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A Bilateral Behavior Sequence Cross-Modeling Method For Person-Job Fit Recommendation

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Abstract:
Matching the right person to the right job is a complex task, and recommendation systems have become an essential tool in streamlining this process. While many existing models focus on either the job seeker's or the recruiter's behavior in isolation, they often miss the richer signals that emerge from the interaction between both sides. In reality, both users and jobs exhibit behavioral sequences—browsing histories, application patterns, and engagement behaviors—that evolve over time and influence each other.
In this paper, we introduce a new approach to person-job fit recommendation that models these bilateral behavior sequences in a unified framework. Our method is built on a dual-stream Transformer architecture, where the behaviors of job seekers and job postings are deeply integrated from both the resume and job sides.This allows the system to capture meaningful relationships between the two sides and learn more effective matching representations.
We believe this work makes three key contributions: (1) it highlights the limitations of modeling job seeker or job-side behaviors in isolation; (2) it presents a new way to capture cross-side behavioral dynamics using sequence modeling and attention mechanisms; and (3) it offers a clear and extensible architecture that can serve as a foundation for future empirical work and practical applications
Key Word: *person-job fit recommendation; bilateral behavior sequences; Transformer.*

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I. Introduction

Background on Person-Job Fit recommendation systems

Online recruitment has become the dominant approach in modern hiring[1], with platforms like LinkedIn attracting hundreds of millions of users and job applications each month. The rapid growth of users and job postings has led to serious information overload in the recruitment field. Traditional keyword-based matching methods often fail to consider important user attributes such as education, salary expectations, and behavior[2]. Moreover, most current systems focus only on job seekers' preferences, ignoring recruiters' needs and job requirements. In fact, person-job fit recommendation is inherently a bilateral problem that requires understanding and matching both sides to improve recommendation quality.

Limitations of existing behavior modeling approaches in Recommendation System

Various User Behavior Modeling (UBM) methods have been developed to enhance the understanding of implicit user interests in traditional recommendation system. Conventional UBM focuses on learning user interests from chronologically ordered behavior sequences, exploring patterns like session structure and pairwise dependency. Long-Sequence UBM[3] extends this by processing longer behavior sequences, enabling the extraction of richer long-term interests, though it poses computational challenges. Multi-Type UBM[4], examines various user behaviors (e.g. click and purchase) within a unified model, addressing issues like behavior definition and prediction. Finally, UBM with Side Information[5] incorporates heterogeneous features linked to behavior records, leveraging advanced NLP and CV models to enhance user interest representations.

Despite significant progress in User Behavior Modeling (UBM)[6], several limitations remain that hinder the effectiveness of person job fit recommendation systems. First, many existing methods rely heavily on posterior fusion of historical behaviors, often lacking deep integration across different types of behavior sequences. This can result in incomplete or inaccurate representations of user preferences. Second, while long-sequence models help capture richer interest patterns, they also introduce substantial computational overhead and latency issues, making them less practical for real-time systems. Third, behavioral data is often noisy, and effectively filtering irrelevant actions remains a technical challenge. Fourth, the integration of heterogeneous side information—such as user demographics or item attributes—is not always seamless, limiting the model's ability to contextualize behavior meaningfully. In this paper, we mainly focus on solving the first problem , which approaches typically focus on posterior fusion of historical behaviors, ignoring the fully integration of the behavioral histories of both job seekers and job postings . This lack of bilateral modeling restricts the system's ability to provide truly personalized and mutually beneficial matches.

Contributions of this paper:

In this paper, we propose a novel bilateral user behavior sequence modeling method designed specifically for person-job fit recommendation. The framework leverages the Transformer architecture to effectively encode the behavior sequences of both users and job postings, capturing rich temporal and semantic patterns on each side. By enabling interaction between the two behavior streams, the model offers new insights into how cross-side dynamics—such as job-seeking activity and recruiter behavior—can be jointly modeled to enhance matching accuracy and personalization.

II. Related Work

Person-Job Fit Recommendation Methods

Person-job fit (PJF) recommendation aims to provide personalized job suggestions by assessing the compatibility between job seekers and job postings[1]. With the rise of online recruitment platforms—offering broad coverage, efficiency, and low cost—vast amounts of user and job data have become available, enabling data-driven matching models. Traditional recommendation methods such as collaborative filtering (CF) and content-based filtering have been applied to this task. However, CF methods often suffer from cold-start issues due to their reliance on historical interactions, and content-based approaches typically rely on static textual features, lacking adaptability to user behavior.

