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DETAILING EXPLANATIONS IN THE RECOMMENDER SYSTEM BASED ON MATCHING TEMPORAL KNOWLEDGE

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The problem of matching knowledge in the temporal aspect when constructing explanations for recommendations is considered. Matching allows reducing the influence of conflicting knowledge on the explanation in a recommender system.

A model of knowledge representation in the form of a temporal rule with the explanation constraint is proposed. The temporal rule sets the order for two sets of events of the same type that occurred at two different time intervals in time. An explanation constraint establishes a correspondence between the temporal order represented by the rule for a pair of intervals and the description of temporal dynamics for a given time period. This dynamic is represented by the explanation of the recommendation. The model is designed to match knowledge, taking into account the explanation constraint, as well as further use the matched knowledge to clarify explanations based on the results of the intelligent system.

A method for clarifying explanations in a recommender system based on knowledge matching in the form of temporal rules is developed. The method uses records of purchases of goods, services or their ratings as input data. The method identifies a subset of rules matched in the temporal aspect, which represent the same dynamics of consumer demand for the target item (increase or decrease) as explanations in the recommender system. Matching of temporal knowledge makes it possible to form a refined list of explanations. This list includes basic and clarifying explanations. The basic explanation reflects the dynamics of user interests for the entire given period of time. Clarifying explanation specifies changes in demand for individual intervals within a given time period. The use of the temporal dynamics of user preferences in the explanation is aimed at increasing confidence in the received recommendations

Keywords: recommender system, explanation of recommendations, temporal rules, knowledge matching

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1. Introduction

Recommender systems provide personalized offers of goods, services, information for users based on available data about their interests and preferences. Initial data for recommendations reflect similarities in the characteristics of goods and services, as well as records of the choice of the same and similar items by other consumers. The specified data are generated based on explicit and implicit feedback from the user. Explicit feedback is provided by user-submitted item ratings. Implicit feedback is reflected by records of purchases of goods and services. The use of such systems makes it easier for users to compare characteristics, as well as to choose a suitable item among many similar products [1]. Therefore, recommender systems are widely used as part of e-commerce systems, streaming services, when promoting online events, hotel reservations [2].

The existing algorithms for constructing recommendations allow you to effectively predict the interests of users in the presence of data on their purchases and ratings submitted by users [3]. However, in some situations, information about users may be inaccurate or incomplete, which leads to distortion of recommendations. The received incorrect recommendations do not meet the interests of users, which reduces the credibility of the recommender system. Inaccuracies and distortions in user preference data result from shilling attacks [4]. Such attacks are used to change the sales of target items in the direction desired by the attacker. The essence of a shilling attack is to artificially change the ratings of the target items. As a result, a personal recommendation is formed with distortions and may not take into account the real preferences of users. The recommender system, using an incorrect personal list of goods and services, "forces" the user to choose those items that the attacker is interested in. In case of incomplete information about the user, recommendations are built for new or irregular users [5]. In such a cold start situation, there are no data obtained as a result of feedback from the user, since the latter has not yet made purchases or posted ratings.

Therefore, at present, one of the trends in the development of recommender systems, which makes it possible to consider the incompleteness and inaccuracy of the initial data, is to supplement recommendations with explanations [6]. In accordance with this trend, personalized information for the user is provided in two aspects: the actual recommendation and the explanation for it. The explanation reveals the reasons for including the item in the recommended list of goods and services in order to increase the user's confidence and subsequently convince him to accept the offers received by this system. When constructing explanations, knowledge about the relationship between the characteristics of a product and its placement in the recommended personal list of items is used. In particular, the explanations use information about the popularity of the item, the distribution of item ratings from similar users, the similarity of topics, authors, interests of users [7]. The use of explanations increases the user confidence in the personalized list of items [8].

The initial knowledge for explanations must be matched in order to reduce the influence of incorrect and inconsistent dependencies on the resulting explanation. The matched knowledge satisfies the chosen set of constraints. In particular, when constructing explanations, an explanation relation established for pairs of elements of a set of matched knowledge can be used as a constraint. This relation is true if one of the elements is an explanation for the second [9].

