**Analysis of Career Pathways Based on the Social Network Analysis**

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# **Abstract**

Changing careers is quite an unusual event. There are always ways to move from one position to another, whether within the same industry or across industries. This study tries to figure out the features and patterns of trajectories from one occupation to another one. Due to the advantages of social network analysis (SNA) for tracking the evolution of a behavior or state, social network analysis is used in this study. The network is constructed with different occupations, which are defined by 2002 Census Occupation Code, as nodes. Each node has attributes representing the importance of some skills. An edge between A and B represents the existence of transition from occupation A to B, and the weight of an edge is proportional to the number of times of the transition.

Some community detection algorithms are used attempting to explore potential classification relationships between different occupations. …

Major findings… Any implications… The conclusions…

**Keywords:** Social Network analysis, Career Trajectory

# **Introduction**

It is quite common for a person to embark on a different work, whether these works are in the same industry or not. There is a claim that people typically change jobs seven times in their lifetime, which there's no real data to support. However, according to a poll conducted by Harris Poll in 2021 exclusively for Fast Company, it shows that more than half (52%) of American employees were considering making a career change that year, and 44% had already planning to make the switch (Dishman 2021). LinkedIn published a blog with the topic of the most common career transitions for recruiters. It found that approximately half (51%) of former recruiters still stayed in the field of human resources only making a transition to another HR role. The top two fields that the former recruiters turned to outside the human resource are sales and business development (LinkedIn 2023). From these, it can be said that making a career change to a lesser or greater extent is a choice for many people, and discovering the characteristics and patterns is a topic worth exploring.

Some research aims at the reasons for career change for some specific groups, either in a particular field, age group, gender, etc. For people who have fieldwork experiences, the existence of violations of rules defining appropriate conduct would result in a change of career path. One of the reasons that encourage people to pursue their academic work is productive and enjoyable field experiences. Contrarily, negative field experiences would directly lead to career stalling, moves, or leaving (Nelson et al. 2017). For workers in STEM, even the birth of a child can affect the career path more than some other fields. 43% of new mothers and 23% of new fathers leave full-time STEM employment switching to part-time work or exiting the labor force after their first child (Cech and Blair-Loy 2019). Moreover, the choice of career path is affected by the perception gained during childhood. Children’s perceived academic, social, and self-regulatory efficacy influence the types of occupational activities for which they judge themselves to be efficacious both directly and through their impact on academic aspirations (Bandura et al. 2001).

Some tools including different models and methodologies are utilized to job mobility related topics. The article (Xu et al. 2015) investigated what extent the job change occasion can be predicted based on the career mobility and daily activity pattern of individuals. They tried to predict whether an employee will change job or not sometime in the following months, based on the professional and social linkage datasets, which include personal resumes and historical check-in records in location-based social networks. With these prior data, some classification algorithms are used, for example, regression trees (CART), support vector machine (SVM), Adaboost, and random forest. The comprehensive importance of features indicated people may keep stable job change preference from their historical experience and follow the job mobility regularity of environment. (Xu et al. 2014) proposed a technique to calculate the professional similarity between two individuals by modeling individuals’ profile on LinkedIn as a time-series sequence of positions.

Social network analysis (SNA) is a method based on sociology and graph theory, which is a powerful tool for tracking the evolution of a behavior or state. It has been applied to many career-related fields, such as e-recruitment. (Milovanović et al. 2022) used SNA for the preselection of candidates. A network was created by the most frequently used terms. (Toteva and Gourova 2011) built a network based on social network sites. A node could represent a person or a web page. A node with high degree could be a person who has many connections to the high-level specialists or who has wide interests and hobbies or published contents on many pages.

