

Part II

DYNAMIC NETWORK ANALYSIS

Jose Pablo Gomez¹, Jerome Baron², Shadira Gordon¹

¹Center for Animal Disease Modeling and Surveillance, Department of Medicine & Epidemiology, School of Veterinary Medicine, University of California, Davis

²National Veterinary Institute of Sweden, Department of Epidemiology and Disease Control

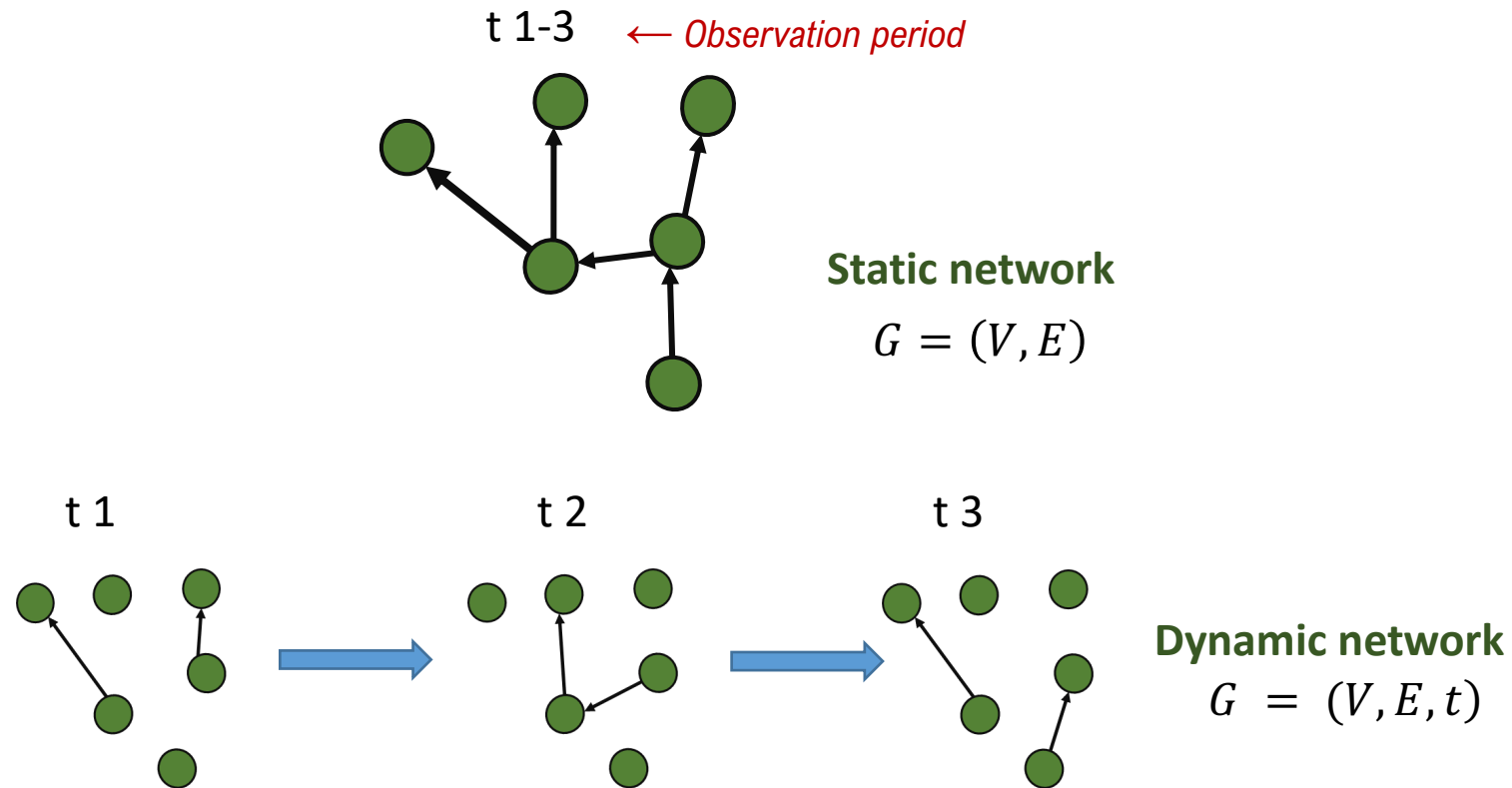
- Emails: jngo@ucdavis.edu, jerome.baron@sva.se

<https://cadms.vetmed.ucdavis.edu/>

Outline

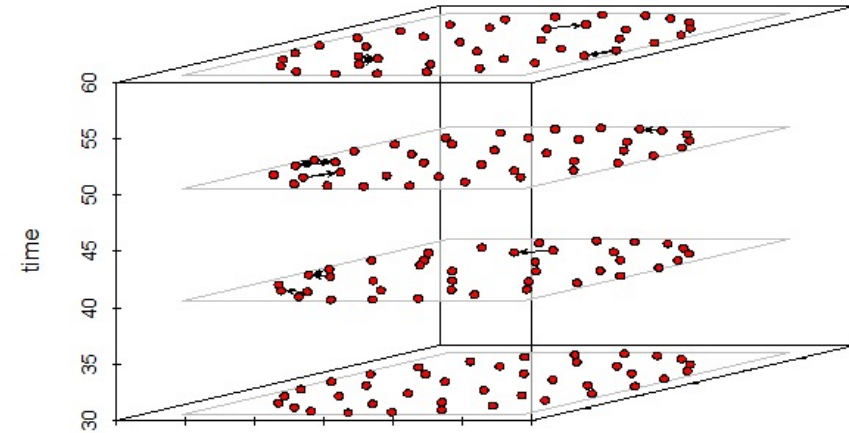
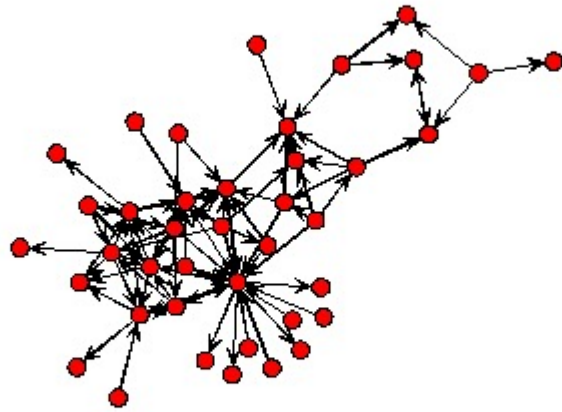
- Static vs Dynamic network analysis
- Dynamic network statistics
- Considerations and limitations

Whats the difference between Static and Dynamic analysis?



Network topology changes over time

Why dynamic networks?