Since consumer requirements change over time, it is advisable to take into account the temporal dynamics of user preferences when constructing explanations [10]. Temporal dynamics is displayed as an ordered sequence of user selections [11]. Taking into account temporal dynamics allows you to quickly adjust the list of recommendations and corresponding explanations when changing user requirements in order to increase sales of offered goods and services [12].

Therefore, the selection and matching of knowledge reflecting changes in user preferences over time and used to form explanations is an important task. The solution to this problem creates conditions for the construction and timely refinement of explanations, taking into account the temporal dynamics of consumer preferences in conditions of incomplete or incorrect data about such users.

2. Literature review and problem statement

The recommender system contains information about the temporal dynamics of preferences in the form of absolute values of the user's choice time, as well as in the form of the order of purchase events, rating, site page selection, etc. Using the available temporal data allows you to take into account both periodic and evolutionary changes in user requirements to improve the accuracy of recommendations and then explain these recommendations [13]. When taking into account temporal changes, time is considered as a special case of the user's decision-making context. The contextual approach involves identifying patterns of user behavior when selecting data for recommendations [14]. The temporal pattern reflects the frequency of changes in the requirements of a group of users. The results of [15] show that the selection of groups of related users, considering the time of setting ratings by these users makes it possible to filter out irrelevant data when building recommendations. In [16], it is shown that considering only long-term cyclical changes in offline mode does not significantly improve the accuracy of recommendations. It is necessary to additionally simulate the current sequence of user actions in the online mode of the recommender system. In [17], it is proposed to use a sequence of actions model to identify context-based user intentions. For the prompt construction of recommendations, the records of the user interaction with the recommender system are used [18]. To improve the accuracy of such operational recommendations, preference trends are identified for individual users or for the community [19].

In general, the approaches based on temporal patterns are intended to describe established, for example, seasonal, cycles of changes in user preferences in the offline mode of the recommender system. When constructing relevant explanations, temporal patterns should be supplemented with information about the current actions of the user. Analysis of the current sequence of user actions in the online mode makes it possible to identify short-term cyclical and evolutionary changes in user requirements. This possibility demonstrates the preference for constructing explanations online. However, approaches focused on current sequences of user actions use limited datasets, making it difficult to generalize temporal changes for multiple clients.

In [20], it is shown that in order to take into account temporal changes, a representation of temporal knowledge is formed based on a relative representation of time. This representation makes it possible to define the order of user actions over time in the form of an adaptable temporal pattern of explanations, taking advantage of pattern-based approaches and sequencing models. Knowledge representation in the form of weighted temporal rules is proposed in [21]. Such rules set the order in time for pairs of events or states that record the execution of an arbitrary process. Unlike traditional causal rules, temporal dependencies only represent the sequence of events without indicating the cause-and-effect relationships between them. The weights of temporal rules are determined taking into account the frequency of processes, knowledge about which is presented in the form of rules [22].

In general, temporal knowledge allows us to describe the processes of functioning of intelligent systems, as well as to form explanations that take into account changes in consumer behavior over time. However, when solving problems of representing temporal dependencies and constructing explanations, the problem of knowledge coherence was not considered, taking into account the limitations characteristic of these problems.

The concept of knowledge coherence is presented in [23]. According to this concept, the task of matching is to split the initial set of dependencies into two subsets: matched and unmatched knowledge. Any pair of elements from the first subset satisfies a matching relation, for example, the explanation relation of the second element by the first element of the pair. For a pair in which the first element belongs to a subset of matched knowledge, and the second to a subset of unmatched knowledge, a knowledge matching relation is satisfied, for example, a knowledge incompatibility relation. In other words, the relations of matching and mismatching of knowledge act as constraints that the elements of the corresponding subsets must satisfy [24]. The main difficulties in implementing the concept of knowledge matching are associated with the definition and formalization of these relations [25]. However, due to the considered features of temporal knowledge, the matching/mismatching relations for them can be unambiguously implemented taking into account the order of the described events in time.

Thus, when constructing recommendations and explanations for recommendations, taking into account the temporal dynamics of users' interests, it is necessary to select only matched temporal rules. Matching allows you to cut off dependencies that contain incorrect knowledge about changing user attitudes towards target items. However, the existing approaches to matching do not take into account the time factor and can be used only when constructing static dependencies, taking into account the specifics of the subject area. Therefore, the problem of matching temporal knowledge when constructing explanations for a personalized list of user items, taking into account the temporal dynamics of the interests of the recommender system, requires a solution.

