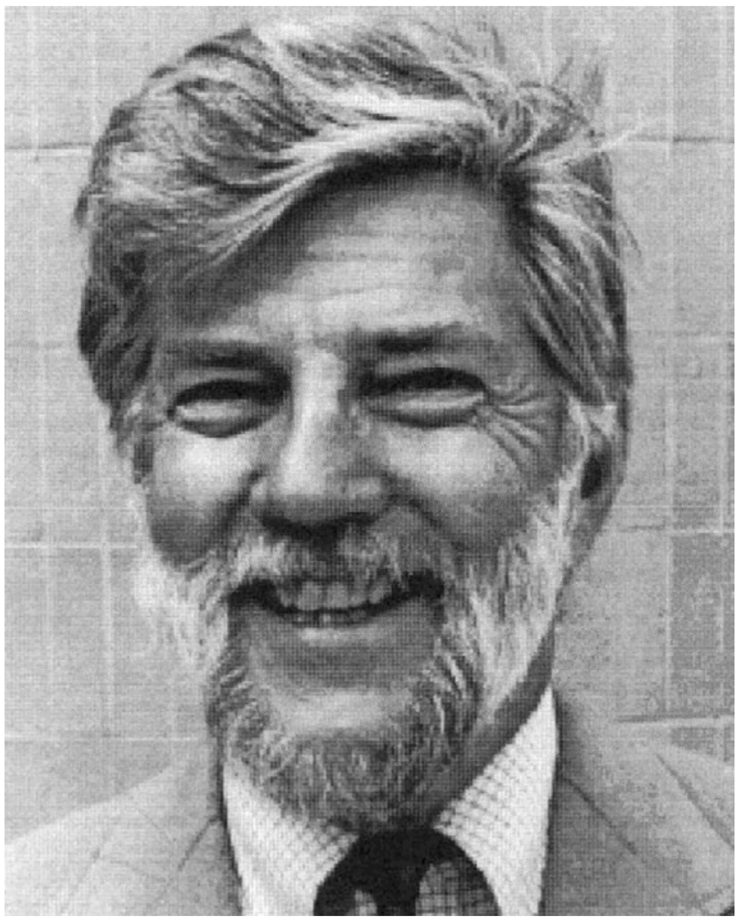
	2005	2006
JAN	**American Politics Group Annual Conference** 1/6-8: Christchurch Univ. College, Canterbury, UK	**Applied Business Research Conference** 1/2-6: Lake Buena Vista, FL, USA
	Southern Political Sciences Association Conference 1/6-8: New Orleans, LA, USA	**Hawaii International Conference on System Sciences** 1/4-7: Kauai, Hawaii, USA
	American Politics Group Annual Conference 1/6-8: Christchurch Univ. College, Canterbury, UK	**ACM-SIAM Symposium on Discrete Algorithms** 1/22-24: Miami, FL, USA
	ACM-SIAM Symposium on Discrete Algorithms 1/23-25: Vancouver, BC, Canada	**Open University Winter Combinatorics Meeting** 1/25: Milton Keynes, England, UK
FEB	**International Sunbelt Social Networks Conference** 2/16-21: Redondo Beach, CA, USA	**FRACTAL 2006 - Complexity and Fractals in Nature** 2/12-15: Vienna, Austria
	American Political Science Association 2/19-21: Washington, DC USA	**The IASTED International Conference on Artificial Intelligence and Applications** 2/13-16: Innsbruck, Austria
MAR	**Western Political Science Association** 3/17 - 19: Oakland, CA, USA	**ICIW: Information-Warfare & Security** 3/15-16: U of Md. Eastern Shore, MD, USA
	Association for Asian Studies Annual Meeting 3/31-4/3: Chicago, IL, USA	**General Online Research (GOR06)** 3/21-22: Ravensberger Park, Bielefeld, Germany
APR	**NCSM 37th Annual Meeting**	**Aveiro Workshop on Graph Spectra**

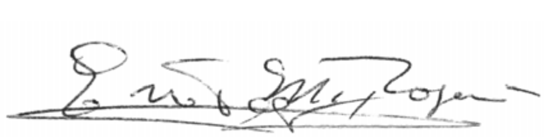
	4/4-6: Anaheim, CA, USA	4/10-12: Aveiro, Portugal
	55th Political Studies Assn Annual Conference 4/4-7: University of Leeds, UK	**European Meetings on Cybernetics and Systems Research (EMCSR)** 4/18-21: Vienna, Austria
	Association of American Geographers 4/5-9: Denver, CO, USA	**21st ACM Symposium on Applied Computing** 4/23-27: Dijon, France
	European Consortium for Political Research Joint Sessions 4/14-19:Granada, Spain	**International Sunbelt Social Networks Conference** 4/25-30: Vancouover, BC, CA
	2nd Brazilian Symposium on Graphs, Algorithms and Combinatorics 4/27-29: Rio de Janeiro, Brazil	
MAY	**The Eighth SIAM Conference on Optimization** 5/15-18: Stockholm, Sweden	**International Congress on Medieval Studies: The Medieval Tradition of Natural Law** 4/4-7: Kalamazoo, MI, USA
	Graph Theory with Altitude 5/17-20: Denver, CO, USA	**5th Intnl. Conference on Drugs and Young People** 5/24-26: Randwick, NSW, Austalia
	International Communication Association 5/26-30: New York, NY, USA	
JUNE	**4th Global Conference on Business & Economics** 6/26-28: Oxford, UK	**Dynamics, Topology and Computations** 6/4-10: Bedlewo, Poland
	National Environmental Health Association 6/26-29: Providence, RI, USA	**International Communication Association** 6/19-23: Dresden, Germany
		Conference on Stochastic Networks

		6/19-24: Univ of Illinois, Urbana, IL, USA **International Conference on Topology and its Applications** 6/23-26: Aegion, Greece
JULY	**Statistical Models for Social Network Analysis Workshop; European Meeting Psychometric Society** 7/4: Tilburg, The Netherlands	**Second Oceanic Conference on International Studies** 7/5-7: Univ of Melbourne, Melbourne, Australia
	20th British Combinatorial Conference 7/11-15: Durham, UK	**Talcott Parsons: Reassessing his contribution to the social sciences** 7/6-8: Manchester, UK
	ASAE Annual International Meeting 7/17-20: Tampa, FL, USA	**Sociolinguistics Symposium 16** 7/6-8: Limerick, Ireland
	Intnl. Union for the Scientific Study of Population 7/18-23: Tours, France	**IEEE World Congress on Computational Intelligence** 7/16-21: Vancouver, BC, Canada
	1st Intnl. Conference on Transportation Logistics July 26-29: Singapore	**ISA World Congress of Sociology** 7/23-29: Durban, South Africa
AUG	**Rivers and the American Experience: From Lewis and Clark to the Bonneville Dam** 8/7-12: Lewis & Clark College, Portland, OR, USA	**American Sociological Association** 8/5-8: San Francisco, CA, USA
	Nordic Political Science Association 8/11-13: Reykjavik, Iceland	**Prague Topological Symposium** 8/13-19: Prague, Czech Republic
	Academy of Management 8/5-10: Honolulu, Hawaii, USA	**International Congress of Mathematicians** 8/22-23: Madrid, Spain
		Diaspora experiences: German-

	Apimondia 2005 9/21-26: Dublin, Ireland **Third European Congress on Social Insects** 8/22-27: St. Etersburg, Russia	**speaking immigrants and their descendants** 8/24-27: University of Waterloo, Ontario, Canada
SEP	**American Political Science Association** 9/1-4: Washington, DC, USA **European Consortium for Political Research** 9/8-11: Budapest **American Sociological Association** 9/13-16: Philadelphia, PA, USA **Apimondia 2005** 9/21-26: Dublin, Ireland	**Fourth Meeting on Celestial Mechanics - CELMEC IV** 9/11-16: San Martino al Cimino, Viterbo, Italy
OCT	**Applications of Social Network Analysis** 10/20-21: Univ of Zurich **Ocean Innovation 2005 conference** 10/23-26: Rimouski, Quebec, Canada **11th Congress of Rhinologic Society** 10/25-29: Sydney, NSW, Australia **Vernacular Colloquium 2005** 10/26-29: Puebla, Mexico	**International Academy of Business and Economics** 10/15-18: Las Vegas, NV, USA
NOV	**4th World Wind Energy Conference & Exhibition** 11/2-5: Melbourne, Australia **ISWC Workshop on Semantic Network Analysis**	**Ass'n for Public Policy Analysis & Management** 11/2-4, Madison, WI, USA

	11/7: Galway, Ireland **American Society of Criminology** 11/15-19: Toronto, Ontario, Canada	
DEC	**Workshop on Internet and Network Economics** 12/15-17: Hong Kong	





A tribute to Everett Rogers

Tom Valente

Ev Rogers was the ultimate networker and so it is not surprising he started his academic career by talking to farmers about their networks in relation to how they adopted farming practices. Ev was a kind and generous man. He was a terrific host, opening his home to everyone whether at Stanford, the Hollywood Hills, or New Mexico. Everyone felt welcome at his home or office, whether a graduate student, a staff member, or esteemed colleague.

He was a pioneer in the study of social networks and human behavior and his name is synonymous with the diffusion of innovations. Starting with the publication of Diffusion of Innovations in 1962, he made the connection between social networks and how new ideas and practices are adopted and spread. He published Communication Networks in 1981 (with Larry Kincaid) which established him as one of the leading contributors to the network paradigm.

He was a wonderful and charming friend to people all over the globe. His legacy of having pioneered the study of network models of diffusion of innovations will live on, and he will always be remembered as someone who saw the “big picture.” His humanistic and global perspective made his work, his research and his company relevant to everyone. He could always look beyond any one study or one observation to truly connect the dots. In fact, his connecting of the dots will be a legacy we all cherish.

Everett M. Rogers, 1931 - 2004

Ronald E. Rice[1]

Everett M. Rogers lived a very full life. And he helped so many others, in so many ways, to live fuller lives as well. Whenever I saw Ev at a conference, students and colleagues would surround him, thanking him for his help when they came from other countries to study with him, setting up times to meet with him to work on joint projects, talking with him about his new book or research, or simply to share in the palpable energy he emitted and harnessed. He was definitely a citizen of the world: he created his own center of gravity, and whatever University he was at was more like a central staging area than a limiting, office-based professional identity.

As a graduate student, I often saw him in his office, with people coming and going, phone calls received and made, notes and ideas being jotted down. At one conference, he sat in the back, seemingly not paying attention to the presenters, revising a proposal, reading a book chapter, edited a paper, writing memos. Then, when the presenter finished the talk, Ev raised his hand and asked a completely informed question about the context of the presenter's research. He was a human time-sharing computer, managing multiple matters in order to respond to many people's questions and needs, and coordinate his multiple projects.

Probably thousands of people have worked with Ev on state, national and international, funded and non-funded, quantitative and qualitative, short-term and long-term projects. At Stanford, he worked with many students there as part of an international Master's program, who went on to become ministers, professors, agency directors, and powerful influences in their home country. I was fortunate to help design and work on several of those projects, along with several other Stanford graduate students and Dr. William Paisley, the Green Thumb agribusiness teletext study. Although a world traveler and international researcher, he was right at home with farmers, agribusiness cooperative managers, and local storeowners. On another project, studying the reinvention of the innovation of dial-a-ride at local departments of transportation throughout the U.S., it took me several trips to become even moderately comfortable with his philosophy of air flight scheduling: "If we get to the airport 10 minutes before the flight takes off, we will have wasted 5 minutes." However, I also learned from him to carry an extra pair of socks in the briefcase to refresh the feet halfway through long days of interviewing, and to always try to present material in ways that people can understand. I have been more successful in following the first than the second advice!

[1] Ronald E. Rice, Arthur N. Rupe Endowed Professor, Dept. of Communication, University of California, President of the International Communication Association, Co-Director, Center for Film, Television and New Media, Santa Barbara, CA 91306-4020

Ev introduced me to communication network analysis possibly by seeing in me an interest that even then I didn't know I had! At that time, around 1977, there were no easily accessible network analysis programs, though Structure and the UCINET series were developing. Many communication researchers used Negopy, which had been developed at Stanford University by William Richards, and fostered by Ev. Negopy was originally written for a CDC computer, and run at a local commercial CDC shop. So communication researchers wanting to analyze their communication networks would send their data to Stanford, where someone would prepare it and take the punch cards to CDC, wait (possibly a day or so) for it to run, look at the output, and revise the commands and re-run the data if necessary. As I had prior management experience in computer systems, it seemed I was a reasonable candidate to take on this job, which provided a little bit of extra funding, but, more importantly, quickly got me involved in the growing network of network researchers, and learning about and understanding network analysis programs and methods. As my dissertation was an over-time network analysis of the development of the 10 primary groups using the EIES computer conferencing system, we also came to share an interest in the study of new media. Later, when we were at the University of Southern California, along with Frederick Williams, we co-authored a book on Research Methods and the New Media. In true southern California fashion, Ev, Fred and I finished revising the last chapter in Fred's hot tub.

Ev published over 500 articles and authored over 30 books, which have been translated into 15 languages in addition to English. He produced many monographs and reports for national and international agencies, such as the United Nations, that were widely used and even available through Amazon.com! His *Diffusion of Innovations* book, now in its fifth edition, is the second most cited book in the social sciences. His book co-authors/editors include: Thomas Backer, Francis Balle, Nancy Bartlit, Rabel Burdge, Steven Chaffee, James Dearing, D. Lawrence Kincaid, Judith Larsen, Roy Prodipto, Rekha Agarwala Rogers, Ronald E. Rice, Floyd Shoemaker, Arvind Singhal, Robert Solo, Pradeep Sopory, Lynne Svenning, Fred Williams. The titles of his primary books, listed below, reveal the range of his expertise, interests, and contributions. These range from explicating and integration fundamental concepts and research literature (communication networks, agenda setting, diffusion of innovations, entertainment-education, intercultural communication, organizational communication, new communication technologies, research methods, health campaigns, development communication), studies of particular issues and contexts (AIDS, India as an information society, new media policy and diffusion, modernization, R&D collaboration, rural social change), and oral and case histories (the foundations of communication study, Navaho code-carriers during WWII, and Silicon Valley).

- *Agenda-setting* / James W. Dearing, Everett M. Rogers.
- *The beginnings of communication study in America: A personal memoir* / Wilbur Schramm; Eds. Steven H. Chaffee, Everett M. Rogers
- *Bibliography of the diffusion of innovations* / Everett M Rogers
- *Combating AIDS: Communication strategies in action* / Arvind Singhal, Everett M. Rogers.
- *Communication and development: Critical perspectives* / Ed. Everett M. Rogers.

- *Communication in organizations* / Everett M. Rogers, Rekha Agarwala Rogers.
- *Communication networks: Toward a new paradigm for research* / Everett M. Rogers, D. Lawrence Kincaid.
- *Communication of innovations: A cross-cultural approach* / Everett M. Rogers, F. Floyd Shoemaker.
- *Communication strategies for family planning* / Everett M. Rogers.
- *Communication technology: The new media in society* / Everett M. Rogers.
- *Designing health communication campaigns: What works?* / Thomas E. Backer, Everett M. Rogers, Pradeep Sopory.
- *Diffusion of innovations* / Everett M. Rogers.
- *Entertainment-education: A communication strategy for social change* / Arvind Singhal, Everett M. Rogers.
- *A history of communication study: A biographical approach* / Everett M. Rogers.
- *India's communication revolution: From bullock carts to cyber marts* / Arvind Singhal, Everett M. Rogers.
- *Inducing technological change for economic growth and development* / Eds. Robert A. Solo, Everett M. Rogers.
- *Intercultural communication* / Everett M. Rogers, Thomas M. Steinfatt
- *The media revolution in America and in western Europe* / Eds. Everett M. Rogers, Francis Balle.
- *Modernization among peasants: The impact of communication* / Everett M. Rogers, Lynne Svenning.
- *Organizational aspects of health communication campaigns: What works?* / Thomas E. Backer, Everett M. Rogers.
- *R & D collaboration on trial: The Microelectronics and Computer Technology Corporation* / David V. Gibson, Everett M. Rogers
- *Research methods and the new media* / Frederick Williams, Ronald E. Rice, Everett M. Rogers.
- *Silent voices: When sons of the land of enchantment met sons of the land of the rising sun* / Everett M. Rogers, Nancy R. Bartlit
- *Silicon Valley fever: Growth of high-technology culture* / Everett M. Rogers, Judith K. Larsen.
- *Social change in rural societies* / Everett M. Rogers, Rabel J. Burdge.

Everett M. Rogers was a massively influential force in the social sciences, from the most personal and individual level, to the most academic and international level. He made our lives fuller, as he filled his life with energy and collaboration.

From Pat Chatiketu:

This is a letter from a stranger from afar.

My name is Pat Chatiketu. I helped Ev and Arvind on their book "Combatting AIDS" when they were in Thailand.

I was shocked by sad news about Ev because when Ev was in Thailand a few years ago he was able to walked up 300-step ladder uphill to Doi Suthep Temple in Chiang Mai and joked with Corrine, Arvind, my wife and I up there by taking a photo with an imaginative camera in his hands and said "Ka-ching!" Corrine jokingly said the photo will be saved in his "memory stick."

During his visit twice to Thailand for writing the book that year, Ev made a lot of impressions to those who met him. Ev gave a special lecture at Chulalongkorn University without caring much for the honorium like many business Gurus do.

Ev also interviewed Kate Bond, your ex-advisee at Johns Hopkins U., and shared some stories about the University and gossiping about you during the conversation. :) (Tom never studied a class in public health... but...)

Personally, I was touched by his amiable manner when we first met at Ohio U. He approached me by calling my name... a supposedly young and unknown PhD student from Thailand. He said he saw my photo from Peer Svenkeruud's (Arvind's advisee) presentations. (Peer worked on a San Francisco-Bangkok AIDS research that I was a research assistant.)

Through out the trip in Bangkok and Chiang Mai, Ev shared stories, his visons, and his experiences that I felt like little a kid listening to another the Lord of the Rings tale.

His legend will last in my "memory stick" as long as I live. May his legend lives longer than Frodo. Rest in peace, Ev. We miss you! :~~~

May the force be with Y'all,

Pat C.

From Joung-Im Kim[2]

When someone who touched so many people and meant so much to so many, I don't know where to begin...

It was such a huge shock to hear that Ev has passed on, especially because this past week I spent a great deal of time talking about him with my graduate students. For three consecutive days (Tuesday-Thursday), many students visited me to discuss how they could develop their dissertation/thesis proposals using the Diffusion of Innovations (DI).

In fact, given the time difference between Albuquerque and Honolulu, I know we must have been talking about Ev while he was passing because all we ended up (I say "ended up" because it wasn't by my design) discussing was the diffusion of innovations and Ev during my research seminar which lasted between 3 - 6:30 pm (running one hour overtime) Hawaii time on Thursday. What is interesting about this phenomenon is that most of these students (mostly with a business school orientation) had only heard of TAM and not much of DI until this semester (which was very hard to believe for me). I'm witnessing a big wave of "diffusion" of DI among many students in the Interdisciplinary Doctoral Program in Communication and Information Sciences at the University of Hawaii, and I know Ev is smiling at us up there.

I even suggested (again this week) to two people organizing two separate conferences to be held here in about a year to invite Ev as a keynote speaker, and was so looking forward to the possibility of seeing him here sometime next year. But how could he pass away so soon? I thought he could easily have another 20 great years ahead. I thought now he is retired he could spend more time gardening which he loves so much. As you can see, it's hard to write in past tense about him. I can still hear his unique, rhythmic "Hi, hi, hi" (in incremental notes, not just one simple "Hi"), coupled with his energetic footsteps, coming from the office hallway ringing in my ears.

Many of us will, of course, remember him as a true international scholar who contributed so much to developing the field of Diffusion of Innovations and who was a source of great intellectual inspiration. And I'm glad that he was able to publish his 5th edition of Diffusion of Innovation last year. But I want to remember him also as a true intercultural and international *person*. Ev had such a compassion for foreign students. While at Stanford, Ev sent an invitation to every foreign graduate student in the department about this time of a year to a Thanksgiving dinner at his house all prepared by himself. "You don't need to bring anything, just wear your national costume," he would say. That was such an annual tradition that warmed the hearts of international students and their families because they had a "home-away-from-home" to go to every holiday season.

I'm so glad that I had the good fortune of meeting him almost 30 years ago and of working with him many years at Stanford, and have many great memories of him. We all lost a great scholar and a dear friend. And we will miss him so.

Good bye, Ev.

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[2] Joung-Im Kim, Ph.D. Associate Professor, School of Communications & Chair, Interdisciplinary Doctoral Program in Communication and Information Sciences, University of Hawaii at Manoa, Honolulu, Hawaii 96822, USA

From Brad Hall

Dear Colleagues and Friends:

It is with regret that I write to let you know that Everett M. Rogers, Distinguished Professor of Communication at the University of New Mexico, has passed away. He died on the 21st of October surrounded by love and peace, after a prolonged battle with cancer.

His was truly a remarkable career and he has influenced countless numbers of lives. He received his doctorate in 1957 from Iowa State University. His 47 years of teaching and research includes faculty positions at Ohio State University, Universidad Nacional de Colombia, Michigan State University, University of Michigan, Stanford University, Universite de Paris, University of Southern California, and finally the University of New Mexico, where as Chair of the department he was instrumental in initiating a doctoral program in 1995.

Professor Rogers had an international impact. He taught or conducted research in Colombia, Ecuador, Brazil, Mexico, India, Nigeria, Korea, Thailand, France, Germany, and Tanzania. He published over 500 articles and authored over 30 books, which have been translated into 15 languages in addition to English. He is perhaps best known for his book Diffusion of Innovations, published in its fifth edition in 2003. He received awards too numerous to mention here, but people throughout the world will note and lament the passing of this truly great scholar.

Brad Hall, Chair

Department of Communication and Journalism

P.S. Arvind Singhal penned a beautiful piece to open the award ceremonies for Ev being named UNM's 47th Annual Research Lecturer. Singhal's tribute touchingly captures Ev's humanity, the depth of his intellect, his love of teaching, and the reach of his compassion. It follows [on the next pages].

Introducing Professor Everett M Rogers
47th Annual Research Lecturer
University of New Mexico, Albuquerque
April 24, 2002

Arvind Singhal[3]

I am honored to introduce to you Dr. Everett M. Rogers. When I first met Professor Rogers in Los Angeles 17 years ago, he was the Distinguished Walter H. Annenberg Professor of Communication at the University of Southern California. I was a first year Ph.D. student. We are here to celebrate Dr. Rogers' "intellectual journey": The journey of a scholar, teacher, writer, and mentor. I hope you will allow me to tell you about Ev, from my privileged vantage point as an advisee, collaborator, and co-traveler.

Ev's journey began on the family Pinehurst Farm in Carrol, Iowa, where he was born. The great depression had just begun. Life was tough everywhere, especially on an Iowa farm. The farm did not have internal plumbing, heating, or electricity. Ev went to a one-room school. He came home to milk the cows, feed the chickens, and do the chores.

That daily hard work ethic, learned on an Iowa farm, defines Ev's intellectual journey. Ev has written 32 books and some 400 refereed journal articles. That's a hard work ethic, and more. Ev's books and articles have shaped and influenced the field of communication, sociology, marketing, and political science.

Hard to believe today, but Ev almost never went to College. He wanted to stay at home and farm. But a highschool teacher packed a bunch of promising high school seniors in his car and drove them to Ames, Iowa. It was Ev's first visit to Ames. Fortunately, for us, he liked Ames, and pursued a degree in agriculture.

Iowa State in those years had great intellectual tradition in agriculture and in rural sociology. Numerous agricultural innovations were generated by scientists at Iowa State. Rural sociologists were conducting pioneering studies on the diffusion of these innovations — like the high-yielding hybrid seed corn, chemical fertilizers, and weed sprays. Questions were being asked about why do some farmers adopt these innovations, and some don't? These questions intrigued Ev.

Back at his farm, Ev saw that his father loved electro-mechanical farm innovations; but was resistant to biological-chemical innovations. His father resisted adopting the new hybrid seed corn, even though it yielded 25 percent more crop, and was resistant to

[3] Arvind Singhal, Ph.D., Professor and Presidential Research Scholar, School of Communication Studies, Ohio University, Athens, OH 45701, USA www.arvindsinghal.com

drought. However, during the Iowa drought of 1936; while the hybrid seed corn stood tall on the neighbors farm; the crop on the Rogers' farm wilted. Ev's father was finally convinced. It took him eight years to make up his mind.

These questions about innovation diffusion, including the strong resistances, and how they could be overcome, formed the core of Ev's graduate work at Iowa State. Ev's doctoral dissertation dealt with the diffusion of the 2-4-D weed spray in two Iowa farm communities (The weed spray has since has been discontinued). Ev's dissertation had an elegant multiple regression, but his committee didn't think much off it. They were, however, intrigued by his review of literature chapter.

In this chapter, Ev reviewed the existing studies of the diffusion of all kinds of innovations — agricultural innovations, educational innovations, medical innovations, and marketing innovations. He found several similarities in these studies. For instance, innovations tend to diffuse following an S-Curve of adoption (Ev will show you some of these S-curves in his presentation).

Ev published this review of literature chapter, greatly expanded, enhanced, and refined, as the *The Diffusion of Innovations* book. The year was 1962. The book provided a comprehensive theory of how innovations diffused, or spread, in a social system. The book's appeal was global. It's timing was uncanny. National governments in countries of Asia, Africa, and Latin America were wrestling with how to diffuse agricultural and family planning innovations in their newly-independent countries. Here was a theory that was useful.

When the first edition of *Diffusion of innovations* was published, Ev was an Assistant Professor of Rural Sociology at Ohio State University. He was 30-years old. But he had also become a world-renowned academic figure. The *Diffusion of Innovations* book, now in its fourth edition, is today the second most cited book in the social sciences. Perhaps someday soon it will be in first place.

Ev's traveled a long way from Iowa to Albuquerque. He has a long vita which humbly notes certain milestones in his career. A chaired professor at Stanford University, Regents' Professor at UNM, and more. One thing you will not find on Ev's academic vita is his illustrious career in the U.S. Air Force between his undergraduate and graduate degrees. Ev, at that time, often flew in-and-out of Kirtland Airforce Base in Albuquerque. He made up his mind then, as a 20-year old, that someday he'd build an adobe house and retire in Albuquerque. In essence, Ev had charted his destination to Albuquerque many decades ago. He just took a circuitous route (about 50 years) to finally land here.

Let me say something about Ev, the teacher. People who know Ev marvel at the ease with which he brings his research experiences into the classroom. At USC, I remember Ev taught a 200-person freshman class. For 16 weeks, Ev moved around an auditorium, microphone in hand. He reminded me of Phil Donohew. The 200 eager-beaver freshman journeyed with Ev to all parts of the world. He discussed his work in Nigeria, Colombia, Korea, Pakistan, and Egypt. He also told them about his work in Indonesia, and how he narrowly escaped a simmering volcano. Ev has a special fondness for teaching large freshman and undergraduate classes. He taught them at Stanford, at USC, and I know he teaches them here at UNM.

This week, Ev and I are putting the finishing touches on our fourth book. The book is titled *Controlling AIDS in the Developing World*. While conducting research for this book, I witnessed his enormous global influence. We visited five countries — South Africa, Kenya, Thailand, India, and Brazil. Everywhere, we ran into former students of Ev Rogers. In Nairobi Kenya, Ev and I visited Dr. Mary Ann Burris, the Ford Foundation Representative for East and Southern Africa. When I tried to introduce Professor Rogers to her formally, she said: "I was Ev's student in a freshman class at Stanford 27 years ago". Our research meeting was quite productive.

Now to Ev Rogers the mentor. At a recent event held in Phoenix to honor Ev, which brought many of his former students under one roof, someone asked Ev the formula for mentoring. Ev replied: "I like to plant little acorns and then watch them grow into trees". You can tell, Ev is at heart, still a farm boy — thinking of plants and trees. Several of Ev's mentees are here in the auditorium today. Some like, Professor William Brown, Dean of Communication at Regent University, have flown in to toast their mentor.

In closing, A year or two ago, Ev and his wife, Corinne, returned to Caroll, Iowa, to Pinehurst Farm, where Ev's journey began. Ev took Corinne to show her the one room school which he attended some 65 years ago. They even posed and took a picture. The one room school with perhaps its most illustrious alumni! To me, this picture, symbolizes the intellectual journey of Ev Rogers, a journey that we are here to celebrate this evening.

Congratulations, Ev.

Barry Wellman

Ties & Bonds

BBS

John Skvoretz is now the Dean of Arts & Sciences at Univ of S. Florida, Tampa. Longtime INSNAniks will remember Tampa as the home of the first 2 Sunbelt conferences, 1981-1982 (at George Steinbrenner's Bayshore Inn), and USF stalwarts Susan Greenbaum and Al Wolfe as the 2nd INSNA coordinator and *Connections* editor after me.... **Susan Bastani** elected Dean of Social Sciences at one of Iran's leading universities, Alzahra University Venak in Tehran. Note the word *elected* the next time you hear a US government rant: Unlike the secretive committees of many North American universities, Susan won an open election against 4 other candidates. She's also the Middle East's first network analyst (except for Israel) and heading the Iranian component of the World Internet Project...

Katy Börner promoted to tenured Assoc Prof, Info Sci, Indiana U..... **Marina Hennig** awarded "Venia Legendi" (5/05) by Humboldt Uni, Berlin where she receives the title of privatdosent (equivalent to US "assistant professor"). She now can be referred to as "PD Dr. habil. rer soc. Marina Hennig." The title of her dissertation: "individuals and social relations: A network theoretical contribution to the overcoming of the community-society dichotomy"....

Andrew Seary awarded PhD from Simon Fraser Univ (Vancouver, Canada): "MultiNet: An Interactive Program for Analysing and Visualizing Complex Networks." My spies tell me that all committee members (+ the external examiner) gave it high praise....

MIT emptying out? **Keith Hampton** moving Summer 05 from Urban Studies to Annenberg School of Communication, U Pennsylvania**....** **Pablo Boczkowski** moving Summer 05 from Sloan B-School to Assoc Prof of Communication at Northwestern U. Pablo also won the 2005 Outstanding Book Award of the International Communication Assoc for *Digitizing the News: Innovation in Online Newspapers* (MIT Press, 2004). The ICA award citation says that the book crosses over research traditions and methods.... It combines archival research and comparative ethnographic studies of specific digital news enterprises. [It is] innovative in approach, meticulous in analysis, and thoughtful in drawing conclusions."

Former INSNA head **Martin Everett** (Provost, Westminster U) has been made an Academician of the Academy of Learned Societies for the Social Sciences. He's now one of the select 350.... Former INSNA head **Steve Borgatti** has won the Outstanding Computing/Teaching Applications Award of the American Soc'gl Assoc's Communication & Info Technologies section.... **Ron Rice** elected president of the International Communication Assoc. He'll also be program chair for the ICA's 2006 meeting in Dresden.... **Harrison White** (Soc, Columbia) received the Distinguished Book Award (of the Amer Soc Assoc's Economic Sociology section) for *Markets from Networks: Socioeconomic Models of Production* (Princeton U Pr, 2002).... **Harriet Friedmann** (Soc, Toronto) spent 3 months on an Agrarian Studies Program fellowship at Yale, followed by 3 months as a Fellow of All Souls College, Oxford.... **David Smith, Judith Stepan-Norris** and

Valerie Jenness (all Soc, Cal-Irvine) selected as editors of *Contemporary Sociology* book review journal.

The first issue of the quarterly, *Social Influence,* will appear, Spring 2006. It is now accepting submissions on such topics as social influence tactics, compliance, advertising and mass media, political process, contagion, rumors, interpersonal influence, influence in democracies, power, as well as other topics related to social influence. The journal accepts long empirical articles, shorter empirical articles, theoretical pieces, literature reviews, historical and biographical pieces, articles on the application of the science of social influence, and commentary. More info at http://www.socialpsych ologyarena.com/ or email Anthony Pratkanis, Editor, at peitho@cats. ucsc. edu.

Frank Harary Graphed

Frank Harary died Jan 4 in Las Cruces, New Mexico, USA, from a post-operative infection at the age of 83. He was a Distinguished Professor at the computer sci dept of New Mexico State U. Frank was the leader in applying graph theory to social network analysis, as he'd be the first to tell you, with a twinkle in his eye. Frank founded the *Journal of Graph Theory* and the *Journal of Combinatorial Theory.* Born in Brooklyn, 1972, he received his Bachelors and Masters from Brooklyn College and PhD from Berkeley. He moved from U Michigan to New Mexico n 1987 and was active in many Sunbelt conferences until recently.

Frank's *NY Times* obit says he "wrote or contributed to 700 academic papers." His 1969 *Graph Theory* "has been credited with giving the field a broader relevance. Theory, which dates from the 18th century or earlier, is concerned with the edges and vertices found in graphs. It is frequently used to model physical or abstract problems in chemistry computer networks, transportation lines *and even sociology."* (my ital). Former student Stephen Hedetniemi (Clemson) said "The elegance of the writing had been crucial to the speciality's acceptance. Harary made a beautiful presentation of the theory that hasn't been equaled since." His dept chair, Desh Raanjan, says Frank delivered > 1K conference and invited lectures in more than 87 countries in 4 languages. He had at least hon docs from universities in Scotland, England, Sweden, Greece and the U.S.

Harary's other books include *Graphical Enumeration* (with Edgar Palmer) and *New Directions in the Theory of Graphs,* and *Structural Models: An Introduction to the Theory of Directed Graphs* (with RZ Norman and Doc Cartwright). You can get a bibliography at "www1.cs.columbia.edu/ ~sanders/graphtheory/ people/Harary.F.htm".

When news of Frank's death circulated on Socnet this past January, former INSNA head Steve Borgatti wrote, "I used to be skeptical when he would begin a sentence with 'When I created graph theory...,' but I have to admit now that his contribution to making graph theory a field was in fact huge. He was an extremely colorful character who [was] quite charming all the time. I remember almost all of my interactions with him (e.g., in the hospitality suite of Sunbelt conferences) quite vividly."

Stan Wasserman notes that Frank would "bring his own wine (bottled at his own 'Harary Winery' label) to conferences.... He almost singlehandedly is responsible for the popularization of graph theory in network analysis" — especially Harary, Norman & Cartwright.

Frank guest taught at Univ of Cal - Irvine. Narda Alcantara remembers becoming "quite fond of him. He was great teaching his stuff and he would lecture his students even using paper napkins ina noisy restaurant."

Scott White (Doug's son) remembers hearing a talk in Mexico. "Being quite the performance artist, he would intermingle colorful and sometimes bawdy jokes with derivations of non-trivial graph theoretic results."

I, too, have fond memories of Frank Harary and regret that our oft-postponed project will never come to be: We were to link my old East York data (1968 variety as in "The Community Question") — the distribution of all the actual egocentric graphs with 5 nodes and 6 ties — with his modeling. I still hope that one day a paper will come from that, with Frank as a spiritual co-author. Or perhaps a posthumous one, as he had an Erdös number of 1 and I only have a 3 (but so do Claude Shannon and John Nash). Frank's had 268 co-authorships compared to Erdös' legendary 509. Should we start a Harary number count in network analysis? One rumor has Frank starting an autobiography, but I haven't been able to get any hard information.

Ev Rogers Remembered

Everett Rogers, the great communication scientist, died this Fall. A memorial service was held for him on December 4, 2004, at the U of New Mexico main campus. He had moved there after many years at Michigan State and Stanford. New Mexico colleague Brad Hall reports that at the memorial service, people not only talked about Ev's "great academic accomplishments, but about his inclusiveness, supportiveness and generosity. These were discussed in regard to young colleagues and graduate students as well as to the communities he researched and served."

Frank and Ev gone in a month -- both in New Mexico. Strange coincidence. Both lovely people, with strong Sunbelt and INSNA presences.

Here is a lovely reminisce from one of Ev's earliest students, Nan Lin.

What I Learned from Ev Rogers – Networking, *By Nan Lin, December 2004*

It was 1964 and I was in the second year of my doctoral studies at Michigan State when someone told me that "an exciting and young professor" had joined the faculty. So, I signed up to take Ev's Diffusion of Innovations course. During the course, we read through his Diffusion of Innovations monograph (I believe it was the first or second edition) and many other monographs and articles, and much discussion took place in and out of the classroom. The course itself was not extraordinarily hard and some parts were even boring. However, Ev was enthusiastic at all times and quickly involved students in his research projects. Along with a fellow graduate student, I soon found myself involved in a study simulating the diffusion process in a rural area in a hypothetical developing country. With Ev urging us on, we worked furiously to write programs in Fortran, keypunch the Hollerith (IBM) cards, submit our decks of cards through the windows at the computing center, anxiously wait for the print-outs, read the error statements, and punch some more cards. After we got the program to work, we then repeatedly changed parameters, examined the outcomes, punched some more cards, and submit the programs again. The harder we worked and the deeper we got into the simulation, the more we became appreciative of Ev's work and enthusiasm.

In less than six months (remember we were using Fortran, Hollerith cards, and relying on the mercy of the humongous and temperamental IBM computer, housed in a conference-room-sized quarters), we succeeded with a working program and obtained some interpretable results. Ev suggested that we write it up and send it to a conference, which we did. The next thing we knew was that Ev was driving us in his car from East Lansing to the conference in Pittsburgh. The three of us were joined by a couple of other graduate students in geography who also had a paper accepted. None of us students had any traveling money and Ev was happy to take all of us and did the driving. Once we checked into the hotel and got into two rooms, one of us had to sleep on a roll-away. So, we drew straws and Ev lost, so he slept on the roll-away for two nights, never losing his smile and always chatting with us about our papers, other papers in the conference and what we needed to do when we went back. Throughout the conference, he introduced us to others (he seemed to know most people at the conference). The participants came from many disciplines, ranging from communication, sociology, political science, and psychology to economics, geography and mathematics. Suddenly, I found myself transformed from being a graduate student into a researcher chatting (as naturally as I could pretend) with colleagues!

