資源和記憶對舊識網路的影響

Resource and Remembering Influences on Acquaintance Networks

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資源和記憶對舊識網路的影響

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摘要

已經有大量的研究採取由上而下的方式來爲社會網路建立模型。這些模型大多直接混合規則網路和隨機網路，它們不但漂亮地造出具備高群聚度及低分隔度的社會網路，用於理論分析時更帶給我們許多重大的洞見。另一方面，由於這類模型忽略了真實社會中的人際互動，所以無法很好地用來解釋發生在社會網路更細部的現象。相對地，我們提出的網路模型採取由下而上的方式，整個網路是以人跟人間的互動規則，隨著時間不斷變化，逐漸演變而成的。這篇論文中，除了考慮到共同的朋友、偶遇、進出朋友圈等因素，我們還考慮了「有限的資源」和「對朋友念不念舊」等對舊識網路造成的影響。基於這些人際間的互動因子，人們彼此可能由陌生到熟識，已建立的友誼除了可能增強、變弱外、甚至還可能因爲久未聯絡，或在資源有限等因素下，再次變得陌生、形同陌路。在一系列的模擬實驗後我們發現：一、一些網路的統計數據，尤其是平均朋友數，和參數的特定分佈無關，只相依於模型各個初始參數的平均值；二、資源、念舊程度、初始友誼等都會增加平均朋友數，且同時降低網路的群聚度及分隔度；三、廣泛用於現場訪查的抽樣方法，無法真正捕捉到社會網路的度分佈特性；四、在我們的舊識網路模型及 Newman 和 Watts 的小世界模型這兩者上，對於感冒等傳染病傳播導致的引爆點發生情形是不同的。這些發現顯示：這類研究需要某種由下而上，基於網路模型，且強調互動規則的模擬實驗。

Resource and Remembering Influences on Acquaintance Networks

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ABSTRACT

To better reflect actual human interactions in social network models, the authors take a bottom-up simulation approach to analyzing acquaintance network evolution based on local interaction rules. Resources and remembering are considered in addition to common friends, meeting by chance, and leaving and arriving. Based on these factors, friendships that have been established and built up can be strengthened, weakened, or broken up. Results from a series of simulations indicate that (a) small world statistics, especially mean degree of nodes, are irrelevant to parametric distributions because they rely on average values for initial parameters; (b) resource, remembering, and initial friendship all raise the average number of friends and lower both degree of clustering and separation; (c) widely used fieldwork sampling methods cannot capture the actual degree distributions of social networks; and (d) the epidemic dynamics and critical thresholds of infectious disease in our acquaintance network differ from those in Newman and Watts' small-world model. These findings indicate a strong need for a bottom-up simulation approach to social network research, one that stresses interactive rules and experimental simulations.

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僅將此論文獻給我家人，父母、妹妹、可愛的外甥女，謝謝他們這段期間給我的關心、支持、鼓勵，祝福他們永遠健康快樂。

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Chapter 1
Introduction

The primary feature of any social network is its small world characteristics of low separation (showing how small the world is) and high degree of clustering (explaining why our friend's friend is often our friend also). Watts' (1999) research has been the basis for models that apply small world techniques to measuring social networks [15-17]. Most of these models [e.g., 13, 15, 17] mix regular and random networks—good for explaining small world features but inadequate for explaining the evolutionary mechanisms of social networks due to their neglect of local rules that affect interactions and relationships between individuals. Furthermore, researchers have generally focused on the final products of network topologies—that is, they have shown a bias toward top-down approaches that facilitate theoretical analyses [13-20]. But actual social network construction involves bottom-up processes entailing local human interactions. Our focus in this study is on the local interaction rules and dynamic processes that affect network formation.

Other complex network models and applications can be referenced when researching social networks. Examples include Albert et al.'s (2000) proposal that the Internet possesses scale-free features, Barabasi and Albert's (1999) use of growth and preferential attachment mechanisms to establish a scale-free Internet model (the BA model). Bianconi and Barabási (2001) added the fitness concept to the BA model, in which new added nodes are possible to attach more edges then old ones. To simulate this kind of complex network more realistically, Li and Chen (2003) have introduced the concept of *local-world* connectivity, which exists in many complex physical networks. Their local-world model exhibits transitions between power-law and exponential scaling; the Barabási–Albert (1999) scale-free model is one of several special (limiting) cases.

As is the case with other complex networks, social networks exhibit the small world phenomenon but differ in terms of characteristic detail (Newman & Park, 2003). Davidsen et al. (2002) have proposed a model based on local rules for building *acquaintance* networks; the rules involve such factors as making acquaintances, becoming familiar with other individuals, and losing connections.

Acquaintance networks are a type of social network that represents the processes and results of people meeting people for the first time. Befriending someone in a social network is an important daily activity, one that more often than not involves two individuals and a go-between who is a friend or acquaintance of both. However, a significant number of acquaintances are made by chance, with two or more individuals coming together at a specific time in a specific place because of a shared interest or activity. As part of their acquaintance network model, Davidsen et al. (2002) identified two local and interactive rules, the first involving introductions and meeting by chance and the second involving the effect of aging on acquaintance networks. Their model is considered more realistic because it acknowledges a simple observation from everyday experience that often one of our friends introduces us to one of his or her friends. However, the model is still inadequate for explaining changes that occur once acquaintances evolve into friendships—for example, strengthening, weakening, or separation that does not involve the death of one party.

In this paper we will introduce a rule that involves limited resources and remembering—the latter a memory factor through which individuals remember or forget their friends. This bottom-up, human-interaction-based simulation approach allows for analyses of how individual interaction factors affect the statistical features of acquaintance networks. For example, researchers can adopt different friend-making resource distributions and probe their effects on entire acquaintance networks and measure correlations between statistical features under different circumstances.

Chapter 2
Complex Networks Applied to Friend-making Simulations

The small world concept reflects the "What a small world!" feeling that two strangers have when they find out they have a friend in common. Milgram (1967) was the first to design experiments involving the small world characteristic; since then, many experiments have been conducted to verify the characteristic in human interactions. To overcome practical barriers, Watts and Strogatz (1998) restated the issue as "general conditions under which the world can be small" [see also 13, 16, 18, and 19]. Based on these efforts, social networks are now graphically expressed as nodes (representing persons) and links (connecting persons who know each other).

According to Watts [16, 17], the small world feature and its characteristics of low separation and high clustering is common to all social networks. Degree of separation is measured using average path length and degree of clustering is measured as a clustering coefficient. Average path length in any given network is calculated as

$$L = \langle d_{u,v} \rangle = \frac{1}{\frac{1}{2}N(N-1)} \sum_{u \neq v} d_{u,v} = \frac{2}{N(N-1)} \sum_{u \neq v} d_{u,v}\ , \tag{1}$$

where N is the number of nodes in the network of interest (i.e., network size) and $d_{u,v}$ denotes the shortest path between u and v. Suppose node v has k_v number of neighbors and a total of E_v edges between k_v nodes The clustering coefficient is defined as

$$C = \langle C_v \rangle = \left\langle \frac{2E_v}{k_v(k_v-1)} \right\rangle = \frac{1}{N}\sum_{v=0}^{N-1}\frac{2E_v}{k_v(k_v-1)} \; . \tag{2}$$

To make sense of the dimension of network separation, the average path length in a network must be compared to that in a random graph with the same average number of neighbors. To make sense of the magnitude of network clustering, a network's clustering coefficient must be compared to that of a regular network with the same average number of degrees.

2.1. Lattice Graphs

Lattice graphs are also called *d-lattices* and *nearest-neighbor coupled networks*. They represent regular networks that have been thoroughly researched. Each node in a d-lattice can only be connected to immediately adjacent neighbors. A two-neighbor (K = 2) periodic 1-lattice is a ring and a four-neighbor (K = 4) 2-lattice is a two-dimensional grid graph. The average path length for a $K > 1$ periodic 1-lattice is calculated as

$$L_{NC} = \frac{N(N+K-2)}{2K(N-1)} \to \infty \quad (N \to \infty) \; . \tag{3}$$

Here the average path length is so large that it cannot be considered a small world characteristic. The clustering coefficient for d-lattices with larger numbers of neighbors is calculated as

$$C_{NC} = \frac{3(K-2)}{4(K-1)} \approx \frac{3}{4} \text{ .} \quad (4)$$

When high clustering is observed in such networks, they are said to conform to social network characteristics.

2.2. Random Graphs

Random graphs are constructed using nodes that have random connection edges. Another way of building a random graph is to determine the p probability of a link between node pairs; the result is an ER random graph [6] consisting of N nodes and $[pN(N-1)/2]$ edges. In their analysis of ER random graphs, Erdös and Rényi (1960) estimated the average number of neighbors (i.e., average degree of nodes) as

$$\langle k \rangle_{ER} = \frac{pN(N-1)}{N} = p(N-1) \approx pN \text{ .} \quad (5)$$

The average path length of an ER random graph is estimated as

$$L_{ER} \propto \frac{\ln N}{\ln \langle k \rangle} \text{ .} \quad (6)$$

As seen in Equation (6), the average path length of an ER random graph (L_{ER}) increases logarithmically with network size (N). This agrees with the small world characteristic observed in social networks. In other words, a common small world feature—the "small" in "small world"—is that even large-scale ($N >> 1$) networks can have short path lengths.

Another small world characteristic is high clustering, which for an ER random graph is estimated as

$$C_{ER} = \frac{\langle k \rangle}{N}, \qquad (7)$$

meaning that unlike social networks, ER random graphs do not have the clustering characteristic.

In cases where the average degree <*k*> is fixed and the node total *N* is large enough, the independent addition of edges results in a Poisson distribution (Bollobàs, 2001) of the ER random graph with the equation

$$P_{ER}(k) = \binom{N}{k} p^k (1-p)^{N-k} \approx \frac{\langle k \rangle^k e^{-\langle k \rangle}}{k!}. \qquad (8)$$

2.3. Small Worlds

Regular networks exhibit high clustering but not small world characteristics; random networks have short average path lengths but not high clustering. Watts and Strogatz (1988) introduced a small world model that we will refer to as the WS model. The WS algorithm starts from a 1-lattice graph in which each node has K neighbors, with each side having $K/2$ edges. The algorithm then determines whether re-linking an edge with a probability β maintains a maximum of one edge between two arbitrary nodes without any self-links. Newman and Watts (1999) simplified the WS model by replacing random edge rewiring with random edge additions. The NW and WS models are equivalent in cases where the probability β of edge rewiring or additions is small and N is sufficiently large. The two models retain the clustering feature of regular networks. Adding a small amount of randomness dramatically shortens the average path length.

The two models just described capture the small world features of complex networks, but social networks have additional characteristics. For instance, clustering in social networks is relatively unmixed, and many social networks are divided into groups (Newman & Park, 2003). Leenders (1996) observed that friendships are not all identical, and can be categorized as acquaintances, "just friends," good friends, best friends, true friends, and so forth.

2.4. Skewed Degree Distributions

In addition to the small-world features of low separation and high clustering, social networks also have the property of *skewed degree distributions* [1, 2]. For example, the degree distribution in a collaboration network of movie actors approximately obeys a power law for a part of its range, and has an apparently exponential cutoff for very high degree. This kind of skewed degree distribution is observed also in coauthoring networks, such as collaboration network of biologists and physicists [21].

On the other hand, the degree distribution of the network of directors of Fortune 1000 companies is much less skewed. It has a sharp peak around a certain mean degree, and a fast decay in the tail—its right-skewed is not noticeably in contrast with that in the collaboration networks. Newman (2001) explained that the network of company directors has a substantial cost associated with it. It takes continual work to be a company director [21, 24].

2.5. Growing Social Networks

The most classical network growth models are that on Internet or on the World-Wild Web, such as Barabasi and Albert's (1999) growth and preferential attachment mechanisms, and Bianconi and Barabási's (2001) addition of fitness on the BA model's vertices. These models continuously add both vertices and edges to the network as time passes (growth); and edges are more likely to connect to vertices of high degree than to ones of low degree (preferential attachment).

Growth models on Internet or on the Web, however, are quite inappropriate as models of the growth of social networks or acquaintance networks. The reasons are (a) the degree distribution of many acquaintance networks does not appear to follow a power-law distribution; (b) the preferential attachment mechanism is not an important one in acquaintance networks; and (c) social networks such as acquaintance networks usually appear high clustering, but growth models of the Web or Internet show weak clustering. Jin, Girvan, and Newman (2001), hence, first attempted at modeling the evolution of the structure of social networks and their model creates a sharply peaked distribution that is conforming to the observation in a lot of real social networks.

