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The Empirical Study of A SNA-based Approach for Identifying KSC of Enterprise

Hui Wu*, Xiaomin Gu, Yuanjun Zhao

Glorious Sun School of Business and Management, Donghua University, Shanghai 200051, China
wdhh429@163.com

In the stage of knowledge economics, Knowledge as a resource is playing an important role, so is the social capital of the enterprise. It has become a hot topic of Management research that from the view of knowledge economics in domestic, as well as international. Based on the present studies in combination with Chinese fact，From the perspective of social network analysis this paper study of the formation and its connotation of social capital in the organization. Analyses the influence to enterprises of each dimension in social capital. The research identifies the key indicators of the three dimensions of social capital.

1. Introduction

With the coming of knowledge, Companies are no longer only depend on the possession of scarce resources, but from Constant learning in order to improve the innovation ability to gain a competitive advantage. How to promote enterprise to improve innovation ability has become the key to the enterprise core-competence.
Social capital theory research developing rapidly in recent decades, in the fields such as social politics, economy, management culture, Scholars ha made a lot of very fruitful research. Abbasi (2014) reportedhave shown that the Disadvantages of formal system in transition economy led to the informal system play an important role in the enterprise development, thus the social capital. Barbieri (2003) reported Social capital has the characteristics of embedded and network structure，These characteristics provide a powerful explanatory power to build enterprise network, Abbasi(2011)reported that using the Internet to integrate internal and external resources of enterprise, and improve enterprise performance etc.
It is generally believed that the social network theory originated in the 1930s British anthropology research，Bogenhold (2013) reported that main consideration of the connection between the economic activity and social relations. British anthropologist Radcliffe brown (1940) first uses Social Network this concept in his book Social structure. 60-70s of the 20th century, Chang (2014) reported that the social network theory in academia expanded rapidly, the influence of the concept of social network have been broad applied and developed in the field of anthropology, sociology, management, economics etc.

2. The establishment of a social network analysis model

2.1The basic concept of social network analysis and modeling

2.1.1The basic concept of social network risk

In recent years, on the statistical characteristics of complex network structure, many of the concepts and methods are put forward. Hancock(2010) reportedthat there are three basic concepts: average path length; clustering coefficient; degree distribution. Actually, the original intention of Watts and Strogatz'swork of small world network model to is to build a large clustering coefficient model, which are similar random graphs. On the other hand, scale-free network model proposed by Barabasi and Albert (2014) reported, which is based on the fact that many practical network degree distributions have a form of power law. Here introduce the several properties of complex networks.

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(1)The representation of a network diagram

A specific network can be abstracted as a figure $G=(V,E)$ of point set V and edge set E. Node Numbers for $N=|V|$. Each side in E has a corresponding point V. If at any point (i,j) and (j,i) corresponding to the same side, then the network is called directed network. Otherwise known as undirected network. If given corresponding weights to each edge, then the network will be weighted network. Otherwise known as unweighted network. Of course weighted network also can be seen as Equal weighted network that each edge weights are 1. In addition a network may contain a variety of different types of nodes. Weighted network and directed-weighted network are more and more attention in recent years.

(2)The average path length

In the network, the distance dij between two nodes i and j is defined as the connection of the two nodes number of edges on the shortest path. The distance between any two nodes in a network of maximum value known as the diameter of the network, denoted as D, that is

$$D=\max dij \tag{1-1}$$

Network of average path length is defined as the average value of the distance between any two nodes, namely

$$L=\frac{1}{\frac{1}{2}N(N+1)}\sum_{i\geq j} dij \tag{1-2}$$

N is the network node number, the average path length also known as the network characteristic path length. To facilitate the mathematical processing, we multiply by the factor $(N+1)/(N-1)$. In the formula (1-2). In practice, such a small difference is completely negligible. Average path length that contains N nodes and M edges can be determined by Breadth limited search algorithm used Time scale $O(MN)$.

