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Developing a Recommender System for a Mobile E-commerce Application

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Abstract

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This thesis describes the process of conceptualizing and developing a recommender system for a peer-to-peer commerce application. The application in question is called Plick and is a vintage clothes marketplace where private persons and smaller vintage retailers buy and sell secondhand clothes from each other. Recommender systems is a relatively young field of research but has become more popular in recent years with the advent of big data applications such as Netflix and Amazon. Examples of recommender systems being used in e-marketplace applications are however still sparse and the main contribution of this thesis is insight into this sub-problem in recommender system research. The three main families of recommender algorithms are analyzed and two of them are deemed unfitting for the e-marketplace scenario. Out of the third family, collaborative filtering, three algorithms are described, implemented and tested on a large subset of data collected in Plick that consists mainly of clicks made by users on items in the system. By using both traditional and novel evaluation techniques it is further shown that a user-based collaborative filtering algorithm yields the most accurate recommendations when compared to actual user behavior. This represents a divergence from recommender systems commonly used in e-commerce applications. The paper concludes with a discussion on the cause and significance of this difference and the impact of certain data-preprocessing techniques on the results.

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1 Introduction

1.1 Overview

The goal of this project is a functional recommendation algorithm integrated into the mobile application Plick. Plick is an e-marketplace application for vintage clothing with a user-base in the thousands. The application was launched in 2013 and has seen an increasing stream of articles of clothing being posted, leading to a huge selection of ads for potential buyers to wade through. This problem of an overwhelming supply is closely related to the more general expanse of available information made possible by the internet, by many researchers referred to as *information overload*.[1] It is exactly this issue that recommender systems are designed to address and is why Plick was considered in need of some form of personalized filtration of the available inventory.

The market for vintage clothes has benefited greatly from the advent of e-commerce, bringing buyers and sellers together with minimal effort. It has been further boosted by an increased interest in environmentally friendly consumption habits in the past few decades. It is in this emerging market that Plick exists, making use of the technologically driven simplicity of connecting consumers with both individual sellers but also larger retailers of used clothes without their own online platforms.

In the recommender systems research field the e-marketplace is a new and very atypical case that brings unique challenges to the fore and that may require novel approaches to tackle.[2] An example of these challenges is the fact that in the selling of used clothes there is usually only one of each item in the inventory and when that is sold it is gone from the system. This makes it impossible to use a recommendation approach like Amazon's "people who bought this also bought…" There are many issues like this that come with the peer-to-peer structure of an application like Plick. These issues are the reason Plick is such an interesting case to apply recommender systems technology on. Meaningful relationships in the data have to be identified in a changeable, almost volatile, environment.

The project was carried out in the Uppsala offices of Swace Digital, Plick's parent company.

1.2 Project Outline

The outline and details of the project were decided on by the master's student in collaboration with the creators and developers of Plick. The project was carried out in three overarching stages:

1. Exhaustive study of the research field and the commonly used techniques. From this baseline a few promising methods were chosen for implementation and evaluation.
2. Implementation and comparison of the selected methods. In this stage the top performing algorithm was selected for implementation in the live system.
3. Evaluation of the implemented solution and reporting.

[1] Francesco Ricci, Lior Rokach, Bracha Shapira, *Introduction to Recommender Systems Handbook*, Springer, 2011, pp. 2

[2] Note the distinction between e-marketplace and e-commerce. E-commerce is the umbrella term for all systems engaged in buying or selling goods and services online whereas an e-marketplace is a system where transactions are peer-to-peer oriented and the goods and services are unique or at least not produced by the owner of the marketplace.

1.3 Questions

As the project is a very practical one the questions that can be answered by it are more specific and technical rather than general and scientific as is often the case with more theoretical projects.

- What are the unique challenges posed by an e-marketplace context when designing a recommender system? How could they be handled?
- What would a recommender system appropriate for implementation in Plick look like?

The first question will be a recurring topic throughout the report and will be answered in the last section. The second question is answered in the form of the system described in section 5 of the report and is further broached in the final discussion. Note that the second question is not asking for the best possible system, only an appropriate one.

1.4 Methods and Tools

As stated above, a project of this type is in its nature very practical. The objective is to deliver a component to a system that will hopefully increase user-activity and sales. However, designing a reasonably high performing recommender system requires knowledge of the existing methods and sufficient understanding of the mathematics they employ to apply them to the case in question. With this in mind the main methodology of this project is to make use of existing recommender system theory and descriptions of practical recommender applications to tailor a system that fits the Plick case.

The tools used to carry out this project came mainly in the form of database management tools and software development tools. To access, track, view and manipulate the data the following technologies were used: MongoDB, MongoHQ, PostgreSQL, PGAdmin3 and Microsoft Excel. The MongoDB-programs were used to extract and insert the new data attributes introduced in this project into the system. The Postgres-programs were used to extract and analyze the existing historical data. To design the system itself these software development technologies were used: Python and IDLE (Python GUI) with the Python libraries Cython, Numpy, PyMongo, Psycopg2 and Pandas. The app-hosting service Heroku and the version control-system Git were used to deploy the finished system. The literature study was carried out using Uppsala University’s library resources and Google Scholar.

1.5 Report Structure

The report is divided into seven sections. Section 1 introduces the project and describes the goal and the questions the project will address. Section 2 gives a background to the research field the project belongs to. This is followed by section 3 which is a brief overview of the system in question, Plick. Section 4 describes the process of selecting the methods to be implemented for testing, based on what was learned in the previous sections. Section 5 describes the fine-tuning of the final system. Finally, section 6 contains a discussion and the concluding remarks about the project. Section 7 holds the reference list.

1.6 Source Criticism

The main source used in the literature study is the Recommender Systems Handbook. This work is an edited collection of 24 papers and reports, each with its own author or set of authors. By including such a vast pool of co-authors it seems the editors of the handbook have attempted to create a one-stop beginner's guide to developing recommender systems and it has to some degree been used as such in this project. Using one source as a theoretical foundation this extensively is not without its risks. Accepting the formulation of, and solutions to, the recommender system problem as proposed in the handbook means that this project begins with an outlook already "zoomed in" on a certain way of doing things. That is, the search for a suitable recommender system begins with a clear definition of what a recommender system is and what kinds of recommender systems are used today. While it would perhaps be more academically rewarding to start by formulating the recommender problem very broadly and drawing up prototype systems mathematically, the practical limitations of the project prohibit such an ambitious scope.

2 Recommender Systems

In this section the results of the literature study are presented, providing an overview of the current research field.

2.1 About Data

The success of any system that hopes to predict the behavior of a user hinges on the type, volume and quality of data available. Availability of some data is usually not a problem in this age of big data, business intelligence and personalized user experiences. In most systems everything is stored somewhere, even if there is no immediate plan to use the information. The issue facing someone designing a recommender system is how to discern what data is usable and what it actually means. In the case of a movie recommendation system of the type that Netflix uses, the data that is used is a very straightforward set of 1 to 5 stars-ratings connected to a user that can be immediately fed to a recommendation algorithm. In other cases it is not as simple to interpret users' preferences. Consider an online edition of a newspaper. There is probably a multitude of data stored for each user-article interaction, everything from time spent reading the article to possible "likes", comments or social media-shares made by the user, a lot of which is potentially useful information. The question is how these data points should be understood when thinking about the preference of the user. How does 5 minutes of reading compare against leaving a comment in terms of interest shown? How to handle slow readers, social media buffs and other outlier-behavior?

2.1.1 What is a Rating?

In order to understand usable data we must first define the concept of ratings. In the context of recommender systems, ratings are used to describe more than just a point on some arbitrary

scale. Every piece of information that implies a user's opinion of or interest in an item[3] can be understood as a rating, or alternatively as a part of an aggregated rating. When aggregating a set of data points it is important to make use of some standardized way of weighting and scaling data with different features. In the case of the newspaper website the problem of aggregating view-time with possible uses of the like-function would be an example of this. What this would require is a formula that could scale the continuous value of reading time and translate it to a score comparable to and combinable with the binary data that for example 'likes' provide.
In order to make use of rating data it is often stored in one big matrix called the user-item rating matrix; Fig 1 is an example of this.[4] It consists of one axis with all users in the system and another with all the items. The elements in the matrix are then the ratings given by each user to each item. Depending on the available data and if the ratings are aggregated this data structure can actually be made cubic and contain a third axis consisting of the data types used by the system. For simplicity's sake only the matrix version will be considered here.

				ITEMS			
		i_1	i_2	i_3	i_4	…	i_n
	u_1	3	5	0	1	→	r_{1n}
	u_2	1	0	0	2	→	r_{2n}
USERS	u_3	3	3	0	3	→	r_{3n}
	u_4	0	0	1	5	→	r_{4n}
	…	↓	↓	↓	↓	↘	-
	u_n	r_{n1}	r_{n2}	r_{n3}	r_{n4}	-	r_{nn}

Fig 1: A generic user-item rating matrix.

2.1.2 On Explicit and Implicit Ratings

With the broad definition of a rating above it is necessary to state that although many things can be considered ratings they can differ from each other greatly. One important difference is the one between explicitly given and implicitly interpreted ratings. The first type is very straightforward, being the type of rating that is consciously provided by a user for no other reason than to indeed rate the item in question. Examples of this are the Netflix star-ratings and the up- and down-votes on the website Reddit.com. Implicit ratings are then every piece of information that says something about a user's attitude towards an item but is not provided consciously by the user.

[3] The term 'item' is used for all objects that recommender systems can be applied to. Anything from a movie to a sweater or a master's thesis report can be an item.

[4] Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich, *Recommender Systems: An Introduction*¸ Cambridge University Press, 2011, pp. 13

Examples of this could be product viewing history on Amazon.com, reading times for different articles on a newspaper's website or even time spent hovering with the mouse over a link. Implicit ratings are more difficult to use in the domain of recommender systems and their role in the system is an active field of research. Among others, how to solve issues of weighting the different types of data against each other and also against possible explicit ratings and how to understand implicit data in terms of positive/negative (does clicking one link over another in a list only imply interest in the clicked link or also a negative preference for the unclicked one?) is still very much up for debate.[5][6] In this project it was assumed that lower than average ratings for an item does not indicate negative preference based on the following reasoning. If the absence of a rating is considered as a neutral preference (it is not possible to discern if a user has actively decided not to interact with an item or simply missed it), then any interest in an item is at worst neutral and at best positive regardless of the level of interest.

2.2 Families of Recommender Algorithms

Most experts on recommender systems divide the popular algorithms into three or more families depending on the fundamental differences in their approaches. The descriptions presented here are based on the research done in the two works *Recommender Systems: An Introduction*[7] and *Recommender Systems Handbook*[8].

2.2.1 Content-based Filtering

Content-based recommendation algorithms are defined by the use of both user- and item *profiles* that the system learns based on users' rating history. These profiles contain information about what item features each user values and are used to recommend items that match these features. A significant advantage of a content-based system is that a new item that is just introduced in the system can be recommended just as easily as an item with a long user interaction-history, assuming that adequate information about the item is provided. Another great advantage is the fact that the system is completely user-independent in the sense that users do not need to be clustered or compared in any way in order to make recommendations. This allows for a diverse model of user-interests rather than predefined "molds" that some approaches use to classify users.[9]

The content-based approach is not without its limits and demands a lot in terms of information and processing power. The main drawback is the need for detailed information on top of the standard need for rating data. This information can take many forms but must be in some way standardized for the algorithm to be able to compare items and preferences. Information of this

[5] Tong Queue Lee, Young Park, Yong-Tae Park, *A Similarity Measure for Collaborative Filtering with Implicit Feedback*, ICIC 2007, LNAI 4682, Springer-Verlag Berlin Heidelberg, pp. 385–397

[6] Peter Vojtas, Ladislav Peska, *Negative Implicit Feedback in E-commerce Recommender Systems*, Proceedings of the 3rd International Conference on Web Intelligence, Mining and Semantics, Article No. 45, 2013

[7] Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich, *Recommender Systems: An Introduction*¸ Cambridge University Press, 2011

[8] Francesco Ricci, Lior Rokach, Bracha Shapira, *Introduction to Recommender Systems Handbook*, Springer, 2011

[9] Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich, *Recommender Systems: An Introduction*¸ Cambridge University Press, 2011, pp. 51-54

type may be readily available and easy to work with, think for example of movie attributes such as genre, director or country. It can however also come in the form of long, user-authored descriptions or other less obvious shapes. In these cases the pre-processing needed for the system to acquire usable representations of the items can be substantial, costing processing power and requiring large amounts of memory to function. Another significant drawback of a system of this type is the lack of support for new users with few or no ratings. Finally, a more subtle problem with using content is that the recommendations will all match a user's preferences and in many cases will never recommend anything outside of the user's "comfort-zone", creating a problem of lack of *serendipity*[10] in the recommendations.[11]

2.2.2 Knowledge-based Filtering

When recommending everyday items of consumption such as music, films, clothes or books there is often an abundance of data about users interactions with the available items. However, in some businesses and industries this is not the case. An example of this is the market for apartments in a city. By the very nature of this item there will not be much data for sales, ratings or anything of the sort. Recommendations of the kind "other users who bought this also bought – ", make no sense in this context. It is in these cases that knowledge-based recommendation approaches can be very successful. The general idea is to make use of as much user-specific, item-specific and domain-specific data as possible to create tailor-made recommendations. This is done by using explicitly defined user preferences together with implicit user data to create user profiles that are constrained by a set of pre-defined rules to have the profile make logical sense, i.e. to match a real type of user. The items are then filtered and matched with users based on how well they suit the profiles.[12] To use an example from the financial instruments industry a knowledge based system would prompt the user with a number of questions to establish a set of constraints such as experience level, willingness to take risks, duration of investment etc. It would then use a set of pre-defined rules to cut down the size of the domain of possible recommendations. These rules could be for example "a financial market novice should not be recommended high-risk stocks unless they report interest in high risk" or "long-term investors should be recommended products with long minimum investment periods".