3. The aim and objectives of the study

The aim of the study is to improve the process of forming explanations in recommender systems, taking into account the multidirectional changes in user interests by matching the temporal knowledge used to form these explanations.

To achieve the aim, the following objectives were set:

– to improve the temporal rule model using a constraint in the form of an explanation relation;

– to develop a method for clarifying explanations based on matching temporal rules;

– to experimentally test the method of clarifying explanations based on matching temporal rules using datasets of product sales.

4. Improving the temporal rule model using an explanation relation

In this work, we use the adaptation of the temporal rule based on the approach proposed in [26]. Temporal rules are based on temporal modal logic, which determines the truth of propositional variables with regard to time. Rules differ in the use of weights to assess the order of events or states over time. Applying rule weights allows you to move from binary to numerical estimation of temporal changes.

The performed adaptation of the temporal rule represents the change in the numerical estimates of two groups of similar events $e_{i,j}$ over time. For example, a rule may reflect changes in user interest in specific items (goods, services) within a given period of time ΔT. With explicit feedback, events occur when ratings are set. Changes in preferences are represented by changes in ratings. In the case of using implicit feedback, the change in the user's interest in an item is described by a decrease or increase in the number of purchases of the specified item for a pair of time intervals $(\Delta\tau_m, \Delta\tau_M)\in\Delta T$ of the same duration. The second interval of the pair corresponds to the moment of constructing the explanation.

The adapted temporal rule $r_{i,m}$ for the i-object relates the numerical estimates of the sets of events $E_{i=\{e_{i,j}\}}$ on the intervals $\Delta\tau_m$ and $\Delta\tau_M$, and has the following form:

$$r_{i,m} = q_{i,m}\ w_{i,m}^{(t)}\ q_{i,M},\ \ m=\overline{1,M-1}, \quad (1)$$

where $q_{i,m}$ and $q_{i,M}$ are the numerical estimates of the sets of events on the intervals $\Delta\tau_m$ and $\Delta\tau_M$, respectively; t is the type of rule; $w_{i,m}^{(t)}$ is the weight of rule.

The numerical estimate is a function of the events $e_{i,j}$:

$$q_{i,m} = f(E_i): \forall e_{i,j}\in E_i\ \exists\tau_j\in\Delta\tau_m, \quad (2)$$

where τ_j is the moment the event occurred $e_{i,j}$.

For recommender systems, the numerical estimate determines the user's degree of interest in the i-target item. When using implicit feedback, the estimate $q_{i,m}$ is determined as the number of purchases of i-goods in the time interval $\Delta\tau_m$. In the case of explicit feedback, the numerical estimate sets the average rating of the i- item at the selected time interval.

The type of rule is determined by the temporal operator used. In particular, the X(NeXt) operator links two consecutive time intervals, the F (Future) operator links two intervals, between which there are other intervals.

The weight of the adapted rule is calculated as the difference between the numerical estimates $q_{i,m}$ and $q_{i,M}$. This approach corresponds to [26] and differs from the resource-intensive estimate proposed in [22]. Calculation of weight based on the difference in estimates allows you to quickly match the rules, taking into account the latest events in the current interval $\Delta\tau_M$. In the case of matching knowledge about various events, such as the purchase of various goods, the estimates $q_{i,m}$ and $q_{i,M}$ must first be normalized.

It is shown in [26] that the explanation g_i that takes into account the temporal dynamics of user interests is represented by a numerical indicator that is equal to the sum of the normalized weights of temporal rules for a given period of time ΔT. When constructing such explanations, F-type rules were used. These rules connect all previous intervals $\Delta\tau_m$ with the current interval $\Delta\tau_M$, for which an explanation is generated. The positive value of this indicator shows the total increase in sales (increase in ratings) in the current interval $\Delta\tau_M$ in relation to the previous intervals $\Delta\tau_m$ for the selected period ΔT.

