

Retraction

Retracted: Serialized Recommendation Technology Based on Deep Neural Network

Wireless Communications and Mobile Computing

Received 1 August 2023; Accepted 1 August 2023; Published 2 August 2023

Copyright © 2023 Wireless Communications and Mobile Computing. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Jin, "Serialized Recommendation Technology Based on Deep Neural Network," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 3216043, 10 pages, 2022.

Research Article

Serialized Recommendation Technology Based on Deep Neural Network

Long Jin 

School of Computer Science and Engineering, Beihang University, Beijing, 100191 Beijing, China

Correspondence should be addressed to Long Jin; longjin@buaa.edu.cn

Received 14 April 2022; Revised 23 May 2022; Accepted 17 June 2022; Published 14 July 2022

Academic Editor: Chia-Huei Wu

Copyright © 2022 Long Jin. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Since the construction of brain network is like organic brain organization, profound brain network has high effectiveness and high accuracy in separating data from profound elements, fit for multifacet learning, conceptual component portrayal, cross-space learning capacity, multisource, heterogeneous data content. This paper presents brain network models, multifacet perceptrons, RBM models, and convolutional brain organizations. In this paper, the experimental design is carried out according to the principle of the model. Compared with the traditional commonly used CMF, PMF, SVD, and item-based algorithms, the proposed two models have lower root mean square error and higher recall rate. The trial brought about by this paper shows that through investigation, it is trusted that because of the impact of the component of the info information, too many secret layers might prompt overfitting. Accordingly, this paper sets the quantity of stowed away layers in the DNN organization to 2.

1. Introduction

As of late, profound brain networks have gained incredible headway in the fields of computerized reasoning and AI, particularly in discourse acknowledgment and picture acknowledgment. Since the design of brain network is like natural brain organization, profound brain organization can remove profound data productively and precisely. It is an abstract representation of functions, learning multiple domains, multiple sources, and heterogeneous content. This provides a new opportunity to solve the inherent problems of recommender systems. Data series refers to normal data or relative positions in a time series. These strings can be univariate or multivariate.

The rapid development of the Internet age provides convenience for people's information exchange, but also brings about the problem of information overload. To solve this problem, recommender systems have been widely used in many fields. Recommendation systems are usually based on user logs and, most importantly, recommendation algorithms, including collaborative filtering and content-based recommendation algorithms. In recent years, in-depth training in the proposed areas has been successfully imple-

mented. This paper uses a deep neural network recommendation algorithm to analyze item scores and user types and proposes a deep neural network-based recommendation algorithm. Recommendation algorithm is a content-based recommendation algorithm. It is fundamentally founded on the similitude among things and thing types and gives proposals in light of the comparability of thing types.

The innovation of this paper is the application of deep neural network to serialized recommendation technology. It has certain experimental value, and it has certain theoretical significance for the research of deep neural network to be applied to other comprehensive applications.

2. Related Work

In fact, the construction of deep neural network models has become a research hotspot. Many scholars have used deep neural network models in various researches. Gong proposed a deep learning-based synthetic aperture radar image change detection method. This method realizes the detection of changing regions and invariant regions by designing a deep neural network [1]. Jiang concentrated on the difficult

issue of ordering recordings in light of undeniable level semantics, like the presence of explicit human activities or complex occasions. He likewise proposes another bound together system that mutually takes advantage of element relations and class relations to further develop order execution. In particular, these two connections are assessed and taken advantage of by forcing regularization during the learning system of profound brain organizations [2]. Bo proposed a deep neural network speech dereverberation framework based on reverberation time perception. It is utilized to deal with a wide scope of resonance times, and there are three critical stages in planning a hearty framework [3]. Deep learning is a group of machine learning techniques capable of learning deep architectures. Research shows that robot perception and action benefit greatly from these technologies. On account of rocket route and control frameworks, this proposes that profound constructions can now be considered to drive all or part of the installed dynamic framework. This guarantee is analyzed in more detail by Sánchez-Sánchez. He prepares a profound counterfeit brain organization to address the ideal control conduct during accuracy landing, accepting that the state data is great [4].

In order to improve the efficiency of computing image similarity, hashing technology has received more and more attention. For most existing hashing strategies, less than ideal double codes are created on the grounds that hand-made highlight portrayals are not ideally viable with parallel codes. Yan proposed a solitary level directed profound hashing system for learning great paired codes. Yan executed a profound convolutional brain organization and constrained the learning code to fulfill the accompanying models [5]. Various leveled profound brain networks are right now famous learning models that mimic the progressive design of the human cerebrum. Single-layer include extractors are the foundation of building profound organizations. Gong proposed an autoencoder-based multiobjective inadequate element learning model to consequently track down a sensible split the difference between the two [6]. To address the problem that other techniques may generate unreliable data, Wang proposed a new computational method to efficiently predict PPI using information from protein sequences. He remakes these removed elements utilizing stacked autoencoders. At last, he utilized another probabilistic characterization vector machine (PCVM) classifier for protein association expectation [7]. On several pattern recognition problems, deep neural networks rival human accuracy. As opposed to conventional classifiers where elements are carefully assembled, brain networks advance progressively complex highlights straightforwardly from information, rather than hand-tailored highlights. It is currently a falsely planned network engineering. Network engineering boundaries, for example, the quantity of layers or channels per layer and their interconnections, are basic for good execution. Pezzotti presented DeepEyes. This is an ever-evolving visual examination framework that upholds the plan of brain networks during preparing [8]. The downside of these studies, however, is that the considerations are not comprehensive enough to adapt to more complex situations, and precision needs to be improved.

