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Research Article

Human Resource Matching Support System Based on Deep Learning

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Aiming at the problem of reasonable recommendation and accurate matching of human resources, a hybrid human resources matching recommendation algorithm based on GBT-CNN is proposed in this article. The advantages of traditional GBT and CNN algorithms are combined and can give full play to the high-level feature abstraction ability of convolution processing. The gradient lifting tree is used to transform the features, complete the feature screening and coding, and then input the hybrid convolution neural network to obtain the high-dimensional feature abstraction by using the hybrid convolution operation, to improve the quality of human resources recommendation. In this article, GBT and CNN algorithms are first described, and then the basic framework and specific implementation of GBT-CNN algorithm are introduced. Finally, the effectiveness of the algorithm is verified by simulation experiments. The results show that the deeper correlation between job seeker information and job information can be effectively captured by the algorithm. Besides, reasonable recommendation and accurate matching of human resources can be realized.

1. Introduction

Recently, more and more recruitment information are published on recruitment websites by companies. At the same time, job seekers will also browse and find companies that meet their satisfaction on the website [1]. However, with the explosive growth of online information and the increasing number of human demand side, the problem of effective matching of human resources gradually appears. In the past decades, with less information on the network, major recruitment websites can extract information according to the location, type, and personnel keywords. However, with the increasing number of job seekers, employers need to take effective measures to quickly obtain the key information of job seekers, to lock the target as soon as possible, which is also a thorny problem faced by enterprises. The traditional way used by the website is to match human resources through keywords such as post, age, education, and even marriage and childbirth, which were more effective in the past. However, with the explosive growth of the amount of information, the traditional methods can no longer meet the needs. Therefore, personalized accurate matching has attracted people's attention. The characteristic of personalized matching is that it can extract qualified personnel from a large amount of information according to more accurate and quantitative information. At present, the traditional recommendation methods used by major recruitment platforms are classified by job nature and keyword search. The above two methods are simple and easy to implement, but in the face of massive data, these traditional methods are difficult to meet the requirements. A large number of recruitment is easy to make job seekers fall into a state of confusion, which makes it difficult for them to effectively screen enterprises that meet their own requirements and even produce ambiguity and uncertainty about their actual needs, which will inevitably require them to spend more efforts to find the job information that is really suitable for them. In this case, the employment difficulty of the talent market also appears. Therefore, how to effectively recommend human resources is the key measure to alleviate the employment difficulties in the talent market. This is also the problem expected to be solved in this article.

Facing the limitations of search engines in dealing with information overload, researchers put forward the solution of a recommendation system. The recommendation system uses the user's historical information to build the preference model, and then matches the content information provided, to recommend the content that the user may like, which makes up for the deficiency of the search engine. The main task of the recommendation system is to locate and push their favorite content to users from a large amount of information. While helping users find the content information they are interested in, the information can be displayed in front of users who can produce value, to achieve a win-win situation for users and service providers. A recommendation system is the main tool to solve the problem of information overload in the Internet environment, which has been widely used in various network information service fields. Because of the application value, recommendation system has not only become one of the research topics in the computer field but also attracted many other researchers from different fields. For example, lots of universities and research institutions (such as Microsoft Research Institute, APEX Laboratory of Shanghai Jiaotong University, and the GroupLens team of the Minnesota University) have carried out a lot of research work on the subject of recommendation system and algorithm. Recently, some open-source recommendation system projects have been developed and put into applications [2]. In the industrial part, the recommendation system is regarded as one of the core contents of enterprise research and development, such as Amazon and Taobao in the field of e-commerce, Facebook and microblog in the field of online social networking, and Google News and today's headlines in the field of news. Similar to e-commerce and social networks, the field of human resources recruitment is also carrying out technological innovation with the development of the Internet. Nowadays, there is a wide range of recruitment websites in China, such as Zhilian recruitment, pull hook, and Wuba company, while foreign successful recruitment websites include Xing, LinkedIn, CareerBuilder, etc. The frequency and proportion of candidates obtaining recruitment information through the Internet are higher and higher, and recruiters are more willing to put recruitment information on the Internet to attract talents than ever before. The amount of human resources information such as talent information and post information has also increased unprecedentedly [3]. Obtaining qualified recruitment information is a key step to find an ideal job. Recruitment websites should better bridge the gap between candidates and enterprises, which is inseparable from the support of a personalized recommendation system. However, although the human resources field is paying more and more attention to the recommendation system, the application value of the human resources recommendation system is improving slowly, and the research results of recommendation algorithm innovation in the human resources field are very few. Therefore, the research topic of the human resources recommendation algorithm in this article has a certain practical significance.

