A Trust and User Personality Trait based Collaborative Filtering Recommender System

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Declaration

We, hereby, declare that the work presented in this thesis is the outcome of the investigation performed by us under the supervision of Muhammad Ibrahim , Senior Lecturer , Department of Computer Science and engineering, East West University. We also declare that no part of this thesis/project has been or is being submitted elsewhere for the award of any degree or diploma.

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Abstract

Recommendation system is a system where a user gets suggestions for the product based on his/her previous preferences to the items. With the monumental growth of web services, developing adequate methods for the recommendation has become dominant in the research area. In terms of Collaborative Filtering(CF) user and item-based methods are the most presiding approaches used in RS. In order to get an improved recommendation, trust value and personality traits of users can play a key role in finding similarity between users.It solves cold start problem where neighbors of the new user are difficult to find as they have not rated any item yet. In our work, the implicit(based on personality),latent(based on trust) and explicit(based on rating) features of user behaviour have been utilized to tackle the problems of Collaborative Filtering.The major benefit of the proposed method is its consideration of direct and indirect trust values and personality similarity compared to traditional collaborative filtering approaches.A comparative review of traditional rating based recommender system,personality based,trust based and their combined approach is presented. Empirical analysis shows that using trust propagation and personality traits substantially increases the efficiency of the CF recommender system.

Acknowledgments

Words are often obscure and have a number of hidden connotations even in one's mother tongue.So we wouldn't prefer finding the best words to express my gratitude rather simply listing those people who contributed in an intrinsic way to this thesis. This research was done in the Department of Computer Science and Engineering at East West University, Bangladesh.

We were introduced to the field of our research are through Data Mining and Machine Learning courses. Our respectable faculties in these courses have given us great insight on our research area which is machine learning and collaborative filtering. As we have good communicative relation with honorable faculty Muhammad Ibrahim sir so at times he guided us by keeping us in the right track of building a recommender system.

First of all, We wish to express gratitude to the Almighty for his profound blessings on us. We would also like to convey our special thanks to our supervisor, Mahamudul Hasan sir, who gave us the chance to have a great learning experience on machine learning field, without whom we could not continue the whole process. His motivation, inventive and insightful ideas and advises, unparalleled encouragement throughout all the stages of our BS.C research have been gratefully received and is of utmost importance for us. His enthusiasm of helping push us enough to finally logically deduce our own doubts is a valuable lesson we learned. He always pointed out our mistakes and provided us enough resources so that we could solve problems ourselves and thus learn by our mistakes. His expertise to bring about the best ability out of us has truly moved us to our core and thus we are forever grateful for his care and guidance.

We would also like to thank all the honorable faculties we have encountered throughout our university life for supporting us. Lastly, We would like to thank our parents for their unending support, encouragement and prayers.

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Chapter 1

Introduction

In the chapter we discussed about every aspect of the mechanism in recommendation system works. Some previous researches of recommender systems are discussed and how we mapped these methodologies in our proposed approach. We also discussed the major driving force that motivated us to go on with this research work. Finally we went though the outline of this book.

1.1 Introduction

Recommenders systems have achieved great success over the past 20 decades as an intelligent information system to help address the issue of information overload.

Nowadays the recommendation system is very popular in every type of field. As the usage of internet is expanding, expectation and demand of user is also on the rise. In this busy life, everyone wants to find things that are best for them as easily as possible. In this circumstance, the recommendation system is a blessing for us. Fields that are most popular for the recommendation system are products recommendation on amazon, friends recommendation on facebook, movies recommendation on Netflix, etc [1]. Mainly the recommendation system is an informatics system that actually predicts the best item and products to the user. Users rate items based on their fulfillment. Using the items evaluated by these users, unrated items can also be rated using many prediction methods and items can be recommended based on that rating. Recommendation system helps overcome information deficiency by providing users with personalized recommendations depending on prior Information of their likes and dislikes. Based on their prior reaction as well as satisfaction, Recommendation System evaluates the user persona because previous interests are often a useful indicator of future choices. In this era of information and technology, the personalized recommendation system is popular in the advertisement on the web, restaurants location service and suggestion of movies. There are 2 most popular approaches of recommender system which are content-based filtering (CB) and collaborative filtering (CF) [2].CF selects mainly items that resemble the preferences of different users or items. Content based filters are fundamentally generated on similarities for both user taste and object substance. [3]. There are few objectives of recommendation system such as prediction version of problems, ranking version of problems, relevance, novelty, serendipity, diversity. BookLens and MovieLens were the respective recommendation systems [4]. Collaborative filtering methods first create a model from the past behavior of a user (e.g. formerly bought items along with ratings of the items), after that utilize that model to estimate items i.e.ratings which can impress the consumer by taking into account opinions of all the other consumers. The higher the comparison between two users ' rating curves, the greater the resemblance between them. This can be appraised through coefficient of correlation of Pearson, Spearman Rank Correlation, Constrained Pearson correlation,Jaccard index,PIP similarity,Adjusted Cosine similarity, or Mean Squared Difference (MSD). In order to get an improved recommendation, personality traits of users and trust matrix plays a key factor in finding similarity between users. It solves cold-start problem where neighbors of users are difficult to find as they have not rated any item yet. From rating dataset (GroupLens) we created a trust matrix and from personality dataset (personality-2018) we created a similarity based on personality and combined them to get final predictionusing z-normalization[5].

1.2 Prior researches on Recommendation system

In the meantime, the recommendations systems have now become a top field for research since the widespread availability of this first publication on CF in the early 90s. Recommendation systems are generally distinguished as helping systems that help users aquire products ,contents or services by combining and analyzing suggestions from several other users. While empirical study has grown significantly on the subject of recommendation systems over the past few years, more study and robust application is necessary in the real circumstances. Since work is still broad therefore, the current papers on RS need to be updated. However, given the nature of recommender system research, restricting the recommender system research to different disciplines would not be easy.

Collaborative filtering (CF) suggests items to users according to their expectations [6]. Basically, CF operates by analyzing user behaviors. There are 17,000 films in their segments in Netflix, and Amazon.com has 4,10,000 titles in its store [6]. Though it has been widely used, it is prone to many problems such as scalability,cold-start problem and so on. Till now, many researchers have suggested some solutions to enhance precision. Such as Ahn et al [1]. proposed PIP(Proximity-Impact-Popularity), a different measure for CFRS. Bobadilla et al[7] paired the Jaccard measure and mean square difference. Also, MJD(Mean-Jaccard-Difference) was created with the objective of solving the cold-start problem. A little while back, SM(Similarity-Measure) was proposed which is a similarity measure based on singularity. Another structure of procedure to improve the recommendation system in CF is data smoothing. Also, some other techniques such as BP neural network, zero-sum reward support vector machines are implemented to solve accuracy but these are not efficient enough to resolve cold-start problem. A traditional rating-based collaborative filtering system is MovieLens that are provided by GroupLens Research [[8],[9]]. In this system, a new user should first give ratings for fifteen movies they have already watched and based on their ratings a user profile is created. Basically, MovieLens then compare the profiles of the user so that it may find similar users which are called 'Neighbors'. So, it may recommend the same movies to the neighbors. Recently, Hu and Pu researched on people's preference in the music domain and the BF personality traits [10]. There are 1,581 songs and 80 users completed TIPI(Ten-Item-Personality-Inventory) questionnaires for their friends and for themselves based on their BF personality traits [11]. This system recommended 20 songs for them and their friends to rate them. A knowledge-based recommending system was used by Hu and Pu with static facts, that is how personalities correlate with music genres. Personality diagnosis (PD) was proposed by Pennock and Horvitz, a method formulated on likelihood which is: every user has an inherent "personality type" and user tendencies are a byproduct of such a type [12]. Rong Hu proposed [13] three approaches: a recommendation process purely based on the personality of users; a linear personality and rating information combination and a cascade mechanism to maximize both. In two cold-start scenarios, they orordinated an experiment to compare proposed moethod with the traditional RBCF: sparse data and new users. Aristomenis S. Lampropoulos [14]proposed Hybrid RS for wireless service. In particular,their system is a scripting engine formulated on a addition of the musical form as well as personality assessment, which complies with the approved protocol. There are lots of researches on trust.But none of them talk about our proposed as it is unique.Paolo Massa proposed [15] a method for spreading trust across the network of trust and calculating a confidence factor which can be used rather than the strength of resemblance. Evaluation on the Epinions dataset shows that RS have the utmost efficiency in terms of reliability at the same time maintaining good coverage.Fu-Guo Zhang [16] claims that trust-based recommendation systems face a new recommendation attack that is distinct from the traditional RS process profile injection attacks. They examine the issue of the attack and consider that in the attack "victim" nodes play an important role. In addition, they suggest a method of data provenance to track malicious users and identify "victim" nodes as recommender framework users of mistrust. The feasibility study of the security system is carried out using the Epinions database crawled dataset.

Reid Andersen [17]focuses on networks representing systems of trust and recommendations incorporating those relationships of trust. A trust-based recommendation system's goal is producing custom recommendations by accumulating other users' conceptions in the trust network. For contrast with previous work on voting and process scoring they use the axiomatic approach from the theory of social selection. They are developing five axioms that could be expected to satisfy a trust-based recommendation system. They then demonstrate that no process can fulfill all the axioms at the same time.

In our work, we measured a different CFRS using personality traits of users and trust matrix that plays a key factor in finding similarity between users. It solves cold start problem where neighbors of the user are difficult to find as they have not rated any item yet.

1.3 Motivation

The main driving force of this research is the effect of taking implicit behavior of users and thus improvement of recommender system. This approach is far better from the traditional way of predicting ratings. Our approach uses the implicit behavior in the form of personality and we take explicit behavior rating and make use of the transitive property of trust to get connections between users who have little to no similarity. Personality traits of users and trust matrix plays a key factor in finding similarity between users. It solves the most common problem of CF which is cold start problem. The problem in this case is neighbors of new user are difficult to find as they have not rated any item yet. From rating dataset (GroupLens) we created a trust matrix and from personality dataset we created a similarity based on personality and combined them to get final prediction.

1.4 Thesis Outline

In our research book, we discussed RS, requirements and kinds of recommendation system, limitations of CF in chapter 2, and chapter 3 presents the five factors of personality, other models of personality ,how does personality relate to user preferences, trust based recommendation system, trust engine. In chapter 4, we prepared our proposed method , And in chapter 5, we evaluate our proposed method. Chapter 6 holds the summary of our thesis work and further discuss about future work as well as some limitation of our work.

Chapter 2

Background Study

2.1 Introduction

Recommendation systems are mainly used in web based sectors to obtain user-wanted information quickly and precisely[18]. It allows the users to find products, content and services through the analysis of suggestions from other users[19]. There are millions of people in the virtual world and it is very easy to identify similarities between users by using collaborative filtering and to suggest the correct item. CFRS is the most frequently employed state of the art of recommendation. Although it has some limitations, it is still the most successful process which helps users discover new items. The recommendations are mainly formulated on two significant approaches discussed below:

Collaborative filtering (CF) functions by collecting users' opinions in contexts of item ratings. The content-based approach suggests products very similar to those already preferred in the past by current user[20]. Two types of CF techniques are used prominently :

- User-Based Collaborative Filtering (UB-CF)
- Item-Based Collaborative Filtering (IB-CF)

Similarity calculation process is carried out using many machine learning algos, like Genetic Algorithm, Bayesian Network, Neural Network and etc in model based CF. Memory-based CF uses popular similarity measures i.e. coefficient of correlation of Pearson, Spearman Rank Correlation, Constrained Pearson correlation,Jaccard index,PIP similarity,Adjusted Cosine similarity etc. In addition, Memory-based CF is divided into user and item-based CF formulated on connection between subjects where either the user or the item can be a subject. Nevertheless, in high quantities of items existing with low ratings in the RS, item-based CF works more efficiently than user-based CF. Work on recommender systems can be divisioned into three kinds: work on the design of technological systems. Studies on user behavior and questions of confidentiality. The study focuses on the development of technical systems. A variety of techniques for recommendations. Such as the mining of data. Recommendation systems based on content provide a consumer with suggestions by automatically matching their interests with product content. For example, web pages and news articles are recommended. Products are defined by a specific collection of attributes in content-based systems.Consumer expectations are predicted through the study of the correlation among user ratings and the related item parameters. For CBRS the necessity to recognize a sufficient number of key features is a critical issue. Clearly, when the collection is too low, there is not enough data to know the profile of the consumer. .