3. Methods of Deep Neural Networks

3.1. Neural Networks

3.1.1. The Connection between Computerized Reasoning, AI, and Profound Learning. AI is the dependable way to man-made consciousness. It contains knowledge of many disciplines. In essence, machine learning is to learn the statistical law of the target to be learned from a large number of training samples so that the computer has human “cognitive” ability and makes reasonable prediction of new objects. Before the approach of profound learning, numerous customary AI calculations were effectively applied. However, in the case of complex problems or nonlinearity, the classification effect of traditional machine learning algorithm is not ideal. The extracted features are put forward by researchers on the basis of rich experience. They are complex and unstable in dealing with the same problem, which mainly depends on the rich experience of researchers. However, deep learning does not require manual intervention in its feature extraction. Researchers need to throw a large amount of data to it, and it can learn by itself. The fields of man-made brain-power (artificial intelligence), AI (machine learning), and profound learning (deep learning) are exceptionally close and incredibly related [9–11]. Figure 1 shows the relationship among the three. Computerized reasoning is a very expansive field, AI is an answer for issues in this field, and profound learning is a part of this arrangement. Since the development of artificial intelligence, there are many remaining problems and development bottlenecks, and the emergence of deep learning has broken these bottlenecks and pushed artificial intelligence to a new height.

3.1.2. Neural Network-Related Concepts. Neural network is a technology that simulates human intelligent behavior. A single neuron structure is shown in Figure 2 [12].

It is similar to a nonlinear threshold device with multiple inputs and only one output. Define the input vector for the neuron:

$$A = [A_1, A_2, A_3, \dots, A_n]^T. \quad (1)$$

Define the weight vector ε :

$$\varepsilon = [\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_n]^T. \quad (2)$$

∂ is the threshold of the neuron, and f is the activation function of the neuron. Then, the neuron output vector B is

$$B = \left(\sum_j^N A_j \varepsilon_j + \partial \right). \quad (3)$$

3.1.3. Multilayer Perceptron. Multilayer perceptron (MLP) is a feedforward neural network; the input data is transformed by nonlinear transformation, which transforms the input data into a linearly separable space. And the learning algorithm it uses is BP algorithm, so MLP is also called BP neural network [13]. MLP is proved to approximate a measurable function with arbitrary accuracy, which is the basis of many

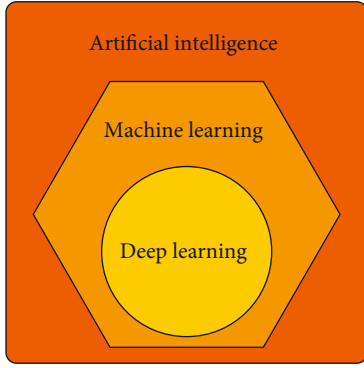


FIGURE 1: The relationship between artificial intelligence, machine learning, and deep learning.

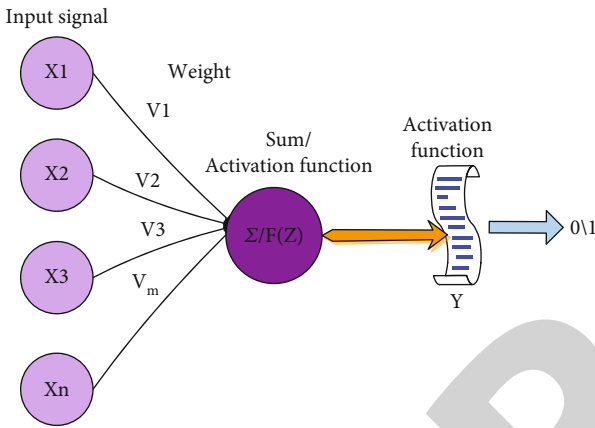


FIGURE 2: Neuron structure.

advanced models. Figure 3 shows the topology of the multilayer neural network. Multilayer perceptron can learn non-linear functions. It is a simple and efficient model, which is widely used in many fields, especially in industrial fields.

3.1.4. Types of Neural Networks. As per the organization engineering, brain organizations can be separated into two sorts: feedforward brain organizations and repetitive brain organizations. The feedforward neural network diagram is shown in Figure 4 [14]. An example of a feedforward neural network is given in Figure 4(a). In feedforward neural network, the input signal starts from the input layer, and the neurons in each layer calculate the output of each neuron in this layer and transmit it to the next layer until the output layer calculates the output result of the network.

3.2. Related Technologies of Deep Neural Network. In real life, deep neural networks are widely used to extract and analyze image semantic features, laying a solid foundation for the study of image classification techniques [15].

3.2.1. Development History of Deep Neural Network Learning. People began to study neural networks very early. The perceptron model is a basic principle based on modern neural networks. It is a network model that can achieve classification and recognition functions through training. It is a true neural network [16].

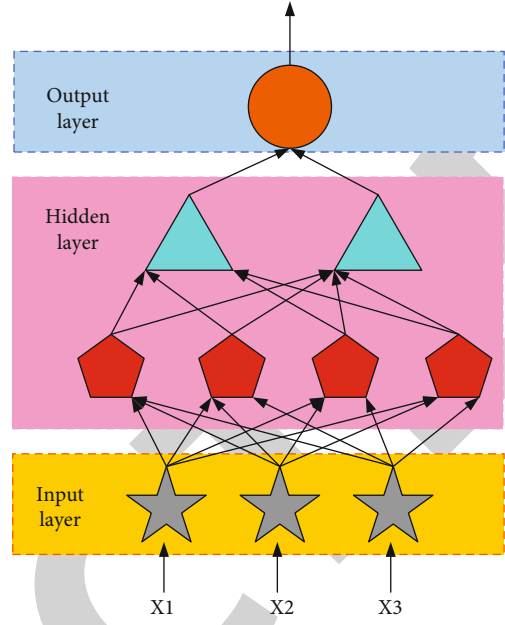


FIGURE 3: Multilayer neural network.

