Recommendation System for Sports Videos

Choosing Recommendation System Approach in a Domain with Limited User Interaction Data

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Abstract

Recommendation systems help users find interesting items and reduce the information overflow problem on websites. Much research has been conducted on such systems the last decades, and there exist several recommendation approaches with different strengths and weaknesses. In this thesis, we investigate which recommendation approach or combination of approaches that can recommend the most interesting content for each individual user of the sports video application Forzify.

We use previous research and literature to find the approaches that are best suited for the data gathered in Forzify and the features wanted in a new recommendation system. Three approaches turn out to be the best suited: item-based collaborative filtering, model-based collaborative filtering and content-based filtering. We implement one algorithm from each of these approaches and a baseline algorithm. The four algorithms are evaluated in an offline evaluation to find out which of the approaches that performs best in terms of recommendation accuracy, both for new and old users, and scalability. As Forzify so far has gathered limited user interaction data, we have to test the approaches on other datasets. To increase the validity, we investigate the accuracy of the algorithms in datasets from different domains. This makes it possible to check whether it is consistencies in the accuracy of the algorithms across the domains.

From our evaluation of the accuracy of the algorithms, we can see both differences and similarities across the domains. The accuracy of the different algorithms is more even in some domains than in others, and some domains generally have higher accuracy, but there is a tendency that the algorithms performing well in one domain also do so in the other domains. Due to this cross-domain consistency, our results provide a good basis for choosing the best approach for Forzify. We conclude that the model-based collaborative filtering approach is the best choice for Forzify. It gives accurate recommendations for both new and old users across the datasets, and it scales well for larger numbers of users and items.

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1 Introduction

In everyday life, we often rely on recommendations from other people when we do not have enough information about our choices. This could be advice from friends and colleagues, recommendation letters, restaurant reviews and travel guides, which all help in decision making. *Recommendation systems* fulfil the same function in a digital context (Resnick and Varian 1997). “Recommendation systems”, “recommender systems”, “recommendation engines” and “recommendation agents” are all terms used interchangeably to describe systems that make recommendations to users about items (Xiao and Benbasat 2007, Ricci, Rokach, and Shapira 2015). In this thesis, we will use the term “recommendation system”. The aim of this thesis is to investigate which recommendation system approaches that are best suited for the sports video application *Forzify*.

1.1 Motivation and background

Websites today often contain a huge amount of information, enough to overwhelm the user. The number of items for the user to choose from is so large, that each item cannot be reviewed, making it a challenge to find interesting items. This is where recommendation systems come in. By recommending items to the user, it becomes easier for the user to explore new material, and the problem with information overload is reduced (Ricci, Rokach, and Shapira 2015). Recommendation systems are used in a wide range of applications and can recommend everything from news, books and videos to more complex items like jobs and travels, or as in our case, sports videos.

The main purpose of a recommendation system is to make easily accessible recommendations of high quality for a large user community (Jannach et al. 2010, xiii). Recommendations can be either personalized or non-personalized. *Personalized* recommendations mean that different users or user groups get different recommendations based on their preferences, while *non-personalized* recommendations mean that all of the users get the same suggestions (Ricci, Rokach, and Shapira 2015). Non-personalized recommendations are much easier to make, and may for instance be a list of the ten most bought books or the top 20 rated movies. Even though this kind of recommendations can be useful in some situations, they do not reflect the individual user’s taste and preferences, and consequently cannot give the same benefits as personalized recommendations. Therefore, they are not typically addressed in research on recommendation systems, and they will not be the focus in this thesis either.

The personalized recommendations give possibilities that would be impossible in the physical world. Jeff Bezos, CEO of Amazon, illustrates this: “If I have 3 million customers on the Web, I should have 3 million stores on the web” (Schafer, Konstan, and Riedl 2001). By giving all users a personalized experience, both the users and the owner of the system benefit. It gives better user satisfaction because the user finds relevant and interesting items, it increases the number of items sold and it helps the company to sell more diverse items (Ricci, Rokach, and Shapira 2015).

Even though recommendation systems are used in a wide range of domains, few studies have examined how the performance of recommendation systems differ across different domains. Most research has either examined algorithmic performance, like algorithms’ accuracy and scalability, or examined applications in a specific area, like music, movies or web pages (Im and Hars 2007).

New websites or applications that want to make good recommendations to their users often have little user data, making it difficult to evaluate the successfulness of their recommendations. One option is to wait for the application to gather enough user data before developing the recommendation system to make sure the system is built on a suitable approach. But then, the system will miss the benefits of recommendations for a period of time. Another option is to evaluate the recommendation system on user interaction data from other applications. Several datasets consisting of user and item data are published on the Internet, making it possible to measure the performance of recommendation systems. However, it is not always possible to find a dataset matching the domain of a given application. In such cases, it is crucial to investigate whether the recommendation system perform consistent across domains.

Herlocker et al. (2004) point out *algorithmic consistency across domains* to be a research problem particularly worthy of attention in recommendation system research. If no differences had existed for algorithms across domains, it would have simplified the evaluation process of recommendation systems, since researchers could use datasets with suitable properties without doing domain-specific testing when evaluating algorithms. Im and Hars (2007) have investigated this problem by comparing the results of two recommendation algorithms in the domain of movies with the results in the domain of books, and found that the accuracy was higher for book recommendations than for movie recommendations. This implies that the accuracy of recommendation algorithms is not domain independent. Much recommendation system research makes generalizations of the performance of algorithms based on testing of the algorithms in a single domain (Im and Hars 2007). This gives weak external validity, i.e., to which degree the results are generalizable to other situations and user groups (Jannach et al. 2010, 168), and can possibly give invalid conclusions.

In this thesis, we will present the case of Forzify, which is a sports video application where users can watch, share and redistribute videos. Forzify does today give recommendations to its users, but a new recommendation system is wanted, that can give the users better and more accurate recommendations. We will look at which recommendation system approaches that are suitable for Forzify and will give the best recommendations for the users. Not much data has yet been gathered in the application, so it will be necessary to use other datasets to test the performance of the new recommendation system. As we are not aware of any datasets for user and item data in the sports video context, we will look at the algorithmic consistency across datasets from different domains.

1.2 Problem statement

In this thesis, the overall goal is to find out which recommendation approach that can recommend the most interesting content for each individual user of the sports video application Forzify. To reach this goal, we first want to answer the following research question:

- Q1: According to previous research and literature, which recommendation approaches are best suited for the case of Forzify?

To answer Q1, we will review the main recommendation approaches, compare these both in terms of advantages and disadvantages, and data required for each approach. Further, we will analyse the case of Forzify, to find appropriate approaches for this case.

Having identified suitable approaches for the case of Forzify, we want to test which of these approaches that produce the best recommendations. A measure for this, is the prediction accuracy, which is the most researched property of recommendation systems (Gunawardana and Shani 2015). This measure, which also is called the correctness of the recommendations, says to which degree the recommendations are correct for the users, by comparing the recommendations given by the recommendation system with real user data (Avazpour et al. 2014). We therefore want to evaluate the accuracy of the recommendation approaches. In addition, we want the recommendation system to scale for larger number of users and items, so the users can get instant recommendations.

Because Forzify at the moment has limited existing data about user interaction, we need to test the approaches on other datasets. Therefore, we want to answer the two following research questions:

- Q2: Do the accuracy of recommendation system approaches differ across datasets from different domains?
- Q3: Which recommendation approach or combination of approaches can give the most accurate recommendations to both new and old users of Forzify, and at the same time give high scalability?

For Q2 and Q3 to be answered, we will test a set of recommendation algorithms on different datasets, to both investigate which recommendation algorithms that have highest accuracy overall in the datasets and to see if the accuracy of the individual algorithm differs across the datasets. The algorithms that will be tested, will be chosen based on the discussion of suitable approaches done for Q1. In addition, we will test a non-personalized baseline algorithm, which is useful to compare the personalized algorithms against. Q2 will give valuable information about the generalisability of the accuracy of the recommendation approaches across domains, which is important when we want to use the results from the tests on the other datasets to decide which approach that are best to use in Forzify. We will also measure the training and prediction times of the algorithms on datasets to evaluate their scalability. In Q3, new users mean users with limited item interaction history, which we define as less than 10 interactions, while old users mean users with more item interaction history.

1.3 Limitations

Ideally, to investigate which recommendation approach that gives the best recommendations for the users of Forzify, we would have tested the approaches on Forzify's data. However, as we explained in the previous sections, this is not possible as Forzify has limited user interaction data.

Recommendation systems is a large research area, consequently we can only cover a small part of it. The success of such systems depends on several characteristics, from quantitative characteristics as accuracy and scalability, to more qualitative characteristics as the usability of the recommendation system. The research problems will be investigated from a user's perspective. This means the recommendation system should be as good as possible for the user, giving accurate and fast recommendations. We will limit ourselves to look at the recommendation approaches and algorithms, not surrounding factors, like usability, which can be more important to look at when the recommendation approaches are decided. We will not use the perspective of the owners of the system, where the aim may be to increase profit, and thereby recommending the most profitable content. We will neither use a system perspective, where the focus is on architecture and how the recommendation system can be integrated with the application.

1.4 Research method

The *design paradigm* specified by the ACM Task Force of Computer Science (Comer et al. 1989) will be used as the research method in this thesis. This paradigm consists of the following four steps:

1. State requirements.
2. State specifications.
3. Design and implement the system.
4. Test the system.

We look at the data that are collected in Forzify and which features that are wanted in a new recommendation system, and use literature to find which approaches that are best suited for this case. Based on this, we choose four recommendation algorithms that we implement. We test the algorithms by conducting an offline evaluation of the algorithms, using recommendation accuracy metrics and scalability metrics, with datasets from three different domains.

1.5 Main contributions

Much research on recommendation systems focuses only on one approach, or one kind of algorithms inside one approach. We instead investigate a practical problem by using an extensive approach where all main recommendation approaches are considered and analysed in order to find the most suitable approaches for Forzify. We further implement four algorithms from different approaches and an evaluation framework for these algorithms. The algorithms are evaluated in this framework on three datasets from the movie, book and song domain, in order to see which approaches that perform best in both accuracy and scalability measures. We evaluate the accuracy both for new and old users. This gives valuable results about how well the different approaches perform in different domains, and in addition, it gives an important contribution to the research on algorithms' consistencies in accuracy across domains, which have not been prioritized much in earlier research, as noted by Im and Hars (2007).

An important part of the thesis is the theoretical background that is presented. Based on this, we can choose the most suitable approaches, datasets and frameworks. We review the main recommendation system approaches and compare them in terms of strengths, weaknesses and data needed. We review the most commonly used datasets in recommendation system research, and compare them in terms of domain features, inherent features and sample features, which are the three levels of dataset features presented by Herlocker et al. (2004). Further, we review four popular recommendation frameworks supporting different algorithms, and compare these and their properties. All of these reviews and comparisons can be useful for other researchers and developers that plan to implement or evaluate a recommendation system.

1.6 Outline

Chapter 2 lays the theoretical foundation of this thesis, and gives the theoretical background for answering which recommendation approaches that are suited for Forzify. In this chapter, recommendation systems are presented more in detail, recommendation approaches are presented and compared in terms of strengths, weaknesses and data needed, and some examples are given of how recommendation systems are used in practice in some well-known applications. We also give a review of how recommendation systems are evaluated, and we present and compare different datasets that can be used for evaluation of recommendation systems.

In Chapter 3, we present the case of Forzify, look at recommendations in this context and review which data that are collected in the application and which features that are wanted in a new recommendation system. Further, we discuss which recommendation approaches that are best suited for the data in Forzify and the wanted features, in order to answer research question Q1.

Chapter 4 describes the implementation of a set of candidate algorithms for Forzify, which are chosen based on the discussion of suitable approaches for Forzify. We review recommendation system frameworks and compare them in term of their properties, to find out which frameworks that are appropriate to use in our case.

In Chapter 5, we present our evaluation of the implemented algorithms. First, we look at the experimental design of the evaluation, which includes which measures and datasets to use, how datasets are split and which experimental setting that is used. We further present and discuss the results of the evaluation. Based on the results, we discuss if there are consistencies or differences in the accuracy across the datasets to answer research question Q2, and we discuss which recommendation approaches that most probably will give high accuracy and scalability for Forzify, in order to answer research question Q3.

In Chapter 6, we present our conclusions by answering the research questions. Finally, we present the main contributions of the work and suggest future research to further explore the main topics of the thesis.

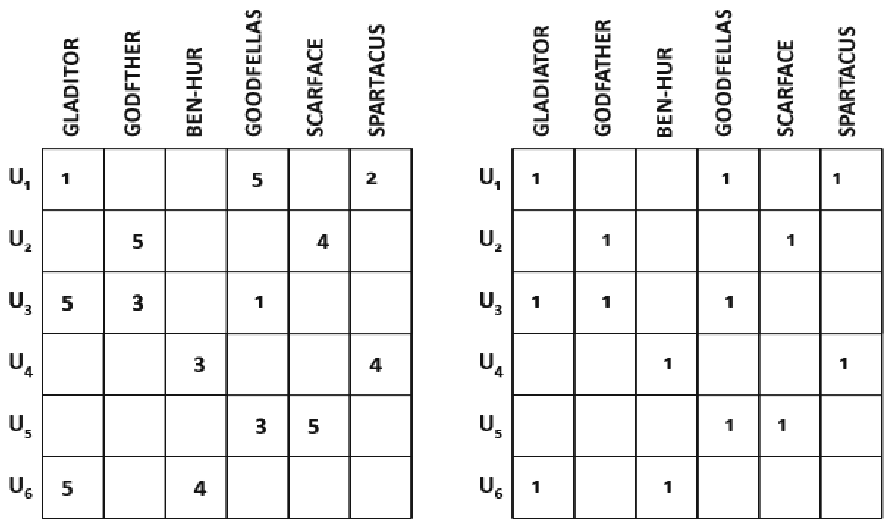
2 Recommendation systems

In this chapter, we lay the theoretical basis of this thesis, and give the theoretical background for answering which recommendation approaches that are suited for Forzify. First, we will look more in detail at recommendation systems and the problems they try to solve. There will be a presentation of different recommendation system approaches, and a comparison of these in terms of their strengths, weaknesses and data needed. There will also be given examples of how recommendation systems are used in practice by some large companies in their applications. Further, there will be a description of how such systems can be evaluated.

2.1 Recommendation systems explored

Recommendation systems are information filtering techniques used for either of the two different, but related problems of *rating prediction* and *top-n recommendation* (Deshpande and Karypis 2004). Rating prediction is the task of predicting the rating a given user will give for a given item, while the latter task is to find a list of *n* items likely to be of interest for a given user, either the *n* most interesting items presented in an ordered list or just a set of *n* items expected to be of relevance for the user (Ning, Desrosiers, and Karypis 2015).

User feedback is essential in most recommendation systems. This information, which can be both explicit and implicit user ratings, is typically stored in a rating matrix R, with ratings $r_{i,j}$, where $i \in 1 \dots n$ and $j \in 1 \dots m$. This matrix stores the ratings of a set of users $U = \{u_1, \dots, u_n\}$, for a set of products $P = \{p_1, \dots, p_m\}$. Figure 1 shows an example of two rating matrices that holds data about six users' ratings for six movies. The first one is a typical example of a rating matrix for explicit feedback, where each rating is given on a scale from one to five, where low values mean dislike and high values mean that the user likes the item. The second one is a rating matrix for unary ratings. Unary ratings are ratings that let the users indicate liking for an item, but where it is no mechanism for detecting a dislike (Aggarwal 2016, 11). This is also called positive only feedback (Gantner et al. 2011). Unary ratings can either have binary values as in this case, where 1 indicates a user interaction and no rating indicates a lack of such interaction, or it can be arbitrary positive values, indicating for example, number of buys or number of views. (Aggarwal 2016, 12). Explicit ratings can be unary ratings, e.g., when there is a like-button and no dislike-button, but unary data are in most cases implicit ratings, collected from user actions. In both of the rating matrices, the missing values indicate that a preference value are missing. For most recommendation systems, most values are missing, i.e., the rating matrix is *sparse,* because most users will only interact with or explicitly rate a small portion of the items (Jannach et al. 2010, 23).



	GLADITOR	GODFTHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			5		2
U_2		5			4	
U_3	5	3		1		
U_4			3			4
U_5				3	5	
U_6	5		4			

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			1		1
U_2		1			1	
U_3	1	1		1		
U_4			1			1
U_5				1	1	
U_6	1		1			

Figure 1: Example of two rating matrices with data about six users' ratings for movies (Aggarwal 2016, 13)

In the rating prediction problem, the recommendation system fills in the missing values of the rating matrix, by utilizing the given values. For this task, the recommendation system needs explicit user ratings for items. This information can, together with implicit ratings, be used to predict the rating a user will give to an item. The predicted rating can then be compared with the real rating for evaluating the prediction. Explicit user ratings can be numerical, as in 1-5 stars, ordinal, as in selection of terms like "loved it", "average" or "hated it", and binary, as in "like"- and "dislike"-buttons (Ning, Desrosiers, and Karypis 2015). Top-*n* recommendation, on the other hand, does not need explicit user ratings. Recommendations in this task can instead be based on only implicit ratings, like user clicks, views and purchases, which are logged as the user interacts with the application. Also in this task, there could be used explicit ratings, but this is not necessary, like in rating prediction.

Explicit user ratings offer the most precise description of users' preferences, but give challenges to the collection of data because the users must actively rate the items (Schafer et al. 2007). Implicit ratings, on the other hand is easier to collect, but gives more uncertainty. For example, if a user rates an element with five out of five stars, we can be sure the user liked the item, but if a user has watched or bought an item, we only know that the user has shown an interest for the item, not that he actually liked it. In the opposite case, lack of item interaction can indicate that the user is not interested in the item or just that she has not discovered the item yet. In other situations, implicit ratings can be as good as explicit ratings, e.g., when play counts are logged for music or video streaming. Then, a high play count can be as indicative for user preference as a rating on a five-star scale.

Recommendation systems have a large and diverse application area. They are today used in areas such as e-commerce, search, Internet music and video, gaming and online dating (Amatriain and Basilico 2015). In highly renowned websites like Amazon, Netflix, Facebook and YouTube, these kinds of systems play an important role, both for the users and for the owners of the systems. How these websites use recommendations will be described more in detail in Section 2.3.

Recommendation systems have in recent years faced a huge increase in interest, not only in the industry, but also in science. Dedicated recommendation systems courses are given at universities around the world, and conferences and workshops are held for this research area, e.g., the annually ACM Recommender Systems (RecSys) conference, which was established in 2007 (Ricci, Rokach, and Shapira 2015).

A major event in the research on recommendation systems was the Netflix Prize, which was announced in 2006 (Amatriain and Basilico 2015). This was a competition for rating prediction on a dataset given by Netflix, with explicit ratings on a scale from 1 to 5. One million dollars were offered to the team that could reduce the root mean squared error (RMSE) by 10 % compared to what was obtained by Netflix' existing system. RMSE is a measure for rating accuracy, where a low RMSE value indicates high accuracy. RMSE and other evaluation methods will be presented in Section 2.5. The Netflix Prize highlighted the importance of personalized recommendations and several new data mining algorithms were designed in the competition (Ricci, Rokach, and Shapira 2015).

Another notable recommendation system competition is the Million Song Dataset Challenge which was held in 2012 (McFee et al. 2012). Here, an implicit feedback dataset consisting of the full listening history for one million users were given, and half of the listening history for another 110 000 users. The task of the competition was to predict the missing half of songs for these users, and mean average precision (MAP), which will be described more in detail in Section 2.5.3, was used as the evaluation metric. This is a typical example of the top-*n* recommendation problem, where the goal is to predict the most interesting items, not to give each item a predicted rating value as in the Netflix Prize.

2.2 Recommendation system approaches

In short, recommendation systems work by predicting the relevance of items for users by analysing the users' behaviour, browsing history, ratings, interaction with items, demography or other information that can learn the system about the users and the items. This can be done in many different ways, with collaborative filtering and content-based filtering as the two main approaches (Bari, Chaouchi, and Jung 2014, 23). Other important approaches are demographic-based, knowledge-based, community-based and hybrid approaches (Ricci, Rokach, and Shapira 2015). Each of these approaches will be presented here.

2.2.1 Collaborative filtering

Collaborative filtering is an approach used to make personalized recommendations that are based on patterns of ratings and usage by the users of a system (Koren and Bell 2011). The idea behind this approach is that if a group of users share opinion on a set of topics, they may also share opinion on another topic (Bari, Chaouchi, and Jung 2014, 23). The system collects large amounts of data, and analyses it to find latent factors or similarities between users or between items. A major advantage of this approach is that no machine-readable representation of the items is needed to generate the recommendations, making the approach work well for complex items like music and movies (Burke 2002). As Figure 2 shows, there are two main groups of collaborative filtering: neighbourhood-based and model-based.

Neighbourhood-based

In the *neighbourhood-based* approach, the ratings are used directly in the computation to predict the relevance of items, by either finding similar items or users, depending on whether it is item-based or user-based (Ning, Desrosiers, and Karypis 2015). This approach is a generalization of the *k*-nearest neighbours problem. The main advantage of neighbourhood-based approaches is their simplicity, which both make them easier to implement and to justify the recommendations for the user (Ning, Desrosiers, and Karypis 2015).

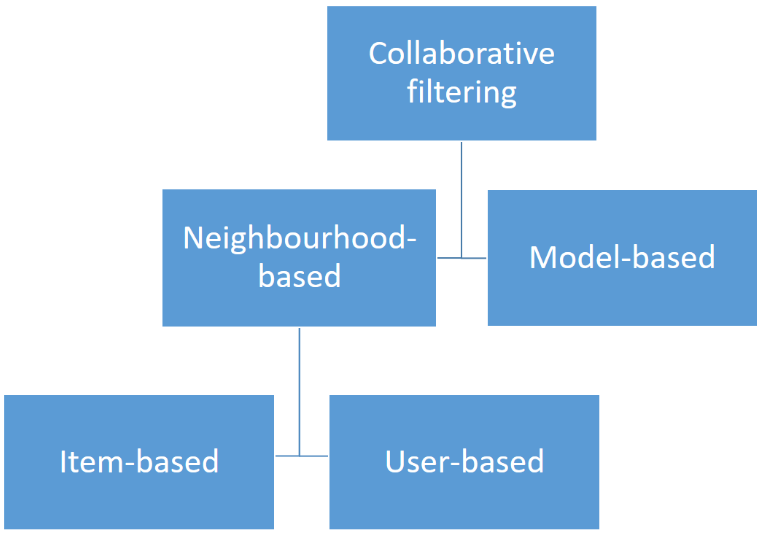


Figure 2: Hierarchy of collaborative filtering approaches

In *item-based* collaborative filtering, recommendations of items are based on the similarity between items (Isinkaye, Folajimi, and Ojokoh 2015). The similarity between one item to another is dependent on the number of people who interacts with both of the items or the similarities of the ratings given to the two items. Two items both watched by a high number of persons will be more similar than two items that are rarely watched by the same persons. In this way, the system can recommend the items most similar to the items a user previously has interacted with. For example, if Martin, who is looking for a good movie, has rated *The Shawshank Redemption* highly, and the users who have rated this movie tend to rate *Forest Gump* similarly, then Martin can be recommended to watch *Forest Gump*.

User-based collaborative filtering is an approach that makes recommendations of items that are highly rated by users similar to the one receiving the recommendation (Desrosiers and Karypis 2011). The similarities between users depend on their resemblance in item interaction history, and the recommended items are those with highest average ratings given by the set of most similar users. For example, if Martin has rated ten movies with highest score and Anna has given the same rating for nine of them, but has not made a rating of the tenth movie, then the system can recommend the tenth movie to Anna. Similarities between users or items are typically calculated with cosine or correlation measures (Isinkaye, Folajimi, and Ojokoh 2015).

Model-based

In model-based collaborative filtering, machine learning and data mining are used to make a predictive model from the training data (Aggarwal 2016, 9). This training phase is separated from the prediction phase. Examples of machine learning techniques that can be used for building such a model are decision trees, rule-based models, Bayesian models and latent factor models (Aggarwal 2016, 9). One of the main advantages of the model-based approaches compared to the neighbourhood-based ones, is that they tend to give better prediction accuracy (Ning, Desrosiers, and Karypis 2015). Another advantage is that they also are more scalable, both in terms of memory requirements and speed (Aggarwal 2016, 73).

Latent factor models are some of the most successful and commonly used of the model-based approaches. They characterize items and users on latent factors based on user feedback (Koren and Bell 2011). For example, if Martin likes to watch biographies and dramas, the recommendation system can identify these latent preferences. Martin can then be recommended *Schindler's List*, which is both biographical and a drama, without the system needing to have a definition of these concepts. The system only needs to know that the movie has the same latent factors as Martin, which the system can find out by conducting a matrix factorization of the rating matrix.

Strengths and weaknesses

Collaborative filtering is the most implemented and most mature of the recommendation approaches (Isinkaye, Folajimi, and Ojokoh 2015). The strength of this approach is that it can recommend items without any domain knowledge and its ability to make cross-genre recommendations (Burke 2002). This is possible because it bases its recommendations on user data, like views, ratings and likes, so that all kinds of complex items can be recommended, also between genres and content. For example, if users who like action movies also tend to like rock music, then a user who likes action movies can be recommended rock music, even though the items have different content. Collaborative filtering also has the advantage of improving its recommendations over time, as more data comes in, and can gather information from the users without needing to explicitly ask for it. Another advantage is that it is generally more accurate than other recommendation approaches (Koren, Bell, and Volinsky 2009).

The downside of this approach is that recommendations cannot be made when there is insufficient data about a user or an item. This is called the *cold start problem*, which can happen when a new user is registered or a new item is added (Felfernig and Burke 2008). User-based collaborative filtering suffers from the cold start problem both when there is a new user and a new item. This is because user history is needed to find similar users, and an item cannot be recommended to similar users if it has not been rated or viewed by a set of users. Item-based collaborative filtering, on the other hand, only has this problem when a new item is added, since data about the use of an item is needed to find similar items. Model-based approaches also have cold start problems, but these are often smaller because they reduce the rating matrix to a smaller model and utilizes both similarities among users and items.

Another problem in collaborative filtering is sparsity (Bari, Chaouchi, and Jung 2014, 31). There is often a huge number of items on a website, and each user may only have rated or viewed a small amount of these. This can result in sparsity in the user ratings, i.e. few users have rated the same items, making it difficult to make recommendations to a user. Model-based approaches have less problems with sparsity compared to neighbourhood-based ones (Su and Khoshgoftaar 2009). Sparsity is particularly a problem in user-based collaborative filtering, where similar users are found by searching for overlap in user ratings. It can also be a problem in item-based collaborative filtering, but in general each item has a higher frequency of interaction than a user has. Sparsity gives challenges in domains where new items are frequently added and there is a huge collection of items, like in online newspapers, where it is unlikely that users have a large overlap in the ratings, unless there is a huge user base (Burke 2002).

The computation in user-based and item-based collaborative filtering is quadratic in either number of users or items respectively. This is because we for each user in user-based, or item in item-based, must compute the similarities to all other users or items, dependent on if it is user-based or item-based. However, item-based filtering is considered more scalable because it allows for precomputation of similarities (Ekstrand, Riedl, and Konstan 2011). This is because the similarities between a user and the other users in a user neighbourhood change when any of the users in a neighbourhood rates a new item, and consequently user similarities must be computed at the time of recommendation in user-based collaborative filtering. The item-similarities are not affected in the same way when it comes a new rating because items usually have more ratings than users have, and they can therefore be precomputed in item-based collaborative filtering. Model-based approaches are usually even more scalable. For example, latent factor models can, like alternating least squares, compute a model which scales linearly in the number of users and items (Hu, Koren, and Volinsky 2008).

The problems with cold start and sparsity, do that collaborative filtering works best for websites with large historical datasets, without frequent changes in items (Burke 2002). If there is not enough user history, the recommendations will be of low quality or it may not even be possible to give recommendations. This makes collaborative filtering an ideal candidate to use together in a hybrid solution with another approach that has less problems with these problems, so that recommendations can be given from the start, but the benefits of the collaborative approach can be achieved when more data is generated.

2.2.2 Content-based filtering

The main idea in *content-based filtering* is to recommend items that have the same features that a user likes (Ricci, Rokach, and Shapira 2015). A user can explicitly state which features he or she likes, or different machine learning techniques can be used to interpret the user's preferences based on former interaction with items (Bari, Chaouchi, and Jung 2014, 32). The features are often tagged keywords or the categories of the item (Felfernig and Burke 2008).

The advantage of this approach, is that recommendations can be made with small amounts of data. There are no problems of recommending new items, because the recommendation system has access to the features of the items (Felfernig and Burke 2008). New users will get recommendations as soon as they have interacted with an item or made a user profile, because the system can recommend items similar to that item or to the preferences expressed in the user profile. The content-based approach thereby avoids the cold start problem. For example, if Martin watches a movie tagged with the keywords "Norwegian" and "thriller", he can be recommended thrillers and Norwegian movies, even if there are no other users in the system. However, the recommendations made to a new user will often be of low quality, because the system has not learned enough about the users' preferences.

Content-based filtering has, like collaborative filtering, the advantage that the recommendations improve as the user interacts with more items, because the system learns more about which features a user likes (Drachsler, Hummel, and Koper 2008). But content-based filtering has one large weakness compared to collaborative filtering; it cannot recommend items of different genres or content (Burke 2002). The reason for this, is that the recommender only recommends items similar, in terms of features, to the ones liked before. This may lead to recommendations that provide nothing new to the user (Bari, Chaouchi, and Jung 2014, 33-35). Another negative aspect of this approach is that domain knowledge is needed to make the feature tags of the items or to place the items in categories.

2.2.3 Demographic-based

Recommendation systems can make recommendations based on demographic information about the users. The idea is that users with different demographic features like age, gender, language, nationality and education will have different interests, and then should get recommendations accordingly. In *demographic-based* recommendation systems, users are categorized in terms of their personal attributes and the recommendations are made based on demographic classes (Burke 2002). For example, Martin who is an 18 years old Norwegian man, will be categorized in a group of persons with the same characteristics, and the items recommended to him will be the items that are most preferred by the other members of the group.

This approach has a resemblance to user-based collaborative filtering, in the way that it finds similarities between users and suggests items based on the preferences of these users. The difference lies in how the approaches find similarities between users. User-based collaborative filtering finds similar users on the basis of interaction patterns, while the demographic-based approach finds similar users on the basis of demographic attributes.

The demographic-based approach is, like collaborative filtering, independent of the domain knowledge, but it does not require the same amount of user history (Drachsler, Hummel, and Koper 2008). Instead, this approach requires the users to fill in demographic information about themselves, so they can get recommendations based on the preferences of users with similar demographic attributes. The advantage of this is that there is no learning period where the system learns about the preferences to the new user. This makes it possible for the system to give recommendations from the first second after registration. Other strengths of this approach is that the recommendations improve with time as more data are gathered, and the ability to recommend items with different genres and content than the items previously interacted with (Burke 2002).

One negative aspect of demographic-based recommenders is that the system must gather the demographic information from the user. This is done in dialogue with the user and cannot be done implicitly, like in collaborative filtering and content-based filtering (Drachsler, Hummel, and Koper 2008). This could be time consuming for the user, and some users do not want to share personal information. If the users choose not to enter the data or some parts of it, the recommendations will suffer (Drachsler, Hummel, and Koper 2008). Another disadvantage of this approach is the "grey sheep" problem, which happens when a user does not fit well in any of the groups used to classify users (Burke 2002). This leads to recommendations that are not based on the user's preferences. The grey sheep problem is also found in collaborative filtering. Demographic-based filtering also has problems with cold start when there are new items, because the item must be interacted with by a set of users for the system to being able to recommend it.

2.2.4 Knowledge-based

Knowledge-based recommendation systems give recommendations based on domain knowledge about how different item features meet user needs and how items are useful for the user (Ricci, Rokach, and Shapira 2015). They do not try to make any long-term generalizations about the users, but instead base the suggestions on an evaluation of the match between a user's need and the options available (Burke 2002). For example, if Martin is going to see a movie together with his little sister, who is eight years old, he will look for a different type of movie than what he usually likes. Therefore, it is better that the recommendations he gets from the system are based on the actual need in this situation, rather than on his usual preferences. With a knowledge-based system, Martin can specify together with his sister which features they would like the movie to have, e.g., "maximum 1 hour" and "children's movie", and the system will find the movies that best fits their needs.

There are two types of knowledge-based recommendation systems: case-based and constraint-based. These two types are similar in terms of used knowledge, but they use different approaches for calculating the recommendations (Felfernig and Burke 2008). While case-based systems base recommendations on similarity metrics, constraint-based systems use explicit rules of how to relate user requirements to items features (Felfernig et al. 2011). Knowledge-based recommendation has its advantage compared to other recommendation approaches when the items have a low number of ratings, e.g., houses, cars, financial services and computers, and when preferences change significantly over time, such that the user needs would not be satisfied by recommendations based on old item-preferences (Felfernig et al. 2011).

The knowledge-based approach does not suffer from the problems of cold start and sparsity. Instead of learning more about the users as more user data comes in, it uses a knowledge base to make recommendations that satisfy a user need. On the one hand, this gives no start-up period with recommendations of low quality, but on the other hand, the recommendation ability is static, not improving over time as in the learning-based approaches (Burke 2002). The approach works better than the others at the start of use, but it cannot compete with the other approaches after some time if no learning methods are used to exploit the user log (Ricci, Rokach, and Shapira 2015). Hence, it can be used successfully for websites where users have few visits and the user data does not make a good fundament for making long time generalizations of the users. It can also be used successfully together with an approach that suffers from the cold start problem.