By that time, I thought I had learned a lot about networks and communications in courses and was rather proud of all the good grades I had received. But during the first year of my exposure to Ev, I learned how to actually practice network research and how to actually do networking. Probably most importantly I learned how a good mentor should treat his/her students (equally) and share the credits with them (eventually we ordered the authorship on a publication by collectively deciding the relative contribution each of us made and Ev was the third author).

In the next two years, I got into more of Ev's research projects (and learned to punch cards faster). By the time I finished my dissertation, I had gone through several iterations of these networking practices. They have since ingrained in me as I have followed the same principles in practicing research and networking for the next four decades. No one can match Ev's enthusiasm, genuine interest in his students, willingness to work with them and giving them full credits. But I am really grateful that I had the opportunity to learn from the great master-mentor himself during my formative years.

Taiwan International Social Capital Conference

Capitalizing on the growth of interest in social capital, a bunch of social networkers descended on Tunghai University, 2 hours south of Taiwan's capital. (And how many meanings of "capital" can *you* use in a sentence?) Organized by Ray-May Hsung (a most capital and capable person), the conference featured presentations by Nan Lin (whom I learned was Fujian born and Taiwan raised), Ron Breiger, Karen Cook, Bonnie Erickson, Henk Flap, Joe Galaskiewicz, myself and Taiwan colleagues.

The themes varied around the overall social capital framework, with discussions about heterophily vs homophily; micro-macro; the impact of ICTs, power-dependence networks; measurement; methods; openness-closure; structural holes; access vs mobilization; instrumental and expressive returns on social capital; contingent effects. Among Ron Breiger's concluding comments were that diversity does not necessarily negate homogeneity, and that diversity does not necessarily negate core values.

Foreign guests also learned that our Taiwanese colleagues make great discussants. The choreography was interesting.

1. Express great honor in being asked to comment on the work of such distinguished scholars in their midst.

2. Apologize in fine English for their poor English and their lack of intellectual worthiness.

3. Announce that despite the great wisdom of the scholars, they would modestly suggest some ways to make already-superb papers even better.

The payoff, of course, is:

4. 10 minutes of extraordinarily perceptive and constructive commenting.

5. Thank the speakers and hope that they had contributed a little bit. "I hold Professor X in the highest esteem. I hope he may find my little contribution useful to improve his masterful work even more.

Collateral learning was also interesting. We learned that the way that Taiwanese drivers keep awake is to chew on betel nuts — stimulants coming from a certain species of palm tree. In normally conservative Taiwan, these are sold by bikini-clad young women in glass booths lit by neon signs

25th Sunbelt Conference in Rainy LA

I'm writing this section in LAX, after successfully convincing the US authorities that my Rockports really are shoes. Bev & I are on our way back from the most successful Sunbelt conference ever by most criteria, in Redondo Beach, suburban LA, Feb 2005.

1. It was the best attended, with upwards of 400 people taking over the Crowne Plaza in Redondo Beach (just south of the airport).

2. We had more papers. There were usually 7

sessions running concurrently, and Thursday has become a full session day instead of an arrival-for-the-banquet day.

3. There were more good papers. At almost every time slot, there was something I wanted to hear. This was achieved partially by the growing success of the field, and by a more selective refereeing process.

4. There were more workshops. Moreover, the workshops were filled, be they "Networks for Newbies" or advanced technical workshops.

5. INSNA itself hit new highs with upwards of 600 members.

6. Not only did we have a plenary keynote speaker — Ron Breiger (Soc, U Arizona) using Spinoza to give relationships true analytic priority — but the Lin Freeman award speaker: Jim Moody (Soc, Ohio State), brought balance theory up to date. (In case you forgot, the Freeman award is for folks under 40 or late-blooming recent PhDs.)

7. The conference was also beautifully run, by Carter Butts & Katie Faust doing the program, Becca Davis & Tom Valente (and their students) running the conference itself, and INSNA Prexy Bill Richards doing computerized registration.

To give you a comparative sense, when INSNA started, we had about 175 members. The first Sunbelt in 1981 probably had about 150 participants. Many of us were upset because we had to run *two* parallel sessions, limiting the extent to which we could hear about each other's work. For many years, INSNA was stable at 300 to 400 members, and the Sunbelt ran 4 to 5 parallel sessions, from Friday morning to Sunday noon.

I spoke briefly after the first night's banquet, doing my INSNA founder schtick. I showed bits from early copies of *Connections* (hand-typed and proofread, and hand-delivered by me and Bev to the postoffice) and pictures of the second Sunbelt. We struggled to ID the then-youthful faces.

It was great to see much representation from outside of North America. In addition to foreign graduate students, studying in North America, I met Italians, Dutch, Slovenians (the Vladi-Anuska duo), Aussies, Taiwanese, Koreans, British, Irish, Mexicans, and Japanese. I didn't meet anyone from mainland China, elsewhere in Latin America (other than my student Juan Carrasco and a Peruvian working at Univ of Southern California) or Africa. Alas, the usually sizable and active French representation seemed to consist of only one person. For better or worse — and I think better — there wasn't a clear difference between North American and unAmerican papers. My guess is that a combination of SocNet, UCINet (et al.), and frequent ocean-crossing has led to coalescence.

One thing that has stayed constant: a continuing stream of formal math model papers. But these have grown more sophisticated in the math and programs used. This year, the buzz is that p* has been developed into EGRM. Not only is UCINet user friendly (and with Steve Borgatti doing saintly advising work on www.ucinet. com) but it is being joined by Pajek, Net Miner, Multinet, and others.

It's not just that we've grown, but that the type of presentations (formal and over coffee) have changed. I've been giving the Networks for Newbies workshop for many years, a vantage point for spotting emerging interests. Originally, much of the action was in social support and community. Then, organizational analysis turned hot, fueled especially by Ron Burt's *Structural Holes.* Bob Putnam's *Bowling Alone* and Nan Lin's 2 *Social Capital* books fostered a move in rhetoric and analysis from social support to social capital.

This year's crop suggests 3 hot areas, fueled by funding, concern and interest:

The epidemiology of disease: in particular, how AIDS/HIV spreads. Both US and Canadian interest was represented. However, I didn't hear anything about SARS, despite its rapid, network-based spread. I would think the models for the rapid spread of SARS would be much different than those for one-person-at-a-time HIV. I also heard about the potential for the spread of bioterrorist diseases. (A nice popular article on this appeared in the March *Scientific American:* Chris Barrett, Stephen Eubank and James Smith, "If

Smallpox Strikes Portland" -- although I can't help but think that they are already infected by the Trail Blazers.)

Computer networks as social networks. For the first time, an appreciable number of people from the computer companies -- software and services -- showed up. Some of us -- like me, Caroline Haythornthwaite and Marc Smith (Microsoft Research) have been preaching to the HCI choir for years, but it has been a slow sell. However, in the past few years the spread of so-called "social software" such as *Friendster*, has gotten a lot of press (see my rant about *LinkedIn* below and now HCI people have starting thinking beyond human-computer interaction to human-computer-human interaction. I saw people from IBM, Parc, and Microsoft, plus a bunch of academics interested in this stuff. (Some CN/SN bits are discussed at the end of my article.)

Defense "intelligence". "Intelligence" of course is often a network phenomena, with connectivity of people, organizations, finances, and materiel. One sometime Sunbelt participant, Olivier Schmidt, has just detailed this in *The Intelligence Files,* published by Clarity Press.

The Sunbelt is open to anybody, and this year we had a larger than ever contingent of folks from the US Defense Intelligence Agency, the US National Security Agency (the folks who listen to phone calls and read emails), an Aussie outfit called the DSTO (Defense Science & Technology Agency), and a Brit. I know of at least 10 spooks who were there. There may have been more, because in previous years, I have met folks from the FBI and the Joint Warfare Analysis Centre. In addition, at least 3 long term INSNA members are actively involved in "terrorism research": two academics and 1 management consultant. They are interested in flows: of funds, drugs, and the well-publicized "weapons of mass destruction". All of these participants seemed like nice people, and at least one was willing to grant that the most sizeable source of WMD was the US government.

To the best of my knowledge, no participants from the other side(s) were there.

Another absence that struck me: no one in the defense "community" (to use their term) seemed interested in the 1950s-1960s hot button question of why people rebel against governments. (Old-timers should remember the CIA's Project Camelot in the Kennedy era; newbies should Google and read Irving Louis Horowitz's book of the time.). This time round, terrorism is dealt with purely as a technical matter of preventing the flow of weapons and funds, rather than an ideological and recruitment issue. Another absence: no one seemed interested in the huge geopolitical cum socioeconomic shift happening with the development of China as an economic power. Yet, the shift of industrial strength and R&D to China is standing world-systems (and its theory) on its head.

Yet Mike Schwartz's (Soc, Stony Brook) recent report documents 2 models of Iraqi opposition. Mike provides evidence that US military leaders believe that there has been a coalescence of a wealthy and savvy Saddamist leadership group with the al-Zaraqi network:

> Pressure from recent American offensives drove the 2 groupings into an increasingly comfortable alliances.... The contacts and networks that Saddam's key cronies began developing months before the invasion now paid off. An understanding with the Islamic fanatics, and the well-funded Baathists appear to have made Syria a protect base of operations. [Quotes from the summary of the Schwartz report in *Intelligence,* number 456, 14March05, part 2. The original essay is, "'Going to War with the Army You Have" at: http://www.tomdispatch.com/indexprint.mhtml?pid=2241].

Mike argues that this coalescence model fits well with the US military's own fixation on command-and-control structures: their own — and through reflective projection *(my term)* — their opposition. It is what the cold-war based US military is set up to deal with, cognitively, procedurally and militarily. By contrast, Mike provides a second model, arguing that the Iraqi opposition is a bunch of scarcely-coupled, autonomous cells, often composed of close kin. [BW: Of all things, this second model reminds me of the hyper US-patriotic movie, *Red Dawn* (John Milius, dir; 1984) in which a bunch of teens harried the Russian-Nicaraguan-Cuban occupying army — heroically, morale-boosting, but to little strategic effect.] Reading Mike's article, I was reminded of his dissertation-based research into a 19th-century American movement.

Network Gelt Flows

Post-Doc and RA-ships at U Illinois: The Science of Networks in Communities (SONIC) at Speech Communic, U Illinois (Urbana) & the local Nat'l Center for Supercomputing Applications has 2 postdocs and 5 graduate RA-ships available to work on an NSF-funded, multinational, multiyear effort. Central goal: develop "cyberservices" to map, nurture and leverage large-scale social networks within distributed communities using "next generation cyberinfrastructure". US & int'l applicants welcomed with expertise in development and testing SNA theories, modeling networks, visualizing networks, data-mining algorithms to detect networks. Info from Nosh Contractor, nosh@uiuc. edu.

Indiana's Field of Network Dreams: The US NSF has also funded at Indiana U & Notre Dame U the "NetWorkBench: A Large-Scale Network Analysis, Modeling and Visualization Toolkit for Biomedical, Social Science & Physics Research" for $1.2M over 3 years. Principals are Albert-Lazlo Barabasi, Katy Börner, Santiago Schnell, Craig Stewart, Alessandro Vespignani & Stan Wasserman. In addition, Börner and Robert Goldstone have received a McDonnell Fdn grant for "Modeling the Structure and Evolution of Scholarly Knowledge" and Börner, Hsinchun Chen (U Arizona) and Lee Giles have a NSF grant to study "Pattern Analysis for Transformational Research.

California Netting: Judith Stephan Norris (Soc, Cal-Irvine) and Rick Grannis (Soc, UCLA) has received a grant to investigate kinship patterns of the American elite. Among other Qs, it asks to what extent the America Revolution marked the end to the power and privilege of families descended from aristocratic families.

Computer Networks are Social Networks

Pseudo Networks from Pseudo Social Network Software: In October 200, I received this information from someone whom I shall keep anonymous:

"I've started using *LinkedIn* to keep up with my professional contacts and help them with introductions. *Since we have worked together and know each other well* (my ital), I would be happy to recommend you and put you in touch with anyone in my network that you may need to contact. I've found quite a few people we both know there as well. I would very like to invite you to join and access my network."

As the name didn't click with me and I do get overloadedly forgetful, I wrote asking how we knew each other. This CEO of a smallish company replied:

"I apologize. I had seen one of your papers online, was impressed and sent the invitation. I used the standard *LinkedIn* invitation."

So here is someone who has never met me — in person or online — writing to tell me that we have worked together and that he knows me well. He also offers to expose his entire LinkedIn network to me, without knowing anything about my often-prickly persona.

Moreover, *LinkedIn* — like some other so-called social network software — assumes each person maintains one big network, whereas we know that people often maneuver among multiple networks — which we might want to keep discrete and discreet.

As I interface between network analysis, computer science and community studies, I consistently find:

1. Many "social networking" programs don't have a clue about social networks. (Pause now, for vigorous response from *Visible Path* folks, who apparently do have a clue.)

2. People in the organizational and computer science world are getting justifiably scornful about such programs — which is good — but are, unfortunately, extending their scorn to social network analysis — which is bad.

Cognitive Networks: Kathleen Carley, among others, has been mapping and analyzing cognitive networks for years. Now "concept mapping" is on the educational software bandwagon. The Florida Institute for Human & Machine Cognition is providing "Cmaps" to schools in Panama, where Gaspar Tarte is an enthusiast as the country's "secretary of governmental innovation." Tarte says "We would like to use tools and a methodology that help children construct knowledge" with Cmaps — a series of concepts (usually nouns) linked by phrases or verbs. Apparently, the kids use the software to construct their own cognitive maps. [Source: Bill Kaczor, "Panama Gets Software to Assess Students," Associated Press, 9July05].

Even some economists are getting the idea that knowledge is networked. See Brian Losby, "Making Connections," *Econ Journal Watch* 2 (April 2005) 56-65.

Been Wiki'ed? Collaborative Software Taking Off A wiki is a website to which many (sometimes all internet participants) can contribute. Sounds like the ultimate amorphous network. We use a restricted wiki in our Connected Lives project to keep up with who is doing what. The most famous wiki is the Wikipedia, an encyclopedia to which all may post and on which all can edit whatever anyone else has written. A good friend got an entry — apparently posted by an undergrad. But it was so inaccurate, that the good editorial fairy came by one night and straightened out some facts. Of course, the wicked witch of the wiki west can then come and edit that one. And so it goes. I find the Wiki pedia useful when I want information quickly, but obviously users need to take the validity of entries with many grains of salt.

As John Markoff points, open collaborative software are vulnerable to antisocial behavior. *(This is a variant of Wellman's Law — "Bad Chat Drives Out Good")*. For example, the *LA Times* was using wikis to create reader-driven editorials until obscene postings drove away serious Los Angelenos. Yahoo My Web folks are reportedly handling such problems with a system in which people invite their friends and colleagues to join them — allegedly creating "overlapping search communities based on mutual trust". CN/SN search-engine maven Eszter Hargatti (Communic, Northwestern U) refers to this as "social bookmarking". Here's her description from her *Crooked Timbers* blog, 29June05:

"Using *del.icio.us* [social bookmarking software] has allowed me to find some great sites that would have been unlikely to show up in my browser otherwise. You go to a Web site, you decide to bookmark it (but doing so on del.icio.-us is like bookmarking it publicly) and then you can add tags to it to classify it according to your liking. The exciting feature of del.icio.us (and other such services) is that they show you how many other people have also tagged that same page. Clearly you share some interest with those people. You can then click to see their entire list of bookmarks or just the ones they have tagged similarly to the shared link. Chances are good that you'll find some additional pointers of interest.

"Yahoo!'s twist on all this is that you don't have to make all the bookmarks public. You can make them completely private (you're the only one with access), available to your community (people you've linked to your Yahoo! account) or completely public... I do think — just like with Yahoo! 360 — that Yahoo! should allow you to distinguish between different communities (e.g. 'make available to friends', 'make available to colleagues')." In her "EList"-serve, Eszter also points out that social bookmarking also gives you portability: you can access your bookmarks from any website ([12July05].

BW: I am more skeptical than my friend Eszter that social bookmarking will be widely used. Why should I want others to know what I am searching for, pix of Paris Hilton or not? And how would it benefit me if they knew? Or, if I knew what they are searching for. There also needs to be much thought into who we give access to, as only the *Friendster* folks believe that we each belong to only one big network.

One good thing. Although the surveillance aspects are potentially ugly — Yahoo is saving the tags (keywords) that people can optionally create to characterize web pages — it does have the cognitive/linguistic fun-ness of creating "folksotomy" — classification systems created by folks rather than by experts. Sounds like the US Supreme Court's approach to porn: "We know porn when we see it." [For more info, and a more positive attitude towards this stuff, see John Markoff, "By and For the Masses," *NY Times,* June 20, 2005: pp. C1, C5].

The Networked iPod: No, I am not talk about file-sharing. Despite being Apple-owned and branded, the original idea came from Tony Fadell, independent contractor hired by Apple in 2001 to develop such a product. In Silicon Valley: the platform design came from Portal Player and the OS to run the interface came from Pixo. The hard disk was developed in collaboration with Toshiba, the flash memory came from Sharp and the flat battery from Sony. There's also a digital > analog converter from Wolfson Microelectronics and a firewire interface controller from Texas Instruments. All of the components are assembled and packaged by Taiwanese company, Inventec. [Source: Satish Nambisan, "How to Prepare Tomorrow's Technologists for Global Networks of Innovation." *Communications of the ACM,* May 2005, p.29]

File-Swapping Networks: I am puzzled by why iPods have captured the cool factor among teens and twenties, when they are the essence of top-down centralized downloading. By contrast, file-swapping networks are more anarchistic — and cheaper. Yet the current nature of file-swapping networks are like very unsafe sex — you don't know who you are networking with to get your copy of "Sympathy for the Devil" — and you are quite likely to get spam and spyware along with it. I've been told — but haven't verified — that when you use Skype, the currently largest peer-to-peer phone service (and largely free), you automatically allow your spare computing power and internet connections to be borrowed by *Skype*. It's made by the same folks who were doing adware on file-swapping *Kazaa* a few years ago. (*Business Week Online*, June 20, 2005). Yet my wife doesn't even let me look in her pocketbook. Why should we let strangers look at our hard disk and possibly leave unwanted droppings there? There is some effort to have computers "gossip" with one another about which files can be trusted when swapped, but I am skeptical. [More info at John Borland, "Cleaning Spam from Swapping Networks", *C/Net News.com*. http://news/com.com/Cleaning+spam_from+swapping+networks/2100-10323-5623848.html, and in Susannah Fox, "Spyware: The Threat of Unwanted Software Programs is Changing the Way People Use the Net." Pew Internet and American Life Project, 6July05. www.pewinternet .org]

Computer Geeks Network: James Gosling and other panelists at a recent Sun deep thinkers conference discussed how computation, and the network, are a fabric that is driving all kinds of interesting things at the edge, not just in the electronic sense but also in a physical sense. "We humans have become part of an ether of computation," said tech wizard Danny Hillis. "If you are in a conversation and you don't know something, you go do Google to search….it's augmenting in a clumsy way. We will get more intimate — when you want a question answered, just think of it and some process will go out on Net and answer will appear to you." Hillis claimed, "I can't think properly unless I am connect," to which Paul Saffo quipped, "that's due to middle age." [Dan Farber, "Views from the Smartest People in Sun's Orbit, *ZDNet,* 30June05]

Musicians Swapping Networks: Musicians often move from band to band. Many play in several bands at once. BandtoBand.com lists how every band they list is connected to every other band through shared or serial membership. Emphasizes recent rock bands. Toscanini's move from La Scala to NYC does not show up.

Family Awareness / Family Surveillance: Microsoft's Cambridge UK lab is designing a tool that uses GPS tech to pinpoint the location of family members. Its called the "Family Awareness Clock" after the one used by Harry Potter's buddy Ron Weasley to learn when his sibs and parents are ind anger or lost. How soon before such sousveillance becomes surveillance by the powers that be? [Source: "News Track, " *Communications of the ACM,* May 2005, p.10]

Network Yourself: By contrast, you use a *personal area network* (PAN) to communicate with yourself: It's a low power network that uses the human body to distribute data signals to devices on or very near the skin. It's shorter range (currently reaching 8 inches from the skin) and possibly securer than Bluetooth, LANs, and certainly WiFi.

CONNECTIONS 26(2): 25-32
http://www.insna.org/Connections-Web/Volume26-2/3.Richards.pdf

A Social Network Analysis into the David Kelly Tragedy[1]

Seth Richards
National Bureau of Economic Research[2]

On July 18, 2003, British scientist and weapons inspector David Kelly was found dead, apparently by suicide. This tragedy capped a two-month controversy over the validity and authorship of an intelligence dossier on Iraq produced by the U.K. government. These events were investigated by a special, independent commission led by Lord Brian Hutton, called the Hutton Inquiry, and its final report was issued in January 2004.

This matter provides an excellent opportunity to study the inner workings of high levels of government because the Hutton Inquiry subpoenaed internal communications and has made them available to the public. From these documents, it is possible to construct the networks of discussion and authority behind the government's actions. An important question in this case is who were the decision-makers that developed the strategy to release Kelly's name to the press. The Prime Minister's Office denied being heavily involved with this process, but the Hutton Inquiry documents reveal otherwise.

This article uses social network analysis to examine internal government communications in the Kelly affair. Social network analysis can quantify the interactions among a group of social actors. It produces measures of actors' power and centrality in a network, and it constructs diagrams, or "network maps," that represent the interactions and relative positions of the actors.

A social network analysis of the Hutton Inquiry documents does not offer any stark, new revelations, because certain documents already made clear that 10 Downing Street was intimately involved in the decision-making. However, this analysis provides a clear visual representation of the coordination among government officials as they confronted a thorny problem. It also quantifies the relative importance of the actors.

This paper begins with a brief background on the immediate controversy over the Iraq dossier and the events leading up to Kelly's suicide. Next I describe the data and methods in detail, then present results, and finally conclude.

[1] Acknowledgements: I am very grateful to Valdis Krebs, the developer of the software InFlow which was used in this analysis, for his assistance with improving the network diagrams presented here. I am greatly indebted to Professor Alasdair Roberts of the Maxwell School of Citizenship and Public Affairs at Syracuse University, as well, for his guidance throughout this research. I also thank the editors for their helpful comments.

[2] Seth Richards. National Bureau of Economic Research, 1050 Massachusetts Ave, Cambridge, MA 02138. Phone: (617) 588-1418. E-mail: richards@nber.org

BACKGROUND

The British dossier on weapons of mass destruction in Iraq had been important and controversial since its release in the fall of 2002. However, the immediate controversy that led to Kelly's suicide began on May 29 of 2003, when BBC journalist Andrew Gilligan reported that a senior government official told him the dossier had been "sexed up" at the request of the Prime Minister's Office (PMO). Gilligan specifically pointed to the added claim that Iraq could launch a weapon within 45 minutes. Gilligan's source supposedly gave this as an example of dubious intelligence that was added after the PMO became involved.

Intelligence agencies in the U.K. government launched an internal investigation after Gilligan's report, to find the source of the leak. Publicly, Prime Minister Tony Blair and his spokesmen strenuously denied the allegations that the report had been "sexed up," while Gilligan and another BBC journalist reported further details. The situation escalated into strong criticisms and counter criticisms between Blair's communications director, Alastair Campbell, and the BBC.

David Kelly had met with Andrew Gilligan on May 22. Kelly was a senior weapons inspector, so it was not unusual for him to talk to reporters. However, on June 30, Kelly wrote his superior at the Ministry of Defence (MOD), Bryan Wells, to say he was beginning to think Gilligan might have used that conversation as a source for his reports. Wells, along with the MOD Personnel Director Richard Hatfield, interviewed Kelly on July 4 and again on July 7 to discuss the matter. At the second meeting they were joined by MOD Deputy Chief of Defence Intelligence Martin Howard, who was in charge of the internal investigation about the leak. From his letter to Wells and the minutes of those meetings, Kelly appears very forthcoming, but he did not mention that he had also spoken with two other BBC journalists in late May.

On July 8, the MOD issued a statement that someone had come forward, without giving Kelly's name, and it used Kelly's account to dispute the credibility of Gilligan's reports. The next day, however, MOD Director of News Pam Teare confirmed Kelly's name when it was put to her by a journalist from the Financial Times. Extensive internal discussions, which are documented in the Hutton Inquiry evidence, preceded that action.

Kelly was brought before the Foreign Affairs Committee of Parliament on July 15. After hearing his testimony, the committee issued a statement calling it unlikely that Kelly was Gilligan's source and criticizing the MOD for its treatment of him. Two days later, Kelly committed suicide. On July 20, after Kelly's body was discovered and identified, the BBC disclosed that Kelly was in fact Gilligan's principal source. After Kelly's death, the PMO strongly denied allegations that they had orchestrated the release of his name. Blair said in response to reporters' questions on July 23, "emphatically not, I did not authorize the leaking of the name of David Kelly" (Hoge 2003). Alastair Campbell testified to the Hutton Inquiry that he had not been involved with the naming, either, saying "I emphasize I didn't do anything to bring it about" (Cordon 2003).

DATA AND METHODS

This analysis is based on internal government documents collected by the Hutton Inquiry. The inquiry has a web site (www.the-hutton-inquiry.org.uk) which makes all its evidence available to the public, except documents that are restricted for personal privacy, national security, or legal process protections. A large portion of the available documents are instances or records of communication from one person to another, such as letters, emails, and minutes from meetings. Many of these communications were intended to be internal to the government, labelled "RESTRICTED" and "CONFIDENTIAL."

From the Hutton Inquiry evidence, I considered documents to be relevant for this analysis based on their subject matter and parties of communication. Relevant documents are those which pertain to the effort to identify the source of Gilligan's story or the strategy in response to Kelly's admission that he had met with Gilligan. Accordingly, they are bounded in time from May 29, 2003, when Gilligan's story ran, through July, 2003. As for parties of communication, only persons inside the executive branch had a role in the internal decision-making process, so correspondence with parliamentary committees is not relevant.

Given the nature of the evidence, the communications in this analysis are directional, meaning there is a "from" person and a "to" person (or persons). This requires an inference in the case of meetings—i.e., that all persons at a meeting talk to all others. Thus, I inputted every meeting as a set of directional communications, one from each participant to every other participant.

There were two other simplifying assumptions. Many documents were copied to persons other than the principal recipients, but I did not count these extra links. Also, I skipped persons who appeared only once or twice and were not readily identifiable from the Hutton Inquiry web site or news reports. My assumption was that these individuals held relatively junior positions in the government and were not major decision-makers in this matter.

The social network analysis software used for this research (InFlow) produces network maps using an algorithm ("Kamada-Kawai") that arranges actors according to their links with other actors. A group of persons who communicate frequently with each other are clustered together, while occasional contacts are placed at a distance. However, there is no unique configuration for these maps because they condense an N x N – dimensional space (where N is the number of actors) down to two dimensions. Still, the clustering of tightly knit groups is usually consistent in multiple maps of the same network.

Numeric measures of actor centrality enhance and clarify the analysis because they provide quantitative estimation of actor positions in a network. Three measures were used: degree, betweenness, and closeness (Freeman, 1979; Krebs, 2001). [3]

Degree is simply a count of the number of different persons each actor communicates with. Because the Hutton Inquiry documents give directional communications, each actor has two measures of degree—one for communications going out, and one for those coming in. Betweenness measures the importance of an actor as a link between other persons. It counts the number of the shortest communication chains throughout the network that include the actor. Closeness measures the ability of an actor to send information out through the network or receive information back in. It reflects the average number of intermediaries needed to reach other actors or receive their information.

RESULTS

From the Hutton Inquiry documentary evidence, 31 individuals emerge as actors in the Kelly affair. They are listed by government position in Table 1. Two of the actors, Simon McDonald and Joe French, only received one communication each and sent none, so they appear to be only tangential to the decision-making.

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[3] The InFlow software makes these measures normalized from zero to one. Thus, the reported values are the actual counts for each actor in proportion to the total number of possibilities for that network property. For example, the degrees value for an actor would be the number of other actors he/she communicated with divided by the total number of other actors in the network.

Table 1: Actors in Hutton Inquiry Documents Related to David Kelly

ORG NAME	POSITION
Prime Minister's Office	
Tony Blair	Prime Minister
Jonathan Powell	Chief of Staff
Alastair Campbell	Director of Communications
Tom Kelly	Prime Minister's Official Spokesman
Godric Smith	Prime Minister's Official Spokesman
David Manning	Foreign Policy Adviser
Clare Sumner	PMO Staff
Cabinet Office	
David Omand	Security and Intelligence Coordinator, Permanent Secretary
John Scarlett	Chairman of the Joint Intelligence Committee (JIC)
Ministry of Defence	
Geoff Hoon	Secretary of State for Defence
Peter Watkins	Private Secretary for Geoff Hoon
Richard Taylor	Special Advisor to Geoff Hoon
Kevin Tebbit	Permanent Secretary
Dominic Wilson	Private Secretary for Kevin Tebbit
Pam Teare	Director of News
Kate Wilson	Chief Press Officer
Richard Hatfield	Personnel Director
Joe French	Former Chief of Defence Intelligence
Martin Howard	Deputy Chief of Defence Intelligence
Bryan Wells	Director of Counter Proliferation and Arms Control
James Harrison	Deputy Director Counter Proliferation and Arms Control
John Clark	Proliferation and Arms Control Secretariat
David Kelly	Chief Microbiologist at Porton Down Facility
Foreign and Commonwealth Office	
Jack Straw	Secretary of State for Foreign and Commonwealth Affairs
Simon McDonald	Principal Private Secretary for Jack Straw
Geoffrey Adams	Private Secretary for Jack Straw
Michael Jay	Permanent Under-Secretary
Menna Rawlings	Private Secretary for Michael Jay
Peter Ricketts	Political Director
John Williams	Director of Communications
William Ehrman	Director General of Defence and Intelligence (and on the JIC)

The list of actors is not surprising. It includes the chain of command up from Kelly to Defence Secretary Geoff Hoon and other senior officials in the government who would be concerned with a high-profile foreign policy issue. Perhaps the only surprise is the number of officials from the Foreign and Commonwealth Office (FCO) who were involved. This makes sense, however, because the press mistakenly thought that the source for Gilligan's story was an FCO employee.

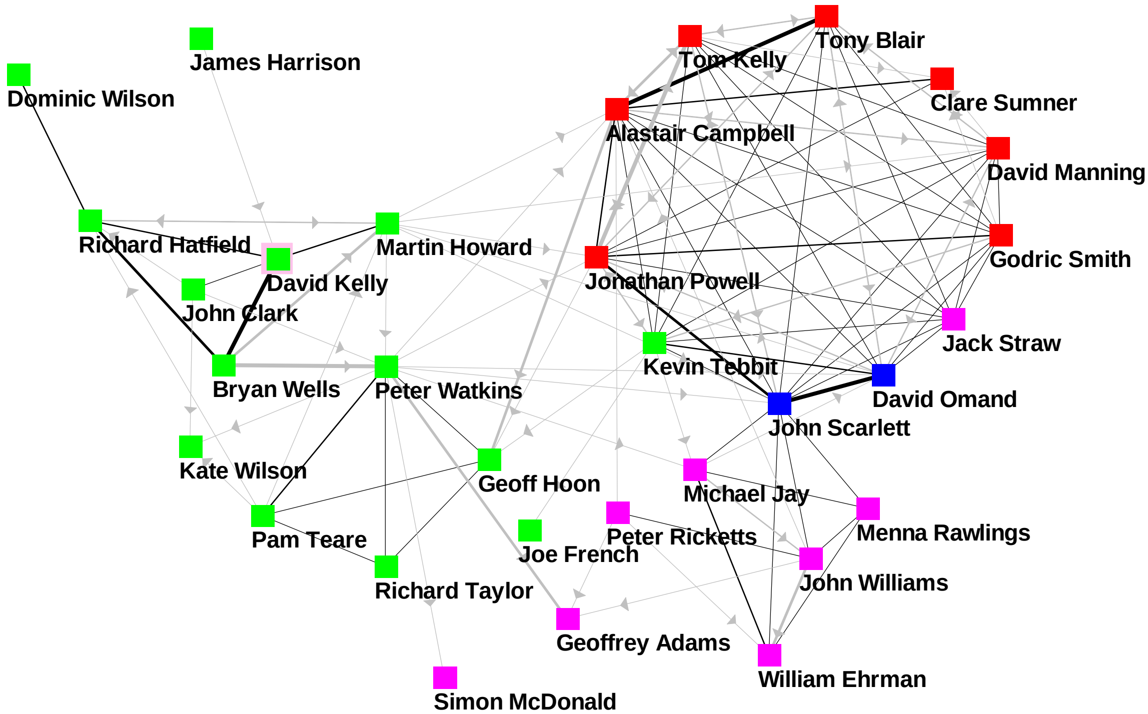

Figure 1: Social Network Map of Communications Related to David Kelly (nodes colored by organization, black links are symmetric).

A network map is presented in Figure 1. It is apparent that the PMO was very active in the Kelly affair, with Jonathan Powell and Alastair Campbell in central positions. Peter Watkins and Martin Howard at the MOD and David Omand at the Cabinet Office also appear as major hubs of activity. The central positions of these actors hold up consistently in additional productions of the map.

As would be expected, the map shows actors mostly clustered by their organization. One exception is that Foreign Secretary Jack Straw is located in the PMO cluster. This aberration is understandable from the data, however, because most of the instances of communication for Secretary Straw come from a meeting with Tony Blair and the PMO staff.

The measures of network centrality refine the picture from this network map. Table 2 lists these measures, with the top five values for each measure in bold. Notably, Alastair Campbell is the only actor who ranks in the top five for all measures of centrality. Also, John Scarlett of the Joint Intelligence Committee emerges as another very important actor with one of top five values in four of the measures, and the same is true of Jonathan Powell. More generally, of the actors with at least one measure scoring in the top five values, four came from the MOD, three from the PMO, two from the Cabinet Office, and one from the FCO.

By examining the measures individually and in comparison, it can be seen that the major actors had different relative strengths in terms of gathering information, giving out information (or commands), and linking other actors. Defence Secretary Hoon did not have a large number of different contacts, shown by degrees, but he was an important link with high betweenness. The same was true of Martin Howard at the MOD intelligence department and MOD Director of News Pam Teare. Alastair Campbell, on the other hand, was slightly stronger in terms of his connections (degrees and closeness) than his betweenness. Not surprisingly, the principals Tony Blair and Jack Straw were not important as links but were well connected for getting information out and in. Finally, Peter Watkins, Private Secretary for Geoff Hoon, gave out more information than he received. This is largely because he sent a key memorandum to Powell, Campbell, Scarlett, Omand, McDonald, and Jay soliciting their advice on how to handle the Foreign Affairs Committee request for David Kelly to testify.

Table 2: Measures of Network Centrality

Actor	Degrees (Out)	Degrees (In)	Betwee n-Ness	Closenes s (Out)	Closenes s (In)
Geoffrey Adams	0.000	0.097	0.000	0.032	**0.161**
Tony Blair	0.290	0.290	0.000	0.287	0.148
Alastair Campbell	**0.355**	**0.452**	**0.167**	**0.326**	**0.159**
John Clark	0.129	0.032	0.009	0.301	0.112
William Ehrman	0.129	0.161	0.002	0.246	0.145
Joe French	0.000	0.032	0.000	0.032	0.151
James Harrison	0.032	0.000	0.000	0.287	0.032
Richard Hatfield	0.129	0.194	0.113	0.284	0.133
Geoff Hoon	0.097	0.194	**0.236**	0.284	0.148
Martin Howard	0.290	0.129	**0.173**	**0.365**	0.132
Michael Jay	0.161	0.194	0.019	0.248	0.149
David Kelly	0.129	0.161	0.074	0.287	0.123
Tom Kelly	0.323	0.290	0.002	0.290	0.148
David Manning	0.323	**0.323**	0.016	0.290	0.153
Simon McDonald	0.000	0.032	0.000	0.032	0.144
David Omand	0.290	**0.387**	0.038	0.287	0.157
Jonathan Powell	**0.355**	**0.387**	0.101	**0.326**	0.157
Menna Rawlings	0.129	0.129	0.000	0.246	0.144
Peter Ricketts	0.129	0.032	0.000	0.274	0.130
John Scarlett	**0.419**	**0.484**	**0.210**	0.304	**0.160**
Godric Smith	0.323	0.290	0.002	0.290	0.148
Jack Straw	0.290	0.290	0.000	0.287	0.148
Clare Sumner	0.065	0.161	0.000	0.252	0.144
Richard Taylor	0.097	0.097	0.000	0.284	0.137
Pam Teare	0.194	0.097	0.163	0.307	0.137
Kevin Tebbit	**0.419**	0.290	0.124	**0.333**	0.148
Peter Watkins	**0.355**	0.194	**0.190**	**0.352**	0.142
Bryan Wells	0.129	0.097	0.015	0.304	0.122
John Williams	0.226	0.161	0.064	0.282	0.145
Dominic Wilson	0.032	0.032	0.000	0.225	0.120
Kate Wilson	0.000	0.097	0.000	0.032	0.147
AVERAGE	0.182	0.182	0.054	0.250	0.140

These measures can be turned back into a network map that shows the “real hierarchy” among the decision-makers in this matter. I ranked the actors by the sum of their betweenness and the average of their in and out closenesses, and positioned them vertically by this rank and horizontally by their organization. The resulting map is shown in Figure 2.

The “real hierarchy” map indicates Geoff Hoon and John Scarlett as the most important actors (Hoon ranks highly because he has the top betweenness value). It also shows Alastair Campbell and Jonathan Powell from the PMO having prominent roles, on par with senior officials at the MOD.

Taken as a whole, the results of this social network analysis support the contention that the PMO officials were misleading when they tried to create the impression that they were not intimately involved with the release of David Kelly's name. Also, this analysis indicates that the political heads of the MOD, *i.e.* Defence Secretary Hoon and his Private Secretary Peter Watkins, had greater influence in the process than did the top civil servant, Permanent Secretary Kevin Tebbit.

