

# Skills-Approximate Occupations: Using Networks to Guide Jobs Retraining

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## Abstract

An issue often confronting economic development agencies is how to minimize unemployment due to disruptions like technological change, trade wars, recessions, or other economic shocks. Decision makers are left to craft policies that can absorb surplus labor with as little pain to workers as possible. The key question, in terms of skills and occupations, is: how can we fill labor gaps with labor surplus efficiently? To address this question, we develop a policy-oriented method to measure the skills proximity of occupations. Using network analysis, we identify key missing skills and determine what occupations are “skills proximate” to one another. Inspired by techniques from ecology, our skills proximities are derived from occupational patterns of geographical co-occurrence. To demonstrate the potential of this method as a policy tool, we provide a case study of a possible worker retraining pathway for Northern Virginia, which was simultaneously impacted by the COVID-19 pandemic and the arrival of a second headquarters for Amazon.

## Intro

We approach our issue from the perspective that regional economies are complex adaptive systems, meaning that they are composed for heterogenous parts that interact in non-random, and often cryptic ways. This view supplements traditional methods in regional economics, which may overlook the fact that interactions between entities are much more than the simple sum of their parts. Furthermore, given the non-linear nature of the systems being examined, it is often difficult to link analysis to concrete policy actions.

Our analysis draws on methods from complexity science to develop a tool targeting regional economic developers. It focuses primarily on worker re-training programs by determining how “close” occupations are to one another within a skills network. That network is constructed by analyzing the co-occurrence patterns of labor occupations across metropolitan areas and translating those patterns into skills patterns.

The novel result has at least two potential policy applications. First, we quantify a metric called “transition potential” to inform policymakers about possible replacement occupations. Thus, if policy makers seek to retrain displaced workers of a specific occupation, such as laid-off coal miners, for other roles in the labor force, this work is intended to help clarify which occupations are more proximate, or more similar in terms of skills, to the original occupation.

Second, for jobs re-training programs, the result is intended to help identify possible issues in transitioning from one occupation to another occupation. That is, once policymakers have chosen the occupations for which they would like retrain workers, specific skills are identified that may hinder the successful retraining of workers.

With these goals in mind, the rest of this paper is organized as follows. First, a brief background is provided for context. The data and methodology are then provided, with key aspects highlighted using illustrative examples. Finally, the methodology is applied to Northern Virginia as a case study of how the tool is anticipated to be used. A brief conclusion summarizes and offers future direction.

## **Background**

Complex systems are generally characterized as systems composed of numerous independent, but interlinked parts whose interactions aggregate non-linearly to more than the simple sum of their parts (Slaper, 2019). Complex systems typically exhibit non-intuitive behavior over time, with outcomes of the system being path-dependent on previous developments and emerging from the myriad interactions of the system's components (Mitchel, 2009).

The leading approach to understanding and quantifying the internal structure and dynamics of complex systems is through network analysis. Network analysis is a set of statistical tools and techniques that examine empirical data in order to understand how both the interactions among individual components of a system and characteristics of the entire network (Jackson, 2008).

Among the most well-known examples of the application of network analysis to economies is that of Hidalgo and Hausman (2009) who examine international trade as a bi-partite network. In this work, the authors imagine both countries and traded goods as nodes, with the linkages between the nodes being trade flows, to build an "atlas of economic complexity".

At the sub-national regional level, the idea of related and unrelated variety (Frenken, Van Oort, Verburg, 2007) can be viewed using network analysis (Hidalgo et al, 2018). An interesting application of network analysis has been the application of networks to Input-Output tables (Essletzbichler, 2015; Han and Goetz, 2019). Others have used the technique to build regional networks of interacting industries (O'Clery et al, 2019).

Examining occupational data, Muneeppeerakul et al (2013) develop a methodology to construct an "occupation space". Using the co-occurrence patterns of occupations within MSAs the authors build a network of inter-connected occupations. The interdependencies between occupations are used as edge weights in this network while the nodes are occupations. Those weights are then used to estimate the likelihood that a region will add a new occupation to existing portfolio of jobs. This likelihood, or "transition potential" was used to estimate the ease with which US regions could transition to a creative (Shutters et al, 2015) or green economy (Shutters et al, 2016).

