Research and Analysis of Recommendation Algorithm Based on Convolutional Neural Network

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Abstract. This paper first introduces the situation that the traditional recommendation algorithms cannot meet the needs of users for accurate and efficient recommendation results because of the continuous growth of data and the increasingly diversified data types. Then it introduces the Deep Learning (DL) algorithm which is getting more and more attention, organizes the research progress of recommendation system based on Convolutional Neural Networks (CNN) in recent years, analyzes its advantages compared with traditional recommendation algorithms. The main research directions and application progress are classified, compared and summarized. Finally, the future development trend of recommendation system based on convolutional neural network is summarized and analyzed.

1. Introduction
In recent years, with the rapid development of Internet applications, the data in the Internet space has also grown explosively. The abundance of data also brings serious problem of "information overload". How to efficiently recommend information that meets user's needs from complex data for users has become one of the popular issues of concern and research in industry and academia. As a tool to filter information, recommendation system is an effective way to solve the problem of "information overload". The core part of the recommendation system is the recommendation algorithm, which can model the user's historical purchase need, behavioral records or similar preferences, find products or services that meet the user's preferences and recommend them to the user.

Although the traditional recommendation methods can realize the recommendation task and alleviate the problems of cold start and sparse matrix to a certain extent. The auxiliary information often has complex characteristics such as multimodality, heterogeneous data and uneven distribution. The traditional recommendation methods still face many problems when dealing with the data fused with multi-source heterogeneous information [1-2].

Deep learning has been widely used in image recognition, speech recognition, text analysis and other fields and has achieved good results. Deep learning is a machine learning algorithm with recognition, analysis, and calculation [3]. Recommendation systems based on deep learning usually take various types of user and item-related data as input, use deep learning models to learn implicit representations of users and items, and generate item recommendations for users based on this implicit representation. It builds a multi-layer neural network to input project or user-related information, and uses regression methods to score and predict input data, which solves the problems of data sparsity and cold start that
tend to occur in traditional recommendation algorithms. This paper analyses and summarizes the application of convolutional neural networks in the field of recommendation systems [4].

2. Traditional Recommendation Algorithm
Traditional recommendation algorithms are mainly divided into three categories: collaborative filtering recommendation algorithms, content-based recommendation algorithms, and hybrid recommendation algorithms. The algorithm classification is shown in Figure 1.

![Figure 1. Classification of traditional recommendation algorithms.](image)

2.1. Content-based Recommendations
Content based recommendation technology recommends products similar to the products that the user likes in the past according to the products that the user likes in the past. The core idea is to use the user's historical records or preference records as a reference, and to mine other unknown records that have high relevance to the referenced content as the content recommended by the system [5].

However, when content-based recommendation technology processes large-scale information content, it often takes too long to obtain the problem of reduced timeliness of information.

2.2. Collaborative Filtering Recommendation
The idea of Collaborative Filtering Recommendation (CF) is to obtain the interaction between users and projects by analysing the score matrix, usually by analysing the user's score on the item, and further predict the relationship between the new user and the item after the model is established. The collaborative filtering algorithm integrates a variety of factors in the recommendation process, such as user preferences, activities, and behaviors, and recommends items based on similarities with other users.

Nowadays, collaborative filtering technology is widely used in music recommendation, movie recommendation, e-commerce and other fields [6].

However, collaborative filtering algorithms are prone to encounter cold start problems when facing new projects.

2.3. Mixed Recommendation
Hybrid recommendation technology integrates different recommendation algorithms into the recommendation system to solve the shortcomings of a single recommendation algorithm. Among them, common hybrid methods include weighted mixing, cross-harmonization, feature mixing, and so on. According to the different recommended strategies, it is divided into front fusion, middle fusion, and post fusion.

Hybrid recommendation requires heavy manual feature engineering and can only grasp the superficial relationship between users and items.

3. Application of Recommendation Algorithm Based on Convolutional Neural Network
CNN is a Multilayer Perceptron (MLP), which is mainly used to process two-dimensional image data [7]. The main application areas of CNN in the recommendation system include image recommendation,
news recommendation, and text recommendation. These application scenarios are for different application areas, but the recommendation models are for a specific target user. In practical problems, the recommendation scenarios are more complex. Therefore, researchers further tried to combine CNN with social relations, time, text and other auxiliary information for recommendation.

3.1. Application of CNN in Recommendation System

3.1.1. CNN-Based Image Recommendation
Lei et al. [8] proposes a comparative deep learning method (Comparative deep learning, CDL), the main idea is to use MLP and CNN to separately feedback from the user's multi-source heterogeneous data (including user portrait, tag information, etc.) and the user's implicit feedback on the image, and finally map the user and the image to the same hidden space. The experimental results of image recommendation on actual data sets show that the performance of the proposed dual-network network model and CDL is much better than other state-of-the-art image recommendation methods.

Wang Yufei et al. [9] dynamically combined the project image and the score, starting from the two aspects of the project image and the project score, using convolutional neural network to extract image features, using the extracted feature values to obtain the similarity between the project images. Dynamically combine it with the similarity of item ratings to generate recommendations. The fusion project image similarity calculation method proposed in the article can effectively alleviate the calculation deviation caused by data sparseness after introducing the project image feature, and improve the accuracy of the recommendation. The disadvantage is that the accuracy of image feature extraction is not high enough.

