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Research on recurrent neural network recommendation algorithm based on time series

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Abstract. In the era of the Internet, all people's behaviors on the Internet will be stored in the server in the form of data, which leads to the image level growth of data today. In the context of big data, how to effectively analyze various existing data to obtain the necessary information is an urgent challenge that various industries need to overcome. Recommendation algorithms are one of them, mainly using existing data to recommend information of interest to users. In traditional recommendation algorithms, collaborative filtering recommendation algorithms encounter difficulties such as cold start and data sparsity. In order to better explore data features, deep learning algorithms have begun to be applied. Recurrent neural networks can not only learn input data but also perform self-learning, which can better extract features between data and improve the accuracy of recommendations. However, the information that users are interested in is greatly influenced by time, in order to improve the accuracy of recommendations. This study investigates the recursive neural network recommendation algorithm with added time series, and experiments have shown that this recommendation algorithm can indeed improve the accuracy of recommendations more accurately.

Keywords: Recurrent neural network, Time series, Recommendation algorithm, Deep learning.

1. Introduction

With the in-depth development of information technology, the Internet has brought more and more convenience to our lives. At the same time, all operations on the Internet will be stored in the form of data, so the amount of data generated is also increasing exponentially. Behind such a vast amount of data, how to make good use of it and extract useful information through the data is also a topic that needs further research, such as the birth of recommendation algorithms to quickly recommend items of interest to users. The traditional recommendation algorithm is best known for collaborative filtering. In order to improve the accuracy of recommendations, scholars have made various improvements to the recommendation algorithm. Although it can effectively improve accuracy and solve some challenges such as insufficient data in the initial stage, there are still many challenges waiting to be overcome. In 2010, deep learning was promoted, and it belongs to a new type of computing model in the field of artificial intelligence[1]. It has become familiar to people and has been effectively used in practical scenarios and results, achieving good results in image and speech processing. Due to its excellent feature learning and data processing capabilities, deep learning can analyze the connections between data at a deeper level. Therefore, since the 2016 seminar on recommendation algorithms based on deep learning,

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many experts and scholars have also conducted research on recommendation algorithms from the perspective of deep learning[2].

Lingyuan Dou proposed a collaborative filtering recommendation algorithm that integrates label features and temporal context[3]. This algorithm utilizes the correlation between information to reveal the relationship between individuals and objects and embeds it into neighbor based methods; In this way, the difficulties of information cold start in traditional recommendation systems can be successfully solved, thereby improving their accuracy level. However, how to incorporate time and situational factors into this algorithm is a tricky issue: as individual preferences and tendencies undergo variable changes over time. However, the introduction of temporal context is a complex issue, as user interests and preferences are dynamically changing over time. The paper mentions considering the temporal context factor of user ratings, but accurately capturing and utilizing this dynamic change remains a challenge. In addition, the impact of different time scales (such as days, weeks, months, etc.) on recommendation results may also vary, and further research is needed. Sun Guangfu proposed a collaborative filtering recommendation algorithm based on temporal behavior in his research, and developed a collaborative filtering recommendation method based on temporal behavior under this architecture[4]. This novel method aims to extract structured connections from the temporal consumption data of users and products, thereby establishing new associations between them. Compared to traditional collaborative filtering techniques, this method focuses more on analyzing the consumption time of users and products, in order to reveal their mutual influence. This method helps to solve the problem of interest drift and can better capture the dynamic preference changes of users. This algorithm has also been tested on the Douban recommendation dataset, and the results show that compared to traditional social network information and tag information recommendation methods, it can more accurately predict the true rating of users, thereby improving the accuracy of recommendations. However, this algorithm faces sparsity in consumer network graphs and cold start issues for users and products. These issues may affect the accuracy and efficiency of recommendation systems, especially when new customers or services are incorporated into this framework; Due to insufficient data interaction information as a basic support, conventional methods are difficult to provide useful solutions. To overcome this problem, Deng Cunbin proposed a novel strategy that integrates dynamic collaborative filtering and deep learning methods: by introducing time factors and utilizing deep learning to deal with problems that exist in ordinary patterns such as insufficient information, initial uncertainty, and the inability to consider differences in consumer demand that arise with time and environmental changes[5]. This algorithm utilizes dynamic collaborative filtering algorithm to integrate temporal features, and then uses higher-level machine intelligence technology to extract more relevant attributes in order to enhance its performance ability. Specifically, they used two algorithms, CNN and MLP, to obtain deep level representation features. Secondly, the dynamic collaborative filtering algorithm and deep learning model were combined to form a hybrid recommendation algorithm, and the rating prediction function and loss function of the dynamic collaborative filtering algorithm were improved. Finally, experiments on the MovieLens dataset have demonstrated that this method improves the accuracy of movie rating prediction. However, this algorithm integrates multiple models and technologies, including dynamic collaborative filtering, convolutional neural networks (CNN), and multi-layer perceptrons (MLP), and its structure may be relatively complex, resulting in reduced interpretability of the algorithm. In practical applications, this may affect the user's understanding and trust in the recommendation results. This study constructs a time series recurrent neural network recommendation algorithm based on previous literature discussions. This algorithm mainly identifies the user's points of interest in the time series and uses deep learning techniques to train the user's features, thereby improving the accuracy of recommendations.

