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Optimization of Intelligent Recruitment Pathways in University Human Resources Systems Using Big Data Models

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Abstract To advance human resources management and talent employment in higher education institutions, this paper proposes a theme-based capability perception person-job matching neural network (TAPJFNN) by incorporating textual theme features into the APJFNN model. Real recruitment data from R University is selected as experimental data to explore the application of big data technology in intelligent recruitment. The results show that the proposed TAPJFNN model can effectively model the matching degree between talent and job positions. Compared to the APJFNN and APJFNN models, the performance of the proposed model is superior. Additionally, in terms of AUC, TAPJFNN outperforms TAPJFNN_preliminary by approximately 3%. This clearly validates the effectiveness of the proposed model in university human resources management systems.

Index Terms APJFNN model, TAPJFNN, university human resources management system, matching degree

I. Introduction

As important bases for talent cultivation and scientific research innovation, the level of human resource management in higher education institutions directly impacts the overall development and competitiveness of the institution [1], [2]. Recruitment and selection are critical components of human resource management in higher education institutions, aimed at identifying suitable candidates for various positions and departments to meet the institution's teaching, research, and administrative needs [3]. Traditional recruitment and selection methods often rely on resume screening, interview assessments, and background checks, which have certain limitations and subjectivity, making it difficult to comprehensively, objectively, and accurately evaluate the abilities and potential of applicants [4]-[6]. This management approach, which heavily relies on experience and intuition and lacks scientific rigor and systematicity, also struggles to effectively match positions with talent in a timely manner, leading to issues such as high recruitment costs, low efficiency, and poor quality [7]-[9]. With the advent of the big data era, competition for talent among universities has become increasingly intense, and how to effectively attract high-quality faculty has become a key issue in current university human resource management.

Under the promotion and application of big data technology, universities possess a wealth of information resources. By conducting in-depth research on these resources, universities can better understand and grasp their current human resource status, enabling them to make scientific and accurate decisions in complex and ever-changing environments [10]-[13]. Additionally, accurate and real-time data can support the formulation of university human resource management strategies, achieving rational allocation and utilization of talent resources [14], [15]. Universities can utilize intelligent recruitment systems to analyze big data, accurately identify talent that meets the school's needs, and enhance the efficiency of recruitment efforts [16], [17]. Furthermore, intelligent recruitment systems employ data mining techniques to predict the potential and future prospects of job applicants, thereby assisting schools in selecting creative and promising talent [18]-[20]. The application of intelligent recruitment systems enables universities to attract more outstanding talent, injecting new vitality into institutional development.

In the big data era, university human resource management faces new opportunities and challenges. Zhi, Y. utilized data mining technology to analyze relevant information about university teacher applicants and constructed an excellent teacher selection model to provide managers with scientific recruitment decisions, addressing the issues of low efficiency and strong subjectivity in traditional recruitment processes [21]. Song, D., et al. proposed a university recruitment management system combining blockchain and text recognition technology. By writing smart contracts, they strictly restricted unfair practices in recruitment reviews while enhancing privacy protection for recruitment information. The integration of text recognition technology enabled automatic application review, significantly improving recruitment efficiency [22]. Minsheng, L. integrated the BP neural network algorithm into a human resources management recruitment system. By analyzing and designing relevant concepts, logic, and the physical structure of data, the system assists universities in achieving long-term progress in human resources management [23]. Okoye, A. C. conducted an empirical investigation into the effectiveness of digital technology in human resources management practices. The study found that while the digitization of school human resources management has achieved significant management outcomes, there is room for improvement in infrastructure development [24]. Mohammed, M. T. et al. used the Analytic Hierarchy Process (AHP) and VIKOR intelligent method to construct a standard weighting system for university course teaching applicants. By inputting applicant information into the system for ranking, the resulting recruitment rankings better align with school requirements and the professional development needs of educators [25]. Sadeghi, S. and Niu, C. addressed racial and ethnic disparities in the teaching workforce by developing an AI-based K-12 teacher recruitment system. By engaging with and supporting the careers of teachers of color, the system aims to minimize inequality in the recruitment process [26]. Therefore, universities can effectively attract and screen talent by leveraging big data and other intelligent technologies to analyze recruitment channels, methods, and timelines, thereby improving human resources management.