Knowledge matching makes it possible to select only those temporal rules that correspond to the explanation indicator for recommendations into a separate subset. The semantics of this correspondence is as follows. Let the explanation of the recommendation be positive and therefore reflect the user's growing interest in the target item. Then the resulting explanation simultaneously explains the rules representing the increase in sales or ratings for pairs of intervals $(\Delta\tau_m, \Delta\tau_M)$ from the selected time period ΔT. The correspondence between the rule $r_{i,m}$ and the explanation g_i can be represented as an $Expl$ relation for the rule. This relation is true if the sign of the rule weight is equal to the sign of the explanation:

$$g_i\ Expl\ r_{i,m} = \begin{cases} \text{true, if}\left(w_{i,m}^{(t)}\ge 0\wedge g_i\ge 0\right)\vee \\ \vee\left(w_{i,m}^{(t)}<0\wedge g_i<0\right), \\ \text{false, otherwise.} \end{cases} \quad (3)$$

The model of the matched temporal rule contains the introduced explanation relation (3) as a constraint:

$$r_{i,m}^{(\mathrm{expl})} = q_{i,m}\ w_{i,m}^{(t)}\ q_{i,M}\ \middle|\ g_i\ Expl\ r_i = \text{true}. \quad (4)$$

According to expression (4), matched rules show the same temporal dynamics with the explanation. Since the type of the temporal operator does not affect the sequence of clarifications of explanations, in the future the weight of the rule will be indicated in a simplified form: $w_{i,m}$.

5. Development of a method for clarifying explanations based on matching temporal rules

The developed method is focused on iterative clarification of explanations for recommendations based on the selection of a subset of matched temporal rules $R_A = \{r_{i,m}^{\exp l}\}$. These rules simultaneously show an increase or decrease in sales, ratings of i–goods, services. Therefore, the weight of all matched rules has the same sign.

Rules for which condition (3) is not satisfied refer to the set of unmatched R_D. During matching by explanation, all the rules from the original set R must be divided between subsets of matched and unmatched knowledge: $R_D = R \setminus R_A$. If the total weight of matched rules exceeds the weight of unmatched rules, then the explanation relation is true for the entire set R:

$$g_i \, Expl \, R = \begin{cases} \text{true, if} \, |W_A| > |W_D|, \\ \text{false, otherwise,} \end{cases} \tag{5}$$

where W_A – total weight of matched rules; W_D – weight of unmatched rules.

In the general case, the task of matching temporal rules is to select rules with the maximum absolute value of the total weight in the set R_A:

$$|W_A| \to \max,$$
$$W_A = \sum_{m=1}^{M-1} \left(w_{i,m} : g_i \, Expl \, r_{i,m} \text{=true} \right). \tag{6}$$

When constructing an explanation for one item, it is enough to check condition (5). The problem in the formulation (6) is solved in the case of forming a unified explanation for a set of items.

The set of rules describes the dynamics of user preferences over a given subset of time intervals [27]. A generalized example of such a description for the problem of matching rules when constructing explanations is shown in Fig. 1. The original explanation g_i is formed from the temporal rules $r_{i,1}$, $r_{i,2}$, $r_{i,m-1}$, $r_{i,m}$, $r_{i,m+1}$ using the method presented in [26]. These rules specify changes in the user's interests for the corresponding pairs of intervals, for example ($\Delta\tau_1$, $\Delta\tau_M$) for the rule $r_{i,1}$, ($\Delta\tau_{m+1}$, $\Delta\tau_M$) for the rule ri, m+1, etc. Some of these rules, namely ri,1, $r_{i,m}$, $r_{i,m+1}$ are matched with the explanation g_i. So, they show an increase in sales of the i-item for the corresponding pairs of intervals if the explanation g_i also shows an increase in sales. These rules belong to the subset R_A. Other rules, such as $r_{i,2}$ and $r_{i,m-1}$, show large sales in the previous intervals $\Delta\tau_2$ and $\Delta\tau_{m-1}$ compared to the current interval $\Delta\tau_M$. Therefore, these rules belong to the subset of unmatched knowledge R_D.