Human resource matching refers to matching the right talents for the right job by effectively connecting the basic information of job seekers with job requirements. Resume recommendation is one of the important links, which mainly automatically recommends suitable talents for enterprises according to the recruitment information of enterprises. Resume recommendation algorithms are mainly divided into three categories. The first category is resume recommendation based on a personalized recommendation algorithm, including content-based recommendation, collaborative filtering-based recommendation, and hybrid model-based recommendation. The second is resume recommendation based on ontology domain knowledge. The third category is a recommendation based on deep learning algorithm. Among them, the recommendation algorithm based on deep learning is the most promising method at present. The purpose of its application in human resources recommendation is mainly to solve the complex matching between resume content and job requirements [4]. At present, an effective processing method is to fuse the surface and deep information in the recommendation results, and the mixed user model is generated and used for recommendation. Then, using the comprehensive feedback information of users, the performance of the human resources recommendation system is strengthened [5, 6]. Another method is to define the human resource recommendation problem as a supervised machine learning problem, and the prediction model is established by using work history and employee information. Then, the future work of employees can be predicted [7–9]. In addition, some deeper research has been carried out. A calculation strategy combining interest sensitivity was proposed in [10], in which the interest sensitivity of enterprise users is calculated by using the recruitment data of different enterprises for job seekers. In this way, the similarity calculation between job seekers is optimized and improved. In ref. [11], combined with the historical information of school, a calculation method based on the correlation between content and school information is proposed, and the factors of interest and preference are also considered. This model is used to solve the problem of information asymmetry in the employment field of graduate job seekers. In ref. [12], slope one algorithm and employment information content are organically combined with similarity, and personalized employment recommendation is optimized.

From the existing algorithm research in the field of human resources, most of the algorithms applied to human resources recommendation are mature and stable traditional recommendation algorithms (such as collaborative filtering recommendation algorithm) or improved algorithms that innovate on traditional algorithms. Generally speaking, the algorithms currently used have the disadvantage of a single implementation mode, and the advantages of emerging technologies have not been effectively utilized, which leads to the unsatisfactory performance and personalized recommendation intensity of these algorithms. This article hopes to make full use of the advantages of emerging technologies such as deep learning, focus on the problems existing in human resource matching, and further study and improve the traditional algorithms. Of course, this does not mean the negation and abandonment of traditional algorithms. In other words, with the help of the efficiency of artificial intelligence and big data, we can process a large amount of information through more powerful computing power, to improve the efficiency of human resource matching. Then the existing problems such as unreasonable human resource matching and waste of human resources are expected to be solved efficiently.

2. Basic Theory and Algorithm

2.1. Introduction of Deep Learning. Deep learning is a machine learning method, which needs representation learning for data. The main task of machine learning is to design a series of algorithms and realize the goal of computer automatic learning related knowledge by analyzing these algorithms. The correlation law is obtained by analyzing the data, and then the unknown data can be predicted, which is an important feature of machine learning algorithms. A large number of reasoning and statistics-related theories are included in machine learning theory, which focuses on practical and efficient learning algorithms. For problems with difficult law exploration, machine learning is replaced by approximate algorithms [13, 14]. For example, there may be a variety of feature description methods for an image, such as pixel intensity value, contour and edge information, or expressed with more abstract features. The use of specific representation methods will make some learning tasks easier to complete. The motivation of deep learning is to simulate the human brain to build a network to interpret sound, text, and image, and solve some tasks efficiently instead of human beings. Nowadays, all aspects of modern society are dominated by deep learning to varying degrees, which provides strong support for social life, such as browser advertising recommendation algorithm and intelligent search; in the fields of smartphones and cameras, such as face recognition, weather recognition, and plant recognition; in the fields of intelligent applications, such as voice and text conversion in voice technology, recommendation of relevant topic videos according to users' preferences in short videos, and products of interest. Before the emergence of deep learning, traditional machine learning technology needs to design strict artificial features. This work requires sufficient professional knowledge reserve and takes a lot of time [15]. The designed feature extractor represents the original picture by means of a feature vector and then completes relevant tasks through the classifier. This feature design method is difficult, costly, and feature representation is very limited, so it cannot be widely applied to the complex tasks of social life.

The underlying logic of deep learning is multilevel representation, and its hierarchical structure is mainly realized by the neural network. The artificial neural network reads the original data as input for processing, extracts the shallow features such as edge information in the shallow layer, and extracts the abstract features such as semantic information in the deep layer. It represents the original data as a more abstract representation through the complex neuron connection mode and updates the parameter weight of each layer of neurons in the training through the back-propagation method. Autonomous learning through the neural network is an important feature of deep learning. With a large number of updatable parameters, deep learning technology can learn different discriminant features for different tasks. For the classification task, the classification features of objects can be learned by the neural network. For the detection task, the classification and position discrimination features of objects can be learned by the neural network. For the segmentation task, the classification of objects and the discrimination characteristics of pixel level can also be learned by the neural network. Therefore, deep learning has a powerful representation function and broad application space.