However, the main disadvantage of knowledge-based recommendation systems is that much time and work is needed for converting domain expert's knowledge to formal and executable representations (Felfernig et al. 2011). In these systems, three kinds of knowledge are needed: catalogue knowledge about the items to recommend, functional knowledge about how items satisfy user needs and user knowledge with information of the user and her needs (Burke 2002). While catalogue knowledge and functional knowledge must be specified by someone with domain knowledge, user knowledge must be gathered, either explicitly or implicitly, from the user.

All recommendation approaches that use the log of user's interactions to make recommendations, have the stability versus plasticity problem (Burke 2007). Users tend to change preferences over time, but this can be difficult for the system to notice when a user profile is made. If the recommendation system makes recommendations based on old ratings, it can result in recommendations that does not reflect the current preferences of the user. For example, if a person who like hamburgers becomes a vegetarian, recommendations of hamburger restaurants will be of low value for the user. The solution to this can be to give a lower weight to old reviews or only use data from a limited period, but this can result in loss of important information. The knowledge-based approach does not have this problem, because it only looks at the user's needs and the options available. Thus, the approach is more sensitive to changes in the user’s preferences, making this a suitable approach for domains where preferences are expected to change frequently.

2.2.5 Community-based

Recommendation systems that are *community-based* gives recommendations based on the likings and preferences of a user’s social connections (Ricci, Rokach, and Shapira 2015). This builds on people’s tendency to prefer recommendations by friends compared to those from an online system (Sinha and Swearingen 2001). The idea is to utilize the ratings from friends to make recommendations that are as good as if they were given by friends. This can be done by collecting information about the user’s social relations at social networks and then recommending items highly rated by the user’s social community (Sahebi and Cohen 2011). For example, if a high proportion of Martin’s friends on Facebook like the same movie, he can be recommended this movie.

People usually have more trust in recommendations from friends than from strangers and vendors, because of the stable and enduring ties of social relationships (Yang et al. 2014). In this approach, the mutual trust between users are exploited to increase the user’s trust in the system (Ricci, Rokach, and Shapira 2015). Recommendations in this approach can be both cross-genre and novel for the user (Groh and Ehmig 2007). This is because the recommendations are based on patterns in user activity of the user’s friends and not on the content tags of the items. There is no need for domain knowledge in this approach either.

The disadvantage of the community-based approach is that data from social networks are needed to generate the recommendations. Not all persons are member of such services, and will thereby not get any recommendations if the system is purely community-based. Sparseness is also a problem because a user has a limited number of friends in online social networks. To cope with this, some variants of the community-based approach traverses the connections in the social network, using the ratings of friends of friends, their friends again and so forth. The ratings provided by users with a nearer connection to the user, are then given a higher weight than those provided by the more distant users. However, this can make the user’s trust in the recommendations suffer, since the recommendations no longer are provided only by first-hand friends.

2.2.6 Hybrid

Each of the presented approaches has advantages and disadvantages. *Hybrid* recommendation systems combine two or more approaches to reduce the drawbacks of each individual approach, and by this getting an improved performance (Burke 2002). For example, collaborative filtering, which in general has good performance, but suffers from the cold start problem, can be combined with an approach that does not have this problem, like the content-based approach. Several methods can be used to make a hybrid recommendation system. The approaches can be implemented separately and combine the results from each, some parts of one approach can be utilized in another approach or a unified recommendation system can be made by bringing together the different approaches (Isinkaye, Folajimi, and Ojokoh 2015).

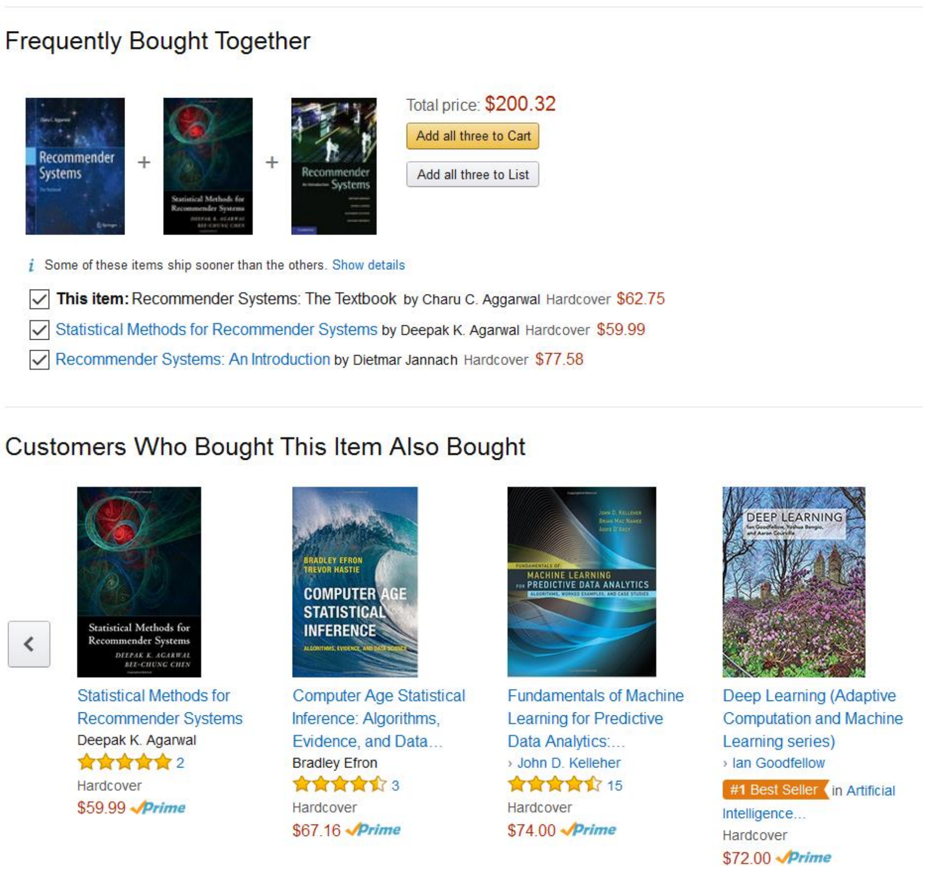
2.3 Recommendation systems in practice

As shown, there are many different recommendation system approaches and combinations of these that can be used. To illustrate how recommendation systems work in real life and the diversity of systems, some recommendation systems used by large companies will be presented here. Note, however, that companies have business secrets, so the presentation of the recommendation systems is based on articles and public information about their recommendation systems, and may have changed from the publication of this information.

2.3.1 Amazon

The American e-commerce company Amazon (amazon.com) was one of the first companies to use recommendations in a commercial setting. They are famous for recommendations like "Customers who bought this item also bought…" and "frequently bought together", as illustrated in Figure 3. Amazon bases its recommendations on buying behaviour, explicit ratings on a scale from 1 to 5 and browsing behaviour (Aggarwal 2016, 5).

Linden, Smith, and York (2003) explains how Amazon uses an item-based collaborative filtering approach to recommend products to its customers. The algorithm builds a similar-items table by finding items often bought together. This is done by iterating over all the items in the product catalogue, and for each customer who bought it, record that this item is bought together with each of the other items bought by this customer. Then, similarity is computed between all pairs of items collected, typically done by a cosine measure. This calculation is made offline, so the most similar products from the similar-items table can be presented fast to the user.


Frequently Bought Together

Total price: $200.32

Add all three to Cart

Add all three to List

Some of these items ship sooner than the others. Show details

This item: Recommender Systems: The Textbook by Charu C. Aggarwal Hardcover $62.75

Statistical Methods for Recommender Systems by Deepak K. Agarwal Hardcover $59.99

Recommender Systems: An Introduction by Dietmar Jannach Hardcover $77.58

Customers Who Bought This Item Also Bought

Statistical Methods for Recommender Systems
Deepak K. Agarwal
2
Hardcover
$59.99 Prime

Computer Age Statistical Inference: Algorithms, Evidence, and Data…
Bradley Efron
3
Hardcover
$67.16 Prime

Fundamentals of Machine Learning for Predictive Data Analytics:…
› John D. Kelleher
15
Hardcover
$74.00 Prime

Deep Learning (Adaptive Computation and Machine Learning series)
› Ian Goodfellow
#1 Best Seller in Artificial Intelligence…
Hardcover
$72.00 Prime

Figure 3: Example of recommendations when visiting an item at Amazon

2.3.2 Netflix

Netflix (netflix.com) is a company that provides streaming of movies and series. It offers its customers a personalized interface, where previous views, ratings and items added to the user's list give basis for the titles presented to the user. Netflix typically recommends a set of videos in a particular genre or a set of videos based on a user's interaction with an item, as Figure 4 shows. The recommendations are then justified by what the set is based on, as "Because you watched …", "Comedies" or "Top list for you". Each set is presented as a horizontal list of items and the user is presented to several rows of such sets.

The recommendation algorithm uses a set of factors to make its recommendations. Which genres the available movies and series have, the user's streaming and rating history and all ratings made by users with similar tastes, are factors that affect the recommendations a user gets (Netflix 2016). This is an example of a hybrid recommendation system, that uses both collaborative filtering – as similar users' ratings are used to recommend, and content-based filtering techniques – as genres are used to recommend. The rating scale in Netflix is, as in Amazon, from 1 to 5 stars.

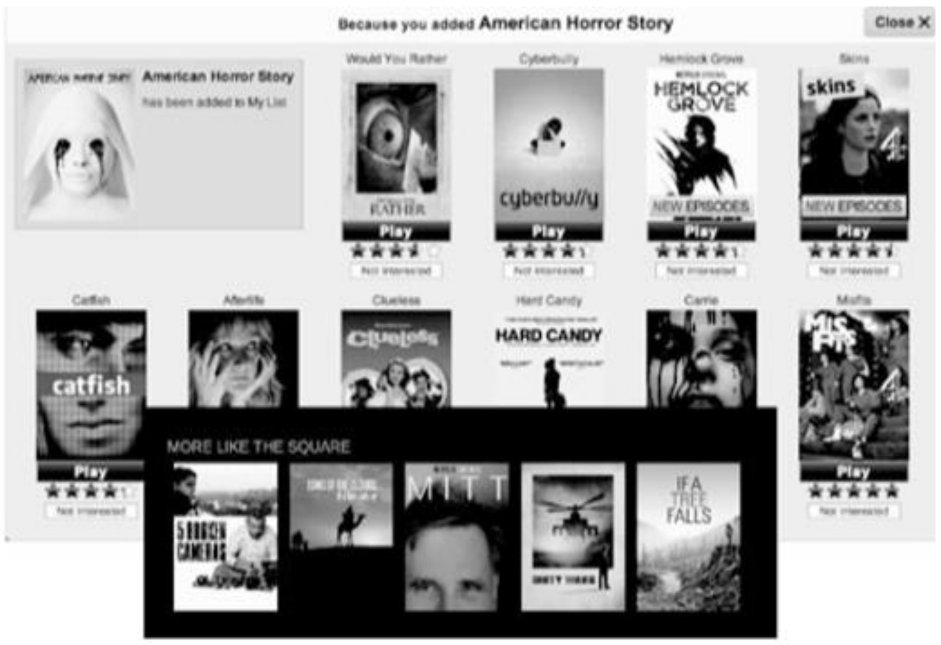


Figure 4: Recommendations of videos in Netflix (Amatriain and Basilico 2015, 393)

2.3.3 Facebook

The social networking site Facebook (facebook.com) makes recommendations to its users at multiple areas of the website. Recommendation systems are used to suggest new friends, choose which posts should be showed at the top of a user's newsfeed, propose pages for a user to like and recommend apps to download. The algorithm used for recommending apps in Facebook's app centre will here be presented to give an understanding of how Facebook recommends content to its users.

The recommendation system used in Facebook's app centre has three major elements (Facebook Code 2012). The first is candidate selection, where a number of promising apps are selected. This selection is based on demographic information, social data and the user's history of interaction and liking of items. The second element in the recommendation system is scoring and ranking. Explicit features like demographic data and dynamic features like number of likes are important when the ranking scores for the apps are calculated, but the most important feature is learned latent features. This is features learned from the user's history of interaction with items. The predicted response for a user to an object, is calculated by the dot-product of two vectors, where one is the latent features of the user and the other is for the characteristic of the object. The last element of the recommendation system is real time updates. With a huge number of users and new apps coming in frequent, the indexes and latent features must be updated in real-time to ensure the best possible recommendations.

This is a good example of a model-based latent factor model that also utilizes the demographic- and community-based approach. Figure 5 shows recommendations of games in the app centre. Facebook is known for its like-rating, but uses also ratings on a scale from 1 to 5, as seen in the figure.

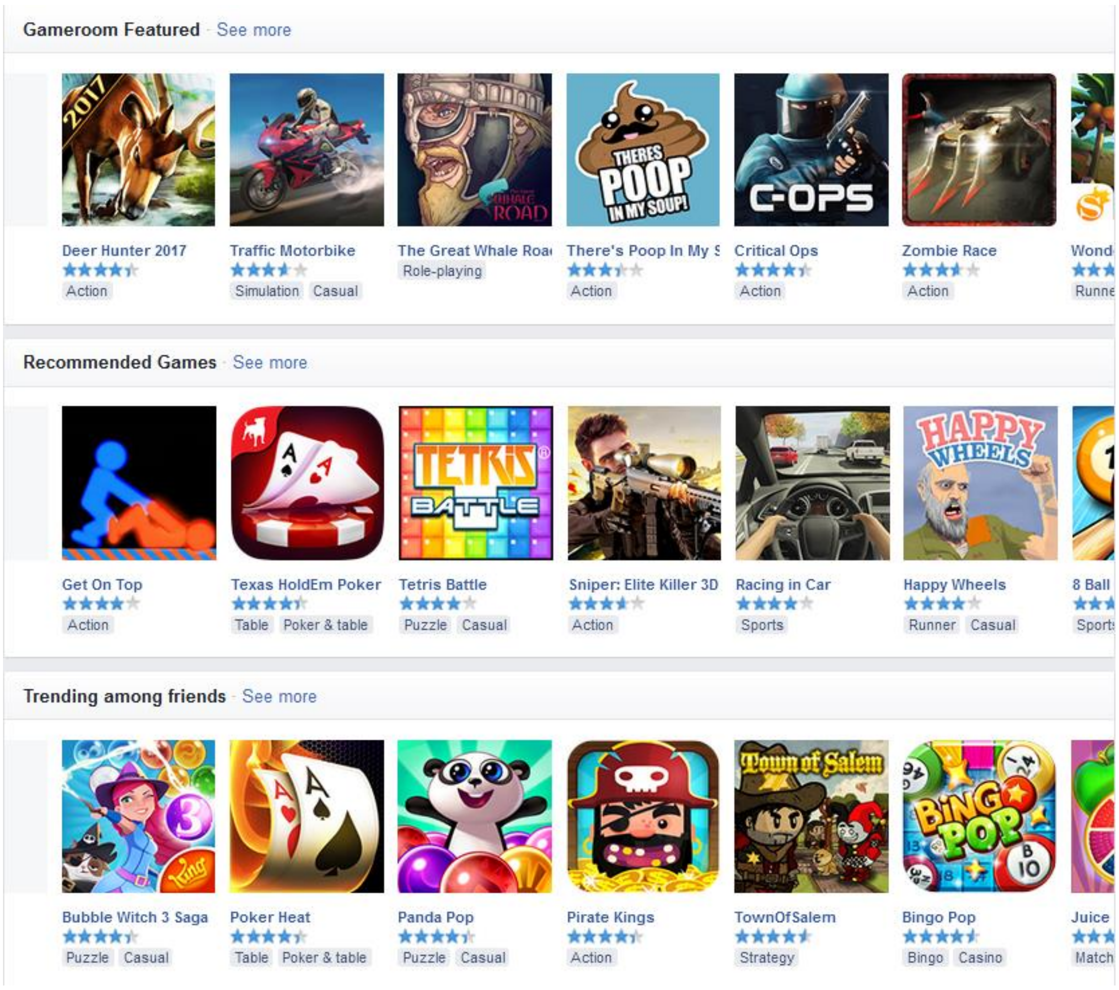
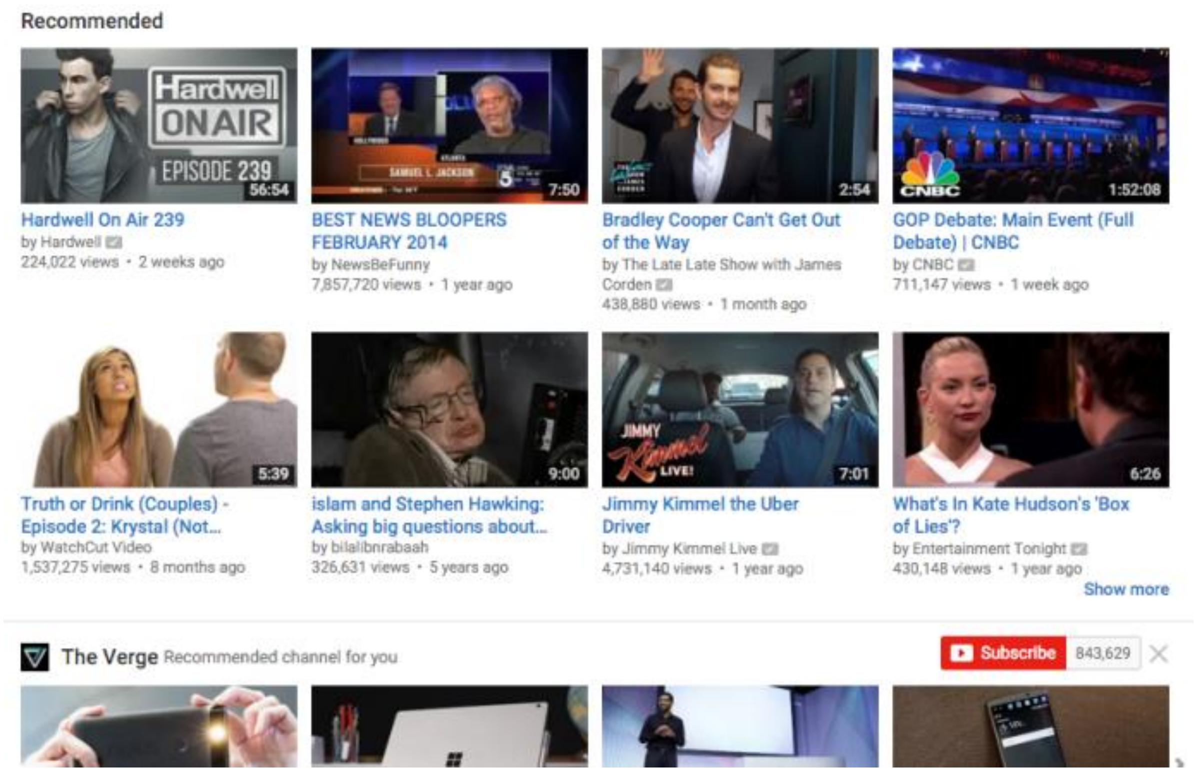


Figure 5: Recommendations of games in Facebook

2.3.4 YouTube

The world's most popular online video community, YouTube (youtube.com), gives personalized recommendations of videos to its users, with a goal of letting the users be entertained by content they find interesting (Davidson et al. 2010). Figure 6 shows an example of recommendations in YouTube. An important part in YouTube's recommendation system is to find the most similar videos for each video. This is done in a similar fashion to the item-based approach to collaborative filtering used by Amazon. Two videos are regarded as similar if they have a high co-visitation count, i.e., if they are watched together by the same user within a given period of time, typically 24 hours. This number is then normalized with a function that takes the video's global popularity into account, to avoid that the most watched videos get an advantage over the less popular ones. A mapping is then made between each video and its *N* most similar videos.

To select the recommendation candidates for a user, a seed set of videos are generated. This is all the videos the user has liked explicitly or implicitly. A candidate set of videos are generated by taking the union of all videos that are similar to the videos in the seed set. The candidate set is then extended with all videos similar to the videos in the set, and this is repeated several times to increase the span of the videos. YouTube wants the recommendations to help the users to explore new content, and then it is important that not all videos are too similar to videos in the seed set.


Recommended
Hardwell On Air 239
by Hardwell
224,022 views • 2 weeks ago
BEST NEWS BLOOPERS FEBRUARY 2014
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7,857,720 views • 1 year ago
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by The Late Late Show with James Corden
438,880 views • 1 month ago
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by CNBC
711,147 views • 1 week ago
Truth or Drink (Couples) - Episode 2: Krystal (Not...
by WatchCut Video
1,537,275 views • 8 months ago
islam and Stephen Hawking: Asking big questions about...
by bilalibnrabaah
326,631 views • 5 years ago
Jimmy Kimmel the Uber Driver
by Jimmy Kimmel Live
4,731,140 views • 1 year ago
What's In Kate Hudson's 'Box of Lies'?
by Entertainment Tonight
430,148 views • 1 year ago
Show more
The Verge Recommended channel for you
Subscribe 843,629

Figure 6: Recommendations of videos on Youtube (Manoharan, Khan, and Thiagarajan 2017)

The videos in the candidate set is then ranked according to video quality and user specificity. Video quality is computed by variables independent of the user, like total view count and the total number of positive ratings for a video. YouTube has explicit data in form of likes and dislikes, and implicit data from for example viewing history, comments and sharing of videos. To ensure the relevance of the video for the user, the user specificity reflects if the video is closely matched with the user's unique taste and preferences. In the end, not only the videos that are ranked highest are recommended. Videos from different categories are selected to increase the diversity of the recommendations.

2.4 Comparison of approaches

The approaches will here be compared in terms of their characteristics, strengths and weaknesses. One of the most important aspects when comparing the different recommendation approaches is what kind of data that are used and how this data is used to make recommendations. Figure 7 illustrates the data inputs and background data that are used in each of the approaches.

In demographic-based, community-based and collaborative filtering, the user rating database for the whole set of users constitutes the background data for the recommendations. Demographic-based filtering uses in addition the demographic information about the users. The individual user's demography, her social connections or her ratings are then used as input data, depending on which of these three approaches it is, so that the system can categorize the user in a group of users. Recommendations can then be made based on the preferences in this group of users. Item-based collaborative filtering, does not use the ratings to find similar users, but instead uses them to find items that are similar to the items rated highly by the user. In model-based collaborative filtering, ratings are used to make a predictive model, which is used to recommend items.

As Figure 7 shows, content-based filtering uses the user's ratings or interests as input data. The database of items and the associated metadata are used as background data, instead of the user ratings, as in collaborative filtering. Based on the user's ratings and interests, items similar in content are found from the item database. The knowledge-based approach is the only approach that does not use any data about user ratings to make recommendations. Instead it uses a knowledge base to map a user need to an item in the item database.

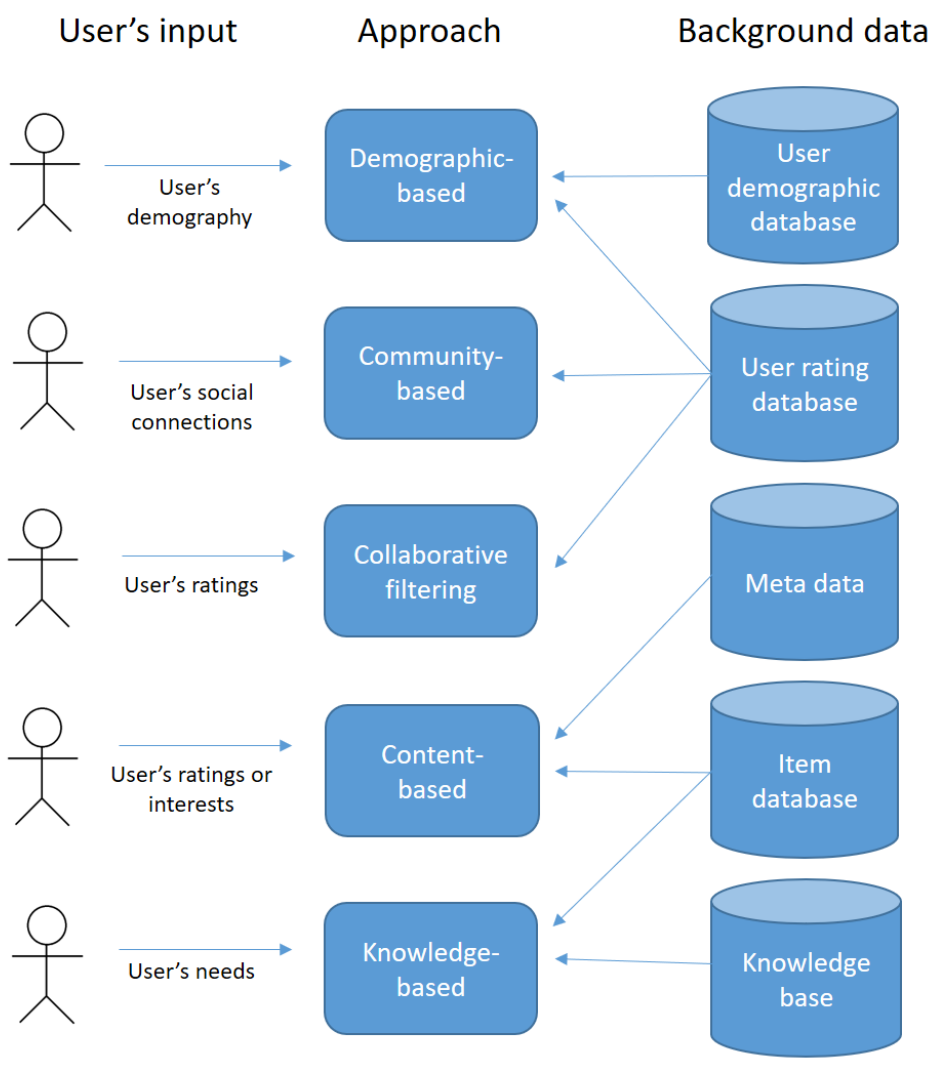


Figure 7: Input and background data used in different recommendation approaches.

All of the approaches have strengths and weaknesses, which is illustrated in Table 1. With the exception of the knowledge-based approach, all the presented approaches use some kind of learning. This means that the systems learn more about the users as more data are gathered about them and the items, and that the recommendations consequently are improved. As a result, the knowledge-based approach is inferior to the other approaches when the system is used for an extended period of time. On the other hand, if the system operates in a domain where the user is likely to change preferences, the learning can lead to recommendations that are not relevant for the user because they are based on the user's old habits. In cases like this, the learning gives a negative impact on the recommendations, and the knowledge-based approach could be a better option because it is more sensitive to changes in preferences. But in general, the learning-based approaches will give the best recommendations for a frequent user.

The absence of learning in the knowledge-based approach gives recommendations of the same quality for new users as for old users. This means the users can get relevant recommendations from the first time they use the system, which is not the case for all of the approaches that use learning. Without enough data about the users' interaction with items, these approaches will generate recommendations of low quality.

Approach / Feature	Collaborative filtering	Content-based	Demographic-based	Knowledge-based	Community-based
Improvement over time	+	+	+		+
Sensitive to changes				+	
Cold start – new user	-			+	
Cold start – new item	-		-	+	-
Only needs implicit data	+		-		+
Needs data from social media					-
Increased trust					+
Needs knowledge engineering				-	
Needs domain knowledge		-		-	
Cross-genre and cross-feature	+	-	+		+

Table 1: Advantages and disadvantages of recommendation approaches. "+" indicates an advantage for this feature, "-" indicates a disadvantage for this feature, while no sign indicates neither advantage or disadvantage

Collaborative filtering, demographic-based filtering and community-based filtering all have the cold start problem. Cold start consists of two different but related problems: the new user problem and the new item problem. Item-based collaborative filtering, demographic-based filtering and community-based filtering do all have the new item problem, while user-based collaborative filtering has problems with both new users and items. Model-based collaborative filtering does also have cold start problems, but not to the same extent.

Content-based filtering does not have the cold start problem because it can explicitly ask for the user's interest, and then recommend items that have content in accordance with these interests. If the system does not collect these interests explicitly, or the user chooses not to enter her preferences, the recommendations will suffer, but as soon as at least one item is interacted with, items with similar content will be recommended. Even if the user is the first user of the system, there will be given recommendations because the approach is independent of the ratings to users other than the one getting the recommendation. When new items are added, they can be recommended from the first second because they have content tags.

As Table 1 tells us, collaborative filtering and community-based filtering have the advantage of only needing implicitly gathered data. Demographic-based filtering, on the other side, must explicitly ask the users for demographic information to be able to categorize the users in terms of demographic attributes, while content-based filtering needs to explicitly ask for the user's interests to avoid the cold start problem, but can otherwise use implicit data to learn content preferences. Knowledge-based filtering can both use explicit and implicit ratings to understand the need of the user.

Despite the fact that community-based filtering only needs implicit ratings, it is dependent on social connections from social networks. Without this information, the approach cannot provide any recommendations. This will be the case when a user is not a member of social networks, or does not want to share this information. However, the strength of using this kind of data is that it can increase the users' trust in the recommendations, by exploiting the trust in social relationships.

One downside of the knowledge-based approach is that knowledge engineering is needed to make the knowledge base. This can be a time-consuming process where domain knowledge is needed. Content-based filtering also requires domain knowledge because knowledge about the items are needed to make the item tags, but this can be added by the owners of the items as they are added. The other approaches, on the other hand, are independent of domain knowledge.

An often-desired feature in recommendation systems is the possibility to make recommendations with different content or genres than the items the user has interacted with in the past. These recommendations that are relevant for the user, but do not contain characteristics that are in the user’s profile, are called *serendipitous* recommendations. Collaborative filtering, demographic-based filtering and community-based filtering can all make these because they base the recommendations on similarities in user data, rather than on the properties of the items. This gives the advantage of letting the user explore new exciting and varying material. This feature is also possible in knowledge-based recommendation systems, but then, this must be specified in the knowledge base, and is not done automatically. In content-based filtering, it is not possible with serendipitous recommendations because the recommendations are made on the basis of preferences in types of content.

2.5 How to evaluate recommendation systems

When making a recommendation system, it is important to evaluate the qualities of the recommender, both for selecting the right approach and to see if the system is successful according to its goals. In this section, there will be a presentation of the different experimental settings that can be used for testing recommendation systems, a presentation of which characteristics that are commonly evaluated and a review of how to measure the accuracy of a recommendation system.

2.5.1 Experimental settings

There are three types of experimental settings that can be used to evaluate recommendation systems, namely offline experiments, user studies and online evaluation (Gunawardana and Shani 2015). In *offline experiments*, the experimenter uses a pre-collected dataset consisting of ratings or users’ item interactions to simulate the behaviour of users interacting with the recommendation system. The advantage of this approach is that no interaction with real users are needed, making it easy to evaluate different implementations and compare them to each other. On the other hand, this approach can only be used to evaluate a small subset of the features of a recommendation system, typically the accuracy of the predictions. Since this approach only simulates how real users interact with the recommender, it is not possible to measure the recommendation system's influence on user behaviour.

The simulation in offline experiments can be carried out by collecting historical data, leaving some of the data out and then comparing recommendations or predictions of ratings with the hidden data. The goal of experiments in this setting is therefore often to find the algorithm with the best prediction or to see how changes to one algorithm influence the accuracy of the recommendations. The data used for training a model is called the *training set*, while the hidden data is called the *test set*. The reason for using a separate dataset is to avoid *overfitting*, i.e., making incorrect generalizations from random properties of the training data (Manning, Raghavan, and Schütze 2008, 271).

While traditional recommendation system research has focused on algorithms' accuracy, research in this area has in recent years started to emphasize the importance of other aspects of recommendation systems, like evaluating recommendation systems from a user experience perspective (Konstan and Riedl 2012). To evaluate the user experience of a recommendation system, the system must be tested in a lab or in the field with real users (Knijnenburg and Willemsen 2015). User studies do the former, while online evaluations do the latter.

In a *user study*, a number of test subjects are asked to do a set of tasks that involves interaction with the recommendation system, so their behaviour can be observed and measured to gain quantitative data (Gunawardana and Shani 2015). In addition, the subjects can be asked questions, to provide qualitative data about their opinions when it comes to the use of the system. The advantage of user studies is its ability to answer a wide set of questions of the qualities of the recommendation system. However, this approach also has a major downside. It is an expensive evaluation method because it is time-consuming and a set of subjects must volunteer or be paid to participate.

Online evaluation is conducted by measuring real users doing real tasks (Gunawardana and Shani 2015). This type of evaluation is commonly carried out as A/B tests (Knijnenburg and Willemsen 2015). An A/B test is done by changing exactly one thing from the original system to an alternative system, and then redirecting a small percentage of the users to the alternative system (Manning, Raghavan, and Schütze 2008, 170). This makes it possible to measure the effects a change in a system makes on the users' behaviour, like for example, if users in one system follow recommendations more often than in another system. For such an evaluation to be successful, it is important that users are randomly redirected to the different systems and only one variable are changed between the systems. Online evaluation gives the best evidence for the true value of a system, but is not conducted without risks (Gunawardana and Shani 2015). For example, if a recommendation algorithm with low accuracy is tested on real users, it can result in dissatisfied users and decreased user visits and product sale. Because of this, it is smart to use this experimental setting after offline evaluation and user studies are carried out.

