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Artificial Intelligence as Assistance in Warranty Claim Handling

Sebastian Kvist

Degree Thesis for Bachelor of Engineering

Degree Programme in Mechanical and Production Engineering

Vaasa 2023

BACHELOR'S THESIS

Author:	Sebastian Kvist
Degree Programme:	Mechanical and Production Engineering
Specialization:	Mechanical Construction Engineering
Supervisors:	Joakim Hägg, Wärtsilä
	Tobias Ekfors, Novia University of Applied Sciences

Title: Artificial Intelligence as Assistance in Warranty Claim Handling

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Date: 3.4.2023 Number of pages: 32

Abstract

This thesis has been completed on behalf of Wärtsilä Marine Power, Customer Assistance Warranty Services. The main purpose of the thesis was to find a solution to the question: is a subpart needed together with this main part? Example: If someone buys a fork, they should also buy a knife as these items are mostly used together.

The theory chapter in this thesis focuses on artificial intelligence, how it is used on daily basis, association rule learning, and the machine learning process. There are multiple different types of AI available which are explained alongside their typical areas of use.

In the method chapter the two different approaches available that could be used to fulfil the purpose of the thesis are explained. In this thesis, an experimental approach was taken, which means that independent variables were changed multiple times to be able to see the difference in the dependants. Furthermore, a careful analysation of the results was done.

The result of the thesis acts as a guideline that the company can follow when going forward with the implementation of the algorithm into their different solutions.

Language: English
Key words: artificial intelligence, warranty claim handling, machine learning

EXAMENSARBETE

Författare:	Sebastian Kvist
Utbildning och ort:	Maskin- och produktionsteknik, Vasa
Inriktningsalternativ:	Maskinkonstruktion
Handledare:	Joakim Hägg, Wärtsilä
	Tobias Ekfors, Yrkeshögskolan Novia

Titel: Artificiell intelligens som hjälp vid hantering av garantianspråk

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Datum: 3.4.2023 Sidantal: 32

Abstrakt

Detta examensarbete har skrivits på uppdrag av Wärtsilä Marine Power, Customer Assistance Warranty Services. Målet med detta examensarbete var att hitta en lösning till frågan: Finns det en tillhörande del som hör ihop med denna huvuddel? Exempel: Om någon köper en gaffel, så borde de också köpa en kniv eftersom dessa föremål oftast används tillsammans.

Teorikapitlet i detta examensarbete fokuserar på artificiell intelligens, hur AI används dagligen, föreningsregelinlärning och maskininlärningsprocessen. Det finns flera olika typer av AI som förklaras tillsammans med deras typiska användningsområden.

I metodkapitlet förklaras de två olika tillvägagångssätt som kunde användas för att uppfylla examensarbetets syfte. I detta examensarbete användes ett experimentellt tillvägagångssätt, vilket innebär att de oberoende variablerna ändrades flera gånger för att kunna se skillnaden i resultatet via de beroende variablerna.

Resultatet av examensarbetet fungerar som en riktlinje som företaget kan följa när de går vidare med implementeringen av algoritmen i sina olika lösningar.

Språk: engelska
Nyckelord: artificiell intelligens, hantering av garantianspråk, maskininlärning

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List of Abbreviations

WE – Warranty Expert

CAWS – Customer Assistance Warranty Services

TS – Technical Services

AI – Artificial Intelligence

ANI – Artificial Narrow Intelligence

AGI – Artificial General Intelligence

CMMS – Computerized Maintenance Management System

BOM – Bill of Materials

1 Introduction

When working as a warranty expert (WE) in the Customer Assistance Warranty Services a lot of technical knowledge is required to be able to perform the work fluently. In this thesis, I have investigated how artificial intelligence (AI) could be used in warranty handling for a smoother operation of claim handling for warranty experts, and alongside my supervisor at Wärtsilä, tested and analyzed the results of a solution to assist with warranty claim handling with the help of AI.

In this chapter, a brief overview of the thesis will be presented, including background, problem area, and purpose.

1.1 Background

As a company selling a multitude of different products directly or indirectly to customers, a warranty is always needed to ensure that the customer is satisfied with the product. To take care of the warranties of the products a warranty team is needed, in Wärtsilä in the Marine Power business, that team is called Customer Assistance Warranty Services. A warranty expert (WE) will take care of the individual claims received either directly from the customer or via the shipyard where the vessel was constructed. These claims are then manually inserted into the system by the WE and then processed accordingly to the issues present.

Sometimes the only request in the claim could be a new spare part, with the spare part number provided, and if that is the case then the only thing the WE need to do is send out the requested spare part. However, the WE also need to look for related subparts that might be required, and that is where the problem area for this thesis job can be found.

1.2 Problem area

Sometimes it can be as easy as sending out a requested spare part with the provided spare part number and the claim can be closed. But other times it can be hard to know, has the customer provided the correct spare part number, *are any other subparts needed in relation to the requested spare part?*

With the latter question in mind, the subject matter for this thesis was created. If you have the technical knowledge there is the possibility to go into the spare part catalogue and manually look if any subparts might be required, or if the technical knowledge is lacking, there is always the possibility to contact the Technical Services (TS) department via a ticket system and ask them for assistance to check if any subparts might be required alongside the main spare part.

But both options can be time-consuming for both the Warranty Expert, either needing to look through the spare part catalogue or to wait for the TS team to answer the ticket created in the system. But what if artificial intelligence could be used? What if AI could suggest if any subparts are needed according to the requested spare part number provided by the customer? A similar kind of AI is already being used by multiple different web stores.

This would improve the time needed to send out needed parts but also reduce the workload for the WE and the TS team.

