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Human Resource Recommendation Using Chinese BERT, BiLSTM, and Short Text Similarity Algorithm

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Nowadays, many job seekers often cannot clearly analyze their job advantages and the real needs of the position, which can easily lead to large job seeking deviations, low admission rates, and waste of talent in the human resources market. The study first uses character embedding technology to pre-train Chinese text. Secondly, to enhance the model's ability to understand contextual information in text, a bidirectional long short-term memory network and attention mechanism are introduced. Finally, the short text similarity algorithm is used to calculate the matching degree between job seekers and job descriptions. The experimental outcomes denoted that the data classification accuracy of the new model reached a high of 97.3%, which was about 5% higher than that of the Chinese BERT module alone. The highest recommendation success rate was 97.6%, the highest job recommendation acceptance rate was 97%, the highest job matching degree was 97.83%, the lowest average processing time was 3.28 seconds, and the highest user satisfaction was 98.88%. From this, the model proposed by the research has excellent performance in occupational data classification and human resource recommendation among many existing models, and can provide an effective technical support for subsequent human resource recommendations and market operations.

Povzetek: V prispevku je predstavljen model, ki združuje ChineseBERT, BiLSTM in algoritem za podobnost kratkih besedil za izboljšanje priporočanja kadrov.

1 Introduction

In the era of big data, enterprises are able to collect and store a large amount of job seeker information, including resumes, social media data, career history, and more. The widespread availability of these data provides abundant resources for building more accurate and personalized recommendation systems [1]. With the intensification of market competition, the demand for high-quality talents in enterprises is also increasing day by day. Finding suitable talents and maintaining their long-term retention has become an important challenge for businesses [2]. Liang et al. developed a new balanced recommendation algorithm for physical education teaching human resources by combining support vector machine algorithm and big data mining to address the drawbacks of traditional physical education teaching human resource recommendation. The experimental results showed that the algorithm had the highest degree of sports resource utilization, with an average recommended value of 96.4% [3]. To further improve the application effect of machine learning in human resource recommendation, Garg et al. proposed a new recommendation model by combining decision trees and text mining algorithms. The experiment findings denoted that this model had a higher recommendation matching degree and credibility for human resources compared to traditional models [4]. Gannoruwa et al. developed a personalized university classification system for subsequent career planning matching and recommendation in order to improve the effectiveness of university recommendations and career demand forecasting. The experiment outcomes indicated that the system had excellent accuracy in classifying and recommending occupations for nearly 20000 college students [5]. Forouzandeh et al. proposed a new human resource multi-criteria decision-making model by combining artificial bee colony algorithm and fuzzy TOPSIS to further improve the recommendation performance of tourism industry practitioners. The experimental results showed that the model could adapt to large-scale employment recommendations for tourism professionals, with a recommendation effectiveness of up to 94.1% [6].

In recent years, as the quick advancement of information technology and artificial intelligence, especially the advancement of big data and natural language processing technology, the application of Short Text Similarity (STS) algorithm in the field of human resource recommendation has attracted widespread attention [7]. Hickman et al. found that existing STS algorithms heavily rely on their own employee data mining and preprocessing performance. Therefore, researchers proposed a text preprocessing STS algorithm by combining computer linguistics and web crawling techniques. The experiment outcomes indicated that the effectiveness of the algorithm for human resource recommendation has increased by about 7.3% compared to before the improvement [8]. Hickman et al. attempted to analyze personnel characteristics to improve the matching of human resource recommendations. A new recommendation method was proposed by combining STS and closed text mining. The experiment outcomes indicated that the average prediction accuracy of this method in 10 fold cross validation was 95.3%, and the highest recommended matching accuracy was 95.7% [9]. To help human resources consultants in the news industry find more suitable talent information, Wu et al. constructed a personalized recommendation system for news professions through personalized recommendations and STS algorithm. The experimental results showed that the system had significant recommendation advantages and could grasp more detailed information about job seekers [10]. Ko et al. conducted an evaluation and analysis of recommendation systems in various service areas and found that there was a common problem of limited recommendation data sources and low recommendation effectiveness. To this end, researchers proposed a new service industry human resource recommendation model by combining cloud data and STS algorithm. The experimental results showed that the recommendation service automation and effectiveness of this model were generally higher than traditional methods, and it had high feasibility and robustness [11].

In summary, existing research has performed well in specific fields, using machine learning and big data mining techniques to improve the matching and credibility of human resource recommendations. However, there are still problems such as high computational complexity, long processing time, and incomplete semantic understanding. To address these issues, an STS algorithm based on ChineseBERT, Bidirectional Long Short-Term Memory (BiLSTM), and Attention Mechanism (AM) is proposed to improve the accuracy and efficiency of recommendation systems by optimizing text feature embedding and contextual information processing capabilities. The innovation lies in the combination of the latest pre-trained language models and deep learning algorithms, which effectively improves recommendation performance and provides a theoretical reference for the development of technology and data management in this field, as shown in Table 1.

Table 1: Comparison of different studies

Using literature	Algorithm/ Model used	Dataset size/Type	Accuracy	Recommendation success rate	Strengths/Limitations
Liang et al. [3]	support vector machine algorithm	/	/	96%	The recommendation trust is high, but the comprehensive recommendation effect still needs to be explored
Garg et al. [4]	machine learning	105 Scopus-indexed articles+20000 college students	/	/	The positive impact of human resource management efficiency has been emphasized, but its comprehensive impact still needs to be further studied and strengthened.
Gannoruwa et al. [5]	ARIMA	/	/	/	Provided better insights for talent resource recommendation, but further research is needed for practical application results
Forouzandeh et al. [6]	ABC+TOPSIS	1015 online questionnaires on the Facebook	/	94.10%	Adapt to large-scale employment recommendations for tourism professionals, but the effectiveness of recommendations in other industries still needs to be verified
Hickman et al. [8]	STS	/	/	Improve 7.3%	The effectiveness of human resources recommendations has increased by 7.3%, and further research is needed on the situation in other industries
Hickman et al. [9]	STS and closed text mining	/	95.30%	96%	Having recommendation advantages, but with a single industry recommendation
Wu et al. [10]	STS	/	/	/	Having recommendation advantages, but with a single industry recommendation
Ko et al. [11]	cloud data with STS	/	/	/	The recommendation effect is good, but the model runs slowly

2 Methods and materials

In response to the problems of computational complexity and low recommendation effectiveness in existing human resource recommendations, this study first uses ChineseBERT as the training basis through word embedding, introduces BiLSTM and AM for optimization, and proposes a human resource data text classification model. Secondly, based on this model, the attribute characteristics and preferences of both job seekers and recruiters are considered, and an improvement is made using the STS algorithm. Finally, a human resource personality recommendation model is proposed.

