INTERNATIONAL
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Product Recommendation System

Paraskevopoulos Athanasios

SID: 3306160004

SCHOOL OF SCIENCE & TECHNOLOGY

A thesis submitted for the degree of

Master of Science (MSc) in Mobile and Web Computing

DECEMBER 2017

THESSALONIKI – GREECE

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Supervisor:	Assistant Professor Dr. Christos Tjortjis
Supervising Committee Members:	Faculty Member Dr. Christos Berberidis
	Academic Associate Dr. Marios Gatzianas
	Assistant Professor Dr. Christos Tjortjis

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Abstract

This dissertation was written as a part of the MSc in Mobile and Web Computing at the International Hellenic University. The aim of this work is to investigate if user's demographics data and ratings entropy0 scores can have an impact on addressing the cold start problem in collaborative filtering. We propose four collaborative movie recommender systems that use ask-to-rate techniques by displaying movies to users for rating.

The implementation of the aforementioned systems was done in Python 3.6 programming language, developing four independent scripts that display movies for rating using different ask-to-rate techniques: random choice of movies, demographic based, entropy0 based , mix of demographic and entropy0 based.

In the evaluation we have taken into consideration both the accuracy of the predictions but also the user effort. The results have shown that there is (almost) a tie for the first place between demographic-based and entropy0-based systems both in terms of user preference score but also in terms of user's effort (entropy0 based system is only marginally better). Furthermore, we can also see that the system with the combination of demographics and entropy0, is slightly better (in terms of user preference score) than the basic (random selection), even if the user effort is much higher. Finally, for a future work we can use a movie-set with newer movies or a completely different dataset with another type of products like electronic devices, books etc. Moreover, a mobile implementation can make recommender systems even more useful and also valuable.

Last but not least, I would like to thank my supervisor Dr. Christos Tjortjis for all his valuable support and guidance that he has given me the past six months.

Student Name: Athanasios Paraskevopoulos

Date: 29/12/2017

Contents

1 Introduction

Over the last decade, the rapid growth of technology has led to an enormous amount of information enabling even an average internet user to have a wide variety of options. Electronic shops like Amazon or E-bay are offering plentitude of products, online newspapers are publishing numerous articles every day while other websites like Netflix are offering thousands of movies to their subscribers. Statistics have also shown that the number of internet users is growing more and more. More specifically we can see that from 2000 to 2017 there is a growth of 976 % in the global internet usage [1].

Although technology evolution is making a huge progress, there are several disadvantages that should be taken into consideration. Using the search engines in order to find something that I would like seem very generic and often has not the desired results. Internet users are facing the problem of information overloading in which it is seems very challenging to find and process the most suitable information in order to extract meaningful information and knowledge [2]. It is obvious that utilizing and manipulating useful information is proven a very demanding and time-consuming procedure.

In order to address this problem, we can use recommender systems which seem an effective solution in many cases. In other words, recommender systems are capable of processing huge amounts of information in order to help users identify meaningful data and knowledge from a wide range of choices. As a result the main goal of these systems is to do all the “hard” work which in other conditions would be executed by human beings.

1.1 Definition of Recommender Systems

Recommender systems suggest items based on users past behavior, preferences and personal data. Because of the diversity of data, the variety of the information and the wide range of products, recommender systems are very essential in order to provide recommendations for products and other items [3]. In other words, a recommender system is a software that process large amounts of data in order to produce useful information. Movies, news or books which are considered by a user as “interesting” can now be presented by these systems that can be very helpful especially in cases with a wide range of items.

We can define a recommender systems as a system that is capable of gathering, processing and suggesting products that might be interesting for a given user. According to [2] a recommender system is every system that outputs personalized recommendations or has the ability to navigate users in order to find interesting and useful products.

Many companies are currently using these systems for commercial reasons. They provide different types of products such as movies, songs or books which means that recommender systems do not focus on specific type of items but they can be generalized in order to operate on a wide range of products. Below we introduce some of the most famous recommendation engines:

- Netflix which is a service for video rental and streaming, is considered as one of the most well-known paradigms because it helps its viewers to find shows that might have not initially chosen.
- Amazon which is a very popular e-commerce website, suggests items that other users have bought based on the item that you have just purchased.
- LinkedIn which is a social networking website designed for business community, makes recommendations for people that you might know, jobs you may like or companies and groups that are interested in.
- Also Hulu which is a streaming video website uses recommender systems is order to suggest content that many users may find interesting.

Recommendations can be optimized if the system can use two different types of input data: explicit (raw user input) and implicit (user's behavior) [5]. For example, when a user is rating some movies on Netflix, this means that he offers explicit input to the system. Various online communities like MovieFinder or MovieLens for movies and Pandora or Last.fm for music, are trying to collect user opinions, in order to recommend items based on this knowledge. However, there are many cases where this type of information is not available for the system. Moreover, user experience will become worse in case the system will keep using long and demanding questionnaires in order to extract useful information from user.

In order to provide accurate recommendations, systems should be aware of users past ratings and tastes. By this way, system should be able to suggest products based on what users like in the past or products that other similar (based on ratings) users like. However, there are many situations where this kind of knowledge is not available for the new users.

In this case systems have to face the cold start problem which is considered a very critical problem. In order to overcome this problem, many different approaches have been adopted: for example systems are capable of exploiting user's demographic data in order to make recommendations for new users based only on this kind of information [6].

1.2 Problem

The main problem of collaborative recommender systems is to make suggestions for new users who have just started to make use of the system. In this problem, which is known as cold start problem, the system has to collect new user information in order to be ready for use by the recently entered user. In case the system does not have sufficient information about new users, it will be very hard to provide accurate predictions.

1.3 Purpose

The main goal of this thesis is to address the cold start problem of collaborative recommender systems in the context of suggesting movies to new users. First of all, we will examine how user's demographic data affects their movies preferences and then we are going to study efficient methods such as the entropy of ratings based on ask-to-rate technique. These approaches will be evaluated for their efficiency and accuracy in the MovieLens 100K dataset.

1.4 Scope

The goal of this study is not to improve the accuracy of collaborative or content based filtering as this is not within the scope of this dissertation. In this study, we are going to investigate if demographic data or/and entropy of information can effectively address the cold start problem. Although there is a wide variety of MovieLens datasets with a lot of movies ratings, the majority of them does not include information about demographic data. In our study, we will use the demographic data of MovieLens 100K dataset combined with small research conducted by us.

1.5 Structure of Dissertation

In the first (Introduction) chapter, we give a brief description of the main features of the recommendation systems and the challenges that they have to face right now. Then, we present the purpose and the scope of this dissertation, and finally we provide a brief summary of the next chapters.

In the second chapter, we present the core concepts of our Thesis. In other words we are trying to describe recommender systems and explain how they work. Furthermore we introduce the main categories of recommender systems and also give a description of their characteristics and their functionality.

In the third chapter, we provide a literature review of the main published work regarding the recommendation systems and how they address the cold start problem. In this point, the main goal is to critique the respective literature and to identify the main problematic areas that can be improved. Moreover, we are trying to define the problem we are working on and also to connect our study with previous knowledge and suggest any further research. More specifically, we are trying to focus on the cold start problem which is a big issue for new users in recommender systems. Also we concentrate on the possibility of addressing it by using user metadata such as demographic data and proving that this kind of information can affect personalized recommendations. Furthermore, we try to focus on how ratings entropy and entropy0 can affect the cold start problem.

In the fourth chapter, we provide a section with the most important functional and non-functional requirements of our proposed system. Moreover, we give a description of the design of our proposed recommender system by providing all the related details and components. In addition, we present some diagrams and also the logic behind our proposed system.

In the fifth chapter, we introduce the implementation of our system by presenting the tools and the programming languages that we have used. For the needs of this thesis the programming language we have used is Python 3.6, and the development environment is PyCharm. Additionally, we present the datasets and all the related knowledge that we have extracted from them. In this case, we have used the MovieLens datasets that include user's demographic data thousands of movie ratings.

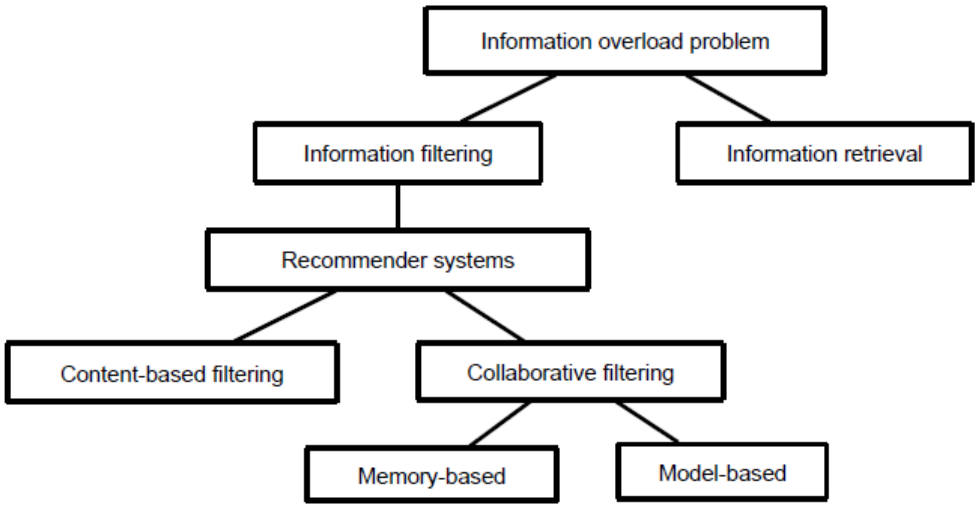
In the final chapter, we evaluate our proposed system, compare it with other systems and present the final conclusions of this study. Furthermore, we are also trying to suggest future work related to our system.

2 Core concepts of Recommender Systems

In this chapter, we introduce the basic idea and some of the most important characteristics that are related with recommender systems. Also, we are trying to explain some of core concepts that are adopted in our dissertation.

2.1 Recommender Systems

In previous chapters we introduced the problem of information overload in which users find it difficult to locate the most suitable information at the right time. The set of solutions that have been proposed can be presented in the following figure:

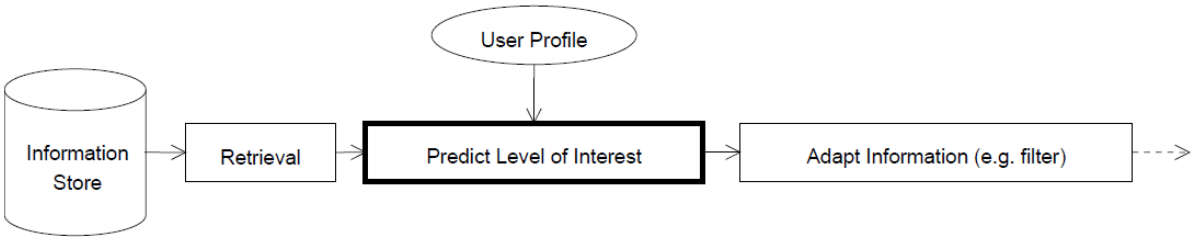


Picture 2.1: The hierarchy of solutions proposed for the information overload problem

As we can see in the above figure, the solutions are located between information filtering and information retrieval. Information retrieval systems ask the users to specify the type of information that is needed. On the other hand, information filtering systems aim to learn the user's main interests and then filter information taking into consideration users' profiles.

As we mentioned in the previous chapters, recommender systems are used to suggest what products to buy, what movies to watch or even who should be your friends on the social media. In 1992 Goldberg created the first recommender system in order to address the problem of the problem of the numerous emails which were presented in user's mail-box. In simple words, this system is a type of collaborative filtering algorithm in which users make reviews for the emails they read [7]. Over the last decade the need for precise and accurate recommender systems is growing more and more, because there are large amounts of data and the demand of personalized recommendations. Universities and companies have developed many techniques because it is proven that recommender systems can be very profitable.

Recommender systems include two main ingredients: the database and the filtering algorithm [8]. All the datasets and the information about users is placed in database. On the other hand, the filtering algorithm is divided into two steps: Firstly, the algorithm calculates the most similar users or items while in the second step the system is trying to make recommendations for the users. All the above can also be seen in the following figure:



Picture 2.2: Information filtering in recommender systems

Below we present the different recommendation techniques that have been developed over the past years:

- Collaborative filtering: The recommendations are based on the similarity between users and their ratings.
- Content-based filtering: The recommendations are based on the similarity between items.
- Demographic filtering: In this case, recommendations are based on the user personal information such as gender, age, occupation, location etc.
- Social filtering: Recommender systems are based on user's social networks
- Hybrid filtering: Combination of the above approaches

It is also worth mentioning that our implementation is based on collaborative filtering. In the next sections, we will give a brief description of some of the above techniques focusing on the methods that are used in our proposed system.

2.1.1 Basic concepts for ratings

The rating system has a big impact on the design of the recommender algorithms. The ratings are usually indicate how much a user likes or dislikes a specific item. There are rare cases, where ratings can take continuous values, for example in the Jester recommendation engine the rating values range between -10 and 10. On the other hand, in most cases the rating values are in intervals, which means that there is a collection of distinct ordered numbers used to indicate whether the user likes or dislikes the item on hand. For instance, a 5-star rating system can use the set {-2, -1, 0, 1, 2} where a rating of -2 represents extreme dislike while a rating of 2 an extreme like. For other implementations we may have other distinct values such as {0, 1, 2, 3, 4}, having the same logic as above.

The number of the rating values depends on the recommendation system. The most common scenarios is to use a 5-star, a 7-star or even a 10-star system rating. In figure 2.3 we can see an implementation of a 5 star rating system.

Picture 2.3: The picture shows a 5-star ratings system that is also referred as interval ratings system

Apart from the ratings, the above picture can also show the semantic meaning of the user's interests. This meaning can be different depending on the system: For example, Netflix uses a 5-star rating system where 4-stars mean that the user "really liked" the movie, while the "middle" 3-star rating means that the user simply "liked" the movie. For that reason, Netfilx has two ratings expressing the "dislike", and three ratings expressing the "like", which is also referred to as unbalanced rating scale. There are other implementations where the number of ratings is even and the neutral rating is absent, which leads to a forced choice rating system.

In case of our implementation, we have the Movielens Dataset where there are users that give their ratings for different items. Users are people who rate items, while items are the movies. Ratings can be explicit which means that users inserted the ratings by himself or they can be implicit which means that the ratings were estimated based up on the users behavior. In our implementation, we use a five point rating scale with ratings ranging from 1 to 5 (1 is the extreme dislike, while 5 is the extreme like).

In table below we can see an example of the *rating matrix* that will be used in our implementation:

	Toy Story	**Men in Black**
User1	1	4
User2	5	Nan
User3	Nan	3

Table 2.1: Example of rating matrix

The above rating matrix includes the ratings which three users gave for 2 movies. As we have mentioned before the ratings are ranging between 1 and 5. Also, the Nan value means that either the user have not rated the movie because either he has not seen it or he he has seen it, he has not managed to rate it.

2.2 Content-Based filtering

Over the past years, a lot of research has been carried out in order to address the problem of information overload, as we have mentioned above. Several items are compared with items that have already rated by users in order to recommend the most suitable items.

The difference between information filtering and information retrieval can be located in this point: The user is not trying to make a query for information, but the filtering system is building a model based on user's past choices and behavior and then tries to recommend the most suitable information to the user. Although there is a difference between these two concepts, information filtering has adopted several approaches from information retrieval, as it can be seen in content-based filtering and in collaborative filtering.

In content-based filtering, the recommendation is constructed based up on user's behavior. In this technique which is also known as cognitive filtering [10], all the available information is used in order to predict its relevance taking into consideration the user's profile. Content-based filtering has many similarities with the relevance feedback of information retrieval literature [11] in which the query vector is constructed by using the relevance of user's opinions on new documents. In Information Filtering (IF), this modified query vector can be considered as a profile model that includes keywords and their relative importance. Based on this profile, the relevance of new items is calculated by measuring the similarity between the query vector and the item feature vector.

In their simplest form, these profiles are user defined keywords or rules that represent users interests and traits. Usually, users would prefer the system to learn their profiles rather than providing it to system by themselves. For that reason, systems have to use machine learning techniques where the main idea is to learn to create rules and classify newly entered items based up on previous knowledge that has been provided by users. Thus, machine learning techniques can be used in order to construct a model that will be capable of predicting whether newly introduced products or items are probably going to be of interest. The ML techniques used in this case are based on text categorization because the IF is mainly focused on textual domains [19].

The process of allocating a Boolean value to each pair $(d_j,c_i) \in DxC$, where D is a set of documents and C is a set of categories. If true is allocated to the pair (d_j,c_i) there is a

tendency to assign the category c_i to the document d_j. On the other hand, if false is assigned to this pair then there is an aversion to assign the category c_i to the document d_j. The aim of this process is to estimate the function F:DxC →{True,False} which determines the way that documents should be classified, by defining a new function F':DxC →{True,False}. The F' function which is called model, should be similar to F as much as possible.

One of the most well-known approaches from the Information Retrieval and Text Categorization domains is the Rocchio Algorithm which describes documents using the vector space representation having as the most important ingredient the TF-IDF weight (Term Frequency/Inverse Document Frequency). TF-IDF can be formulated by the following equation:

$$tfidf(t_k, d_i) = tf(t_k, d_i) x log \frac{N}{n_k} \quad (1)$$

where N represents how many documents there are in the collection, and n_k defines the number of documents that involve the token t_k. Moreover, $tf(t_k,d_i)$ can be considered as the scheme which calculates how many times the token t_k appears in document d_i.

Rocchio algorithm calculates $\vec{c_i} = (\omega_{1i}, \ldots., \omega_{|T|i})$ (where T is the number of the unique tokens in the training set), for the c_i category using the following equation:

$$\omega_{ki} = \beta \cdot \sum_{d_j \in POS_i} \frac{\omega_{kj}}{POS_i} - \gamma \cdot \sum_{d_j \in NEG_i} \frac{\omega_{kj}}{NEG_i} \quad (2)$$

where ω_{kj} represents the tfidf factor of the token t_k in the d_j document, $[\![POS]\!]_i$ is the positive example in the training set for a category c_i and $[\![NEG]\!]_i$ is the negative example respectively.

Moreover β and γ are the factors that set the relative weight of the positive and negative examples. The vector model enables us to estimate how similar two vectors are taking into consideration the correlation. In order to calculate this correlation we can simply measure the cosine of the angle between these vectors. The class $\vec{c}$ is assigned to a document d_j, by computing the similarity between each vector $\vec{c_i}$ and the document $\overrightarrow{d_j}$. The $\vec{c}$ will eventually be defined by the c_i that has the highest similarity score.

2.3 Collaborative filtering

In Collaborative filtering (CF), user similarity is calculated based on user's ratings [9]. The majority of the studies uses this technique because it is easy to implement and also it provides satisfactory results. Most of the research is mainly focused on two points: The first is how to determine the similarity metric and the second is how to make predictions for items that have no ratings.

Collaborative filtering is mainly based on a model that exploits user's behavior. This model can be created by using a single user's behavior or by using the behavior of a group of users that have similar preferences. In other words, this technique makes recommendations based up on the collaboration of many users and focuses on users that have similar traits and behavior.

There are two main groups of Collaborative filtering algorithms: Memory-based Collaborative Filtering and Model-Based collaborative Filtering [12]. In Memory-Based Collaborative Filtering, recommendations are made by using the whole or a large part of the user dataset. One of the most famous and effective algorithms of this category is User-Based Collaborative Filtering. One of the most important disadvantages of this algorithm is that in order to create recommendations, the system has to process the whole dataset which can be proved a very demanding and slow task. On the other hand, model-based algorithms utilize datasets in order to create a more concrete model that will be used in order to make recommendations. The most famous algorithm in this case is Item-Based Collaborative Filtering. Below we are going to introduce the core concepts of the most famous memory and model based collaborative filtering algorithms. Furthermore, we will introduce kNN algorithm, a well-known data science algorithm that will be used in combination with Collaborative Filtering in our implementation.

