Determining An Actor's Network Capacity And Network Utilization: A Markov Model Of Human Agency In Social Networks

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Abstract
The focus of this paper has been to put forth a Markov model that will provide information to actors in a network about the optimum capacity of alters in their social networks and how to maintain social-temporal relations with their contacts and resources with optimum efficiency. This model takes advantage of the similarities between the concept of human agency and Markov random processes. It takes into account the fact that present experiences are the sum total of past iterational and habitual experiences and the present practical-evaluative capacity to evaluate these past experiences. The model then adapts the Markov process and the Erlang blocking formula used in telephony, when it uses the present practical-evaluative experience to create a projective capacity toward the future state of the social network. This will then provide the actor (ego) with information about the efficient utilization of his/her channel/network capacity and the number of contacts or resources he/she would need to maintain to achieve the future stability of the network contacts and resources.

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Introduction

Human agency as described by Emirbayer and Mische (1998), is conceptualized as a temporally embedded process of social engagement, informed by the past (in its "iterational" or habitual aspect), but also oriented toward the future (as a "projective" capacity to imagine alternative possibilities) and toward the present (as a "practical-evaluative" capacity to contextualize past habits and future projects within the contingencies of the moment). Emirbayer and Mische (1998) further make a proposition that actors in the midst of changing situations and contexts that demand the reconstruction of temporal perspectives can expand their capacity for imaginative and or deliberative response. This leads to viewing actors as much more than agents alone in a social situation, in that any agency that they employ in the maintenance of their social structures is both within themselves and simultaneously embedded in their social structures.

This definition of agency provides for the scope that Isocrates (436-338 B.C.E.) a contemporary of Plato in ancient Greece, advocated (Bizzell and Herzberg, 2001) in his definition of rhetoric, involving the use of history to solve present problems depending on the context (following from the Sophistic traditions of Kairos) and making useful contributions for the future in all public and private human affairs. This approach, also taken by Emirbayer and Mische (1998), allows one to view human agency not only from the temporal perspective, but also from the relational dimension of sociality by viewing the embeddedness of actors in multiple cultural, social-structural and social-psychological contexts.

One can approach the task of identifying the settings and situations that tend to keep actors engaged in patterns of behaviors and communication processes from various theoretical perspectives, such as action theory and normative theory which are discussed by Emirbayer and Mische (1998), but the aim of this paper is to propose a theoretical model based on Markov processes to model this human agency so prevalent and embedded in social networks. In socio-temporal relations where kinship relations are generally constant over time and friendship or entrepreneurial networks change with time, the structure of a group is often a function of time. We can then model these relations stochastically in order to better explain the social and network behavior of actors in the social structure.

If we consider the formation of relationships and ties over time between people in a social structure, we can consider this to be both a deterministic process (with kith and kin) and a stochastic process (friends, co-workers, entrepreneurial acquaintances, etc.). These socio-temporal relations depend on the past actions and behaviors of the people, which affects their present actions and their future relationships with one another. In a general random process we have a set of times $0=t_0 < t_1 < \ldots < t_n$ and a set of states $s_i \in S$ so the probabilities $P(Xt_n \,.\, s_n \mid Xt_{n-1} = s_{n-1}, \ldots , Xt_0 = s_0)$ depend on the entire history of events from t_0 to t_n. A stochastic process is a *Markov process* if the probability of the next state depends upon the current state and not the previous states. The current state is the sum total of all past states or in the case of social relations, all past experiences, and is used as a predictor of future states or behavior. We can thus see how the Markovian approach lends itself to the modeling of human agency in social networks and the rest of the paper will be devoted to exploring more of the relevant literature and the development of the model.

Organizations, Networks and Agency

Since we are looking specifically at the stochastic nature of these socio-temporal relations, i.e. between friends, co-workers and entrepreneurial acquaintances, I begin with a discussion of some social network analysis studies, which looked at organizational structures in the context of computer-mediated communication. This is relevant to the understanding and modelling of human agency. One of the questions we would like answered is the one about the contexts that constrain or enable the capacity of people in a social structure like an organization for communicative deliberation, by means of which they judge the particular actions most suitable for resolving the practical dilemmas of emergent situations (Emirbayer and Mische, 1998). Communication and communication patterns then could be viewed in this context of both emergent network structure and emergent situations, such as those that arise in organizations.

Burkhardt and Brass (1990) used social network analysis to examine the organizational impacts of a new information technology, specifically the relationship between *centrality, power, and the timing of adoption* of a new distributed computing system. They reasoned that a new technology would increase uncertainty, raising the power of those able to mitigate that uncertainty, while increasing the need to communicate about that uncertainty and thus altering the social communication network. They found that early adopters increased their power and centrality to a greater degree than later adopters. They also observed changes in the network structure as a result of the new technology.