Knowledge-based algorithms can be very accurate and useful when dealing with a domain where the items are few but of great importance or value to the users. Some examples often cited in literature are the above mentioned financial instruments and services, the housing market and the automobile market. The major drawback of this approach becomes apparent when applying it to something of higher item frequency and lower value. The act of creating and codifying the

[10] Serendipity is an adjective that describes a "pleasant surprise" and should in this context be understood as a measure of the rate of unexpected true positives in a set of recommendations.
[11] Christian Desrosiers, George Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 110
[12] Alexander Felfernig, Gerhard Friedrich, Dietmar Jannach, Markus Zanker, *Recommender Systems Handbook: Developing Constraint-based Recommenders*, 2011, pp. 187-191

profiles for all items in the system is a significant one and becomes more or less insurmountable in cases with millions of users and items.[13]

2.2.3 Collaborative Filtering

The collaborative filtering approach uses a simplified understanding of the recommendation problem and considers only the rating data when predicting user interest. Being easy to understand and relatively easy to implement while still maintaining impressive accuracy, collaborative methods have been the most popular since recommender systems started being used in industry in the 1990s.[14] The various implementations are numerous and getting an idea of the set of collaborative filtering methods that are used today can be a good way of giving yourself a mild headache. For this reason only the higher level classifications will be presented here. First described are the so called “neighborhood”-approaches where the focus is to group entities, either users or items, based on some similarity that is computed based on the rating history. [15] Neighborhood-methods are characterized by the way they operate on the data directly and are for this reason sometimes referred to as being memory- or heuristic-based.[16] The other collaborative filtering approaches are conversely often defined as model-based. This because of the common structure of having a mathematical model *learn* from a set of data to later be able to predict ratings. The model-based methods are numerous and many of them very complex which is why this chapter only includes a description of one such method, the recently popularized matrix factorization method.[17]

2.2.3.1 User-based

The user-based collaborative filtering approach is based on the assumption that there are naturally occurring groups of users in any given system that can be identified by looking at their preferences and/or behavior. By using such information, recommendations for a certain user can be made by first finding the group of users he/she belongs to by computing their similarity to other users based on the ratings they have in common. After having done this every user will have a set of nearest neighbors that can then be used to make recommendations.[18] For example, the set of items that are the most popular in the neighbor-group that the user in question has not yet viewed. The predicted rating $\dot{r}$ for a user u on an item i is in its most simple form calculated using (1). An estimation based on the sum of each rating r (from the user-item rating matrix R)

[13] Alexander Felfernig, Gerhard Friedrich, Dietmar Jannach, Markus Zanker, *Recommender Systems Handbook: Developing Constraint-based Recommenders*, 2011, pp. 187

[14] Francesco Ricci, Lior Rokach, Bracha Shapira, *Introduction to Recommender Systems Handbook*, Springer, 2011, pp. 12

[15] The notion of neighbors in statistics is widely used and should in this case be understood as the top-n (where n is some real number) other users in a list of all users ordered by some similarity measure.

[16] Christian Desrosiers, George Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 111-112

[17] Christian Desrosiers, George Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 112

[18] Christian Desrosiers, George Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 114-115

made by each neighbor *v* multiplied with the similarity weight between the user and the neighbor, normalized by the denominator which is the sum of all similarity weights between the user in question and all neighbors that have rated item *i*, the set N_i.

$$\dot{\mathrm{r}}_{\mathrm{ui}} = \frac{\sum_{v \in N_i(u)} w_{uv} r_{vi}}{\sum_{v \in N_i(u)} |w_{uv}|} \tag{1}$$

The user-based approach is considered best suited for environments where the number of items exceed the number of users and where the user base is fairly stable since it requires a certain amount of historical data about each user to make good predictions.[19]

2.2.3.2 Item-based

In the item-based approach the focus is instead on the items. Some similarity measure is used to calculate the similarity between each and all items, based on the users they have in common in their rating histories. This means that in this case the neighborhood is made up of items rather than users. To make recommendations to a specific user the system then considers that user's previous ratings and suggests items that are most similar to the users' most preferred items.[20] The predicted rating for a user *u* on an item *i* is an estimation based on the sum of each rating made by the user multiplied with the similarity weight between the item and each neighbor item *j*, normalized by the denominator which is the sum of all similarity weights between the item in question and all neighbor-items rated by the user, the set N_u.

$$\dot{\mathrm{r}}_{\mathrm{ui}} = \frac{\sum_{j \in N_u(i)} w_{ij} r_{uj}}{\sum_{j \in N_u(i)} |w_{ij}|} \tag{2}$$

Item-based recommenders are widely used in commercial settings since they are capable of handling the common situation of having a lot more users than items; often the case in markets such as e-commerce and movie-streaming.[21]

Note the relationship between (1) and (2). The calculations are very similar but the focus is on different entities, users or items. Additionally it should be made clear that these are the general formulas and therefore uses the absolute value of the weights to be able to handle negative similarities.

[19] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 115

[20] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 117

[21] Ibid

2.2.3.3 Matrix Factorization

In recent years matrix factorization techniques have gained significant popularity, being featured in many of the top solutions to the Netflix Prize challenge, including the winning submission.[22] Matrix factorization is based around the idea of latent information existing in the user-item rating matrix. This latent information is usually understood to represent certain features that exist in the data, some of which can be readily interpreted (example: people who rate b-action movies highly tend to dislike romantic comedies) and others that are more subtle. This is closely related to the information retrieval concept SVD (Single Value Decomposition) and indeed involves a decomposition of the user-item rating matrix.[23] Mathematically the approach is to map users and items to a latent factor space by creating vectors for each user and item whose inner product corresponds to an element in the rating matrix. These features are learned by minimizing the regularized squared error, meaning that the algorithm changes the values of the features iteratively and calculates how close the resulting product is to the target value during each iteration. This is done for all features considered and is optimized, usually by way of gradient descent or a least squares method, to predict the known elements of the matrix. Combining these vectors will then yield a matrix where all previously unknown values are predicted by using the latent factors. This approach is highly scalable and has been proven to yield very accurate results for many datasets. One of the biggest advantages is that by using latent information this approach can actually find similarities between users or items that have no overlapping information, something that can be crucial when using sparse data. The function that is minimized is generally on the same form as (3) where the first term represents the error ($\mathbf{p}_u\mathbf{q}_i^T$ yields the predicted rating) and the second term is the change. (P and Q are the latent factor matrices, λ is the rate of regularization).[24]

$$err(P,Q) = \sum_{r(u,i)\in R}(r_{ui} - \boldsymbol{p}_u\boldsymbol{q}_i^T)^2 + \lambda(\| \boldsymbol{p}_u \|^2 + \| \boldsymbol{q}_i \|^2) \tag{3}$$

2.3 Recommendation Engines

Recommender systems can take many shapes and forms. In this project, the ideal system structure would be one where the recommender system is a separate from the larger system, to simplify the architecture of the whole application. This can be viewed as a black box component, a component that can be fed data and that returns results without being dependent on the system it is in. The contents of this black box are will themselves be divided into sub-processes that deal with each step of the recommendation process. These components vary depending on the type of

[22] In 2009 Netflix provided access to their rating-data and held a competition where teams worked to come up with a recommendation engine that could out-predict Netflix's own system by at least 10%, awarding the winning team one million dollars. Read more at: http://www.netflixprize.com/

[23] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 132-134

[24] Yehuda Koren, Robert Bell, *Recommender Systems Handbook: Advances in Collaborative Filtering*, 2011, pp. 151

recommender system but generally include some preprocessing of the data, an algorithm that connects or groups either users or items and finally some method of drawing recommendations from the calculated similarities.[25]

2.3.1 Data Preprocessing

There are very few cases where data can be read from a system and used as-is in a recommender system. For the most part some logic is required to have the data make sense from an algorithmic standpoint.[26] Sometimes it is as simple as translating a dataset of likes and dislikes into 1's and 0's and sometimes it can be something requiring very complicated logic, e.g. data mining operations such as clustering entities before using a neighborhood-based method or sampling data to reduce computational cost.

There are many preprocessing schemes designed to cluster, classify or otherwise make sense of the data before it being used by the recommender. Apart from these methods are the more direct normalization measures that are applied directly on the ratings in order to increase the accuracy of the predictions that are to be made using the data. An example of this is subtracting users' mean ratings from all their ratings in order to account for differences in rating behavior.

For methods that use complex data, preprocessing can be very expensive, something that is important to remember when choosing a recommender system. Consider for example a content-based recommender that uses key words to recommend news articles. To search thousands of articles for multiple keywords and create profiles for each item is a huge preprocessing job compared to computing the similarity between two profiles once they are created.

2.3.2 Similarity Measures

Many recommendation algorithms make use of some type of similarity measure. The common collaborative filtering methods use similarities to first decide the top-N neighboring users or items and then again to weigh the "importance" of the input from each of these neighbors (the w's in (1) and (2)). Text based systems often use cosine, or lexical, similarity to compute the similarity between for example articles or reviews.

There are a number of common similarity measures, each with different pros and cons. Two of the most common ones are the above mentioned cosine similarity and another called Pearson correlation. Cosine similarity was first popularized in the field of information retrieval and is defined as the cosine value of the angle between two rating vectors in n-dimensional space where n is the number of elements in the vectors. For example, when computing the similarity between two users in a movie rating database, n will be the total number of movies in the database.[27]

[25] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 121-131
[26] Xavier Amatriain, Alejandro Jaimes, Nuria Oliver, and Josep M. Pujol, *Recommender Systems Handbook: Data Mining Methods for Recommender Systems*, 2011, pp. 40-41
[27] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 124

$$cos(\mathbf{x}, \mathbf{y}) = \frac{(\mathbf{x} \cdot \mathbf{y})}{\|\mathbf{x}\| \|\mathbf{y}\|} \quad (4)$$

Pearson correlation measures the linear relationship between the same two vectors. This is done by dividing the covariance between the vectors by the product of each vectors standard deviation as shown below. [28]

$$Pearson(\mathbf{x}, \mathbf{y}) = \frac{\sum(\mathbf{x}, \mathbf{y})}{\sigma_{\mathbf{x}} \sigma_{\mathbf{y}}} \quad (5)$$

Pearson correlation accounts for the mean and variance caused by differences in user behavior. This is problematic when using implicit ratings. Accounting for the mean in a rating vector is done by subtracting a user's mean rating from each rating made by that user. When applying this on implicit ratings the issue becomes that relatively low magnitude preferences are seen as negative in comparison to the mean which does relay actual behavior well. A newer, more novel similarity measure called inner product similarity has been suggested as a way of better capturing similarities based on implicit ratings, as described below in (6).[29] It is defined simply as the inner product between two rating vectors. The idea is that when it comes to implicit ratings one might not want to normalize the magnitude of the data by user behavior as in the other similarity measures, since it can contain information. Instead the ratings are used as-is. The risk in doing this is of course that very active users or users with very abnormal behavior might influence the recommendations greatly.

$$IP(\mathbf{x}, \mathbf{y}) = \mathbf{x} \cdot \mathbf{y} \quad (6)$$

2.3.3 Predicting and Recommending

The final step of the recommendation process is the recommending itself. This is sometimes fairly trivial but can also turn into an involved process in its own right depending on the system in question.

A recommendation is in most cases the direct product of a prediction. The system predicts either the exact rating a user is likely to assign an item or simply a binary attribute such as "might interest the user" or "probably not interesting to the user". In some algorithms the predictions are produced automatically, for example in the case of matrix factorization algorithms the entire user-item rating matrix is filled with predicted values where there used to be unknowns. In other algorithms each prediction has to be computed individually. This is the case for user- or item-based methods where the predictions are drawn from an aggregate list of neighbors' rating histories. This calculation can be augmented by a variety of extra steps to account for special attributes the data might have.

[28] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 125

[29] Tong Queue Lee, Young Park, Yong-Tae Park, *A Similarity Measure for Collaborative Filtering with Implicit Feedback*, Springer-Verlag Berlin Heidelberg, 2007

3 System Information

This section will provide information about e-marketplaces in general and the Plick case specifically. Its architecture, features, usage and data collection will all be described.

