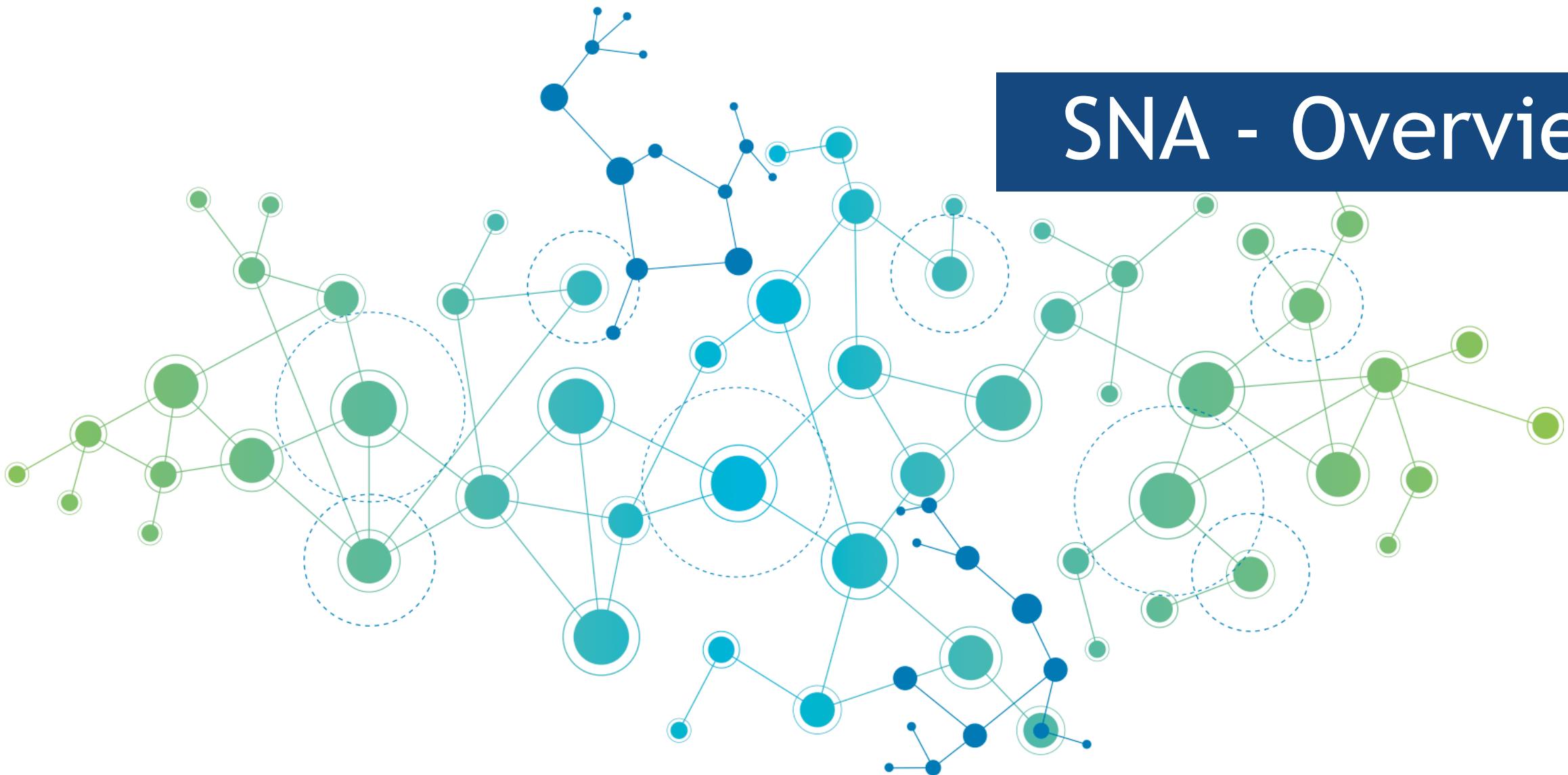
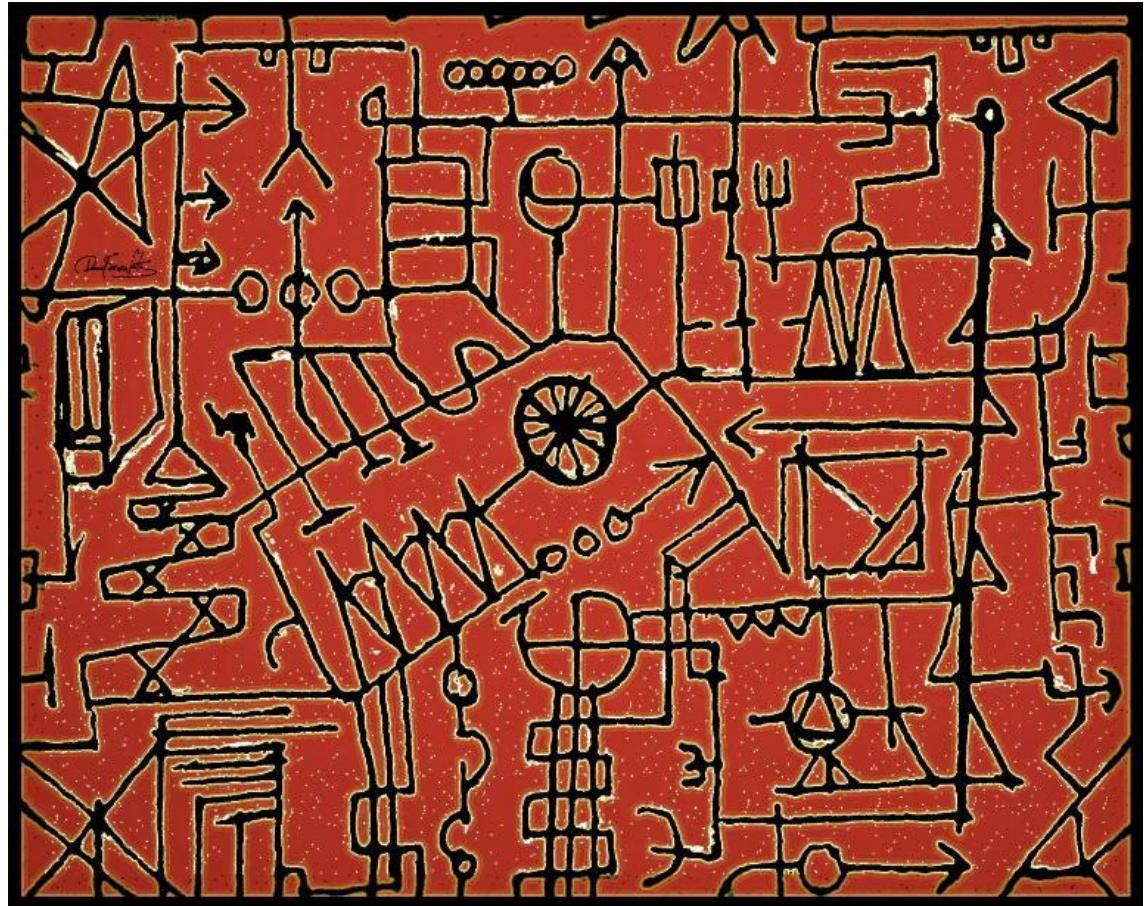


SNA - Overview



Goals

- Provide a ‘big picture’ for workshop
- Provide a systems science context for network analysis
- The wide utility of network analysis
 - In public health
 - In dissemination & implementation science
 - For evaluation (with a pinch of team science)



Complex Systems – Daniel Ferreira-Leites Ciccarino



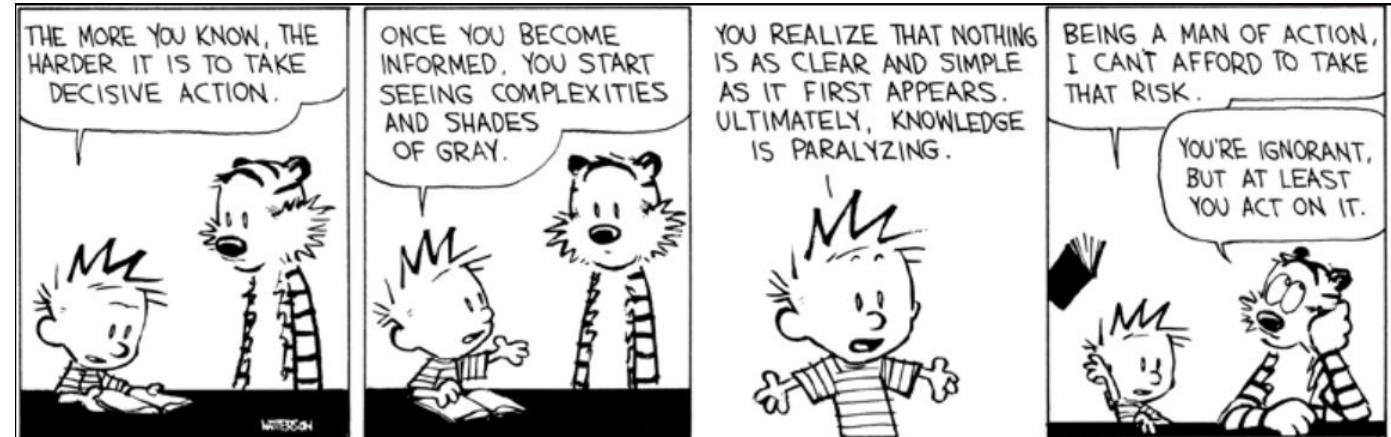
Rationale

Why are systems science and network approaches important for public health?



‘Wicked problems’ and systems science

- Complex problems that resist resolution
- Examples
 - Obesity
 - Poverty
 - Clean air, water
 - Gun-violence
 - Climate change
 - Tobacco control
 - Healthcare access
 - Implementing evidence-based practices in health settings
- Characteristics of wicked problems
 - Many sectors/actors
 - Problem embedded across multiple biological, social, organizational levels
 - Incomplete knowledge
 - High economic/political stakes
 - Interconnectivity with other problems
 - Solution unclear or undefined



Tobacco control as a complex system

- Complex systems are:
 - Made up of heterogeneous members
 - Which interact with each other
- System behavior:
 - Emerges over time
 - Is not described wholly by the behaviors of the individual elements of the system

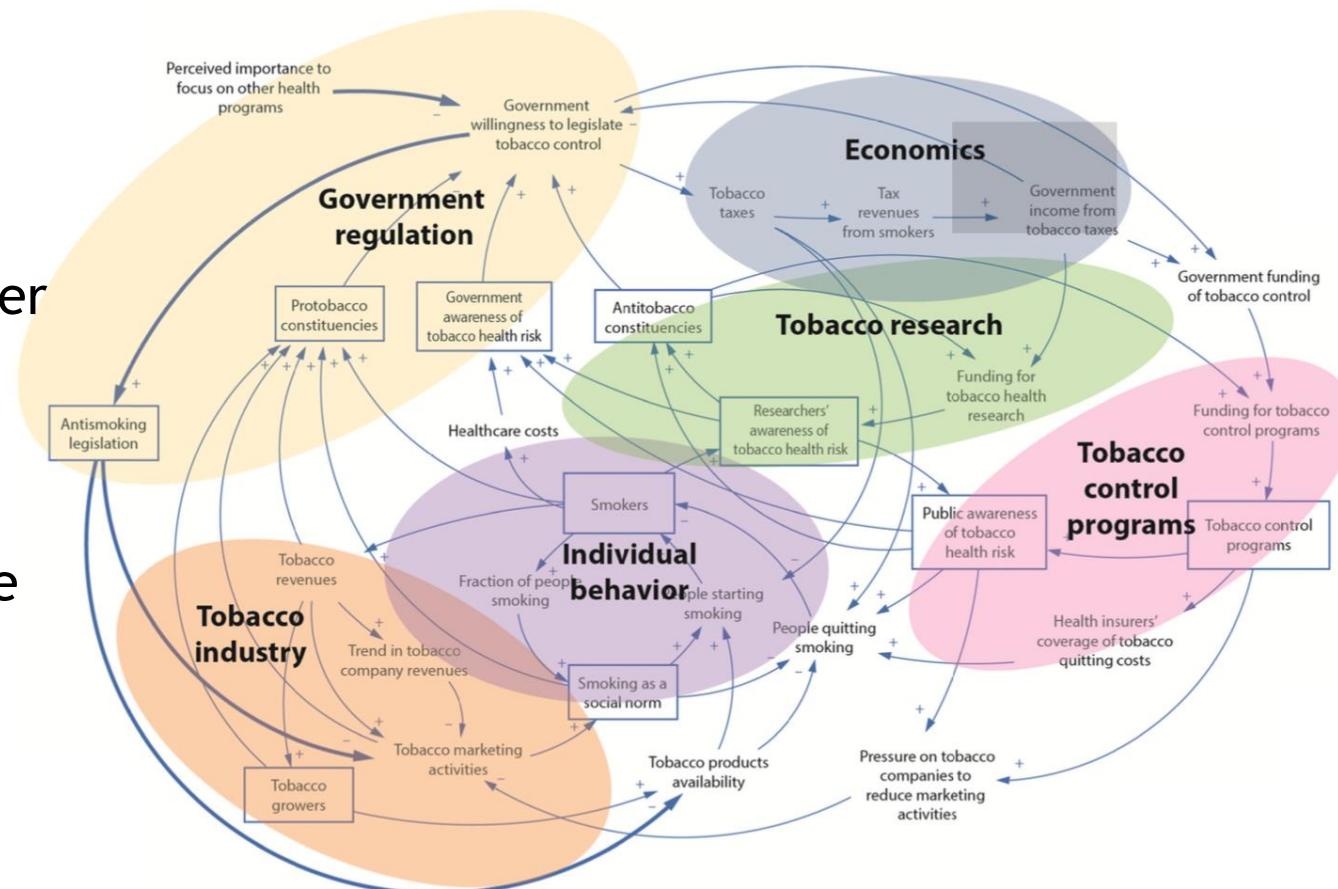


FIGURE 2-2 Complex tobacco landscape.

NOTE: This figure is not drawn to scale, nor is any meaning implied by the relative sizes of elements within the figure. See Kirkwood (1998) for more information about causal loop diagram construction.
SOURCE: NCI, 2007 adapted by Luke, 2013.

Allen Barton, 1968

For the last thirty years, empirical social research has been dominated by the sample survey. But as usually practiced, using random sampling of individuals, the survey is a sociological meatgrinder, tearing the individual from his social context and guaranteeing that nobody in the study interacts with anyone else in it.

It is a little like a biologist putting his experimental animals through a hamburger machine and looking at every hundredth cell through a microscope; anatomy and physiology get lost, structure and function disappear, and one is left with cell biology

...

If our aim is to understand people's behavior rather than simply to record it, we want to know about primary groups, neighborhoods, organizations, social circles, and communities; about interaction, communication, role expectations, and social control.



Systems science methods can handle wider variety of study design challenges and assumptions

Table 1 Comparison of traditional and complex system analytic assumptions

Domain	Traditional analytic techniques assumptions	Complex systems assumptions
Functional form	Linearity	Nonlinearity
Common distributions	Normality	Nonnormality
Characteristics of actors	Homogeneity	Heterogeneity
Level of analysis	Single level	Multiple levels
Temporality	Static or discretely longitudinal	Dynamic, with feedback
Fundamental relationships	Among variables	Interaction of actors
Perspective	Reductionist	Holistic

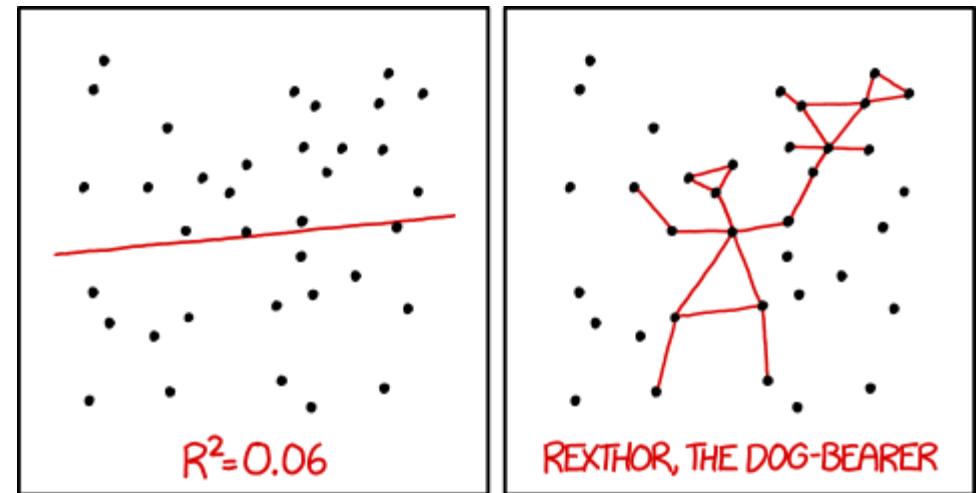
From Luke & Stamatakis,
2012, ARPH



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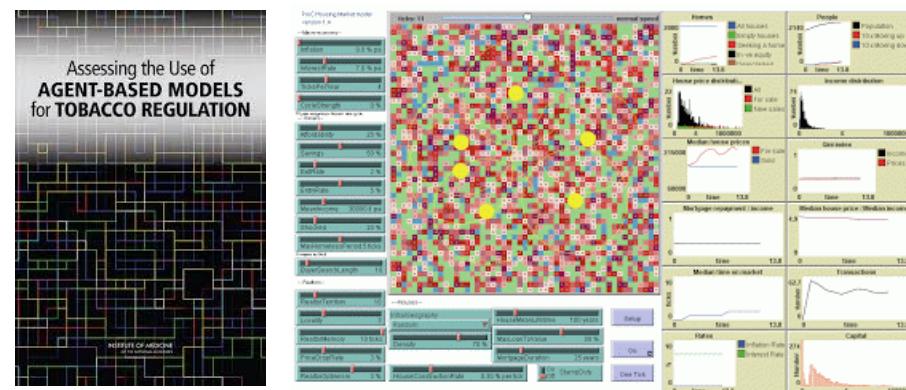
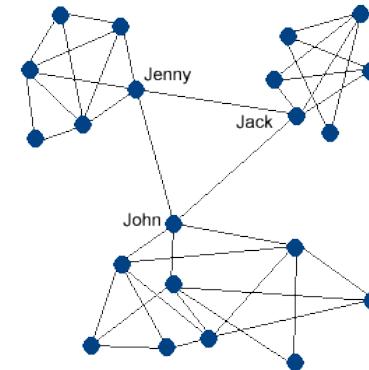
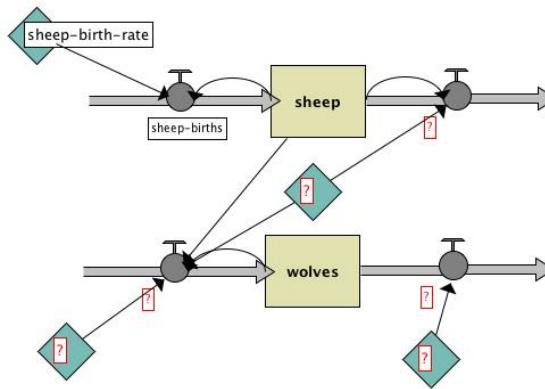
I DON'T TRUST LINEAR REGRESSIONS WHEN IT'S HARDER
TO GUESS THE DIRECTION OF THE CORRELATION FROM THE
SCATTER PLOT THAN TO FIND NEW CONSTELLATIONS ON IT.

