A FUZZY-BASED APPROACH FOR MODELLING PREFERENCES OF USERS IN MULTI-CRITERIA RECOMMENDER SYSTEMS

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By

Odu Nkiruka Bridget

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CERTIFICATION

This is to certify that the thesis titled “A FUZZY-BASED APPROACH FOR MODELLING PREFERENCES OF USERS IN MULTI-CRITERIA RECOMMENDER SYSTEMS” submitted to the school of postgraduate studies, African University of Science and Technology (AUST) Abuja, Nigeria for the award of the Master's degree is a record of original research carried out by Odu Nkiruka Bridget in the Department of Computer Science.

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By

Odu Nkiruka Bridget

A THESIS APPROVED BY THE COMPUTER SCIENCE DEPARTMENT

RECOMMENDED: _____

Supervisor, Prof Mohamad Hamada

_____

Co-supervisor

_____

Head, Department of Computer Science

APPROVED: _____

Chief Academic Officer

_____

December 9th, 2017

ABSTRACT

Recommender systems are web-based platforms or software that use various machine learning methods to propose useful items to users. Several techniques have been used to develop such a system for generating a list of recommendations. Multi-criteria is a new technique that recommends items based on multiple characteristics or attributes of the items. This technique has been used to solve many recommendation problems and its predictive performance has been tested and proven to be more effective than the traditional approach. However, current research has shown that there is still a need to use some machine learning techniques in modelling the criteria ratings in multi-criteria recommendation techniques. The proposed project aimed to present a model that is based on the architecture and main features of fuzzy sets and systems. Fuzzy Logic (FL) is a method of reasoning that resembles human reasoning. It is one of the machine learning techniques that is widely known for its effective application in different fields of study. Its main advantage is that it does not need a lot of data to train, coupled with its ability to combine human heuristics into computer-assisted decision making, which is highly applicable in the domain of recommender systems. The proposed project is designed to test and provide the predictive performance of the fuzzy-based multi-criteria technique and compare it with some of the existing methods. The main focus of this research is to model a system that can optimize the prediction accuracy of an RS, increase in ranking accuracy, and thus obtain high correlation between the predicted and actual values. Experimental results performed on real-world datasets (Yahoo movies) proved that the proposed technique (Fuzzy Multi-criteria Recommender System) remarkably improved the accuracy of prediction in multi-criteria CF RS. The system was implemented using java programming language.

Keywords: Recommender System, Multi-Criteria, Fuzzy Logic, Membership function, rating, linguistic variables, overall rating.

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DEDICATION

From the deepest part of my heart, I sincerely dedicate this prestigious work to God Almighty, for the wisdom, understanding and strength to finish this project.

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LIST OF ACRONYMS

MC	Multi-Criteria
RS	Recommender System
AsySVD	Asymmetric Singular Value Decomposition
CF	Collaborative Filtering
FL	Fuzzy Logic
FS	Fuzzy System
MF	Membership Function
TMF	Triangular Membership Function

AF	Aggregation Function
TFN	Triangular Fuzzy Number
RMSE	Root Mean Square Error
MAE	Mean Average Error
ROCAUC	Area Under the Curve of Receiver Operating Characteristics
FCP	Fraction of Concordant Pairs
NDCG	Normalized Discounted Cumulative Gain

CHAPTER ONE
INTRODUCTION

This chapter presents a general introduction to the Recommender System, the proposed system frameworks, problem statement, research aim and objectives, research questions, and structure of the thesis.

1.1 Background of the Study

The rapid growth of Internet of things (IoT) and fast development of e-commerce websites, has given rise to the pressing need for a recommender system. Users found it difficult to arrive at the most appropriate choice given the immense variety of items (products and services) that these websites offered. The explosive growth and variety of information available on the Web and the rapid introduction of new e-business services (selling products, product comparison, auctions, etc.) frequently overwhelmed users, leading them to make poor decisions. Consequently, the availability of choices, instead of producing a benefit, started to decrease users' well-being. It was understood that while choice is good, extra choice is not always the best, as this leads to information overload, which muddles the user of the system on the right choice to make from the increasing number of options available, therefore, the need for recommender system (RS). Recently, RS has proven to be a valuable means of coping with the information overload problem. Ultimately an RS addresses this phenomenon by pointing a user towards new, not-yet-experienced items that may be relevant to the user's current task.

1.2 Recommender Systems (RS)

Recommender Systems (RS) are software tools and techniques that provide users with suggestions for items that are most likely of interest to them. Recommendation is about

predicting the pattern of taste and using them to discover new and desirable things that you did not already know. Recommender System is a specific type of information filtering technique that tries to present users with information about items (movies, music, books, news, web pages, among others) in which they are interested in (Meier, Pedrycz & Portmann, 2013). RS emerged as an independent research area in the mid-1990's, it is mostly used in e-commerce websites as a technique to provide suggestions to people who lack competency in selecting few out of many overwhelming items in a particular website. Some examples of sites that make use of recommender system are Amazon, Netflix, YouTube, Spotify, LinkedIn, Facebook etc. RSs are mostly directed towards people who lack the adequate personal experience or skill in order to evaluate the possibly overwhelming number of alternative items that a website may offer. A good example is a movie recommender system that assists users in selecting a movie to watch. An example is Netflix which is popularly known for its movie recommendation site and employs an RS to personalize the online store for each customer. RSs can be personalized or non-personalized. The non-personalized recommendations are mostly featured in magazines or newspapers, but they are typically not addressed in RS research. However, since recommendations are usually personalized, different users or user groups benefit from diverse, tailored suggestions. The personalized recommendations are offered as ordered (ranked) lists of items given by the user. Consequently, in order to perform ranking, RS tries to predict what the most suitable products and services are, based on the user's preferences and constraints, and to complete such a computational task, RS collects information from a user's preferences which might be explicitly expressed by the user through their ranking or browse history or implicitly through simple navigation of sites.

The development of RS's begun from a moderately simple observation which showed that individuals often rely on recommendations provided by others in making choices for their

daily routine and decisions. For example, it is often common to rely on what one's peers recommend when selecting a book to read, similarly, school administrators count on recommendation letters given to students during their admission decision process. Furthermore, when selecting a movie to watch, individuals tend to read and rely on the movie reviews and critics. Therefore, in order to mimic this real-life scenario, the first RS was implemented using Collaborative Filtering technique, which follows that if an active user agreed in the past with certain users, then the other recommendations coming from these similar users should be relevant to the other active users. Data used in RS refers to three main objects such as items, users and transactions (Tobergte & Curtis, 2013).

1. **Items:** Items are the objects (movie, books, music, places of interest, services) that are recommended by an RS to a user.
2. **Users:** Users can be described as humans to whom the items are directed to. They are described by their interaction with the RS.
3. **Transactions:** This is generally referred to as a recorded interaction between a user and the RS, comprising of log-like data that store important information generated during the human-computer interaction and which is useful for the recommendation generation algorithm that the system is using. It might be in the form of explicit or implicit feedback that the user has provided, such as the rating for the selected item. Ratings are the most popular form of transaction data that an RS collects. Therefore, an RS rating system is generally classified into two forms as Traditional (single rating) and Multi-Criteria RS.

1.2.1 Traditional Single rating

- Most of the existing Recommender System on the market are based on a single numerical rating that represents user's opinion about the item. The traditional RS operates in two-dimensional space of users and items. The utility of items to users is generally represented by a totally ordered set of ratings R_0. Ratings can take on a variety of forms (Tobergte & Curtis, 2013), such as
- Numerical ratings which involves number ranging from 1 – 5
- Ordinal ratings: it might be in the form strongly agree, strongly disagree, and the user is asked to select the term that best indicate their opinion about an item.
- Binary ratings: it is a model that decides whether a user should choose good or bad for a specific item.
- Unary rating: It indicates whether a user has purchased an item or otherwise rated an item to be positive.

The utility function *R* for single criteria RS can be formally written as follows:

$$R: Users \times Items \rightarrow R_0$$

The utility function is determined based on user inputs, such as numeric ratings that users explicitly allocate to items and/or transaction data that implicitly shows users' preferences (e.g., purchase history). The majority of traditional recommender systems use single-criterion ratings that indicate how much a given user liked a certain item in total (i.e., the overall utility of an item by a user), for instance, consider a traditional collaborative single-rating (between 1 – 10) in movie recommender system, where user u provides a single rating for a movie that they have watched, denoted by $R(u, i)$**,** assuming that the users provide their ratings as shown in Figure 1.1.

The system would estimate any rating that user *u* would give to yet-unseen movie *i* according to how users *u*' who are similar to target user *u* rated movie i. Therefore, as illustrated in **fig. 1**, assuming that there are five users, u1,…,u5 and five movies i1,…,i5 and supposing that the ratings of the users to the movies i are as shown in fig. 1, the RS finds the users who are closer to the active user 1 and who have also watched the movie i5. From Figure 1.1, it is clearly shown that user 2 and user 3 have the same similarity of taste with user 1, therefore the RS will predict the rating of user 1 to movie i5 R (u5, i5) as 9. Thus, the ability to correctly determine the users that are most similar to the target user is crucial in order to have accurate predictions. Single criterion rating hides vital information concerning the exact thing the user liked in the movie, hence mislead an RS into making a wrong prediction for an activity, because the information about the exact feature they liked in the movie are not well- represented. This single rating problem gave rise to the need for Multi-Criteria RS.

