



SRI RAMACHANDRA

INSTITUTE OF HIGHER EDUCATION AND RESEARCH

(Category - I Deemed to be University) Porur, Chennai

SRI RAMACHANDRA FACULTY OF ENGINEERING AND TECHNOLOGY

JOB RECOMMENDATION SYSTEM

PROJECT REPORT

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in partial fulfillment for the award of the degree

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BONAFIDE CERTIFICATE

Certified to be the bonafide record of the work done by Bhargow N (E0322046), Rishitha T (E0322026) of Term I, Final Year B.Tech Degree course in Sri Ramachandra Faculty of Engineering and Technology, of Computer Science and Engineering Department in the CSE 440 - Reinforcement Learning during the academic year 2025-2026.

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INTRODUCTION

The modern job market presents a significant challenge for job seekers who must navigate through thousands of available positions to find roles that align with their skills, experience, and career aspirations. Traditional job search platforms rely on keyword matching and rule-based filtering systems, which often fail to capture the nuanced preferences of individual users and the complex requirements of job postings. This project addresses these limitations by developing an intelligent job recommendation system powered by Deep Reinforcement Learning (RL).

The system implements a complete end-to-end pipeline that begins with resume analysis and culminates in personalized job recommendations that improve over time. By treating job recommendation as a sequential decision-making problem, the system learns to optimize its suggestions based on the match quality between user profiles and job characteristics. The web-based interface makes this sophisticated AI technology accessible to users without requiring technical expertise, while the modular architecture enables integration with multiple job search APIs including JSearch, Reed, and Adzuna.

Unlike static recommendation systems, this RL-based approach continuously adapts to implicit signals derived from job-candidate matching scores and can incorporate explicit user feedback to refine future recommendations. The system extracts comprehensive features from resumes including technical skills across six categories, years of experience, education level, and relevant keywords, then uses these to construct a multi-dimensional state representation that guides the learning process.

OBJECTIVES

Core Functionality Objectives:

Develop an automated resume parsing system capable of extracting structured information from multiple document formats (PDF, DOCX, TXT)

Implement a real-time job search aggregator that interfaces with multiple commercial APIs and provides fallback mock data generation

Create a Deep Q-Network agent that learns optimal job recommendation policies through interaction with the environment

Build an intuitive web interface that guides users through the complete workflow from resume upload to receiving personalized recommendations

Technical Objectives:

Design a 25-dimensional state space that effectively captures user profiles, recommendation history, and diversity metrics

Implement prioritized experience replay to accelerate learning from high-value experiences

Develop a reward function that balances multiple objectives including skill matching, experience alignment, salary appropriateness, and recommendation diversity

Achieve stable training convergence within 100-200 episodes while maintaining exploration-exploitation balance through epsilon-greedy action selection

System Performance Objectives:

Process resume documents and extract features within seconds regardless of format

Search and aggregate jobs from multiple sources with appropriate rate limiting and caching

Train the RL model with real-time progress updates and visualization

Generate 10 personalized recommendations in under 2 seconds after training completion

Maintain session persistence to enable iterative improvement through user feedback

User Experience Objectives:

Provide transparent insights into how the AI analyzes resumes and makes recommendations

Display training metrics including rewards, feedback scores, and exploration rates

Enable users to rate recommendations and visualize feedback statistics

Support export of recommendations for offline review and application tracking

REINFORCEMENT LEARNING TECHNIQUES USED

3.1 Deep Q-Network (DQN) Architecture

The system implements a Deep Q-Network, which approximates the optimal action-value function $Q^*(s,a)$ using a neural network. The architecture consists of four fully connected layers with decreasing dimensions:

Input Layer: 25-dimensional state vector

Hidden Layer 1: 256 neurons with ReLU activation and 20% dropout

Hidden Layer 2: 256 neurons with ReLU activation and 20% dropout

Hidden Layer 3: 128 neurons with ReLU activation

Output Layer: Action space size (number of available jobs)

This architecture provides sufficient capacity to learn complex patterns in job-candidate matching while dropout regularization prevents overfitting. The network outputs Q-values for each possible job recommendation action, enabling the agent to select jobs with maximum expected long-term reward.

