IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 10, 2021, accepted November 7, 2021, date of publication November 10, 2021,
date of current version November 22, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3127201

Application of Intelligent Recommendation for Agricultural Information: A Systematic Literature Review

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This work was supported in part by the Shandong Smart Ocean Ranch Engineering Technology Collaborative Innovation Center; in part by the Research Fund for High-Level Talents of Qingdao Agricultural University under Grant 1119048; in part by the Shandong Agricultural Science and Technology Service Project under Grant 2019FW037-4; in part by the Shandong Technology Innovation Guidance Program under Grant 2020LYXZ023; in part by the Horizontal Project under Grant 20193702010792; in part by the Experimental Technical Project of Qingdao Agricultural University under Grant SYJK18-01; and in part by the Ministry of Education Industry-University Cooperation Collaborative Education Project under Grant 201902005027, Grant 201901029013, and Grant 202101123035.

ABSTRACT With the ever-growing volume of online information, recommender system has been an effective strategy to overcome such information overload. Recommender systems are widely used in many web applications, such as e-commerce, news, agriculture and other fields. Agricultural informatization is an important driving force for the development of agricultural modernization. With the further improvement of agricultural informatization infrastructure construction, the use of modern information technology to achieve personalized agricultural information resource recommendation services and provide users with timely and effective information has become an effective solution. This article aims to provide a comprehensive review of recent research efforts on application of agricultural information based on intelligent recommender systems. Firstly, the method of content analysis used in this article to sort out the papers is introduced. Secondly, the background concepts of recommender systems and the key technologies are presented. Thirdly, the applications of recommender systems/technologies for agricultural information are described in detail. Finally, a summary and outlook on the application of recommender systems for agricultural information are provided.

INDEX TERMS Recommendation algorithm, recommender system, application model, agricultural information, collaborative filtering, hybrid recommendation.

I. INTRODUCTION

With the development of network technology and the further coverage of network globalization, the application of web technology has been extended to all aspects of our lives, such as social network (Micro-blog [1], Twitter and Tencent [2], etc.), e-commerce (Amazon, Jingdong, Netflix and Alibaba [3] etc.), news push (Today's headline [4], Google News and Tencent News etc.), and information acquisition of agricultural products and recommendation of agricultural news. However, with the geometric expansion of data volume and the acceleration of the data update cycle, how to find the content that users are interested in and remove the worthless information in the numerous data is particularly important. Therefore, the Recommender System (RS) become an effective solution [5]–[11].

Recommender system is an intuitive line of defense against consumer over-choice [12], [13]. Given the explosive growth of information available on the web, users are often greeted with more than countless products, movies or restaurants [14]–[16]. As such, personalization is an essential strategy for facilitating a better user experience, which can effectively solve the problem of information overload and confusion when users are looking for the information resources they need. The applications of the recommender system in agriculture, by analyzing the preferences of the agricultural products that farmers are interested in, are mainly to help farmers to obtain the required product information

The associate editor coordinating the review of this manuscript and approving it for publication was Xianzhi Wang.

and related news more conveniently and accurately [17]–[19]. Different from the traditional news recommender system, the recommender system related to agriculture needs to consider the impact of real-time weather and environmental changes on agricultural products [20]–[22], the impact of different environmental conditions on the planting of different varieties of agricultural products [23], and the correlation degree of the same news to different varieties of the same agricultural products [24], [25].

Cyber-Physical System (CPS) is often characterized as a smart system, which intelligently interacts with other systems across information and physical interfaces. CPS is integrated into modern smart agriculture [26], [27]. CPS integrate multiple techniques, including distributed computing, communication and automatic control, to support variety of intelligent services and applications. The smart agriculture or precision agriculture is one of the typical application scenarios of CPS. CPS transmits a wide variety of agricultural information supplies to enable intelligent processing and service. Sensors in fields, livestock farms, etc., will detect changing health conditions, and new recommender system will make personalized agricultural devices interoperable. In smart agriculture, the CPS usually contains three layers: the perception layer, the network layer and the application layer [28]. The perception layer is used to acquire the perceptive information and to execute the feedback decisions. The network layer is used to transfer the information and decisions among different system elements. The application layer, which can also be viewed as the control layer, is mainly used to make decisions according to the analyzed results of the perceptive information. The architecture of CPS recommender system for agricultural Internet of Things (IOT) are showed in Figure 1.

In view of the above requirements and characteristics, this paper mainly discusses and analyzes the research status of recommendation technology and application of recommender system in agriculture. This article aims to provide a comprehensive review of recent research efforts on application of agricultural information based on intelligent recommender systems. It provides a panorama with which readers can quickly understand and step into the field of intelligent recommendation technology and the applications of intelligent recommendation in agriculture. This survey lays the foundations to foster innovations in the area of recommender system in agriculture and tap into the richness of this research area. This survey serves the researchers, practitioners, and educators who are interested in recommender system for agricultural information, with the hope that they will have a rough guideline when it comes to choosing the recommendation technology to solve the problem of agricultural information overload at hand. To summarize, the key contributions of this survey are three-folds:

1) We provide a method of content analysis to sort out the literatures and give the research process.

2) We provide an overview and summary for the state-of-the-arts.

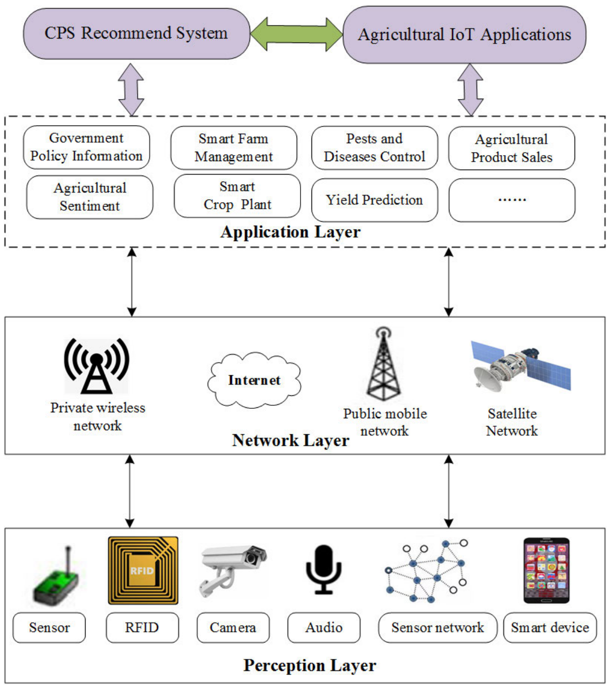

FIGURE 1. The architecture of CPS recommender system for agricultural internet of things.

3) We discuss the challenges and open issues, and identify the new trends and future directions in this research field to share the vision and expand the horizons of recommender system research in agricultural fields.