3.2.2. Deep Neural Network Model. Deep learning technology originated from neuroscience, also known as deep neural network. Because the current deep neural network mainly uses convolution structure, deep neural network is sometimes called deep convolution neural network. Machine learning is a method of realizing artificial intelligence. Machine learning is the process of using algorithms to analyze and train large amounts of data. Deep learning originated from perceptron-based artificial neural networks. The first-generation neural network perceptron model is shown in Figure 5.

(1) *RBM Neural Network.* Further research on the RBM model is one of the core contents of deep learning and is of great significance. The RBM energy model is shown in Figure 6 [17].

RBM is an undirected graph probabilistic model, which is energy based. We combine the energy functions of the input layer vector x and the hidden layer vector h to define the joint probability distribution as

$$p(x, h) = \frac{e^{-\text{energy}(x,h)}}{z}, \tag{4}$$

where the normalizing constant is $Z = \sum_{x,h} e^{-\text{energy}(x,h)}$. The marginal probability distribution of the observed input data x is

$$p(x) = \sum_h p(x, h) = \sum_h \frac{e^{-\text{energy}(x,h)}}{z}. \tag{5}$$

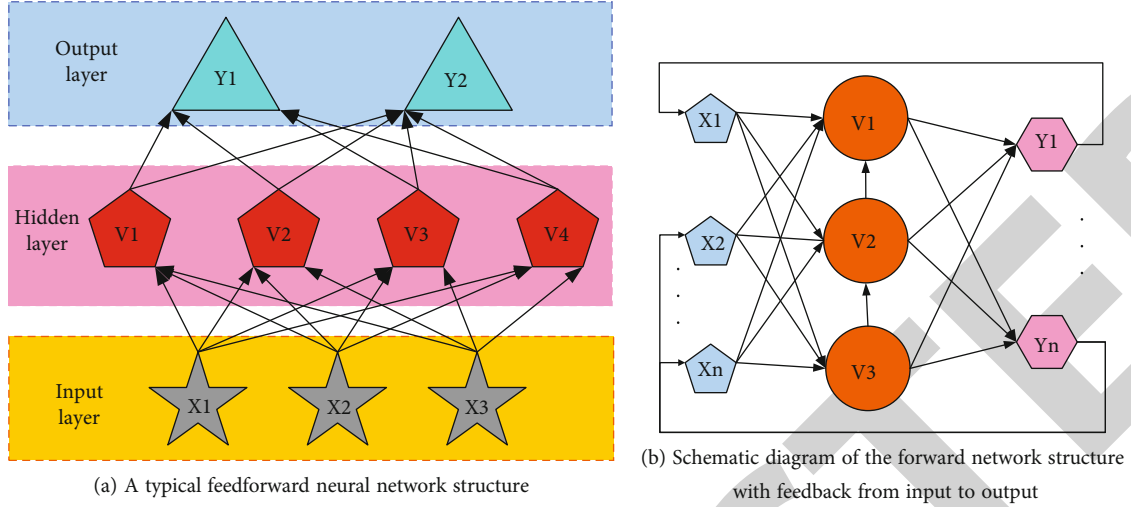


FIGURE 4: Neural network classification.

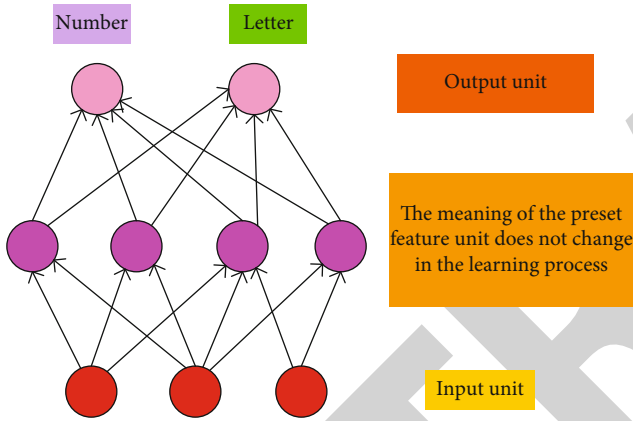


FIGURE 5: The first-generation neural network perceptron model.

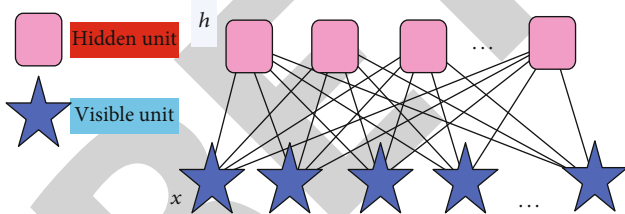


FIGURE 6: RBM energy model.

