A HYBRID VIDEO RECOMMENDATION SYSTEM
BASED ON A GRAPH-BASED ALGORITHM

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submitted by **GİZEM ÖZTÜRK** in partial fulfillment of the requirements for the degree of **Master of Science in Computer Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen ______________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Adnan Yazıcı ______________________
Head of Department, **Computer Engineering**

Assoc. Prof. Dr. Nihan Kesim Çiçekli ______________________
Supervisor, **Computer Engineering Dept., METU**

Examining Committee Members:

Prof. Dr. Mehmet R. Tolun ______________________
Computer Engineering Dept., Çankaya University

Assoc. Prof. Dr. Nihan Kesim Çiçekli ______________________
Computer Engineering Dept., METU

Assoc. Prof. Dr. Ferda Nur Alpaslan ______________________
Computer Engineering Dept., METU

Assoc. Prof. Dr. Ahmet Coşar ______________________
Computer Engineering Dept., METU

Dr. Ayşenur Birtürk ______________________
Computer Engineering Dept., METU

Date: 16.09.2010

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Gizem Öztürk

Signature :

ABSTRACT

A HYBRID VIDEO RECOMMENDATION SYSTEM BASED ON A GRAPH-BASED ALGORITHM

ÖZTÜRK, Gizem
M.S., Department of Computer Engineering
Supervisor: Assoc. Prof. Nihan KESİM ÇİÇEKLİ

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This thesis proposes the design, development and evaluation of a hybrid video recommendation system. The proposed hybrid video recommendation system is based on a graph algorithm called Adsorption. Adsorption is a collaborative filtering algorithm in which relations between users are used to make recommendations. Adsorption is used to generate the base recommendation list. In order to overcome the problems that occur in pure collaborative system, content based filtering is injected. Content based filtering uses the idea of suggesting similar items that matches user preferences. In order to use content based filtering, first, the base recommendation list is updated by removing weak recommendations. Following this, item similarities of the remaining list are calculated and new items are inserted to form the final recommendations. Thus, collaborative recommendations are empowered considering item similarities. Therefore, the developed hybrid system combines both collaborative and content based approaches to produce more effective suggestions.

Keywords: Recommendation systems, collaborative filtering, content based filtering, graph based recommendation, information extraction

ÖZ

GRAFİK TABANLI BİR ALGORİTMAYA DAYALI HİBRİT VİDEO ÖNERİ SİSTEMİ

ÖZTÜRK, Gizem
Yüksek Lisans, Bilgisayar Mühendisliği Bölümü
Tez Yöneticisi: Doç. Dr. Nihan KESİM ÇİÇEKLİ

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Bu tez, hibrit bir video öneri sisteminin tasarım, geliştirme ve değerlendirme bölümlerini sunar. Sunulan hibrit video öneri sistemin temeli Adsorption adındaki bir grafik algoritmasına dayanır. Adsorption, işbirlikçi filtrelemeye dayalı bir algoritmadır ve öneri yapmak için kullanıcılar arasındaki benzerlikleri göz önünde bulundurur. Adsorption, temel öneri listesini elde etmekte kullanılır. Sadece işbirlikçi filtrelemenin kullanılmasıyla oluşan sorunları aşmak için içerik bazlı filtreleme de sisteme eklenir. İçerik bazlı filtreleme, kullanıcının tercihlerine uyan benzer maddeleri önerir. İçerik bazlı filtrelemeyi kullanabilmek için öncelikle temel öneri listesinden zayıf nesneler çıkarılır. Bunun ardından, kalan nesnelerin önerilmeyen nesnelerle olan benzerlik oranları hesaplanır ve yeni nesneler listeye eklenir. Böylece, işbirlikçi öneriler nesneler arasındaki benzerliğe göre güçlendirilir. Buna bağlı olarak da geliştirilen sistem, işbirlikçi ve içerik bazlı yaklaşımları birleştirerek daha verimli öneriler ortaya koyar.

Anahtar Kelimeler: Öneri sistemleri, işbirlikçi filtreleme, içerik bazlı filtreleme, grafik tabanlı öneri, bilgi çıkarma

To Emine Demirkan,

Rest in peace my dear grandmother …

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CHAPTER 1

INTRODUCTION

Internet has already become a part of our lives. There is no doubt that it is the easiest way to reach data so people use Internet in their daily lives. However, the data on the Internet is increasing continuously. Everyday a huge amount of information is uploaded in many different topics so it becomes a difficult task for users to find out the appropriate information available online.

Recommendation systems have arisen to provide convenient suggestions to the users. These systems can be used for different purposes in several domains from offering papers to researchers to helping consumers in e-commerce. There are recommendation systems in different domains such as films, television programs, video, music, books, news, images, web pages [1]. It can be said that, recommendation systems basically aim to overcome the difficulty of finding proper information. Available systems try to help their users to find the correct data they want. Among the most famous ones Amazon is recommending books in book domain. Last.fm helps users to find the songs that they want to listen. MovieLens tries to guide users to reach the movies they might like. IMDb, which is also in movie domain, has a big information archive about movies.

The roots of research on recommendations systems extend to the mid-1990s when the first papers about collaborative filtering are released [2]. As it is also important in business considering especially e-commerce, both industry and academic world has given a great importance to recommendation systems. Thus, a lot of research has been done about recommendation systems. It is still a hot subject in terms of research because current applications have deficiencies suggesting correct items to users.

Former research work was based on the idea of prediction of ratings only. In other words, the problem seems to guess the rating of unrated items by users. Guessing ratings for unseen items can be easily used for recommending new items to the users [2]. Later, researches deals with more complex prediction approaches. Especially, with the improvement of information technologies, recommender systems make use of techniques such as information retrieval, user modelling and machine learning.

Recommender systems can be broadly divided into three categories according to the approach they used to make recommendations. These are content-based recommendation, collaborative recommendation and hybrid recommendation [43]. In content-based recommendation, items are suggested according to their similarity to the items the user selected before. In collaborative recommendation, items are suggested according to the similarity between users with similar habits. Hybrid systems combine these methods to obtain better performance.

Adsorption [27] is a collaborative filtering algorithm which is already applied to YouTube successfully. In YouTube, there are millions of videos available and users can state whether they like the video or not. Adsorption uses this rating information and tries to reach unrated videos using a graph-based algorithm. The newly reached videos are suggested to users as new recommendations.

In this thesis a hybrid system which uses both collaborative filtering and content based approaches is proposed for recommending videos to users. By merging different approaches, it is intended to give more powerful results than using pure methods individually. In this thesis, Adsorption algorithm [27] is enriched by content based approach to provide better suggestions. Besides using rating archives, video and movie content information is also used to suggest new items which help to reinforce recommendations.

In evaluating the proposed hybrid system two data sets have been used: YouTube and MovieLens. The data crawled from YouTube dataset is highly sparse. MovieLens provides a regular dataset containing users, movies and ratings, which make this dataset more appropriate for adding the content based approach. The proposed algorithm is tested on both datasets. The improvements in recommendations were more obvious on the MovieLens data.

Adsorption algorithm [27] is among the new generation graph-based collaborative filtering methods. This method is not used together with content-based recommendation before. In this thesis, the results of Adsorption algorithm are improved by adding content-based techniques to obtain more accurate suggestions. Beside videos in YouTube, Adsorption algorithm is also applied to movie domain in MovieLens.

In summary, the main contribution of this thesis is improving the results of Adsorption algorithm by injecting content-based similarities between videos for the purpose of enhancing recommendations.

The rest of the thesis is organized in the following way:

Chapter 2 focuses on the related work about recommendation systems. A detailed description of the recommendation systems is presented including types of recommendation systems, and different approaches that are used in these systems. As well as a formal classification, works that are already available in the literature are addressed and explained according to the methods they utilize. While explaining existing works, useful parts of these works are featured, deficiencies are also mentioned.

In **Chapter 3**, the main work that is done for the development of the hybrid recommendation system is stated. The system architecture is presented and modules that form the complete design are explained in detail. Approaches and algorithms which are used in the system are discussed.

Chapter 4 is evaluation part in which experiments are involved. Tests that are completed in order to determine the success of the developed system are stated and results are declared.

Chapter 5 concludes the thesis with a brief discussion of the obtained system including specific contributions. In addition, possible future work is stated.

CHAPTER 2

RELATED WORK

In this chapter general concepts and the terminology about recommendation systems (RS) are presented. Different recommendation techniques are explained and algorithms that are used to build RS are referred. Previous works are discussed considering the techniques they are used.

2.1 Recommender Systems

With the increase of the Internet usage and the available huge data, recommendations became a part of life [3]. No matter what the domain is, a huge amount of information is online and it becomes a difficult task to select items that are necessary. Recommender systems try to overcome this challenge and aim to map people with the correct items.

More formally, recommender systems can be defined as systems which generate personal suggestions as an output or guide users individually to reach relevant and useful items among a lot of possible options [4]. Recommender systems generally produce a set of items which are aimed to take the attention of the current user in a high degree, so it can be said that the recommender system is a mapping between users and items involving a value of interest [63].

2.2 Recommendation Techniques

Recommendation techniques can be divided into five main approaches which are summarized in Table 1. The following assumptions are made to construct the table:

First, it is assumed that *I* is the set of items over which recommendations might be made. *U* is the user set, whose preferences are known already. *u* is the user for whom recommendations need to be formed. Finally, *i* is an item which is required to predict *u*'s preference.

Table 1 - Recommendation Techniques [4]

Technique	**Background**	**Input**	**Process**
Content-based	Features of items in *I*	*u*'s ratings of items in *I*	Generate a classifier that fits *u*'s rating behavior and use it on *i*.
Collaborative	Ratings from *U* of items in *I*.	Ratings from *u* of items in *I*.	Identify users in *U* similar to *u*, and extrapolate from their ratings of *i*.
Demographic	Demographic information about *U* and their ratings of items in *I*.	Demographic information about *u*.	Identify users that are demographically similar to *u*, and extrapolate from their ratings of *i*.
Utility-based	Features of items in *I*.	A utility function over items in *I* that describes *u*'s preferences.	Apply the function to the items and determine *i*'s rank.
Knowledge-based	Features of items in *I*. Knowledge of how these items meet a user's needs	A description of *u*'s needs or interests.	Infer a match between *i* and *u*'s need.

2.2.1 **Content Based Methods**

Content based recommendation systems suggest items based on the correlation between the content of the item and user's preferences [5]. They try to suggest items that are similar to the items which are preferred by the user in the past [6].

A content based recommendation system needs user feedback to learn the preferences of the user. Generally, user profiles are constructed in order to represent user choices. The information that is necessary for constructing the user profile can be obtained in two ways. They are implicit and explicit feedbacks [7]:

Explicit feedback: The user provides data willingly. Generally, users are forced to fill forms at the beginning of a sign up process. In these forms basic demographic information such as age, gender, education, occupation, location or user interests, is requested. The user can state interests as "I like action films" or "I don't like horror films". As another option, feedback can be obtained by collecting ratings that are assigned to the items. However, since this technique depends on asking the user to spend time on the system, users might be bothered of this process.

Implicit feedback: The user is not aware of the fact that he/she is providing feedback. This type of feedback can be gathered by monitoring the user activity. For instance, in video domain, a system can keep the list of watched movies or even better, it can be thought that if a user *u*, watches more than half of a video *v*, it can be considered as "*u* likes *v*". In this type, users are not disturbed, but the gathered results might not be as relevant as the results that are collected from explicit feedback.

Early systems start with text-filtering. For instance, a tool called SIFT (The Stanford Information Filtering Tool) is proposed in [59]. In SIFT users are subscribed to the system and they construct a profile by stating the words to favour or block [60]. Profiles can be changed manually by users. For each profile 20 articles are retrieved daily. In [59], it is stated that SIFT usage is increased to 1400 subscriptions in a month and there is a considerable amount of positive user-feedback.

PURE [8] is an article recommendation system which is based on content-based recommendation. The system is tested using PubMed [9] database which is one of the biggest databases about biological and medical sciences. The obtained results show that the system is useful for users to find articles that are appropriate with the user's preference.

Machine learning and information retrieval algorithms are used in order to specify user favorites and create user profiles. Generally, vector space models (VSM) are used in order to characterize user and item profiles [10]. PRES (Personalized Recommender System) [5] is another content-based filtering system which recommends articles related to home improvements. System promises learning with the use of feedback from user. To accomplish learning, relevance feedback [11] method by Rocchio is used which works in the vector space model.

The advantage of content-based methods is that, implicit feedback is enough to construct such a system. Beside this, the database grows with ratings providing the improvement of system performance in time. However, this fact is a clue of a bottleneck which occurs at the early steps of the system because there must be sufficient number of ratings in order to obtain a reliable system.

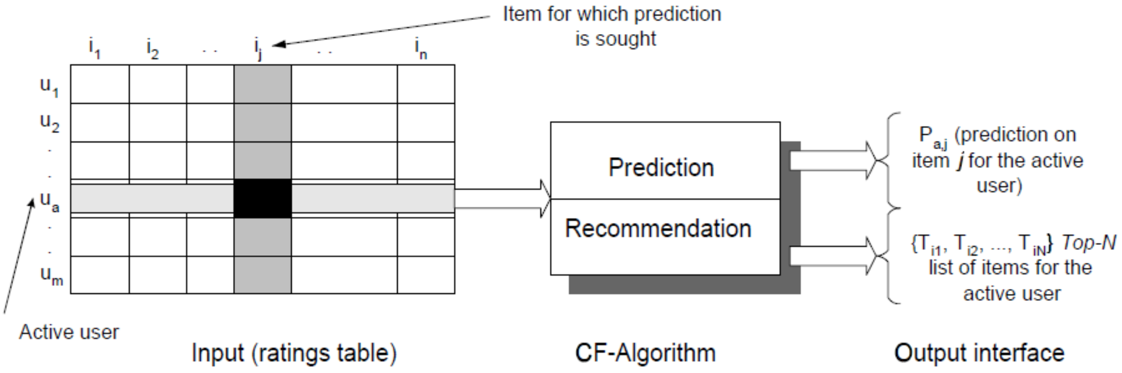
In this thesis, recommendations are firstly done using collaborative filtering (CF). As a result of CF, a recommendation list is obtained. Then, selected items in this list are compared with other items which are not in the list. This comparison is done according to item contents, and new items are suggested as well. So, recommendations are extended using CB filtering methods. Therefore, benefits of content-based approach are obtained.

2.2.2 **Collaborative Filtering Methods**

In collaborative filtering, the basic idea is “similar users have similar preferences” [12]. Or it can be said that, to find the correct suggestions for the current user, other users that are similar to the current user are figured out by observing their choices. By using this information, the preference of the current user can be guessed for specific items and a list of items can be constructed which includes the items that the active user might prefer.

Collaborative filtering can be divided into two as prediction and recommendation [13]. Collaborative prediction is the task of predicting user preferences for items, using currently available preferences, and the relation with the preferences’ of other users. Collaborative recommendation is developing a set of items which the active user might like most.

In the light of these concepts, the general structure of the collaborative filtering process is illustrated in Figure 1 [14]:



Item for which prediction is sought
i_1 i_2 . . i_j . . i_n
u_1
u_2
u_a
u_m
Active user
Input (ratings table)
Prediction
Recommendation
CF-Algorithm
$P_{a,j}$ (prediction on item j for the active user)
$\{T_{i1}, T_{i2}, ..., T_{iN}\}$ *Top-N* list of items for the active user
Output interface

Figure 1 - The Collaborative Filtering Process

Collaborative filtering systems can be divided into two groups according to the algorithms they use. These are memory-based collaborative filtering algorithms and model-based collaborative filtering algorithms [14]. In memory-based algorithms the user database is used in order to make suggestions whereas in model-based algorithms the user database is used in a preparation process to learn a model, later this model is used to make suggestions [13].