xkcd: Linear Regression



Three common systems methods

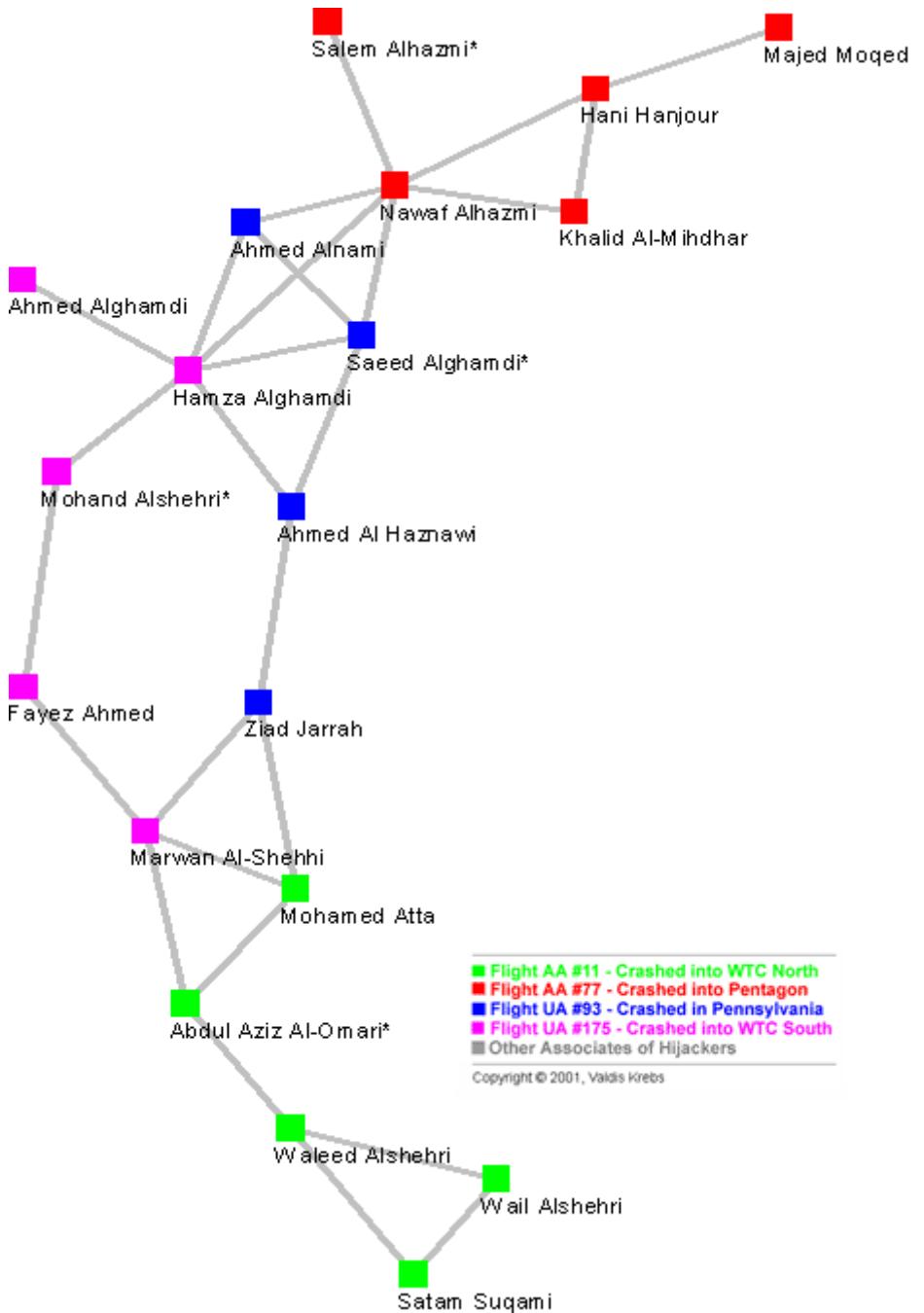
- **System dynamics**
 - Models and computer simulations used to understand endogenous sources of complex system behavior
 - **Network analysis**
 - The study of relationships and flows among social actors, including people and organizations
 - **Agent-based modeling**
 - Use of computer simulations to examine how elements of a system behave as a function of their interactions with each other and their environment
 - (Other methods include microsimulations, discrete event simulation, dynamic forecasting, hybrid models)



Network analysis

Powerful tools to map and model complex systems,
especially social and relational structures



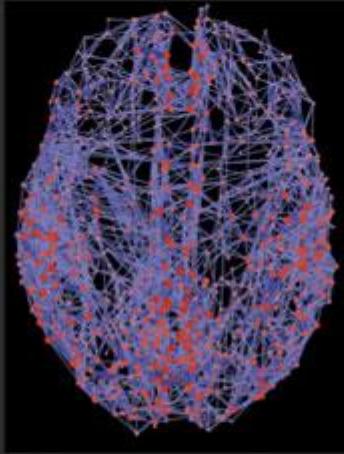


The Human Connectome



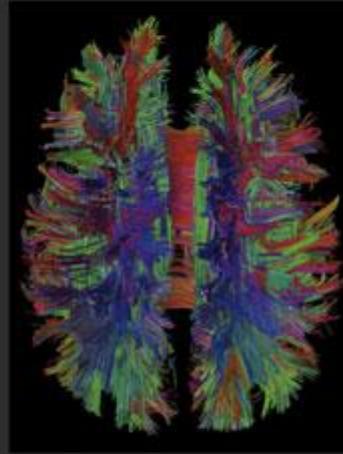
Anatomy

Klingler's method for fiber tract dissection uses freezing of brain matter to spread nerve fibers apart. Afterwards, tissue is carefully scratched away to reveal a relief-like surface in which the desired nerve tracts are naturally surrounded by their anatomical brain areas.



Connectome

Shown are the connections of brain regions together with "hubs" that connect signals among different brain areas and a central "core" or backbone of connections, which relays commands for our thoughts and behaviors.

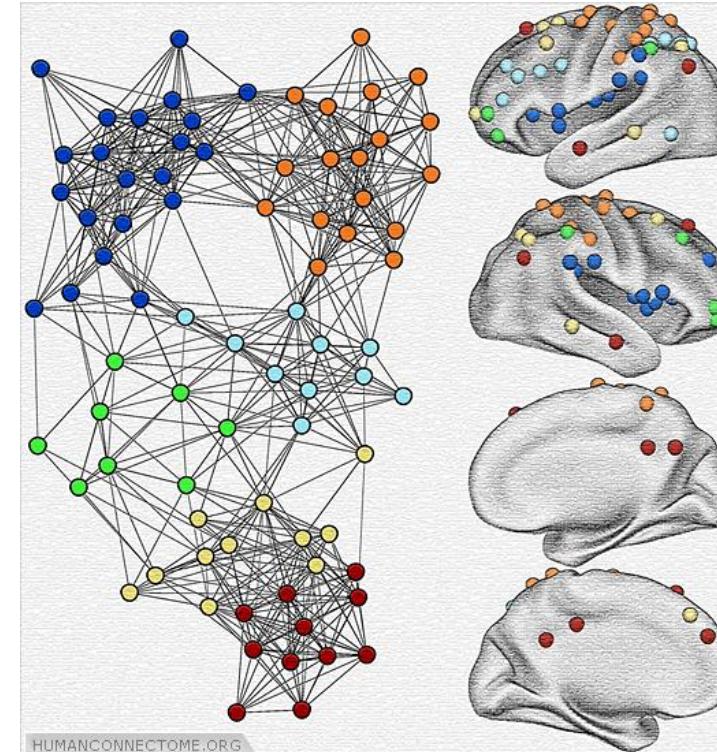


Neuronal Pathways

A new MRI technique called diffusion spectrum imaging (DSI) analyzes how water molecules move along nerve fibers. DSI can show a brain's major neuron pathways and will help neurologists relate structure to function.

The brain as a large network:

- 10^{11} neurons
- 10^{15} synaptic connections

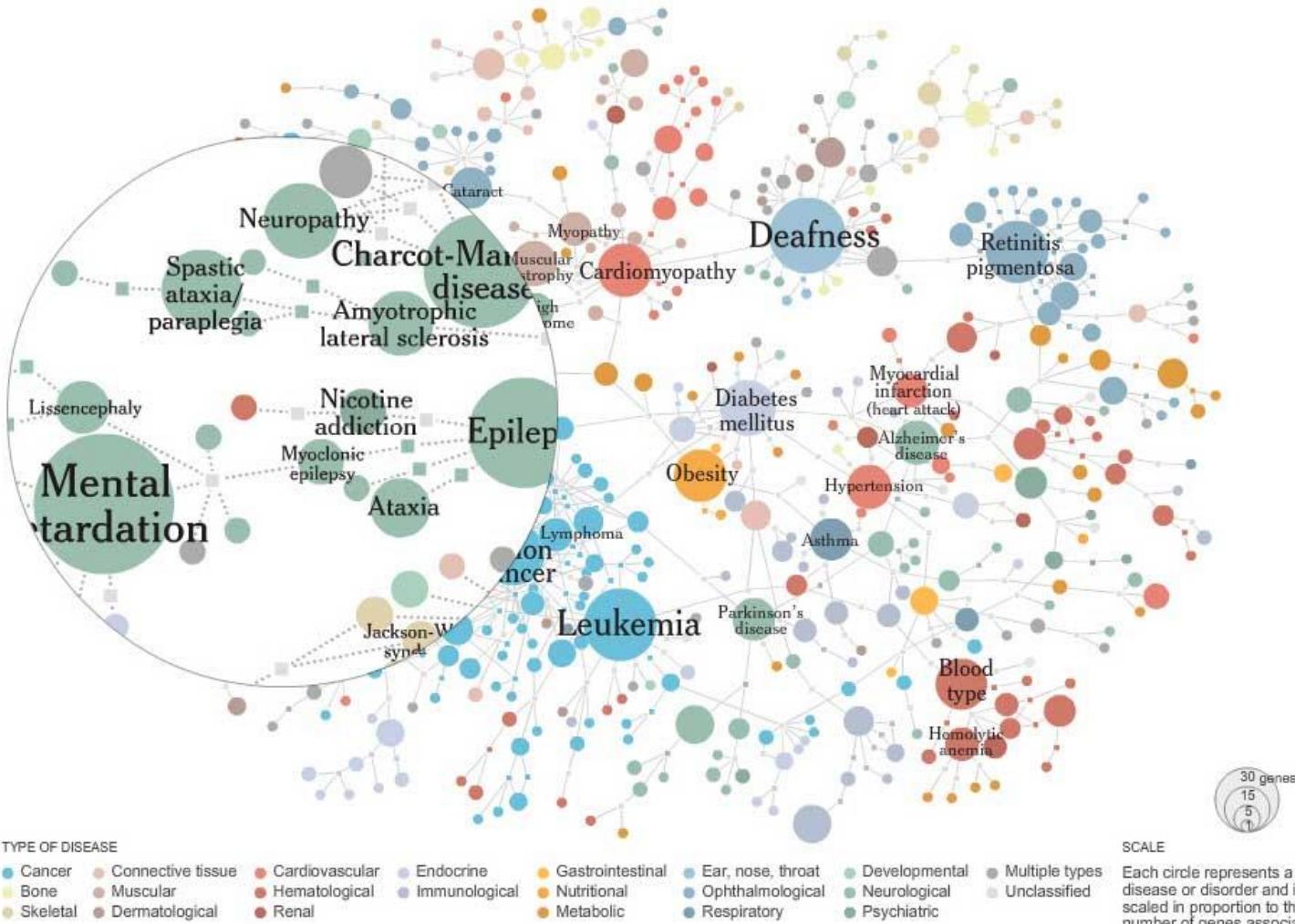


<http://humanconnectome.org/>
<http://13pt.com/projects/nyt110621/>



Mapping the Human ‘Diseasome’

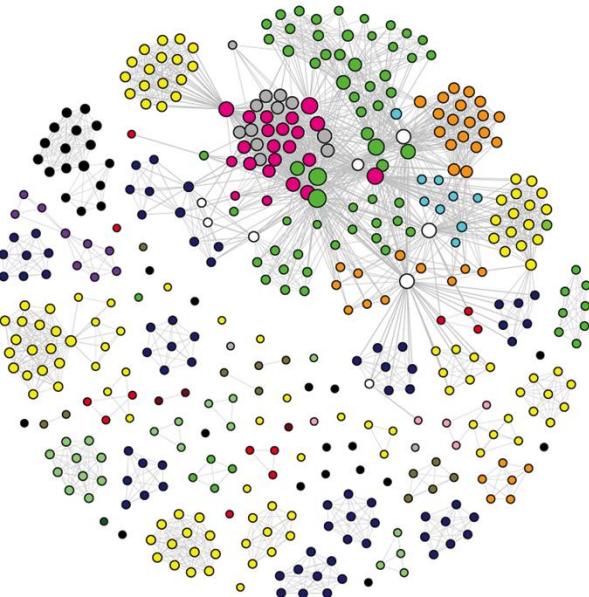
Researchers created a map linking different diseases, represented by circles, to the genes they have in common, represented by squares. Related Article: [Redefining Disease, Genes and All](#)



Sources: Marc Vidal; Albert-Laszlo Barabasi; Michael Cusick;
Proceedings of the National Academy of Sciences

The New York Times

The small world of psychopathology



DSM-IV symptoms

- Disorders usually first diagnosed in infancy, childhood or adolescence
- Delirium, dementia, and amnesia and other cognitive disorders
- Mental disorders due to a general medical condition
- Substance-related disorders
- Schizophrenia and other psychotic disorders
- Mood disorders
- Anxiety disorders
- Somatoform disorders
- Factitious disorders
- Dissociative disorders
- Sexual and gender identity disorders
- Eating disorders
- Sleep disorders
- Impulse control disorders not elsewhere classified
- Adjustment disorders
- Personality disorders
- Symptom is featured equally in multiple chapters

Global properties		
Number of symptoms	208	
Number of explicitly represented disorders	69	
Number of edges	1949	
Average shortest path length	2.60	
Average number of shortest paths between two symptoms	3.01	
Small-worldness index (SWI), based on transitivity	6.20	
Clustering coefficient, based on transitivity	0.68	
Average degree	18.74	
Symptoms with highest degree		
Symptom name	Degree	% Connected symptoms
1. Insomnia	71	34.1%
2. Psychomotor agitation	68	32.7%
3. Psychomotor retardation	61	29.3%
4. Depressed	60	28.8%
Symptoms with highest random walk betweenness		
Symptom name	Betweenness	% Connected symptoms
1. Irritable	0.24	23.6%
2. Distracted	0.17	24.0%
3. Anxious	0.16	23.1%
4. Depressed	0.16	28.8%

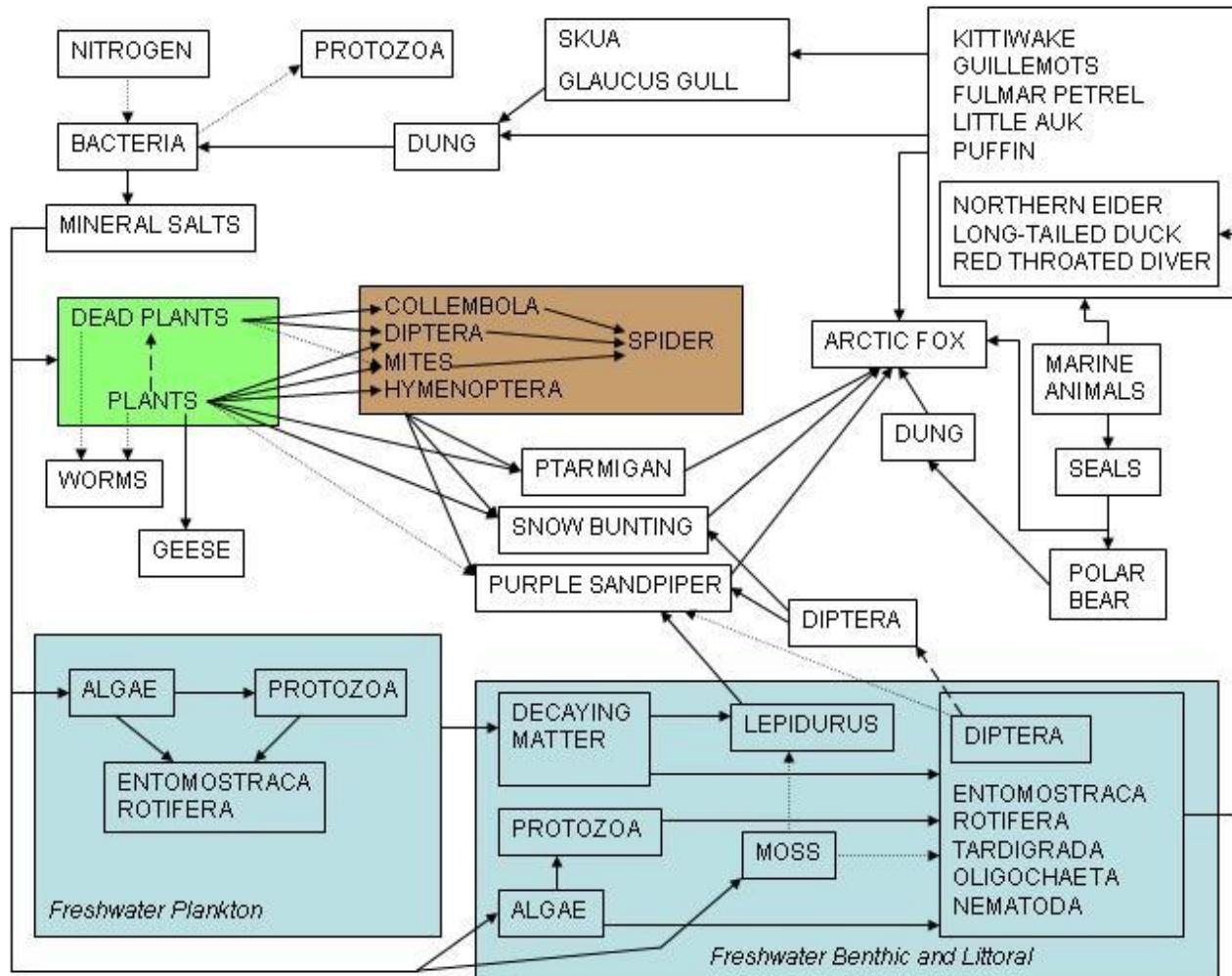
doi:10.1371/journal.pone.0027407.t001

Network properties of symptoms

From Boorsboom, et al., 2011, *PLoS ONE*



Biological networks: Food webs

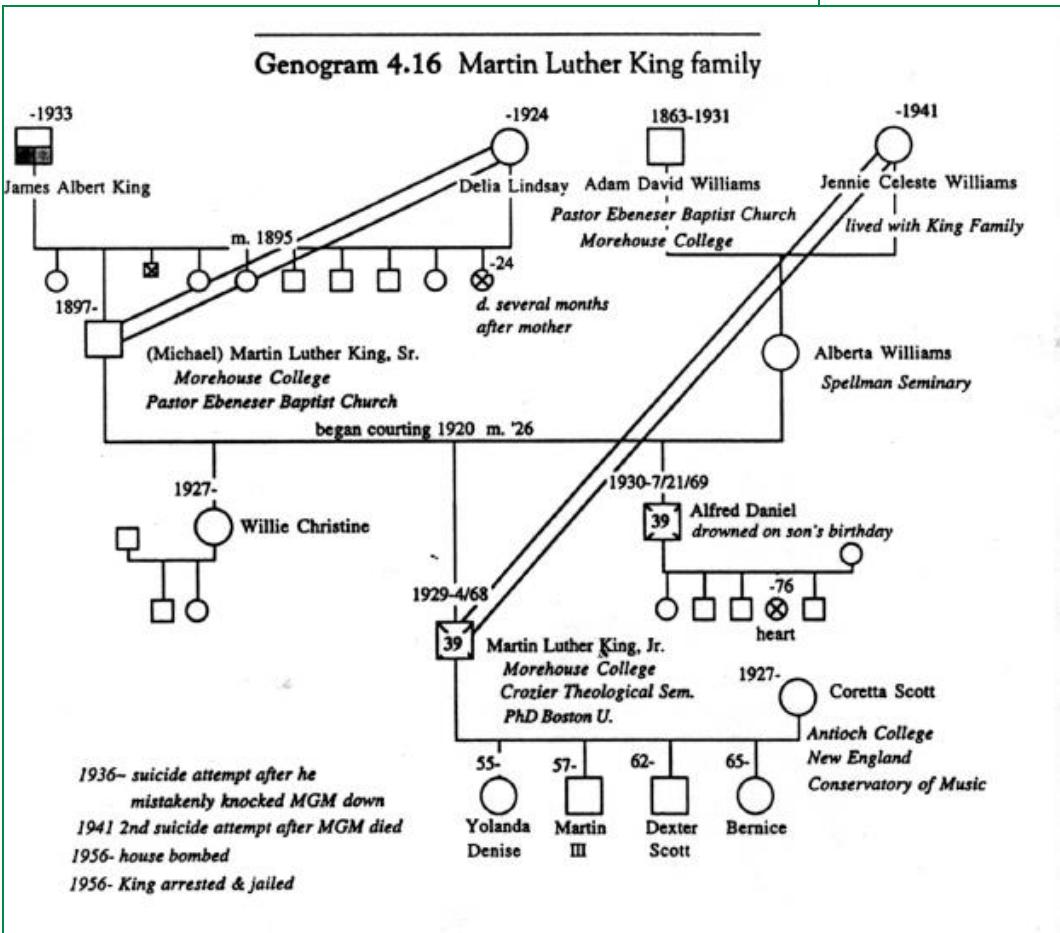


(Wikipedia: Summerhayes & Elton's
1923 food web of Bear Island)



Social networks

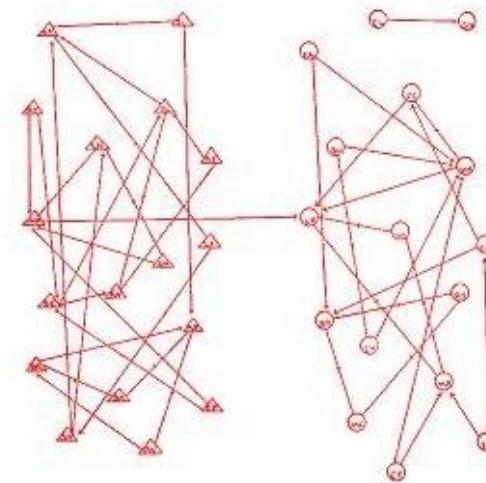
MLK Genogram



EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the Psychological Currents of Human Relationships.

