Research on Recommendation System of Agricultural Product Logistics Scale Control Based on Consumer Behavior

Yanli Jiao, Shanshan Zhang, and Haiyan Lv(✉)

Guangzhou City Construction College, Guangzhou 510990, Guangdong, China
Lhy68@163.com

Abstract. With the rapid development of economy and society, consumers' preferences for agricultural products tend to be diversified and personalized. However, a single recommendation system can hardly meet the rational needs of consumers for the safety, health, personality, culture and services of agricultural products. According to consumer behavior, this paper calculates and optimizes the recommendation algorithm, and uses the information of the agricultural product trading platform to make quick decisions. First, control the production volume, storage scale, circulation volume and logistics cost of agricultural products; Secondly, establish the network structure of the agricultural product logistics recommendation system, realize the optimal and fast distribution of agricultural products, meet the increasingly diversified and personalized needs of consumers, and maximize the economic and social benefits.

Keywords: consumer preference · agricultural product scale control · recommendation system

1 Introduction

The paper "Research on the Scale Control and Recommendation System of Agricultural Products Logistics Based on Consumer Behavior" is the mid-term research result of the second batch of projects in Guangdong Province to help towns and villages (document number: Yue Ke Han Nong Zi [2021] No. 1466). Based on the purchasing behavior of consumers, this research uses the collaborative filtering recommendation algorithm to complete the preprocessing of agricultural product filtering data, and recommends the favorite agricultural products to consumers.

2 Research Background

Over the past 40 years of reform and opening up, my country's logistics industry has made great progress. However, the operational efficiency of the agricultural product origin storage system is still not high. Agricultural products are the daily necessities of ordinary people, and they are placed on the dining table of every household every day.

A. Luqman et al. (Eds.): PMIS 2022, AHCS 6, pp. 569–576, 2023.
https://doi.org/10.2991/978-94-6463-016-9_59

However, the storage of agricultural products cannot satisfy consumers that they can buy the agricultural products they need at relatively stable prices in any season.

With the deepening of reform and opening up, the quantity and quality of agricultural products in our country have grown by leaps and bounds. With scientific and technological progress, supply-side structural reform and rapid economic development, the demand for agricultural products presents three characteristics: miniaturization, specialization and refinement. Agricultural product logistics enterprises should upgrade their new management ideas in a timely manner, and deeply understand the positive application value of computer technology in agricultural product logistics management [1]. The delivery of agricultural products to consumers on time, by quality, by quantity and by variety needs to rely on an information search system to achieve this. The development and application of agricultural product logistics control recommendation system based on the framework of information search system provides the possibility of precise selection and punctual arrival for agricultural product sales and logistics. The demand for agricultural products in my country is showing the trend of miniaturization, specialization and refinement [2].

3 Collaborative Filtering Algorithm of Agricultural Product Logistics Scale Recommendation System

3.1 Identify Consumers' Purchase Intention and Make Personalized Recommendation

The recommendation system is scored and evaluated by consumer a based on the context of the commodity selection system, and then the perceived value model is established by associating the types and varieties of agricultural products owned in the actual warehouse. In the actual operation process, the supplier first completes the unified coding of agricultural product labels, and then puts these coded agricultural products into the warehouse for storage. The association rules of the collaborative filtering algorithm of the recommendation system are to associate this label through data analysis and conduct data modeling to achieve the optimal recommendation scheme and guide the storage management of agricultural products.

3.2 Design of Collaborative Filtering Algorithm

The recommendation behavior of agricultural products is evaluated and scored by collaborative filtering algorithm, and the scoring standard is 1… 5 points. $U = \{\mu_1, \mu_2, \ldots, \mu_n\}$ to represent the set of users; $P = \{p_1, p_2, \ldots, p_n\}$ to represent the set of agricultural products; Use U to represent the $n \times m$ evaluation matrix for rating item $U_{R(i,j)}$. Here $i \in 1 \ldots n, j \in 1 \ldots m$, Among them, 1 indicates special dislike, 2 indicates general liking, 3 indicates moderate liking, 4 indicates relatively liking, and 5 indicates very liking.