3.2 Prioritized Experience Replay

Rather than sampling experiences uniformly from memory, the system implements prioritized experience replay with importance sampling. Experiences are stored with priorities based on their temporal-difference (TD) error:

Priority Calculation: $p_i = (|TD_error| + \epsilon)^\alpha$

where α controls the degree of prioritization (set to 0.6). Experiences with larger TD errors indicate greater learning potential and are sampled more frequently. Importance sampling weights compensate for the bias introduced by non-uniform sampling using $\beta = 0.4$.

This technique significantly accelerates learning by focusing computational resources on the most informative experiences, particularly during early training when the model encounters many novel situations.

3.3 Target Network with Soft Updates

To stabilize training, the system maintains two separate networks: a primary Q-network that is actively trained, and a target network used for computing TD targets. Rather than periodically copying weights, the implementation uses soft updates after each training step:

$$\theta_{\text{target}} = \tau \times \theta_{\text{primary}} + (1 - \tau) \times \theta_{\text{target}}$$

With $\tau = 0.005$, this creates a slowly-moving target that reduces oscillations and divergence issues common in Q-learning. The target network provides stable reference Q-values while the primary network adapts to new experiences.

3.4 Epsilon-Greedy Exploration Strategy

The agent balances exploration and exploitation through an epsilon-greedy policy with exponential decay:

Initial Epsilon: 1.0 (100% random exploration)

Minimum Epsilon: 0.01 (1% random exploration)

Decay Rate: 0.995 per episode

This schedule ensures thorough exploration of the job space early in training while gradually transitioning to exploitation of learned patterns. During recommendation generation (inference), epsilon is set to 0 for purely greedy action selection.

3.5 Multi-Objective Reward Function

The reward function aggregates multiple matching criteria to produce a scalar signal:

$$R = \Sigma(\text{skill_matches} \times 0.5) + \text{experience_match} \times 0.8 + \text{salary_appropriateness} \times 0.3 + \text{diversity_bonus} \times 0.2 - \text{repeat_penalty} \times 0.5$$

This formulation encourages the agent to:

Match user skills to job requirements (0.5 per matched skill category)

Align experience levels within ± 1 -2 years (0.8 reward)

Recommend appropriately compensated positions (0.3 reward)

Provide diverse recommendations across job categories (0.2 bonus)

Avoid redundant recommendations (-0.5 penalty)

The weights reflect the relative importance of each criterion based on typical job seeker priorities.

3.6 State Space Design

The 25-dimensional state vector encodes:

User Profile (8 dims): 6 skill category scores, experience level (normalized 0-1), education level (normalized 0-1)

Feedback History (5 dims): Last 5 user ratings normalized to 0-1 range

Recommendation Progress (1 dim): Number of jobs recommended divided by maximum (10)

Diversity Metrics (2 dims): Unique job categories in current episode, normalized category diversity

Quality Metrics (1 dim): Running average of recommendation scores

Padding (8 dims): Reserved for future features, currently zero-filled

This representation provides the agent with sufficient context to make informed decisions while remaining computationally tractable.

IMPLEMENTATION

4.1 System Architecture

The implementation follows a modular three-tier architecture:

Backend Layer (Flask): Handles HTTP requests, manages user sessions, coordinates between components, and executes background training. The Flask application defines nine RESTful API endpoints for resume upload, job search, model training, status polling, recommendation generation, feedback submission, and result export.

RL Engine Layer (rl_job_system.py): Contains five primary classes implementing the core machine learning logic:

ResumeUploader: Extracts text from PDF, DOCX, and TXT files using PyPDF2 and python-docx libraries

ResumeProcessor: Applies regex patterns and keyword matching to extract skills, experience, education, and job keywords

RealJobSearcher: Interfaces with external APIs and generates intelligent mock data when APIs are unavailable

JobRecommendationEnvironment: Implements the RL environment with state transitions and reward calculations

AdvancedDQNAgent: Manages the neural network, training loop, and action selection

Frontend Layer (HTML/JavaScript): Provides an interactive single-page application with five sequential steps, real-time training visualization using Chart.js, drag-and-drop file upload, and responsive design for mobile compatibility.