3.1 Data in the E-Marketplace

E-marketplaces have been around in some shape or form since the 90s and the concept is now far from novel. Indeed it has now become a key part of the online market with businesses like eBay, Craigslist and Etsy logging huge amounts of traffic and financial transactions. When considering these sites it is important to remember that they are fundamentally different from regular e-commerce sites such as Amazon (or really any retailer's online shop). The most important difference is the fact that in the e-marketplace the goods are being sold by users rather than the provider of the system as is the case for regular e-commerce sites. This fact has a huge impact on what kind of data can be collected for a recommender system. To understand what kind of data is available we have to account for the following:

- Every item in the system is unique (and even if they are not, it has to be assumed that they are). This has huge implications in terms of what data can be known about each item. There will be no historical data for purchases of the item, seeing as it disappears from the system once it is sold. Furthermore, we will lack solid historical data for the item in general. Page views, comments, likes, etc. mostly make sense after a certain period of time when enough data has been built up to rule out anomalies and outlier-behavior. Finally there is the fact that explicit ratings make almost no sense when items can only be purchased once. Only in the sense that users browsing the item like the pictures or description of it can explicit interest be collected, not in the sense of a review given by an owner of the item.
- Items are uploaded and described by each individual seller. This can lead to huge differences in the quality of the description and what kind of information is available about the item. Some users might provide every piece of information they can think of whereas others might just say "worn once, buyer pays for shipping". When this is the case it can make it very difficult for any type of content-based system to find a standardized way of comparing items. It is possible to guard against this however, mainly by requiring users to provide certain pre-defined points of information about what they are uploading.
- The uniqueness of the items causes issues in the user-related data as well. Purchase histories become shaky if a high percentage of transactions take place outside of the system, a high throughput of items might lead to users missing items they would have been interested in which risks skewing the data.

3.2 The Plick Case

Plick was first launched in 2013 and has since grown into a service with thousands of users and tens of thousands of articles of clothing.

3.2.1 System Architecture

The main concept in the architecture of Plick is the focus on feeds. All clothes that are posted can be seen in a “never ending” feed of pictures which is ordered by upload time, showing the newest items first. This feed can be filtered in by gender, category and geographical location. Additionally there is a second feed where items posted by users that you (as a user) follow are shown. To interact with sellers, users can start conversations that are tied to each item where they can work out purchase details, shipping and other practicalities.

This type of architecture has important effects on how users browse items. Both the follow-feed and the browse feed show the newest items at the top, meaning that older items are pushed down further and further as new items are uploaded. After time an item will only be found by browsing for a relatively long time, alternatively by filtering the feed heavily to reduce the amount of items shown. This means that items have a measurable life-span which is the period in which they are viewed regularly and interacted with. Not only is this a strong argument for the implementation of a recommender systems but it is also a reminder that items might be overlooked by users for no other reason than that they did not use the app for the time a particular item was “active”. This has important consequences for the selection of the recommender system and will be covered in the next section.

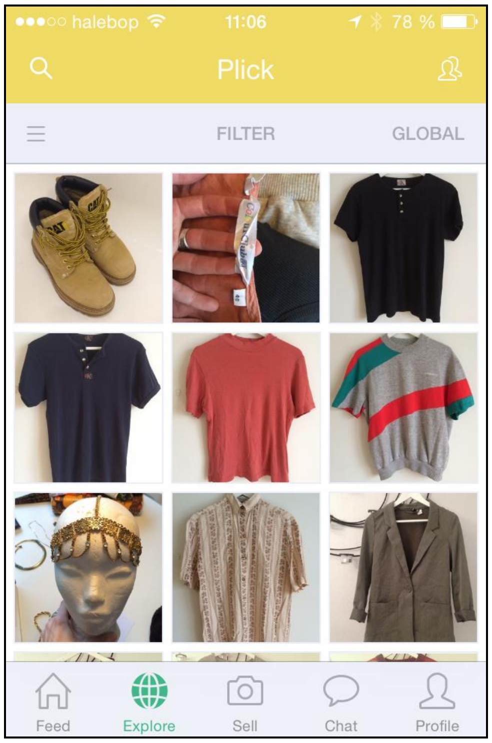
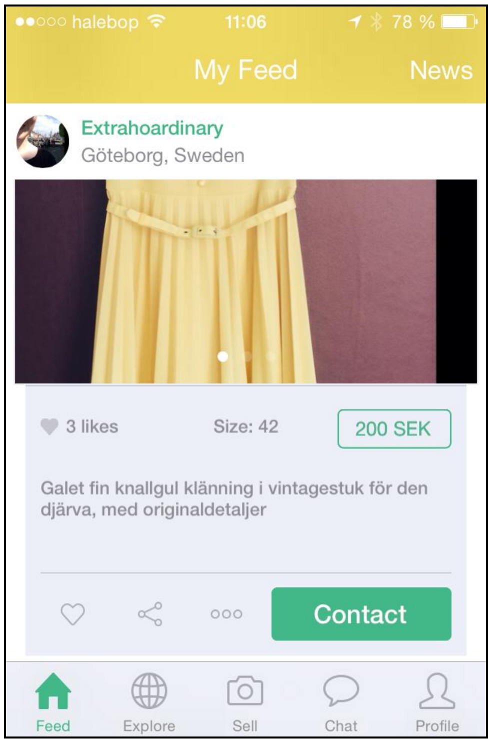
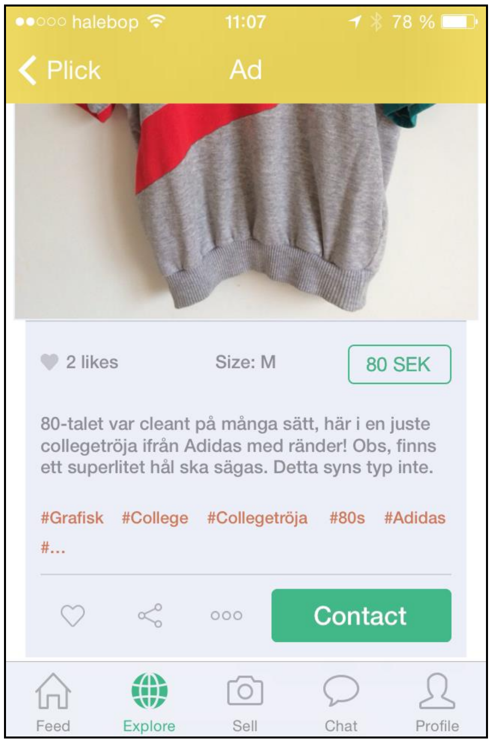


Fig 2: The “Explore” view where most of the browsing happens.



Galet fin knallgul klänning i vintagestuk för den djärva, med originaldetaljer

Fig 3: The "home feed" where ads posted by people you follow are shown.



80-talet var cleant på många sätt, här i en juste collegetröja ifrån Adidas med ränder! Obs, finns ett superlitet hål ska sägas. Detta syns typ inte.

Fig 4: An individual ad's page.

3.2.2 Features

Plick has a light-weight and minimalistic approach to e-commerce, e.g. the main browse-feed contains nothing but pictures of items and only displays other information when a user clicks through to an item’s page. Still, Plick does contain some essential features. There is a guide that tells users how to upload their own items just using the camera on their phone. This guide also gives tips about how to make sure that the item stands out and is displayed in the best possible way. As stated above, users can “follow” other users which means that they subscribe to updates about those users’ activities. Additionally, Plick is connected to Facebook and it is possible for users to create their accounts through Facebook and also to share their ads on Facebook directly through Plick. A user can also “like” an item when on the item’s page.

3.2.3 Users and Items

Users and items in Plick have a couple of different attributes connected to them. Users have a name, email, country, city and description tied to them but everything is user-defined and except for name and email they are optional, making the information known about one user very different from the next. The items have more information tied to them. Seller, location and price are all required to post an item to the system. Additional information consists of gender, size, description but these are not required.

There is a clear division of users into three groups: buyers, sellers and people who do both. The largest group is the buyers but many people do try to also sell items, although more sporadically than the more specialized sellers. In this group we find a set of very active individuals and another set of physical retailers who use Plick to advertise and sell part of their inventory.

Plick is mostly a Swedish phenomenon as of now, with large clusters of users in the four largest cities in Sweden. Little is known about what happens offline when a transaction is initiated in the app. Payment- and shipping methods are mostly unknown and it is not possible to track which user buys a certain item as both the financial and physical transaction happen outside of the app.

By using the information about gender provided with the items it was possible to approximate the ratio of female to male users and it was found that the number of female users far exceeds the number of male users, something that also becomes apparent when scrolling through the app.

3.2.4 Data

With this information in mind we now know what kind of data that can be mined from the system. It is obvious that a lot of the data in the system is unreliable, either because the users are not required to provide it or as a result of the design of the system’s structure. This affects which recommender system methods can be used and what kind of accuracy can be expected. There are no explicit ratings except for likes, which are used by a subset of users. In terms of reliable implicit data there are a few data points in the system that can be of use. Conversations between buyers and sellers are strong indicators of interest and since they are the first step towards a transaction they can be considered the closest thing to purchase history that is available. Another key data point is item views. Whenever a user taps on an item’s image through to the item’s page it indicates a certain interest in the item since the user selects the particular item out of a constant flow of others. At the start of the project this user-action was not logged by the system but that was implemented shortly after the beginning to facilitate the recommender system.

Even with item-views being logged, the data in Plick is very sparse. When the user-item rating matrix is constructed this becomes very clear, having a 99.6% sparseness. However, it is important to remember that this matrix includes many items that were uploaded long before view-tracking was implemented and therefore has very few views since their time of activity is long gone. The sparseness should decrease over time but will remain generally very high for a data set of this type. To improve the data density during testing only data logged after the introduction of view-tracking were used in this project.

4 Selecting a Recommender System

So far we have discussed the most popular types of recommender systems. This section will cover the reasoning and strategy behind selecting the components of a recommender system that works for the e-marketplace case. To do this we must first understand the unique attributes of Plick as an e-marketplace and how its features affect which methods can be implemented.

4.1 Matching Data and Algorithms

The data available in Plick renders certain recommender system methods unusable for this case. Others are usable but may need tweaking. This section covers the reasoning behind the selection of methods to implement and evaluate based on what was learned about the available data in the previous section.

4.1.1 Content-based methods

The content available in Plick could theoretically be used to make recommendations. In practice the huge difference in how extensive and detailed the content is makes it very hard to use a standardized way of translating the content into numerical vectors and measuring them to each other. There would essentially be two options to choose from when doing this. Either the vectors are used as-is, meaning that the items with the most extensive information would be dominate even if they only partly match a profile, leading to skewed recommendations. The second approach would be to normalize all ratings into the same range, regardless of how many attribute vectors are defined. This means that each item would have a certain level of uncertainty connected to it, based on how many of the item’s attributes are defined which in turn would make the user-profiles based on those items poorly defined as well. In the end it would mean that different users would receive recommendations that were based on information of differing quality. It would also mean that certain items could only be recommended with a limited amount of certainty.

Content-based methods were quickly ruled out as a possibility for the above reasons but also because of its computational cost. Considering how sparse the data is, the available item descriptions would almost definitely be used. This would involve a keyword search and match in order to make use of them, something that could become very computationally expensive.

4.1.2 Knowledge-based methods

Knowledge based methods were never really considered for Plick for a number of reasons. The need for detailed information about users and about every individual item posted would require a lot of attention and time from the users and would thereby increase the threshold for creating and using an account in the app. Furthermore it could be argued that there is very little to be gained by knowledge-driven, super accurate recommendations when it comes to clothes and accessories. After all, a t-shirt is not an apartment and there is probably no singular item that is “perfect” for any one user. The goal of a recommendation service for clothes is more along the lines of finding items that are of the size, category and style that a user is interested in rather than their ideal piece of clothing, which for many people might not even exist.

4.1.3 Collaborative Filtering methods

From the very beginning of the research phase of the project it became clear that collaborative filtering would be the most viable approach for the project. Not only is it the earliest, most widely adopted approach for recommender systems out there, collaborative filtering methods also include the most cutting-edge algorithms currently used today in huge online systems such as Amazon, Netflix, Spotify and Etsy. This fact has had an interesting effect on the research being done on recommender systems. A lot of attention has been given to improving the predictions made by collaborative filtering systems, both within the industry but also in academia. An example of this is the research being done on matrix factorization methods in connection to the Netflix Prize competition in 2009 where one such method was part of the winning system and where many notable recommender system researchers participated.[30] After that, Spotify adopted a similar system, based on the research that was carried out during and after the competition.[31]

The issues facing a collaborative filtering approach have mainly to do with three things:

- Availability of historical data: This is the well-known “cold-start” problem that collaborative filtering methods suffer from. It means that the entity focused on by the algorithm is poorly defined until a certain amount of data has been built up.[32] For example, before a user has rated at least a few movies on Netflix it is impossible to say anything about that user’s preferences. Conversely, a movie cannot be compared with other movies in users’ rating histories if the movie has not been rated by anyone. In Plick this problem is present but not insurmountable. By using the most basic action a user can take (viewing item pages), data can be collected quickly and without any complex user

[30] *Grand Prize awarded to team BellKor’s Pragmatic Chaos*, http://www.netflixprize.com/community/viewtopic.php?id=1537, 2009

[31] Christopher C. Johnson, *Logistic Matrix Factorization for Implicit Feedback Data*, Stanford, 2014

[32] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 131

input like explicit ratings which can be connected to a certain “maturity” of the user in the system.