2.2 Recommender System

Recommenders system basically makes decisions based on different users ' choice of product and then shows some recommended items. So, recommendation system is used to make life easier for users by in any way recommending their most likely desired products[21]. Recommender system operates in many ways, it can suggest on the basis of previous buying behavior of users, product quality evaluation, price range, as well as many other categories[22].

2.3 Models of RS

- Collaborative Filtering

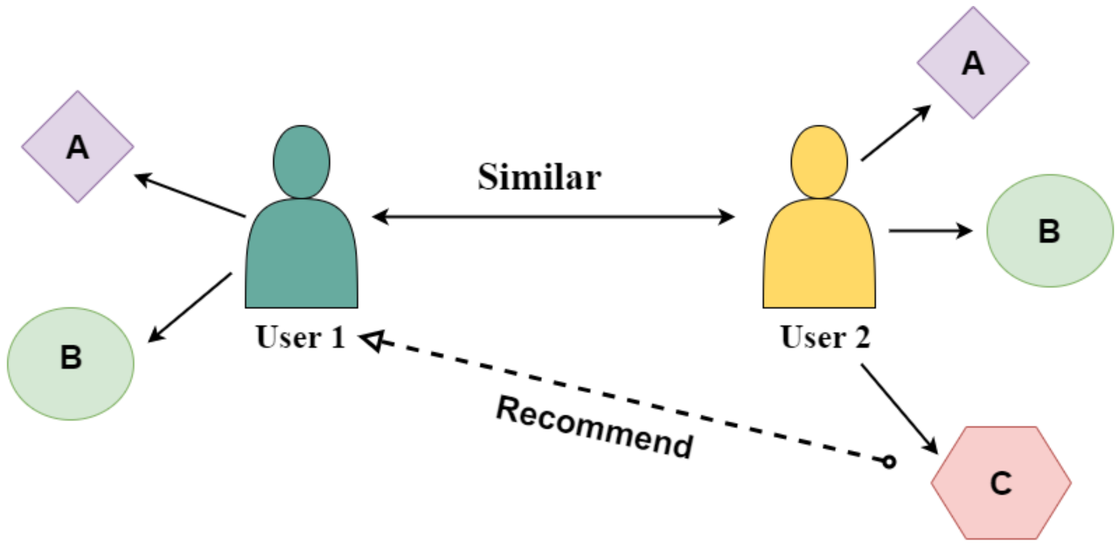

Figure 2.1: Recommender System

- Content Based
- Demographic Based
- Hybrid
- Knowledge Based
- Trust Based
- Utility Based

2.3.1 Collaborative Filtering Recommender System

CF is prevalent algorithm that is formulated on the basis of ratings and actions connected to the different users existing in the system to establish its predictions and recommendations[23] .The core element of CF is the estimation of individual or object

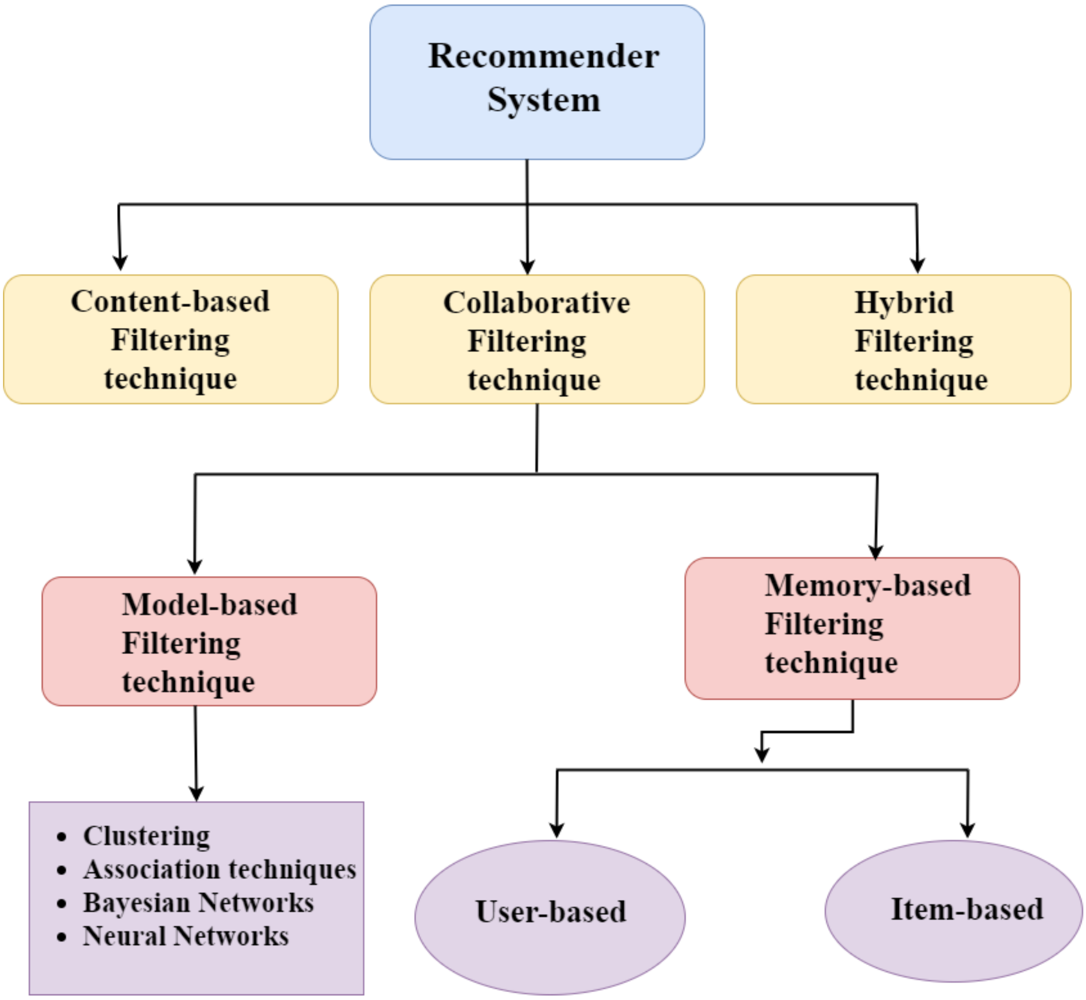

Figure 2.2: Classification of Recommender System

resemblance and then the correct items can be estimated relying on the highest possible resemblance[24]. The fundamental idea to create this process is that different views of users can be analyzed so that the desires of active user can be predicted[25]. Instinctively, they assume users are more willing to agree to certain other items when users meet the quality or significance of certain items[26].

2.3.1.1 Memory-Based CF

There are mainly 2 types of CF which are memory based.

Item-Item Based CF Item-item CF, also known as item-based CF, yields significant step in this direction. It is most frequently used among contemporary collaborative filtering techniques. Sarwar et al and Karypis first described item – item collaborative filtering in the literature though Amazon appears to have used a variation of it. The CF uses resemblances among rating variations of products, rather than estimating inclinations with resemblances between the scoring behavior of the item.

User-Based CF The first of the automatic collaborative filtering approaches was user-user collaborative filtering, often recognised as k-NN collaborative filtering. This was originally incorporated in the GroupLens Usenet recommendation.User-user CF is a straightforward computational expression of the basic idea of collaborative filtering to classify users whose previous scores are similar to current individual then use their scores on other objects to decide what the current person may prefer.

2.3.1.2 Model-Based CF

Algorithms like Bayesian , clustering and dependency networks are studied and investigated to solve memory-based CF algorithm disadvantages.Memory-based approaches maintain a repository of all users ' known perceptions of everything and perform a calculation for each assumption across the repository. Memory-based approaches are easier,

