Bachelor's Thesis

Analysis of list creation with machine learning

By

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Abstract

This Bachelor’s Thesis delves into the category of list generation using machine learning within IKEA. The thesis work involved information gathering, planning, studying machine learning concepts, creating a proof of concept (POC), and analyzing the results. The Technical Background was built upon literature reviews and practical skills acquired through Machine learning courses such as Google’s “Machine Learning for Beginners” and Kaggle’s advanced courses. The methodology involves continuous learning and improvement, with the goal being to understand IKEA, data landscapes and implementing machine learning models.

The authors worked together every step of the way, cooperating to craft the model, construction around it and the thesis. The presentations of findings to IKEA colleagues provided insights and opportunities for more improvements. By using Python tools like NumPy and Pandas and the development environment Visual Studio Code, the authors navigated the theoretical knowledge of machine learning and recommendation systems to develop the model for list generation.

Keywords: Machine Learning, Matrix Factorization, Recommendation System, User Experience, List Generation

Sammanfattning

Detta examensarbete utforskar listgenerering med hjälp av maskininlärning inom IKEA. Avhandlingsarbetet involverade informationsinsamling, planering, studier av maskininlärning koncept, skapande av ett konceptbevis (POC) och analys av resultaten. Den tekniska bakgrunden byggdes på litteratur genomgångar och praktiska färdigheter genom maskininlärning kurser som Google's "Machine Learning for Beginners" och Kaggle's avancerade kurser. Metodiken innefattar kontinuerligt lärande och förbättring, med målet att förstå IKEA, data uppbyggnad och implementera maskininlärningsmodeller.

Författarna arbetade tillsammans varje steg på vägen, samarbetade för att utforma modellen, konstruktionen runt den och avhandlingen. Presentationen av resultaten för IKEA-kollegor gav insikter och möjligheter till ytterligare förbättringar. Genom att använda Python-verktyg som NumPy och Pandas och utvecklingsmiljön Visual Studio Code navigerade författarna den teoretiska kunskapen om maskininlärning och rekommendationssystem för att utveckla modellen för listgenerering.

Nyckelord: Maskininlärning, Matrisfaktorisering, Rekommendationssystem, Användarupplevelse, Listgenerering

Acknowledgments

This Bachelor’s thesis would not be possible without the support and guidance of our thesis supervisor at LTH Christin Lindholm, along with the efforts of our supervisor at IKEA Alper Kilic, who helped us and guided us in the right direction. We also want to thank the collective efforts of employees at IKEA who lent a hand through the spring.

Jonas Thunberg & Aminn Khatib

Contents

1. Introduction

This chapter describes the goals and purpose of the bachelor’s thesis work, as well as the necessary background information needed to understand the scope and delimitations.

1.1 Background

IKEA, formally IKEA Group, is a multinational furniture company that designs and sells furniture, founded in 1943 and today employing over 166,200 workers. It is widely known as a retailer of offering a wide range of products made for furnishing the home. IKEA consists of many different subsidiary companies and sections with different focuses. The largest one is called INGKA which owns most of the retail warehouses owned by IKEA. The convention is to still use the name IKEA when referring to the subsidiary company INGKA. Therefore this thesis will adhere to that practice and use the name convention of IKEA to refer to IKEA or INGKA. The thesis is done as a collaboration with one of the INGKA Digital offices, Hubhult Svågertorp, which handles all forms of e-commerce through a website for IKEA, such as the Swedish IKEA digital store website which mainly sells home products.

In the realm of retail, particularly in companies with an online presence, there exists a persistent drive to enhance the customer experience, aiming for greater efficiency in product sales. Consequently, there's a steady need to explore and assess new methodologies, perpetually evaluating their potential to surpass existing practices and lead to greater success such as increased sales or a better customer experience.

Currently, there is a feature for creating a list called "Favorites list" that is available and linked to each user's profile. Such a list is initially empty but can be expanded with various products by manually adding them. This is done by the user clicking on the heart symbol on each product's display page. This means that creating and adding to a list requires a lot of input from the user.

The use of artificial intelligence (AI) to facilitate decision-making has been known and utilized for some time [1]. The idea is to leverage existing AI and machine learning models to simplify and enhance the user experience for customers of IKEA, shopping on IKEA's website.

A machine learning model will be implemented on IKEA's "Favorites" page to create lists that are relevant and tailored to the user's needs, the users in this thesis context being customers at the IKEA digital store website. The list will consist of products available for purchase on IKEA's commerce website that would be more interesting to the user. The process would streamline and make it easier for a user to find and purchase various IKEA products and reduce the time a user would spend searching for similar and suitable products. The products on IKEA's website are in their internal database where the product consists of a product ID and various tags such as what color the product is or what product category it belongs to.

1.2 Purpose

The purpose of the thesis work at IKEA is to implement a proof of concept machine learning model to create product lists based on a user's preferences and purchase history and then evaluate its effectiveness. The intention is to improve IKEA's webshop user experience and make it more personal and individualized. A part of that is to investigate if the machine learning model can automate the process of creating individual product lists and lessen the need for manual input from the user. In addition, the thesis aims to conduct a thorough analysis of the various input parameters to the machine learning model and assess the balance between these to achieve optimal results. An important part will be to analyze and examine the definition and measurement of success criteria for the result. The work will also evaluate whether the use and implementation of a machine learning model represent an improvement compared to the current methods available.

IKEA can benefit from the service as they can choose which products have higher profit margins and recommend them through the service. The thesis work can lead to a better understanding of the application of AI in list creation for both IKEA and other companies. The work can answer questions about cost-effectiveness in implementing such a service, which in turn can help inform and optimize future decisions and strategies to create a more user-centered platform.

1.3 Goals

Explore and evaluate the use of artificial intelligence, specifically a machine learning model in combination with lists. Create at least one functioning POC based on in-depth analysis. Then conduct an analysis of the POC and its effectiveness based on what a successful outcome looks like. Evaluate the effectiveness of implementing a machine learning model compared to what currently exists.

This evaluation will include an in-depth analysis of the model's effectiveness and comparisons with existing approaches to determine if the implementation of machine learning yields desired results and surpasses existing systems. Through such an approach, the work aims to quantify and qualify the potential improvement compared to existing methods.

1.4 Problem Description

Through the thesis project, the following questions will be answered:

1. How does AI improve the process of list creation and management?
2. What are the challenges and limitations of integrating AI in list generation?.
3. How does AI-driven list creation impact user experience and decision-making processes?
4. How can the results be measured, when does AI list generation reach acceptance levels?
5. How does the integration of AI in list creation align with current web development technologies and principles of user experience?

1.5 Motivation

We chose this thesis work for personal interest. The market is taking a turn to focus more on machine learning and AI. This makes the skills we are going to acquire relevant, and gives us a deeper understanding of what the future of software development might look like.

