbf{S}_0^{-1} + \beta\boldsymbol{\Phi}^T\boldsymbol{\Phi}. \tag{2.15}$$

Here $\boldsymbol{\Phi}$ is the matrix of basis functions with elements like $\phi_j(\mathbf{x}_i)$, naming it the design matrix.

If we choose the prior distribution as a zero-mean Gaussian with a precision parameter α like $p(\mathbf{w}|\alpha) = \mathcal{N}(\mathbf{w}|0, \alpha^{-1}\mathbf{I})$ where $\mathbf{I}$ is the identity matrix we get the posterior distribution over $\mathbf{w}$ given by 2.13 with

$$\mathbf{m}_n = \beta\mathbf{S}_n\boldsymbol{\Phi}^T\mathbf{t} \tag{2.16}$$

$$\mathbf{S}_n^{-1} = \alpha\mathbf{I} + \beta\boldsymbol{\Phi}^T\boldsymbol{\Phi}. \tag{2.17}$$

Taking the logarithm of the posterior distribution, given by the sum of the logarithm of the likelihood and the logarithm of the prior, we get the following

$$ln[p(\mathbf{w}|\mathbf{t})] = -\frac{\beta}{2}\sum_{i=1}^{n}\{t_i - \mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_i)\}^2 - \frac{\alpha}{2}\mathbf{w}^T\mathbf{w} + c. \tag{2.18}$$

As seen, maximising the posterior distribution with respect to $\mathbf{w}$ is equivalent to minimising the sum-of-squares error function with a regularisation term, 2.8 with $q = 2$.

To make predictions t^* on new inputs $\mathbf{x}^*$, evaluation of the posterior predictive distribution need to be made. The predictive distribution is defined as the convolution of the posterior distribution 2.13 and the conditional distribution of the observed values so we get 2.10 (Bishop, 2007),

$$p(t^*|\mathbf{x}^*, \mathbf{t}, \mathbf{w}, \alpha, \beta) = \int p(t^*|\mathbf{x}^*, \mathbf{w}, \beta)p(\mathbf{w}|\mathbf{t}, \alpha)d\mathbf{w} = \mathcal{N}(t^*|\mu^*, \sigma^{2^*}). \tag{2.19}$$

where the mean and variance are defined as

$$\mu^* = \mathbf{m}_n^T \boldsymbol{\phi}(\mathbf{x}^*) \tag{2.20}$$

$$\sigma^{2^*} = \beta^{-1} + \boldsymbol{\phi}(\mathbf{x}^*)^T \mathbf{S}_n \boldsymbol{\phi}(\mathbf{x}^*). \tag{2.21}$$

The Bayesian setting of linear regression extends ordinary linear regression by also providing the ability to measure prediction certainty with a posterior predictive distribution. The ability to model prediction certainty can be very beneficial in some settings. Although the fact that the basis functions need to be fixed before the training data is observed makes the number of basis functions grow rapidly as the feature space dimensionality increases (Bishop, 2007). This problem is a major disadvantage that the two linear regression models exhibits.

2.3.6 Gaussian Processes

Gaussian processes for regression is a machine learning method that defines distributions over functions as apposed to weights in Bayesian linear regression.

To understand Gaussian Processes for regression we need to present the concept of *kernels*. Kernels are similar to basis functions $\phi(\mathbf{x})$, discussed in 2.3.4 and 2.3.5 but with some important differences. We define a kernel function k as a real-valued function of two arguments in abstract space

$$k(\mathbf{x}, \mathbf{x}') \in \mathbb{R}, \tag{2.22}$$

$$\mathbf{x}, \mathbf{x}' \in \mathcal{X}. \tag{2.23}$$

So k is a function that given two input vectors returns a real value that is some measurement of similarity between the inputs (Schölkopf et al., 2005). Returning to the basis functions previously explained we define

$$\phi(\mathbf{x}) : \mathcal{X} \to \mathcal{H} \tag{2.24}$$

such that ϕ is a mapping from the abstract space $\mathcal{X}$ to a *feature space* $\mathcal{H}$. Under the assumption that the feature space is a dot product space we can now write (Schölkopf et al., 2005)

$$k(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x})^T \phi(\mathbf{x}'). \tag{2.25}$$

The introduction of polynomial basis functions in linear regression required the explicit transformation of the inputs to new vectors. With kernels, algorithms can instead replace all dot products $\mathbf{x}^T\mathbf{x}'$ with a call to the kernel function $k(\mathbf{x}, \mathbf{x}')$. This is referred to as the *kernel trick* (Murphy, 2012).

We now turn to the discussion of Gaussian processes for regression. We define a *stochastic process* as a collection of random variables $\{y(\mathbf{x})\}$ where $\mathbf{x} \in \mathcal{X}$, and $\mathcal{X}$ is a index set of possible inputs which could be more general such as $\mathbb{R}^d$. A stochastic process is a Gaussian process if any finite subset of random variables has a joint multivariate Gaussian distribution (Do, 2007). So a set of random variables $\{y(\mathbf{x})\}$ are drawn from a Gaussian process with mean function $m(\mathbf{x})$ and kernel i.e covariance function $k(\mathbf{x}, \mathbf{x}')$, if for a finite set of elements from $\mathcal{X}$, the related finite set of random variables $y(\mathbf{x}_1), ..., y(\mathbf{x}_m)$ have a joint distribution like (Do, 2007)

$$\begin{bmatrix} y(\mathbf{x}_1) \\ \vdots \\ y(\mathbf{x}_m) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} m(\mathbf{x}_1) \\ \vdots \\ m(\mathbf{x}_m) \end{bmatrix}, \begin{bmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & \cdots & k(\mathbf{x}_1, \mathbf{x}_m) \\ \vdots & \ddots & \vdots \\ k(\mathbf{x}_m, \mathbf{x}_1) & \cdots & k(\mathbf{x}_m, \mathbf{x}_m) \end{bmatrix} \right). \tag{2.26}$$

We use the simplified notation

$$y(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')), \tag{2.27}$$

with, for any $\mathbf{x}, \mathbf{x}' \in \mathcal{X}$, mean function and kernel function as

$$m(\mathbf{x}) = \mathbb{E}[y(\mathbf{x})] \tag{2.28}$$

$$k(\mathbf{x}, \mathbf{x}') = \mathbb{E}[(y(\mathbf{x}) - m(\mathbf{x}))(y(\mathbf{x}') - m(\mathbf{x}'))]. \tag{2.29}$$

An example of a Gaussian process model can be obtained from a linear regression model with prior $\mathbf{w} \sim \mathcal{N}(0, S)$ as (Rasmussen, 2006)

$$m(\mathbf{x}) = \mathbb{E}[y(\mathbf{x})] = \boldsymbol{\phi}(\mathbf{x})^T \mathbb{E}[\mathbf{w}] = 0 \tag{2.30}$$

$$k(\mathbf{x}, \mathbf{x}') = \mathbb{E}[(y(\mathbf{x}) - m(\mathbf{x}))(y(\mathbf{x}') - m(\mathbf{x}'))] = \boldsymbol{\phi}(\mathbf{x})^T S \boldsymbol{\phi}(\mathbf{x}') \tag{2.31}$$

For a training set of input-output pairs $M = \{(\mathbf{x}_i, t_i)_{i=1}^n\} = (\mathbf{X}, \mathbf{t})$ we define the model as

$$t_i = y(\mathbf{x}_i) + \epsilon_i, \quad i = 1, ..., n, \tag{2.32}$$

where $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$ is a gaussian distributed random noise variable, independent for every observation i. Further assuming a Gaussian process prior

$$y(\mathbf{x}) \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}')), \tag{2.33}$$

with zero mean and a valid kernel. For example the *squared exponential kernel* defined as

$$k(\mathbf{x}, \mathbf{x}') = exp(-\frac{1}{2l^2}||\mathbf{x} - \mathbf{x}'||^2). \tag{2.34}$$

The goal is to make predictions t^* on unlabelled data $\mathbf{x}^*$, we define a test set of such unlabelled data as $T = \{(\mathbf{x}_i^*, t_i^*)_{i=1}^{n^*}\} = (\mathbf{X}^*, \mathbf{t}^*)$. So, like in bayesian linear regression, the goal is to find a posterior predictive distribution.

For every function $y(\mathbf{x})$ drawn from the Gaussian process prior the marginal distribution over a set of inputs from $\mathcal{X}$ must have a joint multivariate Gaussian (Do, 2007). Under the assumption that the unlabelled data in T and the training data M are drawn from the same unknown distribution we get

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{y}^* \end{bmatrix} |\mathbf{X}, \mathbf{X}^* \sim \mathcal{N}(\mathbf{0}, \begin{bmatrix} K(\mathbf{X}, \mathbf{X}) & K(\mathbf{X}, \mathbf{X}^*) \\ K(\mathbf{X}^*, \mathbf{X}) & K(\mathbf{X}^*, \mathbf{X}^*) \end{bmatrix}. \tag{2.35}$$

Where for n training points and n^* test points the matrix $K(\mathbf{X}, \mathbf{X}^*)$ is the $n \times n^*$ matrix of covariances evaluated at all pairs of training and test points and similarly for the other K matrices. We also have $\mathbf{y} \in \mathbb{R}^n$ and $\mathbf{y}^* \in \mathbb{R}^{n^*}$. For the noise assumption we have

$$\begin{bmatrix} \epsilon \\ \epsilon^* \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} \sigma^2 I & \mathbf{0} \\ \mathbf{0}^T & \sigma^2 I \end{bmatrix}\right). \tag{2.36}$$

Using the rule that sums of independent random Gaussian variables are also Gaussian we get

$$\begin{bmatrix} \mathbf{t} \\ \mathbf{t}^* \end{bmatrix} |\mathbf{X}, \mathbf{X}^* = \begin{bmatrix} \mathbf{y} \\ \mathbf{y}^* \end{bmatrix} + \begin{bmatrix} \epsilon \\ \epsilon^* \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \begin{bmatrix} K(\mathbf{X}, \mathbf{X}) + \sigma^2 I & K(\mathbf{X}, \mathbf{X}^*) \\ K(\mathbf{X}^*, \mathbf{X}) & K(\mathbf{X}^*, \mathbf{X}^*) + \sigma^2 I. \end{bmatrix} \tag{2.37}$$

With for the rules for conditioning Gaussians we get

$$\mathbf{t}^* | \mathbf{t}, \mathbf{X}, \mathbf{X}^* \sim \mathcal{N}(\mu^*, \Sigma^*), \tag{2.38}$$

where

$$\mu^* = K(\mathbf{X}^*, \mathbf{X})(K(\mathbf{X}, \mathbf{X}) + \sigma^2 I)^{-1}\mathbf{t} \tag{2.39}$$

$$\Sigma^* = K(\mathbf{X}^*, \mathbf{X}^*) + \sigma^2 I - K(\mathbf{X}^*, \mathbf{X})(K(\mathbf{X}, \mathbf{X}) + \sigma^2 I)^{-1} K(\mathbf{X}, \mathbf{X}^*) \tag{2.40}$$

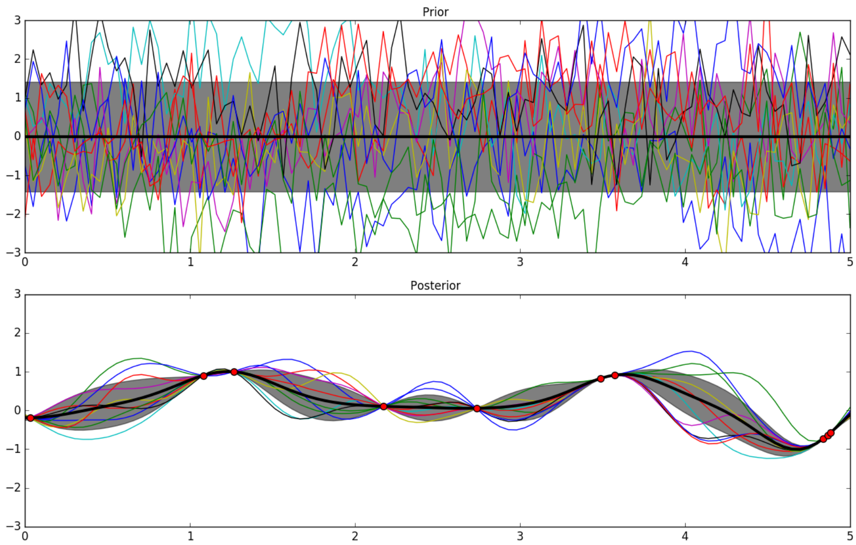

Figure 2.17: Example of 10 functions randomly drawn from a Gaussian Process prior and posterior with a squared exponential kernel. The shaded areas shows plus minus one standard deviation.

As seen in Figure 2.17, we have a Gaussian Process prior with mean function 0 and a squared exponential kernel. The first Figure shows 10 randomly drawn functions from the prior. The second Figure shows 10 randomly drawn functions from the posterior. As seen, the functions becomes bounded to the data and the standard deviation is significantly decreased around the data points.

Utilising kernels makes Gaussian Processes different than ordinary Bayesian linear regression as there is no need to define fixed basis functions prior to fitting the model. With a squared exponential kernel, the Gaussian Process regression model corresponds to a Bayesian linear regression model with infinitely many basis function (Rasmussen, 2006). The advantages of the model comes at the cost of computational complexity. Making predictions with Gaussian Processes has a space complexity of $O(n^2)$ and time complexity of $O(n^3)$ (Rasmussen, 2006).

2.3.7 Model selection and performance estimation

The models presented above all have hyperparameters i.e free parameters that require tuning in order for a model to perform well. In order to tune the hyperparameters and evaluate models performance, some metric of prediction performance is required. This section presents methods for performance measurement and hyperparameter optimisation.

2.3.7.1 Coefficient of determination

The coefficient of determination metric, denoted R^2, provides a measurement of how well future samples are likely to be predicted by the estimator. Best score is 1.0, a constant model that disregards input features would get a score of 0.0. The R^2

score is defined as

$$R^2(\mathbf{t}, \mathbf{t}^*) = 1 - \frac{\sum_{i=1}^{n} (t_i - t_i^*)^2}{\sum_{i=1}^{n} (t_i - \bar{t})^2}. \tag{2.41}$$

Where t_i is the target output, t_i^* is the predicted value, n is the number of samples and $\bar{t}$ is the average over all desired outputs.

2.3.7.2 Cross validation

Training models so that they maximise the R^2 score on the whole set of labelled data can lead to severe overfitting and bad generalisation performance, this because such a regression model would be a function that goes through every point of the training data and if noise is present, this is not desirable as shown in section 2.3.4 and Figure 2.15. Because of this we present the method of cross validation. Cross validation a method for estimating a models performance. We define the complete set of available labelled data as $M = \{\mathbf{x}_i, t_i\}_{i=1}^{n}$. After randomly scrambling the set M we divide M into k folds, i.e into k sets of approximately $\frac{n}{k}$ samples. We denote these sets $C_1, C_2, ..., C_k$. For $j = 1...k$, the model is trained on all data that does not belong to the set j and then measure the models score on data that are in the set j. For every fold we compute the score which can be the coefficient of determination R^2, or some other scoring function, and then average that score.

2.3.7.3 Grid search

A grid search is an exhaustive search over a defined set of hyperparameters. The concern of a grid search is finding the configuration of hyperparameters which maximises the score of the model. The search needs some way of comparing the configurations so naturally k-fold cross validation can be used for evaluation. As an example, for an enumerable set of hyperparameters $H = \{(g_1, h_1), (g_2, h_2), ...(g_m, h_m)\}$ we configure the model with every pair of hyperparameters and for every configuration we evaluate the performance of those hyperparameters with a k-fold cross validation.

In the previous sections, several machine learning models and model selection techniques were presented. As the purpose of this project is to search for a repeatable, scalable and sustainable business model, based on machine learning technology, the previous sections were included to present a theoretical background to machine learning methods and concepts used in the product development. This also concludes the theory section of this thesis. These theoretical frameworks guided the project in the process of finding a repeatable, scalable and sustainable business model based on machine learning technology by applying the Lean Startup Methodology. Theories of the Lean Startup Methodology make it possible to develop a repeatable and scalable business model, while the sustainability theories informs how to make the business model sustainable in deployment and the machine learning frameworks presented a theoretical background for the methods and concepts used to develop a product.

3
Methods

In this chapter, we present the methods applied in this thesis. Since this project is of a practical nature, the methods are centred around the empirical work rather than focusing on scientific method structure.

3.1 Venture Creation

The purpose of this project is to search for a repeatable, scalable and sustainable business model, based on machine learning technology, by applying the Lean Startup Methodology. This means that we are working in the domain of venture creation, as defined by the Cambridge online dictionary the process of turning a new idea or technology into a business that can succeed and will attract investors. Before we can start the process of applying the Lean Startup Methodology, we need to create a set of hypotheses or ideas as a starting point. This section describes concepts and frameworks related to the inception point of venture creation.

Founding a startup to pursue venture creation has a number of dilemmas attached to it (Wasserman, 2013). There is for instance the *Solo-versus-Team* dilemma. Wasserman (2013) argues that data suggests there are different reasons when going solo is the preferred choice. For example, the solo founder could have already attracted the resources necessary to found the startup. She may also choose this path to avoid identified factors that makes startups especially prone to failure (Stinchcombe and March, 1965). These factors are all related to forming a founding team. Forming relationships based on trust with strangers, negotiating distribution of financial rewards, and learning to take new roles within the founding team are all avoided when deciding to be a solo founder. However, there are also arguments for when multiple co-founders are an asset to the startup (Wasserman, 2013). These arguments are mainly based on three kinds of capital: Human, social, and financial capital. The human capital is the sum of the knowledge, skills and experience of the team. Social capital refers to the value of the information and communication based networks the team can amass. The financial capital is an economic resource measured in terms of money that can be leveraged within the team when founding the startup. Taking a capital based approach, having multiple founders could result in a larger base of human, social, and financial capital. Wasserman (2013) summarises these arguments of Solo-versus-Team dilemmas in Figure 3.1. Coupled with a founding of a startup by either a solo founder or founding team, an idea is required to meet the definition of venture creation. Osterwalder et al. (2014) offers a framework to conceptualise two

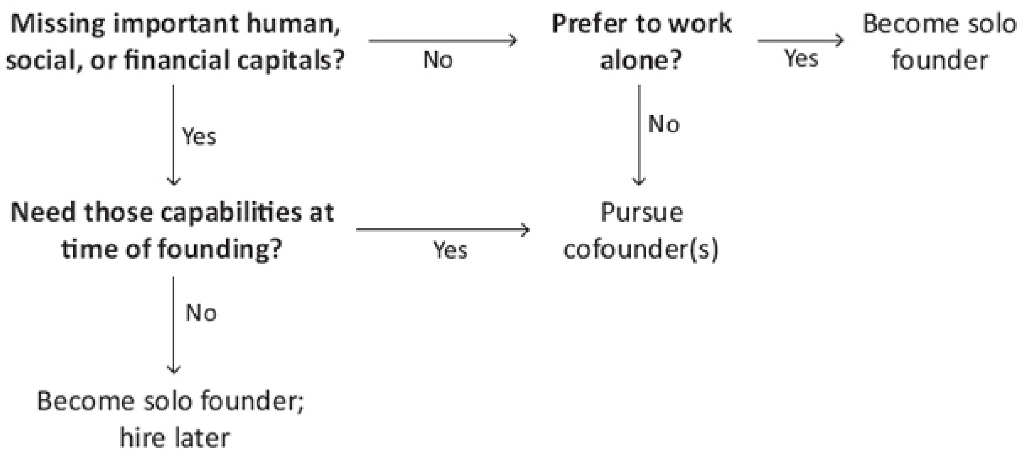

Figure 3.1: Central "Solo versus Team" Questions (Wasserman, 2013)

different approaches from where a business model design can originate from. The first approach is called technology push, in which the starting point is a key resource that could be an invention, innovation or technology. This approach starts from a solution of sorts, and through designing and prototyping ideas looks for a problem to solve as a business. In contrast, the approach of market pull starts from the jobs, pains and gains of a customer segment. Ideas are then designed and prototyped to find a solution to these problems. These approaches are visualised in Figure 3.2 and 3.3. According to Osterwalder et al. (2014), both approaches should be considered viable options depending on the preferences and context of the startup or business.

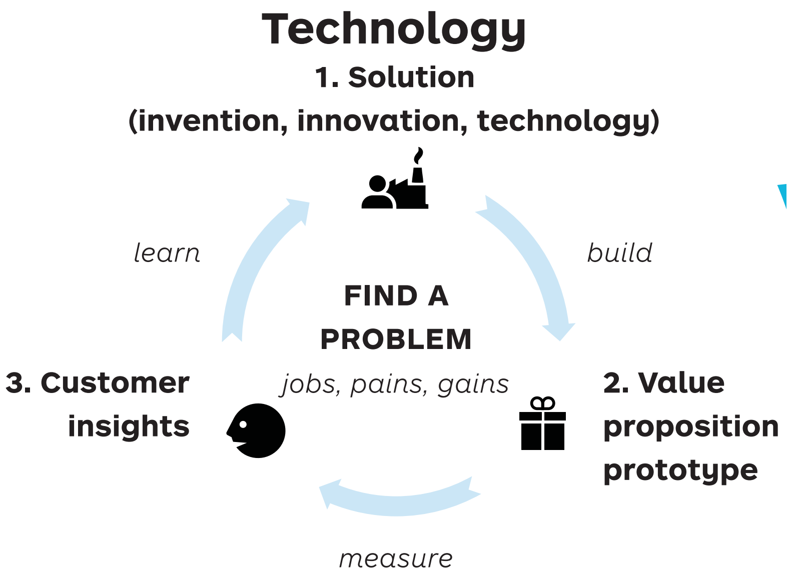

Figure 3.2: Technology Push (Osterwalder et al., 2014)

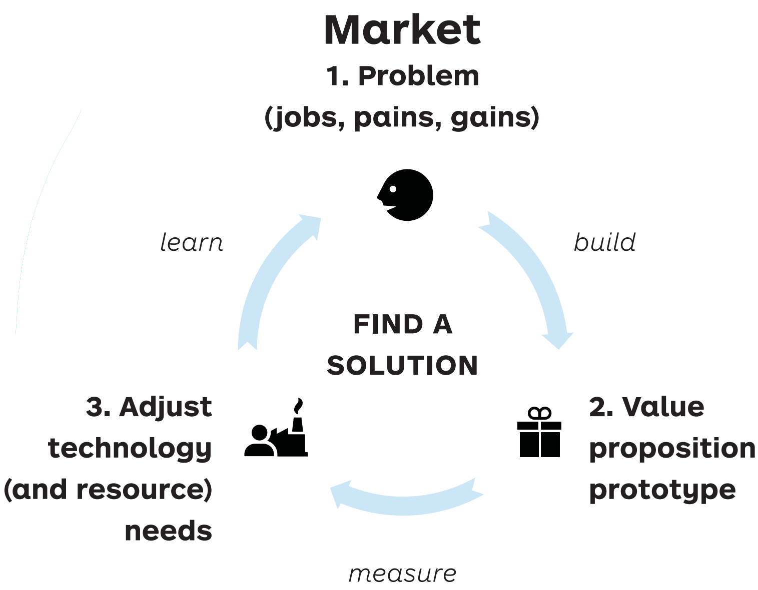

Figure 3.3: Market Pull (Osterwalder et al., 2014)

3.1.1 Team

This project was created within the constraints of a bachelor's thesis at Chalmers University of Technology. The constraints required six students to form a team, which can be visualised as required choices in Figure 3.1 and define their own thesis purpose, which in itself had to have a certain technological level to be accepted by the faculty of the university. Facing these requirements, we decided to start from the approach of technology push, visualised in Figure 3.2, simply choosing to work with a technology we were excited about. The technology domain we chose was machine learning, a sub-field of artificial intelligence, which has a wide range of possible areas of applications such as finance, health care and education just to name a few.

With the choice of having a team of six founders already made for us by the university, the challenge became to maximise the total of human, social, and financial capital when forming the team. This pursuit led to a formation of a team with a wide variety of backgrounds, skills, experiences and networks. Two members studied Industrial Engineering and Management, two studied Software Engineering, one studied Computer Science and one studied double degrees in Industrial Engineering and Management combined with Software Engineering. This mix of backgrounds and skill sets were a reflection of the need to have knowledge and passion for both technology and business to build the startup. Experience wise, members had been or were concurrently working at top technology companies, had started startup projects before, and had good knowledge of implementing machine learning methods. These activities had also resulted in a broad network that enabled us to connect with top technology companies in our pre-study traveling to Silicon Valley, and to ask for domain specific advice in related to both business and technology as the project went on.

3.1.2 Idea

After the team was assembled and the starting point of the technology push approach using machine learning technology, it was time to design our first hypotheses. According the Progress Board, seen in Figure 3.4, the first two stages of progress entails prototyping business model and value proposition, and to asses these designs with competitors. Osterwalder et al. (2014) details how this process can be performed specifically for ideas starting from technology push, using the six steps seen below.

1. Design - State the technology as a key resource.
2. Ideate - Come up with possible value propositions based on this key resource.
3. Segment - Select a customer segment that could benefit from this value proposition.
4. Profile - Sketch out the customer's profile on the value proposition canvas.
5. Sketch - Refine the value proposition map to match the customer profile on the value proposition canvas
6. Assess - Assess the design as initial hypotheses as a starting point of the Lean Startup Methodology.

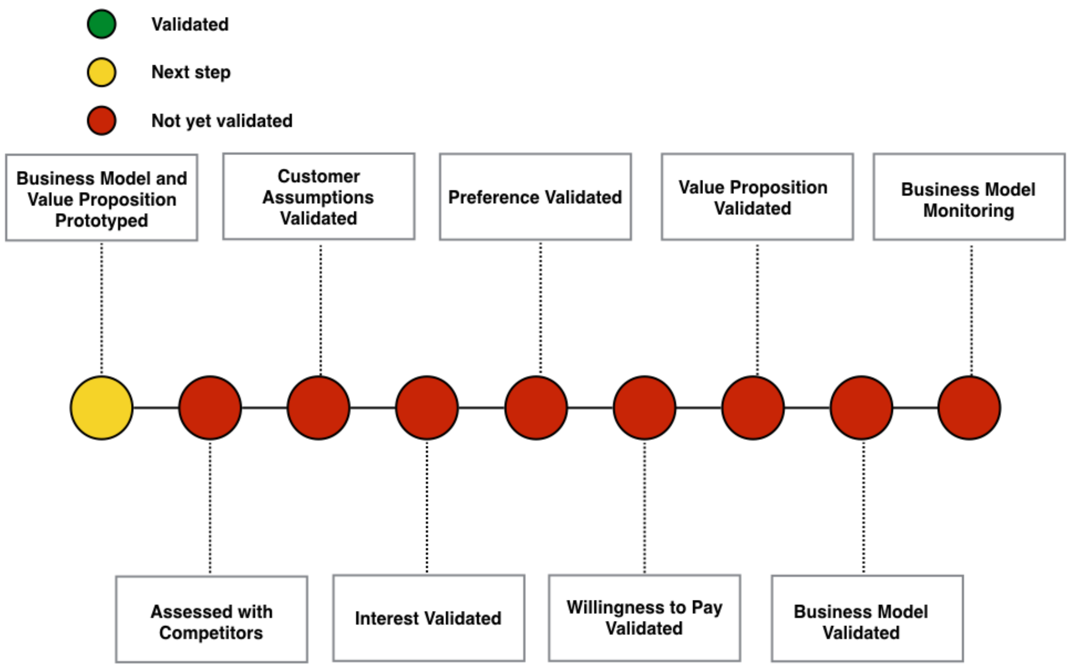

Figure 3.4: Idea Stage on the Progress Board

Our approach to assessment was influenced by the frame of our thesis, where Chalmers University of Technology would both require and excite us for solutions with an element of sustainability. In other words, a great business idea that would by design have a negative effect on environmental, social, or economical sustainability would not be pursued.

We went through these steps twice as a team before finding hypotheses that got us excited to pursue. The result of the first iteration, seen in Figure 3.5 and 3.6, was an idea to offer price recommendation, based on machine learning, as a value proposition to hosts on the travel platform Airbnb. Our assessment was that it would empower hosts to compete against big hotel chains which can afford to develop proprietary price recommendation software for their rental services. This in turn could be a great asset to a sustainable economy where current housing resources could be used more efficiently and private citizens could generate revenue as income. However, after searching for similar offerings on Google.com, it turned out that Airbnb had recently introduced a similar tool on their platform. While possible to work and improve this solution, the team were not as excited to work on the idea as it was not novel.

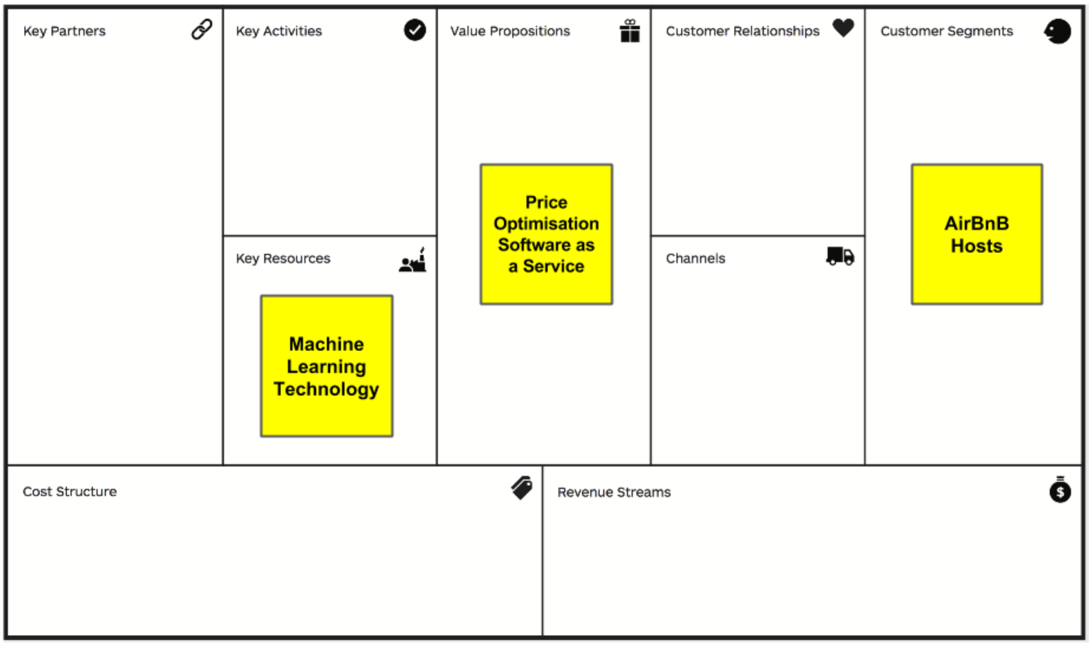

Figure 3.5: Iteration 1 Business Model Canvas Hypotheses

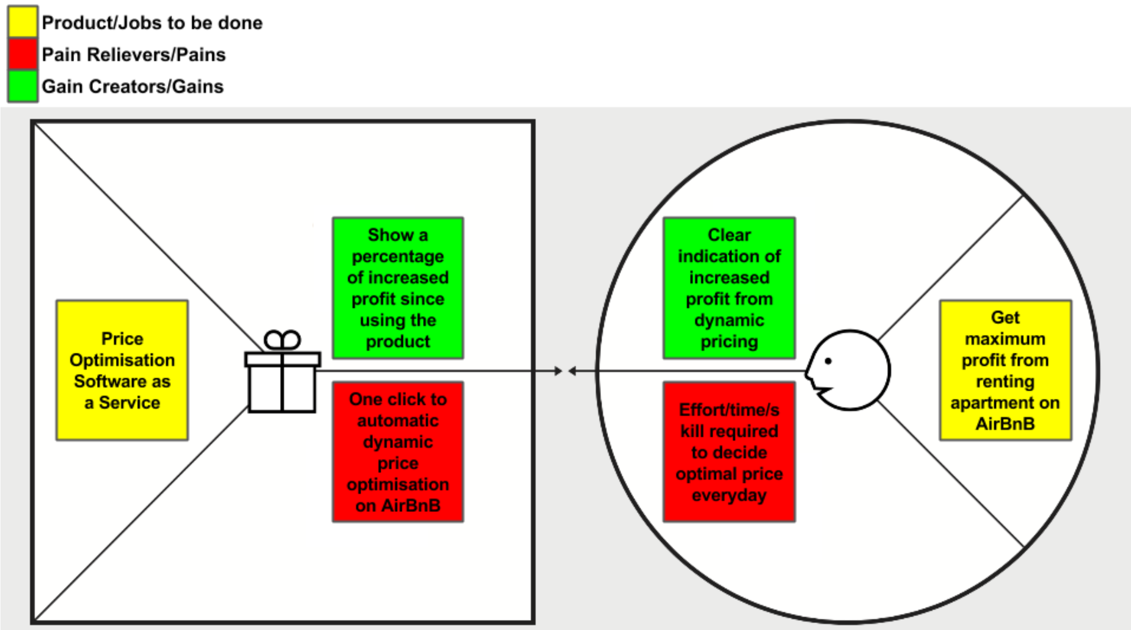

Figure 3.6: Iteration 1 Value Proposition Canvas Hypotheses

The results of the second iteration can be seen in Figure 3.7 and 3.8. Here, our idea was once again to offer price recommendation, based on machine learning, as a value proposition. However, the customer segment would be sellers on online second hand marketplaces. Specifically, we chose sellers of Macbooks since we had some experience with selling Macbooks ourselves. Starting with the narrow scope of Macbooks would make the technological challenge more attainable within a short period of time, with the option to expand in concentric circles on the second hand market to Iphones, Apple products, digital products or even all product categories. Our assessment was that it was an interesting challenge from a sustainability perspective. Utilising second hand resources has an environmental impact, while making the second hand market more accessible and transparent for sellers could improve their personal finance, or economical sustainability. The social aspect of sustainability in this case could be argued to have the potential to alleviate poverty and increase potential for communication and information empowerment through further utilisation of computing platforms and electronic devices. Since Macbooks have a tendency to be replaced by a new generation for the consumer, potential for a repeatable business model is present. Building Software as a Service is also inherently scalable, since there is essentially zero marginal cost for further use of the platform, and the cost structure would be centred around server costs. Our assessment was therefore that the designed business model had potential to be repeatable, scalable and sustainable. Unless a pivot would be made that would change this fundamental nature of the business model, these assessments about the business model would remain intact.

A cursory search on Google.com for similar solutions returned competitors, but none which seemed dominant enough to turn us away from believing it was a problem that had not yet been solved well. These became our initial hypotheses that we designed on our Business Model Canvas and Value Proposition Canvas. Having now prototyped our canvases and assessed them against competitors, this meant that we had graduated from stage one and two on the progress board to stage three, seen in Figure 3.9, where customer tests take place in search for problem-solution fit. At this point, we named our startup project "Selleri".

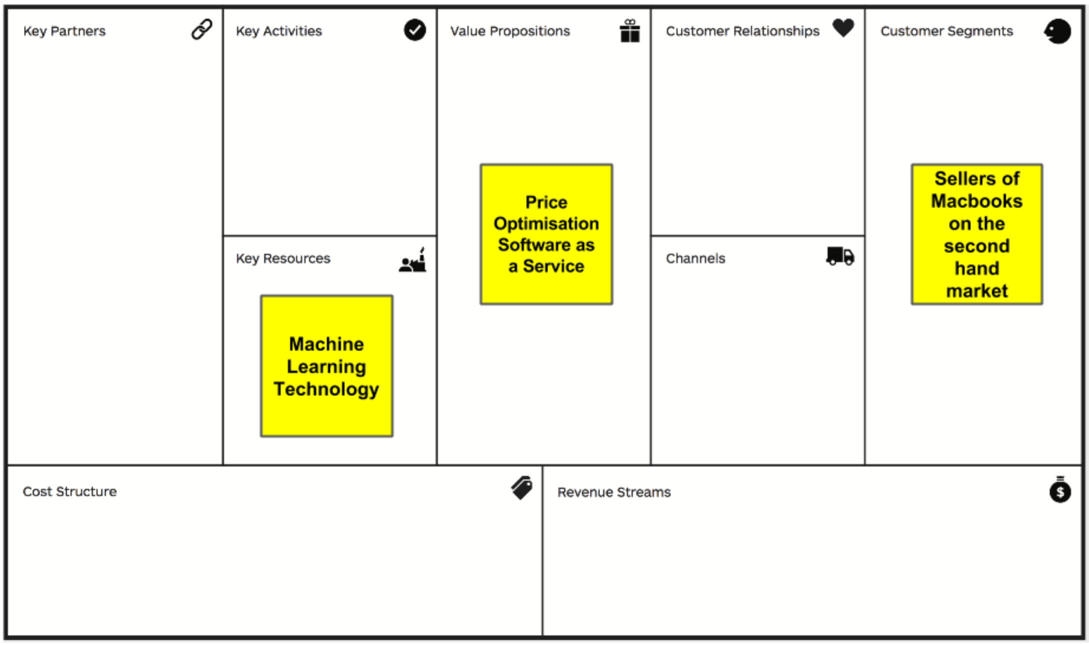

Figure 3.7: Iteration 2 Business Model Canvas Hypotheses

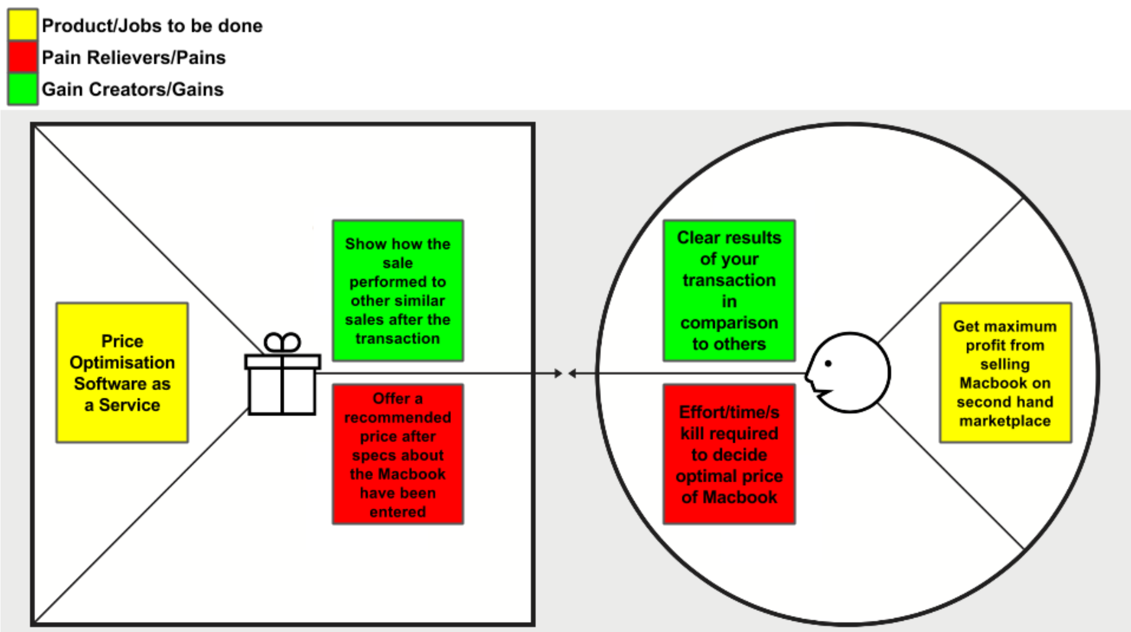

Figure 3.8: Iteration 2 Value Proposition Canvas Hypotheses

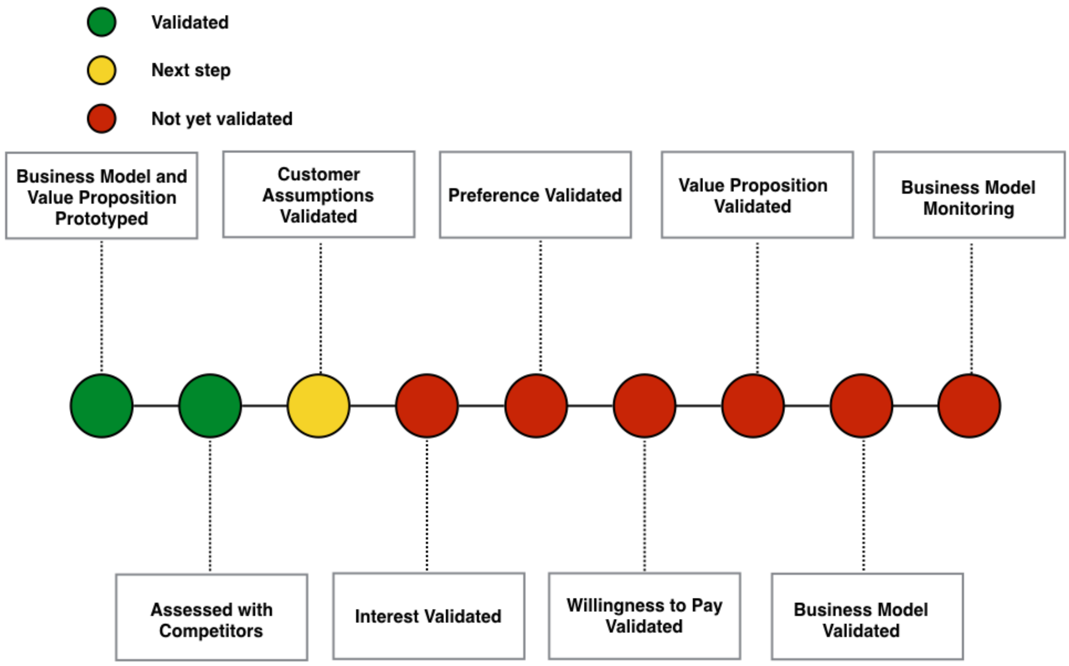

Figure 3.9: Test Stage Progress Board

3.2 Applying Lean Startup Methodology

As previously stated, Blank and Dorf (2012) defines the Lean Startup as a methodology consisting of three components: Business Model Design, Customer Development and Agile Engineering. These components are also umbrella-terms of sorts where different tools and approaches are utilised with the same purpose in mind. For our startup project, we had to define how we would apply the Lean Startup Methodology now that we had designed our initial hypotheses on the Business Model Canvas and Value Proposition Canvas.

3.2.1 Applying Scrum Development

We decided to use the Scrum development framework in the project. The main reason is that we found the structure of working in sprints more suitable than e.g. Kanban or Extreme Programming. This was due to a clear overview of the project through a Scrum board, as well as the defined, yet flexible roles (Sillitti et al., 2011). Using Scrum development meant that we would perform sprints, a timed cycle of a Build-Measure-Learn feedback loop, on a two-week average cycle. This cycle can come from structured tests, where we set up test cards to measure and learn from, or in a more ad-hoc way, such as talking to customers, friends and family, inter-team discussions, or personal findings.

Each sprint would consist of approximately two weeks of work and our plan was to do four to five sprints for the whole duration of the project. These sprints are reported in chapter 4, each one starting with a snapshot of our current progress and hypotheses. In chapter 4 of this thesis, we decided to only illustrate the elements in the Business Model Canvas and Value Proposition Canvas that were directly related to the individual sprints, to make the purpose of each sprint more transparent. This is why some parts of the canvas were left empty at times.

3.2.2 Build

Each sprint consists of building tests, experiments, or developing the product, all towards the purpose of finding a scalable, repeatable and sustainable business model. This was when we decided which test or development we would perform and how we would do it.

The customer tests were designed with the use of *Test Cards*, consisting of our hypotheses, test, metric of measurement, and criteria for validation (Osterwalder et al., 2014). We discuss how critical this test is considered to be to the success of our business model, what costs and data reliability the test has, and ending on how much time the test required to measure the required data. In summary, the Build section describes the **method** used in each individual sprint.

3.2.3 Measure

For everything we built, data were collected to measure the impact towards our purpose of finding a scalable, repeatable and sustainable business model. The data were reported and key points are showcased to inform the successive *Learn* process. In summary, the Measure section describes the **result** of each individual sprint.

3.2.4 Learn

In the last section of each sprint, we conclude with our learnings based on the data we observed and measured. All learnings that generate value and insights for the generation of a business model are considered. The learnings from customer tests leveraged a *Learning Card*, which includes a restatement of our hypothesis, a brief description of the data we observed, the learnings and insights we took from the tests, and the decisions and next actions we decided to take based on this test (Osterwalder et al., 2014). The data reliability was briefly discussed, as well as an indication of the impact these next actions will have on our current business model, being a small iteration or a larger pivot. As the inter-team social capital described by Wasserman (2013) is not captured by the Business Model Canvas, it is evaluated in a final sprint retrospective. In summary, the Learn section describes the **analysis** of each individual sprint.

This concludes the overarching methodologies that were used in the project, and we will now present the results from applying said method.

4

Our Lean Startup Process

In this chapter, the implementation and results of our work is presented and analysed. The process had an iterative nature centred around sprint cycles. Each sprint begins with a snapshot and assessment of our current progress. For each sprint, we present what we built, what we measured, and what we learned.

4.1 Sprint 1

Starting Sprint 1, we were at stage three on the Progress Board, found in Figure 4.1, having prototyped our Business Model Canvas and Value Proposition Canvas as well as assessed these models against competitors. This meant that we had entered the Customer Discovery phase of the Customer Development Process, and the goal was to achieve Problem-Solution Fit by validating our customer assumptions. The current canvases are found in Figure 4.2. and 4.3. We decided to build two customer tests and measure qualitative and quantitative data during Sprint 1, to learn about hypotheses about our customer profile.