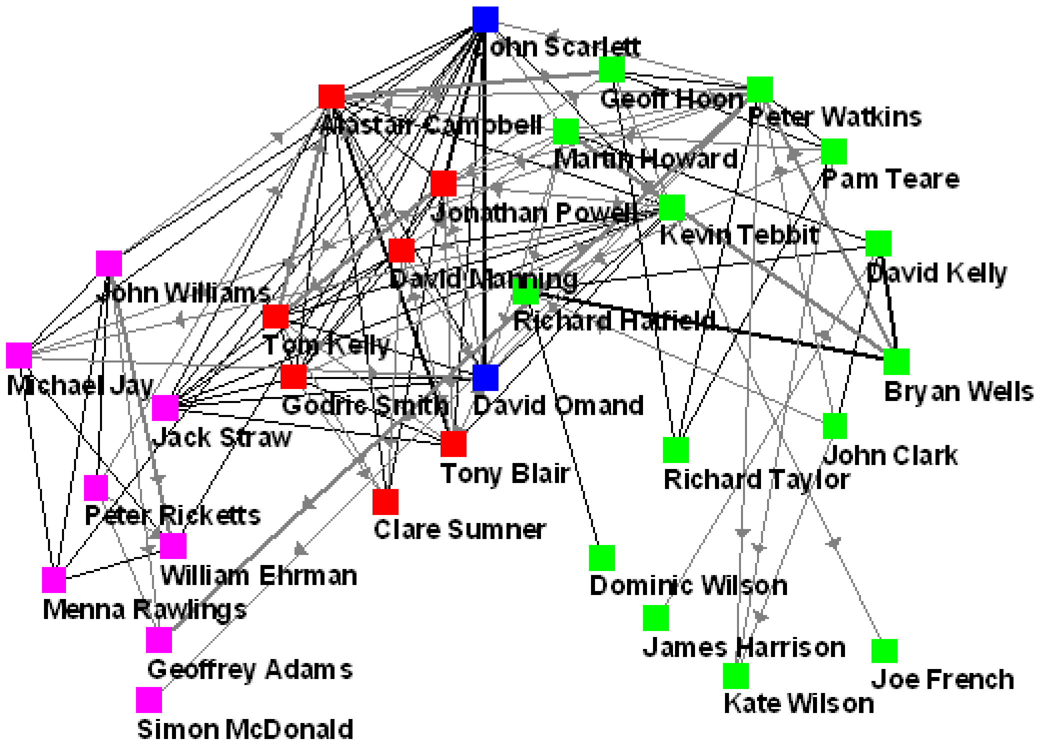

Figure 2: The "Real Hierarchy" (nodes colored by organization, black links are symmetric).

CONCLUSION

When considering the value of this exercise, it is important to recognize two significant limitations of the data. First, the Hutton Inquiry documents do not necessarily provide a representative picture of all internal communications from the Kelly affair. They are not from an unbiased, random sample but rather a collection of preserved communications that the actors consciously retrieved and submitted to the inquiry. Second, this analysis considers the flow of information through a network, not the flow of authority. Although the two are related, it is certainly possible to have a well-connected and well-informed actor who is not calling the shots. Third, the content of the communications has not been analyzed. It could be, for example, that communications in the PMO concerned reaction to the media story and subsequent scandal and is not related to the release of Kelly's name.

Despite these reservations, social network analysis can enhance our understanding of government decision-making in the events surrounding the death of David Kelly. This method synthesizes scores of communications into a form that can be digested as a whole, and it has the potential to add precision to comparisons of different actors in the affair. The results are not surprising, but a clear picture emerges of the central role that the PMO indeed played in this tragedy.

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Interorganizational Coordination in Dynamic Context: Networks in Emergency Response Management[1]

Naim Kapucu, Ph.D.[2]
Department of Public Administration, University of Central Florida

This paper addresses the inter-organizational network in response to an extreme event. Specifically, this paper analyzes interactions among public, private, and nonprofit organizations that evolved in response to the September 11, 2001 terrorist attacks. The research uses a theoretical framework primarily drawn from dynamic network theory and complex adaptive systems theory. The study assumes that the increased efficiency that would likely accrue in mitigation and response to disaster if agencies learned to collaborate more productively. Organizational analysis techniques were used to identify the major organizations that participated in the response system. The research found that effective response and recovery require well-coordinated interorganizational networks and trust between government agencies at all levels and between the public and private sectors.

INTRODUCTION

Public management increasingly takes place in settings of networked actors who necessarily rely on each other. Building networks of effective action is particularly difficult in dynamic environments. Yet, current administrative theorists devote relatively little attention to acting effectively in such situations. The September 11 attacks and their aftermath, along with other major disaster events, revealed much about institutional responses and collective behavior in extreme disaster conditions, underscoring what is already known about the social processes that characterize such events, while at the same time highlighting aspects of disasters that the literature has yet to explore fully.

In drawing lessons from the World Trade Center terrorist attacks in New York City, while the response activities undertaken by official emergency agencies were crucial, those activities constituted only part of the picture. Equally significant was the manner in which those agencies interacted with

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[2] I wish to thank Dr. Louise K. Comfort for her helpful comments on earlier versions of this paper. I also thank Michael Carrigan and Kilkon Ko in helping me conducting the content analysis of *The New York Times* reports and the *FEMA situation reports* for this study. Further, I thank public managers from the Federal Emergency Management Agency, the U.S. Army Corps of Engineers, the Department of Health and Human Services, and managers of the nonprofit organizations in New York City who gave their time and thoughtful observations to this research.

and obtained support from non-crisis organizations. It has long been recognized that disasters represent occasions in which the boundaries between organizational and collective behavior are blurred (Comfort, 1999). This paper discuses how to identify sets of structurally key players, particularly in the context of networks of organizations in response to September 11, 2001. Specifically, this paper examines the interactions among organizations that evolved in response to the September 11, 2001 terrorist attacks on World Trade Center (WTC) in New York City.

The paper addresses the following questions: How did interorganizational coordination among the organizations evolved in response to the extreme event? What primary organizations were involved in response to the attack? What were the primary nodes of interaction among the organizations in their response to the attack? This study assumes that extreme events will lead to greater density of communication among organizations and less centralized networks. As organizations increase their interactions, they share resources and information. As organizations from different sectors shares information and resources, victims in impacted areas will be served better as a result of this collaboration.

METHODOLOGY

The case study and descriptive research methods were used in conducting this research (Yin, 1994). The case study uses the data from the situation reports from the Federal Emergency Management Agency (FEMA) and interviews with selected public and nonprofit managers involved in response to September 11. Data collected through FEMA situation reports and interviews were used to develop a list of organizations that participated in response operations performed by public, nonprofit, and private organizations. Situation reports prepared by the Federal Emergency Management Agency (FEMA, 2001) were used as the official account of organizational operations following the September 11 attacks. This analysis illustrates patterns of communication and information flows among actors. The actual pattern of interaction reported by the organizations is compared with the designated responsibilities of the public organizations under the Federal Response Plan (FEMA, 1999). This comparison illustrates the differences between actual performance and designated roles in the Federal Response Plan.

I identified all the organizations that participated regardless of any interaction from the FEMA situation reports. Then, for the network analysis purposes, I identified only the reciprocal organizational interactions. With these interacting organizations I constructed the matrix for network analysis. I also reduced the number of organizations by aggregation to construct a manageable network matrix. The goal was to choose a level of "granularity" that corresponds to the problem at hand. As in a traditional sociogram, one can aggregate constituents into larger units, if that proven useful (Pentland, 1999). Second, based on identified actors from the content analysis of the FEMA situation reports, I used the stratified random sampling method to construct a sample of organizations that were actively involved in the response system. Third, semi-structured interviews (43) with the staff, managers, and director of the participant organizations were conducted. Interviews helped to clarify and expand some of the issues already discovered in the content analyses with regard to interorganizational networks in response to the attack. The network data collected from my interviews and the FEMA situation reports were analyzed using the UCINET 6.0 social network analysis program.

In the network analysis, we are always interested in how an actor is embedded within a structure and how the structure emerges from the micro-relations between individual parts. The other important factor for the design of network data has to do with what ties or relations are to be measured for the selected nodes (Scott, 2000). The other fundamental properties of a social network have to do with how connected the actors are to one another. Networks that have few or weak connections, or where some actors are connected only by pathways of great length may display slow response to stimuli. Networks that have more and stronger connections with shorter paths among actors may be more robust and more able to respond quickly and effectively. Measuring the number and lengths of pathways among the actors in a network allow us to index these important tendencies of whole network (Hanneman, 2001; Wasserman and Faust, 1994). Indeed, most of the basic measures of networks, measures of centrality, and measures of network groupings and substructures are based on looking at the numbers and lengths of pathways among actors are used for the analysis of the collected data. This paper uses the standard network centrality measures of degree, closeness, betweenness and flow betweenness applied to groups and classes (Everett & Borgatti, 1999). Beside the group centrality, I also measured cliques, subgroups, similarity and structural equivalence.

THEORETICAL BACKGROUND: INTERORGANIZATIONAL NETWORKS

The research uses a theoretical framework primarily drawn from dynamic network theory and complex adaptive systems theory (Scott, 2000; Axelrod and Cohen, 1999; Comfort, 1999; Carley, 1999; Holland, 1995; Wasserman and Faust, 1994; Alter & Hage, 1993; Nohria & Eccless, 1992). In complex and turbulent environments, organizations frequently develop formal or informal relationships in order to work together to pursue shared goals, address common concerns, and/or attain mutually beneficial ends. In recent years, such interorganizational collaboration has become a prominent aspect of the functioning of many different types of organizations. The number and significance of collaborative forms of organizing, including interorganizational teams, partnerships, alliances, and networks, have increased tremendously. The value of effective collaborative relationships as well as the complexities and challenges they present have been recognized by many researchers, and they continue to be a frequent subject of scholarly and practitioner-oriented literature (e.g., Linden, 2002; Powell, 1990; Gray, 1989).

Many researchers have noted that network organizations reflect a qualitatively different form of governance structure than the bureaucratic hierarchies they are beginning to replace (O'Toole, 1997; Powell, 1990). In such a environment, understanding the dynamics of the interorganizational networks and the patterns of interaction have become urgent matters both for policy makers and those who seek to understand the policy making process and implementation (Gidron et al, 1992).

In this paper, the term network is used to describe multiple-organizational relations involving multiple nodes of interactions. A network is group of individuals or organizations who, on a voluntary basis, exchange information and undertake joint activities and who organize themselves in such a way that their individual autonomy remains intact. In this definition important points are that the relationship must be voluntary, that these are mutual or reciprocal activities, and that belonging to the network does not affect autonomy and independence of the members.

A large body of theory and research about inter-organizational networks now exists to explain how these relationships emerge, sustain, and create value for the whole society. A particularly interesting generic type of network involves complex production relationships that benefit from being able to form and dissolve quickly. The participants therefore wish to protect themselves against opportunistic exploitation by their partners without having to suffer the delays and costs of formal contracting. This means that there is some element of trust in the relationship so that post-transaction adjustments to meet the parties' needs and interests can be quickly addressed with minimal inter-personal and inter-organizational resistance (Bardach, 1998).

Public administration scholar Harland Cleveland predicted in 1972 that organizations are moving toward a more horizontal style of management in which leadership is shared and decisions are often made on the basis of expertise rather than positions. "The organizations that get things done will no longer be hierarchical pyramids … they will be systems – interlaced webs of tension in control is loose, power diffused (Cleveland, 1972, p. 13).

Ackoff (1974) points out that many important current problems are "messes" that actually involve sets of interconnected problems. The multifaceted nature of these complex problems makes them extremely difficult to conceptualize and analyze and thus immune to simple solutions (Chisholm, 1998). This interdependence and complexity often require extensive collaboration among different types and various levels of organizations. Forming and developing inter-organizational networks represents a response to this interdependence complexity.

Brinton Milward (1996) uses the "hollow state" to characterize what he regards as the increasingly networked character of public management. Despite the evidence that networks are very important for public administration, much of the discussion of this subject has been vague (Wamsley et al., 1990; Provan and Milward, 2001). Helpful starts have been made in other fields. In particular, sociologists and public choice specialists have developed rich conceptualizations regarding networks (Miller, 1994; Cook and Whitmeyer, 1992; Ostrom, 1990). Public, nonprofit, and private sector resources may blend in a variety of ways. These formats permit the mutual leveraging of resources and the blending of public, nonprofit, and private attributes in ways that might not be possible in more traditional structural arrangements. This governance perspective is connected to the concern about social capital and the social underpinnings necessary to effective collaboration.

Networks in the field of public administration and organization theory are primarily based on the organizations with clearly defined boundaries (Milward, 1996; Chisholm, 1998; Alter and Hage, 1993). The effect of relations in organizations with permeable boundaries may be different. Modern organizational environments are becoming more complex at an increasing rate (Weick, 2001; Emery and Trist, 1965; quoted in Scott, 2001; Kauffman, 1993), largely through technical change (Simon, 1996). This means that uncertainty also increases, and the ratio of externally to internally induced changes also is increasing. There are instances where changing governance structures and technical changes may actually reduce uncertainty (Comfort, 1999; Weick, 2001). The interactions of organizations in a large system can generate greater complexity then the organizations themselves. Moreover, organizations tend to move toward higher levels of complexity, largely through networks. Organizations must balance differentiation and coordination to successfully adapt to the rising environmental complexity. Organizations also must determine the scope of their activities and degree of vertical integration decisions. Depending on one's theoretical perspective, these balancing conflicts are either seen as inefficiencies (rational system) or necessary parts of the negotiation process (natural system) (Scott, 2001).

Social network analysis is a well-developed and fast-growing area of organizational sociology, and it provides tools and concepts for analyzing organizations as networks (Wasserman and Faust, 1994). A meta-matrix, developed by Kathleen Carley (2002), represents a network of interactions that can be analyzed using the same graph-theoretic techniques that have been applied to networks of individuals and other entities. Meta-matrix analysis is a useful method in analyzing the structure of interorganizational response.

INTERORGANIZATIONAL NETWORKS IN EXTREME EVENTS

The dynamics of learning and adaptation, central to the complexities of an ecological system, are increasingly used as an analogy to the collaborative relations between sectors in network based systems of governance. Resilient social systems are characterized by reduced failure, measured in terms of lives lost, damage, and negative social and economic impacts, and reduced time to recovery – that is, more rapid restoration of the social systems and institutions to their normal, pre-disaster levels of functioning. Aaron Wildawsky (1971, p. 77) describes resilience as "the capacity to cope with unexpected dangers after they have become manifest, learning to bounce back." The Resilience Multidisciplinary Center for Earthquake Engineering Research (MCEER) has identified four general properties that can be applied to all systems and to the elements that comprise systems: robustness (ability to withstand the forces generated by a hazard agent without loss or significant deterioration of function; resourcefulness (capacity to apply material, informational, and human resources to remedy disruptions when they occur); redundancy (the extent to which elements, systems, or other units of analysis exist that are capable of satisfying the performance requirements of a social unit in the event of loss or disruption that threaten functionality); and rapidity (the ability to contain loses and restore system or other units in a timely manner). Organizations can contribute to resilience in a society by incorporation other emergency response organizations and by integrating volunteers into emergency operations as appropriate.

Meta Matrix	***People / Agents***	***Knowledge***	***Resources***	***Tasks***	***Organizations***
People / Agents Relations	**Interaction Network** *Who knows whom* **Structure**	**Knowledge Network** *Who knows what* **Culture**	**Capabilities Network** *Who has what resource* **Capital**	**Assignment Network** *Who does what* **Jobs**	**Work Network** *Who works where* **Demography**
Knowledge Relation		**Information Network** *What informs what* **Data**	**Skills Network** *What knowledge is needed to use what resource* **Technology**	**Needs Network** *What is needed to do that task* **Needs**	**Competency Network** *What knowledge is where* **Culture**
Resources Relation			**Substitution Network** *What resources can be substituted for which*	**Requirements Network** *What resources are needed to do that task* **Needs**	**Capital Network** *What resources are where* **Resources**
Tasks Relation				**Precedence Network** *Which task must be done before which* **Operations**	**Sectoral Network** *What tasks are done where* **Niche**
Organizations Relation					**Inter-Organizational Network** *Which organization works with witch* **Partnerships**

Source: Adapted from Kateen M. Carley 2002.

Figure 1. Meta Matrix

Extreme events are occurrences that are notable, rare, unique, and profound, in terms of their impacts, effects, or outcomes. When extreme events occur at the interface between natural, social and human systems, they are often called "disasters" (Red Cross, 2001). Quarantelli and Dynes (1977) define disaster as the disruption to society after the "event." Everybody is affected in extreme events and individuals and single organizations cannot prevent the harm caused by the event. In extreme events standard procedures cannot be followed and they require dynamic system to adapt to unanticipated and rapidly changing conditions. The September 11 2001 terrorist attack is an example of an extreme event with significant impact upon humanity. Extreme events trigger greater density of communication and interaction among organizations that stimulates collective action. A critical aspect of this process is the formation of new and or stronger networks among multi-sector organizations.

1. Interorganizational networks in emergencies can play an important role in facilitating the flow of information across organizational boundaries. Following are the principal pathways through which social networks enhance performance of organizational networks:
2. Social networks increase interaction among organizations that can lead to development of trust which reduce transaction costs (Coleman, 1990),
3. Social networks spread risk by providing individual members with sources of support during times of trouble, and allow the group as a whole to engage in overall higher levels of risk-taking (Fukuyama, 1995),
4. Social networks facilitate the rapid dissemination of information among members and reduce the asymmetries of information that can otherwise discourage profitable transactions,
5. Social capital improves access to resources among network members,
6. Social networks allow members to solve collective action problems more easily with less fear of defection and free riding (Ostrom, 1990)

The capacity of a society to understand and manage extreme events depends on its ability to understand, anticipate, prepare for, and respond to them (Comfort, 1999). Moreover, increasing organizational and technological interconnectedness may create more possibilities of multiorganizational partnerships for the surge of an extreme event. The WTC disaster illustrates how in disaster settings high levels of cooperation and collaboration among organizational and community actors can co-exist. Communities responding to disasters are seen as coping collectively with shared pain, loss, and disruption and as temporarily suspending ongoing conflicts and disagreements in the interest of meeting urgent needs and beginning the recovery process. Trustworthiness and social capital can, especially, play an important role in extreme events within which there is no clear policy or guidelines available to the participant organizations and individuals (Axelrod and Cohen, 1999).

INTERORGANIZATIONAL COORDINATION

Under the Federal Response Plan (FEMA, 1999), eight federal agencies in addition to FEMA play lead roles in disaster operations, with 25 federal agencies assigned responsibilities under twelve specified emergency support functions. The lead agencies include the Departments of Transportation (DOT), National Communications Service (NCS), Defense (DOD), Agriculture (USDA), Health and Human Services (HHS), Housing and Urban Development (HUD), Environmental Protection Agency (EPA), and the General Accounting Office (GAO). Two departments have dual emergency support functions. The USDA has the primary support function for firefighting, carried out by its sub-unit, the U.S. Forest Service (USFS), as well as for food. FEMA is responsible for information management, as well as urban-search-and-rescue operations. The American Red Cross (ARC) is designated as the lead agency for mass care (Figure 2).

Immediately after the attack, an intensive coordinated effort was begun by federal, state, and city government, along with volunteer agencies, in the search, rescue, recovery, and identification of the victims. Extensive assistance was directed toward the needs of victims and their families. While the physical damage was concentrated in a relatively small area, the economic and social effects were pervasive citywide. The pervasive threat of the attack created a situation of shared risk, that is, the risk of the attack is shared by all members of society. This condition of shared risk offers an important alternative perspective on response operations for extreme events. As the risk is shared, so is the responsibility for assessing and responding to that threat (Comfort, 1999). Recognition of shared responsibility immediately broadens the task of confronting the threat with organizations outside the public sector. Individuals, private and nonprofit organizations become resources for this collective response operation (Kapucu & Comfort, 2002).

Coordinating the activities of non-crisis organizations is a complex and difficult task. Public managers are reluctant to rely upon nonprofit voluntary organizations during extreme events. "Because they distrust the intentions of the volunteers, lack confidence in the volunteers skills and resources, fear that volunteer may endanger themselves or others, are concerned that volunteer may get into way of professional responders, and fear that there may be legal liability for volunteers' actions" (Waugh, 2000; p. 47). As noted in Waugh (2000) that emergency management is the quintessential government role. FEMA is the lead federal agency for responding to disasters and may link with nonprofit organizations. According to FEMA regulations, in the event of a residentially declared disaster or emergency, such as 9/11, FEMA is required to coordinate relief and assistance activities of federal, state, and local governments; the American Red Cross; the Salvation Army; as well as other voluntary relief organizations that agree to operate under FEMA's direction. Disaster response and recovery roles cross-cut 28 Federal agencies and the Red Cross, which participates with FEMA in disaster operations guided by the Federal Response Plan (1999).

PATTERNS OF INTERORGANIZATIONAL NETWORKS

In this section of the paper, I measure degree, closeness, betweenness, and flow betweenness centrality and clique and sub-groups (n-clique, c-clans, k-plexes). There are many measures of actor position and overall network structure that are based on whether there are pathways between actors, the length of the shortest pathway between two actors, and the numbers of pathways between actors. I employed UCINET (Version 6.0) for the network analysis of the data. UCINET is a comprehensive program for the analysis of social networks and other proximity data. The program contains several network analytic routines and general statistical and multivariate analysis tools.

Size of the network is critical to the structure of organizational interactions because of the limited resources and capacities that each organization has for building and maintaining networks. Usually, the size of a network is indexed simply by counting the number of nodes. In any network there are (k * k-1) unique ordered pairs of actors, where k is the number of actors. It follows from this that the range of logically possible social structures increases (complexity) exponentially with size. If the size of the network increases, the complexity of the relationships also increases.

The graph from the Federal Response Plan (FRP) is represented in Figure 2 below. We can perceive a number of things in simply looking at the graph. There are a limited number of actors (28), and all of them are connected very well in a very orderly manner as we would not expect from any complex organizational networks. There appear to be some differences among the actors in how connected they are (compare actors HUD and USDA, for example). If we look closely, we can see that some actor's connections are likely to be reciprocated (that is, if A shares information with B, B also shares information with A) but some other actors are more likely to be senders than receivers of information.

As a result of the variation in how connected organizations are, and whether the ties are reciprocated, some actors may be at quite some "distance" from other actors. There appear to be groups of actors who differ in this regard. For example, FEMA, HHS, USDA, ARC, and DOT that seem to be in the center of the action while HUD, DOC, and TVA, seem to be more peripheral.

The graph from the FEMA situation reports is presented in Figure 3 below. We perceive a number of things by simply looking at the graph as well. There are a limited number of actors here (41), and all of them are "connected." But, clearly not every possible connection is present, and there are "structural holes." There appear to be some differences among the actors in how connected they are as usual. If we compare FEMA and NYCEMO with HUD and GSA for example, we can easily see the difference. FEMA and NYCEMO are in the center of the activities. On the other hand, HUD and GSA are not very central or well connected to other organizations. If we look closely, we can see that some actor's connections are likely to be reciprocated in this network but some others are not. FEMA, NYCEMO, NYC government and mayor, and HHS seem to be in the center of the action; HUD, DOJ, OSHA, FAA seem to be more peripheral in the network.

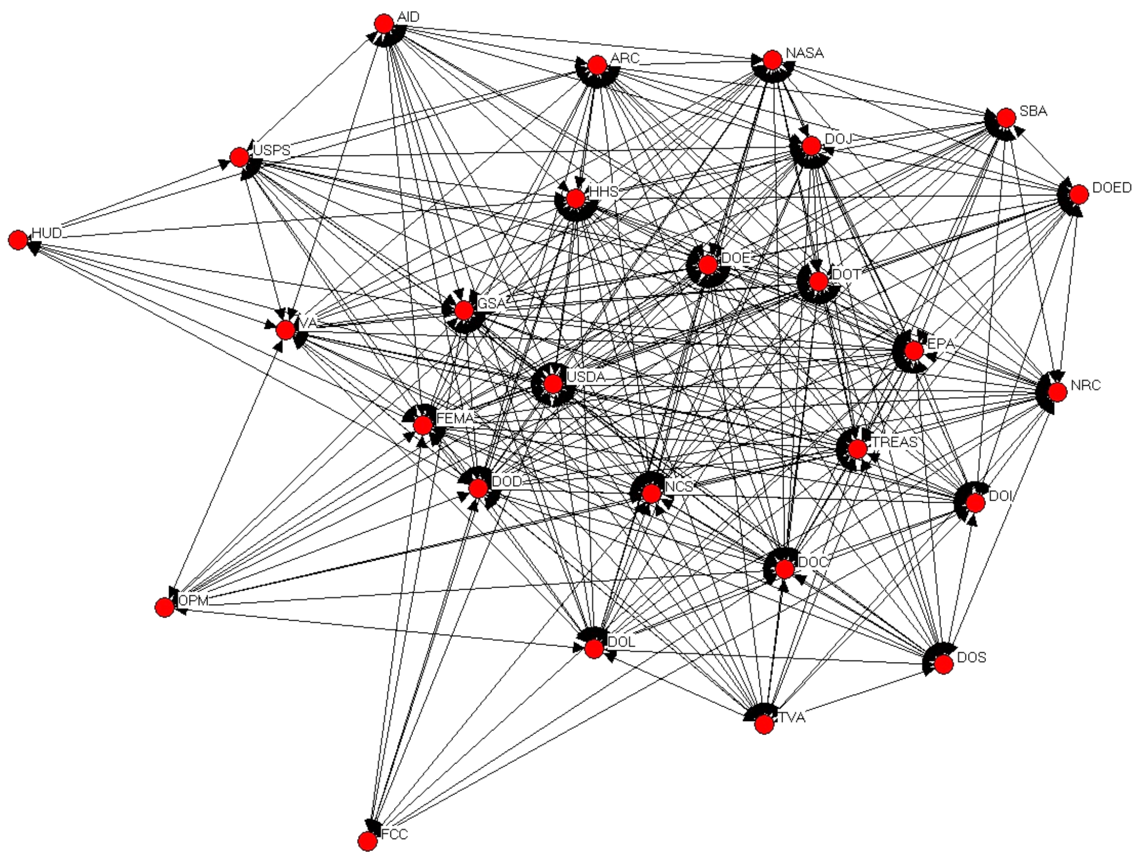

Figure 2. Networks in FEMA Emergency Response Plan

Findings from content analysis of the FEMA situation reports indicate that interactions were limited and occurred primarily between organizations of similar types. For example, public organizations tended to interact most frequently with other public organizations from the same jurisdiction; private organizations with other private organizations; nonprofit organizations with other nonprofit organizations. Interactions were infrequently reported across jurisdictional lines.

Group Centrality: Major Players

With larger populations or more connections, however, graphs may not be very helpful. Looking at a graph can give a good intuitive sense of what is going on, but our descriptions of what we see are imprecise. To get more precise, and to use computers to apply algorithms to calculate mathematical measures of graph properties, it is necessary to work with the adjacency matrix and more complicated calculations instead of the graph.

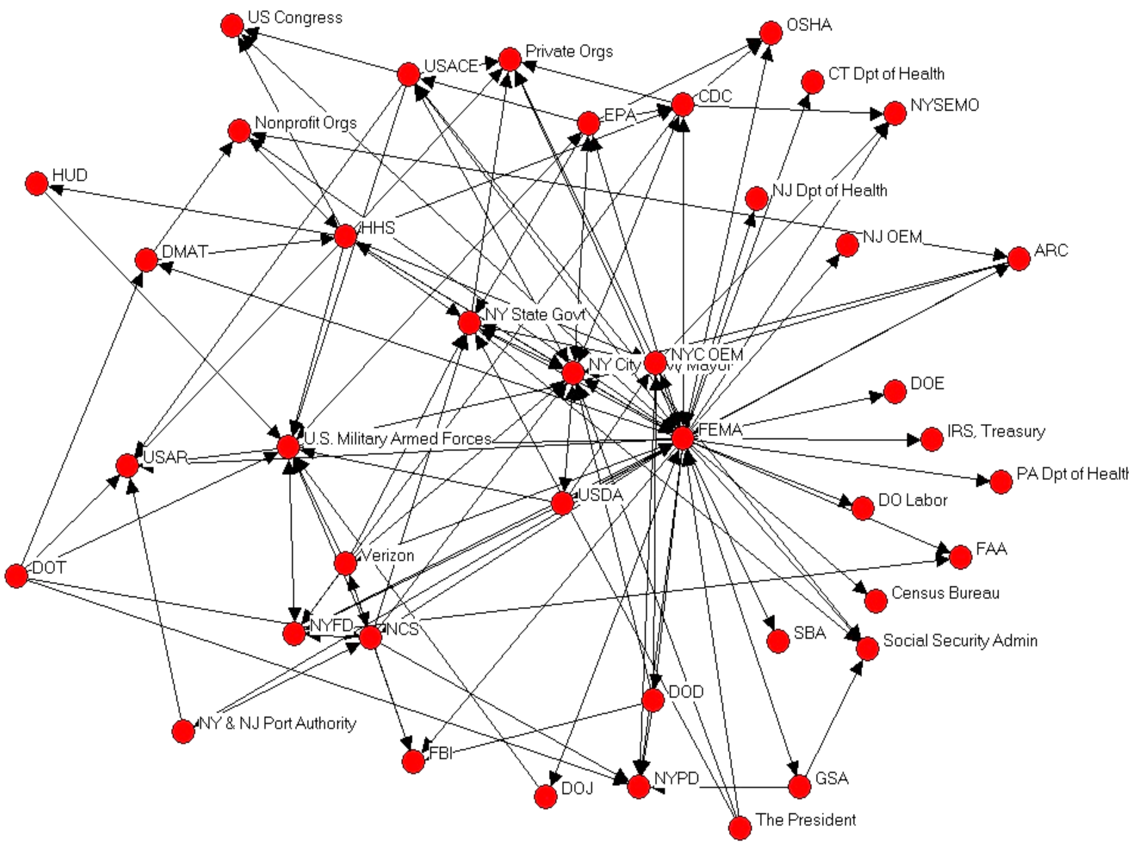

Figure 3. Organizational Network -FEMA Situation reports

One of the methods used to understand networks and their participants is to evaluate the location of actors in the network. Measuring the network location is finding the centrality of an actor. These measures help determine the importance of a node in the network. I use centrality measures as a basic tool for identifying key organizations in the response system network (Everett & Borgatti, 1999). The centrality approaches (degree, closeness, and betweenness) describe the locations of individual organization in terms of how close they are to the center of the action in a network.

Group degree centrality is defined as the number of non-group nodes that are connected to group members (Everett & Borgatti, 1999). Actors who have more ties to other actors may have access to, and be able to call on, more of the resources of the network as a whole. UCINET is used to do the counting, and some additional calculations and standardizations that were suggested by Linton Freeman (1979).

Table 1. Freeman's Degree Centrality Measures

		Degree	NrmDegree
2	FEMA	329.000	822.500
34	NY City Govt/ Mayor	87.000	217.500
41	Nonprofit Orgs	58.000	145.000
13	U.S. Military Armed Forces	42.000	105.000
27	NY State Govt	42.000	105.000
35	NYC OEM	32.000	80.000
39	Private Orgs	32.000	80.000
3	HHS	28.000	70.000
24	US Congress	22.000	55.000
10	USACE	21.000	52.500

Freeman's degree centrality measures show that FEMA (actor #2) and New York City Government/Mayor (actor #34) have the greatest degree, and can be regarded as the most influential in the response operation. Nonprofit Organizations (actor #41) and the US Military and Armed Forces (actor #13) are followed by New York State Government (actor #27). The similarity between the two results, Freeman's degree centrality measures and visual representation of the data in graph, can easily be captured. That other organizations share information with these five would seem to indicate a desire on the part of others to participate in network in response operations.

The following is the result from the degree group centrality calculated by UCINET for the optimal groups in network (Table 2). FEMA, HHS, New York City Government, American Red Cross, USACE, and nonprofit organizations were identified again as central organizations in the network.

Table 2. Degree Group Centrality

Observed # reached=41.000 (100.0%) *Group Members:*	Observed no. reached = 30.000 (88.2%) *Group Members:*
2 FEMA	3 FEMA
3 HHS	6 NYC Govt/mayor
6 DOT	7 Nonprofit Orgs
25 USAR	8 NY & NJ Port Authority
27 NY State Government	14 City Harvest, NY
28 CT Dpt of Health	18 USDA Forest Service
37 NYFD	20 Salvation Army
40 ARC	21 Southern Baptist Kitchens
41 Nonprofit Orgs	24 Catholic Charities of NY
Source: FEMA Situation Reports	Source: Interviews

Closeness Centrality

Degree centrality measures might be criticized because they only take into account the immediate ties that an actor has, rather than indirect ties to all others. One actor might be tied to a large number of others, but these others might be rather disconnected from the network as a whole. In this case, the actor could be quite central, but only in a local neighborhood (Wasserman and Faust, 1994). However, closeness centrality emphasizes the distance of an actor to all others in the network by focusing on the geodesic distance from each actor to all others. The sum of these geodesic distances for each actor is the "farness" of the actor from all others. We can convert this into a measure of nearness or closeness centrality by taking the reciprocal (one divided by the farness) and normalizing it relative to the most central actor. Here are the UCINET results for closeness:

Table 3. Closeness using FEMA situation reports data

		Fairness	nCloseness
2	FEMA	42.000	95.238
13	U.S. Military Armed Forces	67.000	59.701
34	NY City Govt/ Mayor	67.000	59.701
3	HHS	68.000	58.824
35	NYC OEM	69.000	57.971
27	NY State Govt	70.000	57.143
20	NCS	70.000	57.143
10	USACE	72.000	55.556
18	EPA	73.000	54.795
37	NYFD	73.000	54.795
30	NJ OEM	81.000	49.383
29	NJ Dpt of Health	81.000	49.383
6	DOT	93.000	43.011
16	HUD	98.000	40.816

Actor #2 (FEMA) is the closest, or most central, actor using this method, because the sum of FEMA's geodesic distances to other actors (a total of 41) is the least. Four other actors US Military Armed Forces – USACE (actor #13), New York City Government/Mayor (actor #34), Health and Human Services (actor # 3), and New York City Emergency Management Office (actor #35) are nearly as close and thus are highly central organizations, HUD (actor #16) and the Department of Transportation (DOT) (actor #6), on the other hand, have the greatest farness.

Betweenness Centrality

Suppose that FEMA wants to exchange resources and information and work with NYCEMO. FEMA must go through an intermediate agency, NYC Government/Mayor for example. According to the strict rules of bureaucratic hierarchy, FEMA must forward the request through another governmental agency. The intermediate agency could delay the request, or even prevent the request from getting through. This gives a coordinating position to the organization who lie "between" the two organizations with respect to others. FEMA might use other agencies or channels to work with NYCEMO. Having more than one channel makes FEMA less dependent, a more central, and as more independent actor. Betweenness centrality views an actor as being in a favored position to the extent that the actor falls on the geodesic paths between other pairs of actors in the network. UCINET, it is easy to locate the geodesic paths between all pairs of actors, and to count up how frequently each actor falls in each of these pathways. The results from UCINET are:

Table 4. Betweenness

		Betweenness	nBetweenness
02	FEMA	652.629	41.835
34	NY City Govt/ Mayor	116.781	7.486
37	NYFD	90.183	5.781
13	U.S. Military Armed Forces	65.600	4.205
20	NCS	52.167	3.344
27	NY State Govt	46.360	2.972
3	HHS	45.460	2.914
18	EPA	39.943	2.560
41	Nonprofit Orgs	26.667	1.709
35	NYC OEM	21.250	1.362
5	CDC	13.167	0.844
39	Private Orgs	13.110	0.840
15	DMAT	8.000	0.513
10	USACE	6.443	0.413
7	USDA	2.743	0.176
40	ARC	1.500	0.096

It can be seen that there is a great deal of variation in actor betweenness. FEMA (actor #2) andNY City Government/Mayor (actor #34) appear to be relatively a good bit more central than others by this measure.

Flow Betweenness: Dynamics of Interorganizational Networks

The betweenness centrality measure I examined above characterizes actors as having positional advantage to the extent that they fall on the shortest pathway between other pairs of actors. The idea is that actors who are "between" other actors, and on whom other actors must depend to conduct exchanges, will be able to translate this central intermediary role into power.

If the two actors want to have a network relationship, but the geodesic path between them is blocked by an unwilling organization, and if there is another pathway, the two actors are likely to use it, even if it is longer and less efficient. The flow approach to centrality expands the notion of betweenness centrality. It assumes that actors will use all pathways that connect them to others proportionally to the length of the pathways. Betweenness is measured by the proportion of the entire flow between two actors that occurs on paths which connect them. For each actor, then, the measure adds up how involved that actor is in all of the flows between all other pairs of actors (Wasserman and Faust, 1994). Since the magnitude of this index number would be expected to increase with the size of the network and with network density, it is useful to standardize it by calculating the flow betweenness of each actor in ratio to the total flow betweenness that does not involve the actor (Everett & Borgatti, 1999).

Table 5. Flow betweenness

		FlowBet	nFlowBet
1	FEMA	795.727	51.008
2	HHS	97.754	6.266
3	DOD	2.167	0.139
4	CDC	27.294	1.750
5	DOT	0.000	0.000
6	USDA	4.497	0.288
7	GSA	6.167	0.395
8	DOE	0.000	0.000
9	USACE	7.176	0.460
10	SBA	0.000	0.000

By this more complete measure of betweenness centrality, FEMA (actor #2), U.S. Military and Armed Forces (actor #13), HHS (actor #3), and New York City Office of Emergency Management (actor # 35) are clearly the most important mediators. New York State Emergency Management Office (NYSEMO) (actor #31) and American Red Cross (ARC) (actor #40), who were fairly important when we considered only geodesic flows, appear to be rather less important by this calculation. While the overall picture does not change a great deal, the elaborated definition of betweenness does give us a somewhat different impression of who is most central in this network.

