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AI-Driven Talent Matching: Empowering HR Professionals With Reinforcement Learning

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Abstract - The goal of "AI-Driven Talent Matching: Empowering HR Professionals with Reinforcement Learning" is to transform hiring practices by fostering a mutually beneficial partnership between employers and employees. When HR specialists thoroughly specify Job Descriptions (JDs) on the platform, the project gets underway. Meanwhile, job applicants upload their resumes, resulting in the establishment of profiles summarizing their credentials and experiences. After that, the system gathers essential data to create unique JDs for each seeker. The degree to which these customized JDs resemble the HR's JD is measured by a computed similarity score, guaranteeing a data-driven method of candidate assessment. Based on these scores, candidates are ranked, and Recruiters are then presented with top ranked candidates by applying a threshold. The incorporation of reinforcement learning will improve the recommendation model through learning from recruiter's feedback. Feedback in the form of "yes" or "no" from recruiter reviews of candidates enables the model to dynamically modify the similarity score threshold. This research explores the shifting dynamics of the labor market and makes the case for a datadriven strategy that would enable recruiters to make well-informed choices when hiring and selecting candidates. The process ends with a screening test to make sure applicants have the skills that are needed for the job. Better recruitment outcomes are promised by this cutting-edge approach, which will help both Recruiters and job seekers.

Keywords: - Reinforcement Learning, Data-Driven, Job Descriptions, Recommendation Engine, Job Seekers.

1. INTRODUCTION

Recruiters face a daunting problem in the everchanging labor market of today: matching job searchers with acceptable job opportunities. This is an intricate undertaking. To improve the recruiting process overall, sorting through a large number of job seeker profiles requires not just a significant amount of time and effort but also a data-driven strategy. Innovation was made possible by the paradigm shift in hiring practices from manual to automated, marked by the introduction of Applicant Tracking Systems (ATS). These early fixes did, however, have certain drawbacks. While popular online recruitment services provide more convenient channels for both employers and job seekers, it is also faced with the challenge of Person-Job Fit due to the explosion.[3] It is impossible to overestimate the revolutionary effects of artificial intelligence (AI) and reinforcement learning on the employment market.

With the help of AI and reinforcement learning algorithms, this research project aims to develop a platform that enhances and simplifies the work of recruiters. With an emphasis on making highly accurate recommendations for job seeker profiles, the platform seeks to transform the hiring process by enabling more favorable matches between candidates and companies. The project's extensive workflow introduces a fresh method to information extraction, similarity scoring, and reinforcement learning-driven feedback, and it modernizes recruiting by seamlessly integrating recruiters with job seekers.

The process starts when a recruiter posts a Job Description (JD) that includes all of the qualifications for the position. In parallel, job seekers submit their resumes—which include vital details about their qualifications and skills—after creating profiles on the portal. The algorithm mimics the original JD's language by extracting critical information. to create personalized JDs for every job applicant. Stronger match recommendations are ensured by this exact alignment between job needs and job searchers. After that, a similarity score is determined, which ranks candidates according to how closely their customized JD resembles the original JD created by the Firm.

The project introduces a novel approach to recommendation systems by establishing a proximity value, a pivotal metric that governs the quantity of recommendations. This value is dynamically updated through feedback from recruiters and serves as a crucial input to the recommendation system, facilitating ongoing enhancements using the Proximal Policy Optimization (PPO) algorithm.[8] The unique aspect of the project lies in its implementation of reinforcement learning. In response to recruiters' feedback, the algorithm continually refines the similarity score threshold, ensuring that recommendations become more precise over time.

2. PROBLEM STATEMENT

Creating a platform powered by reinforcement learning to offer HR Recruiter precise job seeker profile recommendations, optimizing talent acquisition.

3. OBJECTIVES

3.1 Develop an Intelligent Recommendation System Implementing a model based on Reinforcement Learning Algorithms to create an adaptable and accurate recommendation system. Furthermore, integration of skill matching algorithms to the proposed methodology aims to modernize the recruitment process, fostering seamless communication between HR professionals and job seekers. The process unfolds through a series of well-defined steps, leveraging stateof-the-art technologies and algorithms.