- Sparseness of data: With the number of items in the tens of thousands, it is highly unlikely that users have interacted with more than a couple of hundred at the most. As a result, the user-item rating matrix is largely empty and yet this is all we have to work with in a collaborative setting. This problem is present in most systems and Netflix reports a similar level of sparseness as Plick.[33] Data sparseness is a reality of the system that cannot be avoided but is expected to improve over time as more data is collected (remember that the item-viewing data has only been collected since the beginning of this project). The main effect of a sparse user-item rating matrix is lowered accuracy of predictions.[34] A more active user will create a larger base of implicit data, containing fewer cases of deviating behavior which allows for a better approximation of the user’s actual preferences.
- The burying feed: This issue is mostly specific to the e-marketplace case. It can be assumed that in an e-marketplace the number of items in the system will increase steadily with the number of users since it’s unlikely that all of them will be sold. The problem is that if the method for displaying the items uses a continuous feed structure then there is a risk that users will miss items that are added when they are inactive, especially if they only use the service sporadically to begin with.

  The impact of the burying feed can be mitigated by filtering but will still be a factor in any subset of items that are sorted chronologically. Interestingly, one of the best ways of combating this issue is by recommending items regardless of chronological data, meaning that this problem should be alleviated by the introduction of a recommender system. The recommender system would affect the data it is itself using to broaden the interaction scope for users, bumping up older items and putting them back into circulation. This is one of the main benefits of recommender systems.

  Closely connected to this problem is the problem of older items that lack view-data and are unlikely to be found by users and introduced into the recommender system. There is no straight forward solution to this problem. Artificially assigning them views is not possible since item-views are linked to a user and would introduce extreme skewing into the data. The only mitigating circumstance in the case of Plick is that a couple of other data points (likes, conversations) have been collected since the inception of the system and thus some of these items have a chance of being “activated” by the recommender system.

4.1.3.1 User-based

User-based collaborative filtering seemed to fit Plick well, both in terms of available data and in terms of the system’s architecture and features. It especially seemed to suit the relationship between items and users in the system. Contrary to the classical e-commerce case, the more

[33] Yehuda Koren, Robert Bell, *Recommender Systems Handbook: Advances in Collaborative Filtering*, 2011, pp. 148
[34] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 131

stable group in an e-marketplace is users rather than items. That means that users will have more extensive historical data connected to them seeing as they are in the system indefinitely whereas an item will with time be either sold or “forgotten” by the majority of the users. Users who have been in the system for a while will have viewed a multitude of items and might also have interacted with some of them through Facebook-sharing, likes or even conversations with the sellers. All of these activities leave clues about the users’ interests and tastes which allows us to compare and cluster them based on how similar their tastes are. Of course, new users will be tough for the system to handle (the cold start problem described above). With only few items interacted with (picked out of a small subset from the top of the feed) the new users will have highly questionable behavioral data connected to them. There is a question of how well an approach like this would scale. Computing similarities based on the entire set of items for $\sum_{n=1}^{N} n - 1$ user-pairs is not nothing.

4.1.3.2 Item-based

Using an item-based approach was definitely possible since the system could to a certain degree be regarded as a traditional e-commerce case. Item similarities obviously occur in real life and should be possible to find using user-item interaction data in a reversed fashion from the user-based approach. That is, by looking at how many users an item has in common with another item their similarity can be computed. However, the transient nature of unique second hand items bring the correctness of these similarities into question. As an example: Calculating the similarity between a popular and an unpopular item might often result in a high degree of similarity seeing as the unpopular item will only have been viewed a few times and popular items are likely to have those viewers in their own history. This risks creating false positives between unpopular and popular items. As with most recommendation problems, an increase in data will fix this problem of correctness. The issue is that there is no guarantee that this will happen since items are added to the system continuously and so a large portion of them are always new (which can be considered equal to being unpopular as far as the recommender is concerned).

4.1.3.3 Matrix Factorization

Matrix factorization techniques are difficult to theorize about without testing them because of the complexity of the computations in the algorithm and the hidden nature of user- and item-factors. On paper a correctly built and tuned matrix factorization algorithm should produce good prediction accuracy in Plick. The sparseness in the user-item rating matrix is a similar level to what Netflix reports and items as easily categorized as clothes should have plenty of latent factors. The issue that a matrix factorization method could run into is the same as for most methods, the problem of sparse data for new items. As stated before, this is a problem inherent in the system. However, there is reason to believe that matrix factorization would handle this problem better than other methods, mainly because of the concept of latent factors but also because matrix factorization techniques are trained to fit the data, allowing for tailored parameters that hopefully capture hidden information about the data.

The problem with this is that implementing and evaluating a matrix factorization technique is time consuming and difficult. First, a complicated function describing the user-item rating factors has to be defined, complete with parameters adjusting things like rate of convergence. Then the unknown model parameters need to be learned by the system. This is done by minimizing the function using an optimization technique, usually alternating least-squares or gradient descent search. Both of these alternatives involve complexity and are computationally expensive, making the implementation process a slow affair.

4.2 Implementation and Evaluation of Candidate Algorithms

Based on the knowledge we have of the available methods and the reasoning in the previous subsection about possibility of matching methods with the Plick case, a few candidate algorithms were selected for testing, namely item- and user-based collaborative filtering and also matrix factorization. The selection of only collaborative filtering methods should at this point not be surprising when considering what type of data is available in Plick.

It is important to note that the algorithms that were tested in this stage were implemented in their most basic form, with some improvements being introduced later in the testing phase but most of them being added to the best-performing algorithm during final implementation. This is because testing every single permutation of each algorithm and each conceivable extension is simply unfeasible in a project of this scale. Instead, based on theoretical knowledge about the possible extensions, the ones that were likely to have the same impact on the results no matter the method in question were assumed to be safe to leave for later implementation in the final algorithm.

The testing was carried out in the following manner:

- The algorithms were implemented in the programming language Python using "blueprints" found either in recommender systems literature or online in the form of blog posts by developers involved in companies such as Netflix and Spotify.
- It was decided that the recommender system would only consider users that had interacted with 10 or more items in order to keep the sparseness of the rating matrix under control.
- In every step of the algorithms the value of the variables currently being calculated were cross checked with simplified manual calculations done on paper to make sure that the values made sense.
- The accuracy of the predictions generated by the algorithms was measured using the RMSE (Root Mean Squared Error). This was achieved by letting the system "forget" part of the data, meaning that a certain percentage of all user-item ratings were saved to a separate data-structure and set to zero in the user-item rating matrix. When the system predicted these forgotten values the difference between what was predicted and what was the real rating given by the user could easily be calculated. This is the "error" part of the RMSE and by summing up the squared differences and then taking the root of that number, the RMSE could be readily computed. Mathematically (T is the test set of users and items):

$$RMSE = \sqrt{\frac{1}{|T|}\sum_{(u,i)\in T}(\dot{r}_{ui} - r_{ui})^2} \quad (7)^{35}$$

In order to have a different measure to compare with, the MAE (Mean Absolute Error) was also computed:

$$MAE = \sqrt{\frac{1}{|T|}\sum_{(u,i)\in T}|\dot{r}_{ui} - r_{ui}|} \quad (8)^{36}$$

- In addition to the above measures the results were also analyzed manually by spot checking the top recommendations for some users and making sure that they made somewhat sense to the extent that this was possible. This type of sanity check can be surprisingly effective in ruling out potential changes to the system. Does it differentiate between obvious groups such as men and women or are the recommendations mostly random? Are the recommendations personalized or does everyone get the same set of universally popular items recommended to them?

The testing as described in this report might seem linear and quite straightforward but this is only how it appears when some coherence needs to be maintained, the truth is as always more muddled and complex. There were in fact several rounds of testing for each algorithm. Parameters, settings and the data pre- processing was changed several times during testing, requiring many re-computations to maintain the exhaustive approach of the search. Before getting into the testing of these algorithms we have to discuss which data was retrieved and how it was converted into a format that could be used by the candidate algorithms, the step called data pre-processing.

4.2.1 Data Selection and Preprocessing

As discussed in section 3.2.4 the only piece of explicit rating data in Plick was in the form of likes provided by users on items. Seeing as likes are not on a scale and also sparsely used they simply do not provide enough information to give any kind of clear picture of user interests. Apart from these it became necessary to make use of implicit data. As a substitute for purchasing history, the data on conversations was used to provide information about "purchase interest" and the abundant item-views were used as an indicator of general interest in an item. The conversation data was treated the same way as the like-data and put in a table containing user-item pairs where each pair meant that a user had initiated a conversation about an item. The view-data was considered in a similar fashion with the difference being that duplicates in this table were summed up to the number of views by a user on an item. This was of course not necessary in the case of the other data sets since in their cases each entry is unique.

There were essentially two ways of handling the collaborative data retrievable in Plick. Either the different data-points could be handled separately, essentially running the algorithm as many

[35] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 109
[36] Ibid

times as there were different data sets and then merging the results of the separate runs at the end, simply put a structure on the form: f(a) + f(b) + f(c). The other option was to merge the data sets into a weighted aggregate before feeding it into the algorithm, making the algorithm a unified function on the form: f(a, b, c). The benefit of doing so is that it would reduce complexity and therefore running time but at the possible expense of information, seeing as the data sets might contain different latent information.

For the first round of testing the second option was chosen. The reasoning behind this was twofold. First, it is important to keep the running time to a minimum when running repeated tests. Second, the conversation- and like-data sets are far sparser than the view-data which raises the question of how much information could actually be lost by not considering them in their own right. In the light of this it was decided that the data should be merged using a weighting formula so that a user-item rating matrix could be constructed and fed to the algorithms as if it contained one type of rating. (9) shows the structure of the formula (f is a function that caps the impact of views on the final rating as they can be indefinitely many):

$$\begin{aligned}
&r = w_1 * r_{like} + w_2 * r_{conversation} + w_3 * f(r_{view}) \qquad (9)\\
&r_{like}, r_{conversation} \in \{0,1\}\\
&r_{view} \in [0, \infty)\\
&w_1, w_2, w_3 \in \mathbb{R}
\end{aligned}$$

4.2.2 Item-Based

The implementation of the item-based method was mostly straightforward. It consisted of two parts that each represented the two stages of collaborative filtering prediction, first a function that calculated the item-similarities followed by a function that made predictions on a user-by-user basis. The similarity function was implemented with a choice of two similarity measures: cosine similarity and inner product similarity. Inner product similarity is a relatively new concept in recommender systems but has been shown to improve similarities in some cases where implicit ratings are used.[37]

These two similarity measures were very suitable for data represented on matrix form since they both make use of the inner product between vectors without first manipulating them. This means that it is simply a matter taking the dot product of the user-item rating matrix with its own transpose to get these inner products. As an example let us say we have a set of four users and four items, each of which have been rated by at least one user (remember, the actual user-item rating matrix for Plick is much sparser than this example). In this case we end up with the following:

[37] Tong Queue Lee, Young Park, Yong-Tae Park, *A Similarity Measure for Collaborative Filtering with Implicit Feedback*, 2007

$$
\begin{array}{cc|cccc}
 & & \multicolumn{4}{c}{\text{USERS}} \\
 & & u_1 & u_2 & u_3 & u_4 \\
\hline
 & \mathbf{i_1} & 3 & 1 & 3 & 0 \\
\text{ITEMS} & \mathbf{i_2} & 5 & 0 & 3 & 0 \\
 & \mathbf{i_3} & 0 & 0 & 0 & 1 \\
 & \mathbf{i_4} & 1 & 2 & 3 & 5
\end{array}
\quad \bullet \quad
\begin{array}{cc|cccc}
 & & \multicolumn{4}{c}{\text{ITEMS}} \\
 & & \mathbf{i_1} & \mathbf{i_2} & \mathbf{i_3} & \mathbf{i_4} \\
\hline
 & u_1 & 3 & 5 & 0 & 1 \\
\text{USERS} & u_2 & 1 & 0 & 0 & 2 \\
 & u_3 & 3 & 3 & 0 & 3 \\
 & u_4 & 0 & 0 & 1 & 5
\end{array}
\quad = \quad
\begin{array}{cc|cccc}
 & & \multicolumn{4}{c}{\text{ITEMS}} \\
 & & \mathbf{i_1} & \mathbf{i_2} & \mathbf{i_3} & \mathbf{i_4} \\
\hline
 & \mathbf{i_1} & 19 & 24 & 0 & 14 \\
\text{ITEMS} & \mathbf{i_2} & 24 & 34 & 0 & 14 \\
 & \mathbf{i_3} & 0 & 0 & 1 & 5 \\
 & \mathbf{i_4} & 14 & 14 & 5 & 39
\end{array}
$$

Fig 5: Inner product similarity for items.

The inner product similarity measure is at this stage done and uses the values in the resulting matrix. Cosine similarity includes one more step which is dividing these values by the product of the magnitude of the vectors, thereby eliminating the influence of variance in the vectors. When looking at the resulting matrix above it becomes apparent why this might make sense to do. It appears that item 3 is more similar to item 4 than to itself (a value of 1 for itself as opposed to 5 for item 4 in the similarity matrix)! If we account for variance these values would instead be 1 and 5/11. This shows what strange things can happen if rating magnitudes are not normalized.