Cliques and Sub-groups: Groupings of Organizational Networks

Networks are also built up out of the combining of dyads and triads into larger, but still closely connected sub-structures. Many of the approaches to understanding the structure of a network emphasize how dense connections are compounded and extended to develop larger cliques or sub-groupings (Wasserman and Faust, 1994). A clique is simply a sub-set of actors who are more closely tied to each other than they are to actors who are not part of the group. This view of social networks focuses attention on how connection of large networks structures can be built up out of small and tight components.

Divisions of actors into cliques is a very important aspect of networks in understanding how the network as a whole is likely to behave. For example, suppose the actors in one network form two non-overlapping cliques; and, suppose that the actors in another network also form two cliques, but that the memberships overlap (some organizations are members of both cliques). Where the groups overlap, it can be expected that conflict between them is less likely than when the groups do not overlap (Hanneman, 2001). Where the groups overlap, resources can be mobilized and shared effectively across the entire network; where the groups do not overlap, resource sharing may occur in one group and not occur in others.

Knowing how an organization is embedded in the structure of groups within a net may also be important to understanding its behavior. For example, some organizations may act as "bridges" between groups (boundary spanners). Other organizations may have all of their relationships within a single clique (locals). Some actors may be part of a tightly connected group, while others are completely isolated from this group. Such differences in the ways that organizations are embedded in the structure of groups within in a network can have profound consequences for the ways that these actors see the network, and the behaviors that they are likely to practice to sustain or dysfunction the colloboration.

Table 6. Cliques

```
1:  FEMA NCS NY State Govt NY City Govt/ Mayor Verizon
2:  FEMA EPA NY State Govt NY City Govt/ Mayor
3:  FEMA HHS NY State Govt NY City Govt/ Mayor NYC OEM
4:  The President FEMA NY State Govt NY City Govt/ Mayor
5:  FEMA DOD NY City Govt/ Mayor NYC OEM
6:  FEMA CDC EPA NY City Govt/ Mayor
7:  FEMA HHS CDC NY City Govt/ Mayor
8:  FEMA USDA NY City Govt/ Mayor NYC OEM ARC
9:  FEMA USACE EPA NY City Govt/ Mayor
```

Table 6 suggests a number of things: FEMA, Verizon, HHS, NY City Government/Mayor, NYCEMO, USDA, and U.S. Military Armed Forces appear to be in the middle of the action in the sense that they are members of many of the groupings, and serve to connect them, by co-membership.

