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RESEARCH ARTICLE

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A bilateral heterogeneous graph model for interpretable job recommendation considering both reciprocity and competition

Abstract Amidst the inefficiencies of traditional job-seeking approaches in the recruitment ecosystem, the importance of automated job recommendation systems has been magnified. However, existing models optimized to maximize user clicks for general product recommendations prove inept in addressing the unique challenges of job recommendation, namely reciprocity and competition. Moreover, sparse data on online recruitment platforms can further negatively impact the performance of existing job recommendation algorithms. To counteract these limitations, we propose a bilateral heterogeneous graph-based competition iteration model. This model comprises three integral components: 1) two bilateral heterogeneous graphs for capturing multi-source information from people and jobs and alleviating data sparsity, 2) fusion strategies for synthesizing attributes and preferences to produce mutually beneficial job matches, and 3) a competition-enhancing strategy for dispersing competition realized through a two-stage optimization algorithm. Augmented by granular attention mechanisms for enhanced interpretability, the model's efficacy, competition dispersion, and interpretability are validated through rigorous empirical evaluations on a real-world recruitment platform.

Keywords job recommendation, competition, reciprocity, interpretability

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1 Introduction

Despite the rapid evolution of professional online recruitment platforms, such as LiePin and LinkedIn, which provide job seekers with a vast array of job listings (Yi et al., 2007), sifting through thousands of jobs to identify the handful that aligns with one's specific requirements remains a laborious and intricate endeavor. According to a survey conducted by the Society for Human Resource Management, the process of securing a suitable job takes an average of 42 days for job seekers, incurring recruitment costs of approximately $4000 for companies. Consequently, there exists an immediate market demand for a recommendation system capable of swiftly and accurately presenting job opportunities that closely match the aspirations of job seekers.

In comparison to recommendation systems deployed on conventional e-commerce websites, job recommendation systems possess distinct characteristics, reciprocity and competition. Reciprocity, as elucidated by reciprocal recommender systems, implies that both the end user and the user being recommended must accept the suggested match for the recommendation to be deemed successful (Palomares et al., 2021). Job recommendation serves as a prime example of a reciprocal recommender system, wherein reciprocal job recommendation hinges upon modeling the bilateral matching between people and jobs. This mutual compatibility is contingent upon whether an individual meets a job's prerequisites and whether the job's attributes align with the individual's preferences (Al-Otaibi and Ykhlef, 2012). Therefore, a successful reciprocal job recommendation not only entails a person applying for a preferred job but also entails the human resources (HR) department of the company selecting and engaging with the application, thus deeming it a "successful match" in this context.

The concept of competition in job recommendation diverges from that of typical products on e-commerce platforms, which usually can be recommended to hundreds and thousands of users without limitation, as jobs are inherently limited resources incapable of catering to the needs of all individuals simultaneously (Borisyuk et al., 2017). Consequently, recommending a single job to multiple potential candidates inherently intensifies competition, thereby diminishing the success rate of matches and applications. Beyond these characteristics, job recommendation confronts a substantial challenge rooted in data sparsity pertaining to both people and jobs as well as their interactions. This arises from the dynamic nature of online recruitment platforms, where both jobs and individuals quickly depart from the platform upon fulfilling their needs. The influx of new individuals in need of prompt recommendations further compounds the scarcity of interaction data and associated labels (Sorokin and Forsyth, 2008).

The majority of existing job recommendation systems primarily focus on optimizing the click probability for individuals, such as job seekers, often neglecting the pivotal characteristics of reciprocity, competition, and data sparsity within this domain (He et al., 2023). Consequently, these systems may exhibit a reduced rate of successful job applications for individuals, potentially impacting the equilibrium and sustainability of the job market. Given these distinctive characteristics and the existing research landscape in the realm of job recommendation, the creation of an effective job recommendation system capable of aiding individuals in discovering suitable employment opportunities continues to present several significant challenges.

To effectively model reciprocity within a job recommendation system, it is imperative for the model to learn and align bilateral preferences of both people and jobs. The model should not only consider the personalized preferences of people but also assess the compatibility between their attributes and the prerequisites of available job opportunities. Moreover, in addition to attracting clicks from individuals, which indicate their interest in applying, enhancing application success rates significantly impacts the satisfaction of users in job recommendation models. Therefore, addressing the challenge of mitigating competitive pressure among individuals competing for the same job is crucial. This necessitates recommending the same job to an appropriate number of people based on their unique characteristics and competitive exclusivities.

Furthermore, the ability to cope with data sparsity is a critical factor in determining the practical application and robustness of job recommendation models. Current recruitment platforms prioritize personal information confidentiality, limiting access to detailed text descriptions, such as work experience in resumes. Consequently, recommendation systems increasingly rely on structured features and behavioral data disclosed by individuals on the platforms. However, the limited availability of structured features exacerbates the challenge of addressing data sparsity. Additionally, in practical scenarios, users often require the model to provide transparent recommendation evidence to enhance their trust and comprehension of the recommendations. Therefore, designing an intelligent recommendation model enhanced with interpretability for practical management applications, facilitating quick and informed decision-making, represents a significant challenge within the realm of job recommendation models.

In response to these challenges, we introduce the ReComJob model, a bilateral heterogeneous graph-based competition iteration model that amalgamates the characteristics of reciprocity and competition to implement intelligent job recommendation. First, we construct two heterogeneous graphs, one for individuals and one for jobs, based on their structured attributes and click information, leveraging the versatility of heterogeneous graphs in amalgamating multisource information (Shi et al., 2019). These graphs serve as a foundation for learning information and the connections between nodes, enhancing our understanding of people and job preferences. Building upon this, various fusion strategies are applied to model bilateral matching and achieve reciprocal job recommendations. To harness the structural characteristics and node data within the bilateral heterogeneous graphs, we define first-order and second-order neighbor nodes based on metapaths. This approach effectively addresses information sparsity by facilitating the transfer and integration of information through internode connections (Sun et al., 2011). Moreover, information transfer within heterogeneous graphs aids in propagating labels to unobserved nodes, attributing higher probability scores to relevant but unobserved nodes compared to unrelated nodes (Zhang et al., 2022). To address the challenge of sparse labels, we introduce metapath-based third-order and fourth-order neighbor nodes, enabling the weighted label information to supplement missing click data, taking into account the degree of correlation through the information dissemination of third-order neighbors.

Additionally, we recognize that evaluating the degree of person–job matching solely based on an individual's attributes or skill features has limitations. Instead, it relies on feedback regarding a person's application, such as when HR on the employer side clicks on a person's application (Belavina et al., 2020). Therefore, for assessing bilateral matching in job recommendation, we consider HR clicks (indicative of positive feedback from the job to the individual) rather than individual clicks as the model's learning objective. HR clicks provide valuable information, not only signifying an individual's application but also implying that HR reviewed the individual's resume, thereby reflecting the mutual preferences of the individual and the job.