In terms of categories, deep learning can be roughly divided into two categories: the generative model and the discrimination model. The existing recommendation algorithms based on deep learning mostly adopt the algorithm integrating the deep learning model with the traditional recommendation algorithm. The corresponding models include the Boltzmann machine, convolutional neural network (CNN), cyclic neural network (RNN), trestle denoising self-encoder, etc. [16–18], as shown in Figure 1. Compared with traditional methods, deep learning has significant advantages in image and voice, but it also has the problems of long training time and different convergence speed, which is also the direction of continuous progress of deep learning. Among many deep learning algorithms, the convolutional neural network is the most widely used algorithm with the highest technical maturity.

2.2. Gradient Boosting Tree. Gradient boosting tree (GBT) is based on the boosting idea in ensemble learning and runs in serial mode [19–21]. In each iteration, a weak learner (decision tree $T_1 \sim T_{\mathrm{m}}$) is selected, and a new decision tree is established in the gradient direction of reducing the residual ($F_0 \sim F_{\mathrm{m}}$). The principle of GBT is shown in Figure 2. Through the linear addition model, the results of each decision tree are weighted and accumulated to obtain the final prediction results. The mathematical expression of the model can be expressed as

$$F(x, w) = \sum_{t=0}^{T} a_t h_t(z, w_t) = \sum_{t=0}^{T} f(x, w_t), \tag{1}$$

where x is the total input sample, $h_t(x, w_t)$ is the regression tree for each classification, w_t is the parameters of each classification regression tree, a_t is the weight of each tree, and T is the number of decision trees.

A weak learner is obtained in each iteration, and the loss function is:

$$\widetilde{w} = \arg\min \sum_{t=0}^{N} L\left[y_i, F_{t-1}(x_i, w_t) + h(x_i, w_t)\right], \tag{2}$$

where $F_{t-1}(x_i, w_t)$ is the current model, and the parameters of the weak classifier are determined by minimizing the value of the loss function under GBT.

The choice of loss function itself can include L1, square loss, 0-1, etc. In this study, the square loss function is selected and the corresponding mathematical formula is

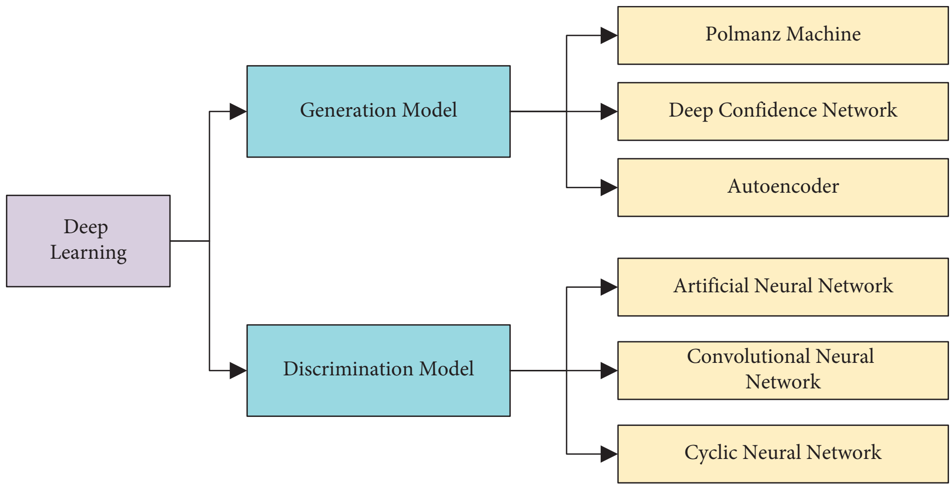

FIGURE 1: System of deep learning.

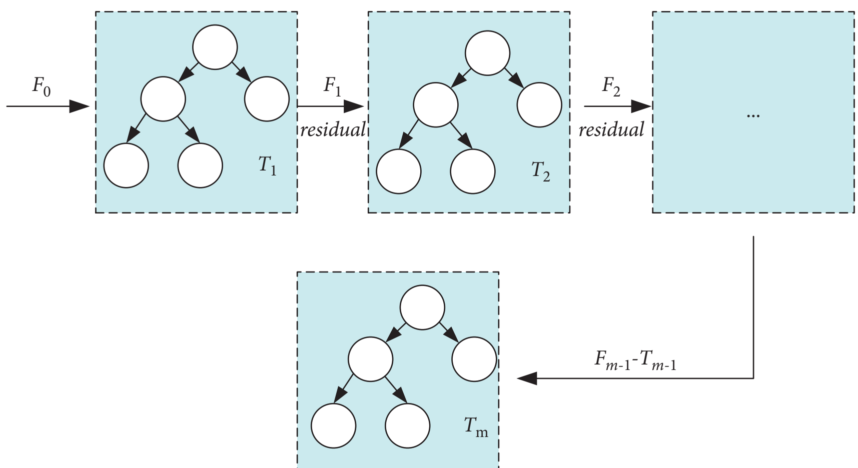

FIGURE 2: Training process of GBT model.

$$e = \frac{1}{2}\left[y_i - h\left(x_i\right)\right]^2, \tag{3}$$

where y_i is the true value, $h\ (x_i)$ is the estimated value of the model, and the corresponding difference is the residual. In each iterative training process of GBT, a new decision tree is created in the gradient direction of reducing residuals. The path of each tree from root node to leaf node represents different feature combinations, which makes GBT have a natural advantage feature combination.