Rice and Aydin (1991) used social network analysis to examine the mechanism by which individual attitudes toward an information system were influenced by the attitudes of socially proximate others. They identified three mechanisms for proximity: *relational, positional and spatial*. Relational and positional proximity were defined following the discussion above, while spatial proximity represented physical location. They found that attitudes towards an information system are socially influenced and that relational and positional proximity have greater influences than traditional occupational roles and spatial proximity.

By mapping the social networks and the computer-mediated communication (CMC) networks for each organization, Zack and McKenney (1995) examined how existing social structure influences the way in which an organization appropriates electronic messaging systems. They were able to make direct comparisons between networks and between organizations. By comparing both networks within organizations, they found that the CMC network closely reflected the social structure. Comparing networks across organizations, they found that where the social structure reflected open, collaborative communication and a participatory management style, CMC was used to broaden the communication networks and make them more responsive. Where the social structure reflected relationships in conflict and a strict, centralized hierarchy, CMC was appropriated in a way that reinforced the hierarchy. They were able to relate performance effectiveness to particular communication patterns to show why the technology enabled effective performance in some organizations while not in others.

Zack (2000) studied the key impact of organizational systems and new information technologies and how they enable new organizational forms - the structural features or patterns of relationships and information flows of an organization. His study also proposed social network analysis as a highly appropriate and useful method for framing and describing the effects of organizational and communication systems on organizational forms and structures. The key finding was that the social structure influenced the way the technology was appropriated, and therefore, mediated its impact on organizational performance.

Wellman, Garton, and Haythornwaite (1997) showed the utility of the social network approach for studying CMC, in either a computer-supported network, in a virtual community, or in less bounded systems like the Internet. However, Ahuja & Carley (1998) empirically measured the structure of a virtual organization and found evidence of hierarchy in the virtual organization, much like in traditional organizations. They recommend the retaining of individuals who are at the center of information exchange networks, designing reward structures so those individuals acting as knowledge centers on specific topics can be retained and promoted, and giving incentives for these individuals to share their expertise with other organization members. Ahuja & Carley go further to say that it is critical to develop and train other individuals who can assume the network positions occupied by other individuals as they are promoted so that the communication structures can remain stable despite the turnover.

The above studies have highlighted the various facets of human agency in organizations, specifically with regard to information flow and the resultant emergent network structures. They bring to the fore both relational and positional issues involving actors in an organization and how these impact their social structures. Emirbayer and Mische (1998) ask whether the changes in agentic orientations allow actors to exercise different forms of mediation (face-to-face and CMC to leverage relational social capital, Lin, 1999) over their contexts of action, and if actors who feel blocked in encountering problematic situations can actually be pioneers in exploring and reconstructing contexts of action.

To attempt an answer to these questions I have proposed to look at these socio-temporal structures from a stochastic modeling perspective. Socio-temporal relations like kinship relations, are generally constant over time, while friendship or entrepreneurial networks change with time, often making the structure of a group a function of time. If we consider the formation of relationships and ties over time between people in a social structure, we can consider this to be both a deterministic process (with kith and kin) and a stochastic process (friends, co-workers, entrepreneurial acquaintances etc.). These socio-temporal relations depend on the past actions and behaviors of the people, which affects their present actions and their future relationships with one another.

Researchers have proposed several such time dependent statistical models which are both deterministic and stochastic (Bernard and Killworth, 1979; Rapoport, 1963; Wasserman and Faust, 1994). Wasserman and Iacobucci (1988, 1991) proposed loglinear approaches to model network changes and Markov chains to represent stochastic block models for structural equivalence and brokerage (Burt, 1992), while Katz and Proctor (1959) applied discrete Markov chain theory to longitudinal sociometric data to demonstrate the possible use of Markov models to explain the dynamic nature of social network structures. Sorensen and Hallinan (1977) applied continuous time discrete state Markov chains to the study of the evolution of triads over time and their model analyzes the tendency toward transitivity at the triad level affecting the social structure at the macro level.

A network triad consists of an unordered set of three nodes and the ties between them. An ordered set of three nodes is called a triplet and a triplet (i,j,k) is defined as transitive from i's perspective if the presence of arcs (directional lines or degrees) from i to j and from j to k implies the presence of an arc from i to k. Sorensen and Hallinan (1977) reported that triads tend to move away from intransitivity over time with the inconclusive/inconsistent assumption that triads behave independently. Snijders (1996) proposed stochastic actor-oriented models for network evolution which combined a rational choice approach with a continuous-time Markovian approach, while Holland and Leinhardt (1977a, 1977b) also proposed a continuous-time Markov approach to model structural change, starting from the dyad level with each dyad following a four state Markov process.