1.3 Purpose

The purpose of this thesis was to determine how subparts that are needed alongside a main spare part for a specific claim can be detected and recommended. This would assist Warranty Experts with the warranty claim handling process in the marine business of Wärtsilä. This is to be done by using the assistance of AI.

Another purpose of the thesis is to increase the efficiency of the warranty handling process of receiving a claim and sending out the needed spare parts, but also to reduce the time spent on these kinds of claims by WE's and the TS team.

1.4 Delimitations

This thesis is created with the focus being to test a provided algorithm to see if it could be implemented in the current machine learning system to simplify the daily work of a Warranty Expert working for the marine business organization. The source code to be used will be created by a data scientist from Wärtsilä hence the creation and/or modification of the code will not be looked into in this thesis, but mainly the testing of the code and analysis

of the results. The AI used to perform relevant tests in this thesis is machine learning, so the other types of AI will only be touched on briefly.

2 Wärtsilä

This chapter will explain Wärtsilä in short, a description of the two main organizations of the company, and a brief explanation of Customer Assistance Warranty Services organization.

2.1 The company

Wärtsilä is constructing and developing different power solutions alongside many other products for the marine and energy markets. The company has taken a path toward shaping decarbonization for the future, as almost a third of carbon emissions in the world come solely from the marine and energy sectors. The company operates in over 80 countries globally, has around 18,000 people employed, and in 2021 the company had a revenue of 4,78 million EUR. (Wärtsilä, 2023)

2.2 Marine business

In marine technology, Wärtsilä is a leader thanks to its substantial portfolio of innovative products and solutions. Wärtsilä enhances the marine business for their customers thanks to the reliability, flexibility, efficiency, and environmental sustainability of the solutions. (Marine, 2023)

Wärtsilä is pushing so that the decarbonization of the maritime can happen as soon as possible. The path to decarbonization is anything but short, but through innovative solutions, Wärtsilä is speeding up the process rapidly. (Bass, 2022)

2.3 Energy business

In the energy business, Wärtsilä is also a leader in the transition towards a 100% renewable energy future and the decarbonization of the future thanks to their market-leading technologies. Some of these technologies are energy storage, power plants being ready for future fuels, hybrid solutions, and optimisation technology. Wärtsilä's track record in regard to the energy business is 76 GW of power plant capacity and 110+ energy storage systems supplied to 180 countries worldwide. (Energy, 2023)

2.4 CAWS – Customer Assistance Warranty Services

CAWS is the organization that provides warranty management services for Wärtsilä Marine projects. A couple of the main activities for CAWS are warranty planning, warranty claim handling, and supplier warranty reclaiming. CAWS cooperates closely with Field Service Operations, Technical Services, and suppliers to be able to work efficiently and offer the best support for Wärtsilä's customers. CAWS has personnel with over 80 warranty professionals who are located in multiple locations globally in areas with significant fleets under warranty. (Wärtsilä, internal document)

3 Theory

This chapter will explain the theories which are relevant to this thesis. This includes an explanation of artificial intelligence, a short description of the different types of AI that exists, and a deeper look into machine learning. A description of the warranty handling process will also be presented.

3.1 Artificial Intelligence

Artificial Intelligence or also known as AI, is a very broad term which can be hard to define correctly but can be described as a field of computer science that aims to create intelligent machines that are capable of performing tasks that would usually require human intelligence. Some of these tasks are understanding natural language, recognizing objects, making decisions, and learning from experience. (Schroer, 2022)

AI is very valuable for the future because it can give businesses a new perspective on their operation and can also perform certain tasks more efficiently than humans. Particularly tasks that are very repetitive and need to be done meticulously can be done with AI quickly and with a minimal number of errors. (Burns, 2022)

Some key advantages and disadvantages of AI according to Burns (2022) are:

- 24/7 availability
- Reduction in human error
- Completes repetitive tasks without complaints
- High costs
- Requires deep technical expertise
- No creativity or out-of-the-box thinking

AI can be placed in two different categories, either weak AI or strong AI. Weak AI or also called artificial narrow intelligence (ANI) is a system that is trained to only perform a specific task and this type of AI is the one mostly used today. Some examples of this AI are industrial robots, Apple's Siri, and autonomous vehicles. (Burns, 2022)

Strong AI, also known as artificial general intelligence (AGI), refers to the type of programming that can reproduce the cognitive abilities of the human brain. This means that in theory, AGI would have the self-aware consciousness of a human being and the capability to solve new issues without previous experience. However currently, there are no practical examples of strong AI in use, and it is entirely theoretical. (IBM, 2022a)

3.1.1 Types of AI

According to Marr (2021), there are four main types of AI, and these are:

- Reactive machines
- Limited memory
- Theory of mind
- Self-aware

Reactive machines are the most simple and oldest type of the AI systems and do only have the possibility to react to what it currently sees; it does not use past experiences or memories. That makes it so the machines behave in the same way when faced with the same scenario which also makes the reactive machines very trustworthy. (Hintze, 2016)

AI of limited memory is the most extensively used type of AI. This AI has the possibility to take in new information or learning data and thus adjust the result based on its past experiences. (Marr, 2021)

As an example, autonomous cars use this technology to observe the surroundings like traffic lights and curves in the road, and add these to the preprogrammed representations of the world. (Hintze, 2016)

Whilst the two previous types mentioned exist in both the past and present, the types of theory of mind and self-awareness are much more advanced machines and do only exist in theory or as work in progress. An AI using the theory of mind would be able to understand more by perceiving the emotions, needs, and thought processes through interactions, this meaning that the AI would essentially understand humans. (Naveen, 2019)

The last type of AI is self-aware, and the name indicates where this is leading. This means that the AI would be so close alike to the human brain that it has developed self-awareness.