II. CONTENT ANALYSIS METHOD AND RESEARCH PROCESS DESIGN

A. SAMPLE EXTRACTION

Generally speaking, compared with monographs, research reports and dissertations, journal articles can more acutely and directly reflect research hotspots and frontiers [29]. Therefore, the sampling principles are as follows:

1) PAPER COLLECTION

We used Google Scholar and Baidu Scholar as the main search engines, and we also adopted the database, CNKI (https://www.cnki.net/), Web of Science and IEEE Xplore, as three important tools to discover related papers. In addition, we have screened most of the relevant well-known conferences, such as RecSys, ACM SIGKDD, ACM SIGIR, ICDM, ACM RecSys, CIKM, WSDM and so on.

2) TIME INTERVAL

From 1992 to 2021.

3) MAJOR SEARCH KEYWORDS

The major search keywords are ‘‘recommender system’’, ‘‘recommendation system’’, ‘‘intelligent recommendation’’, ‘‘recommended algorithm’’, ‘‘Agricultural recommender system’’, ‘‘Agricultural recommendation algorithm’’, "e-business recommendation system", "Artificial intelligence in agriculture", "collaborative filtering", "Knowledge discovery and data mining", etc.

B. CONTENT ANALYSIS CODING

According to the research objectives of this paper, the two researchers discuss and set the analysis coding rule together.

1) BASIC INFORMATION OF THE PAPERS

Title, author, year of publication, the journal name, technique used, applied model, specific content of the model study.

2) RESEARCH CONTENT ANALYSIS

Analysis of the number of recommended algorithms, analysis of advantages and disadvantages of recommendation algorithm, and analysis of recommendation algorithm technology application.

C. RESEARCH STEPS

1) STEP ONE

According to the principle of sample extraction, papers were extracted and screened, and then 351 initial samples were obtained.

2) STEP TWO

Does the paper use recommendation algorithm technology? If yes, it is classified into the statistical sample. Otherwise, it is discard.

3) STEP THREE

Identify the technologies used in the papers and their application models, and this step was done independently by two researchers.

4) STEP FOUR

The preliminary identification results of the two researchers were combined. And the identification results, that were controversial, were discussed and determined by two researchers.

5) STEP FIVE

The preliminary classification was performed by two researchers.

6) STEP SIX

The controversial classifications were discussed and determined by two researchers, and finally the final research samples were obtained.

III. KEY TECHNOLOGIES FOR RECOMMENDER SYSTEM

According to Step two of SECTION II-C, on the basis of the initial research samples, the system architecture or system functional description papers and the papers without any technology are removed, and the final sample papers are determined to be 97. The following analysis is based on these samples. Table 1 shows the various techniques and their number of adoptions in recommender system. It can be seen from the Table 1 that the user-based Collaborative Filtering (CF) algorithm has been used up to 23 times, followed by model-based collaborative filtering algorithm, item-based collaborative filtering algorithm, content-based recommendation algorithm, hybrid recommendation algorithm, etc.

TABLE 1. Various technologies and their number of adoptions in recommender system.

Technology Name	Number of Adoptions
• User-based collaborative filtering algorithm	23
• Model-based collaborative filtering algorithm	21
• Item-based collaborative filtering algorithm	19
• Hybrid recommendation algorithm	15
• Big data-based recommendations	11
• Neighborhood-based social network recommendation	2
• Clustering recommendation algorithm based on cuckoo search	2
• Cookie-based personalized recommendation service	2
• Social network recommendation based on network structure	1
• Collaborative filtering recommendation algorithm based on multi-type implicit feedback confidence	1

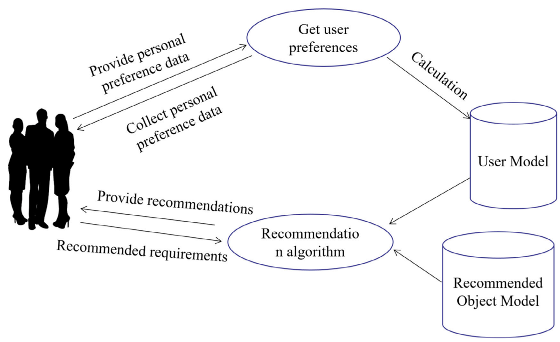

FIGURE 2. General model of recommender system.

Adomavicius G *et al.* gave the definition of a recommender system [13]: Assume that C is the set of users and S denotes the set of all items to be recommended to users, such as books, movies, or agriculture news. Let u be a utility function that measures usefulness of item s to user c, i.e., $u : C \times S \rightarrow R$, where R is a totally order set(e.g., non-negative integers or real numbers in a certain range). Then the goal of the recommendation algorithm is, for each user $c \in C$, to choose such item $s_c \in S$ that maximizes the user's utility. And we have

$$\forall c \in C, s_c = \arg\max_{s \in S} u(c, s) \tag{1}$$

A recommender system should include three elements: users, items, and recommendation methods, as shown in Figure 2.

According to the recommendation target, recommender systems can be usually divided into two types: rating recommendation and Top-N recommendation. The idea of rating recommendation is that the system predicts the user's rating on the item, and then sends the generated recommendation list to the user based on the rating, and the user selects the

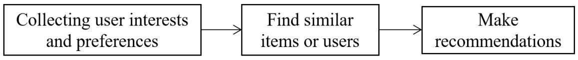

FIGURE 3. Workflow of collaborative filtering recommendation algorithm.

option he is interested in from the received recommendation list. Top-N recommendation is to count the weighted average of users' interest in different items in the ''nearest neighbor'' set, and then take the Top-N items in the set of items that are not rated by users as the Top-N recommendation set [22].

A. INTRODUCTION TO POPULAR RECOMMENDATION ALGORITHMS

1) CONTENT-BASED RECOMMENDATION ALGORITHM

Content-based recommendation algorithm is a simple but important recommendation idea [23]. Content-based recommendation algorithm does not depend on the user's evaluation of the item, but actively creates the documents that the user is interested in based on the user's historical evaluation, forwarding, collecting, downloading, etc. And then the matching degree, between the item to be recommended and the document that the user is interested in, is calculated statistically. Finally, the item with the highest similarity is recommended to the user according to the matching degree. For example, if a farmer has liked and collected related agricultural articles on the website, the related articles of that kind of agricultural products will be placed in a prominent position on the website when he opens the website next time.

The core problem of content-based recommendation algorithm is how to calculate the similarity of the items. The content-based recommendation algorithm mainly uses the Pearson Correlation Coefficient (PCC) [30], [31] and cosine similarity to perform similarity calculation. And in [24] and [25], the two similarity calculation methods are described in detail. Other commonly used similarity calculation methods include modified cosine similarity, Tanomi and Euclidean distance [32] and so on. In addition, common improved similarity measurement methods include proposing a new similarity function [33], adding a correlation weight factor to calculate the similarity [34], [35], and using similarity propagation to improve the similarity function [36].

2) COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM

Since Goldberg *et al.* proposed the CF recommendation algorithm in 1992, this algorithm has been widely studied and applied in recommender systems [37]. The main task of CF is to find the mapping relationship between users and items, that is, to find a group of users with similar interest goals, to analyze the group's evaluation of an item, and finally to predict the group's preference for this item [38]. The workflow of the CF recommendation algorithm is shown in Figure 3.

