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Exploring the technology of machine learning to improve the demand forecasting

A case study at Axis Communications

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ABSTRACT

Title: Exploring the technology of machine learning to improve the demand forecasting
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Background: The technology of artificial intelligence is considered to be one of the most important technological advances of our era and a fundamental driver of economic growth in our society. Axis Communications, a customer-oriented technology company delivering end-to-end solutions that strives to maximize growth is dependent on a scalable and flexible supply chain. The technology of machine learning can be beneficial to investigate when considering strategies of improving the demand forecast.

Problem description: The motivation of this study derives from Axis' supply chain setup. It takes approximately four months to procure 85 % of the cameras' components. Despite this long time period for procurement, Axis offers a lead time of ten days towards their customers. With this setup, it is crucial to have an accurate demand forecast and the current processes facilitating the demand forecasting today are time-consuming, subjective, complex and leads to patterns and trends going undiscovered.

Purpose: The purpose of this research is to explore the phenomenon; ML applications in the demand forecasting at Axis. This purpose is fulfilled by answering the following research questions.

- What kind of ML application could improve the demand forecast at Axis?

- What factors should be considered when implementing machine learning into the demand planning processes at Axis?

Methodology: A single case study was performed at Axis Communications to research the phenomenon of improving the demand forecasting with machine learning. The study was qualitative and explorative by nature and a research process framework was followed. Furthermore, the study's trustworthiness was thoroughly analyzed in terms of validity, reliability as well as generalizability.

Conclusions: The overall conclusions of the research were three independent model propositions. The models presented in the research are an attribute-based model, a prediction model based on distributor data as well as a parameter segmentation model. The proposed models are believed to generate more accurate forecasts, less manual work as well as more quantitative data processing.

Recommendations: The concluding recommendations of the research were the following;

- Form a strategic stance determining the level of acquisition in competence and knowledge.
- Top management needs to communicate the recognized success stories of initiated projects to counteract cultural resistance and unwillingness to allocate resources.
- Clear roles and responsibilities should be set as well as the implementation of data-quality principles, management principles and customized policies within the entirety of the organization to further facilitate the implementation of ML.
- Axis' demand planning department should strive to develop its internal ML competence and knowledge. Knowledge on the most relevant and basic ML would facilitate idea generation as well as generate awareness of benefits and risks.
- Axis is suggested to recruit ML competence that can support implementation projects within business processes at the operations department. This recommendation implies competence allocated to support ML implementation into the demand planning processes.
- When acquiring ML competence, it is recommended that Axis defines and communicates their level of ambition and expectations to avoid the ML competence leaving due to disappointments connected to the working assignments.
- Axis could suggestively develop a ML support network to provide a support system for the implementation team.
- Axis should consider the composing of implementation teams to bridge the gap of knowledge and competence between the demand planning team and the ML competence to ease collaboration, streamline the implementations and trigger the idea generation.
- Axis should also raise awareness to the limited experience in the implementation and usage of ML in Axis' business processes.
- It is crucial to develop an understanding of how ML models should be interpreted and their limitations to reduce overreliance.
- Axis is recommended to strive for shared incentives between functions involved when initiating ML projects.
- Develop a joint and generic data warehouse to consolidate the data available at Axis.
- Take action towards cleaning data and standardizing the usage of information systems

Keywords: *machine learning, demand forecasting, business processes, artificial intelligence, operations*

Glossary of terms

Annual dollar volume - The value of components measured in value of volume distributed per year. Annual dollar volume = annual demand x COGS
Bullwhip effect - A phenomenon where the volatility of the orders increases upstream in the supply chain which affects the efficiency and overall performance
Customer relationship management - CRM, is the management of business processes regarding customer and customer relationships of a company
Cognitive distances - The difference in knowledge, competence and understanding that could lead to misunderstandings as well as missed requirements at the workplace
Dataset - A dataset is a collection of data and each row in a dataset is referred to a member of the dataset. Each column is referred to as the variables of the members of the dataset
Data mining - The process of searching for patterns in large sets of data
Deep learning - An artificial neural network with more than one hidden layer
Enterprise resource planning - In short ERP. This concept usually involves the controlling and monitoring and executing activities related to the business processes in a company
Inventory management - An element of SCM that involves the planning, monitoring and executing of the activities related to the inventory and stock within the supply chain
Organizational distances - Distance connected to the organizational structure of the organization. This can cause difficulties or delays when making decisions connected to conflicting views or allocation of resources
Pattern recognition - A part of machine learning where the aim is to find patterns and regularities in data
Primary commodity group - A segmentation of Axis products connected to their main attributes. Examples of these product segments are the following; fixed box camera, thermal camera, explosion-protected cameras etc.
Product unit - The product unit is the finished hardware configured at the CLCs.
Sales in data - A term used by Axis for the sales from Axis to the distributors and any returns of product has been removed from the data
Sales out data - A term used by Axis for the sales from the distributors to resellers and system integrators
Service level - A measurement related to customer satisfaction in connection with material availability

Abbreviations

AI - Artificial intelligence
Axis - Axis Communications AB
COGS - Cost of goods sold
EMS - Electronic manufacturing services
3PL - Third party logistics partner

Table of content

1. Introduction

The technology of machine learning, ML, can in a simple way be described as machines mimicking the cognitive function to learn. This imitative technology is utilized when optimizing business processes as well as developing completely new innovations. No matter if the hype of this technology is overblown or not, this trend should not be ignored and must be investigated. This chapter provides a short background of the research area and the company where the study is conducted. The remaining part of this chapter describes the problem, the purpose and the scope of the study as well as the outline of the report.

1.1. Background

According to Brynjolfsson and McAfee (2017), ML is a general-purpose technology consisting of a collection of algorithms that enables machines to perform various tasks. Furthermore, the algorithms also have the capability to improve their performance without human interaction. The technology of AI is considered to be one of the most important technological advances of our era. Moreover, it is considered to be a fundamental driver of economic growth in our society (Brynjolfsson & McAfee 2017). According to Carlton (2017), growing volumes of data and computational power is the main driver of ML trends. Furthermore, successful implementation stories where vast improvements have been made are also mentioned as reasons for the growing interest in ML (Carlton 2017).

Axis Communications, a customer-oriented technology company that strives to maximize growth, is dependent on a scalable and flexible supply chain (Hallengren 2018). One way to strive for these targets could be to integrate ML into the demand forecasting. According to Bousqaoui and Achchab (2017), there are major gains when applying ML to supply chain planning processes. ML could act as a facilitator when investigating uncertainties, seasonality, randomness and potential bullwhip effect (Bousqaoui & Achchab 2017). This increased awareness could potentially lead to an improved demand forecast. The focus of this research is exploring ML applications potentially improving the demand forecasting at Axis.

1.2. Axis Communications

Axis Communications is a technology company with a broad product portfolio initially founded 1984 in Lund, Sweden. Axis was the first company to introduce the network camera to the market in 1996. As of today, Axis is still a pacesetter of this market with the vision "*Innovating for a smarter, safer world*". The majority of Axis' products are still within the area of video network solutions and consist of products such as video encoders, network cameras, network speakers, video management systems and other accessories to deliver intelligent security solutions (Axis 2018c).

Figure 1.1. A sample of Axis' cameras available on the market (Axis 2018a)

Currently, Axis has over 2600 employees worldwide and keeps on growing in a rapid pace. Products generated by Axis can be found in all kinds of industries. Some examples of industries are retail, transportation, health care, government, hotels and restaurants, education, infrastructure etc. (Axis 2018b).

1.3. Problem description

The need for this study derives from Axis' supply chain setup. It takes, in general, approximately four months to procure 85 % of the cameras' components calculated in annual dollar volume. Despite this long time period of procurement, Axis offers a lead time of ten days towards their customers (Gard 2018a). With this supply chain setup, conducting a demand forecast is a necessity to be able to deliver and satisfy the customer's demand. Furthermore, it is crucial to have a sufficiently accurate demand forecast to understand the capacity needed to avoid disruptions in the downstream material flow.

As of today, Axis is gathering large quantities of data facilitating the development of the demand forecast. To some degree, data analyzing techniques such as data mining and pattern recognition are used within the demand planning process. However, this is performed manually on a project basis, with the purpose of segmenting cameras, discovering trends as well as measuring the performance of the forecast. This manual process is time-consuming and allows the occurrence of human errors. Due to the short product life cycles and fluctuating demand, this analysis is complex to perform and does not always generate value creation (Hallengren 2018). Other factors increasing the analysis complexity are the large product assortment and numerous external factors with unknown impact in combination with the rapid company growth, making trends hard to identify (Lindroth & Ädelroth 2018). The complexity of these phenomena leads to patterns and trends going undiscovered. There are many different approaches to address this problem and this research investigates solutions connected to the identification of correlations in data utilizing the technology of ML.

1.4. Research purpose & questions

The purpose of the research is to explore the phenomenon; ML applications in the demand forecasting at Axis. This purpose will be fulfilled by answering the following research questions.

- What kind of ML application could improve the demand forecast at Axis?
- What factors should be considered when implementing ML into the demand planning processes at Axis?

1.5. Directives & delimitations

The study conducted is constructed from Axis' directives as well as delimitations presented in this section. The directives from Axis are the following;

- Providing a pre-study that highlights areas where the technology of ML potentially improves the forecast accuracy
- Performing an evaluation and quantification of requirements and competence to ensure a successful implementation ML

The amount of time dedicated to this research is 20 weeks of full time work for two students. This limitation influences the depth of the study. Therefore, the delimitations of this study are the following;

- ML applications not applicable within Axis' demand planning
- Demand forecasting connected to products in Axis' product assortment that are not cameras
- Cameras that are not in the introduction and mature life cycle phase
- Solutions that are not feasible to develop internally at Axis with their current competence and internally collected data available

1.6. Target group

The primary target group of this research is Axis employees with incentive to improve the forecast accuracy, learn more about ML applications and factors to consider when investigating an implementation at Axis. The secondary target group is product-based companies and other Axis employees interested in the development of ML applications in general business processes.

1.7. Outline of the report

The remaining chapters of this research report are demonstrated in figure 1.2. below.

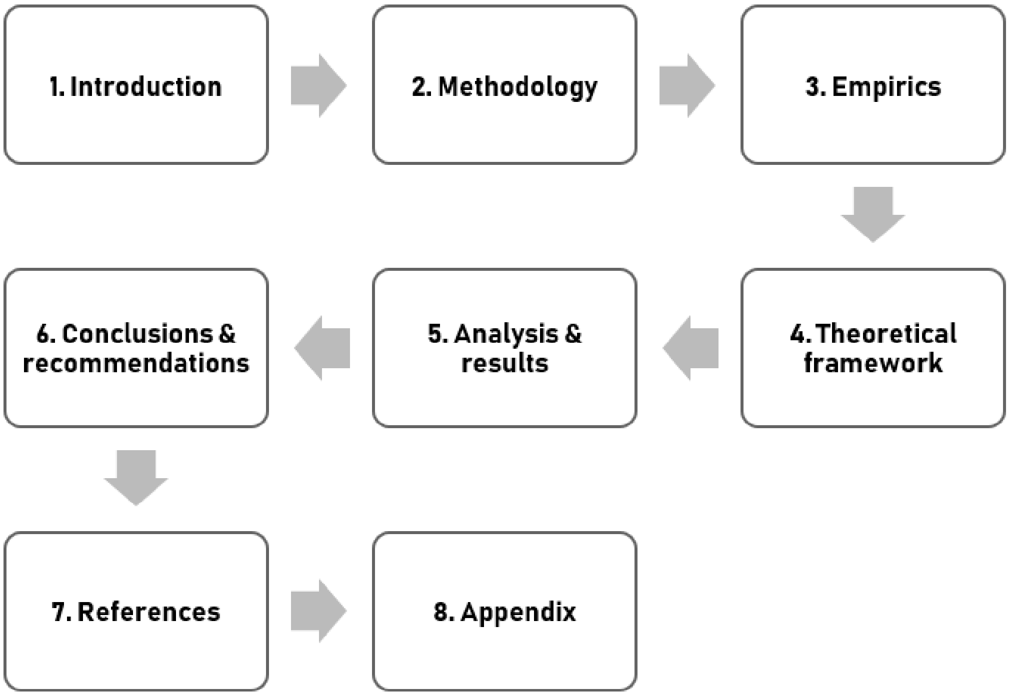

Figure 1.2. Outline of the remaining part of the research report

2. Methodology

To conduct a well-structured and reliable study, it is important to reflect upon the methodology best suited to the field of research and what answers are sought. In this chapter, the choice of methodology for the study is as well as a framework over the research process is presented and motivated. The trustworthiness is also analyzed in order to evaluate the reliability, validity and generalizability of the study.

2.1. Research approach

When choosing a research study approach, the existing amount of knowledge within the field of research, the format of the information as well as the questions problematizing the subject are relevant (Golicic et al. 2005). The research approaches examined for this study were the quantitative and qualitative. According to Golicic et al. (2005), when observing a new and complex phenomenon, a qualitative approach is suitable. This approach facilitates the interpretation and mapping of the complexities related to the subject or situation (Golicic et al. 2005).

When performing a quantitative research, variables and hypotheses are tested, measured and evaluated numerically (Creswell 2013). The objective of the quantitative approach is to create a theory that contributes to an increased understanding of the phenomenon along with the possibility of making predictions and controlling it. Furthermore, a quantitative approach could be suitable when testing the theory built through qualitative research (Golicic et al. 2005).

The selection of research approach for this study is a qualitative one. This choice is motivated by the study being exploratory by nature. The phenomenon, improving Axis' demand forecasting with ML applications, is not measurable because it does not exist. The observation and measuring of variables as well as making and testing hypotheses are therefore not feasible. To achieve the purpose of the research, the environment of the phenomenon, Axis' demand planning process, needs to be mapped and thoroughly reviewed. Only when this has been performed, can the ML applications be investigated in its environment. In conclusion, a qualitative approach enables an understanding of the phenomenon as well as its applicability to the forecasting process at Axis which a quantitative approach cannot do.

2.2. Research framework

The framework presented by Voss, Tsikritsis, Frohlich (2002) is utilized to align the purpose, questions and structure of this research study, see table 2.1.

Table 2.1. Aligning the research study (Voss et al. 2002)

Purpose	**Questions**	**Structure**
Exploration - Uncover areas for research and theory development	- Is there something interesting enough to justify research?	- In-depth case studies - Unfocused, longitudinal field study
Theory building - Identify/describe key variables - Identify linkages between - variables - Identify "why" these relationships exist	- What are the key variables? - What are the patterns or linkages between variables? - Why should these relationships exist?	- Few focused case studies - In-depth field studies - Multi-site case studies - Best-in class case studies
Theory testing - Test the theories developed in the previous stages - Predict future outcomes	- Are the theories we have generated able to survive the test of empirical data? - Did we get the behavior that was predicted by the theory or did we observe another unanticipated behavior?	- Experiment - Quasi-experiment - Multiple case studies - Large scale sample of population
Theory extension - To better structure the theories in the light of the observed results	- How generalizable is the theory? - Where does the theory apply?	- Experiment - Quasi-experiment - Case studies - Large scale sample of population

2.2.1. Research purpose & questions

The research questions were defined early in the study and has been redefined iteratively as the research progressed. When examining table 2.1. together with the research questions for this study, the purpose is defined. The research questions indicate that theory building is the most relevant purpose for this study. However, the study is somewhat exploratory by nature since a large part of the research process has been to understand and investigate a phenomenon that does not exist today as well as its environment. To conclude, the purpose of this study is connected to theory building but it also has elements of exploration.

