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DETERMINING PREFERENCES IN RECOMMENDER SYSTEMS BASED ON COMPARATOR IDENTIFICATION TECHNOLOGY

The **subject** of research in the article is the process of ranking objects in the lists of recommender systems. The **goal** of the work is to increase the efficiency of recommender systems by improving the method of determining preferences between objects in lists using the theory of multi-criteria decision-making. The following **tasks** are solved in the article: review and analysis of the current state of the problem of identifying advantages between objects and their ranking in the lists of recommender systems; analysis of filtering methods used in recommendation systems; decomposition of the decision support problem for selection of objects; development of a combined method for ranking objects in the lists of recommender systems, combining the procedures for selecting a subset of Pareto-optimal objects, structural-parametric synthesis of a scalar multi-criteria estimation model, and evaluating the entire set of selected objects. The following **methods** are used: mathematical modeling, systems theory, utility theory, decision theory, optimization and operations research. **Results.** Based on the results of the analysis of the modern methodology for ranking objects in the lists of recommendation systems, the possibility of increasing their efficiency has been established. To take into account factors difficult to formalize, the knowledge and experience of users, it is proposed to implement the determination of preferences between objects using the theory of multi-criteria decision making. The problem of forming lists of recommendation systems is decomposed into the tasks of selecting a subset of Pareto-optimal objects, structural-parametric synthesis of a scalar multi-criteria estimation model, and evaluating a set of selected objects. A combined method for ranking options has been developed that combines the procedures of ordinalistic and cardinalistic ordering technologies and allows one to correctly reduce the subsets of objects included in the lists of recommendations. Conclusions. The developed method for determining preferences expands the methodological foundations for automating the development and operation of recommendation systems, other multi-criteria decision support systems, allows for the correct reduction of the set of non-dominated objects for the final choice, taking into account factors that are difficult to formalize, knowledge and user experience. The practical use of the obtained results due to more economical method of forming lists when adding new objects will allow to decrease the time and capacity complexity of the procedures for providing recommendations, and due to taking into account of set of weighted local indexes and allocation of set of non-dominated objects - to increase quality of given recommendations.

Keywords: multi-criteria assessment; comparator identification; recommender system; ranking of objects; structural-parametric synthesis.

Introduction

One of the modern trends is the rapid growth of the range and volume of goods and services sold in the market. On the one hand, this allows to better meet the needs of consumers, but significantly complicates for them the task of choosing the object (goods, services, leisure facilities, etc.) that best meets their preferences. In cases when a lot of objects of choice are offered, it creates a potential problem for Internet users [1]. To avoid information overload, consumers need to properly filter objects, prioritize them, and provide relevant information about them. To simplify consumers' choices, recommendation systems are increasingly being used to solve this problem by searching through a large volume of dynamically received information. Due to the use of filtering methods, they allow providing users with the necessary personalized information about the objects that most correspond to their preferences [2].

The information about the similarity of the characteristics of objects or about the acts of selection of objects by users with similar preferences is used for the formation of suggestions in recommendation systems. The most widespread methods for solving the problems of recommendation formation in them are methods of collaborative filtering, recommendations based on content and knowledge [3 - 5]. Their main disadvantage is the high complexity of debugging or use, which creates problems when it is necessary to analyze information from powerful sets of objects for a large number of users. In addition, these methods are focused on the formation of recommendations using generalized evaluations of objects. To improve the accuracy of establishing user preferences, the use of multicriteria decision-making models and methods looks promising [6 - 9]. In this case, it is reasonable to justify a scalar criterion of choice, which would sufficiently fully characterize objects on the basis of some set of contradictory local criteria [10-11]. When decision-making technologies are used in recommender systems, the evaluation of the effectiveness of objects can be performed on the basis of utility theory using methods of individual or collective expert evaluation [12 - 14]. In recommendation systems, their users act as professionals. To form recommendation lists using decision theory, it is necessary to identify a subset of Pareto-optimal objects on the set of admissible objects by local criteria, parametric synthesis of their scalar evaluation model, and calculation of their generalized evaluations. To implement these tasks it is necessary to develop appropriate mathematical models and effective methods for their solution.