(3)Clustering Coefficient

In your friend network, your two friends are likely friend, this attribute is called the clustering characteristics of the network. Generally assume that the node i of the network have k_i edges which is connected to the other nodes. This k_i node called the neighbor of node i. Of course there are at most $k_i(k_i-1)/2$ edge between the k_i nodes. The ratio of the actually exist edges E_i between k_i node and he total possible number of edges $k_i(k_i-1)/2$ is clustering coefficient C_i, that is

$$C_i=2E_i/(k_i(k_i-1)) \tag{1-3}$$

Look from the collection features, an equivalent definition of it is

$$C_i=\frac{\text{The number of triangles connected to node}\,i}{\text{The number of triples connected to node}\,i} \tag{1-4}$$

The triples that are connected to the node i including three node of node i. And there are at least exiting two edges from the node i to the other two nodes. The network-clustering coefficient C is the average of clustering coefficient C_i of all nodes. Obviously $0\leq C\leq 1$. If $C=1$, if and only if all of the nodes are isolated nodes, namely no link. $C=1$ If and only if the network is a global coupled, that any two nodes in the network are directly connected.

(4)Degree and degree distribution

Degree is simple and important concept in the properties of single node. The K_i degree of Node i is defined as the number of the other nodes connected with the node. To a node in directed networkis divided into the out-degree and in-degree. The out-degree of node refers to the number of edges from the node to other nodes. The in-degree refers to the number of edge points to change from the other node. Intuitively, the greater the degree of a node in a sense means that the node is more important. All The degree k_i of Node i average is called the average degree of the network $\langle k\rangle$. The distribution of nodes in the network degree can use distribution function $P(k)$ to describe. $P(k)$ represents the probability of randomly selected node degrees is K.

In recent years, a large number of studies have shown that many of the actual network distribution obviously different from the Poisson distribution.in particular, many degrees can use power-law distribution $P(k)\infty k^{-r}$ to better description. Power-law distribution curve down much more slowly than the index of the Poisson distribution curve.

The scale-free characteristic of power-law distribution function: Consider a probability distribution function $f(x)$, if for any given constant there is constant makes function $f(x)$ satisfy the following Scale-free conditions.

$$f(ax)=bf(x) \tag{1-5}$$

So there must be (IF $f(1)f^{'}(1)\neq 0$)

$$f(x) = f(1)x^{-r},\ r = -f(1)/f'(1) \tag{1-6}$$

That is to say, power-lawis the only meet scale-free distribution function. These properties can be simply deduced as follows：take $X = 1$， we have $f(a) = bf(1)$， then $b = f(a)/f(1)$， thus

$$f(ax) = \frac{f(a)f(x)}{f(1)} \tag{1-7}$$

Due to the above equation is set up to any a, on both sides of the equation of a derivation

$$x\frac{df(ax)}{d(ax)} = \frac{f(x)}{f(1)}\frac{df(a)}{da} \tag{1-8}$$

If have $a = 1$, thus

$$x\frac{df(x)}{d(x)} = \frac{f'(1)}{f(1)}f(x) \tag{1-9}$$

For solutions of differential equations (1-9)

$$\ln f(x) = \frac{f(1)}{f'(1)}\ln(x) + \ln f(1) \tag{1-10}$$

2.2 Modeling

2.2.1A Class of Network Models with Dyad Dependence

To define the dyad dependence, we need to include latent or manifest vertex variables that influence the dyad structure. A dyad dependence model is specified by giving a probability distribution for the vertex variables X_i for $i = 1, \cdots, N$, and, conditionally on the outcomes of $x_1, \cdots, x_N$, the $N(N-1)/2$ dyad variables (y_{ij}, z_{ij}, z_{ji}) are assumed to be independent. The conditional probability distribution of the dyad variable (y_{ij}, z_{ij}, z_{ji}) may be dependent on i and j, but is independent of x_k for all k different from i and j. Formally, we write the probability or probability density function of all network variables as follows.

$$\mathrm{f}(\mathrm{x}_1, \ldots, \mathrm{x}_N)\prod_{i \le j} g_{ij}\ (\mathrm{y}_{ij}, \mathrm{z}_{ij}, \mathrm{z}_{ij} \mid \mathrm{x}_i, \mathrm{x}_j)$$