However, occupations are often used as a proxy for the set of skills embodied by workers of each occupation. Thus, there researchers have begun to analyze the similarity between occupations by analyzing each occupation's underlying skills profile (Kok and Weel, 2014; Alabdulkareem et al, 2018; Farhina et al, 2019). Here we implement the method of Muneeppeerakul et al (2013) as extended by Shutters and Waters (2020) to calculate the skills proximity of occupations. Using so-called occupational elements to decompose occupations into a set of skills, activities, and abilities,

we examine the co-occurrence of elements to uncover otherwise unseen linkages between elements. Hereafter we refer to these elements collectively as “skills”. Skills, and interlinkages between them as defined by their co-occurrences, are then re-imagined as a network. We then locate individual occupations within that skills network and quantify the proximity of any two occupations.

### Data

Our analysis relies on two principal datasets. The first dataset is the Occupational Information Network (O\*Net). O\*Net data depict several hundred attributes of occupations such as required skills, activities, abilities, and other job characteristics, referred to collectively as elements. Two metrics are captured for each element, one depicting the level of at which the element needs to be performed and a second that captures the importance of the element to the occupation. Here, we use the level of each element taken from O\*Net version 24.2 (National Center for O\*NET Development, 2020). For the remainder of this analysis, we synonymously refer to elements as skills.

The second dataset is the Bureau of Labor Statistic’s Occupational Employment Statistics (OES) dataset. OES data are published annually and provide estimates of employment and wages for occupations as defined by the Standard Occupation Classifications system. The May 2018 data are used for this study (US Bureau of Labor Statistics, 2019).

Our units of analysis are U.S. Metropolitan Statistical Areas (MSA). MSAs are defined as regional economic units, based primarily on commuting patterns. While MSAs are the primary regions used, OES data are reported for an alternate geographic unit in the six states comprising New England, called New England City and Town Areas (NECTAs). These regions are used for consistency with OES data and does not impact our analysis as the OES geographic units are the only geographic data used here.

### Method

As a broad overview, the proposed methodology has three basic steps. First, create a skills network that is composed of skills as nodes and co-occurrence values derived from skills co-occurrence at the regional level as edges. Second, identify the origin nodes and the destination nodes. Finally, calculate the transition potential between the origin nodes and each destination node before accumulating transition potentials to produce an aggregate statistic measuring the skills proximity of two occupations.

#### Skills Co-Occurrence

To begin we create a matrix of occupational skills at the regional level. Following the notation of Shutters & Waters (2020), the aggregate level of skill  $i$  for a given MSA is defined as:

$$s_{i,m} = \sum_o l_{i,o} w_{o,m} \quad (1)$$

where  $l_{i,o}$  is the level of skill  $i$  characteristic of occupation  $o$  and  $w_{o,m}$  is the number of workers employed in occupation  $o$  in MSA  $m$ .

MSA skills aggregates are then compared to the total level of skills in the system using location quotients ( $LQ$ ), which are widely used. Formally,

$$LQ_{i,m} = \frac{(s_{i,m}/\sum_i s_{i,m})}{(\sum_m s_{i,m}/\sum_m \sum_i s_{i,m})}. \quad (2)$$

The location quotient matrix resulting from equation 2 is then analyzed with the co-occurrence measure, more commonly used in ecology. Here, co-occurrence compares how often two skills appear together with how often they would appear together if they were independent. Two skills that co-occur more often than would be anticipated at random are interpreted to indicate a possible interdependence between the skills. Formally,

$$x_{i,j} = \frac{P[LQ_{i,m} > 1, LQ_{j,m} > 1]}{P[LQ_{i,m'} > 1]P[LQ_{j,m''} > 1]} - 1, \quad (3)$$

where  $x$  is termed the interdependence between  $i$  and  $j$ . As before,  $m$ ,  $m'$  and  $m''$  are randomly selected MSAs. The interdependence measure is the conditional probability that  $i$  and  $j$  are specialized in the same city over the marginal probability of each appearing in a city at random. We then subtract 1 so that two skills appearing together less frequently than expected by chance have a negative interdependence and those appearing together more frequently have positive interdependence.