The choice of thesis work is also based on the need to create a new service at IKEA that utilizes existing AI and machine learning models. The purpose of the service is to improve and simplify the shopping experience at IKEA. The service can improve customer satisfaction by allowing customers to find products related to their needs more quickly. IKEA can benefit from the service as they can choose which products have higher profit margins and recommend them through the service. Our work can lead to a better understanding of the application of AI in list creation for both IKEA and other companies. The work can answer questions about cost-effectiveness in implementing such a service, which in turn can help inform and optimize future decisions and strategies to create a more user-centered platform.

1.6 Limitations

The thesis project will focus on the analysis of an implemented Proof of Concept (POC) product and will not include broad system changes or in-depth changes to existing IT structures. The thesis will not conduct an in-depth analysis of the science behind machine learning or its principles.

1.7 Division of Labor

The goal was to split the thesis work as evenly as possible and apply the combined knowledge. In any team there is a diversity of knowledge and experience and this was taken into account when there was an uneven split in some of the thesis work. The numbers in the figure represent the percentages of work each part of the group had as shown in figure 1.

	Jonas Thunberg	Aminn Khatib
Analysis	50	50
Design of Base Model	100	0
Design of Frontend/Backend	0	100
Implementation/Construction	50	50
Testing/Utvärdering	70	30
Thesis writing	50	50

Figure 1. The division of work between authors in percentages

2. Technical Background

This chapter explains the tools and software used for gathering data and building the artificial Intelligence model used for this thesis. It will cover the machine learning practices and methodologies that are used in this thesis work.

2.1. Artificial Intelligence

Artificial Intelligence (AI) refers to a technology that simulates human intelligence using computers and machines [2]. In theory, tasks that require human intelligence or decision making can be done by AI on its own. It can also be combined with other technologies. For example, to navigate AI can use geolocation for GPC guidance [3]. One of the most important steps towards AI started as a question of whether machines could think or not in 1950 when Alan Turing published his paper "Computing machinery and intelligence" [4].

2.2. Machine Learning

Machine learning is a subset of artificial intelligence that focuses more on creating a model that can predict outcomes for various inputs given it has knowledge about a large amount of data. The term was first coined in 1952 by Arthur Samuel and defined as "Machine Learning is the field of study that gives computers the ability to learn without being explicitly programmed"[5] .

The basic concept of machine learning system construction is to set up a model with a certain number of parameters that will take in a set of data and produce an analyzed result based on the data, for example, input data could be a random color, and the result data could be the identified color [6]. The model is "trained" through an iterative process where it is "fed" a certain amount of data for which the outcome is already known, then the model compares its own result with the given result and adjusts the model's parameters so that its result becomes as close as possible to the real result. This is called optimizing the model. After the model has been trained, it can be tested with new, unknown data where it can be evaluated to see how effective it is at analyzing, evaluating, and identifying patterns in new or different data.

The data used as both input and output machine learning models can be divided into two types, numerical or categorical [6]. Numerical data types can be either continuous or discrete and has a natural ordering to it. An example would be a person's age or the price of a house. Categorical data on the other hand does not have this ordering and is always discrete , for example color types, red is not inherently higher than blue and vice versa.

Machine learning can be divided into three types with the main difference being how a model is trained on a given set of data. They are called unsupervised, supervised and reinforcement learning, and are used in different ways and have different algorithms to analyze the datasets [6]-[8].

Supervised learning is an approach that uses a dataset, called the training set, that is labeled [7]-[9]. That means that for every input in the dataset there is a known corresponding output. The model can then use different algorithms to map out and learn the relationship between those corresponding variables, or features by a different name. The model is given an amount of test data to try and predict, where it will compare its result with the known result. This in turn will guide the model to make corrections in its algorithm and minimize the difference in the outcome, also known as loss [9], [10].

This process is done iteratively over many iterations. Labeled datasets ensure that the supervised learning model has general knowledge of what the correct intended output values of the model should be.

Unsupervised learning is an approach that uses machine learning algorithms to analyze and cluster unlabeled datasets [7]-[10]. Clustering is a data mining technique that groups similar data points based on their similarities or differences. It is used when there is no known relation between input and output. The name of the method for clustering is K-means, which is used to group data points into K distinct clusters. The algorithm works by repeatedly splitting up the data points in these clusters in a way that reduces the overall variance within each cluster. These algorithms find hidden patterns by themselves, without any human interference, hence the name “unsupervised”. The hidden patterns are found using the association method, which creates association rules that identify relationships between variables in a dataset. A common use for it is a recommendation system for online shops, where the method recommends other items based on the items picked by the user (“Customers who bought this item also bought”). While using high-dimensional datasets, datasets with where the number of features for each observation is comparable or larger than the number of observations, the method called “Dimensionality reduction” within unsupervised learning reduces the number of features while preserving data integrity.

2.3 Recommendation systems

Recommendation systems simply put a system design to function to rank and sort different items according to various inputs [11]-[14]. It can use both supervised and unsupervised learning as a method to learn and rank the different items. Its function is to predict what a user would respond positively towards, depending on the context where this recommendation is given. The goal with such a system is to enhance user satisfaction and drive more engagement with users. By leveraging both supervised and unsupervised learning techniques, recommendation systems can effectively learn from data to tailor recommendations to individual users' tastes and preferences. However both techniques require some historical knowledge about the interaction and evaluation between the users and items. This is also described as the "cold start problem" where the recommendation system in order to function properly needs prior knowledge about for example, a user's interaction with items so evaluate and predict what items that specific user would respond positively and negatively to [15]. [16].

Recommendation systems can be classified into two distinct methods of filtering, content-based filtering and collaborative filtering [11]. Both of them can implement machine learning techniques such as supervised and unsupervised systems.

Content-based filtering is based around the idea that each item in the data consists of a set number of attributes that describes the specific item [11]. These are used as features to create an item-vector to describe that item. This can for example be color, style, and fabric for a clothing item. By comparing the item-vector of each item and the historical data of a user and meaningful interaction with different items, for example if they bought a certain clothing item, an inference

can be made about the preference of that user and which item attributes they have a preference for. Extracting those inferences a user-vector can be constructed with weighted values for each attribute.
It is then possible to measure the similarity between the user-vector and the item-vector by a similarity calculation, one of which is cosine similarity. To get the similarity, the cosine value of the angle between the vectors is calculated. This is useful because the range of -1 to 1, where -1 is opposite similarity and 1 is fully similar.