By having a study with an exploratory and theory building nature, the purpose is to uncover areas for research, acting as a pre-study. Furthermore, the purpose is also to identify key variables related to the phenomenon relevant for Axis. Therefore, the research questions for this study aims to answer "what" kind of ML application could be applied and "what" factors to consider for such an implementation.

2.2.2. Research structure

In connection with the research purpose, six different research structures were considered suitable in table 2.1. The environment and nature of the research affects the suitability of the different research structures. When evaluating the research structures in table 2.1, it is clear that an in-depth case study would be a suitable structure for this research.

In a case study, the phenomenon is examined in its environment. This perspective enables the in-depth understanding of the phenomenon and true to its natural state. Furthermore, conducting a case study is particularly good when the research is of an explorative nature (Voss et al. 2002). Due to the lack of ML in Axis' demand planning process, the need for a deeper understanding of the environment motivates the choice of an in-depth case study. To assess the possibilities of ML in demand forecasting, a thorough evaluation of the present environment is crucial.

2.3. Research process

An iterative research process has been developed for this case study. The process steps are illustrated in figure 2.1. and are described in this section.

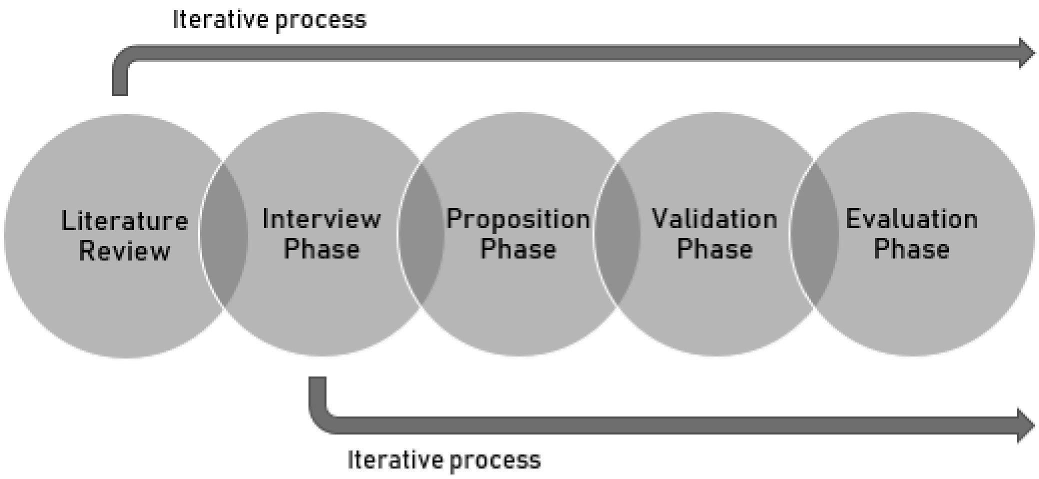

Figure 2.1.The research process developed for this case study

2.3.1. Literature review

In the initial phase of the research, the problematization of the research was not complete. To understand the scope and complexity of the environment, a literature review was initiated. Through the literature review and directives from Axis, the field of research as well as the research questions started to take form. When the environment became gradually clearer, further delimitations could be made on the basis on feasibility.

As illustrated in figure 2.1, the literature review was an iterative process throughout the research progress. It was used as a frame of reference to compare and evaluate the information gained from interviews, workshops as well as facilitating during the construction of the propositions and conclusions. This ensured the quality of the information gathered and reassured that the information given was received and interpreted correctly.

The literature reviewed in the research consisted of books, academic journals, web-based articles, research from industry as well as blog posts. Due to the research conducted within a new and state of the art technology, the most recent and up-to-date information was found in less reliable sources.

2.3.2. Interview phase

According to Voss, Tsikritsis, Frohlich (2002), in a case study, several methods are often used when collecting data of the same phenomenon. Through multiple independent sources of data, a higher reliability can be achieved. Interviews played a central part of the field data collection for this study and followed an unstructured character. The interviews had preformulated questions, but as the interviews progressed, the interviewers' insight on the subject was inadequate to deliver the same depth due to the exploratory nature of the study. The unstructured interview can in many situations provide rich data for the interviewer (Baškarada 2009). This is the motivation to why unstructured interviews were assessed to be suitable for this study.

The first step of the interview phase included conducting interviews with Axis' employees to map the supply chain and their cross-functional activities. The purpose was to understand the infrastructure and the connected limitations of the current processes. When these interviews were completed, the scope of the research was not feasible within the time limitation. Therefore, the research was further delimited, and the final scope was defined.

As can be seen in figure 2.1, the interviews were also conducted iteratively throughout the research process. Follow-up interviews where initiated when new insights would enable the study to go deeper. Interviews were also conducted with employees that possess ML competence as well as all functions within the operations department. Furthermore, a higher concentration of interviews was conducted close to the demand planning and the data relevant to a ML application under investigation.

2.3.3. Proposition phase

In the previous research process phases, information has been gathered and a mapping and visualization of the environment has been obtained. When the demand planning processes were understood, potential improvement areas within the processes could be identified. Together with a thorough literature review on ML technologies that are available and applicable to Axis' processes, propositions started to take form.

When multiple propositions had been developed, the propositions were evaluated and filtered out with respect to their potential benefits and strategic fit. Together with further complementing interviews as well literature reviews, their timing and relevance within the demand forecasting processes were further assessed. The propositions with most potential benefits and considered to have the highest feasibility, in this moment of time, were compiled.

2.3.4. Validation phase

To validate the applicability of the propositions, a few workshops where initiated. The first workshops were conducted with ML knowledgeable personnel within Axis to assess the feasibility of the propositions. A discussion of suitable models and algorithms connected to the propositions were validated depending on the inputs, outputs and the amount of data accessible. If a proposition was considered to be difficult to successfully implement, it was disregarded.

Furthermore, a workshop amongst the employees with knowledge in the demand planning as well as material supply planning processes was conducted. By having the models assessed by practitioners, important validity for this research was generated. The propositions' relevance, feasibility and potential benefits were discussed and assessed.

This step was not only performed for validation purposes, but also to gain insights on how to develop the propositions further and possibly to generate more ideas. The workshop was prepared with questions regarding the propositions' identified factors, inputs and measurements. The intention of this phase was to grasp even deeper insights on the demand planning process than what the interviews provided. The practitioners are familiar with the dimensions of the data sources, giving a more reliable view of the factors and inputs influence on the forecast and to what degree. To be able to obtain a visualization of the propositions and successively construct its elements, both with the ML perspective and the demand planning perspective, the workshops were iteratively performed.

2.3.5. Evaluation phase

The propositions still considered to be feasible, beneficial and applicable to the demand planning process were further analyzed and evaluated. This final phase was carried out through reviewing the propositions against further literature. Efforts to benchmark the propositions were made and finally, conclusions were drawn, and recommendations were formulated.

In addition to the remaining propositions, a framework was constructed. During the interview, proposition and validation phase, this research was confronted with several factors to consider when implementing ML into demand planning processes. These factors were consolidated into a factor assessment framework to act as a basis to structure the recommendations to facilitate more efficient implementations in the future.

2.4. Trustworthiness of the research

When evaluating the trustworthiness of the research, validity and reliability are important aspects to consider when conducting a case study (Voss et al. 2002). A framework by Yin (2009) seen in table 2.2, were utilized to determine the quality of the conducted study.

Table 2.2. Approaches to ensure validity as well as reliability. Based on (Yin 2009)

Test	**Case study tactic**	**Phase of research in which tactics occurs**
Construct validity	- Use multiple sources of evidence - Have key informants review draft case study report	All phases All phases
Internal validity	-	-
External validity	- Examine and compare with other studies of the same phenomenon	Evaluation phase
Reliability	- Research process framework	All phases

2.4.1. Validity

The validation of a study is defined as the evaluation and the assurance that the conducted study is relevant to the context.

Construct validity
This term describes the measures that are taken to establish correct and valid operational measures for the studied phenomenon (Yin 1989).

There are many tactics to ensure construct validity. One tactic, listed in table 2.2, is to retrieve information from multiple sources of evidence. Inputs and perspectives from different parts of the organization, experienced practitioners with various competences were collected and utilized for this study. Furthermore, combining these multiple sources with extensive literature, different types of sources facilitated this research. This approach generates a higher validation that the information is of quality and interpreted correctly.

When conducting this study, the academic literature regarding practical aspects of ML in business processes was scarce. However, articles from technology magazines and blog posts were considered to generate information that the academic literature was found lacking. To ensure that the content was deemed valid, multiple sources covering the same topic were sought. If many sources contained the same information, the sources were considered valid and of value to the research.

During the study, the report draft was regularly reviewed by a few key informants at Axis to ensure that the environment of the research was interpreted correctly. This is also a tactic listed in table 2.2. that contributes with a stronger construct validity.

Internal validity
According to Yin (2009), this test is widely used when performing studies such as experimental or quasi-experimental in nature. This test is not optimal or applicable for explanatory case studies and therefore, this test is disregarded for the research performed (Yin 2009).

External validity
The third test, external validity, is used to verify that the finding from the study is generalizable beyond the scope of the performed study (Yin 1989). Conducting a study with multiple cases has a stronger external validity than single cases (Voss et al. 2002). Since the study performed is a single study, it is important to be conscious of and compensate for this weakness to ensure validity.

To strengthen the external validity, one can examine and compare with other studies of the same phenomenon. The phenomenon of this research does not exist to, but the work has been benchmarked against similar phenomena. The outcome of this benchmark was that organizations experienced similar factors to consider, as mentioned in the assessment framework.

Another approach to ensure external validity, discussions and evaluations with independent consultants possessing knowledge within the relevant field was conducted. This was performed to a limited degree by benchmarking the propositions with multiple external ML knowledgeable students. However, to assess the experience amongst these students was difficult and should be considered when evaluating this approach of ensuring external validity.

2.4.2. Reliability

The reliability of the study is defined by the degree that the study can be repeated and generates the same results (Voss et al. 2002). The work towards ensuring the reliability is especially important for this case study since one of the authors have been employed at Axis. The consciousness of personal bias is therefore something that must be observed and be departed from.

In table 2.2, a tactic to ensure reliability is to document how the study was conducted through the research process framework, see figure 2.1. This could be utilized as instructional guidelines that could facilitate a replication of the study.

Furthermore, mostly semi-structured or unstructured interviews were conducted for this study. This creates a unique environment and the information gathered reflects personal bias to some extent. With that said, every conducted interview as well as its date and agenda were documented. This documentation makes the progress of the study easier to trace and potentially replicate.

2.4.3. Generalizability

According to Hyde (2000), the aim of a qualitative study is to be able to broaden theories through generalizations. Therefore, it is important to critically review the analytical generalizations (Hyde 2000).

A factor that contributes to the generalizability of this case study is that several of the suggested areas of improvements are recognized to be common problems within many organizations today. For example, Axis, like many other organizations, experiences unclean, biased and insufficient amounts of data. The concluded recommendations revolving these issues could therefore possibly be applied in other similar cases. However, it is important to utilize this study's recommendations with caution and properly assess the differences in environments.

Literature sources concerning ML risks and barriers have been reviewed for this research and have facilitated the analysis conducted. These general sources have influenced the recommendations. In the same manner that the general issues are found applicable to Axis demand planning process, it should be assessed as general and applicable to other similar phenomena.

2.4.4. Evaluation of trustworthiness

The trustworthiness of this research may be compromised in regard to this research dependency on references from magazines and blog posts with unconfirmed authors. However, efforts have been taken to overcome these gaps of trust in order to maintain adequate construct validity. Furthermore, efforts to benchmark the results of the study have increased the external validity of this research.

The study has, in an early stage of the research, been carefully and thoughtfully planned. The planned research process is documented and considered to increase the reliability of the research. However, the generalizability of the study is evaluated to be somewhat lacking. This should be taken into consideration when evaluating if the results are applicable to more general cases. In conclusion, the overall trustworthiness of the study is considered to be valid and reliable to a certain degree, but the findings should be applied with caution.

3. Empirics

This chapter aims to introduce the environment of the research which consists of the strategic configuration of Axis' supply chain and their product breakdown referred to as the product pyramid. Furthermore, the demand supply planning, forecasting process as well as relevant information systems is presented. This chapter also includes a brief description of the data collection relevant to the demand forecast and ML competences that can be found at Axis.

3.1. The strategic configuration of the supply chain

Axis is a goods-based company with high quality products focusing on being a customer-oriented player on the market. Supply chain loyalty, cooperation and building a trustworthy quality brand on innovative end-to-end solutions is a priority for Axis (Lindroth 2018). According to Lindroth and Ädelroth (2018), this strategic positioning is reflected in the operational goals. Axis strives to maintain a flexible and scalable supply chain as well as delivering a high service level to satisfy the customer.

To maintain the company growth and prosperity, increasing the cost-efficiency through the supply chain is a prioritized goal (Lindroth & Ädelroth 2018). The lead time towards Axis customers is 10 business days while the components lead time is often 2-26 weeks. In some cases, due to the material scarcity, the component lead time can be up to 52 weeks (Olofsson 2018b). To be able to satisfy customer demand without material flow disruptions, a demand forecast is a necessity.

3.2. Axis supply chain design

Axis supply chain is mapped in figure 3.1. Each stakeholder in the supply chain configuration and their role in Axis' supply chain are described below.

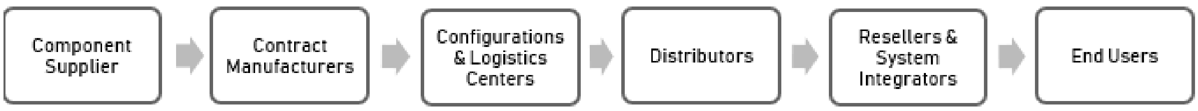

Figure 3.1. Axis Communications supply chain

3.2.1. Component suppliers

The majority of the component suppliers are located in Asia. This is mainly due to the industrial spread of electrical components situated in this area. However, Axis product portfolio consists of various components procured from different parts of the world (Lindroth 2018**).**

According to Olofsson (2018a), the majority of the components are purchased from external component suppliers with a few exceptions developed in-house. Axis strategic choice of this in-house development is motivated by a dissatisfaction of the available market alternatives in terms of quality as well as maintaining a competitive advantage against Axis competitors.

3.2.2. Contract manufacturers

Axis has six, soon to be five, contracted manufacturers, i.e. EMS’. The EMS’ account for the majority of Axis production and they are situated in Asia, Europe and the North America. At this stage in the supply chain, the components are configured into product units. This is when the majority of the hardware configuration is finished but the software is not yet integrated into the product (Lindroth 2018).

According to Olofsson (2018a), some components are quite standardized and the EMS’ can purchase components with less influence from Axis. In other cases, only one or a few specific suppliers are qualified according to Axis. One reason for this is to ensure the desired quality of the components.

3.2.3. Configurations & logistics centers

According to Lindroth (2018), the configuration and logistics centers, so called CLCs, are mainly used for keeping stock as well as some final assemblies and configurations. All CLCs but one are contracted 3PLs but the stock kept is owned by Axis. The postponement of the mentioned products’ value-adding activities is to remain as flexible as possible until an order is received.

Axis has six CLCs located in various parts of the world. By having CLCs close to the different regions, the inventory can be kept closer to the customers and facilitate to maintain a good service level by meeting the requirements of delivering the merchandise within 6-10 working days. To enable this strategy, the same product units can be kept in stock at different geographically located CLCs to meet the markets demand. When the final assemblies and configurations are made and an order arrives from a distributor, the products are consolidated and shipped to the distributor’s location (Lindroth 2018).

