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An Overview of Person-Job Fit Recommendation Approaches

Chuntao Liu[1],Tadiwa Elisha Nyamasvisva[2],Xiuliang Zhang[3]
[1]*Student, Infrastructure University Kuala Lumpur, Faculty of Engineering,Science and Technology, ChunTao,Liu, 232924067@s.iukl.edu.my*
[2]*Professor, Infrastructure University Kuala Lumpur, Faculty of Engineering, Science and Technology, Tadiwa Elisha Nyamasvisva*
[3]*Student, Infrastructure University Kuala Lumpur, Faculty of Engineering,Science and Technology, Chuntao Liu*
Corresponding Author: Liu Chuntao

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ABSTRACT: Person-job fit recommendation is the core technology in online recruitment. While traditional content filtering and collaborative filtering methods have been widely used, they are increasingly being supplanted by deep learning techniques that offer superior matching accuracy by modeling both textual and behavioral data. This paper provides a comprehensive review of current approaches to person-job fit recommendations, with a focus on text-based matching, historical behavior modeling, and hybrid methods. It also evaluates the performance of these models and delves into key challenges such as data sparsity, the cold start problem, and the long-tail effect. The paper proposes innovative solutions for future research in these areas. Nevertheless, despite the promise of these emerging research directions, significant limitations remain, particularly in terms of data access, privacy concerns, and the computational resources required for large-scale implementation.

KEYWORDS:
Person-Job Fit, Online Recruitment, Deep Learning, Text-Based Matching, Historical Behavior Modeling, Cold Start Problem, Long-Tail Effect

I. INTRODUCTION

Person-job fit refers to the alignment between an individual's characteristics, skills, and preferences with the requirements and demands of a job[1]. Traditional recruitment processes often rely on subjective assessments and manual resume screenings, which can be time-consuming and prone to biases. The advent of technology, particularly in the form of recommendation systems, has opened up new possibilities for improving the efficiency and accuracy of person-job matching.

Organizations today face an unprecedented volume of applications for job openings, making efficient filtering of candidates essential. Traditional methods can lead to overlooking qualified candidates or misclassifying applicants, resulting in poor hiring decisions[2]. The integration of automated systems for person-job fit not only enhances the recruitment process but also aligns it with modern technological advancements.

With the increasing focus on data-driven decision-making, the need for sophisticated recommendation systems that go beyond simple keyword matching has become evident. These systems can leverage large datasets and advanced algorithms to provide more accurate and meaningful recommendations, ultimately benefiting both organizations and candidates.

This paper provides a comprehensive survey of current person-job fit recommendation systems, focusing on various methods, their strengths and weaknesses, performance comparisons, and the challenges they face. In addition, the paper identifies and discusses common problems and challenges encountered by existing systems, such as data sparsity, cold start problems, and long-tail effects. These challenges significantly impact the accuracy and effectiveness of person-job fit, particularly when handling large datasets or tailoring recommendations to individual users. As diversity and inclusion become central to organizational objectives, addressing these challenges through more advanced person-job fit recommendation systems is crucial. Finally, the paper explores potential future research directions, considering how new technologies and methodologies, such as contrastive learning, cross-attention mechanisms, and deep learning, can further improve the accuracy, fairness, and

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scalability of these systems, ultimately contributing to more efficient and equitable recruitment practices.

This paper is structured as follows: Section 2 provides a foundational understanding of person-job fit recommendations and distinguishes them from traditional recommendation systems. Section 3 delves into the specific methodologies employed in person-job fit recommendations, including text-based matching, historical user behavior modeling and hybird methods. Section 4 discusses the main challenges and limitations, such as data quality issues, cold start problems, and data sparsity, along with a comparison of current methods. Section 5 concludes with a summary of the findings and an outlook on future research directions, focusing on improving algorithmic efficiency and addressing unresolved challenges.

II. PERSON-JOB FIT Recommendation

Traditional recommendation systems are commonly used in e-commerce and media platforms, aim to predict user preferences based on historical data[3]. The core goal of recommender systems is to study the interaction between humans and information. For a specific target user, the recommendation system processes the input information of numerous candidate "items". By thoroughly processing and modeling this information, the system aims to predict user interest and ultimately generates recommendation results.

