Title: CareerNav: Your career’s personal GPS

1. Introduction

In today's dynamic and rapidly evolving job market, navigating career transitions can be a daunting task for individuals across all cultural, economic, and social backgrounds, even more so for folks with limited access to learning resources and mentorship. CareerNav. was developed with a vision of enabling **equitable access to career opportunities for everyone**, beyond their measures. We aim for our platform to serve as a beacon of hope for economic mobility, providing every individual with equitable access to boundless career opportunities, transcending limitations and leveling the playing field for all.

CareerNav. is a tool that lets individuals, intending to transition from one career domain to another, identify transferable skills and skill-gaps in their profile. The goal is to help the user with a personalized learning map for the skills that matter in the industry. Users first update their background and career goals. The tool takes these into consideration and evaluates the transferable skills they already have, benchmarking them against industry trends. The tool then does a skill gap analysis and recommends a study plan for each skill gap. The user is also provided with an explanation for the recommended learning path.

2. Background & Motivation

In the wake of the pandemic, the landscape of professional employment has undergone a seismic shift. A staggering 46% of workers have ventured into career transitions outside their traditional fields, seeking new opportunities amidst uncertainty [1]. Furthermore, among those who faced job losses during the COVID crisis, a significant 63% opted for a career change [2]. The statistics clearly indicate that career transitions are very common.

Now that we knew career transitions are common, we wanted to validate our hypothesis that career transitions are challenging, and for that we conducted a preliminary user survey across folks who were either undergrad students, early career professionals who are currently not enrolled as a student, early career professionals who are currently enrolled as a student or late career professionals.

This internal survey revealed an even more striking trend, with a remarkable 83% of respondents either having already transitioned or intending to transition to new career domains. Further, based on the responses provided by 36 users, the average difficulty rating for the career transition journey is approximately 3.6 out of 5, where 5 denotes extreme difficulty.

Based on the qualitative insights gathered from these responses, several key challenges emerged within the realm of career transitions:

1. **Leveraging Current Career Skill Sets**: Users expressed uncertainty about how to utilize their existing skill sets effectively when transitioning to a new career path.
2. **Finding Quality Resources for Upskilling:** A common struggle was identifying the best resources and platforms to enhance their skills and knowledge in their desired field.
3. **Determining the Best Fit Job Role:** Users grappled with the challenge of determining which job roles align best with their interests, strengths, and aspirations, necessitating guidance in the decision-making process.
4. **Identifying Essential Hard Skills:** Users seeked clarity on the specific hard skills required to successfully transition into their target career, highlighting the importance of understanding skill requirements.
5. Additionally, users express **challenges in connecting with individuals who have undergone similar transitions** and **maintaining motivation** throughout their career transition journey.

The above problems were highlighted by our respondents who were majorly Berkeley students, have top-class access to career resources and mentors. This highlights the fact that the problem is way more horrifying for folks with limited to no access to career resources.

These statistics underscore the pressing need for a robust platform like CareerNav, poised to address the evolving career aspirations and all-pervasive challenges of individuals navigating the post-pandemic job market.

3. Methodology

As shown in [Fig 1], our career navigation system operates in a multi-stage process, leveraging Large Language Models (LLMs) and Retrieval-Augmented Generation RAG for explainable learning roadmap generation.

3.1. Data Sources

Resume: For the resume parsing phase, we leverage resumes collected without our group in pdf format. We used a resume parser script to extract the skills of the user from their resume.

LinkedIn job postings: We scraped LinkedIn job postings using BeautifulSoup. Filters were applied to the location, experience levels (associate and entry level), and the job title. The dataset contained job descriptions from 86 unique companies for 9 different job titles (Data Scientist, Data Engineer, ML Engineer, Software Engineer ML, Applied Scientist, Data Analyst, Decision Scientist, Research Scientist, Business Analyst). For the scope of this project, we focus on the Data Scientist job description. We used role-based prompt engineering to retrieve the skills from the job descriptions. A sample prompt looks like the following:

> ***### Instruction: Act as a Careers Transition Expert. I will give you a list of JOB DESCRIPTION, JOB TITLE, and COMPANY and you will have to extract the relevant skills for each role as well determine the proficiency level required for***

each skill based on the job description (description field). Your output should be tuples for each job role in the following format: (technical skill or tool, proficiency levels). Proficiency level must be from one of the following - Basic, Intermediate, Expert.

