Moving Beyond Descriptives

Lorien Jasny[1]

[1]University of Exeter
L.Jasny@exeter.ac.uk

A step-change in quantitative social science skills
Funded by the Nuffield Foundation ESRC and HEFCE

EUSN Workshop
11 September 2022

Contents

Hypothesis Testing

Relating Node level indices to covariates

- Node Level Indices: centrality measures, brokerage, constraint

Relating Node level indices to covariates

- Node Level Indices: centrality measures, brokerage, constraint
- Node Covariates: measures of power, career advancement, gender – really anything you want to study that varies at the node level

Emergent Multi-Organizational Networks (EMON) Dataset

- 7 case studies of EMONs in the context of search and rescue activities from Drabek et. al. (1981)

Emergent Multi-Organizational Networks (EMON) Dataset

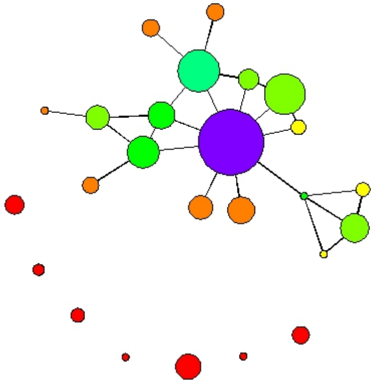
- 7 case studies of EMONs in the context of search and rescue activities from Drabek et. al. (1981)
- Ties between organizations are self-reported levels of communication coded from 1 to 4 with 1 as most frequent

Emergent Multi-Organizational Networks (EMON) Dataset

Attribute Data

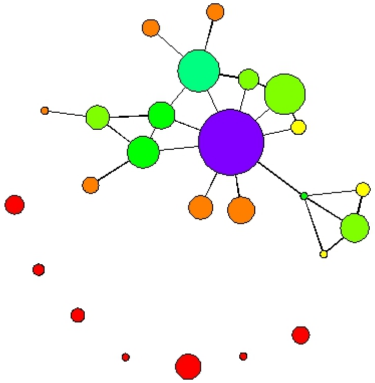
- Command Rank Score (CRS): mean rank (reversed) for prominence in the command structure
- Decision Rank Score (DRS): mean rank (reversed) for prominence in decision making process
- Paid Staff: number of paid employees
- Volunteer Staff: number of volunteer staff
- Sponsorship: organization type (City, County, State, Federal, or Private)

Correlation between DRS and Degree?



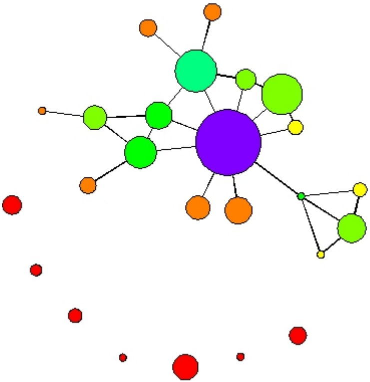
Correlation between DRS and Degree?

- Subsample of Mutually Reported "Continuous Communication" in Texas EMON



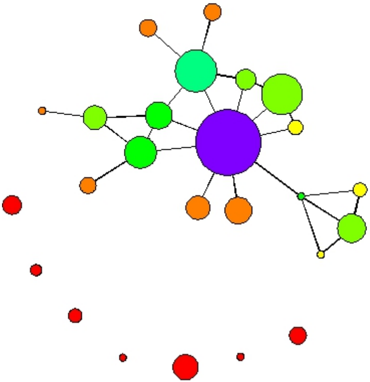
Correlation between DRS and Degree?

- Subsample of Mutually Reported “Continuous Communication” in Texas EMON
- Degree is shown in color (darker is bigger)



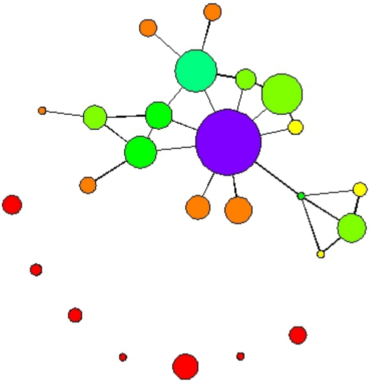
Correlation between DRS and Degree?

- Subsample of Mutually Reported “Continuous Communication” in Texas EMON
- Degree is shown in color (darker is bigger)
- DRS in size

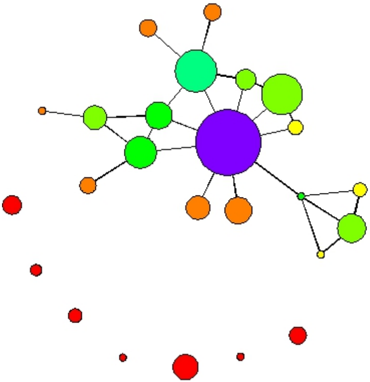


Correlation between DRS and Degree?

- Subsample of Mutually Reported “Continuous Communication” in Texas EMON
- Degree is shown in color (darker is bigger)
- DRS in size
- Empirical corelation $\rho = 0.86$

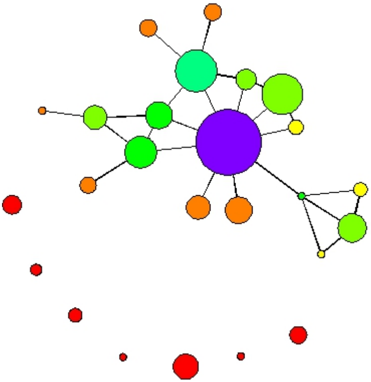


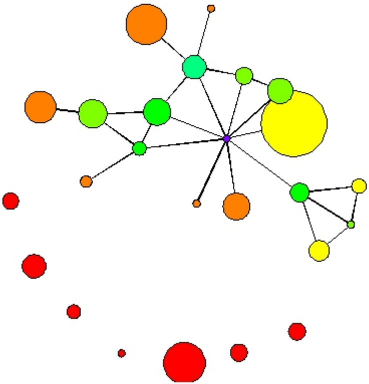
Correlation between DRS and Degree?



$\rho = 0.86$

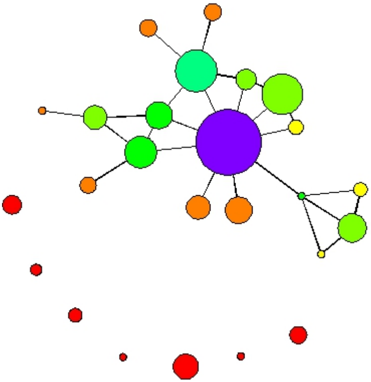
Correlation between DRS and Degree?



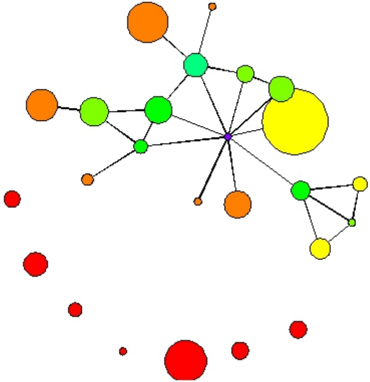


$\rho = 0.86$

Correlation between DRS and Degree?

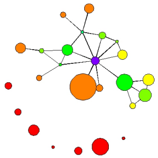


$\rho = 0.86$

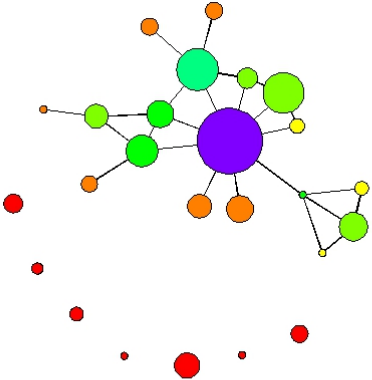


$\rho = -0.07$

Correlation between DRS and Degree?

