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INTELLIGENT RECOMMENDATION ALGORITHM FOR PRODUCT INFORMATION ON E-COMMERCE PLATFORMS BASED ON ROBOT CUSTOMER SERVICE AUTOMATIC Q&A

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Abstract. In order to enhance the shopping experience of customers and retain them, thereby increasing sales volume, the author proposes the research topic of an intelligent recommendation system for product information on e-commerce platforms based on robot customer service automatic question answering. Firstly, starting directly from the question itself, the system can provide feedback to customers by simply segmenting the questions submitted by customers and matching them with semantic templates; Secondly, the system automatically builds and updates the user's personalized knowledge base, using this to predict user purchasing tendencies and achieve the function of recommending products to customers. The implementation of the intelligent shopping robot system has passed 365 question and answer tests on 5G mobile phone sales terms, and is feasible in the professional field. The experimental results indicate that, when the number of training corpora increased to 300, the accuracy of the system was 0.85, 0.90, and 0.98 using 100, 2003, and 300 tests respectively. Such a system is perfect for natural language processing, so we can improve the system by expanding and improving the knowledge base. The intelligent shopping robot recommendation system studied by the author is still in the analysis and demonstration stage, sincerely hope that the processing method used in this project can have reference significance for similar recommendation systems in the near future.

Key words: Robots, Automatic question and answer, E-commerce platforms, Information intelligent recommendation

1. Introduction. The customer service system has evolved from telephone consultation to instant messaging consultation, then to the question answering system of natural language processing with artificial intelligence, it has gone through a long process of development. The intelligent customer service based on language intelligent processing technology solves the problem of increasing service demand and dispersed customer sources, reducing the response speed and processing efficiency of traditional customer service to customer service needs, breaking through the bottleneck of customer service development, promoting the transformation of service methods, and further optimizing customer experience [1].

As an emerging development direction of automatic question answering, intelligent customer service system is an industry oriented automatic question answering system based on large-scale knowledge processing, involving knowledge management, natural language understanding, logical reasoning and other technologies, which can provide an effective technical means for communication between enterprises and a large number of users. In addition, intelligent customer service systems can effectively reduce labor costs, enhance user experience, and provide users with more convenient and comfortable services.

It can also establish a fast and effective natural language based technical means for communication between enterprises and a large number of users, and provide statistical analysis information required for lean management [2]. The intelligent customer service robot provided by the intelligent customer service system can automatically respond to simple customer service needs, achieve a humanized human-machine dialogue experience, divert manual traffic, reduce customer service pressure, improve response rate, and improve customer satisfaction, which is increasingly receiving attention from enterprises.

In order to actively respond to relevant national science and technology innovation policies, the ”National Science and Technology Management Information System Public Service Platform” built by the Institute of Scientific and Technical Information of China was officially launched for service in September 2015 [3]. As an external window and service platform for national scientific research projects, the system needs to address various problems faced by researchers, however, with the increase of projects and rapid policy updates, it is

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difficult for manual customer service to cope with various problems, therefore, building an intelligent Q&A system for the platform is one of the effective solutions. With the development of speech recognition technology and its widespread application in daily life, users have put forward higher requirements for speech recognition in terms of vocabulary and specific people. Researchers have begun to study speech recognition with large vocabulary and non-specific people, and many new technical challenges also need to be solved. For example, the larger the vocabulary of a speech recognition system is, the larger the glossary is required. In this case, it is particularly important to select and establish appropriate templates, which is more difficult to process; Voice information is different for different recognizers. Semantic information is also different when the same person says the same thing at different times [4]; if there is some noise information in the speech signal, the results of speech recognition will also produce errors. Therefore, traditional template establishment and matching methods are no longer suitable for new environments.

In the 1980s, speech recognition researchers successfully broke through the barriers of large vocabulary, non-specific individuals, and speech continuity. Among them, the representative one is the Sphinx speech recognition system developed by Carnegie Mellon University, which is the world's first large vocabulary, non-specific continuous speech recognition system, and has high speech recognition performance. At this point, statistical methods are the mainstream method in speech recognition technology. Among them, representative speech recognition systems include the Naturally Speaking system successfully developed by DragonSystem, the Nuance Voice Platform system developed by Nuance, VoiceTone from Sun, and Whisper from Microsoft [5].