There are three main types of CF recommendation algorithms: user-based collaborative filtering algorithm, item-based collaborative filtering algorithm and model-based collaborative filtering algorithm.

a: USER-BASED COLLABORATIVE FILTERING ALGORITHM

The basic principle of the user-based CF algorithm is as follows: Firstly, the similarity between users is calculated, and the user similarity matrix is thus obtained. Secondly, the nearest neighbors to the target user are selected. Finally, for each item s that the current user has not seen, the current user's interest in the item is predicted based on the rating of the item s by its neighbors, and the item with the largest predicted score (or the top N items with the largest predicted score are) is selected for recommendation.

b: ITEM-BASED COLLABORATIVE FILTERING ALGORITHM

The basic principle of item-based CF algorithm is the opposite of user-based CF algorithm. The item-based CF method analyzes the similarity between items using the aggregated user ratings, and recommends to an active user new items that are similar to the items he liked in the past [39]–[42].

c: MODEL-BASED COLLABORATIVE FILTERING ALGORITHM

The model-based CF recommendation method needs to analyze and mine the existing user data through data mining and deep learning methods, use it as an experimental training set, and then build a user-item rating prediction model. Content recommendations are made to users based on the trained rating prediction model. There are two main model-based CF methods available: matrix-based decomposition models [43], [44] and clustering-based models [45].

3) RECOMMENDATION ALGORITHM BASED ON SOCIAL NETWORK

Due to the popularity of 4G, the impact of the rapid development of the Internet has changed the way of life of contemporary human beings. From children to adults, from rural to urban areas, almost everyone has a smartphone that can be connected to the Internet. With the widespread use of social software such as WeChat and Weibo, social networks have developed at an astonishing speed. Moreover, recommendations based on social networks have also become a hot research topic. Sinha and Swearingen [46], by studying six online recommender systems, confirmed that users are more inclined to choose recommendations from friends rather than those generated by online recommender systems. Bonhard and Sasse [47] investigated whether social context has a significant effect on recommendations, and the experimental results showed that, in the interest domain, people are more likely to receive recommendations from familiar people. There are two main types of recommendation algorithm based on social network: social network recommendation based on network structure and neighborhood-based social network recommendation.

a: SOCIAL NETWORK RECOMMENDATION BASED ON NETWORK STRUCTURE

The recommendation technology based on the network structure does not consider the relationship between users and products, and only abstracts users and products as nodes, and the information used by the algorithm is hidden in the selection relationship between users and products.

Network structure-based recommendation technology does not consider the relationship between users and items, but only abstracts users and products as nodes, and then constructs a new network graph based on the relationship between users and users as well as between users and items [48]. The information utilized by the algorithm is hidden in the selection relationship between the users and the items. In addition, the weights of the edges in the network graph can be defined based on the familiarity and liking between users and their friends and between users and items. After calculating the relevance between all users and items, all items that are not directly connected to the user are selected, and the items are sorted from highest to lowest relevance to form a recommendation list, and the items with high relevance can thus be recommended to the user.

b: NEIGHBORHOOD-BASED SOCIAL NETWORK RECOMMENDATION

The basic idea of neighborhood-based social network recommendation is to comprehensively consider the current user and his or her friends, the user's browsing history, and the user's purchase history, and recommend a collection of items that friends are interested in to the user. On the other hand, as the familiarity and preferences of the same user and different friends are not the same, the algorithm also needs to consider the familiarity and similarity of preferences between the user and friends. The authors in [49] study neighbor-based social network recommendation, which is based on social network friend relationship, social network user interest model and user feedback, respectively.

4) HYBRID RECOMMENDATION ALGORITHM

The collaborative filtering recommendation algorithm, content-based recommendation algorithm and social network-based recommendation algorithm introduced above, all have their have their pros and cons. And few existing problems can be well solved by using only one recommendation algorithm. Therefore, the hybrid recommendation algorithm is born, which abandons the shortcomings of a single recommendation algorithm, learns from each other's strengths, and integrates the mature recommendation technologies to make the best use of their advantages as much as possible, so that the comprehensive ability of the newly generated hybrid recommendation algorithm is significantly improved. In the future, hybrid recommendation algorithms, combining machine learning, clustering, data mining and other knowledge, are the main directions for future research.

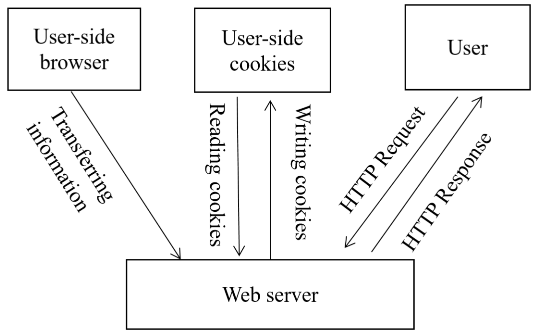

FIGURE 4. **Working process of cookie-based personalized recommendation.**

B. OTHER NEW RECOMMENDED TECHNOLOGIES

1) COOKIE-BASED PERSONALIZED RECOMMENDATION

Cookies were originally created as a solution to HTTP's inability to record memorized visits to the same web site by the same user at different times, that is, the user is considered a new user when logging into the same site multiple times [50]. Cookies are a set of text strings containing relevant variables stored by the Web server on the user's hard disk, which records information about the user's visit to a specific site, and can only be read back by the site that created the cookie. Cookies files are text files, which can track and record the information behavior of online users in real time, and can distinguish users well [51]. Based on this feature of cookies, web servers can provide high quality personalized information services to users according to cookies. The working process of cookie-based personalized recommendation is shown in Figure 4. However, cookies are not perfect, and their security issues and blind obedience issues are key issues that need to be resolved urgently.

2) CLUSTERING RECOMMENDATION ALGORITHM BASED ON CUCKOO SEARCH

K-means, as a better clustering algorithm combined with recommender system at present, is characterized by simple thinking and low time complexity. However, when the data amount is large or the initial clustering center is improperly selected, the clustering accuracy and efficiency will also be significantly affected. In order to solve the above problems, a large number of researchers have devoted themselves to improving k-means algorithm. For example, Liu *et al.* proposed a K-means clustering algorithm based on particle swarm optimization [52]. And this algorithm can effectively overcome the problem that the traditional K-means algorithm is easy to fall into the local minimum value and has good global convergence ability.

Wang, R.H. *et al.* proposed the adaptively adjusted cuckoo search K-mean clustering algorithm (CSSA-OIKM), which enhanced convergence performance of the algorithm, and it can effectively improve the clustering accuracy and has good stability [53]. The Cuckoo Search (CS) algorithm, is a meta-heuristic algorithm. The meta-heuristic strategy usually imposes some requirements on the search process, and then the heuristic algorithm implemented, according to these requirements, is called a meta-heuristic algorithm. The cuckoo search algorithm can maintain a good balance between local search strategy and searching the whole space, so it can significantly improve the recommendation accuracy and the coverage of search results of K-means algorithm.

3) COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM BASED ON MULTI-TYPE IMPLICIT FEEDBACK CONFIDENCE

Farmers' clicks on news, collections and purchases of goods will generate implicit feedback information. Bayesian Personalized Ranking (BPR) algorithm is the more prominent algorithm, which has good mining and analysis capabilities for single-class implicit feedback. However, there are more multiple types of implicit feedback in the actual recommender system. In the case of agricultural e-commerce, operations such as browsing, collecting, purchasing and commenting will comprehensively affect the recommendation results. In which, the purchase operation is a deterministic implicit feedback behavior, and the behaviors of browsing, collecting and commenting are called non-deterministic implicit feedback behaviors. The CF recommendation algorithm based on the confidence of multiple types of implicit feedback is proposed in [54]. Two data processing methods: logistic regression and tree-based feature selection, are used to select the part of the non-deterministic implicit feedback that is most beneficial to the realization of accurate recommendation from the non-deterministic implicit feedback data, thereby improving the accuracy of the recommendation.

4) BIG DATA-BASED RECOMMENDATION

In the context of today's big data, in addition to problems such as data sparsity and cold start, recommender systems also face more and more complex problems caused by big data. The traditional single database storage technology is no longer applicable, and the recommender system based on the centralized central server cannot meet the current requirements. The big data-based recommender system employs distributed file system, which is based on cluster technology, to manage data, and the current problems can thus be solved. Hadoop Distributed File System (HDFS) architecture of Hadoop is a typical recommended big data system architecture that can meet the requirements of high concurrency, scalability, and processing massive data. Data files are stored on multiple nodes. When users call data, the client will call them according to the interface provided by HDFS. The big data-based recommender system is based on the processing of massive data and performs combined recommendation through various algorithms. The essence of big data-based recommendation is personalized ranking, and different recommendation algorithms are adopted in different scenarios.

C. RECOMMENDATION ALGORITHM EVALUATION METHOD

1) COMPARATIVE ANALYSIS OF POPULAR RECOMMENDATION ALGORITHMS

Each algorithm has its own advantages and disadvantages, and the existing algorithms are constantly being improved. Different algorithms have different effects in different fields and requirements. For example, the content-based recommendation algorithm has the disadvantage of not being able to recommend for new users, and the CF recommendation algorithm has a cold start problem, etc. The advantages and disadvantages of the five common recommendation algorithms are shown in Table 2.

2) EVALUATION METRICS FOR RECOMMENDATION ALGORITHM

Evaluation is a means to test the performance of the recommender system and has important guiding significance for the development of the recommender system. With the progress of research work on recommendation algorithms, how to evaluate the efficiency of the proposed recommendation algorithms becomes a focus of research. For example, in [55], the recommendation performance are evaluated from four aspects: accuracy, coverage, diversity, and novelty. The evaluation metric that best fits the target system can be selected based on preferences and whether it relies on conditions such as the length of the recommendation list [56]. The most common algorithm evaluation metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized Mean Average Error (NMAE), recall rate and accuracy rate, as shown in Table 3.

The calculation formulas of the above five evaluation metrics are as follows:

a: MEAN ABSOLUTE ERROR (MAE)

$$MAE = \frac{\sum_{i=1}^{n} |P_i - r_i|}{n} \tag{2}$$

where n denotes the number of sets, and P_i and r_i denote the set of predicted users' ratings and the set of users' actual ratings, respectively.

b: ROOT MEAN SQUARE ERROR (RMSE)

$$RMAE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - r_i)^2}{n}} \tag{3}$$

c: NORMALIZED MEAN AVERAGE ERROR (NMAE)

$$NMAE = \frac{MAE}{r_{\max} - r_{\min}} \tag{4}$$

where $r_{\max}$ is the maximum value of user rating and $r_{\min}$ is the minimum value of user rating.

TABLE 2. Analysis and comparison of commonly used recommendation algorithms.

Recommendation Algorithm	Advantages	Disadvantages
Content-based recommendation algorithm	• No need for users to rate items in advance; • No cold-start problem for new items; • Recommended results are easy to understand and highly interpretable; • High independence of users; • No Matthew effect.	• Restricted by new users, there is a cold start problem for new users; • Unable to tap into items and news that users may be interested in; • Lack of diversity; • Unable to handle multimedia data.
Collaborative filtering recommendation algorithm	• Can dig out items and news that users may be interested in; • The model has strong versatility; • Recommendation performance can be enhanced with continuous training; • High degree of personalized recommendation; • Recommendation results are easy to understand; • Suitable for complex, unstructured objects.	• Cold start problem for new users and new items; • Data sparsity problem exists; • Dependent on user rating; • Low interpretability of recommended results; • Grey sheep problem; • Matthew effect; • There are algorithm scalability issues.
Hybrid recommendation algorithm	• No cold start problem; • No Matthew effect; • Can dig out items and news that users may be interested in; • With recommended diversity; • No data sparsity issue.	• Usually requiring a lot of work to achieve balance; • It is necessary to integrate and sort out the feature information with different scales and uneven distribution.
Social network-based recommendation algorithm	• Recommendation results can be highly trusted; • Conductive to recommend long tail items, not easy to cause waste of resources.	• Restricted by the number and quality of users' friends.
Cookie-based recommendation algorithm	• Can distinguish different users well; • The behavior of online users can be tracked and recorded in real time.	• Security issues; • "Blind obedience" problem; • "Cross-domain" problem.

TABLE 3. Evaluation metrics for recommendation algorithm.

Evaluation Metrics	Meaning	Application Scenarios
Mean Absolute Error (MAE) [57] [58] [59] [60]	The mean absolute error is used to represent the average of the absolute value of the difference between the user's predicted score and the actual score.	Accuracy of predictive scoring, more accurate than RMSE.
Root Mean Square Error (RMSE) [57] [59] [61] [62] [63]	The root mean square error, also known as the standard error, is the square root of the ratio of the square of the deviation of the predicted value from the true value to the number of observations n.	Predict the accuracy of the score, there is a heavier penalty for a large absolute error [64].
Normalized Mean Average Error (NMAE) [57]	Normalize the mean absolute error.	The normalized values are usually in the interval (0,1), and it is easier to interpret from a straightforward point of view.
Recall rate [57] [62]	Recall is used to measure the ratio of correct recommendations to the total number of correct results.	Used to measure the percentage of recommended results.
Accuracy rate [57] [61] [65] [66] [67]	Accuracy rate is used to indicate the ratio of the correct recommendation results to the total number of recommendation results.	Used to measure effective recommendation results.

d: ACCURACY RATE (AR)

$$AR = \frac{TP}{TP + FP} \tag{5}$$

where TP (true positive example) denotes the number of correct recommendation results, that is the number that predict positive samples as positive samples, and FP (false positive example) denotes the number of incorrect recommendation result, that is the number that predict negative samples as positive samples.

e: RECALL RATE (RR)

$$RR = \frac{TP}{TP + FN} \tag{6}$$

where FN (false negative example) denotes the number that predict positive samples as negative samples.

For top-N recommender systems, accuracy rate and recall rate are commonly used to perform system performance evaluation.

