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Measuring Uncertainty to Extract Fuzzy Membership Functions in Recommender Systems

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Abstract: Nowadays, due to the high volume of choices for customers which causes confusion, the use of recommender systems is strongly growing. Of course, existing systems have two problems, one is complexity and the other is failure to consider uncertainty. In this article, we have reduced the complexity of the system by using a fuzzy innovative system and solved the problem of the uncertainty of users' ratings regarding goods. For that purpose, this research attempts to extract fuzzy membership functions from the Yahoo movie dataset for recommendation applications. In the proposed method, a type I fuzzy system with low numbers of membership functions is designed. The uncertainty in users' ratings is handled by clustering users and movies. Moreover, repeated user evaluations of the same movies are used to determine the uncertainty in improved type 1 membership functions. To evaluate the proposed strategy, MAE, confusion matrix, and Classification-report are used. The result demonstrates the superiority of the introduced strategy.

Keywords: Recommender Systems, Uncertainty, Fuzzy Rating, Membership Function Extraction

Introduction

A recommender system is a method for filtering data gathered from internet users to carry out two fundamental tasks: First, predicting user ratings; second, recommending a new item for them that they have not previously studied (Xue *et al*., 2019) Analysts have become interested in the RS in recent years and they have created a number of recommendation models with the same objective of helping both the client and the service provider organization and resolving the issue of data overload. The collaborative filtering approach, which makes recommendations to customers based on the preferences of other users, is one of the most frequently used methods to build an RS (Dogan, 2023). Making a trustworthy forecast for a target user using concepts similar to their own is the most important stage in CF. CF typically employs a two-step process: First, it searches for customers with comparable ratings and then uses those ratings to generate a suggestion for the new consumer. It takes a unique approach to get a high-accuracy proposal. Using multi-criteria ratings is one example. However, using many criteria to rate a huge dataset can complicate the processing (Acharya and Das, 2023). Take the Yahoo movie databases, for instance, which have a rating matrix where users may score films based on the title, director, genre, and so on. This makes the dataset larger since it makes the data more dimensional. Some investigations, such as those by Marzuki and Tee (2014); Aminifar and Marzuki (2012) used fuzzy system for signal processing, and Taha and Aminifar (2022), used k-means clustering to find comparable users, while others used k-nearest neighbors and k-means clustering. We included a novel two-step processing mechanism in our suggested method. We begin by incorporating the super-sub clustering strategy. This study's major goal was to:

1. How to build a model using a large dataset with minimum processing complexity
2. How to reduce search space while recommending a new item to the user
3. How to enhance the performance of our model and recommend an item considering users' rating uncertainty

Employing a large dataset in RS has its benefits, such as acquiring more information with higher accuracy results. However, processing a large dataset causes processing complexity and is time-consuming. To achieve our goal, after applying the fuzzy C means clustering method and assigning each user to its nearest class, the Alfa cut technique has been applied to the sub-cluster supercluster. The sub-clustering method achieves two objectives:

- Decreasing the search area and thus, the search time
- Users who are remarkably similar to one another are grouped together, thus reducing the dissimilarity across users within the same cluster

(1) In the second phase of this study, the top N nearest users to new active users who have rated at least one movie were found using the multinomial logistic regression as a classification model with various distance indicators, such as Euclidean distance indicators.

Proposed Model

The main aim of this study is to present a new method for measuring uncertainty in user ratings in order to extract different membership functions in order to have a certain recommendation for a new user. The key issue in this scenario is how to create membership functions that are consistent with linguistic expressions and result in an output recommendation sphere that can recommend the right things. (In this case movies) so that we get better user satisfaction and less wasting of time.