Chapter 3
Friendship Evolution and the Three-Rule Model

Davidsen et al. (2002) propose a two-rule model of acquaintance network evolution, with the first rule addressing how people make new friends—via introductions or meetings-by-chance. The second rule is that friendships are broken when one partner dies. The model formulates a fixed number of N nodes and undirected links between pairs of nodes representing individuals who know each other. We will introduce a *friend remembering* rule that allows for the weakening and strengthening of friendships (Fig. 1). The model repeats the three rules until the acquaintance network in question reaches a statistically stationary state.

- **Rule 1. Friend Making**: Randomly chosen persons introduce two friends to each other. If this is their first meeting, a new link is formed between them. Randomly chosen persons with less than two friends introduce themselves to one other random person. Thus, we use the term "introduce" to describe meetings by chance as well as meetings via a common friend.

- **Rule 2. Leaving and Arriving**: At a probability p, a randomly chosen individual and all associated links are removed from a network and replaced by another person. Accordingly, acquaintances can be viewed as circles of friends whose members can leave for reasons other than death and enter the circle for reasons other than birth.

- **Rule 3. Friend Remembering**: A certain number of friendships are updated, with the number depending on an update proportion *b*. This proportion and details about updating will be explained in the next two sections.

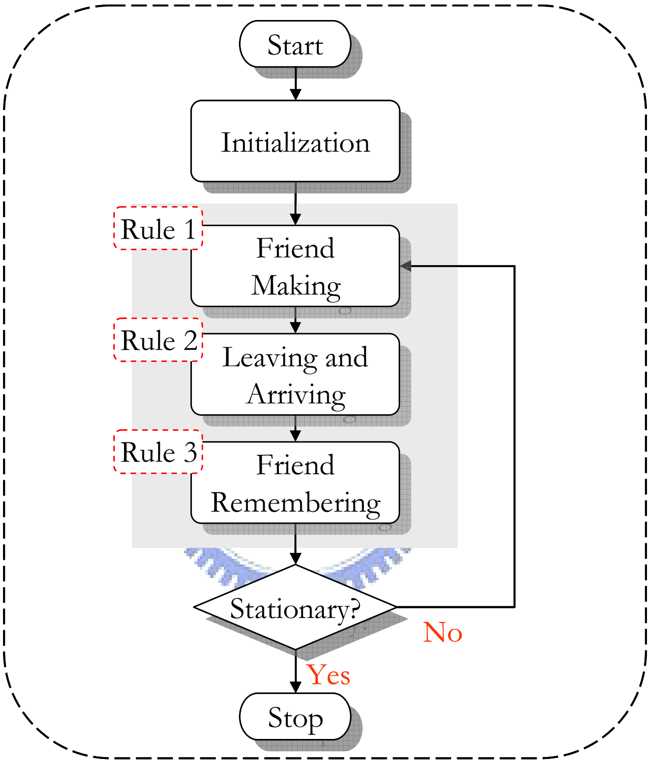

Figure 1. Three-rule model flow diagram.

3.1. Friendship Selection Methods

We considered three selection methods for updating friendships. In the first, *person selection*, an individual chooses $b \times N$ persons before picking a specific friend for each person and updating their friendship. The update does not occur if the chosen person does not have any friends. In this method, b is a proportion factor for deciding how many persons are chosen and N represents the number of persons in the network. In the second method, *pair selection*, the individual chooses $b \times N$ pairs of persons and updates their friendships. Updating is canceled if the paired persons don't know each other—a frequent occurrence, since the network in question is sparse in comparison to a complete graph. In this method, b is a proportion factor for deciding how many pairs are chosen. In the last, *edge selection*, the individual has more direct choice in selecting $b \times M$ friendships for updating. In this method, b is a proportion factor for deciding how many friendships are chosen and M is the number of friendships (or edges) at a specific moment.

We rejected the first two methods because in both cases, the number of chosen friendships is in proportion to N (number of nodes or persons). Since $N \times (N - 1) / 2$ (the upper boundary of the number of friendships) is directly proportional to M (the number of edges or friendships), we adopted the edge selection method for choosing friendships.

3.2. Friendship Update Equation

During friend remembering, the model uses the selection tactic described in the preceding section for choosing a specific number of friendships. If a selected friendship links person u with person v, their friendship is updated using Equation (9), dependent upon individual remembering, resource, and breakup threshold factors:

$$f_{u,v}^{new} = \begin{cases} q \cdot f_{u,v}^{old} + (1-q) \cdot J\left(D\left(\frac{r_u}{k_u}\right), D\left(\frac{r_v}{k_v}\right) \right), & if \ f_{u,v}^{old} \geq \theta, \\ 0, \quad if \ f_{u,v}^{old} < \theta \end{cases} \tag{9}$$

where $f_{u,v}^{new}$ represents the new friendship between *u* and *v*, $f_{u,v}^{old}$ the original friendship, *q* the old friend remembering, θ the breakup threshold, r_u person *u*'s friend-making resources, k_u his or her number of friends, and r_v and k_v person *v*'s resources and friend numbers, respectively. *J* is a joint function and *D* a distribution function. For convenience, the friend remembering *q*, resource *r*, and breakup threshold θ parameters are normalized between 0 and 1.

Simplification without loss of generality is behind our decision to use $D(x) = x$ as the distribution function and $J(a, b) = (a + b) / 2$ as the joint function. The updated equation is written as

$$f_{u,v}^{new} = \begin{cases} q \cdot f_{u,v}^{old} + (1-q) \cdot \left(\frac{r_u}{k_u} + \frac{r_v}{k_v} \right) \cdot \frac{1}{2}, & if \ f_{u,v}^{new} \geq \theta. \\ 0, \quad if \ f_{u,v}^{new} < \theta \end{cases} \tag{10}$$

The equation is divided into two parts by the breakup threshold, θ. The first part consists of the terms *q* (representing the effect of old friendships) and $(1 - q)$ (representing the effect of limited resources). The newly updated friendship may be weakening or strengthening. It may also theoretically equal zero if the new friendship is below the breakup threshold, as shown in the second part of the equation.

3.3. Expected Effects of Local Rules

Acting locally, the three rules influence several aspects of an acquaintance network: (a) the friend-making rule adds links, thereby increasing the average number of friends; (b) the leaving and arriving and friend-remembering rules both remove links, thereby reducing the average number of friends; (c) increases in average number of friends $<k>$ lead to decreases in the average shortest path length L; and (d) the direction of the clustering coefficient C and average shortest path length L will reverse.

As opposed to the large number of factors associated with the friend-remembering rule, the leaving and arriving rule has a single parameter (probability p). The factor q denotes a person's ability to remember friends, thus increasing that person's number of friends. The resource factor r determines an individual's resources for making friends, thereby setting an upper limit. The breakup threshold θ determines the difficulty of cutting off a friendship—a negative influence. The initial friendship factor f_0 is a reflection of how much attention a person is paying when making a new acquaintance—a positive contribution to friend-making. We expect that parameters q, r, and f_0 will exert positive (increasing) influences on $<k>$ and that parameters p and θ will exert negative influences on $<k>$.

3.4. Fitting a Normal Distribution

For sensitivity analyses of skewness and critical parameters affecting distribution, a feasible probability-distribution function (pdf) must be applied. In most situations a normal distribution is considered the best choice, but it does not fit our purposes in this study. Since critical parameters such as initial friendship, old friends remembering, resources, and breakup thresholds have ranges of 0 to 1, we chose a *beta* distribution—a two-parameter family of continuous probability distributions defined according to the interval [0, 1] with a probability density function of

$$f(x;\alpha,\beta) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}, \tag{11}$$

where B is the beta function and α and β must be greater than zero (Larson, 1995).

We used a beta distribution subset called *beta14* that satisfies $\alpha + \beta = 14$ and has $\mu = \alpha / (\alpha + \beta)$ as its average. Figure 2 presents pdf curves for *beta14* distributions with averages of 0.1, 0.5, and 0.9. Figure 3 presents pdf curves for comparing *beta14* and normal distributions.

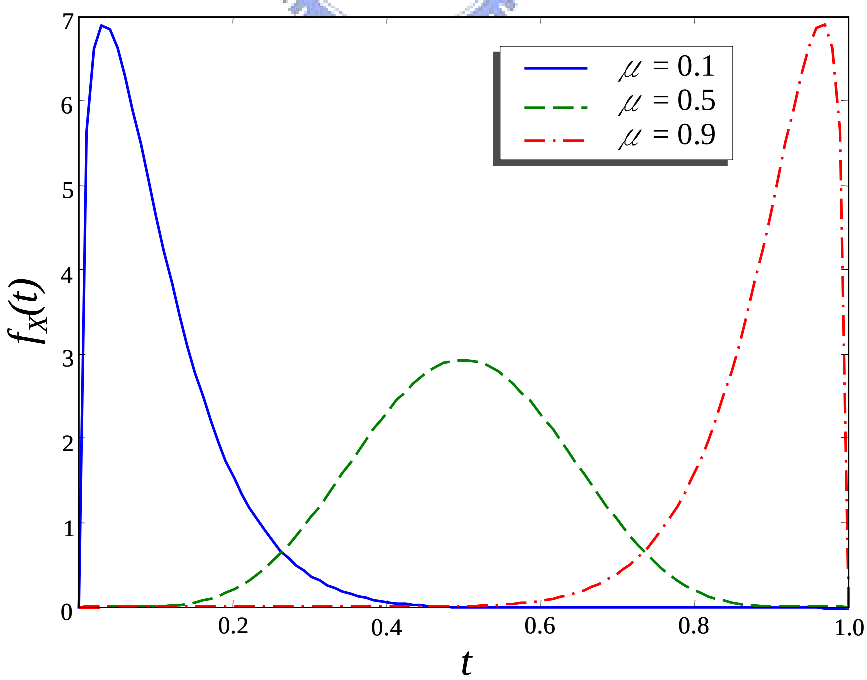

Figure 2. Beta14 pdf curves at different averages of 0.1, 0.5, and 0.9.

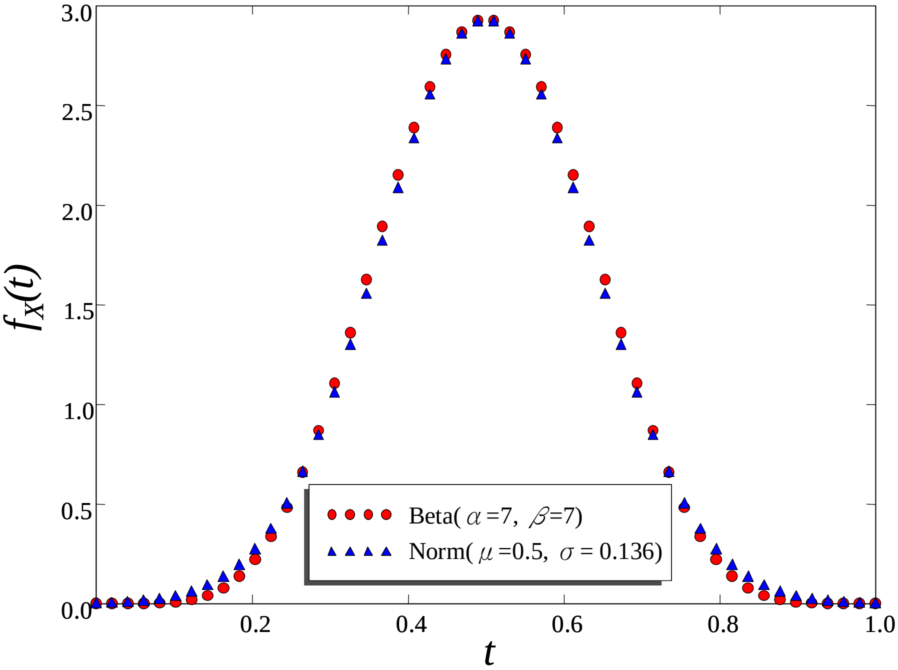

Figure 3. Comparison of beta and normal distributions.

Once a simulation reaches a statistically stationary level, then clustering coefficient, average path length, average degree, average of degree squared, and degree distribution statistics can be collected. Degree distributions in our simulations involved some random rippling, especially for smaller populations. However, since large populations consume dramatically greater amounts of simulation time, we applied Bruce's (2001) ensemble average as follows:

$$\bar{p}(k) = \frac{1}{M}\sum_{m=1}^{M} p_m(k), \qquad (12)$$

where M is the number of curves to be averaged and $p(k)$ a curve that represents, for example, a degree distribution, a time series, and so forth.