At the early steps collaborating filtering systems are categorized into two separate models which are pull-active collaborative filtering and push active collaborative filtering [15]. In pull-active systems such as Tapestry [16], the responsible party is the user to request recommendations from the database. In push-active systems the user pushes the item to a specific group of users, and makes suggestions to them. An example of push-active systems is presented in [17] which is used to recommend a document to the related people in the company. Automated collaborative filtering (ACF) systems save users from making choices.

In [61] collaborative filtering techniques are applied in order to obtain accurate results in movie search. More specifically collaborative filtering algorithms are used to compute personalized item authorities in search [61]. A prototype movie search engine called MAD6 (Movies, Actors, and Directors with 6 degrees of separation) is proposed. In the system besides collaborative filtering information retrieval techniques are also used in order to obtain relevant suggestions. The system is evaluated using online and offline experiments. According to test results, it is stated that both for online and offline experiments proposed collaborative system works better than IMDb and Yahoo! Movies search.

GroupLens [18][19] (newsgroup articles domain), Ringo [20] (music domain) and Video Recommender [21] (movie domain) are among the examples of ACF [22]. Amazon.com is also a famous recommender in which the recommendation system uses item-based collaborative filtering approach [23]. Other successful implementations of collaborative-based systems are MovieFinder.com and CDNow.com which is later purchased by Amazon.com [24].

MovieLens [25] is one of the most popular movie recommendation systems, which uses collaborative filtering. For the watched items a MovieLens user give ratings from 1 to 5 (1 means “Awful” and 5 for “Must See”). If there is no rating on a movie, the system assumes that movie has not been watched yet. Then, ratings of all users are used to suggest unwatched movies to the current user [15].

The problem with the MovieLens is that the system requests information from the user. When a new user joins, he/she should read the list of several movies and give ratings among the ones which are watched before. This operation is very time consuming because MovieLens expects at least 15 ratings to produce coherent recommendations. At the beginning, the user should spare time to fill these forms which is not much desired by many users.

Graph-based approaches are popular for developing collaborative filtering systems. A graph based recommendation algorithm is proposed in [67]. Nodes of the graph are formed by users and edges of the graph are formed by similarity ratios between users. Recommendations are done by traversing the nodes which also enables catching transitive relations [68]. Experiments show that the described algorithm performs successfully on test data.

In [27] a collaborative approach is used which is developed for recommending videos in YouTube [28]. In the system, a graph based semi-supervised [26][29], [30] algorithm called “Adsorption” is proposed. It is actually stated as an algorithmic framework which is appropriate for the systems where the set of labelled items is very small but the number of unlabelled items is larger. So, Adsorption algorithm is used when there are both labelled and unlabeled items in the graph and the aim is to set labels to all unknown nodes.

It is stated that there are several ways of classifying labels in a graph [27]. Some of the most well known of these approached are: nearest neighbour, shortest distance, commute time or electrical resistance [27]. But most of these touches are very time consuming and they are not able to end up in a reasonable time especially in a spread and huge graph structure. Commute distance is more sensible than others but it is also too expensive and generally do not allow improvements. To overcome these difficulties User-Video graph is formed. For better understanding a sample user-video graph can be seen in Figure 2 [27]:

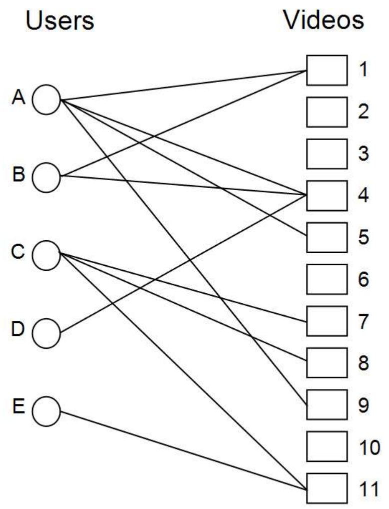


Figure 2 - An Example of User Video Graph

Suppose that there is a video called *v* and user *u*. The User-Video graph is used and recommendation is done considering the following conditions [27]:

1. *u* and *v* have a short path between them
2. *u* and *v* have several paths between them
3. *u* and *v* have paths that avoid high-degree nodes

In [27] three similar understandings of the algorithm are stated: Adsorption via averaging, Adsorption via Random Walks, and Adsorption via Linear Systems. Since these approaches are accepted to be equal [27], Adsorption via averaging is selected in which the main idea is based on forwarding existing labels and collecting new labels.

This thesis is based on this collaborative filtering work, which uses averaging through the user-video graph. First of all, label distribution list is formed using adsorption. Then, this pure collaborative approach is extended with a content based approach. Item similarities are taken into consideration in order to apply content based approach. Half of the distribution list is kept and other items are removed in order to make space. New items are obtained by calculating item similarities and these items are inserted to the empty places. So, a new distribution list is produced. This list is used as the recommendation list in order to obtain more accurate results.

2.2.3 **Demographic Techniques**

Demographic information such as country, age, gender, education can be used in order to cluster users. Demographic information of a user is compared with existing clusters. The most relevant cluster is found for the user. Also, items are separated and weighted according to their characteristics. These classes are compared and finally, items in the most matching cluster are recommended for user.

Generating clusters is the key issue when using demographic filtering. For this reason, Krulwich [31] builds the approach of demographic generalization and used this concept in Lifestyle Finder. With demographic generalization, user profiles are constructed by taking the advantage of a large-scale database of demographic data. In Lifestyle Finder, this approach is tested and results show that the demographic filtering is useful to create user profiles.

Privacy is one of the most important issues in demographic filtering. In [32], this issue is addressed. The system proposes ALAMBIC a system for e-commerce and promises to satisfy the necessities of privacy using demographic filtering. ALAMBIC suggests a system in which recommendations are based on feedback of users with similar demographic information.

Generally, demographic filtering techniques are combined with other recommendation methods. For instance, in [33] collaborative filtering is combined with demographic data for automatic music recommendation and satisfying results are obtained.

The advantage of these kinds of systems is recommendations can be done independent of the user history (ratings, favourites etc.) However it might be difficult to obtain demographic information. This data might be retrieved from users directly. IP addresses can also be used but only limited data such as country / city can be obtained. For these reasons demographic filtering techniques cannot be applied to systems in which anonymous user concept exists [34].

2.2.4 **Utility-based Methods**

Utility-based recommendation methods try to model a user's multi-attribute utility function and recommend items with highest utilities based on this function [10]. So, utility-based methods guess the importance of the items for each user and do recommendations based on the user preferences.

RBFN (radial basis function networks) and SMARTER (Simple Multi-Attribute Rating Technique Exploiting Ranks) are two utility-based methods. In [10] these methods are compared with classical content-based vector-space model method. The comparison is done in terms of recommendation accuracy, time expense, and user perceptions in the contexts of recommending different types of items. According to the results item type has an effect on the recommendation accuracy and time expense. Vector-space model method is more appropriate if the items have nominal attributes. SMARTER should be preferred if items have numerical attributes. Finally, RBFN gives reasonable results independent of the item type.

Utility-based methods do not need statics in order to do suggestions, so new item and new user problems do not affect the results of these systems. The drawbacks of utility-based methods are: system does not come up to new facts, and a utility function must be provided.

2.2.5 **Knowledge-based Methods**

In a knowledge-based system, there are three types of knowledge [4]. These are catalogue knowledge, functional knowledge and user knowledge. First of all in catalogue knowledge, the items and their features should be known clearly. Considering a web-based car recommendation system, the system must know that “Symbol” is also a member of “Renault” which is also a “French” made car. In functional knowledge the system should be able to match the correct items according to the user needs. If a house searching system is considered; when the user enters the keywords “calm” the system should fetch houses such as “not in city centre”, “a detached house not an apartment”, “riverside”, or “around trees”. Finally, in user knowledge, the system needs to know about the user, which is generally the demographic information about the user.

In [35] systems using KB methods are reviewed. One is Entree which is a restaurant recommender. Another one Recommender.com is a web site which provides movie research.

The good point with KB systems is they do not suffer from cold-start problems. Because, the necessary information should already be known and new data is not constructed later on.

The bottleneck of the Knowledge-based recommender systems is that, they suffer from all situations in which there is lack of information. Therefore, in order to obtain required data, a detailed knowledge mining should be done, but since this is a very expensive process, it is generally not preferred. As another disadvantage, KB recommender systems can make suggestions only with the information that is given. KB systems cannot come up with new information as a collaborative system does.

2.2.6 **Hybrid Methods**

Each type of recommendation techniques has its own strengths and weaknesses. The disadvantages of pure systems can be overcome by combining different techniques [36]. Hybrid methods produce recommendation systems in which at least two of the existing techniques are used. The aim is to take benefits of all techniques and obtain more relevant suggestions.

In [4], some of the blending methods are discussed. They are summarized in Table 2.

Table 2 - Hybridization Methods

Hybridization method	Description
Weighted	The scores (or votes) of several recommendation techniques are combined together to produce a single recommendation.
Switching	The system switches between recommendation techniques depending on the current situation
Mixed	Recommendations from several different recommenders are presented at the same time
Feature combination	Features from different recommendation data sources are thrown together into a single recommendation algorithm.
Cascade	One recommender refines the recommendations given by another.
Feature augmentation	Output from one technique is used as an input feature to another.
Meta-level	The model learned by one recommender is used as input to another.

To produce hybrid systems, the most popular approach is to combine content based systems with collaborative filtering systems. One of the early examples of this kind of integration is [37], which is done in online newspaper domain. The system takes into consideration both content based and collaborative filtering and constructs the suggestions by taking the weighted average of the results from these two different approaches.

A personalized news recommendation system is developed for Google News in [38]. The content-based recommendation mechanism which uses learned user profiles is combined with an existing collaborative filtering mechanism to generate personalized news recommendations. Tests are done on the live traffic of Google News website. As a result, it is concluded that the hybrid method improves the quality of news recommendation.

System in [62], works for movie domain. A hybrid system is described in which a content-boosted collaborative filtering approach is followed. In the system, existing user-rating vector is very sparse. First of all, content based predictor is applied to the user-rating vector. The resulting pseudo user-ratings vector contains both real user ratings and predicted ratings for unrated items. Then the obtained vectors are combined to form a user-rating matrix. The constructed matrix is passed to the collaborative filtering system. Collaborative filtering outputs final recommendations. It is reported that the hybrid system gives better results than using pure content based or pure collaborative systems.

In [66], a graph based model is developed for building e-commerce recommender systems. A two-layer graph model is presented in which the nodes represent products and customers accordingly. Edges between customers represent similarity between customers whereas edges between products represent product similarity. On the other hand, links between two layers demonstrate purchase history. A generic data representation is provided and this proposed model can be used with different recommendation techniques which are content-based, collaborative and hybrid recommendations. Content-based approach is used by activating only product information. To apply collaborative approach, customer-layer and inter-layer links are used. Finally, all edges are activated in order to obtain the hybrid approach. Evaluation results show that the hybrid method performs better than both collaborative and content-based methods.

In this thesis, advantages of both collaborative filtering and content based methods are used. Recommendations obtained by collaborative filtering are enhanced using content based methods. Therefore, this work represents a hybrid recommendation system using cascade hybridization method.

2.3 General problems in recommender systems

In recommender systems, different problems can occur, depending on the techniques that are used. These can be summarized as the following:

2.3.1 **Cold Start**

Recommender systems might suffer from cold start problem [39]. These systems use collected information to make reasonable recommendations. There are situations in which there is lack of required data and a recommender system suffers in these situations. These problems can be gathered into three groups which are new user, new item and new system.

New user: When a new user signs up to a recommendation system, there is only little information about that user. So, it is very difficult for the system to produce realistic recommendations.

Both collaborative filtering and content based filtering techniques suffer from the new user – cold start problem. In order to build the user profile and produce coherent results, there should be enough user feedback, which is generally the ratings that are given to the items [2].

New item: This problem is seen when there is a newly added item to the system. In this situation, there is not enough feedback that is provided for that item by users.

Especially collaborative filtering techniques suffer from this problem. Because in collaborative filtering recommendations are based on the previously given ratings to the items by other users. Therefore when a new an item is added there is no data about that item. Considering movie domain, when a new movie is added to the recommendation system, there is no rating that is given to that movie. So, until a sufficient number of ratings are given to that item by users, the new item is not recommended by the system [2].

New system: New system problem is the synthesis of the new user and new item problems which occurs clearly when a systems has just been constructed.

In [40], cold start problem is addressed. Cold-start problem is splitted as: user side and item side. The work concentrates on user side in which there is a new user who does not have any preferences over the existing items. Therefore a hybrid model is constructed which is based on the analysis of two probabilistic aspect models using pure collaborative filtering to combine with the users' data. MovieLens data set is used to test the system. According to the results, it is found out that this model helps to solve the user-side cold-start problem to some extent.

2.3.2 **Data sparsity**

Data sparsity plays an important role in recommendation systems. In [12], data sparsity problem is addressed in collaborative filtering. In the work, it is concluded that the sparsity of the data directly affects the obtained results of collaborative filtering recommendation systems.

Considering movie domain, there may be a lot of movies that are rated by few people. Even if the users, who rate the movie, give high ratings, this kind of movies would not be recommended very often [2].

Systems such as [41] try to eliminate the data sparsity problem. In [41], a method is suggested to enhance similarity matrices under sparse data as well. The evaluation is done using Movie-Lens data. Experiments are done using different sparsity levels. Results show that the proposed Random Walk Recommender algorithm outperforms two other item-oriented methods in different sparsity levels, especially giving best results when the data is sparse.

In this thesis, primary approach is using YouTube data. YouTube has a big database but, it does not share its dataset with public. So, YouTube data is formed by crawling and due to this reason, it is very scattered. For each person, the number of seen movies and ratings are very low and this makes it difficult to work with this data. Because of the high sparsity of YouTube data, one of the regular dataset alternatives MovieLens is also used. In MovieLens dataset, each user has at least 20 ratings and this makes the dataset more uniform than YouTube dataset.

2.3.3 **Over-specialization**

In content-based filtering, the system aims to suggest items that are highly matching with the user profile. This causes a user to face with similar recommendations continuously that are already rated, not different ones that the user might like [42]. This problem is called over-specialization and pure content-based filtering systems often experience this problem [43].

This problem can be solved with inserted randomness in a degree. In [44], it has been proposed that the use of a genetic algorithm can be a solution in terms of information filtering. Beside this, Outside-The-Box (OTB) recommendation [45] proves that taking some risks are helpful to overcome over-specialization problem.

There are several other methods trying to overcome this problem. For instance CHIP (Cultural Heritage Information Personalization) is a CB recommender system which uses semantic relations, claiming that the usage of semantic relations can partially solve the over-specialization problem by providing additional information and retrieving new concepts [46][47].

As over-specialization problem is related with content-based filtering, collaborative filtering techniques can be used in order to eliminate the problem. However, [48] deals with over-specialization problem by presenting a personalization strategy without making use of collaborative filtering approaches. In the system a different reasoning mechanism is used which offers semantically related items, instead of using semantic approaches and finally, the obtained system is used for recommending TV-programs.

2.4 Evaluating Recommendation Systems

After building the recommendation system, the next step is making tests on the system in order to prove its usefulness. Because there are several different methods to evaluate a recommender system, the system designers must decide on a proper approach that will be employed to the system [49]. Selecting proper algorithms is a key issue in order to construct successful systems.

The evaluation of recommender systems can be divided into three main parts which are offline experiments, user studies, and online evaluation.

2.4.1 Offline experiments

Offline experiments are performed using the data that is already available. This data set is generally the ratings that are collected from users. In these methods, it is aimed to simulate the interaction of users to the system [49]. Since offline experiments do not interact directly with the user, the evaluation can be done using different techniques just with a little cost.

In this thesis, data that simulates the user behavior is collected so offline experiments fit very well for the needs. Especially considering the timing issues, offline experiments are used to evaluate the system behavior.

2.4.2 User studies

User studies are generally performed by asking users to interact with the system. During this period user behaviors are monitored and recorded. The goal is to collect quantitative measurements [49]. In most of the cases users are asked to fill questionnaires, before, during and at the end of the task.

