

Livestock Trade Networks

Social network analysis
in one health epidemiology

Hartmut Lentz
Thomas Selhorst
Igor M Sokolov



FLI

Island of Riems

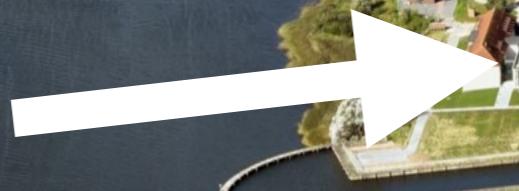
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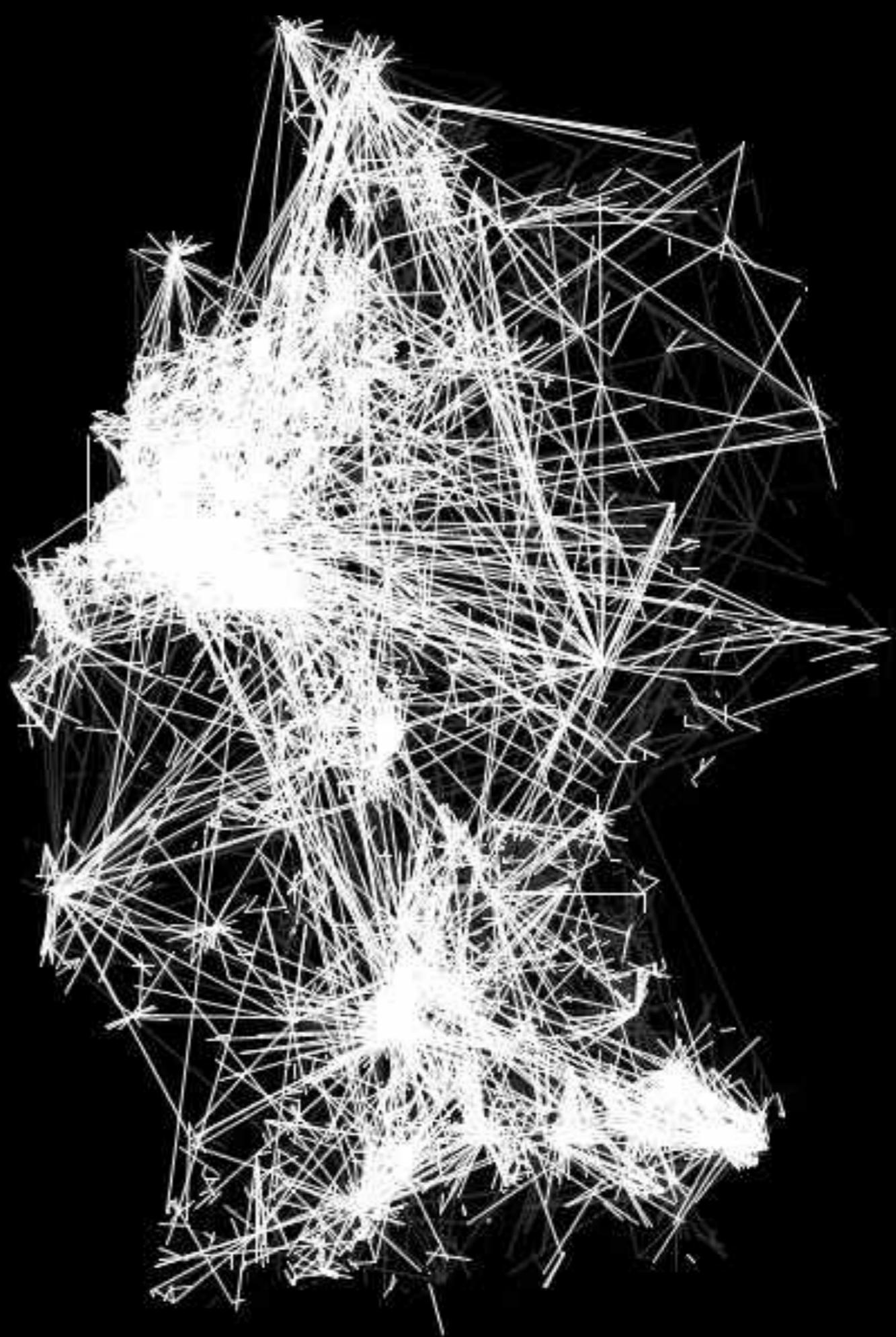


network dataset

**livestock pig
trade**



farm to farm



classical network view: main questions

classical network view: main questions

Where can a disease spread in the network?

classical network view: main questions

Where can a disease spread in the network?

What is a good strategy for targeted vaccination?

temporal network dataset

**livestock pig
trade**



farm to farm

temporal network dataset

**livestock pig
trade**



farm to farm



temporal network dataset

**livestock pig
trade**



farm to farm



Graph. An ordered pair $G = (V, E)$ comprising a set V of nodes together with a set E of edges which are 2-element subsets of V .

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**this is not
a graph!**

temporal network view: main questions

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Where can a disease spread in the network?

temporal network view: main questions

Where can a disease spread in the network?

What is a good strategy for targeted vaccination?

temporal network view: main questions

Where can a disease spread in the network?

What is a good strategy for targeted vaccination?

How much time does it take to traverse?

temporal network view: main questions

Where can a disease spread in the network?

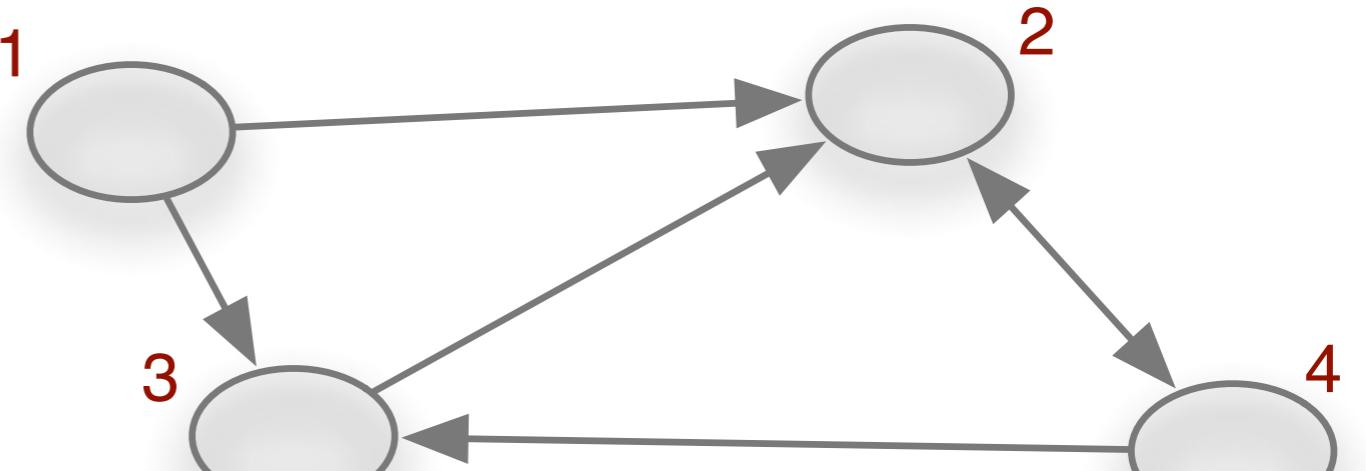
What is a good strategy for targeted vaccination?

How much time does it take to traverse?

Can I pretend it's NOT time dependent?

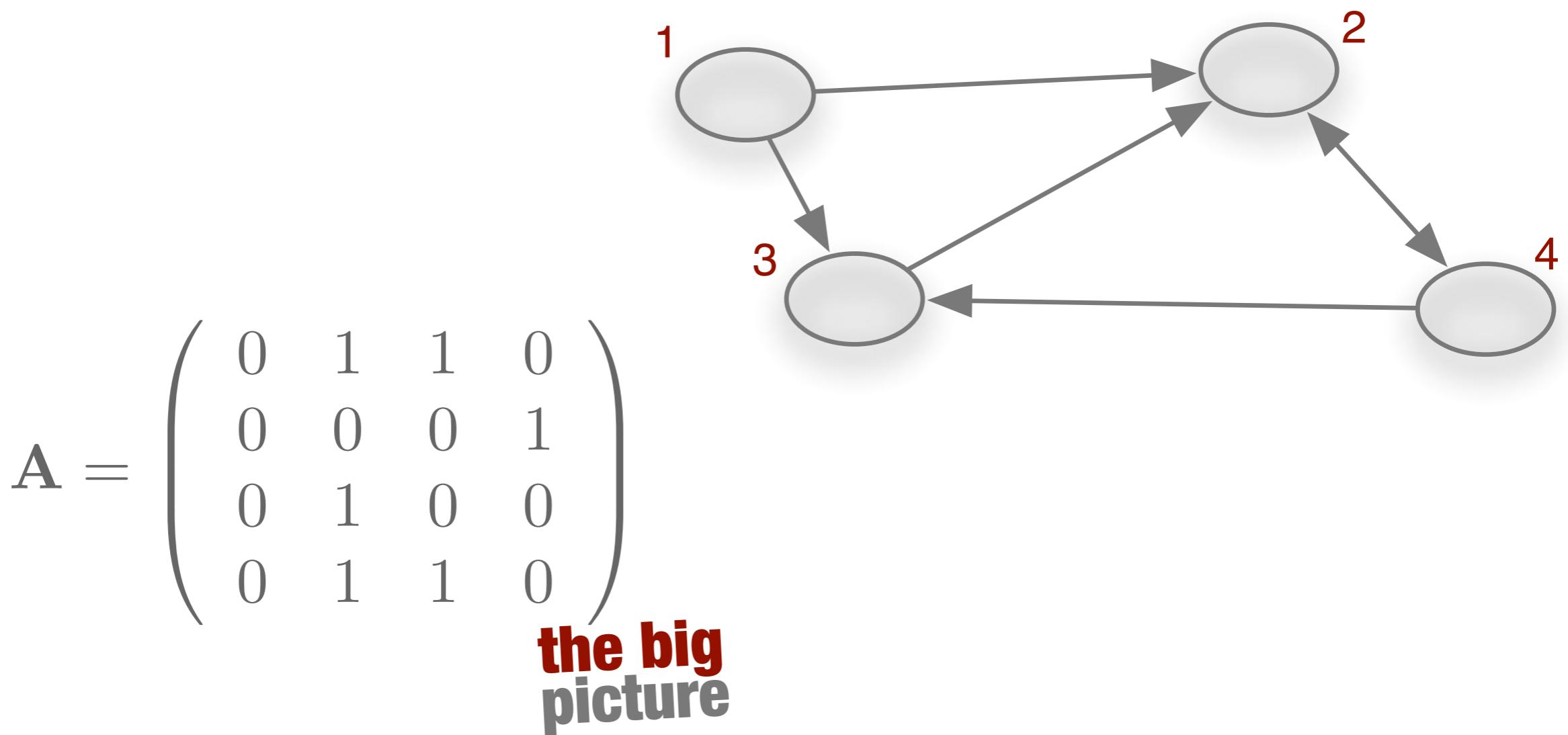
static network representation

representation: Adjacency matrix \mathbf{A}

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$


static network representation

representation: Adjacency matrix \mathbf{A}



temporal network representation

adjacency matrix sequence

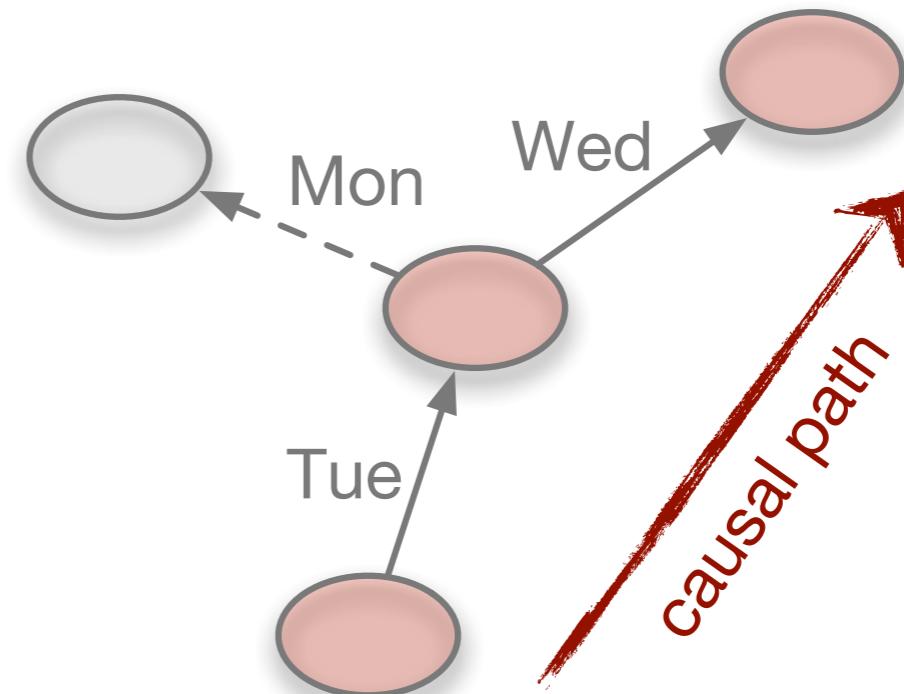
time

$$A_4 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$
$$A_3 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$
$$A_2 = \begin{pmatrix} 0 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$
$$A_1 = \begin{pmatrix} 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}$$

causal paths

chronologic sequence of edges

fundamental difference to static: **causal paths**



static & temporal networks
common ground?

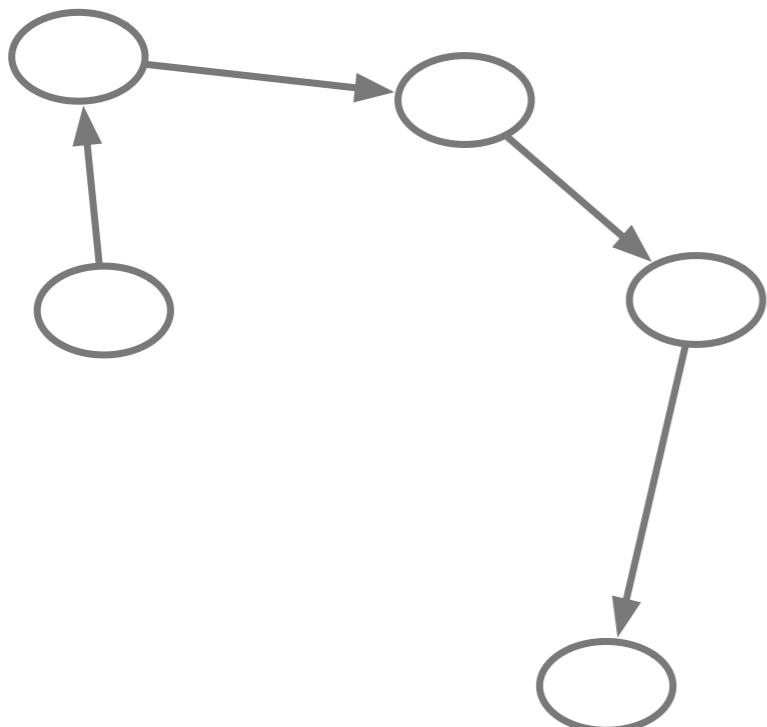
static & temporal networks
common ground?

path structure!

static & temporal networks common ground?

path structure!

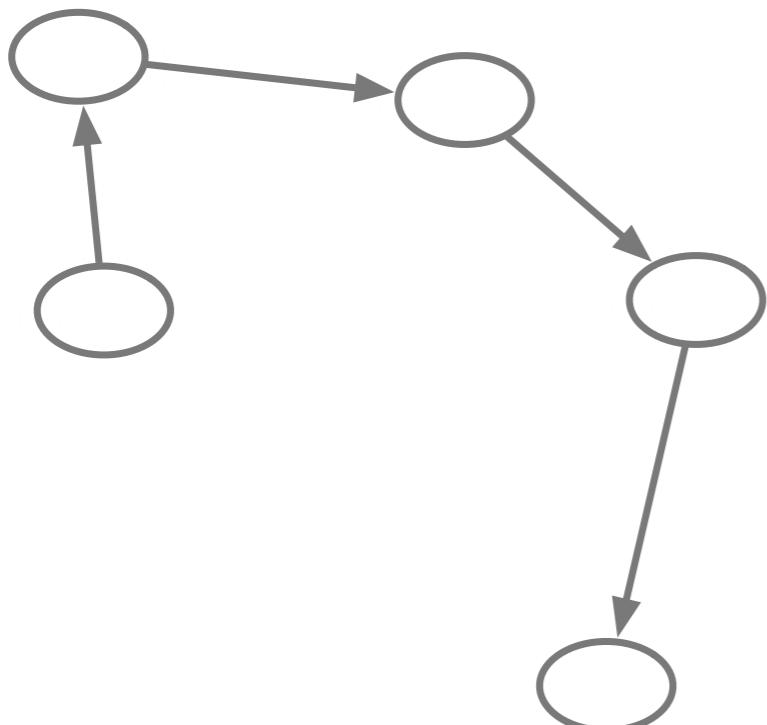
some network



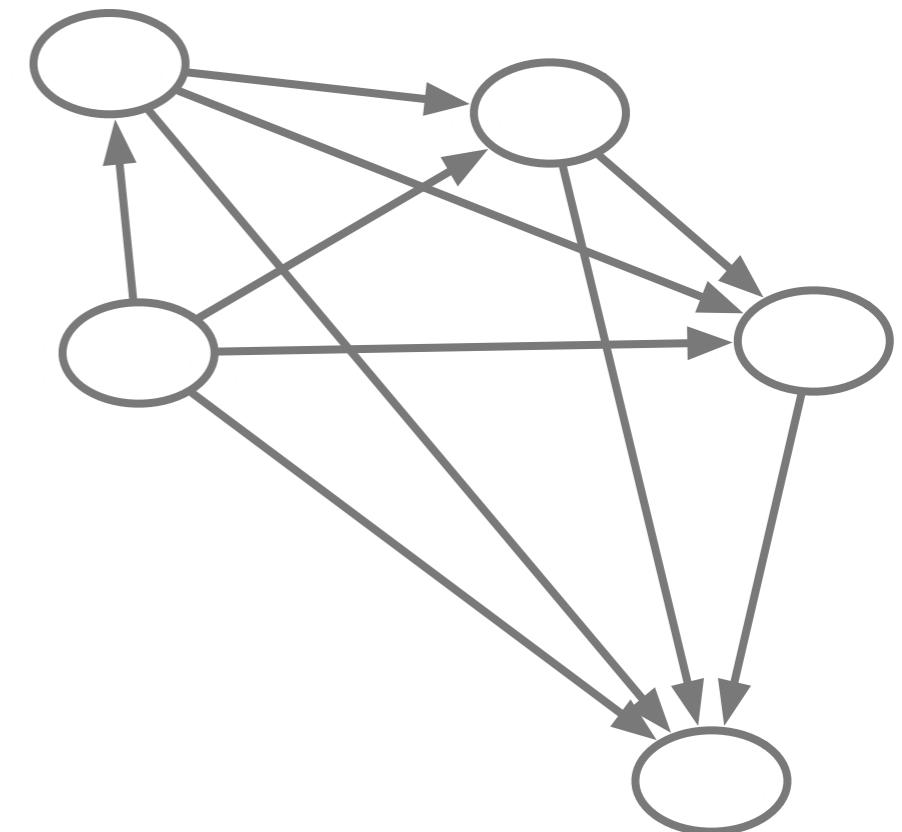
static & temporal networks common ground?

path structure!

some network



its accessibility-graph

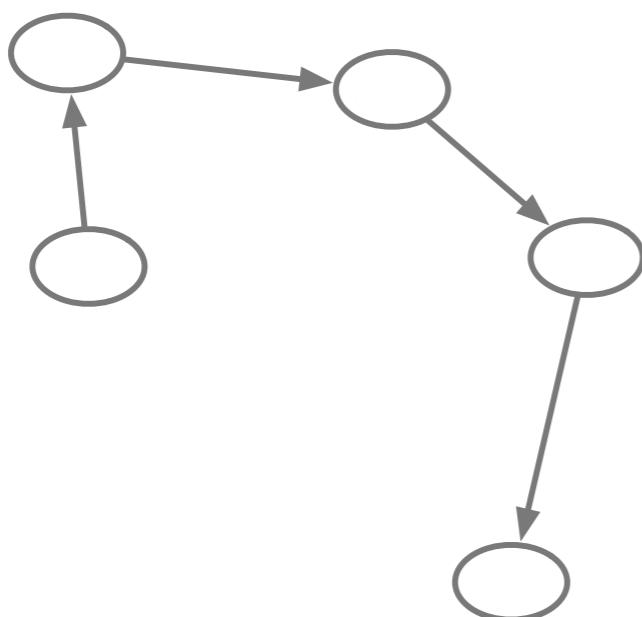


accessibility matrices & accessibility graphs

adjacency matrix A :
number of paths of length 1

square of adjacency matrix A^2 :
number of paths of length 2

Example (static):

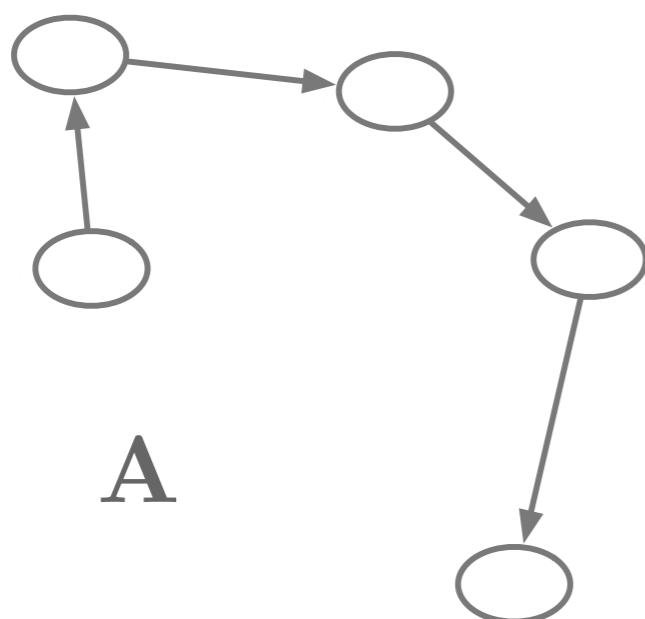


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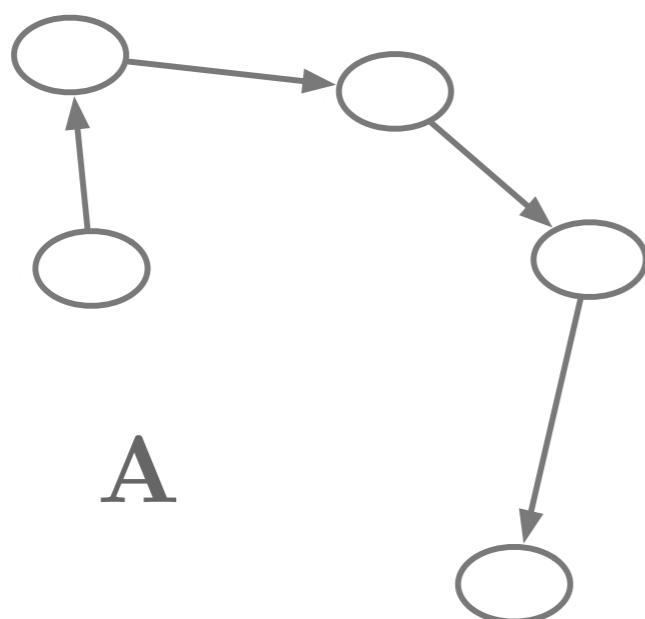


accessibility matrices & accessibility graphs

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Example (static):