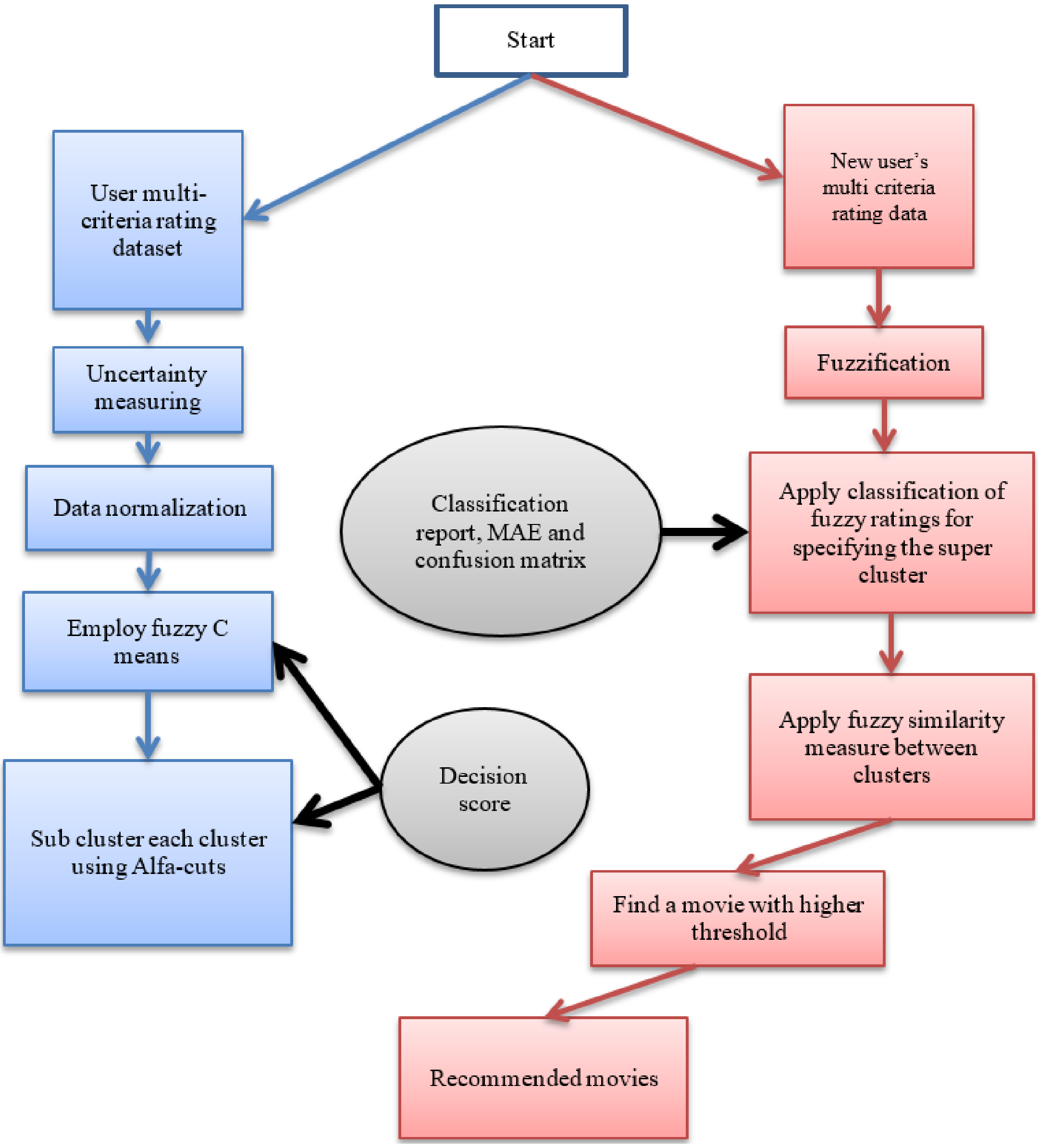

Fig. 1: Fuzzy-based movie recommender system block diagram

The structure in Fig. 1 is utilized in recommender systems for the two main goals of user pleasure and time efficiency, both of which are critical in the recommending process. Figure 1 depicts a recommender system that utilizes speculative user rating data. The recommendation system, which has a high degree of nonlinearity Cao and Li (2007), also requires user evaluation in a variety of situations where the parameters fluctuate and are uncertain Aminifar and Marzuki (2013a). In order to handle a system with such high nonlinearity and difficulty to model it using conventional techniques, this research involves extracting membership functions in order to apply enhanced membership functions Aminifar (2020).