2. Introduction to Recurrent Neural Networks

Recurrent neural network is a deep learning model that captures temporal dynamics by introducing a cyclic structure when processing sequential data[6]. This type of network can store previously inputted information and combine it with the current input for prediction or classification. RNN is different from traditional feedforward neural networks in that it has internal state or memory capabilities, which enable it to process long time series and adapt to time changes. The core feature of recursive neural networks is the cyclic connections of their hidden layers. This architecture indicates that the formation of network output is not only dependent on the data input of the existing input layer, but also influenced by the data loop input of the previous hidden layer and system conditions. Therefore, this feature makes it very suitable for performing complex tasks that require consideration of time, such as voice recognition, text generation, or automatic decoding. During the training phase, RNN uses backpropagation algorithm (BPTT) to adjust and optimize parameters[7]. However, due to issues such as vanishing gradients or exploding data, standardized RNNs may pose challenges for long-term information transmission. To overcome this challenge, scholars have developed many improved versions of RNNs, such as LSTM and GRU, which introduce a technology called "gated loop unit" to effectively manage information flow and more accurately distinguish factors that affect the future. In summary, recurrent neural networks are a powerful tool for deep learning, especially effective for tasks that require consideration of time series. By introducing a loop structure and an improved gating mechanism, RNN can effectively capture temporal dynamics and solve long-term dependency problems[8].A recursive neural network consists of three parts: input layer, hidden layer, and output layer, as shown in Figure 1. The input layer receives external sequence data such as text, audio, or video as input. The hidden layer is a crucial part of RNN, which combines the current information with the previous information through cyclic connections. This loop connection allows the hidden layer to maintain memory of past information and consider this information when processing current input. The output layer is responsible for transmitting the processed results to the next time step or for the final prediction or classification task.

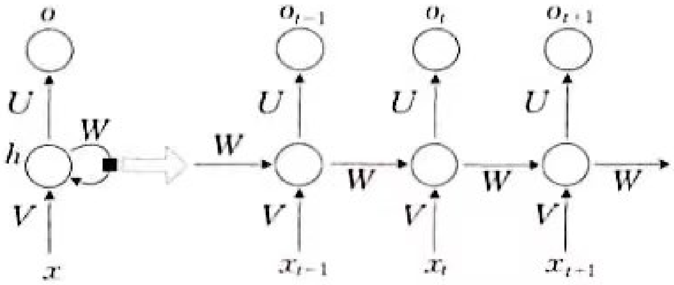

Figure 1. RNN Network Structure Diagram

Recurrent neural networks have significant advantages in recommendation algorithms due to their unique ability to process temporal data, bringing revolutionary improvements to recommendation algorithms. This network structure is particularly suitable for processing sequential data and can capture the dynamic characteristics of user behavior and preferences over time. By introducing a time dimension, RNN can better understand users' long-term interests and short-term behavior patterns, thereby providing more personalized and accurate recommendation content.

