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RECOMMENDER MODEL FOR DATA PREDICTION BASED ON FUZZY LOGIC AND THE COLLABORATIVE FILTERING METHOD

Abstract. *The article proposes a model for data in recommendation in recommender systems, which is based on the implementation of fuzzy logic in the collaborative filtering method to improve the quality of personalized recommendations. Particular attention is paid to the problems of data sparsity, uncertainty of user ratings, and the subjectivitye of interpretation of criteria, which traditionally complicates the work of classical recommendation algorithms. The study substantiates the feasibility of using personalized triangular membership functions, which allow for the reflectingon of the personal preferences and evaluation characteristics of each user. A formalized procedure for constructing and dynamically updating the parameters of such functions for all evaluation criteria is proposed.*

The Mamdani method was used to calculate the degree of similarity between users, which takes into account the fuzziness of ratings and allows logical conclusions to be drawn based on a system of rules. This approach makes it possible to determine the level (degree) of similarity between users, taking into account multidimensional criteria and their qualitative interpretation. In addition, the procedure for defuzzifying the obtained fuzzy similarity values and integrating them into the rating prediction process was demonstrated.

To evaluate the effectiveness of the developed model, a model experiment was conducted on an artificially generated dataset with a controlled structure and a given level of sparsity. Metrics based on mean square error (MSE), root mean square error (RMSE), and sum of squares error (SSE) were used to compare the proposed approach with the results of basic collaborative filtering. The results demonstrate the potential of the modified model to reduce prediction error in conditions of incomplete and fuzzy data, as well as to improve the adaptability of recommendations by taking into account individual evaluation models. The proposed approach can be used as a basis for building more robust, flexible, and interpretable next-generation recommendation systems.

Keywords: *fuzzy logic, Mamdani method, collaborative filtering, data sparsity, uncertainty, fuzzy numbers.*

INTRODUCTION

Recommendation generation in modern recommender systems is based on various approaches, each of which involves the analysis of large volumes of information. Traditional methods are typically focused on precise numerical values, which does not always reflect real-world conditions, where user ratings and item properties are often vague, partially defined, or incomplete. To make well-founded decisions under such conditions, it is advisable to apply approaches based on fuzzy logic.

The introduction of fuzzy logic into recommendation systems makes it possible to formally process uncertainty and inaccuracy in both the input data and the inference rules, to build logically consistent conclusions, and to organize and structure the relationships between factors and recommendations, taking into account the limitations and specifics of the available information. In particular, the use of fuzzy models makes it possible to assess the degree of similarity between users based on fuzzy criteria of their preferences or behavior patterns rather than on rigid ones.

PROBLEM STATEMENT

The traditional task of forming recommendation ratings in any problem area involves the presence of objects to be evaluated and subjects performing such evaluation. Let us consider the procedure for forming a predictive user rating for a given object based on its history of interactions with other objects, as well as historical ratings from other users. For this purpose, a collaborative filtering methodology modified through the incorporation of fuzzy logic methods is employed.

We will assume that each object to be evaluated is characterized by a set of parameters that can be grouped as follows:

1) ratings — numerical values within a predefined range (e.g., 1–5 or 0–1) assigned by users. The interpretation of these ratings is subjective: the same numerical value may have different meanings for different users;

2) criterion-related information — information about specific evaluation criteria of an item (such as the genre of a movie or book, or the type of product) that influence users' perception of the item;

3) individual user characteristics — personal differences in evaluation behavior and preferences, which may vary depending on the evaluation criterion.

Under these conditions, the task is to develop an approach that enables:

- a more accurate approximation of user ratings compared to classical collaborative filtering methods;
- the incorporation of individualized membership functions for different users and evaluation criteria, allowing the system to adapt to subjective preferences;
- the application of fuzzy logic algorithms and methods to assess the degree of similarity between users, which helps reduce data uncertainty and provides a more flexible representation of their preferences.

ANALYSIS OF RECENT RESEARCH

Systems based on fuzzy logical inference are widely used in control systems, knowledge representation, decision support, structural and parametric identification, pattern recognition, and optimization. Fuzzy logic has found broad application in consumer electronics, diagnostics, and various expert systems. In particular, fuzzy expert decision support systems are actively implemented in the military sector, medicine, and economics. They are used for business forecasting, risk assessment, and evaluating the profitability of investment projects. Fuzzy logic tools are also applied to the analysis of global political decisions and the modeling of crisis situations.

Thus, the problem of developing decision support systems using fuzzy logic has been analyzed in a number of scientific works [1–8]. Studies devoted to the development and improvement of recommender systems using fuzzy logic, depending on their application domain, are presented in [9–15]. The effectiveness of collaborative filtering methods modified by the use of fuzzy logic has been analyzed and demonstrated in [16–18].