Chapter 4
Experiment

A simulation of our model begins with parameter initialization and ends once the acquaintance network reaches a statistically stationary state. Initialized parameters included the number of persons N, leaving and arriving probability p, updated friendship proportion b, old friend remembering q, breakup threshold θ, distribution of friend-making resources r, and distribution of initial friendship f_0. Statistically stationary states were determined by observing average degree $\langle k \rangle$, average square of degree $\langle k^2 \rangle$, clustering coefficient C, and average path length L. Each of these four statistics eventually converged to values with slight ripples.

A statistically stationary state of parameter initialization at N = 1,000, p = 0, b = 0.001, q = 0.9, θ = 0.1, r with a fixed value of 0.5, and a *beta14* f_0 (μ = 0.9) is shown in Figure 4. Solid lines indicate the acquaintance network and the dashed lines in Figures 4c and d (which are calculated using Equation 6 and Equation 7) indicate the ER random model at the same average degree as the acquaintance model.

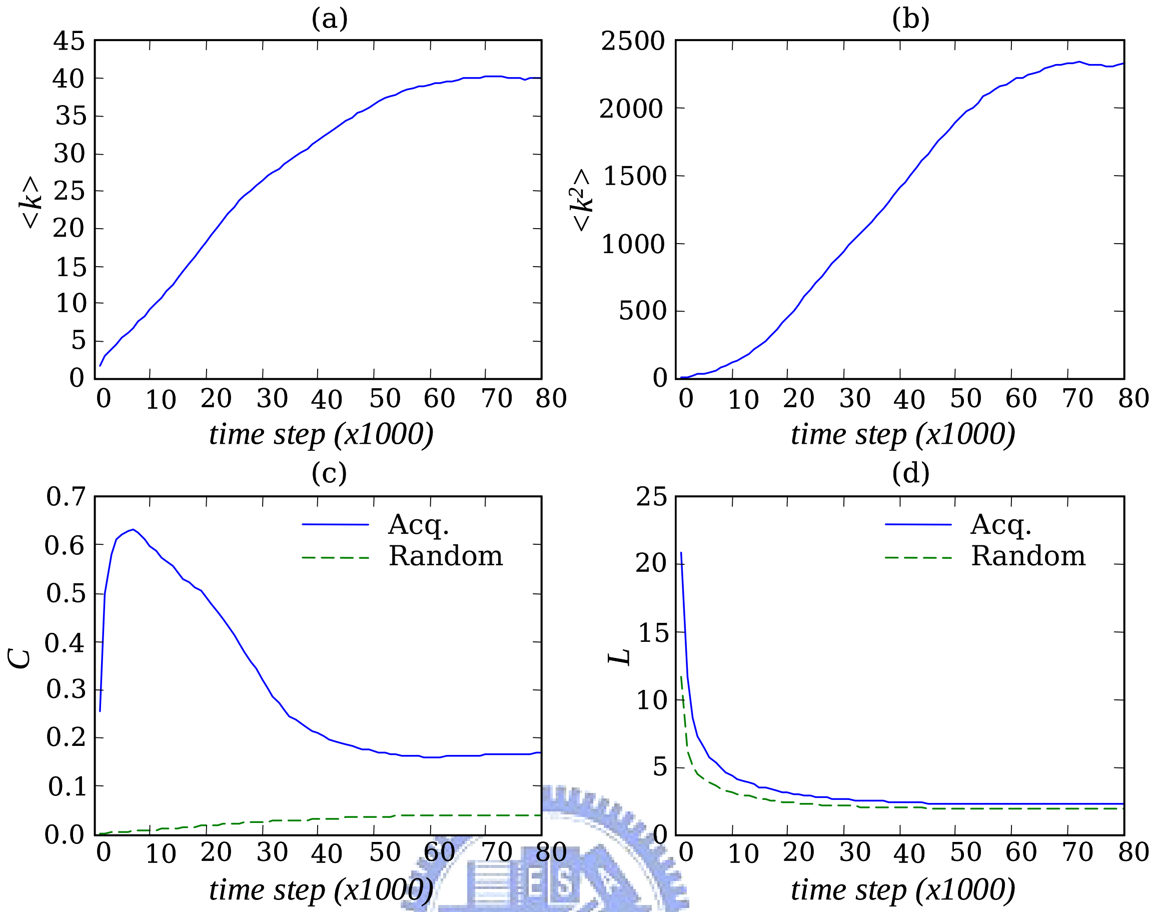

Figure 4. Example of a statistically stationary state using the proposed model.

4.1. Effects of Leaving and Arriving

For comparison, we reproduced Davidsen et al.'s (2002) simulations using their original parameters of N = 7,000 and p at 0.04, 0.01, and 0.0025. We then changed N to 1,000 and tested a broader p range. As noted in an earlier section, the leaving and arriving probability p is the only parameter in rule 2. In addition to using various degree distribution diagrams, we gathered $<k>$, C, and L varying in p and analyzed their correlations to determine the effects of p on the acquaintance network.

The degree distribution $P(k)$ from the two-rule model is shown in Figure 5. All $<k>$, *C*, and *L* values with parameter initializations for various probability *p* values are shown in Figure 6. Correlations among $<k>$, *C*, and *L* are shown in Figure 7. The solid lines in Figure 6 reflect the application of Davidsen et al.'s two-rule model; the dashed lines (which are calculated using Equation 6 and Equation 7) reflect the application of the ER model at the same average degree. Contrasts between the two lines in Figures 6b and 6c indicate that the acquaintance network has the small world characteristic. Figure 6a shows that the number of friends increases as the lifespan of an individual lengthens. According to Figure 7d, the clustering coefficient closely follows average degree not but average path length.

A larger *p* indicates a higher death rate and a lower *p* a longer life span. Thus, parameter *p* acts as an aging factor. Relative to other species, humans require more time to make friends; Davidsen et al. therefore only focused on the $p << 0.1$ regime. To satisfy the needs of integrity theory, we also explored the $p >> 0.1$ regime and found that mean degree $<k>$ decreased for *p* values between 0 and 0.5. The decrease slowed once $p > 0.1$ (Fig. 6a).

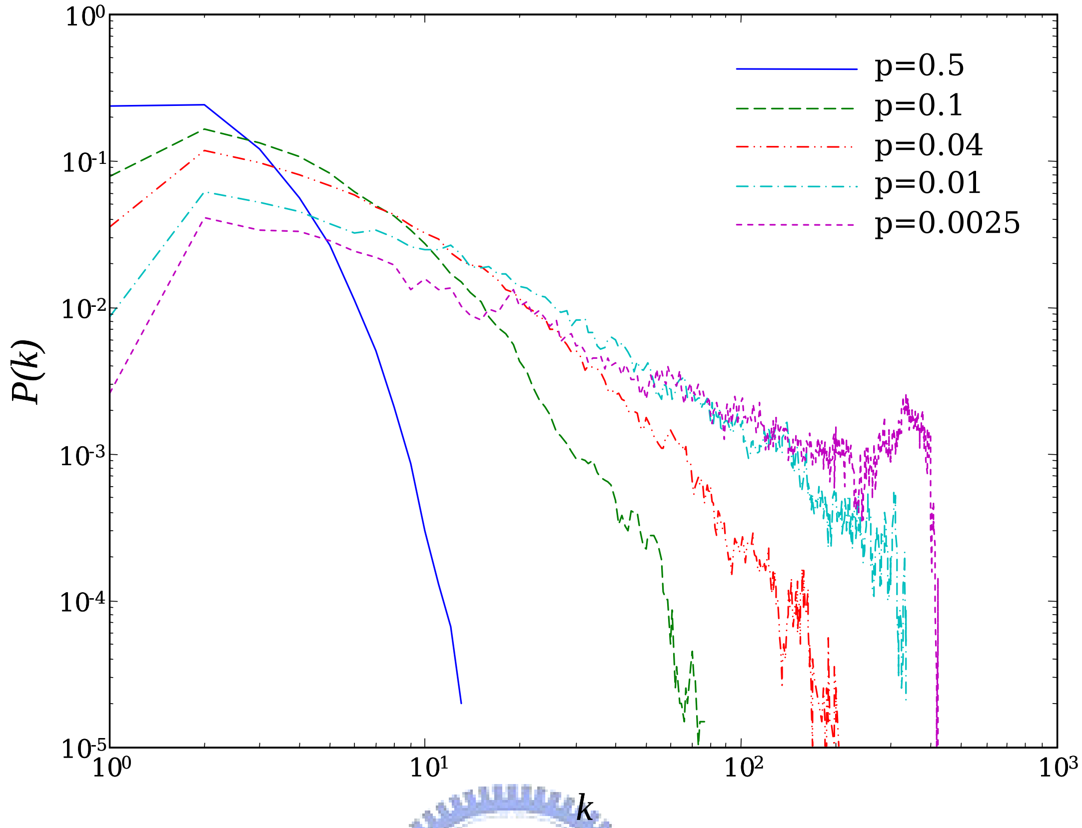

Figure 5. Two-rule model degree distribution $P(k)$.

Table 1. $<k>$, C and L vary in leaving and arriving probability p.

p	.5	.1	.05	.04	.01	.0025
$<k>$	1.55	5.246	10.02	12.64	39.71	115.34
$< k^2>$	4.88	60.13	314.18	467.23	4708.25	29652.69
C	0.213	0.413	0.453	0.465	0.577	0.697
L	17.076	4.226	3.262	3.053	2.416	2.111

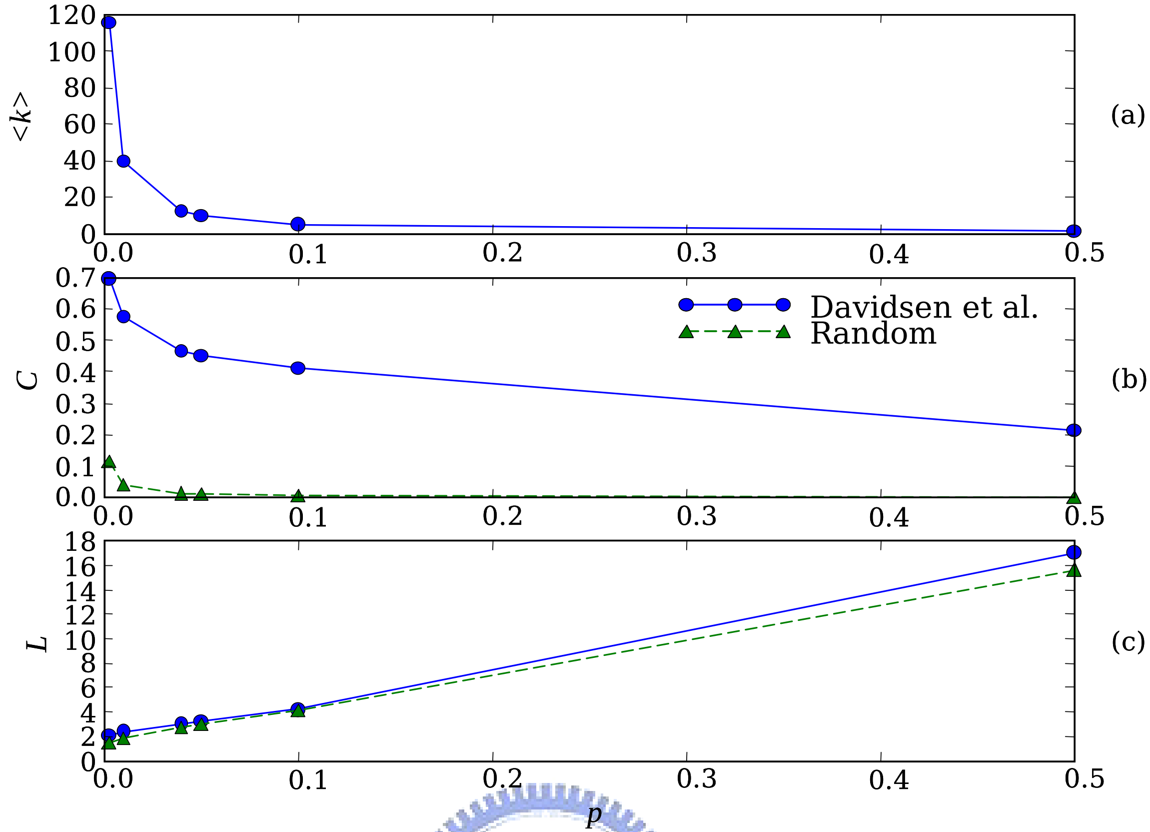

Figure 6. <*k*>, *C* and *L* vary in leaving and arriving probability *p*.

