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Intelligent Employer Matching System for Young Professionals and Students Based on Multifactor Analysis

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Abstract—**The article discusses the development of an intelligent employer matching system based on multifactor analysis. The system uses a career test that evaluates 40 factors, divided into four categories: career development, work environment, social and corporate benefits, and personal values and lifestyle. Machine learning algorithms account for the interconnections between attributes and provide personalized recommendations for students and young professionals. The test results are compared with employer profiles, created based on feedback from company employees. The system is planned to integrate with platforms that scrape job postings from popular websites like dou.ua, which will increase its relevance. Implementing this system will help optimize the employment process and facilitate more accurate matching of specialists to the labor market's needs.**

Keywords—career test; machine learning; multifactor analysis; employer matching; personalized recommendations; employer profile; labor market

I. INTRODUCTION

In today's increasingly competitive labor market, young professionals and students often face significant challenges when trying to identify employers that match their professional and personal needs [1]. One of the major issues is the lack of sufficient information or experience to make informed decisions about which companies best align with their values and career goals.

On the other hand, employers also struggle to find candidates whose priorities align with their company culture and requirements. In response to these challenges, there is growing interest in utilizing automation and data analysis technologies to improve employer matching processes.

Traditional job search platforms like LinkedIn [2] and Indeed rely on basic filters and keyword searches but fail to account for deeper individual priorities such as work-life balance, corporate culture, and growth opportunities. Similarly, while Applicant Tracking Systems (ATS) streamline the recruitment process for employers, they often focus solely on employer needs and overlook candidate-specific preferences [3]. Thus, these tools fall short in providing personalized recommendations that would meet both parties' expectations.

To bridge this gap, career tests that integrate machine learning and big data analysis offer a promising solution [4]. By combining multifactorial analysis with machine learning algorithms, these tests can evaluate candidates based on multiple factors, such as age, education, and professional interests, and provide tailored recommendations. This approach not only benefits candidates by offering personalized matches with employers but also provides employers with a clearer understanding of which candidates are the best fit for their company culture and demands.

II. CAREER TEST DEFINITION

A career test is an evaluative tool that aims to help individuals identify careers or employers that align with their personal and professional values, strengths, and goals. By answering a series of structured questions, users receive insights into potential career paths or companies where they are likely to thrive based on the factors that are most important to them.

The career test in your system is designed to provide personalized recommendations by evaluating 40 carefully selected attributes. These attributes are divided into four key categories: Career Development, Work Environment, Social and Corporate Benefits, and Personal Values and Lifestyle. This structure is purposefully chosen to cover all major aspects that influence a candidate's decision-making process when choosing a job or an employer.

Why This Structure? The decision to structure the test around these four categories is rooted in both research and practical experience from the fields of human resources and career counseling. Studies show that job satisfaction is not solely dependent on salary or job title; instead, it arises from a complex interplay of various factors that fulfill both personal and professional needs . Each of these categories addresses a critical dimension of this satisfaction:

- Career Development: For many young professionals and students, opportunities for learning, mentorship, and career advancement are essential when evaluating potential employers. This category measures factors like availability of promotions, professional training programs, and skill-building opportunities, which are all linked to long-term job satisfaction.

- Work Environment: The workplace culture and conditions can significantly impact an employee's daily experience. Factors such as work-life balance, flexibility in working hours, and the physical or virtual office environment are vital for ensuring that employees feel comfortable and supported in their roles. This category ensures that employers meet these practical needs, which are highly valued by modern job seekers Social and Corporate Benefits: Beyond salary, benefits like health insurance, bonuses, and pension schemes play a crucial role in employment decisions. Research shows that candidates often prioritize comprehensive benefits packages when choosing between job offers . By including these factors, the test helps users identify employers who offer the social and financial security they desire.
- Personal Values and Lifestyle: Alignment between an individual’s personal values and an employer’s corporate culture is becoming increasingly important, particularly for younger generations who are more focused on corporate social responsibility, ethics, and work-life balance . This category assesses how well a company's mission, ethics, and culture align with the candidate's personal beliefs and lifestyle preferences.

The structure of this career test ensures that multiple dimensions of job satisfaction are covered, allowing for a holistic understanding of what makes a particular employer a good match for the candidate. By considering not just professional development and salary, but also personal values and work environment, the test provides a comprehensive picture of employer-employee compatibility.

This structured approach reflects current trends in recruitment, where both employers and employees seek matches that go beyond basic qualifications, focusing on long-term satisfaction and organizational fit.