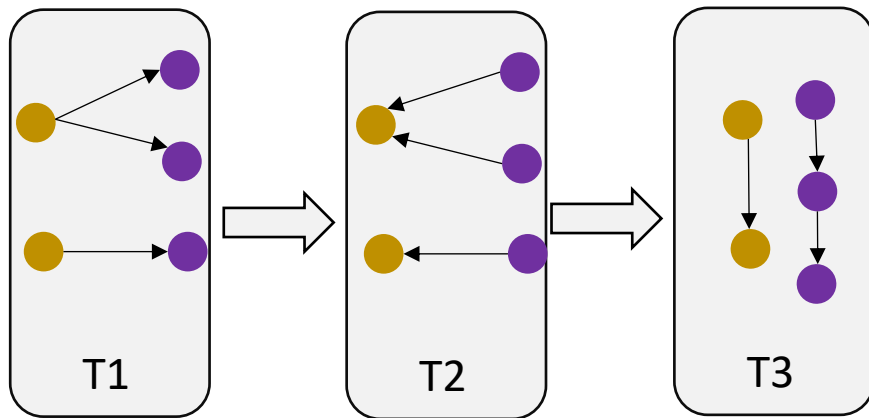


Why is interesting in epidemiology?

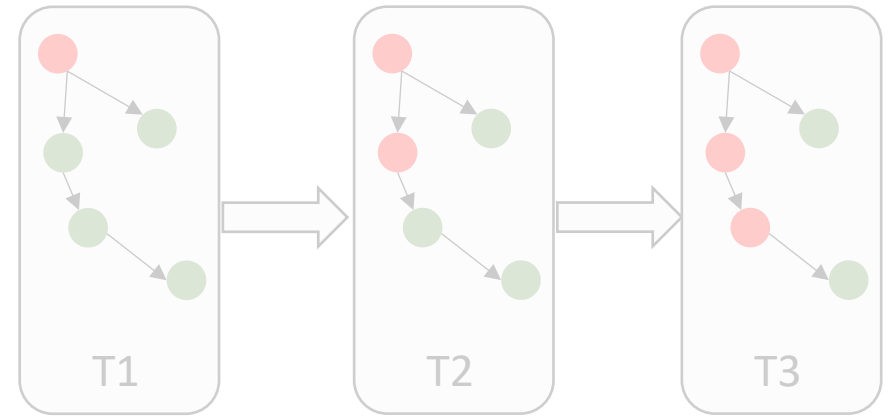
- Contact patterns are usually influenced by extrinsic events (weather conditions, demand, production cycles, etc..)
- Disease transmission has a linear process.
- A static network will always contain edges that were not necessarily present at the time when a transmission event occurred, which could be important for estimating the transmission rates.

Network dynamics in epidemiology

Changes on the structure



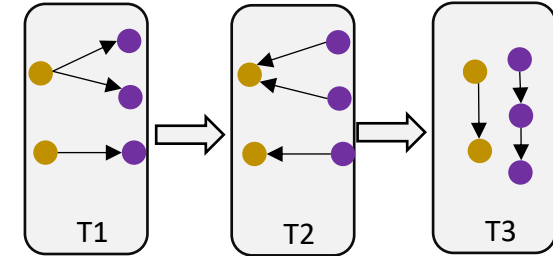
Study disease transmission



DNA for Changes in the network structure

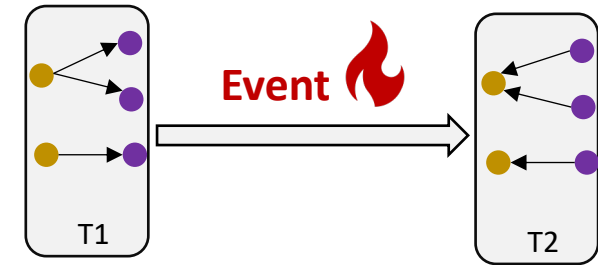
Understanding the evolution of the network over time:

As the environment changes, so does the social behavior of individuals.



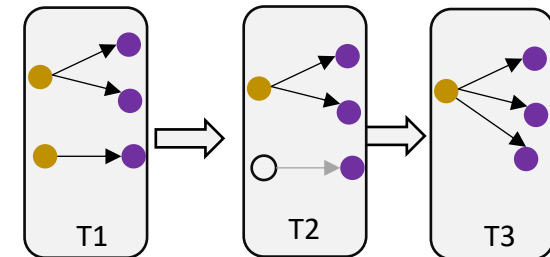
Understanding how changes in the environment impact the network structure:

Environmental changes such as drought, fires, floods, etc. can have an impact on the way individuals interact.



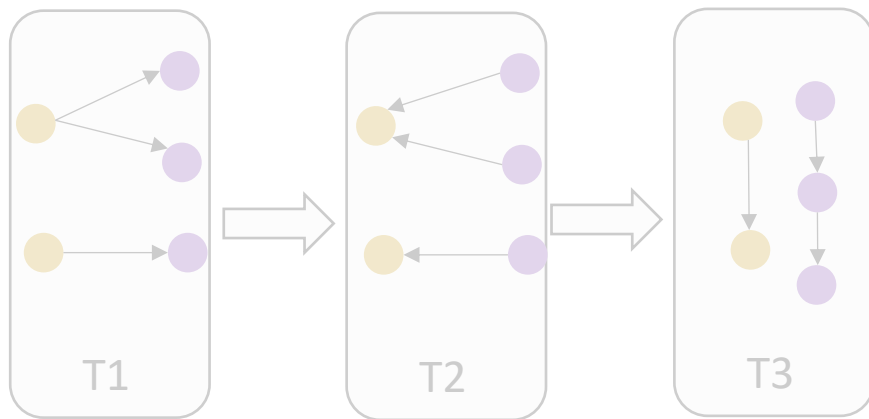
Understanding how changes in individual traits impact the network structure:

Presence or absence of particular individuals can impact the structure of interactions.