3.2.4. Distributors

Currently, Axis has approximately 100 distributors and the strategic goal is to have loyal and long-term partnerships with this category of stakeholders (Hjelmström 2018). According to Lindroth (2018), this is an important factor that distinguishes Axis from their competition.

Most of the finished goods are managed and stocked by the distributors and they are responsible for supplying the system integrators and resellers with goods, see figure 3.1. If the distributor has an excess of products in stock and problem moving the goods, Axis can in some cases buy back the inventory from the distributor (Lindroth 2018).

3.2.5. Resellers & system integrators

According to Lindroth (2018), the resellers and system integrators purchase the products from the distributors. Axis has an established incentive and loyalty program for resellers and system integrators called the Channel Partner Program. The program has different discount levels depending on various factors, for instance, volumes distributed per year. This encourages Axis resellers and system integrators to learn about the Axis products to further climb the incentive program and receive larger discounts and other benefits. Today, Axis has approximately 90,000 partners within this segment in the supply chain configuration (Lindroth 2018).

3.2.6. End users

The last stakeholders in the supply chain are the end users. The end users procure the products from a reseller, system integrator or in a few cases, through a distributor (Lindroth 2018).

3.3. Product pyramid

Axis' products can be defined on different levels. The product line is the most general segmentation which can be broken down to the smallest product level referred to as sales units. The different product levels are described in detail in this section and the product breakdown, referred to as the product pyramid, can be seen in figure 3.2.

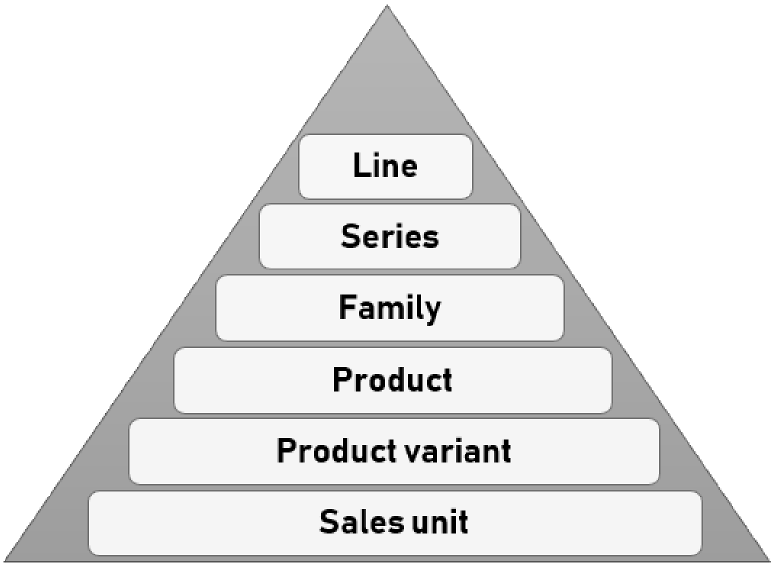

Figure 3.2. The product pyramid at Axis illustrating the product breakdown (Based on Axis Communications 2018)

According to Jeppson (2018), the first product level in Axis' product pyramid is the sales units. The sales units are finished products connected to a specific region. Currently, there are nine regions that the products are broken down to. The differences between product variant, the next product level in the pyramid, and sales unit can be a different cord depending on regional power output for example.

Comparing the third product level, product, with product variant, the product variant can have minor differences in lenses and so forth. On the product level product, this distinction is not made but there are certain extension differences. For example, products can have differences in attributes such as being outdoor adjusted, vandal resistant or wireless. On the following product level, product family, the distinction is that there is no extension segmentation.
The next step in the product pyramid is product series. As the name implies, there are multiple product families within a product series. The definition is that they consist of the same product type or as defined in Axis' ERP system, primary commodity group. The final step in the product pyramid is the product lines. This product level is defined as the most general level where the products are differentiated to cover Axis' different customer segments. The different product lines have individual physical features, different demands on material and quality as well as levels of innovation (Jeppson, 2018).

3.4. Information systems

Information systems facilitating the development of the demand forecast as well as the demand planning processes are presented in this section.

IFS Applications
IFS Applications is the ERP system utilized at Axis. The system is a full coverage system with applications and modules that cover various activities performed by an industrial company (IFS 2018). The system was the first component-based system on the market and the system facilitates a project-based infrastructure (Berns 2004).

IFS Demand Plan Client
The IFS Demand Plan Client is a module to IFS Applications. This module extracts the historical demand data from the main ERP platform and a Bayesian forecast model with standardized parameters is then applied to the data. The demand forecast is updated twice a month. The module also allows the demand planners to enter projects and adjust the demand forecast manually. The standard deviation as well as other measurements monitoring the demand is available in IFS Demand Plan Client for Axis' products (Wikström 2018b).

QlikView
QlikView is a business intelligence application developed by the company Qlik. The application is used by the demand planning team to visualize data and facilitate analysis (Wikström 2018b).

CRM system
This system is internally developed by Axis and gathers data regarding registered projects from the Channel Partner Program. The projects are inserted into the CRM system by Axis' sales personnel when approved and monitored (Andersson 2018). The system's purpose is for resellers or distributors to register their customer projects with the incentive of receiving a discount.The demand planning department utilizes the system to detect larger customer projects in the pipeline (Wikström 2018b; Andersson 2018).

PIA system
The PIA, product information API, system is a database consisting of all Axis' current and previous products. In the system, information regarding the products attributes, placement in the product pyramid described in section 3.3, the predecessors and successors and their assembly properties can be found. Examples of assembly properties can be a product's compatible assembling devices or accessories. This system is mainly used by the demand planning department to extract information about the products as well as their connections to devices and other cameras (Bodin 2018).

Microsoft Excel
Excel, a program developed by Microsoft, is a commonly utilized system for manual data analysis and visualization when conduction demand planning processes. Excel is a manual system were a majority of the demand planning processes and analyses are performed.

3.5. Demand supply planning

The demand supply planning was originally two separated planning processes, material supply planning and demand planning. The purpose of integrating these processes was to strengthen the exchange of information and the strategic alignment between the two processes as well as reducing silo thinking (Magnusson 2018).

3.5.1. Material supply planning

According to Olofsson (2018a), this department's responsibility is the material procurement and inventory management of approximately 4000 SKUs. The material procurement involves securing the material availability at the CLCs with basis in the demand forecast produced by the demand planning department. When the demand forecast is finalized, it is transferred from IFS Demand Plan Client into IFS Applications and broken down to a component level forecast. Depending on the breakdown, the components are divided upon the CLCs to represent the respective regional demand.

3.5.2. Demand planning

The fundamental responsibility of the demand planning department is to secure customer satisfaction through sufficient material flows (Axis Communications 2018). The department develops both short-term, in the near future, as well as long-term forecasts up to 13 months in advance. All hardware in Axis' product portfolio is forecasted in the IFS Demand Plan Client module on sales unit level (Hallengren 2018).

All life cycle phases for an Axis camera can be seen in figure 3.3. below. However, the relevant life cycle phases for the demand planning team are the introduction, mature and decline phase.

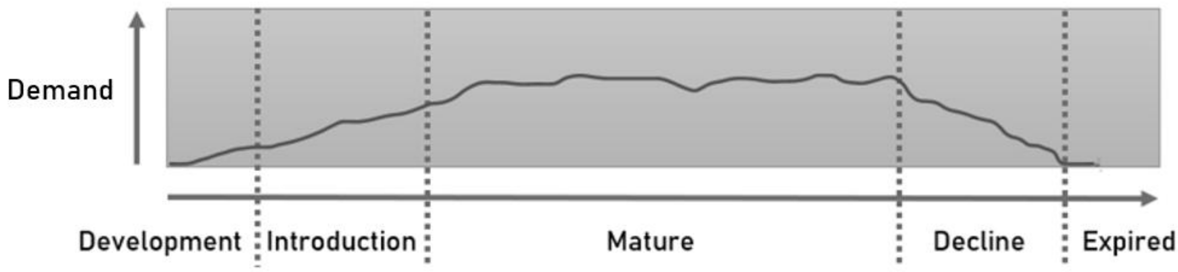

Figure 3.3. The different phases in a product's life cycle (Based on Gidlöf 2018)

Introduction phase
According to Wikström (2018b), when new products are introduced to the market, they are referred to as ramp-up or rollover products. Ramp-up is when a completely new product is being introduced and a rollover when the introduction has a predecessor being phased out. The introduction phase takes place the first six months on the market.

For ramp-ups and rollovers, there is no historical demand data that could derive a forecast. The demand planning process is therefore slightly different for these products. Furthermore, the uncertainty is naturally higher for a ramp-up than a rollover because they lack a predecessor to proceed from (Wikström 2018b).

Mature phase
After the six initial months of demand, the products enter the mature phase. In this phase, the products gradually reach a more stable demand. A Bayesian forecast model is used in the IFS Demand Plan Client to forecast the demand of mature products (Hallengren 2018).

According to Kastor (2018), the parameters in the forecast model are standardized for all forecasted products. However, the products have different demand patterns; some products have a volatile demand while others have a more stable demand (Kastor 2018). The result of having standardized parameters makes it necessary for the demand planner to adjust the forecast manually in a higher degree (Wikström 2018c). The Bayesian forecast model is more thoroughly described in subsection 4.1.2.

Continuous improvement projects
The demand planning team also manually executes projects to improve the demand planning processes, for example, to interpret trends and patterns (Wikström 2018c). The insights from these analyses are limited due to complexity of predicting the demand.

3.6. Data Collection

This section provides a description of the current data sources that is analyzed in the demand forecasting process as well as additional data sources that could provide further insight in this process. The data facilitating the demand forecasting process is located within systems or at different functions of Axis and the extraction is either manual or automatic. Currently, only one data warehouse has been located at Axis during this research. This data warehouse is located within the function called business intelligence. However, the data stored in this warehouse is limited and controlled by this function.

3.6.1. Current data collection

In this section, data currently collected to develop Axis' demand forecast are described. The inputs are mapped in figure 3.4. below.

Figure 3.4. Inputs facilitating the demand forecast development

Historical demand
According to Kastor (2018), the historical demand is the only input to the statistical forecasting model that is the initial basis of the forecast. The historical demand input is the orders registered in IFS Applications aggregated to a monthly customer demand. It is the only forecast input that is automatically entered into the demand forecast in IFS Demand Plan Client (Kastor 2018).

Sales in and sales out data
These data sources are two separate inputs facilitating one analysis. The sales in data are the invoiced orders from distributors whilst the sales out data are collected from the distributors' sales to their customers (Lanni 2018). According to Kastor (2018), the sales in and sales out data are analyzed on a monthly basis to get a rough overview of the distributors' inventory on hand as well as identifying bullwhip effects. This analysis is done on three different levels, see figure 3.5.

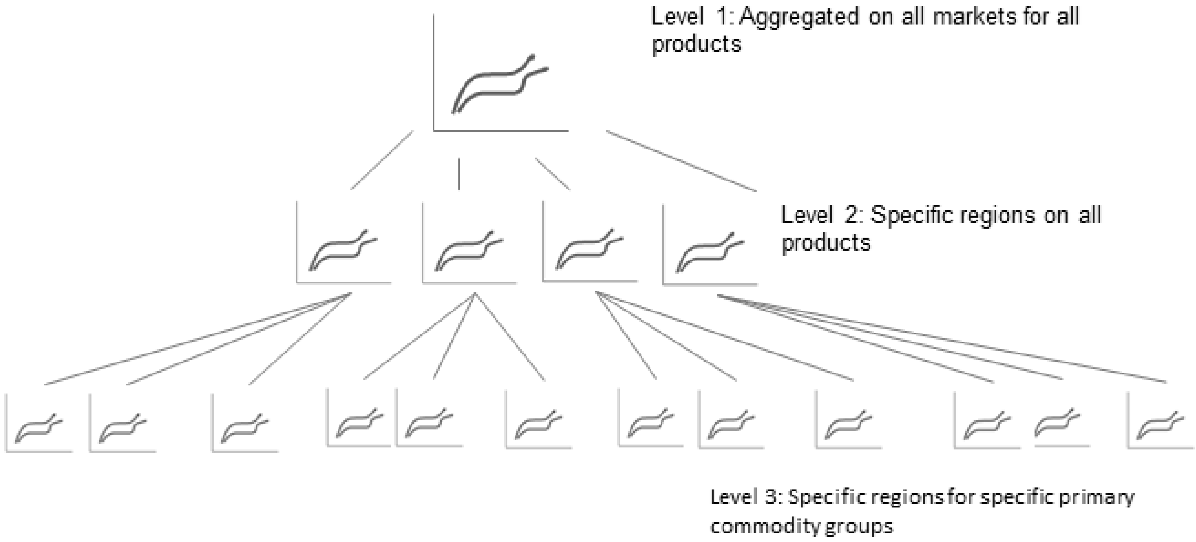

Figure 3.5. Levels of sales in and sales out data analysis (Wikström 2018c; Kastor 2018)

The demand planners utilize this analysis as an indicator rather than quantitative data and are therefore not directly integrated into the demand forecast. This analysis also contributes with insights to how the primary commodity groups are managed by distributors on a very general level (Kastor 2018).

Business analysts

According to Wikström (2018b), the inputs gathered from the business analysts are especially important for product introductions. Their knowledge and experience can give a good indication of whether a product will have a fast, medium or slow ramp-up.

Product managers

According to Wikström (2018c), the product managers contribute with inputs to the forecast since they possess knowledge about Axis' product portfolio. The demand planning team has monthly meetings where they present the demand forecast to the product managers. The product managers share their insights on new product introduction projects and how they believe the project will impact the product demand. The product manager's main expertise is the product portfolio and can to some degree predict how products will cannibalize on each other (Wikström 2018c).

Sales regions

According to Wikström (2018c), the data received from the sales regions are gathered from monthly meetings with the purpose to highlight the most important strategic projects in the CRM. The exchange with the sales regions is also to communicate back when a large strategic project is received too late and risks disrupting the material flow (Wikström 2018c).

CRM project data
The projects registered in CRM are an important data input to the demand forecast. By investigating the CRM project data, potential disruptions in the pipeline can be identified. The manual analysis of these projects enables a proactive counteraction against demand fluctuations through adjusting the demand forecast (Hallengren 2018). According to Kastor (2018), the registered projects are often uncertain, and it is unfeasible to monitor all registered projects. Some of the issues causing the uncertainties are that customers registering the same project at multiple distributors as well as multiple products within one project. The extraction of the projects considered to be of significance by the sales regions are communicated to the demand planning team.

Furthermore, the integration of the projects into the forecast is also a subjective process. These factors could be the product demand in the project in relation to the general monthly product demand as well as the project's perceived probability of falling through. The probability feature in the system is handled differently on the different regions (Wikström 2018).

3.6.2. Potential data collection

In this section, current data collection not facilitating the demand forecast is described.

Website data
According to Frich Welch (2018), there are website data collected in two different systems. The first dataset is collected to the heat map in a system called Hotjar. From the heat map, click-, movement- as well as scroll data can be extracted and further analyzed.

As of today, the click data are used for statistical purposes where two main features are being observed; the content of click as well as the format of the clicked feature. Content refers to the information sought by the website user. The format, on the other hand, is the user's preferred way to obtain information. See Appendix 2. for an illustration of the click data. These two features are being tracked, monitored, evaluated and analyzed to keep the website user friendly and interesting.