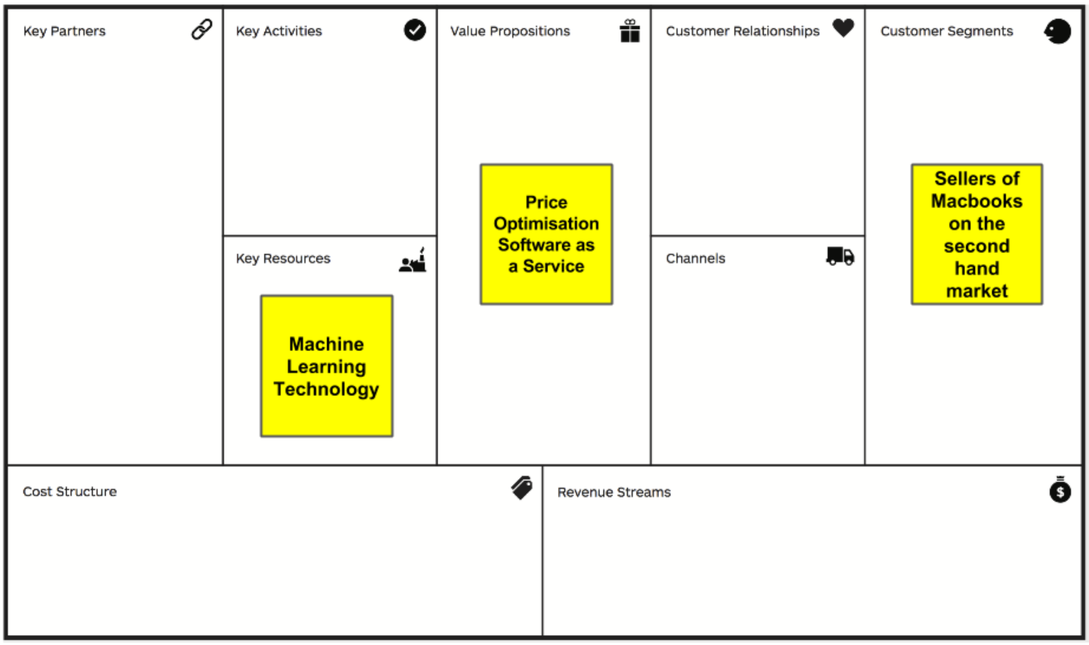

Figure 4.2: Sprint 1 Business Model Canvas Hypotheses

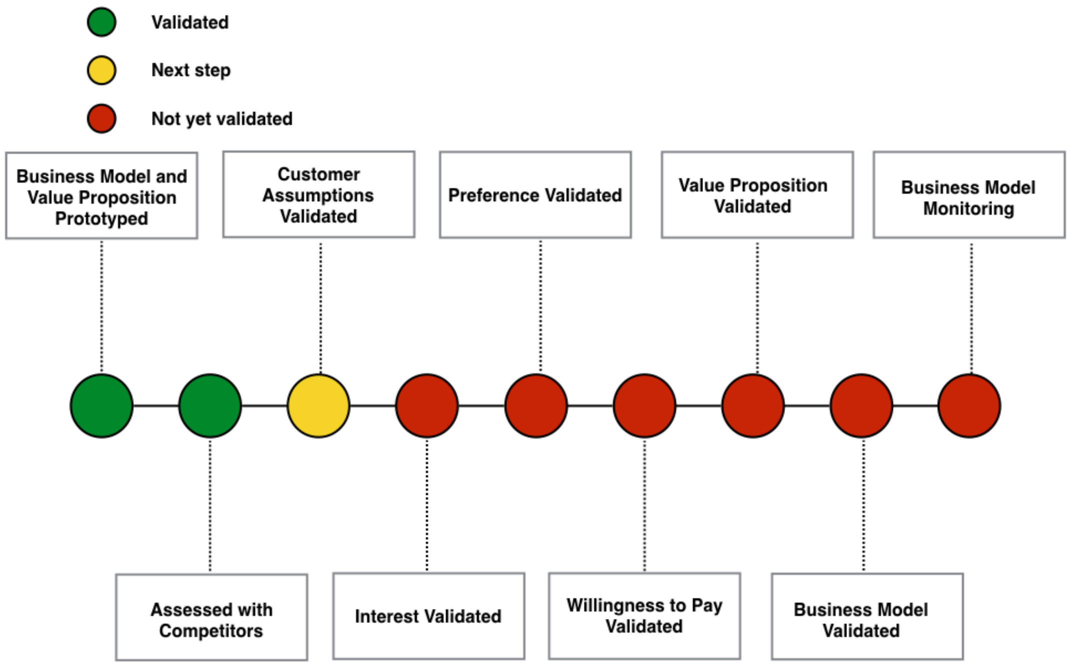

Figure 4.1: Sprint 1 Progress Board.

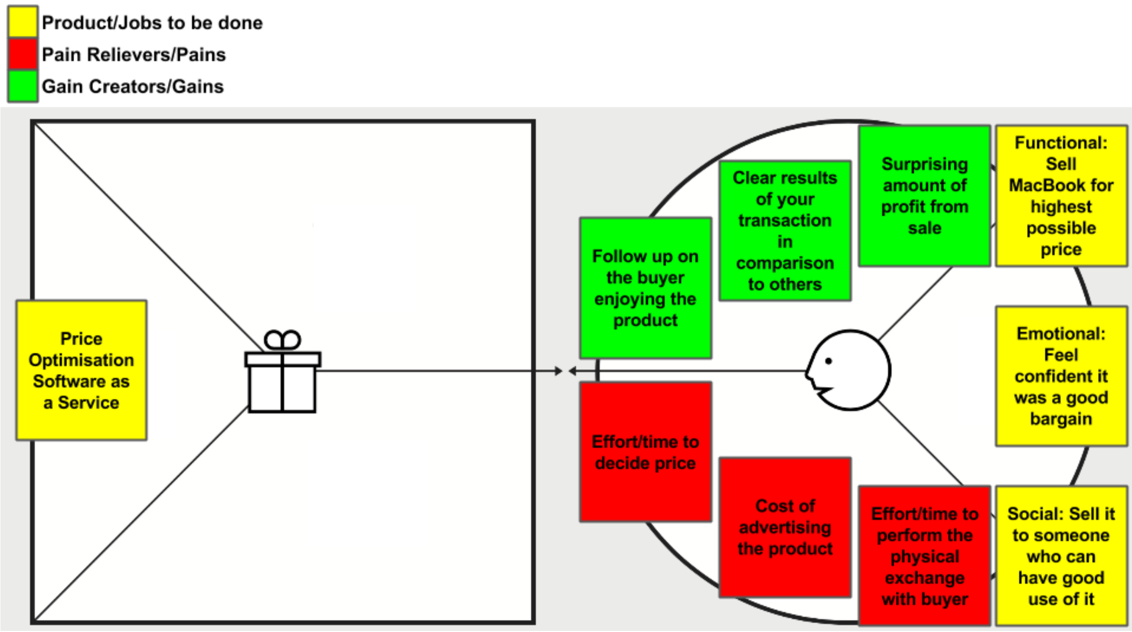

Figure 4.3: Sprint 1 Value Proposition Canvas Hypotheses

4.1.1 Build

In the first sprint, we built two tests for testing our initial customer hypothesis, and started initial development of a *Minimum Viable Product (MVP).*

4.1.1.1 Conducting Interviews to Test the Initial Customer Hypothesis

The customer interviews started from a hypothesis that our designed customer, as stated in the Value Proposition Canvas in Figure 4.3, matched a customer base existing in the real market. To test this hypothesis, we decided to conduct ten interviews with customers who had previously sold a Macbook on the second hand market. The interview questions were based upon what job to be done, pains, and gains. They were also based on the customers experiences in the process of selling a Macbook, and the respective gain creators and pains relievers that exists (Osterwalder and Pigneur, 2010). The full interview questions can be found in appendix B.2. The test card can be seen in Figure 4.4.

The metric we measured was an aggregation of their responses, checking if they matched our initial design or not. The criteria of validation was defined as met if every bullet point on the designed customer profile was mentioned by over 80% of the interviewees.

This test was considered critical since validating the customer profile was required to graduate to the next step on the Progress Board. There were no direct costs related to the test, other than a time. Data reliability was rated as low since establishing trustworthiness in the data might entail interviewer corroboration, prolonged engagement with the interviewees, auditability and confirmability (Lincoln and Guba, 1985). In other words, we believed we could gain a lot of insights from interviewing customers, but would not necessarily trust the data by itself even if it met our criteria of validation. We would rather run more tests with higher data reliability to support these claims. The 10 interviews were decided due to time constraints, and did limit the quality of the data. To counteract this, the questions was designed as to generate as much qualitative information as possible. The time budget for the test was synced to the current sprint, and thus estimated to two weeks, which was rated as moderate.

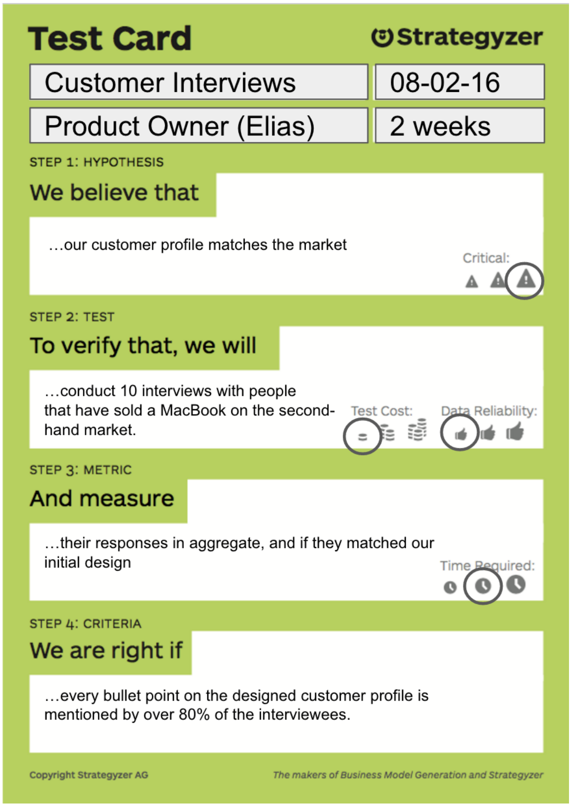

Figure 4.4: Customer interviews Test Card

The Customer Questionnaire was a further test to validate or invalidate our current customer profile hypotheses in the market. Based upon the qualitative data in the interviews, we created a questionnaire to further narrow down on the customer hypothesis. The test card can be seen in Figure 4.5.

Conducting the test involved ten customers meeting the same criteria as the customer interviews, having previously sold a Macbook on the second hand market. These ten customers were given a set of affirmative statements in a questionnaire, found in appendix B.3, and were asked to rate how well they identified with the statements on a five point scale. This was done in order to describe the accuracy of each statement in relation to their experience of selling their Macbook. These ratings were measured and segmented based on their responses. The criteria for a validated hypotheses was that we could identify a customer segment where 80% of the answers matched our customer profile.

Figure 4.5: Customer Questionnaire Test Card

This test was, like the customer interviews, considered critical since validating our customer profile was required in order to move to the next stage on the Progress Board. There was no direct cost related to running this experiment, other than time. Data reliability was rated as moderate, since there were risks of using a questionnaire (Kelley et al., 2003), which were mainly:

1. The high risk of the one answering misunderstanding the questions
2. Different people rate and perceive the questions differently
3. The data that are produced are likely to lack details or depth on the topic being investigated
4. A low response rate makes it less statistically relevant

However, getting responses in the form of numbers was precise in the aggregation of the data (Diriwächter and Valsiner, 2006), in contrast to the more qualitative customer interviews. The time budget was estimated to two weeks which was rated as moderate.

4.1.1.2 Building a Domain Model for Developing an MVP

In order to produce an MVP to represent the value proposition in Figure 4.3 for the customer, the starting point for the technical development was to create a domain model. A domain model is an abstract overview of a system where the parts and connections between the different parts are outlined.

Our model, seen in Figure 4.6, had two main parts. One part was the website that a potential user visited, signed up and filled in specifications of the computer. A REST API was the second part, it was meant to run on a different server and perform the machine learning computations needed for a price recommendation. The API was decided to be built using the *Python* language and the website was decided to be built with a *Node.js* backend and *Angular.js* frontend. The technical decisions were made according to the technical background of the team. Both the website and the REST API were to be hosted on *Heroku* servers to easily scale when needed.

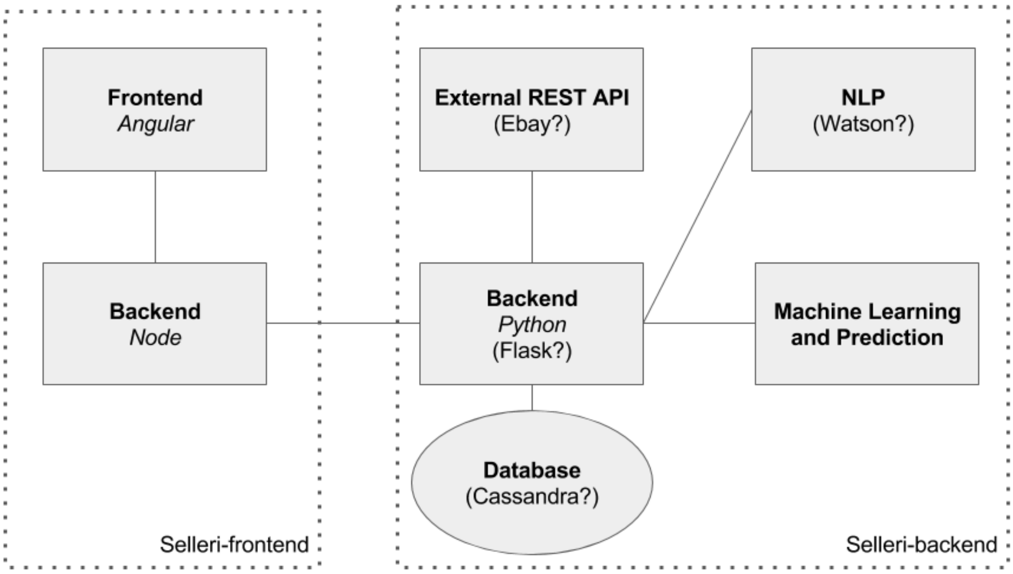

Figure 4.6: Product domain model

4.1.1.3 Researching External APIs for Gathering Data

Our value proposition at its current state required the creation of technology that could predict prices for a set of inputs variables. A lot of data needed to be acquired to use machine learning algorithms, and we needed to evaluate our options for gathering this data.

To get as accurate data as possible we measured the available data filters from different market platforms and vendors. To measure which external API that was most fit for the product, we looked at the Swedish second hand market and where the biggest markets were. Several platforms for data retrieval were evaluated, primarily Blocket, Tradera, and Ebay, since they are the biggest market actors. We also investigate if and how we could use Natural Language Processing (NLP) to analyse data from external APIs.

4.1.1.4 The MVP Development at This Stage

The team discussed various strategies for further developing the fully-functional MVP. At this point the price prediction API had not been implemented but the frontend and backend could communicate with each other. We had a temporary site that was served from the Node.js server.

4.1.2 Measure

We measured data from the customer tests during Sprint 1, and the results from the initial development research.

4.1.2.1 Data From Interviews and Questionnaires

The initial data from the customer interviews, found in appendix B.7.1, was the result of transcribing insights from the audio recordings of the interviews that were conducted in person. These results were further divided into patterns, found in appendix B.8. A key result of this process was that it gave us an opportunity to see common patterns of statements. For example, some customers expressed a desire to sell their Macbooks for the highest possible profit, while others were not very concerned with the price. Finding the data from the customer questionnaires, found in appendix B.9.1, showed that there were some commonalities between customers. For example, the data showed a correlation that customers who had sold their Macbook to a family member or a friend were the ones that did not care much about the pricing. The customers who had sold their Macbook online to a stranger, in contrast, were very interested in maximising the profit from the sale.

4.1.2.2 Evaluating Potential for External APIs and NLP

When evaluating external APIs for data gathering, we found that Ebay's API for fetching products had a REST API. From the API, historical transactions from all markets was accessible. Ebay's API also had the biggest data set in our comparison and it had the ability to filter searches. For example, if a search for "Macbook" was made there would be results for not only Macbook computers, but also Macbook accessories and Macbook cases that were no appropriate to include in training machine learning algorithms as the price would not be representative for what the customer was asking for.

We also found that Tradera's API was built upon Simple object access protocol (SOAP), which was not as easy to use as a REST API. The amount of data that could be extracted was small in comparison to Ebay.

Blocket did not have an API for querying data about historical transactions.
When evaluating different methods for NLP, we found that Natural Language Toolkit (NLTK) had suitable methods for transcribing text, and it was written in Python, which is the same language we had planned to write the machine learning backend in.

4.1.3 Learn

In the first sprint, by analysing the results, we learned that our initial customer hypothesis needed further iteration, and what tools to use for further developing the MVP.

4.1.3.1 Invalidating Original Hypothesis

Before running the customer interviews test, we believed that our customer profile matched the market. However, through the interviews we observed data that invalidated many of our hypotheses. In conclusion this led us to the insight that we needed to re-design our customer profile and test it further.

We needed to remove "Follow up on the buyer enjoying the product" from gain and "Effort/time to perform the physical exchange with buyer" and "Cost of advertising the product" from pain on the Value Proposition Canvas. On the other hand we needed to add "Access to broader marketplace" to gain and "Time to sale" and "Unsure of computer condition" to pain.

As seen in the list above, the only changes that were made affected the gains and pains. Customer jobs remained unchanged since the data either validated the hypothesis or did not support either validation or invalidation. As stated in the build-phase, the data had relatively low reliability, making us more comfortable to label some hypotheses invalidated and test further than to call any part of the customer profile completely validated.

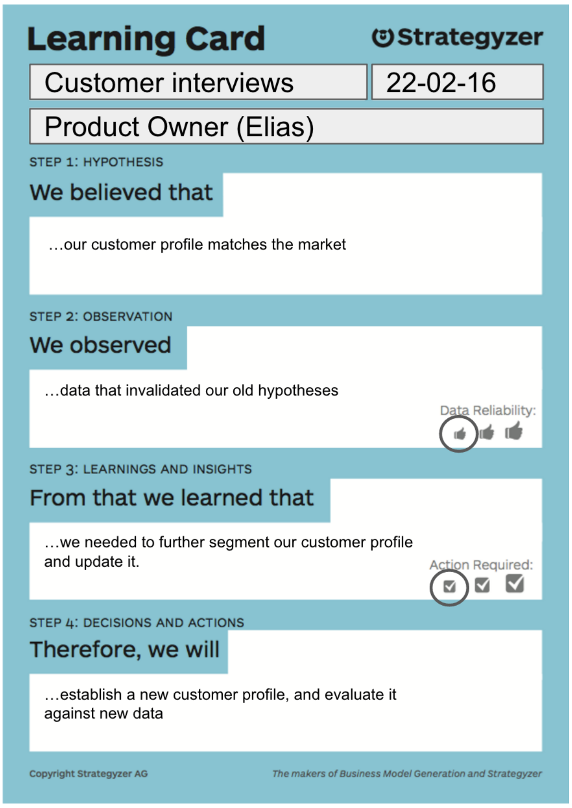

Figure 4.7: Customer interviews Learning Card

The customer questionnaires were based on the qualitative data from the re-designed customer profile, which was coupled with the hypothesis that this would match the real market. Testing this hypothesis led to the observation that some parts of the customer profile were once again invalidated, but other areas were not and instead strengthened our belief in them. From this position, we could once again update our customer profile based on the new data. After once again re-designing the customer profile, we could enter Sprint 2 with new progress in the customer development process.

Figure 4.8: Customer Questionnaire Learning Card

To reiterate, we rated the reliability of this data as moderate in the build phase. The action to re-design the canvas was again considered a small iteration.

4.1.3.2 Deciding upon Architecture and Dividing Responsibility

With the domain model in place, we learned that to develop the MVP we needed to do it in two separate parts, the website part running on Node.js and Angular.js, and the REST API part with a Python server running the machine learning algorithms and accessing external APIs, such as Ebay and Tradera. With this division in place it was easy to assign certain members of the team as responsible for different parts of the MVP. With these insights, the team could start the next sprint with a clear structure of the project.

4.1.3.3 Ebay has the Biggest Macbook Dataset

In our research for how to gather the required data by the machine learning algorithms, we learned that Ebay's API for fetching information about products were easiest to use and had the biggest set of data. This made it very preferable to use for gathering the first batches of data. While the Tradera data set more closely resembled the customers own data, and did have an API with the ability to fetch data, it was deemed too complex to get an outdated SOAP API working with our software. The discrepancy could be compensated for in other ways, such as by adjustment via a conversion index for Macbook prices but we deemed it not worth our development time. However, we were aware of the fact that Ebay's API collected information about products sold worldwide, and not as much in Sweden as Tradera. This could result in the recommended price being more accurate in e.g. the U.S. compared to Sweden, since Macbook computers slightly differ in price, depending on which country they are sold in.

While we found a suitable method to implement Natural Language Processing with, we also found that it would be very time consuming to implement. As such, we chose to prioritise other features before it.

4.1.3.4 Sprint Retrospective

From the first sprint it was clear, based upon the group feedback, that the pre-defined workflow was too structured and unnecessarily complex. Instead of using git and a text editor to edit the document, the group changed to using Sharelatex. The documentation process was changed from a dynamic flow in Slack to a more static documentation process in Google Documents. Technical issues were encountered with using Skype for the daily scrum, therefore it was changed to Google Hangouts. Furthermore, it was unclear what roles the Scrum master and Product owner had, and a more prominent role from both of them was desirable. Overall, a lot of the structure of the work flow was improved.

4.2 Sprint 2

Starting Sprint 2, we were still at stage three on the Progress Board, found in Figure 4.9. Not yet having found Problem-Solution Fit, we needed to run more tests based on the customer profile on the Value Proposition Canvas. The current canvases are found in Figure 4.10 and 4.11 respectively. We decided to build a landing page to measure signups to learn more about our customer profile.

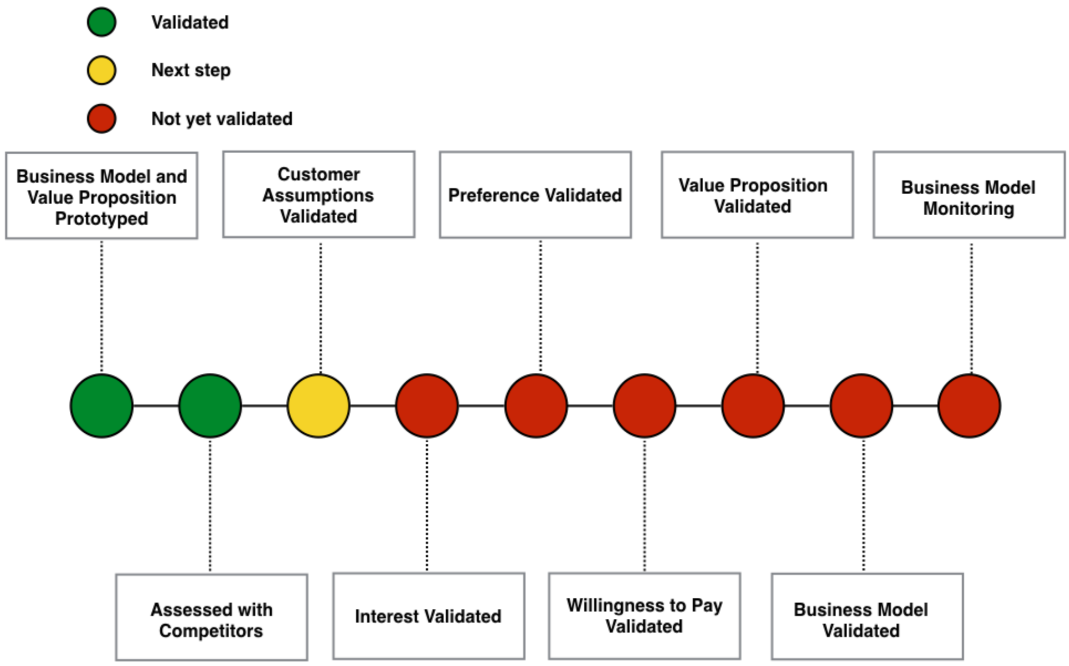

Figure 4.9: Sprint 2 Progress Board.

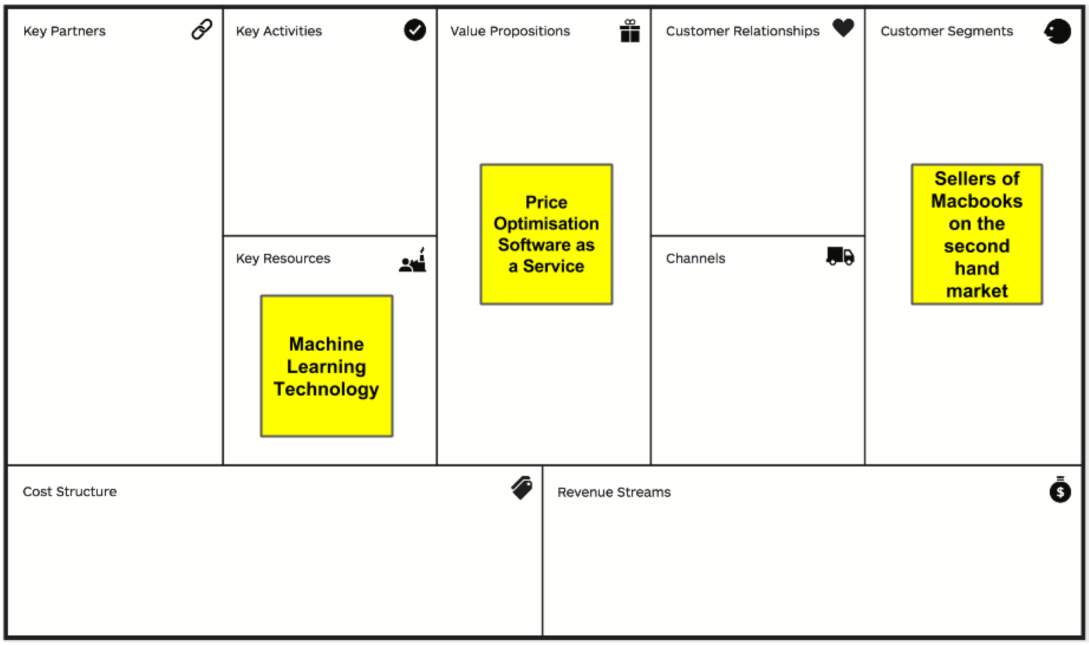

Figure 4.10: Sprint 2 Business Model Canvas Hypotheses

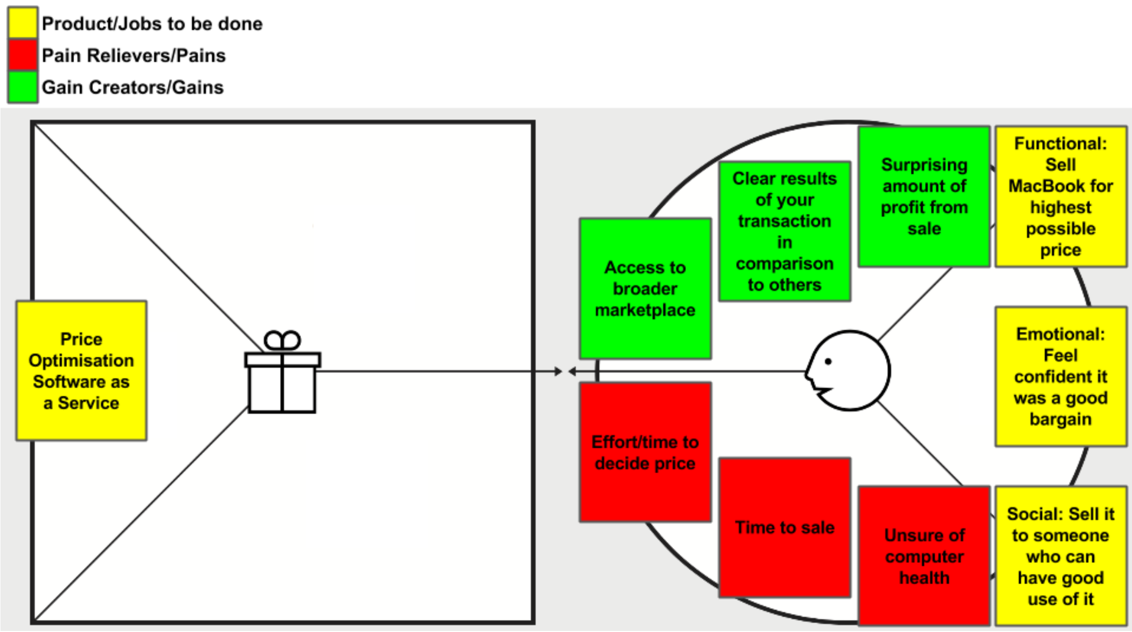

Figure 4.11: Sprint 2 Value Proposition Canvas Hypotheses

4.2.1 Build

We started to build a test using a landing page describing our customer profile, and tools for extracting data from Ebay.

4.2.1.1 Building a Landing Page to Test Customer Interest

Having tested and iterated upon the first customer hypothesis in Sprint 1, we wanted to test the value proposition towards potential customers via a landing page. This would allow us to validate their interest and further progress towards finding a Problem-Solution Fit. According to Osterwalder et al. (2014), a landing page is a "single web page or simple website that describes a value proposition or some aspects of it". The main learning instrument of a landing page is the conversion rate from the number of people visiting the site to visitors performing the Call-To-Action (CTA).

This test involved building a landing page that described our customer profile, to look for resonance in the customers. The metric to be measured was a CTA to sign up to our newsletter using their email address, giving a clear sign of interest through that investment of time and trust. The criteria to pass as validation was if we could generate ten or more signups.

Figure 4.12: Landing page (1) Test Card

In order to produce the site, some design decisions had to be made. We chose a simple layout with a header section, three sub section describing the customer profile and a footer section with a CTA to get people to signup with their email addresses using an external service provider. We decided upon using *Sendgrid*, as this could be implemented in the *Node.js* server. In order to save upcoming email signups we had to create a database using *Mongodb* and thus had to configure database entities to save email signups as customers. We also needed a domain and a host provider for our website. In order to track incoming traffic to the website, we set up a *Google Analytics* account and added it to the website.

This process took longer than expected which led to the consequence of measuring and learning from the test did not occur until Sprint 4.

This test was viewed as a critical since the customer profile hypotheses had to be validated in order to decide what needed to be built next on the MVP. Building the landing page had small related direct costs of hosting online. The data reliability from signups was rated moderate, since friends and family would have the opportunity to sign up, perhaps providing a false positive to the gauging of interest. However, the critical part of the test would be if we could find customers willing to try our product, a process in which friendship with the customers could be considered an asset. Time required for the test was rated as moderate as we estimated a time budget of two weeks to build and collect emails before we measured the result against our test criteria.

4.2.1.2 Building Tools to Extract Price Data for the MVP

During Sprint 1 we learned that the Ebay API was the best choice of where to get our data set. A script for fetching data from the API was implemented in *Python*. Once items had been extracted from the API, Ebay also provided another endpoint for fetching item specific attributes which enabled us to get the non exhaustive list of attributes seen in Table 4.1

Attribute	**Example value**
Product family	Macbook Pro
Screen size	13 Inches
RAM size	4GB
Hard drive size	128GB
Processor speed	2.3Ghz
Processor type	Intel i5
Release year	2014
Condition index	9000
Model identifier	MacBookPro12,1
Ad creation	Time
Product sold	Time
Transaction price	200$
Users description of the product	"Description"

Table 4.1: Table of extracted attributes

4.2.2 Measure

We measured the first draft of our landing page by conducting user tests. We also measured the price data from the Ebay API.

4.2.2.1 Landing Page Draft Development Progress

The development of the landing page had a lot of small iterations. During the development, people inside, as well as, outside the team, gave continuous feedback on our design choices. Feedback included were inputs on where our CTA was situated, what the text should say, and how replies from the email signup should be displayed and how we should record it. We expected the implementation of email signups to be simple, but it proved more complex than expected. This was due to the process of adding a database, plugins in the *Node.js* server to connect to the database and send emails from the site, that made the development process more time consuming than what was anticipated.

4.2.2.2 Ebay Price Data

Limited by Ebay API call limits and our requirement that all the attributes in Table 4.1 should be available, we were able to extract around 4500 data points about historical Macbook sales. Histograms showing distributions of product family, release year, condition index and sale time are shown below. Histograms for all attributes are available in appendix I.1

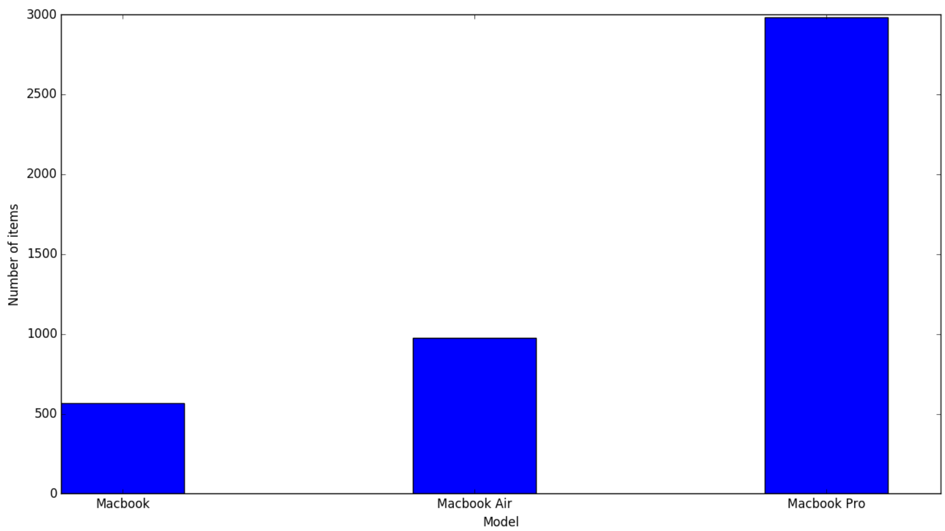

Figure 4.13: Histogram showing the distribution of product family

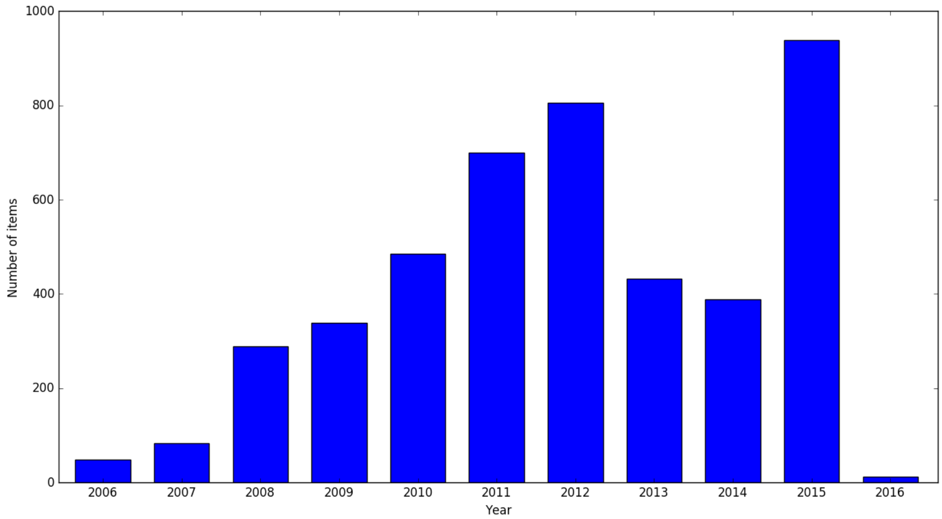

Figure 4.14: Histogram showing the distribution of manufacture year

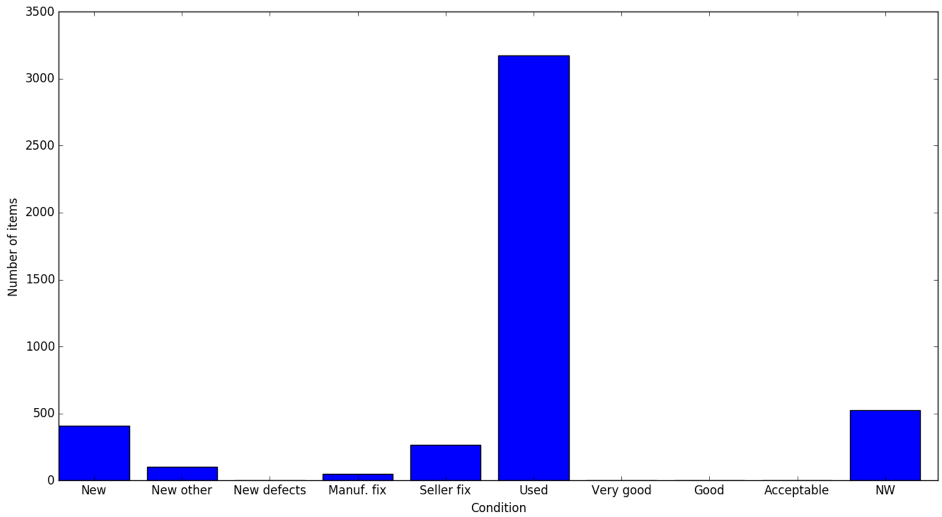

Figure 4.15: Histogram showing the distribution of condition index

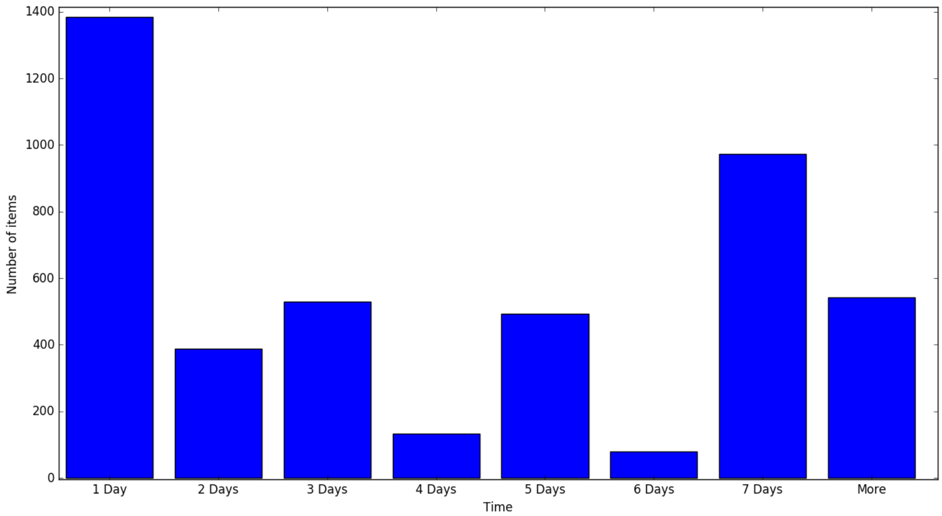

Figure 4.16: Histogram showing the distribution of sale time

As seen in Figures 4.13 and 4.15, computers in product family Macbook Pro and computers with condition index "Used" are overrepresented. The distribution of manufacture years, Figure 4.14, has a better spread but with computers from 2015 being the most. As for the sale time, Figure 4.16, sales within one day are overrepresented but the spread is better than between conditions and product families.

4.2.3 Learn

In the second sprint we learned that Mailchimp was a more appropriate service, also that the data from Ebay API could lead to poor prediction.

4.2.3.1 Changing from Sendgrid to Mailchimp

Due to the complexity of using Sendgrid and a database for the single purpose of saving emails, we decided that it was not worth the time it took. We instead focused on a simpler alternative, Mailchimp, which would serve the same purpose, saving emails and providing feedback to the customer upon signups, but we did not need to implement our own database or mailserver for it. This was to be implemented in the upcoming sprint.

4.2.3.2 Ebay Dataset is Large Enough

The data queried from the Ebay API was thought to be large enough to train machine learning algorithms to perform adequately. As seen in Figure 4.13 and Figure 4.15 the spread between product families and computer condition was quite narrow. Most computers belonged to the product family Macbook Pros and most computers were in "Used" condition. The narrow spread could lead to poor prediction performance on input that is underrepresented in the data set which is undesirable.

4.2.3.3 Sprint Retrospective

For the second sprint, there were problems with the fragmentations within the group, and unclear responsibilities. The unofficial "Technical" group mostly worked on the technical parts, while the unofficial "Business" group worked separately with the Customer Development Process. As such, it felt like there were difficulties communicating between the groups, misleading the development group by not communicating what customers actually want, and thus what they needed to develop for.

The proposed solution was to incorporate fixed meetings every week, where the whole team collaborated together. While each "group" could work on their individual project, we hoped that more cross-pollination of ideas would occur and communication would be made easier. The groups would also become more inclusive and invite the other group for ideas and discussions. To solve the unclear responsibilities, we decided to adopt a "Direct Responsible Individual" (DRI) for each user story, a practice adopted from Company A in Appendix H.2. The DRI would have the utmost responsibility for the user story getting done for the sprint duration. The person would not need to do it in person, but would be responsible for it being executed.

4.3 Sprint 3

Starting Sprint 3, we had not yet captured any more learnings from the landing page that was still in development. This meant that we were still in stage three on the Progress Board, found in Figure 4.17, looking for Problem-Solution Fit. The current canvases are found in figure 4.18 and 4.19. As Sprint 3 stretched over the exam period, the velocity of this sprint was significantly lower than other sprints. Therefore, we continued building the landing page, and started to build a non-functional MVP.

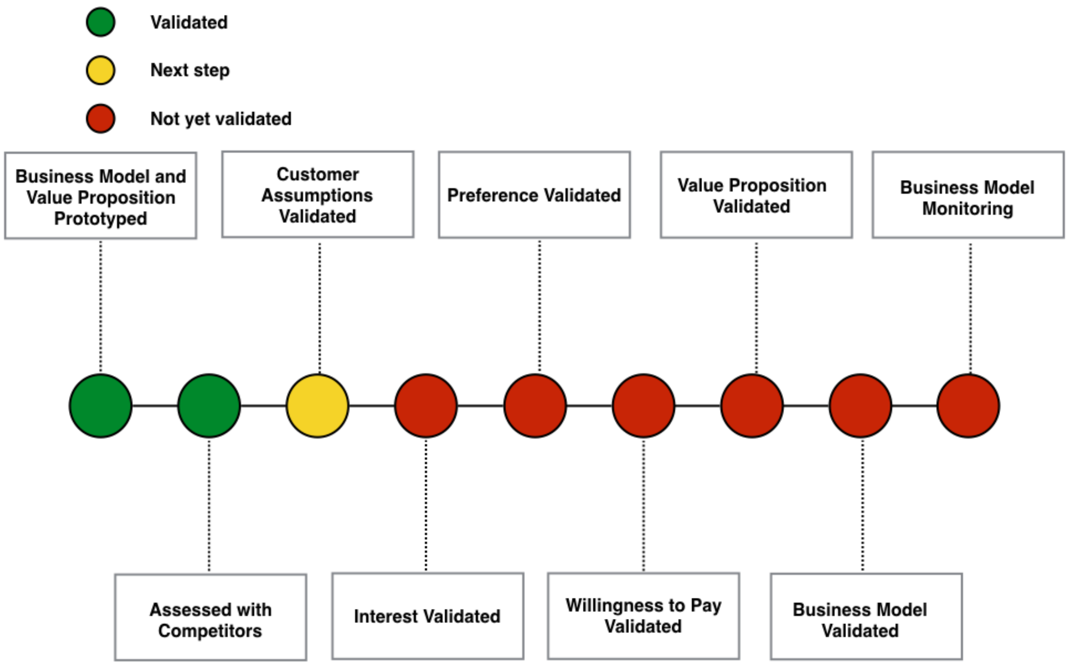

Figure 4.17: Sprint 3 Progress Board

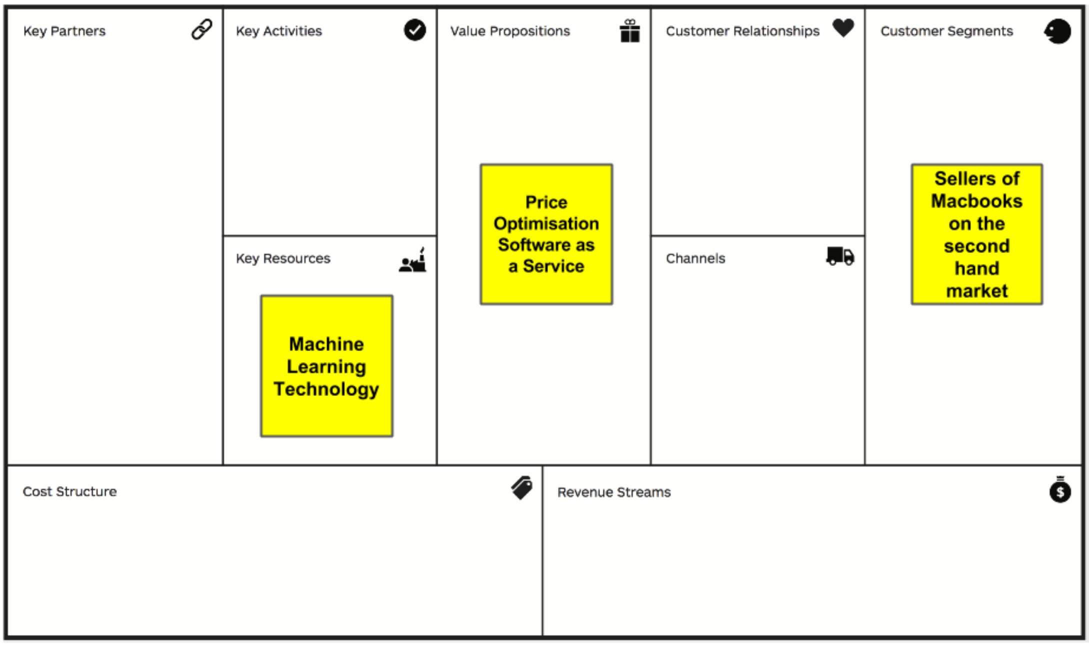

Figure 4.18: Sprint 3 Business Model Canvas Hypotheses

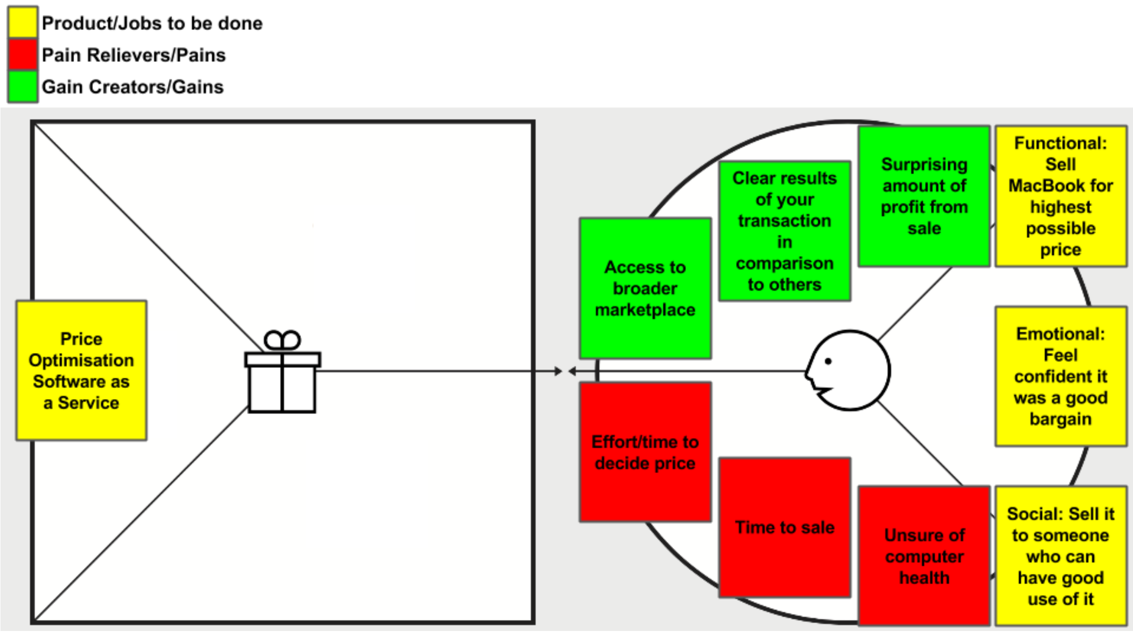

Figure 4.19: Sprint 3 Value Proposition Canvas Hypotheses

4.3.1 Build

During Sprint 3 the landing page was updated, a paper prototype was built, as well as a non-functional MVP. The machine learning methods were built and implemented and a connection to Tradera's API was built.