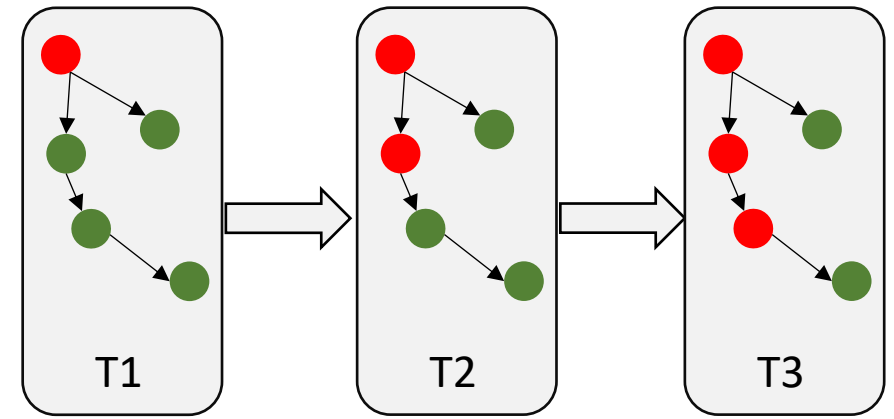


Network dynamics in epidemiology

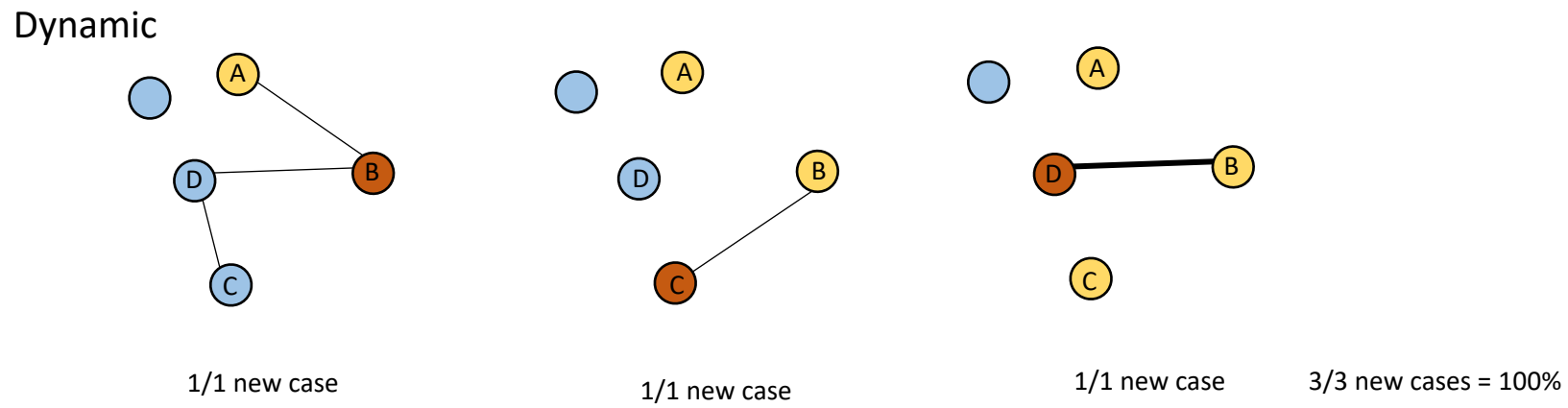
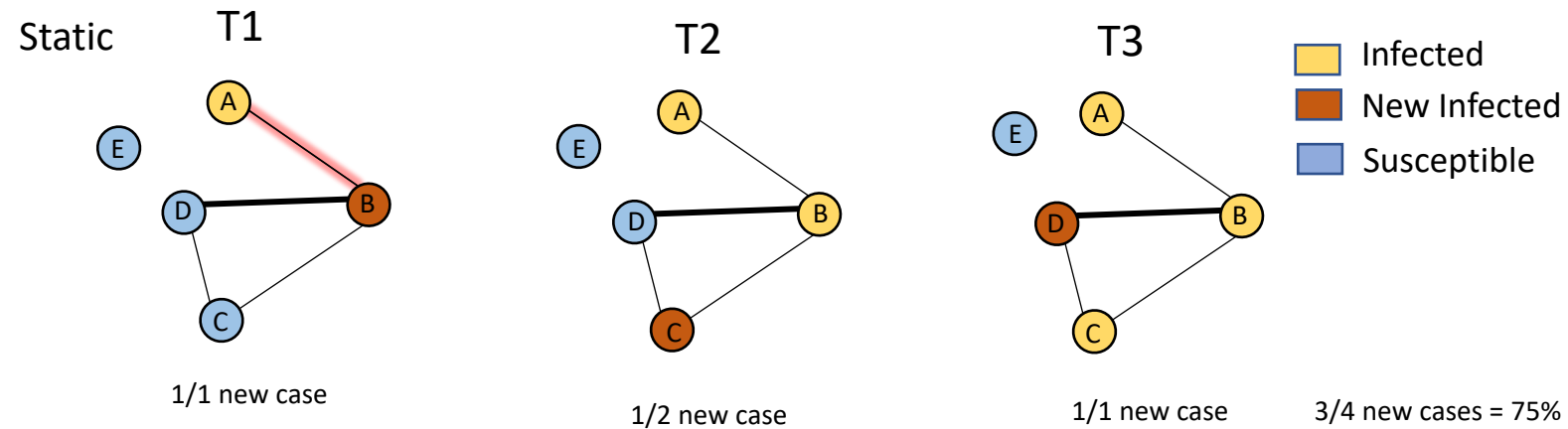
Changes in the structure



Disease transmission



Understand an observed epidemic

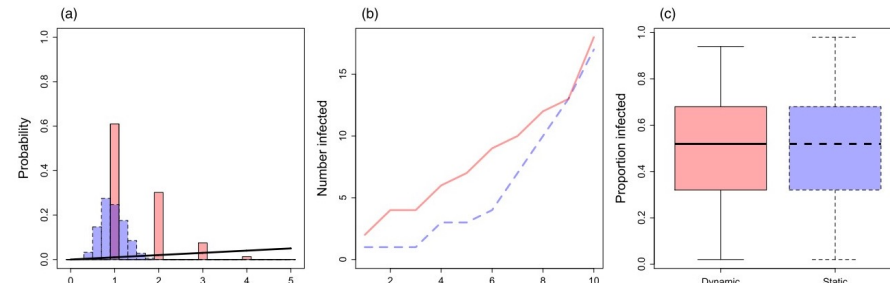


From Damien 2017

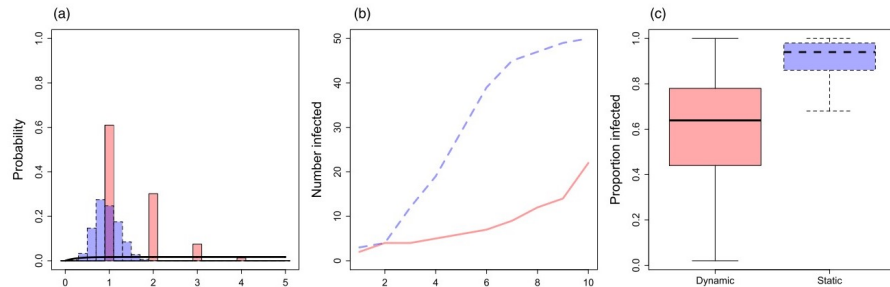
Making general predictions

- A well designed study that uses DN at a **temporal scale that matches the epidemic transmission** profile will generate the most accurate conclusions.

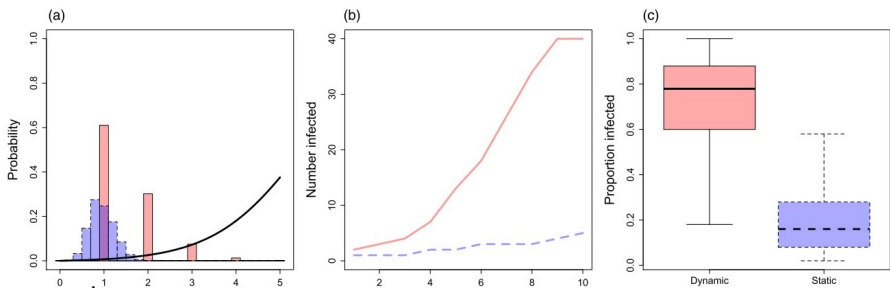
Linear function



Decelerating function



Accelerating function



Transmission rate x Contact strength = Edge weight

Making general predictions

- When the goal of modelling is to make general predictions such as the epidemic size rather than the pathway it takes, SN is often a better representation of the average population

Is the observed dynamic network likely to re-occur?

Same order of contacts?

Same period of time between contacts?

