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TF-IDF Based Contextual Post-Filtering Recommendation Algorithm in Complex Interactive Situations of Online to Offline: An Empirical Study

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Abstract: O2O accelerates the integration of online and offline, promotes the upgrading of industrial structure and consumption pattern, meanwhile brings the information overload problem. This paper develops a post-context filtering recommendation algorithm based on TF-IDF, which improves the existing algorithms. Combined with contextual association probability and contextual universal importance, a contextual preference prediction model was constructed to adjust the initial score of the traditional recommendation combined with item category preference to generate the final result. The example of the catering industry shows that the proposed algorithm is more effective than the improved algorithm.

Keywords: context information; contextual post-filtering recommendation; contextual preference; item category preference; TF-IDF

1 INTRODUCTION

At present, the domestic mobile electronic commerce is in full swing, in addition to the related policies, the trend of online and offline convergence is increasing with each passing day. While promoting the consumption pattern and optimizing the industrial structure, the online mode also faces the problem of information overload. It is increasingly difficult for users to find the information that matches their needs in the vast amount of goods and services. Especially in O2O environment, online and offline interaction is more contextualized and diversified. Personalized preferences are contextually sensitive when users consume and make decisions. How to effectively excavate the user preferences and recommend information that meets their contextual needs is to be studied and deepened.

Personalized recommendation is one of the most effective methods to solve the information overload problem. The personalized preference is mined through the user-item binary relationship, and the information that conforms to his/her interest is recommended to the user [1]. However, the individualized demand in O2O environment is not fixed, but has contextual sensitivity, that is, the personalized preference is different in different contexts. Previous studies have demonstrated that contextual factors play an important role in personalized recommendation. Herlocker et al. think that it is not enough to consider the user score, the factors in the process of experience should be taken into consideration too [2-4], which is the earliest research literature to bring the context into the individualized recommendation. Subsequently, Bettman et al. [6] Yu et al. [5] Gorgoglione et al. [8] and Mallat et al. [9] discussed the influence of contextual factors on user behavior and decision-making mechanism in complex contexts and demonstrated the importance of context to personalized recommendation. Although the related domestic research started relatively late, there are many achievements: Zhuang used Logistic regression model to analyse the user shopping's context factors and found that some contexts have obvious influence on the user's purchase decision [10]. From the four dimensions of physical context, social context, behaviour context and psychological context, Tu Li studied the impulse shopping. The results show that the four dimensions of context have significant positive effects on impulse shopping, but the influence path is different. Physical context and behaviour context affect the purchase, social context and psychological context influence the unplanned purchase [11]. Hu and Cai [12], Li [13], Zhang et al. [14] studied the influence of contextual factors on user demand and preferences from the perspective of user experience. According to the existing research, the context has a great impact on personalized recommendation. This paper puts the context factor in the same position as the user and the item, and develops the personalized recommendation based on the multi-variate relationship between user, context and item.

2 LITERATURE REVIEW

As an important factor to affect user behaviour and decision-making, the context information is combined into the personalized recommendation process, mining the user contextual preferences, recommending information that meets the needs of the user in the current context. This recommendation model can effectively analyse the dynamic user contextual preferences, improve recommendation quality and user satisfaction. However, there are inherent flaws, which are manifested in:

2.1 The Data Sparsity Issue in Personalized Recommendation of Fusion Context

The traditional recommendation almost all faces serious data sparse problem, but the personalization recommendation of the fusion context faces even more serious data sparse problem: on the one hand, the personalized recommendation of fusion context is further deepened in the traditional recommendation, thus the traditional sparse problem still exists. On the other hand, the introduction of context information leads to the transformation of data from traditional user-item two-dimensional data to user-context-item multidimensional data, which invisibly expands the data sparsity, because users do not inter-act with the item under some conditions. In the e-commerce environment, the number of users and products is often counted in millions, but the number of products commented by users is often limited. The ratio is about 3%, and the possibility of selecting overlapping items between two users is very low [15]. The sparsity of the most studied MovieLen data set is 4.5%, the Bsonomy is 0.35% and the Delicious is 0.046% [16]. In the O2O environment, the relevance degree of the user and the item under most of the context instance conditions is 0, or the user does not interact with most items under the condition of many associated context instances, that is, the preference degree under the current context is unknown [17]. At this point, the majority of the elements in the high dimensional matrix are empty values. How to generate a relatively precise recommendation using a few non-empty values of the contextual preference data needs to be studied in depth. There are many ways to solve the data sparsity issue in traditional recommendation, such as Wang et al, who combine the similarity of user attributes and item preference into the traditional similarity calculation, and improve the accuracy of nearest neighbour search [18]. Li et al. improve the accuracy of the nearest neighbour search by weighting item category similarity and scoring similarity. This paper combines the item preference degree and item category preference weighting to find the nearest neighbour of the target user so as to reduce the sparsity of the data [19].

2.2 The Contextual User Preference Extraction [illegible] Based on Context Fusion

Contextual user preference extraction is the key to contextual recommendation. Collaborative filtering recommendation mainly uses quantitative method to analyse user preference, which is, quantifying preference degree by numerical scoring and calculating it. Multi-dimensional vector scoring model and the hierarchical model are used to represent user preference quantification. Preference extraction techniques include nearest neighbour algorithm, clustering, similarity calculation, [20, 21] etc. Shin explicitly gives the preferences of some single context instances, calculates the similarity of contexts by using hierarchical distance and Jaccard coefficient, and then calculates the user preference of multidimensional contexts by weighted aggregation [22]. Jrad et al use clustering and collaborative filtering to model contextual user preferences [23]. Hong et al use rule reasoning to calculate historical contextual preference and use decision tree to extract current preference [24]. Bunningen et al use mathematical statistics to construct an overview model to calculate contextual user preferences [25]. Compared with the traditional user-item two-dimensional scoring matrix, the contextual user preference extraction of the fusion context faces the dilemma of large amount of data and complex calculation, and the dynamic change of user contextual preference. How to acquire contextual user preferences in a timely and effective manner is worthy of further study.

3 RESEARCH THEORIES AND METHODS

3.1 Theoretical Foundation

TF-IDF (Term Frequency-Inverse Document Frequency) is a measure of the importance of a word to a document in a corpus. If a word appears frequently in one document and rarely in the others, it means that the word has a good distinguishing ability. This model mainly involves two factors: word frequency and reverse file frequency.

In a given document set, term frequency (*TF*) refers to the frequency of a word appearing in a document. Considering the length of the document, the same word has a higher frequency in the long document than in the short document. It is necessary to standardize the word frequency (word occurrence frequency divided by the total number of words in the document) to prevent it from biased to the long document. For words in a particular document, their importance can be expressed as:

$$TF_{ti} = \frac{n_{ti}}{N} \tag{1}$$

where n_{ti} is the frequency of the word t appearing in document i and N is the frequency of all words appearing in document D_t.

Inverse Document Frequency (*IDF*) is used to measure the universal importance of words. The more documents it appears in, the lower the distinguishing ability of the word, the lower the importance. It is usually obtained from the quotient logarithm between the total number of documents and the number of documents in which a particular word appears, and can be expressed as:

$$IDF_t = \log\frac{|D|}{n_t} \tag{2}$$

where $|D|$ is the total number of documents and n_t is the number of documents containing the word t.