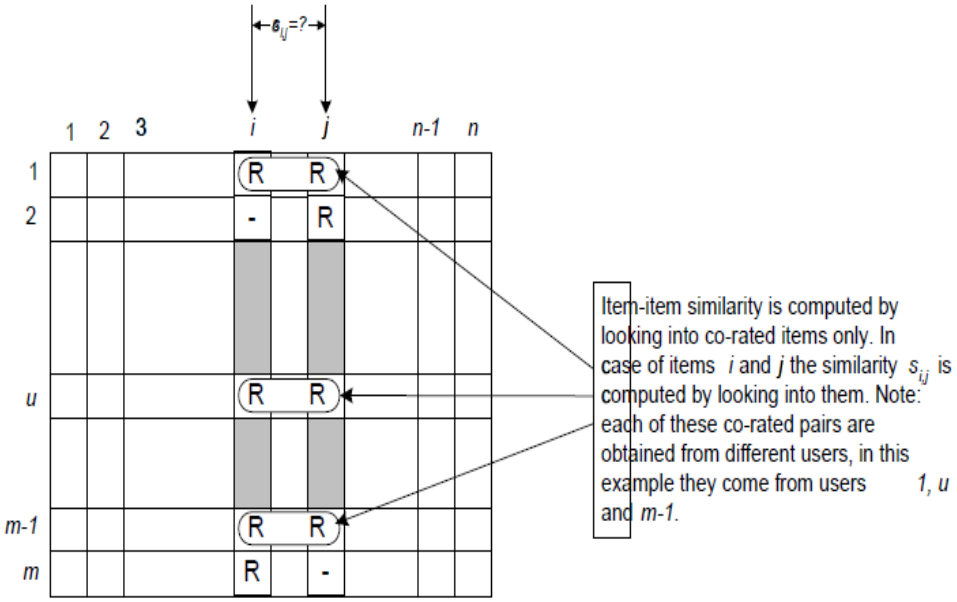
2.3.1 Item – Based Collaborative Filtering (IBCF)

Item Based collaborative filtering [13, 14] is a model-based technique which recommends items taking into consideration the relationship of items from the rating matrix. The main idea of this technique is that users would choose items which have similarities with other items they had already liked in the past.

This approach involves the calculation of similarity matrix which has item to item similarities based on a similarity measure. Some of the most well-known similarity measures are: Cosine Similarity, Pearson Similarity and Adjusted Cosine Similarity.

These similarities are located in a matrix S with n rows and n columns. In order to the size of the matrix to n * k where k <<n, we only save the k most similar items and their corresponding similarity values. The neighborhood of the item i with size k, can be defined by the set S(i) which is translated as the k items that are most similar with the item i. Keeping the k most common neighbors simplifies the problem, however it is obvious that the quality of recommendation is decreasing.

One of the most important parts in item-based recommender systems is to calculate item similarities and then to choose only the most similar items. The main idea behind the calculation of the similarity between two items i and j is to choose only the users who have rated both of these items and then to calculate the similarity s_{ij} based on a similarity measure technique. The above procedure can be visualized in the following Picture 2.4, where there is a matrix with m rows which represent users and n columns that represent items.



Picture 2.4: Elicitation of the co-rated items and similarity computation.

There three main methods that are used in order to calculate the similarity between items. These methods which are described below are: cosine based similarity, correlation based similarity, and adjusted cosine similarity.

2.3.1.a. Cosine-based similarity

In this approach, two items are represented as two vectors in the m dimensional user space. We calculate the similarity between these items by measuring the cosine angle of their corresponding vectors. Looking at the matrix of Picture 2.3 we calculate the similarity between two items i,j (sim(i,j)):

$$sim(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{|\vec{i}| * |\vec{j}|} \quad (3)$$

where "." is the dot product

2.3.1.b. Correlation-based similarity

In this technique, we calculate similarity between two items i,j by computing the Pearson correlation $corr_{ij}$. In order to improve accuracy we have to single out the cases where users have rated both items i and j as we have mentioned in Picture 2.3. Defining as U the set of users that have rated both items i and j, correlation-based similarity is calculated by the following equation:

$$sim(i,j) = \frac{\sum_{u\in U}(R_{u,i} - \bar{\bar{R}}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u\in U}(R_{u,i} - \bar{R}_i)^2}\sqrt{\sum_{u\in U}(R_{u,j} - \bar{R}_j)^2}} \quad (4)$$

where $R_{u,i}$ corresponds to the rating of the user u for the item i, and $\bar{R}_i$ represents the average rating for the i-th item.

2.3.1.c. Adjusted cosine similarity

The calculation of similarity between user-based collaborative filtering and item-based collaborative filtering has some differences. One of the main differences is that in user based collaborative filtering, we calculate the similarity between the rows of the rating matrix while in item based collaborative filtering we calculate the similarity between columns of the matrix (each pair of the co-rated items represents a different user). In case of item based collaborative filtering, the computation of similarity by the cosine similarity technique has one main disadvantage: The variation of the rating scale for different users is not taken into consideration. This problem can be addressed by using the adjusted cosine similarity where the user average is subtracted by each co rated pair.

By using this approach, the similarity between two items i and j is calculated by the equation:

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \overline{\overline{R_u}})(R_{u,j} - \overline{R_u})}{\sqrt{\sum_{u \in U}(R_{u,i} - \overline{R_u})^2}\sqrt{\sum_{u \in U}(R_{u,j} - \overline{R_u})^2}} \quad (5)$$

where R_u denotes the average rating for user u.

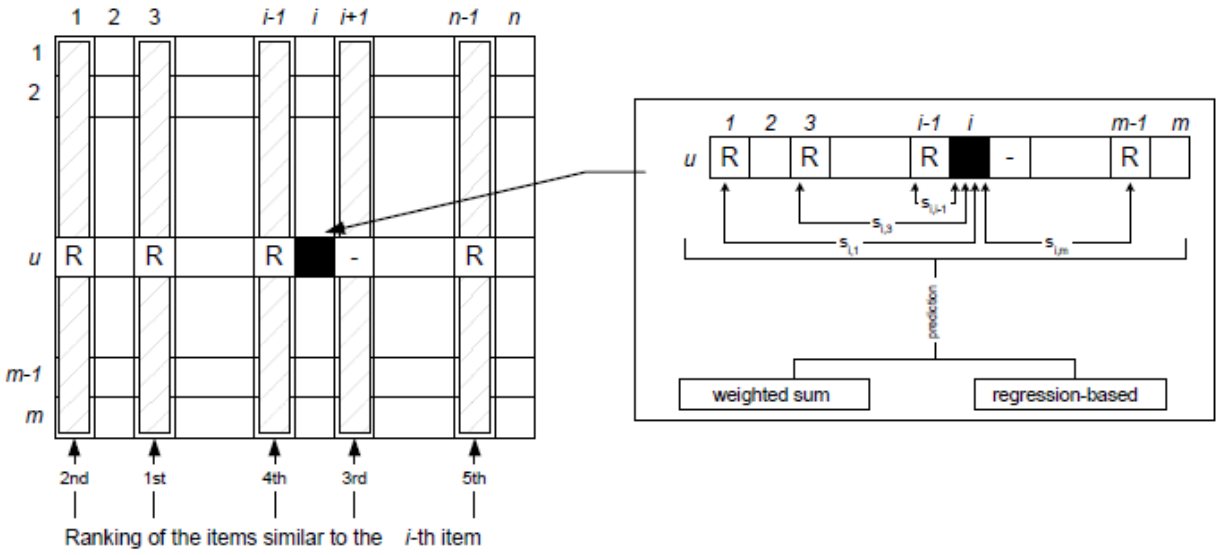
2.3.1.d. Prediction computation

The most crucial part of a collaborative filtering system is to generate the desired predictions. First of all we try to single out the most similar items taking into consideration the aforementioned similarity measures and then we try to focus on the users' ratings and generate predictions based on the weighted sum approach.

In this approach we calculate the prediction for an item i targeting a user u by calculating the sum of all the ratings the user u has given for items that are similar to the item j. The similarity sim(i,j) between items I and j "weights" each one of the ratings. Taking into consideration the idea that is depicted in Figure 2.5 we can define the prediction P(u,i) using the following equation:

$$P_{u,i} = \frac{\sum_{all\ simillar\ items,N}(s_{i,N} * R_{u,N})}{\sum_{all\ simillar\ items,N}(|s_{i,N}|)} \quad (6)$$

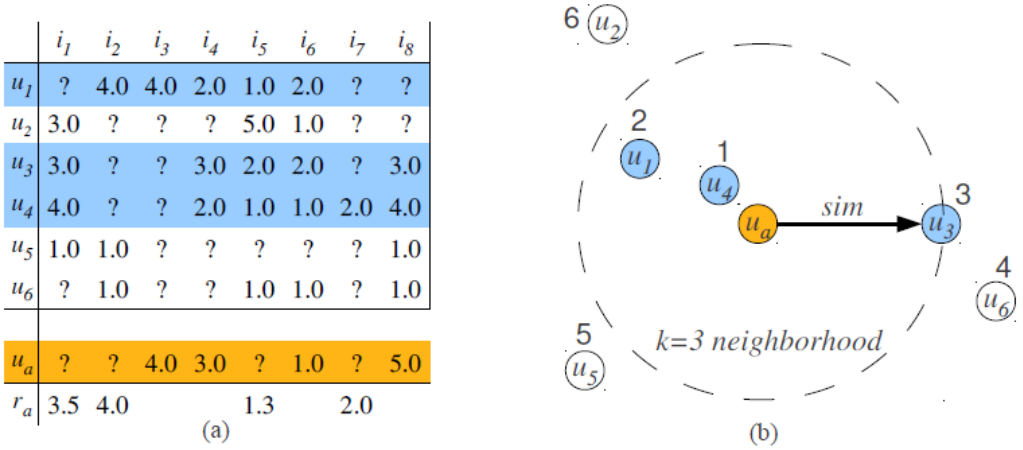
The main idea of this technique is that it tries to describe how a user rates similar items. Moreover we can see that the sum of similar items scales the weighted sum in order to guarantee that the prediction falls within a specified range.



Picture 2.5: Item-based collaborative filtering algorithm. Prediction is done by considering 5 neighbors

2.3.2 User – Based Collaborative Filtering (UBCF)

User based collaborative filtering is memory based approach that uses and process rating data from a wide range of users. The main idea behind this technique is that users with the same or almost the same preferences will also give similar ratings in the items. For that reason, a user's missing ratings can be estimated by finding the k-most common neighbors and then process their ratings in order to create the final recommendations.



	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
u_1	?	4.0	4.0	2.0	1.0	2.0	?	?
u_2	3.0	?	?	?	5.0	1.0	?	?
u_3	3.0	?	?	3.0	2.0	2.0	?	3.0
u_4	4.0	?	?	2.0	1.0	1.0	2.0	4.0
u_5	1.0	1.0	?	?	?	?	?	1.0
u_6	?	1.0	?	?	1.0	1.0	?	1.0
u_a	?	?	4.0	3.0	?	1.0	?	5.0
r_a	3.5	4.0			1.3		2.0	

(a)

(b)

Picture 2.6: User-based collaborative filtering approach. In (a) there is the matrix with all users ratings and also the predicted ratings for the target user u_a,, where in (b) there is the neighborhood with the most similar users for the target user u_a.

The neighborhood with the k most common users is calculated by the similarity of users, choosing the k most similar users or choosing all users that have a defined similarity threshold. For User-based collaborative filtering the most well-known similarity measures are person correlation and cosine similarity (both of them where presented in the previous paragraph 2.3.1). As we have mentioned before, a user's N(a) ⊂ U neighborhood can be estimated either by choosing a number of the most similar neighbors or by defining a threshold on the similarity. After finding the common neighbors, we aggregate their ratings in order to predict the missing ratings for the target user u_a. A simple approach is to take the average of the ratings in the neighborhood by using the below equation:

$$\hat{r}_{aj} = \frac{1}{N(a)} \sum_{i \in N(a)} r_{ij} \quad (7)$$

In order to exploit the case the fact that some neighbors are more similar to the target user than other neighbors, we adopt another approach in which we add weights in equation (7). As a result we now have:

$$\hat{r}_{aj} = \frac{1}{\sum_{i \in N(a)} s_{ai}} \sum_{i \in N(a)} s_{ai} r_{ij} \quad (8)$$

where s_{ai} defines the similarity between a neighbor u_i and the target user u_a.

An even better approach is to measure $\hat{r}_{aj}$ with distinct ratings. In this case, we have the classic user-based collaborative filtering algorithm, in which there is an aggregation of the target user's average rating, considering all the items that the target user has rated. This approach can be defined by the following equation:

$$\hat{r}_{aj} = \bar{r}_a + \frac{\sum_{u=1}^{k} (r_{u,j} - \bar{r}_u) P_{a,u}}{\sum_{u=1}^{k} P_{a,u}} \quad (9)$$

where: k is the number of the k most similar neighbors for the target user a, $P_{a,u}$ denotes the similarity between the target user and the other users u, $\bar{r}_a$ is the average rating for the target user a, $\bar{r}_u$ is the average rating of the neighborhood users for the item j, and $r_{u,j}$ is the rating that user u gave to item j.

2.3.3 kNN Algorithm

In this point, we will give a short description of the kNN algorithm which is used in our implementation. K Nearest Algorithm (known as kNN) is very simple and easy to understand and also has an incredibly well performance. Moreover, it is versatile and robust classifier and has a wide range of applications. The aim of this algorithm is to utilize a dataset where the data points divided into classes, in order to predict in which class belongs a new data point.

Each of the features of the dataset is considered as a different dimension in space and the value of an observation for each of these features is considered as a coordinate, which means that we have a collection of points in the dimensional space. Eventually, the similarity of two points can be regarded as the distance between them.

In order to make predictions for a new observation the algorithm picks the k most similar (closest distance) points to this observation and then chooses the most similar class between them. For that reason the algorithm is referred to as k-Nearest Neighbors Algorithm. [23]

kNN is considered as a non-parametric and lazy algorithm. It is characterized as non-parametric because it does not make any assumptions regarding the underlying data dis-

tribution. This is a big advantage because the majority of the practical data does not usually follow the typical theoretical assumptions. As a result, non-parametric algorithms such as kNN are here to offer the desired solutions.

Moreover kNN is a lazy algorithm. In other words, it does not utilize the training data sets in order to make generalizations. This means that the explicit training phase is absent or is extremely small, which denotes that the training phase is very fast. The absence of generalization indicates that kNN maintains all training data which is needed for the testing phase. Contrary to other methods in which you can remove a portion of the dataset, lazy algorithms such as kNN utilizes the whole dataset in order to make predictions.

In case of kNN, two opposing parts can also be observed: Although the training is absent or almost absent, the testing phase is much more expensive regarding memory and time. Time is demanded because there are cases in which all data had to participate in generating a prediction, while memory is needed when all data must be saved.

The algorithm can be briefly described in four steps:

1. We define a positive integer k, and also a new sample
2. We choose the k points from our dataset, which are mist similar to the new sample
3. We make the classification based up on these points
4. The aforementioned class is given to our new sample

As we have mentioned before, data points are located in a feature space and can be considered as scalars or multidimensional vectors. As a result, there is the concept of distance between these points, which can be calculated by many ways for example the Pearson correlation or simply the Euclidean distance. Furthermore, we take into consideration the integer number k which determines the number of neighbors that defines the classification.

To conclude, considering that the points are m-dimensional the procedure of finding the k-Nearest Neighbors can take O(m) time. Moreover, choosing the value of number k is a challenging task: If the value of number k is small the noise will have a big impact on the final result. On the other hand, if the value of number k is large, then the algorithm becomes more resource demanding. As a result, a compromised solution for this issue is to choose the number k based up on the function $k = sqrt(n)$, where n is the number of data that are included in the dataset.

2.4 Matrix Factorization

Until now we have introduced neighborhood methods which are focused on measuring the relationships between items or users. In contrast to these methods, there are also the latent factor models where both items and users are characterized on factors which are derived from the rating patterns.

The implementation of latent factor models is mainly based on matrix factorization [22]. The basic functionality of the Matrix Factorization is that it characterizes items and users using vectors of factors which are derived from item rating patterns. Recommendations are generated in case there is high similarity between items and users. These approaches are becoming more and more popular in recent years because they combine scalability and precise recommendations. Furthermore, they are also more flexible because they are capable of modeling real life scenarios.

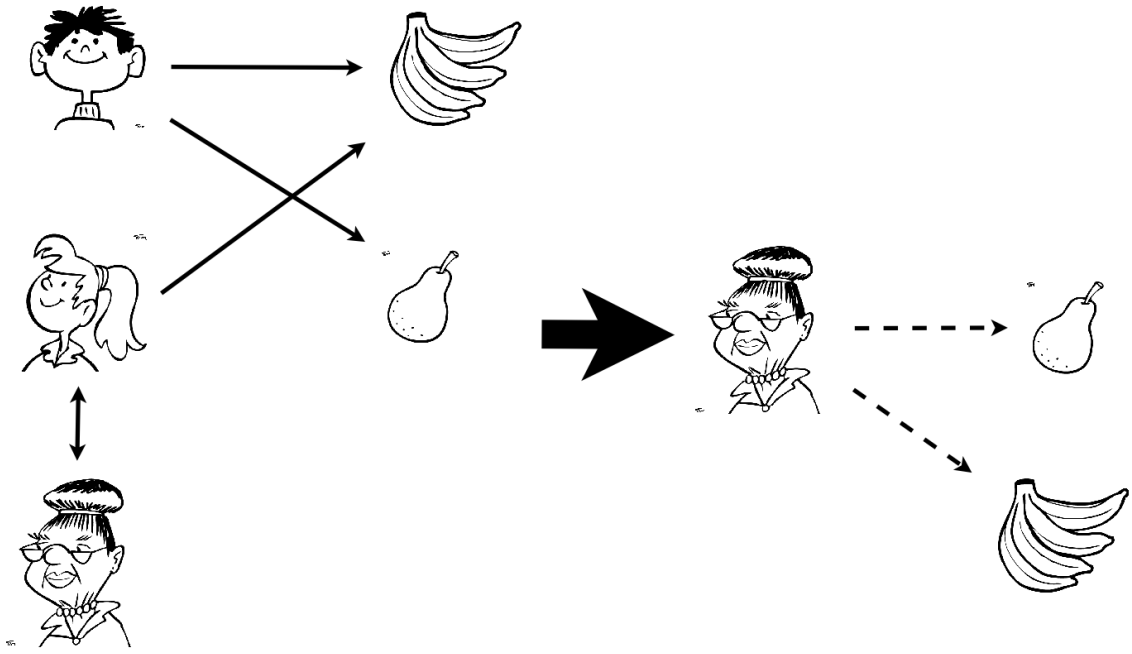
As we have mentioned in the previous section, recommender systems are based on various types of input data. This data is usually located in matrices which have one dimension as the items and the other dimension as the users. One of the most suitable type of data is the explicit feedback, which includes users' ratings for products in interest. For instance, Netflix gives users the opportunity to rate their preferred movies by giving star ratings, while TiVo collects ratings by enabling users to press thumbs up or thumbs down buttons if they like or not the movies respectively. The explicit feedback can also be called as ratings. It is also worth noting that these ratings are often placed in sparse matrices because users have only rated only a small number of the existing movies of the whole dataset.

One of the main advantages of matrix factorization is that it is capable of enabling the integration of additional information. In case explicit feedback is not available, recommender systems can predict user tastes by using implicit feedback. Implicit feedback represents opinions by taking into consideration users' behaviors and habits such as: past purchases, search history and in some cases the movement of mouse. Furthermore, implicit feedback can be depicted by a dense matrix because it often indicates if there is an event or not.

2.5 Hybrid Algorithm

Hybrid techniques combine multiple recommendation algorithms (e.g. content-based, collaborative filtering, etc.) increasing the efficiency and the likelihood to generate more precise recommendations as well as the complexity of recommender systems. In order to combine these methods many approaches have been proposed.

Generated recommendations can be significantly boosted by using a hybrid recommender that utilizes several of the aforementioned methods. A well-known approach is the combination of content-based and collaborative filtering. Hybrid recommender systems may be a smart solution for addressing the cold start problem which is one of the most serious problems of recommender systems. Figure 2.7 illustrates the basic idea of the generated recommendations for a new introduced user based up on a hybrid recommender which combines social links and collaborative filtering.



Picture 2.7: The main idea behind a hybrid recommender system

3 Challenges and related work

Recommender systems have been a subject of a vast number of research studies and discoveries in order to find new approaches capable of enhancing and improving recommendations. In this chapter we are going to present some of the most important research topics over the last years. This analysis is mainly based on papers [15, 16, 17, 18]. Moreover, the majority of the presented work is tightly related with the development and the problems that we have faced in our work. To sum up, we will present the cold start problem, followed by some works that are trying to solve it using various techniques and approaches.

3.1 Cold Start Problem

One of the most challenging problems which recommenders systems have to face is undoubtedly the limited number of the initially available user data. Under these circumstances, it is not easy to apply the aforementioned recommendations techniques and especially the collaborative filtering method. Although knowledge based or content based models proved to be more resistant to cold start problems than collaborative filtering, it is not easy to have this knowledge or content always available. Small numbers of data has negative effect on the performance of recommender systems by downgrading their prediction accuracy to a large extent. For that reason, there is a great interest of researching and studying all the drawbacks of limited data, and also what has to be done in order to address this problem.

Cold start problem affects recommender systems in terms of new users and new products [20]. Many studies have shown that cold start problem affects all types of recommender systems, but it is also proved that collaborative filtering methods have to face bigger problems than content based methods. [5] Below we present the two different categories of the cold start problem which are related with the new user and the new product respectively.