To overcome these limitations, researchers have explored transforming the PJF task into a text matching problem, using resumes and job descriptions as inputs to compute semantic similarity. Deep learning has further advanced this area, introducing CNN[7], RNN[8], and hybrid-based models[9]for end-to-end matching. More recently, behavior-based approaches [10-11]have gained attention, focusing on modeling the sequential interaction histories between users and jobs to better capture dynamic preferences. In addition, addressing long-tail problems and cross-domain matching has become increasingly important to ensure fairness, diversity, and broader coverage in recommendations. Unlike conventional recommendation systems, PJF recommendation is inherently bilateral, requiring consideration of the preferences, constraints, and histories of both job seekers and recruiters—a challenge many existing systems still inadequately address.

User behavior Modeling in Traditional Recommendation Rystems

User Behavior Modeling (UBM) plays a crucial role in learning implicit user interests from historical interactions [12]. Traditional UBM methods typically focus on modeling chronologically ordered behavior sequences to capture user preferences and improve recommendation accuracy. Four main modeling paradigms have emerged:

1. Conventional Behavior Modeling[13-14]： It focuses on short-term sequential behaviors using deep neural networks such as RNNs (e.g., GRU4Rec), CNNs (e.g., Caser, NextItNet)[15], and attention-based architectures (e.g., SASRec, DIN, DIEN)[16-17]. These models extract dependencies and session patterns, though they may struggle with long-range interactions or diverse behavior types.
2. Long-Sequence Modeling：This model extends conventional methods to capture richer long-term interests. Models like DIN and MIMN attempt to leverage longer histories but face challenges in scalability and online latency. SIM addresses this by introducing a retrieval-based paradigm, significantly increasing sequence capacity with minimal processing delay.
3. Multi-Type Behavior Modeling: In this method, it captures user preferences across diverse behavior types (e.g., clicks, purchases, shares). Techniques such as DMT, MBGCN, and NMTR model intra- and cross-type dependencies to improve interest fusion and prediction accuracy. Recent work also considers micro-behaviors to mitigate issues like sample selection bias and data sparsity.
4. Modeling with Side Information ：This is a modeling which enriches behavior sequences using heterogeneous contextual features. These models incorporate auxiliary attributes and multimodal signals—enabled by advanced NLP and CV models—to better reconstruct user interest representations[18].

While these approaches have substantially advanced the field, they also introduce challenges such as high computational cost, noise sensitivity, and integration complexity, particularly in large-scale, real-time environments.

User behavior Modeling in Person-Job Fit Recommendation

User behavior modeling in person-job fit (PJF) recommendation differs fundamentally from traditional recommendation settings due to its bilateral nature. Unlike conventional systems that focus solely on user behavior, PJF requires simultaneous modeling of behavioral sequences from both job seekers and job postings. This introduces added complexity in terms of sequence length, type diversity, and contextual integration. Several recent approaches have been proposed to address these challenges. For example, DPGNN[19] models active and passive preferences through dual graph nodes to represent both sides of the recruitment interaction. JRMPM [20] captures sentence-level preferences from historical interactions and aggregates them into global matching vectors. The DPJF-MBS[21] model further incorporates auxiliary behaviors (e.g., clicks, applications, chats) and uses memory-based mechanisms to refine preference extraction.

Despite these advances, current methods still face several limitations. Many rely on simple posterior fusion of behavior sequences without fully modeling the dynamic interactions between both sides. Modeling long and diverse behavior histories remains computationally expensive and sensitive to noise, limiting real-time applicability. Moreover, integrating side information and context—such as user demographics, job attributes, and interaction semantics—is often fragmented or incomplete. Addressing these issues requires more comprehensive, sequence-aware, and context-rich behavior modeling frameworks tailored to the unique demands of person-job fit recommendation.

III. Proposed Method

Our method is based on the mature recommendation framework and extends one key module: the bilateral sequence cross module. It uses the Transformer's self-attention mechanism to model the relationship between the historical browsing sequences of resumes and positions, and then uses the cross-attention mechanism to cross-fuse the historical behavior data of resumes and positions in real time, solving the problem of inaccurate matching caused by insufficient historical behavior interaction.