2.3. Convolutional Neural Network. Convolutional neural network is connected by multiple neurons, and the task of information transmission is undertaken by neurons [22–24]. The structural diagram of artificial neurons is shown in Figure 3. There is a visual overlap in the sensory field of vision interacted by different neurons so that neurons can cover the whole perceptible field of vision. With the deepening of theoretical research, there are lots of different structures for neural network models currently. The convolution neural network used in this article is a typical model belonging to the neural network structure. The most important feature is to use the operation of convolution operation for model training.

Convolution network is a hierarchical structure, which usually includes an input layer, convolution layer, activation function layer, pooling layer, and full connection layer. Among them, the convolution layer, activation layer, and pooling layer can be stacked in multiple layers according to the actual needs to design a reasonable network structure to meet the task. The input layer is generally used to preprocess the original data, such as mean removal and normalization. Convolution layer is the most important hierarchical structure of CNN. This layer is used for convolution calculation and extracting important features. Each convolution core contains the attention features of response (such as texture and edge), and the set of convolution cores is equivalent to the feature set of the overall information. The function of the activation layer is to make a nonlinear mapping of the results obtained by convolution, which is convenient to obtain the gradient. The function of the pooling layer is to compress the image and reduce parameters, which can reduce overfitting to a certain extent.

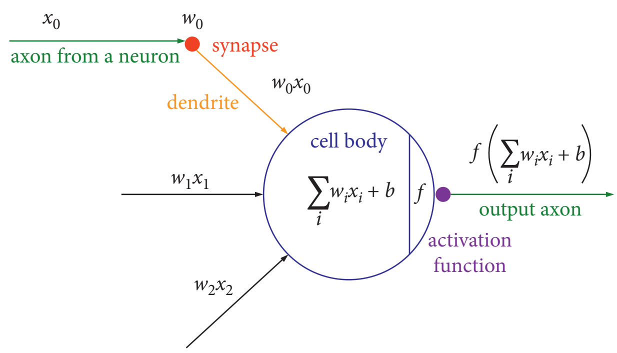

FIGURE 3: Structure of artificial neuron.

Since the application of CNN is also the basis of this article, the hierarchical structure of CNN will be described in detail later. In short, the main operation mode of CNN is layer by layer abstract operation. The mathematical expression is as follows:

$$\begin{aligned} & x^1 \longrightarrow w^1 \longrightarrow x^2 \longrightarrow \ldots \longrightarrow x^{L-1} \longrightarrow w^{L-1} \longrightarrow x^L \longrightarrow w^L \longrightarrow z, \\ & z = f\left(x^L, y\right), \end{aligned} \tag{4}$$

where x^L is the data input of layer L, w^L is the weight of layer L, representing the loss function of this calculation process, and y is the final real classification mark.

At present, more feature extraction networks used in small target detection mainly include VggNet, MobileNet, DenseNet, ResNet, DeepL, and so on. Various novel and efficient convolution models are constantly proposed. Among different network models, the change is to strengthen the relationship between levels, so that the feature information of the target can be extracted more efficiently and quickly.

2.3.1. Convolution Layer. Each convolution layer in CNN contains several convolution subunits, in which the parameters of different convolution subunits are improved and iterated by the back-propagation method. This is a self-renewal process. For example, for some targets that contain a lot of information, the first volume layer can only extract some primary information, which is the basis of other networks. On this basis, more layers of networks further mine complex information from primary features, and then iterate the features, to expand more feature information. The convolution formula is as follows (5) and (6):

$$\begin{aligned} z^{l+1}(i,j) &= [Zt \otimes wl + 1](i,j) + b \\ &= \sum_{K=1}^{Ki} \sum_{x=1}^{f} \sum_{y=1}^{f} \left[Z_K^l \left(s_0 i + x, s_0 j + y\right) w_K^{l+1}(x,y) \right] + b, \end{aligned} \tag{5}$$

$$(i,j) \in \{0, 1 \ldots, L_{l+1}\}, L_{l+1} = \frac{Ll + 2p - f}{s_0} + 1, \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}, \tag{6}$$

where z^{l+1} is the output and input of the l +1 layer respectively, b is the offset, L_{l+1} is the output size of Z_{l+1}, $Z(i,j)$ is the pixel value, K is the number of channels, f is the size of convolution kernel, s_0 is the step size, and p is the number of fills. The principle of convolution operation is shown in Figure 4.

