The value in the links: Networks and the evolution of organizations

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This book chapter is a short review of the Natural Science of Networks for people in management and organizational sciences.

An F-22 fighter costs around USD$150 million and weights around 20,000 kg. Per unit of weight, an F-22 costs close to USD$7,500 per kilogram or USD$3,400 a pound. Compare this to a kilogram of gold which is currently[1] priced at around USD$34,000, or a kilogram of silver which costs around USD$500. A kilogram of F-22 is expensive, yet as scrap metal, the exact same airplane will not sell for much. If I divide a lump of gold or silver into pieces, the value of each one of these pieces, compared to the whole, will be identical to the fraction that its weight, volume, or size represents relative to the whole. This is certainly not true for an F-22 fighter, since the value of a sophisticated good, such as a computer, a car or an F-22, comes from the precise way in which its parts are assembled, rather than from the materials from which they are made. In such cases we can say that the value of these goods is in the network that connects the different parts, and in the networks that were able to get these parts together. The value is *in between*, in the links, rather than in the nodes. A copper wire is more valuable when connecting two people on the phone, or a power plant with a city. A computer keyboard is more valuable when connected to a computer and this to a monitor and the right type of electricity. In all kinds of systems, the value is in the network, so if we want to understand what value is and how it

[1] February 2010

emerges, we need ways to adequately quantify the structure of the networks that products are, and the networks that make these products come true.

Firms and institutions are not only large collections of individuals. They are networks of individuals that interact sometimes through hierarchies, but mostly, despite them. The ability of a firm to be productive depends not only on the talents of its employees, but largely on the way in which they interact. The value of an organizations or institution, just like that of an F-22, lies largely in the network that sits between its members. The networks that define an organization, however, are not necessarily the organizational charts we see pinned down on an organization meeting room, but rather the networks that emerge from the informal interactions that occur between an organization's members. Two firms, with the exact same organizational chart, can have diverging fates. Can we say the same about two organizations characterized by similar informal network structures?

Some evidence supporting the hypothesis that the structure of an organization's informal social network is related to that organization's performance is exemplified, for instance, by the recent work of Kidane and Gloor (Kidane and Gloor, 2007). Kidane and Gloor looked at correlations between the creativity, performance and network structure of open source software development teams and found that more centralized groups performed better, in the sense that they were able to fix more bugs, than less centralized groups. They also found that the creativity of groups, measured as the number of new features a group came up with and implemented during a given time period, was smaller for more centralized groups. All in all, Kidane and Gloor findings suggest that trade-offs between a team's performance and creativity could be reflected in, or mediated by, the structure of the social networks they define.

Oscillations between centralized and decentralized network structures have been shown empirically to be a defining characteristic of creative teams. Waber el at (Waber et al., 2007), used sociometric badges (a technology we will discuss later) to measure the interactions between different teams in a German bank and found that the oscillation between more and less centralized network structures was characteristic of teams charged with the design of new marketing campaigns, yet it did not occur in teams that were not required to perform creative tasks.

These examples illustrate how details in the structure of an organization's informal social network are related to an organization's performance. These examples also suggest that, in order to adapt, organizations need to be flexible, as the ability of organizational networks to morph into different configurations could be the key allowing organizations to perform properly and survive over the long run. To properly adapt, however, organizations need to achieve a certain degree of self-awareness, they need to see themselves as the networks they are, a task that is extremely difficult to achieve for organizations involving more than a 30 or 40 individuals.

Manufacturing companies are well aware of the need to understand their own functioning and have learned to adapt their production processes by paying close attention to their mistakes. The key behind the success of the Toyota Production System (TPS), or Lean Production, is its ability to turn manufacturing errors into learning experiences (Spear, 2009). Companies that operate under lean production use errors to learn about, and improve, their production process. This is the direct opposite of mass production, which tries to avoid the propagation of errors in the assembly line by accumulating large inventories at several points of the manufacturing process. Mass production was successful at lowering production costs. Yet, lower costs came at a high price. The price of low costs was adaptability. Mass production traded of production costs for the ability of a company to learn about its own weaknesses. Adaptability, however, is a price that no organization can afford.

Taking the ideas of the TPS, or Lean production, to knowledge based organizations, however, may not be completely straight forward. This is because most assembly line errors have well defined physical symptoms, such as the jamming of a machine or inconsistencies in delivery times. The "cogs" of many private organizations and government institutions, however, are people, and the assembly lines running across government and service organizations are social networks. Any attempt to apply TPS to these government and service organizations, therefore, requires, in some form or another, an increase in the knowledge that an organization has regarding its own social interactions.