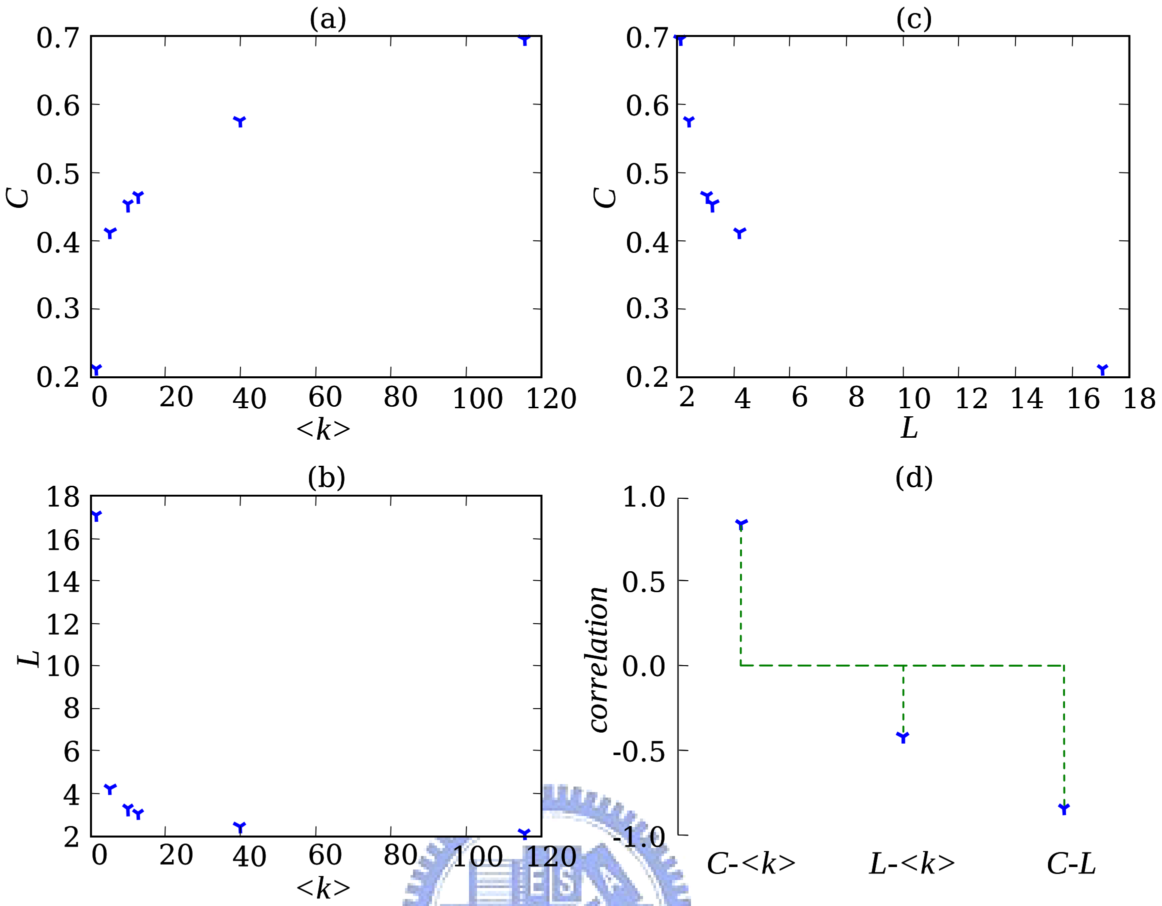

Figure 7. Correlations among <*k*>, *C* and *L* vary in leaving and arriving probability *p*.

Note that in our model, a leaving and arriving probability of 0 means that rule 2 is inactive, and a friendship update proportion of 0 means that rule 3 is inactive. Once rule 3 becomes inactive, our three-rule model becomes the equivalent of Davidsen et al.'s two-rule model. In all of the experiments described in the following sections, *N* was initialized at 1,000 and *b* at 0.001.

4.2. Effects of Breakup Threshold

To determine the effects of the breakup threshold on the acquaintance network, experiments were performed with parameters initialized at different levels of the friendship-breakup threshold θ. Other initialized parameters were q = 0.6 and the constants r = 0.5 and f_0 = 0.5. The solid lines in Figure 8 represent $<k>$, C, and L statistics without rule 2 (p = 0) and the dashed lines represent the same statistics with rule 2 included (p = 0.0025). The data indicate that rule 2—which acts as an aging factor on acquaintances in the network—reduced both average degree $<k>$ and clustering coefficient C and increased average path length L.

According to the data presented in Figure 8, the breakup threshold θ lowers the average degree $<k>$ and raises both the clustering coefficient C and average path length L. The Figure 9 data show that the C–$<k>$ and L–$<k>$ corrections are negative and the C–L correction is positive. The threshold reflects the ease with which a friendship is broken. As expected, a higher θ results in a smaller number of "average friends" and greater separation between individuals.

Table 2. $<k>$, C and L vary in breakup threshold θ with different leaving and arriving probability p.

θ	0.2	0.1	0.05	0.025	0.0125
p			*0*		
$<k>$	5.99	9.94	14.39	22.05	38.21
$<k^2>$	58.84	153.62	256.06	533.08	1528.89
C	0.3778	0.3146	0.1899	0.1284	0.1085
L	4.0986	3.2369	2.8368	2.5431	2.1414
p			*0.0025*		
$<k>$	6.00	9.61	14.30	21.89	34.84
$<k^2>$	60.48	146.94	257.08	531.31	1365.39
C	0.3876	0.3112	0.1532	0.1108	0.1484
L	4.0543	3.3064	2.8975	2.6230	2.3075

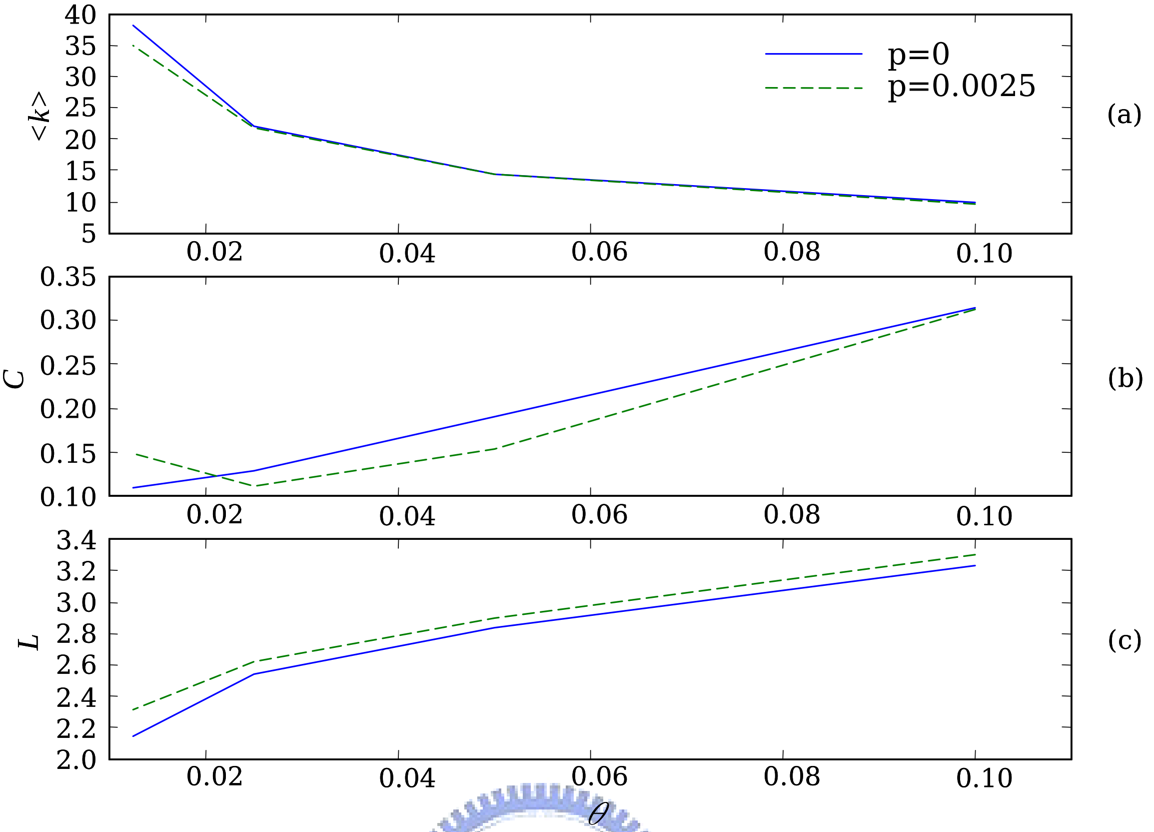

Figure 8. <*k*>, *C* and *L* vary in breakup threshold θ with different leaving and arriving probability *p*

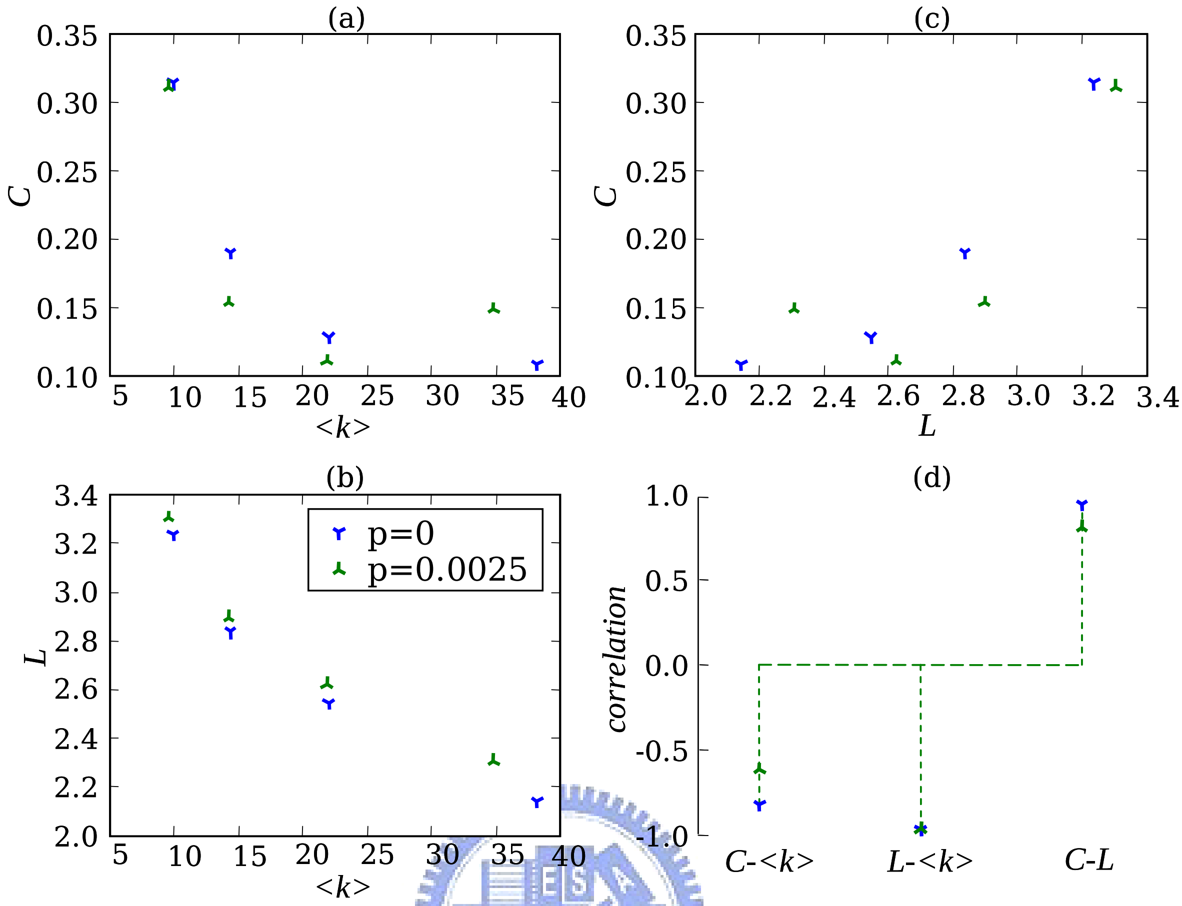

Figure 9. Correlations among <*k*>, *C* and *L* vary in breakup threshold θ.

4.3. Effects of Resources

To determine the effects of resources and memory factors on acquaintance networks, we ran a series of experiments using parameters initialized with different friend-making resource r and friend-remembering q values. Initialized parameters also included $p = 0$, $\theta = 0.1$, and a fixed f_0 value of 1. According to our results, a larger r raised the average degree <*k*> but lowered the clustering coefficient *C* and average path length *L* (Fig. 10). While it is not obvious that statistical characteristics are influenced by different resource distributions, they are clearly influenced by different resource averages. In other words, <*k*>, *C*, and *L* are affected by different resource averages but not by different resource distributions. The Figure 10 data also show that an increase in q raised $<k>$ and lowered both C and L. Furthermore, C–$<k>$ and L–$<k>$ corrections were identified as negative while the C–L correction was positive (Fig. 11).