2.5.2 Dimensions and metrics

Recommendation systems have several characteristics, both quantitative and qualitative, that can be important for determining its quality. Avazpour et al. (2014) list the following 16 dimensions that are commonly used to evaluate the successfulness of a recommendation system:

- *Accuracy*, also called correctness, i.e., how close the recommendations are to a set of predefined correct recommendations.
- *Coverage, i.e.,* the proportion of the items and users that can be recommended or given recommendations respectively.
- *Diversity*, i.e., to which extent the items recommended to the user are not similar to each other.
- *Trustworthiness*, i.e., the users' trust in the system. For example, good recommendations and explanations of why items are recommended can increase a user's trust in the system, while recommendations of low quality can lead to a user losing her trust in the system.
- *Recommender confidence*, i.e., the recommendation system's trust in its recommendations and predictions. For example, a system will get a high confidence in a prediction if there is a high probability for it to be correct, as when the system has a high amount of data about the given user and item. It is desirable that the system have a high confidence in the recommendations presented to the user.

- *Novelty*, i.e., the systems' ability to recommend items the user did not know about.
- *Serendipity*, i.e., the systems' ability to give recommendations that are both surprising and interesting for the user.
- *Utility*, i.e., the value the recommendations give to a user or to the owner of the system. For example, good recommendations will give high utility for the user and bad recommendations will give low utility, while an increase in the revenue will give high utility for the system owner.
- *Risk*, i.e., the risk for a user associated with a recommendation. For example, if a recommendation system is used to recommend stocks, it is important that the items have a minimal risk, not only a possible high profit.
- *Robustness*, i.e., the stability of the system in case of false information, either given by accident or on purpose. For example, if an owner of an item want to increase the popularity of that item by giving good ratings from fake user profiles, a robust recommendation system will be affected to a small extent by these false ratings.
- *Learning rate*, i.e., how fast a recommendation system can adapt the recommendations to new information and trends.
- *Usability*, i.e., how user friendly the interface of the recommendation system is regarded by the users. For example, a recommendation system with a chaotic presentation of items can be of low value for the users, even though the recommendations are accurate.
- *Scalability*, i.e., how the system can scale up to large datasets of items and users, both with regards to time and space requirements. The scalability of a recommendation system is often determined in terms of training time, prediction time and memory requirements (Aggarwal 2016, 235). The training time is usually done offline and can without problems be up to a few hours, while the test time must be very low as the users are not interested in waiting for recommendations.
- *Stability*, i.e., how consistent the recommendations are over a period of time. For example, systems that change its recommendations rapidly, without the user changing

her user habits, can result in confusion for the user and a subsequent decreased trust in the system.

- *Privacy,* i.e., to which degree the users' data stay private, not being available to any third-party.
- *User preference,* i.e., the users' perception of the recommendation systems. For example, users can try several systems, and decide which they prefer.

Because different recommendation systems have different needs and goals, the developers of the system must choose which dimensions that are important to evaluate in order to meet these expectations. Some of the dimensions affects each other, either positively or negatively. For example, an increase in coverage will often increase the accuracy, while an increase in diversity, serendipity or novelty can result in a loss of accuracy.

2.5.3 Measuring accuracy

In Section 2.1, the rating prediction and top-*n* recommendation were presented as the two main problems to solve for recommendation systems. In this section, there will be given a review of how the accuracy of these two problems can be measured in an offline setting. To answer research question Q2 and Q3, we must measure the accuracy of recommendation approaches. This is the reason for reviewing the accuracy metric, and not the other metrics presented in Section 2.5.2.

Predicting user ratings

If the recommendation system's task is to predict users' ratings of items, the metrics *root-mean-squared-error* (RMSE) and *mean-absolute-error* (MAE) can be used to measure the accuracy of the predictions. Ratings are divided into two independent sets: a training set and a test set. The training set is used to learn a function for predicting the ratings, so that the recommender can predict the users' ratings of items in the test set. The predicted rating for each item can then be compared to the actual rating in the test set to find the difference, or the residual, of the ratings. As stated in Section 2.5.1, it is important that the training and test sets are disjoint to avoid overfitting.

RMSE is possibly the most commonly used metric to evaluate the accuracy of rating predictions (Gunawardana and Shani 2015). It was used as the metric in the Netflix Prize, described in Section 2.1. When calculating RMSE for a test set τ, the residuals of the predicted rating $\hat{r}_{u,i}$ and the actual rating $r_{u,i}$ are squared, the average of these values is calculated and the square root is taken on the average:

$$RMSE = \sqrt{\frac{1}{|\tau|} \sum_{(u,i)\in\tau} \left(\hat{r}_{u,i} - r_{u,i}\right)^2} \tag{1}$$

MAE resembles RMSE, but calculates instead the average absolute deviation of the predicted ratings from the correct ratings:

$$MAE = \frac{1}{|\tau|} \sum_{(u,i)\in\tau} \left|\hat{r}_{u,i} - r_{u,i}\right| \tag{2}$$

In both RMSE and MAE, a low value indicates high prediction accuracy. The main difference between the two measures is that RMSE penalizes large differences in ratings more than MAE, because it squares the residuals before calculating the average (Avazpour et al. 2014).

Predicting interesting items

When the task of the recommender is not to predict ratings, but instead to predict the top *n* items for the user, it is necessary to use other metrics for accuracy than RMSE and MAE. *Precision* and *recall* are two commonly used metrics for this case. As basis for these measures are usually the items that a user has accessed, but it could also be the items that are rated positively or are bought by the user. These items are considered as *relevant* for that user. The user data are also in this case split into a training set and a test set. The training set is used to learn a function that predicts for each item in the test set if it is relevant or not for the user, or to produce a recommendation list where items are sorted based on their predicted relevance for the user.

Each item can be classified as either true positive, false negative, false positive or true negative, based on if it is recommended or not and if it is used or not, as Table 2 shows.

	Recommended	Not recommended
Used	True positive (TP)	False negative (FN)
Not used	False positive (FP)	True negative (TN)

Table 2: Confusion matrix for possible classifications of an item

When all items in the test set are classified, precision and recall can be measured as follow, depending on how many items that are classified in each of the classes:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Precision measures the proportion of the recommended items that are actually used, while recall measures the proportion of the used items that are recommended. One weakness of these two measures are that items not accessed are assumed not to be interesting, which is not necessarily true (Gunawardana and Shani 2015). These items could be interesting for the user; they are just not discovered yet. There is a trade-off between precision and recall, in the way that an increase in precision often results in a decrease in recall (Avazpour et al. 2014). For example, if the number of items in the recommendation list is increased, it will probably improve the recall, but worsen the precision.

When the size of the recommendation list is predefined, it is appropriate to use *precision at n*, which means to compute the precision for n recommendations, ignoring the other items. Then we can measure the precision of the *n* recommendations in the recommendation list. Otherwise, it is desirable to measure the precision for various sizes of lists. This can be done by plotting the precision versus recall rates in a graph, which is called a precision-recall curve.

A measure commonly used when the recommendation list is ordered, is *mean average precision* (MAP). MAP emphasizes the top recommendations and was the measure used in The Million Song Dataset Challenge (McFee et al. 2012), presented in Section 2.1. This measure is often used in implicit feedback situations (Aiolli 2013, Wu et al. 2016, Parra et al. 2011). Traditionally, this measure takes all recommendations into account. However, as recommendation systems only recommend a limited number of items, it is common to use a truncated version of this measure, where only the *n* first recommendations are taken into account (McFee et al. 2012). We will therefore present this version of the measure, and refer to this version when saying MAP. For this measure, average precision at *n* (AP@*n*) is first calculated for each user in the following way:

$$AP@n = \sum_{k=1}^{n} P(k) / \min(m, n) \tag{5}$$

Here, *P(k)* is the precision at *k* if the item in position *k* is considered relevant for the given user, or otherwise it equals 0. The symbol *m* is the number of items the user has interacted with and *n* is the size of the recommendation list. This means we take the average precision at each recall point, i.e., each index in the recommendation list with an item considered relevant. The MAP is then computed by taking the average of AP@*n* over all the users, the following way, where *N* equals the number of users and *n* is the recommendation list size:

$$MAP = \sum_{i=1}^{N} AP@n_i / N \tag{6}$$

Other measures often used in implicit feedback situations are *Hit-Rate* (HR) and *Average Reciprocal Hit-Rank* (ARHR) (Ning and Karypis 2011, Deshpande and Karypis 2004). HR measures the partition of users who get at least one correct recommendation in the recommendation list (Jannach et al. 2010, 181). ARHR, which is also referred to as mean reciprocal rank, does, like HR, measure the proportion of users who get at least one correct recommendation, but does in addition take the rank of the correct recommendation into account. ARHR is measured the following way:

$$ARHR = \frac{1}{\#\, users} \sum_{i=1}^{\#\, hits} \frac{1}{p_i} \tag{7}$$

# Hits denotes the number of users who get a correct recommendation in the recommendation list, while p_i is the position of the first correct recommendation for a user *i*, that get at least one correct recommendation. For all of the metrics for predicting interesting items that are presented here, larger values indicate higher prediction accuracy.

2.5.4 Datasets

The dataset used in an offline evaluation should be as similar as possible to the data expected when deploying the system online (Gunawardana and Shani 2015). If the system has been operational for a certain time and has a large user base, a dataset can be created by logging user data. In other situations, this can be problematic, for example when the system is not yet operational or it only has small amounts of data. Then, it is possible to use an existing available dataset. If no existing dataset matches the domain of the recommendation system, an alternative is to use synthesized data that matches the domain, but this does not give accurate modeling of real users and real data (Herlocker et al. 2004).

Several datasets that can be used in recommendation system research are available online with real user data. Some of the most commonly used are:

- *MovieLens*, which consists of several datasets of movie ratings and metadata, where the largest has 20 million ratings by 138 000 users for 27 000 movies, while the smallest have 100 000 ratings (Harper and Konstan 2016).
- *Amazon* dataset, with 144 million reviews of 9 million items (McAuley et al. 2015).
- The *Book-Crossing* Dataset, with both explicit and implicit user data for books (Ziegler et al. 2005).
- The *Jester* Dataset, with explicit user ratings for 100 jokes (Goldberg et al. 2001).
- The *Million Song* Dataset, with 48 million song counts for 380 000 songs and 1.2 million users, with corresponding metadata (Bertin-Mahieux et al. 2011).

Comparison of datasets

When choosing a dataset for evaluation, it is essential to analyze the properties of the datasets to see if they model the tasks of the recommendation system under evaluation in a good way. Herlocker et al. (2004) divide properties of datasets into three categories: domain features, inherent features and sample features. *Domain features* describe characteristics of the content being recommended and rated, *inherent features* describe features of the ratings and data collection practices, and *sample features* describe distribution properties of the data. The different datasets will here be compared in terms of a subset of the features of these properties.

As Table 3 shows, all of the presented datasets have different product domains, i.e., they contain ratings for different types of items. MovieLens operates in the movie domain, Amazon is in the e-commerce domain and has a diverse set of products, while Book-crossing, Jester and Million Song is in the book, joke and music domains respectively. Different domains tend to have different preference heterogeneity, which means they differ in the preference pattern of the users (Im and Hars 2007). For example, there is a tendency that peoples' preferences overlap more in the movie domain than in the domain of research papers (Im and Hars 2007). This can in turn affect the accuracy of the recommendation algorithms on the different domains.

	MovieLens	Amazon	Book-Crossing	Jester	Million Song
Content	Movies	Various products	Books	Jokes	Music
Context	Web	Web	Web	Web	Web
Cost for false negative	Low	Low	Low	Low	Low
Cost for false positive	Low	Intermediate	Low	Low	Low
Benefit	High	High	High	Intermediate	High

Table 3: Comparison of domain features of datasets

However, there are also some similarities for these datasets in the domain features presented by Herlocker et al. (2004). The data for all of them are collected from web-settings and the main user task supported by each of the recommendation systems is to find good items for the user. There are very low costs for false negatives in all of the domains compared to for example a recommendation system for juridical documents, where missing recommendations of good items could be problematic for a lawyer. False positives do also have low costs in the domain of these datasets as incorrect recommendations only could waste small amounts of time and money for the users. The only exception here is Amazon, where incorrect recommendations of retail items could be both costly and time-consuming for the user. In all of the domains, except in Jester's case, the recommendations could give huge benefits for both the users and the companies by dealing with the information overload problem, as the item catalogues are extremely large. Jester does not have this large number of items and are thus not facing such a high potential benefit from its recommendations.

There is also differences in the datasets when it comes to the inherent features, as seen in Table 4. MovieLens, Amazon and Jester have gathered explicit user ratings, The Million Song dataset has gathered implicit data about play counts, while The Book Crossing dataset contains both explicit and implicit data. All of the datasets have only one dimension for the ratings, unlike for example TripAdvisor where one user can rate a hotel stay with several dimensions, as service, location and cleanliness. MovieLens and Amazon do both have ratings on a 1-5 scale, Book-Crossing has a rating scale from 1-10, while Jester has a continuous rating scale from -10.0 to 10.0.

	MovieLens	Amazon	Book-Crossing	Jester	Million Song
Explicit or implicit	Explicit	Explicit	Both	Explicit	Implicit
Scale	1-5	1-5	1-10 and implicit	-10.0-10.0 continuous	Play counts (unary)
Dimensions of ratings	1	1	1	1	1
Timestamps	Yes	Yes	No	No	No
Demographic data collected	Yes	No	Yes	No	No
Content data collected	Tags	Tags	Publisher information	Text of jokes	Tags

Table 4: Comparison of inherent features of datasets

MovieLens and Amazon are the only ones of the datasets that contain timestamps. This information can be useful if a researcher wants to simulate the system at a single test time, where all ratings after that time is hidden. Content data and demographic information about users are additional data that can be valuable in a dataset. MovieLens, Amazon and Million Song have content data in the form of tags, while Jester has its jokes in textual form. The

Book-Crossing has publisher information about each book, as year published, title of the book and the book's publisher. Both Book-Crossing and MovieLens have demographic data about its users.

The possibly largest differences of the datasets are found in the sample features. As Table 5 shows, the number of users ranges from 73 000 to 21 million, the number of items ranges from as little as a hundred to over 9 million, while the number of ratings ranges from around a million to 155 million. All the datasets have more users than items and, not surprisingly, more ratings than items. Amazon has not only the highest number of users, but also the highest number of items and ratings. Jester, on the other hand, has both the smallest number of users and items, while The Book-Crossing dataset has the fewest ratings.

	MovieLens	Amazon	Book-Crossing	Jester	Million Song
Users	138 000	21 M	279 000	73 000	1 M
Items	27 000	9.35 M	271 000	100	384 000
Ratings	20 M	144 M	1.15 M	4.1 M	48 M
Avg. ratings per user	145	7	4.1	56	48
Avg. ratings per item	740	17	4.4	41 000	125
Overall density of ratings (avg. % of the items that are rated per user)	0,54%	0,000075 %	0,0015%	56%	0,0125%

Table 5: Comparison of sample features of datasets

The differences are also visible in the average number of ratings per user and item, but even more significantly in the overall density of ratings. This metric is computed as the average percent of the items that are rated per user. As much as 56 percent of the items are on average rated by the users of Jester, which can be explained by the small number of items, and that smaller amount of time and resources are needed to read jokes compared to the items rated in the other datasets. MovieLens and Million Song also have a high density in the ratings, while

Book-Crossing and especially Amazon have a very low density in the ratings. This is natural because it takes significantly longer time to read a book than to watch a movie or listen to a song, and a user cannot be expected to buy even a small part of Amazon’s huge item catalogue.

2.6 Summary

This chapter has given a general description of recommendation systems and the two main problems concerned with such systems: the rating prediction problem and the top-*n* recommendation problem. There has been a presentation and comparison of the most commonly used recommendation system approaches, namely collaborative filtering, content-based, demographic-based, knowledge-based, community-based and hybrid approaches. All of these approaches have different strengths and weaknesses, and they use different data sources for making the recommendations. Thus, the best recommendation approach in a particular situation depends on the needs and goals of the system and the available data in the system. Hybrid approaches are often used to minimize the disadvantages of two or more approaches while at the same time exploiting the advantages of each approach. This was observable when we looked at the recommendation systems used in practice by Amazon, Netflix, Facebook and YouTube.

Recommendation systems can be evaluated in three different experimental settings: offline experiments, user studies and online evaluation. Offline experiments use pre-collected datasets and are typically used for testing the accuracy of the recommendations. User studies and online evaluation, on the other hand, are conducted by interacting with real users, either in a lab or in a real setting, respectively. These two settings can answer a wider set of questions than offline experiments, but not without a cost; user studies are expensive to conduct and online evaluation can result in dissatisfied users if they are exposed for an unwanted or unsuccessful change in the system.

If the recommendation system aims to solve the rating prediction problem, RMSE or MAE can be used to predict the accuracy of the rating predictions, by comparing the predictions to real ratings. Recommendation systems that is concerned with the top-*n* recommendation problem on the other hand, can use precision, recall, HR, ARHR and MAP for measuring the accuracy, as is often the case when the system bases the recommendations on implicit data.

When evaluating the accuracy in an offline setting, a dataset with item and user data is needed. This can be collected from the application the recommendation system is made for. In other situations, where this is not possible because of small amounts of data or when the system is not yet released, online existing datasets from other application or synthesized datasets can be used. We presented five datasets that contain rating information for movies, e-commerce products, books, jokes and songs. These did not differ only in domain features, but also in inherent and sample features.

Now that we have gotten a general understanding of how recommendation systems work and are evaluated, we can start to look at the case of the sports video application Forzify to find out how recommendation systems can be utilized in this context. This will be the topic of the next chapter.

3 Case: Forzify

In this chapter, we will present the context of the sports video application Forzify, look at recommendations in this context and present the data sources available in Forzify that could be used for making recommendations. Further, there will be a description of wanted features in an improved recommendation system for Forzify and there will be a subsequent discussion of the suitability of different recommendation approaches in terms of the wanted features and available data. This discussion will be done in light of the comparison in Section 2.4, and makes basis for research question Q1, which was specified in Section 1.2.

3.1 Context

Forzify is a system for football events, which aims to give the users an interactive and social experience (ForzaSys 2016). Forzify builds on the same ideas as DAVVI (Johansen et al. 2009, Johansen et al. 2010, Johansen et al. 2012), which is a prototype of the next generation multimedia entertainment platform. The new generation of football supporters are not just watching the games at home or on the stadium. They interact with friends and fellow supporters on social media, sharing experiences, getting updates on the latest scores and discussing the newest actions. These new interaction patterns have been taken into account when making Forzify. The idea is to boost supporter activity on the match day, but also on the other days of the week.

The system is like a sport version of Spotify, where the users can watch video clips of games, make video playlists, share and discuss sport events, create their own events, get recommendations by friends and collect and redistribute their favourite video clips. The system is today in use by Tromsø IL, Viking FK and Vålerenga IF, three football teams from Eliteserien, which is the premier division in Norway. Forzify is made both as a website and as an app for iOS and Android. The version of Forzify used by these three clubs, only include videos of the given club, but in 2017, one Forzify-version will be released for Eliteserien and one for Allsvenskan (the top division in Sweden), where videos for all of the teams will be published, and games will be sent live.

Figure 8 shows a screenshot of the home page of the Forzify-version made for Tromsø IL. Here, the user is presented to three sets of videos: one for the last game, one for trending videos and one for videos recommended to the user. The user can also browse videos by other means. There is a search bar where the user can do text searches, with the possibility of adding tags to the search. The user can choose different categories of videos from the "videos"-tab, e.g., "most popular videos", "newest videos" or "matches", where the user can choose videos from a particular match.

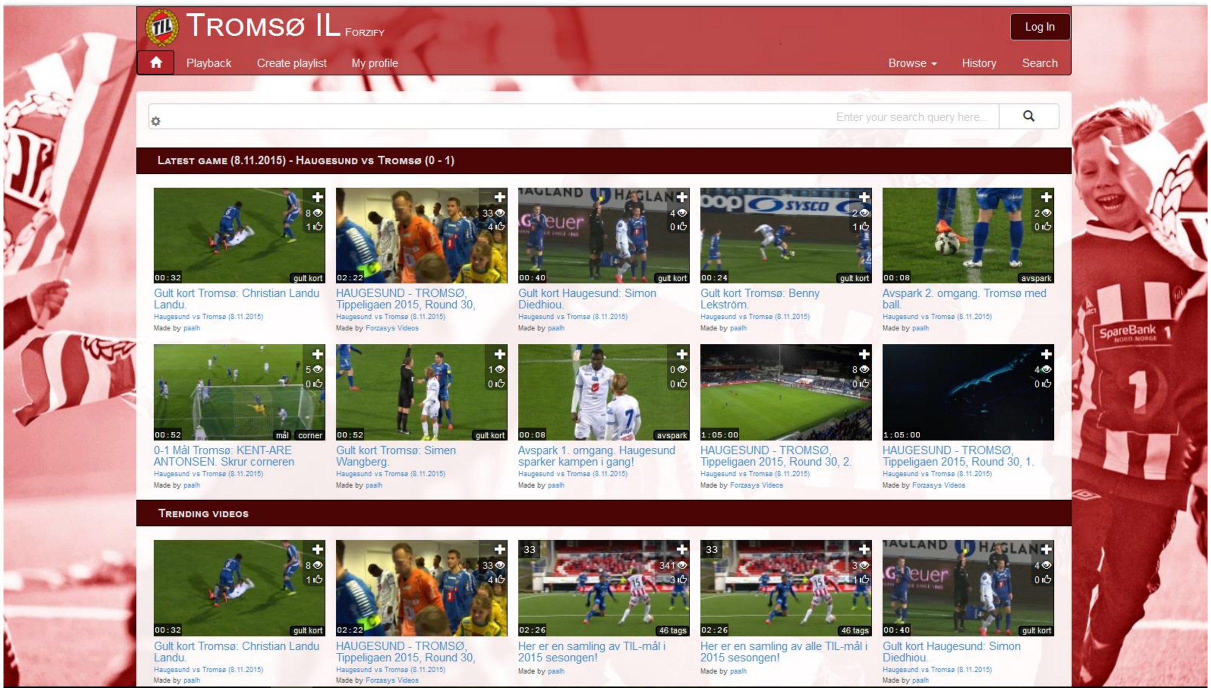

TROMSØ IL FORZIFY
Log In
Playback
Create playlist
My profile
Browse
History
Search
Enter your search query here...
LATEST GAME (8.11.2015) - HAUGESUND VS TROMSØ (0 - 1)
Gult kort Tromsø: Christian Landu Landu.
HAUGESUND - TROMSØ, Tippeligaen 2015, Round 30,
Gult kort Haugesund: Simon Diedhiou.
Gult kort Tromsø: Benny Lekström.
Avspark 2. omgang. Tromsø med ball.
0-1 Mål Tromsø: KENT-ARE ANTONSEN. Skrur corneren
Gult kort Tromsø: Simen Wangberg.
Avspark 1. omgang. Haugesund sparker kampen i gang!
HAUGESUND - TROMSØ, Tippeligaen 2015, Round 30, 2.
HAUGESUND - TROMSØ, Tippeligaen 2015, Round 30, 1.
TRENDING VIDEOS
Gult kort Tromsø: Christian Landu Landu.
HAUGESUND - TROMSØ, Tippeligaen 2015, Round 30,
Her er en samling av TIL-mål i 2015 sesongen!
Her er en samling av alle TIL-mål i 2015 sesongen!
Gult kort Haugesund: Simon Diedhiou.
Haugesund vs Tromsø (8.11.2015)
Made by paalh
Made by Forzasys Videos

Figure 8: Screenshot of the home page of Forzify

3.2 Recommendations in Forzify

To give the users of Forzify a good user experience, it is crucial with recommendations of content that are relevant for the users and which support exploring. This will especially be important when Forzify is released for Eliteserien and Allsvenskan, where several videos will be added for the 16 teams each football round. The majority of the users do not have time or desire to browse through all videos to find new and exciting material. By giving suggestions of interesting videos, the users can use less time searching, and if the suggestions are successful, the user satisfaction will increase, which again can result in loyal users and a higher number of visitors.

Forzify does today present recommendations to its users in two cases. The first is when a user is on the main page, where a set of videos are recommended based on the user's history. These videos can also be watched by clicking on the "Recommended"-tab at the top right corner, as seen in Figure 9. The second case is when a user watches a video, related videos are presented to the right of the video being played, as seen in Figure 10. For the first case, the user must be logged in to get recommendations, while in the second case, the user can be anonymous and still get recommendations, as the related videos are not based on the user's preferences. In both cases, 10 recommendations are shown, but the user can choose to watch the next 10 recommendations by clicking on the next page button. We will in this thesis focus on the personalized recommendations that are presented in the main page, and we will focus on the new version of Forzify where videos are available for all teams in a division. The choice to concentrate on the new Forzify-version and not the club versions, is done because the new version will include many more videos and consequently it will get huger benefits from the recommendations.

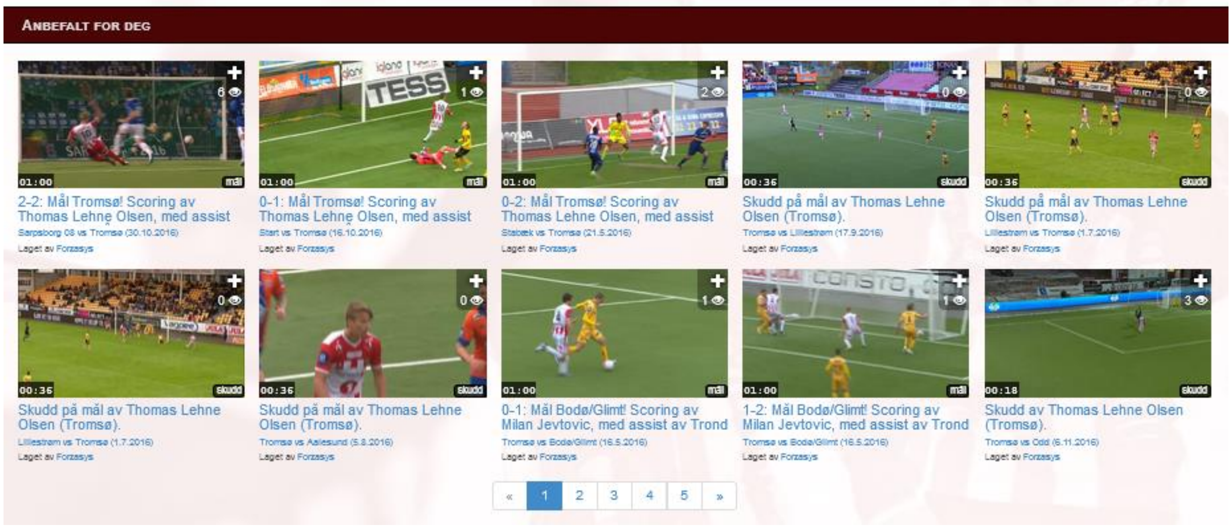
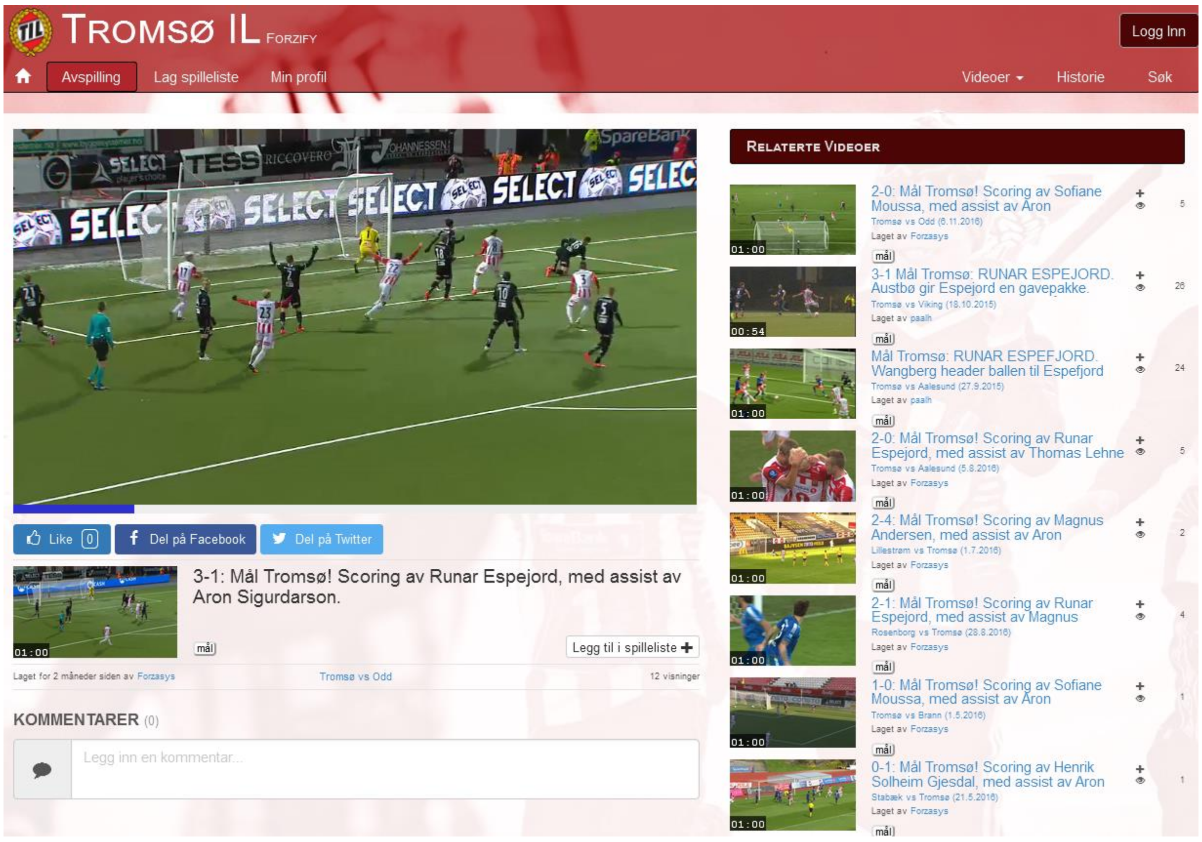

Anbefalt for deg
2-2: Mål Tromsø! Scoring av Thomas Lehne Olsen, med assist
Sarpsborg 08 vs Tromsø (30.10.2016)
Laget av Forzasys
0-1: Mål Tromsø! Scoring av Thomas Lehne Olsen, med assist
Start vs Tromsø (16.10.2016)
Laget av Forzasys
0-2: Mål Tromsø! Scoring av Thomas Lehne Olsen, med assist
Stabæk vs Tromsø (21.5.2016)
Laget av Forzasys
Skudd på mål av Thomas Lehne Olsen (Tromsø).
Tromsø vs Lillestrøm (17.9.2016)
Laget av Forzasys
Skudd på mål av Thomas Lehne Olsen (Tromsø).
Lillestrøm vs Tromsø (1.7.2016)
Laget av Forzasys
Skudd på mål av Thomas Lehne Olsen (Tromsø).
Lillestrøm vs Tromsø (1.7.2016)
Laget av Forzasys
Skudd på mål av Thomas Lehne Olsen (Tromsø).
Tromsø vs Aalesund (5.8.2016)
Laget av Forzasys
0-1: Mål Bodø/Glimt! Scoring av Milan Jevtovic, med assist av Trond
Tromsø vs Bodø/Glimt (16.5.2016)
Laget av Forzasys
1-2: Mål Bodø/Glimt! Scoring av Milan Jevtovic, med assist av Trond
Tromsø vs Bodø/Glimt (16.5.2016)
Laget av Forzasys
Skudd av Thomas Lehne Olsen (Tromsø).
Tromsø vs Odd (6.11.2016)
Laget av Forzasys
« 1 2 3 4 5 »

Figure 9: Recommended videos for a user in Forzify

The existing system uses the open source distributed search engine Elasticsearch (Elastic 2016) both for search and to generate recommendations. The recommendation system uses a content-based approach as the recommendations are produced on basis of the content of the items. Recommendations for a user are made by doing a search in Elasticsearch for the text fields associated with the videos the user has watched, liked or added to playlists, and the previous searches. Related videos are found by using the text fields stored about a video to search for videos with similar content. Newer videos are given a higher weight and are thus more likely to be recommended, while the 20 videos last watched by the user are removed from the recommendation set.



3-1: Mål Tromsø! Scoring av Runar Espejord, med assist av Aron Sigurdarson.

mål

Laget for 2 måneder siden av Forzasys | Tromsø vs Odd | 12 visninger

KOMMENTARER (0)

2-0: Mål Tromsø! Scoring av Sofiane Moussa, med assist av Aron
Tromsø vs Odd (6.11.2016)
Laget av Forzasys
mål
5

3-1 Mål Tromsø: RUNAR ESPEJORD. Austbø gir Espejord en gavepakke.
Tromsø vs Viking (18.10.2015)
Laget av paalh
mål
26

Mål Tromsø: RUNAR ESPEFJORD. Wangberg header ballen til Espefjord
Tromsø vs Aalesund (27.9.2015)
Laget av paalh
mål
24

2-0: Mål Tromsø! Scoring av Runar Espejord, med assist av Thomas Lehne
Tromsø vs Aalesund (5.8.2016)
Laget av Forzasys
mål
5

2-4: Mål Tromsø! Scoring av Magnus Andersen, med assist av Aron
Lillestrøm vs Tromsø (1.7.2016)
Laget av Forzasys
mål
2

2-1: Mål Tromsø! Scoring av Runar Espejord, med assist av Magnus
Rosenborg vs Tromsø (28.8.2016)
Laget av Forzasys
mål
4

1-0: Mål Tromsø! Scoring av Sofiane Moussa, med assist av Aron
Tromsø vs Brann (1.5.2016)
Laget av Forzasys
mål
1

0-1: Mål Tromsø! Scoring av Henrik Solheim Gjesdal, med assist av Aron
Stabæk vs Tromsø (21.5.2016)
Laget av Forzasys
mål
1

Figure 10: Recommendation of related videos in Forzify

The content-based approach used by Forzify has both advantages and disadvantages, as presented in table Table 1. The strength is primarily that the system can learn about the users' preferences and thereby give better recommendations as the users interact with the system. There are also less cold start problems compared to collaborative filtering. In addition, using a distributed search engine, like Elasticsearch, gives time-efficient recommendations. On the other hand, Forzify's recommendations will be restricted to only recommend the same type of content as the user has looked at before. This will not provide serendipitous recommendations that let users explore new types of content. For example, a user who only has watched free kicks of one team, will only get recommendations of free kicks and videos from that team, even though she also might be interested in watching other content, as beautiful goals from other teams. In Figure 9, we can see an illustration of this. The user has watched a few videos of shots and goals by the player Thomas Lehne Olsen, and are then recommended videos of this player in eight out of ten recommendations. Content-based filtering does also tend to give lower accuracy than collaborative filtering. In addition, recommendation systems do generally benefit from using more than one data source, but in Forzify's case, only content information is used for generating the recommendations.