3.1.1 New user

The cold start problem is related with the issue of the new user when a new user has just been introduced himself to the system or when an already existing user has not given enough data to the system and as a result the system is not performing with the normal way. Having this limitation in user's data, the system generates inaccurate predictions which do not fit with the users preferences. In order to address this problem, many systems use the ask-to-rate technique where they ask from users to rate some products. For example MovieLens asks users to rate movies when they sign up [21].

3.1.2 New product

The second instance of the cold start problem is related with the issue of the new product. This problem arises when a new product is introduced to the system because is not related with any user or any of the already existing products. This limitation in data is very challenging especially in case of collaborative filtering systems which usually use information that describe connections between products and users. On the other hand, content based filtering methods are more robust because they classify the items based up on its characteristics. [21]

3.2 Documents addressing the cold start problem

Below we present some solutions that have been proposed in the past, by giving a description of some of the documents which helped us to create our recommender system.

3.2.1 Using Demographic Information to Reduce the New User Problem in Recommender Systems

In [15], the author attempts to build a recommender system based up on the demographics data included in the MovieLens 100K dataset. This dataset which will also be used in our work, has various information including 100,000 movies ratings made by 963 users for 1682 movies. Moreover, the ratings range from 1 –the lowest rating- to 5 – the highest rating. Additionally, the dataset is created by users' personal information which are were provided when users visited the MovieLens website for the first time. The structure of the demographic information is given below:

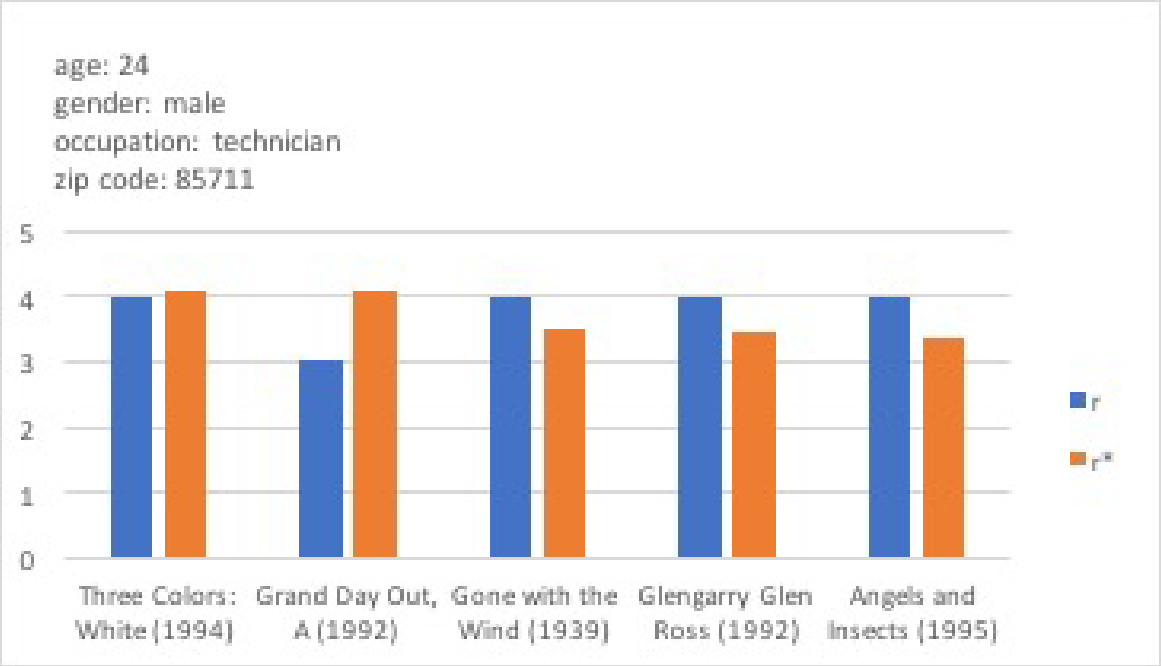
user id | age | gender | occupation | zipcode

Furthermore, the user ratings in the dataset is given as follows:

user id | item id | rating | timestamp

Dividing the above users into training and testing set, we create a model that has K distinct clusters, and we train it, by taking into consideration the users of the training set. This model can be considered as a classifier that defines which of the users of the training set matches a new introduced user (a user from testing set). Also, this model makes the classifications based on the user's demographic data. The ratings of the new introduced user are generated by taking into consideration the rating information which is calculated from users who belong to the same cluster.

Some indicative rating predictions for users in the testing set are plotted along with the actual ratings of the users of training set on some specific movies. These plots are shown in picture 3.1:



Picture 3.1: This plot depicts the predicted ratings r* along with the actual ratings r, for five movies for a male user that is 24 years old, he is technician and his zip code is 85711

The figure shows that the predicted ratings r* are very close with the actual predictions r. However, regarding the final results it was observed that most of the predicted ratings are located around 3-4.

To sum up, the prediction of ratings for new users assuming that there are not any past rating data, cannot guarantee that there is any significant relevance between the number of clusters and the precision of the prediction regarding the MovieLens 100K

dataset. Moreover, it seems that there is a connection between demographic data and movie ratings, but in order to generate more concrete results there is a need for a greater range of demographic data.

3.2.2 Collaborative Filtering Enhanced By Demographic Correlation

In [16], there is an attempt to introduce a specific technique which includes a lot of approaches of existing algorithms combing them with demographic data using MovieLens 100k dataset. The introduced hybrid algorithms called U-Demog and I-Demog, are mainly influenced by the User-based and Item-based collaborative filtering respectively. Additionally, the aforementioned algorithms are also enhanced by the user's demographic data: age, gender, a choice of 21 occupations, and also the zip code for each user that gave his ratings. The aforementioned data is used for the calculation of demographic correlations by taking into consideration the user vector similarities. In other words, each user in MovieLens 100k dataset corresponds to a user demographic vector that is defined as a vector with 27 features and can be seen in detail in the following table:

feature #	feature contents	comments
1	age <= 18	• each user belongs to a single age group, • the corresponding slot takes value 1 (true) • the rest of the features remain 0 (false)
2	18 < age <= 29	
3	29 < age <= 49	
4	age > 49	
5	male	• the slot describing the user gender is 1 • the other slot takes a value of 0
6	female	
7-27	occupation	• a single slot describing the user occupation is 1 • the rest of the slots remain 0

Table 3.2: Description of the user demographic vector

In this point, it is worth mentioning that we will follow the same logic in our implementation where we are also exploiting user's demographic data. This procedure is described in chapter 4 (requirements and design).

The experiments have shown that the performance of the proposed algorithms can be much better than the base algorithms, but on the other hand it can also be worse than them. This deviation is mainly based on the role of the demographic correlations in the process of the prediction generation.

As it has also mentioned in the previous section, it was noticed that the demographic data from the MovieLens 100K dataset, does not have the adequate information in order to generate precise and reliable predictions. However, in case this data is combined with other types of filtering, like collaborative filtering, the recommendation procedure can be boosted and the final predictions can be more precise and reliable.

3.2.3 Cold-start Problem in Collaborative Recommender Systems: Efficient Methods Based on Ask-to-rate Technique

In this document [17], the author is trying to address the cold start problem of a Collaborative filtering recommendation method by proposing some variations of the "ask-to-rate" technique.

In order to generate recommendations, the author uses memory based Collaborative filtering algorithm which was described in the previous Chapter (Chapter 2). In this point we can figure out that this algorithm is mainly based on kNN (k –Nearest Neighbors) algorithm. The whole recommendation procedure can be described as follows:

- ✓ First of all, we calculate the similarity between the active user and the other users who have rated the item by measuring the Pearson's correlation. Defining as U the set of users that have rated both items i and j, correlation-based similarity is calculated by the following equation:

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \overline{\overline{R_i}})(R_{u,j} - \overline{R_j})}{\sqrt{\sum_{u \in U}(R_{u,i} - \overline{R_i})^2}\sqrt{\sum_{u \in U}(R_{u,j} - \overline{R_j})^2}} \qquad (10)$$

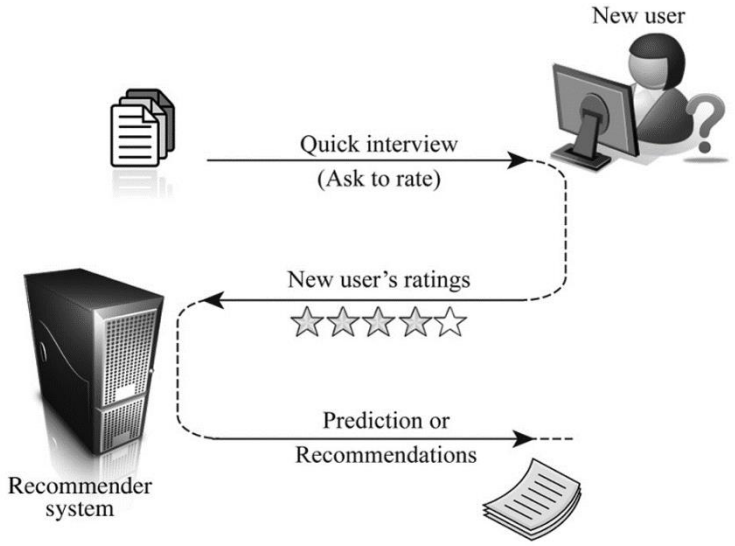
  where $R_{u,i}$ corresponds to the rating of the user u for the item i, and $\overline{R_i}$ represents the average rating for the i-th item.
- ✓ Then, the prediction for a target item regarding an active user can be measured by the following equation:

$$\hat{r}_{aj} = \bar{r}_a + \frac{\sum_{u=1}^{k}(r_{u,j} - \bar{r}_u)P_{a,u}}{\sum_{u=1}^{k} P_{a,u}} \qquad (11)$$

where: k is the number of the k most similar neighbors for the target user a, $P_{a,u}$ denotes the similarity between the target user and the other users u, $\bar{r}_a$ is the average rating for the target user a, $\bar{r}_u$ is the average rating of the neighborhood users for the item j, and $r_{u,j}$ is the rating that user u gave to item j.

Some of the advantages of Collaborative filtering algorithms are that they are simple to implement and relatively easy to understand, and also that new data can be added without any problem. However, the main drawback of these systems is the cold start problem when there is a new user to the system.

In order to find a solution for the cold start problem, the author proposes the "ask-to-rate" technique .The main idea of this technique is to present some items to the new user and ask for explicit ratings. Then, in the user item matrix, the row with the ratings of the new user is not empty anymore and the system is capable of using these ratings in order to make recommendations. The above process can also be depicted below:



Picture 3.2: The main idea behind ask-to-rate technique

It is also worth noting that the system must be capable of presenting the most informative items in order to collect the right information for the new user. If the ratings of the new user are originated from a well-designed selection method rather than a "random selection", then there is a great chance of generating much more improved and accurate predictions. Normally, these techniques should not be difficult but instead they should be understandable and user friendly. An indicative evaluation of the proposed selection techniques on the user effort and the recommendation accuracy can be seen in Table 3.2.

Methods	User Effort	Recommendation Accuracy
IGCN	★★★★	★★★★★
(Log pop)×Ent	★★★	★★★★★
Entropy0	★★★★★	★★★★
HELF	★★★	★★★★
Popularity	★★★★★	★★★
Item-Item	★★★★★	★★
Entropy	★	★★
Random	★	★★

Table 3.2: The evaluation of the proposed selection methods on user effort and on prediction accuracy (5star: Best, 1star: Worst).

For our recommender system we have initially taken into consideration the pure entropy method, which is also referred as non-adaptive method. Non-adaptive methods are able to present similar items to all new users ignoring the existence of changes in knowledge of the user being asked. Pure entropy H(a_t) which is usually characterized by low complexity, represents the scattering of the item ratings in the rating matrix. The basic structure of entropy's algorithm can be seen in the following figure 3.3.

In this point it is worth mentioning that this method is capable of providing a lot of information for each rating. However, this kind of information is not always really useful as the system can present some items that are totally unknown to the majority of the users.

```
Function Entropy ( a_t )
{
    entropy ( a_t ) = 0
    for each item  a_t  in dataset
    {
        for i as each of the possible rating values  //in case of MovieLens, i = 1…5
        {
            if (rating( a_t ) == i):
            {
                value[i] += 1  //rating frequencies
            }
        }
        proportion[i] = value[i]/(total number of users who rate  a_t )
        entropy( a_t ) +=  proportion[i]*Math.log(proportion[i],2)
    }
    entropy( a_t ) = - entropy( a_t )
}
```

Picture 3.3: Algorithm of pure entropy method

The author also examines the Entropy0 method which is the Entropy considering missing values. In the previous method (Pure Entropy), missing ratings were nor taken into consideration. In order to address the problem of an item without evaluation, the method of Entopy0 zero is introduced: All missing ratings belong to a new category referred as "0" while "1-5" continues to be the normal rating scale as it was before. The following equation shows the Entropy0 formulation using a weighted approach:

$$Entropy0(a_t) = -\frac{1}{\sum_i w_i}\sum_{i=0}^{5} p_i w_i \log(p_i) \qquad (12)$$

where $w_0 = 0.5$ represents the weight for the missing ratings, and $w_i = 1$ (for i = 1,…5) represents the original ratings of the dataset. It is also worth noting that if we change w_0 to 0, the Entropy0 is altered to the Pure Entropy. Entropy0 manages to address some of the drawbacks of Pure Entropy, and make a distinction between the unknown items (items that have a small number of ratings) and frequently rated items. It is also observed that Entropy0 generates better results than Popularity method.

3.2.4 Learning Preferences of New Users in Recommender Systems: An Information Theoretic Approach

This paper [18], is trying to address the cold start problem by examining the effectiveness of several item selection methods based on information theory. The basic concept of this procedure is to use each of these methods in order to find a set of items, and then to evaluate how effective these items are in constructing new users profiles. We also have to note that the author is mainly focused on developing methods based on information theory, aiming to extract information about new users' habits and tastes. Similar to the previous section, the author also notices that pure entropy has many limitations and as a result he proposes some variations: Entropy0 and HELF. The methods used by the author are: Popularity, Entropy0 (Entropy Considering Missing Values), HELF (Harmonic mean of Entropy and Logarithm of Frequency) and IGCN (Information Gain through Clustered Neighbors).

Entropy and Entropy0 were presented in the previous section. Regarding the other 3 methods we have:

- Popularity shows how frequently the users rate the items, and it is considered a very easy and inexpensive technique.
- HELF which is the Harmonic mean of Entropy and Logarithm of rating Frequency can be formulated with the above equation:

$$HELF_{a_i} = \frac{2 * LF'_{a_i} * H'(a_i)}{LF'_{a_i} + H'(a_i)} \qquad (13)$$

where LF'_{a_i} is the normalized algorithm of the rating frequency of a_i: $\lg(|a_i|) / \lg(|U|)$ and $H'(a_i)$ is the normalized entropy of a_i: $H(a_i)/\lg(5)$.

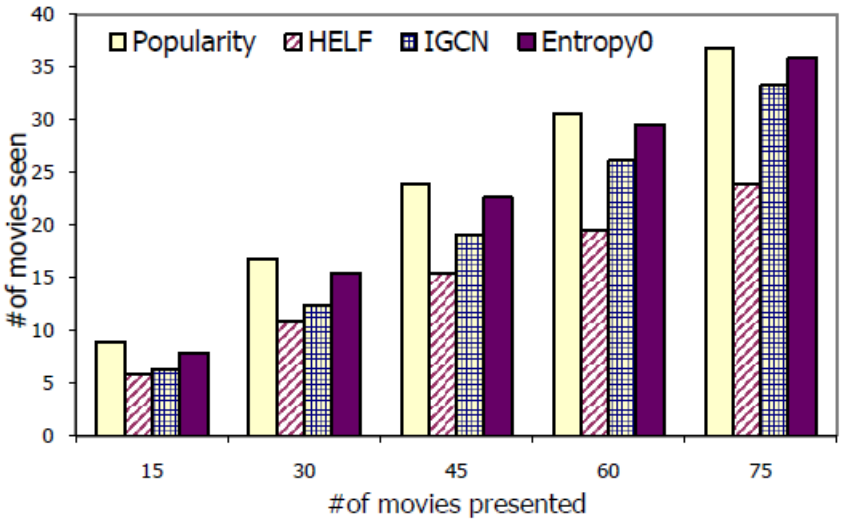
Finally, ICGN which is the Information Gain through Clustered Neighbors, calculates information gain of items. Additionally, the ratings data is selected according to the users that match best with the active's user profile until now. The information gain of an item a_t can be calculated by the below function:

$$IG(a_t) = H(C) - \sum_r \frac{|C^r_{a_r}|}{|C|} H(C^r_{a_r}) \qquad (14)$$

where H(X) represents the entropy of a distinct variable X, while C indicates the distribution of users into clusters defining the number of users that belong to each cluster. $C^r_{a_r}$ indicates the distribution into classes of those users that have rated the

item a_t with value r. $\sum_r \frac{|C_{a_r}^r|}{|C|} H(C_{a_r}^r)$ represents the weighted average of entropies of the partitions of the class distribution (C) caused by the ratings of the item a_t.

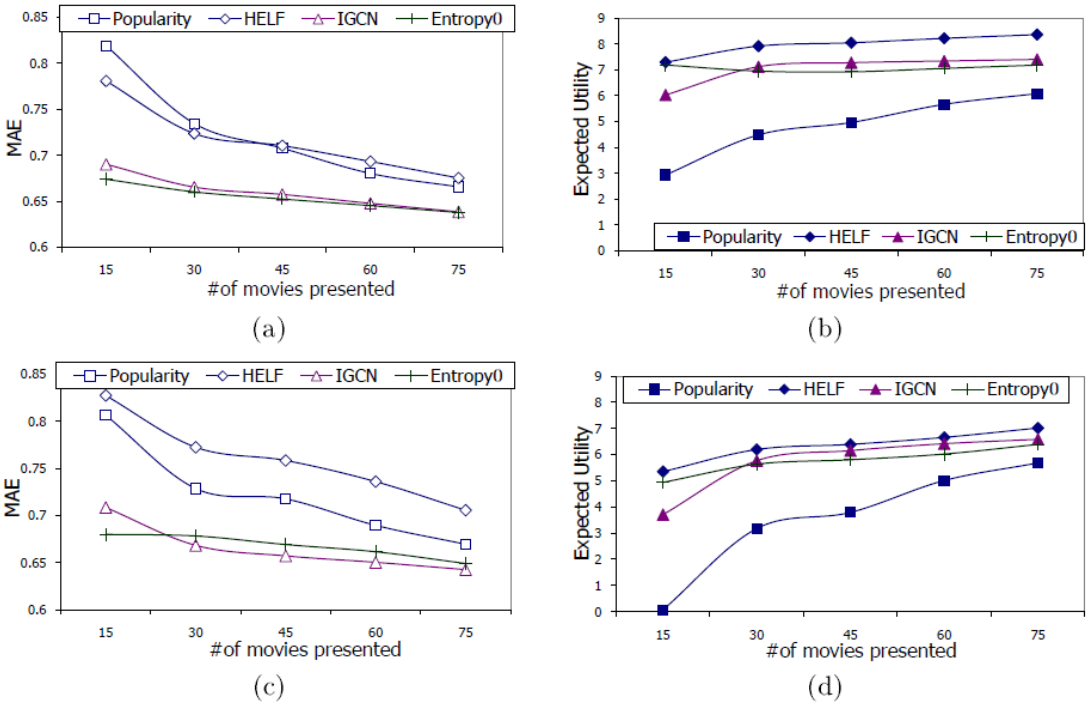
The following figure shows the results of the above methods from the offline simulation:



Picture 3.3: The figure shows how familiar the presented movies are to the users, for each of the aforementioned selection methods.

It is obvious that popularity method selects the most familiar items to users while HELF generates the worst results. Moreover, we can see that Entropy0 is also capable of producing some satisfactory results.

Then, in figure 3.4 we can see the results regarding the accuracy of recommendations. From these results we can see that both IGCN and Entropy0 have a good performance for both of the metrics. However, HELF produces some confusing results because regarding MAE is one of the worst, while regarding Expected Utility is one of the best.



Picture 3.4: The plots show the effectiveness of the generated user's profiles. (a),(b) present the recommendation accuracy of User-based kNN CF algorithm, while (c),(d) present the accuracy of Item-based kNN CF algorithm. Mean absolute error (MAE) is better for lower values, and Expected Utility is better for higher values

4 Requirements and Design

In this chapter, we present the functional and non-functional requirements of our implementation, taking into consideration the cold start problem and the overview of the system model that is described briefly below: The system asks the new user for explicit ratings and then, based on the already existing dataset which has the other users' ratings, generates recommendations for the new user.