To alleviate competitive pressure among people applying for the same job, we introduce a learning strategy that explicitly incorporates competitive relationships into the model's training process. This strategy entails a two-stage adjustment process, wherein a personalized competition adjustment weight is designed based on individuals' job rankings and their competitive preferences. This weight is applied to adjust the initial HR click score, dispersing competition among individuals vying for the same job. An individual's ranking correlates positively with their competitiveness, meaning that higher rankings denote greater competitiveness. Thus, the person's rank among competitors serves as a factor in adjusting the HR click score since an individual's application success is more influenced by their relative advantage over other competitors applying for the same job than by the absolute number of competitors. Furthermore, considering the varying degrees to which competition can either promote or weaken intrinsic motivation (Locke and Latham, 1990), we incorporate personalized competition preferences into the competition adjustment weight, which adjusts the recommendation with a high absolute value but a low ranking of the initial HR click score, to disperse the competition and potentially enhance the success rate of job seeking.

Heterogeneous graphs possess formidable capabilities for representing complex data. However, extracting and learning nodes and structural features necessitates the application of deep learning methods, such as graph neural networks (GNNs) (Zhang et al., 2022). Nevertheless, the intricacies of GNNs introduce complexity, leading to the "black box" problem and compromising their practical reliability (Ying et al., 2019). In the context of job recommendation, enhancing model interpretability becomes crucial because it can bolster people's confidence in the model's credibility and fairness. This is achieved by providing insights into the evidence behind the generation of job recommendations. To tackle this challenge, we have devised attention mechanisms of varying granularities within the GNN-based learning process. These mechanisms facilitate job recommendations tailored to individual preferences. Specifically, metapath-level attention weights are utilized to elucidate the rationale behind recommendations, such as suggesting a job based on geographical similarities to previously favored jobs. Additionally, the ReComJob model furnishes HR click scores and competitive scores in the recommendation results, empowering users to gain deeper insights into the reasons behind the recommendations and aiding them in making informed decisions.

Furthermore, extensive experiments have been conducted using real-world recruitment platform data, affirming the superior performance of ReComJob in comparison to baseline models. Additionally, a case study is presented to illustrate the interpretability benefits inherent to ReComJob.

In summary, we propose an effective job recommendation model, ReComJob, adept at addressing the intricacies of reciprocal matching, competitive exclusivity, and data sparsity within the domain of job recommendation. This model, which amalgamates reciprocity and competition, deviates from conventional recommendation algorithms that focus solely on optimizing accuracy and diversity. Reciprocity, in this context, entails the simultaneous modeling and matching of preferences from both parties, distinguishing it from the simple aggregation of recommendations for people and jobs. Furthermore, we gauge the alignment between people and jobs based on HR clicks, constraining recommended results to attract job applications while fostering positive feedback from jobs to individuals. Additionally, competition is a unique challenge that cannot be resolved through diversity alone. Diversified recommendation is to recommend multiple distinct jobs to an individual, while competition dispersion recommendations aim to reduce the number of recommending the same job to multiple individuals. Our approach, in this paper, centers on competition iteration to maximize clicks from individuals while considering their competitiveness in the job market, ultimately enhancing the likelihood of job application success. We introduce a competition adjustment weight that refines initial HR click scores through a two-stage iterative optimization process. On the one hand, it learns personalized competition preferences to achieve varying degrees of competition dispersion. On the other hand, it offers job seekers a visualized competition ranking, providing insights into the underlying rationales for recommendations and elevating the interpretability of recommendation outcomes.

The remainder of this paper unfolds as follows. Section 2 offers a concise review of related work. Section 3 delves into the technical intricacies of the ReComJob model, while Section 4 provides a comprehensive evaluation of model performance. This is followed by a discussion of the interpretability of the results. Finally, concluding remarks are presented in Section 5.

2 Literature review

2.1 Job recommendation

In recent times, job recommendation algorithms have undergone optimization to accommodate the characteristics of bilateral matching. The primary objective is to align candidates' skills with job requirements efficiently, minimizing wastage (Xu et al., 2016; Lian et al., 2017). Deep neural networks have been utilized as valuable tools for enhancing bilateral matching between people and jobs. For instance, Zhu et al. (2018) introduced a convolutional neural network that assesses the compatibility between a candidate's qualifications and a job's requirements by quantifying the distance between their respective latent representations. Bian et al. (2019) proposed a global matching multilayer deep learning model that captures the global semantic interactions between sentences in job descriptions and resumes. Sun et al. (2019) introduced a "two-way selection" algorithm designed to aid jobs in efficiently selecting suitable candidates. Qin et al. (2020) presented a topic-based ability-aware person–job fit neural network for comprehensive bilateral matching analysis between individuals and jobs. A topic-based ability-aware person–job fit neural network incorporates a refinement strategy to enhance the accuracy of predicting the degree of matching between individuals and jobs.

In the domain of human resources, research has concentrated on the competitive nature within the job market. For example, Collins and Mcnamara (1993) applied game theory to optimize a stopping problem and explored the influence of competition on job search strategies. Anderson and Burgess (2000) investigated the impact of endogenous job competition on the matching function at the state level. Pierrard (2008) studied the effects of cross-regional competition among individuals on the national unemployment rate. These studies primarily examine competitive relationships at the macro level and do not delve into the impact of competition on individual job search success. Some psychological and behavioral studies suggest that competition can either diminish or enhance participants' interest by reducing or enhancing their sense of self-determination, depending on their individual preferences for competition (Deci and Ryan, 1985; Song et al., 2013). Therefore, when designing job recommendation algorithms, it is imperative to incorporate personalized competitive preferences for individuals.

In the context of job recommendations, several studies have underscored the unique characteristic of competitive exclusivity. The scarcity of job opportunities dictates that each job can accommodate only a limited number of individuals. Consequently, unlike general commodities, a job cannot be indiscriminately recommended to numerous individuals solely based on their preferences (Kenthapadi et al., 2017). Borisyuk et al. (2017) proposed a regulatory strategy to manage the number of job applications. However, an individual's success in job seeking is not solely determined by the absolute quantity of applications but is also influenced by their relative ranking compared to other competitors. Therefore, optimizing through competitive rankings, rather than controlling the volume of applications, constitutes a pivotal design element of the job recommendation model presented in this paper.

2.2 Heterogeneous information network

Heterogeneous graphs possess the remarkable capability to represent diverse entities and relationships, and they have found wide applications in real-world scenarios, including bibliographic networks, social media networks, and knowledge graphs (Sun et al., 2011). Various methods for learning heterogeneous graph representations leverage metapaths to manage the complexities of heterogeneous features (Tang et al., 2015; Wang et al., 2016). For instance, Zhao et al. (2017) introduced a metagraph concept, similar to metapaths, to address the challenge of integrating high-dimensional information. Metapath2vec, a heterogeneous graph representation learning model proposed by Dong et al. (2017), employs metapaths to guide random walks within heterogeneous graphs. Shi et al. (2019) introduced the HERec model, which integrates feature representations learned from different metapath schemes to enhance the learning effectiveness on heterogeneous graphs.