Other things to consider

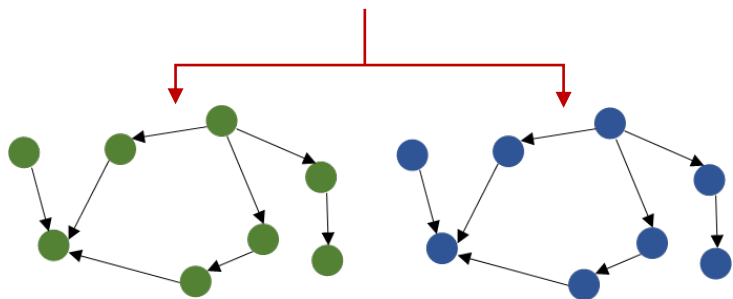
- Is there enough data available to construct each of the temporal snapshots of the network?
- Equal sampling efforts during the study period?

Dynamic Network Statistics

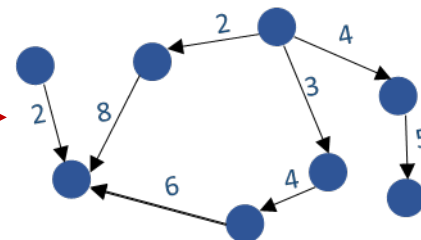
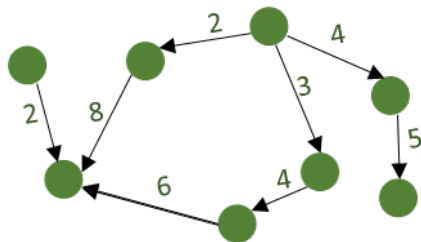
How do we know if a network is likely to re-occur?

Network isomorphism

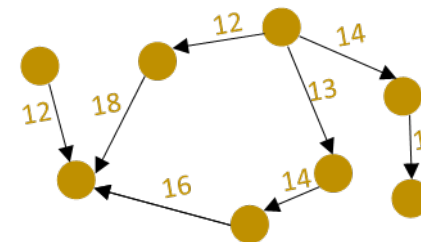
Same adjacency structure



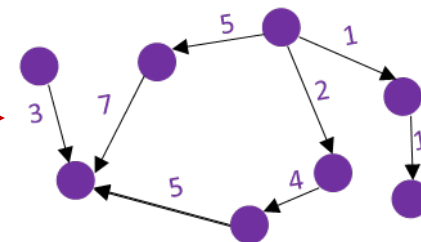
Identify patterns



Strictly isomorphic

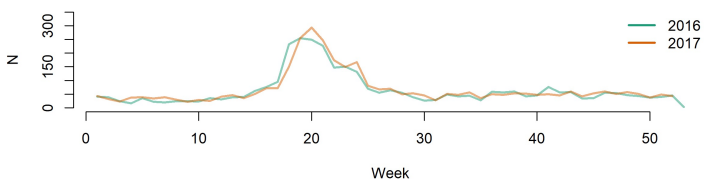


Temporally isomorphic

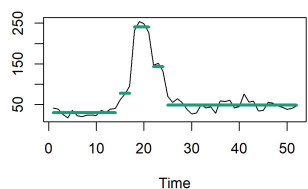


Temporal order isomorphic

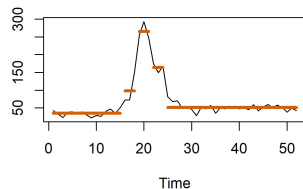
Movements to Pasture (Out of State)



2016

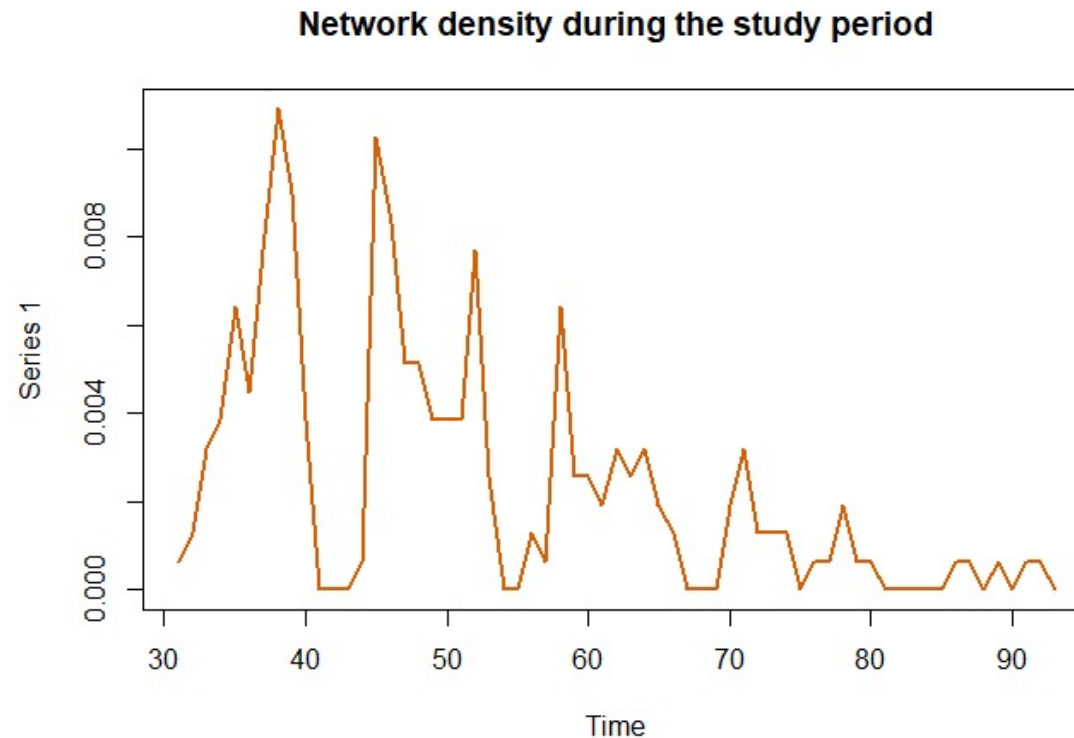


2017



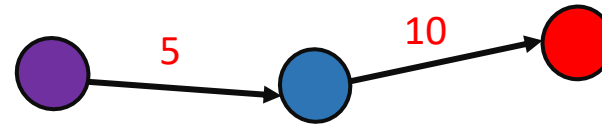
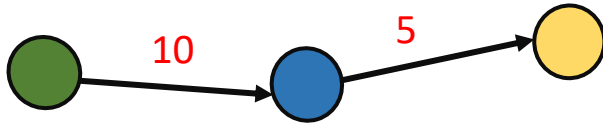
Why Dynamic network analysis?

- Centrality measures and network statistics used in static networks can be adapted for dynamic network analysis.