Analysis of the problem and methods of its solution

Modern recommender systems use explicit (when the user is asked to perform certain evaluations) and implicit (when information is obtained without the user performing evaluation actions) methods of information collection. In the first case, the user makes a quantitative assessment of objects, their ranking, determines the best among the whole set or proposed pairs of objects. In the second case, information about the user's interest in the content of the network, their subscriptions, messages, location, etc. is analyzed. Collaborative filtering first came into use as a

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means of combating excessive information on the Internet, and later filtering systems began to emerge that could automatically identify relevant opinions and aggregate them to provide recommendations. In the simplest case, personalized recommendations are presented as ranked lists of items [15].

One of the key problems of recommender systems is considered a problem of cold start [16]. Such a problem occurs in situations of incomplete data regarding preferences or selection of objects by new users or users who do not regularly perform automated selection of objects (purchase of real estate, vehicles, selection of tourist objects, etc.). The cold start problem is usually solved in two steps: context analysis of the input data and collaborative filtering. The context analysis process uses user behavior characteristics, which can be constructed using gradient descent and represented in the form of temporal graphs or neural network models [5]. A disadvantage of most recommendation systems is considered to be the use of only filters and sorting by user evaluation without taking into account user's individual preferences. More effective is the technology of collaborative filtering, which involves the analysis of object ratings received from users with similar preferences.

In traditional formulations of the problem of providing recommendations the set of system users $U = \{ u_j \}$, $j = \overline{1,m}$ and objects of choice are considered set $O = \{ o_i \}$, $i = \overline{1,n}$. In the process of interaction with the recommendation system, users provide information for forming a matrix of selection objects' ratings $R = [r_{ij}]$, $i = \overline{1,n}$, $j = \overline{1,m}$ (where r_{ij} is object $o_i \in O$ rating of user's $u_j \in U$. Taking into account that the number of objects in modern recommendation systems can be large, and known objects constitute a rather insignificant fraction of them, in practice the matrices of certain ratings $R' = [r_{ij}]$ are usually highly sparse. The main function of such systems is the establishment of prediction and recommendation for users about new objects. Such predictions can be represented by orders, binary relations or numerical values P_{ji} reflecting the value of the whole set of objects $o_i \in O$, $i = \overline{1,n}$ for users $u_j \in U$, $j = \overline{1,m}$. In this case, the recommendation is a list of the most preferred objects for a particular user. In this case, the recommendation is a list of the $N = |O'|$ objects $O' \subseteq O$ most suitable for a particular user.

In practice, it often turns out that a significant number among the objects proposed as alternatives may be ineffective under Pareto [17-18] in their multicriteria evaluation.

Orders on the set of recommended objects can be presented in the following form:

$$o_i \succ o_j \succ \ldots \succ o_z, \quad o_i, o_j, \ldots, o_z \in O' \subseteq O. \qquad (1)$$

A binary strict advantage relation reflecting the relative value of user objects can be represented as a set of arranged pairs:

$$R(O') = \{ < o_i, o_j >: \ o_i, o_j \in O', \ o_i \succ o_j \}. \qquad (2)$$

Most modern recommender systems use only filters and sorting based on the user's score, without taking into account the user's individual preferences. To overcome this drawback, the technology of collaborative filtering is used. It analyzes the ratings of objects given by users with similar preferences (fig. 1) [19]. Due to the sparseness of matrices $R' = [r_{ij}]$ and their high dimensionality (as a result of the growth of the volume of information regarding objects and users), the use of this method in many cases is irrational. In such cases, for practical implementation of collaborative filtering technology it is reasonable to use graph data model. In it, the results are represented as sets consisting of "user-object" pairs $u_j \times o_i$, $j = \overline{1,m}$, $i = \overline{1,n}$. Then for the predicted estimates, each pair of $u_j \times o_i$, $j = \overline{1,m}$ $i = \overline{1,n}$ will correspond the value of the predicted user estimate.

