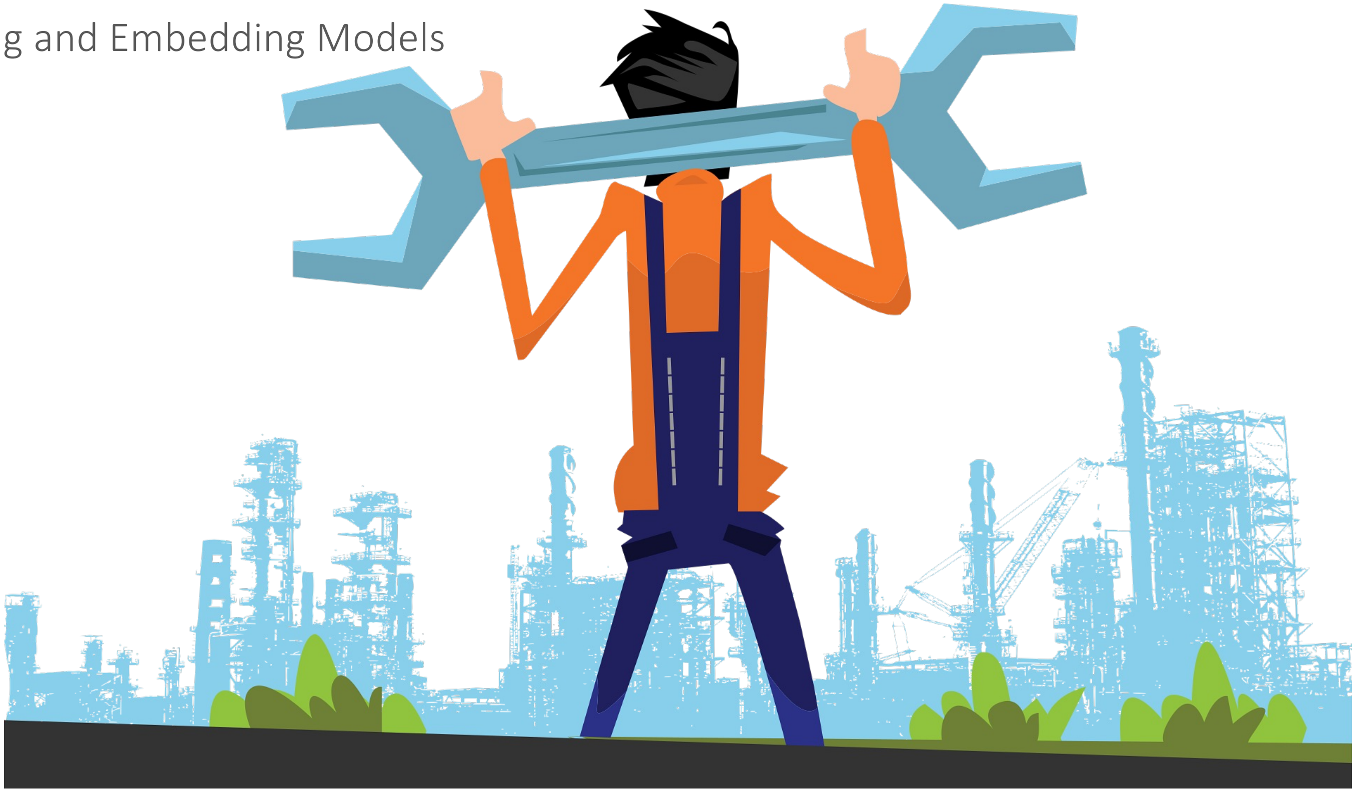
Modelling of Employee Skill Demand Evolution in the US

