Personalised recommendation of smart home products based on convolution neural network

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Abstract: In order to solve the problems of high recommendation error and long recommendation time in traditional personalised recommendation methods for smart home products, a new personalised recommendation method for smart home products based on convolution neural network is proposed. The attributes of smart home products are superimposed, and the square root of the attribute weight vector and all components are calculated. Determine the relationship between the attributes and important factors of smart home products to be recommended, and complete the weight calculation of smart home product recommendation. The personalised recommendation model of smart home products is constructed, and the convolution neural network is used to obtain the global optimal solution of the personalised recommendation model, so as to realise the personalised recommendation of smart home products. The experimental results show that the minimum error of the proposed method is about 0.3%, and the recommendation time is less than 15 s.

Keywords: smart home products; personalised recommendation; product attributes; convolution neural network.

Reference to this paper should be made as follows: Luo, X. and Liu, J. (2022) ‘Personalised recommendation of smart home products based on convolution neural network’, *Int. J. Product Development*, Vol. 26, Nos. 1/2/3/4, pp.52–63.

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1 Introduction

With the in-depth development of online sales business in China, the types and quantity of products recommended by online products are increasing (Zuo et al., 2020). With the continuous improvement of people's living standards, people's choice of household products is not limited to the use of its basic functions, and the personalised functions of household products are constantly improved (Huang et al., 2020). Therefore, the emergence of smart home products continues to meet the spiritual needs of consumers. Under the background of rapid development of electronic information technology, it is difficult for commodity buyers to choose goods recommended online, and it is difficult for product sellers to determine the real needs of consumers due to the huge online data (Wu et al., 2020). Based on this, how to recommend smart home products and improve the accuracy of recommended customer groups has become a hot issue in this field.

According to the method of Wang et al. (2016), a personalised recommendation algorithm integrating comment tags is proposed. This algorithm solves the problem of only paying attention to users' interests in the existing recommendation methods. In this method, the comment tag can design certain rules according to the recommended products, with the help of which the user's features and product features can be analysed in depth, and on this basis, the user interest model and product feature model can be constructed, and the recommendation can be made according to the results of the construction. The process of recommendation is relatively simple, the speed of recommendation is fast, but the error of recommendation is large, so it still needs to be further improved. According to the method of Ren et al. (2019), this paper proposes a personalised recommendation method based on hot diffusion influence propagation in social networks. In this method, the relationship between people in display and users in shopping network is determined, and the relevant information network is constructed. On this basis, the composite similarity in user relationship is determined, and the influence factors in the relationship network are analysed with the help of thermal diffusion probability model, and the user following probability score is obtained to complete the screening of product recommendation users, and the potential needs of potential customers are identified to collect and recommend products effectively. This method considers a variety of relationship factors and improves the accuracy of recommendation, but the anti-interference ability is poor and has some limitations. In Tang et al. (2020), a collaborative filtering recommendation algorithm based on improved canopy clustering is proposed. This method sets the density value of user data, combines user activity, determines the weight value of user data, and summarises it. This paper introduces the theory of canopy, divides the user data into different categories, summarises the determined users, and completes the recommendation. The application of this algorithm in smart home product recommendation is beneficial to product recommendation, but the accuracy of recommendation cannot be guaranteed.

Based on the shortcomings of the above methods, this paper designs a new recommendation method. Through a neural algorithm in artificial intelligence, the optimal solution of the model is obtained to complete the personalised recommendation of products

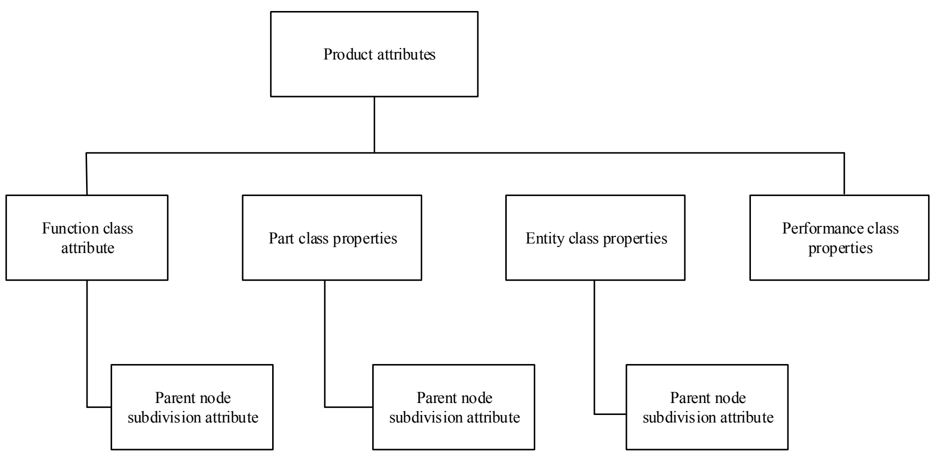
2 Attribute mining and recommended weight determination of smart home

