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Using Graph Theory to Optimize Career Transitions

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Abstract:

Grounded in graph theory, this paper proposes and demonstrates a novel methodology to analyze career transitioning. We collect and integrate official U.S. Government data on 35 general job skills and the annual wage data for over 900 standard occupations. Our research can help people move from unemployment, or a current job, to their desired occupation. We use graph theory to determine the most efficient way to hop between intermediate jobs to gain the necessary set of skills required by the targetted occupation. Our analysis assumes that working in a job proffers the skills from that job to the employee. A potential application involves an employee who wishes to transition to a different occupation, perhaps even in a different industry. The employee does not have the necessary skills to transition directly to the desired career because the skill levels are too different between the jobs. Instead, the employee must make a series of smaller job hops to acquire the skills. This type of analysis can provide valuable insights into the most efficient way to change careers. Our study may be especially relevant and helpful because some employees may need to move from languishing careers or industries to ones less impacted by COVID 19 or less threatened by automation.

Key words: *Career change, Occupational skills, Graph theory, Shortest path*

1. Introduction

Currently, the COVID-19 pandemic has resulted in unprecedented unemployment due to business closures and suppressed consumer demand (Tappe, 2020). For example, squeezed by debt and store closures, luxury retailer Neiman Marcus filed for chapter 11 during the COVID 19 pandemic (Friedman and Maheshwari, 2020). It is a distinct probability that many workers may have to look for jobs both within and across industries when they return to the workforce.

While the pandemic will likely eventually end, industry experts cautioned that the historically low unemployment rates that existed before the pandemic will probably not return anytime soon, as many companies restructure or go out of business (Morath and Guilford, 2020). We note that meanwhile, the pandemic has affected different industries differently. For example, retail, restaurants, travel, and bars that require customers to congregate closely together may see permanently lower employment. It is a reality that millions of workers may have to look for jobs across different industries when they return to the workforce. To add to this unfortunate situation, Frey and Osborne (2017) suggested that "47% of total US employment is in the high-risk category" of being replaced by technology in the next 10 to 20 years.

Our research is intended to guide people moving from unemployment, or from a current job to their desired occupation by determining the most efficient way to hop between intermediate jobs and gain the necessary set of skills required by the targeted occupation. Our analysis assumes that working in a job proffers the skills from that job to the employee.

A potential case involves an employee who wishes to transition to a different occupation, perhaps even in a different industry. The employee does not have the necessary skills to transition directly to the desired career because the skill levels are too different between the jobs. Instead, the employee must make a series of smaller job hops to acquire and accumulate the skills.

This type of analysis can provide valuable insights into the most efficient way to change careers. Our study and methodologies may be especially useful because some employees may need to move from languishing industries to ones less impacted by COVID 19 or less threatened by automation.

This paper is organized as follows. After our literature review in Section 2, we describe our data, how it was collected, and how it is organized for our analysis in Section 3. Our methodology is described in Section 4. Our results and findings are presented in Section 5. We discuss practical implications, research limitations and future research steps in Section 6.

2. Literature Review

Workers must increasingly take responsibility for managing their careers and concern themselves with maintaining and upgrading their skillsets to adapt to fast-changing work environments. Hall (1996) describes the protean career, which is driven by the individual rather than the organization. The protean career requires the individual to personally acquire and use an identifiable set of skills. Laar et al. (2017) argue that the current workplace requires highly skilled workers who must address increasingly complex and interactive tasks. Employees not only need excellent technical preparation; but also need sufficient skills to adapt to the changing requirements of the job (Carnevale and Smith, 2013).

Over their working life, employees change jobs several times. According to the Bureau of Labor Statistics (BLS), the median number of years that wage and salary workers had been with their current employer was 4.2 years in January 2018 (BLS, 2018). Employees can use those job changes to improve their skillsets. Tambe and Hitt (2014) describe the practice of leveraging the learning of on-the-job learning of technical skills acquired at one employer to job hop to another employer. Nzukuma and Bussin (2011) describe senior managers moving from organization to organization to build their repertoire of skills and competence.

In this research, we ground our analysis of job hopping on graph theory, which is the analysis of network structures that are made up of nodes connected by links. Mathematically, a graph is essentially a network. Dating back to the problem of Konigsberg Bridge in 1735, graph theory is concerned with the use of the geometry of position (graphs) to model and study pairwise relations between objects. A graph is comprised of two elements: (1) vertices (endpoints, nodes, objects or entities) , which can be quantified based on various attributes; (2) edges (e.g., links), which connect any two vertices. The links may be symmetrical or uni-directional. From the early Eulerian Graph to modern random graph theory, graph theory has been applied in a wide range of fields, including biology, chemistry, sociology, computer science, project management, operations research, etc. In operation research, notably, the construction of transport networks and vehicle routing have benefited significantly from graph theory (Shrinivas et al., 2010). The classic traveling salesperson problem (TSP), which finds the shortest possible route without visiting any city more than once given a list of cities and the distances between each pair of cities, is another classical application of graph theory.