The AI of this type would as theory of mind be able to perceive emotions with those it interacts with but also have its own emotions, needs, and beliefs. But fortunately, this type of AI is only hypothetical. (Naveen, 2019)

3.1.2 Where is AI being used?

To make it easier to understand how AI is being used, let's take a look at where it is being used at the moment. Whatever we are doing on the internet either on the phone or the computer, AI is always present in the background.

For example, you might have noticed that after visiting an online store, suddenly you receive ads from that particular store while you are on another website. This is AI noticing that you have been looking at the online store for a while and it is now recommending it to you based on your previous browsing history and interests. This is called personalized shopping. (Biswal, 2023)

Another example is that while browsing an online store, a chat can automatically appear in the corner of your screen and ask you if you need any help. These AI-powered chatbots are there to improve the experience of shopping online and by using natural language processing they try to make you believe you are talking to a human. (Biswal, 2023)

Also, when you have been shopping online and added a couple of items to your shopping basket, you might get recommended similar products that have been bought together or are related to each other in one way or another, like in Figure 1 below. This occurs thanks to AI. (Biswal, 2023)

Figure 1. Frequently bought-together items are recommended in a web store. – www.avada.io

To be short, AI is being used everywhere and a few more examples are facial recognition, autonomous vehicles, spam filters, and voice assistants.

3.1.3 Machine learning

Most of the examples of AI mentioned in the subchapter above use a form of AI called machine learning. Machine learning is the most popular form of AI and is hence often used interchangeably with the term artificial intelligence, but this is incorrect as machine learning is a subfield of AI. Machine learning is a type of limited memory and can be categorized as narrow AI. (Brown, 2021)

The point of machine learning is to create a system that can pick up information and use that information to learn and become better. For the system to be able to do this, a programmer needs to design an algorithm that tells the system what to look for and what to collect in the data that the system is presented with. (Banoula, 2023)

3.1.4 Machine learning algorithms and models

When someone is new to AI and machine learning, it can be hard to know the difference between algorithms and models as the words are often used interchangeably with each other. In an AI system, the machine uses the algorithm as a set of instructions when running the data, and the result is the machine learning model. This means that the algorithms are learning from the data, and it is the algorithm that is detecting patterns in the data and the result of this will become the machine learning model. The machine learning model is the representation of what the algorithm has learned from the data and the model can then be used on new data that it has not seen before and be able to make predictions. (Brownlee, 2020)

There are many different algorithms that are used, and these are classified into four different types which are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. The three most popular algorithms in use today according to Tavasoli (2023) are linear regression, logistic regression, and decision tree.

3.1.4.1 Supervised learning

Supervised learning means that the machine is trained under supervision. The machine is supplied with pre-labeled training data, and the variables that are to be analyzed for correlations are specified. This means that the training dataset includes the target answer for the model to learn from. When new input data without any labels are inserted into the model, it can now accurately predict the results based on the training data. Supervised learning can be broken down into two different types, classification, and regression. (Banoula, 2022)

Classification is often used when the result is categorical, for example, true or false, car or house, spam mail or non-spam mail, and so on. Going further with the spam mail or non-spam mail example, in order to accurately be able to predict what type of mail that has been received, the machine first needs to be trained on what spam mail is. This is done by using spam filters on training data, looking through the contents, and the mail header, and looking for certain keywords. All the above and more filters are added together to give the mail a spam score and the lower the score, the less likely it is that the mail is spam. Based on the results the mail is then placed into either the inbox or the spam folder. (Banoula, 2022)

Regression on the other hand is used when the result is a continuous value, meaning that it is based on multiple variables. Some examples of this are automatic gearboxes which use engine revolutions and vehicle speed to know which gear to engage, to be able to predict weather conditions humidity, and temperature is used. If you have humidity and temperature, humidity is dependent on the temperature, meaning that when the temperature increases the humidity decreases. After using training data to teach the model the relation between these, the machine can accurately predict the humidity when provided with a temperature. (Banoula, 2022)

3.1.4.2 Unsupervised learning

As an opposite to supervised learning, unsupervised learning uses unlabeled data, and the machine learns on its own without any supervision. The model then tries to find similarities or differences in the training data provided. As the machine does not know what the correct result should be, it groups the data depending on the similarities or patterns. Unsupervised learning can also be grouped into two types, clustering, and association. (Banoula, 2022)

Clustering is a method that clusters the data into different groups depending on the similarities or differences in the data. An example is seen in Figure 2, where a telephone company wants to provide personalized contracts for their customers. They then need to use clustering to know if the customer uses more internet, more call time, or both. (Banoula, 2022)

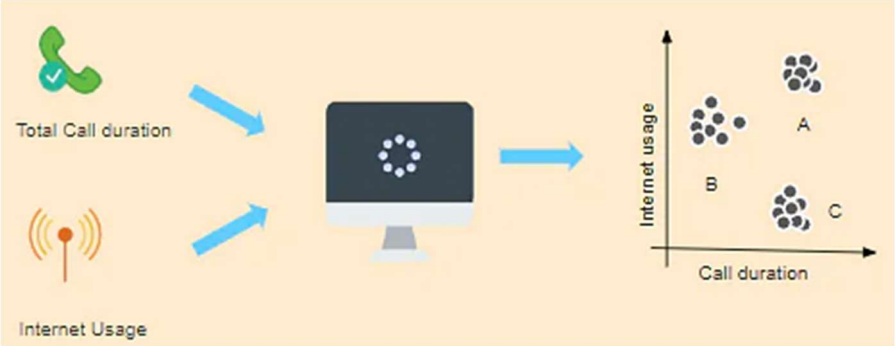

Figure 2. Example of clustering - unsupervised learning. – www.simplilearn.com

Association is the other type of unsupervised learning and uses a rule-based method to find similarities or patterns between variables in the given data. This method is often used in the so-called market basket analysis, with an example shown in Figure 3. Market basket analysis helps companies find different relationships between products and understand how customers consume products to be able to give personalized recommendations. The most popular example of the association type in use is “frequently bought together with” when trying to shop for anything online. There are a couple of different algorithms used to create these association rules, but the most common one is the Apriori algorithm. (IBM, 2022b)