New York Times
April 3, 1933

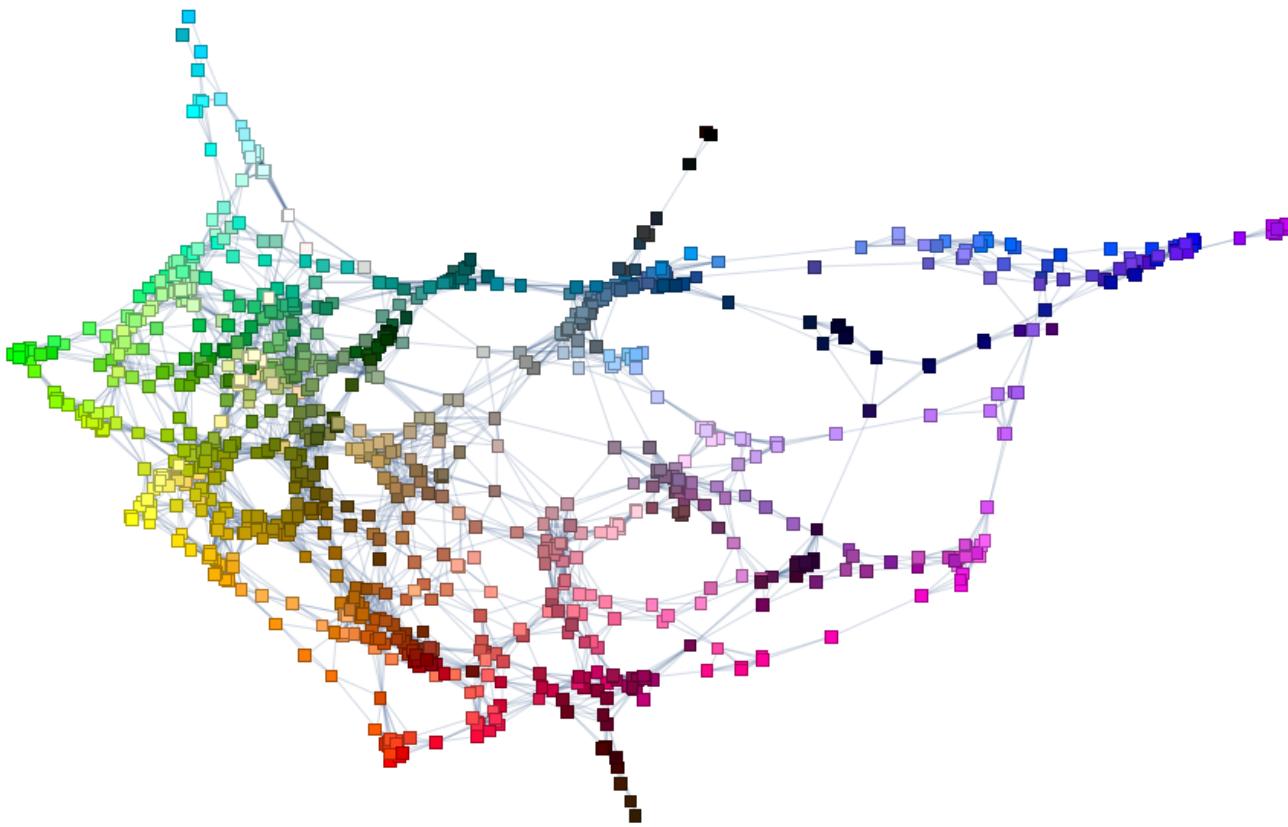


Moreno Sociogram

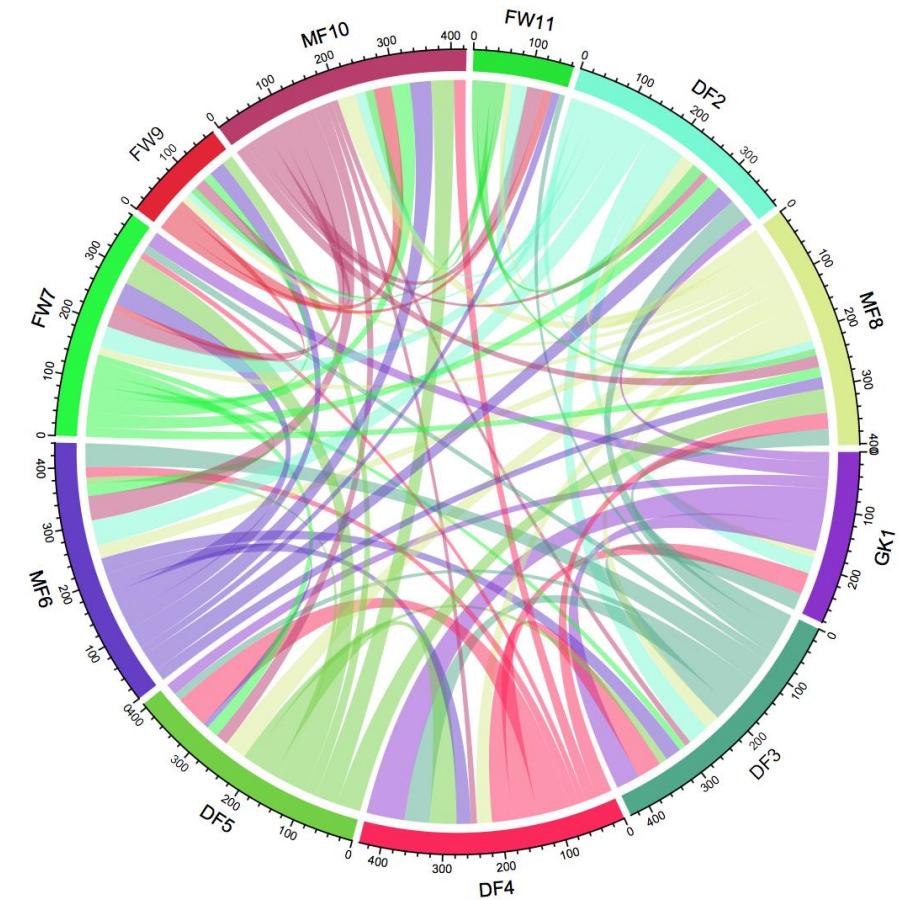


Everything is networked...

Relationships among color labels



Passes between members of Dutch national soccer team

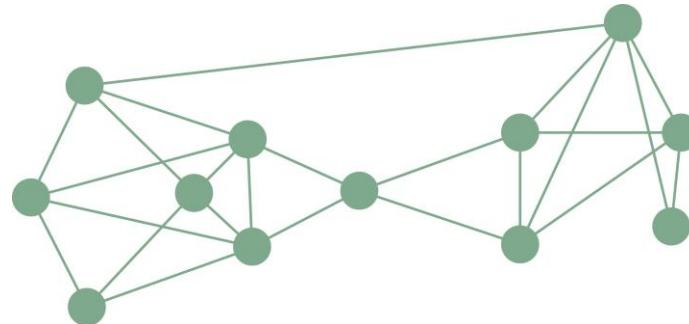


(<http://community.wolfram.com/groups/-/m/t/434022>)

(Luke, *A User's Guide to Network Analysis in R*, 2015)

Analysis modes

1. Visualization



2. Description

Network	Size	Diameter	Density
LGBT	57	5	.17
Latino	46	4	.31
APPEAL	39	4	.12

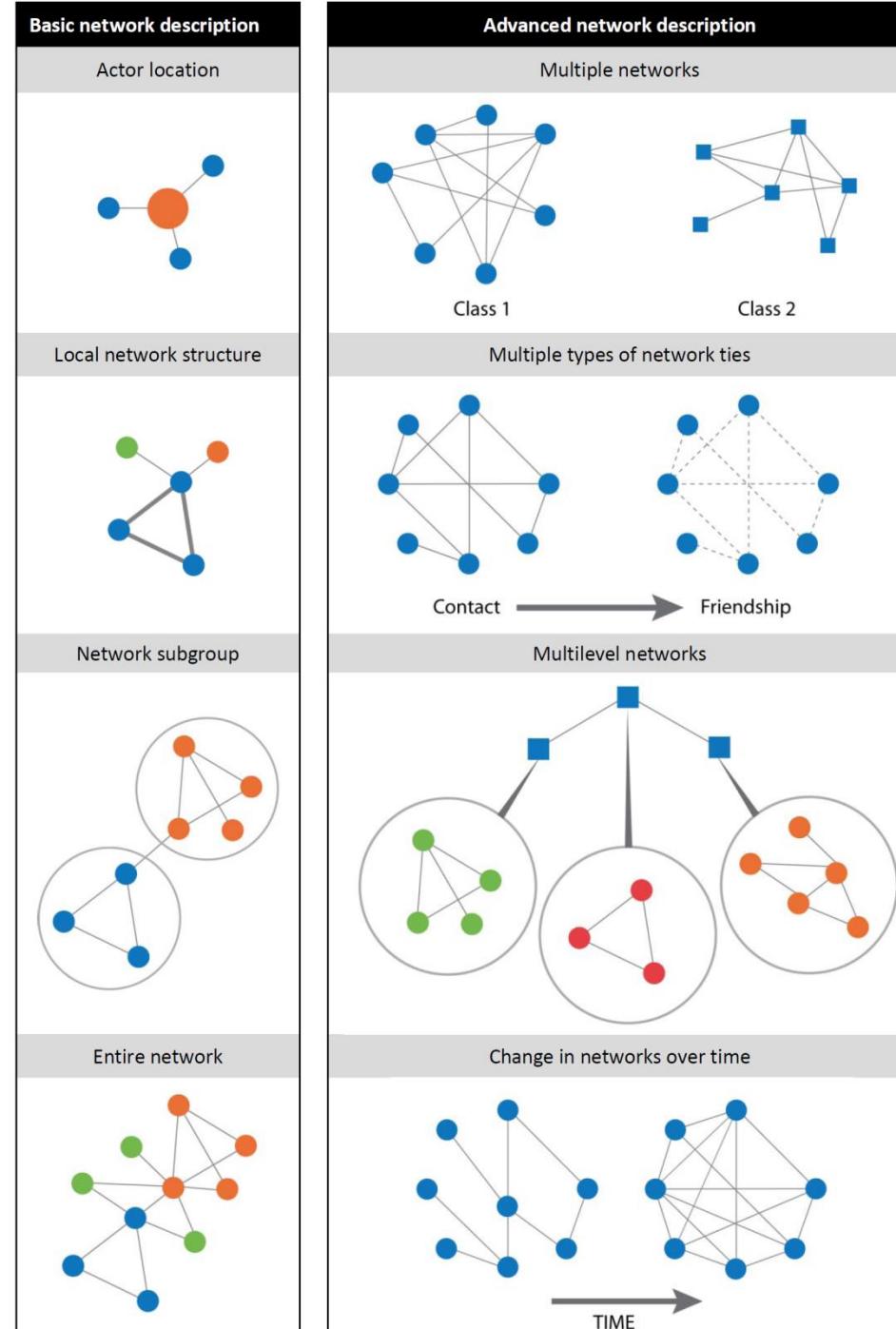
3. Modeling

$$P(Y = y | X) = \exp[\theta^T g(y, X)] / \kappa(\theta)$$



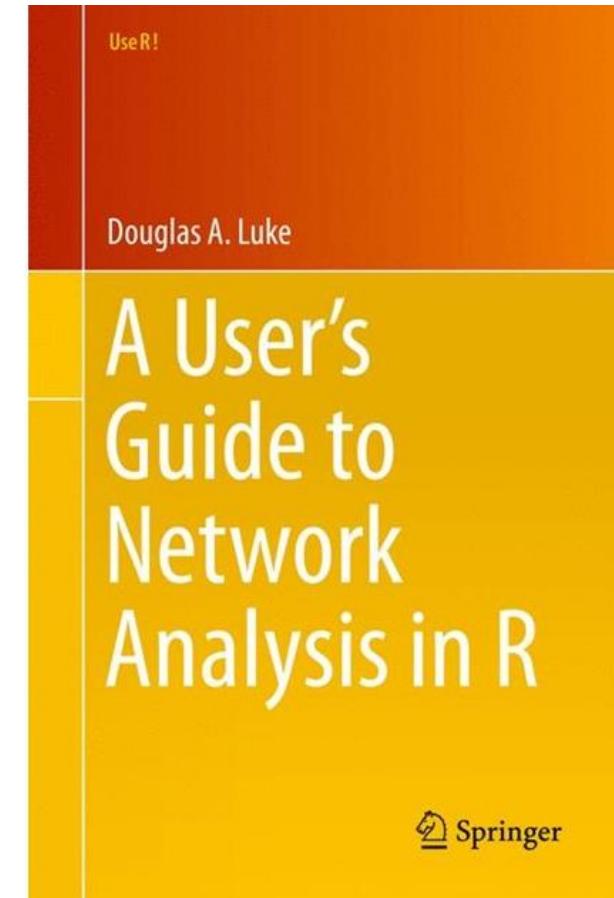
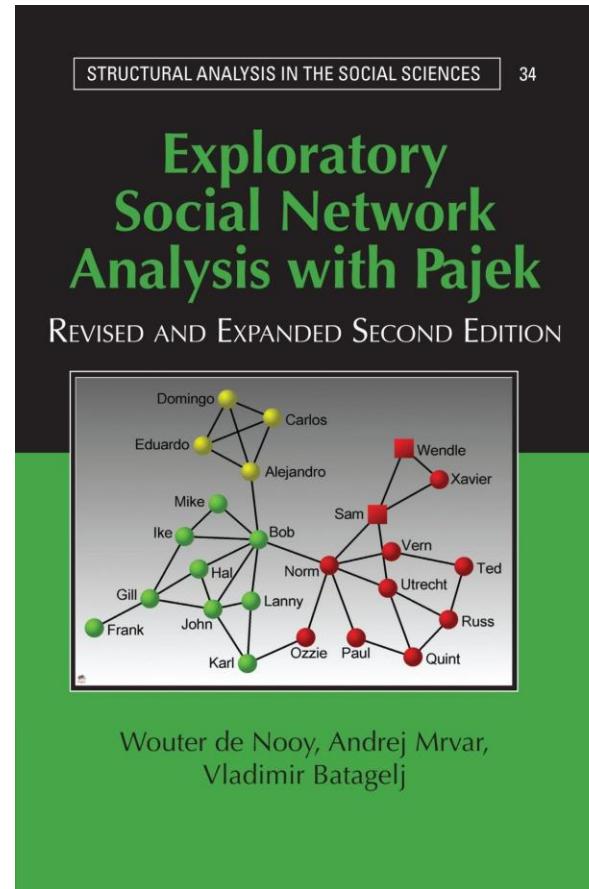
Multiple analytic approaches

Luke & Stamatakis, 2012, ARPH



Network analysis software options

- Stand-alone
 - Pajek
 - UCINet
 - NodeXL
 - Gephi
- Integrated (R, Python)
 - igraph
 - statnet