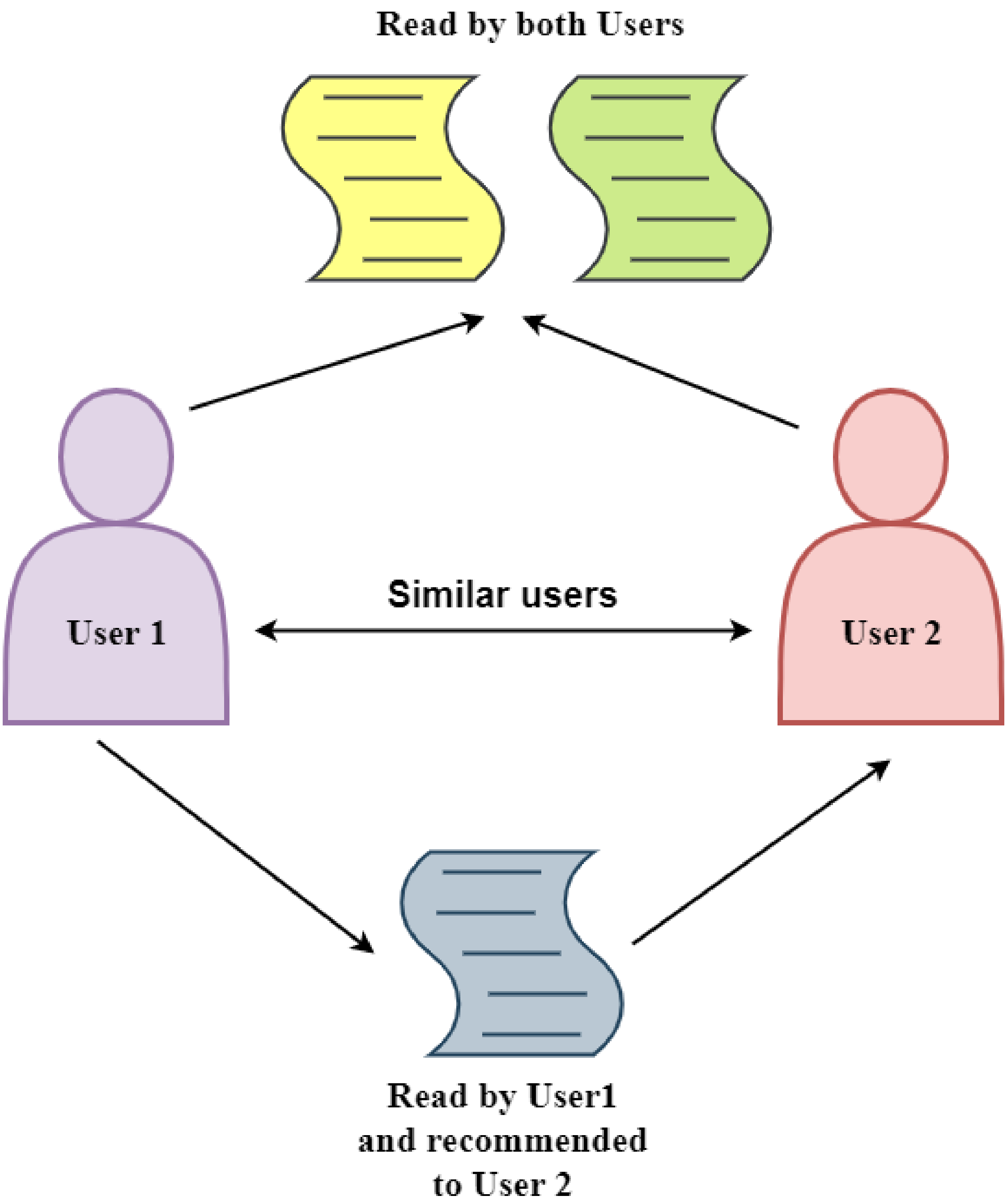

Figure 2.3: Collaborative Filtering

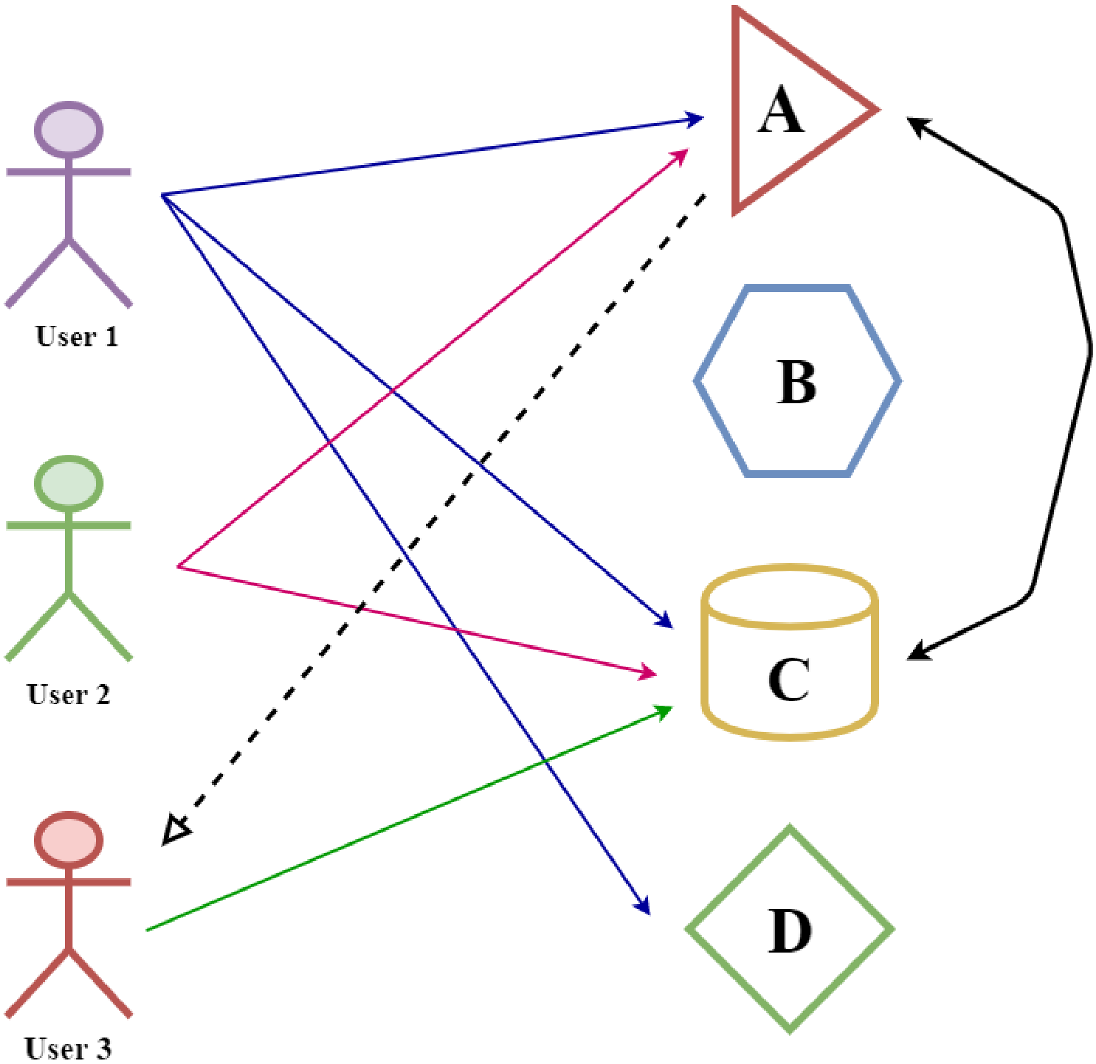

Figure 2.4: Item-Item Based CF

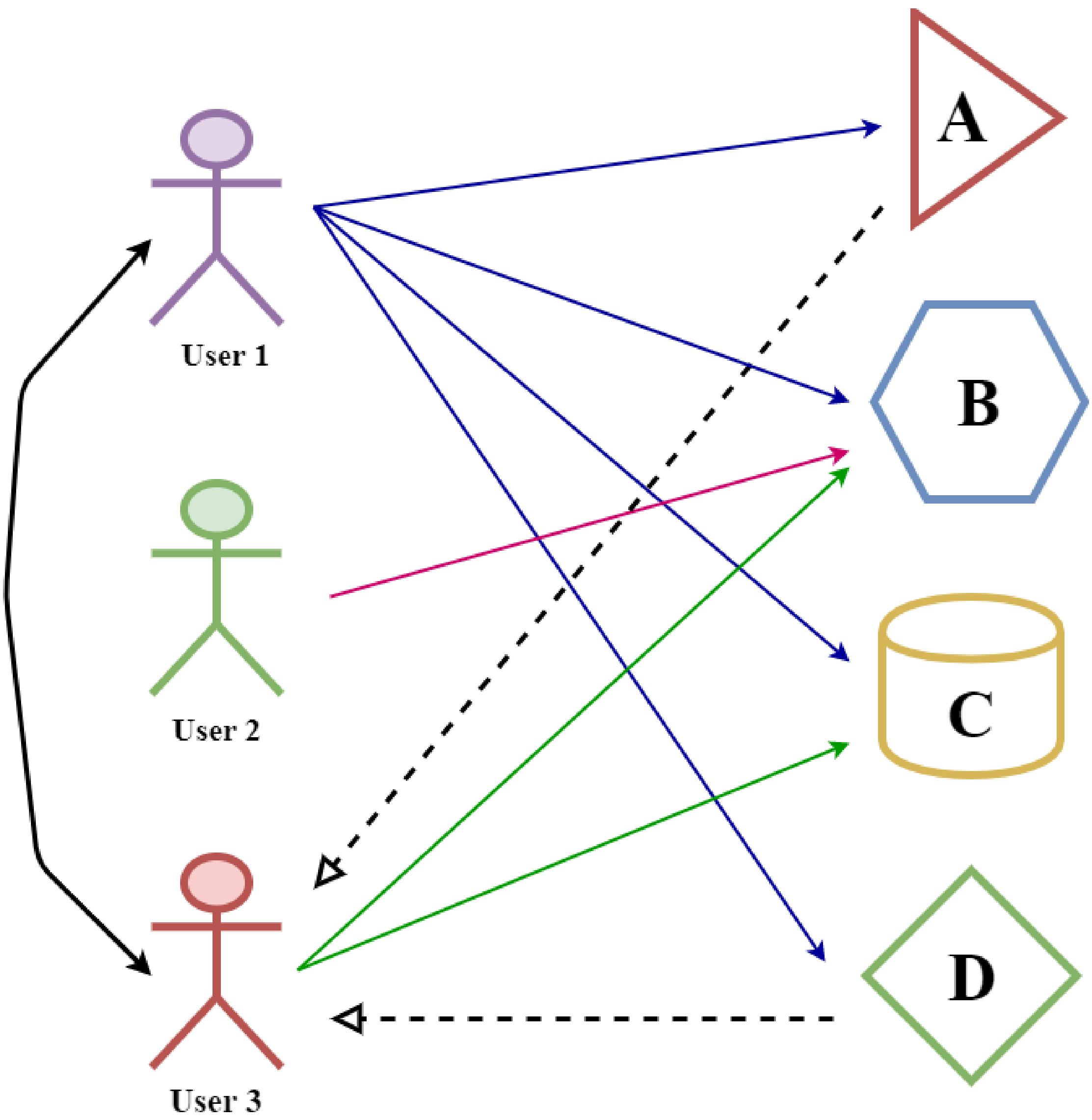

Figure 2.5: User Based CF

in practice they appear to work fairly well, and new data can be quickly and incrementally introduced. Nevertheless, This approach can be computationally demanding when database capacity increases in space time complexity. In addition, these approaches are typically unable to clarify forecasts or provide more insights into the results.The prototype can contribute positively outside the mathematical aptitude of model-based algorithms by focusing these patterns in data, offering an explanatory basis for suggestions or making arbitrary conclusions.. Memory re-opted independently, where the model's first CF algorithms are typically less than the estimation. Both are examples of the complete server being more common. Predictions can be calculated quickly category of memory-based approaches, where the model is generated for each prediconce, although the time complexity factor is measured to some degree over the entire database of compiling the data into a model, and user ratings may be prohibitive.

2.3.2 Content based Recommender System

The content representation of objects that are previously of interest to the user is shown in a personal profile in content-based filtering. The metadata of the product description is represented by a set of features or characteristics that classify this product. In such systems, it typically is appropriate to contrast derived attributes from unexplored and unscored objects with details of user information. The user is suggested things which are much like the user characterestic of that user[27]. Systems that incorporate a content-based recommendation method evaluate a collection of currently scored records and descriptions, and construct a template or profile of user interest based on the features of objects scored by the user[28]. The description is a formal reflection of knowledge of users interest, incorporated in order to suggest new innovative things[29]. In theory, the recommendation method involves comparing the user's profile characteristics with the features of an user object[30]. Content-based information filtering systems allow suitable methods for interpreting and generating the personal profile, and certain approaches for contrasting the personal profile with the item representation. [31].

2.3.3 Demographic Recommender System

The demographic recommendation model separates the consumer based on personal characteristics and recommends age, race, ethnicity, etc. depending on demographic groups. This recommendation system's advantages and disadvantages are close to the knowledge-based recommendation system.The aim of this software is to classify attribute-based users and make demographic-based recommendations.An RS is being designed in five stages, namely data collection, user identification, similarity computing, group choice, and finally predictions and recommendations. RSs may be based on profile data based on content-based RSs (CBRSs), cooperative RSs (CRSs) or quantitative RSs (DRSs). Nevertheless, if the user profile is a set of characteristics describing the demographic class and culture of the user, then we have a DRS.Zhang et al. developed a collaborative hybrid recommendation system that combines CRS-based item-based and user-based solutions for mobile products and operating recommendations. The recommender systems ' main intention is to address the online information that overload problem and improve the system's relationship with its users.Both problems are closely related to how the program represents customers and how much processing time it takes to satisfy the desires of the client.

2.3.4 Hyrbid Recommender System

The combination of various recommending algorithms in a hybrid recommending model is reasonable for optimization. Different types of hybrids have been discovered to exceed individual algorithms in certain applications.Hybrids can be particularly helpful when the algorithms concentrate on different cases of use or different aspects of the data set. Hybrid recommender system could use description text comparison to match the new element with existing items, which could at any level be recommended, thereby increasing the