3.3 Data in Forzify

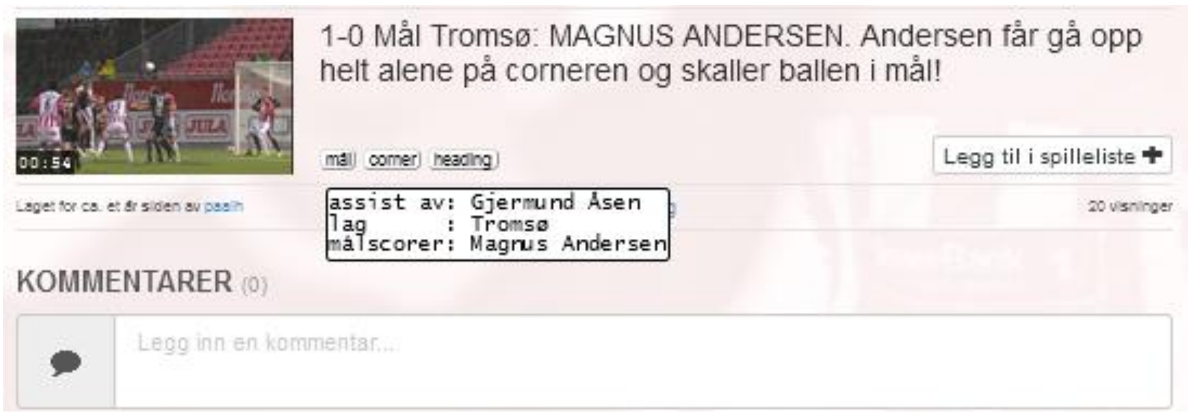
There are several data sources in Forzify that can be used for making recommendations. We will here present these data sources, look at which recommendation approaches that can be used with this data and review what data that are needed to use the other approaches.

In Forzify, data about users' item interaction history are recorded, which includes mostly implicit data, like the videos watched by a user, the number of times each video is watched by a user, which videos that are added to playlists by a user and the searches performed by a user. It also includes explicit rating data about which videos a user has liked. This information can be used to infer the preferences of the user. However, there are no dislike-buttons or scale ratings, i.e., there are only unary ratings, which means it is not possible to know from the ratings if a user dislikes any items, as described in Section 2.1. We can then only know if a user has liked or added a video to a playlist, which indicates a strong preference, or if a user has interacted with an item, which gives a weaker indication of preference. For example, a user can watch a video and not enjoy it, but it is not possible to know this negative preference.

This absence of negative preference data, gives certain implications for the design of the recommendation system. We cannot predict ratings when we have no explicit ratings on a scale from negative to positive. Instead, we can handle the recommendations as a top-*n* recommendation problem, as described in Section 2.1, treating all user-item data as positive indications for preference and then make recommendations for the items most probably preferred by the user. Top-*n* recommendation measures can then be used, as precision, recall, HR, ARHR and MAP, to evaluate the successfulness of the recommender. Items can be considered relevant for a user if there exist any preference data for that user-item pair, or otherwise be treated as non-relevant.

Forzify also has item data. Each video has a title, which tells us about its content, and there is content data, which tells us about the features of the video. The content data is a set of tags that can be added to the videos. For example, one video of a football goal can be tagged with "Goal", the club name, the name of the goal scorer and the name of the player who had the assist. This information gives a valuable description of the items, as the items themselves do not contain any textual content, like in for example a text document. If the content data are combined with users' item history, it can be used to infer the users' preferences in content.

Figure 11 shows an example of the content information for a video in Forzify, which are found under the video. On the top of the figure is the title of the video, which describes the item. Under the title are three tags: “goal”, “corner” and “heading”. All of these tags contain additional information that are shown when the user places the mouse over the tag. In the figure, the mouse is held over “goal”, and metadata for the goal are shown.


1-0 Mål Tromsø: MAGNUS ANDERSEN. Andersen får gå opp helt alene på corneren og skaller ballen i mål!

```
assist av: Gjermund Åsen
lag      : Tromsø
målscorer: Magnus Andersen
```

Figure 11: Example of tags for a video in Forzify

To make an improved recommendation system for Forzify, it is important to look at which approaches that can be implemented with the existing data sources, and which data sources that are needed in order to use the other approaches. If we take a look at Figure 7 again, Forzify has three of the types of background data that are included in the figure; it has a user rating database, an item database and meta data about content features of the items. However, there are no user demographic database or knowledge base. This means that Forzify has not the existing background data needed for the demographic-based and knowledge-based approach.

To use the demographic-based approach, user data and demographic data about the users are needed. While user data are available in Forzify, no demographic information is today gathered about the users. To get this, the system must explicitly ask the users for this information when they register as a new user. This can be considered troublesome by the users, as they do not want to share all information or use time on this, which can lead the user not to enter all the data or not even register at all.

Forzify has the metadata needed for the knowledge-based approach, but lacks both functional knowledge about how the items satisfy user needs, and user knowledge about the user and her need. To get functional knowledge, domain knowledge and time are needed to make a knowledge base, and to gather user needs, information must be gathered from the user. This can be both time-consuming and expensive.

Figure 7 also shows which data inputs that are needed for each approach. Only user ratings are collected of these data types in Forzify today, which means the community-based approach neither is possible to use with existing data sources. This approach needs, in addition to usage data, data from social relations of the users which must be fetched from a social network.

Then, we are only left with two approaches if we are going to base the recommendations on existing data sources. These are collaborative filtering and content-based filtering, which both utilize user ratings to learn about the preferences of the user. After the system has inferred the user's preferences, the collaborative filtering uses the user rating database as background data to find similarities in usage patterns, while the content-based filtering, on the other hand, uses the meta data and item database to find content similar to the preferences of the user.

3.4 Features wanted in the recommendation system

Before we can decide which recommendation system approach that suits the needs of Forzify, we must specify which features that are wanted in the recommendation system. First of all, it is important that the recommendations have as good quality as possible. In a system like Forzify, new content will be uploaded continuously, so it is expected that many users will visit the system repeatedly. Thus, it is beneficial with an approach that uses some kind of *learning* of the users' preferences. In the long run, this will give the best recommendations for the user. The system can then learn, either through content information or associations in user data, about which teams and players the user likes and if she likes any special events, like goals, free kicks or saves.

One important feature of recommendation systems is to help users discover new material. It is desirable that Forzify's recommendation system can make recommendations that are serendipitous. Another important feature, is that the system can recommend as many items as possible to as many users as possible. Then, it is important to *reduce the cold start problem* both for new users and for new items.

Another feature wanted in the system is *scalability*. If the recommendation system uses long time to generate the recommendations, it makes small differences whether the recommendations are good or bad, because the users are not interested in waiting for the content. Therefore, it is important that the system can scale well with large amounts of items and users, to give time-efficient recommendations.

3.5 Discussion of suitable approaches

In the last section, the features wanted in the new recommendation system were presented. Now, we will discuss which approaches that best suit these needs and the data sources of Forzify. Summarized, we want the recommendation system to use some kind of learning, produce serendipitous recommendations, handle cold start situations and scale well for a large set of users and items. As Table 1 showed, no approach is perfect and suits all these needs. Therefore, it is smart to use a combination of approaches in a hybrid solution, which makes it possible to exploit the advantages and at the same time reduce the disadvantages of each approach.

All of the presented approaches, except for the knowledge-based, learn about the users as they interact with the system, and can thereby give improved recommendations over time. Even though the knowledge-based approach cannot make as good recommendations as the others in the long run, it has no problem with making recommendations for new users or items. This lack of cold start problem, makes it an ideal candidate to use together in a hybrid approach with one of the approaches that use learning. Then, it will be possible to give good recommendations from the first second the user visits the site and after some time, even better recommendations since more user data are logged.

Content-based filtering also has less cold start problems than the other approaches. This approach can make recommendations as soon as a user has visited an item or made a user profile. It can then find videos similar in content to that video or to the interests expressed in the user profile. However, it will take some time before the system learns enough about the user’s preferences for content, to make good recommendations.

Collaborative filtering, demographic-based filtering and community-based filtering can all make serendipitous recommendations. Content-based filtering is unable to make these kind of recommendations, while the knowledge-based approaches can do this if a knowledge base is made with rules describing how it should be done. This is the challenge with knowledge-based recommenders. Domain knowledge is needed to make good recommendations, and a certain amount of time must be used to manually make rules based on this knowledge. In cases where little user history is expected, like in a website for selling of cars or apartments, this can be a suitable approach, because good recommendations can be difficult to make otherwise. In the case of Forzify, on the other hand, where the users are expected to interact with several items, it will be better to use other approaches that do not need manual work.

One possible option then, is to use content-based filtering together with collaborative filtering, demographic-based filtering or community-based filtering. This will handle cold start situations well because of the content-based approach, and give serendipitous recommendations that are improved as the user interacts with the system because of the other approach. Since no demographic and social data now are collected in Forzify, while the system collects several data about item interaction, it will be best to use collaborative filtering as the second approach.

Using content-based filtering together with collaborative filtering in a hybrid approach is a common combination because they complement each other well and they only need easy accessible data sources. This will be similar to the way Netflix make recommendations, as described in Section 2.3.2. To ensure that the system scales well, it will be best to use a model-based or item-based collaborative filtering approach, as the user-based approach does not scale good for large datasets. Therefore, the best choice for approaches for the data gathered in Forzify and the features wanted in the system, is the combination of the content-based approach and either item-based or model-based collaborative filtering.

3.6 Summary

In this chapter, we have presented the sports video app Forzify. Forzify lets users watch football videos, make playlists and share experiences with fellow supporters and friends. In such an app, a recommendation system is important for letting users easy find content that are interesting for them. To find which recommendation approaches that could best suit this context, we looked at which data sources that could be possible to get from the existing system, and which characteristics that would be desirable for a recommendation system in this setting. Today, it is collected both explicit data, in form of likes, and implicit data, such as which videos that are watched or added to playlists by a user. In addition, the system contains textual content information about videos. As Forzify only contain unary ratings and mostly implicit data, the recommendation problem must be treated as a top-*n* recommendation problem, not a rating-prediction problem. The features wanted in the new recommendation system are primarily use of learning, serendipitous recommendations, good handling of cold start situations and good scalability.

Further, we discussed how the different recommendation approaches are suited for the data and wanted features in Forzify. We found item-based collaborative filtering, model-based collaborative filtering and content-based filtering as the approaches best suited for Forzify's recommendation system. The next step in the process now, is to look at how these approaches can be implemented, which will be the focus of the next chapter.

4 Implementation of a recommendation system

To answer research question Q2 and Q3, stated in Section 1.2, we will implement a set of algorithms from different approaches that can be evaluated, both in terms of accuracy and scalability. In this chapter, we will therefore look at the implementation of a set of candidate algorithms that will be chosen based on the discussion in Section 3.5, about which approaches that are suitable for Forzify according to the literature. First, we will describe and compare a set of recommendation frameworks that are commonly used for implementation of recommendation systems. Next, we will present the algorithms that we will implement. These algorithms are presented in detail, both in terms of implementation details and underlying calculations needed to make the recommendations.

4.1 Recommendation frameworks and libraries

An important decision when making a recommendation system is if the system should be implemented completely from scratch or if some existing frameworks, libraries or packages should be used. There exist several open source recommendation frameworks. Some commonly used are *Apache Mahout*, *LensKit* and *MyMediaLite* (Said and Bellogín 2014). Another popular framework is the *Apache Spark's* machine learning library *MLlib*, which has shown to be highly efficient for producing recommendations on large datasets (Meng et al. 2016). In this section, there will be a presentation and comparison of these frameworks.

Using existing frameworks and libraries can give multiple benefits. Instead of reinventing the wheel, time can be saved by reusing software libraries and frameworks. Such software is also generally tested thoroughly, reducing the risk for errors in the program. In the case of recommendation systems research, frameworks and libraries can make it easier to compare different algorithm implementations and results. On the other hand, reuse of software can give constraints in technologies, algorithms and data structures.

4.1.1 Mahout

Apache Mahout is a project that provides Java-based machine learning frameworks and libraries for making scalable recommendation systems (Apache Mahout 2016). It offers a set of collaborative filtering techniques, including neighbourhood-based approaches, like user-based and item-based collaborative filtering, and model-based approaches, like SVD++ and alternating least squares (ALS). The framework can be used to run on a single computer or on a cluster with the distributed framework Apache Hadoop using the MapReduce paradigm.

Central parts of Mahout are the Java interfaces *DataModel*, *UserSimilarity*, *ItemSimilarity*, *UserNeighborhood* and *Recommender*. The *DataModel* is used to store information about user preferences, which can be fetched from a database or another source. *UserSimilarity* and *ItemSimilarity* are used to find similarities between users or items, and *UserNeighborhood* defines a mean for determining a neighbourhood of similar users for a user. At the core of the framework, is the *Recommender*, which can recommend items for a user or predict a user's preference for an item (Schelter and Owen 2012). The interfaces can be used to implement new algorithms, or they can be used to implement the algorithms contained in the Mahout library.

4.1.2 LensKit

LensKit is an open source Java-based recommender toolkit (Ekstrand et al. 2011). Its goal is to give an extensible and robust basis for research in recommendation systems, but the framework is also usable in real-world situations, primarily for web-applications. LensKit has implementations of three collaborative filtering approaches: the model-based approach SVD and the two neighbourhood-based approaches user-based and item-based collaborative filtering. It provides the interfaces *ItemScorer* and *ItemRecommender*, which respectively are used to predict ratings for a user for an item and to recommend items for a user. Two of the advantages of LensKit are that different variations of algorithms easily can be configured and that it offers possibilities for easy implementation of new parts to existing algorithms.

4.1.3 MyMediaLite

MyMediaLite is a recommendation system library written in C# (Gantner et al. 2011). It offers libraries containing existing algorithms, and a framework for implementing and evaluating new ones. MyMediaLite is made to be a fast and scalable library for collaborative filtering and is aimed at both academic and industrial purposes. The tasks of predicting ratings and predicting interesting items are supported, both with various neighbourhood- and model-based algorithms.

4.1.4 Spark MLlib

Apache Spark is an open source cluster computing framework for large-scale data processing (Shanahan and Dai 2015). It is well-suited for machine-learning tasks and offers the machine learning library MLlib, which contains a set of fast and scalable implementations of machine learning algorithms (Meng et al. 2016). Spark can either be run distributed in a cluster or on a single machine. MLlib supports two variants of alternating least squares, which is a model-based collaborative filtering algorithm. The first variant is for explicit data and the other is adapted for implicit data.

Spark has APIs in Java, Scala and Python. The advantage of Spark is its ability to scale well for large datasets. Spark has similarities to the MapReduce paradigm, but performs significantly better on iterative jobs (Zaharia et al. 2010). Therefore, its alternating least squares algorithm is very efficient on large datasets compared to the one provided by Mahout, which is based on MapReduce (Meng et al. 2016).

4.1.5 Comparison of frameworks

In this section, there will be a comparison of the four recommendation frameworks presented above. The differences are summarized in Table 6. The frameworks have several properties in common, but there also exist some differences between them. While Spark's MLlib and Mahout are machine learning frameworks with support for recommendation system algorithms, LensKit and MyMediaLite are made to support recommendation algorithms only. All of the frameworks are open source software and are also platform-independent. Except for MyMediaLite, which only supports C#, all of them have Java APIs. Spark has in addition Scala and Python APIs.

The only algorithms supported in these frameworks are collaborative filtering algorithms. This means there is no algorithms for content-based, knowledge-based, demographic-based or community based recommendations, even though there is support for making new recommendation algorithms in Mahout, LensKit and MyMediaLite. In Spark's MLlib, new algorithms must be made from scratch with Spark's data structures, as the API does not support implementation of new recommendation algorithms. Mahout, LensKit and MyMediaLite have both neighbourhood-based and model-based collaborative filtering algorithms, while Spark only have model-based ones. All of them have support for evaluation of the recommendation algorithms, but they differ in how this is done. Spark and Mahout have evaluation classes that makes it possible to evaluate the recommendations inside the Java program, while LensKit and MyMediaLite have evaluation scripts that can be run from terminal. When it comes to scalability, Mahout and Spark has an advantage as they can be distributed over several nodes in a cluster, making it possible to handle large amounts of data. However, Spark outperforms Mahout on computation time for recommendations on large datasets, and is therefore a better option in such cases.

Framework / Property	Mahout	LensKit	MyMediaLite	Spark's MLlib
Machine learning framework	X			X
Dedicated recommendation framework		X	X	
Platform-independent	X	X	X	X
Provides neighbourhood-based collaborative filtering	X	X	X	
Provides model-based collaborative filtering	X	X	X	X
Support for implementing other recommendation algorithms	X	X	X	
Support for evaluation	X	X	X	X
Supports distribution in cluster	X			X

Table 6: Comparison of properties of the recommendation frameworks

This comparison has given an overview over the recommendation frameworks and their properties. We will use this as a basis for choosing one or more frameworks to be used for implementing our recommendation algorithms.

4.2 Algorithms

We will here introduce four candidate algorithms for Forzify's recommendation system, and present their implementations. The first three, item-based collaborative filtering, model-based collaborative filtering and content-based filtering, are chosen based on the conclusion that they were the best choices for Forzify, which we made in Section 3.5. In addition, we will implement a non-personalized algorithm that recommends items based on items' overall popularity. Such a popularity algorithm is good as a baseline to compare the personalized algorithms against, but can also be used successfully for recommending items in cold start situations (Ekstrand, Riedl, and Konstan 2011). Therefore, we have two algorithms that, according to the literature, should give high accuracy for new users and two algorithms that should give high accuracy for old users.

As described in Section 3.3, Forzify has only unary data which are mostly implicitly gathered. Therefore, the algorithms we choose must support unary and implicit data, either given as binary values or arbitrary positive values. This means that rating prediction algorithms, based on negative and positive ratings, cannot be used. Instead we must use a top-*n* approach to the recommendation problem, as described in Section 2.1, where we want to recommend the *n* best items for a user.

As none of the frameworks contain all of these algorithms with support for unary and implicit data, we choose not to stick to one single framework. For the item-based algorithm we choose to use LensKit for our implementation, which offer an item-based *k*-nearest neighbour variant effective in implicit feedback situations. For the model-based algorithm, we choose Spark's alternating least square variant for implicit feedback. This algorithm handles the data type in Forzify well and because of Spark's possibility for distribution, it also scales well.

For the content-based algorithm, we choose to use a content-based implementation built in LensKit (Lin 2013). LensKit has no built-in content-based algorithm, but this content-based implementation uses LensKit's data structures and classes, and is publicly available at GitHub. This implementation is originally made for explicit feedback, but we will adjust it to better handle implicit feedback. Our baseline algorithm will not be implemented in any framework. It is a very simple algorithm, only using the popularity of the items, so we find it more convenient to make it from scratch. All of the code in our implementations will be written in Java, and are available on GitHub from the link provided in Appendix A.

Figure 12 shows the hierarchy of our implemented recommendation algorithms. We have made one interface *Recommender*, and one class for each of the algorithms, which all implement the *Recommender*-interface. *Recommender* has four methods: *initialize()*, *update()*, *recommend()* and *close()*. They are used to initialize the recommender, train the recommender based on a rating file, recommend an array of item-ids for one user, and to shut down the recommender, respectively. By using a single interface, we ensure that all of the recommendation algorithms have the same functionality, which becomes convenient when we are going to evaluate the different recommendation algorithms.

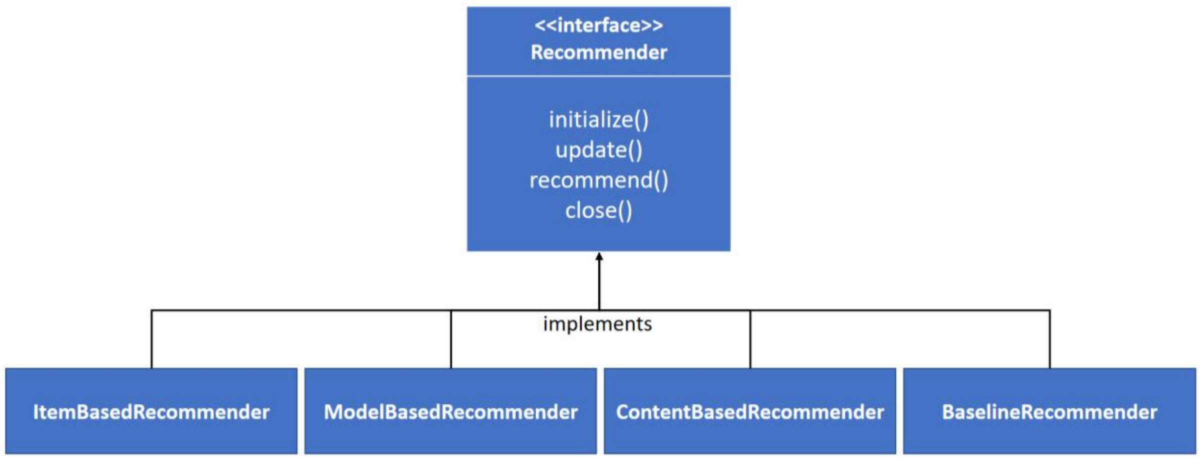


Figure 12: Design of the implementation of our recommendation algortihms

We have decided not to recommend items already rated, to avoid that users get recommended items they already have interacted with. This is the default in LensKit, but in the other two algorithms we must exclude the items already rated by the users. We do this by storing each user's rated items in a hash-map and then removing the recommendations of items that are contained in the user's hash-map. The reason for using hash-maps is to ensure that the check whether items already are rated can be done in constant time.

4.2.1 Item-based collaborative filtering

As explained in Section 2.2.1 the goal for item-based collaborative filtering is to recommend similar items to the ones the user has interacted with in the past. We will here use an *k*-nearest neighbour approach for this, which is the standard method for item-based collaborative filtering (Aggarwal 2016, 40). In short, a *k*-nearest neighbours algorithm for item-based collaborative filtering involves finding the most similar items, also called neighbours, for each item, and then predict each item’s relevance for a user by looking at this item’s *k* most similar items that the user also has interacted with. The predicted score for this item is then based on the user’s rating on these *k* items and the similarities of these to the given item.

We will implement this approach using the framework Lenskit (version 2.1.1), which is built as a generic recommender system. The parts of the recommender can easily be specified to get the recommender approach of choice with the implementation details as needed. The *LenskitConfiguration* class is used to configure the recommendation system by binding together different classes, e.g., binding the *ItemScorer* to *UserUserItemScorer* if one plans to make a user-based recommender, and setting values for different classes, e.g., setting the *NeighborhoodSize* to a certain value. Because we are making an item-based algorithm, we set the ItemScorer to *ItemItemScorer* to specify that we want to score items using an item-based collaborative filtering approach, i.e. using similarities between items and not users. In addition, the input file, which contains the user data, must be bound to the *EventDAO* class, so that data can be added to the model.

Item-based filtering consists of two key steps: (1) Computation of similarities between each item pair and (2) the computation of a prediction score for each item based on the users’ history and the similarities between items (Deshpande and Karypis 2004). The first step then, which is the training phase of this algorithm, is to compute the item-similarities. Several similarity functions can be used for this, but the most commonly used are Pearson correlation coefficient, cosine and adjusted cosine (Sarwar et al. 2001). The two cosine measures are the most used, as they produce the most accurate results (Jannach et al. 2010, 19). Therefore, we decide to use one of those.

To compute the similarities between two items, we must look at the ratings for the two items. Recall the rating matrix presented in Section 2.1, where each column represents an item and each row represents a user. The similarity between two items are computed based on the similarities in the ratings in the two corresponding columns. Only ratings from users who have rated both items are taken into account. Figure 13 illustrates item-similarity computation for two items i and j. The column representing an item is called the rating vector of that item. We thereby use a vector space model to find similar items, where each item is represented by its rating vector in an *n*-dimensional space. Each dimension in the space is corresponding to the rating of a user.

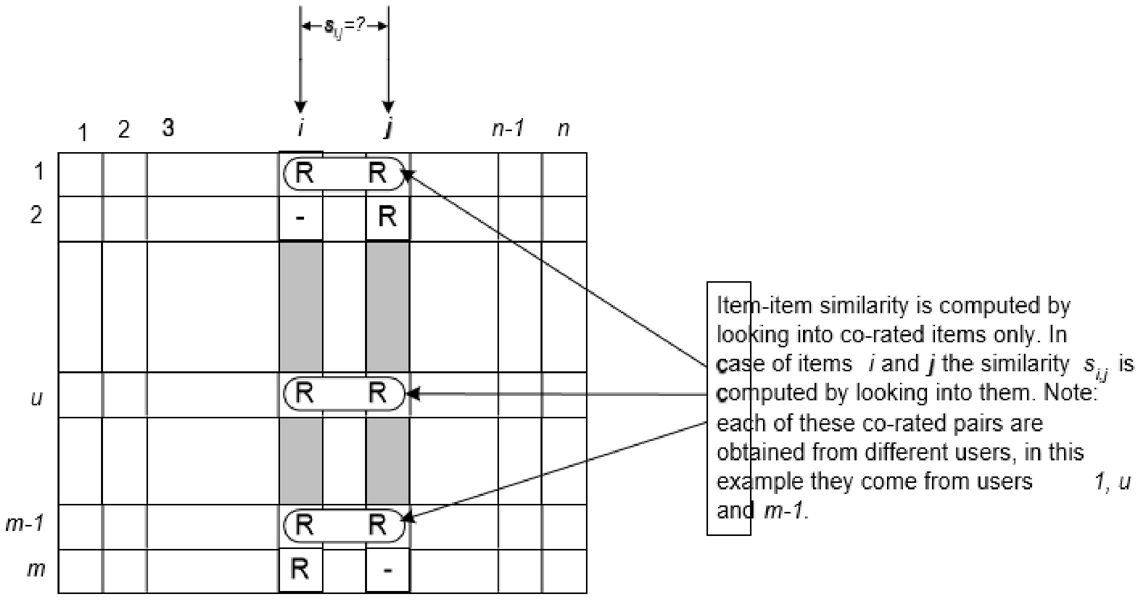

$s_{i,j}$=?
1
2
3
i
j
n-1
n
1
2
u
m-1
m
R
-
Item-item similarity is computed by looking into co-rated items only. In case of items i and j the similarity $s_{i,j}$ is computed by looking into them. Note: each of these co-rated pairs are obtained from different users, in this example they come from users 1, u and m-1.

Figure 13: Similarity computation between items in a rating matrix (Sarwar et al. 2001, 289)

The cosine similarity between two items a and b with rating vectors $\vec{a}$ and $\vec{b}$ are defined as follows:

$$\operatorname{sim}(a,b) = cos(\vec{a},\vec{b}) = \frac{\vec{a}\ \cdot \vec{b}}{|\vec{a}\,| * |\vec{b}|} \tag{8}$$

The symbol · means the dot-product of the two vectors, while $|\vec{a}\,|$ means the Euclidean length of a vector, which is defined as the square root of the sum of the squared values of the vector. The reason for dividing by the Euclidean lengths is to normalize the vectors, to avoid that more rated items get higher similarity scores. One drawback with this measure, is that the rating behaviours of different users are not taken into account in the computation (Sarwar et al. 2001). For example, one user can rate the majority of items with five out of five stars, while another user only rate 10 percent of her rated items with 5 stars, which gives a bias to the similarities. The same can be the case for view counts: some users watch in average more items than others. To avoid this bias, the adjusted cosine can be used, where the user's average rating is subtracted from each corresponding user rating:

$$\operatorname{sim}(a,b) = \frac{\sum_{u \in U}(r_{u,a} - \bar{r_u})(r_{u,b} - \bar{r_u})}{\sqrt{\sum_{u \in U}(r_{u,a} - \bar{r_u})^2}\sqrt{\sum_{u \in U}(r_{u,b} - \bar{r_u})^2}} \tag{9}$$

Here, *U* is the set of all users who have rated both items a and *b*, $r_{u,a}$ is the rating of user *u* for item a and $\bar{r_u}$ is the average rating of user u. This can easily be done by subtracting each rating in the rating database with the user's average rating value before calculating the similarity with a standard cosine measure. When we have explicit ratings on a numerical scale, this similarity measure is the best choice. On the other hand, when we have unary implicit feedback, where 1 indicates that the user has visited an item, the measure cannot be used. This is because the average rating for all users will be 1, and consequently all rating values will be 0 when we subtract the average rating. Cosine will therefore be used as the similarity measure in this item-based algorithm, as we want it to support unary implicit feedback. In Lenskit, this is configurated by binding *VectorSimilarity* to *CosineVectorSimilarity.*

After the similarities are computed, the next step is to predict a score for each item. When the ratings are given as numerical ratings, a prediction of user u's rating for item *a* can be calculated as a weighted average based on the user's ratings and the items' similarities, in the following way:

$$pred(u,a) = \frac{\sum_{b \in S} sim(a,b) * r_{u,b}}{\sum_{b \in S} sim(a,b)} \tag{10}$$

Here, *S* denotes the set of the *k* most similar items to the target item *a*, which also are rated by user u, and $r_{u,b}$ is the rating of user *u* for item *b*. This works well with explicit ratings on a scale, but does not work well with implicit and unary data. If the data are binary unary data where each rating $r_{u,b}$ have value 1, the equation will always be equal to 1. Also, when there are implicit ratings with arbitrary values, as play counts or number of buys, this prediction works poorly. This is because low values, as 1, will be regarded as a negative preference, while they actually indicate some preference for the item. An option then is to add 0-ratings for all the items that are not rated by a user, as the user has shown interest in the implicitly rated items, and not for the others (Aggarwal 2016, 12). However, this will give expensive computations as we for each user must add ratings for each of the items, and use all of them in the computation of similarities and prediction values. This is probably the reason why the addition of 0-ratings is not supported in the positive-only feedback versions of item-based collaborative filtering in both LensKit and MyMediaLite. In these cases, we can instead compute pseudo-predictions $\tilde{p}_{u,a}$ by summing the similarity scores of the *k* most similar items in the user's item interaction history I_u (Ekstrand, Riedl, and Konstan 2011). This can be done as follows:

$$\tilde{p}_{u,a} = \sum_{b \in I_u} sim(a, b) \tag{11}$$

For our item-based algorithm, we will use this as the prediction scorer, which we specify in LensKit by binding *NeighborhoodScorer* to *SimilaritySumNeighborhoodScorer*. Next, we must specify the number of similar items, or neighbours, to use. Normally will 20 to 30 neighbours be sufficient (Ekstrand 2014). We therefore set this value to 20, which also is the default in LensKit. This is done by binding *NeighborhoodSize* to 20.

An important decision is how to store the rating similarities. One possibility is to make an item-item similarity matrix where similarities between each item-pair is stored, but this is ineffective both in memory usage and computation time. This will require $O(n^2)$ space, and to find the most similar items to an item, it will be necessary to iterate over all n items. Instead, a better way is to store the *m* most similar items for each item together with their similarities in decreasing order of similarity. The number of similar items stored for each item, is called the *model size*, and can be specified in LensKit by binding *ModelSize* to an integer. We will set the *ModelSize* to 100 in Lenskit, to reduce problems related to scalability. The risk of setting the model size too small is that it will not be possible to find *k* rated neighbour items for some of the items, which can result in reduced accuracy. To avoid too small neighbourhoods, we set *MinNeighbours* to 2 in LensKit, so that items with less than two neighbour items rated by a given user get no prediction score for that user. The code used for configuring the item-based recommender is presented in Code snippet 1.

Now that the configuration of the recommender is finished, we have to build the recommender, as shown in Code snippet 2. Because we want top-*n* recommendation and not rating prediction, we make an *ItemRecommender*-object. This object can be used to give recommendations by calling its *recommend()*-method with parameters for number of recommendations to give and the user to produce recommendations for. This returns an ordered list of *ScoredId*-objects, one for each recommended item, with the item-id and the predicted value for the user.

```
LenskitConfiguration config;
config = new LenskitConfiguration();
config.bind(ItemScorer.class).to(ItemItemScorer.class);

config.bind(VectorSimilarity.class).
        to(CosineVectorSimilarity.class);
config.bind(NeighborhoodSize.class).to(20);
config.set(MinNeighbors.class).to(2);
config.set(ModelSize.class).to(100);
config.bind(NeighborhoodScorer.class).
        to(SimilaritySumNeighborhoodScorer.class);

String path = "training_data.csv";
String delimiter = ",";
config.bind(EventDAO.class).
        to(new SimpleFileRatingDAO(new File(path), delimiter));
```

Code snippet 1: Configuration of item-based recommender in LensKit

```
LenskitRecommender rec = LenskitRecommender.build(config);
ItemRecommender irec = rec.getItemRecommender();
List<ScoredId> recommendations = irec.recommend(id, num);
```

Code snippet 2: Creating the recommender and getting recommendations in LensKit

4.2.2 Model-based collaborative filtering

We will implement a matrix factorization algorithm as our model-based collaborative filtering algorithm because matrix factorization models are considered the state-of-the-art in recommendation systems (Aggarwal 2016, 91). To implement a matrix factorization algorithm for collaborative filtering, we will use the framework Spark MLlib (version 2.1.0). This library includes two forms of matrix factorization: one alternating least squares for explicit feedback and one for implicit feedback, based on an algorithm introduced by Hu, Koren, and Volinsky (2008). We will use the latter in our implementation because of the data sources in Forzify, which are positive-only feedback that contain no explicit scale ratings and mostly are implicitly gathered.