To explore the application of big data-related technologies in intelligent recruitment within university human resources management systems, this paper builds upon the APJFNN model by integrating textual theme features, proposing a theme-based capability-aware person-job matching neural network (TAPJFNN). First, the Skip-gram algorithm is used to identify keywords in resumes and classify different positions. An attention layer is added to the BiLSTM model to enhance resume perception capabilities. Through a hierarchical capability perception representation process, the model can learn the representations of job requirements and resume experiences. To predict the matching degree between them, real recruitment data from R University is used as the research sample to validate the effectiveness of this model in intelligent recruitment within university human resources management systems.

II. Job-person fit method

In recent years, scholars have begun to actively explore other algorithms based on machine learning to address the challenges of job-candidate matching. By incorporating information such as the job seeker's age, education level, salary, work location, job description, and work experience into a binary classification problem framework, recruitment tasks can be completed in a more accurate and efficient manner, thereby improving recruitment efficiency and enhancing employment quality. Job descriptions and work experience are text-based data, while age, education, and other information are categorized as structured data. Typically, there are interaction records between job seekers and job positions, such as interviews attended or jobs applied for. With the continuous development of data mining technology, research on representing text-based data has achieved significant maturity. By combining deep neural networks with text mining technology, it is possible to effectively analyze the features of job descriptions and job seekers' work experience, thereby predicting the similarity between the two. This method can provide companies with more effective recruitment information, better meeting their needs. The ability-aware job-candidate matching model APJFNN utilizes BiLSTM learning technology to compare a job seeker's abilities with job descriptions. Based on the characteristics of different abilities, it proposes four hierarchical ability-aware strategies to assess a job seeker's ability level and their contribution to job requirements. A storage module dynamically updates job seekers' resumes and job descriptions, and uses a perceptron model to predict job seekers' chances of securing interviews, understand their potential preferences, and provide effective support for their career development [27].

This model transforms the matching problem into a ranking problem, aiming to deeply explore the expectations of job seekers and employers and assess their interest levels based on this. Additionally, this model adopts a multi-task optimization approach to transform the talent matching problem into a more effective solution, thereby improving the efficiency of job seeking. By incorporating textual topic features into the APJFNN model, the topic-based ability perception job-person matching neural network TAPJFNN is proposed. The Skip-gram algorithm is used to identify keywords in resumes, and these keywords are grouped into different job categories based on their similarity. Finally, industry synonyms are used to assess the reliability of job positions, thereby providing job seekers with more precise job recommendations.

Scholars do not limit themselves to analyzing textual data but also incorporate structured features of job postings and resumes, such as education level and salary, into their research scope. Gu Zhenwei utilized his unique technology, combining latent semantic algorithms and deep forest features, to construct a new recruitment recommendation algorithm that accurately reflects the personal characteristics of job seekers, thereby meeting the needs of enterprises in recruitment. Using DeepFM and CNN models, semi-structured feature entities are extracted from job and resume texts, and LSTM models are employed for in-depth analysis to uncover latent semantic information in historical application records, thereby accurately understanding and interpreting the information in job and resume texts. The multi-domain feature representation and interaction learning algorithm MUFFIN, based on self-attention mechanisms, integrates text features, semi-structured features, and other diverse features from job postings and resumes into an end-to-end neural network to enhance learning efficiency and accuracy. The success of talent matching during recruitment depends on the job seeker's interview performance. Given the sensitivity of interview data, research utilizing this information for personnel matching remains relatively scarce [28].

III. Intelligent recruitment based on data technology

After obtaining word-level representations of job postings and resumes, we further extract higher-level representations for them. For job postings, we consider each job requirement to be a specific demand of a particular position, and the overall demands of a position can be further summarized from all its requirements. Based on this, a hierarchical neural network structure was designed to model this hierarchical representation. For resumes, there is a similar hierarchical relationship between a candidate's experience and qualifications, so resumes also adopt a similar hierarchical neural network structure. Additionally, job postings and resumes are both documents with relatively well-defined formats. For example, for ease of understanding, most candidates tend to categorize their past work experience by job content and sort it by time. Therefore, to improve the model's performance and interpretability, four attention mechanisms were designed to optimize the different hierarchical representations extracted by the model. Specifically, this section can be further divided into four parts:

1) Use the attention mechanism to distinguish the importance of each word in a job requirement and obtain the vector representation of the sentence.