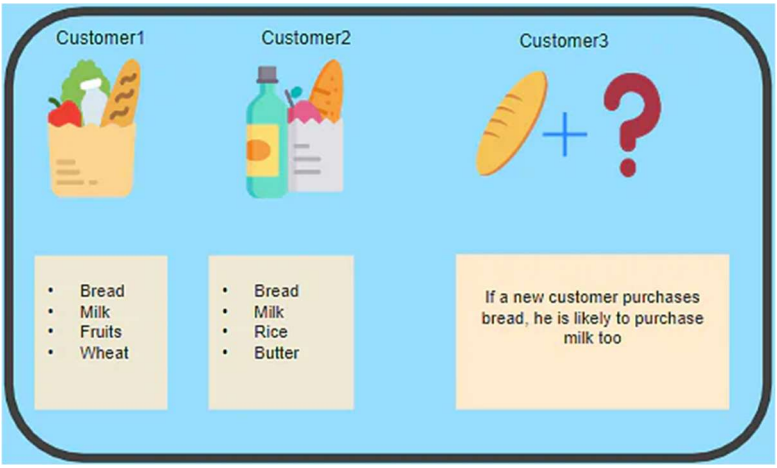

Figure 3. Example of association - unsupervised learning. – www.simplilearn.com

How the Apriori algorithm works is fairly simple. When the support value of an item surpasses a certain limit, the item qualifies as a frequent itemset. When a frequent itemset is identified, it gives a recommendation of the itemset when a single item in the itemset is consumed. An example of this algorithm in use is Spotify's "discover weekly" playlist which suggests music to you based on your listening history. Based on the listening history of other users and what music overall is frequently played together the algorithm suggests music of a similar type to you via the playlist which is updated weekly. (IBM, 2022b)

Testing an Apriori algorithm

As the algorithm itself is simple, the process to test the functionality of the algorithm is not much more difficult. To test an Apriori algorithm one can follow the following steps:

1) The first step is to prepare a dataset that contains a list of transactions. Every transaction should include a set of items that are purchased together. The dataset being prepared should represent the kind of data that the algorithm is to be used on. Preparing the data means removing or filtering unnecessary data.

2) The next step is to set a minimum support value and a minimum confidence value, that determines which itemsets that can be considered frequent. The support value can be an unlimited number while the confidence value is between 0 and 1. This is the main step in testing an Apriori algorithm. These values should be adjusted multiple times to see how they affect the performance of the algorithm.

3) When the data is ready and the necessary values are set, the algorithm can be run. The algorithm will then scan the dataset and create a list of frequent itemsets found in the data.

4) When the algorithm has been run the final step is to evaluate the results. This can be done by, for example, checking the accuracy of the itemsets by comparing them to a known itemset. (Javatpoint, 2021)

3.1.4.3 Semi- supervised learning

Semi-supervised learning is a model which is something in-between supervised and unsupervised learning. The dataset that is used in training consists of a small amount of labeled data and a lot of unlabeled data. This gives the algorithm some labeled data to learn

on and acts as a guide to the unlabeled data. Semi-supervised learning can be a good alternative if there is not enough labeled data available, or if it is too expensive to label enough data to use supervised learning. (IBM, 2022c)

3.1.4.4 Reinforcement learning

Reinforcement learning is a model which is quite much the same as supervised learning, but the key difference is that it does not use any training data, instead the model learns by itself by using trial and error. (IBM, 2022c)

When the model provides a good result, it is rewarded, while bad results get punished. This is done by assigning the results with positive and negative values according to the result. The model then strives for the highest overall reward in the long run-in order to achieve the best outcome. (Carew, 2021)

3.1.5 Machine learning process

The process to create a machine learning system can be divided into 7 major steps.

1. **Collecting data**

The first step in the process is to collect the data that will be used to train and test the system. It is very important to have as much reliable and good quality data as possible, so the system has a good training model to follow. If the data that is used to train the model is of bad quality, the machine will not be able to provide accurate results. (Banoula, 2023)

2. **Preparing the data**

When an appropriate amount of good data has been collected, it must be prepared to be used as training for the machine. This can be done in a couple of different ways, for example by first adding all the data together and then cleaning the data by removing unfavorable data like duplicates, missing values, or invalid data. Cleaning of the data can be done either by manually going through the data or by using filtering techniques. It is also a good idea to randomize the data, so that the order of the data does not influence the learning process for the machine. One last step in the preparation is to divide the dataset into two sets, a training set that should be about 90% of the data, and a test set that is the remaining 10% which is used later to test the system. (Banoula, 2023)

3. Choosing a model

The model that will be chosen and used decides what kind of output that will be received after running the machine learning algorithm on the provided training datasets. Through the years various types of models have been developed depending on what tasks the AI will be performing, so the chosen model will need to be in relation to the task at hand and suited for the dataset, according to if the data is numerical, photographic or any other kind. (Banoula, 2023)

4. Training the model

After the desired model has been chosen, it is time to train it, which is the most important step. Training means that the prepared data is passed on to the model for it to find patterns and be able to make predictions. The outcome of the model is learning from the training data and as it continues to learn it will provide more accurate results. (Banoula, 2023)