A

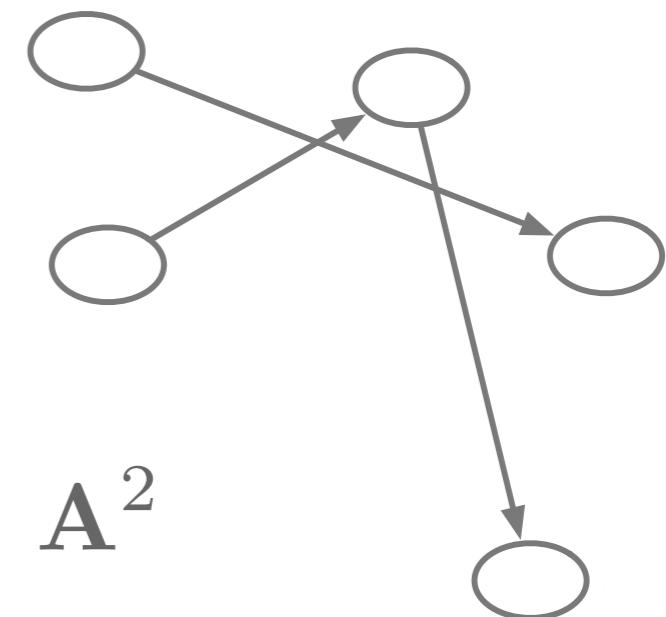
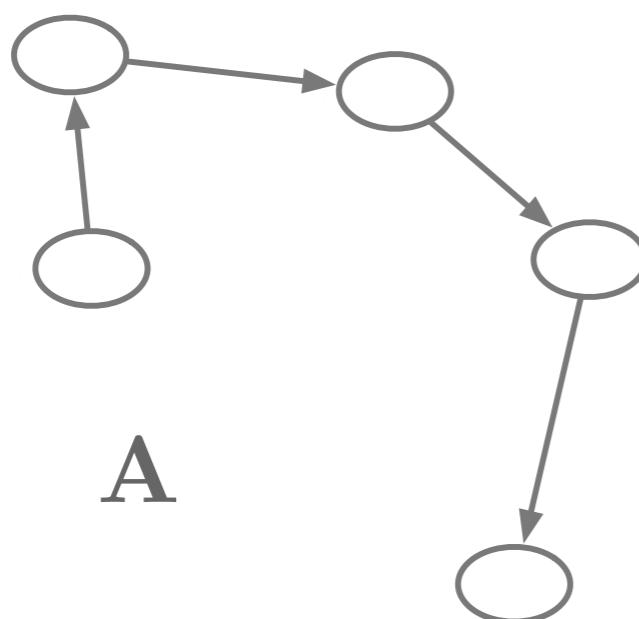
A^2

accessibility matrices & accessibility graphs

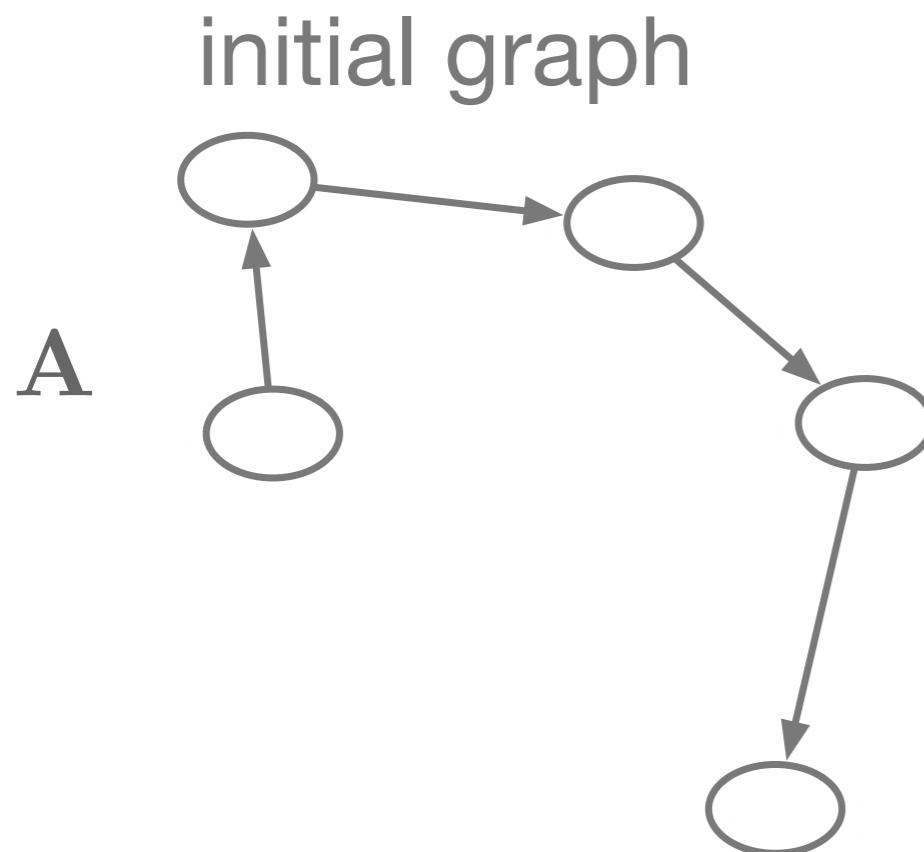
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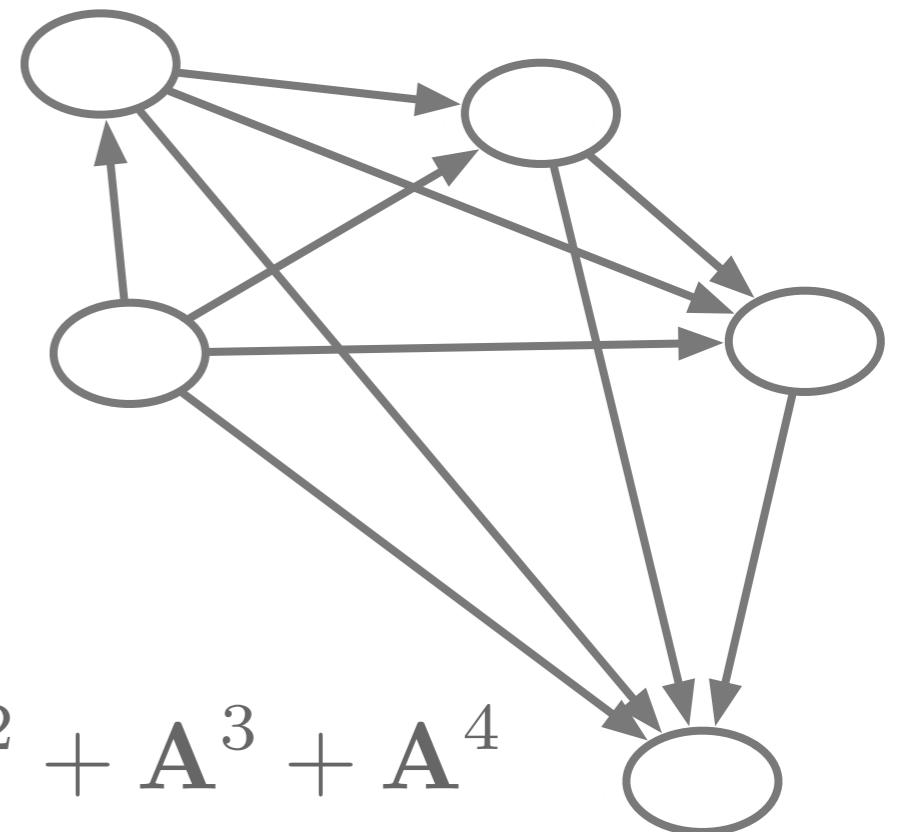


accessibility matrices & accessibility graphs



accessibility-graph

$$P = A + A^2 + A^3 + A^4$$



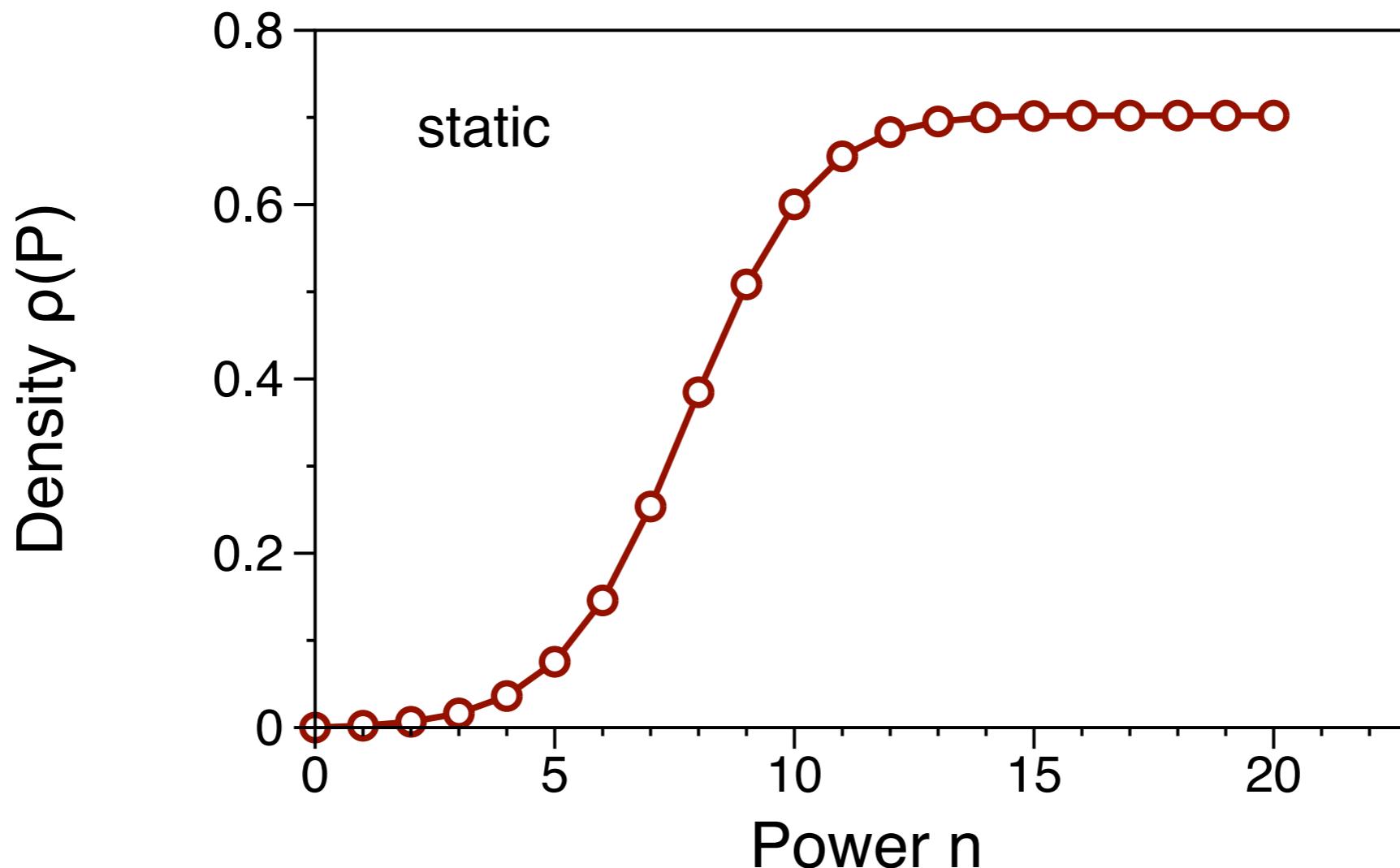
accessibility matrices of **static** networks

example:
Random DiGraph
1000 nodes
2000 edges

$$P = A + A^2 + A^3 + \cdots + A^n$$

accessibility matrices of **static** networks

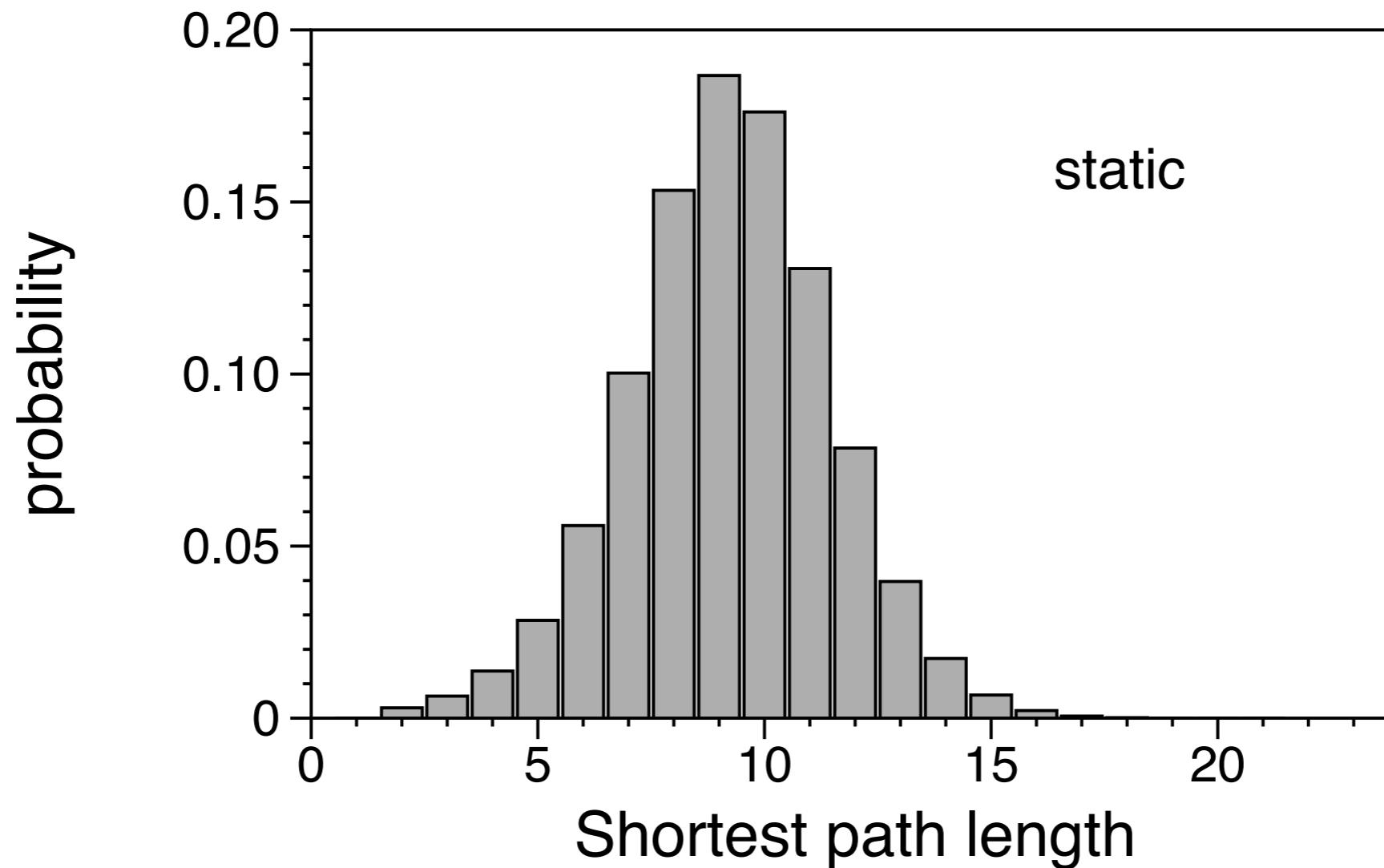
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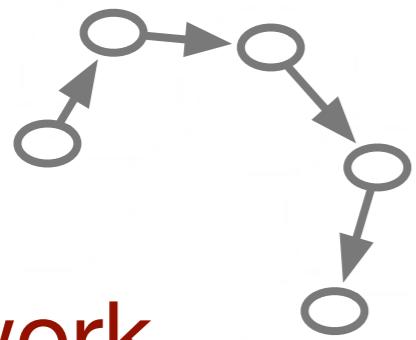
$$P = A + A^2 + A^3 + \cdots + A^n$$

accessibility matrices of **static** networks

example:
Random DiGraph
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recap:
the idea

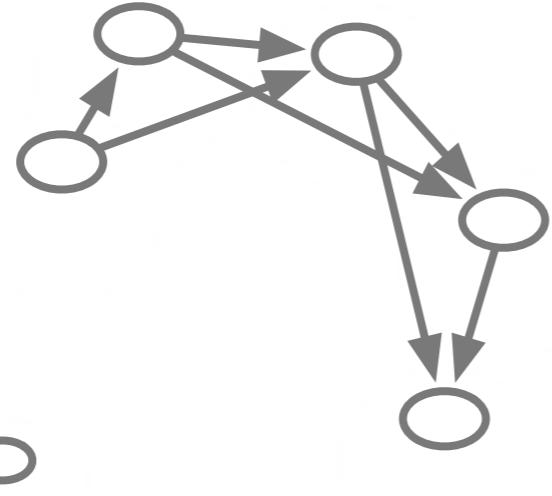


Network

recap: the idea

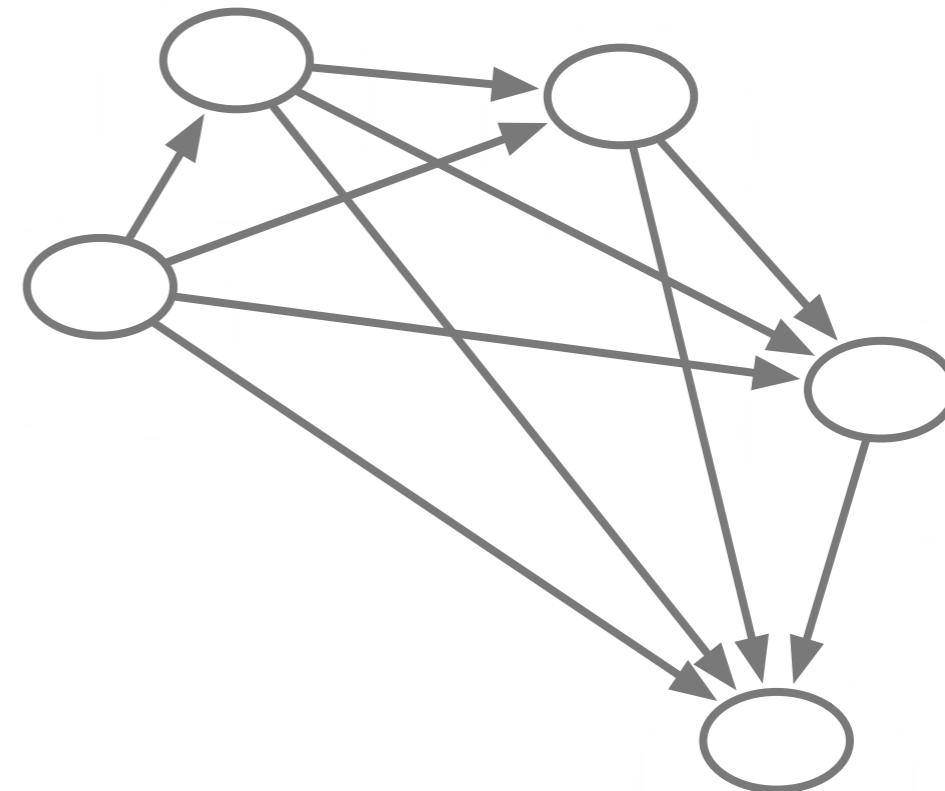


Network



unfold
accessibility

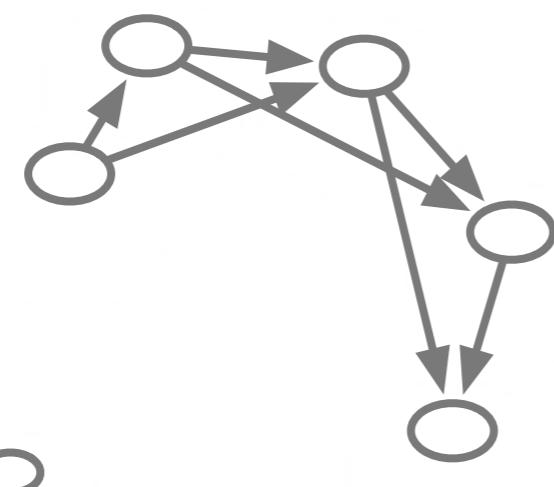
...



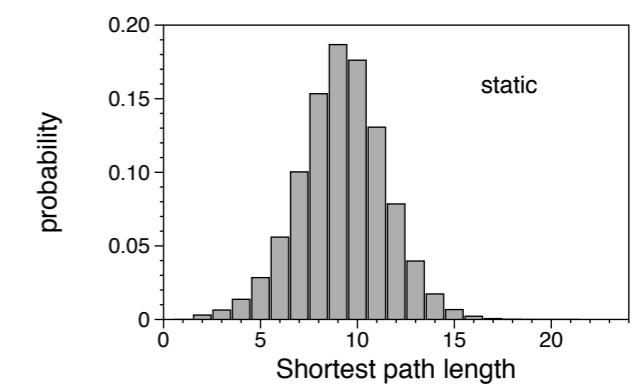
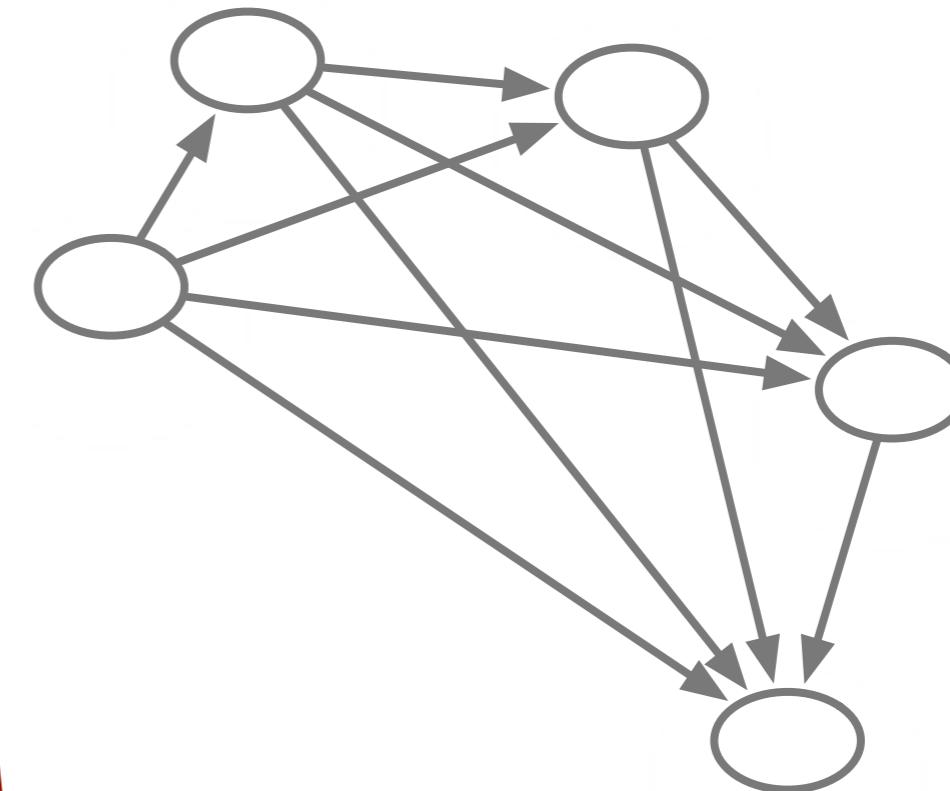
recap: the idea