Dividing the original subset of rules into two subsets allows the user to refine the explanations by constructing two new explanations g_i^* and g_i^{**}. The first of them corresponds to the original explanation and reflects, for example, the general trend of growth in demand for the i-item for the entire period of time ΔT, ending with the current interval $\Delta\tau_M$. Thus, the explanation g_i^* "pushes" the consumer to buy. The second explanation g_i^{**} shows that there are time intervals with a higher demand for the product in relation to the current interval $\Delta\tau_M$. Such a situation may, for example, arise for goods of periodic use, in particular, gift sets that are bought on holidays. Therefore, the second explanation makes it possible to increase the user's confidence both in the first explanation and in the resulting recommendation as a whole.

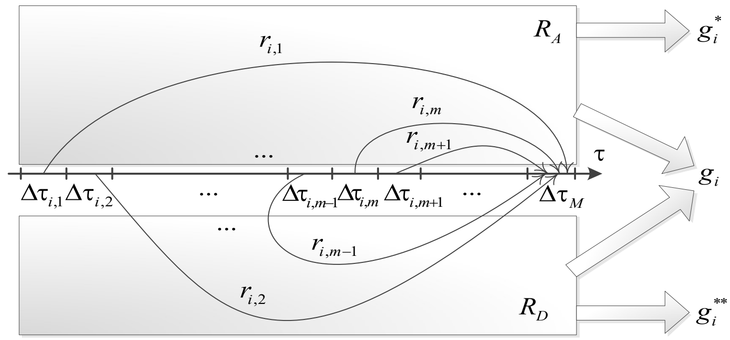

Fig. 1. Scheme of matching rules for an explanation taking into account the temporal dynamics of user interests

The developed method uses data on user behavior presented by the sales or rating log; time period for building temporal rules ΔT; duration of time intervals $\Delta\tau_m$; target i-item as input data. Sales or rating logs contain timestamps. Each sale or rating event $e_{i,j}$ is represented by at least four parameters: user code; item code; quantity (rating), timestamp. The algorithm uses the description of the event in the form of a pair consisting of the number of items sold (rating value) n_i and timestamp $\tau_{i,m}$: $e_{i,j}=(n_i, \tau_j)$.

The method includes the following steps.

Step 1. Formation of prototypes of temporal rules $p_{i,m}$ for the i-item for each pair of time intervals ($\Delta\tau_m$, $\Delta\tau_M$) from the initial data. The prototype differs from rule (1) in the absence of a weight value $w_{i,m}$. A prerequisite for the formation of a prototype: the presence of the user's interest (in the form of a purchase, rating, etc.) in the item in the interval $\Delta\tau_m$:

$$P = \left\{ p_{i,m} : (\forall m) q_{i,m} > 0 \right\}, p_{i,m} = \left(q_{i,m}, q_{i,M} \right). \tag{7}$$

The estimate $q_{i,m}$ differs from zero if there are records ei,j in the original data for the interval $\Delta\tau_m$:

$$q_{i,m} > 0 \Leftrightarrow \exists e_{i,j} : n_i > 0 \wedge \tau_j \in \Delta\tau_m. \tag{8}$$

Prototyping allows you to reduce computations when calculating the weights of the rules, eliminating this procedure for the intervals with $q_{i,m=0}$.

Step 2. Formation of a set of temporal rules R.

Step 2. 1. Calculation of weights $w_{i,m}$ for all prototypes:

$$W_i = \left\{ w_{i,m} : (\forall m) \exists p_{i,m}, w_{i,m} = q_{i,M} - q_{i,m} \right\}. \tag{9}$$

The value $q_{i,m}$ is calculated depending on the type of feedback. In the case of implicit feedback, the number of purchases for the interval $\Delta\tau_m$ is summed up. Alternatively, the total cost of i-items sold can be calculated. In the case of explicit feedback, $q_{i,m}$ is the average rating over the interval $\Delta\tau_m$. More generally, $q_{i,m}$ can also display the number of searches for the i-item, the number of page views with the i-item in an e-commerce system, etc. The value $q_{i,M}$ is calculated in the same way as $q_{i,m}$.

Step 2. 2. Construction of a set of rules R for the i-item according to (1).

Step 3. Formation of the explanation g_i taking into account the dynamics of the user's interest in the i-item. The explanation is constructed by the method [26] based on the summation of the normalized weights of the temporal rules.

Step 4. Construction of a set of matched temporal rules.

At this stage, for each rule, the truth of the explanation constraint (3) is checked and the set R_A of rules (4) is formed for which this relation is true.