TF-IDF is usually obtained by multiplying *TF* value and *IDF* value, which indicates that the importance of words increases with the increase of its frequency in the document, but decreases with the increase of the number of documents it appears in. The formula can be expressed as:

$$TF\text{-}IDF = TF_{ti} \times IDF_t = \frac{n_{ti}}{N}\log\frac{|D|}{n_t} \tag{3}$$

As one of the classical algorithms of weight calculation, *TF-IDF* algorithm is popular in the field of information retrieval and text analysis. Many scholars have extended it to feature selection, domain dictionary construction and user preference modelling. Yan et al. have considered the combination of single word vector and multiple word vectors based on *TF-IDF* model to calculate the similarity of Weibo information flow and evaluate user interest [26]. According to the item label information selected by users, Zhang et al. build preference prediction models using *TF-IDF* algorithm and user support degree for items and combine them linearly with the network structure based on recommendation [27].

This paper introduces *TF-IDF* model into the construction of contextual preference prediction model. The *TF* value is used to measure the probability of user association with each item in the current context, and the *IDF* value is used to measure the universal importance of the current context. A contextual preference prediction model is constructed by combining the two models.

3.2 TF-IDF Based Post-Context Filtering Recommendation

According to the user contextual preference, the post-context filtering recommendation paradigm constructs the preference prediction model and generates the recommendation by adjusting the initial prediction score of the traditional recommendation. In this paper, a *TF-IDF* based contextual post-filtering recommendation algorithm is proposed according to the characteristics of O2O and the deficiencies of existing research. The framework of this algorithm is shown in Fig. 1.