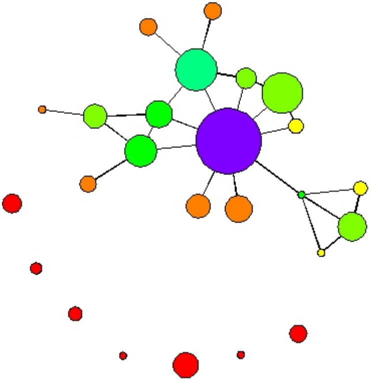


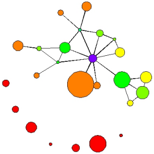
$\rho = -0.07$



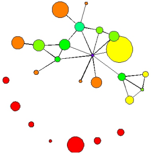
$\rho = 0.86$

Correlation between DRS and Degree?





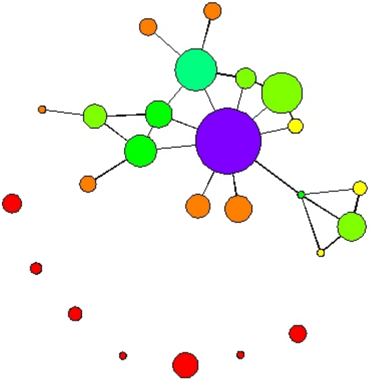
$\rho = -0.07$



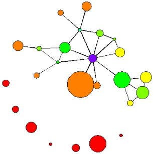
$\rho = -0.12$

$\rho = 0.86$

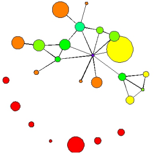
Correlation between DRS and Degree?



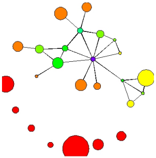
$\rho = 0.86$



$\rho = -0.07$

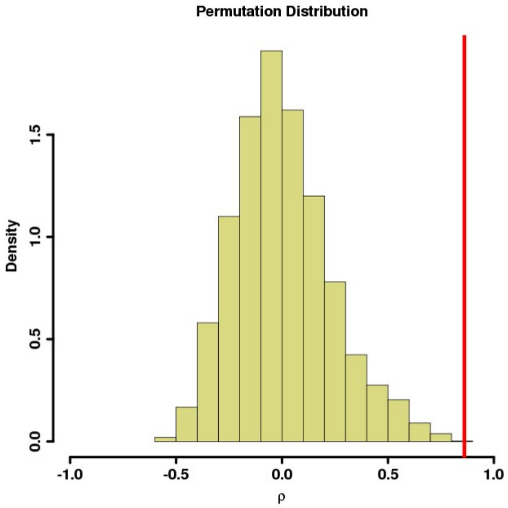


$\rho = -0.12$

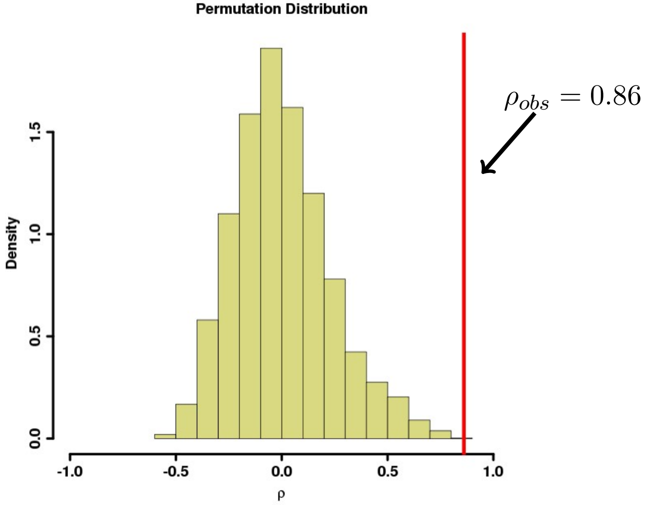


$\rho = -0.39$

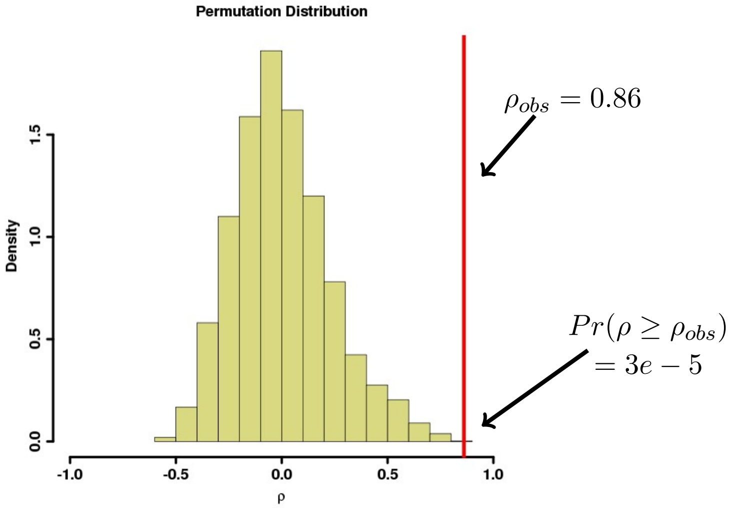
Correlation between DRS and Degree?



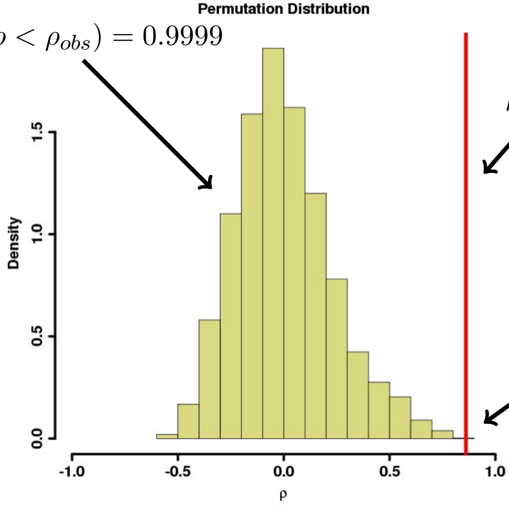
Correlation between DRS and Degree?



Correlation between DRS and Degree?



Correlation between DRS and Degree?



$Pr(\rho < \rho_{obs}) = 0.9999$

$\rho_{obs} = 0.86$

$Pr(\rho \geq \rho_{obs})$
$= 3e-5$

Regression?

Regression?

- Can use Node Level Indices as independent variables in a regression

Regression?

- Can use Node Level Indices as independent variables in a regression
- Big assumption: ***position*** predicts the ***properties of those who hold them***

Regression?

- Can use Node Level Indices as independent variables in a regression
- Big assumption: ***position*** predicts the ***properties of those who hold them***
- Conditioning on NLI values, so dependence in accounted for ***assuming no error in the network***

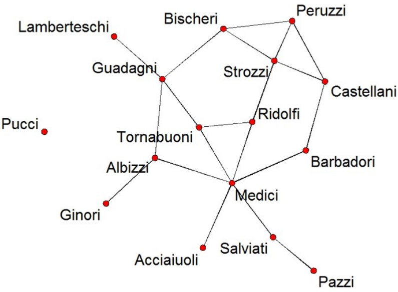
Regression?