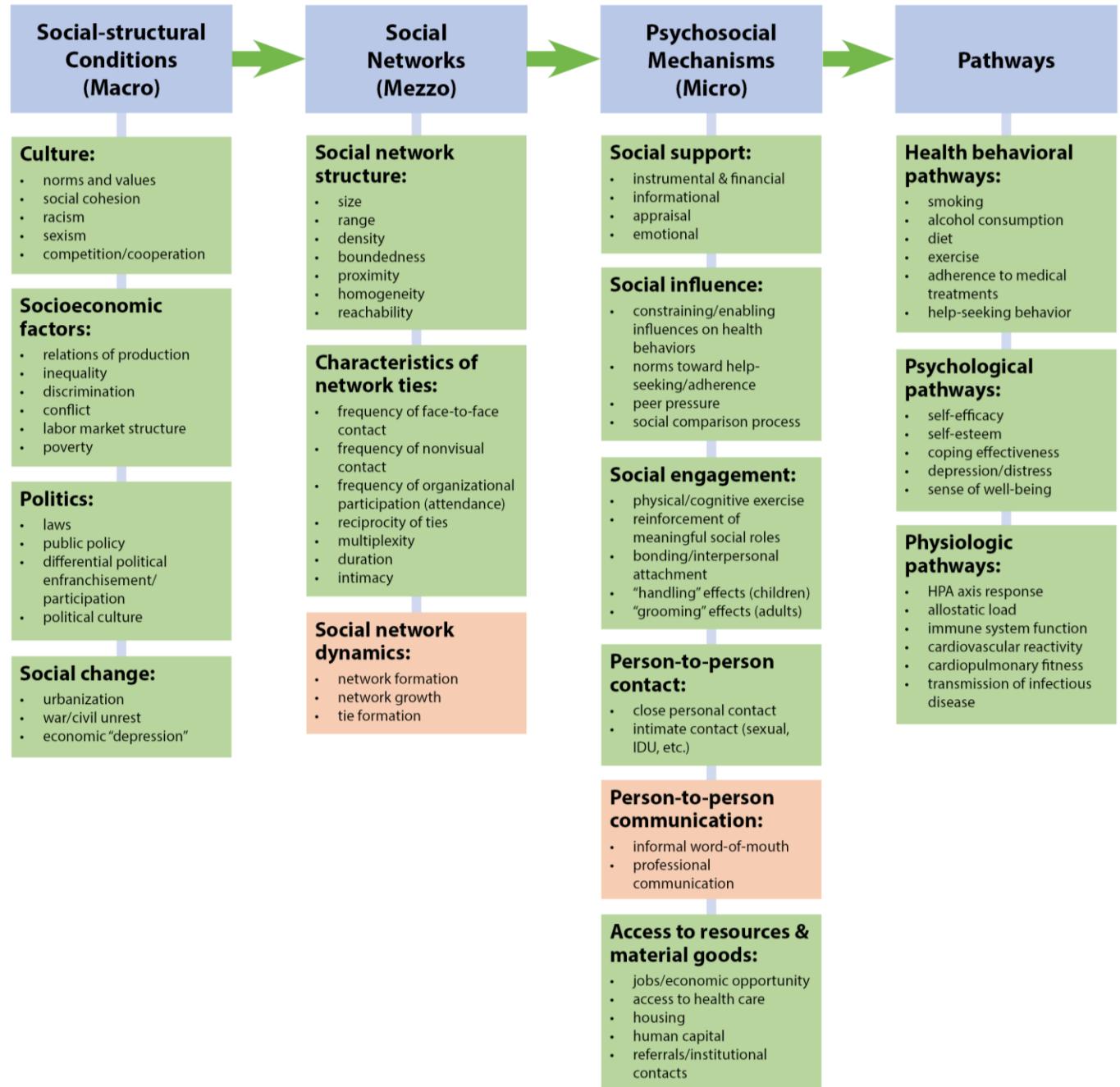


Network Theory

Theoretical frameworks that connect social structures to health/systems

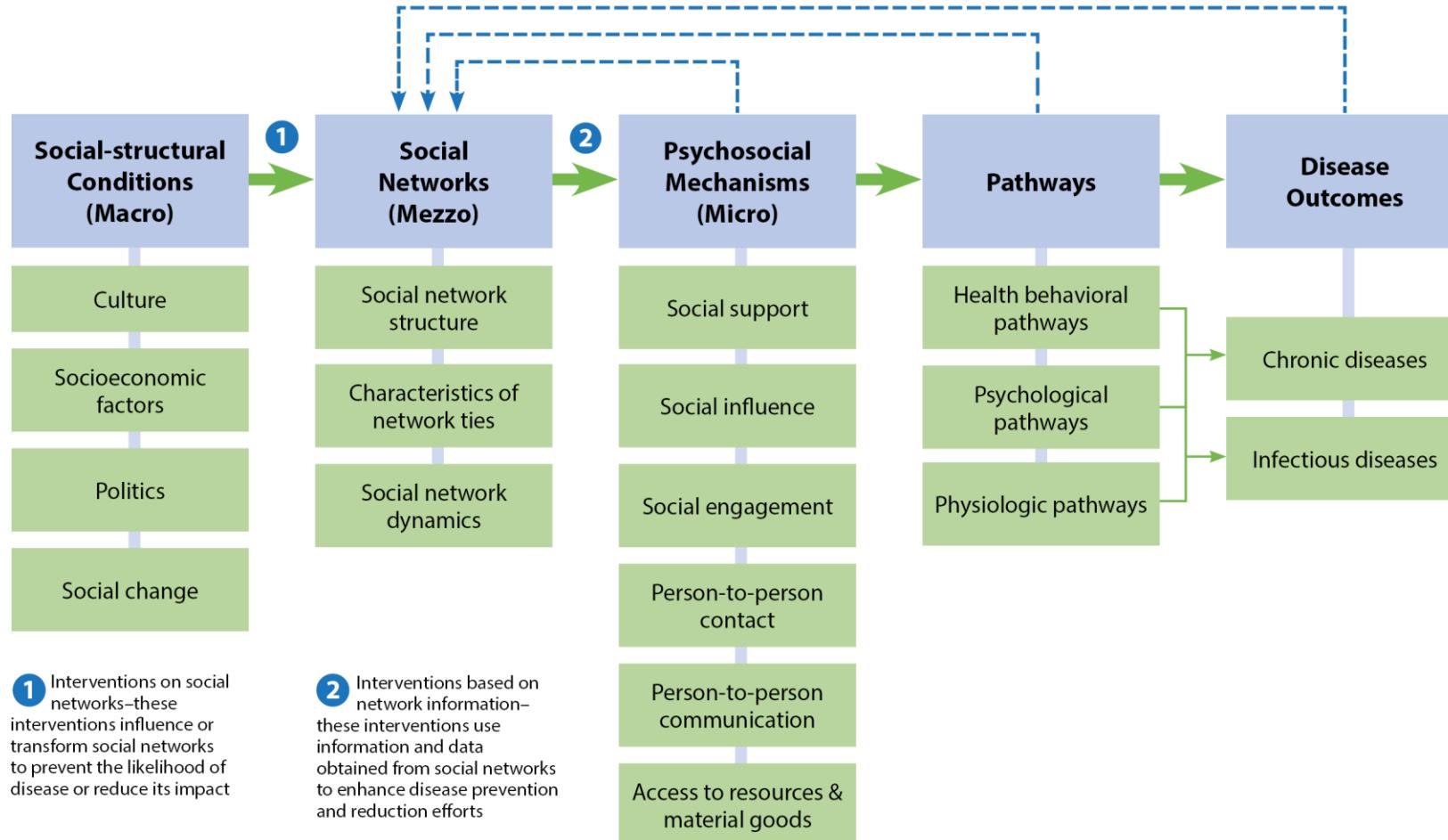


Social networks and human disease conceptual model



Luke & Schoen, 2017; Adapted from Berkman, et al, 2000, SSM

Network dynamics and intervention opportunities



Connecting the social to the biological

Brain connectivity dynamics during social interaction reflect social network structure

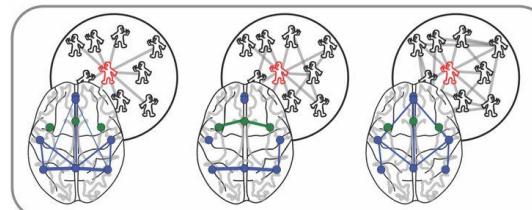
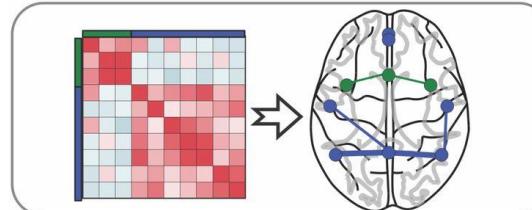
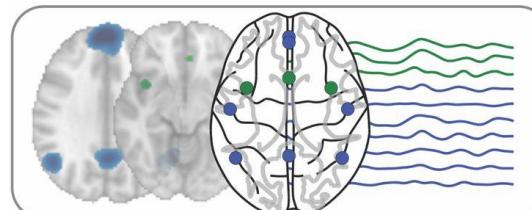
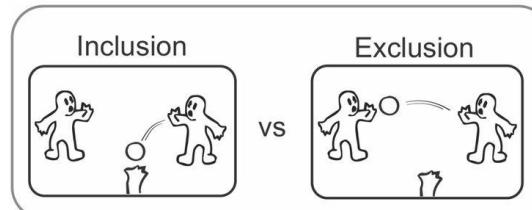
Ralf Schmälzle, Matthew Brook O'Donnell, Javier O. Garcia, Christopher N. Cascio, Joseph Bayer, Danielle S. Bassett, Jean M. Vettel, and Emily B. Falk

PNAS May 16, 2017 114 (20) 5153-5158; published ahead of print May 2, 2017 <https://doi.org/10.1073/pnas.1616130114>

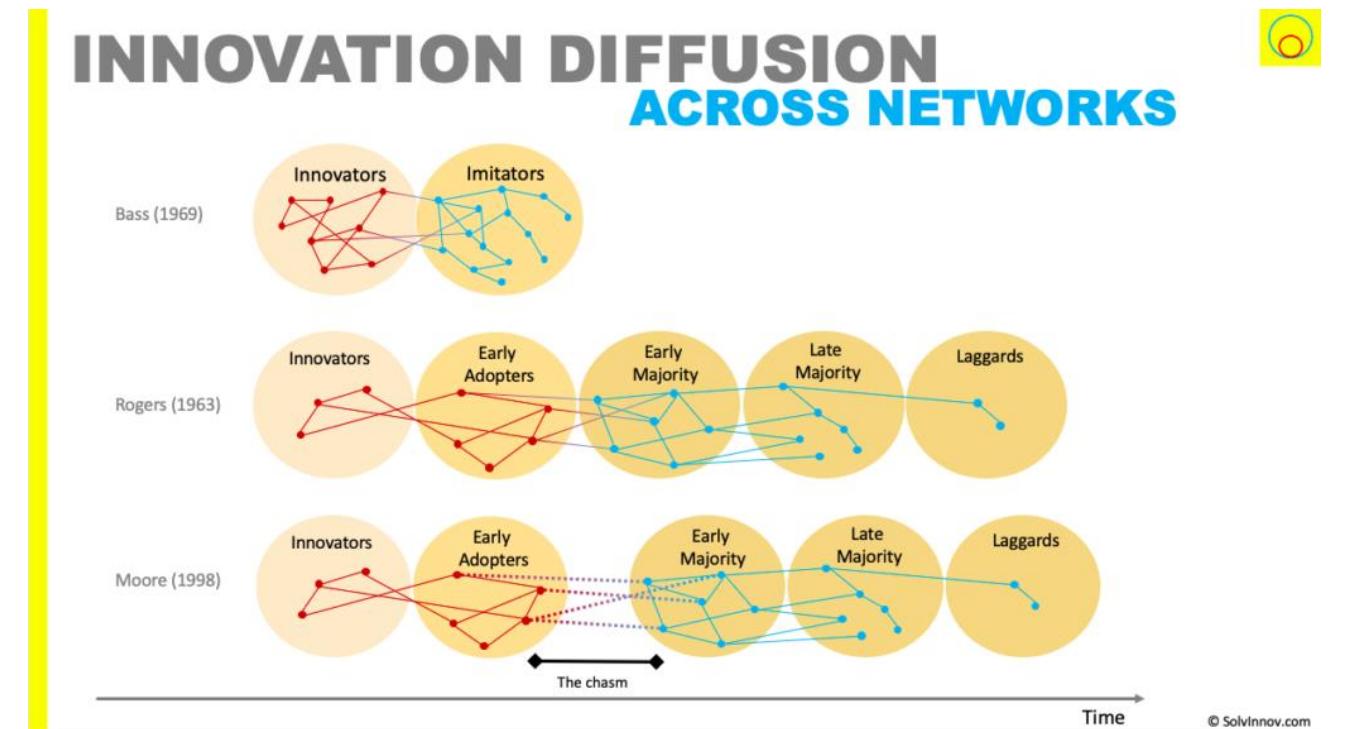
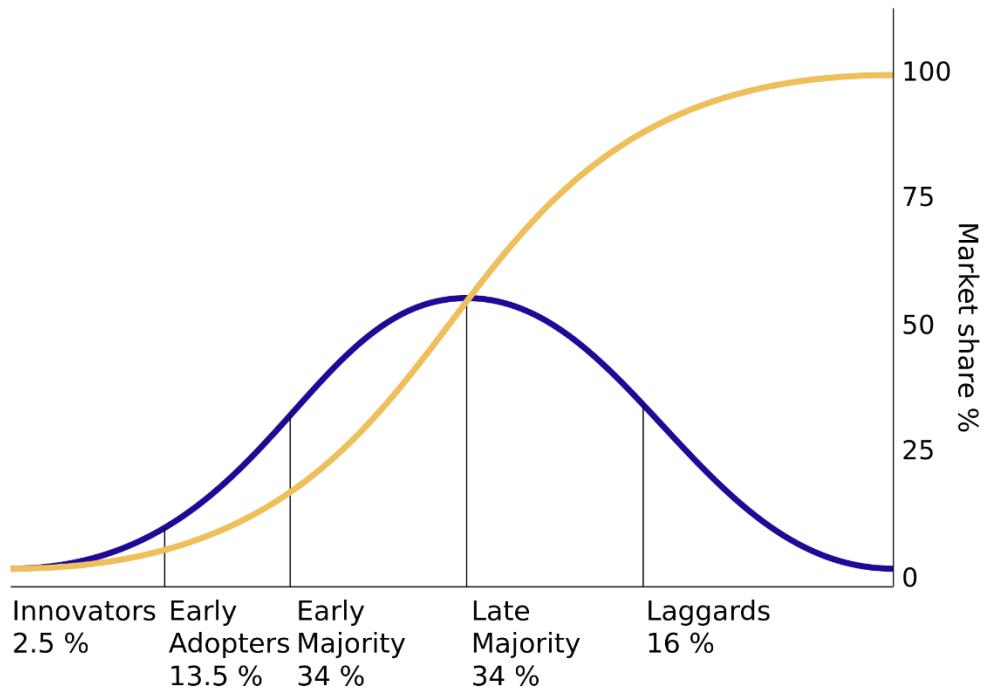
Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 31, 2017 (received for review September 30, 2016)



Experimental Design and Analysis



Diffusion of innovations



https://en.wikipedia.org/wiki/Diffusion_of_innovations

<https://solvinnov.com/innovation-diffusion/>

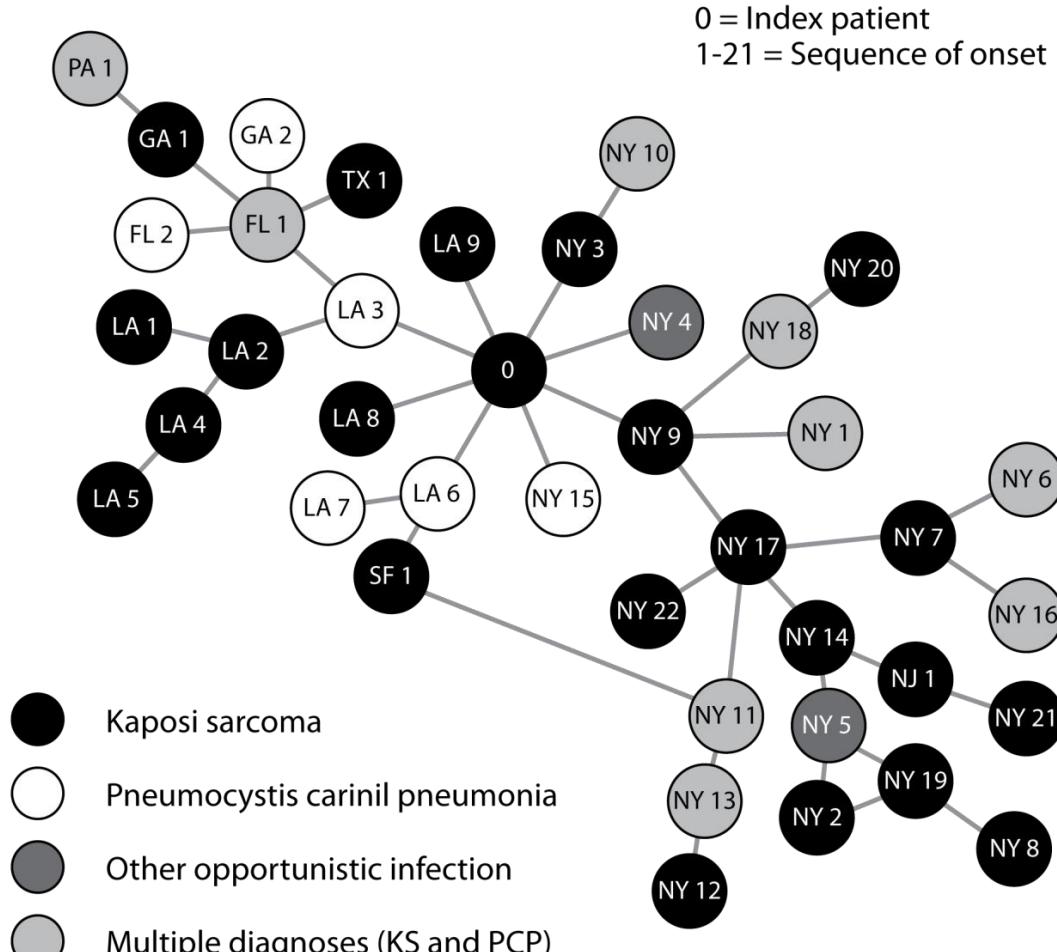


Public Health

Social structure drives many aspects of individual and population health



First HIV/AIDS network graphic



City LA-Los Angeles, NY-New York City, SF-San Francisco
State FL-Florida, GA-Georgia, NJ-New Jersey, PA-Pennsylvania, TX-Texas

(Auerbach et al, 1984; Luke & Stamatakis, 2012)

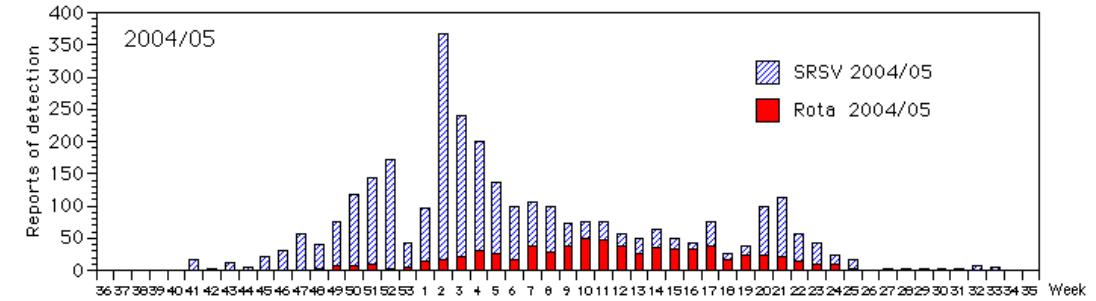
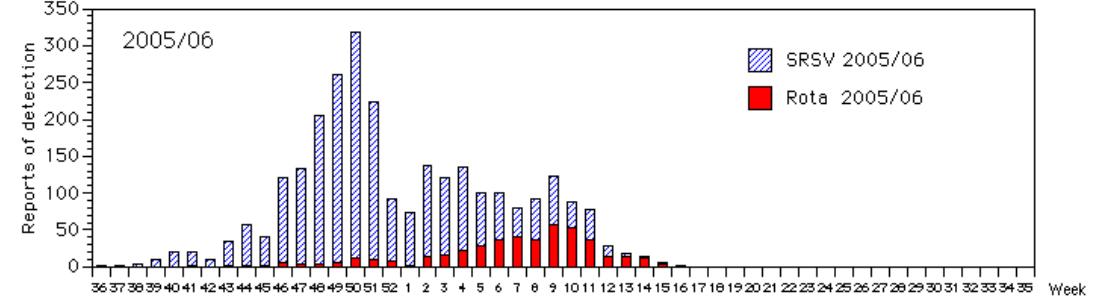


Traditional S-I-R models ignored social structure

Symbol	Name	Definition
S	Susceptible	not infected but can be infected
E	Exposed	Infected but cannot infect others (Latent)
I	Infectious	Infectious TB, can infect others (Active)
T	Treated	Treated either from latent or Active TB
V	Vaccination	vaccinated, no longer susceptible to TB

Symbol	Explanation
Λ	recruitment rate
β	transmission rate (meaning varies)
c	average number of contacts per person per unit time
k	per-capita regular progression rate
μ	per-capita natural mortality rate
d	per-capita excess death rate due to TB
r_0	per-capita treatment rate for recently latently-infected
r_1	per-capita treatment rate for latently-infected
r_2	per-capita treatment rate for actively-infected
ω	per-capita progress rate for early latent-TB progression