In addition to metapath-based approaches, GNNs have garnered significant attention in recent years. GNNs generate embedding representations of nodes by employing spatial filters and propagate structural information through layers (Zhou et al., 2020). Tu et al. (2018) presented the deep hypernetwork embedding model, designed to capture both local and global structures within heterogeneous graphs. Wang et al. (2019) proposed the heterogeneous graph attention network, which employs a hierarchical attention mechanism to capture node and semantic importance. Subsequently, several related studies have introduced attention-based heterogeneous GNNs (Hong et al., 2020; Hu et al., 2020). For instance, Hu et al. (2019) introduced the heterogeneous graph attention network for learning heterogeneous graph embeddings, particularly for short text classification. Heterogeneous graph Structural Attention Neural Network (HetSANN) (Hong et al., 2020) and Heterogeneous Graph Transformer (HGT) (Hu et al., 2020) utilized a single type of node as the focal point to calculate the importance of other types of nodes in its vicinity, assigning different weights to neighbors. In the context of this paper, we leverage heterogeneous graphs to tackle the challenge of data sparsity in job recommendation. We have designed a network and attention mechanism tailored to the domain's characteristics, enabling us to learn individualized preferences of people effectively.

3 Bilateral heterogeneous graph competition iterative model

Suppose that we have a set of people $U=[u_1, u_2, \ldots, u_m]$ and a set of jobs $J=[j_1, j_2, \ldots, j_n]$, where m and n are the total numbers of people and jobs, respectively. Correspondingly, $T=[(u_1, j_1), (u_2, j_1), \ldots, (u_m, j_n)]$ is used to represent the application of people for jobs, and the corresponding job feedback is recorded as $Y=[y_{1,1}, y_{1,2}, \ldots, y_{m,n}]$, where $y\in\{0, 1\}$ indicates whether HR deems the person to be a match for this job, where $y=1$ means matching (i.e., the person applies for the job and HR clicks the application), otherwise, $y=0$.

Drawing from the definitions provided above, we present a formal proposition of the ReComJob model —

a bilateral heterogeneous graph-based competition iteration model — aimed at mitigating the challenges outlined in Section 1. This model leverages individual attributes and job applications to construct a heterogeneous graph for people and utilizes job attributes and clicks to construct a corresponding heterogeneous graph for jobs. The ReComJob model comprises three core components: The creation of heterogeneous graphs and the derivation of metapath-based neighbor nodes, attention-enhanced embedding within the heterogeneous graph, and job recommendation based on bilateral matching and competitive iteration. Figure 1 provides an illustrative representation of the overall architecture of ReComJob.

3.1 Generation of heterogeneous graphs and metapath-based neighbor nodes

To capture the preferences and attributes of people and jobs while respecting privacy considerations, we amalgamate disclosure attributes and click information obtained during the job-seeking processes to construct two distinct types of bilateral heterogeneous graphs. One graph is founded on an individual's applications and attributes, while the other is rooted in a job's clicks and attributes. These graphs, namely, the person application graph and the job (HR) click graph, encapsulate an individual's job preferences and the evaluations conducted by job (HR), respectively. The integration of these two heterogeneous graphs facilitates the acquisition of bilateral preferences learning and matching, which captures and depicts the inherent characteristic of reciprocity within job recommendations.

Within these heterogeneous graphs, nodes encompass person nodes, person attribute nodes, job nodes, and job attribute nodes. These nodes are interconnected through four types of relationships: Individuals possess person attributes, jobs possess job attributes, individuals apply for jobs, and job (HR) interactions with individuals through clicks. In the selection of attribute nodes, we draw upon prior research in the field of job recommendation, which has identified company scale, type, region, salary, person's function, age, and education as pivotal attributes for people and jobs as summarized in Table 1. By meticulously screening nodes based on domain knowledge, we can control over the quantity and effectiveness of metapaths within heterogeneous graphs, ultimately enhancing the algorithm's efficacy (Epasto and Perozzi, 2019).

Table 1 Summary of attributes

Attribute	Job/Person	Reference
Regional factors, salary	Job	Li et al. (2016)
Job type, region, job skills	Job	Yang et al. (2017)
Education level, job function experience, language skills	Person	Malinowski et al. (2006)
Academic requirements, job type, salary, region	Job	Yi et al. (2007)
Company scale	Job	Lu et al. (2012)

Metapaths play a crucial role in discerning the contributions of various attributes or preference paths to the ultimate match, thereby furnishing an explanatory framework for recommendation outcomes (Yang et al., 2023). In the context of the person application graph, heterogeneous neighbor nodes can be derived through metapath-based first-order connections. For instance, the connection denoted as "person–job" signifies jobs to which an individual has applied. Similarly, within the HR click graph,

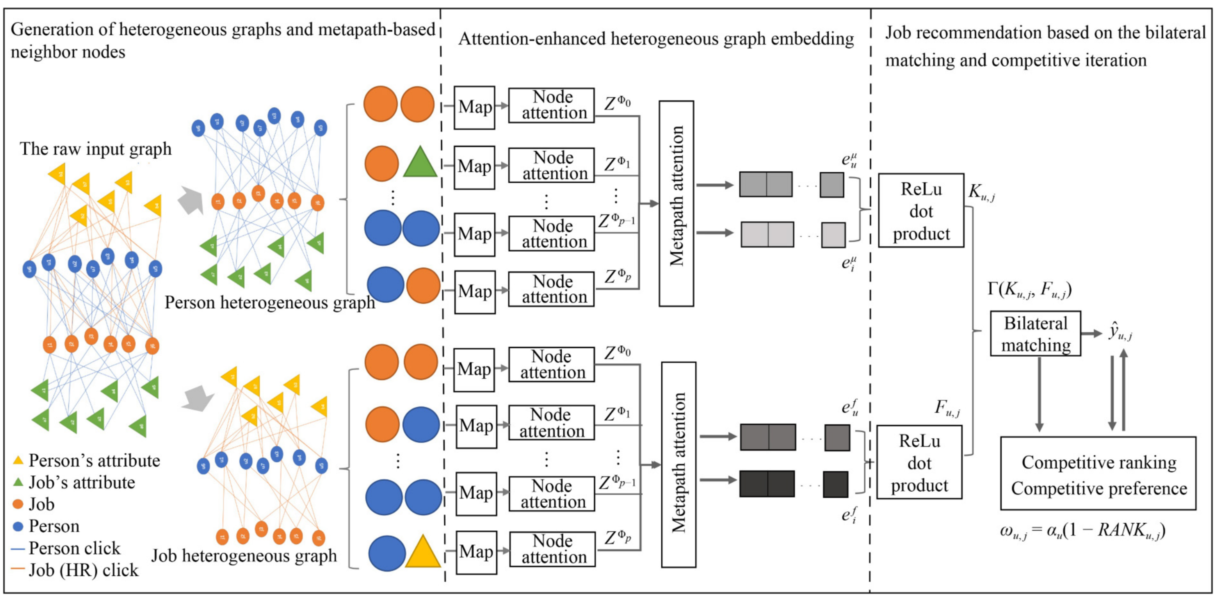

Fig. 1 Bilateral heterogeneous graph competition iteration model.

metapath-based first-order connections enable the extraction of heterogeneous neighbor nodes. Furthermore, metapath-based second-order connections yield homogeneous neighbor nodes. For example, "person–job–person" represents individuals who share a common application relationship, facilitating the identification of connections among individuals based on application similarity.