The interdependence values calculated in equation 4 results in a symmetric matrix. Matrices can be recast as networks (Jackson, 2008). We recast this matrix as a network in which we identify the location of occupations to determine the proximity of all occupations to all other occupations.

#### Skills Approximate Occupations

With the calculated interdependence values of each skill at the regional level, we now turn our attention to a policy application. The policy application pursued here is to use the skills network to help with occupational transitions. Before defining the method by which we use to measure the proximity of two occupations, as well as skills that may cause issues, we provide some broader discussion about when such a tool may be used.

To start, imagine that policy makers want to transition their workforce. Whether the policy makers have a transition in mind or not, the transition may begin by identifying origin and destination occupations. The origin occupation is the occupation that policy makers would like to move workers out of, and the destination occupation is the occupation that policy makers would like to

move workers into. Policy makers are likely to want to identify the workers that will be targeted to help fill the gaps in the destination occupations with workers from the origin occupations.

A policy maker may identify an origin occupation to move workers out of for a number of reasons. For example, a policy maker may be aware of a surplus of workers resulting from a large layoff from a plant or from a shock to the economy that disrupted a sector. Another possibility is that a surplus of workers builds up slowly as the result of regional underperformance in a specific sector. Such occupations could be identified using traditional economic metrics such as shift-share analysis. Or, it may be the case that the policy maker has identified a destination occupation, perhaps that is growing quickly in the region, and is simply interested in the origin occupations that would need the least training to successfully perform the destination occupation.

Similarly, a policymaker may identify an origin occupation for a variety of reasons. For example, a local industry may be growing so fast that firms in the region can't hire qualified labor from within the region. Or, perhaps the policy maker is looking to diversify or specialize for a particular reason. In this case, the policy maker would have identified a destination occupation for some idiosyncratic reason

In general, the local context will be crucial to informing the process of choosing origin and destination workers. While the above examples are provided for illustrative purposes, the list is clearly not exhaustive.

Once origin occupations and destination occupations are chosen, we modify use two metrics to determine skills proximity of the origin and destination occupations. The first metric measures the transition potential to any given skill in the network developed by Muneeppeerakul et al (2013). The second metric aggregates transition potential for all skills specialized by the origin occupation that are not specialized by the destination occupation developed by Shutters et al. (2015).

We start with the transition potential. Here transition potential measures the proximity of specialized skills (SOS) in the origin occupation to a single skill specialized by the destination occupation that is not specialized in the origin occupation. Using the notation from Shutters et al (2015), the transition probability is defined as

$$V_i(SOS) = 1 - \prod_{j \in SOS} (1 - c(\zeta_{ij}P[LQ_i > 1])) \quad (4)$$

where  $j$  is a skill that is specialized in the destination occupation and  $SOS$  are the specialized skills of the origin occupation not specialized in the destination occupation. As in Muneeppeerakul (2013),  $\zeta_{ij}$  is the interdependence determined using co-occurrence,  $LQ_i$  is the single probability that a skill is likely to be specialized in any MSA at random, and  $c$  is a scaling parameter. However, while Muneeppeerakul et al (2013) locate MSAs within an occupation network, we locate occupations within a skills network.

It is important to note that a skills network may be constructed using two different co-occurrence patterns: how skills co-occur across occupations (Alabdulkareem et al, 2018) or how skills co-occur across MSAs (Shutters and Waters, 2020). In this study we use the latter method for two reasons. First, relationships between skills have been found to be robust across aggregation levels, with a dual lobed skills network emerging under both methodologies (Alabdulkareem et al, 2018; Shutters and Waters, 2020). Second, we expect the MSA-based skills network to uncover unexpected interlinkages between skills. That is, there are likely linkages between skills that are not captured within a single occupation but are captured at the more aggregate MSA level. We liken these inter-occupation skills linkages captured at the MSA level to inter-industry spillovers, commonly referred to as Jacobian externalities (Jacobs, 1969).