2.1 Text feature classification of human resources data based on CBCF-BAC

When faced with a massive amount of job information, job seekers often find it difficult to quickly and accurately find positions that match their expertise and abilities, and companies also face the huge challenge of screening candidates who meet the job requirements from a large number of job seekers [12, 13]. Therefore, the research focuses on embedding job features and analyzing details. The existing human resources data text feature classification roughly includes four stages: data preprocessing, data feature extraction, feature classification, and classification effect evaluation. The problems of word ambiguity, word order dependency, and long text dependency have always affected the efficiency of data processing. Therefore, the ChineseBERT module is introduced in the study. ChineseBERT is a pre-trained language model based on Transformer architecture, specifically optimized for processing Chinese text [14, 15]. By introducing character level and word level embedding representations, ChineseBERT can better capture the semantic and syntactic features of Chinese. Its structure is shown in Figure 1.

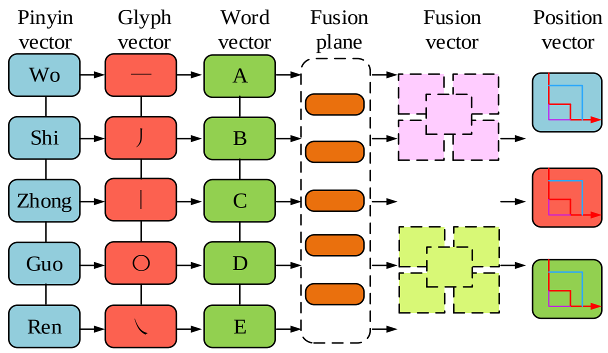


Figure 1: Schematic structure of ChineseBERT

As shown in Figure 1, ChineseBERT is mainly divided into input layer, pinyin vector layer, glyph vector layer, glyph vector layer, fusion vector layer, position vector layer, and output layer. Firstly, the input layer includes input at the character level and input at the pinyin level, where the pinyin corresponding to each Chinese character is also introduced into the model. Then, the embedding vectors of characters and pinyin are processed through the embedding layer to generate embedding representations of characters and pinyin. Next, these embedded representations are input into the BERT model, which encodes them through a multi-layer Transformer structure to generate context sensitive hidden state representations. Finally, the hidden state representation is classified through linear and Softmax layers to generate the final output. The vector calculation of the embedding layer is shown in Equation (1).

$$E = E_{word} + E_{pinyin} + E_{pos} \tag{1}$$

In Equation (1), E represents input vector embedding; E_{word} represents word level embedding; E_{pinyin} stands for Pinyin level embedding; E_{pos} stands for positional embedding. The calculation encoded by the multi-layer Transformer structure is shown in Equation (2).

$$\begin{cases} H_i = LayerNorm(E + Attention(Q_i, K_i, V_i)) \\ H_{i+1} = LayerNorm(H_i + FFN(H_i)) \end{cases} \tag{2}$$

In Equation (2), H_i and H_{i+1} represent the hidden layer states of the i and $i+1$ layers, respectively; $LayerNorm$ represents layer normalization; FFN stands for feedforward neural network; Q_i , K_i, and V_i mean the query, key, and value vectors of AM, respectively. The classification calculation formula of the Softmax layer is indicated in Equation (3).

$$\begin{cases} Z = W_O H_L + b_O \\ \hat{y} = Softmax(Z) \end{cases} \tag{3}$$

In Equation (3), Z represents the result of linear transformation; $\hat{y}$ represents the probability distribution of the output; W_O means the weight matrix of the output layer; H_L represents the hidden state of the last layer of Transformer; b_O means the bias term of the output layer. Through ChineseBERT, text feature embedding can be dynamically quantified. To enhance contextual relevance, a special sequence processing model, BiLSTM, is further introduced in the study. Unlike traditional LSTM, BiLSTM connects two independent LSTM layers together, one processing sequences from front to back and the other processing sequences from back to front, to better understand the global dependencies of input data [16]. The structure of BiLSTM combined with AM is denoted in Figure 2.

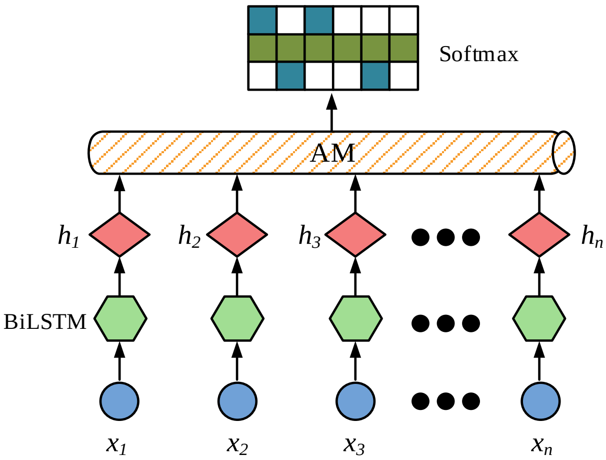


Figure 2: Schematic diagram of BiLSTM-AM structure

In Figure 2, the word vector x_n generated by ChineseBERT feature embedding is processed forward and backward by BiLSTM to generate hidden state representations for each time step, namely h_n. Then, guided by the training weight score α_n of AM, a summary calculation is performed, and finally processed by the Softmax function to obtain the final classification result. The calculation formulas for the optimized hidden layer state vector and feature vector are shown in Equation (4).

$$\begin{cases} H_i^* = v_i \tanh(w_i h_n + b_i) \\ a_i = \exp(H_i^*) / \sum_{j=1}^{n} H_i^* \end{cases} \tag{4}$$