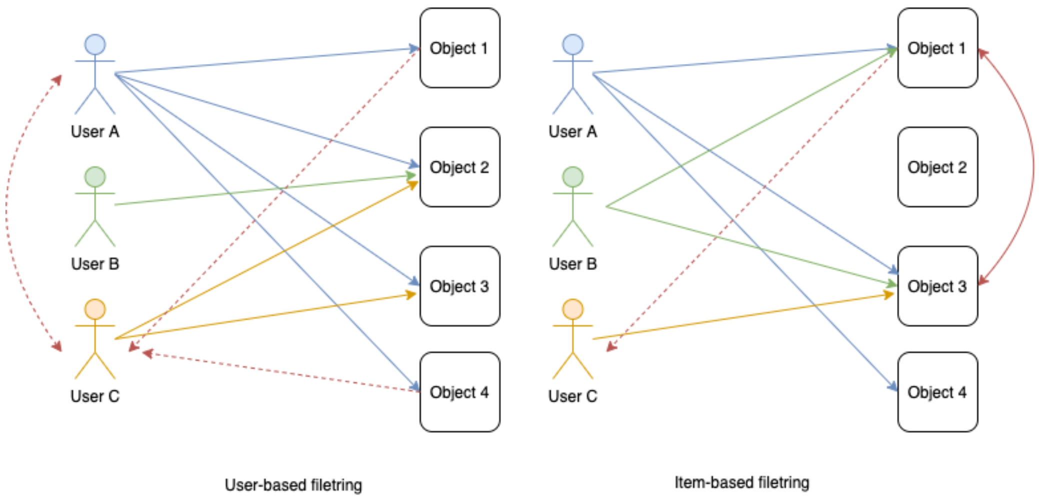

Fig. 1. Schemes of approaches based on the neighborhood of users and objects [19]

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In the projected graph of links

$$G=(V=(U,O'),E). \quad (3)$$

Vertices are elements from the sets $U=\{u_j\}$ and $O'=\{o_i\}$, and the edges E are set by the corresponding tuples $<u_j \in U, o_i \in O'>$, $j=\overline{1,m}$, $i=\overline{1,n}$.

The presence of an arc between the vertices of the graph u_j and o_i means that the object $o_i \in O'$ will be recommended (given a predictive score) to the user $u_j \in U$. Each arc of the graph has a weight corresponding to the value of the "user-object" distance function $d_{UO}=L(u_j \in U, o_i \in O')$.

Each vertex of the graph (3) corresponding to the preferences of an individual system user $u_j \in U$ has a certain number of arcs connecting it with the vertices corresponding to different objects of choice $o_i \in O'$. It is equal to the number of recommendations (or forecasts) requested by the user. Then the development of user's prediction is reduced to finding such a graph of connections, which will have the minimal weight of all arcs. This will correspond to the recommendation of such objects of choice for the user, in the graph of links the average distance between the vertices corresponding to them and the user will be the least.

A review of the current state of the problem of determining benefits in recommender systems found that:

- recommender systems are most likely to be useful to users who do not have sufficient personal experience or competence to evaluate alternative facilities and the reliance on recommendations from other users of the system;
- a significant number among facilities that are offered as alternatives may be ineffective under Pareto;
- content-based recommendations identify similarities in features of object content, but have a strong dependence on subject matter and limited value of recommendations;
- collaborative filtering is a generic approach, it generally produces better results than content-based filtering, but has a cold-start problem in the absence of information about user preferences;
- knowledge-based recommendations are of the highest quality, but the development and use of such systems is expensive;
- in its essence, recommender systems are specific decision support systems, to improve their effectiveness, the use of models and methods of multi-criteria decision making looks promising.

The aim of the study is to improve the effectiveness of recommender systems by improving the method for determining the advantages between objects in lists using the theory of multicriteria decision-making.

Results of the study

To increase the accuracy of user advantage determination, we use a mathematical apparatus to determine on the set of acceptable subsets of Pareto-optimal objects by local criteria, parametric synthesis of their scalar evaluation model, calculation of their generalized evaluations and their ordering [17 - 18].

At the first stages of formalization the essence of the problem of choosing the best user object can be represented by a logical statement «it is necessary to find o^o" or formally $<-,o^o>$ (where $o^o \in O$ is the best user object from the set of considered ones). At that, the situation of choosing the best object d is usually not clearly defined (formally $<d,->$). To proceed to the choice problem $<d,o^o>$, let us decompose the problem into a set of problems of the form: "given $<d,->$, necessary $<d,o^o>$" or "given $<-,o^o>$, necessary $<d,o^o>$", i.e.:

$$<<d,->,<d,o^o>>, \quad <<-,o^o>,<d,o^o>>. \quad (4)$$

The main tasks in the development of recommendation systems obtained as a result of decomposition of the decision-making problem (4) are: $Task_1$ - allocation of the set of admissible objects $O=\{o_i\}$, $i=\overline{1,n}$ satisfying the set of restrictions on the set of local criteria $k_l(o_i)$, $l=\overline{1,p}$; $Task_2$ – allocation of a subset of effective (Pareto-optimal) objects on the set of local criteria $O^E \subseteq O$; $Task_3$ – ranking of objects $o_i \in O^E$.