Continuous Dyad Dependence Models

We consider a dyad dependence model for continuous variables, which is of some interest in connection with other log-linear models considered in network analysis and deserves to be further investigated. Assume that $x_i = (x_{1i}, x_{2i})$ are independent vertex variables with a common bivariate normal distribution

$$\mathrm{N}(\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \boldsymbol{\sigma}_1, \boldsymbol{\sigma}_2, \boldsymbol{\rho}).$$

The two components of the vertex variable represent out- and in-effects or out- and in-capacities of the vertex. Conditionally on the vertex variables, the dyad variables have a trivariate normal distribution that is given by

$$\mathrm{y}_{ij} = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1(\mathrm{x}_{1i} + \mathrm{x}_{1j}) + \boldsymbol{\alpha}_2(\mathrm{x}_{2i} + \mathrm{x}_{2j}) + \boldsymbol{\sigma}_3\boldsymbol{\varepsilon}_{3ij},$$

$$\mathrm{z}_{ij} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\mathrm{x}_{1i} + \boldsymbol{\beta}_{2\mathrm{x}2i} + \boldsymbol{\beta}_{3\mathrm{x}1j} + \boldsymbol{\beta}_{4\mathrm{x}2j} + \boldsymbol{\sigma}_{4\,\boldsymbol{\varepsilon}4ij},$$

$$\mathrm{z}_{ji} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\mathrm{x}_{1j} + \boldsymbol{\beta}_{2\mathrm{x}2j} + \boldsymbol{\beta}_{3\mathrm{x}1i} + \boldsymbol{\beta}_{4\mathrm{x}2i} + \boldsymbol{\sigma}_{4\,\boldsymbol{\varepsilon}4ji}$$

Where the ε-variables are standardized normally distributed with covariance

$$\mathrm{C}(\boldsymbol{\varepsilon}_{3ij}, \boldsymbol{\varepsilon}_{4ij}) = \mathrm{C}(\boldsymbol{\varepsilon}_{3ij}, \boldsymbol{\varepsilon}_{4ji}) = \boldsymbol{\gamma}_3, \mathrm{C}(\boldsymbol{\varepsilon}_{4ij}, \boldsymbol{\varepsilon}_{4ji}) = \boldsymbol{\gamma}_4$$

The edge variable is linearly dependent on the out- and in-effects of its two vertices, and by symmetry the two vertices are equally weighted. The arc variables are also linearly dependent on the out- and in-effects of their two vertices. Here the weights are allowed to differ, but by symmetry they are interchanged for the two arcs. The coefficients in front of the ε-variables are conditional standard deviations. By symmetry, two of them are equal. The distribution of the vertex variables is determined by five parameters, and the conditional distributions of the dyad variables involve twelve more parameters. From the assumptions, it follows that the dyad variables are marginally normally distributed. The marginal distribution is determined by the expected values, variances, and covariance, which are given by the following functions of the parameters

$$E(y_{ij}) = \alpha_0 + 2\alpha_1\mu_1 + 2\alpha_2\mu_2,$$
$$E(z_{ij}) = E(z_{ji}) = \beta_0 + (\beta_1+\beta_3)\mu_1 + (\beta_2+\beta_4)\mu_2,$$
$$V(y_{ij}) = 2(\alpha_1^2\sigma_1^2 + \alpha_2^2\sigma_2^2 + 2\alpha_1\alpha_2\sigma_1\sigma_2\rho) + \sigma_3^2,$$
$$V(z_{ij}) = V(z_{ji}) = \beta_1^2\sigma_1^2 + \beta_2^2\sigma_2^2 + 2\beta_1\beta_2\sigma_1\sigma_2\rho + \beta_3^2\sigma_1^2 + \beta\sigma_2^2 + 2\beta_3\beta_4\sigma_1\sigma_2\rho + \sigma_4^2,$$
$$C(y_{ij}, z_{ij}) = C(y_{ij}, z_{ji}) = \alpha_1(\beta_1+\beta_3)\sigma_1^2 + \alpha_2(\beta_2+\beta_4)\sigma_2^2 + [\alpha_1(\beta_2+\beta_4) + \alpha_2(\beta_1+\beta_3)]\sigma_1\sigma_{2\rho} + \sigma_{3\sigma}4_{\gamma 3},$$
$$C(z_{ij}, z_{ji}) = 2[\beta_1\beta_3\sigma_1^2 + \beta_2\beta_4\sigma_2^2 + (\beta_1\beta_4 + \beta_2\beta_3)\sigma_1\sigma_2\rho] + \sigma_4^2\ \gamma$$