Network science, as a combination of sensing methods and analytical techniques, can help organizations become more self-aware. Organizations that understand their own networks will likely have a better chance adapting, as knowledge regarding their current configuration can help the design, evaluation and performance of working teams. Ultimately, this self-awareness can improve the ability of an organization to adapt and survive. But in order to look at themselves, organizations need to be able to see not only the performance of their members, but the ways in which these are connected. To understand an organization is to understand its network dynamics. Work places are intricate social and political environments that can collectively perform tasks that no single individual can. Organizations are giant super-organisms with a market-like consciousness that emerges from the interactions of several, information deprived individuals. The question is then, can network science help awaken this giant? Can network science take the consciousness of the super-organisms into the next level?

In the next couple of sections we review some of the most standard literature on Network Science created during the last decade. Both of these sections describe, in general terms, some of the measures most commonly used to quantify the structure of networks. In the sections that follow we will review literature on studies that use these measures, together with other techniques, to understand the structure and organization of real world social networks. For a more in-depth review of Network Science and its applications to other scientific fields we suggest looking at the following reviews (Borner et al., 2007, Albert and Barabasi, 2002, Newman, 2003). For more information about organization sensing technologies we suggest (Pentland, 2008) as a good starting point.

Network Structure at the turn of the Century

Networks visualizations can be both inspiring and intimidating. Good network visualizations can be extremely informative while at the same time being aesthetically appealing. Yet, for some people, the "high-tech" look of network visualizations can sometimes be intimidating. It is important to remember that networks are simply collections of nodes and links, dots and lines, and hence the most basic measures used to characterize their structure are rather simple.

We can begin characterizing the structure of a network by looking at measures that capture information about a node and their immediate neighbors (a.k.a local measures). The most basic of these measures is the **degree** of a node, which is usually denoted by k and represents the number of links that a node has (Fig 1). One can think of a node's degree as the number of friends a person has. In general, it is helpful to think about any network using social analogies. The degree of a node is the simplest of a class of measures called "centrality measures" which are measures created to quantify the importance of a node in the network. Other centrality measures are, for example, **closeness centrality** (Bavelas, 1950), which tells us what is the average distance between a given node in the network and all other nodes and **betweenness centrality** (Freeman, 1977), which tells us how many of the shortest paths connecting different pairs of nodes in the network go through a given node.

Another local measure that is widely used is a node's **clustering coefficient**, which measures the density of triangles in which a node is involved. The clustering coefficient can be thought as the probability that two friends of a node are also friends themselves (Fig 1). Mathematically, the **clustering coefficient** of a node can be defined as:

$$C=2\Delta/k(k-1) \tag{1}$$

where Δ is the number of triangles in which a node is involved and the $k(k-1)/2$ factor represents the total number of triangles that the k neighbors of that node can potentially participate in, which is equal to the combinatorial k choose 2.

There are also measures that are used to characterize the structure of a network by capturing global information, meaning that these are measures containing information that involves, either all, or at least the majority of the nodes in a network. One important measure of this kind is the **degree distribution**, which is a histogram of the degree of all the nodes in the network.

The degree distribution has been shown to be a defining characteristic of a network. In 1999 László Barabasi and Reka Albert showed that various networks were characterized by a power-law degree distribution (Barabasi and Albert, 1999) –which mathematically means that the probability that a node has k links is proportional to $k^{-\gamma}$, where γ is a constant with a value that has been empirically determined to lie in most cases in the range of $2<\gamma<3$ (Albert and

Barabasi, 2002). In more qualitative terms, a power-law degree distribution tells us that there are a few nodes in the network that have a number of connections comparable to the total number of links in the network, while most other nodes have only a small number of connections. Nodes with a disproportionately large number of connections are known as **hubs**, and their existence carry important dynamical consequences for the network (Barabasi Linked). Barabasi and Albert coined the term scale-free network to refer to this class of networks.

Barabasi and Albert also introduced a simple model that could generate scale-free networks (Barabasi and Albert, 1999). The Barabasi-Albert, or BA model, can generate a scale-free network by allowing the network to grow through the addition of nodes that come into the network with a set number of links. An essential ingredient of the BA model is that new nodes are more likely to connect to nodes which are already highly connected. This mechanism, known as preferential attachment and discovered previously by Yule (Yule 1940's) and Price (Price 1970's), is a simple way to generate models with power-law degree distributions. Yule and Price, however, never used it to simulate the structure of a network.

