Online Social Networks

Academic Year	2017-18, Hilary Term
Day and Time	Mondays, Weeks 1-9, 14:00-16:00
Location	Seminar Room, Oxford Internet Institute, 1 St Giles, Oxford, OX1 3JS
Course Providers	Dr Bernie Hogan, Oxford Internet Institute, bernie.hogan@oii.ox.ac.uk
Prerequisites	Successful completion of Intro to Scripting with Python is a requirement for this course. The course will be teaching networks using python. It is also encouraged that the student have introductory statistics and is taking data wrangling in parallel although these are optional. Many students will successfully complete a qualitative approach to network analysis without complex statistics. Regardless, python is required for the successful completion of the formatives.

Background
The internet is but one of many networks. Every network is different in its own way but there are striking similarities, whether we refer to traffic routing, infectious diseases, friendships on Facebook or gossip on Twitter. This course represents a primer in social network analysis [SNA], a longstanding approach to the generation and analysis of network data.

SNA, also sometimes called structural analysis, has been at the forefront of many of the most considerably insights in sociology, from inequality in jobs, to political polarization. Yet, network analysis extends beyond sociology in important and significant ways. From computer science, we learn optimizations for graphs and new ways of visualizing them. From statistics we learn which networks are likely to appear by chance. From physics we learn of large scale cascading behaviour and ways of detecting communities. Collectively, these insights comprise a new field called network science.

In this course we introduce many of the fundamentals of social network analysis, from graph theory through personal networks to newer network science approaches and advanced statistical modelling. Each week includes reading summaries and exercises designed to build the student's capacity for network analysis. We conclude the course with a critical interrogation of network analysis to help circumscribe some limits to this otherwise exciting and powerful paradigm. The result is a well-rounded course designed to enable the effective use of networks in research.

Key Themes

- What differentiates social networks as analytical objects from the reality they seek to represent?
- How do the descriptive measures of networks inform us about macro social structures as well as micro social behaviours?
- How do the affordances and constraints of online technologies help facilitate certain kinds of network structures (and indeed, even the notion of networks as analytical tools in the first instance)?
- Why do networks as visual objects persist in having a rhetorical power? Is it that they are merely 'sciency' and complex looking or should we consider the visual presentation of networks as a meaningful scholarly practice?

Course Objectives

The course will familiarise students with the state of network science as a paradigm comprising multidisciplinary approaches to the analysis of relational data. Students will be able to read introductory network metrics and understand how these measures speak to theories of human behaviour as well as put together an original piece of analysis using network data. Students will gain a modest understanding, via the 'sociology of science', as to why network analysis is a highly distributed field where no single software application, journal or conference covers all of the active research on social networks. Students will also learn basic data capture and analysis techniques that can enable them to begin, if not complete, a full social network analysis study.

Learning Outcomes

Upon successful completion of this course students should:

- Have a familiarity with the basic terms and concepts of social network analysis.
- Understand how differing network analysis metrics relate both to each other and to academic research questions.
- Be able to describe how a network can be constructed from an online phenomenon.
- Have a clear understanding of some of the various analytical tools used in network science.
- Be able to construct and theorise a research question that employs social network analysis in order to address a specific topic related to human behaviour and collective dynamics.

Teaching Arrangements

The course will consist of eight classes taught in weeks 1-4 and 6-9 of Hilary term. The date, time and venue will be communicated to students during Michaelmas Term. The lectures will be given by both course conveners alternately, to provide a cohesive mix of social science and network science.

Each class will begin with an hour-long lecture. The second half of the class is typically a guided walkthrough of network analysis techniques. The techniques draw upon a variety of software packages and data sources. Every effort will be made to ensure cross-platform and open source software is used whenever possible, but this cannot always be guaranteed.