2.3.2. Pool Layer. The pool layer is also known as the downsampling layer, which aims to calculate the pixel value in each fixed window in the feature map. Pooling is equivalent to reducing the input feature map so that the model can extract a wider range of features, which is equivalent to expanding the field of perception. In addition, since the pooling operation reduces the length and width of the characteristic graph, the amount of parameters and calculations are reduced. Because the input is unchanged and the parameter is reduced, the model is not overfitted, and the pooling operation is robust to the interference of noise. A typical pool operation is shown in Figure 5.

2.3.3. Active Layer. Neural network is composed of multilayer composite functions, which needs an activation function to ensure the nonlinearity of the network. This is because no matter how the linear function changes, its result is still a linear function, so the activation layer is needed to activate neurons. In other words, the input of neurons is mapped to the output, which makes the feature expression of the small target detection model more specific. In the early stage, the neural network mainly uses sigmoid as the activation function, and its expression is:

$$\sigma(x) = \frac{1}{1 + e^{-x}}. \tag{7}$$

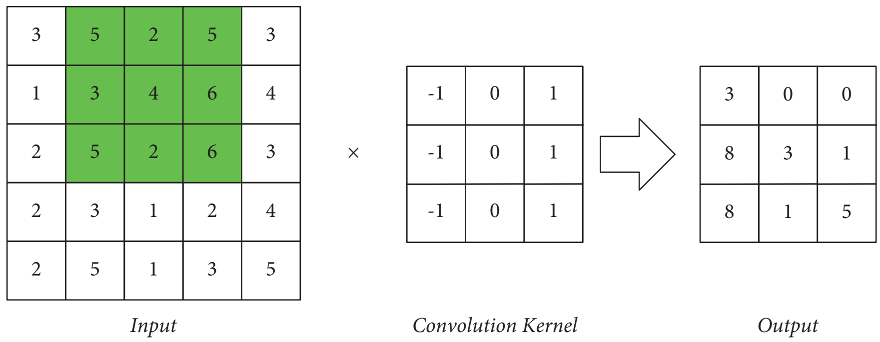

Figure 4: Schematic diagram of convolution operation.

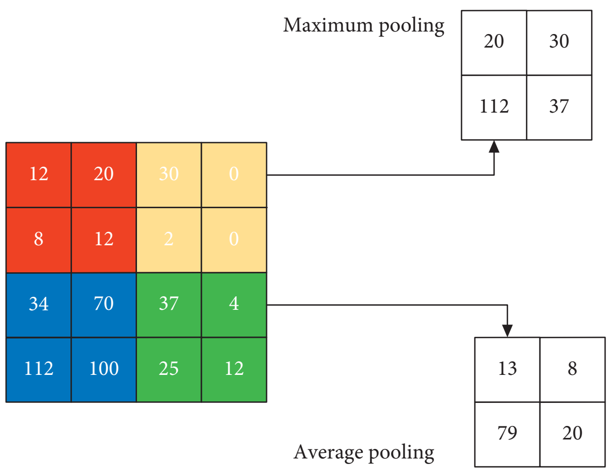

Figure 5: Schematic diagram of pooling mode.

The trend range of this function is [0, 1]. When the input is too large or too small, the gradient of the obtained sigmoid function will be very small. With the deepening of the number of network layers, the network gradient will be attenuated, and finally, the gradient will disappear, which makes it difficult for the network to continue training. To avoid the disappearance of gradient and enhance the convergence of the network model, ReLU is often used as an activation function. The slope of ReLU can be regarded as a nonlinear function near 0, so it can also be regarded as a nonlinear function. When the input value is less than or equal to 0, the calculation of neurons will be stopped by RELU. Such an operation can greatly reduce the amount of calculation. In addition, the interaction between networks is also reduced by the response, which improves the convergence of the model.

$$\mathrm{ReLU}(x) = \max(0, x). \tag{8}$$

2.3.4. Full Connection Layer. The fully connection layer is used for the interconnection of two layers of neurons. Because the convolution layer, pooling layer, and activation function are used to extract features, the full connection layer realizes classification by mapping the features to the sample label space. According to the characteristics of the full connection layer, there are more parameters than other layers. The functional relationship can be expressed in matrix form:

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} w11 & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{33} & w_{33} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix}, \tag{9}$$

where y_1, y_2, and y_3 are the outputs of the full connection layer, and x_1, x_2, and x_3 are the inputs of the full connection layer. For classification tasks such as image recognition and target detection, SoftMax function operation will be carried out after the full connection layer, and each classification result will be output in the form of probability.

2.4. Framework of Deep Learning. With the rapid development of deep learning, different types of deep learning frameworks have been developed. At present, the commonly used deep learning frameworks include TensorFlow, MxNet, Torch, Theano, Keras, etc. It should be noted that different frameworks do not have absolute advantages and disadvantages, but they have different emphases. Table 1 compresses these frameworks.

