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A FUZZY COLD-START RECOMMENDER SYSTEM FOR EDUCATIONAL TRAJECTORY CHOICE

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Abstract. Several approaches to choosing an educational trajectory are considered, and the advantages of using recommender systems are determined. The cold start problem of recommender systems is formulated and solved by creating a hybrid recommender system that combines a rule-based fuzzy expert system and a recommender system with fuzzy collaborative filtering. As one application, the general approach is implemented for choosing the field of study when entering a higher education institution. A modification of Klimov's career guidance test is used as initial data. The rules for estimating the metrics and similarity of fuzzy triangular data are presented. The algorithms of a fuzzy expert system and a fuzzy recommender system with collaborative filtering are described in terms of the fuzzy representation accepted. The two approaches are combined by generating pseudo data using an expert system. This provides a solution of the cold start problem and yields a recommender system whose quality is gradually improved by substituting the values from real user queries into the database. The programs implementing these algorithms are tested to confirm the effectiveness of the fuzzy recommender system.

Keywords: expert system, recommender system, fuzzy description, fuzzy metric, collaborative filtering, cold start, educational trajectory.

INTRODUCTION

Recommender systems are intended to advise in decision-making when there are many alternatives to choose from, by analyzing the behavior of others who have made choices under similar conditions [1]. A recommender system selects and suggests decisions to the user based on the available knowledge about him, the decision space, and the interaction between the user and the decision space. Thus, the choice of a decision is determined by the properties of the user and the properties of the alternatives proposed. The algorithms of such systems differ in the type of data to generate recommendations. The methods implemented based on the data about the previous application of the system are called collaborative filtering. In collaborative filtering, a close group of users with the same private preferences as those of a particular user is identified. Then, the user's preferences are extended to the complete set of preferences of the entire close group. Content-based filtering rests on metadata, i.e., the descriptions of objects from the user's catalog. Depending on the algorithm, the system can generate recommendations by selecting objects similar to those previously chosen by the user, by matching objects with the data from the user's profile, or by searching for similar objects from the entire content. In fact, recommender systems are developed in order to create decision tools with the maximum possible consideration of the user's data-based preferences [2]. Due to the role of psychological factors in the choice process, the problem of designing perfect recommender systems is of great interest and leads to significant challenges.

The formal problem statement is as follows. Consider a set of users and a set of objects. For the set of users, the preference matrix for choosing objects is known. The problem of a recommender system is to fill the missing values in the preference vector of the user under study by analyzing the available data of the object rating matrix for the entire set of users. Thus, technically, tools are needed to fill the existing gaps in a matrix. Different algorithms serve for this purpose [3–5], including those exploring additional object and user data. In many practically important cases, the data underlying recommendation search are imprecise and fuzzy. It is natural to describe such data within probabilistic or fuzzy models. The advantages of probabilistic models [6] show up when working with big data. Under small initial samples, for solving the cold start problem, one has to be content with a priori expert assessments of probabilities. In this case, the approach based on fuzzy calculations turns out to be more suitable [7].

Fuzzy versions of clustering and factorization methods of the rating matrix [8–25] have been developed for fuzzy recommender systems. Fuzzy expert recommender systems are quite convenient for development and application [26–28], but they do not accumulate data during operation. According to the survey of available solutions, the choice of an appropriate algorithm for a recommender system essentially depends on a particular problem to be solved.

1. PROBLEM STATEMENT

Due to the diversity and complexity of large systems, various tools are needed to control them [29], including machine learning methods. In the recent decade, the problem of a more flexible response of the education system to global dynamic changes has arisen, followed by a steady trend to personalize the educational trajectory of students in higher education institutions (HEIs). The complexity and scale of this problem require developing intelligent control systems [30–33] with recommender systems that facilitate the rational choice of the fields of study by enrollees and their filling with courses (the profiles of educational programs) to link current learning with future professional careers. The real demand behind this task is that the labor market has many free vacancies due to the mismatch between the application forms submitted and the requirements of employers [34]. Therefore, deliberate efforts are made to develop user systems in order to determine the best educational trajectory for subsequent successful careers [35, 36]. Many factors and attributes can help in determining a career. They include skills, relationships, decision-making, home address, education, parents’ jobs, etc.