Table 3. $<k>$, C and L vary in friend-remembering q value with different distributions of friend-making resource r.

q	0.	.2	.4	.6	.8	.9
r	*beta14(μ=0.1)*					
$<k>$	4.00	4.05	6.00	8.17	18.00	39.95
$<k^2>$	24.62	25.60	68.48	135.10	616.24	2338.91
C	0.3588	0.3816	0.3582	0.3590	0.2969	0.1780
L	0.5254	5.4701	3.9116	3.4143	2.7518	2.2644
r	*beta14(μ=0.5)*					
$<k>$	4.96	6.03	7.99	11.43	21.20	41.25
$<k^2>$	30.59	49.21	105.52	237.55	753.64	2438.32
C	0.4554	0.3840	0.3642	0.3245	0.2382	0.1802
L	6.0173	4.4481	3.4747	3.0483	2.5915	2.2003
r	*beta14(μ=0.9)*					
$<k>$	8.18	9.73	11.60	14.00	23.97	43.99
$<k^2>$	71.30	109.03	161.57	252.06	821.56	2625.60
C	0.1905	0.2246	0.1737	0.1778	0.1705	0.1461
L	3.8626	3.3340	3.1260	2.8912	2.4840	2.1564
r	*fixed_value(μ=0.5)*					
$<k>$	4.68	6.02	8.01	11.37	19.97	40.30
$<k^2>$	26.03	46.23	95.12	226.93	659.40	2356.56
C	0.486	0.386	0.348	0.319	0.275	0.189
L	6.954	4.611	3.575	3.067	2.624	2.201

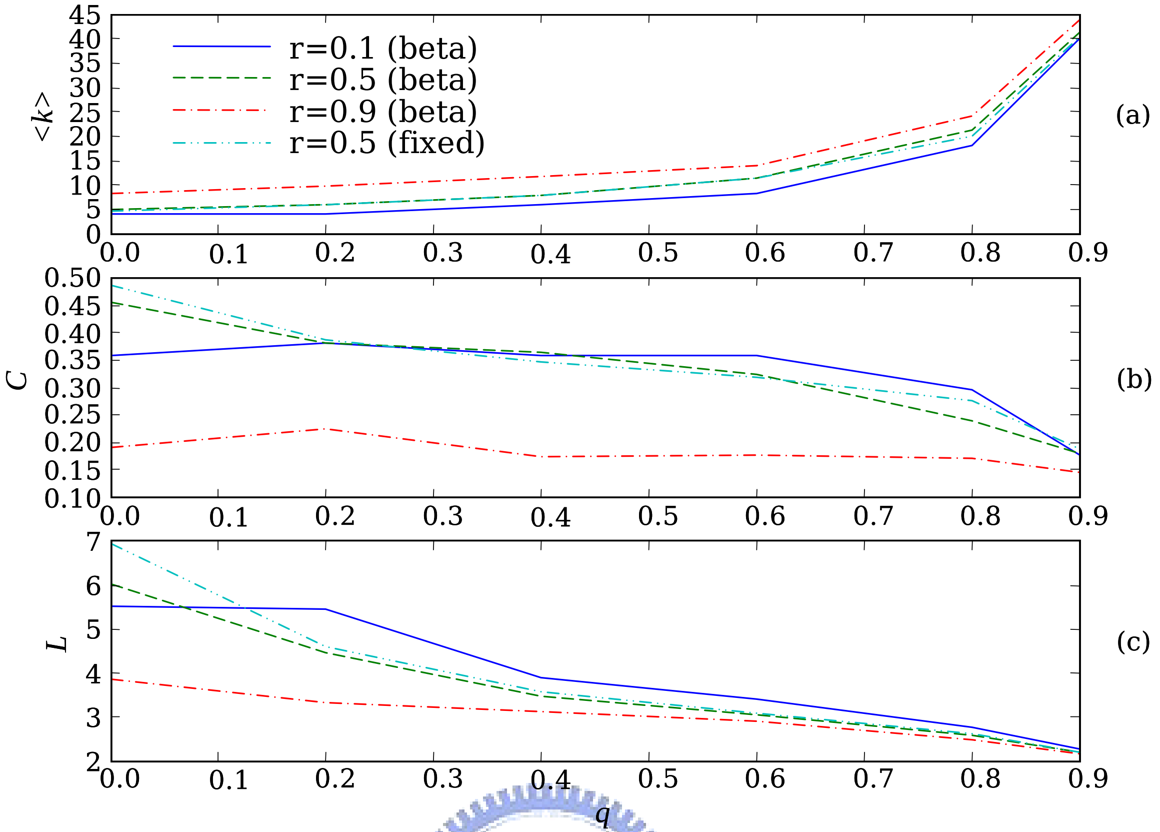

Figure 10. <*k*>, *C* and *L* vary in friend-remembering *q* value with different distributions of friend-making resource *r*.

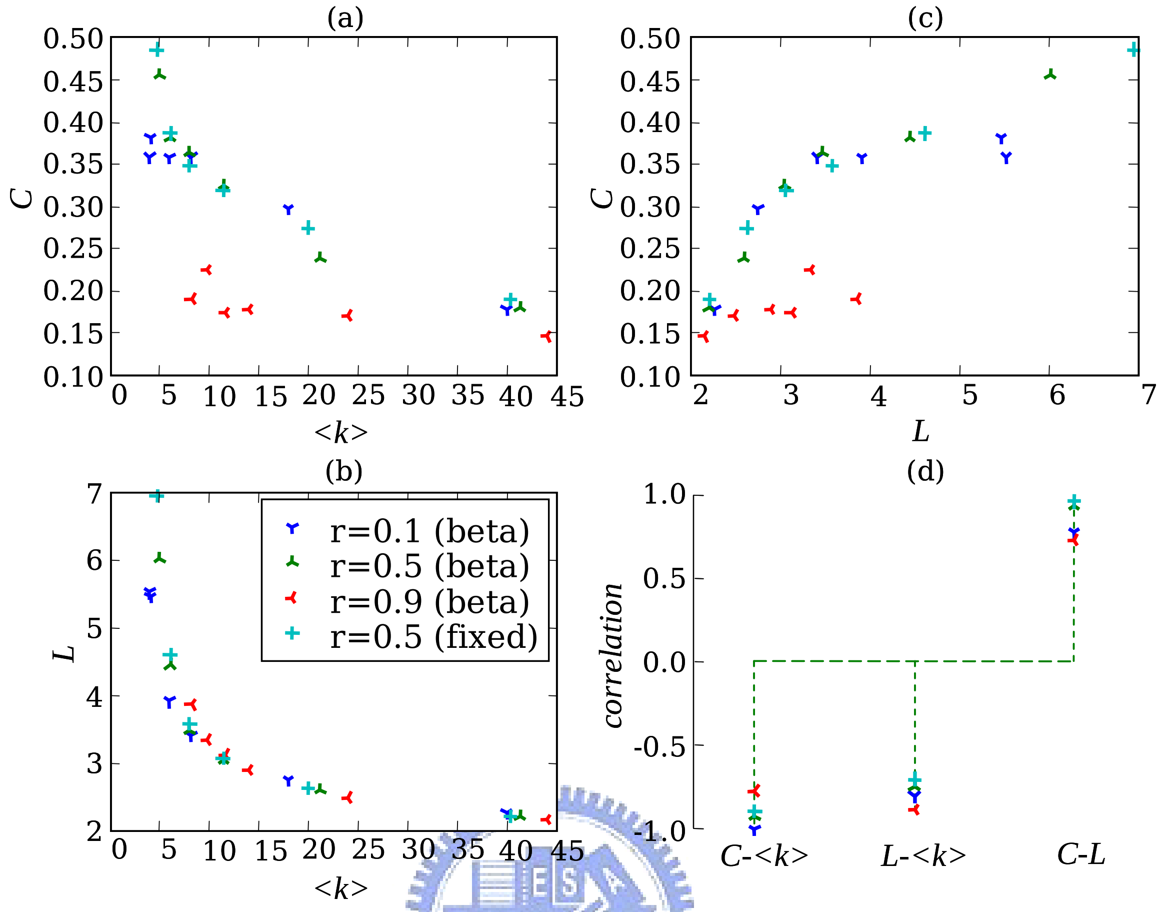

Figure 11. Correlations among <*k*>, *C* and *L* from the different distributions of friend-making resource *r*.

4.4. Effects of Initial Friendship

Experiments were run using parameters initialized at different initial-friendship f_0 and friend-remembering q values for the purpose of determining the effects of those factors on acquaintance networks. Other initialized parameters were $p = 0$, $\theta = 0.1$, and a fixed r value of 0.5. Our results show that a larger f_0 raised the average degree <*k*> but lowered both the clustering coefficient C and average path length L (Fig. 12). That different distributions of initial friendship influenced the statistical characteristics was not obvious, but different averages of initial friendship clearly did. In other words, <*k*>, C, and L were affected by different initial friendship averages but not by different initial friendship distributions. The Figure 12 data also show that the friend remembering q factor raised $<k>$ and lowered both C and L. Both C–$<k>$ and L–$<k>$ corrections were negative and the C–L correction positive (Fig. 13).

Table 4. $<k>$, C and L vary in friend-remembering q value with different distributions of initial friendship f_0

q	0.	.2	.4	.6	.8	.9
f_0	*beta14(μ=0.1)*					
$<k>$	4.01	4.14	4.58	5.05	6.00	8.00
$< k^2>$	19.00	19.59	24.33	30.8	44.01	84.36
C	0.5007	0.4788	0.4539	0.4512	0.3547	0.2886
L	9.2204	9.7683	7.7325	6.6268	4.7783	3.7074
f_0	*beta14(μ=0.5)*					
$<k>$	4.74	6.00	7.03	9.52	15.96	29.98
$< k^2>$	25.41	47.06	69.95	141.19	442.85	1342.34
C	0.4892	0.4023	0.3652	0.3232	0.2939	0.2065
L	8.1108	4.5738	3.8898	3.2932	2.7749	2.3597
f_0	*beta14(μ=0.9)*					
$<k>$	4.66	5.99	7.99	10.59	20.04	40.04
$< k^2>$	25.24	45.92	92.82	179.43	625.14	2330.23
C	0.5064	0.4068	0.3370	0.3031	0.2313	0.1691
L	8.2640	4.7841	3.6030	3.1511	2.6172	2.2277
f_0	*fixed_value(μ=0.5)*					
$<k>$	4.66	6.00	7.37	9.94	16.01	30.46
$< k^2>$	24.85	46.29	76.41	153.62	395.63	1352.15
C	0.4950	0.4299	0.3670	0.3146	0.2312	0.1862
L	7.9614	4.8324	3.8830	3.2369	2.7998	2.3541

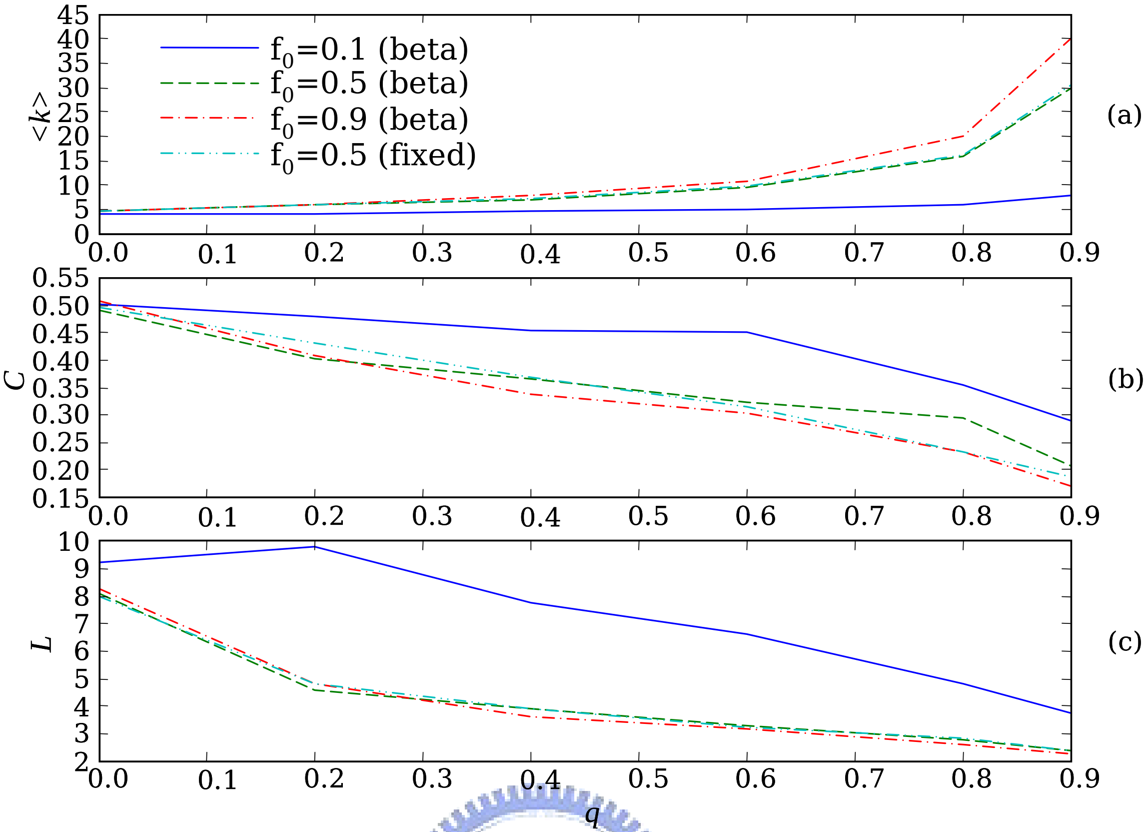

Figure 12. <*k*>, *C* and *L* vary in friend-remembering *q* value with different distributions of initial friendship f_0.