In this current research, we treat each occupation as a node or vertex with attributes (skill levels and importance values). The path from one occupation to another is considered a link. The link is weighted by Euclidean distance based on the values of attributes (skillsets). Our goal is to identify the shortest path between two vertices (occupations) in a graph. Cheng, Xie, Chen, Agrawal, Choudhary, and Guo (2013) use a graph network to find companies with dense job-hopping connections between them. That is, company communities that tend to share many job hoppers between them. Based on social network data to track the careers of 262 Michelin-starred chefs, Aubke (2014) uses graph theory to create a chef affiliation network that diagrams how chefs are related based on such attributes as the restaurants they have worked for, and their Michelin rating.

3. Data

We collect and integrate occupation skills and wage data sponsored by the U.S. Government. This data is used to create our graph nodes and connections. The occupation skills data, including Skill Level Ratings and their related Skill Importance Ratings, are collected from the Occupational Information Network (O*NET), which is sponsored by the U.S. Department of Labor Employment and Training Administration. Updated annually, the O*NET database contains hundreds of standardized and occupation-specific descriptors on nearly a thousand job occupations covering the entire U.S. economy. It is considered the primary source of U.S. Governmental occupational information (O*NET, 2019). Listed in Table 1, the 35 different occupational skills are organized into six categories by O*NET, including basic skills, social skills, technical skills, complex problem-solving skills, systems skills, and resource management skills

Table 1: Occupational Skills

Skill Category	**Skill Category Description**	**Skill**
Basic Skills (10)	Developed capacities that facilitate learning or the more rapid acquisition of knowledge	*Active Learning, Active Listening, Critical Thinking, Learning Strategies, Mathematics, Monitoring,*

		Reading Comprehension, Science, Speaking, Writing
Social Skills (6)	Developed capacities used to work with people to achieve goals	*Coordination, Instructing, Negotiation, Persuasion, Service Orientation, Social Perceptiveness*
Technical Skills (11)	Developed capacities used to design, set-up, operate, and correct malfunctions involving the application of machines or technological systems	*Equipment Maintenance, Equipment Selection, Installation, Operation and Control, Operation Monitoring, Operations Analysis, Programming, Quality Control Analysis, Repairing, Technology Design, Troubleshooting*
Complex Problem-Solving Skills (1)	Developed capacities used to solve novel, ill-defined problems in complex, real-world settings	*Complex Problem-Solving*
Systems Skills (3)	Developed capacities used to understand, monitor, and improve socio-technical systems	*Judgment & Decision Making, Systems Analysis, Systems Evaluation*
Resource Management Skills (4)	Developed capacities used to allocate resources efficiently	*Management of Financial Resources, Management of Material Resources, Management of Personnel Resources, Time Management*

Each skill in Table 1 is described along with descriptive anchors for low, medium, and high skill level ratings, ranging from 0 to 100. In addition to the Skill Level Rating, the related importance of each skill (Skill Importance Rating) to each occupation is also provided.

For example, the *Marketing Manager* occupation requires mathematic skills at a Skill Level Rating of 45 out of 100, with a Skill Importance Rating of 44 out of 100. Contrast that occupation with the *Refuse and Recyclable Material Collectors* occupation, which requires a *mathematics* Skill Level Rating of 7 out of 100, with an Importance Rating of 10 out of 100. Thus, the level of *mathematics* skills required of *Marketing Managers* is much higher and significantly more important for them, than for *Refuse and Recyclable Material Collectors*.

In addition to occupational skills data, we also collect annual wage data from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES). The BLS is the principal federal agency responsible for measuring labor market activity, working conditions, and price changes in the economy (U.S. Bureau of Labor Statistics, 2019). The BLS OES provides nationwide, average annual wage data for close to 1000 occupations in the U.S. across numerous industries and job types. Their dataset includes wage data from high-level positions, such as chief executives, to lower-wage employees, such as fast-food workers.

We integrated this annual wage data with the O*NET occupational skills data via job codes to create a consolidated dataset that links the 35 skillsets and wage data for 967 occupations. The initial dataset was then pruned to 937 occupations to eliminate records with missing and incomplete data. Note that we assigned a level of zero (0) for skill level ratings or skill importance ratings with 'Not available' or 'Not relevant' as their value.