The idea in matrix factorization for recommendation systems is to discover a set of latent factors from the user ratings and characterize each user and item by vectors of these factors (Jannach et al. 2010, 27). While user-based collaborative filtering looks for correlations between users and item-based collaborative filtering looks for correlations between items, matrix factorization methods utilize both correlations among users and items to predict item preferences, which is one of the reasons why matrix factorization is the state-of-the-art in collaborative filtering (Aggarwal 2016, 91).

An m x n ratings matrix *R* of *m* users and *n* items, can be factorized into an $m \times k$ matrix *U* and an $n \times k$ matrix *V*, where *k* is the number of latent factors and the symbol *T* means matrix transposition, in the following way:

$$R \approx UV^T \tag{12}$$

Each row of *U* is a *user-factor* vector x_u, with *k* entries representing the preference of user *u* towards the *k* latent factors, while each row of *V* is an *item-factor* vector y_i that represents the association of item *i* to the *k* latent factors. The prediction $\hat{r}_{u,i}$ of a user's preference for an item, is the dot product of the two associated vectors, given as:

$$\hat{r}_{u,i} = x_u^T y_i \tag{13}$$

Figure 14 illustrates a simple matrix factorization of user ratings, where *R* is a rating matrix for 7 users and 6 movies, and the ratings are integers ranging from -1 to 1, where larger numbers indicate larger preferences. The first three movies are historical movies and the next three are romantic movies. We can infer from the ratings that users 1-3 like historical movies and are neutral to romantic movies, that users 5-7 like romantic movies and dislikes historic movies, while user 4 likes both genres. Matrix *R*, can then be factorized into two matrices *U* and *V* with rank 2, i.e., two latent factors. The matrix U shows the seven users' preferences for the two latent factors, while matrix V shows the six movies' associations to the two latent factors. Next, we can imagine the movie "Gladiator" being added to matrix *V*, with value 1 for "History" and 0 for "Romance", and we want to predict user 1's rating for this movie. The prediction can then be computed by taking the dot-product of the factor-vectors for the given item and user, which contain the values (1,0) and (1,0), and consequently give the prediction value 1, which means the user is predicted to like the item. In this example, we knew which genres the movies were in, but when a recommendation system uses matrix factorization, it does not know these facts. Instead, the system must find the latent factors to use from the rating patterns.

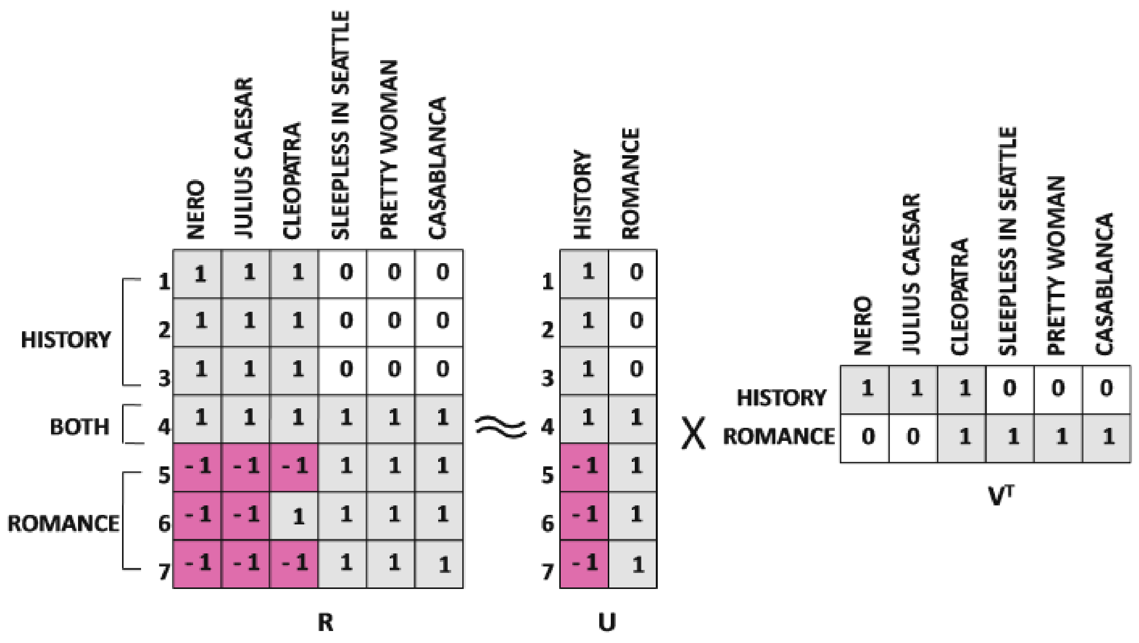


Figure 14: Example of matrix factorization for a rating matrix (Aggarwal 2016, 95)

Several approaches can be used to solve the matrix factorization problem. The approach proposed by Hu, Koren, and Volinsky (2008), which we will implement, uses an alternating least square solution. This algorithm scales linearly for both users and items, and are well-suited for parallelization. However, it scales cubic with the number of latent factors, but this number is independent of the input data and typically is very small, usually between 10 and 200.

In explicit feedback situations, the factor vectors can be learnt by minimizing the regularized squared errors on the set of known ratings (Koren, Bell, and Volinsky 2009). This can be done the following way:

$$\min_{x_*,y_*} \sum_{r_{u,i}\ is\ known} \left(r_{u,i} - x_u^T y_i\right)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right) \tag{14}$$

Here, the $\left(r_{u,i} - x_u^T y_i\right)^2$ is the squared difference between the known ratings and the predicted ratings based on the dot product of the factor vectors x_u and y_i. The function thereby tries to find the user factor vectors and item factor vectors that best reduce the RMSE, which is described in Section 2.5.3. The part $\lambda(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2)$ is the regularization term used to avoid overfitting, which we explained in Section 2.5.1. Larger values of λ will increase the regularization.

Hu, Koren, and Volinsky (2008) adjusts this model to better handle implicit data. This is done by taking the different confidence values for a prediction into account and optimizing for all user-item pairs, not only those that corresponds to observed data. The following cost function is used as basis for computation of the factors in this approach:

$$\min_{x_*, y_*} \sum_{u,i} c_{u,i} \left(p_{u,i} - x_u^T y_i \right)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right) \tag{15}$$

In this equation, $p_{u,i}$ is a binary variable indicating the preference of a user u towards an item i. It is set to 1 if user u has interacted with item i, i.e., rating $r_{u,i} > 0$, and otherwise is set to 0. The variable $c_{u,i}$ is a confidence value which measures the confidence in prediction $p_{u,i}$, and is computed as follows:

$$c_{u,i} = 1 + \alpha r_{u,i} \tag{16}$$

This gives a certain confidence level for every user-item pair, which increases if a user has interacted several times with an item. The α determines how much the confidence should increase when we have a higher rating value. Confidence values are included in the model because of the problems of distinguishing positive from negative feedback in implicit feedback datasets.

A problem of the cost function in Equation (15), is that the computation must be done for each user-item pair, which easily can become a bottleneck. By differentiation, Hu, Koren, and Volinsky (2008) therefore find an analytic expression for x_u and one for y_i which each minimizes the cost function in Equation (15). Then we can use an alternating least square optimization process, alternating between re-computing the user-factors (x_u) and item-factors (y_i) in an iterative process until convergence. A typical number of iterations is 10 and typical number of factors are 10 to 200 (Hu, Koren, and Volinsky 2008). The idea of alternating least squares is to hold one of the factor matrices constant, while the other one is computed, and afterwards holding the second matrix constant, computing the first one. The computation of each of the user factor vectors are independent of the other user factors vectors, making this approach well-suited for parallelization (Aggarwal 2016, 105). The same is the case for the computation of each of the item-factors.

When implementing this approach in Spark, we must first initialize the Spark configuration, which is done in Code snippet 3. Here, we name the Spark application, and specify that the program should be run locally on one machine. If we had wanted to use a cluster, we could have entered the URL of the master node as a parameter to *setMaster()*, but in this thesis we are only going to run the code on a single machine.

```
SparkConf conf = new SparkConf().
      setAppName("Implicit ALS-recommender").
      setMaster("local");
JavaSparkContext sc = new JavaSparkContext(conf);
```

Code snippet 3: Initialization of Spark configuration

The next step, as seen in Code snippet 4, is to read the user data into *Rating*-objects stored in a Resilient Distributed Dataset (RDD), which is the parallelizable data structure used by Spark. This is done by first calling the *textFile()*-function of the *JavaSparkContext*-object *sc*, which makes an RDD of the strings in the input file. Afterwards, the map function returns an RDD of *Ratings*, by passing each *String*-object from the dataset through a function where each String is split by a delimiter into a user-id, item-id and rating, which subsequently are sent as parameters to a new *Rating*-object.

```
String path = "training_data.csv";
JavaRDD<String> data = sc.textFile(path);
JavaRDD<Rating> ratings = data.map(
        new Function<String, Rating>() {
            @Override
            public Rating call(String line) {
                String[] parts = line.split(",");
                return new Rating(Integer.parseInt(parts[0]),
                    Integer.parseInt(parts[1]),
                    Integer.parseInt(parts[2]));
            }
        }
);
```

Code snippet 4: Reading user data into an RDD in Spark

The implicit feedback alternating least square matrix factorization can then easily be carried out by calling *trainImplicit()*, which returns a *MatrixFactorizationModel*-object that can be used to get recommendations. The code for this is presented in Code snippet 5. *TrainImplcit()* needs a set of parameters to conduct the matrix factorization. First, we must give the ratings and number of latent factors – which is the rank of the factorization. The number of iterations, the regularization value λ and the α-value must also be set. In our implementation, we use the default values in Spark's MLlib for these parameters, which are 10 iterations, 10 latent factors, 0.01 for the regularization value and 1.0 for the α-value, which ensures a reasonable trade-off between accuracy and scalability (Apache Spark 2016).

When we call *recommendProducts()* on the trained model, an array of *Rating*-objects are returned. The user-id for the user to get the recommendations for and the number of recommendations must be given as parameter in this method. The returned ratings are sorted based on predicted rating values in decreasing order.

```
MatrixFactorizationModel model = ALS.trainImplicit(
     JavaRDD.toRDD(ratings), rank, iterations, lambda, alpha);
Rating[] ratings = model.recommendProducts(id, num);
```

Code snippet 5: Train an implicit model in Spark and get recommendations

4.2.3 Content-based filtering

Our content-based filtering algorithm relies on a vector space model, where both items and users are represented by term vectors, which is a standard way of doing content-based filtering (Lops, De Gemmis, and Semeraro 2011). The algorithm is implemented in the framework LensKit (version 2.1.0), and is a continuation of the implementation of Lin (2013). The main idea behind the algorithm is to represent each user and each item with a content representation, and for each user find the most similar items based on similarities in the representations of the user and the items.

The first step in content-based algorithms is to make a content representation for each item. This is the training phase of this algorithm. Each item must be associated with a document, which typically are content tags or terms gathered from the item itself, e.g., books, or from descriptions of the item. Each item can then be represented by the terms, also called the *features*, of the document. We store these features in a *feature vector* for each item**,** where each feature gets a value based on its frequency in the document. This could simply be a binary vector where each feature that appears in the document gets value 1, and otherwise gets value 0, or a vector containing the raw frequencies of the features, but this can give several biases. We will therefore use normalized *term frequency-inverse document frequency* (TF-IDF) values for the features, which ensures that rare terms are not considered less relevant than common terms, that multiple occurrences of a term is considered more relevant than single occurrences and that long documents are not considered more relevant than smaller documents (Lops, De Gemmis, and Semeraro 2011).

The TF-IDF value for term t_k in document d_j is computed by taking the product of the *term frequency* (TF) and the *inverse document frequency* (IDF):

$$TFIDF = TF\left(t_k, d_j\right) * IDF(t_k) \tag{17}$$

$TF\left(t_k, d_j\right)$ is the frequency of term t_k in document d_j, while the IDF for a term is computed as follows, where N is the number of documents, and n_k is the number of documents which contain term t_k:

$$IDF(t_k) = \log \frac{N}{n_k} \tag{18}$$

The computation of IDF values ensures that rare terms overall in the document collection get a higher score than more common terms.

Next, we normalize the TF-IDF values in each feature vector, by dividing each TF-IDF value by the Euclidean length of the feature vector, to ensure that the lengths of the documents do not affect the similarity. This is done as following, where $n_{k,j}$ is the normalized TF-IDF value for term k in document j, and $\sqrt{\sum_{s=1}^{|T|} TFIDF\ (t_s, d_j)^2}$ is the euclidean length of the feature vector:

$$n_{k,j} = \frac{TFIDF\left(t_k, d_j\right)}{\sqrt{\sum_{s=1}^{|T|} TFIDF\ (t_s, d_j)^2}} \tag{19}$$

Because we want to find items that are similar to the user's preferences in content, we must make a feature vector for each user. After each item is represented with a feature vector, a feature vector is made for each user based on which items the user has interacted with. This could be done by making a feature vector with the sum of all of the feature vectors a user has rated. However, we want the tags of highly rated items to count more than the tags of items rated with low ratings by the user. Therefore, we weight each TF-IDF value for the features in a rated item by a user u as following, where $w_{k,j,u}$ is the weighted TF-IDF value for term k in document j for user u, $n_{k,j}$ is the normalized TF-IDF value for term k in document j, and $r_{u,j}$ is the rating of user u for document j:

$$w_{k,j,u} = n_{k,j} * (1 + \log(r_{u,j} + 1)) \tag{20}$$

The reason for multiplying with $(1 + \log(r_{u,j} + 1))$ and not the user's rating of the document, is because we want the recommendation system to work for implicit data, where larger ratings indicate larger preferences, but the differences in ratings do not precisely show differences in the user's preferences. For example, an implicit rating, like a play count, of 4 will not necessarily mean the user likes the item twice as good as another item with rating 2, which is the case for explicit ratings. Therefore, we want all tags of rated items to count, but the tags of higher rated items to count a little more, which is achieved by this weighting. We add 1 to the rating in $\log(r_{u,j} + 1)$ because some of the datasets presented in Section 2.5.4 contains 0-ratings for implicit data, and the log of 0 is undefined.

After this weighting is done, we can make a feature vector for each user by summing all the weighted feature vectors of the items the user has rated, the following way, where $\vec{a}$ is the feature vector of user u, R_u is the set of rated items by user u, and $\overrightarrow{t_{i,u}}$ is the feature vector for item i weighted for the user u based on his rating for the item:

$$\vec{a} = \sum_{i \in R_u} \overrightarrow{t_{i,u}} \tag{21}$$

Now, we can use a vector space model to find items similar to the users, where each item and user is represented by its feature vector in an n-dimensional space. Each dimension in the space corresponds to a term. The next step is to calculate the similarities between users and items, which means we need a similarity function. The cosine measure is the most commonly used similarity function and it is well suited for the text domain (Aggarwal 2016, 151). We will therefore use this measure, as we did in the item-based approach in Section 4.2.1, to compute similarities. The similarity between user *a* and item *b* is then computed by the cosine of the two feature vectors $\vec{a} = (a_1 \dots a_d)$ and $\vec{b} = (b_1 \dots b_d)$, where the values for the i'th word are given as a_i and b_i. Feature vector $\vec{b}$ for an item, contains the normalized TF-IDF values as computed in Equation (19), and not the weighted values that were used to compute the user's feature vector. The equation for cosine was given in Equation (8), but it will be repeated here to simplify the reading:

$$\text{sim}(a, b) = cos(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}\,| * |\vec{b}|} \tag{8}$$

After the similarities between a user and all items are computed, we can recommend the *n* items with highest similarity to this user. This algorithm scales linearly in number of users, items and features, as we for each user must iterate over all features for each item to compute the similarities between the users and the items.

As this algorithm is implemented with LensKit, the algorithm is configured in a similar way to how the item-based collaborative filtering algorithm was configured, which was presented in Section 4.2.1. Again, we use the *LenskitConfiguration* to bind together the components we want to use. The *ItemSimilarity* is bound to *TFIDFItemScorer* to specify that we want to find similar items for a user in terms of their TF-IDF values. In addition, we have to set the ratings file, tag file and title file, so that the feature vectors can be updated with the right values. To train the recommender and produce recommendations, the exactly same procedure is used as for the item-based implementation, as shown in Code snippet 2.

4.2.4 Popularity baseline

The last algorithm we will implement, is a non-personalized baseline algorithm. This type of algorithm does not depend on the individual user's ratings. It can therefore be used to recommend items for new users and is useful as a baseline that the personalized algorithms can be compared to (Ekstrand, Riedl, and Konstan 2011). We will use the popularity of the items as basis for our baseline algorithm. The baseline score b_i for item i will be calculated by counting the number of ratings for item i for the whole set of users U. This is done as follows:

$$b_i = \sum_{u \in U} p_{u,i} \tag{22}$$

Where $p_{u,i}$ is defined as follows:

$$p_{u,i} \begin{cases} 1 & r_{u,i} > 0 \\ 0 & r_{u,i} = 0 \end{cases} \tag{23}$$

Here, $r_{u,i}$ is the rating of user *u* for item *i,* and a rating value of 0 indicates that there is no rating for this user-item pair. In situations where the user data are explicit ratings on a scale, a better baseline can be to use the average rating of an item, because we then get both positive and negative ratings for the items. However, as we want the baseline to work for implicit unary data where no negative ratings are collected, it is better to use the number of ratings for each item to measure the items' popularity. For example, one video played by 1000 users will be more popular than a second video played by 5 users, even though the second video has a higher average number of plays.

In our implementation, we represent users, items, and predicted relevance of an item with *User, Item* and *Prediction* classes, respectively. *Item* only contains a parameter for the item id, while *User* contains a parameter for user id and a hash map of *Item*-objects the user has rated. *Prediction* contain an *Item*-object and a frequency for how many users who have rated the item. All *Prediction*-objects are stored in a hash map, *predictions,* in the *BaselineRecommender* class. To train the recommender, a *Prediction*-object is added for each item, and for each rating of an item, the frequency in the *Prediction*-object associated to that item is increased. In the end, all *Prediction*-objects are sorted in a list, with descending order of frequencies, so that the items with highest frequencies are found first in the list. To recommend the best *n* items, the item ids belonging to the first *n Prediction*-objects in the list can be recommended.

4.3 Summary

In this chapter, the focus has been on implementation of recommendation system algorithms suited for Forzify. We started by looking at some of the most commonly used recommendation frameworks: Mahout, LensKit, MyMediaLite and Spark's MLlib. These have both some similarities and some differences. LensKit and MyMediaLite are dedicated recommendation frameworks, while Spark and Mahout are machine learning frameworks with support for distribution.

We implemented the following algorithms: item-based collaborative filtering, model-based collaborative filtering, content-based filtering and a non-personalized baseline. The three first algorithms were chosen based on the discussion of approaches suited for Forzify in Section 3.5, while the last was chosen because it is good to compare the other algorithms against and can give good recommendations for new users. All the algorithms had to support unary implicit data, as Forzify has no mechanism to detect users' dislikes of items. Because none of the reviewed frameworks supports all these algorithms for this kind of data, we decided not to stick to only one framework. The item-based and the content-based algorithm was implemented in LensKit, the model-based in Spark, while the popularity baseline algorithm was implemented from scratch. The item-based algorithm uses a *k*-nearest neighbours approach, where similar items are computed by cosine. The content-based algorithm also uses cosine to find similarities, but in this algorithm, the similarities are computed between users and items. The model-based algorithm uses an alternating least square approach for matrix factorization, and the baseline algorithm bases its recommendations on the items' overall popularity.

We now have implemented four candidate algorithms for Forzify, but we do not know how well they work on real data. In the next chapter, we want to test these algorithms on different datasets to see which have the best scalability and accuracy, and if the performances differ from domain to domain.

5 Evaluation

In this chapter, we will evaluate the algorithms presented in Section 4.2. We will present the design of the evaluation, which includes the datasets, methodology, and metrics that will be used. Then, there will be a presentation and discussion of the results of the evaluation, and finally, there will be a discussion concerning the research questions Q2 and Q3, which were specified in Section 1.2.

5.1 Experimental design

The aim of this evaluation is to investigate how accurate the algorithms we have implemented are for top-*n* recommendation both for new users and users with more item interaction history. As stated in the problem statement in Section 1.2, we will evaluate the recommendation algorithms on different datasets, and not on Forzify's own dataset, because Forzify has limited amount of existing data. We want to find out which of the algorithms that gives best accuracy across the datasets, and to investigate if the accuracy is consistent across the datasets. If one algorithm performs better for all the datasets, this algorithm will most probably be the best option also in Forzify's case, but if the algorithms vary in the performances on the datasets, it will be more difficult to choose the best approach. Additionally, we want to investigate the scalability of the algorithms, as a recommendation system must give its recommendations to users in real-time and must be able to handle large amounts of data.

In this section, we will first present the experimental setting and metrics that will be used in the evaluation. There will be a part about the datasets we will use, where we first compare the features of Forzify's dataset to the other presented datasets, in order to find the best suited datasets for our evaluation. Next, there will be a description of how we will treat the data and we will present the characteristics of the sampled datasets. Then, we will describe how the evaluation is implemented.

5.1.1 Experimental setting and metrics

The experimental setting used for this evaluation, will be offline evaluation, which was described in Section 2.5.1. This setting is well-suited for measuring accuracy and scalability, and is more time- and cost-efficient than user studies. Online evaluation was not an option because the version of Forzify, made for all clubs of a division, which we are making the recommendation system for, are not yet released. Online evaluation is not a good option for testing new algorithms either, because they can introduce risks when the algorithms are not effective or contain errors. Therefore, offline evaluation is the best option for our evaluation, which also is the most common method used in recommendation system research (Jannach et al. 2010, 175).

Offline evaluations use pre-collected datasets of users' ratings of items. The datasets we will use, will be presented in Section 5.1.2. An important decision when measuring accuracy in an offline evaluation, is how the dataset should be divided into separate training and test sets, which only are used for either training or testing of the recommendation system. If a parameter tuning of the model is required, there is also necessary to make a separate tuning set. This set can be used for training after the tuning, but cannot be used for testing, as it can lead to overfitting (Aggarwal 2016, 236). Figure 15 shows a typical example of a partitioning of a dataset, where half of the ratings are placed in the training set, a quarter of the ratings are placed in the validation set, and the last quarter are used as test set. This is a common division of ratings, but if the dataset is large, the test and validation sets can be reduced to a smaller proportion of the ratings (Aggarwal 2016, 236). This was the case in the Netflix Prize, which had 100 million ratings, as shown in Figure 16.

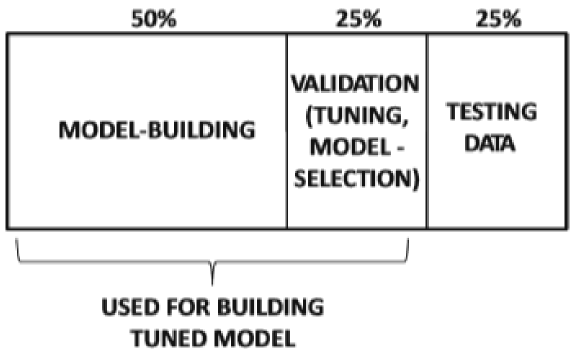

50%
25%
25%
MODEL-BUILDING
VALIDATION (TUNING, MODEL - SELECTION)
TESTING DATA
USED FOR BUILDING TUNED MODEL

Figure 15: Typical partitioning of ratings for recommendation evaluation (Aggarwal 2016, 237).

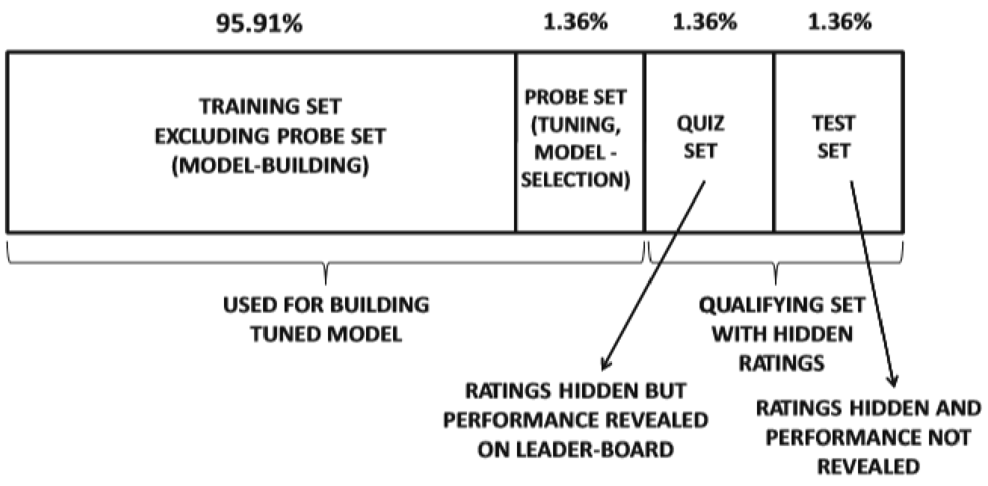

95.91%
1.36%
1.36%
1.36%
TRAINING SET EXCLUDING PROBE SET (MODEL-BUILDING)
PROBE SET (TUNING, MODEL - SELECTION)
QUIZ SET
TEST SET
USED FOR BUILDING TUNED MODEL
QUALIFYING SET WITH HIDDEN RATINGS
RATINGS HIDDEN BUT PERFORMANCE REVEALED ON LEADER-BOARD
RATINGS HIDDEN AND PERFORMANCE NOT REVEALED

Figure 16: Netflix Prize partitioning of ratings (Aggarwal 2016, 237)

To avoid bias from the users in the test set, *N-fold cross validation* will be used as selection technique in the evaluation. This is a stratified random selection method often used in recommendation system research (Jannach et al. 2010, 177). In this technique, the users are randomly assigned to *N* different user partitions of size $\frac{1}{N}$. Each of these partitions is then selected for testing once, while the remaining partitions are used for the training of the model. This means the testing are done *N* times, and the results are consequently averaged from the results of all *N* repetitions. We will use 5-fold cross validation, which means we divide all the users in 5 partitions of equal sizes. For each *fold* or repetition, one of the partitions are used for testing and the others are used for training, and this is repeated 5 times, so that each user is used once for testing and four times for model training. Our partitioning of users and use of folds are illustrated in Figure 17.

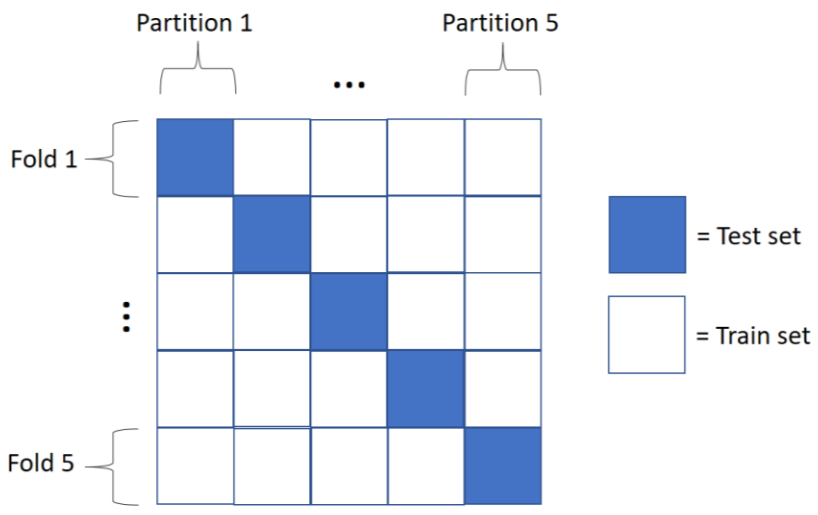


Figure 17: The 5-fold cross validation method used in our evaluation

Because all of the presented recommendation algorithms, except for the baseline algorithm, base their recommendations on users' previous history, it is necessary to include some of the test users' ratings in the dataset used for training. There are two methods commonly used for this: given-*N* and all-but-*N* (Jannach et al. 2010). The *given-N* method assigns *N* random ratings to the training set for each evaluated user, and assigns the rest of the ratings to the test set. *All-but-N*, on the other hand, assigns *N* random ratings for the evaluated user to the test set, while all the others of the user's ratings are assigned to the training set. These methods have different advantages and can therefore be used for different purposes. Given-*N* has the advantage that we get the same background information for each of the tested users, while all-but-*N* ensures equal conditions when using classification metrics (Jannach et al. 2010), such as top-*n* metrics, where the top *n* recommendations are classified as relevant or not. Another strength of all-but-*N*, which is desirable when evaluating the general accuracy of the recommender, is that we get different number of ratings as background information for the different users, which best models a real recommendation system.

Because given-*N* and all-but-*N* have different purposes, we will use both methods, but to investigate different problems. In the problem statement in section 1.2, we stated that we will find out which recommendation approaches that give best accuracy for both new and old users. Therefore, we will use given-*N*, with different sizes of *N*, to evaluate the accuracy for users with limited item interaction history, and all-but-*N* to evaluate the general accuracy of the recommendation system. All-but-*N* gives the best opportunity to examine how the top-*n* accuracy differs across the datasets, as it gives equal numbers of correct recommendations for each user. If we had used a rating prediction problem, the number of ratings in the test set would not have been important, because the accuracy in such cases measure the variations in predicted scores from the original ratings, not if the top *n* recommendations are considered correct. But, as stated in Section 3.3, Forzify only contain unary data, which mean we must treat the recommendation problem as a top-*n* recommendation problem, and consequently use top-*n* metrics.

We will measure the general accuracy by using all-but-10, i.e., for each test user we will hide 10 ratings in the test set. These items are considered relevant, and the rest of the ratings are used as training data. The choice of 10 is made of various reasons. Forzify presents its recommendation in lists of 10 items, and we will therefore evaluate the recommendation algorithms with a recommendation list size of 10. By using all-but-10, it will then be possible to make a perfect recommendation list, by recommending all the 10 relevant items. As we will come back to in Section 5.1.2, we will only choose users with 20 to 200 ratings, to ensure equal conditions for the different datasets in the accuracy measurement. By choosing all-but-10, we ensure all users have at least 10 given ratings, and mostly 190. For the evaluation of accuracy of recommendations for new users, we will use given-2, given-5 and given-8, because we then can see how the accuracy changes when more information about the user is known.

In Section 2.5.3, we presented top-*n* measures for recommendation systems. We will use MAP as the main metric in the evaluation of the accuracy of the algorithms. MAP is commonly used in research on recommendation systems which use unary data and implicit feedback, and it was used as the metric in the most famous recommendation system challenge for top-*n* recommendations: The Million Song Dataset Challenge, as we presented in Section 2.1. The strength of this measure is that it both takes into account the number and positions of the correct recommendations among the top *n* recommendations, not only the position of the first correct recommendation (as ARHR), the number of users who get at least one correct recommendation (as HR), the proportion of correct recommendations in the recommendation list (as precision) or the proportion of the correct items that are recommended (as recall). To get reliable data about accuracy, we will include HR, ARHR and precision, to ensure that the results are not biased by the metric. The reason for including precision and not recall, is that we mean precision gives a better measure for top-*n* recommendations, as it considers the number of recommendations in the list, not the total number of possible correct recommendations. We could have included both, but we expect them to give much the same scores in our case. This is because all-but-10 gives 10 relevant items, and the recommendation list size will, as we come back to later, mainly be set to 10. Precision and recall are, as stated in Section 2.5.3, found by dividing the number of correct recommendations on the recommendation list size or the number of relevant items in total, for precision and recall respectively.

All the items that a user has interacted with, will be regarded as relevant for that user because we want to simulate implicit feedback recommendations, similarly to The Million Song Dataset Challenge. This is because Forzify mostly gathers implicit feedback, this kind of data is easiest to collect, and all datasets can be transformed to implicit feedback datasets, which means it makes it easier to compare accuracy results across datasets. As Forzify presents the recommendations in a set of 10 items, we will measure the MAP for the 10 best recommendations for each evaluated user, i.e., we have a top-10 recommendation problem, where we try to predict which items a user will interact with. In addition, we will include results for recommendation list sizes of 20 when we evaluate the general accuracy, to see how this affects the accuracy.

To measure the scalability of the recommendation algorithms, we will for each dataset and for each recommendation algorithm, measure the average time used for training the recommender and the average time used for producing recommendations to a user. In addition, we will test the training time and time used for making recommendations for three different subsets, with varying sizes, of the MovieLens dataset, to show how the recommendation algorithms scale up to larger ratings sizes. Our experimental setting is summarized in Table 7, and more details about the datasets will be presented in the next section.