3.3 Near Field Recommendation Model of Agricultural Products

First, compare the score vectors of other agricultural products to find agricultural products with similar scores to agricultural product 5. In this case, the score of agricultural product 5 (2, 5, 4, 3) is very similar to the score of agricultural product 1 (3, 4, 1, 2), and it is partly similar to the score of agricultural product 4 (3, 3, 5, 2). Through the agricultural product recommendation algorithm, Ms. Zhang's ratings of these similar agricultural products can be found. Ms. Zhang rated Agricultural 1 out of 5 and Agricultural 4 out of 4, and the agricultural product-based recommendation algorithm averaged these scores by weight, predicting that Agricultural 5 would be rated between 4 and 1.

3.4 Cosine Similarity Measure [3]

This metric measures similarity as the angle between two n-dimensional vectors. This method is also widely used for document comparison in information retrieval and document mining. Where documents can be represented as vectors of words. The two agricultural products a and b are represented by the corresponding score vectors r and l, and their similarity can be defined as follows:

$$sim(\vec{a}, \vec{b}) = \frac{\vec{a} \times \vec{b}}{\left|\vec{a}\right| \times \left|\vec{b}\right|} \tag{1}$$

3.5 Collaborative Filtering Recommendation Algorithm

User-based collaborative filtering algorithm is to discover consumers' likes of a certain agricultural product or content (such as commodity purchase, collection, content comment or share) through consumers' historical behavior data, and measure these preferences.

3.6 Data Preprocessing Based on Agricultural Product Filtering

A similarity matrix of agricultural products is constructed in advance to describe the similarity between all agricultural products. At runtime, by determining the most similar produce to p and computing μ. The weighted sum of the scores of these neighboring agricultural products is used to obtain Consumer μ's predicted score for Agricultural Product p.

The number of neighbors is limited by the number of agricultural products currently rated by consumers. Since the quantity of such agricultural products is generally relatively small, the calculation of the predicted value can be completed in a short time as allowed by the online interactive application. Considering the memory requirements, the similarity matrix of N agricultural products will theoretically have $2N$ items, but in practice the number of items will be lower, and further methods can be taken to reduce the complexity.

3.7 Credit Rating

Typically, a five- or seven-point Likert feedback scale is used, ranging from "very dislike" to "very much liked." After the scores are internally transformed into numerical values, the previously mentioned similarity method can be applied. Cosley et al. proposed a behavior-aware approach (2003) and discussed the effect of using different rating scales. For example, when different scales need to be used, how does the consumer's rating behavior change; when the rating scale increases, how does the recommendation quality change. The five-point scale for evaluating agricultural products may have made user choices too few, and the ten-point scale was more acceptable; again discussed choosing a finer scale in quality recommendations, using a continuous scale from -10 to $+10$, and Graphical input is taken.

4 Storage System Recommendation Using Association Rules Method of Data Mining

Data mining can capture and discover implicit, previously unknown, and potentially valuable knowledge for decision-making from large-scale data volumes. A typical application of this method is to unearth pairs or groups of produce from produce that are often purchased at the same time in a supermarket. That is, consumers have purchased their favorite agricultural products and require warehouse management to quickly find the agricultural products of this variety. In this case, the probability of realizing the purchase is about 70%.

Knowing this relationship, you can use this scheme to make marketing and cross-selling strategies, and can also be used to design the storage layout of the warehouse and promote it to collaborative recommendation. For example, if consumer Ms. Wang likes the first two types of agricultural products, she is likely to like the third type of agricultural products (ie, all three types of agricultural products).