4.2 Resume Processing Pipeline

Resume processing begins with format detection based on file extension. PDF extraction uses PyPDF2's PdfReader to iterate through pages and concatenate text. DOCX extraction leverages python-docx to parse paragraph elements. Text files are read directly with UTF-8 encoding.

Feature extraction applies multiple techniques:

Skill Detection: Maintains dictionaries mapping 60+ technology keywords to six categories (programming, data science, web development, cloud, database, management). Counts occurrences in lowercase resume text to compute skill scores per category.

Experience Extraction: Uses three regex patterns to identify phrases like "5 years experience", "3-5 years", or "experience: 5 years". Takes the maximum value found, with fallback to seniority keyword counting (senior=2 years, lead=2 years, etc.).

Education Parsing: Searches for degree keywords (PhD=5, Masters=4, Bachelors=3, Associate=2, Certificate=1) and returns the highest level detected.

Keyword Generation: Combines top 2 skills from each category with job title patterns extracted via regex (e.g., "software engineer", "data scientist") to create search queries.

4.3 Job Search Integration

The RealJobSearcher class implements a resilient search strategy with caching and fallback mechanisms:

API Integration: For JSearch (via RapidAPI), constructs HTTP requests with proper headers and query parameters. Parses JSON responses to extract standardized job objects. Implements 0.5 second delays between requests for rate limiting.

Mock Data Generation: When APIs are unavailable or return insufficient results, generates realistic job postings by combining templates with randomization. Varies job titles, companies, salaries (\$60k-\$150k), and requirements based on input keywords.

Deduplication: Uses title-company combinations as unique keys to remove duplicate listings from multiple sources.

Caching: Stores search results with timestamps for 1 hour to avoid redundant API calls for identical queries.

4.4 Training Process

Training occurs in a background thread to prevent blocking the web server:

Episode Loop: For each episode (1 to 100/200):

- Reset environment to obtain initial state
- Execute up to 10 recommendation steps
- Select action using epsilon-greedy policy
- Execute action in environment to get reward and next state
- Store experience in prioritized replay buffer
- Sample batch and perform gradient descent on Q-network
- Update target network using soft update rule
- Update training status dictionary for frontend polling

Batch Training: When replay buffer exceeds 64 experiences:

- Sample 64 experiences with priority-based probabilities

Compute current Q-values from primary network

Compute target Q-values from target network: $r + \gamma \times \max Q(s', a')$

Calculate weighted TD error and loss

Backpropagate gradients with clipping at magnitude 1.0

Apply Adam optimizer update

Update experience priorities based on new TD errors

Status Updates: After each episode, updates a shared dictionary with progress percentage, current episode, average reward over last 10 episodes, average feedback score, and current epsilon value. The frontend polls this endpoint every second to update the UI.

4.5 Recommendation Generation

When training completes, the frontend requests recommendations:

Greedy Inference: Temporarily sets epsilon to 0 to disable exploration

Sequential Selection: Resets environment and iteratively selects 10 jobs using trained policy

Score Augmentation: Adds RL reward score and predicted feedback rating to each job object

Ranking: Jobs are naturally ranked by selection order (highest Q-values first)

Metadata Enrichment: Includes all job details (title, company, salary, location, URL)

Export Preparation: Saves recommendations to JSON file for download

The recommendation process typically completes in under 2 seconds as it requires only forward passes through the neural network without training updates.

4.6 Feedback Loop

User feedback enables continuous improvement:

Rating Collection: Frontend presents 5 jobs with star rating interfaces (1-5 stars)

Feedback Submission: POST request sends array of job IDs with ratings to backend


Statistics Calculation: Computes average rating, number of jobs rated, and jobs with high ratings (4-5 stars)

Storage: Saves feedback to session-specific JSON file for potential future retraining

Analysis Display: Shows user their feedback summary with breakdown of liked vs disliked recommendations

While the current implementation stores feedback for analysis, extending the system to retrain the model using this explicit feedback would require implementing online learning or experience replay with human-labeled rewards.