Figure 4. Hierarchical Clustering of Equivalence Matrix

```
        1   1 1 1 1     1 2       1 1 1 1   2     2
Level   8 9 5 6 1 2 5 8 7 0 1 2 4 0 9 3 4 3 1 6 7 2
-----   - - - - - - - - - - - - - - - - - - - - - -
4.000   . . . . . . . . . . . . . . . . . XXX . . .
3.000   . XXX . XXX XXX . . XXXXX . . XXX XXX XXX .
2.667   . XXXXX XXX XXXXX . XXXXX . . XXXXXXX XXXXX
2.222   . XXXXX XXX XXXXX . XXXXX . . XXXXXXXXXXXXX
2.178   . XXXXX XXXXXXXXX . XXXXX . . XXXXXXXXXXXXX
1.915   . XXXXX XXXXXXXXX . XXXXX . XXXXXXXXXXXXXXX
1.810   . XXXXX XXXXXXXXXXX XXXXX . XXXXXXXXXXXXXXX
1.641   . XXXXX XXXXXXXXXXX XXXXX XXXXXXXXXXXXXXXXX
1.507   . XXXXX XXXXXXXXXXX XXXXXXXXXXXXXXXXXXXXXXX
1.299   . XXXXXXXXXXXXXXXXX XXXXXXXXXXXXXXXXXXXXXXX
1.249   . XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
1.057   XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

We see that actors #2 and #21 are joined first as being close because they share 4 clique memberships in common. At the level of sharing only three clique memberships in common, actors #9, # 15, # 11, # 12, # 5, # 8, # 1, # 4, # 13, # 14, 3 6, and # 7 join the core. If we require only one clique membership in common to define group membership, then all actors are joined except # 18.

Much of what was observed on 9/11 and in the days and weeks that followed in New York City's massive destruction and social disruption, was a complex organized response. The immediate impact area was evacuated rapidly and in an orderly manner. After the collapse of the towers, the absence of panic saved numerous lives. Assisted by emergency workers, occupants of the World Trade Center and people in the surrounding area helped one another to safety, even at great risk to themselves. Prior experience with the 1993 Trade Center bombing had led to significant learning among organizational tenants and occupants of the Twin Towers, and planning and training contributed to their ability to respond in an adaptive fashion to highly ambiguous and threatening conditions.[3]

It has long been recognized by academics that disasters represent occasions in which the boundaries between organizational and collective behavior are blurred. Local capabilities are enhanced through the active involvement of nonprofit organizations. In the World Trade Center disaster, all these organizational patterns observed at Ground Zero: NYC emergency response organizations were assisted by counterpart organizations from throughout the tri-state region[4] and ultimately from communities around the country, by nonprofit organizations offering whatever assistance they could. Collective behavior brings charitable organizations with their needed resources to disaster areas while simultaneously creating substantial management challenges.

CONCLUSION

The insight of both network and complexity theories can help constructs interorganizational networks and help us understand their workings. Multi-sectoral collaboration involves creating new forms of relationships among organizations. In order to foster linkages and the trust that would enable accelerating coordination in emergency management response operations, the government should provide incentives and information to promote multi-sectoral colloborations.

The idea of interdependency has long been at the heart of organization design in complex environments. Despite the richness of theoretical developments, there has been relatively little formal investigation as to the extent to which interdependency among organizations can influence organizational adaptation over time in dynamic environments. This research represents a modest step towards understanding how organizational design can be used to help track the interorganizational coordination in emergencies.

Effective response and recovery operations require colloborations and trust between government agencies at all levels and between the public and nonprofit sectors. Ongoing collaboration raises trust, and the importance of broad collaboration among various governmental levels and between government, the private sector, the nonprofit sector, and the public cannot be overemphasized. In response to 9/11 a resilient emergency response was achieved through integrating the resources and capacity of emergency response organizations with other governmental agencies, private, and nonprofit organizations.

[3] Interview with NY & NJ Port Authority, 11/28/2003

[4] The Tri-State Metropolitan Region consists of nearly 20 million people living in Connecticut, New Jersey, and New York.

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Social Network Analysis and Estimating the Size of Hard-to-Count Subpopulations[1]

Daniel Jackson, John Kirkland[2], Barry Jackson and David Bimler
Massey University, Palmerston North, New Zealand

Social Network Analysis (SNA) is a social research tool that investigates both individuals and their relationships within a population. Complete network analysis is used to examine closed populations, while personal network analysis examines the set of people ('alters') that an individual ('informant') is connected to. Personal network analysis may be performed in the context of a survey to provide information on a larger group of individuals than a traditional survey of the same sample size. This review of the literature discusses the need for networks to be carefully defined and generated to reflect the population of interest, and examines the issue of informant accuracy in social network data. It also discusses an SNA model for estimating subpopulation sizes and how subpopulation characteristics may affect these estimates. Finally, it suggests some guidelines for potential SNA researchers.

INTRODUCTION

Traditionally, when researchers have sought to investigate the characteristics of society the focus has been on the use of polls or surveys of individuals. The combined data over all participants is then scaled up in order to generalise about the size of and demographic make-up of subpopulations. However, any population is more than just the sum of its individuals. The relationships and interactions between individuals are also important elements of a population. Traditional survey methods may identify groups within the population, but tell us little about how individuals within these groups are related to and affect one other. For example, a traditional survey may tell us that girls are outperforming boys at a school, but cannot tell us about the social influences that contributed to this outcome. A method that specifically examines relationships may explain more about subgroups in the population.

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[2] Correspondence concerning this article should be addressed to John Kirkland, Department of Health and Human Development, Massey University, Private Bag 11-222, Palmerston North. E-mail: j.kirkland@massey.ac.nz

Social Network Analysis (SNA) is an alternative method of gathering data about populations. Social network researchers come from a diverse range of backgrounds and are interested in many different relationships and populations. These differences have led to the creation of two basic kinds of network analysis, reflecting two different kinds of data: complete (sociocentric) network analysis, and personal (egocentric) network analysis (Marsden, 1990).

Researchers interested in a small group such as an office or a classroom commonly use complete network analysis. Researchers attempt to obtain all the relationships among a set of respondents, such as all the friendships among employees of a given company. Statistical techniques are then employed in order to identify subgroups (cliques), power bases, whether relationships are reciprocated, how well respondents know each other and other network properties.

Personal network analysis examines the open-ended group of people (known as 'alters') that an individual (known as an 'informant') knows. Each informant is asked about the people they interact with, and about the relationships among those people. Personal network analysis is extremely convenient because it can be used with random sampling in the context of a traditional survey. Standard statistical techniques can then be used to generalise the results to describe the characteristics of the greater population and the distribution of relationships within it. However, because of the open-ended nature of personal networks, it is not possible to verify every detail. Findings from complete network studies are often used to build theories that personal network studies draw from. For example, studies of informants' forgetting allow researchers to modify their models of personal networks (Brewer & Webster, 1999).

An emerging field of personal network analysis is the use of social network data in the estimation of hard-to-count subpopulations. A sample of informants provides information about the members of their personal social networks. This social network data serves as a substitute for directly interviewing these network members ('alters'). Each informant provides information on many alters, so a small sample leads to a large data set. Bernard, Johnsen, Killworth & Robinson (1989) reasoned that the proportion of alters in an informant's network that are members of a subpopulation, averaged over all informants should give an approximation of the proportion (and hence the number) of people in the greater population who are members of the subpopulation. This can be expressed as $m/c=e/t$, where m is the average number of alters that informants know in the subpopulation, c is the average size of an informant's network, e is the total size of the subpopulation and t is the total population.

The value of c needs to be determined in order to estimate the size of e (Bernard & Killworth, 1997). One method of estimating personal network sizes is through the use of network generators. The average number of subpopulation members known m is determined by informant reports and therefore depends on informants' accuracy of recall.

Additionally, this simple model of the network scale-up method ($m/c=e/t$) works only under three assumptions (Killworth, McCarty, Bernard, Shelley, & Johnsen, 1998a):

1. Everyone has an equal chance of knowing someone in a given subpopulation.
2. ‘c’ (network size) is a constant.
3. Everyone has ‘perfect’ knowledge about the members of their network.

These assumptions are not met for all subpopulations (Johnsen, Bernard, Killworth, Shelley, & McCarty, 1995; Killworth, Johnsen, McCarty, Shelley, & Bernard, 1998b; Laumann, Gagnon, Michaels, Michael, & Schumm, 1993), so future models must take specific subpopulation effects into account (Killworth, McCarty, et al., 1998a).

SOME FEATURES OF NETWORK SURVEYS

A number of approaches have been made to determine the size of rare and concealed populations . Kalton, for instance, identified a number of practical methods for sampling rare and mobile populations (Kalton, G, 2003). Other approaches have been adopted; the multiplicity method (Rothbart, Fine, & Sudman ,1982), geographical clustering method (Kalton & Anderson, 1986) and network sampling, "Locating the seriously ill," (Sudman & Freeman, 1988) and "Estimating incidence of missing children," (Sudman, 1986).

Sampling errors common to traditional survey methods are also present in network surveys. The problem of non-response bias (where certain individuals are less likely to complete the survey than others) is compounded in the alter generation process. However, a small sample of informants can provide information on a much larger section of the population than a traditional survey of the same size. Although the cost of interviewing each informant is higher, the increased data yield reduces the overall cost of the survey. Network surveys provide information about the relationships between individuals as well as about the individuals themselves.

Informants may be more willing to identify alters who are members of a stigmatic subpopulation than they are to identify themselves. However, informants may not be aware that an alter is a subpopulation member. There are unknown errors in the estimates of network sizes, which carry through to the analysis of network properties, and subpopulation estimates.

NETWORK GENERATION

There are several different possible definitions of personal networks used by social network analysts. The total personal network of an informant is the set of people that he/she has known over the course of his/her lifetime. It is obviously impossible to enumerate anyone's total personal network. And even if an informant were to successfully recall everyone he/she had ever met, he/she would not be able to supply detailed information about each alter. Informants are more likely to recall, and to have detailed knowledge of the members of their active personal networks.

The relationships in personal networks can be defined in either situational or conceptual terms. Situationally defined relationships such as 'family', 'co-workers', 'classmates' and 'neighbours' are consistently defined, leading to a reliable network generator, but at the expense of including other sectors of an informant's network. Conceptual relationships such as 'acquaintances', 'friends', 'close friends' and 'best friends', may be considered as being like successive layers of total personal networks, with relationship strengths and alter knowledge increasing as each layer is removed.

Personal networks of alters can be elicited by using one or more 'name generators'. The number of names generated by an informant is taken as a measure of his/her network size 'c'. McCallister and Fischer (1978) were unsatisfied with previous methods of network generation. They noted that asking informants to list 'friends' excluded network alters from other social contexts, and that there were individual differences between informants' interpretation of terms like 'best friend' or 'close friend'. As an alternative, they asked informants to name alters who they interacted with in several unambiguously defined situations. They also observed that informants had poor recall of the people they know, and that extensive probing could help to generate more alters.

McCallister and Fischer (1978) limited their study to core personal networks, that is those alters who most influenced informants' attitudes and behaviour, so they used a variety of name generators centring on important interactions. McCallister and Fischer emphasised the importance of carefully specifying what properties of networks are of interest and using name generators that capture a representative sample of the relevant alters.

Fischer (1982) noted that the concept of 'friend' was central to studies of social networks. Noting the ambiguity of dictionary definitions, 'class' and cultural differences in interpretation, Fischer investigated 1050 informants' interpretations of the term 'friend', and found significant variation between informants. There was variation between informants as to whether they included family members, co-workers or neighbours as 'friends'. Fischer's study demonstrated the importance of clearly defined terms in network generation.

Two network generators were considered particularly important in determining the size of "hard-to-count" subpopulations: The (American) General Social Survey (GSS); and the Reverse Small World (RSW) technique. The General Social Survey (GSS) is a nationally representative, cross-sectional survey that has been conducted almost every year since 1972. The General Social Survey includes information on American demographics, beliefs, attitudes and participation in social life. The Reverse Small World (RSW) technique was developed by a group of researchers notably Killworth and Bernard (1978), Bernard, Killworth and Sailer (1981) and Bernard, Killworth, and McCarty (1982). The two approaches were compared by Bernard, Shelley & Killworth (1987) in order to estimate how many people are in an average network, to attempt to understand what the differences in network size depend on and to look for the rules governing whom people know and why they know each other. The GSS question asked informants to simply name as alters those who they had "talked about important matters with in the last six months". In the RSW task, informants were asked to name alters that they would use to get in touch with 500 fictional 'targets'. Informants generated an average of 160 alters in the RSW and were limited to 5 in the GSS. These researchers admitted that although networks produced by the RSW were much larger, they did not know whether they were any more useful than networks produced using the GSS. They found some overlap between the networks elicited by the two techniques but speculated that they were tapping into different cognitive sets of alters: intimate alters and instrumental alters.

Freeman and Thompson (1989) noted that the RSW technique seemed to be estimating a different parameter to personal network size, so they adapted the phonebook approach to network generation first used by Pool and Kochen (1978, cited in Freeman & Thompson, 1989). Three hundred and five surnames were randomly selected from a phonebook and presented to 247 informants who generated an average of 15 alters. Scaling up to match the total number of names in the phonebook yielded a 'c' of 5500. Freeman and Thompson acknowledged that it was an order of magnitude larger than that estimated by Killworth and Bernard (1978, cited in Freeman & Thompson, 1989) and Killworth, Bernard and McCarty (1984), but note that the RSW mode is concerned with social contacts and not total personal networks. Freeman and Thompson believed that their estimate was merely a lower bound for informants' total personal networks due to errors of recall.

In a second investigation of different network generators, Bernard, Johnsen, Killworth, McCarty, Shelley, & Robinson (1990) compared the networks generated by the GSS 'important matters' technique, the RSW method, a social support instrument and Freeman and Thompson's (1989) phonebook method. Bernard et al. acknowledged that their RSW technique does not produce alters who are representative of informants' total personal networks, and that the RSW did not elicit key social support alters either. Bernard et al. found that the phonebook method yielded a network that was the most representative of an informant's total personal network.

Killworth, Johnsen, Bernard, Shelley & McCarty (1990) had a closer look at the phonebook method. They found that if only the 7 most common names in the phonebook were used, a correlation of 0.81 was found with the data for 305 names. They also found that a phonebook for a part of the area had a good correlation with the full version. This indicated that the phonebook instrument could be reduced to a smaller size and still retain its reliability. However, they found that some unusual names that were similar to more conventional names elicited many responses even though there were few listings in the phone book, leading them to predict that the Freeman and Thompson (1989) estimate of network size was an overestimate.

Campbell and Lee (1991) investigated the consequences of name generators for network data. They considered network size, age and education heterogeneity and found that the average tie characteristics were strongly affected by the name generator used. In particular, they found that racial and sexual heterogeneity were the least affected by name generator choice. Campbell and Lee also found that network data gathered using name generators tend to reflect stronger ties, stronger role relations or ties associated with local geographical areas.

In order to elicit a representative sample of any informant's network, cues are required that stimulate unbiased recall of alters in that network. McCarty, Bernard, Killworth, Shelley, & Johnsen (1997) examined the use of 50 first names common to both blacks and whites in the United States. However, Asians respondents were biased against selection because there were no Asian names on the list. Some names on the list were more common in older or younger people which resulted in an alter selection bias. An alter selection bias was also found against females because of the wider range of female names. The seven most popular male first names in the US accounted for 7.9% of the population compared to only 3% for female first names. McCarty et al. suggest that both the respondent selection bias and alter selection bias could be rectified by randomly assigning respondents to a unique list drawn from a larger pool of names, with a probability of a name being drawn equal to its prevalence in the population. McCarty et al. believe that the first-name method captures a more representative sample of the personal network than other methods. The proportion of alters recalled with a given first name agreed well with the prevalence in the greater population. This was not found to be the case for the phonebook method (Killworth et al., 1990).

Brewer (1997) re-examined the McCarty et al. (1997) data looking for associative biases in the network generation process. Associative biases occur when the recollection of an alter prompts the recollection of a contextually related alter. Recall of a workmate may prompt the recall of another workmate, for instance. The informants in the McCarty et al. study had been asked whether various pairs of alters knew each other. Brewer found that successively recalled alters were no more likely to know each other than separately recalled alters. Brewer speculated that the presentation of first name cues served to restart the recall process because the informant could not control or anticipate the order of cue presentation.

The average number of people known to an individual is far from measured. Informants are fallible and as a result the size of a personal network can never be measured directly, and so a useful proxy for personal network size has to be determined instead. The first-name method does not require the informant to make a subjective judgement about 'friendship' and with the improvements to their method proposed by McCarty et al. (1997) seems well designed to elicit a representative sample of alters from informants' total personal networks.

Name generators are complex instruments that not only require a consistent interpretation by informants but also need to be consistently applied by interviewers. Marsden (2003) examined interviewer effects on the network size of informants participating in the 1998 General Social Survey (GSS) in the United States. Although Marsden found no strong effects of interviewer characteristics on network size, he did find significant variation in network sizes between interviewers. Marsden suggested interviewer effects may be limited by providing extensive interviewer training, 'probing' guidelines for the elicitation of additional alters and computer assisted interviewing. Such improvements would increase the consistency and reliability of a network generation instrument.

INFORMANT ACCURACY

The accuracy of social network data depends upon the accuracy of informant reports in the data collection process. If the network data is skewed significantly by informant inaccuracy then the nature of this error must be understood in order to draw meaningful conclusions from the data. However, there are several possible sources of informant inaccuracy such as forgetting, cognitive schemas, biases and, as discussed in the next section, the properties of certain subpopulations.

In the first of a series of informant accuracy studies, Killworth and Bernard (1976) examined a partial network of 32 deaf informants who communicated with each other using Teletype machines. The informants logged their interactions with each other and were later asked to rank each other by the amount of communication with them in the study period. Overall they found that informants tended to communicate more with the people they ranked higher, but surprisingly they also found that the person ranked as being communicated with the most was only in the top four 52% of the time. This disparity between perceived interactions and observed interaction led Killworth and Bernard to speculate that informants' interactions are interpreted through a cognitive structure that systematically distorts informant recall.

In a review of their informant accuracy studies, Bernard, Killworth, Kronenfeld & Sailer (1984) found that informants who recorded their behaviour were no more accurate than those who didn't, and that informant accuracy decreased as the time elapsed increased. Over all their datasets they found that informants could recall or predict less than 1/2 of their communications. No demographic differences were found between accurate and inaccurate individuals.

Many studies have found poor informant accuracy in a wide range of situations. Some researchers have also found specific factors that affect accuracy. Hyett (1979, cited in Bernard et al., 1984) surveyed 354 telephone users and found that infrequent users over reported the number of calls made while frequent users under reported the number of calls made. Young and Young (1961, cited in Bernard et al., 1984) found greater accuracy and agreement amongst informants in Mexico when asked about publicly available information compared to private information. Kronenfeld (1972, cited in Bernard et al., 1984) asked informants who were leaving restaurants to describe what the waiters and waitresses were wearing. Informants showed much higher agreement about the waiters' clothes than the waitresses' despite the fact that there were no waiters in the restaurant! Kronenfeld suggested that without specific memories of the waiters, informants turned to cultural norms for descriptions of what they had 'seen'. It is clear that if social scientists wish to use recall data about actions and interactions as a substitute for those actions and interactions, then they must understand something of how informants' cognition affects the storage and retrieval of information.

Why should informants' cognitive processes conflict with accurate recall? Freeman and Romney (1987) believed that long-term social structure was not well represented by any particular set of recorded interactions. Instead, they asserted that social structure might be a relatively stable pattern of interpersonal relations that is well represented by informants' cognitive structures. When asking informants to recall information about a particular event there are two main sources of recall error: some facts are lost, and the remainder are supplemented with pseudo-facts. Freeman and Romney asked informants who attended a series of weekly meetings about the attendees of the final meeting. Informants were inaccurate about the attendees of the final meeting. They forgot those who attended few prior meetings and falsely recalled those who were the most regular attendees. This was a systematic bias towards the social structure norm showing that informant recall may be a better measure of long-term social structure than is a single observation. In addition, recall data is much easier and less costly to collect than observational data, especially for large or open-ended networks.

In a follow-up study investigating attendance recall of a series of University meetings Freeman, Romney & Freeman (1987) found that just under half of the attendees of the final meeting were forgotten and there were a small number of false recalls leading to an error ratio of 52%. However, the correlation between recall and attendance at all sessions was greater than the correlation between attendance at the final session and attendance at the previous sessions. Therefore Freeman et al. concluded that recall provides a better index of the long-term pattern of social structure than that derived from direct observation. Based on their cognitive outlook of recall Freeman et al. hypothesised that those informants who were in the in-group (faculty members with central offices) were more experienced and had developed complex internal mental structures that represented social structure and would therefore forget fewer attendees but also falsely recall more attendees. They also hypothesised that those who have attended more sessions would be seen as more typical elements of the sessions and would therefore be less likely to be forgotten and more likely to be falsely recalled. Both of the hypotheses were supported by the data indicating that informant recall is mediated by cognitive structure. At the same time as supporting the Bernard et al. (1984) figures for informant accuracy (around 50%), the results of this study indicated that the problem of informant inaccuracy is not as great as originally supposed.

The persons recalled in a network elicitation task are only a sample of the possible set of persons who could be named. Sudman (1985) examined five closed groups (3 work departments and 2 church groups) varying in size from 18 to 283 members. He compared recall, recognition and numerical estimation (guessing) of acquaintances and friends as different methods for estimating personal network size. He found that recognition procedures produced substantially larger estimates of network size than recall. However, he also found that the numerical estimates of network size, though highly variable, were closer to recognition estimates than recall estimates were. Sudman found that as group size increased the accuracy of recall estimates decreased. Sudman cautioned against simply asking an informant to name everyone they know because of the variation between informants' power of recall and also their interpretation of the term 'knowing'.

Brewer and Webster (1999) examined the effects of the forgetting of friends on the measurement of personal social networks. They asked 217 residents at a student hall to recall their friends in the hall and then presented them with a list of all residents at the hall from which they were asked to recognise any additional friends. On average, they found that 20% of friends had been forgotten. Informant characteristics were found to have no correlation with forgetting and no difference was found between those recalled and those recognised. However, relationship strength was found to be slightly stronger for recalled friends. A higher proportion of best (97%) and close (91%) friends was recalled than 'just friends' but 26% of those with a best or close friend forgot at least one of them. However, 21% of informants didn't forget any friends. Recalled friendships were slightly more likely to be reciprocated than recognised ones, but this difference was slight. Recognised friends were slightly more peripheral (distant) in an informant's network than recalled friends. Recall data was found to correlate very strongly ($r=0.92$) with combined (recall + recognition) data regarding personal network density. In addition, recall data correlated strongly ($r=0.89$) with combined data in the measurement of network size. Brewer and Webster concluded that although estimates of personal network sizes using recall data were underestimates due to forgetting, they were still good proxies for the combined data estimates of personal network sizes and should retain the network size order of informants.

In a study of social support in the social networks of 8 classes of 31 17-year old high school students Ferligoj and Hlebec (1999) also investigated the difference between free recall and recognition network data. In a different approach to that of Brewer and Webster (1999), Ferligoj and Hlebec separated informants into recall or recognition groups. They found that in their study (where informants knew each other well) that free recall had as high a test-retest reliability as recognition.

However, they found that the recognition task yielded more and weaker relationships than the recall task. Although recall was found to be a stable method, they concluded that if a full list of membership is available then the recognition method should be used in order to include weaker relationships.

As already noted, informants have imperfect recall of their interactions. However, in addition to memory errors, informants may also exhibit various biases in the reporting of their interactions. Some informants may over/understate the characteristics of their relationships, and others may have different minimum requirements for reporting a relationship to exist. Feld and Carter (2002) define this tendency to over/underreport others as "expansiveness bias". Informants may also tend to exaggerate their relationship strength and interactions with desirable people and/or overlook their relationships with undesirable people. This is defined as "attractiveness bias". Feld and Carter re-examined a 1960 dataset of 930 college students to examine these biases and found evidence for expansiveness bias but not for attractiveness bias. This suggests that the cumulative reports about each informant yield better network data than informants' reports about themselves, which may be exaggerations/understatements. Although it is not possible to collect reciprocated data for each informant in an open network design, a sample of informants could be studied to give a general indication of expansiveness bias. In order to reduce expansiveness bias in further studies, Feld and Carter suggest minimising the variation in individual interpretation by asking solid practical questions that minimise distortion.

SUBPOPULATION EFFECTS

The network scale-up method of estimating the size of hard-to-count subpopulations produced good initial results. Laumann, Gagnon, Michaels, Michael & Coleman (1989) and Laumann et al. (1993) found very good agreement between their estimate of the number of homicide victims and the FBI official statistics for the United States.

McCarty, Killworth, Bernard, Johnsen and Shelley (2000) also compared two methods for estimating the size of personal networks using a nationally representative sample of the United States. Both methods rely on the ability of respondents to estimate the number of people they know in specific subpopulations of the U.S. (e.g., diabetics, Native Americans) and people in particular relation categories (e.g., immediate family, coworkers). The results demonstrate a remarkable similarity between the average network sizes generated by both methods (approximately 291). Similar results were obtained with a separate national sample.

Homicide statistics are considered to be the most reliably reported of the FBI index of seven serious crimes (Gove et al., 1985, cited in Johnsen et al., 1995). Homicide victims were found to have personal networks of similar size to the general population, and because the knowledge of their homicides propagated throughout their networks quickly and thoroughly, it was therefore used as a benchmark subpopulation for comparative purposes (Johnsen et al., 1995).

However, when network scale-up methods were used to estimate the seropositive (HIV+) subpopulation and then checked against the benchmark (homicides) Johnsen et al. (1995) found an over-count by a factor of 3.7. This implied that the social network size of a seropositive individual was only 27% of the size of the population average. Although seropositive individuals have been hypothesised to cut back their networks, the definition of an acquaintance used in the alter generation process specified contact within the last two years, therefore limiting the possible shrinkage of a seropositive's network. Johnsen et al. concluded that the most likely explanation was that due to the stigmatising nature of HIV infection that information about an individual's HIV status was limited to about 1/3 of their active personal network.

The difficulty in estimating seroprevalence highlights the limitations of Bernard and Killworth's model, which makes three main assumptions (Killworth, McCarty, et al., 1998):

1. Everyone has an equal chance of knowing someone in a given subpopulation.
2. Network size 'c' is a constant.
3. Everyone has ‘perfect’ knowledge about the members of their network.

It is clear that these assumptions are not met in the case of HIV+ individuals. The demographic makeup of the HIV+ subpopulation in the USA is different to that of the general population, with homosexual males and intravenous drug users making up a disproportionate number of cases. Given that similar individuals are likely to interact more with each other, this means that a male homosexual or an IV drug user has a greater chance of knowing an HIV+ individual than do other individuals. This is referred to as a 'barrier' effect or as a 'buried' subpopulation (Killworth, Johnsen, et al., 1998; Killworth, McCarty, et al., 1998). Where certain demographics are related to subpopulation membership it is preferable to include a representative number of individuals with those demographics. However, some linked demographic variables may be of a sensitive or private nature (i.e. sexuality). Given a fairly large sample, though, the distribution of most demographics would be expected to be representative, and the chance of missing any 'buried' populations would be low.

Data from Johnsen et al. (1995) suggest that network size of HIV+ individuals is smaller than the norm, and/or that information about HIV status is limited in the network. This imperfect knowledge of HIV status is called a transmission effect (Killworth, Johnsen, et al., 1998; Killworth, McCarty, et al., 1998). For some subpopulations (first name "Michael" for instance) membership is immediately apparent and informants can be considered to have 'perfect' knowledge. For other subpopulations, information of subpopulation status may be limited by one or more transmission errors. There are three main sources of transmission errors (McCarty, Killworth, Bernard, Johnsen & Shelley, 2001):

1. Doesn't come up in conversation (e.g. left-handedness, twin).
2. Stigma (e.g. HIV+ or drug use).
3. Personal information (e.g. weight, IQ, income)

In order to make a more accurate estimate of seroprevalence the characteristics of HIV+ social networks need to be more explored (Johnsen et al., 1995; Killworth, Johnsen, et al., 1998; Laumann et al., 1993; Shelley, Bernard, Killworth, Johnsen & McCarty, 1995). The composition of relationship types within the social networks of both HIV+ and 'normals', as well as the relationship paths that HIV status information propagate through need to be more thoroughly investigated. Any barriers that surround the networks of HIV+ individuals and the difference in network size between HIV+ individuals and 'normals' must also be identified. If these properties are better understood, then the simple model of the network scale-up method can be modified to give weightings to:

1. The probability of knowing someone in the HIV+ subpopulation, given an individual’s demographic information.
2. The ratio of HIV+ network size to 'normal' network size.
3. The proportion of alters in an HIV+ person’s network that know of their status.

The problem of transmission errors is perhaps the largest obstacle in the estimation of hard-to-count subpopulations. There are two potential methods of accounting for transmission errors. The first method is to investigate the networks of subpopulation members, in order to determine the proportion of their alters that know of their subpopulation status. The second method is to seek to quantify the stigma level of the subpopulation. Either method produces a scaling factor for the subpopulation.

In an effort to better understand the characteristics of the personal networks of HIV+ individuals, Shelley et al. (1995) interviewed 70 HIV+ patients. They found that their sample of HIV+ patients did have smaller personal networks than the control group, and that they also limited information about their HIV status within their networks. Shelley et al. also investigated the socio-demographic characteristics that govern who receives HIV status information and found that medical personnel and support group members have the most knowledge of HIV status. Friends and former lovers had the next best knowledge followed by relatives and acquaintances. Males and whites were found to have slightly more knowledge of HIV status than women and blacks.

Shelley et al. (1995) speculated that if informants were to know information that was less well known than HIV status then maybe they would also know HIV status. However, they found that informants could not accurately judge how difficult a given piece of information was to know, and also that black men had the greatest knowledge of alters' blood types (the hardest piece of information to know) but had the worst knowledge of alters' HIV status.

Exploring the possibility of quantifying transmission and barrier errors, Killworth, Johnsen, McCarty, Bernard and Shelley (2003) found that informants may be responding based on imperfect knowledge. Although Killworth et al. were unable to assign a scaling factor to estimate the actual size of a hard-to-count subpopulation, they found that it is possible to determine an effective subpopulation size. This effective size could be used to compare different geographical areas or demographics sectors in the population to find relative differences in subpopulation membership. The validity of the probabilty model in describig the distribution of peoples' personal networks to improve the estimate has been undertaken by Bernard, Johnsen, Killworth and S. Robinson (1989).

APPLYING SOCIAL NETWORK ANALYSIS

Care must be taken to obtain a sample of alters that represent the population. The first step is to collect a representative sample of informants. If the sample of informants is skewed, then any resultant pool of alters will also be skewed. Some groups of informants are more likely to respond than are others and some demographic groups are over/under represented in some subpopulations. Attention must be paid to the respective merits of targeted samples (better validity) and of random samples (less costly).

A network generation method that elicits alters that are representative of each informant's personal network is also vitally important. A network generator such as the first-name method is a reliable instrument because informants are not required to interpret terms, and there is no bias towards alters from certain social contexts.

Although suitable in other respects the first-name method has been criticised for its ethnic bias. It has been suggested by McCarty et al. (1997) that each informant be presented with a list of 50 names that have been randomly selected from a greater pool of names that is representative of all ethnic groups in the greater population. In New Zealand for instance special care must be taken to ensure that Maori are represented in the sample. Interviewers need to be trained to administer the network generation method consistently. Interviewers must follow a set procedure in the initial generation of alters, a set of guidelines must be developed for the probing for additional alters also for the recording and interpretation of informant responses. Ideally, interviewers would be tested for consistency in a trial phase before interviewing their first informant in the study group.

Network size 'c' is estimated by multiplying the number of alters generated from the list of first names by the ratio of names in the population to names on the list. It is reasonable to use this number as a proxy for 'c' without further modification. Those informants who generate more alters can justifiably be seen as having larger networks than those informants who generate fewer alters.

The standard approach of investigating alters is to ask the informant about each alter as he/she is generated. Although identifying information is not sought about alters, some informants may be unwilling to label an alter as a subpopulation member. As an alternative, after the generation process, informants could be asked, "How many of the people that you have listed meet these criteria?" This would reassure informants that they weren't 'dobbing in' any of their alters.

Transmission effects have been found to interfere with the estimation of some hard-to-count subpopulations such as HIV+ individuals in the US. Investigation of the social networks of the members of different stigma-bearing subpopulations of known size may allow for the quantification of stigma that can then be applied to unknown subpopulations with equivalent levels of stigma.

Although the estimation of exact subpopulation sizes may in some cases be unobtainable, relative differences between areas, demographic groups and related subpopulations may still be obtained. Any investigation would need to take into consideration a number of factors. The final research method will depend upon the subpopulation of interest.

One possible avenue for future research is the use of computer modelling to investigate the effects of informant accuracy, biases, barrier effects and transmission effects on network data. Such a model may help in the design of subsequent experiments and to identify distortions in future network data.

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A Modified Elicitation of Personal Networks Using Dynamic Visualization

Christopher McCarty[1]
Bureau of Economic and Business Research, University of Florida, Gainesville, FL

Sama Govindaramanujam[2]
Bureau of Economic and Business Research, University of Florida, Gainesville, FL

Several algorithms and software packages have been developed for displaying the relationship between actors within a whole (sociocentric) network. These visualization packages use as input an adjacency matrix representing the relationship between actors, and have occasionally been applied to personal (egocentric) network data. Personal network adjacency matrices require respondents to report on all alter-alter ties. This is an enormous respondent burden when the number of alters goes much beyond 30. We report here on an effort to reduce that burden by having respondents build their own personal networks, interactively, on the Internet. In a study on smoking, 100 respondents (50 smokers and 50 non-smokers) listed 45 network alters and provided data on whether each of the 990 pairs of alters talked to each other. We used a program called EgoNet to collect these data. Fifty of the respondents (25 smokers and 25 nonsmokers) then completed a similar exercise over the Internet, using a visual interface, called EgoWeb. There are clear mode effects on personal network composition and structure.

BACKGROUND

Many advances have been made in the visualization of network data over the past decade. Until the past couple of years, virtually all network visualization packages were oriented toward whole (sociocentric) networks. These packages, such as PAJEK, NETDRAW, KRACKPLOT, NETVIZ (among others), typically provide a variety of visualization algorithms using an existing adjacency matrix as input. The result is a two or three dimensional representation of the links within the group, and often the ability to display attributes of network nodes (or actors) using size, shape, color or some combination of these.

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[1] Chris McCarthy, Survey Director, University of Florida Survey Research Center, Bureau of Economic and Business Research, PO Box 117145, University of Florida, Gainesville, FL 32611-7145, chrism@bebr.ufl.edu, fax: (352) 392-4739.

[2] Sama Govindaramanujam, Graduate Research Assistant, University of Florida Survey Research Center, Bureau of Economic and Business Research, PO Box 117145, University of Florida, Gainesville, FL 32611-7145, samag@bebr.ufl.edu.

Unlike whole networks, egocentric networks are centered on a focal individual. In the field of social network analysis, egocentric analyses are often done of members of a whole network. Some network visualization packages allow the user to visualize the egocentric network of a member of that whole network. For example, NETDRAW has a module that allows the user to pick a node in a whole network and display ties to the nodes to which it is connected. In practice, for example, one may want to toggle between viewing the entire set of ties between children in a classroom, or the egocentric network of a single student.

The logical extreme of an egocentric network is the personal network. Unlike any of the prior examples, a personal network is an egocentric network existing within the whole network defined by the population of the world. In other words, personal networks are not constrained by a sub-structure, such as geographic or social space. Personal networks can vary between structurally cohesive networks that are compositionally homogenous in terms of member characteristics, to compositionally heterogeneous networks that exhibit extensive bridging and reach across geographic and social space. Unlike their constrained counterparts, egocentric networks include the influences of all the whole networks to which a respondent belongs, the effect of the overlap between those whole networks, and the potential to use these characteristics as explanatory or dependent variables.

Researchers who want to understand the effect of personal networks face an enormous data collection problem. One cannot know at any given time the names of all the members of the world, and there is no practical way to present this list to a respondent. One can only ask respondents to whom they are tied. There is, however, bias in the way respondents list alters. Brewer (2000) found that both close and weak ties could not be recalled by respondents in a free-listing task. Brewer and Webster (1999) found that forgetting in a free list of alters affected the estimated structural features of a whole network. This research suggests that names are not recalled randomly from respondent memory. Other research has focused on cueing mechanisms to enhance recall to correct for this bias (Brewer and Garrett 2001; McCarty et al. 1997; Brewer 1997).

Another solution to the problem of recall bias is to generate a sample of personal network alters so large that the bias towards strong ties or those with particular characteristics is minimized. Some research suggests that personal networks consisting of active ties (those contacted in the past two years) are roughly size 290 (McCarty, et al. 2000; Killworth, Bernard and McCarty 1984). McCarty (2002) had respondents list 60 alters in a study of personal network structure. A sample of 60 alters would account for nearly 20 percent of the personal network and would presumably minimize recall bias.

Most personal network studies are on a small number of alters and almost never consider personal network structure, instead relying on personal network composition for explanatory power. While explorations of personal network compositional variables (such as the percent of network alters that are family, women or who smoke) are useful, the analysis of personal network structural variables (such as closeness or betweenness centrality and the number of components) remains largely unexplored. Previous studies have limited their analyses mostly to network density (Latkin et al. 1998; Haines, Hurlbert and Beggs 1996; Latkin et al. 1995; Fischer and Shavit 1995)