2.1 Smart home product attribute mining

Before personalised recommendation of smart home products, it is necessary to mine the product attributes. Smart home products belong to the product of the development of intelligent technology. Its product attributes overlap with those of traditional home products. In order to better adapt to social development, smart home products introduce intelligent technology on the basis of traditional product attributes to change the product attributes. Product attributes mainly refer to the characteristics of the product itself, the set of differences between smart home products and common home products (Wang and Fu, 2020). In fact, the attribute mining of smart home products refers to the mining of the unique nature of the use effect of its evaluation in many home products.

In this paper, smart home product attribute mining, due to the different types of smart home products, there are some differences. Therefore, this paper designs a smart home product attribute set and sets the rules to Cao et al. (2020) the smart home product attribute set. Based on this, the organisational structure of the smart home product attribute set designed in this paper is shown in Figure 1.

Figure 1 Structure of smart home product attribute set



In the smart home product attribute collection organisation designed in this paper, the smart home product attribute is mainly the functional attribute of the home product, including the attribute of its components, and subdivides it into the parent node attribute. According to the above division, its attributes are deeply mined.

In this study, the new attributes of smart home products are added to the common product set, in which the mutual information of the added household product attributes is expressed as:

$$H[a,b] = \log \frac{H(a,b)}{H(a)H(b)} \tag{1}$$

In the formula, a represents the parent node property value of a smart home product, $H[a, b]$ represents new feature values in smart home products, $H(a)$ represents the probability of new attributes appearing in household products, $H(b)$ represents the new attribute value of the candidate.

On the basis of determining the attribute mutual information of smart home products, a set of attributes of smart home products is constructed, that is:

$$G = \begin{cases} G_{11}, G_{12} \cdots G_{1N} \\ G_{21}, G_{22} \cdots G_{2N} \\ \cdots \\ G_{U1}, G_{U2} \cdots G_{UN} \end{cases} \tag{2}$$

In the formula, a weight vector G_{UN} represents the relationship between the attributes of smart home products, contains multiple components, N the dimension of smart home product attributes.

On this basis, the smart home product attributes are superimposed, and the superposition matrix of smart home product attributes is constructed, that is:

$$G = \begin{cases} DG_{11}, DG_{12} \cdots DG_{1N} \\ DG_{21}, DG_{22} \cdots DG_{2N} \\ \cdots \\ DG_{U1}, DG_{U2} \cdots DG_{UN} \end{cases} \tag{3}$$

In the formula, DG_{UN} represents the component factors in the attribute superposition matrix of smart home products. The values are:

$$DG_{UN} = \sum D_{i=1}^{N} w_{ik} \tag{4}$$

In the formula, w_{ik} represents the component of smart home products. The values of the constituent factors in the superposition matrix are obtained by formula (5), that is:

$$w_{ik} = \sqrt{\frac{w'_{ik}}{\max\left(w'_{ik}\right)}} \tag{5}$$

In smart home products, the weight vector and all components of the attributes are calculated by superposition, which can avoid the same (Zhao et al., 2020) between the attributes of smart home products and other general household product attributes.

2.2 Determination of recommended weight for smart home products

On the basis of the above intelligent home product attribute mining, the recommended weight of intelligent furniture products should be determined before recommendation. This paper uses the HITS method to determine the recommended weight (Kaur et al., 2020) smart home products. First of all, the attribute set after mining smart home products is considered as all the important factors recommended, and the main smart home products are considered as the key factors in the recommended weight factor. The relationship between the attributes and important factors of smart home products to be recommended is expressed as a directed graph, that is:

$$Y = \left(C, F, K, L\right) \tag{6}$$

In the formula, C represents the collection of smart home product attributes to be recommended, F represents the set of recommendation factors, K represents a collection of key factors for smart home product attributes, L represents the rest of the smart home product attributes to be recommended.