Using Dynamic Topic Modelling and Embedding Models



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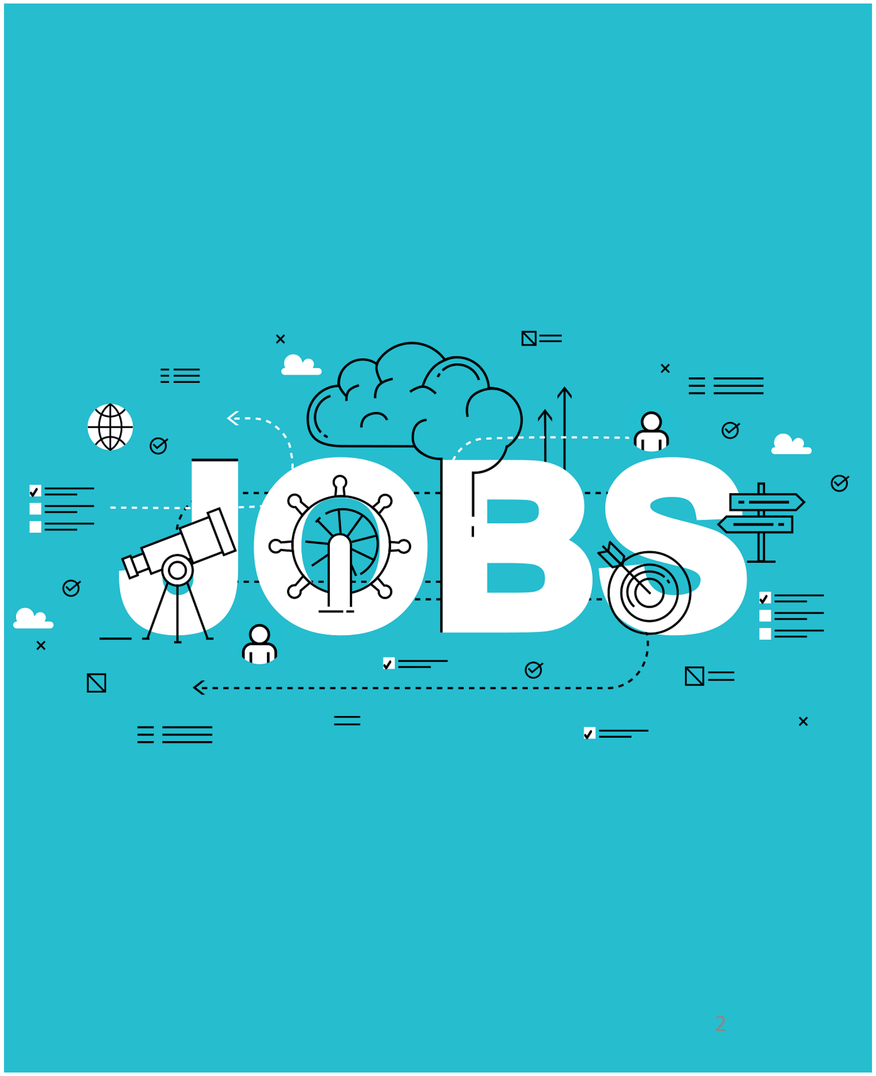
Introduction/Background

- Presently, the concept of human resource has moved beyond availability and lack of availability, and has extended to cover skill and demand (Grama & Todericiu, 2025).

- Analysis is hence needed for contextualizing of human resource at a skill demand level.

- Given the evolution of business, and markets as a product of technology, companies and policy makers would benefit from a good understanding of human resource in terms of the skills demand and how it evolves (Jotabá, 2022; Dhuniganh et al., 2024).

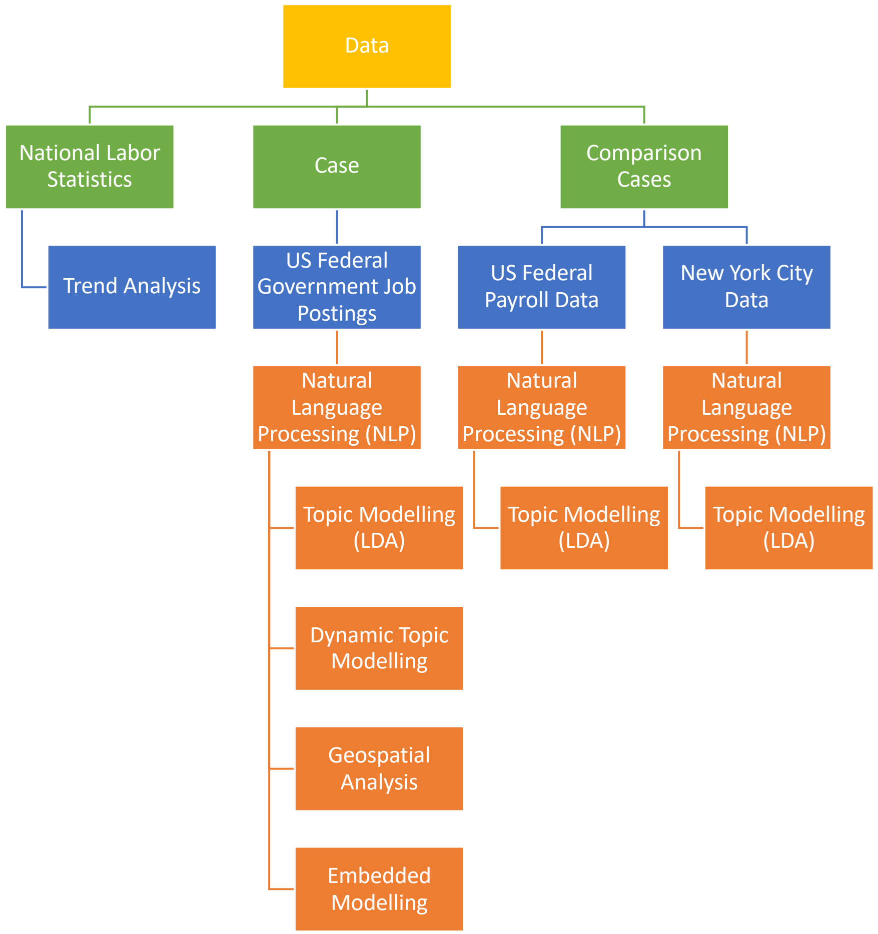


Employment Evolution and Big Economies

- Magnitude in terms of the organization or economies amplify the critical nature of the evolution in skill demands in human resource (Israel & Rutainurwa, 2025).
- The ability of skills to overlap job positions make the analysis of skill demand complex (Jotabá, 2022; Mishra et al., 2025).
- Hence, skills demand would benefit from interrogation using data analysis methods such as in the case, Dynamic Topic Modelling and Embedding Models