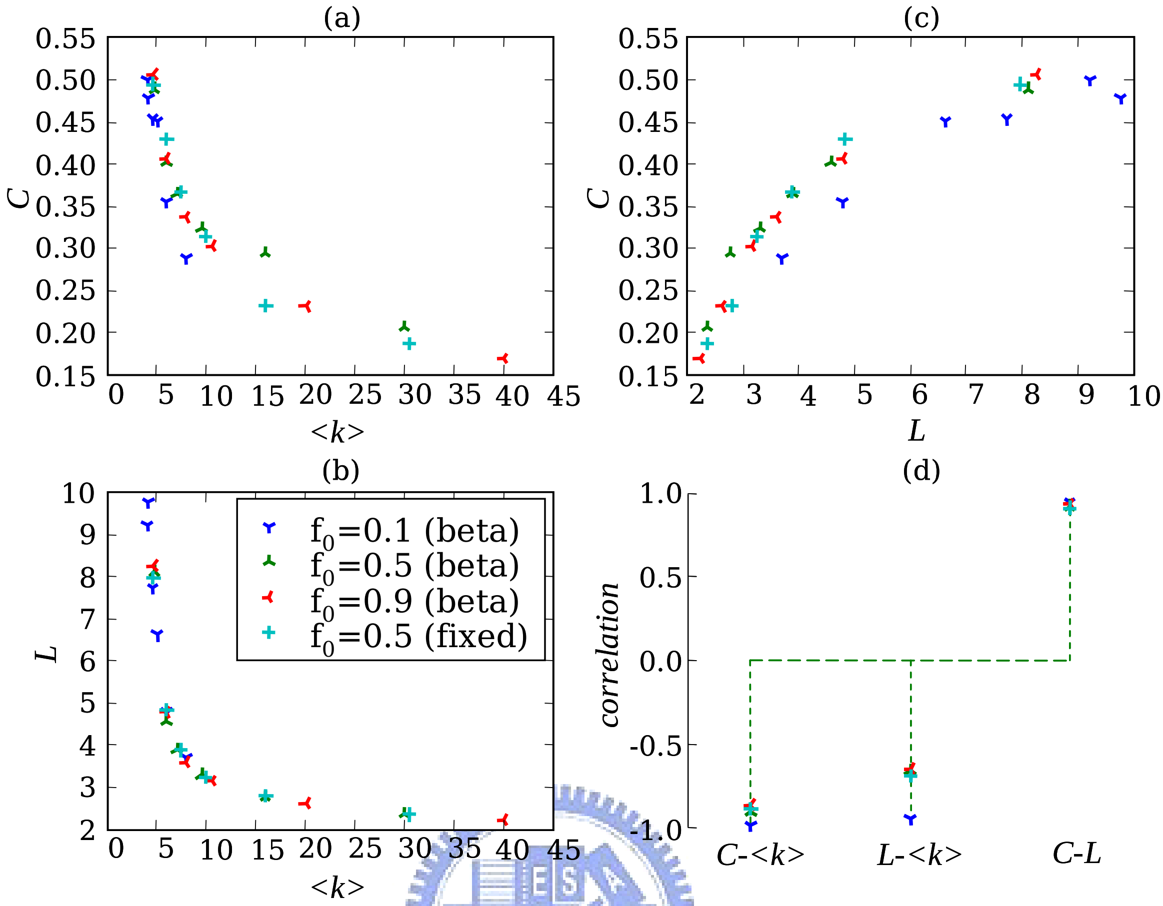

Figure 13. Correlations among <*k*>, *C* and *L* from the different distributions of initial friendship f_0.

We analyzed the effects of different parameters on our proposed model by relationally cross-classifying all experiments; our results are shown in Tables 5 and 6. The plus/minus signs in Table 5 denote positive/negative relations between parameters and statistics. In Table 6 the plus or minus signs denote the strength and direction of correlations. As Table 5 indicates, in addition to the effects of rule 1, *q*, *r*, and f_0 had positive correlations with average degree <*k*> and *p* and θ had negative correlations with <*k*>. Furthermore, each average degree had a negative relationship with its corresponding average path length. All of the rule 3 parameters affected the clustering coefficient *C* and average length *L* in a positive manner, while rules 1 and 2 affected *C* and *L* negatively. Note that friendships are initialized in rule 1 and updated in rule 3.

Table 5. Effective directions of the parameters on <*k*>, *C*, *L*.

Statistics	Rule 1	Rule 2	Rule 3			
		p	q	θ	r	f_0
<*k*>	+*	-	+	-	+	+
C	+*	-	-	+	-	-
L	-*	+	-	+	-	-

Table 6. Summary of the correlations between <*k*>, *C*, *L* from above experiments

Experiments	Variational Parameters	*C*-<*k*>	*L*-<*k*>	*C*-*L*
4.1	p	+++	--	---
4.2	θ, p	--	---	+++
4.3	q, r	---	--	+++
4.4	q, f_0	---	--	+++

4.5. Sampling

Surveys, questionnaires, and sampling techniques stand at the center of traditional social science research and are considered cheaper and more practical than collecting large amounts of census data. However, the effectiveness of these methods for analyzing social networks has not been examined. We therefore ran an arbitrary simulation of our model after reaching a statistically stationary state and collected a sample of nodes. Initialized parameters were N = 1,000, p = 0, b = 0.001, q = 0.4, and θ = 0.1; constants were r = 0.5 and f_0 = 0.5.

Figure 14 presents the degree distribution $P(k)$ after sampling at 100, 300, 500 and 700 nodes. Figures 14a and 14b are log plots with log scaling on the x and y axes; these were used to determine if distributions were scale-free. Figures 14c and 14d are semi-log plots with log scaling on the x axis only; these were used to determine if distributions were exponential. Degrees in Figures 14b and 14d are post-normalization, as required for different numbers of sampled nodes. Each curve in Figure 14 represents an ensemble average of 100 sampling repetitions. The solid lines in Figure 14 reflect a lower sampling ratio of 0.1—considered common for traditional surveys and sampling techniques. The dotted lines reflect a higher sampling ratio (0.7) considered common for a census. Turns in the direction of the y-axis were observed for high sampling but not for low. The degree distribution clearly lost its original shape after sampling.

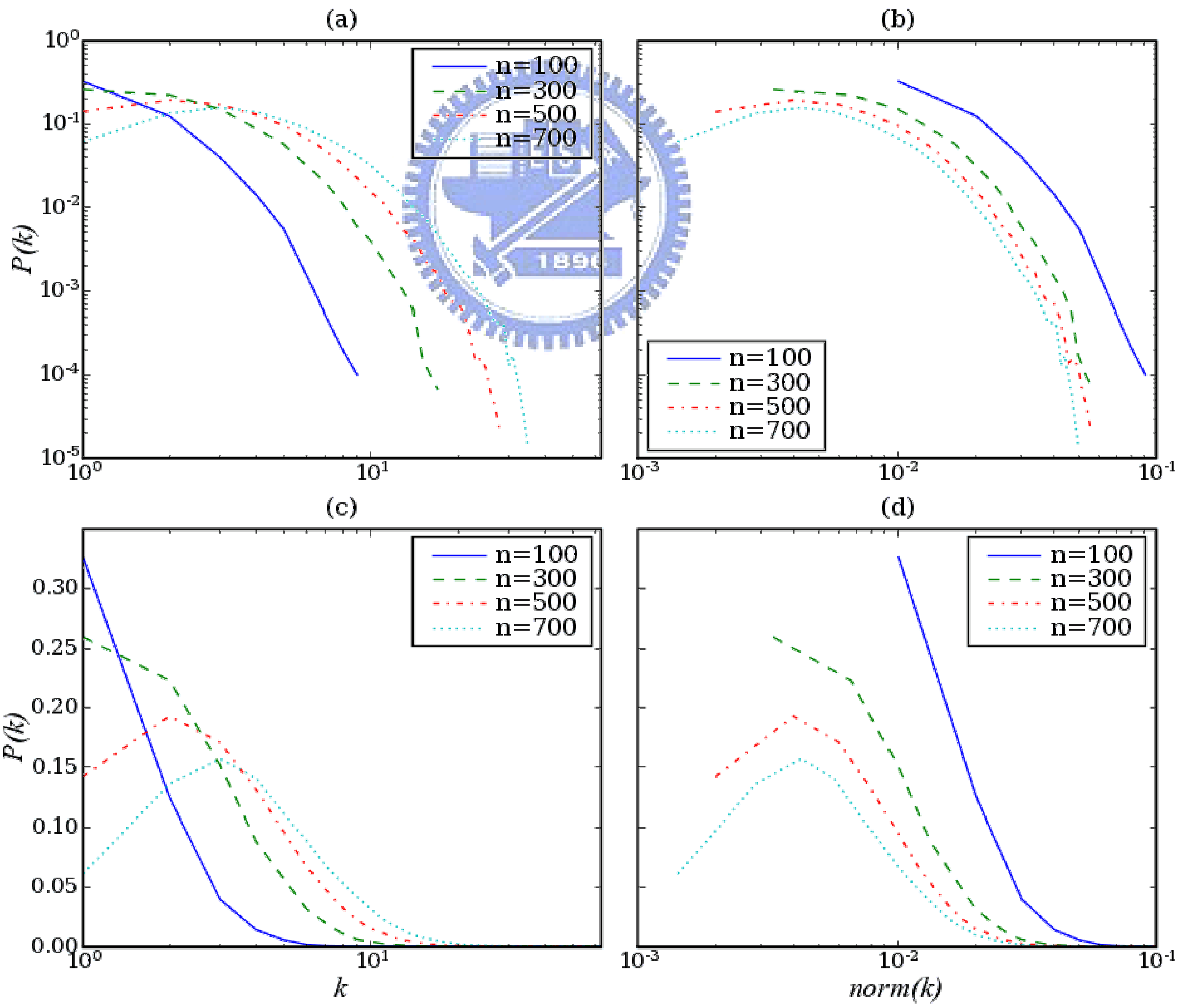

Figure 14. Model acquaintance network samples.

Chapter 5
Conclusion

Most small world models of social networks are analyzed by mixing regular graphs with random networks. This practice is based on Watts and Strogatz's (1988) model, which mixes one regular and one random graph to facilitate theoretical analysis. While the WS model has had a strong impact, there is growing awareness that social network research should not be restricted to issues associated with separation and clustering (Newman & Park, 2003).

Exploring how people make new friends is a meaningful task. In most cases, people make new social connections via introductions by friends in common, but there are many cases in which strangers become friends through chance meetings with no introductions. With few exceptions, most of us can only give limited attention or spend limited resources on friend-making, therefore friends who were once considered close can become distant over time. To gain a better understanding of acquaintance networks, we propose a three-rule model of network evolution. In rule 1, acquaintances are made via introductions and chance meetings; an aging factor is added in rule 2; in rule 3, friendships are altered according to such factors as limited resources, friend remembering, breakup thresholds, and initial friendships.

In our model, small world statistics (especially mean degree for each node) were solely dependent on the average for each parameter. For example, we used a fixed friend-making resource value to compare resources with *beta14* distributions of different averages, and found that the <*k*> statistic says more about average than resource distribution. A similar phenomenon was also found for the initial friendship factor f_0.