Furthermore, we are going to introduce the design of our proposed system and how is it possible to satisfy the aforementioned requirements. We will give a brief description about the architecture of the system, the data that we used, the assumptions we made, and finally the basic execution flow.

4.1 Requirements

4.1.1 Functional requirements

In this section, there will be a brief explanation of the non-functional requirements of the user interaction with the software

FR ID	Title	Description
1	Display movies for rating	The system should provide an interface that presents movies to users
2	Request users demographic data	The system should provide an interface which asks users to give their demographic information
3	Display movies for rating based on their entropy	The system should be able to calculate movies entropy, and present (for rating) the movies with the highest scores of entropy
4	Display movies for rating based on users' demographic data	The system should be able to find the k most common neighbors (based on demographics) for the target user, and present (for rating) their corresponding movies.
5	Ask user for explicit ratings	The system should provide an interface that asks users for explicit ratings
6	Generate recommendations using collaborative filtering	The system should be able to generate recommendations by processing the ratings given by the target user and other similar user from the existing dataset.

Table 4.1: Functional requirements of our proposed system

4.1.2 Non-Functional requirements

In this section, there will be a brief explanation of the non-functional requirements of the user interaction with the software

NFR ID	Title	Description
1	Accurateness	The system should provide precise recommendations which correspond to the target user actual movie preferences
2	Simple	The system should provide a simple interface that will be understandable and easy to use.
3	Interesting	The system should not be boring and should be capable of capturing user's attention during the whole procedure
4	Fast	The system should be fast, both in terms of producing the recommendations but also in terms of collecting user's ratings and his demographic information.

Table 4.2: General Non-Functional requirements of our proposed system

The software must also be compliant with ISO 9126 quality characteristics (http://www.sqa.net/iso9126.html).

Category	Subcategory	Description
Functionality	Compliance	The system should minimize intrusiveness and be compliant with privacy laws
Reliability	Maturity	The software should face very rarely failures
	Fault tolerance	Software should be able to withstand and recover from failures
	Recoverability	Ability to bring back a failed system to full operation, including data
Usability	Understandability	Ease of which the software's functions can be understood
	Learnability	It should be easy to learn for every kind of user (i.e. no tech savvy)
	Operability	Ability of the software to be easily operated by a given user in a given environment.
Efficiency	Time Behavior	Response time < 5 sec
	Resource behavior	Use a little amount of memory
Portability	Adaptability	Characterizes the ability of the system to change to new specifications or operating environments.

Table 4.3: ISO 9126 quality characteristics

4.2 System architecture

The user interacts with the system through an interface that we have developed. The interface is capable of displaying movies to user, and also asking for explicit ratings. It is also asks for users demographic data and store all this information on the disk. Finally the system is capable of generating recommendations based on user's ratings and his demographic information. This can be implemented by finding the top k most common neighbors and then using collaborative filtering bias subtracted technique.

In order to provide an optimal service to users, the system must be able to generate fast and precise recommendations. Furthermore, the ask-to-rate method should be simple and not boring, but instead should capture user's attention throughout the duration of the whole procedure of information gathering.

The aforementioned functional and non-functional requirements should be satisfied by designing a recommender system with various components and operations. Below, we provide the key points of its operation:

- *Input*: MovieLens 100k Dataset, new user movies ratings and his demographic data
- *Output*: Generated recommendations based on: 1) select movies for rating randomly, 2) select movies for rating, considering users demographic data, 3) select movies for rating, considering their entropy0 score, 4) combination of 2, 3 methods.
- *Basic steps of the systems functionality*:
    1. User starts the system
    2. System loads the MovieLens 100k dataset
    3. Target user gives his demographic data – *optional (only in case the algorithm requests user's demographic data)*
    4. System calculates movies entropy – *optional (only in case the algorithm take into consideration movies entropy)*
    5. System displays movies for rating
    6. User rates movies
    7. System generates and displays recommendations
    8. User exits the system

In this point it is worth mentioning that our proposed system consists of four independent and different algorithms (scripts):

1. The first algorithm (basic algorithm) displays movies for rating randomly, and then generates recommendations based on collaborative filtering.
2. The second algorithm (demographic based algorithm) displays movies for rating based on users demographic data, and then generates recommendations like the basic script.
3. The third algorithm (entropy0 based algorithm) displays movies for rating based their entropy0 scores (movies with the highest entropy0 scores are presented first), and then generates recommendations like the basic script.
4. The fourth algorithm (demographic and entropy0 based algorithm) which is a combination of the third and the fourth script, displays movies for rating based on users demographics and movies entropy0 scores, and then generates recommendations like the basic script.

4.2.1 Recommendation engine

As we have mentioned above, the recommendation engine is implemented by using the kNN algorithm and bias subtracted user based collaborative filtering, and the users similarities are calculated by the Pearson correlation scheme. In other words, we will have the user-similarity matrix that includes the similarities (Pearson correlation) between users. Also the recommendations are calculated by taking into account only the top-k most similar users (kNN algorithm). Finally, in the collaborative filtering technique we have managed to prevent biases related with the users by subtracting each user's average rating from each user's rating, and then add that average at the end (bias subtracted collaborative filtering).

4.3 Used dataset

For this project we have used the MovieLens 100k dataset as we have already mentioned in previous chapters. This dataset, was developed by GroupLens Research Project and contains 1682 movies with 100.000 ratings on the rating scale 1-5 provided by 943 users. Moreover, it is based on explicit information given by users during their sign-up on MovieLens website. It is also worth mentioning that every user included in the dataset has rated at least 20 movies.

The MovieLens dataset contains a lot of files, however for our implementation we have singled out and used the following files:

- *u.user*: This file contains demographic data about users. This information has the following format:

  user id | age | gender | occupation | zipcode.

  From the above structure, the zipcode feature was removed because it is not needed for our project. Below we present the first 3 users of the u.user file:

user id	age	gender	occupation
1	24	M	Technician
2	53	F	Other
3	23	M	Writer

Table 4.4: A sample containing the first 3 rows of the u.user file

The users are classified based on their demographic data by converting the above features (age, gender and occupation) to numeric scales in order to estimate their similarity. As a result we have:

a) Age is represented within the ranges: 0-18, 19-24, 25-30, 31-40, 41-50, 51-60, 61-70, 71-100. So for a 24 year old user, we have value 1 for the 19-24 age range and 0s for the other ranges.
b) Gender is specified by 0 and 1
c) Occupation is also specified by 0s and 1

Combining the above features we develop the below model:

- ✓ *age* = ['18', '24', '30', '40', '50', '61', '70', '100']
- ✓ *gender* = ['M', 'F']
- ✓ *occupation* = ['administrator', 'artist', 'doctor', 'educator', 'engineer', 'entertainer', 'executive', 'healthcare', 'homemaker', 'lawyer', 'librarian', 'marketing', 'none', 'other', 'programmer', 'retired', 'salesman', 'scientist', 'student', 'technician', 'writer']
- ✓ *combined_features* = ['18|0', '24|1', '30|2', '40|3', '50|4', '60|5', '70|6', '100|7', 'm|8', 'f|9', 'administrator|10', 'artist|11', 'doctor|12', 'educator|13', 'engineer|14', 'entertainer|15', 'executive|16', 'healthcare|17', 'homemaker|18',

'lawyer|19', 'librarian|20', 'marketing|21', 'none|22', 'other|23', 'programmer|24', 'retired|25', 'salesman|26', 'scientist|27', 'student|28', 'technician|29', 'writer|30']

Applying the same logic as the author of 3.2.2 in chapter 3, the above data is used for the calculation of demographic correlations by taking into consideration the user vector similarities. The user demographic vector is defined as a vector with 31 features and can be seen in detail in the following table:

feature #	**feature contents**	**comments**
0	age <= 18	• each user belongs to a single age group, • the corresponding slot takes value 1 (true) • the rest of the features remain 0 (false)
1	18 < age <= 24	
2	24 < age <= 30	
3	30 < age <= 40	
4	40 < age <= 50	
5	50 < age <= 60	
6	60 < age <= 70	
7	70 < age <= 100	
8	Male	• the slot describing the user gender is 1 • the other slot takes a value of 0
9	Female	
10-30	occupation	• a single slot describing the user occupation is 1 • the rest of the slots remain 0

Table 4.5: Description of the user demographic vector

For example, considering the first user of the table 4.4 (24 year old, Male technician) we can see that the corresponding *combined_features* list contains the below values:

[0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0]

- *u.data*: This is our main dataset that includes 100000 ratings for 1682 movies given by 943 users. Information is formatted on a table with four columns (user id, movie id, rating, timestamp). Users are numbered consecutively from 1 to 943 and every use rid is unique for each user. Moreover the same logic applies for movies (movie id ranges from 1 to 1682). Also as we have mentioned before, ratings range from 1 to 5. Finally the timestamps are unix seconds since 1/1/1970 UTC, but in our implementation we will not take them into consideration. Below we give a small sample of the first 5 rows of this dataset where we have omitted the timestamp column as we mentioned before:

user id	**movie id**	**rating value**
196	242	3
186	302	3
22	377	1
244	51	2
166	346	1

Table 4.6: A sample containing the first 5 rows of the u.data file

- *u.item*: Finally, this file includes the metadata for our movies. More specifically it is formatted as a table with rows where each row corresponds to a movie. Also the table has 23 columns where: the 1st column is the movie id, the 2nd is the movie title, the 3rd is the release date of the movie, the 4th is the imdb link for this movie, and the remaining columns corresponds to the movie genres. All the possible genres can be: | unknown | Action | Adventure | Animation |Children's | Comedy | Crime | Documentary | Drama | Fantasy |Film-Noir | Horror | Musical | Mystery | Romance | Sci-Fi |Thriller | War | Western |. A 1 indicates the movie is of that genre, while a 0 indicates it is not. Also movies can be in several genres at once. It is also worth noting that the movie ids are the ones that are used in the u.data dataset. For our implementation we care only about the titles, as a result we keep only the first two columns (movie id and movie title). Below we give a small sample of the first 5 rows of this dataset:

movie id	movie title
1	Toy Story (1995)
2	GoldenEye (1995)
3	Four Rooms (1995)
4	Get Shorty (1995)
5	Copycat (1995)

Table 4.7: A sample containing the first 5 rows of the u.item file

4.4 Assumptions

For the sake of simplicity, and in order to overcome various problems, we are going to make some assumptions that are applied within the constraints of our project. The assumptions are described as follows:

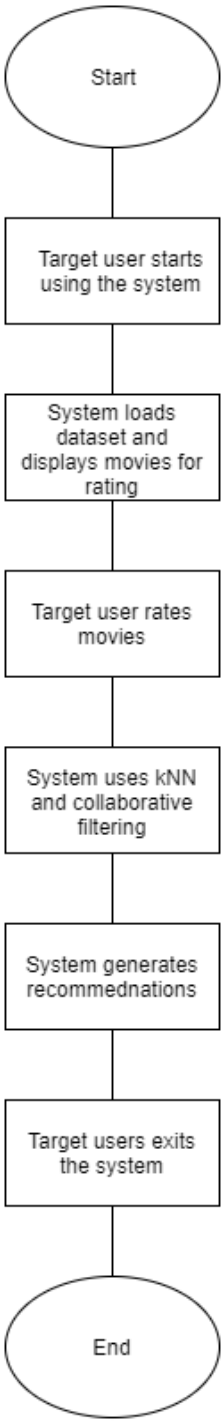
- The u.item dataset which contains metadata about movies, remains stable and does not change from the start till the end of our implementation. In other words, there are not new movies that are added, or there are not movies characteristics that are altered.
- The u.users dataset that contains user's demographic information does not change. This means that neither new users are added nor existing users demographic data changes throughout the whole procedure of our implementation. Even if a new user is introduced to the system, his demographic data is saved only temporarily.
- The same logic is also applied for the u.data dataset, as all the including information (users' movies ratings) does not change. Similarly, in case a new user enters the system, his movies ratings are only saved temporarily and are discarded when the user exits the system.
- There is always a fixed number of movies displayed to target user for rating.
- The number of recommended movies is also fixed.
- Each algorithm (script) provides recommendations when user has rated 10 movies.

4.5 Flowchart diagrams

The following sections provide a brief description of the functions of the four algorithms that were discussed in 4.2: Basic algorithm, Demographics based algorithm, Entropy0 based algorithm and Demographics-Entropy0 based algorithm. Moreover we introduce the procedure of inserting user's demographics and providing ratings for movies.

4.5.1 Basic algorithm flowchart diagram

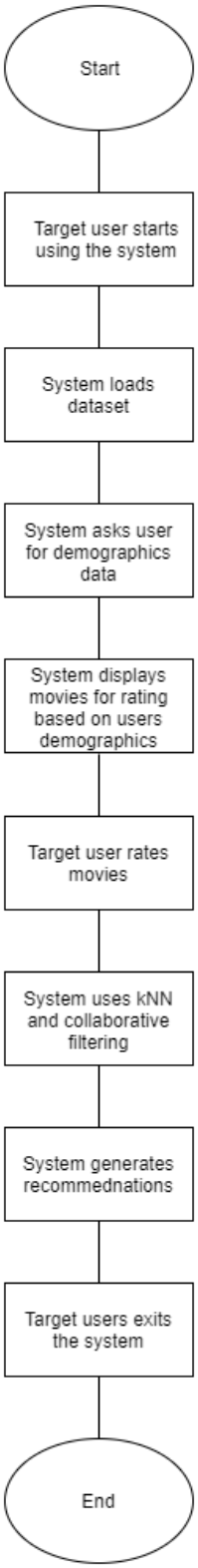
In this section we introduce the flowchart of the basic algorithm which only uses collaborative filtering. Movies are displayed for rating randomly without using a specific approach.



Picture 4.1 Basic algorithm

4.5.2 User Demographics based algorithm flowchart diagram

In this section we introduce the flowchart of the user demographics based algorithm which displays movies for rating based on users' demographic data and uses collaborative filtering for recommendations.



Picture 4.2: User Demographics based algorithm

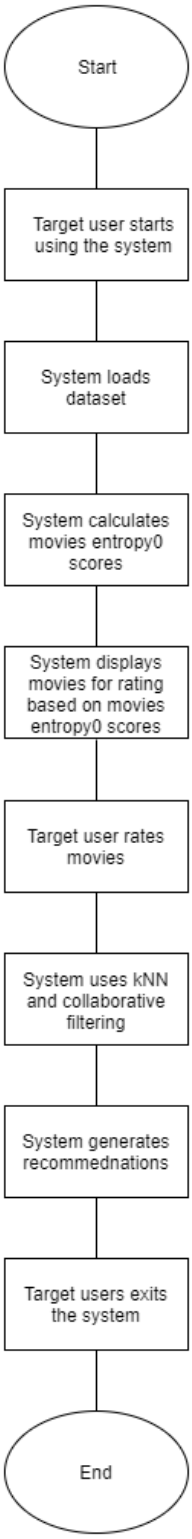
Below we present a screenshot of how the system asks user to insert his demographic data:

```
Select your age range:
 1. <=18
 2. 19-24
 3. 25-30
 4. 31-40
 5. 41-50
 6. 51-60
 7. 61-70
 8. 71-100

Choose the corresponding number: 3
Select your gender:
 1. Male
 2. Female

Choose the corresponding number: 1
Select your occupation:
 1. administrator
 2. artist
 3. doctor
 4. educator
 5. engineer
 6. entertainer
 7. executive
 8. healthcare
 9. homemaker
 10. lawyer
 11. librarian
 12. marketing
 13. none
 14. other
 15. programmer
 16. retired
 17. salesman
 18. scientist
 19. student
 20. technician
 21. writer

Choose the corresponding number: 15
```

Picture 4.3: System asks target user to insert his age, gender and occupation

4.5.3 Movies Entropy0 based algorithm flowchart diagram

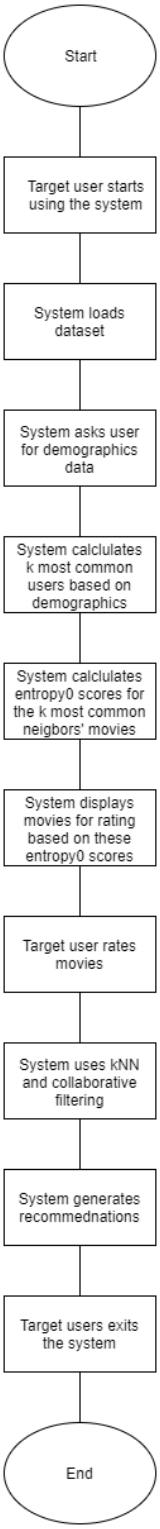
In this section we introduce the flowchart of the movies entropy0 based algorithm which displays movies for rating based on their entropy0 scores and uses collaborative filtering for recommendations.



Picture 4.4: Movies Entropy0 based algorithm

4.5.4 User Demographics and movies entropy0 based algorithm flowchart diagram

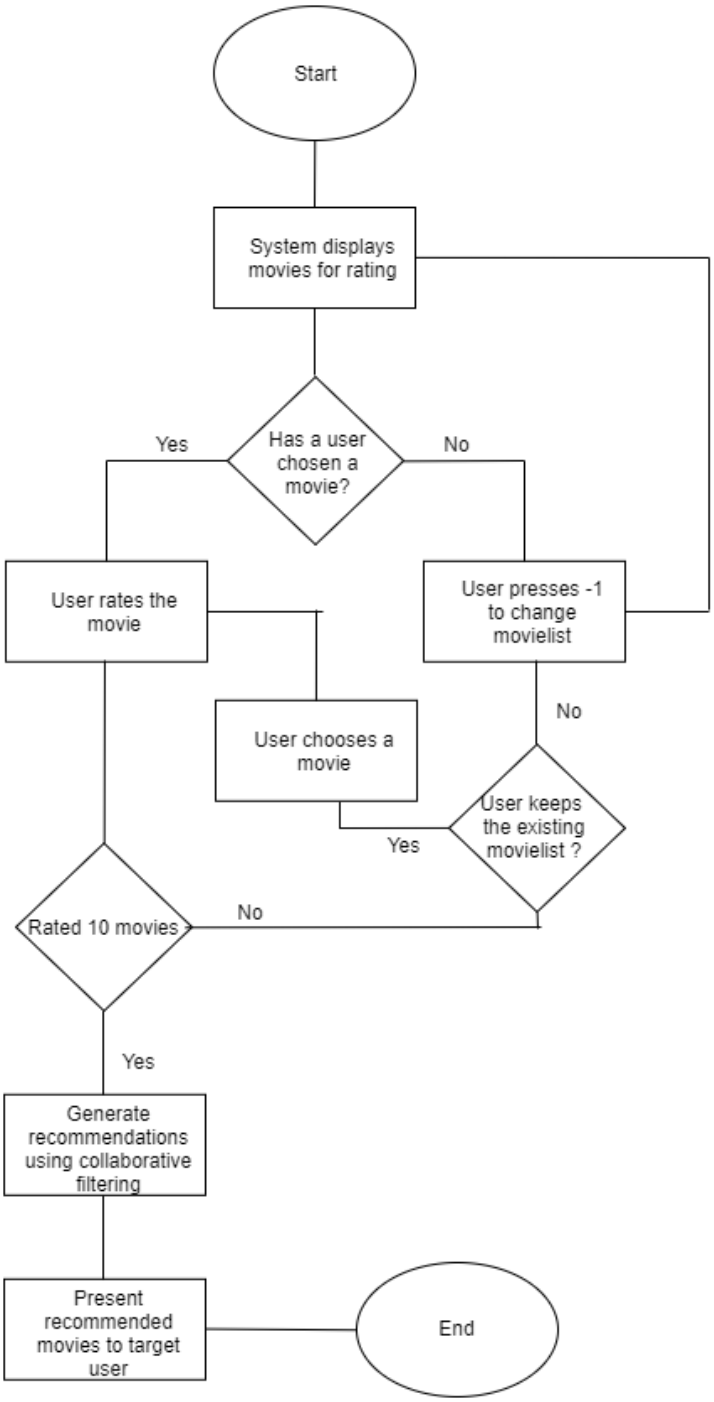
In this section we introduce the flowchart of the user demographics and movies entropy0 based algorithm which displays movies for rating based on users' demographics and movies entropy0 scores and uses collaborative filtering for recommendations.



Picture 4.5: Users demographics and Movies Entropy0 based algorithm

4.5.5 Movies rating function flowchart diagram

In this point we provide the flowchart diagram for the movie rating procedure. User starts the system and the system displays movies for rating. User either choses a movie for rating or presses -1 to load a new movielist. If he has rated 10 movies, the system provides recommendations by using collaborative filtering. On the other hand, if he has rated less than 10 movies the user either changes the movielist or keeps the already existing movielist.