Temporally reachable sets

Temporally reachable sets



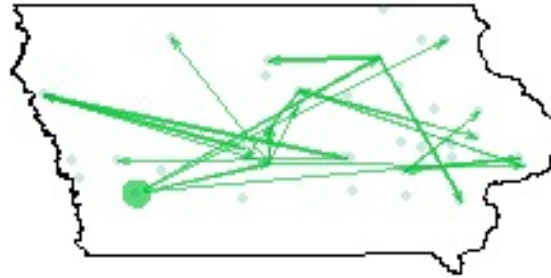
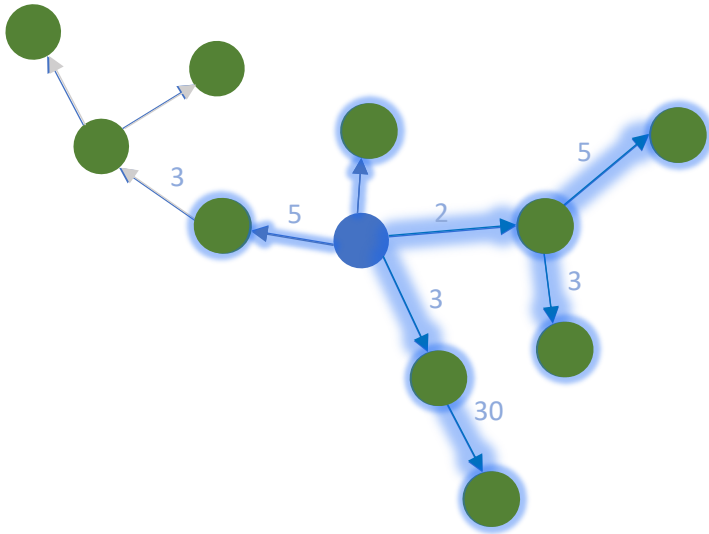
The temporally reachable set of a node, represents the set of other nodes that can be reached following a temporal path.

Temporally reachable sets

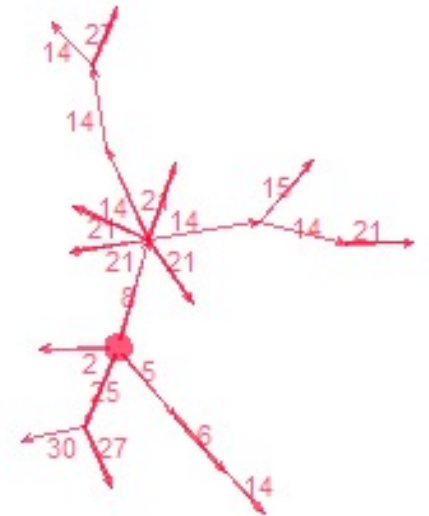
$e_1 = (i, j, t_1, \delta t_1)$ **Event 1**

$e_2 = (j, k, t_2, \delta t_2)$ **Event 2**

$i \rightarrow j \rightarrow k$ **If** $t_2 > t_1 + \delta t_1$

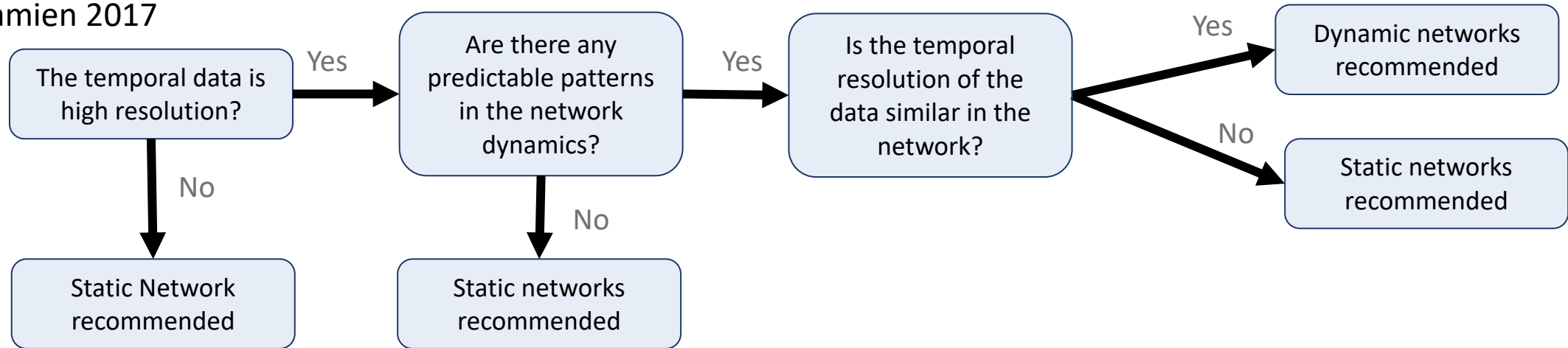


Reachability of Farm 23



Recap

Damien 2017



Limitations

- Time resolution will have an impact on our analysis
- When using dynamic network analysis for modeling or prediction we have to consider how likely is that the observed network will happen again.
- Implementing DN adds complexity to the model, can reduce generality and overinflate the perceived quality of predictions.

Questions?

Time for Lab 3!

[CADMS](#)[Home](#)[Pre Workshop ▾](#)[Contact ▾](#)[1 Exploratory analysis](#)[2 Species range maps](#)[3 Defining the network:](#)

Lab 3

In this section we will use a different dataset which consist on GPS locations of 3 different species.

We will define our contact network based on proximity between two animals from the GPS location records.

1 Exploratory analysis

```
# libraries we will use
library(dplyr) # for data manipulation
library(sf) # For spatial data manipulation
library(sp) # for spatial data
library(ggplot2) # for making figures
library(purrr) # for network transformation
library(tidygraph) # for network manipulation
library(ggraph) # for plotting networks
# We get the data from the STNet package
GPSc <- STNet::GPSc
```

First we will see how many locations were recorded during the observation period by species:

```
GPSc %>%
  count(species_type) # count by species
```

```
##   species_type    n
## 1      cattle  9309
## 2       deer 11511
## 3        pig  4428
```

Now lets create a dataset for the nodes.

```
Nodes <- GPSc %>%
  mutate(CollarID = as.character(CollarID)) %>% # convert to character
  distinct(CollarID, species_type) # unique IDs
```

Further applications

**CENTER FOR ANIMAL DISEASE MODELING AND SURVEILLANCE (CADMS),
SCHOOL OF VETERINARY MEDICINE, UC DAVIS**

**Jose Pablo Gomez*, Jerome Baron,
Shadira Gordon**

Center for Animal Disease Modeling and Surveillance (CADMS)
Department of Medicine & Epidemiology
School of Veterinary Medicine
University of California, Davis

* Presenter: Email: jpgo@ucdavis.edu
<https://cadms.vetmed.ucdavis.edu>



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Outline

- Statistical Models
- Simulation Models

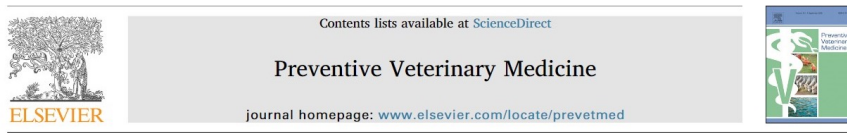
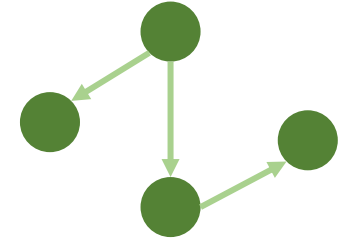
Network Analysis and Regression

Regression assumptions:

- Linearity
- Independence
- Normality
- Equal variance



SNA recognize the influence of community members on each other.