- Can use Node Level Indices as independent variables in a regression
- Big assumption: ***position*** predicts the ***properties of those who hold them***
- Conditioning on NLI values, so dependence in accounted for ***assuming no error in the network***
- NLIs as dependent variables more problematic due to autocorrelation

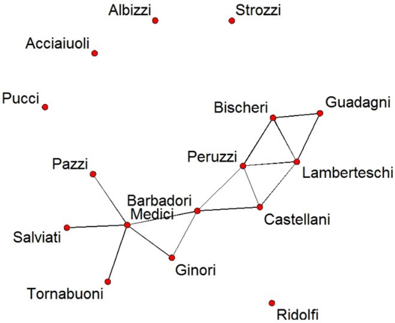
Code Time

Sections 1-2.3

Quadratic Assignment Procedure

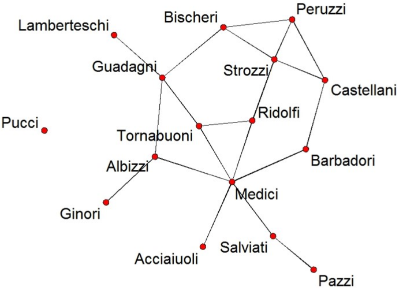


Marriage

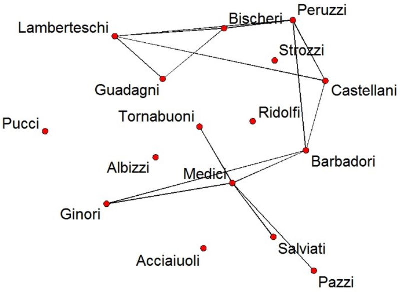


Business

Quadratic Assignment Procedure



Marriage



Business

Graph Correlation

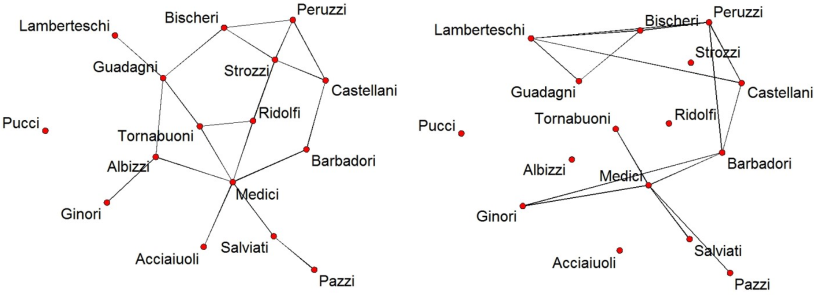
Graph Correlation

- Simple way of comparing graphs on the same vertex set by element

Graph Correlation

- Simple way of comparing graphs on the same vertex set by element
- $gcor\left(\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix} \right) = cor([1,1,1,0],[1,1,2,2])$

Do business ties coincide with marriages?

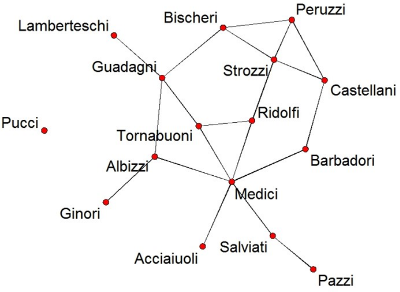


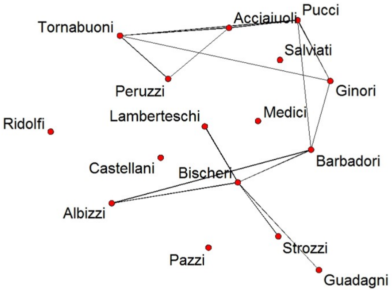
Marriage

Business

$$\rho = 0.372$$

Do business ties coincide with marriages?

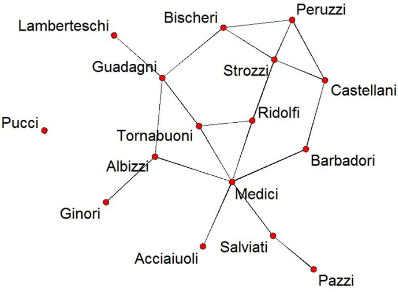




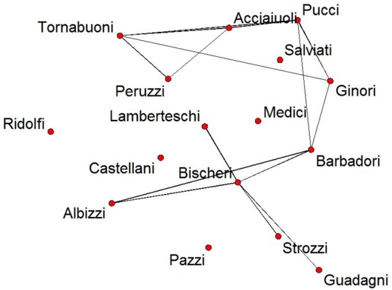
Marriage

Business

Do business ties coincide with marriages?



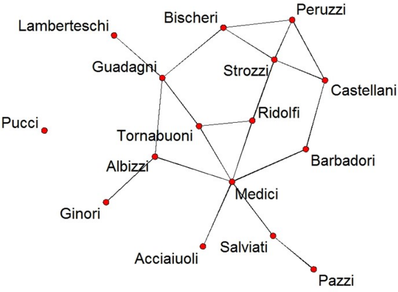
Marriage



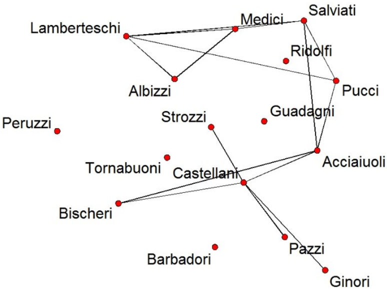
Business

$$\rho = 0.169$$

Do business ties coincide with marriages?



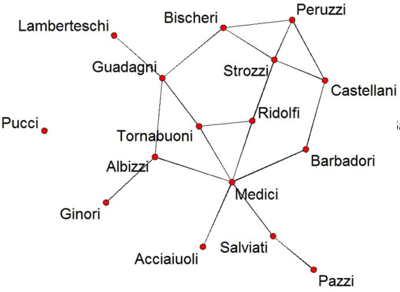
Marriage



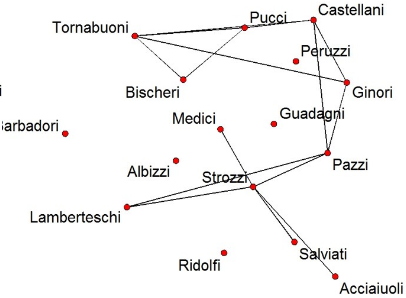
Business

$$\rho = -0.034$$

Do business ties coincide with marriages?



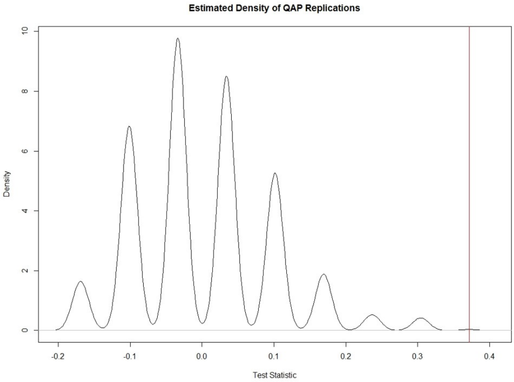
Marriage



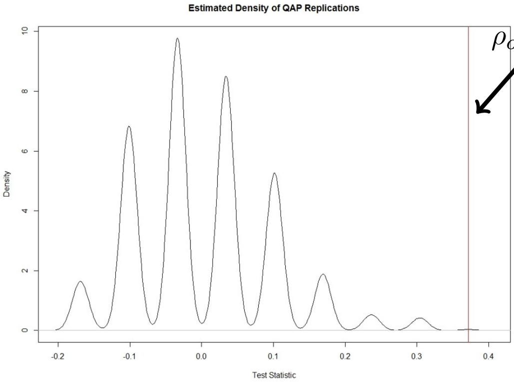
Business

$$\rho = -0.101$$

QAP Test

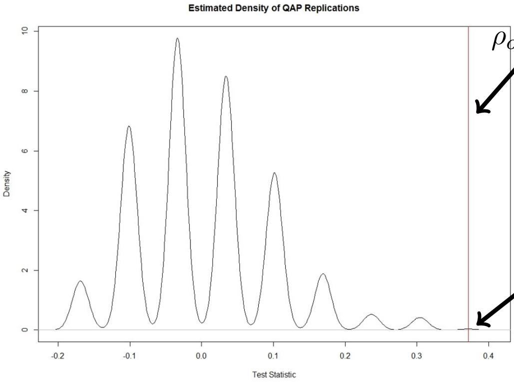

Estimated Density of QAP Replications
Density
0
2
4
6
8
10
-0.2
-0.1
0.0
0.1
0.2
0.3
0.4
Test Statistic

QAP Test



$\rho_{obs} = 0.372$

QAP Test

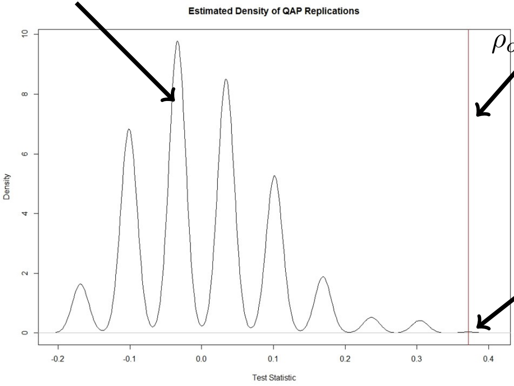


$\rho_{obs} = 0.372$

$Pr(\rho \geq \rho_{obs})$
$= .001$

QAP Test

$Pr(\rho < \rho_{obs}) = 0.999$

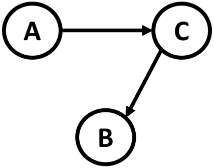


$\rho_{obs} = 0.372$

$Pr(\rho \geq \rho_{obs})$
$= .001$

Why can't we use the same permutation test?