The method of our modeling of users' behavior here is under base of redundancy of ratings for extracting the special type 1 fuzzy membership functions Hamad *et al*. (2020). Based on the information that we have about user recommending criteria, it must follow a specific curve or specific area for each type of user Jader and Aminifar (2022). For these implementations, we used a special case in recommending systems Aminifar and Bin Marzuki (2013b).

For our case study, in the recommending system the rating should start from a cold rating and then ratings go up linearly up to 95 times during a specific period. After that, it must stay in the ratings around the last seen movies for 15 times Jader *et al*. (2022).

According to Fig. 2, the idea of uncertainty in fuzzy systems is interpreted in a novel way. In contrast to traditional Type-1 (T1) fuzzy systems, which are depicted in Fig. 2 and discussed in more detail in Aminifar and Yosefi (2007) this research takes into account the presence of uncertainty injectors and removers. These two blocks are absent from T1 fuzzy systems in comparison to the suggested fuzzy system Jader and Aminifar (2023).

Uncertainty of User's Ratings

The recommender system which is our proposed system has one input as a fuzzy evaluated rate of users' satisfaction. An auto-rating input is available for an online rating of users. Sources of uncertainty in the system are as follows.

The first rating of the user can never be absolute because the user's hepatise is affected by another experiment and its taste is stabilized over time. However due to all environmental and systematic conditions used to stabilize the user rating, whenever measuring the user rating using more redundancy, we can see fluctuations around the first rating. These variable fluctuations affect the next recommendations. Depending on the recommending system, sometimes these fluctuations may make wrong recommendations. One of the uncertainty sources originated from non-rating cases and sparse data problems. If rating times go higher then the averaging is done to settle down the overfitting.

Since the movie types are of different types, i.e., the combination and the percentage of tiny components are never the same, the rate of satisfaction by the users is not the same even for seemingly identical movies. This also affects the function of the recommendation.

The rating even for the same user has a small hysteresis. If the hysteresis is as much as it is identified as a hysteresis range, we cannot consider uncertainty for this user. Here we mean the inherent and minor hysteresis available in most user ratings.

Users' ratings, due to their voting circumstances, have both noise and variable delay. Ratings in the same circumstances are different. The difference is the low and variable.

Collaborative Filtering

A popular machine-learning technique for producing predictions and suggestions based on system users who share similar likes is collaborative filtering Aminifar *et al*. (2018). By combining notions that are comparable to each new user's own, CFRS aims to help them find an accurate prediction. The CF typically completes two steps: Finding users with ratings comparable to those of the newly active user first and then using those ratings to provide suggestions for the newly active user Karthik and Ganapathy (2021). The CF utilizes a cosine, Pearson correlation coefficient, and Euclidean distance, among other indicators, to determine user similarity.

Dataset

The Yahoo movie dataset, which consists of two files (movies and ratings) and includes 1,000 multi-criteria ratings from webscop@verizonmedia.com, is the basis for all analyses. Table 1 provides an overview of the dataset along with some statistical data.

As we know, employing large datasets, that have high dimensional features has its benefits, such as acquiring more information and achieving higher accuracy results than using a small dataset, especially in RS. Using multi aspects rating of items will help the scientist to discover a user favorite more realistically. However, time consumption and complexity problems occur while processing such large datasets. Additionally, it is difficult to visualize high-dimensional datasets Serrano-Guerrero *et al*. (2011).

Table 1: Summary of used dataset

Rows present	100867
How many people rated	610.000000
Number of films	9742.000000
Rating range	0-5
The typical number of movies each user has rated	25.000000
Row-column null count	1000.000000
The total number of user IDs	100836.000000

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We prepared our dataset based on our study strategy by deleting an unwanted column, checking null rows and columns, combining necessary information from both files and normalizing rating features.