4.3.1.1 Building a New and Updated Landing Page

To continue testing our value proposition we implemented the Value Proposition Canvas into the text during the third sprint. The text was presented in three sections with three bullet-points in each section, that described our hypothesis about the customer profile as seen in Figure 4.20. We also switched from Sendgrid to Mailchimp for the email sign-ups. The landing page was rewritten in *Jade* to make the readability of the *HTML* easier when developing.

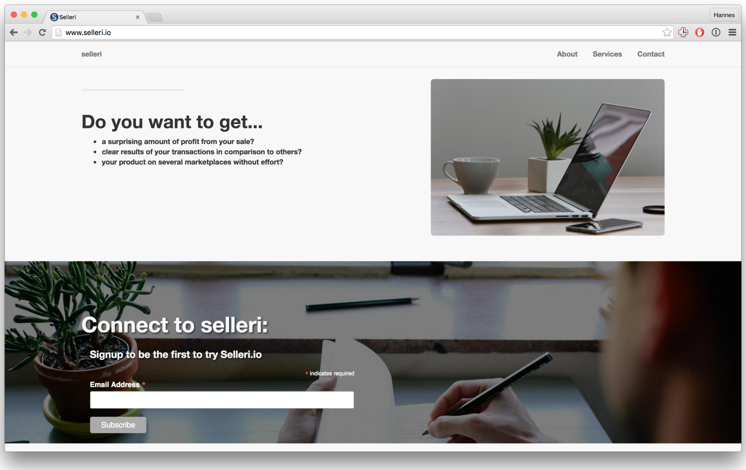

Figure 4.20: Selleri, Landing Page

4.3.1.2 Building a Paper Prototype

As for the sprint planning of Sprint 3, a prototype was to be created to allow further development on a frontend client and to allow easy testing and iterating for the customer. Using a whiteboard to develop and brainstorm ideas, a simplistic product was developed, taking inspiration from the Macbook ordering system on Apples website. To avoid information overload, the user was presented with a maximum of four choices. When a user had made a choice, a maximum of four more choices appeared, narrowing down what Macbook the user wanted to sell.

The user was first presented with a choice of model (Macbook Pro, Macbook Air, Macbook, or "other"), followed by screen size, size of hard drive, and the condition of the Macbook. The paper prototype was created using the "POP" Ios app. All images of the paper prototype can be found in Appendix C.3.

As the initial MVP, based upon the paper prototype, was completed in short notice after the paper prototype, we decided to measure impact from the MVP instead of the paper prototype. This was done due to it being closer to the final product, and the data would thus better represent interaction of the final product, improving quality.

4.3.1.3 Building and Implementing the Machine Learning Methods

To test our value proposition we needed a functional MVP. This MVP needed to have a machine learning method that estimated a price for a given computer model. In order to make the best prediction for our customers we needed to implement different algorithms and testing them against each other.

The implementations of the machine learning models presented in theory were made in the *Python* language due to the availability of several machine learning packages and the ability to deploy it is as a web application. The package *Numpy* was chosen as a math and matrix package due to its efficiency in matrix computations and *Scikit-learn* was chosen as the primary machine learning package due to its many and sufficient machine learning implementations.

In order to utilise the implemented machine learning methods, the raw data extracted from Ebay's API had to be transformed to be used as inputs in the algorithms. A first step was to decide which features were applicable and important for predicting the price of the item. The process of identifying relevant features, also known as feature selection, was primarily carried out with the use of our knowledge of the problem domain. Supporting plots of single features plotted against the price, available in Appendix I.1, were also made to support our assumptions. These plots can though be misleading since they omit the impacts of other features.

We chose to discard the processor type, the model identifier and the users textual description of the product. These decisions were made because of the difficulties of transforming this data into machine learning input. The processor type and model identifier were not floating point values and could not be converted to such, hence they needed to be divided into independent binary features. The problem with converting them to independent features was that there existed many possible values and the dimensionality of the input would become very high which would not be desired because it would increased the complexity of the model and hence the run time of the algorithms. The users textual description of the computer was also discarded due to the complexity of performing feature construction on it. Constructing features from free text would require a natural language processing step which we had decided not to do due to a limited amount of time. Also, the textual description of the computer would not provide that much new data since the API enabled us to extract relevant features directly.

We stated the hypothesis that all the other attributes listed under 3.2.1.1 contributed in different amounts to the determination of a computers price. Some of these features required transformations before they could be efficiently used in the algorithms. Due to its natural categorical values, the product family attribute with three possible values was divided into three binary features. With the learnings from the last spring we also knew that the spread of the condition attribute was quite narrow. Because of the vast majority of computers taking the value "Used", the condition index attribute with ten possible values was merged and divided into three binary features, the new histogram of the condition distribution is shown in

Figure 4.21. In order to predict prices based on users preference on sale time we also transformed and divided the sale time attribute into three binary features. The resulting histogram is shown in Figure 4.22.

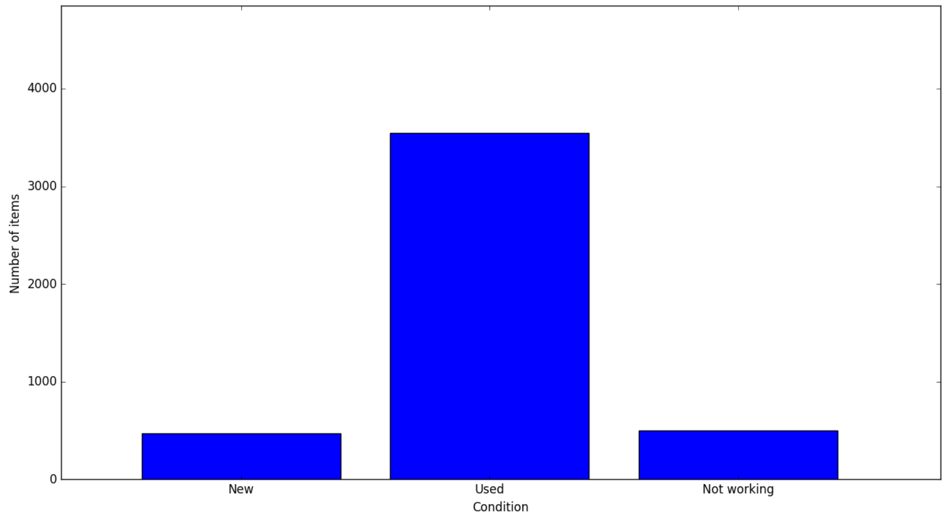

Figure 4.21: Histogram showing the new distribution of condition index

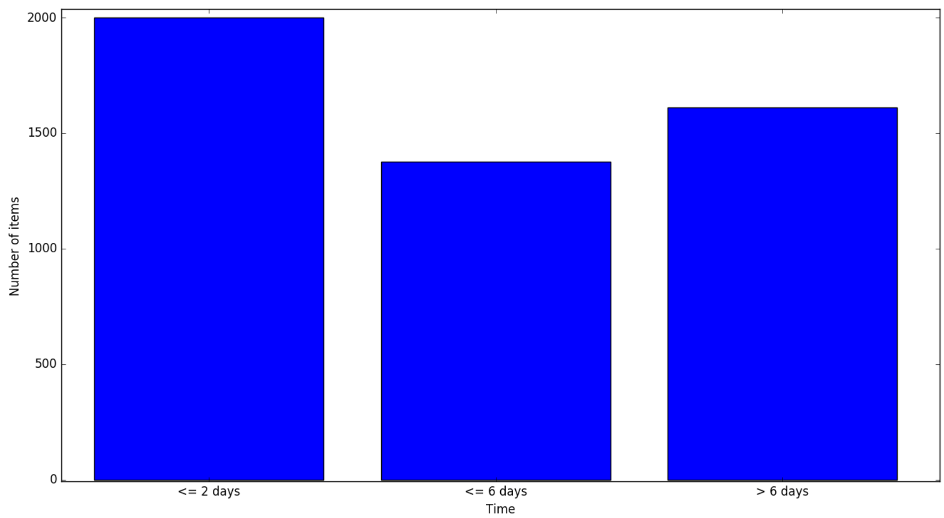

Figure 4.22: Histogram showing the new distribution of sale time

The transformations and selections resulted in the following feature vector which served as input to the machine learning algorithms, as seen in Table 4.2.

Feature	**Datatype**
Macbook	Binary
Macbook Air	Binary
Macbook Pro	Binary
Screen-size	Continuous
RAM size	Continuous
HDD size	Continuous
CPU speed	Continuous
Manufacture year	Continuous
Short sell time	Binary
Medium sell time	Binary
Long sell time	Binary
Condition New	Binary
Condition Used	Binary
Condition Broken	Binary

Table 4.2: Table of input features

4.3.1.4 1st MVP Iteration: Building the Non-Functional MVP

It was during this sprint that our first version of the MVP was created. We had decided upon a form structure, where the user would choose between different properties of their Macbook, so we could return an applicable price. Due to the fact that the machine learning algorithms were not yet properly trained for making sharp predictions, this MVP only returned dummy price data. However, the focus was upon the user experience, and not the quality of the predictions. As such, we defined it as a *non-functional MVP*.

In order to not overwhelm the user with choices, the same principles as with the paper prototype was included. This led to a form where only the question being asked until an answer was provided. The user would choose an option and a new question would appear below it. This would repeat until all the questions were asked and a button to "request a price" would appear. A snapshot of the MVP at this stage can be seen in Figure 4.23.

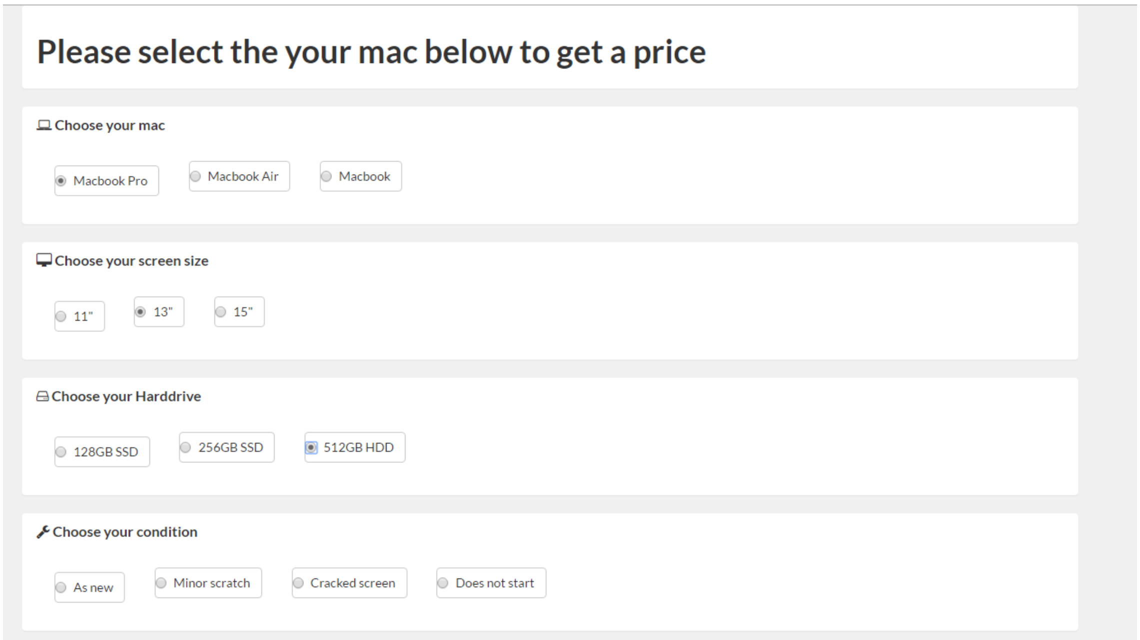

Figure 4.23: Selleri, non-functional MVP

4.3.1.5 Building a Connection to Tradera's API

One of the proposed features in MVP was to be able to publish an ad directly from our service to an online second hand marketplace. Due to the Swedish market focus, we chose to investigate Tradera. In order to do this, we needed to connect their API to our site. The API was built with *XML* and *SOAP*. This means that when an application wanted to connect to the API, they needed to send a request with a XML file in a predefined format. Because we wanted to publish ads on our customer's own Tradera page we also needed a method to log in to Tradera. When a user logged in, Tradera sent a token that we then could use to publish an ad on their page.

The Publishing flow worked by sending an initial request with basic information about the user and the object being published. Afterwards the application needed to send several requests to add extra information, for example images, and at last sent the final request that published the ad.

4.3.2 Measure

We measured the progress of developing the API connections, the landing page, and the initial MVP.

4.3.2.1 Tradera API Connection Progress

After a lot of hours working with this, we had developed a solution which could only log in to Tradera, which was not the complete feature set we needed. The format specified by Tradera was not compatible with *Node.js* directly and there were no available packages to work with. In the end, when we tried to upload an ad to

Tradera, we got the error message "500 - Internal Server Error" which made it hard to measure any other results.

4.3.2.2 Landing Page Development Progress

During the development of the landing page, we realised that the site was loading very slowly. We identified that this was due to optimisation problems, including that pictures used were far too big for their use on the site. We had issues with maintainability and potential scalability due to increasing amounts of files to compile.

4.3.2.3 MVP User Experience

As the initial MVP, based upon the paper prototype, was completed in short notice after the paper prototype, we decided to measure impact from the non-functional MVP instead of the paper prototype. This was done due to it being closer to the final product, and the data would thus better represent interaction of the final product, improving quality. The MVP was developed iteratively during this sprint and to measure the user experience, both team members and outsiders were asked for inputs of the usability of it.

4.3.3 Learn

We learned what to iterate on, and where to focus our development resources

4.3.3.1 Iterating on the Design for the Initial MVP

The form needed new design iterations after the initial testing of the design. We found that users did not like the approach of not knowing how many questions that needed to be asked before completion. This could be solved using breadcrumbs *(a graphical control element used as a navigational aid in user interfaces)*, or similar elements to show where in the process the user is. This needed to be addressed in the upcoming sprint by building a new interface based upon this design.

4.3.3.2 Easier Development Tools

To solve problems with allowing the product to scale, as mentioned above, a new build system was introduced. This made it easier to develop for the site, as updates could be seen right away with the help of build tools like *gulp-livereload*. The readability was increased with the use of templating languages instead of uncompiled languages, such as *Jade* vs *HTML* and *Coffeescript* instead of *Javascript*.

4.3.3.3 Developing Automatic Ad Posting Deemed Too Time Consuming

As the development did not generate the desired outcome, our learnings from the implementation of the Tradera API was that it did not work properly and was too time consuming to implement with our choice of language. After several retries to contact them for help without results we decided to not use it in our product. We had two options, use another market to try our proposed feature or to not include the feature in our MVP. We chose to test it on customers in the next sprint using a feature test.

4.3.3.4 Sprint 3 Retrospective

For the third sprint, there were still problems with the fragmentation within the team. Exams had been taking time, a lot of work was being done asynchronously, and we did underperformed in regards to our planning for Sprint 3.

We decided that not too much had to be radically changed, and we instead should work on incremental improvements on the current structure. With exams no longer being a concern, we expected to have enough time for a successful sprint.

4.4 Sprint 4

Starting Sprint 4, we were still lacking any learnings if we had achieved Problem-Solution Fit. This meant that we were still in stage three on the progress board, seen in Figure 4.24. However, the landing page was ready to be tested. Being constrained by time we started to build tests for value proposition hypotheses as well. Our current Value Proposition Canvas can be found in Figure 4.25, describing our hypotheses about both the customer profile and our value proposition map. The current Business Model Canvas is found in Figure 4.26.

During Sprint 4, we finished building the landing page. A feature test was built, along with an early functioning MVP. Measuring data from all three tests, we were trying to learn if we had achieved a Problem-Solution Fit and could start to look for Product-Market Fit.

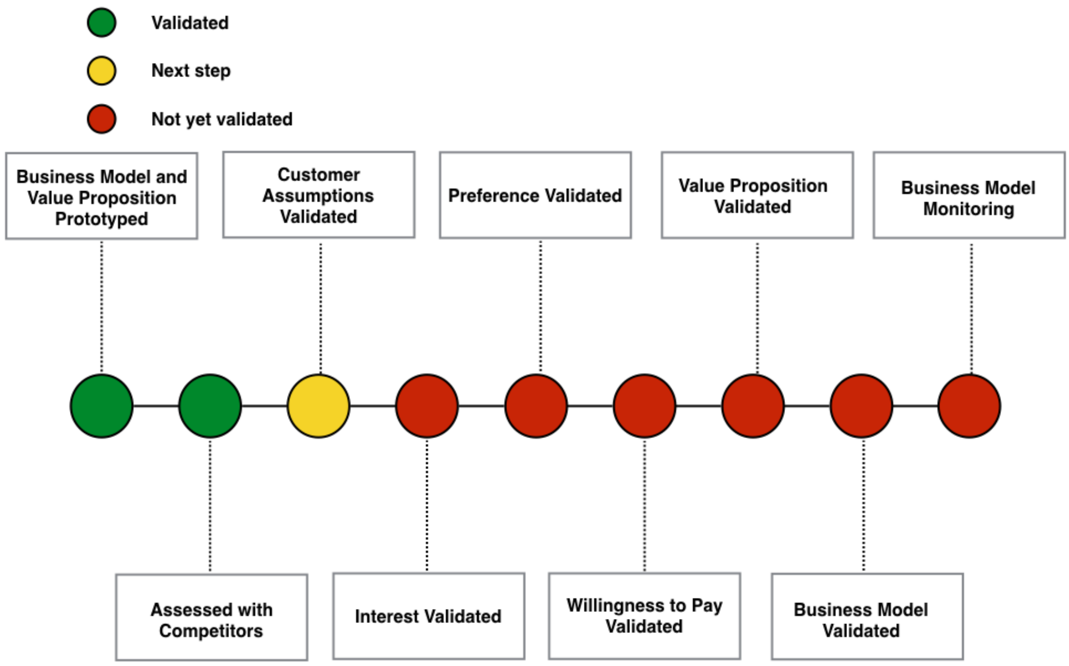

Figure 4.24: Sprint 4 Progress Board

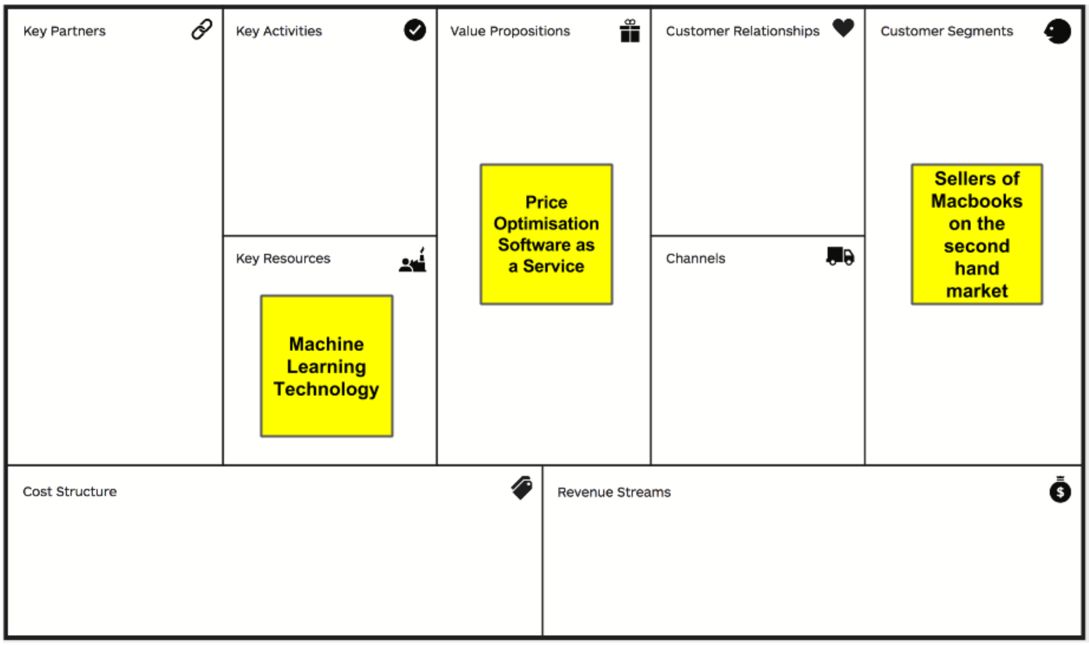

Figure 4.25: Sprint 4 Business Model Canvas Hypotheses

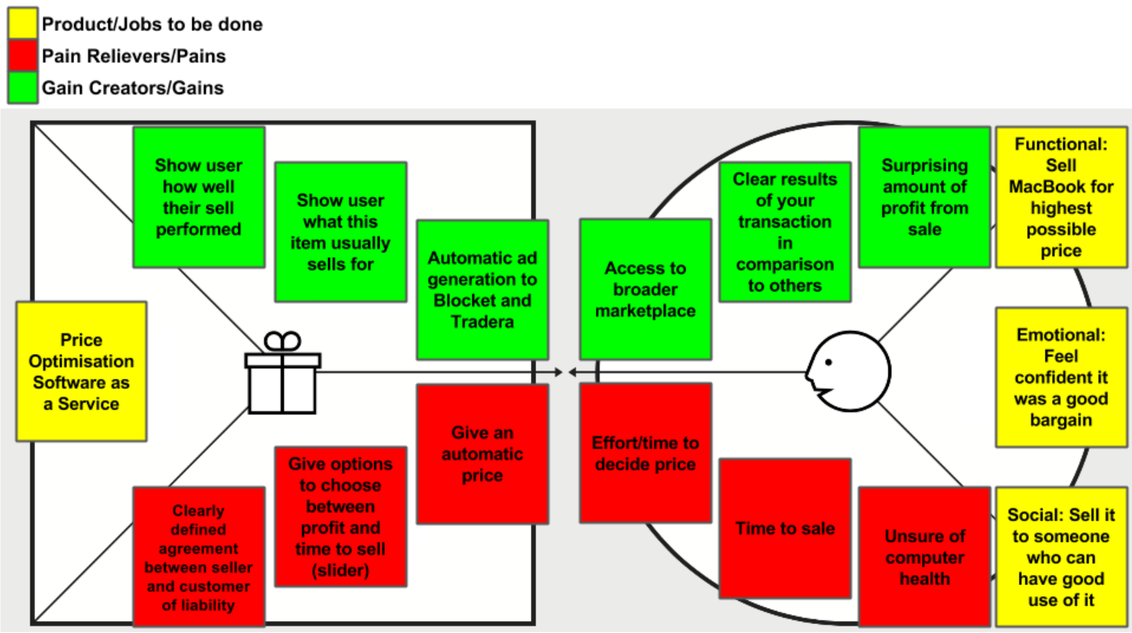

Figure 4.26: Sprint 4 Value Proposition Canvas Hypotheses

4.4.1 Build

We finished building the landing page and a first functioning MVP. Working fast, we also built a feature test in the sprint.

4.4.1.1 Conducting Interviews to Test Features to Prioritise

This test, which we called a *feature test* was carried out for the purpose of testing our hypothesis that our value proposition map matched our customer profile, and that we were building features in the priority that matches what was important in the customer's experience. To validate this hypothesis, we decided to use Surveymonkey to conduct ten customer interactions where the customers could rank the features of our value proposition in order of importance to them. The metric of measurement was which rank each feature got prioritised to in aggregate. The criteria of validation was defined as if our current prioritisation of building features matches how the customer ranks our features in aggregate. The test card can be found in Figure 4.27.

Figure 4.27: Feature Test Card

This hypothesis was critical since we needed to find and validate the customers' priorities and preferences to continue advancing on the Progress Board, and building only the necessary features in order of priority could save us a lot of time. There were no direct costs related to this test. Data reliability of the test was rated as moderate, with similar arguments raised for the customer questionnaire test which was built in Sprint 1. The time budget was estimated to two weeks which was rated as moderate.

4.4.1.2 Conducting Interviews to Test the Non-Functional MVP User Experience

In the last sprint, the non-functional MVP was completed. To ensure a good user experience, we wanted to test and gather feedback about it. This test was run to test our hypothesis that our first non-functional MVP had a user friendly way to present our value proposition map to our potential customers. To test this hypothesis, we put the first MVP in the hands of ten customers and collected feedback from them. The metric of measurement was a rating of each question displayed on the frontend of the MVP. The criteria for validation of the hypothesis was that the average feedback from customers was positive on their rating scale. The test card for this test can be found in Figure 4.28.

Figure 4.28: Form Test Card

This UX test, which we called a *form test*, was not viewed as highly critical for the purpose, since it was merely an expression of how to present the value proposition map, which would be tested in the test where we evaluate what features to prioritise. However, it would be very useful from a software development standpoint to know how to design the frontend of the MVP. There were no direct cost related to building this test. Data reliability was rated as moderate, with the same arguments raised in the customer questionnaire which was built in Sprint 1. Time required to run the ten interviews was rated as moderate when estimated to two weeks.

4.4.1.3 Training Machine Learning Algorithms

After Sprint 3, the software implementations of the machine learning algorithms had been done and a set of training data about Macbook transactions had been constructed. To compare the performance of the machine learning models on our data set, we implemented a test suite to measure predictive and time performance.

Finding the optimal hyperparameters for each model was done using a grid search over each possible pre-defined configuration with 3-fold cross validation. Each models predictive performance was measured and optimised on the R^2 score. After the best set of hyperparameters had been found, we retrained the model with that configuration on 70% of the full data set, our training set, and evaluated the model on the remaining 30% of the data, our validation set. We measured how many of the predictions on the data in the validation set that were within 10% and 20% of their target value.

Training and prediction times were also measured. The training time was measured on 70% of the full data set, our training set. Prediction time was measured as an average over all predictions on the remaining 30% of the full data set, our validation set.

4.4.1.4 2nd MVP Iteration: Building the Fully Functional MVP

A first version of a non-functional MVP was completed in the previous sprint. With the feedback received from potential customers it was redesigned. The new design had a much clearer approach, with steps in the header and animated transitions between the steps. The Angular.js app was rewritten completely to serve this purpose. Thanks to the use of templating, it was easy to see a result quick. Since a test to find out what features our customer prioritised was done in parallel, the inputs received during this could be applied directly. One of those was a help box that had information and images to guide the user to an answer for the question. An image of the help box can be found in appendix A.2.2. At the same time we developed our REST-API with endpoints to send in details about a computer and to return a price generated by the machine learning algorithms. With all parts connected, the user could input details about a Macbook and get a price based on historical data. As such, we defined it as a *fully functional MVP*. The MVP can be seen in Figure 4.29

4.4.2 Measure

We measured signups on the landing page, prioritisation of features development, user experience of the MVP paper prototype as well as the learning algorithm performance.

4.4.2.1 Measuring Interest From Landing Page Sign-Ups

Launching the landing page, sharing it on our social media and collecting emails led to 18 independent sign-ups out of a total 192 visits. We also did receive some

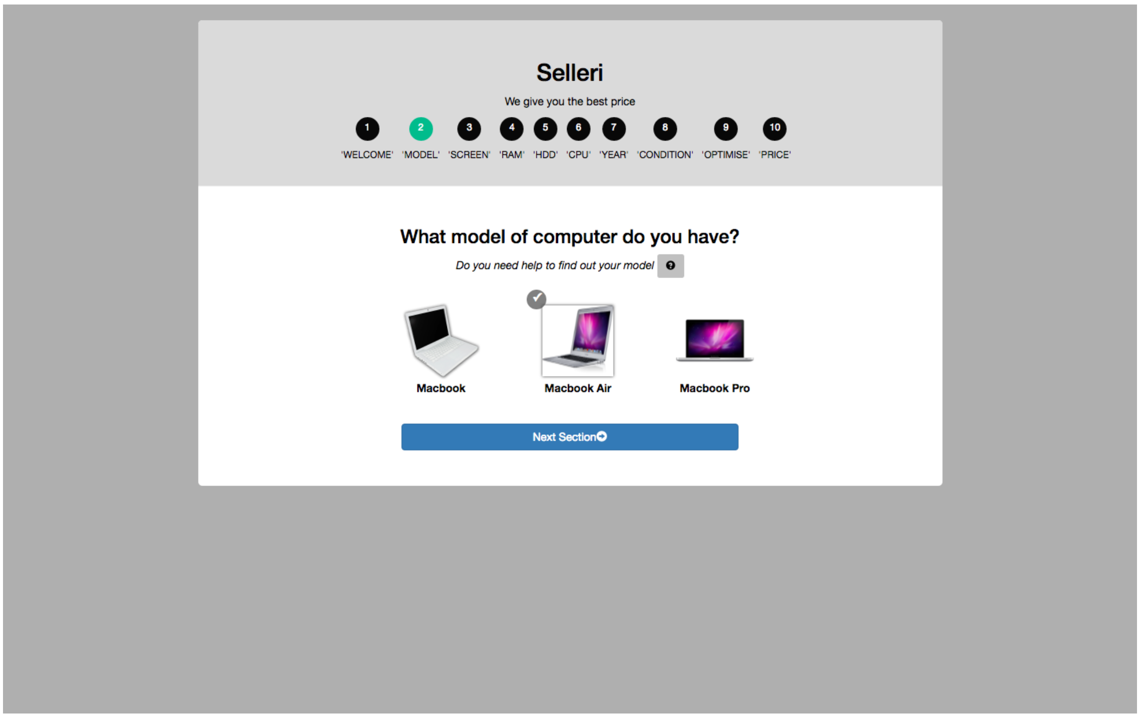

Figure 4.29: Selleri, functional MVP

feedback about the layout of the site. A lot of people thought it looked like a scam and did not communicate enough about the actual product, just what jobs that the customer had to be done.

4.4.2.2 Measuring How to Prioritise Feature Development

The feature test resulted in data showing the order of how proposed features were prioritised by the customers. The rankings are presented in Figure 4.30, and the full list can be found in appendix B.6. Notably, there were three features that consequently got prioritised high. These were to show statistics or data collected to give a recommended price, the possibility to optimise the price for profit or time to sale, and to get a recommended price as a number. On the low end were the features to show statistics of how well the customer's sale performed compared to others after the sale was done, and to generate an ad to directly post to marketplaces like Blocket.se or Tradera.se. The feature test also resulted in free flow insights collected by asking the customers why they decided to prioritise the features in this way. All feature insights can be found in appendix B.9.

4.4.2.3 Measuring the User Experience

Testing the user experience for our first MVP draft resulted in the data that can be found in appendix B.4. It showed that some questions were easy to answer for the customers. For example, nine out of ten answered that they had the knowledge required to tell if they owned a Macbook Pro, Macbook Air, or a Macbook. However, other questions resulted in confusion. Asking the customer about the condition of

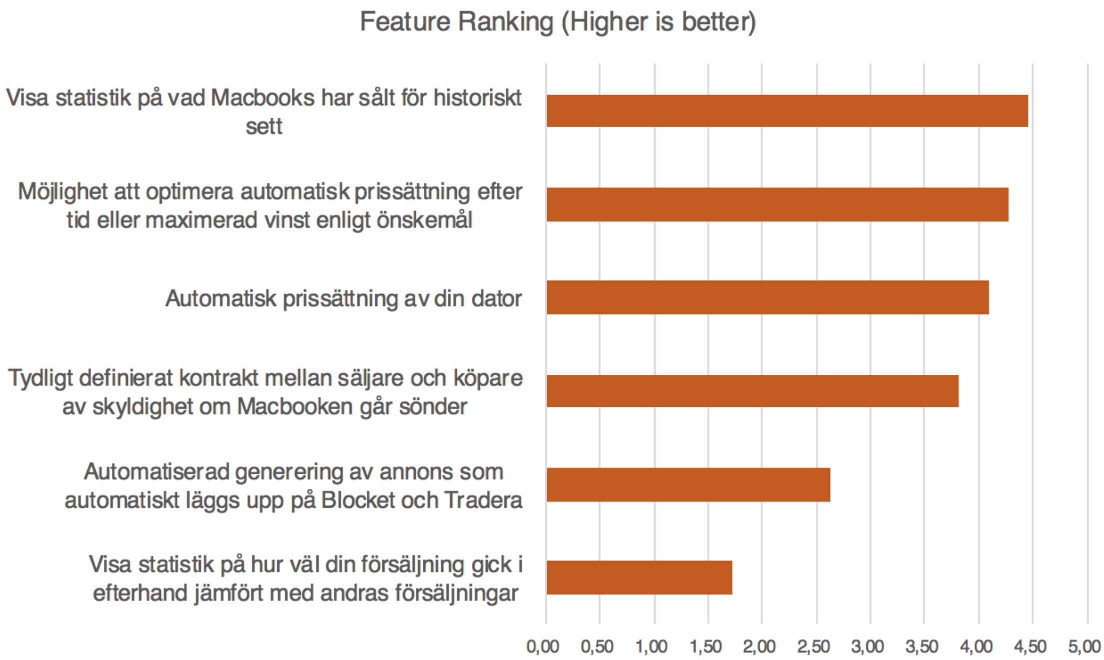

Figure 4.30: Feature ranking (In Swedish)

their Macbook was in aggregate rated as a poorly formulated question and four out of ten customers did not feel they had enough knowledge to answer this question.

4.4.2.4 Measuring Machine Learning Algorithm Performance

Running our tests defined in section 4.4.1.3 gave us the results shown in Table 4.3 and 4.4. For simplicity, all tests were carried out on a local computer with *Intel i5, 2.3Ghz CPU (2 Cores)* and with a *RAM* size of *8Gb*.

Model	**R^2-score**	**Within ±10%**	**Within ±20%**
k-nearest neighbours	0.830	41.15%	66.35%
Decision Tree	0.852	39.34%	65.62%
Random Forrest	0.859	44.71%	68.43%
Linear regression	0.842	38.40%	63.87%
Bayesian linear regression	0.832	37.53%	61.26%
Gaussian Process	0.852	41.55%	67.09%

Table 4.3: Table of machine learning models prediction performance

Model	**Training time**	**Avg. pred. time**	**Avg. pred. time with std.**
k-nearest neighbours	0.0076	0.00160	—
Decision Tree	0.0082	0.00009	—
Random Forrest	0.4500	0.00590	—
Linear regression	0.1786	0.01020	—
Bayesian linear regression	2.8290	0.01140	—
Gaussian Process	149.00	0.00067	4.48580

Table 4.4: Table of machine learning models time performance in seconds

4.4.3 Learn

During Sprint 4 we learned that we were able to generate interest among customers, that the user experience needed improvements, and also that automatic ad generations was necessarily not a customer need.

4.4.3.1 Validating Our Ability to Generate Interest

Before testing the landing page, we believed that our customer profile matched the market and would resonate with customers if presented to them as a website. We observed that 18 customers signed up using their emails, which overshot the criteria of getting ten signups. From this we learned that we could generate interest based on our current customer profile and scope. Because of these learnings, we decided to continue towards testing our value proposition and regard our customer profile as validated. The learning card can be found in Figure 4.31.

Figure 4.31: Selleri, Landing Page 1

The reliability of the data was considered moderate as stated in the build phase, and the insight did not entail any iteration or pivot.

4.4.3.2 The User Experience Needs to Improve

The MVP paper prototype was the first test of our value proposition map hypothesis, testing if our MVP was a user friendly way to present our value proposition to our customers. We observed from the data we measured that our current paper prototype was not user friendly. From that we learned which information the users did not have about their computers, how to formulate our questions and which questions to add to the MVP to be a better reflection of our value proposition. Learning these things, we decided to redesign our MVP paper prototype in order to make it more user friendly. The learning card can be found in Figure 4.32.

Figure 4.32: Form test Learning Card

In the build phase, we rated the data reliability as moderate. The action required after these insights was a relatively small iteration of re-designing the frontend of the MVP.

4.4.3.3 Automatic Ad Generation Unnecessary - Focus on Making Data Transparent

The Feature test was run to test our hypothesis that the priority we were building our value proposition by matched our customers' priorities and preferences. Running the test, we observed that their ranking of features did not align with our current priorities of building our next iteration of the MVP. From that we learned which features we needed to prioritise based on our customers' input. We realised that there was some bias in the data, since we interviewed mostly engineers and highly technically competent people, but we decided that it still was viable for our product. Because of the data presented in Figure 4.30 we decided to build the features of the next iteration of the MVP in the order prioritised by our customers. The learning card can be found in Figure 4.33.

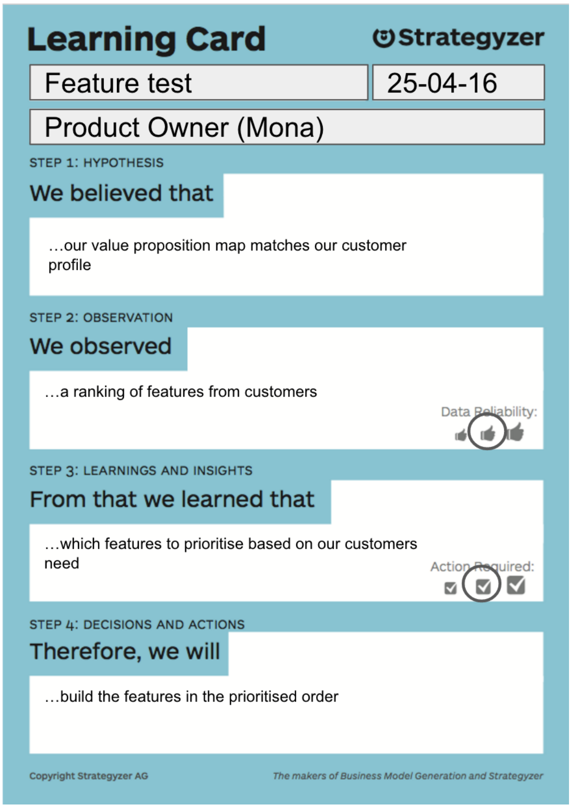

Figure 4.33: Feature test Learning Card

The data reliability was considered moderate as stated in the build phase, and the action required was moderate since it entailed dropping features from the product backlog.

4.4.3.4 Evaluating and Deciding a Machine Learning Model

The results of the machine learning model evaluation presented in Section 4.4.2.4 shows that the predictive performance between the models are quite similar but with the two Linear regression models having the poorest predictive performance and the Random Forest having the best. The linear regression models relatively poor performance can be explained in the choice of basis function. During the grid search with cross validation, different polynomial basis function were tested and the one maximising the R^2 score was the third degree polynomial for both the Bayesian and the ordinary linear regression. High polynomials, such as of degree > 7 were not included in the grid search due to the very high time complexity in the learning phase and could hence explain the relatively poor performance of those models. The overall predictive performance of the models are heavily dependent on the choice of hyperparameters. An attempt to find good hyperparameters for each model was done with the use of grid search and cross validation but as the set of hyperparameters to evaluate was defined manually, we could not conclude that the optimal choice of hyperparameters were in our manually defined set. Since the range of some features in our data set were quite narrow, this could also have an impact on the predictive performance of the algorithms. Making predictions on inputs were we have little or no data often does not result in accurate predictions. A proposed solution to increasing the predictive performance was to increase the size and spread of our data set and introduce more hyperparamters to evaluate in the grid search.

As for the time performance of the models we can clearly see that the prediction time for the Decision tree model is, by far, the shortest. This is easily explained by the nature of the model. A binary tree has, as discussed in the theory chapter, $O(log(n))$ time complexity. The shortest training time is achieved by the k-NN algorithm. This is not surprising since the k-NN is an instance based learning algorithm, meaning that no model is actually learned, the training data is instead retained in the model and used to predict new input (Russell and Norvig, 2009). The longest prediction and training times are both achieved by the Gaussian process regression model. As discussed in the theory chapter this is not surprising since the model requires heavy computations, having a time complexity of $O(n^3)$.

Since the Random Forest regression algorithm outperforms the other models in every predictive performance measurement and the training and average prediction time were not high enough to become problematic in small scale, the data clearly stated that this model should be used for the price recommendation software. Although, the insights from customer interviews showed that a point estimate is not the only information the customer is interested in. The customer insights showed that without presenting arguments of why this point estimate is relevant, this information is of no interest.

Due to the customer insights we turned our discussion to the Bayesian models. The two Bayesian models, Bayesian linear regression and Gaussian Process regression, could provide a standard deviation of the point estimate and hence give some measure of confidence for each prediction. In practice this allowed the model to communicate when there is none or very little data that can be used by the model to make predictions on user input. As shown in Table 4.3, the Gaussian process had better predictive accuracy than the Bayesian linear regression in every metric. Therefore our choice of machine learning model for the task of price prediction landed in the Gaussian Process regression. Several negative aspects also came with the choice of a Gaussian Process as our prediction model, the most significant was the long time to train the model and make predictions with a standard deviation estimate.

4.4.3.5 Sprint 4 Retrospective

The fourth sprint was the most productive so far. Even though all team members were not geographically present, it was still a very productive one. A continuous problem from Sprint 2 had been that the development team was not always in sync with the insights from the business team, but the problem had been alleviated.

Further improvements could be to not only pass further the information from the learning cards, but to jointly analyse the cards between the business team and development team in coordination with focused work together.

4.5 Sprint 5

Starting Sprint 5, we first and foremost had just learned from the landing page test that we could generate customer interest based on our customer profile and scope of Macbooks. This meant that we could move to stage four on the Progress Board, seen in Figure 4.34. The non-functional MVP was an attempt to validate interest from customers, while the feature test was an attempt to validate their preferences and priorities of features. Since our hypotheses on these areas were both invalidated, we were still on stage four on the Progress Board. However, we could update our value proposition canvas with new hypotheses which can be found in Figure 4.36. The Business Model Canvas found in Figure 4.35.

During Sprint 5, we built an *MVP think aloud test*, and an *MVP funnel test*. This data had the potential to measure if customers had an interest for our value proposition. These learnings could allow us to start testing their willingness to pay.

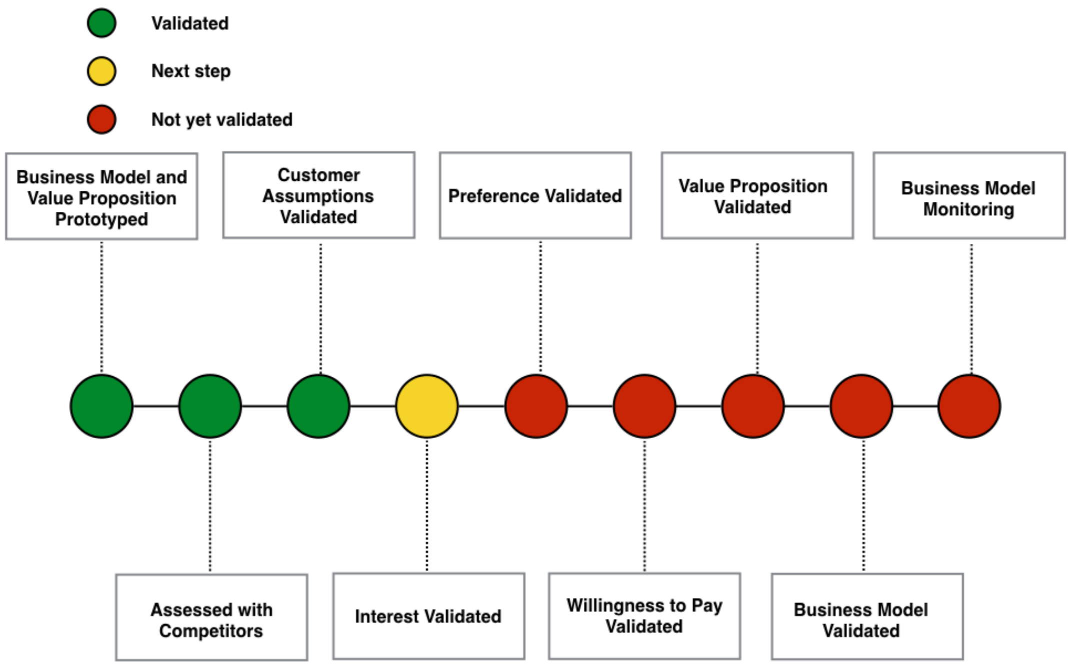

Figure 4.34: Sprint 5 Progress Board.

