Social Networks: From Sexual Networks to Threatened Networks

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Abstract. Our scientific goal is to uncover common principles governing the behavior of a range of social networks. Our practical goal is to use this understanding to develop specific strategies to destroy threat networks and, in parallel, to develop specific strategies to defend threatened social networks against attack. There are recent hints that progress toward achieving both goals can be achieved applying new approaches from modern statistical physics to social network structure and dynamics.

1 Introduction

Populations, which can be viewed as networks of social acquaintances, are vulnerable to disease epidemics such as AIDS. Any random immunization of people against such disease attacks is problematic because it must encompass almost the entire population in order to successfully stop the spreading epidemic [1–5]. Other types of social networks are organizations, e.g., security agencies, in which working relations are represented by links. To be effective, these organizations must be stable and allow rapid data flow in the network. We have begun addressing these problems — using concepts and tools of both social sciences and statistical and nonlinear physics — by designing more stable social network structures, enabling them to resist both random and intentional attacks. For this purpose, we need to better understand the topological structures of existing social networks, and to improve our understanding of transport in such systems.

Our methods in statistical physics are based on relatively new concepts, such as correlated site-bond percolation theory [6–10]. The applications of percolation theory range from predicting the amount of oil that can be extracted from an underground reservoir, to understanding the network formation mechanism involved in the hardening of a boiled egg. The use of percolation theory has already proven valuable in the study of social networks. The Bar-Ilan group has generalized percolation theory in order to analyze the structure and stability of general networks under random failures [11] and intentional attacks [12]. Based on this generalization, we are following up on a novel approach for designing new social networks that are more resilient to attack. We are also developing methods based on the percolation approach [13] that will enable us to immunize populations more effectively against different types of epidemics.

2 Recent Advances on Scale-Free Social Networks

Very recent analysis of social networks, as well as many other networks (such as trust networks and sexual networks), reveals that some of these networks display the important property of being scale-free [6,2,14], i.e., there is a very wide distribution of the number of links per vertex. Most vertices have a small number of connections. However, there are a small number of vertices that have a very large number of connections, and there are vertices in the full range between these extremes. Further, it seems that there is a possible explanation for this scale-free behavior [2,15], and that the results for sexual networks extend to other social networks [16].

Our groups are studying the structure of a wide range of social network types [17], and are building mathematical models and tools for large social networks [13]. In studies conducted about the stability of scale-free social networks, it was proven that these networks are optimally resilient to the random failure of individuals [11]. Even if almost all elements of a network malfunction, a large fraction of the individuals will be left connected, allowing continuing interactions between a large fraction of the population. This situation is unlike that of homogeneous networks, in which such a failure will break the entire network into small, unconnected islands. On the other hand, a deliberate, successful attack on the most-connected elements in the network will lead to failure of the entire network after only a small fraction of nodes have been targeted [12]. Further, studies show that search can be conducted in such heterogeneous networks in a much more efficient way than in homogeneous networks [18].

A connection exists between (a) the stability of a network and (b) the propagation of disease. Heterogeneous networks are prone to the rapid spread of epidemics. If the individuals to be immunized are chosen randomly, spreading is unavoidable, even if almost all individuals in the network are immunized. However, if the individuals to be immunized are chosen using "smart" strategies, it becomes possible to reduce the number of infected individuals to almost zero. Using models, it is possible to forecast the consequences of epidemic outbursts and to try to control them. It is established that random immunization of a large fraction of the population fails to prevent epidemics of diseases that spread upon contact between infected individuals; for example, Malaria requires 99% of the population to be immunized in order to stop epidemic spreading [4,5]. On the other hand, targeted immunization of the most-connected individuals requires global knowledge of the topology of the social network in question, rendering 99% immunization impractical. We recently proposed an effective strategy, based on the immunization of a small fraction of *acquaintances* of randomly-selected individuals, that prevents epidemics without requiring global knowledge of the social network [19].