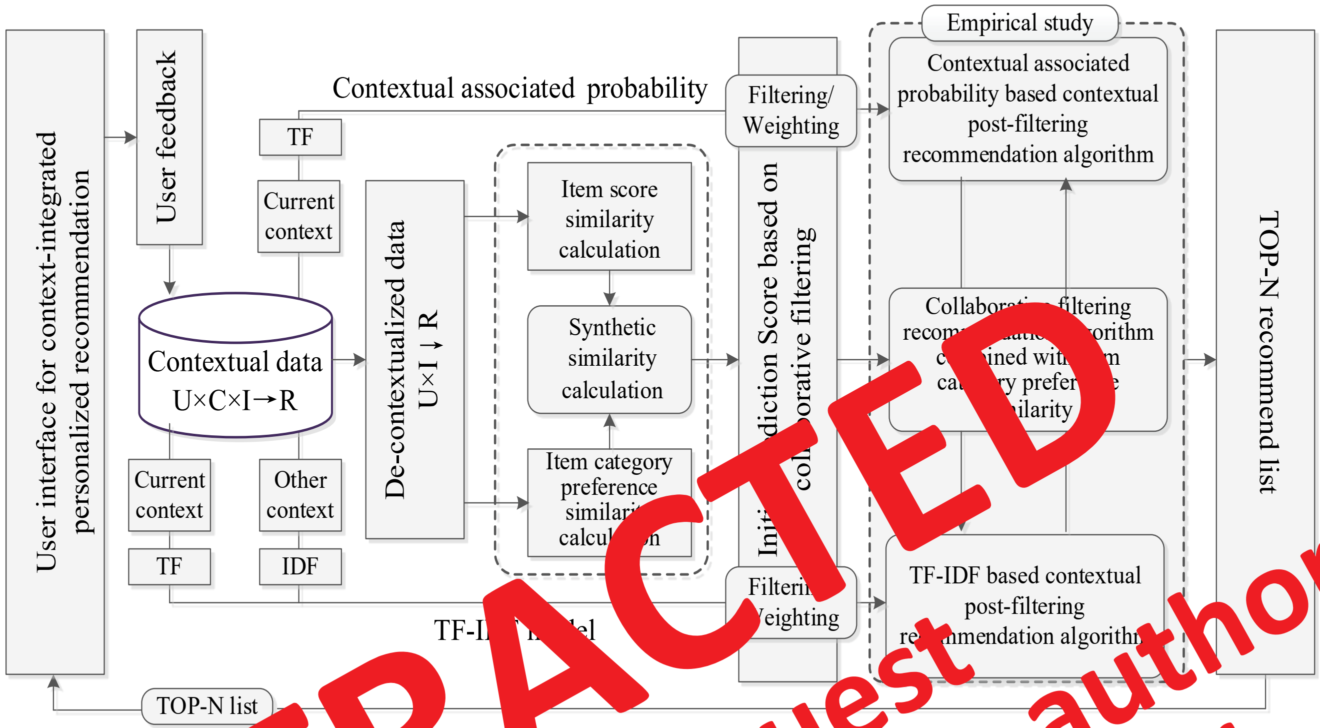

Figure 1 Post-Context Filtering Recommendation Process Based on *TF-IDF*

3.2.1 Improvement on the Initial Prediction Score Algorithm

The accuracy of the initial prediction score is directly related to the final recommendation quality, but in O2O environment, [illegible] only score a few items, most users do not have common score items, the data sparsity problem is extremely serious, which directly restricts the accuracy of the prediction score. At the same time, in O2O scenario, the user pays attention to the item itself as well as the category of the item, which is mainly reflected in the user preference for the item category. For example, the O2O users pay attention to the category of food and beverage (Sichuan cuisine, Hunan cuisine, etc.). Compared with the item, the number of item categories is limited, and the user common score on the item category is much higher than the common score on the item itself.

In this paper, the similarity of item category preference is incorporated into the nearest neighbour search, and the traditional item score similarity and item category preference similarity are combined and weighted to calculate the synthetic similarity to search for nearest neighbour user, predict the user initial score of the item and improve the accuracy of the prediction score.

Item score similarity calculation. The consumption behaviour in O2O environment mostly belongs to regular and high frequency consumption behaviour. Users may have multiple scores for the same item in different contexts or the same context. The similarity calculation of item scoring needs to construct the user-context-item multidimensional scoring matrix which integrates context information, and uses *AVG* (mean value) method to de-context and construct the user-item two-dimensional scoring matrix. The calculations are as follows:

$$R_{AVG}(u,i) = allScore_d(u,i,d)/n_d \tag{4}$$

The $allScore_d(u,i,d)$ is the sum of user u score on item i under the context condition d, and n_d is the frequency of user u scoring on item i under the context condition d. The user-item two-dimensional scoring matrix can be constructed by calculation and the similarity of user score can be calculated by using Pearson Correlation Similarity. The similarity between a and u can be calculated as follows:

$$Sim_R(a,u) = \frac{\sum_{i \in I_{au}} \left(R_{a,i} - \bar{R}_a\right)\left(R_{u,i} - \bar{R}_u\right)}{\sqrt{\sum_{i \in I_{au}} \left(R_{a,i} - \bar{R}_a\right)^2} \sqrt{\sum_{i \in I_{au}} \left(R_{u,i} - \bar{R}_u\right)^2}} \tag{5}$$

where a is the target user, u is the other user, I_{au} represents a set of items commented by user a and u.

Item category preference similarity calculation. For a given contextual data set *CD* in the O2O environment, the set of items being commented on is I, $I = \{I_1, I_2, \ldots, I_j\}$, The items generated by clustering or categorization belong to a collection of categories V, $V = \{V_1, V_2, \ldots, V_l\}$, The items contained within the categories are as similar as possible, and the items in each category are as different as possible, and the items are satisfied with the requirements of $I = V_1 \cup V_2 \cup \ldots \cup V_l$, $V_i \cap V_j =$, $(1 \le i \le l,\ 1 \le j \le l)$, According to the user score on the item and the corresponding scoring frequency, the item category preference degree is calculated, and the user-item category preference matrix is constructed. The calculation of item category preference [26] is as follows:

$$P_{u,v_i} = \frac{allScore(u,v_i)}{allScore(u,V)} \tag{6}$$

where $allScore(u,v_i)$ is the sum of the item scores included in category by user u, and $allScore(u,V)$ is the sum of item scores in all item categories by user u. The Pearson Correlation Similarity is used to calculate the item category preference similarity in the constructed user-item category preference matrix. The formula is as follows:

$$Sim_V(a,u) = \frac{\sum_{v \in V_{au}} (P_{a,v} - \bar{P}_a)(P_{u,v} - \bar{P}_u)}{\sqrt{\sum_{v \in V_{au}} (P_{a,v} - \bar{P}_a)^2} \sqrt{\sum_{v \in V_{au}} (P_{u,v} - \bar{P}_u)^2}} \tag{7}$$

where V_{au} represents a set of item categories commented by user a and u.