The second stage of this method is the prediction of user interest based on the similarity between an item and a user's "favorite" items. Since the goal is not to predict a certain user's interest in a certain item but all user's interest in all items this becomes in practice very expensive and the implementation only allowed for testing using a reduced test set size, about 25% of the actual data.

The results of the testing were very underwhelming. Not only was the RMSE very high, the predictions were in a lot of cases zero. After debugging and evaluating each step of the algorithm it became apparent that the sparseness of the data was a big problem for the item-based method. The issue was identified as the lack of data shared between a target item (the item for which the rating is being predicted) and the very limited set of rated items in the user's history. Simply put there seemed to be many cases where an item did not have a single user in common with the set of items in the active user's viewing history. When considering some of the attributes of the system this is not very surprising. Consider the average case. The average user has only viewed a small subset (in the order of ~1%) of the items in the system. This means that the average item has been viewed by an even smaller portion of users since there are more items than users. When predicting the rating a user *u* is going to give an item *i* we want to take the ratings given by *u* to the set $N_u(i)$, items rated by *u* that are similar to *i*, and multiply them with the similarity between *i* and the items in $N_u(i)$. The problem is that in the set of ~1% of items that the user has viewed, the number of items with any defined similarity to *i* will be small and sometimes zero when the data is this sparse. This comes from the fact that the average item only has views from one in a hundred users, making it unlikely that it will have a user in common with any given item, the basis for a similarity to be calculated. Even if it does have some defined similarities there needs to be a certain number of them for *all* items since the item-similarities used should come from a top-k selection from a sorted set $N_u(i)$. When there are only a few defined similarities, the top-k selection becomes the same as all defined similarities which makes the predictions very unreliable.

These issues could not really be handled by any change in the algorithm since they were a direct effect of the data distribution in the system. As a result the item-based algorithm was discarded in stark contrast to the common practice in the e-commerce field. In the recommender systems literature it is generally considered wise to base predictions on the entity that has the most data connected to it and it seems like this could be the reason why.

4.2.3 Matrix Factorization

The first thing to decide when implementing a matrix factorization algorithm is to either use a pre-existing library of factorization functions or to define one yourself. The testing of matrix factorization consisted of both of these approaches. First, a standard factorization function (specifically a single value decomposition function) from the Python library Nimfa was implemented and tested with the full Plick data set. The results were underwhelming. The predicted ratings were very low and the only higher ones were for universally liked items, indicating that the method had missed key latent factors.

The second attempt at matrix factorization therefore consisted of a custom made algorithm that trained multiple latent factors, based largely on the method Simon Funk developed for the Netflix Prize competition, together with a more simplistic algorithm from Albert Au Yeung at Quuxlabs.[38][39]

$$
\begin{array}{|c|c|c|c|c|c|}
\hline
 & & \multicolumn{4}{c|}{\text{ITEMS}} \\
\hline
 & & i_1 & i_2 & i_3 & i_4 \\
\hline
 & \mathbf{u_1} & r & 0 & 0 & 0 \\
\hline
\text{USERS} & \mathbf{u_2} & 0 & r & 0 & r \\
\hline
 & \mathbf{u_3} & r & r & 0 & 0 \\
\hline
\end{array}
\rightarrow
\begin{array}{|c|c|c|c|}
\hline
 & \multicolumn{3}{c|}{\text{LATENT}} \\
\hline
 & \multicolumn{3}{c|}{\text{FACTORS}} \\
\hline
 & & \mathbf{l_1} & \mathbf{l_2} \\
\hline
 & \mathbf{u_1} & l & l \\
\hline
\text{USERS} & \mathbf{u_2} & l & l \\
\hline
 & \mathbf{u_3} & l & l \\
\hline
\end{array}
\times
\begin{array}{|c|c|c|c|c|c|}
\hline
 & & \multicolumn{4}{c|}{\text{ITEMS}} \\
\hline
 & & i_1 & i_2 & i_3 & i_4 \\
\hline
\text{LATENT} & \mathbf{l_1} & l & l & l & l \\
\hline
\text{FACTORS} & \mathbf{l_2} & l & l & l & l \\
\hline
\end{array}
$$

$$
\approx
\begin{array}{|c|c|c|c|c|c|}
\hline
 & & \multicolumn{4}{c|}{\text{ITEMS}} \\
\hline
 & & i_1 & i_2 & i_3 & i_4 \\
\hline
 & \mathbf{u_1} & r' & r' & r' & r' \\
\hline
\text{USERS} & \mathbf{u_2} & r' & r' & r' & r' \\
\hline
 & \mathbf{u_3} & r' & r' & r' & r' \\
\hline
\end{array}
$$

Fig 6: Decomposition of a user-item rating matrix into latent factor matrices.

[38] Simon Funk, *Netflix Update: Try This at Home*, http://sifter.org/~simon/journal/20061211.html, 2006
[39] Albert Au Yeung, *Matrix Factorization: A Simple Tutorial and Implementation in Python*, http://www.quuxlabs.com/blog/2010/09/matrix-factorization-a-simple-tutorial-and-implementation-in-python/, 2010

This approach allowed for better insight into each step of the algorithm and a better understanding of what parameters were appropriate. The results from this implementation were equally underwhelming but also came with some insight into the factorization process. Almost all users were recommended the exact same items, mostly in the same order. However, the predicted rating-scores differed wildly between users and seemed to be connected to the user's own rating behavior (active users with high rating scores received strong predictions, less active users received lower). It seems like the user- and item-biases were not being handled well by the algorithm. To combat this, baseline predictors were introduced. Baseline predictors could be said to be crude predictions made purely from information about averages. They are found by blending the average rating for a user with the average rating given to an item by all users. Thus, there is a baseline predictor for each user-item pair. The effect of baseline predictors on the matrix factorization method's results were positive and did result in an improved RMSE-score found when training 12 latent factors. The matrix factorization method's ability to predict the "forgotten" ratings was ultimately at a level that implied that the predictions made for unknown ratings also should have decent accuracy. However, this is not necessarily the case. This will be discussed at the end of this section.

4.2.4 User-Based

After having exhausted the two other collaborative filtering approaches with mixed results it became clear that a user-based model not only made the most sense intuitively but also seemed to be supported by lessons learned from the previous attempts. User-based filtering would focus on the ratings collected for users and by doing so would avoid the crippling sparseness that haunted the item-based approach as the average user has interacted with far many more items than the average item has had users interacting with it. The questions that had to be answered when implementing the user-based approach had mainly to do with the issue of computing similarities and making sure that highly active users did not end up skewing results too much. The same similarity measures that were used for the item-based approach were also used in this approach. The idea is to calculate the similarity between all users and then by taking the top-k most similar users for each individual, compiling lists of the *nearest neighbors* for each user. The selection of these neighbors is very important for the accuracy of the predictions for a number of reasons. Since the prediction for each item is a weighted sum of all of the ratings given by a user's neighbors, it is paramount that these neighbors are actually similar users and not just a selection of active users that have interacted with some of the same items as the user by chance. It is also important to note that the number of neighbors, k, is also very important. If too few neighbors are used the predictions run the risk of becoming undefined because no neighbors have interacted with a particular item. Furthermore, there is an issue of too much influence being given to a small number of users which could lead to predictions becoming unreliable if some of these similarities are high because of chance rather than real similarity. On the other hand, if too many users are used as neighbors the risk is that predictions are made from more universal agreement, leading to generalized recommendations rather than personalized ones. Simply put, for this approach it is extremely important to tune the parameters right.

The similarities were calculated in the same way as for the item-based approach, simply by computing the dot product of the user-item rating matrix with itself. From the resulting similarity matrix a collection of users and their top-k neighbor-lists was compiled, containing the neighbors id and the level of similarity to the user (to be used as a weight when predicting). The standard way of producing recommendations from a collection like this would be to create a list of all items that occur in the neighbors' rating histories to be used as candidate items for prediction.[40] In this case however it was of interest to predict *all* items in the system, mainly to be able to compare the predictions for different algorithms and settings. It was also discovered to be faster to simply compute predictions for all items rather than searching and compiling rated items into lists for each set of neighbors, making any limitation on predicted items illogical. Thus the structure of the algorithm came down to the following:

			ITEMS		
		i_1	**i_2**	**i_3**	**i_4**
	u_1	3	5	0	1
USERS	u_2	1	0	0	2
	u_3	3	3	0	3
	u_4	0	0	1	5

•

			USERS		
		u_1	**u_2**	**u_3**	**u_4**
	i_1	3	1	3	0
ITEMS	i_2	5	0	3	0
	i_3	0	0	0	1
	i_4	1	2	3	5

=

			USERS		
		u_1	**u_2**	**u_3**	**u_4**
	u_1	35	5	27	5
USERS	**u_2**	5	5	9	10
	u_3	27	9	27	15
	u_4	5	10	15	26

↓

		USERS		
	u_1	**u_2**	**u_3**	**u_4**
NEAREST	u_3	u_4	u_1	u_3
NEIGHBORS	u_2	u_3	u_4	u_2
	u_4	u_1	u_2	u_1

Fig 7: Inner product similarity for users. The nearest neighbors are easily extracted in the last step.

The first version of the user-based approach was simple but produced reasonable results. The recommendations were however global rather than personalized and when looking at the nearest

[40] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 115-116

neighbors-lists it became apparent that a small number of super active users were dominating predictions for nearly all users. This was to be expected as the basic implementation did not contain any corrections for user-bias. A way of accounting for this would be to normalize the ratings by subtracting a user's mean rating from all of the user's ratings.[41] However, as described in section 2.1.2, there is the issue of what happens to the lower than average ratings that suddenly become negative in that scenario. As all implicit feedback should be considered positive, even if it is lower than a user's average interest, there is simply no good way of handling this kind of bias and instead one has to properly cap the magnitude of ratings when the user-item rating matrix is constructed so that "outlier behavior" is reined in before the similarities are computed. This was an important tool when improving predictions for all algorithms and will be described in section 4.3. It was however found that the cosine similarity measure produced more personalized similarities which probably comes down to the fact that although it does not account for differences in mean and variance of users, cosine similarity does account for the magnitude of the rating vectors and will curb the impact of extreme user behavior somewhat.

4.3 Extensions and Improvements

This section describes the various extensions that were tested in order to improve the predictions made by the candidate algorithms. It is important to note that not all extensions were applicable to all three algorithms.

4.3.1 Rating Aggregation

The aggregation of the views, conversations and likes into unified ratings is one of the most crucial components of this recommender system. Simply counting views as a binary data point, viewed vs not viewed, might seem logical but would result in a huge loss of information if the reality of user behavior is considered. Re-viewing the same item a couple or many times may indicate a huge interest, especially when considering the concept of the burying feed described earlier. A user that specifically seeks out the same item for viewing multiple times even when it has been pushed down far in the feed indicates a significantly higher level of interest compared to a single view on an item at the top of the feed. Another problem with this model is that the relatively small subset of items that have likes or conversations connected to them will dominate and skew ratings. On the other hand considering the number of views the same as likes and conversations is also unreasonable as a user can have viewed the same item 40 times but can only have liked or conversed about it once. There is need of a middle ground.

The formula that is proposed here is based on the following logic: likes and conversations indicate a level of interest comparable to re-viewing the same item more than two times. One or two views on the same item indicates a browsing preference, the item has been picked out and clicked out of a set of many items. Re-viewing an item a couple of times indicates a stronger preference and possibly an interest in purchasing the item. However, the impact of views on the same item is curbed after this as there must be a maximum level of interest that can be interpreted from a user viewing an item. Essentially, there should be no difference in the rating

[41] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 121-122

given an item based on 20 views by the same user as compared to the rating given by 50 views, both indicate a strong interest and the more extreme data should be understood as an expression of anomalous user-behavior. Finally, there is need of a base rating value given to an item with a single view that can be used as an easy controlling parameter for the interval of ratings and the impact of views versus other data. With this reasoning the proposed structure for the rating aggregation becomes:

$$r = w_1 * r_{like} + w_2 * r_{conversation} +* f_{viewcap}(r_{view}, w_3) \tag{9}$$

$$f_{viewcap}(r, w) = w + 0.5 - \frac{0.5}{r} \tag{10}$$

With this formula the value of $f_{viewcap}$ will be bounded by its second and third terms which will create the domain [w_3, w_3 + 0.5] for the view-part of ratings. Keeping in mind that likes and conversations can take the values 1 or 0 this means that the maximum rating becomes $w_1 + w_2 + w_3 + 0.5$.

4.3.2 Rating Normalization

Despite the issues brought up in previous sections concerning rating normalization there was some testing and investigating carried out in an attempt to fully exhaust the option of normalizing ratings to account for user- and item biases. First, the previously mentioned Pearson correlation was used as the similarity measure in both the user- and the item-based collaborative filtering methods. The results produced by the user-based algorithm matched the results when using cosine similarity but when taking a closer look at the recommendations given by the algorithm it became clear that this measure did a much better job at blocking recommendations made from low but broad support among the neighbors than it did limiting the influence of highly active users.