In Equation (4), H_i^* represents the hidden layer state vector processed by BiLSTM-AM; v_i and w_i both represent weight coefficient matrices; j represents the number of processed items; a_i represents the optimized hidden layer feature vector. For the embedded information of BiLSTM input, a 3-layer convolution kernel is first used for convolution operation to extract local features of the text. The convolution calculation formula for this process is shown in Equation (5).

$$c = f(w_i \cdot M + b) \tag{5}$$

In Equation (5), c represents the convolution result of embedded information; M stands for convolutional kernel matrix; b represents the bias of the convolutional layer. After the convolution is completed, the feature selection is performed by the max pooling layer to retain the maximum feature, and then input into the fully connected layer. The calculation for the maximum feature is shown in Equation (6).

$$k = c(c_1, c_2, c_3, \cdots c_n) \tag{6}$$

In Equation (6), k represents the maximum feature retained after pooling. From this, it can be seen that word embedding and feature extraction are performed separately using ChineseBERT and BiLSTM-AM, and after full connection using a loss function, classification is ultimately guided by Softmax. A novel feature embedding text classification model ChineseBERT Collaborative Filtering and BiLSTM Attention Classification (CBCF-BAC) was proposed, and its structure is shown in Figure 3.

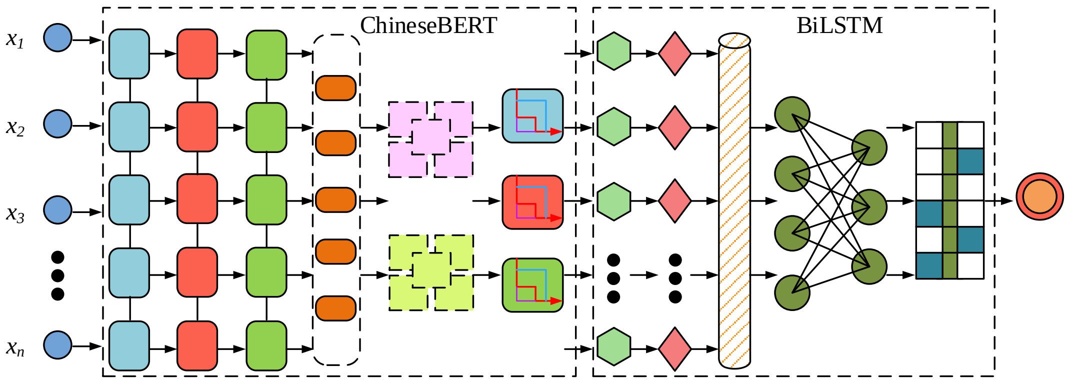


Figure 3: CBCF-BAC structure

In Figure 3, firstly, the ChineseBERT module performs character level and word level embedding processing on the input text to generate preliminary embedding representations. Then, these embedded representations are input into the BiLSTM-AM module through collaborative filtering combined with historical user behavior and content information. The BiLSTM network simultaneously processes the forward and backward information of the sequence, generates context sensitive hidden state representations, and assigns weights to different time steps through AM. Finally, the hidden state representation is processed through convolutional neural networks and max pooling layers to extract high-level features, and then classified through a Softmax layer to generate the final output result.

2.2 Construction of human resource recommendation model integrating STS algorithm

After constructing the CBCF-BAC human resources text classification model, it is found that most existing methods can only statically obtain bilateral feature information, and the data is single. The personalized human resources recommendation model constructed is not successful [17]. Therefore, based on the CBCF-BAC human resources text classification model, this study classifies and preprocesses the information provided by both sides, while associating upper and lower semantic information, to achieve accurate recommendation [18]. Firstly, using web crawling technology, it conducts data crawling on popular websites such as Wuyou Qiancheng Recruitment Network, Zhilian Recruitment Network, and BOSS Direct Recruitment Network. Various text attributes and data information are shown in Figure 4.

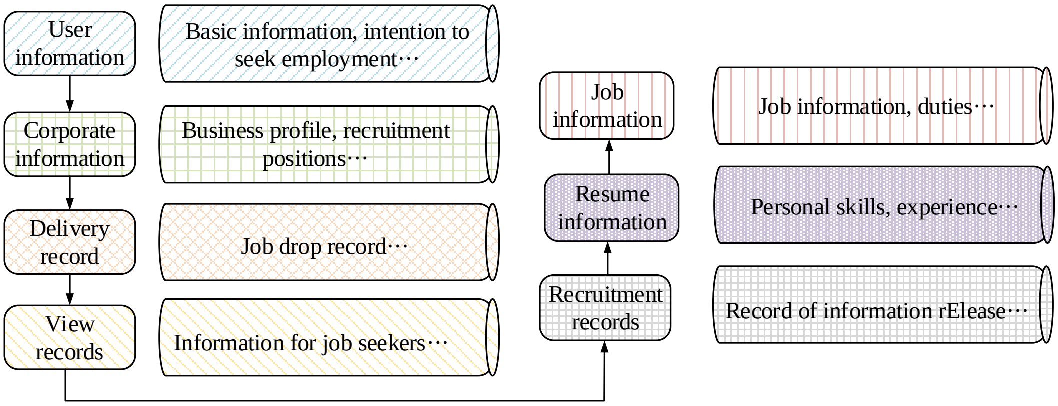


Figure 4: Schematic diagram for displaying various types of text information

As shown in Figure 4, the content of these data mainly includes user information, enterprise information, delivery and viewing records, job information, and resume information of job seekers. For example, user information includes basic information of job seekers, job intentions, educational background, and work experience, etc; Enterprise information includes company profile, job positions, company size, and industry type. The above information can be divided into short text and long text based on the length of the text. Short text can more intuitively reflect the key matching information between job seekers and positions compared to long text, and has faster processing speed and lower computational resource consumption. STS, as an algorithm used to measure the similarity between texts, can effectively identify the degree of match between job seekers and job descriptions [19, 20]. However, traditional STS algorithms face problems such as high computational complexity, long processing time, and incomplete semantic understanding when dealing with large-scale and diverse human resource data [21]. Therefore, the research improves its operation process, and the improved STS algorithm is shown in Figure 5.