3 Recent Advances on Traffic Flow in Networks

We are adapting recent results on traffic flow to social network analysis. In 1994, Leland et al. [20] found that Ethernet LAN traffic is self-similar; "bursts" occur on every time scale. These findings show that long-range correlations in the interval times of arriving packets and extreme variability (or infinite limit of the variance). Paxson and Floyd [21] have found evidence for self-similarity of Wide Area Network (WAN) Traffic, and showed the failure of Poisson modeling in this case. New empirical findings challenge the validity of the traditional queuing models, and new models have since been proposed. In contrast to the above measurements, Takayasu et al. [22–24] have measured a $1/f$ power spectrum only at the critical point of a phase transition, and it is still not clear whether the flow is always self-similar in such networks. They found finite correlation times in the fluctuations of network traffic, and identified phase transitions between "sparse" and "jam" phases of the network.

The empirical phenomena mentioned above can influence the design of control schemes for traffic. However, the empirical description of the traffic is not yet complete. As the Bar-Ilan group has demonstrated recently in the case of vehicular traffic [25], a careful nonlinear statistical analysis of measured data may lead to the finding of several congested phases. One of our goals is to clarify this issue, and one method that we will use in the analysis of measured time series is Detrended Fluctuation Analysis (DFA). DFA was developed by the Boston group [26] and has been successfully applied by us and others to many systems, e.g., to DNA sequences [27,28], the analysis of climate changes [29,30], heart rate variability [31–34], economics [35], and even prime numbers [36]. One of the advantages of this method is its ability to detect long-range correlations in the records in the presence of trends and other nonstationarities.

4 Characteristic Properies of Real Networks

4.1 Classification of Real Networks

We have developed a method that classifies complex real-world networks according to their statistical topological properties [17]. By studying a wide range of different types of networks, we find evidence for the occurrence of three classes of small-world networks:

(a) scale-free networks,
(b) broad-scale networks, characterized by a connectivity distribution that has a power-law regime followed by a sharp cut-off;
(c) single-scale networks, characterized by a connectivity distribution with a fast-decaying tail.

4.2 Percolation

A percolation approach for general networks has been developed, with surprising results for scale-free networks [11–13]. The network is fully resilient to the random failure of sites and is extremely vulnerable to intentional attack. This analytical approach is being developed to study realistic social networks—e.g., where known correlations between individuals are included—where the measured clustering property and real geographical distance, measured experimentally, are being taken into account. Preliminary findings show that the geographical effect has a strong influence on the stability and transport of the network [37–39].

4.3 Structural and Transport Properties of Networks

We are studying several topological properties of networks—e.g., clustering and correlations. Some preliminary results already exist, such as the work on clustering in trust networks [40]. The clustering coefficient [41,42], which quantifies the extent to which nodes adjacent to a given node are linked, seems not to be affected when the network collapses. This may be relevant to terrorist organizations that are comprised of small, strongly-connected cells that are connected to each other by a few, highly-connected individuals [43]. The clustering was found to be important also in electric power networks, e.g., the power grid in the Western States in which the clustering coefficient is significantly larger than that of random networks. A useful method to quantify correlations (by measuring assortative tendencies, i.e., the tendency of high-degree vertices to associate preferentially with other high-degree vertices) was suggested recently by Newman [44].

We have preliminary results extending these studies to other real social networks. We are also studying the degree distribution for sites at a given distance from the most-connected site [45]. We are also studying the effect of geographical distance in real networks. This information is important for evaluating the stability and the immunization threshold. We are also analyzing the transport properties of data flow in social networks. We are applying DFA analysis and multifractal analysis [46] to better understand transport in complex social networks. We also are developing structural and transport modeling that will enable a better understanding of the structure and transport in such networks.