Purpose. The purpose of this study is to develop and justify an approach aimed at improving the quality of personalized recommendations in collaborative filtering under conditions of data sparsity, as well as in the presence of uncertainty and subjectivity in user ratings, through the integrated application of fuzzy logic methods. In particular, the work focuses on the use of personalized membership functions and the application of fuzzy logic to take into account users' personal preferences and improve the accuracy of rating prediction.

RESULTS AND DISCUSSION

Fuzzy logic is a mathematical tool used to analyze and model situations involving uncertainty, imprecision, or ambiguity, through a system of fuzzy rules and inferences. It is based on the theory of fuzzy sets and fuzzy relations proposed by Lotfi Zadeh in 1965, which allows working with intermediate values between "true" and "false" and introduces formalized measures of membership (correspondence) of available data to certain concepts or events. Let us formulate some concepts of fuzzy set theory.

Definition 1. A fuzzy set $\tilde{A}$ of a universal set X is defined as a set of pairs $\tilde{A} = \{(\mu_{\tilde{A}}(x), x)\}$, where $\mu_{\tilde{A}}(x): X \rightarrow [0,1]$ is a mapping of the set X onto the unit interval [0, 1], called the membership function of the fuzzy set.

The value of the membership function $\mu_{\tilde{A}}(x)$ for an element $x \in X$ determines the degree of its membership in the fuzzy set. The interpretation of the membership degree $\mu_{\tilde{A}}(x)$ is a subjective measure of how well the element $x \in X$ corresponds to the concept whose meaning is formalized by the fuzzy set $\tilde{A}$.

The processing of fuzzy quantities is associated with the construction and application of binary relations. Most commonly, the concept of a fuzzy binary relation from a universal set X into a set Y is used. Thus, a fuzzy binary relation is understood as a fuzzy set $\tilde{R}$ defined on the Cartesian product $X \times Y$ with a membership function $\mu_{\tilde{R}} : X \times Y \rightarrow [0, 1]$.

Let us consider the set of real numbers X as the universal set, that is, $X + R^1$.

Definition 2. A *fuzzy triangular number* $\tilde{A}$ is defined as an ordered triple of numbers (a, b, c), $a \le b \le c$ with a given membership function $\mu_{\tilde{A}}(x)$:

$$\mu_{\tilde{A}}(x) = \frac{x-a}{b-a}, x \in [a,b]; \quad \mu_{\tilde{A}}(x) = \frac{c-x}{c-b}, x \in [b,c]; \quad \mu_{\tilde{A}}(x) = 0, x \notin [a,c]. \tag{1}$$

The use of fuzzy numbers and fuzzy relations in conditions of situational or informational uncertainty makes it possible to construct fuzzy inference schemes, within which logical conclusions are formed based on a system of fuzzy rules and operations on fuzzy values in order to obtain target (output) values,. and Moreover the combination of fuzzy logic tools with basic collaborative filtering methods contributes to the formation of more accurate and transparent personalized recommendations, especially in conditions of incomplete or fragmentary data with a high level of inaccuracy (uncertainty). This approach creates additional opportunities for improving the quality of recommendation systems and increase their effectiveness.

Taking into account the positive impact of fuzzy logic on the recommendation generation process, it is proposed to apply the Mamdani method [19] to compute the degree of similarity between users, which makes it possible to account for the fuzziness of ratings and to ensure well-grounded rating prediction.

Suppose there is a set of users $U = \{u_1, u_2, \dots, u_m\}$, a set of items $I = \{i_1, i_2, \dots, i_n\}$, each of which can be rated by a value $r \in N$ (according to a certain numerical scale), and a set of criteria $K = \{k_1, k_2, \dots, k_s\}$. Each criterion describes properties of the items in the set I, for example, "acting performance", "plot", and so on.

The rating matrix R of size $m \times n$, is given, where each element r_{ui} represents the rating assigned by user u to item i. A three-dimensional matrix RK of size $m \times n \times k$ is also given, where each element r_{ui}^k describes the rating assigned by user u to criterion k when evaluating item i.