The movement data tracks the click sequence of a user see Appendix 3. This data is utilized to analyze trends and customer orientation (Frick Welch 2018). The scroll data are currently used to plan and change the website content to ensure a suitable layout of interesting formats and information. For example, if certain information is viewed by the user, it is often removed from the website. See Appendix 4. for an illustration of this data.

Hotjar is a newly integrated tool at Axis and since the structure is not fully modified to reflect the website user's movement and therefore, the data are uncertain. In addition to this, the website data collected are limited.

The second website dataset is collected at Axis and is gathered in a system called Google Analytics. This system also gathers click data to facilitate the development of Axis' website through a statistical analysis to understand the customers and their website behavior (Frick Welch 2018). Some products are being clicked on or searched through the search engine directly while other products are being located by the website user through a longer clicking trail (Lading 2018). These user patterns can be analyzed in Google Analytics.

Site Designer data
According to Sandberg (2018), the Site Designer is an internally developed system utilized by system integrators to draw up end-to-end solutions for end users. The projects registered in the system target smaller projects with 12-50 cameras. These data have similar uncertainties as the CRM data in some aspects. For example, many end users can register projects at different Axis system integrators. However, there is no incentive to register multiple products within the projects which occurs in the CRM system. The success of the system has triggered the development of a new Site Designer tool. The purpose is the same but with a further optimized platform and with a larger target group covering the remaining business segments (Sandberg 2018).

PIA data
All products with their respective attributes and relations to other products are registered in the PIA system. According to Bodin (2018), the system visualizes a product breakdown from product line to sales unit. The attributes can be expressed in different data types such as integer, boolean, string etc. The majority of the attributes are of type string, but the type boolean is also common (Bodin 2018; Axis Communications 2018).

3.7. Machine learning at Axis

Currently, there are different projects involving ML at Axis. The majority of these projects are related to integrating intelligence into the products such as machine vision. These machine vision projects are conducted internally by Axis personnel or master thesis students.

Exceptions to projects involving intelligence integrated into the products are ML related applications to improve business processes. These types of ML projects have been on a more experimental level to recognize patterns. These identified projects are small and locally initiated making them hard to locate and the insight limited. Competence related to machine vision is not directly applicable to business processes performed at the demand planning department. The datasets are different both in regard to size and format and other models as well as requirements are connected to the processes (Andreen and Pendse 2018). Currently, the authors of this study have not located any type of mapping of the ML competence or ongoing projects at Axis.

4. Theoretical framework

This chapter introduces some of the theory behind Axis' statistical forecast model facilitating the demand forecast. Furthermore, the coefficient of variation, a measurement on demand volatility utilized in the propositions is introduced. This chapter also introduces the technology of ML as well as common ways of segmenting ML models and algorithms. Lastly, some risks and requirements connected to the technology is also described to facilitate with the comprehension of the study's environment.

4.1. Statistical theory

In this subsection, theory related to the forecasting model utilized at Axis and its most relevant parameters for this study is presented. Furthermore, a demand volatility measurement, the coefficient of variation is assessed to be needed to be able to follow the reasoning for this research.

4.1.1. The Bayesian forecasting model

The Bayesian model is an equally weighted result from four different forecasting models, *the moving average, adaptive EWMA, least squares and Brown's level and trend model* (Anon 2018a; Gard 2018a). These forecasting models are briefly described in this subsection and its parameters are summarized in table 4.1.

Table 4.1. The parameters of the Bayesian forecast model

Parameters	**Description**
alpha, α	The selected level smoothing parameters
beta, β	The selected trend smoothing parameters
delta, δ	The smoothing parameters used by the tracking signal
rho, ρ	The selected damping parameters

Moving average
According to Axsäter (2006), the concept of the moving average is to compute the mean of the N most recent values.

$$\widehat{a_t} = estimate\ of\ a\ from\ observing\ the\ demand\ in\ period\ t$$
$$\widehat{x_{t,\tau}} = forecast\ period\ \tau > 1\ when\ the\ demand\ of\ period\ t\ is\ observed$$

The moving average is calculated by equation (1)

$$(1)\ \widehat{x_{t,\tau}} = \widehat{a_t} = (x_t + x_{t-1} + \cdots + x_{t-N+1})/N$$

Adaptive EWMA
According to Anon (2018), in adaptive EWMA, adjusted weights are applied to historical

data. The adjustment is regulated exponentially, i.e. the model emphasizes recent observations more and the emphasis decreases for previous observations. The formula below is used to compute the forecast with Adaptive EWMA with the trend parameter, β, see table 4.1.

$$F_t^{(t+\tau)} = forecast\ for\ period\ t+\tau\ in\ period\ t$$
$$D_t = actual\ demand\ for\ period\ t$$

The forecast is calculated by equation (2) together with equation (3), (4), (5) and & (6).

$$(2)\ F_t^{(t+\tau)} = \alpha_t * D_t + (1-\alpha_t) * F_t$$

$$(3)\ \alpha_{t+1} = |\frac{E_t}{M_t}|$$

$$(4)\ E_t = \beta * e_t + (1-\beta) * E_{t-1}$$

$$(5)\ M_t = \beta * |e_t| + (1-\beta) * M_{t-1}$$

$$(6)\ e_t = D_t - F_t$$

Least squares

This model is a regression model and is suitable for intermediate and long-term forecasts since little weight is set for short-term fluctuations in comparison to the moving average and EWMA (IFS 2009). According to Anon (2018), the forecast of the least squares model is calculated according to the following formulas.

$$(7)\ \widehat{Y_t} = L_{t-n} + t * T; \ni min\left\{\sum_{i=1}^{n}(Y_i - \widehat{Y_i})^2\right\}$$

$$(8)\ L_{t-n} = \overline{D} - \frac{T*(n+1)}{2}$$

$$(9)\ T = \frac{\sum_{i=1}^{n} i*D_i - \frac{(n+1)}{2} * \sum_{i=1}^{n} D_i}{n * \frac{n^2-1}{12}}$$

$$(10)\ F_t^{(t+\tau)} = L_{t-n} + (\tau + n) * T * \rho^{\tau}$$

The equations are calculated with the following parameters;

$$n = the\ number\ of\ time\ periods\ observed$$
$$\rho = see\ table\ 4.1.$$
$$L_t = estimated\ level\ of\ period\ L$$
$$Y = expected\ yearly\ demand$$

Brown's level and trend
According to Anon (2018), Brown's level and trend is similar to Adaptive EWMA and the parameters are calculated as seen in equation (11) and (12).

$$(11)\ \alpha_B = 1 - \ (1-\alpha)^2$$

$$(12)\ \beta_B = \frac{\alpha^2}{1-(1-\alpha)^2}$$

The level and trend are computed with the formulas below.

$$(13)\ L_t = \alpha_B * D_t + (1-\alpha_B)(L_{t-1} + T_{t-1})$$

$$(14)\ T_t = \beta_B(L_t - L_{t-1}) + (1+\beta_B) * T_{t-1}$$

The forecast is calculated with the following relationship.

$$(15)\ F_t^{(n)} = L_t + n * T_t * \rho^n, n = 1,2,3, \ldots$$

4.1.2. The forecast model parameters

The parameters of the Bayesian forecasting model should be set differently depending on various factors such as industry as well as demand trends and patterns. For example, new product introductions such as ramp-up and rollover products need to have more reactive trend and level parameters than mature products (Olhager 2018).

The level and trend factors, referred to as α and β, have a significant impact on the forecast. Both parameters have an interval [0, 1] and depending on the value set, the forecast is more or less reactive. For example, at 0, the parameter is non-reactive compared to very reactive at the value 1 (Olhager 2018).

4.1.3. Coefficient of variance

A common statistical measure is the coefficient of variation and it is defined as the standard deviation divided by the mean for a unit (Huynh et al. 2016). The coefficient has many different areas of application (Huynh et al. 2016; D'Alessandro and Baveja 2000). In this subsection, an example of how it could be utilized is presented. In the study by D’Alessandro and Baveja (2000), the coefficient of variation was used to measure and compare products’ demand volatility where the unit of measure was the average weekly demand, see figure 4.1. The way to utilize the figure can be seen below.

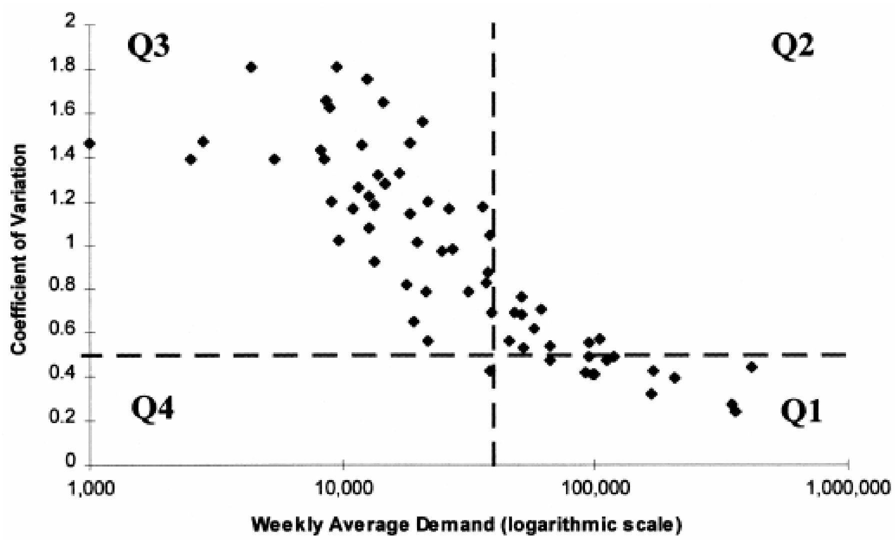

Figure 4.1. Differentiation with coefficient of (D'Alessandro & Baveja 2000)

In the quadrant Q1, visualized in figure 4.1, includes products with a high volume and a low demand volatility and in Q2, products with high volume and demand volatility. Furthermore, Q3 includes products with a low volume and high demand volatility were as in, Q4, products with low volume and demand volatility can be seen. This segmentation of demand volatility could ease the understanding of how the demand predictions vary between the quadrants to further create differentiated strategies for the products (D'Alessandro and Baveja 2000).

4.2. The technology of machine learning

According to Gerbert et al. (2017), ML is a sub area within AI and the technology is used when detecting and identifying connections in data. ML manages both linear and nonlinear problems. This technology with the ever-increasing amounts of data within organizations today, a multitude of optimization potential within business processes can be found (Gerbert et al. 2017). As demonstrated in figure 4.2, ML and technology areas overlapping this concept are many and the lines between the different concepts can sometimes be hard to distinguish.

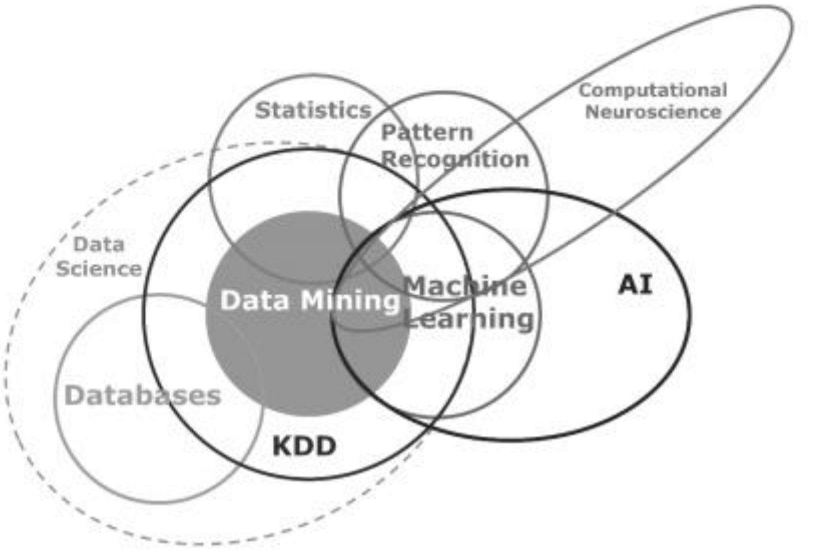

Figure 4.2. Machine learning and overlapping technologies (Hall et al. 2014)

The term *learn* is used when referring to the training of the algorithms but of course, the algorithms don't have that actual cognitive ability to learn. It is simply a way of explaining the process of optimizing a set of model parameters numerically with the purpose of minimizing a cost function (Farber 2017).

According to Abu-Mostafa (2012), there are three components vital for a problem to be solved with ML. These three components are the following;

- A sufficiency in the amount of data available
- An inability to mathematically pin down the problem
- An actual existence of a pattern

The first component of having a sufficient amount of data available is the most crucial component. The motivation behind this is that if there is insufficient amount of data, the output received will be deceptive. The algorithm can make a prediction, but it may not be reliable. Secondly, if the problem can be pinned down mathematically, it means that the function is known, and ML is not necessary to solve the task. However, ML may still solve the problem in a sufficient and effective way. Lastly, if no pattern exists, this would be the resulting output from a correctly trained algorithm. Even if this fact doesn't lead to any improvements, it would be the correct answer (Abu-Mostafa 2012). According to Schapire (2018), the best approach of finding a suitable algorithm for the problem is to select a few algorithms that have a good fit in regard to their area of application. These algorithms should further be tested and compared in terms of their success before a deliberation of what algorithm would be the most suitable for the application in question (Schapire 2018).

There are several types of ML models and they can be segmented in various ways. In the coming two sections, the process- and function-based segmented models are explained.

4.3. Process-based segmentation

There are three commonly used process-based models to characterize ML algorithms (Abu-Mostafa 2012). These models are supervised learning, unsupervised learning and reinforcement learning (Jones 2017). This division is derived from how the learning process is performed within ML (Suthaharan 2015). This section will describe the categories supervised and unsupervised learning.

4.3.1. Supervised learning

According to Jones (2017), the algorithms associated with supervised learning have the common factor of being trained with labeled data. By processing labeled output data, the model receives feedback during the training and this is the key attribute for the learning process. Supervised learning algorithms can be utilized for different algorithms depending on what type of prediction is sought. The most commonly used estimator types within supervised learning are classification and regression models (Microsoft 2017).

4.3.2. Unsupervised learning

In contrast to supervised learning, the main concept of unsupervised learning is that the training procedure is performed on unlabeled data (IBM 2018b). When processing unlabeled data, there is no feedback loop that measures the performance of the algorithm (McKinsey 2018a). An unsupervised algorithm finds a structure in the unlabeled dataset and then classifies the dataset members into different segments that are characterized by a similar behavior (McKinsey 2018b). The most common unsupervised learning model is a clustering model (Anon 2017a).

4.4. Function-based segmentation

Some of the most commonly used ML models segmented on their functionality are regression, classification and clustering models. This segmentation has its basis in how ML could be modeled (Suthaharan 2015). A simplified function-based decision model can be seen figure 4.3.