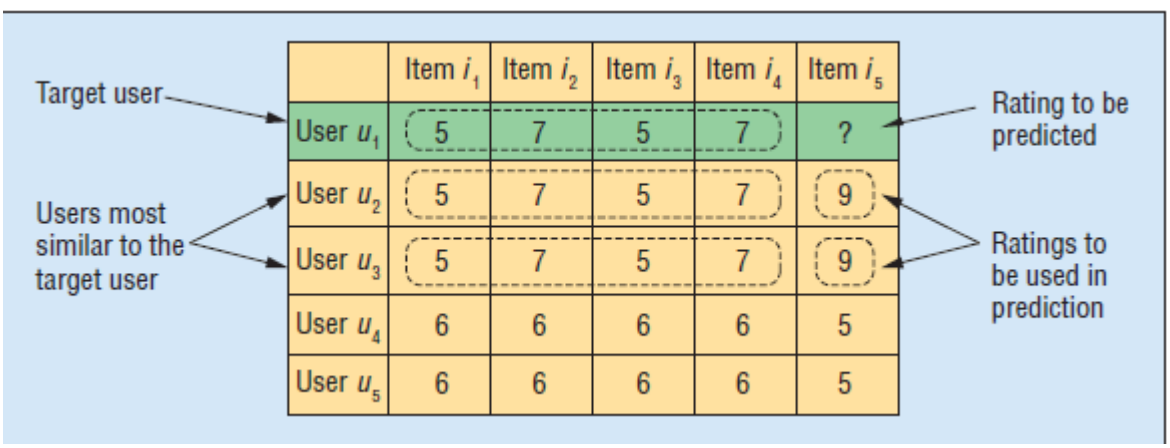


Figure 1.1: Collaborative Filtering in a Single Criteria RS (Adopted from New Recommendation Technique for Multi-criteria Recommender System)

1.3 Multi-Criteria Recommender System

Multi-Criteria are the different attributes of items that can be put together to describe the quality of items. For instance, in a Music RS, the criteria or attributes might be the lyrics, visual, audio, sound, beat, genre, etc. Its utility function is represented as $R: Users \times Items = R_0 \times R_1, \ldots, R_k, where R_0 is the overall rating, \wedge R_1 R_k are the criteria rating.$ In multi-criteria ratings, users can provide their subjective preference ratings on multiple attributes of an item. This additional information provided by multi-criteria ratings could help to improve the quality of recommendations as it represents more complex preferences of each user as well as modelling the user preferences more accurately. Users might have different reasons for liking an item (Tobergte & Curtis, 2013). Research in multi-criteria problems is extensive in both operations research and decision science fields (Adomavicius & Kwon, 2007).

Similarly, consider the same scenario in a multi-criteria RS, having five users *u*1,…, *u*5 and five movies, *i*1, …, *i*5, an unknown rating *R*(*u*1, *i*5) that must be predicted, and known overall ratings of all users to different movies that are exactly the same as shown in Figure 1.1, assume that the system asks each user to provide the feedback for each movie on four explicit criteria—story, acting, direction, and visuals, assume that the overall rating in this case is a simple average of the four individual criteria ratings. Using the same CF method, the additional information available in the multi-criteria ratings shown in fig 2 makes it clear that *u*2 and *u*3 are rather different in their tastes from *u*1, even though their overall ratings for each movie match perfectly, *u*1 disliked the movie aspects (story and acting) that *u*2 and *u*3 liked and liked the aspects (direction and visuals) they disliked. However, recommender systems that are based on single-criterion ratings would hide this information in the aggregated rating. As shown from the example, the aggregation can lead to inaccurate insights about the true similarity between user preferences.

Users *u*4 and *u*5 seem to make better matches for user *u*1 in this example, because their overall ratings and preferences are similar for different movie features. Both *u*4 and *u*5 rate movie *i*5 as 5, so the system would predict a value of 5 for the target rating *R* (*u*1, *i*5). This result is varied from the one obtained in a single-rating scenario in section 1.2.1. From these two scenarios, it is clearly shown that the overall rating that users provide to an item explicitly describes how much they like the item, and multi-criteria ratings provide some insights regarding why they like it. Therefore, multi-criteria ratings enable more accurate estimates of the similarity between two users.

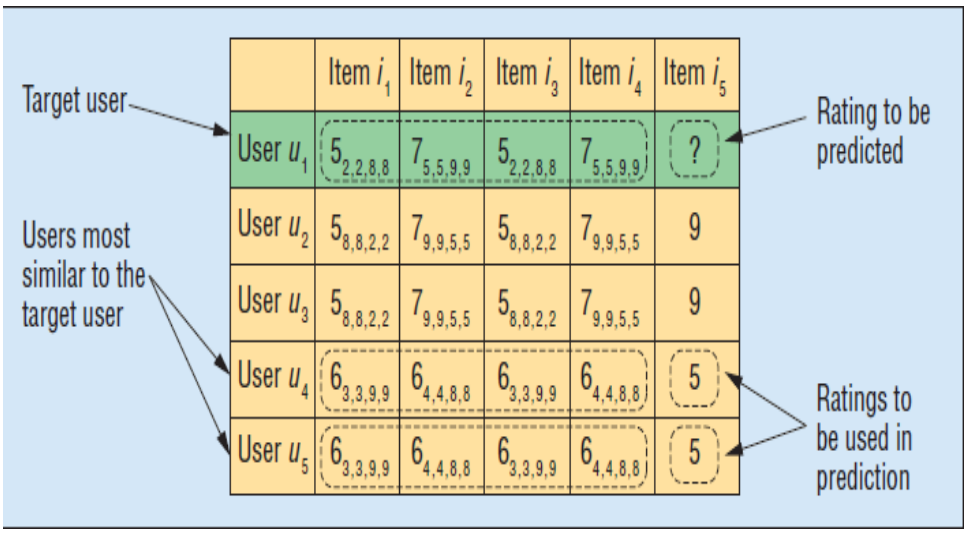


Figure 1.2: Collaborative Multi-criteria Rating. (Adopted from New Recommendation Technique for Multi-criteria Recommender System)

1.4 Recommendation Techniques

Recommender Systems are classified according to the taxonomy given by (Burke, 2007) :

1. Content-Based: This describes a system that is designed to recommend items that are related to the ones that the user liked in the past. This technique tends to learn more about the user's preference and so extracts keywords that describes what the user has liked before and perhaps, recommends similar item (s) to the user in their next transaction.

2. Collaborative Filtering (CF): It is the most popular and widely used approaches for RS which makes recommendations to the active user based on the items that other users with similar tastes liked in the past. It does this by collecting an explicit rating done by a user for an item and computes similarities between the users or items to provide a recommendation. Collaborative Filtering is a people-to-people correlation (Owen, Anil, Dunning, & Friedman, 2011). CF is basically in two forms, Memory-based and Model-based Techniques. These techniques will be further discussed in Chapter 3.

3. Hybrid: This Recommender technique is based on the combination of both Content based and Collaborative filtering. "A hybrid system combining techniques A and B tries to use the advantages of A to fix the disadvantages of B (Tobergte & Curtis, 2013).

1.5 Reasons for using Recommender Systems: The following are reasons why we need a Recommender system:

- To increase sales and productivity: when a user is being provided with the best suggestions, it maximizes the purchases made since the user is provided with the best item that matched their preferences.
- Increase in sales of diverse items: RS does not provide users with only popular items or services, it also creates opportunity to users to view other items that might not be of interest to others; this would not have been possible without a recommender system.
- Maximize the satisfaction of the user: RS matches the users with their right preferences, this increases consumer satisfaction of the user, perhaps, maintains the user's interest in the system which leads to frequent visits to the site and an increase in traffic for goods purchase.

- Increases user fidelity: When a system acknowledges the user for being an active customer, it gives the user the value.

1.6 Summary of task done by the RS

- Helps users find the best items that can satisfy their needs.
- Provide list of all available items
- Random generation of user preference without the user explicitly requesting for it

1.7 Fuzzy Set and Logic

The word fuzz or fuzzy means “nap” or “pile”, and it is a word used with textiles, and from “fuzz” comes the idea of a hazy outline, which means something that is not clearly seen. Therefore, the word “fuzzy” means “unclear” or “ambiguous”. In the real world, things are not always in their extremes, in the form; yes or no, or yet there are so many issues that we may not wish to give an exact response to, for example, one might ask this question, “do you like chicken pie?” the response might be “I like it, but it is not really tasty”, another might decide to reply with “I don’t really like it, but if that is the only option, let me have it” it might be very difficult to determine the degree of these responses based on their likeness for the chicken pie. For this cause, Prof. L.A Zadeh in 1975 proposed the fuzzy theorem and then further extended the two valued evaluation of 0 or 1 to infinite values between the intervals 0 to 1. At the inception of fuzzy sets, curly brackets $\{\}$ were used to indicate sets, while square brackets [ ]denote real number closed interval.

A fuzzy set A defined as a function $A \rightarrow X[0,1]$ where X is the universe of discourse is represented by membership function that enhances its characteristic function of a set. In a fuzzy set A, a membership function (MF) expressed as $\mu A$is defined as $\mu A: X \rightarrow [0,1]$.

The value $\mu A(x)$ at element $x \epsilon X$ determines the degree of membership of the element in the fuzzy set A.

Fuzzy logic describes a set of truth values in the interval [0, 1]. fuzzy logic is derived from fuzzy set theory. One might ask why fuzzy theory have the wide applications? The answer to this is that fuzzy theory is the only theory that can deal with the meaning of human language mathematically.

Furthermore, there has been a movement toward trying to use fuzzy theory in the humanities and social sciences recently. In the near future, starting with models of human activity, thinking, psychology, reliability, and economics, it will probably be used actively in education, law, and analysis and evaluation of things such as public opinion. In summary, fuzzy methods will probably serve all fields that relate to control and information.

1.8 Aim and Objectives

The thesis aims to implement a fuzzy-based algorithm that would model the preferences of users in multi-criteria recommender system. The thesis would be tested to ensure that it improves the predictive performance of the fuzzy-based multi-criteria technique and compare it with some of the existing methods (traditional RS). The thesis is aimed at achieving the following objectives:

1. Decrease in prediction errors, increase in ranking accuracy,

2. To obtain high correlation between the predicted and actual values.

1.9 Research Question

This section provides critical questions that describe the goals and scope of this research. During the implementation stage, the following questions shall be reviewed:

1. How can Multi-criteria RS improve the traditional method of recommender system?

2. How can fuzzy-logic be applied in multi-criteria recommender system?

3. Which best model would be used for the development of a fuzzy-based RS?

1.10 Thesis Structure

This thesis is organized into five chapters, viz:

Chapter 1: This Chapter introduces the Recommender System, Traditional RS, Multi-criteria RS, Fuzzy sets & logic, Aim and Objectives, Research questions and methodology are discussed.

Chapter 2: Review of some existing literature, previous works done on Recommender system, Multi-criteria RS and fuzzy logic systems.

Chapter 3: This Chapter describes the various frameworks and techniques used, Collaborative Filtering (CF) techniques, Model Based approach, Aggregation function, Asymmetric Singular Value Decomposition, general architecture of a fuzzy-based RS and the architectural framework of the proposed system.

Chapter 4: This Chapter focuses on the implementation of the proposed thesis, it presents experiments and evaluations carried out and the results achieved.

Chapter 5: This Chapter provides the conclusion drawn from the findings, contributions and challenges encountered during this research and anticipation for possible future research.

CHAPTER TWO
LITERATURE REVIEW

In this chapter, we presented a review of the existing related works done to determine what has been done before and current thinking in the interest of this research area. Therefore, we looked at the various works done in solving the problems of Collaborative filtering RS and the various approaches used. Issues of prediction accuracy were discussed as well as the technique applied in improving them, some benefits of applying multi-criteria in RS were also discussed.