Network



unfold
accessibility



accessibility of
temporal networks

accessibility of **temporal networks**

static

$$P = A + A^2 + A^3 + \dots$$

accessibility of **temporal** networks

static

$$P = A + A^2 + A^3 + \dots$$

temporal

$$A \rightarrow A_1, A_2, A_3, \dots$$

accessibility of **temporal** networks

static $P = A + A^2 + A^3 + \dots$

temporal $A \rightarrow A_1, A_2, A_3, \dots$

replace $A^2 \rightarrow A_1 A_2$

accessibility of **temporal networks**

static

$$P = A + A^2 + A^3 + \dots$$

temporal

$$A \rightarrow A_1, A_2, A_3, \dots$$

replace

$$A^2 \rightarrow A_1 A_2$$

but also

$$A^2 \rightarrow A_1 A_3$$

accessibility of temporal networks

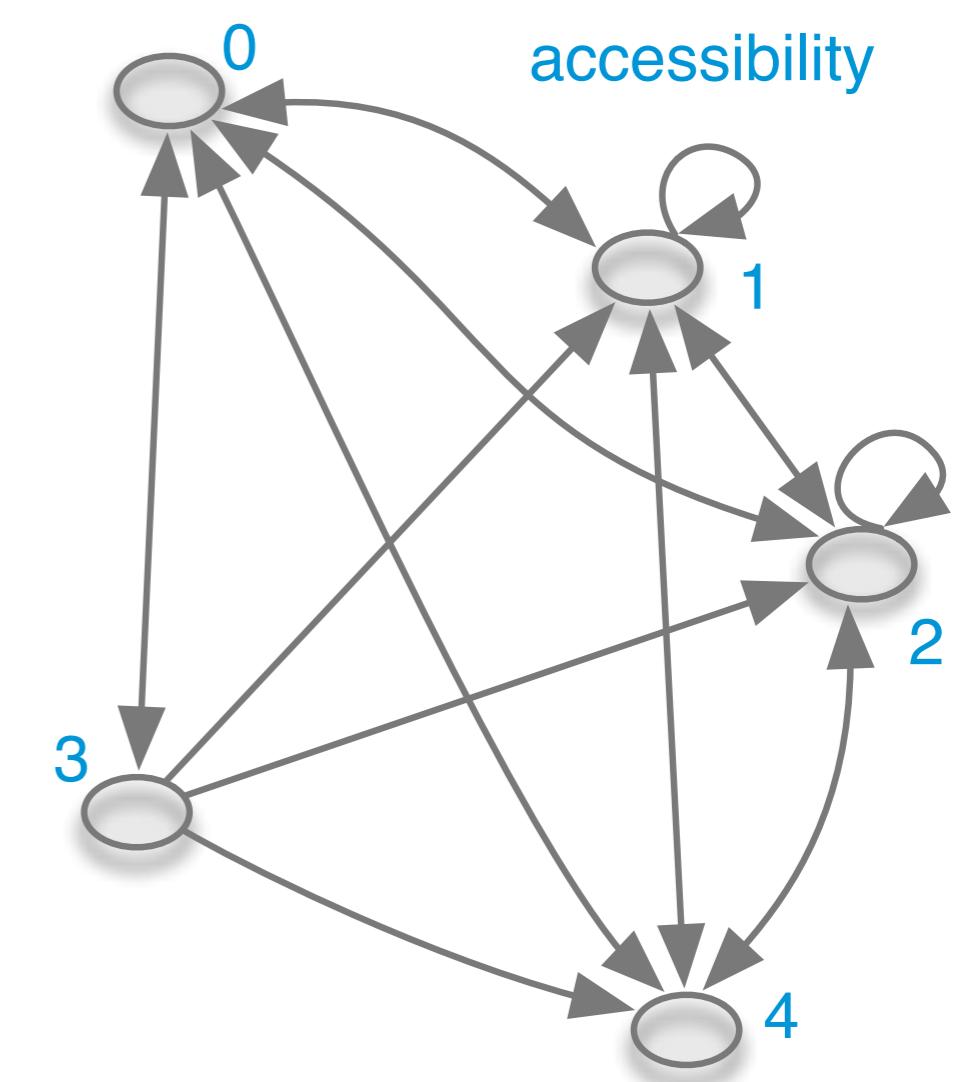
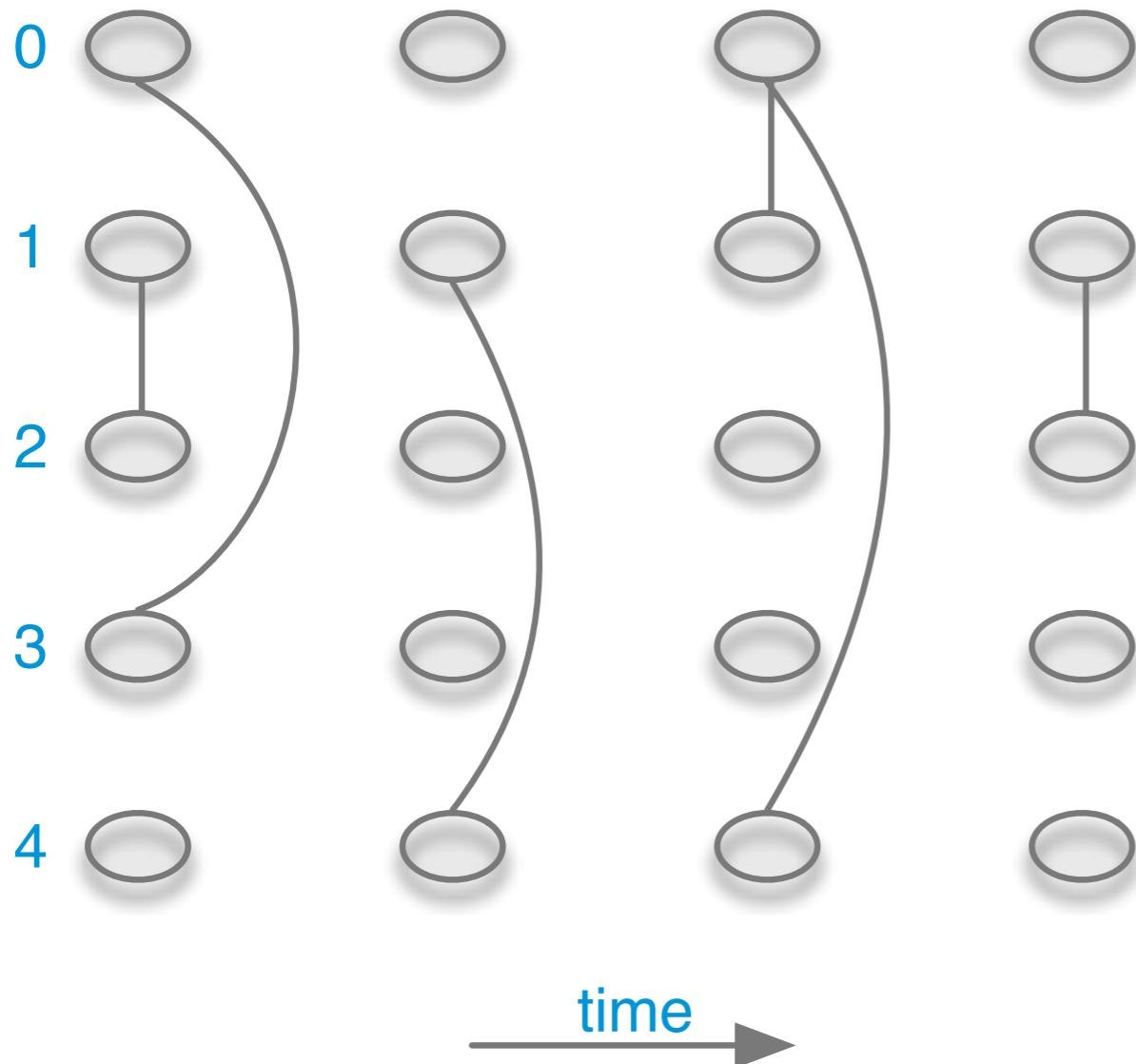
$$\begin{aligned}\mathcal{P}_t = & \mathbf{I} + \underbrace{\mathbf{A}_1 + \mathbf{A}_2 + \mathbf{A}_3 + \cdots + \mathbf{A}_t}_{\mathbf{A}} + \\ & + \underbrace{\mathbf{A}_1 \mathbf{A}_2 + \mathbf{A}_2 \mathbf{A}_3 + \mathbf{A}_1 \mathbf{A}_3 + \mathbf{A}_1 \mathbf{A}_2 \mathbf{A}_3 + \cdots}_{\mathcal{O}(\mathbf{A}_i^2)} \\ = & \prod_{i=1}^t (\mathbf{I} + \mathbf{A}_i)\end{aligned}$$

accessibility of **temporal networks**

$$\begin{aligned}\mathcal{P}_t = & \mathbf{I} + \underbrace{\mathbf{A}_1 + \mathbf{A}_2 + \mathbf{A}_3 + \cdots + \mathbf{A}_t}_{\mathbf{A}} + \\ & + \underbrace{\mathbf{A}_1 \mathbf{A}_2 + \mathbf{A}_2 \mathbf{A}_3 + \mathbf{A}_1 \mathbf{A}_3 + \mathbf{A}_1 \mathbf{A}_2 \mathbf{A}_3 + \cdots}_{\mathcal{O}(\mathbf{A}_i^2)} \\ = & \prod_{i=1}^t (\mathbf{I} + \mathbf{A}_i)\end{aligned}$$

**easy to
implement**

Compute **temporal** accessibility graph Tutorial.



implementation.

implementation.

$$\mathcal{P}_n = \bigwedge_{i=1}^n (\mathbf{I} \vee \mathbf{A}_i)$$

Boolean matrices

implementation.

Sparsity

dense matrix

sparse matrix

$$\mathcal{P}_n = \bigwedge_{i=1}^n (\mathbf{I} \vee \mathbf{A}_i)$$

The diagram consists of two arrows originating from the words 'dense matrix' and 'sparse matrix' respectively. Both arrows point towards the variable 'n' in the equation below. The 'dense matrix' arrow originates from the word 'dense' and points to the top of the 'n'. The 'sparse matrix' arrow originates from the word 'sparse' and points to the bottom of the 'n'.

Boolean matrices

implementation.

Partitioning. For each node

$$i(t) = \left[\prod_{t'=0}^t (\mathbf{I} + \mathbf{A}_{t'}) \right] i(0)$$

Sparsity

dense matrix

sparse matrix

$$\mathcal{P}_n = \bigwedge_{i=1}^n (\mathbf{I} \vee \mathbf{A}_i)$$

Boolean matrices

unfolding accessibility software-tool

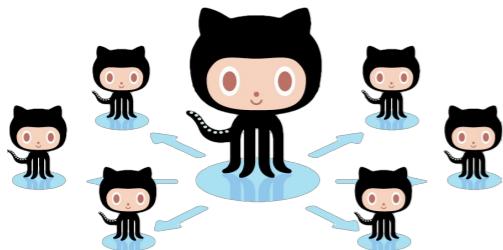
easy-usage object based tool

github repositories:

[hartmutlentz/TemporalNetworkAccessibility](#)

[andreaskoher/TemporalNetworkEpidemics](#)

Download



Language



Uses



example

usage

example usage

Input:

0	1	0
2	1	0
3	1	0
0	4	21
5	6	47
5	6	73
7	8	105
9	10	121
11	12	124
13	12	126
7	14	168
15	16	171
17	12	172
18	19	179
18	20	179
21	19	179
22	23	184
24	25	185
26	27	192
17	28	193

example usage

```
from AdjacencyMatrixSequence import AdjMatrixSequence
```

example usage

```
from AdjacencyMatrixSequence import AdjMatrixSequence
```

```
At = AdjMatrixSequence(„Edges.txt”, directed=True)
```

example usage

```
from AdjacencyMatrixSequence import AdjMatrixSequence  
  
At = AdjMatrixSequence(„Edges.txt”, directed=True)  
  
c = At.unfold_accessibility()  
h = np.gradient(c)
```

application.

livestock network data-set

**livestock pig
trade**



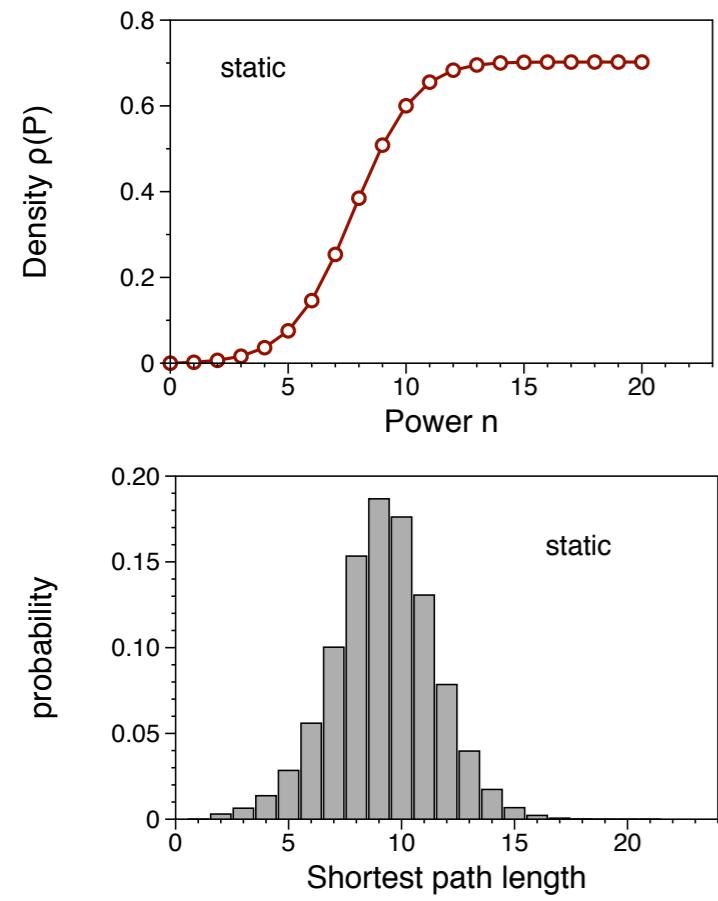
livestock network data-set

**livestock pig
trade**



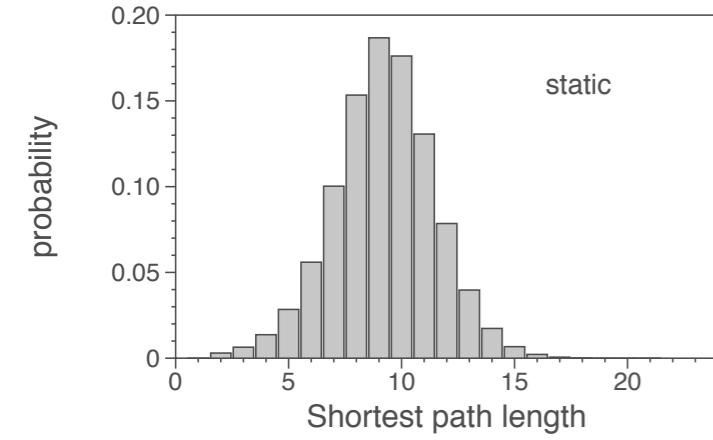
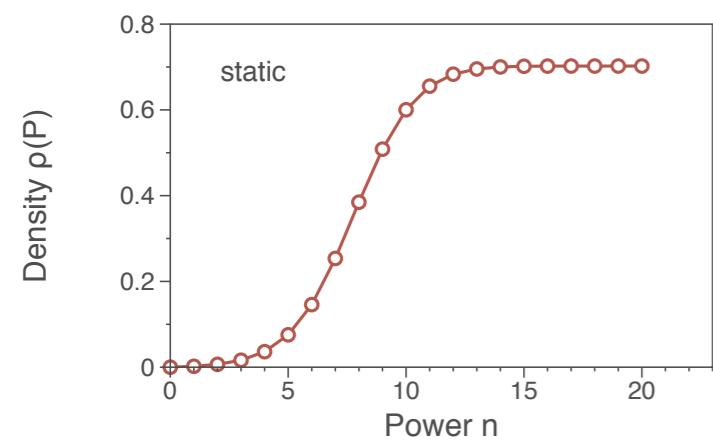
characteristic time scales results I

static random network

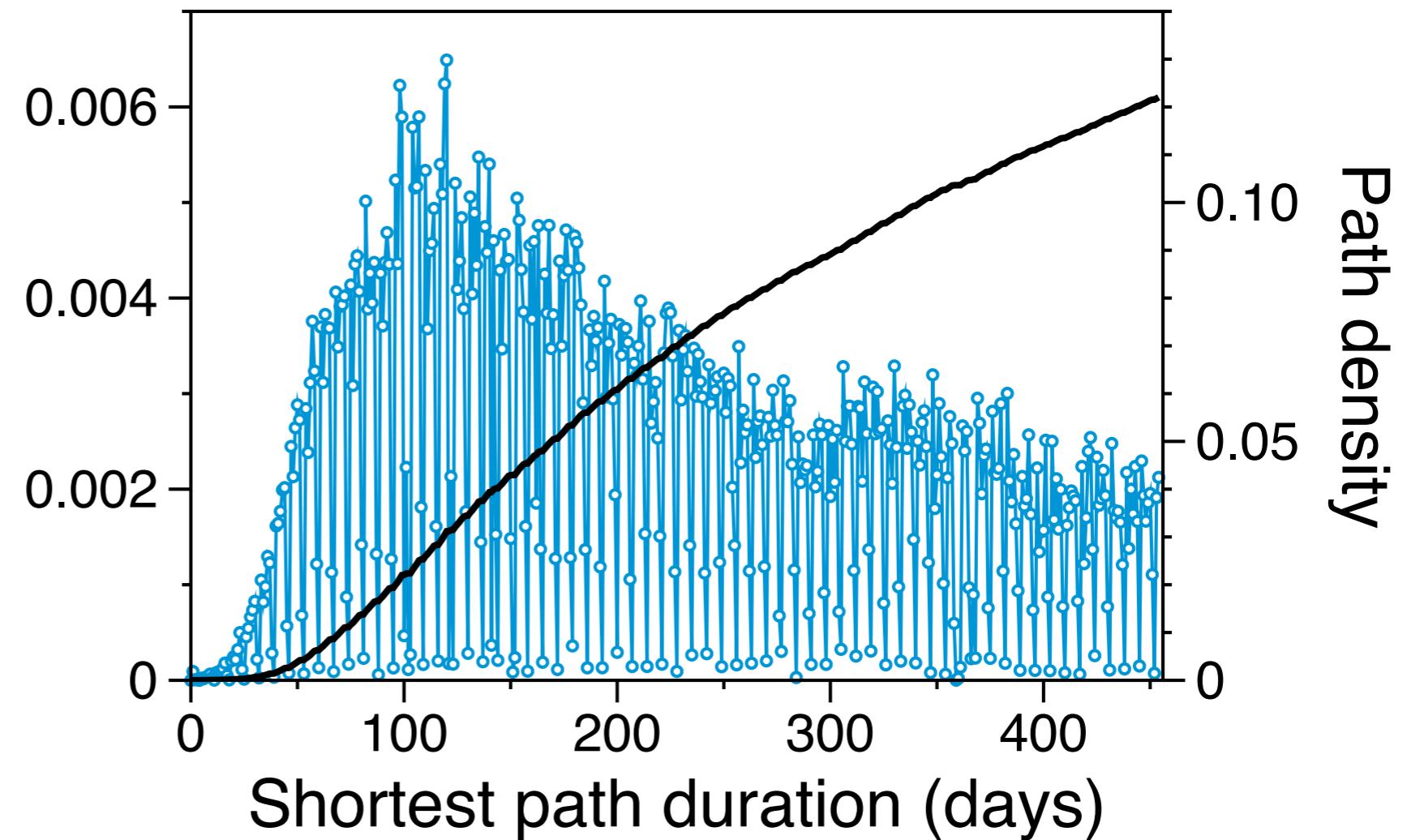


characteristic time scales results I

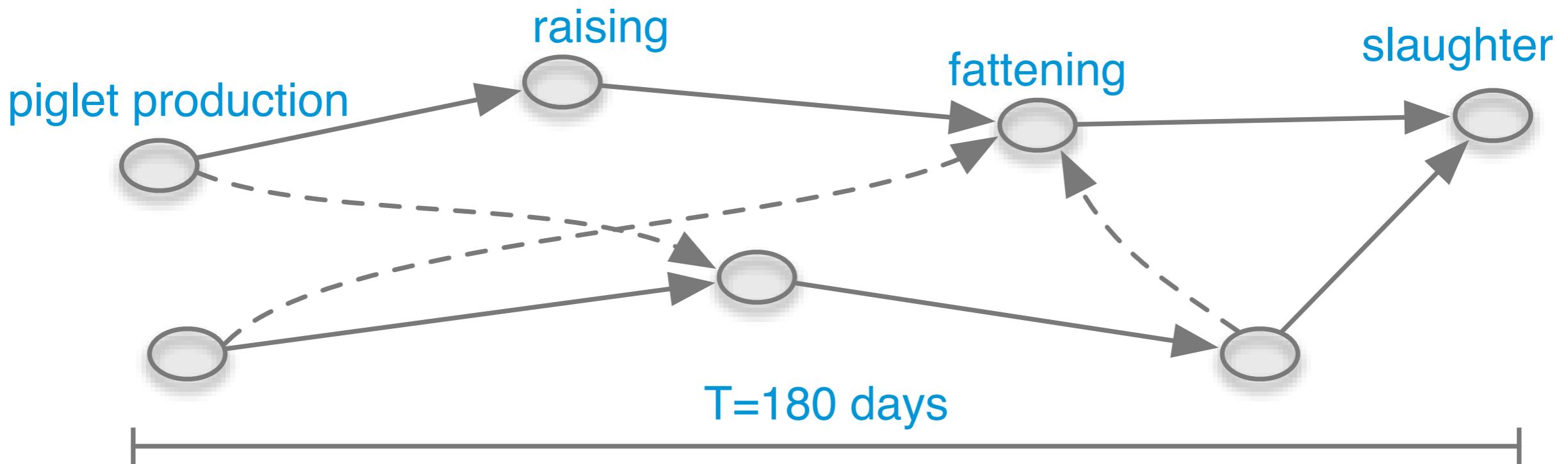
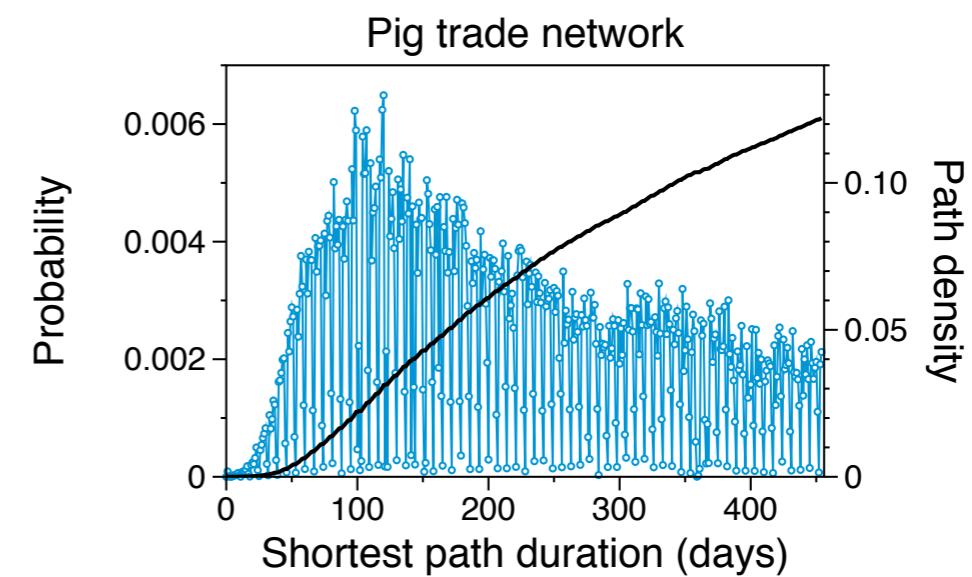
static random network



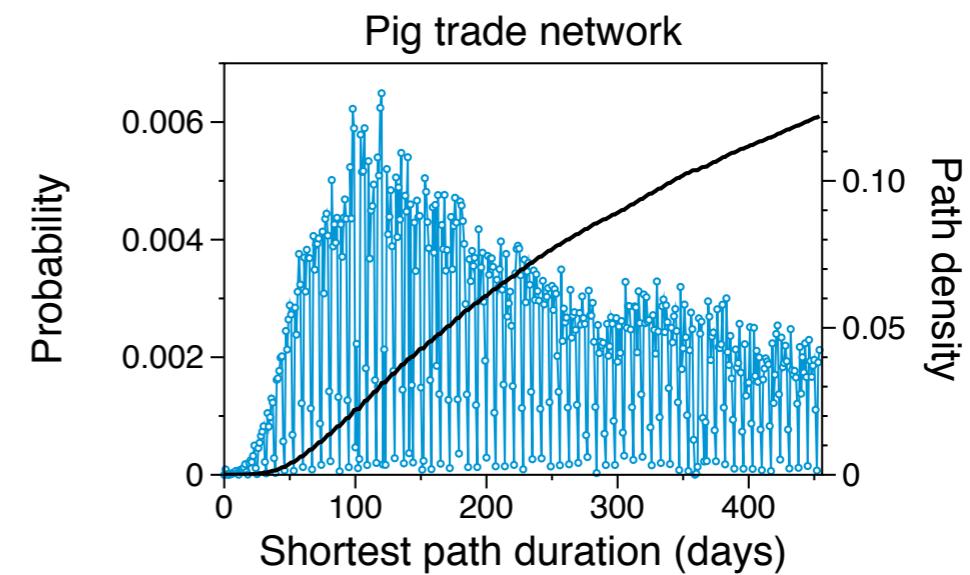
Pig trade network



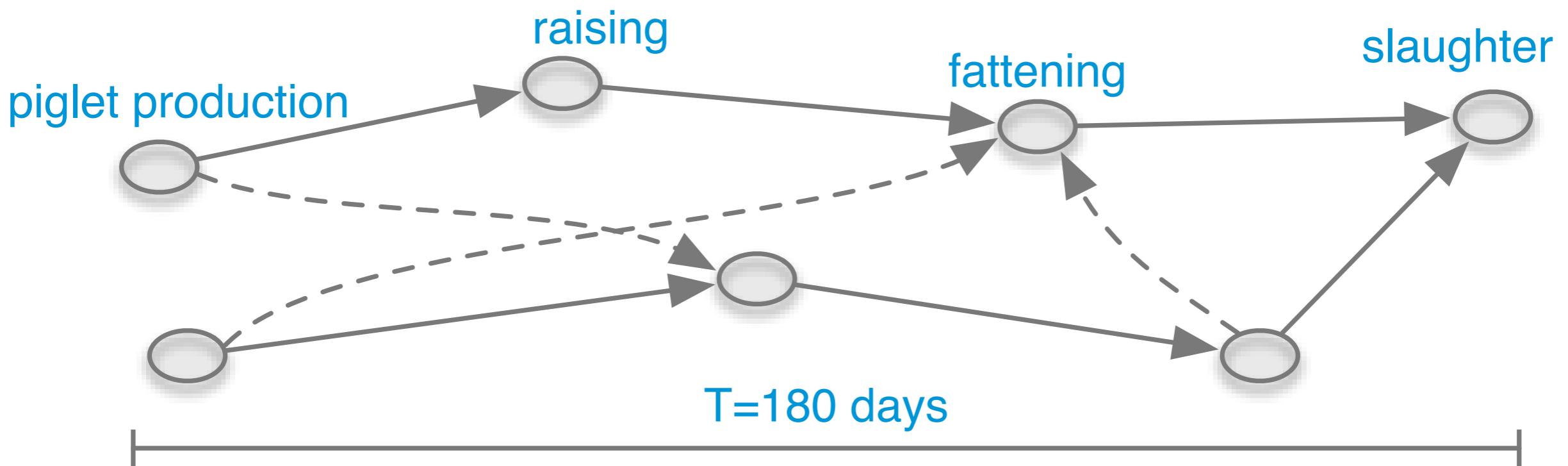
characteristic time scales results I



characteristic time scales results I



Pork production chain



causal fidelity **results II**

causal fidelity **results II**

comparison:
static vs. temporal accessibility-graph

causal fidelity **results II**

comparison:
static vs. temporal accessibility-graph

number of paths:

static representation: 1.4 billion

temporal representation: 1.0 billion

causal fidelity results II

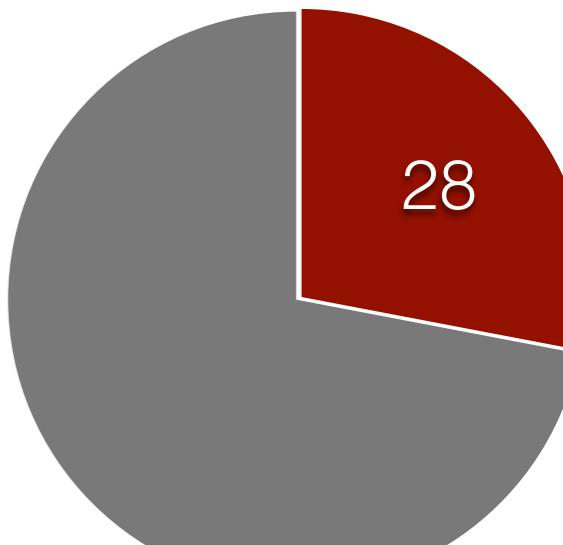
comparison:
static vs. temporal accessibility-graph

number of paths:

static representation: 1.4 billion

temporal representation: 1.0 billion

28
out of **100 paths**
in the aggregated network
do actually not exist!