D. KEY ISSUES TO BE ADDRESSED FOR RECOMMENDER SYSTEM

Although both academia and industry have done a lot of in-depth research on recommender systems, there are still many problems in recommender algorithms, such as cold start problem, data sparsity problem, real-time recommendation issues and scalability issues, etc. In this paper, we discuss the meanings of cold start problem and data sparsity problem, and give the solutions for them, as shown in Table 4.

1) COLD START PROBLEM

Cold start is divided into user cold start and item cold start. User cold start refers to the fact that when a new user interacts with the recommender system, no information about the user is stored in the recommender system, so the system cannot recommend items according to the user's interests. Item cold start refers to how to recommend an item that has just been added to the system to users who may be interested in it. Collaborative filtering algorithm usually encounters cold start problems. A proposal to solve the cold-start problem is proposed in [78], which combines content and collaboration data in a probabilistic framework and introduces a new performance metric, the CROC curve, which has been validated and proven to be a good solution to the cold-start problem.

2) DATA SPARSITY PROBLEM

Data sparsity refers to the fact that due to the development of the Internet, there are a large number of items in today's e-commerce system, and in such a large matrix, only a few entries have values. For example, according to Taobao.com data statistics at the end of 2014, every day, the number of online users reaches 120 million and the number of online items exceeds 800 million. Assuming that the collaborative filtering algorithm based on User-Item (U-I) is to be used, the size of the U-I matrix can then reach 120 million * 800 million. In such a large matrix, only a few entries have values, which make the overlap rate of data between users very low. Although CF recommendation algorithm based on item clustering proposed in [79] and the user clustering-based recommendation algorithm for heterogeneous social networks proposed in [80], alleviate data sparsity to certain extent. However, due to the increasing number of users and the characteristics of items, the recommendation quality is getting worse and worse. Therefore, the problem of data sparsity is urgently needed to be solved.

IV. APPLICATIONS OF RECOMMENDATION ALGORITHMS IN AGRICULTURE

With the continuous development of ''Internet + Agriculture'', its advanced technology has gradually been applied to the agricultural field. Smart agriculture is a type of agriculture that emphasizes the use of information and communication technologies in the networked farm management cycle. Therefore, new technologies such as the Internet of Things, cloud computing and big data are expected to take advantage of this development and introduce more advanced technologies into agriculture. Agricultural products are selling better and better on online platforms. A good online marketing platform for agricultural products can promote users and businesses to conduct efficient transactions, and intelligent recommendation plays an indispensable role. Table 5 shows the direction of application of recommendation algorithm in agriculture. Table 6 shows how the recommendation algorithm solves problems in agriculture. Table 7 shows some companies or regions have applied the big data recommendation systems /algorithms to agriculture and integrated them into real life.

A. APPLICATIONS OF CONTENT-BASED RECOMMENDATION ALGORITHM IN AGRICULTURE

Similar to general news websites, a large number of agricultural information portals providing agricultural information services are mostly in the form of articles. When users look up news and information, they will generate a large number of browsing records, as well as real-time interaction and feedback information. For example, reading, likes, comments, etc. can quickly reflect the user's interest preferences in a short period of time. Long-term accumulation and calculation of this information can form historical data close to the user's daily personality preferences. Therefore, a similarity matrix can be established based on real-time feedback information and a large amount of historical browsing information. Based on the similarity matrix, it is possible to consider the user's long-term inherent preferences while also pay attention to the user's short-term interest focus changes. In order to enable agricultural workers to discover new agricultural science and technology knowledge that suits their preferences, and to enable the agricultural science popularization service system to provide agricultural knowledge to appropriate users, authors in [110] proposed a content-based agricultural science recommendation algorithm based on Convolutional Neural Networks (CNN). In the CNN model, a language model based on labeling latent Dirichlet assignment and a latent factor model with inherent characteristics are established. The experimental results on the public database show that compared with the classic method, it has better improvements in the recommendation algorithm, and it has a better effect in solving the problems of cold start and data sparsity. In view of the problem of poor pertinacity of agricultural science and technology information service, Song and his team [122] provide a content-based recommendation algorithm for agricultural science and technology information on the basis of trustworthiness, which can improve the credibility of similar users' selection and is beneficial to improve the recommendation accuracy. According to the characteristics of online agricultural products trading, an agricultural products recommendation model based on agricultural products attributes and categories is constructed. And Guan's team calculates on the similarity of agricultural products attributes, using a similarity improvement algorithm that incorporates the weighted Jaccard coefficient of information entropy, and

TABLE 4. The solutions to problems related to cold start, data sparsity.

Problem	Literature	Solutions
Cold start problem	[68] [69]	Methods for building probabilistic statistical models: initialize the content information of users or items to a specified probability distribution instead of the rating probability distribution in collaborative filtering recommendations, and utilize Hofmann's Expectation Maximization (EM) iterative algorithm on the probability distribution of content information instead of rating information.
	[68] [70] [34]	Use user or item content information to find the intrinsic connection between content and ratings through machine learning.
	[71]	Create a new user orientation process: use decision trees to guide users to learn the items and provide feedback.
Data sparsity problem	[72] [73]	Default filling: default filling using the mean or plurality method.
	[74] [75]	Predictive fill: predict item ratings based on similar users and similar items.
	[76]	Apply singular value decomposition techniques to collaborative filtering to reduce data sparsity by reducing the dimensionality of the input matrix.
	[77]	Prediction of missing data to fill the original scoring matrix by the constructed Radial Basis Function (RBF) neural network.

introduces a user preference factor, so that the sparsity problem of data can be better solved [123].

B. APPLICATIONS OF RECOMMENDATION ALGORITHM BASED ON COLLABORATIVE FILTERING IN AGRICULTURE

At present, the most widely used recommendation algorithm based on agricultural products at home and abroad is the CF algorithm. Experts and scholars both at home and abroad have conducted almost uninterrupted research on collaborative filtering recommendation algorithms, and have done a lot of research on similarity, accuracy, scarcity and system security in collaborative filtering recommendation technology [34], [69]–[74]. China's research on information push technology is relatively late, domestic first push technology product named WebAngle, which can accurately and reliably track the initiative, and the user's attention, as well as the pre-determined information transmitted to the user, achieves the classification of the collection of Internet information and pushes the information to the hands of users in a timely manner. Founded by Hunan Huinong Technology Co., Ltd, the Huinong.com platform [124] includes ten categories covering more than 20,000 varieties of conventional agricultural products, and is one of the essential tools for agricultural practitioners. Based on the real transaction prices and unique data channels, Huinong.com collects the latest price data from the supply side, purchasing side and wholesale market, and provides agricultural practitioners with real-time and accurate agricultural production and marketing quotes through intelligent cleaning and filtering of big data [125].

