Project Proposal Team 149

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February 25, 2025

1. What are you trying to do? Articulate your objectives using absolutely no jargon.

Our aim is to forecast employment opportunities, trends in salary fluctuations, and the requisite skills for these positions within the United States. This project will empower job seekers by highlighting where opportunities exist and the knowledge they must acquire. Simultaneously, it will aid companies in strategizing for the workforce they will require and determining appropriate compensation in the future. We aim to create an interactive job market map that displays job availability and regional salary projections for the next 2-3 years. The project will be executed in phases: first, we will gather and clean employment data from sources like the National Labor Exchange and US DOL. Then, we will analyze regional job trends and use machine learning models to forecast future employment patterns. These insights will be visualized on an interactive map, allowing users to explore job data by region, industry, and time frame. By incorporating predictive analytics, our tool will offer a unique, forward-looking perspective that goes beyond traditional job market reports.

2. How is it done today; what are the limits of current practice?

Job market forecasting relies on historical employment data, economic models, and time-series analysis to predict job demand, salary trends, and required skills. Government reports [3] and industry studies provide foundational insights into labor market trends [1] [2]. Machine learning and NLP techniques enable the extraction of structured insights from unstructured job postings, predicting skill adjacencies and emerging roles [11] [8] [14]. Tools and frameworks offer robust methodologies for time series forecasting and workforce planning [15] [18]. Studies assess automation risks and workforce shifts based on past trends [7] [6] and explore how external shocks like the COVID-19 pandemic accelerate demand for specific skills [9]. Collectively, these approaches provide a broad understanding of the labor market but lacks actionable insights for stakeholders.

Limits of current practice:

- **Lack of Regional Insights**: Most forecasts provide only national-level trends, failing to address localized labor market dynamics [3][2].
- **Narrow Industry Focus**: Studies often analyze only specific sectors, limiting their applicability to broader workforce planning [5] [16].
- **Outdated Data Usage**: Many studies rely on data that is 2–3 years old, resulting in stale and insufficient insights for real-time decision-making [1] [7].
- **No Direct Guidance for Job Seekers**: Insights from reports are often broad and do not provide clear, actionable guidance for career planning or skill acquisition [2] [3].

3. What's new in your approach? Why will it be successful?

We aim to take a holistic approach to tackling the problem by giving the user a complete picture of the employment market. This includes **forecasting job demand**, **analyzing salary trends**, and **skill requirements forecasting** across location and occupation. To achieve these goals, we will incorporate job data from National Labor Exchange APIs to enhance forecasting accuracy. We also plan to use techniques like clustering, time series analysis, and regression analysis. We plan to develop an interactive dashboard showing job availability and salary projections at both national and regional levels.

4. Who cares?

- **Job seekers** looking for the best locations for their careers,
- **Employers** assessing hiring trends and talent availability,
- **Policymakers & economists** analyzing regional labor market shifts, and
- **Educators & students** planning skills development based on future demand.

5. If you're successful, what difference and impact will it make, and how do you measure them (e.g., via user studies, experiments, ground truth data, etc.)?

Our tool will help users make better job-related decisions, reducing skill mismatches and improving workforce planning. Success will be measured by user engagement (site visits, interactions with the map), accuracy of job projections (compared to real employment trends), and feedback from stakeholders.

6. What are the risks and payoffs?

Risks:

- Data Quality and Availability: Incomplete, outdated, or inconsistent data from public sources or APIs.
- Model Accuracy: Machine learning models may not perform well due to insufficient training data.
- Technical Challenges: Aggregating APIs, large datasets, and visualization could face logistical hurdles.
- Resource Constraints: Limited budget or computational resources.
- Privacy and Ethical Concerns: Handling sensitive employment data could raise privacy/bias issues.

