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Assignment Report: Intelligent Job Recommendation System for Job Seekers Using Artificial Intelligence.

Abstract :

It is a challenging task for job applicants to get a suitable job since the traditional job search websites are ineffective. The websites employ keyword-based search and manual filtering, which are likely to provide wrong job recommendations. This research suggests an AI-based job recommendation system that enhances the matching process between employers and job applicants.

The proposed system will utilize Natural Language Processing (NLP) and Machine Learning techniques to analyse job listings and resumes. The model will be created using a hybrid approach, combining content-based filtering (that compares job applicants based on their qualifications and experience) and collaborative filtering (that considers the interests and actions of similar users).

To implement this system, job datasets will be gathered from open-source job postings and synthetic resume datasets.

Data pre-processing methods will be used to sanitize and structure the data for training AI models. The system performance will be gauged with metrics such as Precision, Recall, and F1-score to ensure precise job suggestion.

The expected outcome of this research is an intelligent job recommendation system that increases job search efficiency, reduces time incurred in searching for jobs that match, and provides personalized job recommendations to users. Such a system can be implemented in job portals to enable better job matching and benefit both the recruiters and job seekers.

Background and Motivation

In today's competitive job market, finding the right career opportunities that align with our interests and skills can be challenging. However, with the advancement in AI/ML technologies, we can leverage data-driven systems to provide personalized job recommendations based on user preferences and historical job data. I have been diligently trying to find a job in Riyadh for the past 11 months, but I have failed to get a satisfactory opportunity that fits my area of expertise. My experience in sales, maintenance & operations, and business development is not easily translatable to a formal job-matching process. In addition, most companies do not adequately define their employment needs, making it difficult to identify appropriate opportunities. This has motivated me to develop an AI-driven job recommendation system that can help job seekers identify the right jobs more efficiently.

Problem Statement

Traditional job search websites rely on keyword searches, which often provide irrelevant and misleading job recommendations.

It is difficult for the majority of job applicants to find a job that matches their level of qualifications, skills, and career objectives. The majority of job applicants still employ manual applications, which include visiting companies in person and submitting their resumes. The process has several drawbacks, including:

- Making sure the resume really finds the HR staff doing the hiring.
- Securing that the resume is duly considered rather than overlooked.
- Even if the HR personnel goes through the resume, will it be interesting enough to compel them to call the candidate?

These problems translate into wasted effort and time without any guaranteed results, which annoy job seekers.

Employers can also lose best fit candidates because manual screening fails.

Therefore, a job recommendation system powered by AI is essential that enhances the efficiency and precision of job matching to make job seeking easier for job seekers and ease employers' task of identifying the best-fitting candidates.

Research Objectives

Openings to job applicants depending on their experience, skill, and interest to enhance job satisfaction Implement Natural Language Processing (NLP) and Machine Learning techniques to match job postings and cvs with more precision.

Run a hybrid approach to recommendations wherein content-based filtering (matching candidates on resume) and collaborative filtering (learning trends from similar candidates) are employed. Save time spent on job hunting and improve the job hunting process by suggesting appropriate jobs.

Literature Review

The first paper, **An Intelligent Job Recommendation System Based on Semantic Embeddings and Machine Learning**, proposes a novel job recommendation system based on semantic embeddings and NLP techniques for enhancing the accuracy of job matching. As opposed to traditional systems that are content-based alone or collaborative filtering, this work proposes a two-way matching system where employers and candidates are both given personalized suggestions. The method integrates Bag of Words (BoW), n-grams, TF-IDF, and Parts-of-Speech (PoS) tagging, which are further augmented with Sentence-BERT (SBERT) to extract more meaningful semantic relationships between job descriptions and resumes. Using multiple real-world datasets, the system avoids problems of dataset sparsity and outdated recommendations. The study concludes that combining machine learning and semantic similarity metrics improves the trustworthiness and versatility of job recommendation systems, making them more dynamic and personalized.

The second paper, **Enhancing Job Recommendations Using NLP and Machine Learning Techniques**, suggests a hybrid recommendation framework that embraces content-based filtering and collaborative filtering to generate job recommendations based on specific requirements. The framework utilizes Word2Vec embeddings to represent job descriptions and candidate profiles as vectorized data to facilitate more precise matching through cosine similarity. Additionally, it applies named entity recognition (NER) to recognize prominent skills and qualifications that can be gleaned from job descriptions and improve recommendation quality. Unlike the standard keyword-based matching method, the system is deeper in examining text meaning, thereby providing more accurate matching of candidates with job descriptions. Furthermore, the study is concerned with fairness by assigning higher priority to skills and qualifications over demographic factors to eliminate bias in hiring. The evaluation of the system using precision, recall, and F1-score indicates great improvement in precision over conventional recommending techniques.