In this article, social network analysis is applied to explore the features and patterns of trajectories from one occupation to another one no matter what industry they are in. Data used for this study is from the official website of U.S. department of labor. The datasets include data from large nationally representative longitudinal surveys, as well as licensed data on occupational transitions from online career profiles, etc. (“Career Pathways Descriptive and Analytical Study Data,” n.d.), which provide the individual information about career trajectories over time. The network is constructed with different occupations as nodes. The occupations are defined according to the 2002 Census Occupation Code (US Census Bureau 2023), which is a four-character code that identifies the generic occupation. Each node has attributes that come from the dataset representing the importance of some skills. An edge between A and B represents the existence of transition from occupation A to B, and the weight of an edge is proportional to the number of times of the transition. The following research questions were formulated:

1. Which occupations have the highest/lowest outflow/inflow rates?
2. Are there occupations that are suitable as intermediate bridges from one occupation to another?
3. Are there any occupations that can be seen as core occupations?
4. Are there clear categories for career transitions?
5. Does the occupation transition show a tendency to cluster according to the skills required?
6. What characterizes a career change in the field of computer technology?

# **Methods**

## **Data Preparation**

The datasets are public use datasets that conform to federal policy guidelines and are checked for disclosure risk prior to release, originally released by the U.S. department of labor. The main dataset used for this study records workers’ career trajectories and transitions within three years. Their work status, including occupation, wage, sector, etc. were updated every month during the time when the data was collected. The granularity of the occupational division is based on the 2002 Census Occupation Code Lists. The OCC is a 4-digit number representing primary occupations, coded into a contemporary census classification scheme.

Additionally, this dataset contains variables denoting the importance of skills, such as problem solving, communication, teaching, etc. These variables are extracted on a per-occupation basis.

## **Social Network Analysis**

Social network analysis is a powerful method for visualizing and analyzing complex connections among lots of entities. It has applications in various fields, including sociology, anthropology, business, information science, and more. It helps to identify patterns of relationships and information flow among them to gain a deeper understanding and insights into the whole structures and the features of the research object.

For this study, a directed network is constructed. All the occupations that exist in the dataset are regarded as nodes. The edges among these nodes represent the existence of career transition. Each edge is weighted with a standard of the number of transitions between two nodes. Figure. x shows the general overview of the whole network. Due to the length of occupations titles that are too long to be shown clearly in the network, OCC codes are shown instead as node labels.

This network has 472 nodes and 8370 edges in total with density at roughly 0.038. The average clustering coefficient at 0.368 is considered moderate, which means there is a tendency for the neighbors of nodes to be connected with each other and form clusters. The negative degree assortativity coefficient suggests a moderate level of disassortative connection, meaning that nodes with different degrees tend to be connected to each other more frequently than expected by chance.

Table x. General information about the network

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Number of nodes** | **Number of edges** | **Density** | **Average Clustering Coefficient** | **Degree Assortativity Coefficient** |
| 472 | 8370 | 0.038 | 0.368 | -0.214 |

A network of circles and dots

Description automatically generated

Figure 1 Overview of the whole network with OCC code as node labels (nodes sized and colored by “out-degree”)

## **Turnover Rate Calculation**

Here the turnover rate is defined as:

TR = sum(weights of all out-edges)/sum(weights of all in-edges)

This turnover rate describes the labor mobility for each occupation. If the value is greater than 1, it means the labor outflow in this occupation is greater than inflow. If the value is less than 1, the flow is exactly the opposite. If it is equal to 1, it means that the occupation from a perspective of the whole labor market is relatively stable.

## **Community Detection**

Community detection refers to the process of identifying cohesive groups of nodes within a network where nodes within the same community are more densely connected to each other than to nodes in other communities. The results of community detection typically reveal the underlying network structures. Within this study, the purpose of community detection is to answer whether there are clear clusters for career transitions. In other words, is there a tendency for career transitions to move from one occupation to another, making these occupations connected closer to each other?

The main methods for community detection in this study are Louvain algorithm and greedy algorithm aiming to modularity maximization. As shown in the Tabel x, no algorithm produces significantly superior results, either for directed or undirected graphs. The highest modularity at 0.2136 suggests the presence of meaningful community structure.