2) Using attention mechanisms to distinguish the importance of different sentences across all job requirements, thereby further extracting the representation of the entire job position.

3) Highlighting specific skills in a candidate's experience based on the skill requirements listed in the resume.

4) Conducting multi-skill perception of a candidate's experience and ultimately describing the candidate using the sum of all skills.

III. A. Single-skill perception of job requirements

This attention layer is the weighted sum of the semantic vectors of each word in each ability requirement. For example, for the l th ability requirement j_l, we first use the word-level representations $\left\{h_{l,1}^l, h_{l,2}^l, \ldots, h_{l,m}^l\right\}$ as input to a fully connected layer and calculate the similarity with the word-level context vectors. Then, we use the softmax function to calculate the weight score α, i.e.:

$$\alpha_{l,t} = \frac{\exp\left(e_{l,t}^J\right)}{\sum_{z=1}^{m} \exp\left(e_{l,z}^J\right)} \tag{1}$$

$$e_{l,t}^J = v_a^T \tanh\left(W_a h_{l,t}^J + b_a\right) \tag{2}$$

Among them, v_a, W_a, and b_a are parameters to be learned during the training process. Specifically, v_a represents the context vector of j_l, which is randomly initialized. The weight score α can be regarded as the importance of each word in j_l. Finally, we calculate the single-item ability perception demand representation s_l^J of j_l in the following way:

$$s_l^J = \sum_{t=1}^{m} \alpha_{l,t} h_{l,t}^J \tag{3}$$

III. B. Multi-skill perception of job requirements

The importance of educational background is far less significant than professional skills. Additionally, the order of skill requirements listed in job descriptions also reflects their importance. Based on this, we first utilize a BiLSTM model to model the sequence information of skill requirements. Then, we add an attention layer to learn the importance of each skill requirement. The sequence of skill representations learned from the single-skill perception in the previous step, $\left\{s_1^J, s_2^J, \ldots, s_p^J\right\}$ as input to the BiLSTM, generating a series of hidden state vectors $\left\{c_1^J, c_2^J, \ldots, c_p^J\right\}$ as follows:

$$c_t^J = BiLSTM\left(s_{i,p}^J, t\right), \forall t \in [1, \ldots, p] \tag{4}$$

Similar to the first attention layer, we add another attention layer on top of the LSTM to learn the importance of each competency requirement. Specifically, we calculate the importance β_t of each competency requirement j_l based on the similarity between its hidden state c_t^J and the context vector J_p of all competency requirements, i.e.:

$$\beta_t = \frac{\exp\left(f_t^J\right)}{\sum_{z=1}^{p}\exp\left(f_z^J\right)} \tag{5}$$

$$f_t^J = v_\beta^T \tanh\left(W_\beta c_t^J + b_\beta\right) \tag{6}$$

Among them, parameters W_β, b_β, and context vector v_β are learned during training. Then, the multi-capability-aware job requirement vector is calculated by the weighted sum of the hidden state vectors of capabilities, i.e.:

$$g^J = \sum_{t=1}^{p}\beta_t c_t^J \tag{7}$$

III. C. Perception of single abilities in resumes

Unlike job requirements, candidates' experiences often overlap in meaning, while job requirements are generally distinct. Therefore, for a given job requirement, all candidates' experiences are relevant, but the same experience may have different meanings for different job requirements. Formally, for a candidate's l th experience r_l, we compute its word-level semantic representation using BiLSTM. The relationship score $r_{l,k,t}$ based on the Attention mechanism is used to limit the contribution of each semantic representation $h_{l,t}^R$ to the perception of the k th capability requirement j_k. It can be calculated as follows:

$$r_{l,k,t} = \frac{\exp\left(e_{l,k,t}^R\right)}{\sum_{z=1}^{n}\exp\left(e_{l,k,z}^R\right)} \tag{8}$$

$$e_{l,k,t}^R = v_\gamma^T \tanh\left(W_\gamma s_k^J + U_\gamma h_{l,t}^R\right) \tag{9}$$