4. Methodology

In this section, we describe how to use graph theory and pathfinding algorithms to determine how best a person should move between jobs to get from a current occupation to a final desired occupation.

Figure 1 provides a conceptual diagram of our approach. Here the objective is to find the shortest total path between the current job (Job_1) and the desired job (Job_8). For the purpose of illustration, in the example that is diagrammed in Figure 1, we set a constraint for hops between jobs such that the maximum distance between two job's skillsets must be less than 50. In the example, this constraint eliminates the hop from Job_3 to job_6 (with a Euclidian distance of 51). Using the Dijkstra shortest path algorithm, we can then determine that the most efficient path (shortest distance) between Job_1 and Job_8 follows this path: Job_1->Job_4->Job_6->Job_8.

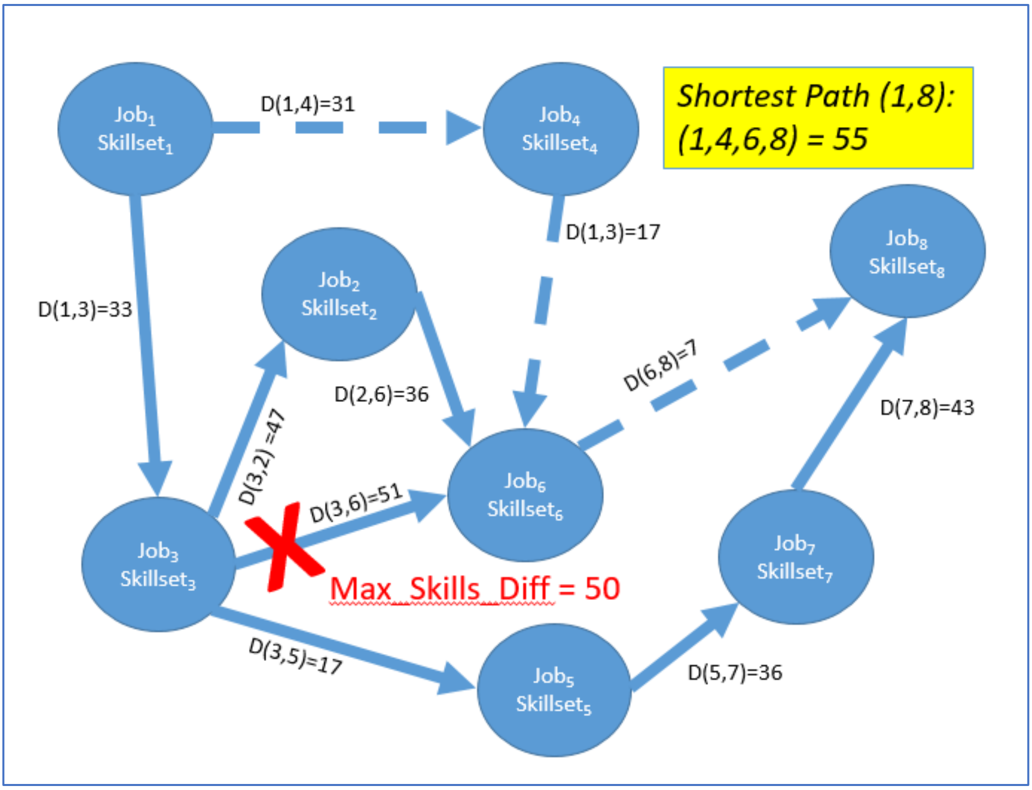

Figure 1: Job Hopping Example

A potential use case for this analysis involves an employee who wishes to transition to a different occupation, perhaps even in a different industry. The employee does not have the necessary skills to transition directly to the desired career because the skill levels are too different between the jobs. Instead, the employee must make a series of smaller job hops. Each job hop increases the employee's skillset towards the skill levels required by the final desired occupation.

Our analysis assumes that employees are limited by how far (in skill distance) they can hop between occupations. The allowed hops are those where the distance between the current set of job skill levels that must be increased, and the skill levels required by the next job, is less than some constraint maximum.

We calculated skill distance from job_p to job_q based on the Euclidian distance between the two sets of occupational skills $d(p,q)$ as shown in Equation 1. Note that in the conditional equation, r_i is zero if p_i (the skill level of the originating occupation) is equal to or larger than q_i (the required skill level in the destination occupation). This eliminates those skills that already equal or exceed the required levels of the destination occupation.

