

Lecture 10 Networks 5

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CIVIL 534: Computational systems thinking for sustainable engineering

7 May 2025

Outline

- Percolation
- Network applications
 - Naturally-defined networks
 - Model-defined networks
 - Data-defined networks
- Networks and systems thinking
- Reading: Honti et al. 2019 (on Moodle)
- Networks Midterm next week
- Project milestone 2 due Friday
- Project final presentation on May 28

Final project deliverable

- Presentation on May 28
 - 15 minutes followed by Q+A
- What to cover:
 - What is your group's definition of sustainable development in the context of the world dynamics models?
 - Be explicit in how you construct your metric(s)
 - How did you design your automated exploration of different policies?
 - What did you find in analyzing the system dynamics model as a network?
 - Did your network analysis affect your policy development?
 - What parameters did you adjust in your final policy, and which had the biggest impact in moving your model toward your sustainable development target?
 - How does the model perform in the end?
 - What are the biggest strengths and weaknesses of both the model and your approach?

Final project presentation

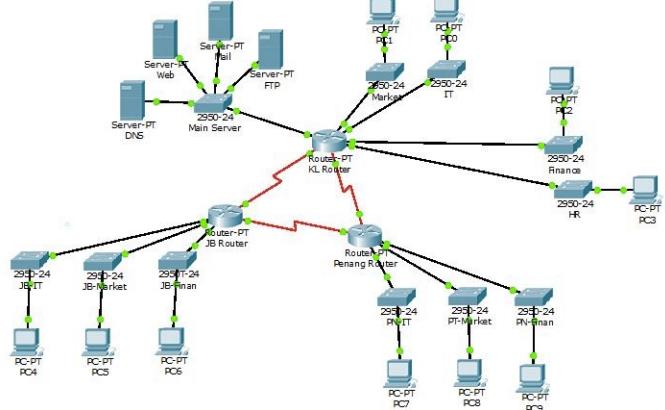
- Introduction to the project context (10 pts)
- Definition of sustainable development in the world dynamics models (20 pts)
- Network analysis of systems model (20 pts)
- Automated process for policy development (20 pts)
- Discussion of results and implications (20 pts)
- Conclusion, limitations, and outlook (10 pts)

Final project deliverable

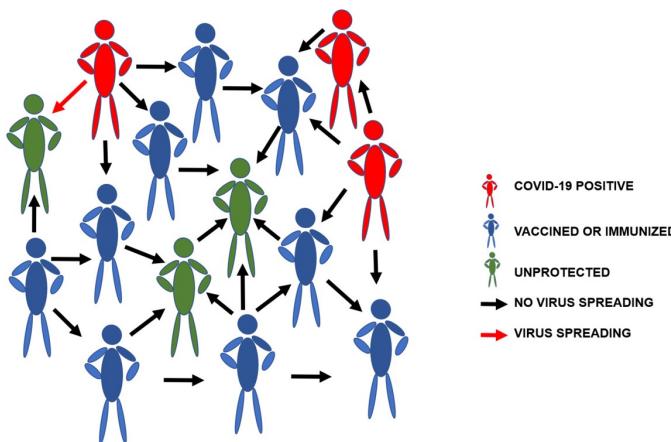
- You also need to submit a final version of your code for analysis
- Grading criteria:
 - Does it contain all the code you reference in your final presentation? (75%)
 - Is it well-documented (i.e. commented)? (25%)

Percolation

- The process of removing nodes from the network and the associated edges
- Helps us understand “what-if” scenarios
- Examples:



Internet



“Herd immunity”



Lots of urban systems!

Simulating percolation

- Key parameter: ϕ (occupational probability)
 - $\phi = 1 \rightarrow$ all nodes are present
 - $\phi = 0 \rightarrow$ all nodes have been removed
- Process of removing nodes
 - Uniform: all nodes have same probability of removal
 - Non-uniform: based on node properties (e.g., different forms of centrality)
 - The choice is normally driven by the domain

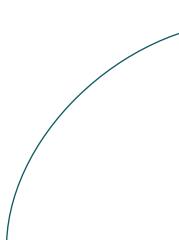
Percolation theory

- Newman goes into detail in Chapter 15
 - (And there can be a lot of mathematical detail)
- Percolation is an entire subfield of network science
- Offers an understanding of network resilience and robustness

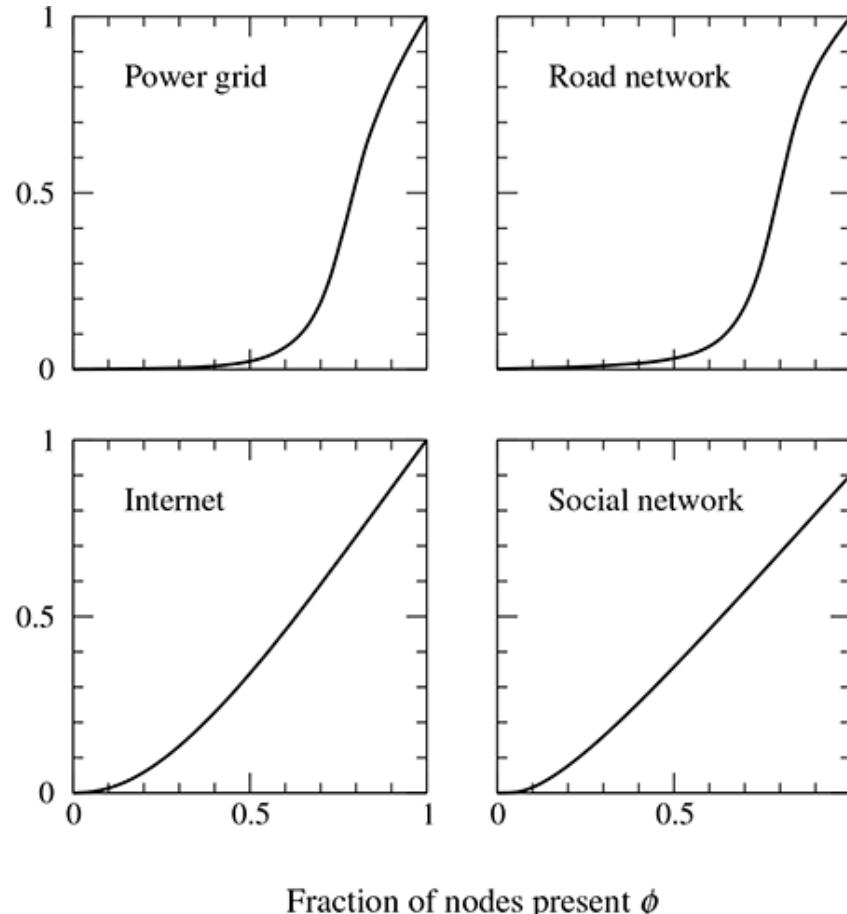
Qualitative percolation analysis example

Uniform removal
of edges

What does this signify?

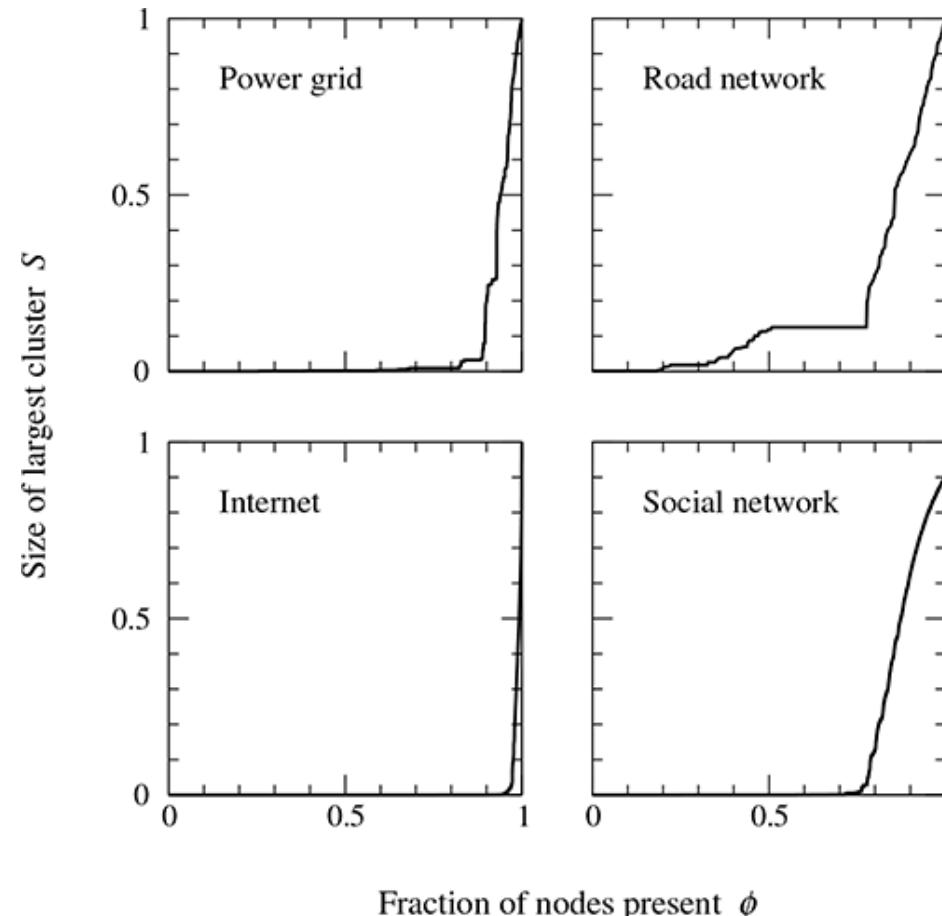


Size of largest cluster S



Qualitative percolation analysis example

Targeted edge removal (target largest degree first)



General network analysis procedure



Define network structure



Analyze structure & extract insights



Perturb structure to understand how changes impact performance



Make design changes / recommendations for the system

Networks in urban systems

Naturally-defined network structure

Network is defined by the physical or natural structure of the data / system:

- Social network (people, relationships)
- Transportation network (roads, intersections) (destinations, paths)
- Water network (valves, pipes)
- Power grid (homes/transformers/etc., power lines)

Model-defined network structure

Network is defined by a model (models are imperfect):

- Theoretical between two entities in a city
 - How similar are two buildings?
 - How much do two buildings impact one another?
- Dynamic networks (processes or changes across edges/nodes)

Data-defined network structure

Network structure is learned from data

- Open problem in many domains
- Can help to understand interdependencies between infrastructure / systems / people
- Example: data on human behavior – learn social network structure?

Naturally-defined networks



Define network structure



naturally defined



Analyze structure & extract insights

Structure: metrics from class

Insights: e.g. node importance, edge importance

What can we say about the system as currently designed?



Perturb structure to understand how changes impact performance

How does changing the capacity of edge **x** or node **y** affect performance?