Let us describe the stages of constructing personalized triangular membership functions. We will define a set of linguistic terms $A = \{A_1, A_2, \dots, A_t\}$ used to describe subjective evaluations of elements r_{ui}^k given by users. Each of the terms corresponds to a certain range of quality levels, for example: A_1 — "very bad", A_2 — "bad", A_3 — "neutral", A_4 — "good", A_5 — "very good", etc. Next, for each user u, item $i \in I$, and criterion $k \in K$ personalized membership functions of triangular shape are introduced based on the terms $w \in A$:

$$\mu_{\tilde{A}_{ku}}^{(w)}(r_{ui}^k) = \begin{cases} 0, r_{ui}^k \le a_{ku}^{(w)}, \\ \frac{r_{ui}^k - a_{ku}^{(w)}}{b_{ku}^{(w)} - a_{ku}^{(w)}}, a_{ku}^{(w)} < r_{ui}^k < b_{ku}^{(w)}, \\ \frac{c_{ku}^{(w)} - r_{ui}^k}{c_{ku}^{(w)} - b_{ku}^{(w)}}, b_{ku}^{(w)} < r_{ui}^k < c_{ku}^{(w)}, \\ 0, r_{ui}^k \ge c_{ku}^{(w)} \\ 1, r_{ui}^k = b_{ku}^{(w)} \end{cases} \quad (2)$$

where R_{uk} is the set of user u's ratings of objects from set I according to criterion $k, k \in K, a_{ku}^{(w)} = \min_{r \in R_{uk}} r$ is the lowest rating that user u gave to any of the objects according to criterion $k \in K, c_{ku}^{(w)} = \max_{r \in R_{uk}} r$ the highest rating given by user u to any of the objects according to criterion $k, k \in K$ and $b_{ku}^{(w)} = median(R_{uk})$ is the median rating of user u for all objects according to criterion $k \in K$.

As a result, we obtain sets of fuzzy triangular numbers in the form of triples $(a_{ku}^{(w)}, b_{ku}^{(w)}, c_{ku}^{(w)})$. The construction of the initial values $(a_{ku}^{(w)}, b_{ku}^{(w)}, c_{ku}^{(w)})$ for the membership functions is carried out according to the following sequence of steps:

1. Determine the number of evaluation criteria.
2. Set the upper and lower bounds of the rating scale for each criterion.
3. Identify the set of items evaluated by the corresponding user.
4. For each criterion and each user, find the minimum and maximum values of the ratings assigned by that user.
5. The obtained rating scale is divided into $c = t - 1$ overlapping intervals (where t is the number of linguistic terms), as shown in **Figure 1**.

After this, the parameters for representing fuzzy numbers are defined according to the following procedure:

$$\begin{gathered} \sigma = \{r_1, r_2, \dots, r_c\}, \\ \underline{r} = \min \sigma, \overline{r} = \max \sigma, \\ b_k = \underline{r} + k * h, h = \frac{\overline{r} - \underline{r}}{c-1}, \\ a_k = b_k - h, c_k = b_k + h, \\ a_0 = \underline{r}, c_{n-1} = \overline{r}, k = \overline{1, c}. \end{gathered} \quad (3)$$

The need to introduce personalized fuzzy membership functions is explained by the fact that different users interpret the significance of item criteria differently, based on their own subjective perceptions. For example, when watching movies, the same film might be rated highly by one user due to the appeal of its genre, despite a mediocre plot or acting, whereas another user might give a low rating solely because the genre is not to their taste.

Since users' preferences change over time, it is proposed to update the corresponding triples $(a_{ku}^{(w)}, b_{ku}^{(w)}, c_{ku}^{(w)})$ each time a new rating from user u is received. This allows the system to dynamically adapt to the user's interests, thereby providing more accurate personalized recommendations.

The update of these triples is performed according to the following scheme:

$$\begin{gathered} a_{ku}^{(w)\,new} = \min(a_{ku}^{(w)\,old}\ r_{ui}) \\ c_{ku}^{(w)\,new} = \max(c_{ku}^{(w)\,old}, r_{ui}) \\ b_{ku}^{(w)\,new} = \alpha r_{ui} + (1-\alpha) b_{ku}^{(w)\,old}, \alpha \in [0,1]. \end{gathered} \quad (4)$$

The value $b_{ku}^{(w)\,new}$ is calculated as a smoothed intermediate value, which helps to avoid abrupt changes in the membership function. Exponential smoothing is used for this purpose, providing gradual updating of the parameter and reducing its sensitivity to individual anomalous ratings assigned by users.

Next, the Mamdani method will be applied to compute fuzzy similarity between users and to identify those whose interests are most alike, even before including them in the recommendation generation process.