Assessment

Students will be assessed through a final essay that is no longer than 5000 words which must be submitted via Weblearn by 12 noon of Monday of Week 1 of Trinity Term (23 April). Your essay for this course can be in one of any of the following three styles:

1. A critical review of a concept in social network analysis. In this sort of essay, you will have to select a concept that has been introduced in the course and provide a review of the concept that includes a thorough review of empirical research, an outline of the outstanding issues with the concept and contemporary analytical or methodological approaches to the concept. This should also contain some novel synthesis rather than mere description.
2. A novel analysis of an existing data set. This is an analytical route that is suitable for a student planning to explore complex statistical approaches such as ERGms / SOAMs / big data analysis / network econometrics. As these models are tedious and slow to run as well as mathematically formidable, most of the work will involve the building and testing of the models alongside diagnostics and visualizations.
3. A descriptive analysis of novel data. This requires you to collect your own data. The emphasis in the essay will not be on complicated modeling so much as the methodological concerns involved in collecting the data. You will be expected to provide basic descriptives and visualizations where appropriate. You should report on the network(s) in such a way that their description will speak to a relevant research question.

Essays should be formatted using APA style and absolutely must contain a guiding research question. The essay topic should be agreed upon by the student and the course instructor prior to submission (see the following section).

Formative Assessment

Each week there will be a formative assignment. In weeks 1-4 the assignment will be a small analysis of a network done in an ipython notebook. In week 5 the student is expected to submit a final essay topic for approval. This will be a title and a <200 word summary of the topic. In weeks 6,7 and 8 the students will again have short exercises to do in ipython (or related software) based on the course material. In week 9 the student will be expected to submit a preliminary piece of writing (between 1000-1500 words) that will form part of the final essay. The course instructor will provide written feedback of the writing and seek to schedule a meeting to discuss the writing after term ends and before papers are due. The purpose of this second piece is to demonstrate to the instructor that the proposed topic has sufficient literature / theoretical motivation and data to continue pursuing.

In addition to the formative assignments the course instructor will direct students to a wiki, housed at http://wiki.oii.ox.ac.uk/ . It will include headers for each of the readings for the weeks. Students are each expected to write a brief summary of at least two papers featured in the course. This way, by the end of course, every student will have a shared, thorough annotated bibliography to help them with their summative essay.

Submission of Assignments

The summative assignment for this course is due on Monday of Trinity Term Week 1 (23 April) by 12.00pm and should be submitted electronically via the Assignment Submission WebLearn Site. The assignment should also be submitted electronically by 5:00 pm on the same day to teaching@oii.ox.ac.uk. If anything goes wrong with your submission, email teaching@oii.ox.ac.uk immediately. In cases where a technical fault that is later determined to be a fault of the Weblearn system (and not a fault of your computer) prevents your submitting the assessment on time, having a time stamped email message will help the Proctors determine if your assessment will be accepted. Please note that you should not wait until the last minute to submit materials since Weblearn can run slowly at peak submission times and this is not considered a technical fault.

Full instructions on using WebLearn for electronic submissions can be found on Plato under General Information. There is also an FAQ page on the Assignment Submission WebLearn Site.

Please note that work submitted after the deadline will be processed in the standard manner and, in addition, the late submission will be reported to the Proctors' Office. If a student is concerned that they will not meet the deadline they must contact their college office or examinations school for advice. For details on the regulations for late and non-submissions please refer to the Proctors website at https://www.admin.ox.ac.uk/proctors/examinations/candidates/ .

Any student failing this assessment will need to follow the rules set out in the OII Examining Conventions regarding re-submitting failed work.

Topics

1. Introduction
2. Ego-centred network data collection
3. Sociocentric and partial data collection
4. Dyads and homophily
5. Communities and clusters
6. Dynamic and Generative models
7. Network cognition and visualization
8. Theorizing beyond the network

Week 1. Introduction

The readings for this week are all introductory works on networks. I would recommend reading the Hogan piece first for a general overview of social network analysis from the perspective of online data. The Harrington piece then is as gentle an introduction to graphs as one is likely to get (given that it discusses teaching graph theory to high school students). The Borgatti et al. chapters comprise a very thoughtful conception of different kinds of networks and discuss this from a distinctly social network perspective.