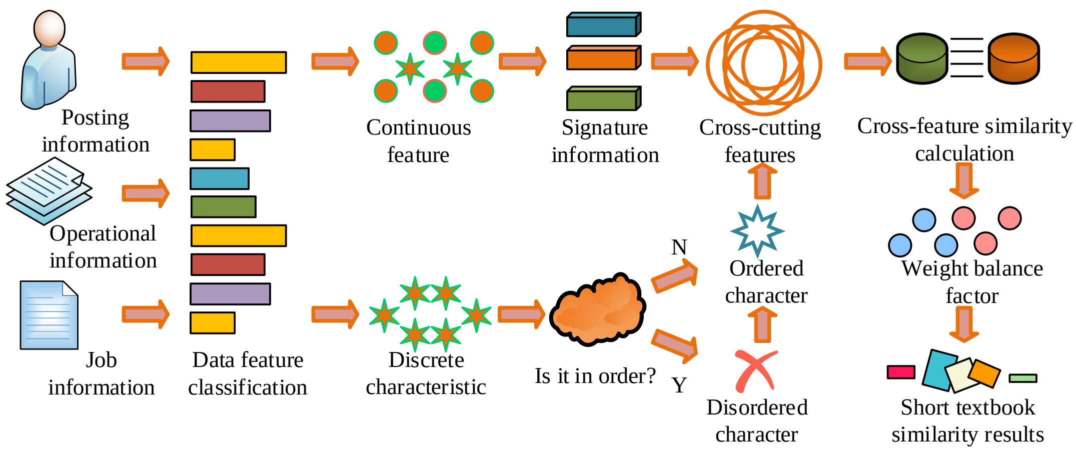


Figure 5: Improved STS process

In Figure 5, first is to obtain user delivery information, operation information, and job information, clean, integrate, standardize, and transform them through data preprocessing. Then, it classifies them into discrete features and continuous features according to the feature partition table. Discrete features are further classified based on order and disorder. Ordered features construct cross features, unordered features directly calculate similarity, and continuous features are normalized. Next, cross feature similarity calculation and feature vector weight factor calculation are performed. The similarity of discrete features and continuous features is weighted and summarized through the comprehensive similarity calculation module to obtain the final text similarity score. Among them, constructing cross features of short texts is crucial for the mutual screening between job seekers and recruiters, for example, expected cities and actual work cities, expected salaries and actual wages, expected occupations and actual work occupations, etc. The similarity of cross features are calculated using cosine values as shown in Equation (7) [22].

$$Similarity(A,B)=\frac{A\cdot B}{\|A\|\times\|B\|}=\frac{\sum_{i=1}^{n}(A_i\times B_i)}{\sqrt{\sum_{i=1}^{n}A_i^2\times\sqrt{\sum_{i=1}^{n}B_i^2}}} \tag{7}$$

In Equation (7), both A and B represent word vectors; A_i and B_i represent the eigenvector components of A and B, respectively. At this point, according to the improved STS process, if it meets the main types of text, such as desired city, salary, position, major, and other attribute characteristics, it is marked as matching degree 1, otherwise it is 0. The comprehensive classification calculation formula is shown in Equation (8) [23].

$$Similarity(R_i,J_i)=\begin{cases}1 & Conformity\\ 0 & Non\text{-}conformity\end{cases} \tag{8}$$

In Equation (8), R_i and J_i denote the expected and actual values of the i th attribute, respectively. Taking urban characteristics as an example, job seekers can choose multiple cities of interest for work, and there are also many expected positions in these cities. The set operation matching of the two is shown in Equation (9) [24].

$$Similarity(R_c,J_w)=\begin{cases}1 & \delta_1\cap\varphi_1\neq\varnothing\\ 0 & \delta_1\cap\varphi_1=\varnothing\end{cases} \tag{9}$$

In Equation (9), δ_1 denotes the set of expected work cities for job seekers; φ_1 denotes the set of expected job positions in these cities that meet the expectations of job seekers. After setting the key user preference attributes of the job seeker, the similarity between each attribute is calculated in a weighted manner. At this point, the similarity calculation of the preferences between the job seeker and the recruiter is shown in Equation (10).

$$\begin{cases}Similarity_u=\sum_{1}^{7}\mu_i Similarity(R_i,J_i)\\ Similarity_u=\sum_{6}^{7}\mu_i Similarity(R_i,J_i)\end{cases} \tag{10}$$

In Equation (10), μ_i represents the weight of each attribute. In addition, to avoid differences in preference similarity calculation caused by different weights, weight weighting adjustment is needed. At this time, the adjusted STS preference calculation between job seekers and recruiters is shown in Equation (11).

$$Similarity_Y(R,J)=\psi Similarity_u+(1-\psi)Similarity_c \tag{11}$$

In Equation (11), ψ represents the weighted balance factor. If the value is 1, it indicates that the short text preference direction of the job seeker $Similarity_u$ is consistent with that of the recruiter, and the recommendation degree is high. If it is 0, it indicates that the recommendation matching degree between the two is low, even 0. At this point, the final human resources recommendation model process is shown in Figure 6.

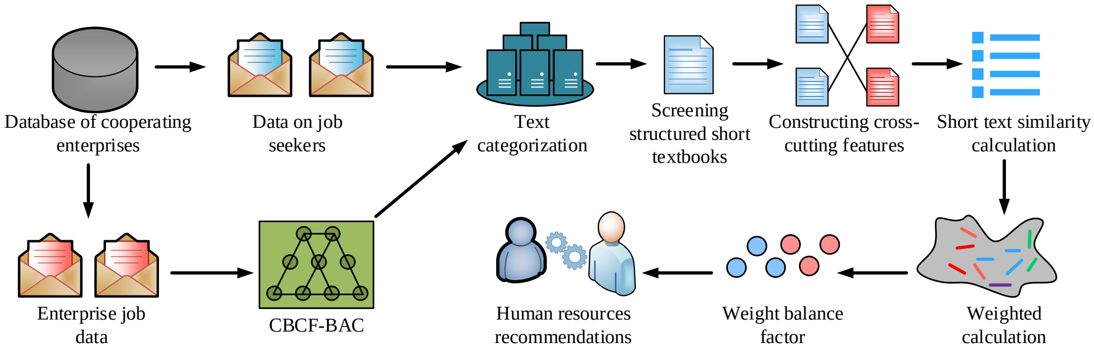


Figure 6: New HR personalized recommendation model process

In Figure 6, the entire model is broken into three main modules: data preprocessing module, STS calculation module, and weighted inference module. The data preprocessing part first provides relevant data source information through enterprise interfaces, including enterprise job data and global employee data. Next is to preprocess these data and use the CBCF-BAC model for data feature extraction and classification. Then, the improved STS algorithm is used to induce short texts with discrete, ordered, and unordered attributes, construct a cross feature set, and calculate the similarity of short texts. Finally, the weighted similarity is calculated based on the weight value and weighting factor. If they match, a recommendation is generated. If they do not match, the structured short text is readjusted and recalculated.