JOB DESCRIPTION: {job_descriptions}

JOB TITLE: {job_title}

COMPANY: {company}

Answer:

- **User Input:** Users provide their resume and desired data science role.
- **Job Description Dataset:** A collection of scraped Linkedin job descriptions for data science-related roles is used to fine-tune the LLM for skill extraction.[filters used - Region: United States, Experience - Associate or Entry Level]
- **Knowledge Base:** A curated collection of learning resources (courses, videos, articles) vetted by domain experts serves as the foundation for recommendations.

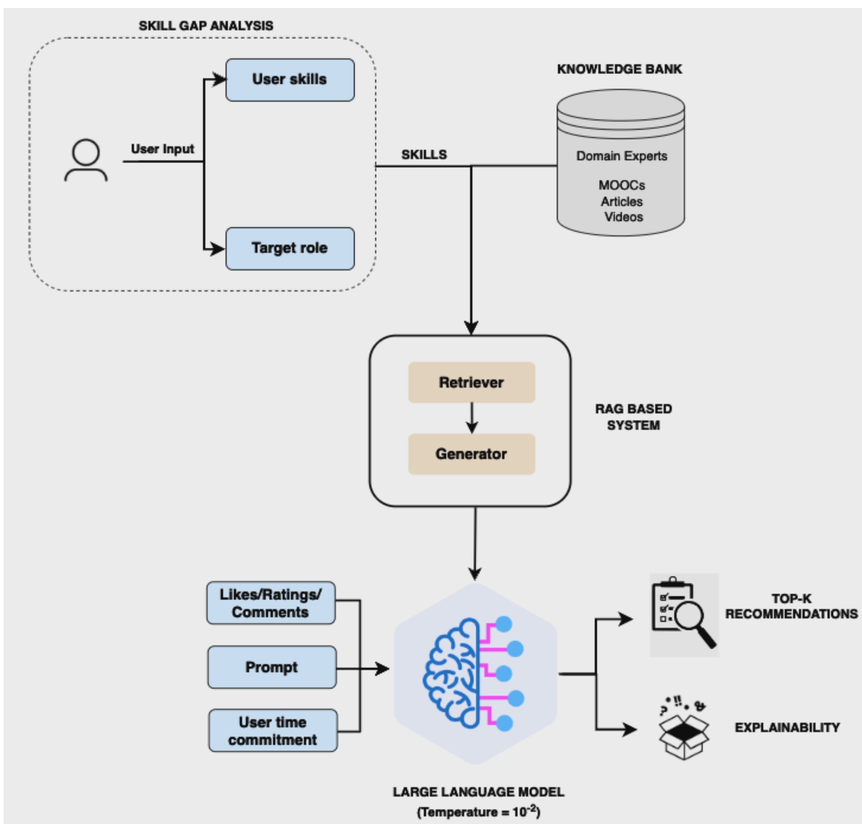


Fig.1

3.2. Process Flow

1. **Skills Gap Analysis:**
    - The pre-trained LLM (in our case, Gemini) extracts skills from the user's resume and the target job description.
    - The system analyzes the user's skill proficiency against the requirements of the target job description and devices the skill-proficiency table.
2. **Learning Roadmap Recommendation:**
    - The user specifies their time commitment.
    - The RAG system retrieves relevant learning resources from the knowledge base based on the user's skill gaps and target job description (refer to Section 3.3 for details).
    - Gemini, fine-tuned with instruction data as well as appropriate prompts, generates a personalized learning roadmap incorporating the retrieved resources.
    - The system provides explanations for each recommended resource, enabling user understanding.

3.3. RAG-based Recommendation

The core of the system lies in the RAG approach. Here's a deeper look at why RAG excels in this task:

- **Retrieval Accuracy:** A retrieval model based on vector embeddings stored in our Pinecone database (a vector similarity search engine), that efficiently searches the knowledge base for learning resources most relevant to the user's needs.
- **Explainable Generation:** The fine-tuned LLM utilizes retrieved resources and the user's profile to generate a personalized learning roadmap with clear explanations. This transparency builds user trust and engagement - this is the highlight of our product.