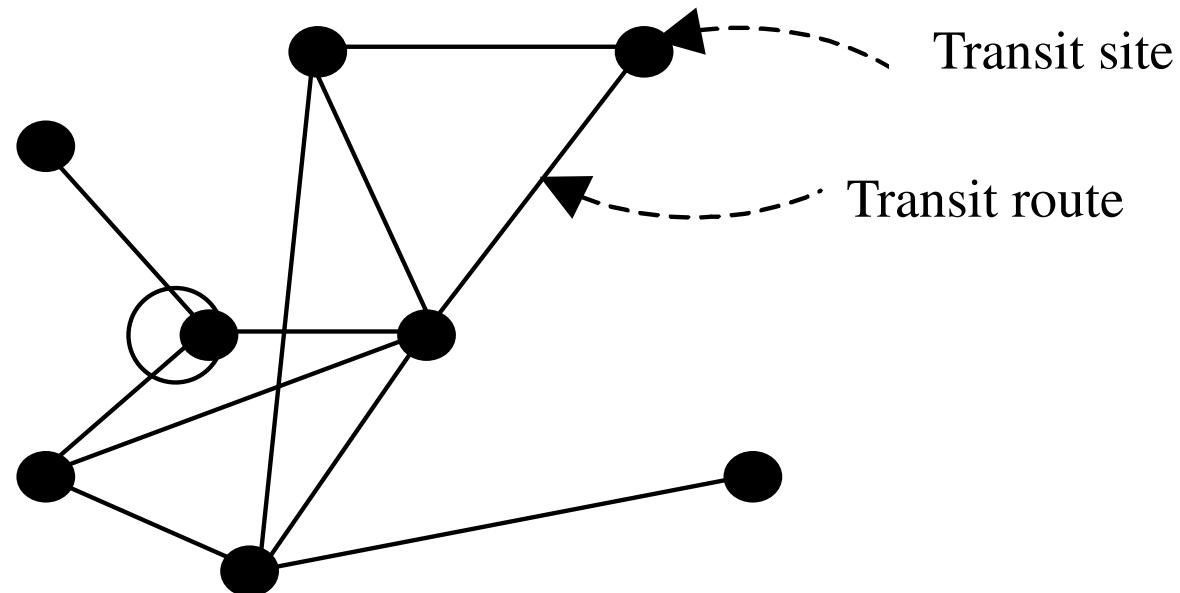


Make design changes / recommendations for the system

Make decisions based on alternative analysis

Example: Beijing transit network

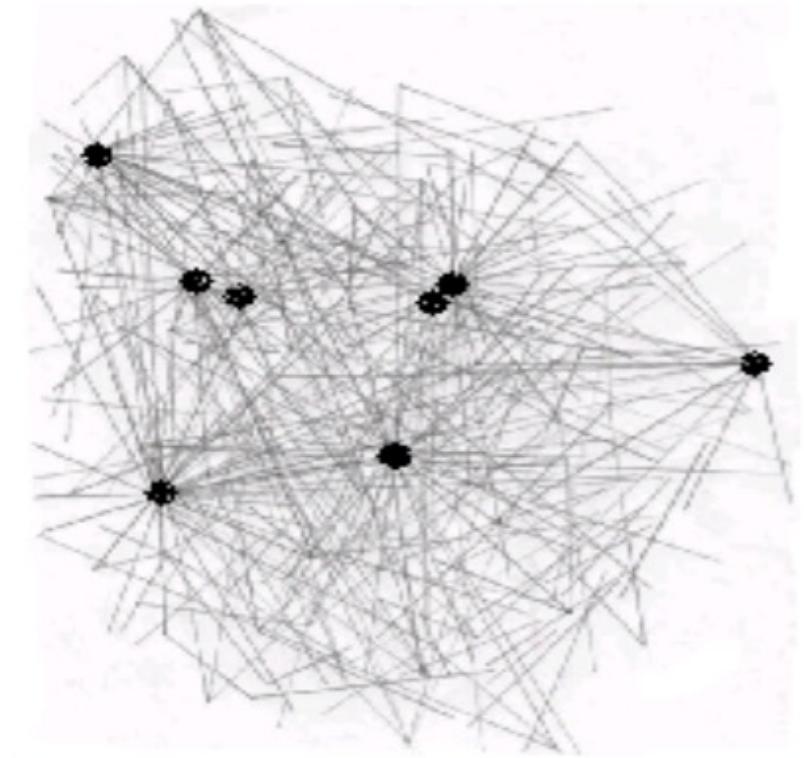
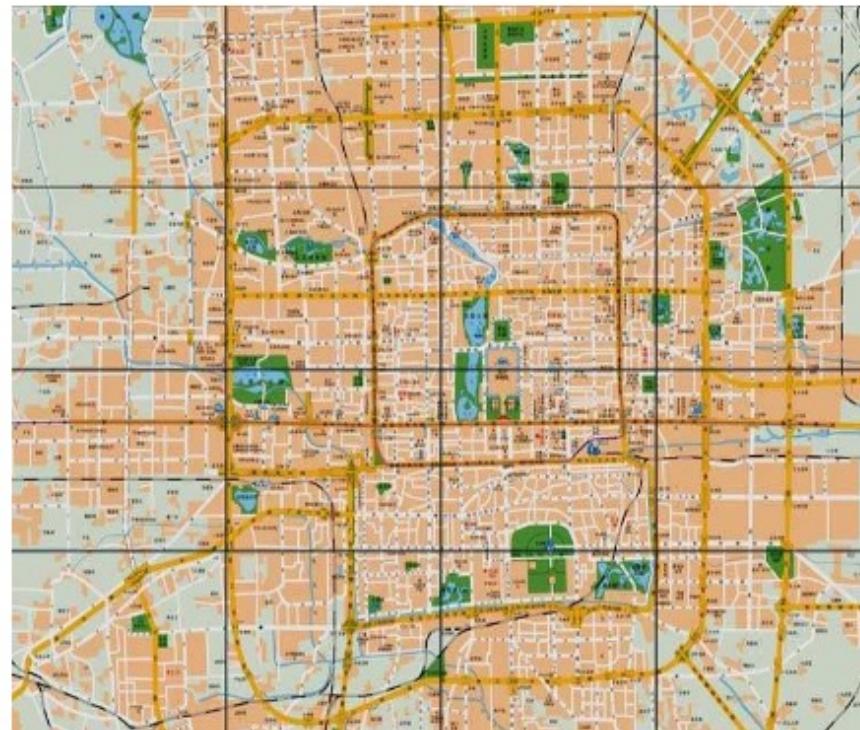
Model transit sites as nodes and transit routes as edges



Wu, J., Gao, Z., Sun, H., & Huang, H. (2004). Urban transit system as a scale-free network. *Modern Physics Letters B*, 18(19n20), 1043-1049.

Example: Beijing transit network

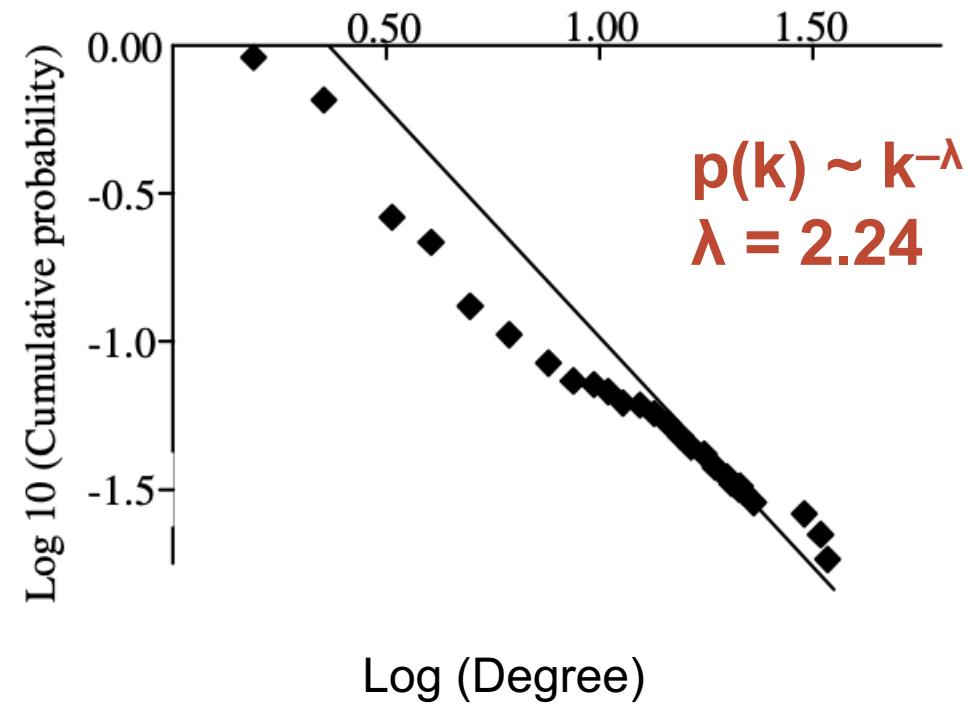
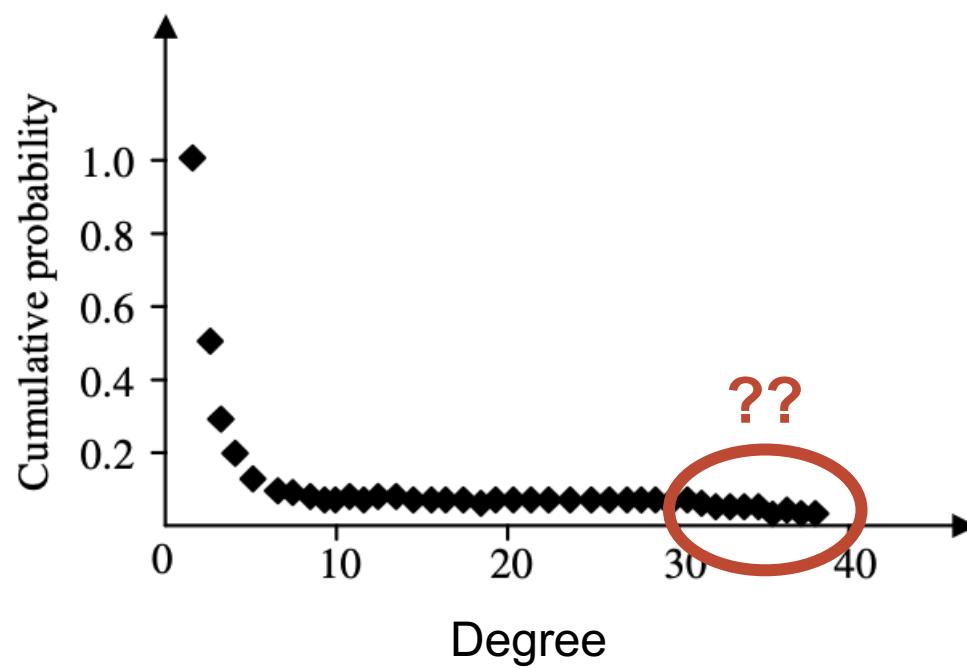
Empirical analysis of Beijing urban transit network (*441 nodes, 776 edges*)



Wu, J., Gao, Z., Sun, H., & Huang, H. (2004). Urban transit system as a scale-free network. *Modern Physics Letters B*, 18(19n20), 1043-1049.

Example: Beijing transit network

Demonstrates properties of a scale-free network

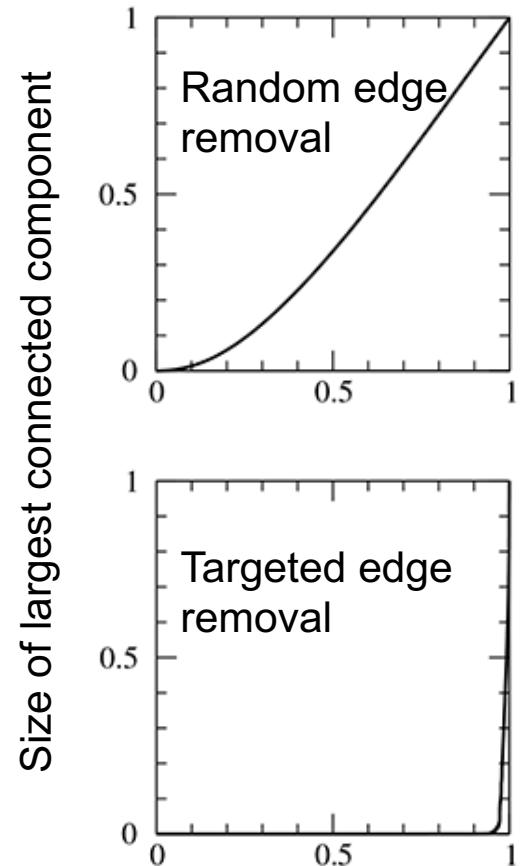


Example: Beijing transit network

Implications for urban transit:

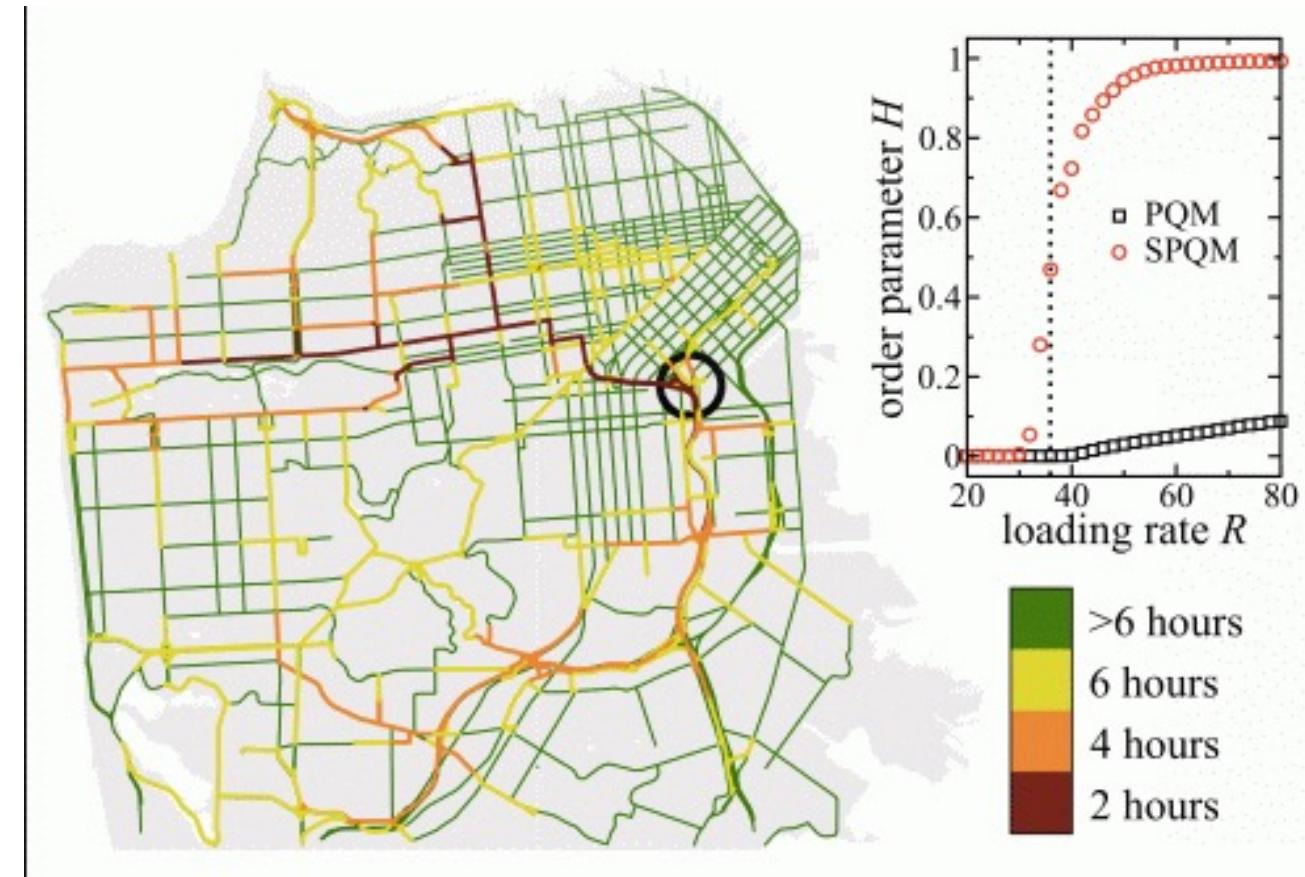
- *Effective in propagation* – people can move around across the entire network efficiently (hubs facilitate this)
- *Resistant to accidental (random) failures* – this is because of its nonhomogeneous topology (a few very important hubs); non-hub breakdowns/accidents won't destroy connectivity
- *Vulnerable to targeted attacks* – breakdown at a hub can be devastating to the network (ex: July 11 rainstorm); where should you put resources for resiliency planning?