Weekly reports of SRSV(norovirus,sapovirus) & rotavirus detection, 2005/06
 (Infectious Agents Surveillance Report: Data based on the reports received before April 21, 2006 from public health institutes)



(<http://dimacs.rutgers.edu/Workshops/EpidTutorial>)

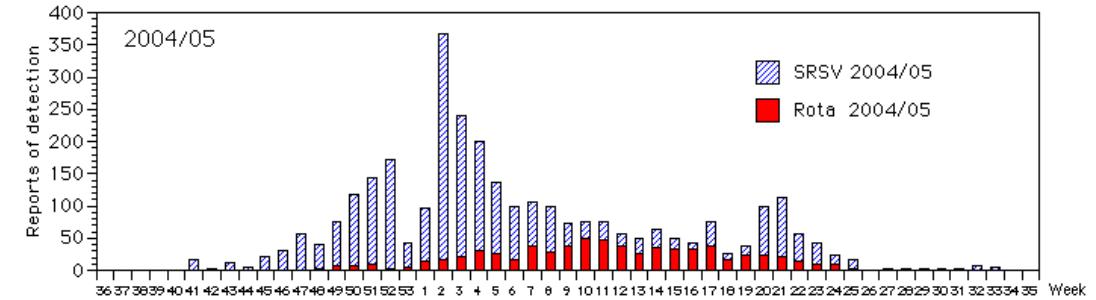
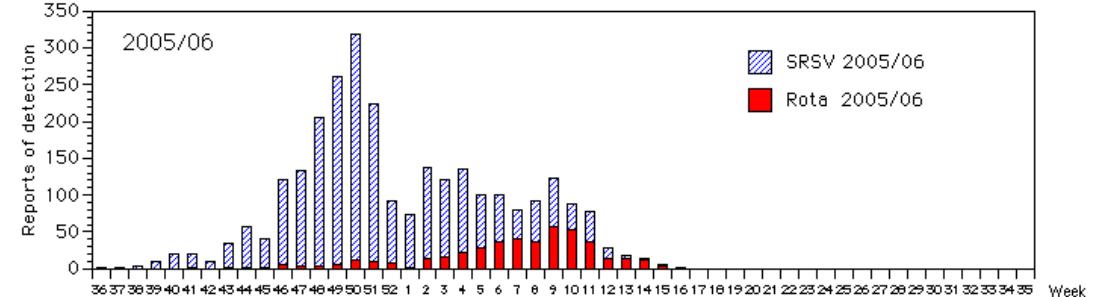


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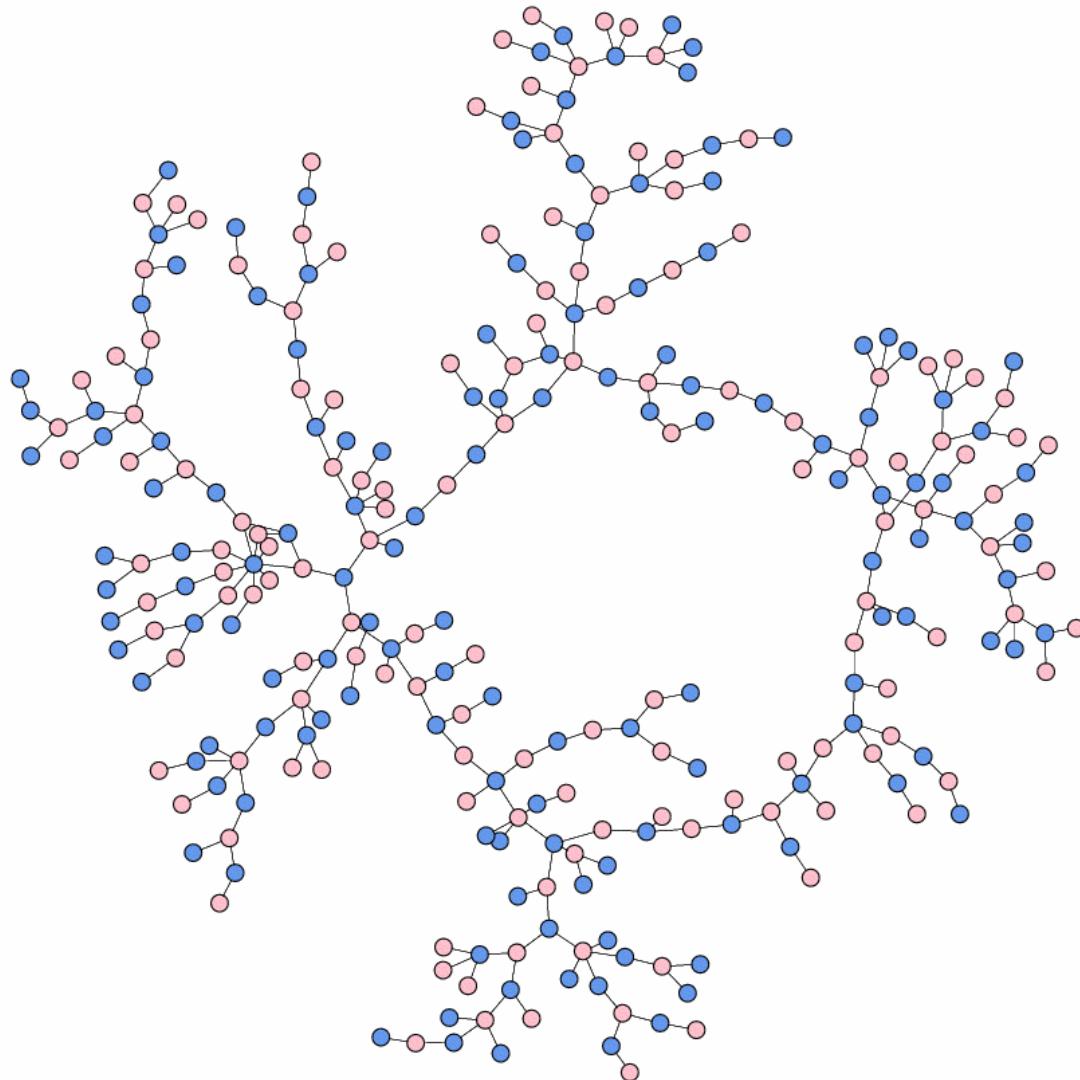


Assumes random mixing

(<http://dimacs.rutgers.edu/Workshops/EpidTutorial>)



High school romantic contacts



Peter S. Bearman, James Moody, and Katherine Stovel, [Chains of affection: The structure of adolescent romantic and sexual networks](#), *American Journal of Sociology* 110, 44-91 (2004).



General association of social support and network size with cancer mortality

Table 1

Association of perceived social support, network size, and being married with cancer survival.

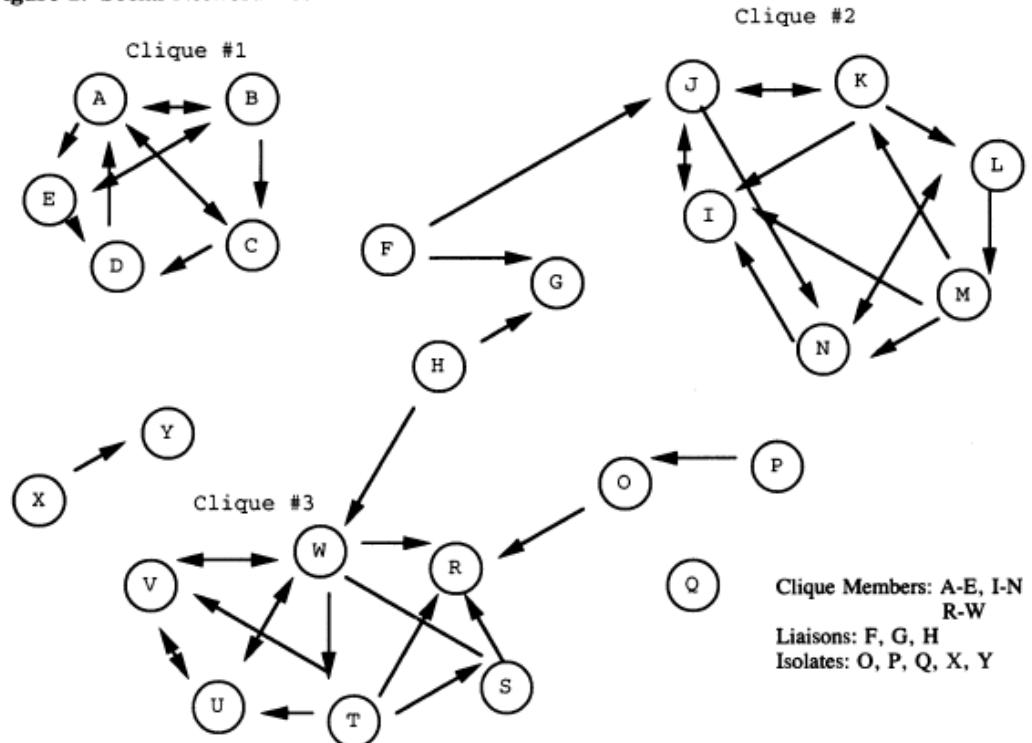
Study characteristic	k	N	RR	95% Confidence interval	Z	p
<i>Association of social support with mortality in cancer patients</i>						
Uncontrolled effect sizes	18	2,867	.92	.84 .99	-2.03	.0427
Controlled effect sizes	21	17,481	.75	.65 .87	-3.79	.0002
Averaged effect size	31	18,828	.82	.75 .89	-4.56	.0001
<i>Associations of social network with mortality of cancer patients</i>						
Uncontrolled effect sizes	6	94,794	.73	.60 .88	-3.30	.001
Controlled effect sizes	23	3,997	.80	.72 .89	-4.30	.0001
Averaged effect size	23	97,088	.80	.72 .88	-4.33	.0001
<i>Associations of being married with mortality in cancer patients</i>						
Uncontrolled effect sizes	64	11607,245	.84	.81 .86	-12.52	.0001
Controlled effect sizes	40	610,837	.88	.82 .94	-3.74	.0002
Averaged effect size	88	12159,656	.87	.84 .90	-7.92	.0001



Network analysis in chronic disease

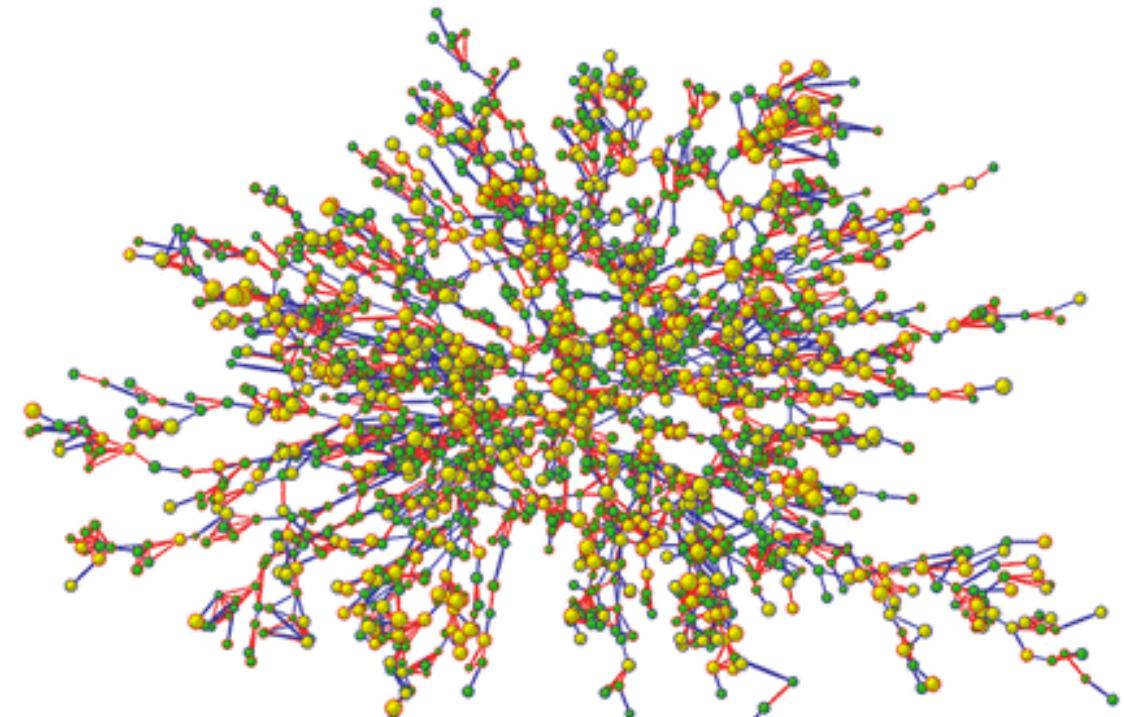
Peer group structure and smoking

Figure 1. Social Network Positions



From Ennett & Bauman, 1993, *JHSB*

Clustering of obesity in personal networks



Christakis & Fowler, 2007, *NEJM*



Peer Group Structure and Adolescent Cigarette Smoking: A Social Network Analysis*

SUSAN T. ENNETT

Research Triangle Institute

KARL E. BAUMAN

University of North Carolina, Chapel Hill

Figure 1. Social Network Positions

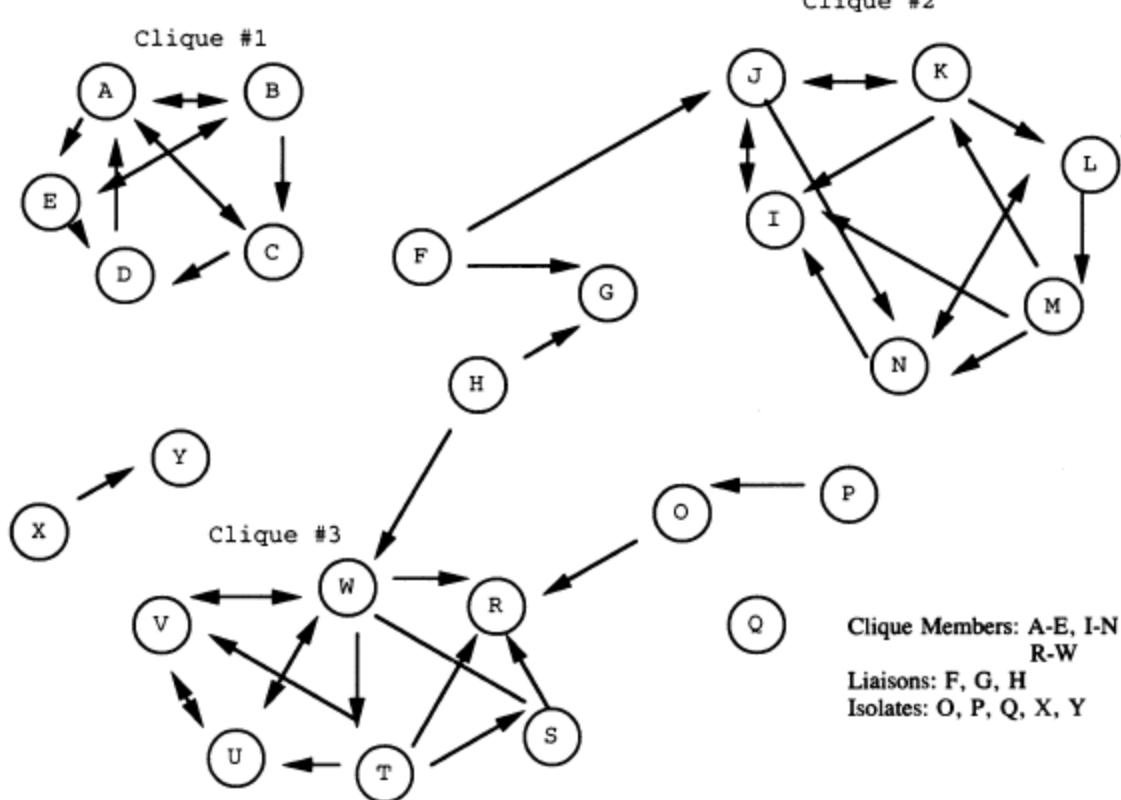


TABLE 3. Results of Logistic Regression Analysis of Current Smoking Status on Social Position, By School

	Adjusted Odds Ratio ^a	95% CI
School A (<i>N</i> =164)		
Network Isolate ^b	6.46***	2.08, 20.04
School B (<i>N</i> =164)		
Network Isolate	3.66***	1.67, 8.03
School C (<i>N</i> =257)		
Network Isolate	2.92***	1.54, 5.54
School E (<i>N</i> =288)		
Network Isolate and Male	6.05**	.81, 45.51
Network Isolate and Low Mother's Education	4.84*	1.37, 17.09

^a Adjusted for gender, race, and mother's education.

^b Reference is clique member/liaison.

* $p < .05$; ** $p < .01$; *** $p < .001$.

From Ennett & Bauman, 1993, *JHSB*



Dissemination & Implementation Science

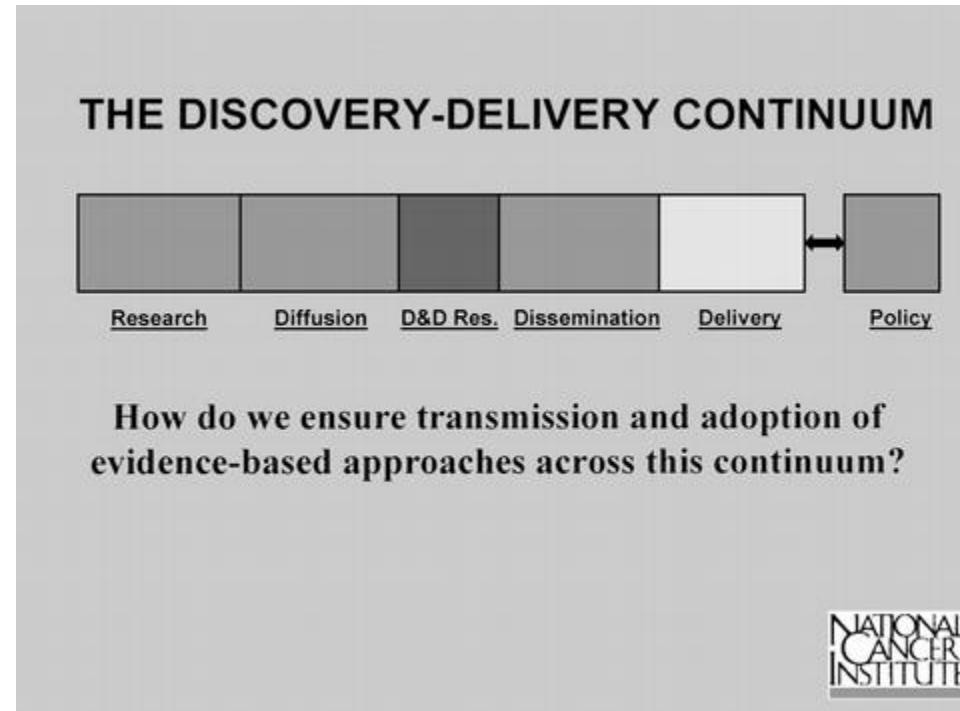
Networked systems are integral to the processes and outcomes relevant to implementation science