In addition, we introduce a more in-depth connection-based information transfer mechanism that incorporates metapath-based third-order and fourth-order neighbor nodes. These nodes establish potential connections based on the similarity between cold start data and introduce potential applications or click tags for new people or jobs. These deeper connections not only address the issue of sparsity but also effectively tackle the problem of unbalanced labels. Similar to the metapath-based first-order and second-order neighbor nodes, metapath-based third-order and fourth-order neighbor nodes are generated for people and jobs within the two heterogeneous graphs. Exemplary connections are provided in Table 2.

Link weights exhibit distinct assignments contingent upon the type of the connection. Links connecting either a job or an individual to an attribute node are endowed with a weight of 1. Conversely, for other links, such as those signifying clicks or applications, the weight aligns with the count of such clicks or applications. To differentiate between directly connected neighbor nodes and potential neighbor nodes generated through information transmission, namely, first-order, second-order, third-order, and fourth-order neighbor nodes, the link weight of the nth-order neighbor nodes is set as the reciprocal of the number of transmissions, denoted as $1/n$.

3.2 Attention-enhanced heterogeneous graph embedding

To effectively capture the job-seeking preferences of people, the ReComJob model employs a multigrained attention mechanism for learning heterogeneous graphs. A node-level attention mechanism is introduced to consolidate semantically specific node embedding representations within the context of metapaths. Concurrently, a metapath-level attention mechanism is utilized to apprehend and amalgamate individualized preferences at the metapath level. The metapath-level attention mechanism also serves the purpose of elucidating recommendation outcomes, thereby bolstering people's trust in and comprehension of the model's recommendations. The process of representation learning within heterogeneous graphs is visually outlined in Fig. 2.

Formally, in a heterogeneous graph $G=\{V, R\}$ with the sets of predefined node and link types Ω and ε, V represents nodes and R represents links. For the node set V^{τ} with type $\tau \in \Omega$, the representation matrix of nodes is denoted as $X^{\tau} \in \mathbb{R}^{|V^{\tau}| * q^{\tau}}$, where q^{τ} is the representation dimensionality. For a node $i \in V^{\tau}$, its corresponding representation vector is the ith row of X^{τ}. According to Banach's fixed point theorem (Oltra and Valero, 2004), for any initial point x_0, the Cauchy sequence $f(x_0)$ converges to a fixed value. Hence, for the initial feature vector of each node, we adopt a straightforward approach by employing one-hot encoding of the node degree. This approach has been empirically proven to enhance performance (Errica et al., 2019). To render these diverse node features commensurate, we employ a type-specific transformation matrix, denoted as M_{τ}, to project distinct node

Table 2 Examples of metapath-based third-order and fourth-order neighbor nodes

Graph	Metapath based third-order neighbor nodes	Metapath based fourth-order neighbor nodes
Person application network	person–job–city–job: Potential applications from person who prefer the same work city …	person–job–city–job–person: People who prefer the same city of job …
Job (HR) click network	job (HR)–person–education–person: Potential clicks from job (HR) that prefer person in the same education level …	job (HR)–person–education–person–job (HR): Jobs that prefer person in the same education level …

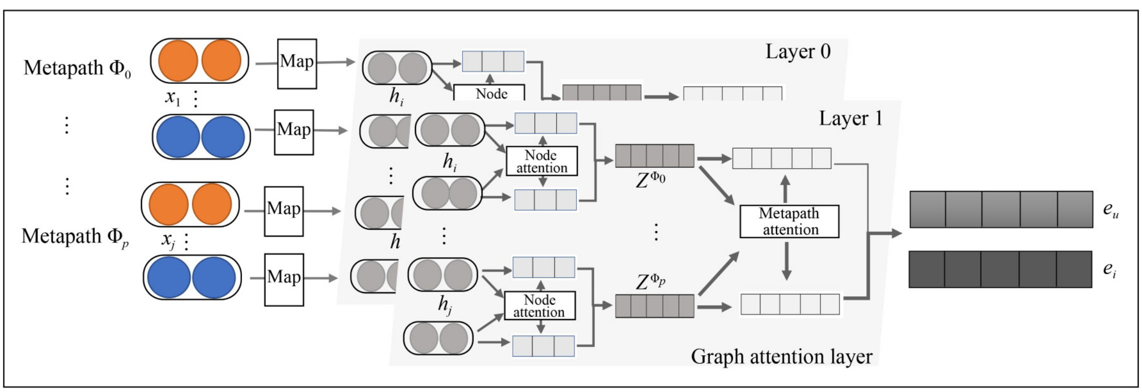

Fig. 2 Attention-enhanced heterogeneous graph representing learning.

features into a uniform dimensional space. The transformation process is elucidated in Eq. (1):

$$h_i^{\tau} = M_{\tau} \cdot x_i^{\tau}. \tag{1}$$

In a heterogeneous graph, the metapath Φ between nodes of types Ω_1 and Ω_{l+1} is expressed as $\Omega_1 \to (\varepsilon_1) \to \Omega_2 \to (\varepsilon_2) \ \dots \ \to (\varepsilon_l) \to \Omega_{l+1}$, where Ω_l is the node type and ε_l is the link type. Building upon this foundation, the heterogeneous graph can be partitioned into multiple isomorphic subgraphs based on the type of metapath. Within each subgraph, a graph attention layer is meticulously crafted to extract and assimilate the embedding representation of each node by considering the adjacency relationships. Specifically, for node i, Eq. (2) learns and normalizes the importance relationship between nodes under each metapath, where σ represents the activation function, $\|$ is the connection operation, and β_{Φ} is the node-level attention vector under metapath Φ. Therefore, the embedded representation of node i under metapath Φ can be obtained by integrating the attention coefficients and by mapping features corresponding to neighboring nodes, as shown in Eq. (3), where h_j^{Φ} is the embedding representation vector of node j in metapath Φ, and N_i^{Φ} is the set of metapath-based neighbors linking with node i via metapath Φ. For clarity, the layer indices Ψ of all the layer-specific notation are omitted in the following.

$$\alpha_{ij}^{\Phi} = \frac{\exp\left(\sigma\left(\beta_{\Phi}^{\mathrm{T}} \cdot \left[h_i' \,\|\, h_j'\right]\right)\right)}{\sum_{k \in N_i^{\Phi}} \exp\left(\sigma\left(\beta_{\Phi}^{\mathrm{T}} \cdot \left[h_i' \,\|\, h_k'\right]\right)\right)}, \tag{2}$$

$$z_i^{\Phi} = \sigma\left(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot h_j^{\Phi}\right). \tag{3}$$