Introducing free energy transforms formula (5) into

$$p(x) = \frac{e^{-\text{freeEnergy}(x)}}{Z}, \quad (6)$$

$Z = \sum_x e^{-\text{freeEnergy}(x)}$, in formula (6), namely,

$$\text{freeEnergy}(x) = -\log \sum_h e^{-\text{energy}(x,h)}. \quad (7)$$

Introducing θ to represent the parameters of the model, taking the logarithm of formula (6) and taking the derivation to obtain

$$\begin{aligned} \frac{\partial \log p(x)}{\partial \theta} &= -\frac{\partial \text{freeEnergy}(x)}{\partial \theta} + \frac{1}{Z} \sum_{\tilde{x}} e^{-\text{freeEnergy}(\tilde{x})} \\ &\quad \cdot \frac{\partial \text{freeEnergy}(\tilde{x})}{\partial \theta} \\ &= -\frac{\partial \text{freeEnergy}(x)}{\partial \theta} + \sum_{\tilde{x}} p(\tilde{x}) \frac{\partial \text{freeEnergy}(\tilde{x})}{\partial \theta}. \end{aligned} \quad (8)$$

In order to deal with the difficult calculation of RBM partition function, the approximate value of log likelihood gradient $\partial \log p(x)/\partial \theta$ is usually used for training. The model parameter update rule is defined by the free energy gradient on the sample $x \sim p(x)$ subject to the data distribution and the sample $\tilde{x} \sim p(\tilde{x})$ subject to the model distribution as follows:

$$E_{\hat{p}} \left[\frac{\partial \log p(x)}{\partial \theta} \right] = -E_{\hat{p}} \left[\frac{\partial \text{freeEnergy}(x)}{\partial \theta} \right] + E_p \left[\frac{\partial \text{freeEnergy}(\tilde{x})}{\partial \theta} \right], \quad (9)$$

where p is the model probability distribution, $E_{\hat{p}}$ and E_p are the expected values under the corresponding probability distribution, and \hat{p} is the empirical probability distribution of the training dataset. The first term of formula (9) is relatively simple and is generally replaced by the training sample expectation; the second term contains the samples obtained from the model p . The samples are generally sampled by means of the Monte-Carlo Markov Chain (MCMC) algorithm [18].

(2) *Self-Encoding Network*. Autoencoder network is a special feedforward neural network, which is mainly used in tasks such as dimensionality reduction, nonlinear feature extraction, and expression learning. The overall structure is shown in Figure 7.

Autoencoders mainly consist of an encoder and a decoder that generates reconstructions [19]. The encoder

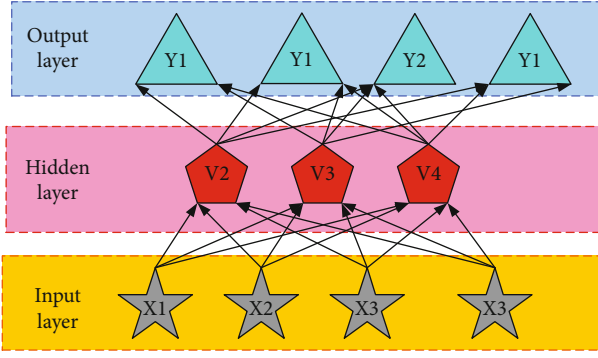


FIGURE 7: Autoencoder network structure with only one hidden layer.

can be represented by the function $D = F(x)$, and the decoder can be represented by the function $S = J(D)$. Its related formula is as follows:

$$D_i = F(Qx_i + B), \quad (10)$$

$$\hat{x}_i = F(Q'x + A). \quad (11)$$

Among them, F represents the nonlinear activation function, which is generally a sigmoid function. Among them, $Q = \sum_{i=1}^N Q_{ij}x_i$ and $Q' = \sum_{i=1}^M Q_{ij}x_i$ are the weight matrices of the encoder and decoder, respectively. B and A are the biases of hidden layer D and input layer x , respectively. Due to the limited ability of a single-layer autoencoder to extract signal features, classifiers such as SVM and SoftMax are generally added to the autoencoder [20].

3.3. Convolutional Neural Networks. As indicated by the organization engineering, brain organizations can be isolated into two sorts: feedforward brain organizations and intermittent convolutional neural network (CNN) are a profound feedforward brain network with nearby association and weight sharing qualities. CNN is primarily utilized for different assignments in pictures and recordings, like face acknowledgment and picture division. It has been generally utilized in normal language handling, recommender frameworks, and different fields. This paper utilizes convolutional brain organizations to handle text and get text feature networks [21]. The schematic diagram of CNN is shown in Figure 8.

A convolutional neural network is essentially an end-to-end mapping that goes from one end to the other. What the network model needs to learn is this end-to-end mapping rule. There is no explicit mathematical expression for this rule; it is learned through training and learning from a large amount of training data. All weights need to be initialized during training. It generally initializes the network with a small random number. The purpose of this is to avoid saturation in advance due to the influence of some abnormal weight items during the training process, because too large weights will lead to training failure. Secondly, due to the random nature of random numbers, different values will be generated, and these different values can ensure the normal

training and learning of the model [22]. The training process is described.

The preparation interaction comprises 4 stages, which can be partitioned into two fundamental stages:

- (1) The main stage, the forward engendering stage
 - (i) Extract an example (A, B_v) from the dataset and input it into the organization
 - (ii) Calculate its comparing real result U_v

In this stage, the example data goes through the change of each layer from the info layer, lastly arriving at the result layer. The statement of the execution cycle of the organization is

$$U_v = g_n(\dots(g_2(g_1(A_v T^1) T^2) T^m \dots)). \quad (12)$$

- (2) The subsequent stage, the back spread stage
 - (i) Take the contrast between the real result esteem U_v and the ideal result B_v as the blunder esteem
 - (ii) Adjust the weight coefficient as indicated by the technique for limiting the blunder

The two phases of activity have accuracy prerequisites. Here, E_v is characterized as the mistake size of the v th preparing test in the model. The general blunder of the whole organization model is characterized as E , and the numerical depictions are as per the following:

$$E_v = \frac{1}{2} \sum_{j=1}^n (B_{vj} - U_{vj})^2, \quad (13)$$

$$E = \sum E_v. \quad (14)$$

It can be seen from the description that the input sample data is firstly forwarded to calculate the error and then back-propagated to pass the error layer by layer to adjust and update the weights. In order to fully describe the training process, let the number of input layer, hidden layer, and output layer be O , P , and Q , respectively.