For scale-free networks:



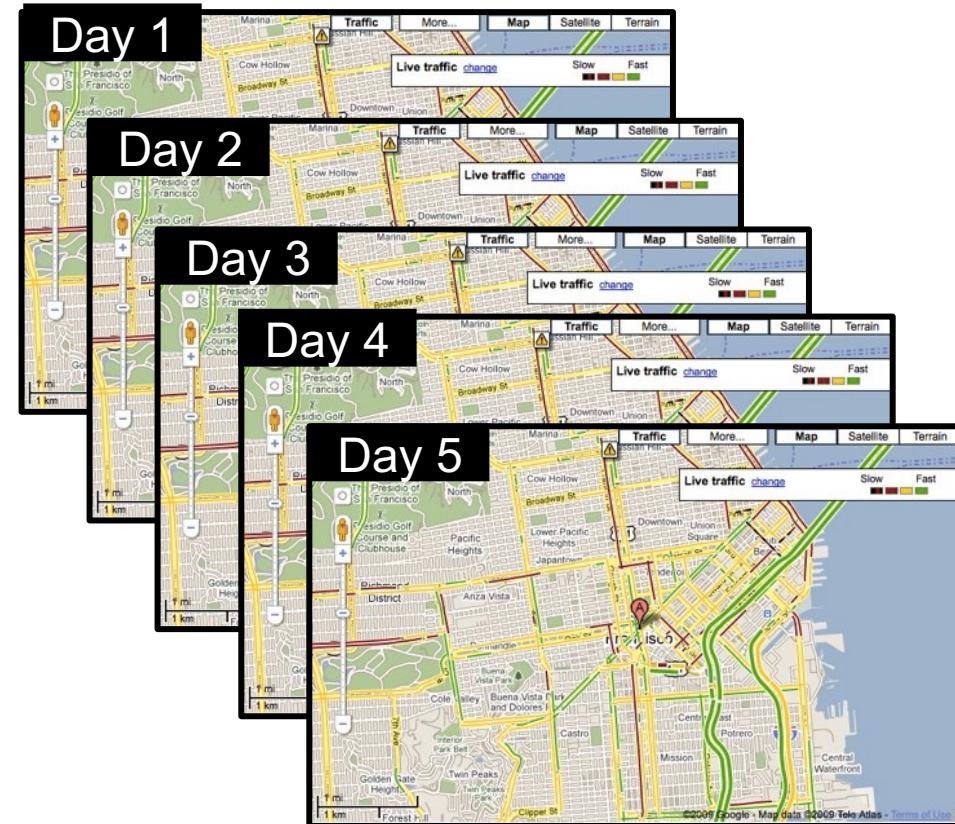
Example: Traffic on a road network

- Nodes: Intersections
- Edges: Roads
 - Weight: capacity or traffic (depending on analysis)
- Process:
 - Analyze structure
 - Extract insights
 - Perturb network
 - Make design recommendations



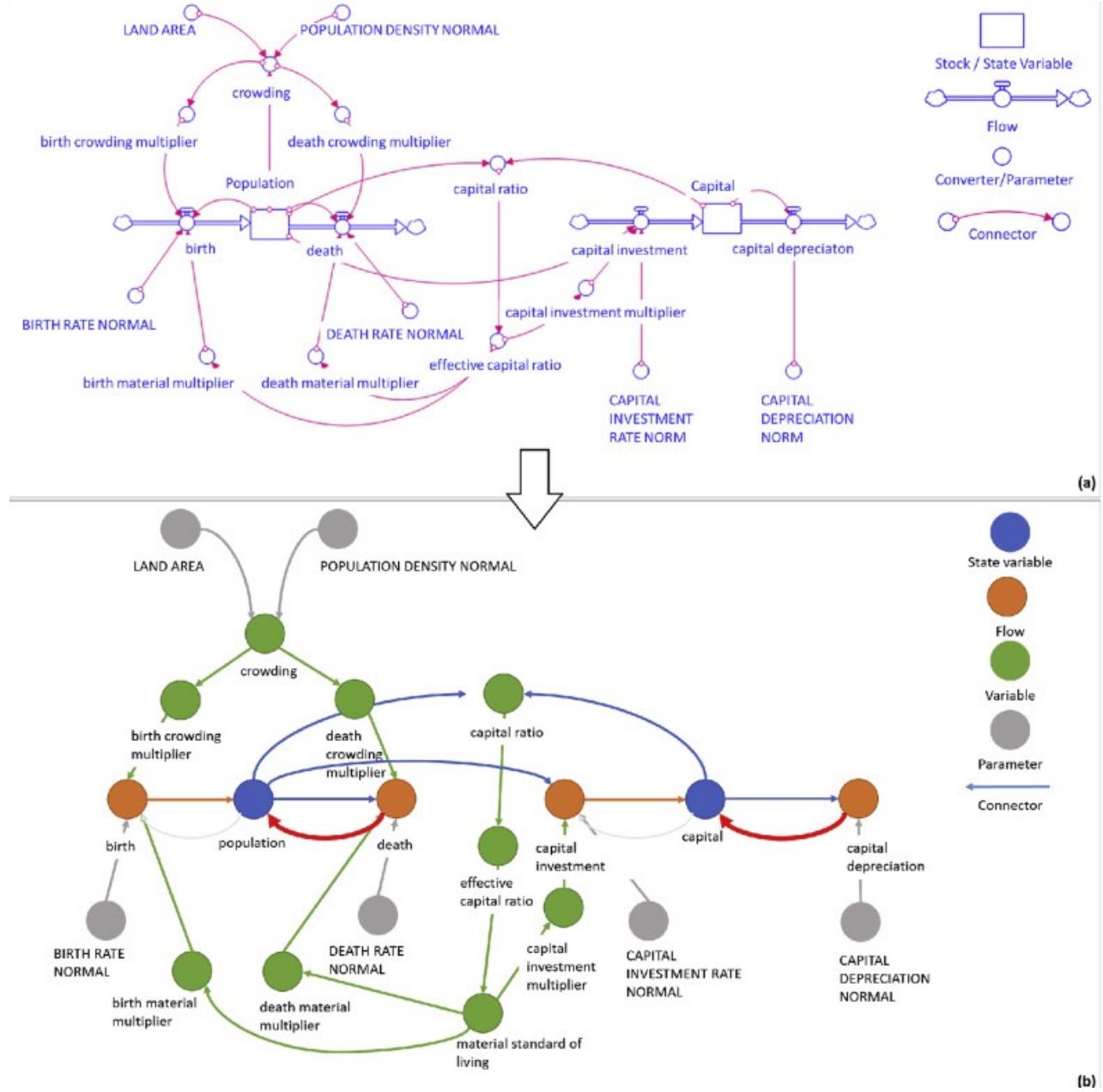
Example: Traffic on a road network

- Nodes: Intersections
- Edges: Roads
 - Weight: capacity or traffic (depending on analysis)
- Process:
 - Analyze structure
 - **Extract insights**
 - **What if networks is dynamic with time-series data? How do things change?**



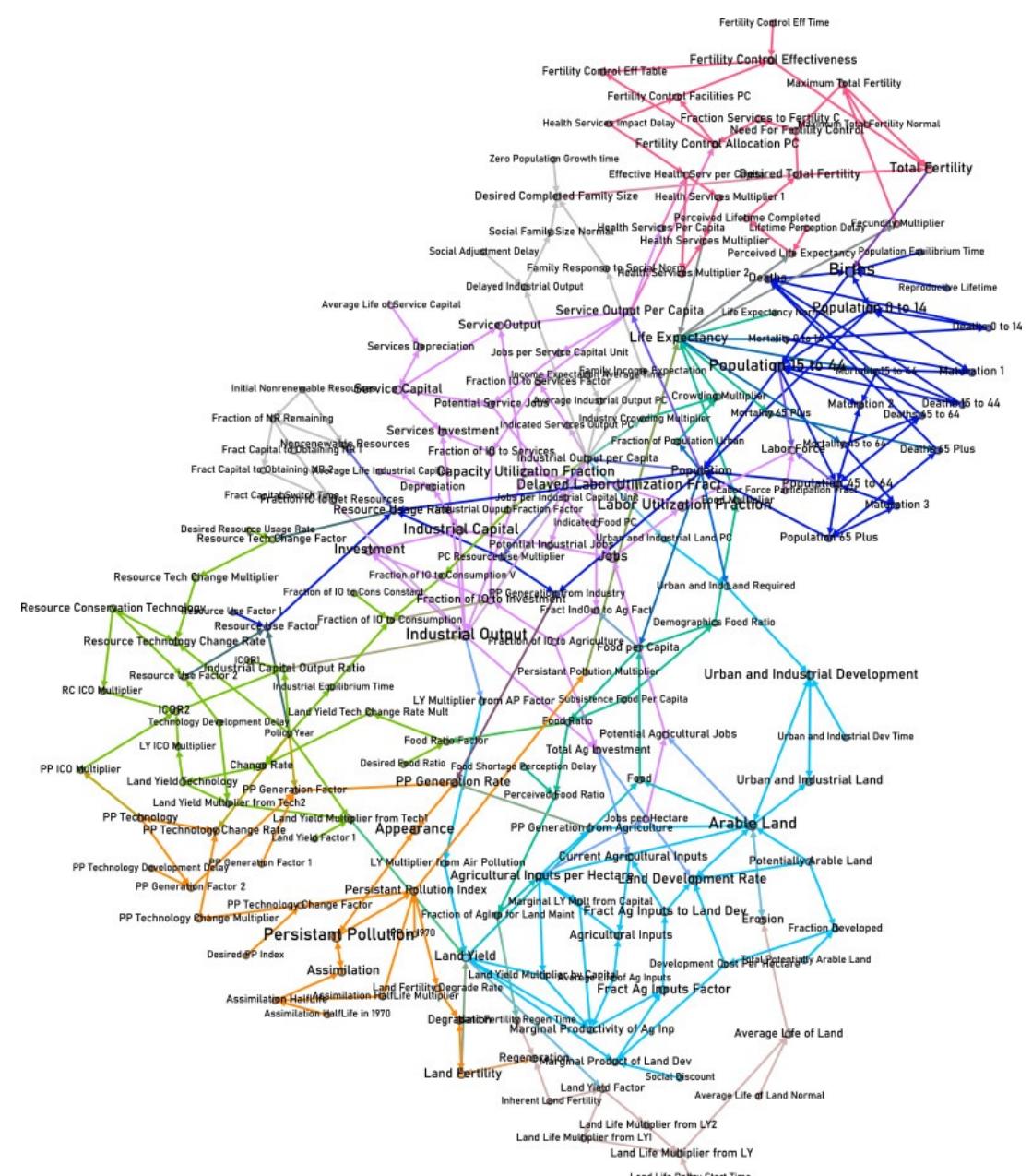
Example: System dynamics model

- All types of variables become nodes
 - Stocks
 - Flows
 - Parameters/Variables
- All influence arrows become edges
- All flow-stock pairs become edges



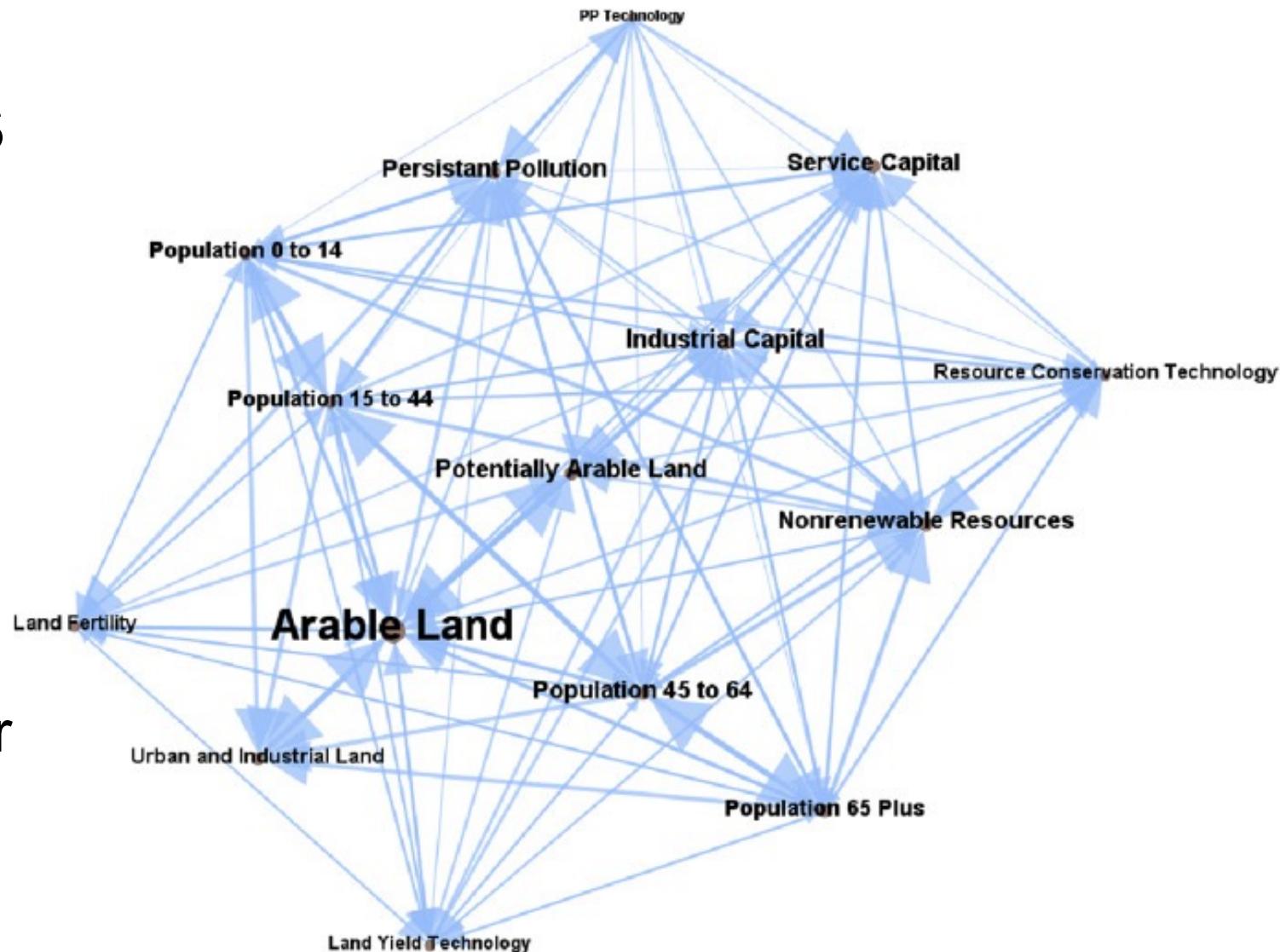
Example: System dynamics model

- Network diagram of world3 model



Example: System dynamics model

- Example where authors created a subgraph with only the stocks
- The size of the text corresponds to the eigenvector centrality
- How could this impact our understanding of the system?
- See reading on Moodle



Model-defined networks



Define network structure

Derive relationships / network based on known model
Remember: all models are wrong (imperfect), but some are useful

- Useful to compare to ground truth network if known



Analyze structure & extract insights

Do patterns emerge that match the model?