As an example, a *Refuse and Recyclable Material Collector* hopping to a *Music Therapist* job already possesses a skill level of 30 for the *Troubleshooting* skill (see Figure 2). The *Music Therapist* occupation requires a *Troubleshooting* skill level of 11. Thus, the skill gap is zero (0) for Troubleshooting for those hopping from a *Refuse and Recyclable Material Collector* position to a *Music Therapist* job. However, there is a *Troubleshooting* skill gap of 19 for the reverse situation, where someone hops from *Music Therapist* to a *Refuse and Recyclable Material Collector* job.

The allowed hops are constrained by a maximum distance between hops. That is, where *d*(p,q) does not exceed a maximum hop distance (HD_{max}) as defined by Equation 1.

$$d(\mathrm{p},\mathrm{q}) = \begin{cases} \sqrt{\sum_{i=1}^{n} r_i} \leq HD_{max}, & p_i \leq q_i \rightarrow r_i = (p_i - q_i)^2 \\ & p_i > q_i \rightarrow r_i = 0 \end{cases}$$

Equation 1: Calculating Distances Between Skillsets

We designed the employment skills graph in the following way. Each node of the graph represents an occupation. Each node includes several attributes that describe the occupation that it represents. These attributes include the occupation skill level ratings (SL), skill importance ratings (SI), and annual wages (AW) as diagrammed in Figure 2.

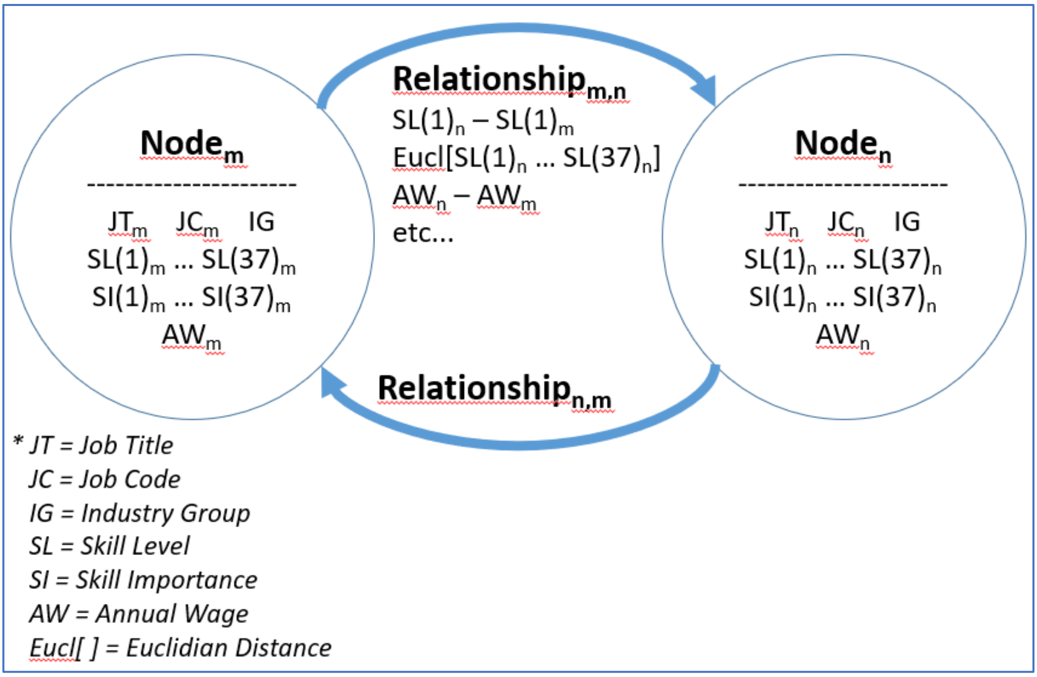

Figure 2: Node and Relationship Attributes

Table 2 provides a specific example of the type of attribute data found in a node. In the table, we see that the Laborers and Freight, Stock, and Material Movers, Hand occupation, the average national yearly wage is \$22,999. This occupation requires a skill level rating of 37 for the Management of Material Resources skill, with a skill importance rating of 28.

Table 2: Occupational Node Attributes

Job Title (JT)	Laborers and Freight, Stock, and Material Movers, Hand
Job Code (JC)	53-7062
Industry Group (IG)	Transportation and Material Moving Occupations
Skill Title (ST)	Management of Material Resources
Skill Level (SL)	37
Skill Importance (SI)	28
Annual Wage (AW)	\$22,999

The weightings of relationships (or edges) between the nodes are directed. The Euclidean distance link weightings are calculated via Equation 1.