Dependent variable	Technique	Variation	Dataset	Measures
General accuracy	5-fold cross validation, all-but-10	10/20 recommendations	Datasets from different domains, using original / binarized ratings	MAP, ARHR, HR, precision
Accuracy for new users	5-fold cross validation, given-2/5/8	10 recommendations	Datasets from different domains, using binarized ratings	MAP, ARHR, HR, precision
Scalability	5-fold cross validation, all-but-10	Training recommender / predicting recommendations	Datasets from different domains	Average time used
Scalability	Use whole dataset as training data, produce recommendations for 100 users, repeat all 5 times	Training recommender / predicting recommendations	Subsets of one dataset in 3 varying sizes	Average time used

Table 7: Summary of our experimental design

5.1.2 Datasets

To decide which datasets that are best suited for our evaluation, we will compare Forzify's data to the datasets presented in Section 2.5.4. Further, there will be a description of how we will make the selected datasets ready for evaluation, and we will present the properties of these datasets.

Selection of datasets

In Section 2.5.4, we presented 5 datasets from different domains that are commonly used for recommendation system evaluation, namely Book-Crossing, MovieLens, Amazon, Million Song and Jester. These vary not only in domain features, but also in inherent features and sample features. In this section, we will compare Forziy's data to the other datasets when it comes to these features, so the datasets that are best suited for the evaluation can be selected. We want to use the datasets that are most similar to Forzify, even though the item types recommended in each dataset naturally differ from the one in Forzify.

When it comes to domain features, Forzify has both resemblances and differences to the other presented datasets. The domain features of Forzify are shown in Table 8, and the domain features of the other datasets are summarized in Table 3. The context is, as in the other datasets, a web setting, but the content type is different from the others. Forzify recommends sports videos, while each of the other datasets contains data about one of the following: books, songs, movies, jokes and e-commerce products. Forzify's content type can be seen as most similar to MovieLens' content, i.e., movies. Both Forzify and MovieLens recommend videos, but on the other hand, the videos differ in content and duration, as most movies are not about sport and are 90 to 120 minutes long, while sports videos typically last for a few minutes. In this perspective, the items are more similar to the ones in Million Song, because a song usually is a few minutes long.

Forzify has low costs for both false negatives and for false positives, because recommendations of low quality or missing recommendations of relevant items do not introduce any risks to the users, as can be the case in other domains. On the other hand, successful recommendations can give a high potential benefit for the users and the owners of the system, as it simplifies the browsing and information filtering process. This is similar to all datasets except for Amazon, which has higher costs for false negatives, and Jester, which have smaller potential benefits of recommendations, as the item catalogue is very small.

Content	Context	Cost false negatives	Cost false positives	Benefit
Sports videos	Web	Low	Low	High

Table 8: Domain features of Forzify's data

The inherent features of Forzify are summarized in Table 9, while these features for the other datasets are summarized in Table 4. Forzify has both explicit and implicit data, similar to Book-Crossing. However, there is unary data only, in the form of presence of user actions and play counts. The scale of ratings is therefore most similar to Million Song, where only number of plays are recorded. However, all of the datasets can be used because explicit user data can be transformed to unary data. This can for example be done by substituting all ratings with 1-values - indicating an item interaction, substituting high ratings with 1-values and removing the other ratings - indicating likes, or by treating the explicit ratings as arbitrary unary ratings, where all ratings indicate preference, but higher values indicate larger preference, as in playcounts. This can be done because explicit data are richer data than implicit data, and it is not possible to transform the data the other way, i.e., from implicit to explicit.

Like all of the other datasets, Forzify has only one dimension of ratings, because the ratings are not related to special qualities or characteristics of the videos, as video quality or sound quality. There is not collected any demographic information, but each item has associated tags, which is also the case in MovieLens, Million Song and Amazon. In Book-Crossing and Jester, on the other hand, publisher information and the text of the jokes are collected respectively as content data.

Explicit or implicit	Scale	Dimensions	Demographic data	Content
Both	Presence of user actions and play counts	1	No	Tags

Table 9: Inherent features of Forzify's data

Forzify has today only gathered data from the three individual club versions of Forzify, which are not representative for the new versions that will be released for Eliteserien and Allsvenskan for the 2017-season. We will therefore discuss the sample features of Forzify in terms of how these are expected to be for the new version, where all clubs in a league are included. These will be compared to the sample features of the other datasets, which were summarized in Table 5.

Several hundred thousand persons watch Eliteserien each match day, either live at the stadium or on TV (Sponsor Insight 2016). All of these are potential users of the new Forzify version for Eliteserien. If only a small percentage of these starts to use Forzify, the application will get several thousand users. Consequently, the number of users will be more similar to MovieLens, Book-Crossing and Jester, which have between 73 000 and 279 000 users, than to Amazon and Million Song, which have 1 M and 21 M users, respectively.

Because both explicit and implicit data are gathered, and videos typically are short, several ratings can be expected from each user. It will probably be more ratings per user than in Book-Crossing and Amazon, as it is more time-consuming to read a book than to watch a sports video, and users typically do not buy as much items online as they watch online videos. Ratings per user will therefore be more similar to Jester, MovieLens and Million Song. However, users will only be expected to interact with a small fraction of the items. In both Tippeligaen and Allsvenskan, there are 8 matches each match day, and there are 30 rounds in one season. For each match, typically 30-50 videos are added, which means it most likely will be uploaded around 10 000 videos for each league in a season. Forzify's dataset will therefore be most similar to MovieLens, Million Song and Book-Crossing in number of items and percentage of items rated per user, as Jester and Amazon have an extremely small and large number of items, respectively.

Summarized, Forzify has both similarities and differences to all of the other datasets. We choose to use MovieLens, Book-Crossing and Million Song as datasets for this evaluation, because they have the highest similarities to Forzify in sample features, as number of items and items rated per user, and they are most similar to Forzify in domain features, although the type of content varies in all of them. The inherent features of these three datasets are all suitable for Forzify's case, as they all contain content data and have ratings that can be transformed to unary data, like the data in Forzify. Jester and Amazon could both have been used also, but we rather want to go into the depth of the results for a few datasets, than to look at the results for all of the datasets. The main reason for not choosing these two datasets, are the number of items and the consequential density of ratings. Jester has an extremely dense dataset, where most users have rated nearly all of the items, while Amazon has an extremely sparse dataset, where most users only have rated an extremely small fraction of the items.

Sampled datasets

Here, we will describe how we make the datasets ready for the evaluation, and present the characteristics of the sampled datasets. We will sample one subset of 6000 random users with 20 to 200 ratings for each of the datasets. This is because we want to make the evaluation setting as similar as possible for all of the datasets, so the number of users or previous ratings do not affect the recommendation accuracy. This is important to get reliable data about the differences in accuracy across the datasets. In addition, carrying out simulation of recommendations for up to a million of users can take unreasonable amounts of time when we are using 5-fold cross-validation and running repeated tests. The choice of 6000 users are made because previous studies have shown that this number of users is sufficiently large and lets the simulation being done in reasonable time (Im and Hars 2007).

The datasets differ in rating scales and type of ratings. MovieLens contains only explicit feedback, Million Song Dataset contains only implicit unary feedback, while Book-Crossing contains both explicit and implicit feedback. Because Forzify only contain unary ratings and because we want to compare the accuracy across the datasets, we will transform the data to implicit unary ratings. By doing this, the type of ratings will not affect the accuracy in the different datasets. We will do this by substituting all rating values by 1-values, so that each rating indicates an equal implicit preference. In addition, we will run one test with the unmodified ratings, to examine if we get higher accuracy with the original data. Then, the ratings will be treated as arbitrary value unary ratings, where a 1-value indicates a small preference and larger values indicates larger preferences, so that the ratings are as similar as possible to the play counts collected in Forzify. This can give valuable information about which ratings that are best to use in the new recommendation system for Forzify.

The characteristics of the users, items and ratings for the sampled datasets are presented in Table 10, where we can see that the number of items varies to a great extent across the datasets. In the Million Song Dataset, there are more than ten times as many items as in MovieLens, while Book-Crossing nearly has twice as many items as Million Song. We can expect this to give a higher accuracy for the recommendations in MovieLens, because the recommendation system solves a top-*n* recommendation problem, where the items are classified as relevant or not for a user based on the previous user-item interactions, and the accuracy is calculated on the basis of how many of the recommended items that are classified as relevant and their positions in the list. For example, it is easier to get a high number of relevant recommendations when recommending 10 items out of 100 items, compared to recommending 10 items out of 10 000 items when the number of relevant items remains the same.

	# Users	# Items	# Ratings	Avg. ratings per user	Avg. ratings per item
Book-Crossing	6000	150 771	336 051	56.00	2.23
Million Song Dataset	6000	87 957	337 867	56.30	3.84
MovieLens	6000	7 359	407 571	67.92	55.38

Table 10: Statistics about ratings, items and users for the sampled datasets

We sampled users with number of ratings in the range of 20 to 200, however we can see a difference in the number of ratings and average ratings between MovieLens and the two other sampled datasets. Book-Crossing and Million Song have nearly the same number of ratings, while MovieLens has a larger number. The high number of ratings and low numbers of items, gives a much higher average of ratings per item in MovieLens than in the two other datasets. Book-Crossing and Million Song can therefore give valuable information about the accuracy for items with low number of ratings.

As can be seen in Table 11, there are large differences in the content information in the sampled datasets. MovieLens has a default set of tags, while the tagging in Million Song are user specified. The tags in Book-Crossing is taken from the publisher information. This results in a much larger tag set for both Book-Crossing and Million Song. To reduce the number of tags in these two datasets, we have removed all tags with a frequency of 1 and in the Million Song Dataset, we have removed tags for items where the tag values are lower than 30 for the item-tag combination (the tags have values from 0-100 indicating the relation between item and tag, where larger values indicates stronger association). In addition, we have removed stop-words, which are commonly used words that give little information, as "a", "the" and "on" (Jannach et al. 2010, 56). The numbers in Table 11, show the properties of the datasets after these removals. MovieLens has only 19 different tags, while Million Song Dataset has 52 291 tags and Book-Crossing has a total of 47 921 different tags. Book-Crossing has the highest number of tags associated to items, both in total and in average per item, but Million Song has also a considerably larger number of tags than MovieLens.

	# Distinct tags	# <Item, tag>-pairs	# Items with tags	Avg. tags per item
Book-Crossing	47 921	872 117	124 626	7.00
Million Song Dataset	52 291	365 191	70 095	5.21
MovieLens	19	15 468	7 359	2.10

Table 11: Statistics about the content information for the sampled datasets

For the evaluation of scalability, we will also test the algorithms on three different subsets of MovieLens, one with 100 000 ratings, one with 1 M ratings and one with 5 M ratings. The properties of these subsets are shown in Table 12.

	MovieLens 100 K	MovieLens 1 M	MovieLens 5 M
# Users	730	7 316	35 029
# Items	6 373	9 626	10 527
# Tags	19	19	20
# <Item,tag>-pairs	13 678	19 740	21 291

Table 12: Properties of the MovieLens subsets used for scalability testing

5.1.3 Implementation of an evaluation framework

All of the presented frameworks in Section 4.1 have built-in support for evaluating recommendation algorithms. However, none of them support evaluation of external algorithms. We have made one algorithm from scratch and used two recommendation frameworks for our implementations, so it was not possible to evaluate all the algorithms in one framework. We decided to make our own tests in Java because it is important to use exactly the same evaluation procedure for each algorithm in order to get reliable data. The program code used to prepare and conduct the evaluation can be obtained from GitHub, see link in Appendix A. The splitting of ratings into training and test sets is done in the *DataSplitter*-class, while the evaluation itself is carried out in the *Evaluator*-class.

5.2 Results

In this section, we will present and discuss the results of the evaluation. First, we will look at the results necessary to examine how accurate the recommendation algorithms are in general for the different datasets. This is done with an all-but-10-approach. Next, we will look at the results of accuracy measures with given-2, given-5 and given-8 for the different datasets, to investigate how accurate the recommendations are for users with limited item interaction history. Further, we will look at the time used for training the recommendation model and for producing the recommendations, which tells us about the scalability of the different algorithms.

All tests were performed on the same computer, at a Linux-based operating system with 2.30 GHz (Intel Core i5-6200U) and 6GB memory. The algorithms will use parameters as specified in Section 4.2. To get the best possible accuracy for these algorithms, we could have done parameter tuning on every dataset, where different parameters are tested for the algorithms on a validation set. However, as we want to test the suitability of the same algorithms across datasets, we have chosen not to do this.

5.2.1 General accuracy

Here, we will present and discuss the results important for investigating the general accuracy of the recommendation algorithms. By general accuracy, we mean the accuracy for users with some item interaction history, as opposed to the accuracy for new users, which will be the focus of the next section. The results are presented for the three selected datasets, i.e., MovieLens, Million Song and Book-Crossing, and can therefore give us valuable information about how the accuracy differs across different domains. All the results in this section are obtained by using an all-but-10 approach, which means 10 ratings are assigned to the test set and between 10 and 190 ratings are assigned to the training set for each user, as we only included users with between 20 and 200 ratings. As we solve a top-*n* recommendation problem, the accuracy is determined by how many of the items placed in the test set for a user we are able to recommend in the recommendation list for that user, and their position in the recommendation list. These items are considered relevant for that user.

First, we will present the accuracy obtained by using binarized data and the accuracy obtained by using the original arbitrary value ratings, to see which difference this makes for the accuracy. In Figures 18-20, the MAP, which was described in Section 2.5.3, is shown for both original ratings and binarized ratings, for all of the three datasets. The number of recommendations used are 10. Higher MAP-values indicate higher accuracy. Overall, there are small differences between the accuracy when comparing the values obtained using original ratings with the ones obtained using binarized ratings. However, in three situations, the accuracy is considerably higher for binarized ratings than for the original ratings. This is the case two times for the item-based algorithm, in Million Song and Book-Crossing, and one time for the model-based, in the Book-Crossing. This implies that binary ratings give at least as good accuracy as arbitrary valued ratings for top-*n* recommendations for the three datasets. The rest of the results in the evaluation is gathered from binary ratings, as was stated and justified in Section 5.1.2.

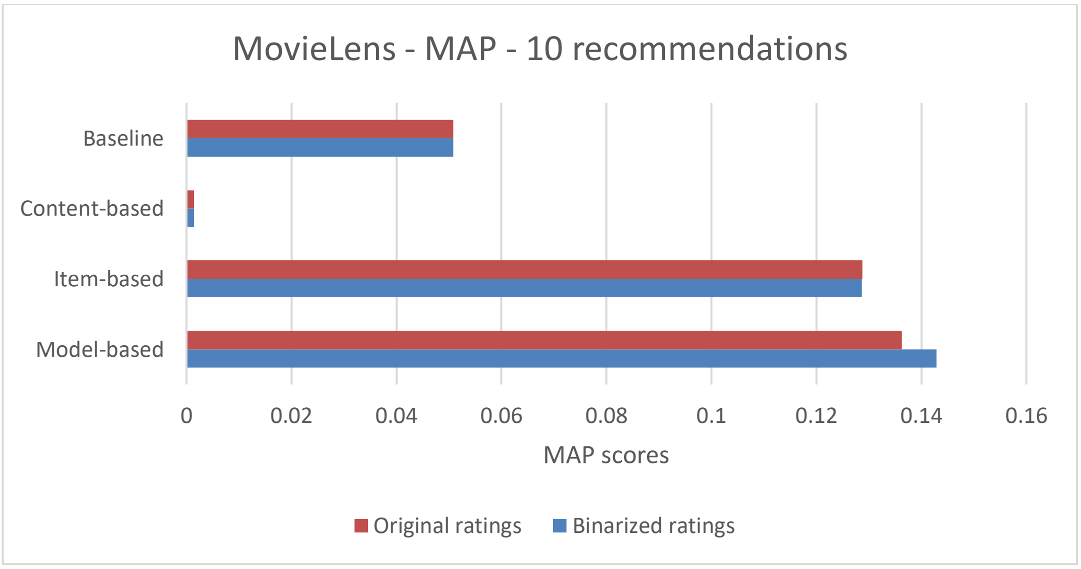


Figure 18: MAP for our algorithms performed on MovieLens

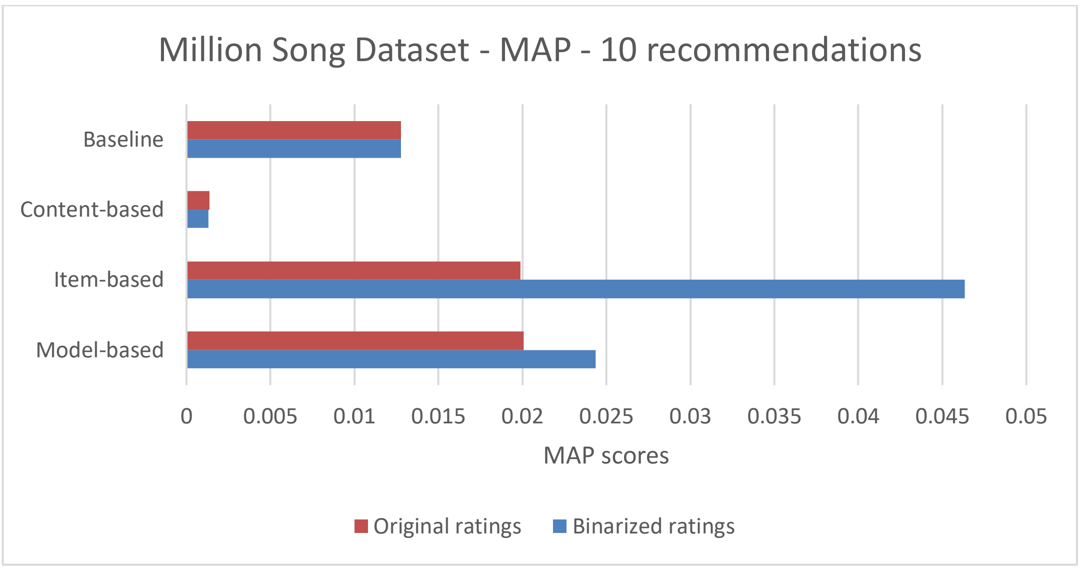


Figure 19: MAP for our algorithms performed on Million Song Dataset

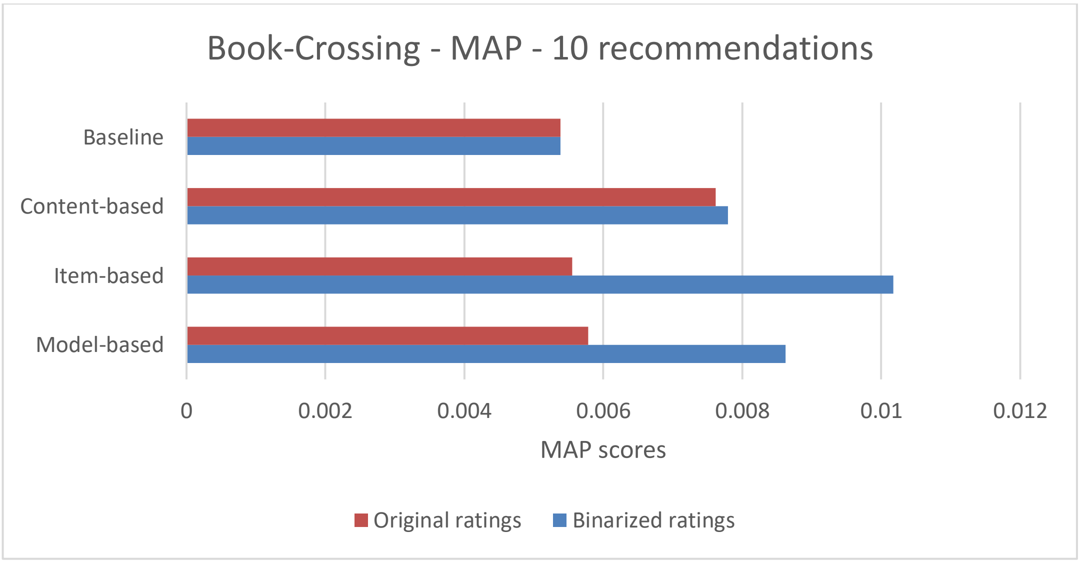


Figure 20: MAP for our algorithms performed on Book-Crossing

To get an idea of what the MAP scores mean, a MAP value of 1.0 indicates that all users either are recommended only relevant items or are recommended all the relevant items (if the number of relevant items is less than the number of items in the recommendation list). A MAP value of 0, on the other hand, means that none of the relevant items are recommended. However, it is not easy to see what each individual MAP score tells about how good a recommendation algorithm is, as the metric both takes into account the number of correct recommendations and the index of the correct recommendations in the recommendations list. There is no universal defined range of good values, as the values depend on number of hidden items in the test set and items in total. Therefore, to get an indication of how good an algorithm performs, one can compare the algorithm with a popularity baseline algorithm (Ekstrand, Riedl, and Konstan 2011), which commonly is done in evaluation of recommendation algorithms (Deshpande and Karypis 2004, Rendle et al. 2009, Hu, Koren, and Volinsky 2008). A successful recommendation algorithm gives a certain improvement in accuracy from what is achieved by the baseline. By using this comparison, we can see in Figures 18-20 that the content-based algorithm performs weak in the MovieLens and Million Song dataset, while it gives a good accuracy in Book-Crossing. In all of the binarized datasets, the item-based and model-based give a considerably better accuracy than the baseline, which mean they have a good performance in all of these datasets.

In Figures 21 and 22, we can see how the MAP varies for the recommendation algorithms and for the datasets. In the first of the two, the results are gathered with a recommendation list size of 10, while in the second, the number of recommendations used for testing is 20. First of all, it is clearly visible that the accuracy follow the same pattern, regardless of the recommendation size. The only notable difference between the results for the different recommendation sizes, is that the accuracy is slightly higher for 20 recommendations than for 10.

There are large differences between the accuracy across the three domains. The algorithm with largest accuracy in the MovieLens dataset, have more than three times as high accuracy as the best scoring algorithm for Million Song, and around 14 times higher accuracy than the best scoring algorithm for Book-Crossing. There are also differences across the datasets in how evenly the algorithms perform in each domain. In Book-Crossing, the algorithms perform evenly, while in Million Song, there are larger differences between the different algorithms. The largest differences inside a domain, however, are found in MovieLens.

There is also some consistency in the accuracy across the domains. The two collaborative filtering algorithms perform best in all three domains. Especially in MovieLens, but also in Million Song, they perform clearly superior to the two other algorithms. The model-based algorithm is the one with the best accuracy in MovieLens, while the item-based is the best-performing one in Million Song. In Book-Crossing, their accuracy is quite even, although the item-based performs slightly better. Therefore, these two algorithms seem to be the most accurate approaches across the domains when using MAP as accuracy measure, but it is not easy to decide which of them that is the most accurate.

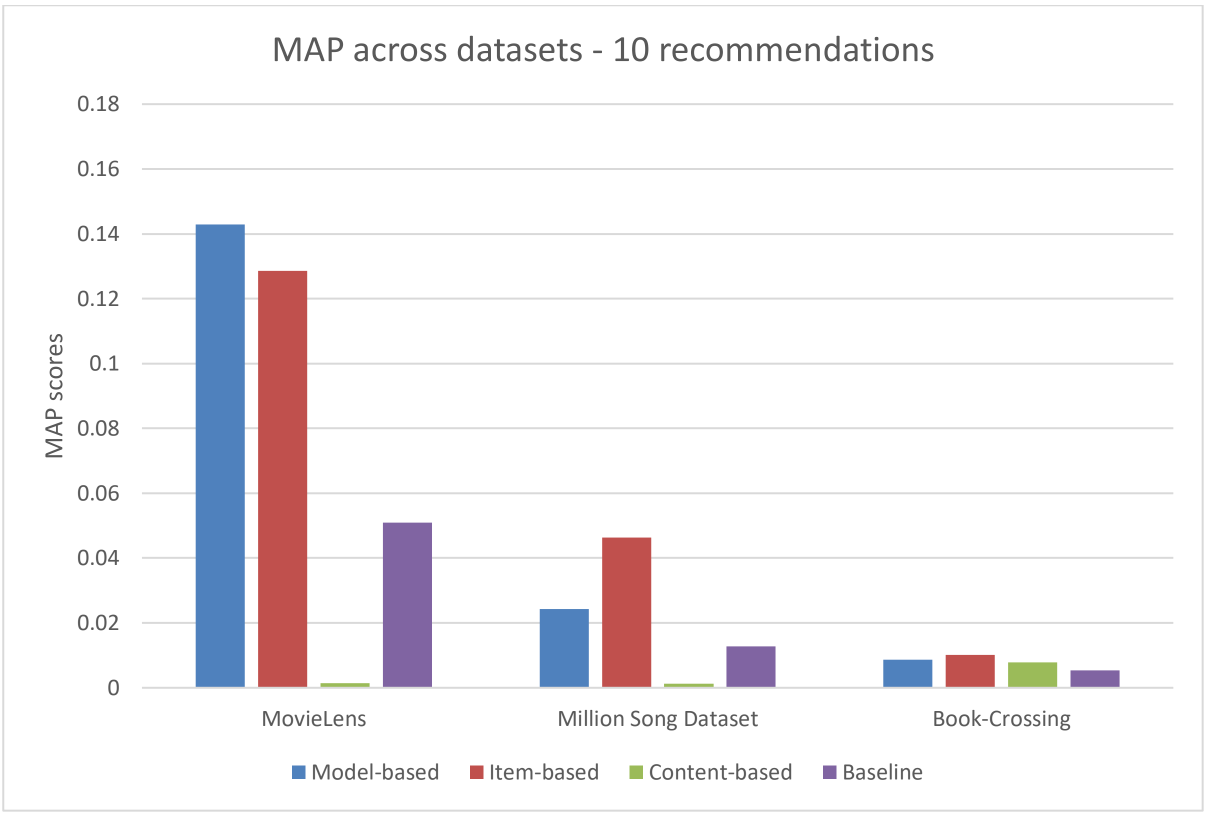


Figure 21: MAP for our algorithms for the different datasets, with recommendation list size = 10

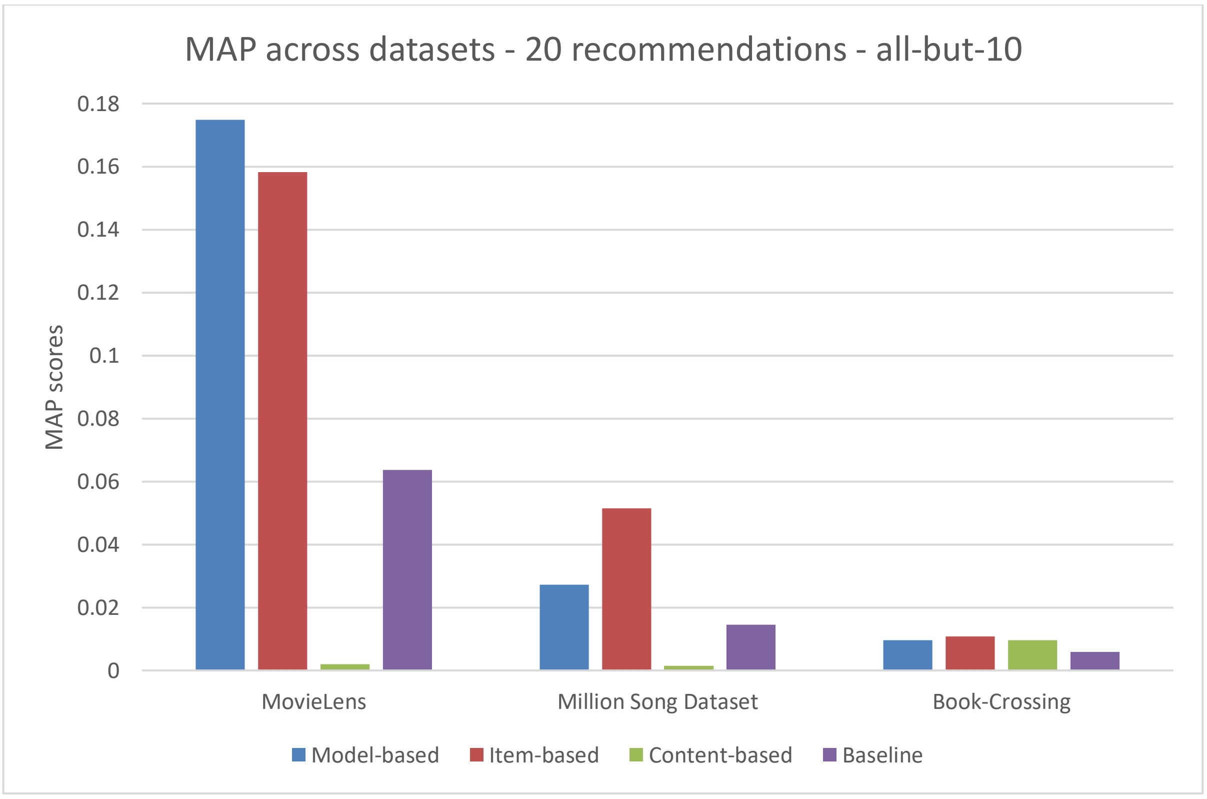


Figure 22: MAP for our algorithms for the different datasets, with recommendation list size = 20

For both MovieLens and Million Song, the content-based algorithm scores very low, while the baseline algorithm's accuracy lies between the ones of the two collaborative filtering algorithms and the content based algorithm. In the Book-Crossing dataset, the accuracy of the algorithms is more even, although the two collaborative filtering algorithms score best, once again. In this domain, the content-based algorithm performs better than the baseline algorithm, unlike the results in the two other domains. The content-based algorithm performs better in Book-Crossing than it does for the two other datasets. All the other algorithms tend to perform better in Million Song, and even better in MovieLens.

To avoid possible biases from the MAP measure, we will also present the results of ARHR, HR and precision, which were explained in Section 2.5.3, for the algorithms on the different datasets. This enhances the validity of the data for accuracy. A value of 1.0 for HR means that all users get at least one correct recommendation, a value of 1.0 on ARHR means every user get a correct recommendation on the first index in the recommendation list, and a 1.0 score in precision means all of the recommended items are correct, i.e., the items are in the users' test sets. A 0-score, on the other hand, means for all of the metrics that none of the users get any correct recommendations. Again, as with MAP, the best indication of an algorithm's successfulness is found by comparing its accuracy with the baseline accuracy.

In Figures 23-28, the results for these measures are presented for all combinations of algorithms and datasets that are presented, for both 10 and 20 recommendations. Also for these measures, there are little differences in the accuracy when the recommendation sizes differ. The patterns are the same for the algorithms, regardless if it is 10 or 20 recommendations, on all of the datasets. The only notable differences, are that HR and ARHR tend to increase with more recommendations, and the precision tends to decrease when more recommendations are given. This is a consequence of how the different metrics measure the accuracy. Precision is found by dividing the number of relevant recommendations to the number of recommended items, and therefore tends to decrease its score when more recommendations are given. HR and ARHR sum up values based on the number of hits, i.e., the first relevant recommendation for a user, and the hits' positions (only in ARHR), and ignores items outside the recommendation list. Therefore, it is as expected that the accuracy increases for these two measures when more recommendations are given.

For the MovieLens dataset, the metrics in Figures 23 and 24 show the same tendency as for the MAP, as shown in Figures 21 and 22, with the collaborative filtering approaches as the most accurate. However, the difference in accuracy seems to be smaller between item-based and model-based for HR, ARHR and precision than for MAP. Figures 25 and 26 show that all of HR, ARHR and precision give the same accuracy pattern as for MAP when it comes to the Million Song dataset: The item-based is the most accurate, and model-based the second most accurate.

In the Book-Crossing dataset, there are larger differences between the results of the different metrics, as can be seen in Figures 27 and 28. Content-based scores best for HR, with model-based second, and item-based and baseline last. The same tendency is present for the precision. This is different from the MAP for the same dataset, shown in Figures 21 and 22, where the order from best to worst was: item-based, model-based, content-based and baseline. The results of ARHR, on the other hand, show more similarity to MAP, with model-based and item-based performing best. A possible reason for this, is that these two metrics take into account the positions of the correct recommendations in the recommendation list when computing the scores. Overall, this implies that the algorithms have more similar accuracy in this domain. It is not clear which algorithm that performs best: this depends on the metric used. However, item-based, model-based and content-based seem to give the best overall scores among the metrics.