Super-Sub Clustering Model

The obtained inertia values (sum of distance between each point in a dataset and its assigned cluster) with the same number of clusters as shown in Fig. 2 after calculating a distortion score for the original dataset and extracted feature dataset were quite different between them, with values of (125107.54698020557) and (4906.362764013522) for the original and extracted features dataset, respectively.

After the preparation approach, we conducted the fuzzy C means clustering approach as a super clustering phase to group those users who were similar. The next step was assigning each user to one of the predetermined centers by calculating the distance between centroids and each user using the Euclidean distance indicator.

The original dataset was clustered using the generated cluster labels and the subsequent step involved sub-clustering the supercluster using the Alfa cut technique.

Classification and Recommendation

We must decide which cluster in our supercluster model the newly active user who has rated at least one movie will belong to after constructing the super-sub cluster strategy. Based on the rated film, which alfa cut corresponds to new-active users? Which film ought to be suggested to the new user? Calculating the most comparable case in an alpha cut by comparing a new user's fuzzy similarity to the nearest alpha cut set was the best solution to this problem.

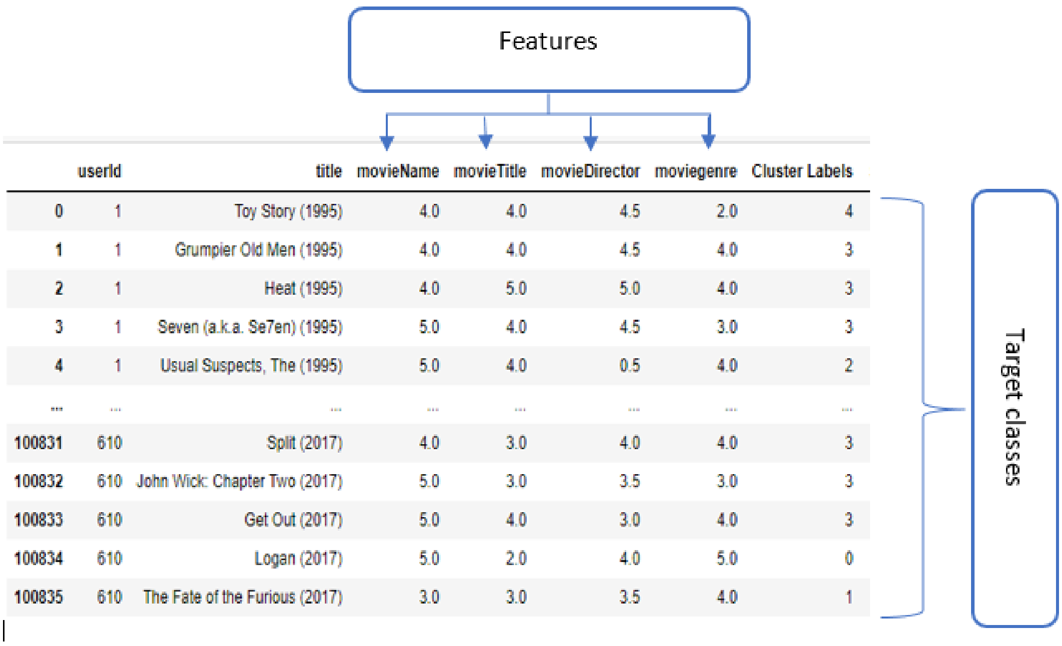
To predict a class, fuzzy similarity measurement will first compute the probability for each of the classes in the training phase and then make a prediction using the cross-entropy function.

The similarity measurement formula is shown in Eq. 1:

$$\cos\left(\boldsymbol{u}_x, \boldsymbol{u}_y\right) = \frac{\sum_{s_k \in S_{xy}} r_{x,k} r_{y,k}}{\sqrt{\sum_{s_k \in S_{xy}} r_{x,k}^2 \sum_{s_k \in S_{xy}} r_{y,k}^2}} \qquad (1)$$

The result of the fuzzy similarity measurement with the target one-hot encoding will be sent into the cross-entropy approach in the last stage of the models to produce a predicted class.