Payoffs:

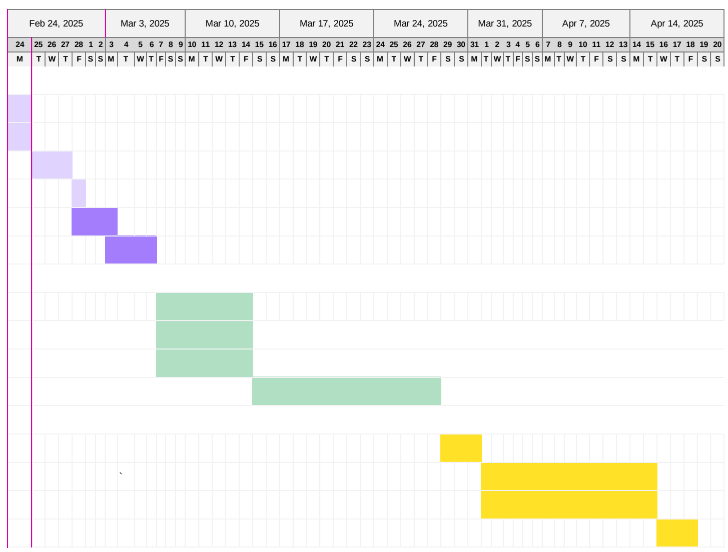
- Improved Workforce Planning: Enhance data-driven decision-making.
- Empowered Job Seekers: Enhances data-driven decision-making.
- Competitive Advantage: Foresee labor market trends providing a competitive edge in talent.
- Scalability and Expansion: Scalability to other sectors and regions.

7. How much will it cost?

- **Data acquisition**: Free (public sources) to moderate (API subscriptions).
- **Development**: Moderate (depending on tech stack and hosting costs).
- **AI/ML modeling**: Could require computational resources (cloud services).
- **Total estimate**: Low to moderate for an initial MVP, scalable with funding.

8. How long will it take?

TASK	ASSIGNED TO	PROGRESS	START	END
Initiation				
Proposal Writing	Mansi, Vrinda, Prakshi, Utkarsh, Tanima	100%	2/10/25	2/24/25
Proposal Slides	Vrinda	100%	2/22/25	2/24/25
Propsal Video	Tanima	100%	2/25/25	2/27/25
Proposal Submission	Tanima	100%	2/28/25	2/28/25
Data Collection	Tanima, Mitchell, Mansi	0%	2/28/25	3/3/25
Data Cleaning	Prakshi, Utkarsh, Vrinda	0%	3/3/25	3/6/25
Execution				
Job Demand Forecast Model	Utkarsh, Mansi	0%	3/7/25	3/14/25
Salary Trends Assessment	Vrinda, Mitchell	0%	3/7/25	3/14/25
Skills Requirements Forecasting	Prakshi, Tanima	0%	3/7/25	3/14/25
Visualization	Utkarsh, Prakshi, Vrinda	0%	3/15/25	3/28/25
Evaluation				
Testing / Fine tuning	All	0%	3/29/25	3/31/25
Final Report Writing	All	0%	4/1/25	4/15/25
Final Slide Deck and Video	All	0%	4/1/25	4/15/25
Project Submission	All	0%	4/16/25	4/18/25



9. What are the midterm and final "exams" to check for success? How will progress be measured?

Midterm checks: Data should be retrieved, cleaned, and stored in a structured format with no major gaps or inconsistencies. Preliminary models should be built and tested on a subset of data, showing reasonable accuracy like low RMSE (Root Mean Squared Error) or low MAE (Mean Absolute Error). A basic version of the interactive map is functional, displaying job demand and salary trends for a few regions.

Final Success Metrics will be a **f**ully functional interactive tool with real-time and projected job data where the tool's predictions align with real-world employment trends over time. We will compare forecasted job demand, salary trends, and skill requirements with actual data (e.g., BLS reports) after 6–12 months. We will also test user engagement levels (Google Analytics/Dashboard usage).

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Appendix

LITERATURE SURVEY (EXTENDED):

Name	**Paper Title**	**Article Link**	**Main Idea**	**Why It Will Be Useful**	**Potential Shortcomings**
Vrinda	Projecting Changes in the US Labor Face (link)	https://www.nber.org/brd-20221/projecting-changes-us-labor-force	The study examines the impact of population aging on labor force participation in the U.S. and Germany, projecting workforce trends up to 2060. Using a dynamic microsimulation model, researchers find that while the U.S. labor force is expected to grow by 16.2% (25.2 million workers) due to population growth, education, and pension reforms, Germany's labor force is projected to decline by 10.7% (4.4 million workers) due to demographic shifts.	By contrasting U.S. projections with those of Germany—where the labor force is expected to decline by 10.7% (4.4 million workers) between 2020 and 2060—the report offers a broader context for understanding how different demographic and policy environments can influence labor force trends.	The projections assume current policies remain unchanged. Future alterations in immigration laws, retirement benefits, or education funding could significantly impact labor force dynamics, potentially rendering these projections less accurate.
Vrinda	Preparing for the Future of Work:	https://gfoundr	The study examines the evolving labor	The report notes the rapid	The report provides a global overview