Step 5. Clarification of the explanation based on the set of rules R_A.

The main goal of this step is to refine the value of the explanation indicator using only matched rules. The result of the step is a refined explanation g_i^*. This explanation by virtue of condition (5) represents the main trends in the attitude of users to the target item.

Step 6. Construction of additional explanation g_i^{**} on the set R_D. The explanation represents the local change in user preferences at separate time intervals.

6. Experimental verification of the method of clarifying explanations based on matching temporal rules

The "Online Retail" set from the UCI repository was used as input data for the experimental verification of the method [27]. This set contains sales records for a gift store chain. An example of the source data is shown in Fig. 2.

An essential feature of the used dataset for testing the method is that each record contains a timestamp in the "InvoiceDate" field. Also, each record contains information about the product (code in the "StockCode" field and the name in the "Description" field), as well as information on the number of units sold within the current transaction in the "Quantity" field. The customer ID is in the "CustomerID" field.

The purpose of the experiment is to determine the possibility of separating explanations depending on the prevailing trend of changing user interests for a given period of time. This separation will allow showing the user an explanation only if the temporal dynamics indicates an increase in ratings, sales, views, etc. Detailed experimental results for three items are presented in Table 1.

The sequence of processing experimental data consists of two groups of steps. Steps 1–2 pre-select the input data, and steps 3–7 implement the steps of the developed method.

Step 1. Selection of a subset of recommended items for which explanations are generated.

In order to illustrate the difference in the explanations, during the experimental evaluation, the items were selected for which the temporal dynamics should differ significantly. The first two items, "poppy's playhouse bedroom" (1), "lovebuildingblockword" (2), are mainly focused on children's games, the interest in which can change rapidly. The third item, the "inflatablepoliticalglobe," is designed for schooling and therefore has a long cycle of use. The aim of selecting heterogeneous items based on their purpose was to compare detailed recommendations for different items with potentially short (items 1 and 2) and long (item 3) cycles of changing user preferences.

Table 1

Results of the explanation refinement method

Explanation items		Items		
		1	2	3
Evaluation of events by days	$q_{i,1}$	11	14	2
	$q_{i,2}$	17	10	2
	$q_{i,3}$	27	16	3
	$q_{i,4}$	15	23	1
	$q_{i,5}$	16	17	3
Normalized rule weights	$w_{i,1}$	0.14	0.09	0.03
	$w_{i,2}$	−0.03	0.2	0.03
	$w_{i,3}$	−0.31	0.03	0.0
	$w_{i,4}$	0.03	−0.17	0.06
Explanation	g_j	−0.17	0.14	0.11
Matched rules	$w_{i,m}$	$\{w_{1,2}, w_{1,3}\}$	$\{w_{2,1}, w_{2,2}, w_{2,3}\}$	$\{w_{3,1}, w_{3,2}, w_{3,3}, w_{3,4}\}$
Corrected explanation	g_i^*	−0.34	0.31	0.11
Alternative explanation	g_i^{**}	0.17	−0.17	absent

Step 2. Selecting sales for a given subset of items for a time period ΔT.

During the experiment, the sales period ΔT with a duration of 5 working days was considered. This period was divided into 5 intervals $\Delta\tau_m$ of 1 working day each. This division into short intervals is determined by two factors. First, when constructing explanations, it is important to take into account the most recent changes in consumer preferences. Second, the raw data contain records of wholesales. Therefore, the dataset contains a sufficient number of events $e_{i,j}$, in order to form the rules describing changes in sales for pairs of days within one work week. The total number of sales of the selected items by day obtained as a result of this step is given in the lines $q_{i,1}$–$q_{i,5}$.

Step 3. Formation of temporal rules and calculation of their weights in accordance with stages 1 and 2 of the method of clarifying explanations based on matching temporal rules.

Rule weights are calculated as the difference in sales between the current 5th day and the previous days of the selected time period. The weights of the rules were normalized to the maximum number of sales of all items in one day during the period ΔT. The results of this step are presented in the rows $w_{i,1} - w_{i,4}$ in Table 1.

Step 4. Construction of an explanation as the sum of the weights of all temporal rules in accordance with stage 3 of the developed method. The results of this step are represented in the line g_j in Table 1.