The problem of developing a recommender system for education has a characteristic feature as follows: there are fuzzy values among the initial parameters reflecting such factors as preferences, expectations, and other qualitative assessments [37]. There exist two different approaches to designing recommender systems with fuzzy logic. The first one is to develop rule-based expert systems [38, 39], whereas the second approach rests on big data [40–43]. Both approaches have their advantages and drawbacks. The rule-based method involves explicitly formulated rules with the experience of experts [44]. In this case, the system’s operation does not affect its quality. Methods for designing recommender systems based on machine learning assume that the decision rules are unknown in advance but require big data. In other words, a recommender system based on machine learning is unable to formulate relevant inference rules under small initial data in the database. This limitation is known as the cold start problem [45]. At the same time, as the data volume increases, the quality of such a recommender system will grow reflecting real correlations and relations. This paper aims to overcome the limitations of both approaches by combining them. At the initial stage, a recommender system will therefore be rule-based, generating an appropriate database. As the data volume increases, the simulated examples will be gradually replaced by real data, and the recommender system will be redesigned in accordance with machine learning results, thereby overcoming the cold start difficulties.

2. METHODS AND DATA

In the Russian multilevel education system, the problem of choosing an educational trajectory considering the future career arises several times: at the stage of determining the field of study and the profile of the educational program when entering an HEI, when choosing a master’s degree in the case of continuing higher education and, finally, when entering a graduate school. An individual educational trajectory can also be detailed using a set of elective courses. This paper proposes a recommender system [46], which can be applied at different education levels and adapt to the changing structure and priorities of Russian education. To provide a cold start for the system, a hybrid fuzzy recommender system is used, combining a rule-based expert system and a recommender system based on the collaborative filtering of user characteristics [9].

The approach is validated using a modification of Klimov’s career guidance test [44], where crisp estimates are replaced by fuzzy ones. This test is based on a classification of professional interests to determine a better field of study for an individual. According to this classification, all modern professions can be divided into five main types: “man–nature” (N, work with natural objects), “man–technology” (T, work with technical devices), “man–sign system” (S, work with abstract symbolic systems, models, and natural and artificial languages), “man–art” (A, creative work), and “man–man” (M, work involving direct communication and interaction with people). The table below shows the test [44] used by the recommender system.

Klimov's career guidance test

No.	User characteristics	Type of professions				
		N	T	S	A	M
1	I get acquainted with people easily.	–	–	–	–	1
2	I can make something willingly and for a long time.	–	1	–	–	–
3	I like to go to museums, theaters, and exhibitions.	–	–	–	1	–
4	I take care of plants and animals willingly and constantly.	1	–	–	–	–
5	I can calculate and draw something willingly and for a long time.	–	–	1	–	–
6	I am happy to communicate with peers or kids.	–	–	–	–	1
7	I enjoy caring for plants and animals.	1	–	–	–	–
8	I usually make a few mistakes in writing.	–	–	1	–	–
9	My products usually arouse the interest of my friends and seniors.	–	2	–	–	–
10	People think I have artistic abilities.	–	–	–	2	–
11	I like to read about plants and animals.	1	–	–	–	–
12	I take part in plays and concerts.	–	–	–	1	–
13	I like to read about the design of mechanisms, devices, and machines.	–	1	–	–	–
14	I can spend much time solving puzzles, problems, and rebuses.	–	–	2	–	–
15	I settle disagreements between people easily.	–	–	–	–	2
16	People think I have a knack for technology.	–	2	–	–	–
17	People like my artwork.	–	–	–	2	–
18	I have an aptitude for working with plants and animals.	2	–	–	–	–
19	I can state my thoughts in writing clearly.	–	–	2	–	–
20	I rarely quarrel with people.	–	–	–	–	1
21	Even the unknowns approve the results of my technical creativity.	–	1	–	–	–
22	I learn foreign languages without much difficulty.	–	–	1	–	–
23	I often help even the unknowns.	–	–	–	–	2
24	I can spend a long time practicing music, drawing, reading books, etc.	–	–	–	1	–
25	I can influence the development of plants and animals.	2	–	–	–	–
26	I like to comprehend the design of mechanisms and devices.	–	1	–	–	–
27	I usually manage to convince people of the truth of my words.	–	–	–	–	1
28	I am eager to observe plants or animals.	1	–	–	–	–
29	I read popular science, critical literature, and journalism willingly.	–	–	1	–	–
30	I endeavor to understand the secrets of skill and try my hand at painting, music, etc.	–	–	–	1	–
Results		8	8	8	7	8