	Trends in Job Market 2030 (link)	y.com/future-of-jobs-2030/	market influenced by technological advancements, demographic shifts, and changing consumer preferences. It highlights the dual impact of automation and artificial intelligence (AI), which are expected to automate 42% of tasks by 2027, potentially displacing jobs in routine and repetitive sectors such as data entry and manufacturing. Conversely, these technologies are projected to create approximately 97 million new roles in fields like data science, AI, cybersecurity, and healthcare.	expansion of the gig economy, significantly impacting the nature of work and employment patterns, this means it could be helpful to see the effects of other macroeconomic factors on employment.	but lacks detailed regional or country-specific data, which may limit the applicability of its findings to localized projections.
Vrinda	After Everything: Projections of Jobs, Education, and Training Requirements through 2031 (link)	https://cew.georgetown.edu/cew-reports/projections2031/	The study forecasts that by 2031, 72% of jobs in the U.S. will necessitate postsecondary education or training. This marks an increase from 68% in 2021. On average, there will be 18.5 million job openings annually between 2021 and 2031, with approximately 12.5 million of these requiring at least	The study delineates a bifurcated economy into managerial and professional economy and blue-collar and skilled-trades economy. This helps further alienate our project into more focused sectors and allows us to take into consideration	The report, published in March 2024, relies on data projections that may not fully account for unforeseen economic shifts, technological advancements, or global events occurring after its release.

			some college education.	differences in macro sectors and their needs.	
Utkarsh	AI's Labor Market Impact via NLP of Job Postings	https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4710299	The paper proposes a novel methodology to assess AI's impact on labor markets by analyzing unstructured job postings using NLP and deep learning. Traditional approaches rely on structured databases like O*NET, which have limitations in timeliness and coverage. The authors develop a two-stage model: 1. Task Extraction: A BERT-based model identifies specific tasks from job descriptions with 87.6% accuracy. 2. Feasibility Prediction: A classifier predicts whether each task can be performed by AI within 0-5 years (short-term), 5-10 years (medium-term), or 10+ years (long-term), achieving 73.4% accuracy. Empirical analysis of 12,000 business operations jobs suggests 25% of tasks could be AI-driven within 5	Repurposing the paper's regression analysis to link salary data with skill requirements will be very helpful in the group project. Adapting the BERT-based NLP pipeline to identify skill clusters using SHAP explanations.	The potential shortcomings of the paper include - 1. Narrow occupational scope: The paper focuses exclusively on "business operations" jobs from Monster.com. This should be expanded to multiple sectors (healthcare, tech, manufacturing) using diverse sources like LinkedIn, Indeed, and government databases. 2. Temporal Resolution issues: In light of the rapidly evolving tech landscape, using 5-10 year horizons without real-time adaptability causes problems. This should be changed to tiered forecasting like 0-2 years, 3-5 years and 5-10+ years.