Apart from the Pearson correlation there were also some attempts made to normalize ratings before similarities were calculated. Subtracting mean ratings for both users and items and capping negative ratings to 0 produced acceptable results but eventually led to similar loss of information as when using Pearson correlation. It became apparent that fixed intervals and clear bounds (as described in section 4.3.1) was the only way of maintaining a good balance between the impact of few extreme ratings and many low ratings. This was further improved by introducing significance weighting, described in 4.3.3.

4.3.3 Frequency Weighting

When trying to extract the most informative parts of a dataset it is important to account for variance. In this case it can be understood as adjusting the impact of certain ratings on user-similarities based on how much information the ratings are thought to provide.[42] In practice this means penalizing the impact of universally liked items and favoring less known items as it is likely that two users having such an item in common in their rating history is telling of a greater

[42] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 129

degree of similarity. This is done by applying a factor calculated as the log-ratio of users that have rated an item as compared to the total number of users.

$$\lambda_i = \log \frac{|U|}{|U_i|} \tag{11}$$

A good example of this is in movie ratings where high ratings given to a movie like *The Godfather* are essentially disregarded as they are considered almost default. In the case of Plick it became apparent that there exists a subset of very popular items that affect predictions negatively and the introduction of frequency weighting reflected positively in the results when applied to the user-based method and matrix factorization method.[43]

4.3.4 Significance Weighting

There have been a number of strategies suggested to account for the significance of a similarity, either between two users or two items. The problem that these strategies are trying to solve is that in a sparse environment it is not uncommon for two entities to have very little data in common which can create situations were recommendations are unknowingly based on very weak similarities.[44] As an example, take two low- to medium active users in Plick. Say that they have viewed only a few items each but have one item in common. Their similarity will be fairly significant and they will probably have each other as neighbors in a user-based system. Recommendations will then be made to both of them based on their respective historical interactions with the items in the system even though their actual preferences may differ wildly. The proposed solution to this problem is an intermediate step just after the similarity calculation called *significance weighting*. The idea is very straightforward: if the number of commonly rated items is below a certain threshold the weight will be penalized by a factor proportional to the difference between the number of rated items in common and the threshold, as described in (12) [45] (for a user-based model, the w_{uv} represents the similarity weight between users u and v, I_{uv} the set of items u and v have both interacted with. γ is the threshold value):

$$w'_{uv} = \frac{\min\{|I_{uv}|, \gamma\}}{\gamma} * w_{uv} \tag{12}$$

This strategy had a powerful impact on predictions and when examining the lists of neighbors assigned each user it was found that they became more diverse in terms of activity and more homogenous in terms of demographics, something that indicates real similarity in this context (e.g. women have more in common with other women than men when it comes to clothing preferences).

Still, significance weighting applied on similarities may have helped account for low confidence neighbors but it did not address the issue of recommendations being made based on a

[43] Ibid

[44] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 127-128

[45] Ibid

small subset of neighbors. That is, recommendations made based on a neighbor with a large similarity weight and generally high ratings (from a liberal use of likes for example) would out-weigh recommendations based on the ratings made by several neighbors with mid-range similarity weights. This could result in unexpected and low-accuracy recommendations being made based on singular strong neighbors. For example, two users may have very similar tastes in almost all clothing but one of them is also a huge fan of hats whereas the other user just does not wear hats. This would lead to them being very close neighbors in preference and result in one user being recommended hats that they are not interested in (made even more likely by the fact that they probably have not viewed any hats in the system). To prevent this from happening a novel use of significance weighting was introduced. This time it was not the similarity weights being penalized but the predicted ratings themselves. When considering (12) and (13) it is apparent that the formula is very closely related to the one for similarities ($\dot{r}_{ui}$ is the predicted rating for user u on item i, N_{ui} is the set of neighbors that have interacted with item i and θ is the threshold value).

$$\dot{r}'_{ui} = \frac{\min\{|N_{ui}|, \theta\}}{\theta} * \dot{r}_{ui} \tag{13}$$

The danger of applying this type of arbitrary factor on ratings became apparent when going over the results. The RMSE was found to be affected negatively every time this weighting was used as it heavily penalized a large portion of predictions which resulted in many of them ending up significantly lower than the average rating. This penalization is however necessary to re-order the recommendations in the final stage to rein in the prevalence of recommendations based on one or two strong neighbors over a larger number of medium confidence neighbors. In order to review the success of this weighting scheme a different measure than the RMSE was needed. This measure, known as gender recall, is introduced in the following section.

4.4 Choosing an Algorithm: Evaluating Recommendations

In the end it came down to two algorithms: Matrix factorization and collaborative user. Both algorithms had strengths and weaknesses. The first one with exceptional predictive capabilities but highly generalized recommendations and the second one having good predictive capabilities but in need of several add-ons to achieve decent recommendations. However, once these add-ons were implemented and their parameters tuned it was obvious that the user-based collaborative algorithm outperformed matrix factorization in the quality of recommendations. Below are the final and best RMSE and normalized RMSE scores achieved by the two competing algorithms.

Table 1: The best scores for the two top performing algorithms.

	RMSE	**MAE**
Matrix Factorization	0.29	0.23
Collaborative User	0.27	0.21

These scores only tell half the story. Something needs to be clarified about the RMSE. As this measure is based around the *squared* error between prediction and reality it punishes large differences significantly compared to smaller errors. This leads to a situation where, in terms of RMSE, it is preferable to have four mediocre predictions rather than one perfect prediction, two mediocre ones and one bad one. When considering that recommendations are delivered in top-10 lists it seems that it is less relevant how many mediocre recommendations there are further down in the top-list as long as the top 10 recommendations are as good as they can be. The fact that the matrix factorization algorithm will always predict all unknown ratings means that it will not suffer any penalties in the RMSE for missing to predict a forgotten rating, a rather large penalty as the squared difference between zero and a rating will be relatively big. Also, the RMSE is based on the algorithms ability to predict a known subset of ratings that were intentionally "forgotten" by the system. The logic is that if these real ratings are predicted accurately then the predictions made for completely unknown items should also be accurate. Still, it is not a measure of how good the actual recommendations are. The quality of the recommendations can only be measured with some type of user feedback, something that was unavailable when this project was carried out. Some type of approximation of user input was needed.

4.4.1 Gender Recall

The solution was found when going back to the other part of the data that was on hand, the content. By matching a user attribute with an item attribute it would be possible to measure some degree of qualitative accuracy in recommendations. That is if it was known about users what their favorite colors were and the items were all color coded, then that could be used to check if the recommendations made sense. In lieu of something that obvious the only data point that could be used in this way was the gender. Specifically the substantial difference between male and female users allowed for a type of sanity check of the top recommendations made to male users. As the average male users rating history contained mostly male and unisex items it was expected of the system to produce recommendations in these categories. This should be achieved despite about 65% of items in the system being tagged as female, including the most popular items. Under these circumstances it could be considered a decent measure of some basic accuracy that the system can identify a user's gender and recommend accordingly. Important to note is that this is still not a real measure of user feedback like measuring click-through rates for example. It also does not say anything about the actual taste of the user and how the recommendations match that. The test function measured the percentage of items tagged as male or unisex in the top 10 recommendations for a subset of male users. These users were manually identified by username or email as the gender is not specified by users themselves. The performance of the algorithms on this gender recall index is presented below.

Table 2: Best gender recall score for the two top performing algorithms.

	Gender Recall
Matrix Factorization	38%
Collaborative User	74%

When taking these scores together it becomes obvious that the collaborative user algorithm is the only one that can actually produce recommendations pertinent to each individual user. With this evaluation done, the collaborative user algorithm was selected for implementation in the final system.

5 Final System

5.1 Parameter Tuning

Optimal parameters for the collaborative user method were found in the last stage of testing using a three dimensional grid search. Parameters were increased or decreased in different permutations within certain viable value ranges found in earlier testing phases. When all permutations were calculated the vertices defined by each combination of parameter values formed a honeycomb-like structure in three-dimensional vector space. The cuboid in this space containing the best target values would then become the next interval for another grid search, thus “zooming in” on the optimal parameter values iteratively.[46] The targets were RMSE and gender recall and the variables were the number of neighbors and the threshold values for significance weighting, both for low confidence neighbors and for low confidence recommendations. This way of estimating parameters is not ideal and there are better ways of minimizing functions but when considering the running time of just one round of the user based method (~4 minutes) it is simply not feasible to use a strategy that requires thousands of iterations.

5.1.1 Algorithm Parameters

Because of the three-dimensional nature of the target function during parameter optimization it is difficult to convey graphically where the optimal parameters were found. We can however represent the optimization process in two parts; the number of neighbors and the connected significance threshold value with RMSE as a target and the low confidence prediction penalty threshold. The first two parameters have the same target and can be represented graphically.

[46] James Bergstra, Yoshua Bengio, *Random Search for Hyper-Parameter Optimization*, Journal of Machine Learning Research 13, 2012, pp. 281-305

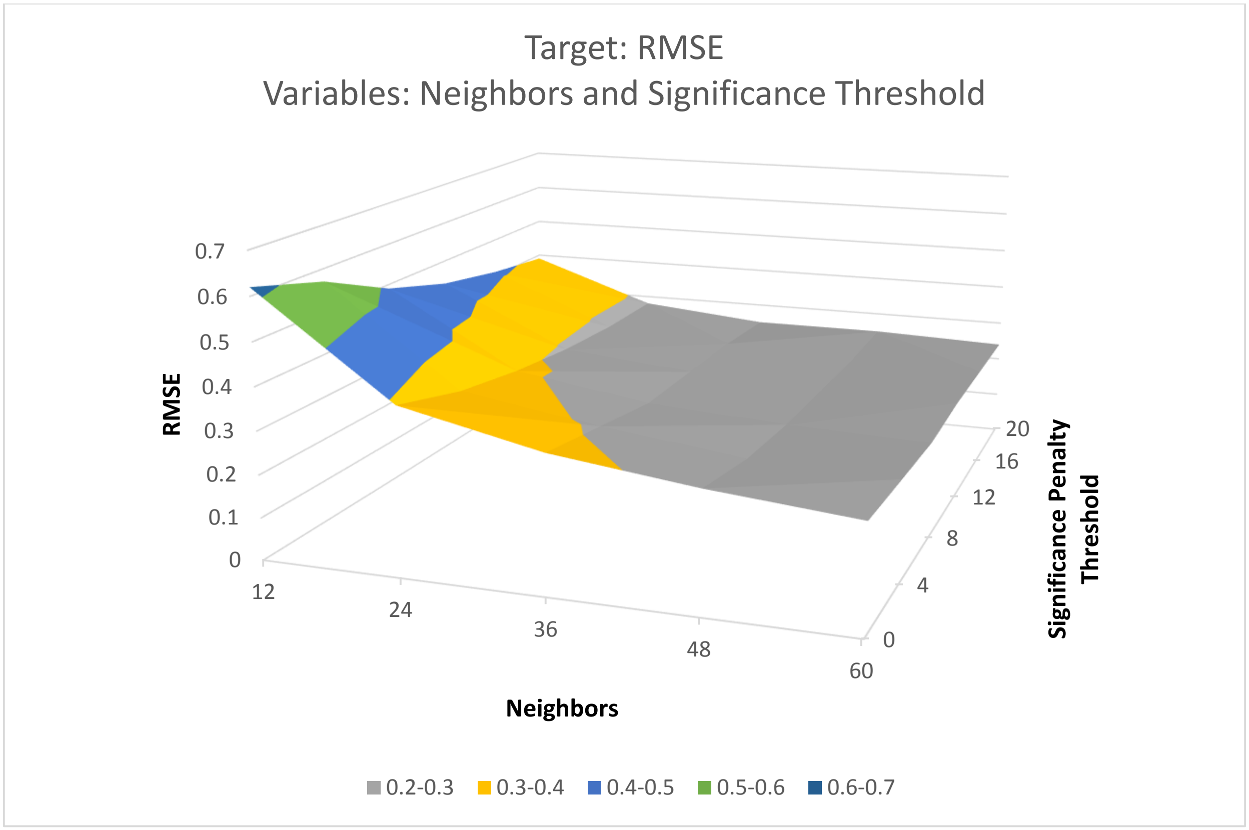


Fig 8: The RMSE for different neighbor- and significance threshold-settings.

From Fig 8 it becomes apparent that a low RMSE (indicated by the grey area in the graph) is achieved with an increasing number of neighbors. It can also be gleaned that a similar low RMSE is achieved by increasing the significance threshold, almost regardless of the number of neighbors more than 24. In recommender systems literature it is generally considered bad to use more neighbors than necessary as recommendations taken from a large set of weak neighbors will conform more and more to general opinion rather than personal opinion, resulting in non-personalized recommendations.[47] With this in mind the most interesting part of this grid becomes the 24-36 span for the number of neighbors and a significance threshold value of between 12 and 20. Important to note is that although it is hard to see in the graph, the RMSE increases with a significance threshold value over 20 which is why that is the upper bound for that variable in the grid search.

Another view of this is presented in Fig 9. The series of graphs show the impact of the significance threshold on the RMSE and it can be seen that the effects are similar almost regardless of the number of neighbors.