3 Results

To identify the performance and effectiveness of the new human resource recommendation model proposed in the study, after setting up an experimental environment, the effectiveness of the new model was first verified through ablation testing, and a multi-index comparative test was conducted by introducing similar methods. In addition, recommendation tests were conducted on four different positions, and advanced models were reintroduced for comparison to verify the true performance of the new model.

3.1 Performance testing of human resources recommendation model

The performance of the proposed model was validated through a series of subsequent experimental tests, with the CPU set to Intel Core i7 and a base frequency of 3.5 Hz. The GPU was set to NVIDIA GeForce RTX 3060ti, with 32 GB of VRAM and 64 GB of RAM. The operating system was Windows 10, the algorithm language was implemented in Python 3.9, and the algorithm integration development environment was Anaconda. The hidden layer size of BiLSTM was 128, the amount of layers was 2, the batch size was 128, and the learning rate was 2e-5. The Job Recommendations Dataset (JobRec) and XING Challenge Dataset (XingCD) were used as the testing data sources. Among them, the JobRec dataset contained users' resume information, work experience, skills, and job recommendation history, totaling about 20000 records. The JobRec dataset included job seekers' educational background, work experience, skills, certificates, etc. The class distribution is classified according to industry, job category, and years of work experience. The XingCD dataset includes users' work experience, educational background, career field, etc. User activity records on the platform, such as searching for positions, browsing resumes, sending invitations, etc. The distribution of classes is classified according to occupational fields, industries, job levels, etc. The XingCD dataset contained over 50000 pieces of users' career information, activity logs, skills, and recommended job information. The study first validated the performance of the proposed human resource recommendation model through ablation testing, and the test outcomes are denoted in Figure 7.

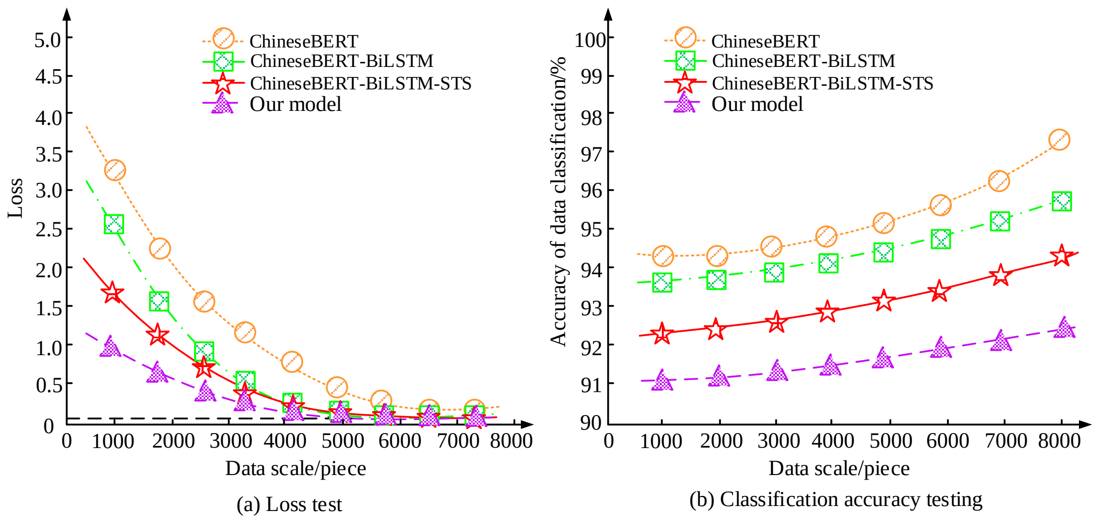
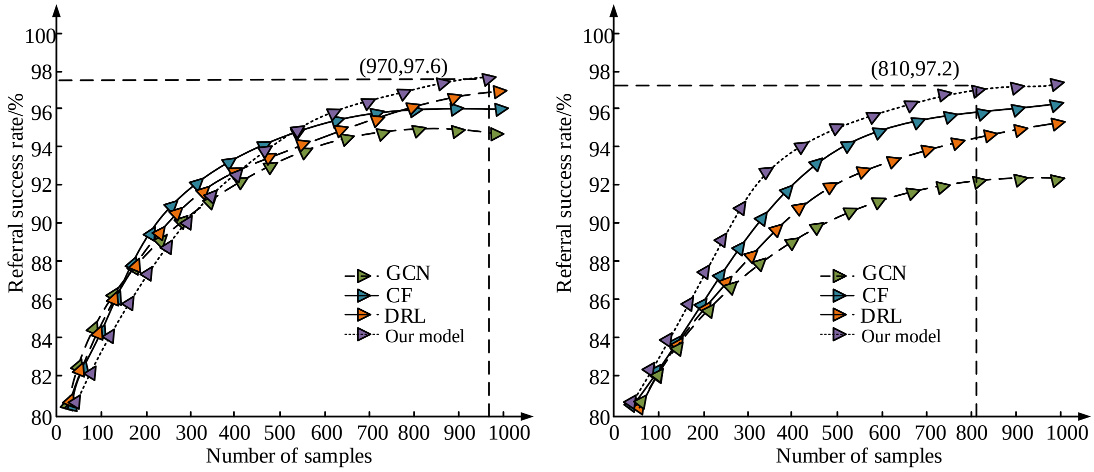


Figure 7: Ablation test results for human resource recommendation model

Figure 7 (a) showcases the loss value test results of each module in the model, and Figure 7 (b) shows the data classification accuracy test results of each module in the model. In Figure 7, with the increase of the amount of test samples, the loss test values of each module showed a significant decrease, among which the ChineseNERT module alone had the smallest slope of the decrease curve. After adding BiLSTM, its efficiency was significantly improved. The lowest loss value after stable introduction of STS was close to 0.2, which was similar to the final proposed new human resource recommendation model, but required significantly more training samples. In addition, in the classification of human resources data, the performance of the final model was the best, reaching 97.3% in the later stage. This value increased by about 5% compared to the standalone ChineseNERT module. The study used recommendation success rate as an indicator and introduced similar algorithms for comparison, such as Graph Convolutional Networks (GCN), Collaborative Filtering (CF), and Deep Reinforcement Learning (DRL). The test results are shown in Figure 8.