			years, rising to 69% within a decade.		
Utkarsh	Generative AI for Labor Market Extraction	https://www.amazon.science/publications/extracting-structured-labor-market-information-from-job-postings-with-generative-ai	The paper discusses application of generative AI to extract structured labor market insights from unstructured online job postings, addressing gaps in traditional survey-based data collection. By analyzing 6,800 job postings divided across 68 occupational groups, the authors developed a scalable method using Amazon Bedrock's foundation models to parse details such as educational requirements, remote-work flexibility, and benefits offerings with high accuracy.	The paper provides actionable insights that directly align with our project's objectives. 1. The GenAI framework extracts structured data from unstructured job postings, enabling analysis of emerging roles and skill adjacencies faster than traditional surveys. 2. Aggregating data at a hyperlocal level and providing forecasts will be a massive value proposition for the project.	There are some key shortcomings in the current research. 1. Skill Demand Analysis Gap: Focuses on high-level attributes (education, remote work) but lacks granular skill extraction (eg. Python vs R proficiency etc.) We can improve upon this by applying NLP to map skill adjacencies (e.g., "TensorFlow → machine learning engineer") and forecast demand surges. 2. Aggregates data nationally, missing metro-specific trends (eg. AI engineering demand in Austin vs Boston). We can improve upon this by getting geographic data from BLS to localize forecasts.
Utkarsh	A Machine Learning-Based Job Forecasting System	https://rgu-repository.worktribe.com/OutputFile/1993469	The paper proposes a machine learning-based system to forecast job market trends, specifically targeting the software industry, to aid job seekers, organizations, and academic institutions in adapting to evolving employment	The paper provides a few foundational ideas which can be used in our project. 1. Data Collection Strategy: The paper's use of web scraping to gather 522,180 job listings validates this approach for	The paper has the following limitations, which can be improved upon: 1. Skill extraction method: It uses TF-IDF for keyword extraction, which lacks nuance in detecting emerging or context-specific skills. This can be

			demands. It tries to address gaps in prior research by incorporating real-time data from job boards and combining quantitative analysis (e.g., job posting frequency) with qualitative aspects like skill requirements.	employment trend analysis. 2. Skill Extraction: While the paper uses TF-IDF for keyword extraction, we can improve semantic analysis by applying BERT/GPT-4 embeddings to detect emerging skills.	improved by applying BERT or GPT-4 embeddings for semantic skill clustering. 2. Forecasting approach: The paper uses Bi-LSTM which focuses on historical patterns without validating against unforeseen disruptions. This can be improved by combining quantitative models (ARIMA, Prophet) with qualitative inputs (like Delphi method).
Mansi	Labor Market 2050: Automation & Policy	https://docs.iza.org/pp148.pdf	The main idea of the paper, *The US Labor Market in 2050: Supply, Demand and Policies to Improve Outcomes* by Harry J. Holzer, is an analysis of the anticipated changes in the U.S. labor market by 2050. The paper explores the effects of demographic shifts, automation, and changing employment practices on labor supply and demand. Key points including demographic changes, automation , employment trends etc.	Use real-time job market data (e.g., LinkedIn, Glassdoor, Bureau of Labor Statistics) to refine and validate the paper's projections. Develop predictive models for employment and salary trends using machine learning or statistical methods. Provide industry-specific insights rather than broad economic trends. Incorporate regional labor market variations to make your findings more actionable for job seekers and employers.	There are several potential shortcomings in the paper like Limited Use of Data-Driven Forecasting , lack of granular, industry-specific forecasts, regional analysis and company specific forecasts.

Mansi	ML for Workforce Planning in Mental Health	https://pmc.ncbi.nlm.nih.gov/articles/PMC10424701/	The paper titled "Applying Machine Learning to Human Resources Data: Predicting Job Turnover among Community Mental Health Center Employees" explores the use of machine learning techniques to analyze HR data for predicting employee turnover in community mental health centers. By identifying patterns and factors associated with staff departures, the study aims to enhance retention strategies and reduce turnover rates in these critical healthcare setting	We can apply similar predictive modeling techniques to analyze broader employment trends, such as job demand across industries or salary progression over time. We can expand the variable set to include skills, industry trends, automation impact, and regional economic factors to enhance forecasting accuracy.	The paper focuses on a single sector (mental health centers), making its findings less generalizable to broader employment trends across multiple industries. The study primarily examines job turnover, which is a subset of workforce trends but does not address broader employment opportunities, salary trends, or future skill requirements. The study does not explore how salaries fluctuate over time or what factors influence salary growth within an industry.
Mansi	Forecasting Unemployment Using Labor Force Flows	https://www.brookings.edu/articles/the-ins-and-outs-of-forecasting-unemployment-using-labor-force-flows-to-forecast-the-	This paper presents a model that leverages labor force flow data to predict unemployment rates. By analyzing transitions between employment, unemployment, and non-participation, the model offers real-time forecasts that outperform traditional methods, such as the Survey of Professional Forecasters and the	These insights can help predict job openings and workforce stability by understanding how workers transition between jobs and how industries experience employment fluctuations. We can integrate real-time job postings, wage data, and economic indicators to	The paper primarily forecasts unemployment rates, rather than providing a broader analysis of job opportunities, salary trends, and skill requirements. The paper treats the labor market as a whole and does not differentiate between industries or occupations. The paper does not analyze which skills will be in demand or how workers can