Set up, respectively,

$$A = (a_1, a_2, \dots, a_o). \quad (15)$$

Input vector added to the network:

$$R = (r_1, r_2, \dots, r_p). \quad (16)$$

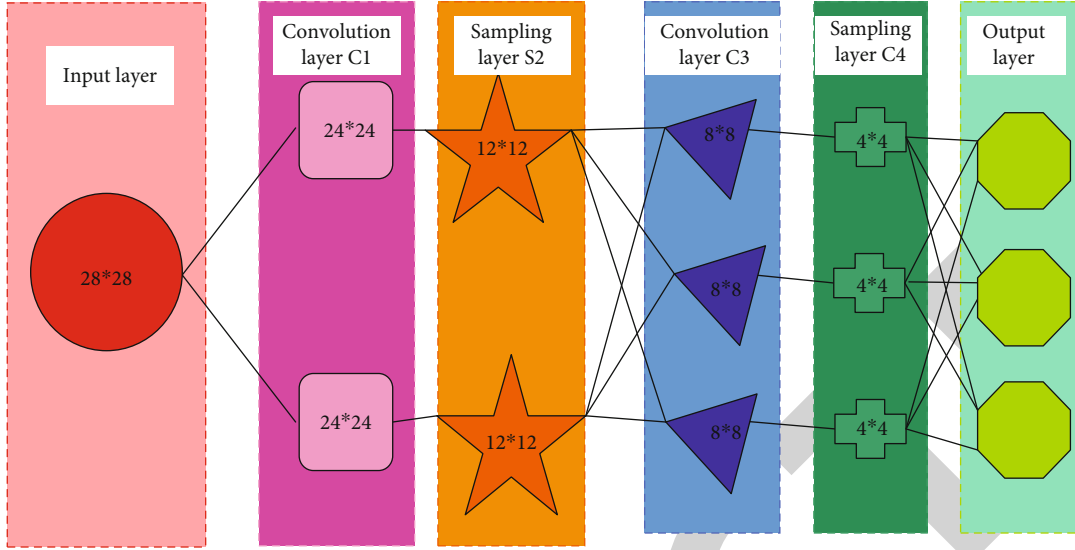


FIGURE 8: CNN schematic.

Intermediate layer output vector:

$$B = (b_1, b_2, \dots, b_q). \quad (17)$$

The actual output vector of the network and use

$$C = (c_1, c_2, \dots, c_q). \quad (18)$$

Addressing the objective result vector of every module of the preparation information, the load from the result unit I to the halfway unit j is set as W_{ij} , and the load from the transitional unit j to the result unit m is set as T_{jm} . Utilize ε_m and φ_j to signify the edges of result cells and halfway cells.

Accordingly, the result of the center layer is the equation

$$S_j = g \left(\sum_{i=0}^o W_{ij} A_i + \varphi_j \right). \quad (19)$$

The output of the output layer is the formula

$$B_m = g \sum_{j=0}^p T_n R_j + \varepsilon_m, \quad (20)$$

where $g(\bullet)$ is the excitation work and the sigmoid capacity is utilized, which is communicated as follows:

$$g(A) = \frac{1}{1 + E^{-ma}}. \quad (21)$$

4. Experiment and Analysis of Serialized Recommendation Algorithm Model Based on Deep Neural Network

The general model of the personalized recommender system is shown in Figure 9.

4.1. Dataset Introduction and Processing. Sequence recommendation is also called next item/basket recommendation. There will be a time limit when evaluating. The evaluation index considers that the user visits the recommended location within a period of time after the system recommends, and it is considered a hit.

The experiments in this section use the MovieLens datasets ml-100k, ml-1M, ml-10M and amazon datasets. The ml-100k, ml-1M, and ml-10M data are obtained by collecting the real ratings of the movies by users on the Movie Recommender System website, and the ratings range from 1 to 5 points. The larger the rating value, the more interested the user is in the movie. The ml-100k contains 94901 rating pairs for 1550 movies by 951 users. ml-1m contains 993,583 rating pairs for 3552 movies by 6052 users. ml-10m contains 9945935 rating pairs for 10085 movies by 6991 users. Amazon contains 238456 rating pairs for 18119 items by 81441 users.

In the trial, the scoring informational index was arbitrarily isolated into preparing set and test set by the proportion of 8:2 or, at least, the preparation set represented 80% and the test set represented 20%. Amazon data contains user data, item data, and rating data. The user data includes user ID, gender, occupation, and region. In the data, the gender of the user is represented by 0 and 1 to represent "female" and "male," the age field is represented by 7 consecutive numbers 0~6, the occupation is represented by 1-20 consecutive integers, and the area code is converted into a numeric field. Movie data includes movie number, title, release year, and movie genre. Because the data for the movie only has the name and genre. In order to make up for the sparse data, this paper adds movie content information and uses convolutional neural network to process the movie content information. Since the MovieLens dataset does not contain item description documents, it needs to obtain the description documents of the corresponding items from IMDB, that is, movie abstracts. This article uses the user's comment data file on the item in the amazon dataset as the description

The general model of the personalized recommender system is shown in Figure 9.