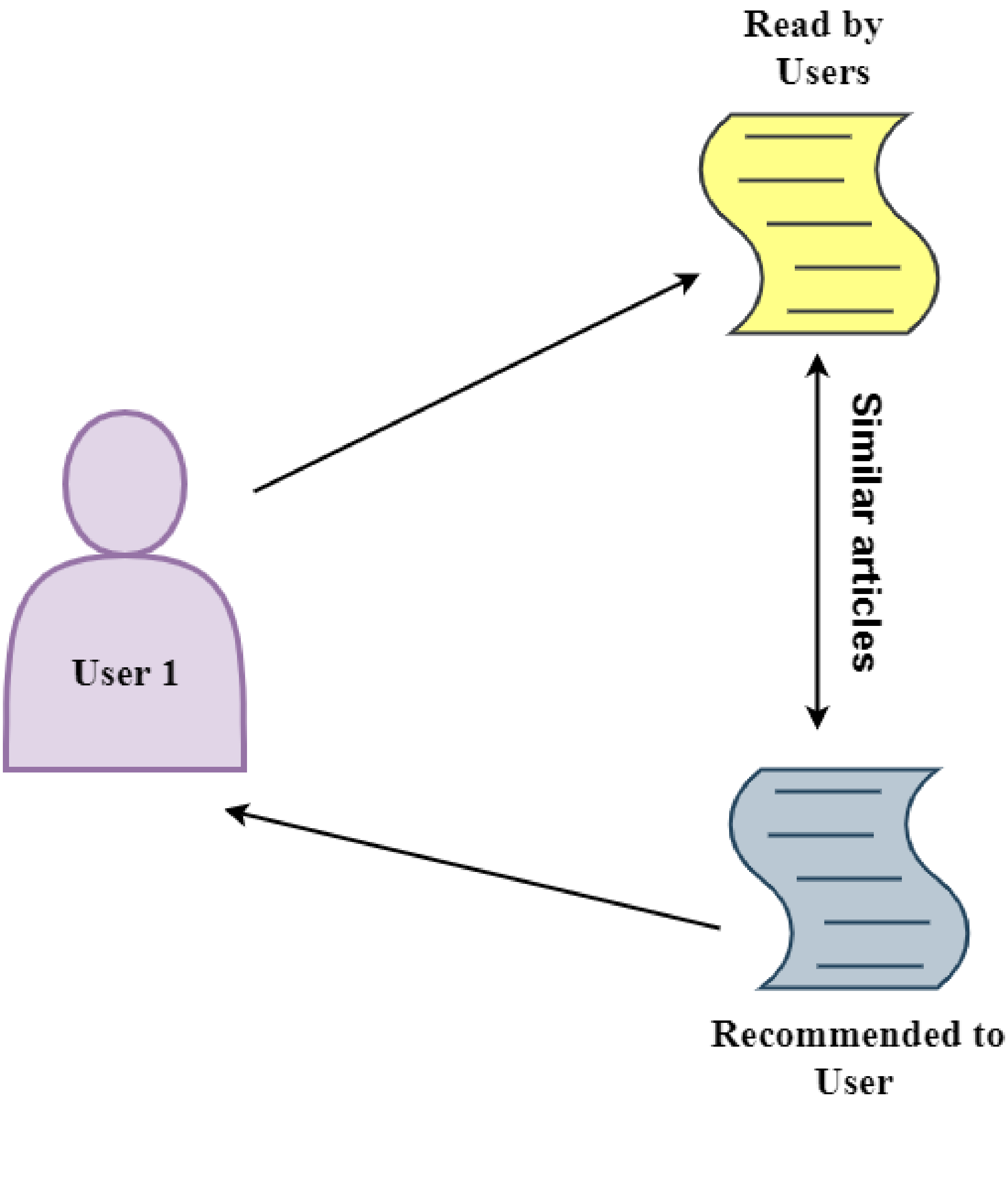

Figure 2.6: Content based Recommendation system

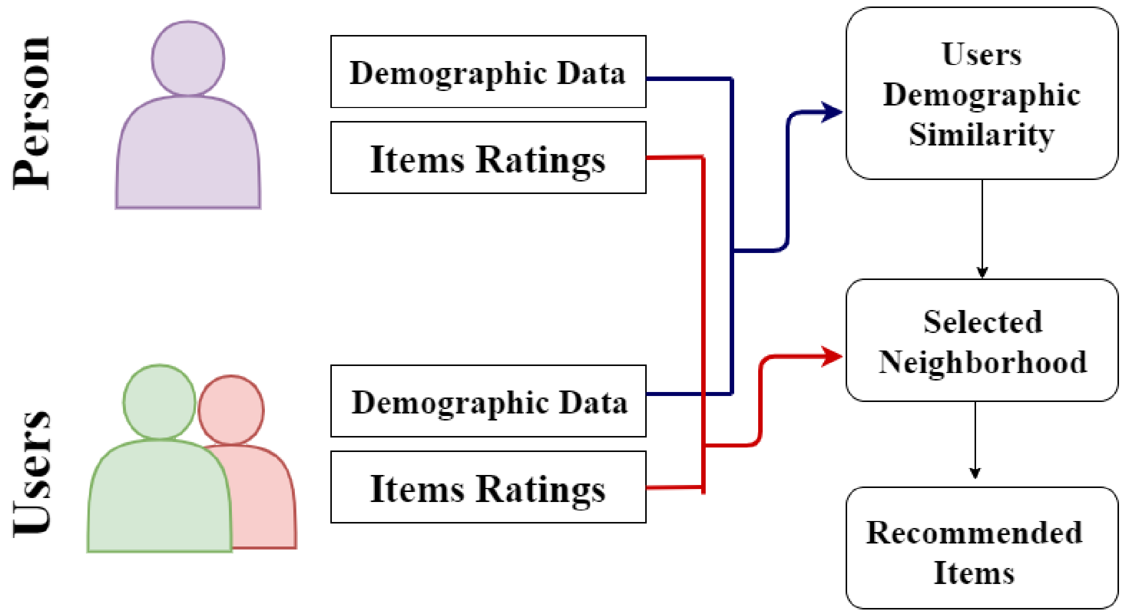

Figure 2.7: Demographic Recommendation system

effect of mutual filtering as users rate the item. The users can therefore identify the information of things that the users like and objects themselves[26].

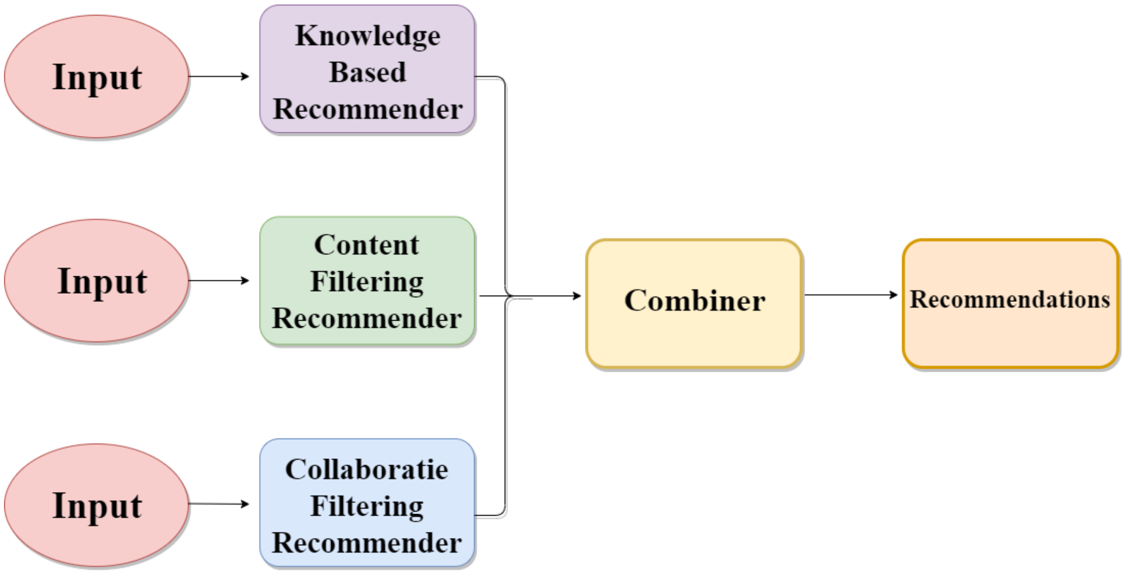

Figure 2.8: Hyrbid Recommender System

2.3.5 Knowledge based Recommender System

The principle of the knowledge base depends a lot on the KBRS type. This can be in the form of a simple data base, or the knowledge can contain a database ontology, formalized knowledge, or a case base. The essence of the knowledge base and strategy are closely linked and mutually influential. In fact, quantitative metadata of a knowledge base is coupled with a recommendation system that involves some kind of estimate of similarity. On the contrary, a qualitative knowledge base content is connected to a recommendation strategy that involves some sort of a matching methodology[32]. Recommendation systems provide users with product recommendations that they may want to buy or review. Recommendations from such systems can help users access a wide range of product descriptions, news articles, or other data objects.This is the third type of recommender system that includes customer and brand awareness to adopt an information-based approach to generate a recommendation which rationalizes that goods meet the needs of the client. A knowledge-based counseling program removes certain advantages. Since its recommendations are not dependent on user ratings, it has no ramp-up problem. It does not need to gather information about a particular user as its evaluations are independent of individual tastes.

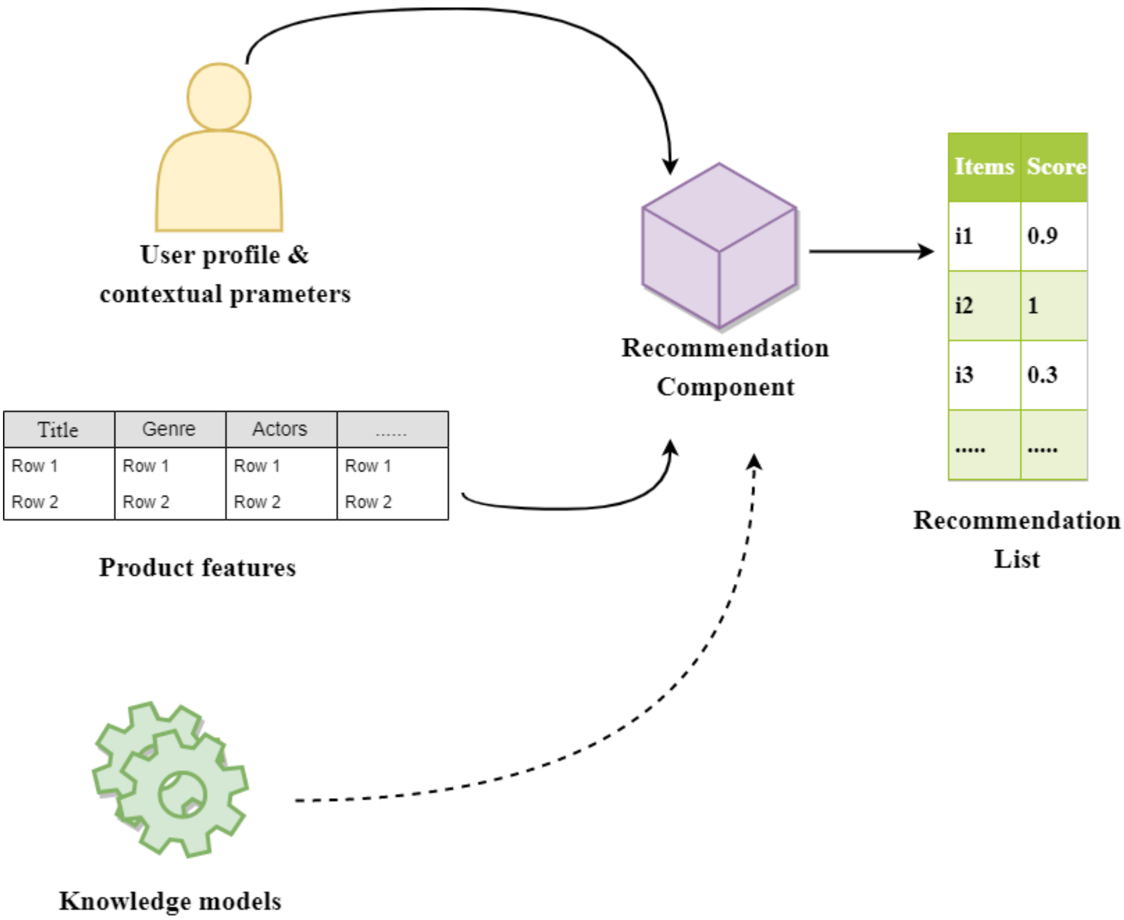

Figure 2.9: Knowledge based Recommender System

2.3.6 Trust based Recommendation System

Due to some inherent problems of CF, the usual recommendation approaches may yield poor results. Trust-based recommendation systems are adopted to solve these problems and provide more credible recommendations[33]. Researchers have also recently proceeded to incorporate information about distrust into such systems. It is experimentally established that people depend more on trusted fellows ' recommendations; like friends, family members; than recommendations from an automated recommendation system. It is also established that a positive relationship exists between trust and similarity of interest. Furthermore,This indicates that people who have been familiar with them or have been identical tend to receive recommendations from users. It therefore shows that using trust or reputation systems along with the other recommendation systems (CF) can increase performance[34].

2.3.7 Utility based Recommender System

Utility-based recommendation systems generate recommendations based on the user's calculation of the utility of each item. Utility-based recommendation approaches use items features as background information, generate utility functions over users' items to define user preferences, and use the function to evaluate a user's rank of items (Burke, 2002). The advantage of utility-based recommendations is that they do not face problems involving new users, new items, and sparsity (Burke, 2002). The central issue, nevertheless, is how to create a utility function for each user. The user should first create a full preferential function and weigh the importance of each attribute. This often gives rise to a substantial liability of interaction Hence, in building utility-based recommender systems, defining the procedure of making precise recommendations with very little user initiative is a critical issue[35].

