Dynamic Analysis of Social Networks of Equids

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Grevy's zebra are endangered species of zebra found in Eastern Africa. Onagers are very common wild Asses widespread from Middle East to India. Both species are equids of roughly the same size, similar physiology, and living in semiarid environment. Both were previously described as having the same social organization: social fission-fusion species with territorial males and harem females. While traditional social network analysis has revealed some differences in the structure of their interactions, it was not sufficient to fully differentiate and explain the differences. We use dynamic social network analysis, specifically, we use the method we have previously developed for identifying dynamic communities, to compare same-size populations of Grevy's and onagers.

Dynamic Communities Identification

Communities are loosely defined as collections of individuals who interact consistently and frequently [9–12, 16, 30]. Community structure often reveals interesting properties shared by the members, such as common hobbies, occupations, social functions or rank, etc. [4, 5, 8]. In particular, many researchers have shown that communities tend to evolve gradually over time [2, 13, 14, 18–21, 29], as opposed to assembling or disbanding spontaneously. Thus, it is desirable to use temporal information not only to identify communities with high intra-community interaction, but also to study their development, persistence, and decline over their life time.

Recent explosion of data collecting technology created an abundance of data on dynamic social networks and spurred the development of computational approaches to the analysis of those data, including analysis of dynamic community structure [1, 3, 6, 7, 15, 17, 22, 23, 26–28, 31]. For a survey of the recent computational techniques for dynamic communities identification, with a particularly detailed description of the method proposed by the authors of this abstract see [25].

Our approach to identifying dynamic communities is to derive an objective from first principles of social behavior. Specifically, we proposed an axiomatization of the persistence of social interactions and their dynamics, in a way that explicitly draws a connection between latent community structure and observed interactions [27]. This axiomatization is based on the tenets that members usually participates in interactions of their own community, rarely participate in interactions or meetings of other communities, and rarely make long-term switches of community affiliation. Based on this formalism, we formulate a combinatorial optimization problem. Dynamic communities are viewed, essentially, as dynamic clusters, where some notion of "social cost" is minimized within communities. The optimization problem itself is computationally intractable and we therefore proposed various methods for speeding up the computation, including a recent approximation algorithm [26].

Grevy's and Onager data sets

Data sets of affiliations of the two species of species of equids were obtained in similar ways, by observing spatial proximity of members of a population over a period of time. Predetermined census loops were driven approximately 5 times per week. Individual animals were identified by their unique markings such as stripe patterns of zebras, scars and ear notched of onagers [24]. The Grevy's zebra data set was collected by observing a population of 27 animals over three months in 2002 in Kenya. The onager data set was collected by observing a population of 29 animals in the Little Rann of Kutch desert in Gujarat, India, from January to May in 2003. The data was collected by ecologists making visual scans of the herds, typically once a day over periods of several months. Each entity in the dynamic network is a unique animal and an interaction represents social association, as determined by spatial proximity and the domain knowledge of ecologists.

Results and Discussion

The static (aggregate) network of Grevy's zebra shows most individuals in one large cluster [24]. However, dynamic community identification exposes that within the major cluster, we find two large communities, whose members come together and split apart repeatedly. These two communities are those of lactating females who need to stay by the water and non-lactating females, who can go further from the water where the grass is better but come to drink every now and then. In addition, the dynamic approach informs us of individuals with distinctive interaction behavior, such the territorial male who roves between the lactating and non-lactating members of his harem.

In addition to offering novel insights for a single population, our dynamic community identification method provides powerful metrics with which to compare societies. Our analysis shows that the onager society has a higher number of smaller communities, and individuals switch their affiliations a lot, compared to Grevy's zebra. While Grevy's have a cohesive (although fluid) structure of communities, onagers' communities are ephemeral and constantly mixing. Our analysis suggests that onagers may have a lower social cost of switching their affiliations than Grevy's. The ecological reasons behind these differences may be the difference in predation pressure and water availability and predictability. The dynamic community analysis points to the ecological aspects of the two species that influence their social structure and elucidates the reasons of why individuals are found in groups in nature in the first place.