4.1 Weighted Mean Prediction Evaluation

For convenience and speed, we simplified the five-point rating into a binary choice of "like/dislike". 0 corresponds to "dislike" and 1 corresponds to "like". 1 if the score is greater than average, 0 otherwise. The standard rule mining algorithm will analyze this data, calculate the list of association rules and the corresponding credibility and support for verification. In the collaborative recommendation environment, the recommendation algorithm is as follows:

- Determine the set of association rules $X \Rightarrow Y$ related to Ms. Zhang (that is, the judgment rule that X determines Y), that is, all elements in X that Ms. Zhang has sold (or liked). Because Ms. Zhang is familiar with and sells this agricultural product.
- Calculate the set of agricultural products that are not sold by Ms. Zhang in the Y set of these rules.
- Rank these agricultural products according to the credibility of the rules. If multiple rules recommend the same agricultural product, the one with the highest reliability is selected.

Table 1. Consumers' evaluation of agricultural products (5-point scale) [4]

name	dish name				
	Shanghai watch	mushroom	Green pepper	lotus root	fish
Ms. Lee	4	2	2	3	4.5
Ms. Wang	2	3	2.5	2	4.5
Ms. Zhang	2.5	3	3	4	4
Ms. Xie	3	3	3.5	4	4

- Return the top N elements of the sorted list as recommendations. This method of searching for rules can not only improve the efficiency of the algorithm, but also discover rules that rarely buy agricultural products, which may be filtered out in the global search due to limited support. In addition, the algorithm can set lower and upper bound parameters to adjust the number of rules to be identified.

4.2 Bayesian Recommendation Method Based on Probability Analysis

Typically, the entire scoring data is marked with an R. All the scores of a certain consumer are stored in an incomplete array $U = \{\mu_1, ..., \mu_n\}$, and μ_i is the score of agricultural product i by consumer μ. Lemire and Mac Lachlan (2005) call this array the scores, which correspond to a row in the matrix R. Given two produce j and i, let the token contain the set of ratings for both produce i and produce j. The average deviation value dev for two agricultural products i and j can be calculated as follows:

$$dev_{i,j} = \sum_{(\mu_i.\mu_j \in s_{(j,r)}(R)} \frac{\mu_j - \mu_i}{\left|S_{(j,r)}(R)\right|} \tag{2}$$

The overall effect is that the program focuses only on those ratings that consumers agree on, whether positive or negative. While this can be problematic for an already sparse rating database, the desired effect is that the prediction scheme does not predict when consumer A likes agricultural product K and consumer B does not like agricultural product K. See Table 1.

4.3 Recommendation System Design Using Multiple Evaluation System Platforms

- For each user to input query data individually, it is hoped that the more data returned by the query, the less interaction between the system and the user, to avoid the user's repeated input operations.
- Each user inputs data separately to complete the same data query task. The more data input, the less interaction between the system interfaces, avoiding the input window switching back and forth.

- Associating wizards between the entire programs, the more control screens, the more complex the wizard model of the control screens, and the higher the impedance (interference) between the user and the system interface, to avoid operational errors or omissions. Calculate the cost of each action by properly arranging LA (Layout Appropriateness), and calculate by the frequency of the action:

$$\cos t = \sum allmotition \times immigration - shiftout \tag{3}$$

$$LA = 100 \times \frac{\text{optimum}}{\text{cost - evaluating}} \tag{4}$$

Find the best recommendations. Recommendation activities are carried out according to community behavior and association rules between consumers and agricultural products. Consider inputting a set of actions, denoted as $\{p_1, p_2 \ldots, p_n\}$, defined as follows: p_1 single-line evaluation and scoring action, action weight ω_1 determined by the difficulty of clicking a single action on the keyboard. p_2: Single-line scrolling action, multiple scoring actions are assigned a weight of ω_2 which is determined by the difficulty of scoring a single action.