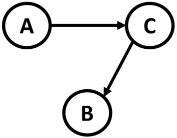
QAP Test



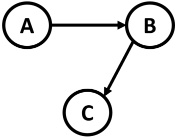
	A	B	C
A	-	0	1
B	0	-	0
C	0	1	-

$$\begin{bmatrix} - \\ 0 \\ 1 \\ 0 \\ - \\ 0 \\ 0 \\ 1 \\ - \end{bmatrix}$$

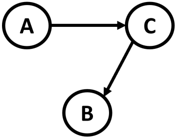
QAP Test



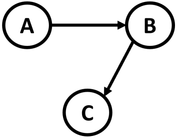
	A	C	B
A	-	0	1
C	0	-	0
B	0	1	-



QAP Test



	A	B	C
A	-	1	0
B	0	-	1
C	0	0	-



Network Regression

Network Regression

- Family of models predicting social ties

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression
  - Dependent variable is a network adjacency matrix

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression
  - Dependent variable is a network adjacency matrix
- $\mathbf{E}Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_\rho X_{\rho ij}$

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression
  - Dependent variable is a network adjacency matrix
- $\mathbf{E}Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_\rho X_{\rho ij}$
  - Where $\mathbf{E}$ is the expectation operator (analagous to "mean" or "average")

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression
  - Dependent variable is a network adjacency matrix
- $\mathbf{E}Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_\rho X_{\rho ij}$
  - Where $\mathbf{E}$ is the expectation operator (analagous to "mean" or "average")
  - Y_{ij} is the value from i to j on the dependent relation with adjacency matrix Y

Network Regression

- Family of models predicting social ties
  - Special case of standard OLS regression
  - Dependent variable is a network adjacency matrix
- $\mathbf{E}Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_\rho X_{\rho ij}$
  - Where $\mathbf{E}$ is the expectation operator (analagous to "mean" or "average")
  - Y_{ij} is the value from i to j on the dependent relation with adjacency matrix Y
  - X_{kij} is the value of the kth predictor for the (i, j) ordered pair, and $\beta_0, \ldots \beta_\rho$ are coefficients

Data Prep

Data Prep

- Dependent variable is an adjacency matrix

Data Prep

- Dependent variable is an adjacency matrix
  - Standard case: dichotomous data

Data Prep

- Dependent variable is an adjacency matrix
  - Standard case: dichotomous data
  - Valued case

Data Prep

- Dependent variable is an adjacency matrix
  - Standard case: dichotomous data
  - Valued case
- Independent variables also in adjacency matrix form

Data Prep

- Dependent variable is an adjacency matrix
  - Standard case: dichotomous data
  - Valued case
- Independent variables also in adjacency matrix form
  - Always takes matrix form, but may be based on vector data

Data Prep

- Dependent variable is an adjacency matrix
  - Standard case: dichotomous data
  - Valued case
- Independent variables also in adjacency matrix form
  - Always takes matrix form, but may be based on vector data
  - eg. simple adjacency matrix, sender/receiver effects, attribute differences, elements held in common

Code Time

Sections 2.4-2.5

Network Autocorrelation Models

Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties

Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties
  - Special case of standard OLS regression

Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties
  - Special case of standard OLS regression
  - Dependent variable is a vertex attribute

Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties
  - Special case of standard OLS regression
  - Dependent variable is a vertex attribute
- $y = (I - \Theta W)^{-1}(X\beta + (I - \psi Z)^{-1}v)$

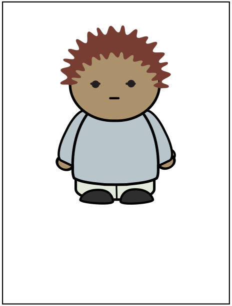
Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties
  - Special case of standard OLS regression
  - Dependent variable is a vertex attribute
- $y = (I - \Theta W)^{-1}(X\beta + (I - \psi Z)^{-1}v)$
  - where Θ is the matrix for the Auto-Regressive weights

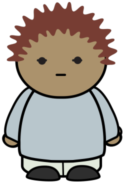
Network Autocorrelation Models

- Family of models for estimating how covariates relate to each other through ties
  - Special case of standard OLS regression
  - Dependent variable is a vertex attribute
- $y = (I - \Theta W)^{-1}(X\beta + (I - \psi Z)^{-1}v)$
  - where Θ is the matrix for the Auto-Regressive weights
  - and ψ is the matrix for the Moving Average weights

