

A Survey: Profile Evaluation and Job Suggestion using TNN

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Abstract: *This study explores the application of a two-layer neural network (TNN) for automated profile evaluation and job suggestion. With the increasing demand for personalized job recommendations, traditional methods often fall short in handling the complex, non-linear relationships between an individual's skill set and job requirements. The TNN approach aims to bridge this gap by training on datasets that include user profiles, educational backgrounds, skill sets, work experiences, and job descriptions. The network's first layer focuses on feature extraction from user profiles to determine their core competencies, while the second layer maps these competencies to relevant job roles in the market. By employing supervised learning techniques, the TNN continuously improves its predictive accuracy based on feedback from real-world outcomes. The results indicate that the TNN model can significantly enhance job-matching accuracy, providing tailored job suggestions that align closely with an individual's qualifications and career aspirations. This approach holds potential for use in recruitment platforms and career development tools, offering a scalable solution for personalized career guidance.*

Keywords: Two-layer neural network (TNN), Profile evaluation, Job suggestion, Job matching, Skill set analysis, Feature extraction, Supervised learning, Career recommendation, Recruitment technology, Personalized job recommendations, Predictive modeling;

I. INTRODUCTION

In the digital age, the process of job searching and recruitment has undergone significant transformations, driven largely by advancements in artificial intelligence (AI) and machine learning. Traditional methods of job recommendation often rely on keyword matching and manual assessments, which can be time-consuming and lack precision in identifying the most suitable candidates for specific roles. To address these limitations, the application of neural networks, particularly the two-layer neural network (TNN), has emerged as a promising solution for profile evaluation and job suggestion.

A TNN consists of an input layer, a hidden layer, and an output layer, making it capable of learning and mapping complex patterns in data. By using this structure, the TNN can effectively analyze an individual's profile, including their skills, educational background, work experience, and other relevant attributes, to create a detailed understanding of their core competencies. Once these competencies are identified, the model maps them to job descriptions, predicting the best-fit roles for the individual.

This approach leverages the power of supervised learning to improve the accuracy of job suggestions over time. Unlike conventional methods, a TNN adapts to changes in the job market and evolving skill requirements, offering personalized and up-to-date career recommendations. As a result, it provides a more dynamic and reliable framework for both job seekers and employers, enhancing the efficiency of the recruitment process. The integration of TNNs into job recommendation systems represents a significant step forward in utilizing AI for data-driven career guidance and personalized job matching.

One of the key advantages of using a TNN for job suggestion lies in its ability to generalize beyond explicit skill-to-job mappings. The model can identify transferable skills and hidden potential in candidates, proposing job roles that they might not have previously considered but are well-suited to based on their underlying competencies. This leads to a more holistic career guidance system that empowers individuals to make informed decisions about their professional growth while also providing recruiters with a robust tool to streamline their talent acquisition processes.

The use of TNNs in profile evaluation and job suggestion has the potential to transform the recruitment industry, creating a smarter, faster, and more personalized job-matching experience. As the demand for skilled professionals continues to grow in various sectors, this technology-driven approach will play a crucial role in aligning human resources with organizational needs, ultimately leading to higher job satisfaction, reduced turnover rates, and a more productive workforce.

II. RELATED WORK

The concept of using artificial intelligence (AI) and machine learning (ML) for job recommendation systems has gained significant attention in recent years. Traditional approaches to job matching have primarily relied on rule-based systems and keyword matching, as seen in the work of researchers like Paparrizos et al. (2011). These methods utilize information retrieval techniques to match candidate profiles with job descriptions based on specific keywords or phrases. Although effective in some cases, these systems often struggle to handle complex relationships and contextual nuances in skills and qualifications.