4.4 Optimizing the Stability of Threatened Networks

We are using the analytical approach we developed to calculate the percolation threshold for a given network [11,12], in order to design topologies that improve the stability of scale-free networks under both random failures and intentional attacks. This is being done by calculating the percolation threshold while keeping the average number of links for an individual in the network constant (for safety and security reasons) and then varying parameters such as the form of the degree distribution, the type of correlations, and the clustering coefficients. We are also testing the effect of geographical distances on the stability of scale free networks. This will enable us to propose ways to design more stable networks and to improve the stability of existing networks.

4.5 Immunization of Networks

Random immunization fails to prevent epidemics of diseases that spread in populations upon contact between infected individuals [4,5]; the same is true for immunization of computers against viruses [47]. Unless almost the entire system is immunized, the virus continues to spread through the population or computer network. To deal with this problem, the Bar-Ilan group has developed an analytical method that can accurately determine, for various scenarios, the threshold needed to stop spreading epidemics [13]. Among these possible scenarios are (i) immunizing people who are acquaintances of an infected individual and (ii) immunizing only those people who are acquaintances of at least two infected individuals.

Our recent results on social networks are complemented by analogous strategies for protecting other threatened networks, such as communication networks. For example, the Bar-Ilan group has already demonstrated that, in scale-free uncorrelated networks, if we immunize the neighbors of randomly-chosen sites, the critical threshold can be reduced by a factor of five [19]. This result has dramatic practical implications.

Our analytical approach is enabling us to study efficient immunization strategies in more realistic networks where, e.g., correlations, clustering effects, and geographical topology are taken into account. The immunization approach is also helping to develop methods to disintegrate targeted organizations, since by removing the nodes that are most relevant for immunity, the targeted network will collapse.

5 Possible Contributions of Social Network Research

(a) We are improving the tentative explanation [15] of scale-free social networks, and develop a better understanding of the range of social networks that are scale-free [16].
(b) We are developing a better understanding of the topological structures and the tomography of threatened social networks.
(c) We are developing new algorithms to improve the stability and safety of threatened networks. We are designing networks for optimal resistance to epidemics, malfunctions and attacks, and we are designing efficient and secure algorithms for organizational data flow.
(d) We are designing efficient methods for effective "immunization" that will greatly reduce spreading in threatened networks—the same mathematics describes spread of infectious agents in social networks, or "viruses" in communication networks. These methods will also help to identify weaknesses and thereby protect threatened networks.

6 Discussion

We are seeking to test whether concepts and methods of statistical physics such as scaling and percolation theory can be usefully applied to social networks, with special emphasis on social networks such as sexual networks and threatened networks. Many of the primary methods being used in our network research have been developed by our research group. These include the analytical percolation approach to general networks [11–13], the efficient immunization theory [19,13], and the DFA method [26]. We also were among the first to identify scale-free networks in certain social systems and sexual networks [14–16], and we developed an approach for classifying network topologies [17].