Perturb structure to understand how changes impact performance



Make design changes / recommendations for the system

Example: Building pollution

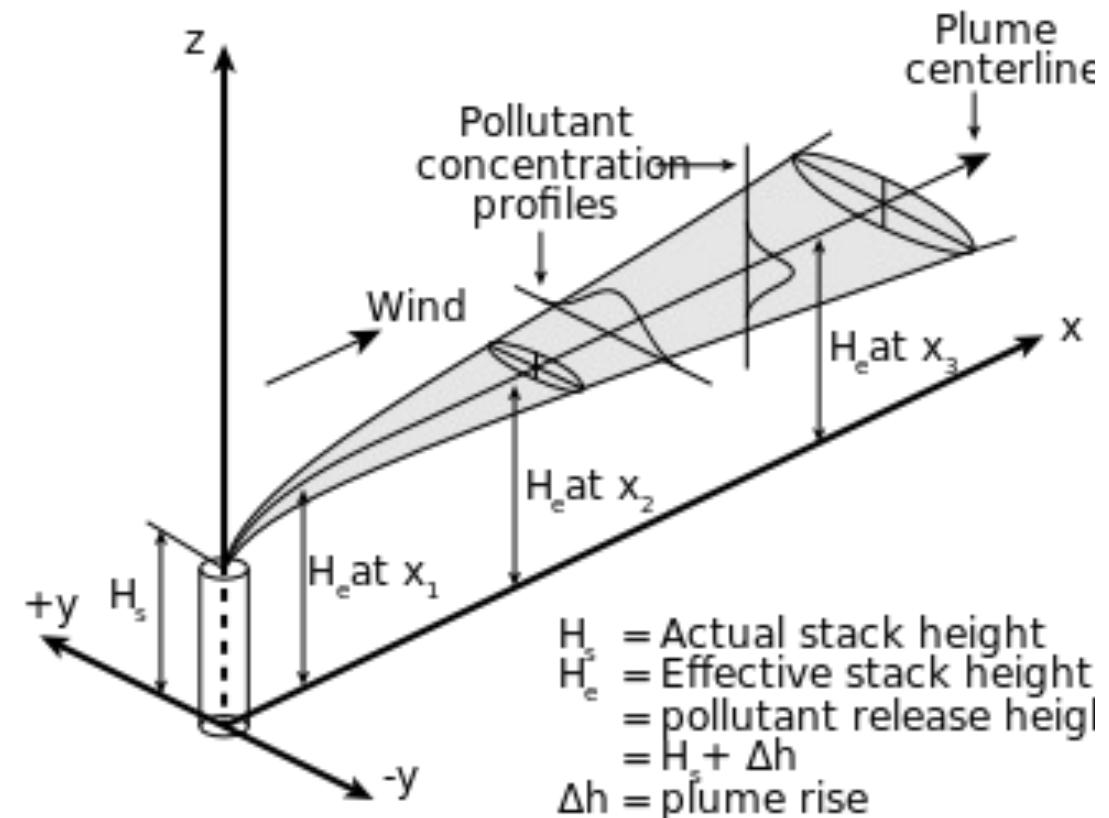


Photo taken on Jan 8, 2014 in downtown Brooklyn, NY
by Rishee Jain, Stanford University

- Boilers produce more PM_{2.5} than cars and trucks (City of NY, 2012)
- Local pollution: +2,300 deaths; +4,800 ER asthma visits
(City of NY, 2013)
- **Goal: identify clusters of buildings for infrastructure re-design**

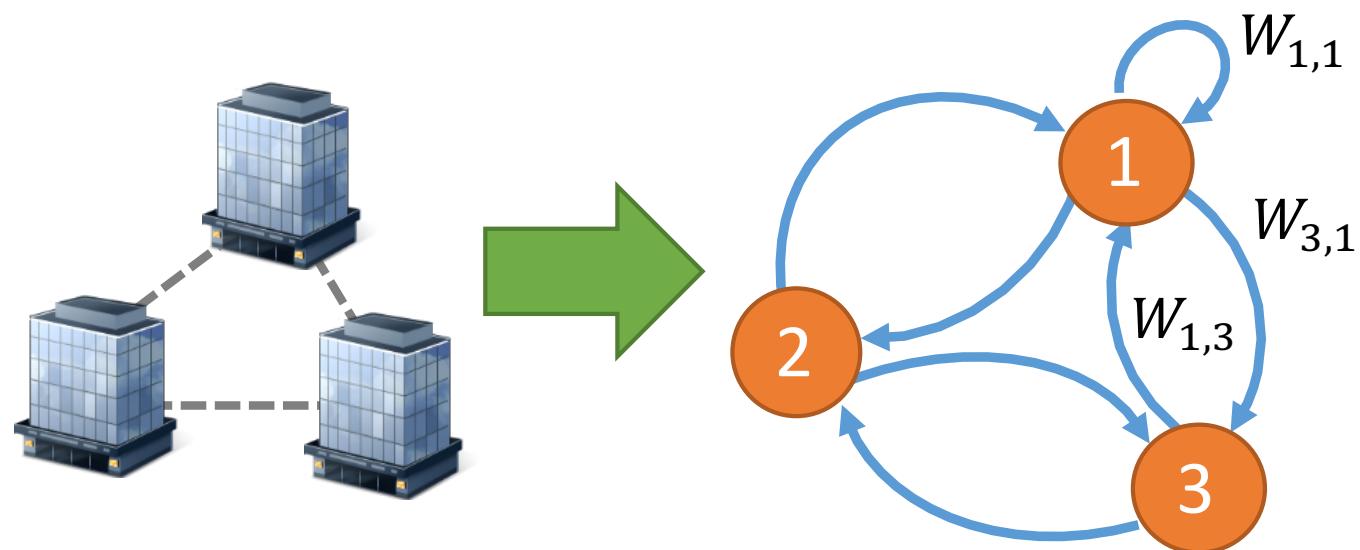
Example: Building pollution

Model to define network:
Gaussian Plume Model



Example: Building pollution

Nodes = buildings; Edges = pollution dispersion relationship



$$\mathbf{x}_1 = \begin{bmatrix} EC_1 \\ \vdots \\ FLRS_1 \end{bmatrix}$$

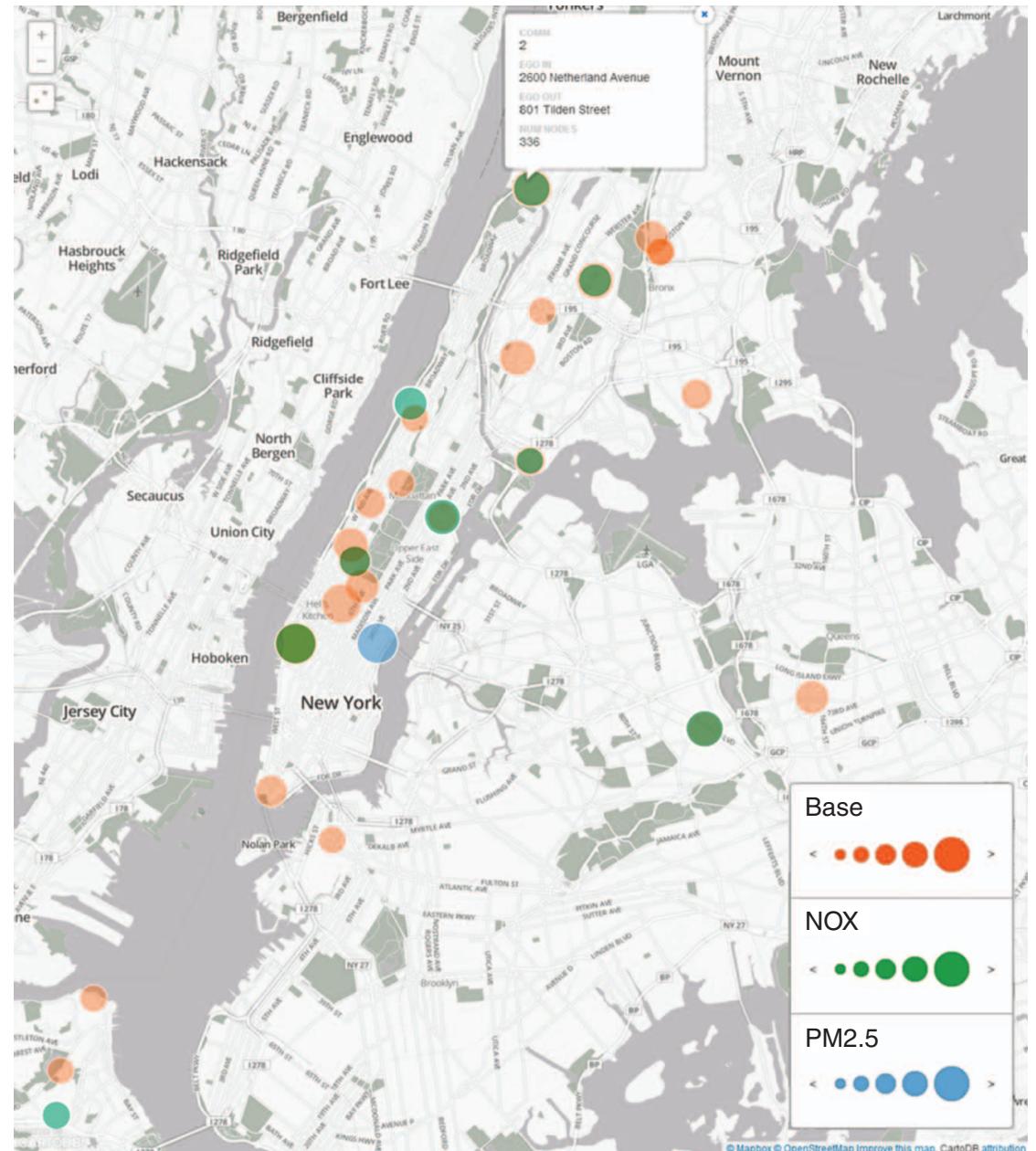
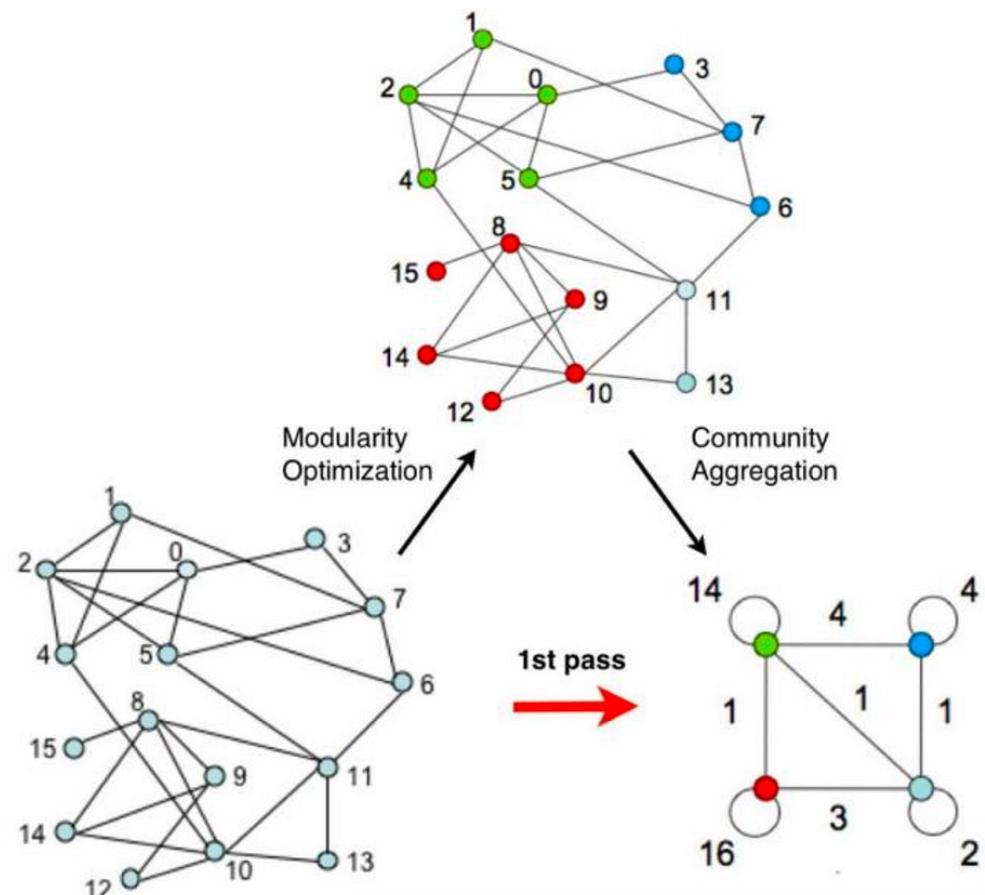
\mathbf{x}_1 is the signal vector of building (node) 1 with
 EC = energy consumption,
 $FLRS$ = number of floors

Example: Building pollution

[TABLE 2] THE COMMON GRAPH METRICS APPLIED TO URBAN AIR POLLUTION.

GRAPH METRIC	FORMAL DEFINITION (DEFINITIONS ADAPTED FROM [11])	MATHEMATICAL FORMULATION	APPLICATION TO URBAN AIR POLLUTION
SELF-LOOP OF A VERTEX	THE VALUE OF AN EDGE CONNECTING A VERTEX TO ITSELF.	$W_{i,j}$ WHERE $i = j$	A MEASURE OF THE EMISSIONS OF BUILDING i .
IN-DEGREE OF A VERTEX	THE VALUE OF ALL IN-GOING EDGES CONNECTED TO A VERTEX ON A DIRECTED GRAPH.	$k_i^{\text{in}} = \sum_{j=1}^N W_{i,j}$	A MEASURE OF HOW MUCH NEIGHBORING BUILDINGS ARE CONTRIBUTING TO BUILDING i 's AIR QUALITY.
OUT-DEGREE OF A VERTEX	THE VALUE OF ALL OUT-GOING EDGES CONNECTED TO A VERTEX ON A DIRECTED GRAPH.	$k_j^{\text{out}} = \sum_{i=1}^N W_{i,j}$	A MEASURE OF HOW MUCH BUILDING j IS CONTRIBUTING TO THE AIR QUALITY OF ITS NEIGHBORS.