Synthetic similarity calculation. The value of user score similarity $Sim_R(a,u)$ and the item preference similarity $SimV(a,u)$ weight calculation is called synthetic similarity, that is $Sim(a,u)$.

$$Sim(a,u) = \beta Sim_R(a,u) + (1-\beta) Sim_V(a,u) \tag{8}$$

Among them, β is the weight coefficient, which is used to adjust the proportion of score similarity and item category preference similarity, and its value range is [0,1]. Choosing the value of β reasonably can combine the advantages of two similarity measures to improve the accuracy of the nearest neighbour search, so it is very important to determine the value of weight coefficient β.

Improved initial prediction score calculation. Calculate the item synthesis similarity $Sim(a,u)$, and select the neighbour of the top K as the nearest one set to predict the target user a's traditional recommended initial score for each item. The calculation formula is as follows:

$$P_{a,i} = \bar{R}_a + \frac{\sum_{u \in U} sim(a,u) \cdot (R_{u,i} - \bar{R}_u)}{\sum_{u \in U} |sim(a,u)|} \tag{9}$$

where the $\bar{R}_u = \left(1/|I_u| \sum_{u \in I_u} R_{u,i}\right)$ is user u's average score on items, and $I_u = \{i \in I \mid R_{u,i} \ne \varnothing\}$, U is a set of all items.

3.2.2 Construction of Contextual Preference Prediction Model

Contextual preference prediction model directly affects the accuracy of filtering recommendations and user satisfaction. How to construct an effective contextual preference prediction model is the key to this recommendation paradigm. Panniello et al. use the current context and the associated probability of the item to construct the contextual preference prediction model, which can excavate the user preference for each purpose in the current context, but the method treats the importance of the current context in each item equally, and the importance of the same context in different items is ignored. Generally speaking, the more contexts an item involves, the lower its contextual importance is; in addition, the less the number of contexts involved in an item, the higher its contextual importance, that is, the contextual importance is inversely proportional to the number of contexts involved in the item.

In order to effectively measure the importance of context, this paper uses TF-IDF algorithm to construct a prediction model of contextual preference, TF is used to calculate the probability of user association with each item in the current context, and IDF is used to calculate the importance of the current context in each item. If the user has a higher probability of associating an item in the current context, and the importance of the current context in the item is higher, then the user is more inclined to the item in the current context. Thus, it could be seen that the prediction model of contextual preference based on TF-IDF algorithm mainly involves two aspects: the probability of user association with each item in the current context and the importance of the current context in each item.

The probability of the user association with each item in the current context. It is usually measured by the ratio of the target user's positive feedback frequency to the positive feedback frequency of all items in the current context. The higher the contextual association probability is, the greater the user preference for the item in the current context. Positive feedback is the user preference for this item. In a five-point scoring system, a score of 3-5 points indicates "like" (positive feedback, expressed by t=1). The probability of contextual association of target user a to item i in current context c can be calculated as:

$$TF_{a,c,i} = \frac{count\{t=1 \mid i, C=c\}}{count\{t=1 \mid I, C=c\}} \tag{10}$$

where $count\{t = 1|i,\ C = c\}$ is the total number of positive feedbacks of user a to the item i under the current context c, $count\{t = 1|I,\ C = c\}$ is the total number of positive feedbacks of user a to all items I under the current context c.