2. Literature Review. Almost all large e-commerce systems, such as Amazon, eBay, Dangdang, etc., use various forms of recommendation systems to varying degrees. However, with the vigorous and rapid development of e-commerce websites, the products provided to customers have almost exponentially increased. For customers, facing these "rich" information, they are no longer able to quickly obtain the products they want from personalized recommendation service systems, the services of personalized recommendation systems have shown to lag behind customers' shopping needs. Since the 21st century, due to the popularity of the Internet, computer processing of natural language has become an important means of acquiring knowledge from the Internet. Almost all modern people living in the information network era have to deal with the Internet, and more or less use the research results of natural language processing to acquire or mine various kinds of knowledge and information on the vast Internet, therefore, countries around the world attach great importance to relevant research and have invested a large amount of manpower, material resources, and financial resources [6].

The intelligent shopping robot system is a requirement for e-commerce innovation. The traditional e-commerce model has developed to the extreme, Chinese e-commerce websites represented by Alibaba, Taobao and others have encountered development bottlenecks, how to get the goods they want more quickly, how to solve the adhesion between merchants and customers, how to let customers experience the pleasure of shopping, how to let more consumers participate in online shopping, how to involve more farmers in e-commerce transactions has become an urgent issue that needs to be addressed. The development of e-commerce in China requires a disruptive innovation revolution.

Currently, almost all large e-commerce systems, such as Amazon, CDNOW, eBay, Dangdang, etc., use various forms of recommendation systems to varying degrees. With the vigorous and rapid development of e-commerce websites, the number of products provided to customers has almost exponentially increased. For customers, facing these "rich" information, they are no longer able to quickly obtain the products they want from personalized recommendation service systems, the service of personalized recommendation systems has shown to lag behind customers' shopping needs. In an increasingly competitive environment, intelligent shopping robot systems can effectively retain customers and improve sales on e-commerce websites.

Zhang, X proposed a collaborative filtering recommendation algorithm to improve the user model. Firstly, the algorithm takes into account the scoring differences caused by different user scoring habits when expressing preferences, and adopts a decoupling normalization method to normalize user scoring data; Secondly, considering the forgetting transfer of user interest over time, a forgetting function is used to simulate the forgetting law of scores, and the weight of time forgetting is introduced into user scores to improve the accuracy of recommendations; Finally, improvements were made to the similarity calculation when calculating the nearest neighbor set. On the basis of Pearson similarity calculation, an effective weight factor is introduced to obtain a more accurate and reliable nearest neighbor set [7]. Sharma, S. N extracts tweets or comments from the database

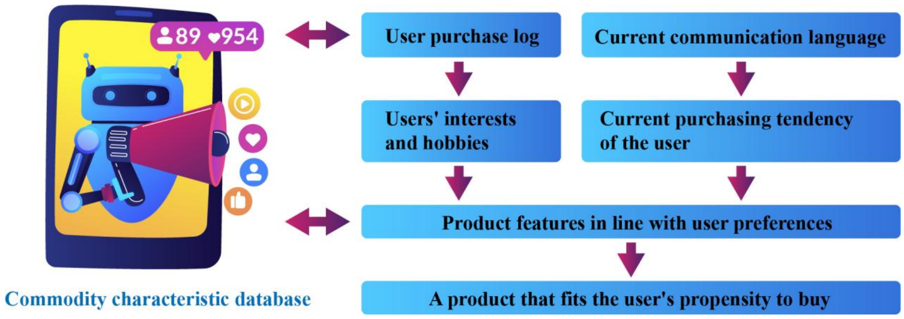

Fig. 3.1: Personalized recommendation algorithm structure diagram of intelligent shopping robot system

through preprocessing, which includes three processes: word segmentation, stemming, and space deletion. In the process of semantic word extraction, the semantic words in the dictionary will be extracted by matching with the extracted keywords. The next process is feature extraction, extracting the joint holographic entropy and cross holographic entropy of all keywords, and further conducting feature selection based on conditional holographic entropy. Finally, a deep belief network (DBN) is used to classify the selected features, which is a high-performance deep learning algorithm [8]. Qi, X adopts an intelligent information retrieval method based on human-computer interaction (HCI-IRM). The proposed method focuses on customer satisfaction, which is the main success evaluation indicator. It identifies the set of related records at a given time in the set. The main goal of information retrieval systems is to obtain information [9].

In addition, for some small sellers, such as shops on Taobao, employees are still traditionally employed to do online customer service. Firstly, due to time constraints on users' purchases of goods (the service hours of online customer service are usually from 9:00 pm to 9:00 am), a portion of customer traffic will flow away; Secondly, hiring online customer service will increase payment costs, which is a significant expense for small businesses. If intelligent shopping robots are used to replace online customer service, it will save sellers a lot of costs.