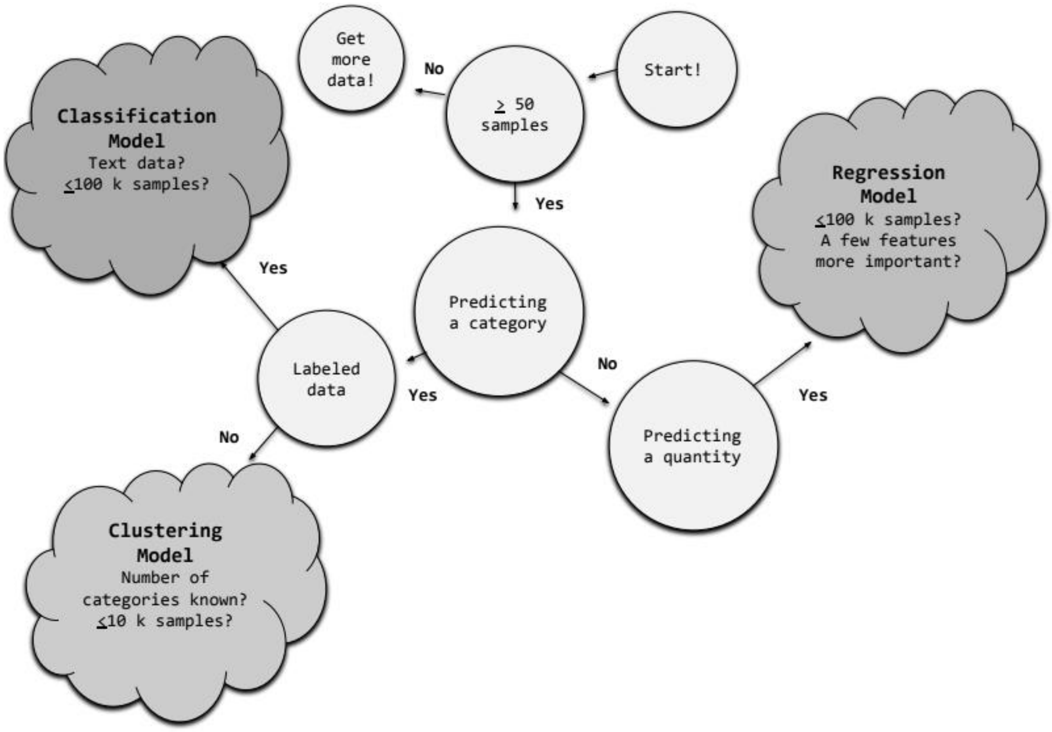

Figure 4.3. Function-based decision model (Anon 2017b)

4.4.1. Regression modeling

A regression model is a supervised learning model that is utilized to make predictions on quantity. The model makes predictions through identifying the relationship between the input and output variables in a dataset, see x and y in figure 4.3. (Bousqaoui & Achchab 2017; Suthaharan 2015).

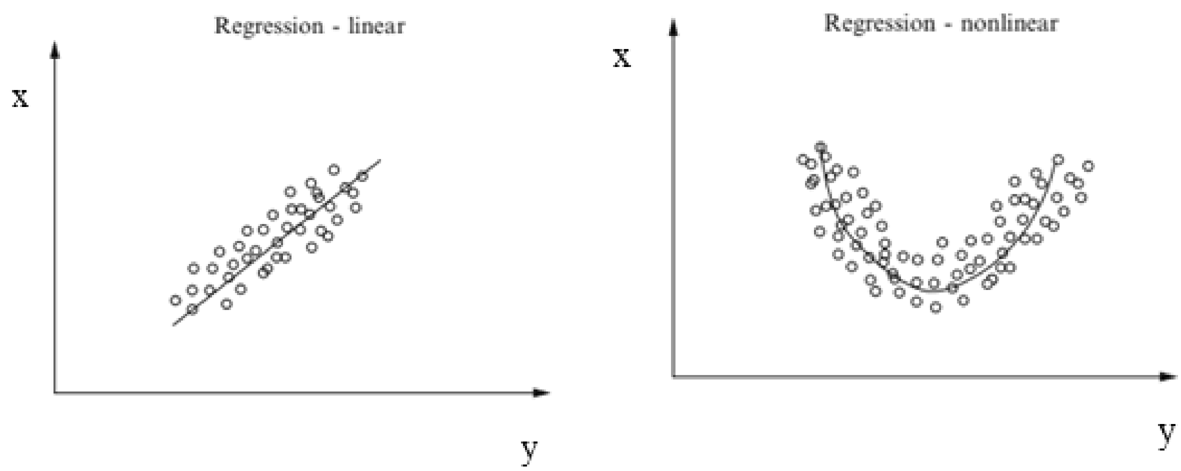

Figure 4.4. An example of linear and nonlinear regression models (Suthaharan 2015)

As can be seen in the figure 4.4, there are both linear and nonlinear regression models (Witten & Frank 2005; Suthaharan 2015). In linear regression, the dataset variables fit a linear equation. The same principle applies for nonlinear regression models were the variables fit a nonlinear equation. When the equation is fitted by the data, a prediction of the y value can be obtained for a given x value (Suthaharan 2015). A practical example of a typical application for a regression model is predicting stock prices (Anon 2018b).

4.4.2. Classification modeling

A classification model is a supervised learning model and is used make a prediction on category for members of a dataset. Since the data is labeled, it is possible to train the algorithm to find rules that in a later stage forms the basis for classifying other unlabeled datasets. Figure 4.5. illustrates an example of a dataset labeled into to two classes, visualized as black and white dots. The straight line in the right graph is the identified rule and is the basis for the classification of new data (Suthaharan 2015).

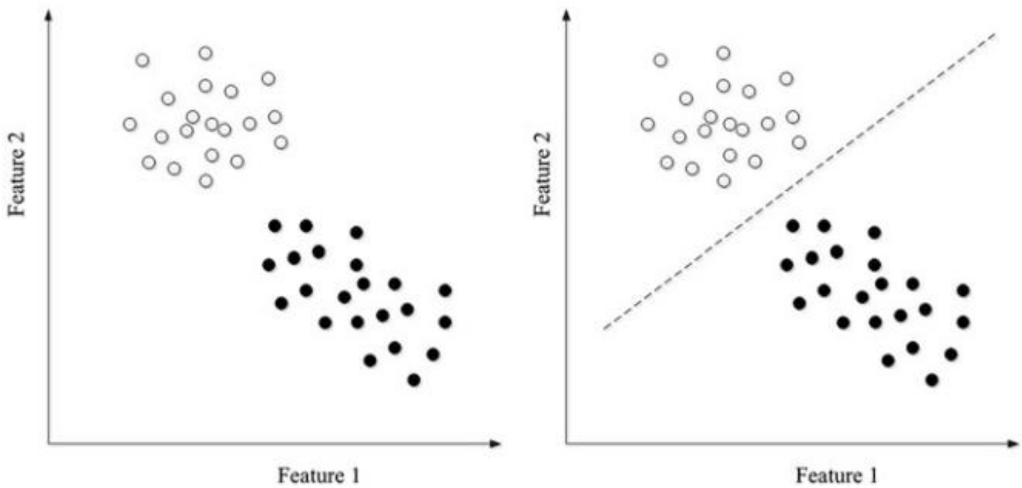

Figure 4.5. Class formation in a classification model (Suthaharan 2015)

Classification models could be used to determine a medical diagnosis, evaluate whether an email is spam or to interpret the meaning of a handwritten letter (Wendler & Gröttrup 2016).

4.4.3. Clustering modeling

Clustering is a form of unsupervised learning where the algorithm sorts the members in a dataset into clusters. Since there are no labels that could derive a rule as in a classification model, clustering is performed through a different approach. The formation of the clusters has its basis in the geometrical pattern of the dataset members which are plotted in their graphs from their variables, see figure 4.6. The members of the dataset are allocated to the cluster where the distance between the member and the cluster's members are minimized for a single or few variables (IBM 2018a; Suthaharan 2015).

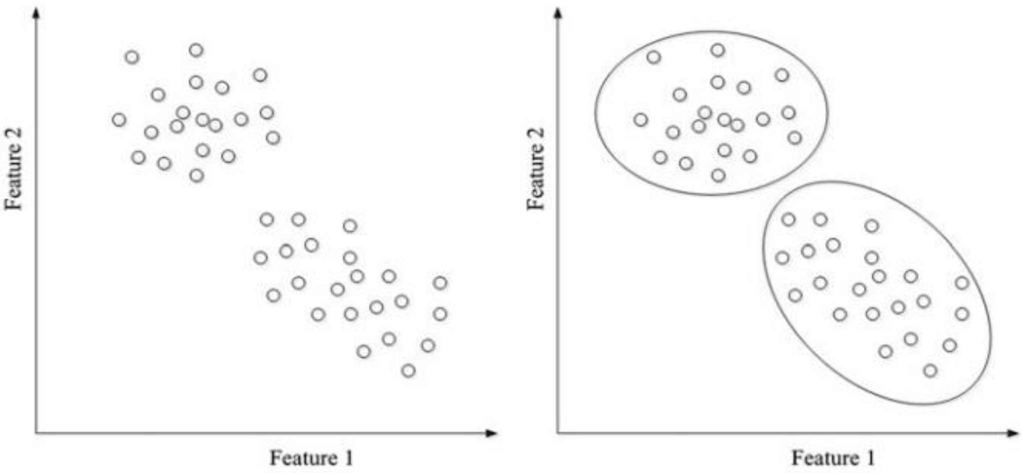

Figure 4.6. An example of a cluster formation (Suthaharan 2015)

An example of application for a clustering model could be to discover unknown ways to structure data (California Institute of Technology 2018; Hetu 2017; Carlton 2017). A situation where this kind of analysis would be relevant may be when a marketing campaign should be targeted to new customer groups with less noticeable characteristics (McKinsey 2018a).

4.5. Risks associated with machine learning

ML is a complex technology and when implemented into business processes, it may imply exposing the business to new risks. According to Brynjolfsson and McAfee (2017), the risks associated with an implementation should therefore be properly identified, analyzed and if necessary, mitigated. This section aims at clarifying common risks with ML.

A human can easily explain and trace her thought of reasoning that derives a decision. This implies an important transparency in the human decision-making process, often taken for granted (Davenport & Ronanki 2018). This is however a large risk with ML. A model's output is often developed through a vast amount of connections in data which makes the reasoning behind the decisions hard to trace and interpret (Brynjolfsson & McAfee 2017). This is particularly a problem with the extensive networks of deep learning where it is almost impossible to trace the decision-making elements of the algorithms. This phenomenon is often referred to as the black-box dilemma (Davenport & Ronanki 2018) and raises the question of whether the results of a ML algorithm should be trusted or not. This is especially an important question to evaluate in highly regulated industries where it is crucial to maintain a transparency of the decisions made (Davenport & Ronanki 2018). Therefore, this black-box dilemma poses a risk that should be evaluated depending on the intended environment.

According to Brynjolfsson and Mcafee (2017), an additional risk is that there is always a certain amount of uncertainty in predictions. A larger amount of data may increase the accuracy and therefore, reduce the uncertainty connected to the prediction. However, it will not diminish it completely. This is an important aspect to take into consideration when utilizing the technology. Uncertainty in predictions poses a serious threat if the technology is applied to critical processes. For instance, a process performed at a nuclear power plant. Furthermore, processes where the uncertainty can generate a major disaster if the unlikely outcome occurs, ML may not be an appropriate technology to apply (Brynjolfsson & McAfee 2017).

There is also a risk associated with hidden biases. Even if the algorithms per se do not involve personal bias, there is a risk of bias that stems from the datasets used to train the algorithm. An example of this could be a ML algorithm that is trained by data from manual processes. Furthermore, the algorithms can also contain bias from the code it is built on. This may not be a deliberate intention by the designer of the algorithm and they are often unaware of the existence of the bias (Brynjolfsson & Mcafee 2017).

Lastly, the human brain performs generalizations well and if ML should replace manual tasks, it is crucial that the model performs sufficiently in this feature as well (Jensen 2018). Under- and overfitting are two identified risks when developing and training a ML model. Underfitting is when the developed model is too simple to pick up on trends of the data. This phenomenon can be seen in the graph to the left in figure 4.7. In contrast, overfitting is when the model is too sensitive causing the model to recognize noise too well. This leads to the model over-interpolating the data which results in an impaired ability to make reliable predictions. This phenomenon can be seen in the graph to the right in figure 4.7. The performance of a balanced ML algorithm can be found in the middle of figure below (Jensen 2018).

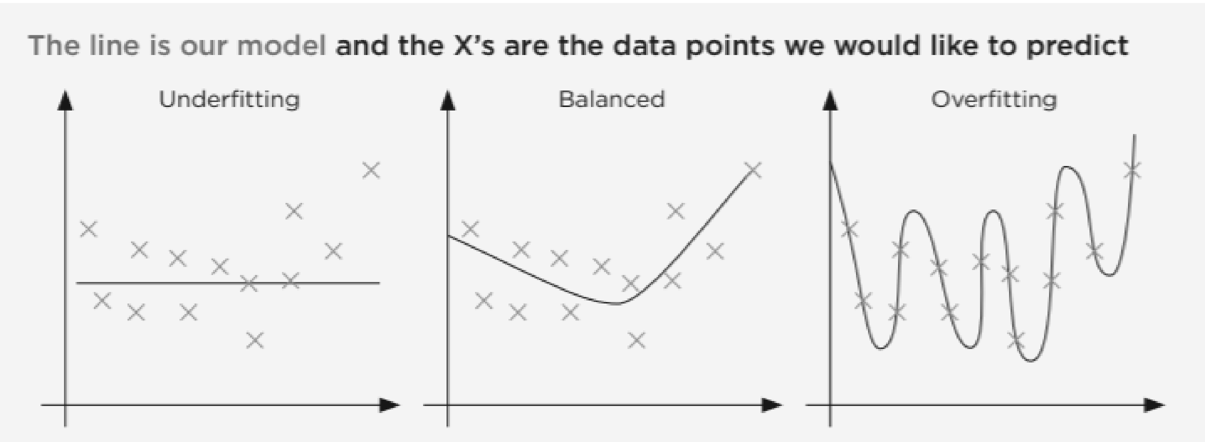

Figure 4.7. Over- and underfitting models in machine learning (Jensen 2018)

4.6. Artificial intelligence requirements

Despite the hype of AI, several studies illuminate the gap between ambition and execution amongst organizations considering an implementation (Ransbotham et al. 2017; Küpper et al. 2018). In the study by Ransbotham et al. (2017), 84 % of the respondents believed that AI would obtain or sustain competitive advantage for their company. However, just a fraction of these companies has implemented AI in a larger scale. This section aims to clarify AI requirements that may be relevant when enhancing the implementation success of ML in business processes.

Corporate strategy and management
In a survey presented by Baan et at. (2017), it is concluded that the biggest barrier of implementing AI applications is AI not being a strategic priority by top management. One of the motivations behind this was that top management is not being clear about the value of AI. Furthermore, to consider launching an AI transformation, the importance of an established corporate strategy is also highlighted in the study by Küpper et al. (2018). According to Baan et al. (2017), when defining the corporate strategy of AI, it is important to conduct an analysis of the impact of AI on the industry. From this analysis, a strategic stance should be taken depending on the environment of the organization and the benefits that can be made.

If top management is onboard, continuous communication of the potential gains is an important element to reduce the cultural resistance towards AI. It is also essential to ensure a clear delegation of roles and responsibilities during the implementation of AI (Küpper et al. 2018). Pyle & José (2015) also stresses that top management must influence and encourage the implementation of the technology throughout the organization. The authors suggest that success stories should be communicated to ease the change of ML (Pyle and José 2015).