The five option papers this week range in importance. Granovetter is probably the most important work in social network analysis to date. It will come up repeatedly in class discussions but it is not strictly speaking an introductory piece. The Wellman article clarifies that networks are a paradigm and not merely a “turbo-charger” for existing types of social research. Its claims still ring true today. Butts is an extremely technical piece for those looking for a more statistically-oriented intro to networks and contemporary network analysis thinking. Hildago does a fine job of clarifying the relationship between social network analysis and network science. Finally, the Hennig et al. chapter is a gentle introduction to networks that is similar in tone and spirit to the Borgatti et al. chapter.

Required readings

Hogan, B. (2017). Online Social Networks: Concepts for Data Collection. In N. Fielding, R. Lee, & G. Blank (Eds.), *The SAGE Handbook of Online Research Methods* (Second Ed, pp. 241–258). Thousand Oaks, CA: Sage.

Harrington, H. A., Beguerisse-díaz, M., Rombach, M. P., Keating, L. M., & Porter, M. A. (2013). Commentary : Teach network science to teenagers. *Network Science*, *1*(2), 226–247. http://doi.org/10.1017/nws.2013.11

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. Thousand Oaks, CA: SAGE Publications Limited. Chs. 1-2.

Optional readings

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*, 1360–1380.

Wellman, B. (1988). Structural Analysis: From Method and Metaphor to Theory and Substance. In B. Wellman & S. D. Berkowitz (Eds.), *Social Structures: A Network Approach* (pp. 19–61). Cambridge, UK: Cambridge University Press.

Hidalgo, C. A. (2016). Disconnected, fragmented, or united? A trans-disciplinary review of network science. *Applied Network Science*, *1*(6), 1–19. http://doi.org/10.1007/s41109-016-0010-3

Butts, C. T. (2008). Social network analysis: A methodological introduction. *Asian Journal Of Social Psychology*, *11*(1), 13–41. http://doi.org/10.1111/j.1467-839X.2007.00241.x

Hennig, M., Brandes, U., Pfeffer, J., & Mergel, I. (2012). *Studying social networks: A guide to empirical research*. Campus Verlag. Ch. 1. Pp. 13-26.

Week 2. Ego-centred network data collection

Personal networks (a.k.a. ego-centred networks, egocentric networks or simply ego-nets) are a critical part of social network analysis. It is the set of connections from which an individual operates. In this sense, it is the reference group for all activity for any given person. While a large social structure may exert hidden forces on an individual, the personal network exerts immediate forces on the individual. The required readings focus on the collection and analysis of egocentered network data, both online and offline. Hogan (2016) highlights modern approaches to data collection alluded to in Crossley et al., and Dunbar discusses whether it is meaningful to thing about networks at the scale of online egonets like Facebook.

The optional readings for this week dig deeper into egocentric network analysis. Hogan (2017) highlights how online data collection is no longer as feasible in many contexts. Van Duijin et al., show an exemplary statistical technique for egonets called multilevel analysis. This is also discussed in later chapters of Crossley et al. The Reyes paper shows how one can do very qualitative egonet research and the Giannella and Fisher paper describes a contemporary technique for classifying egonets using random forests.

Required readings

Crossley, N., Bellotti, E., Edwards, G., Everett, M. G., Koskinen, J., & Tranmer, M. (2015). *Social Network Analysis for Ego-Nets*. London, UK: Sage Publications. Ch. 3. Pp. 44-75

Hogan, B., Melville, J., Phillips II, G., Janulis, P., Contractor, N., Mustanski, B., & Birkett, M. (2016). Evaluating the Paper-to-Screen Translation of Participant-Aided Sociograms with High-Risk Participants. In *Proceedings of the 2016 Conference on Human Factors in Computing. CHI '16.* (pp. 5360–5371). San Jose, CA. http://doi.org/http://dx.doi.org/10.1145/2858036.2858368

Dunbar, R. I. M. (2016). Do online social media cut through the constraints that limit the size of offline social networks? *Royal Society Open Science*, *3*(150929), 1–9.

Optional readings

Reyes, Cornelia. Eliciting data on social relationships: The use of hand-drawn network maps in tracing the perception of digitally mediated social ties. *International Review of Social Research*. 6(4): 256-268.