(a) JobRe (b) XingCD

Figure 8: Recommendation success rate test results for different models

Figures 8 (a) and (b) show the recommendation success rate test results of four models in the JobRe and XingCD datasets, respectively. In Figure 8, the traditional GCN model performed average in both datasets, with the highest recommendation success rates of 94.3% and 92.1%, respectively. Although the test data results of CF model and DRL model had advantages over GCN, they were still inferior to the proposed model. Overall, the model proposed by the research achieved the highest recommendation success rates of 97.6% and 97.2% in the JobRe and XingCD datasets, respectively, achieving the above recommendation effects. The required data sample sizes were 970 and 810, respectively. Upon investigation, the model proposed by the research effectively enhanced its ability to capture text semantics and contextual information by introducing ChineseBERT and BiLSTM-AMs, thereby improving the accuracy of recommendations. Continuing to test the above models using precision, recall, F1 score, Gini coefficient, and cross entropy as test indicators, the test results are denoted in Table 2.

Table 2: Performance testing of indicators for 4 models

Collection	Algorithm	P/%	R/%	F1/%	Gini coefficient	Cross entropy
JobRe	GCN	81.36	82.47	81.78	0.52	19.77
	CF	84.22	85.78	85.04	0.53	14.68
	DRL	85.79	88.69	86.83	0.33	7.94
	Our model	90.17	91.47	90.87	0.17	2.68
XingCD	GCN	82.07	83.47	82.41	0.41	28.47
	CF	85.69	84.21	84.67	0.37	18.69
	DRL	86.08	87.61	86.53	0.22	6.72
	Our model	91.97	89.36	90.59	0.13	3.51

According to Table 2, the proposed model outperformed the other three models in all indicators. In terms of precision, the new model achieved 90.17% and 91.97% respectively. In terms of recall rates, they were 91.47% and 89.36% respectively. In terms of F1 score, they were 90.87% and 90.59% respectively. The Gini coefficient values on the two datasets were 0.17 and 0.13, respectively, and the cross entropy values were 2.68 and 3.51, respectively. Overall, the model proposed by the research performed well in various indicators such as precision, recall, F1 score, Gini coefficient, and cross entropy, verifying its advantages in recommendation effectiveness and model stability.

3.2 Simulation testing of human resource recommendation model

To further verify the effectiveness of the new human resource recommendation model in practical applications, simulation tests were conducted on data from Wuyou Qiancheng Recruitment Network, Zhilian Recruitment Network, and BOSS Direct Recruitment Network. Firstly, resume screening was used as the testing object, such as technical positions, management positions, marketing positions, and logistics positions, and then popular recommendation models were tested separately such as Content-Based Filtering (CBF), Wide and Deep Learning for Recommendation (WDL), and Attention-Based Recommendation Model (ABRM). The test results are shown in Figure 9.

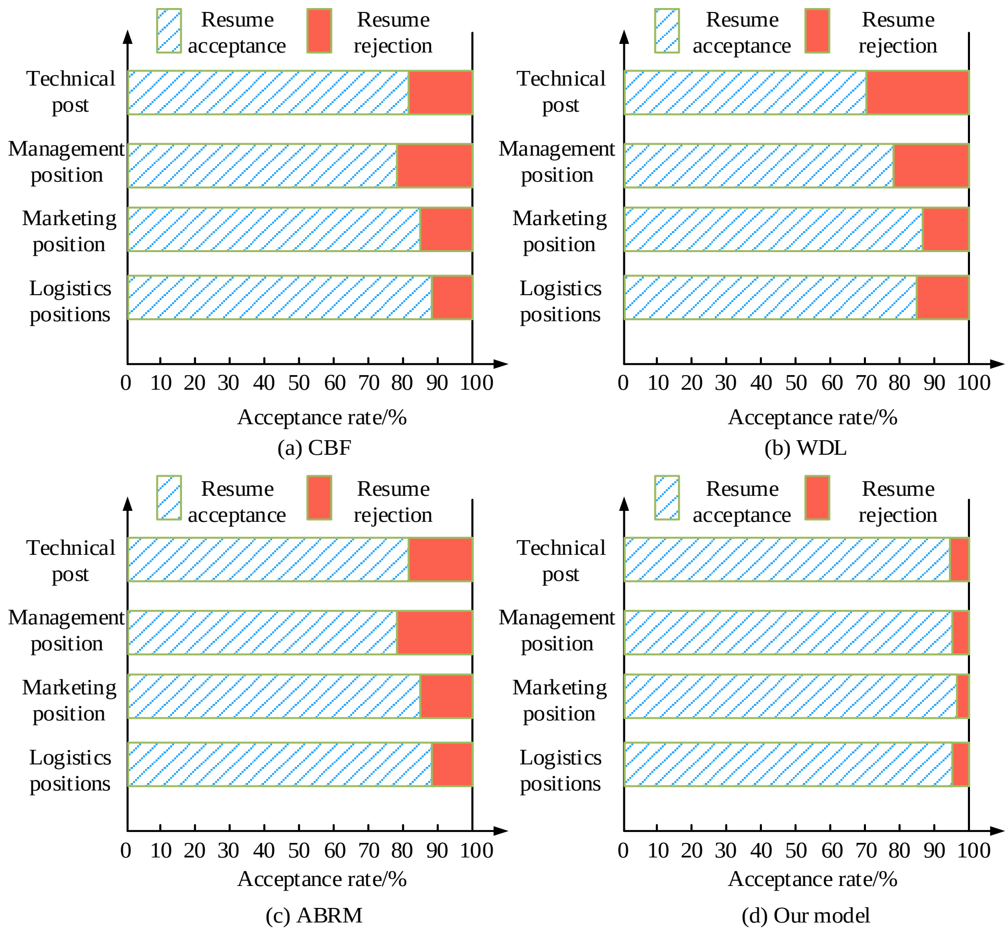


Figure 9: Results of recommended acceptance rates for four jobs with different models