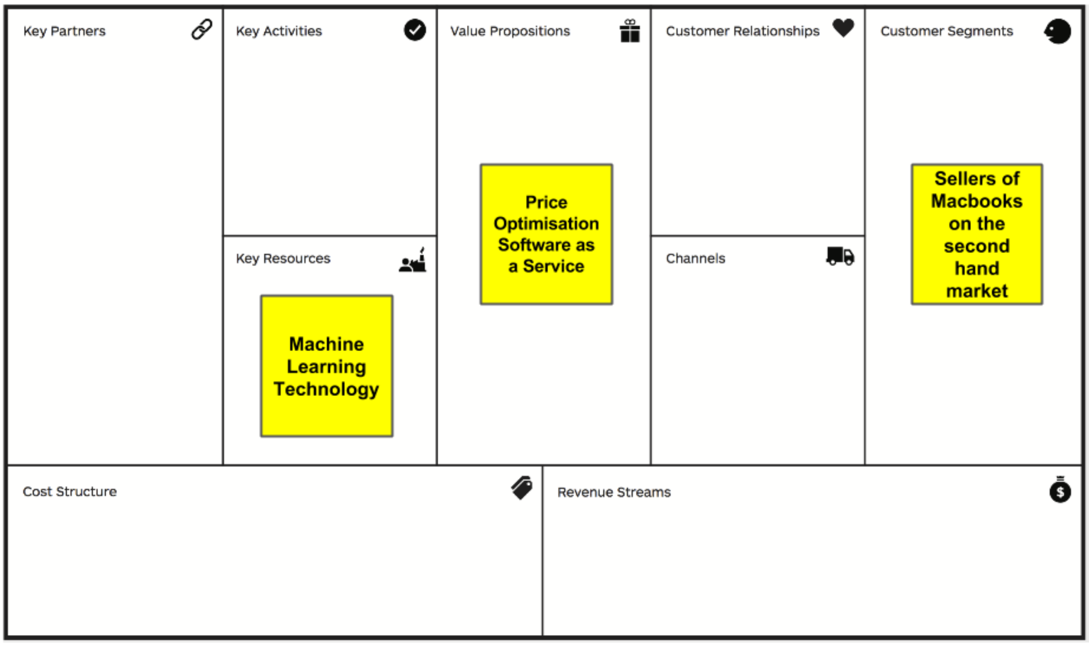

Figure 4.35: Sprint 5 Business Model Canvas Hypotheses

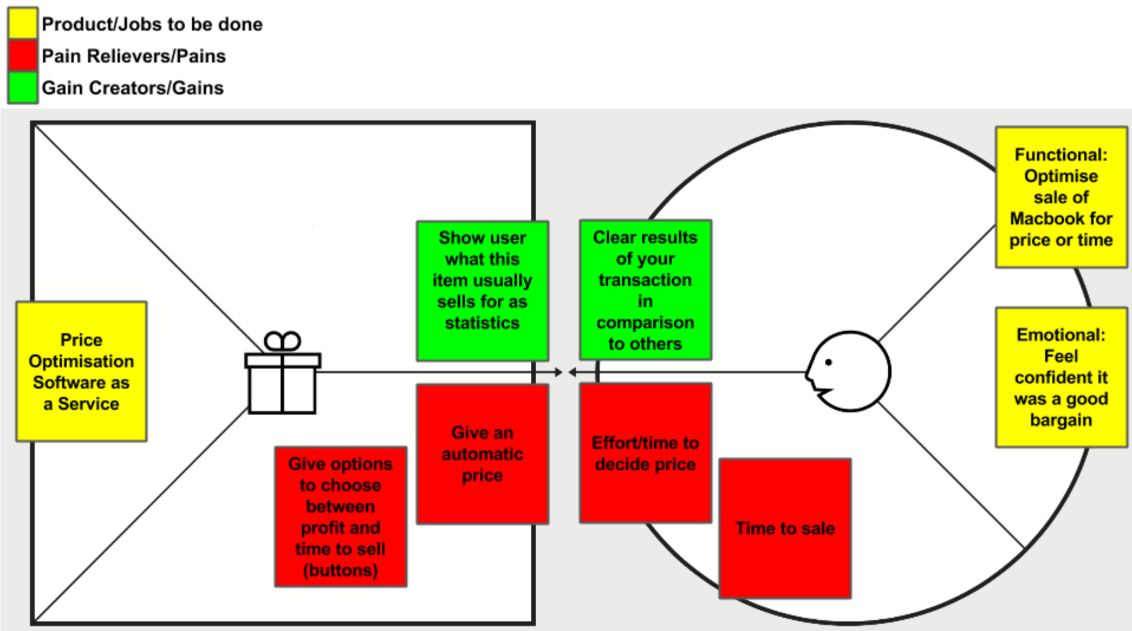

Figure 4.36: Sprint 5 Value Proposition Canvas Hypotheses

4.5.1 Build

For the build phase in Sprint 5, we built an MVP think aloud test, as well as a Google and Facebook ads test. We also altered the MVP and improved the landing page as well as the machine learning performance.

4.5.1.1 Conducting Interviews to Learn more about the User Experience

The MVP think aloud test was conducted to test the hypothesis that we knew our target customers' prioritisation and preferences for our value proposition. To test this hypothesis, we presented our MVP to ten customers, asking them to think aloud when interacting with it and thus providing feedback. The metric of measurement was the usability in each step of the product, the overall impressions and a call to action asking if they would like to use our product themselves. The criteria to validate the hypothesis was set to if a majority of the customers said they wanted to use the product themselves. The test card can be found in Figure 4.37.

Figure 4.37: Qualitative Test Card

This test was a holistic impression of our value proposition to our customers, and as such we viewed this test as highly critical and a necessity to move on the Progress Board. There were no direct costs related to this test. Data reliability was considered moderate, since it had similar characteristics to the arguments raised in the customer questionnaire test which was run in Sprint 1, in the question related to the test criteria. The time budget was two weeks which was considered moderate.

4.5.1.2 Using Google and Facebook ads to Test Interest

We had from previous tests learnt that we could generate an interest with a click-through-rate of over 10 percent for our value proposition when we shared the first draft of the landing page on social media. To further investigate customer interests, we decided to iterate on these learnings and design another test.

The test was designed to test our hypothesis that our target customers had an interest for our value proposition. To validate the hypothesis, we decided to drive traffic through paid ads, using Google Adwords and Facebook ads, to our landing page. The metric we measured was the conversion rates through the funnel from the landing page, to our product website, and to generating a recommending price and reaching out to us using email or phone.

Passing criteria for validation of the hypothesis was if the conversion rate was over 5% on the generated price button and over 1% conversion rate on personal contact through email or phone. The test card can be found in appendix 4.5.1.2.

Figure 4.38: Quantitative Test Card

Again, like the MVP think aloud test, this was a holistic test of our MVP which we deemed to be of critical importance. Driving payed traffic pushed up the cost of running this test to a high rating in our current phase, setting a maximum budget of 1000 SEK. The data reliability was high since we had decoupled ourselves and our personal relationships from the test, which was an important factor considered in mix-method research related to qualitative and quantitative data (Diriwächter and Valsiner, 2006). Time budget for the test was considered small as we estimated it would only take one week.

4.5.1.3 Altering the MVP due to User Feedback

In Sprint 4 we learned that users did not trust the given price and wanted more data to support it. To achieve this we added a graph of the predictive distribution computed by the Gaussian Process to give users some understanding regarding how the price and probability are connected to each other. We also added a graph showing how many computers with similar configuration that had been sold in recent time and what their prices were. The result view of the MVP can be seen in Figure 4.39.

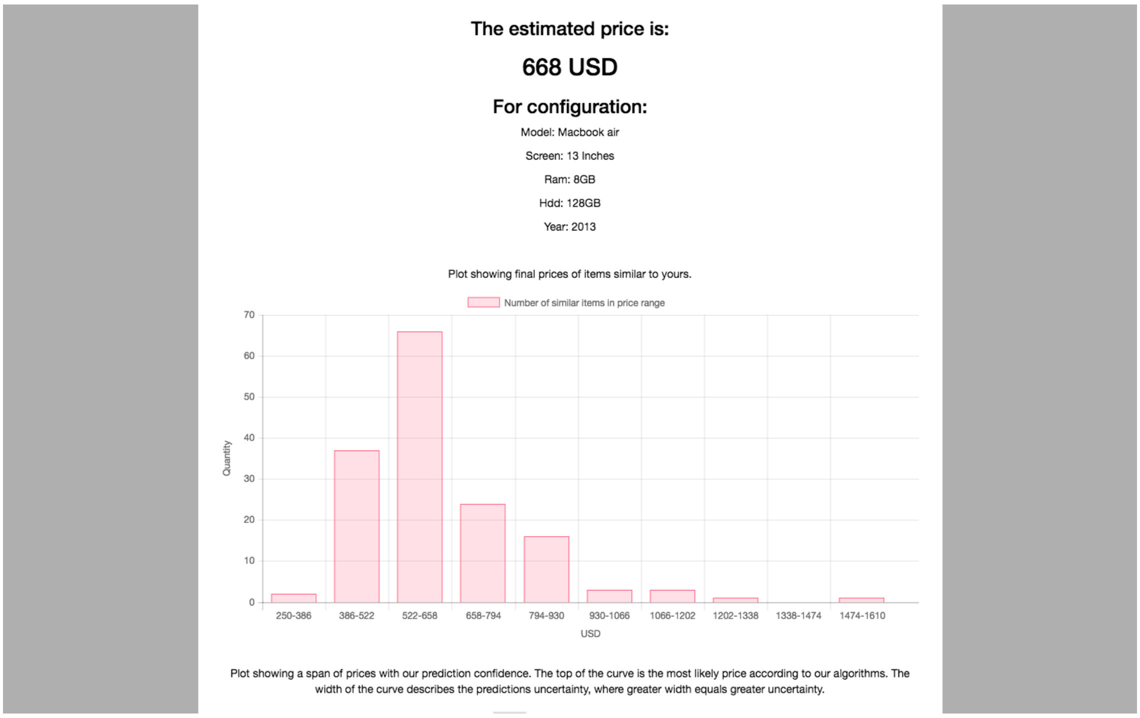

Figure 4.39: Selleri, MVP, Search Result image 1

When added the above metadata about the estimated price the time to fetch a price increased. A change in the communication module of the MVP was made to address this problem. Instead of sending a request, keeping it alive and waiting for a response, we sent a request and then waited for 20 seconds. After having waited, the client polled our backend to see if a result was available every five seconds. The backend waited for results from the price calculation server, saved it to a list and returned the correct data if the user had a result and asked for it.

In order to address the feature request about the possibility to optimise the price for profit or time to sale, we added a new choice to be made in the MVP. This choice can be seen in Figure 4.40

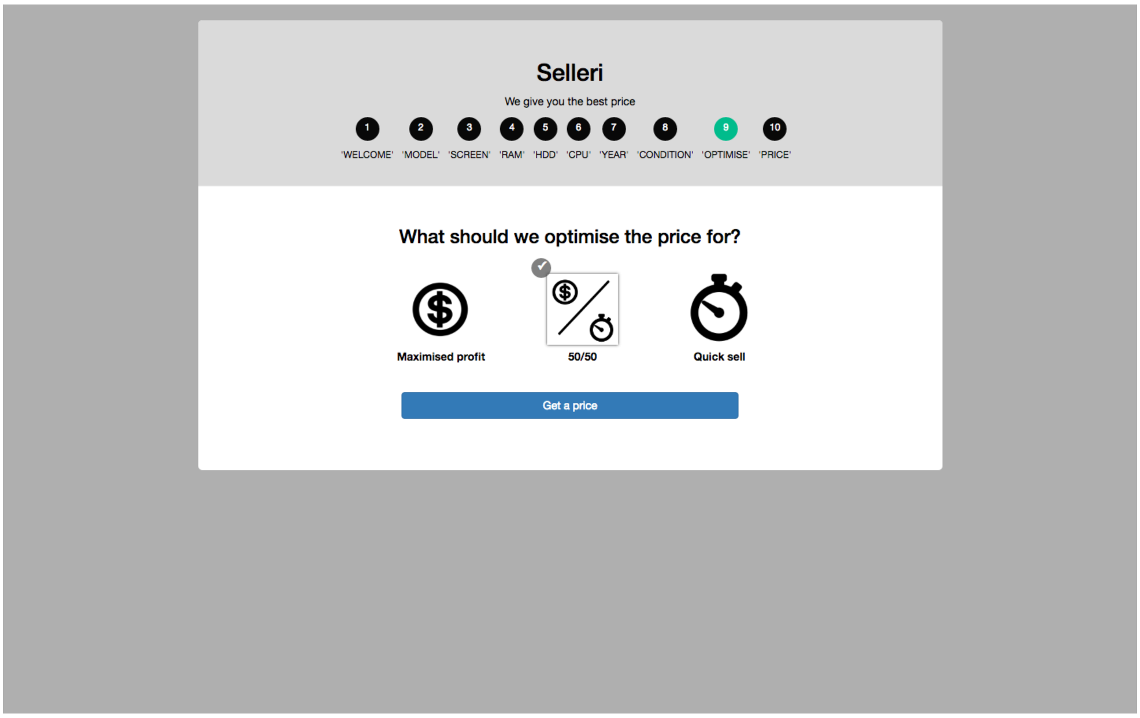

Figure 4.40: Selleri, MVP, Price vs Time to sale

4.5.1.4 Improving Landing Page 2

The idea of the landing page was to inform the customer, and guide him or her towards the product. As such, it is an integral part of testing the MVP. After Sprint 4, we had learned that our Landing Page looked "Scammy", and that it did not explain the product well. We redesigned it to look less scammy and giving a clearer understanding for the product. A part of the new landing page can be seen in Figure 4.41

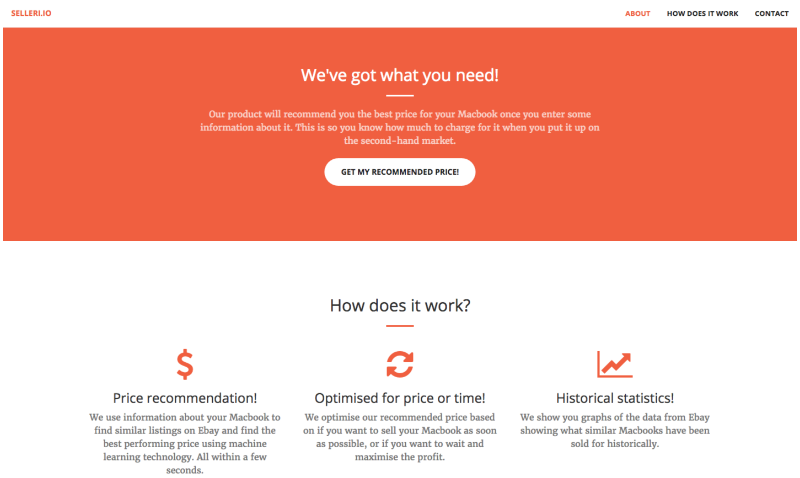

Figure 4.41: Selleri, Landing Page v2

4.5.1.5 Improving Machine Learning Performance

From the learnings in Sprint 4 we made the decision to use a Gaussian Process as our predictive model. This choice came with a trade-off. The learning and prediction times were very long. In this sprint, focus was on decreasing the learning and prediction times.

To decrease the learning time we utilised a pre-learning step, performed on a local computer, saving a trained model and then importing it on the server. To decrease the prediction time we utilised the scaling abilities on *Heroku*, increasing our servers RAM size and CPU speed. The predictive computations were also offloaded on separate worker dynos, servers dedicated for the task of prediction, freeing the web dyno to receive new requests.

4.5.2 Measure

We measured data about the functional MVP user experience, data from Google and Facebook, as well as tested the latest MVP and the machine learning performance.

4.5.2.1 Measuring Data About the functional MVP User Experience.

The MVP think aloud test resulted in data found in appendix B.9.2. The key metric of this data was the answer to the question of their interest in using the product again after trying it. Nine out of ten customers said yes. There was also data collected on the user experience in every step of the MVP. For example, there were mentions of design flaws regarding inappropriate colour themes, placement of buttons and interactive content, text explanations, etc.

4.5.2.2 Measuring Data from Google and Facebook ads

After running the MVP funnel test, we had collected data on how customers' sessions on the website converted between different funnel metrics. These funnel metrics were:

- Conversion rate from landing page to product page.
- Conversion rate from product page to generated price.
- Conversion rate from landing page to personal contact by email or phone.

The result was that 29% of sessions on the landing page converted to the product page. From sessions on the product page there was a 125% conversion rate, which meant that some sessions led to multiple generated prices. There were however a 0% conversion rate to personal contact. The full list of the funnel data can be found in appendix B.9.3.

4.5.2.3 Measuring on Altering the MVP from User Feedback

With our previous version of the MVP, only a price was returned and after implementing the changes we had a price and two graphs, one was the predictive distribution computed by the Gaussian Process and the other one was for what prices computers with similar configurations had been sold. In conclusion, we increased the transparency of our calculation by giving the user more background to the estimated price.

Before updating the communication module only one request per client could be sent every 30 seconds, and the server could only calculate one price at the same time. After the upgrade, a client could send unlimited requests that would be queued in the backend until the server was done calculating the result.

4.5.2.4 Measuring Machine Learning Performance

With the pre-learning, scaling in *Heroku* and the separate worker dynos we were able to decrease the time to train and make predictions with the Gaussian Process model. Using the pre-trained model instead of training directly after initialising the server significantly increased the time until the server was ready to receive requests, from about 140 to only a few seconds. Prediction time was decreased from around 60 seconds on the *Heroku* server to roughly 30 seconds.

4.5.3 Learn

The learnings from the fifth sprint was that a clear majority of the potential customers wanted to use our product and that we had a very high conversion rate on the landing page. Also, that the data visualisation could be improved in the product and other machine learning methods should be investigated since the Gaussian Process is very computationally expensive.

4.5.3.1 UX Test Allowed Us to Validate Customer Preferences

The MVP think aloud test was designed to challenge our hypothesis that we know our target customers' priorities and preferences for our value proposition. We observed that nine out of ten customers wanted to use our product again after using it, which was above the set criteria of a majority. From this we learned that we had data showing that we know our target customers' priorities and preferences regarding our value proposition. Based on these insights, we decided to regard our customers' priorities and preferences as validated and would continue towards testing their willingness to pay for using the product. The learning card can be found in Figure 4.42.

Figure 4.42: Quantitative Learning Card

In the build phase, we stated that the data reliability was considered moderate. The action required after the test was primarily in regard to the design and not the core functionality, which was why it was rated as small.

4.5.3.2 Interest Validated, but Google and Facebook Ad Data Was Inconclusive

The MVP funnel test was carried out to test the hypothesis that our target customers had an interest for our value proposition. We observed that the funnel metrics were above our validation criteria for the conversion rate of generating a price, where 37% of the sessions converted whereas the criteria was 5%. However, 0% of sessions converted to a customer reaching out through email or by phone which did not meet our conversion criteria of 1%. From this we learned that our value proposition created interest among our customers, but that question remain regarding their need or excitement of reaching out to us. Because of these insights, we decided it would be possible to increase our marketing test budget and start to test our customers' willingness to pay for using the product. The learning card can be found in Figure 4.43.

Figure 4.43: Quantitative Learning Card

The data reliability was considered moderate as stated in the build pahse, and the action required as a result of the test were no direct iterations or pivots.

4.5.3.3 The Data Visualisation in the MVP Was Hard to Understand

Users wanted more data on how the price was calculated and this was achieved with by showing the two graphs. Although the graphs improved the transparency and amount of data we believed that the predictive distribution was hard to interpret. We could alter the graph to have made it more understandable. For example, percentages would have made it easier to understand than decimal numbers or adding a small explanation to the graph. We also learned the limitations of the MVP implemented in Sprint 4. It could only handle very few requests, making it a bottleneck for future development. However, it was altered to allow more customers using the product at the same time during the sprint.

4.5.3.4 Gaussian Process Regression Proved too Computationally Expensive

Although the performance of the *Gaussian process regression* was significantly increased, several problems was still present. Without a big budget, scaling *Heroku* to perform very well on such heavy computations is problematic. If the traffic to our web site were to increase heavily we would require a big budget for scaling the servers which is undesirable for an unfunded startup. Pre-learning the model also exhibited problems since it requires us to, from time to time, relearn the model to new data locally then pushing the new model to *Heroku* which is unwanted due to the amount of manual work it requires. Training the model on new data directly on the *Heroku* servers would we beneficial for a robust application.

The *Gaussian Process* is very computationally expensive in both time and space which has been proven problematic for our application. Even with a very large budget to increase the computational power, the Gaussian process regression cannot scale adequately as our traffic and data set increases. To deal with this problem, we could investigate other methods for Bayesian inference that are less computationally expensive whilst still having good prediction performance and giving prediction standard deviation estimates. Investigating alternative Gaussian Process models that intend to improve the computational complexity, such as models presented by Saatçi (2012) could also be an option.

4.6 Summary of our Lean Startup Process

In this section we conclude with the final results in the end of Sprint 5 in three parts; our progress in the business, the status of our MVP and the current Machine Learning method.

4.6.1 Customer Development

In the end of Sprint 5 we had learnt that nine of ten users wanted to use the product, 29% of sessions on the landing page continued to the product page and 125% of user sessions on the product page generated a price. With this data as background we could conclude that we had validated customer interest and customer preference and we could move to the next step on the progress board, shown in figure 4.44, that is validating willingness to pay. Both the Business Model Canvas, figure 4.45, and the Value proposition, figure 4.46, were the same as before Sprint 5 because they were validated.

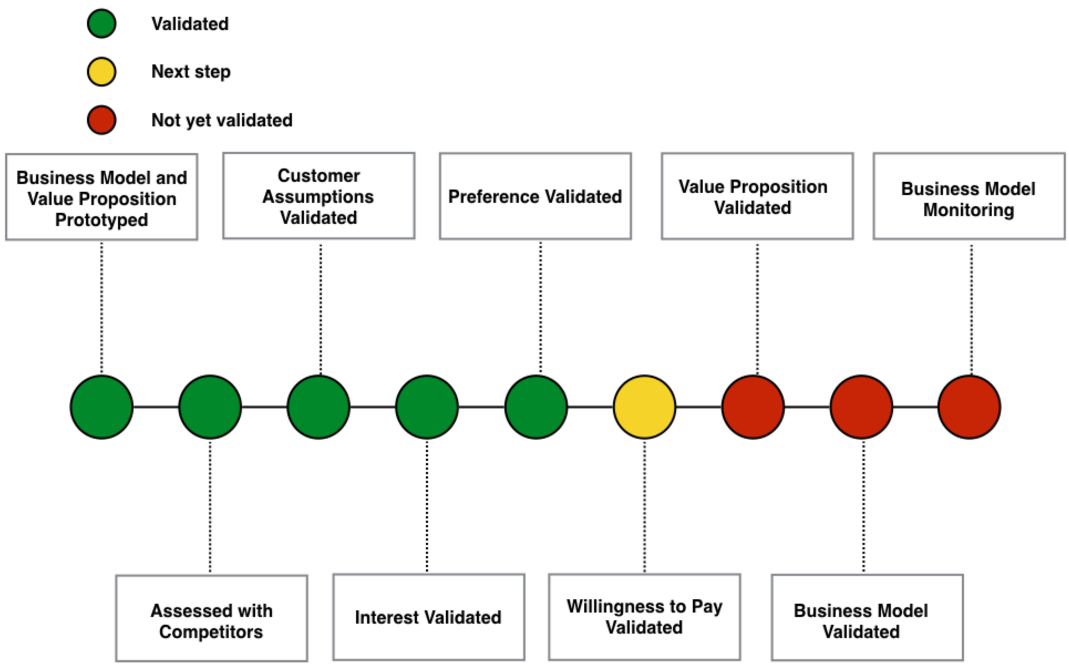

Figure 4.44: Resulting Progress Board.

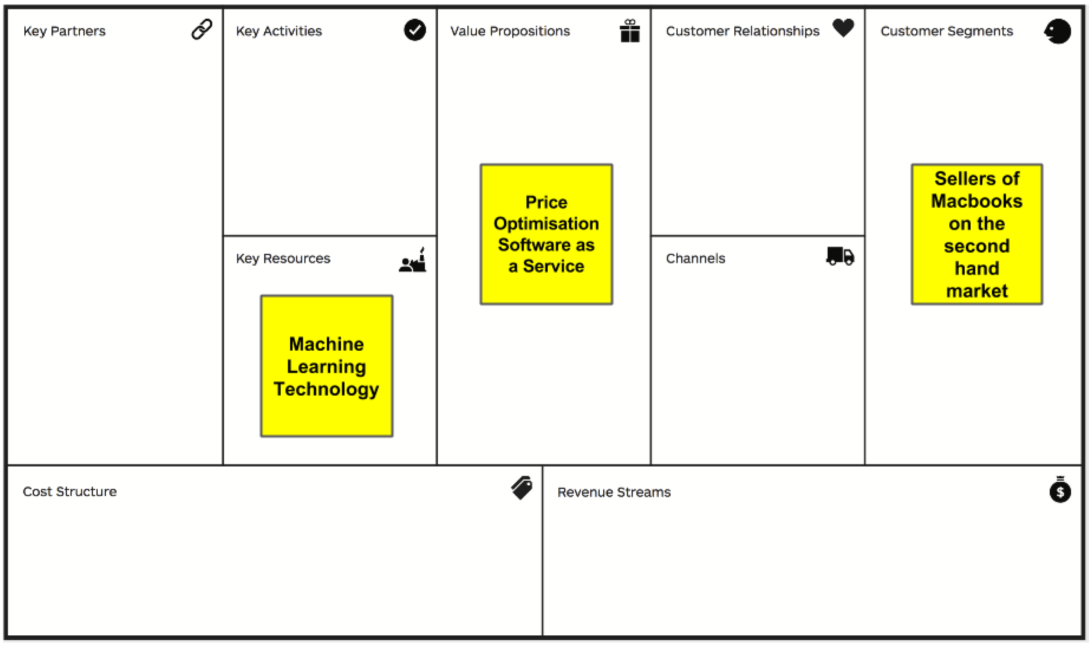

Figure 4.45: Resulting Business Model Canvas Hypotheses

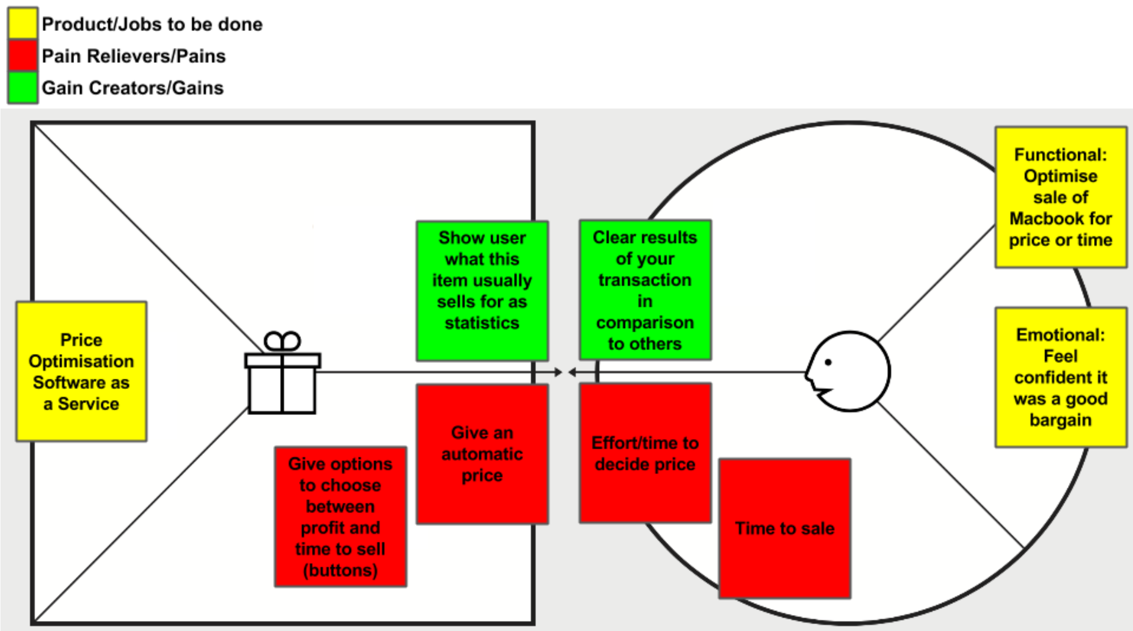

Figure 4.46: Resulting Value proposition Canvas Hypotheses

4.6.2 Product Development

At the end of Sprint 5, we had a functional MVP. The frontend had a graphical user interface in which the user could enter information about their computer and receive a price, with two supporting graphs explaining the reasoning behind the price. The graphs were shown in the form of a predictive distribution of the price, and a bar plot showing what prices similar products had been sold for historically.

4.6.3 Machine Learning Development

At the end of Sprint 5, we had successfully implemented and deployed a trained Gaussian process regression model. The accuracy of the final model predicted 41.55% correct prices within ±10% of the target values, and 67.09% of the prices within ±20% of the target values. The R^2 score of the model was estimated to 0.852. The Gaussian process regression was not the model with the best predictive performance, nor the best time performance. It was chosen due to it being the best performing model of the models that provided an estimate of the prediction error. This meant that we could offer customers further insights, knowing that some statistical arguments needed to be presented in order for the customers to trust the price predictions.

4.6.4 Next Steps

The initial hypothesis of the project was that our customers were the same as our users, selling Macbooks on the second hand market. However, data showed that the web application in it self did not attract many views. At the same time, the majority of the people wanted to use the product. We believe that the fact that our web application did not attract as many views as we would have wanted depended on the lack of brand recognition, where people simply did not have enough information about Selleri. At the same time, the nature of the product meant that the user only visited the website when selling a Macbook, which usually only happens with the frequency of once every few years. These factors resulted in the team having a hard time building a hypotheses around our customers willingness to pay. Instead, we realised that a significant pivot in the business model was necessary.

As seen in figure 4.47, our new customer segment became online marketplaces for electronic devices instead of sellers of Macbooks on the second hand market, who would be the actual end users. In other words, the business would change focus from B2C to B2B, but now with our previous customer segment becoming the end users, and previous key partners (online marketplaces) becoming the new customer segment. The reason is that the current online marketplaces already have a customer base and can drive traffic to our product without us having to build up a brand and invest in marketing. Furthermore, since our product was very focused on one specific job to be done, we were worried that the incitement was not enough for the customers to pay for Selleri as a standalone product. Consequently, our revenue streams would be a regularly paid fee from the marketplaces, since working as software as a service. The customer relationship would basically be us selling our service by showing statistical data and results from users tests, where proving how Selleri meets customers' needs. The Customer Development Process would still be a necessary key activity towards our new customer segment. Our key partner would be Ebay since all the data that the machine learning algorithm use, was obtained from their API. Our key resources would be the same as during this project, the founding team and machine learning technology, but in order to continue developing the business, we would potentially need additional funding. The funding would in turn cover costs such as salaries and server costs.

Based on the hypotheses about the forming of the new business model, a next step Value Proposition Canvas was created (figure 4.48), where translating the different parts in the business model into pains, gains and jobs to be done. As mentioned before, the jobs to be done would be increasing revenue to marketplaces for electronic devices, based on the pain to help end users, who were the customers on our previous business model, to maximise their profit from sale and the gain to make end users use the marketplaces more often and therefore sell in higher quantity. This would in turn, from a sustainable perspective, further promote re-usage of electronic devices instead of producing new ones, as well as enable people with a lower income, afford a Macbook. The features would be built upon these pains, gains and jobs to be done by offering end users a recommended price for their product within that specific marketplace, as well as a list of additional electronic devices to sell.

If we would apply these hypotheses and perform the pivots presented by creating a new business model as well as a new value proposition canvas, the position on the progress board would have to be updated. The next position Selleri would go to, is Customer Assumptions Validated as seen in figure 4.49, were having to validate all the hypotheses presented in figure 4.47 and figure 4.48. This would mean taking multiple steps back on the Progress Board. However, the validated learning about the end users could still offer us leverage in selling our value proposition to the online marketplaces, since their business models rely on the very same users who are their paying customers. Having data that these end users already want to use our value proposition could be a critical selling point towards these online marketplaces.

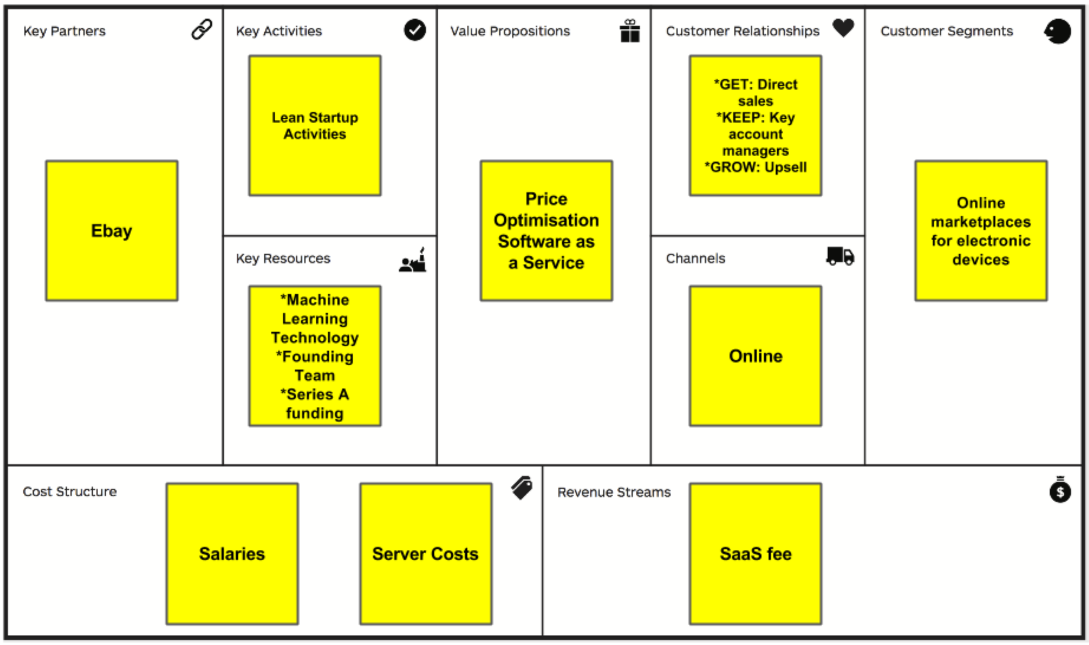

Figure 4.47: Next Steps Business Model Canvas Hypotheses

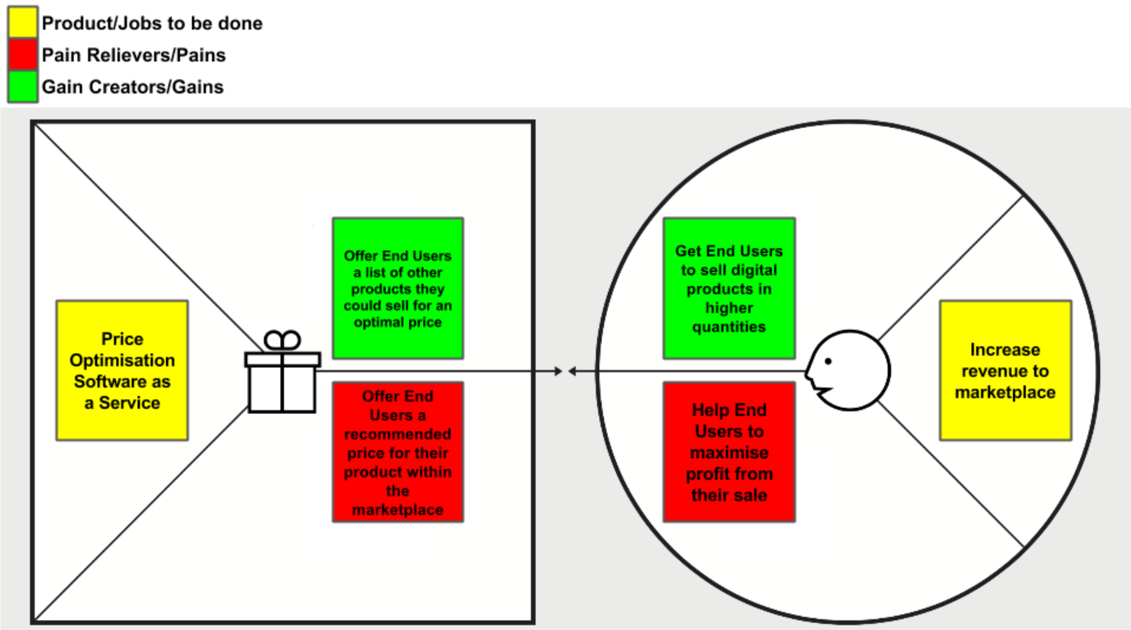

Figure 4.48: Next Steps Value Proposition Canvas Hypotheses

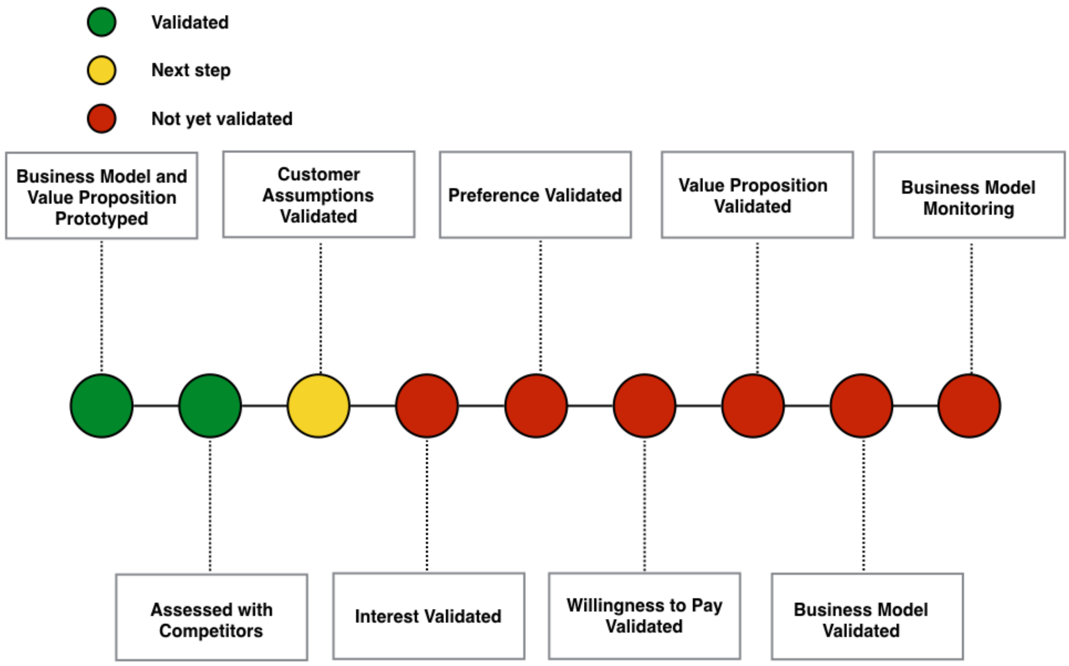

Figure 4.49: Next Steps Progress Board

5
Conclusion

In this chapter, we conclude and reflect over the results, purpose and problem statements of this project. We end with finishing thoughts on future work and research.

5.1 Purpose achievement and project outcome

During a university semester, we managed to turn an idea into an MVP and validate potential customers' interest and preferences by following the Lean Startup Process. The journey contained several invalidation, as well as validation of hypotheses.

A functional MVP, with a Gaussian Process machine learning model as the core technology, was built and can be found at http://selleri.io/. The MVP helped sellers on the second hand market who wanted to sell their Macbooks by offering them insights into the market with a selling price recommendation interfaced through a web application. This unlike our competitors who only work as a platform for buying and selling. The customers' jobs to be done was to optimise the process of selling a Macbook for profit and/or time. The pains related to this job were summarised as the amount of effort and time they had to put on deciding the price and that the time to make a sale was too long. The customers' desired gains from performing the job were clear results and visualisation of sales numbers of similar Macbooks to compare with.

Analysing the results of this project lead to insights that reflect the purpose of this project, which was to search for a repeatable, scalable and sustainable business model based on machine learning technology by applying the Lean Startup Methodology. Looking at the progress board, we found that the project successfully did prototype a Business Model and Value Proposition, as well as assessed our Business Model and Value Proposition with competitors. We found Problem-Solution Fit and validated customer interest and preference in our value proposition.

The problem statements were answered by the finding that Business Model Design could, through tools like the Business Model Canvas and Value Proposition Canvas, be used as a shared language to communicate hypotheses and insights within the team. Also, at the start of every sprint, a snapshot of the current Business Model Canvas and Value Proposition Canvas could be used to prioritise the most critical hypotheses that needed to be tested in a build-measure-learn cycle. Furthermore, the Scrum framework could be applied to work in development sprints that allow a product to be built iteratively and incrementally. A business model based on machine learning could, in our case, be sustainable in deployment when solving customer problems in the second hand market, addressing environmental, economical and social perspectives.

5.2 Further work and research

If not constrained by time, we would have kept sprinting, aiming to learn more to share in this thesis, and accomplish all the steps on the progress board. The next step would have been to pivot the business model according to our new hypotheses based on results and insights from previous sprints. More specifically, we would replace the target customer from sellers of Macbooks on the second hand market, to online marketplaces for electronic devices. In the scenario of having online marketplaces as target customer, the focus would go from B2C to B2B, and a Software as a Service revenue model. The changes in the business model would according to our hypotheses result in increasing revenue to marketplaces as jobs to be done, help user to maximise their sales profit as pain and increase usage of marketplace as gains. The features would be offering end users a recommended price for their product within that specific marketplace, as well as a list of additional electronic devices to sell. This would, in turn, result in Selleri also taking steps back on the progress board, with the next step being to pursue validation of customer assumptions. Furthermore, it would be possible to increase the scope of our product, and to scale it until we would cover several, or all, electronic devices, using the same core technology.

As to further research, this project could serve as a template to be replicated and improved. If a student would want to work on his or her own thesis, or if an entrepreneur would want to become more structured and principled in his or her work, this thesis could help and guide their way to success.

6 Discussion

In this chapter, we discuss the challenges and learnings during the process of going from idea to results using the Lean Startup methodology.

6.1 Lean Startup within the constraints of a Bachelor's thesis

The Lean Startup Methodology has been at the core of this project. We used different frameworks of the methodology within the constraints of a Bachelor's thesis. However, some modifications of the process were made, in order to adapt it to our business idea, our team and the format of a Bachelor's thesis. Furthermore, we believe that this kind of adaption should be made by everyone using the Lean Startup Methodology, and should be regarded as guidance and a set of tools rather than a detailed plan of operational work. One of the adaptations that were made was additional user interaction. We collected feedback regarding the user interface and the user experience, which was executed outside the explicit scope of the progress board. We realised the fact that interaction with customers created more value than expected when developing the product, which we wanted to integrate more in the project. By constantly executing user tests and sharing the insights with the whole team, we could easily stay aligned both in deciding next steps in the developing process, as well as in the overall vision for the product.

A valuable insight from this cross functional project was the importance of customer insights in technical development. If this project had been purely technical, the choice of machine learning model would have been solely data driven. As the Random Forest model gave the highest predictive accuracy this would have been the choice of model in a purely technical development. But as this project was not purely technical, a worse performing model was chosen due to the fact that it offered more valuable insights to the customers.

This project was founded on the approach of technology push. This means that the choice of technology was static but the choice of customer segment was dynamic. This allowed us to, from the very start, pick a team with machine learning technology skills, since the pivots would revolve around the choice of customer segment rather than the underlying technology. Our project had constraints requiring six students to form a team and an idea of a certain technological level to be accepted by the faculty of the university. While the technology push approach was helpful within these constraints, we contemplated what the implications would have been if we had chosen the market pull approach instead. This approach would have made the customer segment static but the choice of technology dynamic, allowing us to stay motivated towards solving a specific problem, rather than to keep pivoting to new customer segments as soon as we encounter problems with our current customers.

We started the project with high technical ambitions, creating a feasible product and business model by integrating several different technologies, and using advanced machine-learning algorithms as the core technology. This in turn resulted in a long implementation time, giving us only one sprint to iterate on the product and test it on customers. An easier product to implement would allow us several sprints to develop the product continuously with the help of feedback from customers, towards the goal of finding a product-market-fit. In other words, there was a trade off between advancing the product and advancing in the lean startup process.

On the other hand, testing too much requires excessive time from development while waiting for insights and analysis. Instead of regarding the development process, as well as the testing process, as linear, we divided the work into sections and tested them as they the development was finished. Eventually the mindset became to test as soon as a part was finished, even if we were not fully satisfied with details. The customers' feedback became a guidance when continuing to develop and build the product. Moreover, a lesson which we learned further into the project, was to allow the customer feedback to be considered as dynamic guidelines, rather than static requirements, and to run the testing process in parallel, allowing us to gain more insights without being dependent on earlier tests.

6.2 The team

We were a group consisting of students from three different programs; Computer Science and Engineering (D), Software Engineering (IT) and Industrial Engineering and Management (I). Initially, the high degree of diversity in competence resulted in both positive and negative consequences. But as the project moved forward and the team learned to work together and integrate the two major competencies, business and technology, the negative consequences were not as present.