2.1 Problems of Collaborative Filtering Recommender System

RS constitutes a problem-rich research area whose abundance of practical applications has helped users to deal with information that has continuously improved businesses. The major problems of CF RS would be discussed in this section together with the various approaches used by different scholars in solving these problems.

2.1.1 Data Sparsity

Recommender Systems became an important research area since the appearance of the first paper on collaborative filtering since the mid-1990s (Gediminas, 2005). Over the past decades, information technology and the internet have resulted in e-commerce flourishing and emerging as an important gateway to business papers on collaborative filtering (Nilashi, M., & Ibrahim, O. Bin. 2014). Recommender System has been a vast growing tool that has enhanced the massive growth of e-commerce websites (Adomavicius & Tuzhilin, 2003). Yet, interest in this area remains high because it constitutes a problem rich research area and its abundance of practical applications has helped users to deal with information overload.

However, although there is vast growth of RS, Multi-Criteria rating problems have recently emerged in the recommender systems research literature as an important next-generation issue (Adomavicius & A. Tuzhilin 2005). Multi aspects in the CF recommender systems presents new challenges such as sparsity problem in criteria and overall ratings, scalability problem with increasing new dimensions, representation and rating (Nilashi, 2014). Therefore, there is a need to address these problems of RS. Researchers have proposed that the problem of inflexibility has been addressed using Recommendation Query Language (RQL) (Adomavicius & Tuzhilin, 2007). Using user profile information when calculating user similarity may overcome the problem of rating sparsity (Adomavicius & Tuzhilin, 2007). Sparsity problem has been circumvented due to the application of matrix factorization (Chen, G., Wang, F., & Zhang, C. 2009).

Clustering-based privacy preserving collaborative filtering is a technique proposed to solve the problem of scalability and sparsity in order to enable users to supply their information without fear of insecurity trusting that their privacy is well protected. This is achieved through masking the user's confidentiality before submitting them to the data holder and disguising the rated items and the ratings (Bilge, A., & Polat, H. 2013). The use of self-organizing map (SOM) clustering to CF schemes is designed to preserve users' confidentiality (Alper & Polat, 2012). SOM is a type of artificial neural network that reduces dimensions by producing a map of usually one or two dimensions that plots the similarities of the data by grouping similar objects together. Fuzzy methods can predict the users' preference more accurately and even better alleviate the sparsity problem in overall rating by considering user perception about items' features (Nilashi & Ibrahim, 2014).

Orthogonal Non-negative Matrix Tri-Factorization (ONMTF) is a novel framework for collaborative filtering that alleviates the sparsity problem via matrix factorization and also solves the scalability problem by simultaneously clustering rows and columns of the user-item matrix (Chen, Wang, & Zhang, 2009). Integrating both subjective and objective information to generate recommendations for an active consumer is a novel collaborative filtering framework proposed to solve the problem of sparsity and the cold-start (Li-Chen Cheng & Hua-An Wang 2014). Fuzzy linguistic model, which is a more natural way for the consumer to present their preferences, is adopted within their proposed framework, based on their concepts, two algorithms, a simple aggregated (SA) algorithm and aggregated subjective was proposed.

2.1.2 Cold Start

Cold start problem occurs when a new user or item has just entered the system and it is difficult to find similar ones because there is not enough information about the user nor the item (Su & Khoshgoftaar, 2009). Multi-criteria CF recommender systems suffer more from this problem on two sides, missing values in overall and criteria, with the system having to predict these missing ratings with new approaches. Recommendation problem is reduced to the problem of estimating ratings for the items that have not been seen by a user (Bilge & Polat, 2013). Many recommender systems are intrusive in the sense that they require explicit feedback from the user and often at a significant level of user involvement, leading to new user problems (Breese, et al. 1998). The unrated items of an individual user in a group can be predicted by using the rating information from a group of closely related users (Gediminas, 2005). However, prediction of an unrated item can be derived by the composition of matrix operation (Cheng & Wang, 2014) and Hybrid Recommender System to solve the New items problem of CF (Adomavicius & Tuzhilin, 2001).

User profile information can be used when calculating user similarity which means that two users could be considered similar if they belong to the same demographic segment (Cheng, & Wang, 2014). This approach relatively solved the cold start problem, but it is not a reliable approach. Person/actor aspect model is a novel approach that combines collaborative with content data in one model, where casts of actors can act as substitute for items, such that recommendations are now made based on the similarity of the cast to the item that the user has already rated (Schein, et al 2002), the result of the evaluation showed that this method solved some problems of cold start.

2.1.3 Scalability

As more people got oriented in the use of e-commerce sites, the dimensions *n* and *m* grew and it became harder to expand such systems thus leading to the scalability problem. Scalability occurs when numbers of existing users and items grow at a tremendous rate (Su & Khoshgoftaar, 2009). Traditional *CF* algorithms suffer serious scalability problems, with computational resources-based recommendations. Clustering is widely used to cope with the scalability problem by reducing the size of datasets involved in the CF process (Bilge, A., & Polat, H. 2013). High Order Singular Value Decomposition (HOSVD) was used for dimensionality reduction to alleviate the scalability problem (Nilashi, et al, 2014) In their same work, they also proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for extracting fuzzy rules from the experimental dataset, thus, alleviating the sparsity problems in overall ratings, representing and reasoning the users' behaviour on items' features. In conclusion, these experimental results on real-world dataset showed that a combination of the two techniques remarkably improves the predictive accuracy, leads to a reduction in new user problem, and provides recommendations for the quality of multi-criteria CF.

2.2 Improvements in Prediction Accuracy

Accuracy is by far the most discussed property in the recommendation system literature (Tobergte & Curtis, 2013). Two more common tasks related to recommender systems are the prediction of user opinion (e.g. rating) over a set of items as the prediction task, and the recommendation of a set of good (interesting, useful) items to the user as the recommendation task (Gunawardana & Shani, 2009). Recommended systems are personalized information filtering technology used to either predict whether a certain user will like an item (prediction problem) or to identify a set of N items that will be of interest to a certain user (top-N recommendation problem) (Karypis, G. 2015).

Accuracy and confidentiality are two major goals that should be achieved by online vendors to attract customers (Oliver, 1999). Multi-Criteria recommendation techniques came into existence in an attempt to solve prediction accuracy problems found in traditional Recommender systems. The Multi-Criteria approach extends the traditional approaches by increasing the number of ratings to cover various attributes of the items and incorporate their ratings for improving the prediction accuracy of the RS. Neural network model trained with Simulated Annealing Algorithm (SMA) is a novel approach proposed to improve the prediction accuracy of multi-criteria recommender systems (Hassan & Hamada, 2017). Their results indicated that modelling MCRS's with artificial neural networks significantly improved the prediction accuracy of the systems. Prediction accuracy could improve if we assume some default rating value for the missing ratings collaborative recommender systems by trying to predict the utility of items for a specified user based on the items previously rated by other users (Breese et al 1998). Mathematical approximation theory can also contribute to developing better rating estimation (Gediminas, 2005).

However, Multi-Criteria Decision Making (MCDM) methods were proposed to facilitate the recommendation process (Manouselis & Costopoulou, 2007). Accuracy measures can either be statistical or decision-supportive, decision-support measures determine how well a recommender system can make predictions of high-relevance items (i.e., items that would be rated highly by the user (Herlocker, et al., 1999). There is a need for new techniques to effectively incorporate the multi-criteria rating information into the recommendation process. Fuzzy approach offers a low-cost solution for producing high quality recommendations and enhances robustness of Privacy Preserving Collaborative Filtering (PPCF) systems due to its approximation-based model (Bilge & Polat, 2013). Support Vector Regression is a technique used to determine the relative importance of the individual criteria ratings (Dietmar et.al., 2001). This approach (SVR) also helped to handle sparse data which improved the quality of recommendation of the system.

Trust–Semantic Fusion (TSF) based recommendation approach is a technique that incorporates additional information from the users' social trust network and the items' semantic domain knowledge to alleviate the prediction error (Shambour et al 2012), TSF approach significantly outperformed existing recommendation algorithms in terms of recommendation accuracy. A new recommendation method uses Classification and Regression Tree (CART) and Expectation Maximization (EM) for accuracy improvement of multi-criteria recommender systems (Mehrbakhsh Nilashi, 2014). Other scholars suggested that for prediction to be improved, the customer’s satisfaction for an item must also be considered (Oliver 1999, Kim et al 2009). Therefore, satisfaction is also a crucial factor for repurchase intention; this gives rise to the need to improve the prediction accuracy of the top *n* items recommended to users in the e-commerce sites.

During an electronic survey of online shoppers and hotel customers totalling 1,743 samples, it was discovered that customers' information satisfaction and website quality are an important factor of online behavioral intentions and essential for information satisfaction, respectively (Kim et al., 2009). Satisfied consumers exhibit a greater intention to purchase online products, have a greater re-purchase intention and have a lower desire to look for alternative providers (Oliver, 1999). Therefore, in the search to improve prediction accuracy in RS, customer's satisfaction must also be considered.

2.3 Advantages of Multi-Criteria Recommender System

Multi-Criteria are the different attributes of items that can be put together to describe the quality of items (Yera & Mart, 2017). Although multi-criteria ratings have not yet been examined in the recommender systems literature, they have been extensively studied in the Operations Research community (Dwyer, et al., 1995). The difference between single-rating and multi-criteria rating systems is that the latter have more information about the users and items to be used in the recommendation process (Adomavicius, et al, 2007). Single-criterion rating systems have proved successful in several applications, but many industries have begun employing multi-criteria systems (Adomavicius & Kwon, 2007). Several basic strategies were proposed to exploit multi-criteria ratings to improve the predictive accuracy of a recommender in terms of typical information retrieval measures.

Later, many additional techniques to leverage the detailed ratings in the recommendation process were proposed. Multi-Criteria ratings enable more accurate estimates of the similarity between two users. In addition to the overall rating, multi-criteria ratings provide information about user preferences for different aspects or components of an item, recommender systems should benefit from leveraging this additional information because it can potentially increase the recommendation accuracy.

Research in recommender systems is now starting to recognize the importance of multiple selection criteria to improve the recommendation output (Liu & Xu, 2011). Research indicates that Multi-criteria system provides more information about user's preferences than a single-rating system and by adopting a decision theory, multi-criteria systems can provide rich tools for system designers to build more interesting systems (Lakiotaki, et al, 2011). However, in some applications where single criteria recommendation does not meet users' personalized needs, multi-criteria ratings are considered.