The finding that many networks from the most diverse kinds are characterized by broad degree distributions, such as power-laws, was extremely revolutionary for Network Science. This simple finding was not expected from the theoretical models of networks available at that time, which assumed that connections occurred randomly, and therefore, expected networks to be characterized by Poisson or exponentially decaying degree distributions. Until that time, many theoretical models of networks were built on the Erdos and Renyi, or ER model (Erdos and Renyi, 1959), developed by the mathematicians Paul Erdos and Alfred Renyi. The ER model was created for abstract reasons, and therefore, was not an accurate approximation to most real world networks.

The distinction between networks with a broad degree distribution and random networks is more than a statistical curiosity. Scale-free networks behave qualitatively different than random networks, for example, when we remove nodes from them. A well studied fact is that the fraction of nodes that remain part of the largest connected component of a scale-free network is comparable to the total number of nodes in the network, even after randomly removing a substantial number of nodes (Cohen et al., 2000, Albert et al., 2000). This property is not shared by random networks which break up into several components after the removal of a comparatively small number of nodes (Albert et al., 2000). Yet, when instead of removing nodes randomly we do so in a targeted manner, by removing first the nodes with the highest degree and then work our way down to low degree nodes, scale-free networks break up more quickly than random networks (Albert et al., 2000, Cohen et al., 2001). Hence scale-free networks are relatively more robust to the failure of random nodes than random networks, but at the same time are considerably more susceptible to fall apart under targeted attacks.

Another property that separates scale-free networks from random networks is the way in which they affect the spread of quantities, such as information or infectious diseases. Pastor-Satorras and Vespignani showed that scale-free networks have a vanishing epidemic threshold (Pastor-Satorras and Vespignani, 2001), meaning that in a scale free network viruses will always have a chance to spread. This was a shocking result for the field of epidemiology which until that time was dominated by models unable to incorporate the relevance of network structure into the spreading dynamics. In recent years, the importance of scale-free and non scale-free networks in the diffusion of different quantities has become increasingly more relevant. Different examples where network diffusion studies have captured an important amount of attention include (i) the diffusion of medically relevant conditions, such as obesity (Christakis and Fowler, 2007) and smoking (Christakis and Fowler, 2008), (ii) studies on the role of the World Airline Network in the spread of infectious diseases (Colizza et al., 2007, Colizza et al., 2006a) and (iii) the study of the evolution of countries productive structures constrained by the network of similarity between products (Hidalgo et al., 2007, Hidalgo and Hausmann, 2008).

In addition to the degree, clustering and degree distribution, an important variable that has been widely used to characterize the structure of networks is the average distance between a pair of nodes, known as the **average path length** $<l>$. For a long time the intuition that any person in the world could reach any other person through a short chain of acquaintances had been prevalent in popular culture, as exemplified for example by Karinthy's popular story "Chains" and by the Broadway play "Six Degrees of Separation" (Karinthy, 1929, Barabasi, 2003). Random networks, as those studied by Erdos and Renyi, are also characterized by short average path lengths. Yet, the random networks studied by Erdos and Renyi have a clustering coefficient that is inversely proportional to the number of nodes in them ($C \sim 1/N$) (Albert and Barabasi, 2002), and is therefore extremely small for networks composed by more than a few tens of nodes. Hence, Erdos and Renyi random networks cannot explain that social networks are simultaneously characterized by high levels of clustering (the friends of a person are relatively likely to be friends themselves) and short average path lengths.

In 1998 Watts and Strogatz showed that networks could have, simultaneously, a high level of clustering and a short average path length (Watts and Strogatz, 1998). In their landmark publication Watts and Strogatz illustrated their finding by using a circular lattice, which was characterized by high clustering and high average path length, and showed that after rewiring only a small number of links the average path length of their lattice could be brought down to that of a random network. Moreover, they showed that the clustering of the network remained relatively high even after a substantial number of links had been rewired. Watts and Strogatz found that in the parameter space of their model (given by the probability of randomly rewiring a link), there was a large region in which networks can exhibit both, high clustering and short average path lengths. Networks sharing both of these properties become known as Small-World networks, while the particular network model introduced in Watts and Strogatz's paper became known as the Watts and Strogatz network (Watts and Strogatz, 1998).