5. Evaluating the model

When the model has been trained, it is needed to evaluate how well it accomplishes the requested task. The data which has not been used in training will now be used to test the model. It is very important to not use the data that was used in training to test the model, because since the model is familiar with the data it already knows the patterns and the results would not be an accurate representation of the model. (Banoula, 2023)

6. Tuning parameters

Now with the model created and tested, it is good to see if the accuracy could be improved via parameter tuning. The variables in the model are called parameters, which are most often chosen by the programmer. When doing parameter tuning, you are looking for the value of the variables that provides the most accurate results. (Banoula, 2023)

7. Deployment

The machine learning model is now completely finished and is now ready to be deployed and tested on new unseen data. (Banoula, 2023)

3.1.6 Association rule learning

Association rule learning is categorized as unsupervised learning. This method uses simple If/Then statements to help discover common patterns or associations in different types of datasets, and when a pattern is found an association rule is created. (Rai, 2022)

An association rule is composed of two components, an antecedent (if) and a consequent (then). To simply describe this, an antecedent refers to an item that is found in the data, and an item that can be found in conjunction with the antecedent is called a consequent. See the following example:

> If a customer buys sausage, he is 80% likely to also buy ketchup.

In the statement above, the sausage is the antecedent and the ketchup is the consequent. After the association rule has been created, the strength of the correlation between the antecedent and the consequent can be noted by looking at the values of support, confidence, lift, leverage, and conviction. (Rai, 2022)

Support

Continuing the example above, we have one itemset that consists of sausage and ketchup, and we have one itemset that consists of sausage and candles. There will automatically be more purchases of sausage and ketchup than sausage and candles since sausages and candles do not relate in any way, hence giving the first itemset a bigger support than the second one. In mathematical terms, support is the fraction of the total number of purchases which includes the itemset. (Garg, 2018)

$$Support(X > Y) = \frac{Purchases\ including\ X\ and\ Y}{Total\ amount\ of\ purchases}$$

The support metric can have a value of between 0 and 1. Support serves as a tool to help determine how often a specific item set occurs. If the support value is for example 0.01, this means that the itemset has been bought together 10 times over a total of 1000 purchases or 1% of the total amount of purchases. If the support value is very low, it means that the items are very rarely purchased at the same time and an association of the items should not be assumed. (Garg, 2018)

Confidence

Confidence is another metric available in association rule learning. Confidence can be defined as the probability of the consequent already being in the shopping cart, assuming that the antecedents are already in the cart. Confidence answers the following question:

Of all the purchases including sausage, how many also included ketchup?

As most people use ketchup together with sausage, it can be assumed that this association rule should have high confidence. This means that the probability of the consequent being purchased together with the antecedent is high. (Garg, 2018)

$$Confidence(X > Y) = \frac{Purchases\ including\ X\ and\ Y}{Purchases\ including\ X}$$

Confidence can have a value of between 0 and 1. A high confidence value, for example 0.8, means that the consequent is being bought together with the antecedent 8 times out of 10, so a high confidence means that the consequent and antecedent already are being purchased together most often. However, a high confidence value does not always mean that the items are associated with each other, continuing the example, sausage and fruits might also have a high confidence value since fruits are popular shopping item, but that does not mean that sausage is being consumed together with fruits, hence gives a false high confidence value. (Garg, 2018)

Lift

Lift is the third metric available and acts as a ratio value between the confidence of Y and support of X. This means that a high lift value indicates that the occurrence of X and Y being purchased at the same time is very likely to happen. A lift value of exactly 1 means that there is no association, and a negative value means that there is a negative association. (Garg, 2018)

$$Lift(X > Y) = \frac{Support\ (X\ \cup\ Y)}{Support(X) \cdot Support(Y)}$$

To easier describe this, when the sausage causes the fruits to be purchased at the same time, the lift value will be greater than 1. A lift value of lower than 1 in this scenario

indicates that having fruits in the basket instead decreases the likelihood of sausage being purchased at the same time, even though the confidence value was high. (Garg, 2018)

Leverage

Leverage is almost defined the same way as lift, but instead of using ratio, it is the difference that is being used. This leads to leverage often favoring itemsets with a higher support value. (Herbold, n.d.)

$$Leverage(X > Y) = Support\ (X\ \cup\ Y) - Support(X)\ \cdot Support(Y)$$

Conviction

Conviction is another method for measuring the association between antecedents and consequents. Conviction evaluates the probability of X appearing without Y independently against the actual occurrence of X appearing without Y. (Dobilas, 2021)

$$Conviction(X > Y) = \frac{(1 - Support(Y))}{(1 - Confidence(X > Y))}$$

When using the formula above, even if the lift value is the same for (Sausage > Ketchup) and (Ketchup > Sausage), the conviction value for (Sausage > Ketchup) is much higher. This indicates that even though sausage and ketchup are frequently bought together, sausage more often leads to ketchup also being purchased instead of ketchup leading to sausage being purchased. Thus, the conviction can be utilized to evaluate the directional relationship between the items. (Dobilas, 2021)

3.2 QlikView

QlikView was founded in Sweden in 1993 and is a comprehensive business intelligence tool created for data integration, analytics, and conversion of raw data into a knowledge base. Some advantages of using QlikView are:

- Easy-to-use platform
- Fast response time
- Ability to visualize data in an innovative way
- Data can be accessed, analyzed and retrieved from multiple devices
- Short implementation period

Thanks to these advantages and many more, QlikView makes it easy to work with large amounts of data that can easily be shared between coworkers or to other people. (Taylor, 2023)