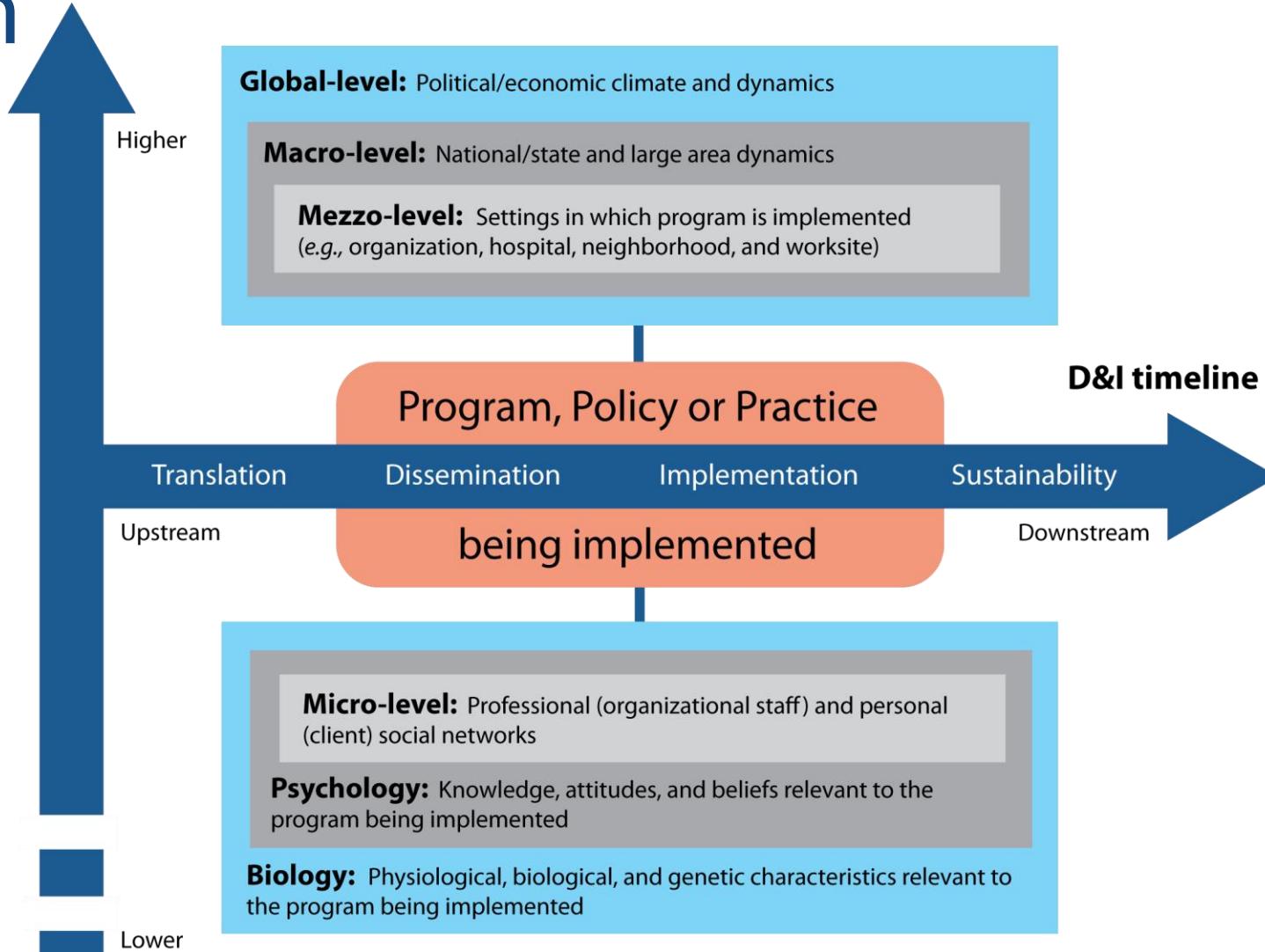
The Promise of D&I Science

...there is still an enormous gap between what we know can maximize the quality of health care and what is currently being delivered in practice and community settings.

...to optimize public health we must not only understand how to create the best interventions, but how to best ensure that they are effectively delivered within clinical and community practice.



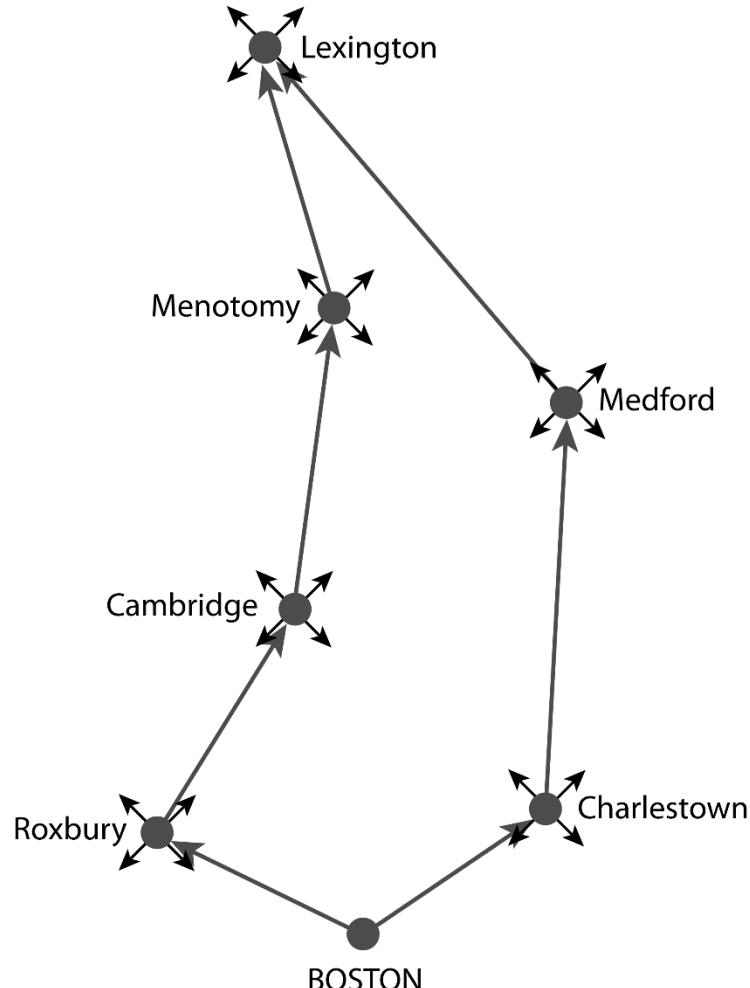
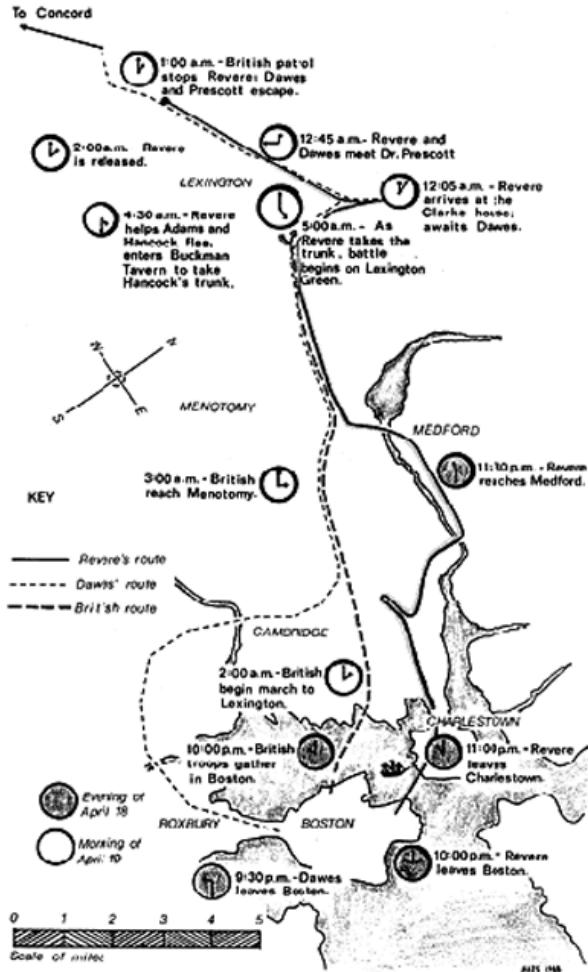
A social-ecological framework for D&I research



Inspired by Glass & McAtee, 2006, SSM

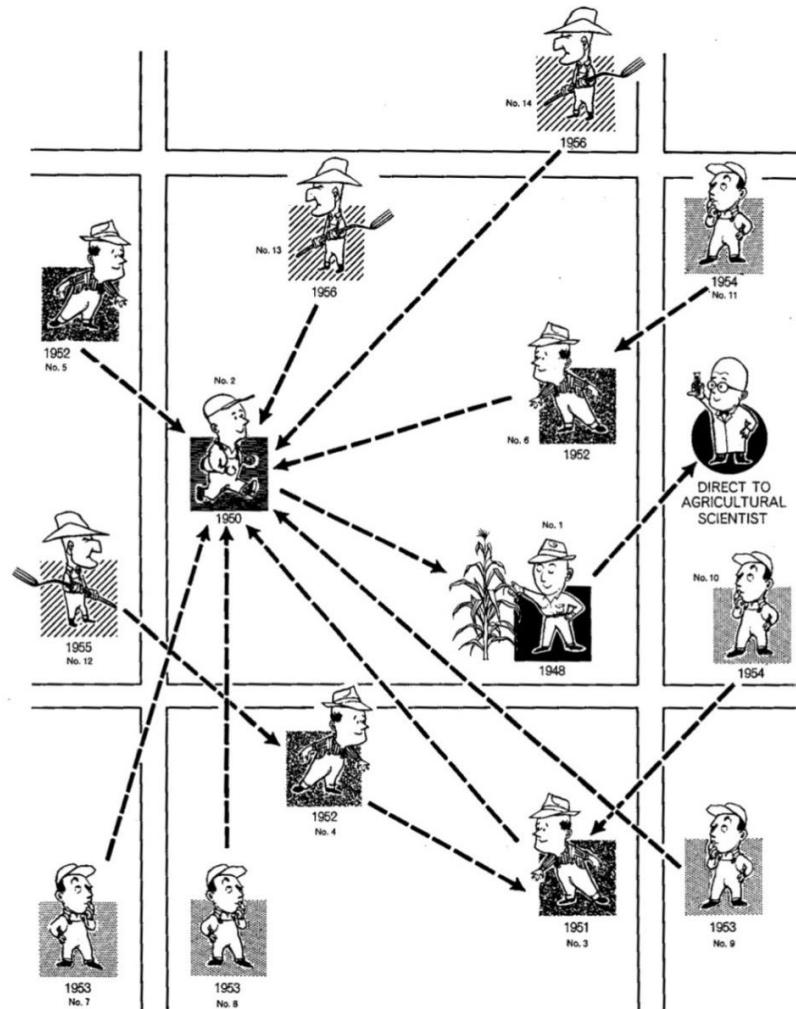


Network science - diffusion of information across a social system



Diffusion of innovations as a networked process

- Seminal article in 1943 on diffusion of hybrid seed corn in two Iowa communities (Ryan & Gross, 1943)
- Key findings:
 - Adoption as key variable
 - Change agents
 - Importance of different communication channels
- Diffusion and networks
 - Rogers, Dearing, Valente



How fourteen Midwest farmers obtained information on a new farm practice. Farm locations are shown against a mile grid.



Dissemination also takes too much time in tobacco control

Forty Years of Secondhand Smoke Research The Gap Between Discovery and Delivery

Jenine K. Harris, PhD, Douglas A. Luke, PhD, Rachael B. Zuckerman, BA, Sarah C. Shelton, MPH, CHES

Context: Public health initiatives often focus on the discovery of risk factors associated with disease and death. Although this is an important step in protecting public health, recently the field has recognized that it is critical to move along the continuum from discovery of risk factors to delivery of interventions, and to improve the quality and speed of translating scientific discoveries into practice.

Evidence acquisition: To understand how public health problems move from discovery to delivery, citation network analysis was used to examine 1877 articles on secondhand smoke (SHS) published between 1965 and 2005. Data were collected and analyzed in 2006–2007.

Evidence synthesis: Citation patterns showed discovery and delivery to be distinct areas of SHS research. There was little cross-citation between discovery and delivery research, including only nine citation connections between the main paths. A discovery article was 83.5% less likely to cite a delivery article than to cite another discovery article ($OR=0.165$ [95% CI=0.139, 0.197]), and a delivery article was 64.3% less likely ($OR=0.357$ [95% CI=0.330, 0.386]) to cite a discovery article than to cite another delivery article. Research summaries, such as Surgeon General reports, were cited frequently and appear to bridge the discovery-delivery gap.

Conclusions: There was a lack of cross-citation between discovery and delivery, even though they share the goal of understanding and reducing the impact of SHS. Reliance on research summaries, although they provide an important bridge between discovery and delivery, may slow the development of a field.

(Am J Prev Med 2009;xx(x):xxx) © 2009 American Journal of Preventive Medicine

Introduction

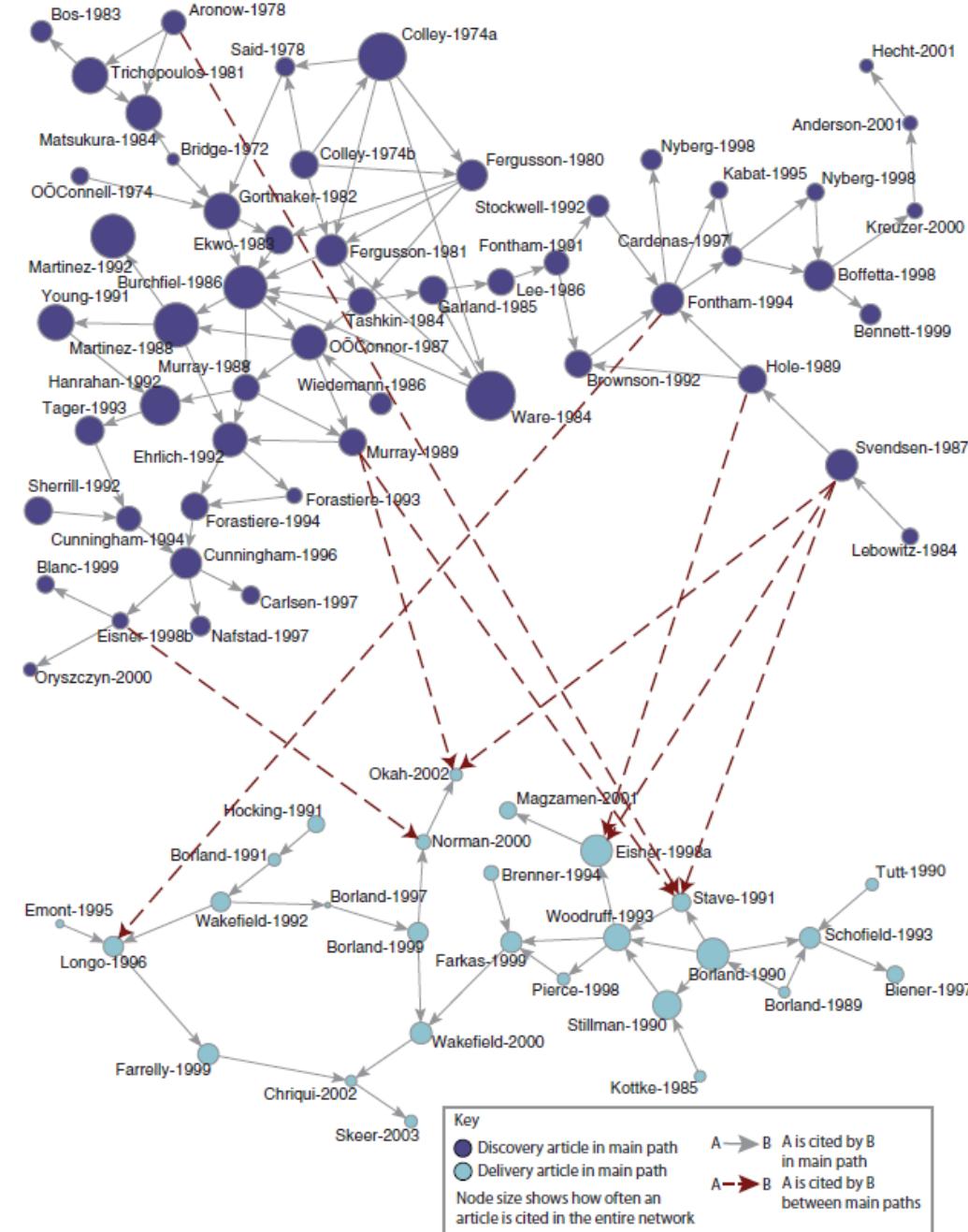
Efforts in public health often focus on discovery of risk factors associated with disease and death.¹ However, discovery is only half the story; it is critical to move along the continuum from discovery of health information to delivery of interventions that improve public health.^{1–4} For example, although understanding the nature and extent of a new virus is important, vaccine development and other interventions to combat the virus are equally important, as is the delivery of these interventions to appropriate populations.

The path from discovery to delivery is a fundamental process in public health; however, it is not well understood. A few models showing the relationship between discovery and delivery have recently emerged (e.g., the

National Cancer Institute Discovery-Development-Delivery model⁵). For example, in relation to cancer science, the "... research process spans a continuum from discovery of new knowledge about the process of cancer, to development of new interventions, to the ultimate delivery of new, more effective, and safer interventions to all who need them."³

One helpful framework for understanding the path from discovery to delivery is the Diffusion of Innovations (DOI) theory.⁵ The DOI theory consists of three major steps: become aware of and learn about the innovation, develop a positive or negative attitude toward the innovation, and put the innovation to use.⁵ This theory has often been used to describe how innovations travel through social networks. For example, one exemplar study examined how interpersonal communication among physicians facilitated adoption of a new drug.⁶ Using DOI theory, scientific progress can be seen as a highly formalized process in which scientific discoveries are the innovations that are communicated (at least partially) through peer-reviewed studies.

Recent work in systems thinking and transdisciplinarity related to public health further elucidates how information and innovation move along the discovery-



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The full text of this article is available via AJPM Online at www.ajpm-online.net.