References

1. C. C. Aggarwal and P. S. Yu. Online analysis of community evolution in data streams. In *Proceedings of SIAM International Data Mining Conference (SDM 2005)*, 2005.
2. L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group formation in large social networks: Membership, growth, and evolution. In *Proc. 12th ACM SIGKDD Intl. Conf. on Knowledge Discovery and Data Mining*, 2006.
3. T. Y. Berger-Wolf and J. Saia. A framework for analysis of dynamic social networks. In *KDD '06: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 523–528, New York, NY, USA, 2006. ACM Press.
4. R. L. Breiger. The duality of persons and groups. *Social Forces*, 53(2):181–190, December 1974.
5. A. Davis, B. B. Gardner, and M. R. Gardner. *Deep South*. The University of Chicago Press, Chicago, IL, 1941.
6. T. Falkowski. *Community Analysis in Dynamic Social Networks*. Dissertation, University Magdeburg, 2009.
7. T. Falkowski, J. Bartelheimer, and M. Spiliopoulou. Mining and visualizing the evolution of subgroups in social networks. *Web Intelligence, IEEE/WIC/ACM International Conference on*, 0:52–58, 2006.
8. K. Faust. Scaling and statistical models for affiliation networks: patterns of participation among soviet politicians during the brezhnev era. *Social Networks*, 24(3):231–259, July 2002.
9. L. Freeman. Finding social groups: A meta-analysis of the southern women data. In R. Breiger, K. Carley, and P. Pattison, editors, *Dynamic Social Network Modeling and Analysis*. The National Academies Press, Washington, D.C., 2003.
10. L. C. Freeman. On the sociological concept of "group": a empirical test of two models. *American Journal of Sociology*, 98:152–166, 1993.
11. M. Girvan and M. E. J. Newman. Community structure in social and biological networks. *Proc. Natl. Acad. Sci.*, 99:8271–8276, 2002.
12. J. Hopcroft, O. Khan, B. Kulis, and B. Selman. Natural communities in large linked networks. In *9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 541–546, 2003.
13. A. Iriberri and G. Leroy. A life-cycle perspective on online community success. *ACM Comput. Surv.*, 41(2):1–29, 2009.
14. R. Kumar, J. Novak, P. Raghavan, and A. Tomkins. On the bursty evolution of blogspace. *World Wide Web*, 8(2):159–178, 2005.
15. Y.-R. Lin, Y. Chi, S. Zhu, H. Sundaram, and B. L. Tseng. Facetnet: a framework for analyzing communities and their evolutions in dynamic networks. In *WWW '08: Proceeding of the 17th international conference on World Wide Web*, pages 685–694, New York, NY, USA, 2008. ACM.
16. M. Newman, A.-L. Barabási, and D. J. Watts, editors. *The Structure and Dynamics of Networks*. Princeton University Press, 2006.
17. G. Palla, A. Barabási, and T. Vicsek. Quantifying social group evolution. *Nature*, 446:664–667, 2007.
18. M. Pearson and P. West. Drifting smoke rings: Social network analysis and markov processes in a longitudinal study of friendship groups and risk-taking. *Connections*, 25(2):59–76, 2003.
19. T. Snijders, C. Steglich, and G. van de Bunt. Introduction to actor-based models for network dynamics. *Social Networks*, 2009.

20. T. A. Snijders. Models for longitudinal network data. In P. Carrington, J. Scott, and S. Wasserman, editors, *Models and methods in socialnetwork analysis*, chapter 11. Cambridge University Press, New York, 2005.
21. T. A. B. Snijders. The statistical evaluation of social network dynamics. *Sociological Methodology*, 31:361–395, 2001.
22. M. Spiliopoulou, I. Ntoutsi, Y. Theodoridis, and R. Schult. Monic: modeling and monitoring cluster transitions. In *KDD '06: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 706–711, New York, NY, USA, 2006. ACM.
23. J. Sun, C. Faloutsos, S. Papadimitriou, and P. S. Yu. Graphscope: parameter-free mining of large time-evolving graphs. In *KDD '07: Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 687–696, New York, NY, USA, 2007. ACM.
24. S. R. Sundaresan, I. R. Fischhoff, J. Dushoff, and D. I. Rubenstein. Network metrics reveal differences in social organization between two fission-fusion species, Grevy's zebra and onager. *Oecologia*, 2006. doi 10.1007/s00442-006-0553-6.
25. D. K. T. Y. Berger-Wolf, C. Tantipathananandh. Community identification in dynamic social networks. In C. F. Philip S. Yu, Jiawei Han, editor, *Link Mining: Models, Algorithms and Applications*, chapter 8. Springer, 2010.
26. C. Tantipathananandh and T. Berger-Wolf. Constant-factor approximation algorithms for identifying dynamic communities. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, New York, NY, USA, 2007. ACM.
27. C. Tantipathananandh, T. Berger-Wolf, and D. Kempe. A framework for community identification in dynamic social networks. In *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 717–726, New York, NY, USA, 2007. ACM.
28. H. Tong, S. Papadimitriou, J. Sun, P. S. Yu, and C. Faloutsos. Colibri: fast mining of large static and dynamic graphs. In *KDD '08: Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 686–694, New York, NY, USA, 2008. ACM.
29. M. Toyoda and M. Kitsuregawa. Extracting evolution of web communities from a series of web archives. In *HYPERTEXT 2003: Proceedings of the fourteenth ACM conference on Hypertext and hypermedia*, pages 28–37, New York, NY, USA, 2003. ACM.
30. S. Wasserman and F. K. *Social Network Analysis.* Cambridge University Press, Cambridge, MA, 1994.
31. T. Yang, Y. Chi, S. Zhu, Y. Gong, and R. Jin. A bayesian approach toward finding communities and their evolutions in dynamic social networks. In *Proceedings of the 2009 SIAM International Conference on Data Mining*, February 2009.