The Classical Regression Model

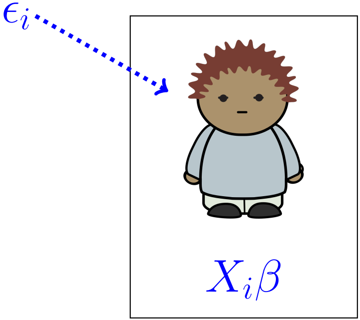


The Classical Regression Model

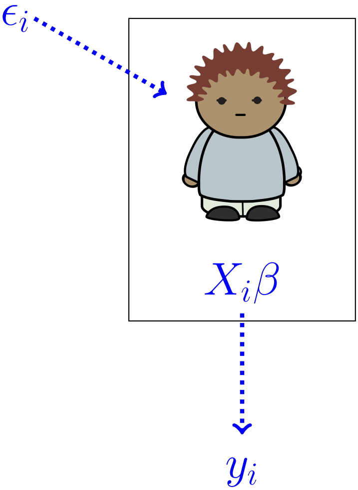


$$X_i\beta$$

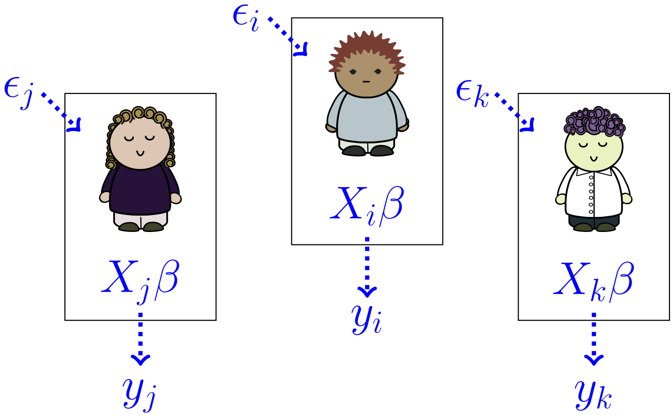
The Classical Regression Model



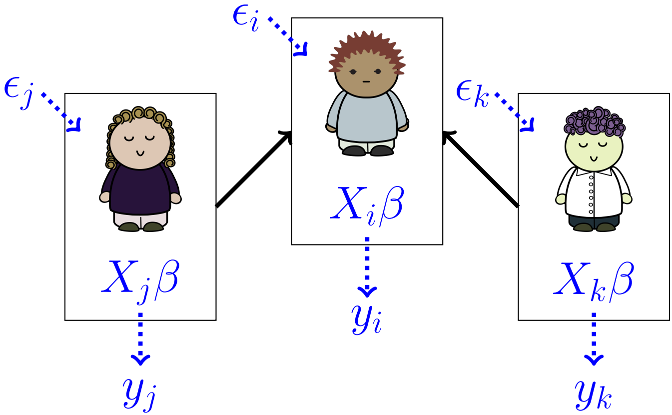
The Classical Regression Model



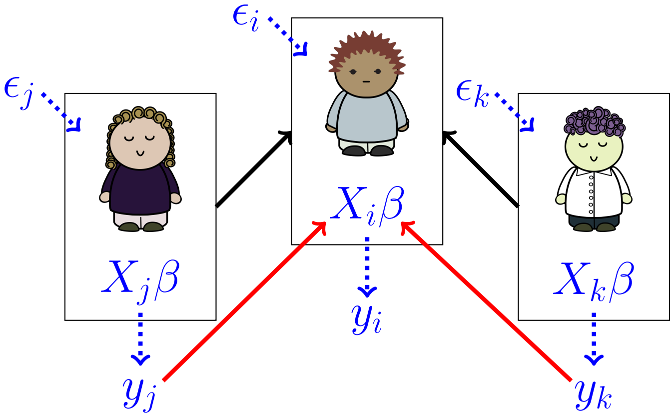
Adding Network AR Effects



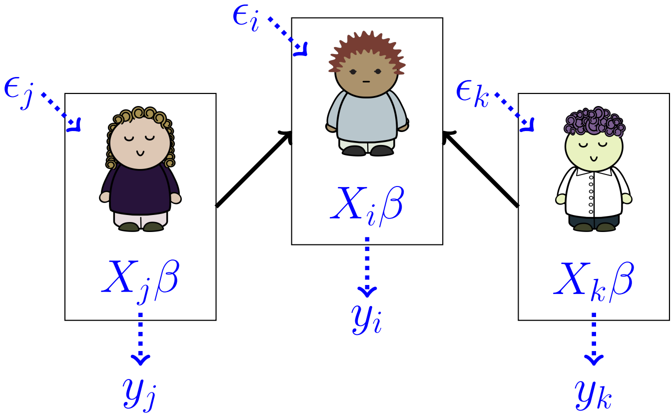
Adding Network AR Effects



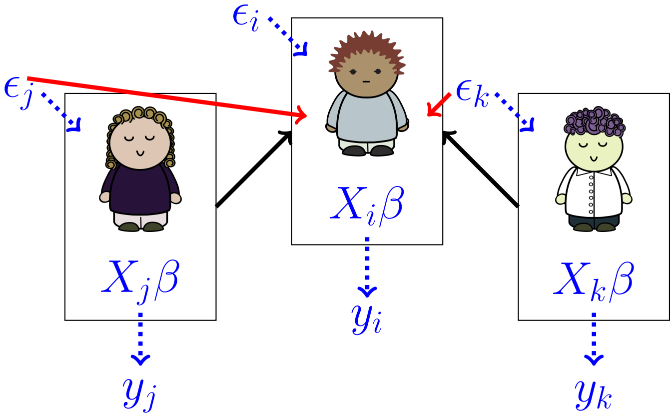
Adding Network AR Effects



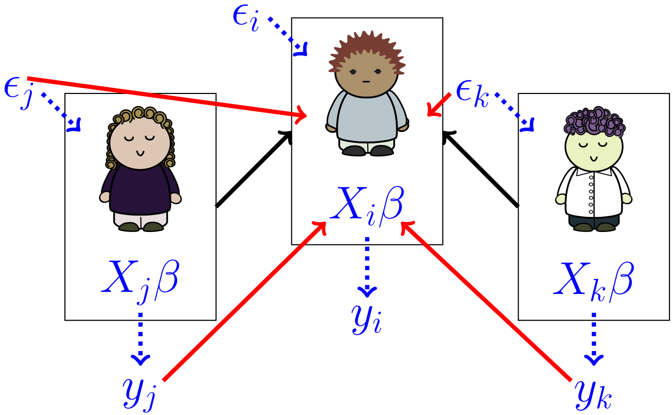
Adding Network MA Effects



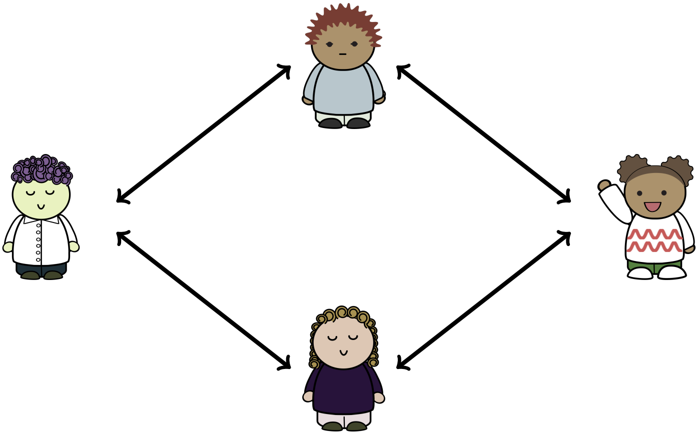
Adding Network MA Effects



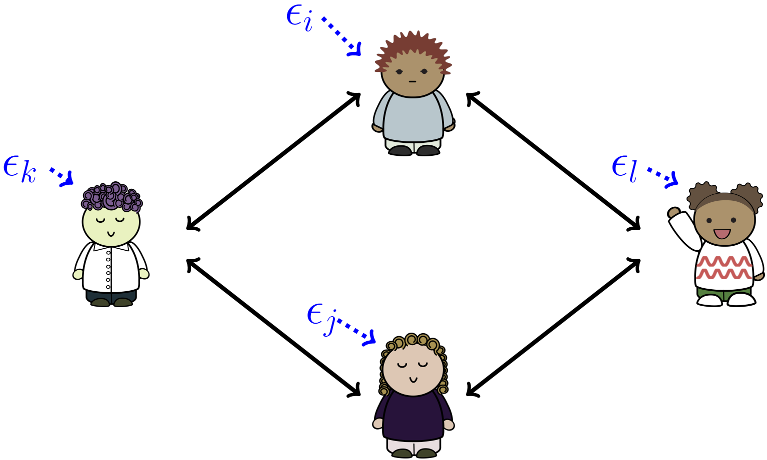
Network ARMA Model



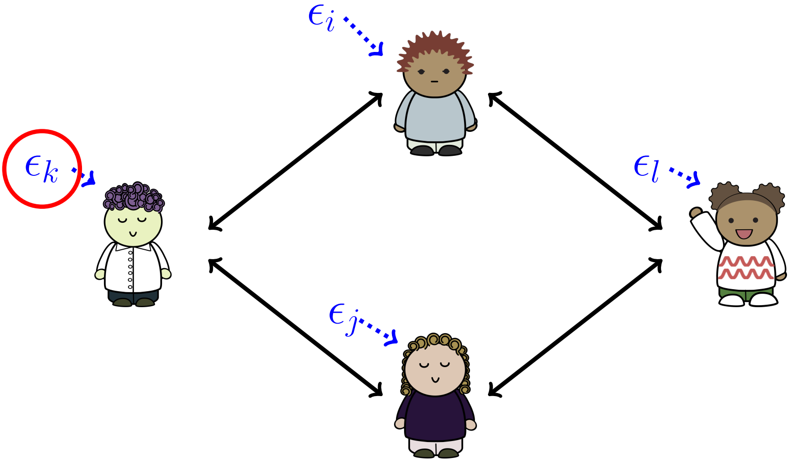
Network ‘Resonance’