2.4 Fuzzy Logic Recommender Systems

Fuzzy Logic System (FLS) can be defined as the non-linear mapping of input datasets to a scalar output dataset (Ojokoh, B. 2012). The use of Fuzzy Sets Theory has given very good results for modeling qualitative information (Zadeh, 1975). Fuzzy set theory and logic provide a way to quantify the non-stochastic uncertainty that is induced from subjectivity, vagueness and imprecision (A. Zadeh, 1994). Fuzzy logic provides high-value properties to recover items stored in a database to provide recommendations for users. Since fuzzy sets have the ability to manage concepts such as similarity, preference and uncertainty in a unified way, they also have the aptitude to perform rough reasoning (Darwish, 2014). Fuzzy logic can help to minimize the sparsity problem, which is the main drawback current recommender systems suffer from (Nadi et al., 2011). From the foregoing, it can be seen that Fuzzy Logic has wide application in various domains of study, as well as the domain of recommender systems. Some works that employed fuzzy logic for handling the graded/uncertain information in recommender systems, includes the work of Darwish (2014) in his paper "Collaborative Filtering Based on Soft Computing to Enhance Recommender System for e-Commerce".

In their work to improve the recommendation quality conducted towards hybridization between CF and type-2 fuzzy linguistic modelling to enhance the CF accuracy in recommender systems in order to deal with the sparsity and scalability problems, the suggested method makes predictions by using only the user-item interaction information. From their experimental results it was shown that the proposed approach gave better performance when compared with traditional fuzzy recommendation approaches in all the sensitive parameters.

Linguistic Hierarchy, LH, which is a set of levels $l(t, n(t))$ where each level t is a linguistic term set with different granularity$n(t)$ from the remaining levels of the hierarchy (Cordón et al., 2001). The fuzzy linguistic modelling (FLM) is a tool based on the concept of linguistic variable which has given very good results for modelling qualitative information in many problems, e.g., in decision making (Zadeh, 1994). Fuzzy Ant based RS for web users applied fuzzy logic in accordance with ant colony optimization to increase the accuracy and relevance of predictions (Nadi, et al., 2011). The system analysed the user's navigational behaviour during a period of time to determine the most ideal recommendations for him. This was done by extracting the user's interests to the web pages from web server log files and further applying Fuzzy Clustering Means (FCM) and ant based clustering algorithms to group users that has the similarity in taste. This proposed method helped in providing optimal more qualified recommendations. Another fuzzy linguistic approach proposed to capture the uncertainty in user preferences in a knowledge-based recommender system (Martinez, 2008). Fuzzy linguistic variables can be realized through the fuzzy membership function (MF), the following includes the merits of MF:

(i) The membership function in fuzzy theory is intentionally designed to treat the vagueness and imprecision in the context of the application. Therefore, it is more reliable and accurate to use fuzzy theory to model subjectivity and vagueness in the attributes.

(ii) The membership function can be continuous, which are more accurate in representing the attributes of items and user feedbacks.

(iii) The fuzzy mathematical method is easy to perform once the membership functions of attribute have been defined.

They further said that these properties promise to provide the framework for addressing the representation and inference challenges faced in recommender systems research (S.-M. Hsu, 2011). Our work was motivated by the work done by (Hadjali, et al., 2014) which entails fuzzy modelling of user multi-criteria preferences by using linguistic terms and the analysis of their experiment showed that their approach did pretty well in predicted ratings.

Our proposed fuzzy logic approach using model based collaborative filtering approach is based on a user's previous rating, and the use of CF techniques to find users who are related to the active user, we aim at using machine learning (Fuzzy logic algorithm) and aggregation function approach to analyse the predictive performance of a Multi-Criteria RS.

CHAPTER THREE
RESEARCH FRAMEWORK AND METHODOLOGY

This Chapter presents the different approaches used during implementation of the proposed system. This research adopted collaborative filtering techniques for the traditional (single) rating RS using Asymmetric Singular Value Decomposition, it further discussed the model based CF, aggregation function that was used to find the relationship f between the $\mathbf{r_0}$ (overall rating) and $\mathbf{r_1}$ (criteria rating). It described how the model was trained to determine a user's preference. It presented the fuzzy logic system, the flow diagram and the programming language used.

3.1 Fuzzy logic system

Fuzzy logic is used to represent things in the real world that are crisp or put simply so unclear. The concept of Fuzzy Logic (FL) is derived from fuzzy set theory and was conceived by Lotfi Zadeh in 1975, a professor at the University of California at Berkley. It was not presented as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership. Fuzzy Logic (FL) is a method of reasoning that resembles human reasoning. The approach of FL imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO. The conventional logic block that a computer can understand takes precise input and produces a definite output as TRUE or FALSE, which is equivalent to a human's YES or NO, whereas a fuzzy set is determined by a membership function with a range of values between 0 and 1.

Definition 1.1: A fuzzy set A defined as a function $A \rightarrow X[0,1]$ where X is the universe of discourse is represented by membership function that enhances its characteristic function of a set.

In a fuzzy set A, a membership function (MF) expressed as $\mu A$is defined as $\mu A: X \rightarrow [0,1]$. The value $\mu A(x)$ at element $x\varepsilon X$ determines the degree of its membership of the element in the fuzzy set A. consequently,

$$if\mu A = 0itimpliesthatxcompletelydoesnotbelongA$$

$$if\mu A = 1, itimpliesthatxcompletelybelongsA$$

3.1.1 Basic Fuzzy operations:

Empty set: The fuzzy set A is defined as empty is and only if:

$$A = \emptyset = \{x|x\varepsilon \cup \mu A(x) = 0,\}$$

Equal sets: Two fuzzy sets A and B are defined as equal if and only if:

$$A = B = \{x \vee x\varepsilon \cup, \mu A(x) = \mu B(x)\}$$

Subset: The fuzzy set *A* is defined to be contained in another fuzzy set *B* if and only if:

$$A \subseteq B = \{x \vee x\varepsilon \cup, \mu A(x) < \mu B(x)\}$$

Complement: The complement of fuzzy set *A*, denoted by *A*, is defined by:

$$A = \{x|x\varepsilon \cup, \mu A(x) = 1 - \mu A(x)\}$$

α-cut: The α-cut of fuzzy set A is a crisp subset defined by:

Aα =$\{x \vee x\varepsilon \cup, \mu A(x) \leq \alpha., \alpha\}$

3.1.2 General Structure of Fuzzy Logic System

Fuzzification: It involves the conversion of crisp set of input data to a fuzzy set using fuzzy linguistics variables, fuzzy linguistic terms and membership functions.

Linguistic variables: These are the input or output variables of the system whose numerical values are the equivalent of words or sentences from human language, A linguistic variable is generally decomposed into a set of linguistic terms.

Membership Function: It is a graphical representation of the magnitude of participation of each input that associates the weighting with each of the inputs that are processed, it determines the functional overlap between inputs and ultimately determines an output response. MF are used in the fuzzification and de-fuzzification steps of FLS, it is one of the most important part of fuzzy system. Because it displays the degree to which an item satisfies a particular user. It contains linguistic parameters known as hedges, measured on the interval of [0, 1]. The membership function is used as a quantifier to quantify the linguistic term. There are many types of membership functions, for example:

- Triangular
- Trapezoidal
- Singleton
- Gaussian

Fuzzy Rule: Fuzzy Logic system uses a fuzzy rule to control the output variable. It is like the backbone of the fuzzy system. It is simply in the IF-THEN structure where IF structure is the antecedent block and THEN represent the consequent block.

De-fuzzification: This is done according to the membership function of the output variable. The main purpose of de-fuzzification is to get a crisp value.

3.2 Multi-criteria Recommender System:

Multi-criteria recommender system is the use of different attribute of a specific item to recommend items to users. Its utility function is defined as $R: Users \times Items \rightarrow R_1 \times R_{2,\ldots,} R_k$. Single criteria ratings hide the users' preferences and mislead the system when predicting the items that users are interested in whereas multi-criteria ratings provides additional information to the user and this concept has helped to improve the performance in MC RS. MC predicts the overall rating for an item based on past ratings regarding both the item overall and individual criteria and perhaps recommends to the user the item with the best overall score. MC RS can be built using basically any of these three *approaches, viz;*

- Content based RS
- Collaborative RS
- Hybrid RS

3.3 Collaborative Filtering:

Collaborative Filtering is an RS technique that recommends items to the user based on what other people with similar tastes and preferences has liked before. CF methods produce user specific recommendations of items based on patterns of ratings or usage without need for exogenous information about either items or users (Tobergte & Curtis, 2013). To establish recommendations, CF systems need to relate two fundamentally different entities: items and users. CF which has been widely adopted regardless of the facts that recommenders may not explicitly collaborate with recipients and recommendations may suggest particularly interesting items.

The basic assumption of *CF* is that if users *X* and *Y* rate *n* items similarly, or have similar behaviours (e.g., buying, watching, listening) there is a likelihood that they both rate or act on other items similarly (Su & Khoshgoftaar, 2009). *CF* techniques use a database of preferences for items by users to predict additional topics or products a new user might like. However, CF can be divided into two: The memory based CF and model based CF.

3.3.1 Asymmetric Singular Value Decomposition (AsySVD)

Asymmetric SVD is one of the matrix factorization techniques that represents users as a combination of items features. It can directly compute recommendations for users not yet parameterized and providing an immediate feedback to his or her activity. The following are the reasons for choosing Asymmetric SVD (i) it allows the use of fewer parameters, for example, in our dataset, the number of users is much larger than the number of items this helps to lower the complexity of the model. (ii) It has the ability to handle new users as soon as they provide feedback to the system since it does not parameterize users, without needing to re-train the model and estimate new parameters. (iii) it explains and gives reasons for prediction, since predictions are a direct function of past user's feedback (Koren, Ave, & Park, 2008.).

Therefore, the overall average rating can be computed using this general prediction rule:

$$(u) \vee \quad \frac{1}{2}\sum_{j\epsilon R}(\mu)\left(r_{uj} - b_{uj}\right)x_j + N(\mu) \quad -\left(\frac{1}{2}\right)\sum_{j\varepsilon R}(\mu)\, y_i \qquad (1)$$

$$\hat{r}_{ui} \quad \vee R$$

From (1) each item i is associated with 3 factor vectors $q_i, x_i, y_i \varepsilon R^f$, and users are represented through the items that they liked.