More recently, Robins and Pattison (2003) have proposed a generalized graphical modelling approach of *p** (Wasserman and Faust, 1994) social influence models to develop discrete time models for the temporal evolution of social networks. They report that systematic temporal processes are construed as effects that are homogeneous across the network, and that reflect dynamics inherent in a particular social relation. Any one actor cannot control these dynamics, especially given that non-dyadic configurations may be implicated, for instance, tendencies for various triadic configurations to be constructed or collapsed over time. Robins and Pattison (2003) further report that non-systematic processes, may pertain to the changing nature of a particular dyadic tie, or to change involving a particular socio-temporal neighbourhood of the network. Non-systematic processes are inhomogeneous across time and across the network, and are modelled as random. To separate non-systematic from systematic temporal processes Robins and Pattison (2003) use the constant tie assumption – whereby ephemeral ties are assumed not to have influence across time. They illustrate these models with an analysis of the Freeman EIES data, and then with data from a newly-formed small training group involving trust and friendship networks.

Random or Stochastic Processes

A stochastic process is a family of random variables $\{X_t \mid t \in T\}$ where T is a parameter space indexing the set. We can consider $\{X_t \mid t \in T\}$ to be the path of a particle moving randomly. The particles' position at a time t is X_t. For example, Brownian motion can be analyzed as such a random process as can data packets moving in a computer network or information flow in a social network. T can belong to $[0,\infty]$ or T can be $\{0,1, \ldots \}$. Therefore, the indexing can be done for all real numbers, and in such a case we have a continuous process; alternatively, T can be the set of non-negative integers, and we have a discrete process.

We can characterize a joint cumulative distribution function (CDF) as $F\mathbf{x}(\mathbf{s};\mathbf{t})$ for a given set of random variables $\{X_{t1}, X_{t2},\ldots , X_{tn}\}$ as follows. Given the parameter vector $\mathbf{t}=(t_1,\ldots,t_n)$, t_i non negative, real or integer and $t_i < t_{i+1}$ with state vector $\mathbf{s}=(s_1,\ldots,s_n)$ then $Fx(s;t) = P(x_{t1} < s_1, x_{t2} < s_2,\ldots x_{tn} < s_n)$ and the joint density function is given by $fx((s;) = (\partial^n)/(\partial_s \ldots \partial_{sn}) * Fx(s;t)$. Stochastic modeling allows us to do the following:

- Find $P(x_t \in s')$ where s' is a particular state or set of states, and t is a particular time. We usually let t

$\rightarrow \infty$ (t tend to infinity), which is steady state. So we wish to find the probability of being in a particular state at a particular time.

- For t_i, t_j Є T the relationship between x_{ti} and x_{tj}. That is, determine the relationship between the values of random variables at two times.
- Find $P(x_t = s_i)$ where s_i is a particular state. That is, the probability that the system enters a particular state.
- Since a system may enter into a state many times, one frequently wishes to know the first time of entry into a state.

Often, we have increments that occurs at times t_i and t_{i+1}. Within these increments we can have independent increments. For $t_i < t_{i+1}$ Є T then each $(x_{ti+1}- x_{ti})$ for $i < i+1$, is independent. This says that an event, such as an arrival, occurring at increments $[t_i,t_{i+1})$ was not influenced or affected by events in (t_{i-1},t). We can consider this event to be the arrival of a data packet at a network switch or the establishing of a contact between two actors in a social network by way of an email or a visit.

Markov Processes and Markov Chains

As mentioned earlier, in a general random process we have a set of times $0=t_0 < t_1 < \ldots < t_n$ and a set of states s_i Є S so the probabilities $P(X_{tn} . s_n \mid X_{tn-1} = s_{n-1}, \ldots , X_{t0} = s_0)$ depend on the entire history of events from t_0 to t_n. A stochastic process is a *Markov process* if the probability of the next state depends upon the current state and not the previous states.

Several of the most powerful analytic techniques for evaluation of computer system performance (and many other systems) are based on the theory of *Markov chains*. A Markov chain is a special case of a *Markov process*, which is itself a special case of a *random process*. Random (stochastic) process as discussed above is a family of (ordered set of related) random variables *X*(t) where *t* is an indexing parameter (usually time). There are many kinds of random processes. Two of the most important distinguishing characteristics of a random process are whether or not the values that the random process can take on are continuous over some interval(s) and whether or not the indexing parameter is continuous or discrete.