We define a set of output fuzzy terms $S = \{S_1, S_2, \dots, S_q\}$, to describe the level of similarity between users, where each term represents a similarity level. For example, for (q = 5):

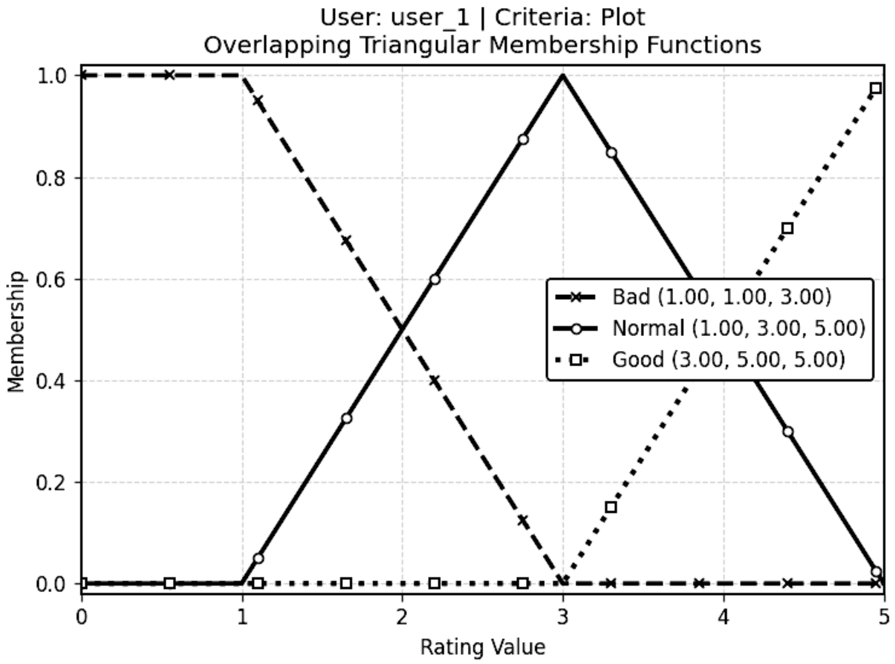

Fig. 1. Example of initial values $(a_{ku}^{(w)}, b_{ku}^{(w)}, c_{ku}^{(w)})$

- S_1 — "very low similarity",
- S_2 — "low similarity",
- S_3 — "medium similarity",
- S_4 — "high similarity",
- S_5 — "very high similarity".

Considering the fuzzy nature of the terms $\tilde{S}_p$, triangular membership functions are defined for each of them, similarly to (2), which determine the corresponding fuzzy sets:

$$\mu_{\tilde{S}_p}(s_{uv}) = \begin{cases} 0, s_{uv} \leq a_p, \\ \frac{s_{uv}-a_p}{b_p-a_p}, a_p < s_{uv} < b_p, \\ \frac{c_p-s_{uv}}{c_p-b_p}, b_p < s_{uv} < c_p, \\ 0, s_{uv} \geq c_p \\ 1, s_{uv} = b_p \end{cases} \quad (5)$$

Here the triple (a_p, b_p, c_p) represents the parameters of the membership function for each fuzzy assessment of the similarity level S_{uv} of users u and v based on the corresponding term S_p, $p,=\overline{1\ q}$, which are specified in advance. Since the Mamdani method is based on the use of a rule-based system to generate an inference, we introduce an appropriate set of production rules for calculating the degree of similarity between users:

$$IF\ \mu_{\tilde{A}_{ku}}^{(w)}(r_{ui})\ IS\ FUZZY\ OF\ A_w \wedge \mu_{\tilde{A}_{kv}}^{(l)}(r_{vi})\ IS\ FUZZ$$
$$OF\ A_l\ THEN\ s_{uv}\ IS\ FUZZY\ OF\ S_p,$$

where A_w, A_l are the linguistic terms of the ratings given by users u and v, S_p is the corresponding term of the users' similarity level, and **IS FUZZY OF** is a conventional notation indicating the degree of membership of a fuzzy similarity assessment to the corresponding linguistic term. For example:

- if the rating of user u for object i under criterion k is "Very good" AND the rating of user v for object i under criterion k is "Good", THEN their similarity is "High";
- if the rating of user u for object i under criterion k is "Neutral" AND the rating of user v for object i under criterion k is "Poor", THEN their similarity is "Medium";
- if the rating of user u for object i under criterion k is "Very good" AND the rating of user v for object i under criterion k is "Poor", THEN their similarity is "Low".

Then, by applying the Mamdani method to compute the fuzzy similarity between users u and v based on the evaluation of commonly viewed objects $i \in I' \subset I$ for each criterion $k \in K$, we obtain:

$$\mu_{\tilde{S}_{uvi}}^{p}(s_{uvi}) = \max_{l=\overline{1,M}} \mu^l(y),$$
$$\mu^l(y) = \max_{w \in A, k \in K} \min(\mu_{\tilde{A}_{ku}}^{(w)}(r_{ui}^k), \mu_{\tilde{A}_{kv}}^{(w)}(r_{vi}^k)), \quad (6)$$

where $\mu_{\tilde{S}_{uvi}}^{p}(s_{uvi})$ denotes the degree of membership of the possible values s_{uvi} of the similarity between users u and v when evaluating object $i, i \in I'$, in the output fuzzy set $\tilde{S}_{uvi}^{p}$ corresponding to the given term.