To comprehensively incorporate and discern the influence of metapaths on the ultimate vector representation in an interpretable manner, a metapath-level attention mechanism is harnessed. This mechanism serves to differentiate between various preferences and intentions exhibited by people and jobs. The optimized metapath weight is recorded as γ^{Φ} shown in Eq. (4), where c is the attention vector at the metapath level, V^{Φ} represents the set of nodes under the metapath Φ, and W and b are the weight matrix and bias vector, respectively. By using the learned attention weight γ^{Φ} as the coefficient, metapath-based representations can be integrated to obtain the comprehensive representation for nodes, as shown in Eq. (5), where p is the number of metapaths. The obtained representation E is in turn used as the input of the blocks in the next layer.

$$\gamma^{\Phi} = \frac{\exp\left(\frac{1}{|V^{\Phi}|}\sum_{i \in V^{\Phi}} c^{\mathrm{T}} \cdot \tanh\left(W \cdot z_i^{\Phi} + b\right)\right)}{\sum_{k \in metapaths} \exp\left(\frac{1}{|V^{k}|}\sum_{i \in V^{k}} c^{\mathrm{T}} \cdot \tanh\left(W \cdot z_i^{k} + b\right)\right)}, \tag{4}$$

$$E = \sum_{\Phi=1}^{p} \gamma^{\Phi} \cdot Z^{\Phi}. \tag{5}$$

3.3 Job recommendation based on bilateral matching and competitive iteration

The final representations of the people and jobs in the person application heterogeneous graph and the HR click heterogeneous graph are output by the blocks in the last layer, denoted as e_u^{μ}, e_i^{μ}, and e_u^{f}, e_i^{f}, respectively. Afterward, to model the connection between the job vector and the person vector, the dot product and a single-layer perceptron are employed to learn the preference matrix K for people and the preference matrix F for jobs, which are implemented as follows:

$$K_{u,j} = ReLu\left(e_u^{\mu} \cdot e_j^{\mu}\right), \tag{6}$$

$$F_{u,j} = ReLu\left(e_u^{f} \cdot e_j^{f}\right). \tag{7}$$

To quantify the extent of reciprocal alignment between people and jobs, the preference matrices extracted from the two heterogeneous graphs are amalgamated using various fusion strategies, denoted as $\Gamma(K, F)$. Commonly employed fusion strategies in reciprocal recommendation encompass the harmonic mean, the arithmetic mean, and the cross-ratio function (Neve and Palomares, 2019a; 2019b). Each of these strategies exhibits distinct advantages and is suitable for different problem scenarios. Consequently, all three methods — harmonic mean, arithmetic mean, and cross-ratio function — are applied to derive the reciprocal recommendation score (Eqs. (8)–(10)). A comparative analysis is conducted during experiments to ascertain the most effective approach for achieving optimal reciprocal recommendation results. Ultimately, the widely employed quadratic loss function is adopted to gauge the disparity between the predicted value and the actual ground-truth value (Eq. (11)).

$$\hat{y}_{u,j} = \Gamma_{\mathrm{h}}(K_{u,j}, F_{u,j}) = \frac{2}{K_{u,j}^{-1} + F_{u,j}^{-1}}, \tag{8}$$

$$\hat{y}_{u,j} = \Gamma_{\mathrm{a}}(K_{u,j}, F_{u,j}) = \frac{K_{u,j} + F_{u,j}}{2}, \tag{9}$$

$$\hat{y}_{u,j} = \Gamma_{\mathrm{c}}(K_{u,j}, F_{u,j}) = \frac{K_{u,j}F_{u,j}}{K_{u,j}F_{u,j} + (1-K_{u,j})(1-F_{u,j})}, \tag{10}$$

$$L_1 = (y_{u,j} - \hat{y}_{u,j})^2. \tag{11}$$

After the initial matching prediction based on reciprocity features, the model proceeds to incorporate an iterative optimization module grounded in the concept of competition. The introduction of personalized competition adjustment weights proves pivotal in the realm of job recommendation, given the inherent exclusivity of job competition and the substantial impact of relative rankings on an individual's likelihood of being selected and hired by an employer. Studies have demonstrated that individuals exhibit varying intrinsic motivations contingent upon their proclivity for competition, with some experiencing increased motivation while others face a decrease (Song et al., 2013). Hence, it becomes imperative to integrate personalization factors such as competitive ranking and preferences into the optimization process to enhance the final match score.

To establish rankings for individuals with regard to each job, the initial matching score $\hat{y}_{u,j}$ is used to generate an initial ranking. Data analysis revealed a general negative correlation between rankings and job (HR) clicks, as illustrated in Fig. 3.

Therefore, the personalized competition adjustment weight assigned to person u is influenced by their relative ranking among all candidates on job j, denoted by $\omega_{u,j}$. The higher the ranking value, the lower the relative ranking in the competition, making it more difficult to succeed. Furthermore, it is worth noting that the competition adjustment weight is also influenced by variations in an individual's inclination toward competition. When confronted with equivalent levels of competition, distinct individuals may elicit varying degrees of motivational response (Song et al., 2013). Consequently, the personalized competition adjustment weight must be derived through a process that takes into account each individual's ranking and their specific proclivity for competition, as depicted in Eq. (12):

$$\omega_{u,j} = \alpha_u(1 - RANK_{u,j}) = \alpha_u\left(1 - \frac{rank_{(u,j)\in T_j}(\hat{y}_{u,j})}{|T_j|}\right), \quad (12)$$

where α_u represents the personalized preference of person u for competition, T_j represents the set of applications of people related to job j and $|T_j|$ is the number of applications for job j.

During training, the problem can be treated as a two-stage process. First, we iterate over the personalized

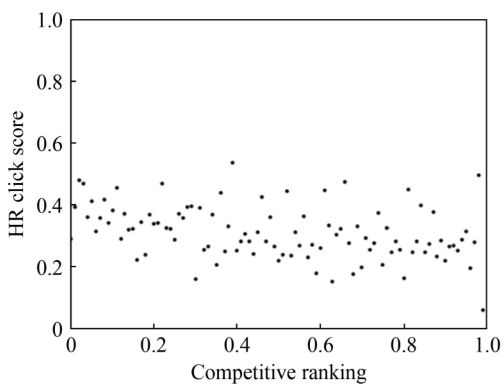

Fig. 3 The relationship between HR click score and ranking.

competitively adjusted weights $\omega_{u,j}$ and initial matching scores $\hat{y}_{u,j}$. Then, $\hat{y}_{u,j}$ is adjusted by using the latest relative ranking information until the relative size of $\hat{y}_{u,j}$ stabilizes to a fixed value, resulting in convergence, thus obtaining each parameter of the model. The final objective function is shown in Eq. (13):

$$\begin{aligned} L_2 &= (y_{u,j} - \omega_{u,j}\hat{y}_{u,j})^2 \\ &= \left(y_{u,j} - \alpha_u\left(1 - \frac{rank_{(u,j)\in T_j}(\hat{y}_{u,j})}{|T_j|}\right)\hat{y}_{u,j}\right)^2. \end{aligned} \quad (13)$$

During the testing phase, the ultimate recommendation score is calculated by factoring in both the ranking and the predicted matching score. This approach ensures that jobs with higher recommendation scores are suggested to each individual, effectively mitigating the intensity of job competition and enhancing the prospects of job-seeking success.