We learn the values of the parameters by minimizing the regularized squared error function associated with (1) as shown in (2)

$$uj - b_{ij}$$
$$r$$

$$+(N(u)|^{-\left(\frac{1}{2}\right)} \sum_{j\epsilon N(u)} y_i$$

$$R(u) \vee \quad {}^{-\left(\frac{1}{2}\right)} \sum_{j\in R(u)} \qquad (2)$$

$$r_{ui} - u - b_u - b_i - q_i^T$$

$$\min_{a \;\; x \;\; y \;\; b} \sum_{(u,i)\in k}$$

With far integration of implicit feedback, more accurate results were gotten leading to this model:

$$ui + q_i^T \left(P_u + \left| |N_{(u)}| \right|^{\frac{-1}{2}} \sum_{j\epsilon N(u)} y_i \right) \qquad (3)$$
$$ui = b$$
$$\hat{r}$$

Where user u will be modelled as $P_u + |N_{(u)}|^{\frac{-1}{2}} \sum_{j\epsilon N(u)} y_i$.

Where $\gamma = 0.002 \wedge \lambda$ =0.04 on a 10-fold Cross Validation rule for dataset selection

3.4 Model based Approach

Model based is a Collaborative Filtering technique that uses prior user activities, ratings or history to first learn about a predictive model.

This is done by using some statistical, domain expertise, or machine-learning method, through which the system then uses to make recommendations. It involves many approaches such as simple aggregation functions, probabilistic modelling, singular value decomposition (MSVD), and support vector regression (SVR).

3.4.1 Aggregation function:

An aggregation function is a function of n >1 arguments that maps the (*n*-dimensional) unit cube onto the unit interval, $f: [0,1]n \rightarrow [0,1]$. The purpose of aggregation function is to combine inputs that are typically interpreted as degrees of membership in fuzzy sets, degrees of preference, strength of evidence, or support a hypothesis and so on. It is a function with multiple arguments that always returns single value (Tobergte & Curtis, 2013). This approach assumes that the multi-criteria ratings represents user preferences for different characteristics of the item and suggests that the overall rating is not a rating that is dependent on other ratings, but rather serves as some "aggregation" function of the multi-criteria ratings of the item r_0 = f (r_1, …, r_k). The following steps summarize the aggregation function approach for n criteria recommendation problems: Fig 3.1 summarizes the general structure of Recommender System techniques.

1. Decompose the multi-criteria rating problem into single-rating problems.

2. For each k_m, use a single-rating technique to predict the unknown rating r_0 i for each criterion

3. Learn the relationship between r_0 and r_{i0s} using fuzzy based approach.

4. Integrate steps 2 and 3 to predict $r'_{0=f(r'_{1,}r'_{2,\ldots,}r'_{n})}$

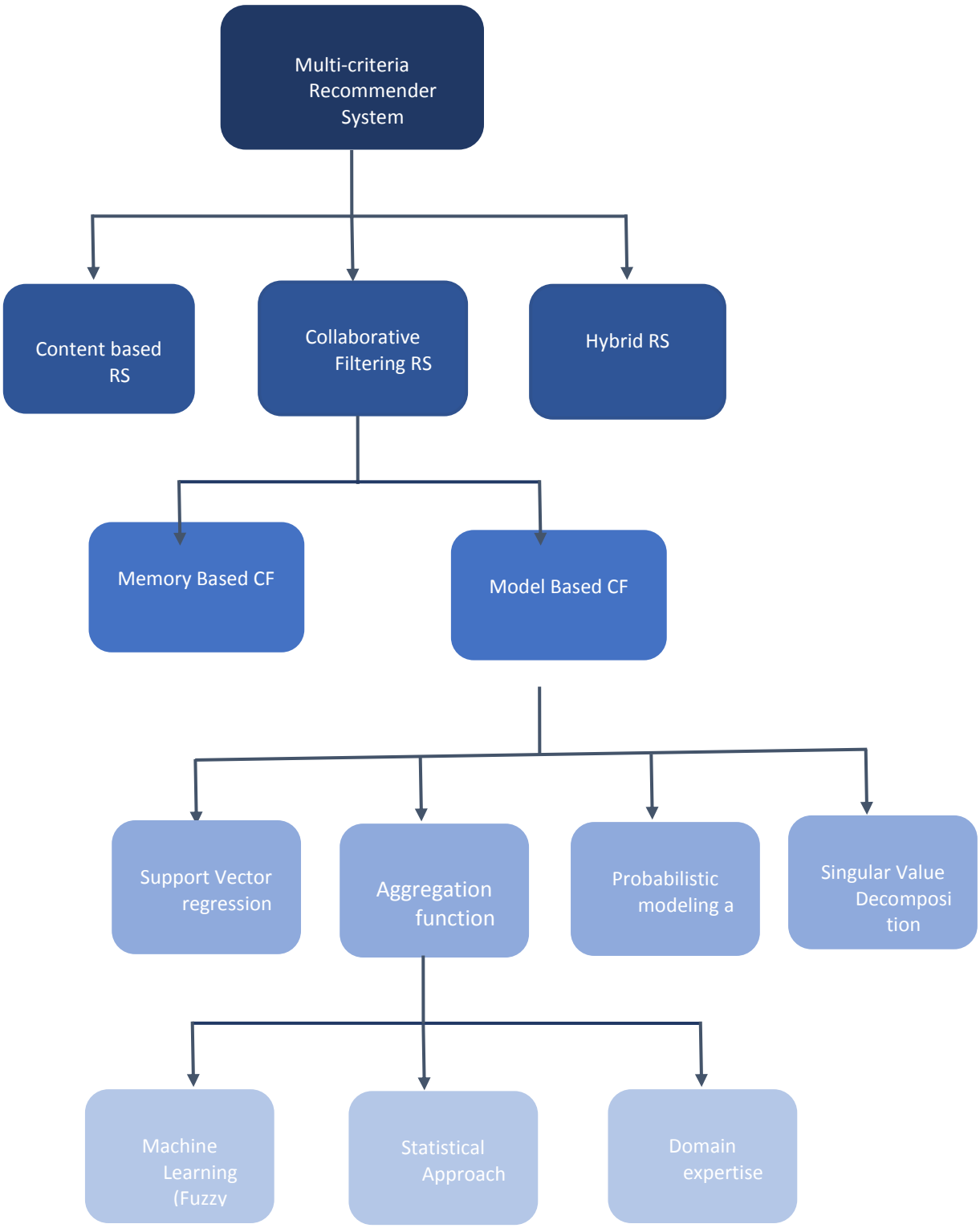


Figure 3.1 General Structure of Multi-criteria Recommender System

3.5 The Proposed System framework

To build the proposed MCRS using the aggregation function approach typically involves 4 basic steps as shown in fig 3.2. Step 2a involves decomposition of the k-dimensional ratings space into k-single rating space. At this stage, each problem is represented with a traditional user x item matrix. Step 2b estimates the unknown rating for each individual criterion using the proposed traditional recommendation technique (Asymmetric SVD). Step 3a and 3b, provides an estimation of the relationship f $0 = f(r_1, \dots, r_k)$ r between the overall rating and the multi-criteria ratings of items.

An appropriate aggregation function should be chosen to act on the k-dimensional ratings to estimate the relationship f. Our aggregation function f, was obtained using the proposed fuzzy logic machine learning technique. Then at step 4, we integrated the predicted rating computed with the traditional rating in step 2b together with the obtained aggregation function in step 3b to compute the unknown overall rating and thus provide the top -N recommendations in step 4. Fig 3.2 illustrates the basic steps involved in building an aggregation function based system.

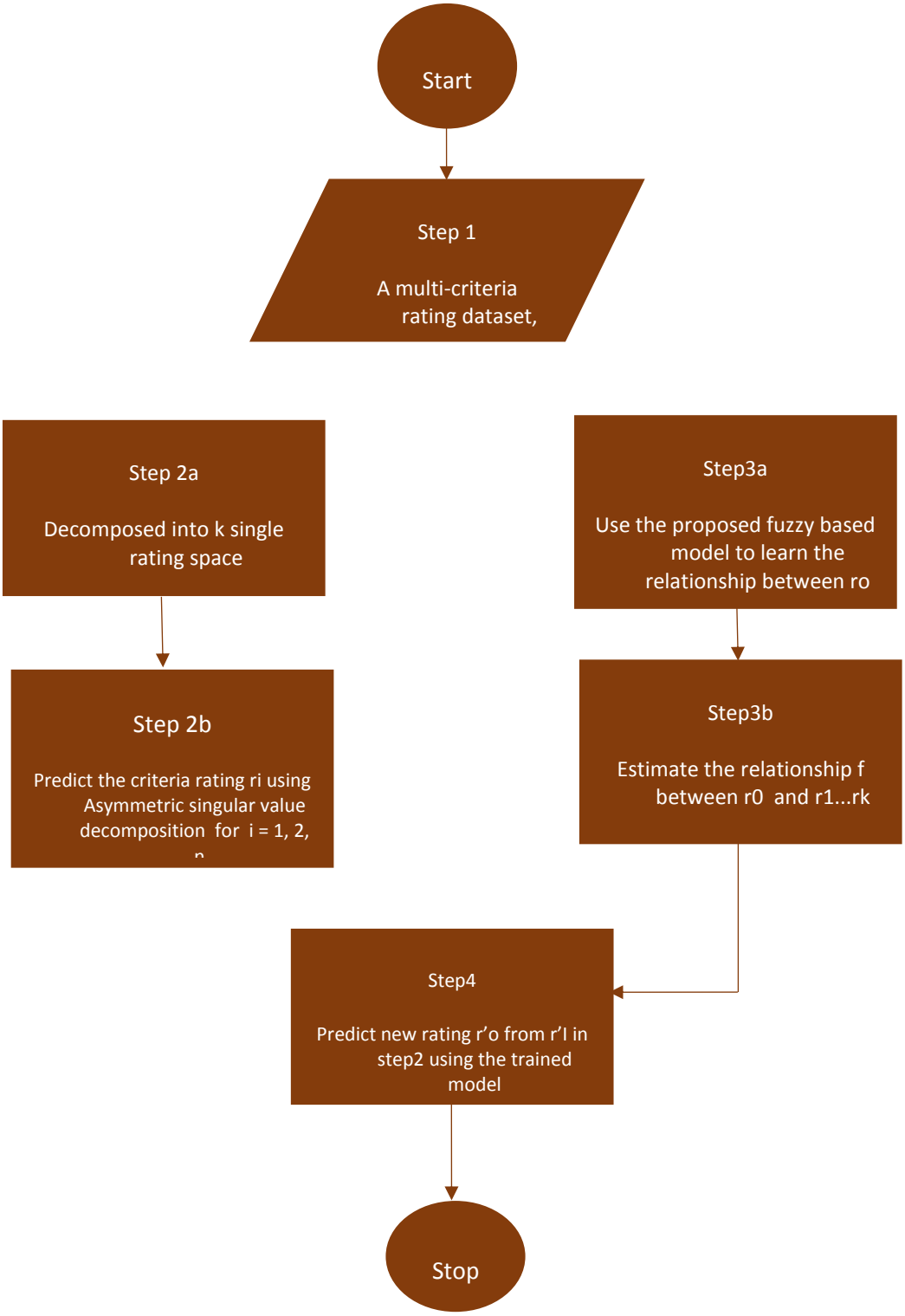


Figure 3.2: Framework of the aggregation function Multi-Criteria Recommender System

3.5.1 General Algorithm for the Proposed System:

Input data: Yahoo movie multi-criteria data set

Output: Accurate prediction and recommendation to the active users.