Given the alteration of scale, one modification to the original metric is required. The modification here is with regard to how origin and destination skills within occupations are selected. In Shutters et al (2015), the authors examine the possibility of transitioning to a “creative economy”. To do this, the authors create an interdependence matrix using occupations. In this process, the authors identify location quotients of occupations greater than one as the “origin” and “destination” occupations. Because the current work locates an occupation in a skills network, we need an alternate way to define the set of skills of the origin occupation to compare to the destination’s skills. Here we use the location quotient of skills within occupations to select origin and destination skills. This step closely follows the work of Alabdulkareem et al (2018). A matrix of the occupations by elements is constructed. Elements are weighted by the national employment levels in each occupation.

$$LQ_{i,o} = \frac{(w_o s_{i,o} / \sum_i w_o s_{i,o})}{(\sum_o w_o s_{i,o} / \sum_o \sum_i w_o s_{i,o})}. \quad (5)$$

The skills  $LQ$  of an occupation is the skills share of employment weighted skills for the occupation of interest as a ratio of the skills share of employment weighted skills for all occupations. A skill  $LQ$  greater than 1 implies that the skill is specialized in the occupation compared with all occupations and is thus a part of the origin or destination skill set used to calculate the transition potential.

The second metric from Shutters et al. (2015) used here is a version of their Creative Jobs Index. However, we re-term the metric the “skills proximity” of two occupations for generality. The skills proximity metric measures the transition potential of one occupation to another by averaging the transition potential of all the skills associated with the destination occupation from the origin occupation. Formally,

$$C_j^{(occ)} = \frac{1}{N_c} \sum_{i \in SOS_D} V_i(SOS_0^{(occ)})^{1-\delta_i} \quad (6)$$

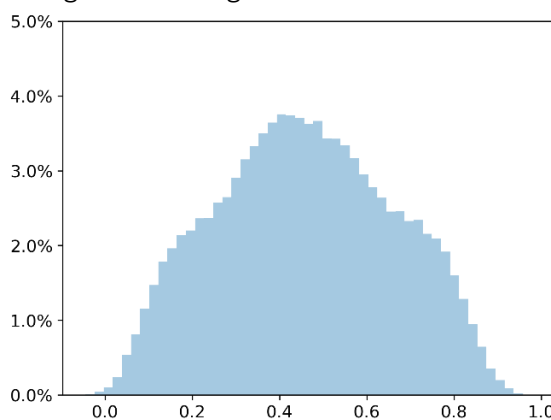
where  $SOS_D$  is the set of skills that defines the destination occupation  $j$ . The parameter  $\delta$  takes on a binary value; it is 0 when the origin occupation does not specialize in the destination skill and 1 when the origin occupation specializes in the destination skill. See Shutters et al (2015) for a decomposition of this function.

As final notes, for all  $V$  and  $C$  presented here, the same scaling parameter as Muneeppeerakul et al. (2013) is used,  $c = 0.002$ . Also, it should be noted that the proximity of two occupations is not symmetric. Given that the single marginal probabilities for the destination occupations are used, the resulting  $V$  and  $C$  measures are unequal between the same two occupations. The skills proximities of all occupation permutations are provided in Table 1 and Figure 1.

Table 1. Summary Statistics of Skill Proximities

Summary Stats	
Count	566,256
Mean	0.460
Std. Dev.	0.202
Min.	-0.045
25th Percentile	0.308
Median	0.456
75th Percentile	0.613
Max.	1.000

Figure 1. Histogram of Skill Proximities



We note at least two potential uses of this network technique in policy applications. First, the skills proximity measure can be used to select between two or more competing origin or destination occupations. For example, policy makers deciding between two or more destination occupations would choose the destination occupation that has a closer skills proximity, as it would provide the worker the shortest retraining path to a new position. This could also be the case for competing origin occupations from which to draw labor from. For a full example, we turn to a case study of Northern Virginia.

Second, once occupations have been selected, the transition potential can be used to identify destination skills that may be problematic in the transition process. Policy makers examining origin and destination occupations could identify which skills are the most distant from the destination occupation and flag these as skills requiring additional training to increase the likelihood of successful worker transitions to a new position.

### **Case Study: Northern Virginia**

We use occupation switching from leisure and hospitality in Northern Virginia as a case study to illustrate the proposed methodology. Two simultaneous events make this case study an illustrative example, the location of the second headquarters of Amazon and the Covid-19 pandemic.