3.3 Jupyter

Project Jupyter is a non-profit organization that was started in 2014 and focuses on developing open-source software and tools for interactive computing across various programming languages. While the project started with iPython, it now offers support for over 50 other programming languages. (Jupyter, 2023a)

3.3.1 Jupyter Notebook

Jupyter's main application is called Jupyter Notebook and is a web application that enables users to create interactive narratives using text, code, and multimedia. It is also suitable for recording the entire computation process which is code development, documenting, executing the code, and result communication. (Jupyter, 2015)

3.3.2 JupyterHub

JupyterHub is a multi-user version of Jupyter Notebook and is designed to be used by companies or research laboratories. It gives users access to the needed computational environments without the users having to manage installation and maintenance. JupyterHub can run in either the cloud or on the user's own hardware, this also means that users can work from anywhere on shared resources. (Jupyter, 2023b)

3.4 Warranty claim handling process

The warranty claim handling process starts with a warranty issue received from the customer either via e-mail or online customer portal. The warranty expert in charge of the vessel's warranty will register the claim and depending on the issue coordinate a resolution either via sending out spare parts, requesting manpower via Field Service Operations, or contacting Technical Services when there is a need for deeper technical expertise. In many cases when sending out spare parts the warranty expert will also need to request the old parts back for further investigation of the issue present. After needed action has been taken

a request to close the claim will be sent to the vessel to ensure that both parties are on the same page. (Wärtsilä, internal document)

3.5 Spare part management

To be able to provide good support efficiently and consistently for customers, good spare part management is required. This means that when a spare part is required, if it is a usual service part or a part known to be prone to failure, it always needs to be in stock, or if it is an unusual part, there needs to be set instructions on how to proceed with obtaining the part within a reasonable timeframe. (G3P, n.d.)

According to G3P (n.d.) a good spare part management system needs to follow these practices:

Implement a computerized maintenance management system (CMMS)

A CMMS main objective is to centralize information and processes. By having a CMMS, it will give a clear overview of inventory stock, assist with removing delays due to out-of-stock items, and will reduce inventory inaccuracies.

Spare part classification

Different spare parts need different classifications depending on, for example, the importance of the part and the movement of stock. By classifying spare parts, it will be easier to balance the inventory.

Keeping bill of materials up to date

A bill of material (BOM) is a source of information that includes all items needed to produce a product. By keeping these up to date it will greatly improve the time it takes to order materials and produce a part.

Optimized warehouse

By optimizing the warehouse, it will ensure the accuracy of inventory stock and ease the process of stocking and retrieving spare parts.

4 Method

This chapter will present the two different approaches which were considered and how the data available was used.

4.1 Manual approach

A manual approach would have consisted of manually looking through data from thousands of claims that have been marked as completed and looking at what parts that have been delivered. By then finding parts that seem to have a connection, have been sent out on multiple occasions, and share similarities within the claim form, then an itemset would be created for these parts. When all the itemsets have been found, these would then be saved and included in the ordering system. This means that when the main item in the itemset is a part of the order, the whole itemset would be recommended.

Whereas this method would work, the process would be very time-consuming as there are thousands of claims that need to be looked through, and the system would also need to be kept up to date by continuously looking through new claims that are finished for new item sets. If this was to be completed in one go, it would take a lot of time and be very repetitive which could also induce fatigue which leads to decreased accuracy.

4.2 AI approach

Another possible approach was using AI. This means that instead of manually looking through the data, AI would do it instead. This can be done by using an unsupervised machine learning method called association rule learning. As also described in the theory chapter, this method is used to find relationships between items in a dataset. The items with relationships can then be considered as itemsets and be used to create association rules. Association rule learning is a great tool when trying to find relationships between items in large amounts of data, which was the case in this thesis job.

I decided to use the AI method because it seemed more engaging and interesting, whereas the manual method seemed slow and repetitive.

Furthermore, an experimental approach was taken, which means that the independent variables (the parameters) were adjusted multiple times and the dependent variables (the results) were saved, and in the end, the results were compared to each other to be able to know which values for the independent variables that work best and draw conclusions between the variables.

5 Association rule learning process

This chapter will go through the process of finding itemsets, testing the algorithm and analyzing the results.

In this thesis, the machine learning method that was used is called association rule learning. The first step in the process was to prepare the data. All the data needed for this thesis was stored in QlikView, which made it easy to clean and filter the data. The data was then sorted so only relevant and needed data was available.

Collecting itemsets for testing the algorithm

The process started with manually looking for itemsets in the data to use when testing the algorithm. The QlikView was set up so there was one column showing all parts that had ever been ordered and were sorted by the number of times they had been ordered. By then choosing a part in the first column, in a second column all the order baskets where the selected part has been included were displayed, and sorted by the number of times the specific basket has been ordered, as illustrated in Figure 4 below.

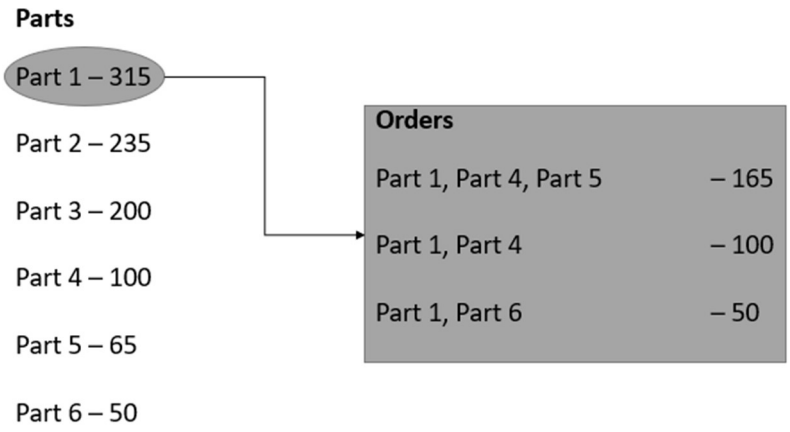

Figure 4. A visualization of how QlikView was used when looking for itemsets.