Another strategic aspect mentioned in literature is organizational flexibility. According to Ransbotham et al. 2017, this is a requirement to handle the difficulties connected to AI initiatives. To adopt AI in a broader sense, cross-functional collaboration needs to be facilitated within the organization. Baan et al. (2017) proposes a centralized unit that supports the organization's AI initiatives across business units. Ransbotham et al. (2017) also presents a similar structure to support AI within the organization. The authors of this study suggest that companies should both have a centralized unit that collaborates cross-functionally as well as a number of decentralized units with AI analytics competence. The purpose of the central unit is not to take responsibility for all AI initiatives within the organization but to provide expertise, support and guidance to the decentralized internal units (Ransbotham et al. 2017).

Knowledge and competence
The acquisition of knowledgeable personnel with competence within programming, data management and analytics are important requirements when launching an AI transformation (Küpper et al. 2018). In this study, the recommendation is to form a clear perception of the competence needed in order to bridge the gap between the company's already existing competence and what is needed for implementing AI (Küpper et al. 2018; Bughin et al. 2017). In the study by Küpper et al. (2018), 93 % of the survey respondents believed that they had insufficient competence to implement AI into their operational processes (Küpper et al. 2018).

Moreover, in the study by Baan et al. (2017) the lack of talent and knowledge were highlighted as the biggest barrier for implementing AI applications. The study described common situations where companies experienced difficulties with both attracting as well as maintaining talent within AI. The outcome of the study was that the recruitment requires more dedication and concretization of the company's AI ambitions. Whereupon, the study further illuminated the common occurrence of AI talent leaving a company as disappointment of what the career actually turned out to be arises (Baan et al. 2017; Bughin et al. 2017).

Data infrastructure

The data accessibility is the fundamental requirement for ML. Several studies illuminate the importance to gather and consolidate data available in an organization to an accessible data warehouse. This enables a clear overview of data available and eases its accessibility (Baan et al. 2017; Bughin et al. 2017). Moreover, it is important that the IT systems a company has in place are compatible and able to communicate with each other (Küpper et al. 2018) .

According to Baan et al. (2017), there are a few major dimensions to prepare for an AI transformation. One of these dimensions is to redesign the work flows to be aligned with the requirements accompanying AI integration. This competence should be distributed throughout the organization to facilitate the new processes. Some examples of competences to be distributed are AI customized policies, data-quality and management principles to generate an improved and more efficient data infrastructure.

5. Analysis & results

The first part of this chapter aims to present potential areas of improvement in Axis' demand planning process based on the findings in the empirics and the theoretical framework. Proposed ML models that address the identified areas are then presented and discussed. The second part of this chapter aims at presenting a framework that illuminates the factors to consider when implementing ML in the demand planning process.

5.1. Connecting areas of improvement with propositions

In the beginning of this study, a thorough investigation of Axis' demand planning and cross-functional processes affecting the demand forecast was conducted. This investigation resulted in an identification of several areas that were considered to be improved by ML. Together with the theoretical framework describing the complexities of the ML technology and its potential benefits, various propositions started to take form. The propositions that were assessed to be feasible and have high improvement potential were selected and further developed.

These selected propositions are presented in a simplified form and believed to have potential to generate value by a somewhat easy implementation if successful. However, if correlations are found as the propositions suggest, the applications could be developed to generate further value. These propositions are visualized in figure 5.1. and are presented in detail in the coming subsections.

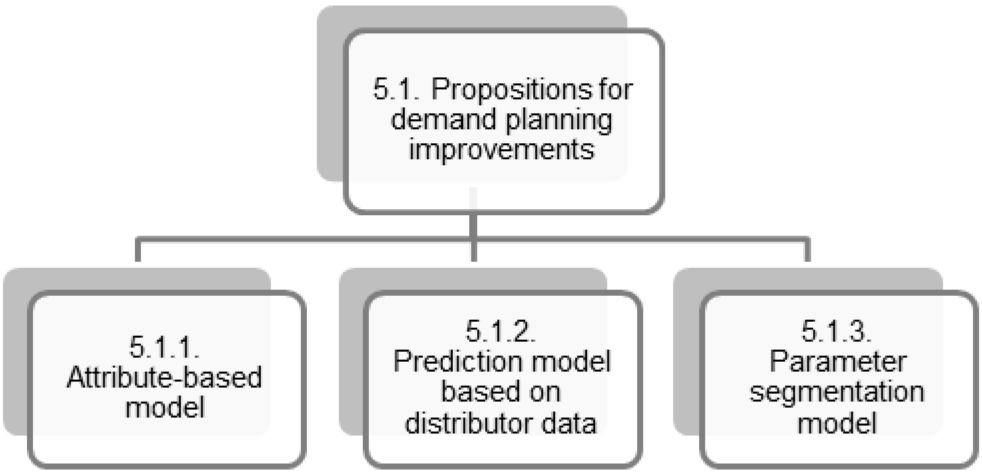

Figure 5.1. Visualization of the proposed applications

5.1.1. The attribute-based model

A recurring issue when developing the demand forecast is the lack of data. For new products, there are for obvious reasons, no historical demand data that could derive a forecast. As of today, the current demand forecasts for new products are based on subjective analyses and discussions among different functions at Axis, see subsection 3.5.2. Furthermore, Axis' products generally have short product life cycles which implies less data than products with a longer product life cycle would generate. This issue is also amplified by Axis' historical demand data being aggregated on a monthly basis generating even less data points. It is possible that a higher forecast accuracy can be achieved if more data, reflecting the demand complexity, was available.

Purpose of the proposition
The purpose of this proposition is to make more data available to facilitate the development of the demand forecast. This proposition suggests the utilization of historical demand data from other Axis products with similar attributes to the forecasted product. This is motivated by the assumption that products with similar attributes may have similar demand patterns. The purpose of this proposition is therefore to analyze whether this assumption holds true and if the product attributes could be used as additional dimensions when forecasting a product's demand.

Proposed modeling
A regression model is suggested for this proposition because it enables a quantitative prediction of the sought output, product demand, see subsection 4.4.1. The suggested initial inputs for this proposition are the product's attributes, price level and historical demand. The inclusion of these inputs could enable the regression model to find the relationship between similar products and their product demand. The inputs for the model and the motivation for their inclusion are described below.

The expectation of including the product's attributes is that the model displays the weighted importance of the attributes by identifying connections in the historical demand from multiple products. The price level of the products is an important dimension to integrate into the model. This input is believed to differentiate the customer's choice of products, a dimension that would not be reflected in a model with only the product's attributes.

The last input, the historical demand is an important dimension to integrate into the model for two reasons. Firstly, Axis has a rapid company growth, see section 1.3. This dimension is likely to affect the overall product demand and should therefore be included to this model. This aspect may also indicate external trends affecting the product assortment as an entirety, for example socio-economic trends and seasonality. Secondly, the model is a supervised learning model, see subsection 4.3.1. This implies that the training of the model requires the historical demand to produce a sufficient prediction of the future demand. The suggested inputs and where they can be extracted from Axis are summarized in table 5.1.

Table 5.1. The suggested inputs for the attribute-based model

Model inputs	**Data source**
Attributes/sales unit	PIA system
Price/sales unit	IFS Applications
Historical demand/sales unit	IFS Demand Plan Client

It is necessary to evaluate the inputs in regard to how they should be specified in the model. The input product attributes is suggested to be specified on the sales unit level. The product's attributes are fully represented on this level and is assessed to reflect the dimensions of the product attributes sufficiently. The input of the product's price level should be specified on sales unit level. These specifications should be discussed and evaluated further on suitability as well as feasibility.

The historical demand input is suggested to be specified on a monthly basis on sales unit level. The motivation behind this suggestion is that Axis most likely has not had a homogenous growth on all markets. This input would therefore reflect the demand on a specific region. Furthermore, the input should be aggregated to the monthly demand for a sales unit because that is how it is specified in the system today.

The output of the model is the predicted demand on sales unit level. The reasoning behind this is that the demand forecast is currently performed on sales unit level, see subsection 3.5.2. It would therefore be beneficial to ensure that the model's result is compatible and comparable with the current forecast.

Discussion

This proposition aims to extend the current analysis beyond the product predecessors and retrieve insights from non-predecessors, see subsection 3.5.2. The nature of this regression model is multidimensional, and it has a few complex elements. If the model is not generating accurate predictions, it may be advantageous to simplify the model even further or investigate if isolated markets or other product levels would generate a better result.

Firstly, the model can be further simplified by decreasing the attributes integrated into the model that are strongly believed to correlate. There are risks of having large amounts of dimensions in such analyses. If the number of dimensions is too many in relation to the number of cameras analyzed, the weighted importance of the attributes may not be sufficiently reliable. The limitation of attributes reflecting the dimensions could reduce this risk (Bodin 2018; Saknini 2018; Gustafsson 2018). It is therefore recommended to adapt an approach to limit the attributes successively. However, it should be noted that this could integrate subjectivity into the model and associated risks should be taken into consideration when contemplating an advancement of this simplification.

Furthermore, some markets may, for various reasons, be more stable and standardized than others contributing to correlations more easily located. Testing this proposition on different markets may generate different results, where some are of value, and others not.

The suggested specification of the model output is on sales unit level. However the same aspects could be applied to the product level of the model. If this analysis on sales unit level is not generating the results expected, a prediction could be done on product, product family and product series level. However, the more aggregated level the analysis is performed on, the less takeaways can be retrieved. The potential takeaways on the respective level should be evaluated individually.

Lastly, Axis is a company that has experienced a rapid company growth and large organizational changes the last years. This may cause older historical demand data not to be fully representative of the future demand. Together with the amount of data available and what is assessed to be required for a successful implementation of the model, it might be necessary to limit the data collected deemed representative.

Further development
If this proposition would be implemented successfully, it could be utilized as an indicator to complement to the current demand forecasting process. However, depending on the performance of the model, it may be assessed beneficial to integrate the indicator to the demand forecast in a later stage.

A potential development of this model may be the integration of a dimension reflecting the scarcity of components. This potential input to the model could facilitate with higher prediction accuracy by filtering out events concealing the actual customer demand in that moment in time.

Another aspect that may further develop the model could be the integration of other inputs reflecting external trends and patterns. The historical demand might capture some of these dimensions mentioned. However, if this would be further assessed, other inputs reflecting these aspects in a better and more representative way may be found. The inclusion of other inputs, internal or external, is therefore suggested to be further discussed and assessed at a later stage to develop this model further.

Lastly, it is possible that additional data could be integrated into this model at a later stage. The site designer data as well as heat map data could be interesting for this analysis. If products are registered in the site designer tool with increasing or decreasing frequency, this could indicate a trend or change in demand, see section 3.6. A similar analysis could be done for the heat map data, see section 3.6. In these data, the click, movement and scroll data may give indications of the future demand. For example, if the frequency of clicks for a certain product increases, this may be an indication of an increased interest for a product. The movement and scroll data could be used to analyze the customer interest based on how he or she moves on the website. For example, an immediate search on a product may indicate a higher interest than sequential clicks towards the product since it may indicate a stronger purpose in the search. The scroll data could possibly reveal the customers' interest by measuring how much the customer reads about the product on the website.

5.1.2. Prediction model based on distributor data

There are currently efforts taken to analyze and interpret the interplay between the sales in and sales out data from distributors, see subsection 3.6.1. These analyses are mainly done on an aggregated primary commodity group level, summarized on all markets. The potential insights of this analysis are therefore limited to an overall perception of the current state and no quantitative prediction on product demand can be extracted. Moreover, this analysis is performed when considered necessary and not on a regular basis. This makes it difficult to draw conclusions regarding the quality of the results and furthermore, to continuously improve the performance of the analysis. With this model, it is possible that deeper insights from the data and a quantitative prediction on product demand could be achieved.

Purpose of the proposition

This proposition aims to explore if a quantitative analysis on the sales in and sales out data could enable a sufficiently accurate demand prediction on sales unit level. If the demand prediction can be conducted on this level, it may contribute with more useful results than the current analysis and form a more compatible complement to the current forecast. Moreover, this analysis may contribute to deeper insights on the market trends and patterns as well as how the distributors manage their inventory.

Proposed modeling

A regression model is suggested for this proposition enabling a quantitative prediction of the sought output, the product demand, see subsection 4.4.1. The suggested inputs for this proposition are the product's historical demand and their sales in and sales out data, see table 5.2. The inputs for the model are presented in detail below.

The historical demand per month is an important dimension to integrate into the model since Axis has undergone a rapid economic growth the last years, see section 1.1. This dimension is likely to affect the product demand and should therefore be included to this model. The training of this supervised learning model also requires the historical demand to produce a product demand prediction, see subsection 4.3.1.

The interplay between the sales in and sales out data is believed to represent the distributor's inventory on hand, see subsection 3.6.1. The sought insights are the distributor's procurement patterns, on an aggregated as well as individual level which motivates this input inclusion to the model.

Table 5.2. Suggested inputs for the prediction model based on distributor data

Model inputs	**Data source**
Sales in data/distributor/sales unit	QlikView
Sales out data/distributor/sales unit	QlikView
Historical demand/sales unit	IFS Demand Plan Client

For the suggested inputs and outputs, it is necessary to evaluate them in regard to how they should be specified in the model to optimally reflect the dimensions they are intended for. Firstly, both the sales in and sales out data per distributor should be specified on sales unit level. These specifications should be discussed and evaluated further on suitability as well as feasibility.

The historical demand input is suggested on sales unit level. The motivation behind this suggested specification is that Axis most likely has not had a homogenous growth on all markets. This input should therefore reflect the demand on a specific region.

Lastly, the output of the model is a prediction of the demand on a sales unit level. The reasoning behind this, similar to the attribute-based model, is that the current demand forecast is performed on this level. A desired outcome would be four months of sufficiently accurate predictions into the future. This is motivated by the time span to procure 85 % of the cameras' components mentioned in section 1.3. and is considered to enable the possibility of taking action based on most cases risking disruption in material flow. However, the application could still improve the demand forecast with less reliable outcome.

Discussion

This proposition aims to extend the sales in and sales out data analysis at the demand planning department today through a more quantitative approach. If correlations in the demand patterns of the distributors are found, a quantitative demand prediction on sales unit level may be achieved. Since the sales in and sales out data today is already extracted and collected over a longer period of time, these data are assumed to be feasible and clean, as well as relatively simple to implement into this model.

It is at this point unclear how many months forward the model can produce sufficiently reliable demand forecasts. Factors that influence the reliability of the output are dependent on the amount and quality of the data. Aspects that can affect the quality of the data are for example the distributor's standardization of processes as well as how uniform the distributors handle their inventory. If the inventory is handled unstandardized, there is a risk of the application needing more data to draw valid predictions.

It may be interesting to see if these patterns vary on other levels, for example, with product lines or primary commodity groups. Furthermore, it is possible that trends and patterns for the respective level could generate insights on region and customer trends that could be useful to both the demand planning analyses as well as other functions at Axis. The demand forecast is believed to perform well in the near future if the distributors' inventory management, trends and patterns are identified. Furthermore, the data for this model are at this point assessed to require a smaller amount of cleaning and preparation. However, the potential correlations and predictions detected in the data are uncertain.

Further development
If this proposition would be implemented successfully, it could be utilized as a complementary indicator or a parallel forecast facilitated to a degree suitable to the performance of the application. Additionally, it is possible that this model could be developed in a similar way as the attribute-based model in regard to the site designer and heat map data, see subsection 5.1.1.

5.1.3. Parameter segmentation model

The parameters facilitating the forecast model are standardized for all products, see subsection 3.5.2. This is not considered to be a suitable parameter setting due to variations in the product demand pattern, see subsection 4.1.2. Firstly, the parameters are not reactive enough for volatile products which causes the model to level out new trends too slowly. The second issue is that the parameters are too reactive for some products which causes the forecast to reflect the demand peaks too much. These issues make it necessary for the demand planners to adjust the forecast manually, see subsection 3.5.2. The manual adjustment is both time-consuming and opens the possibility of integrating human biases as well as mistakes into the demand forecast.