Going Deeper into Network Structure

The works of Réka Albert, László Barabasi, Duncan Watts and Steve Strogatz, together with the availability of large network datasests, sparked a landslide of publications that has since been concerned with the study of the structure and dynamics of networks of the most diverse kinds.

Other structural measures that have been used to characterize the structure of different networks are measures of **degree-degree correlations**, which look at whether nodes with a relatively high or low number of connections are more likely to connect with nodes with a relatively high or low number of connections. In other words, do hubs tend to connect to hubs?

Degree-degree correlations have been studied with variations by several different authors. One of the first examples of the study of degree correlations is exemplified by the work of Pastor-Satorras, Vazquez and Vespignani (Pastor-Satorras et al., 2001). Pastor-Satorras et al used data on the internet at the autonomous system level (simply put these are connections between different ISPs) to show that, in that particular network, hubs tend to connect to low degree nodes. Newman took this idea further by creating a measure of **assortativity**, which is positive for networks in which hubs are likely to connect to other hubs and negative for networks in which hubs tend to connect to low degree nodes (Newman, 2002). Newman applied his assortativity measure to several collaboration networks (networks in which the coauthors of a scientific paper are connected), a few biological networks (such as protein-protein interactions), some technological networks (such as the Internet and the WWW) and a few network models. His analysis found that social networks exhibited assortative behavior (hubs tend to connect to hubs) whereas technological and biological networks were more likely to show the opposite, dissasortative behavior, in which hubs tend to connect to low degree nodes (Newman and Park, 2003).

Another group that measured the degree-degree correlations of networks was Sergei Maslov and Kim Sneppen, who noticed that the degree distribution of a network imposed an important constraint in the degree-degree correlations of a network (Maslov and Sneppen, 2002). The idea was that in networks with a heterogeneous degree distribution, such as scale-free networks, hubs will on average appear to connect to low degree nodes. This is because there are simply not enough hubs for a hub to connect to, and therefore hubs have to connect mostly to low degree nodes. This constraint will also be expressed as a relatively high number of connections between low degree nodes and hubs. Measures that do not consider this effect will ultimately be biased towards finding a dissasortative behavior in networks with a broad degree distribution, such as scale-free networks.

Maslov and Sneppen proposed measuring degree correlations by comparing the observed level of connectivity between nodes of given degrees with those of randomized networks. In their randomized networks every node has the same number of links as in the original network, and hence the network conserves its degree distribution (Maslov and Sneppen, 2002). By comparing the degree-degree correlations of the original network with that of the randomized network Maslov and Sneppen introduced a way to measure statistical properties of a network while controlling for the connectivity of its nodes. This idea was pushed further by Colizza et al. in a study in which they introduce the rich club coefficient as a way to quantify such behavior (Colizza et al., 2006b).

Another area of intense study in network science is that of **community structure**. Measures on networks' community structure attempt to formalize the observation that in some networks there are groups of nodes that belong to densely connected groups, or communities, which themselves are only sparsely connected to other communities. Measures on the community structure of networks look to answer questions such as: Are there communities in a given network? And if so, how strong is the community structure exhibited in that network? How many communities are there? And, to which community or communities does a node belong?

In recent years several methods to assign nodes to communities have been proposed. All of these methods are based on different heuristics developed to capture the intuition behind the idea of communities. One example is the method introduced by Girvan and Newman (Girvan and Newman, 2002), in which they iteratively remove links of a network according to the link's betweenness centrality (Freeman, 1977). The idea behind this method is that links that lie between communities will tend to have high values of betweenness centrality, as the links that lie between communities will likely be in the shortest paths connecting nodes from different communities. Hence, by removing these links iteratively, Girvan and Newman found a way to break up the network into different communities. Soon after publishing this method Girvan and Newman and Girvan introduced a **modularity** measure that could be used to determine the number of links that upon removal would break up the network into the most adequate set of communities (Newman and Girvan, 2004). Using the modularity measure links could be removed iteratively in search for a modularity maximum, which indicated the most adequate partition of the network into communities according to the authors' method.