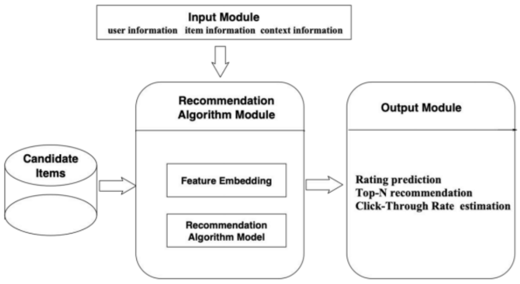

Figure 1. Logical Framework of Recommender System

As shown in Figure 1, clearly demonstrates the interaction between each component and the overall recommendation workflow. The input module collects user, item, and context data, generating features like user behavior, item attributes, and context for the recommender system. The recommendation algorithm module uses these features to suggest items matching user preferences, with CTR estimation being the primary task in person-job fit recommendations. The output module then produces recommendation results, tailored to the system's specific goals, such as Top-N recommendations or CTR prediction.

Traditional recommendation metholds are mainly categorized into three types[: content-based recommendations, collaborative filtering-based recommendations, and hybrid recommendations[4]. Each model has its advantages, disadvantages, and applicable scenarios depending on the algorithm principles. Traditional recommendation systems are effective in many domains but often lack the depth needed for complex human resource applications, particularly in the nuanced field of person-job fit.With the rapid development of deep learning ,it has been used in recommendation system as well. Deep learning recommendation algorithms have stronger feature representation capabilities, capable of uncovering more hidden nonlinear features in user and item data. Additionally, the structure of deep learning models is highly flexible, enabling end-to-end representation learning for recommendation systems, and can be adapted to various recommendation scenarios by flexibly changing the model structure to accommodate different types of recommendations.

Unlike traditional recommendations that only focus on users' interests and preferences for products or movies, both parties in PJF, a bilateral scenario, have active behaviors and their own preferences. It is so called bilateral recommendation . Which is used in online dating platform, online recuriment ,etc. For instance, while a traditional recommendation system might suggest a movie based on previous viewings, a person-job fit system must analyze a candidate's educational background, work experience, and even personality traits to recommend suitable job openings. This holistic view is essential for creating meaningful matches that contribute to long-term success in the workplace.

For person-job fit problem, in this scenario, job seekers have their own target positions, and job positions also have ability requirements for job seekers. Because of this bilateral modeling requirement, various models and methods different from traditional recommendations have emerged in PJF. Currently, common personjob matching algorithms are mainly divided into text-based matching [5-6], historical behavior preference-based [7-8] and hybrid recommendation algorithms[9]. The first category calculates the matching degree based on the text content of job postings and resumes. This method believes that whether a job seeker matches a position mainly depends on whether the skills or work experience in the job seeker's resume correspond to the job requirements description. Therefore, this approach models the PJF problem as a text matching problem between resumes and job descriptions. Different from text-based matching methods, models based on historical behavior preferences focus more on extracting preference information from the interaction history records of both job seekers and positions. PJF methods that combine text matching with historical behavior preference modeling are also a research hotspot among researchers. These methods often combine explicit preferences extracted from the text of both parties with implicit preferences obtained from historical behaviors to complete recommendations

III. Existing Person-Job Fit Recommendation Methods

The early research on person-job fit (PJF) can be traced back to[1], where the authors proposed a bilateral recommendation system using the archival information of candidates and job postings to find good matches between talents and positions. Some of the early related studies mainly relied on traditionalrecommendation algorithms such as collaborative filtering (CF) [10-11]and content-based filtering[12] The limitation of CF methods lies in their heavy dependence on historical interactions between users and job positions. Recently, the widespread application of deep learning in various fields has led to the development of end-to-end neural networks designed to comprehend semantic representations for calculating matching degrees. These models include CNN-based approaches [5] RNN-based models [6] and hybrid models that combine RNN and CNN techniques[13]. Furthermore, research has started focusing on modeling behavior sequences, utilizing historical interaction sequences between job seekers and positions to enhance the model's understanding of user preferences, thereby improving matching efficiency[7]

3.1 Text-Based Matching Method

Text-based matching methods involve analyzing the textual content of resumes and job descriptions to identify keywords, skills, and other relevant features. Techniques such as natural language processing (NLP) and semantic similarity measures are employed to assess the degree of match between a candidate's profile and a job requirement.

