IMPROVEMENT OF THE METHOD OF COLLABORATIVE FILTERING, TAKING INTO ACCOUNT THE CHARACTERISTICS OF THE CONSUMER TO PERSONALIZE RECOMMENDATIONS IN THE E-COMMERCE SYSTEM

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Abstract. The purpose of the article. The purpose of the article is to improve the method of collaborative filtering with implicit feedback by combining the characteristics of the consumer and his behavior to improve the efficiency of building recommendations in cases of lack or insufficient information about consumer preferences.

Research methods. Collaborative filtering methods with implicit feedback used in the process of sales personalization.

The main results of the research. The problem of improving the method of collaborative filtering with implicit feedback for personalizing sales in the recommendatory subsystem in the e-commerce system, taking into account the characteristics of the consumer and the characteristics of his behavior when choosing goods and services, is considered. The importance of using additional contextual filters to improve the quality of recommendations received is shown. It is shown that the existing hybrid methods of collaborative filtering take into account separately the characteristics of the consumer or the characteristics of the domain. At the same time, in situations of "cold start" for personalizing sales, there is a practical need to build recommendations taking into account changes in the interests of users of different demographic groups. Hybrid method of collaborative filtering was improved. The main idea of the improved method is to complement the algorithm of collaborative filtering with implicit feedback, taking into account the attributes of the user, as well as the dynamics of changing his interests. The method uses as input data information about purchases without user ratings and with the date of purchase, as well as demographic information about the user. This information can be obtained from other subsystems of the e-commerce system. The result of the method is a refined list of recommended purchases for the user. This list corresponds to the age group of the user and the context-sensitive sequence of changes in his interests.

Scientific novelty. The method of collaborative filtering with implicit feedback has been improved by taking into account additional features of users, as well as changes in consumer interest over time.

Practical significance. In practical terms, the proposed method allows to increase the relevance of the recommendations when personalizing sales to the user in the recommender subsystem in the e-commerce system. Experimental verification showed an increase in the effectiveness of the recommendations received according to the AUC criterion. The improved method can also be used in the promotion of promotional offers in social networks.

Keywords: *collaborative filtering, implicit feedback, recommendation subsystems, personalization of sales, e-commerce.*

Problem statement.

Recommendation systems are designed to form the most relevant list of consumer goods and services in e-commerce systems [1]. They use the similarity between the characteristics of the goods that the consumer chooses, or between the characteristics of consumers to form a list of recommendations. Ratings or information about user selection are considered as feedback. In the first case, an explicit feedback is used, and in the second case it is implicit [2].

Such systems provide the possibility of personalized consumer choice in a large number of alternative options and lack of consumer detailed knowledge of goods or services [3].

Personalization of products and services in recommendation systems has been widely used in search engines and e-commerce, for example, in Amazon stores and Netflix streaming services [4, 5].

Recommendation systems that forms list of the consumer-friendly products and services are mainly based on collaborative filtration and content filtering methods [1, 3]. In the first case, the recommendations are based on the similarity of consumers, and in the second - the goods. To improve the effectiveness of the basic approaches, hybrid methods are also used, taking into account the semantic characteristics of the product and the context of the choice of the consumer [6, 7].

However, in the lack of information about consumer or incomplete product information, existing hybrid approaches do not always allow us to form relevant recommendations. This indicates the relevance of the problem considered in this paper.

Analysis of recent research and publications.

One of the basic and most common algorithms for constructing recommendations that take into account the similarity of consumers is collaborative filtration (CF). This algorithm allows you to recommend products and services that have received high ratings by other users with similar preferences and interests [2].

A user profile is determined based on a set of ratings assigned to different products and services. These ratings can be recorded explicitly, that is, based on the results of user replies or implicitly, as a result of analysis of its interaction with the advisory system [1].

The rating can be represented by unary (only relevant elements), binary (which distinguishes between good and bad elements) or more generally as a numerical value on the corresponding final scale.

Existing methods of collaborative filtration do not solve a number of similar issues of issuing recommendations in non-typical conditions. These include, in particular, the problems of cold start, spam attacks, inconsistency of consumer interests, and scalability [8].

The problem of a cold start is due to the complexity of providing advice to new users, information about which was only recently introduced in the recommendation system. The users have not yet chosen and appreciated a sufficient number of products, so the recommendation system cannot predict their interests [6].