The recommendation system that is going to be used is Collaborative Filtering (CF)[17]-[19]. Using collaborative filtering, the user will be recommended items based on reactions by similar users. This is done by searching through a larger group of users and picking out a smaller set of users with a similar preference as a particular user.
In general there exist two different techniques for CF which is either neighbor-based, also known as memory-based, or model based [15]. Memory-based CF systems is a filtering technique where the system identifies the nearest "neighbor" of a user or an item, depending if it's user- or item-based, by the use of an algorithm designed to find similarities between the entities [18]. This can be done with various methodologies, one being the earlier mentioned cosine similarity. The system then outputs the top N number of nearest neighbors most similar to the user/item and recommends them.

Model-based CF general principle is that a model is trained with predictions, using for example matrix factorization, with the objective of predicting the preferences of a specific user based on their historical interactions with the items that are included in the systems dataset [11]. The model-based CF methodology has been used for its general fast speeds, scalability and accuracy given it gets enough data to train on [19]. It also overcomes the issue of low accuracy that exists for memory based CF for users that do not supply enough ratings to adequately use a k-nearest neighbor method on them.

2.3.1 Matrix Factorization

A widely used method, according to Ken-Lin, Du within Collaborative Filtering which is model based is Matrix factorization [20]. It works by decomposing the user-item interaction matrix into the product of two rectangular matrices, one matrix representing the users and the other one representing the items. This will break down each user's preference of items. However, because users have not interacted with each item, some values will be left empty. To fill these empty values, the user matrix and item matrix will be multiplied back together, which gives an approximation of the original matrix, but now with all the missing values filled in. These filled-in values are the ratings which have been predicted that the user would give to the movies they haven’t rated yet.

There are three methods of matrix factorization that relate to this topic. The Singular Value Decomposition (SVD) is used in collaborative filtering to create low-rank approximations before the neighborhood calculations [21], [22]. The formula for this is:

$$A = U \cdot \Sigma \cdot V^T$$

Where U is an orthogonal matrix. The columns of V are the right-singular vectors.

The second one is Probabilistic Matrix Factorization(PMF), which takes a large matrix with many missing values and breaks it down into smaller matrices [11]. The formula for PMF is:

$$R_{ij} = U_i^T \cdot V_J + E_{ij}$$

Where R_{ij} is the rating given by user i to item U_i and V_J are vectors that represent the features of the user and the item. E_{ij} is a term that represents the error which is the difference between the actual rating and the rating predicted by the model. PMF assumes that the user and item use vectors that follow a Gaussian distribution, a certain statistical distribution.

A third one is called non-negative matrix factorization [23], which concept centers around the idea that the vectors used in the matrix factorization are non-negative, they are in other words positive. This requires however that the matrix that is being decomposed is non-negative, that its elements are all positive [23].
The matrices are approximated using the formula:

$$V \approx WH$$

Where V is the original matrix that is being decomposed into the matrix factors of W and H, which are repeatedly updated with every iteration of approximation until a given level of quality in the approximation is found. This can be found using a loss-function, one being:

$$|A - B|^2 = \sum_{ij} (A_{ij} - B_{ij})^2$$

Which calculates the euclidean distance between the two non-negative matrices.

2.4 Tools

The tools used in the thesis will be presented and explained in this section. These are all the tools that were used to develop the machine learning model that this thesis is based on.

2.4.1 NumPy

NumPy (Numerical Python) is an open-source Python library that's a standard for working with numerical data in Python [24]. It has all the fundamentals for calculations, providing support for arrays, matrices and high-level mathematical functions to operate on these data structures. This will be used to conduct all calculations for matrices in this thesis.

2.4.2 Pandas

Pandas is an open-source Python library that is used for data manipulation and analysis [5]. The name comes from the term "panel data" which is an econometrics term for datasets that include observations over multiple time periods for the same individuals. This will be used to implement all data in this thesis.

2.4.3 Visual Studio Code

Visual Studio Code (VSCode) is the IDE that was used in the process of developing Python scripts [25]. VSCode supports many programming languages and comes with features such as refactoring, command-line interface and syntax highlighting. It is a Microsoft developed source code editor, which is also free. It was used to build and train the model for this work using the VSCode Python extension.

3. Methodology

This chapter describes all processes and methods used during this thesis work.

3.1. Thesis work process

The process for this thesis work can be broken down to three parts in Figure 2. These parts are:

1. Information gathering, planning and studying
2. Creating the proof of concept (POC)
3. Analysis of POC results

The parts have been done in order, but also by going back to either improve the POC or understand IKEA. For example, studying machine learning was a process that continued from the first part all the way to the last part. It has been a continuous learning experience.

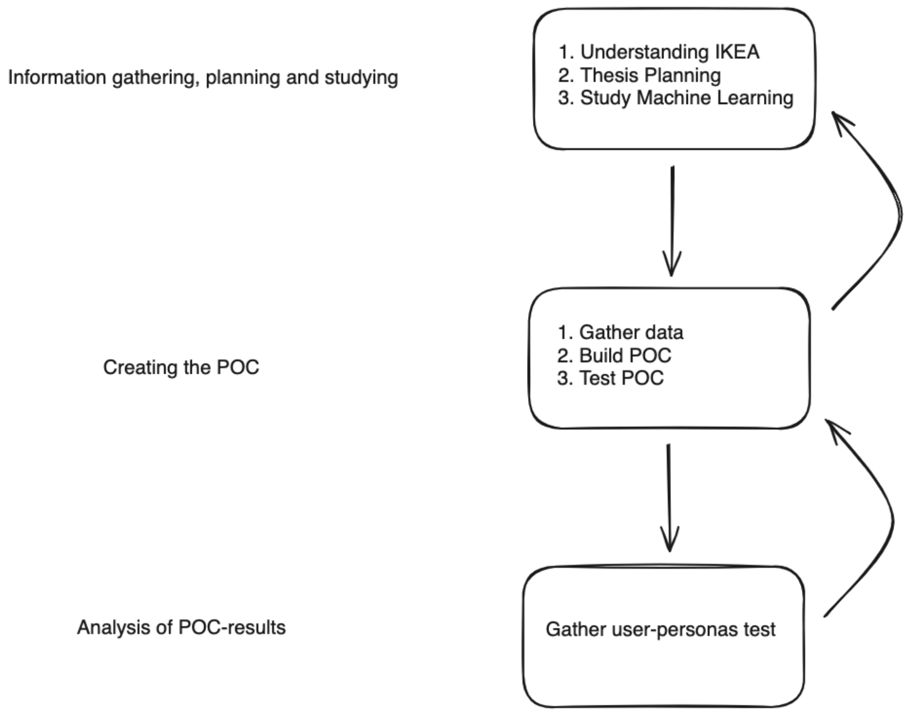

Figure 2. The process for the thesis work

The first part was Information gathering, planning and studying. This part was to get a general idea of how IKEA operates, creating a timeline and plan for the thesis and studying machine learning. The planning included deciding what type of model to create. Studying machine learning was done through online courses.
The second part, Creating the POC, could be broken down to three parts. Gathering data from the companies databases after understanding IKEA, building the proof of concept with the knowledge from machine learning courses and later testing it.
The final part, Analysis of POC-results, consisted of letting users test and gather the data from it, then documenting the results and discussing them.