3.4. Retrieval and Ranking

The retrieval and ranking stages within RAG work together to ensure relevant and well-ordered recommendations:

- **Retrieval:**
    - Vector embeddings of learning resources and user skills/job description data enable efficient similarity search for relevant resources.
- **Ranking:**
    - A ranking model prioritizes retrieved resources within the learning roadmap based on factors like:
        - Skill Alignment: How effectively does the resource address a user's skill gap?
        - Content Quality: Popularity metrics, domain expert approval, and learning outcomes are considered.

- Learning Style: The system might account for preferred learning styles (e.g. video vs. text).
- Time Commitment: The roadmap adheres to the user's specified time constraints.

3.5. Explainability

A recent study talks about the use of building Explainable Recommender Systems using LLMs [3]. As stated in the paper, one of the advantages of using a LLM-based recommender system is being able to explain in natural language, instead of using weights and activation values. We fine-tuned a LLM model by providing the model with the input of the user specification (missing skills, proficiency, and their proposed deadline) and recommendation output (from the knowledge-base) and ask the model to return the intention of the model's output (the explanation).

4. Results

Skill Gap Analysis:

The following are the accuracy score for the tasks of skill extraction from CV and skill-proficiency extraction from the LinkedIn job description. We note that Gemini showed a better performance for skill extraction from CV, while GPT-4 performed better for the skill-proficiency pair extraction.

	Gemini	***Mistral 7b***	***GPT-4***
Skills extraction from CV	0.92	0.88	0.88
Skills and Proficiency extraction from LinkedIn JD	0.801	0.731	0.871

Recommender System:

We also report the Precision, Mean Reciprocal Ranking (MRR), and mean Average Precision (mAP) for our resource recommendation.

Predictive quality metrics	
Precision	0.77
Ranking quality metrics	
MRR	0.64
mAP	0.72

Sample of the Knowledge bank

Based on the output of the skill-gap analysis and the user preference (for timeline), and the popularity of the content (using likes, comment sentiment), the LLM suggests resources for the users to learn from. The following is a table that shows a representation of the recommended resources for different skill levels for Python.

			Resources		
Skill	**Level**	**Topics**	**Video**	**Article**	**MOOC**
Python	Beginner	Basic syntax (variables, data types, operators) Control flow (if statements, loops) Functions and modules Data structures (lists, dictionaries, tuples) File handling (reading and writing files) Exception handling Basic OOP concepts (classes and objects)	Link	Link	Link
	Medium	Advanced data structures (sets, comprehensions) Working with libraries (NumPy, Pandas) Error handling and debugging techniques Regular expressions Functional programming (lambda functions, map, filter) Decorators and generators Unit testing	Link	Link	Link
	Advanced	Advanced OOP concepts (inheritance, polymorphism) Concurrency and parallelism Design patterns Meta-programming Profiling and optimization techniques Advanced libraries (Scikit-learn, TensorFlow, PyTorch) Web development frameworks (Django, Flask)	Link	Link	Link

5. UI Evaluation

Methodology

The user testing process involved 5 participants assuming the persona of Priyamvada Radhakrishna, a Business Analyst at Deloitte, with a Bachelor's in Chemical Engineering, looking to transition to Data Science. Participants were guided through specific tasks on the CareerNav platform prototype, encouraging them to think aloud and provide feedback on their experiences.

- Task 1: Identify transferable skills and fill skill gaps
  - Participants evaluated the platform's ease of use in identifying relevant skills.
- Task 2: Explore explainability features.
  - Participants navigated through the platform to understand why certain skills were considered transferable and why specific learning resources were recommended. They then provided feedback on the clarity and helpfulness of the explanations provided.
- Task 3: Compare and contrast CareerNav. With existing approaches.