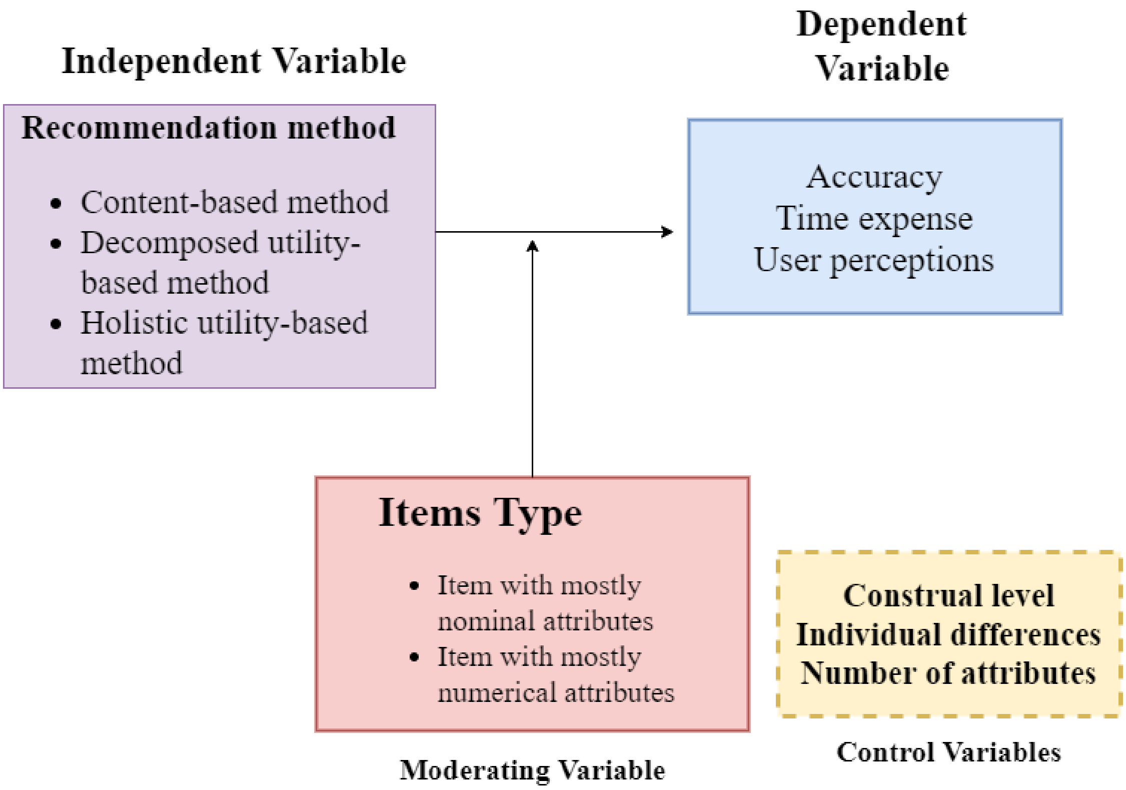

Figure 2.10: Utility based Recommender System

2.4 Limitations of collaborative filtering

Even though collaborative system is the most widely used recommender system,still there are some limitations in CF. If we recall about relationships and recommend items based on relationships between items and individuals, our minds prefers to think about people-to-people relationships. So we want to find like minded people and recommend things the user might like. This is something intuitive to do, but it is not the best thing to do. Some of the major drawback of this method are:

- Cold start problem
- Data sparsity
- New user problem
- New Item problem

2.4.1 Cold Start Problem

The cold start issue affects individual suggestions for users with no or no previous backgrounds (new users). Cold start occurs when new users or items appear on e-commerce sites. It is challenging for CF models to generate recommendations to people with a small past experience because their ability to learn and predict is limited.

2.4.2 Data Sparsity

Sparsity of ratings and users can cause difficulties in making accurate recommendations.

2.4.3 New User problem

To make accurate recommendations, the recommendation system must know the preferences of the user. Before the recommendations system can begin to make recommendations, the user must therefore rate enough products.

2.4.4 New item problem

Since the recommendations are based solely on the preferences of the user, an item must be rated by a considerable number of users before it can be recommended. The problem of "gray sheep" takes place when a user could be categorized into several user group. This user's similarity with two or more categories is equivalent, resulting in inaccurate recommendations for the user.

2.5 Limitations of Content based recommender system

One of the major setbacks of Content based recommender system is:to generate recommendations, an adequate set of features is required. It will also be impossible to differentiate two different items depicted by the very same set of features.

2.5.1 Over-Specialization

The collection of suggested items is likely to be very homogeneous, the items are expected to be very close to those already rated by the user.

2.5.2 New user problem

To grasp the preferences of the user and generate concise recommendations, the user must rate a certain number of items.

2.6 Summary

In this chapter of the book, collaborative filtering has been thoroughly discussed. We discussed how collaborative filtering works and many types of approaches of collaborative filtering .

The drawbacks of the methods used in CF are also discussed. A brief comparison was made to better understand the ways of solving the problems of one approach through using another approach.

Chapter 3

Relevant Approaches

Here we discused very common relevant approaches of recommender system.

3.1 Personality based recommender system

3.1.1 What is Personality?

Computer scientists want to use human psychological factors and want to use that into recommender systems. So that the recommendation may be more correct. Recommenders are not always able to produce successful user suggestions based solely on raw data. From this point of view personality based recommendation system has created[36].

3.1.2 The Five Factor Model of Personality

Hu and Pu have recently been studying people's interest in the music field and the features of the BF. There are 1,581 songs and 80 users who have completed TIPI (Ten-Item-Personality-Inventory) questionnaires for their friends and for themselves based on their characteristics of BF. For them and their mates, this program recommended 20 songs to score them. Using static information, Hu and Pu used a knowledge-based recommendation system, which is how personalities associate using music genres. Pennock and Horvitz have suggested personality diagnosis (PD), an implicit parameter approach based on the basis that a fully new user has an fundamental "type of personality" and user proclivity are a by-product of this kind. Recommendation system using rating and personality characteristics measures a new recommender system for collaborative filtering and improves accuracy. Researchers found that human personality and taste have a strong relationship. It will resolve the cold-start problem and also be used in collaborative filtering for achieving precision efficiency. We believe personality is essential because the recommendation has a distinct preference for users with distinct personality. So it is important to recommend any item not only for rating-based but also for user personality. Recommendation of any product based not only on ranking, but also on user personality is therefore important.

The five main personality traits are openness, acceptability, emotional stability, empathy, extraversion. These factors have many different personality characteristics provided by research known as Five factors and six subordinate traits known as facets. It gives a better result. If a user in a definite dimension receives a high score such as extraversion. It shows that, on the other hand, they are strong, bold, friendly, sociable, energetic, and enthusiastic, a lower score shows that they are introverted. Recommendation system based on user personality is important to find similar users or solve the cold star problem. Because there is an important link between the taste of consumers and their attitudes or behaviors. Many users enjoy watching comedy or action movies, others like watching romantic or horror, some like adventures, and some souls are always seeking something different. Therefore, if we only know the users' inner feelings, we can perfectly match the users' similarity. And then there will be a better estimate for the recommendation system. This research paper is different from others as we propose a fresh strategy based on rating and user-personality characteristics. Not only does our document make recommendations by using rating, but it also handles user-personality. Therefore, the prediction should be more accurate.

3.1.3 Some Other Personality Models

Some other personality models are

Table 3.1: The Big Five Framework of Personality Traits

Trait Dimension	High score	Low score
Openness	open to new ideas	conventional,incurious
Agreeableness	trusting,lenient	suspicious,antagonist
Emotional stability	calm,secure	anxious,stressed
Conscientiousness	organized	negligent,lazy
Extraversion	passionate,active	sober,passive

RIASEC vocational model

Bartle model

Thomas-Kilman conflict model

3.1.4 In which way Personality is Related to User Preferences?

Many studies have recently shown that personality is closely related to user preferences. Users of various personalities may like to prefer different types of content styles. Such relationships depend on the field. To design a recommender system for any particular domain, such information is very useful. They classified each piece of music into four categories. The first category is reflective nuanced had to do with openness to new experiences. Similarly, there was also a positive relationship between the intense rebellious category and openness to new experience. While this class includes music in negative emotions, however,that was not linked to consent. It was found that the upbeat traditional classification is positively linked to extraversion, cohesion, and perception. Ultimately, the active rhythmic group was found to be linked to extraversion and acceptability. Rentfrow expanded the field to general entertainment in a similar study. This content was classified into the following categories: visual, analytical, personal, exciting and dark[37].

3.2 Trust based recommendation system

3.2.1 What is Trust based recommendation system?

Trust is one's belief in others' ability to deliver valuable ratings. There are primarily two forms of trust: explicit confidence and implied confidence. The user ratings infer the former trust. Users indicate later trust explicitly and it indicates to whom and to what degree they trust[38].

3.2.2 How does trust work?

Trust has also extended to a broad range of scenarios, including access issues, including who should be trusted in sharing content or services, justifying issues, or targeting network nodes that are wrong in a particular context, and indicating: or making users decide whether to access a service or not.Information overload explanations warn us that users generally don't have a lot of content to search for all the information they want and recommend systems to minimize this issue by helping each user to decide what kind of content they may want to access [39]. Therefore, here we propose:

- Trust-based neighborhood selection: The choice of neighborhoods based on model similarity is overtaken by the a realistic assessment of the importance that the customer gives towards others and trust is adequately granted[40].
- Data shortages are informative: our system awards user ratings to everyone who

were eventual recommenders varying degrees of confidence in each item and rebalances trust scores to users that were unable to continue providing data[41].

- Recover ratings from Recommenders, Not Neighborhoods: Restricting users to a top-k neighborhood harm that can be expected.
- It can be useful to have different ratings.

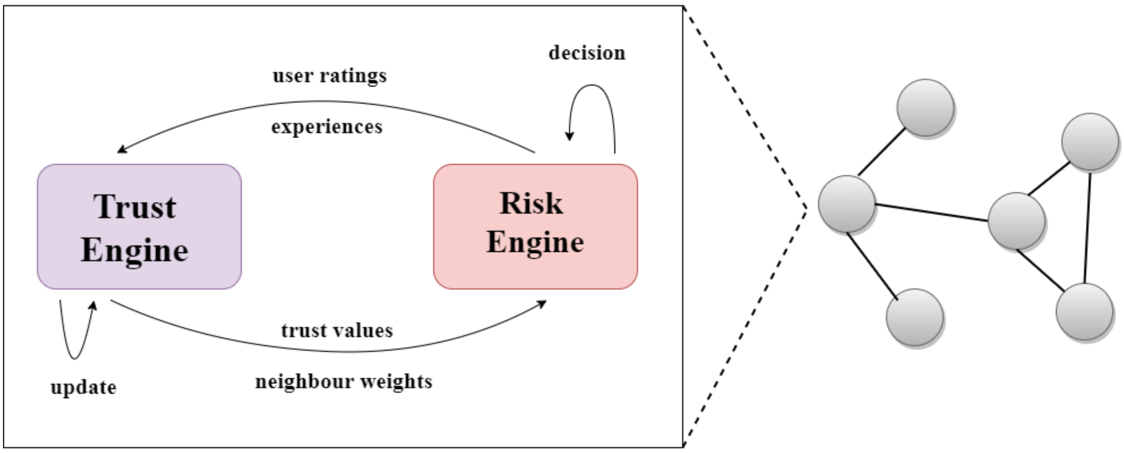

Figure 3.1: Trust based Recommender System

3.2.3 Refining as a Trust Problem

For using trust system properties instead resolve the challenges faced by recommender systems, we have to recognize how a trust system operates and then analyze is not whether the approaches mentioned relate to CF. A trust system is an interconnected network of peers or trust managers. Formal trust models also divide the process of establishing a trusting relationship with another individual into an interaction between two components as shown in the figure 3.1.The first one is the risk engine that decides whether to enter into a transaction with the entity or not.If this transaction is performed, the threat engine will then analyze the outcomes and send these findings to the confidence engine. That principal has a personal view of the surrounding world, and the entire community of leaders is creating a network of trust. Through CF, every client can be represented as a confidence manager who has to determine which content to access. To do this, the risk engine must decide whether to recommend an item to the end user by generating predicted ratings. Each forecast rating is measured by gathering rating information from the other principals of a subset of the system. What members are to be selected? Here the threat engine challenges the confidence engine, which keeps current and maintained a table of trusted peers. Standard CF specifies that it should be considered only probatively identical neighbors and that the others should be disregarded.Once the final rating is obtained from the final user, the actual product experience is understood, and the trust principal will think back on the assumption he made not only to see if it was accurate, but also to better assess the feedback he got from the surrounding directors and adjust his confidence values accordingly. Therefore, a CF atmosphere may be defined as an example of a trust-based system in which a decision mechanism is required to select an acceptable subset of users to serve as recommenders. If CF is seen as an example of a trust-management problem, the opposite approach can be accepted; we start from a trust-management system perspective and create a CF algorithm by describing the operation of each main component of the trust.

