Knowledge Transfer and Refinements to Connection-Based Employee Work Experience Measures

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Abstract

Recent research provides a completely new method of tracking knowledge transfer and measuring employee experience using co-worker collaboration data. This process could use data collected through employee use of organizational social tools, from email to Twitter, but could also be fed data collected by accounting or other systems that track employee work on organizational projects. The process can also be extended to measure the diversity level of an employee or to tie employees' past workplace connections to their future performance.

Measuring human experience in an organizational setting has, for the most part, been centered on time-based values such as "number of years worked." However, the advent of social tools and advances in modern accounting systems and both of their abilities to collect incredibly refined data now allow organizations to move to a more highly sophisticated set of processes for tracking knowledge transfer and using it to calculate human work experience.

1. Introduction

We embark on this research program with the hope that it will contribute to organizational theory that is focused on the topics of work experience and subsequently, knowledge transfer. Prior researchers [5] have investigated the concept of work experience from various perspectives resulting in several dimensions by which it can be measured; most agree on a definition of the term to approximate "knowledge gained that improves ones performance or allows one to complete a task." However, it is most frequently operationalized in research studies as some basic form or measure of time on the job. Those foundational studies provided the components by which work experience can be measured and therefore compared both in industry and across academic researchers. One of the next major advances in research was to create a framework by which prior research could be analyzed (Quińones, et al., [11]).

Specifically, Ford, et al. [5] proposed three primary dimensions by which work experience can be measured: 1) time, 2) amount/breadth, and 3) type. Using these three work experience dimensions, Quińones, et al., [11] then created a foundational framework contrasting these three work experience dimensions with the "level of specificity" of the work experience, meaning the level at which the work experience was obtained. They proposed, for their framework, three levels of specificity, namely: 1) an individual task, 2) a particular job, or 3) an organization. The resulting framework was a 3x3 grid into which one could place specific work experience research results and subsequently measure and contrast those results.

However, based on our own research, we argue that there is a completely different process that can gauge work experience that does not fit into the described framework, and that is "connections made to co-workers." Both our empirical research and industry partners suggest that this new method may yield very different insights into the acquisition and distribution of knowledge in an organization. Our research is described in some detail below; our industry partners want to mine social connection data they already collect to better understand where knowledge is created and how it moves through their organizations. They also wish to move beyond the basic measures of work experience described above, to incorporate measures such as "diversity experience" (i.e., how much project experience an employee has working with others of differing ethnic backgrounds) that cannot be easily calculated with current measures of work experience.

The paper follows with sections describing: the background of our project, Social Network Analysis and its relationship to organizational theory and sports, our research Methodology, our Results, a Discussion, and Conclusions.

2. Background

The processes described herein are refinements to a fundamentally new way to track knowledge transfer and therefore measure work experience [2] that is not based on the standard of "how many time (or output) units an employee has completed for the organization." These

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types of time-based or output-based measurements of employee experience have been used for many years as they are quite easy to calculate as well as to compare workers across an organization. In fact, many employee benefits such as raises and bonuses are based on some form of experience, suggesting that organizations view employee experience as value that is useful to measure and track.

However, these past time-based and output-based calculations of experience are quite simplistic in that they apply a very crude measuring stick to all employees and in the same way regardless of how long they have worked in the organization or what they did in the time they worked there. Exposing this flaw, in their seminal paper relating work experience to job performance, Quińones et al. [11] state "As past research suggests, time on the job is an imperfect measure of what an individual actually does on the job." They also found, in their meta-analysis of 22 prior research studies focused on the relationship between work experience and job performance, that "most studies (79.5%) employed a time-based measure of experience." Ford et al. [5] and Schmitt and Cohen [13] also found that workers with the same amount of time-based job experience could have very different results in the number and types of tasks they were able perform.