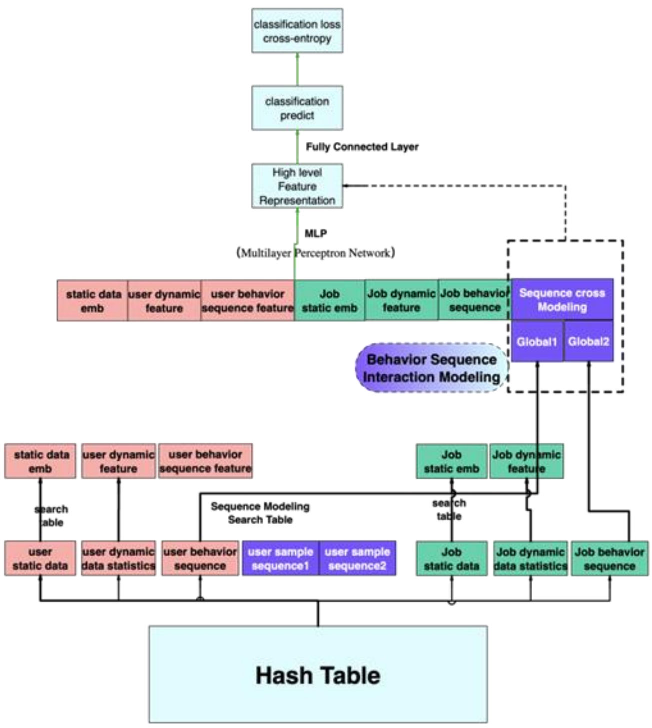

Figure 3-1 Person-Job Fit with Interaction Modeling

The specific process of the overall algorithm is shown in Figure 3-1. The algorithm receives two types of data input: static data and dynamic data. Static data includes basic information of users (such as gender, age, industry, etc.) and fixed attributes of positions (such as position category, position ID, etc.). Dynamic data covers the historical browsing sequence of users and the historical browsing sequence of positions, and constructs user behavior sequence features and position browsing sequence features through the attention mechanism. Secondly, the algorithm cross-integrates the historical behavior data of users and the historical browsing data of positions in real time through the self-attention and cross-attention mechanisms of Transformer. Finally, in the feature fusion stage, the static/dynamic features of the above sequence cross-feature users/positions, as well as the user behavior sequence features and position browsing sequence features are fused, and further processed through the multi-layer perceptron network (MLP) to generate the final prediction results.

Motivation and Challenges

When there are frequent interactions between a job seeker's historical browsing sequence and a job's historical resume viewing sequence, it indicates a strong mutual interest and potential match between the two. To accurately capture this strong signal, the model should perform real-time cross-integration of behavioral data from both the resume and the job, thereby improving matching accuracy. Once such high-frequency interaction patterns are detected, the system can automatically prioritize recommending the relevant job, making the results more personalized and aligned with user needs. However, many existing approaches model the historical behaviors of resumes and jobs separately, overlooking the interactions between them. This separation makes it difficult to capture the complex matching relationships effectively, leading to suboptimal recommendation outcomes.

Implemention Details

To describe the person-job matching task, we consider two types of historical behavior data: the job browsing history of a resume R, noted as LR (j1, j2, ... ji), and the resume browsing history of a job J, noted as LJ (r1, r2, ... rm). If a resume rm has viewed a job ji, we record this interaction as 1 in an interaction matrix; otherwise, it's 0. Our main goal is to predict how well a specific resume and job match, based on their respective historical behavior. At the same time, we aim to discover as many meaningful matches as possible to improve the system's coverage. Each resume-job pair is associated with a binary label y∈{0,1}, indicating whether the job seeker has shown interest. Ideally, the model should accurately identify positive pairs (where y=1), increasing the chances of successful job matches.

To do this, we adopt a Transformer-based approach that models not only the behavior sequences of resumes and jobs individually but also the interactions between them. Self-attention helps the model understand internal patterns within each sequence, such as a job seeker's career preferences or a job's target profile. Cross-attention, on the other hand, allows the model to connect the two sequences, capturing signals that reflect mutual interest. This combination leads to more personalized and accurate recommendations.

In practice, we represent each resume's job browsing history as a sequence of job IDs SeqR={aR1,aR2,...,aRn}, and each job's resume viewing history as a sequence of resume IDs SeqJ={aJ1,aJ2,...,aJm}. aRi represents the job ID of resume R browsed for the i-th time,aJi is the resume ID of position J browsed for the i-th time .These IDs are mapped into embedding vectors that carry additional information, such as job categories or skill tags. These enriched representations allow the model to learn both behavioral and content-based features, improving the overall matching performance.

Self-Attention in User Behavior Sequence Modeling

In the actual business of job matching, the historical behavior sequences of job seekers and positions contain rich information, which is crucial for accurate matching. In order to deeply explore the complex relationships within these sequences, we introduced the self-attention mechanism to internally model a single sequence. The application of the self-attention mechanism helps the model to more accurately understand the historical behavior patterns of job seekers and positions.