3.2.4 The Trust Engine

The first choice to be taken in a CF program is the one that to connect with; that user wants a neighborhood that is recommended.This step is driven by the assumption that collecting information from everyone (and baseline judgments on item reputations) will not be as effective as simply aggregating the information from the "right" sources; and thus involves deciding who will be the appropriate users. A user's neighborhood has traditionally been packed with the most connected users of the top-k network. Transferring the present CF idea into a trust-based context means "I trust the best k users who can show that they have similar views to my own, and I don't trust anyone else." However, the broader approach advanced by trust-management research is also worth exploring. The equivalent quote would be "I trust the users with whom I've had a positive experience and don't know how much to trust the others." This quote incorporates two new important concepts that can provide an escape route from the CF algorithm risks:

- Uncertainty: Users ought not automatically be disqualified if they do not have a measurable value of similarity to add to the expected ratings of each other.
- Value:Being the optimal recommender is not only a matter of high similarity, but can be defined in conjunction with two additional qualities. The best neighbors will have the information necessary to engage in the user's predicted ratings and will have a positive influence on the user's predicted score. In other words, the neighbor's opinion should be heavily weighted in the user's expectations, and therefore similarity will be an evolving property of the trust relationship rather than its source[42].

Trust-based recommendation systems are based on recommending that only trust scores or a combination of trust scores and similarity scores be used when making suggestions.

3.3 Neighborhood model for recommender system

3.3.1 Jaccard Similarity

Jaccard only takes into account the number of common ratings between two users. The basic idea is that if users have more popular scores, they will be more similar. The drawback is that the absolute ratings are not considered. For instance, in item 1 and item 2, user2 rates 1 and 2, user3 rates 4 and 5, user1 rates 5 and 4. User1 and user 3 are, of course, more similar.

$$J\_S(a,b) = \frac{M_a \cap M_b}{M_a \cup M_b} \tag{3.1}$$

3.3.2 Mean Square Deviation

MSD only takes into account absolute ratings, but does not take into account the number of common ratings. The downside is that it lacks the similarity's legitimacy. As in the previous example, assume that user1, user2 and user3 have respectively rated 5, 8 and 100 objects.It is possible to combine Jaccard and MSD to form a new metric.

Jaccard is essentially the most common measure used in CF. This calculation only takes into account the number of items classified by two users as compared to the scores, meaning the more corated items, the more similar. Therefore, in some instances the similarity measure is incorrect. Mean Squared Difference (MSD) looks at the absolute scores separately from Jaccard.

$$MSD\_S(a,b) = 1 - \frac{\sum_{p \in M} (rat_{a,p} - rat_{b,p})^2}{M_a \cap M_b} \tag{3.2}$$

where M_a is set of items rated by user a and M_b is set of items rated by user b. Mean squared difference between user a and b.

3.3.3 Jaccard Mean Square Deviation

In order to avoid the disadvantages of traditional measures, Bobadilla et al. developed a method combining Jaccard and Mean Squared Difference (JMSD), using Jaccard to capture the proportion of co-rated items and using MSD to obtain rating information[43]. The formula of JMSD is expressed in

Jaccard Mean square difference

$$JMSD\_S(a,b) = J\_S(a,b) \times MSD\_S(a,b) \tag{3.3}$$

3.4 Summary

In this chapter we discussed about some basics of collaborative recommender system. Here we described few standard similarity metrics.

Chapter 4

Proposed Method

In Chapter 4 we discussed about proposed method, similarity, prediction model.

4.1 Introduction

In the section we discuss about totally new proposed method which has inherent feature personality and trust-based similarity model. We go through each of the steps taken in order go get the desired prediction using our proposed approach.Here we explain how our proposed technique of evaluating a target user's similarity with other users and compare it with other approaches based on similarity.

4.2 Method

In our experiment, the analysis from the dataset in personality 2018, there are 2 types of dataset, ratings based and personality-based. From rating based dataset, we first calculated Jaccard and then calculated Mean squared difference (MSD), after that we multiplied both method and combined new similarity method which called Jaccard and Mean squared difference (JMSD).Merger of Jaccard and MSD solves some partial problems.Merger method can find out similarity matrix of both direct and indirect user to user. For example,between User1 and User2 similarity can find that they how much rated on the same items. We consider this similarity matrix is direct trust based similarity. After that we calculated indirect trust based similarity matrix on this direct trust based similarity. We calculated this method for which have no direct similarity between two users. For example, User1 and User2 rated same items other side User2 and User3 rated another same item, but User1 and User3 are not related with each other. So that the concept of trust we can find out indirect trust based similarity matrix, where we shown the similarity between User1 and User3. Also calculated a weighting factor sigma. Sigma represents the changes of weights between direct and indirect trust matrix of two users. After that we sum these two matrices together by multiplying with this weighting factor and present total trust-based similarity. In our another dataset, from personality based dataset we calculated similarity matrix using MSD. We average this two similarity matrix. From this average result we can get our final similarity. On this final similarity we calculated prediction method using by mean-centering and Z-score normalization.

4.3 Trust Based Similarity

In this section, the rating of users is considered to gain the direct trust matrix. A person rating of any item is predicted based on the rating of the closest neighbors. Therefore, similarity measure must be defined between users. A method must be selected to merge the ratings of top nearest neighbors on item [44] which will eventually give the value for direct trust between two users.

4.3.1 Direct Trust Matrix

Direct trust measure is obtained through tradition similarity measure. To enumerate trust based similarity Jaccard and (MSD) Mean Squared Difference [45] are used. They are the two popular similarity measures used in the system. Jaccard compares the ratings of two individual users. Users are compatible when the same products are rated. As it considers the number of general rating, we multiplied the Jaccard with MSD to get error-free and more accurate similarity result. MSD does not consider number of general rating rather we considers absolute ratings.As MSD considers absolute ratings so both these measures combined increases precision of similarity between users. The formula for Jaccard and MSD have been depicted using equation 4.1 and 4.2 respectively.

$$J\_S(a,b) = \frac{M_a \cap M_b}{M_a \cup M_b} \tag{4.1}$$

where M_a is a set of items rated by peoples a and M_b is a set of items rated by user b. Mean squared difference between user a and b.

$$MSD\_S(a,b) = 1 - \frac{\sum_{p\in M}(rat_{a,p} - r_{b,p})^2}{M_u \cap M_v} \tag{4.2}$$

Direct trust based matrix

$$DT(a,b) = J\_S(a,b) \times MSD\_S(a,b) \tag{4.3}$$

4.3.2 Indirect Trust Matrix

According Trust concept trust is famous by defining the similarity between peoples [46]. To generate indirect trust matrix we used this equation. Calculating indirect trust based similarity matrix gives us those similarities between two users who are not related with each other. Their preference easily can be predicted using this similarity.

$$IDT(a,b) = \frac{\sum_{m\in C}(DT_{a,m} \times DT_{m,b})}{\sum_{m\in C} DT_{a,m}} \tag{4.4}$$

where C is all the users associated with user a and b.

4.3.3 Weighting Factor

The two matrices are combined together using this weighting factor. So this weighting factor helps to get a summary of total equation.

$$sigma = \frac{DT_{a,b}}{DT_{a,b} + IDT_{a,b}} \tag{4.5}$$

4.3.4 Final Trust matrix

For our proposed method we get total trust from adding these two matrices while multiplying each matrix with the weighing factor sigma.

$$T\_S(a,b) = sigma \times DT_{a,b} + (1 - sigma) \times IDT_{a,b} \tag{4.6}$$

4.4 Personality Based Similarity

Section we talk about each users' personality trait to calculate similarity between different peoples. We treat the personalities of a user as a vector.User a's personality qualifier is a vector of a n dimension, $Q{=}Q_a^1, Q_a^2, Q_a^3, ..., Q_a^n$ and each dimension represents a feature that consists of its own personality.For instance, if the users are evaluated by big 5 factor mode [47] describing a user's personality in five main features. Here Q_a is a 5 dimensional vector, each dimension refers to one of the 5 traits of personality. Hence, the proximity of personality between 2 users p and q can be calculated as the MSD Similarity of their personality qualifiers.

$$P\_S(a,b) = 1 - \frac{\sum_{i=1}^{k} (Q_{a,i} - Q_{b,i})^2}{M_u \cap M_v} \tag{4.7}$$

Here an important factor to notice is that jaccard was not applicable for personality-based similarity as the common count will always be 5 .So similarity will always end up being 1.

Now we put forth an integration model in order to use personality and ratings more competently to create user profile [13]. We take the average of both trust and personality based similarity.

Final similarity model:

$$Sim(a,b) = \frac{T\_S(a,b) + P\_S(a,b)}{2} \tag{4.8}$$

4.5 Prediction Method

The mean-centering and Z-score are two of the most common rating normalization systems to transform individual rating to a more worldwide scale.

Mean Centric Rating of item m by user b, rat_{bi} converted to mean-centered one by deducting average $\bar{r}at_b$ from rat_{vb}.

$$rat_{bi} - r\bar{a}t_b$$

Then guess of a rating r_{ai} is acquire as

$$rat_{a,i} = r\bar{a}t_a + \frac{\sum\limits_{b \in N_i(a)} w_{ab}(rat_{bi} - r\bar{a}t_b)}{\sum\limits_{b \in N_i(a)} w_{ab}} \tag{4.9}$$

where w_{ab} presenting the preference sameness between a b gained from final similarity measure [48].

Z-score Normalization Although mean-centering eliminates offsets due to contrasting impression of an average rating, Z-score normalization takes spread of rating scales into consideration as well. Here, mean-centered rating is divided by the standard deviation σ_b

$$\frac{rat_{bi} - r\bar{a}t_b}{\sigma_b}$$

Then guess of a rating r_{ui} is achieve as

$$rat_{a,i} = r\bar{a}t_a + \sigma_a \frac{\sum\limits_{b \in N_i(a)} w_{ab}(rat_{bi} - r\bar{a}t_b)/\sigma_b}{\sum\limits_{b \in N_i(a)} w_{ab}} \tag{4.10}$$

In this research we worked with Z-normalization. As this approach considers all the aspects needed to get correct predictions.

4.6 Algorithms

Algorithm 1 Proposed Method

Input: Train Datasets

Output: Personality and Trust-based Matrix

```
for u ← mxuid do
    for v ← mxuid do
        array userlist= userCluster
        similarity ← calculateJaccard
for u ← mxuid do
    for v ← mxuid do
        similarity ← calculateMSD
for u ← mxuid do
    for v ← mxuid do
        if denominator != 0 then
            calculate indirect Trust Matrix
        else
            indirect Trust Matrix= 0
if calculate weighting Factor then
    sigma ← weightingFactor
for u ← mxuid do
    for v ← mxuid do
        trustBasedSimilarity ← CalculateTrustBasedSimilarity
for u ← mxuid do
    for v ← mxuid do
        if calculate personality MSD metrix then
            finaltrustBasedSimularity ← calculatefinaltrustBasedSimularity
```