		labor-market/	Federal Reserve Board's Greenbook. This approach provides a more dynamic and accurate tool for anticipating labor market conditions	create up-to-date employment forecasts.	adapt to labor market changes.
Prakshi	Optimizing Workforce Efficiency: Leveraging Integrated Business Analytics and Machine Learning for Enhanced Performance Prediction	(PDF) Optimizing Workforce Efficiency: Leveraging Integrated Business Analytics and Machine Learning for Enhanced Performance Prediction	The paper proposes a framework using business analytics and machine learning to predict employee performance, optimize workforce efficiency, and enable proactive decision-making through systematic data collection, preprocessing, modeling, and validation	Its methodology of leveraging historical and real-time data to forecast trends aligns with your goal of identifying employment opportunities, salary fluctuations, and requisite skills for job seekers and companies.	Reliance on high-quality data, lack of granularity for specific roles/regions, ethical concerns, and potential resistance to adoption may limit its effectiveness despite its robust methodology.
Prakshi	Evaluation of the trends in jobs and skill-sets using data analytics:	Evaluation of the trends in jobs and skill-sets using data analytics: a case study | Journal of Big	The study uses data analytics (LSI, LDA, FA, NMF) to analyze job market trends, skill demands, and education-industry mismatches, focusing on the oil and gas sector.	It provides a data-driven framework to forecast employment opportunities, salary trends, and required skills, aiding job seekers and companies in workforce planning.	It lacks regional specificity and does not address emerging industries, remote work trends, or demographic shifts, limiting its broader applicability.

		Data | Full Text			
Prakshi	On the radar: Predicting near-future surges in skills' hiring demand to provide early warning to educators	On the radar: Predicting near-future surges in skills' hiring demand to provide early warning to educators - PMC	The paper proposes an AI-driven methodology to predict emerging skills in the labor market by analyzing job ad trends, focusing on skills with sudden surges in hiring demand. This approach aims to provide early warnings to educators and training providers, enabling them to adapt curricula and training programs to meet future workforce needs.	This methodology aligns with the goal of forecasting employment opportunities, salary trends, and requisite skills. By identifying emerging skills early, it can help job seekers understand where opportunities lie and what skills to acquire, while assisting companies in workforce planning and compensation strategies. The use of job ad data and predictive analytics offers a data-driven approach to understanding labor market dynamics.	The methodology relies heavily on job ad data, which may not capture all labor market trends, especially in emerging industries or regions with limited job ad availability. It also focuses on granular skill predictions but may lack broader insights into macroeconomic factors, such as recessions or geopolitical shifts, that could impact employment trends. Additionally, the approach may struggle with predicting skills that emerge very rapidly or are not well-represented in job ads.
Tanima	Occupational projections overview, 2021-31	https://www.bls.gov/opub/mlr/2023/article/occupational-projections-overview-2021-31.htm	The paper provides a comprehensive overview of occupational projections in the United States from 2021 to 2031, as developed by the Employment Projections program of the U.S. Bureau of Labor Statistics. It highlights anticipated changes in employment across 24	The paper directly aligns with forecasting job demand by projecting growth trends across different occupational groups and identifying key drivers of employment changes. It provides detailed insights into salary trends by reporting on	While the paper offers a broad national overview, it lacks regional specificity, which could be crucial for understanding localized job market trends. Furthermore, the analysis primarily focuses on occupational groups and does not delve deeply into granular predictions for individual