3. Model building

The traditional collaborative filtering recommendation algorithm is mainly based on the user's past behavior records, and generates recommendation results by calculating the similarity between users or items[9]. This algorithm relies on common interests among users, and when the number of users is large and their interests are widely distributed, the recommendation effect may be affected to some extent. The recursive neural network recommendation algorithm is a deep learning model that can capture sequential information of user behavior, thereby better understanding users' long-term interests and short-term preferences[10]. By learning recursive neural networks, it is possible to more accurately predict the future behavior of users. So improving traditional recommendation algorithms combined with deep learning techniques can achieve better recommendation results. In this project, a recursive neural network based on time series will also be used to establish a recommendation algorithm model.

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In this project, the method of time series modeling will be used to design a recommendation algorithm model that integrates time series analysis and recurrent neural network technology. This model can effectively analyze the trend of user behavior over time, thereby improving the personalization and accuracy of recommendation services. In recommendation systems, time series data reflects the evolution process of user behavior, such as purchasing, browsing, or rating. By analyzing the changes of these data over time, it is possible to reveal user preference patterns and interest trends. However, traditional recommendation algorithms often overlook the time factor, resulting in a lack of timeliness and adaptability in recommendation results. To overcome this limitation, a time series based recurrent neural network is introduced into recommendation algorithms. Recurrent neural networks (RNNs) are particularly suitable for processing sequential data because they have memory capabilities and can retain previous information to influence current decisions. This enables RNN to effectively learn the temporal dependence of user behavior.

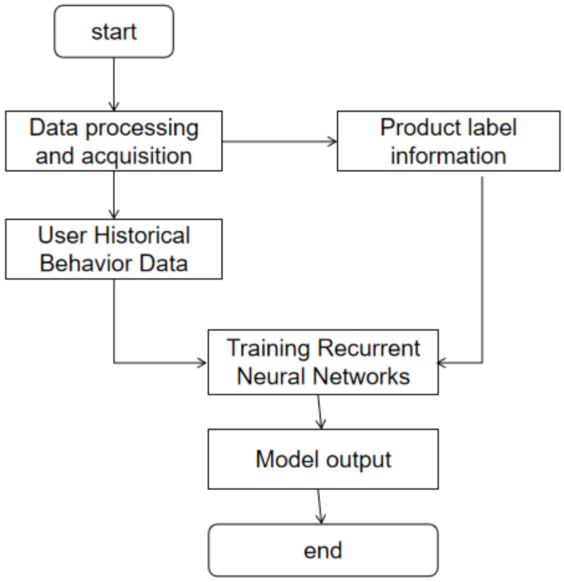

Figure 2. Recurrent neural network construction recommendation algorithm model

4. Experimental design

This project uses open-source data provided by Alibaba Algorithm Competition as the dataset, which consists of two tables: one is the operation data of all users on a certain e-commerce website within a month, and the other is the product information data. Both tables have undergone data desensitization processing. Before conducting the experiment, we first need to clean the data. Firstly, we process the user operation data table, such as adding operation labels based on user behavior such as bookmarking, commenting, adding shopping carts, etc; Add a time series to the data based on its timestamp; Eliminate suspicious data with a significant amount of operations.

In classic collaborative filtering recommendation systems, the first step is to calculate the similarity between users, which can be achieved by calculating cosine similarity, correlation similarity, and corrected cosine similarity. Next, the target user's rating on the item is predicted based on the rating of the nearest neighbor user. Finally, the highest rated item is fed back to the user as the recommendation result. For example, if user A likes items 1, 2, and 3, user B likes items 1 and 3, and user C likes items 1 and 4, then we would assume that user A and user C are similar users, while user B did not choose item 2. Therefore, we can recommend item 2 to user B.