Each item in the table is assessed using a five-point fuzzy scale; the results are multiplied by the weight indicated in the corresponding column. A real number from 0 to 5 is indicated to reflect adequately the user's estimate of his (her) answer to each test question. Klimov's test is supplemented with the average grade points of the user's high school diploma by the disciplines of interest in order to consider not only the user's subjective estimates but also the available accurate and verifiable external data with a weight of 2:

– Type N: biology, geography, life safety, and informatics;

– Type T: algebra and elements of analysis, geometry, physics, and informatics;

– Type S: algebra and elements of analysis, geometry, Russian language, and informatics;

– Type A: Russian language, Russian literature, universal history, and history of Russia;

– Type M: social studies, universal history, history of Russia, and life safety.

As a result, the vectors of fuzzy data are formed, and the priority type of professions is selected based on the maximum-length vector. The length of fuzzy estimate vectors is adopted instead of the simple sum of features to increase the contribution of the most pronounced features to the resulting estimate. As in the paper [9], we use triangular fuzzy numbers $\tilde{a}$ with a membership function μ defined using a triplet of numbers $(a^-,\ a,\ a^+)$ as

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, \ x < a^-, \\ \dfrac{x - a^-}{a - a^-}, \ a^- \le x \le a, \\ \dfrac{a^+ - x}{a^+ - a}, \ a \le x \le a^+, \\ 0, \ a^+ < x, \end{cases} \qquad (1)$$

where $x \in X$.

When the fuzziness definitional domain exceeds the boundaries of the interval $\left[c,\ d\right]$, it is necessary to set $a^{-} = c$ (on the left) or $a^{+} = d$ (on the right).

For triangular fuzzy numbers, arithmetic operations are defined by simple triplet transformation rules [47, 48]:

$$\tilde{a} + \tilde{b} = (a^{-} + b^{-},\ a + b,\ a^{+} + b^{+}),$$

$$\tilde{a} \cdot \tilde{b} = (a^{-}b^{-},\ ab,\ a^{+}b^{+}),$$

$$\tilde{a} - \tilde{b} = (a^{-} - b^{+},\ a - b,\ a^{+} - b^{-}),$$

$$\frac{\tilde{a}}{\tilde{b}} = \left(\frac{a^{-}}{b^{+}}, \frac{a}{b}, \frac{a^{+}}{b^{-}}\right).$$

The distance between fuzzy numbers is given by [47]

$$d\left(\tilde{a},\ \tilde{b}\right) = \sqrt{\frac{1}{3}\left[(a^{-} - b^{-})^{2} + (a - b)^{2} + (a^{+} - b^{+})^{2}\right]}. \qquad (2)$$

The Euclidean distance between fuzzy vectors $\tilde{\mathbf{a}}$ and $\tilde{\mathbf{b}}$ [49] is calculated by analogy, i.e., the quadratic sum for one pair of triplets in (2) is replaced by the sum of the squared differences of the corresponding triplets of the fuzzy coordinates:

$$d\left(\tilde{\mathbf{a}},\ \tilde{\mathbf{b}}\right) = \sqrt{\frac{1}{3}\sum_{jk}\left(a_j^k - b_j^k\right)^2}. \qquad (3)$$

In this formula, the subscript j is associated with vectors whereas the superscript k with triplet parameters. For crisp numbers, the expression (3) coincides with the conventional distance formula used in the Euclidean space. The relations presented above are sufficient for processing fuzzy test data and selecting a prioritized decision.

An expert system based on fuzzy parameters makes conclusions based on the user data but neglects the history of queries, which may contain information differing from expert assessments. One possible reason is a significant hidden factor, absent or disregarded when developing the expert system. Such a factor may systematically distort the result.