4 Experiments

4.1 Experimental setup

We conducted an extensive evaluation of our model using a real-world dataset obtained from one of China's largest online recruiting platforms, denoted as S. This dataset comprises 22552 job listings and 176069 individuals, with a total of 357832 application records. To safeguard individuals' privacy, all records were anonymized by removing any identifying information. An analysis of HR click patterns in the data revealed the ratio of the number of job applications to the number of HR clicks for each job. The statistics indicated an average HR click rate of 0.448 for each job. This observation suggests the presence of a significant number of invalid applications in the job-seeking process, highlighting the importance of considering factors such as reciprocity and competition to enhance efficiency.

The preprocessed data were split into three subsets: The training set, the validation set, and the test set. The training and validation sets were utilized for training the model parameters, while the test set was employed to assess the model's performance and provide explanations for the recommendation results based on metapaths.

The comparative analysis in this study encompasses two facets. The first part focuses on job recommendation models, including the traditional matrix factorization (MF) model (Lee and Seung, 2000), as well as state-of-the-art models such as the Person–Job Fit Neural Network (PJFNN) (Zhu et al., 2018) and MUlti-Field Features representation and INteraction (MUFFIN) (He et al., 2023). The second part centers on graph processing models, encompassing methods such as DeepWalk (Perozzi et al., 2014), Metapath2vec (Dong et al., 2017), and advanced models such as HERec (Shi et al., 2019) and Heterogeneous Graph Convolutional Network (HGCN) (Yang et al., 2023). Our evaluation metrics include accuracy, precision, recall, and the $F1$ score. Given that the matching degree measured in this study is a continuous value ranging from 0 to 1, we also include the mean squared error (MSE) and mean absolute error (MAE) in the evaluation.

In the following four subsections, we will present the results of extensive experiments conducted on a real-world recruitment dataset to address the following motivation questions:

Q1: How does the proposed ReComJob model perform compared to other state-of-the-art models?

Q2: Does the proposed competition-based iterative optimization module successfully achieve the objective of dispersing competition in job recommendations?

Q3: How does the proposed ReComJob model effectively tackle the issue of data sparsity by utilizing a bipartite heterogeneous graph model?

Q4: How does the proposed ReComJob model generate interpretable job recommendation results?

4.2 Overall performance evaluation

The overall performance of all models is summarized in Table 3. First, it is evident that the ReComJob model proposed in this study demonstrates significant advantages across all evaluation metrics. Specifically, the cross-rate fusion strategy outperforms the other two fusion strategies in terms of $F1$ score, precision, and recall. The arithmetic mean performs best in terms of MSE and accuracy, while the harmonic mean outperforms the other two fusion strategies in terms of MAE.

Second, among the job recommendation models, the MF model, which focuses solely on people's job applications, performs poorly in reciprocal bilateral matching. In contrast, the PJFNN and MUFFIN, which consider bilateral feature matching between people and jobs based on neural networks, exhibit significant improvements in accuracy.

Third, in the graph processing models, DeepWalk adds attribute nodes for people and jobs but does not effectively handle heterogeneity, leading to subpar results influenced by considerable noise in data learning. Metapath2vec considers node heterogeneity but struggles with managing node relationships in the graphs, resulting in unsatisfactory results. HERec optimizes the integration model with different metapaths, achieving an accuracy approximately 6% higher than that of Metapath2vec. HGCN combines object-level aggregation and path-level aggregation to automatically extract useful metapaths for each object, achieving the best performance among the comparison models with an accuracy of 0.844. However, this accuracy is still lower than that of the ReComJob model proposed in this paper.

Fourth, ReComJob considers the information provided by multiorder metapath-based neighbor nodes and takes the weight of nodes and people preferences for different paths into account, significantly improving the model's learning effect through the personalized competition weights. Compared to MUFFIN, which performs the best among the job recommendation models in the comparison, ReComJob's accuracy improves by approximately 2%. Compared to the best-performing graph processing model, HGCN, the accuracy of ReComJob improves by 4%.

Finally, to assess the performance of the job recommendation model in terms of reciprocity and competition on people's click-through rate (CTR), we calculated the CTR of people based on the recommendations provided by the trained ReComJob model and other comparison models. The results are presented in the last column of Table 3. Notably, since HR (job) clicks encompass information regarding both people's and jobs' preferences, optimizing for maximizing HR clicks does not compromise the CTR score of people. As a result, the ReComJob model proves highly effective in enhancing the job application experience for people, ensuring increased success rates while maintaining a desirable CTR.

Impact of Hyperparameters. The hyperparameter Ψ

Table 3 The overall performance of the baselines and ReComJob model

Models	MSE	MAE	Precision	Recall	Accuracy	$F1$	CTR
ReComJob Γ_c	0.047	0.133	0.902	0.881	0.881	0.891	0.912
ReComJob Γ_a	0.042	0.166	0.901	0.880	0.888	0.890	0.898
ReComJob Γ_h	0.049	0.122	0.900	0.880	0.879	0.890	0.887
MF	0.132	0.236	0.434	0.659	0.659	0.523	0.668
PJFNN	0.057	0.180	0.852	0.807	0.853	0.829	0.862
MUFFIN	0.055	0.151	0.870	0.775	0.868	0.820	0.878
DeepWalk	0.222	0.497	0.510	0.591	0.591	0.548	0.605
Metapath2vec	0.129	0.211	0.565	0.606	0.665	0.585	0.674
HERec	0.072	0.172	0.779	0.705	0.705	0.740	0.715
HGCN	0.060	0.138	0.890	0.814	0.844	0.850	0.853

controls the number of layers in the graph, and the hyperparameter q determines the representation dimensionality of nodes. We evaluated the impact of performance with different Ψ ranging from 1 to 6 and q ranging in {4, 8, 16, 32, 64, 128}, which are shown in Fig. 4. We can observe that the performance is generally stable for different parameter settings and thus shows good robustness, and when $\Psi = 2$ and $q = 16$, the performances are good enough.

Ablation Study. To assess the necessity of each module's design and its contribution to the final effectiveness, ablation experiments were conducted, and the results are presented in Table 4.

First, when the competition iteration module was removed (i.e., ReComJob−competition), the model's accuracy experienced a slight drop of approximately 2%. The competition module is designed to disperse competition intensity and to diversify recommendations, and while it has a minor impact on matching accuracy, its presence contributes positively to the model.

Second, the removal of metapath-based third/fourth-order neighbor nodes (i.e., ReComJob−third/fourth order neighbors) resulted in a significant decrease in accuracy. This highlights the importance of incorporating metapath-based third/fourth-order neighbor nodes, which facilitate longer-distance information learning and potential label dissemination, addressing the sparsity issue and enhancing the model's accuracy.