After fuzzy similarity values have been obtained for each pair of users u and v for each linguistic term, there arises a need to defuzzify them for further use in computing the predicted recom-

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mendation rating. In this study, the centroid (center of gravity) method of fuzzy set defuzzification is employed [6].

$$s_{uvi}^{*} = \frac{\sum_{p=1}^{q} s_{uvi}\mu_{\tilde{S}_{uvi}}^{p}(s_{uvi})}{\sum_{p=1}^{q} \mu_{\tilde{S}_{uvi}}^{p}(s_{uvi})}. \quad (7)$$

Next, the Mamdani method is applied to all objects from I' that were jointly viewed and rated by users u and v, respectively. As a result, a set of similarity values is obtained, and for the final calculation of the similarity between two users it is necessary to compute the average value s_{uv}^{*} of the resulting set of values:

$$s_{uv}^{*} = \frac{\sum_{i\in I'} s_{uvi}^{*}}{|I'|}. \quad (8)$$

The calculated value provides an approximate measure of the level of similarity in how users v and u evaluate common objects. Then, a relationship can be defined for predicting the rating that user u may potentially assign to object i, which has not been previously viewed by the user, taking into account the ratings provided by other users:

$$\hat{r}_{ui} = \frac{\sum_{v\in N_u} s_{uv}^{*} r_{vi}}{\sum_{v\in N_u} s_{uv}^{*}}, \quad (9)$$

where N_u is the set of users most similar to user u according to the calculated values s_{uv}^{*} and R_{vi} is the rating assigned by user v to object i. After performing the calculations required to generate recommendations, all predicted ratings are ordered in descending order, and the top L values corresponding to the respective objects are selected (L — a parameter that can be varied).

Model Experiment

To validate the proposed approach, an artificial test dataset was created consisting of 7 users, 3 evaluation criteria, 2,100 user-object ratings, and 6,300 criterion-based ratings. The use of generated data made it possible to fully control the structure of the sample, the level of sparsity, and to repeat the experiment under identical conditions.

First, a set of users and a set of objects that they could rate were formed. For each “user-object” pair, a rating was generated with a certain probability, which allowed the desired level of density in the rating matrix to be specified. Rating values were generated in the range from 1 to 5, taking into account possible differences in user preferences and object characteristics. Separately, for each object, the values of the criteria according to which it was evaluated were generated, and these criteria were used as input data for constructing personalized fuzzy membership functions.

As a result, a model dataset was obtained that reproduces a typical information structure of recommender systems: a set of users, a set of objects, a partially filled rating matrix, and descriptive object criteria. This made it possible, under controlled conditions, to study the operation of the model, verify its ability to process sparse and partially uncertain data, and assess the impact of the proposed fuzzy mechanisms on recommendation quality.

Three metrics were used for comparison: MSE, RMSE, and SSE. All of them reflect the error