3.2 Information gathering, planning and studying

The first part consisted of understanding IKEAs software-development teams to find out which tools were accessible for the thesis work. Studying machine learning would help narrow down the methodologies to work with which gives the opportunity to plan more precisely.

3.2.1 Understanding IKEA

The first section was for getting to know the company in which the thesis was conducted. This includes understanding all the communication channels applications like Slack for direct messages and Microsoft Teams for digital meetings. For software documentation, INGKA mainly uses Confluence. This is where all information about the data and data parameters can be found. For API's (Application Program Interfaces) INGKA uses Allen for instructions on how to get access to and call any API within INGKA to fetch data onto the devices. These structures are learned for the purpose of being able to communicate the thesis work to employees in the company and also use the resources that already exist within the company to build a POC as close as possible to IKEAs standards.

3.2.2 Studying Machine Learning

The second section of this thesis work involved exploring and researching different machine learning methodologies and how they could be used in the context of this thesis. This process required both a theoretical understanding of machine learning and its underlying concepts and principles and practical skills to implement them in order to build the POC in an acceptable manner. Acquiring theoretical knowledge took the form of mainly literature study of various

academic works and research papers, while for the practical proficiency the courses taken for machine learning models were Google's own course ‘Machine learning for beginners’ and also Kaggles beginner and advanced courses [6]. The courses were a good way to get introduced into the practical side of machine learning and how it should be used when trying to write code. Furthermore it added to the theoretical knowledge in seeing how those concepts and principles were expressed in examples. It was also very helpful to learn and expand the thesis workers knowledge about the various libraries commonly used like above mentioned Pandas in section 2.4.2 and Python as a language in general.
These helped create an understanding of what practical approach to take towards the goal of creating a list generation.

3.2.3 Thesis Planning

The third part of the thesis work involved planning every aspect, focusing on setting up a timeline with all milestones and tasks. To do this, a detailed GANTT chart was created to visualize the projected timeline.

The timeline was roughly followed, however there were delays in the implementation part of the work as it took longer than expected.

3.2.4 Presentations

In the month of March the thesis was presented in IKEAs company wide presentation held over Microsoft teams. It was open to all colleagues in the different departments of Ingka and around ten people attended the presentation. This was done not only to inform other employees and coworkers about the thesis work and idea and what the goal is to accomplish with the finished thesis. It was also done in order to find out if there was any employee that could provide more information about the current data structure of IKEA. This was done for a better understanding of the data that the thesis would need for the models dataset. The response for this presentation gave a helpful tip to where the data the thesis needed could be found.

Another presentation was also held in the middle of the thesis at the end of april. This time with an updated presentation, the model had progressed and showcased in a demo during the presentation. This was more of a general presentation for a bigger audience within IKEA where many different thesis works were presented. This however did not yield any useful tips or new information.

3.3 Creating the POC

Building the POC model took a lot of work and time. Throughout the process of creating code different hyperparameters values were tried and three different datasets were used. The work was mainly done in three stages that are outlined below.

3.3.1 Gathering data

The information and data for the thesis work was gathered through setting up online meetings with data analysts within IKEA using IKEAs internal communications channel. The next step was getting access to IKEAs data, specifically three types of data which were the Profile data to get the users perspective, item data to get all the items that IKEA sell and lastly sales data to find the event interactions. The first data for items and sales data(rating data) that was used to train the model was mock data.

The mock data was generated by Mockaroo, a website that randomly generates data based on prompts and parameters [32]. Three columns were generated which were item-id, category and item-type. The item_id was used to identify the mocked items, the category was to place the item in certain categories such as “Living Room” or “Bedroom” and the item type was to identify what type of item such as “Lamp” or “Bed”. In the rating data, used-id and ratings were included as well. The user-id represents mocked users and items representing mockitems. The mock items were used to link the two different datasets, one being the ratings and the other representing the items more in depth.
In the data that consists of the users, items and user-items interaction each cell represents the rating that the user has given the item. In the mock data this is an abstract representation of a rating and is randomly assigned to each cell with a value between 1 and 5, only using natural numbers. A 5 would indicate a high rating and a 1 would indicate a low rating. An actual rating system could be as simple, for example only measuring the given “stars" on a product as seen in many e-commerce sites. It could also be more complex, taking into account not only customer reviews but also purchases, interactions, if IKEA wants to push certain products to the forefront more than others, and so on.

$$min\sum_{u,i}(R - g - b_u - b_i - U \cdot I^T)^2 + \lambda(||U||^2 + ||I||^2 + b_u^2 + b_i^2)$$

Where R is the whole matrix, U, I is the user and item matrix, g is the global average bias, b is the bias and λ is the regularization parameter.

Since the goal for the model is to in principle create a large matrix over each inputted user and item where each cell in the matrix is given a value of either real observed user-item interactions or values

that are predicted by the model, this would create a very large matrix if the input is large. Given a large enough data this matrix would be immensely large, for example a data set with 5 million users and 1 million items would yield a matrix that would have 5 million rows and 1 million columns.
This was observed to cause problems when the model switched input data from the mock data to the Amazon data where there wasn't enough memory available for the program to run the model and store the matrix.

The problems were solved by implementing two strategies. The first was to divide the input data into smaller chunks and then iteratively feed each of those chunks into the model and train it on that chunk, and then take the mean result of all the chunks as the result of the model. To expedite the process of each chunk the previous iterations user and item matrix was used as a starting point instead of randomized values, in order for the model to converge faster.
The second was not keeping the entire full matrix of each user and item but instead keeping and storing the matrices that the model would use to calculate the full matrix and using them to calculate the ratings for the specific item or user when the list creation function, which is discussed below, is called.

This data was used to build the first version of the proof of concept model just to get the model to work and see if it could process data without problems or bugs. The input data was later changed to a dataset randomly generated from Mockaroo, which is a dataset containing data about users, products and their user-item interactions. This dataset is not only more complex but also taken from the real world making it inherently much more valuable to analyze than the mock data which was randomized. This was also done in order to see what patterns the model could plot using data that was not randomized.

This data was however random so its result was also random and not really fit to be used other than testing the functionality of the model to see if it worked.