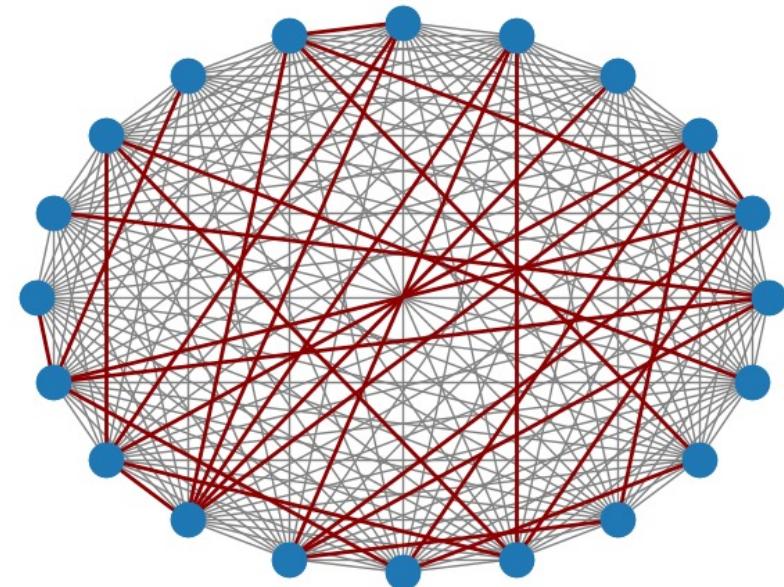
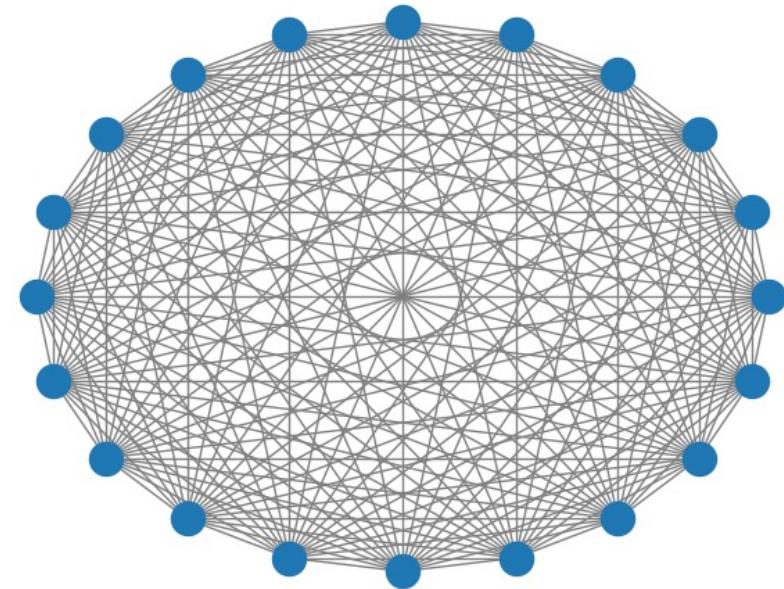
Example: Building pollution Community detection



Network thresholding

- Some models / data give you a fully connected network
 - Example: network defined as the similarity in building energy use profiles
- We often threshold such graphs to identify edges deemed “significant”

$$e_{ij} = \begin{cases} e_{ij}, & e_{ij} \geq \alpha \\ 0, & e_{ij} < 0 \end{cases}$$



Data-defined network



Define network structure



Analyze structure & extract insights



Perturb structure to understand how changes impact performance



Make design changes / recommendations for the system

1. Feature extraction from data
2. Need to find graph structure that is the “best” fit
 - Difficult problem and domain specific

Example: Occupant network inference

- Example from our lab's research



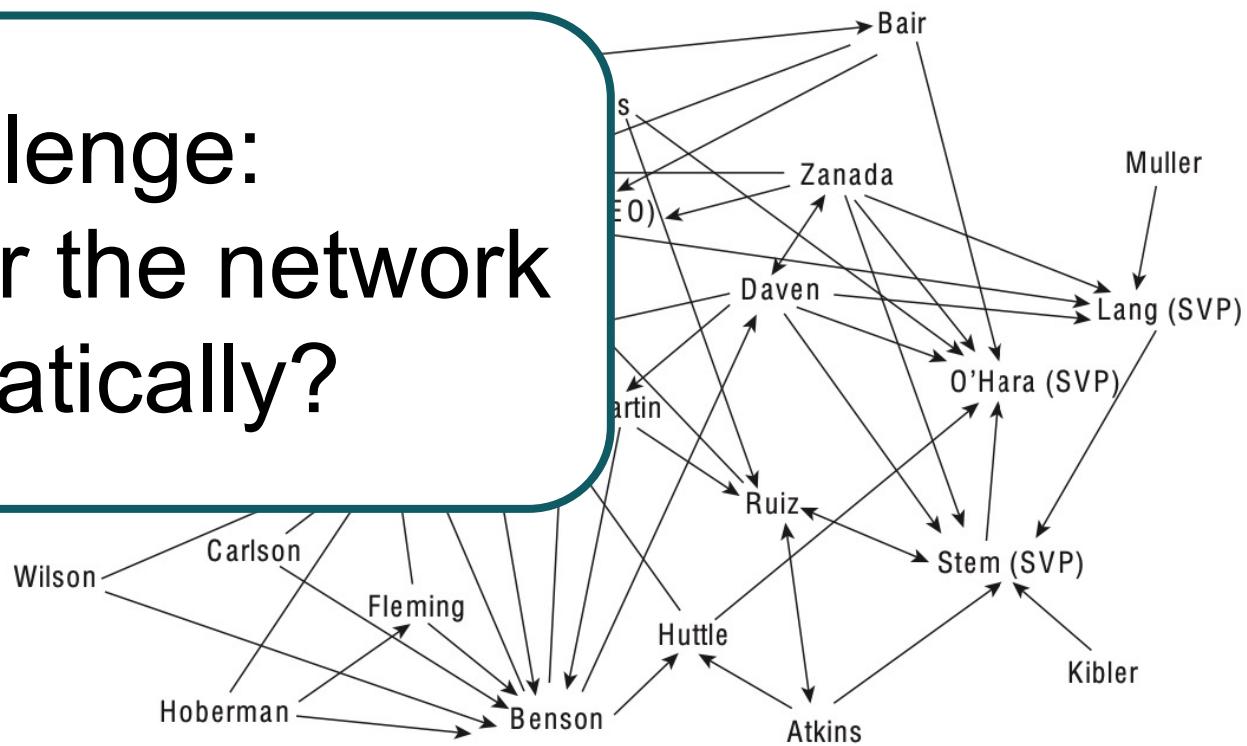
Research gap: understanding networks

The formal chart shows who's on top

The advice network reveals the experts

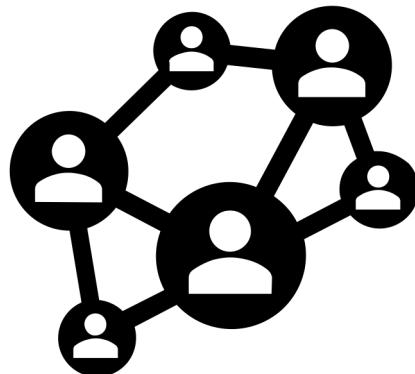
Challenge: How to infer the network automatically?

Software Applications	Field Design	Integration
O'Hara (SVP)	Calder (SVP)	Lam (SVP)
– Bair	– Harris	–
– Stewart	– Benson	–
– Ruiz	– Fleming	–
	– Church	–
	– Martin	–
	– Lee	–
	– Wilson	–
	– Swinney	–
	– Carlson	–
	– Hoberman	–
	– Fiola	–



How to infer network automatically?

Learn graph $G = (\mathcal{V}, \mathbf{A})$
from time series



\mathcal{V} : set of nodes (occupants)
 \mathbf{A} : weighted adjacency matrix



Develop or adapt method
to infer network

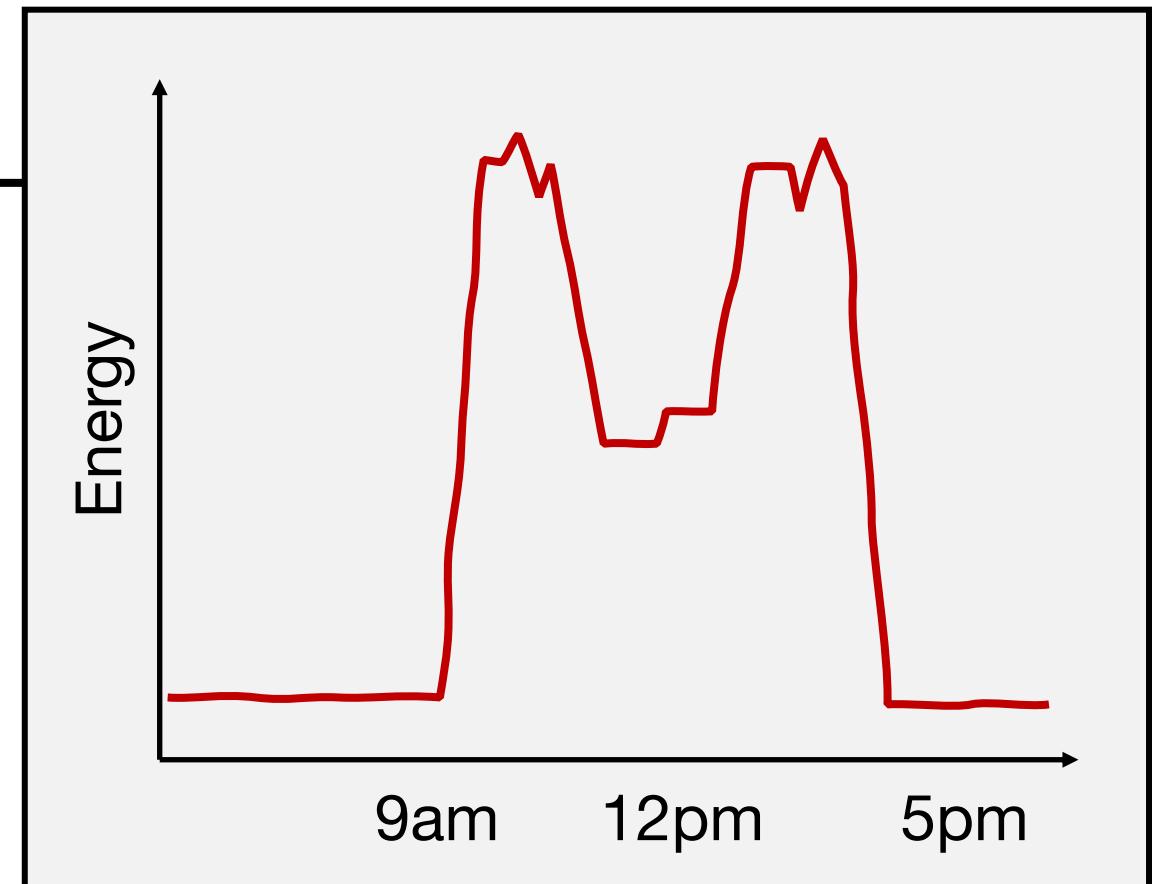
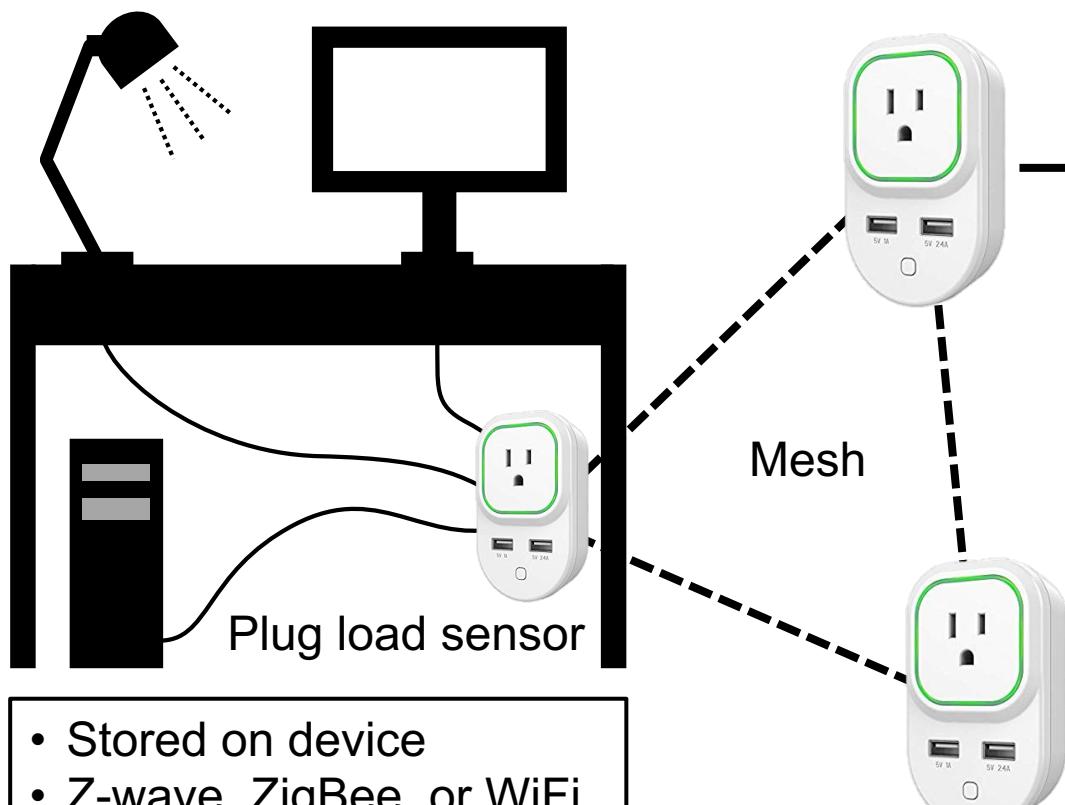