Results

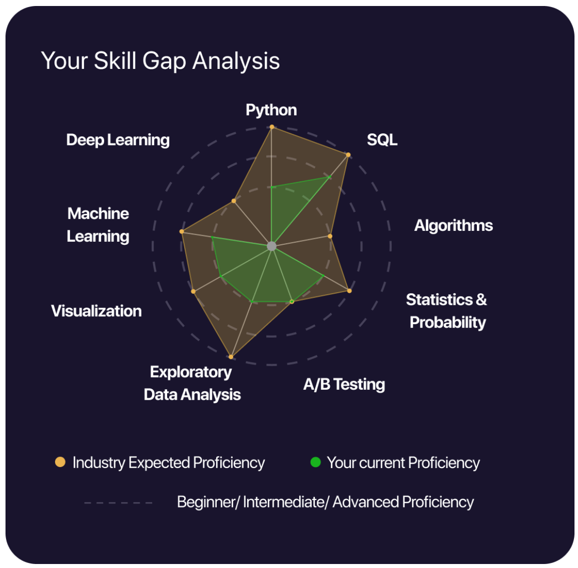
Participants found the platform's interface highly intuitive, with positive feedback on features such as identifying transferable skills and recommending learning resources. The explanations provided for transferable skills and recommended resources were generally well-received. The average rating on ease of use was 4.5 out of 5, across five users.

While contrasting CareerNav. with existing approaches, users expressed similar challenges as highlighted in the Background & Motivation section. They rated the satisfaction with existing approaches a 3.2 out of 5, while for CareerNav. their average likelihood to recommend the platform was 4.6 out of 5. This rating was driven by their perception of CareerNav. as a one-stop solution that takes away the hassle of handling ten different tasks on ten different platforms. Further, the element of explainability improved their ability to trust the platform. Our effort of sprinkling elements of motivation throughout the platform, gave the users a constant feeling of incremental progress, which they found essential in maintaining their motivation levels while approaching a career transition.

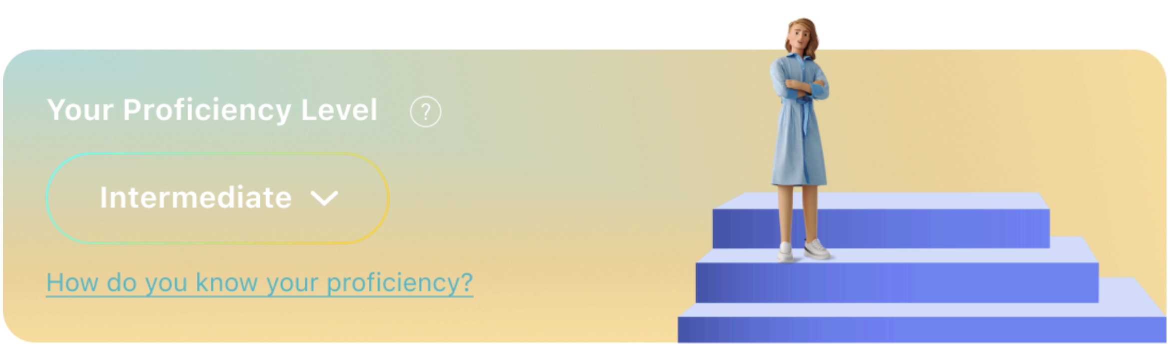
6. User Journey and Features

CareerNav offers a user-centric platform designed to facilitate smooth career transitions by leveraging the power of machine learning and user agency. This section details the user journey, outlining the key interaction points for individuals seeking to navigate a career shift.

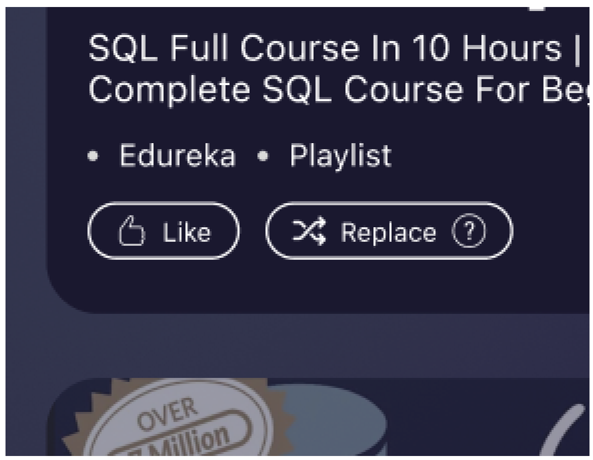
1. **Profile Creation (Initiation):** The user journey begins with a small set of questions, a streamlined process requiring approximately five minutes. Users provide information regarding their current professional role, their desired career path, their educational background, and the amount of time they can commit in a week to fill the learning gap. Users can also simply upload their resume (which we do not store), which the system then parses to extract all the information needed.
2. **AI-Powered Skill Analysis (Assessment):** Upon profile completion, CareerNav's machine learning engine takes center stage. It analyzes the user's input data, identifying transferable skills relevant to their target career. This analysis is instantaneous, providing the user with an initial assessment of their skillset in relation to their desired trajectory.