Markov chains

A *Markov chain* is a discrete-state random process in which the only state that influences the next state is the current state. To be more precise:
X_{n+1} depends only on X_n and not on any X_i , $1 \leq i < n$
$\Pr [X_{n+1} = s_i \mid X_n = s_j, X_{n-1} = s_k, \ldots X_1 = s_1] = \Pr [X_{n+1} = s_i \mid X_n = s_j]$. This equation is referred to as the *Markov property*.

<u>Continuous-time Markov chain:</u>

Consider a continuous-time random process in which the number of times the random variables *X*(t) change value (the process changes state) is finite or countable. Let $t_1, t_2, t_{3,\ldots k}$ be the times at which the process changes state. If we ignore how long the random process remains in a given state, we can view the sequence $\{X_{t1}, X_{t2}, X_{t3,\ldots,K}\}$ as a discrete-time process embedded in the continuous-time process. Thus a continuous-time Markov chain is a continuous-time, discrete-state random process such that the embedded discrete-time process is a discrete-time Markov chain, and the time between state changes is a random variable with a memory-less distribution.

A distribution function $FT(.)$ is memory-less if and only if $FT(t) = FT(t + \tau | T > \tau)$. This says that the distribution of the time until the next state change is not a function of the time since the last state change. This can be restated as $FT(t) = \Pr[T \leq t + \tau | T > \tau]$. Using the definition of conditional probability,

$$\boldsymbol{FT(t) = \Pr[T \leq t + \tau \;\&\; T > \tau] / \Pr[T > \tau]}$$

$$= \frac{FT(t+\tau) - FT(\tau)}{1 - FT(\tau)} \quad (1)$$

Dividing both sides by t and taking the limit as $t \to 0$, we get a linear first order differential equation with the solution $FT(t) = 1 - e^{-FT(0)t}$. Hence, the only continuous-time, memory-less distribution is the exponential distribution, and the time between state changes in a continuous-time Markov chain is exponentially distributed. For discrete-time Markov chains, the next state may be the same as the current state: $X_{n+1} = X_n$. If p is the probability that the current state is as described above, then the probability that X_{n+1} is different from X_n is (1-p). Also, the probability that X_{n+1} is the same as X_n and X_{n+2} is different from X_{n+1} is p(1-p). Therefore, the number of state transitions between state changes is geometrically distributed.

One special type of Markov chain is a *birth and death* process, in which the states take on all non-negative integer values on a (possibly infinite) range. In this case, we can just refer to s_i as i and define a birth and death process as: if $X_n = i$, then $X_{n+1} = i+1$, i, or $i-1$, i.e., state transitions are always between neighboring states. If the inter-arrival times of data packets or agentic contact between two actors in a social network are independent and identically distributed (IID) and also exponentially distributed as shown above then the # of arrivals, n, over a given interval $(t, t+x)$ has a Poisson distribution with a mean rate of arrival, λ, and a service rate of μ. The properties of the Poisson distribution allow the modeling of information flow in a communication channel like a telephone or computer network or, in our case, the social network of information flows in an organization or society in general.

Markov Chains and Agency

Suppose there are N communication terminals. In our case, N actors in a social network require a connection when the terminal (actor) becomes active (ready to make contact). Suppose there are C connections available. Normally, there will be fewer connections than actors, because not all terminals (actors) are active at the same time. It is also possible that all connections are temporarily busy and a terminal is blocked (the actor is inaccessible or has not yet made the social connection or the tie is weak). Then, the blocked terminal (actor) goes back to idle state without reattempts (will retry at a different time) or the blocked terminal (actor) is put on hold until the connection becomes available in which case the actor may need to establish a stronger tie with the alter. We can model the problem with birth-death Markov process.

- If state i represents the number of active terminals (i.e., the number of connections used),
- When i terminals are active, the rate at which these terminals become idle is given by i_m. The other N-i idle terminals may become active with a total rate of $(N\text{-}i)\,\lambda$. We can depict this Markov process as shown in Figure 1.