Initial ratings are used to solve this problem, that is, the system forces the user to first evaluate a particular set of goods. However, this creates inconvenience to the user. Also, these primary ratings may lead to erroneous recommendations, as consumer responses do not always reflect their interests. The cold start issue also affects new products, as they will not be in the list of recommendations until sufficient users have been rated [8].

The problem of spam attacks occurs when unscrupulous consumers mislead the recommendation system [1, 8].

The issue of user inconsistency (or Gray Sheep problem) occurs if there are users whose opinions are not consistently consistent or inappropriate with any group of people. Such consumers do not benefit from the use of the advisory system [9].

The problem of scalability arises as a result of finding recommendations for the entire database of consumer ratings. This does not allow for personalization of recommendations.

Hybrid methods integrating collaborative filtration with user profile analysis are used to solve a set of problems. [6] A more generalized approach proposed in [7, 10] relates to the consideration and generalization of the context of consumer choice.

To clarify the recommendations, associative rules are also found, and they form a list of goods and services using these [11, 12].

However, these methods do not allow solving the problem of the formation of recommendations in the absence of detailed information about the consumer.

To solve this problem it is necessary to combine information about the user and his behavior when choosing goods and services, that is, taking into account not only the properties of objects, but also the temporal aspect. Temporal characteristics are used in the construction of knowledge bases [13, 14], as well as the formation of recommendations using these knowledge bases [15].

This indicates the importance of completing the collaborative filtration method taking into account the temporal characteristics of the consumer and the product.

The aim of the study.

The purpose of the article is to improve the method of collaborative filtering with implicit feedback by combining the characteristics of the consumer and his behavior, and to increase the effectiveness of constructing recommendations in cases of lack or insufficient information about consumer preferences.

To achieve the research objectives are solved the following tasks:

– to substantiate the possibility of obtaining additional data on the consumer taking into account the structure of e-commerce systems;

– formalize additional characteristics of consumers and goods that may affect the resulting recommendations;

– to supplement the method of collaborative filtration on the basis of taking into account the characteristics of the consumer and his preferences.

Presentation of research material.

E-commerce is a form of trade in which the selection and ordering of goods is carried out through computer networks, and settlements between the buyer and the supplier are carried out using electronic documents and / or payment methods.

Therefore, the e-commerce system combines a number of subsystems that control internal processes and interact with customers:

– ERP-subsystem, which is intended to control the state of the warehouse and movement of goods and money;

– PIM - subsystem of content support for goods and categories of goods;

– CRM - subscriber interaction seller with customers;

– Service desk - automation module for customer request processing;

– Cost accounting module;

– Recommender subsystem.

The presented structure of the e-commerce system makes it possible to conclude that the Recommender subsystem may use additional data about the consumer and goods received from other subsystems in addition to purchasing information.

Input data of the developed method is:

– Data about the purchase of goods;

– Consumer data for which recommendations are being generated.

Data on purchases of goods are presented in the form of an ordered table: $P = \{p_k\}$.

Each item in this table contains information about the selected product, the consumer who chose the product, and the date of purchase:

$$p_k = \{e_i, u_j, d_k\}, \qquad (1)$$

where e_i - the goods or services chosen by the consumer; u_j - consumer data; d - the date of purchase.

Each purchase is displayed as a separate item in this table.

Product information can also be detailed using additional attributes, such as the name and product group, the physical characteristics of the product (size, resolution, weight, etc.), etc.

$$E=\{e_i\},\ e_i=\{Ie_i,n_i,c_i,A_i\}, \qquad (2)$$

where Ie_i - the unique product code in the e-commerce system; n_i - the name of the product; c_i - the price of the goods; $A_i=\{a\}$ - additional attributes of the goods.

Every consumer $u_j \in U$ in the advisory system has the following demographic characteristics:

$$u_j=\{Id_j,n_j,D_j\}, \qquad (3)$$

where Id - the unique consumer code in the recommendation system (or e-commerce system); n_j - the registration name of the consumer; $D_j=\{d_{jm}\}$ - additional attributes of the consumer.