To get as good results as possible, the 10 most ordered baskets were inserted into an Excel document as in Figure 5, and then all the parts were separated and added up to get a number for the total amount of times they had been ordered, which can be seen in Figure 6.

Figure 5. Screenshot from Excel document where itemsets are being collected. (Internal information)

The part that was originally chosen from the parts list in QlikView, will also be the most ordered part as it was included in every order basket, and will hence be the antecedent. By then dividing the number of the "total amount of times ordered" with the antecedent, a percentage result is obtained, which tells how often the part has been ordered together with the antecedent. If the percentage is of sufficient size this indicates that the parts are often ordered together and can be seen as a consequent to the antecedent, which means that this can be seen as an itemset. An example of this calculation can be seen below in Figure 6.

Figure 6. Screenshot from Excel document in which the expected results from the algorithm have been calculated. (Internal information)

This procedure was done multiple times to have a couple of itemsets that could be used when testing the algorithm.

Running the algorithm

After enough itemsets were ready to be used in testing, JupyterHub was opened via a web browser. By using JupyterHub it was possible to easily test and execute the code created by the data scientist from home. There are several intermediate steps from start to finish, but some of the main steps in the code are the following:

- All the notifications and material numbers are imported from the database and saved as a csv file. (A csv file is a plain text file format that is commonly used to store tabular data, such as spreadsheets or databases)
- Then all the material names are imported from another database, this makes the results easier to read and understand.
- All the materials are grouped according to their notification.
- Then a transaction matrix is created.

- Now the first parameters confidence and support are to be entered.
- Frequent itemsets are created based on the first parameters.
- Then the confidence, price and consequent sum parameters are to be entered.
- Based on the entered parameters, the association rules are now created, and an example of the rules can be seen in Figure 7 below.

Figure 7. The association rules are created based on all the inputs from the parameters. (Internal information)

- Now the association rules can be tested either part-by-part in Jupyter, or all the rules can be saved in an Excel document.

The parameters

Inside the code, there were a couple of parameters that could be changed, and these affect the end results. The parameters that could be changed were:

Max_Itemset_len: This parameter decides the maximum amount of consequents there can be in a solution.

Min_support_n: This parameter decides how many times a part must have been ordered before it can show up as a consequent.

Min_Confidence: This parameter decides the minimum confidence value needed in the relationship between the antecedent and the consequent before it can show up as a consequent and is a value between 0 and 1.

A zero value means that all parts that have ever been ordered together even once will be displayed, while a value of one means that only parts that have been ordered together every time will be displayed.

Price_factor: This parameter decides how much more or less expensive a consequent can be than the antecedent. A value of 0.5 means that the consequent

can be half the price of the antecedent. A value of 2 means that the consequent can be two times more expensive than the antecedent.

Consequents_filter_sum: This parameter decides how high the maximum price of the consequents summed together can be. A value of 300 means that the consequents added together can have a maximum price of 300€.

The main parameters are min_support_n and min_confidence as these change the results drastically. The antecedents from different itemsets that were earlier determined were now entered into the algorithm and the results with the consequents are saved. The parameters are then changed, the algorithm is run again, and results are saved. This was done systematically multiple times to get a wide range of results.

Analyzing the results

The results from the algorithm were saved as an Excel document. In the document all the association rules are listed along with the following data in different columns: antecedents, consequents, support value, confidence, lift, leverage, conviction and final solution. By having all the data in an Excel file, it was now easy to read and search for an antecedent using the filtering option. When searching for an antecedent with the filter, all scenarios where an antecedent and any other parts were activated, and all other rows were hidden.

By now looking at the row which only has the antecedent, and the last column named final solution, it was easy to see what recommendation was made. If all final solutions where the antecedent is present are the same, that means that there was a good result. If there was no result found when using the filter, that meant that no recommendation was made.

Figure 8. Example of final solution when searching for an antecedent using the filtering function in Excel. (Internal information)

As seen in Figure 8 above, I have searched for the antecedent and when looking at the last column one can see, that while using the specific parameters that were used to get these association rules, the final solution is the same in all scenarios including this antecedent.

Figure 9. The expected results in relation to Figure 8. (Internal information)

When now comparing the final solution to the expected results seen in Figure 9, we can see that they are the same. This means that in this case, the results are very positive.

Data from different timeframe

The data that was used in the first test had no limitations, which means that all data that had ever been collected was used. In a second test, I decided to use data from 2018 to 2023 to see how the results differentiate. This means that the process of manually collecting itemsets was done again and the code had to be modified to be able to use data from a certain timeframe and new tests were run.

6 Results

This chapter will present the results of the thesis and how it can be used.

Due to the limited timeframe of the thesis job, there was not enough time for the model to be put into a real practical test and hence there are no concrete results from the model being implemented anywhere. However, the results of this thesis can be used as guidance when going forward with the implementation of the algorithm.

Algorithm parameters

When changing the parameters you get different results, and based on the testing that was done for this thesis the following conclusions can be taken:

When using a high confidence value (over 0.8) the suggestions will be very accurate and there will be a very low number of false positives or errors, and the suggestions by the algorithm can be trusted. However, due to the high confidence value, the total amount of recommendations based on the association rules will be low and would not bring as much value to the table as one would like.