At the beginning of this project, the work tended to be divided into two separate parts, depending on the two groups of competencies and the want to start working with both development and business right away. We realised that in order to integrate both parts to create a cohesive product, the two parts would have to communicate and work more together by sharing insights and cooperating on the different parts of the project. As a result we introduced weekly work slots, where we met, went through the overall status of the project, and finally worked together during a few hours. These sessions resulted in the team communicating more about insights and issues, which in turn lead to a deeper integration of business and technology development during the rest of the project.

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A

Appendix - Minimum Viable Product

A.1 Non-functional MVP

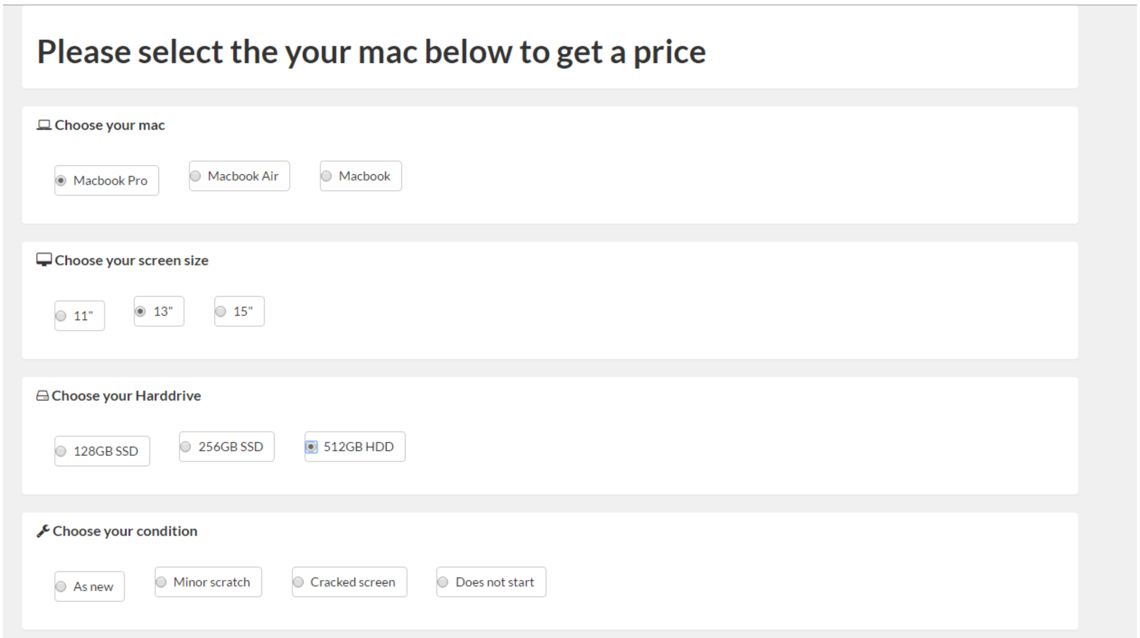

Figure A.1: Selleri, non-functional MVP

A.2 Functional MVP

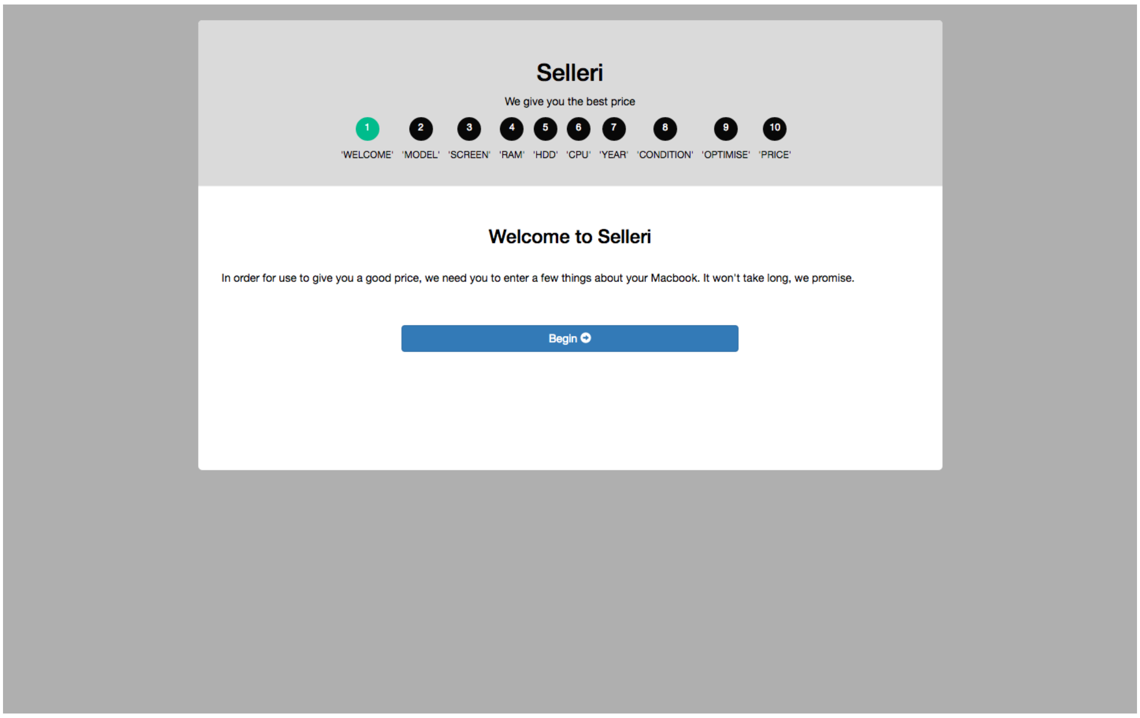

Figure A.2: Selleri, MVP, image 1

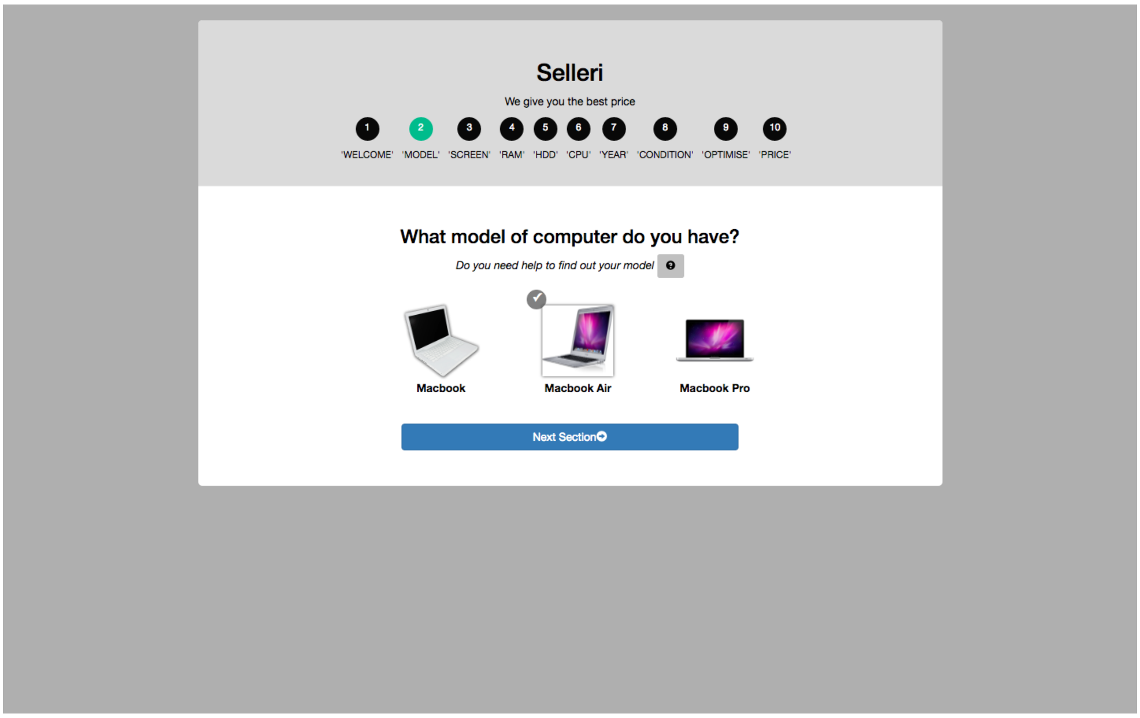

Figure A.3: Selleri, MVP, image 2

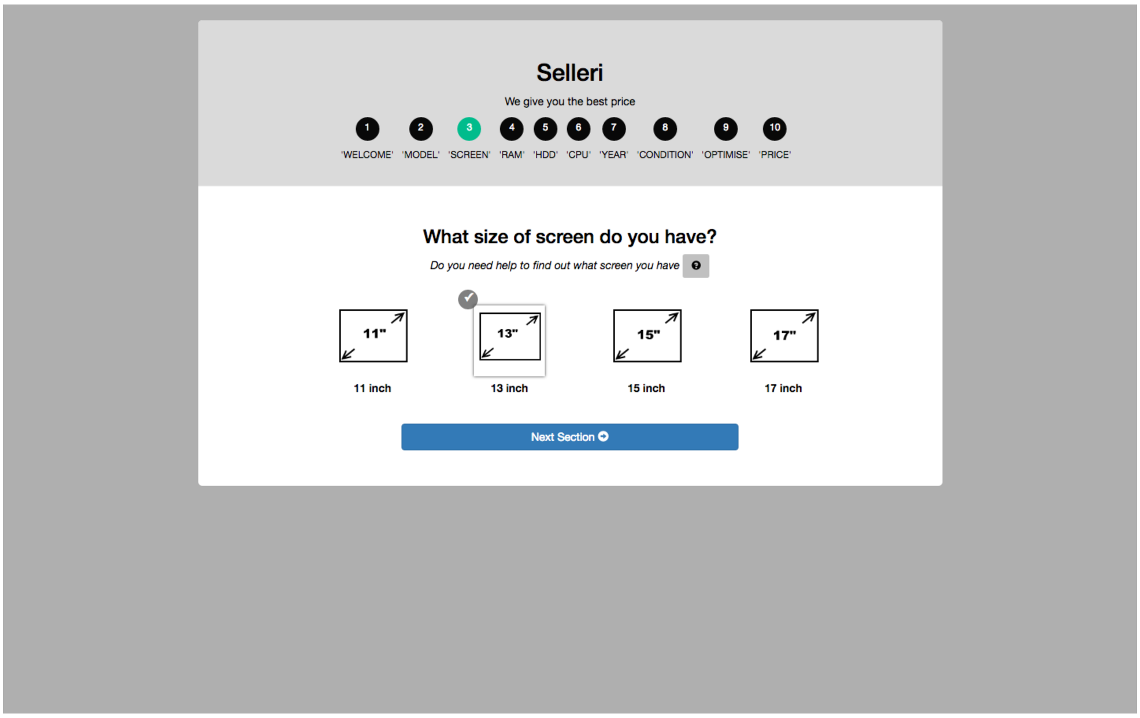

Figure A.4: Selleri, MVP, image 3

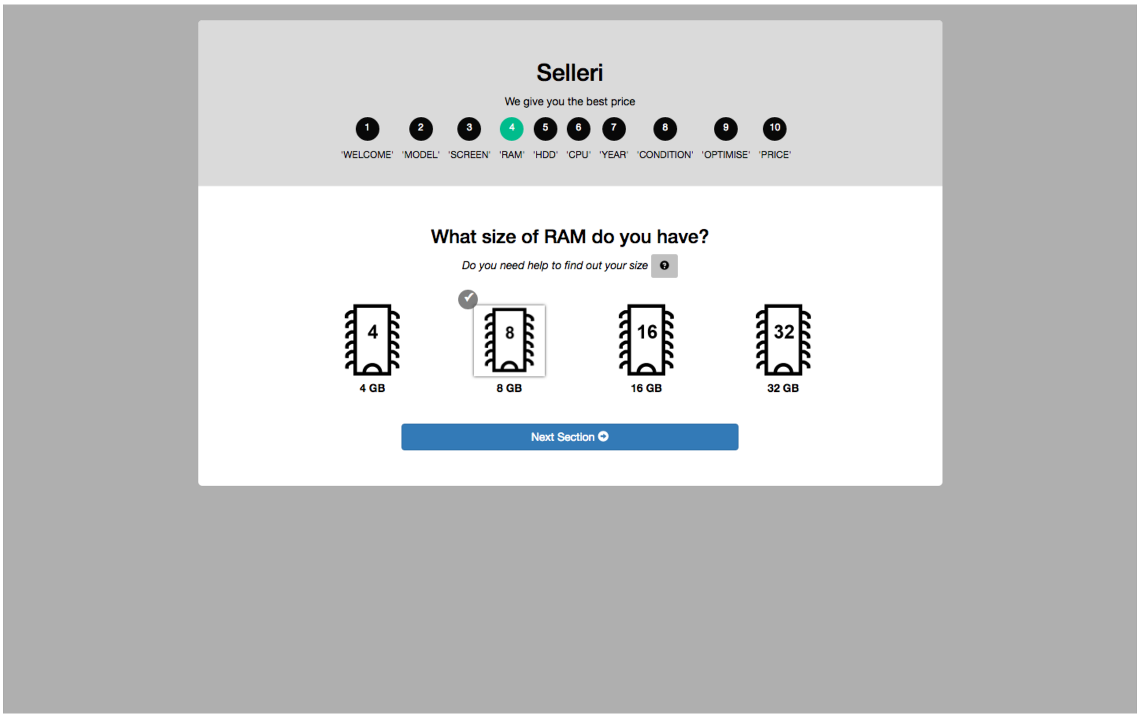

Figure A.5: Selleri, MVP, image 4

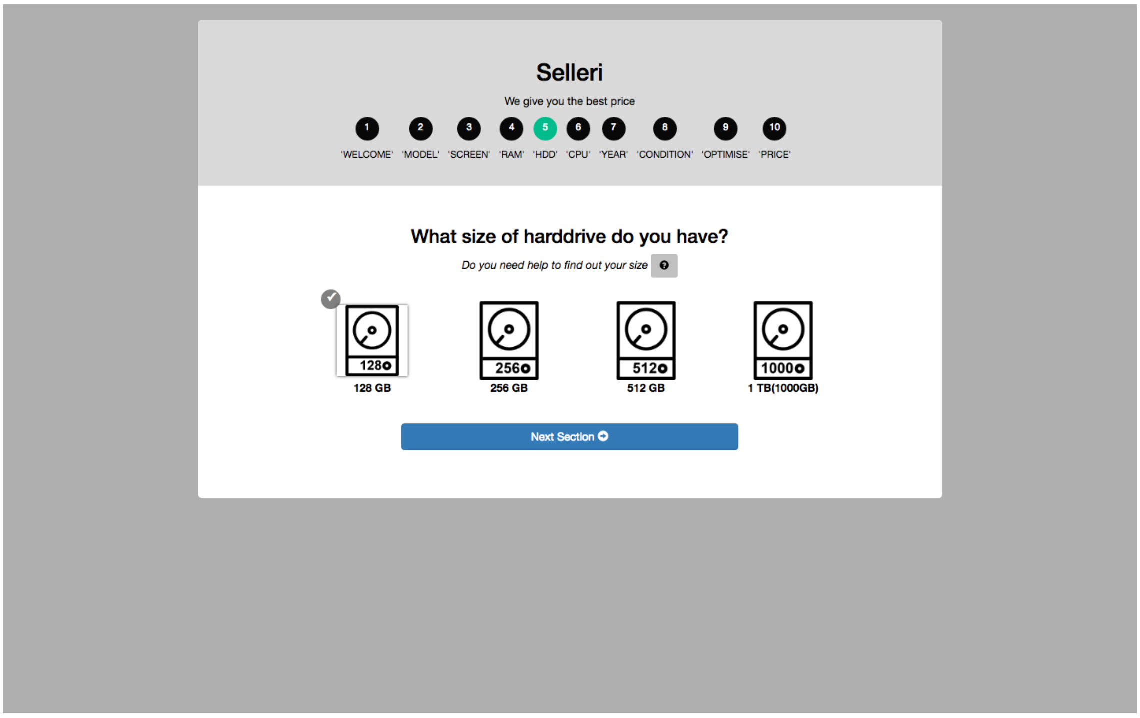

Figure A.6: Selleri, MVP, image 5

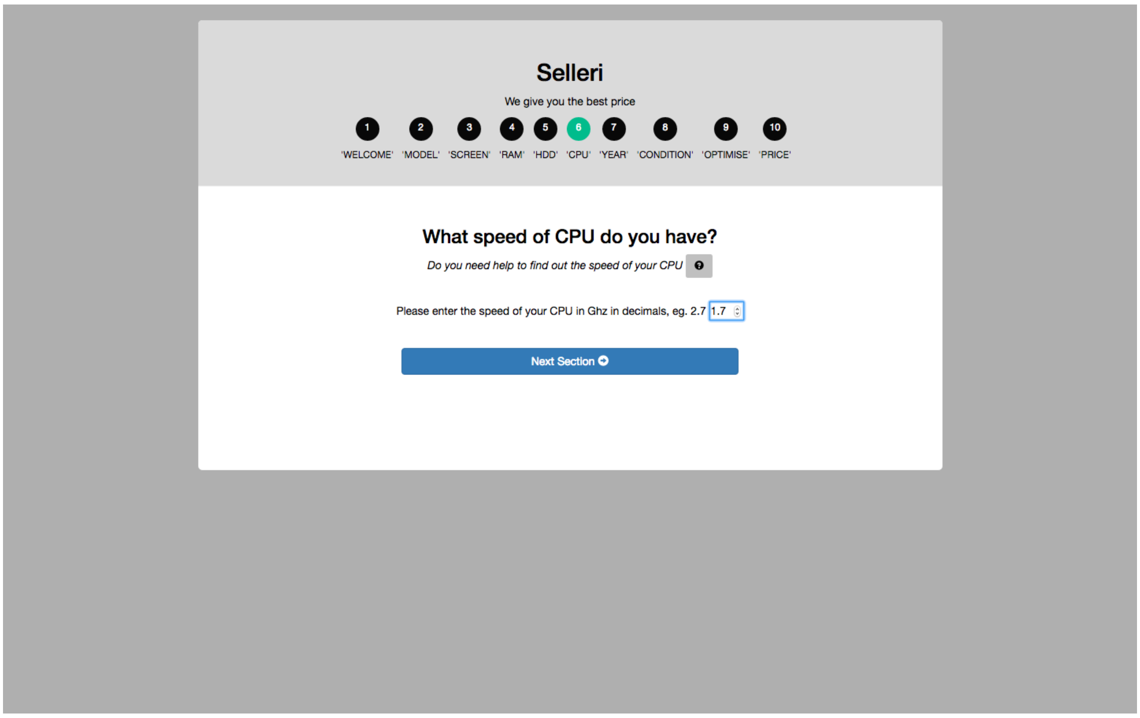

Figure A.7: Selleri, MVP, image 6

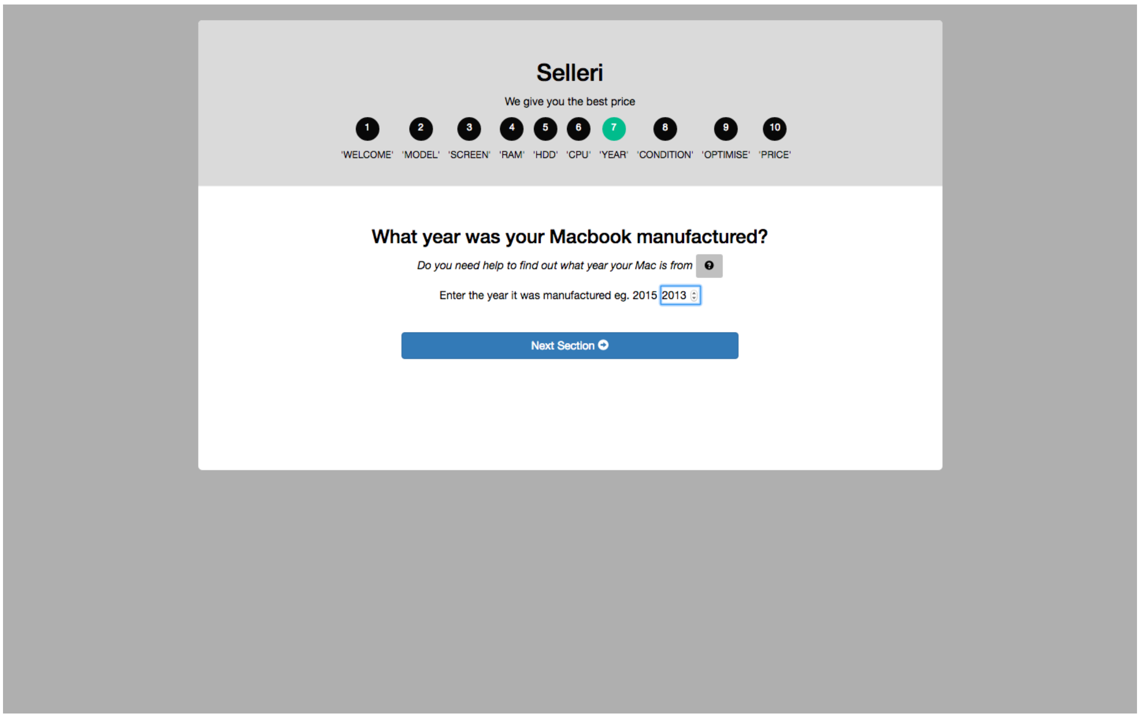

Figure A.8: Selleri, MVP, image 7

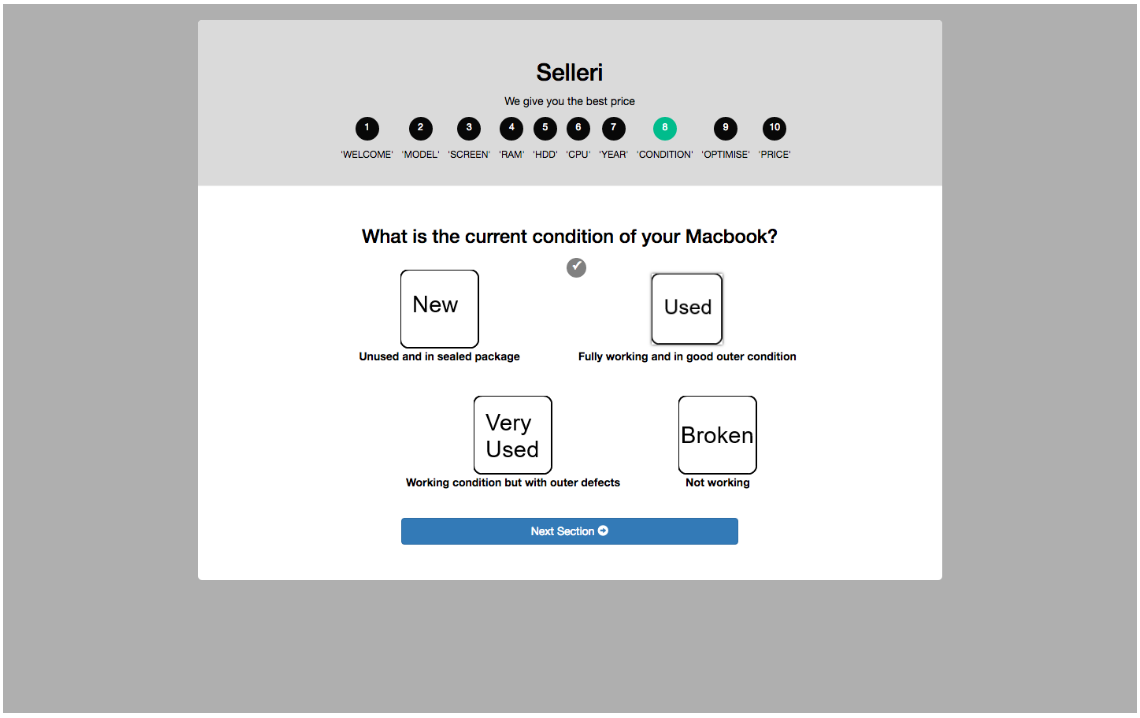

Figure A.9: Selleri, MVP, image 8

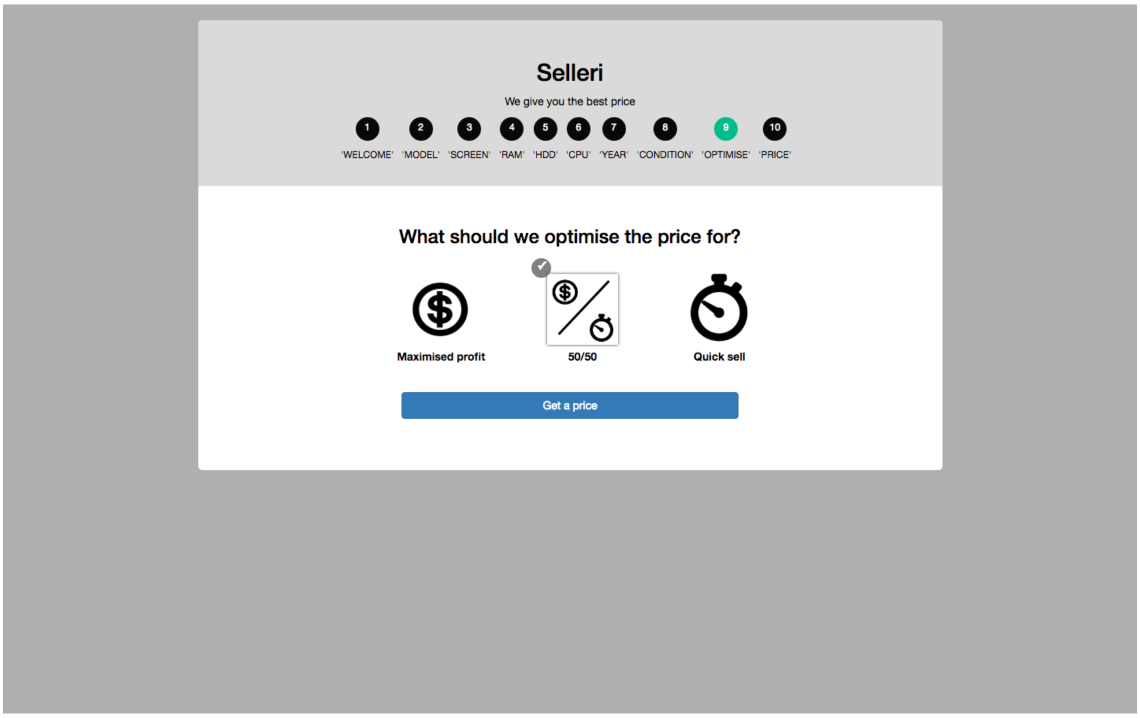

Figure A.10: Selleri, MVP, image 9

A.2.1 Results of form

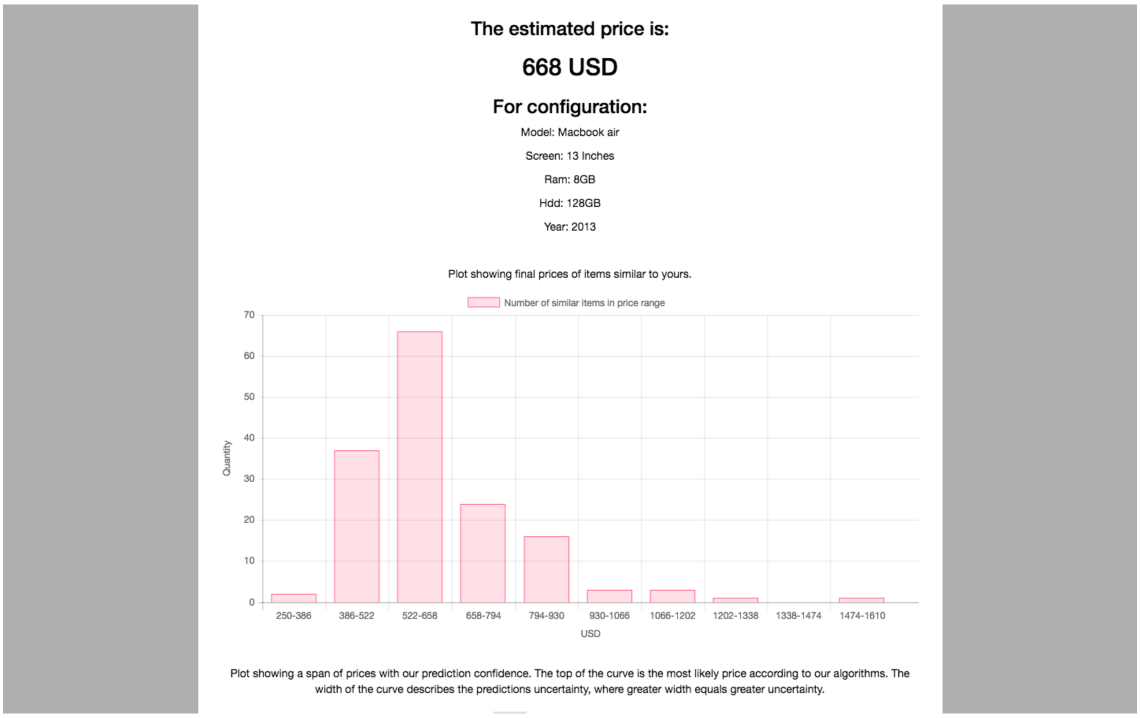

Figure A.11: Selleri, MVP, Search Result image 1

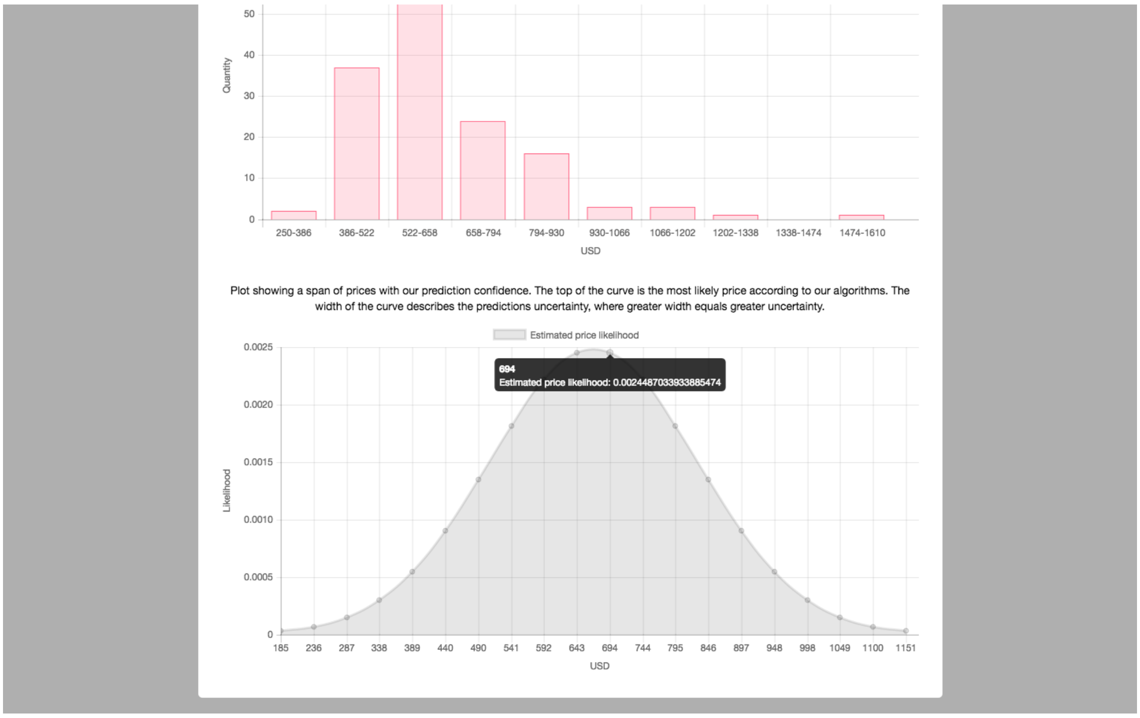

Figure A.12: Selleri, MVP, Search Result image 2

A.2.2 Help box

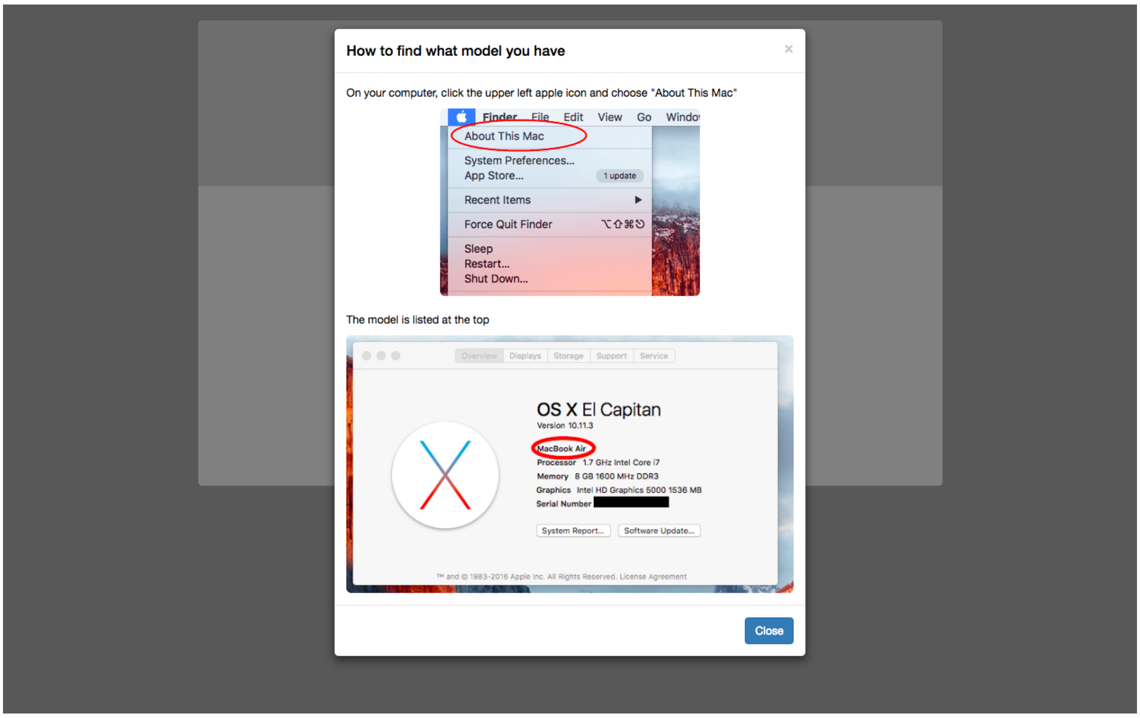

Figure A.13: Selleri, MVP, image of help popup

B

Appendix - Test Data

B.1 Customer Interviews Demography

- Namn
- Email
- Telefon
- Land - Bor i vilket land? (Alternativ: Sverige,annat)
- Kön? (Alternativ: Man, Kvinna, ignorera)
- Digitala enheter - Vilka enheter äger du idag? (Alternativ: PC, Mac(Stationär), Macbook, Laptop, Smartphone, Tablet, konsol)
- Digital försäljning i andrahand - Vilka enheter har du sålt i andra hand? (Alternativ: PC, Mac(Stationär), Macbook, Laptop, Smartphone, Tablet, konsol)
- Operativsystem - Vilket operativsystem använder du? (Alternativ: OS X, Windows, iOS, Andriod, Övriga)

B.2 Customer Profile Interview

Jobs to be done: Varför vill du sälja din gamla Macbook? Vilket jobb utför försäljningen för dig?

Pains: Var du frustrerad eller orolig för någoting?

Gains: Blev du glad/hoppades du på något?

Products/Services: Vad använde du för lösning för att sälja?

Pain Relievers/Gain Creators: Hur fungerar funktioner som du älskar med denna lösning?

Kontext: På vilka platser/situationer hanterar du försäljning/titar du för att sälja din gamla Macbook?

Kontext: När på dygnet/veckan/året gjorde du detta?

Revenue Stream: Har du betalt för denna lösning? Hur mycket? Hur ofta?

B.3 Questionnaire 1 questions

- var fick du sålt din macbook?
  - Jag fick sålt den till någon okänd inom samma stad som jag bor.(T.ex. Någon från blocket köpte den och bodde i samma stad) Hur väl stämmer detta?
    - Stämmer inte alls

        * Stämmer inte så väl
        * Neutral
        * Stämmer väl
        * Stämmer mycket väl
    - Jag fick sålt den inom "hemmet".(T.ex. ett syskon, en förälder eller en släkting köpte din gamla Macbook) Hur väl stämmer detta?
    - Jag fick sålt den inom skolan. (T.ex. Sålde till en klasskamrat eller någon inom skolan) Hur väl stämmer detta?
- När fick du sålt din Macbook?
    - Jag sålde utan koppling till specifik tid eller datum. (T.ex. Försäljning utan koppling till juletid, ny utkommen version av Macbook, etc.) Hur väl stämmer detta?
    - Jag sålde den inför Juletid. (T.ex. November - December) Hur väl stämmer detta?
    - Jag sålde under kvällstid. (T.ex. efter jobbet/skolan, runt middagstid, innan läggdags, etc.) Hur väl stämmer detta?
    - Jag sålde i samband med att en ny Macbook-modell släpptes.(T.ex. modelluppgradering eller ny generation) Hur väl stämmer detta?
- Vad var anledningen till att du sålde din Macbook?
    - Jag ville maximera vinst från försäljning. (T.ex. Du ville hellre ha datorn sålt för bra pris än en snabb försäljning) Hur väl stämmer detta?
        * Stämmer inte alls
        * Stämmer inte så väl
        * Neutral
        * Stämmer väl
        * Stämmer mycket väl
    - Jag ville ha en snabb försäljning. (T.ex. Du ville hellre ha datorn sålt snabbt än att spendera mycket tid för att maximera vinst) Hur väl stämmer detta?
    - Jag prioriterade att sälja till vänner och familj. (T.ex. gick du först och kollade om någon i din närhet behövde en Macbook, och prioriterade den kunden högst) Hur väl stämmer detta?
    - Jag tyckte att det var enklare att sälja till vänner och familj. (T.ex. enklare att ta kontakt, enklare leverans) Hur väl stämmer detta?
    - Jag tyckte att det var viktigt att kunna ha ett bra pris till vänner och familj. (T.ex. vill du kunna påvisa att det är ett korrekt marknadspris) Hur väl stämmer detta?
    - Jag sålde min gamla Macbook på andrahandsmarkanden efter uppgradering till ny dator. Hur väl stämmer detta?
- Vilka problem stötte du på när du sålde din MacBook?
    - Jag hade svårt att veta marknadsvärdet av Macbooken. (T.ex. Svårt att veta vad just min dator är värd med modell och slitage) Hur väl stämmer detta?
        * Stämmer inte alls
        * Stämmer inte så väl
        * Neutral

        * Stämmer väl
        * Stämmer mycket väl
    - Jag hade svårt att sätta ett schysst kompispris. (T.ex. svårt med tradeoff mellan marknadsvärde och vara schysst mot kompis/familj vid försäljning) Hur väl stämmer detta?
    - Jag kände oro för att datorn skulle gå sönder efter försäljning. (T.ex. vad händer om Macbook:en kraschar i efterhand) Hur väl stämmer detta?
    - Jag var irriterad på att försäljningen tog lång tid. (T.ex. Tog tid att få svar på annons) Hur väl stämmer detta?
    - Jag kände oro och irritation inför att ge lågt pris för att få MacBook såld (T.ex. Behövde sänka priset för att få den såld, oro att den inte skulle stiga i pris på auktion) Hur väl stämmer detta?
    - Jag hade problem och oro med transaktionen vid försäljningen. (T.ex. Var tvungen att ta tillbaka datorn då man aldrig fick hela summan, oro för säkerhet vid transaktion av pengar) Hur väl stämmer detta?
    - Jag kände oro för att sälja produkten till främmande om all data inte skulle vara rensad korrek. (.ex. Svårt att med säkerhet ha rensat all data ur MacBook) Hur väl stämmer detta?
    - Jag tyckte att det var jobbigt att lägga upp annons på flera olika marknadsplatser. (T.ex. Jobbigt att sätta sig in i andra marknader än Blocket) Hur väl stämmer detta?
    - Jag hade problem och oro med transaktionen vid försäljningen. (T.ex. Var tvungen att ta tillbaka datorn då man aldrig fick hela summan, oro för säkerhet vid transaktion av pengar) Hur väl stämmer detta?
- Vilket värde skapade försäljningen av din macbook?
    - Jag kände trygghet på grund av rättvis prissättning. (T.ex. Det pris som din Macbook såldes för kändes rättvis för både dig och köparen) hur väl stämmer detta?
        * Stämmer inte alls
        * Stämmer inte så väl
        * Neutral
        * Stämmer väl
        * Stämmer mycket väl
    - Jag kände att köparen fick användning av min Macbook. (T.ex. En till person kunde använda din gamla Macbook till stor fördel för sig själv) Hur väl stämmer detta?
    - Jag kände att det fanns en efterfrågan på marknaden vid försäljningen. (T.ex. mjukvaran stöttades fortfarande och tekniken var aktuell och många ville därför ha datorn) Hur väl stämmer detta?
    - Jag tyckte att den såldes för ett bra pris. (T.ex. din Macbook såldes för ett bra pris som gav dig en rimlig summa pengar) Hur väl stämmer detta?
    - Jag fick den såld för ett högre pris än väntat. (T.ex. du förväntade dig behöva sänka det satta priset på 4000kr, men lyckades få den såld) Hur väl stämmer detta?

  - Jag tyckte att köpet gick snabbare/smidigare än väntat. (T.ex. du sålde din Macbook snabbare än väntat eller att det var en oväntat okomplicerad process) Hur väl stämmer detta?
  - Jag kände oro för att sälja produkten till främmande om all data inte skulle vara rensad korrek. (.ex. Svårt att med säkerhet ha rensat all data ur MacBook) Hur väl stämmer detta?
  - Jag tyckte att det var jobbigt att lägga upp annons på flera olika marknadsplatser. (T.ex. Jobbigt att sätta sig in i andra marknader än Blocket) Hur väl stämmer detta?
  - Jag hade problem och oro med transaktionen vid försäljningen. (T.ex. Var tvungen att ta tillbaka datorn då man aldrig fick hela summan, oro för säkerhet vid transaktion av pengar) Hur väl stämmer detta?
- Vad använde du för tjänster för att sälja din Macbook?
  - Jag använde mig vid försäljning/research inför försäljning av Blocket. hur väl stämmer detta?
    - Stämmer inte alls
    - Stämmer inte så väl
    - Neutral
    - Stämmer väl
    - Stämmer mycket väl
  - Jag använde mig vid försäljning/research inför försäljning av Tradera. Hur väl stämmer detta?
  - Jag använde mig vid försäljning/research inför försäljning av Facebook. Hur väl stämmer detta?
  - Jag använde mig vid försäljning/research inför försäljning av Macrumors. Hur väl stämmer detta?
  - Jag använde mig vid försäljning/research inför försäljning av Telefonsamtal. Hur väl stämmer detta?
  - Jag använde mig vid försäljning/research inför försäljning av direkt (IRL) kontakt med köparen. Hur väl stämmer detta
- Vilka funktioner hjälpte dig att sälja din Macbook?
  - Jag hjälptes av att kunna se pris på liknande produkter. (T.ex. Att kunna se Macbooks som ligger ute på marknadsplatser och deras pris) Hur väl stämmer detta?
    - Stämmer inte alls
    - Stämmer inte så väl
    - Neutral
    - Stämmer väl
    - Stämmer mycket väl
  - Jag hjälptes av att kunna se hur längre liknande produkter legat uppe på annons/auktion. (T.ex. Att kunna se hur länge produkter har legat uppe på sin marknadsplats) Hur väl stämmer detta?
  - Jag hjälptes av att känna trygghet i att sätta rätt pris. (T.ex. Att en hemsida visar vad "rimliga" priser är vilket man kan visa för den man säljer till) Hur väl stämmer detta?