Step 5. Matching of rules in accordance with stage 4 of the developed method. The matched rules are presented in the line $w_{i,m}$ in Table 1.

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01.12.2010 8:26	2,55	17850	United Kingdom
536365	71053	WHITE METAL LANTERN	6	01.12.2010 8:26	3,39	17850	United Kingdom
536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01.12.2010 8:26	2,75	17850	United Kingdom

Fig. 2. An example of source data from the "Online Retail" set

Step 6. Construction of a revised explanation in accordance with step 5 of the explanation refinement method. The revised explanations are presented in the line g_i^*.

Step 7. Construction of an alternative explanation according to stage 6 of the developed method.

As can be seen from Table 1, in accordance with condition (5), knowledge about a decrease in demand for the first item is matched. However, user preferences change cyclically. This feature may be associated with short demand cycles for the first item, or with promotions. Considering this additional information, the user can be provided with explanations g_1^* and g_i^{**}, representing the multidirectional change in demand for the proposed item. Without such a significant adjustment, it is impractical to provide the user with the original negative indicator of the explanation, since it shows a decrease in interest in the first item. The dynamics of user preferences for the second item is also positive, even taking into account the increased sales on the fourth day. The data of $q_{2,1}$–$q_{2,5}$ show a short cycle of demand change, commensurate with the period ΔT. Therefore, both explanatory indicators can be provided to the user. For the third item, sales are small and change insignificantly, which corresponds to its purpose and indicates a long cycle of use. The explanation corrected after the rules have been matched is the same as the original one. The indicator g_i^* can be displayed only optionally.

Thus, the refinement made it possible to detail two of the three explanations. The explanation for the first item has received significant changes, reflecting the multidirectional dynamics of user preferences. Therefore, in contrast to the negative explanation g_1, the corrected explanation in the form g_1^* and g_1^{**} can be presented to the user.

In a sample of 52 items in this set, explanations were clarified for 56 %, and a significant adjustment, taking into account multidirectional dynamics, for 21 % of goods.

Additionally, an experimental test of the method was performed on a time-ordered dataset without timestamps on the choice of books [31]. The purpose of the experiment was to test the possibility of matching rules and constructing explanations based on the selection of subsets of time-ordered records without taking into account time intervals. During the experiment, the size of the record sets changed. The results of the experiment showed that explanations reflecting the user's preference cycles are formed by highlighting subsets of records from several thousand items. This level of granulation allows you to display the temporal dynamics of user preferences for individual books and build appropriate explanations. As the subset size grows over 10,000 records, the temporal rule weights decrease due to inconsistency with user preference cycles, which makes it difficult to build explanations. With a subset size of about 100,000 records, the temporal rules average growth and then reflect a long-term, without significant fluctuations, decrease in new book sales. This steady decline in sales does not allow using temporal explanations.

7. Discussion of the results of developing a method for clarifying explanations based on matching temporal rules

The result of the work is a method that allows correcting the explanation of the items from the recommended list. The recommender system proposes this list after the temporal rules have been matched with this explanation. The refined explanation contains numerical estimates of typical changes in user preferences within a given period and alternative changes in separate time intervals.

The method uses information about user behaviour, represented by events of purchases or product ratings, indicating the occurrence of these events.

At the first step, the method forms prototypes (7) of temporal rules. Rule prototypes connect groups of events belonging to pairs of different time intervals. The prototype is created after checking (8) the records of the user's activity in the corresponding time interval. At the second step, the weights of the rules (9) are calculated, and the temporal rules (1) are formed by complementing the prototypes with the obtained weights. Rule weight is a numerical estimate of the change in user interest in a given product or service for a pair of time intervals. In the third step, basic explanations are formed that take into account the temporal dynamics of user interests. At the fourth step, a set of matched temporal rules is formed (4). All rules from this set satisfy the constraint (3). Steps 5 and 6 refine the original explanation. This refinement consists in adjusting the weight of the basic explanation and forming an additional explanation that reflects the dynamics of the user's interests at certain time intervals.

The feature of the proposed method lies in the fact that the explanations refined after matching reflect the peculiarities of the user's behaviour at different time intervals, making it possible to satisfy the confidence criterion presented in [7].