2.4.3 **Online evaluation**

This kind of experiments collect more accurate results than other techniques as they measure the system behavior in reality. Measurements are done while the system is running. However, there is a risk that unexpected results might occur and this might cause the system even crash [49]. Therefore, before applying online evaluation, basic tests should be done in offline environment to provide safety.

CHAPTER 3

A HYBRID VIDEO RECOMMENDATION SYSTEM BASED ON GRAPH-BASED ADSORPTION ALGORITHM

3.1 General System Overview

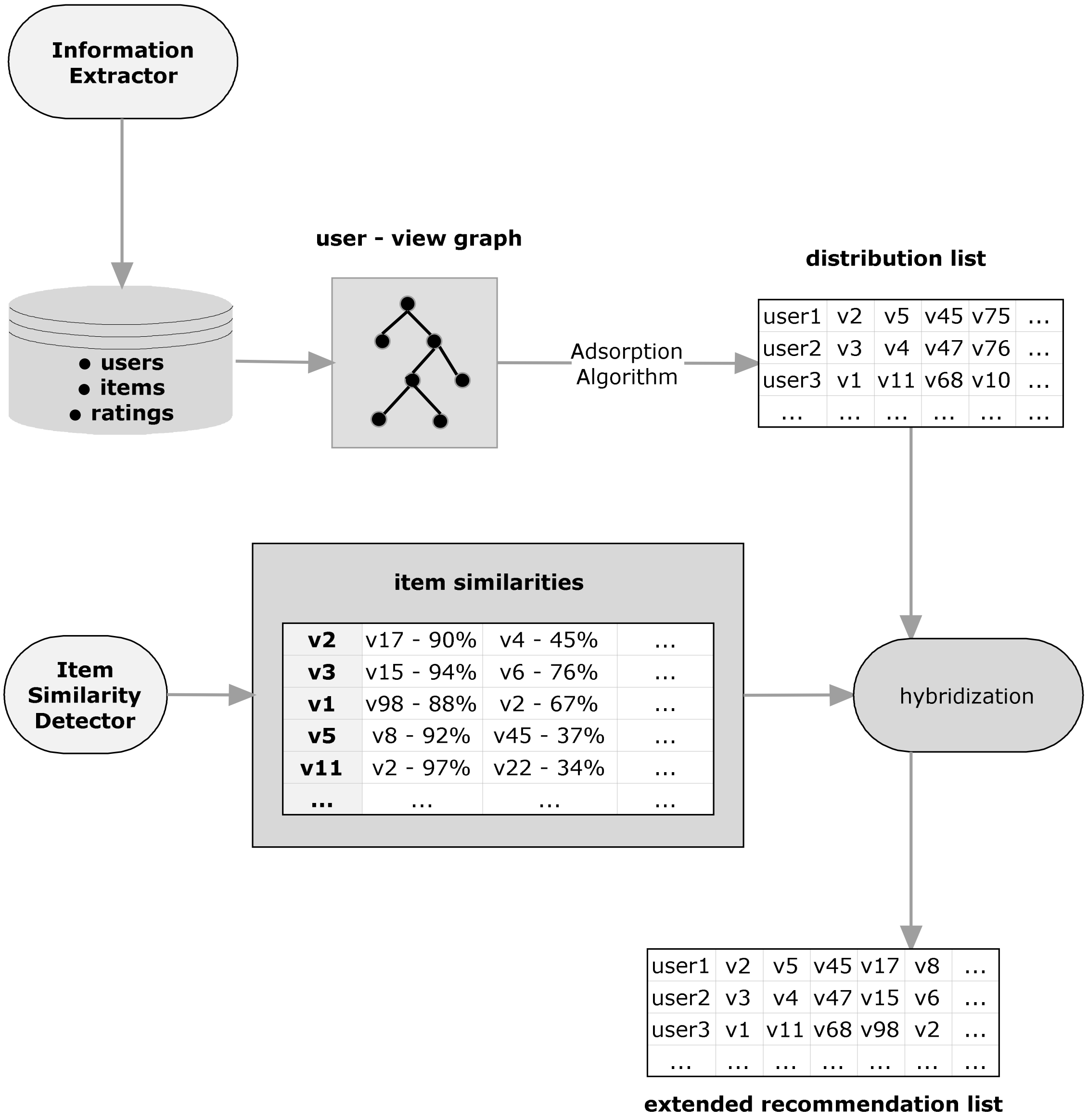
The hybrid recommendation system that is developed in this thesis is an application which aims to select appropriate videos or movies for users.

The developed recommendation system can be used both for YouTube and MovieLens.

Recommendations are done according to both collaborative and contend based features. First, ratings are guessed according to collaborative relations. Then, content based features are injected to provide a hybrid system.

3.2 System Architecture

The generated hybrid recommendation system consists of different modules. Each module is developed for a specific task. The general system architecture is presented in Figure 3.



user1	v2	v5	v45	v75	…
user2	v3	v4	v47	v76	…
user3	v1	v11	v68	v10	…
…	…	…	…	…	…

v2	v17 - 90%	v4 - 45%	…
v3	v15 - 94%	v6 - 76%	…
v1	v98 - 88%	v2 - 67%	…
v5	v8 - 92%	v45 - 37%	…
v11	v2 - 97%	v22 - 34%	…
…	…	…	…

user1	v2	v5	v45	v17	v8	…
user2	v3	v4	v47	v15	v6	…
user3	v1	v11	v68	v98	v2	…
…	…	…	…	…	…	…

Figure 3 - General System Architecture

The distribution list consists of users and the list of videos for each user. The items in the video list are found to be related to that user and can be recommended accordingly.

Item similarities table demonstrates how much two items are similar to each other. In first column items are listed. The aim is to find the similarity ratio of other items to these selected items. Other columns in the table show the likeliness proportion of different items. For instance, the similarity between v2 and v17 is 90%, v2 and v4 is 45%, v3 and v15 is 94%, etc.

3.3 Design Issues

The designed recommender system is able to work with two different databases. The first one is YouTube database, the second one is MovieLens database. Besides in order to insert content based techniques IMDb database is also used together with the MovieLens dataset.

3.3.1 **Database**

MySQL [50] which is one of the most popular open-source databases is used during the development of the recommendation system. Java Persistence Architecture API (JPA) [51] is used in the design of the system. JPA is a Java specification which enables accessing, persisting and managing data between Java objects / classes and a relational database. Currently, JPA is admitted to be a standard for Object-Relational Mapping (ORM).

JPA cannot make any actions by itself as it is just a set of interfaces. So, it needs implementation. Recently, there are implementations of JPA and in this work Hibernate is used. Hibernate is an open-source implementation of JPA. So by the help of JPA and Hibernate a Java class is mapped to the relational database table. So, the user does not have to think about neither table structures nor joining tables.

In JPA, there is an EntityManager API. This API provides processing queries and transactions on the objects against the database. Beside this, there is also an object level query language, JPQL [52]. JPQL is used for querying objects in the database. These recent technologies simplify database modelling and shorten queries that are needed to reach database items.

The created database structures are the same for YouTube and MovieLens and they are shown in Table 3.

Table 3 - Database Structure for YouTube and MovieLens

Table Name	Fields in Table	Summary
user	Name	This table contains user names. User names are unique. This table is constructed from user Java class that is described in the application.
video_rating	id, rating, videoId	This table contains videoId, and rating pairs which are kept together using unique id for each pair. This table is constructed from movie_rating Java class that is described in application. Only rating and videoIds are stated in class. id field is formed by Hibernate.
user_video_rating	User_name, ratings_id	This table is used for joining user and video_rating tables. This table is entirely formed by Hibernate. Since the user class actually contains a list of movie-rating objects, the connection between users and movie-rating pairs is satisfied by this table.

3.3.1.1 **YouTube Database**

In this thesis, the database tables are handled using JPA and Hibernate. To construct YouTube database, objects are passed to Hibernate and the related tables are constructed as in Table 3.

3.3.1.2 **MovieLens Database**

GroupLens Lab. shares their MovieLens data for developers. Currently, the data is available on Internet and it is in text format. MovieLens data includes user_id, item_id and rating for the related item. Therefore, the data can be downloaded and inserted into the database.

For MovieLens database a MovieLensConverter is created in order to use the same data structures that are previously created. The converter reaches the existing MovieLens table, extract users, movies and ratings accordingly. Then, Java objects are developed and they are inserted into the database using Hibernate. , both YouTube and MovieLens databases have same structures and this enables applying same techniques on both databases similarly.

3.3.1.3 **IMDb Database**

MovieLens does not include features of movies, but IMDb does. So, in order to reach movie features there is a need to extract the data from IMDb. In order to gather movie data an information extractor is developed in [53] and [54]. This information extractor processes movies in IMDb and add their information to the local database. We have also used their IMDb database in this thesis. Their database includes features of movies and a connection table for MovieLens-IMDb IDs which enables mapping movies between MovieLens and IMDb.

In IMDb database there are various sections and features but not all of them are used. The details of selected features and fields are summarized in Table 4.

Table 4 - Database Structure for IMDb

Used Table Name	Used Fields in Table	Summary
title	kind_id	Describes kind information of the movie.
cast_info	role_id, person_id, movie_id	Includes cast information of a movie
name	id, name	Involves names of actors and actresses. cast_info and name are used together to obtain cast of movie and name of the writers as well.
movie_info	info_type_id, info, movie_id	Stores movie id, info and info type ids of movies. According to the info_type_id genre, language and country of movie can be obtained.
keyword	keyword, id	Stores keyword for a movie
movie_keyword	keyword_id, movie_id	Stores movie id and keyword id. When used together with keyword table, keywords for the related movie can be extracted.
movie_companies	company_id, movie_id, company_type_id	Includes company id, movie id and company type id
company_name	name, id,	Stores company name. Used together with movie_companies table in order to get company information.

3.3.2 Item and User Modelling

In the proposed hybrid recommendation system, first collaborative filtering technique is applied and then the content based approach is injected to the results. The input to the CF approach should be a graph. To construct this graph, users and items are formed as nodes of the graph.

At the beginning items and item ratings are structured together as item-rating pairs. Then, these objects are used in order to model users. User objects contain user names and a list of item-rating pairs.

For each user a graph node is constructed. While examining the list of item-rating objects, a graph node is inserted for each distinct item. Weighted edges are added between nodes considering the ratings that are given to the items by the corresponding users. An example of a constructed graph structure is given in Figure 4. It should be noted all user names and video IDs are unique in the system.

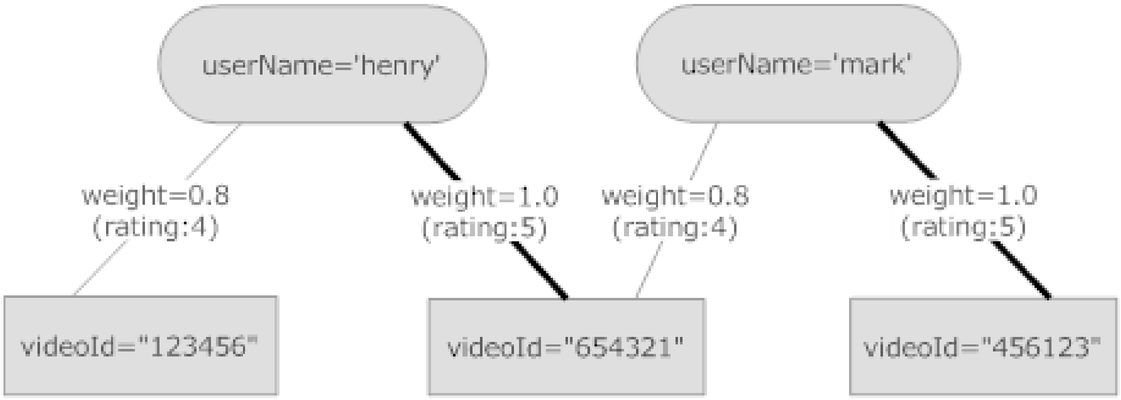


Figure 4 - Modelled Graph Structure

3.4 YouTube Information Extractor

YouTube does not provide a database that can be used in this thesis. For this reason it was necessary to develop a module to crawl YouTube and construct the YouTube database.

YouTube provides an API [55] in order to help developers to implement client applications. With the API methods, only a limited amount of information can be extracted. But the available methods are helpful to implement a data set extracting module. We used this API to retrieve the necessary data to construct our data set.

There are different YouTube APIs available for different programming languages. These are Java, .NET, PHP and Python [55]. In this thesis, Java API is preferred for the reason that it is object-oriented and there are numerous libraries available for Java. Besides, Java is used within Eclipse which is an open-source IDE [56]. Especially in Eclipse, Java is very well supported which makes easier for a developer to build applications using Java and Eclipse together.

The YouTube dataset module is implemented by using the Java Platform, Eclipse IDE and the API which is provided by YouTube. The extracted data includes user information, such as user name, list of pre-watched and rated videos, and given ratings. Periodically, the system checks for updates in user information and inserts new data accordingly. This enables the data to stay up to date.

The task of collecting data for our database continued nearly four months. During that period 15,090 users are added to the system with 117,604 videos and 177,733 ratings.

3.4.1 Video Fetcher

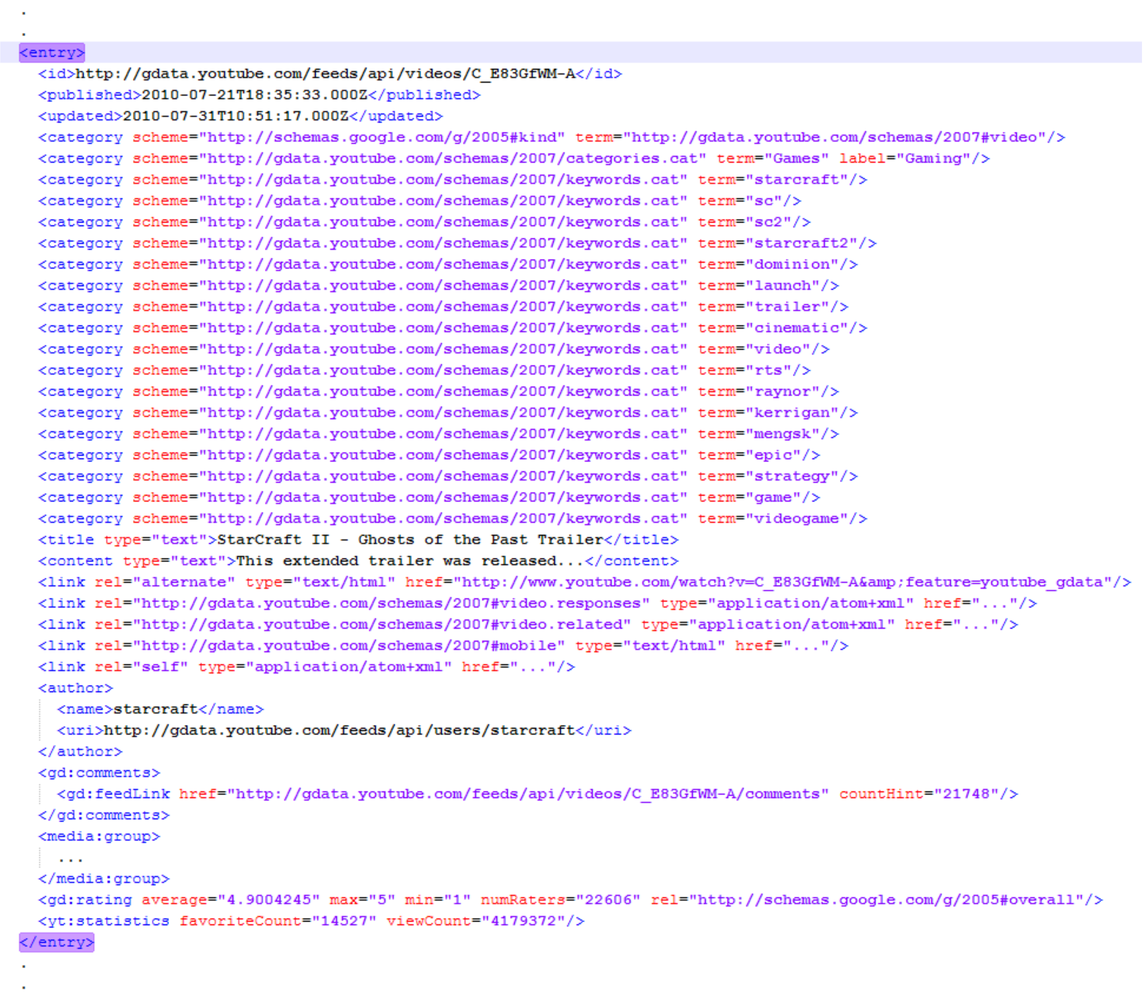
Since the list of YouTube users is not readily available via YouTube API, various videos are visited as a first step to collect user data. There are standard feeds such as top_rated, most_viewed, top_favorites, most_popular, most_recent, most_discussed which are provided by YouTube. These standard feeds can be used as in the following:

http://gdata.youtube.com/feeds/api/standardfeeds/recently_featured

http://gdata.youtube.com/feeds/api/standardfeeds/most_popular

http://gdata.youtube.com/feeds/api/standardfeeds/top_rated?time=today

The returned feeds are in xml format. For each movie there is an <entry> tag and all information about the movie exists in the <entry> tag. Figure 5 is an example of an entry tag for the video in most_popular feed (less important parts are eliminated):



```
.
.
<entry>
  <id>http://gdata.youtube.com/feeds/api/videos/C_E83GfWM-A</id>
  <published>2010-07-21T18:35:33.000Z</published>
  <updated>2010-07-31T10:51:17.000Z</updated>
  <category scheme="http://schemas.google.com/g/2005#kind" term="http://gdata.youtube.com/schemas/2007#video"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/categories.cat" term="Games" label="Gaming"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="starcraft"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="sc"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="sc2"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="starcraft2"/>
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  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="kerrigan"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="mengsk"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="epic"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="strategy"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="game"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="videogame"/>
  <title type="text">StarCraft II - Ghosts of the Past Trailer</title>
  <content type="text">This extended trailer was released...</content>
  <link rel="alternate" type="text/html" href="http://www.youtube.com/watch?v=C_E83GfWM-A&amp;feature=youtube_gdata"/>
  <link rel="http://gdata.youtube.com/schemas/2007#video.responses" type="application/atom+xml" href="..."/>
  <link rel="http://gdata.youtube.com/schemas/2007#video.related" type="application/atom+xml" href="..."/>
  <link rel="http://gdata.youtube.com/schemas/2007#mobile" type="text/html" href="..."/>
  <link rel="self" type="application/atom+xml" href="..."/>
  <author>
    <name>starcraft</name>
    <uri>http://gdata.youtube.com/feeds/api/users/starcraft</uri>
  </author>
  <gd:comments>
    <gd:feedLink href="http://gdata.youtube.com/feeds/api/videos/C_E83GfWM-A/comments" countHint="21748"/>
  </gd:comments>
  <media:group>
    ...
  </media:group>
  <gd:rating average="4.9004245" max="5" min="1" numRaters="22606" rel="http://schemas.google.com/g/2005#overall"/>
  <yt:statistics favoriteCount="14527" viewCount="4179372"/>
</entry>
.
.
```

Figure 5 - Sample video feed

Beside standard feeds, videos are also retrieved by key-based searches. For instance when “flute” is typed and the related videos are searched, a list of videos are returned that fits the search criteria. The list of returned videos is inserted as new videos to the system database.

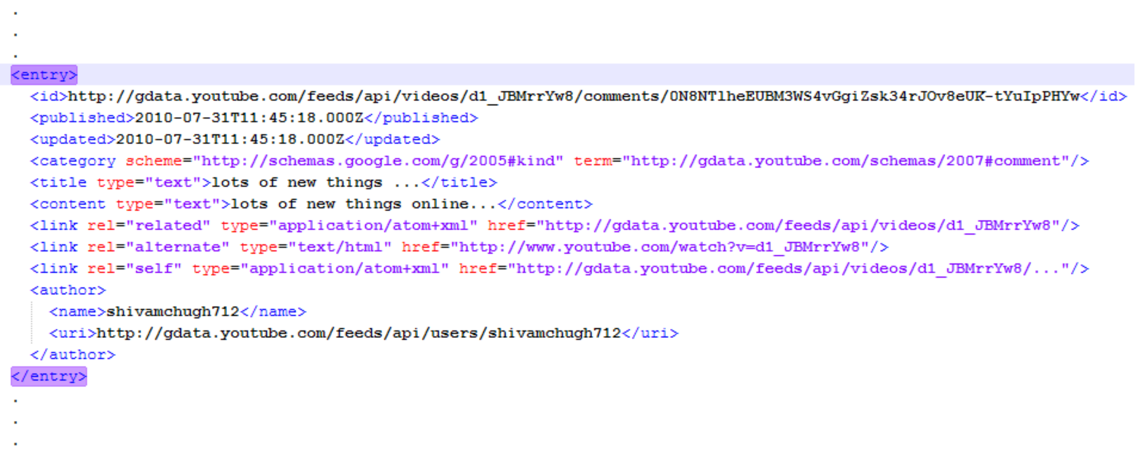
3.4.2 **User Fetcher**

The obtained xml files contain video information including a feed link for comments of the corresponding video. Its format is as follows:

http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/comments

The keyword ‘d1_JBMrrYw8’ is the video-id for video ‘Avatar Movie Trailer [HD]’. Each video has a unique video id which identifies the video.

Each comment stays in a separate <entry> tag as it is like in video feeds. Its format is shown in Figure 6.



```
.
.
.
<entry>
  <id>http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/comments/0N8NTlheEUBM3WS4vGgiZsk34rJOv8eUK-tYuIpPHYw</id>
  <published>2010-07-31T11:45:18.000Z</published>
  <updated>2010-07-31T11:45:18.000Z</updated>
  <category scheme="http://schemas.google.com/g/2005#kind" term="http://gdata.youtube.com/schemas/2007#comment"/>
  <title type="text">lots of new things ...</title>
  <content type="text">lots of new things online...</content>
  <link rel="related" type="application/atom+xml" href="http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8"/>
  <link rel="alternate" type="text/html" href="http://www.youtube.com/watch?v=d1_JBMrrYw8"/>
  <link rel="self" type="application/atom+xml" href="http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/..."/>
  <author>
    <name>shivamchugh712</name>
    <uri>http://gdata.youtube.com/feeds/api/users/shivamchugh712</uri>
  </author>
</entry>
.
.
.
```

Figure 6 - Sample comment feed

Comment feed is retrieved because it contains the list of users who share their opinions about the video. But YouTube does not allow getting all comments (therefore users). The number of comments that can be retrieved for each video item is limited to 1000 and it can be taken in groups of 50.

3.4.3 **Rating Fetcher**

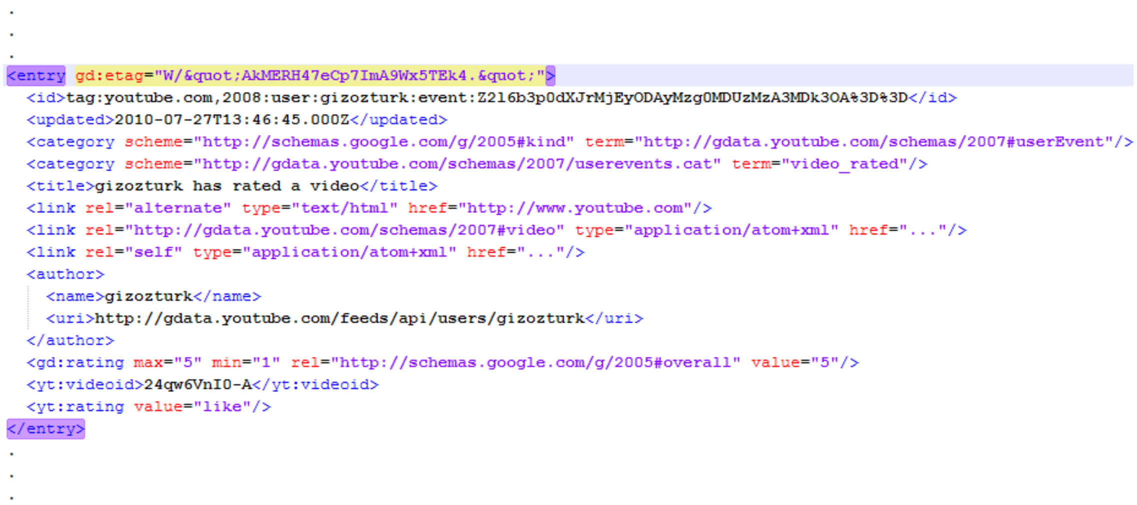
User names are extracted from comments, and they are added to the database. The next step is getting ratings of users. In YouTube, each user has their events feed. If the users agree to share their activities, these feeds can be retrieved from YouTube system. Activity feeds contain information such as rated videos, favourite videos and commented videos. But, in order to fetch this data YouTube requests developer-key which can be obtained with Google accounts [57]. This developer-key is used in requesting feeds. A sample request is as follows:

http://gdata.youtube.com/feeds/api/users/gizozturk/events?v=2&key=AI39si4ysIkjnbqC5TNtBZMPXBsuLqzWHtw6TuvZoBiCvchRIXnmiV_H8aaSLF-3gd_cuwDN6AvqSwENct-b6nAU3gGOdTHdOw

This link retrieves the events of the YouTube user ‘gizozturk’. However, there is also a restriction in YouTube such that a developer is not allowed to retrieve feeds which occurred more than 60 days before the time of request [55]. Activity feeds are parsed and rated videos are added to the database with the given ratings. In addition, favourite videos are also added assuming the user has given a rating 5.

During the time of collecting data, YouTube has changed their rating system. Previously, users were giving ratings in a range of [0, 5]. However in the new version of YouTube, users explain their tastes by marking ‘like’ or ‘dislike’ options. In order to provide compatibility, prior ratings are converted to values between [0, 1]. In other words, if a user likes a video it is assumed that the user has given a rating of 1 to that video, and 0 otherwise.

Figure 6 presents an entry tag which contains rating information.



```
.
.
.
<entry gd:etag="W/&quot;AkMERH47eCp7ImA9Wx5TEk4.&quot;">
  <id>tag:youtube.com,2008:user:gizozturk:event:Z216b3p0dXJrMjEyODAyMzg0MDUzMzA3MDk3OA%3D%3D</id>
  <updated>2010-07-27T13:46:45.000Z</updated>
  <category scheme="http://schemas.google.com/g/2005#kind" term="http://gdata.youtube.com/schemas/2007#userEvent"/>
  <category scheme="http://gdata.youtube.com/schemas/2007/userevents.cat" term="video_rated"/>
  <title>gizozturk has rated a video</title>
  <link rel="alternate" type="text/html" href="http://www.youtube.com"/>
  <link rel="http://gdata.youtube.com/schemas/2007#video" type="application/atom+xml" href="..."/>
  <link rel="self" type="application/atom+xml" href="..."/>
  <author>
    <name>gizozturk</name>
    <uri>http://gdata.youtube.com/feeds/api/users/gizozturk</uri>
  </author>
  <gd:rating max="5" min="1" rel="http://schemas.google.com/g/2005#overall" value="5"/>
  <yt:videoid>24qw6VnI0-A</yt:videoid>
  <yt:rating value="like"/>
</entry>
.
.
.
```

Figure 7 - Sample rating feed

This rating feed is in the new rating structure. It can be seen that the rating value in this example is ‘like’ which is automatically assumed to be ‘5’.

There is also a module that scans through all users, fetches their activities and update ratings if there are changes. This module runs periodically to gather up-to-date information.

3.5 Recommender

The proposed recommender system uses both collaborative filtering and content based approaches in order to provide suggestions. Collaborative filtering technique forms the predictions for the movies and content based approach aims to improve the obtained results.

The following sections clarify both the collaborative filtering recommendation and insertion of content based features within the generated system.

3.5.1 **Pure Collaborative Filtering Approach**

Collaborative filtering is one of the most successful techniques in recommendation systems and it makes use of preferences of many users in order to predict interests of the current user. Here, the underlying assumption is that users who have similar interests in the past would have similar interests in the future too.

In general, it can be said that collaborative filtering examines the previously given ratings of all users to the items and use them in order to guess the ratings of unrated items for the active user.

In this work, a graph-based collaborative filtering algorithm is used. The algorithm is called Adsorption.

3.5.1.1 **Adsorption Algorithm**

Adsorption algorithm is a general framework when there is a rich graph structure, in which there are both labelled and unlabeled items and it can be used for classification and learning [27].

There are different versions of Adsorption algorithm and the basis of the algorithm arises from the idea of finding the optimum way of classifying items in a graph in terms of labels that are already put on some other items. In other words the problem is giving labels to the unlabeled items using labelled items in the graph structure. The versions of adsorption algorithm are ‘Adsorption via Averaging’, ‘Adsorption via Random Walks’ and ‘Adsorption via Linear Systems’. According to the theorem given in [27] all three version of the Adsorption algorithms are equal. In this work ‘Adsorption via Averaging’ version is used due to memory and time issues.

As Adsorption algorithm is a graph based method, there is a need to represent items as nodes of graph to apply it in YouTube domain. To achieve this, the graph architecture is built involving YouTube users and available videos and Adsorption is thought to work through that developed User-Video graph. An instance of user-view graph is illustrated in Figure 8.

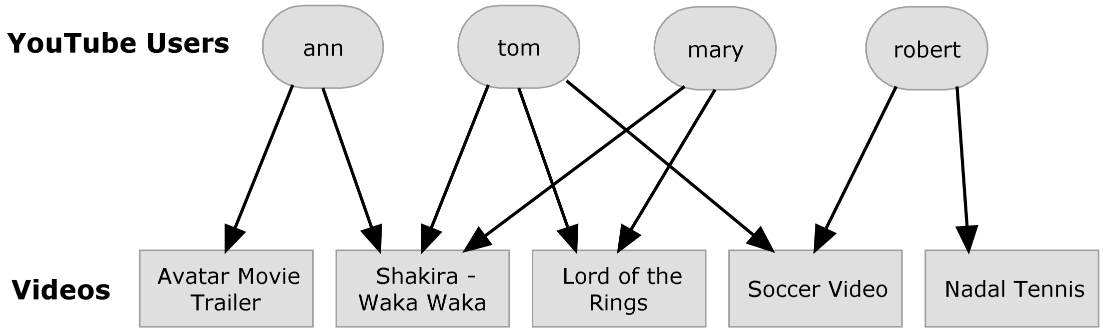


Figure 8 - An instance of User-View Graph

As it can be seen in Figure 8 relations between videos and users can be determined. Besides, by tracking a movie that is watched by a user, other unseen videos can be found collaboratively.

3.5.1.2 Adsorption via Averaging

The main idea in adsorption via averaging is forwarding labels from the labelled items to the neighbour items, and saving the received labels by neighbours. The important part of the algorithm is to make sure keeping important information while guaranteeing to converge with a reasonable number of label assignments. More formally it can be explained as the following [27].

A graph $G = (V, E, w)$ is given where V is the set of vertices, E denotes the set of edges, and $w : E \rightarrow \boldsymbol{R}$ denotes a non-negative weight function on the edges. L denotes a set of labels. Assume each node v in a subset $V_L \subseteq \mathrm{V}$ carries a probability distribution L_v on the label set $L. V_L$ represents the set of labelled nodes.

At this point some pre-processing is necessary. For each vertex $v \in V_L$, a shadow vertex $\tilde{v}$ is created with exactly one outgoing neighbor v, which means v and $\tilde{v}$ are connected by an edge with a weight of 1.