At present, text matching between job seekers' resumes and job descriptions, as well as extracting preference information from the historical interaction between job seekers and positions, have become the focus of research. Next, we will introduce the popular text matching methods in the current person-job matching research. After consulting relevant materials, here we lists the current classic and mainstream matching algorithms, which are introduced as follows:

A representative study proposed the Deep Structured Semantic Models (DSSM)[14], which maximizes the conditional likelihood between queries and clicked documents through click data. DSSM uses convolutional layers to extract semantic information for final matching predictions. This method achieves matching between job applicants and positions by learning the representations of queries and documents separately and then scoring them using a matching function. This method performs well in capturing deep semantic information in text and has become the basis and important reference for subsequent research.

PJFNN[5]proposes a CNN-based method that calculates matching degree through cosine similarity.It can effectively learn the joint representation of PersonJob fitness from historical job applications.In this model, PJFNN uses a binary neural network architecture, and uses two similar CNNs to encode the job requirements and the work experience in the job applicant's resume.

Unlike PJFNN based on CNN, APJFNN[6] uses LSTM+attention to encode the job seeker's work experience and job requirements. , First, the vector representation of all words in the resume and job text is learned through a bidirectional long short-term memory network (Bi-LSTM). Then, the vector representation of the resume and the job is obtained through a hierarchical skill perception module. Then, the two vectors are subtracted element by element and concatenated with the original vector and input into a fully connected network to predict the matching degree between the resume and the job.

DGMN[13] is a deep model designed to enhance job and resume matching by focusing on global sentence interactions, particularly addressing the issue of limited labeled data through domain adaptation. The model comprises two main components: a Hierarchical Attention-based RNN Encoder, which utilizes BiGRU and attention mechanisms to convert job postings and resumes from word-level to global representations, and a

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Global Match Representation, which uses CNNs to model the matching between these representations.

Text-based matching is particularly effective in fields where hard skills are critical, such as IT and engineering. However, it may overlook softer skills and cultural fit, which are often essential for long-term success in a role. To enhance the effectiveness of text-based matching, organizations can incorporate additional data sources, such as personality assessments or cultural values, to provide a more comprehensive evaluation of candidates.

3.2 Historical Behavior Preference-Based Method

Text-based person-job matching algorithms primarily focus on the textual content of resumes and job descriptions, but incorporating historical behavioral data offers a more accurate reflection of user preferences. Historical behavior preference-based methods leverage user behavior data, such as past job applications, interview outcomes, and career progression, to infer preferences and predict future job suitability. Several methods have been proposed to model this sequence of user behavior:

DPGNN [7]: This model introduces a dual-view interaction graph with separate nodes for active and passive representations of job seekers and jobs. It uses BERT for encoding and GCN for preference propagation, accounting for bidirectional matching between job seekers and positions.

BOSS[15]: BOSS is a bidirectional recommendation system that considers the reciprocity, bidirectionality, and sequence characteristics of recruitment. It uses a multi-group MoE module for preference learning and a multi-task learning module for behavioral sequence modeling, improving recommendations through probabilistic methods.

JRMPM[16]: This model extracts latent preferences from historical interactions using a memory-based preference update mechanism, which updates preferences in chronological order. These preferences are then used to generate a global preference vector for matching predictions.

DPJF-MBS[8]:Focuses on auxiliary behaviors (e.g., clicks, applications) before matching, which are denser and more informative than direct matching behaviors. The model uses a memory matrix to update and read preference information, considering the cascade relationship between behaviors for final match predictions.

PJFFF[17]: Combines feature fusion, text matching, and historical behavior modeling. It uses explicit and implicit features from resumes and job descriptions, modeled through CNNs and LSTMs, to predict matching scores.

PJFCANN [9]: Combines text matching with relationship graphs derived from historical interactions. The model encodes text using mashRNN and co-attention, while relationship graphs enhance predictions through GNNs and attention mechanisms, leading to improved matching results.

Hybrid methods are advantageous as they can address the limitations of single-method approaches. By considering both textual content and behavioral history, hybrid systems can deliver more personalized and relevant job recommendations. However, implementing these systems can be resource-intensive, requiring significant investment in data infrastructure and computational power.

IV. Discussion

In this section, we will compare the various person-job matching methods discussed, highlighting their strengths and weaknesses. We will also address the key challenges and limitations these methods face, such as data sparsity, cold start issues, and the complexity of accurately modeling user preferences and behaviors across diverse domains.