Hogan, B. 2017. (Forthcoming) Social Media Giveth, Social Media Taketh Away: Facebook, Friendships and the decline in access via APIs. *International Journal of Communication.*

van Duijin, M. A. J., van Busschbach, J. T., & Snijders, T. A. B. (1999). Multilevel analysis of personal networks as dependent variables. *Social Networks*, *21*(2), 187–209.

Giannella, E., & Fischer, C. S. (2016). An inductive typology of egocentric networks. *Social Networks*, *47*(1), 15–23. http://doi.org/10.1016/j.socnet.2016.02.003

Week 3. Sociocentric and partial data collection

Whole networks and partial networks are where we either define a boundary or just keep collecting links until we exhaust criteria. In either case, they are networks that transcend the reference group of any individual. As such, we can start to think about qualities and behaviours that occur on account of the large scale patterns which emerge from the aggregation of these links. The core papers in this section highlights some of the novel findings at the sociocentric level. As this is a class on online social networks, I have included as mandatory the recent papers that employ big data and online data to explore networks at this larger scale alongside a chapter on roster-based data collection. The optional papers are the classic papers that introduce these ideas.

Required readings

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. Thousand Oaks, CA: SAGE Publications Limited. Chs. 3-4.

Ugander, J., Karrer, B., Backstrom, L., Marlow, C., & Alto, P. (n.d.). The Anatomy of the Facebook Social Graph, 1–17. Avialable online: http://arxiv.org/abs/1111.4503

Hodas, N. O., Kooti, F., & Lerman, K. (2013). Friendship Paradox Redux : Your Friends Are More Interesting Than You. In *Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media* (pp. 225–233). Boston, USA.

Optional readings

Feld, S. L. (1991). Why Your Friends Have More Friends Than You Do. *American Journal of Sociology*, *96*(6), 1464–1477.

Travers, J., & Milgram, S. (1969). An Experimental Study of the Small World Problem. *Sociometry*, *32*(4), 425–443. http://doi.org/10.2307/2786545

Pool, I. deSola, & Kochen, M. (1978). Contacts and Influence. *Social Networks*, *1*(1), 1–48.

Week 4. Dyads and homophily

Dyads are a core building block of social networks. While there are important phenomena that occur once we add in triads, there is a huge amount of work that is successful at the dyad level. Many qualities of dyads make a difference. For example, whether one is a relationship or not can aid in resilience. Having people like you in your network can help you feel a sense of solidarity, but it can also bog you down with responsibilities. At a level just slightly more interconnected than standard social science, we can already see the power of networks. Rivera et al., explore features of dyads and dyadic analysis. The McPherson et al., paper is the key paper on homophily. If you are doing anything with homophily in your final paper this will be worth reading. Bakshy et al., is a great paper on how Facebook manages homophily (with some potential unintended consequences). Finally, Crossley et al., show how to calculate homophily scores using EI indices and Yule's Q. In the class we will also cover assortativity and mixing matrices.

The option papers dive deeper into the matters of dyads and homophily. The Cyberbalkans paper explored the Filter Bubble thesis almost two decades before it became a big deal on social media sites. It was first presented in 1997 and published a decade later. One of the authors of that paper, Marshall Van Alstyne, also wrote a great paper on brokerage with Sinan Aral. That is included as well. Gould and Fernandez are not the originators of the notion of brokerage and structural holes, but their paper on it is excellent and still in use today. Finally, Mizruchi and Marquis show how dyadic level analysis can have more explanatory power than other levels, thus reinforcing the importance of work at this level.

Required readings

Rivera, M. T., Soderstrom, S. B., & Uzzi, B. (2010). Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms. *Annual Review of Sociology*, *36*, 91–115. http://doi.org/10.1146/annurev.soc.34.040507.134743

Bakshy, E., Messing, S., & Adamic, L. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130–1132.

McPherson, J. M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*, 415–444.