The pseudo-code of the algorithm is as follows:

```
**Input:** $G = (V, E, w), L, V_L$.
repeat
    for each $v \in V \cup \tilde{V}$ do:
    Let $L_v = \sum_u w(u, v) L_u$
    end-for
    Normalize $L_v$ to have unit $L_1$ norm
until convergence
**Output:** Distributions $\{L_v \mid v \in V\}$
```

In order to apply the algorithm, the first step is to create the user-view graph. Considering effective usage of memory and processor, videos which have a rating lower than the decided threshold are pruned and not added to the graph. After experimenting with different values it is decided to set this threshold value to 4. That is, if a user has given 4 to a movie, that movie is added to the graph by adding an edge between that user and the movie. If the rating of the movie is 2 it is not added to the graph.

After the pruning step, a shadow node is created for each user and video, which is the end of the graph construction part.

Each node of the graph is traversed one by one and its label distribution list is updated according to its neighbours. First, the label distribution list of the current node is cleared. Then, this list is reconstructed by traversing its neighbours and copying their label distribution lists. The edge weight between the current node and its neighbour is also taken into account in this process. For instance, if the edge weight is 0.6 between the current node and its neighbour, neighbour label distribution list is multiplied with 0.6 and copied to the distribution list of the current node. This copying process is continued with the neighbour of the neighbour of the current node and so on. While going deeper, the effect of labels reduces dramatically and time and memory constraints become crucial. For this reason, the system uses only the first 3 levels of the neighbour label distributions.

The size of the label distribution list limits the labels which will be carried to the next iteration. Therefore, after the label distribution list is formed, it is sorted and poor labels are deleted from the list.

This process continues until the label distribution list of all nodes converges. To be more precise, whenever the label distribution list of all nodes remains same on an iteration, the algorithm terminates.

3.5.2 **Injection of Content Based Methods to Collaborative Filtering**

To increase the strength of recommendations it is decided to add content based filtering to the results obtained by collaborative filtering.

The content based method that is used in this thesis does not provide recommendations itself. Instead, it is used to recommend videos/movies to the users that are similar to the ones obtained with the Adsorption algorithm. The aim is to suggest different but also relevant items to the users.

Content based approach is added by using item similarities. As two different datasets are used in this thesis, two different similarity methods are applied, one for YouTube dataset and one for MovieLens dataset. Collaborative results are sorted by relevance and less relevant results are replaced with content based similarity results.

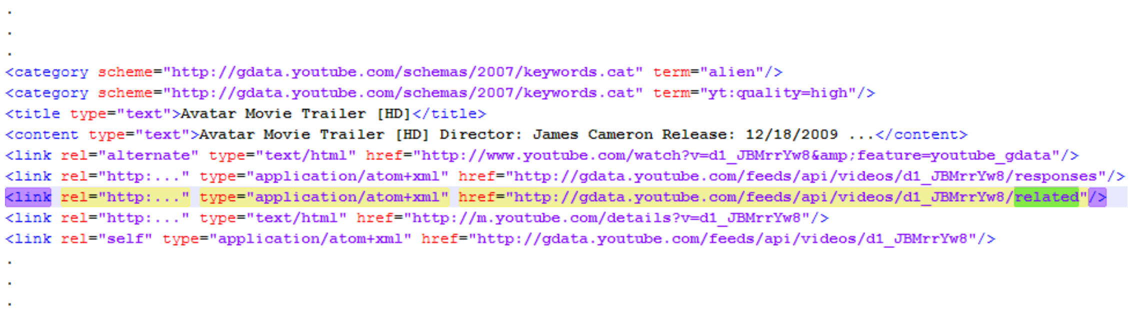
3.5.2.1 Item Similarities for videos in YouTube

YouTube has its own algorithms to decide the similarities between videos. This is exactly the necessary property to obtain item similarities in this thesis. In YouTube API there is a feed which retrieves the related videos to a specific one.

In order to retrieve the related videos of a selected video, the first step is to determine the video id of the selected video. As it is explained in Section 3.4, there is a list of videos containing YouTube video ids for each video in the database. Using the id of the video, an HTTP GET request is sent to the related URL. An example URL of 'Avatar Movie Trailer [HD]' is as the following:

http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8

The retrieved xml file contains a link which can be used for retrieving related videos of the current video. The structure of the retrieved xml file is shown in Figure 9 (some parts are shortened to focus on the related videos URL).



```
.
.
.
<category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="alien"/>
<category scheme="http://gdata.youtube.com/schemas/2007/keywords.cat" term="yt:quality=high"/>
<title type="text">Avatar Movie Trailer [HD]</title>
<content type="text">Avatar Movie Trailer [HD] Director: James Cameron Release: 12/18/2009 ...</content>
<link rel="alternate" type="text/html" href="http://www.youtube.com/watch?v=d1_JBMrrYw8&amp;feature=youtube_gdata"/>
<link rel="http:..." type="application/atom+xml" href="http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/responses"/>
<link rel="http:..." type="application/atom+xml" href="http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/related"/>
<link rel="http:..." type="text/html" href="http://m.youtube.com/details?v=d1_JBMrrYw8"/>
<link rel="self" type="application/atom+xml" href="http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8"/>
.
.
.
```

Figure 9 - Related-videos URL in a Singe Video Feed

So, the part that is used to obtain related videos is:

http://gdata.youtube.com/feeds/api/videos/d1_JBMrrYw8/related

When this feed is retrieved the list of related videos are gathered including the basic video information such as category, title, content, author, comments and ratings. If a related video is already in the recommendation list, another related item is added to recommendation list.

3.5.2.2 Item similarities for movies in MovieLens

It is necessary to find similarities between movies for MovieLens. The relationships between movies can be found according to their features such as year, actors, genre etc. However, in MovieLens database only basic information related to the movies exist. These are movie name, movie year, movie genre, movie IMDb URL, user gender, age, occupation and zip code. So, it is required to gather more detailed movie information from IMDb. IMDb stores extra information about movies like movie kind, writer list, cast list, country, language, company and keywords. As it is stated in Section 3.3.1.3 gathering movie information is handled by the database that is prepared for [53] and [54].

At this point IMDb information of movies are obtained. There are various methods to find similarity between objects. In classic methods such as cosine similarity or Euclidian similarity, the same weight is given to all features. However in movie domain it is not reasonable to give the same importance to all attributes. To be more precise, writer, genre or country of the movie cannot have the same significance with each other for a movie to be preferred. Therefore, the second issue is to decide the importance values of the features. This problem is studied in [58] and feature weighs for movies are determined experimentally.

In [58], similarity is defined with the equation:

$$S(O_i, O_j) = \omega_1 f(A_{1i}|A_{1j}) + \omega_2 f(A_{2i}|A_{2j}) + \cdots + \omega_n f(A_{ni}|A_{nj})$$

According to the equation, S describes the similarity between objects O_i and O_j where ω_n is the weight applied to the similarity between object attributes A_n. The difference is calculated by the function $f(A_{ni}|A_{nj})$. The definition of f varies according to the attribute. It might be numeric, nominal or Boolean. But generally it is numeric and calculated by the ratio of the number of matched items to the number of overall items. In addition, values of f are normalized to have range [0, 1].

In [58], it is also stated that these attribute weights are independent from movies and datasets. Therefore, in this thesis same feature weights are used in order to find the similarities between movies.

Table 5 shows the feature weight values as determined in [58].

Table 5 - Feature Weight Values

Feature	**Mean**
Type	0.18
Writer	0.36
Genre	0.04
Keyword	0.03
Cast	0.01
Country	0.07
Language	0.09
Company	0.21

The related videos of a movie are found by using the values above and IMDb database.

As a result of Adsorption algorithm, a distribution list is obtained which is aimed to be used as the recommendation list itself. Half of bad results are deleted from the distribution list of user. As a result of calculating item similarities, new items are added to the recommendation list of the active user. Therefore, the recommendation list contains items from both collaborative filtering and content based filtering providing a hybrid recommendation to the user.

CHAPTER 4

EXPERIMENTS AND EVALUATION

This chapter presents the experiments that were carried out in order to evaluate the performance of the system. First, the datasets that are used for evaluating the system are described. Then, the used metrics are specified. Next, the evaluation of the hybrid system is performed including comparisons with two different datasets. Finally, results are presented with graphical charts.

4.1 Data Sets

In this thesis two different datasets are used in order to evaluate the proposed system. These are YouTube data set and MovieLens data set.

4.1.1 **YouTube Data Set**

There is not enough information available in the YouTube site to be used as a dataset. For this reason an information extractor is implemented to form the YouTube dataset. This dataset includes:

- 177733 ratings
- 117604 videos
- 15090 users

As the values indicate, the YouTube dataset is very sparse, which is clearly an undesirable property for evaluation.

In addition, similar videos are extracted and added to database for the content-based approach. So, the similar videos also become part of the YouTube dataset.

4.1.2 **MovieLens Data Set**

There are three different data sets available in MovieLens to help developers to evaluate their recommendation systems [25]. These are:

1. 100,000 ratings for 1682 movies by 943 users
2. 1 million ratings for 3900 movies by 6040 users
3. 10 million ratings and 100,000 tags for 10681 movies by 71567 users

In this thesis the first of these available datasets is used. The selected dataset has the following features:

1. Ratings are assigned from 1 to 5 (1 means very bad, 5 means very good)
2. Each user has rated at least 20 movies
3. Simple demographic information of the users (age, gender, occupation, zip) is provided

In order to use the available MovieLens dataset, there is a need to map the information in the database to the current data structure. For this purpose, as it is stated in Chapter 3, MovieLensConverter is constructed. Users and ratings are extracted from database and they are converted to the available format.

For the content-based part it is necessary to calculate similarities of movies. IMDb IDs are necessary for this purpose. Data in IMDb contains information about movies such as genre, writer, country and company. Therefore, IMDb data is used and movie features are also taken into consideration.

4.2 Evaluation Metrics

There are different approaches to evaluate the performance of an information retrieval system. One can investigate time / space efficiency, effectiveness of results or pleasure of user [64]. This thesis focuses on evaluating the effectiveness of results.

In order to evaluate effectiveness, precision and recall are among the most preferred metrics. Precision and recall are set-based metrics, so they can be used when the output is a cluster of items. This exactly fits the generated recommender system as results come with a list.

Precision is the ratio of the number of relevant items which are retrieved to the total number of retrieved items [65].

Recall is the ratio of the number of relevant items which are retrieved to the total number of relevant items [65].

For better understanding precision and recall can be expressed using sets:

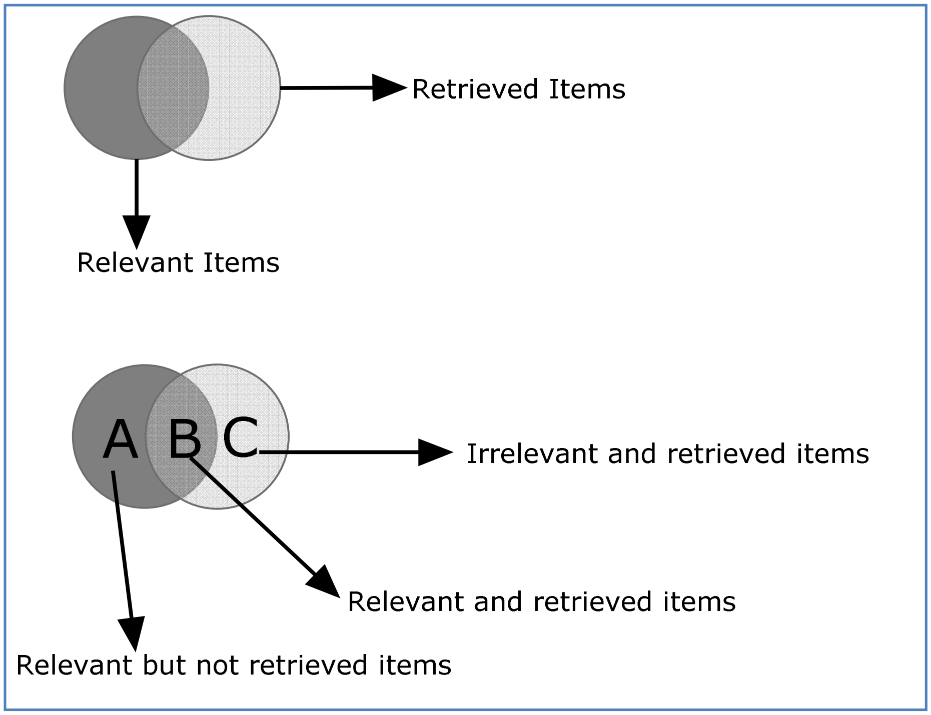

Retrieved Items
Relevant Items
A
B
C
Irrelevant and retrieved items
Relevant and retrieved items
Relevant but not retrieved items

Figure 10 - Precision and Recall

The precision and recall can be formulated as [64]:

$$precision = \frac{B}{B+C} * 100\%$$

$$recall = \frac{B}{A+B} * 100\%$$

F-measure is also a metric for evaluation which combines precision and recall. Actually F-measure is the harmonic mean of precision and recall. So, F-measure can be calculated by the formula:

$$F = 2 * \frac{(precision*recall)}{precision+recall}$$

In this thesis precision, recall and F-Measure values are calculated in order to evaluate the system performance.

4.3 Parameters

There are various parameters that may be changed in order to examine results in different perspectives. These are $U, Y, \beta, \gamma, \delta$ parameters and their explanations are given in the following.

4.3.1 Parameters U and Y

In order to evaluate the system, different user groups are formed according to the number of ratings they gave to items. U denotes the user groups for MovieLens users and Y denotes user groups for YouTube users.

User groups are formed differently for YouTube and MovieLens dataset. Because of the high data sparsity of YouTube, only one group of users is formed. This group contains 20 users and average rating of the group is 70. On the other hand, in MovieLens dataset three types of user groups are constructed. The groups $U1$, $U2$ and $U3$ are formed according to their average number of ratings. The details for both YouTube and MovieLens user-sets are shown in

Table 6.

Table 6 - Test User Groups

User Group	Average # of ratings
Y	70
$U1$	250
$U2$	150
$U3$	60

For each group $U1$, $U2$ and $U3$, 20 users are selected. For each user in each group, recommendations and precision/recall values are obtained. The average of these metric values constitutes the user group value.

4.3.2 Parameter β

The parameter β denotes the depth value. It represents how deep the Adsorption algorithm goes in the user-view graph. 3 is selected for this parameter because of time constraints.

4.3.3 Parameter γ

The parameter γ is the size of the label distribution list. The length of the distribution list affects precision and recall values. Since increasing this parameter also increases the memory usage dramatically, an upper bound value of 40 is selected for its maximum value. On the other hand, there must be sufficient number of recommendations in order to evaluate the recommendation system properly. Low values are inadequate to provide successful recommendations. So, lower boundary of this parameter is set to 20. In addition to lower and upper boundaries, intermediate values are also considered to see the effect of this parameter on overall evaluation. Therefore, calculations are done for five different γ values. These are 20, 25, 30, 35 and 40.

4.3.4 **Parameter δ**

The parameter δ is the threshold value of ratings. While traversing the videos that are rated by a user, related video is added as a video node only if its rating is equal to or higher than the value of δ. It is assumed that, users give ratings above 3 (in a 1 to 5 rating system) to videos they like. Because of this, 4 is selected for this parameter.

4.4 Constraints

Since there are lots of users and ratings in YouTube database (which form a huge graph with many nodes), it becomes a necessity to reduce the number of users. So, randomly selected 10000 users are kept and others are not included in the graph.

4.5 Experiments

This section present the results of experiments that were carried out for both CF and hybrid systems. Experiments are done using both YouTube and MovieLens datasets. Therefore precision/recall values are indicated for both datasets and related curves are plotted accordingly.

4.5.1 **Pure Collaborative System using YouTube Data**

Because of the data sparsity problem, common videos between users are very rare and this makes it harder to traverse the graph and reach new videos. Besides, even if there are common videos, they are usually popular videos which may be watched by millions of people who are most probably do not have common interests. In addition, the nodes that are reached through popular nodes may not reflect the effectiveness of recommendations. So, it is a challenging task to suggest different videos other than popular ones.