4.1Performance Comparison of different Methods

In evaluating the effectiveness of various person-job fit (PJF) recommendation methods, the Area Under the Receiver Operating Characteristic Curve (AUC) serves as a crucial metric, offering insights into the discriminative power of these models. Higher AUC values reflect a model's enhanced ability to distinguish between suitable and unsuitable job matches, thereby indicating its overall robustness in real-world applications.

Method		AUC
Hybrid Method	PJFFF	0.953
Behavior Preference Modeling	JRMPM	0.913
	BOSS	0.852
Text Based Mathing	PJFNN	0.775
	APJFNN	0.831
	BPJFNN	0.7818

Figure 2.
AUC For Different PJF Recommendation

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The performance comparison of different person-job fit recommendation methods, as shown in Figure 2, highlights the distinct advantages of hybrid approaches and behavior-based models over traditional text-based methods. Hybrid models, represented by PJFFF, achieve the highest AUC scores, demonstrating the effectiveness of combining both text-based features and historical behavioral data. This integration enables a more comprehensive understanding of candidate-job compatibility by capturing both explicit qualifications and implicit user preferences. Behavior-based models, suchas JRMPM and BOSS, also show strong performance, underscoring the importance of leveraging past user interactions to refine recommendation accuracy. These models outperform purely text-based methods by dynamically modeling user preferences over time. In contrast, text-based approaches like APJFNN and BPJFNN achieve relatively lower AUC scores, reflecting the limitations of relying solely on semantic matches between job descriptions and resumes. While these models are effective in matching qualifications, they struggle to address more nuanced aspects of fit, such as long-term aspirations and behavior-driven preferences. Overall, the comparison illustrates that hybrid and behavior-based models offer superior performance by providing a more holistic view of candidate-job fit, making them better suited to the complexities of modern recruitment needs.

4.2 Challenges and Limitations

Although significant progress has been made in the field of job matching, there are several challenges and limitations in this domain that need to be addressed for improving job matching systems[18]. They are mainly categrized to data quality,coldstart,userperferene,interpreterbility,bias and fairness and scalability.

Data quality is a big challenge in person-job fit recommendation, as they handle diverse data sources including CVs and job descriptions, which vary in quality and often contain implicit facets like skills. Key issues include the need for data cleaning and preprocessing due to noisy textual data, bridging the semantic gap caused by varied terminology, extracting crucial skills from unstructured data, supporting multi-lingual content, and addressing data sparsity due to infrequent usage by job seekers and rapid turnover of job postings.In this paper we mainly focus on data sparsity issue .

To address the data sparsity issue in e-recruitment recommendation systems, several approaches have been explored. One method involves reducing the number of distinct job positions by separating a job into its title and company name[19]or by clustering similar positions[20]. Shalaby et al. proposed densifying the job interaction graph by adding content similarity links between entities, thus enhancing recommendation generation[21]. Bied et al. utilized both application and hire interaction graphs to mitigate data sparsity[22]. Yan et al. developed a multi-task approach that integrates various interaction types by sharing text and graph embeddings[23]. Additionally, Shi et al. created a multi-objective person-job fit matching model that leverages multiple interaction types to tackle data sparsity effectively[24].

The cold start problem in person-job fit recommendation systems refers to the challenge of making recommendations for new users or job postings with little or no interaction data. This issue is more acute in person-job fit because job openings are often treated as distinct items, even with identical titles and descriptions. To alleviate this, content-based approaches can be employed. These include using interactions of similar job seekers or jobs to compute matching scores and predicting recommendation scores based on features extracted from job seekers' and job postings' content. Two approaches are used in the literature for job recommendations based on similar interactions: 1) computing matching scores between jobs and new job seekers by finding similar job seekers based on content features and using their known matching scores with jobs [20][25]; 2) computing matching scores between new jobs and job seekers by finding similar jobs and using their known matching scores with job seekers[[26-27]Some studies also predict matching scores using job seekers' and jobs' features to address the cold start problem [28-29]. Other papers provide recommendations based on job seekers' and jobs' content, addressing both job seeker and job cold start problems[30-31]. Additionally, studies extract features for job seekers based on their past job interactions to tackle the job cold start problem[32-34].