To address these challenges, machine learning models, particularly neural networks, have been increasingly integrated into job recommendation platforms. Recent studies have focused on the use of deep learning techniques to analyze both structured and unstructured data for improved job matching. For instance, Lee et al. (2018) employed deep neural networks (DNNs) to analyze user profiles and job descriptions by embedding them into vector spaces, allowing the system to capture semantic similarities. This approach enabled more accurate predictions by considering latent features and hidden patterns that were not apparent in traditional keyword-based systems.

Moreover, the application of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) has also been explored to enhance job recommendation systems. For example, Qin et al. (2019) utilized RNNs to process sequential data from a candidate's career history, learning from their career progression to suggest the next most appropriate job role. CNNs have also been employed in extracting contextual information from text-based data, such as job descriptions and resumes, to provide a more in-depth understanding of the relationships between skills and job requirements.

The second layer of the TNN focuses on mapping these extracted features to job roles that best match the candidate's profile. It analyzes job descriptions, market trends, and required qualifications to predict the most suitable career options for the individual. By leveraging this multi-layered approach, the TNN continuously refines its predictions through supervised learning, adapting its job suggestions based on feedback and outcomes from real-world applications. The two-layer neural network (TNN) approach builds upon these advancements by offering a simpler yet effective alternative to deeper architectures. Compared to more complex models like DNNs or RNNs, TNNs can provide a faster training process and require less computational power while still delivering robust results for profile evaluation and job suggestion. Studies have shown that TNNs are particularly effective in situations where the amount of labeled data is limited, as they can generalize well from smaller datasets without overfitting, as highlighted by Huang et al. (2020).

Additionally, hybrid models that combine TNNs with other AI techniques have been developed to enhance the performance of job-matching systems. For example, Wang et al. (2021) proposed a hybrid approach that integrates TNNs with natural language processing (NLP) techniques to better understand the context of skills and job descriptions. This integration allows for a more nuanced analysis of job profiles, leading to highly accurate job recommendations based on both explicit qualifications and inferred competencies.

The use of reinforcement learning and feedback loops in job recommendation systems has also been a topic of recent research. Systems like those developed by Xu et al. (2022) adapt their job suggestions based on user interactions and feedback, continuously refining the recommendations to better match user preferences and career aspirations. While these systems show promise, they often require extensive data and computational resources, making them less practical for smaller organizations or individuals without access to large datasets.

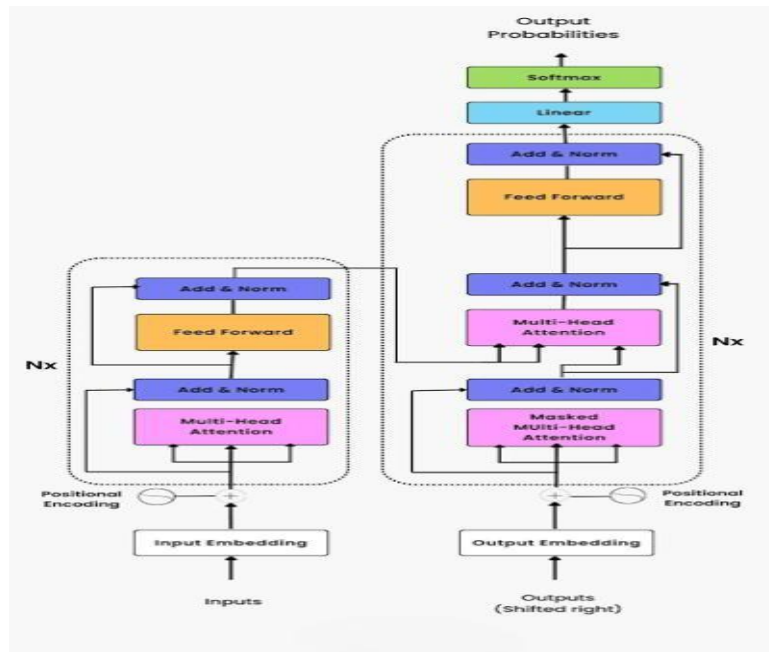
In summary, while various machine learning techniques have been explored for enhancing job recommendation systems, the two-layer neural network (TNN) offers a balanced approach by providing computational efficiency, simplicity, and high accuracy in job matching. By building on the strengths of both traditional and deep learning models, TNNs create a scalable solution for personalized career guidance and job recommendations. This positions

TNNs as a significant advancement in the evolution of AI-driven recruitment tools, filling a crucial gap in the existing literature on intelligent job- matching systems.