The seventeen parameters can be estimated by the moment method. The require equation system with seventeen moment equations consists of six equations corresponding to the previous parametric expressions, together with eleven equations corresponding to the parametric expressions among the following moments:

$$V(x_{1i}) = \sigma_1^2,\ V(x_{2i}) = \sigma_{22},$$
$$C(x_{1i}, x_{2i}) = \sigma_1\sigma_{2\rho},$$
$$C(x_{1i}, y_{ij}) = C(x_{1j}, y_{ij}) = \alpha_1\sigma_{21} + \alpha_2\sigma_1\sigma_{2\rho},$$
$$C(x_{2i}, y_{ij}) = C(x_{2j}, y_{ij}) = \alpha_2\sigma_2^2 + \alpha_1\sigma_1\sigma_{2\rho},$$
$$C(x_{1i}, z_{ij}) = C(x_{1j}, z_{ji}) = \beta_1\sigma_{21} + \beta_2\sigma_1\sigma_2\rho,$$
$$C(x_{2i}, z_{ij}) = C(x_{2j}, z_{ji}) = \beta_2\sigma_{22} + \beta_1\sigma_1\sigma_2\rho,$$
$$C(x_{1i}, z_{ji}) = C(x_{1j}, z_{ij}) = \beta_3\sigma_{21} + \beta_4\sigma_1\sigma_2\rho,$$
$$C(x_{2i}, z_{ji}) = C(x_{2j}, z_{ij}) = \beta_4\sigma_{22} + \beta_3\sigma_1\sigma_2\rho.$$

The parametric expressions that apply to two different moments are equated to the average of the two moments. The others are just equated to their moments. For the resulting equations, replace the expected values, variances, and covariance by empirical quantities obtained from data and solves the equation system numerically for the parameters.

So far, we have considered networks that have simultaneously both edge and arcvariables. Without this combined occurrence of symmetric and unsymmetrical relationships, the degrees of freedom are reduced. If there is no edge variable but only vertex and arc variables, twelve of the seventeen parameters remain. If there is no arc variable but only vertex and edge variables, nine parameters remain. In all these cases, the model is a log-linear network model with a log-likelihood function that is a linear function of moment statistics of the types considered previously.

2.2.2Discrete Dyad Dependence Models

Aparticular version of the dyad dependence model for categorical edge and arc variables generalizes in a nice way the Holland-Leinhardt model for a simple digraph. At the same time, it provides an interpretation of the model in terms of actor preferences for local structure. It also suggests an extension of the Holland-Leinhardt model with tie dependence, which is not so evident with the usual formulation of the model. To demonstrate these results, we now consider the following dyad dependence model. Let $x_1, \ldots, x_N$ be independent identically distributed categorical variables of type $(a_1, \ldots, a_p)$ with $a = a_1 \ldots a_p$ categories. Thus, their log-likelihood equals.

$$\log f(x_1, \ldots, x_N) = i \log f(x_i) = x N(x) \log f(x)$$

Where $N(x)$ is the number of vertices with $x_i = x$ for $i = 1, \ldots, N$. Conditionally on $(x_1, \ldots, x_N)$ the $N(N-1)/2$ dyad variables (y_{ij}, z_{ij}, z_{ji}) are independent and (y_{ij}, z_{ij}, z_{ji}) has a distribution that does not depend on x_k for any k different from i and j. Assume first that the dyad distributions are also independent of the labels i and j.