The cluster with the shortest distance will receive the new active user. Now, we calculated the Euclidean distance between the newly active user and each user in the same cluster in order to identify the top N comparable individuals. The new user will be suggested to watch movies with the highest threshold rating based on that information.



	userId	title	movieName	movieTitle	movieDirector	moviegenre	Cluster Labels
0	1	Toy Story (1995)	4.0	4.0	4.5	2.0	4
1	1	Grumpier Old Men (1995)	4.0	4.0	4.5	4.0	3
2	1	Heat (1995)	4.0	5.0	5.0	4.0	3
3	1	Seven (a.k.a. Se7en) (1995)	5.0	4.0	4.5	3.0	3
4	1	Usual Suspects, The (1995)	5.0	4.0	0.5	4.0	2
...	...	...	...	...	...	...	...
100831	610	Split (2017)	4.0	3.0	4.0	4.0	3
100832	610	John Wick: Chapter Two (2017)	5.0	3.0	3.5	3.0	3
100833	610	Get Out (2017)	5.0	4.0	3.0	4.0	3
100834	610	Logan (2017)	5.0	2.0	4.0	5.0	0
100835	610	The Fate of the Furious (2017)	3.0	3.0	3.5	4.0	1

Fig. 2: K-Means clustering result

The Measurement Platform

The major component of the platform that makes use of the extracted fuzzy membership function is a fuzzy controller that manages the behavior of the autoclave.

Here, according to the knowledge of the system based on the expert operators, the start point is considered as a type I fuzzy function in Fig. 3. In fact, this point is the start point for the design.

The ratings in the mentioned recommender system are considered as three symmetric T1MFs having 50% overlap with adjacent membership functions as shown in Fig. 3. The distance parameter, in alfa cut sub-clusters, is considered as five intervals. To select the T1FMs, we consider two points: 1- The start mode is considered symmetric with equal partitioning to be generalized to all similar problems. However, if we have more feasible and more information about the system, we can consider the slope of membership functions sides and the partitions otherwise. 2- We consider the number of membership functions small. Based on the sensitivity of the problem, we can consider more or less functions. The objective and the benefit are using fewer membership functions to be more consistent with linguistic descriptions Rutkowski *et al*. (2018).

The primary membership functions are considered as shown in Fig. 3. The next step is to extract modified T1MF based on several measurements of the system. Five equal and symmetric membership functions are assigned for distance. We will explain how to measure and extract modified T1MFs in the following.