Among them, $W_\gamma, U_\gamma, v_\gamma$ are parameters, and s_k^J is the semantic vector of capability requirement j_k, calculated by formula (10). Finally, the weighted sum of the word-level semantic representations $r_{l,k,t}$ is used to calculate the single capability perception representation of the resume:

$$s_{l,k}^R = \sum_{t=1}^{n} r_{l,k,t} h_{l,t}^R \tag{10}$$

Here, the attention score r further enhances the interpretability of APJENN. It allows us to understand whether a candidate meets the competency requirements and why they meet those requirements.

III. D. Multi-skill perception in resumes

For job seekers, resumes are generally filled out in chronological order, and this time information is also useful for assessing their abilities. To capture this temporal relationship between experiences in resumes, another BiLSTM is used. First, an average pooling layer is added on top of the single-ability-perceived resume experience representation to generate a potential semantic vector u_l^R for the l th resume experience r_l:

$$u_l^R = \frac{\sum_{t=1}^{p} s_{l,t}^R}{p} \tag{11}$$

Obtain a set of semantic vectors for the resume experiences, i.e., $\left\{u_1^R, u_2^R, \ldots, u_q^R\right\}$. Considering that there is a temporal relationship between $\left\{u_1^R, u_2^R, \ldots, u_q^R\right\}$, BiLSTM is used for encoding, i.e.:

$$c_t^R = BiLSTM\left(u_{i,q}^R, t\right), \forall t \in \left[1, \ldots, q\right] \tag{12}$$

Finally, we use the weighted sum of $\left\{c_1^R, c_2^R, \ldots, c_q^R\right\}$ to generate a multi-capability-aware resume experience representation, namely:

$$\delta_t = \frac{\exp\left(f_t^R\right)}{\sum_{z=1}^{q} \exp\left(f_z^R\right)} \tag{13}$$

$$f_t^R = v_\delta^T \tanh\left(W_\delta g^J + U_\delta c_t^R\right) \tag{14}$$

$$g^R = \sum_{t=1}^{q} \delta_t c_t^R \tag{15}$$

III. E. Job-person fit prediction

Through the layered ability perception representation process, job requirements and resume experience representations can be learned. To predict the degree of match between them, they are finally input into a fully connected network, which uses a logistic function to learn the degree of job-person match for the prediction label y:

$$D = \tanh\left(W_d\left[g^J; g^J; g^J - g^R\right] + b_d\right) \tag{16}$$

$$\hat{y} = Sigmoid\left(W_y D + b_y\right) \tag{17}$$

Among them, W_d, b_d, W_y, and b_y are network optimization parameters, and $\hat{y} \in [0,1]$. At the same time, we train our model by minimizing the binary cross-entropy.

The data sources used in the data model are provided by Zhaopin in the problem "Intelligent Matching of Job Seekers and Positions" from the Second Alibaba Big Data Intelligence Cloud Programming Competition. The data includes three tables: the resume description table table1_user, the job description table table2_id, and the behavior table table3_action. The resume description table contains approximately 60,000 user basic information records, the job description table contains approximately 1.1 million job basic information records, and the behavior table contains approximately 4.84 million user application behavior records. Using this data source, after initial data cleaning, we constructed the aforementioned job-candidate matching model to intelligently recommend jobs to job seekers. We trained three models using the labels "browse," "apply," and "accept," and obtained three prediction values from these models. The prediction values from these three models can be combined in the following format:

$$\begin{aligned} &Final\ score\ =\ Browsin\,g\ score^{\alpha} \\ &*Aubmission\ score^{\beta} * Approval\ score^{\gamma} \end{aligned} \tag{18}$$

Among them, α, β, and γ are parameters that need to be determined based on testing. After testing, a set of relatively suitable values is $\alpha = 0.1$, $\beta = 0.2$, and $\gamma = 0.7$.