The third paper, **Job Recommendation System Using Hybrid Filtering**, seeks to develop a hybrid recommendation model that uses content-based filtering and collaborative filtering in an effort to mitigate the loopholes of both approaches. TF-IDF vectorization is applied for content-based filtering and Singular Value Decomposition (SVD) for collaborative filtering in such a way that accurate job recommendation can be made even if data provided by users is sparse. The hybrid method ensures both new and experienced job candidates receive suitable recommendations in accordance with their past experiences, skills, and profession interests. The work also highlights the effectiveness of weighted hybrid filtering, where multiple recommendation techniques are weighted to enhance accuracy. The work also addresses the cold start issue, a common in recommendation systems where limited user data leads to poor

suggestions. Through the integration of various machine learning approaches, the study demonstrates that a combination of the systems yields more accurate and timely job recommendations.

Critical Analysis

The three papers present novel approaches to job recommendation systems, but each of them has its pros and cons in methodology, efficiency, and computational cost. The first paper stands out in the way that it applies bi-directional matching, whereby both employers and job seekers receive suitable recommendations, thereby being more dynamic than conventional systems. However, though it employs advanced NLP techniques like SBERT, it does not utilize deep learning-based classification methods that would additionally enhance accuracy. The second paper is based on a hybrid approach that combines content-based and collaborative filtering and uses Word2Vec and cosine similarity to measure textual relationships. This deep learning-based text classification provides a more contextualized understanding of job roles and resumes, with higher accuracy at the expense of computational complexity. Unlike the first and third papers, the second paper directly addresses bias and fairness by focusing on skills and qualifications rather than demographic characteristics, thus being more in line with the ethics of AI. The third paper, while using a hybrid filtering model, is focused on efficiency in the sense that it employs TF-IDF and Singular Value Decomposition (SVD) rather than complex embeddings or deep learning. While this ensures computational efficiency and safeguards against cold start problems, it may lack in sharing a similar contextual understanding that the first two papers are capable of enabling. In general, while each of the three papers contributes valuable enhancements, there is a trade-off between deep learning-based accuracy, computational efficiency, and the ethical concern of fairness in recommendation systems.

Connections

Despite methodological variation among the three studies, the three share similarities in purpose and methodology towards improving job recommendation precision. The three are all based on the union of NLP and machine learning methods to surpass keyword-based matching. Hybrid filtering approaches, through content-based and collaborative filtering, are both used by the second and third papers in order to improve recommendation quality, while bi-directional matching is unique to the first paper. In addition, all three papers touch on the problem of feature extraction, with techniques such as TF-IDF, semantic embeddings, and deep learning models being used to analyze job descriptions and resumes of applicants. Measurement of performance is also a recurring theme, with each paper measuring the performance of the system using standard metrics such as

precision, recall, and F1-score. Another key similarity is the focus on overcoming dataset limitations—either by using multiple datasets (first paper), collaborative filtering for new user adaptation (second paper), or cold start prevention (third paper).

These similarities indicate a broader trend in recommendation systems towards more intelligent, more personalized, and adaptive approaches.

Conflicts

While the three papers have so much in common, they vastly diverge when it comes to approach and agenda. The most striking difference comes from bi-directional vs. uni-directional recommendation approaches. While the first paper stands single-handedly taking the employer preference into account, the second and third papers look at ways to increase job recommendations alone for seekers.

Another important difference is the handling of bias and fairness—the second paper addresses fairness head-on by prioritizing skills and qualifications over demographics, while the first and third papers fail to address bias mitigation, which could allow for hidden biases to persist in their recommendations.

On a computational complexity level, the first and second papers employ deep learning-based text processing, such as SBERT and Word2Vec, hence they are more sophisticated

but more computationally complex. Conversely, the third paper employs antiquated machine learning techniques such as TF-IDF and SVD in order to ensure efficiency at the expense of sacrificing some contextual accuracy. There is also methodological diversity along the lines of measuring text similarity—the first paper relies on SBERT for semantic deep understanding, the second paper on cosine similarity with Word2Vec, and the third paper is largely focused on TF-IDF-based similarity. Lastly, while all three papers intend to improve job recommendations, the second paper explicitly mentions ethical AI principles, which is largely absent in the other two.

These distinctions also bring into question the controversy of whether precision, effectiveness, or justice is most important in job recommender systems.

Conclusion

These papers distinguish between different techniques to job recommendation systems, where hybrid systems (Paper 2 & 3) are a realistic solution and semantic embeddings (Paper 1) are an enhanced, context-aware system. Future research must integrate deep learning, hybrid filtering, and fairness-aware approaches to better job recommendations.

Reference

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