Compare against ground
truth

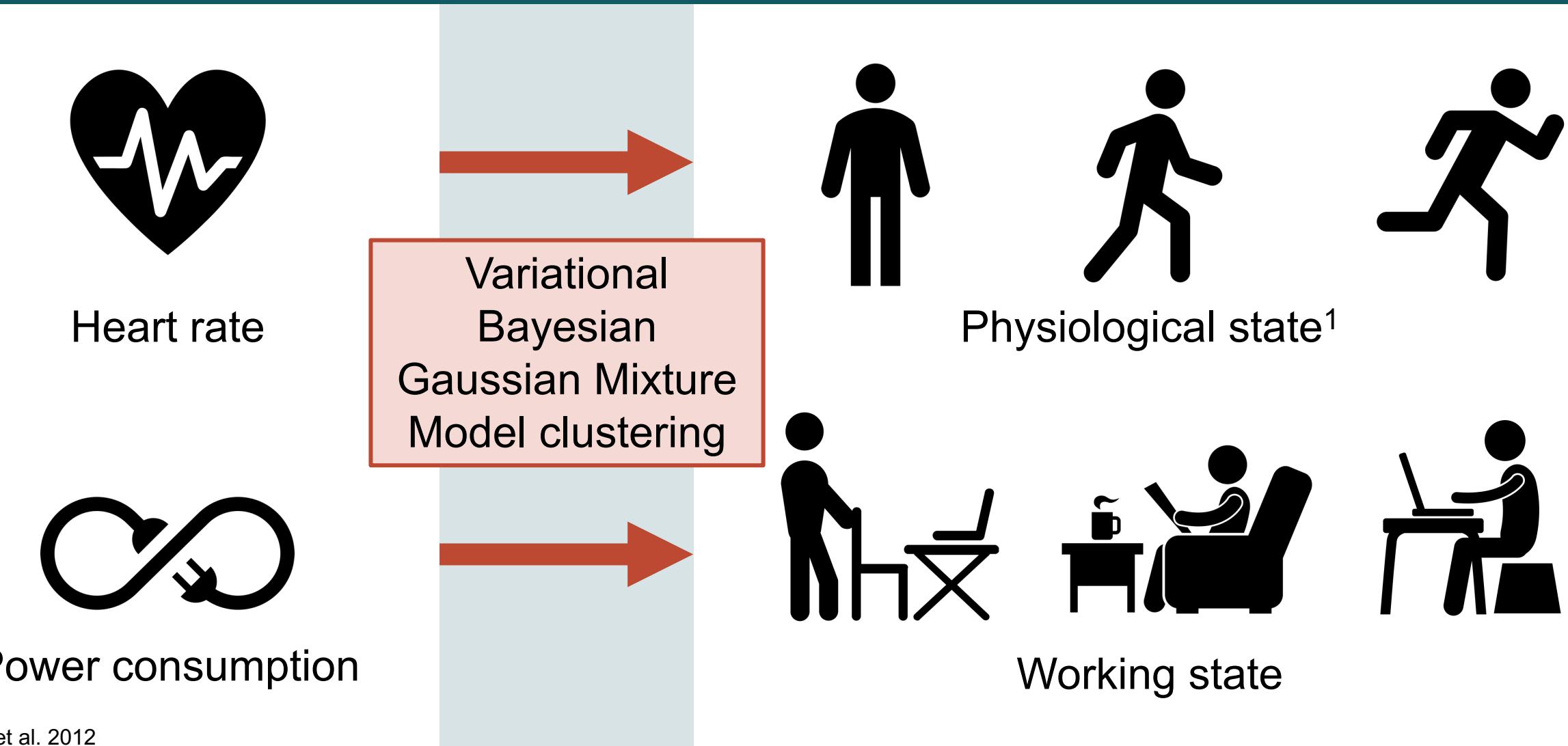


Hypothesis: novel method
infers network structure
similar to ground truth

Sensor deployment details

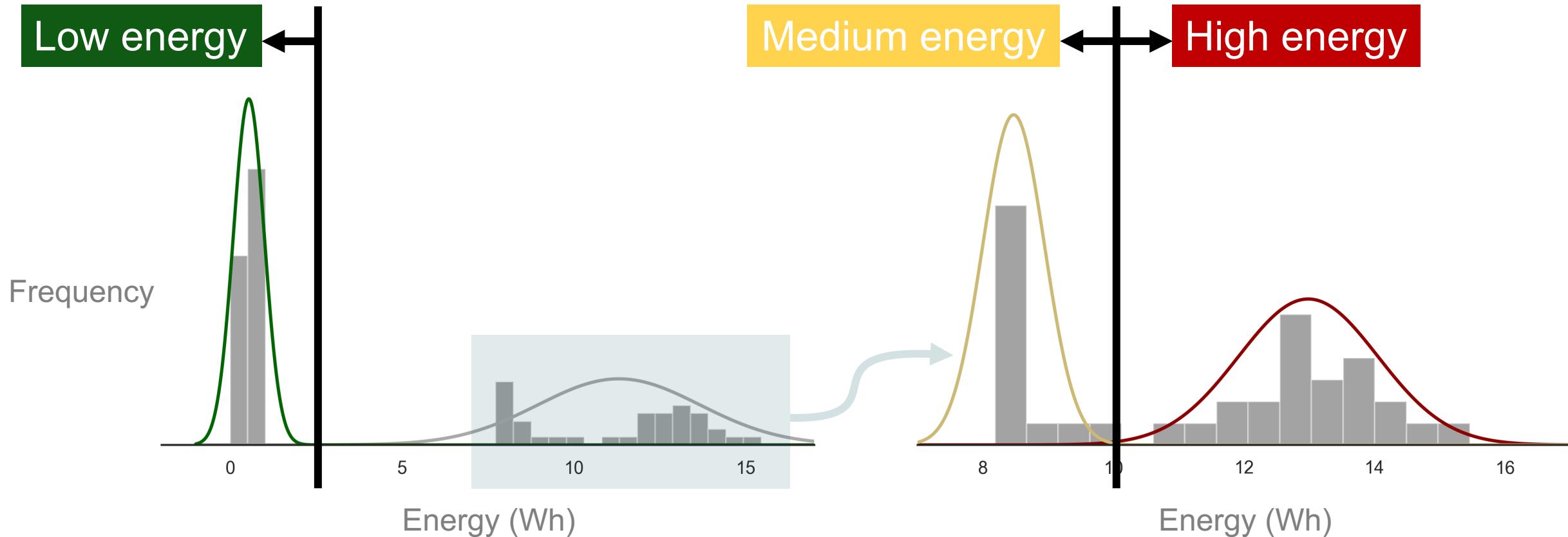


Method inspiration: Gaussian Mixture Model



¹ Costa et al. 2012

Variational Bayesian Gaussian Mixture Model

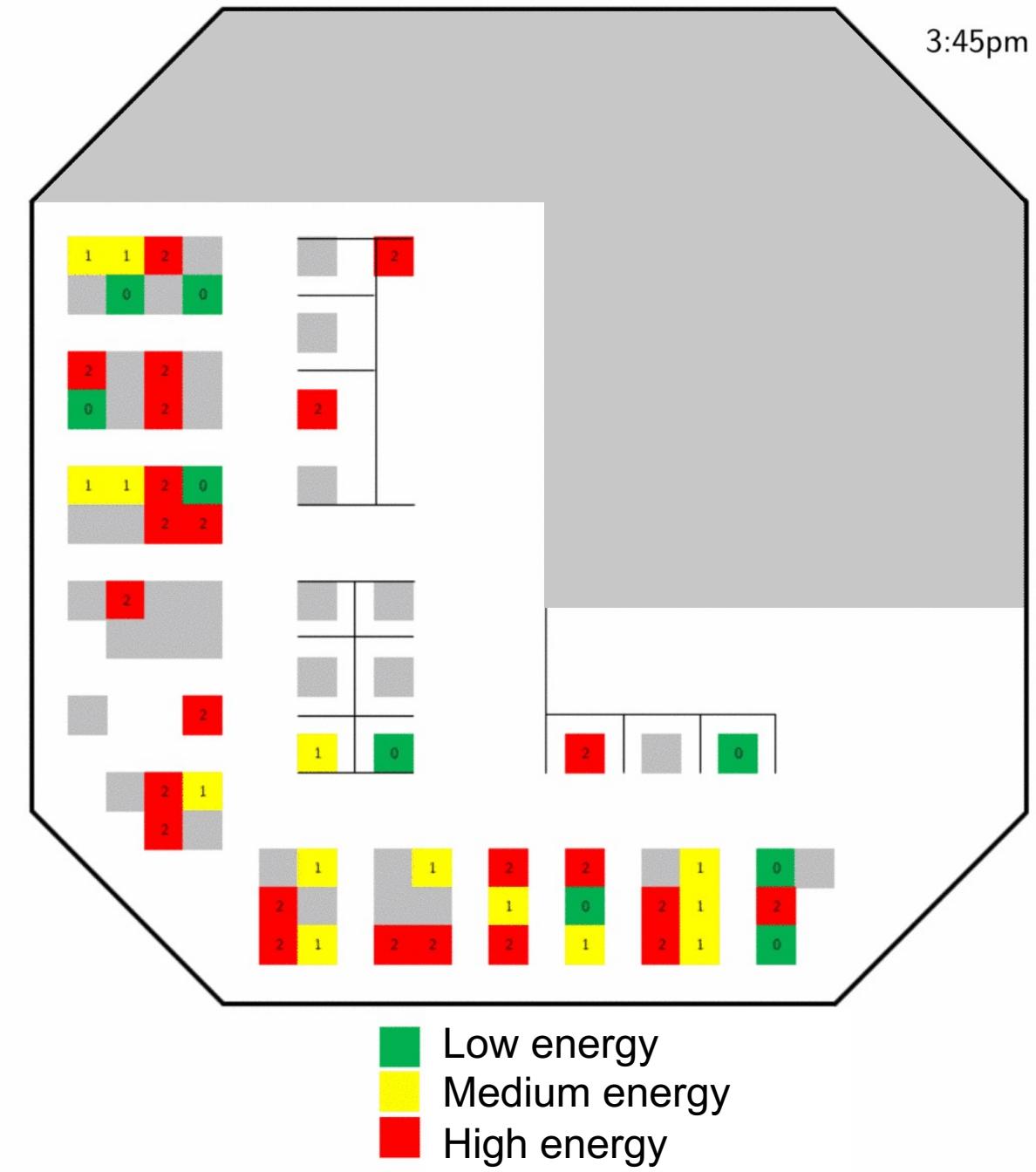


Distribution of 15-min energy consumption
(1 occupant over 1 day)

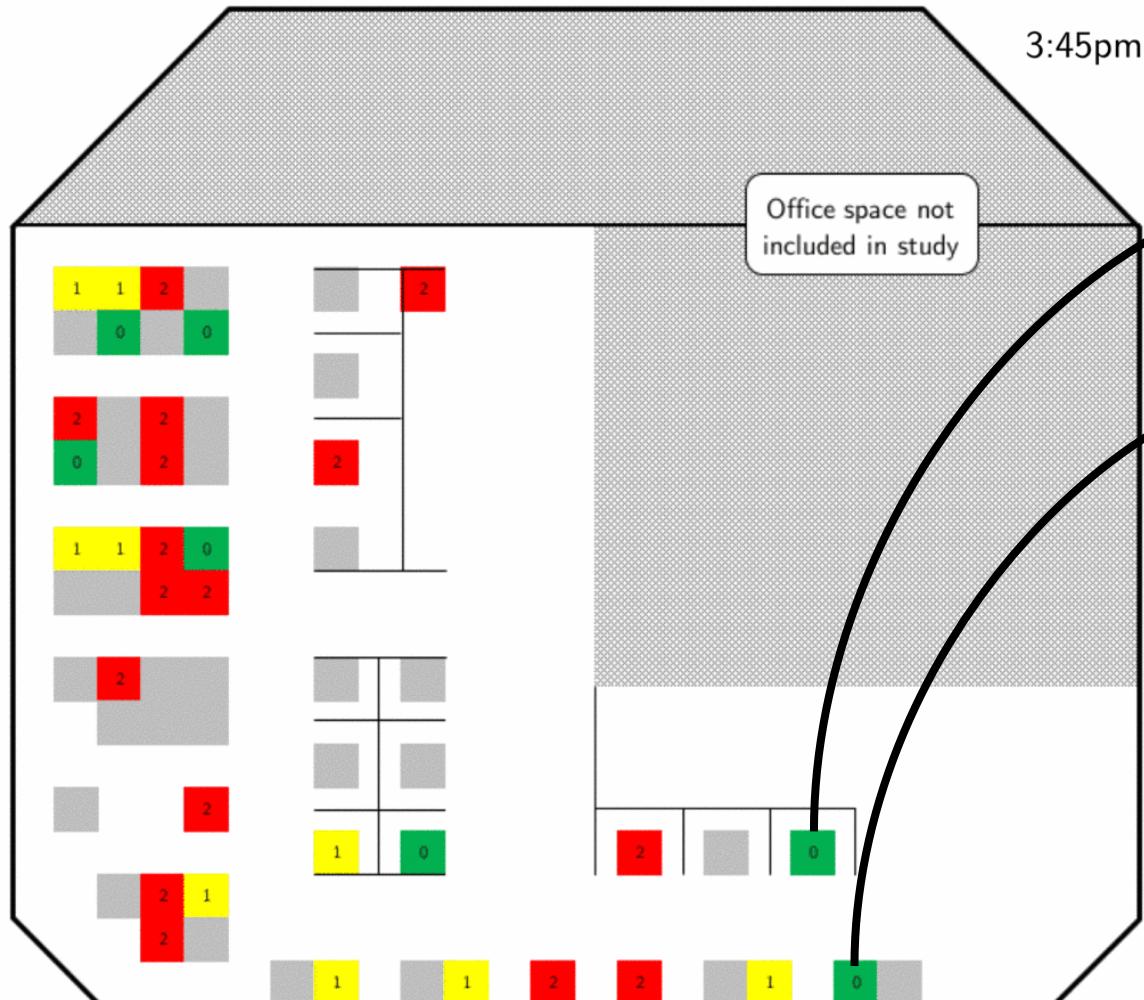
Activity States Visualized

(Real office in San
Francisco)

3:45pm



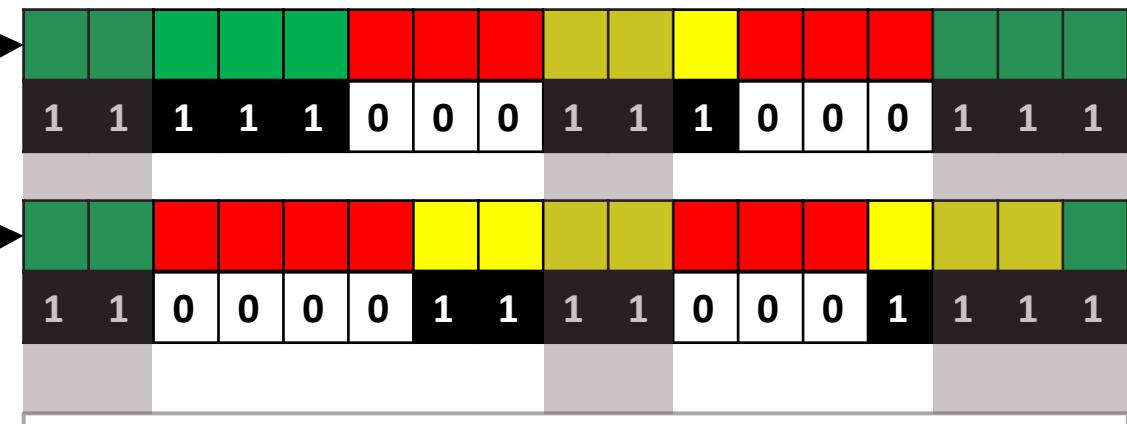
Sonta, A. J., Simmons, P. E., & Jain, R. K. (2018). Understanding building occupant activities at scale: An integrated knowledge-based and data-driven approach. *Advanced Engineering Informatics*, 37, 1–13.