3.2 Enhance User Experience and Decision-Making Justifying the candidate's selection by clarifying the reasons behind the selection of the job recruiters. Simultaneously, with the developments in Natural Language Processing (NLP), user experience would be enhanced by allowing flexible and intuitive search.

3.3 Improving the efficiency of the process of hiring by introducing an Interview scheduling feature that will automate communication and scheduling, which will help in reducing delays.

3.4 The candidates will appear for a screening test which will test the knowledge of the skillsets they mention in their profile. Along with that, the test will include questions befitting the job requirements. This will help check the knowledge and authenticity of the candidates, hence, making the job easier for the recruiter.

3.5 A feedback mechanism based on reinforcement learning for the recruiter will facilitate the continuous learning and system improvement based on the insights given by the model. The integration of candidate matching confidence scores will enhance the decision-making by providing an indication of the credibility of the recommended candidates.

3.6 Integration of email templates and automated rejection emails with constructive feedback support for the development of the candidates' professional career even in cases of non- selection.

3.7 Offering Customizable Data Visualizations and Reports, the system enables HR professionals to analyze hiring trends and make informed, data-driven decisions.

4. METHODOLOGY AND ARCHITECHURE

The proposed methodology aims to modernize the recruitment process, fostering seamless communication between HR professionals and job seekers. The process unfolds through a series of well-defined steps, leveraging state-of-the-art technologies and algorithms.

4.1 Job Description Posting

The recruiters start the procedure by posting thorough job descriptions (JDs) on the website. These JDs lay the groundwork for a subsequent candidate evaluation by outlining the precise job requirements and qualifications for a specific position.

4.2 Profile Creation

Candidates seeking jobs have already registered on the site and included vital details about their backgrounds, experiences, and abilities. A comprehensive database of possible applicants is created in this step.

4.3 Profile Verification

The implementation of a verification process serves to guarantee the legitimacy of profiles. This involves verifying the authenticity and existence of related projects by checking GitHub links that candidates submit. In order to examine only sincere and honest candidates, this step is essential.