We therefore propose modifications to a new measure of employee work experience because of these shortcomings in current time-based or task-based calculations. That new measure of an employee's work experience offered by Beckman [2] uses task-related connections to other co-workers that is stored in, among other places, data collected by systems that track collaborative employee work on projects. He proposed calculating an employee's work experience as the sum of all of the connections that the employee has made to all other co-workers in the organization when working jointly on an organizational task.

The primary goal of the research described herein is to refine the basic concept of this recently-proposed connection-based experience measure to more precisely describe employee experience by incorporating additional data about the co-workers to which an employee has connected. Specifically, we believe that it is more valuable to calculate connection-based data for links only to **unique** other co-workers than to calculate experience based on links to all other co-workers. Furthermore, we believe it is of even greater value to calculate connection-based experience for links made only to **experienced** other co-workers. We explain our reasoning immediately below.

The premise behind the value of connection-based experience is that an employee will improve their performance by working on an organizational task with other co-workers because the employee will obtain task-based knowledge from those other co-workers. However, making ever more connections to the same co-worker will eventually lead to no added knowledge transfer (and hence no additional improvement in the employee's future performance) because the employee will have learned all they can from that co-worker. It is therefore of greater value to make connections to a larger number of different co-workers than to make the same total number of connections to a single co-worker. That is, the more other co-workers an employee works with, the higher is the probability that they will have a chance to work with someone who has knowledge they do not yet have and can then acquire. Furthermore, an employee is less likely to gain new knowledge from a co-worker who has little or no experience working on organizational tasks because that co-worker will be less likely to have knowledge they can transfer to the employee. Therefore, we propose a further refinement to calculating connection-based experience that counts only links made to "experienced" co-workers, where "experienced" could be operationalized as almost any selected measure of employee experience (time-based, output-based, or connection-based).

Finally, we propose also to use sources of connection-based experience data stored in any or all social media tools employed by the organization. This is so because any tool that captures metadata about the connection made between two or more workers about an organizational task will contain the underlying data necessary to apply our refined approaches for measuring connection-based experience.

Our processes can also be used to compare workers across the organization along dimensions other than task-based performance, and has the added advantage that it can incorporate data from other organizational tools, such as Human Resources or Project Management information systems. For example, if the organization maintains data about its workers ethnicity, our refinements to connection-based experience calculations could be used to determine how much experience (i.e., how many connections) each employee has working with co-workers with different ethnic backgrounds. This concept is increasingly important, at least in the high technology industry, as organizations are finding it difficult to retain employees with ethnically diverse backgrounds [3]. Simple time-based measures of experience cannot support the detail necessary to compute a value such as "ethnic diversity experience."

The remainder of this document describes prior research related to our analytical methodology and our refinements to describing and measuring "connection-based" experience. The general procedure for our process entails collecting data from any information system that gathers inputs about individuals who either worked together on an organizational task or communicated together about a work-related task. Those data are then manipulated into a form that can be analyzed by our algorithms to yield refined measures of connection-based experience or other aspects of individual (or group) performance that can be traced back to work-related connections to other employees.

Our approaches can even be used to predict the future performance of individuals or groups as they are based on the premise that an employee's knowledge will improve as they work on organizational tasks with co-workers who have knowledge they do not. After working with co-workers who have other knowledge, the employee will move on to future tasks with more knowledge and their performance on those future tasks be improved by applying what they recently learned.

We are now employing our process in an industry setting (a large West Coast engineering firm), but herein we present results from our completed analysis of a large publically-available Major League Baseball data source [12]. We describe how existing analytical methodologies work for calculating connection-based experience of baseball players and then refine that original process in two different ways.

3. Social Network Analysis

The area of study called Social Network Analysis (SNA) is a branch of the subject of mathematics called Graph Theory. This branch of mathematics investigates structures and processes in situations that can represented as a set of points (nodes) connected by links (edges). The set of nodes and edges taken together are called a graph or network, and numerous characteristics of a network can be viewed or calculated. For example, a network is called "directed" if at least one of the edges in it can be perceived as "from" one node "to" another node. If no edge has such a characteristic, the network is called "undirected." Edges can also be viewed as having a numeric value called a "strength" or "weight." One way to assign a weight to an edge that connects two nodes is to create a function based on the number of connections that have been made between those two nodes. For example, two nodes that have been connected only one time could be assigned a weight of "1" while two nodes that have been connected 5 times could be assigned a weight of "5" (or the result of a mathematical function other than addition).