Table x. Modularity from two algorithms applied to both directed and un-directed networks

|  |  |  |  |
| --- | --- | --- | --- |
| **Louvain Algorithm + Directed Network** | **Louvain Algorithm + Un-directed Network** | **Greedy Algorithm + Directed Network** | **Greedy Algorithm + Un-directed Network** |
| 0.2118 | 0.2133 | 0.2136 | 0.2130 |

# **Results**

## **Basic network information**

1. Educational background exaltation

When looking for a job as a graduate with limited work experience, educational background plays an important role to some extent. At the same time, for those who have already started their careers, it is also possible for them to enhance their educational background in search of a better position or a higher salary. Within the three years during the data tracking, 20.07 percent of respondents succeeded in pursuing educational background exaltation. 68.89 percent started with no degree, and of those people, 0.16 percent of them got a bachelor's degree in three years. The percentages of those who started with a HS diploma or equivalent (no college degree) and an associate degree (no bachelor's) and ended up with a bachelor's degree were 19.54 and 1.93, respectively.

2. Wage change

After three years, 54.77 percent of all respondents finally got a raise. Among those people who improved their academic degree, 59.61 percent of them got a raise. All respondents got an average of a 3.36 percent increase in wage, and people who improved their academic degree got an average of a 7.05 percent increase, which is more than twice times than the average.

3. Turnover rate

More than 58 percent of occupations that have a high turnover rate, in other words, outflow is more significant than inflow, are in transportation and production industries.

The rates of the five occupations that have the highest centralities are also greater than 1, meaning that while there was a significant labor inflow to these occupations over the three years, more people left these jobs. This result conforms with the flexibility of these occupations.

Occupations having lower turnover rate mainly concentrate in the office and administrative support industry and construction industry. Computer and information systems managers, lawyers, architects, medical and health services managers, and human resources managers are top 5 occupations with the lowest turnover rate. Within the three years, 21 transitions to and only 1 transition from computer and information systems managers occur.

## **Network Centrality**

There are five measures for network centrality being used in this study, including in-degree, out-degree, closeness, betweenness, and Eigenvector centrality. When unemployed status and student status are taken into account, these two nodes have the highest centrality under all measures of centrality. This is reasonable because it is common that there will be a short gap between two different jobs when career transition occurs and the time of two jobs does not fit seamlessly. Also, for those people who pursued educational background exaltation, there must be a period of student life between the different jobs. Thus, there are a large number of edges pointing in or out the ‘unemployed’ and ‘student’ nodes, which contribute to make them the highest centrality nodes. In order to obtain clearer information on career transitions, these two nodes are excluded from the study.

Generally, five occupations, including (1) retail salespersons, (2) cashiers, (3) waiters and waitresses, (4) stock clerks and order fillers, (5) laborers and freight, stock, and material movers, hand, take up the top five positions in terms of all measures of in-degree, out-degree, and closeness in both inward and outward directions. This means that these occupations have a great deal of flexibility. There are no high requirements to meet to switch to or from these occupations. Particularly, for the betweenness centrality, the values of nodes are all less than 0.055, meaning that all the node's position as a bridge or intermediary in facilitating career transition is low. On the other hand, all the occupations with the least centrality, such as (1) ship engineers, (2) subway, streetcar, and other rail transportation workers, and (3) fabric and apparel patternmakers, mainly concentrated in the productions and transportation industry.

## **Community Detection**

The result of community detection that gets the highest modularity contains six communities in total. Figure x. displays the general distribution of nodes in different communities. The occupations in the community containing only two nodes are (1) Shoe and leather workers and repairers and (2) shoe machine operators and tenders. Three occupations including (1) locomotive engineers and operators, (2) railroad conductors and yardmasters, and (3) subway, streetcar, and other rail transportation workers are in another community. The four remaining communities focus on construction, office and administrative support, production, and healthcare, respectively.