It is known that in practice a significant part among the objects of multicriteria choice $O=\{o_i\}$, $i=\overline{1,n}$, the information about which is in the system, can be dominated [17 - 18]. Relative to them there are objects best simultaneously on all quality indicators $k_l(o_i)$, $l=\overline{1,p}$.

An object of choice $o^E \in O$ belongs to a subset of non-dominated (Pareto-optimal, efficient) $O^E \subseteq O$ if there is no object for which the inequalities are fulfilled:

$$k_l(o_i) \ge k_l(o^E), \text{ if } k_l(o_i) \to max, \; l=\overline{1,p}, \quad (5)$$

$$k_l(o_i) \le k_l(o^E), \text{ if } k_l(o_i) \to min, \; l=\overline{1,p} \quad (6)$$

and at least one of them was strict.

The results of experimental studies for uniform distribution of object characteristics in the space of local criteria $k_l(o_i)$, $l=\overline{2,7}$ showed that: the powers of Pareto-optimal object subsets $|O^E|$ depending on the number of local criteria p and the powers of the sets of admissible objects $|O|$ have a stable tendency to growth, and the relative sizes of Pareto-optimal object subsets $|O^E|/|O|$ have a stable tendency to reduction (table 1, fig. 2).

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Table 1. *Relative power of a subset of Pareto-optimal objects*

p	**Number of objects of choice, *n***									
	10	20	30	40	50	60	70	80	90	100
2	0,200	0,150	0,133	0,100	0,100	0,083	0,071	0,075	0,078	0,080
3	0,400	0,300	0,233	0,225	0,160	0,150	0,286	0,275	0,278	0,260
4	0,600	0,450	0,400	0,350	0,240	0,317	0,400	0,350	0,300	0,280
5	0,700	0,600	0,500	0,650	0,580	0,567	0,500	0,475	0,422	0,430
6	0,900	0,750	0,767	0,725	0,700	0,683	0,600	0,575	0,656	0,630
7	1,000	0,900	0,933	0,900	0,840	0,783	0,729	0,713	0,722	0,710

On this basis, using the method of even comparisons, a preliminary separation of a subset of non-dominated objects of choice is proposed [17]. To further reduce the set of non-dominant objects and to compose them, it is proposed to use the idea of the combined method [18].

Its use implies that each object of choice $o_i \in O^E$ is assigned a scalar estimate of its generalized utility, reflecting its value for the user $P(o_i)$:

$$o_i \succ o_j \leftrightarrow P(o_i) > P(o_j), \quad (7)$$

the value of which will determine the ordering of the whole set of objects: $o_i \succ o_j \succ \ldots \succ o_z$, $o_i, o_j, \ldots, o_z \in O' \subseteq O$.

For quantitative scalar estimation of generalized utility of objects the classical additive convolution of local criteria can be used [17 - 18]:

$$P(o_i) = \sum_{l=1}^{p} \lambda_l \xi_l(o_i), \quad (8)$$

$$\xi_l(o_i) = [(k_l(o_i) - k_l^-)/(k_l^+ - k_l^-)]^{\mu_l}, \; l = \overline{1,p}, \quad (9)$$

where λ_l, $l = \overline{1,p}$ – parameters that characterize the importance of the individual properties of the object of choice $k_l(o_i)$, $\lambda_l \geq 0$, $\sum_{l=1}^{p} \lambda_l = 1$ for the user; $\xi_l(o_i)$ – value of the utility function of the local criterion value $k_l(o_i)$; k_l^+, k_l^-, $l = \overline{1,p}$ – best and worst values of the l-th local criterion; μ_l – parameter determining the type of dependence (9): linear, convex or concave.

