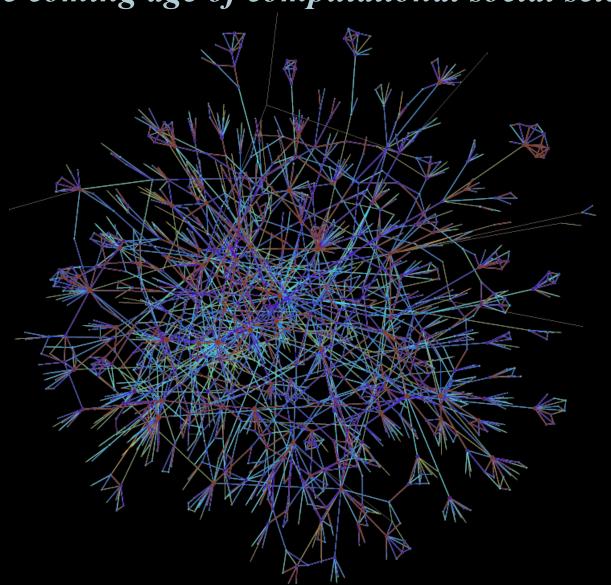
Life in the network

The coming age of computational social science



Computational social science



Computational social science

- The capturing and analysis of human activity represented in digital form
 - Increased computational capacity to manipulate data
 - Incidental, vast archives of human activity (e.g., Internet, e-mail)
 - Instrumentation of human behavior (e.g., cookies, GPS devices)
 - Creation of virtual worlds to experiment with
- What are the implications for our understanding of collective human behavior?
- What are the obstacles to the emergence of a "computational social science"?



What can data like these tell us?

- How do "things" spread through a network?
 - Ideas?
 - Avian flu?
- How do people/organizations work together?
 - Collaboration and coordination?
 - Who is in key positions in the network?
- Form an empirical basis for various types of policy recommendations
- Possibly even real-time feedback for effective interventions



Computational social science

- Orders of magnitude increase in data being collected about human behavior over last decade
- Constant increase in computational power
- Shift in social science research over the next generation
 - Thinking relationally: what is flowing among people? How are people working together?

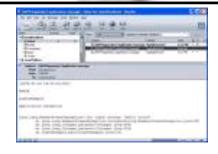


Existing approaches to studying networks

- Exponential growth in social network analysis in last decade, especially in the study of organizations, but generally across the academy
- In social sciences, generally rely on self reports
- Static generally based on snapshots
- Shaky reliability— what is being measured by self reports?
- Small scale— mostly systems in the hundreds or less
- Inferential challenges in existing research
- Many important phenomena are neglected



Life in the network













Life in the network

- E-mail
- Instant messaging
- Text messaging
- Telephone logs
- Link structure among websites (google algorithm)
- References (e.g., social science index)
- What can data like these tell us?