Evaluation of the impact of live pig trade network, vaccination coverage and socio-economic factors in the classical swine fever eradication program in Peru

J.P. Gómez-Vázquez^{a,*}, M. Quevedo-Valle^{b,1}

^a Center of Animal Disease Modeling and Surveillance (CADMS), Department of United States

^b Dirección de Sanidad Animal SENASA, Lima, Peru



Unraveling the contact patterns and network structure of pig shipments in the United States and its association with porcine reproductive and respiratory syndrome virus (PRRSV) outbreaks

Kyuyoung Lee^{a,*}, Dale Polson^b, Erin Lowe^b, Rodger Main^c, Derald Holtkamp^c, Beatriz Martínez-López^a

^a Center for Animal Disease Modeling and Surveillance (CADMS), Department of Medicine and Epidemiology, School of Veterinary Medicine, University of California, Davis, CA, USA

^b Boehringer - Ingelheim Vetmedica, Inc., St. Joseph, MO, USA

^c Veterinary Diagnostic and Production Animal Medicine, College of Veterinary Medicine, Iowa State University, Ames, IA, USA

Multilevel Logistic Regression for Repeated measures

$$y_{ij} \sim \text{Binomial}(n_{ij}, \pi_{ij})$$

$$\text{logit}(\pi_{ij}) = \beta_{0j} + \beta_1 X_{1ij} + \beta_2 X_{2ij} \cdots \beta_n X_{nij} + \mu_j$$

y_{ij} : Occurrence of the event i at time j

π_{ij} : Expected probability of PRRS occurrence

β_{0j} : The intercept

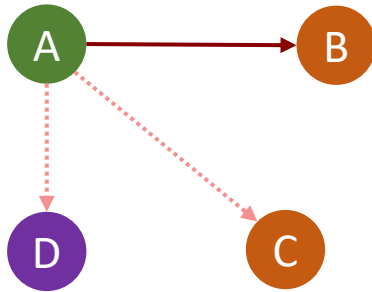
$\beta_1, \beta_2, \cdots \beta_n$: The slopes

μ_j : The random effect

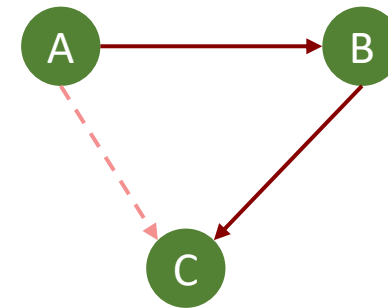
ERGMs

- **Exponential Random Graph Models:** Predicting dichotomous ties. What is the probability of observing our network?
- Evaluate a cross sectional structure

Individual covariates: are sow farms more likely to contact GDUs?



Network structure: If Farm A contacts Farm B, and Farm B contacts Farm A, what are the chances of farm A contacting Farm B? (Triangles formations)



Exponential Random Graph Models

```
## =====
## Summary of model fit
## =====
##
## Formula:  n ~ edges + mutual
##
## Iterations:  2 out of 20
##
## Monte Carlo MLE Results:
##      Estimate Std. Error MCMC % p-value
## edges   -1.7634     0.2047      0 <1e-04 ***
## mutual    2.3290     0.4154      0 <1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*'
0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 424.2  on 306  degrees of
freedom
## Residual Deviance: 332.3  on 304  degrees of
freedom
##
## AIC: 336.3    BIC: 343.7    (Smaller is
better.)
```

RESEARCH ARTICLE

Modeling the live-pig trade network in Georgia: Implications for disease prevention and control

Esther Andrea Kukiella¹*, Beatriz Martínez-López¹, Daniel Beltrán-Alcruo²

¹ Center for Animal Disease Modeling and Surveillance (CADMS), Department of Medicine & Epidemiology, School of Veterinary Medicine, University of California, Davis, California, United States of America, ² Food and Agriculture Organization, FAO Budapest, Hungary

© These authors contributed equally to this work.

* ekukielka@ucdavis.edu

$$P(Y_{ij} = 1|y_{ij}^c) = \ln \frac{P(Y = 1|y_{ij}^c)}{P(Y = 0|y_{ij}^c)} = \theta' \delta(g(y))_{ij}$$

Y_{ij} is the random variable for the state of the actor pair i,j

y_{ij}^c is the compliment for y_{ij} (All the dyads in the network other than y_{ij})

$\delta(g(y))_{ij}$ equals $g(y_{ij}^+) - g(y_{ij}^-)$, where:

$g(y_{ij}^+)$ is defined as y_{ij}^c along with y_{ij} set to 1

$g(y_{ij}^-)$ is defined as y_{ij}^c along with y_{ij} set to 0

$g(y)$ is the statistic of the model and $\delta(g(y))$ the change statistics for actor pair y_{ij}

Transboundary and Emerging Diseases



ORIGINAL ARTICLE

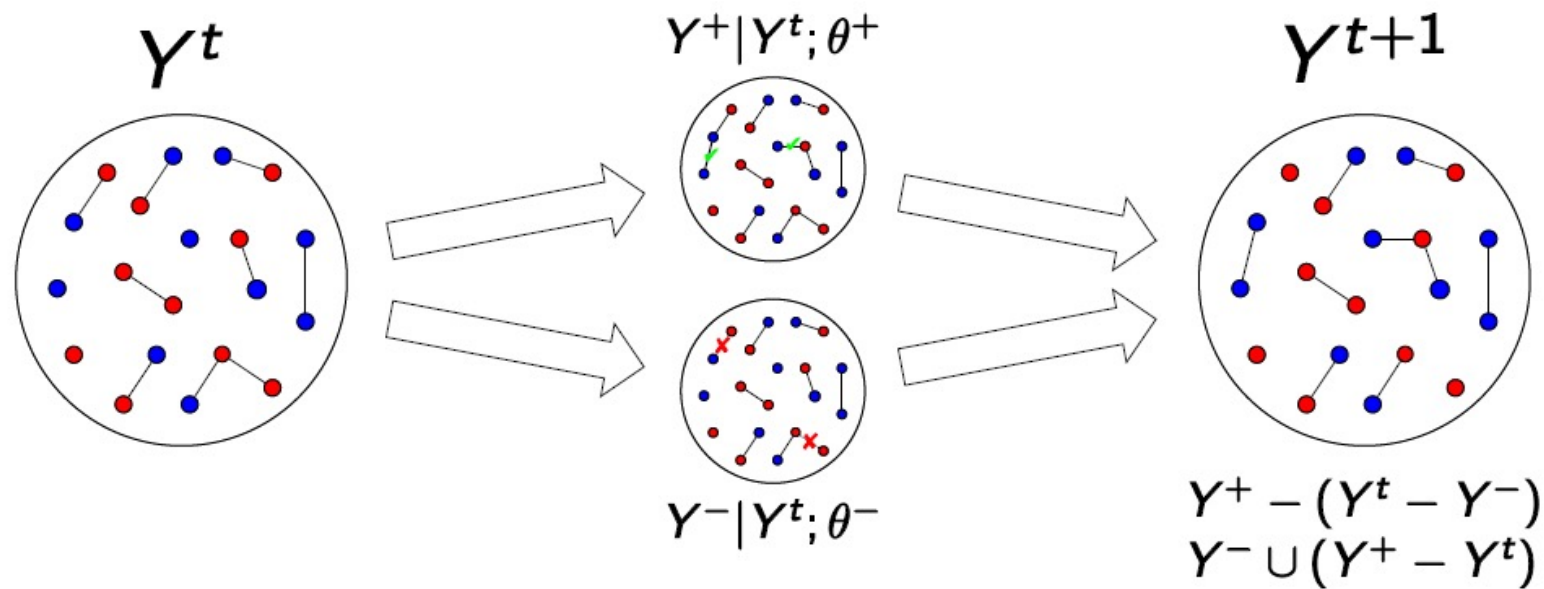
Application of exponential random graph models to determine nomadic herders' movements in Senegal