4.5.1.1 **Results For Y**

In this experiment, the effectiveness of pure CF system is evaluated using YouTube data. For user-set Y calculations are done and the results are presented in Table 7.

Table 7 - YouTube Test Results with pure CF System

User Group Y					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.255556	0.220311	0.173333	0.171984	0.171429
recall	0.046589	0.051023	0.057757	0.070678	0.077599
F-Measure	0.07881	0.082857	0.086644	0.100184	0.106837

Figure 11 shows precision – recall values of the system for user group *Y* using pure collaborative filtering technique.

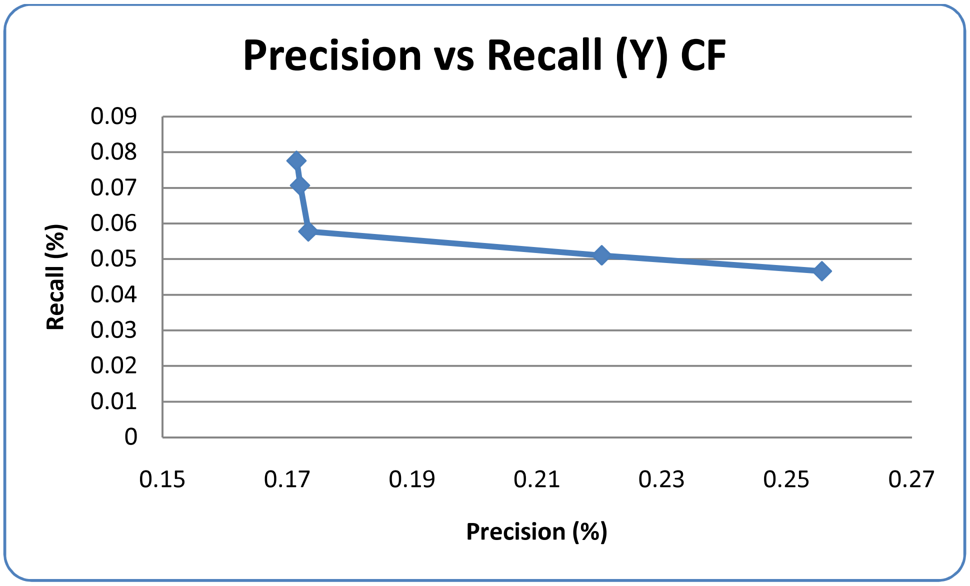


Figure 11 - Precision vs. Recall (Y) CF

While the values for precision are increasing, recall values are decreasing. As it can be observed, especially recall values are very low. This happens because of data sparsity. It can also be deduced from Table 7 that recall is directly proportional to γ values whereas precision is inversely proportional to γ.

Figure 12 shows pure collaborative F-measure of the system for YouTube user group *Y*.

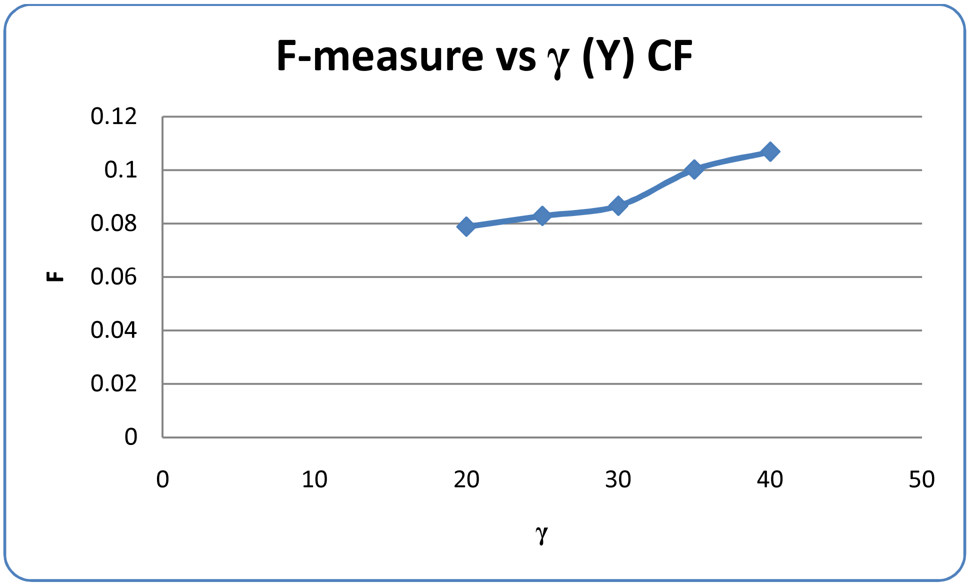


Figure 12 - F-measure vs. γ (Y) CF

Figure 12 demonstrates the relationship between γ and F-measure. It can be concluded that F-Measure tends to increase with increasing γ values.

4.5.2 Pure Collaborative System using MovieLens Data

This part of the experiment evaluates the effectiveness of pure CF system using MovieLens dataset. In the chosen MovieLens data set, users have at least 20 ratings. This amount is high enough to form the graph structure for Adsorption and obtain satisfactory results.

4.5.2.1 Results For $U1$

Table 8 shows the results for the pure CF system using MovieLens user-set U1.

Table 8 - MovieLens Group U1 Test Results with pure CF System

User Group U1					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.9373062	0.9327172	0.925128	0.918103	0.908077
recall	0.1147386	0.1198197	0.126901	0.150324	0.167748
F-Measure	0.2044499	0.2123591	0.223187	0.258348	0.283184

Figure 13 shows pure collaborative precision – recall of the system for user group $U1$.

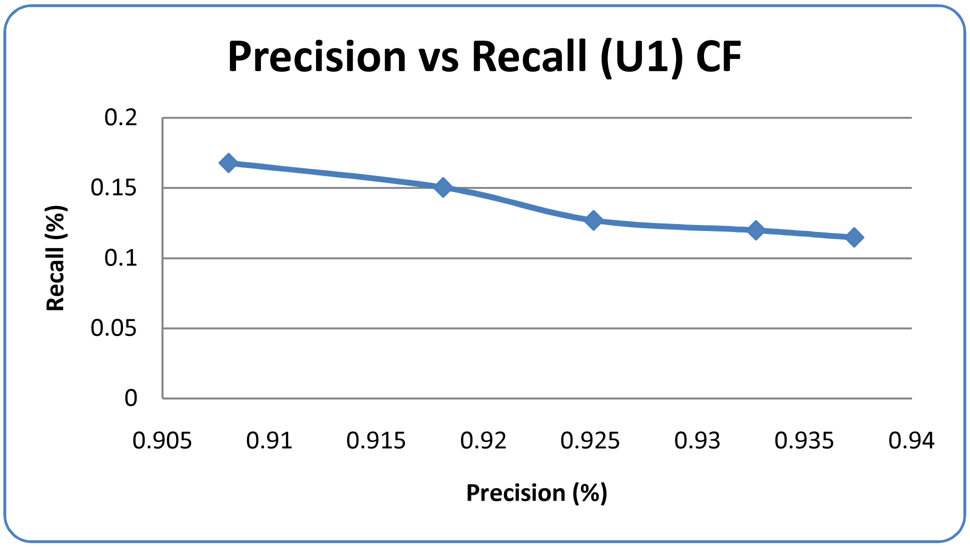


Figure 13 - Precision vs. Recall (U1) CF

It known that precision and recall are generally inversely proportional. Figure 13 confirms this fact. Recall decreases with decreasing γ-value, on the contrary, precision increases. In order words, according to Figure 13, the size of distribution list is directly proportional to recall but inversely proportional to precision.

Figure 14 shows pure collaborative F-measure of the system for user group $U1$.

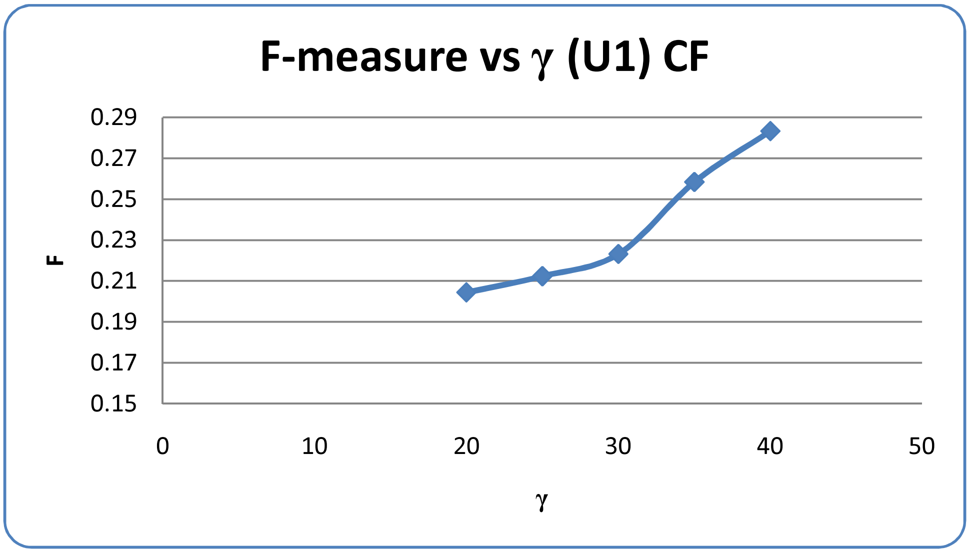


Figure 14 - F-measure vs. γ (U1) CF

It can be inferred that, F-measure increases while the size of the distribution list increases.

4.5.2.2 Results For $U2$

Table 9 demonstrates calculations done for MovieLens user-set U2.

Table 9 - MovieLens Group U2 Test Results with pure CF System

User Group U2					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.6644737	0.6630913	0.662069	0.639113	0.624157
recall	0.0938765	0.1269281	0.13998	0.150174	0.172368
F-Measure	0.164511	0.2130706	0.231099	0.243202	0.270136

Figure 15 shows precision – recall of the system for user group $U2$ running with pure CF approach.

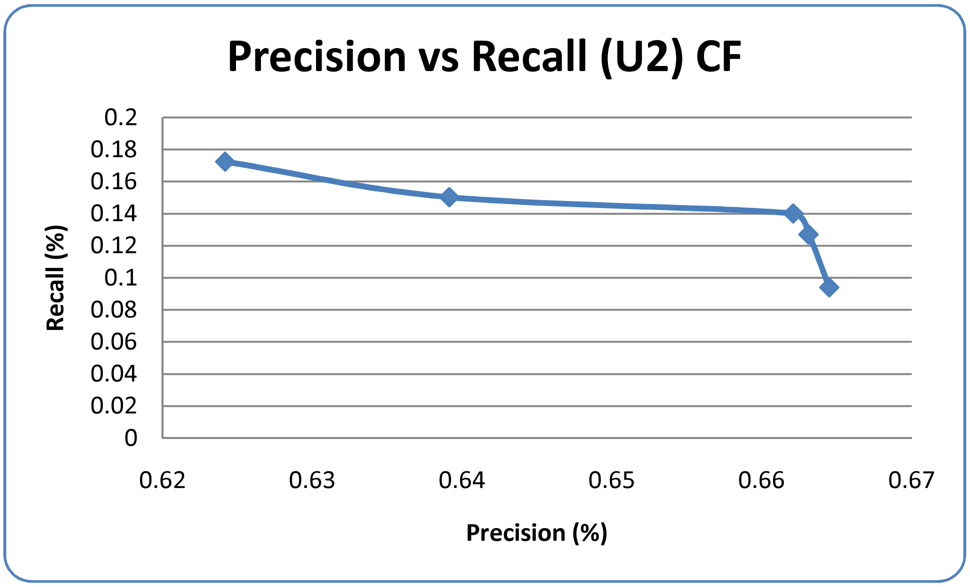


Figure 15 - Precision vs. Recall (U2) CF

For user group U2, recall decreases while precision increases with decreasing γ values.

Figure 16 shows pure collaborative F-measure of the system for user group $U2$.

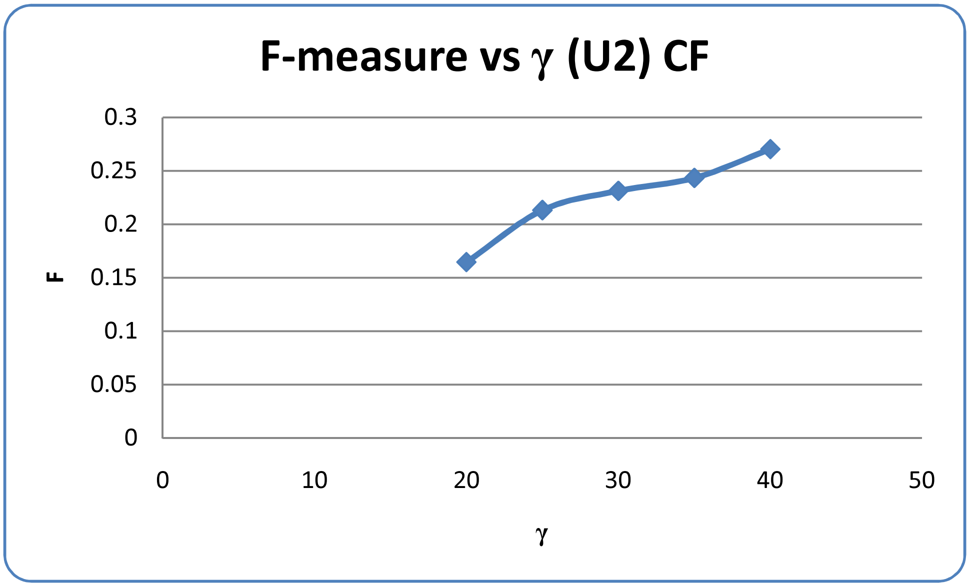


Figure 16 - F-measure vs. γ (U2) CF

F-measure is again directly proportional to the size of the distribution list (γ). The graph is in similar form with the F-measure graph for U1.

4.5.2.3 Results For *U*3

This test is done to get values for MovieLens user group *U*3. Only CF is applied over the dataset and Table 10 presents the results for this test.

Table 10 - MovieLens Group U3 Test Results with pure CF System

User Group U3					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.5127851	0.5107345	0.508484	0.489266	0.462048
recall	0.2313595	0.2296903	0.226021	0.269245	0.292469
F-Measure	0.3188566	0.3168742	0.31294	0.347345	0.358202

Figure 17 is the related curve for results in Table 10. Results are obtained with pure collaborative system and Figure 17 denotes precision – recall of the system for user group $U3$.

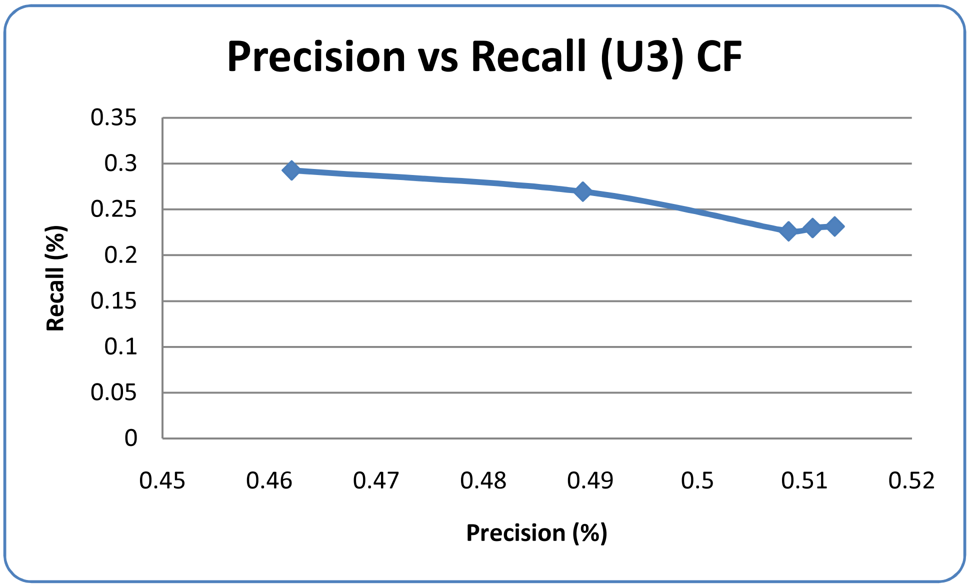


Figure 17 - Precision vs. Recall (U3) CF

Precision – recall curve shows that recall reduces with rising precision. It is exactly the same behaviour as in previous user groups U1 and U2.

