

**Large-scale structural organization of social networks**Adilson E. Motter,<sup>1,2,\*</sup> Takashi Nishikawa,<sup>1,†</sup> and Ying-Cheng Lai<sup>1,3</sup><sup>1</sup>*Department of Mathematics, Arizona State University, Tempe, Arizona 85287, USA*<sup>2</sup>*Max Planck Institute for the Physics of Complex Systems, Nöthnitzer Strasse 38, 01187 Dresden, Germany*<sup>3</sup>*Departments of Electrical Engineering and Physics, Arizona State University, Tempe, Arizona 85287, USA*

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The characterization of large-scale structural organization of social networks is an important interdisciplinary problem. We show, by using scaling analysis and numerical computation, that the following factors are relevant for models of social networks: the correlation between friendship ties among people and the position of their social groups, as well as the correlation between the positions of different social groups to which a person belongs.

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**INTRODUCTION**

Application of concepts and tools from physics to the understanding of large-scale structural organization of social networks is an interesting interdisciplinary topic. This is particularly so when we consider that a social network is typically a complex network [1] that possesses the small-world property [2]. There is now a large amount of recent literature concerning complex networks, for which ideas and methodologies from statistical and nonlinear physics have proven to be useful [1,2]. The purpose of this paper is to present a quantitative analysis elucidating some fundamental ingredients required for models of complex, social networks.

The problem that motivates our analysis is the *small-world phenomenon*, according to which any two people are connected by a short chain of acquaintances [3–5]. Although sociological in origin, the small-world phenomenon has been observed in a variety of natural and man-made systems [1,2], with examples ranging from word association [6] to the Internet [7]. The *existence* of short paths in these systems has been successfully described by network models with some degree of randomness [8–10]. However, since short paths are present in most random networks, it is not clear which models are sociologically more plausible, and the real structure of the network of social ties still remains widely unknown.

A more involved and entirely different issue concerns the *discovery* of short paths based only on local information, such as in a process of target search [11–16], which has been only partially understood. In particular, the phenomenon of quick and easy identification of acquaintances has not been explained yet at a fundamental level. When two people are introduced to each other, they are naturally inclined to look for social connections that can identify them with the newly introduced person. In this process, they often discover that they share common friends, that their friends live or work in the same place, etc. Considering the typically large size of the communities and the limited number of acquaintances a

person has, this happens with a surprisingly high probability, even if we accept that people systematically underestimate the likelihood of coincidences. The often successful identification of acquaintances is even more striking in view of the very small number of friends usually mentioned in an introductory conversation. As we show, the existence of short paths connecting people, although to some extent necessary, is not a sufficient condition for the frequent identification of common friends to occur, even when we consider that strangers who meet are more likely to have mutual friends than randomly selected people. Indeed, the networks that account for this phenomenon contain both random and *regular* components and are necessarily *highly correlated* (to be described below). This result constrains the possible structure of the actual network of acquaintances and provides insight into the properties of social networks. These properties are potentially relevant to a variety of other networks as well.

A class of social network models has been recently proposed by Watts, Dodds, and Newman (WDN) [13], which can explain the letter-sending experiment of Travers and Milgram [17]. In this model, people are organized into groups according to their social characteristics. These groups in turn belong to groups of groups and so on, forming a *hierarchy* of social structure. A different hierarchical scheme is defined for each social characteristic [18], which is assumed in the WDN model to be *completely independent* of one another. The network is then constructed using the notion of social distance defined in terms of this set of hierarchies. However, social groups are often correlated. For example, people who work or study together are more likely to engage in other activities together. As we show, a proper level of correlation among social groups is the key to discovering social connections between individuals.

**NETWORK MODEL**

We consider a community of  $N$  people, which represents, for instance, the population of a city. People in this community are assumed to have  $H$  relevant social characteristics that may correspond to professional or private life attributes. Each of these characteristics defines a nested hierarchical organization of groups, where people are split into smaller and smaller subgroups downwards in this nested structure [see Fig. 1(a)]. Such a hierarchy is characterized by the number  $l$  of levels, the branching ratio  $b$  at each level, and the

\*Electronic address: motter@mpipks-dresden.mpg.de

†Present address: Department of Mathematics, Southern Methodist University, Dallas, TX 75275, USA.