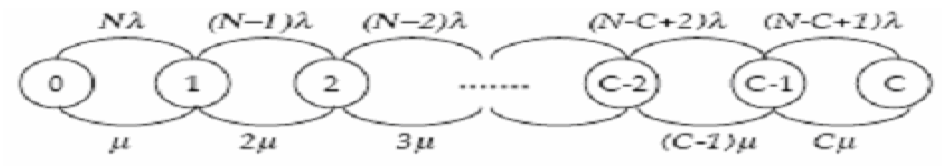

Figure 1: Markov Chain for Engset Blocking Formula – Human Agency

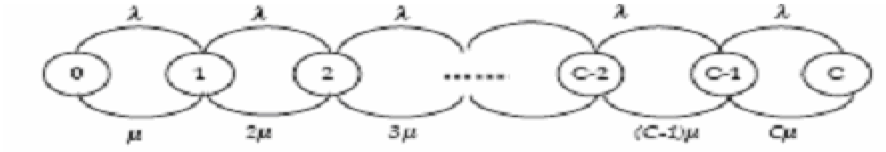

Figure 2: Markov Chain for Erlang Blocking Formula – Human Agency – Utilization and Efficiency

To simplify the analysis and observe that only adjacent states are connected, then the probability flow between states i and i-1 must be balanced. Using the fact that probability sums up to 1, we get **Probability of blocking = P(other N-1 terminals are using C connections).** This means that the probability of the actor's agentic attempt to establish the connection with the 'alter' in his/her social network is given by the above equation. In telephony this is called the Engset Blocking formula.

If we do not restrict the population size and let N go to infinity,[1] while keeping the call arrival rate[2] at a constant **λ** and taking limits for the binomial terms of the Engset distribution, the blocking formula becomes

$$B(C,\rho) = \frac{[\rho^C/C!]}{\sum_{k=0}^{C} [\rho^k/k!]} \quad (2)$$

[1] N going to infinity means increasing the number of contacts for the actor in the social network.

[2] The call arrival rate is the actor's attempt to either build newer and newer entrepreneurial contacts or maintain the existing contacts.

Equation 2 is called the Erlang blocking formula, depicted in Figure 2 and in telephony provides information about trunk utilization and efficiency, while in the case of the social network, we can get information about the actor's agentic capacity and the ability to maintain his/her social network efficiently.

- Offered load = $\rho = \lambda / \mu = \lambda\, E[x]$, where **λ** is the mean arrival rate; **μ** is the service rate over a given interval of (t, t+x).
- Blocking probability, $P_b = B(C, \rho)$
- The blocked load is ρP_b & the carried load is $\rho(1 - P_b)$
- Efficiency = trunk utilization
- Average number of trunks (connections/ties) in use divided by total number of trunks (connections/ties) gives
- Utilization = $\frac{\rho(1 - P_b)}{C}$ (3)
- Where C = total number of trunks (connections/ties).

This means that given a particular load (number of actors in the network), the ego would need a specific number of trunks (connections), C, to meet the target blocking probability (e.g., 1%). From these, you can compute the trunk utilization or efficiency. Based on past experiences, the actor can take decisions on current states, and this is the iterational process as described by Emirbayer and Mische (1998). The actor can then go further and predict his/her future human agentic capability and capacity to make newer friend or entrepreneurial contacts.

The following is an example of this process. Let there be 5 (the offered load **ρ**) actors in a network. Then, total number of ties or connections in the network is C = n(n-1)/2 (Scott, 1991). C then equals 5(5-1)/2 = 10. Assuming a target probability of blocking ($\mathbf{P_b}$) to be 1% (0.01), we can now look at the trunk or connection utilization of the central actor from equation 3 above as

$$\mathbf{U = (5*(1-0.01))/10 = 0.495}$$

This means that with five actors in the network, the efficiency of utilization of the connections or ties is 49.5%. If you now increase the number of actors in the network to 10, the total number of connections rises to 45 and the connection utilization efficiency drops to 22%, keeping the target probability of blocking constant at 1%. Lowering the probability of blocking will only lower the efficiency, so the central actor will then have to determine his ideal or optimal connection utilization and based on this percentage, limit or manage his/her contacts. Thus, for an actor in an organizational or entrepreneurial network, it becomes imperative to know which contacts to retain, which to let go, and which to keep in abeyance by delegating or occasional communiqués so that she/he can best benefit by the efficient utilization of the network's resources. Since everything depends on the flow of information between actors and the social relations that they have developed, each actor will be in a position to allocate a priority to the contact based on the history of their previous interactions with that actor, their present relationship and determine their individual optimum for connection utilization in the future with that actor in the network.

Example From a Recent Study

In a recent study involving distance students using a computer-supported collaborative learning (CSCL) environment, a network of the usage of the CSCL's instant messenger (IM) system by the students revealed a few central actors, one of them being the instructor himself. Of the others who also participated in IM discussions, N = 11, it was found that they were also active in the electronic bulletin boards, regularly posting messages (task related, administrative and social). Figure 3 depicts the IM social network.