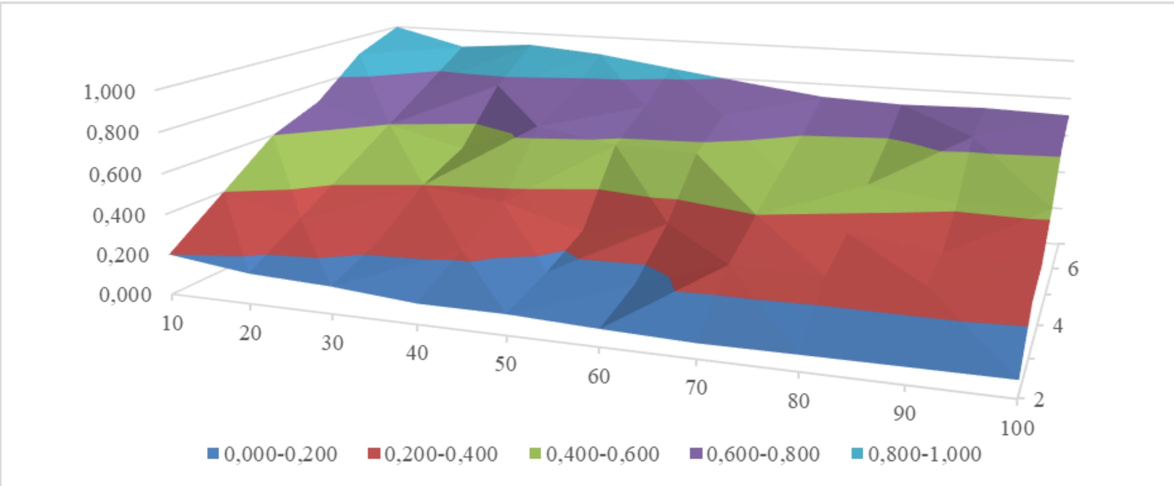

Fig. 2. Relative power of a subset of Pareto-optimal objects

The user of the system by the results of the analysis of proposals among the Pareto-optimal objects on the set of local criteria $k_l(o_i)$, $l = \overline{1,p}$ determines its advantages. In the easiest case, he chooses the best object $o^o \in O^E$ in his opinion. This choice corresponds to the binary relation of the strict advantage of this kind:

$$R(O^E) = \{<o^o, o_i>: \; o^o, o_i \in O^E, \; o^o \succ o_i\}. \quad (10)$$

In general, using quantitative or qualitative estimates, the user can set the order among the non-dominant objects offered to him:

$$o_i \succ o_j \succ \ldots \succ o_z, \; o_i, o_j, \ldots, o_z \in O^E. \quad (11)$$

or determine the advantages among the pairs of objects offered for comparison:

$$R(O^E) = \{<o_i, o_j>: \; o_i, o_j \in O^E, \; o_i \succ o_j\}. \quad (12)$$

On the basis of the established relation of strict advantage (10), (11) or (12) let us make a system of inequalities of the form:

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$$P(o_i,\lambda)>P(o_j,\lambda),\ <o_i,o_j>\in R(O^E),\ \sum_{l=1}^{p}\lambda_l=1,\ \lambda_l\ge 0,\ (13)$$

where $\lambda=[\lambda_1,\lambda_2,...,\lambda_p]$ – vector of model weighting coefficients (8).

The problem of parametric synthesis of the model (8) consists in determining the coordinates of the vector $\lambda=[\lambda_l]_{l=1}^{p}$ corresponding to the established system of inequalities (13), as well as the condition of its normalization.

If the user preferences (10), (11) or (12) are non-contradictory, the system (13) can have many solutions. To regularize the problem, it is proposed to reduce the process of its solution to the search for its Chebyshev point [17 - 18]. In this case, if the user-defined binary relation (10), (11) or (12) is consistent, the system of inequalities (13) will be compatible. Then the resulting set of model parameters $\lambda=[\lambda_1,\lambda_2,...,\lambda_p]$ (8) will be as stable as possible to probable changes in user preferences.

Using the set parameter $\lambda=[\lambda_1,\lambda_2,...,\lambda_p]$ values, let's calculate the value of the generalized value function (8) of the proposed user objects of the recommender system $P(o_i),\ o_i\in O^E$. On the basis of obtained values of parameters $\lambda=[\lambda_1,\lambda_2,...,\lambda_p]$ and properties of objects set by values of local criteria $k_l(o_i)$, $l=\overline{1,p}$ the correct orders will be formed when changing a set of objects of choice for the user of the system $O=\{o_i\}$, $i=\overline{1,n}$.

Let us consider the problem of putting in order 8 objects of the recommender system by solving the problem using the general utility model (8). Each of the objects is estimated by four local criteria $k_l(o_i)\to max$, $l=\overline{1,4}$ on a ten-point scale. Let's calculate by relation (9) the value of utility functions of local criteria $\xi_l(o_i)$, $l=\overline{1,4}$ for $\mu_l=1$ (table 2).