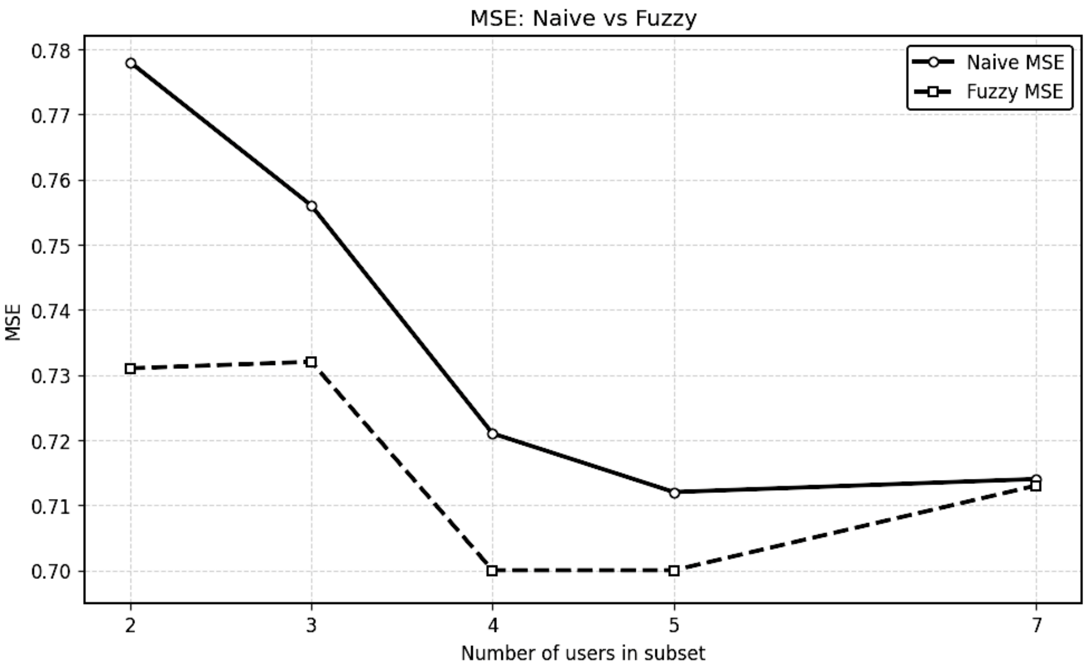

Fig. 2. Comparison of the mean squared error for Naive and Modified methods

between predicted and actual ratings, where lower values indicate better model performance.

The graph shown in **Figure 2** presents a comparison of the mean squared error (MSE) values for the naive collaborative filtering method and the modified fuzzy approach across samples with different numbers of users. The X-axis represents the number of users, while the Y-axis represents the MSE values. It can be observed that, for the considered subsamples, the MSE values of the modified approach are lower than or close to those of the naive method, which indicates better or at least no worse rating prediction accuracy.

The graph shown in **Figure 3** illustrates the change in RMSE for the two approaches depending on the number of users in the sample. The X-axis shows the number of users, while the Y-axis represents the RMSE values. As can be seen, the results are similar to those shown in the previous graph. The modified method demonstrates a reduction in error.

The graph shown in **Figure 4** presents a comparison of SSE for the naive and fuzzy approaches. The X-axis represents the number of users in the subset, while the Y-axis shows the SSE values. Since SSE reflects the total accumulated error for the entire sample, a reduction in this measure in our approach indicates that the overall number of rating prediction errors is lower compared to the baseline model.

Figure 5 shows a chart illustrating the percentage improvement of the modified approach compared to the naive method across three metrics: MSE, RMSE, and SSE. The X-axis represents the number of users in the sample, while the Y-axis indicates the percentage change in the metrics. Positive values correspond to improvements in quality (i.e., error reduction) for the fuzzy approach relative to the baseline, allowing a clear visualization of how the proposed modification enhances results for each subset size.

When comparing the modified approach with the naive collaborative filtering method on artificially generated data, a heterogeneous pattern is observed: for some user subsets, the modified method demonstrates better error metrics, while for others, its performance is close to that of the baseline model.

One key factor explaining this behavior is the nature of the input data. In the proposed approach, when calculating similarity between users, additional criteria based on movie attributes are considered. For real-world data, these criteria typically correlate with user preferences (e.g., genre, cast, release year), allowing for more accurate modeling of the structure of user preferences.

In such situations, the added complexity of the proposed model does not necessarily reveal useful patterns, but rather amplifies the influence of random factors. The naive method, relying solely on the rating matrix, proves to be more robust in the absence of meaningful dependencies, whereas the modified approach, which incorporates membership functions and weighted coefficients based on the criteria, becomes sensitive to random