3. Case Study

Here with Chinese companies a practical example to illustrate how to use social network analysis to identify the key social capital. In view of the space. We analyzed the strategic target of a China's high-tech enterprisesonly emphasis on social network analysis part, and analysis the Structure dimension, relationship dimension and the cognitive dimension, of high technology enterprise social capital. Through the questionnaire, we get the constituent elements of social capital and Correlation matrix between the elements, as shown in table 1.

Table 1: The adjacency matrix of social capital

0uninfluenced2moderate	1weak 3strong		1	2	3	4	5	6	7	8	9	10	11
Structure dimension	Internet connection strength	1		3	2	1	1	0	0	0	2	1	1
	Network density	2	1		3	2	3	0	2	1	2	2	2
	Network stability	3	1	1		2	2	1	2	1	3	2	2
Cognitive dimension	Common vision	4	0	2	2		3	3	1	2	2	1	1
	Teamwork	5	0	3	2	3		1	3	2	2	1	1
	Team needs	6	0	2	3	1	2		1	1	1	1	1
	Knowledge platform	7	0	3	3	1	3	1		2	2	1	1
Relationship dimension	Common language	8	0	1	2	2	3	3	1		3	3	3
	Shared goals.	9	0	2	3	3	2	2	3	3		1	2
	Reciprocity	10	0	3	2	2	1	1	1	1	1		2
	Goodwill trust	11	0	2	2	2	1	1	1	1	2	2	

Table 2 to calculate out-degree and out-degree of various factors, by the two center degree index and network connection degree index we can seen that out-degree and out-degree of most factors, and the connection degree is higher. This suggests that many factors are considered to have an impact on other factors also influenced by other factors. This shows the high technology enterprises to think they are a highly interactive, dynamic and flexible organization, but this analysis considers only the manage relationships between these elements, and has yet to consider the effect of each element to the whole network. As a result, this also can't decide which element is the key social capital.

Table 2: Based on the out-degree and out-degree to identify the key social capital

Social capital	The components of social capital	Output close to the center	Input degree	Whether the key social capital
Structure dimension	Internet connection strength	0.87	0.75	
	Network density	0.87	1	
	Network stability	0.91	0.85	Yes
Cognitive dimension	Common vision	0.95	1	
	Teamwork	1	1	
	Team needs	0.95	0.75	Yes
	Knowledge platform	1	0.95	Yes
Relationship dimension	Common language	0.95	1	
	Shared goals	1	0.95	Yes
	Reciprocity	0.95	0.8	Yes
	Goodwill trust	0.91	0.8	Yes

In order to identify the high technology enterprise social capital, we need to calculate the close to the center degree of the matrix. Against to the directed matrix, using social network analysis pajek calculating the output close to the center of the matrix and input degree. Finally get the results shown in table 2. From the calculation result shows that there are six elements into the scope of social capital, they are Network stability，Team needs，Shared goals，Reciprocity and Goodwill trust.

4. Conclusions and Prospects

This paper studies the social capital's influence on the economy as well as the mechanisms. We take advantage of social network analysis model to analyze the key elements of social capital, including the interactive relationship between the economic subjects. Social capital mainly plays the role of the following four aspects: (1) It offers economic subject information about options and opportunities which reduce the transaction costs of the organization. (2) Social connections can affect some of the organizations and agencies, which can bring more value to the members of the network resources. (3) Personal integrity through social ties are recognized by the network of organizations and institutions, and generate positive externalities, form the credit on the individual in society. (4) The relationship between the members of the network to strengthen the trust and recognition, allows members to share common interests and resources.

In the practice of corporate social capital, How to accurately find out the effect of social capital to enterprise strategic target, all the elements of personnel can correctly identify the elements of social capital, the relationship between the subjective activity directly affect the efficiency and accuracy of key social capital recognition. Enterprise in the enterprise in addition to strengthen the study and research in the theory of social capital, formed a set of rely on social capital for the red backbone enterprise management ideas and management thinking. From this perspective, to identify the enterprise social capital purpose is to improve enterprise management level.

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