Note that the weightings can be changed, if needed, to conduct different analyses. For example, the weightings could be changed to occupational wage differences. That is: Wagem - Wagen. A person could use this type of graph to calculate the fewest number of hops (versus the shortest total distance) to reach a target annual wage. For this analysis, one would first delete all the relationships that exceed the maximum hop distance. Then, all distance weightings would be set to the same arbitrary value above zero (for example, d(p,q) = 1), since we are minimizing the total number of hops instead of the total hop distance.

5. Results

Given the extensive data, our graph is extremely large. It contains 967 nodes (for the exact 967 occupations). And since each node is connected to all other nodes, including itself, there are 935,089 paired relationships (9672). Figure 3 provides a snapshot of our graph. The nodes are labeled with the occupation and the links are labeled with the Euclidian distance between skillsets. For clarity and illustration purposes, the graph shows just 7 of all occupations and their interconnections.

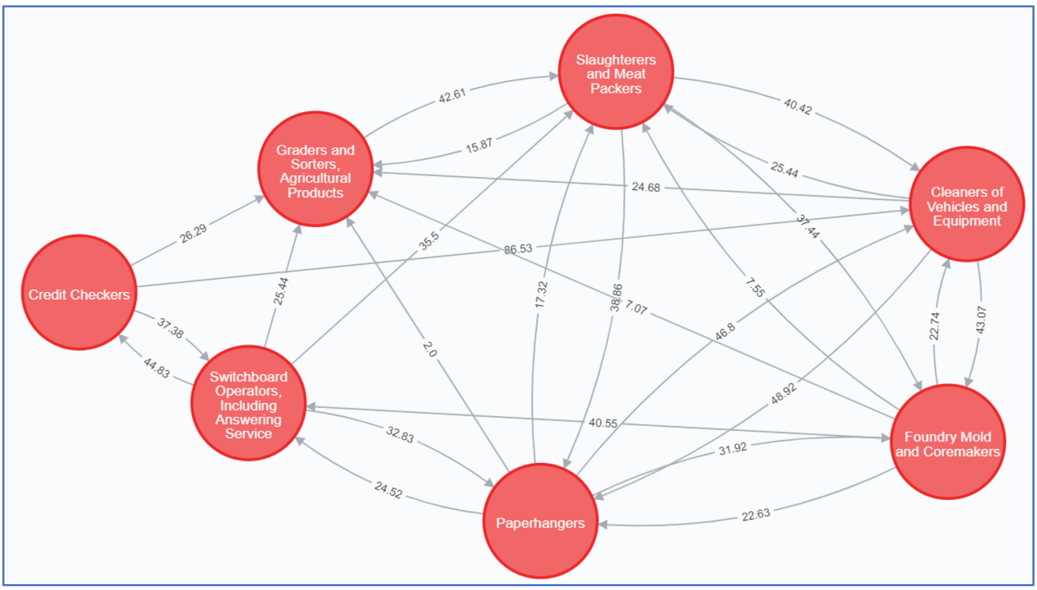

Figure 3: Graph Nodes and Relationships

Figure 4 plots the required skill levels of *Refuse and Recyclable Material Collectors* (*RC*) (in black) and *Music Therapists* (*MT*) (in yellow), along with the required increases in skill levels (red bar) that are needed for an *RC* to transition to an *MT*. As perhaps expected, the *RC* already have sufficient skills related to dealing with machines (e.g., Equipment Selection, Repair, Operation Monitoring, etc.), but will need to increase their human-related skills (e.g., Active Listening, Persuasion, Instructing, etc.) to meet the required *MT* skill level requirements. The overall Euclidean skill level distance from *RC* to *MT* (122) is calculated by taking the square root of the sum of the required skill level increases (the red bar) squared.