3. Detailed description of recommendation algorithms for intelligent shopping robot systems.

3.1. Algorithm Overview and Structure Diagram . The first step is to obtain the user's current purchasing tendency based on their basic information or purchase logs, in preparation for recommendations.

The second step is to compare and analyze the current purchasing tendency data with the product feature data, obtain the user's current preference for product features and recommendation reference groups, and combine the product feature database and product recommendation evaluation function to make the current recommendation [10].

The third step is to make real-time recommendations based on the dynamically updated user personality knowledge base, guiding users to be satisfied. The structure of the recommendation algorithm is shown in Figure 3.1.

3.2. Explanation of concepts and formulas in algorithms.

3.2.1. Product characteristics. The requirement for product features in this algorithm is that product features are objective and descriptive, and these features are consistent with the descriptions in the product knowledge base that records product features, such as price, color, pixels, etc [11]. In order to describe product features, the product feature database we have established can be represented by vectors as follows:

$$P(m) = (f_{11}, \cdots, f_{1k}, \cdots, f_{ik}, \cdots, f_{ij}), m = 1, 2, 3, \cdots, M \tag{3.1}$$

M is the total quantity of a physical product (such as a mobile phone) m, i is the product feature number (such as color, price), and j represents the jth feature value of feature i (white, 2000 yuan), the meaning of feature k is that the feature domain of each product feature is not fixed, and each f_{ij} is represented by a true or false value. If the product has this feature, the value is 1, otherwise it is 0.

3.2.2. Current purchasing tendencies of users . Generally speaking, users always frequently inquire about the products they care about when purchasing, reflecting their willingness to purchase. Therefore, we believe that among all the product categories that users are currently consulting, the one with the highest number of inquiries is the user's current purchasing tendency, and the type of product also belongs to the category of product features. Therefore, the user's current purchasing tendency is also a feature entity of product features. For the feature entity set $K = (K_1, \cdots, K_i, \cdots, K_n)$ of category features, the user's current purchasing tendency $K_t = K_i$, and K_i are the category feature entities with the highest number of user inquiries [12].

3.2.3. User preference for product features. Analyze the user's preference for product features based on their purchase logs during a certain period of time, and then assign corresponding weights to these product features based on their preference, that is, the user's current preference for features.

The definition of favoritism is as follows: Statistical analysis of some product features purchased by users during a certain time period, preference C_i for feature i; The ratio of the number of features i included in the product purchased by the user to the total number of features in the purchased product is calculated using the formula:

$$C_i = \frac{m_i}{\sum_{j=1}^{n} m_j} \tag{3.2}$$

Among them, n represents the number of statistical product features (such as the brand and color of the phone), m_j refers to the number of products purchased by users within a certain period of time that contain a certain feature [13].

3.2.4. Similarity matrix of product feature entities.

(1) Similarity of entities. Let the user's ratings of feature entity i and feature entity j in the M-dimensional space be expressed as the similarity S (i, j) between feature entity i and feature entity j in vectors $\bar{i}$ and $\bar{j}$, respectively

$$S(i, j) = cos(\bar{i}, \bar{j}) \tag{3.3}$$

$$cos(\bar{i}, \bar{j}) = \frac{\bar{i} \cdot \bar{j}}{||\bar{i}|| \times ||\bar{j}||} \tag{3.4}$$

Among them, the numerator is the inner product of two feature entity rating vectors, and the denominator is the product of the modules of the two feature entity rating vectors.

The rating matrix is considered as a rating on an m-dimensional space, $u_1, \cdots, u_m$ represents m types of products (such as m different models of mobile phones). If a user does not rate a feature entity, the user's rating for that feature entity is set to 0.

(2) Similarity Matrix of Product Feature Entities. For the feature entity set $I = \{i_1, i_2, \cdots, i_{n-1}, i_n\}S$ of a certain feature, use matrix S to represent the similarity matrix. The similarity value is calculated using formula 3.2.

Through observation, it is not difficult to find that matrix S has the following characteristics:

$$S(i, j) = S(j, i) = 1 \tag{3.5}$$

Therefore, only upper triangular matrix or lower triangular matrix can be considered in the calculation, which is conducive to simplifying the calculation[14].