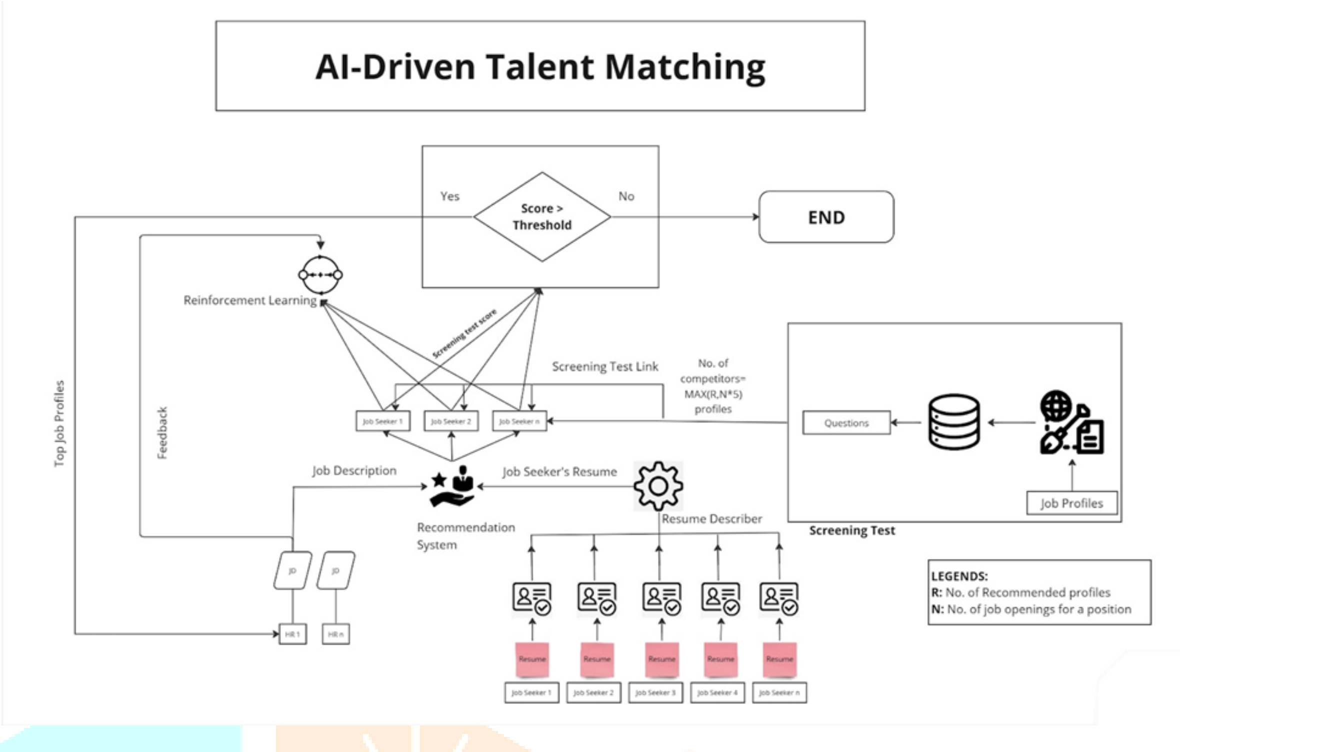

Fig 1. AI-Driven Talent Matching Architecture

4.4 Profile Describer

This stage attempts to standardize profiles to match the format of the related job description by using the Mistral algorithm. Sentences that make sense are used to summarize profiles, which improves readability and makes analysis easier.

4.5 Recommendation Model

To measure the degree of alignment between candidate profiles and Recruiter 's JD, a similarity score is calculated. This score is an essential indicator for evaluating how well candidates match particular job requirements.

4.6 Candidate Ranking

The similarity scores of candidates are used to rank them. The number of job opportunities multiplied by a predetermined factor yields the number of suggested applicants. A list of possible candidates is created at this step for review

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4.7 Screening Test

Those who make the cut are invited to take a screening exam that is tailored to the job description. A thorough database with questions for different job responsibilities is used, and assessments are used to determine which candidates are sent to the recruiter.

4.8 Reinforcement Learning Integration

Reinforcement learning is integrated into this unique feature. The model's adaptation is guided by recruiter's input, which is given as a "yes" or "no" when examining recommended applicants. The model's alignment with recruiters' expectations is improved by this iterative learning process, which also refines the similarity score threshold.

4.9 Recommendation Refinement

Reinforcement learning and recommendation models are connected using the Proximal Policy Optimization (PPO) method. Through this interface, the recommendation engine is continuously improved, guaranteeing exact matches between job seekers and opportunities. Facilitating continuous improvement yields a system that adjusts to changing recruiter preferences and eventually maximizes results for recruiters and job seekers alike.

Profile Describer Mistral 7B

A new artificial intelligence startup called Mistral AI unveiled Mistral 7B, a 7 billion parameter language model. Being one of the most potent 7 billion parameter models accessible, this model has drawn attention.

Presented as a foundational model, Mistral 7B signifies its importance as a fundamental building component of natural language processing. It is a component of the vast language models' changing environment.

Mistral 7B is a small model in comparison to some larger models, yet it does remarkably well in a variety of natural language understanding and interpretation tasks. It performs exceptionally well in tasks such as code completion, text completion, text classification, and text summarization.

Mistral 7B has a unique architectural style. The model makes use of a novel architecture that, while not fully detailed, offers a different approach to design than popular models such as GPT-3. It makes use of "Sliding Window Attention" (SWA) to handle longer sequences at a lower cost and "Grouped-query attention" (GQA) for faster inference. As a result, the model performs incredibly well for its size.

At the moment, Mistral 7B is largely focused on English with coding skills. On the other hand, compared to other models like GPT-3, it is renowned for having an exceptionally big context window, which allows it to comprehend and produce text in a wider context.

Recommendation Model

To create a similarity score between candidate profiles and a job description (JD), you can use a cosine similarity measure. This involves representing both the candidate profiles and the JD as vectors and then calculating the cosine of the angle between these vectors.