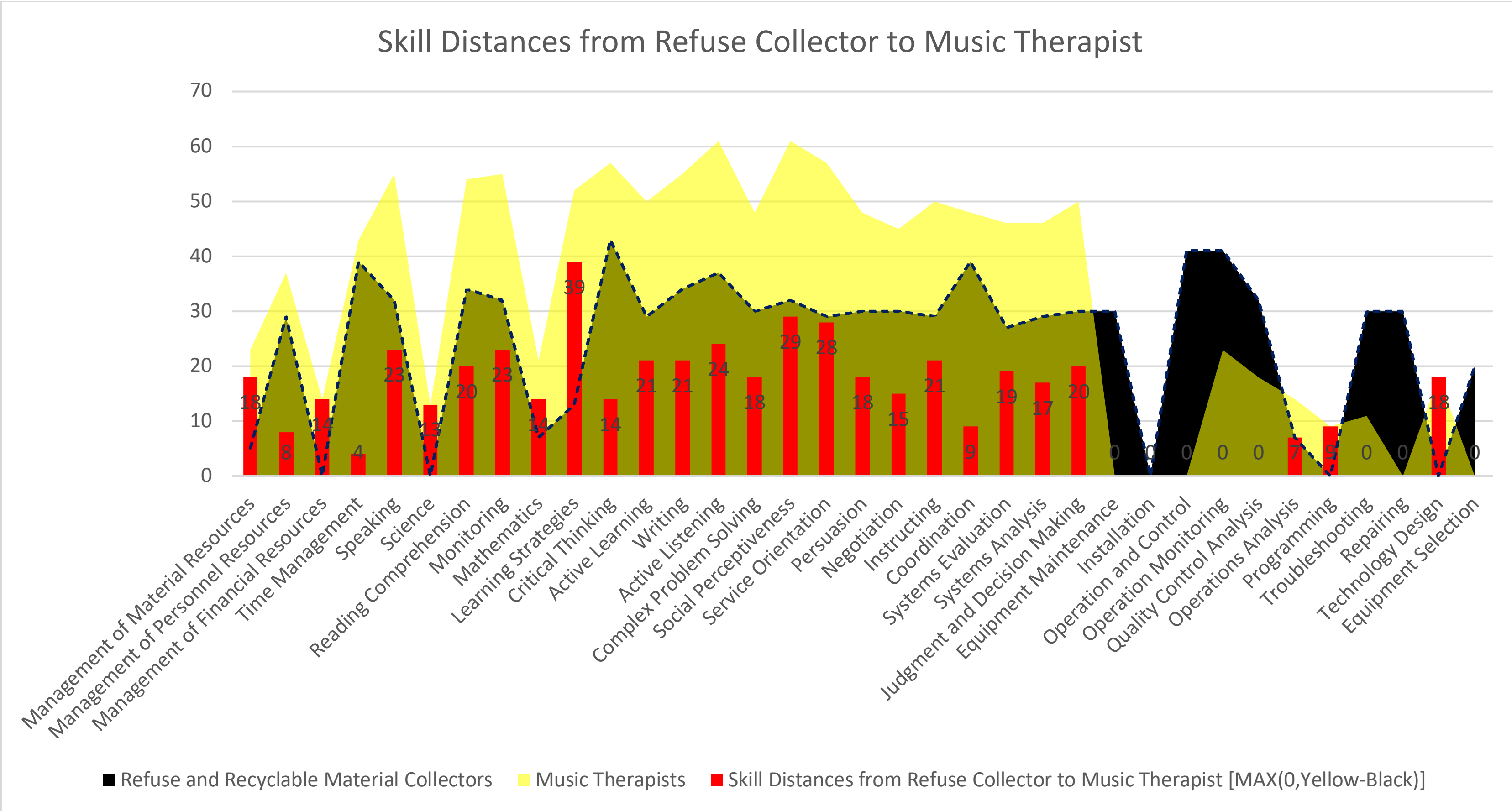

Figure 4: Skill Distances Between Two Occupations

We randomly selected the occupations of *Credit Checkers (CC)* and *Cleaners of Vehicles and Equipment (CV)* as the starting and ending occupations, respectively, from the 967 occupations available for analysis. We calculated the hops for an unconstrained maximum hop distance as well as for maximum hop distance constraints of 20, 40, and 50. The shortest paths to move from the *CC* occupation to the *CV* occupation for the four cases are listed in Table 3.

Table 3: Hopping from *Credit Checker* to *Cleaner of Vehicles and Equipment*

Job Title	**Cum Hop Distance**
Case 1: Unconstrained Job Hop Distance	
Credit Checkers	0.00
Cleaners of Vehicles and Equipment (***Hop1=86.53***)	86.53
Case 2: Maximum Job Hop Distance = 50	
Credit Checkers	0.00
Graders and Sorters, Agricultural Products (***Hop1=26.29***)	26.29
Slaughterers and Meat Packers (***Hop2=42.61***)	68.90
Cleaners of Vehicles and Equipment (***Hop3=40.42***)	109.32
Case 3: Maximum Job Hop Distance = 40	
Credit Checkers	0.00
Switchboard Operators, Including Answering Service (***Hop1=37.38***)	37.38
Paperhangers (***Hop2=32.83***)	70.21
Foundry Mold and Coremakers (***Hop3=31.92***)	102.13
Cleaners of Vehicles and Equipment (***Hop4=22.74***)	124.87
Case 4: Maximum Job Hop Distance = 20	
A feasible solution does not exist	Not Applicable

As can be seen in Table 3, the unconstrained case will always only require a single hop, since all nodes are connected to all other nodes in our graph. And as shown in the left-hand column of the table, each hop distance does not exceed the constraints defined by the cases. For example, note that the largest hop for Case 2 is 40.4, which is under the maximum hop distance of 50.