causal fidelity **results II**

comparison:
static vs. temporal accessibility-graph

Definition: **causal fidelity**

$$c = \frac{\rho(\mathcal{P}_T)}{\rho(\mathbf{P}_T)}$$

causal fidelity results II

comparison:
static vs. temporal accessibility-graph

Definition: causal fidelity

$$c = \frac{\rho(\mathcal{P}_T)}{\rho(\mathbf{P}_T)}$$

temporal (real) path density

static path density

causal fidelity results II

comparison:
static vs. temporal accessibility-graph

Definition: **causal fidelity**

$$c = \frac{\rho(\mathcal{P}_T)}{\rho(\mathbf{P}_T)}$$

temporal (real) path density

pig trade net
 $c = 0.72$

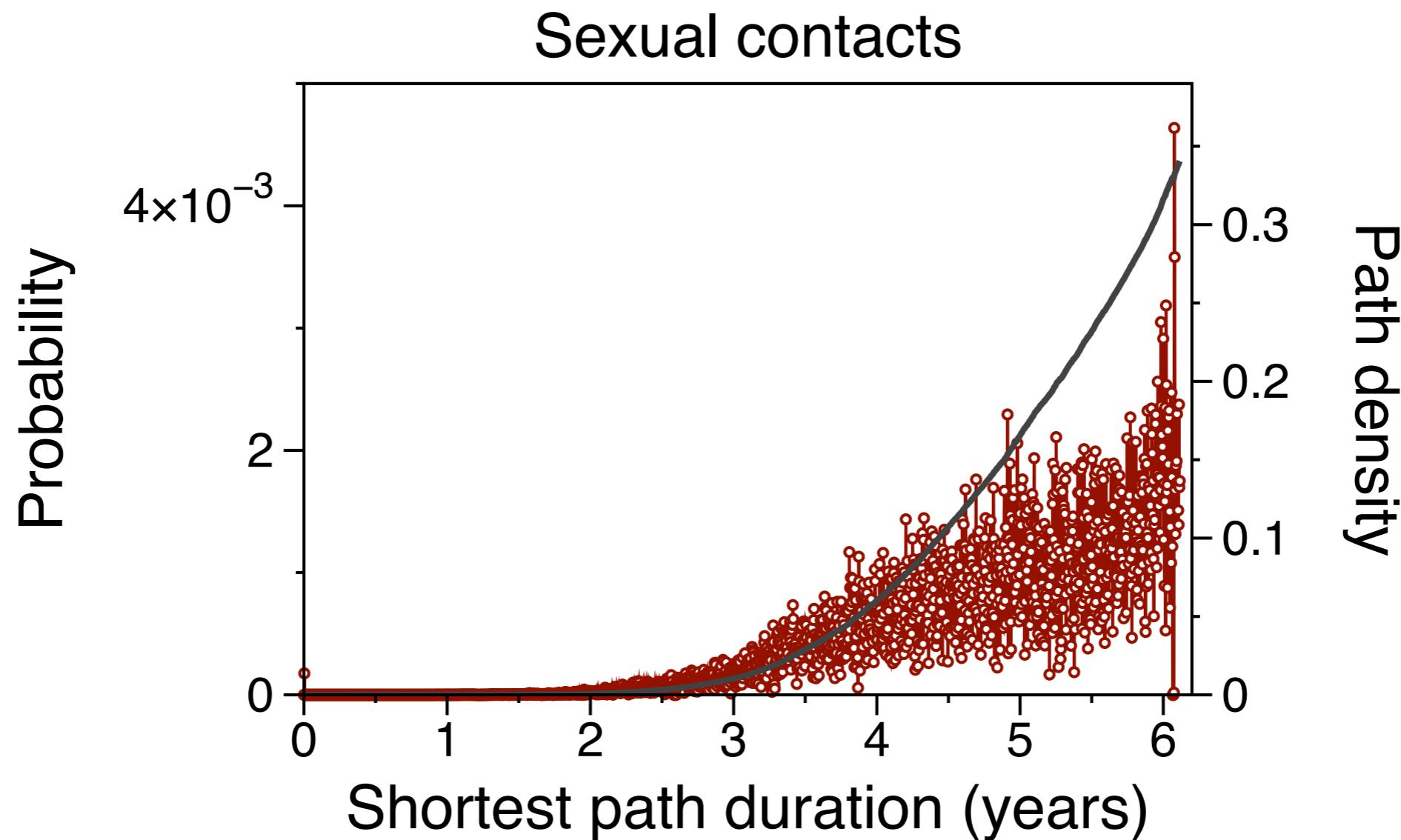
static path density

Further datasets.

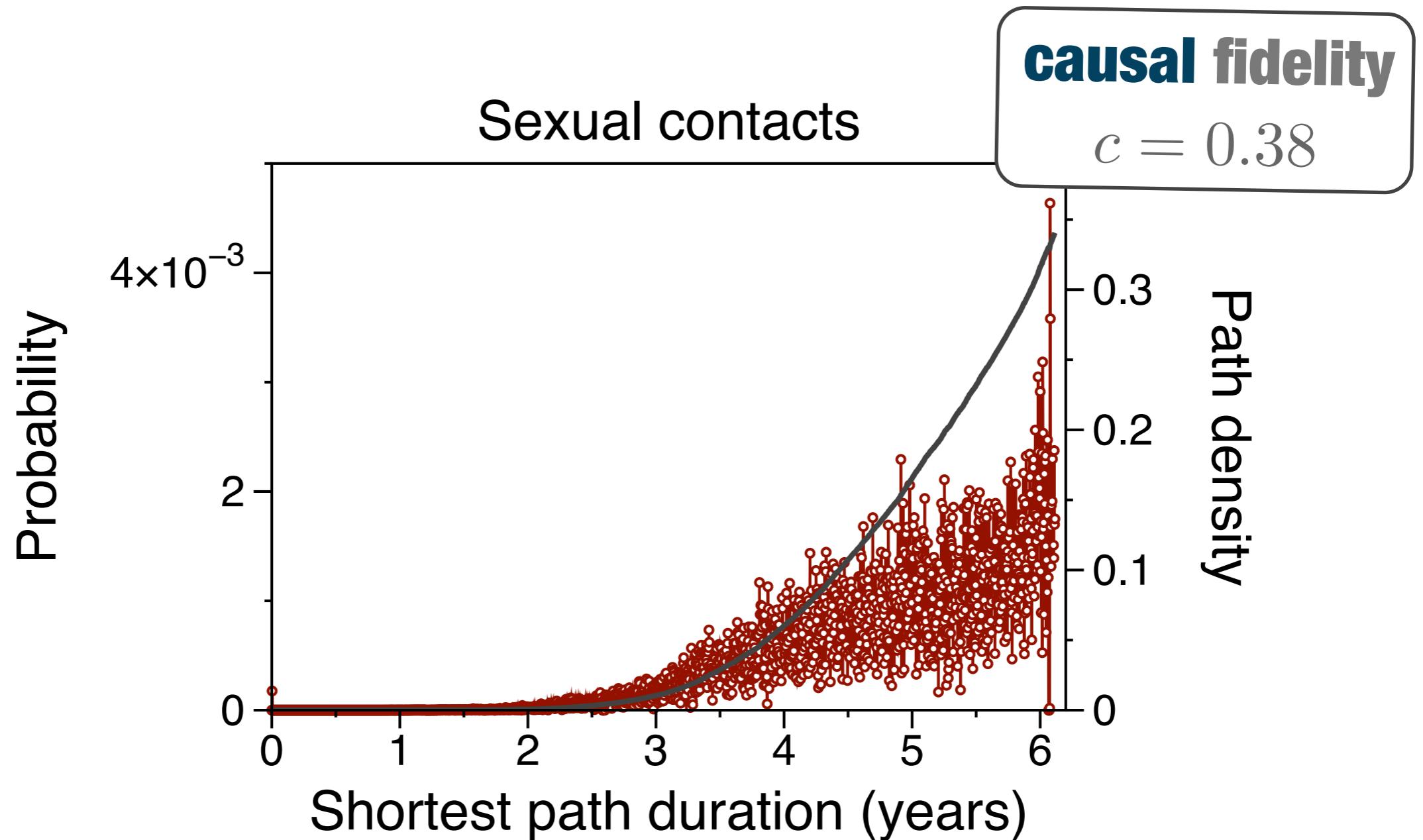
sexual contact network
Rocha et al., PNAS 2010

face-to-face conference contacts
sociopatterns.org

sexual contact network results III

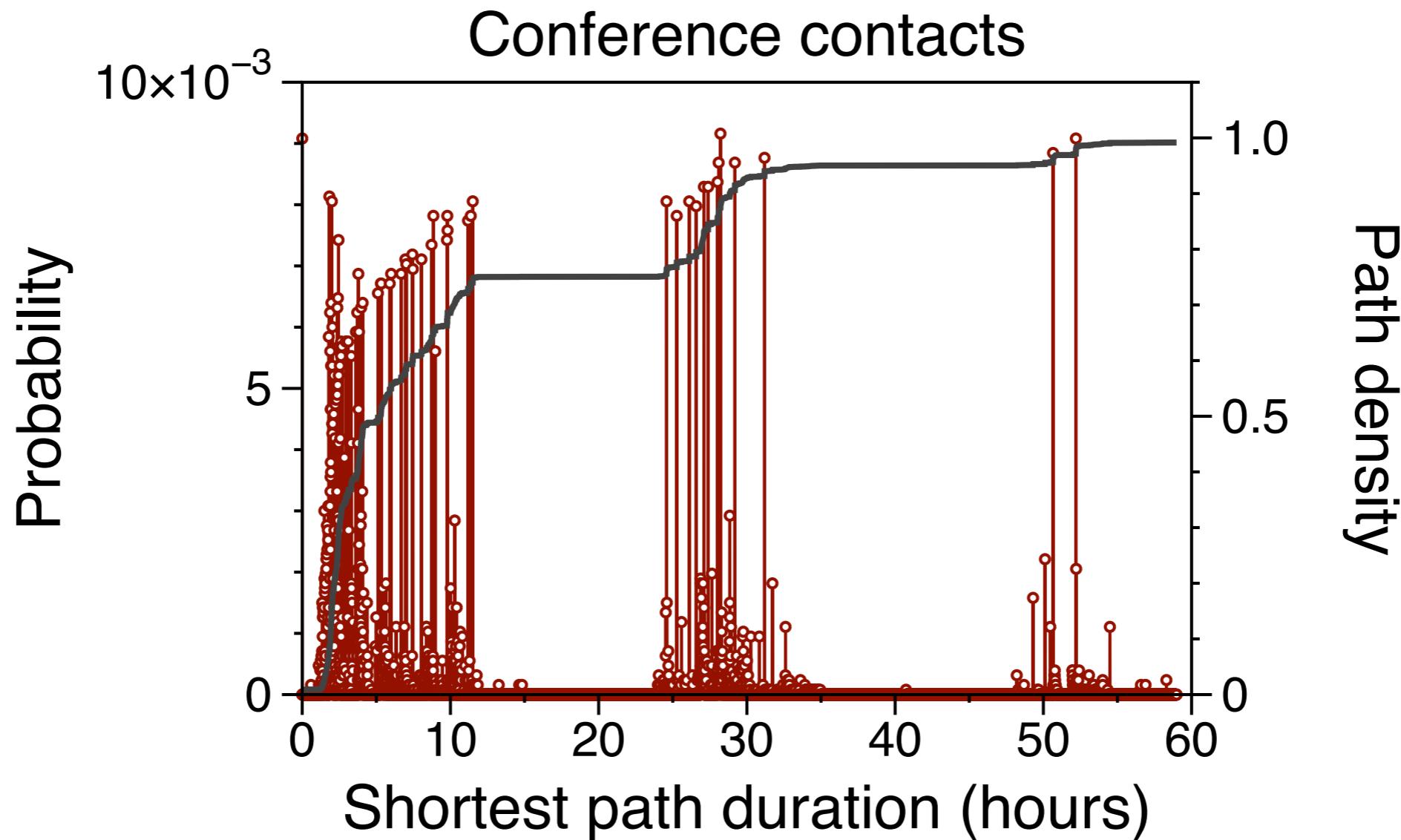


sexual contact network results III



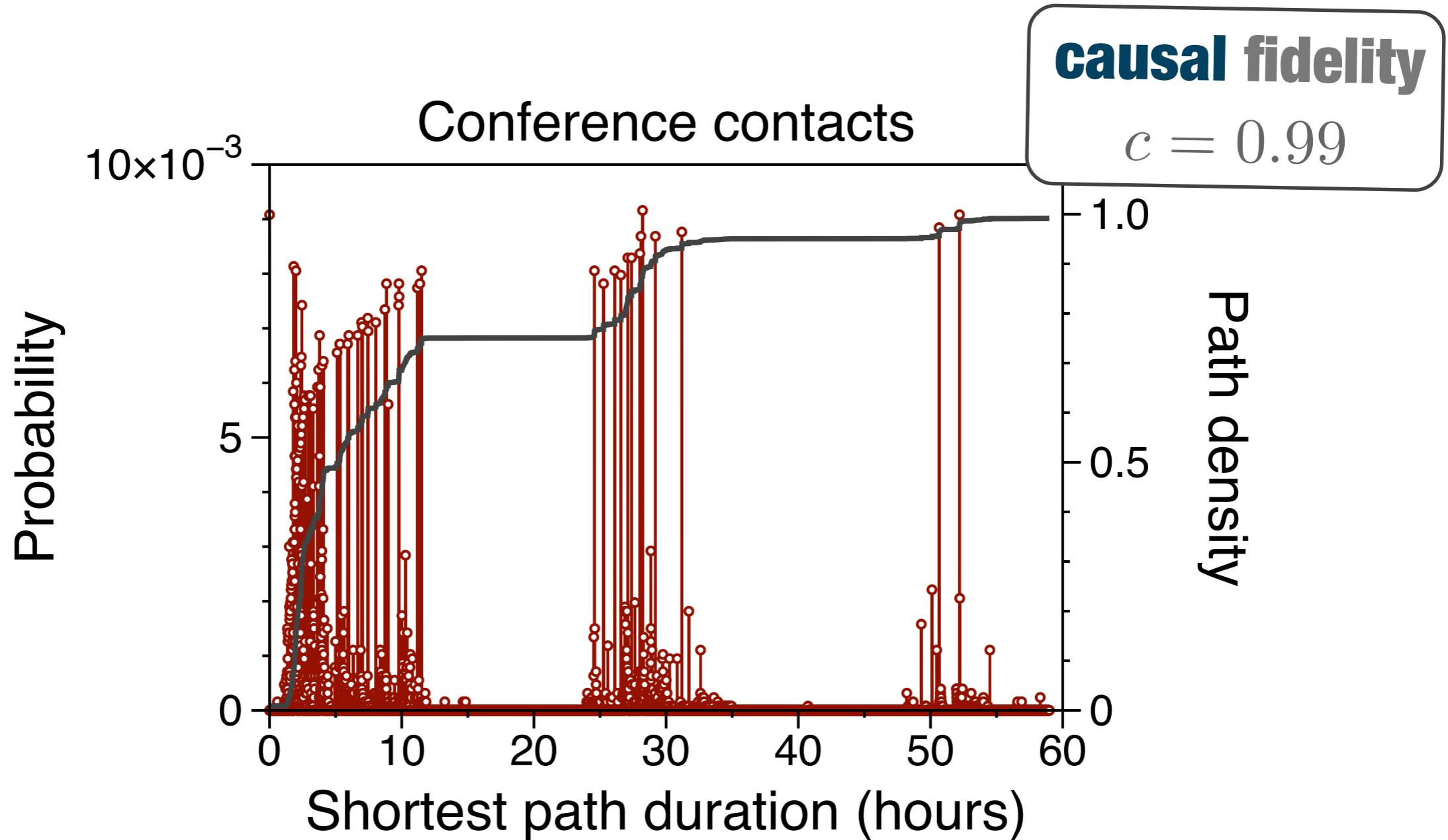
conference contacts

results III

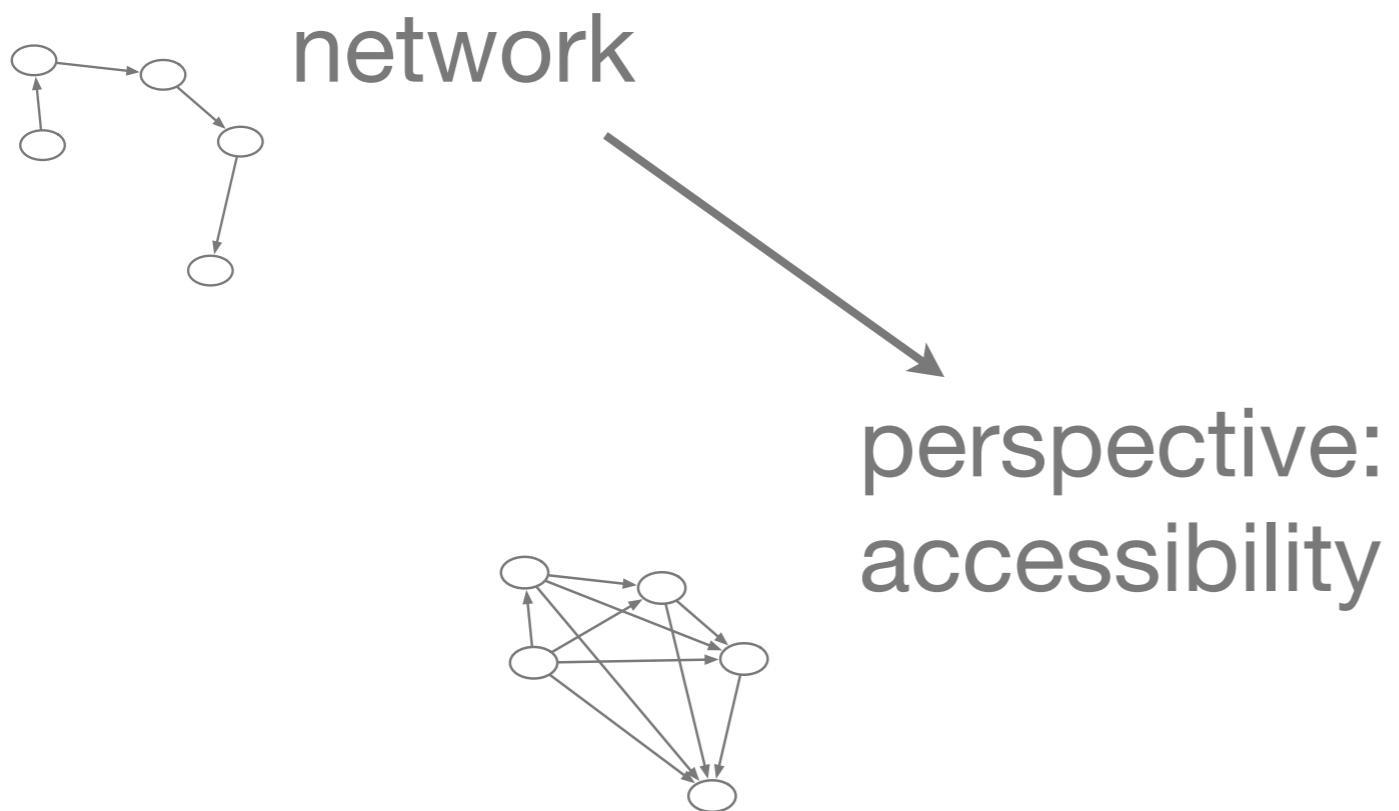


conference contacts

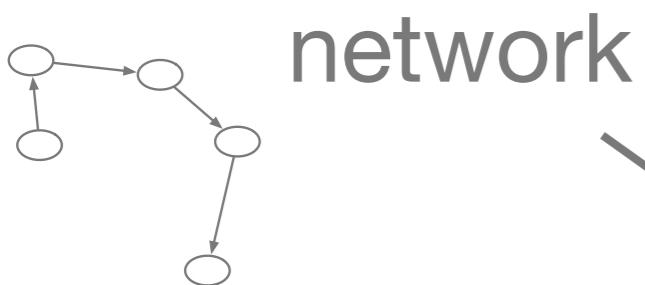
results III



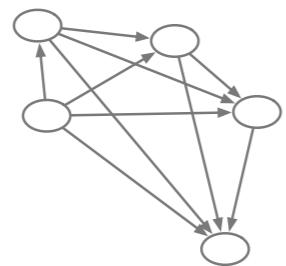
recap.



recap.



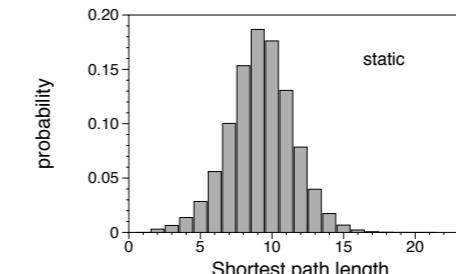
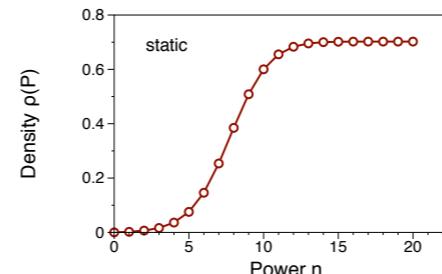
network



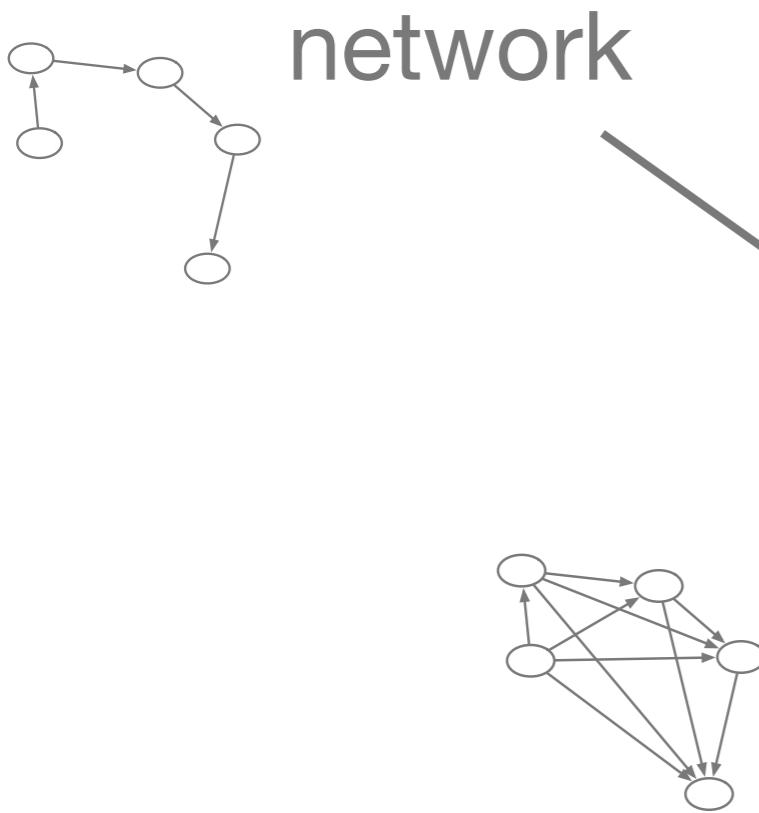
perspective:
accessibility

new

path-lengths



recap.