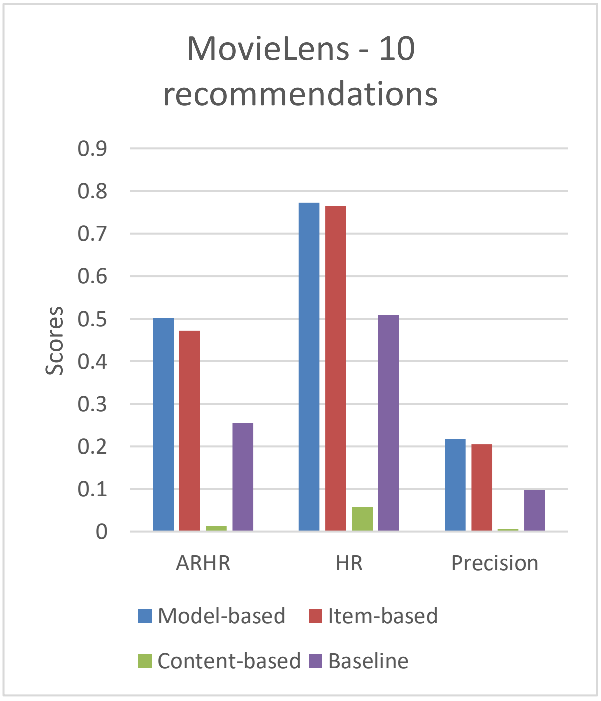


Figure 23: Various accuracy measures for algorithms on MovieLens, tested with 10 recommendations

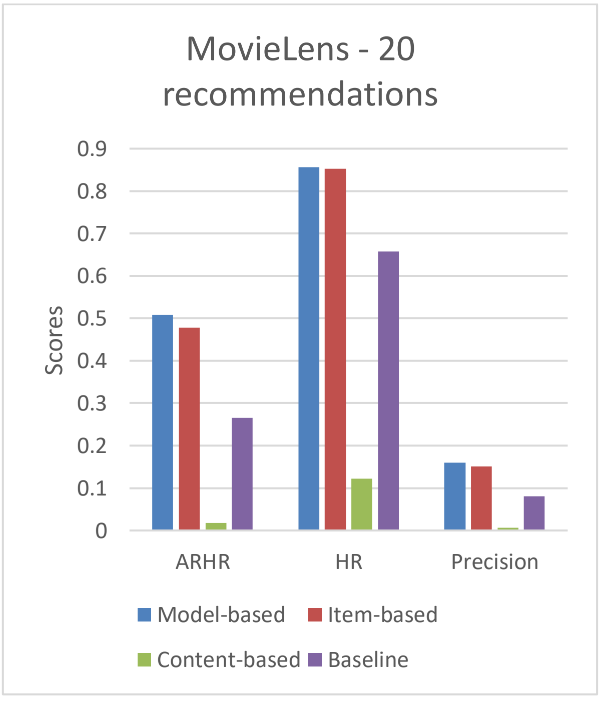


Figure 24: Various accuracy measures for algorithms on MovieLens, tested with 20 recommendations

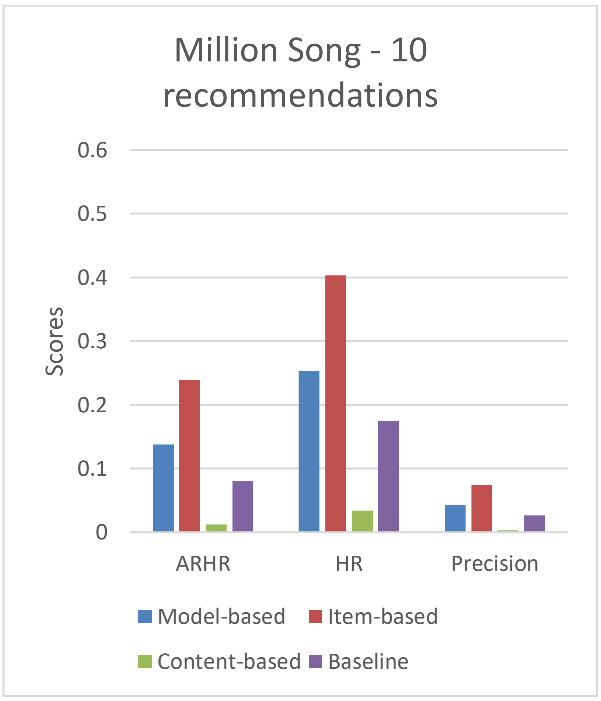


Figure 25: Various accuracy measures for algorithms on Million Song, tested with 10 recommendations

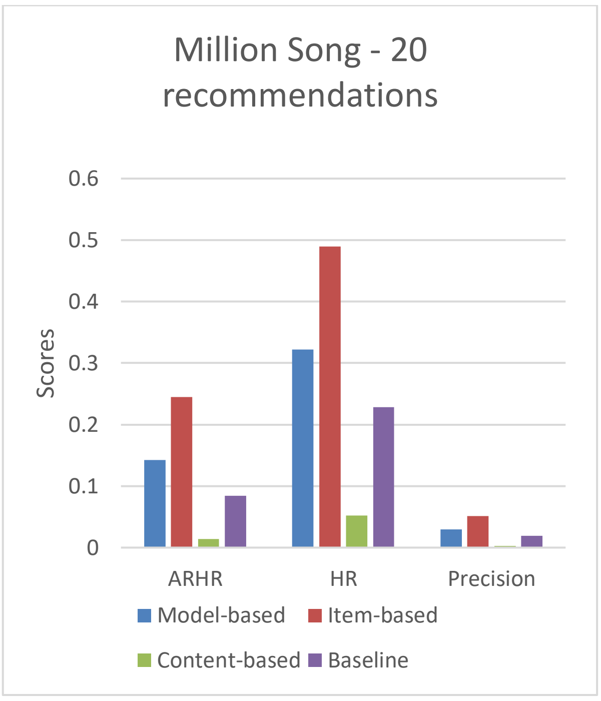


Figure 26: Various accuracy measures for algorithms on Million Song, tested with 20 recommendations

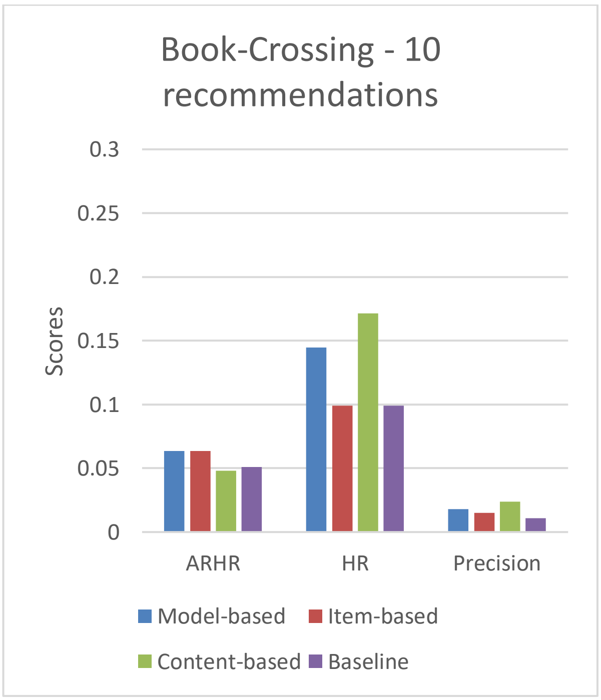


Figure 27: Various accuracy measures for algorithms on Book-Crossing; tested with 10 recommendations

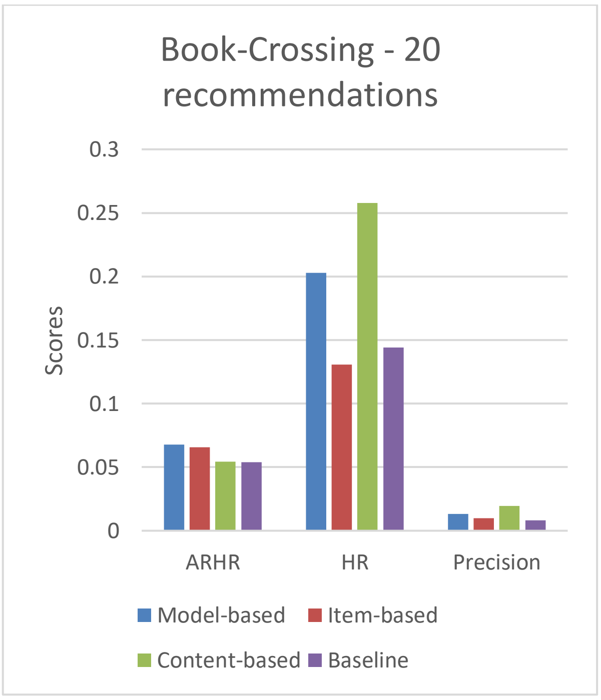


Figure 28: Various accuracy measures for algorithms on Book-Crossing, tested with 20 recommendations

If we take all metrics into account and look at which algorithms that are most accurate overall in the datasets, it is clear that the two collaborative filtering approaches, i.e., model-based and item-based, give the highest accuracy. In MovieLens and Million Song, they perform considerably better than the two other algorithms, while they in Book-Crossing perform best together with the content-based algorithm. When it comes to which of them that is the most accurate, it is quite even. Model-based is the best performing algorithm in MovieLens, item-based is the best-performing in Million Song, while they perform similarly in Book-Crossing.

Content-based is performing as good as the collaborative filtering algorithms in Book-Crossing, but shows very weak accuracy for the two other domains, which can be caused by differences in the tags for the different datasets or other domain differences. The baseline is not giving the best accuracy in any of the domains, but gives some accuracy for all three domains, which is understandable as it always recommends the most popular content, not personalizing its recommendations.

To summarize, the two collaborative filtering algorithms – item-based and model-based – are the most accurate algorithms, but it is not easy to decide which of them that gives the best accuracy all in all. Therefore, using one of these algorithms, will be a good option to give the long-time users recommendations with high accuracy. This is as expected since collaborative filtering algorithms are known as the most mature and most implemented recommendation approaches, and are known to give recommendations of high accuracy, as stated in Section 2.2.1.

5.2.2 Accuracy for new users

Here, we will present and discuss the results necessary to find out which of the recommendation algorithms that give best accuracy for new users, i.e., users with little item interaction-history. This is simulated by using a given-*n* approach. We will use given-2, given-5 and given-8, which means we will use either 2, 5 or 8 ratings for each test user as training data, while the rest of the test users' ratings will be used as test data. All of the results are obtained by using a recommendation list size of 10 and using binarized ratings. The metrics HR, ARHR and precision will not be included in this section, as we found that they overall give the same results as MAP for the given-*n* approach.

In Figure 29, the MAP for our algorithms are shown for the different datasets with a given-2 approach. For MovieLens, the best accuracy is obtained by the model-based algorithm, with baseline and item-based not far behind. In both Million Song and Book-Crossing, the model-based and the baseline algorithm give the highest values of MAP. Content-based is the least performing in both MovieLens and Million Song, but has higher accuracy than item-based in Book-Crossing. Model-based therefore seems to give the best results for users with 2 known ratings, but also the baseline algorithm performs good at this task.

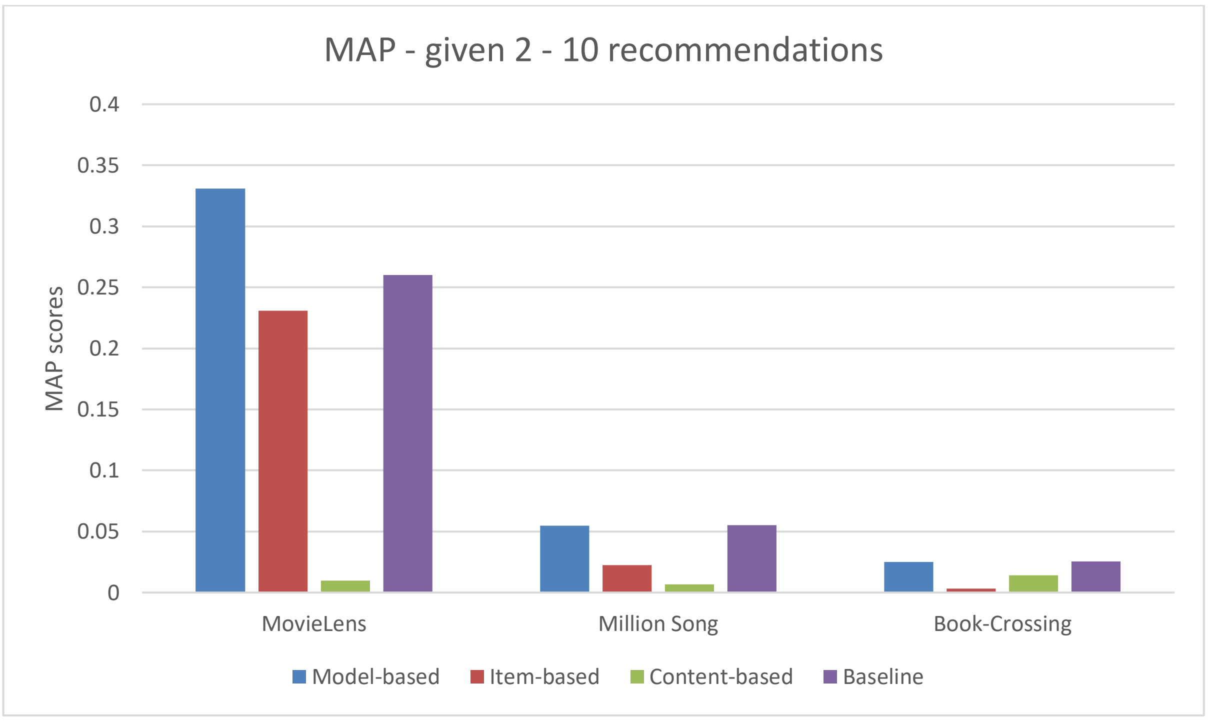


Figure 29: MAP for our algorithms on datasets with a given-2 approach

In Figure 30, we can see how the accuracy of the algorithms differs for the datasets when 5 ratings are known for each test user. Again, as in given-2, the model-based algorithm performs best for MovieLens, but this time with item-based right behind. Item-based also performs well in Million Song, together with model-based and baseline, but performs poorest of the algorithms in Book-Crossing. In this dataset, the model-based and the baseline perform best, right in front of content-based filtering. Model-based and baseline therefore seem to be the most accurate algorithms across the datasets for the given-5 approach, as also was the case for given-2, but now with item-based performing good for two of the datasets.

The accuracy of the algorithms with the given-8 approach, shown in Figure 31, shows much of the same tendencies as the accuracy for given-5, as seen in Figure 30. In short, the two collaborative filtering algorithms give best accuracy for MovieLens and Million Song, while model-based and baseline give best accuracy for Book-Crossing. The most notable difference between given-5 and given-8 is that the item-based is the best performing algorithm for the Million Song with given-8, when it in given-5 performed similar to the model-based and baseline algorithm. Overall, the model-based seems to be most accurate for given-8. The baseline performs quite good in all of the domains, while the item-based performs well in two of the domains and weak in the last.

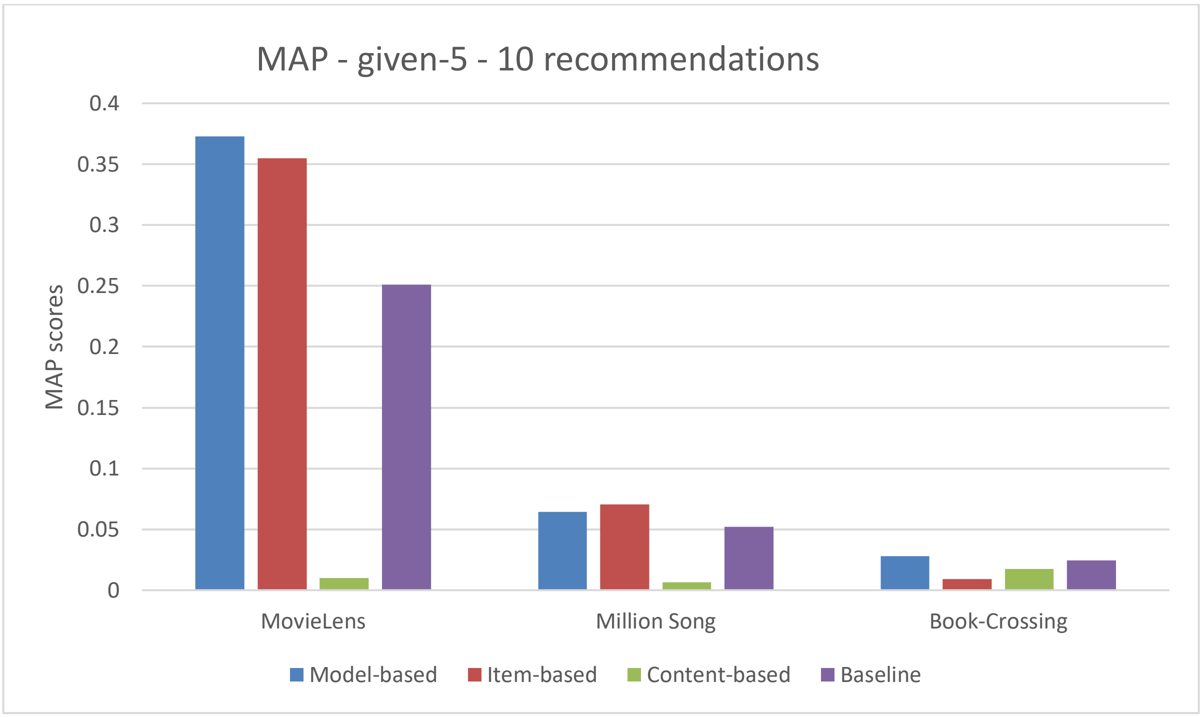


Figure 30: MAP for our algorithms on datasets with a given-5 approach

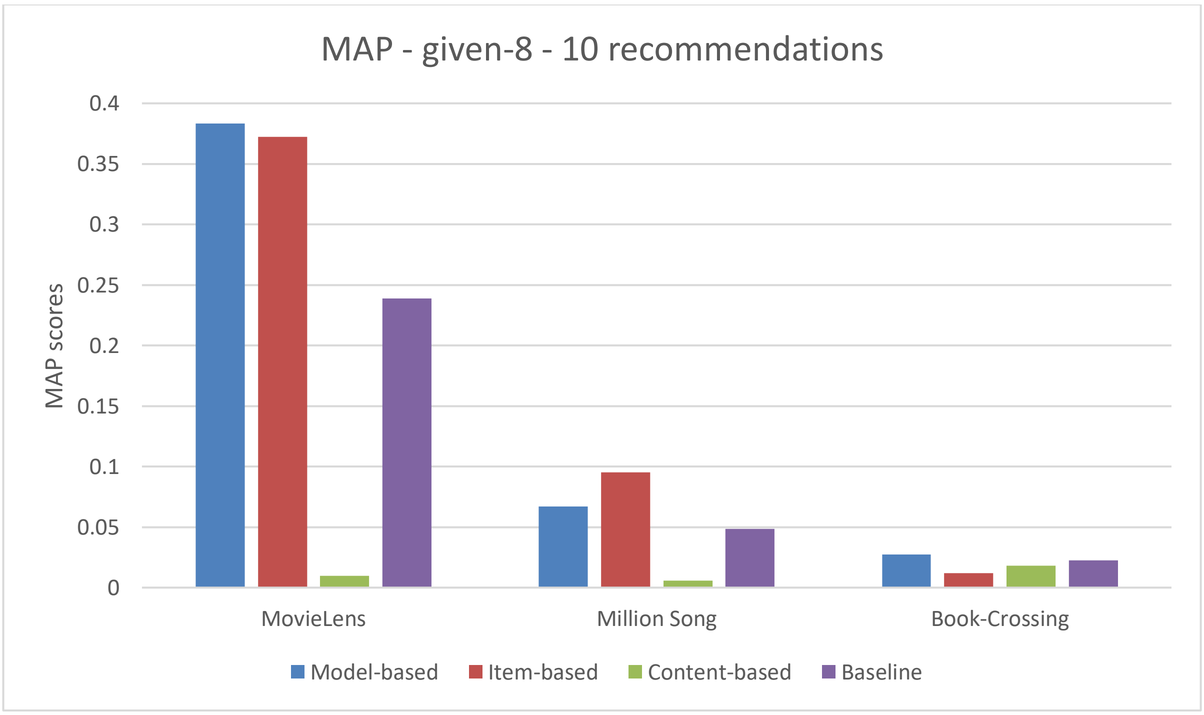


Figure 31: MAP for our algorithms on datasets with a given-8 approach

The results of accuracy for users with limited rating history show the overall same tendencies as for the general accuracy, with two main differences: (1) the item-based algorithm does not perform as good for new users as it does for old users when compared to the other algorithms, and (2) the baseline performs better for new users. For both users with 2 and 5 ratings, the model-based and the baseline give the best accuracy across the datasets. Therefore, these two algorithms seem to be the best options in order to give high accuracy for new users.

This is as expected as the baseline does not need any previous ratings for the user the recommendations are made for. It only needs to know which items that are most popular among all the users, and can therefore recommend items to new users as accurate as to users with more item interaction history. The model-based approach is also known to be better for cold start situations than the item-based because it can reduce the rating matrix to a smaller model and utilize both similarities among users and items, as stated in Section 2.2.1. Therefore, the fact that this algorithm performed well was not a surprise either.

The most surprising with the results of the accuracy for new users, however, was the weak performance of the content-based filtering. The content-based filtering is in recommendation system literature often mentioned as the best approach for cold start situations for both new users and new items (Koren, Bell, and Volinsky 2009, Bari, Chaouchi, and Jung 2014, 36), but this was absolutely not the case in our experiments. This algorithm performed clearly poorest of the algorithms for new users in two of the datasets, and third best, out of four, in the Book-Crossing dataset. One reason for this, may be that the datasets do not contain enough content information for the content-based algorithm to work properly. For both MovieLens and Million Song, genre tags were used as content information, while for Book-Crossing, publisher information was used as content data. The accuracy in Book-Crossing was better than in the two other datasets, which can indicate that this kind of content information is better suited for content-based filtering. However, the differences may come from differences in the domains; maybe this algorithm only is better suited for the book domain than for the movie and song domain. One could also wonder if there were any errors in the algorithm, causing the weak results, but when choosing the algorithms, we also tested an alternative content-based filtering implementation, which used a *k*-nearest neighbours approach – where similarities were computed between items based on their tags, and predictions were computed based on the *k* most similar items to the ones the user has rated before, and this gave even worse accuracy.

To give an overview of how the accuracy changes for different levels of known ratings, Figures 32-34 show for each of the datasets how the MAP changes from given-2, 5 and 8. “g2”, “g5” and “g8” in the figures mean given-2, 5 and 8 respectively. The accuracy for the model-based and the item-based algorithm increase from given-2 to given-5 and increase further to given-8 for all of the three datasets. The content-based, on the other hand, performs on the same level when more items are given for MovieLens and Million Song, while it in Book-Crossing has a positive change in accuracy from given-2 to given-8. In all three datasets, the baseline algorithm has a small decrease in accuracy when more ratings are known. This is probably due to the fact that when more ratings are given in the training set, the number of items in the test set is reduced.

For MovieLens, the best accuracy for new users is obtained by model-based collaborative filtering. When more ratings are given, the item-based algorithm’s accuracy increases and is almost on the same level as the model-based. In both Million Song and Book-Crossing, the model-based and the baseline algorithm perform best for new users. With some more ratings, the item-based performs best in Million Song, while the model-based and baseline continues to perform best in Book-Crossing.

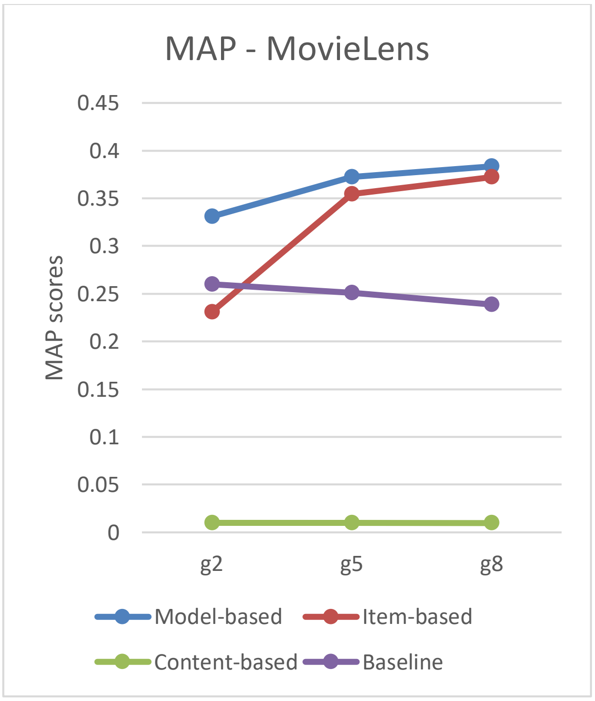


Figure 32: MAP for MovieLens for different rating splitting conditions

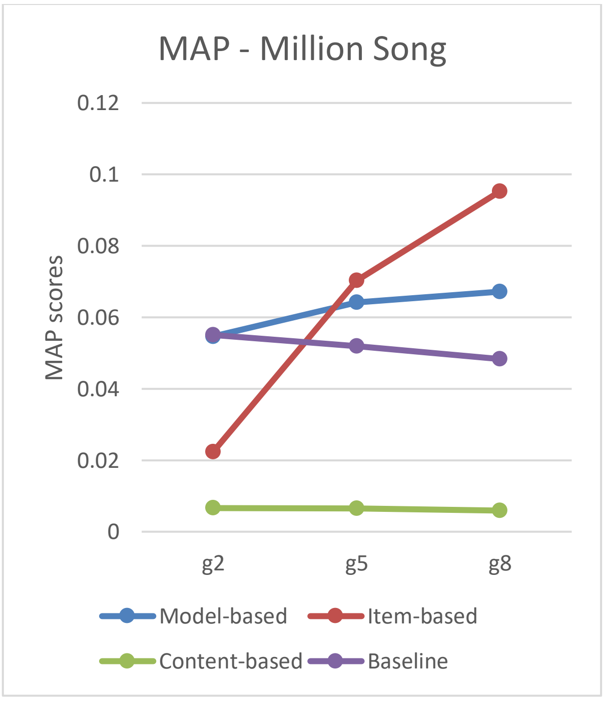


Figure 33: MAP for Million Song for different rating splitting conditions

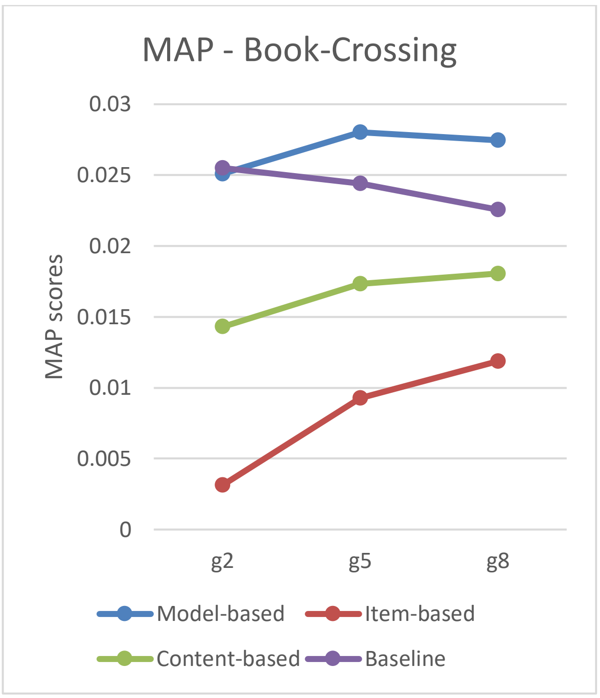


Figure 34: MAP for Book-Crossing for different rating splitting conditions

These results show that when more ratings are given for each user, the accuracy evolves different for the different algorithms in our experiments. Both item-based and model-based perform better when the number of given ratings is increased from 2 to 8, but the increase is clearly larger for the item-based algorithm. The baseline, on the other hand, shows no improvements with more ratings, which is as expected as the recommendations are independent of the user's ratings. The content-based algorithm shows improvements with more known ratings for the Book-Crossing dataset, but performs steadily in the two other domains with more known ratings.

In our experiments, all algorithms show lower accuracy for all-but-10 than for given-8, even though more ratings are given for all-but-10. The reason for this comes most probably from how the accuracy is measured for top-*n* recommendations. In all-but-10, fewer items are hidden and it becomes harder to recommend the hidden items. Therefore, we shall be careful comparing the accuracy across the different number of known and hidden ratings. A better measure for this, would be a rating prediction measure, as RMSE or MAE, which is not affected by number of hidden ratings. Another limitation of our evaluation of algorithms' accuracy for new users, is that we evaluated only three different levels of given-*n*. Ideally, we would have measured the accuracy for more values of *n*. This would have given a more complete picture of the change of accuracy when more user interaction data are available.

However, there is no reason to believe that this would change the clear tendencies in the results.

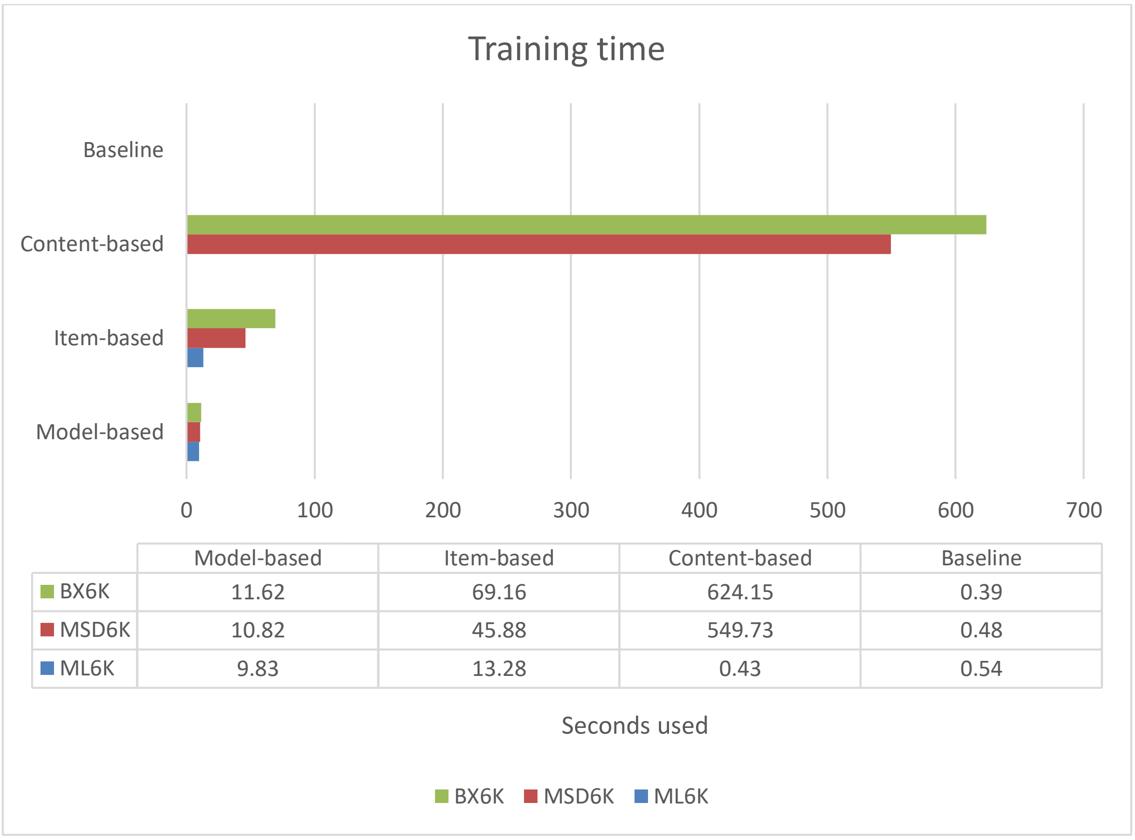
To summarize this section, the best accuracy for new users is obtained by the model-based and the baseline algorithm. The algorithms differ in how their accuracy changes with more ratings.

5.2.3 Scalability

In this part, we will look at the scalability of the recommendation algorithms. We will use the training time and prediction time of the algorithms to determine their scalability. Training time is the time used for training the model, so that recommendations can be made, while the prediction time is the average time used for producing a list of recommendations for one user. We will first look at the training and prediction times for the three datasets used for testing of accuracy in Sections 5.2.1 and 5.2.2, and afterwards, we will look at the same measures for three subsets of MovieLens with different sizes.

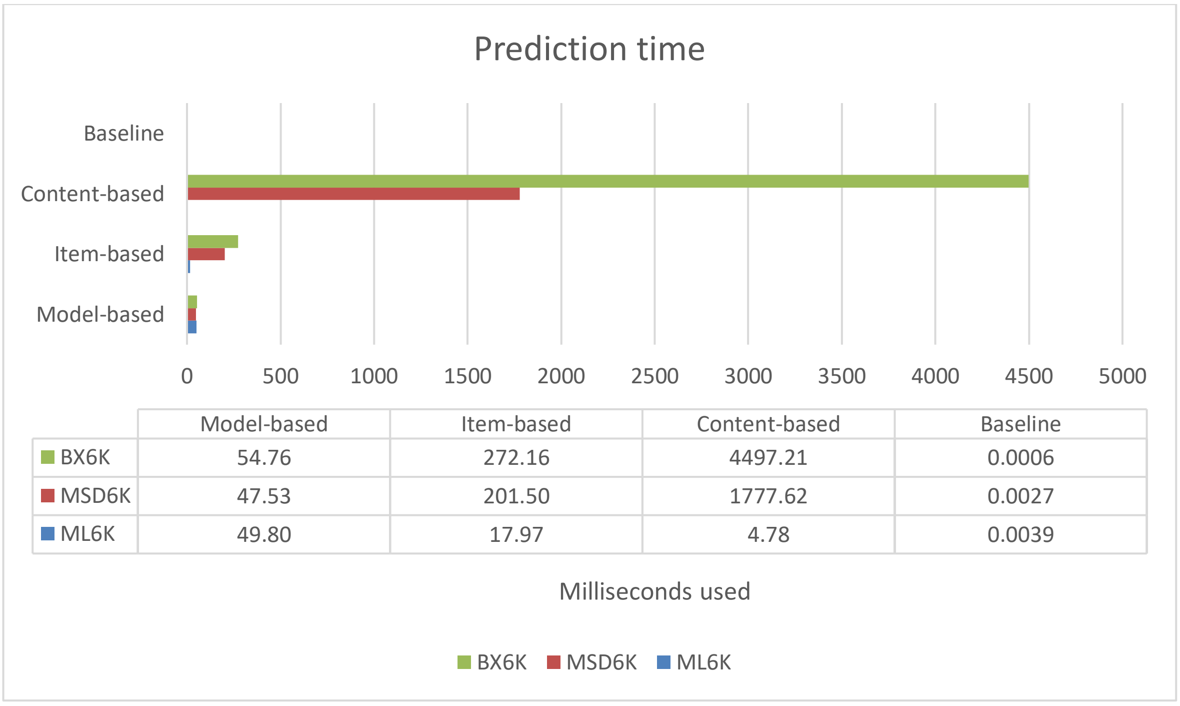
In Figure 35, the training time for the presented algorithms are shown for the sampled subsets of MovieLens, Million Song and Book-Crossing. There are large differences for the algorithms in the time used for training the recommender. The baseline algorithm uses less than 1 second for training in all three datasets, while the model-based uses around 10 seconds for all three. The item-based varies more. It uses 13 seconds on MovieLens, 46 seconds on Million Song and 69 seconds on Book-Crossing. The largest differences, however, are found for the content-based algorithm. This algorithm uses from under 1 second on MovieLens to around 600 seconds on the two other datasets.