The next step was to gather data that was more “real” and hence more useful. However during this time an issue had arisen with the collecting of data from IKEA. The process of finding the correct data was taking much longer time than expected and for the sake of the thesis and need to progress the POC to see if it could handle bigger and more “real” datasets a decision was made to use publicly available datasets that is review data from Amazon, this includes information about the the many various different products, users/customers and the reviews and ratings they have given the products listed on the online retailer. The complete dataset of all products and users was however incredibly large with over 18 million products and 54 million users all in a csv file. A subset was chosen, one most closely related and similar to IKEA products, being the product category of “Home and Kitchen” with 23.2 million users, 3.7 million items and 67.4 million ratings [26]. After consideration it was deemed that this data would be very helpful in building the POC and could be used as data to test the thesis as it is similar to IKEA data in terms of customers, items, its features and user-item interactions with regard to reviews.

3.3.2 Build POC

The matrix factorization model that was implemented and used for testing in this thesis is a form of Singular Value Decomposition matrix factorization model, using the algorithm and definition found in Yehuda Koren paper about matrix factorization techniques for recommender systems [12]. It was implemented using Python and consists of several methods and functions but the most important parts being how the model implements the matrix factorization, and

how it evaluates its error rate.
The main idea of the model is that it takes in a user-item matrix R with MxN dimensions and tries to decompose it into two smaller matrices, one for the users U and one for the items I. These matrices are of the MxK and KxN dimensions where K is the amount of the latent features for the users and items. These latent features could be things like item categories or user characteristics, it's not inherently important that these features were named, what matters is that it is part of how the model discovers underlying patterns in the dataset. Having made an estimate of the value of the latent features for both matrices the model then recompose them back into a matrix R using the dot product of U and I, I being transposed.

Equation 1: $R \; = \; UI$

An example picture is shown in figure 3 [31] shows the concept. The big matrix is the main matrix R with some unknown values. This R matrix can be viewed as the resulting matrix of two smaller matrices dot product where the known values match.

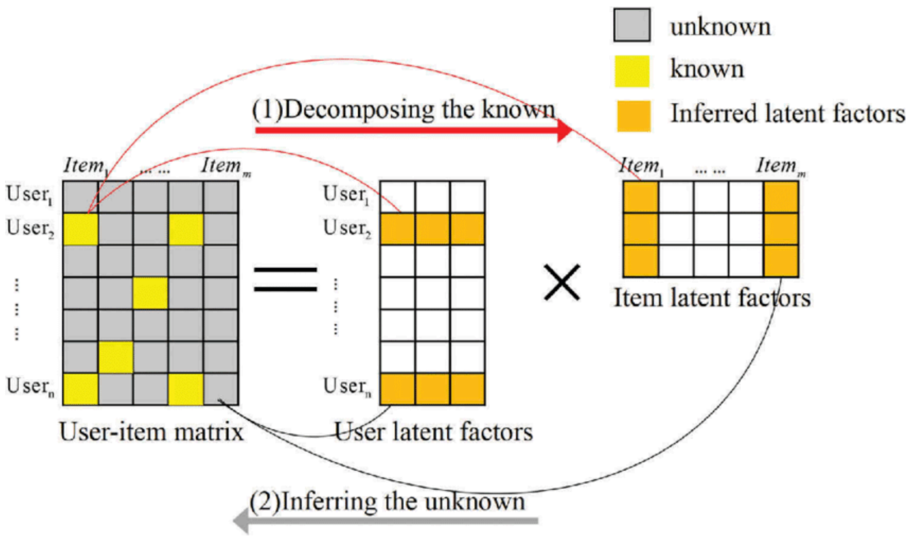

Figure 3. Matrix Factorization

This new matrix P is the prediction of the values that existed in R and is not entirely correct with those values. The training process of the model is to iteratively and progressively update its parameters to make better U and I matrices so that the difference between the predicted value in P and the real value in R is as little as possible. It is then possible to predict the value of yet unknown user-item interactions in the main matrix R.

The model also incorporates bias into its prediction, where the bias for a specific user-item interaction is the global mean average for all observed item-user interactions, and specific biases for the specific user and item.
Some user for example have a tendency to rate items on average higher than other users, this should be taken into account when trying to make a user-item interaction prediction.

The model utilizes stochastic gradient descent in order to minimize the error in the loss function as seen in equation 1 by modifying the internal parameters in the model by a magnitude proportional to the learning rate Y. This modifying continues until the model has run all of its iterations or the model converges, that is the change in the loss function is smaller than the tolerance of change that is allowed. In other words the progress is not enough to justify its continued computation. The model also utilizes L2 regularization in order to prevent overfitting to the input data. Lastly it evaluates itself with use root mean square error(RMSE), where is iteratively goes through the user-item interactions and measuring the difference between the produced predicted user-item interactions and the actual observed user-item interaction and adding the root square of each difference all together and then dividing by the amount of observation made.

The output from the model was then used as the basis for the list generation functions. wherein the output from the model, in other word the predictions, is used as the input for the list generation functions.

INGKA has a component library written in the programming language Javascript and Javascript framework React [27]. This component library is a set of standardized React components to be reused on IKEAs website. This is for users of the website to have the same visual and user experience throughout all the pages in the website. Two of the components that will be used are “Accordion” and “Carousel”. The Accordion is a list of dropdown components where when an arrow is clicked, the component dropdown reveals anything within the component. When the dropdown is clicked, it will reveal a set of items, which in this case will be IKEA products, in the form of a carousel that can be scrolled horizontally. The items shown will be recommendations to the user.

The “Favorites” page on the IKEA website uses NextJS which is a React framework for handling the tooling and configuration needed for React, and provides additional structure, features, and optimizations for applications [28]. Using this framework, a page was created to build the visualization, also known as the frontend for the thesis.

3.3.3 Test POC

To test the POC, it was run on a local production server on a computer for the thesis work. The visual tests were conducted manually by the thesis writers, checking that all the buttons and components work as intended in other parts of the website. The functionality tests were done by using IKEAs own user-personas, which are discussed below, to create a user with preferences that align with IKEAs personas.

3.4 Analysis of POC

The analysis of the result was done via the user-persona method [29]. Which is a way to analyze and understand the general types of users who interact with a system, product or a service, in this case the “Favorites” page on the IKEA web store. The personas are a fictional representation of actual users and groups of users based on data and research collected from them. It's a way to understand their needs, goals, preferences and behaviors of the users, instead of learning the specifics of each specific user.

3.4.1 Gather persona-tests on POC

In order to analyze the lists generated but the model and list functions and their impact on user experience, IKEAs own user-personas were used. This included five different types of users with different preferences and needs in regards to how they use lists within the user page of IKEAs website. They were also specifically designed to be user-personas that are based around users and potential users using the “Favorites”, the same page previously mentioned, page in IKEAs webshop. They are not user-personas that include all users and potential users for the whole of IKEAs online retail website. By using the personas a general assessment could be made about favorite and list users and the thesis workers could gauge how each of these user-personas would react to the different list generated based on the result of the model.