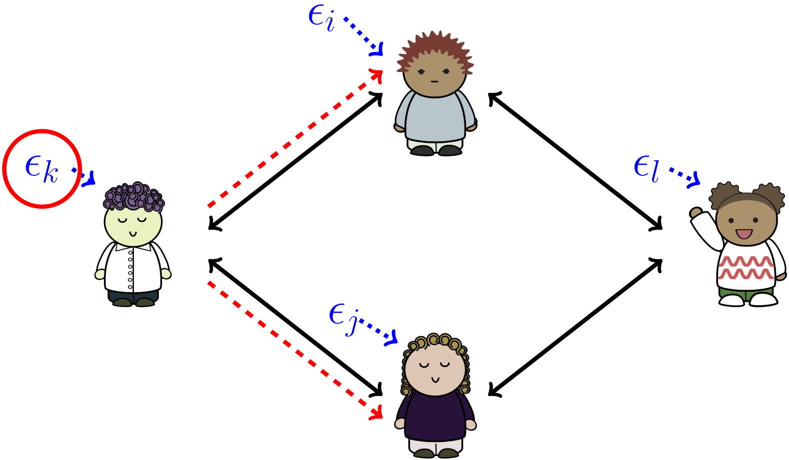
Network 'Resonance'



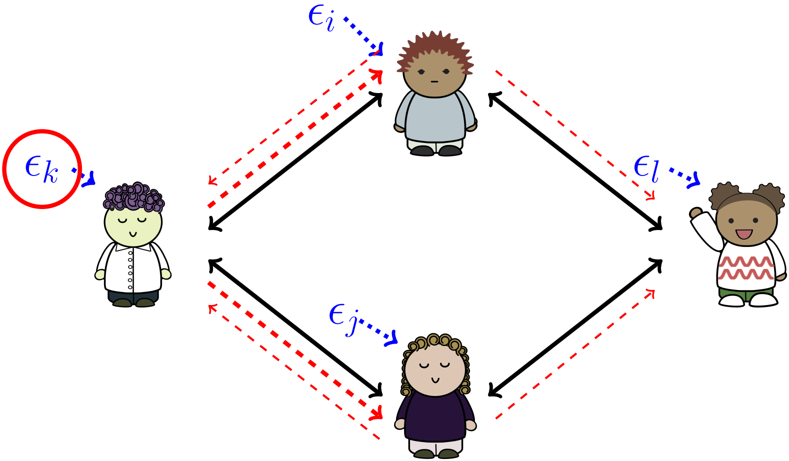
Network ‘Resonance’



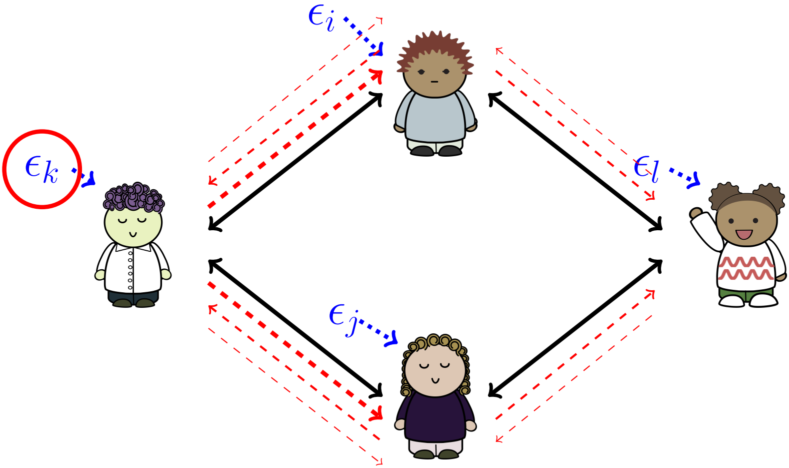
Network 'Resonance'



Network ‘Resonance’



Network 'Resonance'



Inference with the Network Autocorrelation Model

Inference with the Network Autocorrelation Model

- Usually observe $\mathbf{y}$, $\mathbf{X}$, and $\mathbf{Z}$ and/or $\mathbf{Z}$, want to infer β, θ, and ϕ

Inference with the Network Autocorrelation Model

- Usually observe $\mathbf{y}$, $\mathbf{X}$, and $\mathbf{Z}$ and/or $\mathbf{Z}$, want to infer β, θ, and ϕ
- Need each $\mathbf{I} - \mathbf{W}, \mathbf{I} - \mathbf{Z}$ invertible for solution to exist

Inference with the Network Autocorrelation Model

- Usually observe $\mathbf{y}$, $\mathbf{X}$, and $\mathbf{Z}$ and/or $\mathbf{Z}$, want to infer β, θ, and ϕ
- Need each $\mathbf{I} - \mathbf{W}, \mathbf{I} - \mathbf{Z}$ invertible for solution to exist
- error in disturbance autocorrelation, v, assumed as iid, $v_i \; N(0, \sigma^2)$

Inference with the Network Autocorrelation Model

- Usually observe $\mathbf{y}$, $\mathbf{X}$, and $\mathbf{Z}$ and/or $\mathbf{Z}$, want to infer β, θ, and ϕ
- Need each $\mathbf{I} - \mathbf{W}, \mathbf{I} - \mathbf{Z}$ invertible for solution to exist
- error in disturbance autocorrelation, v, assumed as iid, $v_i \ N(0, \sigma^2)$
- Standard errors based on the inverse information matrix at the MLE

Inference with the Network Autocorrelation Model

- Usually observe **y**, **X**, and **Z** and/or **Z**, want to infer β, θ, and ϕ
- Need each $\mathbf{I} - \mathbf{W}, \mathbf{I} - \mathbf{Z}$ invertible for solution to exist
- error in disturbance autocorrelation, v, assumed as iid, $v_i \ N(0, \sigma^2)$
- Standard errors based on the inverse information matrix at the MLE
- Compare models in the usual way (eg AIC, BIC)

Choosing the Weight Matrix

Choosing the Weight Matrix

- crucial modeling issue to choose the right form

Choosing the Weight Matrix

- crucial modeling issue to choose the right form
    - standard adjacency matrix

Choosing the Weight Matrix

- crucial modeling issue to choose the right form
  - standard adjacency matrix
  - row-normalized adjancecy matrix

Choosing the Weight Matrix

- crucial modeling issue to choose the right form
  - standard adjacency matrix
  - row-normalized adjancecy matrix
  - structural equivalence distance

Choosing the Weight Matrix

- crucial modeling issue to choose the right form
  - standard adjacency matrix
  - row-normalized adjancecy matrix
  - structural equivalence distance
- Many suggestions given by Leenders 2002

Data Prep

Data Prep

- Dependent variable is a vertex attribute

Data Prep

- Dependent variable is a vertex attribute
- Covariates are in matrix form with one column per attribute

Data Prep

- Dependent variable is a vertex attribute
- Covariates are in matrix form with one column per attribute
- Can include an intercept term by adding a column of 1s

Data Prep

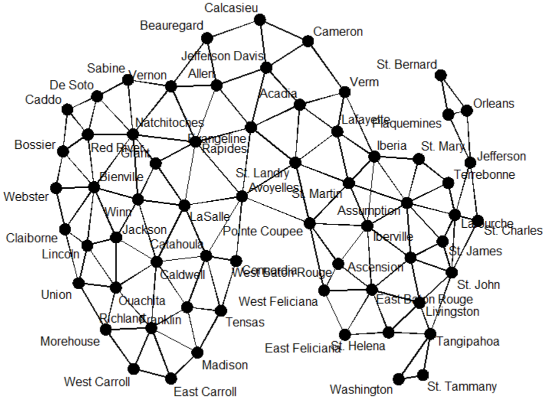
- Dependent variable is a vertex attribute
- Covariates are in matrix form with one column per attribute
- Can include an intercept term by adding a column of 1s
- Weight matrices for both AR and MA terms in matrix form

Data Prep

- Dependent variable is a vertex attribute
- Covariates are in matrix form with one column per attribute
- Can include an intercept term by adding a column of 1s
- Weight matrices for both AR and MA terms in matrix form
- Can include multiple weight matrices (as a list) for both AR and MA

Leenders 2002

Leenders 2002



Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:
    - B is the percentage of African American residents in the parish

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:
  - B is the percentage of African American residents in the parish
  - C is the percentage of Catholic residents in the parish

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:
  - B is the percentage of African American residents in the parish
  - C is the percentage of Catholic residents in the parish
  - U is the percentage of the parish considered urban