Crossley, N., Bellotti, E., Edwards, G., Everett, M. G., Koskinen, J., & Tranmer, M. (2015). *Social Network Analysis for Ego-Nets*. London, UK: Sage Publications. Ch. 4. Pp. 76-104

Optional readings

Gould, R. V, & Fernandez, R. M. (2017). Structures of Mediation : A Formal Approach to Brokerage in Transaction Networks. *Sociological Methodology*, *19*(1989), 89–126.

Mizruchi, M. S., & Marquis, C. (2006). Egocentric, sociocentric, or dyadic? Identifying the appropriate level of analysis in the study of organizational networks. *Social Networks*, *28*(2), 187–208.

Alstyne, M. Van, & Brynjolfsson, E. (2005). Global Village or Cyber-Balkans ? Modeling and Measuring the Integration of Electronic Communities. *Management Science*, *51*(6), 851–868. http://doi.org/10.1287/mnsc.1050.0363

Aral, S., & Alstyne, M. Van. (2011). The Diversity-Bandwidth Trade-off. *American Journal of Sociology*, *117*(1), 90–171. Retrieved from http://www.jstor.org/stable/10.1086/661238

Feld, S. L. (1982). Social Structural Determinants of Similarity Among Associates. *American Sociological Review*, *47*, 797–801.

Week 5: BREAK

NOTE. Remember to submit your formative this week detailing your proposed essay topic.

Week 6. Communities and clusters

Homophily does not simply lead to dependence between dyads. As these dyads have friends who are also similar, we end up with forms of clustering in networks. This has been known for ages. What has been less clear is how to identify the communities and what makes for an accurate representation of community. For example, does every individual need to be in a community? Must communities be non-overlapping? Many unresolved questions remain in this space. The first paper by Smith et al., is a simple read that highlights how different twitter hashtags show clear and distinct community signals. The second paper is a review of community detection written deliberately to get new and interested academics up to speed. As a counterweight, the third shows how we should not get too excited by community detection where most of the network structure is in other dimensions than the network topology. This is especially relevant in the high dimension networks found among people.

The option papers this week range considerably in scope. The Fortunado paper is the mammoth paper on community detection from which Porter is but the abridged version. The Newman paper is an early community detection paper that ties many different conceptual strands together, particularly modularity. Leskovec shows an alternative form of partitioning based on conductance rather than modularity. Moody and Gest show the performance of early community detection algorithms and a matrix-based method referred to as blockmodelling. Brooks et al., and Watts and Kossinetts focus on communities and clustering using data traces.

Required readings

Smith, M. A., Rainie, L., Himelboim, I., & Shneiderman, B. (2014). Mapping Twitter Topic Networks: From Polarized Crowds to Community Clusters. *Pew Research Center*, *1*, 1–56.

Porter, M. A. P., Onnela, J.-P., & Mucha, P. J. (2009). Communities in Networks. *Notices of the AMS*, *56*(9), 1082–1166.

Hric, D., Darst, R. K., & Fortunato, S. (2014). Community detection in networks : Structural communities versus ground truth. *Physical Review E*, *62805*(June), 1–19. http://doi.org/10.1103/PhysRevE.90.062805

Optional readings

Newman, M. E. J. (2006). Modularity and Community Structure in Networks. *Proceedings of the National Academy of Sciences*, *103*, 8577–8583.

Gest, S. D., Moody, J., & Rulison, K. L. (2008). Density or Distinction? The Roles of Data Structure and Group Detection Methods in Describing Adolescent Peer Groups. *Journal of Social Structure*, *8*(1). Retrieved from http://www.cmu.edu/joss/content/articles/volume8/GestMoody/

Brooks, B., Hogan, B., Ellison, N., Lampe, C., & Vitak, J. (2014). Assessing structural correlates to social capital in Facebook ego networks. *Social Networks*, *38*(1), 1–15. http://doi.org/10.1016/j.socnet.2014.01.002

Kossinets, G., & Watts Duncan, J. (2006). Empirical Analysis of an Evolving Social Network. *Science*, *311*(5757), 88–90.