The possibilities of using the developed method are shown by the example of constructing explanations considering the temporal dynamics of user preferences for three items. These items are sold in a chain of gift stores (Table 1). Clarification of explanations allows you to change the list and numerical values of the explanation indicators presented to the user. The first indicator before the adjustment is negative, which indicates a decrease in interest in the first item. This indicator will contradict the recommendation and therefore, cannot be provided to the user. At the same time, the revised indicator obtained after matching the rules can be displayed to the user if additional information shows the cyclical demand or atypical changes on individual days. Such abnormal changes could, for example, reflect a promotional sale. The adjustment of the second indicator allows us to clarify the value of the constant growth in demand for this item without considering external factors that cause one-time increased sales. The third indicator does not change after adjustment and therefore reflects the general trend of a slight increase in interest in the third item. Thus, the proposed method allows a more detailed explanation of the change in interest in the recommended item, which creates conditions for the user to select this item.

The advantage of the method is that it allows you to promptly supplement the set of explanations regarding recommendations, taking into account the latest user actions, which allows building and refining explanations in the online mode of the recommender system.

The disadvantage of this method is that the composition of the matched set of rules largely depends on the level of detail of time intervals, which can significantly change the numerical values of explanations. This disadvantage can be overcome by building a set of explanations for different levels of time detail.

The proposed approach has limitations associated with the form of presentation of the initial data. The input log must contain data on user behaviour with timestamps, or the data must be ordered by time. The level of time detail in the source data can affect the results of matching the rules.

This method is focused on constructing explanations within the online subsystem of the recommender system. The method is intended for use in the explanation module. In accordance with the architecture of the recommender system presented in [28], this module interacts with the module for building recommendations using information about a ranked list of recommended items. The explanation is presented in the form of a diagram that visualizes the numerical values of the considered indicators with possible decoding in the form of rule weights. This form is widely used by the Amazon recommender system to present explanations in the form of a rating distribution for a recommended item. The explanation is traditionally placed on the page describing the characteristics of the recommended item.

The developed method can be applied in related subject areas, provided that temporal rules are adapted to the description of processes occurring in such areas. Adaptation consists in defining a procedure for calculating numerical estimates of events that correspond to the antecedent and consequent of the temporal rule. For example, within the framework of solving the problem of calculating resources in process control [29], matching of temporal knowledge about controlled processes can be performed. Matching is based on data from the logs of events that have occurred at the facility.

One of the directions of further development of the proposed approach to knowledge matching within the problem of constructing explanations is based on the use of feedback, which conveys knowledge about the user's emotional state in the process of perceiving explanations. To obtain such knowledge, it is advisable to use online tools to recognize emotional patterns in real time, particularly using fuzzy neural networks [30].

8. Conclusions

1. The model of the temporal rule with the explanation relation makes it possible to match knowledge when constructing explanations in intelligent systems in accordance with changing user preferences. The model contains a pair of numerical estimates of events at two time intervals, connected by a temporal operator, as well as a rule weight. The operator sets the type of relationship between the specified pair of intervals in time. Weight indicates the importance of the rule. The explanation relation acts as a constraint that allows the formation of a set of matched rules. This relation establishes the correspondence of the changes in time represented by the rule to a more general explanation of an intelligent system's behaviour. The model is intended to clarify explanations regarding the results of the work of an intelligent system by using matched knowledge.

2. The method of clarifying explanations regarding the recommended personalized list of items considers the multidirectional changes in user preferences over time. Clarifying is performed based on matching temporal rules. The method uses information about user behaviour in relation to the target item (purchase, rating) to match knowledge by forming a subset that satisfies the explanation constraint. Knowledge matching allows you to refine the numerical estimate of the explanation and supplement the basic explanation with an alternative clarifying explanation describing the behaviour of the users of the recommender system at individual intervals within a given period.

3. Experimental evaluation of the method shows that knowledge matching allows detailing the numerical estimate of the explanation. Detailed assessment makes it possible to increase the number of provided explanations by more than 20 % in the conditions of multidirectional temporal dynamics of user preferences. Supplementing the basic explanation with an alternative one that is applicable for specific time intervals increases the user's confidence in the basic explanation and, consequently, in the recommendations received. This creates conditions for improving the efficiency of the recommender system.

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