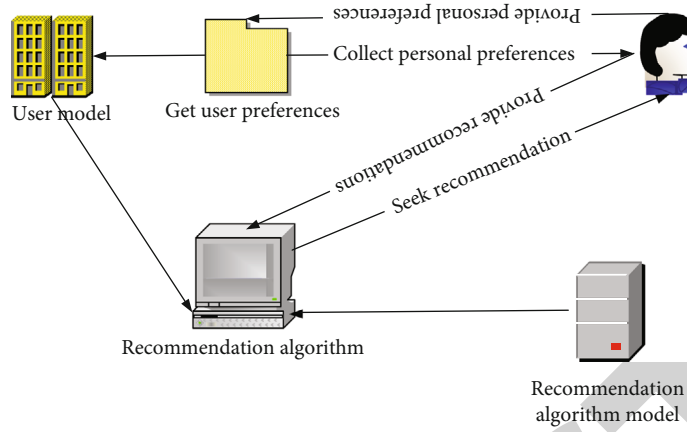


FIGURE 9: Generic model of a personalized recommender system.

TABLE 1: Dataset assignment.

Dataset	Number of users	Number of items	User item scoring items
ml-100k	951	1550	94901
ml-1m	6052	3552	993583
ml-10m	6991	10085	9945935
Amazon	81441	18119	238456

TABLE 2: The effect of the number of iterations on the experimental results.

Dataset	20	40	60	80	100
ml-100k	0.815	0.7155	0.7052	0.7022	0.6856
ml-1m	0.7422	0.6881	0.6751	0.6666	0.6577
ml-10m	0.7571	0.7009	0.6549	0.6711	0.6679
Amazon	0.9705	0.9466	0.9228	0.9066	0.8944

document of the item. In the experiment, the item data without text auxiliary information was deleted, the document size was set within 300 words, and the missing value in the original score matrix was set to 0. The dataset assignments are shown in Table 1.

4.2. Influence of the Number of Iterations on the Experimental Results. While preparing the model, the preparation impact of the model will be impacted by the quantity of epochs of preparing, and tries are done on the informational collection in regard to the impact of the quantity of cycles on the consequences of the calculation. The particular root mean square mistake values are displayed in Table 2.

It very well may be seen from the trial results that the quantity of emphases increments constantly under the four datasets. The RMSEs of all four datasets gradually decrease, indicating that the recommendation quality improves with increasing iterations. Between epochs = 80 and epochs = 100, the reduction in RMSE becomes smaller, so the number of iterations between [80, 100] is preferred. The RMSE drops to around 0.7 after 100 iterations. And it can also be seen that the experimental effect of the model on the denser dataset is better than that of the sparse dataset.

4.3. Comparison and Analysis of Results of Different Models. To verify the performance of the DNCF algorithm proposed in this chapter combining user and item attribute information, it is compared with the following commonly used recommendation algorithms.

- (1) CMF (Collective Matrix Factorization): it is a model that decomposes multiple sources at the same time, including the user-item rating matrix and the matrix containing auxiliary edge information
- (2) PMF: it is a broadly utilized lattice factorization model, which means to deteriorate the client thing rating grid, which is the client and thing highlight vectors
- (3) SVD: this calculation depends on the solitary worth disintegration technique, where the client thing rating grid is deteriorated into three networks, and these lattices are utilized for rating forecast
- (4) Item-based: the thing-based cooperative sifting calculation computes the similitude between things as per the client thing rating framework and afterward prescribes comparable things to the client in the run-down of things they like. RMSE and recall are used to evaluate the results of the algorithm model and other methods in this chapter. The length of the produced suggestion list is 50 and the quantity of emphases is 80. The particular outcomes are displayed in Table 3 and Figure 10

It can be seen from Figure 10(a) that the traditional recommendation model does not add auxiliary information. It only uses a sparse scoring matrix for scoring prediction, and the effect is relatively poor. Compared with the other three traditional methods, the effect of CMF is better due to the addition of side information to the model. However,

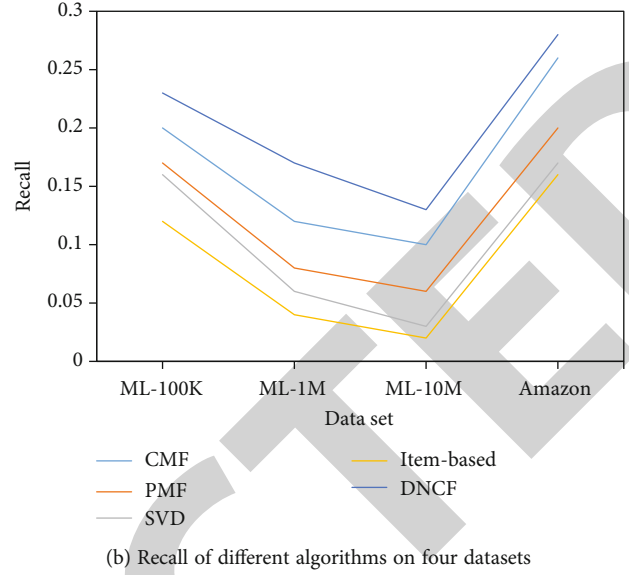
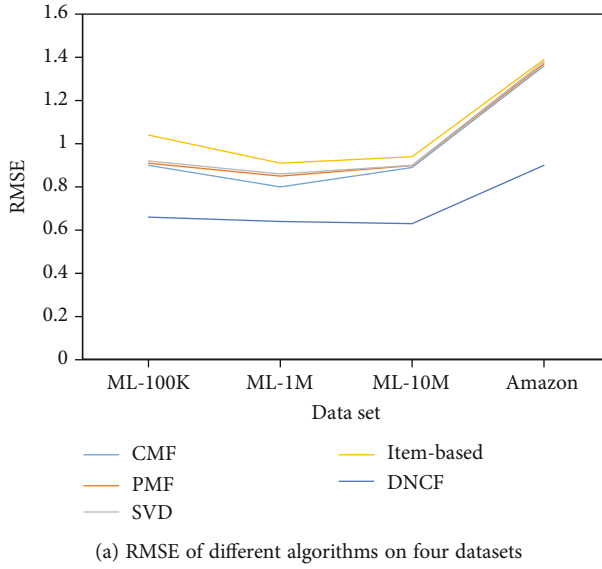