First, Amazon recently announced that Northern Virginia would be the location of its second headquarters. While the company already has a significant footprint in the region, most notably with its Amazon Web Services unit, the opening of its second headquarters promises to bring more

than 25,000 well-paying technical and administration jobs. Technology workers were already scarce before the announcement, but since Amazon has begun to hire for computer related occupations, the availability of qualified labor has become scarcer.

Second, the covid-19 pandemic led to a rapid and dramatic decline in the region's leisure and hospitality employment. The Washington, D.C. region is a well-known tourist destination with numerous attractions and museums stemming from the presence of the federal government. Directly following the onset of the pandemic, employment in the region's leisure and hospitality sector declined by more than 155,000 workers, a 46.2 percent decline from April 2019 to April 2020. While the sector is recovering the pace of recovery has slowed as the pandemic has worn on. From September 2019 to September 2020, employment in the region's leisure and hospitality sector was down approximately 87,000 workers, a 25.9 percent year-over-year decline.

This local context provides the backdrop to identify the region's strengths and weaknesses. In 2020, the regional strength is a glut of workers stemming from mass layoffs from the covid-19 pandemic. It should be stressed that while this is identified as a strength, the enormous toll that these layoffs have taken is not underestimated. In this scenario, the dearth of technology workers is the region's weakness. That is, the region cannot find enough qualified workers for computer-related occupations. It should also be noted that the strength of the industry in the region here is noted as a weakness, given that the region is unable to produce enough workers.

For the case study we examine the potential of retraining workers from an occupation with high unemployment to occupations with high demand. We use waiters and waitresses, SOC Code 35-3031 as the origin occupation, and computer user support specialists, SOC Code 15-1151, and computer network support specialists, SOC Code 15-1152 as the destination occupations. We estimate the transition potential of waiters and waitresses to both destinations, comparing their proximities as a means of informing a potential policy decision.

As discussed, the first potential policy use is to examine two or more destination occupations. In the Northern Virginia case study, there are two destination occupations. The skills proximity of waiters and waitress to computer support specialists is 0.360. In comparison, the skills proximity index between waiters and waitresses and computer network support specialists is 0.241. Using the skills proximity index suggests that, between the two destination occupations sought, worker retraining programs attempting to fill the gap should choose computer user support specialists as the destination occupation for waiters and waitresses.

It is important to note that the skills proximity of both destination occupations to waiters and waitresses are more distant than the mean and the median. This suggests that the transition from waiters and waitresses, to either computer user support specialists or computer network support specialists, may be more difficult than the average occupation transition. The five closest occupations, along with the mean salaries and LQ's in the Washington, DC MSA for 2018 (which encompasses Northern Virginia) are provided for context.



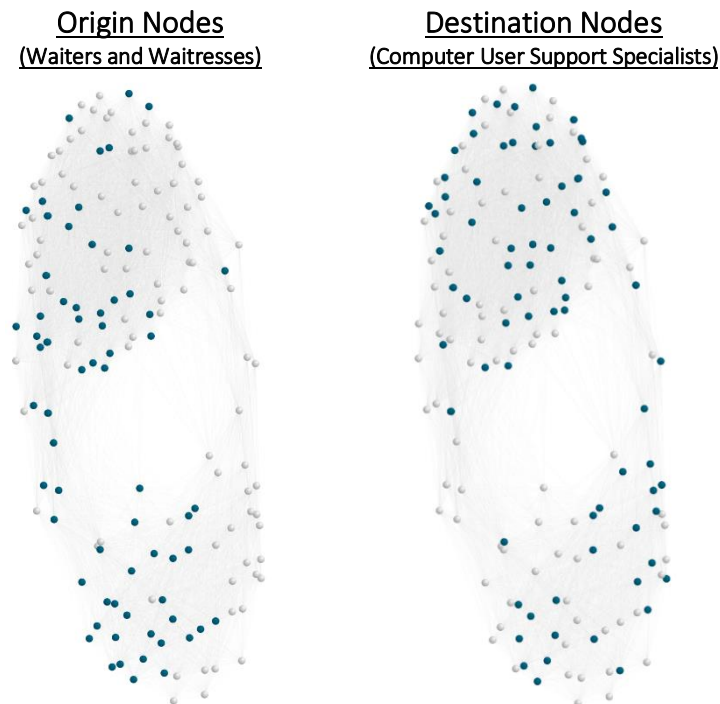
Table 2. Occupations Most Proximate to Waiters and Waitresses – Annual Salary and LQ in the DC MSA