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:
  - B is the percentage of African American residents in the parish
  - C is the percentage of Catholic residents in the parish
  - U is the percentage of the parish considered urban
  - BPE is a measure of 'black political equality'

Variables

- Dependent variable: proportion of support in a parish for democratic presidential candidate Kennedy in the 1960 elections
- Covariates:
  - B is the percentage of African American residents in the parish
  - C is the percentage of Catholic residents in the parish
  - U is the percentage of the parish considered urban
  - BPE is a measure of 'black political equality'
- Weight matrix (ρ): simple contiguity network

Leenders 2002

Table 3
Network effects model for the Louisiana voting data

	OLS	$w_{ij}^{[1]}$	$w_{ij}^{[2]}$	$w_{ij}^{[6]}$	$w_{ij}^{[9]}$
ρ	–	0.31* (0.10)	0.07 (0.06)	0.12 (0.25)	0.04 (0.12)
Constant	21.03* (4.40)	13.87* (4.67)	19.83* (4.34)	16.78 (10.06)	19.80* (5.62)
B	0.01 (0.08)	−0.00 (0.07)	0.00 (0.08)	0.01 (0.08)	0.01 (0.08)
C	0.30* (0.04)	0.22* (0.05)	0.28* (0.04)	0.29* (0.05)	0.29 (0.05)
U	−0.11* (0.04)	−0.10* (0.04)	−0.11* (0.04)	−0.11* (0.04)	−0.11* (0.04)
BPE	0.39* (0.06)	0.30* (0.06)	0.37* (0.06)	0.38* (0.06)	0.38* (0.06)

* $P < 0.05$.

Table 4
Network disturbances model for the Louisiana voting data

	$w_{ij}^{[1]}$	$w_{ij}^{[2]}$	$w_{ij}^{[6]}$	$w_{ij}^{[9]}$
ρ	0.69* (0.10)	0.53* (0.13)	0.22 (0.42)	0.74* (0.15)
Constant	26.99* (4.50)	24.98* (4.22)	21.52* (4.30)	24.51* (5.06)
B	−0.11 (0.07)	−0.07 (0.07)	−0.00 (0.08)	−0.09 (0.08)
C	0.37* (0.05)	0.35* (0.04)	0.31* (0.04)	0.38* (0.04)
U	−0.07* (0.03)	0.08* (0.03)	−0.11* (0.04)	−0.10* (0.04)
BPE	0.24* (0.06)	0.30* (0.06)	0.38* (0.06)	0.29* (0.06)

* $P < 0.05$.

Leenders 2002

Table 5
Order of W matrices and autocorrelation models according to AIC

	Weight matrix	AIC	Order within model	Overall order
Network effects model	$w_{ij}^{[1]}$	439.12	1	3
	$w_{ij}^{[2]}$	445.52	2	5
	$w_{ij}^{[9]}$	446.78	4	8
	$w_{ij}^{[6]}$	446.44	3	6
Network disturbances model	$w_{ij}^{[1]}$	431.92	1	1
	$w_{ij}^{[2]}$	436.33	2	2
	$w_{ij}^{[9]}$	446.69	4	7
	$w_{ij}^{[6]}$	440.95	3	4
OLS	–	446.82	–	9

Code Time

Section 2.6

Baseline Models

Baseline Models

- treats social structure as maximally random given some fixed constraints

Baseline Models

- treats social structure as maximally random given some fixed constraints
- methodological premise from Mayhew

Baseline Models

- treats social structure as maximally random given some fixed constraints
- methodological premise from Mayhew
  - identify potentially constraining factors

Baseline Models

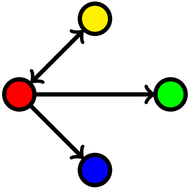
- treats social structure as maximally random given some fixed constraints
- methodological premise from Mayhew
  - identify potentially constraining factors
  - compare observed properties to baseline model

Baseline Models

- treats social structure as maximally random given some fixed constraints
- methodological premise from Mayhew
  - identify potentially constraining factors
  - compare observed properties to baseline model
  - useful even when baseline model is not ‘realistic’

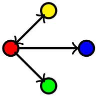
Types of Baseline Hypotheses

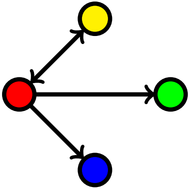
Types of Baseline Hypotheses



Empirical Network

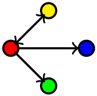
Types of Baseline Hypotheses

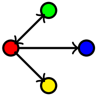


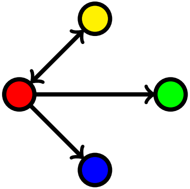


Empirical Network

Types of Baseline Hypotheses

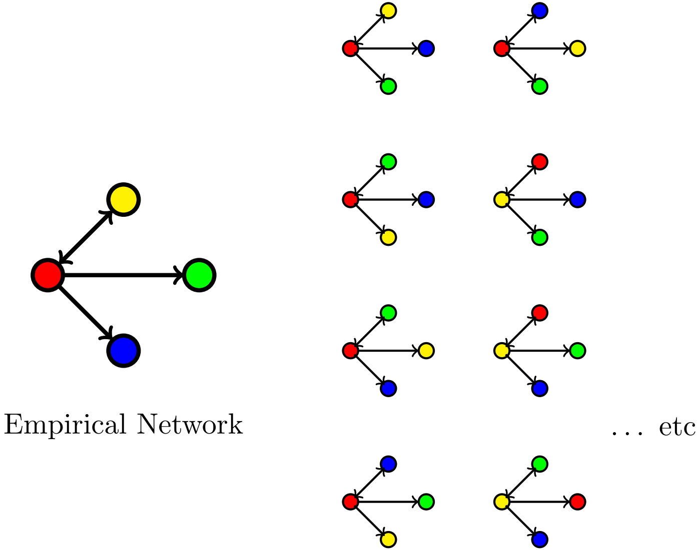




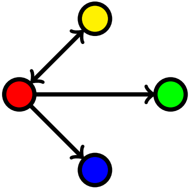


Empirical Network

Types of Baseline Hypotheses

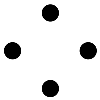


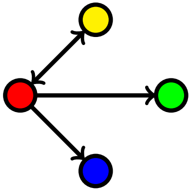
Types of Baseline Hypotheses



Empirical Network

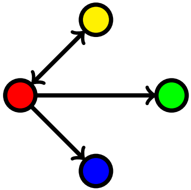
Types of Baseline Hypotheses

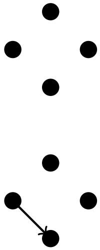




Empirical Network

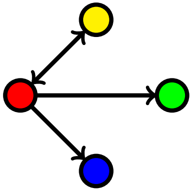
Types of Baseline Hypotheses



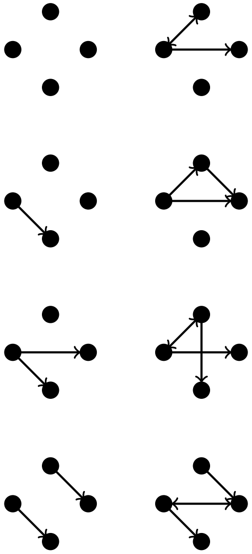


Empirical Network

Types of Baseline Hypotheses



Empirical Network



. . . etc

Types of Baseline Models

Types of Baseline Models

- **Size:** given the number of individuals, all structures are equally likely

Types of Baseline Models

- **Size:** given the number of individuals, all structures are equally likely
- **Number of edges/probability of an edge:** given the number of individuals and interactions (aka Erdös-Renyi random graphs)

Types of Baseline Models

- **Size:** given the number of individuals, all structures are equally likely
- **Number of edges/probability of an edge:** given the number of individuals and interactions (aka Erdös-Renyi random graphs)
- **Dyad census:** given number of individuals, mutuals, asymmetric, and null relationships

Types of Baseline Models

- **Size:** given the number of individuals, all structures are equally likely
- **Number of edges/probability of an edge:** given the number of individuals and interactions (aka Erdös-Renyi random graphs)
- **Dyad census:** given number of individuals, mutuals, asymmetric, and null relationships
- **Degree distribution:** given the number of individuals and each individual's outgoing/incoming ties

Types of Baseline Models

- **Size:** given the number of individuals, all structures are equally likely
- **Number of edges/probability of an edge:** given the number of individuals and interactions (aka Erdös-Renyi random graphs)
- **Dyad census:** given number of individuals, mutuals, asymmetric, and null relationships
- **Degree distribution:** given the number of individuals and each individual's outgoing/incoming ties
- **Number of triangles:** not implemented due to complexity – with ERGM, can condition on the *expected* number of triangles

Method

Method

- Select a test statistic (graph correlation, reciprocity, transitivity. . .)