3.1.2. News Recommendation Based on CNN
Gabriel et al. [10] used a "two-stage" news recommendation method, that is, "model first, then user" distribution modeling. The author proposes the first deep learning meta-architecture for news recommendation. The meta-architecture can be instantiated into different architectures with similar characteristics to complete a common task. The architecture consists of two modules: the Article Content Representation (ACR) and the Next-Article Recommendation (NAR). The ACR module is responsible for learning the distributed representation (embedding) of news content. The input of the ACR module consists of two pieces: 1) article metadata attributes (for example, publisher) 2) article text content, expressed as a series of word embeddings. The article content embedding is trained as an auxiliary task-to classify the article category. Its content representation module is based on CNN to perform convolution calculation on news text content from word level to generate news content embedding representation [11].

Khattar et al. [12] used a "fusion-style" news recommendation method to integrate news and user information, and learn news and user characteristics at the same time. The author proposes a new deep learning news recommendation model, which uses the content of news articles and the order in which users read the articles. The first part is based on a three-dimensional convolutional neural network, which takes as input the word embeddings of articles appearing in the user's history. Using this method enables the model to automatically learn the space (features of specific articles) and time features (features of users reading articles) that represent user interests. During the test, the author combined a two-dimensional convolutional neural network to recommend articles to users. On real data sets, this model is superior to the most advanced neural network-based models.

3.1.3. CNN-Based Text Recommendation
Ma Xiaosuan et al. [13] proposed a text recommendation algorithm based on tagged convolutional neural network (Tagged Convolutional AutoEncoder, TCAE), which encodes text information to mine semantic information, at the same time, the tag information is used to group the convolution kernels of the convolutional neural network, so that articles with different labels will use different convolution kernels for feature learning. The articles collect some relevant information in the system based on user-
oriented articles, such as text information, tag information, etc., to help the recommendation system better recommend articles. Compared with the control experimental model, the algorithm proposed in the article can obtain better recommendation results.

Hu Chaoju et al. [14] proposed a deep fusion model (DeepFM), which uses the MLP structure to capture the user and item preferences of the rating matrix, and expands it to learn the user potential feature vector $p_u$, and use the CNN structure to obtain the text information related to the project. And then combine the output vector $v_l$ and the document latent vector $o_i$ to construct the project latent feature vector. Finally, by constructing a fusion layer method, the user potential feature vector and the item potential feature vector are fused to better get the predicted score. Experiments show that the performance of the model is improved compared to traditional algorithms, and the model has a greater performance improvement when the data density is small. The model structure is shown in Figure 2.

![Model structure diagram.](image)

### 3.1.4. CNN-Based Hybrid Recommendation

As a kind of effective auxiliary information in the hybrid recommendation system, knowledge graph has attracted the attention of a large number of researchers in recent years [15-16]. Shen Dongdong et al. [17] proposed a sequence recommendation algorithm (KGAttCRNN) based on knowledge graph embedding and multiple neural networks. First, a more effective project embedding method is proposed based on the knowledge graph. Then, the user's sequence is divided into different periods according to the user's historical interaction sequence, and CNN is used to learn the context information of the user's sequence to generate the user's interest point vector. Finally, the use of LSTM (LongShort-TermMemory) neural network and self-attention mechanism dynamically merge the user's points of interest to generate user preferences, and then generate recommendations. The algorithm has the advantages of high recommendation accuracy, can alleviate data sparsity, alleviate the cold start problem, and the recommendation is more interpretable. However, longer training time and more expensive hardware equipment are required. The overall flow of the algorithm is shown in Figure 3.
3.2. Comparative Analysis
Table 1 lists future improvement directions that CNN needs in different recommendation fields.

Table 1. Future improvement directions.

| Application direction | Future direction of improvement | Application direction | Future direction of improvement |
|-----------------------|--------------------------------|-----------------------|--------------------------------|
| Image[18]             | 1) Unified processing of heterogeneous data  
2) Improve the accuracy of image feature extraction | Text                  | 1) Add the user's document information to the algorithm  
2) Add users and projects impact factor |
| News                  | 1) Accurate user modeling, how to accurately portray users' long-term preferences and short-term interests  
2) Privacy and security in news recommendations | Mixed recommendation  | 1) Consider more project information for user interaction  
2) Build a unified hybrid recommendation framework for all data |

4. Concluding Remarks
With the continuous maturity of deep learning, data mining and other technologies, improving the accuracy and security of the recommendation system will become a hot topic for future research on the basis of satisfying the recommendation of users who meet their needs. This paper briefly introduces the advantages and disadvantages of traditional recommendation algorithms, focuses on the research progress of CNN-based recommendation algorithms in various application fields in recent years, compares their application effects in various fields, and tries to summarize their future improvement directions. In the subsequent research, cross-domain recommendation can be considered as the focus of research, and the fusion of multiple deep learning models and machine learning models can be tried in the recommendation algorithm to improve the generalization ability of recommendation. A unified hybrid recommendation model can also be attempted for all auxiliary information. Better use of knowledge graphs in hybrid recommendation algorithms enables them to produce better recommendations for new systems. I hope to provide useful help to researchers in related fields.
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