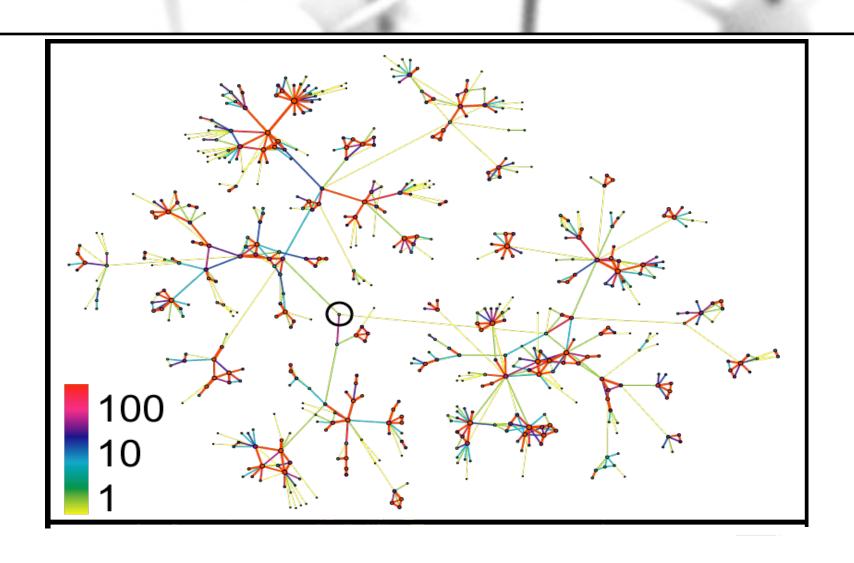


Study 1: Call log analysis

- "Structure and tie strengths in mobile communication networks" (PNAS, with J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, K. Kaskil, J. Kertész, A.-L. Barabási)
- Examination of call log data from mobile phone company in moderate sized European nation— a total of approximately **7,000,000** users, 49 trillion dyads
- What does network structure look like?



Call log network data



Results...

- Hub-spoke structure (scale free)
- Small world (on average, 13 degrees of separation)
- But poorly structured for dissemination: Strong ties tend to be clustered, and weak ties bind clusters together (consistent with Granovetter)
- But simulations suggest that weak(est) ties are not effective at spreading (inconsistent with Granovetter)
- Potentially powerful tool for studying evolving social structures of communities
- Possible use of data for a variety of policy purposes, from criminal investigations to "early warning" system for avian flu
- But: what does a phone call between two people mean??



Study 2: Instrumentation of human behavior

- Paper: "Revealing Social Relationships using Contextualized Proximity and Communication Data" (with Nathan Eagle and Sandy Pentland)
- Collaboration with Media Lab
- Program mobile phones of ~100 students for 9 months:
 - Call log data
 - Physical proximity (using Bluetooth)
 - Location (using cell tower triangulation)
- Also collected self report data on friendship, satisfaction
- What is the information in these data?
- Compare observations to self reports



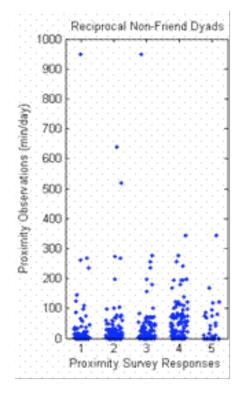
Self reported vs observed proximity

- Substantial recency effects: recent interactions weighted more heavily
- Reciprocal non-friends: 99.5% accurate at reporting 0's
- Reciprocal friends: 35% accurate at reporting 0's
- Friends more accurate at non-0's



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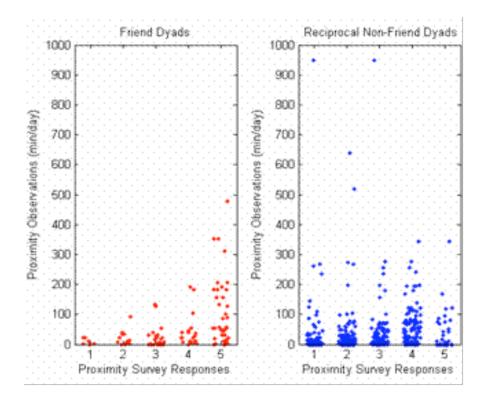


	Survey Key
Response	Reported Avg. Proximity
0	< 5 minutes
1	5-10 minutes
2	10-30 minutes
3	30 minutes - 2 hours
4	2-4 hours
5	> 4 hours