Figure 18 shows pure collaborative F-measure of the system for user group $U3$.

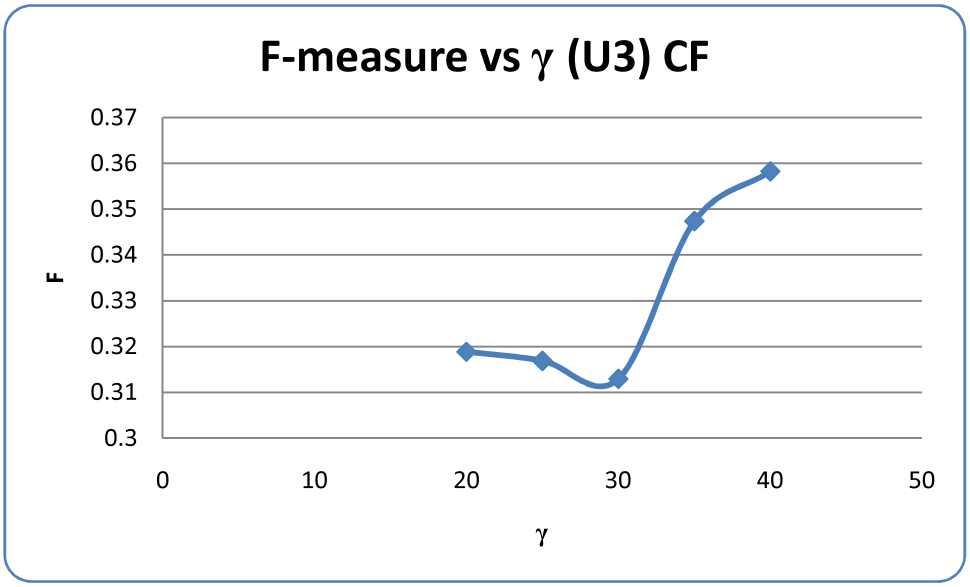


Figure 18 - F-measure vs. γ (U3) CF

As it is seen in Figure 18, for user group U3, F-measure generally tends to increase again with increasing γ values.

As expected, in all precision vs. recall graphs that are presented, recall is directly proportional to γ-values. Recall measures the relevant and retrieved items over all relevant items. The number of relevant items is fixed, so when the number of distribution list is small, the number of both relevant and retrieved items is limited to the size of distribution list. Therefore, obtained relation between γ and recall makes sense.

However, precision is inversely proportional to γ. This is also reasonable, as precision is the ratio number of retrieved and relevant items to the number of retrieved items. Because, this time the probability of retrieving irrelevant items gets higher as the size of distribution list grows.

For all user groups U1, U2 and U3 precision, recall and F-measure values do not change very much. For each user group precision, recall and F-measure graphs follow similar patterns. Therefore, there is not a certain relation considering only user groups, and this shows that Adsorption is insensitive to user groups. As a result, CF system gives coherent results with all user groups.

Better F-measure results mean better results, and it can be concluded for all user types that, with larger distribution lists the collaborative system produces better results.

4.5.3 Hybrid System using YouTube Data

As Adsorption is affected very much from sparsity, content based approach gives a chance to increase the quality of suggestions.

Table 11 - YouTube Test Results with Hybrid System

User Group Y					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.20744	0.184444	0.161333	0.122381	0.101429
recall	0.076589	0.081209	0.089757	0.118986	0.159599
F-Measure	0.111873	0.112767	0.115344	0.12066	0.124032

This experiment is done in order to see the effect of content-based filtering over the existing CF system. The results are obtained using YouTube dataset. Figure 19 demonstrates the change of precision vs. Recall.

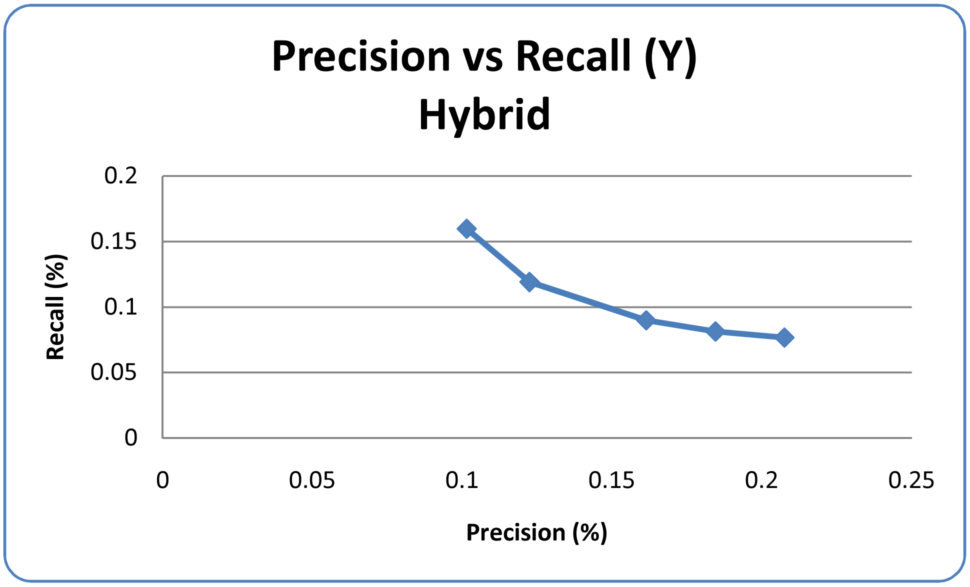


Figure 19 - Precision vs. Recall (Y) Hybrid

Figure 20 presents F-measures, obtained for the hybrid system.

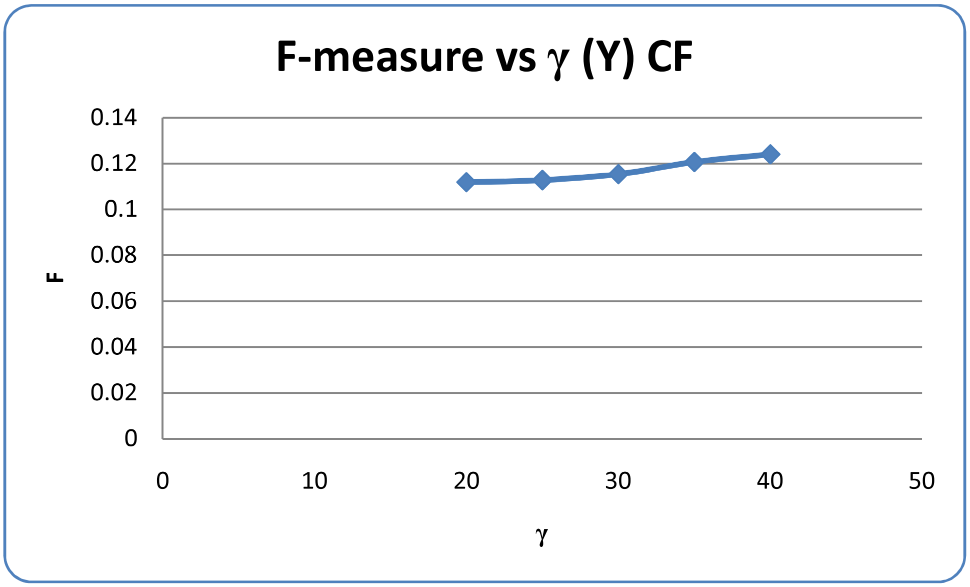


Figure 20 - F-measure vs. γ (Y) Hybrid

So, as it is seen from the results, hybrid system curve has a similar form with CF curve. Similarly, it can also be seen that hybrid system has higher values which means hybrid system performs better results than pure collaborative system when using YouTube data.

4.5.4 Hybrid System using MovieLens Data

These experiments are done in order to detect the impact of CB approach over CF approach. This time, hybrid system is tested using MovieLens data. For each user-group $U1$, $U2$ and $U3$ calculations are done. Results can be seen in following subsections.

4.5.4.1 Results For $U1$

Table 12 denotes the results for $U1$. All precision, recall and F-Measure values are represented in the table.

Table 12 - MovieLens Group U1 Test Results with Hybrid System

User Group U1					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.8006507	0.7562651	0.73188	0.730212	0.724491
recall	0.1999656	0.2285986	0.273631	0.309294	0.379793
F-Measure	0.320008	0.3516076	0.398335	0.434534	0.498344

Figure 21 shows related graph for Table 12. Curve, includes hybrid system results in terms of precision – recall values for user group $U1$.

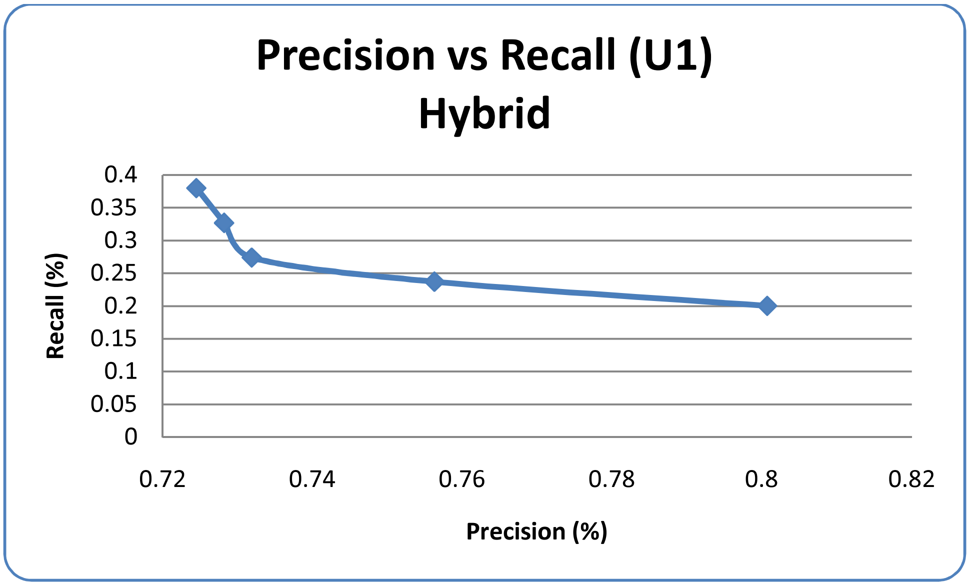


Figure 21 - Precision vs. Recall (U1) Hybrid

Figure 22 shows corresponding F-measure values of the hybrid system for user group $U1$.

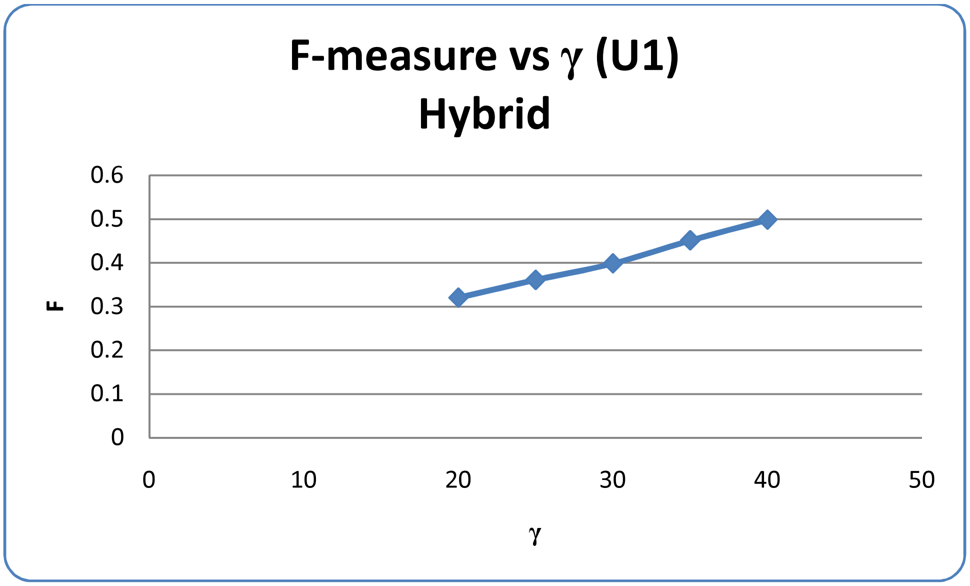


Figure 22 - F-measure vs. γ (U1) Hybrid

4.5.4.2 Results For $U2$

This test is done with MovieLens user-group $U2$ using both CF and CB approaches. Table 13 includes the corresponding values.

Table 13 - MovieLens Group U2 Test Results with Hybrid System

User Group U2					
γ-value	**20**	**25**	**30**	**35**	**40**
precision	0.5030189	0.4623454	0.440393	0.429093	0.421672
recall	0.187753	0.2089604	0.23168	0.264984	0.301366
F-Measure	0.2734429	0.2878328	0.303629	0.327638	0.35151

Figure 23 shows hybrid precision – recall of the system for user group $U2$.

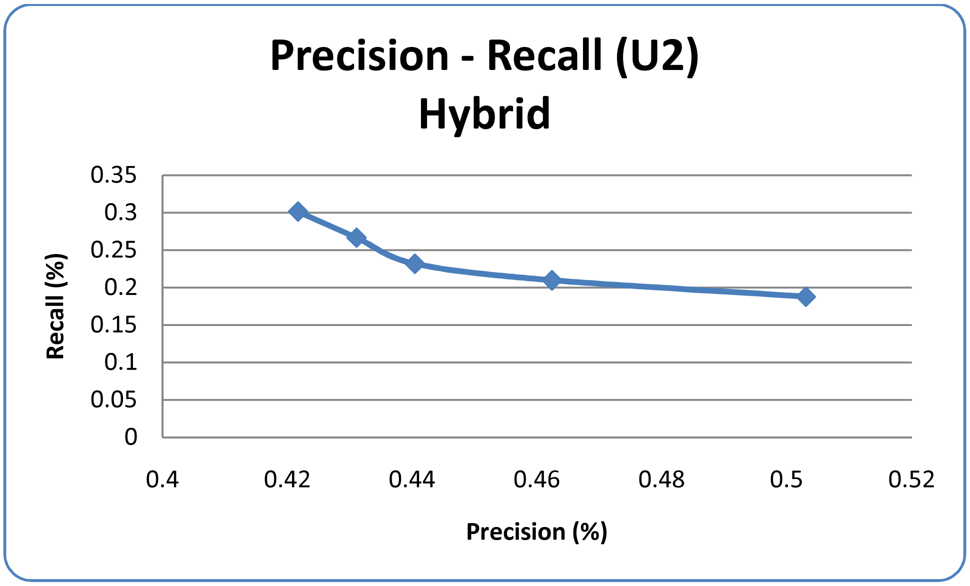


Figure 23 - Precision vs. Recall (U2) Hybrid

Figure 24 shows hybrid F-measure of the system for user group $U2$.