Purpose of the proposition
This proposition aims to explore if the products can be segmented based on their demand volatility. Depending on the outcome, the forecast model parameters could be adjusted accordingly, and the statistical model optimized after the products it is applied to. A statistical forecast model with an optimized parameter setup may contribute with several improvements. Firstly, a more accurate demand forecast could be generated. Secondly, the forecast would require less adjustments in retrospect. This aspect may further lead to a reduction of the manual work as well as human bias and mistakes entering the demand forecast.

Proposed modelling
A clustering model is suggested for this proposition because it would enable a segmentation of products with similar demand volatility. In this proposition, these segments would be the basis for a differentiated parameter setup. This is motivated by the assumption that products with similar demand patterns should have similar parameters in the forecast model.

This proposition would be an early ML application to optimize the models' parameters in regard to their demand volatility. To enable this proposed segmentation through ML, a measurable variable that reflects the degree of the demand volatility for each product must be specified. For this proposition, the coefficient of variation is suggested as a model input. The potential clustering factors are visualized in table 5.3.

Table 5.3. Suggested clustering inputs to segment Axis products

Clustering factors	**Model inputs**	**Data source**
Demand volatility	Coefficient of variation	IFS Demand Plan Client /Excel
Demand	Historical demand/sales unit	IFS Demand Plan Client

This proposition suggests forming clusters based on the clustering factors in table 5.3. and in a later stage, optimize the forecast parameters for these clusters. As stated in subsection 4.1.2, the parameters α and β, are assessed to have a significant impact on the demand forecast. When the clusters have taken from, the next step is to optimize these parameters with regards to the formed clusters. In this initial modeling, the optimization of the parameters aligned with the segmented clusters, is suggested to be adjusted manually.

Discussion

For this proposition, the demand volatility was assessed to reflect the issue at hand when optimizing α and β. However, there might be other dimensions advantageous to integrate into the model. It was not considered feasible to investigate this further within the scope of this study. It is assessed to be important to thoroughly analyze and evaluate alternative dimensions before going further with this model. Furthermore, the success of this model is dependent on the segmentation parameters' ability to reflect the actual demand volatility. The suggested variable, the coefficient of variation, is evaluated to be a good starting point for this dimension. The motivation behind this is the accessibility of the standard deviation on product demand in IFS Demand Plan Client as well as the support in literature, see subsection 4.1.3. Whether the coefficient of variation is the most suitable variable for implementing this proposition at Axis should be further tested and investigated.

The proposed segmentation could be performed with both a clustering as well as a classification model. However, with the few dimensions and the manual work required to label the data, a clustering model is the recommended option. In the suggested initial application, the parameters are manually adjusted after the segmented clusters.

The parameter setting of α and β should be assessed after the clusters have be formed. As mentioned in subsection 4.1.2, the products considered to be more stable should be matched with a lower value of both α and β while the products identified with more fluctuating demand should be given a higher parameter setup.

Lastly, this proposition presumes that the parameters in IFS Demand Plan Client can be adjusted and accessed by the demand planning team.

Further development

As mentioned, the proposed model is a simplified model generating limited amounts of value but is assessed to have more potential long-term. The ultimate target in a later stage is to implement an automated parameter setup for the formed clusters. However, the complexity of the model makes the simplified version assessed to be a suitable initial application to assess the feasibility and benefits. Furthermore, the automation of the parameter setup requires an investigation of how to optimize the parameters accordingly as well as developing a system when this automation occurs. This further development could have elements of ML, but this is not a necessity and is outside the scope of this study.

A further development of the model could be to add more segmentation parameters to reflect more dimensions than demand volatility.

Lastly, the number of clusters formed could also be developed. Note that there is no suggested number of clusters for this proposition at this stage. This was a deliberate choice from the authors since this decision would be easier addressed when tested.

5.2. Current state analysis of implementation environment

In this section, Axis' current state is analyzed in regard to factors to consider when implementing ML at the demand planning department.

5.2.1. Cross-functional collaboration

The demand planning department has an interest in improving the demand forecast with ML. However, a ML application often includes cross-functional collaboration when allocating resources and data from other functions. When developing the propositions for this research, there has seldom been shared incentives between the functions involved which have hindered the development. Moreover, Axis does not have an established strategic stance on ML that could align business processes with ML. Nevertheless, when gathering information for this research, it has worked relatively well due to Axis' open company culture. However, a higher engagement from other functions may be required together with a clear strategy for allocating ML resources for business processes, if ML would be implemented to a more extensive degree than today.

5.2.2. Competences within the organization

As of today, there is ML knowledge at Axis, see section 3.7. However, this knowledge is mostly related to machine vision which is not directly applicable to business processes performed at the demand planning department. The datasets are often different both in regard to size and format and other models as well as requirements are connected to the processes. Throughout this research, a lack of ML competence related to the process setup in question has been identified as a barrier. Furthermore, the knowledge related to ML at Axis is scattered and isolated throughout the organization. This makes it difficult to find the right competence, even if it would be present in some function within Axis.

In this research, it has been difficult to communicate between functions even if ML competence is located. This is assessed to be a result of the limited amounts of insights into the different functions’ responsibilities, incentives as well as the knowledge required to understand the general processes. Within functions at Axis aiming to utilize ML in business processes, a lack of understanding for the technology has been found. This makes the identification of key variables and basic algorithm requirements difficult to communicate with ML knowledgeable in a project. These cognitive distances have often hindered the drafting of the ML propositions.

5.2.3. Data architecture

The organizational structure at Axis implies vast amounts of data locally collected at different functions. This is no efficient way to find data collected at Axis since it requires involvement of other functions. This is both time-consuming and risks an unawareness of the actual data available at Axis. The absence of an overview of data available at Axis often hindered this research from moving forward. Moreover, some of Axis’ data sources have inconsistencies due to data uncleanliness and an unstandardized utilization of the information systems. This is a big issue when implementing ML that utilizes these data.

5.3. Factor assessment framework

The development of the ML propositions has provided reflections of factors to consider when implementing ML at Axis, see section 5.2. Together with the theoretical framework highlighting common implementation requirements, an assessment framework was constructed, see table 5.4. The purpose of this framework is to identify, structure and assess the factors to consider when implementing ML at Axis.

Table 5.4. Proposed framework for identifying factors related to ML implementations

Categories	**Factors to consider**
Strategic alignment	• Establish & communicate strategic stance • Provide a sufficient resource allocation • Form machine learning support network • Support cross-functional collaboration
Competence management	• Acquire and maintain knowledge & competence • Bridge the competence gap • Develop reality-based expectations
Data accessibility	• Construct a data warehouse • Facilitate data extraction • Generate consistent & cleaned data

5.3.1. Strategic alignment

It is important to develop a strategic alignment regarding the degree of ML integrated into Axis and how it should be implemented. Pushing the technology and integrating ML into

Axis’ products has been a natural step for Axis. However, no major efforts have been identified to ease the implementation of ML into the demand planning process.

Establish & communicate strategic stance

As mentioned in section 4.6, the biggest barrier when implementing AI in an organization is the lack of strategic priority by top management. Therefore, Axis should establish a strategic stance on degree of ML integration into their business processes such as the demand planning processes. When the potential value of ML in the industry is assessed, the next step is to evaluate and quantify the value of ML for Axis by top management. This strategic stance as well as the potential value with ML should be clear and continuously communicated to the functions involved in the implementation, see section 4.6. The continuous communication would encourage the involved functions, reduce cultural resistance and knowledge barriers as well as facilitating when clarifying roles and responsibilities. These aspects are also highlighted as common requirements to implement AI in an organization, see section 4.6.

Provide a sufficient resource allocation

The lack of a clear established strategy for allocating ML resources to implementation projects within business processes has been identified at Axis, see subsection 5.2.1. The ML resources available within Axis are scarce and assessed to be prioritized to the existing processes and projects at other departments than the operations department or the demand planning department for that matter, see section 5.2.2. This implies difficulties to obtain resources to support a ML initiative within these departments. As mentioned in section 4.6, more than 9 out of 10 companies believe that they have insufficient resources to implement AI and here, Axis is not considered to be an exception. It is necessary for Axis to recruit ML competence that can support ML projects within business processes at the operations department. Furthermore, this implies competence allocated to support ML implementation into the demand planning processes.

Form machine learning support network

It should be noted that Axis already has some ML competence located at other functions, see section 3.7. To join this competence with newly recruited ML competence could be a good starting point to gather the scattered competence. Axis could suggestively develop a ML support network to provide a support system for the implementation teams as well as enabling the sharing of knowledge and experiences. Moreover, it is possible that this initiative would trigger the idea generation of ML improvements and facilitate a mapping of where personnel with the right knowledge can be located. The importance of having a ML support network is also something illuminated in section 4.6.

Support cross-functional collaboration

When implementing AI in broader sense, it is important to develop cross-functional collaboration throughout the organization, see section 4.6. It may be beneficial to establish shared incentives among the functions to facilitate cross-functional collaboration needed to help clean, locate, transfer data, see subsection 5.2.1. This may engage the involved functions and generate a higher success rate. An example of this is that if the demand planning and supply planning department would collaborate when initiating ML improvements in demand planning processes. A more accurate demand forecast generates less manual labor to solve last minute supply issues, hence, beneficial for both functions. It is recommended that when considering a ML implementation, the establishment of shared incentives between functions should be strived for.

5.3.2. Competence management

This subsection mainly focuses on the cognitive distances and how competence should be managed for a successful ML implementation.

Acquire and maintain knowledge & competence
In section 4.6, the lack of talent and knowledge was highlighted to be the biggest barrier for implementing AI and this is also a barrier experienced at Axis, see subsection 5.2.2. Even if this issue is addressed and competence acquired, there are still factors to consider. As mentioned in the theoretical framework, attracting competence is not the sole issue at hand but also maintaining it. It is important for Axis to be as concrete as possible when communicating the ML ambitions during the recruitment processes. By giving the recruited a fair chance to assess if the position is aligned with his or her own ambitions, the competence will less likely to leave the company.

Bridge the competence gap
The importance of a clear perception of the competence needed to bridge the gap between the company's existing knowledge and what is required for an AI implementation is highlighted in section 4.6. In this study, cognitive distances are assessed to exist between the demand planning department and other functions within Axis. The cognitive distances between the different departments in need of collaboration, some common issues are misunderstandings and missed requirements. This was experienced when drafting model propositions within Axis, see section 5.2. The gap of knowledge and competence between the demand planning team and the ML competence is a time-consuming and difficult barrier to overcome. To bridge this, personnel with experience within both operations and ML should be integrated into the composed implementation team.

As of today, the demand planning team possesses deep knowledge of the department’s processes like many other specialized functions. To integrate this knowledge when developing a ML model is crucial to ensure value creation. However, the integration of this competence into a ML project can be difficult due to the significant the mentioned cognitive distances between the demand planning team and ML knowledgeable personnel at Axis. To overcome these challenges, a high level of knowledge integration and collaboration is needed. To develop ML knowledge and experience in the demand planning team to any larger extent is not a reasonable solution due to the amount of resources required. However, it may make a significant difference if some elemental knowledge was developed. The relevant knowledge for the demand planning team could for example be the typical problems that could be solved with ML as well as the benefits and risks that accompany the model. The expectation with this knowledge enhancement is to trigger proposition generation when reflection on ML solutions in demand planning processes is possible.

Develop reality-based expectations
It is important to understand the level of expectations reasonable for a ML application. For example, even if the forecast prediction is improved through ML, it is still just a prediction as discussed in section 4.5. It is important to grasp the prediction's direct dependency on the data the model is trained on and the connected risks. The data cleanliness dimensions and data amount available define the quality of the data. The limitations connected to the model should be understood prior to an implementation but most importantly, when utilizing the ML application. Together with the black-box dilemma that occurs with many ML applications, making it is hard to trace how the decisions have been made, the true value of the ML applications should be assessed to avoid overreliance.

5.3.3. Data accessibility

During this research, the inaccessibility and lack of standardized and clean data often hindered the development of the ML propositions. In this subsection, factors to consider revolving data accessibility when implementing ML in the demand planning at Axis is presented.

Construct a data warehouse
With the independent and decentralized organizational structure at Axis, the visibility and the understanding of other functions is low, see section 5.2. To retrieve data from other functions and understand the connected dimensions was both time-consuming and not always feasible. This causes ML implementations to be costly, complex and time-consuming. Furthermore, these problems may hinder the initiation of ML projects. One way to make the data accessible is to consolidate the data through a joint and generic data warehouse. To devote resources and personnel to gather and consolidate the data as well as facilitate the extraction of standardized data are assessed to be a key factor to streamline ML implementations, see section 4.6.

Facilitate data extraction
This factor is mainly due to the cross-functional data extraction requirement of efforts and resources allocated from the functions involved. To facilitate efficient and effective processes, it is considered a requirement to redesign the work flows, see section 4.6. Depending on the strategic stance, Axis should integrate customized policies as well as data-quality and management principles within the entirety of the organization. By standardizing some management policies and principles, a more efficient data infrastructure can be acquired.

Generate consistent & clean data
Some of Axis' data sources are as of today unclean and some of the information systems are used in an unstandardized way, causing the data to be inconsistent, see section 5.2. The consequence is therefore that these data sources cannot successfully be used for ML. It is possible that the correlations in potential ML application goes unnoticed and that false

correlations are found. This would of course hinder the success of an implementation in demand planning and other business processes at Axis. Efforts should therefore be taken to evaluate and work towards ensuring cleanliness consistency in the data.

6. Conclusions & recommendations

In this chapter the fulfillment of purpose is discussed as well as conclusions and recommendations formulated with the research questions as a platform. A discussion of the research contribution, the research limitations as well as relevant future research that could generate further findings.

6.1. Fulfillment of purpose & research questions

The purpose of this research was to explore what kind of ML applications could improve the demand forecast at Axis Communications as well as evaluating which factors to take into consideration when performing such an implementation. This section evaluates and discusses the degree of fulfillment accomplished during this research.

6.1.1. What kind of ML applications could contribute to improving the demand forecast at Axis?

The first research question is relatively open in its nature but is limited by the delimitations defining the scope of the research. To answer the question, an analysis of the current state has been performed and areas of improvement identified. These areas are then connected to ML concepts that together developed and evaluated to be the most feasible and beneficial for Axis demand planning. These concepts and their respective contribution to the demand forecast are summarized in table 6.1.

Table 6.1. Machine learning propositions and their potential contributions

Proposition	**Contribution**
Attribute-based model	Making more data available to facilitate the development of the demand forecast both for new and mature products.
Prediction model based on distributor data	Exploring if a quantitative analysis from the sales in and sales out data could contribute with more beneficial and useful results.
Parameter segmentation model	Exploring if the products can be segmented based on their demand volatility to differentiate the forecast model's parameters.

There are two aspects that all models address which are the reduction of the amount of manual work and the enabling of a more quantitative data processing approach. The amount of manual work performed affects the objectivity of the output. Even if all propositions still contain subjective elements, this is a natural way to start integrating ML into the demand planning processes or business processes in general. Through experience and further development, more benefits as well as the applicability of the models start to become more accessible.