The reason that there have been few studies of personal network structure on large numbers of alters is that respondents must report on the ties between alters. Getting respondents to assess all alter-pair combinations is a tedious task that increases geometrically as alters are added (see Figure 1). Even though the process of evaluating an alter pair tie is relatively quick (rarely more than five seconds), it can easily take an hour for a respondent to complete all 990 alter pair evaluations for a 45 alter network. Combining this with information elicited about the respondent themselves, and about each of their network alters, it is difficult for researchers to justify obtaining structural data on large numbers of alters. On the other hand, given that elicitations of very few network alters typically result in mostly strong ties, the structural data from these samples are less interesting than large samples of alters that demonstrate structural variability. A method that maximizes structural variability while lowering respondent burden would advance the field of personal network analysis.

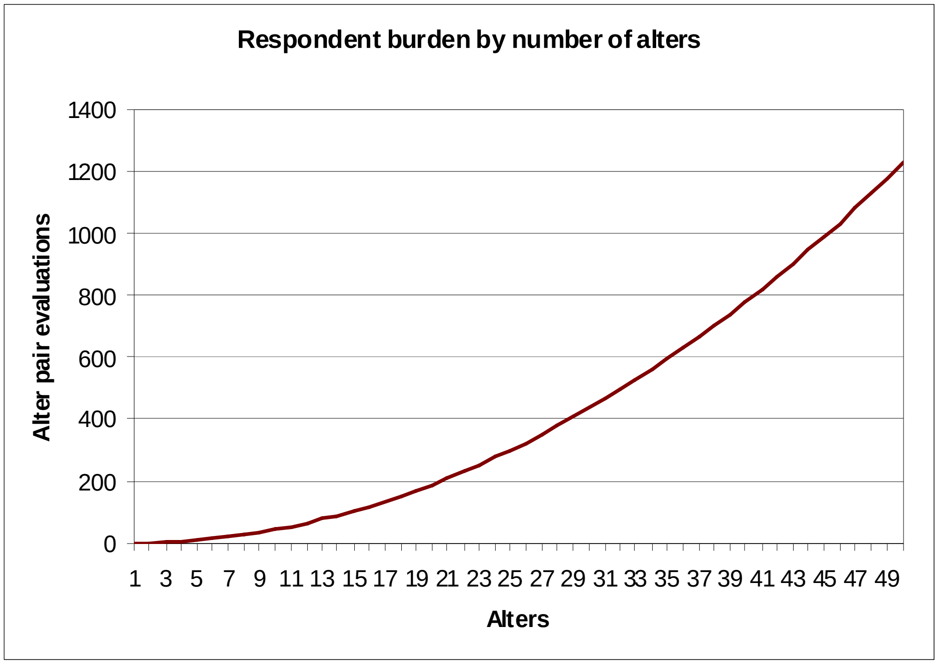

Figure 1. Respondent Burden by number of alters.

METHOD

The data for this study were generated as part of a grant to develop a web-based personal network intervention for adolescents at risk of smoking. This technology is founded on literature that identifies social influences as the primary factor explaining adolescents transitioning from non-smokers to experimenting, and experimenting to regular smokers (Flay et al. 1994). Ennett et al. (1994) demonstrated the importance of the network structure of peer groups on smoking, although the alters for that study were constrained to be from a whole network consisting of a set of schools. By visualizing the structure of their personal network and the structural placement of key alters, including smokers, adolescents can then use simulation tools to understand both the effect of smokers on them and the consequences of changing those relationships. This software is viewed as a potential interface for other intervention tools as well.

All participants were college freshman and sophomores, as we wanted respondents who were as close to high school age as possible. The study began with an EgoNet interview of 100 respondents, 50 smokers and 50 non-smokers. EgoNet is a personal network data collection and analysis package freely available through the Internet (http://survey.bebr.ufl.edu/egonet/). It consists of two programs, one for creating a study and one for running it. A study consists of four sections: questions asked of the respondent about themselves, questions asked to elicit a set number of alters, questions asked of the respondent about each alter, and a question about the tie between each unique pair of alters. The last module is used to generate adjacency matrices for structural analysis.

EgoNet uses the adjacency matrix to generate a network visualization based on the open source software library JUNG (Java Universal Network/Graph Framework), developed primarily at the University of

California at Irvine. EgoNet also calculates several structural measures (degree, closeness and betweenness point centrality, degree, closeness and betweenness network centralization, the number of components greater than size 2, the number of dyads, the number of isolates and the number of cliques). These measures can be viewed for an individual personal network in EgoNet or output as a summary file that combines respondent data, compositional data about all alters and structural data about the network in a comma delimited file with one line per respondent. All 100 respondents completed a 45 alter EgoNet study. The last module of EgoNet requires the respondent to evaluate all alter-alter pairs, in this case 990 ties. For this particular study, respondents typically finished in less than two hours. Respondents were paid $30 to complete the EgoNet study and submit to a short interview following the study where they were asked questions about their personal network visualization.

EgoWeb was developed to reduce respondent burden and to deliver a personal network interview over the web. EgoWeb relies on dynamic network visualization, whereas other network visualization packages (including EgoNet) expect as input a completed adjacency matrix. EgoWeb uses a visual interface for collecting personal network data and redraws the network visualization with the addition of each alter. The purpose of the study was to test the EgoWeb interface that was designed to reduce respondent burden and to make the interface more appealing to respondents.

Unlike the EgoNet study that relied on a free-list of 45 alters, the EgoWeb study was designed to elicit alters in such a way as to maximize network structural features early on. Respondents were asked to list a single alter, but not one who is closest to them. They were then asked to name someone they knew who also talked to that alter. As these alters were added to EgoWeb a dot was placed on the screen with the alter's name below it and a line placed between the alters and the dot representing the respondent, indicating a network tie.

Next respondents were asked to name an alter who they knew, but who did not talk to any of the other two alters already depicted. They were then asked to name an alter who talked to the one just mentioned. If they couldn't think of someone that talked to that alter, that alter was an isolate. This process of naming pairs or singles that were unrelated continued until the respondent couldn't name any more. The idea was to force the respondent to nominate people from the variety of whole networks to which they belonged. Only when all such groups were exhausted did the respondent proceed to the next stage.

Once all whole networks had been represented, respondents were asked to name more alters until the visualization contained 45 names. At this time they were asked to concentrate on very close alters, that is, those they would not want to leave out. Close alters were avoided for the first part of the elicitation task as close alters tend to be bridges in a network and would make it difficult to name pairs of alters that were not tied to each other. For this part of the elicitation, as a new alter was named the respondent clicked on existing nodes, selecting those alters to which the new nominee was tied. The respondent indicated when they were finished making those ties and the visualization was refreshed and the respondent could list a new alter. This process continued until 45 alters had been named.

The EgoWeb elicitation differs from the EgoNet elicitation in several ways:

1. Respondents are forced to list pairs of unconnected, and less-close alters before listing more close alters. This maximizes network structural features.
2. Respondents see the visualization as they enter alters. This no doubt affects who they list next. Some respondents may actually use the visualization to try to fill out groups they see clustering on the screen.

3. Respondents only provide existing ties using the visual interface. In EgoNet all ties must be evaluated, including null ties. In a less cohesive network, null ties can easily represent the majority. This dramatically increases respondent burden in EgoNet.
4. Respondents in EgoWeb determine which ties they evaluate; often based on their perceptions of groupings they see through the visualization. For example, a respondent creating ties for a co-worker may easily avoid making any tie to family if they know there is no link between the work and family alters. Shifting control of which ties to evaluate from the researcher (via EgoNet) to the respondent (via EgoWeb) is perhaps the biggest change. With EgoWeb the researcher must rely on the respondent to provide the ties as the respondent burden is determined entirely by the respondent, rather than by the researcher.

Of the 100 respondents to the EgoNet study, 50 were selected to pilot the EgoWeb study and were paid $60 to complete it via the web. The EgoWeb study was a much shorter version of the EgoNet study, including only the 45 alter elicitation using the dynamic visualization described above, and a question about alter smoking. The purpose was to get respondent feedback about the two methods and to test differences in selected structural measures between the two methods.

RESULTS

Given that the 50 respondents from this study used both the EgoNet and the EgoWeb interfaces, they were in an ideal position to make a comparison. It is not surprising that 70 percent of those respondents preferred EgoWeb. On average, the EgoWeb task consisting of simultaneous alter elicitation and alter-alter tie evaluation took about half the time of the EgoNet alter elicitation and alter-alter tie evaluation modules combined. The EgoWeb interface would have no effect on questions asked of the respondent about themselves or about their alters.

Specific comments about the comparison were more varied. Most respondents found it easier to point and click rather than to muddle through the arduous task of responding to the 990 alter-pair evaluations. Most also found the visualization interesting and appealing. One respondent suggested that having the visualization on the screen helped her to recall certain respondents. This is a factor that must be examined further. It is unclear whether the feedback is a positive influence, helping the respondent describe their network the way they perceive it to be, or a negative by stimulating them to fill out clusters that would otherwise be less represented.

On the negative side, some respondents actually felt it was harder to think of people to list, having the natural flow of the free-list disrupted by seeing their network structure. Many respondents found it difficult to read the names in tightly knit groupings of alters, even though the visualization allowed the nodes to be dragged aside. This is a technical issue that should be possible to correct by adding the capability to isolate an area of the visualization for expansion across the screen. Most respondents found it difficult to think of people they knew who did not talk to each other. This was to be expected given that it was designed to exhaust all of these groups.

Personal network composition refers to the summary characteristics of the alters who the respondent lists. This is in contrast to personal network structure that refers to the summary measures that capture the pattern of relations between those alters. While we cannot compare summary alter attributes of the two methods, we can determine to what extent respondents listed the same people in the two studies. Of the fifty respondents to EgoWeb, respondents on average used 22.4 (SD 6.5) of the alters they used in EgoNet. This represents only half of the alters from the free-list. The minimum that were the same was 1 and the maximum was 36. It is apparent that the EgoWeb interface generated a much different set of alters. The differences could have been due to the elicitation method, the feedback from the visual interface or both. It is important to note that the two studies were conducted within a time gap of 2 months, so it is doubtful that the differences between the networks were due to actual changes in the respondent's personal network.

One obvious question is whether those that were substituted between the EgoNet and EgoWeb studies tended to be strong or weak ties. By comparing the average closeness score for each alter on a scale of 1 to 5, we found the average for those included in the EgoWeb study was 3.3 compared to 2.5 for those who were left out. The difference between these averages was significant ($p < .001$). As expected, both methods pick up the core network members and vary in the weak ties that are used to list a 45 alter network.

The structural differences between the two elicitation methods are summarized in Table 1. We expected that the EgoWeb method would elicit members of all the groups a respondent belongs to, which would in turn maximize both mean betweenness point centrality and mean betweenness centralization. In fact, these were the only two structural measures that were not significantly different. On average, these measures differed less then either degree or closeness centrality. While EgoWeb does result in higher numbers for both betweenness measures, the differences between these two measures is so highly variable (as demonstrated by the coefficient of variation) that significant differences between them were not found. There were, however, about 30 percent more network components of size three or more using EgoWeb than EgoNet. Although the bridging capability of alters was not significantly different, EgoWeb did result in more subgroups.

Table 1. Comparison of structural measures between EgoNet and EgoWeb elicitation for 50 respondents.

Variable	Mean – Egonet	Mean – Egoweb	Mean Difference	Coefficient of Variation of Mean Difference	Probability Difference > 0
Mean point degree centrality	10.90	7.50	3.41	1.00	0.0001
Mean degree centralization	36.20	31.20	4.99	3.25	0.03
Mean point closeness centrality	30.50	21.20	9.32	2.28	0.003
Mean closeness centralization	20.20	12.50	7.69	4.07	0.09
Mean point betweenness centrality	19.60	21.60	-1.97	-7.28	0.34
Mean betweenness centralization	22.40	23.80	-1.43	-15.11	0.64
Number of components	1.50	1.90	-0.44	-3.37	0.04
Number of isolates	1.50	0.70	0.76	2.95	0.02
Number of Cliques	46.90	32.20	14.62	2.53	0.008

All of the other measures exhibited significant differences. The most significant difference was mean point degree centrality, which was much lower in EgoWeb than in EgoNet. There were also about half as many isolates using EgoNet versus EgoWeb. The difference in degree centrality is likely due to the fact that respondents to EgoWeb choose which alter-alter pairs to enter, rather than having to individually evaluate each one as they do in EgoNet. The lower number of isolates was probably affected by the respondents' use of the network visualization in EgoWeb as a cue once they got to the stage where they were entering individual alters. Respondents may have been less likely to enter isolates than members of groups they saw before them in the visualization.

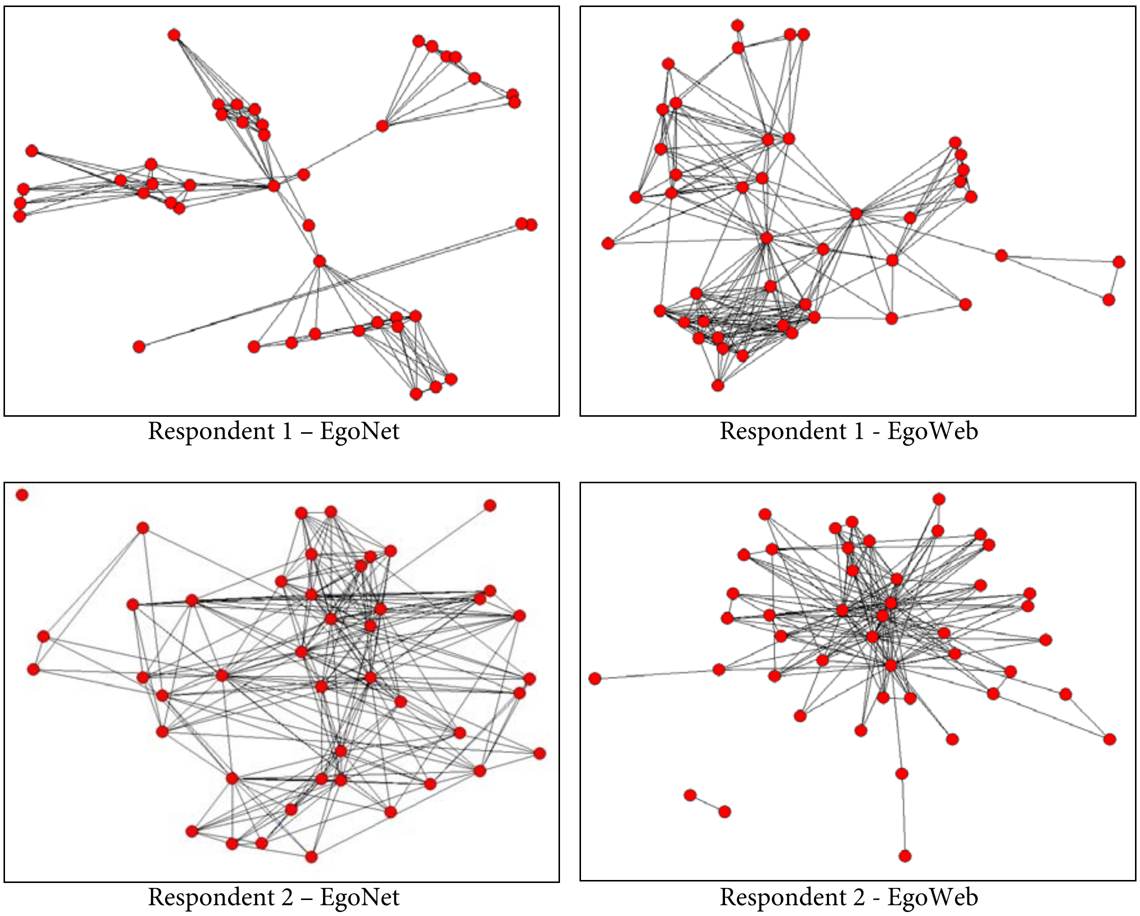

Figure 2. Selected network visualizations using EgoNet and EgoWeb.

Figure 2 compares personal network visualizations of two respondents using EgoNet and EgoWeb. Respondent 1 reflects most of the differences detailed in Table 1. In contrast, Respondent 2 reflects very few of the differences in Table 1. These two visualizations demonstrate the variability that one can expect using the modified elicitation of EgoWeb. Although most of the groups Respondent 1 listed in EgoNet are also represented in EgoWeb, the structural features appear quite different.

DISCUSSION

In this article we have compared two methods for collecting structural data on personal networks. The practice of visualizing personal networks, that is unconstrained egocentric networks, is not common, and the analysis of structural data on personal networks is relatively unexplored. We believe that the variability in structural features of personal networks is a good source for explaining variability in many outcome variables. We also believe that future network applications will use visualizations of personal networks as an interface, and thus understanding the best way to elicit these data is essential. Much research is needed in extracting valid and reliable data from respondents.

The two methods reported here, EgoNet and EgoWeb, are operationalized in two software programs. EgoNet is designed for researchers to collect personal network data across many respondents. It does not use a visual interface and collects structural data from respondents by presenting all possible alter pairs. EgoNet presents a network visualization to the respondent after all data are collected.

In contrast, EgoWeb is oriented toward an individual respondent. It is an attempt to create a personal network interface that can be used over the Internet to deliver network interventions. Given this constraint, it is designed to lower respondent burden and be visually appealing. This is done through the personal network dynamic visualization.

There are two big differences between the two methods. EgoNet relies on a set of elicitation questions typical of personal network research. EgoWeb is an attempt to extract the groupings a respondent belongs to without the bias of pre-conceived groupings used by researchers (e.g. family, work, church). McCarty (2002) found that groupings derived from alter-alter interaction often did not fall into these pre-conceived groupings. Thus, a method that forces respondents to list groups without using these prompts may better reflect their social environment without imposing a set of common cognitive groups upon them.

Perhaps the biggest difference between the two methods is that in EgoNet respondents are forced to evaluate each alter pair tie (990 evaluations for a 45 alter personal network) whereas the visual interface of EgoWeb allows the respondent to use the visualization to tie a new alter to those already depicted. Although this is designed to reduce respondent burden by allowing respondents to avoid evaluating null ties, it makes it possible for unmotivated respondents to leave out ties that may not be null. The consequences of that are evident in that EgoNet generated 493 ties and EgoWeb 340 ties out of the possible 990. EgoWeb results in significantly ($p < .001$) fewer ties.

Although the visual interface of EgoWeb reduces respondent burden by about half, it results in a much different structure. It is unknown which of the two structures is closest to the existing communication between the alters, yet it is likely that the EgoNet structure is more reliable given that each alter tie evaluation must be made. For research, particularly in cases where respondents are compensated, it is still advisable that respondents evaluate all alter pair combinations. This ensures that the respondent burden is the same for all respondents.

It is unclear, however, that the modified elicitation that attempts to elicit all groups a respondent belongs to before listing the remaining alters is advisable. In hindsight, it would have been useful to have the 50 respondents who had used EgoWeb evaluate all 990 alter pair combinations and see how close that structure is to EgoNet.

While the dynamic visualization presents some problems, for the purposes of a network intervention, some form of this interface will likely be necessary. More research must be done to reduce respondent burden and to maximize the validity and reliability of the structural data that result. For example, several algorithms may be used to predict ties based on existing data. One approach would be to have the software assume ties by completing triads. Another would be to use attributes of alters, such as the relationship category, to assume ties. Any algorithm that assumed ties would have to test some sample of them, introducing more ties to evaluate if the assumptions were proven incorrect.

The future application of personal networks as a tool for intervention will undoubtedly involve some type of visual interface as has been tested here. We assume that a respondent that is motivated, that is one who hopes to get something from the intervention, would take the time to ensure that the structure of their network is as accurate as possible, and that a user of a personal network intervention would be motivated. Further research will hopefully yield an interface that is both entertaining and accurate.

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A Complement-Derived Centrality Index for Disconnected Graphs[1]

Benjamin Cornwell
University of Chicago, Department of Sociology

Freeman's (1979) measure of closeness centrality is valuable in network analysis, but its use is limited to connected networks. In this paper, I describe an approach for calculating actor closeness centrality that circumvents the problem of disconnectedness. I show how the complement, G_C, of a disconnected network, G, can be used to obtain weights that transform Freeman's measure, C'_C, into a universal measure, C'_{CW}, for actors in both connected and disconnected networks. In essence, this method incorporates information about how an actor is not proximate to all other actors in a network (captured by the structure of the complement network) to weight within-component closeness. C'_{CW} has several attractive properties. Aside from being universally applicable and ranging from 0 to 1, the value of C'_{CW} equals C'_C in connected networks. Furthermore, C'_{CW} cannot reach 1 for actors in disconnected networks.

INTRODUCTION

Centrality is a much-analyzed actor-level property of social networks. Measures of centrality attempt to identify the "most important" actors in a network using nomination degree, closeness, betweenness, or some comparable notion. Perhaps the most useful and popular of these measures, Freeman's (1979) closeness centrality index, relies on geodesic distances among actors. The measure is useful because it captures independence from the control of others in terms of accessing (the resources of) others in a network, but it can only be applied to connected networks. Though several attempts to calculate actor centrality measures for disconnected networks have been made, none seem to possess as much intuitive appeal or are as substantively interpretable as the original measure for connected networks.

I begin by describing some existing actor centrality measures and by summarizing the problem of disconnectedness. I follow with a discussion of the complement of a network (the network of ties that do not exist), and how it can be used to infer properties about actor closeness centrality across disconnected components. I show that one can extend Freeman's (1979) measure to actors in a disconnected network by considering the extent of disconnectedness in conjunction with a given

[1] Correspondence concerning this manuscript should be addressed to Benjamin Cornwell, Department of Sociology, University of Chicago, 1126 E. 59th St., Chicago, Illinois 60637. Email may be sent to: cornwell@uchicago.edu., and faxes may be sent to 614-292-6687. I wish to thank Jim Moody for his always indispensable counsel, Robert Poulin and Marie-Claude Boily for technical clarification, Erin York for her meticulous reading and thoughtful suggestions, and the Connections editor and reviewers for valuable advice.

actor's position in its complement. Finally, I compare the closeness measure that I derive from the complement (which I will call C'_{CW}) to another measure, C''_{CN}, developed in previous attempts to overcome the problem of disconnectedness.

C'_{CW} has attractive properties in that it ranges from 0 to 1 (it can only reach 1 in connected networks), and it is comparable across components and networks containing different numbers of actors and levels of disconnectedness. Freeman's (1979) closeness centrality is a special case of C'_{CW} that is found in fully connected networks, since the amount of disconnectedness experienced in these networks is constant for all actors (0). *C'_{CW} reflects independence from the limits on access posed by reachable others in the network and by disconnectedness in the overall network*. This operationalization results from conceiving of centrality as a dimension of an actor's local importance that is contextualized by a broader structure.

ACTOR CENTRALITY MEASURES

Early measures of actor centrality that focused on closeness were developed by Bavelas (1950), Harary (1959), and Beauchamp (1965; see Wasserman and Faust 1994). Measures of closeness centrality developed later are somewhat more useful because they convey the minimum number of steps separating actors from others (see Hakimi 1965; Sabidussi 1966). According to Freeman (1979), the simplest and most useful actor closeness measure was developed by Sabidussi (1966). The appeal of Sabidussi's measure is that it uses geodesic distances to measure actor closeness centrality. The measure is calculated as the inverse of the sum of the distances from a given actor, *i*, to all the other actors in a network (Wasserman and Faust 1994). The formula can be expressed as:

$$Cc(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

where g is the number of actors in the network, and d is the number of links in the shortest path from actor n_i to actor n_j.

Note that Sabidussi's (1966) measure depends on the number of actors in the network. *Ceteris paribus*, networks with fewer actors will have larger closeness centrality scores, since the sum of distances (which ends up in the denominator) is greater in larger groups. However, following Beauchamp (1965), we can set the ceiling of this index to 1 by dividing g-1 by the sum of the path distances, which is the same as multiplying the inverse of the sum of the path distances by g-1 (Freeman 1979). In essence, we are dividing by the maximum possible distance. This technique standardizes the measure, making it comparable across groups of different sizes. Thus, the revised closeness centrality index is:

$$C'c(n_i) = (g-1)\,Cc(n_i)$$

While Freeman's (1979) standardized closeness centrality index is useful, it has one major drawback: it can be calculated universally only for actors in *connected* networks. Connected networks are those in which each actor in the network can reach all of the others through direct or indirect ties. There are no isolated actors in connected networks. The reason is that the distance between disconnected actors (actors who are not connected—directly or indirectly) is infinite, or undefined. Therefore, "the distance sum for every actor is infinity, and the actor closeness indices are all 0" (Wasserman and Faust 1994:185). This limitation sometimes leads researchers to compute a localized index of closeness centrality *within* connected components of networks, thereby ignoring isolated actors or entire components that exist separately elsewhere in the network. The major drawback of this method is that one cannot adequately compare actor closeness centrality across networks when at least one of those networks is disconnected (see Donninger 1986; Stephenson and Zelen 1989; Altmann 1993). Another approach is to assign a distance to all unreachable nodes. One might use some arbitrary large number, such as 1,000, which simulates infinity in a more mathematically manageable way. Alternately, a researcher could use a value such as one plus the diameter (the largest observed distance) to imitate the distance between unreachable nodes (e.g., see Valente and Forman 1998). This approach is probably more realistic, particularly when the nodes are people, because it assumes that we are all connected to each other in a relatively modest number of steps (Milgram 1967; Watts 1999). These approaches are useful fixes but require imputing somewhat arbitrary values.

Attempts at Bypassing Graph Disconnectedness

Poulin et al. (2000) provide a detailed account of several options that exist for circumventing the problem of accounting for infinite distances among disconnected actors when calculating centrality. Stephenson and Zelen's (1989; see also Altmann 1993) S-Z index of centrality (C'_{Inf}) is one example. While such approaches often have reasonably good discriminant power (i.e., the ability to recognize obscure differences in closeness within components), they still suffer from some problems with comparability among actors in different components/networks. Poulin et al. (2000) argue that other limitations of these methods include the fact that they are computationally difficult (e.g., inversing large matrices), and can be time- and memory-consuming when analyzing large networks. Thus, they propose a centrality measure, C''_{CN}, for disconnected networks that overcomes these problems. Theirs is a mapping-based method that uses a *c*umulative *n*omination scheme to explore all of the possible paths between pairs of individuals in a network. Their idea is as follows:

> Initially . . ., every individual gets one nomination. Then, after the first round of nominations (stage 1), each individual gets additional nominations from their contacts, weighted by the number of nominations their contacts already have, which is 1 at this stage. Thus, a contact with many nominations will be considered more important than a contact with only few nominations. The process is repeated such that [an] individual cumulates nominations every new round . . .. After a while, individuals are ordered in the function of their cumulated number of nominations; more central individuals having cumulated more nominations. (Pp 199-200).

They normalize the measure (at this stage referred to as C_{CN}) by the level of nomination activity within the component of interest (a measure of the rate of growth of the cumulated nominations), yielding a new measure, C'_{CN}. Finally, they improve the discriminatory power of the score for each actor by multiplying it by its component size, yielding C''_{CN}.

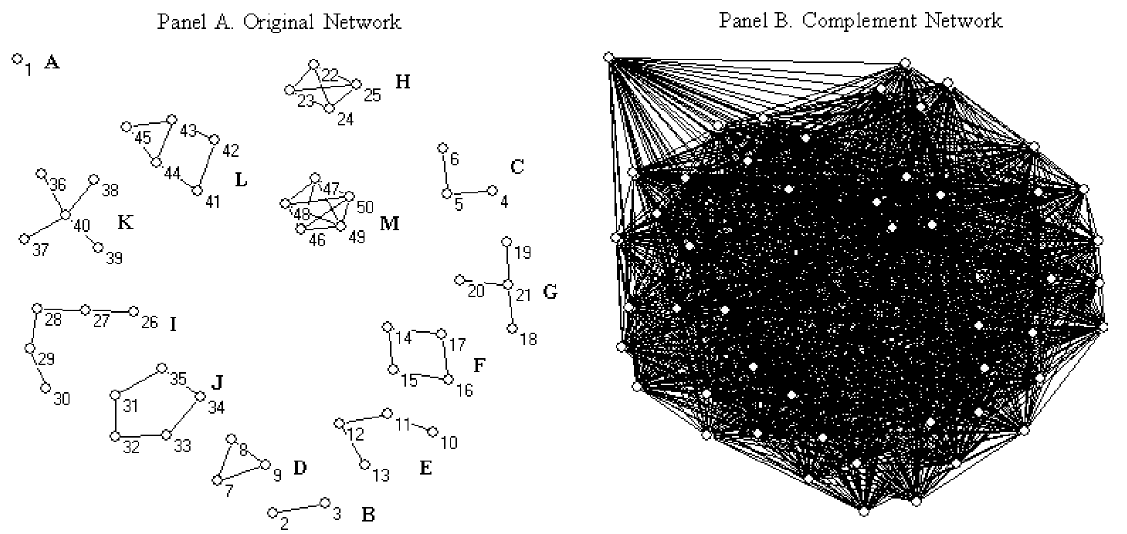
The application of Poulin et al.'s (2000) measure to a 50-person contact network is shown in Table 1, which is discussed in greater detail in the section on discriminatory power. The network is sparsely connected, and contains multiple autonomous subgroups of varying sizes, as shown in Panel A of Figure 1 (see Poulin et al. for a more visually organized layout of the network). The complement of this network, which is exceedingly busy and difficult to comprehend, is depicted in Panel B.

Despite the usefulness of the Poulin et al. (2000) measure for overcoming the problem of disconnectedness, it suffers from a lack of comparability and interpretability.[2] One problem is that the comparability of the measure in various networks is questionable. It is difficult to tell what is a "high" or "low" centrality score in this scheme. That is, the measure does not appear to be standardized within a certain range because its theoretical maximum has not been determined. [3] Relatedly, C''_{CN}

[2] See Poulin et al. (2000) for a detailed discussion of the limitations of the other measures.

[3] I thank Marie-Claude Boily and Robert Poulin for providing clarification of this point in a personal communication.

does not permit direct interpretation. The measure provides little language that can be used to discuss the relative centrality of one point versus another. Overall, while cumulative nomination mapping may be a useful and computationally convenient tool for examining disconnected networks it is neither comparable across disconnected and connected networks nor substantively interpretable.



Note: The network appearing in Panel A is from Poulin et al. (2000), which includes a clearer portrayal of the network and its components. In these panels, nodes are in fixed positions, determined by a spring embedding algorithm in NetDraw (Borgatti 2002). For example, the node in the upper left hand corner of Panel A (node 1) is the same as the node in the upper left hand corner of Panel B. Panel A provides both node labels(numbers) and names of the components in which the nodes appear (bolded etters,appearing to the right of the components). Node and component labels are not included inPanel B due to lack of space.

Figure 1. A Disconnected Network of 50 Actors, and its Complement

Below, I propose a method of calculating a closeness centrality measure which applies to actors in both connected and disconnected symmetric networks. This new measure is based on Freeman's (1979) original closeness centrality index, but it includes information about how an actor is *not* connected to others to infer its closeness centrality with respect to the entire network. In effect, this method generates a value representing the extent of disconnectedness in a network, which can be used to weight an actor's centrality within connected components. In the next section, I describe how information concerning an actor's disconnectedness can be generated and analyzed using standard network methods.

Complement Weighting

Examining the connections that *do not* exist in a network is potentially as interesting and useful as examining the connections that *do* exist. This idea, as applied to directed networks, is mentioned briefly by Wasserman and Faust (1994):

> . . . the complement of a digraph might be used to represent the absence of a tie, or as *not* the relation. For example, in the digraph representing the relation of friendship the arc $< n_i, n_j >$ means *i* "chooses" *j* as a friend. In the digraph representing the complement of the relation of friendship, the arc $< n_i, n_j >$ means *i* "does not choose" *j* as a friend. (P. 135.)

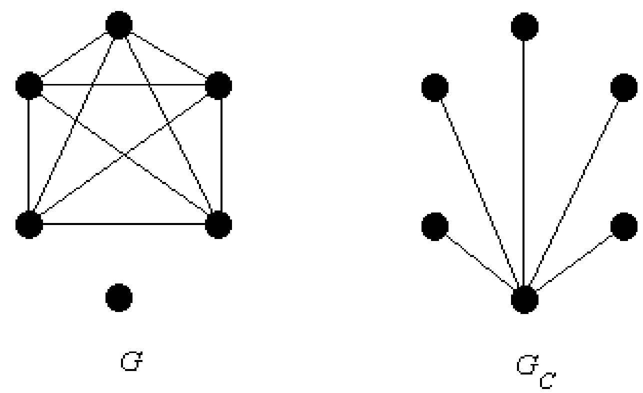


Figure 2. A Disconnected Graph, G, and its Complement, G_C.

In other words, the complement is a network of non-existent ties among actors. Thus, G_C has the same number of nodes as G, but has the exact opposite pattern of ties. If actor i is connected to actor j in an undirected network G, it is not connected to j in G_C. Unfortunately, the above passage from Wasserman and Faust (1994) is the most in-depth discussion of the complement that I could find in current social network research. Possibly because it is simply the "opposite" of a given network, the properties of the complement have not been fully explored. However, as we will see, this very fact makes the complement useful for overcoming limitations in G with respect to at least one unique network measure—actor closeness centrality. Figure 2 provides a clear example of the relationship between a given disconnected network, G, and its connected complement, G_C.

An important point is that, *if a symmetric network is disconnected, its complement will be connected*, because any isolate (or groups of disconnected actors) will have ties to *all* actors in other components, linking those actors together indirectly. Other isolates or actors in other components will have the same pattern of ties, linking them indirectly to each other. Applying this idea to the problem of calculating actor closeness centrality in disconnected networks, one can work backward from knowledge concerning which actors are and which actors are not central in the pattern of *non-existing ties* in a network to determine who is not and who is, respectively, central in the pattern of *existing* ties in a network. As I will show, one can calculate actor closeness centrality for nodes in all networks, including disconnected ones, by considering the extent to which actors contribute to a network's overall disconnectedness, and using that value to weight their within-component closeness centrality scores.

Obtaining the Complement Graph

Obtaining G_C is easily accomplished using matrix algebra. We simply solve:

$$G_C = 1 - G,$$

where

G_C = The $n \times n$ adjacency matrix of the complement of the disconnected graph;

1 = An $n \times n$ matrix containing all ones;

G = The adjacency matrix of the disconnected graph.

In a binary matrix, this operation effectively transforms 0s into 1s, and all 1s into 0s, since 1 - 0 = 1 and 1 – 1 = 0. Thus, this method works for undirected as well as directed networks. Any statistical program capable of solving matrix algebra expressions can generate the complement matrix with ease.

Complement-Weighted Centrality

The idea behind a complement-weighted centrality measure is to adjust observed closeness among connected actors by non-closeness among all actors. First, we calculate Freeman's (1979) centrality index for actors within connected components (see above), and set those values aside. Next, we evaluate the distance relationships among actors in the complement. The distance matrix for G_C can be obtained relatively easily using network analysis programs (e.g., Borgatti et al. 2002). The complement's distance matrix allows one to consider how close actors are to each other in the "opposite" reality. If an actor, *i*, is not reachable to an actor, *j*, in *G*, *i* is reachable to *j* in the connected complement, G_C. Distance in the complement represents what we might refer to as anti-distance, or distance to others given the exact counterfactual of the reality we observe in the original network. The structure of an anti-distance matrix, as derived from the complement, is unique and cannot be determined simply by reversing distances in the original networks of ties. It is this pattern of anti-distances that I use to derive weights for observed closeness among connected actors.

Recall that Freeman's (1979) closeness centrality measure is calculated as the inverse of the sum of the distances from actor *i* to all the other actors in the original network, *G*, normalized by *i*'s component size. Likewise, to obtain the complement-weighted measure, C_{CW}, I first calculate the inverse of the sum of the *anti*-distances for each actor, given in the complement's distance matrix. Those in small components in *G* will be more central (less anti-distant) in G_C, so I normalize the inverse of *i*'s anti-distances to others by multiplying it by the number of actors outside of *i*'s connected component in *G* (because distances to these persons will always equal 1 in the complement). Theoretically, an actor retains centrality status in *G* by being non-central in the complement, G_C. If *i* is central in this counterfactual reality, which presents the structure of non-connectedness, then *i*'s centrality in *G* should be adjusted downward to account for *i*'s actual disconnectedness. Because the weight should be a relatively low number for cases that are disconnected in G_C, I subtract the normalized complement centrality measure from 1 before using it to weight Freeman's measure. The final step is to multiply this complement-derived weight by Freeman's measure of centrality. Thus, the formula for the complement-derived closeness centrality index for a given actor, *i*, is:

$$C'_{CW}(n_i) = \left(1 - \left(\left[\sum_{j=1}^{g_C} d_{G_C}(n_i, n_j)\right]^{-1} (g_C - g(n_i))\right)\right) C'_C(n_i)$$

where

> g_C = the number of nodes in G_C, the complement of *G*;
>
> $d_{Gc}(n_i, n_j)$ = the distance between n_i and n_j in G_C;
>
> $g(n_i)$ = the number of nodes in *i*'s component in *G*; and
>
> $C'_C(n_i)$ = Freeman's within-component closeness centrality score for actor n_i.

This formula makes the complement-derived measure comparable to Freeman's (1979) measure for actors in connected networks. We can interpret a complement-weighted closeness centrality value for any given actor, *i*, as the closeness centrality of *i*, adjusting for the non-closeness of *i*. Freeman's centrality measure for actors in connected networks can be interpreted in the same way. Thus, C'_{CW} provides a way of comparing the centrality of actors in connected and disconnected networks against each other.

Table 1. Summary Statistics for Nodes in the Disconnected Network Pictured in Figure 1.

Node	Comp. Size	C'_C	Rank (C'_C)	C''_{CN}	Rank (C''_{CN})	C'_{CW}	Rank (C'_{CW})	Node	Comp. Size	C'_C	Rank (C'_C)	C''_{CN}	Rank (C''_{CN})	C'_{CW}	Rank (C'_{CW})
1	1	.000	9	.020	18	.000	12	26	5	.400	8	.183	13	.040	11
2	2	1.000	1	.080	17	.040	11	27	5	.571	6	.317	6	.067	7
3	2	1.000	1	.080	17	.040	11	28	5	.667	4	.366	3	.078	4
4	3	.667	4	.127	16	.040	10	29	5	.571	6	.317	6	.067	7
5	3	1.000	1	.180	14	.078	5	30	5	.400	8	.183	13	.040	11
6	3	.667	4	.127	16	.040	10	31	5	.667	4	.300	7	.078	4
7	3	1.000	1	.180	14	.078	5	32	5	.667	4	.300	7	.078	4
8	3	1.000	1	.180	14	.078	5	33	5	.667	4	.300	7	.078	4
9	3	1.000	1	.180	14	.078	5	34	5	.667	4	.300	7	.078	4
10	4	.500	7	.160	15	.040	11	35	5	.667	4	.300	7	.078	4
11	4	.750	3	.259	9	.074	6	36	5	.571	6	.250	10	.057	8
12	4	.750	3	.259	9	.074	6	37	5	.571	6	.250	10	.057	8
13	4	.500	7	.160	15	.040	11	38	5	.571	6	.250	10	.057	8
14	4	.750	3	.240	11	.074	6	39	5	.571	6	.250	10	.057	8
15	4	.750	3	.240	11	.074	6	40	5	1.000	1	.500	1	.151	1
16	4	.750	3	.240	11	.074	6	41	5	.667	4	.283	8	.078	4
17	4	.750	3	.240	11	.074	6	42	5	.667	4	.283	8	.078	4
18	4	.600	5	.185	12	.048	9	43	5	.800	2	.419	2	.108	3
19	4	.600	5	.185	12	.048	9	44	5	.800	2	.419	2	.108	3
20	4	.600	5	.185	12	.048	9	45	5	.667	4	.338	4	.078	4
21	4	1.000	1	.320	5	.115	2	46	5	1.000	1	.500	1	.151	1
22	4	1.000	1	.320	5	.115	2	47	5	1.000	1	.500	1	.151	1
23	4	1.000	1	.320	5	.115	2	48	5	1.000	1	.500	1	.151	1
24	4	1.000	1	.320	5	.115	2	49	5	1.000	1	.500	1	.151	1
25	4	1.000	1	.320	5	.115	2	50	5	1.000	1	.500	1	.151	1

Note: Measures for C''_{CN} and C'_C are from Poulin et al. (2000).

Properties of the Complement-Derived Centrality Measure

One of the most useful properties of C'_{CW} is that it can be calculated for any node in any symmetric network. Its use is limited to neither connected nor disconnected networks. When a network is connected, the complement-derived weight will always equal 1, because there are no outside-component nodes in the parenthetical expression. Thus, *when a network is connected, the complement-weighted closeness centrality measure will equal Freeman's (1979) within-component actor closeness centrality measure*. In this section, I describe some of the additional properties, including the range and discriminatory power of the complement-weighted centrality measure, C'_{CW}. I also discuss its interpretation and comparability across networks.

Range

C'_{CW} is attractive because it is standardized and interpretable. Isolates receive a centrality score score of 0, and the centrality score of nodes that are maximally connected within their components depends on the degree of disconnectedness elsewhere in the entire network, *G*. In the network shown in Figure 1, Panel A, the largest observed complement-weighted centrality value is .151. This centrality score is modest—despite the fact that the nodes that receive that score (nodes 40, 46 - 50) are maximally connected within their components—because of the extensive disconnectedness characterizing the rest of the network. As connectedness within an actor's component (in an otherwise disconnected network) increases, that actor's centrality also increases, but can never reach a value of 1. In fact, *the measure only equals 1 when there are no isolates or separate components in the network*. This makes sense, because an actor should not achieve a centrality score of 1 unless it is directly connected to *every* node in a network. Imagine that this network contains one complete component of size 999 and one isolate. In this case, the centrality of any of the actors in the connected component would be .999 (not 1, as Freeman's index would indicate), because some of the possible ties (999 of them, to be exact) are non-existent in this network.

Table 1 (above) shows how this measure applies to the disconnected graph given in Poulin et al. (2000), and Figure 3 plots them together on a scatter plot. As you can see, the measures are closely related (r = .97), but are slightly different in several respects. These discriminatory differences are described below.

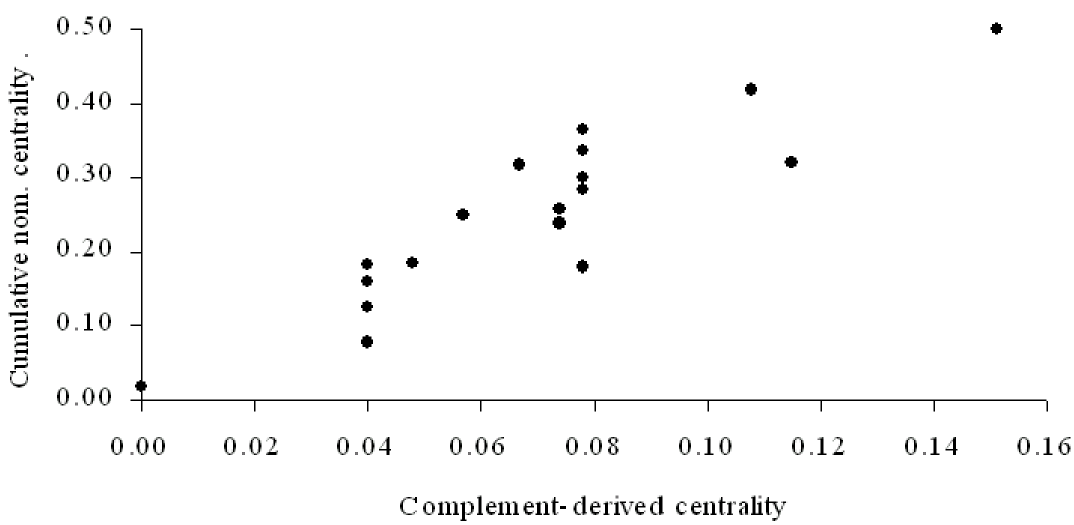


Figure 3. Scatterplot of Poulin et al.'s (2000) Centrality Measure against the Complement-Weighted Closeness Centrality Measure for a Disconnected 50-Actor Network

Discriminatory Power

Compare Freeman's (1979) C'_C, Poulin et al.'s (2000) C''_{CN}, and the complement-weighted centrality measures shown in Table 1. The differences in the node centrality ranks generated by each one are notable. For instance, while nodes 2 and 3 take on the maximum possible centrality values when using Freeman's measure within components, they have the 11th and 17th highest centrality values, respectively, when using the cumulative nomination mapping and complement-weighted methods.[4] This is a direct result of bringing the measure out of the within-component context.

One of the most striking (and I argue, useful) aspects of the complement-weighted measure is that the centrality values are small given the 0 - 1 range, and thus the differences among the raw complement-weighted values obtained for this network are small (ranging from .000 to .151). This is a direct result of the level of disconnectedness in the rest of the network as experienced by each node. After all, this is a 50-node network, containing only 51 lines, and we are dealing with components that are small relative to the total number of nodes in the overall network. This is an attractive property of C'_{CW} because it forces us to consider the overall properties of the network in determining an actor's centrality.

Because this method is based on geodesic distances, the relative centrality rank of a given node within its component is the same as indicated by Freeman's (1979) measure. Poulin et al.'s (2000) C''_{CN} does not always correspond to C'_C within components. For instance, C'_{CW} assigns the same centrality to nodes 41, 42, and 45, whereas 45 takes on a larger C''_{CN} value than that assigned to 41 and 42. Thus, while the complement-weighted method also considers disconnectedness in a network, it retains the emphasis on geodesic distance found in classic treatments of centrality.

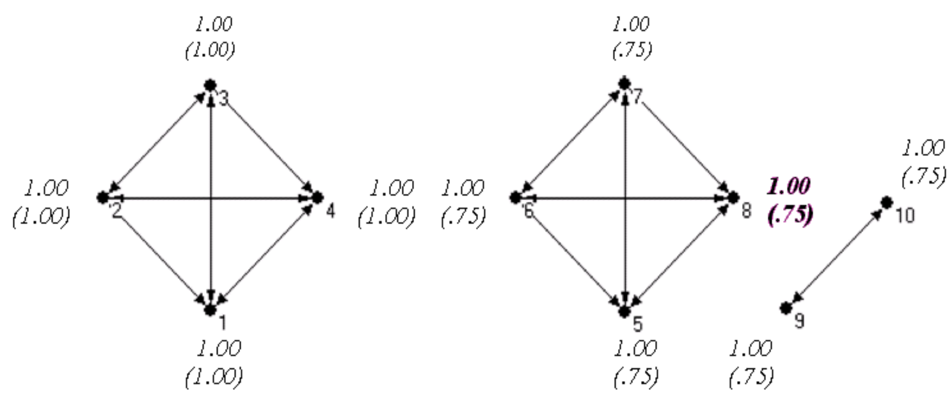
There are some other discriminatory differences between the complement-weighted centrality measure and C''_{CN}. Both measures allow nodes within larger components to take on values that are lower than some nodes in smaller components. For instance, both measures indicate that nodes 10 and 13 are less central than nodes 7 thru 9, despite the fact that the former two are in a larger component. However, the complement-weighted method allows this to happen more frequently. For instance, according to C'_{CW}, 5 is more central than 30, whereas it is less central according to C''_{CN}. This occurs because the complement-weighted method places greater emphasis on *closeness*. Node 30's lack of closeness to others within its component is weighted more heavily than its general connectedness to them, while node 5's closeness to the others in its component is weighted more heavily than its lack of connectedness to others in the network.

The final difference in the discriminatory powers of C'_{CW} and C''_{CN} is revealed in an examination of centrality of nodes in component *J* (31 thru 35) versus that of node 28. C''_{CN} gives more weight to node 28 (by .066). Freeman's (1979) measure does not discriminate between nodes 31 thru 35 and node 28, and neither does C'_{CW}. The average distance of node 28 to others in component *I* is the same as those in *J* with each other (avg. = 1.5) and at the same level of consistency (captured by the standard deviation, which is .578). The only difference is that node 28 binds the other nodes in *I* together, whereas those in *J* are similarly connected to each other. If we were to impute a direct link between nodes 26 and 30, components *I* and *J* would be identical. Thus, C''_{CN} gives weight to the structural role of node *28 relative to the other nodes within I* (resembling more of a betweenness centrality measure), which is somewhat irrelevant if what we are interested in is its geodesic closeness centrality.

[4] The reader should note that the rank scales are different for each measure.

When to Use the Complement-Weighted Centrality Measure

Versus C'_C Calculated within Components. As I will show, the choice between Freeman's (1979) closeness centrality measure, C'_C, and C'_{CW} hinges on whether one is interested in the local or universal conditions of nodes. C'_C is calculated as the inverse of the sum of the distances between *i* and the actors to whom *i* is connected divided by the number of other actors in *i*'s component. Because it is based on geodesic distances, the measure cannot be calculated for disconnected networks. C CW is appropriate when one wishes to calculate actor closeness centrality in any network, connected or disconnected. The complement-weighted method can be used for comparisons between actors across components, disconnected networks, connected networks, and even between a node in a connected network and a node in a disconnected network. The measure can be compared across components/networks of different sizes and levels of disconnectedness. It has the same range as Freeman's centrality index. In fact, C'_C is a special case of C'_{CW} , occurring when an actor is at least indirectly connected to all others in a network. C'_{CW} simply has the added benefit of allowing us to incorporate a node's lack of connectedness in determining centrality in disconnected networks.



Note: C_{CW} values are presented in parentheses below C_C values

Figure 4. C_C and C_{CW} Centrality Scores for a Connected and a Disconnected Network

Figure 4 compares two simple networks: one connected network made up of four actors and one disconnected network made up of six actors (split up into a maximally connected component containing four actors and one dyad). C'_C can be calculated for actors in both networks—though it must be calculated within components in the disconnected network—and is presented next to each node. C'_{CW} is calculated for actors in both, and is presented in parentheses under C'_C . As you can see, the complement-weighted measure conveys the centrality of a given actor, *i*, that is due to how close *i* is to actors to whom *i* is connected and relative to its level of disconnectedness to everyone else in the network.

This complement-weighted method allows us to improve our understanding of the extent to which actors can independently access all other actors in a network, which takes us away from mere local structural context. We can see that actors 1 and 5 have direct and indirect access to the resources of the same number of actors (four) at the same distance (one step away from the other three actors). To make the comparison across networks, one simply uses C'_{CW} for all actors. Using this measure, we see that actor 1 has more independent access to the resources held by others in his or her network than actor 5 because actor 5 also must deal with not having any access to the resources of actors 9 and 10.

Actors 9 and 10 have relatively little access independence, which is reflected in the relatively low centrality scores. With C'_C, we can only assess centrality relative to others in one's own component. It is not as useful when we are considering conditions across subgroups. Therefore, C'_C values calculated within components might be more appropriate for studying context-specific conditions, such as relative deprivation (Davis 1959; Gurr 1970; Runciman 1966), whereas C'_{CW} is better for understanding overall conditions.