Data and Methodology

- For the project, the data was sourced from:
  - US Federal Government Job Postings API (https://developer.usajobs.gov/api-reference/)
  - US Federal Payroll Data API (https://www.census.gov/data/datasets/2024/econ/apes/annual-apes.html)
  - National Labor Statistics API (https://data.bls.gov/oes/#/industry/000000)
  - New York City API Data (https://data.cityofnewyork.us/resource/k397-673e.json)



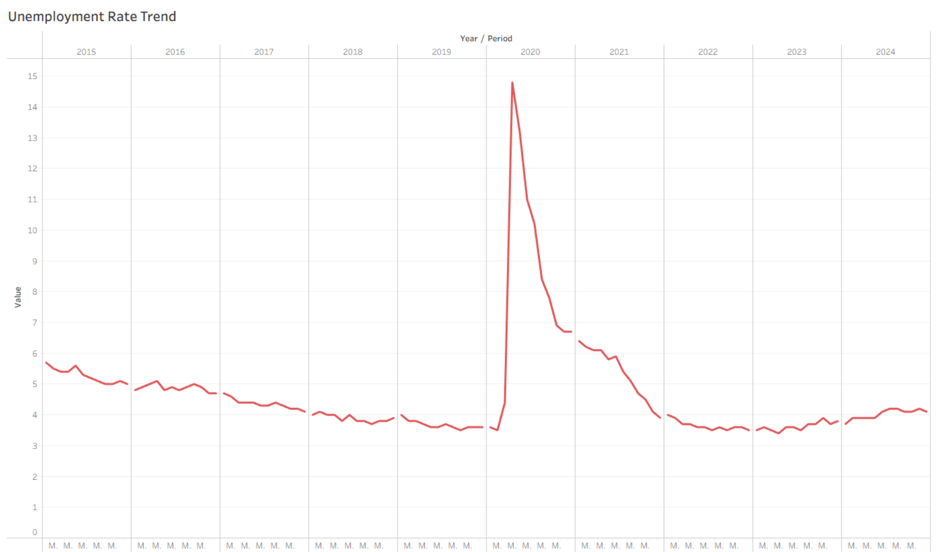
Data and Methodology

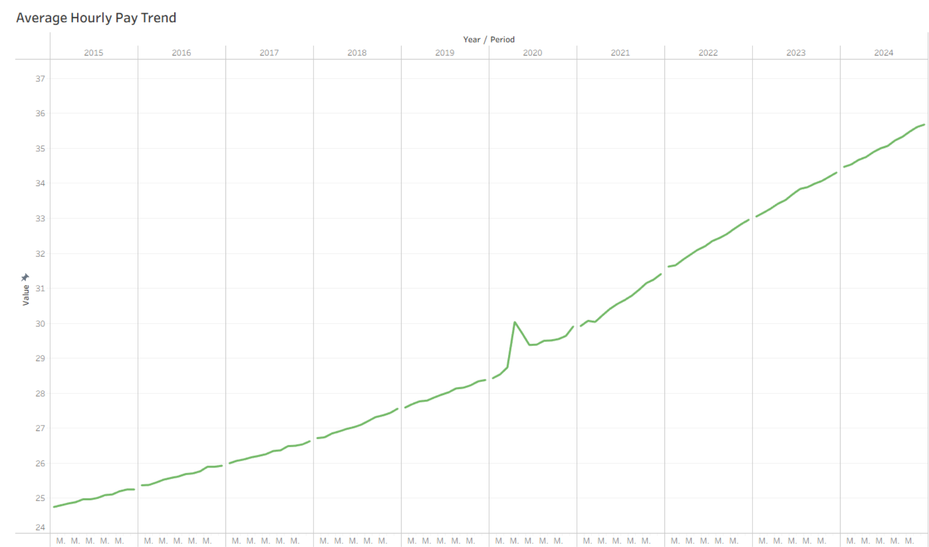
- The first set of data analytics approaches employed were:
  - Natural Language Processing (NLP) extracts key terms from textual data (O'Shaughnessy, 2026). In this case extraction of skill signals from job description.
  - Trend Analysis provides overview of time series data (Siswanto et al., 2025). In this case, overview of the time series for current and historic employment indicators; unemployment rate and average hourly pay.
  - Geospatial analysis plots attributes based on spatial characteristics of record into maps (Muhammad et al., 2025). In this case mapping of topics from the LDA across the US.

Data and Methodology

- The second set of data analytics approaches employed were:
  - Topic Modelling employs the Latent Dirichlet Allocation(LDA) to group terms into topics based on thematic analysis (Hairani et al., 2024). In this case grouping of skill demand terms that provide signals for the skill demand.
  - Dynamic Topic Modelling conducts LDA overtime to capture evolution of skill demand.
  - Embedded Models evaluates the similarity and semantics in textual data (Ajallouda et al., 2025). In this case similarity and semantics of skills.