From discovery to delivery, via monographs

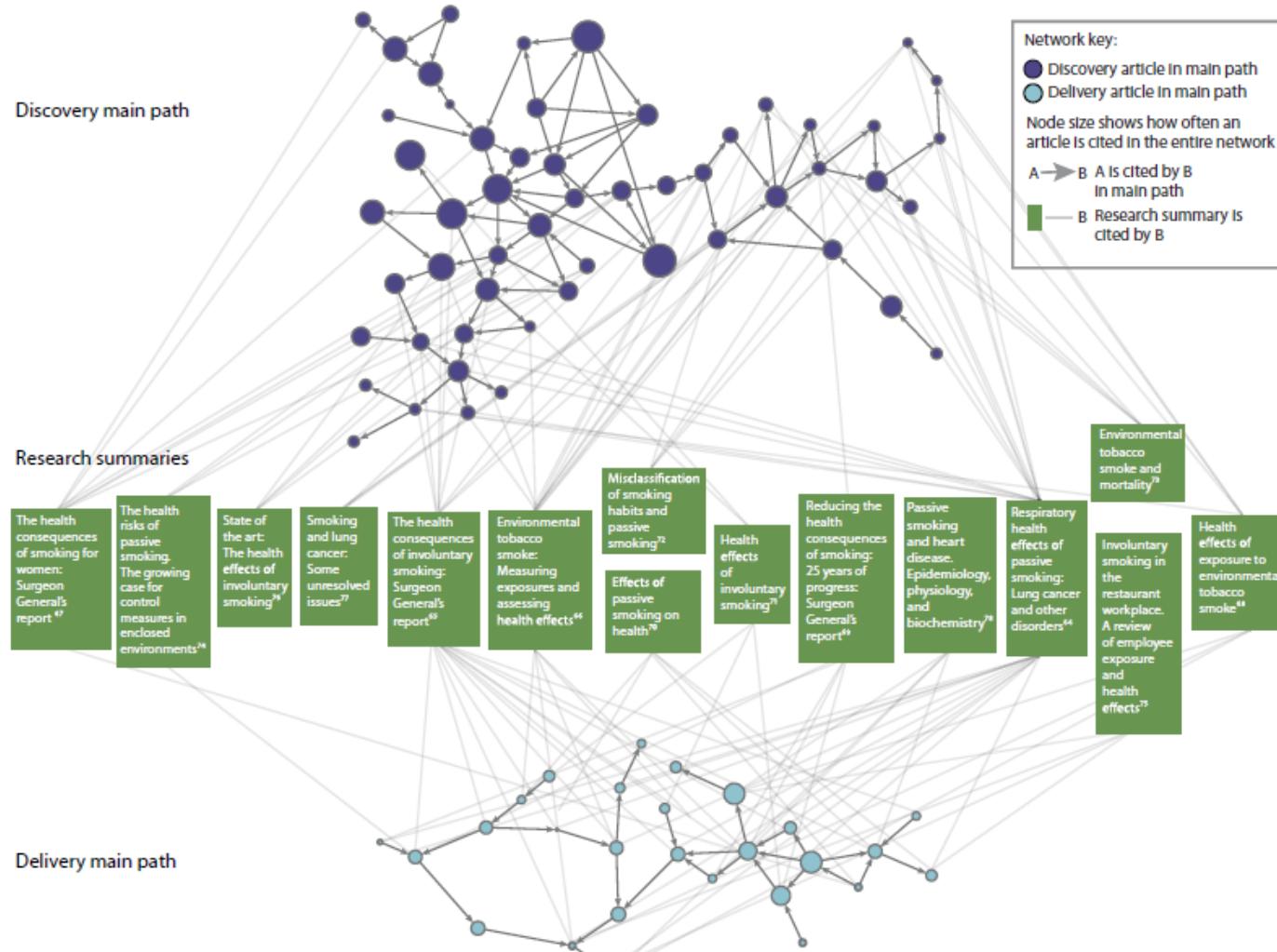


Figure 2. Main citation paths through discovery (top) and delivery (bottom) research articles related to SHS exposure, and the 120 citation links to the 15 research summaries cited most often by main path articles



Modeling dissemination of *Best Practices* in Tobacco Control

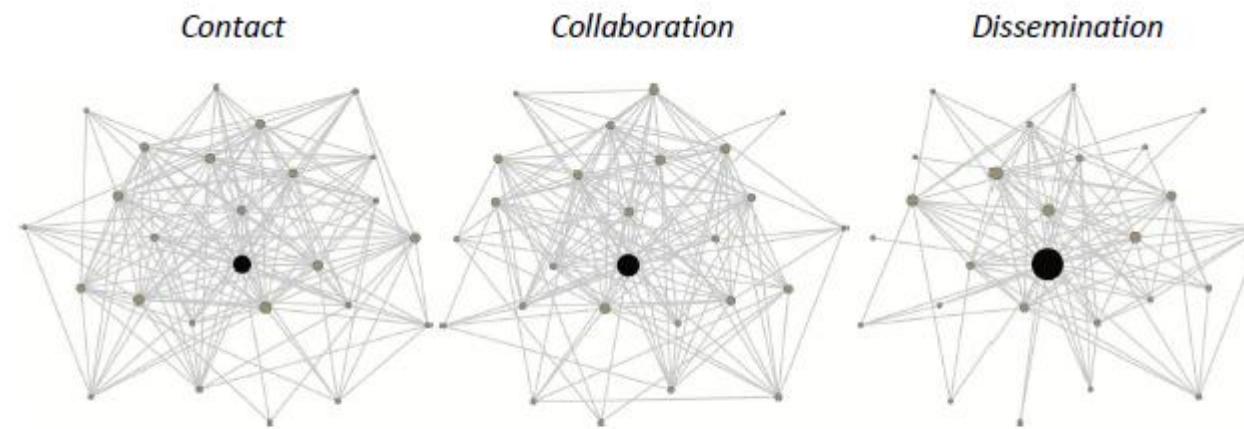


Figure A1. Contact, collaboration, and dissemination networks in Indiana. Nodes sized by betweenness centrality. Betweenness centrality for the lead agency (darker node) was .127 for contact, .207 for collaboration, and .423 for dissemination.

Odds ratios for final model (M3) for all states

	Indiana		Texas		Wyoming		DC	
	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
Edges	0.01	(0.00-0.02)	0.23	(0.09-0.63)	0.07	(0.04-0.15)	0.00	(0.00-0.00)
Degree (GWDegree)	0.06	(0.03-0.11)	0.05	(0.02-0.19)	0.02	(0.01-0.03)	0.12	(0.04-0.35)
TC Experience	1.08	(1.03-1.13)	0.95	(0.88-1.02)	1.08	(1.02-1.15)	1.24	(1.12-1.37)
Geographic Reach (Homophily)	1.72	(1.44-2.04)	5.33	(3.84-7.42)	0.62	(0.50-0.77)	3.95	(3.00-5.20)
Agency Distance	1.00	(0.98-1.02)	0.92	(0.91-0.92)	0.99	(0.98-0.99)	0.99	(0.98-1.01)
Network Contact	2.38	(2.28-2.48)	1.64	(1.43-1.88)	1.64	(1.57-1.71)	1.46	(1.34-1.59)
Network Collaboration	1.78	(1.70-1.86)	2.99	(2.67-3.35)	1.76	(1.68-1.84)	7.29	(6.55-8.12)



Modeling dissemination of *Best Practices* in Tobacco Control

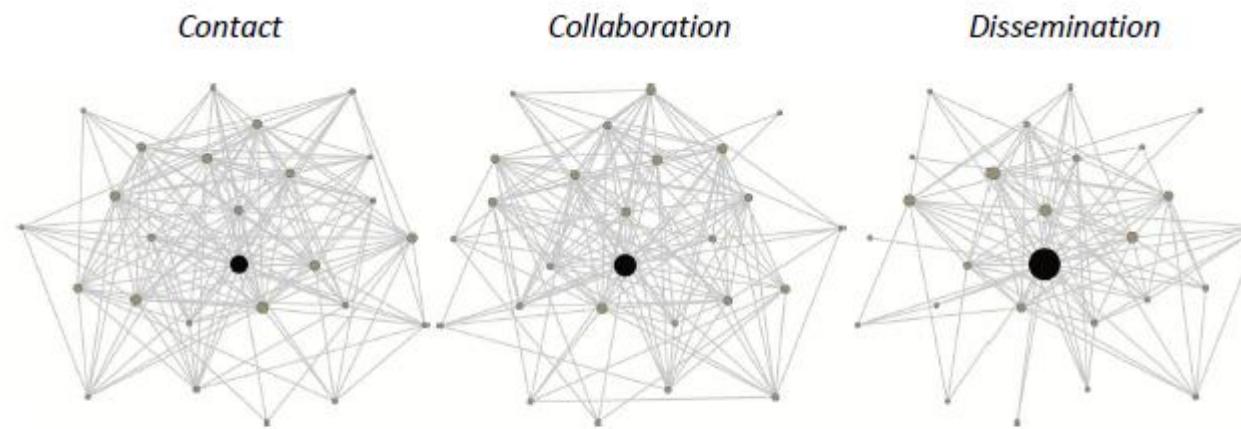


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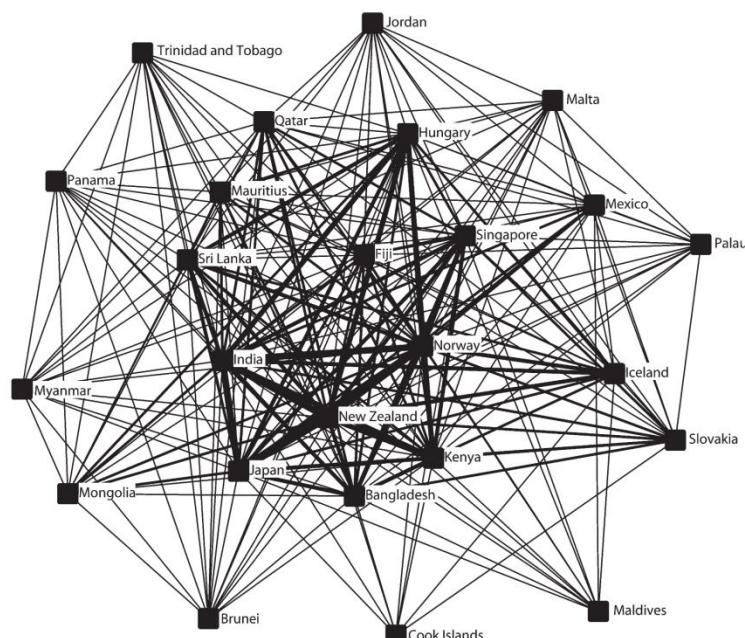
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Network predictors of Framework Convention on Tobacco Control treaty adoption

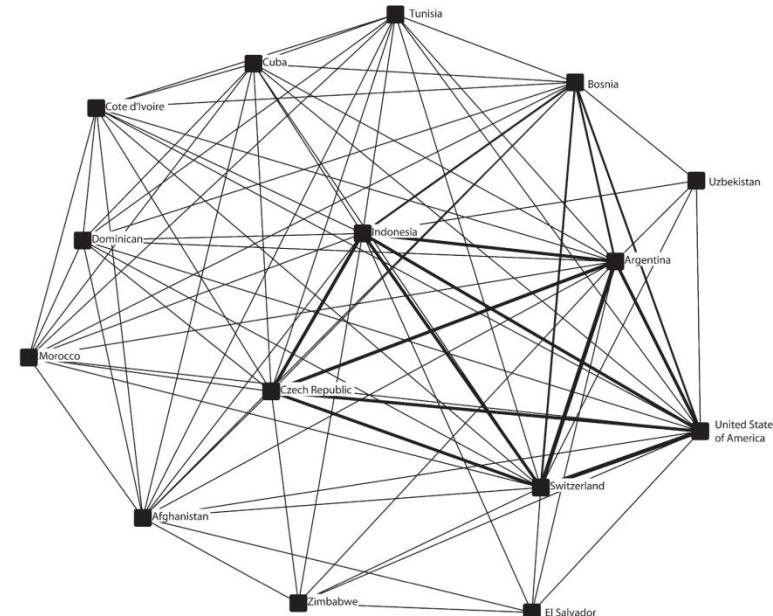
Adopted FCTC



Note. Figure created using Netdraw.¹⁸ For example, Norway and India had at least 1 member (although not necessarily the same individual) who subscribed to GLOBALink for at least 9 years from 1993 to 2005. Conversely, Jordan and Palau only had 1 member during the same period. There were 5 outlying countries. Thicker lines indicate stronger links on GLOBALink.

FIGURE 2—Network of the 30 countries that were the earliest to adopt the Framework Convention on Tobacco Control (first 15.5% of all countries), with links indicating the magnitude of comembership on GLOBALink.

Did not adopt FCTC



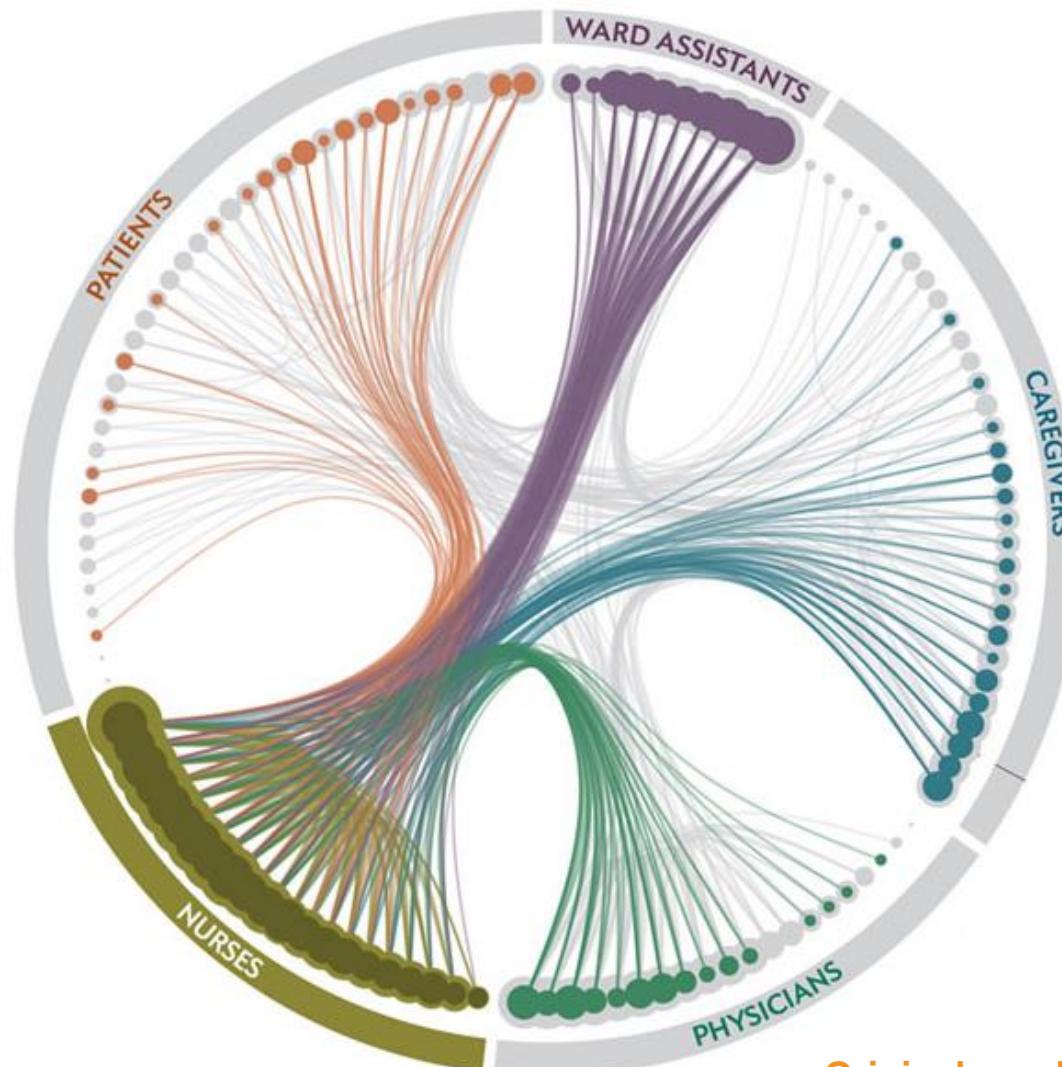
Note. Figure created using Netdraw.¹⁸ There were 18 outlying countries. Thicker lines indicate stronger links on GLOBALink.

FIGURE 3—Network of the 33 countries that did not adopt the Framework Convention on Tobacco Control, with links indicating the magnitude of comembership on GLOBALink.



From Wipfli, et al., 2010, AJPH

Who are the critical players in a pediatric hospital ward?



Original graphic by Jan Willem Tulp.
Based on Isella, 2011, *PLOS One*.

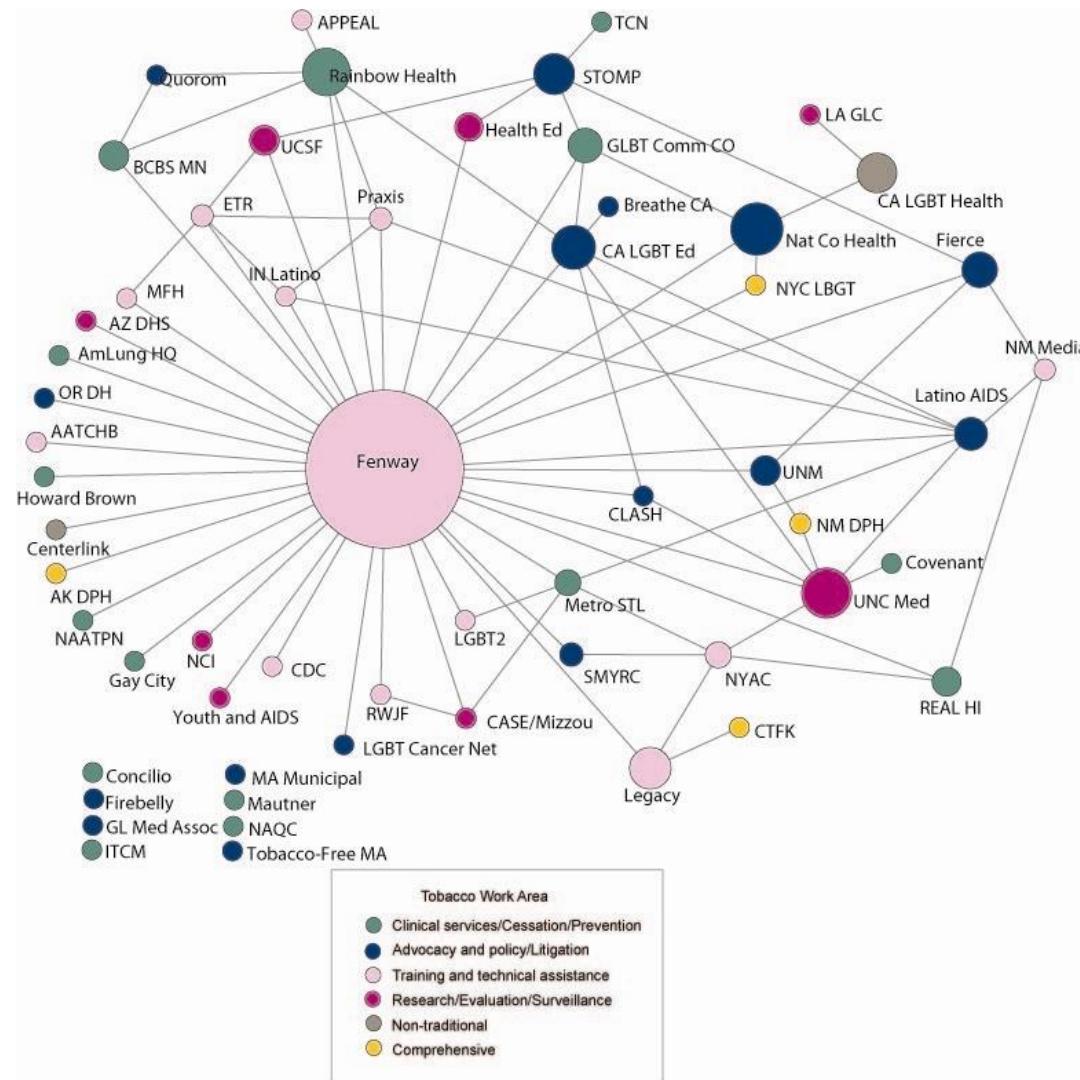


Evaluation & Team Science

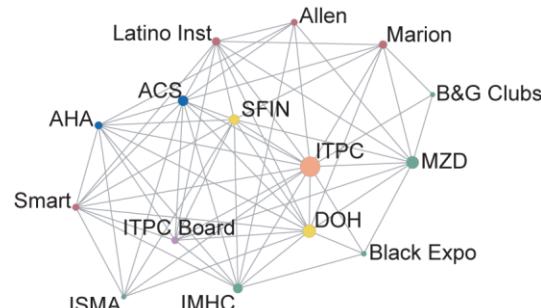
Network analysis as a powerful tool for assessing organizational and program processes and outcomes



Mapping of organizational systems



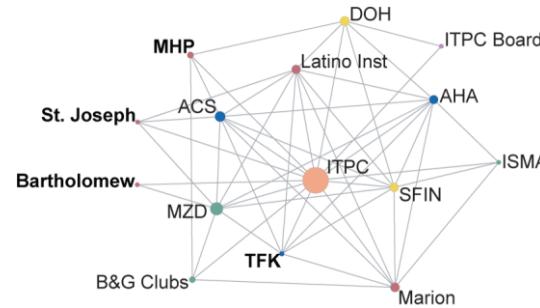
Example: Network mapping of dynamic systems