3:45pm

12 pm

4 pm



Opportunities for social interaction

Fill adjacency matrix with
Jaccard similarity:

$$A_{1,2} = \frac{|V_1 \cap V_2|}{|V_1 \cup V_2|} = \frac{|V_1 \cap V_2|}{|V_1| + |V_2| - |V_1 \cap V_2|}$$

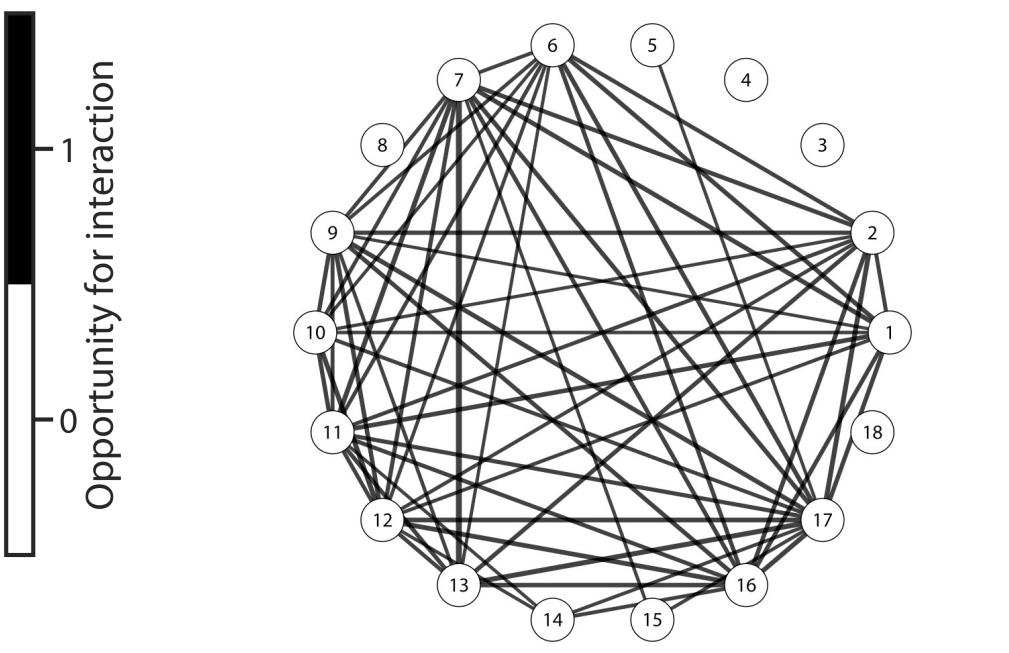
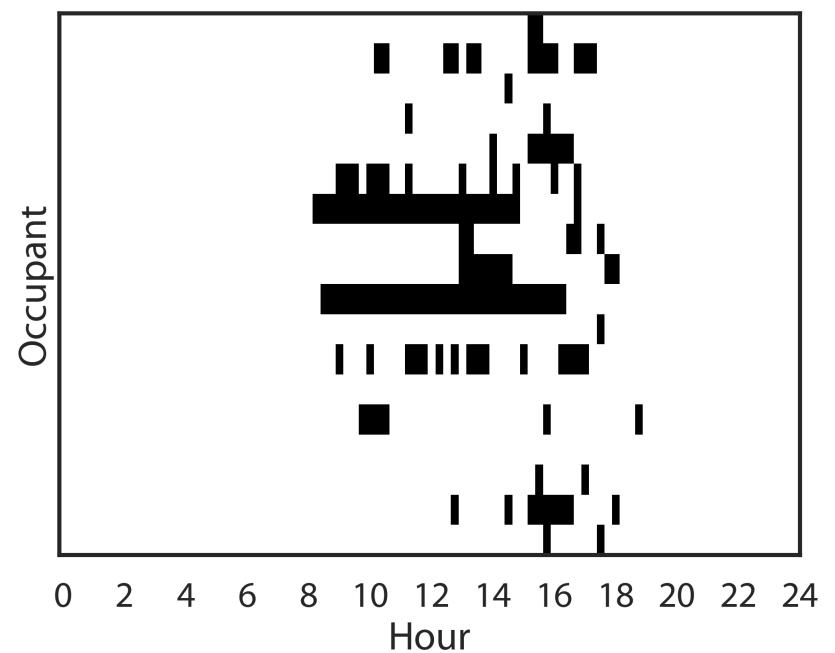
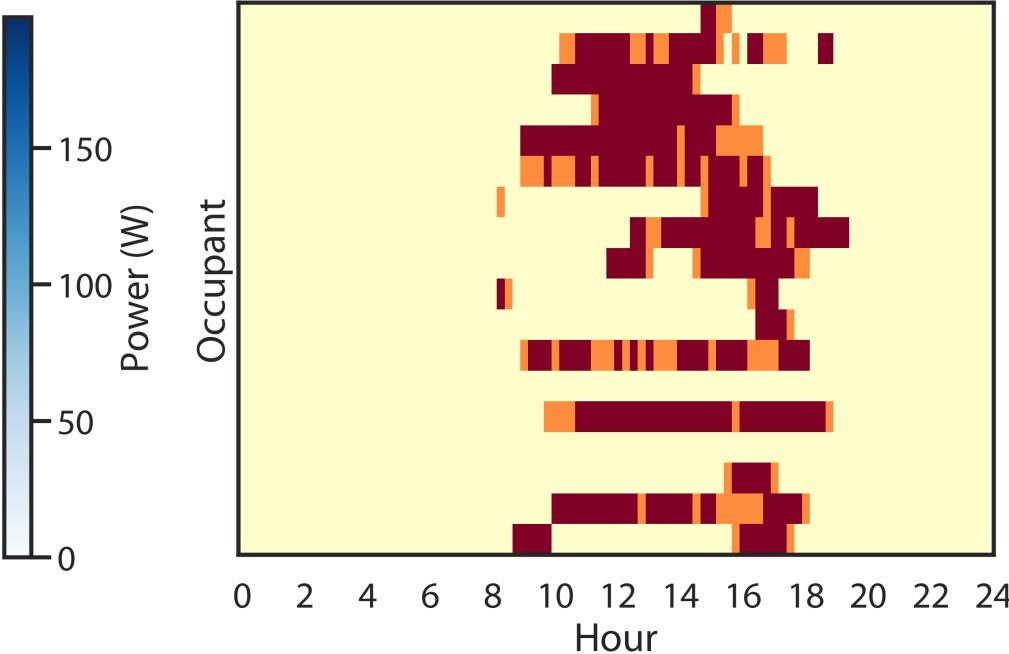
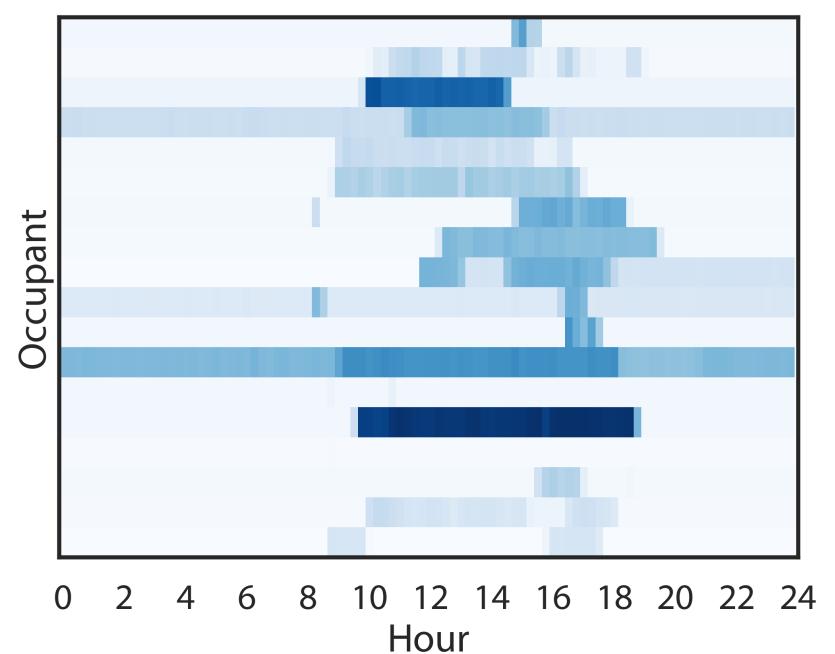
$$|V| = \sum_i V^i$$

$$|V_1 \cap V_2| = \sum_i V_1^i \cdot V_2^i$$

The Interaction Model

Example data
from one day

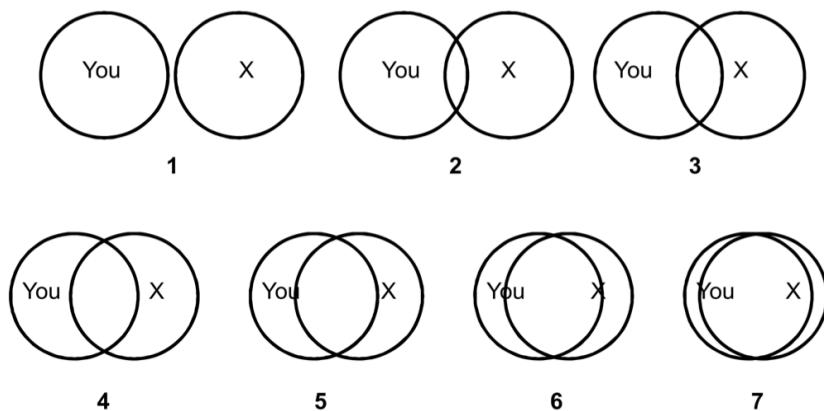
Office building
in Berkeley



Survey to measure ground truth network

Social

“Inclusion of the other in the self” scale¹



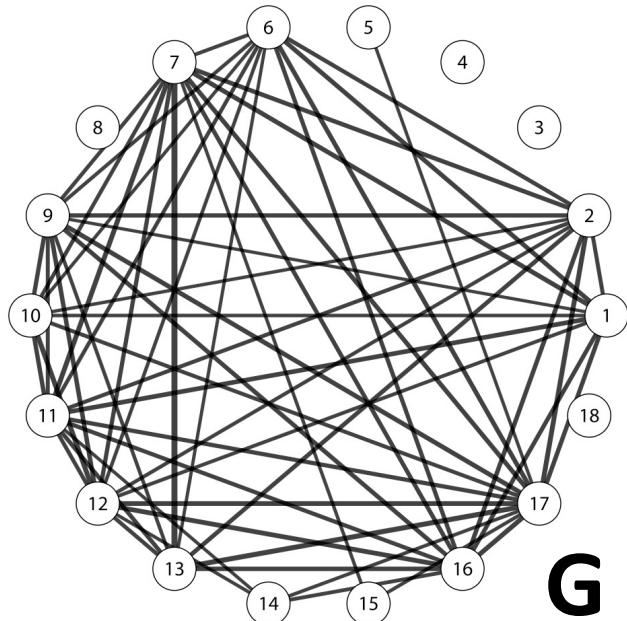
Organizational

Survey questions measure 3 key attributes²

1. **Communication** (information sharing)
2. **Advice** (problem solving)
3. **Trust** (work-related support)

¹ Gachter et al. 2012 | ² Krackhardt & Hanson 1993

Network comparison

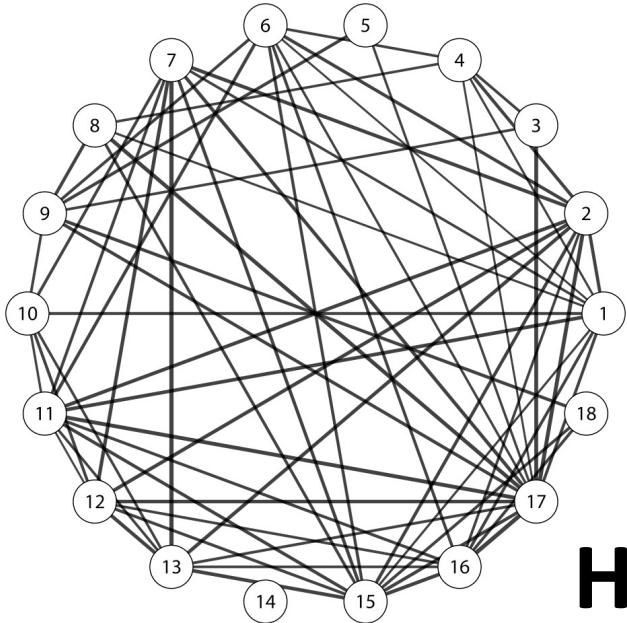


Inferred from model

- Graphical Lasso
- Influence Model
- Interaction Model

Ground truth from survey

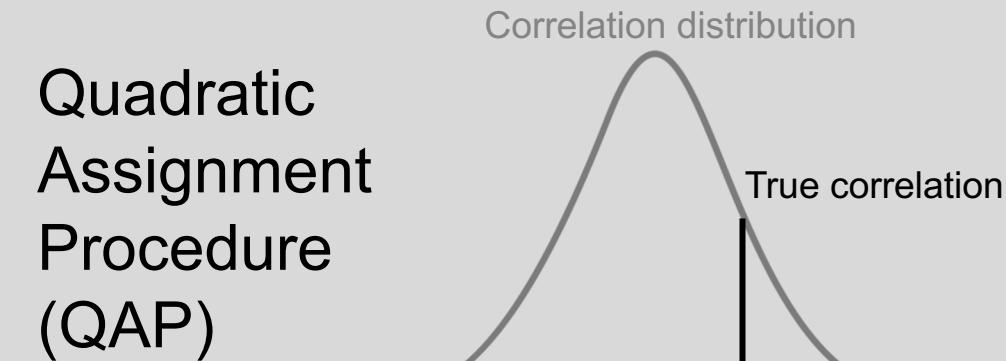
- Organizational (communication, advice, trust)
- Social



Graph correlation

$$\text{cor}(\mathbf{G}, \mathbf{H}) = \frac{\text{cov}(\mathbf{G}, \mathbf{H})}{\sqrt{\text{cov}(\mathbf{G}, \mathbf{G}) \cdot \text{cov}(\mathbf{H}, \mathbf{H})}}$$

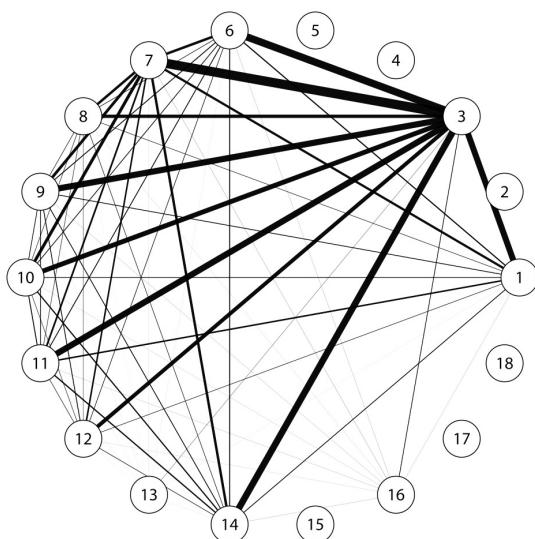
$$\text{cov}(\mathbf{G}, \mathbf{H}) = \frac{1}{|V|^2 - |V|} \sum_{i=j} (\mathbf{A}_{ij}^{\mathbf{G}} - \mu_{\mathbf{G}}) (\mathbf{A}_{ij}^{\mathbf{H}} - \mu_{\mathbf{H}})$$



Quadratic Assignment Procedure (QAP)