    - Jag hjälptes av att kunna lägga upp annons/auktion snabbt och smärtfritt. (T.ex. Att det går snabbt att lägga in uppgifter om produkten och få upp annonsen/auktionen) Hur väl stämmer detta?
    - Jag hjälptes av att sälja till vänner som är lättare att kommunicera med. (T.ex. Att vänner kontaktar en för ens annons så att man kan hålla en mer flödande diskussion om försäljningen jämfört med någon man inte känner) Hur väl stämmer detta?
    - Jag hjälptes av att veta när en ny Macbook släpps så att man kan sälja sin egen Macbook i rätt tid för att köpa en ny (IRL) kontakt med köparen. (T.ex. Att se på en hemsida om det är god tid att köpa en ny Macbook) Hur väl stämmer detta
    - Jag hjälptes av att kunna sköta försäljningen IRL för att slippa transaktionskostnader, etc.. (T.ex. Att sköta diskussion och transaktion i person med vänner/familj, etc.), (T.ex. Att sköta diskussion och transaktion i person med vänner/familj, etc.) Hur väl stämmer detta?
- Hur mycket betalade du för att sälja din Macbook?
    - Jag betalade en avgift för annons eller auktion. (T.ex. 30 kr för annons på Blocket, etc.) Hur väl stämmer detta?
        * Stämmer inte alls
        * Stämmer inte så väl
        * Neutral
        * Stämmer väl
        * Stämmer mycket väl
    - Jag betalade ingenting för att sälja min Macbook(T.ex. Såldes utan transaktionsavgifter, annonsavgifter, etc.) Hur väl stämmer detta?
    - Jag hjälptes av att känna trygghet i att sätta rätt pris. (T.ex. Att en hemsida visar vad "rimliga" priser är vilket man kan visa för den man

B.4 First MVP UX test

- Mac type:
    - Choose your macbook:
        * Macbook
        * Macbook Pro
        * Macbook Air
    - Please rate how hard it was to answer the question above between 1-5.
    - Did you have enough knowledge to answer the question?
        * Yes
        * No
        * Kind Of
    - How well-formulated was the question? Between 1-5
    - Any Other thoughts?
- Screen
    - Choose your screen size
        * Screen 11
        * Screen 13

        * Screen 15
    - Please rate how hard it was to answer the question above between 1-5
    - Did you have enough knowledge to answer the question?
        * Yes
        * No
        * Kind Of
    - How well-formulated was the question? Between 1-5
    - Any Other thoughts?
- Hard Drive
    - Choose your hard drive
        * 128 GB
        * 256 GB
        * 512 GB
    - Please rate how hard it was to answer the question above between 1-5
    - Did you have enough knowledge to answer the question?
        * Yes
        * No
        * Kind Of
    - How well-formulated was the question? Between 1-5
    - Any Other thoughts?
- Computer Condition
    - Choose your condition
        * New
        * Scratched
        * Cracked
    - Please rate how hard it was to answer the question above between 1-5
    - Did you have enough knowledge to answer the question?
        * Yes
        * No
        * Kind Of
    - How well-formulated was the question? Between 1-5
    - Any Other thoughts?
- Overall feedback

B.5 Feature test

Features

- Automatisk prissättning av din dator
- Möjlighet att optimera automatisk prissättning efter tid eller maximerad vinst enligt önskemål
- Tydligt definierat kontrakt mellan säljare och köpare av skyldighet om Macbooken går sönder
- Visa statistik på hur väl din försäljning gick i efterhand jämfört med andras försäljningar
- Visa statistik på vad Macbooks i liknande försäljningar har sålt för vid prisrekommendation innan försäljning
- Automatiserad generering av annons som automatiskt läggs upp på Blocket och Tradera

B.6 Think Aloud Test Manuscript

Välkommen till detta test. Tack för att du tar dig tiden. Vi har som kandidatarbete utvecklat en produkt som tar fram ett optimerat pris på Din Macbook, baserat på vad liknande Macbooks sålts för på andrahandsmarknaden. Produkten är en webbsida där man som kund får fylla i specifikationer kring sin Macbook för att sedan få ett rekommenderat pris.

Det kommer att ta 15-30 min att utföra detta test. Du kommer att få använda vår produkt och gå igenom alla steg. När du går igenom varje steg vill jag att du tänker högt kring hur du tolkar informationen och frågorna, samt generella tankegångar medan du svarar. Jag kommer inte att svara på några frågor kring produkten under tiden du fyller i enkäten.
Efter att alla frågor är ifyllda, kommer jag att ställa lite frågor kring den övergripande upplevelsen men också om specifika delar. Du kommer även få chansen att lägga till övriga kommentarer. Jag kommer att berätta mer om detta när du gått igenom samtliga steg.
STARTA “THINK-ALOUD” TESTET

MAIN
Under “think-aloud” testet Som testare ska du inte svara på några frågor kring produkten. Skriv istället ned vilka oklarheter och missförstånd som uppstått. Försök inte korrigera testaren eller reagera starkt på svar. Agera neutralt under hela testet. Le smått och nicka uppmuntrande funkar.

Frågor efter think-aloud testet Behöver inte fråga alla dessa, välj ut några utifrån resultat från testet.

Holistic/other Vad tycker du övergripande om produkten? Tycker du att processen som du togs igenom var logisk? Utveckla Vilka frågor hakade du upp dig på? Varför? Några övriga tankar kring produkten?

Any features missing Var det någonting som saknades i produkten? Hade du velat lägga till, ändra eller ta bort någon information?

Would you use the product Hade du använt produkten om du behövt/velat sälja din Macbook? Varför/varför inte?

END
Tusen tack för att du tog dig tiden för att utföra detta test. Dina åsikter är väldigt värdefulla för oss. Nästa steg för oss är sammanfatta resultatet från dessa tester. Efter det kommer vi att dokumentera allt i vårt kandidatarbete.

B.7 Interview Results

B.7.1 Customer Profile Interview Data

Table B.1: Customer Profile Interview Data

Timestamp	[JOBS to be done] Varför vill du sälja din gamla Macbook? Vilket jobb utför försäljningen för dig?	[Pains] Var du frustrerad eller orolig för någonting?	[Gains] Blev du glad/hoppades du på någonting?	[Products/Services] Vad använde du för lösning för att sälja?	[Pain Relievers/Gain Creators] Hur fungerar funktioner som du älskar med denna lösning?	[Kontext] På vilka platser/situationer hanterar du försäljning du/tittar du för att sälja din gamla Macbook?	[Kontext] När på dygnet/veckan/året gjorde du detta?	[Revenue Streams] Har du betalat för denna lösning? Hur mycket? Hur ofta?
18/02/2016 10:57:47	*Köpt en ny, ville bli av med gamla, *Ville sälja för pengarna med bra andrahandsvärde, *Inte nödvändigtvis få ut varje krona utan sälja för marknadsvettigt pris	*Sätta ett icke-rimligt pris, *Svårt att hitta exakt vad "min"" specifika produkt är värd"	*Trygghet genom att se att prissättningen är rättvis genom oberoende part (se att andra sätter typ samma pris), *Snabb och smidig process att få den såld	*Blocket, *Macrumours	Blocket: *Kolla pris på andra liknande produkter, *Se hur länge produkter legat uppe, *Se specs för produkter som ligger uppe (garanti, etc.), *Se skick av andra produkter för samma pris, *Benchmarka mot andras spec för kostnad, *Trygghet i att sätta rimligt pris, *När folk har använt tydlig syntax och beskrivit exakt vad deras produkt är så den är sökbar, Macrumours: *Kolla om det är bra tillfälle att köpa/sälja	*Inom stad där han bor	*Ingen speciell tid utöver att få den såld så snabbt som möjligt för att inte förlora tidsvärde	*30kr för annons på blocket
18/02/2016 13:21:36	*Hade köpt ny dator och ville sälja gamla, *Hjälpa systern få en billig dator, *Hade ingen nytta av datorn själv och ville att den skulle kunna användas	*Datorn höll på att dö och vågade inte använda den till arbete, *Rädd för att den skulle gå sönder efter försäljning, *Svårt att sätta pris för tradeoff med marknadsvärde + att vara schysst mot systern, *Svårt att rensa ut gammal dator och undrar vad som finns kvar om sälj till utanför familjen, *	*System fick användning av den och den höll bra	*Sålde via telefonsamtal till systern	*-	*Inom hemmet (till syster)	*Nya Macbooks hade släppts och sålde den direkt efter	*kontoöverföring av pengar, inga kostnader
18/02/2016 13:32:36	*Ville uppgradera till ny macbook och sålde för pengar till detta, *Ville sälja till syster för att hon behövde ny dator, *Känna att han gör systern en tjänst	*Svårt att sätta pris tradeoff mellan att hjälpa syrran och få behövda pengar, *Svårt men viktigt att det blir en fair deal för båda	*Glad att systern fick en bättre dator, *Kunde sen köpa ny dator själv	*Sålde i person till syster, *Blocket för att kolla priser, *Macforum för rekommendation av när sälja	Blocket: *Alla typer av produkter och subprodukter finns sökbara, *Flera exempel på samma datorer med olika priser och tid hjälper beslut av pris, Macforum: *Veta när den nya macbooken kommer ut och då är det dags att sälja	*Inom hemmet till syster	*När nya macbooks släpptes	*Bankkonto överföring ingen direkt kostnad
18/02/2016 13:51:55	*Datorn var för långsam för skolarbete och behövde pengar till ny dator	*Svårt att veta vad han skulle få för den prismässigt	*Glädje då han fick betydligt mer pengar för den än trott, *Köpet gick snabbare än förväntat vilket var skönt	*Blocket	*Kollade andras prissättning, *Kollade upp info om modellen	*Samma stad som boende	*Började på skolan och upptäckte att datorn var för långsam för skolan	*30kr för annons på blocket
18/02/2016 14:34:31	*Hade redan ny och ville sälja av för pengar innan pris gick ner, *Ville ge schysst pris till vän vid försäljning	*Svårt att sätta pris för att vara schysst men ändå få någon vettig summa, *Tog tid med processen av att sälja, *Tog tid att få svar på "annons""	*Drygt att ge underpris för att få den såld	*Lyckades inte få allt betalt	*Tvungen att ta tillbaka datorn då han aldrig fick alla pengar	*Rädsla om datorn skulle krasha efter försäljning"	*Kul att någon som fick användning av den fick den	*Facebook, *Frågade runt i person på skolan, *Blocket
18/02/2016 14:46:29	*Sålde sin farfars macbook för att hjälpa till, *Farfar ville bli av med den då den inte används, *Farfar ville även få lite pengar från den, *Han fick lite pengar för att han hjälpte sin farfar sälja datorn	*Orolig för hur transaktionen och bytet skulle ske rent praktiskt för säkerhet	*Skönt då det gick snabbt att få sålt den	*Blocket	*Möjlighet att se vad liknande produkter och modeller kostar	*Sålde till okänd i samma stad som boende	*ingen specifik tidsaspekt	*30 kr för blockets avgift
20/02/2016 07:19:27	*Få pengar för något som inte används längre	*För att hitta seriösa budare, *Behöva sänka priset, *prissättning generellt	*Glad för att han gick plus, *Hoppades på att sälja för högre pris	*Blocket, *Kollade priser som folk hade satt på sina Macbooks (samma modell) under ett års tid	*Man kan se vilket pris andra satt, *Lätt att lägga upp, *Ville inte köra auktion	*Hemma och i hemstad	*Kvällstid, höst/tidig vinter	*Ett par hundra kronor men nuvarande pris (ca 20kr) känns rimligt
20/02/2016 07:28:11	*Gamla datorn var lite långsam och fick en ny i julklapp så kunde lika gärna sälja	*Lite nervös över att hon lade upp den för 1kr och att den inte skulle stiga så mycket i pris	*Ja mycket, hon hade hoppats på att få 3000kr, hade kollat runt och sett att de sålts för 3-3500 kr, hon fick den sålt för 4000 kr vilket var över förväntan	*Tradera	*Gillar auktionen då den med största sannolikhet säljs för marknadspris, *slipper sätta pris, *gillar inte blocket då man måste sätta fast pris och då finns risk för att sätta fel	*Lade upp annons hemma, såldes på skolan då hon som köpte också gick på Chalmers	*I februari (efter jul då hon fick en ny dator i julklapp)	*Tror tradera tog ca 30 kr men hade kunnat betala ca dubbla
02/03/2016 15:50:27	* Pengar till att köpa en ny dator med bättre processor och bättre batteritid* Pappa behövde ny dator	* Nej, enkel process genom familjen.	* Enkel försäljning via familjen	* Försäljning via familjen	* Enkel leverans till någon man känner* Enkel betalning* Pappa accepterade priset jag satte efter att ha kollat på vad som låg ute på blocket	* Hemma* Visste att pappa behövde dator	* Kvällstid	* Nej
02/03/2016 15:55:05	* Behöver ha pengar	* Jobbigt att hitta specifika auktioner för just min typ av Macbook* Jobbigt att sätta sig in i andra marknader än Blocket	* Macbooks har bra andrahandsvärde* Senaste mjukvaran stöds fortfarande* Haft mini sju år och det finns fortfarande efterfrågan	* Blocket* Kontaktnät	* Go-to-platsen för att handla nätprodutker	* Hemma	* Söndag eftermiddag.	* Yes. 20-40 kronor.

Table B.2: Demography results

Timestamp	Kön	Ålder	Digitala enheter	Digital försäljning i andrahand	Operativsystem	Land
11/02/2016 12:37:13	Man	07/08/1993	Macbook, Smartphone, Konsol	Macbook, Laptop, Smartphone, Konsol	OS X, Windows, iOS	Sverige
12/02/2016 12:48:28	Man	16/05/1989	Macbook, Laptop, Smartphone, Tablet	Macbook, Smartphone	OS X, iOS	Sverige
12/02/2016 14:01:44	Man	05/05/1987	Macbook, Smartphone, Tablet	Macbook	OS X, iOS	Sverige
16/02/2016 11:46:12	Man	13/11/1994	Macbook, Smartphone	PC, Macbook, Smartphone, Konsol	OS X, Android	Sverige
17/02/2016 12:09:37	Man	07/01/1991	Macbook, Smartphone, Tablet	Macbook, Smartphone	OS X, Android	Sverige
18/02/2016 12:12:59	Man	11/04/1992	Macbook, Smartphone, Tablet, Konsol	Macbook, Laptop	OS X, iOS	Sverige
18/02/2016 12:44:12	Kvinna	15/12/1992	Macbook, Laptop, Smartphone, Tablet	Macbook	OS X	Sverige
18/02/2016 21:36:12	Man	12/02/1991	Macbook, Laptop, Smartphone, Tablet, Konsol	Macbook, Laptop, Smartphone	OS X, Windows, iOS, Android	Sverige
02/03/2016 21:39:23	Man	29/08/1989	PC, Macbook, Konsol	Macbook	OS X, Windows	Sverige
07/03/2016 22:03:16	Man	03/06/1992	Macbook, Smartphone	Macbook	OS X	Annat

B.8 Interview pattern data

Var?

Inom samma stad där du bor
- Inom stad där han bor
- Samma stad som boende
- Kompis i samma stad som boende
- Sålde till okänd i samma stad som boende

- I hemstad

Inom hemmet

- Inom hemmet till syster
- Inom hemmet till syster
- Hemma
- Hemma
- Hemma
- Visste att pappa behövde dator

Inom skolan
- Lade upp annons hemma, såldes på skolan då hon som köpte också gick på Chalmers

När?

Kvällstid/eftermiddag
- Kvällstid/eftermiddag
- Kvällstid, höst/tidig vinter
- Söndag eftermiddag.

Höst/tidig vinter
- Kvällstid, höst/tidig vinter
- I februari (efter jul då hon fick en ny dator i julklapp)
- Började på skolan och upptäckte att datorn var för långsam för skolan
- Precis innan jul

När ny Macbook släpptes
- Nya Macbooks hade släppts och sålde den direkt efter
- När nya Macbooks släpptes

Ingen speciell tid
- Ingen speciell tid utöver att få den såld så snabbt som möjligt för att inte förlora tidsvärde

- ingen specifik tidsaspekt

Varför (Jobs To Be Done)

Ville tjäna pengar
- Ville sälja för pengarna med bra andrahandsvärde, Inte nödvändigtvis få ut varje krona utan sälja för marknadsvettigt pris
- Behövde pengar till ny dator
- Vill sälja av
- Ville få pengar från försäljning
- Få pengar för något som inte används längre
- Behöver ha pengar

Ville hjälpa släkt och vänner
- Ville sälja för pengarna med bra andrahandsvärde, Inte nödvändigtvis få ut varje krona utan sälja för marknadsvettigt pris
- Behövde pengar till ny dator
- Vill sälja av
- Ville få pengar från försäljning
- Få pengar för något som inte används längre
- Behöver ha pengar

Vill bli av med överflödig dator efter nyköp
- Köpte en ny, ville bli av med gamla
- Hade köpt ny dator och ville sälja gamla, hade ingen nytta av datorn själv och ville att den skulle användas
- Ville sälja av innan pris gick ner
- Ville bli av med den då den inte används
- Få pengar för något som inte används längre

Vill uppgradera till ny dator
- Ville uppgradera till ny macbook och sålde för pengar till detta
- Datorn var för långsam för skolarbete
- Gamla datorn var långsam, och fick en ny i julklapp så kunde lika gärna sälja
- Pengar till att köpa en ny dator

Pains

Svårt att veta marknadsvärde av produkt
- Sätta ett icke-rimligt pris
- Svårt att hitta exakt vad "min" specifika produkt är värd
- Svårt att veta vad han skulle få för den prismässigt
- Prissättning generellt

Svårt att sätta schysst kompispris
- Svårt att sätta pris för tradeoff med marknadsvärde + att vara schysst mot systern
- Svårt men viktigt att det blir en fair deal för båda

- Svårt att sätta pris för att vara schysst men ändå få någon vettig summa
- Svårt att sätta pris tradeoff mellan att hjälpa syrran och få behövda pengar

Oro för att produkten skulle gå sönder efter försäljning
- Datorn höll på att dö och vågade inte använda den till arbete
- Rädd för att den skulle gå sönder efter försäljning
- Rädsla om datorn skulle krasha efter försäljning

Irriterad på att försäljningen tog lång tid
- Tog tid med processen av att sälja
- Tog tid att få svar på "annons"

Oro och irritation för att ge lågt pris för att få produkten såld
- Drygt att ge underpris för att få den såld
- Behöva sänka priset
- Lite nervös över att hon lade upp den för 1kr och att den inte skulle stiga så mycket i pris

Problem med faktiska transaktionen
- Tvungen att ta tillbaka datorn då han aldrig fick alla pengar
- Lyckades inte få allt betalt
- Orolig för hur transaktionen och bytet skulle ske rent praktiskt för säkerhet
- För att hitta seriösa budare

Oro för att sälja produkten till främmande om all data inte skulle vara rensad korrekt
- Svårt att rensa ut gammal dator och undrar vad som finns kvar om sälj till utanför familjen

Svårt att hitta info om just min produktmodell för prissättning
- Jobbigt att hitta specifika auktioner för just min typ av Macbook

Jobbigt att lägga upp annons på flera olika ställen/marknader
- Jobbigt att sätta sig in i andra marknader än Blocket

Gains

Trygghet på grund av rättvis prissättning
- Jobbigt att sätta sig in i andra marknader än Blocket

Köparen fick användning av den
- Systern fick användning av den och den höll bra
- Glad att systern fick en bättre dator, *Kunde sen köpa ny dator själv
- Kul att någon som fick användning av den fick den

Fick mer pengar än förväntat
- Glädje då han fick betydligt mer pengar för den än trott,
- Ja mycket, hon hade hoppats på att få 3000kr, hade kollat runt och sett att de sålts för 3-3500 kr, hon fick den sålt för 4000 kr vilket var över förväntan

Sålde för ett bra pris
- Glad för att han gick plus
- Macbooks har bra andrahandsvärde

Köpet gick snabbare/smidigare än förväntat
- Köpet gick snabbare än förväntat vilket var skönt

- Skönt då det gick snabbt att få sålt den
- Enkel försäljning via familjen
- Snabb och smidig process att få den såld

Fanns en efterfrågan
- Senaste mjukvaran stöds fortfarande
- Haft datorn i minst sju år och det finns fortfarande efterfrågan

Vad

- Använde Blocket (6)
- Använde Kontakter via släkt och vänner (5)
- Använde Tradera (1)
- Använde Facebook (1)
- Använde Macrumours (1)
- Använde Telefonsamtal (1)

Hur

Att kunna se pris på liknande produkter
- Kolla pris på andra liknande produkter
- Se specs för produkter som ligger uppe (garanti, etc.)
- Benchmarka mot andras spec för kostnad
- När folk har använt tydlig syntax och beskrivit exakt vad deras produkt är så den är sökbar
- Flera exempel på samma datorer med olika priser och tid hjälper beslut av pris
- Kollade andras prissättning
- Kollade upp info om modellen
- Tittar på andras priser
- Möjlighet att se vad liknande produkter och modeller kostar
- Man kan se vilket pris andra satt
- Se skick av andra produkter för samma pris
- Alla typer av produkter och subprodukter finns sökbara

Att se hur länge produkter legat uppe
- Se hur länge produkter legat uppe

Att känna trygghet i att sätta rätt pris
- Trygghet i att sätta rimligt pris

Att kunna lägga upp annons snabbt och smärtfritt
- Lätt att lägga upp

Att slippa sätta pris själv
- Gillar auktionen då den med största sannolikhet säljs för marknadspris
- Slipper sätta pris

- Gillar inte Blocket då man måste sätta fast pris och då finns risk för att sätta fel
- Pappa accepterade priset jag satte efter att ha kollat på vad som låg ute på blocket

Att sälja till vänner som är lättare att kommunicera med

- Lade upp som status och då ser vänner som litar på en
- Känns minst meckigt att förklara status av datorn till vänner

Att veta när ny ekvivalent produkt kommer ut för att veta god tid att sälja

- Kolla om det är bra tillfälle att köpa/sälja
- Veta när den nya macbooken kommer ut och då är det dags att sälja

Att kunna sköta saker IRL och slippa transaktionskostnader/tid

- Enkel leverans till någon man känner
- Enkel betalning

Övrigt

- Ville inte köra auktion
- Go-to-platsen för att handla nätprodutker

Betalat

Kostnadsfri transaktion via bank eller cash, inga övriga kostnader

- Bankkonto överföring ingen direkt kostnad
- Cash i person inga konstader
- Nej
- Kontoöverföring av pengar, inga kostnader

B.9 Feature Interview Insights

Automatisk prissättning av din dator

- Skeptisk när man inte ser hur algoritmen tänker/optimerar.
- Hade kännt bättre om den tog in både datorns inre och yttre.
- Bra för att få ett hum om vad priset ligger på för att få sålt inom rimlig tid.
- Inte fel, men man vet inte hur det optimeras och känns otryggt. Förstår inte hur det skulle kunna bestämmas bra.
- Smidigt om jag slipper leta upp detta själv
- Om man får ut priset kan man ordna resten själv, detta känns som det viktigaste.
- Vill själv ha kontroll över prissättning
- Vill helst prissätta själv, är ett kontrollfreak. Vill bara ha data och transparens, inte rekommendation.
- Osäker på hur vår prisoptimering fungerar, litar inte på den. Optimerar den efter tid? Cash? Average?
- Vettigt att se, men datan är viktigare.
- Kan minska ockerpriser. Viktigt att vara transparent med hur prissättningen görs.

Möjlighet att optimera automatisk prissättning efter tid eller maximerad vinst enligt önskemål

- Bättre att välja själv
- Vill kunna kommunicera att man bara bryr sig om maximal vinst, etc.
- Vill som säljare kunna påverka parametrar som ingår i optimeringen
- Litar inte på algoritm utan att se egen input av parametrar.
- Tidsaspekten är viktig - vill kunna justera den
- Nice, men optimerar hellre själv. Vet ej hur vi gör det– därför gör det hellre själv. Känns som risk att förlora pengar på bordet annars.
- Vill välja efter pris 100
- Vill bara maximera cash, bryr sig inte om tid. Nice att få välja.
- Kan vara bra så att man slipper justera själv efter tid

Tydligt definierat kontrakt mellan säljare och köpare av skyldighet om Macbooken går sönder

- Undvika dåligt samvete, datorn är sällan i toppskick vid försäljning.
- Vill slippa argument med köpare efter.
- Viktigt att skapa säker transaktion där båda parter känner sig trygga
- Trodde inte detta var ett problem, känns inte viktigt. Har ju fungerat utan detta verktyg förr.
- Gör helst detta själv
- Grundförutsättning för god transaktion
- Skönt att slippa krångel - bra med tydligt och lättolkat kontrakt
- Idag finns ej men tycks fungera ändå– ser ingen större poäng då detta är underförstått.
- Känns viktigt för lugn! Inga komplikationer efter hade varit nice.
- Vill aldrig lägga tid på datorn efter jag sålt den - ett bra kontrakt skulle gör att jag känner mig tryggare

- Känns mer legitimt med en tredjepart som Selleri.
- Bryr sig ej jättamycket om deta. Okej, men ingen erfarenhet eller excitement för featuren.

Visa statistik på hur väl din försäljning gick i efterhand jämfört med andras försäljningar

- Ingen poäng, bara deppigt.
- Spelar ingen roll vad andra ha sålt för– vill bara vara nöjd själv.
- Vill inte veta hur "kursen förändras efter köp på aktiemarknaden". Blir bara deppig!
- Kul att följa upp sin framgång i affärerna. Kan lära sig om man säljer för billigt.
- Inte intresserad av. Man har redan förlikat sig med detta och vill inte se jämförelse med andra.
- Vill ej veta. Bara en tidssänka, och försäljningen är redan en sunk cost.
- Kul att veta
- Bra för framtida transaktioner, man kan lära sig.
- Bryr sig inte. Gör all research själv innan. Feedback behövs ej.
- Vad hjälper det? Efteråt spelar det ingen roll för målet att sälja datorn. Alla andra funktioner hjälper mot detta mål, men inte detta.

Visa statistik på vad Macbooks i liknande försäljningar har sålt för vid prisrekommendation innan försäljning

- Vill använda samma app inför köp också.
- Bra att det finns historisk data om man inte litar på den automatiska prissättningen
- Bra beslutsstöd
- Känns mest relevant– även för köpare.
- Gillar idé av rå data, se spridning, bedömma själv efter behov.
- Älskar att jämföra priser och säljare på egen hand, och prisoptimerar sedan själv i huvudet. Älskar idén av att se statistik/data bättre.
- Vill gärna se statistik, men i slutändan välja själv ut efter detta, inte bara få en siffra.
- Bryr mig inte om jag vet att man kan lita på prissättnings-algoritmen

Automatiserad generering av annons som automatiskt läggs upp på Blocket och Tradera

- Fett skeptisk till att inte ha all kontroll själv.
- Tänkte inte ens på fler marknadsplatser än blocket -> nice. Men vill kunna ha egen kontroll i sälj-rollen och föredrar att inte automatisera.
- Bryr sig inte jättemycket om hur annonsen ser ut - smidigt om någon annan gör det åt mig
- Vill själv ha kontroll
- Smidigt, men kan göra det själv. Minskar iallafall tröskeln.
- Känns som att annonsen inte blir bra och unik, vilket gör att den säljer sämre
- Kontrollfreak och vill inte överlämna till någon annan.
- Vill agera SÄLJARE själv, men gillar att få hjälp att se data, osv.
- Irrelevant innan säkra och rättvisa förhållanden för transaktionen kan garanteras

- Vill lägga så lite tid på försäljning som möjligt - detta hjälper mig med det
- Skapa gärna en annons som man kan länka till för information, osv. Men lägg inte upp den. Vill kunna länka till den t.ex. På facebook för att visa att allt kommer från en legitim tredjepart. Nice att inte behöva känna sig dum av att lägga sig högt eller lågt. Legitimt. Men vill inte att den åker upp på marknadsplatser. Bara genererat.

B.9.1 Customer Profile Questionnaire Data

Table B.6: Interview results

Points	6	5	4	3	2	1	Total	Score
Visa statistik på vad Macbooks har sålt för historiskt sett	4	1	3	2	1	0	11	4,454545455
Möjlighet att optimera automatisk prissättning efter tid eller maximerad vinst enligt önskemÍl	1	6	1	1	2	0	11	4,272727273
Automatisk prissättning av din dator	4	1	2	2	0	2	11	4,090909091
Tydligt definierat kontrakt mellan säljare och köpare av skyldighet om Macbooken gÍr sönder	2	2	2	3	1	1	11	3,818181818
Automatiserad generering av annons som automatiskt läggs upp på Blocket och Tradera	0	1	2	2	4	2	11	2,636363636
Visa statistik på hur väl din försäljning gick i efterhand jämfört med andras försäljningar	0	0	1	1	3	6	11	1,727272727

B.9.2 Think aloud test results

Table B.3: Ranking of interview question 1

Timestamp	Jag fick sålt den till någon okänd inom samma stad som jag bor [Hur väl stämmer detta?]	Jag fick sålt den inom "hemmet" [Hur väl stämmer detta?]	Jag fick sålt den inom skolan [Hur väl stämmer detta?]	Jag sålde utan koppling till specifik tid eller datum [Hur väl stämmer detta?]	Jag sålde den inför Juletid [Hur väl stämmer detta?]	Jag sålde under kvällstid [Hur väl stämmer detta?]	Jag sålde i samband med att en ny Macbook-modell släpptes [Hur väl stämmer detta?]	Jag ville maximera vinst från försäljning [Hur väl stämmer detta?]	Jag ville ha en snabb försäljning [Hur väl stämmer detta?]	Jag prioriterade att sälja till vänner och familj [Hur väl stämmer detta?]	Jag tyckte att det var enklare att sälja till vänner och familj [Hur väl stämmer detta?]	Jag tyckte att det var viktigt att kunna ha ett bra pris till vänner och familj [Hur väl stämmer detta?]	Jag sålde min gamla Macbook på andrahandsmarkanden efter uppgradering till ny dator [Hur väl stämmer detta?]	Jag hade svårt att veta marknadsvärdet av Macbooken [Hur väl stämmer detta?]
04/03/2016 14:28:49	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl
07/03/2016 10:09:10	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer väl	Stämmer inte alls	Neutral	Stämmer mycket väl	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl	Neutral
07/03/2016 12:42:16	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer mycket väl	Stämmer inte så väl	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer väl	Neutral	Stämmer väl
07/03/2016 13:27:56	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer väl	Stämmer mycket väl	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl
07/03/2016 18:39:23	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer väl	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Neutral	Stämmer inte alls	Neutral	Stämmer mycket väl	Stämmer väl
08/03/2016 10:01:10	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Stämmer inte så väl	Neutral	Neutral	Neutral	Stämmer väl	Neutral	Stämmer mycket väl	Neutral
09/03/2016 15:10:40	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Neutral	Neutral	Neutral	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte så väl	Stämmer mycket väl	Stämmer väl
09/03/2016 18:56:04	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer inte så väl	Stämmer inte alls	Stämmer inte så väl	Stämmer väl	Neutral	Stämmer väl	Stämmer väl	Stämmer mycket väl	Stämmer inte så väl	Stämmer inte alls	Stämmer väl

Table B.4: Ranking of interview question 2

Timestamp	Jag hade svårt att sätta ett schysst kompispris [Hur väl stämmer detta?]	Jag kände oro för att datorn skulle gå sönder efter försäljning [Hur väl stämmer detta?]	Jag var irriterad på att försäljningen tog lång tid [Hur väl stämmer detta?]	Jag kände oro och irritation inför att ge lågt pris för att få MacBook såld [Hur väl stämmer detta?]	Jag hade problem och oro med transaktionen vid försäljningen [Hur väl stämmer detta?]	Jag kände oro för att sälja produkten till främmande om all data inte skulle vara rensad korrekt [Hur väl stämmer detta?]	Jag tyckte att det var jobbigt att lägga upp annons på flera olika marknadsplatser [Hur väl stämmer detta?]	Jag kände trygghet på grund av rättvis prissättning [Hur väl stämmer detta?]	Jag kände att köparen fick användning av min Macbook [Hur väl stämmer detta?]	Jag kände att det fanns en efterfrågan på marknaden vid försäljningen [Hur väl stämmer detta?]	Jag tyckte att den såldes för ett bra pris [Hur väl stämmer detta?]	Jag fick den såld för ett högre pris än väntat [Hur väl stämmer detta?]	Jag tyckte att köpet gick snabbare/smidigare än väntat [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av Blocket [Hur väl stämmer detta?]
04/03/2016 14:28:49	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer väl	Stämmer mycket väl
07/03/2016 10:09:10	Stämmer väl	Stämmer väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer väl	Neutral	Stämmer mycket väl	Stämmer väl	Stämmer väl	Stämmer inte så väl	Stämmer väl	Stämmer väl
07/03/2016 12:42:16	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer väl	Stämmer väl	Stämmer väl	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer väl
07/03/2016 13:27:56	Stämmer väl	Stämmer väl	Stämmer mycket väl	Neutral	Stämmer mycket väl	Stämmer inte alls	Neutral	Stämmer inte så väl	Stämmer mycket väl	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer inte alls
07/03/2016 18:39:23	Stämmer inte alls	Neutral	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Neutral	Stämmer inte så väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer väl
08/03/2016 10:01:10	Stämmer väl	Stämmer mycket väl	Stämmer inte så väl	Stämmer väl	Stämmer inte alls	Stämmer inte så väl	Neutral	Stämmer väl	Stämmer väl	Stämmer väl	Neutral	Stämmer inte så väl	Stämmer väl	Stämmer mycket väl
09/03/2016 15:10:40	Stämmer inte så väl	Stämmer inte så väl	Stämmer inte så väl	Stämmer inte så väl	Stämmer inte alls	Stämmer inte så väl	Neutral	Stämmer väl	Stämmer väl	Stämmer väl	Stämmer väl	Neutral	Neutral	Stämmer mycket väl
09/03/2016 18:56:04	Neutral	Stämmer väl	Stämmer väl	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer inte alls	Neutral	Stämmer väl	Neutral	Neutral	Stämmer inte så väl	Stämmer inte så väl	Stämmer mycket väl

Table B.5: Ranking of interview question 3

Timestamp	Jag använde mig vid försäljning/research inför försäljning av Tradera [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av Facebook [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av Macrumors [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av Macforum [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av Telefonsamtal [Hur väl stämmer detta?]	Jag använde mig vid försäljning/research inför försäljning av direkt (IRL) kontakt med köparen [Hur väl stämmer detta?]	Jag hjälptes av att kunna se pris på liknande produkter [Hur väl stämmer detta?]	Jag hjälptes av att kunna se hur längre liknande produkter legat uppe på annons/auktion [Hur väl stämmer detta?]	Jag hjälptes av att känna trygghet i att sätta rätt pris [Hur väl stämmer detta?]	Jag hjälptes av att kunna lägga upp annons/auktion snabbt och smärtfritt [Hur väl stämmer detta?]	Jag hjälptes av att slippa sätta pris själv [Hur väl stämmer detta?]	Jag hjälptes av att sälja till vänner som är lättare att kommunicera med [Hur väl stämmer detta?]	Jag hjälptes av att veta när en ny Macbook släpps så att man kan sälja sin egen Macbook i rätt tid för att köpa en ny [Hur väl stämmer detta?]	Jag hjälptes av att kunna sköta försäljningen IRL för att slippa transaktionskostnader, etc. [Hur väl stämmer detta?]	Jag betalade en avgift för annons eller auktion [Hur väl stämmer detta?]	Jag betalade ingenting för att sälja min Macbook [Hur väl stämmer detta?]
04/03/2016 14:28:49	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Neutral	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls
07/03/2016 10:09:10	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer väl	Stämmer inte alls	Neutral	Stämmer inte alls	Stämmer inte så väl	Stämmer väl	Stämmer mycket väl	Stämmer väl	Stämmer inte alls	Stämmer mycket väl
07/03/2016 12:42:16	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Neutral	Stämmer väl	Neutral	Neutral	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl
07/03/2016 13:27:56	Stämmer inte alls	Stämmer mycket väl	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte så väl	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte så väl	Stämmer väl	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl
07/03/2016 18:39:23	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Stämmer väl	Stämmer inte alls	Stämmer väl	Stämmer mycket väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls
08/03/2016 10:01:10	Stämmer väl	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer väl	Stämmer väl	Neutral	Stämmer inte så väl	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Stämmer mycket väl	Stämmer inte alls
09/03/2016 15:10:40	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer väl	Stämmer inte så väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Neutral	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl	Stämmer inte alls	Stämmer mycket väl
09/03/2016 18:56:04	Stämmer inte alls	Stämmer inte alls	Neutral	Stämmer inte alls	Stämmer inte alls	Stämmer inte alls	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer väl	Stämmer inte så väl	Stämmer väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer mycket väl	Stämmer inte så väl

Table B.9: Interviews part 2

	What is the current condition of your Macbook?	Optimise price for...	Your price is...	Holistic/other	Any features missing?	Would you use the product?
Interviewee 1	*Used but fully working, ser lite tveksam ut och tittar runt på sin dator. *Tror han kan rusta upp den till att se ännu bättre ut,	*Laggar med bilderna, *Väljer 50/50, *Förstår vad optimeringen står för	*751 USD, *Kollar diagram och försöker förstå dem. *Förstår inte den övre, estimated price likelihood, ignorerar den och går vidare till nästa graf, *Tittar länge på nästa graf, förstår inte om detta är för "alla liknande produkter" eller alla macbooks, ingen aning. *Priset är värdefullt, det förstår han. *Känner sig lite besviken på priset, känns lite lågt, *Tar priset som 100% legitimt, litar på oss, *Vill ändå prissätta lite högre själv som plan, sätter alltså inte priset i sig som eget pris vid försäljning, mer som ribba han vill minst komma över.	*Funktionallitet var 100%, riktigt nice, logisk *Färgerna var tråkiga, gärna djusare och finare, mer indragande, kändes stel nu med tråkig bakgrund, hade han inte kännt oss utan bara klickat sig till sidan hade han studsat direkt från förstasidan för den såg så tråkig ut, men så fort han fyllde i något så såg han hur nice den var. Måste ha en mer tilldragande förstasida/bakgrund. Ser oproffsigt ut nu.	*Fattas inte direkt någonting, *Gav mer än han förväntade sig, *Den gav mycket av jobbet, vilket han var tacksam för,	*Kommer kontakta oss när han ska sälja sin macbook, helt ärligt! *Kommer också berätta för sina familjemedlemmar och vänner om de ska sälja om de ska göra samma sak, istället för att göra de själva, *Känner inte till någon annan sida som gör samma jobb, *Känner att han har lärt sig något, speciellt om hur han tar reda på info om sin egen mac
Interviewee 2	*Tittar över alternativen, *Vet på rak arm att den är i gott skick, *Förstår direkt	*Väljer maximised profit direkt, gillar det!	*Väntar en stund, gillar att man får feedback att det laggar så man inte tror att det har hängt sig., *Gillar att han får en uppskattning på hur lång tid det borde ta, *Verkar ändå lite rastlös och vet inte om det kommer fungera (observation), *Börjar nynna i väntan och säga "ska vi se här....", inget händer...., *Väntar i 1+min, *Inget kommer upp. *Får göra om allt och då fungerar det, *Fick 715USD, *Verkar typ förstå estimated price likelihood, "mest chans att det blir runt 700 USD", *Hade gärna velat se svenska kronor, måste annars googla runt själv, *Förstår den undre grafen helt utan problem, *Brydde sig mest om priset, *Gillar ändå statistiken, men bättre grafiskt lätt att urskilja, svårt att förstå på rak arm nu	*Bra produkt, smidigt att ta sig igenom, även när han fick göra om det en gång, gick på 30 sekunder den gången, *Gillar att vi använder grafiska medel i de flesta fallen så man slipper läsa– kan direkt klicka på utseende, *Saknade detta vid "used", osv. där grafiska represantation hade fungerat och varit riktigt nice, *Gillar att snabbt kunna kolla upp priset så det snabba flödet var riktigt nice, *Gillar att hela tiden se hur nära målet han är i progress bar + var han befinner sig i flödet, *Kanske hade ändrat "inches"-vyn till olika storekar på ikonerna, *Reagerade på varför inte "late" eller "early" 20XX är med, *Hade gärna haft mer description på "used"-vyn så att man snabbt förstår & kan gissa vad han har	*Kanske kunna fylla i mer för att få ett ännu bättre estimate? Kanske inte går, men om det går vore det nice, *Kunna visa att hans dator är "pedantiskt bra" medan någon annan kanske har "bra" med några skråmor, mer detaljnivå på "skick" hade känts vettigt, *Tycker det är bra att det inte är för många features, saknar egentligen inte något. Får gjort det han vill :)	*Skulle kunna fråga i senare skede om vår produkt fortfarande är uppe, om den hade varit mer specificerad. Han beskriver sig som en poweruser och vill ha extremt utförlig koll. *Hade kunnat använda produkten för att få ett snabbt värde, men hade ändå försökt att toppa det på egen hand, sett vårt pris som ett "mini-pris" som han åtminstone vill slå, *Hade lätt rekommenderat till någon vän/-familjemedlem om de visar att de inte vet vad man ska sälja för, tror verktyget är perfekt för någon som inte gillar att själv reseracha sånt här.
Interviewee 3	*Checkmarken hamnar lite skumt. Hade varit mer nice om den hade varit mer centrerad.	*Nice feature! *Väljer 50/50	*Ser HDD i historiken, och blir lite osäker på om han har en SSD eller en HDD. Kollar upp det men han är osäker* Graferna gillar jag!* Får jag samma grafer som andra oavsett optimise-villkor?	* Övergripande nice! Man behöver inte tänka speciellt mycket, och så får man fram ett vettigt pris.* Processen var logiskt. Ja. Absolut. Vet inget sätt man skulle göra det annorlunda på.* Hakade inte upp mig på några frågor. Det var väl på year, så var det oklart för man kunde inte välja mid, eller late osv.*Inga övriga tankar	* Skulle på price vilja se hur olika optimise påverkar. Om jag hade valt något annat, hur hade det sett ut?* Vill inte lägga till eller ta bort information	* Ja, om jag skulle sälja dator, så varför inte?
Interviewee 4	* Kollar efter skador* Har inte så mycket defekter	* Har inte så jättebråttom	* Lägger sig ner på bordet och väntar* Tror inte på 15-60 sekunder* Har något gått fel?* Testar att göra det igen* Fungerar andra gången* Man förstår ju om man kollar på graferna	* Lätt att följa stegen. Väldigt tydliga grejer. Kan inte nödvändigtvis alla exempel, men gött att det fanns exempel.* Gött att se en överblick över stegen* Ja, en logisk rocess. Tyckte i alla fall inte ologiskt.* Inget jag hakade upp mig på* Inga övriga tankar* Behövs snyggas till innan den blir helt färdig* För mycket tid man fick vänta första gången	* Nej, inget saknades.* Ingen jätterolig design mot slutet. Bara siffror och grafer* Hade inte velat lägga till eller ta bort något	* Ja, det hade varit rimligt om man hade velat göra det, om den visar rimliga svar, vilket man inte riktigt vet.
Interviewee 5	* Oj, ingen aning* Alignment är skum?* Jag tycker det är good outer condition men inte inner condition* Vad väljer jag om batteriet är kasst?* Tar det som är närmast	* Oj.. ingen aning* Det är en dator, kanske kan ta tid?* Väljer maximum profit	* Tabbar ut medan han väntar * Kollar in sporadiskt då och då* Nu händer det grejer!* Hade varit soft att veta vad det var i SEK* Verkar vara ett rimligt pris* Jag har en dålig macbook! Like* NEGATIVA PRISER WTF!?!* Har ingen aning om hur den undre grafen fungerar* Har ni bara slått ut histogrammet över en normalfördelning?* Fattar inte alls* Läser igenom källkoden	* Verkar vara nice, man vill ju veta vad man ska sälja den för* Jag hade inte trott på det här priset för fem öre* Det känns "buzzigt"* Man litar inte på det, men annars asnice* Processen var väldigt logisk* Skulle gärna vilja veta vilka som var avklarade.* Om jag bara går till price, vad fan händer då liksom?* Skulle vilja klicka in "vet inte"* Hakade lite upp mig på CPU speed, men gissade eftersom jag inte visste och inte satt på min macbook* Visste inte riktigt vad jag skulle svara på condition, det passade inte för min* Hade gärna vilja toggla optimeringen på price istället för att välja det direkt.* Nyfiken på vad som händer om jag inte klickar in priset* (Kollar i källkoden) Ser bra ut med angular* Ingen fattar grafen i slutet* Utav fördelningen, är det av min modell eller är det mot alla macbooks?* Var tydlig med prismodellen och att ni inte lägger på något* Optimise for time - är det en feature?* Starkt fan av tada-animationen i CSS	* Lägga till fler produkter? Varför bara Macbooks? Då har ni overfittat algoritmen* Lägg till mer info om hur det fungerar och varför vi litar på det* Förtydliga vad grafen gör* Flytta upp knappen så att man slipper åka karusell	* Tänker en stund* Vet inte riktigt* Tror att jag skulle använda den* Man vill ju alltid sälja lite högre än marknadspris* Bra dataverktyg för att kolla på vad jag borde sälja det för* Ja. Jag hade använt det här. Bra skit
Interviewee 6	* Spillde öl på den. Trackpaden lite konstig ibland. Very used?	* fegar lite och tar 50/50	* (Denna personen är duktig på matte och statistik)* Scrollar sakta neråt tyst* Säger "Whaat" * 6k för att vara en likadan verkar bra* Låter som ett högt pris.	* Genomsnittsanvändaren har ju ingen aning, och detta hjälper dig att ge bra, och det är ju bra* Samarbete med prisjakt kanske för att få saker på nypris också?* Processen var logisk* GHz hade jag ingen aning om* Hårddisk-frågan. Jag har ju en SSD* Inga övriga tankar* Säljer gärna min datorn nu för detta priser	* Någon dummy-variabel om vilken skärm man har* Hade inte velat ändra eller ta bort.*	* Ja. Varför inte? Man får ju ett pris. Jag har ju ingen aning om vad denna är värd idag.
Interviewee 7	*Inte snygg layout av boxarna för condition	*Bra sida, gillar frågan	*Gillar informationen	*Ojämnt mellan plupparna som visar vilket steg man är på *Väldigt lättanvänd och intuitiv. *Hakade inte upp sig på nåt - hjälpknappen hjälpte*Design kan förbättras	*Kanske ska ange om man haft problem och löst det, e.g. bytt skärm eller haft virus	*Förmodligen inte använt produkten, hade gått in på blocket för att det känns mer trovärdigt
Interviewee 8	*Lätt att svara på, väldigt tyst och snabb	*Lätt att svara på	*Bra sida, intressant med datan och priset kändes rimligt*Tycker om graferna, spännande. *Vet inte vad första grafen innebär dock - oklara axlar. Förstod andra grafen bra.	*Bra, enkel att svara på, såg bra ut, fräsch	*Inga features men kanske lite mer designgrejer tex mer färg	Ja förmodligen
Interviewee 9	*Funderade lite, svårt att svara på. *Ojämna kanter på alternativen (boxarna) för condition. *Lätt att svara på dock	*Vad innebär 50/50 undrar han först, förstod sedan när han såg ikonerna.	*Tydligt, förvånad över så högt pris. *HDD bör stå i stora bokstäver. *Någon förklaring till hur priset tagits fram (t.ex. data har hämtats från Ebay) så att alla kan förstå. Man vill gärna veta som användare, skapar förtroende	*Allmänt om produkten - knapparna ligger inte symmetrisk (som visar vilket steg man är på)*borde ha en mer munter färgskala. *Väldigt smidig och snabb upplevelse. Nöjd. *Snyggare layout/design hade skapat mer förtroende till sidan, ser scammig ut annars - slarvigt.	*"Go back to first screen" - knapp hade varit nice så kan man göra det igen	*Hade använt den om den hade varit lite mer känd - man vill att folk ska tro på varumärket - t.ex. genom att berätta hur priset räknats ut
Interviewee 10	Inte så snyggt visuellt	*50/50 bör stå sist för man förstår inte ikonen för tid	*Allting ser scammigt ut, "B". *Få priset att poppa upp mer som en ruta. *Svårt att förstå andra grafen. Inte så användarvänligt för icke-analytiska personer.	*Smidigt, finns guider vilket är bra. *Saknas dock "back" -knappar och "börja om". *Hade velat ha en knapp som är "optimera för snabb försäljning istället" på sista sidan om man inser att man kan tänka sig att sänka priset för snabbare försäljning, när man sett det rekommenderade priset	*Saknar fråga ang antal kärnor i processorn (relevant för pris?)*Vill ha en "ändra" knapp om man upptäcker att man gjort fel. *Hade varit nice om man fått lite miniatyrer från Ebay där man ser annonser på liknande datorer och priset de säljts för. Skapat förtroende*Hade varit bra att visa vilka regioner priserna är baserade på, t.ex. är Macbooks billigare i USA, vet man det kan man ju lägga på någon tusing. Bör vara någon slags viktning beroende på geografi.	*Hade nog kunnat tänka sig att använda den. Framför allt om man vill sälja snabbt.
Suggested changes						9 st (av 10 st)