Employment Trend Analysis: Unemployment Rate and Average Hourly Pay

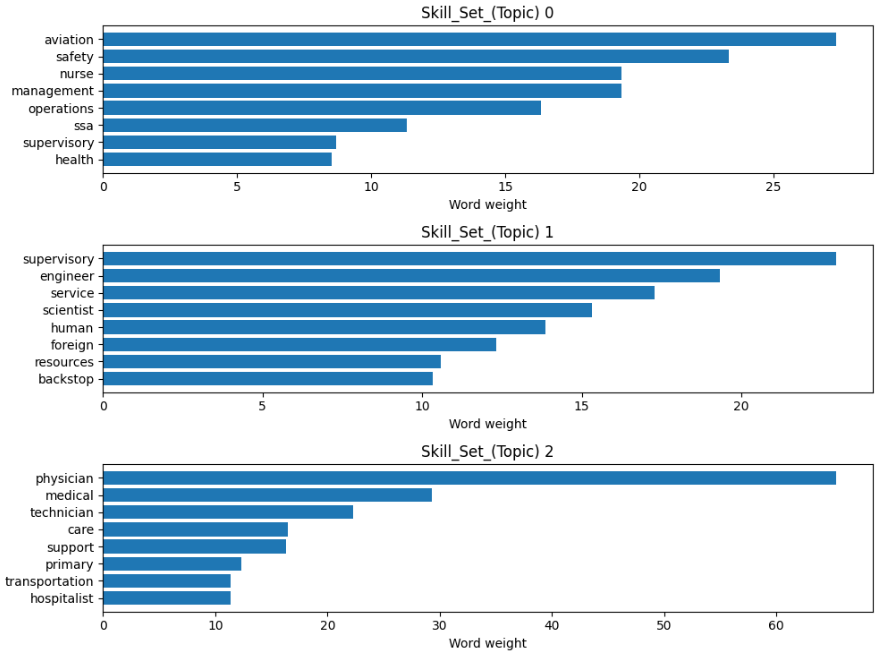




The line chart above on the left shows the trend in the unemployment rate, we note that the unemployment rate has largely been stagnant, fluctuating over a range of values. The period between 2020 and 2021 represented an outlier where there was a very steep spike in unemployment followed by a steep then gentle fall in the unemployment rate; due to the COVID-19 pandemic .

On the right, the average hourly pay trend in shown in the line chart. The plot show a steady rising trend over time with a notable jump in the year 2020 followed by a drop; this can similarly be attributed to the COVID-19 pandemic.

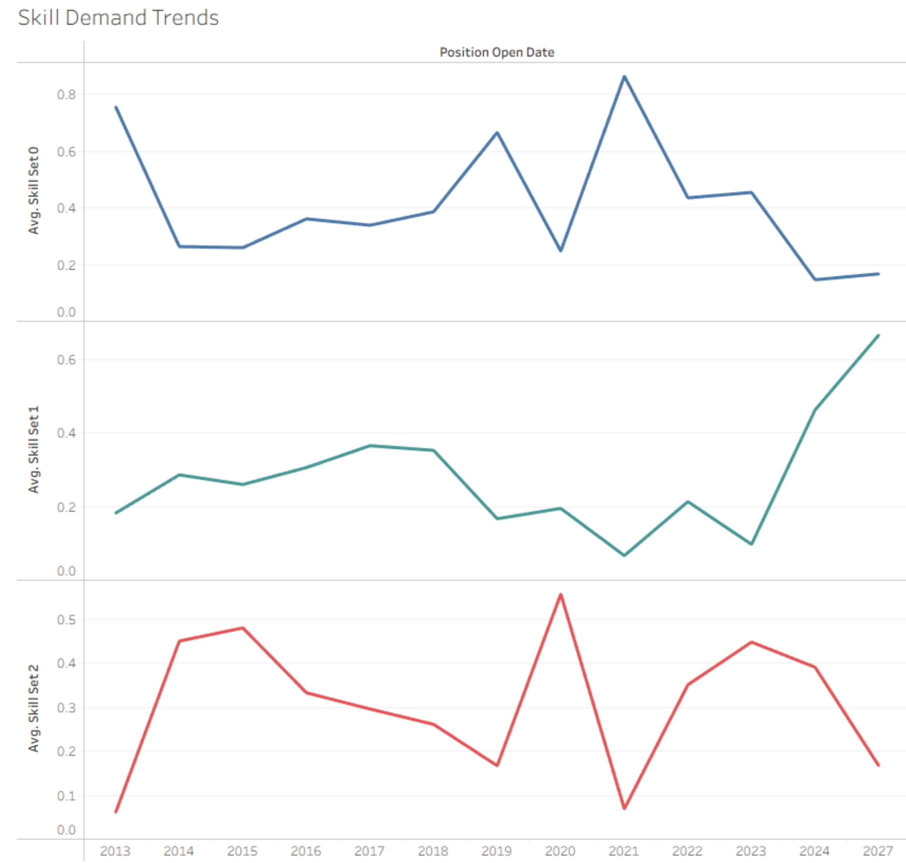
Natural Language Processing (NLP) and LDA Topic Modelling – US Federal Government Jobs



- The output given in the bar chart on the left shows that;
  - From the first topic, the skill demand related to the aviation, safety, management and medical fields.
  - From the second topic, the skill demand related to engineering and human resource.
  - From the third topic, the skill demand related to the medical and engineering fields.