Method

- Select a test statistic (graph correlation, reciprocity, transitivity. . .)
- Select a baseline hypothesis (what you're conditioning on)

Method

- Select a test statistic (graph correlation, reciprocity, transitivity...)
- Select a baseline hypothesis (what you're conditioning on)
- Simulate from the baseline hypothesis

Method

- Select a test statistic (graph correlation, reciprocity, transitivity. . .)
- Select a baseline hypothesis (what you're conditioning on)
- Simulate from the baseline hypothesis
- For each simulation, recalculate the test statistic

Method

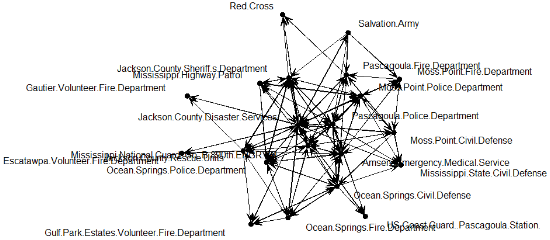
- Select a test statistic (graph correlation, reciprocity, transitivity. . .)
- Select a baseline hypothesis (what you're conditioning on)
- Simulate from the baseline hypothesis
- For each simulation, recalculate the test statistic
- Compare empirical value to null distribution, just as in standard statistical testing

Example

Transitivity in the Hurricane Frederic EMON

Example

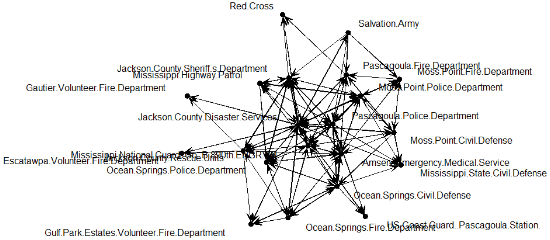
Transitivity in the Hurricane Frederic EMON



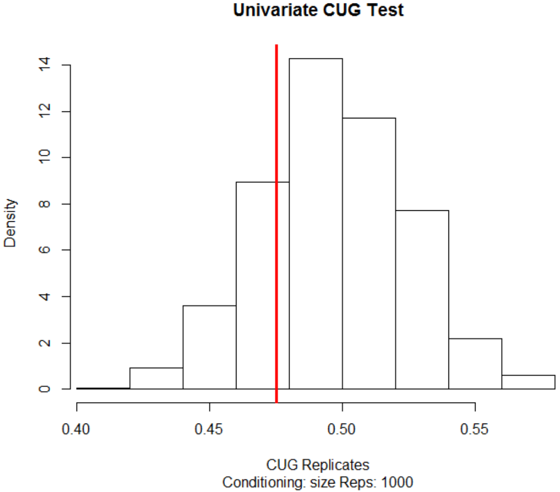
Example

Transitivity in the Hurricane Frederic EMON

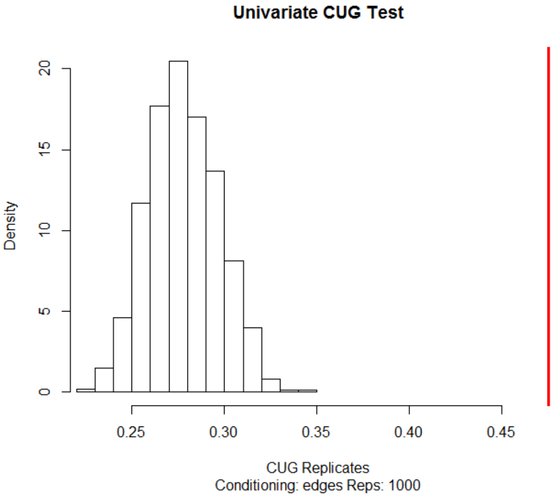
- $\rho = 0.475$
- indicates that roughly half the time that $i \to j \to k$, $i \to k$



Example


Univariate CUG Test
Density
0
2
4
6
8
10
12
14
0.40
0.45
0.50
0.55
CUG Replicates
Conditioning: size Reps: 1000

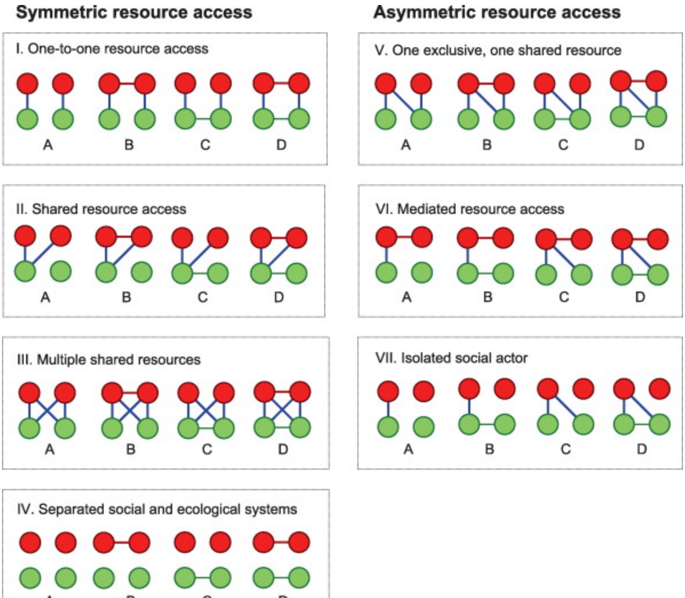
Example


Univariate CUG Test
Density
0
5
10
15
20
0.25
0.30
0.35
0.40
0.45
CUG Replicates
Conditioning: edges Reps: 1000

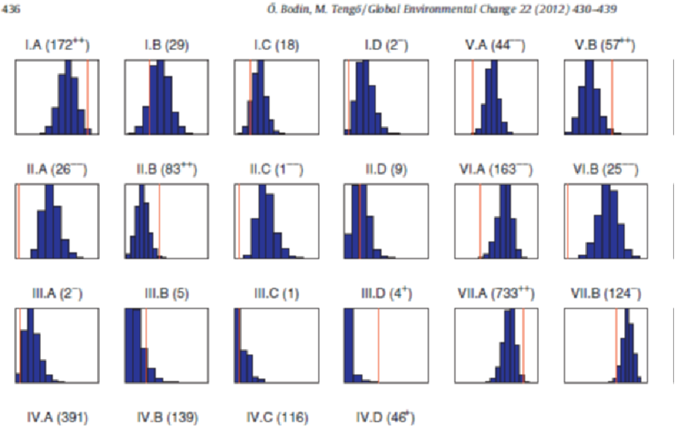
Bodin and Tengo

"Disentangling intangible social–ecological systems"

Bodin and Tengo



Bodin and Tengo



Summary

Summary

- Network indices as independent variables in regression

Summary

- Network indices as independent variables in regression
- QAP regression (edges are the dependent variable)

Summary

- Network indices as independent variables in regression
- QAP regression (edges are the dependent variable)
- Network Autocorrelation Model (vertex attribute is dependent variable)

Summary

- Network indices as independent variables in regression
- QAP regression (edges are the dependent variable)
- Network Autocorrelation Model (vertex attribute is dependent variable)
- CUG tests (network is dependent variable)

Code Time

- the rest! whew!