3.2.5. Recommended values for product feature recommendation groups . Multiply the similarity in each feature similarity matrix by the preference of the product features in the recommendation group, and then add them to obtain the recommendation value of the recommendation group, expressed in RV. The calculation formula is as follows:

$$RV_{ij} = \sum_{i=1}^{n} S_{m,n} \times C_m \tag{3.6}$$

Among them, i represents the i-th reference group, j represents the recommended group for group j, and $S_{m,n}$. The similarity between feature entity m of a certain feature and feature entity n, which is the element in the product feature entity similarity matrix, C_m is the user's preference for feature m, and n is the number of selected main features.

3.3. Personalized recommendation algorithm based on product features . We determine the user's current purchasing intention based on the number of inquiries they make about a certain product during human-machine communication, and use the feature entity with the highest number of inquiries as the user's current purchasing intention. For example, for the entity feature set K=Huawei, Samsung, Apple..., firstly, based on the consulting statistics of current users, it can be concluded that the user's current purchasing tendency is: K==Apple. Secondly, by analyzing customer purchase logs, the preference degree C of each feature is calculated using formula (2), and then sorted based on the size of the preference degree value, considering the accuracy of the calculation, only the features with preference ranking in the top n are used for recommendation in actual recommendations. For example, by analyzing the purchase logs of a user during a certain period of time and calculating according to formula (2), the sorted result is: The preference for brand, color, weight, and corresponding features is 0 285 0. 197 0. 135...

3.4. Recommended Reference Group for Obtaining Features . After obtaining the user's preference for features, first sort the preference horizontally, through further analysis of user purchase logs, the physical features of each feature are vertically sorted based on the number of customer inquiries. Each set of feature entities serves as a basic recommendation reference group. Select the first n basic reference groups as the recommendation basis[15]. Consider further expanding the scope of recommendations, we can cross the features of each group of feature entities with the highest similarity and those with a preference ranking second to others to form a new feature recommendation group. If we take the first n groups, theoretically we can obtain n recommended reference groups. For example, the features sorted based on preference values are: brand, color, weight.

3.5. Calculate the recommended value of the recommendation group for product recommendation . After obtaining the recommended reference group, recommendations can be made based on the first group and the recommended value of the recommended group can be calculated. Based on the reference group, recommend the recommendation group through the similarity matrix of each feature.

The reference group itself is the first recommended group obtained, because the entities of each feature have the highest similarity (similarity of 1) in the similarity matrix [16]. Then find the feature with the second highest similarity in the similarity matrix, which can result in the 2nd, 3rd, and i-th groups, here, i is related to the recommendation accuracy and can be limited according to actual needs. Then, based on the formula for calculating the recommended value, relevant calculations can be performed to obtain the recommended value for the recommended group. Taking the first set of reference groups as an example, because the similarity of the same entity features between the first set of features is 1, the first recommended group obtained is the first set of reference groups themselves, namely apples, white, according to the formula, the recommended value is RV11=1 * 0.285+1 * 0.197+... next, for the first reference group, find the second most similar feature in the similarity matrix of each feature, for example, in the brand similarity matrix, after comparing and searching, it is found that Samsung ranks second to Apple, with a value of 0.82, in the color similarity matrix, black comes next to white with a value of 0.62, and other features follow suit, so, through the first reference group, the second recommended group was obtained, namely Samsung, black, according to the formula, the recommended value is RV12=0.82 * 0.285+0.62 * 0.197+... The same method can be used to obtain the recommended group and its recommended value RV based on the i-th reference group.

3.6. Product recommendation based on recommendation group. The feature recommendation groups were obtained above, and all recommendation groups were sorted according to their recommendation values. Select the feature recommendation group ranked in the top n as the recommendation group for users. At this point, the user's current purchasing intention (i.e. the feature entity of the category feature) is combined with the recommended n sets of feature recommendation groups to obtain n products. Then, based on the obtained n products, the product feature knowledge base is matched, if the product exists, recommend it. Otherwise, add the recommendation group one by one after the recommendation value reaches n digits, and

Table 4.1: Experimental results of the first group

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers
100	20	14
100	50	40
100	80	72

Table 4.2: Experimental results of the second group

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers
200	20	15
200	50	42
200	80	73

then continue to recommend and match until it is added to the recommendation group with the recommendation value ranking last. For example, RV11 ranks first and calculates that the type of entity that customers are currently inclined to purchase is an Apple phone, based on the combination, the features obtained are white, etc. Then, based on the features, match the product feature library. If there are products that meet the feature conditions, recommend them. If it does not exist, proceed to the next group of recommendations [17].

4. Experimental Results and Analysis. The training data for this experiment comes from 365 5G mobile phone store Q&A phrases provided by PT37 company, which means the training set consists of 365 question answers. The test data adopts 100 randomly selected questions from user question records.