IV. Applications and Explorations in Intelligent Recruitment

IV. A. Analysis of the Current Status of Human Resource Recruitment Management at R University

R University has a total of six departments, including four functional departments and two business departments. Functional departments generally do not directly interact with customers or provide services, but instead are responsible for supervision, support, guidance, and after-sales service. These departments typically include Human Resources, Finance, Art, and Technology, among others. Operational units directly provide services to clients or deliver projects, including the Business Department and Operations Department. Among these, the Technical Department has the largest number of staff, totaling 290 people, with the majority in technical roles such as R&D, operations, and planning. The Finance Department has 15 staff, the Business Department 64, the Operations Department 38, the Human Resources Department 27, and the Art Department 80. The human resources composition of R University is shown in Table 1.

Table 1: Composition of human resources of R company

Corporate sector	Number of employees	Proportion
Technical department	290	56.42%
Finance department door	15	2.92%
Commerce Department	64	12.45%
Human resources department	27	5.25%
Operation door	38	7.39%
Art department	80	15.56%

According to an analysis of R University's human resources data, the current employee structure at R University is characterized by a young workforce, a concentration of employees with bachelor's degrees, and a higher proportion of male employees. As shown in Table 2, in terms of age distribution, employees aged 30 or younger account for the majority of the workforce, making up 57.79% of the total, with an average age of 27. Employees aged 30–40 (including 40) are the next largest group, accounting for 35.41% of the total workforce, with an average age of 29.

Table 2: Analysis of personnel age structure of R company

Age interval	Number	Proportion
<25	87	16.93%
25-30	210	40.86%
30-40	182	35.41%
40-50	35	6.81%
Mean age	29	

Internet recruitment is a recruitment method that leverages the vast information resources and instant communication capabilities of the internet to quickly obtain information on a large number of candidates. Due to its low recruitment costs, it is often the preferred method for small and medium-sized enterprises. According to the R University Enterprise Database, the current internet recruitment channels for R University are compared in Table 3.

Table 3: Analysis of current Internet recruitment channels of R company

Channel name	Positioning	Talent distribution	Merit	Shortcoming
Zhaolian	Traditional channel	Traditional industries, the type of position is more than average	Excellent recommendation algorithm	There are fewer Internet and high-end talent, and resume searches are inaccurate
Hook	Internet channel	1-3 years Internet technology, the operating class position industry ranked first	Low cost	The main search function is inconvenient
Hunting	Medium high end talent channel	In the market, the operation class is mainly, more is the high end talent	The resume is more timely	The Internet technology is less expensive and expensive
Linkedin	High-end talent channel	High level talent concentration	More high-end talent	Social, hiring properties are weak and inefficient
51job	Traditional channel	New graduates, traditional industries, and language media are more concentrated	Lower cost and quick resume	There are fewer Internet positions and high-end talent
58	Traditional channel	Job classification, service class, sales class concentration	Lower cost	Middle and low level talent concentration
Boss	Emerging Internet channels	There are more customer service classes and the average distribution of other jobs	The position is unlimited and the cost is low. Chat recruitment	The recruitment efficiency is low and can't get a lot of resumes quickly

Internal referrals are a recruitment method that leverages the professional networks of existing employees to recommend suitable candidates to universities, while also providing incentives to the referring employees. This approach is cost-effective and enables the swift identification of candidates who are well-suited for specific roles.

The internal referral process at R University primarily involves recruitment specialists identifying job requirements, then sending them to employees' corporate email accounts and notifying them in the university's work group. If the talent recommended by an employee is successfully hired and passes the probationary period, the employee is given a corresponding reward, the amount of which is determined based on the importance of the position. The current internal referral reward mechanism at R University is shown in Table 4.