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References

1. R. Albert, H. Jeong and A.-L. Barabási, "Attack and Error Tolerance of Complex Networks," *Nature* **406**, 378–382 (2000).
2. R. Albert and A.-L. Barabási, "Statistical Mechanics of Complex Networks," *Rev. Mod. Phys.* **74**, 47–97 (2002).
3. S. N. Dorogovtsev and J. F. F. Mendes, "Evolution of Networks," *Adv. in Phys.* **51**, 1079–1187 (2002).
4. R. M. Anderson, and R. M. May, *Infectious Diseases of Humans* (Oxford University Press, Oxford, 1991).
5. A. L. Lloyd and R. M. May, "How Viruses Spread among Computers and People," *Science* **292**, 1316–1317 (2001).
6. H. E. Stanley, "Scaling, Universality, and Renormalization: Three Pillars of Modern Critical Phenomena," Reviews of Modern Physics **71**, S358–S366 (1999).
7. A.-L. Barabási, *Linked: The New Science of Networks* (Perseus Publishing, Cambridge, 2002).
8. H. E. Stanley, J. S. Andrade, S. Havlin et al., "Percolation Phenomena: A Broad-Brush Introduction with Some Recent Applications to Porous Media, Liquid Water, and City Growth," Physica A **266**, 5–16 (1999).
9. A. Bunde and S. Havlin, eds., *Fractals and Disordered Systems* (Springer, New York, 1996).
10. D. ben-Avraham and S. Havlin, *Diffusion and Reactions in Fractals and Disordered Systems* (Cambridge University Press, Cambridge, 2000).
11. R. Cohen, K. Erez, D. ben-Avraham, and S. Havlin, "Resilience of the Internet to Random Breakdown," Phys. Rev. Lett. **85**, 4626 (2000).
12. R. Cohen, K. Erez, D. ben-Avraham, and S. Havlin, "Breakdown of the Internet under Intentional Attack," Phys. Rev. Lett. **86**, 3682 (2001).
13. R. Cohen, S. Havlin, and D. ben-Avraham, "Structural Properties of Scale-Free Networks" in *Handbook of Graphs and Networks: From the Genome to the Internet*, edited by S. Bornholdt and H. G. Schuster (Wiley-VCH, Berlin, in press, 2002).
14. F. Liljeros, C. R. Edling, L. A. N. Amaral, H. E. Stanley, and Y. Åberg, "The Web of Human Sexual Contacts," Nature **411**, 907–908 (2001) cond-mat/0106507.
15. L. A. N. Amaral, C. R. Edling, F. Liljeros, and H. E. Stanley, "Mechanisms for the Formation of a Web of Sexual Contacts" (preprint).
16. F. Liljeros, L. A. N. Amaral, and H. E. Stanley, "Scale-Invariance in the Growth of Voluntary Organizations," Europhys. Lett. (submitted).

17. L. A. N. Amaral, A. Scala, M. Barthélémy, and H. E. Stanley, "Classes of Behavior of Small-World Networks," Proc. National Academy of Sciences **97**, 11149–11152 (2000).
18. L. A. Adamic, R. M. Lukose, A. R. Punyani, and B. A. Huberman, "Search in Power Law Networks," Phys. Rev. E **64**, 046135 (2001).
19. R. Cohen, D. ben-Avraham, and S. Havlin, "Efficient Immunization of Populations and Computers," cond-mat/0207387 (2002).
20. W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the Self-Similar Nature of Ethernet Traffic (Extended Version)," IEEE/ACM Trans. Netw. **2**, 1 (1994).
21. V. Paxson and S. Floyd, "Wide Area Traffic: The failure of Poisson Modeling," IEEE/ACM Trans. Netw. **3**, 226 (1995).
22. K. Fukuda, H. Takayasu, and M. Takayasu, "Spatial and Temporal Behavior of Congestion in Internet Traffic," Fractals **7**, 23 (1999).
23. M. Takayasu, H. Takayasu, and K. Fukuda, "Dynamic Phase Transition Observed in Internet Traffic Flow," Physica A **277**, 248 (2000).
24. M. Takayasu, H. Takayasu, and K. Fukuda, "Application of Statistical Physics to Internet Traffic," Physica A **274**, 140 (1999).
25. E. Tomer, L. Safonov, and S. Havlin, "Presence of Many Stable Nonhomogeneous States in an Inertial Car-Following Model," Phys. Rev. Lett. **84**, 382 (2000).
26. C. K. Peng, S. Havlin, H. E. Stanley, and A. L. Goldberger, "Quantification of Scaling Exponents and Crossover Phenomena in Nonstationary Heartbeat Time Series" [*Proc. NATO Dynamical Disease Conference*], edited by L. Glass, Chaos **5**, 82–87 (1995).
27. C.-K. Peng, S. V. Buldyrev, S. Havlin, M. Simons, H. E. Stanley, and A. L. Goldberger, "On the Mosaic Organization of DNA Sequences," *Phys. Rev. E* **49** (1994) 1691–1695.
28. S. V. Buldyrev, A. L. Goldberger, S. Havlin, R. N. Mantegna, M. E. Matsa, C.-K. Peng, M. Simons, and H. E. Stanley, "Long-Range Correlation Properties of Coding and Noncoding DNA Sequences: GenBank Analysis" Phys. Rev. E **51**, 5084–5091 (1995).
29. A. Bunde, H. J. Schellnhuber, and J. Kropp, eds., *The Science of Disasters: Climate Disruptions, Heart Attacks, and Market Crashes* (Springer-Verlag, Berlin, 2002).
30. R. B. Govindan, D. Vyushin, A. Bunde, S. Brenner, S. Havlin, and H. J. Schellnhuber, "Global Climate Models Violate Scaling of the Observed Atmospheric Variability," Phys. Rev. Lett. **89**, 028501 (2002).
31. A. Bunde, S. Havlin, J. W. Kantelhardt, T. Penzel, J. H. Peter, and K. Voigt, "Correlated and Uncorrelated Regions in Heart-Rate Fluctuations during Sleep," Phys. Rev. Lett. **85**, 3736–3739 (2000).
32. J. W. Kantelhardt, E. Koscielny-Bunde, H.H.A. Rego, S. Havlin, and A. Bunde, Physica A **294**, 441 (2001).
33. K. Hu, Z. Chen, P. Ch. Ivanov, P. Carpena, and H. E. Stanley, "Effect of Trends on Detrended Fluctuation Analysis" Phys. Rev. E **64**, 011114-1 – 011114-19 (2001) physics/0103018.
34. Z. Chen, P. Ch. Ivanov, K. Hu, and H. E. Stanley, "Effect of Nonstationarities on Detrended Fluctuation Analysis" Phys. Rev. E **65**, 041107-1 to 041107-15 (2002). physics/0111103.
35. Y. Liu, P. Gopikrishnan, P. Cizeau, M. Meyer, C.-K. Peng, and H. E. Stanley, "The statistical properties of the volatility of price fluctuations" Phys. Rev. **60**, 1390-1400 (1999).