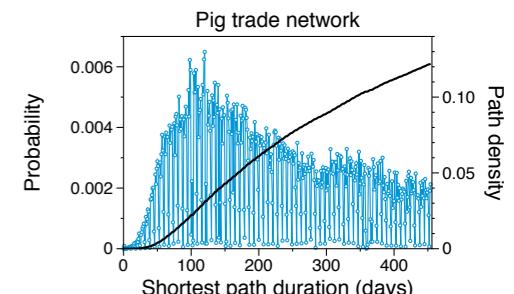
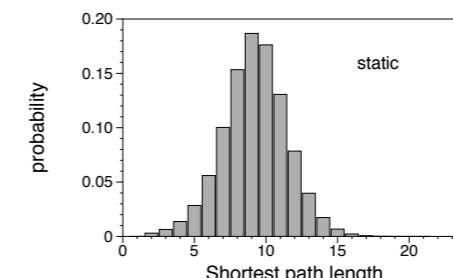
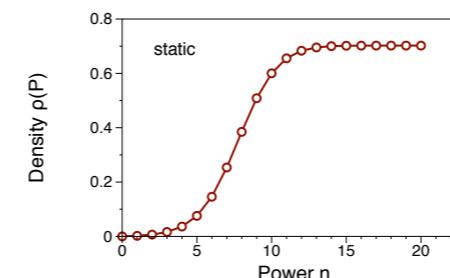
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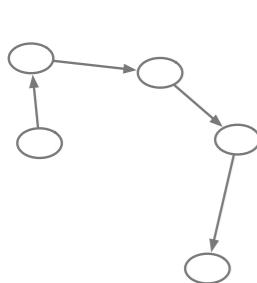
path-lengths

new:
**temporal
accessibility**

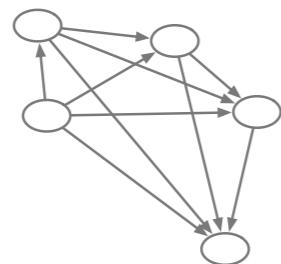
$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$



recap.



network



perspective:
accessibility

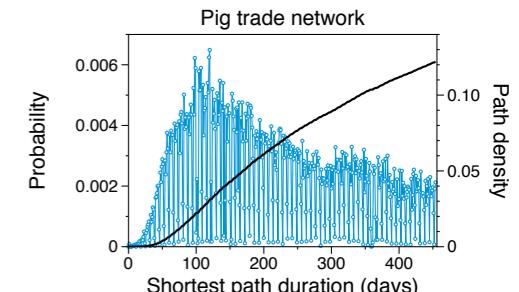
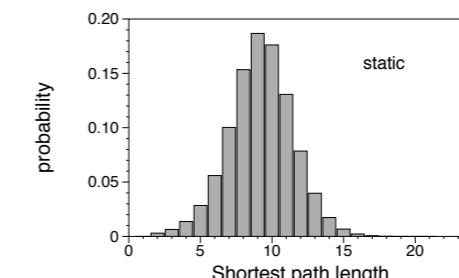
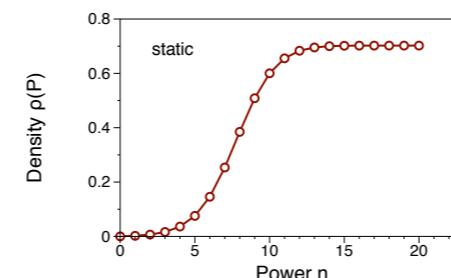
new

new:
causal
fidelity

$$c = \frac{\rho(\mathcal{P}_T)}{\rho(P_T)}$$

new:
temporal
accessibility

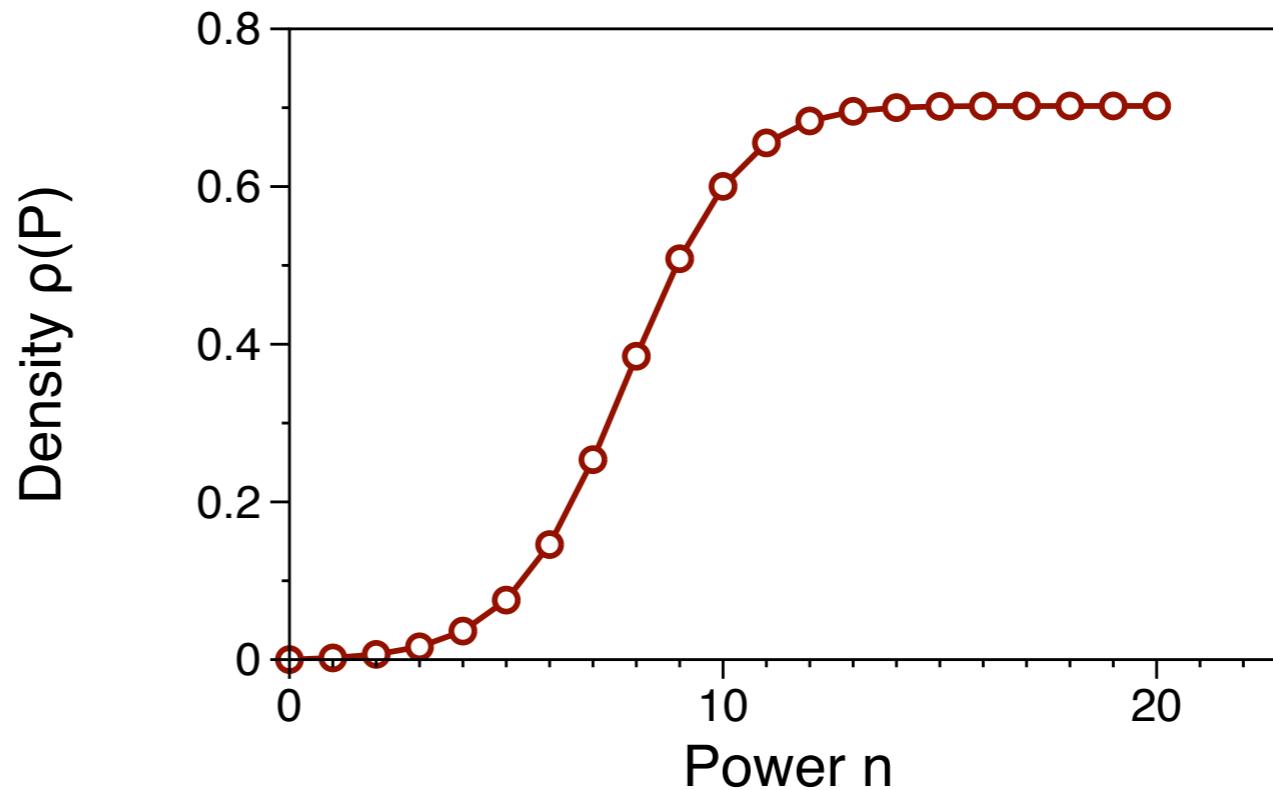
$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$



**paths vs.
epidemic models**

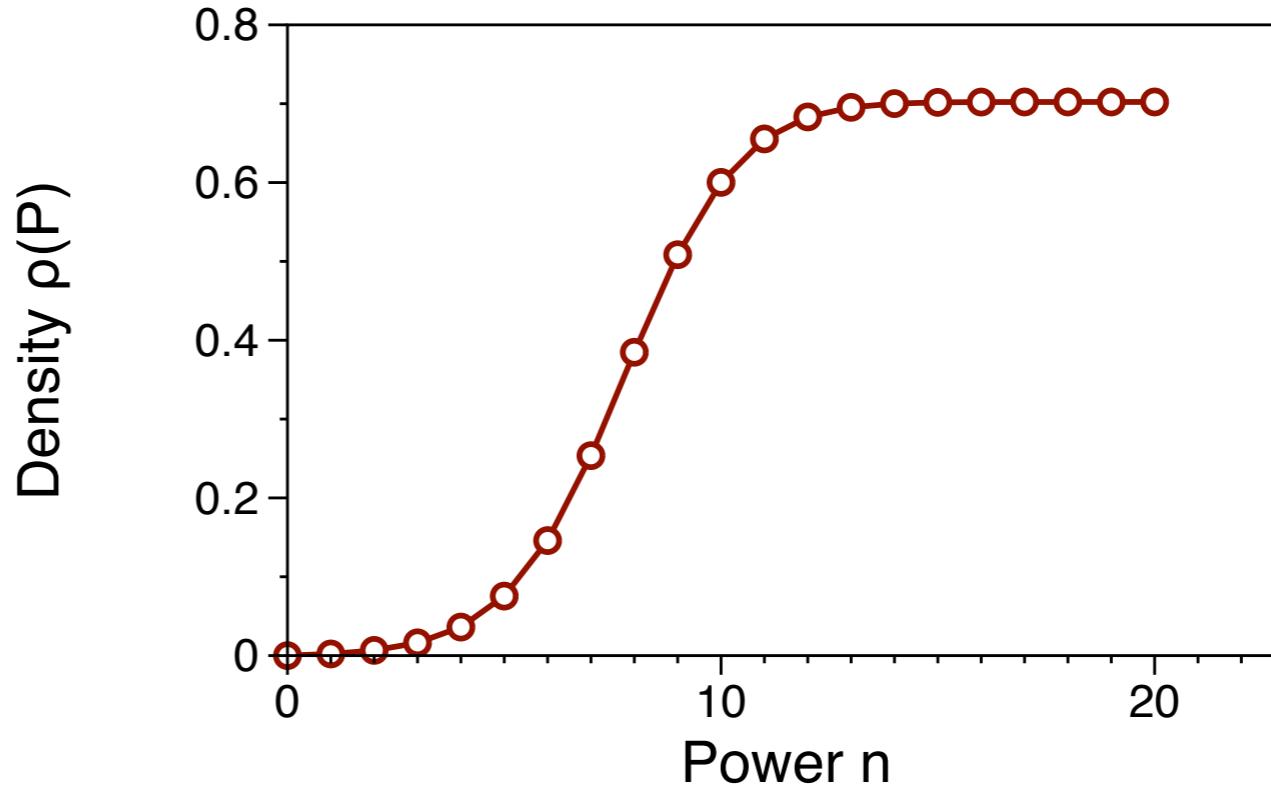
**so far...
.**

so far... ■■■



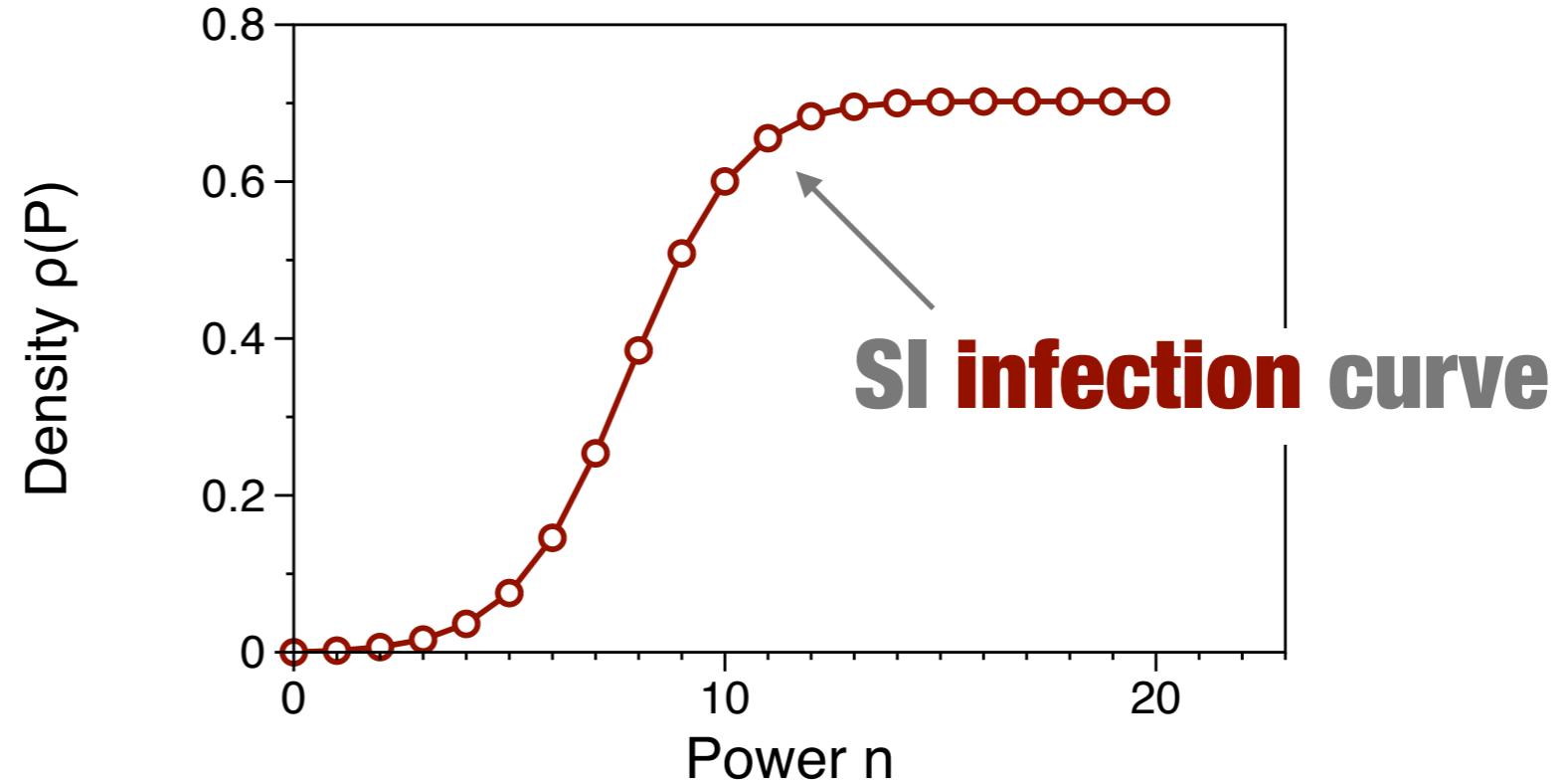
so far....

density of
infectious paths



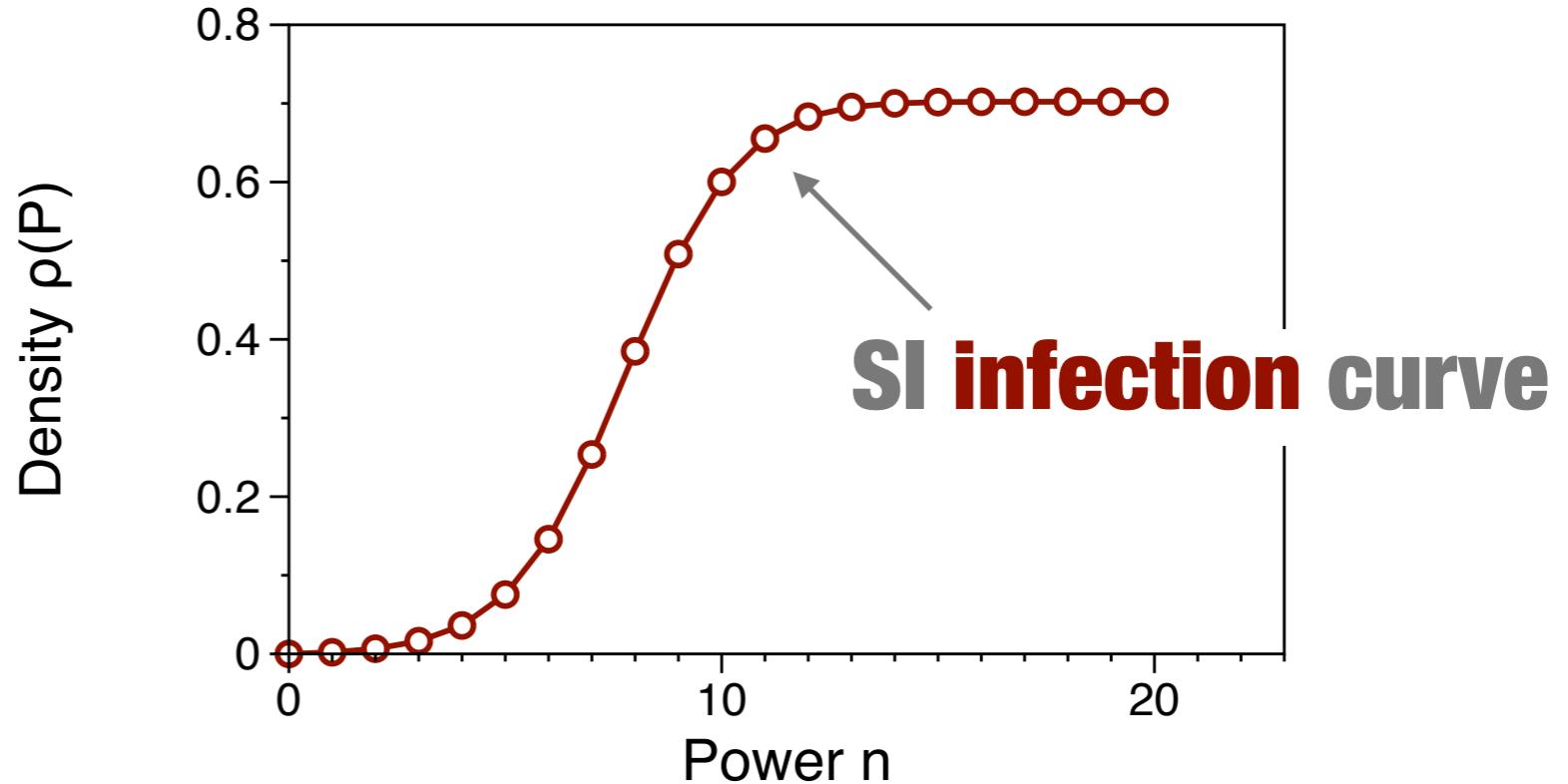
so far....

density of
infectious paths



so far....

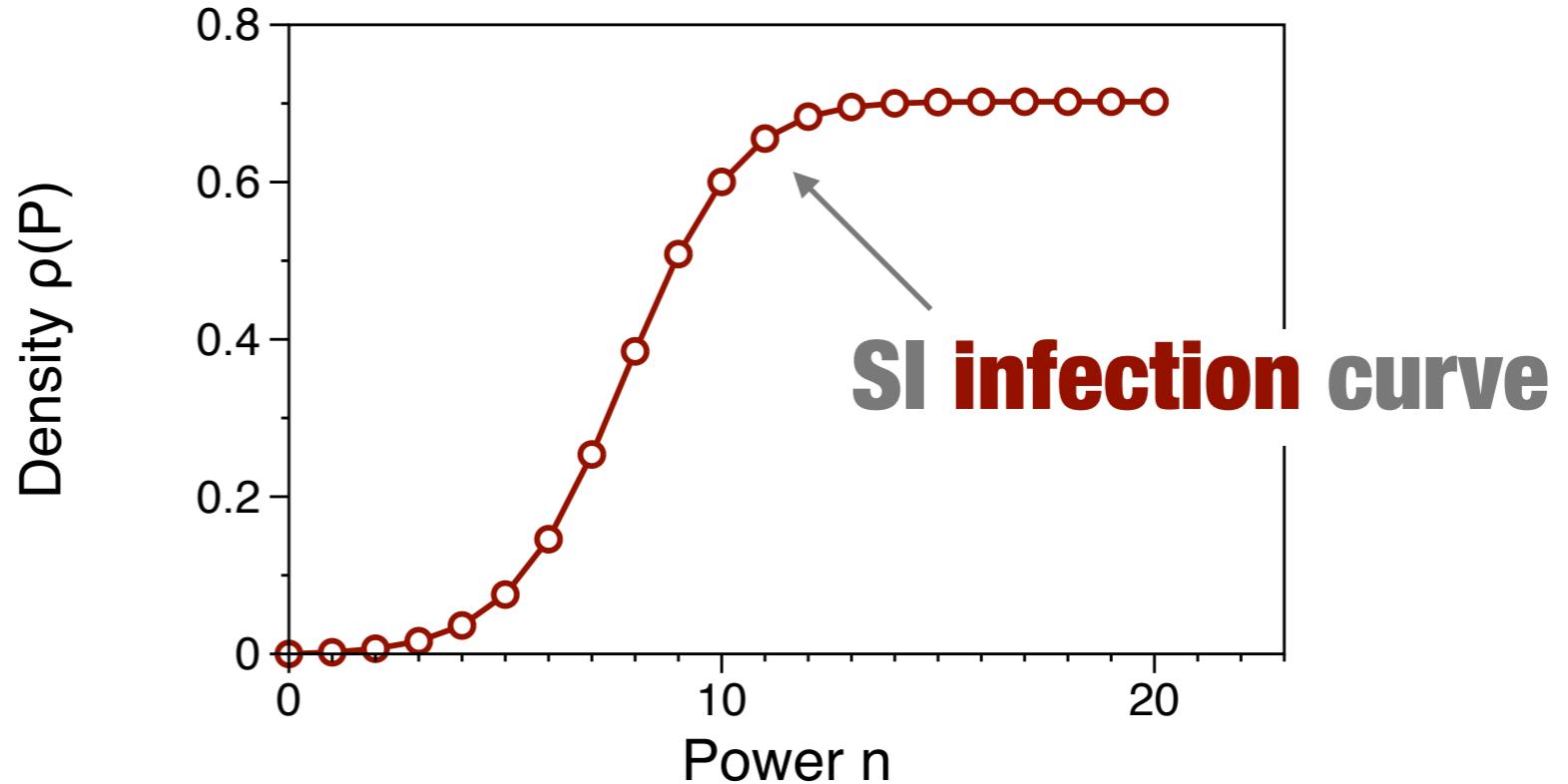
density of
infectious paths



SI type process with infectious period $\tau = \infty$

so far....

density of
infectious paths



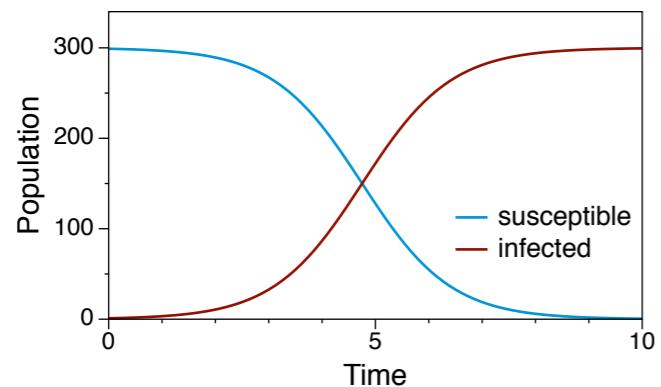
SI type process with infectious period $\tau = \infty$

What if infectious period τ is finite?

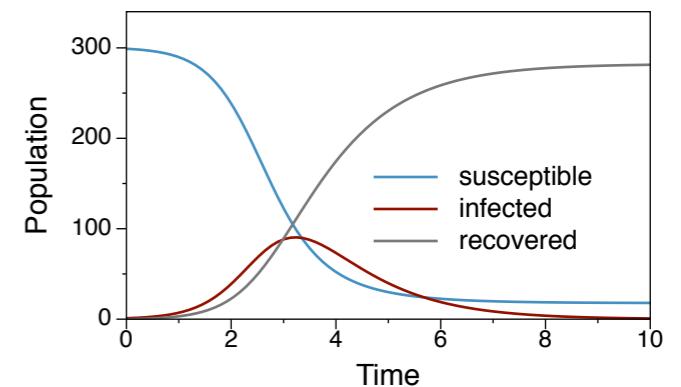
→ SIR type process!