To demonstrate whether the career transition is related to the skills required, the K-means clustering algorithm is implemented to get the same number of clusters as in community detection. If the ways how these occupations are partitioned based on the community detection and K-means are highly similar to each other, it means that career transitions are relevant to the skills, which means career transitions tend to occur between jobs requiring similar skills.

Normalized mutual information (NMI) is a measure used to evaluate the similarity between two clusterings or partitions of a dataset. The value derived from these two partitions is 0.22. This denotes a moderate level of agreement between the two partitions. It indicates that there is similarity between them at a lower level, but there are more differences in the way the clusters are defined. It is concluded that the career transition is not closely related to the skills required for occupations. Skills could be a factor that impacts the direction of job change, but it is not a significant one.

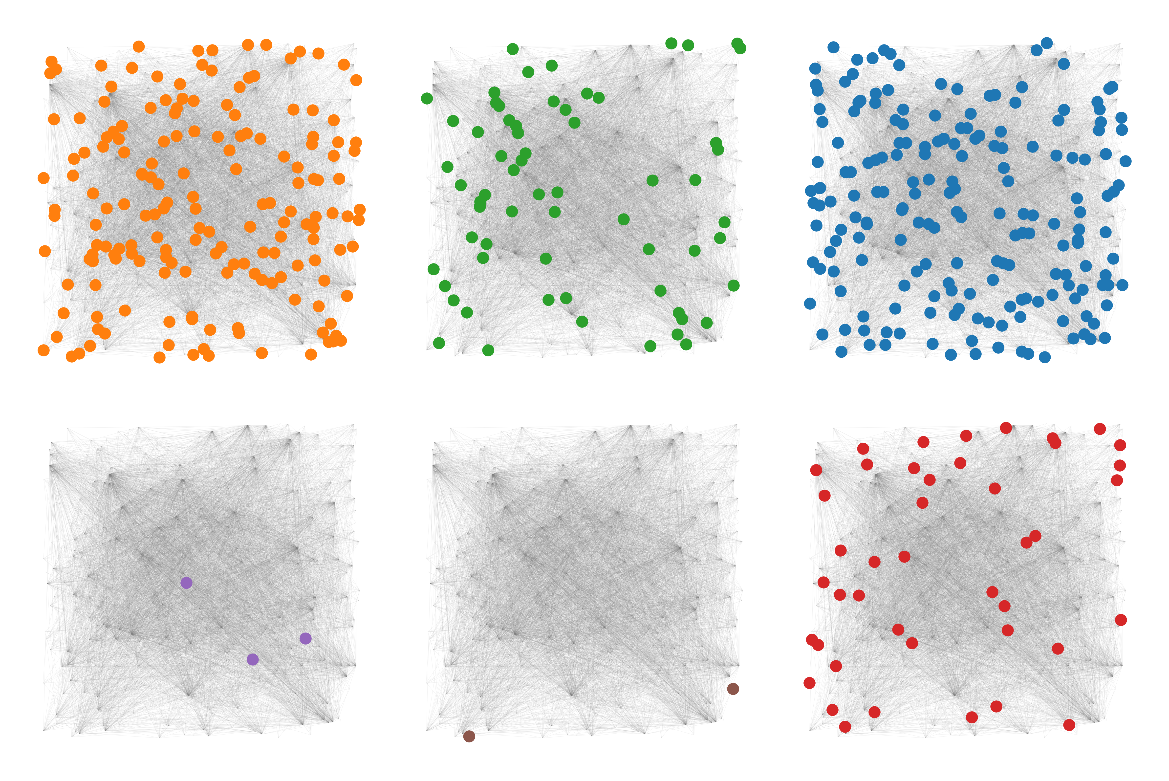


Figure 2 Distribution of the nodes in communities

# **Conclusions**

Which occupations have the highest/lowest outflow/inflow rates?

Are there occupations that are suitable as intermediate bridges from one occupation to another?

Are there any occupations that can be seen as core occupations?

Are there clear categories for career transitions?

Does the occupation transition show a tendency to cluster according to the skills required?