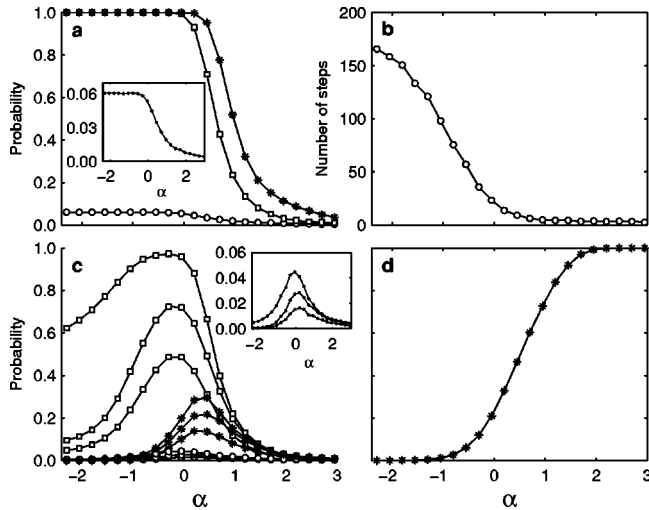


FIG. 2. Identification of acquaintances. (a) Probability that two randomly chosen people have common acquaintances (circles), acquaintances in the same lowest group (squares), and acquaintances who know each other (stars). Inset: blow-up of the probability of having common acquaintances. (b) Average number of steps two strangers need to find a common acquaintance, given that it exists. (c) Probability that randomly chosen strangers find common acquaintances (circles), acquaintances in the same lowest group (squares), and acquaintances in the same lowest group who know each other (stars), in up to  $m = 1, 2,$  and  $20$  steps (from bottom to top). Inset: blow-up of the probability of finding common acquaintances. (d) Probability that two people in the same lowest group know each other. In the computations shown, we set  $\beta = \alpha$ , but similar results were observed for any path in the  $\alpha\beta$  plane interpolating from random to regular networks. The other parameters are  $N = 10^6$ ,  $n = 250$ ,  $g = 100$ ,  $b = 10$ , and  $H = 2$ , which makes  $l = 5$ . The size  $N$  of the networks is typical for the population of a large metropolitan city, and the average number of acquaintances  $n$  is consistent with empirical values [23].

$= \min_i d(x_i^h, x_j^h)$ ; and (2) the other stranger recognizes if the cited person is a mutual acquaintance or an acquaintance within social distance  $D = 1$  of some of his or her acquaintances. The two strangers then repeat steps (1) and (2) switching their roles at every time step, until the identification in step (2) succeeds or they run out of acquaintances to cite.

The probability that two randomly chosen people have common acquaintances, acquaintances at social distance  $l$  (i.e., in the same lowest group), or acquaintances who know each other, decreases to very small values as the network is made more and more regular, as shown in Fig. 2(a). This happens because in a regular configuration, most of the social ties connect people at short distances and hence the acquaintances of two people will overlap only if they are socially close, which is unlikely to be the case for pairs of randomly chosen people in the community. For a random configuration, on the other hand, there is a non-negligible probability of overlap for any two people because their acquaintances are uniformly distributed over the entire network. One might then be tempted to think that the quick discovery of common acquaintances is due to the random-

ness of the network. This, however, is far from being the case, as shown below.

In Fig. 2(b), we display the average number of steps needed for randomly chosen strangers to find a common acquaintance, *given that it exists*. In contrast to Fig. 2(a), the number of steps increases sharply as the randomness of the network is made larger, which means that it is extremely difficult to identify common acquaintances in random networks. Indeed, while in the regular regime only a few steps are required on average, in the random regime it requires well over a hundred steps. This happens because, in the random limit, the social coordinates of a person are completely uncorrelated with his or her social ties, and hence do not give any clue for the position of the person's acquaintances. Accordingly, since only a few among  $n$  acquaintances are typically shared with the other person, they need to go through many steps to identify the overlap. When there is a single common acquaintance, the average number of steps approaches  $n$ , which is of the order of hundreds. Therefore, the probability that two people have common acquaintances is larger for random networks, but if common acquaintances exist it is easier for these people to find them when the underlying network is regular.

Gathering all these together, we have that the identification of acquaintances is most probable in between these two extremes, which is verified in Fig. 2(c). In this figure, we display the probability that two randomly chosen people identify a common acquaintance or acquaintances in the same lowest group in  $m$  or less steps. For small  $m$ , these probabilities are small in the regular and random regimes, but they are significantly larger for a class of networks within the small-world region. This result expresses a trade-off between the overlaps and the clues for people to find the overlaps based only on local information [22].

In addition, our model justifies a tacit assumption people make about the structure of the social network. When the introduced people find that they have acquaintances in the same social group, they *tacitly* assume that those two acquaintances probably know each other. This probability is much higher for regular than for random networks, as shown in Fig. 2(d). In fact, in a completely regular network the probability approaches 1 as every pair of people at social distance 1 know each other, while in the random limit it approaches  $n/(N-1)$ , which is nearly zero. In Fig. 2(c), we show the corresponding probability that, in the process of introduction, the strangers identify acquaintances at social distance 1 who actually know each other (stars). This probability also presents a pronounced maximum in the small-world region, consistent with the intuition that people belonging to the same group are likely to be acquainted.