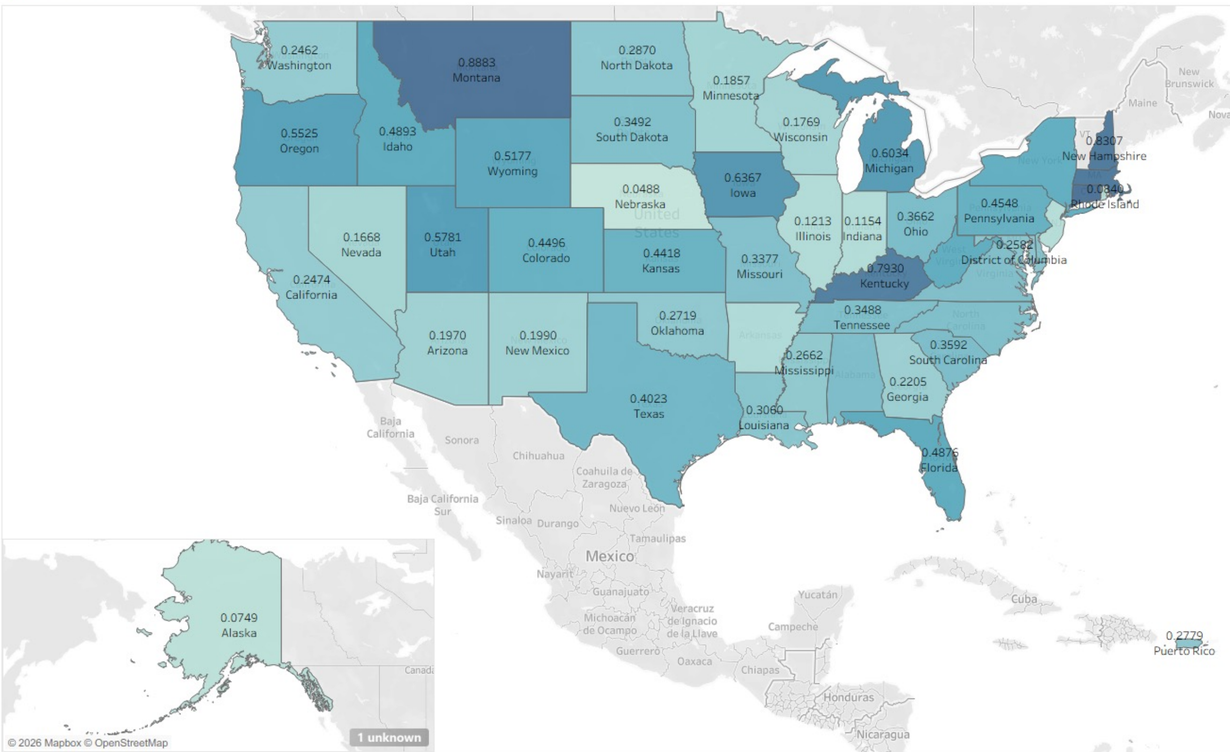
Trends in Skill Demand

- We observe for the trend chart on the right that;
  - The demand for skill set 0 is initially high, then flattens between 2014 and 2018 before having a series of jumps and falls with a decline in recent time.
  - The demand for skill set 1 is relatively flat from 2013 to 2023, but shows a rising trend in recent time.
  - The demand for skill set 2 has three peaks showing possible seasonality (unequal season lengths) with the demand experiencing decline in recent time; a rise might characterize the next season.