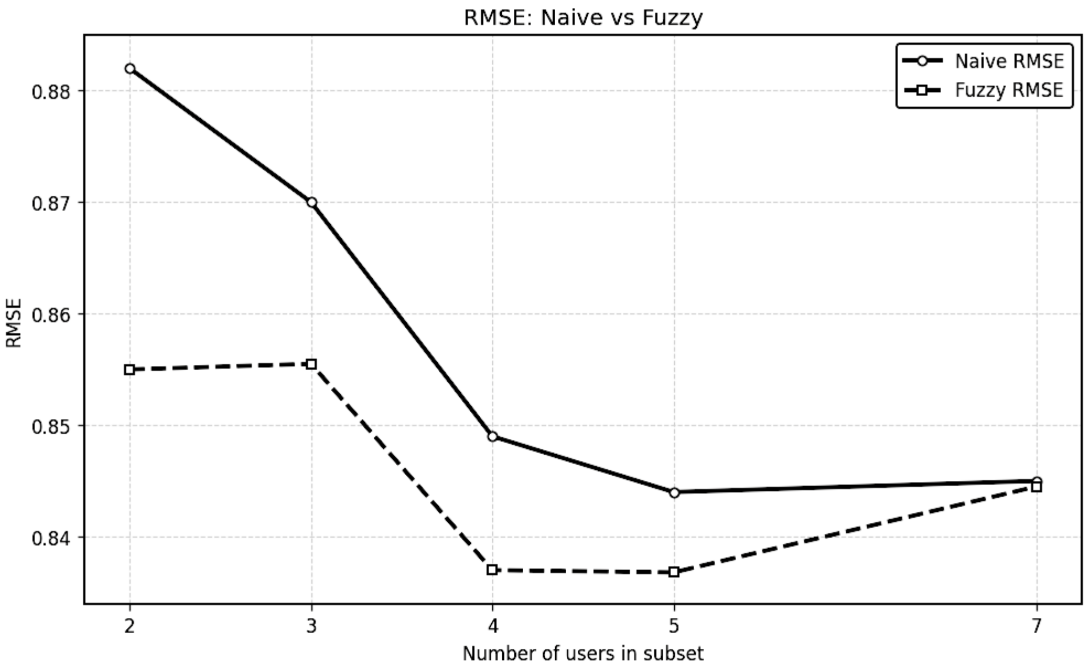

Fig. 3. Comparison of the root mean squared error for Naive and Modified methods

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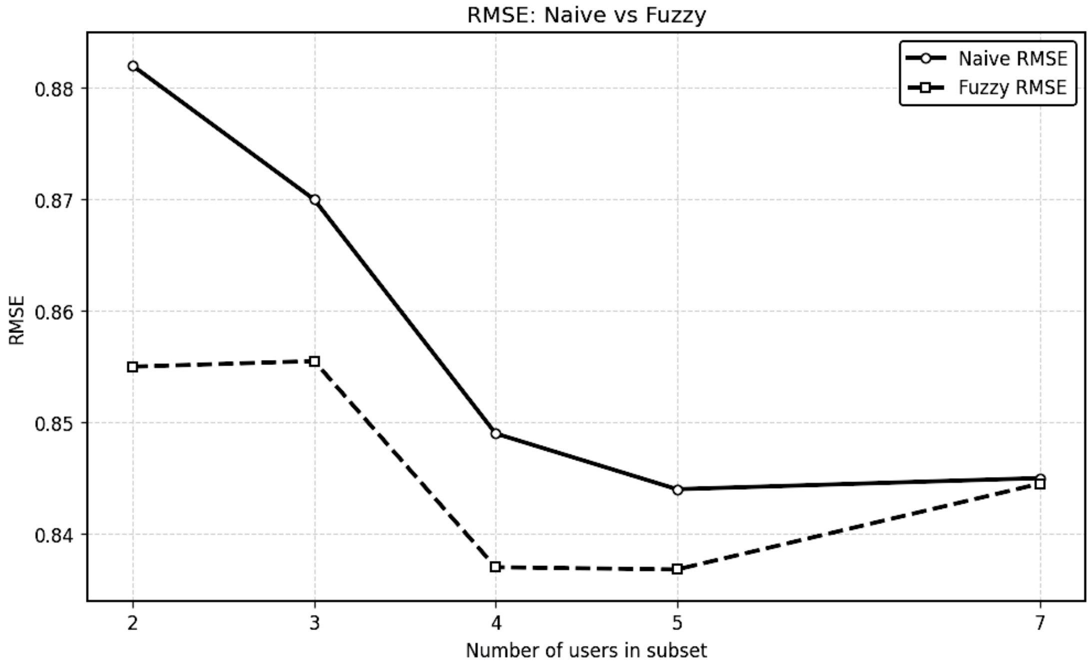