We now consider the scaling with the system size  $N$ . The probability that the identification of acquaintances happens in the first step is  $P_1 = \sum_{k=1}^l \sum_{k'=1}^k Q(k) R(k, k') S(k')$ , where  $Q(k)$  is the probability that the strangers are at social distance  $k$  from each other,  $R(k, k')$  is the probability that the acquaintance first cited (by the first stranger) is at social distance  $k'$  from the second stranger, and  $S(k')$  is the probability that the second stranger recognizes this acquaintance either for being his or her own acquaintance or for being in the

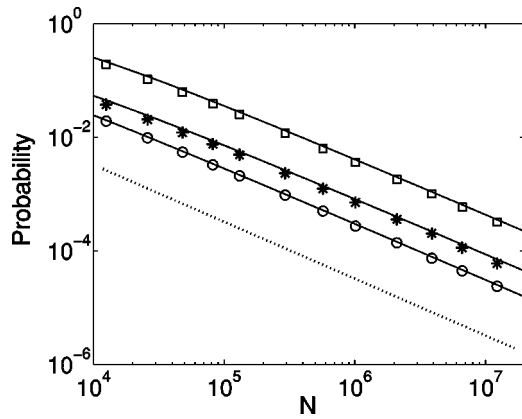


FIG. 3. Probability that the identification of acquaintances happens in up to  $m$  steps as a function of the number  $N$  of people in the community. The continuous lines correspond to our theory and the symbols to the numerical verification. We set  $m=2$ ,  $H=1$ ,  $n=19$ ,  $g=20$ ,  $l=5$ , and  $\alpha=0$ . The legends are the same as in Fig. 2(c). The dotted line is plotted for reference and corresponds to  $P \sim 1/N$ .

same social group of one of them. Because of the symmetry, the probability after two steps is  $P_2 = P_1 + (1 - P_1)P_1$ . To be specific, consider the case  $H=1$  for  $b \gg 1$ ,  $g \gg 1$ ,  $n < g$ , and strangers randomly chosen in the community. Then we have  $Q(k) \approx b^{k-l}$ ,  $R(k, k') \approx [1 - b^{k'-2}/A_k]^{B_k} - [1 - b^{k'-1}/A_k]^{B_k}$ , and  $S(k') = B_{k'}/(gA_{k'})$  for common acquaintances,  $S(k') = C_{k'}/A_{k'}$  for acquaintances in the same lowest group, and  $S(k') = nP_\alpha(1)C_{k'}/(gA_{k'})$  for acquaintances in the same group who know each other, where  $A_k = b^{k-1}$ ,  $B_k = nP_\alpha(k)$ , and  $C_k = A_k[1 - \exp(-B_k/A_k)]$ . The asymptotic behavior of the probabilities  $P_1$  and  $P_2 \approx 2P_1$  is roughly  $P \sim 1/N$ , where  $N = N(b)$ , as shown in Fig. 3 for  $\alpha=0$ . The same scaling is observed for any  $\alpha$ . Therefore, the probabilities do not scale with the diameter of the social network, which in the small-world region increases only logarithmically with  $N$ . The rationale behind this result is that the probability of identification of common acquaintances is limited by the probability that common acquaintances

actually exist, which for randomly chosen pairs of people decreases as  $1/N$ . Incidentally, although the probabilities in Fig. 2(c) decrease if the number  $N$  of people is increased, a sharp maximum in the intermediate region is always observed.

## CONCLUSIONS

We have shown that the network of social ties must be a small world *with* high degree of correlation for the empirically observed frequent identification of acquaintances to be possible. This sheds new light on the large-scale organization of the society, as it imposes constraints for the possible structure of the network of acquaintances. These constraints give a criterion for plausible models of social networks, which has implications for issues of critical concern such as spread of diseases, homeland defense, and propagation of influence in economic and political systems, where the formation and behavior of social groups play important roles. In particular, since the dynamics of many biological agents is driven by social contacts, reliable models of social networks are essential for efforts to reduce the threat of biological pathogens and for making decisions in the case of massive biological attacks. Another important conclusion of our work is that the probability of finding a short chain of acquaintances between two people does not scale with typical distances in the underlying network of social ties neither with respect to system size nor across different degrees of correlation. For instance, random networks are usually “smaller” than small-world networks, and because of that they are sometimes called themselves small-world networks. But our work shows that a random society would not allow people to find easily that “It is a small world!”

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- [21] Our model is potentially relevant to other classes of networks, such as scientific-citation networks. Suppose that the citation is the actual tie linking the papers. Scientific papers can be classified according to author, subject, date, etc., which, along with citation, are not completely independent variables. This defines a network with different correlated hierarchies, similar to the social network of friends.
- [22] We have focused on strangers randomly chosen from the community, but similar results hold when the two strangers to be introduced are correlated. In particular, if they are chosen at social distance  $z$  apart according to the distribution  $P_\gamma(z) \propto \exp(-\gamma z)$ , where  $\gamma$  is a constant, the probabilities corresponding to Fig. 2(c) will still display a maximum in the intermediate region, although continuously shifted to the right as  $\gamma$  is increased. Moreover, the same conclusions are expected if the hierarchies are formed as a realization of a stochastic branching process rather than the deterministic one considered here.
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