classical models: SI vs. SIR

SI model

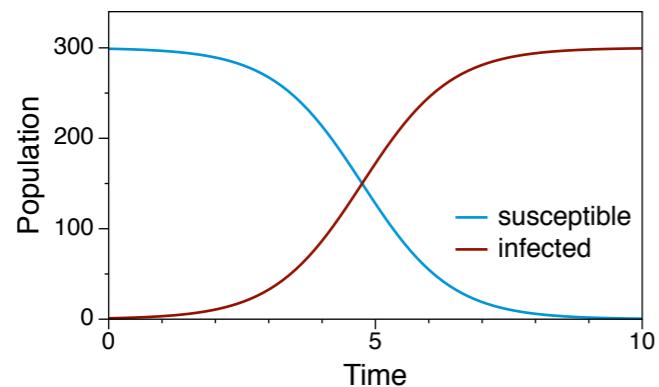


SIR model

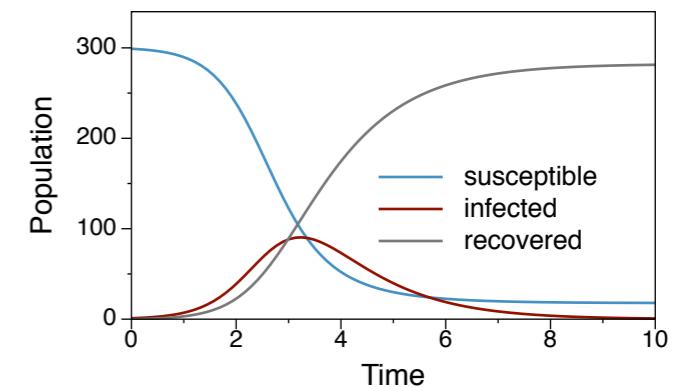


classical models: SI vs. SIR

SI model



SIR model



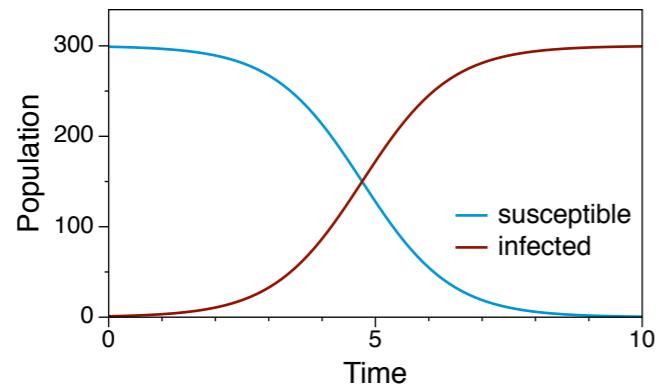
model

$$\frac{dS}{dt} = -\beta SI$$

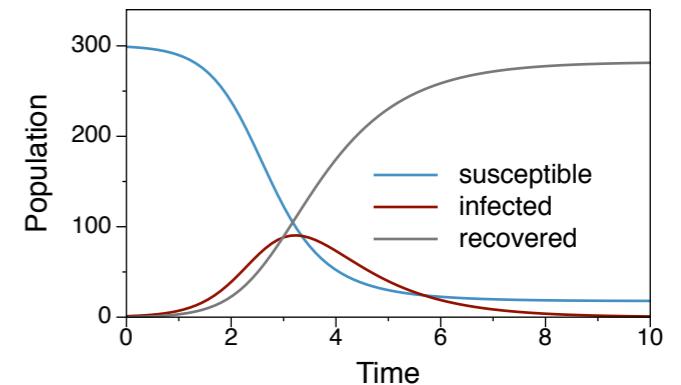
$$\frac{dI}{dt} = \beta SI$$

classical models: SI vs. SIR

SI model



SIR model



model

$$\frac{dS}{dt} = -\beta SI$$

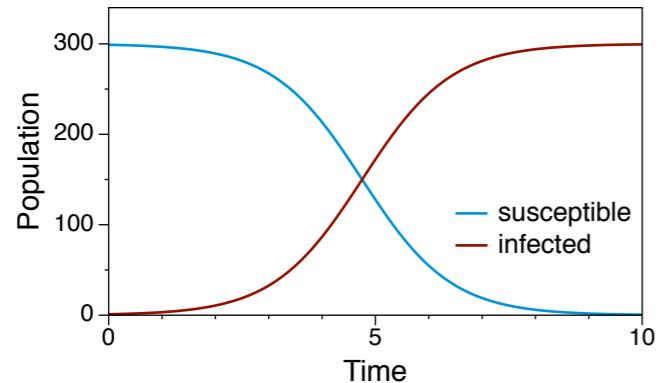
$$\frac{dI}{dt} = \beta SI$$

incidence

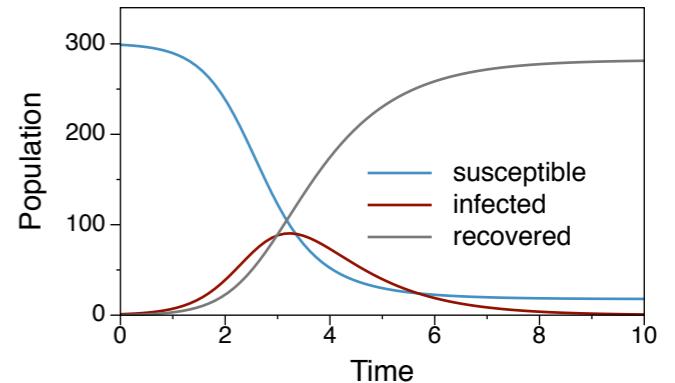
$$\frac{dI}{dt} = \beta(N - I)I$$

classical models: SI vs. SIR

SI model



SIR model



model

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI$$

incidence

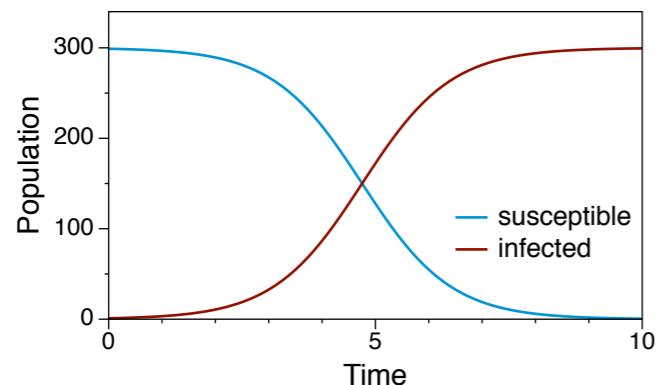
$$\frac{dI}{dt} = \beta(N - I)I$$

solution

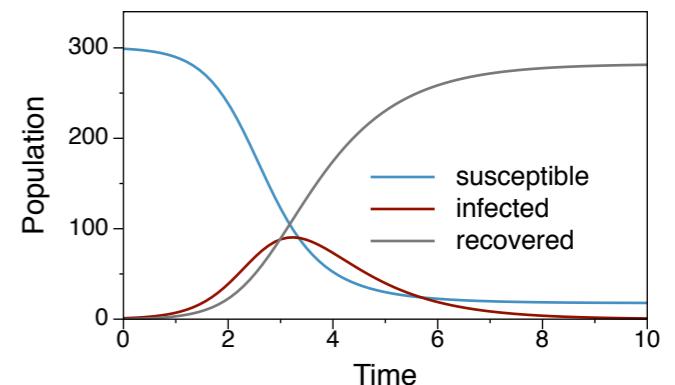
$$I(t) = \frac{I_0 N}{I_0 + (N - I_0)e^{-\beta N t}}$$

classical models: SI vs. SIR

SI model



SIR model



model

dS

$\sim \propto -\beta I$

temporal network case

$$\langle I(t) \rangle = \rho(\mathcal{P}(t))$$

$$\beta = 1$$

dt

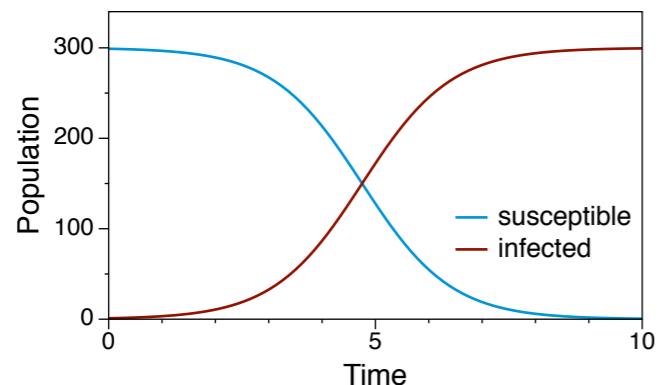
incidence

$$I(t) = \frac{I_0 N}{I_0 + (N - I_0) e^{-\beta N t}}$$

solution

classical models: SI vs. SIR

SI model



model

$\frac{dS}{dt} = -\beta SI$

temporal network case

$$\langle I(t) \rangle = \rho(\mathcal{P}(t))$$

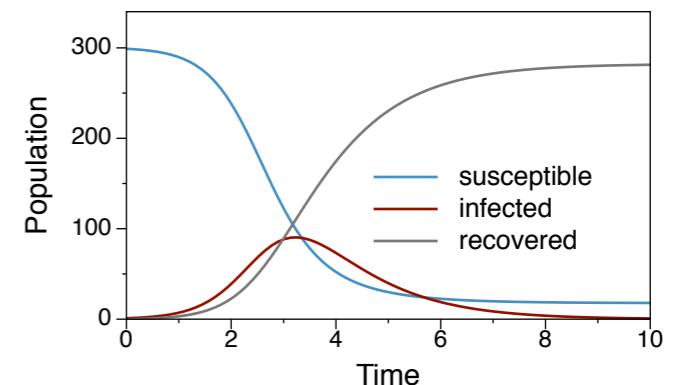
$$\beta = 1$$

$$dt$$

incidence

$$I(t) = \frac{I_0 N}{I_0 + (N - I_0) e^{-\beta N t}}$$

SIR model



model

$$\frac{dS}{dt} = -\beta SI$$

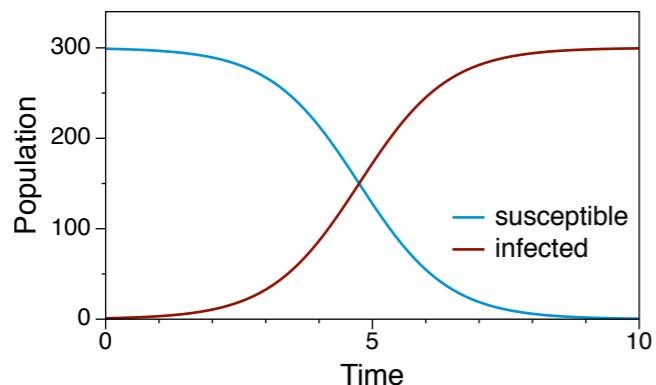
$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

solution

classical models: SI vs. SIR

SI model



model

$$\frac{dS}{dt} = -\beta SI$$

temporal network case

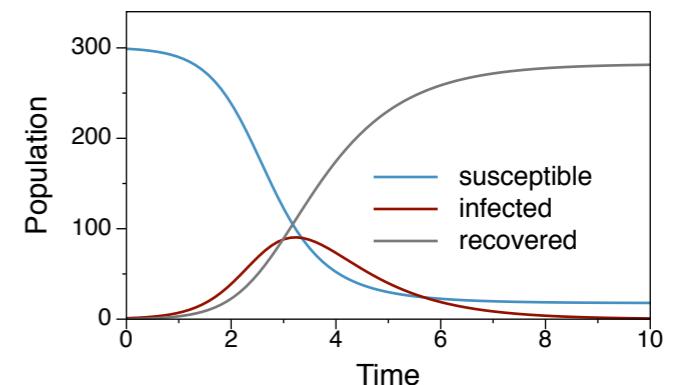
$$\langle I(t) \rangle = \rho(\mathcal{P}(t))$$
$$\beta = 1$$

incidence

$$I(t) = \frac{I_0 N}{I_0 + (N - I_0)e^{-\beta N t}}$$

solution

SIR model



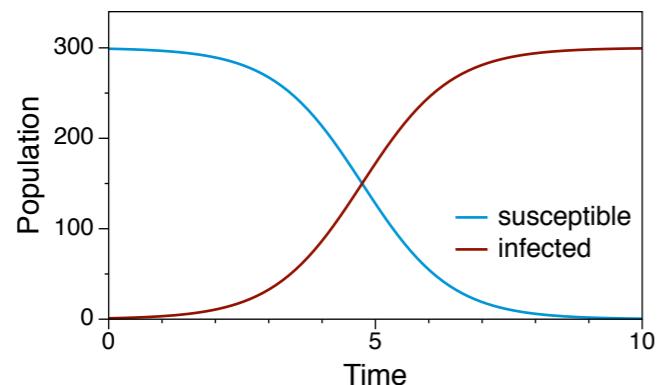
model

$$\frac{dS}{dt} = -\beta SI$$
$$\frac{dI}{dt} = \beta SI - \gamma I$$
$$\frac{dR}{dt} = \gamma I$$

no explicit solution!

classical models: SI vs. SIR

SI model



model

$$\frac{dS}{dt} \approx -\beta SI$$

temporal network case

$$\langle I(t) \rangle = \rho(\mathcal{P}(t))$$

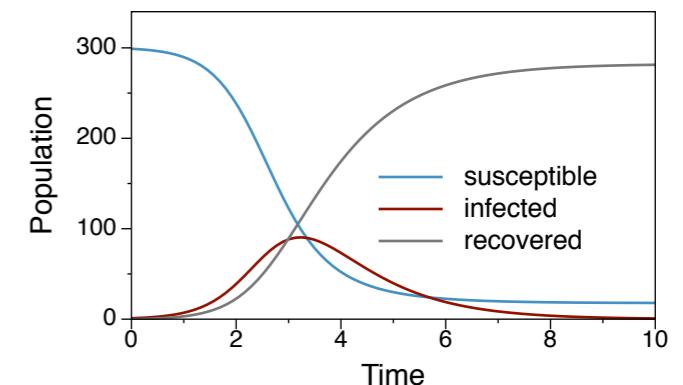
$$\beta = 1$$

incidence

$$I(t) = \frac{I_0 N}{I_0 + (N - I_0)e^{-\beta N t}}$$

solution

SIR model



model

"incidence"

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

no explicit solution!

incidence formulation from SI to SIR

incidence formulation from SI to SIR

1. Starting point.

SI model

$$\mathcal{P}(t) = \prod_{t'=1}^t (\mathbf{I} + \mathbf{A}(t'))$$

incidence formulation from SI to SIR

1. Starting point.

SI model

$$\mathcal{P}(t) = \prod_{t'=1}^t (\mathbf{I} + \mathbf{A}(t'))$$

2. Rewrite.

SI model as incidence

$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{t-1} \mathcal{I}(t' - 1)$$

$$\mathcal{P}(t) = \sum_{t'=0}^t \mathcal{I}(t')$$

incidence formulation from SI to SIR

1. Starting point.

SI model

$$\mathcal{P}(t) = \prod_{t'=1}^t (\mathbf{I} + \mathbf{A}(t'))$$

2. Rewrite.

SI model as incidence

$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{t-1} \mathcal{I}(t' - 1)$$

$$\mathcal{P}(t) = \sum_{t'=0}^t \mathcal{I}(t')$$

3. Finite memory.

$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{\tau} \mathcal{I}(\underline{t - t'})$$

incidence formulation from SI to SIR

1. Starting point.

SI model

$$\mathcal{P}(t) = \prod_{t'=1}^t (\mathbf{I} + \mathbf{A}(t'))$$

2. Rewrite.

SI model as incidence

$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{t-1} \mathcal{I}(t' - 1)$$

$$\mathcal{P}(t) = \sum_{t'=0}^t \mathcal{I}(t')$$

3. Finite memory.

$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{\tau} \mathcal{I}(\underline{t - t'})$$

4. Recovered state.

subtract recovered paths

incidence formalism SIR model



$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{\tau} \mathcal{I}(t - t') - \sum_{t'=1}^t \mathcal{I}(t - t')$$

new
infectious
paths

contacts
within
infectious
period

path was not
infectious before

incidence formalism SIR model



$$\mathcal{I}(t) = \mathbf{A}(t) \sum_{t'=1}^{\tau} \mathcal{I}(t-t') - \sum_{t'=1}^t \mathcal{I}(t-t')$$

new
infectious
paths

contacts
within
infectious
period

path was not
infectious before

$$\mathcal{I}(t) = \mathbf{A}(t) \bigvee_{t'=1}^{\tau} \mathcal{I}(t-t') \wedge \neg \left[\bigvee_{t'=1}^t \mathcal{I}(t-t') \right]$$

**Boolean
formulation**

application.

pig trade network

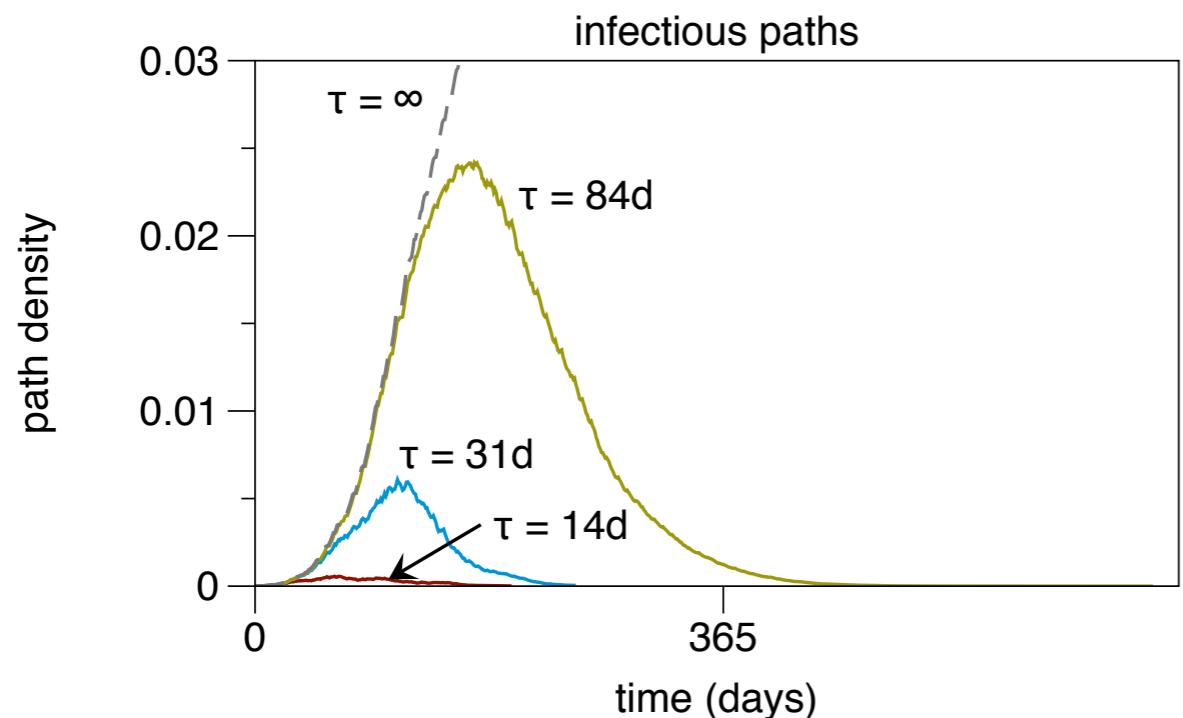
sexual contact network
Rocha et al., PNAS 2010

face-to-face conference contacts
sociopatterns.org

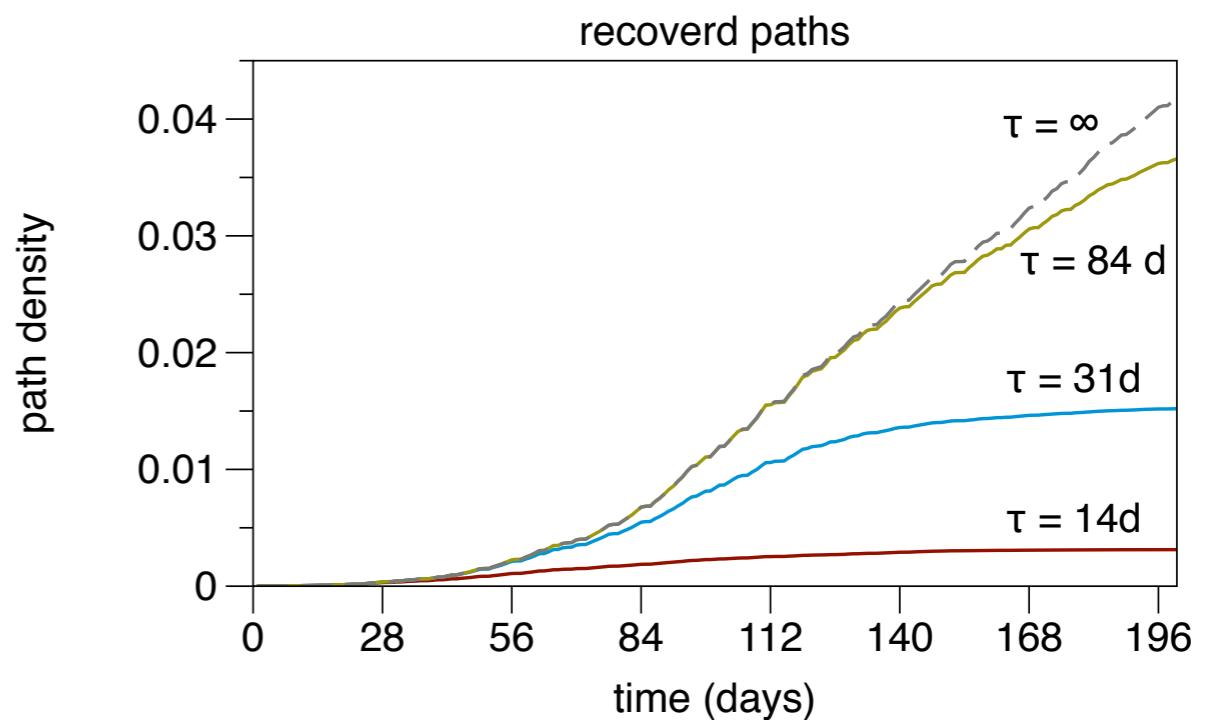
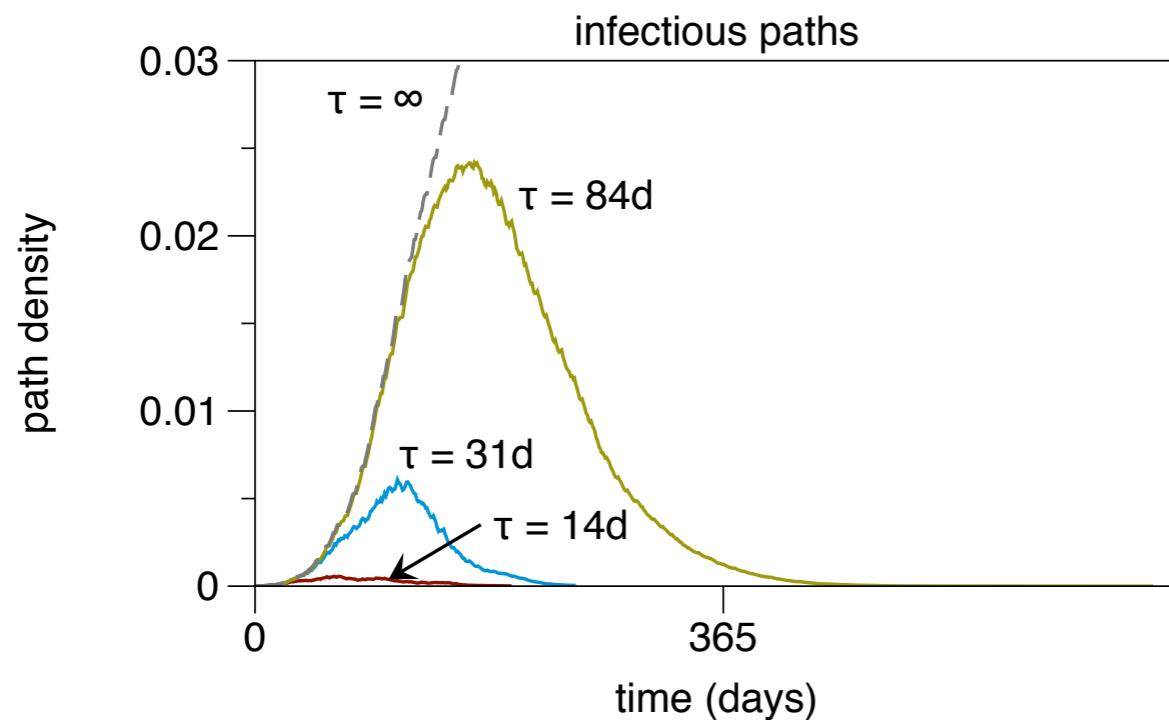
pig trade network