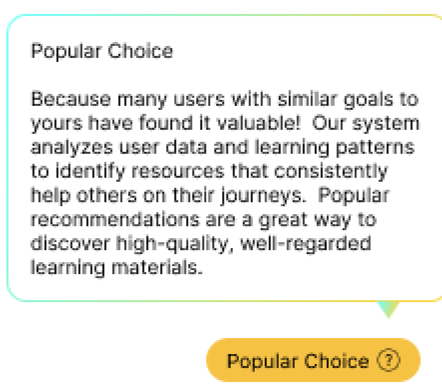
3. **Skill Refinement and User Feedback (Iteration and User Agency):** Following the AI analysis, users engage in a crucial step – refining their skillset. CareerNav presents the identified skills and their proficiency levels. Users can review these levels, adjusting them to accurately reflect their current expertise. This user feedback loop allows the platform to learn and improve its analysis over time. Additionally, users can provide qualitative feedback on the skill identification process, further enhancing the platform's accuracy.



4. **Personalized Learning Path Generation (Recommendation):** Building upon the refined skillset, CareerNav generates a personalized learning path. This roadmap highlights high-quality learning resources specifically tailored to bridge the identified skill gaps and propel the user towards their desired career. The platform leverages various data sources to curate these resources, ensuring users have access to relevant and up-to-date learning materials.
5. **Curating the Learning Journey (User Control):** CareerNav empowers users to take ownership of their learning journey. While the platform offers curated recommendations, users can explore alternative resources that better suit their learning styles or specific goals by simply clicking on the “Replace” button. This flexibility allows users to personalize their learning experience further, catering to individual preferences.



6. **Explainable AI for Transparency (Exploration):** CareerNav prioritizes user trust and transparency. For users who desire a deeper understanding of the platform's recommendations, an "Explainable AI" feature is available. This allows users to explore the rationale behind the AI's skill analysis and resource suggestions, providing a clear picture of how their learning path is constructed.



By following these steps, CareerNav empowers users to navigate their career transitions with confidence. The platform provides a user-centric approach, combining the power of machine learning with user agency to create a personalized and effective learning experience.

7. Future Scope

In line with our product vision of enabling equitable access to career opportunities, the future roadmap for our product would include:

Short term

1. **Suggesting possible career paths** based on an individual's past skill sets, for folks who are not clear on which career path could suit their past experiences best. This aligns with a core user problem we noted in our user research: users grappled with the challenge of determining which job roles align best with their interests, strengths, and aspirations.
2. **Fostering a network of study-buddies** by connecting folks with similar backgrounds and similar career aspirations. This would strengthen the motivation quotient ensuring people hold each other accountable in this journey.
3. Catering to transitions **beyond Data Science.** This involves Fine Tuning the LLMs to provide resource recommendation.
4. **Diversify the sources for job descriptions**. There might be selection bias when only LinkedIn acts as our sole Job Description source. Therefore, we plan to extend the scraping tool to support other job boards.

Long term

1. **Integrating a job-board** helping folks find jobs suited to their current level of preparation, making CareerNav. truly a one-stop solution for career transition.
2. Creating an asynchronous pipeline / scheduled job for **maintaining the knowledge base** for resource recommendation, job descriptions, and resume. This is essential in the long run since the meaning of a specific job keeps evolving over a time period. Why is this important? When we tried scraping the job description for specific companies, we encountered a challenge of not finding adequate job postings since the company constantly adds and takes down job postings. Therefore, it was vital to periodically scrape and maintain the knowledge repository.

Through this process, we aim to allow user-feedback to consistently shape our UI and UX to meet the needs of our users.

8. References:

1. https://arc.net/l/quote/qnkhkmhe
2. https://www.jobscan.co/career-change#carrer_changehow
3. https://arxiv.org/pdf/2403.06465
4. https://www.evidentlyai.com/ranking-metrics/evaluating-recommender-systems