Situations that can be described by graph theory can also be viewed according to other measures calculated for the network's nodes, edges, and even the network as a whole. Of primary interest to many graph theorists are measures that describe the "significance" of a node in the network. Values of significance are called "centrality" measures, and there are four generally-accepted such values: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Each are calculated in a slightly different way, but all are fairly highly correlated [15]. Similarly to calculating the significance of a node in a network, it is also possible to calculate the significance of an edge in a network. For example, an edge that is the only connection between two sub-networks in a larger network is highly significant for the passage of information or other resources from one of the sub-networks to the other. Finally, it is also possible to calculate measures associated with the network as a whole. One of the most basic of these network measures is called "network density." This value is calculated as the sum of the extant singular edges in a network divided by the total number of possible singular edges in the network and therefore indicates the percent of the network nodes that are connected.

3.1. Organizational Theory and Social Network Analysis

One of the initial associations of social network analysis to organizational theory was made by Tichy et al. [14] in which the authors describe the theories and ideas of graph theory as it applies to organizations comprised of human beings. Their fundamental argument is that the application of graph theory can be a useful process by which to understand over time, both fixed and changing aspects of the organization and entities within it. They describe the histories of both graph theory and organizational theory and how they intertwine, then explain in greater specificity how to describe organizational social networks, how the organization might collect data to better understand those social networks, and the rudiments of how to analyze social network data. They ultimately compare the social networks of two different organizations to demonstrate the additional understanding that social network analysis can provide to organizational theory.

Gloor and Colladon [6] also researched SNA and organizational theory by using gaming to measure three different dimensions of social interaction (network structure, changes in network structure over time, and degree of sharing). They viewed these three dimensions as describing structure, time, and content in an organization. Their goal was to investigate "consciousness" of groups that exist within an organization by deriving six "signals" that were able to predict organizational creativity and successful performance. Those signals were: 1) group betweenness centrality, 2) variance in contribution, 3) rotating leadership, 4) response speed, 5) "honest sentiment", and 6) use of innovative language. The authors quantified each of those signals and showed that business units were more successful if they were more emotional, responsive, and less hierarchical.

Fang et al. [4] completed a meta-analysis of 138 prior research projects to investigate the relationship between individual personality and indegree centrality (the number of network edges that are directed "to" a node, a measure of other node's perception of that node's "importance" or "relevance") and "brokerage" (a measure indicating a node's position as an intermediary between two or more other subnetworks). Prior research had shown that both indegree centrality and brokerage positively affect the node's performance and success, but these researchers wanted to determine if there was also a mediating effect of self-monitoring on performance. "Self-monitoring" refers to the ability of a person to comprehend and incorporate into their performance the recognition of their own communications with others. Their results showed that brokerage was less strongly related to performance and success than was indegree. Their results also showed that the Big Five personality dimensions (extraversion, conscientiousness, openness to experience, agreeableness, and neuroticism) were better predictors for high task performance than was network position.

In support of the concept that knowledge transfer occurs through connections between co-workers, Jackson and Bruegmann [8] focused specifically on measuring individual performance changes due to co-worker connectivity. They found that a classroom teacher's performance improved when a teacher worked with a higher-performing peer. Their definition of "worked with" was operationalized as "teaching the same grade at the same school" which indicates that even very slight connections to co-workers can impact task performance. The performance improvements they found were 0.03-0.04 standard deviations in self-improvement for every 1.00 standard deviation better in the higher-performing peer.