Yang, J., & Leskovec, J. (2015). Defining and evaluating network communities based on ground-truth. *Knowledge and Information Systems*, *42*(1), 181–213. http://doi.org/10.1007/s10115-013-0693-z

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3–5), 75–174. Retrieved from http://www.sciencedirect.com/science/article/pii/S0370157309002841

Week 7. Dynamic and Generative models

Because of the way networks imply that nodes are linked to each other, we cannot typically assume independence of actors. For this reason, we have to think about alternative specifications for statistical tests. There are a number of alternative specifications, yet one of the most important is the exponential random graph model [ERGm] and its variants. The Robins chapters introduce ERGms and the Wimmer and Lewis paper apply this model to Facebook data collected in the Taste, Ties and Time data set, a controversial but highly informative data set of undergraduates.

Other specifications are worth considering and will be considered in class. A good review of some of the material to this point and some other novel specifications are found in Borge-Holthoefer and Gonzalez-Bailon. One of the most important of these specifications is the class of models known as Stochastic Actor-Oriented Models [SAOMs]. These models are excellent for disentangling selection effects from influence effects. Snijders et al., introduce SAOMs and Lewis et al., applies these to the same data set as featured above. The short

PNAS paper gives the summary and findings but the supplementary information goes into excellent detail.

Required readings

Lusher, D., Koskinen, J., & Robins, G. (2012). *Exponential random graph models for social networks: Theory, methods, and applications*. Cambridge University Press. Chs. 2-4. Pp. 9-36

Wimmer, A., & Lewis, K. (2010). Beyond and Below Racial Homophily : ERG Models of a Friendship Network Documented on Facebook. *American Journal of Sociology*, *116*(2), 583–642.

Optional readings

Snijders, T. A. B., Bunt, G. G. Van De, & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics ಙ. *Social Networks*, *32*(1), 44–60. http://doi.org/10.1016/j.socnet.2009.02.004

Borge-Holthoefer, Javier & González-Bailón, Sandra. (2016). Chapter 15: Scale, Time, and Activity Patterns: Advanced Methods for the Analysis of Online Networks. In N. Fielding, R. Lee, & G. Blank (Eds.), *The SAGE Handbook of Online Research Methods* (Second Ed, pp. 259–276). Thousand Oaks, CA: Sage.

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences*, *109*(1), 68–72. http://doi.org/10.1073/pnas.1109739109

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Supporting Information. *Proceedings of the National Academy of Sciences*, *109*(1), 1–16.

Week 8. Network cognition and visualization

Visualization has been at the heart of network analysis since the very beginning. What is starting to come into focus is that the reason why some visualizations in particular have made sense is because they appear to coherently represent underlying network structure using only simple rules. Where much of networks draws from physics, statistics and maths alongside social science, graph drawing draws from much work in computer science including the sizeable graph drawing community.

The first required paper is by Freeman. As a precursor to his book on the history of social network analysis is an extensive paper detailing the history of visualization. It highlights the centrality of visualization to the field social network analysis. The Welser paper shows how three different visualizations can lead to different insights about the same networks, in this case, networks of usenet participants. The Lee and Archambault paper and the Brashears paper both discuss how people can interpret clusters detected and possibly remember networks as clusters.

The optional readings show the expanse of this field. The oldest by Fruchterman and Reingold highlight how people have been thinking about graph drawing for a long time. Their layout algorithm is crucial to networks today. The Noack piece suggests there are important mathematical reasons why the Fruchterman-Rheingold algorithm makes sense that can be linked to community detection. The second oldest paper here, by Purchase et al., show how people prefer certain styles of network visualizations. This can be paired with the Kieffer piece showing that we can learn from human-drawn layouts to optimize other layout algorithms. The McGrath piece is a cautionary tale on the fact that some layouts can deceive and finally the Borgatti et al., piece is an instructional chapter on how to present a visualization of a network.

Required readings

Freeman, Linton C. (2000). Visualizing Social Networks. *Journal of Social Structure*. 1(1):0.