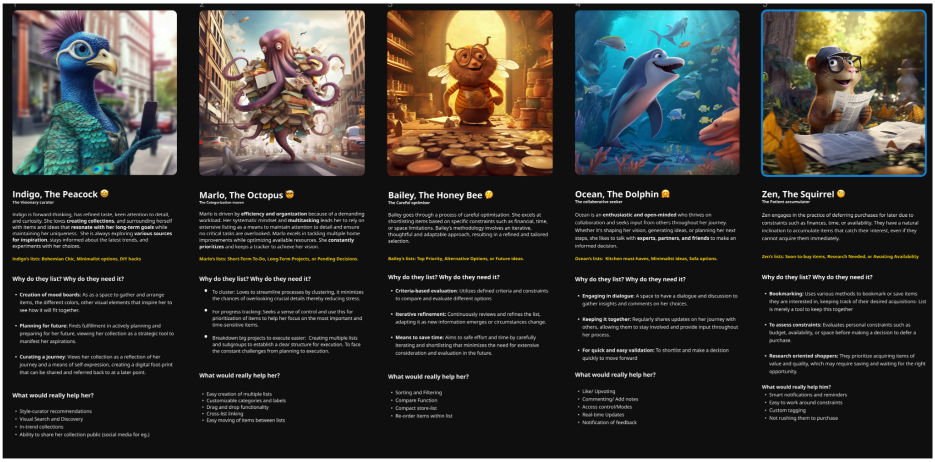

Figure 4: IKEAs User Personas

These five different user-personas shown in figure 4 are specifically about users who would use item lists and why they would use them. It is from their perspective the result from the thesis will be analyzed and judged to see if the AI assisted lists are something that would increase user satisfaction and what, if any, user experience impact the lists have.

3.5 Source criticism

An evaluation was made for each source based on certain factors such as if the publisher is a known established publisher or entity, if the source is peer-reviewed, with more recent publications being preferred.

The sources [5], [24]-[28] are linked to tools and official documents from well known and established sites and are therefore judged as acceptable sources.

The source [6] is from a known and established website that are developed and driven by a community of experts in data science and machine learning and are considered reliable.

The following sources [14,][16], [21] are from various blogs from websites that either have a focus on tech and computer science or they are self published with the ability of the public being able to comment. These are considered lower than the rest of the sources in the thesis but reliable enough to be used to get a better understanding and grasp about the foundational concepts. These concepts are checked and validated in the more academic sources.

The following sources [1], [2], [4], [7]-[13], [15], [17]-[20], [22], [23], [30] come from various known scientific publications where each piece of work has been peer reviewed. They are therefore considered reliable sources.

4. Results

The results from the model was the user and item matrix which was then later used in the list generation for a specific user to get the predicted rating for all items for that user. Four different users were chosen by the authors at random and a list for the specific category of “Kitchen & Dining” was made from them. These users are given the names of John, Gustav, Matilda, and Karin.

The following are each of the users lists with the different items that were included in their lists for the specific category “Kitchen & Dining”. Each product in the list is described with a description by the author and the corresponding item ID. The list is of the predicted top rated product for the different users.

	User Johns List
Product 1	Item Description: Place Mat, fresh mint colored Item ID: B01J663PAA
Product 2	Item Description: Spice Rack, Rotating Spice Holder Item ID: B082DXCN3L
Product 3	Item Description: Airtight Food Storage Container Item ID: B000SI9ZAA
Product 4	Item Description: Checkerboard cake decorating set Item ID: B07175N569
Product 5	Item Description: 4 cup Coffee Maker Item ID: B000F7FM9W
Product 6	Item Description: Cutting Mats containing Bamboo fibers Item ID: B072JTXMPV

Product 7	Item Description: Glass Olive Oil Dispenser Bottles Item ID: B092VH4BYG
Product 8	Item Description: Multi Purpose Grater Item ID: B07TWCKN7D
Product 9	Item Description: Ziplock Bag Organizer Item ID: B09XWVZ9G8
Product 10	Item Description: Ice Cube Trays Item ID: B088D8526M

Figure 5. User Johns Recommendation List in the category "Kitchen & Dining"

	User Gustavs List
Product 1	Item Description: Gothic Rose Cupcake Stand for Halloween Item ID: B0B5LGW926
Product 2	Item Description: Kitchen Hanging Rack Rail Item ID: B07DLVWWH3
Product 3	Item Description: Digital Price Computing Scale Item ID: B0B2VQ5HFD
Product 4	Item Description: Set of 16 Coastal Cups Item ID: B087B77M8J
Product 5	Item Description: Cup reading "His" on front Item ID:B00IGN8KG4
Product 6	Item Description: Porcelain Serving Dishes Item ID: B071HXP93F
Product 7	Item Description: Two Level Fruit Basket Item ID: B08PVJDXFF

Product 8	Item Description: Mandoline Slicer Item ID: B013JL2SVU
Product 9	Item Description: Precision Toaster, Two Slots Item ID: B08DQ75249
Product 10	Item Description: Juicer Machine Item ID: B07WGP9SKM

Figure 6. User Gustavs Recommendation List in the category "Kitchen & Dining"

	User Matildas List
Product 1	Item Description: Wood Kitchen Utensils Item ID: B01N35N9U4
Product 2	Item Description: Magnetic Sand Timer for Cooking Item ID: B00MBCLA2C
Product 3	Item Description: Measuring spoon set Item ID: B08B64JCZ8
Product 4	Item Description: Insulated Cup Carrier Item ID: B07PRMN1VW
Product 5	Item Description: Egg Holder Item ID: B00149FS3A
Product 6	Item Description: Vacuum Sealer Bags Item ID: B08JPC61N2
Product 7	Item Description: Brownie Pan with Dividers Item ID: B09WT9BXTK
Product 8	Item Description: Jar Opener Kit Item ID: B097H9VX4F
Product 9	Item Description: Measuring Cups 20PCS Item ID: B08G1N5KKW

Product 10	Item Description: Oven Mitts and Pot Holder Sets Item ID: B08N9XLK3G

Figure 7. User Matildas Recommendation List in the category "Kitchen & Dining"

	User Karins List
Product 1	Item Description: Bottle Compressor Cooler Item ID: B06XY75SBW
Product 2	Item Description: Stainless Cup 17 Ounce Item ID: B0BM9CKB3Y
Product 3	Item Description: Nonstick Loaf Pan Item ID: B07BST328N
Product 4	Item Description: Airtight Container Set with Handle Item ID: B012TSGXVK
Product 5	Item Description: Wirsh Espresso Machine Item ID: B08X627458
Product 6	Item Description: Mini Smart Oven Item ID: B00DM6GZPS
Product 7	Item Description: Wooden Spoons for Cooking Item ID: B08GZ4W193
Product 8	Item Description: Fruit Basket, 2-Tier Item ID: B094ZC1Y3F
Product 9	Item Description: Count Your Blessings Cups, 2PCS Item ID: B00TYV8FEE
Product 10	Item Description: Sheet Cake Pan, Rectangular Item ID: B01DR6ZN0K