Also in prediction time, there are large differences for the algorithms on the three datasets. This can be seen in Figure 36. The results of the algorithms in prediction time show the same tendency as for the training time. The baseline algorithm does again use the least amount of time, from 0.0006 to 0.0039 milliseconds, while the model-based overall is the second fastest, using around 50 milliseconds for all three datasets. The item-based varies from 17 milliseconds on MovieLens to between 200 and 300 milliseconds for Million Song and Book-Crossing. Also, this time does the content-based algorithm vary the most, from around 5 milliseconds for MovieLens to 1778 milliseconds (1.778 seconds) for Million Song and 4497 milliseconds (4.497 seconds) for Book-Crossing.



	Model-based	Item-based	Content-based	Baseline
🟩 BX6K	11.62	69.16	624.15	0.39
🟥 MSD6K	10.82	45.88	549.73	0.48
🟦 ML6K	9.83	13.28	0.43	0.54

Figure 35: Training time for our algorithms on the different datasets



	Model-based	Item-based	Content-based	Baseline
🟩 BX6K	54.76	272.16	4497.21	0.0006
🟥 MSD6K	47.53	201.50	1777.62	0.0027
🟦 ML6K	49.80	17.97	4.78	0.0039

Figure 36: Prediction time for our algorithms on the different datasets

In these results, we can see large differences both between the algorithms and between the domains when it comes to training and prediction times. The most notable from the results, is how much time the content-based algorithm uses for both training and prediction in Million Song and Book-Crossing. This algorithm is several times slower on these datasets than the algorithm that uses second most time. However, the content-based algorithm is among the fastest in the MovieLens dataset, both for training and prediction. The reason for this is most probably the number of tags in the datasets, which varies from 19 distinct ones in MovieLens to around 50 000 ones both in Million Song and Book-Crossing. This algorithm's computation has a linear time complexity in number of items and tags, because each user and item is represented by feature vectors, and similar items to a user are found by computing the dot-product of the user's feature vector and all items' feature vectors, as mentioned in Section 4.2.3. However, when both number of items and tags get larger, as in Million Song and Book-Crossing, this algorithm gets very time-consuming.

A possible solution to increase the efficiency of the content-based algorithm, is to use *feature selection*, which means to keep only a subset of the tags (Jannach et al. 2010, 72). Then, statistical techniques can be used to select the most informative words to keep, usually around 100. This does not only reduce the computation time needed for the content-based algorithm, but also decreases overfitting, which was explained in Section 2.5.1. However, using this strategy can remove important information describing items, and therefore reduce the number of items that contain metadata and consequently decrease the number of possible items to recommend.

The results also show that the baseline algorithm is the fastest algorithm for both training and prediction in all of the datasets. This is as expected as it only counts items' user interaction frequencies to find out which items that are the most popular. The model-based algorithm gives the second best results overall, performing better than the item-based in both Million Song and Book-Crossing. However, it performs not as good as the item-based for MovieLens. Item-based has a quadratic complexity in terms of items, as stated in Section 2.2.1, because it for each item must compare the item to all other items to find similarities among items. The model-based algorithm, on the other hand, has a linear time complexity in both number of items and users, but scales cubic with number of latent factors, as stated in Section 4.2.2, but the number of latent factors is usually a small number, set to 10 in our implementation. The item-based algorithm's quadratic complexity for number of items can explain why it performs weakly for Million Song and Book-Crossing, which have the largest number of items, but performs better on the MovieLens dataset, which has a smaller number of items. The model-based algorithm's cubic complexity in number of latent factors, does not make it the fastest algorithm with smaller number of users and items, but its linear complexity in number of items and users makes it perform more steadily across the datasets.

In Figure 37, the training times for the algorithms are shown for three subsets of MovieLens of different sizes. The content-based and the baseline algorithm shows only very small differences in the training time when the number of ratings increase. The model-based algorithm and especially the item-based increase more in training time when the dataset contains more ratings.

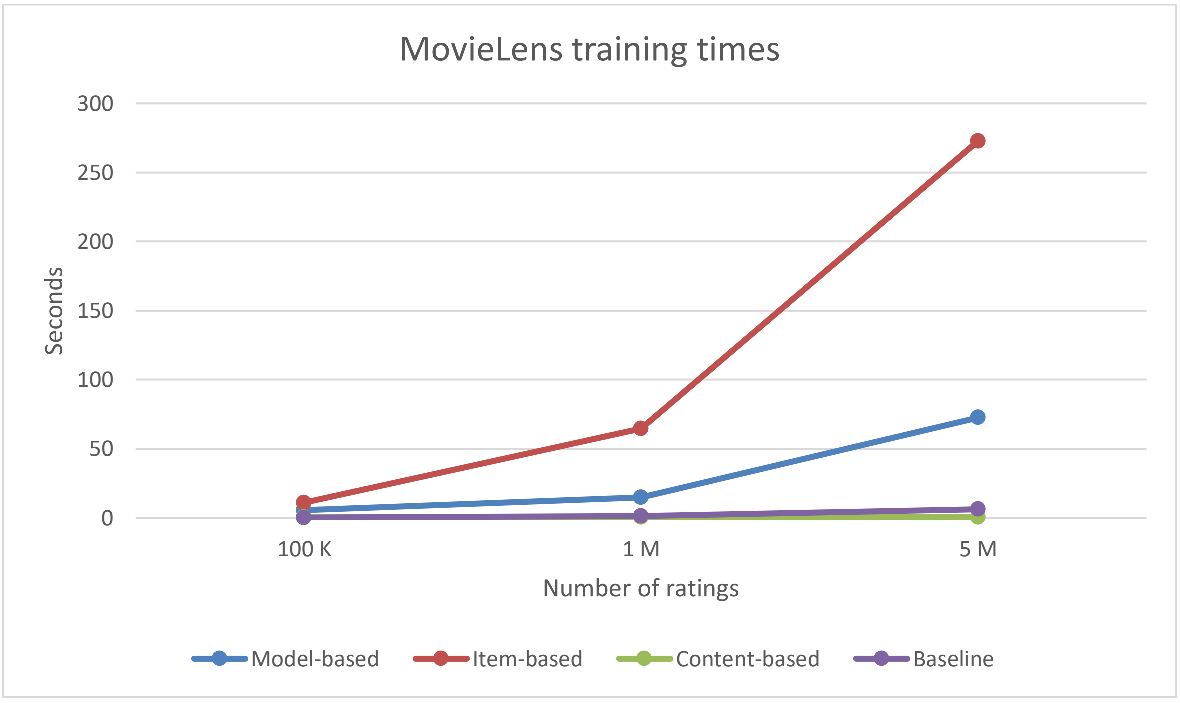


Figure 37: Training time used by our algorithms on different subsets of MovieLens

Figure 38 shows the prediction times of the algorithms on the three same subsets of MovieLens. Again, baseline uses the least amount of time for producing recommendations. The largest growth in prediction time is seen for the item-based algorithm, but also the content-based algorithm shows some increase when the number of ratings increase. Model-based, on the other hand, is the slowest on the smallest subset, but performs almost stable over the three rating sizes.

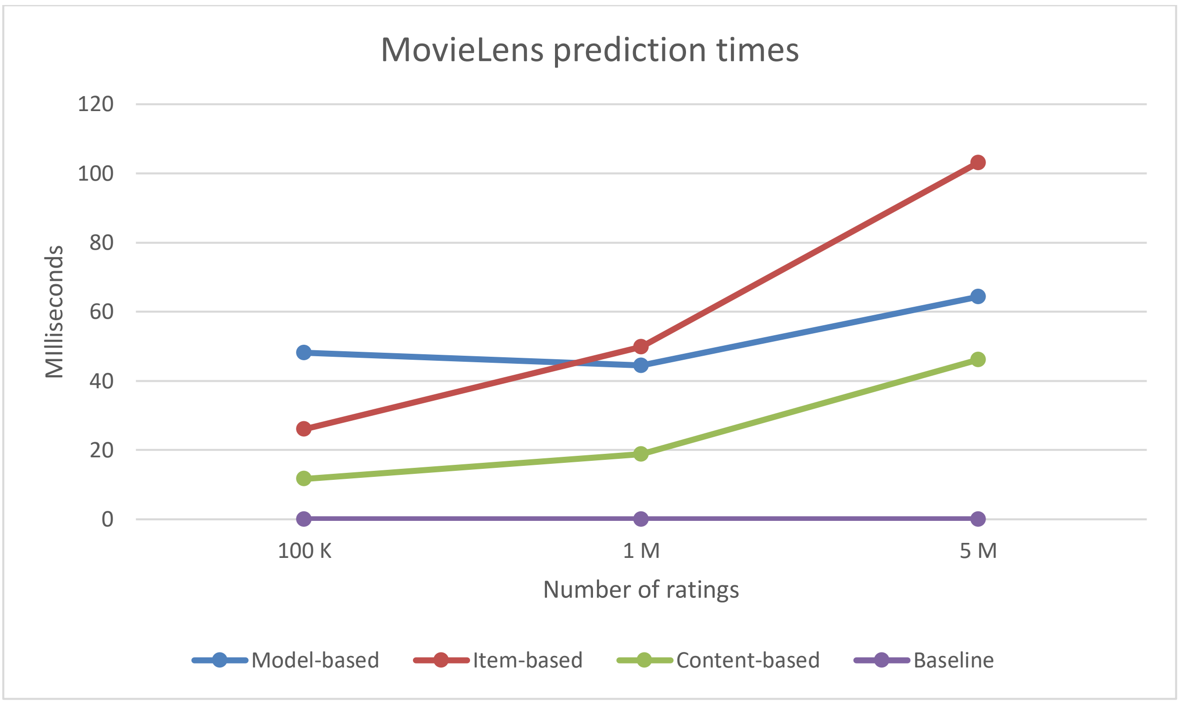


Figure 38: Prediction time used by our algorithms on different subsets of MovieLens

The results from the three different subsets of MovieLens, show that the baseline algorithm is the fastest overall for training and prediction, showing little signs of increase in time-usage when the number of ratings increases. Content-based scales well for training time, while model-based and especially item-based show a large increase in time spent with more ratings. The prediction time also increases fast along the number of ratings for the item-based algorithm. The model-based, on the other hand, performs more steadily across the rating sizes for this, while content-based shows a small increase. The largest difference between the results for the three subsets of MovieLens and those from the three different domains, is that the content-based performs much better in the three subsets of MovieLens, which most probably is caused by the small number of tags in the MovieLens dataset.

Overall, taking all results into account, the baseline algorithm seems to be the most scalable algorithm, both in training and prediction time, which is unsurprising as it only counts the frequencies of the items. The model-based algorithm seems to give the second best scalability. In the training time, it shows some increase, but in the prediction time it performs steadily with more users and items, which is the most important to give users fast recommendations. The training time can be done offline in the background, and are therefore not as important as the prediction time as long as it is within a reasonable time frame. The content-based algorithm scales rather good with the number of items and users, as long as the number of tags is kept to a small number. If the number of tags gets large, however, this algorithm gets very slow. This algorithm performs steadily in training time when more ratings are given, but shows a certain increase in prediction time with more ratings. Therefore, this algorithm does not seem to be as good as the baseline and the model-based when it comes to giving fast recommendations to a large user base. The item-based algorithm scales poor for larger numbers of items both for training and prediction, and therefore seems to be the least scalable of the implemented algorithms in terms of number of users and items.

All of the training and prediction times for the MovieLens subsets are in an acceptable time frame for all of the algorithms. The highest training time for the largest subset, with 5 million ratings, is just below 300 seconds, which is for the item-based algorithm. As the training can be done offline and not in real-time for each user, this number is tolerable. The prediction time, on the other hand, is more important for giving the users fast recommendations and a good user experience. The highest prediction time for the 5 million ratings subset, is also found for the item-based algorithm and are just over 100 milliseconds. This means all of the algorithms can produce recommendations for such a number of ratings in a reasonable amount of time, where the user does not need to wait for the recommendations to appear. However, if the number of ratings or tags increase, both the item-based and content-based will have problems with recommending items in a reasonable time frame, as they do not scale well for number of items and tags, respectively.

To get even better data about the scalability of the algorithms, we could have tested the algorithms with even larger datasets, and also with varying sizes of users, items and tags. This has not been conducted because of time limits in the thesis, but can be interesting for further research. However, our evaluation of the scalability, has given an overall picture of how our algorithms scale, and given good indications of which algorithms that scale best and worst.

To summarize, the baseline and the model-based algorithm show the best scalability, while the item-based seems to be the least scalable. The content-based can scale rather good if feature selection is done or the number of tags are kept to a small number.

5.3 Discussion of cross-domain accuracy

In this section, we will discuss which differences and similarities that are found in the general accuracy of our implemented algorithms across the datasets. We want to find out if there are any consistencies in the accuracy across the domains. This is important for answering research question Q2, and for the findings to be generalizable to Forzify's case. If no consistencies exist, we cannot generalize to Forzify's case, but if the algorithms perform consistent across the different domains, we get good indications of what can be the best choice for Forzify.

It is clear in our results that the accuracy in the different domains differs to a large extent. Overall, the algorithms perform much better in MovieLens than in Million Song, and they perform clearly the poorest in Book-Crossing. The only exception here, is the content-based algorithm which performs better in Book-Crossing than in the other datasets. There could be various reasons for these differences. First of all, it could be domain differences that make the algorithms work better or worse. For example, as Im and Hars (2007) point out, different domains have varying preference heterogeneity, i.e., the tendency for peoples' preferences to overlap varies from domain to domain. This can make the algorithms perform better in one domain than in another. The differences in preference heterogeneity of the sampled datasets is visible in Table 10, where the characteristics of the sampled datasets are presented. For each dataset, we randomly chose 6000 users which all have rated between 20 and 200 items, so the average number of ratings per user are quite similar for the sampled datasets. The number of different items rated in total, however, differ to a large extent in the sampled datasets: from 7 359 in MovieLens to 87 957 and 150 771 in Million Song and Book-Crossing respectively. This shows there is larger preference homogeneity in MovieLens than in the two other domains, which can be one reason for the higher accuracy in this domain. The differences in the content-based algorithm's results across domains may in addition be explained by differences in the type of tags across the datasets.

The differences in accuracy can also be a result of the measures used. We used top-*n* measures for measuring the accuracy because this type of measure is the only one that can be used for unary ratings. This kind of measures is affected by the item catalogue sizes, in the way that it is easier to recommend relevant items from a small item catalogue than from a large one, when the number of relevant items to predict remains the same. Therefore, a better measure for detecting domain differences in accuracy can be rating prediction metrics, such as RMSE and MAE, where the number of items in the item catalogue does not affect the accuracy. However, this was not an option in our case, as we were interested in measuring accuracy across datasets with unary ratings, to get results from data as similar as possible to the data gathered in Forzify.

Also, inside each domain, we found large differences in accuracy. The differences among the algorithms were largest in the MovieLens dataset, while they also were considerable in the Million Song dataset, even though not to the same extent. In Book-Crossing, the algorithms performed much more evenly. This also points towards that the accuracy of the algorithms is domain dependent which supports the research of Im and Hars (2007). On the other hand, there are some clear tendencies in the accuracy of the algorithms that can be seen across the datasets. The two collaborative filtering algorithms tend to perform better than the two other algorithms for users in general. This tendency is strong in MovieLens and Million Song, where these algorithms are superior to the others, but also in Book-Crossing, where these algorithms perform best together with the content-based algorithm. This is consistent with recommendation system literature stating that collaborative filtering gives better accuracy than content-based filtering (Koren, Bell, and Volinsky 2009). This also indicate a cross-domain consistency in accuracy, which is advantageous as we want to use these results to find the algorithm that will be best for Forzify.

5.4 Discussion of best algorithms for Forzify

Here, we will discuss which algorithm or combination of algorithms that are best for Forzify based on the general accuracy, the accuracy for new users and the scalability of the algorithms for the different datasets. This will lay the fundament for answering research question Q3, stated in Section 1.2. In Table 13, we summarize how the implemented algorithms performed in our tests when it comes to scalability and accuracy, both in general and for new users.

When it comes to the general accuracy, the two collaborative filtering algorithms showed that they overall are superior to the other algorithms across the three domains we tested in. This does not necessarily mean that they will give the best accuracy for Forzify, but it is reason to believe that they also will perform good in Forzify's case, as the datasets used for testing have several similarities to Forzify's data and these algorithms perform better than the other algorithms in two of the datasets and among the best in the third. This means they both perform well and consistent across the datasets. Therefore, either of the item-based or the model-based collaborative filtering algorithms will most probably be the best algorithm for giving accurate recommendations for users with some interaction history on Forzify.

	Item-based	Model-based	Content-based	Baseline
General accuracy	+	+	-	-
Accuracy for new users		+	-	+
Scalability	-			+

Table 13: Summary of findings relevant for choosing recommendation approach. "+" indicates good performance, "-" indicates low performance, while no sign indicates medium performance

The model-based and the baseline algorithm gave the best accuracy for new users in our evaluation, and also performed more consistent across the datasets than the other two algorithms. The item-based algorithm needed more ratings to achieve the same accuracy, while the content-based algorithm never was able to get the same level of accuracy. Therefore, the best algorithms to use for new users of Forzify are the model-based or the baseline algorithm. One option is then to use the item-based algorithm for old users, and the baseline for new users. Another option is to use the model-based algorithm both for new and old users, as it handles both situations well.

After looking at the general accuracy and the accuracy for new users, we are left with two options. Therefore, we will look at the scalability of the two options, to decide which is the best choice for Forzify. In the first option, the baseline is used for new users, while the item-based is used for old users. From our evaluation, the baseline was the definitely most scalable of the presented algorithms, while the item-based algorithm did not scale well for larger number of items. In the second option, we stick only to the model-based algorithm. This algorithm did not scale as good as the baseline, but seems to scale better than the item-based algorithm. Therefore, from our evaluation, the best option for Forzify is to use the model-based algorithm for both new and old users. This ensures that the recommendation system scales well and at the same time can give good accuracy, both in general and for users with limited item interaction history.

In Section 3.5, we discussed which of the approaches that were best for Forzify's case according to previous research and literature, and concluded it would be best with a combination of approaches. Our conclusion based on our evaluation, however, tells the opposite: The model-based seems to perform better than a combination of approaches, both in terms of scalability and accuracy for new and old users. The main reason for this, is the low accuracy of the content-based algorithm, which was expected to perform best for new users. This algorithm only performed well in the Book-Crossing dataset. It is not easy to say why this algorithm performs weaker than expected, but it can be differences in the tags across the domains that makes this algorithm's performance more domain dependent. Another possible explanation is that this algorithm do not perform as well on top-*N* recommendation as for rating prediction, which has been the recommendation problem studied most in recommendation system research.

By using only the model-based approach, we do not utilize the content-based information that are available in Forzify. One option to get advantage from this data, without using the content-based approach that gave low accuracy, is to make different set of recommendations that are grouped together based on one or more characteristics of the items, which is similar to what Netflix does, as mentioned in Section 2.3.2. The user can then see recommendations in different categories based on the tags that most often are present in the videos the user has watched. In Forzify's case, this can mean to make one set of recommendations based on the team that has been most watched, one set for the player that are most watched and one set for the overall best recommendations for the user. These set of recommendations can then easily be explained by texts like "because of your interest in Tromsø IL", "goals by Thomas Lehne Olsen" and "top recommendations for you".

Lastly, it is important to note that our selection of algorithm for Forzify is not guaranteed to give good accuracy. When more data is gathered in Forzify, the algorithms must be tested again on this data to show how they actually perform in Forzify's case. However, as we pointed out in Section 5.3, there are consistencies in which algorithms that perform best across the domains in our results. Therefore, our evaluation has given a good indication of which algorithm that will perform best until an evaluation on Forzify's data can be carried out.

5.5 Summary

In this chapter, we have evaluated the four candidate algorithms presented in Section 4.2. The focus has been to investigate the accuracy of the algorithms, both for new and old users, and to find out which algorithms that scale best for larger datasets. We chose to use an offline evaluation, as this is a well-suited approach for measuring accuracy and scalability, and at the same time is a time- and cost-effective approach. Because Forzify has limited existing data, we had to test the algorithms on other datasets. Therefore, we wanted to find out if the accuracy differs across different datasets. If they perform the same way in different domains, it is reason to believe that they will give good accuracy also in Forzify's case.

We compared all of the datasets presented in Section 2.5.4 to the data in Forzify, and found the MovieLens, Million Song and Book-Crossing datasets to be the most similar to the data in Forzify. These datasets were therefore chosen to be used for the evaluation. We sampled one subset of 6000 random users, who each had rated between 20 and 200 items, for each of the selected datasets to ensure equal conditions for the datasets when conducting the evaluation and to make sure the evaluation could be done in a reasonable time frame. In addition, we sampled three subsets of different sizes from the MovieLens dataset, in order to test how the algorithms scale to different sized datasets.

Because Forzify only has unary data, the recommendation algorithms presented solves a top-*n* recommendation problem. Therefore, we had to choose a top-*n* recommendation metric to measure the accuracy. We selected MAP as the main measure as it both takes into account the number of correct recommendations and their positions in the recommendation list. Also, we chose to use HR, ARHR and precision to the enhance the validity of the data for accuracy. The measures for scalability was chosen to be the training and prediction times of the recommendation algorithms.

An important decision in offline evaluation, is how the datasets are split into training and test sets. To avoid bias from the users assigned to the test set, the dataset splitting was conducted with 5-fold-cross-validation, which means the evaluation is repeated 5 times, where all users are used for testing once and for training four times. As we wanted to investigate the accuracy both for new users and for old users, we decided to use two different techniques for splitting the data of the test users: all-but-*n* and given-*n*. All-but-10 was chosen for testing the general accuracy, because it gives equal number of correct recommendations for each user, and at the same time varies the number of known ratings for the user, which best models the users of a real recommendation system. To evaluate the accuracy for new users, we decided to use given-2, 5 and 8, to see how well the algorithms work for three different levels of limited user-history.

The evaluation gave us several valuable findings relevant for our research questions. There were both similarities and differences in the accuracy for the recommendations algorithms across the datasets. First of all, the accuracy varied to a large extent between the different datasets, which can be caused by domain differences, such as preference heterogeneity, but also the measures used, which are affected by the number of items in the datasets. Secondly, there were some differences in the patterns across the datasets: In MovieLens and Million Song, there were large differences between the algorithms, while in Book-Crossing, the algorithms performed much more even. However, there was a clear tendency that the algorithms performing well in one domain also do so in the other domains. Therefore, the accuracy measured of the algorithms in the three datasets, gives valuable indications of what will be the best choice of algorithms for Forzify.

For users with some item interaction history, the item-based and the model-based algorithm gave the best accuracy overall in the datasets, while the baseline and model-based gave the best accuracy for users with less item interaction history. When it comes to scalability, the baseline seems to be the most scalable of the algorithms, both for training and prediction time. The content-based algorithm does not scale well with large number of tags, but if feature selection is used or the number of tags are kept to a small number, it scales better. The model-based algorithm scales well for prediction time, while it shows a certain increase in training time when the number of items increase. However, the poorest scalability is found for the item-based algorithm which shows a large increase in both training and prediction times when number of ratings increases. In the end of the chapter, we discussed which algorithm or combination of algorithms that would be the best choice for Forzify. We concluded that the best choice, based on our evaluation, is to use only the model-based algorithm. It ensures good recommendations for both new and old users, and scales well for larger datasets.

To summarize our main findings, we list them here:

- Binarized ratings give at least as good results as arbitrary valued ratings.

- Using recommendation list sizes of 10 and 20 give small differences in accuracy, and the same patterns are present in both.

- There is both similarities and differences in the algorithms' accuracy across domains: There is higher accuracy in some domains than others, the accuracy of the algorithms is more even in some domains than others, and there is a tendency that the same algorithms perform best across the datasets.

- MAP, precison, HR and ARHR give the same tendencies for the algorithms' accuracy in all of the datasets, except for the general accuracy in the Book-Crossing dataset. In this dataset, it differs from metric to metric which algorithms that perform best.

- The accuracy of the algorithms evolves differently when more ratings are known. The highest increase is found for the item-based algorithm. The model-based shows a small increase, while the baseline does not show any increase with more ratings. The content-based shows an increase in the Book-Crossing dataset, but performs steadily in the two other datasets when more ratings are given.

- The two collaborative filtering algorithms give best accuracy for users in general.

- The model-based and baseline algorithm give best accuracy for new users.

- The baseline algorithm is the most scalable algorithm, while the model-based also scales well. The content-based scales well if the number of tags is small, while the item-based seems to be the least scalable of the algorithms.

6 Conclusion

In this chapter, we will present our conclusions by answering the research questions of the thesis. Then, we will explicitly state the main contributions of the work and address possible future research to further explore the main topics of the thesis.

6.1 Research questions

In the problem statement in Section 1.2, we formulated the following three research questions:

- Q1: According to previous research and literature, which recommendation approaches are best suited for the case of Forzify?

- Q2: Do the accuracy of recommendation system approaches differ across datasets from different domains?

- Q3: Which recommendation approach or combination of approaches can give the most accurate recommendations to both new and old users of Forzify, and at the same time give high scalability?

We will here answer these questions based on the work that has been done in this thesis.

6.1.1 Q1: Approaches suited for Forzify according to literature

To answer research question Q1, we presented the main recommendation approaches and compared them in strengths, weaknesses and in needed data. We presented the case of Forzify, and discussed which of the approaches that best suit Forzify's data and wanted features. Forzify gathers data about users' interaction with items, both explicitly and implicitly. In addition, there is content information about the videos. Our review of approaches showed that only the collaborative filtering and content-based filtering can be used with these data sources. It was wanted that the system should learn about users' preferences, produce serendipitous recommendations, handle cold start situations and scale well for a large set of users and items. We concluded that no single approach support all these features. Therefore, according to the literature, it is beneficial to use a combination of approaches, so that the advantages of one approach could reduce the disadvantages of another.

Based on these wanted characteristics and the data gathered in the application, the best choices of approaches would be collaborative filtering and content-based filtering. Both of these approaches learn about the users as they interact with the system. The collaborative filtering can produce serendipitous recommendations, while the content-based filtering can handle cold start problems in a good way. Among the collaborative filtering approaches, the item-based and model-based seemed to be the best choices, as they scale better than the user-based one.

6.1.2 Q2: Differences in accuracy across domains

To investigate research question Q2, we implemented four algorithms from different approaches: one item-based, one model-based, one content-based and one non-personalized baseline. We studied the accuracy of these four algorithms on the MovieLens, Million Song and Book-Crossing datasets. The first three algorithms were chosen based on the conclusion of the first research question. The non-personalized algorithm was primarily chosen as a baseline to compare the performance of the other algorithms against, but it is also of interest because it does not require any user data to produce recommendations. As Forzify only has unary data, the algorithms solved a top-*n* recommendation problem, and we consequently used the top-*n* recommendation accuracy metrics MAP, HR, ARHR and precision.

The results showed that there are both differences and similarities in the accuracy of the algorithms across the datasets from the different domains. On the one hand, the accuracy was generally higher in some domains than in others. In addition, the variation in the accuracy of the algorithms inside a domain was higher in some domains than in others. This supports earlier research by Im and Hars (2007) that states that the accuracy of algorithms is domain dependent. On the other hand, the two algorithms with best accuracy for general users were the same in all three datasets. This indicates that the accuracy from these datasets also will give a good basis to choose which recommendation approaches that will give good accuracy in Forzify's case.

6.1.3 Q3: Best approach for Forzify according to evaluation

To answer research question Q3, we measured the accuracy of our four algorithms on the same three datasets as in the previous section. We used an all-but-10 approach and a given 2, 5 and 8 approach, in order to simulate recommendations for users with different levels of previous interaction with items. The results showed that the item-based and model-based gave highest accuracy for users in general, while model-based and baseline gave highest accuracy for users with less item interaction history.

We also tested the training time and prediction time for these three datasets and for three different subsets with varying sizes of the MovieLens dataset. The baseline algorithm showed the best scalability, the model-based algorithm showed good scalability, while the item-based algorithm showed the poorest scalability for number of users and items. The content-based algorithm scaled well for larger number of items and users, but did not scale well for higher number of tags.

Based on these results, the best choice of recommendation approach for Forzify, is the model-based, because the algorithm from this approach gave good accuracy both for new and old users across the datasets, and at the same time scaled well for larger number of users and items. The other possible choice of approaches that could give high accuracy for both new and old users based on our results, was a combination of the baseline and the item-based approach. However, due to the poor scalability of the item-based approach, this combination will not scale as good as the model-based. Therefore, our results are contrary to the literature, as one approach seems to be a better choice than a combination of approaches.

6.2 Main Contributions

In this thesis, we have both used a theoretical and practical approach to find the best suited approach for Forzify – an application with limited existing user data. We have reviewed and compared the main recommendation approaches in terms of strengths, weaknesses and data needed, to find out which recommendation approaches that are suited for Forzify’s case. We have reviewed and compared datasets from different domains in terms of domain, sample and inherent features, so we could choose the datasets that are most similar to Forzify’s data for our evaluation. Further, we have looked at a set of commonly used recommendation frameworks, and made a comparison of these based on their properties, to let us choose the ones that are best suited for the approaches we decided to implement. These reviews and comparisons have therefore given a theoretical background for our choices in the implementation and evaluation process, but these can also give valuable contributions to other researchers or developers that plan to build or evaluate a recommendation system, especially in cases where limited user data have been gathered and other datasets are needed for testing.

We have implemented four recommendation algorithms from different approaches that are suited for the wanted features and data collected in Forzify. The first is a *k*-nearest neighbours item-based collaborative filtering algorithm implemented with Lenskit, the second is an alternating least squares model-based collaborative filtering algorithm implemented in Spark, the third is a content-based algorithm implemented with LensKit and the fourth is a popularity baseline algorithm made from scratch.

We have made an evaluation framework to evaluate the scalability and the accuracy, both for new and old users, of our implemented recommendation algorithms. The accuracy is measured by the top-*n* recommendation metrics MAP, precision, HR and ARHR. The scalability is measured by the training and prediction times of the recommendation algorithms. Our evaluation framework is also used to make the datasets and content information ready for evaluation, which includes dataset splitting and reformatting of data. The source code of the recommendation algorithms and the evaluation framework is available online, see link in Appendix A.

We have tested all of the implemented algorithms on datasets from three different domains with this evaluation framework. This has given an overview of the performance of the different algorithms and contributed to the research on how the accuracy of recommendation algorithms is affected by the domain they are evaluated in. The results showed that the model-based and the item-based algorithm give the best accuracy for users in general, while the model-based and baseline give the best accuracy for new users. When it comes to scalability, the baseline is the clearly most scalable algorithm, but also the model-based algorithm scales well. The content-based does not scale well for larger number of tags, while the item-based seems to be the least scalable for larger number of items and users. Our results show that the accuracy of recommendation algorithms is domain dependent. However, the two algorithms performing best, did so in all datasets.

Based on the testing, we have concluded with the model-based approach as the best choice for Forzify, as it gives accurate recommendations both for new and old users across different domains, as well as it can scale to larger sizes of users and items. As this approach performed among the best in terms of accuracy in all of the domains, it is likely that it will perform well also in the domain of Forzify. A combination of the other approaches seemed not to be a better choice according to our tests, which is contrary to what most recommendation literature state. Another unexpected finding from our tests was that the content-based approach did not perform well in accuracy for new users.

6.3 Future Work

In this thesis, we have found out which recommendation approaches that are best suited for the case of Forzify, and we have investigated the differences in accuracy for recommendation approaches across different domains. There is more research that can be done to further explore both of these topics.

First of all, the best way to find the most suitable approach for Forzify is to test the approaches on Forzify's own data, when sufficiently data are gathered. This can be done both as an offline experiment, as we have done in this thesis, but the best data will be obtained by doing an online experiment with real users. Comparing the accuracy of the algorithms on Forzify's data with our test results can give us valuable information regarding how successful our choice of approach was. In our tests, we have focused on accuracy and scalability, but as we saw in Section 2.5.2, there are several other dimensions relevant for evaluation of recommendation systems. Testing the approaches on more of these dimensions will give additional valuable data about the successfulness of the approaches.

Our implementations and testing were limited by time and space. To further investigate the research topics in this thesis, it could be interesting to conduct more thorough testing, e.g., test more algorithms from each approach, test on larger datasets and more datasets, do parameter tuning to find the best possible accuracy for each algorithm in each domain or test with more variations of *n* in given-*n* to get an even better understanding of how the accuracy evolves with more ratings.

To further investigate the algorithmic consistencies in accuracy across domains, it would be interesting to test with even more algorithms and on more datasets from different domains, and look if the same tendencies can be seen. We have only tested the accuracy with top-*n* recommendation measures and algorithms. To get a better understanding of the differences across the domains in general, we could use a rating-prediction problem and see if this gives the same patterns. Using rating prediction algorithms and metrics can be a better way to investigate domain differences in accuracy, because these measures are not affected by the number of hidden items, as the top-*n* recommendation measures.

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Appendix A – Source code

The source code used for our recommendation system algorithms and our evaluation framework is accessible on GitHub:

https://github.com/simenrod/recsys_simenrod