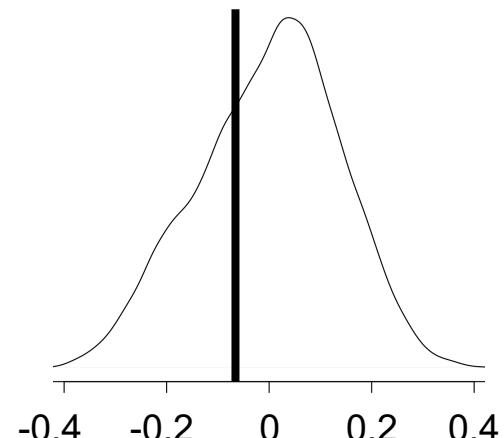
Network visualization

Graphical Lasso

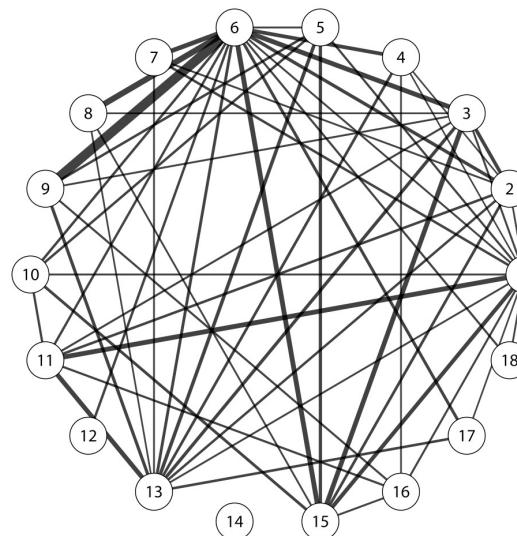


Graph correlation & estimated density from QAP test

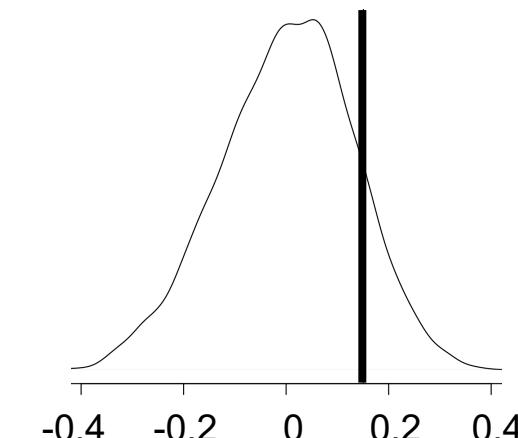
-0.06, p = 0.66



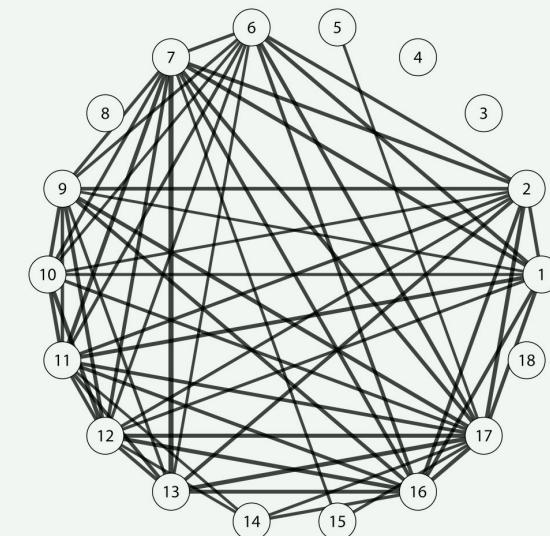
Influence Model



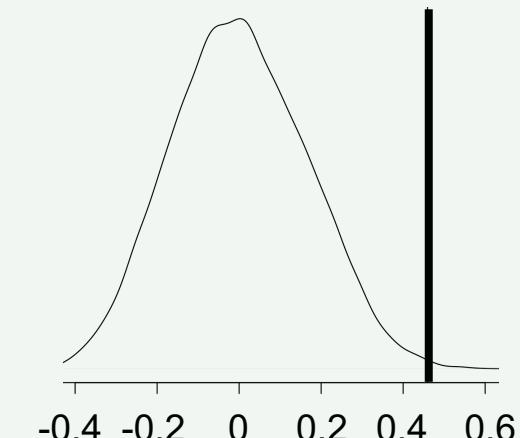
0.15, p = 0.25



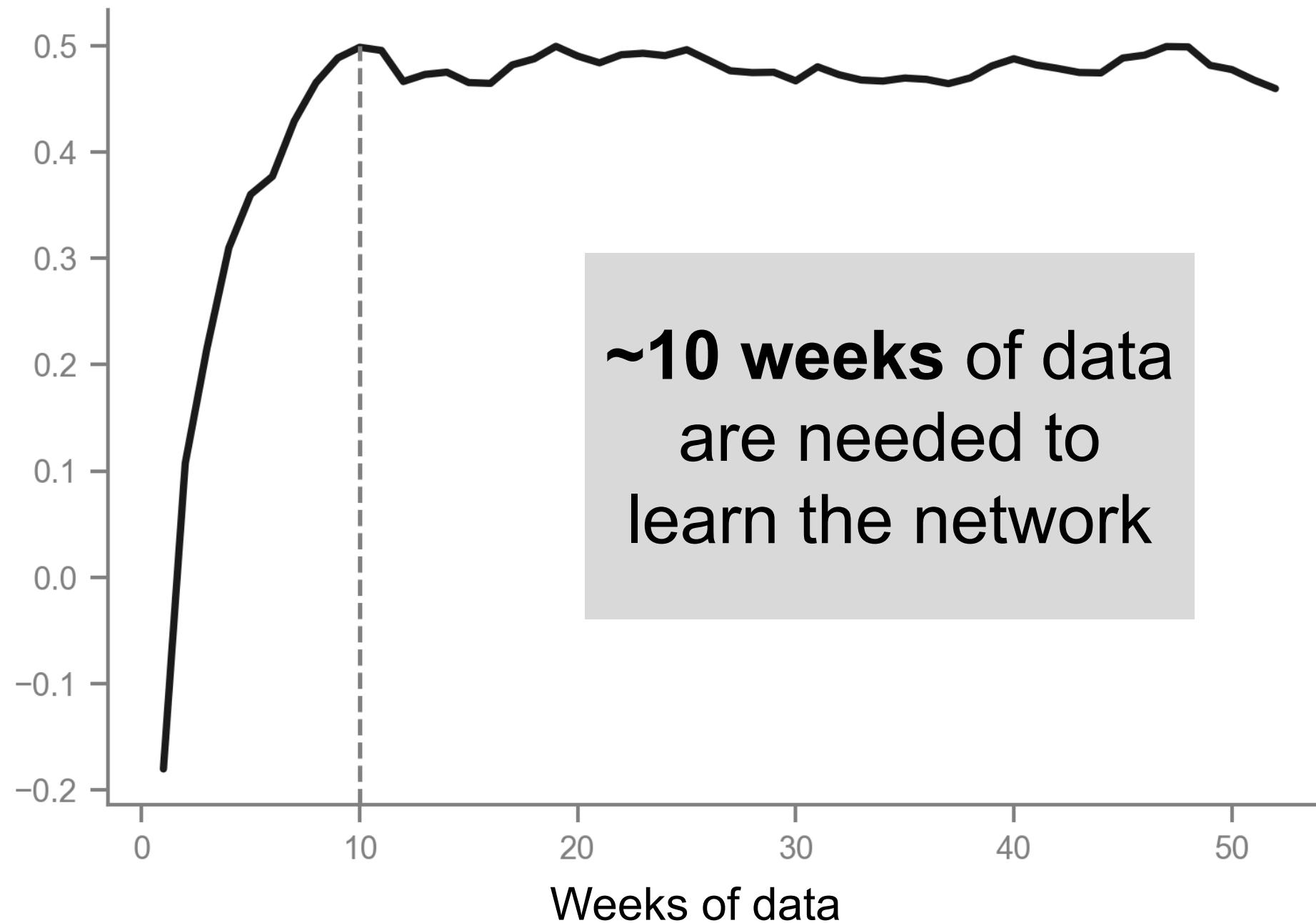
Interaction Model



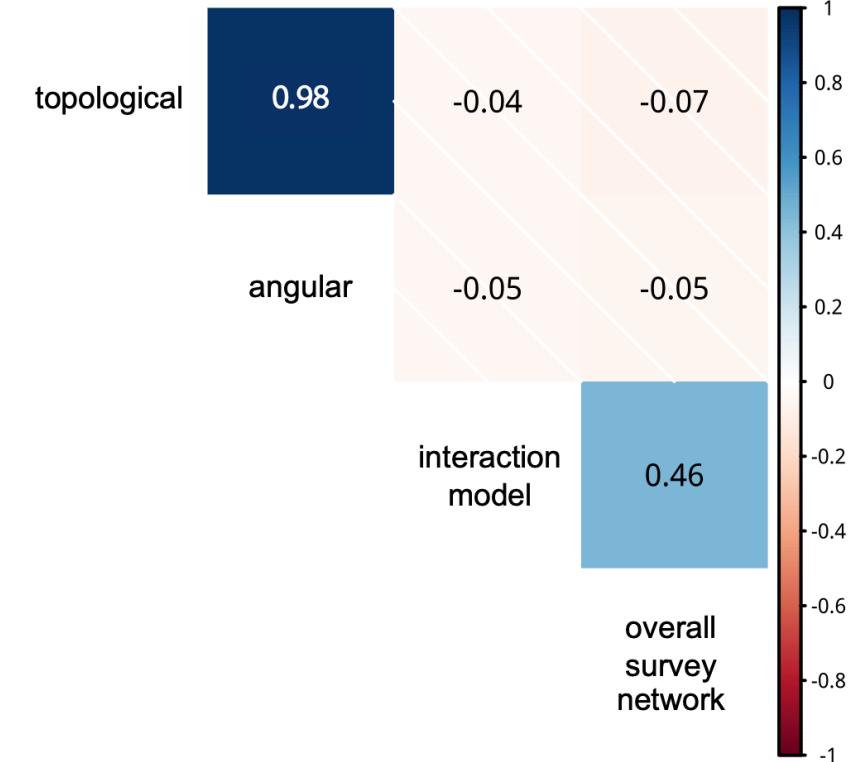
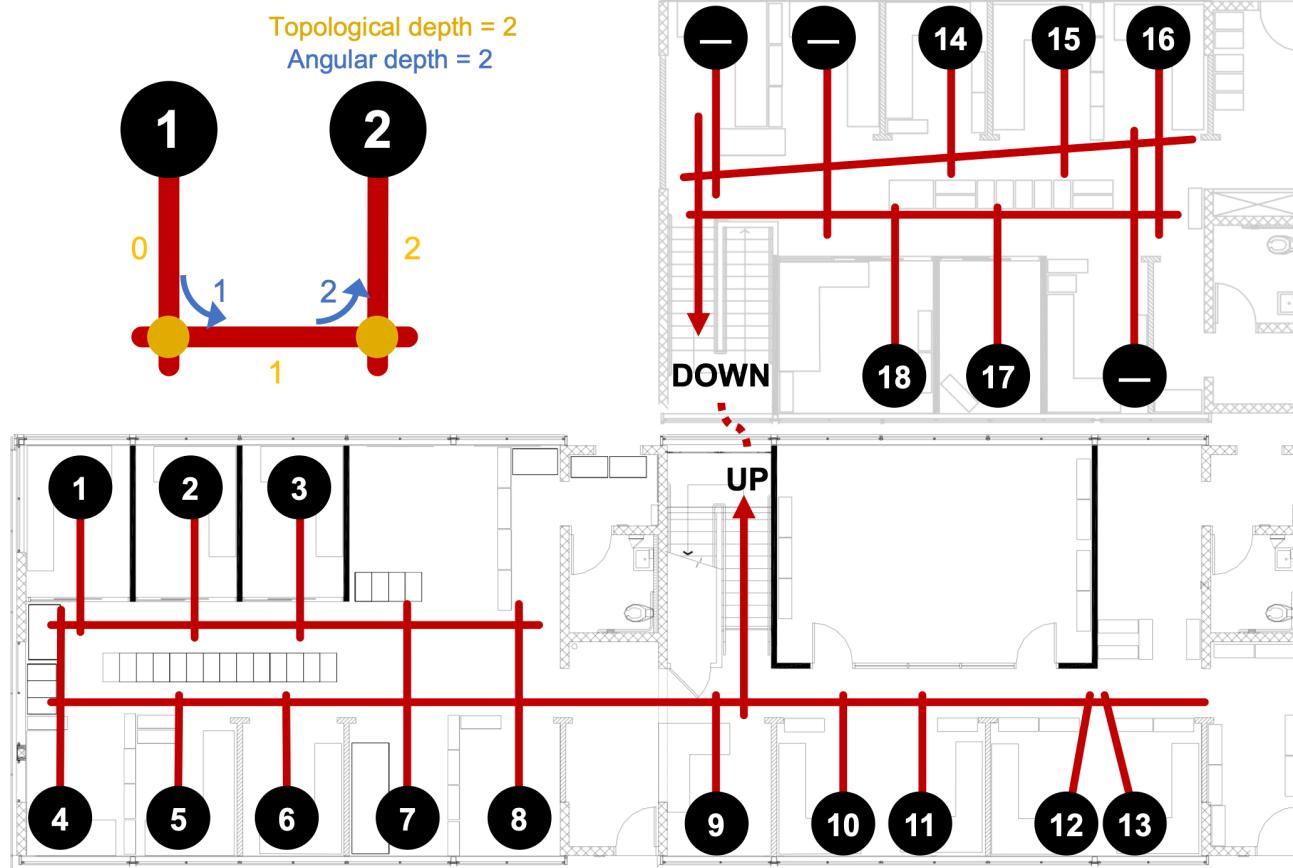
0.46, p = 0.002



Graph
correlation
with ground
truth



How does social network compare with spatial network?



Exam 2 details

- Next class time – Wednesday 8th (9:15 to 11:00 am)
- Closed book and notes
- **You may (and should) bring 1 sheet of paper with notes**
- Content: based on materials in Lectures 6-10
- Format:
 - Multiple choice questions
 - Open-ended questions – application-oriented
 - If network calculations require matrix manipulation (e.g., eigendecomposition), this will be provided
 - No coding

Lecture 06

- Network notation
- Adjacency matrix
- Types of networks
- Degree
- Paths
- Independent paths / connectivity
- Cut sets
- Min-cut/max-flow

Lecture 07

- Components
- Graph Laplacian matrix
- Spectral partitioning; Fiedler method
- Centrality
 - Degree
 - Eigenvalue
 - Katz
 - PageRank
 - Closeness
 - Betweenness

Lecture 08

- Roles
 - Structural equivalence
 - Regular equivalence (intuition)
- Groups of nodes
 - Cliques
 - (k-)Cores
 - (k-)Components
- Clustering coefficient
- Homophily / assortative mixing
- Modularity and community detection
- Motifs

Lecture 09

- Random graph models
 - Erdős–Rényi
 - Configuration model (intuition)
 - Preferential attachment (Barabási–Albert)
- Network structure metrics
 - Degree distribution
 - Clustering coefficient
 - Size of largest connected component
 - Average shortest path length
- Network archetypes
 - Scale free
 - Small world

Lecture 10

- Percolation
- Natural, model, and data defined networks