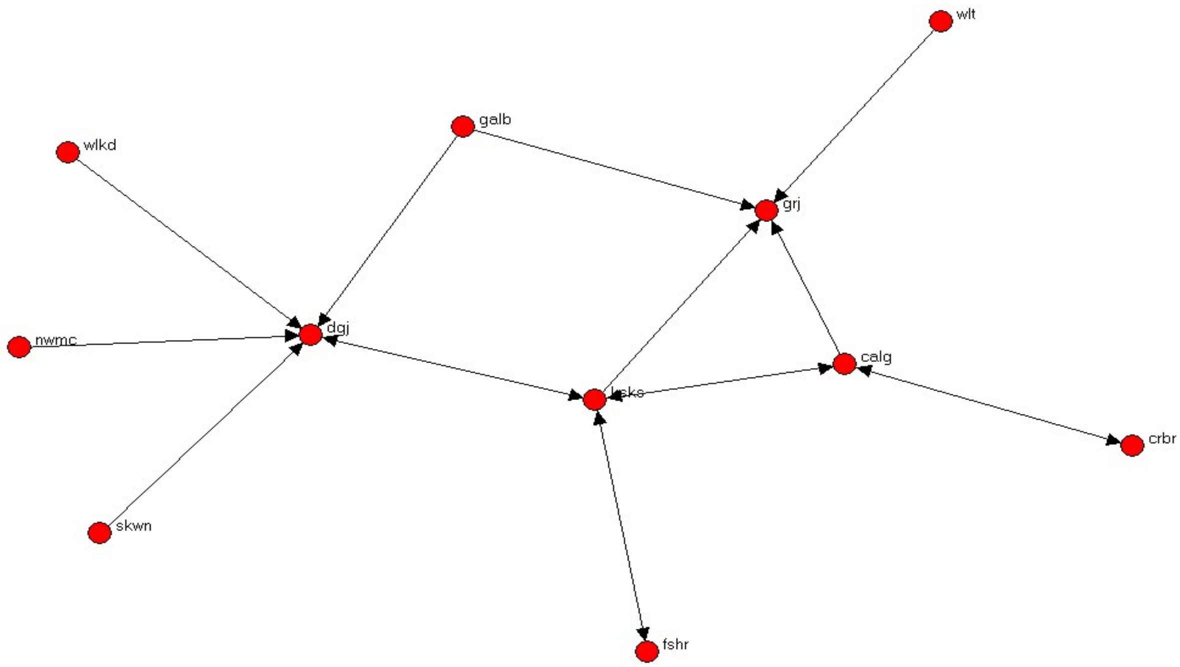

Figure 3: Social Network of Students in a CSCL IM Discussion (Ucinet 6.0 - Borgatti, Everett, and Freeman, 2002)

As you can see from Figure 3, actor dgj is the instructor and has the highest degree of connections, while actor grj is second, and actor ksks, third, with higher in-degree than actor calg. Actor ksks however, had highest flow betweenness centrality score (32.5) compared to dgj (20) and calg (11), while actor grj not being connected to dgj directly had a flow betweenness centrality score of (0). Surprisingly, in the discussion board posts, spanning eleven sessions over a six-week period, grj had the highest number of message posts (54 out of a total of 211) while actor calg had 12 posts and actor ksks had only six message posts.

This interesting phenomenon can be better explained when we use the modified Erlang Blocking formula described earlier (Utilization = **ρ (1- P_b)/C --** eq. 3). We can work with the number of actors in this network. The offered load **ρ** (actors in a network) is 11. The total number of ties or connections in the network is C = n(n-1)/2 (Scott, 1991). C then equals 11*(11-1)/2 = 55. Assume a target probability of blocking (**P_b**) to be 1 % i.e. 0.01, we can now look at the trunk or connection utilization of the central actor from equation 3 above as

U = (11*(1-0.01))/55 = 0.198

Table 1 gives the network utilization for the whole network and for each of the actors calculated based on their in-degree and out-degree being the offered load **ρ** with the probability of blocking set at 1% (0.01). The offered load for each actor, when calculating the in-degree includes the ego and all alters to which the ego is connected. This is done in the case of the out-degree count also. Table 2 gives the network utilization for the whole network and for each of the actors calculated based on their in-degree and out-degree being the offered load **ρ** with the probability of blocking set at 10 % (0.1).