Experimental simulations are a necessary aspect of social network research, not only because of the expenses and other difficulties involved with fieldwork, but also because widely used sampling approaches cannot capture real social network distributions, since distributions for higher sampling rates differ from those for lower sampling rates.

Taking a bottom-up, human-interaction-based simulation approach to modeling is a reflection of the evolution mechanism of real social networks. Building on insights from previous studies, we applied local and interactive rules to acquaintance network evolution. This approach produced new findings that can be used to explore human activity in specific social networks—for example, rumor propagation and disease outbreaks.

Appendix A

Terms and Abbreviations

Table 7. Terms and abbreviations for parameters.

Abbreviation	Description
N	Number of persons (nodes) in acquaintance network. （結點數、人數）
M	Number of friendships (edges) in acquaintance network. （友誼數、邊數）
f_0, $f(t=0)$	Initial friendship distribution. （初始友誼）
p	Leaving and arriving probability in rule 2.（出入機率）
b	Proportion of updated friendships in rule 3.（友誼更新比）
f	Friendships. (友誼深淺)
q	Old friend remembering.（念舊度）
r	Friend-making resource distribution. （交友資源）
θ, th	Breakup threshold. （斷交門檻）
μ, mu	Mean.（平均值）

Table 8. Terms and abbreviations for statistics.

Abbreviation	Description
<k>	Average degree. （度均值）
<k^2>	Average square of degree. （度方均值）
C	Average clustering coefficient. （群聚係數）
L	Average shortest path length. （平均最短路徑長度）

Table 9. Terms and abbreviations for initial distributions.

Abbreviation	Description
fixed_value(μ)	A distribution that sets its random variable as a fixed value μ.
beta14(μ)	A *beta* distribution instance in [0, 1] that forces $\alpha + \beta = 14$ with $\mu = \alpha / (\alpha + \beta)$.

Appendix B
Application to Examining Scales Effects

A model acquaintance network can be used to examine the effects of network scales. An arbitrary simulation of our model after reaching a statistically stationary state was selected to sample its maximum connected components for the purpose of selecting a connected subgraph with a specific number of nodes. The selected network contained five connected components, with the maximum connected components holding 986 of 1,000 nodes. Selected acquaintance network parameters were initialized at N = 1,000, p = 0, b = 0.001, q = 0.4, θ = 0.1, r = 0.5 (fixed) and f_0 = 0.5 (fixed).

Figure 15 shows the degree distribution $P(k)$ after sampling for selecting a connected subgraph with the number of nodes set at 100, 300, 500 and 700. Subfigures a and b are log plots with log scaling on the x and y axes (for determining if the distribution is scale-free). Subfigures c and d are semi-log plots with log scaling on the x axis only (for determining if the distribution is exponential). Degrees for subfigures b and d are post-normalization. Each curve in the figure is from an ensemble average of 100 sampling repetitions.

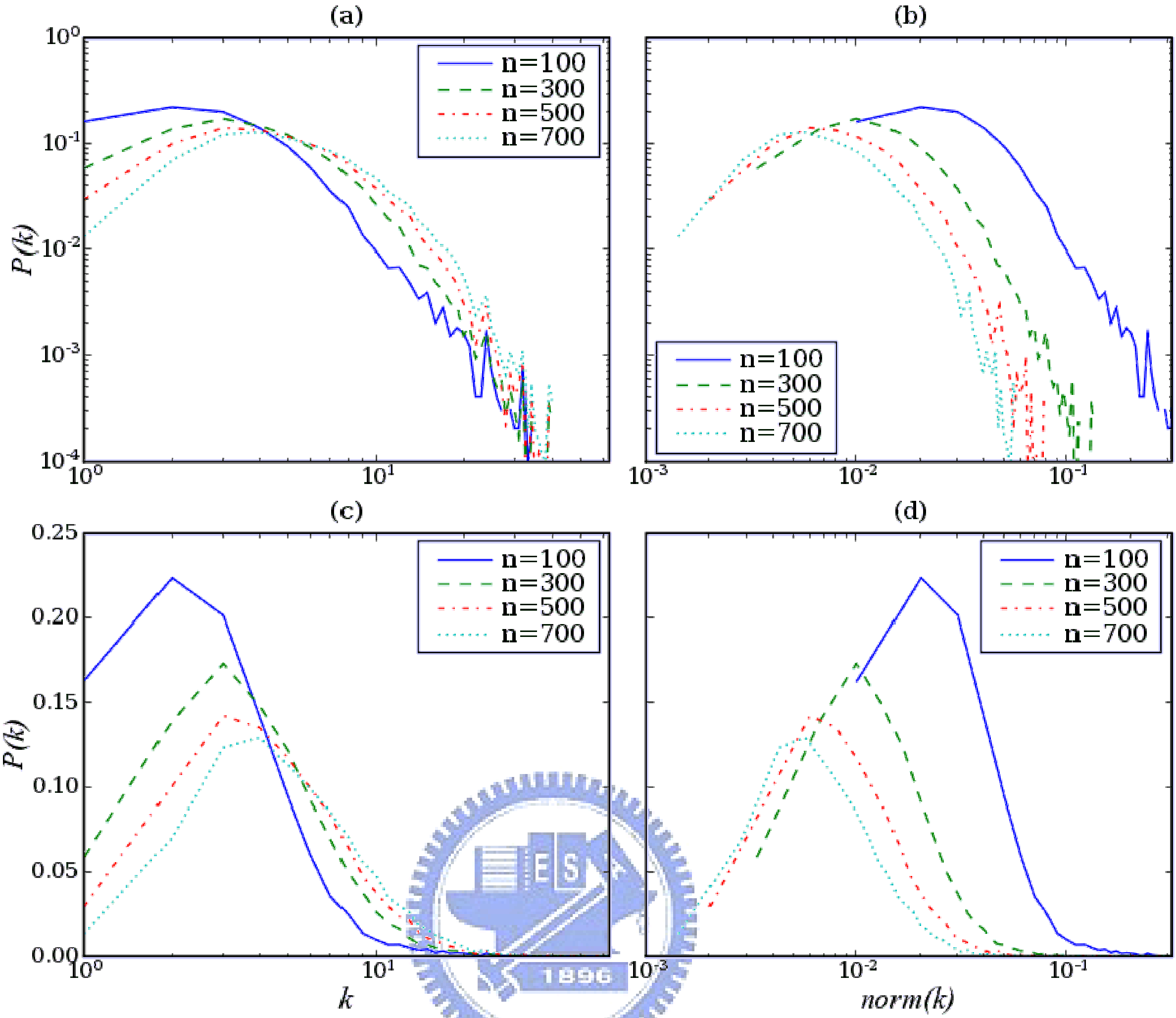

Figure 15. Model acquaintance network scales.

Appendix C
Application to Epidemiology

Some infections (e.g., common colds) do not confer long-lasting immunity. Accordingly, such infections do not have a "recovered" state and individuals become repeatedly susceptible. We applied our model acquaintance network to a simulation of the SIS model (SIS stands for Susceptible, Infected, and Susceptible). An acquaintance network and its analogous NW model were selected to make comparisons of time series and phase transitions with the SIS model.

Selected acquaintance network parameters were initialized at N = 1,000, p = 0, b = 0.001, q = 0.4, θ = 0.1, r = 0.5 (fixed) and f_0 = 0.5 (fixed). Table 10 compares the statistics between an instance of our acquaintance network and its analogous NW model. Table 11 lists the SIS parameters using for Figure 16 and Figure 17. Figure 16 shows the time series during SIS model simulation process. Figure 17 shows the phase transitions of SIS model.

Table 10. Network statistics.

	Our Acquaintance Network	Analogous NW Model
Mean of degree $<k>$	7.844	8.092
Clustering coefficient C	0.346	0.346
Average shortest path length L	3.712	4.109

Table 11. SIS model parameters.

	Figure 16	Figure 17
Infection rate	0.13	from 0 to 0.4 in rules of 0.02
Recovery rate	0.9	1
Initial ratio of infected people	0.005	0.5
Repetitions	20	20

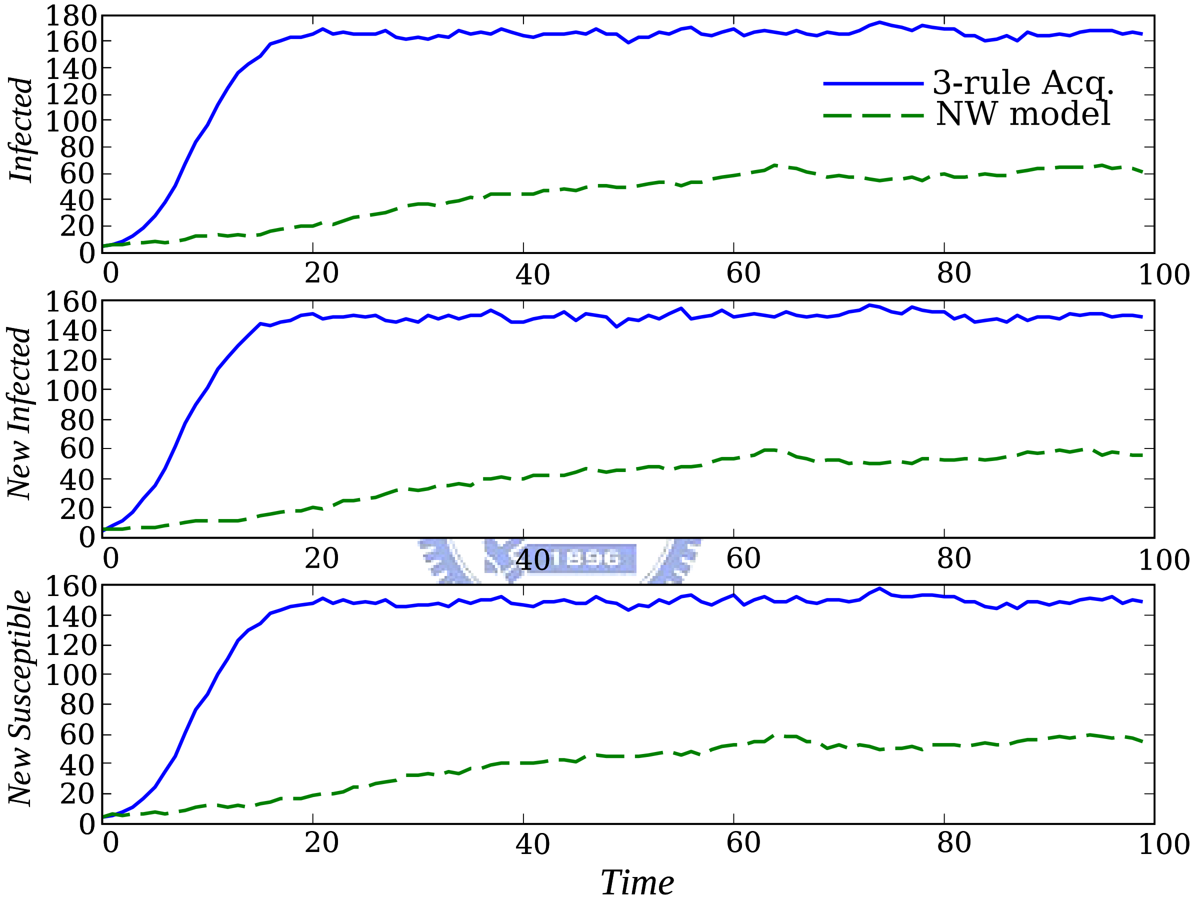

Figure 16. Time series during SIS model simulation process.