When using a much lower confidence value (under 0.2) the number of recommendations would greatly increase and hence also bring more value to the end results. But a low confidence value could instead create more false positives meaning that the algorithm might suggest a part to be sent even though there is no real relationship between the recommended part and the antecedent.

The final solution of each itemset according to the parameters was rated from 0 points (bad) to 2 points (good) and then added up. By looking at the graph in Figure 10 on the next page, one can see the difference between the results when the parameters have been changed. A higher points value means that the specific combination of parameters made more or better recommendations. It is visible that when using an extremely low confidence value (0.01), more recommendations were made and when using a high confidence value (0.8) fewer recommendations were made. The name of each column in the graph represents the values of the parameters that were used, in the same order as described on page 25, meaning the middle value is the confidence value.

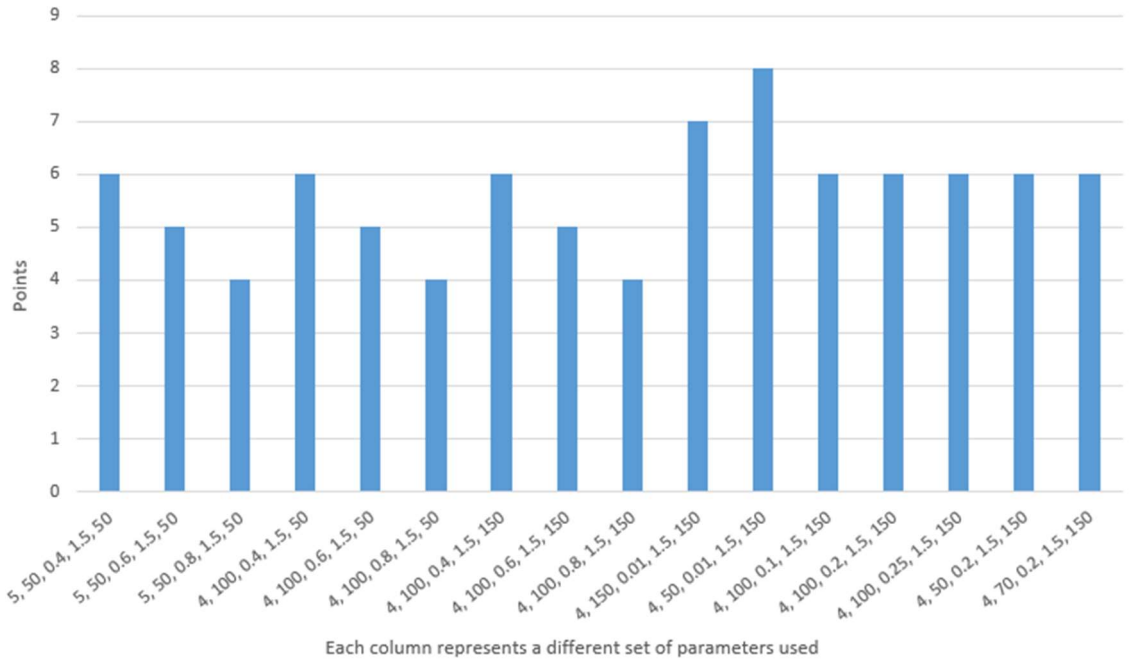

Figure 10. Graph of the results from testing when using all data available.

The optimal confidence value to be used when going forward would be between 0.4 and 0.5. This would eliminate most if not all the false positives but will also find most of the sensible relationships. A confidence value of 0.4 paired together with a minimum support_n value of 100 leads to the best end results when using the data available at the time of testing. This means that before the consequents can show up as a recommendation, they need to have been ordered together with the antecedent every two and a half times, and a minimum of 100 times.

Further conclusions

Some further conclusions that can be taken based on the results of the testing are that it is much better to use all the data available instead of data from a limited timeframe. The more data used leads to more relationships between parts which also leads to more recommendations.

A possibility to manually activate or deactivate relationships between parts should be investigated, as there was found multiple scenarios where a recommendation should be made, but due to the low number of times being ordered together or the low total amount of times ordered, no recommendations were made. An example of this is the original problem described earlier.

While the future of this algorithm at the time of writing the thesis is unclear, it can be concluded that the algorithm will be able to fulfil its purpose efficiently by utilizing the results from the thesis. Some possible solutions where the algorithm could be implemented are:

- In its own system, purposely built to give recommendations on subparts that are needed alongside main parts for warranty experts during claim handling.
- In the online store to help customers find related parts when looking for spare parts.

7 Discussion

When looking at the overall results that were achieved from the testing in this thesis, it can be concluded that the algorithm is working well, and it can absolutely be used in the future for the intended purposes, thus, the main objective of this thesis has been achieved.

7.1 Challenges

There have been a few challenges during the process of writing the thesis, but nothing major. Mostly in the beginning of the process, it was hard to get a grasp of the subject as it is a very complex and broad topic, together with the fact that I was not very familiar with AI overall. It was also hard to get the big picture on how the model would work and what results that were to be expected, but thanks to the weekly meetings with Joakim I was able to discuss any questions I had regarding the thesis and the subject, and he helped me to stay motivated and keep progressing during the process. In the end, I am satisfied with the results.

7.2 Final words

To end this thesis, I would like to thank Wärtsilä and Joakim Hägg, who gave me the opportunity to write this thesis and study a new topic I was not very familiar with before working on this thesis. A thank you also goes to Tobias Ekfors from Novia UAS, who has been my supervisor during the writing of this thesis, for the great constructive feedback that I was given.

The topic of artificial intelligence is very interesting, and I believe it will have a big part in the future in multiple ways. Thanks to this thesis I have been able to broaden my perspective on AI and how different problems can be solved, especially with the help of AI.

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