Picture 4.6: Movies rating function

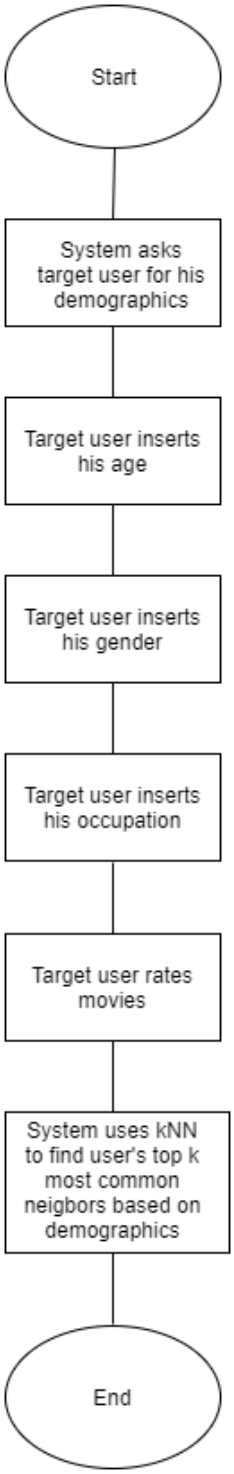
Below we present an example of how movies are displayed by the system to the target user for rating:

```
{1: 'Toy Story (1995)'}
{2: 'GoldenEye (1995)'}
{3: 'Four Rooms (1995)'}
{4: 'Get Shorty (1995)'}
{5: 'Copycat (1995)'}
{6: 'Shanghai Triad (Yao a yao yao dao waipo qiao) (1995)'}
{7: 'Twelve Monkeys (1995)'}
{8: 'Babe (1995)'}
{9: 'Dead Man Walking (1995)'}
{10: 'Richard III (1995)'}
{11: 'Seven (Se7en) (1995)'}
{12: 'Usual Suspects, The (1995)'}
{13: 'Mighty Aphrodite (1995)'}
{14: 'Postino, Il (1994)'}
{15: "Mr. Holland's Opus (1995)"}
{16: 'French Twist (Gazon maudit) (1995)'}
{17: 'From Dusk Till Dawn (1996)'}
{18: 'White Balloon, The (1995)'}
{19: "Antonia's Line (1995)"}
{20: 'Angels and Insects (1995)'}


Choose a movie, or press -1 to change movieset:
```

Picture 4.7: Movies displayed to user for rating

4.5.6 Inserting target user demographics

In the following flowchart we describe how user inserts his demographic data. First of all he inserts his age, then he inserts his gender and finally he enters his occupation. Finally the system uses the kNN algorithm to find user's top k most common neighbors based on demographics



Picture 4.8: Insert users demographics function

5 Implementation

5.1 Basic parts of our implementation

As we have already mentioned in the previous chapter, we developed four different scripts: basic, demographic-based, entropy0-based and demographic & entropy0-based. The aforementioned scripts were developed in Python (version 3.6) language using the PyCharm development environment. Furthermore in order to manage some important Python packages we have used the Anaconda package manager. Below we are going to give a brief description of the main functions of the four scripts:

5.1.1 Functions of the Basic script

- *readFullDataset(dataSetFilePath)*: This function reads the full dataset (u.data) which contains the 100000 ratings. It takes one argument (dataSetFilePath) of type string, which is the path of the u.data file and finally returns the full dataset as Pandas dataframe with the following names as columns: 'user_id', 'item_id', 'rating', 'timestamp'

- *readMovieSet(movieSetFilePath)*: This function reads the movie dataset (u.item) which contains information about movies. It takes one argument (movieSetFilePath) of type string, which is the path of the u.item file and finally returns the movie dataset as Pandas dataframe with the following names as columns: 'item_id', 'title'

- *insertNewUserRatings(ids_titles, fullDataSet, newUserID, timestamp, known_positives, mySelMovies):* This function displays movies to the new user and asks for explicit ratings. It takes 6 arguments: *ids_titles* from the readMovieSet(movieSetFilePath) function, *fullDataSet* from the readFullDataset(dataSetFilePath) function, the *newUserID*, a random *timestamp*, and *known_positives*, *mySelMovies* are both Python lists. Finally returns the full dataset that includes the new user with his ratings.

- *numberOfUsers(fullDataSet)*: This function returns the number of users in the dataset. It takes the full dataset as an argument.

- *numberOfMovies(fullDataSet)*: This function returns the number of movies in the dataset. It takes the full dataset as an argument.

- *getUserItemMatrix(n_users, n_items, fullDataSet)*: This function returns the user-item matrix. It takes the number of users, the number of movies and also the full dataset as arguments.

- *calculateUsersPearsonCorrelation(user_item_matrixTrain)*: This function returns a matrix with the users Pearson correlation based on their ratings. It takes the user-item matrix as an argument.

- *predict_Top_K_no_Bias(ratings, similarity, k=40)*: This function returns a numpy array with the predictions for each user (kNN Collaborative filtering-bias subtracted). It takes the user-item matrix, the matrix with Users Pearson Correlation and a number for the kNN algorithm (default is 40) as arguments.

- *printPredictedMoviesUserBased(user, n)*: This function prints the top–n recommended movies for a given user id. It takes the user id and the number of recommended movies as arguments.

5.1.2 Functions of the Demographic-based script

- *_read_raw_data(path)*: This function reads the demographic data of the existing users. It takes one argument (path) of type string, which is the path of the zip file that contains all the datasets and finally returns the demographic data.

- *createUserMetaDataList (users_raw, users_age, users_occup, user_meta_raw)*: This function asks the new user for his demographic data (age, gender and occupation) and then append this data to the previous dataset with the users demographics. It takes 4 lists as arguments: the first 3 lists are from the demograhic model that we have created, and the 4th list is demographics of the dataset.

- *_parse_user_metadata (num_users, user_meta_raw, users_combined_features):* This function transforms users demographics list (with the new user) into a list with zeros and ones and return this list. It takes as arguments the number of users, the demographics of all users (including the new user), and the user's combined features from the demographic model.

- *euclideanDistance(instance1, instance2, length)*: This function calculates and returns the Euclidean distance of two instances (instance 1 and instance 2).

- *getNeighbors(trainingSet, testInstance, k)*: This function calculates and returns the k most common neighbors of a specified testInstance from a given dataset.

- *readFullDataset(dataSetFilePath)*: The same as Basic script.

- *readMovieSet(movieSetFilePath)*: The same as Basic script.

- *insertNewUserRatings(ids_titles, fullDataSet, newUserID, timestamp, known_positives, mySelMovies, neighborsmovies):* The same as Basic script, taking into consideration the most common neighbors movies.

- *numberOfUsers(fullDataSet)*: The same as Basic script

- *numberOfMovies(fullDataSet)*: The same as Basic script

- *getUserItemMatrixDemographicsBased(n_users, n_items, fullDataSet, neighbors)* The same as the *getUserItemMatrix* of the Basic script, taking into consideration only the common neighbors.

- *getUserItemMatrix(n_users, n_items, fullDataSet)*: The same as Basic script

- *calculateUsersPearsonCorrelation(user_item_matrixTrain)*: The same as Basic script

- *predict_Top_K_no_Bias(ratings, similarity, k=40)*: The same as Basic script

- *printPredictedMoviesUserBased(user, n)*: The same as Basic script

5.1.3 Functions of the Entropy0-based script

- *readFullDataset(dataSetFilePath)*: The same as Basic script.

- *readMovieSet(movieSetFilePath)*: The same as Basic script.

- *insertNewUserRatings(ids_titles, fullDataSet, newUserID, timestamp, known_positives, mySelMovies, entropy_indexes):* The same as Basic script taking into consideration movies entropy (entropy_indexes).

- *numberOfUsers(fullDataSet)*: The same as Basic script

- *numberOfMovies(fullDataSet)*: The same as Basic script

- *calcMoviesEntropy0(fullDataSet, n_users, n_items, neighbors)*: This function calculates and returns the entropy0 values of the full dataset. It takes as arguments the full dataset and the number of users and movies.

- *getUserItemMatrix(n_users, n_items, fullDataSet)*: The same as Basic script

- *calculateUsersPearsonCorrelation(user_item_matrixTrain)*: The same as Basic script

- *predict_Top_K_no_Bias(ratings, similarity, k=40)*: The same as Basic script

- *printPredictedMoviesUserBased(user, n)*: The same as Basic script

5.1.4 Functions of the Demographic & Entropy0-based script

- *_read_raw_data(path)*: The same as Demographic based script.
- *createUserMetaDataList (users_raw, users_age, users_occup, user_meta_raw)*: The same as Demographic based script.
- *_parse_user_metadata(num_users, user_meta_raw, users_combined_features)*: The same as Demographic based script.
- *euclideanDistance(instance1, instance2, length)*: This function calculates and returns the Euclidean distance of two instances (instance 1 and instance 2).
- *getNeighbors(trainingSet, testInstance, k)*: This function calculates and returns the k most common neighbors of a specified testInstance from a given dataset.
- *readFullDataset(dataSetFilePath)*: The same as Basic script.
- *readMovieSet(movieSetFilePath)*: The same as Basic script.
- *insertNewUserRatings(ids_titles, fullDataSet, newUserID, timestamp, known_positives, mySelMovies, entropy_indexes):* The same as Basic script
- *numberOfUsers(fullDataSet)*: The same as Basic script
- *numberOfMovies(fullDataSet)*: The same as Basic script
- *calcMoviesEntropy0(fullDataSet, n_users, n_items, neighbors)*: The same as Entropy0 based script.
- *getUserItemMatrix(n_users, n_items, fullDataSet)*: The same as Basic script
- *calculateUsersPearsonCorrelation(user_item_matrixTrain)*: The same as Basic script
- *predict_Top_K_no_Bias(ratings, similarity, k=40)*: The same as Basic script
- *printPredictedMoviesUserBased(user, n)*: The same as Basic script

5.2 Basic flow of each script

Below we are going to present and highlight the most important points of the basic flow of each script. The corresponding scripts can be seen in detail in the Appendix (source code section).

5.2.1 Basic script

- Lines 198-201: The system initializes the new user and also some lists.
- Lines 203-206: The system reads the full dataset and the full movieset,
- Lines 209-213: The system displays movies and asks for explicit ratings., then it calculates the number of users and movies
- Line 216: The system creates the user item matrix taking into consideration the new user.
- Line 219: The system calculates users similarity by Pearson correlation
- Line 222: The system generates predictions for users
- Line 238: The system prints the top 10 recommended movies for the new user

5.2.2 Demographic-based script

- Lines 369-372: The system initializes the new user and also some lists.
- Line 375: The system fetch the users demographic data
- Lines 378-392: The system creates the model for the demographic based system by creating some lists
- Line 395: The system asks for the demographic data of new user and appends it to the list with the demographics of existing users.
- Lines 397-400: The system reads the full dataset and the full movieset
- Line 404: The system creates a list with zeros and ones that corresponds to users demographic data including the new user
- Line 406: The system creates a list with zeros and ones that corresponds to users demographic data without the new user
- Line 408: The system creates a list with zeros and ones that corresponds only to new user demographic data.
- Line 411: The system finds the 20 most common neighbors of the new user, taking into consideration users demographics.
- Lines 413-415: The system calculates the number of users and movies

- Line 417: The system returns all the rated movies of the 20 most common users based on demographics
- Lines 421: The system displays movies and asks for explicit ratings, taking into consideration only the movies of the 20 most common users.
- Lines 424-425: The system calculates again the number of users and movies
- Line 428: The system creates the user item matrix taking into consideration the new user.
- Line 431: The system calculates users similarity by Pearson correlation
- Line 434: The system generates predictions for users
- Line 450: The system prints the top 10 recommended movies for the new user

5.2.3 Entropy0-based script

- Lines 253-256: The system initializes the new user and also some lists.
- Lines 258-261: The system reads the full dataset and the full movieset.
- Line 263-265: The system calculates the number of users and movies
- Line 267: The system calculate movies ratings entropy0 values and return movies indexes starting from the highest entropy0 values to the lowest
- Lines 271: The system displays movies and asks for explicit ratings, considering movies entropy0 values.
- Line 273-275: The system re-calculates the number of users and movies.
- Line 278: The system creates the user item matrix taking into consideration the new user.
- Line 281: The system calculates users similarity by Pearson correlation
- Line 284: The system generates predictions for users
- Line 300: The system prints the top 10 recommended movies for the new user

5.2.4 Demographic & Entropy0-based script

- Lines 408-411: The system initializes the new user and also some lists.
- Line 414: The system fetch the users demographic data
- Lines 417-431: The system creates the model for the demographic based system by creating some lists
- Line 433: The system asks for the demographic data of new user and appends it to the list with the demographics of existing users.

- Line 437: The system creates a list with zeros and ones that corresponds to users demographic data including the new user
- Line 439: The system creates a list with zeros and ones that corresponds to users demographic data without the new user
- Line 441: The system creates a list with zeros and ones that corresponds only to new user demographic data.
- Line 444: The system finds the 20 most common neighbors of the new user, taking into consideration users demographics.
- Lines 446-449: The system reads the full dataset and the full movieset.
- Lines 451-453: The system calculates the number of users and movies
- Line 457: The system calculates movies ratings entropy0 values taking into consideration the ratings of the 20 most common neighbors, and returns the corresponding movies indexes from the highest to the lowest.
- Lines 460: The system displays movies and asks for explicit ratings, taking into consideration the movies indexes of the previous line
- Line 462-464: The system calculates the number of users and movies
- Line 467: The system creates the user item matrix taking into consideration the new user.
- Line 470: The system calculates users similarity by Pearson correlation
- Line 473: The system generates predictions for users
- Line 489: The system prints the top 10 recommended movies for the new user

6 Evaluation and future work

6.1 Results and evaluation

In this part, we proceed in the evaluation of our system: We have tested each of the four scripts on 25 different users. 10 of them were female and 15 were male with their age ranging from 20-60.

In order to remove bias from the evaluation, we do not disclose in which of the four scripts each predicted movieset corresponds to. For that reason, we modified the *printPredictedMoviesUserBased(),* function of each script by commenting out the last line and adding another line that saves the predicted movieset in excel format. As a result, the modified function will be:

```
def printPredictedMoviesUserBased(user, n):
    user = user - 1
    n = n - 1
    pred_indexes = [i + 1 for i in np.argsort(-user_prediction_User[user])]
    pred_indexes = [item for item in pred_indexes if item not in known_positives]
    movies_ids_titles = pd.read_csv('u.item', sep="|", header=None, encoding='latin-1', names=['itemId', 'title'], usecols=[0, 1])
    pd_pred_indexes = pd.DataFrame(pred_indexes, columns=['itemId'])
    pred_movies = pd.merge(pd_pred_indexes, movies_ids_titles, on='itemId')
    print('\n')
    print("******************user-based collaborative filtering (Top-K neigbors and Bias-subtracted)*****************************")
→   pred_movies.loc[:n].to_csv("Predicted_Moviesets\D", sep='\t', encoding='utf-8')
→   #print(pred_movies.loc[:n])
```

Picture 6.1: Modified version of the printPredictedMoviesUserBased() function

As we can see from the above figure, the blue arrow indicates the added line of code that writes the predicted movieset into an excel file, while the red arrow indicates the commented code. By this way, the program hides the predicted movieset and the user is completely unaware of which predicted movieset corresponds to each of the 4 scripts.

The evaluation process is presented as follows: First of all, every user have to execute each of the four scripts (systems). Then, the four predicted moviesets are shown to the user: The A set corresponds to the demographic-based script, the B set corresponds to the entropy0-based script, the C set corresponds to the basic script and finally the D set corresponds to the demographic & entropy0 based script, however the user is not aware of that matching in order to remove bias as we have mentioned before. Finally, the users have to rank their most preferred to least preferred movieset by declaring his preferences.

For example: Firstly I choose movieset B, secondly I choose movieset A, then I choose movieset D and finally I choose movieset C. The first preference is awarded with four points, the second with 3, the third with 2 and the final with 1 point. By this way we can get the required preference scores for each of the 4 scripts in order to complete the evaluation.

In order to calculate the final scores of the evaluation for each script, we created an excel file with all the required information. This can be seen below:

User info			User preference scores for each system				User effort time (min.)			
Age	**Gender**	**Occupation**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
27	F	Student	4	3	2	1	6	4	9	15
55	F	Technician	2	4	1	3	3	3	9	16
54	M	Technician	4	2	3	1	3	4	9	15
30	M	Scientist	3	4	1	2	4	3	7	10
20	F	Artist	4	3	2	1	5	4	8	12
22	M	Student	1	3	4	2	4	4	9	13
25	F	Programmer	4	2	3	1	4	5	8	11
30	M	Engineer	3	4	1	2	5	6	7	16
31	M	Doctor	1	4	2	3	3	3	9	17
18	M	Student	4	3	1	2	4	6	7	13
62	F	Retired	4	1	2	3	6	4	7	12
65	M	Retired	1	4	3	2	6	3	8	15
38	M	Programmer	3	4	2	1	5	5	6	15
31	F	Lawyer	2	1	3	4	3	4	8	14
27	M	Salesman	3	4	2	1	4	3	7	14
26	M	Healthcare	3	4	1	2	7	4	9	16
28	F	Educator	3	4	1	2	5	6	9	17
27	M	Marketing	2	4	3	1	6	5	7	11
25	M	Salesman	4	2	1	3	7	3	8	18
24	F	Educator	3	2	1	4	3	3	9	12
29	M	Engineer	1	4	2	3	7	4	8	14
33	M	Programmer	4	2	3	1	3	5	6	12
35	F	Homemaker	2	4	3	1	3	6	6	13
25	M	Technician	3	4	1	2	4	3	7	17
21	F	Artist	4	1	2	3	6	4	9	17
SUM			72	77	50	51	116	104	196	355
AVG			3,13	3,34	2,17	2,21	5,04	4,52	8,52	15,43

Table 6.1: Evaluation table containing user demographics, the preference scores for every script and also the effort time to complete each script

As we can see, demographic-based and entropy0 based systems are topping the list of most preferred systems. Entropy0 based is in the first position with average preference score 3,34, while demographic based comes second with 3,13. Surprisingly, the demographic and entropy0 based system is in the third position with 2,21 average preference score, while the basic system (random selection) is the last with 2,17.

In terms of user effort time, entropy0 based system is again the first with 4,52 minutes average user effort time, demographic based is second with 5,04 minutes, basic system is third with 8,52 minutes while demographics and entropy0 based system is the last with 15,43 minutes (double than that of basic).

Finally, excluding the system that combines demographics and entropy0, we compare and contrast entropy0 based and demographic based systems with the basic system. As a result we have the following table:

	Demographics based	Entropy0 based	Basic
SUM	72	77	50
Percentage	36,18%	38,69%	25,12%

Table 6.2: Comparing the best two systems with the basic in terms of user preference score

6.2 Conclusions

Taking into consideration the above evaluations, we conclude that ratings entropy0 values as well as users demographics can play an important role in addressing cold start problem on collaborative filtering systems. Users tend to prefer entropy0 based systems, while demographics based systems rank second with small difference from the first. Surprisingly, the system that combines both demographics and entropy0 is in the third place with almost the same user preference score as the basic system that offers random selection.

More specifically, the entropy0 based system not only is first in terms of user preference scores, but also requires less user effort than the other three systems. The average user effort for entropy0 based system is 4,5 minutes while demographics based system requires 5 minutes on average. Users seemed happy as both of the aforementioned systems and especially entropy0 based displayed movies that were known to them. Moreover, they were a little concerned about the demographic based system because it displayed for rating only a small portion of the total available movies of the dataset. Furthermore, the system that combines both demographics and entropy0 values, is in the last position

because it mostly displays unknown movies, so the users have to make a great effort in order to complete this test.

To sum up, we can see that entropy0 based system is in the first place both in terms of users preference scores and also in terms of effort time. This can also be depicted better if we see the tables 6.1 and 6.2 where entropy0 based system is better than the basic by 13% while it requires much less user effort (the average user effort for entropy0 based is 4,5 minutes while for the basic is 8,5 minutes). By this way, we have significantly improved the collaborative movie recommender system both in terms of user preference scores and also in user effort time.

6.3 Future work

As we have seen from the evaluation part, the majority of users were complaining that many movies were old and completely unknown to them. As a result, in a future work there a need to use newer dataset with more known movies. Furthermore, except from the release year, the movie-set should be enhanced with more demographic features such as income level, marital status, number of children, religion etc. By this way we can better understand how much demographics affect recommender systems.

Another idea for future research is to use completely different datasets that include other kind of products such as music, books, electronic devices and more (this can be achieved by using Amazon datasets).

Finally, another addition that will surely attract a lot of attention is to develop recommender systems for mobile devices. As we can see, in the past 10 years there is a rapid growth of mobile devices and more and more people are using smartphones and tablets. As a result, there is a need to develop recommender systems that fit in these mobile devices. The main idea is that the user will send all the required data from his mobile device using an easy and friendly graphical user interface. Then the recommendation engine running on a powerful server will receive and process the user input, generate recommendation and send it back to user's device. By this way the user will be able to see the predictions through a simple and friendly interface of his mobile device.