Geospatial Analysis

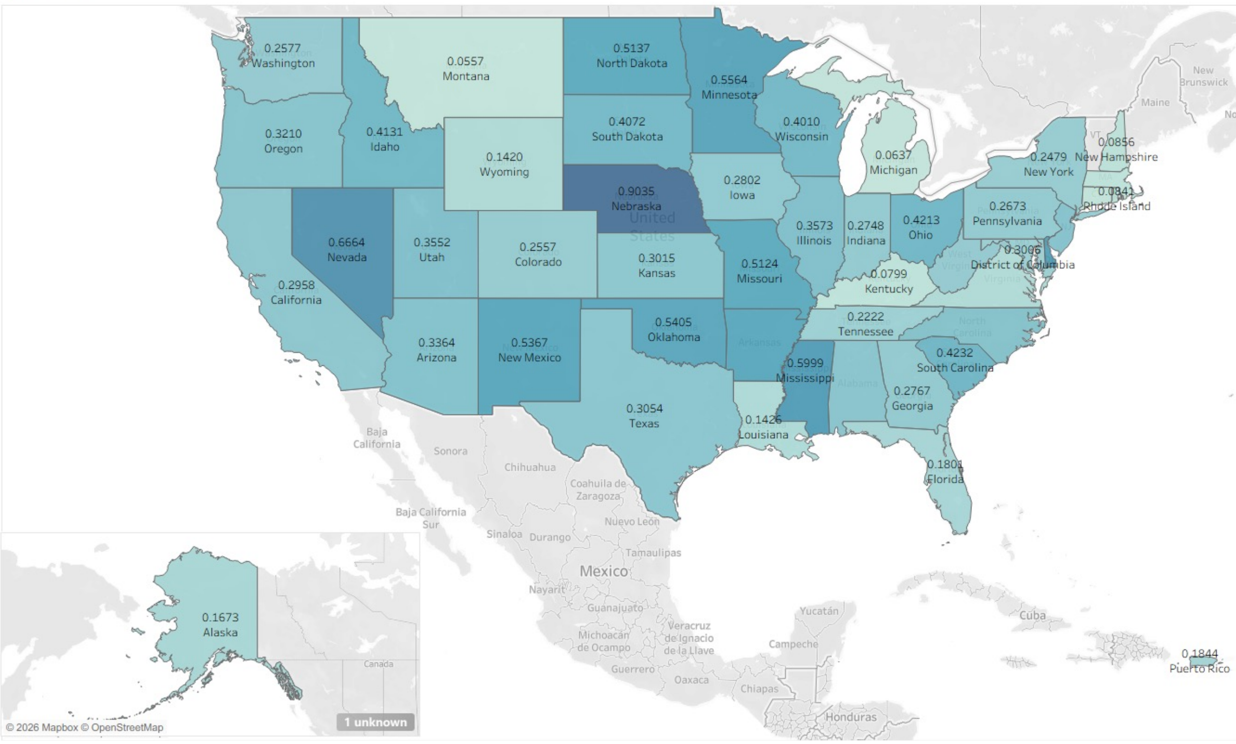
Skill Set 0



- The demand for the skills in skill set 0 are shown in the map on the left to be;
  - Highest in the states of Montana, Maine, Connecticut, New Hampshire, Massachusetts and Kentucky.
  - Lowest in the states of Nebraska and Alaska.

Geospatial Analysis

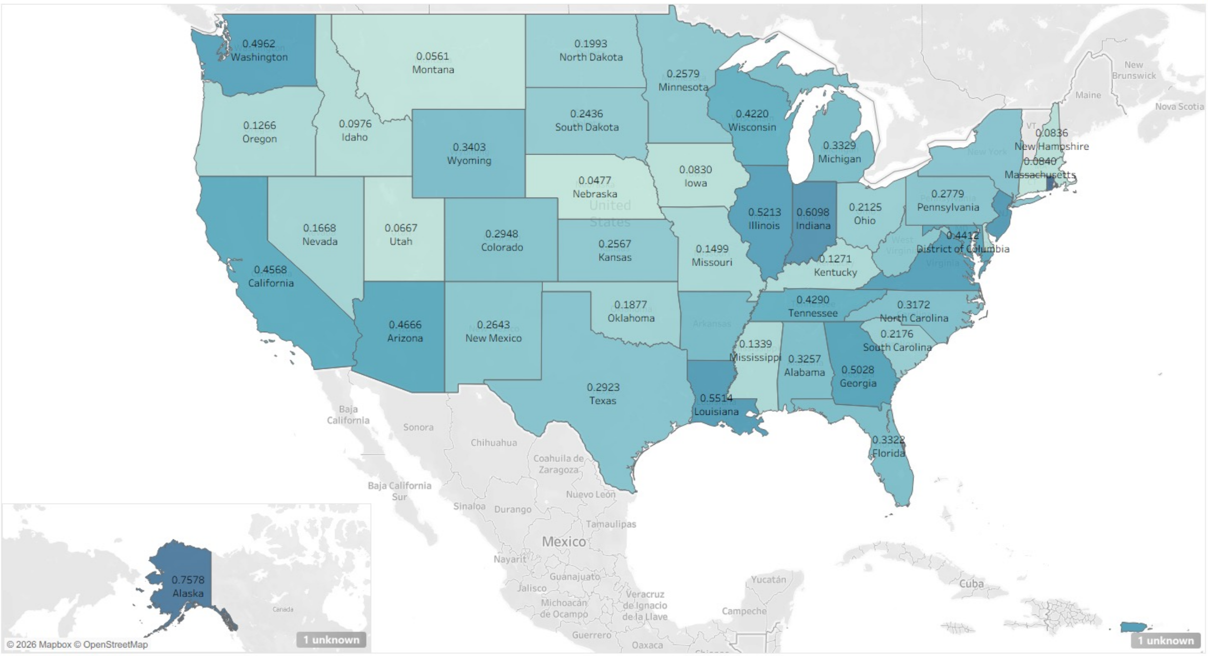
Skill Set 1



- The demand for the skills in skill set 1 are shown in the map on the left to be;
  - Highest in the states of Nebraska, Nevada, and Mississippi.
  - Lowest in the states of Montana, Kentucky, New Hampshire, Rhode Island and Massachusetts.