Versus C''_{CN}. The centrality measure proposed by Poulin et al. (2000) involves a cumulative mapping technique, which weights the number of nominations an actor receives from contacts by the number of nominations those contacts receive, and subsequently weights those values by the amount of nomination activity in the component. Making a choice between the complement-derived C'_{CW} and C''_{CN} boils down to the relevance of the measures to one's substantive question. Both measures are useful because they overcome the problem of disconnectedness. C'_{CW} is more appropriate for those interested in the combined effects of within-component closeness and disconnectedness outside of components, but again with less emphasis placed on the local context.

C''_{CN} is perhaps most useful when one is interested in determining the effectiveness of a given node in distributing resources to others (though not necessarily in a shorter time frame). *C''_{CN} gives more weight to general connectedness, whereas C'_{CW} is more concerned with closeness*. This property also could have implications for diffusion. Closeness is important when the accuracy of a message is crucial, particularly when message accuracy breaks down with each successive relay. In such a case, the message is best left in the hands of an actor who can insure that the information is diffused using the *minimum number of steps* possible. In this case, the choice of node 36 over node 27 in Figure 1, for instance, is clear, since information beginning with node 27 takes three steps to reach node 3 (requiring both nodes 28 and 29 to "forward" the message along). Starting with node 36, though, the remaining nodes in component *K* can receive the message in two steps, at most. A logical implication is that C'_{CW} is perhaps better suited for analyzing a network where the quality of the information being relayed decays substantially with each step. This property of centrality might be relevant when studying diffusion among nodes that are inaccurate or prone to malfunction, or when the information conveyed is intimate in nature, thus translating best among intimate contacts. The use of C''_{CN} is advisable where we assume that all nodes are equally efficient and accurate, and where the researcher is concerned about modeling information relay to as many others as possible without constraints on time or rate. Relatedly, C'_{CW} is probably the better choice if we are interested in evaluating the influence status of a node on others, where independence from others' control over information flow in a given structure is relevant (see Freeman 1979).

Most importantly, it does not appear that the cumulative nomination mapping technique generates estimates of centrality that are comparable across networks. I have already shown that C''_{CN} is not comparable across networks because it assigns values based on the average centrality observed within a network. This average will vary from network to network. Thus, to say that a node has a higher C''_{CN} value in one network than a given node in another does not really convey to us which actor is better off overall, as they are evaluated relative to others in their respective networks.

CONCLUSION

The complement of a disconnected network can be employed to overcome problems with calculating measures related to closeness. Measures that rely on geodesic distances are limited to connected networks because the theoretic distance between two disconnected nodes is not defined. This paper describes how an existing and popular closeness centrality measure for connected networks—Freeman's (1979) measure of actor closeness centrality—can be extended to disconnected networks by adjusting for non-connectedness. The new measure proposed here, C'_{CW}, has several attractive properties. For one, it ranges from 0 to 1 and is comparable across connected and disconnected components and networks. C'_{CW} can be interpreted as the amount of closeness centrality that an actor, *i*, has in a network given the amount of disconnectedness in the network.

The method described here provides one way of circumventing the problem of disconnectedness while retaining the basic principles behind the measure of interest. The complement provides us with a snapshot of the counterfactual of an observed relational reality, which makes it attractive as a weighting tool. It is best suited to issues involving universal access to resources in a network other than local access within connected components.

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Conceptual and Empirical Arguments for Including or Excluding Ego from Structural Analyses of Personal Networks

Christopher McCarty
Bureau of Economic and Business Research, University of Florida, Gainesville, FL

Amber Wutich
Department of Anthropology and Bureau of Economic and Business Research, University of Florida, Gainesville, FL

The structural properties of personal networks are potentially fruitful variables for explaining differences in attitudes, behaviors and conditions across individuals. When researchers apply structural measures to personal network data, they must decide whether to include or exclude ego from the adjacency matrix. This research note discusses several conceptual and empirical issues that should be considered in making that decision.

Most personal network research over the past forty years has focussed on network composition (summaries of alter attributes) rather than network structure (analysis of the pattern of ties between alters). While compositional analyses yield vital information about the network and how it impacts the respondent, structural properties of networks offer a unique perspective and are a worthwhile pursuit (McCarty, 2002). As researchers create new software that makes it easier to construct studies that collect alter-to-alter tie evaluations from respondents (the basis for structural analyses of personal networks), structural features will add to the set of network features that are used to explain respondent attitudes, conditions, and behaviours.

There is, of course, an established tradition of constructing egocentric networks within sociocentric networks. For example, Burt's notion of structural holes is a concept derived from looking at the egocentric network of individuals within a corporate setting (Burt, 1992). While this approach is useful, it is vastly different than the case of personal networks where the list of alters is constrained only by the existence of a link to ego and may span across many groups. We suggest that personal network research should be used primarily to determine the effects of ego's network on ego, or to compare differences in interaction patterns across egos.

Given the novelty of the structural approach in personal network studies, we expect questions to emerge over how personal network data and structural measures should be handled. For instance, when analysing personal network structure, particularly for personal networks with more than 30 alters, researchers will have to determine whether or not ego's ties to her alters should be included in the adjacency matrix that is the input for structural analyses. In this paper, we will explore the conceptual and empirical issues that go into making this decision.

CONCEPTUAL ISSUES

Analyses of whole (sociocentric) networks, though often complex, are conceptually straightforward. A whole network is a group of actors who, to the outside observer, appear more likely to interact than a randomly selected group of actors of the same size. For example, we expect that the 25 members of a drama club in a high school will have more opportunity and reason to interact than 25 randomly selected students from the entire high school population. Network structural measures applied to the drama club are likely to show patterns of interaction where the measures applied to the group of randomly selected students will not.

The conceptual issues surrounding personal networks are more difficult. Nobody considers the analysis of the composition of personal networks to be problematic. We understand how the proportion of a person's network that is female, White, or provides emotional support, or the average age and strength of tie of alters, might affect that person's attitudes, conditions, and behaviors. It is less clear whether the network structure derived from the assessed interactions between alters is meaningful. In other words, is the structure of a personal network of any practical importance?

The interaction within a social group where membership is defined by having some relationship to a single person is meaningless, unless the impact on or of that person (ego) is somehow involved. One may know 300 people, but those 300 people may span large geographic and socioeconomic distances.

Without reference to ego, they are conceptually somewhere in between the examples of the drama club and the random selection of students given above. They are more likely to interact than a random sample of people, but those interactions are hardly interesting or meaningful. This may seem an obvious point, but we believe that structural results should be interpreted only in terms of how the network affects ego or how ego affects the network. To interpret them as a network with innately meaningful structure, as in a sociocentric network, assumes that members perceive the personal network to be social group – an assumption not generally borne out by the data.

The approach researchers use to include ego in data collection and analysis should be determined by the needs of the research question. There are three ways to include ego in the analysis. First, one can leave ego out of the adjacency matrix. Second, one can include ego as a network member, forcing a tie from ego to all other members. Finally, ego can be included as a member of the network, using a tie definition that allows for null ties between ego and each alter. We will discuss conceptual issues involved in each of these in turn.

Leaving ego out

The first option is to exclude ego from the adjacency matrix. This is, in fact, the approach suggested by Scott (1997). At first glance, conducting analysis on a personal network without ego included may appear strange. It is, after all, ego's network and would not exist if not for ego. However, the social environment in which we live is, for many things, not brokered by us, even though we are at its center. One obvious example is gossip. Gossip tends to transfer within the network of people we know without our control over that flow. It can affect us without our knowledge, facilitation, or control.

Another example is social support. Consider a person who is elderly and in need of daily home care. The structure of that person's informal support network may determine if such care is administered informally, by network members, or by strangers, through some formal home care organization. The support network may not be brokered by the elder concerned, even if he is at least partially responsible for its structure. In cases where ego is seeking support, she may not be driving the avenues of delivery of that support. For many things ego is a passive receiver of information and resources from the network. The structural pattern of the network without ego's influence provides a unique picture of the social material ego has to form their attitudes, conditions, and behaviours.

Including ego, with forced ties

Consider the second option, that is, to include ego in the network but force a tie to all alters. Any time the same prompt is used to elicit ego's network and to determine alter-alter ties, ego must be linked to each alter. In such a case, null values cannot exist between ego and the alters. For example, if the researcher asks ego to list every person she conducts business with, and then asks ego if each pair of alters conduct business together, then ego would necessarily be tied to every alter in the network. Similarly, when the prompt used to elicit alters is subsumed by or included in the definition of ties used to evaluate connections between them, ego will always be linked to each alter. For example, if the researcher asks ego to list every person she conducted business with in the last month, and then asked ego if each pair of alters had conducted business together in the last year, then ego would necessarily be tied to each alter.

Connecting ego to every alter is a very intuitive approach since we usually are interested in using the same kind of tie to elicit ego's network and to find out about interactions within that network. Given the compositional analysis approach, we are used to thinking of personal networks as stars. It seems natural that adding ties between alters should just result in an appended star structure.

By virtue of the fact that ego is now tied to all alters, ego will affect network structure more than any other alter – perhaps an unintended consequence. The focus is no longer on how the network affects ego, but instead on how ego affects the network. However, a personal network is not an independently existing social group whose structural patterns we want to predict.

A primary reason for collecting personal network data is to understand how the network impacts ego. By including ego, this impact has largely been removed because we can now only analyze issues where ego's overwhelming influence is a valid question. There are examples of this. If we imagine ego being the focal point of some special knowledge or condition, we might want to know the impact of ego on all of the alters we elicit, given the pattern of relations between those alters. For instance, if ego has a condition that is typically transmitted in every instance of face-to-face contact, such as a highly infectious disease, we can imagine that understanding the structure of face-to-face interactions in ego's personal network, and how structures differ across egos, might be of great interest to some researchers.

Including ego, allowing null ties

The third option is to include ego, but allow for null ties between ego and some subset of alters. This seems odd at first, but it may be the most appropriate approach to take to compare patterns of interaction across egos. By allowing the tie to be null, we separate the elicitation task from the tie definition. We can think of many examples where ego knows someone, but has no tie connection. For example, we may choose to do an analysis where we ask ego to list the 50 people he knows best, and then to assess the likelihood of each pair of alters discussing politics. In this case, there may be ties between alters where politics are discussed (e.g. father and son), but ego is unlikely to discuss politics with either of those alters. Again, the focus is now not on how this network impacts ego, but on how ego, as any other alter, impacts the network. The tie definition should reflect that.

We can imagine some cases where this approach may be quite useful. Again consider an epidemiological study, this time examining the personal networks of HIV positive IV drug users. In such a case, we may be interested in using instances of needle sharing or sexual relationships to define ties between alters. Although ego may know the people in his network, ego probably does not share needles or have sex with all of them. In this case, we can examine how the potential for the spread of HIV is mediated by structural variability in the personal network. We might be able to design interventions that take this network structure under consideration. Under this scenario, ego plays a vital role in the structure of the personal network and must be included, but allowing for null ties.

EMPIRICAL ISSUES

Aside from the conceptual issues, the application of structural measures to personal networks presents empirical problems as well. First, we must keep in mind that we are asking respondents to report on the nature of the relationship between alters. We know that respondents can assess, in general terms, whether their network alters know each other. This is demonstrated by the sensible groupings of alters that respondents can identify using network visualizations and personal network adjacency matrices. If respondents could not make these assessments, the resulting structural patterns they see through network visualizations would appear arbitrary. Further, McCarty (2002) found respondents' alter-alter tie evaluations to be reliable when asked to reassess tie evaluations they had already made.

We are less confident in the ability of respondents to assess more subtle relations between alters. For example, respondents may be able to assess the strength of relationship between alters as non-existent, weak tie and strong tie, but may not be able to assess those ties on a five or ten point scale. Since the data quality is of such crucial importance in network studies, where even a few missing ties could significantly alter network structure, we recommend proceeding cautiously with such studies. The ability of respondents to make these evaluations would vary depending on the size of the personal network and their familiarity with their alters. If the elicitation were limited to close family, the respondent may be able to provide more detailed information. However, it is not enough for respondents to report accurately on some alter-alter ties. They must be able to report accurately on all of them. The level of knowledge required to make that assessment must be driven by the tie the respondent knows the least about.

We are cautiously optimistic about the prospect of personal network researchers finding ways to study subtle or asymmetrical relationships with relatively small personal networks or networks where all of the alter-alter ties are extremely well-understood by ego. For instance, if we elicit ego's network of closest family members and how much money alter A has lent alter B in the last year, we may be able to ascertain a fairly accurate picture of the family loan network, using asymmetrical, interval-level data.

Because of these limitations on what respondents can reasonably report, we believe that the typical adjacency matrix for a personal network will be symmetric, not directed, and will have at most three levels of tie strength (no tie, weak tie, strong tie). This precludes the use of some structural measures. However, others are still valid. We will proceed with a discussion of how structural measures could be used to study adjacency matrices that exclude ego and adjacency matrices with ego included, forcing ties to all alters In terms of execution, there is no difference between adjacency matrices that exclude ego and those that include ego but allow for null ties between ego and alters. Therefore, we will discuss the feasibility of using nine common network measures for adjacency matrices that do and do not force ties between ago and all alters.

Density is the proportion of existing ties out of all possible ties. It is valid for all approaches. Adding ego and forcing a tie increases the number of ties by the number of alters over the no ego approach.

Degree Centrality for a given alter is the number of alters they are directly connected to. It is valid for all approaches. Adding ego and forcing a tie increases the point centrality of each alter by one compared to the no ego approach.

Closeness Centrality for a given alter is the inverse of the distance from that alter to all other alters. Personal networks can (and often do) have network isolates. Closeness centrality is not meaningful with unconnected graphs (the presence of isolates or components). Ego must be included for closeness to be reliably calculated. While we may be able to calculate closeness centrality for some respondents, when we are comparing across respondents we cannot count on a valid closeness centrality result.

Betweenness Centrality for a given alter is the number of geodesics (shortest paths) between all alters that the alter is on. Although this is a valid measure when ego is included and a tie is forced, it becomes strongly correlated with degree centrality. In a graph without ego, there is opportunity for alters to serve key bridging roles. When ego is included they, by default, lie on the most geodesics, except when alters have direct ties.

Components are connected graphs within a network. When ego is included and a tie is forced, the graph is by definition connected and there can only be one component.

Cliques are maximally complete subgraphs. With ego networks, the difference between one clique and another is often the substitution of a single alter. Given that ego is automatically a member of every clique, the addition of ego and forcing a tie does not generally change the number of cliques. The same holds true for other measures in the same family (n-clique, n-clan, k-plex).

Core-Periphery attempts to identify a network core of alters who are all mostly connected. The procedure is less stringent in its definition of a subgroup than the clique routines and it results in only one core. Unlike the other procedures, the addition of ego may serve to bind groups that otherwise would not. Conceptually, this procedure may make more sense with ego included and forcing a tie to all alters as it defines the core group of people on which ego relies.

Structural Equivalence clusters alters together based on the structural role they serve in the network. Adding ego and forcing a tie adds an alter with what is usually a unique position, that is, they are connected to all alters. Adding ego does not change the structural role of the other alters.

Network Visualization routines are used to graphically depict the relations of nodes to each other. Although there are many algorithms for displaying network data, most will be affected the same way by the addition of ego and forcing a tie to all alters. Ego will be at the center of all connections. Like core-periphery, this may be a helpful anchoring for respondents who are being interviewed about their network. Figures 1 and 2 show a network of 45 alters collected in a recent study. It is visualized with Netdraw, the first excluding ego and the second including ego. The structures look very similar.

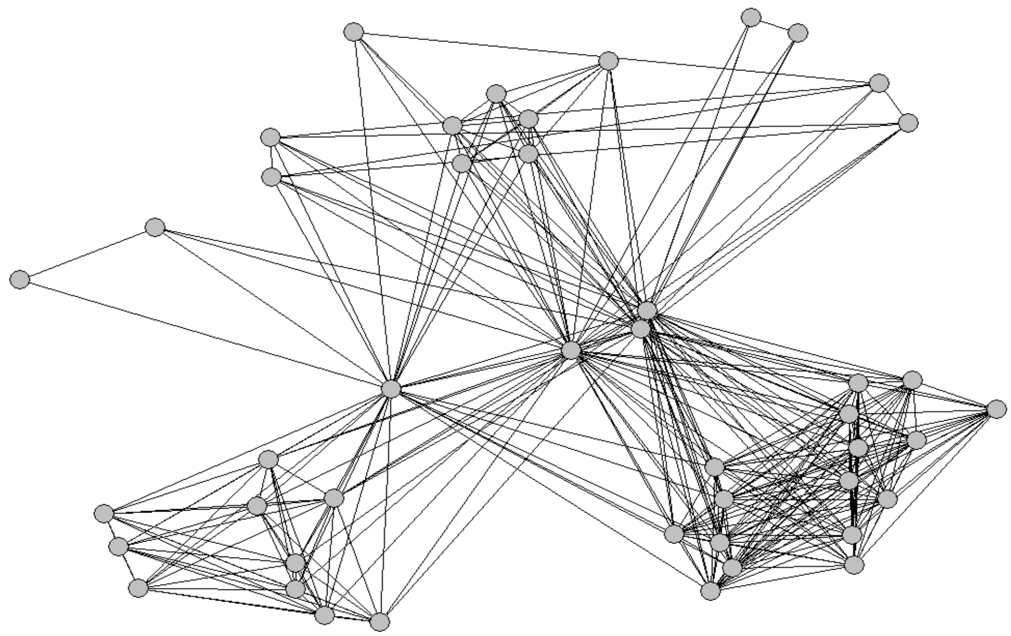

Figure 1: Network Visualization Excluding Ego

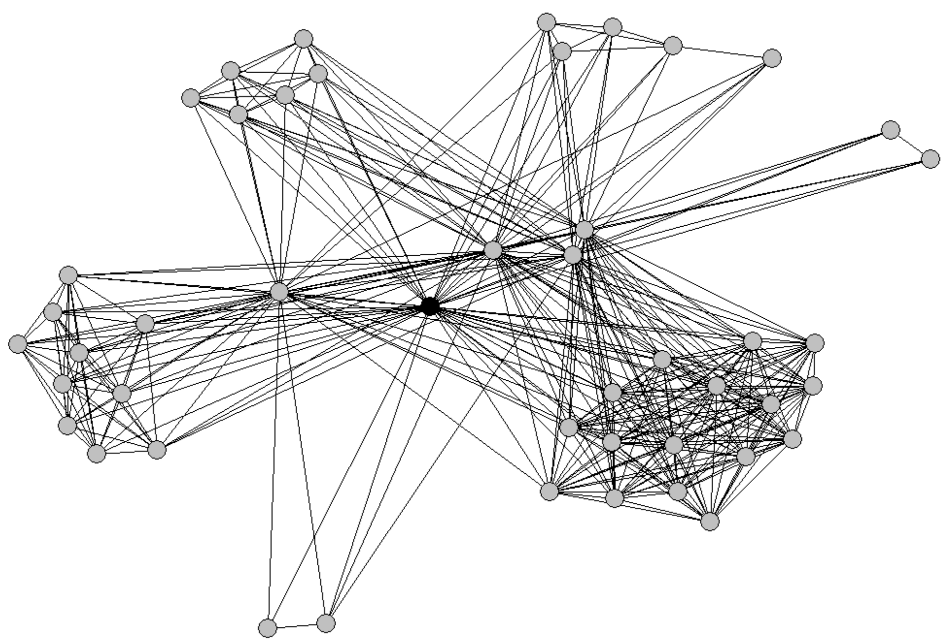

Figure 2: Network Visualization Including Ego and Forcing a Tie to All Alters

CONCLUSION

These conceptual and empirical issues can be summarized as follows. If we are interested in the impact of social networks on ego, then analyses should be limited to adjacency matrices that do not include ego. We should think of ego as a passive receiver of information and resources that are transmitted across the network. In this case closeness centrality, and any other measure that requires a connected graph, cannot be calculated.

If we are interested in the impact ego has in brokering their network, then we should include ego. We should think of ego as an active participant in information and resource exchange. Many of the structural measures will be functionally the same as the case where ego is excluded. If a tie is forced, components will be meaningless, and betweenness centrality will reduce to degree centrality.

Finally, we may be interested in how ego impacts their network, but using a definition that allows for null ties. The empirical issues are the same as those for adjacency matrices without ego, that is, closeness centrality cannot be calculated.

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Complete Network Analysis in Research of Organized Interests and Policy Analysis: Indicators, Methodical Aspects and Challenges[1]

Alejandra Real T.
Institute for Forest Policy and Nature Conservation, University of Goettingen, Germany

Nicolas D. Hasanagas
Institute for Forest Policy and Nature Conservation, University of Goettingen, Germany

This article aims at presenting advantages and weaknesses of complete network analysis in policy analysis and research of organized interests. Indicators (actor- and network-related factors) that have proven to be significant for power dimensions (trust, incentive giving and irreplaceability) will be presented. These have been derived from a policy research project in 2002. Advantages of a complete analysis of policy networks are the disclosure of latent structures, the operationalisation of power in policy arena, the measurement of policy impact of subjective factors (attitudes like radicalism, trustworthiness etc), and the "objective" bounding of the network. Challenges for future improvement are the relative "small size" of a network as a sample, the weakness of telephone queries, and the self-selection which characterizes the snowball sampling. Further questions could concern research on information, financial incentives, oligarchy and corruption.

1. INTRODUCTION

This article aims at presenting advantages of applying network analysis to policy research as well as weaknesses of this method which can be questions for future research and improvement. Indicators (actor- and network-related factors) that specify previous qualitative concepts and have proven to be significant for power dimensions (trust, incentive giving and irreplaceability) will be presented as basis for future applications. The actor-related factors interest researchers of organized interests, while the network-related factors can be useful for policy analysis. The operationalization of power is relevant to both areas.

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[1]Alejandra Real T., University of Gottingen, Institute for Forest Policy and Nature Conservation, Buesgenweg 3, 37077, Gottingen, Germany, Tel. +49-551-3913391, E-mail: areal@gwdg.de; Nicolas D. Hasanagas, Tel. +49-551- 393413, E-mail: nhasana@gwdg.de

Our conclusions are based on experience derived from a survey that was carried out in 2002[2]. General aim of this research was to find out actor- and network-related factors that influence the power status of an interest group in a network[3]. We will briefly present the network-related factors as well as certain actor-related factors which are not internal structures (e.g. multidisciplinary team) but rather depend on the network in which an actor participates (e.g. communication properties of an actor, behavioral aspects, partners). We are going to argue that the advantages of the complete analysis of policy networks are the potential of disclosing latent structures (e.g. oligarchy), the operationalisation of power in political arena, the measurement of policy impact of subjective factors (attitudes like radicalism, trustworthiness, information "importance"), and the "objective" bounding of the network. Challenges for future improvement are the relative "small size" of a network as a sample, the weakness of telephone queries (which usually is the only cost-effective technique), and the self-selection which characterizes the snowball sampling (complete network). Further questions and applications could concern research on information, financial incentives and corruption.

2. APPLYING COMPLETE NETWORK ANALYSIS TO POLICY ARENA

All contacts have taken place by phone using standardized query (see operationalized variables in appendix II). In each network, the first actor to be interviewed was selected randomly by internet or catalogues of environment-related conferences. The initial question was "please, mention an environmental issue of the last 2 years, where you were successful". And the next question was "please name all actors that you have contacted in the framework of this issue". Afterwards, we contacted and interviewed the actors named. This snowball technique permitted us to contact the whole network for each issue (appendix III). We conducted a snowball sample until the network was completely enumerated (no new actors named), and not simply until we reached a certain number of actors that we would consider to be sufficient. Thus, a complete network analysis has taken place.

3. OPERATIONALISATION AND INDICATORS

The main task of the empirical social research is the precise operationalisation of variables specified in Bryman (2001). Valid and reliable measures of these constructs were made which can be difficult when measuring latent constructs like trust. In that case researchers have the responsibility not only for the operationalisation (in our case formulation of the standardized queries) but also for the clear definition of the variables. The clearer the definitions and the more integrated in the social theory, the more objective and transferable knowledge they produce. Simultaneously, empirical researchers are also confronted with possible measurement error due to insincerity or ignorance stemming from subjectivity and misunderstanding (Krott & Suda 2001, p.7, 8). A solution to the insincerity problem can be approached by means of indirect indicators derived from qualitative interviews (e.g. our economic indicators). Error from ignorance or misunderstanding can be prevented by selecting interview partners with access to the relevant information and by previous testing of the query.

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[2] This survey has covered 12 issue networks consisting in total of 234 actors (public services, interest groups, enterprises, universities) in 8 European countries. This article aims to describe only the methodological aspect of this research and part of the results as example, but not the policy content of these issue networks. We only make clear that these are of environmental interest. Briefly, we mention these as follows: 1. Denmark: Certification of sustainable management of natural resources, 2. Finland: Certification of sustainable management of natural resources, 3. Spain: Certification of sustainable management of natural resources, 4. Germany- Bavaria: Eco-account, 5. Germany- Bavaria: Mapping of biotopes, 6. Sweden: Key biotopes, 7. Greece: Revision of constitution regarding environmental policy, 8. Sweden: Governmental forestry strategy, 9. UK- Scotland: Scottish forestry strategy, 10. UK- Scotland: Loch Lomond and Trossachs National Park, 11. Ireland: Provisional marketing services in natural resources, 12. Spain: Research project castanea.

[3] The initial hypothesis was that the power status of an organisation depends both on its own characteristics and on the characteristics of the policy network in which it is involved (Blom-Hansen 1997)

A basic mathematical entity for the following formulas is the link from an actor *i* to actor *j*. If there is a link (e.g., information exchange[4]) from actor *i* (e.g., forest service) to actor *j* (e.g., a certain environmental group), then this link is defined as:

$$Z_{ij} = 1$$

If there is no link in this direction ($i \to j$) then:

$$Z_{ij} = 0$$

A link (e.g. trust exchange) can also be valued: $Z_{ij} = 1,2,3...$

The total number of actors participating is defined as N.

The minimum, maximum and averages of all variables over all 234 actors and 12 networks are presented in appendix IV. The significance of each independent variable for each of the three power dimensions is presented in appendix V.

3.1 Dependent variable: power

The power (P) of each actor has been measured as a sum of trust that an actor gains, the (financial) incentives it offers and the irreplaceability that it is supposed by the other participants to have. Power was first measured in a 5-level scale (P=1 to 5) where 1 means no trust at all[5] and 5 means total trust (3), incentives (1), and irreplaceability (1)[6]. Afterwards, power was converted into a percentage variable (%) through the formula of "status" (Katz, 1953) (T) using special software for quantitative network analysis, "visone". The status illustrates an informal or formal hierarchy, which is based on power relations. The formula of "status" (formula 1) includes matrix multiplication:

$$T = aC + a^2C^2 + \ldots + a^kC^k + \ldots = (I - aC)^{-1} - 1 \qquad (1)$$

Where T is a matrix including the status values of all elements, C is the matrix presenting the real network (of power exchange), and a the value of the exchange z. In our case, a is not constant. Thus, this algorithm becomes more complicated and is practically calculable only by special software (e.g., "visone"). We also measured the status of each dimension separately (trust status, incentive-giving status, irreplaceability status).

The practical meaning of status is that, if an actor X gains power from an actor Y, the actor Y from an actor Z and an actor Z from an actor J, then the actor X gains indirectly power from the actors Y, Z

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[4] Other exchange relations we measured were: exchange of trust, recognition of irreplaceability, and incentives, namely the three dimensions of power. In 2.2.2 we have emphasized that in our analysis, power has been expressed though asymmetric relations: power is to concentrate trust, to give incentives and to be regarded by the others as irreplaceable (exchange of recognition). So, power cannot practically exist without (asymmetric) exchange. The information links can also visualise power centres: the most powerful actor imposes its own information as "important" and also controls to a large extent the communication. But information is a means to implement power rather than a power source (discussion to follow).

[5] P=0 has been not defined for technical and measuring-theoretical reasons; in "visone" (our network analysis software), 0 means "no relation". However, there is a relation of weakness, which should also be measured so that totally weak actors (P=1) are also included in status calculation. Otherwise, the whole network structure and the relative power position of all actors and the oligarchy would have been deformed. If we had defined P=0, it would have meant no existence of the actor of the network and this would be deceptive, because the actor, even with quite little power (P=1), still exists in the network. In other words, "weak participation" means for us more power than "no participation" at all.

[6] There are two equivalent medium situations:
- When an actor gains full trust (P=3) only
- When an actor gains incentive and irreplaceability (P=3) only

and J. In so far, actor X presents a certain specialization in this kind of exchange (in this case, an aptness in concentrating trust, incentive or irreplaceability recognition.). Through this dependence chain, the actor X can (mis)lead all others. In other words, the (power) status of each actor expresses its position in the hierarchy generated in the network through this power exchange. The practical meaning is presented in appendix I.

3.2 Independent variables

3.2.1 Actor-related factors

Communication-related indicators

We distinguish scientific and general information (Henning & Wald, 2000) based on the cross-assessment of the interviewees (see appendix I). The scientific information is a specific part of the general information that is supposed to be characterized by a higher image of objectivity.

We measured five information variables:

- "importance" (image) of:
  a. general information and
  b. scientific information

and

- control of:
  a. general information and
  b. scientific information

The fifth information variable is the occasional receiving of general information.

Information importance is quantified through using closeness centrality, while control through betweenness centrality. Because of their critical role in the quantification of the information they will be more extensively discussed.

The closeness centrality (%) of general or scientific information (CCGI and CCSI respectively) is defined as follows:

$$CC_{(i)} = \left[\sum_j d(j,i)^{-1}\right] \tag{2}$$

where $d(j,i)$ is the distance (shortest path) from actor *j* to actor *i*.

This practically means, how directly the others want to receive information from an actor (without intermediate paths) (see also Brandes et al. 2003); the more directly the others seek to receive information from a certain actor, the more "important" they consider it to regarding the specific kind of information. The "importance" of scientific information that an actor is supposed to have has proven relevant to the actor's trust status and, the importance of general information has additionally proved relevant to incentives and irreplaceability. According to Simon (1949) there is no objectively "important" information that produces these dimensions of power but rather who already possess power (trust or irreplaceability) can impose its information as "important" (the less powerful actors pay attention to the more powerful one). Namely, the information is used in the network as a means of implementing existing power rather than as a power source. This hypothesis seems to be verified by our findings. The relevance of CCGI is relevant to incentive-giving because the powerful actor - using plausible arguments- can draw the attention of the others away from possible competitors (other incentive-givers) and so impose its own offering as unique and legitimate (Heidenheimer & Johnston 2002).

The betweenness centrality (%) of general information (CBGI) is mathematically defined as follows:

$$CB_{(i)} = \sum \frac{|P_i(i,j)|}{|P(i,j)|} \tag{3}$$

where $P(i,j)$ is the set of all shortest paths between *i* and *j*, $P_i(i,j)$ is the set of shortest paths passing through *i*.

This practically means, in how many communication paths an actor plays the "go-between" and thus other actors will be lost if the actor quits the network (see also Brandes et al.2003). The CBGI thus indicates thus a form of control of information. This operationalizes the coordination as described by Simon (1949): coordination means that several participants in a network make the same decision at the same time, which may happen only if a central actor controls the information distribution. This indicator has proven favorable to the offering of financial incentives for reasons similar to those described above (see Heidenheimer & Johnston 2002).

The occasional reception (%) of general information (or abbreviation of indegree of need of general information GINEEDIN) is expressed as an indegree of each actor in general information (cf. Knoke & Kuklinski 1982).

$$Indegree_j = \frac{\sum_{i=1}^{N} Z_{ij}}{\sum_{i=1}^{N}\sum_{j=}^{N} Z_{ij}} \tag{4}$$

where Zij is the information sent ? from i to j and N is the number of actors in the network. Namely, this variable expresses how much information an actor receives from the first contacted actors in comparison to each other. It is named "occasional" because it is only the percentage of the first contacted actor and not for example a dependence chain like the power status or the closeness centrality. This indicator operationalizes the need of monitoring the whole situation which is a prerequisite for self-governance of the network (Ostrom et al. 1994, Ostrom 1999). The GINEED IN is positively correlated both with trust status and irreplaceability.

Behavioral indicators

- Radicalism (RADICALI)

This has been measured through cross-assessment (each actor has characterized all others) and expresses to what extent the organization uses legal and system-conform means or follows extreme practices like e.g. these of Greenpeace. This variable fluctuates from 1 to 3 in a metric scale. Radicalism has been regarded as a behavior which negatively affects the power of an association as it hinders the cooperation with the state (Krott 2001, Alemann 1996). We have specifically found that subversive actions negatively affect the trust status and the irreplaceability of an organization.

- Trustworthiness (TRUSTWOR)

The trustworthiness has been measured through cross-assessment. Trustworthiness is distinct from trust status. Trustworthiness is the average of the characterization of the first contacted actor to a certain organization regarding trust. In contrast to trust status which embeds an organization in an objective hierarchy (dependence chain) throughout the whole network, trustworthiness is a subjective impression of the other actors which have directly contacted this organization. Trustworthiness ranges from 1 to 3 in a metric scale and is an operationalization of what Buskens (1999) and Burkolter-Trachtel (1981) have regarded as reputation. It strengthens both the trust status and the irreplaceability of an organization.

Coalition indicator

- Partner strength (PARTNSTR)

This is the average of power of the partners that a particular organization has. It is measured as the power above in percentage. It operationalizes what in the literature is mentioned as coalition or political support (Henning & Wald 2000, Krott 2001). It proves to noticeably strengthen the trust status.

3.2.2 Network variables

Structural indicators

- Number of actors (ACTORS)

This is the number of actors that participate in the network. It has been mentioned as a descriptive dimension by many authors and has been expected to relate to the stability of a network (van Waarden 1992, Blom-Hansen 1997, Marsh & Rhodes 1992, Henning & Wald 2000, Jordan & Schubert 1992). Here we have found that trust status and the irreplaceability of an organization decrease with the "crowdedness" of the network in which it participates. This is understandable because the possibility of monopoly decreases with the proliferation of alternative contacts. Moreover, trust development decreases with size because participants cannot become "familiar" with so many actors.

- Potential lobbying (POTLOBB)

This expresses the percentage (%) of existing relations Z that are contacts from private to state actors and can thus develop in potential lobbying. This operationalizes what Henning & Wald (2000) have conceived as segmentation of a network. This means how many alternative contacts a private actor has established to the public sector. The more alternative contacts it has, the higher the chance to receive a convenient answer for a request, or obtain new financing resources etc. In our survey this has proven very favorable for the trust status and the irreplaceability of an organization.

$$potlob = \frac{\sum Z_{privateActors \rightarrow stateActors}}{\sum_{i}^{N}\sum_{j}^{N} Z_{ij}} * 100 \qquad (5)$$

- Density (DENSITY)

The density means how much percent (%) of all possible contacts in the network have been already established, and is an indicator for the complexity of a network or of the extent to which all possible contacts have been exhausted (Knoke & Kuklinski 1982). This operationalizes what in relevant literature has been described as "structure" (van Waarden 1992) and is expected to relate to uncertainty and social entropy (O' Toole & Meier 1999, Meier & O' Toole 2001). This has proven to negatively affect the development of trust status and irreplaceability by each single association.

$$DENSITY = \frac{\sum_{i}^{N}\sum_{j}^{N} Z_{ij}}{N^2 - N} * 100 \qquad (6)$$

where Z and N as defined above.

- Oligarchy or power inequality (POWERINE)

The oligarchy fluctuates from 0 to indefinite. This is the concentration of power on few actors and it affects the individual power status of each actor. Here, it has been mathematically defined as follows:

$$Oligarchy = \frac{Status\ \max - Status\ \min}{StatusAverage} \tag{7}$$

The oligarchy can be visualized by "visone" using the formula of Status (1) as a pyramid (see figure 1). The sharper a pyramid is, the higher the oligarchy. The highest oligarchy was recorded in the Irish network and the lowest oligarchy in the Finish network.

Ireland: Provisional marketing services in natural resources management	UK: Scottish strategy for natural resources management	Finland: Certification of sustainability

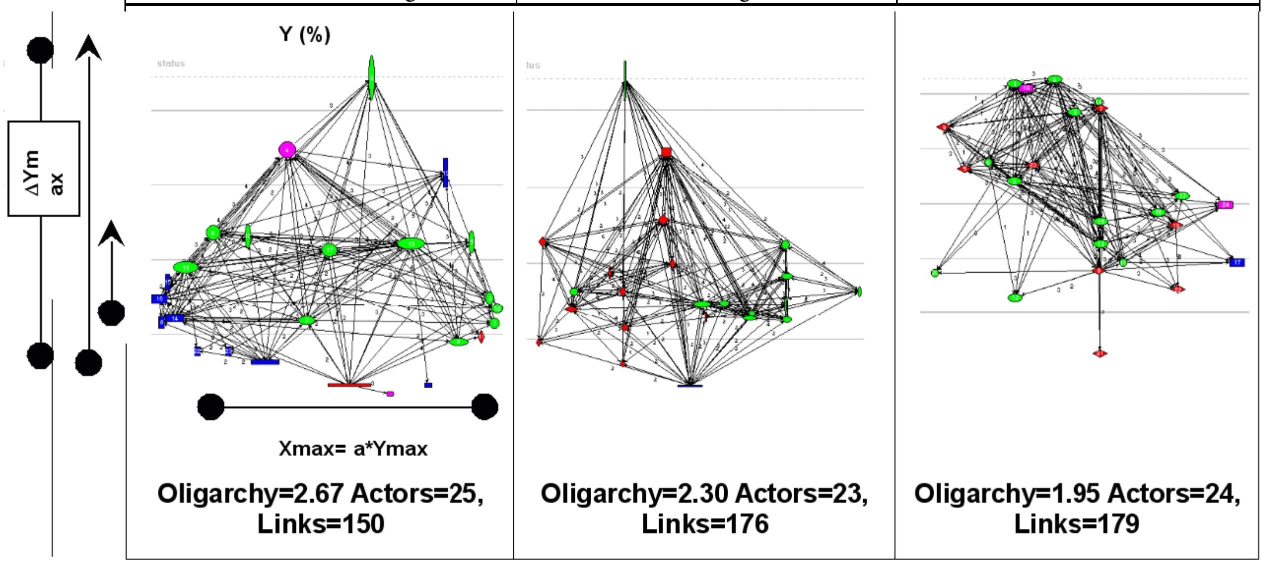

Figure 1: Examples of networks with different status oligarchies and pyramid sharpness

The practical meaning of the status axis (vertical y and horizontal x) can be critically discussed at this point; the practical meaning of the axis Y is clear: the higher an actor is layered, the higher its status. Namely, Y is a vector size (oriented distance from 0 to 100%). However, the X axis is not a vector but a scalar size. Consequently the horizontal placement of each actor does not give any direct information about the status or any other property of the actor. Brandes et al. (2001, p.12) have recognized this deficit in the status graphic of "visone". They have clarified that the only logic for horizontal positioning is the ergonomic optimization of the graphic: the actors are positioned in horizontal layers so as to ensure that long lines run vertically as much as possible and so that the number of crossings is reduced as much as possible. In this way, the graphic obtains a clear form.

However, the X axis has a practical value for the political interpretation of the network: Considering a network in a certain scale, then we should compare the Xmax with the DYmax. Then, we will extract a coefficient a, where Xmax=a*DYmax. The higher the coefficient a is, the higher the proportion of actors that are placed on the respective status layer. Also, the shorter the distance b of the layer Xmax from the bottom of the pyramid is, the sharper the pyramid[7].

[7] Consequently, an alternative definition of oligarchy could be Oligarchy=$\Delta Ymax*(a/b)$. This indicator would have the advantage that it includes the horizontal distance Xmax=a*$\Delta Ymax$. On the other hand, such an indicator would not be so easy measurable because it needs geographical characteristics (a and b) and a standard scale of the graphics and it is not always so clear to be measured (e.g. in Finland). For this reason, we will continue to use the formula 7. However, it is noticeable that $\Delta Ymax$=*Status*max-*Status*min. Thus, if in a future research one proves that the quantity (a/b) is equal or analogous to the (*Status* average)$^{-1}$, then the two indicators will be homologous and replaceable by each other.

This indicator is an additional operational dimension of the "structure" introduced by van Waarden (1992), and an alternative dimension of "hierarchy" which has been defined by O' Toole & Meier (1999, 2001) as the inverted value of the number of horizontal links of a public service to other actors (linking pattern). The operationalisation of O' Toole & Meier resembles what we have above measured as intersectorality. However, the oligarchy seems to express more accurately the hierarchy of aspects of dependence on the superior actors. The oligarchy proves to have the same properties as these of intersectorality; it impedes the development of trust status and irreplaceability by each single association.

- Intersectorality (INTERSEC)
This is the number of sectors that are involved in the network; or in other words the number of sectors to which the involved actors belong to. It has been measured on basis of a standard sector list[8]. This operationalizes what Jordan & Schubert (1992) have mentioned as "scope of policy-making", and Ostrom (1999), O' Toole and Meier (1999, 2001) have connected with uncertainty and social entropy. Indeed, intersectorality has here proved to negatively affect trust status of an organization. This may be similarly explained as in the case of actor proliferation above: in a cross-sectoral labyrinth, an organization cannot become familiar enough with new chances and risks. Thus, its cooperation steps are only incremental ones as they are not based on trust (Nee 1998).

Administrative-instrumental indicators

- Relative importance of state (RELIMPST)
This is the ratio of the possibility of state monopoly to the possibility of private monopoly and can fluctuate from 0 to indefinite. In this way, the role of state and private actors does not depend on the absolute number of the actors and a comparison across all networks becomes possible (cf. Raab 2002, p.619). The possibility of state monopoly is the average irreplaceability of a state actor, namely the sum of the irreplaceability assigned by all the other actors to state actors divided by the number of sate actors. (This can fluctuate from 0 to N-1.) It has been measured through cross-assessment. Similarly, we have measured the possibility of private monopoly. This operationalizes what in the relevant qualitative models has been mentioned as power distribution, state dominance, autonomy of private actors etc (see van Waarden 1992 and Ostrom 1999). It has proven that the higher this indicator is in a network, the more difficult it becomes for the private associations to develop trust or to become irreplaceable.

$$RELIMPST = \frac{pos.st.m.}{pos.pr.m} \tag{8}$$

- Relative density of incentive (RELDEINCE)
This expresses the ratio of the exchange of material support between actors (i,j) to the total existing links (cf. Knoke & Kuklinski 1982):

$$reldenince = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} Incentive_{ij}}{\sum_{i=1}^{N} \sum_{j=1}^{N} Z_{ij}} * 100\% \tag{9}$$

This indicator operationalizes the "structure" mentioned by van Waarden (1992) in the sense of multiplexity of a network and has proven to impede the development of trust status; if material needs can directly be satisfied for a concrete return service (balanced exchange), then there are no conditions suitable for developing generalized exchange (trust-based promises). Namely, the incentive is a direct control means, which overpowers a long-term trust relation (Vogt 1997, cf. Eisenstadt 1995).

[8] Nature conservation, forestry, general agriculture, industry, consulting, general enterprising (except for industry or consulting), water management, tourism / recreation, hunting / fishing, science (units producing knowledge as first priority), energy, general culture and education, employment, regional / rural development

- Scientific information links (SILINKS)

This is the number of the links of scientific information exchange. It operationalizes the concept expert information introduced by Henning & Wald (2000) and has proven to impede the development of trust status (if there is pluralism of scientific information and everyone has contacts to expertise resources, then an actor can hardly be plausible using scientific arguments because it is easily controlled by the others).

4 METHODICAL ASPECTS

4.1 Strengths and weaknesses of complete network analysis

4.1.1 Strengths

Complete network analysis is the operationalization of the general system theory, which assumes that each element (actor) of a system (network) does not possess its own independent properties but these should be attributed to its interaction with other elements. The advantage of complete network analysis is that one can measure the relative position of each actor in a network and disclose latent structures (informal hierarchies like oligarchy) [9]. Moreover, subjective characterizations and other subjective characterizations that an actor is assigned in a network (such as "importance" of information, radicalism, and trustworthiness) can also be measured through cross-assessment. The significance of the aggregated results for power and other policy-relevant factors can be examined. Additionally, the bounding, which takes place through snowball procedure is quite close to reality and not arbitrary or dependent on personal feeling or observation of each surveyor. It is thus an "objective" and legitimate bounding[10].