Table 1: Actor's network utilization for in-degree and out-degree with target blocking probability set at 1 %

Actor	ρ - indegree # of actors	P_b - prob	C - # of ties	U - Utilization	Actor	ρ - outdegree # of actors	P_b - prob	C - # of ties	U - Utilization	# of posts in Discussion Boards
Whole	11	0.01	55	0.198	Whole	11	0.01	55	0.198	100
ksks	4	0.01	6	0.66	ksks	5	0.01	10	0.495	6
Dgj	6	0.01	15	0.396	dgj	2	0.01	1	1.98	0
Calg	3	0.01	3	0.99	calg	4	0.01	6	0.66	12
Grj	5	0.01	10	0.495	grj	0	0.01	0	no value	54
Fshr	2	0.01	1	1.98	fshr	2	0.01	1	1.98	3
Crbr	2	0.01	1	1.98	crbr	2	0.01	1	1.98	3
Galb	3	0.01	3	0.99	galb	3	0.01	3	0.99	6
nwmc	2	0.01	1	1.98	nwmc	2	0.01	1	1.98	7
skwn	2	0.01	1	1.98	skwn	2	0.01	1	1.98	6
wlkd	2	0.01	1	1.98	wlkd	2	0.01	1	1.98	1
Wlt	2	0.01	1	1.98	wlt	2	0.01	1	1.98	2

Table 2: Actor's network utilization for in-degree and out-degree with target blocking probability set at 10 %

Actor	ρ - indegree # of actors	P_b - prob	C - # of ties	U - Utilization	Actor	ρ - outdegree # of actors	P_b - prob	C - # of ties	U - Utilization	# of posts in Discussion Boards
Whole	16	0.1	120	0.12	Whole	17	0.1	136	0.1125	100
ksks	4	0.1	6	0.6	ksks	5	0.1	10	0.45	6
Dgj	6	0.1	15	0.36	dgj	2	0.1	1	1.8	0
Calg	3	0.1	3	0.9	calg	4	0.1	6	0.6	12
grj	5	0.1	10	0.45	grj	0	0.1	0	no value	54
fshr	2	0.1	1	1.8	fshr	2	0.1	1	1.8	3
crbr	2	0.1	1	1.8	crbr	2	0.1	1	1.8	3
galb	3	0.1	3	0.9	galb	3	0.1	3	0.9	6
nwmc	2	0.1	1	1.8	nwmc	2	0.1	1	1.8	7
skwn	2	0.1	1	1.8	skwn	2	0.1	1	1.8	6
wlkd	2	0.1	1	1.8	wlkd	2	0.1	1	1.8	1
wlt	2	0.1	1	1.8	wlt	2	0.1	1	1.8	2

From the two tables we can see that the actors who had higher centrality from the network depicted in Figure 3 have differing values of network utilization **U**. While actor grj, who is central in that she had a higher in-degree than other students (with the exception of dgj the instructor), her out-degree is zero. Actor ksks, with in-degree = 4 and out-degree = 5, has **U** = 0.6, $\mathbf{P_b}$ = 10% for in-degree (0.66 with the target probability of blocking set at 1 %), and **U** = 0.45, $\mathbf{P_b}$ = 10% for out-degree (0.495 with target probability of blocking set at 1%) respectively. Coupled with his higher flow betweenness centrality score (32.5, the highest) and his judicious use of discussion board message postings (only 6), actor ksks is better placed in the network to not only utilize it in an optimum manner, but also leverage his network position in a manner that does not greatly reduce his efficiency. He was able to manage the capacity of actors and information in the network, and thus, used it to his benefit (found from self-reported survey questions, where he found the CSCL system Elluminate™, with its IM, videostreaming, voice-in and whiteboard features suitable for content delivery and that he found it facilitated his learning process). He also reported that it helped him learn new conceptual knowledge and gain new insights into collaborative distance work; he was completely satisfied with his performance in the course, felt he had the respect of his distance classmates, and was confident of getting an A in the course.

Though the other actors in the network have a greater utilization value, they only have 2 actors in their degree calculations, and, as the number of connections 'C' is in the denominator of equation 3, fewer connections will definitely give higher utilization values, but this does not mean that they are utilizing the network well, as can be seen from both their positions in the network (Figure 3) and their activity in the discussion board message postings. Actor, grj though very active in the message postings, and occupying a good network position, because of her lack of out-degree, her own self-reported views on the CSCL system and that she considered herself to be the most knowledgeable person in the network, her network utilization values are lower and apparently not beneficial to her.

Discussion

This modeling of human agency provides one way to answer the questions raised by Emirbayer and Mische (1998), namely, what kinds of contexts provoke or facilitate actors toward gaining imaginative distance from those multi-cultural and socio-cultural responses and thereby reformulating past patterns through the projection of alternative future trajectories? And, what sorts of contexts constrain or enable their capacity for communicative deliberation, by means of which they judge which particular actions are most suitable for resolving the practical dilemmas of emergent situations?