Likewise, in Case 3, the largest hop is 31.9, which is under 40. It is also interesting to note that Case 2 and Case 3 took different paths through the graph, with a different number of hops, to get to the *CV* node. For the case where the maximum hop distance cannot be over 20, there is no feasible solution.

In another example with a maximum hop distance of 50, Figure 5 shows how a *Chief Executive* can move between jobs, using the highlighted links to arrive at the desired occupation as a *Computer Network Architect*.

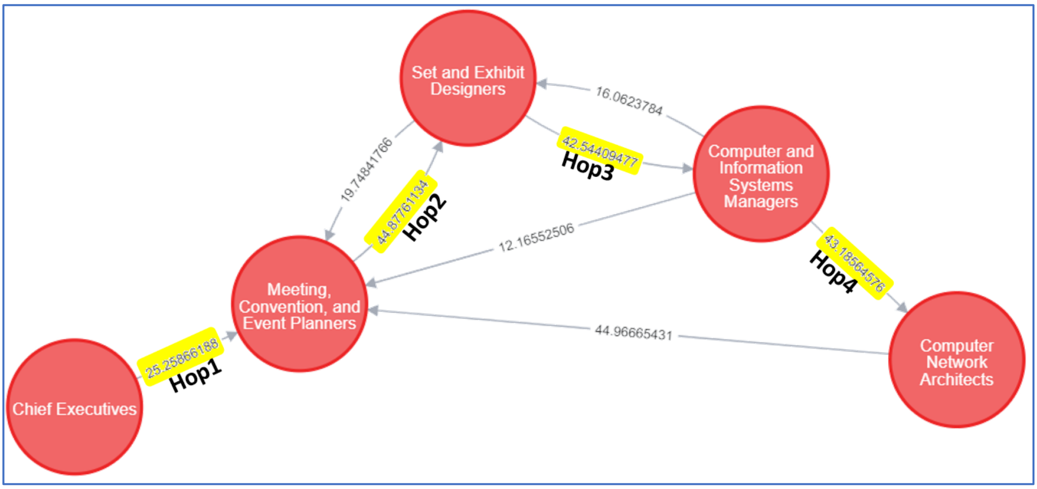

Figure 5: Hopping Between Occupations

Figure 6 shows how five of the skills change when moving from a *Chief Executive* (the bright red bar on the left) to a *Computer Network Architect* (the bright green bar on the right) given the maximum hop distance of 50. The final required skill levels are in bright green. Thus, we can see that the starting *Chief Executive* Systems Analysis skill (77) exceeds the final required *Computer Network Architect* level of 55.

On the first job hop from *Chief Executive* to *Meeting, Convention, and Event Planner*, the Systems Analysis skill level drops to 45. On hop2, hop3, and hop4, the job hopper's System Analysis skill level first drops to 43, then increases to 50, then finishes at the required 55 Systems Analysis skill level.