The importance of current context in each item. In order to measure it, this paper uses the IDF method to measure the universal importance of the current context in each item. The more contexts the item involves, the more disperse the preferences of each context to the item, the lower the importance. The universal importance of the current context c in item I can be obtained by dividing the total number of contexts N_I involved in all items by the number of contexts N_i that item i relates to, and then taking the resulting quotient logarithm, that is:

$$IDF_{c,i} = \log \frac{N_I}{N_i} \tag{11}$$

Contextual preference calculation based on *TF-IDF* algorithm. According to the *TF-IDF* algorithm, the calculation formula of the target user contextual preference for all items in the current context is as follows:

$$P(a,c,i) = TF_{a,c,i} \cdot IDF_{c,i} = \frac{count\{t=1|i,C=c\}}{count\{t=1|I,C=c\}} \cdot \log \frac{N_I}{N_i} \tag{12}$$

The above formula can be expressed as the degree the user preference for an item in the current context increases with the increase of the user preference frequency for the item in the current context, but decreases with the increase of contexts in which the user chooses the item. To make it easy to quantify, the TFC weight algorithm [29] is used to normalize the calculated values of formula (12), and the contextual preference values with a value range of [0,1] are obtained.

3.2.3 Generation of Contextual Post-Filtering Recommendation

That is to use the contextual preference value to adjust the traditional recommendation initial score to generate the final score. There are two methods for adjustment: direct filtering and score correction. Empirical studies have shown that neither of the two adjustment methods is superior to the other [30]. This paper combines the two to adjust the traditional recommended prediction score, the specific process is as follows:

Direct filtering. Some items that have high scores but no relation with the current context need to be filtered out directly. Set the contextual preference threshold μ in advance, when $P(a,c,i) < \mu$, change the original prediction score of the traditional recommendation to 0, that is $P_{a,c,I} = 0$.

Score correction. The remaining items weighted the initial prediction score $P_{a,i}$ and the contextual preference value $P(a,c,i)$, that is, the user a's final score for the item in current context c is $P_{a,c,i}$, TOP-N recommendation was generated. The calculation is shown as follows:

$$P_{a,c,i} = P_{a,i} \cdot P(a,c,i) \tag{13}$$

4 EMPIRICAL ANALYSIS

4.1 Experimental Data

This paper takes Wuhan catering industry of Dianping.com as the experimental object, using crawler tools to grab eight data segments including store information, user consumption information and comment information, including user name, consumption time, store name, address, store style, user rating and comment content etc. A total of 132 users, 60142 review records and 3295 stores are involved.

4.2 Associated Context Information Acquisition

The context acquisition method includes explicit acquisition and implicit acquisition; explicit acquisition is the most accurate but difficult to most valid contexts. This paper uses implicit acquisition method to associate relevant context information in food and beverage O2O environment:

Location. According to the Wuhan geographical location of the stores, including seven examples: Wuchang, Hongshan, Qingshan, Hanyang, Jiangan, Jianghan, Qiankou;

DayType. According to the user consumption date associated to the user status and combined with the general office of the State Council holiday adjustment arrangements to adjust the acquisition including three examples: working days, weekends and holidays.

Weather. According to the user consumption date associated with the weather, including five examples: overcast, sunny, rain, snow and cloudy.

Companion. Extract the personal pronouns for association from the user comment information, including four examples: alone, friend, partner and family.

Emotion. The emotional polarity of user comments is calculated to obtain the emotional context, including three examples: positive, negative and neutral.

In conclusions, the context dimension and its example in O2O environment are shown in Tab. 1.

Table 1 Context dimension and its example in O2O environment

Context dimension	Context example
Location	Wuchang, Hongshan, Qingshan, Hanyang, Jiangan, Jianghan, Qiankou
DayType	working days, weekends and holidays.
Weather	overcast, sunny, rain, snow and cloudy.
Companion	alone, friend, partner and family
Emotion	positive, negative and neutral.