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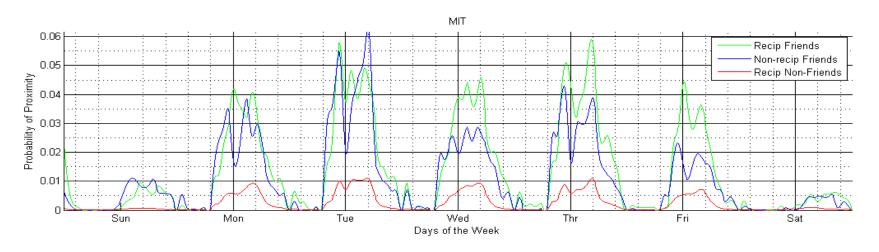
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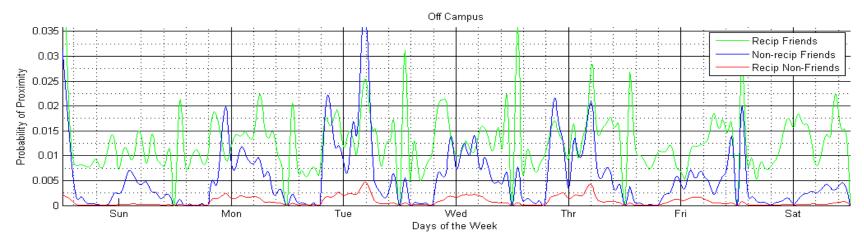


Is friendship observable?

- Friendship is important at individual and collective levels due to the resources that flow among friends
- "Purely" cognitive relationship: in principle, you could be friends with someone with whom you do not interact.
- But generally we all make inferences about who is friends with whom based on our observations
- Can the types of information that inform our inferences be captured via our mobile phones?
 - Certainly, one anticipates that (for ex) friends will tend to be proximate to each other
- If high accuracy is possible, then possible to look at evolution of friendship structure in larger populations over time (as well as other cognitive relationships, such as advice)









Self reported versus observed friendships

- We were able to categorize correctly ~95% of reciprocated friendships and reciprocated non-friendships with a single parameter
- Unreciprocated "friendships" came from high scores in-role communication, perhaps capturing cultural ambiguity
- Created continuous construct from dichotomous self report

 perhaps a more valid measure of friendship?
- Second layer of validation: predicting satisfaction based on (a) actual friendships and (b) inferred friendship. Second model does slightly better.
- Results suggest potential for inferring friendship on much larger scale.



The future...

- Bridging narrow and deep versus broad and shallow data collections...
 - Scale up "deep" data collection
 - Build capacity to infer deeper things about "shallow" data
- Development of designs that match unique characteristics of data: quantity of data is no substitute for quality of design
- Examine substantive phenomena within network, evolution of friendship structures, social capital and demography, epidemiology, etc



HUGE privacy issues

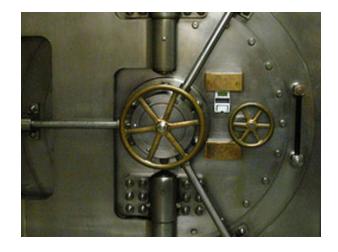
- Many (not all) of these data involve privacy concerns
- Examples: movement, e-mail data, instant messaging, etc.
- Current model of "let 1000 flowers bloom" is good for innovation, bad for potential privacy breaches
- IRBs are generally not savvy to all of the ways data can be de-anonymized
- Ex of recent pulling down of NIH data





HUGE data access issues

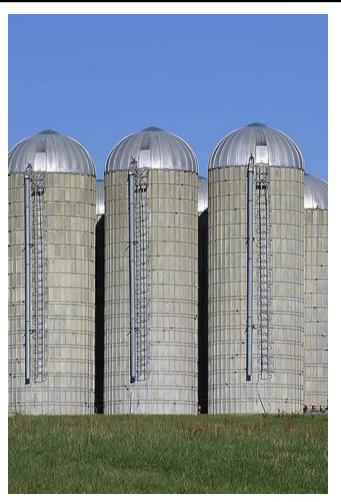
- Two possible dystopias
 - CSS remains the domain largely of corporations and government agencies
 - Dead sea scrolls model, where researchers gain access to data, but don't share





And major institutional challenges for the academy...

Overcoming silo's of academia, particularly wide between the sciences and social sciences





Issues to think about:

- What network data are meaningful? There are potentially serious heterogeneity with behavioral data.
- When are strong statistical regularities interesting? [often, they are not so interesting]
- When are large quantities of data valuable? (as compared to small, high quality, samples)
 - Russian military proverb: Quantity has its own quality.