Jaber Belkhiria✉, Modou Moustapha Lo, Fafa Sow, Beatriz Martínez-López, Veronique Chevalier

First published: 08 April 2019 | <https://doi.org/10.1111/tbed.13198> | Cited by: 1

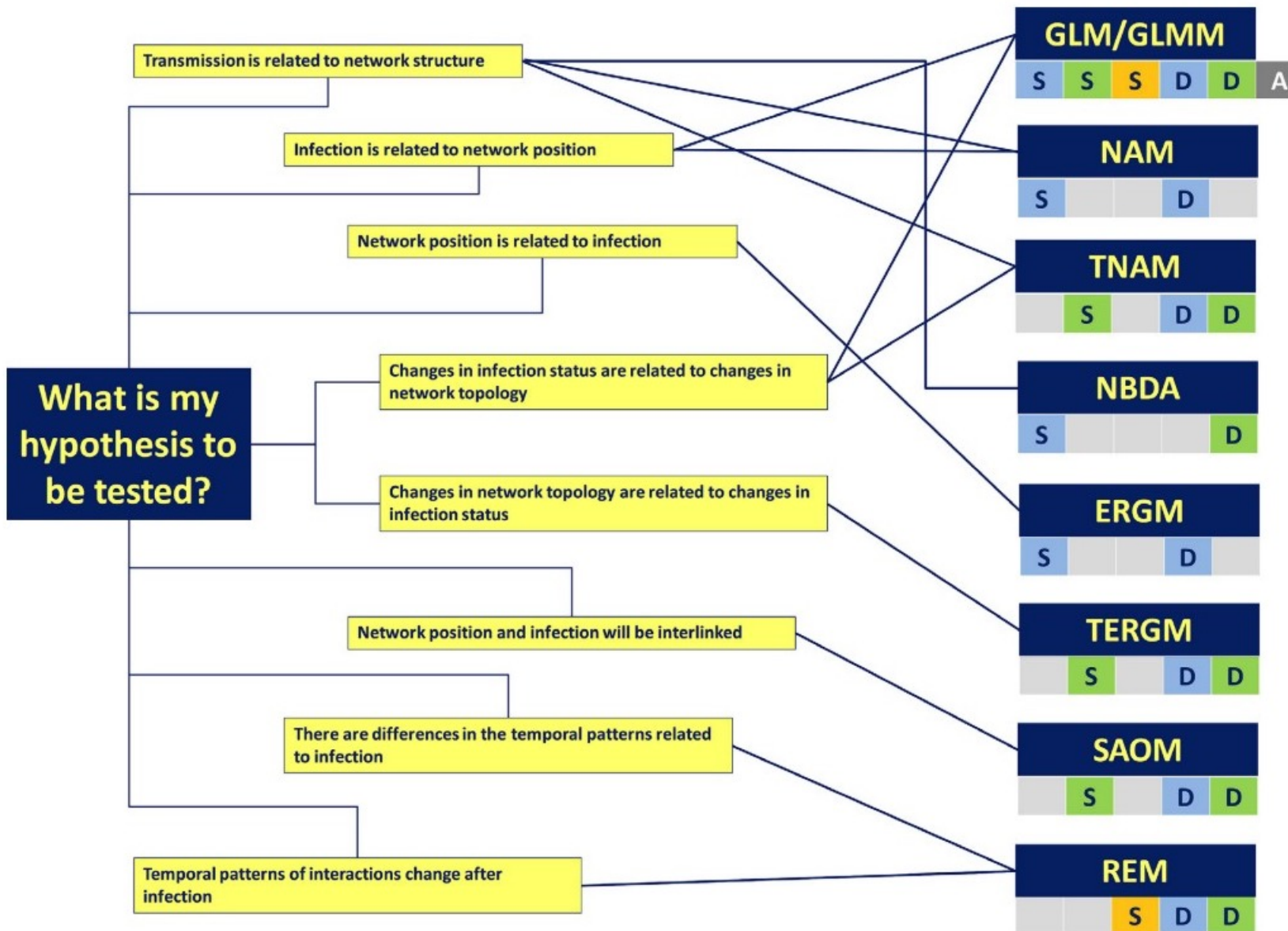
STERGMs

Separable Temporal ERGM



Y^+ = network in the formation process after evolution
 Y^- = network in the dissolution process after evolution
This is the origin of the “S” in STERGM

Statistical Models in Network Analysis



GLM Generalized linear model
GLMM Generalized linear mixed model
NAM Network autocorrelated model
TNAM temporal autocorrelated model
ERGM exponential random graph model
NBDA Network based diffusion analysis
SAOM stochastic actor-oriented model
TERGM Temporal ERGM
REM Relational events model

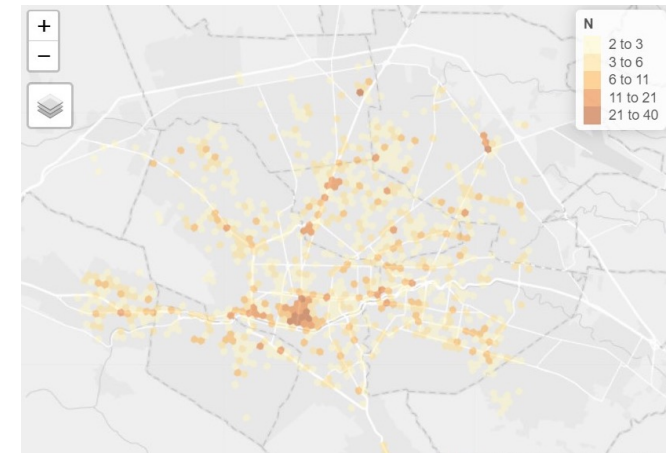
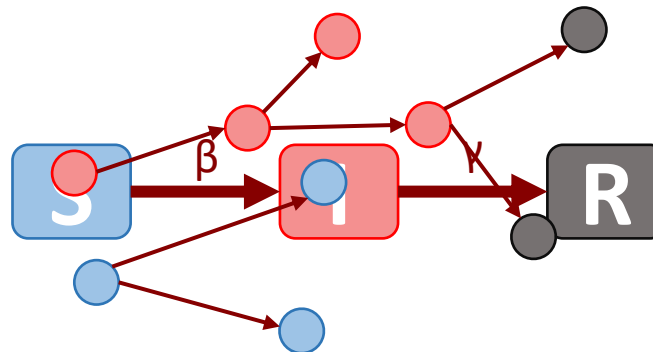
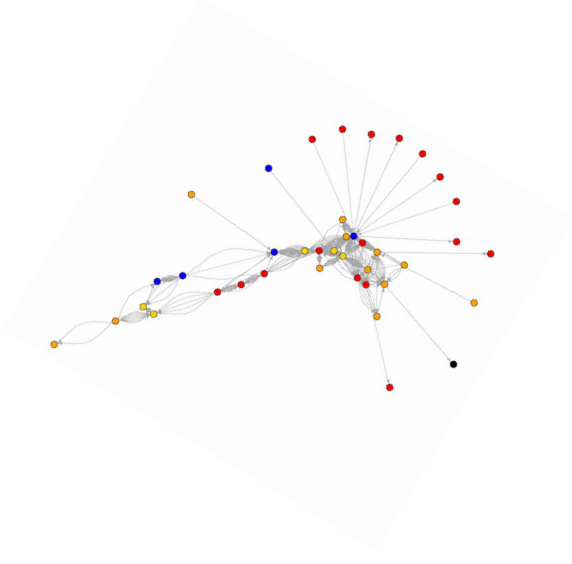
Network data	
S	Static network
S	Temporal snapshots/aggregations
S	Temporally-explicit interaction data
A	Association-based data

What data am I using?