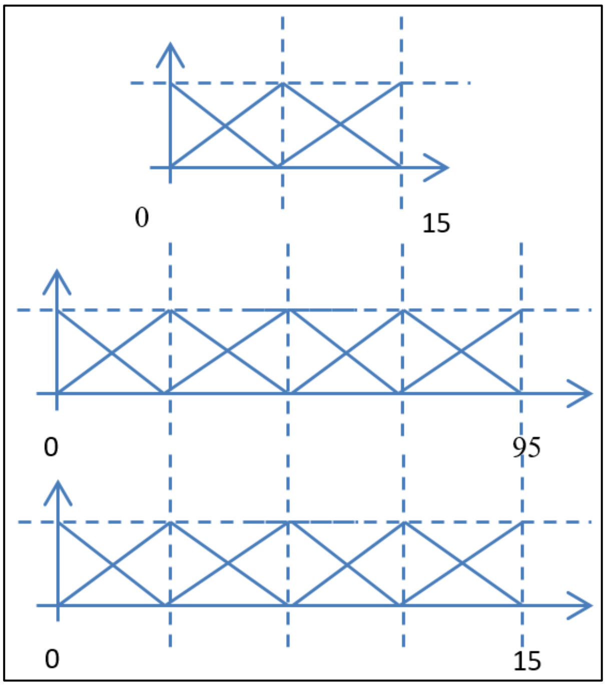


Fig. 3: The primary type 1 membership functions

Extracting Membership Functions

While type-1 fuzzy sets have been extensively studied for their ability to model uncertainty and have been demonstrated to produce acceptable results, interval type-2 fuzzy sets have recently been discovered to offer an even higher potential for modeling significant quantities of uncertainty (Terán and Meier, 2010; Yera and Martinez, 2017; Zhang *et al*., 2021; Sulthana and Ramasamy, 2019). One of the main challenges during the design of any fuzzy-based system (interval type-2) is the specification of the fuzzy Membership Functions (MFs). The choice of type of membership function (such as Gaussian, triangular, etc.) as well as the choice of their specific parameters strongly affects the performance of the fuzzy system. A variety of methods to alleviate this problem have been researched for mainly type-1 and interval type-2s. Such methods are generally based on the use of expert knowledge, evolutionary techniques (such as genetic algorithms), and neural networks (Walek and Fojtik, 2020; Logesh *et al*., 2020). To standardize and streamline the choice of suitable MFs, however, there is still significant work to be done.

Here, we discover the interval type 2 type 1 fuzzy MFs with type 1 membership functions that handle uncertainty.

The method used to implement modified T1MF is similar to the method specified in Aminifar *et al*. (2006). And the method specified by Khanal *et al*. (2020) is consistent more with T2-Z-slice applications. We present a new method for modified T1MF consistent with specifications of the present uncertainty in the recommender systems. Here, we will analytically describe the method.

Our aim is to extract the membership function based on information collected from users and their redundant evaluation of seen movies. To extract the membership function based on information collected from the users, different users are asked about rating the seen movies as low, medium, and high in order to design a type 1 fuzzy MF to extract decision scores. Then the results are analyzed. The problem with users rating seen movies in most similar conditions is often fail to describe their evaluation quantitatively. Now, if we intend to extract a T1FM for the volume of gas to be injected based on analysis of the data collected from an appropriate number of skilled drivers, the best way is to utilize a device to automatically measure and record the angle of the gas pedal while the driver acts. To recommend a movie to a new user that can be several times rated by several people, we should record the rates of users during a relatively long period and then use them to extract the T1FM.

This method uses the ratings at different times and conditions to create the histogram. The differences in various measurements in the same condition, besides the variable behavior of the user and the noise which is produced by outlier users are considered. This indicates that the uncertainty applied to the membership function is not only due to the current rating of the user but due to the uncertainty of the user during a long time and considering noise as well.

This is basically an algorithm proposed to convert the histogram to T1MF in which more parameters are used than the conventional forms of type I fuzzy functions. In the algorithm, the top of bars in the bar graph of the histogram are connected to meet the peak point. Connecting the bars starts from the left side of the side with a positive slope. If the connection to a bar top causes a negative slope, that bar is neglected. This process is repeated at the right side of the peak point by connecting the top of bars, but starting with the rightmost bar and neglecting the negative slope. In the next step, in which modified T1MF is generated using interpolation between the simple T1MF, a large number of parameters are involved.

Creating Histogram

In a given situation, the desired parameter is measured with a high number of repetitions (Depending on the possibility of the measurement and sensitivity of the problem, the number of these repetitions maybe 10, or 50, in the problem under study, the measurements are repeated 25 times). The parameter is measured by a two-dimensional Cartesian graph whose horizontal axis is the measured parameter and whose vertical axis is the frequency of each measurement as shown in Fig. 4.

Normalization

In the created histogram, a horizontal line cuts off the histogram bars at several points. This horizontal line is located in 90% area of the highest frequency. The distance between the leftmost and rightmost side of the bars cut by the line is considered the upper side of the trapezius while the center of the latter distance is considered as apex of the triangular membership function.