results

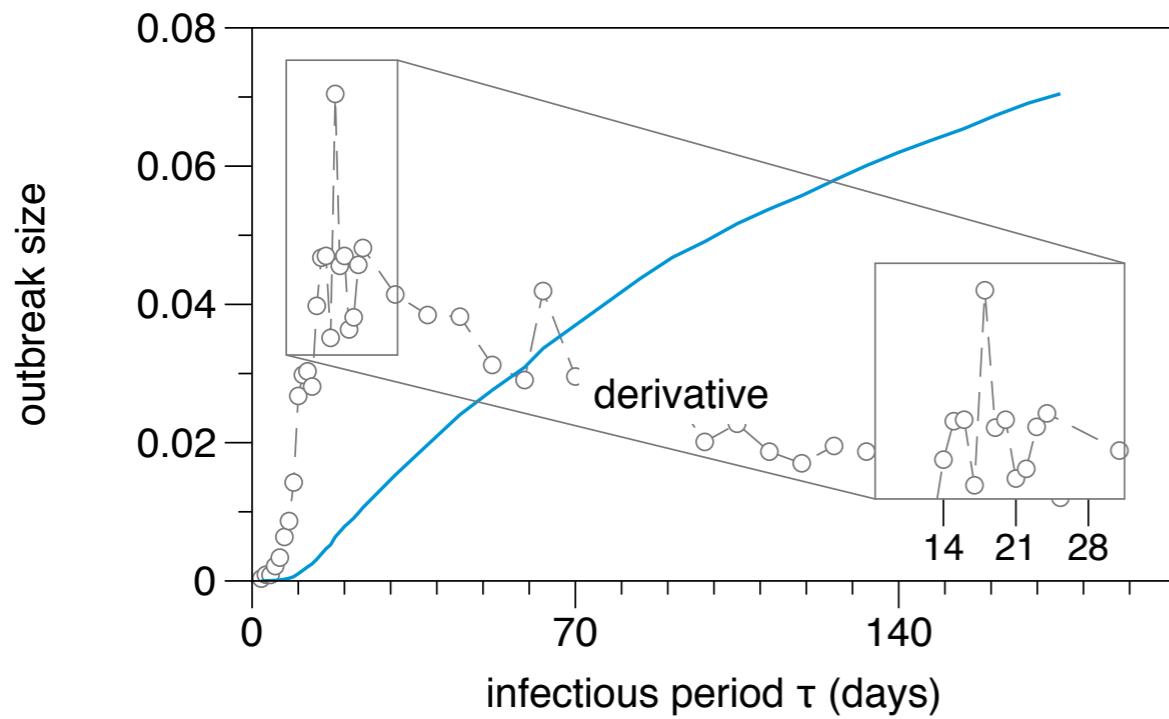
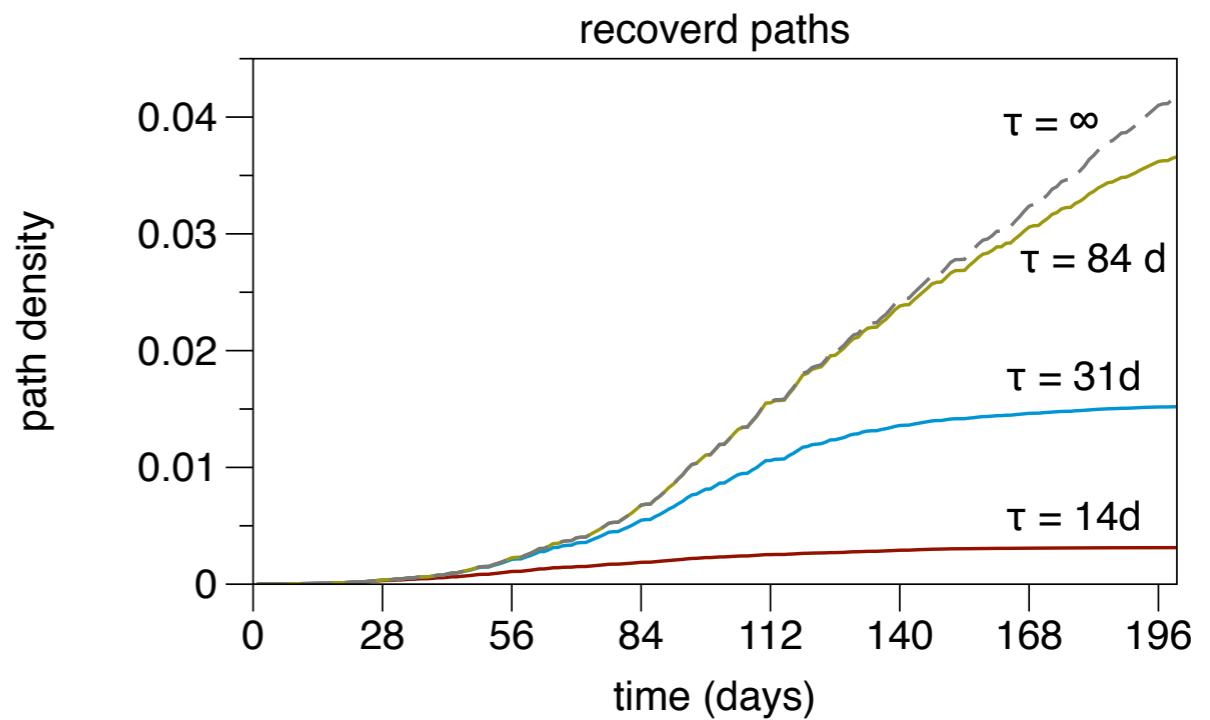
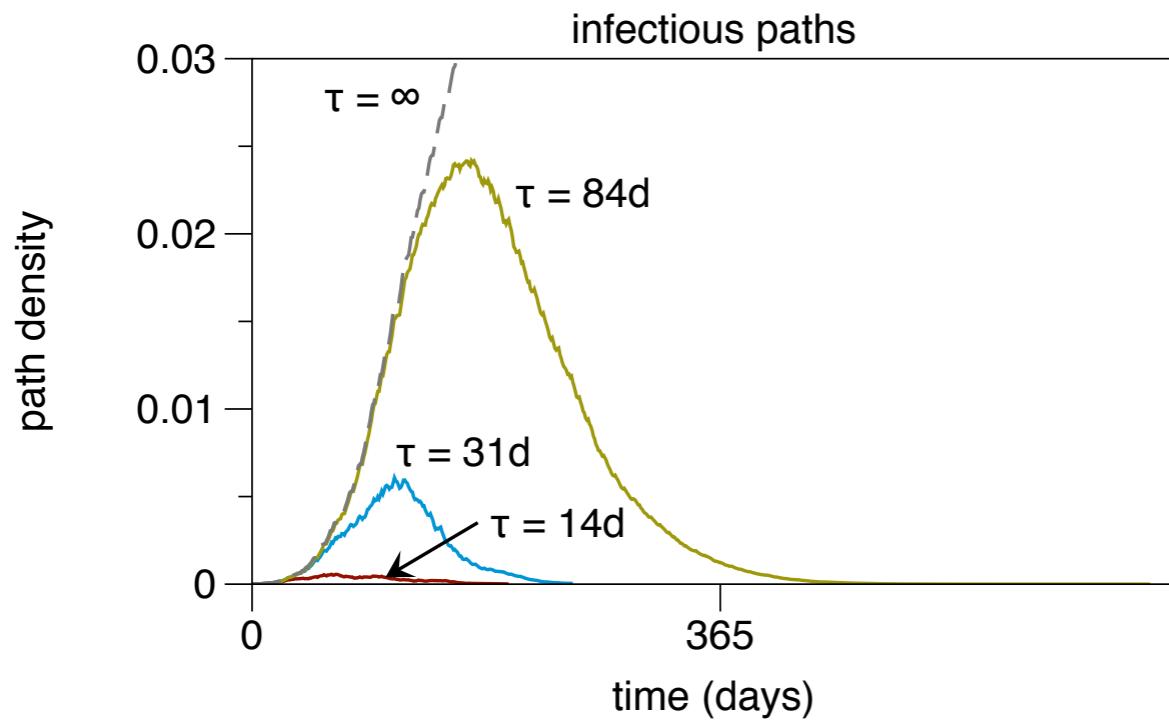
pig trade network results



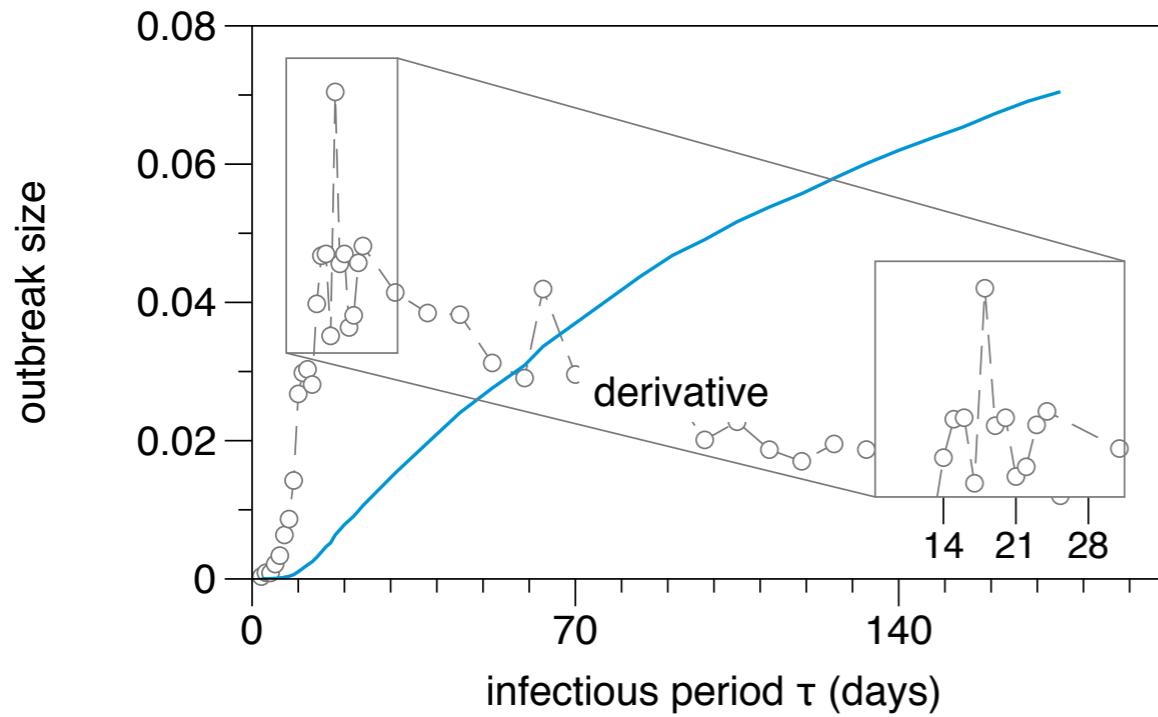
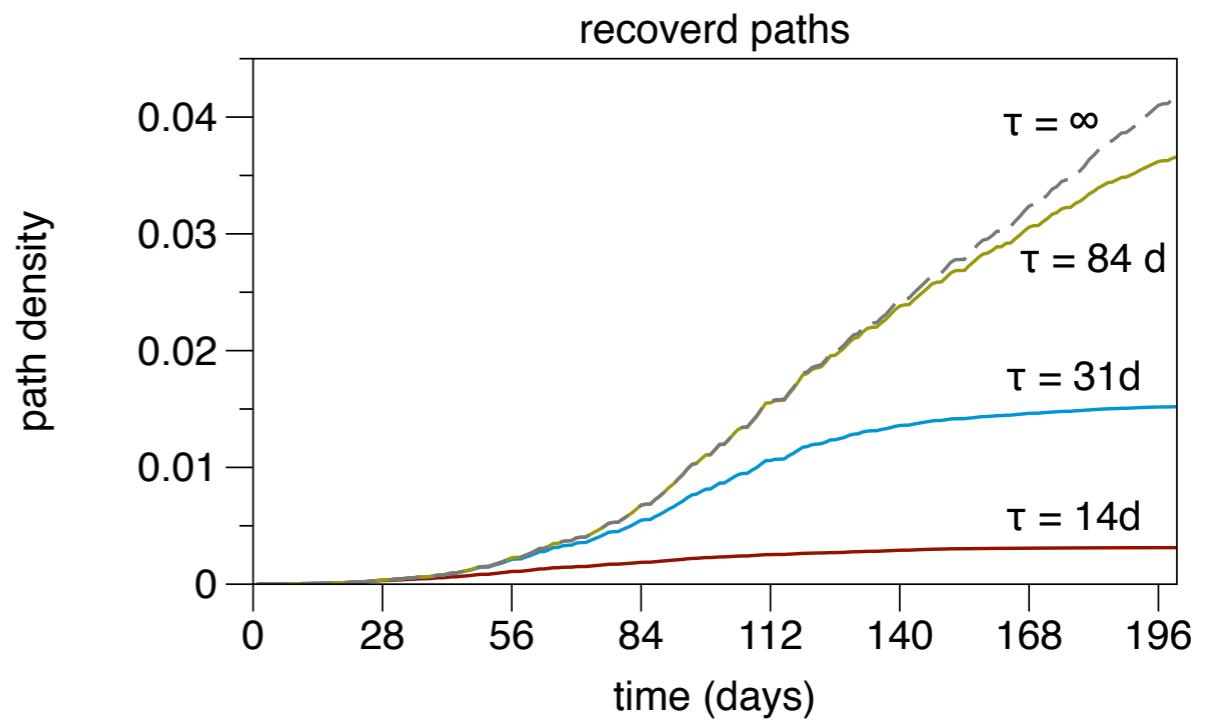
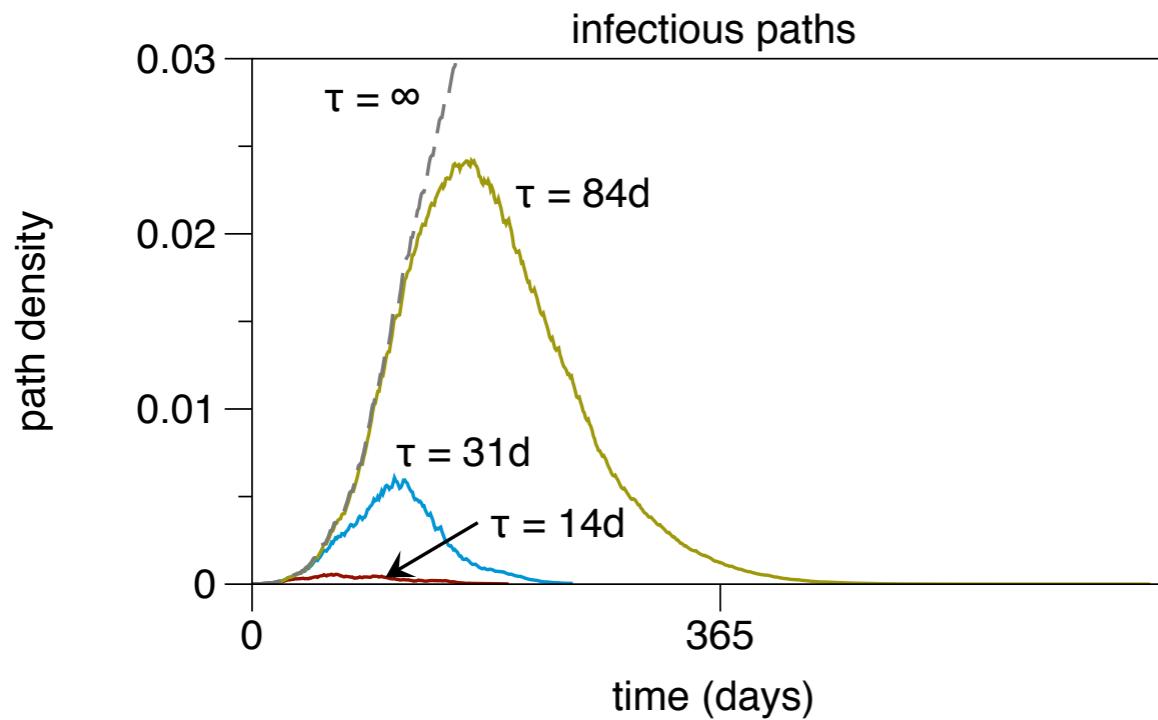
pig trade network results



pig trade network results

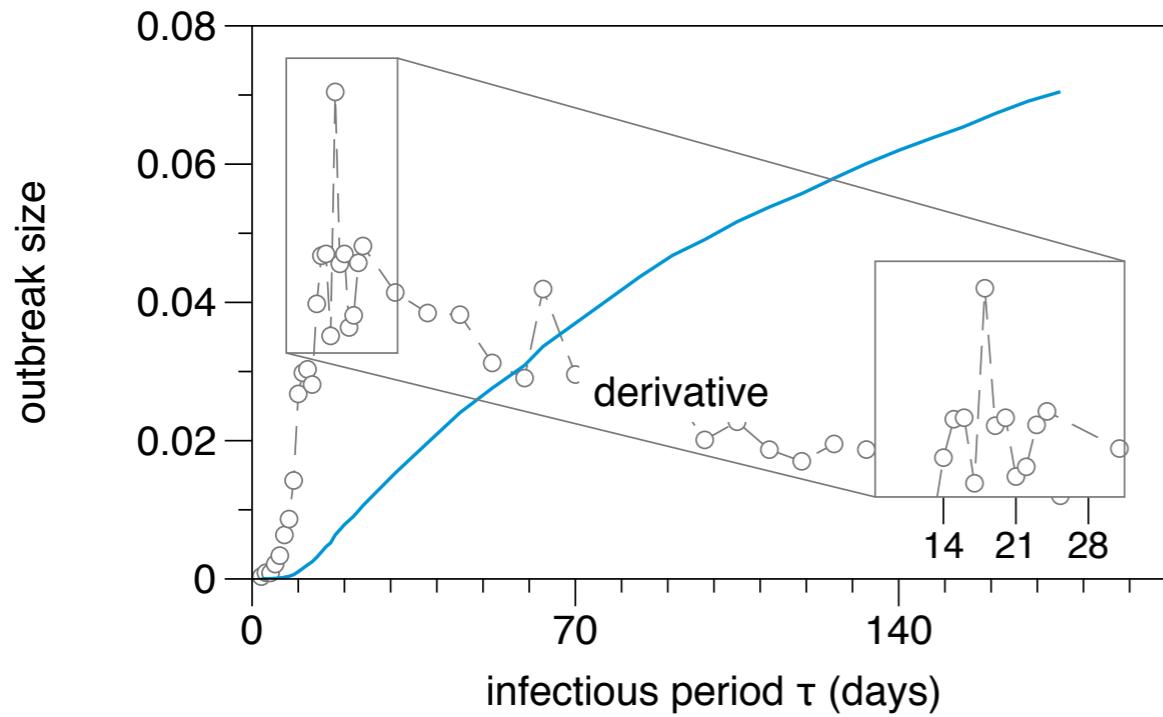
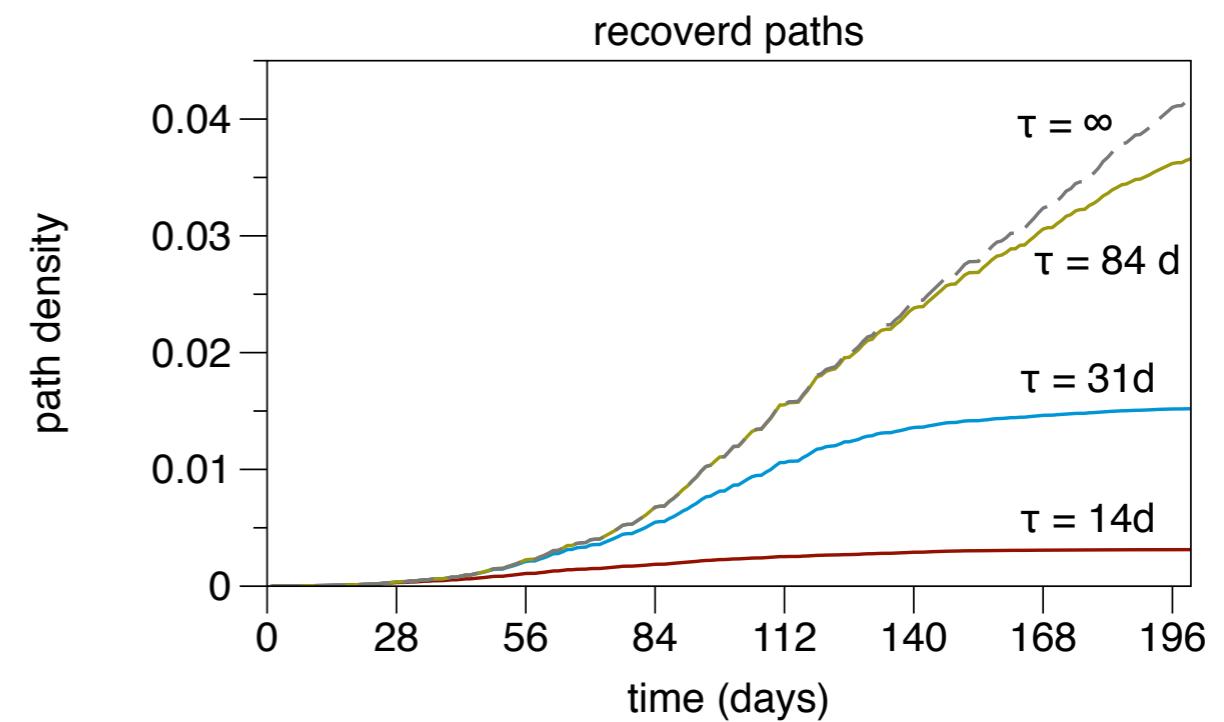
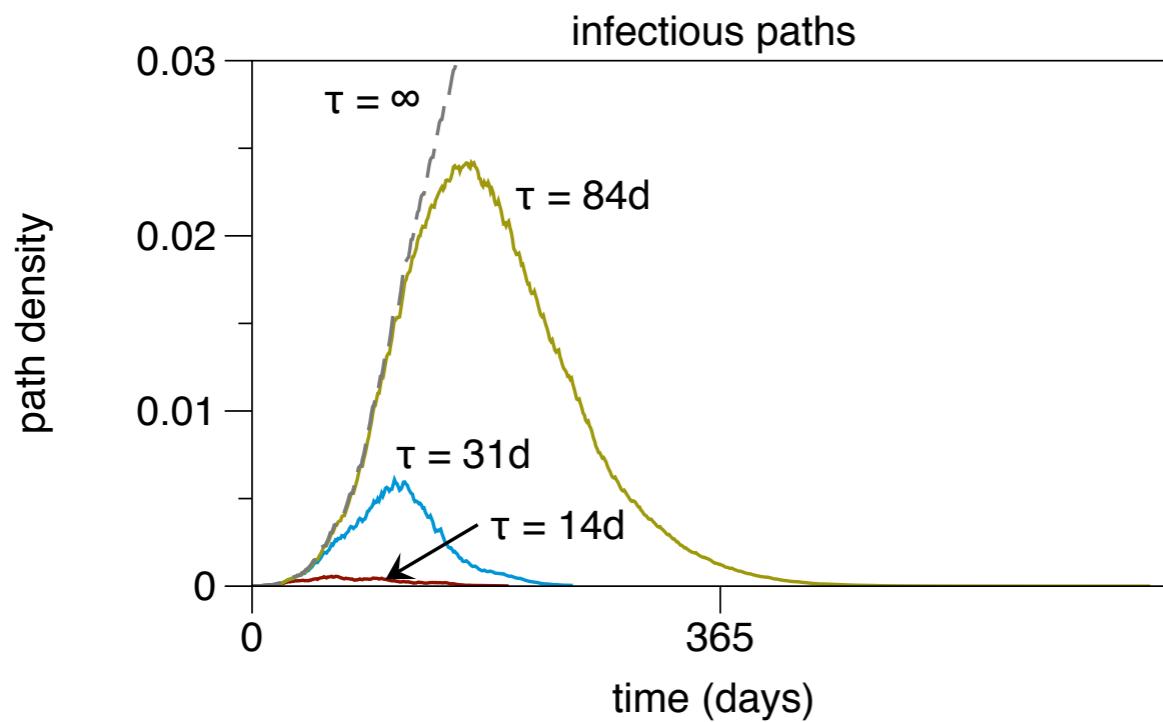


pig trade network results



**critical
infectious
period**
 $\tau_c \sim 20\text{ d}$

pig trade network results



**critical
infectious
period**

$$\tau_c \sim 20 \text{ d}$$

**example:
classical
swine fever**

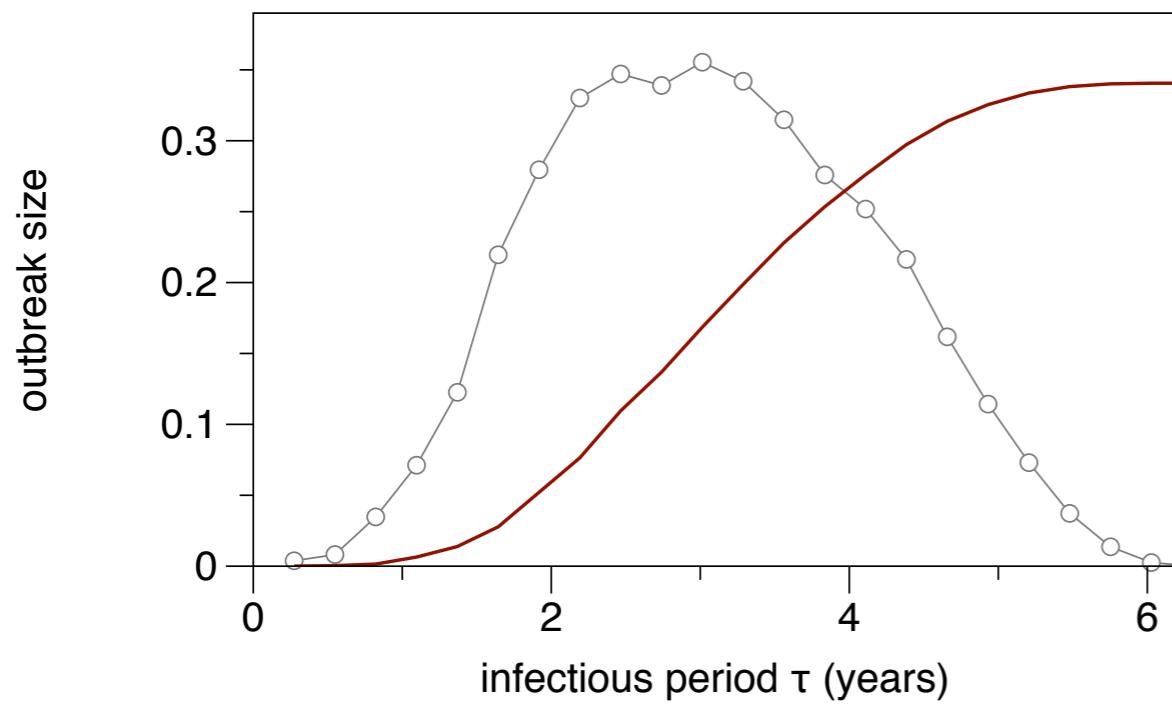
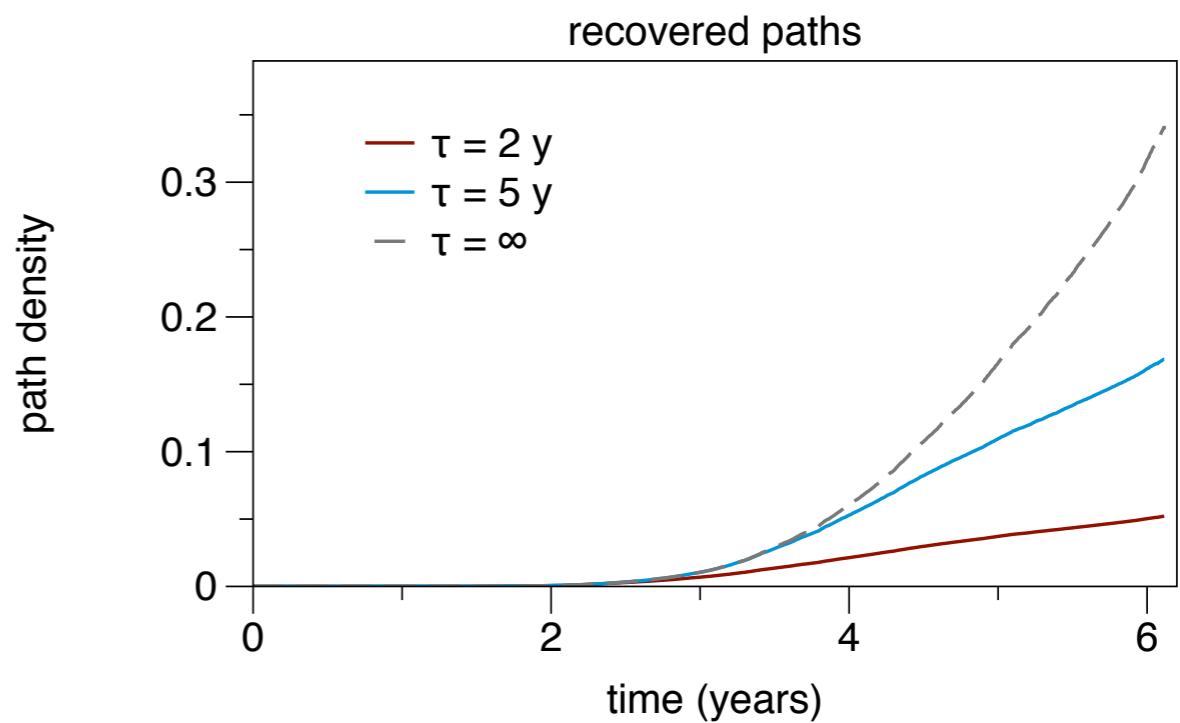
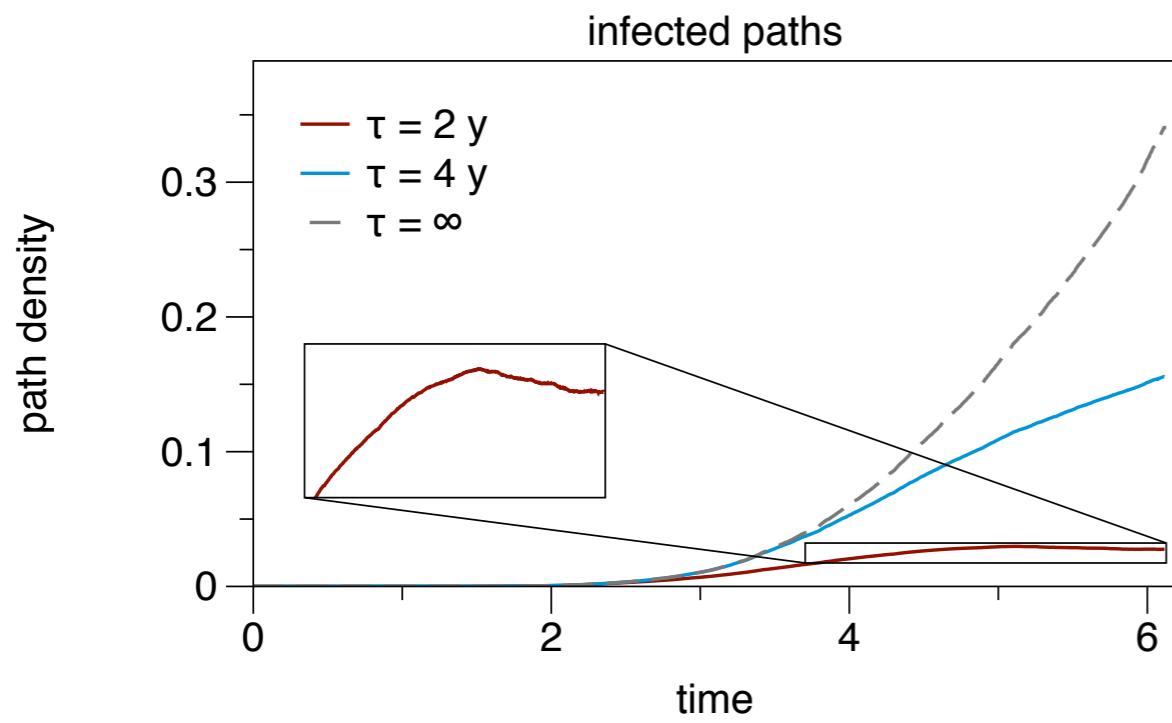
$\tau \sim 28 \text{ d}$