Third, the importance of metapath-based second-order neighbor nodes (i.e., ReComJob−second order neighbors) was verified. A notable decline in accuracy was observed, with recall and accuracy decreasing by approximately 7% and 4%, respectively. This demonstrates that the inclusion of second-order neighbor nodes, which capture direct homogeneous node relationships such as people's applications for the same job, is effective in promoting information transmission in the heterogeneous graph and improving job recommendation accuracy.

Finally, the need for attention mechanisms of various granularities was confirmed by excluding word-level attention (i.e., ReComJob−word attention) and metapath-level attention (i.e., ReComJob−metapath attention) and simply connecting the vectors using a single-layer perceptron. Removing word-level attention led to a reduction in accuracy by approximately 4%, emphasizing the effectiveness of the word-level attention mechanism in integrating node information and learning feature representations of people and jobs. Additionally, removing metapath-level attention resulted in a decrease in accuracy of approximately 2%, underlining the importance of learning individual preferences for metapaths.

4.3 Competition dispersion analysis

To assess the efficacy of the job recommendation model in contrast to the competitive iterative optimization module and the model designed for maximizing user clicks in dispersing competition, we conducted an experiment wherein both models were employed to suggest employment opportunities to the same subgroup of people. The distributions of recommended job outcomes for these two models are depicted in Fig. 5.

The job recommendation model implementing competitive iterative optimization exhibits a more dispersed and uniform distribution of recommended results, characterized by a lower frequency and broader job coverage. Conversely, in the context of job recommendation results oriented toward optimizing user CTRs, the recommended job listings are more concentrated, displaying a higher

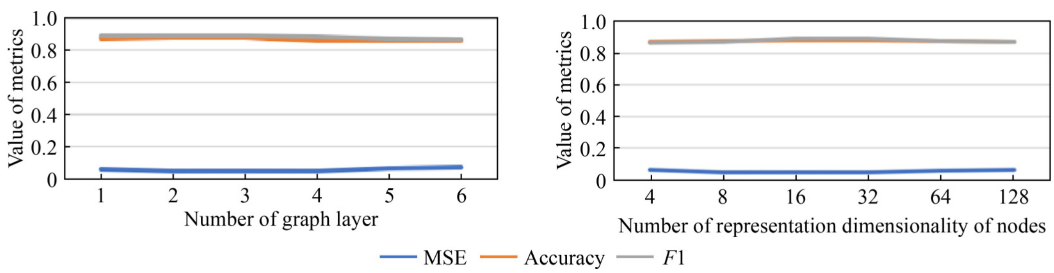

Fig. 4 The impact of hyperparameters.

Table 4 The effects of different model modules

Model module	MSE	MAE	Accuracy	$F1$	Precision	Recall
ReComJob	0.047	0.133	0.881	0.891	0.902	0.881
ReComJob−competition	0.071	0.143	0.863	0.885	0.893	0.878
ReComJob−third/fourth order neighbors	0.100	0.125	0.852	0.878	0.874	0.882
ReComJob−second order neighbors	0.090	0.122	0.841	0.844	0.869	0.820
ReComJob−word attention	0.101	0.158	0.843	0.858	0.865	0.851
ReComJob−metapath attention	0.067	0.131	0.864	0.880	0.890	0.871

frequency and narrower coverage.

Through this comparative analysis, it is evident that the job recommendation model employing competitive iterative optimization can concurrently ensure recommendation accuracy and mitigate competition, thus offering job suggestions that better align with the distinct preferences of diverse individuals. This model is adept at aligning job recommendations with individuals' preferences, diminishing the risk of competition-induced failure, and enhancing the overall success rate of job applications.

4.4 Robustness analysis on sparsity

To demonstrate the robustness on copying with sparsity, we juxtapose the ReComJob model with both the MF model and the MUFFIN model across varying degrees of data sparsity, the latter of which exhibits superior performance among the models in comparison. Following Hu et al. (2018)'s validation approach, we partitioned the entire dataset into five equal segments, incrementally increasing the training data from one to four, corresponding to 20%, 40%, 60%, and 80% of the data serving as the training set.

Figure 6 visually conveys the stability of the ReComJob model's accuracy across distinct proportions of training data. The vertical axis denotes accuracy, while the horizontal axis signifies the proportion of the different training sets. Notably, the accuracy of the conventional MF model experiences a substantial decline as the proportion of training data diminishes, indicating a significant impact on the model's learning performance as data sparsity intensifies. On the other hand, MUFFIN, which amalgamates multidomain features and click data to glean potential preferences, exhibits relative stability when compared to the MF model. Only when data sparsity reaches a critical threshold (training data falling below 40%) does MUFFIN's accuracy observe a notable reduction. These comparative experiments underscore the efficacy of the heterogeneous graph model in adeptly amalgamating diverse information types, demonstrating its capacity to effectively mitigate data sparsity challenges in job recommendation through information propagation between interconnected nodes.

4.5 A case study on interpretability

The job recommendation model proposed in this manuscript possesses the capability to furnish personalized job suggestions to people based on their potential career preferences. The recommendation results can be explained through the utilization of metapath attention in

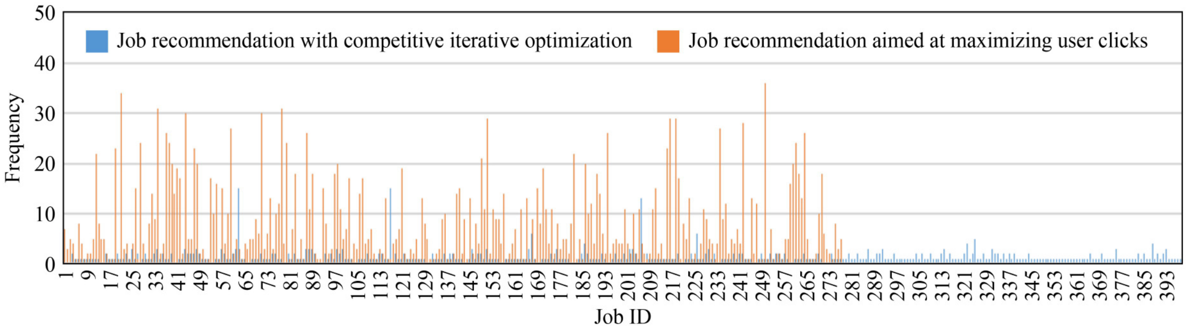

Fig. 5 Job recommendation with intensity comparison.