p_3 and p_4 repeat keys: Repeat the operation for multiple actions, press ω_3 once, press 2 times, 3 times, 4 times,•••••, to assign weight ω_4... in turn…p_5 is the α input. When entering data, it is necessary to switch to another user evaluation system navigation button, which requires additional navigation, and assigns the value of ω_5 and p_6 to the front navigation button After multiple navigation keys are finished, press the OK keyboard to confirm. Different operations have different navigations, and each specific navigation is assigned a weight ω_6. The cost of user interaction with the system:

$$\text{interactive cost} = \sum_{i=1}^{6} n_i \times \omega_i \tag{5}$$

User evaluation combination:

- A disturbed factor is obvious, whether virtual or visible can apply. Visualizing data can reveal the truth and laws contained in the data, and dummy variables are interactive.
- Appropriate interaction between objects, adapt to diversity, multi-type cross-platform system software support.
- Directly use the object combination for immediate use, and cannot prevent the loss of existing interactive type data. The experimental data (%) of various recommender systems analysis are shown in Table 2.

It can be seen from Table 2 that the recommended proportion of agricultural products fish is larger. The consumer single option is 0.96, and the social network information fusion recommendation is 0.95. Therefore, the storage scale of agricultural product producers and sellers should maintain a relatively large proportion. Figure 1 Ontology of product reviews [4].

Table 2. Types of Consumer Behavior Recommendations [5].

Recommended type	Shanghai Green	mushroom	Green pepper	lotus root	fish
Consumer preferences	0.9	0.8	0.8	0.8	0.90
Cost-effective	0.6	0.1	0.2	0.3	0.7
content	0.5	0.33	0.4	0.5	0.8
similarity match	0.9	0.8	0.6	0.6	0.9
Hybrid Information	0.3	0.5	0.6	0.5	0.95

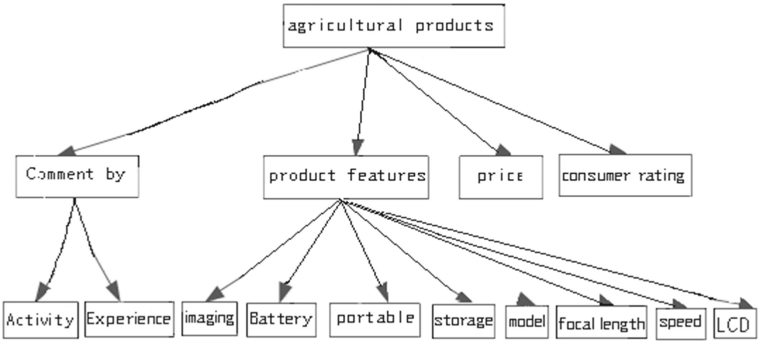

Fig. 1. Ontology of product reviews

5 Conclusion

Regarding the recommendation algorithm, multiple combinations are selected, dynamic modeling is adopted, and the correlation between agricultural products is developed according to the metadata of the recommended agricultural products, and then similar agricultural products are recommended to consumers according to the consumers' previous preference records. This algorithm analyzes and predicts on the basis of the search engine classification model, and is suitable for recommending optimal and worst conditions, but it is difficult to make decisions for similar agricultural products in the middle. This paper analyzes the scores of agricultural products and fish, and determines the first recommended share for the scale of agricultural products and fish for production and storage based on market demand.

6 Conclusion

The Internet is infiltrating all aspects of today's society and is gradually changing the marketing model of various industries [6]. The content displayed to users through the recommender system is of interest to users, and what each user sees is different [7]. Agricultural product warehousing is a science. In order to facilitate consumers to choose their preferred agricultural products and prevent agricultural products from becoming moldy and deteriorating, the agricultural product warehousing recommendation model has more flexible analysis methods. The big data method is used for analysis and statistics, to study all the purchasing behaviors of consumers, and to make a combination recommendation, that is, to purchase a combination of agricultural products and several other agricultural products can enjoy a preferential price, and then achieve the ideal recommendation results.

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