4.3 Utility Evaluation of the Recommendation Algorithms

In order to verify the validity of the proposed recommendation algorithm, this paper uses the Mean Absolute Error (*MAE*), Precision and Recall to determinate the optimal weight coefficient and the optimal contextual preference threshold [31], and to evaluate the utility of the *TF-IDF* based post-filtration recommendation algorithm.

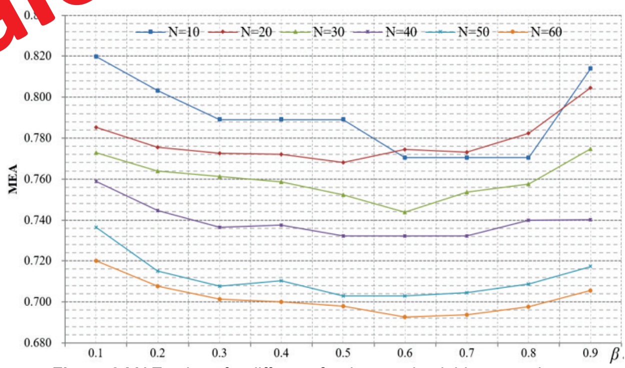

Figure 2 MAE values for different β values and neighbour numbers

4.3.1 The Optimal Weight Coefficient Determination

During initial prediction scoring, the traditional score similarity and the item category similarity are weighted.

The weight coefficient is closely related to the accuracy of the prediction score. In this paper, the weight coefficient β is increased from 0.1 to 0.9 at 0.1 intervals, the nearest neighbour number increases from 10 to 60 at 10 intervals, and the corresponding *MAE* value is calculated as shown in Fig. 2. It can be seen from the graph that the average absolute error *MAE* value is the smallest, that is, the best weight coefficient occurs when $\beta = 0.6$.

4.3.2 The Optimal Contextual Preference Threshold Determination

In direct filtering, the contextual preference threshold μ is too large, which results in the items related to the current context being filtered out, and the items that are irrelevant to the current context being mixed into the recommendation list, both of which will lead to the poor quality of the recommendation.

To explore the most suitable threshold, the contextual preference threshold is set from 0.9 to 0.1, decreasing by 0.1, and the initial prediction score is adjusted by direct filtering and score correction. When the threshold η is 0.9, 0.8 and 0.7, respectively, the number of items with a score which is not 0 is too small to calculate the corresponding evaluation index value, so the three thresholds are abandoned. The Precision and Recall statistics are shown in Fig. 3 and Fig. 4. It can be seen from the diagram that when the threshold $\eta = 0.2$, the corresponding Precision and Recall values are better than the other contextual preference thresholds, so $\eta = 0.2$ is the best one.