After determining the relationship between smart home product attributes and important factors, the weight matrix of the key factors in smart home product attributes is determined, and the weight of the important factors is determined by this matrix, that is:

$$Y_{ij} = \begin{cases} P(C_i, F_i) \\ 0 \end{cases} \tag{7}$$

In the formula, C_i, F_i represent the probability of the emergence of important factors in smart home product attributes.

Assuming that Q_i will represent the authoritative value of the smart home product attribute set to be recommended, z_i represents the central value in the collection of smart home product attributes to be recommended, at this point, the relationship between the two is related to that is:

$$Q_i = \sum_i^n L_{ij} \times Z_i \tag{8}$$

For the above relationship determination, set the $\vec{k}$ as a column vector of the collective weights of the smart home product attributes to be recommended, $\vec{v}$ represents the central column vector of all smart home product attributes set weights to obtain:

$$\vec{k} = L_{ij} \times \vec{v} \tag{9}$$

According to the central column vector of the weighted value of the smart home product attribute set obtained above, the ordered ranking is carried out, that is, the important degree of the intelligent furniture product attribute set is sorted (Liu et al., 2019), which is first initialised. Then iterative update to determine the importance of smart home product recommendation, as follows:

$$\vec{k}^{(n+1)} = L_{ij} \times \vec{k} \tag{10}$$

In the formula, $\vec{k}$ represents the number of iterations.

3 Personalised recommendation of smart home products based on convolution neural network

3.1 Design of personalised recommendation model for smart home products

According to the determination of the recommended weight of smart home products, this paper constructs a personalised recommendation model of smart home products to realise the recommendation of smart home products (Wei et al., 2019). First of all, the recommended weight values of smart home products are standardised pre-processing, and the processing matrix is set up:

$$M = (m_{ij})_{m \times n} \tag{11}$$

In the formula, m_{ij} represents the smart home product index weight vector.

To label it, that is:

$$\varepsilon_{ij} = \begin{cases} \dfrac{m_{ij}}{\sqrt{\sum_{i=1}^{n} m_{ij}^2}} \\ \dfrac{\frac{1}{m_{ij}}}{\sqrt{\sum_{i=1}^{n} 1/m_{ij}\delta}} \end{cases} \tag{12}$$

In the formula, δ represents the recommended benefits of smart home products, ε_{ij} represents the standardised matrix.

According to the weight value standardisation matrix of smart home products, the ideal effect value of product recommendation is obtained, that is:

$$\varepsilon'_{ij} = \left\{x_1^+, x_2^+ \ldots x_n^+\right\} \tag{13}$$

$$x_n^+ = \max \varepsilon'_{ij} \tag{14}$$

Because after standardising the recommended weight value of intelligent household products, due to various influencing factors, there are still some errors in the effect of the treatment, so it needs to be further optimised. In order to build a more perfect recommendation model (Xie and Kumar, 2019). Optimised through the following standardised value optimisation model, namely:

$$\min \varepsilon'_{ij} = \sum_{i=1}^{n} \left(x_n^+ - x_n^-\right) w_{ij} \tag{15}$$

On this basis, the smart home product recommendation model is determined, namely:

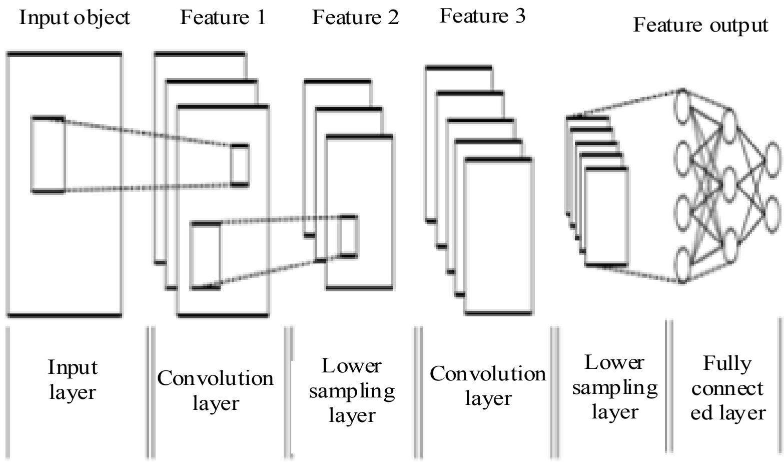
$$P = \begin{bmatrix} a_1 \\ a_2 \\ \cdots \\ a_n \end{bmatrix} \begin{cases} p_{11}, p_{12}, p_{1n} \\ p_{21}, p_{22}, p_{2n} \\ \cdots \\ p_{m1}, p_{m2}, p_{mn} \end{cases} \tag{16}$$

In the formula, p_{11} to p_{mn} the order of recommendation, P represents the matrix recommended for smart furniture products, a_1 to a_n represents the weight of smart home products recommended successively.

3.2 Intelligent home product recommendation optimisation based on convolution neural network

Convolutional neural network is a neural intelligence method processed by convolution kernel. This method is widely used in many fields. Because of the advantages of script perception, weight contribution and talent sampling, this method can the depth of the research object quickly and deeply (Gorban et al., 2020). The neurons in the algorithm break through the link mode in the traditional neural algorithm and only connect with the key parts, which results in the continuous iteration of the weight parameters and reduces the complexity of the algorithm. The smart method is constructed as shown in Figure 2.

Figure 2 Basic structure of convolutional neural network



Because the smart home product recommendation model constructed in this paper is prone to local recommendation optimisation and cannot consider global optimisation, this paper introduces convolution neural network to search for the global optimal solution of the smart home product recommendation model, so as to improve the effect of personalised recommendation of smart home products (Tao et al., 2021). The global optimal search process of convolutional neural network for personalised recommendation model of smart home products is as follows:

First of all, the personalised recommendation model of smart home products is characterised by:

$$\text{Ø}_{ij} = r_i \sqsupset v_j \tag{17}$$

In the formula, Ø_{ij} represents the local feature submatrix of the personalised recommendation model for smart home products, r_{ij} represents the row vector of the highest similarity in the personalised recommendation model for smart home products, v_j represents the column vector of the highest similarity in the personalised recommendation model, $\sqsupset$ represents a two-dimensional matrix.

Because the recommendation effect is local in the personalised recommendation of smart home products, the weight of recommended products is confirmed in convolution neural network. Therefore, with the help of this intelligent neural network, it is divided into: recommended data input layer, convolution layer and regulation layer, and local feature the recommended effect. Among them, in the processing of convolution layer, a linear weighting operation is carried out on its recommended model, and the convolution kernel of $a \times n$ size is used for convolution processing. The final recommended model features are as follows:

$$T_j\left(j \in p \times q\right) = n\left(\sum\nolimits_{i \in n} R_i \times K + e\right) \tag{18}$$

In the formula, e represents bias, $p \times q$ represents the convolution kernel size of the output recommendation model.

On this basis, according to the local features of the recommended model, the recommended model effect after convolution kernel processing is normalised, and the new input data in the recommended model is the most recommended data according to the normalised smart home recommended data here. That is:

$$\gamma_{nor} = \frac{\gamma - \gamma_{\min}}{\gamma_{\max} - \gamma_{\min}} \tag{19}$$

In the formula, γ represents the data recommended by the original smart home product recommendation model, $\gamma_{\min}$ and $\gamma_{\max}$ represent the maximum and, respectively.

The normalised data is input into the convolution kernel in the convolution neural network, and the recommended results are as follows:

$$t = \mu\left(e + \sum_{i=1}^{n} (\gamma \times R_i) L + U\right) \tag{20}$$

In the formula, t represents the new recommendation after convolution kernel processing, L/U represent the ranks of the recommendation matrix, R_i new data for personalised recommendations for smart home products, μ represents the activation function.