			occupational groups, including detailed data on growth trends, numeric and percentage changes, factors driving these changes, median annual wages, and educational or training requirements for occupational entry. The paper's primary contribution is serving as a resource for job seekers, career counselors, researchers, and policymakers, offering insights into future labor market demands.	median wages for each occupational group and specific occupations. Additionally, the discussion of typical education and training requirements for occupational entry supports skills analysis, helping individuals and organizations understand the competencies needed to meet future labor market demands.	occupations beyond some examples. Additionally, it does not address the potential impact of emerging industries, remote work trends, or international factors on the U.S. job market. The paper also does not explicitly consider how demographic shifts or socioeconomic disparities might affect workforce opportunities across different groups.
Tanima	Growth trends for selected occupations considered at risk from automation	https://www.bls.gov/opub/mlr/2022/article/growth-trends-for-selected-occupations-considered-at-risk-from-automation.htm	The article "Growth trends for selected occupations considered at risk from automation," published in the Monthly Labor Review in July 2022, examines the employment growth trends of occupations identified as susceptible to automation. It critically analyzes previous studies that have predicted significant job displacement due to automation, such as the claim that 47 percent of U.S. jobs	By analyzing historical employment data of occupations deemed at risk from automation, the article offers valuable insights into job demand trends. Understanding which occupations have experienced growth or decline despite automation concerns can inform future job demand forecasts. While the article primarily focuses on employment trends, it indirectly	The paper does not provide granular predictions about future employment trends or consider emerging technologies' potential impact on these occupations.

			were at risk between 2010 and 2030. The paper contributes to the discourse by providing empirical data on how these at-risk occupations have fared in terms of employment growth, offering a nuanced perspective on the actual impact of automation on the labor market.	informs salary trends and skills analysis by identifying which occupations remain resilient, suggesting a continued or evolving demand for specific skill sets.	
Tanima	What the long-term impacts of the COVID-19 pandemic could mean for the future of IT jobs	https://www.bls.gov/opub/btn/volume-11/what-the-long-term-impacts-of-the-covid-19-pandemic-could-mean-for-the-future-of-it-jobs.htm	This article examines how the COVID-19 pandemic has influenced employment projections for Information Technology (IT) occupations. It highlights that, prior to the pandemic, IT jobs were already expected to see significant growth; however, the pandemic has further amplified the importance of IT professionals, leading to increased employment projections in this sector. The article provides insights into how the accelerated adoption of digital technologies and remote work has heightened the demand for IT expertise.	The article directly relates to forecasting job demand by presenting updated employment projections for IT occupations in the context of the pandemic. It suggests that the surge in remote work and digital transformation has led to a heightened demand for IT professionals, potentially influencing salary trends upward due to increased competition for skilled workers. Additionally, the article implies a shift in the requisite skills for IT positions, emphasizing the need for expertise	The analysis does not delve into the granularity of predictions for individual IT roles, nor does it address potential disparities in employment opportunities across different regions or industries. Furthermore, the article does not explore the long-term sustainability of the increased demand for IT professionals or how emerging technologies, such as artificial intelligence, might impact future job prospects and skill requirements within the IT sector.

				in areas such as cybersecurity, cloud computing, and IT infrastructure to support remote operations.	
Mitchell	Degrees of Return: Estimating Internal Rates of Return for College Majors Using Quantile Regression	https://www.aera.net/Newsroom/Degrees-of-Return-Estimating-Internal-Rates-of-Return-for-College-Majors-using-Quantile-Regression	Going to college is still valuable but it depends on the degree	Answers the question about whether college is worth it	Assumes that the majors valued in the past will continue to be valued in the future.
Mitchell	Even Harvard M.B.A.s Are Struggling to Land Jobs	https://www.wsj.com/lifestyle/careers/harvard-mba-employment-rate-job-hunt-difficulty-addfc3ec	A MBA may not be as valuable as it once was	Signals that the job market may be valuing different skills	The desired skills for the job market will change over time and this looked at initial job placement not necessary career growth.
Mitchell	Forecasting at Scale (Prophet)	https://peerj.com/prepr	Prophet can be a strong time series forcasting method	Justifies why we may want to use prophet to forecast the job	Relies on historical patterns being persist.

		ints/3190/		market and salary growth	
Mitchell	Modeling and Predicting Individual Salaries: A Study of Finland's Unique Dataset	https://www.actuaries.org/pbss/colloquia/helsinki/papers/koskinen.pdf	Wages for the middle quartile earners can be predicted more accurately than the lower or upper quartiles.	Wages can be more accurately predicted during times of economic growth.	The data is from Finland and may not be representative for the world