1. *Start*
2. ***First Phase:*** *Multicriteria dataset preprocessing*

a. *Preprocessing of dataset to detect and to remove inconsistency in the datasets*
b. *Subsequent filtering to remove users with less than five rated movies*

R(user X items) = $(R_0, R_1, \ldots, R_k)$.

3. ***Second Phase:*** *Generating the Aggregation function*
4. ***Step1: Predict the multi-criteria ratings***

a. *Decompose the k-multicriteria ratings into single criterion ratings*

$$R: User \times Items \rightarrow Ro \times R_1 \times, \ldots, \times R_k$$
$$R: User \times Items \rightarrow Rc(c = 1,2, \ldots, k)$$

b. *Use Collaborative filtering technique to predict each unknown ratings Ri.*

5. ***Step2: Learn the function***

a. *Use the fuzzy logic technique to learn the relationship between the output and input in order to generate f.*
b. *Estimate the relationship f such that* $Ro = f(R_1, R_2, \ldots., R_k)$

6. ***Step3: Predict the Overall rating***

a. *Predict the overall ratings using the predicted criterion rating Rc and the estimated appropriate relationship f.*
b. *Compute the overall rating* $R'o = f(R'_1, R'_2, \ldots., R'_k)$

7. ***Third Phase: Recommendation***
8. *Step1: Recommend items to active users.*
9. *Stop.*

The algorithm presented in section 3.5.1 summarizes the basic steps we followed in implementing the proposed system. It is basically structured into 3 phases. The first phase involves the multi-criteria datasets pre-processing. Our experimental datasets obtained from the yahoo movie site, contained some inconsistencies as at the time of extraction of these datasets, therefore, pre-processing was done to remove inconsistencies from the datasets. The second phase involves obtaining the aggregation function, which was done by following the steps explained in section 3.5, also, see fig 3.2. The third phase involves providing the top-N recommendations to the target user based on the strength of the corresponding r'_0 of the items computed in phase 2.

From the architectural framework shown in Figure 3.2 and the general algorithm presented in section 3.5.1 for the system implementation, the three models implemented are listed below:

(a) Traditional RS was built using the proposed Asymmetric Singular Value Decomposition to learn and predict the unknown decomposed k-dimensional ratings from the datasets

(b) A fuzzy logic MCRS was implemented and trained with the datasets to learn the relationship f between criteria ratings and the overall rating

(c) Integration of the fuzzy MCRS with the traditional technique to obtain the overall prediction r'0.

3.5.2 Multi-Criteria rating decomposition

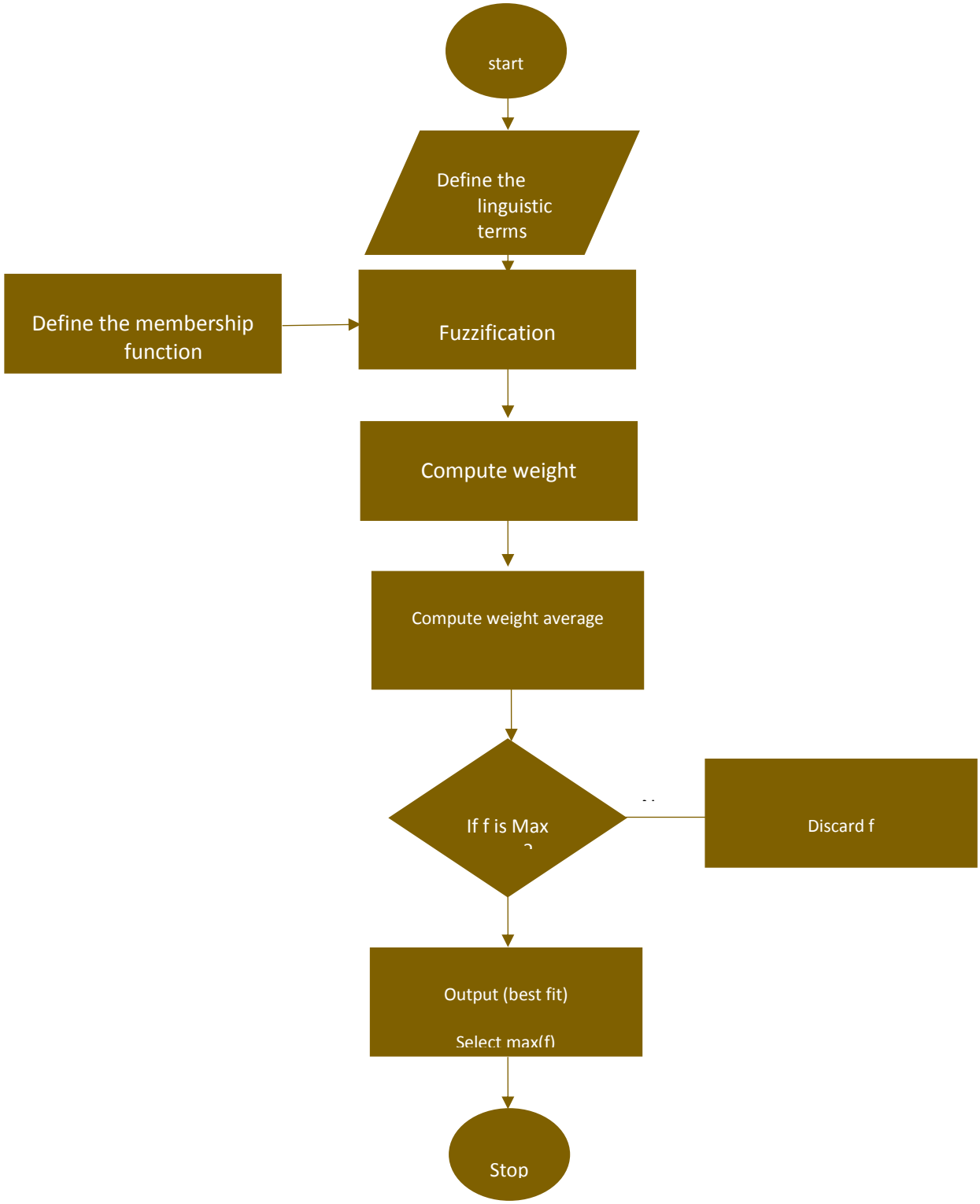
Multi-Criteria decomposition involves the disintegration of k-dimensional multi-criteria rating space $R: Users \times Items \rightarrow Ro \times R_1 \times \ldots \times Rk$where (i = 1,…,k) into k single-rating recommendation problems $R: User \times Item \rightarrow R_c (c = 1,2, \ldots k)$.This is done in order to obtain information on the behaviour of users with respect to each feature of the item. The proposed Asymmetric SVD learns and predicts the criteria ratings for new items. Note that the overall rating is not considered here.

3.5.3 Learning the Function

In order to estimate the relationship *f* between the overall rating and the underlying multi-criteria ratings of items, the datasets were separated by removing the overall rating and working with only the four criteria rating (r_1, r_2,r_3,r_4) with the User ID, this was done to train the fuzzy based MCRS to identify the relationship f between the criteria ratings and r_0 as shown $r_0 = f(r_1, \ldots, r_k)$.

Fuzzy based algorithm was mainly used here to determine the degree to which an item satisfied a user. The success of fuzzy systems in recommender systems is usually associated with its efficiency in modelling of users' preference using linguistic terms. Figure 3.3 presents the summary of how the fuzzy system works.

Figure 3.3: Flowchart of the fuzzy logic model



As shown in fig. 3.3, the process starts by fuzzifying user's preferences into linguistic terms such as (high, medium low, etc.) as shown in Figure 3.4 and Table 3.1 Triangular Membership function is special class of Fuzzy Number whose membership function is defined by the real numbers expressed as (a, b, c) as shown:

$$f(a,b,c) = \begin{cases} 0, for x \leq a \\ \frac{x-a}{b-a} for a \leq x \leq b \\ \frac{c-x}{c-b} for b \leq x \leq x \\ 0 for x > c \end{cases}$$

The criteria rating, which is measured in 13- fold scale as shown in Table 3.1, was used to determine the interests of users in the domain of story, action, direction and visual. Therefore, we have a membership function defined by 13 linguistic terms (see Table 3.1) to diversify the user interest and to determine the degree to which each criterion is chosen. We then compute weight to determine the degree of membership of each criterion from the membership function using equation (4) below:

$$w_i = \frac{R_i}{n} \qquad (4)$$

Where, $R_i = user rating for each item$

$n = total number of fuzzy lingusitic value$

Note that the weighting of each criterion was estimated by dividing each preference rating by the total of the fuzzy number i.e. (13). Our main goal here is to estimate the relationship f, therefore the relationship f, is defined by the equation (5) below:

$$f\left(x_u^j\right) = \frac{\sum_{i=1}^{n} w_i \, c_i}{\sum_{i=1}^{n} c_i} \qquad (5)$$

Where:

C_i = user's criteria ratings (i=1, 2,...,n)

W_i=weight attached to each criteria rating (for $i = 1, 2,...,n$)

$$f(x_u) = max\{f(x_u^j)\} \quad (6)$$

Fuzzy logic algorithm was employed here, to present mainly the degree to which a user attached much preference to a specific feature of an item, however, after computing the function f for each user criteria rating, a selection process is carried out in order to select the function that has the highest weight (degree of membership). The criteria ratings that produces the highest weight for user u, for j ratings (j = 1, 2, 3,…n) are chosen to be the best fit and preference for the user as shown in equation 6.