Because there are more similar data in the personalised recommendation data after convolution layer processing, it is necessary to connect the number of neurons in the convolution layer with the number of rows of the feature matrix. Finally, the optimal solution in the personalised recommendation model of smart home products is determined, that is:

$$o_i = \mu\left(\sum_{z=1}^{s} t_i f\right) \tag{21}$$

In the formula, o_i represents the number of neurons identified in the convolution layer, t_{if} represents the optimal value recommended for personalised features of smart home products, s and z represent the number of rows and numbers of neurons in the intelligent convolution layer, respectively.

4 Experimental analysis

In order to prove that the proposed method can realise the personalised recommendation of smart home products, the experimental analysis is carried out. In order to highlight the effectiveness of the proposed method, Ren et al. (2019) method and Tang et al. (2020) method are selected as reference methods.

4.1 Experimental environment

In this experiment, taking a smart home product market as the research object, the furniture product data of the famous brand are collected, and the experiment is carried out through the WINDOWS 10 system, which supports the experiment. The memory of the system is 8 GB, and the core processing is 3.6 GHz.

4.2 Experimental parameters

The relevant test data in the experiment are shown in Table 1.

Table 1 Test data

Parameters	*Data*
Sample smart home product quantity/pieces	1000
Number of common furniture products/pieces	500
Recommended interval/s	10
Number of iterations/times	200

4.3 Experimental index

Based on the above experimental data and experimental parameters, comparative verification experiments were carried out. The overall experimental scheme is set as follows: Taking the recommendation error and recommendation time as the experimental comparison indexes, the method in this paper is compared with the methods in Ren et al. (2019) and Tang et al. (2020).

1 *Recommendation error*: recommendation error refers to the error between the recommendation results of different methods and the household products that users actually need. The higher the recommendation error is, the worse the recommendation performance of the method is. The calculation formula of prediction error is as follows:

$$W = \frac{1}{n-1} \sum_{i=1}^{n} y - y_i \tag{22}$$

In the formula, y represents the predictive value of personalised recommendations for smart home products, y_i represents the actual value of personalised recommendation for smart home products.

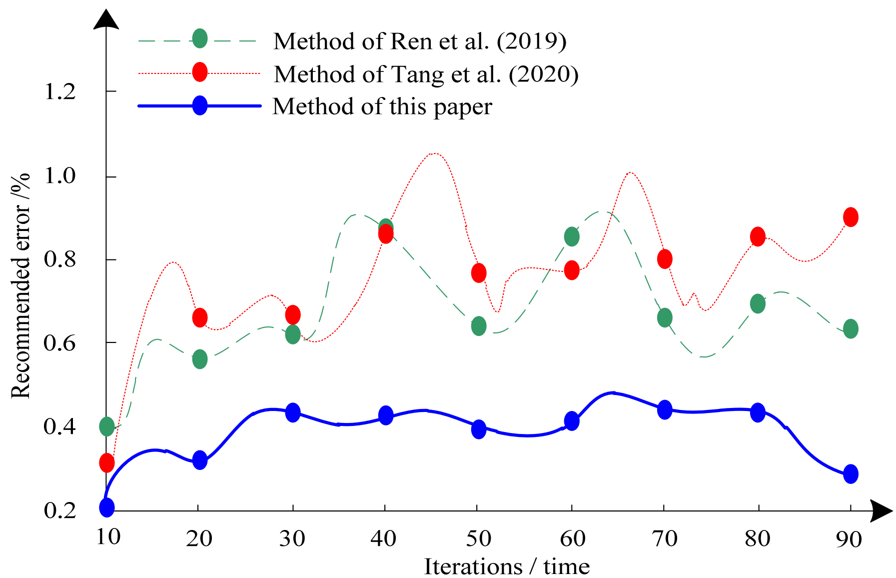
2 *Recommendation time*: recommendation time refers to the time consumed by different methods when recommending the same number of home products. The shorter the time, the higher the recommendation performance of the method.

4.4 Comparison of recommendation errors

To verify the reliability of this method, the error of personalised recommendation of sample smart home products by this method, Ren et al. (2019) method and Tang et al. (2020) method is used in the experiment. In order to ensure the effectiveness of the recommendation, the three methods are iterated several times under the same experimental environment to ensure the accuracy of the experimental data. The final recommendation error is shown in Figure 3.