III. Machine Learning Model

The machine learning model implemented in the career test system is designed to analyze the responses provided by users and deliver personalized recommendations for employers that best match their priorities. Given the complexity of matching individuals with employers based on multiple interrelated factors, the model leverages a combination of machine learning techniques, including classification and clustering algorithms. Here are the key Components of the Model:

- Data Preprocessing: The first step involves cleaning and preparing the data gathered from user responses. Each response to the test's 40 attributes is converted into a structured format suitable for machine learning analysis. Normalization techniques are applied to ensure that all data points are within a consistent range, which is particularly important when different attributes have varying scales.
- Feature Engineering: To capture meaningful insights from the test results, the model must identify important features, or characteristics, that influence job satisfaction and employer matching. These features are derived from the four main categories: career development, work environment, social and corporate benefits, and personal values. Correlation matrices are used to explore relationships between the attributes and assess how changes in one factor may influence others.
- Clustering Algorithm (K-Means): The test utilizes K-Means clustering to group users and employers into distinct clusters based on their similarities. The algorithm analyzes the responses of each user and groups them with other candidates who share similar preferences. This allows for more personalized recommendations by identifying patterns in the data. For example, users who prioritize career development and mentorship opportunities will be clustered together, while those who value work-life balance and remote work options will form another group.
- Classification Algorithm (Random Forest): After clustering, a Random Forest classifier is employed to predict which employers are the best match for each user. This supervised learning model processes the user's input (the test results) and compares it to historical data on employers and candidates, making predictions about which employers align most closely with the user's preferences. Random Forest is particularly effective because it handles large datasets and can manage multiple input variables without overfitting. This robustness makes it ideal for the multifactorial nature of the career test.
- Model Training and Validation: The model is trained on historical data, which includes past user preferences and employer profiles. During training, the model is fine-tuned by adjusting hyperparameters and evaluating its performance using metrics like accuracy, precision, and recall. Cross-validation is applied to ensure that the model generalizes well and does not overfit the training data.
- Real-Time Recommendations: Once the model has been trained, it can generate personalized employer recommendations in real time. Users are provided with a ranked list of employers that align with their responses to the test. The model continuously learns from new data, allowing it to refine its recommendations over time.

Here are the main model advantages:

- Scalability: By leveraging AWS SageMaker, the system can scale to handle large datasets and multiple users simultaneously, ensuring that recommendations are generated quickly and efficiently [5].
- Accuracy: The use of clustering and classification algorithms ensures that the recommendations are highly personalized and relevant to each user's unique preferences.
- Adaptability: The model can adapt to changes in the labor market and evolving user preferences by continuously learning from new data inputs.

In conclusion, the machine learning model plays a central role in the career test system by processing multifactorial data, identifying patterns, and providing personalized employer recommendations. The combination of clustering (K-Means) and classification (Random Forest) ensures that users receive accurate and tailored results, ultimately improving the job search process for students and young professionals.

IV. Infrastructure

The infrastructure supporting the career test system is designed to ensure both seamless performance and scalability through modern cloud technologies. At its core, Python handles data processing, making it wellsuited for integrating machine learning algorithms. Python’s powerful libraries like Pandas and Scikit-learn ensure efficient data manipulation, making it the ideal choice for this project [6].

Hosted on Amazon Web Services (AWS), the platform is designed to scale and adapt to varying loads. AWS SageMaker powers machine learning operations, enabling real-time model training, deployment, and updates, ensuring that large datasets are processed efficiently. The backend communicates with the frontend through a RESTful API, quickly converting user input into actionable recommendations. AWS Lambda, a serverless service, manages requests in real-time, optimizing performance and costs by activating only when needed.

The frontend, developed with frameworks like React.js or Angular, delivers a responsive and intuitive experience, optimized for performance across devices. With progressive web app (PWA) features, users enjoy smooth, lag-free interactions on desktops, tablets, and smartphones.

For secure and reliable data storage, Amazon RDS manages structured data such as user profiles, while Amazon S3 handles unstructured data like logs. These cloud-based solutions ensure data security, accessibility, and performance even during high traffic, while the infrastructure scales effortlessly as user engagement increases. This design ensures the system continually evolves to provide real-time, accurate recommendations while maintaining smooth front-end and back-end operations.

CONCLUSION

The career test system developed in this project represents a significant advancement in the way young professionals and students can navigate the increasingly competitive job market. By focusing on personal and professional priorities across key categories such as career development, work environment, corporate benefits, and personal values, the system goes beyond traditional job-matching platforms. It offers users tailored recommendations that take into account the multifaceted nature of job satisfaction, helping them find employers that align with their long-term goals and values. The implementation of machine learning algorithms like clustering and classification ensures that recommendations are not only accurate but also adaptive to user preferences. The system's real-time analysis capabilities, powered by AWS, make it scalable and efficient, allowing for continuous improvement and personalization. This results in a more intelligent and responsive job-matching experience compared to conventional methods.

Moreover, the system's integration with a previously developed tool that parses job advertisements from dou.ua enhances its practical value [7]. By pulling in real-time data on current job vacancies, the system ensures that users are matched with employers not only on the basis of cultural fit and priorities but also in terms of real, available opportunities. This synergy between the career test and the job parsing system creates a robust ecosystem for job seekers, providing them with both personalized guidance and access to up-to-date market information.

In conclusion, this career test system bridges the gap between traditional job search tools and the need for personalized, data-driven recommendations. As it continues to evolve, the system holds the potential to significantly improve the job search experience for young professionals and students, ensuring that they find positions and employers that truly match their ambitions and values.

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