4.7 Flow Chart of Proposed Method

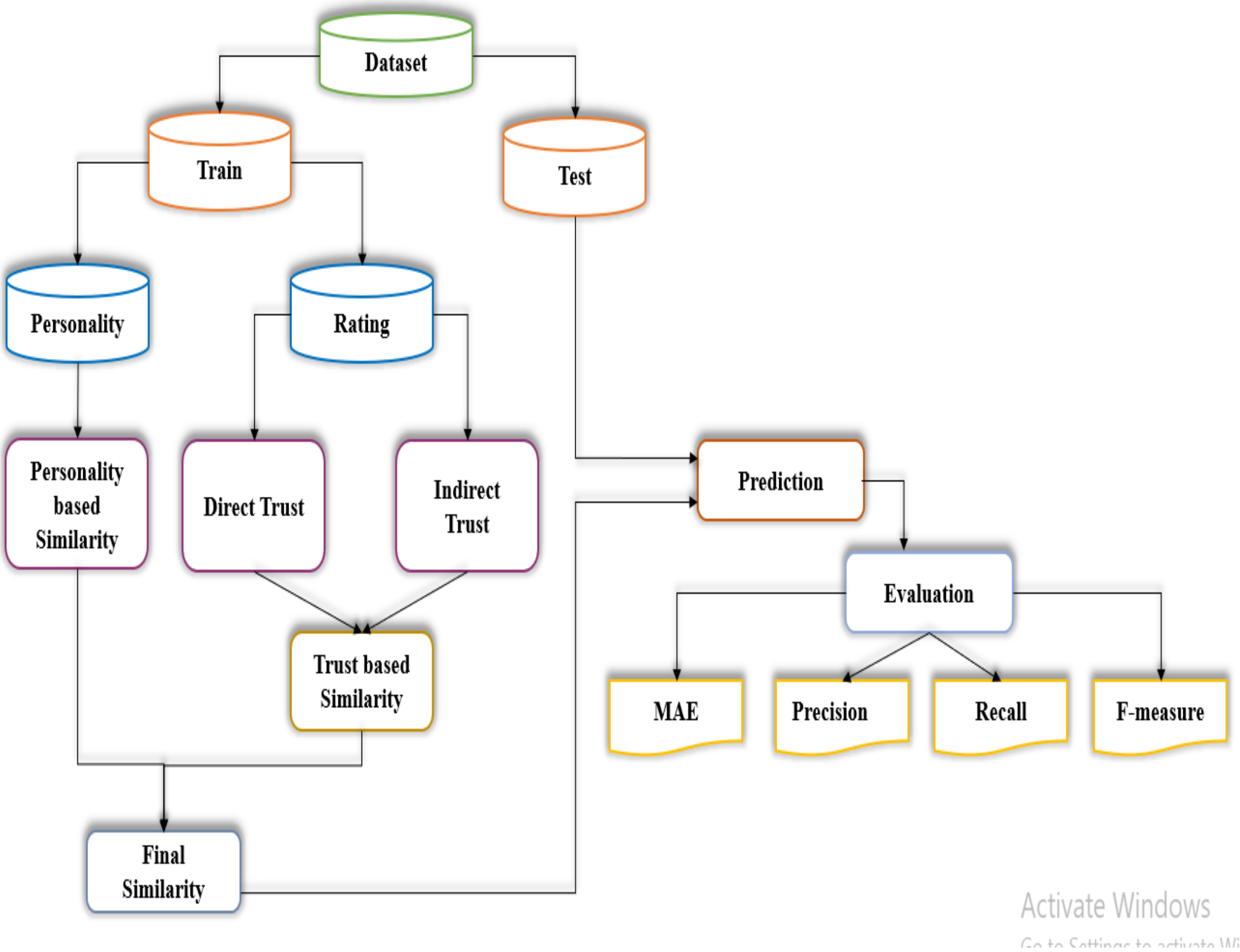

Figure 4.1: Flow Chart of Proposed Method

In this Flow chart we simply visualized the steps of our proposed approach.

4.8 Summary

In this chapter, we have shown our full process which is our proposed method. Flow chart and algorithm were demonstrated in order to give a clear visualization of our proposed method. We combine trust-based similarity and personality based similarity to generate new similarity for calculating prediction using z-score normalization. And then we tested 20% of our data to evaluate our approach.

Chapter 5

Performance Evaluation

This chapter shows the detailed discussion of experiments conducted in our approach. Here is a comparative analysis of state-of - the-art initiatives .

5.1 Dataset

In our experiment, the analysis is mainly offline based and the dataset is from Grouplens Personality 2018 dataset. Grouplens mainly a social computing research for the university of Minnesota. This system was actually used by real users (https://grouplens.org/). There are different types of datasets are present, but we choose the dataset of personality 2018. Which is more relatable and connected for our method.

5.1.1 GroupLens Datasets

In personality 2018, there are 2 types of dataset, ratings-based and personality-based. 1820 user and 11781 movies with 1028751 ratings are included in the dataset as shown in Table 5.1. In personality dataset there are 5 types of personality which are shown in Table 3.1. This dataset is widely used and beneficial for researchers in personality based collaborative filtering domain. We split the data into training sets and test sets. 80% movie rating of each user is selected for training data and 20% is selected for test data.

Table 5.1: Variables of the Data set

Data set	Users	Items	Rating Range	Prediction Range
Personality 2018	1820	11781	0.5-5	1-7

5.2 Evaluation Metrics

We have used four most popular metrics of evaluation. These metrics estimate the precision of predicted ratings with respect to actual ratings. These are mean absolute error [49], Precision, Recall and F-Measure. Such metrics help users to classify highly desired movies from the range of available movies [50]. Though we used offline based data sets, so our evaluation process also offline based. Whereas online based evaluation process is more time consuming rather than our evaluation process.

5.2.1 MAE

As the name suggests, The mean absolute error is the mean deviation from the actual rating of the expected rating [51]. The absolute error between pair of predicted and actual rating of user u is treated equally for each pair. The MAE is measured by adding up those absolute errors and then by calculating the average[4]. This value should be low to indicate good performance. The formula is:

$$MAE = \frac{\sum_{i=1}^{N_u} |p_{u,i} - r_{u,i}|}{N_u} \tag{5.1}$$

where $r_{u,i}$ is actual rating and $p_{u,i}$ is predicted rating and N_u is total rating of user u.

5.2.2 Precision

Precision is an accuracy measure that measures the percentage of relevant items from all items collected [52].This measure should be as high as possible. It is computed as:

$$Precision = \frac{n}{topN} \tag{5.2}$$

We can also demonstrate it like:

$$Precision = \frac{true\,positive}{true\,positive + true\,negative}$$

In terms of rating, true positive are the ratings that are predicted good and they are also actually rated good.Rating can be termed as good or bad within a certain threshold. In our case rating below 2.75 is considered negative which indicates bad rating.

5.2.3 Recall

Recall is a completeness metric that determines the percentage of the retrieved relevant items collected from all the relevant items. M_T MT is the number of items that users like in the test set, and N is the number of items that users like in the recommended list.

$$Recall = \frac{N}{M_T} \tag{5.3}$$

Another way of demonstrating recall is:

$$Recall = \frac{true\,positive}{true\,positive + false\,negative}$$

false negative are the values that are rated good but predicted bad.

5.2.4 F-measure

The f-measure metric actually combines Precision and Recall and blends into a single value for comparison purposes. Also used for more balanced view of performance.

$$F_{Measures} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5.4}$$

5.3 Our Experiment and Measurement

Here we demonstrate our result and talk about it. Figs 5.1 -5.6 show the results using Personality-2018 dataset. According to the evaluation metrics : MAE, Precision, Recall and F-measure our proposed method is more better than other tradition approaches

5.3.1 Performance Evaluation

We used Grouplens (personality-2018) dataset to evaluate our proposed method. Using the trust matrix based on ratings and similarity measure based on personality we generated better similarity measure and therefore generated better prediction method .

5.3.1.1 TOP N Neighbour vs Evaluation Metric MAE Comparing Proposed and Traditional methods

In the figure 5.1 of Our experimental results show that our model proposed for Mean Absolute Error is better than any other similar method. In our approach MAE is decreasing for increase the size of neighbor rather than traditional method. We consider The traditional method are Personality-Rating based similarity, Rating with Trust-based similarity and Personality-based similarity. After comparing, here traditional method is greater than our proposed method.

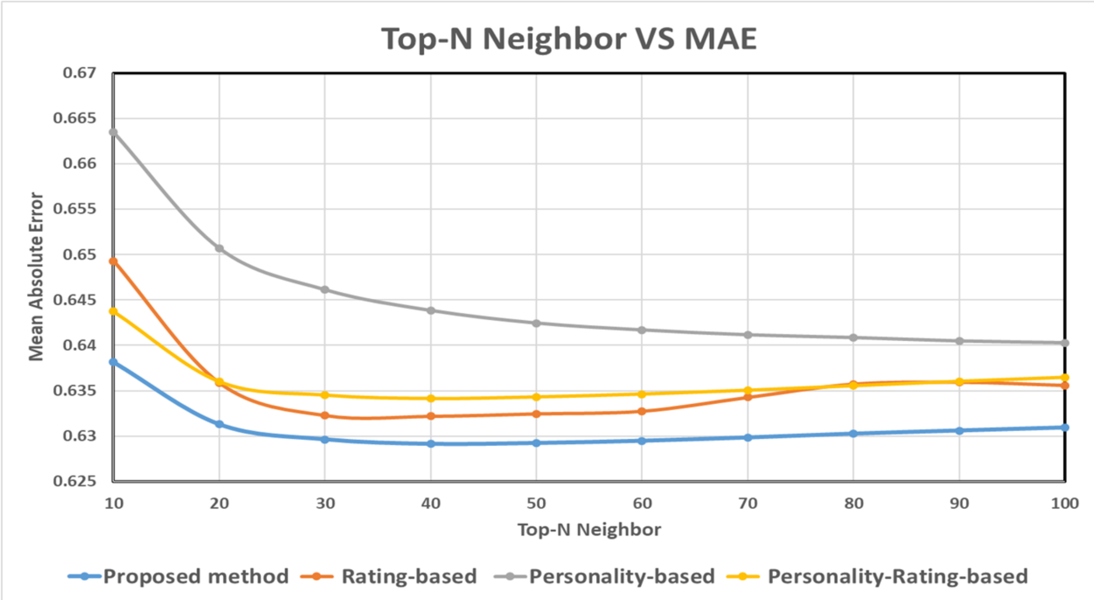

Figure 5.1: Top-N Neighbor vs MAE

5.3.1.2 TOP N Neighbour vs Evaluation Metric Precision Comparing Proposed and Traditional methods

In the figure 5.2 of Our experimental results show that our proposed method is better for precision than any other similar method. After comparing, here traditional method is less than our proposed method. At some point Precision is decreasing for increase the size of neighbor, because the nature of our data sets. Neighbor are behaving in such a way that our Precision is going down.

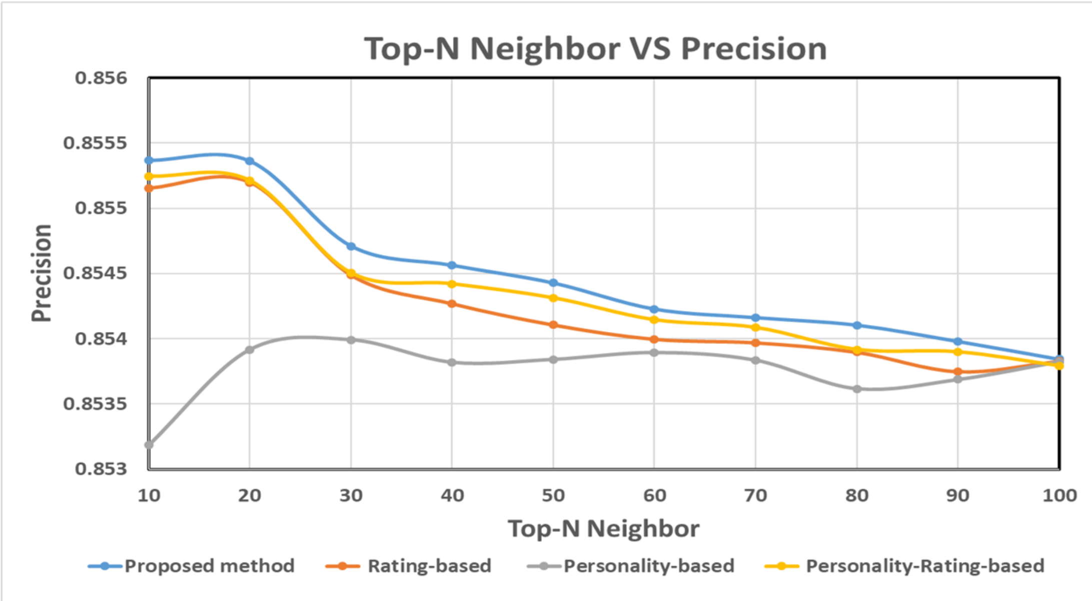

Figure 5.2: Top-N Neighbor vs Precision

5.3.1.3 TOP N Neighbour vs Evaluation Metric Recall Comparing Proposed and Traditional methods

In the figure 5.3 of Our experimental results show that our method proposed for recall is better than other similar methods. In our approach Recall is increasing for increase the size of neighbor rather than traditional method. We consider The traditional method are Personality-Rating based similarity, Rating with Trust-based similarity and Personality-based similarity. After comparing, here traditional method is less than our proposed method.