Table 3.1: Linguistic terms and its respective membership function

Criteria Number	TFN	Linguistic terms
1	(0 1 2)	VVVVlow
2	(1 2 3)	VVVlow
3	(2 3 4)	VVlow
4	(3 4 5)	Vlow
5	(4 5 6)	Low
6	(5 6 7)	Medium low
7	(6 7 8)	Medium
8	(7 8 9)	Medium high

9	(8 9 10)	High
10	(9 10 11)	V high
11	(10 11 12)	VVhigh
12	(11 12 13)	VVVhigh
13	(12 13 14)	VVVVhigh

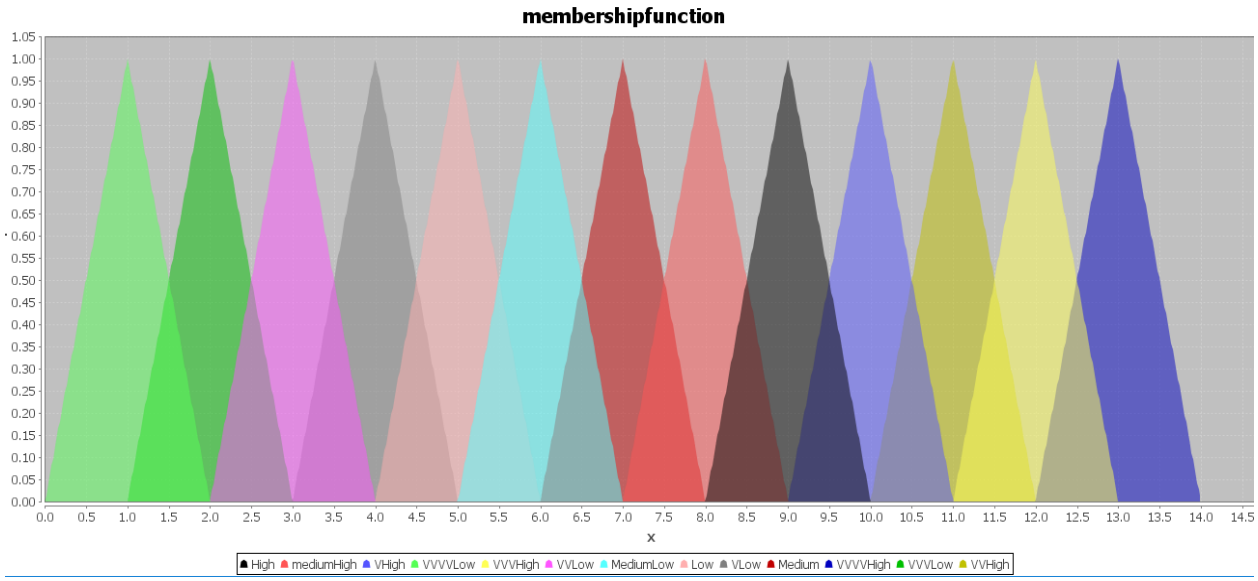


Figure 3.4: Graphical representation of a membership function

3.5.4 Predicting the overall rating:

The model predicts the overall rating $r'_o = f(r'_1, r'_2, \ldots, r'_k)$, for the active user u_a, by combining the trained fuzzy MCRS and the single rating technique (Asymmetric SVD) to provide the top-N recommendation to user u_a. Therefore, to compute the overall rating for the user u_a, we use the weighted sum defined in equation (7)

$$r'_i = \left(\sum_{i=1}^{n} \frac{w'_i \times P'_i}{w'_i}\right) \qquad (7)$$

Where:

W_i = selected weight for the user u_a for item i

P_i = Predicted rating for the user u_a for the item, i.

CHAPTER FOUR
IMPLEMENTATION

This Chapter presents how the proposed system was modelled and simulated, it discussed the datasets used, the programming language used as well as the different evaluation metrics used to measure the prediction accuracy of the system, the experiment carried out and the results of the experiments.

4.1 Implementation of the Proposed System

To implement the proposed system using the framework presented in chapter 3, Java was chosen as the programming language to implement all the systems used for this study. Java was chosen because it is a general-purpose computer programming language that is concurrent, class-based, object-oriented with richness in fuzzy logic library, which enhanced the speed of the implementation of this project. Java is one of the most popular programming languages used to create Web and other applications and platforms, it is well known for its flexibility that allows developers to write code that would run on any machine, regardless of architecture or platform.

The system was built by integrating the Aggregation function based RS and the traditional Asymmetric SVD. The test data was selected using a 10-fold cross validation rule which is the most popularly used selection rule. Cross-validation is one of the techniques employed in evaluating Machine Learning (ML) models through training several ML models on subsets of the available input data and evaluating them on the corresponding subset of the data. The reason behind the choice of cross-validation rule was to enable more data in the ranking algorithm to be used and its high considerations on the effect of the variation in the training set.

4.2 Experimental dataset and setup

To evaluate the proposed system, a set of users submitted ratings which were collected from the Yahoo Movie Recommender System. It is a multi-criteria dataset where preference ratings on movies was provided by users based on four different movie aspects viz., the direction (c1), action (c2), story (c3), and visual (c4) effect of the movie. Ratings of each criterion were measured on a 13-fold scale which ranges from F through A^+. F represents the lowest preference while A+ represents the highest preference. In addition to the criteria ratings, an overall rating (c_0) that measures the final level of users' satisfaction on movies was also contained within the dataset. For easy modelling of the system using these data findings, the rating scale was changed into a numerical rating. The user rating F and A^+ was transformed to 1 and 13 respectively. Table 4.1 displays the sample of the dataset extracted directly from Yahoo! Movies website that contains the alphabetical user ratings.

Table 4.1: Sample of user ratings in yahoo movie RS before conversion

User ID	C1	C2	C3	C4	Overall rating	Movie ID
10	A^+	A^+	A^+	A	A^+	52
	C^-	A	B^-	B	C^-	262
	C	B	B	C	C	289
	A	A	A	B	B^+	682
11	A^+	B^+	A	A^-	A	230
	A	B^+	B^+	A^+	A^-	296
	A^+	A	A^+	A^+	A^+	318
	B	A^+	A	A	A^+	69

14	C^+	B^-	C^+	C^-	C	163
	B^-	B^+	B^+	B^+	B^+	381
	C^-	B^-	B^-	C^+	C^-	434
	B^+	A	A	A	A	465

Moreover, in order to detect and remove variations from the dataset and to improve its quality, the dataset was cleaned to eliminate cases of missing ratings for at least one of the four criteria and the overall ratings. In addition, in order to ensure that an adequate set of evaluated items for each user was collected and analysed, the cleaning process was again applied to remove users who rated less than five movies. At the end, the dataset contained a total of 6078 users and 976 movies which gave a total of 62,156 ratings, with the total sparsity estimates as 0.0105, with the following estimates 9.5221, 11.0000, 3.5232, realized as the global average, global median and standard deviation respectively from the dataset. Table 4.2 shows the user ratings extracted from the yahoo movies dataset after conversion.

Table 4.2: Sample of user rating matrix after conversion

User ID	C1	C2	C3	C4	Overall rating	Movie ID
10	13	13	13	11	13	52
	5	11	8	9	5	262
	6	9	9	6	6	289
	11	12	12	9	10	682
11	13	10	12	11	10	230
	12	10	10	13	11	296
	13	11	13	13	13	318

	9	13	12	12	13	69
14	7	8	7	5	6	163
	8	10	10	10	10	381
	5	8	8	7	5	434
	10	11	11	12	11	465

Furthermore, to analyse the frequency of each rating value (1 through 13), the dataset was divided into five distinct portions (the four criteria rating and the overall rating) comprising the UserID, movieID and value. Table 4.3 shows the summary of the basic statistics of the rating values by computing the number of times each value appears in the dataset, the approximate percentage, and cumulative percentage rounded to the nearest whole numbers.

Table 4.3: Ratings frequency of the user x item in yahoo movie datasets

Value	Frequency.	Percentage	Cum. Percentage
1.0	3395	5%	5%
2.0	1340	2%	8%
3.0	1522	2%	10%
4.0	1329	2%	12%
5.0	2051	3%	16%
6.0	2428	4%	19%
7.0	2489	4%	23%
8.0	3251	5%	29%
9.0	5586	9%	38%

10.0	7006	11%	49%
11.0	6702	11%	60%
12.0	12153	20%	79%
13.0	12904	21%	100%

4.3 The Evaluation metrics

In order to measure the prediction accuracy of the proposed system, we used the three broad classes of prediction accuracy measures as described below:

1. Measuring the accuracy rating predictions: we used two rating techniques to measure the accuracy of the system's predicted ratings, Mean Average Error (MAE), Root mean Squared Error (RMSE).

(a) Root Mean Square Error: RMSE is popularly used evaluation metric used to evaluate the accuracy of the predicted ratings. It is defined by the equation below:

$$-r_{ui}$$
$$\hat{p}_{ui}$$

$$\frac{i}{T_s \vee} \sum_{(u,i)\epsilon T_s} \qquad (8)$$

$$RMSE = \sqrt{}$$

(a) Mean Average Error (MAE): it is defined as, see equation (8) below:

$$MAE = \frac{1}{T_s} \sum_{(u,i)\epsilon T_s} |\hat{p}_{ui} - \hat{r}_{ui}| \qquad (9)$$

Where $T_s = theTestsetsofuseritempairs(u, i)$

$\hat{p}_{ui} = thepredictedratinggeneratedbythesystem$

$r_{ui} = theactualratingoftheuser$

2. Measuring the accuracy of the usage prediction: Here, we want to evaluate how accurate the system properly predicts that the user will add the movie to their content list or perhaps watch the movie later. We used recall for top-10 recommendation defined as:

$$recall = \frac{\#tp}{\#tp + \#fn} \tag{10}$$

$$where, \# \ tp = numberoftruepositiveusefulitems$$

$$\# \ fn = numberofusefulpredictionsthatarenot \in thetop - nrecommendationlist$$

3. Measuring the ranking accuracy of the prediction: This accuracy measure tends to evaluate the ordering of the recommended items according to the user's preference. We used three approaches such as (i) Area under the curve of receiver Operating Characteristics (ROCAUC), (ii) Fraction of Concordant Pairs (FCP), (iii) Normalized Discounted Cumulative Gain (NDCG).