Figure 8. User Karins Recommendation List in the category "Kitchen & Dining"

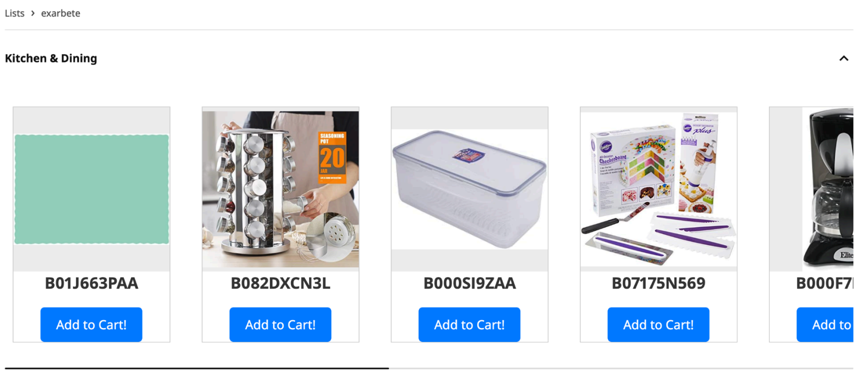

Figure 9. User Johns Recommendation List in the category “Kitchen & Dining” on the IKEA website

An example picture to show how a list would be shown in a users favorites tab on figure 7.

4.1 User personas analysis

The following is the different personas views and how they perceive the generated lists. This is done by assuming that each of the sample users are of the different user personas personalities. For example how would John in Figure 5 react to his list if he was of an Indigo personality versus how he would react if he were a Marlo personality. The user-personas are each given a rating of -1, 0 or 1, denoting if the persona would have a positive, negative or indifference user-experience and view of the lists, 1 being positive, -1 negative and 0 being indifferent.

4.1.1 Indigo

Rating: 1

Viewing the lists from Indigo's perspective there are both positive and negative aspects to the overall user experience of having made lists for them to view and use. It would resonate positive with Indigo because of the list being more personalized and that the items recommended would work as complementary pieces. It can also work as a great way to visually explore different new products and can work as a form of curated exploration of items. The user experience is also heightened by the visual elements of the list, with the ease of use drop down lists.

There are however some negative aspects with the list for Indigo. The two main ones being that the personalized list is based on the historic user-item interactions so new trending items would not show up to the rate that indigo would want. Indigo also seems to enjoy trying out different styles and collections which is also counter intuitive if those styles are very dissimilar to the item indigo have previously liked.

Indigo also finds enjoyment and satisfaction in creating and crafting the item list by themselves, having already made lists could then be seen as something indigo would disregard or even view negatively because they didn't craft and handpick the items themselves.

4.1.2 Marlo

Rating: 1

From Maslow's perspective the lists seem to have a great user experience impact. The central motivations for the list being having and creating lists to cluster items, having multiple lists and so on. Having already made lists tailored to their personal taste and different categories fits well within their want to cluster items where efficiency and organization is a prime motivator. This would save them time and help them multitask and minimize the amount of workload they would need to do to create lists.

4.1.3 Bailey

Rating 0

Bailey approaches the list with the view that they want to research items with depth, carefully and iteratively adding and refining the items within with a thoughtful approach. For this person, having made personalized lists based on categories would serve as a good starting point where they can fine tune and review the lists, in order to further personalize and tailor them to their taste. Thous since they find motivation and satisfaction in the research and comparison of different items, the AI assisted list may not add much to their overall user experience because the even if the list has been perfectly predicted to their preferences, it's highly likely that the would still engage with their previous behavior and motivation factors, such as wanting to the deep research and comparison of items. So in that regard having a made list already wouldn't affect the user experience in a positive or negative manner since they would likely ignore it in favor of doing the “models” work manually.

4.1.4 Ocean

Rating: 0

For Ocean AI-assisted list is not something of interest for them. Their motivations for lists are much more hinged on collaboration with others, such as friends or experts. They are much more suited to manually crafted lists shared to them by other people or in other words they harness the collective knowledge and opinions for insights.
While an AI made list might not affect them negatively in the user experience necessary it's doubtful they would find it positive. Most likely they would disregard it in favor or dialog they can have with other people.

4.1.5 Zen

Rating: 1

Zen have a tendency to use their lists as a practice to defer purchases for later d to various constraints. From the view of Zen the AI assisted item lists would have an overall positive user experience impact as it both works as a good starting point for them to research the items while still giving them personalization would fall into theri want of items of value of quality to them. Since they are motivated by a personal connection to the item, having such a level of personalization with the list would yield good results in regards to their user satisfaction. However there are points to consider that might impact the overall user experience negatively which is that a key motivator for Zen is deriving a sense of achievement and accomplishment for building their lists gradually and over time. Having already built lists might take away from this but at the same time it could work as a good baseline to where to start for them.

5. Conclusions

In this chapter the result will be analyzed and the problem descriptions defined in chapter 1 will be discussed and answered.

Problem 1: How does AI improve the process of list creation and management?

Implementing an AI algorithm, in this case a collaborative filtering recommendation engine utilizing a model based on matrix factorization, improves the process of list creation by making the lists that are created more personalized than a list of the most commonly bought items or items that have a high global rating average. In essence the application of such an AI method embedded a high degree of personalization to the lists, only that only the user themselves could make themselves more personal by manually creating and editing them. An item that is generally disliked by the average user might be of interest for a specific user and recommending it and including it in a list helps the user discover and possibly purchase that specific item.
Implementing a matrix factorization model is also helpful to inform the system about what the predicted satisfaction and rating a user might have about an item they have not yet seen. One positive is that the model learns the “categories” of both users and items in the form of latent features which means it is not necessary to manually categorize or collect user information such as age for the model to make the predictions.

Problem 2: What are the challenges and limitations of integrating AI in list generation?.

Integrating artificial intelligence into list generations presents a multitude of challenges and limitations that one must consider. While the benefits are improved personalized lists it has to be weighed against the cost of time and resources in implementing a model and overcoming the challenges. Which is that it can be somewhat difficult in picking the right model to solve it as there are many different approaches one could take. The one chosen in this thesis was a matrix factorization model. This was done to overcome one of the biggest challenges and that is the lack of “correct” results to train the model towards. Since there is no data about specific users specific lists it's hard to tell the model what the end result should look like. Instead we opted to make a model based on the principles of unsupervised learning, in essence the model was asked to find the patterns and then from that use that result to create lists.