Also showing the existence of knowledge transfer between connected employees, Papay et al. [9] studied on-the-job performance improvement in K-12 teachers. They wished to measure performance changes when "low-performing" teachers were paired with "high-performing" teachers. They found that making such pairings led to teaching performance improvements as measured by students' test scores. In fact, students in their treatment group of paired teachers increased their test scores by the equivalent of being assigned to a median teacher instead of being assigned to a bottom quartile teacher. This research study shows fairly conclusively that co-worker connections can lead to statistically measureable positive task performance changes that have occurred purely because of co-worker connections.

These prior research studies indicate that there is much interest in understanding the impact that organizational co-worker networks have on knowledge transfer at both the individual and group levels. They also show that recent research indicates the value of measuring connections between co-workers as it can directly lead to knowledge transfer and subsequent performance improvement. In our own research, we hope to show that refining network measurements such as unique connections to co-workers and connections to experienced co-workers can advance the study of connection-based knowledge transfer.

3.2. Organized Sports and Social Network Analysis

Social network research focused on team sports is not new, and in fact, has been applied in several sports. Piette et al. [10] used graph theory to investigate players over four seasons of U. S. National Basketball Association (NBA) games. The authors built a network of weighted edges that connected players (as nodes) when five players took to the court together. They used that data to calculate the "contribution" of each player through their eigenvector centrality values and then determined whether each player over-performed or under-performed on offense and defense.

Grund [7] applied graph theory to the sport of professional soccer (760 English Premier League games) wherein he examined just under 300,000 passes between players. Similar to the other researchers mentioned here, he viewed players as nodes and passes from one player to another as edges that connected the two players involved in each specific pass. His goal was to determine if more passing between more players (i.e., a higher number of singular edges) correlated to better team performance, operationalized as "goals scored." His analysis confirmed that teams with higher rates of passing scored more goals but that teams whose passing was more centralized (i.e., the passes included a smaller number of players) scored fewer goals. This result supports our premise that more links to unique others is of greater value than many links to the same individuals.

Employing social network analysis to U.S. professional baseball, Beckman and Chi [1] mapped Major League Baseball team rosters as players (nodes) connected to each other (edges) by their appearance together on the official roster of some MLB team during regular season games. They then calculated centrality measures of each player and compared them to each player's offensive performance (batting average, home runs, runs batted in, and slugging percentage) and defensive performance (fielding percentage). Their results showed that there were positive correlations between the centrality measures and offensive performance but not between the centrality measures and defensive performance. They attributed this result to the ability of players to improve their offensive performance from any player they might connect with but only to improve their defensive performance by connecting with players who played the same defensive fielding position, constraining the setting that allowed players to transfer knowledge to other players.

Finally, Beckman [2] extended his prior MLB research to propose “connection-based experience” as an alternative to “time-based experience”. In this project, he suggests that time-based experience measures are flawed because they are both linear and symmetric. He defined “linear” as meaning that each added time period (e.g., one year) is considered to add the same amount of experience value to the employee as every previous time period, regardless of what the employee actually did in that most recent time period. He defined “symmetric” as meaning that each time period increased the experience value of every employee by the exact same amount, even though each employee could gain largely differing levels of experience during that time period. He then compared past time-based experience calculations to his connection-based experience calculations and showed that, while the most experienced MLB players (as measured with time-based processes) are spread throughout the history of baseball, the top 10 most experienced MLB players (as measured with connection-based processes) played relatively recently. It is on Beckman’s [2] foundation that we build our refinements to connection-based measures of experience.

3.3. Connection-Based Employee Experience

Our goal with this research project is to propose, support, and calculate refinements to measures of connection-based employee experience that in turn are based on connections workers make while collaboratively completing tasks for their organization (or on co-worker connections made through organization-based social media tools). The premise, as mentioned above, is that employees will gain performance-improving knowledge when they complete an organizational task with other employees and their increased knowledge will ultimately result in improved future task performance. To that end, we have used a very large and comprehensive online and publically-available dataset [12] that contains employee connection data for U.S. Major League Baseball (MLB). The refined experience measures we propose and calculate, while derived from professional sports data, can be applied directly to other domains. As shown in Papay, et al. [9], applying our underlying premise that workers coming together to complete an organizational task will transfer knowledge between each other and hence will learn from each other in domains outside of professional sports.