4.1.2 Weaknesses

On the other hand, network analysis has the disadvantage of small sample size[11]. Each network usually includes from 15 to 35 actors. The ideal "solution" for this would be to open up and survey a much larger number of networks, but this requires much more personnel and communication costs as well as achieving the opening of a very wide number of existing networks. Nevertheless, even if the technical-economic difficulties had been overcome, it would have still remained disputable whether we can find an acceptable number of networks that can interest a special research terrain (e.g. European agricultural policy). Although the systemic approach focuses only on polities (structures) and not on politics (processes) or policies (contents), the generalization of the results from one policy sector on different ones remains questionable. This because, politics may be different in other sectors or perhaps the different processes or policy standards may be relevant to certain power dimensions (e.g. to financial incentives in a banking network). Therefore, including as many sectors as possible in a survey is desired (as said, each network includes at any rate actors of several sectors, but the main sector is this one to which e.g. the ministry responsible for the initial issue belongs to).

Another disadvantage of the complete network analysis is that it can be only based on snowball sampling which is characterized by self-selection (Heckmann, Royal Swedish Academy 2000, p.2).

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[9] This method also improves the chance to minimize the effect of "tactical" and "misleading" answers, as an actor expresses a comment (even a negative one) on a third actor much more freely than on itself. Additionally, in complete network analysis there is also the advantage of mutual verification and of general overview (it is improbable that all actors lie).

[10] In certain disciplines the bounding is normatively defined and leads to subjective conclusions. For example, historical institutionalism seems to practise an arbitrary and normative bounding of events and "responsibilities" exactly like historians who often want to play the role of a national "public prosecutor" depending on personal observing and interests; why, for example, should only the Environmental Ministry be considered to be responsible for the lack of acceptance of a conservation area and not the Prime Minister too because he has appointed this environmental minister. And why not the EU that imposed the relevant directive…? etc.

[11] This is not a problem if we regard the particular networks as the whole population which we want to make generalizations on, but it is problematic if we try to generalise the results outside of these networks.

With self-selection we mean a non-random sample that depends on the individual decisions by the agents under study (participating actors that refer the surveyors successively to each other), or depend on administrative rules or decisions on the part of surveyors (selection of initial actor and successful character of policy issue)[12]. In snowball sampling the sample does not only depend on the – at any rate - arbitrarily defined population (environmental-related actors) but on the individual decision of them to participate. According to Heckmann, we have the problem that we can measure the power significance of actor- and network-related variables only for the actors that participate and not for them that potentially could participate in future.

We tried to overcome the shortcomings that the snowball sampling is considered to have as follows: the basic goal of 'randomness' is to assure the independence of data capture from subjective preferences or personal observation capacity of each surveyor and thus to increase the reliability (reproducibility) of the results. In a similar way, we tried to increase the randomness of the snowball samples (networks) selecting the first actor randomly[13]. Then, this actor was contacted and interviewed. The environmental issue was not selected by the researchers but by this actor ("please, mention an environmental issue that you have been successful[14] in the last two years"). Afterwards, with successive contacts and references ("please, mention which other actors you have contacted in the framework of this issue") the whole network was opened up. So, we have also achieved a bounding independent from the arbitrary definition of the researchers or of another single actor[15].

5 CONCLUSIONS: STRENGTHS AND CHALLENGES

On table 1, we concisely present the advantages and disadvantages:

Table 1: Evaluation of complete network analysis

Complete network analysis	
Advantages	Disadvantages
- Disclosure of latent structures (oligarchy)	- Self-selection
- Operationalisation of power and measurement of relative positions and policy impact of subjective factors	- Small size
- "Objective" (legitimate) bounding of the network (by all the participants themselves)	- Weakness of telephone interviews

[12] Form this viewpoint, no sample should be considered to be "random" according to the strict definition of statistics because even in the random selection the whole population is defined by the samplers (Kuehnel & Krebs 2001).

[13] Concerning the definition of population, like in the so called 'random' sampling, we worked with a defined population. This was the actors involved in environmental networks and the networks they have built together in the selected countries (which were independent of the will or observation capacity of the samplers). We may have not known the exact names of these actors from the beginning but exactly the same process is followed in 'random' sampling: the population is defined and delineated as a whole and not in its single units. When a 'random' sampler says that he has defined the population, he means that he has bounded a certain group of units that present specific general properties e.g. final class of pupils at secondary school. The population is in this sense already an independent variable which simply does not appear in the multivariate analysis as such one because it is stable. The sampler does not know each single unit with "all" its peculiarities separately. In contrast, he is aiming to measure certain of these peculiarities in order to see whether they appear frequently "enough" so as to be considered correlated to each other.

[14] We have asked the first actors to mention an issue where they were successful according to their self-evaluation in order to encourage the answering. After a test we have ascertained that almost none was willing to accept a defeat and to mention an issue where it was "unsuccessful".

[15] Additionally, we have examined a dimension of policy, the intersectorality, as an independent variable which finally proved relevant to the power development. The "environmental" networks offer a good chance for measuring intersectorality because they are very cross-sectoral networks.

Because of the relatively "small" size of our sample, the results could be confronted with critical comments of empirical researchers or practitioners. These comments would be also not definitive and complete because they would be based on restricted parts of the reality (normative bounding according to the observation capacity or interests of each commentator) or on norms (feelings, prejudices or political tasks and values) that the practitioners often call 'experience'. The telephone interview is not considered to be the most reliable technique for data capture. Much more reliable in future research would be the employment of additional methods like document analysis, (participant) observation, and group discussion through conferences and workshops which should be designed and planed for this purpose in a research project of several years (e.g. 3-6 years). In these, not only researchers but also stakeholders of the networks would play a role. A diachronic observation of network interactions and developments and a comparison between different conditions would be possible and thus the results would become more reliable for further generalizations.

The following compromise could be acceptable at this point: the advantages of complete network analysis are obvious, but the disadvantage of the "small" size makes results open to empirical criticism. Thus, future policy research should be carried out on the advantageous way of complete network analysis but employing much more scientific resources in order to increase the sample size (e.g. from 12 networks and 234 actors to 100 networks and 2000 actors). Apart from that, the disadvantage of the self-selection characterizing snowball sampling and making thus its statistical properties ambiguous, can present a future research point for Heckmann's models.

5.1 Open questions for future research

The first question would be how we could improve the use of issue-oriented networks as a statistical sample as long as it can only be relatively small and not "random" according to the conventional definition. The main correcting strategy that we have followed in our work was to outweigh the disadvantage of the few cases with the advantage of the many variables and to open up the networks with successive contacts unknown to the researcher. In the future it would be useful to know the optimal balance between cases and variables so as to achieve the highest number of acceptable regressions in a number of networks.

A second question could be the application of the Heckmann's methods to network sampling. The improvement suggested by Heckmann takes the propensity of the missing actors to participate into account. This requires implementation of probability theory. The self-selection problem can be viewed as a problem of missing observations. Political power cannot be observed among non-participating organizations. To obtain unbiased estimates of basic structural parameters, the estimation procedure has to recognize that the sample of the participating actors is not the result of random selection, but the result of individual actors self-selection implied by success maximization. This can be a future project that could present an additional interest because the networks are systems and not additive samples (like working individuals in a labor market). Leenders (1995, p.208) suggested that statistical models, which can test theories of social networks, do not exist because of the interdependence that characterizes social networking. Therefore, networks can only be studied through complete analysis, meaning self-selection. Thus, we suggest that Heckmann's methods could be a solution.

A Heckmann's insight is that observations are often missing because of conscious choices made by actors. The relation between reasons for missing observations and nature of non-missing observations thus takes on an intriguing theoretical structure. He suggested the following correction (also known as the two-stage method) (formula 10, 11 respectively):

$$P_i = x_{1i} b_i + E_{1i} \quad (10)$$

$$e_i^* = x_{2i} b_2 + E_{2i} \quad (11)$$

Formula 10 determines the power status of an actor, whereas formula 11 is a "participation equation" describing the individual propensity to participate. Thus, P_i is the observed power status for actor *i* if it participates and e_i^* a latent variable that captures the propensity to participate; $x_{1i}b_1$ and $x_{2i}b_2$ are vectors of observed explanatory variables, such as internal features like chairperson age or member number etc. E_{1i} and E_{2i} are finally stochastic errors representing the influence of unobserved variables affecting P_i and e_i^*. The parameters of participation interest are the b_1 and b_2. Based on these two equations, Heckmann further developed a method for the estimation of the influence of the unobserved variables on the sample. In a network sampling we could also estimate the non-networked actors, if previous research showed these vectors were important in case of policy networks.

A third research point could be a deeper qualitative analysis of the role of the information and other possible organizational and network factors in the generation of financial incentive. It is already remarkable that non-financial factors appear as directly relevant to the incentive. Further research on the incentive could be also useful in corruption research.

A fourth question could concern the geometric meaning of the status oligarchy as presented using "visone" in figure 1. Apparently, the sharpness of the pyramid is related to oligarchy and the visualization of status is thus useful to make a quick comparative estimation between networks. But the further mathematization of sharpness and its exact relation to oligarchy can be a point for further research.

Finally, a fifth question would be how we could distinguish the "scientific" from the rest "general" information without being dependent on the cross-assessment of the actors. For this purpose a clear definition of science would be necessary (for example maximum acceptable limit of norms that are mixed in objective facts). Through a cross-assessment as we have practiced in this survey, one can rather measure "scientific image" of each actor than science as an objective entity.

APPENDICES

I. Practical meaning of power values

Trust (1,2,3)	Incentives (0,1)	Irreplaceability (0,1)	Power value	Meaning	Aggregation
1	0	0	1	Lowest authoritative and instrumental power – mere existence in the network	1= Only existence
1	1	0	2	Only part of instrumental power	Only part of one power form 2=1*part
1	0	1	2	Only part of instrumental power	
2	0	0	2	Only part of authoritative power	
1	1	1	3	Only total instrumental power	One total power form or parts of two forms 3=1*total or 3=2*parts
2	1	0	3	Part of authoritative power and part of instrumental power	
2	0	1	3	Part of authoritative power and part of instrumental power	
3	0	0	3	Only total authoritative power	
2	1	1	4	Part of authoritative power and total instrumental power	One total power form and part of one other form 4=1*total+1*part
3	1	0	4	Total authoritative power and part of instrumental power	
3	0	1	4	Total authoritative power and part of instrumental power	
3	1	1	5	Total authoritative power and total instrumental power	Both total power forms 5=2*total

II. Operationalisation of variables

Variable	Question
Issue	1. Please mention an environmental-forest policy affaire (issue) of the last 2 years, in which your association was successful
1. Power %	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+) 2b. Please, mention which of these associations, services or other institutions were for you irreplaceable+. 4. Please, mention which of them could you trust (V+): 1 'not at all', 2 'to certain extent', 3 'completely (let make a decision for you)' 7. Which of these actors provided you relatively often with cheap equipment, personnel, members or other kind of material support? (A+)
2. Closeness centrality of general information (ccgi) %	5a. Which of them provided your organisation with enough information (I+)
3. Betweeness centrality of general information (cbgi) %	5a. Which of them provided your organisation with enough information (I+)
4. Closeness centrality of scientific information (ccsi)%	5b. Please, mention 3 of them which provided the scientifically most important information
5. Occasional reception (%) of general information (gineedin)	5a. Which of them provided your organisation with enough information (I+)
6. Radicalism (radicali)	8. How radical-activist do you find each of the other associations? (Ex+) - As radical-activist as Greenpeace or more 3 - only exceptionally 2 - not at all (1)
7. Trustworthiness	4. Please, mention which of them could you trust (V+): 1 'not at all', 2 'to certain extent', 3 'completely (let make a decision for you)'
8. Partner strength (partnstr)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+). 3 . Please, mention which of them you had a conflict with (K+). 2b. Please, mention which of these associations, services or other institutions were for you irreplaceable+. 4. Please, mention which of them could you trust (V+): 1 'not at all', 2 'to certain extent', 3 'completely (let make a decision for you)' 7. Which of these actors provided you relatively often with cheap equipment, personell, members or other kind of material support? (A+)
9. Intersectorality (intersec)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+).
10. Potential lobbying (potlob)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+).
11. Actors (actors)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+)
12. Density (density)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+)
13. Relative density of incentives (reldenince)	7. Which of these actors provided you relatively often with cheap equipment, personnel, members or other kind of material support? (A+)
14. Possibility of state monopoly (pos.st.m)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+). 2b. Please, mention which of these associations, services or other institutions were for you irreplaceable+.
15. Possibility of private monopoly (pos.pr.m)	2a. Please, mention all associations, services or other institutions, with which you have cooperated in this affaire (Z+). 2b. Please, mention which of these associations, services or other institutions were for you irreplaceable+.

III. Network matrix

Actors → ↓	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	..	..	..
1.	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex
2.	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex	Z K V I A Ex
.																			
.																			

Key: Z: general contact, K: conflict, V: trust, I: information (general or scientific), A: incentive, Ex: radicalism

IV. Descriptive statistic of all data

Descriptive statistic of all networks	Minimum	Maximum	Average
Organizational factors			
POWER	0.00	15.62	4.9716
TRUST	0.44	13.84	5.0584
INCENTIVE	0.00	100.00	5.1276
IRREPLACEABILITY	0.00	40.00	5.1179
RADICALISM	1.00	3.00	1.3202
TRUSTWORTHINESS	1.00	3.00	2.3424
PARTNER STRENGTH	1.97	13.66	6.3852
CCGI	.00	23.08	5.0141
CCSI	.00	60.00	5.0825
CBGI	.00	75.00	5.0410
GINEEDIN	.00	53.85	5.0496
Network factors			
ACTORS	11.00	38.00	23.2179
POTENTIAL LOBBYING	4.73	63.16	21.9933
RELATIVE IMPORTANCE OF STATE	.35	4.21	1.7791
INTERSECTORALITY	4.00	11.00	6.6197
OLIGARCHY	1.20	2.67	1.9399
DENSITY	19.76	52.73	28.6099
RELATIVE DENSITY OF INCENTIVES	2.63	23.51	15.6929
SCIENTIFIC INFORMATION LINKS	4.00	38.00	21.9744

V. Stepwise regressions

	Dependent variables					
	Trust status		Incentive status		Irreplaceability	
	Standardized Coefficients	P	Standardized Coefficients	P	Standardized Coefficients	P
Actor-related variables						
RADICALI	-,230	,005	-,043	,709	-,221	,020
………..	……..	..	…….	….	………	…
TRUSTWO	,244	,003	-,006	,959	,227	,016
………..	……..	..	…….	….	………	…
PARTNST	,448	,000	,113	,464	,164	,209
………..	……..	..	…….	….	………	…
CCGI	,505	,000	,243	,003	,371	,000
………..	……..	..	…….	….	………	…
CCSI	,159	,003	,020	,794	,077	,284
………..	……..	..	…….	….	………	…
CBGI	,074	,103	,249	,000	,132	,029
………..	……..	..	…….	….	………	…
GINEEDIN	,145	,001	,107	,091	,162	,005
Network-related variables						
INTERSEC	-,228	,020	,017	,902	-,238	,038
………..	……..	..	…….	….	………	…
POTLOBB	,327	,000	-,057	,612	,367	,000
………..	……..	..	…….	….	………	…
RELIMPST	-,245	,003	-,063	,593	-,372	,000
………..	……..	..	…….	….	………	…
ACTORS	-,447	,000	-,172	,200	-,241	,028
………..	……..	..	…….	….	………	…
POWERIN	-,407	,000	-,097	,535	-,520	,000
………..	……..	..	…….	….	………	…
DENSITY	-,251	,003	,052	,658	-,329	,001
………..	……..	..	…….	….	………	…
RELDEINCE	-,256	,000	-,030	,640	-,111	,069
………..	……..	..	…….	….	………	…
SILINKS	-,239	,000	-,009	,895	-,075	,235

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Connecting the Dots without Forgetting the Circles[1]

Alvin W. Wolfe
Distinguished University Professor Emeritus Department of Anthropology
University of South Florida,Tampa, FL, USA

The steep slope of the increase in human population over the past century has been accompanied by increased complexity of the various systems that serve the six billion human beings that growth has produced. Network analysis has been a response by social scientists to the necessity to develop better methods of analysis. Now other scientists are finding network models more and more useful for understanding their own fields — in the study of materials from quarks to the cosmos, in the study of biology from DNA to ecosystems, and in the study of humans from domestic networks to the internet. The randomness that was earlier assumed is being questioned at all levels of analysis. We need to step back and review our own culture's ontological conceptions of what is really out there and how it is organized. That can be done properly only in some kind of comparative perspective. Because of its holistic and comparative perspective, anthropology has a role to play. Its interdisciplinary leanings and connections – biological, linguistic, historical, social, cultural and humanistic — are valuable in these times of increasing specialization of scientific enterprises. Judgments, as to what we know and what we do, are based on experience, and experience is interpreted by each of us in terms of our own culture, what we have learned to believe is known. There is much that is yet unknown about connecting the dots and interpreting the circles. Circles — cohesive and structural clusters, domains, and fields — at one level of analysis become dots at higher levels in one of the three major hierarchies of systems and subsystems — in the hierarchy of physical and material systems, in the hierarchy of evolving biological systems, and in the hierarchy of our rapidly developing human social or cultural systems. If we open our minds to the possibilities that can be generated in the interactions among the dots and circles of these systems and subsystems, all of which are relatively open networks, we social scientists may make enormous contributions to understanding the whole.

The steep slope of the increase in human population over the past century has been accompanied by increased complexity of the various systems that serve the six billion human beings that growth has produced. Figures 1 and 2 illustrate the marked spike in human population after more than a million years of fairly regular growth.

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[1] Originally prepared for presentation as the Keynote Address at the Twenty-third Annual Sunbelt Social Network Conference of the International Network for Social Network Analysis, in Cancun, Quintana Roo, Mexico, February 13, 2003

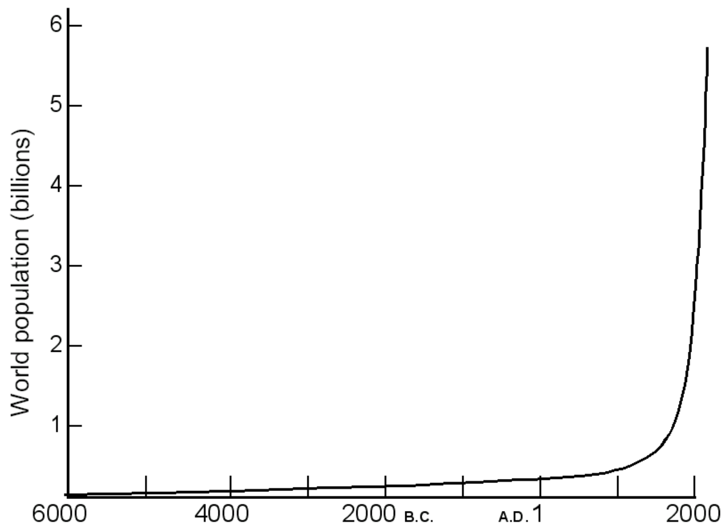

Figure 1. World Population Curve, adapted from Figure 10.4 in The Natural History of Man, by Carl Swanson (1973).

Figure 2 points up some of the many notable events that anthropologists find along this timeline: the outstanding art in the Paleolithic Cave paintings, beginnings of pottery making, the origin of agriculture, the invention of metalworking, etc.

Figure 2. Human Population Growth, with Human Events Marked (From Figure 7.1 in Mackenzie, 1998).

The figure reminds us also that anthropologists are interested in so many different things that the field is almost itself "interdisciplinary" — biological anthropology, archaeology, linguistics, and cultural anthropology. Those interests extend to philosophical ideas as well. Anthropologists are interested in our own ideas about the nature of things and in the cosmological ideas of other peoples as well — cross-cultural cosmology.

No matter what problem the anthropologist is studying, it can be considered in its broadest relevant context. The four fields of anthropology — physical/biological anthropology, archaeology, linguistics, and social/cultural anthropology involve systems, and thus the systemic whole is relevant. The scientific view of the physical universe is a set of nested subsystems down to molecules, corpuscles, atoms, and quarks, and beyond (Figure 3).

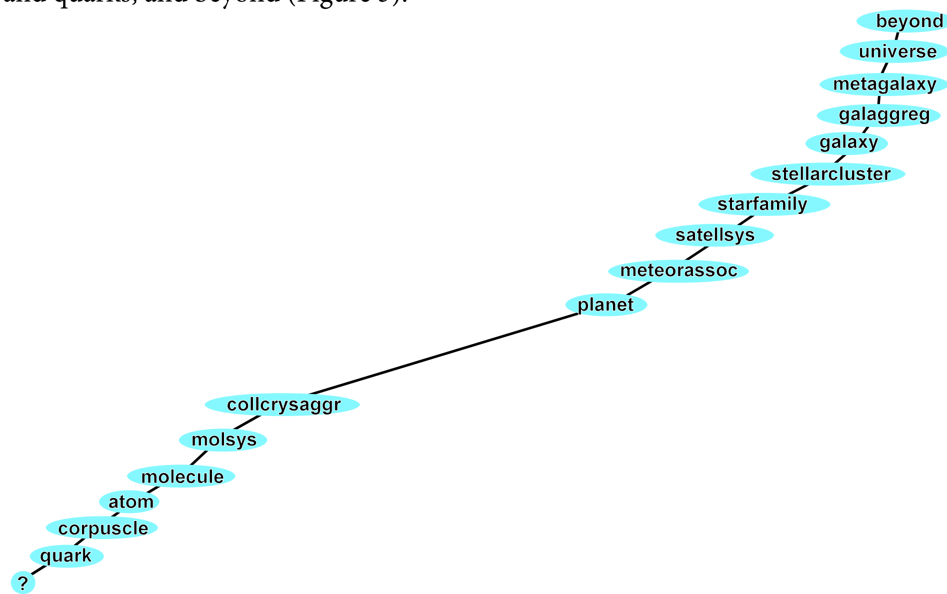

Figure 3. A Hierarchy of Materials Systems. [Note: This figure and all the succeeding ones, except for figure 6, were created using the network drawing program, Krackplot (Krackhardt, et al. 1994)]

There is no question that the material world is hierarchical. If you were a scientist fifty billion years ago this material world is all that you could have known. That is all there was — anywhere. Only very recently did scientists of our kind, the "modern" kind, start understanding it "scientifically," and that knowledge began with some positive understandings about levels somewhere in the middle of its range, in the area between the crystalloid aggregates and the planets. We have increased our knowledge of material systems in both directions — up and down the hierarchy, using empirical methods wherever possible. The evidence suggests it is constantly expanding — evolving (Figure 4).

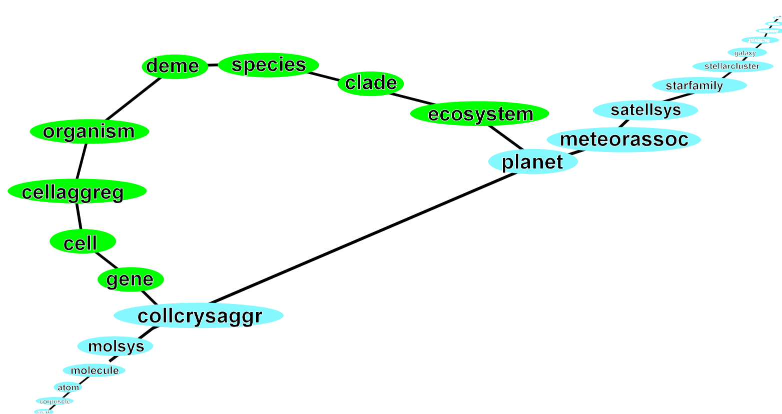

Figure 4. Biological Systems Hierarchy

Somewhere in the middle of the hierarchy of physical systems, something quite different "evolved" and there is no doubting that it has a directionality to it — at one point there was no life on earth, but life emerged from the interactions of colloidal components, and then took off. The original system generated new forms and new systems at hierarchically organized levels (Gould, 1981; 2002).

At each level there are different systems, in some cases billions of systems, and each of those systems is a network. And the whole is also a network, a network of networks. Having emerged out of the physical systems, the biological "life systems" form their own hierarchy: cells, organs, organisms, species, clades, etc.

What followed that was just as startling. After some billions of years of biological development the interactions of components already there generated another extremely interesting new systemic pathway. We call it culture, or the sociocultural system. It was new in the sense that there was a time when it did not exist, several million years ago, and then, when the interaction of elements in the biological world reached one of those equilibrium-punctuating events, it appeared. Now, a million years later, socio-cultural systems in a variety of forms, are very prominent on our planet (Figure 5).

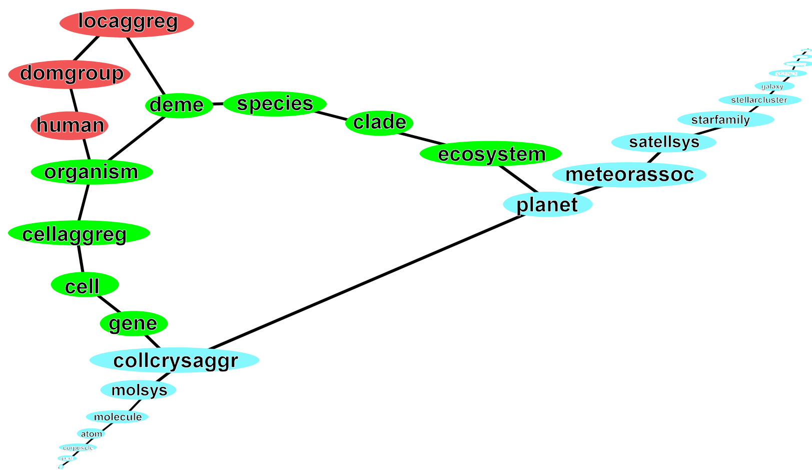

Figure 5. Origins of Cultural Systems

Human culture is quite different from other cultures you might know or might believe to exist. This new pathway – along which human socio-cultural systems are developing -- may be as different from the biological as the biological was from the material. But it is still made up of networks, and some network generalizations apply to it at every level.

One principle that applies in these cultural circles is "cultural relativism," affirming that judgments are based on experience, and experience is interpreted by each of us in terms of what we have learned in our enculturation (Herskovits, 1956, p. 49). This is a principle quite analogous to the general principle of relativity applicable to the physical universe. It does not tell you what you should or should not do. It is a statement of how things relate to each other. Mass, gravity, and movement are interrelated in the one case; judgment, experience, and learning, in the other. Relativism does not mean an end to scientific activity, rather it changes the way we conduct science.

Theories of "cultural evolution" are not popular these days, but empirically there can be no question that there has been a general trend represented in the systems that are associated with culture: greater numbers of people can organize themselves, and there has been a tendency toward more complexity because of the numbers of levels at which people do organize themselves.

For millennia, human beings lived in small local groups or bands of multi-family local groups that followed some learned, cultural, systems of mating, getting food, educating their young, procreation, and so on. At some point, some of these thousands of autonomous bands organized multi-band systems that were more successful in achieving goals. So, thousands of years after they already could have done so, we find evidence on all continents that that many of these populations developed what anthropologists have tended to called "tribal" organization.

Just as there are hundreds or thousands of ways to organize atoms into molecules and animal organs into organisms, so there are hundreds or thousands of ways to organize human groups into tribes at a level of integration higher than the band. One tribal example is that of the Ngombe of the Congo Basin, in equatorial Africa, whom I studied in the early 1950s (Wolfe, 1961). At that time the Ngombe were organized in a particular kind of "tribal" system that anthropologists have labeled a "segmentary lineage system." In this system every man is surrounded by his patrilineal kin who form a series of fluid yet fully functioning social groups. In such a system each local grouping had as its basis the males of a lineage.

Figure 6 simply reminds us that although there is emphasis on lineage segments at many levels – domestic lineage, economic lineage, exogamic lineage, village lineage , and political lineage -- the full bilateral kinship network is necessary for the functioning of a segmentary lineage system such as that of the Ngombe. Surrounding a male ("ego" at center right) are some eighty-six specific types of kinsmen who, in Ngombe terminology are classified under nine terms (represented by "a" through "i" on this chart).

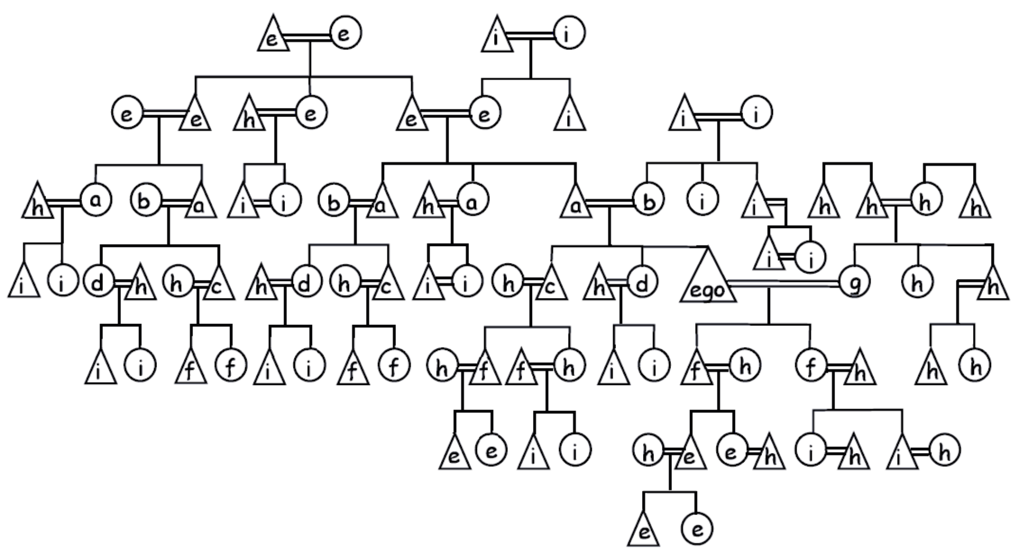

Figure 6. Kinsmen of importance to the Ngombe (copied from Wolfe 1961)

Each line indicates some kind of relation, vertical lines tend to indicate descent, while single horizontal lines indicate sibling relations, and double horizontal lines marriage relations. Those persons of either gender who are descended from a common father, grandfather, great-grandfather, etc. tend to fall into the same class. Each of those who share patrilineal descent will be called by one of three terms, depending on whether the person is: in ego's generation "mwangwambi"(c), above ego's ge neration "sangwambi" (a), or below ego's generation "mwambi" (f). Each kinsmen whose relation to that crucial male lineage is through a marriage relationship is in a category of affines, "mokiombi"(h), except that those who are related to ego through his own biological mother are a very special category for him, called "nokembi"(i).

Understanding this seemingly complex network of relations is fairly straightforward when one knows something of the wider system. Keeping in mind the crucial importance of the patrilineal descent relation, brothers are virtually identical, always living adjacent to each other and only the slightest removed from their male patrilineal cousins. With those cousins they form what might be called an "economic lineage segment" so called because they share whatever goods they have. What kind of goods? Goods like knives, spears, other "hard" valuables that are passed among lineage units as part of a system of bridewealth. Every marriage involves long term obligations that the husband's patrilineal group undertakes to give bridewealth to the patrilineal group of the wife for a period of many years, as long as the marriage lasts. A result of this system of marriage is that every lineage relates to a number of other lineages in two ways – either it is obligated to give goods to that other lineage because one of its males married a woman from that lineage, or it has the right to demand goods from that lineage because one of its "daughters" married a man from that lineage.

The rules are such that there can be only one marriage relationship between any two "economic lineages," so that ego's sister or daughter cannot marry into the same economic lineage as ego's son or cousin gets his wife from. There can be no "exchange marriages" that might reduce transaction costs, so to speak. Furthermore, a rule of exogamy prohibits marriage between persons belonging to the same lineage segment at a wider level than the economic lineage. The consequence of these rules is a very highly connected network of bridewealth obligations over a broad area of Ngombe territory. This is terribly important, because there is among these people no tradition of market exchange. This bridewealth system was the primary method of not only distributing useful capital goods but also of generating a stock of capital goods that was thus available for use when needed. Modern economists would label that stock as "savings."

Figure 7 is meant to illustrate how the patrilineal segments are woven together into a very complex network not only through their descent ties but through lateral ties of kinship and marriage. Marriage was definitely a contract among lineage segments, generating obligations extending not just through the existence of one couple (represented in a bride-wealth pattern) but beyond the lives of those partners through a pattern of levirate and through a special relationship between each person and the patrilineal group of his or her mother.

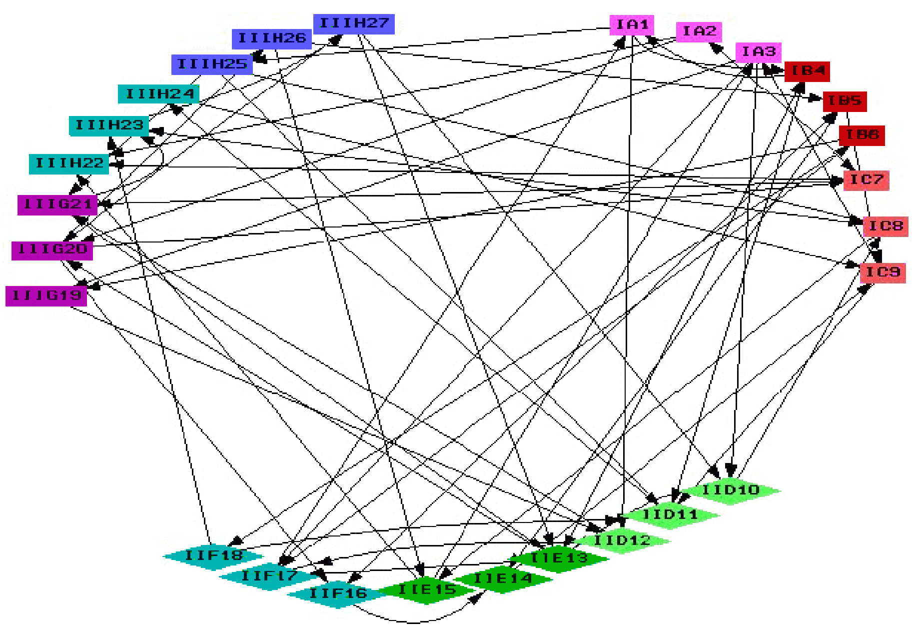

Figure 7. Flow of Bridewealth Among Segments at Different Levels of Organization.

Each node is an "economic lineage" composed of several households with depths of two or three generations. The arrows show the direction of flow of bridewealth – goods flow from the lineage of the husband toward the patrilineal lineage of the wife. Commonly three economic lineages make up an exogamic lineage, so marriage relations must reach out beyond adjacent lineages. In this illustration, three exogamic lineages make up a village lineage, so that the illustration is a model of a three-village social situation. Some marriages (not shown) would connect with economic lineages and exogamic lineages in villages not shown in this figure. Between any two economic lineages there can be only one marriage relationship. This, and the rule of exogamy, forces the establishment of a fairly wide well-connected network. Well-connected is a good description, for each line represents major obligations to transfer capital goods important to these Ngombe villages. If there are any market-based transactions, or if ideas of maximization enter into the Ngombe system at all, they are completely embedded within this wider matrix. Translated to an American or European setting, it is as if all the major institutions – corporations, churches, non-profit organizations – in a metropolitan area had mutual assistance agreements with one another.

What is important to appreciate is that such a "tribal" system is a complex network with a hierarchical structure – household level, economic lineage level, exogamic lineage level, village lineage level, political lineage level – even though there is not really centralization of power in the hierarchy. A multitude of ties actually exist in such a system because there are as many ties as there are ma rriages and offspring of marriages, and no two marriages can connect the same two segments. Such a system enables collaboration and communication and cooperation on a fairly broad scale without centralized control.

Such tribal systems -- and the Ngombe exemplify only one of many types that coexisted on every continent of the world -- evolved many millennia ago from the pre-existing band-level systems providing human beings with ways of organizing larger populations. The best way of conceptualizing and visualizing such evolution is to see it as a process of interaction among units at these several different levels such that out of the interaction new concepts (e.g., lineage and life-force through descent) and new rules (e.g., importance of mother's brother" are generated.

Julian Steward generalized the development of these many different ways of organizing people in what came to be called "multilinear evolutionary theory." (Steward, 1955). When new social formations evolve, older forms do not necessarily die out or remain stagnant as useless survivals. Those earlier forms at lower levels often change and adapt to form parts of new systems at the higher level of integration.

So there are multiple developments along the socio-cultural evolutionary line. With more reliance on domesticated plants and animals we have more stable and dense, clustered, populations, and there is considerable differentiation evidenced. Some of these, when there is evidence of greater centralization, are labeled by those who study them, "chiefdoms" or "kingdoms." There is a tendency toward specialization of organizations (call them corporations, if you will) and toward organizing by territorial boundaries more than lineage and other principles. Those would be represented on Figure 8 by the bubbles labeled either trans-local or territorial systems, depending on the extent to which territoriality is emphasized.

Only within the last ten thousand years have we seen the generation of very dense urban populations and evidence of control over bounded territory that is associated with nation-states. Figure 8 illustrates that further development in sociocultural evolution, as an extension building upon all those that were developed earlier.

The pattern of development of these kinds of systems can be seen as creating a hierarchy not unlike the materials hierarchy, and not unlike the biological systems hierarchy. Certainly, these hierarchies can be seen as networks. There are the smaller networks nested within the larger ones at all levels. Components of the subsumed networks have some connections with components of the broader networks. Hierarchical clustering expresses the general structure, but of course it is more complicated than any representation can show.

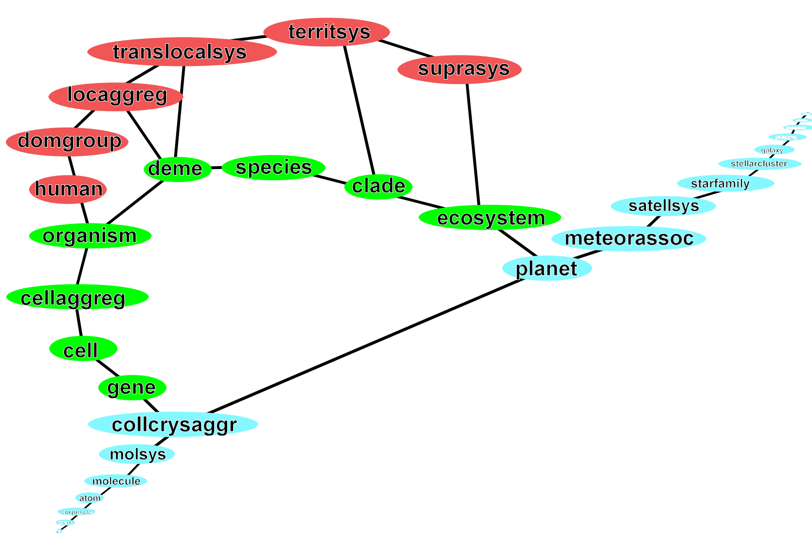

Figure 8. Hierarchical Arrangement of Socio-Cultural Subsystems

How many socio-cultural levels are there? People everywhere learn to see some things as being natural, fixed and real while other things are believed to be merely probable or even only possible. European cultures, from which most American ideas derive, have tended to see market transactions (rational exchange, maximization of returns, getting the most you can for what you give) as natural, while altruism, reciprocity, and other modes of transaction are seen as unnatural. These latter must be explained when they occur, whereas the former don't require explanation.

That narrow vision of human interaction has led to the fairly specialized development of economics as the study of the consequences of transactions of the first type, and it has led to our society's over-reliance on economics in all aspects of life. Isn't it strange that it took generations of work by anthropologists and sociologists to get some recognition of the fact that market transactions are embedded in a much more complex network of transactions? Anthropologists, at least, had been talking about that for generations (Malinowski 1922; Bohannan and Dalton 1962).

The political state or nation-state is another construct that Europeans and Americans have come to see as a natural phenomenon. It seems to be treated by scholars and the public alike as the inevitable outcome of thousands of years of evolution. Scholars have somehow got it into their heads that the State is the highest level of integration, something natural and permanent.

Common concepts like state, nation-state, country, firm, company, and corporation are imbued with cultural meanings that have been fixed in our languages and institutional memories. We put states in a categorical box, and we put business firms in a completely separate box, making it difficult to see that their interactions are generating a system at a still higher level of integration. Although many speak of globalization as a process, few have seen that process as a network development process leading to a genuinely new social form. That new formation is at a "supranational" level, above the level of any given nation or set of nations (Wolfe 1977).

While states and business firms have been around for thousands of years, in the perspective of millions of years of evolution these are both relatively recent emergents, having been constructed through the processes of adaptation that generate all social formations. Anthropologists have not given these forms the kind of attention we have lavished on institutions of family and kinship and community. Now, when it is critical that we understand them and their relations, we seem to be accepting the wisdom of conventional political scientists and economists. We have not subjected these concepts -- business firm, corporation, state -- to analysis in the light of our own comparative and emic/etic perspectives.

In this beginning of the twenty-first century, one cannot talk about the world economy without deliberately taking into account the actions and transactions of multinational firms and enterprises. Many multinational corporations are engaged in transactions of greater dollar value than the entire trade of many of the nation-states studied. The argument has been made that every firm is included in one or another nation-state. While there is a certain legal truth in that view, there are also good reasons to view the situation differently. We are talking here about control over resources and control over persons. Of course, every corporation is registered in one or more state, and many transactions of multinational corporations are included in the statistics for countries or states, but if you really want to know about the world economy, you must also attempt to trace the decisions major corporations make about the disposition of the goods and services under their control. Multinational corporations make a variety of arrangements to assure that transactions do not appear as transactions in order to avoid duties, taxes, imposts, publicity, etc.

At the 1986 Sun Belt Social Network Conference, Linton Freeman, Kim Romney, and Sue Freeman (1986, but see also Freeman 1992) presented an interesting paper on the problem of informant accuracy. That paper has a parallel in our situation at the supranational level. "Somewhere between experience and recall," they said, "our informants were somehow warping the information about the event(s)." Freeman, Romney and Freeman explained that persons develop mental structures that reflect the regularities of their experience. Those structures then intrude on perception and recall in such a way that experience is shaped by expectations as they are stored in memory.

True as this may be for individual informants, such mechanisms operate in an exaggerated fashion as we move up from individuals through institutional levels. And when we reach that cultural construction that goes by the name of nation-state those institutional memory distortions get fixed almost indelibly. Anthropologist Cyril Belshaw's (1976) statement that the concept of national boundary distorts our analyses of social reality was a far too mild complaint. Social science interpretations are falsely biased by nationalistic assumptions and the national bases of data collection. We seem to have built national states so firmly into our culture that even a school of social history that purports to be interested in World Systems ends up merely cataloging and ranking nation-states on a core-periphery scale.

All of our institutions are so biased in that way that it is difficult to find data that are independent of the nationalist assumption. Mary Douglas makes a pithy observation in her 1986 book, How Institutions Think: "Institutions have the pathetic megalomania of the computer whose whole vision of the world is its own program" (1986:92). How appropriate an image for this network problem! While that highest supranational level is of great interest, it is difficult to get the data needed to describe it well in network terms. At least it has not been done.

The failure to see that states and firms are major players in a unique supranational "circle" makes it very difficult for us to study the structure of that highest level comp lex system. It may be possible, however, to study complex systems that are similar even though they are at lower levels.

I am working on such a task – a pilot for the real thing, one might say. The set of public and private organizations involved in matters relating to children and families is a system that probably is structured very much like the entire supranational network.

My study of approximately 600 organizations, public and private, policy making and service providing, in the Tampa Bay Area of the west coast of Florida, is an attempt to do something like that. Using network techniques for measuring centrality, clustering, and equivalencies, I found a three-level structure such as that Illustrated in Figures 9 and 10.

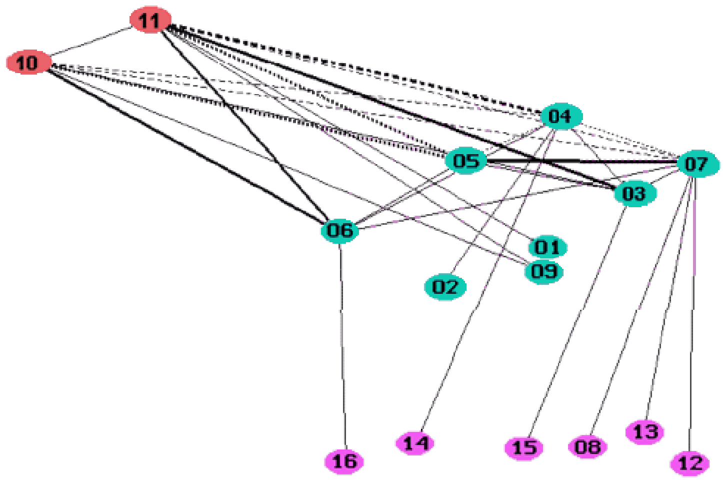

Figure 9. Structure of Regular Equivalence Relationships among 600 Agencies in the Tampa Bay Area. Each node represents a set of regularly equivalent agencies, and each color represents a cluster of sets based on their regular equivalence scores.

Figure 10 shows those same equivalence clusters distributed according to their closeness in terms of average geodesic distances between the (unseen) nodes within the different clusters. Each visible node actually represents a set of agencies that are regularly equivalent. The network as a whole has a closeness centralization index of 0.58, and a betweenness centralization index of only 0.23. If this is not quite as centralized as the view in Figure 10 makes it appear, this is partly because (1) each node represents a set of agencies that have regular equivalence, and (2) this is a two-dimensional view of what is obviously a multidimensional network.

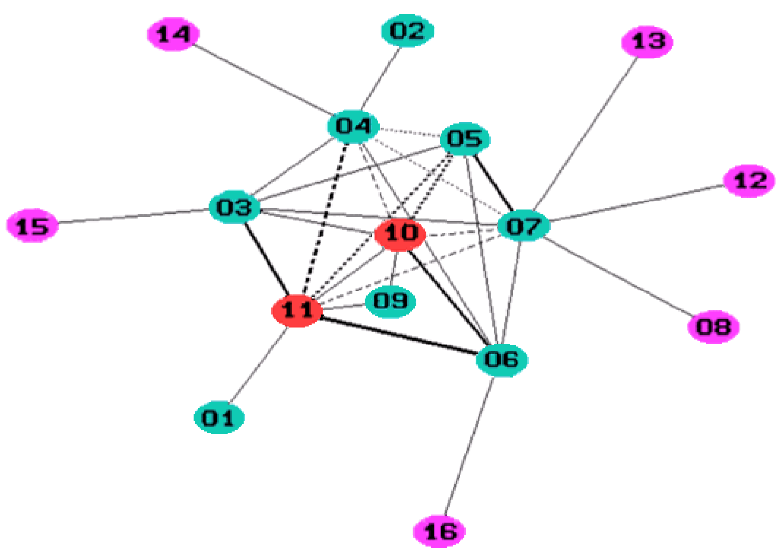

Figure 10. Average Geodesic Distances among the Clusters of 600 Agencies in the Tampa Bay Area.

The distribution of these six hundred nodes in sets of regularly equivalent nodes and the fact that those sets fall into three hierarchically arranged levels needs to be carefully studied and interpreted. It does appear to be quite consistent with the general idea that complex systems tend to be constituted of hierarchically arranged subcomponents.

Herbert Simon has put it well: A complex system, made up of a large number of parts that interact in a nonsimple way, will evolve from simple systems much more rapidly if there are stable intermediate forms, "sub-assemblies," than if there are not, and the resulting complex form in the former case will be hierarchic (1977:209). "In hierarchic systems we can distinguish between the interactions among subsystems, on the one hand, and the interactions within subsystems -- that is, among the parts of those subsystems -- on the other. The interactions at the different levels may be, and often will be, of different orders of magnitude" (Simon 1977:209).

The clusters of regularly equivalent agencies that we find in the subject metropolitan area are analogous to the supranational system of firms and states because they are both constituted of a mixture of public and private organizations. I believe the structure of the supranational system might well be discovered by methods such as we have used in this local project, by graphing both states and firms (government corporations and business corporations) in the same way.

Before closing, I would like to mention another way in which network analysis or at least network imagery can help us interpret a large modern governmental structure. Within the past ten years there have been enormous changes in the government of the State of Florida. In a few years a set of small adjustments moved the state from one in which the governorship was very weak (Jreisat and Wolfe 1995) to one in which the governor is extremely powerful (Jreisat and Wolfe 2002). Network-like images of a major portion of the governmental structure of Florida are shown in Figure 11, for the year 1995, and in Figure 12, for the year 2002. Shown here are three major functions of state government – higher education (Educational Commissioner, Board of Regents, University Presidents), child and family welfare (Secretary, Department of Children and Families, District Administrators, Health and Human Services Boards, Nominee Qualifications Review Committees), and the state judiciary (Florida Bar, Judicial Nominating Commission, Judges).

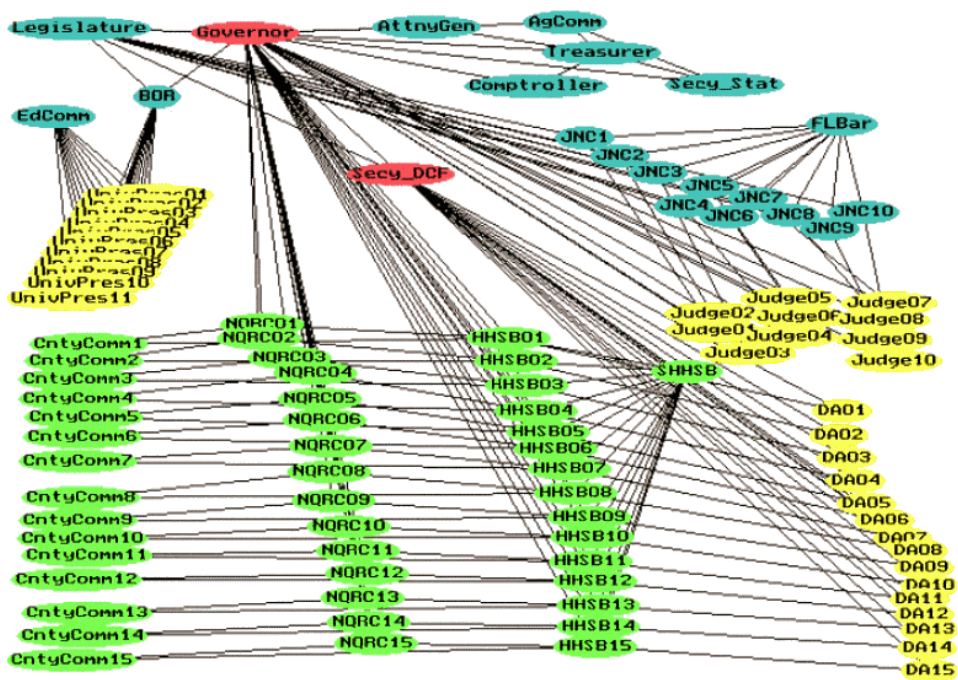

Figure 11. Graphic Illustration of Florida Governance Structure in 1995.

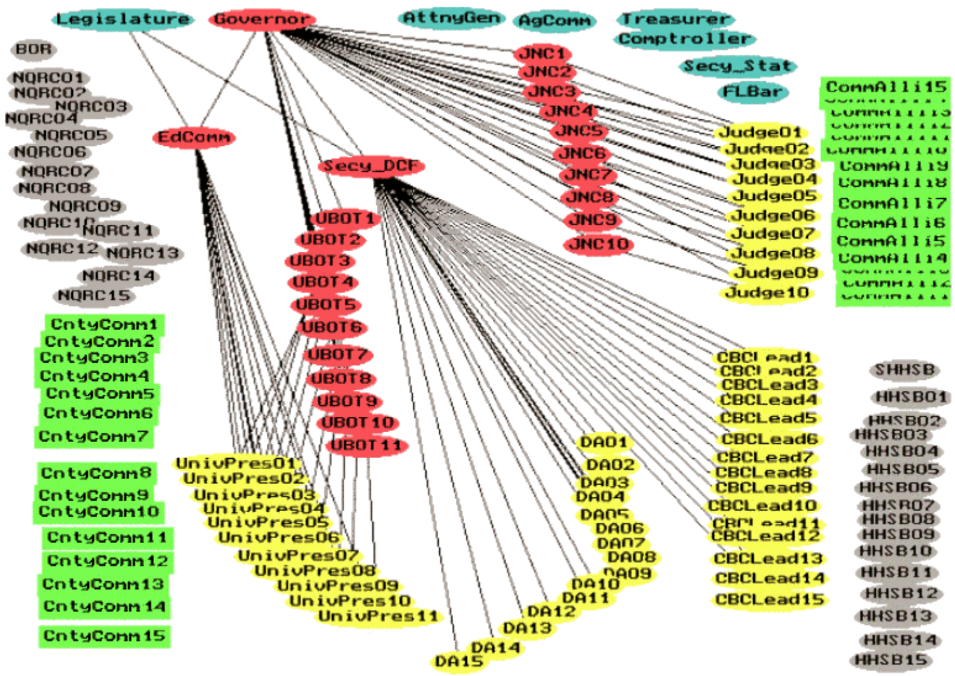

Figure 12. Graphic Illustration of Florida Governance in 2002.

The color coding is important here: The governor and agencies directly controlled by the governor are red. Nodes that are cyan are statewide offices that have some independent status such as being elected statewide. Green indicates nodes that represent local input into policy, e.g. county commissions. Nodes that are essentially administrative, carrying out policies established elsewhere, are yellow. In Figure 12, the nodes colored gray are ones that were deleted by legislation in 2000, each of those nodes having had significant local input in 1995, in which figure they are green. In Figure 12 they are gray shadows and completely disconnected. Some nodes, such as county commissions, remain green in 2002 because they represent local communities, but they are disconnected, virtually powerless in the governance structure of these state functions in 2002. They no longer have ties to the state implementing agents whose appointments they once could influence. The network that remains is obviously a highly centralized one, with the governor having much more direct control than the office had in 1995.

Conclusion

I have not been concerned to define either dots or circles carefully. Circles -- the cohesive and structural clusters, the domains, and the fields -- at one level of analysis become mere dots at higher levels in one of the three major hierarchies of systems and subsystems -- in the hierarchy of physical and material systems, in the hierarchy of evolving biological systems, and in the hierarchy of our rapidly developing sociocultural systems. Dots – the nodes in networks at any level – become complex networks themselves when viewed in the right perspective.

We present-day human beings should keep our minds open to all the possibilities that can be generated through the interactions among the dots and circles of these systems and subsystems at so many different levels. An occasional glance backward along the paths we have travelled in the evolution of these complex systems will help prepare us to see the possibilities ahead.

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