However effective this model is in predicting users rating for items there are certain limitations to it. One being a well known problem for these sorts of models that is coined the “cold start” problem. If the user or item is new the model won't have any historic data about them nor any data about any user-item interaction. This makes it very hard for the model to make any accurate predictions about the new item or user. A way to solve it is to either the average global bias until more history is collected and retaining the model with the new entry with the newer data. In this case there will be a very rough estimate of the predicted user-item interaction until more accuracy can be obtained.

Another limitation of this thesis work has been that it's specifically made for lists and not overall recommendations. Therefore its current potential use is only to generate personalized user lists, and even though it yields good results in this, it is unclear if this method leads to actualized sales of the items and if so in what amount. In that regard it is up to IKEA to make an evaluation if the POC and list generation has good enough results to make the investment of time and resources of implementing worth the cost.

Problem 3: How does AI-driven list creation impact user experience and decision-making processes?

AI-driver list creation impacts user experience and decision-making processes differently for each user profile.
For the user persona Indigo, AI-driven list creation seems to resonate positively, as it gives a personalized experience where it visually provides products that are easy to use. While that's presented however, the AI may not always give results in new and trending items, which may not fit Indigo's want for exploration.
Marlo also benefits greatly from AI-driven list creation thanks to their motivation for being efficient and organized. It's efficient in the way that it saves time and aligns with Marlos desire to cluster items and lay off the workload. Overall this enhances Marlos experience.
When it comes to Bailey however, AI-driven lists may not give a big impact when it comes to deeper research. The lists could be a starting point but Bailey prefers to manually research and compare, which is where something made for Bailey does not fulfill.
From Ocean's perspective, AI-driven lists are not aligned with their Interests of collaboration and collective insights. Ocean prefers lists that come from others and are manually picked, which shows Oceans disinterest for AI-driven list generation.
Zen finds that AI-driven list generation positively impacts their user experience, because of its personalization and helps in delaying purchases. However, there is a chance that the AI generated lists

might slightly stray away from their sense of achievement in building lists over time.

This shows that AI-driven list generation impacts users differently when it comes to user experience and decision making processes depending on individual preferences and motivations. For some users it may enhance the experience when it comes to time efficiency and personalization, but for other users it might not align with their goals and preferences, which can result in the user completely ignoring the list-generation.

Overall it seems to have a positive impact with user experience for most of the personas and therefore one could infer that it would have an overall positive impact on the majority of users. However more work can be done, especially with implicit data, to classify the users into which would respond positively and who would respond negatively to the lists, this could then be used as a filter so that only users, who are enough similar to the user-personas, who are predicted to have an positive perception would have implemented lists.

Problem 4: How can the results be measured, when does AI list generation reach acceptance levels?

Measuring the result can be somewhat difficult, because of its inherent predictive nature in its results. The recommendation model is built and tested with historic data but that in itself does not necessarily mean that generating lists from that will have the same result compared to, for example, listing recommended and similar items underneath or the sidebar of a items webpage.

Problem 5: How does the integration of AI in list creation align with current web development technologies and principles of user experience?

Implementing this AI machine learning list creation currently exists in web shops for the purpose of recommending the right products to the right customer. With AI list-creation, shopping becomes more personalized to users by recommending items in lists that cater to users needs and possible wants based on user-data that the website has gathered. The user-data that has been gathered by events, which are for example what the user has searched for in the past or what items the user has clicked on. These lists are then presenting users with personalized lists, with the idea to make it simpler to shop in the way that the user's specific needs are met which in itself is a principle of personalization within user experience [30].

5.1 Ethical aspects

A non-disclosure agreement was signed between the thesis workers and IKEA during the start of the thesis. The use of IKEAs internal user-personas was discussed with the corresponding supervisor at IKEA and was approved for use in this thesis. That withstanding no other confidential information about IKEA or its internal structure has been disclosed within the thesis.
The thesis used real data about real users in its work that is publicly available where non-confidential information about the users is available. However there is no need to use or disclose those parts of the data for this thesis, rather only the user ID variable within the data was used for the model. The thesis does not disclose this variable however, instead it uses pseudonyms such as John or Matilda for the ID variable. Without knowing ID there is no reasonable way a person or entity could find out and connect who “John” is.

Another interesting ethical aspect is how the use of AI affects the user, and in which manner it is ethical. Whenever a developer strives to create personalization for a user they run the risk of such a system feeling invasive to a users privacy, it might create a feeling of not being private with the system they engage in, something there is reasonable expectation of. An example would be the common example of getting target advertisements in a way a user feels inappropriate. This is because a user perceives that the data collected to make this personalization was done in an unethical manner.
Since the POC created in the thesis only uses explicit data such as ratings, which are public, the model should not cause any ill feelings of a breach of privacy or a feeling of it being invasive. Even if it used implicit data that is contained to what the user is willing to “give” to the system, in other words they would have to agree to it, for example creating an account. And the usage of that data is contained to the website and its systems. Its not remarkably different from having a store clerk in a retailing shop asking what each customer would rate the products they bought and writing it down, along with the perceived characteristics.

The lists being generated are also private to the user, the data about them and their interaction history within the systems can therefore be viewed as a private thing, unique to each user. Even if it relies on other users' historic data to generate the lists, that data will never be disclosed to other users.

In the end the use of AI in the way this thesis is done is just a new more advanced tool to try to persuade the user to, in thesis work context, purchase a certain item. Trying to persuade customers to buy certain products has been done for a very long time and is nothing new.

6. Future Improvement

Further improvement on the model could be made such as using implicit data to make the model more accurate. It could also measure user similarity, using for example a cosine similarity algorithm to reduce the cold start problem of adding new users. In this a new user's attributes would be measured and an initial assessment would be made that they would want items that a user that is very similar also wants.

In regards to the list generation some further improvements could be made such as filling out a users already existing list. This however would need to be tested and measured to see the user satisfaction impact. It could also “add” to the user-item interaction score of certain items that the company would be more keen in showing regardless of the users actual preference for it might be, for example a new item or an item the company wants to increase sales for.

Also having real users test the thesis work for a correct evaluation from the target audience of the thesis work, which are IKEAs webshop customers. This would help with making observations of the way the real users navigate the thesis work, and also get feedback from surveys and interviews from the users on the experience of using this thesis work. With the feedback and observations, changes could be made to the model with the goal of it being more user friendly and having improved user experience.

The data that was used for the thesis work in the end was extracted from an older (2023) Amazon dataset through a github link [26]. This data was similar in terms of both webshops selling furniture and kitchen products, however for a more tailored thesis work, acquiring IKEAs dataset would change the results. Since IKEA offers its own range of products, acquiring the dataset would allow for a more focused analysis. It would offer a more comprehensive understanding of user preferences and purchasing patterns.

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