Figure 3 shows that, using this method, Ren et al. (2019) method and Tang et al. (2020) method, there are some differences in the recommended errors in the three methods. When the number of iterations is 50, the recommended error of this method for smart home products is about 0.4%, Ren et al. (2019) method recommendation error is about 0.62%, about 0.92% error of Tang et al. (2020) method; when the number of iterations is 90, the recommended error of this method for smart home products is about 0.3%, Ren et al. (2019) method recommendation error is about 0.6. By contrast, the recommended error of this method for smart home products is the lowest, which is due to the analysis of the properties of the proposed method before the recommendation is made, and the convolution neural network is used to find the optimal solution of the proposed model, which improves the and reduces the error of recommendation.

Figure 3 Comparison of personalised recommendation error of smart home products

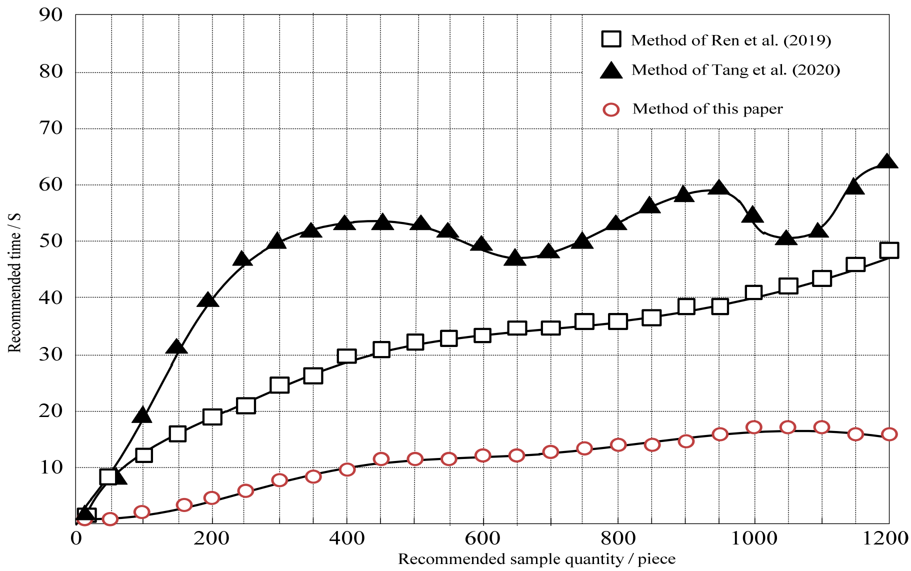


4.5 Comparison of recommended time

On the basis of ensuring the personalised recommendation accuracy of smart home products, the sample data are recommended by this method, Ren et al. (2019) method and Tang et al. (2020) method respectively. The recommended time is shown in Figure 4.

Figure 4 shows that, three ways to recommend sample data, there is a certain gap in the recommended time of the three methods. Among them, when the sample data is 600 pieces, about 10.1 s is the recommended time of this method. The recommended time of Ren et al. (2019) method is about 31 s, the recommended time of Tang et al. (2020) method is about 50 s. When the sample data is 1200 pieces, about 15 s, of the recommended time for this method, the recommended time of Ren et al. (2019) method is about 50 s, the recommended time of Tang et al. (2020) method is about 63 s. By contrast, the recommended method takes the shortest time, The method of this paper is verified Effectiveness.

Figure 4 Comparison of personalised recommended time for smart home products



5 Conclusions

This paper proposes a personalised recommendation method for smart home products based on convolution neural network. The attributes of smart home products are superimposed, and the attribute weight vector and the square root of all components are calculated to complete the mining of the attributes of smart home products; with the help of hits method, the important factors of the attributes of smart home products are obtained, and the relationship between the attributes of smart home products to be recommended and the important factors is determined to complete the weight calculation of smart home products. The weight value of smart home product recommendation is standardised and optimised, and the personalised recommendation model of smart home product is constructed. On this basis, the convolution neural network is used to obtain the global optimal solution of the personalised recommendation model to realise the personalised recommendation of smart home products. Compared with the traditional method, it has the following advantages:

1 The lowest error of personalised recommendation for smart home is about 03 and has certain reliability.

2 Adopting the proposed method for personalised recommendation of smart home takes less than 15 s, and the speed of recommendation is faster.

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