Data sparsity occurs due to the vast amount of job postings and the relatively sparse interaction history of individual job seekers. This issue is further compounded by the cold start problem, where new job seekers or job postings have little to no historical interaction data, making it difficult to generate accurate recommendations. Traditional collaborative filtering methods, heavily reliant on historical interactions, perform poorly in such scenarios[35]. Additionally, the long-tail problem closely relates to data sparsity and refers to the challenge of dealing with low-frequency job positions and job-seeking behaviors. While high-frequency data points, such as popular job postings and common job seeker profiles, are well-represented and easier to model, low-frequency data points are often neglected. This can lead to a lack of comprehensiveness and fairness in the recommendations, as the system might favor popular positions and overlook niche opportunities that could be a perfect fit for certain job seekers.

V. CONCLUSION

5.1 Conclusions and directions for further research

In this paper, we have provided an overview of various person-job fit recommendation approaches, with particular attention to hybrid models that integrate text-based matching with historical behavioral data. Our exploration of existing literature underscores the effectiveness of combining different methods to enhance the accuracy and relevance of job recommendations. However, while the field has made significant strides, there are still challenges and opportunities that require further investigation.

One of the persistent challenges in person-job fit recommendation systems is the "long-tail problem," where infrequent or niche job postings and job seekers are often underserved by current models. To address this, we introduce a contrastive learning mechanism in job matching, which significantly improves the matching performance for long-tail jobs and resumes. This approach enhances both the coverage—how many long-tail jobs and applicants can be effectively matched—and the recall — the proportion of successful matches among all relevant long-tail jobs. Future research should further refine and test this mechanism, exploring its scalability and generalizability across different domains.

Additionally, the issue of inaccurate matching due to insufficient behavioral interaction remains a critical concern. To tackle this, we propose a cross-attention mechanism that leverages historical behaviors, improving the overall matching accuracy. This mechanism enables the model to focus on relevant user interactions, thereby enhancing the precision of job recommendations. Further research could explore the integration of this cross-attention approach with other sequence modeling techniques to better capture the temporal dynamics of user behavior.

Moreover, "user behavior sequence modeling" represents another promising direction for future research. While several studies have leveraged historical interaction data to model user preferences, there is still considerable potential in developing more sophisticated models that can capture the sequential patterns in job seekers' behaviors over time. Improved sequence modeling can further augment the system's ability to predict future job suitability, especially when dealing with evolving user preferences and career trajectories.

Furthermore, as the field advances, it will be crucial to address the ethical implications of these models, particularly concerning fairness and bias in job recommendations. Ensuring that all candidates, regardless of their profile's frequency in the data, receive fair consideration is an ongoing concern that future research must continue to prioritize.

In conclusion, while person-job fit recommendation systems have made considerable progress, future work focusing on overcoming the long-tail problem, advancing user behavior sequence modeling, and enhancing matching accuracy through mechanisms like cross-attention will be essential for developing more robust and equitable recommendation systems. These areas hold the potential not only to improve recommendation performance but also to ensure a fairer and more inclusive job market.

5.2 Limitations

Although these future research directions are promising, several limitations must be acknowledged.

First, data limitations remain a significant challenge. Many job recommender systems, including those that employ hybrid models or advanced learning techniques such as contrastive learning and cross-attention, rely heavily on the availability of large and diverse datasets. However, access to comprehensive interaction data between job seekers and recruiters is often restricted due to privacy concerns, proprietary data limitations, or a lack of collaboration between academia and industry stakeholders. This limited access hinders the training of models that require rich interaction data to accurately capture user preferences and the nuances of job postings.

Second, there are computational challenges associated with implementing complex mechanisms like cross-attention and contrastive learning, especially at scale. While these techniques can improve the accuracy of job matching, they often require higher computational costs and significant infrastructure for deployment in real-world applications. The increased complexity of these models may limit their accessibility to smaller organizations or systems with constrained resources, making it difficult to generalize the proposed approaches across different environments. Research into more computationally efficient versions of these mechanisms could alleviate some of these issues, but this remains an area for further exploration.

Finally, while the long-tail problem is partially addressed through contrastive learning, it continues to be a persistent challenge in job recommender systems. Its performance may vary depending on the characteristics of the specific domain or dataset. Niche job categories and highly specialized applicant profiles often exhibit unique traits that are difficult to capture with generalized models. Ensuring that the long-tail solution is not overly domain-specific also poses a significant challenge.

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