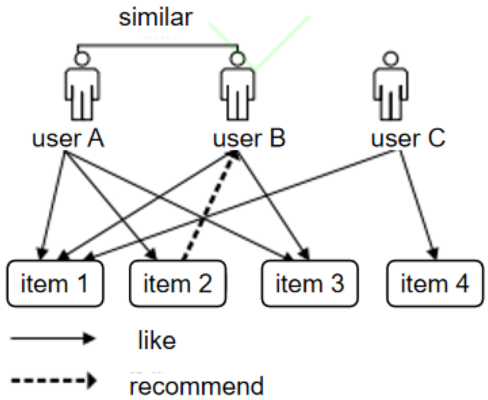

Figure 3. Collaborative filtering recommendation

The similarity of feature vectors for items is calculated using the formula:

$$w_{\mathrm{ij}} = \frac{\sum_{u\in N(i)\cap N(j)} \frac{1}{\log\left(1+N(u)\right)}}{\sqrt{|N(i)| \times |N(j)|}} \tag{1}$$

Among them, w_{ij} represents the item similarity between item i and item j.

When calculating a set of similar items, we used the heap sorting method to select a set of k items that are the same as the target item. The specific calculation formula is:

$$S(u,K) = \max\{v_1, v_2, \ldots, v_n\} \tag{2}$$

In this experiment, U={ u_1, u_2,..., u_n }To represent the user set, use V={ v_1 , v_2 ,..., v_n }Representing user operation data, we can use conditional probability to predict the probability that an item may be recommended:

$$\mathrm{P}(\mathrm{v_n} \mid v_1, v_2, v_3, \ldots v_{n-1}) \tag{3}$$

But as mentioned earlier, a person's interests and hobbies are greatly influenced by time, so the degree to which an item is loved cannot be predicted solely by the nearest neighbor conditional probability. The preferences of users during a certain time period are generally greatly influenced by recent preferences. In order to more accurately predict user preferences, we have improved formula 3:

$$\mathrm{P}(\mathrm{v}_n \mid v_{n-m}, \ldots, v_{n-1}, v_{n+1}, \ldots, v_{n+m}) \tag{4}$$

Mid term m is the time parameter we define, which means that when we want to calculate the neighboring items of a certain item, we only need to refer to the items within the last 2m time period. Under these conditions, we can predict the probabilities of consumers clicking on products and within 2 meters, and then use sorting algorithms to determine the items with a click probability of TOP-N.

After understanding the reasoning foundation of the algorithm, we will continue to establish a collaborative filtering suggestion pattern and a Time Recurrent Neural Network (RNN) modeling approach based on temporal information. For this RNN model, it consists of three parts: input module, implicit module, and output module. In this model, the input data consists of two types of elements included in our dataset: product behavior data and product attribute data. At the same time, we will convert these data into time series form according to the order in which customer behavior occurs. After

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processing the input layer and the previous hidden layer through the hidden layer, the data is passed into the output layer, as shown in Figure 4.

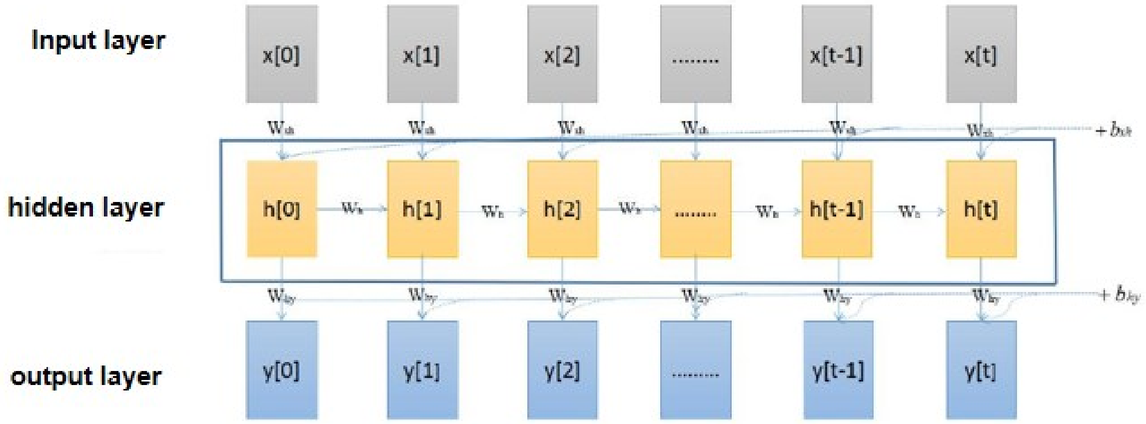

Figure 4. Recurrent neural network model

To confirm the accuracy of this algorithm, we used the publicly available version of the Alibaba recommendation algorithm competition data as our test sample and compared the time-based recursive neural network recommendation method with the traditional collaborative filtering recommendation method based on products. After the experiment, we obtained the following results: the prediction accuracy, recall, and user coverage of the algorithm all performed well. Through the experiment, we obtained the following data:

Table 1. Comparison of Recommended Results

algorithm	Prediction accuracy	Accuracy	recall	User coverage
Collaborative filtering of items	10.7%	43.3%	14.5%	93.7%
Time series recurrent neural network model	42.2%	38%	7.6%	87.2%

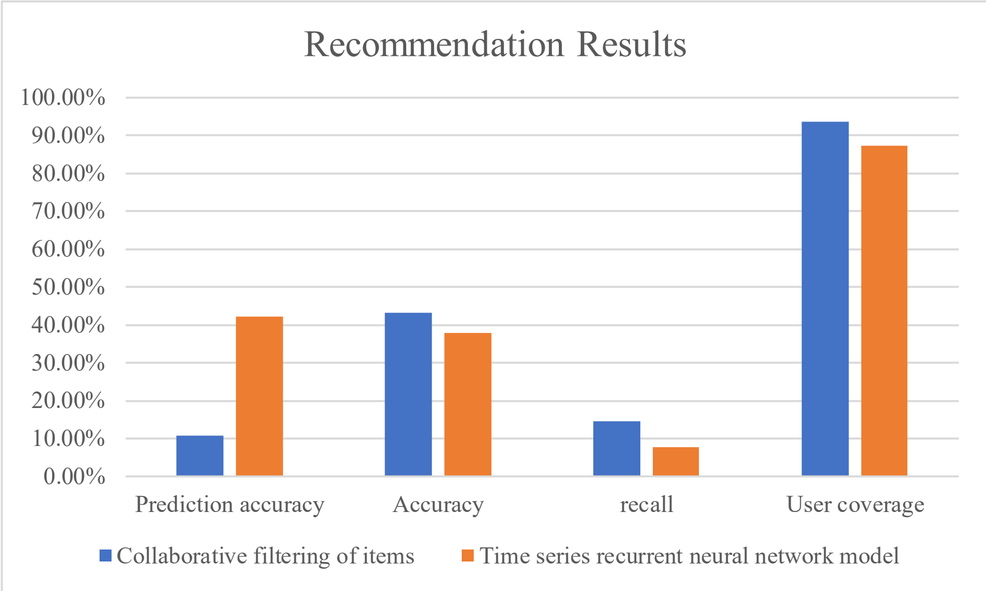

Figure 5. Recommendation Results

From the experiment, it can be seen that the recursive neural network model based on time series significantly outperforms traditional collaborative filtering recommendation algorithms in terms of recommendation accuracy. This also indicates that time series based recommendation algorithms have strong time feature extraction capabilities, and can to some extent calculate user interest preferences based on time when making user preference recommendations.

5. Conclusion

With the rapid development of Internet technology, personalized recommendation systems have been widely used in various fields. Traditional recommendation algorithms mainly rely on user's historical behavioral data, such as ratings, purchase records, etc. However, these data often overlook the time series characteristics of user behavior. In fact, user interests and needs change over time, so recommendation algorithms that consider time series characteristics have higher practical application value. Recurrent neural networks, as a deep learning model for processing sequential data, can capture potential patterns in time series, providing new ideas for building more accurate recommendation algorithms. Future research can improve and optimize existing models from the following aspects: firstly, research more efficient training algorithms and network structures to reduce computational burden and improve training speed. Secondly, explore model regularization and optimization strategies to enhance the model's robustness to noisy data and improve its generalization ability. Once again, conduct more research on the characteristics of time series in order to better understand the impact of different types of data on model performance. Finally, research how to combine RNN with other types of deep learning models, such as Convolutional Neural Networks (CNN) or Transformers, in order to discover new breakthroughs.

Fund Project

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