A fuzzy expert system with collaborative filtering based on the cosine similarity measure of fuzzy data is chosen to consider the information contained in the history of queries and the decisions made. The measure has the form

$$\mathrm{sim}\left(\mathbf{a},\ \mathbf{b}\right) = \frac{\sum_{jk} a_j^k b_j^k}{\sqrt{\sum_{jk}\left(a_j^k\right)^2 \sum_{jk}\left(b_j^k\right)^2}}.$$

This criterion is similar to the classical Pearson correlation coefficient of vectors, coinciding with the latter in the case of crisp data. It takes the maximum value (equal to 1) when the vectors compared have the same direction. Due to this property, the search procedure in the database yields a precedent closest to the case under consideration. For small databases, this solution is the best one. Under big data, it is reasonable to cluster them and make a decision by comparing the case under consideration with the centers of clusters.

3. THE ALGORITHM AND NUMERICAL SIMULATION RESULTS

The software implementation of the fuzzy cold-start recommender system requires operation algorithms for the rule-based expert system and the recommender system with collaborative filtering as well as their coupling that generates pseudo data based on the expert system and given decision statistics.

The algorithm of the fuzzy expert system based on the user properties and rules includes the following steps.

Step 1. User data are entered.

Step 2. Crisp data are transformed into fuzzy data.

Step 3. Based on the fuzzy representation and rules, the weights of decisions are determined as the magnitudes of the fuzzy vectors of characteristic indicators related to different decisions.

Step 4. The weights of decisions are normalized and are compared, and the results are outputted in the form of ranked recommendation ratings.

To form the pseudo-data base, we use a random generation of five data blocks; in each block, a particular type of professional preferences dominates over the other decisions, which have a reduced but close proportion. The variations of the estimates of individual properties within a given type are smaller than the difference between the major type and the minor types for each block.

The algorithm of the fuzzy recommender system with the collaborative filtering of the user's query and the history of queries in the database includes the following steps.

Step 1. The database is formed and is loaded.

Step 2. The indicators are transformed into fuzzy characteristics.

Step 3. The current user's data are entered.

Step 4. The current user's crisp data are transformed into fuzzy data.

Step 5. The closest sample is searched in the fuzzy database.

Step 6. The decision for this sample is outputted as the recommended decision.

Running the collaborative filtering algorithm requires a relevant database. It is often unavailable in the initial stage of system operation, causing the well-known cold start problem. To solve this problem using the fuzzy rule-based expert system, we generate an initial pseudo-data base reflecting the observed decision statistics of users. Then, during the operation of the second recommender system with collaborative filtering, the pseudo-data are gradually replaced by the data taken from real examples. Thus, the relevance of the entire system is improved during operation.

Before the system operation, it is necessary to check the quality of the pseudo-data base by comparing the answers given by both recommender systems on the same test examples. *FuzzyExpert* and *FuzzyRecommend*, the programs implementing the fuzzy rule-based expert system and the fuzzy recommender system with collaborative filtering in MATLAB, have the same interface (a menu column).

Consider a numerical example. Let the input data matrix A with row distribution by the type of professions be

$$A = \begin{pmatrix} 2.00 & 2.00 & 4.00 & 2.00 & 2.00 & 3.00 & 5.00 \\ 4.00 & 4.00 & 4.00 & 4.00 & 5.00 & 4.00 & 5.00 \\ 5.00 & 4.00 & 4.00 & 4.00 & 0.50 & 4.00 & 4.75 \\ 3.00 & 1.00 & 2.00 & 0 & 4.00 & 1.00 & 4.75 \\ 3.00 & 2.00 & 3.00 & 3.00 & 2.00 & 3.00 & 5.00 \end{pmatrix}.$$

The first six columns contain 30 user answers to the questions of Klimov's test. The last column provides the average grade points of the user's high school diploma by the disciplines of interest (the five groups of professions with four related disciplines). The value of fuzziness, which determines the scatter of test parameter estimates in each direction, is taken equal to 1. The average grade points for the disciplines are treated as crisp values during processing. The weights of the estimates form the matrix

$$r = \begin{pmatrix} 1 & 1 & 1 & 2 & 2 & 1 & 1 \\ 1 & 2 & 1 & 2 & 1 & 1 & 1 \\ 1 & 1 & 2 & 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 2 & 1 & 1 & 1 \\ 1 & 1 & 2 & 1 & 2 & 1 & 1 \end{pmatrix}.$$