FY03

Stability	--
Density	0.61
Betweenness	0.14

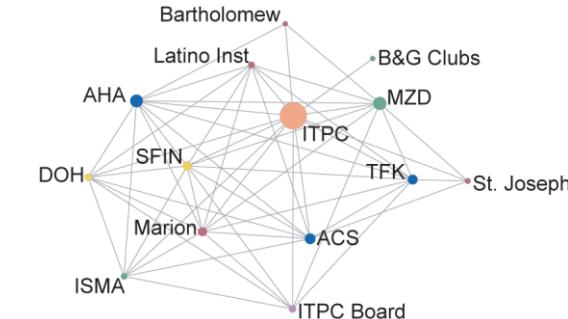
\$33.8M Tobacco Control Funding



FY04

Stability	--	73%
Density	0.48	▼
Betweenness	0.30	▲

\$850M State Budget Deficit



FY05

Stability	97%	▲
Density	0.59	▲
Betweenness	0.23	▼

\$595M State Budget Deficit

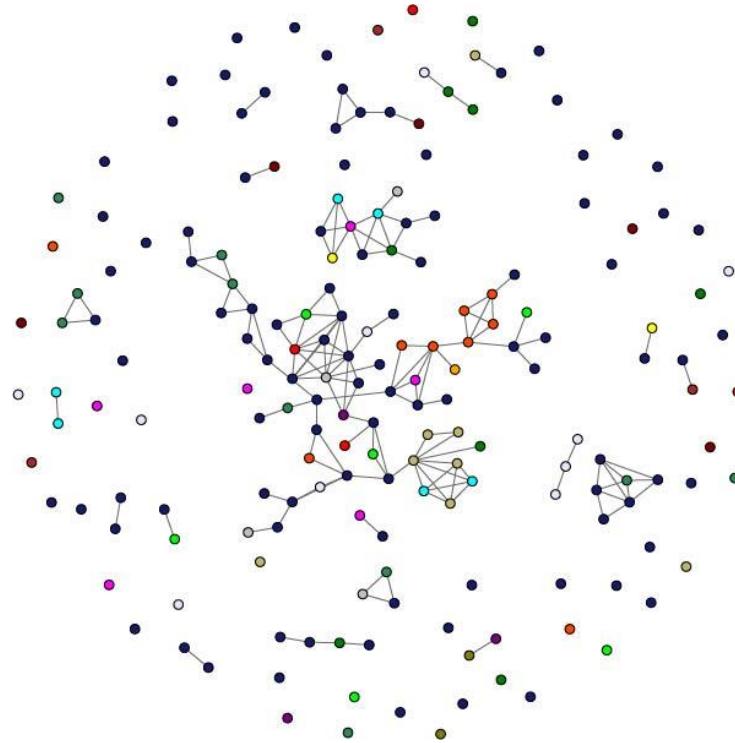
\$300M State Budget Deficit

\$18.2M Tobacco Control Funding

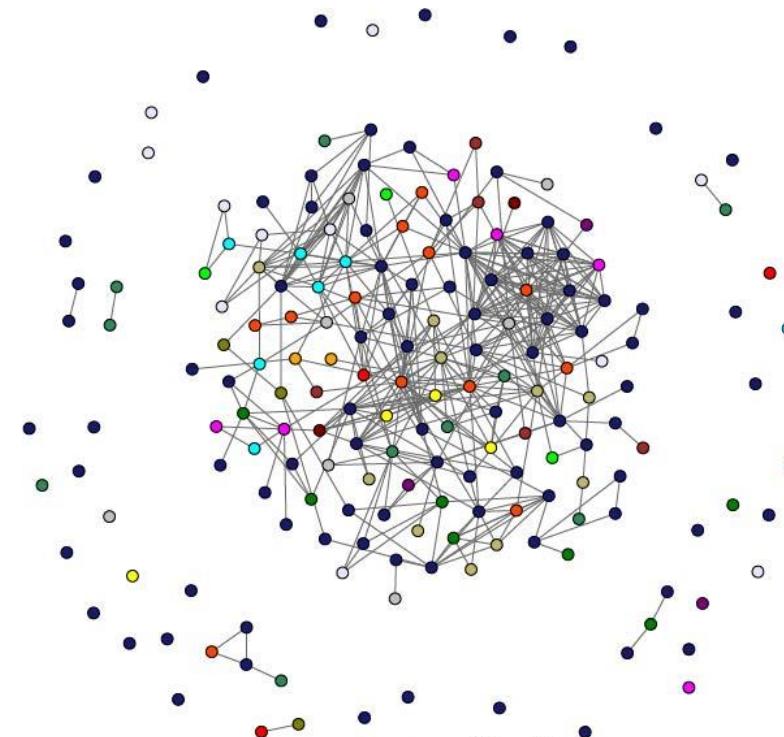
\$12.4M Tobacco Control Funding



Changes in collaboration over time



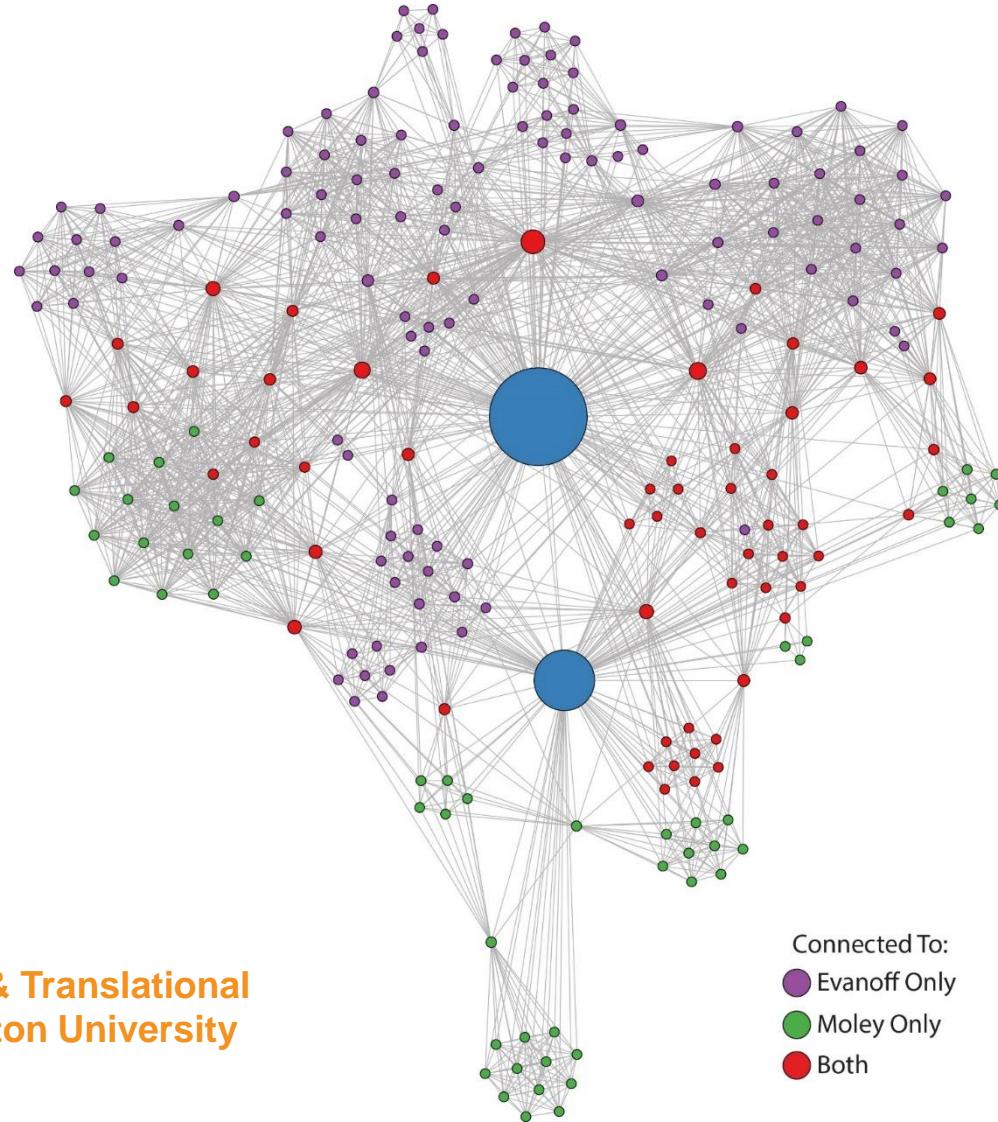
**ICTS grant collaborations -
2007**



**ICTS grant collaborations -
2010**



Demonstrating need for co-leadership in a large translational research system



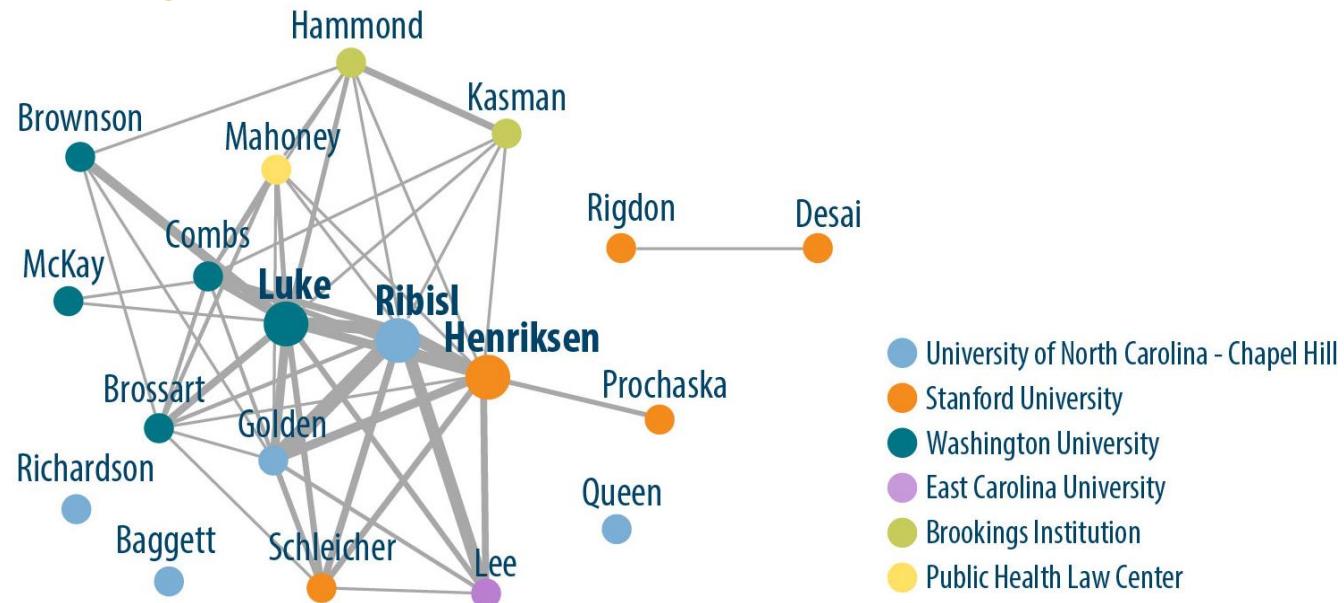
Institute of Clinical & Translational
Sciences, Washington University

Connected To:
● Evanoff Only
● Moley Only
● Both



Demonstrating strong collaboration history

Figure 10: ASPIRE Collaboration Network



Ribisl, Henriksen, Luke; Advancing
Science and Practice in the Retail
Environment; NCI P01



RESEARCH

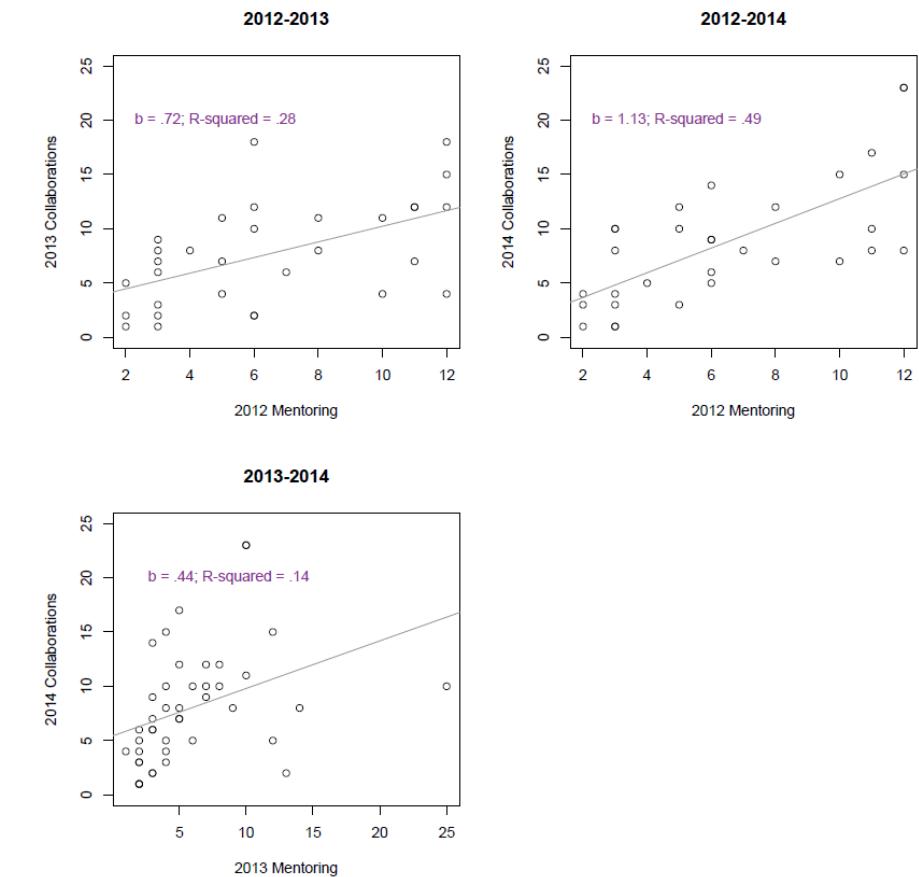
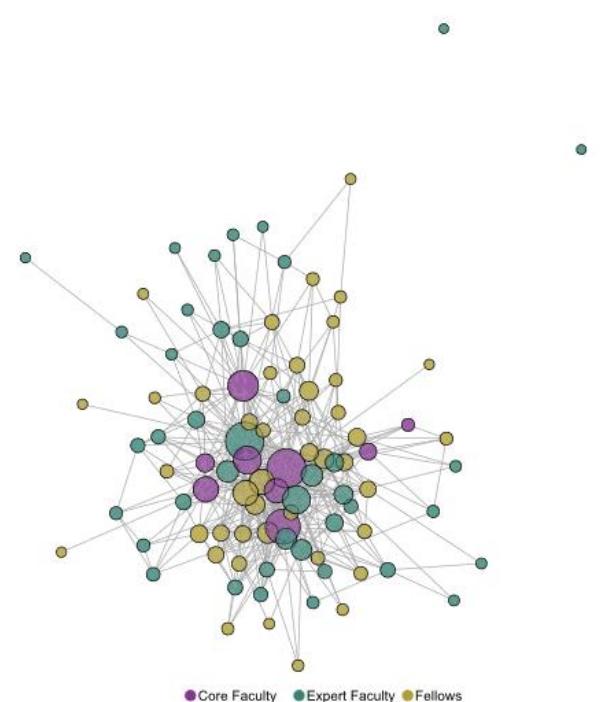
Open Access



Forging a link between mentoring and collaboration: a new training model for implementation science

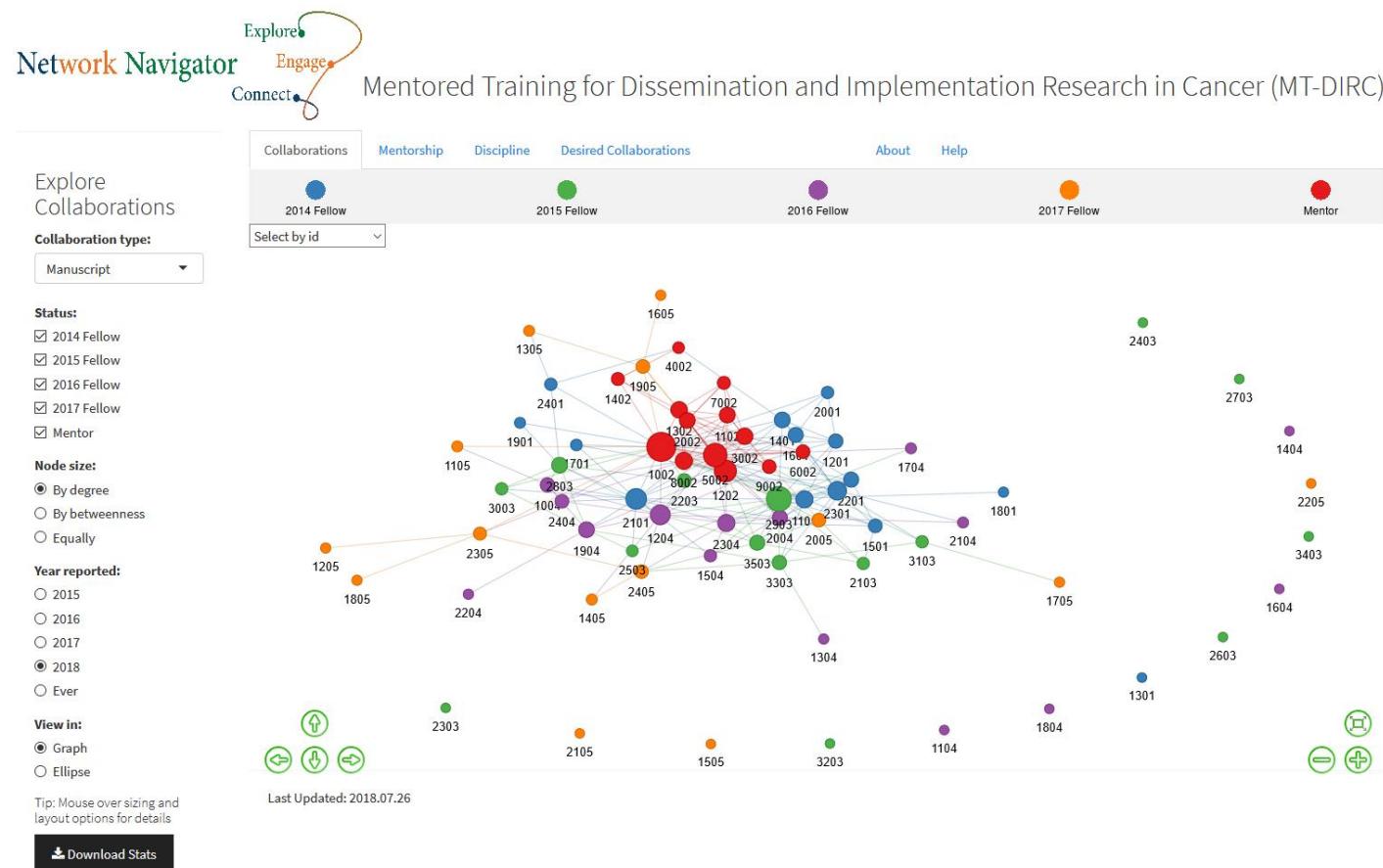
Douglas A. Luke^{1*}, Ana A. Baumann¹, Bobbi J. Carothers¹, John Landsverk² and Enola K. Proctor¹

- Evaluation of implementation science training institute
- Significant relationship between mentoring and future scientific collaborations
- For every additional mentoring relationship, likelihood of scientific collaboration two years later is increased by almost 7%



Interactive network displays for evaluation partners

- Goal: design interactive dashboards that facilitate network exploration
 - Uses off the shelf technology
 - R, Shiny, shinydashboard, visNetwork
 - Try out a demo
 - <https://netnav.shinyapps.io/demonet/>



Conclusion