The combination of recommendation system and machine learning will produce intelligent agricultural systems to help farmers in crop management and other activities, including applications in yield prediction, disease detection, weed detection, crop quality and growth prediction, etc [102]. India ranks second in the world in terms of agricultural production, but its share of Gross Domestic Product (GDP) is declining. A number of factors are contributing to the decline in agricultural GDP, including inadequate irrigation, inadequate power supply, changing environmental conditions, and traditional agricultural methods. The system proposed in [107] has helped Indian farmers to understand their farm soils and maximize crop yields. In Bangladesh, agriculture is the main source of economy, but with limited knowledge of cultivation, local farmers are often unable to choose the most suitable crops to grow. Based on this situation, Miftahul Jannat Mokarrama and his team proposed a Recommendation System for Farmers (RSF) [96], which first detects the user's location, uses different agro-ecological and agro-climate data at the upazila level, and calculates the similarity between upazilas using Pearson's synergistic similarity algorithm. Finally, using seasonal information and crop yields for each upazila-like crop, it recommends top K crops to upazila-like users. The system helps farmers produce the right crops. The system can help farmers to produce proper crops due to its advantages in climatic conditions, Kerala is marked as one of the climatic centers for many food crops like rice, coconut, banana etc. But improper production planning of items can eventually cause huge losses to the farmers. Therefore, proper projections and recommendations are needed for the items. Researches in [101] focused on vegetables, fruits and their related products, such as chili powder, rice flour, banana chips, pineapple fruit, etc., and designed the RS by analyzing the purchasing behavior of customers buying the items. Using this system, farmers will analyze the interaction with customers through a web interface to obtain information about all the items to be planted in the next season. For example, Amazon.com [116] designed a RS to personalize each customer's transaction through an online store. Most RS are personalized, and since a person's buying behavior is different, there are non-personalized RS as well. To accomplish these tasks, customer preferences are clearly expressed

TABLE 5. Direction of application of recommendation algorithm in agriculture.

Applications direction	Goal	Method	Reference
Climate	• Recommend suitable crops according to climatic conditions. • Optimal use of agricultural resources.	(1) Recommend crops by predicting future climate conditions. (2) A planting time recommendation system is proposed, which predicts the best sowing date of winter cereal crops on newly reclaimed land in Farafra Oasis in the western Desert of Egypt.	[81] [82]
Fertilizer and soil	• Recommend suitable fertilizers. • Fertilizers are recommended to improve the soil environment. • Help farmers recommend the right crop for their soil type.	(1) Recommending the right fertilizer based on understanding the soil type for better yields. (2) Providing a fertilizer recommendation system to enrich soil and improve land productivity, and the system was evaluated by using appropriate timing and accuracy measures. (3) Combing different models such as naive Bayes random forest and linear Support Vector Machine (SVM) to construct a recommender system to recommend crop types based on input soil data sets. (4) A recommender system based on a machine learning approach is developed which suggests the type of crop and the fertilizer may be used to increase their productivity and consequently, their income.	[83] [84] [85] [86]
Agricultural information	• Recommend the latest agricultural information, such as seed information, farming advice, agricultural trends, government schemes and programs, etc. to farmers.	(1) Build a RecOrgSeed model, which is based on web mining techniques and semantics, as well as organic farmers or growers' requirements and needs, to recommend organic seeds information to farmers and growers. (2) A web-based collaborative recommendation system is proposed, which answers farmers' questions and pushes them the agricultural information, such as the latest agricultural trends, new government schemes and programs. (3) Propose a semantic and rule based event-driven Services-Oriented Architecture, to facilitate the information integration and interoperation of distributed and heterogeneous web hosted agricultural information systems services.	[87] [88] [89]
Agricultural sentiment	• Accurate prediction of agricultural sentiment to the policy makers to conduct expensive and logistically difficult surveys about the agriculture aid programs. • Access public opinion about certain issues or products, such as commodity and food price prediction, pest control, etc.	(1) Propose a model based on deep learning approach to perform sentiment analysis on extracted agriculture tweets from twitter. (2) Text mining technique is used to resolve agricultural problems or extract knowledge. (3) A sentiment analysis approach for agriculture is proposed, to obtain the polarity about pests control in crops from the comment and entity levels from texts.	[90] [91] [92]
Pests and diseases	• Identify pests and diseases and recommend accurate solutions. • Provide better solutions to pests and diseases encountered by crops.	(1) Analyze data on symptoms, disease types, and medical treatments to provide the best solutions for treating diseases. (2) Provide the construction of a recommendation system that facilitates the identification of pests and the selection of suitable treatments. The core of this system is an ontology that models the interactions between crops, pests and treatments. (3) Authors implement a deep convolutional neural network model to detect whether crops are infected or not. And a content-based crop recommendation system is designed. (4) A model is used to predict the most suitable crops for farmers, detect the possible pests and diseases, and put forward the pest control technology.	[86] [93] [94] [95]
Crop plant	• Recommend the best crops according to different areas, different agro-ecological and agro-climatic, soil type, etc.	(1) Provide advice on the fertilizer and amount to use to achieve the best yield, and make better farming decisions by recommending a suitable crop based on soil type. (2) RSF recommendation system firstly detects the user's location and uses different agro-ecological and agro-climatic data to calculate the similarity between different regions using Pearson relational similarity algorithm to recommend the most suitable crops. (3) An intelligent crop recommendation system is used to help Indian farmers decide which crops to plant based on parameters such as nitrogen, phosphorus, humidity, temperature and rainfall. (4) A cooperative recommendation system is proposed, which suggests suitable crops to farmers according to their location and weather conditions. (5) An ensemble model with majority voting technique is proposed, which uses random tree, CHAID, K-nearest neighbor and naive Bayes as learners to recommend a crop for the site specific parameters, such as soil types, soil characteristics, crop yield data. (6) Use the technology of data mining to provide recommendations to farmers for crops, crop rotation and identification of appropriate fertilizer. (7) A crop recommendation system based on fuzzy logic is proposed, which uses site-specific chemical parameters of soil, rainfall and topographic properties, to deal with eight major crops grown in the state of West Bengal.	[86] [96] [19] [97] [98] [99] [100]
Agricultural products	• Recommend agricultural products to customers and recommend farmers to plant different products based on their sales. • Help farmers to choose the right organic seeds.	(1) Use prior model and mixed filter model to build a web-based recommendation system, which recommends products to users based on the historical purchase and best-selling agricultural products. (2) A RecOrgSeed recommendation model is used to provide farmers with exactly what seeds they need.	[101] [87]
Crop yield	• Forecasting of crop yields.	(1) The effect of observing, measuring crop variability in the field and within the field on crop yield was determined.	[102]

TABLE 6. Recommendation algorithms to solve problems in agriculture.