From the comparison in Table 1, MxNet has obvious advantages in execution efficiency, flexibility, and the completeness of files. Users are allowed to adopt mixed symbolic programming and imperative programming, which ensures that the memory can be used efficiently, and GPU can be applied for parallel and distributed computing. Based on this, MxNet is selected as the basic research framework in this article.

3. Human Resource Matching System Based on GBT-CNN

According to the previous analysis, the computational efficiency of GBT and CNN can provide a feasibility guarantee for more diversified recommendations. To improve the problem of low recommendation quality caused by the limited ability of model feature extraction in traditional recommendation algorithms, the gradient lifting tree and convolutional neural network are synthesized in the paper. In this way, a human resource matching and recommendation algorithm based on GBT-CNN is designed. The core design idea of the algorithm is: firstly, GBT is used for feature

Table 1: Typical deep learning framework.

Framework	Langue	Efficiency	Flexibility	File
TensorFlow	Python/C++	General	High	General
MxNet	C++	High	High	Comprehensive
Torch	Lua/C	High	General	Comprehensive
Theano	Python	General	High	General
Keras	Python	High	High	Comprehensive

transformation processing to complete the screening and coding of the original features, and then the transformed features are input into CNN. Using the high-level feature abstract learning ability of convolution processing, a personalized list of human resources recommendation results is obtained. Based on this hybrid algorithm, a system suitable for human resource matching and recommendation can be constructed. Firstly, human resource data need to be collected, secondly, data preprocessing is carried out in combination with the relevant properties of the human resource field, thirdly, the algorithm used in the human resource recommendation field is realized, and finally, the recommendation result is generated. The overall flow chart is shown in Figure 6.

4. Experiment and Analysis

4.1. Experimental Data Set and Test Environment. To evaluate the performance of the proposed algorithm in human resources recommendation, experiments and analysis are carried out using real data sets. The data set used is the real data collected from a human resources employment platform. Through a series of data preprocessing work, a human resources data warehouse suitable for recommendation is obtained. The data set contains 4784 candidates, 12,000 jobs, and 194,756 user behavior records. The software and hardware environment of the experiment in this article is shown Table 2. The algorithm is implemented through the deep learning framework MxNet, which is built under the operating system Ubuntu kylin 16.04 LTS.

4.2. Evaluation Criteria. To objectively evaluate the simulation results, it is necessary to introduce some quantitative standards. Generally speaking, the indicators recognized by scholars include Precision, Recall rate, and F1_ score. Here, the Recall rate and F1_score are selected for model evaluation, and their expressions are as follows:

$$\begin{aligned} \text{precision} &= \frac{\alpha}{\alpha+\beta}, \\ \text{Recall} &= \frac{\alpha}{\alpha+\gamma}, \\ \text{F1\_Score} &= \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}, \end{aligned} \tag{10}$$

where α is the number of positions that are correctly recommended to job seekers who are really interested in; γ indicates the number of neglected positions, which are actually of interest to job seekers. β is the number of positions wrongly recommended, which are actually not of interest to job seekers.

The reason why recall rate rather than accuracy rate is used as the evaluation standard is that in the human resources recommendation scenario, job seekers will only browse, collect, or apply when they are attracted by the post information. Therefore, it is more valuable to evaluate the recommendation quality of the job information that the job seekers are interested in. In addition to using the recall rate, the evaluation standard of F1_score is also adopted. This evaluation standard comprehensively calculates the accuracy rate and recall rate, and can take into account the measurement of both. This is an overall evaluation standard for integrating the performance accuracy rate and recall rate.

4.3. Result Analysis. Here, the effectiveness of the proposed algorithm is verified. At the same time, to highlight the advantages of the proposed algorithm, it is also compared with the traditional GBT and CNN method. To ensure the credibility of the calculation results, the parameter configuration adopted by the different methods is the same as that of the calculation platform. The experimental results are shown in Figures 7 and 8.

From the above experimental comparison results, it can be seen that when the recommended length of the proposed algorithm is 70, the recall rate is about 0.834 and F1_score is about 0.738, while the recall rate of CNN algorithm excluding GBT is about 0.772 and F1_score is about 0.719. Its effect is not as good as that of the proposed algorithm. In the two recommended quality evaluation criteria, the proposed algorithm improves by 8.03% and 2.64%, respectively, compared with the CNN algorithm without GBT. This proves that directly convoluting the data set can not give full play to the role of high-level feature learning of convolution, but can give better play to the role of convolution through GBT transformation, and the recommendation quality of the model can be effectively improved.

To further compare the advantages of the proposed algorithm with the traditional algorithms, several recommended algorithms which are widely used at present are selected as the comparison object, including user-based collaborative filtering (UserCF), item-based collaborative filtering (ItemCF), content-based recommendation algorithm (CBF), probability-based matrix decomposition (PMF), and four-layer deep neural network (DNN). Similarly, to ensure the credibility of the calculation results, the parameter configuration adopted by the different methods is the same as that of the calculation platform. The experimental results are shown in Figures 9 and 10.