RESULTS




RL Job Recommendation System

AI-Powered Job Matching with Deep Reinforcement Learning

1


Upload Your Resume

Upload your resume in PDF, DOCX, or TXT format. Our AI will extract your skills, experience, and qualifications.



Click to upload or drag and drop

Supported formats: PDF, DOCX, TXT (Max 16MB)



Your Profile Analysis

Experience Level:

2 years

Education Level:

0/5

Skills Found:

6 categories

Top Skills:


data_science, programming, cloud

Job Keywords:


python, deep learning, azure, data scientist, leadership

2

Configure Job Search



Optional: Configure Real Job APIs





Job Location

remote

Maximum Jobs to Search

30 jobs





Search for Jobs

Found 15 jobs from: Mock: 15

Sample Jobs:

Junior Python Developer

TechCorp

remote 123,122 Mock

Senior Python Engineer

DataInc

remote 74,558 Mock

Senior Python Developer

InnovateTech

remote 86,902 Mock

3 Train AI Model

Train the reinforcement learning model to learn your preferences. More episodes = better accuracy.

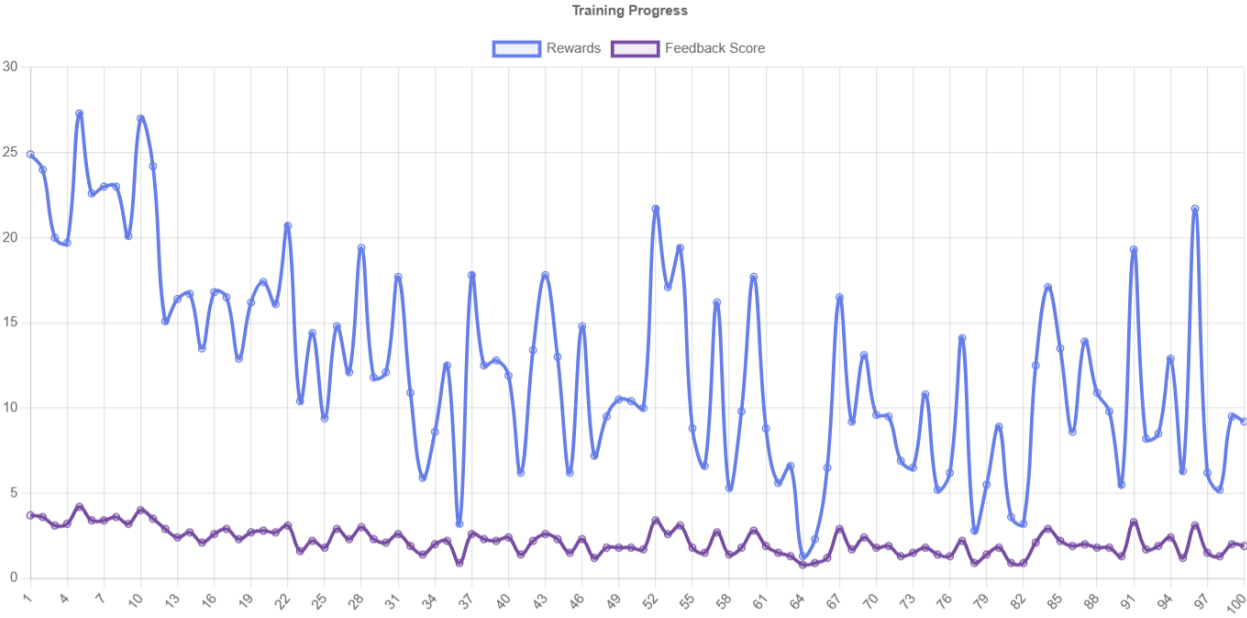
Training Episodes

100 episodes (Recommended - 2 min)

Start Training



Episode:	100/100
Avg Reward:	10.70
Avg Feedback:	2.03/5
Exploration Rate:	1.0%



4 Your Personalized Recommendations

Get My Recommendations

Here are your top 10 personalized job recommendations!