Fig. 4. Comparison of the sum of squared errors for Naive and Modified methods

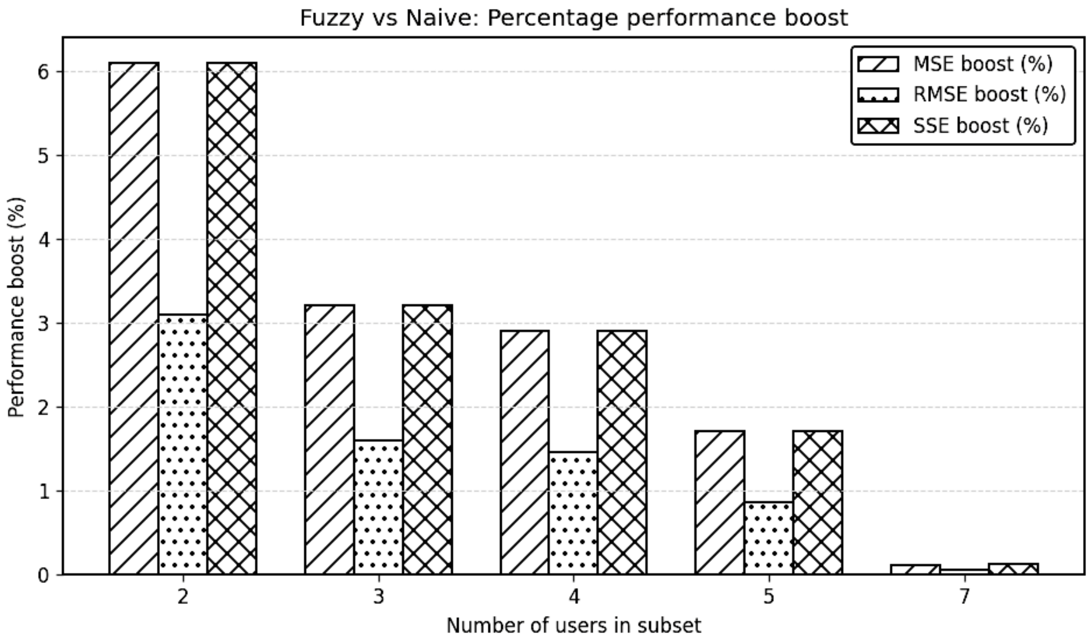

Fig. 5. Percentage improvement of the modified approach

fluctuations. As a result, for certain user subsets, the method demonstrates only a slight improvement in metrics compared to the naive approach.

CONCLUSIONS

In this work, a modification of the naive collaborative filtering method was proposed by introducing elements of fuzzy logic, which allowed for the consideration of additional evaluation criteria for objects and the construction of a more flexible model of user preferences. A comparative experiment was conducted on an artificially generated dataset that reproduces the typical structure of information in recommendation systems, comparing the naive method with the proposed approach.

The results of the numerical experiments showed that even under conditions of artificially generated data, where the relationship between the criteria and user ratings does not fully reflect real behavioral patterns, the modified approach demonstrated a reduction in error values compared to the naive method. This indicates the potential effectiveness of incorporating evaluation criteria and using fuzzy membership functions to improve recommendation quality. At the same time, these results should be regarded as a conservative estimate of the model's capabilities, since the absence of real correlations in synthetic data partially limits the advantages of the modified approach.

Future research will focus on testing the proposed model on real-world data, where evaluation criteria are genuinely related to user preferences. This will allow for the assessment of the model's adequacy in real-world conditions, its robustness to random variations in preferences, and a comparison with other modern recommendation approaches. An additional task is the fine-tuning of fuzzy membership function parameters and criterion weights, which is expected to further enhance the quality of generated recommendations.

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РЕКОМЕНДАЦІЙНА МОДЕЛЬ ПРОГНОЗУВАННЯ ДАНИХ НА ОСНОВІ НЕЧІТКОЇ ЛОГІКИ ТА МЕТОДУ КОЛАБОРАТИВНОЇ ФІЛЬТРАЦІЇ

Резюме. *У статті запропоновано модель представлення даних у рекомендаційних системах, що ґрунтується на впровадженні апарату нечіткої логіки в метод колаборативної фільтрації для підвищення якості формування персоналізованих рекомендацій. Особливу увагу приділено проблемам розрідженості даних, невизначеності користувацьких оцінок та суб'єктивності інтерпретації критеріїв, що традиційно ускладнюють роботу класичних алгоритмів рекомендацій. У межах дослідження обґрунтовано доцільність використання персоналізованих трикутних функцій належності, які дають змогу* *відобразити персональні уподобання та особливості оцінювання кожного користувача. Запропоновано формалізовану процедуру побудови та динамічного оновлення параметрів таких функцій для всіх критеріїв оцінювання.*

Для обчислення міри подібності між користувачами застосовано метод Мамдані, що забезпечує врахування нечіткості оцінок і дає змогу формувати логічно узгоджені висновки на основі системи правил. Такий підхід надає можливість визначати рівень (міру) схожості між користувачами з урахуванням багатовимірних критеріїв та їхньої якісної інтерпретації. Окрім того, продемонстровано процедуру дефазифікації отриманих нечітких значень подібності та їхньої інтеграції в процес прогнозування рейтингів.

Для оцінювання ефективності розробленої моделі проведено модельний експеримент на штучно згенерованому наборі даних із контрольованою структурою та заданим рівнем розрідженості. Застосовано метрики на основі значень середньоквадратичного відхилення (MSE), квадратного кореня з середньоквадратичного відхилення (RMSE) та суми квадратів відхилень (SSE) для порівняння запропонованого підходу з результатами базового методу колаборативної фільтрації. Отримані результати демонструють потенційну здатність модифікованої моделі зменшувати похибку прогнозування в умовах неповних і нечітких даних, а також поліпшувати адаптивність рекомендацій завдяки врахуванню індивідуальних моделей оцінювання. Запропонований підхід може бути використаний як підґрунтя для побудови більш стійких, гнучких та інтерпретованих рекомендаційних систем нового покоління.

Ключові слова: *нечітка логіка, метод Мамдані, колаборативна фільтрація, розрідженість даних, невизначеність, нечіткі числа.*

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