Figures 9 (a), (b), (c), and (d) show the recommendation acceptance test results under the CBF, WDL, ABRM, and the proposed models. According to Figure 9, the CBF model had a lower acceptance rate and higher rejection rate for resumes in technical and management positions. The WDL model slightly improved the resume acceptance rate in marketing positions, but the overall effect was not significant. The ABRM model had a good resume acceptance rate in logistics positions, but the acceptance rate in other positions was still not ideal. The resume acceptance rate of the model proposed by the research was significantly higher than other models in all positions, especially in management and marketing positions with the highest acceptance rates of 95% and 97%, respectively. In addition, there was a significant improvement in the acceptance rate in technical and logistics positions, indicating that the model proposed by the research had excellent recommendation performance in various positions and had high practicality and promotional value. The study used recommendation coverage as an indicator and continued to test four types of positions using a confusion matrix. The test results are shown in Figure 10.

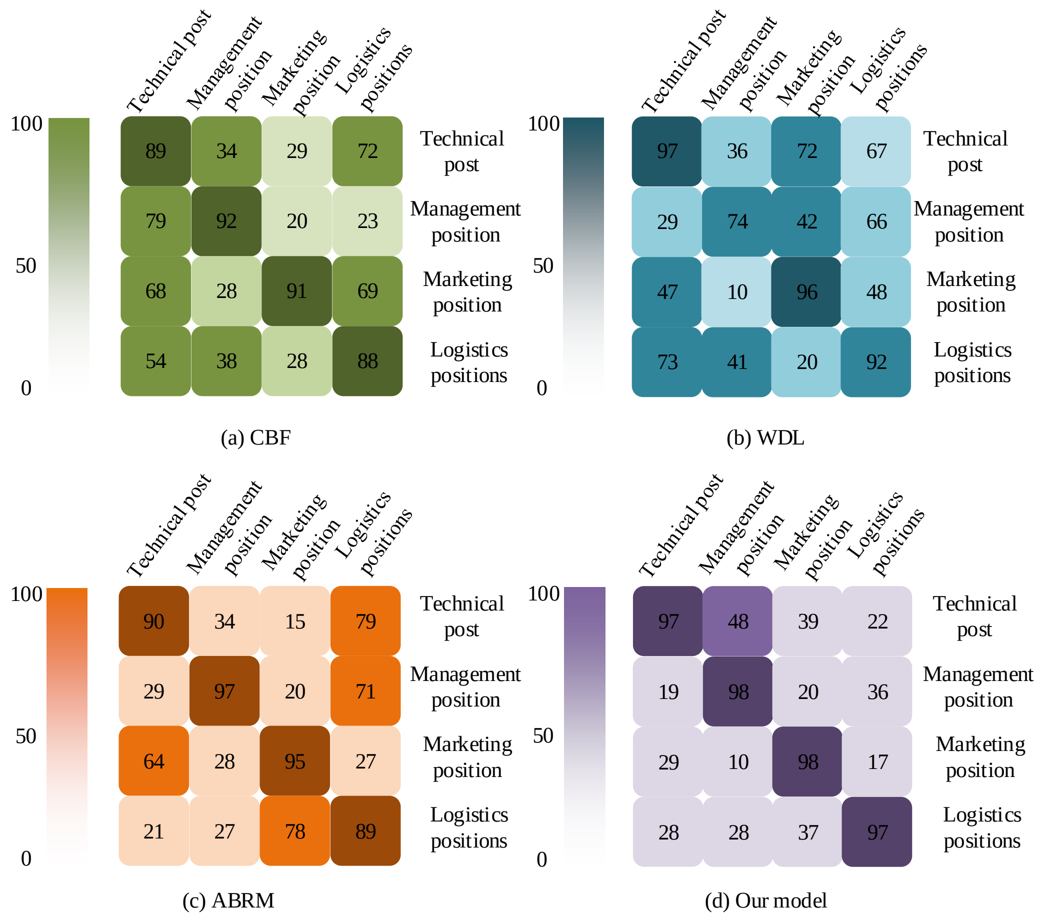


Figure 10: Recommendation coverage test results for four models

Figures 10 (a), (b), (c), and (d) show the recommended coverage test results of the CBF, WDL, ABRM, and the proposed model for four positions, respectively. From Figure 10, in the recommendation process of the four positions, the CBF model and WDL model had a high degree of confusion. For example, in the CBF model, technical positions were easily confused with management positions, while in the WDL model, technical positions were easily confused with logistics positions. Although the ABRM model had low recommendation confusion, its average coverage rate for normal recommendations for four positions was 93%. Compared to other models, the four job recommendations proposed by the research had higher clarity and almost no confusion. The average recommended coverage rate was 98%. The test was conducted using job matching degree, employee turnover rate, average processing time, and user satisfaction as indicators, and the test results are denoted in Table 3.

Table 3: Multi-metric test results for different models

Collection	Model	Job match/%	Employee turnover rate/%	Average processing time/s	User satisfaction/%	Run time/s	Used memory/GB
JobRe	CBF	95.13	18.27	7.68	95.64	8.6	2.6
	WDL	92.44	15.39	7.21	91.28	6.5	2.8
	ABRM	94.17	9.92	5.38	94.26	7.2	1.9
	Our model	97.83	5.18	3.28	98.88	4.8	0.7
XingCD	CBF	91.22	13.27	8.57	94.18	9.2	3.1
	WDL	92.89	11.39	8.14	93.16	8.2	2.7
	ABRM	93.58	8.48	6.26	94.86	7.3	2.0
	Our model	96.18	5.29	4.08	98.73	4.6	0.9

According to Table 3, under two types of real datasets, the test results of the four indicators of CBF, WDL, and ABRM models were inferior to those of the proposed model. The best performing ABRM model had the highest job matching degree of 94.17%, the lowest employee turnover rate of 8.48%, the lowest average processing time of 5.38 s, and the highest user satisfaction rate of 94.86%. In comparison, the proposed model had the highest job matching degree of 97.83%, the lowest employee turnover rate of 5.18%, the lowest average processing time of 3.28 s. The highest satisfaction rate among users using the model in the JobRe dataset was 98.88%. At the same time, the running time of the proposed model had minimum values in different datasets, which were 4.8 s and 4.6 s, respectively. The minimum memory usage for the research model was only 0.7 GB and 0.9 GB, respectively. This indicates that the proposed model has excellent recommendation performance and practical application value among numerous models. To test the actual performance changes of the current model after adding different modules, the performance of the modules before and after adding different modules was compared as shown in Table 4. The JobRe dataset was used for the study.