Additional attributes of the consumer include at least the year of birth, gender and region of residence. The year of birth and sex is usually set when forming a consumer profile in the e-commerce system. The region or city of residence is usually determined automatically.

$$D_j=\{b_j,g_j,r_j\}, \qquad (3)$$

where b_j - data on the year of birth of the consumer; g_j - human sex; r_j - place of residence of the consumer.

Recommendations are formed for a specific customer, which has characteristics (3) and (4).

In this paper, the construction of recommendations based on implicit feedback is considered., That is, the input data only contains information about the fact of purchases and do not contain the ratings given by the consumer.

The main idea of the proposed hybrid method of collaborative filtering with implicit feedback is to filter out irrelevant input data, taking into account temporal and object characteristics.

Temporal characteristics specify changes in the interests of consumers in time. Such changes can be cyclic, one-time or permanent.

Cyclical changes are related, for example, to the seasonal selection of goods. One-time changes occur in cases of single external influences. For example, increasing the availability of transport in the remote area may change the range of goods in demand in this city.

Permanent changes are characteristic of areas related to the creation and use of computer technology, technology, computer games, and the like. Also, such changes are typical for choosing things based on fashion trends.

In general, the input data can be represented as a set of pairs (e_i,u_j) for a specified time interval.

$$M=\{M_l\},M_l \subseteq E\times U:\forall(e_i,u_j)\in M_l\ \exists d_k,d_{\min}\le d_k\le d_{\max}, \qquad (4)$$

where $d_{\min},d_{\max}$ - they determine the time interval for which the preferences of the consumer are considered to be unchanged.

Representation (4) shows that the input data can be filtered in the temporal aspect, for example according to the seasonal preferences of the consumer. Only topical purchases can be selected.

The temporal aspect should also be taken into account when filtering goods based on the proximity of consumer interests. Obviously, the demand for certain groups of goods depends on the age of the consumer:

$$M_l=\{(e_i,u_j)\}:b_{\min}\le b_j\le b_{\max}, \qquad (5)$$

where $b_{\min},b_{\max}$ - determine the age of the consumer with the eastern interests of goods and services.

Similarly, input data can be detailed according to consumer attributes and attributes:

$$M_l=\{(e_i,u_j)\}:a_{ls}\in A_l,A_l\subseteq A, \qquad (6)$$

$$M_l = \{(e_i, u_j)\} : d_{lm} \in D_l, D_l \subseteq D, \quad (7)$$

where a_{il} - the attribute of the goods; A_l - a set of attributes defining a group of goods for consumer choice; d_{lm} - attribute of the consumer; D_l - set of attributes defining a group of consumers; A - set of attributes of all goods; D - the set of attributes of all consumers.

The improved method involves the following steps.

Stage 1. Selection of a subset of input data for consumer attributes:

$$M^{(1)}_l{}_l = \{(e_i, u_j)\} : \forall u_j \forall m \; d_{lm} \in D^*_l \middle| d^*_{lm} \in D^*_l, \quad (8)$$

Where d^*_{lm} - the attribute of the target consumer; D^*_l - a subset of attributes that characterize the target group of consumers.

At this stage, consumers are selected in the target group with properties similar to the consumer for whom the recommendations are made.

Stage 2. Selection of a subset of input data for attributes of goods. At this stage, the selection of such goods, the properties of which are similar to the properties selected by the target consumer is carried out:

$$M^{(2)}_l = \{(e_i, u_j)\} : M^{(2)}_l \subseteq M^{(1)}_l, \; \forall e_i \forall s \; a_{ls} \in A^*_l \middle| \forall s \; a^*_{ls} \in A^*_l, \quad (9)$$

where a^*_{ls} - the attribute of the product chosen by the target consumer; A^*_l - a subset of attributes that characterize the target group of goods; a_{ls} - the attribute of the product from the target group.

Data filtering in the second stage is performed only if the consumer has selected at least one item. Therefore, for the cold start situation, this stage is optional, unlike filtering according to the customer.

Stage 3. The subset of input data by temporal characteristics of the consumer is selected.

Selection at this stage is performed according to the expression (5). The date range $[b_{\min}; b_{\max}]$ is based on the input data using the configuration parameter ε_1:

$$b_{\min} = b^*_j - \varepsilon_1, \; b_{\max} = b^*_j + \varepsilon_1. \quad (10)$$

The result of the phase is a subset of input data $M^{(3)}_l \subseteq M^{(2)}_l$.