Table 4: Current internal recommendation and reward of R company

Recommended post	Bounty	Auditor
Grassroots staff	550	Recruitment specialist
Core technician	1200	Department management
Middle manager	1800	Department manager
Senior manager	3200	General manager

Recruitment specialists determine, based on interview results and job requirements, whether further recruitment is necessary or whether the recruitment process should be closed. They also schedule the start dates for new hires, send offer letters to prospective employees, and submit onboarding approval forms to superiors for approval. Although R University has expanded rapidly in recent years, the overall recruitment effectiveness has been poor. An analysis of R University's human resources data over the past few years reveals significant employee turnover. This has made it difficult to stabilize the university team, which has remained in a state of flux, severely impacting team collaboration efficiency. The results are shown in Table 5, which details R University's employee turnover over the past few years.

Table 5: Statistics of turnover of new recruits of R company from 2020 to 2024

Year		Interview number	Employment	proportion	Drain	proportion
2021	General employee	325	65	20.00%	36	11.08%
	Middle management	84	15	17.86%	19	22.62%
	Senior management	20	10	50.00%	5	25.00%
2022	General employee	236	54	22.88%	42	17.80%
	Middle management	64	22	34.38%	9	14.06%
	Senior management	12	5	41.67%	4	33.33%
2024	General employee	85	22	25.88%	20	23.53%
	Middle management	30	5	16.67%	5	16.67%
	Senior management	8	3	37.50%	1	12.50%

IV. B. Case Study Results

This section presents real recruitment data from a university in R as experimental data. To protect the privacy of candidates, all sensitive personal information has been removed to ensure anonymity. In total, 2,312,220 recruitment application records were collected, covering several years of recruitment data. The distribution of successful applications over time is shown in Table 6. After removing incomplete job postings and resumes (e.g., resumes with no work experience information, job postings with no job requirements), a total of 34,985 job application records were obtained. This section details the experimental setup, including word embedding settings, TAPJFNN parameters, and training phase specifics.

Table 6: Match data set statistical description

Statistical index	Value
Spot number	5812
Resume number	70015
Successful application number	20196
Failed application number	14789
The number of job requirements (job responsibilities) per position	9786
On average, each resume is a number of projects	4558
The average number of words per job requirement	15498
The average number of words per job/project experience	106382

IV. C. Overall experimental results analysis

The initial talent screening dataset was constructed based on real-world job-candidate matching data, using successful job applications as positive samples and unsuccessful job applications as negative samples to train the model. To mitigate the impact of data imbalance, negative samples were randomly sampled in equal quantities to the positive samples to evaluate the proposed model. Based on this, 80% of the dataset was randomly selected as training data, 10% was used for parameter tuning, and the remaining 10% served as test data to validate performance. The overall experimental results are shown in Table 7. It is evident that TAPJFNN performs best across all evaluation metrics, demonstrating that the proposed framework can model the matching degree between talent and job positions, thereby achieving talent screening. Specifically, the proposed TAPJFNN and APJFNN outperform BPJFNN. It can be observed that the proposed attention mechanism not only distinguishes key abilities or experiences for better feature extraction but also aids in better predicting job-talent matching outcomes. Additionally, the TAPJFNN model effectively utilizes historical recruitment data by introducing a topic-based ability perception attention mechanism and a re-training mechanism. Furthermore, it was found that all comparison methods based on bag-of-words features outperform those using pre-trained word vectors as input features. This indicates that pre-trained word vectors are insufficient to represent the semantic features of recruitment text data, thereby highlighting the importance of using BiLSTM to extract character-level semantic word representations in the embedding layer.

Table 7: Experimental results of the initial screening of talents

Method	Accuracy rate	Accuracy rate	Recall rate	F1	AUC
LR	0.6859	0.7014	0.6698	0.6839	0.7348
AB	0.7359	0.7458	0.7211	0.7318	0.8025
DT	0.7114	0.7745	0.6028	0.6893	0.7584
RF	0.7284	0.7379	0.7159	0.7269	0.7994
GBDT	0.7796	0.8046	0.7579	0.7748	0.8559
LR (with word2vec)	0.6689	0.6942	0.6528	0.6678	0.7436
AB (with word2vec)	0.6679	0.6684	0.6522	0.6639	0.7284
DT (with word2vec)	0.6228	0.6287	0.6008	0.6178	0.6723
RF (with word2vec)	0.6589	0.6674	0.6714	0.6428	0.7196
GBDT (with word2vec)	0.6748	0.6789	0.6728	0.6728	0.7520
BPJFNN-RNN	0.845	0.7956	0.7625	0.7784	0.8547
PJFNN	0.8046	0.8147	0.7896	0.8007	0.8739
APJFNN	0.8279	0.8714	0.7698	0.8169	0.9017
TAPJFNN_preliminary	0.8389	0.8674	0.8002	0.8625	0.9096
TAPJFNN	0.8512	0.8779	0.8163	0.8475	0.9358