Bibliography

1. Internet usage statistics - The big picture of world Internet users and population stats. http://www.internetworldstats.com/stats.htm.
2. P. Resnick, N. Iacovou, M. Suchak, P. Bergstorm, and J. Riedl. GroupLens: An Open Architecture for Collaborative Filtering of Netnews. Proceedings of ACM Conference on Computer Supported Cooperative Work, citeseer.ist.psu.edu/resnick94grouplens.html, 1994.
3. Leskovec,J.,Rajaraman,A.,&Ullman,J.D.(2014). Mining of massive datasets. Cambridge University Press.
4. Burke,R.(2002). Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12(4), 331-370.
5. Hu,Y.,Koren,Y.,&Volinsky,C.(2008).Collaborative filtering for implicit feedback datasets. Data Mining,2008. ICDM'08.Eighth IEEE International Conference (pp. 263-272).IEEE.
6. Ricci,F.,Rokach,L.,& Shapira,B.(2011). Introduction to recommender systems handbook (pp. 1-35).Springer US.
7. D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, "Using collaborative filtering to weave an information tapestry," Commun. ACM, vol. 35, pp. 61–70, Dec. 1992.
8. G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems a survey of the state-of-the-art and possible extensions
9. J. Bobadilla, F. Serradilla, and J. Bernal, "A new collaborative filtering metric that improves the behavior of recommender systems," Knowledge-Based Systems
10. Hanani U., Shapira B., Shoval P., (2001). "Information Filtering: Overview of Issues, Research and Systems", User Modeling and User-Adapted Interaction, 11 (3), 203–259.
11. Salton G., McGill M.J., Introduction to Modern Information Retrieval, McGraw-Hill, 1983.

12. Breese J. S., Heckerman D., Kadie C., (1998). “Empirical Analysis of Predictive Algorithms for Collaborative Filtering.” In Uncertainty in Artificial Intelligence. Proceedings of the Fourteenth Conference, pp. 43–52.
13. Deshpande M., Karypis G., (2004). “Item-based top-N recommendation algorithms.” ACM Transations on Information Systems, 22(1), 143–177. ISSN 1046-8188.
14. Linden G., Smith B., York J., (2003). “Amazon.com Recommendations: Item-to-Item Collaborative Filtering.” IEEE Internet Computing, 7(1), 76–80.
15. Callvik, Johan, Liu, Alva, (2017) “Using Demographic Information to Reduce the New User Problem in Recommender Systems.” Kth Royal Institute of Technology School Of Computer Science And Communication
16. Manolis Vozalis, Konstantinos G Margaritis, (2004). “Collaborative Filtering Enhanced By Demographic Correlation.” AIAI symposium on professional practice in AI, of the 18th world computer congress.
17. MH Nadimi-Shahraki, M Bahadorpour, (2014). “Cold-start Problem in Collaborative Recommender Systems: Efficient Methods Based on Ask-to-rate Technique”. CIT. Journal of Computing and Information Technology 22 (2), 105-113
18. Rashid, A.M., Karypis, G., Riedl, J. (2002) “Learning preferences of new users in recommender systems: an information theoretic approach” 127–134. ACM Press
19. Sebastiani F., (2002) “Machine Learning in Automated Text Categorization”, ACM Computing Surveys, 34 (1), 1–47.
20. Shani,G., & Gunawardana,A. (2011). Evaluating recommendation systems. Recommender systems handbook (pp. 257-297). Springer US.
21. Burke,R.(2007).Hybrid web recommender systems. The adaptive web (pp. 377-408).Springer Berlin Heidelberg.
22. Koren, Yehuda; Bell, Robert; Volinsky, Chris. Matrix factorization techniques for recommender systems. Published by the IEEE Computer Society, 0018 9162/09, 2009.
23. Oliver Sutton, (2012). Introduction to k Nearest Neighbor Classification and Condesed Nearest Neighbor Data Reduction
24. Konstantinos Chatzisavvas, George Sarigiannidis, Machine Learning Algorithms for Recommendation System and a Social Recommender System.

Appendix

Source Code

basic.py

```
    import numpy as np
    import pandas as pd
    from sklearn.metrics.pairwise import pairwise_distances
    from random import randint


#############################################################################
################################################
    #We read in the u.data file, which contains the full dataset.
    def readFullDataset(dataSetFilePath):
        header = ['user_id', 'item_id', 'rating', 'timestamp']
        return pd.read_csv(dataSetFilePath, sep='\t', names=header)
    #-------------------------------------------------------------------
-----------------------------------------------#


#############################################################################
################################################
    #we read the the movies titles from the movie dataset
    def readMovieSet(movieSetFilePath):
        df_ids_titles = pd.read_csv(movieSetFilePath, sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],usecols=[0,
1])
        ids_titles = np.empty(1682, dtype=np.object)
        for line in df_ids_titles.itertuples():
            ids_titles[line[0]] = line[2]
        return ids_titles
    #-------------------------------------------------------------------
-----------------------------------------------#


#############################################################################
################################################
    #insert new user by creating gui in python console
    def insertNewUserRatings(ids_titles, fullDataSet, newUserID,
timestamp, known_positives, mySelMovies):
        i=0
        j=20
        f=0
        while(f < 10):
            userList = []
            for x in range(i,j):
                userList.append({x%20+1: ids_titles[randint(0,
1681)]})
```

```
            print('\n')
            for p in userList:
                print(p)
            print('\n')
            while(True):
                try:
                    var = int(input("Choose a movie, or press -1 to
change movieset: "))
                except ValueError:
                    print("Wrong input, please insert an integer")
                    continue
                if((var<-1 or var>20) and var ==0):
                    print("Value must be -1 OR between 1 and 20.
Please insert a valid integer")
                    continue
                if(1<=var and 20>=var):
                    selMovie = str(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
                    if selMovie in mySelMovies:
                        print("You have already selected that movie,
please choose another movie")
                        continue
                    mySelMovies.append(str(ids_titles.tolist().in-
dex(userList[var-1][var])+1))
                break
            if (var == -1):
                if ((1681 - j) >= 20):
                    i = j
                    j += 20
                elif ((1681 - j) > 0):
                    i = j
                    j = 1682
                else:
                    i = 0
                    j = 20
                continue
            else:
                print('\n')
                print("You selected the movie: " + userList[var-
1][var] + " with ID: " + str(ids_titles.tolist().index(userList[var-
1][var])+1))
                print('\n')
                while (True):
                    try:
                        rating = int(input("Rate the movie: "))
                    except ValueError:
                        print("Wrong input, please insert an inte-
ger")
                        continue
                    if (rating < 1 or rating > 5):
                        print("Value must be between 1 and 5. Please
insert a valid integer")
                        continue
                    break
                known_positives.append(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
                fullDataSet.loc[len(fullDataSet)] = [newUserID,
ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
                f = f + 1
                while(f < 10):
```

```
85                    while (True):
86                        try:
87                            ch = int(input("To change the movieset
press -1, to keep press 1: "))
88                        except ValueError:
89                            print("Wrong input, please insert an in-
teger")
90                            continue
91                        if (ch != 1 and ch != -1):
92                            print("Value must be 1 or -1. Please in-
sert a valid integer")
93                            continue
94                        break
95                    if(int(ch) == -1):
96                        break
97                    else:
98                        print('\n')
99                        for p in userList:
100                           print(p)
101                       print('\n')
102                       while (True):
103                           try:
104                               var = int(input("Choose a movie: "))
105                           except ValueError:
106                               print("Wrong input, please insert an
integer")
107                               continue
108                           if ((var < -1 or var > 20)):
109                               print("Value must be between 1 and
20. Please insert a valid integer")
110                               continue
111                           selMovie = str(ids_titles.tolist().in-
dex(userList[var - 1][var]) + 1)
112                           if selMovie in mySelMovies:
113                               print("You have already selected that
movie, please choose another movie")
114                               continue
115                           mySelMovies.append(str(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1))
116                           break
117                       print('\n')
118                       print("You selected the movie: " + us-
erList[var - 1][var] + " with ID: " + str(
119                           ids_titles.tolist().index(userList[var -
1][var]) + 1))
120                       print('\n')
121                       while (True):
122                           try:
123                               rating = int(input("Rate the movie:
"))
124                           except ValueError:
125                               print("Wrong input, please insert an
integer")
126                               continue
127                           if (rating < 1 or rating > 5):
128                               print("Value must be between 1 and 5.
Please insert a valid integer")
129                               continue
130                           break
131                       known_positives.append(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1)
```

```
                        fullDataSet.loc[len(fullDataSet)] = [newUse-
rID, ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
                        f = f + 1
                if((1681-j) >= 20):
                    i = j
                    j += 20
                elif((1681-j) > 0):
                    i = j
                    j = 1682
                else:
                    i = 0
                    j = 20
            print('\n')
        return fullDataSet
    #-------------------------------------------------------------------
-------------------------------------------------#


#####################################################################
##############################################
    #we count the number of unique users and movies.
    def numberOfUsers(fullDataSet):
        n_users = fullDataSet.user_id.unique().shape[0]
        return n_users

    def numberOfMovies(fullDataSet):
        n_items = fullDataSet.item_id.unique().shape[0]
        return n_items
    #-------------------------------------------------------------------
-------------------------------------------------#


#####################################################################
##############################################
    #we create user-item matrix
    def getUserItemMatrix(n_users, n_items, fullDataSet):
        user_item_matrix = np.zeros((n_users, n_items))
        for line in fullDataSet.itertuples():
            user_item_matrix[line[1] - 1, line[2] - 1] = line[3]
        return user_item_matrix
    #-------------------------------------------------------------------
-------------------------------------------------#


#####################################################################
##############################################
    #we use the pairwise_distances function from sklearn to calculate
the pearson correlation
    def calculateUsersPearsonCorrelation(user_item_matrixTrain):
        user_similarityPearson = 1 - pairwise_distances(user_item_ma-
trixTrain, metric='correlation') #943*943
        user_similarityPearson[np.isnan(user_similarityPearson)] = 0
        return user_similarityPearson
    #-------------------------------------------------------------------
-------------------------------------------------#


```

```
179
##########################################################################
##############################################
180   #make predictions combining Top-K neigbors and Bias-subtracted
collaborative filtering
181   def predict_Top_K_no_Bias(ratings, similarity, k=40):
182       pred = np.zeros(ratings.shape)
183       user_bias = ratings.mean(axis=1)
184       ratings = (ratings - user_bias[:, np.newaxis]).copy()
185       for i in range(ratings.shape[0]):
186           top_K_users = [np.argsort(similarity[:,i])[:-k-1:-1]]
187           for j in range(ratings.shape[1]):
188               pred[i,j] = similarity[i, :][top_K_users].dot(rat-
ings[:, j][top_K_users])
189               pred[i,j] /= np.sum(np.abs(similarity[i, :][top_K_us-
ers]))
190       pred += user_bias[:, np.newaxis]
191       return pred
192   #-------------------------------------------------------------------
-------------------------------------------------#
193
194
195
##########################################################################
##############################################
196   ##############################################BASIC
SCRIPT#########################################################################
197
198   newUserID = 944   # new user's id
199   timestamp = '883446543'   # random timestamp, we dont care about
that
200   known_positives = []
201   mySelMovies = []
202
203   #read the movieset
204   ids_titles = readMovieSet('u.item')
205   #read the full dataset
206   fullDataSet = readFullDataset('u.data')
207
208   #insert new user
209   fullDataSetNewUser = insertNewUserRatings(ids_titles, fullDa-
taSet, newUserID, timestamp, known_positives, mySelMovies)
210
211   #calculate number of users and items
212   n_users = numberOfUsers(fullDataSetNewUser)
213   n_items = numberOfMovies(fullDataSetNewUser)
214
215   #calculate user item matrix
216   user_item_matrix = getUserItemMatrix(n_users, n_items, fullDa-
taSetNewUser)
217
218   #calculate user similarity(Pearson correlation)
219   user_similarityPearson = calculateUsersPearsonCorrela-
tion(user_item_matrix)
220
221   #apply bias subtracted user-based collaborative filtering with
Top-40 most common neigbors algorithm
222   user_prediction_User = predict_Top_K_no_Bias(user_item_matrix,
user_similarityPearson, k=40)
223
```

```
224  #function for printing the top n recommended movies for a given
user id -
225  def printPredictedMoviesUserBased(user, n):
226      user = user - 1
227      n = n - 1
228      pred_indexes = [i + 1 for i in np.argsort(-user_predic-
tion_User[user])]
229      pred_indexes = [item for item in pred_indexes if item not in
known_positives]
230      movies_ids_titles = pd.read_csv('u.item', sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],
usecols=[0, 1])
231      pd_pred_indexes = pd.DataFrame(pred_indexes, columns=['item-
Id'])
232      pred_movies = pd.merge(pd_pred_indexes, movies_ids_titles,
on='itemId')
233      print('\n')
234      print("********************user-based collaborative filtering
(Top-K neigbors and Bias-subtracted)*******************************")
235      print(pred_movies.loc[:n])
236
237  #print the top 10 recommended movies for the new User (id = 944)
238  printPredictedMoviesUserBased(944, 10)
```