What characterizes a career change in the field of computer technology?

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# **Appendices**

**Tabel x.x. Ten Occupations with Highest Centralities**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **In-degree** | **Out-degree** | **Closeness Centrality (inward)** | **Closeness Centrality (outward)** | **Betweenness Centrality** | **Eigenvector**  **Centrality** |
| 1 | Retail salespersons  (4760) | Laborers and freight, stock, and material movers, hand  (9620) | Retail salespersons  (4760) | Laborers and freight, stock, and material movers, hand  (9620) | Retail salespersons  (4760) | Cashiers  (4720) |
| 2 | Cashiers  (4720) | Retail salespersons  (4760) | Cashiers  (4720) | Retail salespersons  (4760) | Laborers and freight, stock, and material movers, hand  (9620) | Waiters and waitresses  (4110) |
| 3 | Waiters and waitresses  (4110) | Cashiers  (4720) | Waiters and waitresses  (4110) | Cashiers  (4720) | Waiters and waitresses  (4110) | Retail salespersons  (4760) |
| 4 | Stock clerks and order fillers  (5620) | Driver/sales workers and truck drivers  (9130) | Customer service representatives  (5240) | Driver/sales workers and truck drivers  (9130) | Stock clerks and order fillers  (5620) | Receptionists and information clerks  (5400) |
| 5 | Customer service representatives  (5240) | Waiters and waitresses  (4110) | Stock clerks and order fillers  (5620) | Waiters and waitresses  (4110) | Cashiers  (4720) | Customer service representatives  (5240) |
| 6 | Construction laborers  (6260) | First-line supervisors/managers of retail sales workers  (4700) | Laborers and freight, stock, and material movers, hand  (9620) | First-line supervisors/managers of retail sales workers  (4700) | Driver/sales workers and truck drivers  (9130) | Childcare workers  (4600) |
| 7 | Laborers and freight, stock, and material movers, hand  (9620) | Stock clerks and order fillers  (5620) | Receptionists and information clerks (5400) | Stock clerks and order fillers  (5620) | Construction laborers  (6260) | Stock clerks and order fillers  (5620) |
| 8 | Cooks  (4020) | Customer service representatives  (5240) | Cooks  (4020) | Customer service representatives  (5240) | Customer service representatives  (5240) | Secretaries and administrative assistants  (5700) |
| 9 | Grounds maintenance workers  (4250) | Cooks  (4020) | Secretaries and administrative assistants  (5700) | Cooks  (4020) | First-line supervisors/managers of retail sales workers  (4700) | Cooks  (4020) |
| 10 | Secretaries and administrative assistants  (5700) | Cleaners of vehicles and equipment  （9610） | Construction laborers  (6260) | Cleaners of vehicles and equipment  （9610） | Cooks  (4020) | Nursing, psychiatric, and home health aides  （3600） |