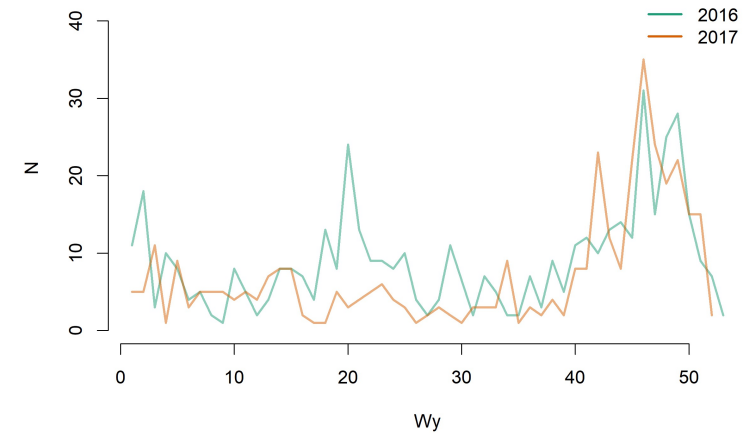
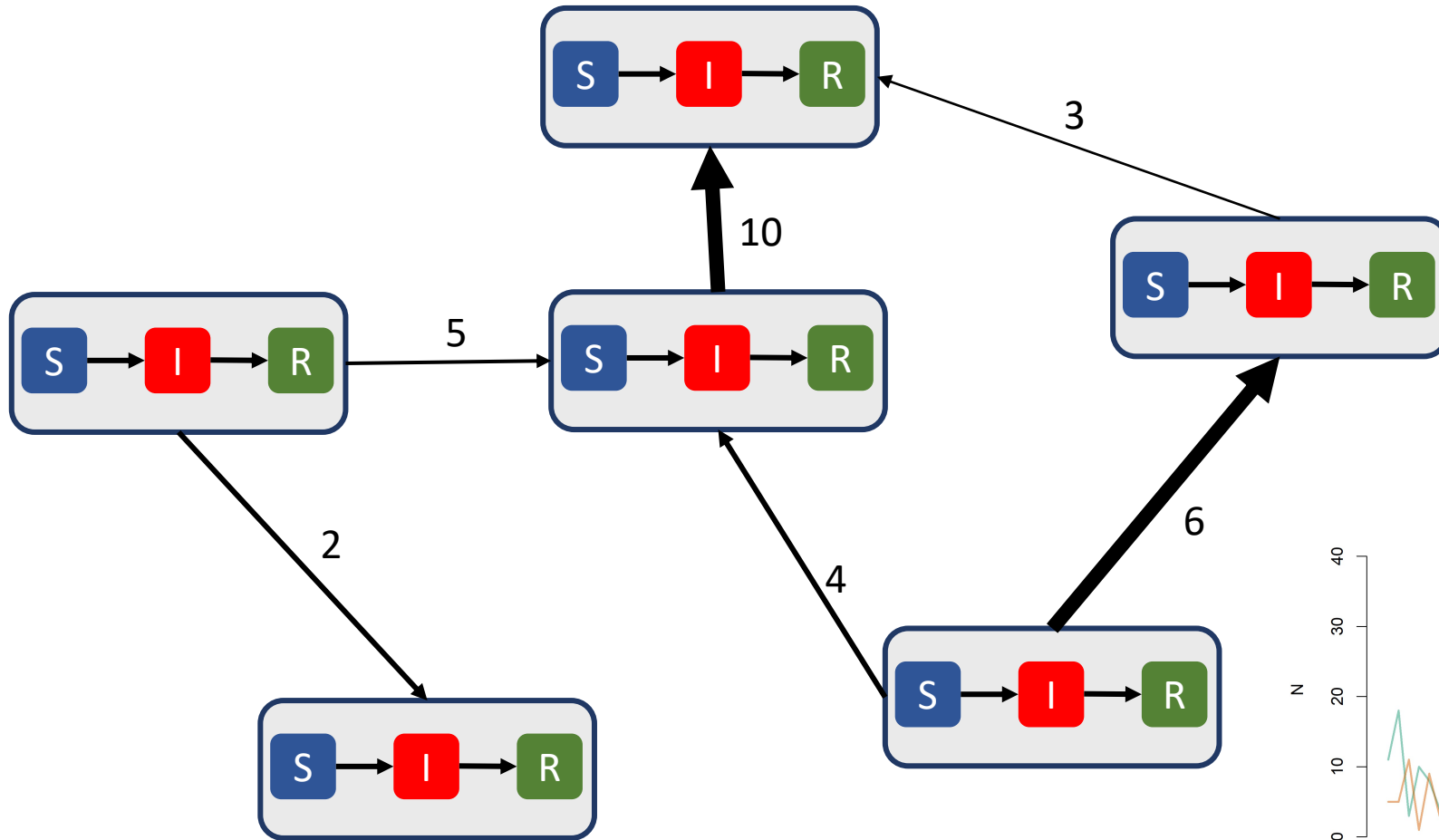
Disease data	
D	Presence/absence or infection load
D	Timing of changes in infection known

Disease spread models

- Most epidemic models incorporate homogenous mixing assumption (Law of mass action).
- This for some scenarios this assumption is unrealistic but simplifies the mathematical computation of the model.
- Populations are not homogeneously mixed, population structure can arise from spatial and social interactions.



Disease spread models



Disease spread models

- Using R:

- Statnet, <http://statnet.org/nme/index.html>
- GEMFsim <https://ece.k-state.edu/netse/software/index.html>

Using Agent-based models:



GAMA Platform

<https://gama-platform.github.io/wiki/Home>



NetLogo

<https://ccl.northwestern.edu/netlogo/>

GEMFsim implementations

Language	Author	Manual	Code
MATLAB	Faryad Sahneh	Matlab_Manual	MATLAB
Python	Heman Shakeri	Python_Manual	PYTHON
R	Aram Vajdi	R_Manual	R
C	Futing Fan	C_Manual	C
MATLAB	Haotian Wu	Animation_Manual	

Please email faryad@ksu.edu or caterina@ksu.edu if you are interested in GEMF

<http://contagion.principate.org/>

Questions?