FIGURE 10: Comparison of different distributions on the four datasets.

TABLE 3: RMSE of different models on different datasets.

Method	ml-100k	ml-1m	ml-10m	Amazon
Item-based	1.045	0.9211	0.9640	1.3842
SVD	0.9295	0.8619	0.9049	1.3859
PMF	0.9138	0.8521	0.8966	1.3779
CMF	0.9056	0.8266	0.8878	1.3668
DNCF	0.7022	0.6678	0.6601	0.9055

the edge information is relatively sparse, so it is not as good as the model DNCF proposed in this chapter. The DNCF model uses CNN to process textual information, makes more full use of textual information, and integrates it into the corresponding item features. It enriches the project data more effectively and also shows that the deep neural network structure can better obtain the features of auxiliary edge information. Therefore, the effect of the DNCF model is relatively good.

From Figure 10(b), it can be seen that item-based algorithm has the worst effect, because this method mainly calculates the similarity between items by scoring and does not consider other relationships between data. The other three recommendation algorithms are based on matrix factorization to obtain other hidden features of users and items, but only use rating data. Due to the sparsity of the data, the generated recommendation effect is not ideal. Simultaneously, it very well may be seen that the model DNCF proposed in this section is better compared to the famous SVD calculation. The adequacy of DNCF should be visible from the test aftereffects of RMSE and recall.

4.4. Influence of the Number of Hidden Layers in the MLP Network on Performance. To confirm the impact of the quantity of stowed away layers in the DNN network on RMSE, the quantity of stowed away layers in the investiga-

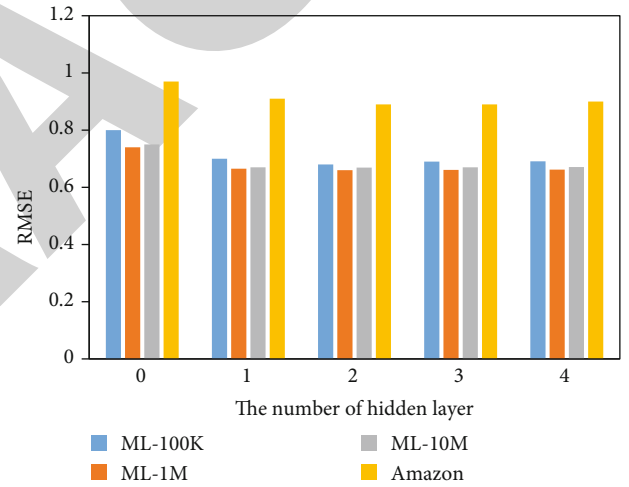


FIGURE 11: The effect of the number of hidden layers on RMSE.

tion is set to be 0~4. The exploratory outcomes are displayed in Figure 11.

It very well may be seen from Figure 11 that properly expanding the quantity of stowed away layers can altogether work on the presentation of the model, yet assuming in excess of 2 secret layers are utilized, the exhibition of the model will scarcely get to the next level. Through analysis, it is believed that due to the influence of the dimension of the input data, too many hidden layers may lead to overfitting; therefore, the number of hidden layers in the DNN network is set to 2.

5. Discussion

Whenever there are an enormous number of stowed away layers and secret hubs in the brain organization, the customary techniques unite gradually or even neglect to merge. With the quick improvement of data innovation, recorded

information has gathered a lot of information in different fields. The information shows a pattern of dramatic development.

A large amount of information is stored in the time series, and there are also many operating rules. Therefore, through the analysis of these time series data, the evolution law of the data can be found, so as to realize the prediction before the system runs. It has important practical significance and application value.

By observing and studying time series data, we can predict future changes and allow people to make reasonable adjustments ahead of time. This is why it is very important to make reasonably efficient time series forecasts. Be that as it may, with the improvement of distributed computing, portable Internet and the Internet of Things, how much information has expanded significantly, and how to make forecasts rapidly and precisely has turned into a pressing issue to be tackled.

6. Conclusion

The main research purpose of this topic is to combine deep learning with serialized recommendation techniques. This paper uses the advantages of deep learning to automatically extract features to obtain higher-level user and item features from user and item information, alleviating the cold-start problem in recommender systems. This paper proposes two recommendation models. The main work of this paper is to test two models on the MovieLens and Amazon datasets. Experimental results show that the two models proposed in this paper outperform CME, PMF, SVD, and item-based algorithms, and the mDAE model outperforms DNCF. The two models proposed in this paper also have shortcomings. Since the combination of different neural network models makes the experiment time-consuming, the model needs to be further optimized.