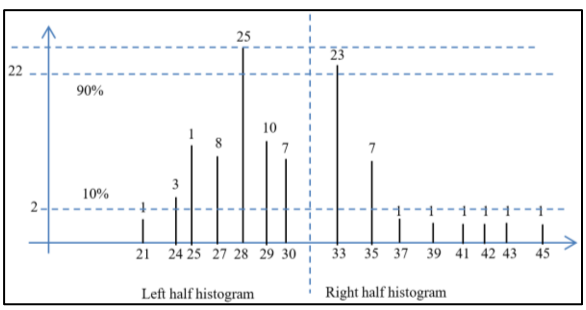


Fig. 4: Redundancy Histogram of 100 measurements (10% line and 90% line for choosing more reliable data)

Creating Membership Functions

In the created histogram, a horizontal line cuts off the histogram bars at several points. This horizontal line is located in a 10% area of the highest frequency. The distance between the leftmost and rightmost sides of the bars cut by the line is considered to support the membership function. If more than 10% of the frequency of each half of the histogram covers the outside area of the membership function, the support should be expanded so that it may cover more than 10% frequency of that half of the histogram. Half of the histogram is the distance between each end of the parameter with 1 frequency and the perpendicular line to the support which passes through the vertices of the triangle (or the center of the upper side of the trapezoid). The 10 and 90% lines as well as the left and right half of the histogram are shown in Fig. 4. The extracted triangular and trapezoidal membership functions based on the proposed algorithm are presented in Fig. 5a. The member function derived based on the algorithm (Shokeen and Rana, 2020) are shown in Figs. (5b-c).

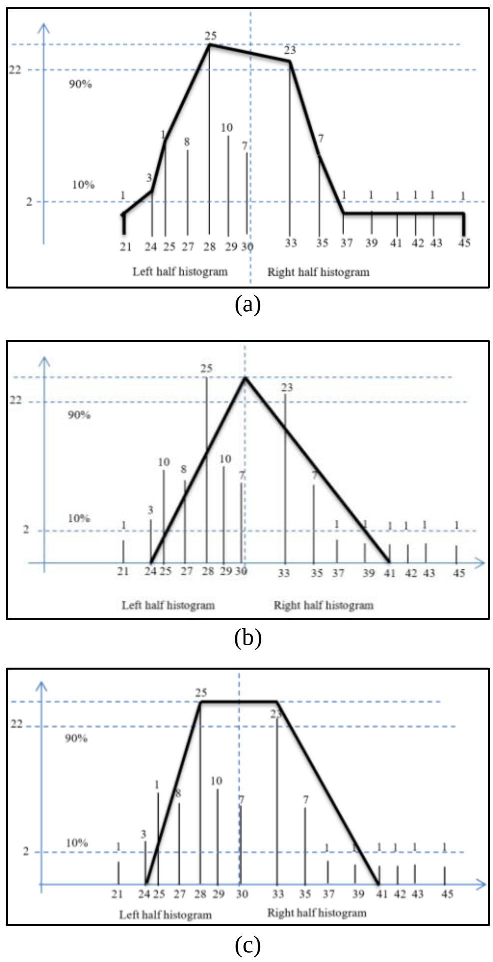


Fig. 5: (a) Extracted MF based on proposed method; (b) Triangular MF based on proposed method; (c) Trapezoidal MF based on proposed method

Figure 5 in 90% bound, a question may arise as to why all the points located in the 90% bound are considered with a high frequency while for instance, the measurements at 30°C show 7 times repetitions. This action, i.e., considering high frequency for all the points located in the 90% bound, is due to the following reasons. First, in a part of the process (considering the continuous property of the parameter under measurement), when the frequency of two sides of a specific bound is high, the frequency in the gap between two bounds should also be high.

This is because obtaining high frequencies in these points requires a greater number of measurements. For example, the number of measurements should be greater than or equal to 2, 5, 10, and 100. Second, in the processes that the parameter under measurement is not continuous, if we had maximum measurement (or better to say the same measurement) at the ends of the bounds, it may show the lack of availability of any information to distinguish between the priority of the points between the two bounds. In other words, there is the highest uncertainty in the distance between these two points.

Performance and Evaluation Metrics

The two main focuses of this study were reducing complexity and time consumption a confusion matrix was employed to measure the classification techniques and the proposed model code was built in Python. Our study included a variety of comparative criteria, including recall %, accuracy, and precision. Accuracy determines the number of accurately recognized predictions and the formula is provided in Eq. 4. The proportion of correctly identified true positives to all positive samples is known as precision. The sum of correctly and erroneously identified samples equals the total number of positive samples. Equation 5 displays the formula, which includes the total number of positive samples, the total number of erroneous negative samples, and the recall percentage of positively classified samples. Equation 2 displays the equation.