Depending on the situation, actors may decide to use past values or information and change as the need arises by establishing newer communication patterns as they seek to imagine alternative futures for a problematic present. However, certain sets of actors might resist change and hold tightly to past routines (such as local or national traditions) in an attempt to ward off uncertainty. By looking at periods of stability and change, as do telephony engineers when monitoring peak and off-peak telephone traffic, much insight into such processes can be gained by looking at these agentic orientations. Thus, the socio-temporal dimension of actors engaged in emergent events sees them positioned between the old and the new, and forces them to develop new ways of integrating past and future perspectives by understanding and using their embedded human agency in multiple cultural, social-structural, and social-psychological contexts.

Emirbayer and Mische (1998) state the implication of Rose Laub Coser's (1975, p. 239) missive that actors who are located in more complex relational settings must correspondingly learn to take a wider variety of factors into account, to reflect upon alternative paths of action, and to communicate, to negotiate, and to compromise with people of diverse positions and perspectives. All of these qualities, she argues, support more autonomous personal and occupational identities (and, by extension, more imaginative and reflective engagements with the contexts of action).

In this paper, I began with a review of organizational communication practices and how social network analysis reveals the emergent network structure in organizational information flows. DiMaggio (1991) argues that the creation of a professional environment at the inter-organizational level leads to more critical discourse, formal equality, and purposeful search for alternatives. This is in contrast to the routine, hierarchy and scripted forms of rationality that predominate inside organizations, highlighting the variation in agentic capacity to institutional complexity. Other researchers have looked at how choice-making and careers are embedded in complex network interactions (Abbott and Hrycak, 1990; Pescosolido, 1992), and the model proposed in this paper may shed light on how differently structured networks and careers support variable agentic orientations. These agentic orientations take into account actors' roles and position, (i.e. in brokerage, central and/or boundary spanner roles) to leverage these socio-temporal relational contexts and develop greater capacities for creative and critical intervention).

We are aware that entrepreneurs and actors in organizations embed their business decisions in social structures (Borch, 1994; Hansen, 1995; Larson & Starr, 1993; Reynolds, 1991; Starr & MacMillan, 1990). Social networks are not fixed; they are the social context of businesses and can be activated according to different needs (Granovetter, 1985; Burt, 1992). To fit their organizational needs, entrepreneurs bring both those that are closer and distant to them into their business decisions. However, kinship relations are usually stable over time and can be modeled deterministically.

The focus of this paper has been to put forth a Markov model that will aid in providing information to entrepreneurs on the capacity of their social networks and how to maintain social-temporal relations with their contacts and resources, despite their tendency to connect to a "friend of a friend" or the ability to select new contacts (acquaintances) from their networks.

This model takes advantage of the similarities between the concept of human agency and Markov random processes. It takes into account the fact that present experiences are the sum total of past iterational and habitual experiences and the present practical-evaluative capacity to evaluate these past experiences. The model then adapts the Markov process when it uses the present practical-evaluative experience to create a projective capacity toward the future state of the social network, by providing the actor (ego) with information about the efficient utilization of his/her channel/network capacity, and the number of contacts or resources he/she would need to maintain to achieve the future stability of the network contacts and resources.

Conclusions

From Rapoport (1963), we view the creation of new network ties as a trade-off between two opposing forces: "order" and "randomness." "Order" is defined in terms of a *triadic closure bias* (Rapoport, 1963), i.e., the tendency of an individual to connect to a "friend of a friend." "Randomness," on the other hand, means that new acquaintances are to be selected by drawing uniformly from the population at large.

Further research in this vein would involve designing a study which would collect the present N of the ego (entrepreneur), the present and past number of contacts, and make a prediction about the capacity of the ego's network and the future capacity and network utilization in order to have a healthy and productive association with the contacts and resources. We can then bring in notions of other factors like "network trust" (Burt, 1992), the "order & randomness" (Rapoport, 1963) that play a role in the selection, and maintenance of network contacts.

A longitudinal study may also estimate transition probabilities and contingencies for transition to another phase or dropping out of the establishment process. Further, longitudinal network data on successful and unsuccessful entrepreneurs, and the conditions forcing entrepreneurs to drop out of the establishment process, would help shed more light on the efficacy of the model. We need more research to describe the development and composition of efficient social structures that are conducive to entrepreneurship and the integral role played in these networks by human agency.

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