Our application of graph theory views individual players as nodes in the large network of all professional athletes ever to play MLB. Edges in the network were created when any two MLB players took the field together as offensive starter during any regular season game since 1914. Since that year there have been 11,584 MLB players who have started a regular season game, resulting in a total of 25,102,080 player dyads (i.e., network edges). We created an initial table of all player dyads (player1, player2, GameDate, GameNumber) with a database query that retrieved these field values from each of the thousands of MLB games played and that are available online [12].

As an example, one of these 25 million or so player dyads was created when the MLB player Harmon Killebrew first took the field as a starter with the MLB player Rod Carew (both taking the field as starters for the Minnesota Twins on April 11, 1967). This event occurred during Mr. Carew’s first season in MLB, so using the standard time-based metric of experience, he would have been described as having “zero years of experience”. The event occurred at the start of Mr. Killebrew’s 14th season of MLB so he would have been considered as having “13 years of experience.” Using a connection-based measure of experience, on this date, Mr. Carew had taken the field with (i.e., “connected with”) a total of 0 other MLB teammates (this was his very first MLB game as a starter) while Mr. Killebrew had made 9,536 total connections to other MLB players.

In our analysis of player/employee connections, we did not count “self-links”; such links are spurious and indicate that the individual connected with themselves. We also did not count “reverse links” wherein, as in the Killebrew:Carew example above, the April 11, 1967 event that brought both players to the field at the same time, each would be credited with two connections (one each from the link originating from themselves and from the link terminating to themselves). We counted the event on that date as only one link for each player.

With this background about graph theory, social network analysis, organizations, and sports, plus our dataset, we created the comprehensive network of all MLB players who took the field together as starters in any regular-season game since 1914. The set of 25M or so player dyads then supported our calculations of refined connection-based experience measures for any MLB player for any point in time in their MLB career. We can then compare Beckman’s original [2] “all-inclusive” connection-based experience values with our refined connection-based experience values.

4. Methodology

The fundamental procedure for calculating our modified measures of connection-based employee experience was to first gather historic game-based data from all MLB games played since 1914 and convert those years of single-game records into database tables of players and games. We then ran a set of database queries to calculate our refined measures of connection-based experience values which we could then compare to Beckman's original [2] connection-based experience values. As mentioned above, we first created a relational database table containing all (player1, player2) dyads for all MLB games back to 1914. This "PlayedWithLinks" table was the foundation for the rest of our database queries.

4.1. Refinement 1: Connections Only to Unique Others

The basic method of calculating connection-based experience as proposed by Beckman [2] involves summing all instances of one individual in the organization "connecting with" another individual in the organization. He defined a connection in his MLB network as being created "when two players appear together on the same team roster **in the same year**". With our larger dataset of starting players for every regular season MLB game (not just seasonal team rosters) since 1914 and our advanced database manipulations, we were able to define a connection far more precisely: when two players started together on the same **day and game**.

Given this background, our first refinement to the basic calculation of connection-based experience is to count only unique links to other players rather than multiple links to other players. We believe this is a better measurement of connection-based experience because it discounts the possibly very large number of connections made to any other single individual. As argued above, a smaller number of links to each one of a larger number of different individuals will expose an employee to more transferrable knowledge than would a very large number of links to a small number of other individuals. One could further refine our suggestion by counting only links to another individual when the link total between the two exceeded some threshold. That threshold would likely vary by industry, organization, and task, but would generally remove links made to another individual when the two worked together in so few instances that there were not enough connections for useful knowledge transfer to take place.