Equation 3: $$Accuracy = \frac{total\ currect\ predictions}{total\ predictions}$$

Equation 4: $$Precision = \frac{TP}{TP + FP}$$

Equation 5: $$Recall = \frac{TP}{TP + FN} \qquad (2)$$

We employed the classification report, Mean-Absolute Error (MAE) for training and test and confusion matrix to assess the classification model. The outcome is shown in Figs. 6-7.

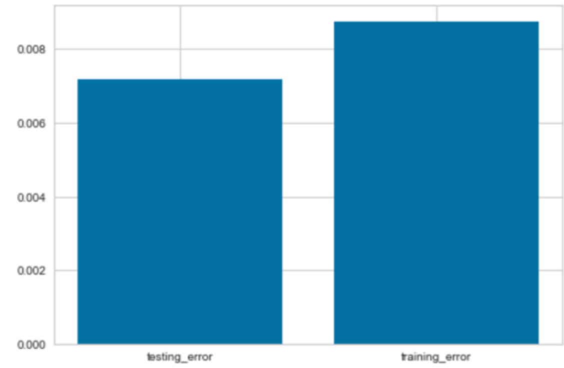


Fig. 6: Classification train-test MAE

	precision	recall	f1-score	support
0	1.00	1.00	1.00	2212
1	1.00	1.00	1.00	3718
2	1.00	0.99	1.00	4050
3	0.99	1.00	1.00	4951
4	1.00	1.00	1.00	2706
5	1.00	0.99	1.00	2531
accuracy			1.00	20168
macro avg	1.00	1.00	1.00	20168
weighted avg	1.00	1.00	1.00	20168

Fig. 7: Result of Classification-report based on multinomial logistic regression

Discussion

A Recommender System's recommendations will each carry a certain level of uncertainty. The quantification of this uncertainty can be useful in a variety of ways. Estimates of uncertainty might be used externally; for example, showing them to the user to increase user trust in the abilities of the system.

The accuracy, processing speed, and complexity of RS have all been improved by various researchers. The papers we looked at (Yan *et al*., 2022; Mohammadi and Rasoolzadegan, 2022) claimed that their methods had superior accuracy, response times, etc. However, many researchers (Forouzandeh *et al*., 2022; Asgarnezhad *et al*., 2022) wanted to focus on only one aspect of RS. In our suggested method, we concentrated on how to quickly and accurately recommend products that users would value.

Conclusion

In this study, a new method for the extraction of membership functions for recommender systems with uncertain ratings is described in detail. The procedure is described in which it is shown how to extract and apply the extracted membership function to a movie data set for improving recommendations to a new user.

The obtained results in this study confirmed the higher efficiency of the proposed membership functions in a substantial reduction in the level of error compared to similar methods.

When compared to single-criteria evaluations, multi-criteria ratings can help describe customers' favorite products more accurately. When people score a product based on a variety of criteria, it is possible to determine what they are entitled to. However, multi-criteria ratings complicate the procedure, take a long time, and lead to multidimensionality issues in the dataset. In this study, we present the super-sub clustering CF-MRS CFRS, a unique CFRS. Furthermore, the proposed strategy outperforms comparable work in terms of item recommendations in the lowest amount of time thanks to the sub-clustering technique, which condensed the search space. Enhanced multinomial logistic regression, a potent classification model that relies on probability value to predict a class label, has been created to predict the closest cluster to a new active user this model had a minimum MAE that reaches nearly (0.009 and 0.007) in training and testing process. This study is done using the Yahoo movie (multi-criteria ratings) dataset and implemented in Python using the Numba package to enhance processing speed by about 30%.

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Author's Contributions

Heersh Azeez: He participated in all experiments, coordinated the data analysis and contributed to the written of the manuscript.

Sadegh Aminifar: He designed the research plan and organized the study.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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