[47] Desrosiers, Karypis, *Recommender Systems Handbook: A Comprehensive Survey of Neighborhood-based Recommendation Methods*, 2011, pp. 131

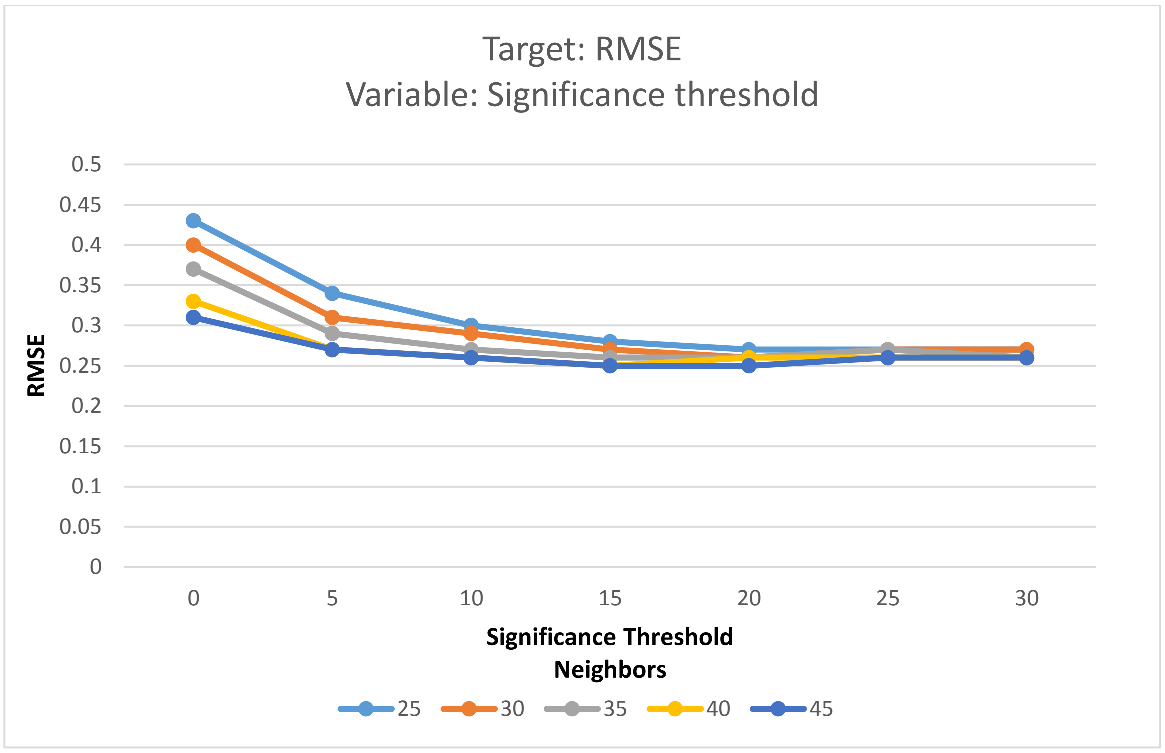


Fig 9: The RMSE for five selections of the number of neighbors with different significance threshold-settings.

Looking at the gender recall measure in the same intervals without the use of the confidence penalty showed a recall of between 40% and 45% for all combinations of neighbors and significance penalties. This is very close to the 38% percent achieved by the matrix factorization method and does not reach very high in the interval between picking an item at random (35% likelihood of it being male or unisex) and the average rating behavior of male users (about 74% of items viewed by males are male or unisex). When introducing the confidence penalty the impact is obvious as can be seen in Fig 10. The graph shows the *average* development of the gender recall as a function of the confidence penalty threshold over the vertices in the first grid.

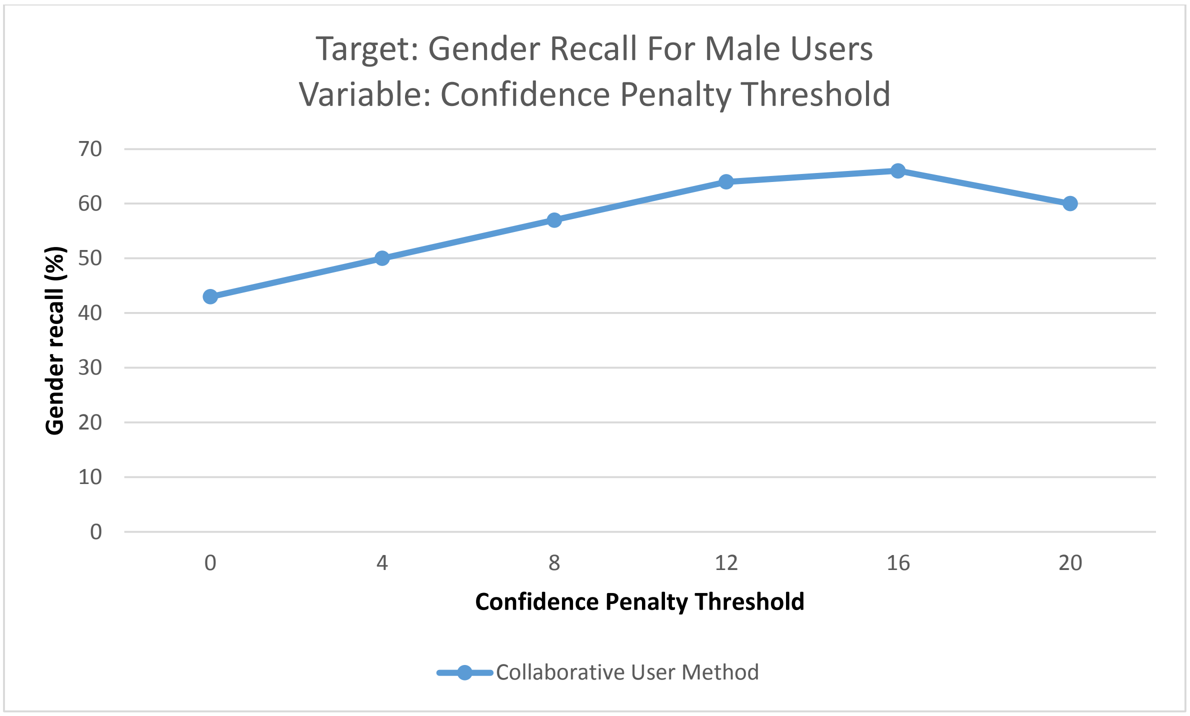


Fig 10: The average gender recall for different confidence penalty threshold-settings over the whole interval of neighbor and significance threshold values.

Increasing on average from just above 40% to just under 70% shows that this way of weighting recommendations based on how many neighbors contributed to them has a real impact on the quality of recommendations. The best performing grid for the gender recall measure was also found within the 24-36 neighbor-span while the significance weighting parameter did not seem to influence the gender recall measure much. The best values for the confidence penalty parameter were exclusively found in the 8-20 interval.

In the second round of optimization the search was zoomed in on the grid defined by the intervals mentioned above. The difference in RMSE for the different settings in this grid was, as expected, very small.

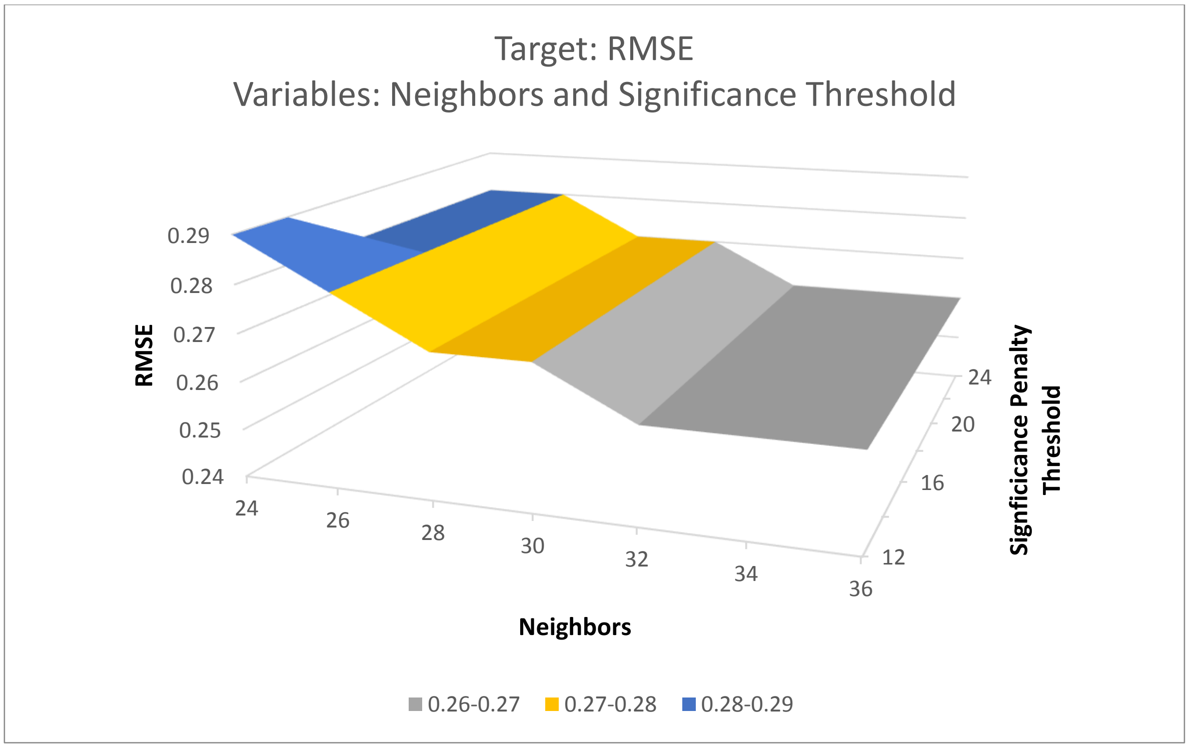


Fig 11: The RMSE for different neighbor- and significance threshold-settings in the zoomed in grid.

Since the highest and lowest achieved RMSE scores only differed by ~0.04 it could be considered that any combination found in this grid would be very likely to produce the same set of top-k neighbors. Increasing the number of neighbors would likely only add low-similarity users to the prediction, diluting the recommendations with input from low-significance neighbors. This was further confirmed when looking at the MAE for the same grid. It showed that the improvement gained by increasing the number of neighbors and the significance weighting was miniscule (~0.01 change in the MAE) which implied that the slight improvement in RMSE with more neighbors was simply very low confidence recommendations being made on items that were not covered by the top neighbors but were rated by the user, resulting in a noticeable difference in RMSE since the error caused by missing a rated item is rather large when squared, regardless of what the recommendation is.

Finally, the gender recall measure in the same grid was found to reach a ceiling between 72% and 78%. The fact that the gender recall could be brought above the average viewing behavior of male users is not very surprising as the average rating given by a male user to a male or unisex item is probably higher than for female items (i.e. a male user is more likely to like or start a conversation about a male or unisex item), resulting in more gender-specific items in the top recommendations. In Fig 12 the significance weighting parameter was fixed to 12 to allow the other two parameters to be plotted as an area.

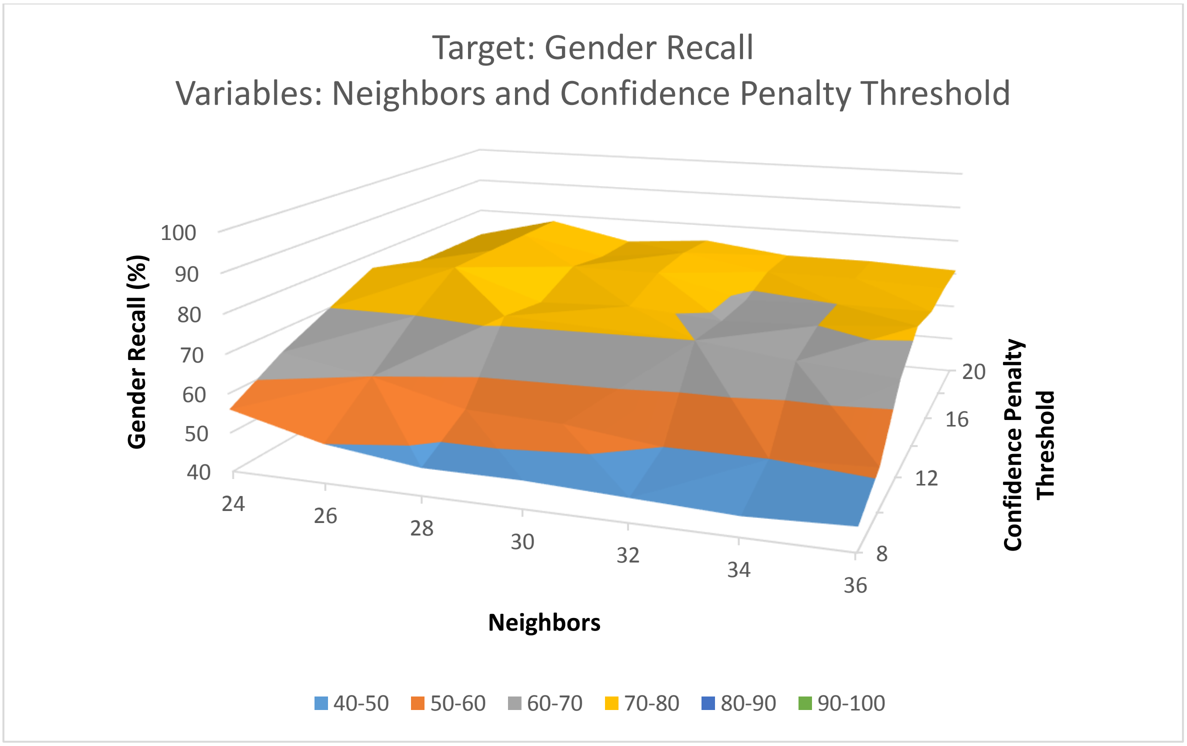


Fig 12: The gender recall for different neighbor- and confidence penalty threshold-settings.