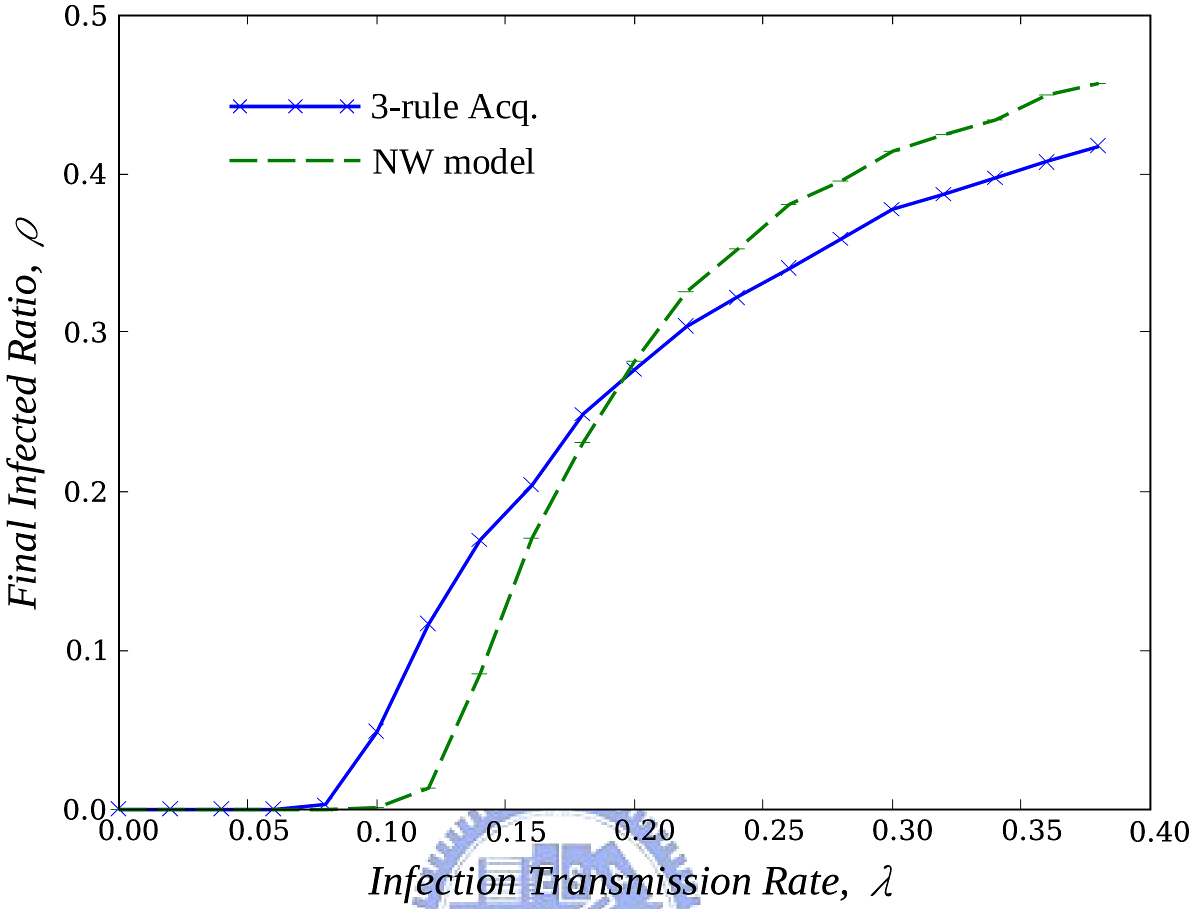

Figure 17. SIS model phase transition.

Appendix D
Distribution of Co-directors

The three main properties of social networks are (a) the small-world phenomenon, (b) the high-clustering characteristic, and (c) skewed degree distribution. In this chapter, we focus on the third property. Networks of board and director interlocks reveal a remarkable degree distribution that is different by far from either scale-free or normal random networks [24]. For example, the nearly 8000 directors on the board of Fortune 1000 companies in 1999 are connected, and the corresponding degree distribution has a strongly peak and a fast approximately exponential decay in the tail, much faster than a power-law distribution but slower than a Poisson or normal distribution [see also 19 and 21].

Figure 18 shows the degree-distribution comparison between one of our acquaintance networks after at a statistically stationary state (solid curve) and co-directors for Davis' boards-of-directors data (dashed curve). Selected acquaintance network parameters were initialized at N = 1,000, p = 0, b = 0.001, q = 0.4, θ = 0.1, r = 0.5 (fixed) and f_0 = 0.5 (fixed). Davis' data is about the nearly 8000 directors on the board of Fortune 1000 companies in 1999 [23]. Both curves exhibit distinct peaks and then a long tail that doesn't appear to decay smoothly.

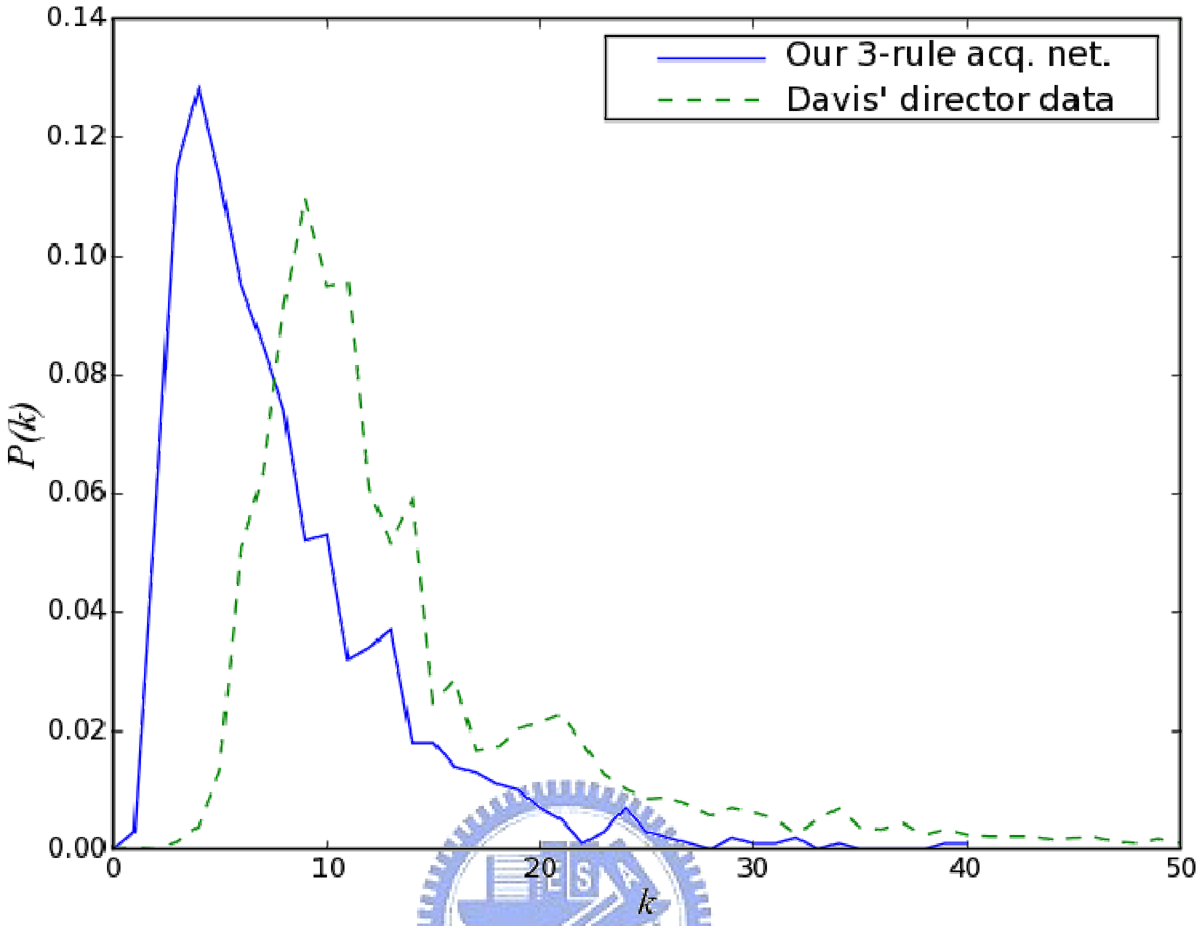

Figure 18. Degree distribution comparison with Davis' boards of directors data.

Appendix E
Source Code

The simulation was coded in Python using the NetworkX package. Statistical data collection was performed using Python with the matplotlib package. Information about Python and relative package installation is available at http://yukuan.blogspot.com/2006/08/graph-based-modeling-on-python.html. Table 12 briefs the files in our acquaintance network project.

Table 12. Summary of source files.

Directory	File Name	Description
./src/	acq2006.py	Our three-rule model.
./src/	acq2002.py	Davidsen et al.'s two-rule model.
./src/acq2006log/	*.log	Log files for experimental simulations of our model.
./src/acq2002log/	*.log	Log files for experimental simulations of Davidsen et al.'s model.
./src/	*.adjlist	Files for storing acquaintance networks in stationary states using adjacency-list.
./src/acq2006log/	stats_fig.v1.8.py	For generating all other figures.
./src/acq2006log/	base.py	For parsing log files.
./src/acq2006log/	acq2002Figs.py	For generating Figures 5, 6 and 7.
./src/acq2006log/	plotKCL.py	For generating Figures 8, 10 and 12.
./src/acq2006log/	plotCorr.py	For generating Figures 9, 11 and 13.
./src/	pdf_fig.py	For generating Figures 2 and 3.
./src/	sis.py	For application to SIS model (Figs. 16 & 17).
./src/	sampleNode.py	For sampling an acquaintance network to select a sub-net with k nodes (Fig. 14).
./src/	sampleMaxCmp.py	For sampling max connected component of an acquaintance network to select a connected subgraph with k nodes (Fig. 15).
./src/	components.py	To gather statistics for connected components.
./src/	assortCoef.py	To gather statistics of Assortativity Coefficients
./src/	direct99.csv	Gerald (Jerry) Davis' boards of directors data
./src/	direct99.py	To process Davis' boards of directors data
./src/	acqCk.py	To plot C-k diagram for our acq. net.
./src/	Davis99AcqCmp.py	For generating Figure 18

Appendix F
Core Algorithm

```
def fixed_value(mu):
    """Generate a fixed value.

    - mu: mean in [0, 1]
    """
    return mu


def beta14(mu):
    """Generate random variates with beta distribution
    and satisfies alpha+beta=14.

    While mu=.5 The distribution is similar to normal
    distribution with mu=.5, sigma=.136

    ref. http://en.wikipedia.org/wiki/Beta_distribution
    ref. http://docs.python.org/lib/module-random.html

    - mu: mean; must in [0, 1]
    """
    a = 14 * mu
    b = 14 - a
    return rnd.betavariate(a, b)


def _create():
    """Initialize the acquaintance network.

    Adds _N nodes to _G, and _G contains no any edges.
    """
    global _G
    _G = nx.XGraph()  # The acquaintance network
    for ID in xrange(_N):
        _G.add_node(Person(ID))


def _step1():
    """Friend making of two persons.

    One randomly chosen person picks any two his friends and introduces
    them to each another. If they have not met before, a new link
    between them is formed. In case the person chosen has less than two
    acquaintances, he introduces himself to one other random person.
    """
```

```
    u, v = rnd.sample(_G.nodes(), 2)
    nb = _G.neighbors(u)
    if len(nb) > 1:
        u, v = rnd.sample(nb, 2)
    if not _G.has_neighbor(u, v):
        _G.add_edge(u, v, _rv_f(_mu_f))


def _step2(p):
    """Leave and Arrive of a chosen person.

    With probability p, one randomly chosen person is removed from the
    network, including all links connected to this node, and replaced by
    a new person.
    """
    if rnd.random() < p:
        v = rnd.choice(_G.nodes())
        _G.delete_node(v)
        _G.add_node(Person(v.ID))


def _update_friendship(u, v):
    """Friend remembering between two persons.

    The two persons update their friendship via the following:
    - f_new = q*f_old + (1-q)*J(D(r_u/k_u), D(r_v/k_v))';
    - The friendship breaks when f_new is less than a threshold.
    """
    f_old = _G.get_edge(u, v)
    r_u, r_v = u.res, v.res
    k_u, k_v = _G.degree([u, v])
    q = (u.q+v.q)/2

    D = fixed_value  # Distribution function
    J = lambda x,y: (x+y)/2  # Join function
    f_new = q*f_old + (1-q)*J(D(r_u/k_u), D(r_v/k_v))

    th = (u.th+v.th)/2
    if f_old < th:
        _G.delete_edge(u, v, f_old)  # breaks the friendship
    else:
        _G.add_edge(u, v, f_new)  # updates the friendship


def step3e(b):
    """Friend remembering for any b*M friendships.

    M means the total friendships/edges of the whole network.
    """
    S = int(b*_G.number_of_edges())
    for i in xrange(S):
        u, v, f = rnd.choice(_G.edges())
        _update_friendship(u, v)


def _loop(i_ttl=0):
    """Loop the three steps of Iters times and gather statistics.

    This function uses yield statement and returns the total iterations of loop

    - i_ttl: total loops for now
```

```
"""
import time
t_start = time.time()  # records the start time
t_ttl = 0  # clears the total time spent
i_cnt = 0  # clears the loop counter

while 1:
    i_cnt += 1

    _step1()
    _step2(_p)
    _step3(_b)

    if i_cnt == Iters:
        i_ttl += i_cnt
        i_cnt = 0

        if _TURN_STAT_ON:
            _stat()

        t_inc = time.time() - t_start
        t_ttl += t_inc
        if _TURN_STAT_ON:
            print "Time spent (increment,total): (%f,%f)" % (t_inc, t_ttl)
        yield i_ttl
        t_start = time.time()
```

(For details please see acq2006.py)

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