Destination Occupation (SOC)	Skills Proximity	Mean Annual Salary*	DC-MSA LQ*
Dining Room and Cafeteria Attendants and Bartender Helpers (35-9011)	0.675	\$28,410	1.25
Orderlies (31-1015)	0.671	\$30,080	0.72
Ushers, Lobby Attendants, and Ticket Takers (39-3031)	0.663	\$25,000	0.85
Food Servers, Nonrestaurant (35-3041)	0.654	\$27,880	0.88
Crossing Guards (33-9091)	0.640	\$31,610	0.87

\*2018 OES MSA

The second potential policy use of this tool is to identify skills in target occupations that may be problematic and thus require additional training. To find potentially problematic skills, we calculate the transition potentials for the specialized skills of waiters and waitresses as well as computer user support specialists. For illustration purposes, the specialty skills of the selected occupations are highlighted in the networks provided in Figure 2.

Figure 2. Occupational Positions in Skills Network



For policy purposes, the top and bottom transition potentials for each element needed to successfully be a computer user support specialist are provided in table 2. The transition potential measures the ease at which a waiter or waitress, given their skill set, could perform this skill. Given

this, skills that may be problematic are “mechanical” and “troubleshooting” skills, which have low V scores. These skills would likely require specific attention in a worker retraining program. In comparison, waiters and waitresses would be well positioned for the skills “oral comprehension” and “oral expression” required by computer support specialists. These skills represent strengths that waiters and waitresses already have that could be leveraged in a new position as a computer support specialist.

Table 3. Transition Potentials from Waiters and Waitresses to Computer User Support Specialists

Rank	Element ID	Element Name	Transition Potentials
1	1.A.1.a.1	Oral Comprehension	0.0153
2	1.A.1.a.3	Oral Expression	0.0153
3	2.A.1.d	Speaking	0.0147
4	2.A.2.c	Learning Strategies	0.0136
5	2.B.1.e	Instructing	0.0136
...	...	...	...
44	2.B.3.j	Equipment Maintenance	-0.0171
45	2.B.3.c	Equipment Selection	-0.0173
46	2.B.3.l	Repairing	-0.0176
47	2.B.3.k	Troubleshooting	-0.0177
48	2.C.3.e	Mechanical	-0.0177

### **Conclusions**

This paper has developed a methodology for identifying the skills proximity of two occupations. The analysis uses co-occurrence of skills at the MSA level to identify interdependence of skills and builds a network from these skills. The analysis then provides a method to locate occupations within the skills network and measure the transition potential and skills proximity of the two occupations. This methodology was developed with the goal of building a useful policy tool. First, the proposed tool works towards helping to select between competing occupations that may be considered in a worker-retraining program. Second, the proposed tool helps to identify skills in the origin and destination occupations that may help or hinder the occupational transition. Skills that may hinder the occupational transition may require additional consideration in the worker retraining work, while skills that may help can be used as confidence boosters.

After providing the framework, a case study for Northern Virginia is provided. The Northern Virginia region of the Washington D.C., MSA had two simultaneous events unfolds that led to an interesting policy application. First, the growth of Amazon’s second headquarters resulted in a dearth of people qualified for computer-oriented occupations. Second, the covid-19 pandemic resulted in the unemployment of a large portion of the leisure and hospitality sector. Applying the policy tool developed to this situation suggested that the region would be better off retraining waiters and waitresses to computer user support specialists instead of computer network support specialists. Furthermore, the tool identified several skills required to be a successful computer

user support specialist that are distant from the specialty skill-sets of waiters and waitresses, and thus may require additional training.

The demonstration of the tool suggests that abstract concepts from Complexity Theory are entirely applicable to real-world issues. While additional testing is needed, the policy tool developed would fit nicely into the tool-box of policy makers looking for insights into how to best transform their regional economies.

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