Table 2. *Characteristics of user choice objects*

o_i	$k_1(o_i)$	$k_2(o_i)$	$k_3(o_i)$	$k_4(o_i)$	$\xi_1(o_i)$	$\xi_2(o_i)$	$\xi_3(o_i)$	$\xi_4(o_i)$	$P(o_i)$
o_1	8,51	9,74	5,95	9,78	0,851	0,974	0,595	0,978	0,8692
o_2	9,26	7,07	7,91	9,43	0,926	0,707	0,791	0,943	0,8346
o_3	9,72	8,86	8,45	5,93	0,972	0,886	0,845	0,593	0,8296
o_4	9,58	7,01	7,87	8,78	0,958	0,701	0,787	0,878	0,8244
o_5	6,51	8,62	7,89	9,65	0,651	0,862	0,789	0,965	0,8193
o_6	7,99	9,15	9,02	4,35	0,799	0,915	0,902	0,435	0,7692
o_7	4,58	8,34	9,75	8,17	0,458	0,834	0,975	0,817	0,7639
o_8	9,84	5,25	3,51	8,15	0,984	0,525	0,351	0,815	0,6743
o_9	5,19	8,38	6,95	4,97	0,519	0,838	0,695	0,497	0,6488
o_{10}	8,92	0,62	8,19	8,51	0,892	0,062	0,819	0,851	0,6072
o_{11}	9,81	7,67	2,75	2,16	0,981	0,767	0,275	0,216	0,5919
o_{12}	9,89	3,45	3,06	6,32	0,989	0,345	0,306	0,632	0,5666

Let the user, based on his preferences, determine the order of the form (11) on a given set of objects:

$$o_1\succ o_2\succ o_3\succ o_4\succ o_5\succ o_6\succ o_7\succ o_8\,. \qquad (14)$$

To solve the problem of parametric synthesis of the general utility model (8) by the method of comparator identification, let us make a system of inequalities and equations (13) and reduce the process of its solution to the search for its Chebyshev point:

$$\begin{cases}\eta_j(\lambda)\equiv\sum_{l=1}^{4}\lambda_l\,\xi_l(o_i)-\sum_{l=1}^{4}\lambda_l\,\xi_l(o_j)>0,<o_i,o_j>\in R(O^E),\ j=\overline{1,7},\\ \eta_8(\lambda)\equiv\sum_{l=1}^{4}\lambda_i=1,\ \lambda_l\ge 0,\ l=\overline{1,4}.\end{cases} \qquad (15)$$

Stable estimates of the vector of model parameters $\lambda=[\lambda_1,\lambda_2,\lambda_3,\lambda_4]$ (8) is a solution of the problem of searching the Chebyshev point [17 - 18]:

$$\begin{cases}\eta_j(\lambda)+\lambda_5>0,\quad j=\overline{1,7},\\ \eta_8(\lambda)\equiv\sum_{l=1}^{4}\lambda_l=1,\quad \lambda_l\ge 0,\quad l=\overline{1,4},\\ \lambda_5\to min.\end{cases} \qquad (16)$$

The solution of problem (16) will be a vector of weight coefficients of local criteria. $\lambda=[0{,}250;\ 0{,}314;\ 0{,}198;\ 0{,}238]$. The values of the generalized value function (8) of the objects $P(o_i)$, $i=\overline{1,8}$ calculated on their basis fully correspond to the user's preferences (14). Using the obtained values of weighting coefficients, the estimates $P(o_i)$ of new objects $i=\overline{9,12}$ added to the system are calculated. On the basis of the expanded table on the basis of the necessary number of objects in the list and values of the function of the generalized value, the new list of recommendations is formed (tab. 2).

According to the results of experiments, it was found that the proposed method of order formation based on comparator identification technology has lower temporal complexity when including new objects in the system than the method of collaborative filtering.

For more adequate identification of the user benefits of the recommender system, if sufficient computational resources are available, an additive-multiplicative model based on the Kolmogorov-Gabor polynomial can be used [17 - 18]:

$$P(o_i)=\sum_{j=1}^{p}\lambda_l\xi_l(o_i)+\sum_{j=1}^{p}\sum_{k=j}^{p}\lambda_{jk}\xi_j(o_i)\xi_k(o_i)+\sum_{j=1}^{p}\sum_{k=j}^{p}\sum_{l=k}^{p}\lambda_{jkl}\xi_j(o_i)\xi_k(o_i)\xi_l(o_i)+... \quad (14)$$

where λ_j, λ_{jk}, λ_{jkl} – weighting coefficients assessing the mutual importance of local criteria $k_i(o_i)$, $k_j(o_i)$, $k_l(o_i)$ and their products; $0<\xi_j(o_i)<1$, $j=\overline{1,p}$ – value of the utility function of the local criterion $k_j(o_i)$, $j=\overline{1,p}$ for an object from the set of non-dominant $o_i \in O^E$.