Stage 4. The subset of input data by temporal characteristics of the product is selected. Selection at this stage is performed according to the expression (4). The temporal interval $[d_{\min}; d_{\max}]$ is determined on the basis of the input data using a configuration parameter ε_2 similar to the previous step.

The result of the phase is a subset of input data $M^{(4)}_l \subseteq M^{(3)}_l$.

Stage 5. Collaborative filtering with implicit feedback is used to build recommendations. The input subset is $M^{(4)}_l$.

At this stage, there are latent factors that connect users and goods. Recommendations are formed using these latent factors.

The result of this phase is the recommended list of products $E_R \subset E$ that may be of interest to consumers with the characteristics specified in the input data.

The developed method was tested on the data on the sale of goods in the Internet stores in the UK.

To evaluate the proposed method, we compared the results of traditional collaborative filtration and the improved hybrid method using the area under the ROC (Receiver operating characteristic) indicator – AUC.

The Receiver operating characteristic is an indicator used to assess the quality of a binary classification. It represents the ratio between the proportion of correctly classified objects from the total number of sign attributes and the proportion of mistakenly classified, not relevant attributes.

The AUC reflects the area that is limited by the ROC curve and the axis of the fraction of false positive classifications. The value of the indicator is less than 0.5 indicates that the classifier inverts the results, that is, it works with the exact opposite. The value of indicator 0.5 demonstrates the unsuitability of the selected classification method. The quality of the classification depends on the AUC value.

In the course of an experimental verification, 2 calculations of the AUC for the sample with regard to the filtration were performed.

The first calculation was carried out using traditional collaborative filtration, the second - taking into account the temporal characteristics of the goods.

The results of the experiments are as follows. With traditional filtration $AUC = 0,872$. When filtering using temporal characteristics of goods $AUC = 0,881$. Thus, even without taking into account the characteristics of the consumer, the quality of the recommendations increases.

Conclusions.

The problem of hybrid collaborative filtration is considered. It is shown the importance of using additional filters to improve the quality of the recommendations.

It is shown that the methods of collaborative filtration during personalization of sales, especially in the "cold start" situation, do not allow giving recommendations of high accuracy. Therefore, in the case of new consumers, there is a practical need for constructing recommendations taking into account the combination of attributes of users and goods.

The result of the work is the improved method of collaborative filtering with implicit feedback, which takes into account additional signs of users and goods, including temporal ones.

The difference between the proposed methods consists in generalization of several methods of filtration. This synthesis makes it possible to combine the benefits of each method to increase the effectiveness of providing recommendations.

In practical terms, the proposed method allows to increase the relevance of the recommendations when personalizing sales to the user in the Recommender subsystem in the e-commerce system.

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УДОСКОНАЛЕННЯ МЕТОДУ КОЛАБОРАТИВНОЇ ФІЛЬТРАЦІЇ ІЗ УРАХУВАННЯМ ХАРАКТЕРИСТИК СПОЖИВАЧА ДЛЯ ПЕРСОНАЛІЗАЦІЇ РЕКОМЕНДАЦІЙ В СИСТЕМІ Е-КОМЕРЦІЇ

Анотація. Мета статті. Метою статті є удосконалення методу колаборативної фільтрації з неявним зворотним зв’язком шляхом комбінування характеристик споживача та його поведінки для підвищення ефективності побудови рекомендацій у випадках відсутності або недостатньої кількості інформації про вподобання споживача.

Методи дослідження. Методи колаборативної фільтрації з неявним зворотним зв'язком рекомендаційних системах.