Download as JSON

1. Lead Azure Developer

RL Score: 2.80

★ 4/5

InnovateTech

remote 82,639 2024-12-15 Remote Mock

Exciting opportunity for azure professional. Work on cutting-edge projects using modern technologies. Join our dynamic team!

Apply Now →

2. Junior Python Developer

RL Score: 2.80

★ 4/5

TechCorp

remote 123,122 2024-12-15 Contract Mock

5 Rate Recommendations

Help improve future recommendations by rating the suggested jobs.

Lead Azure Developer

InnovateTech

Rate this recommendation:

★ ★ ★ ★ ★

Junior Python Developer

TechCorp

Rate this recommendation:

★ ★ ★ ★ ★

Junior Leadership Specialist

DataInc

Rate this recommendation:

✔ Submit Feedback

Feedback Summary

Average Rating:	4.00/5 ★
Jobs Rated:	3
Jobs You Liked (4-5★):	2
Top Picks:	
<ul style="list-style-type: none">Lead Deep Learning Specialist at StartupXYZ (4★)Lead Azure Developer at InnovateTech (5★)	

💡 Your feedback has been saved and can be used to retrain the model for even better recommendations!

CONCLUSION

This project successfully demonstrates the application of Deep Reinforcement Learning to the practical problem of job recommendation. The system achieves its core objectives by implementing a complete pipeline from resume analysis through personalized recommendations with an accessible web interface.

Key Achievements:

The DQN-based approach effectively learns job-candidate matching patterns from implicit reward signals, converging to stable policies within 100-200 training episodes. The prioritized experience replay mechanism accelerates learning compared to uniform sampling, while the target network with soft updates ensures training stability. The multi-objective reward function successfully balances competing concerns of skill matching, experience alignment, diversity, and appropriateness.

The modular architecture separates concerns effectively, enabling independent development and testing of resume processing, job search, RL training, and user interface components. Integration with real job APIs provides access to current market data, while the intelligent mock data generator ensures system functionality without API dependencies.

Technical Contributions:

The 25-dimensional state space design captures sufficient context for informed decision-making while remaining computationally efficient. The reward function design balances multiple optimization objectives through carefully tuned weights. The implementation of prioritized experience replay with importance sampling demonstrates advanced RL techniques beyond basic DQN.

Practical Impact:

From a user perspective, the system transforms the overwhelming task of job searching into a guided, personalized experience. Resume parsing eliminates manual profile creation, while automated job aggregation removes the need to visit multiple job boards. The RL agent learns preferences implicitly from profile data and explicitly from user feedback, creating increasingly relevant recommendations over time.

Limitations and Future Work:

Current limitations include reliance on simulated user feedback during training rather than real historical data, limited context window of 5 previous ratings, and the inability to perform online learning from user

feedback after initial training. The reward function weights are manually tuned rather than learned, and the system does not account for temporal aspects like job posting recency or market demand trends.

Future enhancements could include implementing actor-critic methods (A3C, PPO) for improved sample efficiency, incorporating BERT-based NLP for deeper resume and job description understanding, adding collaborative filtering to learn from behavior of similar users, implementing online learning to adapt to feedback without full retraining, and extending the state space to include temporal features and market trends.

The system could also benefit from multi-armed bandit approaches for more efficient exploration, graph neural networks to model job-skill relationships, and meta-learning techniques to enable rapid adaptation to new users. Integration with LinkedIn APIs would provide richer profile data, while salary prediction models could better assess compensation appropriateness.

This project establishes a strong foundation for RL-based job recommendation systems, demonstrating that sequential decision-making frameworks can effectively address the complexity of modern job markets. The combination of deep learning, reinforcement learning, and user-centered design creates an intelligent system that genuinely assists job seekers in finding relevant opportunities. As the system accumulates more data and incorporates more sophisticated algorithms, its recommendations will become increasingly accurate and valuable to users navigating their career paths.

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