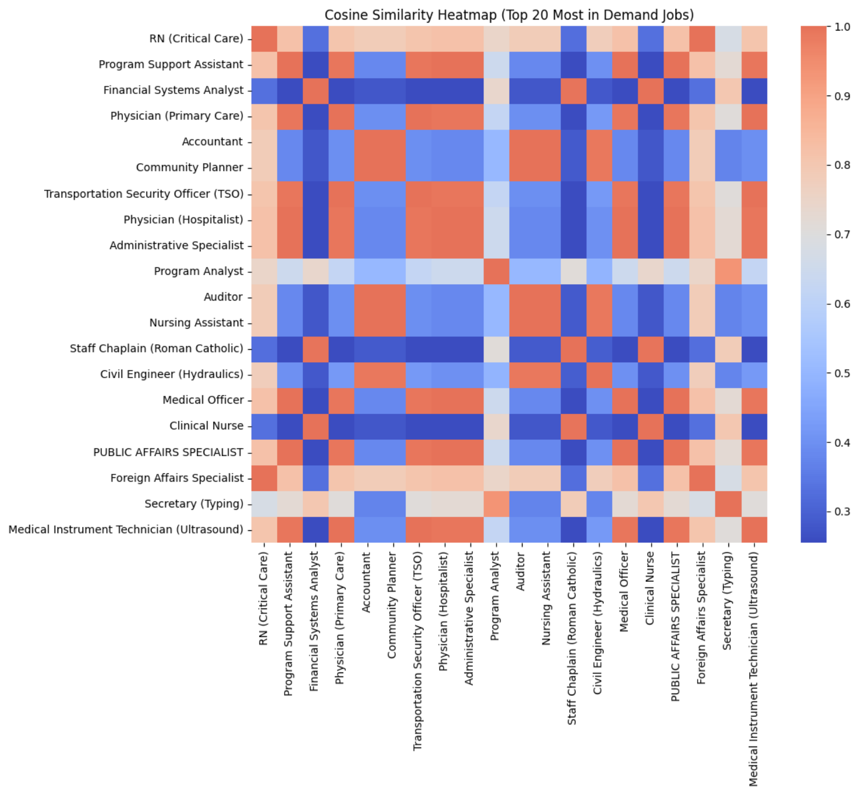
Geospatial Analysis

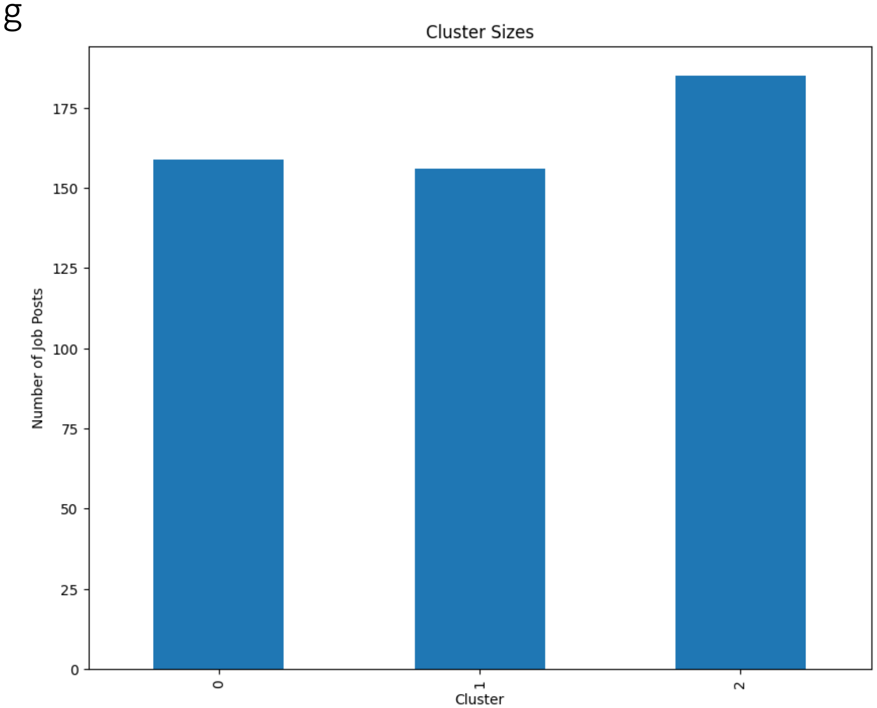
Skill Set 2



- The demand for the skills in skill set 2 are shown in the map on the left to be;
  - Highest in the states of Rhode Island, Alaska and Indiana.
  - Lowest in the states of Nebraska, Montana, Utah and Iowa.

Skill Demand similarity and K-Means Clustering





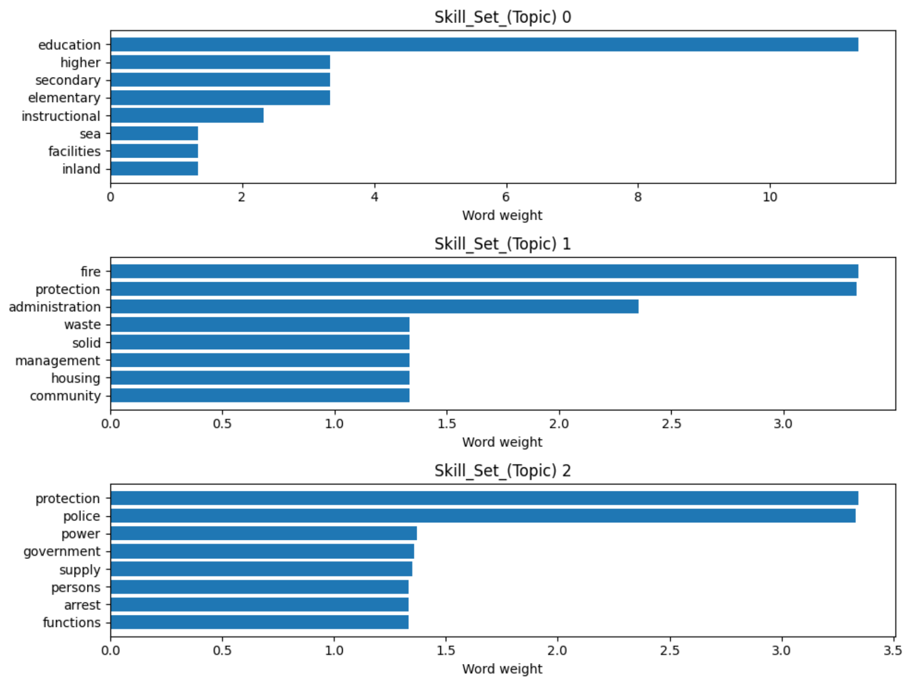
	Skill Demand Clusters	skill_set_0	skill_set_1	skill_set_2
0	0	0.111313	0.770370	0.118317
1	1	0.676366	0.157676	0.165959
2	2	0.110621	0.130044	0.759335