Model (14) is universal and allows to describe all possible advantages of the system users. Its special case under $\lambda_{jk}=0$, $\lambda_{jkl}=0$, $j,k,l=\overline{1,p}$ is the classical additive model of scalar multicriteria estimation (8). In addition, the accuracy of determining user benefits of recommender systems based on models (8) and (14) can be improved by using universal utility functions that allow to realize both linear and nonlinear (including S- and Z-shaped) dependences on the values of local criteria [20 - 22].

The proposed method allows to take into account the set of object characteristics defined by the values of local criteria, has a lower time complexity than the method of collaborative filtering, allows to take into account the advantages of users of recommender systems more accurately, provide recommendations only to those objects that belong to the Pareto-optimal set and on this basis improve the quality of orders of proposals formed for them.

Conclusions

According to the results of the review of the current state of the problem of determining benefits in recommender systems, it was found that they use information about the similarity of the characteristics of objects or the acts of selection of objects by users with similar preferences to form suggestions. Existing methods for providing recommendations based on content, collaborative filtering, and knowledge use only generalized evaluations of objects and have relatively high temporal complexity. At the same time, it is known that a significant number among the objects that make it to the recommendation lists may be inefficient under Pareto. Proceeding from the fact that recommendation systems are essentially specific decision support systems, models and methods of the theory of multicriteria decision making are used to improve their efficiency.

To improve the quality of recommendations, it was proposed to use the evaluation of objects by the set of indicators, which will be considered as local criteria of their effectiveness and to carry out a preliminary filtering of objects included in the lists by checking them for Pareto-optimality. For the inclusion of objects in the lists of recommended, it turned out to be expedient to perform their scalar multicriteria evaluation with the use of generalized value functions. Depending on amount of data, available computational and time resources, both classical additive model and universal additive-multiplicative model based on Kolmogorov-Gabor polynomial can be used for this purpose. For the structural-parametric synthesis of the model, it is proposed to use the comparator identification technology, which allows to solve the problem using both active experiments and collection of information about the facts of users' choices.

The developed method of benefits establishment extends the methodological foundations of automation of development and operation of recommender systems, other multicriteria decision support systems, allows to carry out correct reduction of the set of non-dominant objects for the final choice taking into account the knowledge and experience of users, which are difficult to formalize. Practical use of the received results at the expense of more economical method of formation of lists at addition of new objects will allow to lower time and capacitive complexity of procedures of granting of recommendations, and at the expense of consideration of set of weighted local indicators and allocation of set of non-dominant objects – to raise quality of the given recommendations.

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ВИЗНАЧЕННЯ ПЕРЕВАГ У РЕКОМЕНДАЦІЙНИХ СИСТЕМАХ НА ОСНОВІ ТЕХНОЛОГІЇ КОМПАРАТОРНОЇ ІДЕНТИФІКАЦІЇ