Further datasets.

sexual contact network
Rocha et al., PNAS 2010

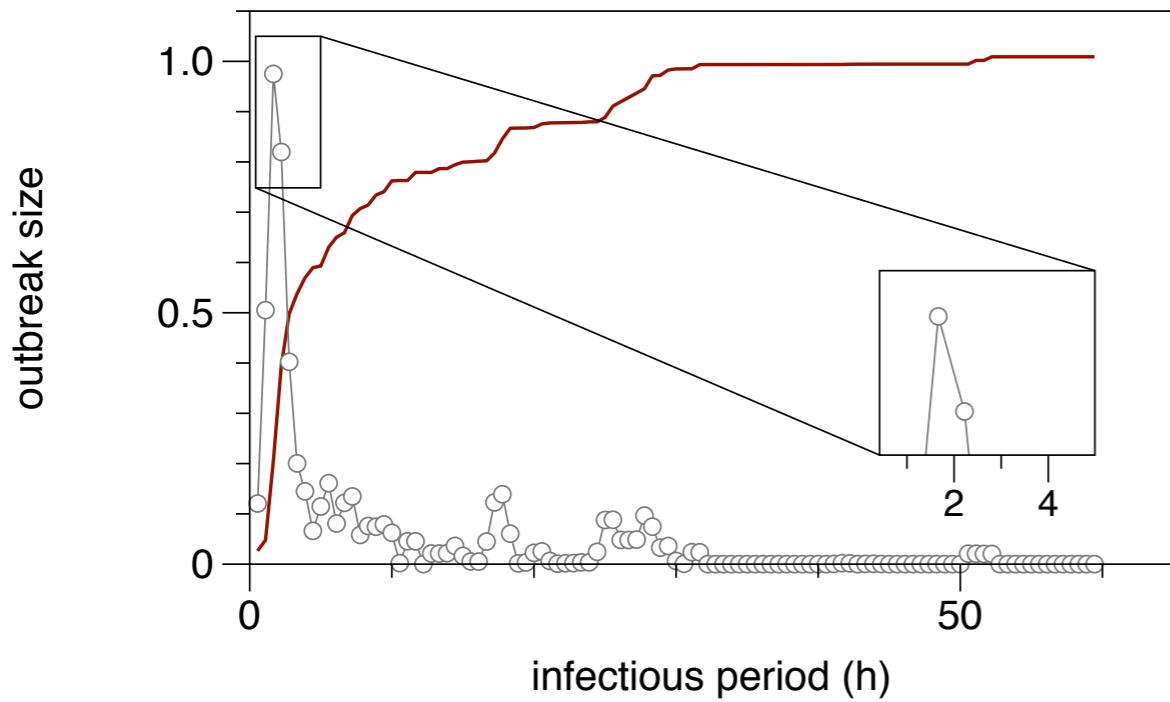
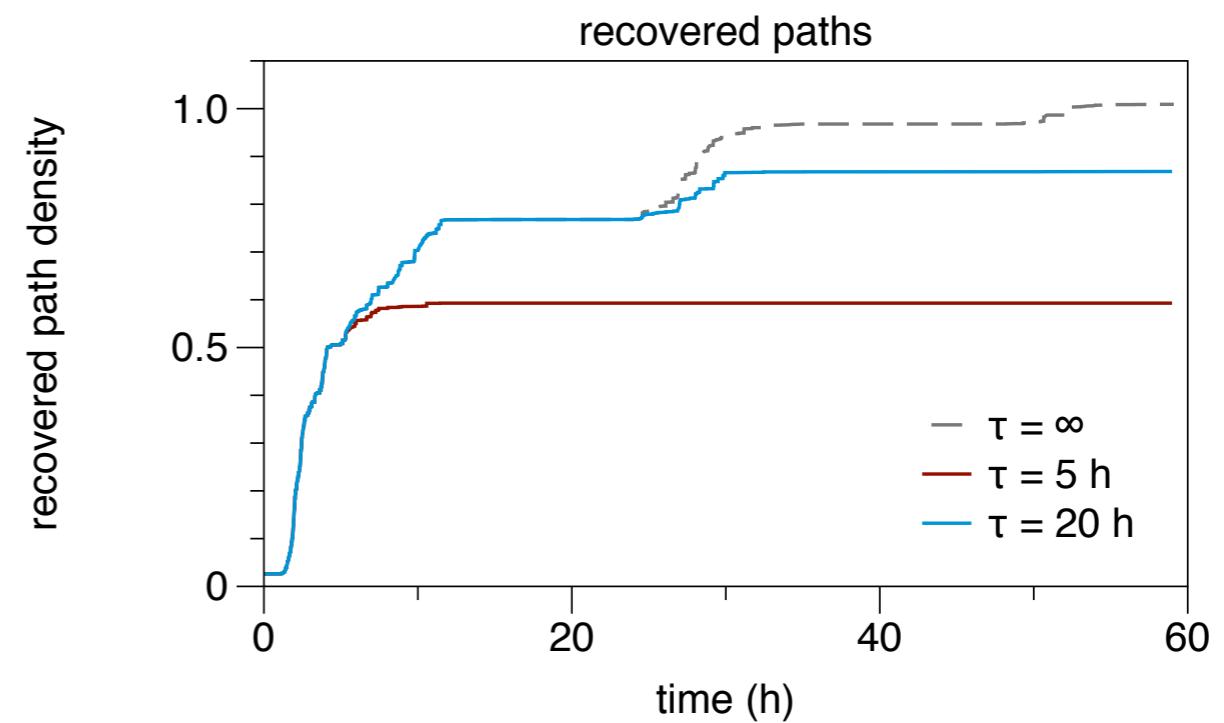
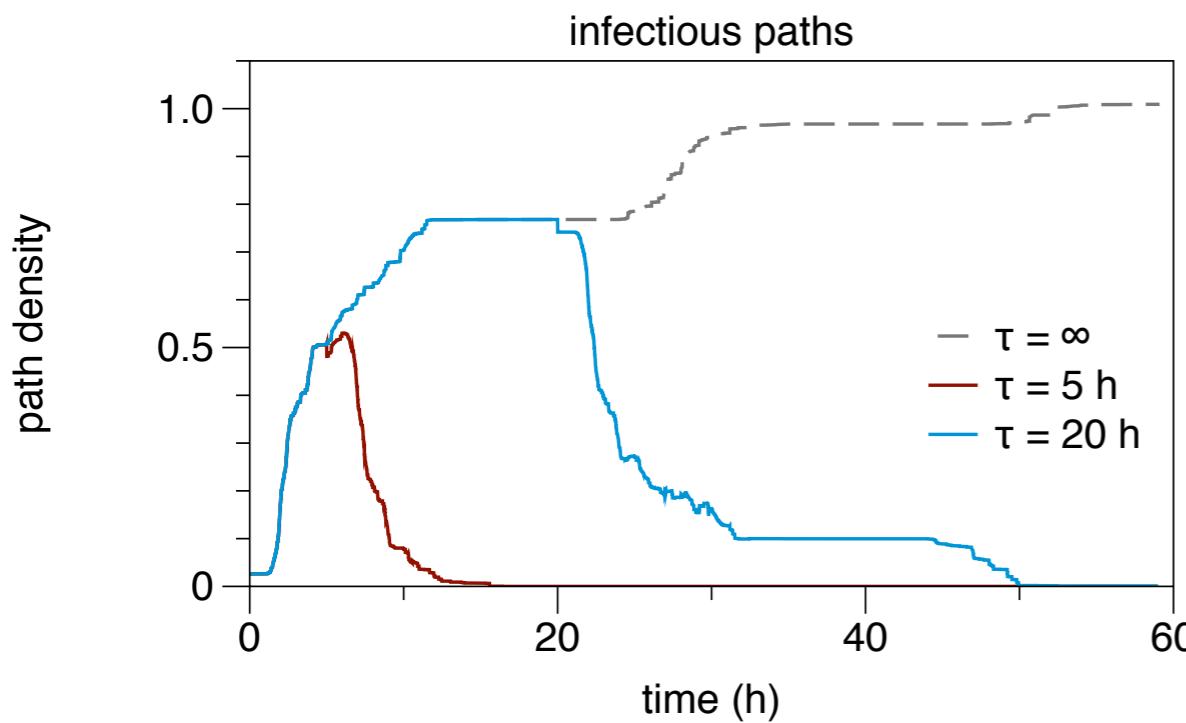
face-to-face conference contacts
sociopatterns.org

sexual contacts results



**critical
infectious
period**
 $\tau \sim 3 \text{ y}$

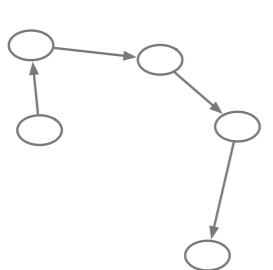
conference contacts results



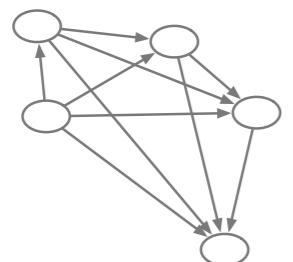
**critical
infectious
period**
 $\tau \sim 2\text{ h}$

recap.

network

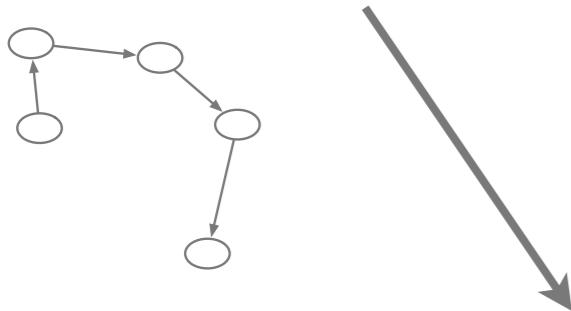


perspective:
accessibility

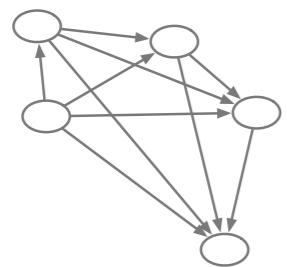


recap.

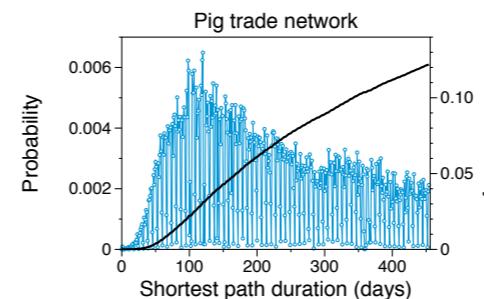
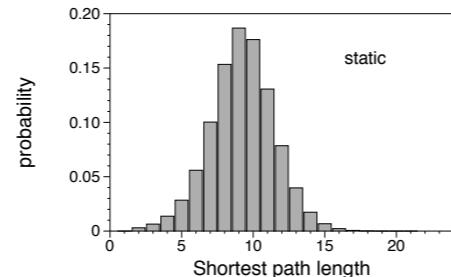
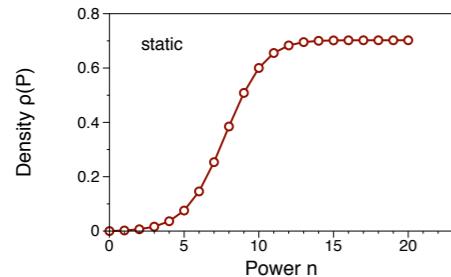
network



perspective:
accessibility

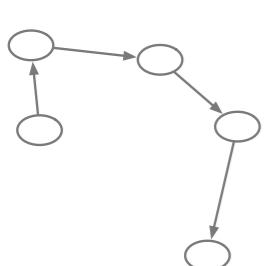


path lengths/durations

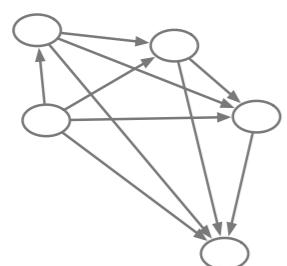


recap.

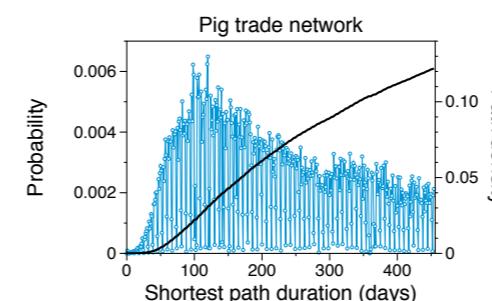
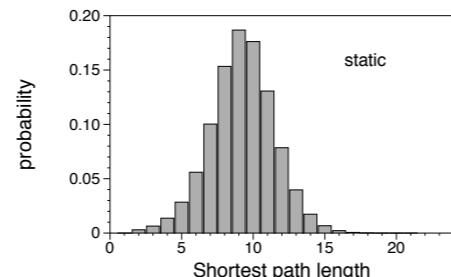
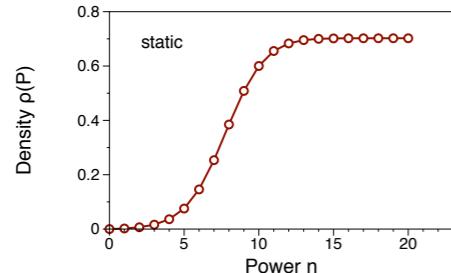
network



perspective:
accessibility



path lengths/durations



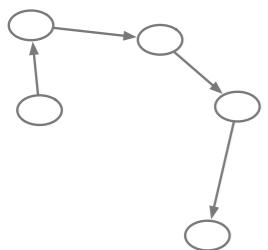
**causal
fidelity**

**temporal
accessibility**

$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$

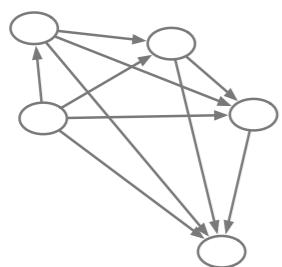
recap.

network

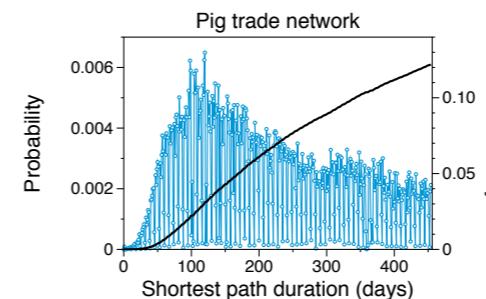
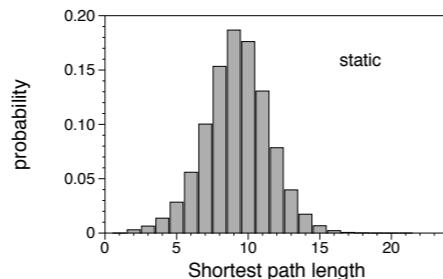
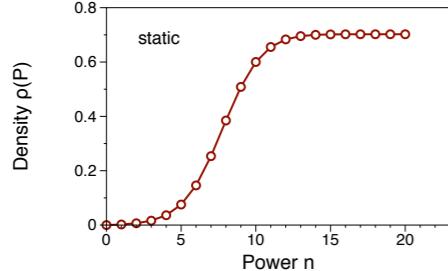


incidence
formulation

perspective:
accessibility



path lengths/durations



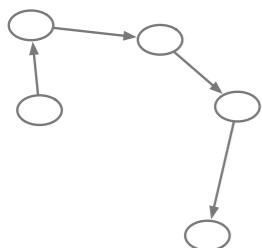
**causal
fidelity**

**temporal
accessibility**

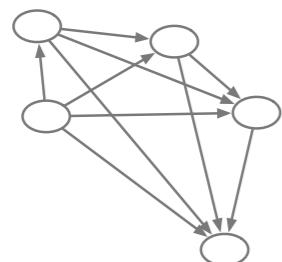
$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$

recap.

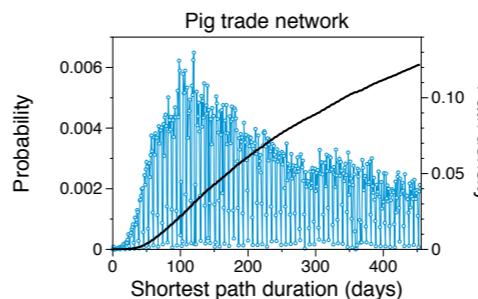
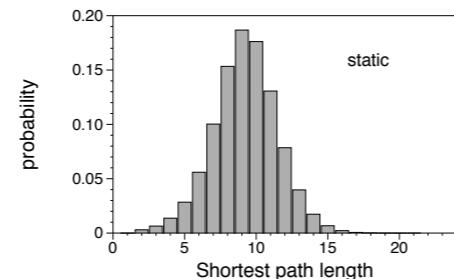
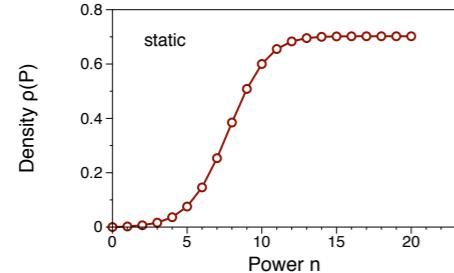
network



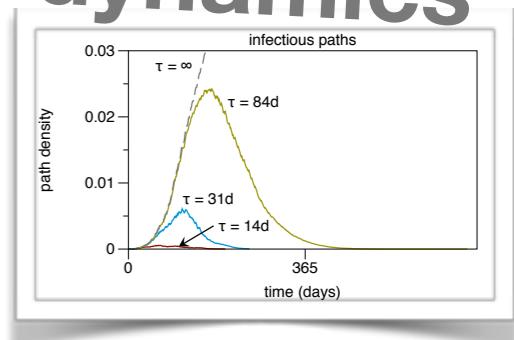
perspective:
accessibility



incidence
formulation



SIR
dynamics



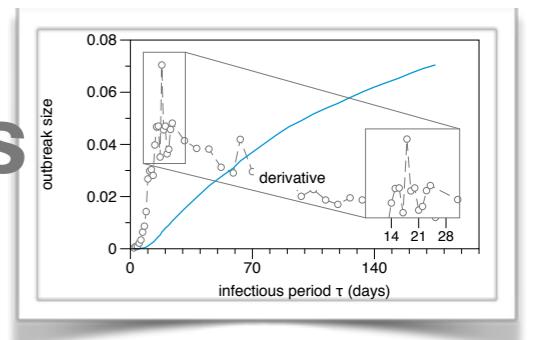
causal
fidelity

temporal
accessibility

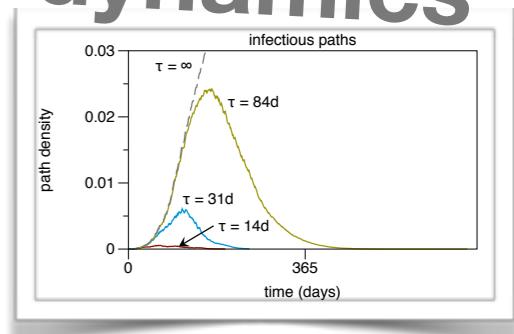
$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$

recap.

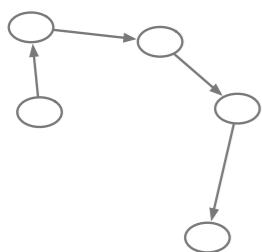
critical infectious period



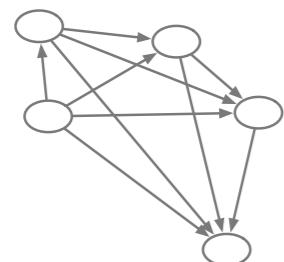
SIR dynamics



network

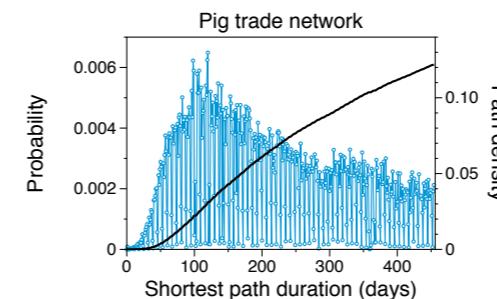
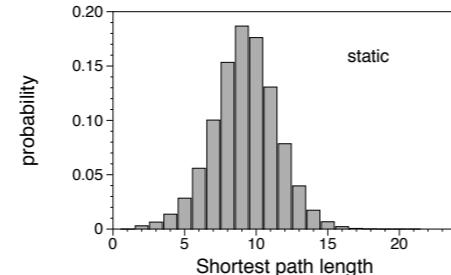
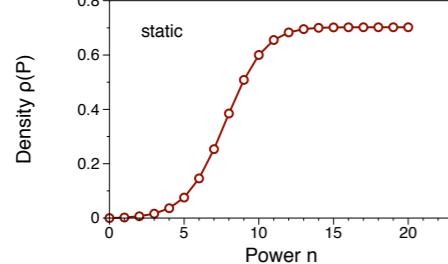


perspective:
accessibility



incidence formulation

path lengths/durations



causal fidelity

temporal accessibility

$$\mathcal{P}_n = \prod_{i=1}^n (\mathbf{I} + \mathbf{A}_i)$$

papers.

Unfolding Accessibility provides a
Macroscopic Approach to
Temporal Networks

Hartmut H K Lentz et al.
Phys. Rev. Lett, 2013

Infections on Temporal Networks—
A Matrix-Based Approach

Andreas Koher et al.
PLOS ONE, 2016

Disease Spread through Animal
Movements

Hartmut H K Lentz et al.
PLOS ONE, 2016