To validate the effectiveness of each component of the model, an ablation experiment was conducted by progressively removing each component. Specifically, the following comparison method was constructed. The results are shown in Figure 1. First, it can be seen that TAPJFNN improved the AUC by approximately 3% compared to TAPJFNN_preliminary, clearly validating the effectiveness of the retraining mechanism for job-person matching prediction. Additionally, it was found that using only the max pooling layer or the attention pooling layer reduces the AUC by approximately 1%. Since using the average pooling layer did not result in significant improvement, it was not included in the retraining strategy. Furthermore, gradually removing the LSTM from the representation under the ability perception significantly degrades performance. Finally, as individual and multiple attention mechanisms under ability-aware conditions are progressively removed, performance deteriorates increasingly, clearly validating the crucial role of the proposed hierarchical attention mechanism.

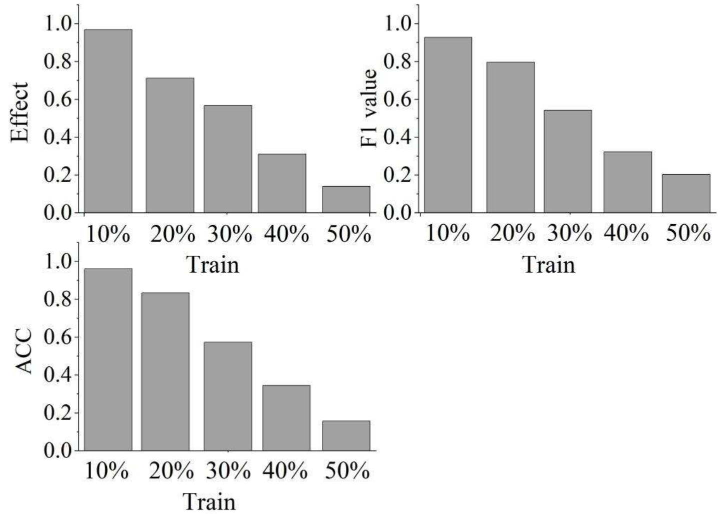

Figure 1: Each component of the model

When using the job-person matching retraining mechanism, the hyperparameter k controls the number of successful and unsuccessful applications. Therefore, we evaluated different ranges of k, from 3 to 15, to observe the impact on performance. The results are shown in Table 8. It can be observed that when k = 7, the performance is already good enough.

Table 8: The experimental effect of post recommendation

Method	HR@10	HR@20
ItemPop	0.2423	0.3204
BPJFNN-RNN	0.2697	0.3452
PJFNN	0.2748	0.3784
APJFNN	0.3154	0.4156
TAPJFNN_preliminary	0.3296	0.4445
TAPJFNN	0.3498	0.4586
TAPJFNN-K	0.4085	0.5448

V. Conclusion

The theme-based capability-aware job-person matching neural network TAPJFNN model proposed in this paper incorporates textual theme features into the APJFNN model, thereby achieving full informatization of the on-site recruitment process between universities and job seekers. This enables informatized management, intelligent application, and paperless communication in on-site recruitment. Using real recruitment data from R University as the research sample, the results show that the performance of the proposed TAPJFNN and APJFNN models is superior to that of the BPJFNN model. Additionally, the TAPJFNN model achieves an AUC that is approximately 3% higher than that of the TAPJFNN_preliminary model. Therefore, this innovative management model can enhance job-seeking efficiency, optimize the recruitment experience, facilitate communication between universities and job seekers to reach employment agreements, and comprehensively improve the service standards of human resources service institutions.

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