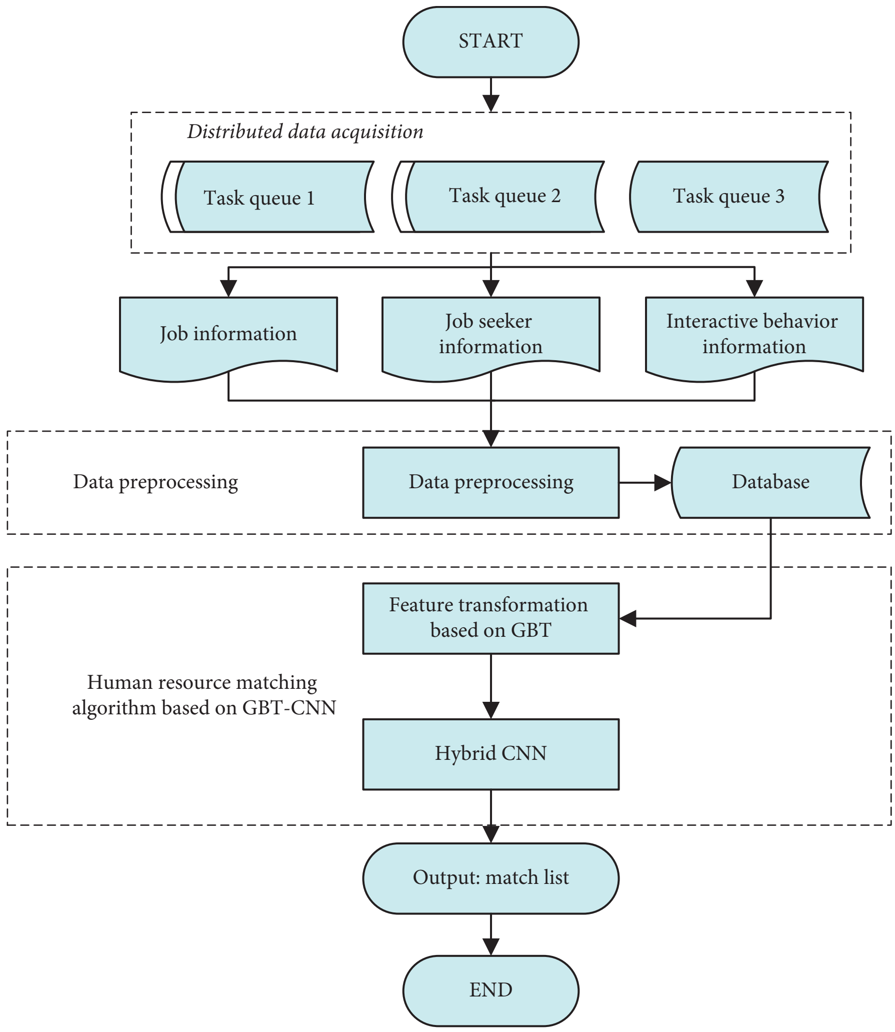

Figure 6: Human resource matching and recommendation process based on GBT-CNN.

Table 2: Simulation platform configuration.

Project	Parameter
CPU	Intel core i5-3360P CPU @3.5GGHz×8
RAM	32 GB DDR3 @1800 MHz
GPU	GeForece GT 860
Operating system	Ubuntu kylin 16.04 LTS
Kernel version	GNU/Linux 4.4.0-53-generic x64
Python version	Python 3.9.6
MXNet version	MXNet 0.12

From the experimental results, compared with the commonly used recommendation algorithms, the proposed algorithm achieved a good improvement in the recall rate and F1_score, which proves the feasibility and effectiveness of the combination of the GBT model and CNN model. In addition, the GBT model is used for feature transformation, and the multichannel convolution is used to enrich the overall feature abstraction. Combined with convolution processing and local connection processing, the job seeker

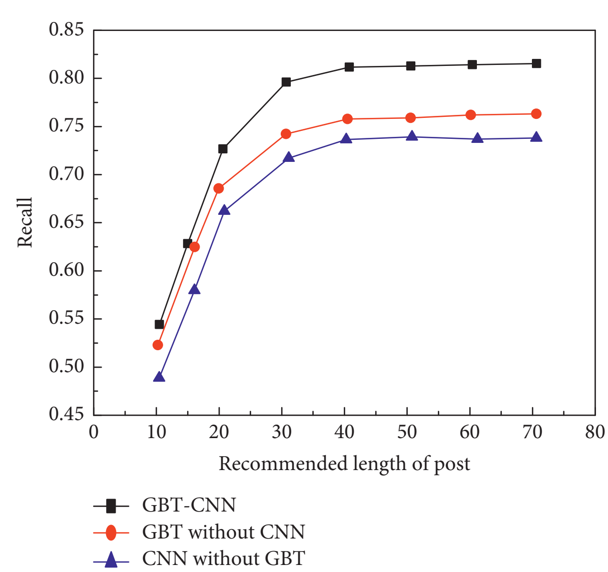

Figure 7: Comparison of parameter recall rates.