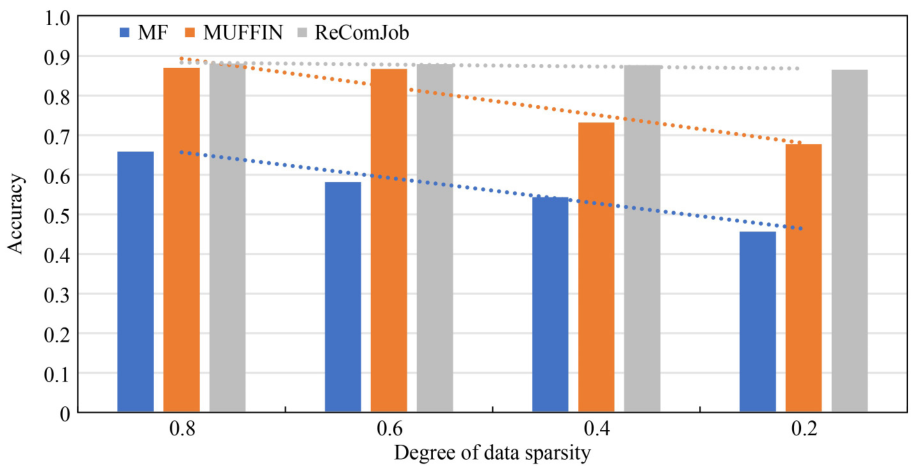

Fig. 6 Accuracy change under various proportions of training sets.

the final layer, thereby augmenting individuals' trust and comprehension of the recommendation system and facilitating a streamlined application process. Figure 7 elucidates the preference weights of people based on metapath attention for jobs sharing analogous attributes such as type, salary, city, and scale. It can be observed that most people tend to accord priority to job type and salary, which rightfully should be the central focus in job recommendations. While some people may exhibit preferences for jobs located in similar cities, the influence of company scale appears to exert less sway on their decision-making. These divergent inclinations in people's preferences highlight the significance of integrating personalized preferences into the job recommendation paradigm.

Table 5 serves as an illustrative example of how the ReComJob model explains recommendation instances predicated on metapath weights, illuminating a strong inclination of the individual toward jobs located in similar cities. Additionally, the competition adjustment weight that correlates with rank is explicitly designed in ReComJob. Throughout the recommendation process, the model expounds upon the rationales behind each recommendation via metapath attention weights and concurrently conveys the competitive ranking within the recommendation score. This multifaceted approach aids individuals in comprehending the detailed information of the recommendation, thereby augmenting their perception of the recommendation results and their confidence in the application process.

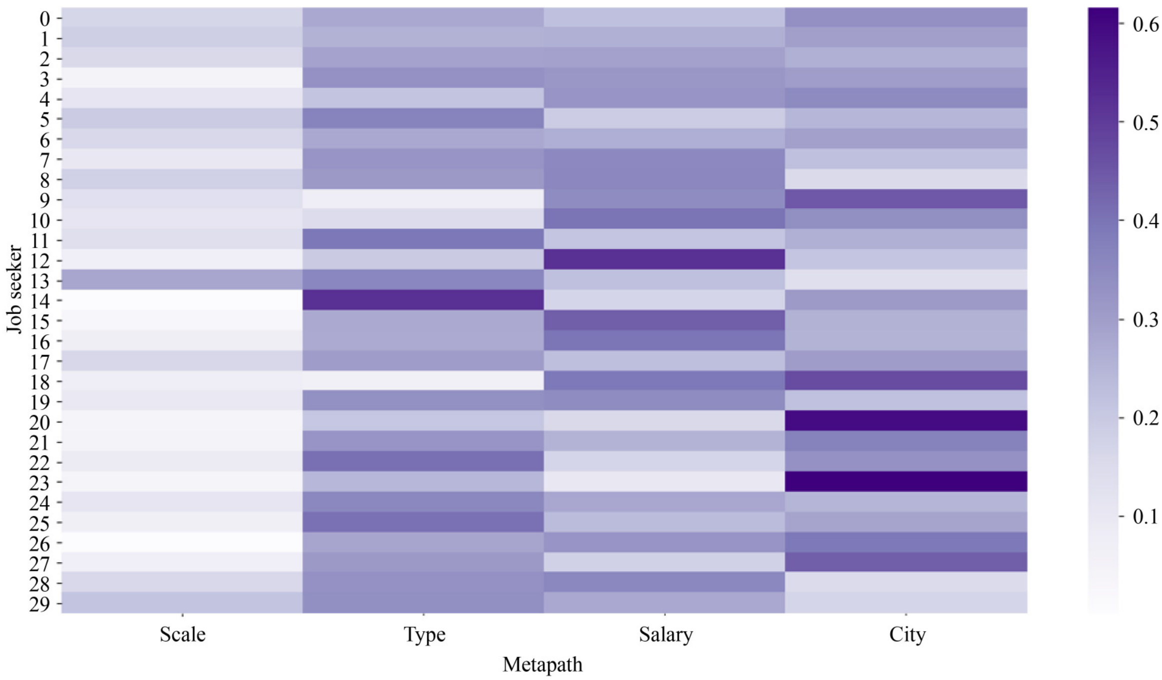

Fig. 7 People's preference path.

Table 5 An example of job recommendation

Job	HR click	City	Type	Salary	Scale
Person: 38774743, historical application and HR feedback information					
Job	HR click	City	Type	Salary	Scale
3691116	1	Shanghai	Embedded software development	9.6	30
12842727	0	Shanghai	Embedded software development	12	80
Recommendations with metapath preference: [0.1744, 0.1188, 0.1638, 0.5431]					
Job	HR click	City	Type	Salary	Scale
7744504	Recommendation score: 0.9273 Rank: 1/7 (true: 1)	Shanghai	Embedded software development	13	40
7744429	Recommendation score: 0.8361 Rank: 1/3 (true: 1)	Shanghai	Software engineer	11	40
5662789	Recommendation score: 0.3972 Rank: 5/7 (true: 0)	Wuhan	Embedded software development	9.6	50

5 Conclusions

In this manuscript, we introduce an innovative job recommendation approach employing a bilateral heterogeneous graph competition iterative model, which takes into account the principles of reciprocity and competition. The model uses heterogeneous graphs and fusion mechanisms to acquire an initial recommendation score, aligning with the concept of reciprocal bilateral matching. Furthermore, we present an iteratively optimized module that factors in individuals' competitive rankings and preferences, strategically dispersing competitive pressures. This enables the model to proffer job recommendations with elevated absolute matching scores and relative rankings, consequently enhancing the rate of successful job applications. The incorporation of a metapath-based attention mechanism and the explicit optimization of competitive rankings equip the model with the capacity to discern and adapt to each individual's unique preferences while also elucidating the rationale behind its recommendations.

This research is situated within the framework of design science (Gregor and Hevner, 2013) and effectively tackles the challenges posed by sparse data, concentrated competition, and low matching success rates inherent to the competitive two-sided job-seeking market. In practical terms, this study furnishes an efficient job recommendation model that expedites the job-seeking process by augmenting the proportion of favorable feedback received from jobs. Methodologically, the proposed heterogeneous graph model incorporating competitive iteration holds promise for broader applications in other two-sided market recommendations. However, it is important to note that this study primarily concentrates on unilateral subjects (i.e., job seekers) within the bilateral market. In future research endeavors, with access to more extensive datasets, we can delve deeper into the preferences of both job seekers and employers, paving the way for recommendations tailored to bilateral subjects.

Competing Interests The authors declare that they have no competing interests.

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