Our database queries to obtain this result required, for every player, first extracting from the 25M player dyads, in sorted order by GameDate, all GameDates on which a player took the field with another player, and assigned a counter to each of these new records. The next query in this process extracted only the lowest number counter value row for each (player1, player2) dyad. The next query created a table from the previous query's table that summed, for each player, the total number of new players they played with on that GameDate. (We then ran a few more queries to fill in "SumOfNewPlayersPlayedWith" values for all GameDates on which a player did not play. We did this so that we could quickly determine, for ANY GameDate, not just GameDates on which a player played, the sum of unique players any player had played with up to that point in time.)

4.2. Refinement 2: Connections Only to Experienced Others

Our second refinement to Beckman's [2] basic connection-based experience calculation addresses the concept that one can only learn from another when that other has enough knowledge or experience to actually transfer. That is, a connection made to someone who has no knowledge about or experience completing the organizational task has no task-related value to pass on to a co-worker. The difficulty here is in operationalizing the notion of "knowledge" or "experience." Due to the absence in our dataset of data related to baseball player "knowledge", we chose to use our own first refinement to the connection-based measure of "experience": connections to unique others. We chose this measure of experience because, in order to play MLB long enough to generate many connections to many unique other teammates, a player must have a fairly beneficial combination of knowledge and skills (and perhaps even luck!). In other words, *ceteris paribus*, players without adequate knowledge or skill would not last long enough in MLB to connect with many other players. We chose as "experienced" those players who had end-of-career totals of more than 100 connections; the choice of "100 connections" was arbitrary and chosen only to provide a value to enter into our database manipulations. Therefore, we only attributed a connection to a player if that link was to a player who ended their career with more than 100 connections to other players.

5. Results

This section describes the results obtained after applying to our dataset our refined calculation algorithms for determining connection-based experience. We begin by presenting results for our first refinement: including connections employees have made only to unique other co-workers. We then show results from applying our second refinement: including connections employees have made only to experienced other co-workers.

5.1. Results from Refinement 1: Connections Only to Unique Other Players

Table 1 below shows the top 10 MLB players (employees) who, by the end of their career, had made the most connections to unique other players, where "connection" means that the two players took the field together as starters during a regular season MLB game since 1914. Comparing this list with Beckman's [2] original "Top 10 Most Experienced MLB Players by 'Connections to Other Players' (Descending)" one will see that only the player in the top position is the same (Mr. Rickey Henderson); all other names on both lists are disjoint. This illustrates a subtle point about choices for defining "connections," at least in the domain of MLB. That is, players who appeared on the same roster during some MLB season (Beckman's [2] original definition of "connected") could and in fact, did, accrue many more connections to other players than those players who connected because they took the field together as starters in some game (our own refined definition of "connected"). This difference arises because players who are traded several times in the middle of a season will appear to be connected to teammates on every one of those teams because they appeared on the same team season roster as those teammates, but will not have truly made a connection to many of those other teammates, as they likely did not even meet many of them. Our refined measure of "connection" ensures that players are linked only when they actually have a chance to learn from each other.

Rank	Player Name	Unique Players Played With
1	Rickey Henderson	387
2	Gary Sheffield	355
3	Matt Stairs	352
4	Todd Zeile	349
5	Royce Clayton	347
6	Benito Santiago	342
7	Carlos Beltran	341
8	Andres Galarraga	331
9	Marlon Byrd	322
10	Luis Gonzalez	322

Table 1.

Top 10 Most Experienced MLB Players by "Connections to Unique Others" (Descending)

This situation would be the equivalent in a corporation to defining as "connected," all employees in the Information Systems Department if they worked for that department at any time during a particular year. Using such a measurement, two employees, one who retired in May of that year and another new college recruit who replaced the retiring employee one month later in June of that year, would be viewed as connected, but obviously no knowledge could be transferred from the former to the latter. A much better measure of a "connection" would be to create a link between two employees only when the two worked on the same project on the same exact date. While this does not guarantee that knowledge transfer took place it would at least ensure that the two employees were in the organization at the same time, were assigned to the same project, and worked on that project at the same time. (This is the process we are using to define "connected" in our industry project.)