Предметом дослідження в статті є процес ранжування об’єктів у списках рекомендаційних систем. **Мета** роботи – підвищення ефективності рекомендаційних систем за рахунок удосконалення методу визначення переваг між об’єктами у списках з використанням теорії прийняття багатокритеріальних рішень. У статті вирішуються наступні **завдання:** огляд і аналіз сучасного стану проблеми встановлення переваг між об’єктами та їхнього ранжування у списках рекомендаційних систем; аналіз методів фільтрації, що використовуються в рекомендаційних системах; декомпозиція проблеми підтримки прийняття рішень з вибору об’єктів; розробка комбінованого методу ранжування об’єктів у списках рекомендаційних систем, який об’єднує процедури виділення підмножини Парето-оптимальних об’єктів, структурно-параметричного синтезу моделі скалярного багатокритеріального оцінювання та оцінювання всієї множини виділених об’єктів. Використовуються такі **методи:** математичного моделювання, теорії систем, теорії корисності, теорії прийняття рішень, оптимізації та дослідження операцій. **Результати.** За результатами аналізу сучасної методології ранжування об’єктів у списках рекомендаційних систем встановлена можливість підвищення їхньої ефективності. Для врахуванням факторів, що важко піддаються формалізації, знань і досвіду користувачів запропоновано реалізувати визначення переваг між об’єктами з використанням теорії прийняття багатокритеріальних рішень. Виконана декомпозиція проблеми формування списків рекомендаційних систем на задачі виділення підмножини Парето-оптимальних об’єктів, структурно-параметричного синтезу моделі скалярного багатокритеріального оцінювання та оцінювання множини виділених об’єктів. Розроблено комбінований метод ранжування варіантів, який об’єднує процедури технологій ординалістичного та кардиналістичного впорядкування та дозволяє коректно скорочувати підмножин об’єктів, що включаються до списків рекомендацій. **Висновки.** Розроблений метод встановлення переваг розширює методологічні засади автоматизації процесів розробки та експлуатації рекомендаційних систем, інших систем підтримки прийняття багатокритеріальних рішень, дозволяє здійснювати коректне скорочення множини недомінованих об’єктів для остаточного вибору з урахуванням факторів, що важко піддаються формалізації, знань і досвіду користувачів. Практичне використання отриманих результатів за рахунок більш економного методу формування списків при додаванні нових об’єктів дозволить знизити часову й ємнісну складності процедур надання рекомендацій, а за рахунок врахування множини зважених локальних показників і виділення множини недомінованих об’єктів – підвищити якість рекомендацій, що надаються.

Ключові слова: багатокритеріальне оцінювання; компараторна ідентифікація; рекомендаційна система; ранжування об’єктів; структурно-параметричний синтез.

ОПРЕДЕЛЕНИЕ ПРЕДПОЧТЕНИЙ В РЕКОМЕНДАТЕЛЬНЫХ СИСТЕМАХ НА ОСНОВЕ ТЕХНОЛОГИИ КОМПАРАТОРНОЙ ИДЕНТИФИКАЦИИ

Предметом исследования в статье является процесс ранжирования объектов в списках рекомендательных систем. **Цель** работы – повышение эффективности рекомендательных систем за счет усовершенствования метода определения предпочтений между объектами в списках с использованием теории принятия многокритериальных решений. В статье решаются следующие **задачи:** обзор и анализ современного состояния проблемы определения предпочтений между объектами и их ранжирование в списках рекомендательных систем; анализ методов фильтрации, используемых в рекомендательных системах; декомпозиция проблемы поддержки принятия решений по выбору объектов; разработка комбинированного метода ранжирования объектов в списках рекомендательных систем, объединяющего процедуры выделения подмножества Парето-оптимальных объектов, структурно-параметрического синтеза модели скалярного многокритериального оценивания и оценки всего множества выделенных объектов. Используются следующие **методы:** математического моделирования, теории систем, теории полезности, теории принятия решений, оптимизации и исследования операций. **Результаты.** По результатам анализа современной методологии ранжирования объектов в списках рекомендательных систем установлена возможность повышения их эффективности. Для учета трудно поддающихся формализации факторов, знаний и опыта пользователей предложено реализовать определение предпочтений между объектами с использованием теории принятия многокритериальных решений. Выполнена декомпозиция проблемы формирования списков рекомендательных систем на задачи выделения подмножества Парето-оптимальных объектов, структурно-параметрического синтеза модели скалярного многокритериального оценивания и оценки множества выделенных объектов. Разработан комбинированный метод ранжирования вариантов, объединяющий процедуры технологий ординалистического и кардиналистического упорядочения и позволяющий корректно сокращать подмножества объектов, включаемых в списки рекомендаций. Разработанный метод определения предпочтений расширяет методологические основы автоматизации процессов разработки и эксплуатации рекомендательных систем, других систем поддержки принятия многокритериальных решений, позволяет **Выводы.** осуществлять корректное сокращение множества недоминированных объектов для окончательного выбора с учетом трудно поддающихся формализации факторов, знаний и опыта пользователей. Практическое использование полученных результатов за счет более экономного метода формирования списков при добавлении новых объектов позволит снизить временную и емкостную сложности процедур предоставления рекомендаций, а за счет учета множества взвешенных локальных показателей и выделения множества недоминированных объектов – повысить качество предоставляемых рекомендаций.

многокритериальное оценивание; компараторная идентификация; рекомендательная система; ранжирование объектов **Ключевые слова:**; структурно-параметрический синтез.

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