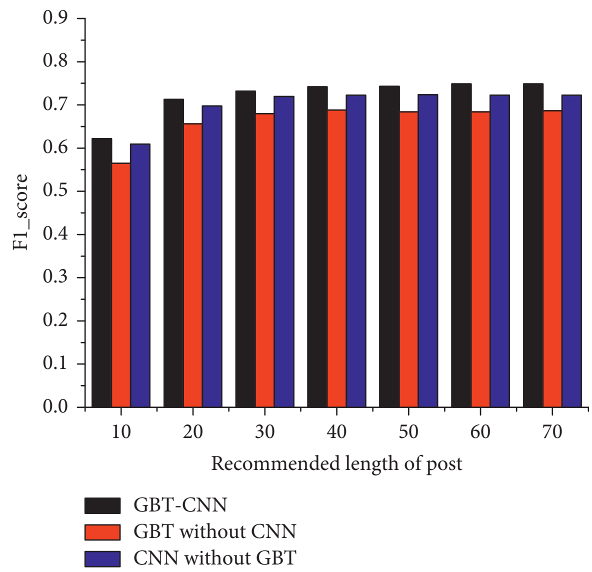

Figure 8: Comparison of parameter F1_score.

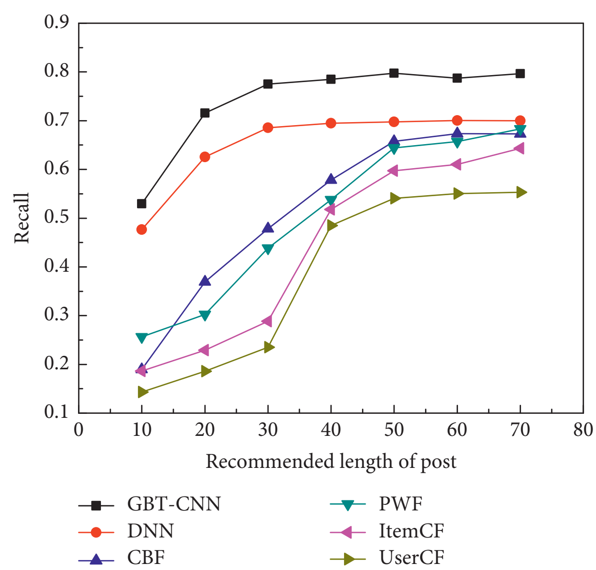

Figure 9: Comparison of recall rates of different algorithms.

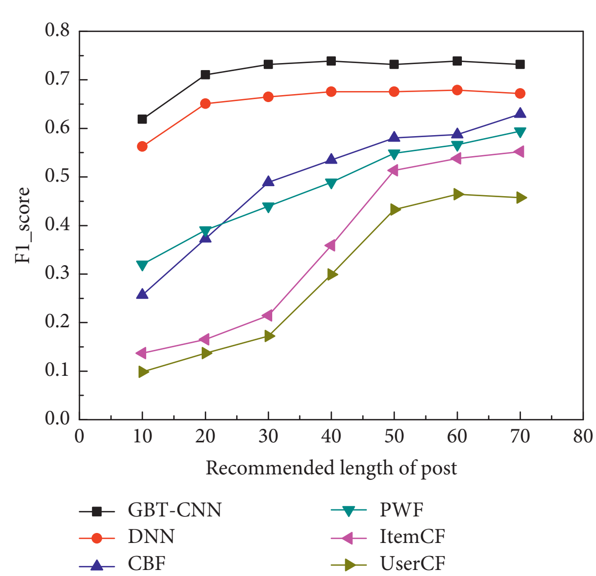

Figure 10: Comparison of F1_score of different algorithms.

information and job information can be more effectively associated and mined, and the high-level abstract feature information can be learned. Then the recommendation quality of the model on human resources can be effectively improved.

5. Conclusion

Aiming at the problems of traditional and single recommendation methods, a recommendation algorithm applied to the field of human resources is implemented in this article. With the help of the feature transformation ability of GBT and the high-level feature learning ability of CNN, the problem of limited model feature extraction ability of traditional recommendation algorithm is solved, and the recommendation quality is improved. Based on the collected human resources data set, the proposed algorithm is compared with various existing algorithms for recommendation quality evaluation. The effectiveness of the proposed algorithm in the field of human resources recommendation is proved. There are issues with the proposed algorithm that need to be improved in the future. In the field of human resources recommendation, the job intention of job seekers is time-varying. However, the timing factor is not considered here, which is tried to be added in subsequent improvements. Maybe using the cyclic neural network model to deal with the timing factor is a promising method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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