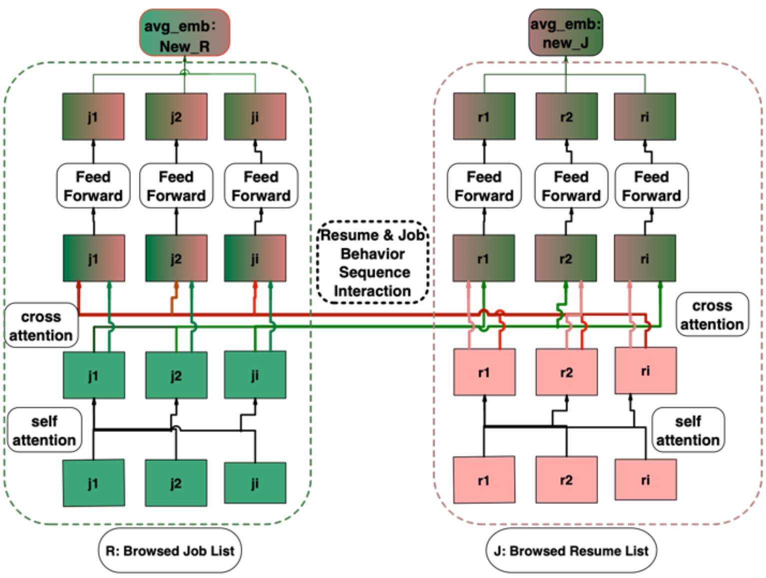

Figure 3-2 Bilateral sequence cross modeling

When we use the self-attention mechanism to encode the historical job browsing sequence SeqR of resume R and the historical browsing resume sequence SeqJ of job J, its core goal is to generate new representations for each job or resume element, which can more accurately reflect its importance in the entire sequence and its complex relationship with other jobs or resumes.

The self-attention mechanism is used to encode the historical job browsing sequence SeqR of resume R and the historical browsing resume sequence SeqJ of job J to capture the long-range dependencies within the sequence. The self-attention mechanism calculates the new representation zi of each job or resume ai through the following steps:

(1) Generation of query, key and value:

For each job (resume) ai in the sequence, we use the learnable parameter matrix Wv to transform its original representation hj into query qi, key ki and value vi. Although in actual implementation, the query, key and value may be transformed by different parameter matrices, for the sake of simplicity, we assume that they share the same transformation matrix Wv.

(2) Calculation of attention weight:

For each element ai in the job or resume history sequence, we calculate the attention weight αij between it and all other jobs (resumes) aj (including itself) in the sequence. This is achieved by comparing the similarity between the query qi and all keys kj, and the score function is usually calculated by scaling the dot product:

$$\mathrm{score}(q_i, k_j) = \frac{q_i k_j^T}{\sqrt[2]{d_k}}$$

Among them, $\sqrt[2]{d_k}$ is a scaling factor used to prevent the gradient vanishing problem caused by the dot product result being too large. Then, the score is normalized to a probability distribution through the softmax function to obtain the attention weight αij:

$$\alpha_{ij} = \frac{\exp(\mathrm{score}(q_i, k_j))}{\sum_{l=1}^{L} \exp(\mathrm{score}(q_i, k_l))}$$

When αij is large, in the case of job matching, this means that there is a strong correlation between the currently considered job ai (or resume ai) and another job aj (or resume aj) in the sequence. For example, when ai and aj are the historical job browsing sequences of a resume, when αij is large, it means that job ai and job aj are closely related, which may indicate that job ai and job aj have similarities in terms of skill requirements, job responsibilities or industry background, thus attracting similar groups of job seekers. Similarly, when αij is small, it means that job ai and job aj are less correlated and have fewer similarities.

(3) Weighted summation to generate new representation:

Finally, we use the attention weight αij to perform a weighted summation on the values vi of all elements in the job (resume) sequence to obtain a new representation zi of element ai. This new representation zi incorporates the information of other jobs (resumes) in the sequence, especially those that are strongly correlated with ai:

$$z_i = \sum_{j=1}^{L} \alpha_{ij} V_j$$

The self-attention mechanism directly calculates the similarity between any two elements in the historical browsing sequence of resumes (positions), assigns attention weights, and effectively captures interactive behaviors that span a long distance but have an important impact on the matching results. For example, when a job seeker browses a position in the early stage and browses related positions multiple times later, the self-attention mechanism can identify and emphasize this long-distance dependency. When encoding the historical browsing sequence, the self-attention mechanism helps the model to understand the job seeker's career interests and job requirements in detail.

The new representation zi of each position or resume element incorporates information from other elements in the sequence, allowing the model to more comprehensively consider the complex relationship between job seekers and positions when matching. By capturing unique interaction patterns, the self-attention mechanism enables the person-job matching algorithm to generate more personalized recommendation results. For each job seeker, the model generates a specific list of job recommendations based on its historical browsing behavior, thereby improving the satisfaction and effectiveness of the recommendation.