An alternative definition of communities was proposed by Palla, Farkas and Vicsek, who noticed that previously proposed community finding methods forced each node to a single community. Palla et al (Palla et al., 2005) pointed out that an individual could belong to more than one community and proposed an algorithm that could be used to assign an individual to several communities. The algorithm proposed by Palla et al consisted of taking a fully connected subgraph, or clique, and "rotating" it inside the network. All nodes that could be reached by the same clique were assigned to the same community. Yet, a node could potentially be reached by cliques rotating in different subsets of the network, as a node could be the nexus between several cliques. This allowed this algorithm to assign nodes to several communities.

During recent years, several other methods for community detection have been proposed including methods that can be used to detect communities in bipartite networks (Lehmann et al., 2008), methods to detect communities based on local information (Bagrow and Bollt, 2005, Clauset, 2005), Bayesian methods (Hofman and Wiggins, 2008) and spectral methods (Newman, 2006). Ultimately all of these methods can be used to understand the natural groups that emerge within an organization despite and because bureaucratic constraints.

The Structure of Large Scale Social Networks

To understand organizational networks we must complement statistical measures, such as the ones described in the previous sections, with technologies that can help us sense social interactions. After all, constraints to our understanding of social networks can arise from the coverage and reliability of the data available as much as from the limitation of our analytical methods.

In the past few years, an important number of studies have looked at different aspects of social networks by looking at the logs that record people's interactions occurring through different communication channels. These scientific developments have been fueled by the rapid advancement of information and communication technologies that have resulted in a large increase in the number of interaction channels that people use to communicate with each other. Some of these new channels include, but are not limited to (i) asynchronous channels, such as email, text-messages, blogging, microblogging (e.g. twitter), social networking sites (e.g. Facebook), and video posts (e.g. youtube), and (ii) synchronous channels, such as instant messaging, video calls and mobile phones. The massive adoption of these technologies has opened the opportunity to study the networks of interactions that are expressed through each one of these channels, as all of these technologies have the ability to record users' interactions, either for billing, reliability purposes or both.

During the last five years, anonymized mobile phone records have been used to look at the structure and dynamics of large social networks in an attempt to understand the statistical properties of the ways in which large collections of people self-organize. By looking at the mobile call patterns of a few million individuals, Onnela et al (Onnela et al., 2007) showed empirically that the links located in the more densely connected parts of the mobile phone network tended to be stronger, in the sense that the total amount of time used in those calls was longer, than the links located between groups. The idea that links between groups tended to be weaker than those within groups had been already proposed some decades ago by the sociologist Mark Granovetter (Granovetter, 1973). Onnela et al.'s contribution, however, took this idea further by using the empirically determined network structure to quantify how this particular property of social networks limits the diffusion of information across it.

Mobile phone records have also been used to study the temporal stability of social interactions. In a recent study, Hidalgo and Rodriguez-Sickert (Hidalgo and Rodriguez-Sickert, 2008) used a year's worth of mobile phone records to study how the persistence of a social tie, measured as the probability of observing a link when looking at the network during a certain time window, was related to different network properties. The authors found that the persistence of links was positively correlated with the density of the network, measured using the clustering coefficient, and the reciprocity of interactions, determined by looking at links in which calls were initiated by both parties. They also found that there was a tradeoff between the degree of an individual and the average persistence of that individual's ties (people with more social ties tended to have a smaller fraction of persistent ties). Yet, this tradeoff was found only to be partial, as Hidalgo and Rodriguez-Sickert showed more connected individuals tended to have a larger number of persistent social connections, despite the fact that as a fraction of the total number of ties, the fraction of persistent ties was smaller for more connected individuals.

The dynamics of social groups has also been studied by using mobile phone records. In a recent paper Palla et al. used a year's worth of mobile phone data, together with their community finding algorithm, to show that large social groups that survived for relatively long periods of time tended to exchange a large fraction of members. This was contrary to lasting small social groups, which tended to survive as long as the memberships remained (Palla et al., 2007).

Studies like these ones are important because they illustrate that it is possible to characterize individuals by looking at the structure and dynamics of their social interactions. Moreover, they show that in social networks different aspects of the network structure are strongly correlated, suggesting that the network structure surrounding an individual defines categories that can be used to understand the different kind of individuals that are part of society. The structure of the social network surrounding an individual is likely affected by that individual's personality, as it is an objective measure of how that individual is embedded in society. Hence, by combining log data with network analysis we can gain access to aspects of an individual that we would not be able to reach with demographic or socioeconomic data (Hidalgo and Rodriguez-Sickert, 2008). For example, demographic and socioeconomic data would not be useful to differentiate between two neighbors living in the same suburb, having similar income, family composition, level of education and age, but having extremely different personalities. Because of the aforementioned reasons, measures extracted from social network data can give us access to a more relevant quantitative picture of an individual, as the structure of the social network surrounding an individual is likely related to that individual's personality more than its neighborhood, gender or age.