From this grid search it could be deduced that the optimal parameters existed in the vicinity of ~26 neighbors, ~12 significance penalty threshold and ~14 confidence penalty threshold. Note that these parameters did not yield the very best RMSE-score or the very best gender recall score but did best overall, while minimizing the impact of the penalties on the scores which theoretically should lead to the best balance between recommendations given by a small number of high-similarity neighbors and recommendations given by a larger number of medium-similar neighbors.

5.1.2 Rating Aggregation Weights

Since there was no user feedback to measure the success of the recommendations it was not possible to optimize the weights given to the three data points used by the algorithm; views, likes and conversations. Consider the measure with which two of the other parameters were optimized, the RMSE. If the same logic was applied to optimizing the aggregation weights the system would be changing both the recommendation value but also the value it was being compared to since the whole rating matrix would be re-computed. In this scenario the optimal weights would simply be zero since that would result in an error of zero.

That having been said, the weights were not chosen at random. Currently the system uses the following weights: 2.0 for views, 0.5 for likes and 0.5 for conversations. These weights were found through trial and error and are essentially at a rough balance between not letting the relatively rare occurrence of a like or a conversation influence ratings too much while maintaining the information provided by these two data points. Also remember that the views can be many but are on a logarithmic scale that converges at about 2.5, making the maximum possible rating ~3.5, occurring when a user has liked an item, started a conversation with its owner and also gone back to view it again >10 times.

5.2 Schemas

5.2.1 Algorithm

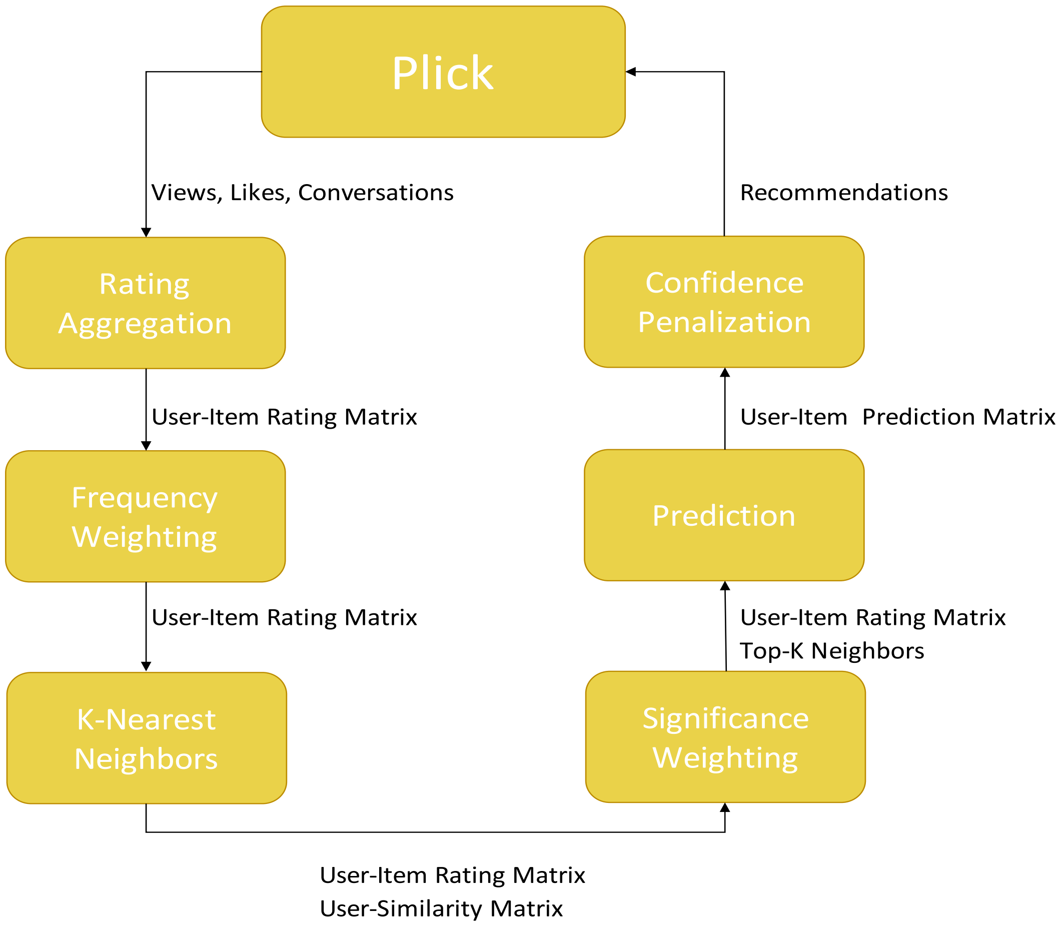


Fig 13: The structure of the final recommender algorithm.

5.2.2 System

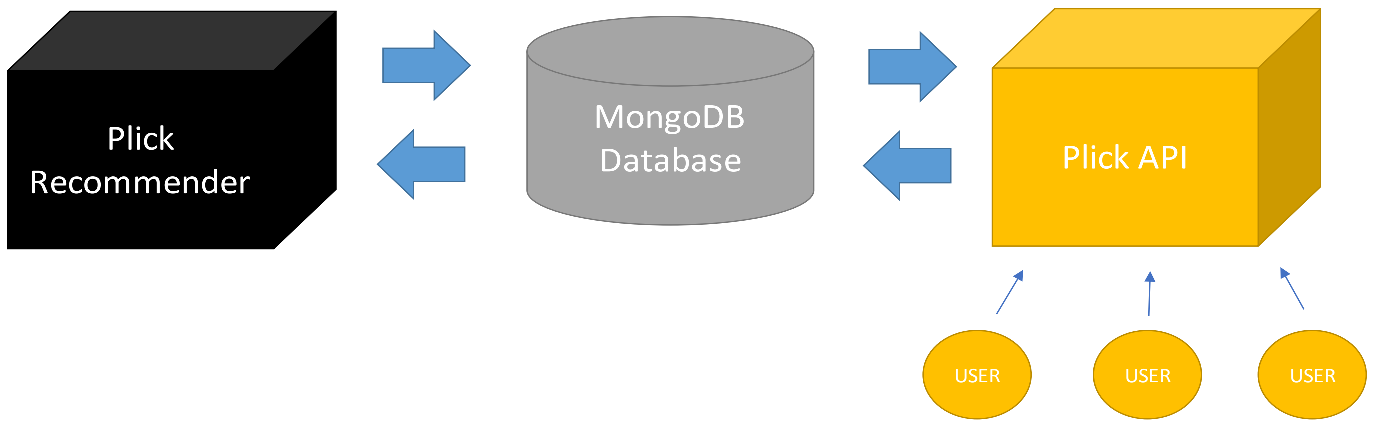


Fig 14: The placement of the recommender system within the larger system.

6 Discussion and Conclusions

When it comes down to it, the business of recommending things to people is more involved than you might expect. In the age of big data and data mining the tools and methods used to make sense of the behavior and opinions of everyone are getting increasingly complex. Even so, the amount of data produced by people going about their daily digital routine leave even the most high-end computing hardware playing a hopeless game of catch up in terms of processing and analyzing.[48] This requires smarter and more efficient algorithms which in turn means approximations, simplifications and compromises. In the case of designing a recommender system this means a trade-off between things like picture analysis and geo-tracking for computational speed. Straightforward data such as likes, star-ratings and views become more attractive in that they are simply numerical values right of the bat.

There is a second trade-off when designing a recommender system that is decided outside the scope of the recommender itself which can be understood as a trade-off between usability and information. That is, how much information is explicitly provided by users and how much can you realistically ask for before it becomes a hindrance when using the system. A choice of a 5-star rating next to a movie in Netflix is a far cry from a filling out a compulsory form explaining exactly what you liked about the movie after watching it. That would however allow for exceptionally accurate recommendations. With Plick the main idea has always been to allow users to post their clothes quickly and without any hassle which means that the explicitly given information is sparse and recommendations need to be based mainly on whatever implicitly provided data that is available. Earlier it was established that implicit data can represent different preferences compared to explicit data. On the one hand explicit ratings have a very clear

[48] The Economist, *Data, data everywhere*, 27-02-2010

meaning but users might be hesitant to provide explicit ratings for every part of their preference. Comparatively, implicit ratings will in an ideal world show the true preference of the user as it monitors actual behavior. The risk when using this data is of course that a lot of this behavior might not be indicative of any particular preference and that any hidden patterns remain unfound. In Plick it remains largely unknown what is actually observed in the user-logs but as shown in the results in the previous section, the ability to produce a portion of predictions with a matching gender larger than what a random selection of items would yield demonstrates that there is some degree of information about actual preferences in the logs.

The challenges of recommending in an e-marketplace environment posed in the beginning of this report were met and to some degree dealt with during the process of testing and tuning the different candidate algorithms. The algorithms tested during this project did not exhaust the multitude of methods that have been explored in recommender systems research in recent years, but it did touch upon most of the major approaches used today. Entire categories such as knowledge-based and content-based systems were quickly dismissed based on the data available. The item-based method could have been dismissed for similar reasons but was considered interesting to evaluate as a way of confirming the idea that the relationship between items and users in a system decides which entity to base recommendations around. It was found that this is at least true for a system like Plick, as the item-based method produced essentially undefined results and the user-based method was the best performing one. While it this find cannot be extrapolated over the whole e-marketplace sector it is a clear indication that quite contrary to the standard e-commerce scenario, the e-marketplace revolves around users. There is every reason to believe that if the content is sparse, there is no explicit rating system and the items in the system have a short lifespan then the best choice for a recommender system is a user-based collaborative method based on implicit user feedback like the one presented in this report. The data necessary for a system like this should in most cases be available as most environments where users both buy and sell items requires users being logged into an account when using the system. However, to make sure that a system of this type is sufficiently accurate there is a need to alpha and beta test recommendations to collect user feedback. Advisable would be to use a scheme of displaying random items in one view and recommended items in another to measure how well the recommendations outperform lazy browsing behavior. It was not possible to carry out such a test during this project which meant that the results existed in a kind of darkness were the user was left out of the loop. This further meant that weights deciding the impact of different data types could not be optimized. In general, optimizing the impact of different types of data to construct singular user-item ratings is something that has been mostly overlooked in recommender system research; at least in what was covered in this project's literature study. As it stands they could probably most easily be found in a very late stage of testing by observing changes in the click-through rate for recommendations while adjusting the weights.

In contrast to what was learned about the effectiveness of user-based collaborative filtering over item-based, the appropriateness of matrix factorization methods for marketplace-applications is still a big question mark. Where the item-based method failed because of its most fundamental attributes, the matrix factorization method failed for reasons not well understood. One explanation might be the complexity of the approach. Where the other collaborative filtering algorithms are intuitive and easy to follow, the matrix factorization techniques are, apart from the most simplistic versions (like the one implemented here), very intricate and often involve multiple stages of calculation and re-calculation of large data structures. There is no doubt that a system of that caliber would perform very well in an application like Plick. Another reason might be a stronger sensitivity to the weighting of the data points. It is possible that the boost in scores for items that had been liked or conversed about over those that had not was not adequately addressed in the algorithm used in this project.

The issue of new users was unsurprisingly not completely resolved. The final system could not handle brand new users but seeing as the testing incorporated users with an interaction history of as few as ten items and still achieved decent results, there seems to be something to be gained by using such a fundamental statistic as a click to build recommendations from. Page views build up incredibly fast in almost any system and making use of that resource as a way of handling cold-start issues is something that deserves more attention. When it comes down to it, it is actually a very minor problem that users who have not clicked more than ten ads are not given recommendations; if they are that inactive, why would they be interested in personalized recommendations anyway?

One of the major limitations of the project was the lack of data about usage and feedback from users themselves. Obviously, this could not be helped since the recommender system was not implemented into the live system during the course of the project. Going forward however, the system is to be deployed in the first half of 2015 which will allow for additional testing and tuning of the collaborative user algorithm and its parameters. The increasing number of users and activity in Plick will provide denser data and it will be interesting to see how this will affect the quality of recommendations. As the application is developed, more types of data will become available which will allow for the recommender system to be further developed as well. Incorporating things like categories or brands by making the algorithm a content-based/collaborative filtering hybrid could certainly add another level of ingenuity to the system. Remember, if the processing power is there, you can never have too much information in a recommender system.

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