Data Availability

No data were used to support this study.

Disclosure

The author declares that the manuscript is an original manuscript, without plagiarism, and the repetition rate is qualified.

Conflicts of Interest

There are no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal.

References

- [1] M. Gong, J. Zhao, J. Liu, Q. Miao, and L. Jiao, "Change detection in synthetic aperture radar images based on deep neural networks," *IEEE Transactions on Neural Networks*, vol. 27, no. 1, pp. 125–138, 2016.
- [2] Y. G. Jiang, Z. Wu, J. Wang, X. Xue, and S. F. Chang, "Exploiting feature and class relationships in video categorization with regularized deep neural networks," *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 40, no. 2, pp. 352–364, 2018.
- [3] W. Bo, K. Li, M. Yang, and C. H. Lee, "A reverberation-time-aware approach to speech dereverberation based on deep neural networks," *IEEE/ACM Transactions on Audio Speech & Language Processing*, vol. 25, no. 99, pp. 102–111, 2017.
- [4] C. Sánchez-Sánchez and D. Izzo, "Real-time optimal control via deep neural networks: study on landing problems," *Journal of Guidance, Control, and Dynamics*, vol. 41, no. 5, pp. 1122–1135, 2018.
- [5] C. Yan, H. Xie, D. Yang, Y. Jian, and Q. Dai, "Supervised hash coding with deep neural network for environment perception of intelligent vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 99, pp. 284–295, 2017.
- [6] M. Gong, J. Liu, H. Li, Q. Cai, and L. Su, "A multiobjective sparse feature learning model for deep neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 12, pp. 3263–3277, 2015.
- [7] Y. B. Wang, Z. H. You, X. Li et al., "Predicting protein–protein interactions from protein sequences by a stacked sparse auto-encoder deep neural network," *Molecular Bio Systems*, vol. 13, no. 7, pp. 1336–1344, 2017.
- [8] N. Pezzotti, T. Höllt, J. Van Gemert, B. P. Lelieveldt, E. Eisemann, and A. Vilanova, "Deep eyes: progressive visual analytics for designing deep neural networks," *IEEE Transactions on Visualization & Computer Graphics*, vol. 24, no. 1, pp. 98–108, 2018.
- [9] S. P. Samyuktha, P. Kavitha, V. A. Kshaya, P. Shalini, and R. Ramya, "A survey on cyber security meets artificial intelligence: AI-driven cyber security," *Journal of Cognitive Human-Computer Interaction*, vol. 2, no. 2, pp. 50–55, 2022.
- [10] Y. Jiang, K.-K. R. Choo, and H. Ko, "A special section on deep & advanced machine learning approaches for human behavior analysis," *Journal of Information Processing Systems*, vol. 17, no. 2, pp. 334–336, 2021.
- [11] R. Surendran, O. I. Khalaf, and C. Andres, "Deep learning based intelligent industrial fault diagnosis model," *CMC-Computers, Materials & Continua*, vol. 70, no. 3, pp. 6323–6338, 2022.
- [12] K. Sachdeva and S. Aggarwal, "A hybrid approach for neural network in pattern storage," *Fusion: Practice and Applications*, vol. 6, no. 2, pp. 43–49, 2021.
- [13] P. Yin, S. Zhang, J. Lyu, S. Osher, Y. Qi, and J. Xin, "BinaryRelax: a relaxation approach for training deep neural networks with quantized weights," *SIAM Journal on Imaging Sciences*, vol. 11, no. 4, pp. 2205–2223, 2018.
- [14] Y. Cheng, D. Wang, P. Zhou, and T. Zhang, "Model compression and acceleration for deep neural networks: the principles, progress, and challenges," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 126–136, 2018.
- [15] A. A. Elngar, M. Arafa, A. Fathy et al., "Image classification based on CNN: a survey," *Journal of Cybersecurity and Information Management*, vol. 6, no. 1, pp. 18–50, 2021.
- [16] H. Li, L. Zhang, X. Zhou, and B. Huang, "Cost-sensitive sequential three-way decision modeling using a deep neural network," *International Journal of Approximate Reasoning*, vol. 85, pp. 68–78, 2017.

- [17] H. Hu, T. Bo, X. Gong, W. Wei, and H. Wang, "Intelligent fault diagnosis of the high-speed train with big data based on deep neural networks," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 4, pp. 2106–2116, 2017.
- [18] Y. H. Chen, J. Emer, and V. Sze, "Using dataflow to optimize energy efficiency of deep neural network accelerators," *IEEE Micro*, vol. 37, no. 3, pp. 12–21, 2017.
- [19] W. Wei, Y. Sheng, J. Wang, X. Zeng, and Z. Ming, "HAST-IDS: learning hierarchical spatial-temporal features using deep neural networks to improve intrusion detection," *IEEE Access*, vol. 6, no. 99, pp. 1792–1806, 2018.
- [20] Z. Qawaqneh, A. Abu Mallouh, and B. D. Barkana, "Deep neural network framework and transformed MFCCs for speaker's age and gender classification," *Knowledge-Based Systems*, vol. 115, pp. 5–14, 2017.
- [21] H. S. Gill, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Multi-model CNN-RNN-LSTM based fruit recognition and classification," *Intelligent Automation & Soft Computing*, vol. 33, no. 1, pp. 637–650, 2022.
- [22] S. Mandour, "An improved equilibrium optimizer algorithm for tackling global optimization problems," *Fusion: Practice and Applications*, vol. 3, no. 1, pp. 1–28, 2021.