Problem	Solution	Reference
Farmers are unable to choose the crops to plant in a timely and accurate manner, and for some organic crop selection issues.	(1) An agricultural product planting recommender system was proposed. The system first detected the user's location, obtained different agro-ecological and agro-climate data of the region, and then calculated the similarity between the regions. Then the similarity top-n recommendation was made for the users of a certain crop.	[96] [103] [86]
	(2) A recommender system model for predicting and recommending the consumption of various agricultural products was designed and developed by using a priori algorithm.	[101]
	(3) The Recorgseed recommendation model is proposed, which extends the technology based on network use by incorporating semantic annotation to meet the needs of farmers and growers.	[87]
	(4) An architecture based on semantic network is proposed to generate agricultural recommendations based on spatial data and agricultural knowledge base.	[104]
Many farmers are not experienced enough to scientifically and accurately identify the types of pests and diseases encountered by their produce.	A cooperative model of recommender system and machine learning is proposed, which can preprocess images and extract features from crop photos, and then recommend preventive measures or solutions according to the analysis results.	[86]
The inability of countries and regions to accurately predict farmers' sentiments has made the relevant agricultural assistance programs unable to be implemented.	Sentiment analysis can accurately analyze the polarity (sentiment rate) of agricultural tweets in social networks such as Twitter.	[105]
When farmers encounter external problems such as weather and soil, they cannot accurately analyze the causes of the problems, so they cannot quickly respond to the problems they encounter.	(1) Through the establishment of soil management and recommendation system and the use of different data mining classification algorithms, people can better understand the soil category, reduce the dependence on chemical fertilizer and provide crop yield.	[106] [107]
	(2) A genetic algorithm was proposed to maximize crop yield while maintaining soil fertility properly.	[108]
	(3) Applying big data analysis to agriculture, the correct crop protection strategy can be implemented by analyzing external big data sources.	[20]
	(4) A recommender system based on rough total score was proposed to predict the weather and the best planting date. Based on the hybrid, recommendation algorithm the best crops suitable for production under specific weather were predicted and analyzed.	[109] [81]
Agricultural workers are not able to quickly discover the agricultural science and technology they are interested in.	A content-based recommendation algorithm based on convolutional neural network was proposed to promote agricultural science. This paper proposes a recommender system based on data mining technology for recommending crop related content.	[110] [111]
How to increase crop yields.	(1) An agricultural recommender system was proposed to improve crop yield by considering factors such as climatic conditions and soil fertility.	[112]
	(2) Precision agriculture was proposed to predict crop yields through, rainfall data surface temperature and other data.	[113] [102]
Food security is a major problem in Egypt, and the temperature difference between day and night in Egypt's western desert has a big impact on the growth of crops.	This research proposes cultivation-time recommender system for predicting the best sowing dates for winter cereal crops in the newly reclaimed lands in Farafra Oasis (the Egyptian western desert).	[82]
Agriculture plays a vital role in Bangladesh, but local farmers do not have enough knowledge to assess which crops to grow.	A recommender system is proposed to guide farmers to find the most suitable crops for a particular soil to solve this problem. Using a mobile application, the proposed system works with the user's soil type and geological information to perform Pearson correlation similarity calculation for determining specific areas.	[114]
Integrated analysis of agricultural and soil ecosystems is in nascent stages, there are often-conflicting objectives (e.g. cost environmental and social).	An adaptive Sensor-Drone-Satellite (SeDS) system for promoting farming operations and sustainability via balancing often-conflicting objectives (e.g. cost environmental and social) was developed. SeDS system understands the ramifications of agro-ecological systems, complex compounds, mechanisms, multi-functional performance and commercial viability, as well as elucidation of the effects of various parameters.	[27]

TABLE 7. Recommendation systems in agriculture that have been implemented.

Company or region	URL	Introduce	Reference
Organics at a Glance	http://ec.europa.eu/agriculture/organic/eu-policy/seed-databases_en	To help farmers, an innovative recommendation system is proposed, which growers or companies obtain organically produced seeds and recombinant seeds. This mechanism can be incorporated into online databases (governmental or commercial) where suppliers register their organic seeds. Benefits for users include reducing search time and effort, comparison of product prices, and decision support. The latest is perhaps the most important benefit. Users help users make good decisions on a personal (personalized) level.	[87]
Huinong Network	https://www.cnhnb.com/	Corresponding networks serve as a platforms for mediation, sellers farmers and buyers. Buyers and sellers can get to know each other and connect with each other, so that farmers can display their types of agricultural products. It is also convenient for buyers to purchase and sellers to sell online transactions, and a variety of agricultural products trade and sales markets are docked, and sales channels are expanded.	[115]
Amazon	https://www.amazon.com/	At Amazon.com, recommendation algorithms are used to personalize the online store for each customer. For large retailers like Amazon.com, a good recommendation algorithm can still work across a very large customer base and an extended catalog of products, and generate online recommendations with only second processing time. Recommendation systems can immediately respond to changes in user data and give a convincing recommendation based on the number of purchases and ratings of similar users.	[116]
Local Harvest	https://www.localharvest.com/	In the United States, there are more than 100 million small farms owned by farmers or families, who sell their products directly to consumers primarily through this Local Harvest. Local Harvest's online sales of agricultural products contain intelligent recommendation module, and its background algorithm is supported by associated recommendation technology.	[117]
Hello Fresh	https://www.hellofresh.com/	As one of the largest fresh food e-commerce providers in Europe, Hello Fresh's online sales platform adopts a hybrid recommendation algorithm based on content and collaborative filtering.	[118]
The Climate Corporation	https://www.climate.com/	According to the growth characteristics of agricultural crops, the Climate Corporation of the United States collects and processes big data samples of the environment, soil and crop roots, so as to effectively avoid the adverse effects of natural disasters on crop growth.	[119]
Silent Herdsman	https://www.thoughtworks.com/	Uk-based Silent Herdsman applies agricultural big data processing technology to animal husbandry, real-time monitoring of cows' body item indicators and movement trajectory, such as abnormal information and real-time warning, to get rid of problems behind traditional agricultural technology.	[120]
Farmigo	https://www.farmigo.com/	Farmigo was the first truly high-volume e-commerce company. Farmigo sells monomers at a discount after the number of purchased monomers reaches a certain scale within a specified time. Farmigo has more than 20 users in each community. The leaders of the user community place orders on the exclusive website. Local farms collect orders from the same community every week and distribute them at designated points.	[121]

in the form of an implicit rating of the project that is important to the design of the project. Other customer decisions play an important role in making recommendations for individual purchase items. For example, people who relied on what a movie critic had said about a movie before they saw it looked at a similar situation when buying produce.