Основні результати дослідження. Розглянуто проблему удосконалення методу колаборативної фільтрації з неявній зворотним зв'язком для персоналізації продажів в рекомендаційної підсистемі в системі електронної комерції з урахуванням характеристик споживача і особливостей його поведінки при виборі товарів та послуг. Представлено важливість використання додаткових контекстних фільтрів для підвищення якості отриманих рекомендацій. Показано, що існуючі гібридні методи колаборативної фільтрації враховують окремо характеристики споживача або характеристики предметної області. У той же час в ситуаціях «холодного старту» для персоналізації продажів існує практична потреба в побудові рекомендацій з урахуванням змін інтересів користувачів різних демографічних груп. Удосконалено гібридний метод колаборативної фільтрації. Основна ідея вдосконаленого методу полягає в доповненні алгоритму колаборативної фільтрації з неявним зворотним зв'язком з урахуванням атрибутів користувача, а також динаміки зміни його інтересів. В якості вхідних даних метод використовує інформацію про покупки із зазначенням їх дати та без рейтингів користувачів, а також додаткову інформацію про користувача. Ця інформація може бути отримана із других підсистем системи електронної комерції. Результатом роботи методу є уточнений список рекомендованих покупок для користувача. Цей список відповідає віковій групі користувача і контекстно-залежною послідовності зміни його інтересів.

Наукова новизна. Удосконалено метод колаборативної фільтрації з неявним зворотнім зв’язком шляхом врахування додаткових ознак користувачів, а також зміни інтересу споживачів у часі.

Практична значимість. В практичному плані запропонований метод дозволяє збільшити релевантність рекомендацій при персоналізації продажів для користувача в рекомендаційній підсистемі в системі електронної комерції. Експериментальна перевірка показала підвищення ефективності отриманих рекомендацій згідно з критерієм AUC. Вдосконалений метод може використовуватися також при просуванні рекламних пропозицій в соціальних мережах.

Ключові слова: *колаборативна фільтрація, неявний зворотній зв'язок, рекомендаційні підсистеми, персоналізація продажу, електронна комерція.*

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УСОВЕРШЕНСТВОВАНИЕ МЕТОДА КОЛАБОРАТИВНОЙ ФИЛЬТРАЦИИ С УЧЕТОМ ХАРАКТЕРИСТИК ПОТРЕБИТЕЛЯ ДЛЯ ПЕРСОНАЛИЗАЦИИ РЕКОМЕНДАЦИЙ В СИСТЕМЕ Е-КОММЕРЦИИ

Аннотация. Цель статьи. Целью статьи является усовершенствование метода коллаборативной фильтрации с неявной обратной связью путем комбинирования характеристик потребителя и его поведения для повышения эффективности построения рекомендаций в случаях отсутствия или недостаточного количества информации о предпочтениях потребителя.

Методы исследования. Методы коллаборативной фильтрации с неявной обратной связью в процессе персонализации продаж.

Основные результаты исследования. Рассмотрено проблему усовершенствования метода коллаборативной фильтрации с неявной обратной связью для персонализации продаж в рекомендательной подсистеме в системе электронной коммерции с учетом характеристик потребителя и особенностей его поведения при выборе товаров и услуг. Показана важность использования дополнительных контекстных фильтров для повышения качества полученных рекомендаций. Показано, что существующие гибридные методы коллаборативной фильтрации учитывают отдельно характеристики потребителя или характеристики предметной области. В то же время в ситуациях «холодного старта» для персонализации продаж существует практическая потребность в построении рекомендаций с учетом изменений интересов пользователей различных демографических групп. Усовершенствован гибридный метод коллаборативной фильтрации. Основная идея усовершенствованного метода заключается в дополнении алгоритма коллаборативной фильтрации с неявной обратной связью учетом атрибутов пользователя, а также динамики смены его интересов. В качестве исходных данных метод использует информацию о покупках без рейтингов пользователей и с указанием даты покупок, а также демографическую информацию о пользователе. Эта информация может быть получена из других подсистем системы электронной коммерции. Результатом работы метода является уточненный список рекомендованных покупок для пользователя. Этот список соответствует возрастной группе пользователя и контекстно-зависимой последовательности изменения его интересов.

Научная новизна. Усовершенствован метод коллаборативной фильтрации с неявной обратной связью путем учета дополнительных признаков пользователей, а также изменения интереса потребителей во времени.

Практическая значимость. В практическом плане предложенный метод позволяет увеличить релевантность рекомендаций при персонализации продаж для пользователя в рекомендательной подсистеме в системе электронной коммерции. Экспериментальная проверка показала повышение эффективности полученных рекомендаций согласно критерию AUC. Усовершенствованный метод может использоваться также при продвижении рекламных предложений в социальных сетях.

Ключевые слова: *коллаборативная фильтрация, неявная обратная связь, рекомендательные подсистемы, персонализация продаж, электронная коммерция.*

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