6.1.2. What factors should be considered when implementing machine learning into the demand planning processes at Axis?

The second research question is answered through the construction of a framework integrating two aspects. The first aspect is common implementation requirements illuminated in literature that are assessed to be relevant for Axis. The second aspect is the topics highlighted in the current state analysis in regard to an implementation at the demand planning department. The identified factors were consolidated into three categories; strategic alignment, competence management and data accessibility. The categories are summarized and motivated in table 6.2. below.

Table 6.2. Categories of the factors to consider and their motivations

Categories of factors	**Motivation**
Strategic alignment	Strategic aspects to consider when developing support systems and aligning Axis with integrating ML into business processes.
Competence management	An area closely related to strategic alignment is competence management which mainly focuses on the cognitive distances and how competence can be managed to decrease these distances.
Data accessibility	These factors revolve the improvement of data quality, accessibility as well as creating efficient data extraction processes.

The framework offers an overview of the factors to consider when implementing ML at Axis. The factors are highlighted to facilitate with achieving more efficient processes or to overcome aspects acting as barriers. The expectation with this framework is to first visualize the requirements an implementation may require to further initiate a discussion and an evaluation of factors that may affect a potential implementation and how to overcome them.

6.2. Recommendations

The research questions of this study, discussed in the previous section, stem from the directives provided upon Axis request:

- Providing a pre-study that highlights areas where the technology of ML potentially improves the forecast accuracy
- Performing an evaluation and quantification of requirements and competence to ensure a successful implementation ML

To follow up on these directives, this section aims to clarify further recommendations to Axis in regard to these directives.

6.2.1. Proposition recommendations

Firstly, in regard to the pre-study of areas where ML could be implemented, Axis is recommended to evaluate the propositions of this research in regard to their benefits, feasibility and risks reflected upon. Moreover, Axis is recommended to further assess these propositions in terms of what they may contribute with for Axis that is discussed in the further development for each proposition.

6.2.2. Machine learning implementation recommendations

The second directive from Axis, to perform an evaluation and quantification of requirements and competence to ensure a successful ML implementation, is assessed in this subsection.

An evaluation and recommendation of factors to consider for a successful implementation has been addressed in the factor assessment framework presented in section 5.3. However, to quantify the requirements and competence necessary was not assessed to be feasible within the scope of this study. The motivation behind this was the time limitation, literature available as well as the scarcity of machine learning competence available at Axis. The final recommendations to Axis when going forward with the integration of ML in business processes in general as well as the demand planning processes are summarized below.

- Form a strategic stance on ML based on an investigation of the industry impacts of ML into business processes. This strategic stance should determine the acquisition of competence and knowledge. Furthermore, the strategic stance and ambition with ML at Axis should be continuously communicated throughout the organization.

- Top management should communicate the recognized success stories of initiated projects to counteract cultural resistance and unwillingness to allocate resources. Clear roles and responsibilities should be set and customized policies as well as data-quality and management principles within the entirety of the organization should be implemented.

- Demand planning and other departments utilizing business processes, should strive to develop its internal ML competence and knowledge. Knowledge on the most relevant and basic ML would facilitate idea generation as well as generate awareness of benefits and risks. Furthermore, Axis is suggested to recruit ML competence that can support implementation projects within business processes at the operations department. This recommendation implies competence allocated to support ML implementation into the demand planning processes. When acquiring ML competence, it is recommended that Axis defines and communicates their level of ambition and expectations to avoid the ML competence leaving due to disappointments connected to the working assignments.

- Develop a ML support network to provide a support system for the implementation team. This enables access and sharing of knowledge and experiences when conducting or preparing for a ML project. This support network should be the existing and future recruited ML competence consolidated.

- To bridge the competence gap between the demand planning team and ML knowledgeable employees, personnel with experience within both operations and ML should be integrated into the composed implementation team. This would ease the collaboration, streamline the implementations and trigger the idea generation at the demand planning department as reflection on the current processes in relation to ML is possible. Axis should also raise awareness to the limited experience in the implementation and usage of ML at Axis. It is crucial to develop an understanding on how ML models should be interpreted as well as the limitations to reduce overreliance. This would facilitate a true value of the ML application and how it should be assessed.

- Strive for shared incentives between functions involved when initiating a ML project. This would also imply creating mutual gains from the involved parties and thus generate a higher success rate for the initiated projects.

- Develop a joint and generic data warehouse to consolidate the data available at Axis. This would ease the data accessibility for ML projects and thus streamline their execution as well forming a platform for ML and big data analysis.

- Take action towards cleaning data and standardizing the usage of information systems to militate current inconsistencies in some of Axis' data sources. These inconsistencies are important to address to enable the finding of true correlations for the proposed ML models.

6.3. Research contribution

This research presents three propositions contributing to an increased understanding of what applications may be possible to implement within Axis' demand planning. The setup of the inputs and the potential benefits are developed to improve demand planning processes. However, they could generate contribution to other functions. The propositions can enable an understanding of associated benefits and limitations as well as ideas on how these concepts could be developed.

Another contribution is that the propositions may be relevant for other product-based companies or organizations with a similar supply chain setup. To be able to draw conclusions from this research from an external point of view, it is important to get an accurate and developed understanding of the culture and strategy at Axis. The motivation behind this is to accurately assess the benefits and applicability for their specific setup. Even if the propositions are deemed not applicable to an organization, the concepts can still contribute with inspiration on how ML applications can be applied on business processes.

Regarding the factor assessment framework, it is more general than the propositions and can initiate a preparation phase when considering factors such as strategic alignment, competence management as well as data accessibility. An example of this is the assessing of cognitive distances is not only applicable to Axis or companies that are product-based or have a similar supply chain setup.

A basic introduction to the different function-based segmentation of the most utilized ML models is presented. This gives the reader a basic knowledge of how a model could be built as well as which type of model to focus on depending on the data available as well as the result sought. The propositions are suggestions that may generate ideas and further development amongst the demand planning team. It is evaluated as such that personnel with both knowledge and experience about the datasets is crucial when building a model to truly be able to identify the potential benefits and, especially, the weakness of the data or dimensions lacking in the model.

6.4. Limitations

The research was limited due to multiple factors that are addressed in this section. To accurately assess the conclusions in this report, these factors should be taken into consideration.

With the time constraint as well as lack of human resources with ML knowledge and experience available at Axis to facilitate this research, no thorough preparation work of the data or testing the algorithms was possible. This fact excluded any type of feasibility evaluation further than with the support of literature and interview material. Furthermore, the propositions should be evaluated further in terms of benefits, feasibility and risks. To evaluate the suitability of inputs and algorithms would also require practical tests and may vary in regard to the situation. It is clear that extensive work remains to be done before initiating a project to develop any of the propositions. The propositions should be treated as idea suggestions that needs to be further analyzed before a project is initiated.

The data needs to be extracted as well as thoroughly cleaned with regards to dimensions reflected. Furthermore, a thorough risk evaluation performed on the biases that could be hidden in the datasets and the data amounts available is needed.

As mentioned as a delimitation, the focus has been centered to propositions and improvements feasible to be developed internally at Axis. In other words, no propositions are connected to acquiring external systems, external data or external competence. However, it is an aspect that could be evaluated when initiating projects revolving the propositions.

To validate and improve the propositions, efforts towards benchmarking against other solutions has been taken. This was performed when further developing the models as well as facilitating the evaluation of the propositions feasibility and benefits. However, despite the efforts, a benchmarking against other companies was not deemed successful. The reason for this was the lack companies willing to participate in the study as well as finding relevant literature on the subject. It is believed that if the propositions would have been successfully benchmarked against other applications on the market, it would have enabled a higher credibility of the proposed applications.

This research is limited to the results improving the demand planning processes. Even if the propositions and the framework could be applicable in other environments, it has not been evaluated or assessed for any other field not concerning the demand planning at Axis. Furthermore, the limitation of improving the demand forecast for cameras in introduction or mature phase leads to aspects revolving decline phase is not properly investigated for the propositions. This limitation was motivated by the fact that the introduction and mature phase was assessed to be more important to Axis in the sense that there is high uncertainty and the majority of the annual dollar volume is connected to these phases according to Axis' demand planning team.

This research only presented three ML propositions even though more applications were found and to some extent developed throughout the research. The time limitation and scope of the study limits the number or propositions presented in the research even if more areas of improvement were identified and connected to a concept within the demand forecasting process.

In section 4.6, AI implementation requirements are consolidated and utilized as the theoretical basis in the factors assessment framework. This theory, together with the current state analysis on the demand planning at Axis, factors to consider as a recommendation basis was formulated. However, AI and ML implementation requirements can differ a large deal. The motivation behind facilitating AI literature to formulate ML recommendations for Axis was based on the scarcity of ML literature found for this study. This aspect can contribute to some of the recommendations being less suitable for Axis' demand planning processes.

6.5. Future research

As the limitations suggest, this research strives to form an understanding of the ML applicability at Axis. However, to develop new areas of applicability within other organizations, further research is suggested. Moreover, the scope of this research has only encircled results that improve the demand forecast. Further research may achieve additional insights outside of this scope.

The authors of this research want to illuminate the essence of developing research connected to the factors to consider as well as the propositions. To further test the actual feasibility and the value that these propositions would enhance the knowledge of ML applications within the demand forecasting.

The research had delimitations to achieve a feasible scope of the research. However, within all the propositions, external data sources could be applied. To further apply external data sources to the propositions, the feasibility and risks should be further researched.

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8. Appendix

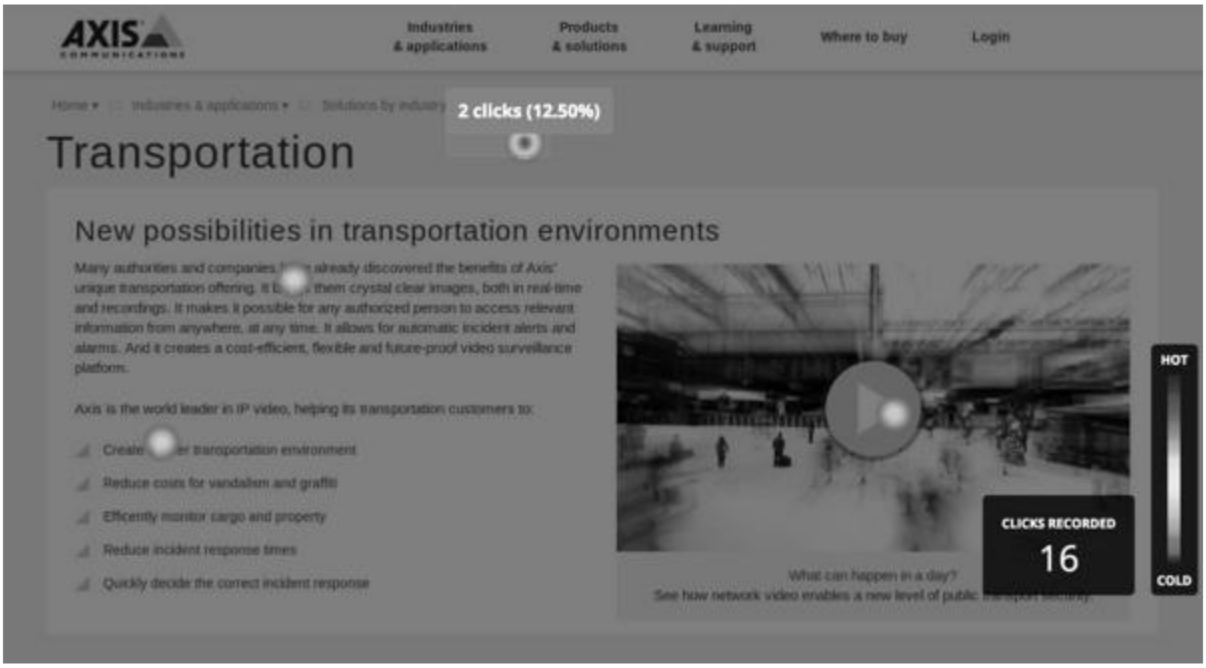
Appendix 1: List of conducted interviews

Name	Title of interviewee	Subject of interview	Date of interview
Jacek Malec	Professor, Department of Computer Science	Artificial intelligence	8/1, 2018
Tobias Gard, a	Sales & Operations Planner	Project management and forecasting accuracy	11/1, 2018
Anna Olofsson, a	Material Supply Manager	Material supply mapping	10/1, 2018
Robert Lindroth	Operations Development Manager	Supply chain mapping	17/1, 2018
Ulrika Magnusson	Director, Demand & Supply	Supply chain mapping	18/1, 2018
Maria Hallengren	Manager Demand Planning	S&OP and the CRM system	24/1, 2018
Anna Olofsson, b	Material Supply Manager	Material supply planning	24/1, 2018
Simon Steiner	Business Intelligence Manager	Data warehousing and business intelligence at Axis	25/1, 2018
Sara Östlund	Supply Process Development at Material Supply	Inventory management	29/1, 2018
Mikael Persson	IFS Applications Expert	IFS interface & data collection	30/1, 2018
Malin Gidlöf	Project Manager, Operations Development	Inventory management	30/1, 2018
Ulrika Andersson	Insides Sales Account Manager New Business	Sales regions functionality	7/2, 2018
Robin Gustavsson	System Development, Applications	Software and hardware requirements for ML	14/2, 2018
Tobias Gard, b	Sales & Operations Planner	Forecast model	16/2, 2018
Alexandra Wikström, b	Sales and Operations Planner	Information systems within demand planning	22/2, 2018
Liselott Lading	Manager Web and	AI at Axis	7/3, 2018

	Business Integrations		
Anna Olofsson, c	Material Supply Manager	Material Supply mapping follow-up	8/3, 2018
Göran Sandberg	Tools Specialist, Software Solutions	The Site Designer system	28/3, 2018
Magnus Bodin	Information Architect, IT Governance	PIA system	4/4, 2018
Robin Gustafsson & Adham Saknini	System Developer & Student Worker	Validation of ML concepts	5/4, 2018
Peter Rietz	Director, Product Management	Marketing analysis	9/4, 2018
Fredrik Nilsson	Vice President, Americas	Marketing and demand planning and the INC market	9/4, 2018
Alexandra Wikström, c	Sales and Operations Planner	Forecasting new product demands	11/4, 2018
Lena Kastor	Sales and Operations Planner	Sales in and sales out Analysis	11/4, 2018
Alexandra Wikström & Ola Sjöholm	Sales and Operations Planner & Process Development Administrator	Validation of ML concepts in demand planning	12/4, 2018
Alexandra Wikström, d	Sales and Operations Planner	Validation of demand planning inputs	18/4, 2018
Robin Gustafsson & Adham Saknini	System Developer & Student Worker	Validation of ML concepts	18/4, 2018
Cecilia Frick Welch	Digital Marketing Manager	Heat map and click data	24/4, 2018
Alexandra Wikström	Sales and Operations Planner	Validation of the demand planning process	25/4, 2018
Jan Olhager	Professor, Supply Chain and Operations Strategy	Demand forecasting models and optimizing parameters	27/4, 2018
Meghan Lanni	Team Lead, Demand Planning	Sales in and sales out data & sales region structure	2/5, 2018

Maria Hallengren & Henrik Ekström	Manager Demand Planning & Purchaser	Feasibility evaluation of ML models	3/5, 2018
Liselott Lading	Manager Web and Business Integrations	Heat map and click data	7/5, 2018
Susanna Jeppson	Product Data Coordinator, Product Specialists	Product Pyramid	28/5, 2018

Appendix 2: Click data



Appendix 3: Movement data

Appendix 4: Scroll data