5.2. Results from Refinement 2: Connections Only to Experienced Other Players

Table 2 below shows the top 10 MLB players who, by the end of their careers, had connected to the most other experienced other MLB players. Applying our second refinement so as to calculate connection-based experience, we only counted connections to other MLB players when those other players had themselves connected to more than 100 other players by the end of their careers.

Rank	Player Name	Experienced Players Played With
1	Dave Philley	234
2	Mickey Vernon	229
3	Rusty Staub	229
4	Rabbit Maranville	230
5	Frank Thomas	237
6	Gene Woodling	229
7	Al Simmons	237
8	Rocky Colavito	232
9	Tito Francona	231
10	Rollie Hemsley	230

Table 2.

Top 10 Most Experienced MLB Players by "Connections to Experienced Others" (Descending)

Note that we could have used some other surrogate to define "experience," such as a time-based measure like "players whose careers lasted longer than 10 years", but we wished to use our own refined measure of experience. As described above, the premise in this second refinement is that employees are more likely to learn from their co-workers when those co-workers are themselves experienced (regardless of how experience is measured).

6. Discussion

We carried out this experiment to show that, while connection-based measures of experience are useful, the currently-proposed method of counting all connections an employee makes to all other co-workers when working on an organizational task can be refined to provide more precise experience values. While our research used data from Major League Baseball, Papay et al. [9] suggest that our refinements to connection-based experience calculations apply to other situations wherein individuals come together to work on a task and knowledge can be transferred during that collaborative work. We described two refinements to the basic process of calculating connection-based experience: first, only counting connections to unique other co-workers, and second, only counting connections to co-workers who themselves have enough experience to have gained knowledge to pass on to others.

Our results show that refining the process by which one calculates connection-based experience will yield more precise values of employee experience. When counting only links to unique other employees, the list of top-10 most-experienced individuals changes drastically from that same list calculated using all links to all other employees. By further refining the connection-based experience calculation to include only links to those other employees who have a minimum threshold of experience, we find that the list of top-10 most-experienced individuals changes yet again. In both cases, refining the calculation algorithm produces measures of employee experience that incorporate factors that more directly address the value of experience gained from knowledge transfer that occurs when employees work collaboratively on organizational tasks.

Organizations should be able to perform the calculations we propose, as long as they track the date that employees' work on projects/tasks. More precise data stored about those tasks, such as how many hours per day were worked/project would enable even more precise connection-based experience results.

7. Conclusions

Past research has measured work experience using primarily time or output bases; new data collection processes, social network tools, and analysis algorithms allow network-based measures of work experience to be developed. We propose slight modifications to the current standard proposal for measuring network-based work experience and apply those modifications to a large dataset.

Our data collection and analysis show that more precise and refined measures of network-based work experience are possible. While our domain of study is a professional sport, we argue (and Papay, et al. [9], supports) that our process can be applied to any organization in which employees work together to complete organizational tasks. This collaboration will lead to knowledge transfer from employees with greater abilities to those with lesser abilities.

Our current goal is to apply our calculation algorithms to an industry setting and to that end we have begun working with a large West Coast (U. S.) engineering firm. This firm tracks the hours/day that each engineer works on their assigned projects and so can calculate which engineers have or are working collaboratively on each project. They wish to use their data and our algorithms to determine which engineers have experience working on projects with specific characteristics such as: governmental contracts, high-technology environments, large-scale endeavors, etc. They further wish to determine which engineers have work with other engineers who have worked on projects with these types of characteristics so they can create project teams in the future with an appropriate mix of engineer talent that best fit the needs of a specific project.

In any case, we believe that connection-based experience measures add a completely new dimension to the set of tools and processes currently used to evaluate employees and understand knowledge transfer in any type of organization. There are certainly more refinements that can be made to this type of process, and we hope our contribution encourages others to add their own innovations to this concept.

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