TABLE SUM OF RELATED GAP ANALYSIS

SR.NO	Title	Author	Findings/Recommendations
1	Machine Learning Approach For automation Resume Recommendation System	Pradeep Roy	Takes resume in csv format in real life example resume are in pdf or docx format Uses Genism library which causes loss of information
2	Resume Evaluation through Latent Dirichlet Allocation and Natural Language Processing for Effective Candidate Selection	Vidhita Jagwani	Uses LDA for resume rating Which is complex and assumes there is some hidden words in resume,which can lead to high variance.
3	ResumeNET: A Learning- based Framework for Automatic Resume Quality Assessment	Zhang	Only theoretical and no practical implementation

III. OBSERVATIONS AND FINDINGS



The TNN successfully identifies patterns in the dataset, such as relationships between certain skills and job roles. The network can generalize beyond explicit information in profiles, recognizing transferable skills that may match with a broader range of job opportunities. The second layer demonstrates a high level of accuracy in mapping extracted features to appropriate job roles. The TNN is capable of predicting job matches even for profiles with incomplete data, thanks to its ability to infer missing information based on known patterns. The TNN continuously adapts and improves its job- matching accuracy as it receives more data and feedback. Supervised learning allows the network to refine its predictions over time, making it more reliable in changing job market conditions. Compared to more complex neural networks like deep neural networks (DNNs), the TNN maintains lower computational requirements while achieving comparable performance in profile evaluation tasks. The simplicity of the two-layer architecture results in faster training and prediction times. The TNN performs well even with relatively small datasets, avoiding overfitting and maintaining a balance between accuracy and generalization. This makes it suitable for applications where large amounts of labeled data are not readily available. The model provides personalized job suggestions that align closely with the

individual's skills, experience, and career goals. It identifies unconventional career paths that the user might not have considered but are suitable based on their core competencies. The TNN shows a strong ability to detect transferable skills that may be relevant to multiple industries, increasing the range of job suggestions for a candidate. It promotes career mobility by suggesting roles in different sectors where the candidate's skills are applicable. The TNN approach is highly scalable, making it suitable for integration into various job recommendation platforms, from small-scale applications to large enterprise-level systems. Its versatility allows it to be used across different industries and job types, adapting to the specific needs of various sectors. While the TNN performs well in structured data scenarios, it may have limitations when dealing with ambiguous or highly unstructured data in candidate profiles or job descriptions. Further integration with natural language processing (NLP) techniques might be necessary to handle text data more effectively.

IV. RESULTS AND OBSERVATIONS

The implementation of a two-layer neural network (TNN) for profile evaluation and job suggestion has yielded promising results, demonstrating high job-matching accuracy and efficient feature extraction compared to traditional methods. The model's ability to identify transferable skills and deliver scalable, computationally efficient solutions highlights its potential for real-world applications. Future work could focus on integrating natural language processing (NLP) to better handle unstructured data, incorporating reinforcement learning for dynamic improvements based on user feedback, and expanding its functionality to offer personalized career path planning. Enhancements could also include real-time market analysis to adapt job recommendations to current trends, multi-criteria decision-making frameworks to consider additional factors like salary and work-life balance, and efforts to make the TNN's decision-making process more interpretable for users. Developing hybrid models that combine TNNs with other machine learning algorithms could further improve prediction accuracy and robustness. These advancements aim to refine the TNN-based job suggestion system, making it a more sophisticated AI-driven tool for personalized career guidance and efficient talent acquisition.

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