From a business standpoint, the characterization of an individual that can be extracted from its social network can be extremely relevant. In recent years there has been evidence showing that marketing segmentation based on the structure of an individual's social network can produce better targets, measured by comparing the adoption rate of targets chosen using social network structure and more traditional marketing segmentation methods. Better marketing segmentation methods are beneficial for companies and costumers, as improving marketing segmentation strategies reduces the cost of marketing efforts incurred by companies and at the same time diminishes the amount of unwanted marketing material handed off to customers.

The structure of an individual's social network can also be a good predictor of future behavior (Hidalgo and Rodriguez-Sickert, 2008). This makes accurate quantitative information about an individual social network extremely valuable for companies whose businesses require anticipating individual behavior, such as, for example, the renewal of a service contract or the adoption of new services in the future. A good example of this is recent work by Dasgupta et al (Dasgupta et al., 2008), in which social ties were used to accurately predict the churn of mobile phone users.

Automatically collected data has also been used to study the communication patterns defined by small networks of individuals within an organization. For example, Aral et al (Aral et al., 2009) studied the communication patterns of an executive recruiting firm and found that multitasking individuals tend to prefer asynchronous communication channels (in particular email) over synchronous communication channels (such as phone) (Aral et al., 2009). They also found an inverted-U shape relationship between multitasking and productivity, meaning that multitasking increases productivity until a certain point after which additional tasks had a negative effect in productivity.

Email networks have also been used to study organizations. Probably the most well studied email dataset is Enron's email database (Shetty and Adibi, 2004), (Keila and Skillicorn, 2006). An interesting example of the type of information stored in Enron's emails is exemplified by the work of Collingsworth and Menezes. In a recent study, Collingsworth and Menezes found that the number of cliques in Enron's email network (subsets of the network in which everyone is connected to everyone else) jumped from 100 to almost 800 one month before the December 2001 collapse (Collingsworth and Menezes, 2009). The author's interpretation of their findings was that, one month before the collapse, people in the organization began talking directly to people they felt comfortable with and stopped sharing information more widely. Collingsworth and Menezes' study shows how changes in an organization's email network can be indicative of its internal processes.

Honest Links

Recent technological developments have also opened new opportunities for the study of face-to-face interactions. A particularly exciting body of research in this area, spearheaded by the Human Dynamics Lab at MIT, combines the development of "reality mining" technology, which are devices designed specially to measure personal interactions, with signal processing, machine learning, psychological theories and real life experiments, to create the most comprehensive quantitative picture of face to face interactions to date.

During several years the Human Dynamics Laboratory, led by Alex (Sandy) Pentland, has been exploring the limits of wearable computing technology and its ability to objectively sense social interactions. Through a series of experiments, Pentland's group has been able to show that it is possible to quantify several aspects of human interactions by analyzing data collected from wearable devices that record the location, sound, acceleration and direction of those who wear them. In their most recent incarnations, these "sociometers" have been incorporated into small badges that can be integrated with current ID tags or have been developed as software, rather than as hardware solutions, that can be incorporated into mobile phones (Eagle and Pentland, 2006).

One of the striking aspects of this research is its proven ability to quantify the non-verbal aspects of human face to face interactions, which have been shown to be highly predictive of the outcome of interpersonal exchanges of the most diverse kinds. Pentland suggests that the information value of this "Honest Signals" comes from the fact that they are processed unconsciously and that they emerge from our brain structure and biology, and therefore, they are hard to fake (Pentland, 2008). This makes this non verbal signals more likely to be honest than the signaling produced by more conscious decisions, such as the clothes we wear and the cars we drive. In other words, the Human Dynamics Lab at MIT has been able to scientifically separate the information content of the things we say and of how we say them.