demographic-based.py

```
    import zipfile
    from numpy import array
    import numpy as np
    import pandas as pd
    from sklearn.metrics.pairwise import pairwise_distances
    import math




##########################################################################
#################################################
    #fetch demographic data
    def _read_raw_data(path):
        with zipfile.ZipFile(path) as datafile:
            return datafile.read('ml-100k/u.user').decode(errors='ig-
nore').split('\n')
    #-------------------------------------------------------------------
-------------------------------------------------#


##########################################################################
#################################################
    # create the user_meta-data list
    def createUserMetaDataList(users_raw, users_age, users_occup,
user_meta_raw):
        # first create the user_meta-data list by the existing da-
taset
        for line in users_raw:
            if not line:
                continue
            #print(line)
            splt = line.split('|')
            # Zero-based indexing
            userid = int(splt[0])
            age = int(splt[1])
            gender = splt[2]
            occup = splt[3]
            i = 0
            for m in users_age:
                if(age <= int(m)):
                    #print(i)
                    break
                else:
                    i = i + 1

            if(gender == 'M'):
                j = 8
            else:
                j = 9
            k = 10
            for n in users_occup:
                if(occup == n):
                    #print(k)
                    break
                else:
                    k = k + 1
            s = str(userid) + "|"
            for l in range(0,31):
```

```
53              if(l == i or l == j or l == k):
54                  s = s + "1|"
55              else:
56                  s = s + "0|"
57          s = s[:-1]
58          user_meta_raw.append(s)
59      #then, append the new user to the above user_meta_data list
60      while (True):
61          try:
62              print('Select your age range:\n', '1. <=18\n', '2.
19-24\n', '3. 25-30\n', '4. 31-40\n', '5. 41-50\n',
63                    '6. 51-60\n', '7. 61-70\n', '8. 71-100\n')
64              newage = int(input("Choose the corresponding number:
"))
65          except ValueError:
66              print("Wrong input, please insert an integer")
67              continue
68          if (newage < 1 or newage > 8):
69              print("Value must be between 1 and 8. Please insert a
valid integer")
70              continue
71          if (1 <= newage and 8 >= newage):
72              newage = (newage) - 1
73          break
74
75      while (True):
76          try:
77              print('Select your gender:\n', '1. Male\n', '2. Fe-
male\n')
78              newgend = int(input("Choose the corresponding number:
"))
79          except ValueError:
80              print("Wrong input, please insert an integer")
81              continue
82          if (newgend < 1 or newgend > 2):
83              print("Value must be 1 or 2. Please insert a valid
integer")
84              continue
85          if (1 == newgend or 2 == newgend):
86              newgend = (newgend) - 1 + 8
87          break
88
89      while (True):
90          try:
91              print('Select your occupation:\n', '1. administra-
tor\n', '2. artist\n', '3. doctor\n', '4. educator\n',
92                    '5. engineer\n', '6. entertainer\n',
93                    '7. executive\n', '8. healthcare\n', '9. home-
maker\n', '10. lawyer\n', '11. librarian\n',
94                    '12. marketing\n', '13. none\n', '14. other\n',
95                    '15. programmer\n', '16. retired\n', '17.
salesman\n', '18. scientist\n', '19. student\n',
96                    '20. technician\n', '21. writer\n')
97              newoccup = int(input("Choose the corresponding num-
ber: "))
98          except ValueError:
99              print("Wrong input, please insert an integer")
100             continue
101         if (newoccup < 1 or newoccup > 21):
102             print("Value must be between 1 and 21. Please insert
a valid integer")
```

```
103                 continue
104             if (1 <= newoccup and 21 >= newoccup):
105                 newoccup = (newoccup) - 1 + 10
106             break
107 
108         s = str(944) + "|"
109         for l in range(0, 31):
110             if (l == newage or l == newgend or l == newoccup):
111                 s = s + "1|"
112             else:
113                 s = s + "0|"
114         s = s[:-1]
115         user_meta_raw.append(s)
116         return user_meta_raw
117     #-----------------------------------------------------------------
---------------------------------------------------#
118 
119 
120 
#####################################################################
#################################################
121     #transform users metadata to a list with zeros and ones
122     def _parse_user_metadata(num_users, user_meta_raw, users_com-
bined_features):
123         user_features = np.zeros((num_users, len(users_combined_fea-
tures)))
124         for meta in user_meta_raw:
125             if not meta:
126                 continue
127             splt = meta.split('|')
128             # Zero-based indexing
129             iid = int(splt[0]) - 1
130             item_meta = [idx for idx, val in
131                          enumerate(splt[1:])
132                          if int(val) > 0]
133             for gid in item_meta:
134                 user_features[iid, gid] = 1.0
135         return user_features
136     #-----------------------------------------------------------------
---------------------------------------------------#
137 
138 
139 
#####################################################################
#################################################
140     #calculate the euclidean distance of users and then find the
k(k=20) most common neigbors based on demographics
141     def euclideanDistance(instance1, instance2, length):
142         distance = 0
143         for x in range(length):
144             distance += pow((instance1[x] - instance2[x]), 2)
145         return math.sqrt(distance)
146 
147     def getNeighbors(trainingSet, testInstance, k):
148         distances = []
149         length = len(testInstance)
150         for x in range(len(trainingSet)):
151             dist = euclideanDistance(testInstance, trainingSet[x],
length)
152             distances.append(dist)
153         a = array(distances)
```

```
154         sorted_indexes = np.argsort(a)
155         index_neighbors = sorted_indexes[:k]
156         return index_neighbors
157     #-------------------------------------------------------------------
----------------------------------------------------#
158
159
160
###########################################################################
###############################################
161     #We read in the u.data file, which contains the full dataset.
162     def readFullDataset(dataSetFilePath):
163         header = ['user_id', 'item_id', 'rating', 'timestamp']
164         return pd.read_csv(dataSetFilePath, sep='\t', names=header)
165     #-------------------------------------------------------------------
----------------------------------------------------#
166
167
168
###########################################################################
###############################################
169     #we read the the movies titles from the movie dataset
170     def readMovieSet(movieSetFilePath):
171         df_ids_titles = pd.read_csv(movieSetFilePath, sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],usecols=[0,
1])
172         ids_titles = np.empty(1682, dtype=np.object)
173         for line in df_ids_titles.itertuples():
174             ids_titles[line[0]] = line[2]
175         return ids_titles
176     #-------------------------------------------------------------------
----------------------------------------------------#
177
178
179
###########################################################################
###############################################
180     #we count the number of unique users and movies.
181     def numberOfUsers(fullDataSet):
182         n_users = fullDataSet.user_id.unique().shape[0]
183         return n_users
184
185     def numberOfMovies(fullDataSet):
186         n_items = fullDataSet.item_id.unique().shape[0]
187         return n_items
188     #-------------------------------------------------------------------
----------------------------------------------------#
189
190
191
###########################################################################
###############################################
192     #we create user-item matrix with the k most common users based on
demographics
193     def getUserItemMatrixDemographicsBased(n_users, n_items, fullDa-
taSet, neighbors):
194         user_item_matrixTrain = np.zeros((n_users, n_items))
195         for line in fullDataSet.itertuples():
196             if line[1] - 1 in neighbors:
197                 user_item_matrixTrain[line[1] - 1, line[2] - 1] =
line[3]
```

```
198       neighborsmovies = []
199       for i in range(0, n_items):
200           for u in neighbors:
201               if ((user_item_matrixTrain[u, i] == 5) and (i not in
neighborsmovies)):
202                   neighborsmovies.append(i)
203       return neighborsmovies
204
205   #-------------------------------------------------------------------
-------------------------------------------------#
206
207
208
#########################################################################
#################################################
209   #insert new user by creating gui in python console
210   def insertNewUserRatings(ids_titles, fullDataSet, newUserID,
timestamp, known_positives, mySelMovies, neighborsmovies):
211       i=0
212       j=20
213       f=0
214       while(f < 10):
215           userList = []
216           for x in range(i,j):
217               userList.append({x%20+1: ids_titles[neighborsmov-
ies[x]]})
218           print('\n')
219           for p in userList:
220               print(p)
221           print('\n')
222           while(True):
223               try:
224                   var = int(input("Choose a movie, or press -1 to
change movieset: "))
225               except ValueError:
226                   print("Wrong input, please insert an integer")
227                   continue
228               if((var<-1 or var>20) and var ==0):
229                   print("Value must be -1 OR between 1 and 20.
Please insert a valid integer")
230                   continue
231               if(1<=var and 20>=var):
232                   selMovie = str(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
233                   if selMovie in mySelMovies:
234                       print("You have already selected that movie,
please choose another movie")
235                       continue
236                   mySelMovies.append(str(ids_titles.tolist().in-
dex(userList[var-1][var])+1))
237               break
238           if (var == -1):
239               if ((len(neighborsmovies)-1 - j) >= 20):
240                   i = j
241                   j += 20
242               elif ((len(neighborsmovies)-1 - j) > 0):
243                   i = j
244                   j = len(neighborsmovies)-1
245               else:
246                   i = 0
247                   j = 20
```

```
248                 continue
249             else:
250                 print('\n')
251                 print("You selected the movie: " + userList[var-
1][var] + " with ID: " + str(ids_titles.tolist().index(userList[var-
1][var])+1))
252                 print('\n')
253                 while (True):
254                     try:
255                         rating = int(input("Rate the movie: "))
256                     except ValueError:
257                         print("Wrong input, please insert an inte-
ger")
258                         continue
259                     if (rating < 1 or rating > 5):
260                         print("Value must be between 1 and 5. Please
insert a valid integer")
261                         continue
262                     break
263                 known_positives.append(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
264                 fullDataSet.loc[len(fullDataSet)] = [newUserID,
ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
265                 f = f + 1
266                 while(f < 10):
267                     while (True):
268                         try:
269                             ch = int(input("To change the movieset
press -1, to keep press 1: "))
270                         except ValueError:
271                             print("Wrong input, please insert an in-
teger")
272                             continue
273                         if (ch != 1 and ch != -1):
274                             print("Value must be 1 or -1. Please in-
sert a valid integer")
275                             continue
276                         break
277                     if(int(ch) == -1):
278                         break
279                     else:
280                         print('\n')
281                         for p in userList:
282                             print(p)
283                         print('\n')
284                         while (True):
285                             try:
286                                 var = int(input("Choose a movie: "))
287                             except ValueError:
288                                 print("Wrong input, please insert an
integer")
289                                 continue
290                             if ((var < -1 or var > 20)):
291                                 print("Value must be between 1 and
20. Please insert a valid integer")
292                                 continue
293                             selMovie = str(ids_titles.tolist().in-
dex(userList[var - 1][var]) + 1)
294                             if selMovie in mySelMovies:
```

```
295                                 print("You have already selected that
movie, please choose another movie")
296                                 continue
297                             mySelMovies.append(str(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1))
298                             break
299                         print('\n')
300                         print("You selected the movie: " + us-
erList[var - 1][var] + " with ID: " + str(
301                             ids_titles.tolist().index(userList[var -
1][var]) + 1))
302                         print('\n')
303                         while (True):
304                             try:
305                                 rating = int(input("Rate the movie:
"))
306                             except ValueError:
307                                 print("Wrong input, please insert an
integer")
308                                 continue
309                             if (rating < 1 or rating > 5):
310                                 print("Value must be between 1 and 5.
Please insert a valid integer")
311                                 continue
312                             break
313                         known_positives.append(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1)
314                         fullDataSet.loc[len(fullDataSet)] = [newUse-
rID, ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
315                         f = f + 1
316                 if((len(neighborsmovies)-1-j) >= 20):
317                     i = j
318                     j += 20
319                 elif((len(neighborsmovies)-1-j) > 0):
320                     i = j
321                     j = len(neighborsmovies)-1
322                 else:
323                     i = 0
324                     j = 20
325             print('\n')
326         return fullDataSet
327     #-----------------------------------------------------------------
-------------------------------------------------#
328
329
330
################################################################################
##############################################
331     #we create user-item matrix
332     def getUserItemMatrix(n_users, n_items, fullDataSet):
333         user_item_matrix = np.zeros((n_users, n_items))
334         for line in fullDataSet.itertuples():
335             user_item_matrix[line[1] - 1, line[2] - 1] = line[3]
336         return user_item_matrix
337     #-----------------------------------------------------------------
-------------------------------------------------#
338
339
```

```
340
##########################################################################
##################################################
341   #we use the pairwise_distances function from sklearn to calculate
the pearson correlation
342   def calculateUsersPearsonCorrelation(user_item_matrixTrain):
343       user_similarityPearson = 1 - pairwise_distances(user_item_ma-
trixTrain, metric='correlation') #943*943
344       user_similarityPearson[np.isnan(user_similarityPearson)] = 0
345       return user_similarityPearson
346   #---------------------------------------------------------------------
-------------------------------------------------#
347
348
349
##########################################################################
##################################################
350   #make predictions combining Top-K neigbors and Bias-subtracted
collaborative filtering
351   def predict_Top_K_no_Bias(ratings, similarity, k=40):
352       pred = np.zeros(ratings.shape)
353       user_bias = ratings.mean(axis=1)
354       ratings = (ratings - user_bias[:, np.newaxis]).copy()
355       for i in range(ratings.shape[0]):
356           top_K_users = [np.argsort(similarity[:,i])[:-k-1:-1]]
357           for j in range(ratings.shape[1]):
358               pred[i,j] = similarity[i, :][top_K_users].dot(rat-
ings[:, j][top_K_users])
359               pred[i,j] /= np.sum(np.abs(similarity[i, :][top_K_us-
ers]))
360       pred += user_bias[:, np.newaxis]
361       return pred
362   #---------------------------------------------------------------------
-------------------------------------------------#
363
364
365
366
##########################################################################
##################################################
367   ##################################################BASIC
SCRIPT#####################################################################
368
369   newUserID = 944   # new user's id
370   timestamp = '883446543'   # random timestamp, we dont care about
that
371   known_positives = []
372   mySelMovies = []
373
374
375   #fetch dempgraphic data
376   users_raw = _read_raw_data("C:/Users/Sak/lightfm_data/mov-
ielens100k/movielens.zip")
377
378   #create models
379   users_age = ['18', '24', '30', '40', '50', '61', '70', '100']
380   users_occup = ['administrator', 'artist', 'doctor', 'educator',
381                                     'engineer', 'entertainer', 'ex-
ecutive', 'healthcare', 'homemaker',
382                                     'lawyer', 'librarian', 'market-
ing', 'none', 'other', 'programmer',
```

```
383                                     'retired', 'salesman', 'scien-
tist', 'student', 'technician',
384                                     'writer']
385
386   users_combined_features = ['18|0', '24|1', '30|2', '40|3',
'50|4', '61|5', '70|6',
387                                     '100|7', 'm|8', 'f|9', 'admin-
istrator|10', 'artist|11', 'doctor|12', 'educator|13',
388                                     'engineer|14', 'enter-
tainer|15', 'executive|16', 'healthcare|17', 'homemaker|18',
389                                     'lawyer|19', 'librarian|20',
'marketing|21', 'none|22', 'other|23', 'programmer|24',
390                                     'retired|25', 'salesman|26',
'scientist|27', 'student|28', 'technician|29',
391                                     'writer|30']
392
393   user_meta_raw = []
394
395   user_meta_raw = createUserMetaDataList(users_raw, users_age, us-
ers_occup, user_meta_raw)
396
397   #read the movieset
398   ids_titles = readMovieSet('u.item')
399   #read the full dataset
400   fullDataSet = readFullDataset('u.data')
401
402
403   #users demographic data with new user
404   usr_feat = _parse_user_metadata(944, user_meta_raw, users_com-
bined_features)
405   #users demographic data without the new user
406   usr_feat_no_newUser = np.delete(usr_feat, (943), axis=0)
407   #new user demographic data
408   new_usr_feat = usr_feat[-1]
409
410   ##The 20 most common neighbors for the new user based on de-
mographics are:
411   neighbors = getNeighbors(usr_feat_no_newUser, new_usr_feat, 10)
412
413   #calculate number of users and items
414   n_users = numberOfUsers(fullDataSet)
415   n_items = numberOfMovies(fullDataSet)
416
417   #neigbors movies the k most common users based on demographics
418   neighborsMovies = getUserItemMatrixDemographicsBased(n_users,
n_items, fullDataSet, neighbors)
419
420   #full dataset with new users ratings
421   fullDataSetNewUser = insertNewUserRatings(ids_titles, fullDa-
taSet, newUserID, timestamp, known_positives, mySelMovies, neigh-
borsMovies)
422
423   #calculate number of users and items
424   n_users = numberOfUsers(fullDataSetNewUser)
425   n_items = numberOfMovies(fullDataSetNewUser)
426
427   #calculate user item matrix with new dataset
428   user_item_matrix = getUserItemMatrix(n_users, n_items, fullDa-
taSetNewUser)
429
430   #calculate user similarity(Pearson correlation)
```

```
user_similarityPearson = calculateUsersPearsonCorrelation(user_item_matrix)

#apply bias subtracted user-based collaborative filtering with Top-40 most common neigbors algorithm
user_prediction_User = predict_Top_K_no_Bias(user_item_matrix, user_similarityPearson, k=40)

#function for printing the top n recommended movies for a given user id -
def printPredictedMoviesUserBased(user, n):
    user = user - 1
    n = n - 1
    pred_indexes = [i + 1 for i in np.argsort(-user_prediction_User[user])]
    pred_indexes = [item for item in pred_indexes if item not in known_positives]
    movies_ids_titles = pd.read_csv('u.item', sep="|", header=None, encoding='latin-1', names=['itemId', 'title'], usecols=[0, 1])
    pd_pred_indexes = pd.DataFrame(pred_indexes, columns=['itemId'])
    pred_movies = pd.merge(pd_pred_indexes, movies_ids_titles, on='itemId')
    print('\n')
    print("********************user-based collaborative filtering (Top-K neigbors and Bias-subtracted)*******************************")
    print(pred_movies.loc[:n])

#print the top 10 recommended movies for the new User (id = 944)
printPredictedMoviesUserBased(944, 10)
```

entropy0-based.py

```
1    import numpy as np
2    import pandas as pd
3    from sklearn.metrics.pairwise import pairwise_distances
4    import math
5
6
7
8
#########################################################################
#################################################
9    #We read in the u.data file, which contains the full dataset.
10   def readFullDataset(dataSetFilePath):
11       header = ['user_id', 'item_id', 'rating', 'timestamp']
12       return pd.read_csv(dataSetFilePath, sep='\t', names=header)
13   #-----------------------------------------------------------------
-------------------------------------------------#
14
15
16
#########################################################################
#################################################
17   #we read the the movies titles from the movie dataset
18   def readMovieSet(movieSetFilePath):
19       df_ids_titles = pd.read_csv(movieSetFilePath, sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],usecols=[0,
1])
20       ids_titles = np.empty(1682, dtype=np.object)
21       for line in df_ids_titles.itertuples():
22           ids_titles[line[0]] = line[2]
23       return ids_titles
24   #-----------------------------------------------------------------
-------------------------------------------------#
25
26
27
#########################################################################
#################################################
28   #we count the number of unique users and movies.
29   def numberOfUsers(fullDataSet):
30       n_users = fullDataSet.user_id.unique().shape[0]
31       return n_users
32
33   def numberOfMovies(fullDataSet):
34       n_items = fullDataSet.item_id.unique().shape[0]
35       return n_items
36   #-----------------------------------------------------------------
-------------------------------------------------#
37
38
39
#########################################################################
#################################################
40   #calculate existing movies entropy0 values
41   def calcMoviesEntropy0(fullDataSet, n_users, n_items):
42
43       user_item_matrixTrain = np.zeros((n_users, n_items))
44
45       for line in fullDataSet.itertuples():
46           user_item_matrixTrain[line[1] - 1, line[2] - 1] = line[3]
47
```

```
48        values = np.zeros((n_items, 6))
49
50        for i in range(0,n_items):
51            for u in range(0,n_users):
52                for j in range(0,6):
53                    if user_item_matrixTrain[u, i] == j:
54                        values[i, j] += 1
55
56        voters = np.zeros((n_items))
57
58        for i in range(0,n_items):
59            voters[i] = values[i,1] + values[i,2] + values[i,3] +
values[i,4] + values[i,5]
60
61        prop = np.zeros((n_items, 6))
62
63        w = np.zeros(6)
64        for i in range(0,6):
65            if i == 0:
66                w[i] = 0.5
67            else:
68                w[i] = 1
69
70        for i in range(0,n_items):
71            prop[i, 0] = values[i, 0]/voters[i]
72            prop[i, 1] = values[i, 1]/voters[i]
73            prop[i, 2] = values[i, 2]/voters[i]
74            prop[i, 3] = values[i, 3]/voters[i]
75            prop[i, 4] = values[i, 4]/voters[i]
76            prop[i, 5] = values[i, 5]/voters[i]
77
78        entropy = np.zeros((n_items))
79        for i in range(0,n_items):
80            entropy[i] = 0
81            for rat in range(0,6):
82                if prop[i,rat] != 0:
83                    entropy[i] = entropy[i] +
prop[i,rat]*w[rat]*math.log(prop[i,rat],2)
84            entropy[i] = entropy[i]/5.5
85
86        entropy = -entropy
87        entropy_indexes = [i for i in np.argsort(-entropy)]
88        return entropy_indexes
89    #-------------------------------------------------------------------
----------------------------------------------------#
90
91
92
##########################################################################
##############################################
93    #insert new user by creating gui in python console
94    def insertNewUserRatings(ids_titles, fullDataSet, newUserID,
timestamp, known_positives, mySelMovies, entropy_indexes):
95        i=0
96        j=20
97        f=0
98        while(f < 10):
99            userList = []
100           for x in range(i,j):
101               userList.append({x%20+1: ids_titles[entropy_in-
dexes[x]]})
```

```
102             print('\n')
103             for p in userList:
104                 print(p)
105             print('\n')
106             while(True):
107                 try:
108                     var = int(input("Choose a movie, or press -1 to
change movieset: "))
109                 except ValueError:
110                     print("Wrong input, please insert an integer")
111                     continue
112                 if((var<-1 or var>20) and var ==0):
113                     print("Value must be -1 OR between 1 and 20.
Please insert a valid integer")
114                     continue
115                 if(1<=var and 20>=var):
116                     selMovie = str(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
117                     if selMovie in mySelMovies:
118                         print("You have already selected that movie,
please choose another movie")
119                         continue
120                     mySelMovies.append(str(ids_titles.tolist().in-
dex(userList[var-1][var])+1))
121                 break
122             if (var == -1):
123                 if ((1681 - j) >= 20):
124                     i = j
125                     j += 20
126                 elif ((1681 - j) > 0):
127                     i = j
128                     j = 1682
129                 else:
130                     i = 0
131                     j = 20
132                 continue
133             else:
134                 print('\n')
135                 print("You selected the movie: " + userList[var-
1][var] + " with ID: " + str(ids_titles.tolist().index(userList[var-
1][var])+1))
136                 print('\n')
137                 while (True):
138                     try:
139                         rating = int(input("Rate the movie: "))
140                     except ValueError:
141                         print("Wrong input, please insert an inte-
ger")
142                         continue
143                     if (rating < 1 or rating > 5):
144                         print("Value must be between 1 and 5. Please
insert a valid integer")
145                         continue
146                     break
147                 known_positives.append(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
148                 fullDataSet.loc[len(fullDataSet)] = [newUserID,
ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
149                 f = f + 1
150                 while(f < 10):
```

```
151                     while (True):
152                         try:
153                             ch = int(input("To change the movieset
press -1, to keep press 1: "))
154                         except ValueError:
155                             print("Wrong input, please insert an in-
teger")
156                             continue
157                         if (ch != 1 and ch != -1):
158                             print("Value must be 1 or -1. Please in-
sert a valid integer")
159                             continue
160                         break
161                     if(int(ch) == -1):
162                         break
163                     else:
164                         print('\n')
165                         for p in userList:
166                             print(p)
167                         print('\n')
168                         while (True):
169                             try:
170                                 var = int(input("Choose a movie: "))
171                             except ValueError:
172                                 print("Wrong input, please insert an
integer")
173                                 continue
174                             if ((var < -1 or var > 20)):
175                                 print("Value must be between 1 and
20. Please insert a valid integer")
176                                 continue
177                             selMovie = str(ids_titles.tolist().in-
dex(userList[var - 1][var]) + 1)
178                             if selMovie in mySelMovies:
179                                 print("You have already selected that
movie, please choose another movie")
180                                 continue
181                             mySelMovies.append(str(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1))
182                             break
183                         print('\n')
184                         print("You selected the movie: " + us-
erList[var - 1][var] + " with ID: " + str(
185                             ids_titles.tolist().index(userList[var -
1][var]) + 1))
186                         print('\n')
187                         while (True):
188                             try:
189                                 rating = int(input("Rate the movie:
"))
190                             except ValueError:
191                                 print("Wrong input, please insert an
integer")
192                                 continue
193                             if (rating < 1 or rating > 5):
194                                 print("Value must be between 1 and 5.
Please insert a valid integer")
195                                 continue
196                             break
197                         known_positives.append(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1)
```

```
198                         fullDataSet.loc[len(fullDataSet)] = [newUse-
rID, ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
199                         f = f + 1
200                 if((1681-j) >= 20):
201                     i = j
202                     j += 20
203                 elif((1681-j) > 0):
204                     i = j
205                     j = 1682
206                 else:
207                     i = 0
208                     j = 20
209             print('\n')
210         return fullDataSet
211     #-----------------------------------------------------------------
------------------------------------------------#
212
213
214
###########################################################################
##############################################
215     #we create user-item matrix
216     def getUserItemMatrix(n_users, n_items, fullDataSet):
217         user_item_matrix = np.zeros((n_users, n_items))
218         for line in fullDataSet.itertuples():
219             user_item_matrix[line[1] - 1, line[2] - 1] = line[3]
220         return user_item_matrix
221     #-----------------------------------------------------------------
------------------------------------------------#
222
223
224
###########################################################################
##############################################
225     #we use the pairwise_distances function from sklearn to calculate
the pearson correlation
226     def calculateUsersPearsonCorrelation(user_item_matrixTrain):
227         user_similarityPearson = 1 - pairwise_distances(user_item_ma-
trixTrain, metric='correlation') #943*943
228         user_similarityPearson[np.isnan(user_similarityPearson)] = 0
229         return user_similarityPearson
230     #-----------------------------------------------------------------
------------------------------------------------#
231
232
233
###########################################################################
##############################################
234     #make predictions combining Top-K neigbors and Bias-subtracted
collaborative filtering
235     def predict_Top_K_no_Bias(ratings, similarity, k=40):
236         pred = np.zeros(ratings.shape)
237         user_bias = ratings.mean(axis=1)
238         ratings = (ratings - user_bias[:, np.newaxis]).copy()
239         for i in range(ratings.shape[0]):
240             top_K_users = [np.argsort(similarity[:,i])[:-k-1:-1]]
241             for j in range(ratings.shape[1]):
242                 pred[i,j] = similarity[i, :][top_K_users].dot(rat-
ings[:, j][top_K_users])
```

```
243                 pred[i,j] /= np.sum(np.abs(similarity[i, :][top_K_us-
ers]))
244         pred += user_bias[:, np.newaxis]
245         return pred
246     #-------------------------------------------------------------------
-------------------------------------------------#
247
248
249
250
#########################################################################
#################################################
251     ##############################################BASIC
SCRIPT#############################################################
252
253     newUserID = 944   # new user's id
254     timestamp = '883446543'   # random timestamp, we dont care about
that
255     known_positives = []
256     mySelMovies = []
257
258     #read the movieset
259     ids_titles = readMovieSet('u.item')
260     #read the full dataset
261     fullDataSet = readFullDataset('u.data')
262
263     #calculate number of users and items
264     n_users = numberOfUsers(fullDataSet)
265     n_items = numberOfMovies(fullDataSet)
266
267     #calculate movies ratings entropy0 values and return movies in-
dexes with the highest entropy0 values to the lowest
268     entropy_indexes = calcMoviesEntropy0(fullDataSet, n_users,
n_items)
269
270     #insert new user
271     fullDataSetNewUser = insertNewUserRatings(ids_titles, fullDa-
taSet, newUserID, timestamp, known_positives, mySelMovies, entropy_in-
dexes)
272
273     #calculate number of users and items with new user
274     n_users = numberOfUsers(fullDataSetNewUser)
275     n_items = numberOfMovies(fullDataSetNewUser)
276
277     #calculate user item matrix
278     user_item_matrix = getUserItemMatrix(n_users, n_items, fullDa-
taSetNewUser)
279
280     #calculate user similarity(Pearson correlation)
281     user_similarityPearson = calculateUsersPearsonCorrela-
tion(user_item_matrix)
282
283     #apply bias subtracted user-based collaborative filtering with
Top-40 most common neigbors algorithm
284     user_prediction_User = predict_Top_K_no_Bias(user_item_matrix,
user_similarityPearson, k=40)
285
286     #function for printing the top n recommended movies for a given
user id -
287     def printPredictedMoviesUserBased(user, n):
288         user = user - 1
```

```
289       n = n - 1
290       pred_indexes = [i + 1 for i in np.argsort(-user_predic-
tion_User[user])]
291       pred_indexes = [item for item in pred_indexes if item not in
known_positives]
292       movies_ids_titles = pd.read_csv('u.item', sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],
usecols=[0, 1])
293       pd_pred_indexes = pd.DataFrame(pred_indexes, columns=['item-
Id'])
294       pred_movies = pd.merge(pd_pred_indexes, movies_ids_titles,
on='itemId')
295       print('\n')
296       print("********************user-based collaborative filtering
(Top-K neigbors and Bias-subtracted)*****************************")
297       print(pred_movies.loc[:n])
298
299   #print the top 10 recommended movies for the new User (id = 944)
300   printPredictedMoviesUserBased(944, 10)
```