Lee, A., & Archambault, D. (2016). Communities Found by Users -- Not Algorithms: Comparing Human and Algorithmically Generated Communities. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 2396–2400. http://doi.org/10.1145/2858036.2858071

Brashears, M. E. (2013). Humans use compression heuristics to improve the recall of social networks. *Scientific Reports*, *3*, 1513. http://doi.org/10.1038/srep01513

Welser, Howard T. et al. “Visualizing Social Networks”. 2008. *Journal of Social Structure.* 8(1). Online: http://www.cmu.edu/joss/content/articles/volume8/Welser/

Optional readings

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph Drawing by Force-directed Placement. *Software Practice and Experience*, *21*(11), 1129–1164.

Purchase, H. C., Cohen, R. F., & James, M. (1996). Validating graph drawing aesthetics. In F. J. Brandenburg (Ed.), *Graph Drawing: Symposium on Graph Drawing, GD ’95 Passau, Germany, September 20--22, 1995 Proceedings* (pp. 435–446). Berlin, Heidelberg: Springer Berlin Heidelberg. http://doi.org/10.1007/BFb0021827

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. Thousand Oaks, CA: SAGE Publications Limited. Ch. 7.

McGrath, C., Blythe, J., & Krackhardt, david. (1997). The effect of spatial arrangement on judgements and errors in interpreting graphs. *Social Networks*, *19*, 223–242.

Noack, A. (2009). Modularity clustering is force-directed layout. *Physical Review E*, *79*, 26102. Retrieved from doi:10.1103/PhysRevE.79.026102

Kieffer, S., Dwyer, T., Marriott, K., & Wybrow, M. (2015). HOLA: human-like orthogonal network layout. *IEEE Transactions on Visualization and Computer Graphics*, 1. http://doi.org/10.1109/TVCG.2015.2467451

Week 9. Theorizing beyond the network

By week eight students should already be underway in their final paper. As a consequence, it is not a good time to introduce new data collection techniques or analytical strategies.

Instead, we will try to think deeply about the relationship between networks as operationalised and the social structures they represent. We will cover relationalism from Emirbayer and performativity from Healy. The first paper asks us to think about what exactly are relations; can we even think of them as things? Healy makes the intriguing case that networks are not representations anymore as we are making the world in the image of networks. Hogan and Wellman show how social network sites were made in the image of networks.

The optional papers again dig deeper into these ideas. Abbott's paper pairs well with Emirbayer by critiquing standard regression techniques. Latour's paper is a alternative to Healy's, but still within STS, of how networks constitute their nodes. Pachuki and Brieger's paper and Levi-Martin's paper both ask us to think about how much of social structure is really just a manifestation of culture.

Required readings

Emirbayer, M. (1997). Manifesto for a relational sociology. *American Journal of Sociology*, *103*(2), 281–317.

Healy, K. (2015). The performativity of networks. *European Journal of Sociology*, *56*(2), 175–205.

Hogan, B., & Wellman, B. (2014). The relational self-portrait: Selfies meet social networks. In M. Graham & W. H. Dutton (Eds.), *Society and the Internet: How networks of information and communication are changing our lives* (pp. 53–66). Oxford, UK: Oxford University Press.

Optional readings

Abbott, A. (1988). Transcending general linear reality. *Sociological Theory*, 169–186.

Latour, B., Jensen, P., Venturini, T., Grauwin, S., & Boullier, D. (2012). "The whole is always smaller than its parts" - a digital test of Gabriel Tardes' monads. *British Journal of Sociology*, *63*(4), 590–615. http://doi.org/10.1111/j.1468-4446.2012.01428.x

Martin, J. L. (2010). Life's a beach but you're an ant , and other unwelcome news for the sociology of culture. *Poetics*, *38*, 228–243. http://doi.org/10.1016/j.poetic.2009.11.004

Pachucki, M. A., & Breiger, R. L. (2010). Cultural Holes : Beyond Relationality in Social Networks and Culture. *Annual Review of Sociology*, *36*(1), 205–224. http://doi.org/10.1146/annurev.soc.012809.102615

Please note: Option papers will only run if selected by at least four students.