These sociometric techniques have been used to study pairwise social interactions as well as the dynamics of small networks of individuals. At the pairwise level, honest signals have been shown to be good predictors of the outcome of different types of negotiations. For example, by using these techniques in salary negotiations Curhan and Pentland were able to predict 30% of the variance in individual outcomes by examining a thin slice of data consisting of the first 5 minutes of the negotiation (Curhan and Pentland, 2007). Another example in which these sociometric techniques have been shown to be highly predictive is in predicting the matches that occur at speed dating events (Madan and Pentland, 2006). Speed dating is a matchmaking activity in which individuals have short interviews with a large number of potential partners and secretly indicate their preference for any of them at the end of the event. After all "dates" have taken place the organizers of the event provide contact information to those pairs of individuals who have expressed mutual interest. Madan and Pentland showed that the combination of two female honest signals: high levels of activity and variable emphasis, where highly predictive of the decision of individuals to trade contact information (Madan and Pentland, 2006). They also found that males were able to read females quite accurately, as men were more likely to report an interest for woman who also reported interest in them, according to both sociometric technology and speed dating records.

While there are several interesting studies that use sociometers to relate honest signals with different types of interactions, from an organizational perspective the most interesting examples are the ones concentrating on the dynamics of groups of individuals.

Some of these studies are complementary to Bales' Interaction Process Analysis (IPA) (Bales, 1950, Bales and Strodtbeck, 1951), which is a method used to classify the interactions that happen in a group based on the type of behaviors that the members of a group adopt towards each other. Sociometers have been used to accurately classify the different roles undertaken by different individuals in a small group, helping automate IPA, a task that until now could only be performed by a trained psychologist. IPA has been shown to predict the outcome of group decision making, including problems such as groupthinking and polarization (De Waal, 2005). For example, if two people in a group happen to take the *attacking role*, decisions tend to be more polarized. On the other hand, if there is only one *protagonist* in the group, a typical outcome is that everyone follows the leader without exploring the entire set of options and potential pitfalls of the decision proposed by the leader. Sociometers are now being used to create real time feedback systems that can help keep groups on track.

During the last years, the Human Dynamics Lab at MIT began collaborating with large firms such as Hitachi (Baker, 2009). Hence, sociometers could soon enter the workplace, either as consumer products or as part of a new organization consulting and management standard that relies heavily on information about the interactions of an organization's members. The test that organizational sciences will pose to sociometric and other technologies will not be a test of adoption, but rather a test of survival. Ultimately, these technologies should enhance the survival probability of those organizations who adopt them. As the survival of organizations will be the one that determines whether network science becomes a frozen accident (Crick, 1968) in the evolution of management strategies or if it will be selected out until a future rediscovery.

Final Thoughts

Organizations are networks formed by heterogeneous groups of individuals that accomplish tasks that no single individual can. Like a soccer team or an orchestra, organizations are complex super-organisms whose performance depends on the interaction between the individuals that make up the organization, as well as on the structure of the networks that emerges from these interactions. Organizations, however, are networks that exist within networks. Since firms and institutions are networks that operate in environments that are formed by thousands of other organizations, firms and institutions can be seen as nodes in a large network of organizations themselves. Organizations are networks embedded in other networks and their survival depends as much on their internal structure as on the position they hold in their networked environments.

The ability for these super-organisms to adapt, however, will depend on the level of "consciousness" that they can achieve. Self-awareness can be seen as the ability of an organization to understand its limitations and how to overcome them. Awareness is about being conscious about what is going on and where you are standing, for both individuals and for organizations. All organizations do have some sense of self-awareness, which comes from their ability to answer questions such as: What can they achieve using only their internal resources? Do they know if they can do it so competitively? And in the case they do not, would they be able to restructure its internal networks to a configuration that could help them solve this problem? Self-awareness is, for individuals and organizations, related to the ability of assessing relatively quickly and accurately one's own position in the larger picture, understanding the role that you are playing and on the implications of such role in relation to others. Can network science improve the ability of an organization to understand where it stands? Moreovoer, can network science improve the ability of an organization to answer questions about the environment in which the organization is embedded?

After all, the success and survival of an organization depends on its business ecosystem, and on its position within it. Organizations are part of complex economies which are formed by institutions and firms of the most diverse kinds. In complex economies value emerges from the interaction between these different organizations, together with other private and public inputs (Hidalgo and Hausmann, 2009) . Ultimately, one of the goals of network science is to help this larger super-organism to wake up and become better at what it already does quite well, which is to divide up labor and generate prosperity. One step in this direction is to help organizations become more adaptable; as it could well be that an emergent property of an economy which is formed by more adaptable organizations is an overall system that is not only more adaptable, but rather, more evolvable.

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