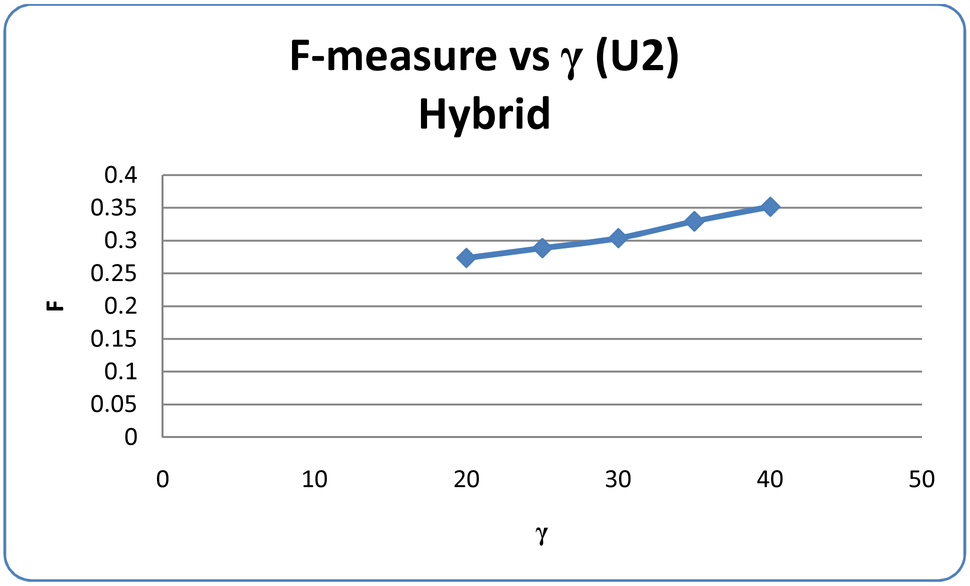


Figure 24 - F-measure vs. γ (U2) Hybrid

If the values are compared, it can be seen easily that results of hybrid system has higher values than in pure CF system.

4.5.4.3 Results For $U3$

This test id done to show the hybrid system behaviour for $U3$. Table 14 presents the related results.

Table 14 - MovieLens Group U3 Test Results with Hybrid System

User Group $U3$					
γ-value	**20**	**25**	**30**	**35**	**40**
Precision	0.489434	0.4408214	0.434959	0.402182	0.387097
Recall	0.4154839	0.4786412	0.483871	0.538212	0.580645
F-Measure	0.4494373	0.4589535	0.458113	0.460359	0.464516

Figure 25 shows hybrid precision – recall of the system for user group $U3$.

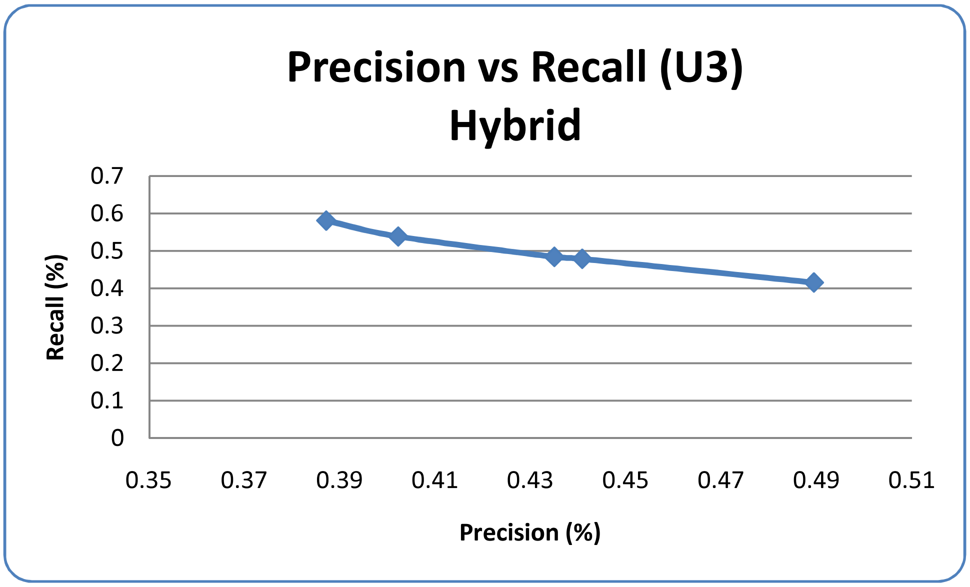


Figure 25 - Precision vs. Recall (U3) Hybrid

Figure 26 shows hybrid F-measure of the system for user group $U3$.

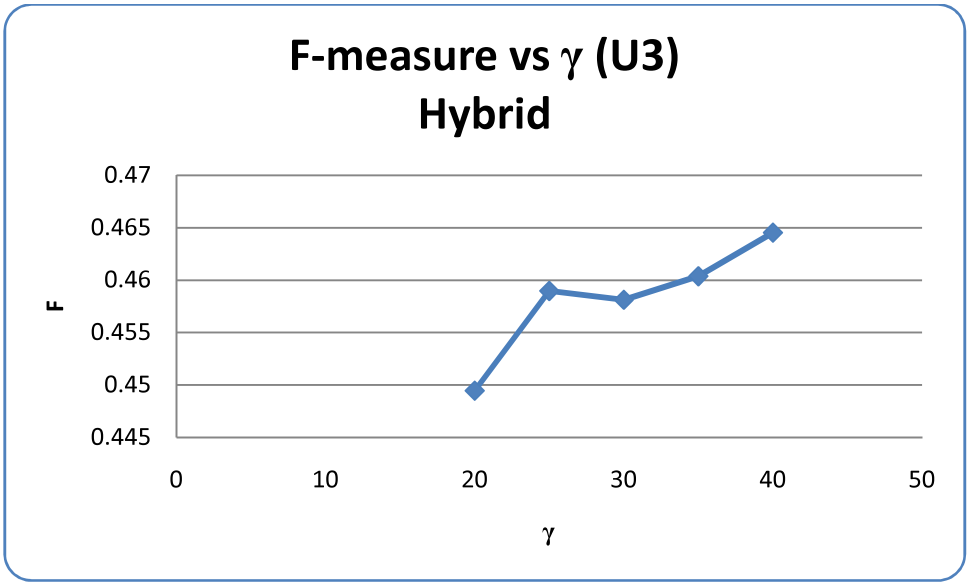


Figure 26 - F-measure vs. γ (U3) Hybrid

As it is obtained in previous MovieLens tests, F-measure values are increased with insertion of CB method.

4.5.5 **Comparison using YouTube Data**

Comparative values for both CF and hybrid systems are presented in Figure 27. Curve includes test results for YouTube. These values are the same as represented in previous sections. Figure 27 is represented in order to compare results easily.

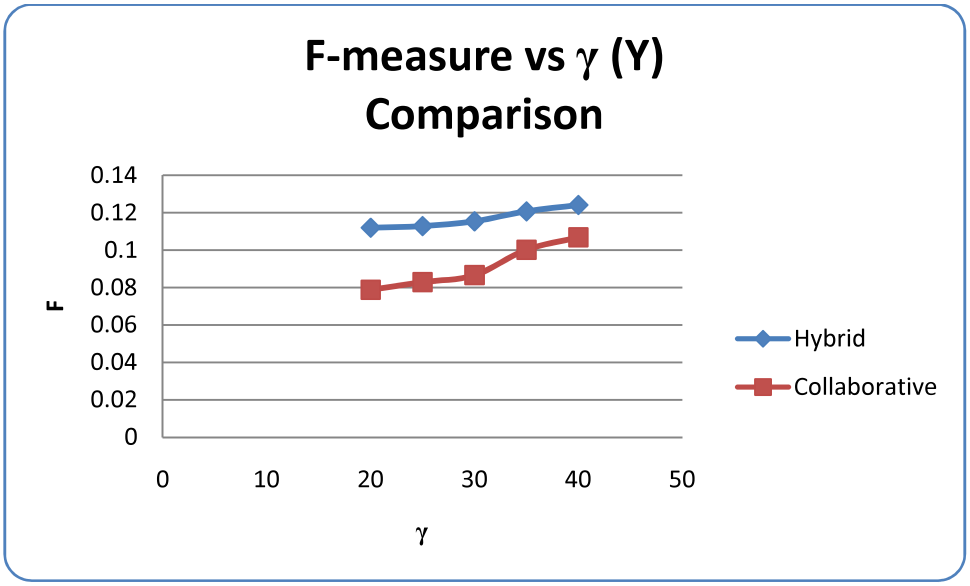


Figure 27 - F-measure vs. γ (Y) Comparison

In Figure 27, it can be seen that both values are small (for CF and for hybrid). This is because of the sparsity characteristic that YouTube data has. However, it can be said that values are consistent; as it is expected the hybrid system has higher values than pure collaborative system.

4.5.6 **Comparison using MovieLens Data**

Following figures are presented in order to provide better understanding. Results for CF and hybrid system are demonstrated on the same graph. Figures are for MovieLens data.

4.5.6.1 Results For $U1$

It can be seen in Figure 28 hybrid system beats CF system considering F-Measure values.

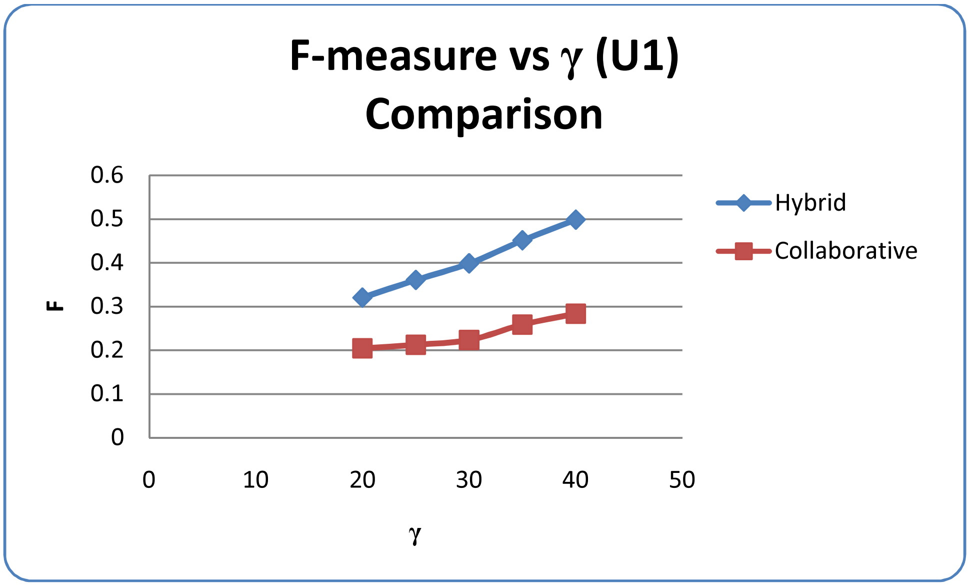


Figure 28 - F-measure vs. γ (U1) Comparison

4.5.6.2 Results For $U2$

As in it is in $U1$, same situation occurs for $U2$ and hybrid system performs better results and it can be seen in Figure 29.

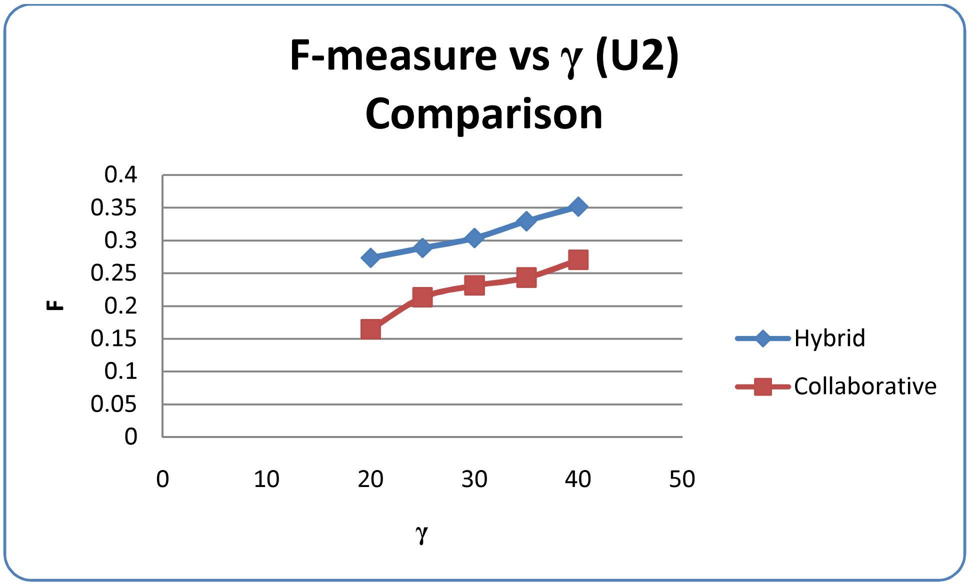


Figure 29 - F-measure vs. γ (U2) Comparison

4.5.6.3 Results For $U3$

The effect of item similarities again can be seen here in Figure 30 with increased F values.

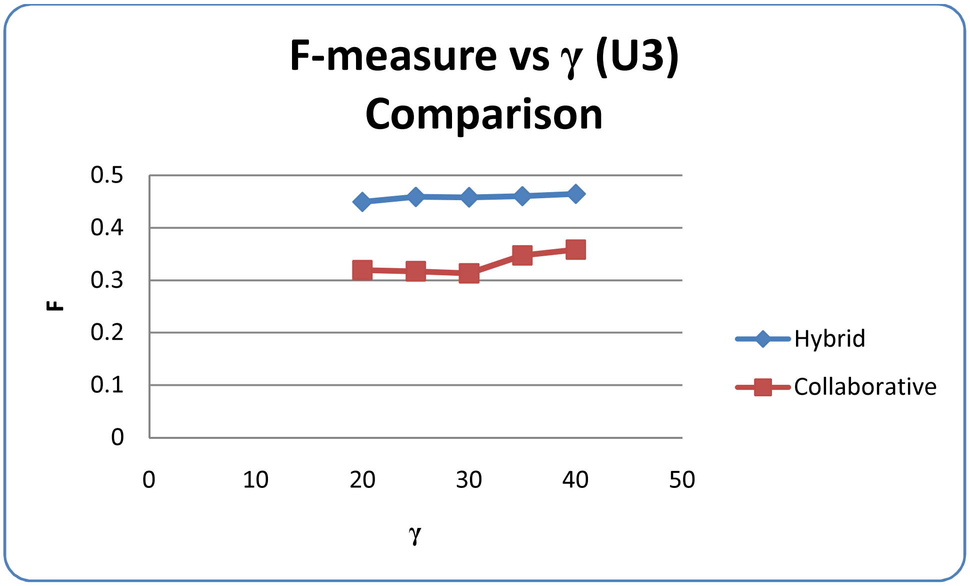


Figure 30 - F-measure vs. γ (U3) Comparison

In all figures, hybrid curves have higher values than CF curves. This means that more accurate results are obtained by inserting CB approach in CF approach. So, it can be said that considering item similarities and applying CB filtering approach improves result for recommendation system.

CHAPTER 5

CONCLUSION AND FUTURE WORK

In this thesis, a hybrid recommendation system is presented. The system uses both collaborative filtering and content-based recommendation techniques. Base is the collaborative part in which a graph based algorithm called Adsorption is used. Content information is retrieved from both IMDb and YouTube and this is used in order to propose a better system.

The design, implementation and evaluation parts of the work are described in detail. First Adsorption algorithm, which is a graph-based collaborative filtering algorithm, is implemented. The implementation is done so that the collaborative filtering recommendations are generated with both YouTube and MovieLens datasets. Secondly, content based recommendation techniques are used. Enhancement is done on the distribution list which is retrieved from the collaborative filtering. To make use of content based approaches item-item similarities are found. According to the similarity results new movies which are not included in the result of collaborative recommendation are inserted to the list and recommended to the user.

Experiments are done and the effect of the hybrid system is evaluated. Results show that the hybrid system has a better performance on recommendations than using pure collaborative algorithm. It is also found out that system gives more successful results when MovieLens dataset is used which means good results are obtained when the data is not sparse.

The recommendation system proposed in this thesis works offline and makes offline predictions. Considering video domain, the next step can be to integrate this system to an online organization where users watch videos online.

The system gives better results when the data is not sparse. That is why results with MovieLens data is better that YouTube. As a future work the system can be extended so that even with sparse data the system can give more appropriate suggestions to users.

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