B.9.3 Funnel test data

Figure B.1: Test data from our funnel test

C

Appendix - Prototypes

C.1 Landing Page

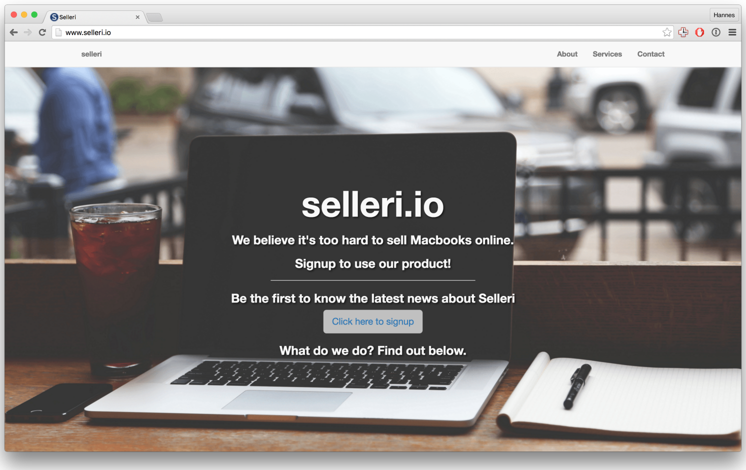

Figure C.1: Selleri, Landing Page 1, image 1

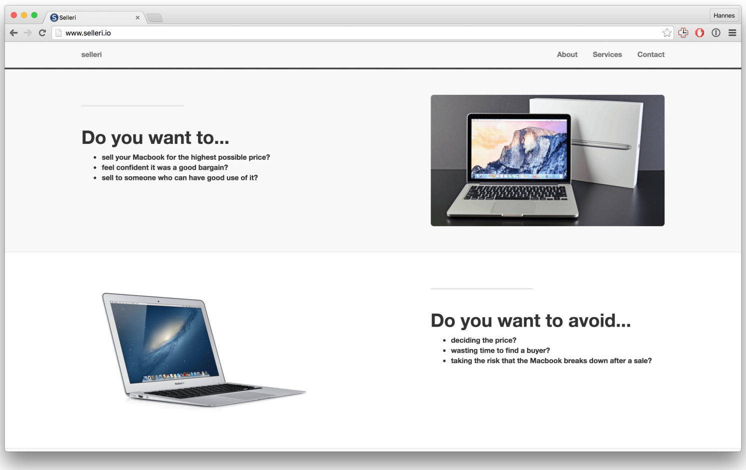

Figure C.2: Selleri, Landing Page 1, image 2

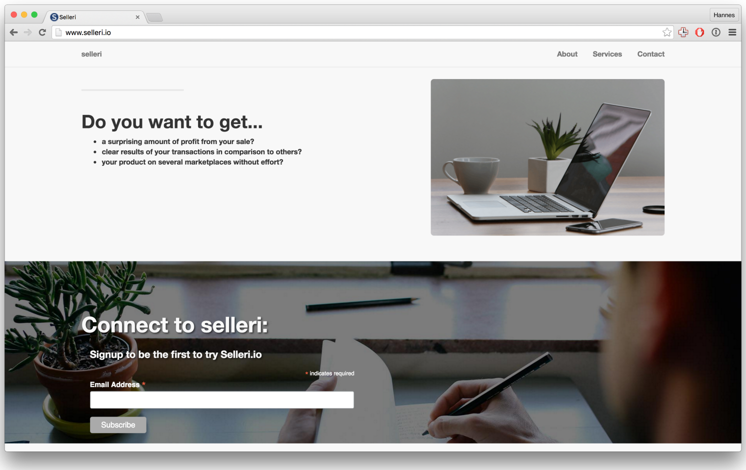

Figure C.3: Selleri, Landing Page 1, image 3

C.2 Landing Page 2

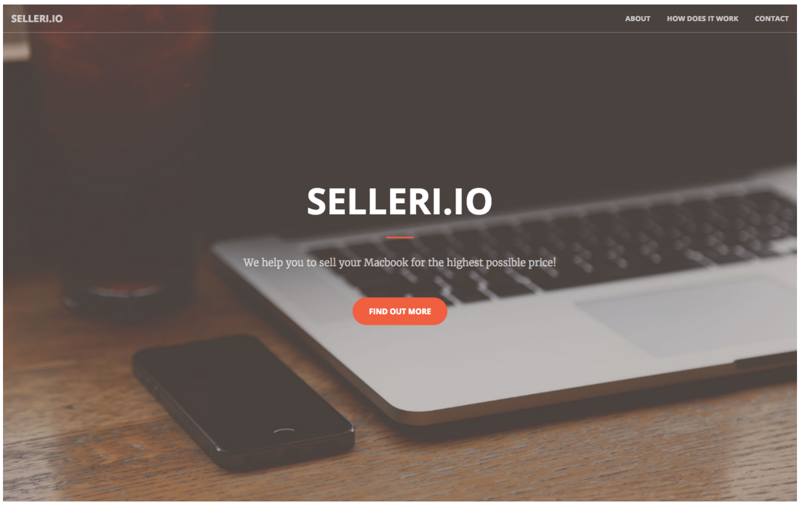

Figure C.4: Selleri, Landing Page 2, image 1

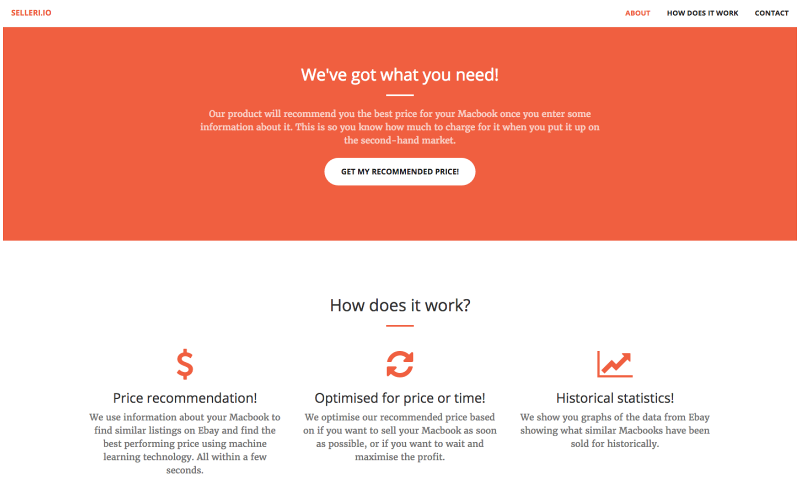

Figure C.5: Selleri, Landing Page 2, image 2

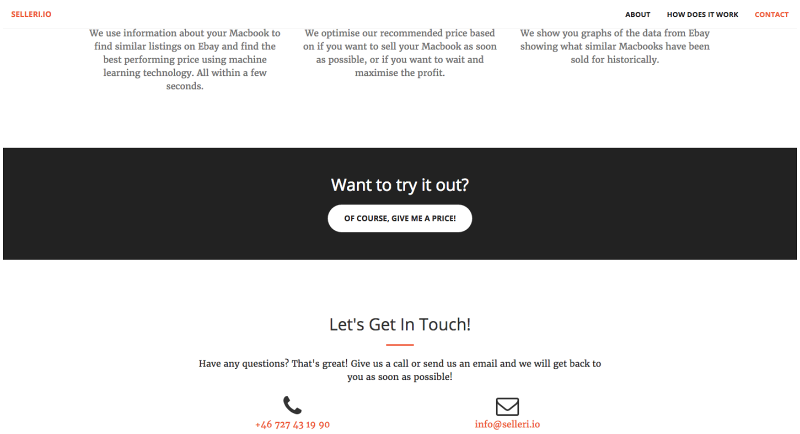

Figure C.6: Selleri, Landing Page 2, image 3

C.3 Paper prototype images

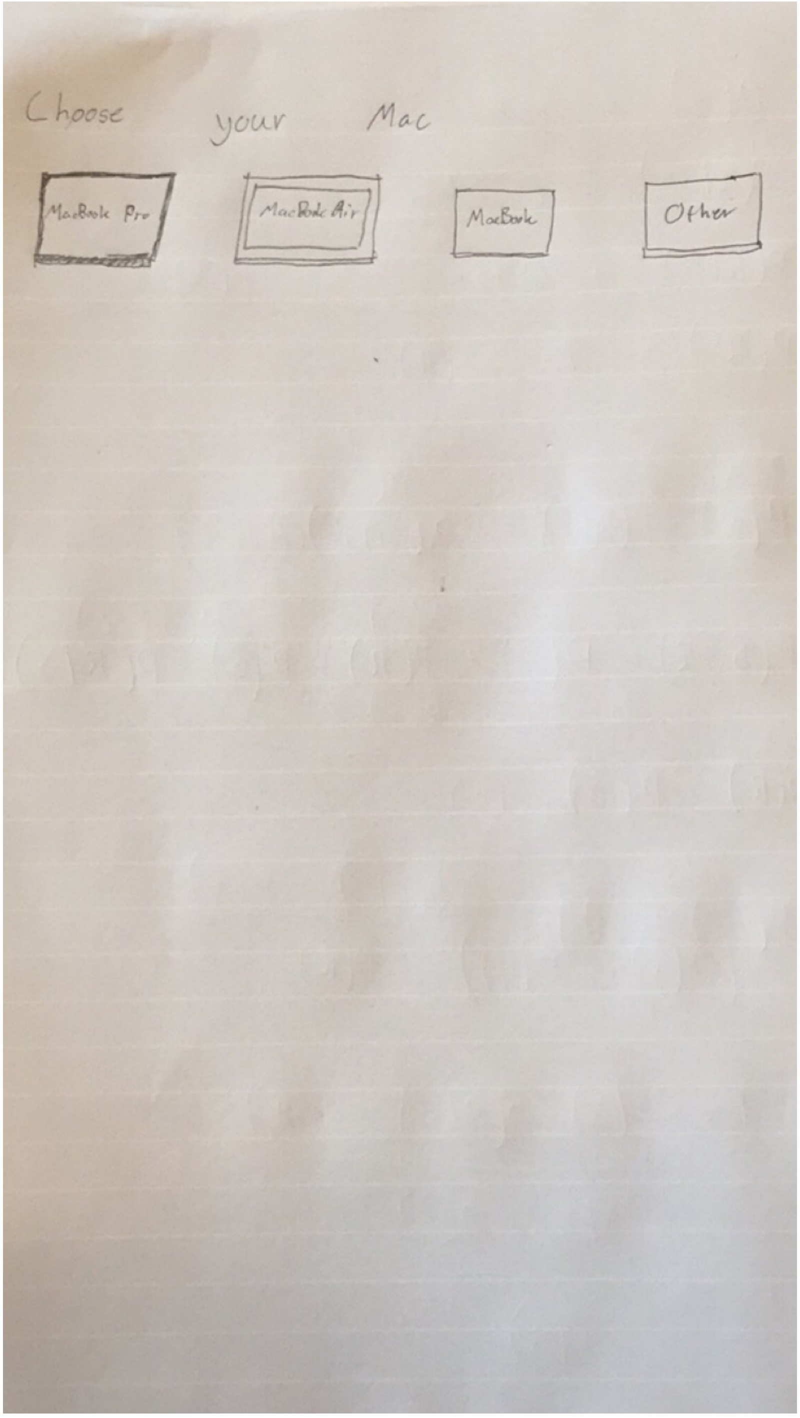

Figure C.7: Selleri, Paper Prototype 1, image 1

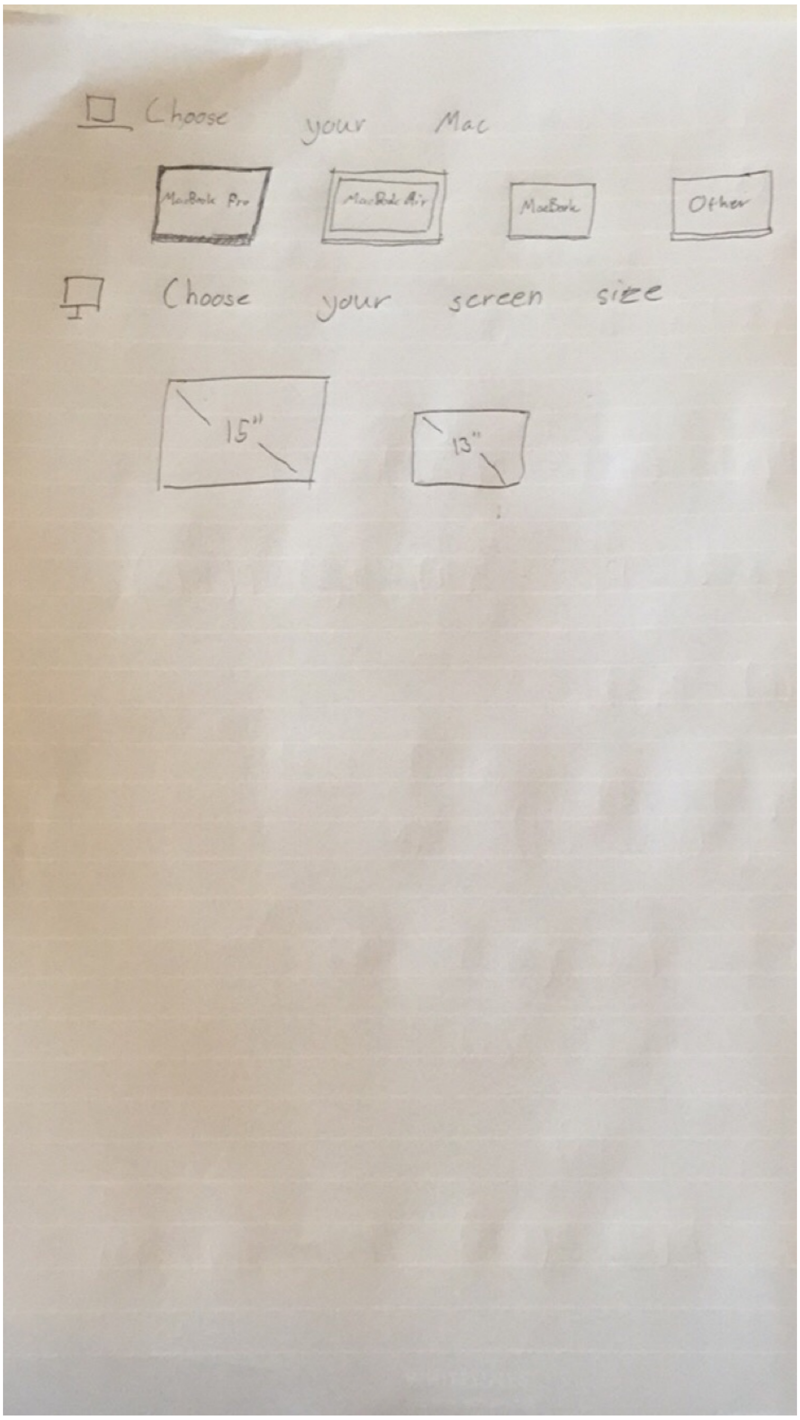

Figure C.8: Selleri, Paper Prototype 1, image 2

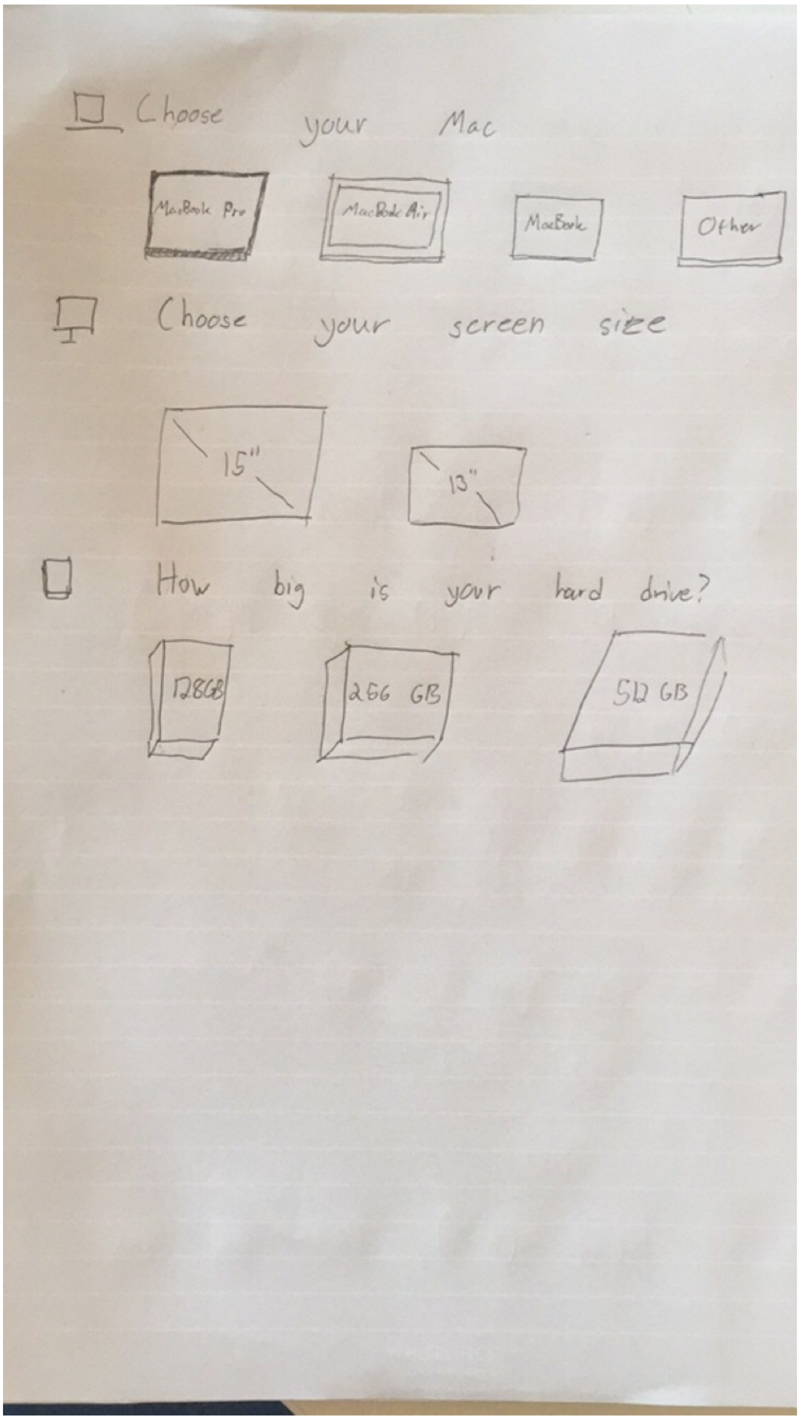

Figure C.9: Selleri, Paper Prototype 1, image 3

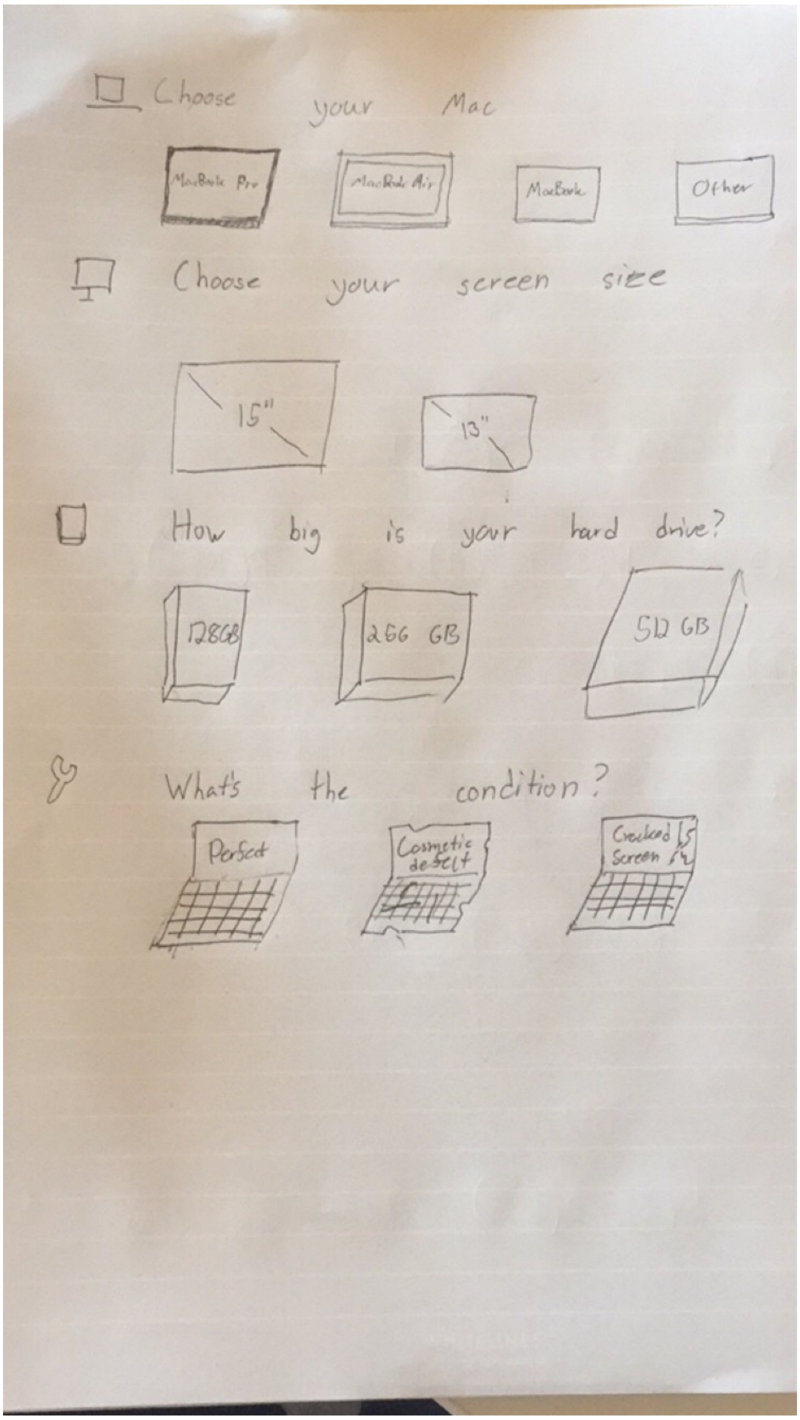

Figure C.10: Selleri, Paper Prototype 1, image 4

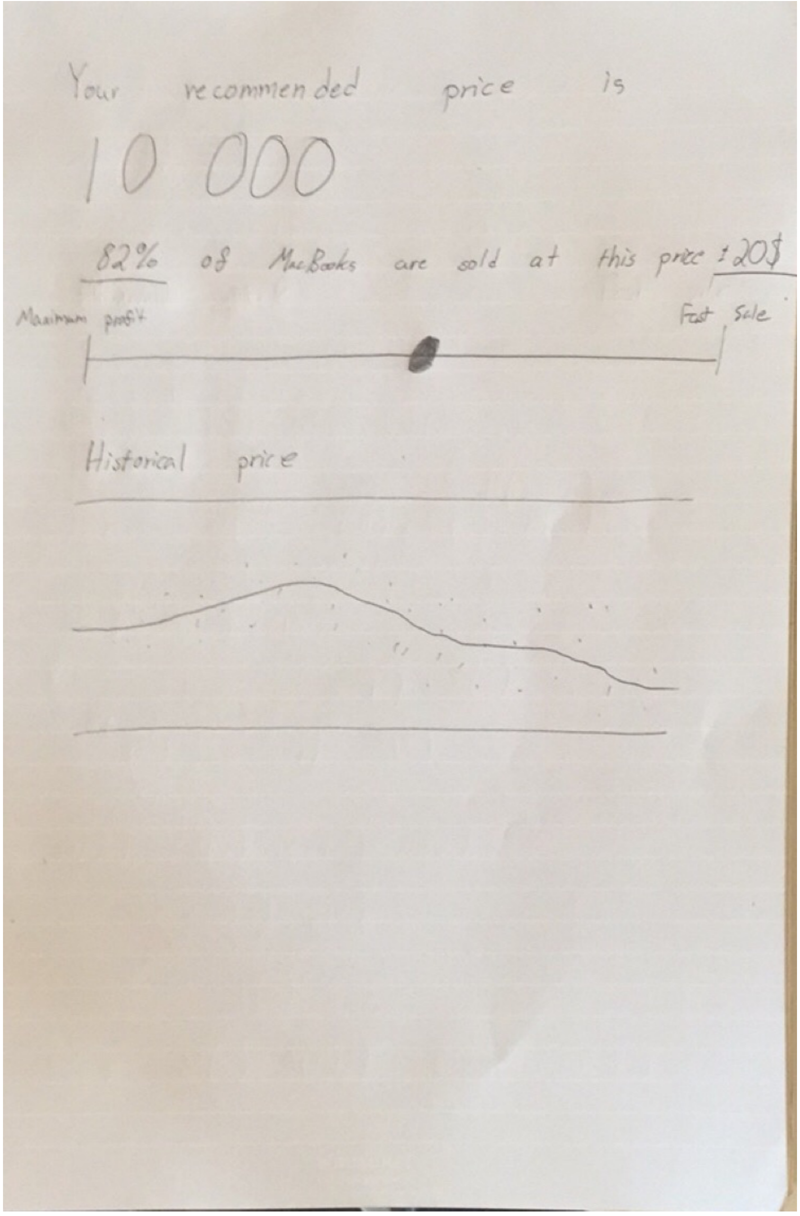

Figure C.11: Selleri, Paper Prototype 1, image 5

D

Appendix - Test Cards

D.1 Landing Page

Figure D.1: Selleri, Landing Page 1

D.2 Customer Interview Test Card

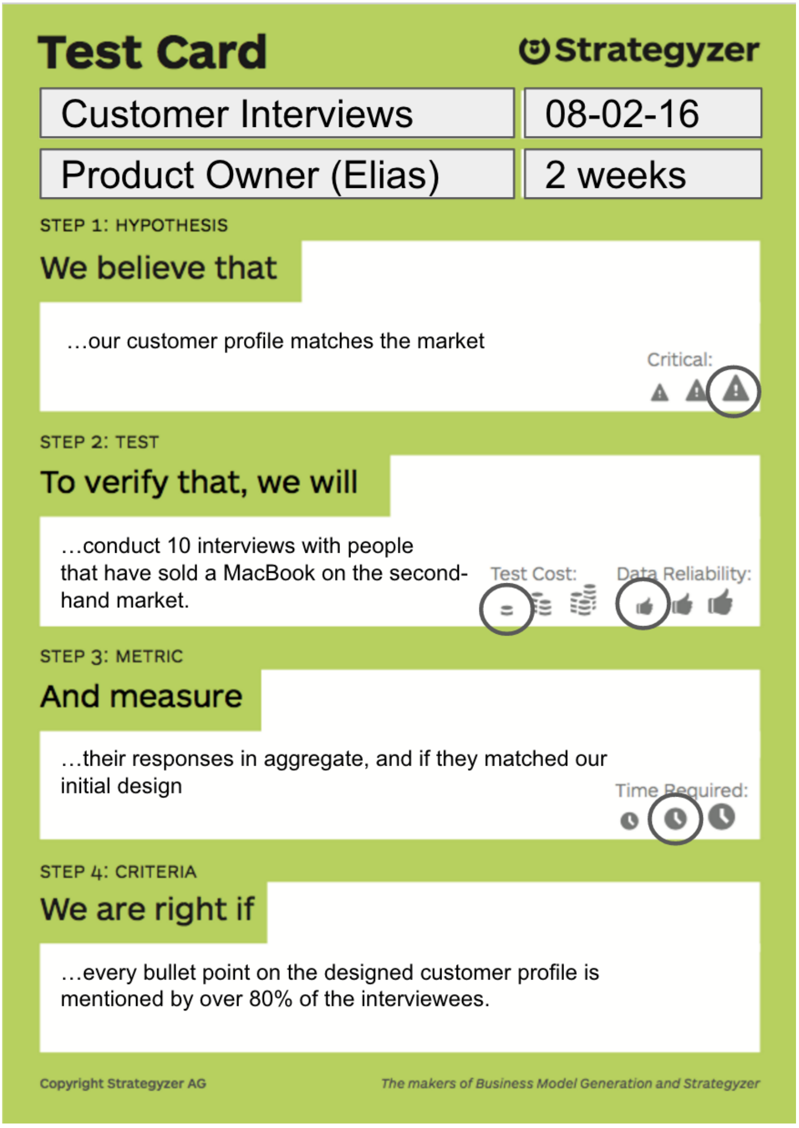

Figure D.2: Customer Interview Test Card

D.3 Customer Questionnaire Test Card

Figure D.3: Customer Questionnaire Test Card

D.4 Customer Form Test Card

Figure D.4: Customer Form Test Card

D.5 Feature Test Card

Figure D.5: Feature Test Card

D.6 Qualitative Test Card

Figure D.6: Qualitative Test Card

D.7 Quantitative Test Card

Figure D.7: Quantitative Test Card

E

Appendix - Learning Cards

E.1 Landing Page Learning Cards

Figure E.1: Selleri Landing Page Learning Card

E.2 Customer Interview Learning Card

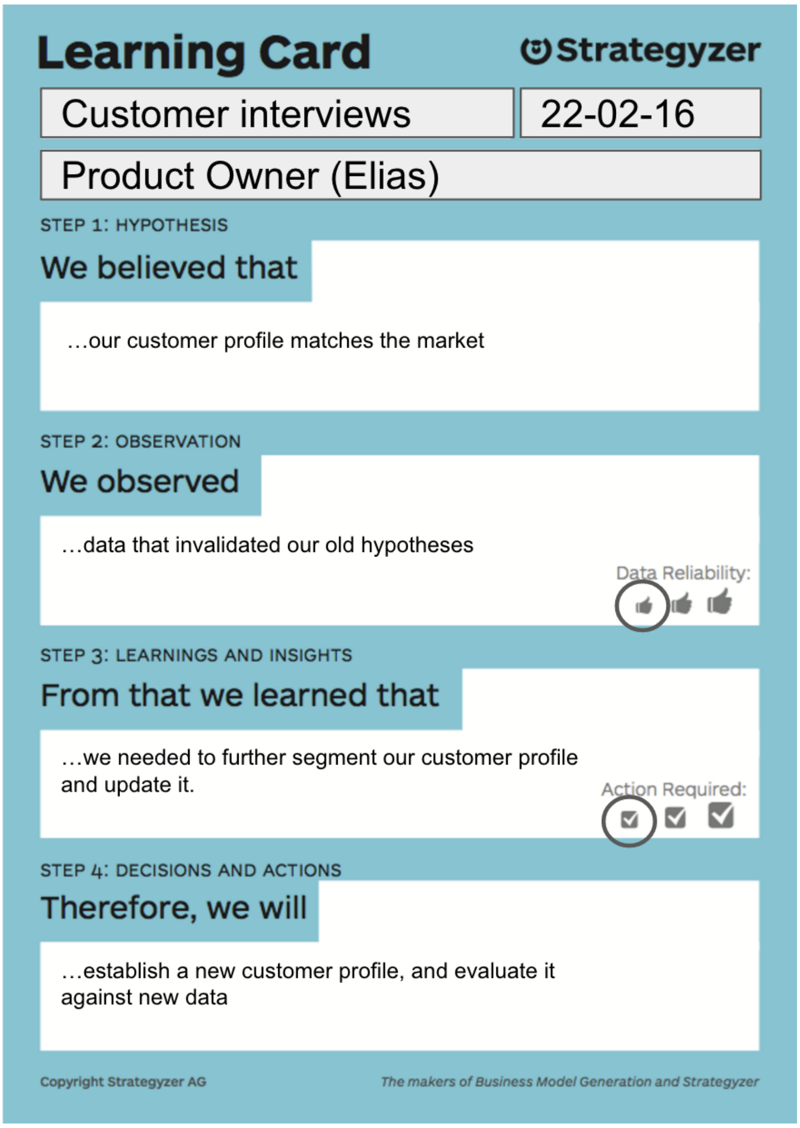

Figure E.2: Customer Interview Learning Card

E.3 Customer Questionnaire Learning Card

Figure E.3: Customer Questionnaire Learning Card

E.4 Customer Form Learning Card

Figure E.4: Customer Form Learning Card

E.5 Feature Learning Card

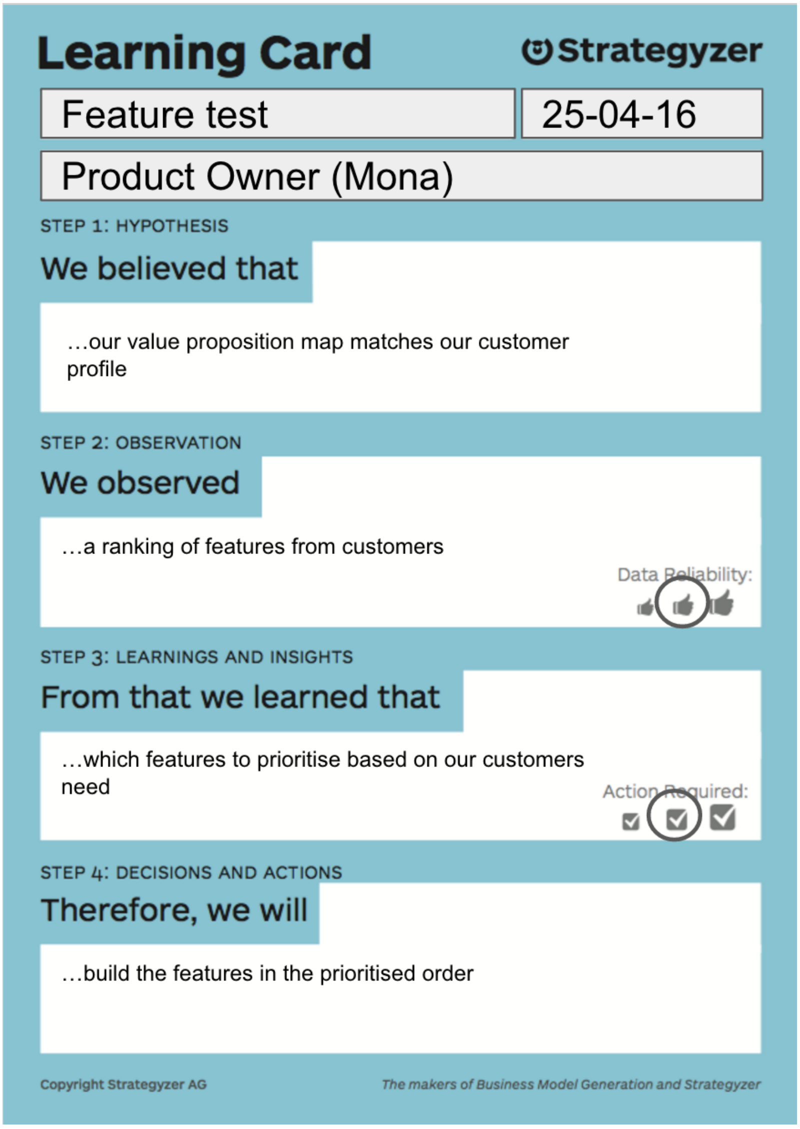

Figure E.5: Feature Learning Card

E.6 Qualitative Learning Card

Figure E.6: Qualitative Learning Card

E.7 Quantitative Learning Card

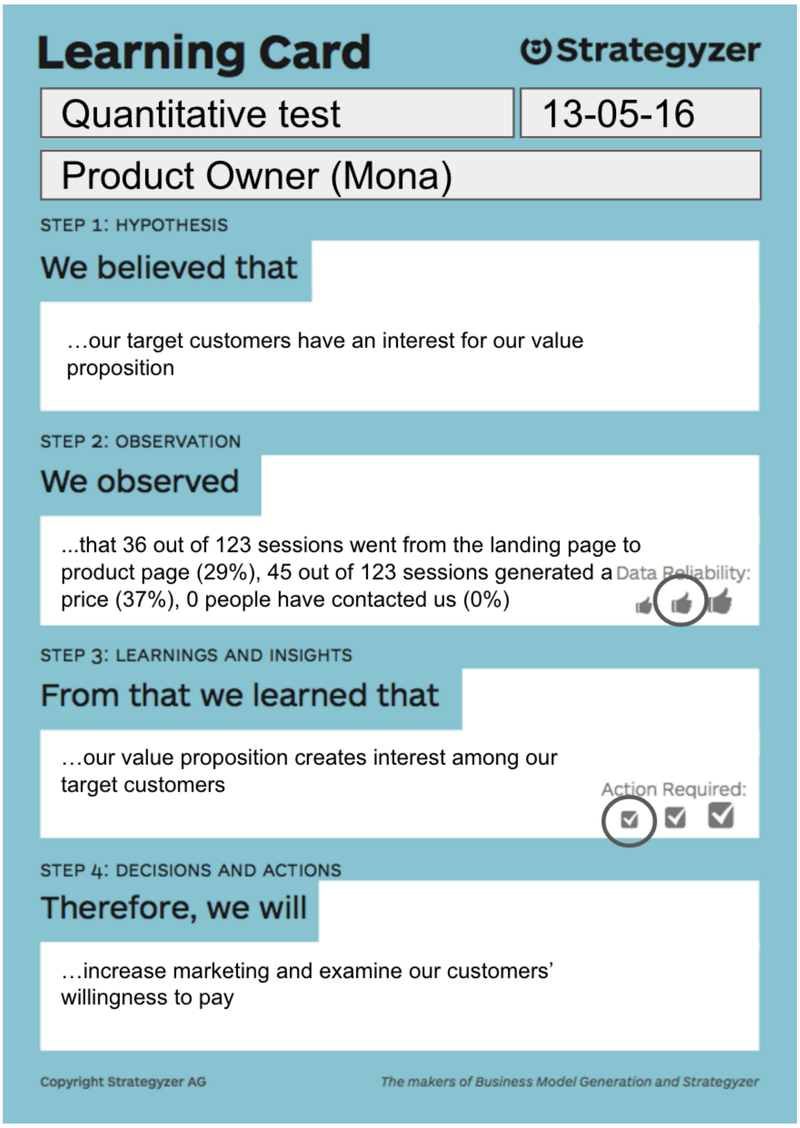

Figure E.7: Quantitative Learning Card

F

Appendix - Value proposition

F.1 Airbnb Value Proposition Canvas

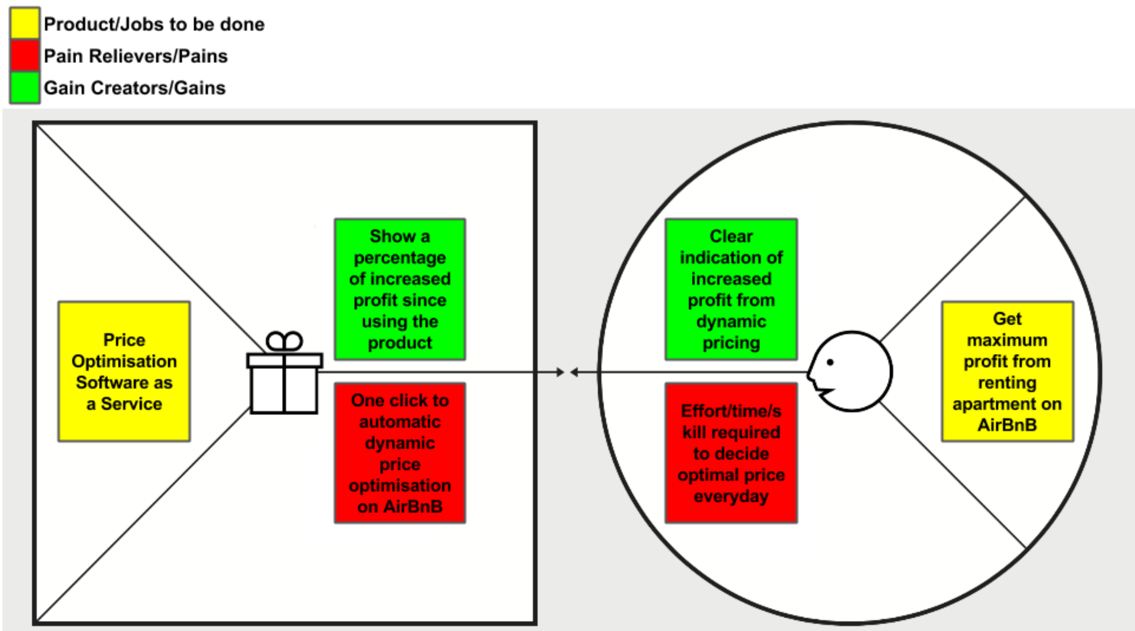

Figure F.1: AirBnb Value Proposition Hypotheses

F.2 Selleri Value Proposition Canvas

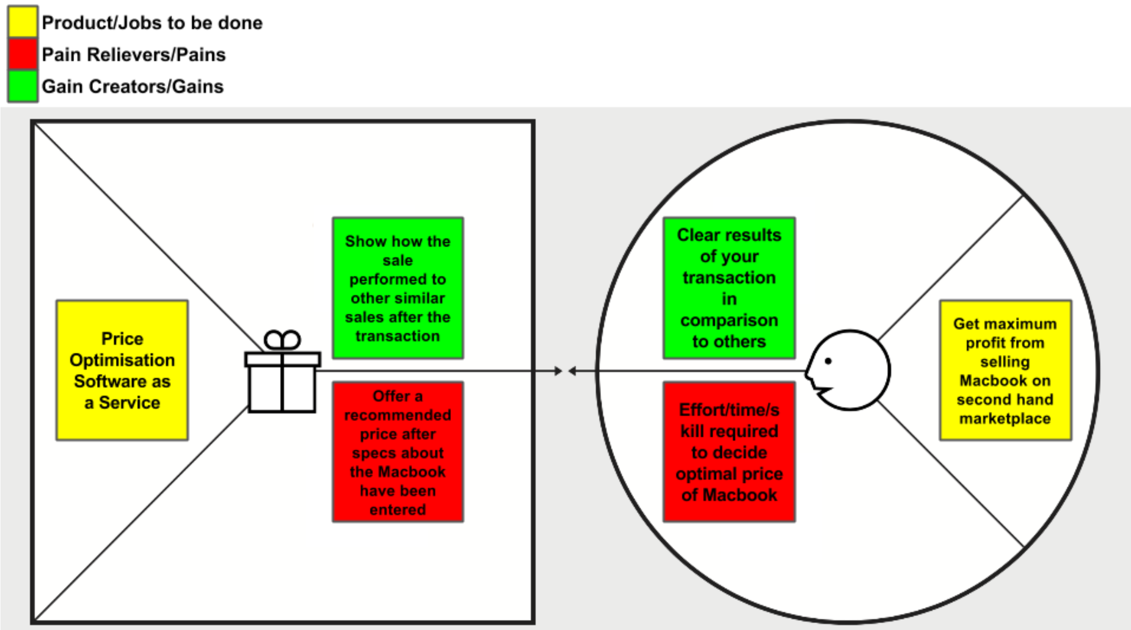

Figure F.2: Selleri Value Proposition Canvas Hypotheses

F.3 Sprint 1 Value Proposition Canvas

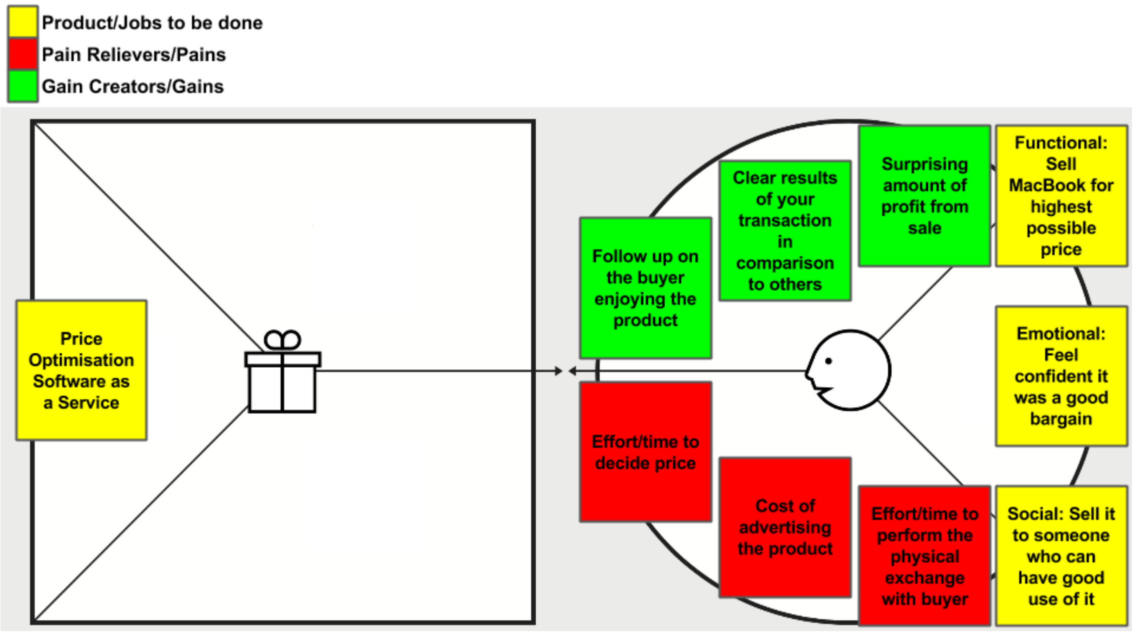

Figure F.3: Sprint 1 Value proposition Canvas Hypotheses

F.4 Sprint 2 Value Proposition Canvas

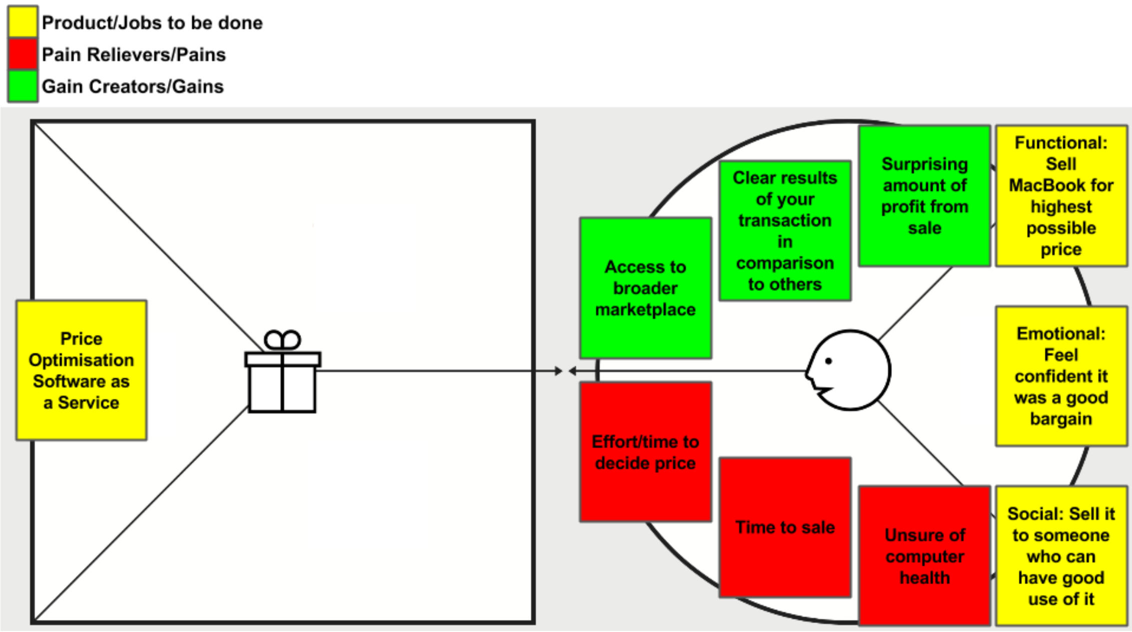

Figure F.4: Second sprint Value proposition Canvas Hypotheses

F.5 Sprint 4 Value Proposition Canvas

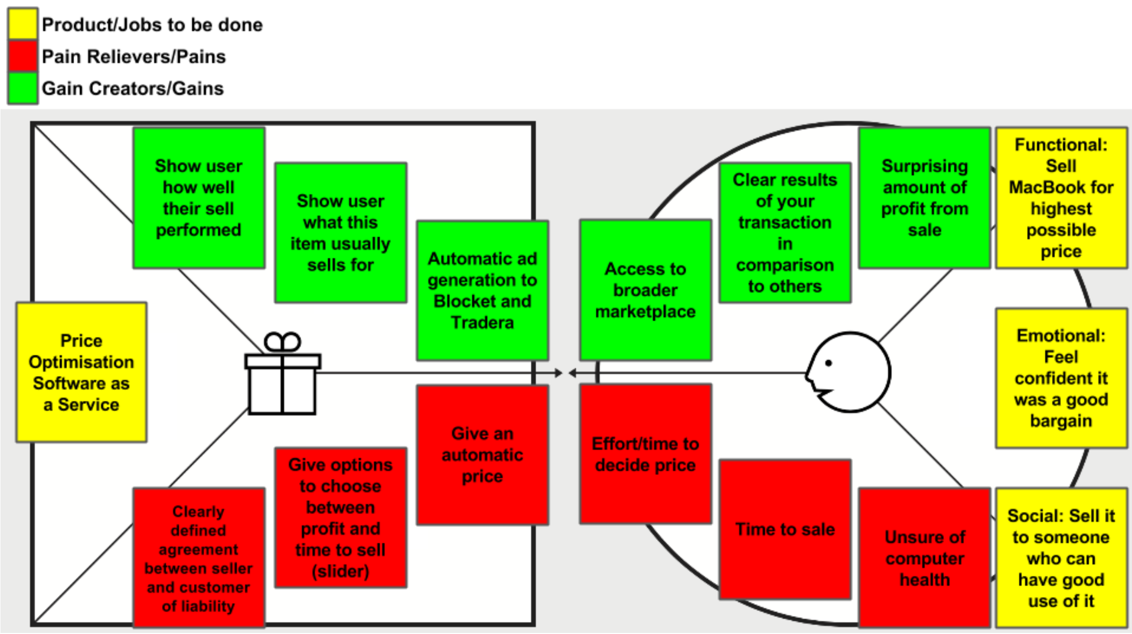

Figure F.5: fourth Value proposition Canvas Hypotheses

F.6 Sprint 5 Value Proposition Canvas

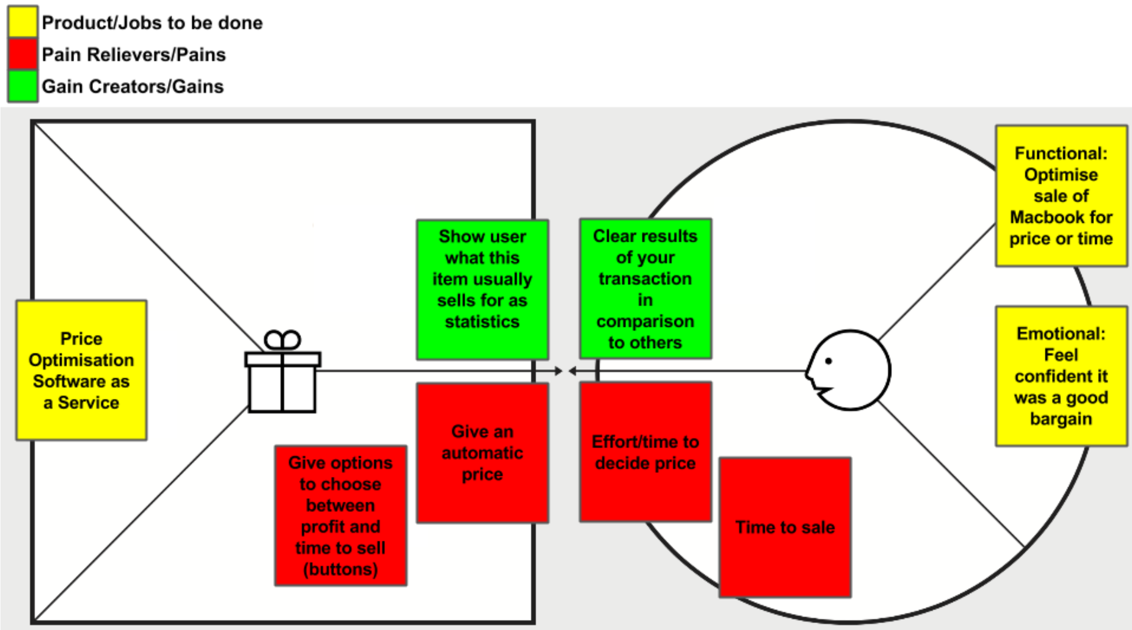

Figure F.6: fifth Value proposition Canvas Hypotheses

F.7 Resulting Value Proposition Canvas

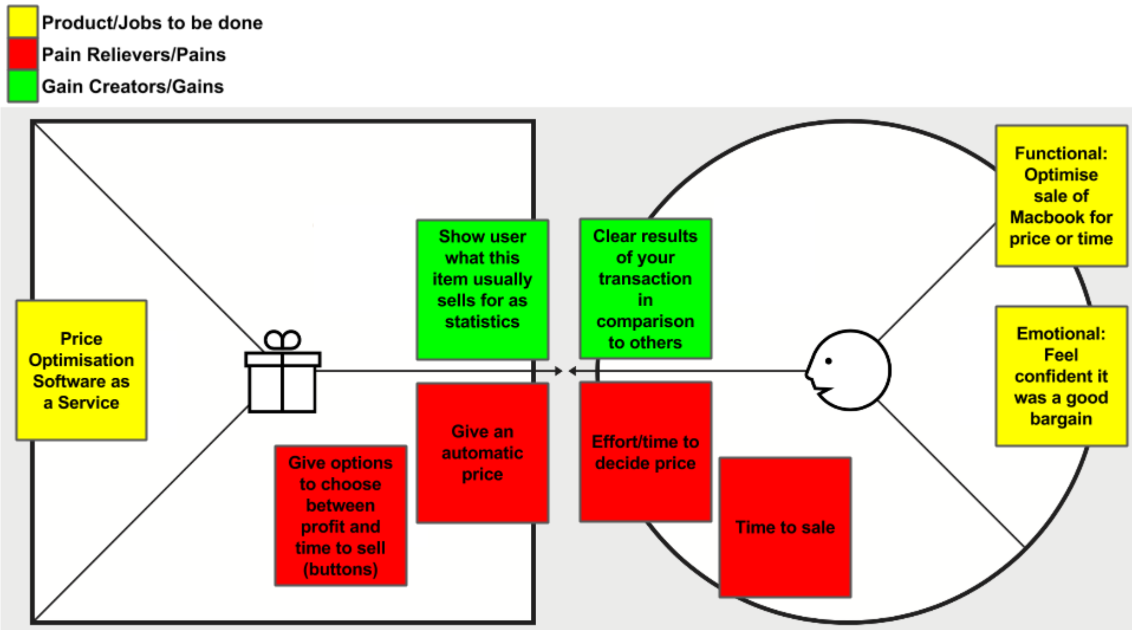

Figure F.7: Resulting Value proposition Canvas Hypotheses

G

Appendix - Business Model Canvas

G.1 Airbnb Hypotheses - Business Model Canvas

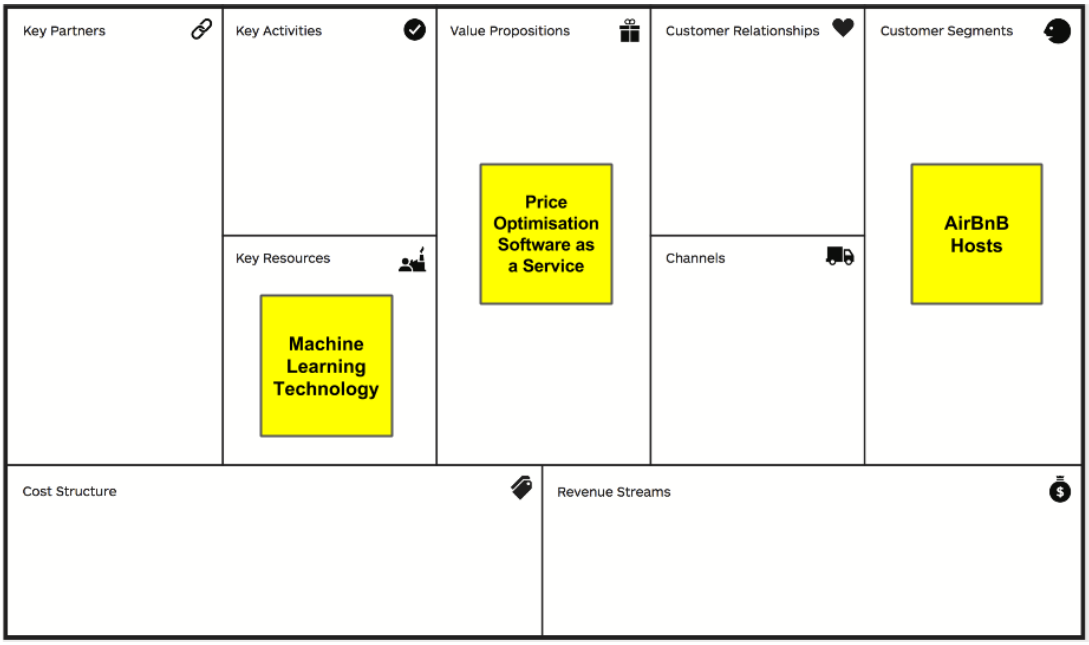

Figure G.1: Airbnb Hypotheses - Business Model Canvas

G.2 Selleri Hypotheses - Business Model Canvasa

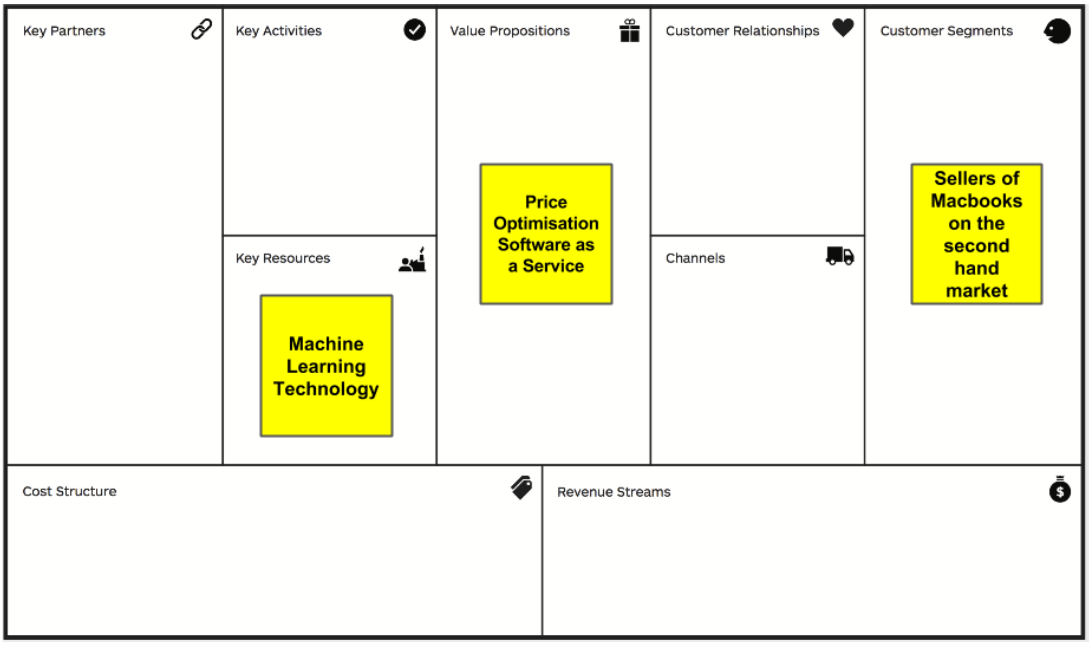

Figure G.2: Selleri Hypotheses - Business Model Canvas

H

Appendix - Pre-Study

H.1 Startup Grind Global Conference

Startup Grind is a startup community with 215,000 members in over 185 cities. Startup Grind educates and mentors entrepreneurs via monthly events focusing on networking and presentations. The global conference is a yearly gathering in Silicon Valley with 3,000 participants.
The event was highly inspirational, with several founders and influential academics weighing in on different issues regarding startups and the challenges they face. The speakers include Clayton Christensen (Author, Innovator's Dilemma), Marc Andreesen (Co-Founder, Andreesen Horowitz), Steve Blank (Author, Startup Owner's Manual), Aaron Levie (CEO, Box), Stewart Butterfield (CEO, Slack) and several more. The event also included more practical presentation in agile development methodologies, that were more applicable in our own workflow.

H.2 Company A

Company A was the first visit and interview of the week. Company A is a large hardware and software company. From our informal interview, working at Company A was described as a free environment where you were very much able to contribute with your own ideas. However, all information was delivered on a need-to-know basis, and separate sections were shut down from each other.
We were surprised to know that Company A does not implement Scrum or any other standardised agile methodologies. Rather, Company A directs the responsibilities of specific work flows down to individual employees and instead applies a "DRI" (Direct Responsible Individual) methodology for assigning responsibilities. All projects within Company A is assigned with a DRI and only one DRI. It is then this person's individual responsibility to make sure the specified project is completed within specifications.

H.3 Company B