(a) $$ACU = \frac{1}{N} \sum_{i=1}^{\#tp_u} \left(\left| + \frac{tp+1}{2} \right] \right. rank_{uj}^{+} \tag{11}$$

$where, rank_{uj}^{+}$ = position of the kth relevant item on the top-N recommendation

(b) $$FCP = \frac{n_c}{n_c + n_d} \tag{12}$$

$where, n_c = numberofconcordantpairsdefinedas$:

$$n_c = \sum_{u \epsilon U} |(i,j)| \{\hat{r}_{ui} > \hat{r}_{uj} \Longrightarrow \hat{r}_{ui} > \hat{r}_{uj}\} \tag{12a}$$

$where, n_c = numberofcorrespondingdiscordantdefinedas$:

$$n_d = \sum_{u \epsilon U} |(i,j)| \{\hat{r}_{ui} > \hat{r}_{uj} \Longrightarrow \hat{r}_{ui} \leq \hat{r}_{uj}\} \tag{12b}$$

- $NDCG = \frac{rel_1 + \sum_2^N \frac{rel_k}{log_2 k}}{rel_1 + \sum_2^{tp_u} \frac{rel_k}{log_2 k}}$ (13)
- rel_1 takes 1 if position of k is relevant or 0 if otherwise
- log_2^k = free parameter between 2 & 10

4.4 Results and Discussion

For us to compare the proposed MCRSs with the corresponding traditional single rating techniques built, several experiments were carried out to ensure the accuracy of the proposed MCRS. Hence, this section presents the basic experiment done and the discussion of the results obtained from the experiments.

4.4.1 Experiment

To prove the accuracy and efficiency of the proposed system, a series of experiments was carried out using the Yahoo! Movie dataset. The proposed system was tested using the offline experiments to simulate the interactions of real users with the real systems before the systems could predict the user preferences and then make recommendations. The simulation was done by recording the interactions between the users and the systems using datasets obtained from the yahoo movie site and hiding some of the interactions (test data) to assess how users would rate some items and measure the degree of satisfaction of the recommendations proposed by the system.

The proposed system was compared with the traditional collaborative filtering techniques (Asy SVD) that was described in chapter three. The test was carried out using 10-fold cross validation rule, and in order to analyse the prediction performance of the two techniques, we used the evaluation metric described earlier in section 4.3 viz:

Fraction of concordant pair (FCP), Area Under the Curve Receiver Operating Character (ROCAUC), Normalized Discounted Cumulative Gain (NDCG), Mean Average Error (MAE), Root Mean Square Error (RMSE) and recall for top-N recommendation. From Table 4.4, the two techniques are named as AsySVD and MCRS to represent the proposed Asymmetric SVD and Asymmetric MCRSs respectively, the results of the evaluation of their predictive performance are presented in Table 4.4

Table 4.4: Summary of Result of the Evaluation

	RMSE	MAE	NDCG	ROCAUC	FCP	Recall
Asy SVD	3.0895	2.4677	0.9830	0.6986	0.7118	0.9992
MCRS	2.4176	1.8753	0.9978	0.9558	0.9467	0.9998

It can also be seen from Table 4.4 that the proposed MCRS resulted in lower prediction error in RMSE and MAE when compared to the traditional AsySVD, in the same vein, NDCG, ROCAUC and FCP has higher usage accuracy level than the AsySVD. Consequently, Table 4.5 also shows the arithmetic differences in accuracies between the Fuzzy based MCRS and the traditional (single rating) System. Table 4.5 shows the decrease in RMSE and MAE and increase in AUC, NDCG, FCP and recall which significantly proved the positive performance of Fuzzy based MCRS.

Table 4.5, Level of accuracy improvement between Fuzzy MCRS and AsySVD

$\overset{-}{\Delta RMSE}$	$\overset{-}{\Delta MAE}$	$\overset{+}{\Delta NDCG}$	$\overset{+}{\Delta ROCAUC}$	$\overset{+}{\Delta FCP}$	$\overset{+}{\Delta Recall}$
0.6719	0.5924	0.0148	0.2572	0.2349	0.0006

In addition, The symbol **"- "** in $\overset{-}{\Delta RMSE}$, $\overset{-}{\Delta MAE}$ indicates reduction in RMSE and MAE between MCRS and the AsySVD whereas the symbol **"+"** in $\overset{+}{+, \Delta Recall}$ $+, \Delta FCP$ $\Delta ROCAUC$ indicate increase in ranking and usage predictions accuracy between MCRS and the AsySVD. The chart in fig 4.1 also shows the relationship between the proposed fuzzy MCRS and AsySVD, which concisely summarizes the decrease in RMSE and MAE in MCRS, and increase in usage prediction and ranking accuracy of the MCRS.

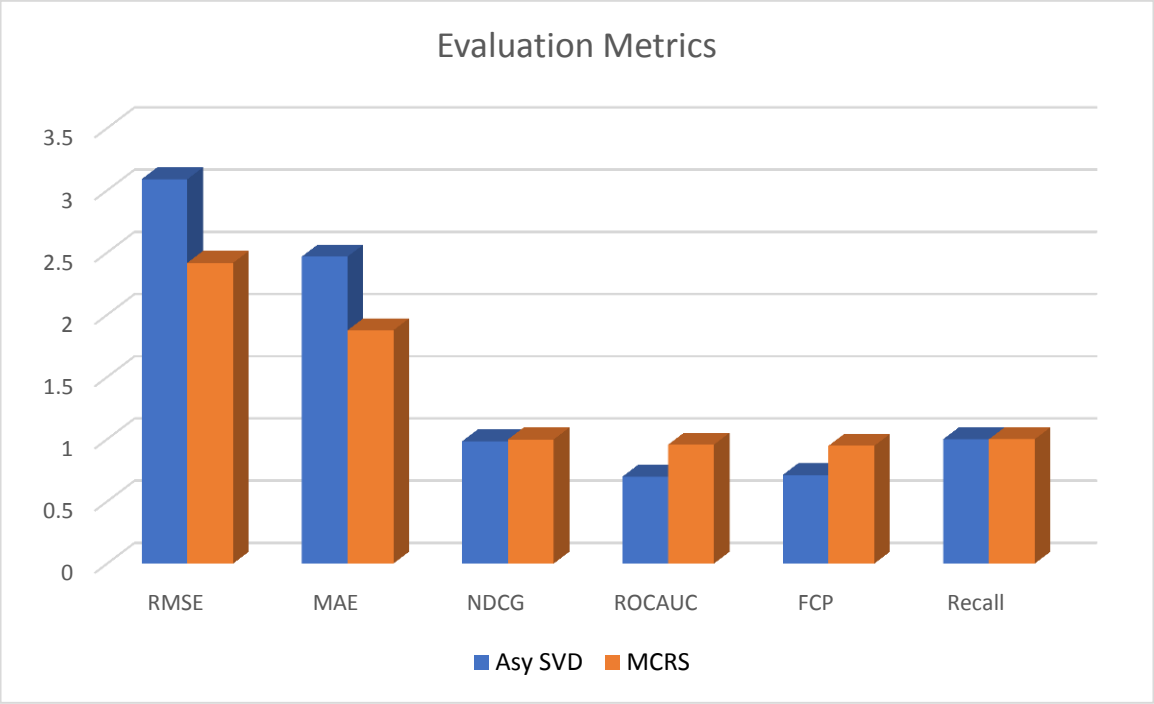


Figure 4.1: Chart to show the relationship between AsySVD and MCRS

In summary, it can be clearly seen that the resulting RMSE, MAE, NDCG, AUC, FCP, and Recall, confirmed that the proposed Multi-Criteria aggregation function model built with fuzzy logic algorithm are more accurate than their corresponding traditional single rating algorithms.

CHAPTER FIVE
CONCLUSION

This chapter presents the summary of all the work conducted during this research, the contributions made as well as suggestions for future work in this subject matter.

5.1 Conclusion

Recommender System (RS) is well known for its great contribution in e-commerce and decision making. They are software tools and techniques that provides users with suggestions for items that are most likely to be of interest to them. RS makes these suggestions based on the implicit or explicit user feedback or rating submitted by the user in the form of transaction log that describes the amount of satisfaction they derived from an item. User ratings in RS might be in single rating, or multi-criteria rating, the single rating RS also known as traditional RS is an RS that determines the right item to direct to users using single rating techniques, whereas Multi-Criteria RS uses several features of an item to predict an item that a user might like. The main goal of this thesis was to improve the prediction accuracy of the system; a goal which was achieved by adopting the model based approach. This Collaborative Filtering technique uses prior activities or history of the users to learn the predictive model, and uses the aggregation function to determine the relationship between the overall rating and the criteria rating. To obtain the aggregation function f, we applied fuzzy logic features as the machine learning technique. Fuzzy logic is a model of reasoning that resembles human reasoning. With all these put together we built two RS, a single rating Recommender System using Asymmetric Singular Value Decomposition and a multi-criteria RS using fuzzy logic integrated with Asymmetric SVD. The dataset obtained from the Yahoo movie site is defined as ratings provided by users on four different rating aspects; story, direction, action and visual.

The test data was selected on a 10-fold cross validation and offline experiments were conducted to simulate the interactions of real users with the real-world system, while different evaluation metrics were used to measure the prediction of the proposed system and the traditional RS to determine the RS that can provide better prediction accuracy under the same circumstance. The results from these experiments showed that the proposed Fuzzy based MCRS provided the highest accuracy compared to the single rating Asymmetric SVD technique used. From indication, this study proposes that using Fuzzy logic together with single-rating technique built with Asymmetric SVD proved to be the best way to model an MCRS.

5.2 Challenges

During this research, many a challenge was encountered. However, we strategized different means to surmount these underlying challenges. Among some of these challenges are:

Time constraint: Research is usually time consuming, this is because of the optimal need for the thoroughness at all stages of the research process, hence, a lot of hard work was applied to manage the limited timeframe and meet the deadline without compromising the quality of the research.

Insufficient material: Sourcing for research materials for this thesis was challenging because of the practical nature of our work, very limited amount of resources was available both in the library and on the internet, but we made maximum use of the resources we had which finally lead to the success of this work.

5.3 Future work

Although the fuzzy based approach used improved the prediction accuracy of the system, there is still a need to incorporate other features and techniques that can enhance the efficiency and precision of MCRS. In our work, we focused more on using the linguistic terms to model the user preferences, there is however still a need to consider incorporating the user mood, climatic and seasonal conditions as part of the criteria to which an item would be recommended. We also suggest applying other machine learning techniques such as combining Adaptive Genetic algorithm and Fuzzy logic, artificial neural network and fuzzy logic, Bayesian deep learning and Convolutional Neural Network on different datasets to enhance the prediction accuracy in modelling a MCRS.

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