C. APPLICATIONS OF HYBRID RECOMMENDATION ALGORITHM IN AGRICULTURE

Recommender systems based on CF are better than content-based systems in terms of recommendation quality, but they have the problem of cold start, that is, they cannot recommend items with little or no rating information. Content-based recommender systems, on the other hand, can recommend both old and new items at the same time, but the recommendation quality is low based on the user's preferences. Reference [105] combines CF and content-based recommendation into one system to address the relative inaccuracies of content-based and cold start issues associated with collaborative filtering. Establishing links between meteorological and climate data and agricultural decision-making is a daunting task. Therefore, a method to improve crop yield by weather forecast using the recommender system is proposed. At present, farmers have access to a large amount of weather and climate information, but weather information alone cannot enable farmers to make decisions quickly. The best way to benefit from natural factors is to take them into account in the decision-making process and to understand them in the best way possible. Meteorological information related to agriculture, particularly climate data, is an important aspect of planning in the context of agricultural production, and climate conditions must therefore be an integral part of the decision-making process. These factors can be determined by recording hourly, daily, and weekly temperature data, rainfall, solar radiation, wind speed, evaporation, relative humidity, and evapotranspiration. Reference [81] provides a predictive analysis to analyze the best crop that can be produced under specific weather conditions, and proposes a hybrid recommender system that uses Case-Based Reasoning (CBR) to improve the success rate of the system. The proposed hybrid system is a combination of collaborative filtering technology and case-based reasoning. The novel feature of this model is that it can be used to analyze regional agricultural data to predict future climatic conditions and recommend crops according to these climatic conditions, taking into account the regional model of agricultural mixed recommender system. In this paper, a new food recommender system is introduced for the recommendation of agricultural food. Various items can be found according to the customer's interests. Mehdi proposed a hybrid technology for recommendation combining collaboration and content-based recommender systems [126]. In this study, users' comments on recommendation quality and system availability were collected, and the interaction design of a mobile food recommender system was focused. Through a new interaction process, users' long-term and short-term preferences for recipes were elicited. Users' long-term preferences were obtained by asking users to rate and label familiar recipes. In order to gather short-term preferences, the user is asked to choose which ingredients she wants to include in the recipe she wants to prepare. Based on a combination of these two types of preferences, a personalized set of recommendations is generated. The results showed that most users rated the quality of the recommendations highly, and the system's usability score was higher than the benchmark score.

D. APPLICATIONS OF OTHER RECOMMENDATION ALGORITHMS IN AGRICULTURE

According to the main technologies of Jilin Province in 2016, Jilin Precision Agriculture and Big Data Engineering Research Center has 22 technical documents, involving the main and characteristic planting and breeding technologies of Jilin Province. The spatio-temporal recommendation algorithm [127] has been proposed to solve the problems existing in the traditional collaborative filtering algorithm, such as inconsistency with the actual agricultural production and low precision of personalized recommendation. In view of the problem of ''information overload'' in agricultural products system, traditional recommendation methods seldom consider the seasonal characteristics of agricultural products, and the recommended effect is not ideal. Based on the consideration of the time effect of agricultural products, changes in user interest and the integration of agricultural seasons, Xu *et al.* introduced traditional collaborative filtering recommendations to improve the quality of recommendations [128]. Since the collaborative filtering algorithm mechanism is to recommend users according to the behavior of similar users, the similarity between the target users and the information text can only be calculated after it has been read by enough users. Therefore, the cold start problem of newly released information appears. Gao and his team proposed hybrid recommendation algorithm can take into account diversity and personalized recommendation results, in the study found that hybrid collaborative filtering algorithm and two algorithms content recommendation algorithm combined to produce the new text information, not only can solve the problem of personalized, also solve the problem of the diversity, and the problem of cold start can be avoided [129]. In [109], for agricultural farming, a recommender system based on rough aggregate score was proposed to predict the weather and the optimum cultivation date of wheat in Sinai Peninsula, Egypt. Because the Egyptian economy has always depended on the income of the agricultural sector in food, feed, fiber and so on and wheat is the most important crop in Egypt. So better forecasting of the weather and predicting the best time to grow wheat could boost Egypt's economy. As hardware devices become more complex and cheap, and fast and broadband wireless Internet connections are available not only in towns but also in remote rural areas, the use of sensors to collect all kinds of data is becoming common in agriculture, and the use of large databases to apply these sensors to a wide range of locations. However, despite the presence of many highly qualified agricultural experts and the vast amount of data collected, much useful information remains hidden. Naturally, there was a need for software that could process these huge databases and extract the underlying information to facilitate decision-making in important agricultural situations. After reviewing the ''farm accounting data network'' provided by the Hungarian Institute of Agricultural Economics, the results of its work are described and a recommender system for agricultural data sets based on matrix decomposition is proposed [130]. Authors' main interest is to find questions that can be answered by using Matrix Factorization (MF) models, and when the real information of high quality is obtained, the explicit data collection is mentioned, such as in their project where they collect data directly from grain growers through questionnaires.

V. FUTURE DIRECTION

With the ever-growing volume of online information, recommender system has been an effective strategy to overcome such information overload. In the past three years, the research on recommender systems for agriculture has attracted more and more attention from the academia and industry. This section discusses the future development direction of intelligent recommendation in agriculture.

A. AGRICULTURAL INFORMATION ACCESS

Agricultural production is easily affected by nature, market and policies. Applying big data to agriculture and scientific analysis and deep mining of massive data generated in the agricultural production process can well predict the development trends of agriculture, enabling farmers to obtain advanced agricultural information in time even in remote rural areas. Seed selection and breeding, agricultural consultation, national policies and so on are full of the network. How to obtain information more accurately and quickly from the large amount of information is the focus of the future development of the recommender system. According to the actual needs, the agricultural industrial structure and crop varieties should be adjusted in time, and the superior resources should be focused on the agricultural production with good development momentum in a targeted way, so as to develop agriculture with local characteristics and provide impetus for regional economic development.

B. EXPERT RECOMMENDATION

If the generalization of information can arm farmers, then experts are there to tell them how to use the weapons at their disposal. Simply finding information by farmers themselves is not only slow but the results obtained may not be a good solution to the problems they face. At this time, the above problem can be solved by recommending experts in the field of the farmer's problem, and how to accurately analyze the farmer's problem and recommend the right expert is also the focus of future research.

C. INTELLIGENT PRODUCTION

Intelligent production includes the construction of a system platform for improving agricultural production technology in terms of planting and breeding production. Typical aspects include: using the IoT technology to build an agricultural production automation system integrating environmental physiological monitoring, crop model analysis and precise regulation. In the field of food safety, the agricultural product traceability system can query and authenticate all kinds of information related to the production, processing and sales of agricultural products, and trace the whole process of information.

With the rapid development of deep learning, reinforcement learning and big data processing technologies, the integrated application of deep learning, reinforcement learning and big data processing technologies in agriculture has become a hot issue nowadays. The fundamental way out of agriculture depends on science and technology, and the future development of agriculture needs the joint action of various advanced technologies, and smart agriculture is the future development direction. To truly realize smart agriculture, biotechnology, information technology and intelligent equipment need to be combined into one, from biological breeding, black land protection, technical equipment to unmanned farms, regional services and agricultural data centers, all of which are intelligent. The intersection of new technology concepts and agriculture is deepening, and smart agriculture is ushering in a profound change in which recommendation algorithms will surely play an irreplaceable role.

VI. CONCLUSION

The creation of the recommender system has largely alleviated the problems of untimely information access and ineffective access to news of interest due to information overload in agricultural production and marketing. Collaborative filtering, content-based recommendation, social network-based recommendation, and hybrid recommendation are all common recommendation methods today. This paper synthesizes the relevant algorithms and their corresponding advantages and disadvantages, and lists other novel and effective recommendation algorithms, so that the reader can learn about the common algorithm evaluation criteria and the practical applications of the relevant algorithms in agriculture. Recommender systems and recommendation technology are ongoing hot research topics in the recent decades, especially in agriculture. There are a large number of new developing techniques and emerging models each year. We hope this survey can provide readers with a comprehensive understanding towards the key aspects of this field, clarify the most notable advancements and shed some light on future studies.

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