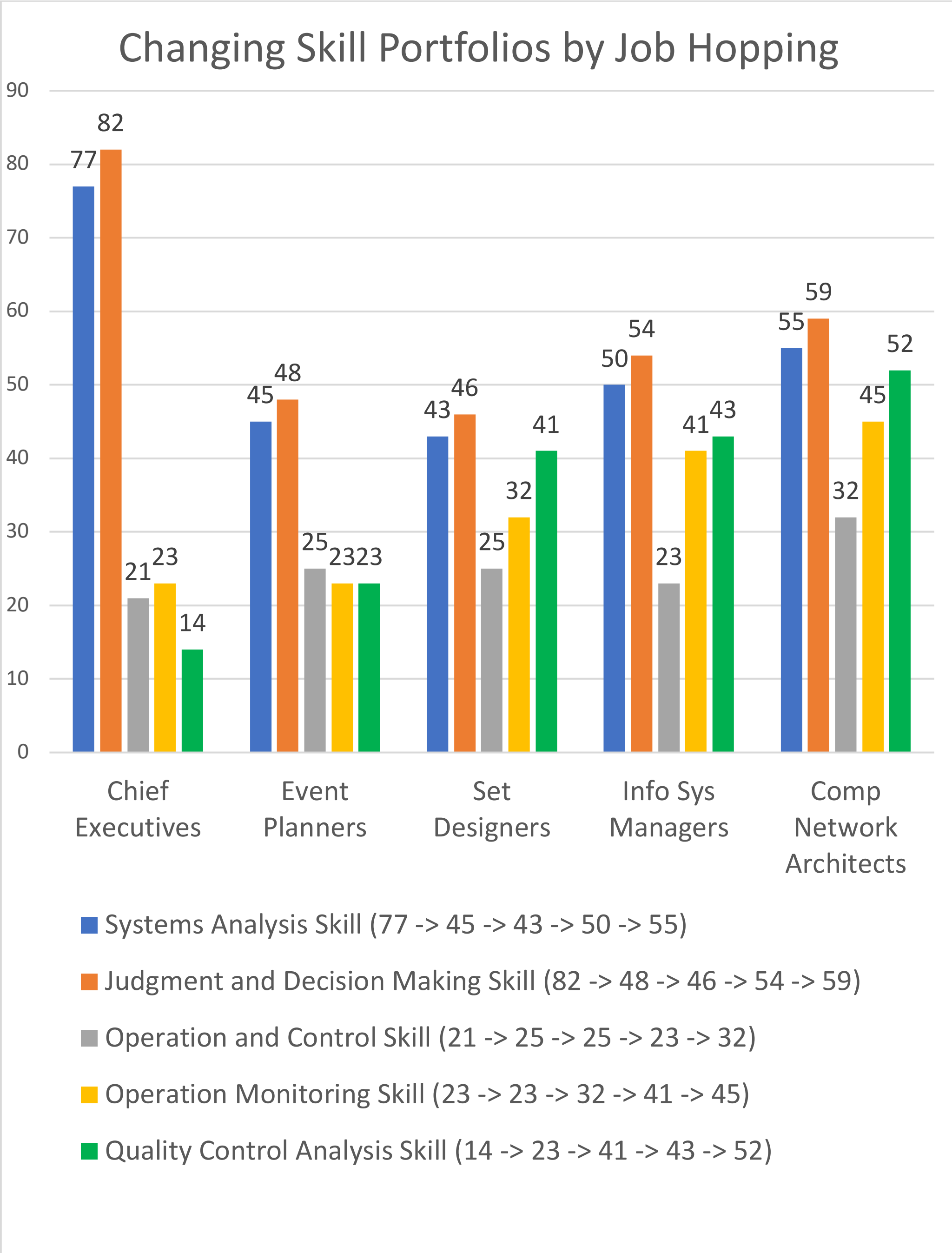

Figure 6: Skill Level Changes with Hops Between Occupations

6. Practical Implications and Future Research Steps

We have developed and demonstrated a novel method using graph theory to analyze career transitioning. Our approach is aimed to enable employees to find the shortest path for moving between jobs (job-hopping) to navigate to a final objective occupation due to a desirable job function, or better compensation.

This type of analysis has become more important and relevant as workers must be able to move between careers as automation and exogenous events (such as pandemics) impact their occupations and disrupt their careers. Meanwhile, government agencies and career organizations may be able to provide customized training and effective assistance to workers who need to find new jobs after layoffs. To companies who need to find and train new employees, our path analysis may serve as guidance to identify employees with the most relevant skillsets.

Our research and findings are subject to several limitations. First of all, our career path analysis is based on the levels and importance values of skillsets. Many other situational or non-quantifiable factors may affect job hops, incluidng general economic health, overall job market, educational background, personalities, cultural fits, etc. Our findings can only serve as a starting point. We could also invite a group of industry executives and career experts to review and validate our results and refine our methodology. Second, our research is limited to the 35 skills and wage data for occupations. For future research, our analysis may be extended by analyzing additional occupational data), incluidng abilities (enduring attributes of the individual that influence job performance) and knowledge (organized sets of principles and facts applying in general domains). Types of ability include cognitive, physical, psychomotor and sensory abilities. Areas of knowledge are even more extensive, including management, biology, chemstry, psychology, computer science, marketing, design, accounting, engineering, construction, geography, mechanical, medicine, human resources, security, transportation, etc. Apparently, each occupation requires a unique set of ability levels and knowledge areas (O*NET, 2020). Third, further analyses based on additional factors and varations of assumptions and restrictions could be conducted. Some examples include (1) finding the largest possible wage increase given a limit on the total number of hops in addition to the maximum hop distance; (2) adding nodes to represent specific certifications or degree requirements to enter professions; (3) incorporating occupation skill importance ratings allow with skill level ratings; (4) calculating all the nearest neighbor for all occupations, for both within the same industrial area and between different industrial areas; and (5) determining the hop distance based on a few specific skills instead of using all the skills.

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