Cross-Attention in User Behavior Sequence Modeling

The historical interaction between resumes and positions is an important basis for evaluating the degree of match between the two. Traditional methods often process the historical behavior sequences of resumes and positions separately, ignoring the potential correlation information between them. To overcome this limitation, we further use the cross-attention mechanism to achieve the correlation modeling of bilateral sequences. This process aims to capture the historical interaction information between resumes and positions, so as to more accurately evaluate the degree of match between the two.

The core idea of the cross-attention mechanism is to use the historical interaction matrix M between resumes and positions to construct the attention weights between the two, so as to achieve real-time cross-fusion of the historical behavior sequences of resumes and positions. The workflow of the cross-attention mechanism is as follows:

Cross-attention weight calculation: For each resume element aRi in the job history behavior sequence, we use the learnable parameter matrix Wv to transform its original representation into query QRi, key KRi and value VRi, and for each job element aJj in the resume history behavior sequence, we transform its original representation into query QJj, key KJj and value VJi, and calculate the attention weight between aRi and aJj.

$$\mathrm{score}(\mathrm{QR_i}, \mathrm{kJ_j}) = \frac{\mathrm{QR_i} \cdot \mathrm{kJ_j^T}}{\sqrt[2]{\mathrm{d_k}}}$$

The scores are normalized to probability distributions through the softmax function to obtain the attention weights:

$$\beta_{ij} = \frac{\exp(\mathrm{score}(\mathrm{qR_i}, \mathrm{kJ_j}))}{\sum_{l=1}^{L} \exp(\mathrm{score}(\mathrm{qR_i}, \mathrm{kJ_l}))}$$

The attention weight βij represents the strength of association between the i-th resume in the historical browsing sequence of position J and the j-th position in the historical access sequence of resume R. When βij is large, it indicates that there is a strong correlation between resume aRi in the historical sequence of the current position J and position aJj in the historical sequence of resume R. When aRi and βij of multiple positions in the historical position browsing sequence of resume R are both large, it means that position J and resume R have a close connection, which may indicate that position J and resume R have similarities in skill requirements, job responsibilities or industry background, thus attracting similar groups of job seekers. Similarly, when βij is small, it means that position J and resume R are less correlated and have fewer similarities.

(2) Generation of new representation: Based on the calculated cross-attention weights, we perform weighted summation on the value representations of the position elements to generate a new representation of the resume:

$$\mathrm{Z_{Ri}} = \sum_{j=1}^{m} \beta_{ij} \cdot \mathrm{V_{Jj}}$$

Similarly, we can perform a weighted summation on the value representation of the resume to generate a new representation of the position:

$$\mathrm{Z_{Jj}} = \sum_{i=1}^{n} \gamma_{ji} \cdot \mathrm{V_{Ri}}$$

Among them, γ_{ji} is the attention weight between the jth browsing of job J and the ith browsing of resume R.

After introducing the cross-attention mechanism, the model can generate new representations for each job or resume element, which incorporates information from other sequence elements, so that the model can capture the interactive relationship between resumes and jobs more finely. Specifically, the mechanism directly calculates the similarity between any two elements in the resume sequence and the job history browsing sequence, and assigns attention weights accordingly, effectively capturing those interactive behaviors that span a long distance but have an important impact on the matching results. For example, when a job seeker browses a job in the early stage, and this job is also browsed by job seekers with similar backgrounds, if the job seeker browses related jobs many times in the future, and these jobs are also followed by similar job seekers, the cross-attention mechanism can help the model deeply understand the job seeker's career interests and the specific needs of the job. In this way, the model can capture more complex interaction patterns, and then generate more personalized and accurate recommendation results, ultimately improving the satisfaction and overall effect of the recommendation.

IV. Furture Work And Conclusion

While this paper focuses on the design and motivation of a bilateral behavior sequence cross-modeling method for person-job fit recommendation, several important directions remain for future exploration. First, we plan to conduct a comprehensive empirical evaluation to assess the performance of the proposed framework on real-world recruitment datasets. This includes benchmarking against traditional and deep learning-based recommendation baselines. Second, we aim to integrate contrastive learning techniques into our current architecture to enhance representation learning and improve generalization, especially in sparse or long-tail scenarios. Additionally, we are interested in extending the model to handle multi-modal inputs, such as textual job descriptions, resume semantics, and recruiter feedback, to further enrich the behavioral context. Finally, considerations for real-world deployment, including scalability, latency, and interpretability, will be essential as we move from conceptual design toward practical application.

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