**Tabel x.x. Ten Occupations with Lowest Centralities**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **In-degree** | **Out-degree** | **Closeness Centrality** | **Betweenness Centrality** | **Eigenvector**  **Centrality** |
| -10 | Ambulance drivers and attendants, except emergency medical technicians  (9110) | Animal breeders  (6020) | Power plant operators, distributors, and dispatchers  (8600) | Tire builders  (8940) | Power plant operators, distributors, and dispatchers  (8600) |
| -9 | Heat treating equipment setters, operators, and tenders, metal and plastic  (8150) | Sales engineers  (4930) | Locomotive engineers and operators  (9200) | Textile bleaching and dyeing machine operators and tenders  (8360) | Locomotive engineers and operators  (9200) |
| -8 | Upholsterers  (8450) | Postmasters and mail superintendents  (0400) | Railroad conductors and yardmasters  (9240) | Shuttle car operators  (9730) | Railroad conductors and yardmasters  (9240) |
| -7 | Fabric and apparel patternmakers  (8440) | Economists  (1800) | Fabric and apparel patternmakers  (8440) | Locksmiths and safe repairers  (7540) | Fabric and apparel patternmakers  (8440) |
| -6 | Parking enforcement workers  (3840) | Veterinarians  (3250) | Parking enforcement workers  (3840) | Subway, streetcar, and other rail transportation workers  (9260) | Parking enforcement workers  (3840) |
| -5 | Fire inspectors  (3750) | Animal control workers  (3900) | Fire inspectors  (3750) | (6740) | Fire inspectors  (3750) |
| -4 | Hoist and winch operators  (9560) | Textile bleaching and dyeing machine operators and tenders  (8360) | Hoist and winch operators  (9560) | Conservation scientists and foresters  (1640) | Hoist and winch operators  (9560) |
| -3 | Shuttle car operators  (9730) | Rail-track laying and maintenance equipment operators  (6740) | Shuttle car operators  (9730) | Model makers and patternmakers, metal and plastic  (8060) | Shuttle car operators  (9730) |
| -2 | Subway, streetcar, and other rail transportation workers  (9260) | Conservation scientists and foresters  (1640) | Subway, streetcar, and other rail transportation workers  (9260) | Heat treating equipment setters, operators, and tenders, metal and plastic  (8150) | Subway, streetcar, and other rail transportation workers  (9260) |
| -1 | Ship engineers  (9330) | Heat treating equipment setters, operators, and tenders, metal and plastic  (8150) | Ship engineers  (9330) | Ship engineers  (9330) | Ship engineers  (9330) |

**Tabel x.x.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **In-degree** | **Out-degree** | **Closeness Centrality** | **Betweenness Centrality** | **Eigenvector**  **Centrality** |
| 1 | Unemployed | Unemployed | Unemployed | Unemployed | Unemployed |
| 2 | Student | Student | Student | Student | Student |
| 3 | Retail salespersons (4760) | Retail salespersons (4760) | Retail salespersons (4760) | Retail salespersons (4760) | Retail salespersons (4760) |
| 4 | Cashiers  (4720) | Cashiers  (4720) | Cashiers  (4720) | Laborers and freight, stock, and material movers, hand  (9620) | Cashiers  (4720) |
| 5 | Waiters and waitresses (4110) | Laborers and freight, stock, and material movers, hand  (9620) | Waiters and waitresses (4110) | Cashiers  (4720) | Waiters and waitresses (4110) |
| 6 | Laborers and freight, stock, and material movers, hand  (9620) | Waiters and waitresses (4110) | Laborers and freight, stock, and material movers, hand  (9620) | Waiters and waitresses (4110) | Customer service representatives  (5240) |
| 7 | Customer service representatives  (5240) | Stock clerks and order fillers  (5620) | Customer service representatives  (5240) | Customer service representatives  (5240) | Laborers and freight, stock, and material movers, hand  (9620) |
| 8 | Stock clerks and order fillers  (5620) | Customer service representatives  (5240) | Stock clerks and order fillers  (5620) | Construction laborers (6260) | Stock clerks and order fillers  (5620) |
| 9 | Driver/sales workers and truck drivers (9130) | Driver/sales workers and truck drivers (9130) | Driver/sales workers and truck drivers (9130) | Stock clerks and order fillers  (5620) | Driver/sales workers and truck drivers (9130) |
| 10 | First-line supervisors/managers of retail sales workers (4700) | Cooks  (4020) | Construction laborers (6260) | Driver/sales workers and truck drivers (9130) | First-line supervisors/managers of retail sales workers (4700) |
| 11 | Construction laborers (6260) | Secretaries and administrative assistants  (5700) | First-line supervisors/managers of retail sales workers (4700) | Secretaries and administrative assistants  (5700) | Receptionists and information clerks  (5400) |
| 12 | Secretaries and administrative assistants (5700) | First-line supervisors/managers of retail sales workers (4700) | Secretaries and administrative assistants (5700) | Grounds maintenance workers (4250) | Secretaries and administrative assistants (5700) |