demographic_entropy0-based.py

```
    import zipfile
    from numpy import array
    import numpy as np
    import pandas as pd
    from sklearn.metrics.pairwise import pairwise_distances
    import math




##########################################################################
################################################
    #fetch demographic data
    def _read_raw_data(path):
        with zipfile.ZipFile(path) as datafile:
            return datafile.read('ml-100k/u.user').decode(errors='ig-
nore').split('\n')
    #-------------------------------------------------------------------
-------------------------------------------------#


##########################################################################
################################################
    # create the user_meta-data list
    def createUserMetaDataList(users_raw, users_age, users_occup,
user_meta_raw):
        # first create the user_meta-data list by the existing da-
taset
        for line in users_raw:
            if not line:
                continue
            #print(line)
            splt = line.split('|')
            # Zero-based indexing
            userid = int(splt[0])
            age = int(splt[1])
            gender = splt[2]
            occup = splt[3]
            i = 0
            for m in users_age:
                if(age <= int(m)):
                    #print(i)
                    break
                else:
                    i = i + 1

            if(gender == 'M'):
                j = 8
            else:
                j = 9
            k = 10
            for n in users_occup:
                if(occup == n):
                    #print(k)
                    break
                else:
                    k = k + 1
            s = str(userid) + "|"
            for l in range(0,31):
```

```
53                  if(l == i or l == j or l == k):
54                      s = s + "1|"
55                  else:
56                      s = s + "0|"
57              s = s[:-1]
58              user_meta_raw.append(s)
59          #then, append the new user to the above user_meta_data list
60          while (True):
61              try:
62                  print('Select your age range:\n', '1. <=18\n', '2.
19-24\n', '3. 25-30\n', '4. 31-40\n', '5. 41-50\n',
63                        '6. 51-60\n', '7. 61-70\n', '8. 71-100\n')
64                  newage = int(input("Choose the corresponding number:
"))
65              except ValueError:
66                  print("Wrong input, please insert an integer")
67                  continue
68              if (newage < 1 or newage > 8):
69                  print("Value must be between 1 and 8. Please insert a
valid integer")
70                  continue
71              if (1 <= newage and 8 >= newage):
72                  newage = (newage) - 1
73              break
74
75          while (True):
76              try:
77                  print('Select your gender:\n', '1. Male\n', '2. Fe-
male\n')
78                  newgend = int(input("Choose the corresponding number:
"))
79              except ValueError:
80                  print("Wrong input, please insert an integer")
81                  continue
82              if (newgend < 1 or newgend > 2):
83                  print("Value must be 1 or 2. Please insert a valid
integer")
84                  continue
85              if (1 == newgend or 2 == newgend):
86                  newgend = (newgend) - 1 + 8
87              break
88
89          while (True):
90              try:
91                  print('Select your occupation:\n', '1. administra-
tor\n', '2. artist\n', '3. doctor\n', '4. educator\n',
92                        '5. engineer\n', '6. entertainer\n',
93                        '7. executive\n', '8. healthcare\n', '9. home-
maker\n', '10. lawyer\n', '11. librarian\n',
94                        '12. marketing\n', '13. none\n', '14. other\n',
95                        '15. programmer\n', '16. retired\n', '17.
salesman\n', '18. scientist\n', '19. student\n',
96                        '20. technician\n', '21. writer\n')
97                  newoccup = int(input("Choose the corresponding num-
ber: "))
98              except ValueError:
99                  print("Wrong input, please insert an integer")
100                 continue
101             if (newoccup < 1 or newoccup > 21):
102                 print("Value must be between 1 and 21. Please insert
a valid integer")
```

```
103             continue
104         if (1 <= newoccup and 21 >= newoccup):
105             newoccup = (newoccup) - 1 + 10
106         break
107
108     s = str(944) + "|"
109     for l in range(0, 31):
110         if (l == newage or l == newgend or l == newoccup):
111             s = s + "1|"
112         else:
113             s = s + "0|"
114     s = s[:-1]
115     user_meta_raw.append(s)
116     return user_meta_raw
117 #-----------------------------------------------------------------
----------------------------------------------------#
118
119
120
#####################################################################
################################################
121 #transform users metadata to a list with zeros and ones
122 def _parse_user_metadata(num_users, user_meta_raw, users_com-
bined_features):
123     user_features = np.zeros((num_users, len(users_combined_fea-
tures)))
124     for meta in user_meta_raw:
125         if not meta:
126             continue
127         splt = meta.split('|')
128         # Zero-based indexing
129         iid = int(splt[0]) - 1
130         item_meta = [idx for idx, val in
131                      enumerate(splt[1:])
132                      if int(val) > 0]
133         for gid in item_meta:
134             user_features[iid, gid] = 1.0
135     return user_features
136 #-----------------------------------------------------------------
----------------------------------------------------#
137
138
139
#####################################################################
################################################
140 #calculate the euclidean distance of users and then find the
k(k=20) most common neigbors based on demographics
141 def euclideanDistance(instance1, instance2, length):
142     distance = 0
143     for x in range(length):
144         distance += pow((instance1[x] - instance2[x]), 2)
145     return math.sqrt(distance)
146
147 def getNeighbors(trainingSet, testInstance, k):
148     distances = []
149     length = len(testInstance)
150     for x in range(len(trainingSet)):
151         dist = euclideanDistance(testInstance, trainingSet[x],
length)
152         distances.append(dist)
153     a = array(distances)
```

```
154         sorted_indexes = np.argsort(a)
155         index_neighbors = sorted_indexes[:k]
156         return index_neighbors
157     #-------------------------------------------------------------------
----------------------------------------------------#
158
159
160
###########################################################################
#################################################
161     #We read in the u.data file, which contains the full dataset.
162     def readFullDataset(dataSetFilePath):
163         header = ['user_id', 'item_id', 'rating', 'timestamp']
164         return pd.read_csv(dataSetFilePath, sep='\t', names=header)
165     #-------------------------------------------------------------------
----------------------------------------------------#
166
167
168
###########################################################################
#################################################
169     #we read the the movies titles from the movie dataset
170     def readMovieSet(movieSetFilePath):
171         df_ids_titles = pd.read_csv(movieSetFilePath, sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],usecols=[0,
1])
172         ids_titles = np.empty(1682, dtype=np.object)
173         for line in df_ids_titles.itertuples():
174             ids_titles[line[0]] = line[2]
175         return ids_titles
176     #-------------------------------------------------------------------
----------------------------------------------------#
177
178
179
###########################################################################
#################################################
180     #we count the number of unique users and movies.
181     def numberOfUsers(fullDataSet):
182         n_users = fullDataSet.user_id.unique().shape[0]
183         return n_users
184
185     def numberOfMovies(fullDataSet):
186         n_items = fullDataSet.item_id.unique().shape[0]
187         return n_items
188     #-------------------------------------------------------------------
----------------------------------------------------#
189
190
191
192
###########################################################################
#################################################
193     #calculate existing movies entropy0 values
194     def calcMoviesEntropy0(fullDataSet, n_users, n_items, neighbors):
195
196         user_item_matrixTrain = np.zeros((n_users, n_items))
197
198         for line in fullDataSet.itertuples():
199             if line[1] - 1 in neighbors:
```

```
            user_item_matrixTrain[line[1] - 1, line[2] - 1] =
line[3]

    values = np.zeros((n_items, 6))

    for i in range(0,n_items):
        for u in range(0,n_users):
            for j in range(0,6):
                if user_item_matrixTrain[u, i] == j:
                    values[i, j] += 1

    voters = np.zeros((n_items))

    for i in range(0,n_items):
        voters[i] = values[i,1] + values[i,2] + values[i,3] +
values[i,4] + values[i,5]

    prop = np.zeros((n_items, 6))

    w = np.zeros(6)
    for i in range(0,6):
        if i == 0:
            w[i] = 0.5
        else:
            w[i] = 1

    for i in range(0,n_items):
        if voters[i] !=0:
            prop[i, 0] = values[i, 0]/voters[i]
            prop[i, 1] = values[i, 1]/voters[i]
            prop[i, 2] = values[i, 2]/voters[i]
            prop[i, 3] = values[i, 3]/voters[i]
            prop[i, 4] = values[i, 4]/voters[i]
            prop[i, 5] = values[i, 5]/voters[i]

    entropy = np.zeros((n_items))
    for i in range(0,n_items):
        entropy[i] = 0
        for rat in range(0,6):
            if prop[i,rat] != 0:
                entropy[i] = entropy[i] +
prop[i,rat]*w[rat]*math.log(prop[i,rat],2)
        entropy[i] = entropy[i]/5.5

    entropy = -entropy
    entropy_indexes = [i for i in np.argsort(-entropy)]
    return entropy_indexes
#-----------------------------------------------------------------
-------------------------------------------------#


#####################################################################
##############################################
 #insert new user by creating gui in python console
 def insertNewUserRatings(ids_titles, fullDataSet, newUserID,
timestamp, known_positives, mySelMovies, entropy_indexes):
    i=0
    j=20
    f=0
    while(f < 10):
```

```
254             userList = []
255             for x in range(i,j):
256                 userList.append({x%20+1: ids_titles[entropy_in-
dexes[x]]})
257             print('\n')
258             for p in userList:
259                 print(p)
260             print('\n')
261             while(True):
262                 try:
263                     var = int(input("Choose a movie, or press -1 to
change movieset: "))
264                 except ValueError:
265                     print("Wrong input, please insert an integer")
266                     continue
267                 if((var<-1 or var>20) and var ==0):
268                     print("Value must be -1 OR between 1 and 20.
Please insert a valid integer")
269                     continue
270                 if(1<=var and 20>=var):
271                     selMovie = str(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
272                     if selMovie in mySelMovies:
273                         print("You have already selected that movie,
please choose another movie")
274                         continue
275                     mySelMovies.append(str(ids_titles.tolist().in-
dex(userList[var-1][var])+1))
276                 break
277             if (var == -1):
278                 if ((1681 - j) >= 20):
279                     i = j
280                     j += 20
281                 elif ((1681 - j) > 0):
282                     i = j
283                     j = 1682
284                 else:
285                     i = 0
286                     j = 20
287                 continue
288             else:
289                 print('\n')
290                 print("You selected the movie: " + userList[var-
1][var] + " with ID: " + str(ids_titles.tolist().index(userList[var-
1][var])+1))
291                 print('\n')
292                 while (True):
293                     try:
294                         rating = int(input("Rate the movie: "))
295                     except ValueError:
296                         print("Wrong input, please insert an inte-
ger")
297                         continue
298                     if (rating < 1 or rating > 5):
299                         print("Value must be between 1 and 5. Please
insert a valid integer")
300                         continue
301                     break
302                 known_positives.append(ids_titles.tolist().index(us-
erList[var - 1][var]) + 1)
```

```
303                 fullDataSet.loc[len(fullDataSet)] = [newUserID,
ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
304                 f = f + 1
305                 while(f < 10):
306                     while (True):
307                         try:
308                             ch = int(input("To change the movieset
press -1, to keep press 1: "))
309                         except ValueError:
310                             print("Wrong input, please insert an in-
teger")
311                             continue
312                         if (ch != 1 and ch != -1):
313                             print("Value must be 1 or -1. Please in-
sert a valid integer")
314                             continue
315                         break
316                     if(int(ch) == -1):
317                         break
318                     else:
319                         print('\n')
320                         for p in userList:
321                             print(p)
322                         print('\n')
323                         while (True):
324                             try:
325                                 var = int(input("Choose a movie: "))
326                             except ValueError:
327                                 print("Wrong input, please insert an
integer")
328                                 continue
329                             if ((var < -1 or var > 20)):
330                                 print("Value must be between 1 and
20. Please insert a valid integer")
331                                 continue
332                             selMovie = str(ids_titles.tolist().in-
dex(userList[var - 1][var]) + 1)
333                             if selMovie in mySelMovies:
334                                 print("You have already selected that
movie, please choose another movie")
335                                 continue
336                             mySelMovies.append(str(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1))
337                             break
338                         print('\n')
339                         print("You selected the movie: " + us-
erList[var - 1][var] + " with ID: " + str(
340                             ids_titles.tolist().index(userList[var -
1][var]) + 1))
341                         print('\n')
342                         while (True):
343                             try:
344                                 rating = int(input("Rate the movie:
"))
345                             except ValueError:
346                                 print("Wrong input, please insert an
integer")
347                                 continue
348                             if (rating < 1 or rating > 5):
```

```
                                print("Value must be between 1 and 5.
Please insert a valid integer")
                                continue
                            break
                        known_positives.append(ids_ti-
tles.tolist().index(userList[var - 1][var]) + 1)
                        fullDataSet.loc[len(fullDataSet)] = [newUse-
rID, ids_titles.tolist().index(userList[var - 1][var]) + 1, rating,
timestamp]
                        f = f + 1
                if((1681-j) >= 20):
                    i = j
                    j += 20
                elif((1681-j) > 0):
                    i = j
                    j = 1682
                else:
                    i = 0
                    j = 20
            print('\n')
        return fullDataSet
    #-------------------------------------------------------------------
-------------------------------------------------#


#########################################################################
#################################################
    #we create user-item matrix
    def getUserItemMatrix(n_users, n_items, fullDataSet):
        user_item_matrix = np.zeros((n_users, n_items))
        for line in fullDataSet.itertuples():
            user_item_matrix[line[1] - 1, line[2] - 1] = line[3]
        return user_item_matrix
    #-------------------------------------------------------------------
-------------------------------------------------#


#########################################################################
#################################################
    #we use the pairwise_distances function from sklearn to calculate
the pearson correlation
    def calculateUsersPearsonCorrelation(user_item_matrixTrain):
        user_similarityPearson = 1 - pairwise_distances(user_item_ma-
trixTrain, metric='correlation') #943*943
        user_similarityPearson[np.isnan(user_similarityPearson)] = 0
        return user_similarityPearson
    #-------------------------------------------------------------------
-------------------------------------------------#


#########################################################################
#################################################
    #make predictions combining Top-K neigbors and Bias-subtracted
collaborative filtering
    def predict_Top_K_no_Bias(ratings, similarity, k=40):
        pred = np.zeros(ratings.shape)
        user_bias = ratings.mean(axis=1)
        ratings = (ratings - user_bias[:, np.newaxis]).copy()
```

```
394       for i in range(ratings.shape[0]):
395           top_K_users = [np.argsort(similarity[:,i])[:-k-1:-1]]
396           for j in range(ratings.shape[1]):
397               pred[i,j] = similarity[i, :][top_K_users].dot(rat-
ings[:, j][top_K_users])
398               pred[i,j] /= np.sum(np.abs(similarity[i, :][top_K_us-
ers]))
399       pred += user_bias[:, np.newaxis]
400       return pred
401   #-------------------------------------------------------------------
-------------------------------------------------#
402
403
404
405
#########################################################################
#################################################
406   ################################################BASIC
SCRIPT#################################################################
407
408   newUserID = 944   # new user's id
409   timestamp = '883446543'   # random timestamp, we dont care about
that
410   known_positives = []
411   mySelMovies = []
412
413   #fetch dempgraphic data
414   users_raw = _read_raw_data("C:/Users/Sak/lightfm_data/mov-
ielens100k/movielens.zip")
415
416   #create models
417   users_age = ['18', '24', '30', '40', '50', '61', '70', '100']
418   users_occup = ['administrator', 'artist', 'doctor', 'educator',
419                                       'engineer', 'entertainer', 'ex-
ecutive', 'healthcare', 'homemaker',
420                                       'lawyer', 'librarian', 'market-
ing', 'none', 'other', 'programmer',
421                                       'retired', 'salesman', 'scien-
tist', 'student', 'technician',
422                                       'writer']
423
424   users_combined_features = ['18|0', '24|1', '30|2', '40|3',
'50|4', '61|5', '70|6',
425                                       '100|7', 'm|8', 'f|9', 'admin-
istrator|10', 'artist|11', 'doctor|12', 'educator|13',
426                                       'engineer|14', 'enter-
tainer|15', 'executive|16', 'healthcare|17', 'homemaker|18',
427                                       'lawyer|19', 'librarian|20',
'marketing|21', 'none|22', 'other|23', 'programmer|24',
428                                       'retired|25', 'salesman|26',
'scientist|27', 'student|28', 'technician|29',
429                                       'writer|30']
430
431   user_meta_raw = []
432
433   user_meta_raw = createUserMetaDataList(users_raw, users_age, us-
ers_occup, user_meta_raw)
434
435
436   #users demographic data with new user
```

```
437  usr_feat = _parse_user_metadata(944, user_meta_raw, users_com-
bined_features)
438  #users demographic data without the new user
439  usr_feat_no_newUser = np.delete(usr_feat, (943), axis=0)
440  #new user demographic data
441  new_usr_feat = usr_feat[-1]
442
443  ##The 20 most common neighbors for the new user based on de-
mographics are:
444  neighbors = getNeighbors(usr_feat_no_newUser, new_usr_feat, 10)
445
446  #read the movieset
447  ids_titles = readMovieSet('u.item')
448  #read the full dataset
449  fullDataSet = readFullDataset('u.data')
450
451  #calculate number of users and items
452  n_users = numberOfUsers(fullDataSet)
453  n_items = numberOfMovies(fullDataSet)
454
455
456  #calculate only neigbors movies ratings entropy0 values and re-
turn movies indexes with the highest entropy0 values to the lowest
457  entropy_indexes = calcMoviesEntropy0(fullDataSet, n_users,
n_items, neighbors)
458
459  #insert new user
460  fullDataSetNewUser = insertNewUserRatings(ids_titles, fullDa-
taSet, newUserID, timestamp, known_positives, mySelMovies, entropy_in-
dexes)
461
462  #calculate number of users and items with new user
463  n_users = numberOfUsers(fullDataSetNewUser)
464  n_items = numberOfMovies(fullDataSetNewUser)
465
466  #calculate user item matrix
467  user_item_matrix = getUserItemMatrix(n_users, n_items, fullDa-
taSetNewUser)
468
469  #calculate user similarity(Pearson correlation)
470  user_similarityPearson = calculateUsersPearsonCorrela-
tion(user_item_matrix)
471
472  #apply bias subtracted user-based collaborative filtering with
Top-40 most common neigbors algorithm
473  user_prediction_User = predict_Top_K_no_Bias(user_item_matrix,
user_similarityPearson, k=40)
474
475  #function for printing the top n recommended movies for a given
user id -
476  def printPredictedMoviesUserBased(user, n):
477      user = user - 1
478      n = n - 1
479      pred_indexes = [i + 1 for i in np.argsort(-user_predic-
tion_User[user])]
480      pred_indexes = [item for item in pred_indexes if item not in
known_positives]
481      movies_ids_titles = pd.read_csv('u.item', sep="|",
header=None, encoding='latin-1', names=['itemId', 'title'],
usecols=[0, 1])
```

```
482       pd_pred_indexes = pd.DataFrame(pred_indexes, columns=['item-
Id'])
483       pred_movies = pd.merge(pd_pred_indexes, movies_ids_titles,
on='itemId')
484       print('\n')
485       print("********************user-based collaborative filtering
(Top-K neigbors and Bias-subtracted)*******************************")
486       print(pred_movies.loc[:n])
487
488   #print the top 10 recommended movies for the new User (id = 944)
489   printPredictedMoviesUserBased(944, 10)
```