36. P. Kumar, P. Ch. Ivanov, and H. E. Stanley, "Statistical Physics and Prime Numbers" (preprint).
37. A. F. Rozenfeld, R. Cohen, D. ben-Avraham, and S. Havlin, "Scale-Free Networks on Lattices," Phys. Rev. Lett. **xx**, xxx–xxx (2003) cond-mat/0205613.
38. R. Cohen and S. Havlin, "Ultra Small World in Scale-Free Networks," Phys. Rev. Lett. **xx**, xxx–xxx (2003) cond-mat/0205476 (2002).
39. D. ben-Avraham, A. F. Rozenfeld, R. Cohen, and S. Havlin, "Geographical Embedding of Scale-Free Networks," cond-mat/0301504 (2003).
40. X. Guardiola et al., "Macro- and Microstructure of Trust networks," cond-mat/020640 (2002).
41. D. J. Watts and S. H. Strogatz, "Collective Dynamics of 'Small-World' Networks," Nature **393**, 440–442 (1998).
42. D. J. Watts, *Small Worlds: The Dynamics of Networks between Order and Randomness* (Princeton University Press, Princeton, 1999).
43. V. E. Krebs, "Mapping Networks of Terrorist Cells," Connections **24**, 43–52 (2002).
44. M. E. J. Newman, "Assortative Mixing in Networks," cond-mat/0205405 (2002).
45. R. Cohen, D. Doler, S. Havlin, T. Kalisky, O. Mohryn, and Y. Shavitt, "On the Tomography of Networks and Multicart Trees," Tech. Report TR 2002-49, Hebrew University, Israel.
46. P. Ch. Ivanov, L. A. Nunes Amaral, A. L. Goldberger, S. Havlin, M. G. Rosenblum, Z. Struzik, and H. E. Stanley, "Multifractality in Human Heartbeat Dynamics," Nature **399**, 461 (1999).
47. R. Pastor-Sattoras and A. Vespignani, "Epidemic Dyanamics and Endemic States in Compex Networks," Phys. Rev. E **63**, 066117 (2001).