Company B is a large software company. At Company B, we learned about several tools and resources that could be valuable for our project. This included an API for leveraging machine learning algorithms, and a collection of Startup resources and communities. As with Company A, we were surprised to find out that Company B does not use any specified Scrum methodology, or any other agile methods. Company B instead leaves the specific methodologies and processes up the the teams themselves. Company B fosters innovation by allowing workers to allocate a specified amount of their work hours to private projects, although from our interview, this often becomes just additional time, since all ordinary work must still be completed on regular time, leaving very little free time to work on private projects.

H.4 Company C

Company C is a medium-sized startup, that works primarily as a clothing company. Their business consists of a subscription-based service, where they send you five pieces of clothing on a regular interval, and you return the ones you do not want. What makes Company C special, and why we wanted to interview them, is the way the whole company is focused around data, and ways of using that data. Company C uses Artificial Intelligence technologies to get the customer as accurate of a recommendation of new clothing as possible. We met with three people form the data-science team, and learned concrete examples of how to apply machine learning technologies to an actual business, and how they develop and implement them in practice.

H.5 Company D

Company D is a medium-to-large sized company delivering online collaboration and storage tools. We met with a design intern, and talked about how Company D works with design, and what to focus in developing a good user experience. It gave us valuable insight into the design process, and what to evaluate when focusing on developing our own user experience.

H.6 Company E

Company E is a very small startup employing focusing on automated B2B sales, that currently employs just the two founders. Since they're the smallest company by far of all those we visited, they have a strong relevance to our project. By interviewing them and learning about their story, we gained insight into the difficulties of the startup process, the grit and dedication required, and the success factors of Company E. Company E established their motto as "Always be hustling", meaning that you always have to work all angles towards a goal, with often unconventional means. They laid forward a concrete example, when after being declined into 500 Startups (A prestigious startup accelerator) for three times, sending personalised and aggressively selling emails to the founder finally got them accepted. This idea of "always be hustling" is a recurring one, and absolutely something that we have come to value highly.

H.7 Company F

Company F is a large company delivering an online social service. At Company F, we talked to a person within the design team, and talked about how Company F works with design. While we did not interact with any software engineers directly, Company F seemed to be one of the few companies where there was an actual agile methodology in place.

H.8 Company G

Company G is a large company delivering online streaming services. We met with a senior person from the design team, and discussed how the design process works at Company G. Compared to our interviewees previous positions, Company G design process was described as much more data-driven, with a sole focus on subscriber retention as the primary key performance index. As we discovered was the case in other large companies except Company F, Company G did not use Scrum or similar agile methods. Our interviewee detailed his previous experience at Microsoft, where they did use Scrum, and explained that he did not find Scrum a valuable method, citing problems with quality control, and the lack of focus on single projects.

I

Appendix - Machine learning training data

I.1 Training set histograms

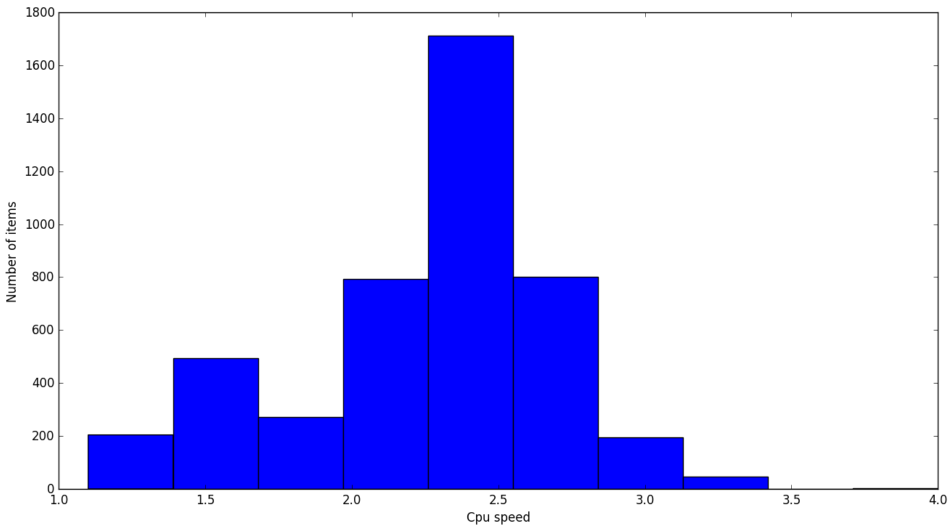

Figure I.1: Histogram showing distribution of CPU speed

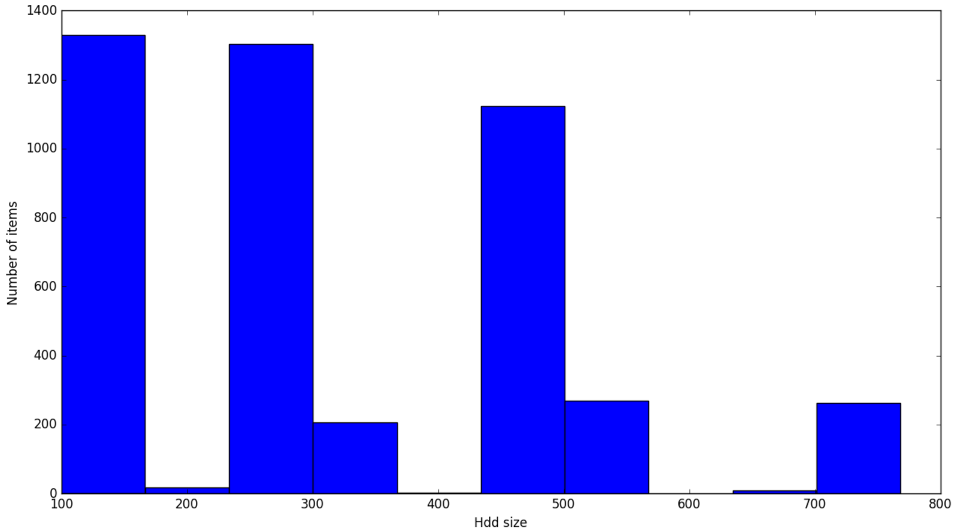

Figure I.2: Histogram showing distribution of HDD size

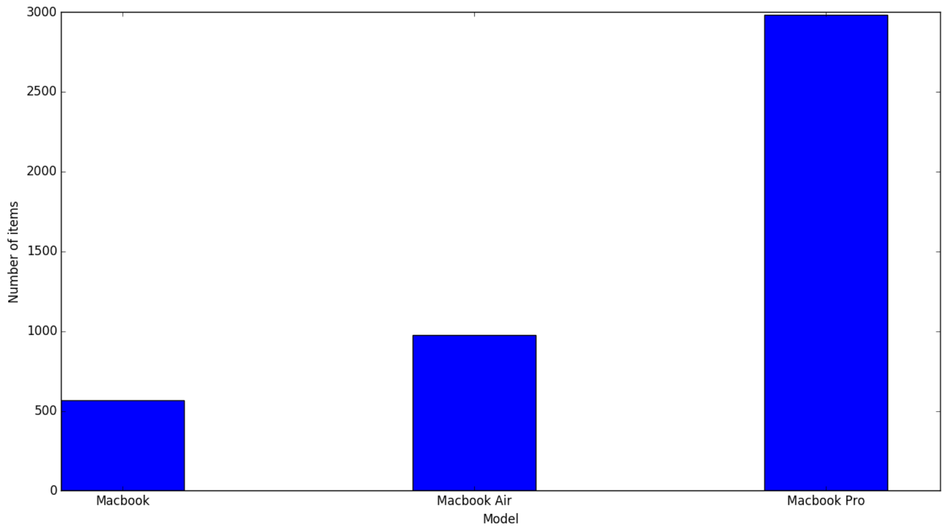

Figure I.3: Histogram showing distribution of product family

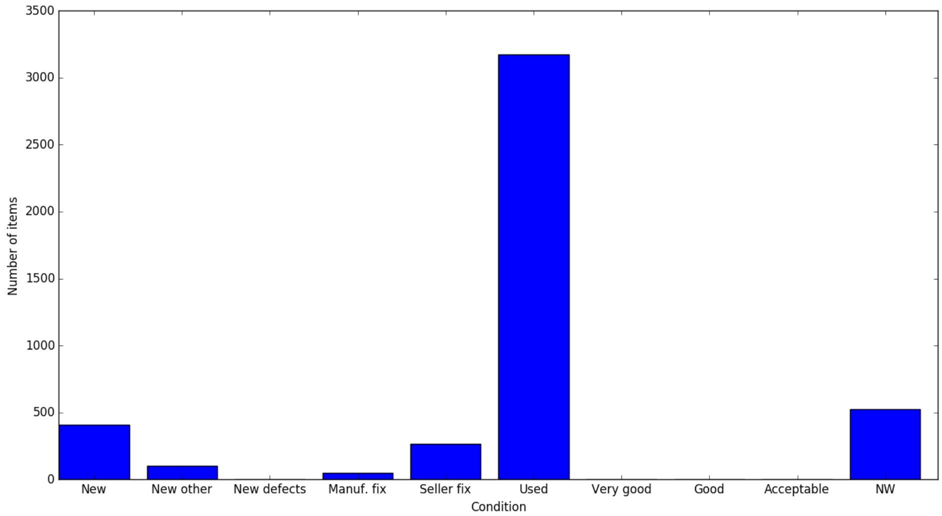

Figure I.4: Histogram showing distribution of conditions before conversion

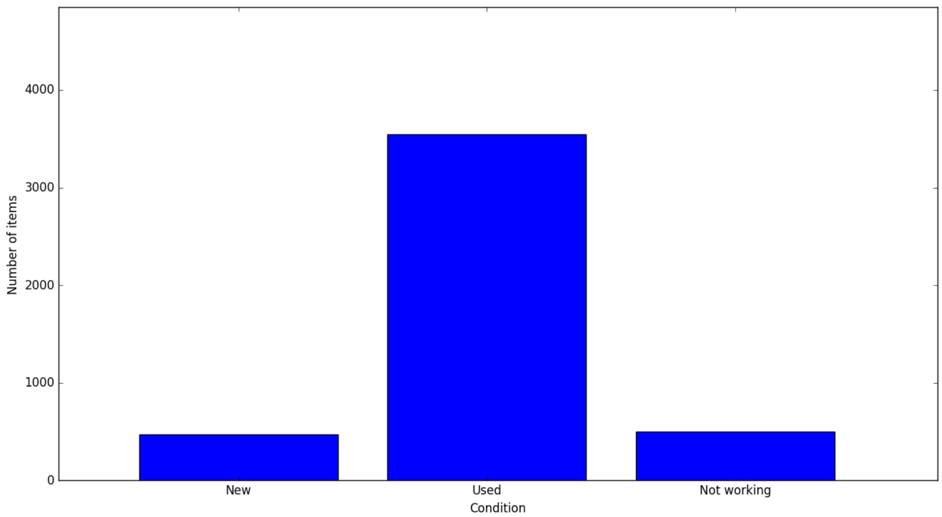

Figure I.5: Histogram showing distribution of conditions after conversion

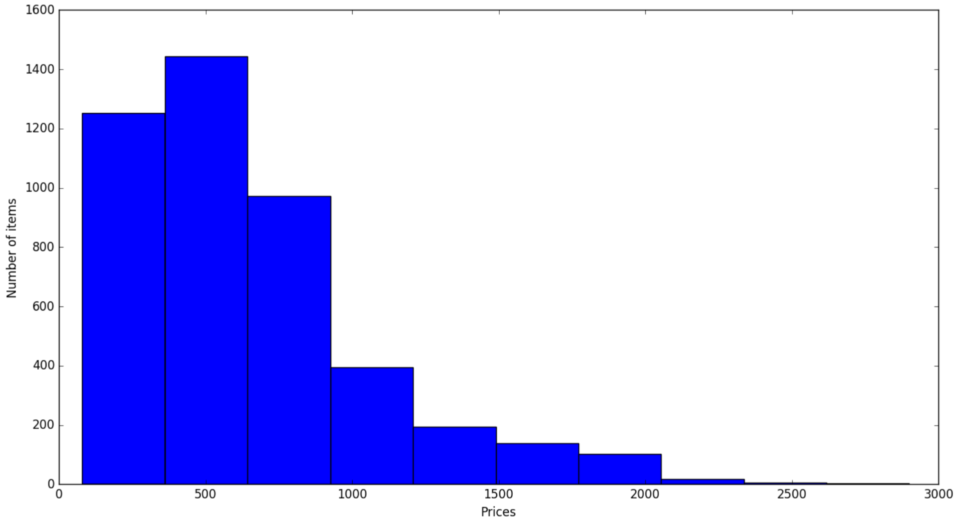

Figure I.6: Histogram showing distribution of prices

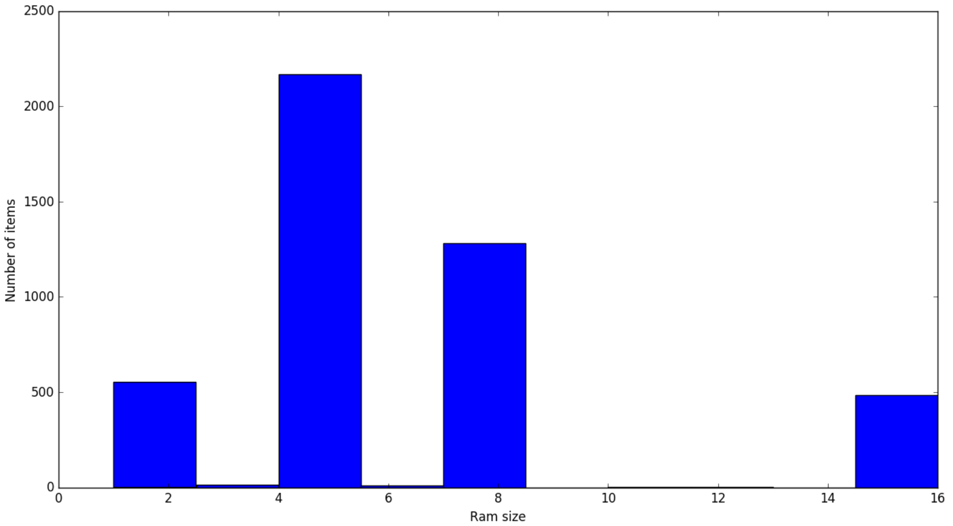

Figure I.7: Histogram showing distribution of RAM size

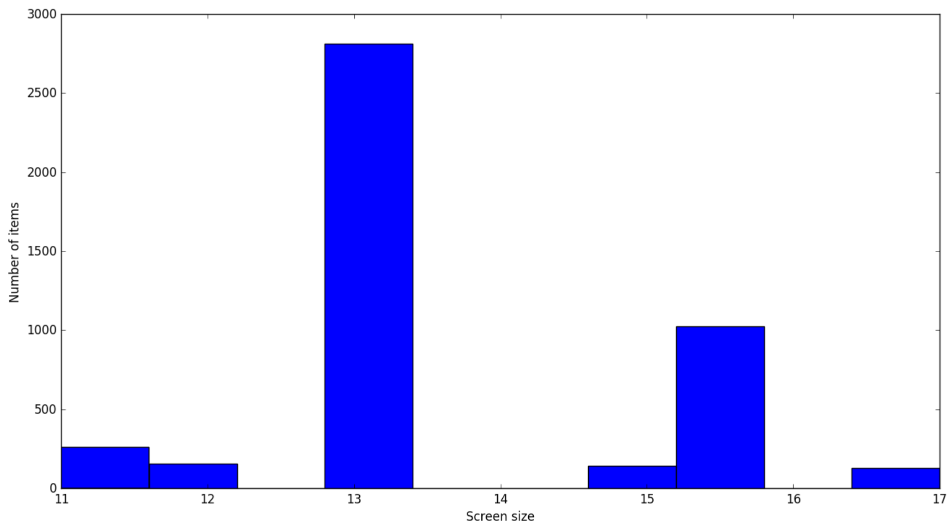

Figure I.8: Histogram showing distribution of screen size

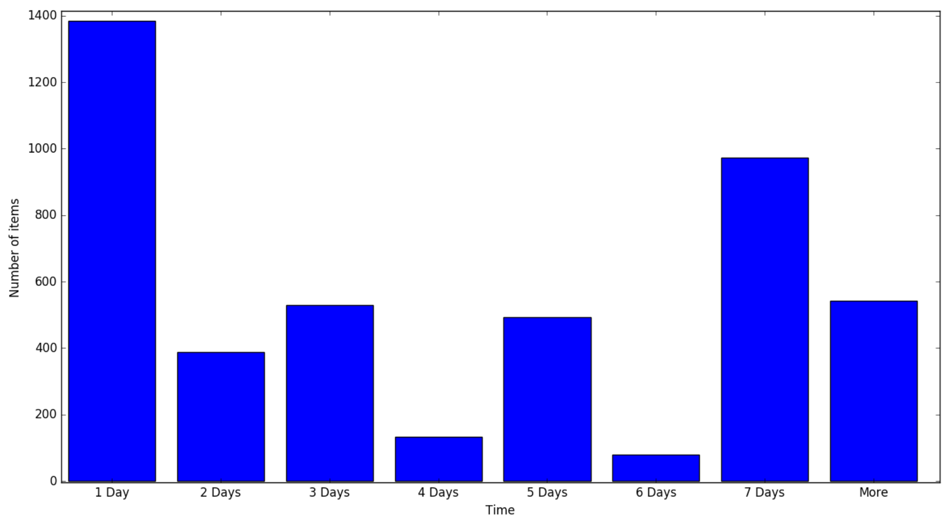

Figure I.9: Histogram showing distribution of time to sale before conversion

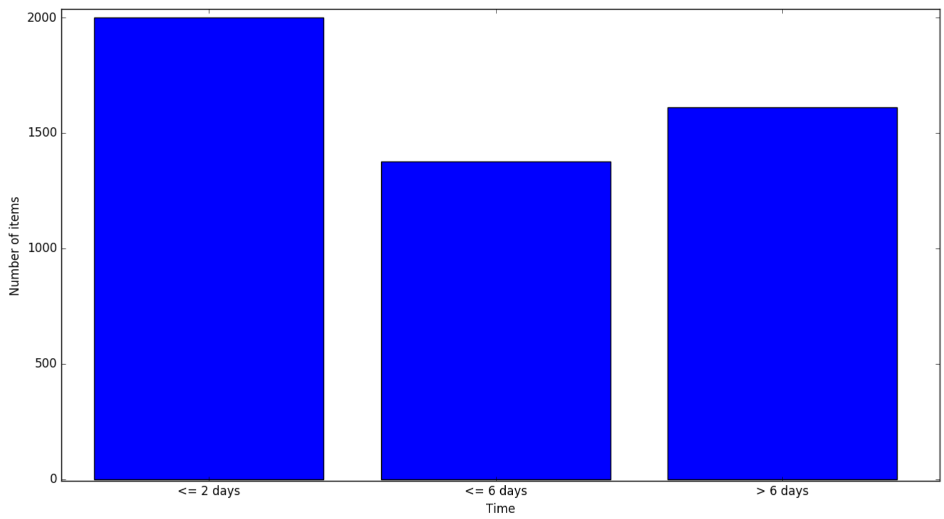

Figure I.10: Histogram showing distribution of time to sale after conversion

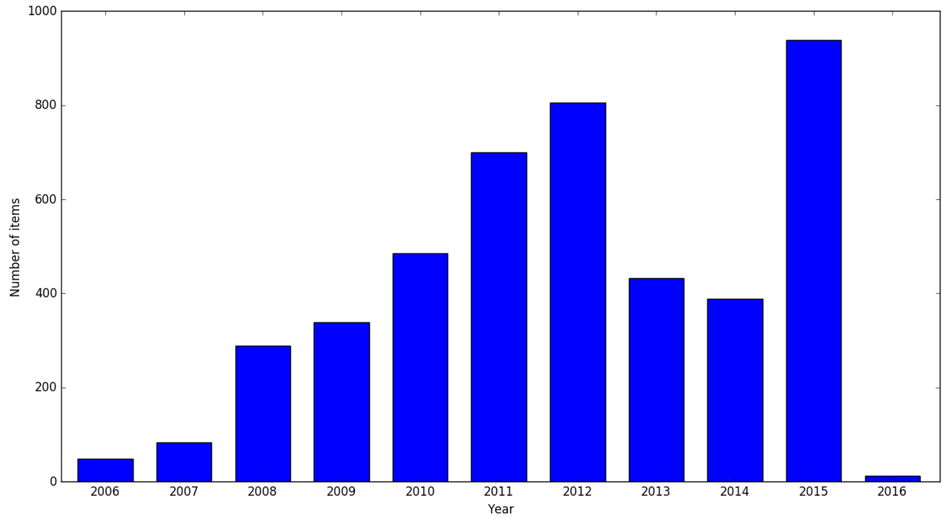

Figure I.11: Histogram showing distribution of manufacture year

I.2 Individual features against price

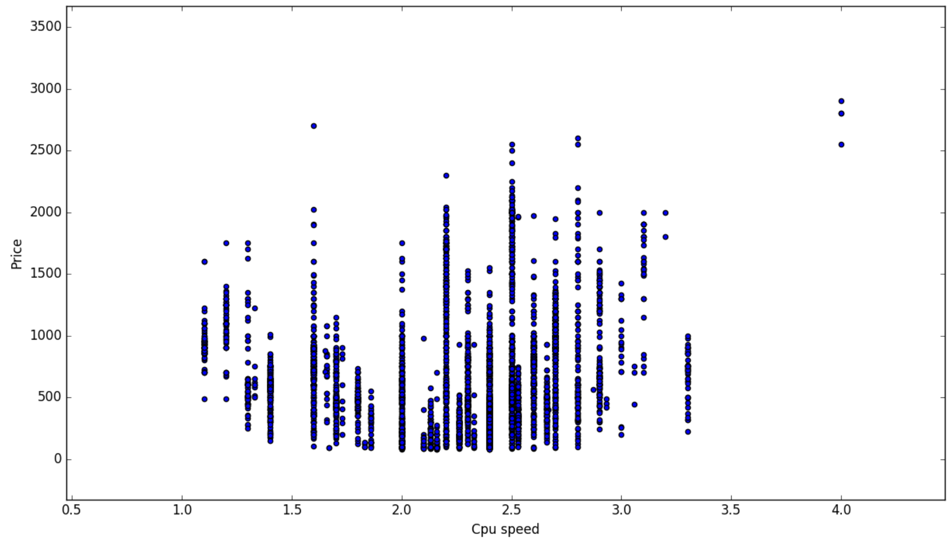

Figure I.12: CPU speed plotted against price

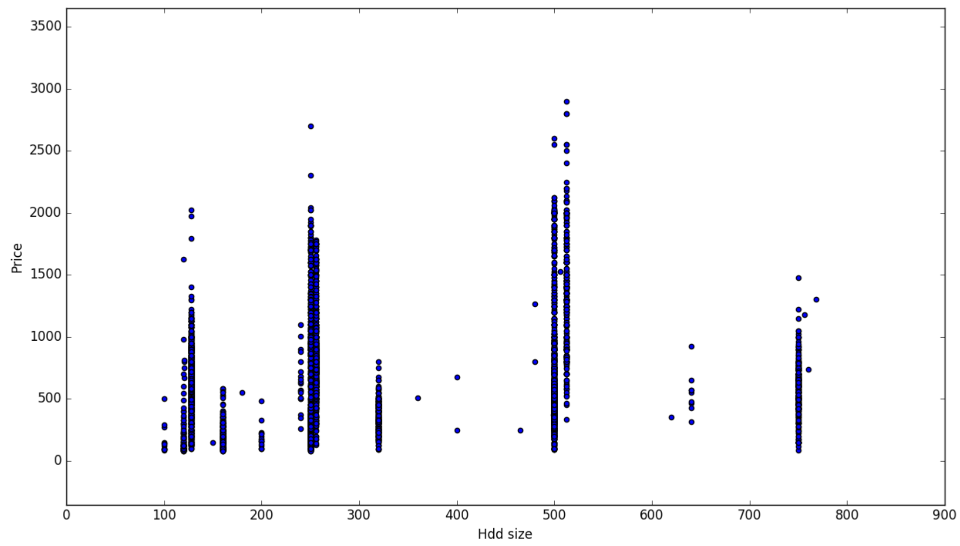

Figure I.13: HDD size plotted against price

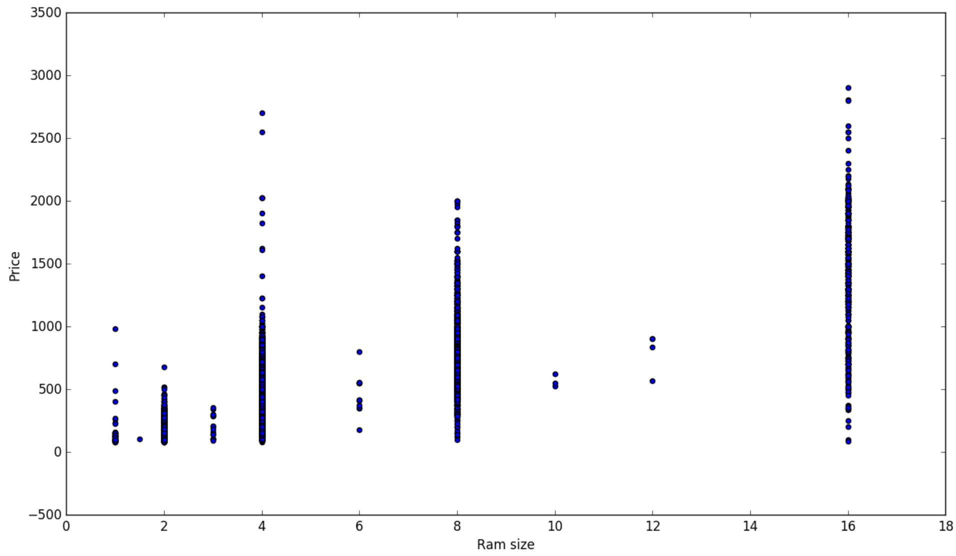

Figure I.14: RAM size plotted against price

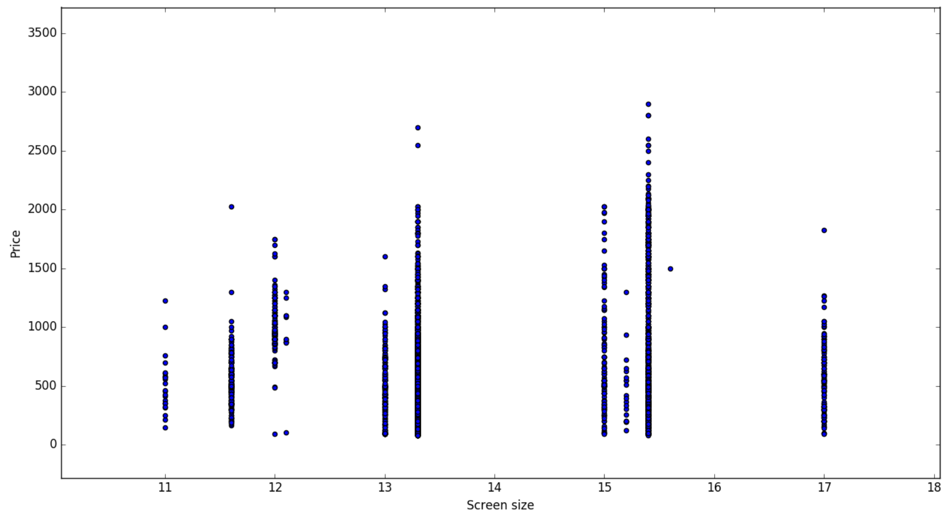

Figure I.15: Screen size plotted against price

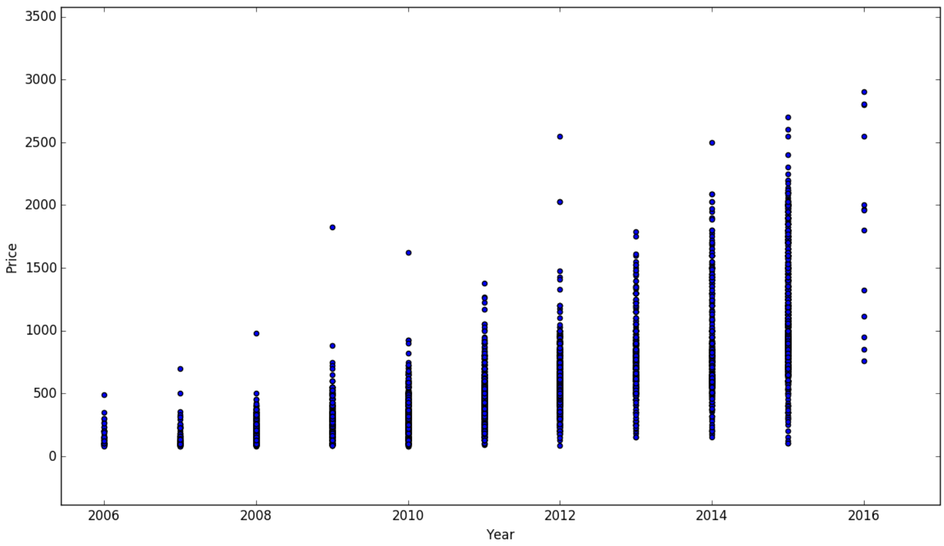

Figure I.16: Manufacture year plotted against price