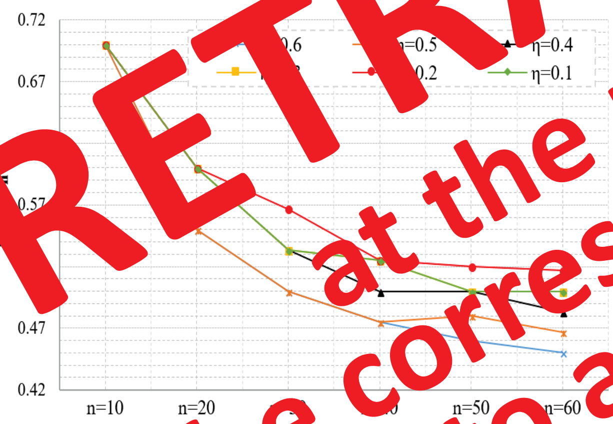

Figure 3 Precision values under different contextual preference thresholds

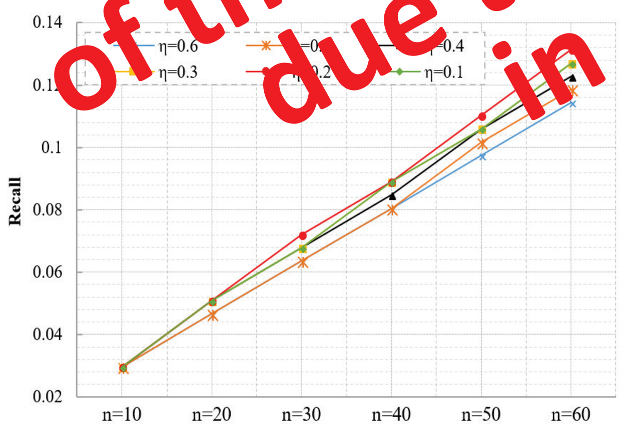

Figure 4 Recall values under different contextual preference thresholds

4.3.3 The TF-IDF Based Contextual Post-Filtering Recommendation Algorithm's Utility Evaluation

To verify the validity of the *TF-IDF* based contextual post-filtering recommendation algorithm (*TF-IDF*_based_*CPF*), this paper compares it with the collaborative filtering recommendation algorithm combined with item category preference similarity (*ICPS*_combined_*CF*) [32] and the contextual associated probability based contextual post-filtering recommendation algorithm (*CAP*_based_*CPF*) [30]. Related index statistics are shown in Fig. 5 and Fig. 6.

Figure 5 Precision values under different contextual preference thresholds

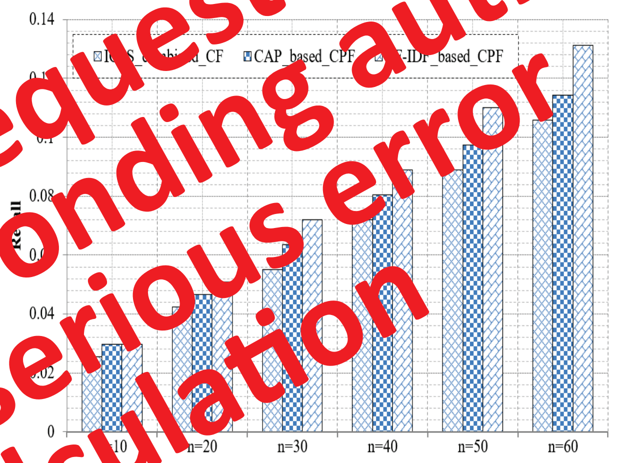

Figure 6 Recall values under different contextual preference thresholds

As can be seen from the graph:

The *TF-IDF* based contextual post-filtering recommendation algorithm is obviously superior to the collaborative filtering recommendation algorithm combined with item category preference similarity, the reason is: The users' personal needs have contextual sensitivity and change with the context change, which is not fixed, and it shows that the context information plays an important role in the process of personalized recommendation.

Compared with the contextual associated probability-based contextual post-filtering recommendation algorithm, the *TF-IDF* based contextual postfiltering recommendation algorithm has advantages in Precision and Recall values, and the advantages become more obvious as the recommended item number increases. This shows that the proposed algorithm can effectively improve the contextual preference extraction quality and then improve the recommendation quality by further analysing the item's context importance based on considering the contextual association probability. It is proved that the algorithm is effective.

5 CONCLUSIONS

This paper studied the information overload problem in O2O environment, improved the contextual associated probability-based contextual post-filtering recommendation algorithm, constructed contextual preference prediction model based on contextual association probability and contextual universal importance to extract the contextual preference degree. Based on this, the direct filtering and score correction were applied to the initial prediction score of collaborative filtering recommendation combined with item category preference to generate the recommendation. The utility evaluation verifies that the best weight coefficient is 0.6 and the optimal contextual preference threshold is 0.2. Furthermore, the proposed *TF-IDF* based contextual post-filtering recommendation algorithm is obviously superior to other algorithms, and with the increase of the recommended items number, the advantages are more obvious.

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