1. **Define Features:** Identify the key features or attributes important for the job. These could include skills, education, experience, etc.

2. **Create Feature Vectors:** Represent each candidate profile and the JD as vectors. Each element in the vector corresponds to a feature, and the value represents the importance or relevance of that feature.

3. **Normalize Vectors:** Normalize the feature vectors to ensure that the scale of values doesn't skew the similarity calculation. You can use techniques like z-score normalization or min-max normalization.

4. **Calculate Cosine Similarity:** Use the cosine similarity formula to calculate the similarity score between the candidate profile vector C and the JD vector J:

   Cosine Similarity = C.J / (‖C‖·‖J‖)

   Where: C·J is the dot product of the two vectors.

   ‖C‖ and ‖J‖ are the magnitudes (Euclidean norms) of the vectors.

5. **Interpret the Score:** The cosine similarity score ranges from -1 (completely dissimilar) to 1 (completely similar), with 0 indicating no similarity. Set a threshold above which you consider candidates as a good fit. **Proximal Policy Optimization (PPO)**

1. Initialization:

i. Define actor model (G_a) for action selection, critic model (U_c) for state value estimation.

ii. Set training parameters: iterations (K), minibatch size (B_r), epochs per iteration (E), learning rates (α_am, α_cm), clipping parameter (ε), KL coefficient (λ).

2. Iteration Loop: For each iteration (1 to K):
Sample and Generate trajectories:

i. Sample a set of "collected states and values" (C_r) from the training data.
ii. For each state in C_r, use the actor model (G_a) to generate a complete "generated trajectory" (J_r) of actions and rewards.

3. Compute Advantages and Rewards: Calculate discounted rewards ("r_i") and advantages ("a_i") for each step in each trajectory (J_r) using Equations (5) and (6) (not provided here).

4. Model Updates:

i. Actor Model (G_a):
   - **a.** Run for E training epochs.
   - **b.** Shuffle the training data and divide into minibatches (size B_r).
   - **c.** For each minibatch:
     - **i.** Compute the policy loss (L_am) based on the sampled data and generated trajectories.
     - **ii.** Clip the ratio of action probabilities before calculating the loss to prevent large policy updates.
     - **iii.** Update the actor model parameters (θ(G_a)) with the clipped policy loss and learning rate (α_am) using gradient descent.

ii. Critic Model (U_c):
   - **a.** Run for E training epochs.
   - **b.** Shuffle the training data and divide into minibatches (size B_r).
   - **c.** For each minibatch:
     - **i.** Compute the policy loss (L_am) based on the sampled data and generated trajectories.
     - **ii.** Clip the ratio of action probabilities before calculating the loss to prevent large policy updates.

iii. **End**: After K iterations, the trained actor model (G_a) outputs optimal actions for unseen states, and the critic model (U_c) estimates their values for improved decision-making.

5. SCOPE

Looking ahead, the project's future scope includes the integration of an Interview Scheduling feature, introducing automated coordination to simplify the process for both HR professionals and job seekers. The extension of the system to cover various job domains is envisioned to enhance its versatility, ensuring its effectiveness across diverse industries and professions. The implementation of Customized Email Templates tailored for HR communication aims to elevate the user experience by providing a personalized touch to interactions. Additionally, the introduction of an Explanations feature for Top Job Seekers will contribute to a culture of continuous improvement, offering detailed feedback and insights. These advancements collectively signify the project's commitment to adaptability, user-centric design, and continual refinement to meet the dynamic needs of HR professionals and job seekers in the evolving landscape of recruitment.

6. CONCLUSIONS

The Research introduces a novel platform utilizing reinforcement learning to enhance hiring processes. This user-friendly tool offers personalized job seeker suggestions, blending advanced computing with human expertise. As organizations adopt this innovative approach, we anticipate improved and streamlined hiring decisions. This research contributes to the evolution of talent acquisition, envisioning a future where the synergy of technology and human insights simplifies and enhances the hiring experience for all stakeholders. The platform represents a significant advancement, offering a harmonious blend of technological assistance and human intuition, ultimately redefining the landscape of contemporary hiring practice.

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