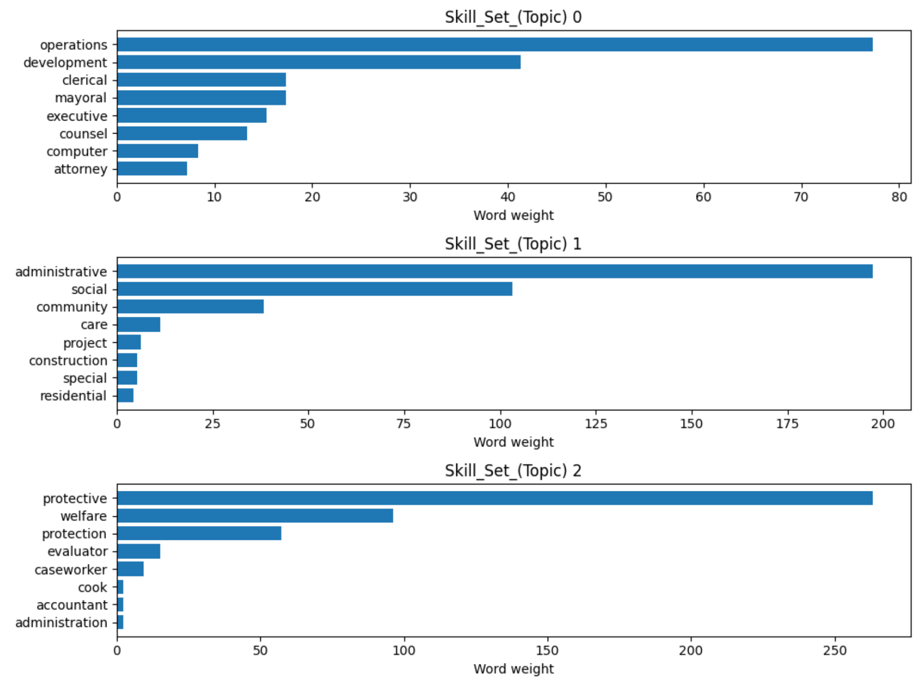
- From the heatmap, we note that skills in Financial System Analyst, Staff Chaplain (Roman Catholic) and Clinical Nurse are the most unique skills among the top 20 most in demand positions.

Comparison Cases: Natural Language Processing (NLP) and LDA Topic Modelling

For the US Federal and Local Government Job Posts Case, the LDA plot below shows that for first topic, skills in education were most predominant. For the second and third topics, skills in fire and safety management, and, governance and policing were respectively predominant.

For the New York City Case, the LDA plot below shows that for the first topic, administration and governance were most predominant. For second and third topics, skills associated with social services and administration were predominant.





Key Insights

- The trend plots show that the drop in unemployment in 2020 to 2021 was consistent with the rise in demand for skill set 0, skills related to the aviation, safety, management and medical fields. Also, the drop in average hourly pay in 2020 to 2021 was consistent with the drop in demand for skill set 2, skills related to engineering and human resource.

- The states with highest likelihood of skill demand for skills in skill set 0 are shown to have the lowest likelihood of skill demand for skills in skill set 1, and vice versa.

- Skills in skills in Financial System Analyst, Staff Chaplain (Roman Catholic) and Clinical Nurse are the most unique skills among the top 20 most in demand positions.

Key Insights

	Case	Comparison Cases	
	National Level - Federal Government Level (Longitudinal)	**Local Government and Federal Government (Cross-sectional)**	**City Level – New York City**
Skill Set 0	Aviation, Safety, Management and Medical fields	Education-Related skills	Administration and Governance related skills
Skill Set 1	Engineering and Human Resource	Fire and Safety Management skills	Administration and Social Service skills
Skill Set 2	Medical and Engineering skills	Governance and Policing skills	Administration and Social Service skills

Conclusion

- Consistency exist between skill demand trends and trends in both unemployment and wage rates.
- The skill demand at national level, local government level and the business level largely differ, pointing a difference in needs across the three levels of employment.
- The distribution of skills across the US states was such that the states with highest likelihood of skill demand for skills in skill set 0 are shown to have the lowest likelihood of skill demand for skills in skill set 1, and vice versa.

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