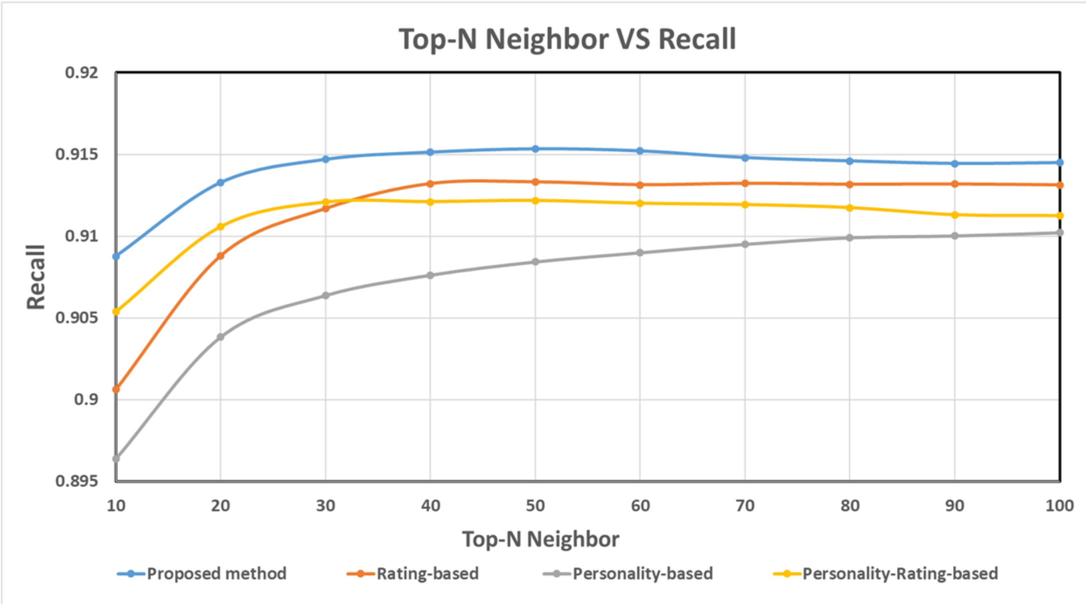

Figure 5.3: Top-N Neighbor vs Recall

5.3.1.4 TOP N Neighbour vs Evaluation Metric F-measure Comparing Proposed and Traditional methods

In the figure 5.4 of Our experimental results show that our proposed method is better than any other F-measure similarity system. In our approach F-measure is increasing for increase the size of neighbor rather than traditional method. We consider The traditional method are Personality-Rating based similarity, Rating with Trust-based similarity and Personality-based similarity. After comparing, here traditional method is less than our proposed method. At some point F-measure is decreasing for increase the size of neighbor, because the nature of our data sets.

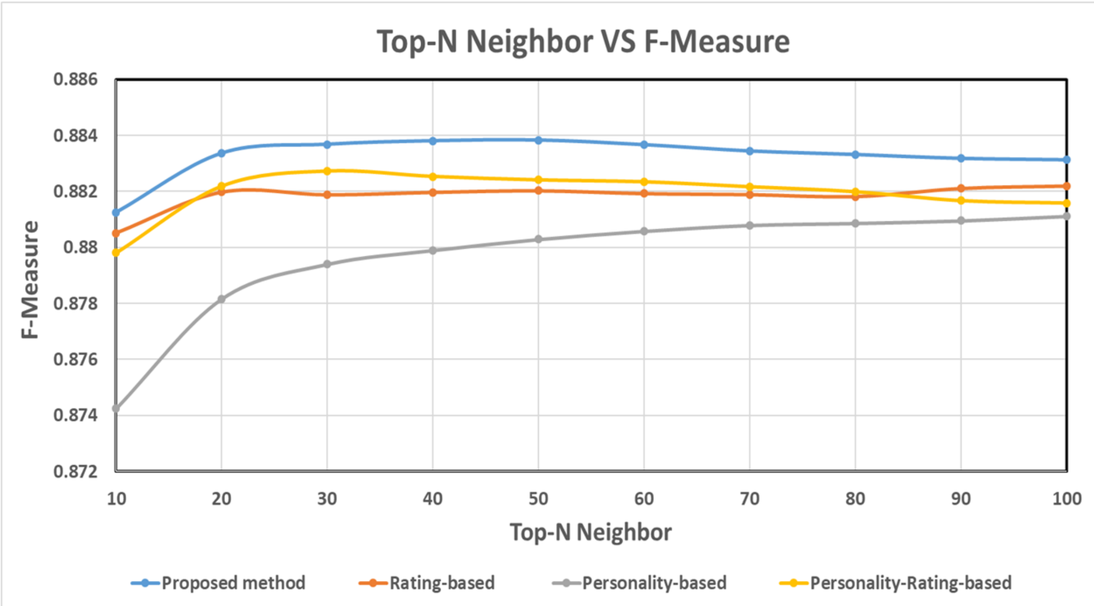

Figure 5.4: Top-N Neighbor vs F-measure

5.3.1.5 TOP N Neighbour vs Evaluation Metric Recall Comparing Proposed and Relevant Paper method

We contrasted our research with relevant paper to further prove the competence of our work. As our approach is new so there is no other work/paper that resemblance our work. So the most relevant one that we found was Hu et al's [10] work on Personality and Rating based Recommender System. In figure 5.5 we can see the MAE measurement of that paper is quite larger than our proposed method which proves compatibility of our work.In figure 5.6 we can see the recall measurement of that paper is quite low than our proposed method which further proves compatibility of our work.

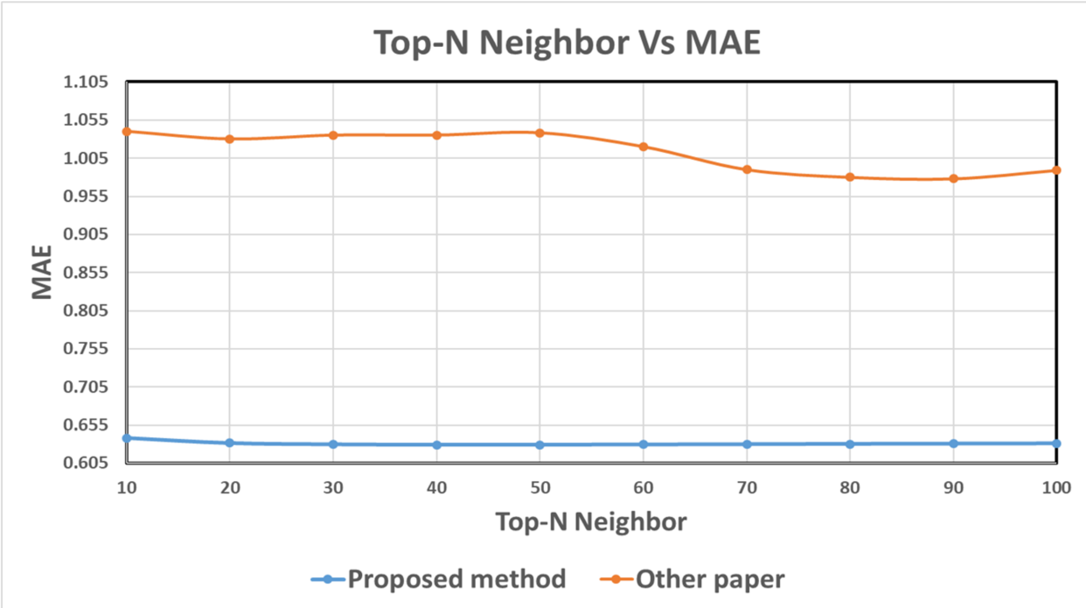

Figure 5.5: Top-N Neighbor vs Mae comparison

5.4 Summary

In this chapter, after evaluating the performance of MAE, Precision, Recall and F-Measure our The approach suggested is much better than other approaches for the data sets of Grouplens. Our results varied at some point for behaving neighbor, so that results might look uncoordinated.

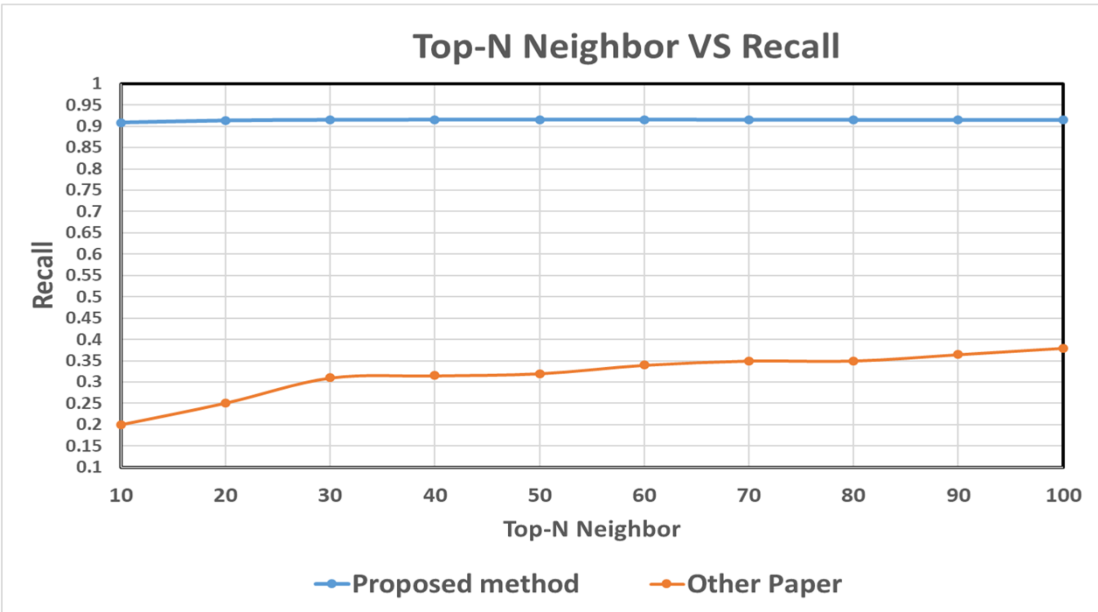

Figure 5.6: Top-N Neighbor vs Recall comparison

Chapter 6

Conclusion

Here we discussed our thesis summary and introduced few possible future works based on our work and the limitations of our work.

6.1 Thesis Summary

At first we introduced the collaborative filtering method. And then we write about different variations of collaborative filtering. We also discussed about personality trait and trust matrix. We analyzed about cold start problem and described how cold start problem can be solved using our approach. After that we demonstrated our own proposed method. There we introduced the combination of trust based matrix and personality trait. Then we evaluated our algorithms. Then we calculated MAE, precision, recall, f-measure to analyze performance.

6.2 Future Work

Our article proposed a completely new technique or new method in collaborative filtering. We combined personality trait and trust matrix so that the result we get is more effective. We develop a different algorithm for recommender systems using both users' trust and personality. In order to get an improved recommendation, personality traits of users and trust matrix plays a key factor in finding similarity between users. It solves cold start problem where neighbors of the user are difficult to find as they have not rated any item yet. From rating dataset (MovieLens) we created a trust matrix and from personality dataset we created a similarity based on personality and combined them to get final prediction[53].

For this purpose, we use different types of algorithms such as MSD, Jaccard, JMSD. For future research, we will use datasets of different domains. In this paper the context of our dataset was based on movies, we can implement our approach on music domain, books domain and on online products. To cope with cold users, we generated implicit behavior of users through their similarity which is based on personality so even if they haven't rated any item yet they will still have neighborhood of similar user[54].

So the future works can be: (1) finding other approaches to get accurate similarity between users (2) implement the models on our dataset (3) use different datasets and comparing that with our approach. (4) the algorithms will be strengthened to generate better recommendation and in order to give a further assessment on cross domain recommendation testing with more dataset will be performed.

6.3 Limitation

One prospective limitation of our work is that we consider only one dataset. It should be enhanced and matured enough to use for commercial purpose.

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Appendix A

List of Acronyms

CF	Collaborative Filtering
CFRS	Collaborative Filtering Recommender System
CBRS	Content based Recommender System
MSD	Mean Squared Deviation
JMSD	Jaccard Mean Squared Deviation
MAE	Mean Absolute Error
TopN	Top Most N Recommended Items

Appendix B

List of Notations

J_S(a,b)	Jaccard Similarity
MSD_S(a,b)	Mean Squared Deviation
JMSD_S(a,b)	Jaccard Mean Squared Deviation
DT(a,b)	Direct Trust Matrix
IDT(a,b)	Indirect Trust Matrix
T_Sim(a,b)	Trust based Similarity
P_Sim(a,b)	Personality based Similarity