Based on the matrices A and r, the system calculates the preference vectors $B_{ij} = \left\{A_{ij} \cdot r_{ij}\right\}$ of the ith profession with projections $j = 1, 2, \ldots, 7$ by the number of indicators compared. Then the fuzzy triangular preference vectors $\tilde{R}_{ij} = \left\{B_{ij}^-, B_{ij}, B_{ij}^+\right\}$, where $B_{ij}^{\pm} = B_{ij} \pm \delta$ with $\delta = 1$, are formed. If the value of a triangular number boundary goes beyond the range [0, 5], it is replaced by the corresponding boundary value of the interval (0 or 5). Next, the lengths of the vectors $R_i = d\left(\tilde{\mathbf{B}}_i, 0\right)$ are calculated using formula (3), and the results are normalized by the total length, yielding the output vector $R_i / \sum_k R_k$ of recommendations in percentage. In the example under consideration, the recommendation vector is (15.4695; 26.4630; 24.3394; 14.2747; 19.4534). According to the simulation results, the user tested should choose professions related to technical devices or, with a slightly lower rating estimate, work with abstract symbolic systems, models, and natural and artificial languages.

These rating estimates are consistent with the results of individual interviews conducted by experts with different users. The fuzzy representation used instead of the initial estimates increases the consistency of the final results with the expert assessments by pushing the mean estimates apart and relaxing the limit estimates at the interval ends. Re-testing shows the robustness of prioritized choice with respect to the ranking of the results.

A pseudo-data base with one hundred entries was generated for the fuzzy recommender system with collaborative filtering. According to the numerical simulation results, this number of random entries ensures the robust identification of the priority profession; in the case of restricting the number of entries to a few tens, the generated data will not reproduce correct prioritization.

CONCLUSIONS

Due to the rich variety of the fields of study and the profiles of educational programs at an HEI, the choice of an appropriate educational trajectory is a serious task for enrollees. For effective assistance in this issue, it is necessary either to form a staff of expensive experts or to implement a special computer-based recommender system.

We have developed an approach to making recommendations on the choice of a general field of study based on Klimov's career guidance test. The initial data are treated as fuzzy values to be processed based on a fuzzy metric and fuzzy comparisons. The cold start problem has been dealt with using an expert estimation system algorithm with the integral length criterion of the fuzzy estimate vector. The fuzzy expert estimation program can be used separately and independently of databases. The cold start problem has been solved by generating a random pseudo-data base with the distribution of answers by priority.

The relevance of the pseudo-data base has been validated by comparing the results of fuzzy collaborative filtering with the answers produced by the fuzzy expert system. According to the numerical simulation results, the optimal size of the pseudo-data base in terms of fast operation with reliable answers is about one hundred entries.

During system operation with real users, pseudo-data are updated by replacing the entries with new data based on the tests passed. With regular updates, the database maintains correct operation and adapts to the changes in the user population.

Note an alternative approach to determining the educational trajectory using fuzzy artificial neural networks as follows: the data of students are clustered, and the neural network undergoes supervised learning at the stage of big data accumulation. Compared to the methodology of artificial neural networks, the approach presented in this paper has the advantage of possible operation under data volumes insufficient for machine learning during the cold start period.

We expect to apply this recommender system in Voronezh State Technical University (VSTU). The corresponding fields and profiles of study for VSTU enrollees are divided into five types:

– type N: geodesy and remote sensing, land management and cadastres, and environmental management and water use;

– type T: construction, radio engineering, and instrumentation;

– type S: economics, applied informatics, and computer and information sciences;

– type A: architecture, design of architectural environment, and reconstruction and restoration of architectural heritage;

– type H: journalism, advertising, and public relations.

The educational trajectory of an individual is further refined after entering an HEI (through choosing elective disciplines), after receiving a bachelor's or specialist degree when entering a master's program, and, finally, when entering a graduate school. This problem is topical due to organizational changes in the Russian higher education system. Further research is needed to develop intelligent support tools for forming an individual student's roadmap.

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