(1) The first group of experiments.

1.Training corpus 100, evaluation corpus 20

2.Training corpus 100, evaluation corpus 50

3.Training corpus 100, evaluation corpus 80

(2) Second set of experiments.

1.Training corpus 200, evaluation corpus 20

2.Training corpus 200, evaluation corpus 50

3.Training corpus 200, evaluation corpus 80

(3) The third group of experiments.

1. Training corpus 300, evaluation corpus 20
2. Training corpus 300, evaluation corpus 50
3. Training corpus 300, evaluation corpus 80

(4) Group 4 Experiment.

1. Training corpus 300, evaluation corpus 100
2. Training corpus 300, evaluation corpus 200
3. Training corpus 300, evaluation corpus 300

The statistical results of the first group of experiments are shown in Table 4.1.

The statistical results of the second group of experiments are shown in Table 4.2.

The statistical results of the third group of experiments are shown in Table 4.3.

The statistics of the fourth group of experimental results are shown in Table 4.4.

Set the number of evaluation corpora to fixed values (set to 20,50,80 respectively), and gradually increase the number of training corpora (100200300) to obtain Tables 4.5, 4.6, and 4.7.

Summarizing Tables 4.5, 4.6, and 4.7 it is clearer to see the trend of increasing the number of training corpora and testing expectations, resulting in an increase in system accuracy.

Table 4.3: Results of the third group of experiments

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers
300	20	18
300	50	46
300	80	78

Table 4.4: Experimental results of the fourth group

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers
300	100	93
300	200	192
300	300	294

Table 4.5: The number of evaluations in Table 5 is 20, and the number of training corpora gradually increases from 100 to 300

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers	Accuracy
100	20	14	0.7
200	20	15	0.75
300	20	18	0.9

Table 4.6: The number of evaluations in Table 6 is 50, and the number of training corpora gradually increases from 100 to 300

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers	Accuracy
100	50	40	0.8
200	50	42	0.84
300	50	46	0.92

Table 4.7: The number of evaluations in Table 7 is 80, and the number of training corpora gradually increases from 100 to 300

Number of training corpus	Number of evaluation corpus	Returns the number of correct answers	Accuracy
100	80	72	0.85
200	80	73	0.9
300	80	78	0.975

Through the comparison and analysis of the experimental results in Tables 4.5, 4.6, and 4.7, we can clearly see that the accuracy of the system is constantly improving under the condition of increasing question/answer knowledge pairs [18].

Especially when observing Table 4.7 obtained from the fourth group of experiments, when the number of training corpora increased to 300, 100, 200300 tests were used to predict the evaluation, and the accuracy of the system was 0.85, 0.90, and 0.98, respectively, as shown in Figure 4.1.

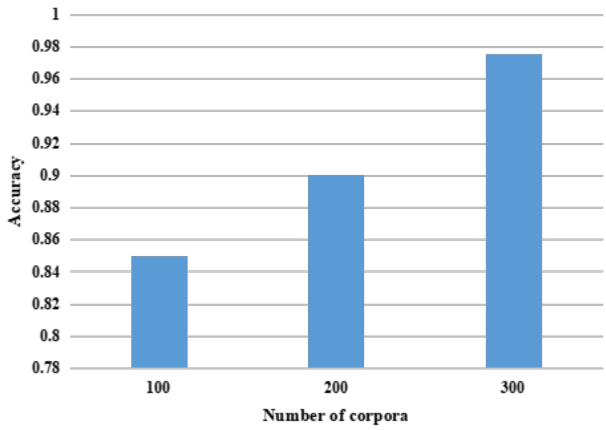

Fig. 4.1: Accuracy of the system

Such a system is perfect for natural language processing, so we can improve the system by expanding and improving the knowledge base.

The intelligent shopping robot recommendation system studied by the author is still in the analysis and demonstration stage, sincerely hope that the processing method used in this project can have reference significance for similar recommendation systems in the near future[19].

5. Conclusion. The author proposes natural language processing algorithm based on semantic template and personalized recommendation algorithm based on knowledge base. The natural language processing algorithm based on semantic template proposed by the author is more accurate and effective than the traditional natural language processing algorithm. The recommendation algorithm proposed by the author starts from the user's personal basic information and past purchase logs, analyzes the user's purchase behavior, obtains the user's current purchase intention, and updates the user's personalized knowledge base by tracking and recording the user's consultation and browsing behavior, it continuously makes real-time recommendations for the user, and ultimately recommends products that meet their interests.

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