Table 4: Performance changes of different modules

Algorithm	P/%	R/%	F1/%
ChineseBERT	81.45	83.84	80.52
BiLSTM	83.58	84.96	83.84
AM	84.86	87.38	84.86
ChineseBERT+BiLSTM	89.57	89.84	87.62
ChineseBERT+AM	88.65	90.25	88.62
BiLSTM+AM	89.48	89.99	89.12
Proposed model	90.17	91.47	90.87

From Table 4, the performance of the model was improved after adding different modules. Among them, the traditional ChineseBERT model performed the worst in performance parameter comparison. After adding the BiLSTM model, its model precision was significantly improved, reaching 89.57%. But compared to the research model, its accuracy was about 0.60% lower. The recall rate of the ChineseBERT+AM model was relatively high at 90.25%, but compared to the research model, its recall rate was about 1.22% lower. In the comparison of model F1 score, the BiLSTM+AM model had a relatively high F1 score of 89.12%, but its recall rate was 1.75% lower compared to the research model. The performance of the model significantly improved after adding new modules, but the performance of the proposed model was better compared to other models. This may be due to the fact that the research model combines the advantages of other models.

To reduce the impact of factors such as gender, race, and education level on the results of the human resources recommendation system, before inputting data into the model, it needs to ensure that the training data is representative in terms of gender, race, education level, etc., to avoid excessive or insufficient representation of a certain group. At the same time, when developing algorithms, it is important to consider indicators such as democracy, equal opportunities, and individual fairness. Diversity and inclusiveness indicators were introduced into the algorithm. At the same time, it should avoid using social attributes that are unrelated to job performance. Fairness constraints, such as equal opportunity constraints, were added during the model training process to reduce prediction differences between different groups, and optimize multiple related tasks simultaneously through a multi-task learning framework. Finally, fairness metrics were regularly used to evaluate the performance of recommendation systems, such as differential fairness, statistical fairness, etc. In the process of system evaluation and data analysis, some biased data information that has a significant impact on the system was removed to achieve accurate analysis of human resource recommendation data by the system and model.

4 Discussion

In the comparison of the models used in the study, it was found that the GCN model had recommendation success rates of only 94.3% and 92.1% in the dataset, which were 3.3% and 5.1% lower than the algorithm recommendation success rates of the model used in the study. The GCN model had a lower recommendation success rate compared to the proposed model. At the same time, the recommendation success rates of the CF model in the dataset were only 96.2% and 95.6%, which were 1.4% and 1.6% lower than those of the proposed model. The recommendation success rates of the DRL model were 97.1% and 95.2%, which were 0.5% and 2.0% lower than those of the proposed model. In the comparison of traditional algorithm models, the success rate of recommendation using the model was higher, and the actual running effect of the model was better. This may be due to the introduction of AMs in the model, which may focus more on key information in job seekers' resumes and job descriptions, thereby improving the relevance and accuracy of recommendations. The proposed model may have found the optimal parameter settings through a more detailed tuning process, resulting in significant improvements in recommendation success rate and job matching.

In the performance testing and comparison of the model, it was found that the highest recommendation success rate using the model could reach 97.6%, the best job matching degree could reach 97.83%, and the highest user satisfaction could reach 98.88%. This may be due to the research using a model architecture that combines ChineseBERT, BiLSTM, and AMs, providing deeper semantic understanding and context awareness capabilities. At the same time, by introducing STS algorithm and other optimization techniques, the model could more effectively process and analyze a large amount of job seeker and position data. The model could also provide personalized recommendations and make adjustments based on user feedback and preferences, thereby improving user satisfaction. From this, it can be seen that the research on using models can demonstrate good model performance in both recommendation effectiveness and performance, which has a good guiding role for human resource recommendation research.

5 Conclusion

As the advancement of information technology and big data, companies are able to collect a large amount of job seeker information, but matching suitable talents remains a challenge. Therefore, the research aims to improve the matching accuracy of human resource recommendation systems. Firstly, a text data classification model was constructed by integrating ChineseBERT and BiLSTM-AM. Secondly, STS was introduced and its STS calculation was optimized, ultimately proposing a new human resource recommendation model. The experimental results showed that the lowest loss value of the new model in the later stage of training was close to 0.2, and the highest data classification accuracy was close to 97.3%, which was about 5% higher than the ChineseBERT module alone. The highest recommendation success rates in the JobRe dataset and XingCD dataset were 97.6% and 97.2%, respectively. The highest F1 scores were 90.87% and 90.59%, respectively. The highest Gini coefficient values were 0.17 and 0.13, respectively, and the lowest cross entropy values were 2.68 and 3.51, respectively. Compared to the other three types of models, the new model had the highest acceptance rate for the four real job positions, especially for management and marketing positions, with acceptance rates of 95% and 97%, respectively. After conducting multiple indicator tests, it was found that the new model had the highest average recommendation coverage rate of 93%, the highest job matching degree of 97.83%, the lowest employee turnover rate of 5.18%, the lowest average processing time of 3.28 s, and the highest user satisfaction rate of 98.88%. In summary, the proposed model performs well in various indicators, verifying its effectiveness in practical applications. This model can help financial services, healthcare, and manufacturing industries make more data-driven decisions in recruitment, employee performance evaluation, training, and development. However, human resource recommendation is a broad research topic, and this study only considers the results and process of recommendation, without addressing other non-objective factors such as market environment and policy influence. Therefore, subsequent research can be taken into consideration to enhance the comprehensiveness of the study.

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