Social influence models: Autologistic Actor Attribute Models (ALAAMs)

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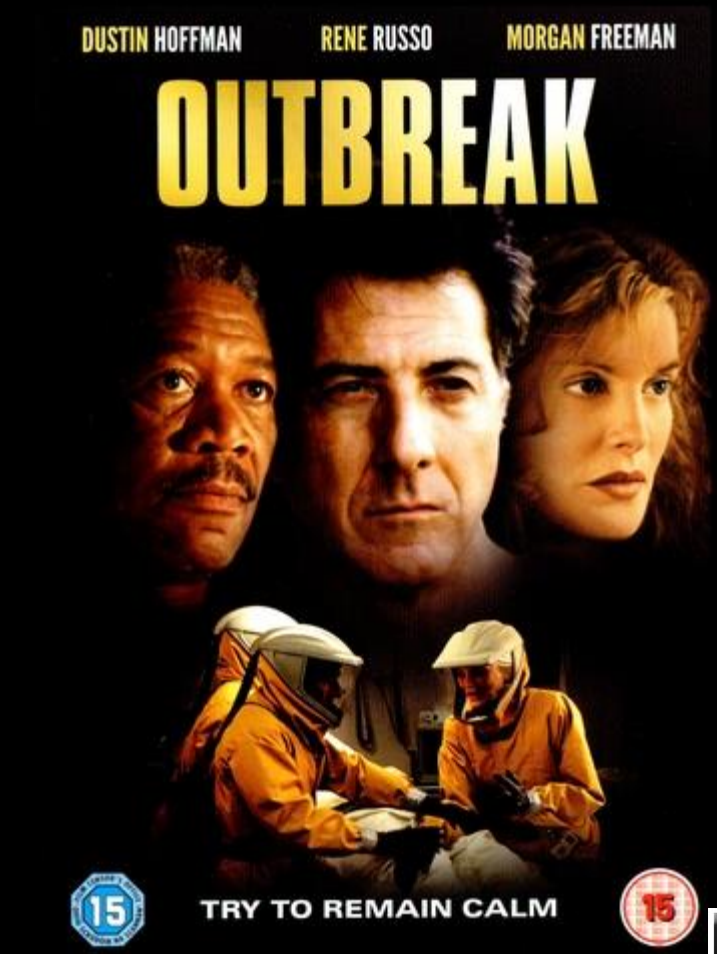
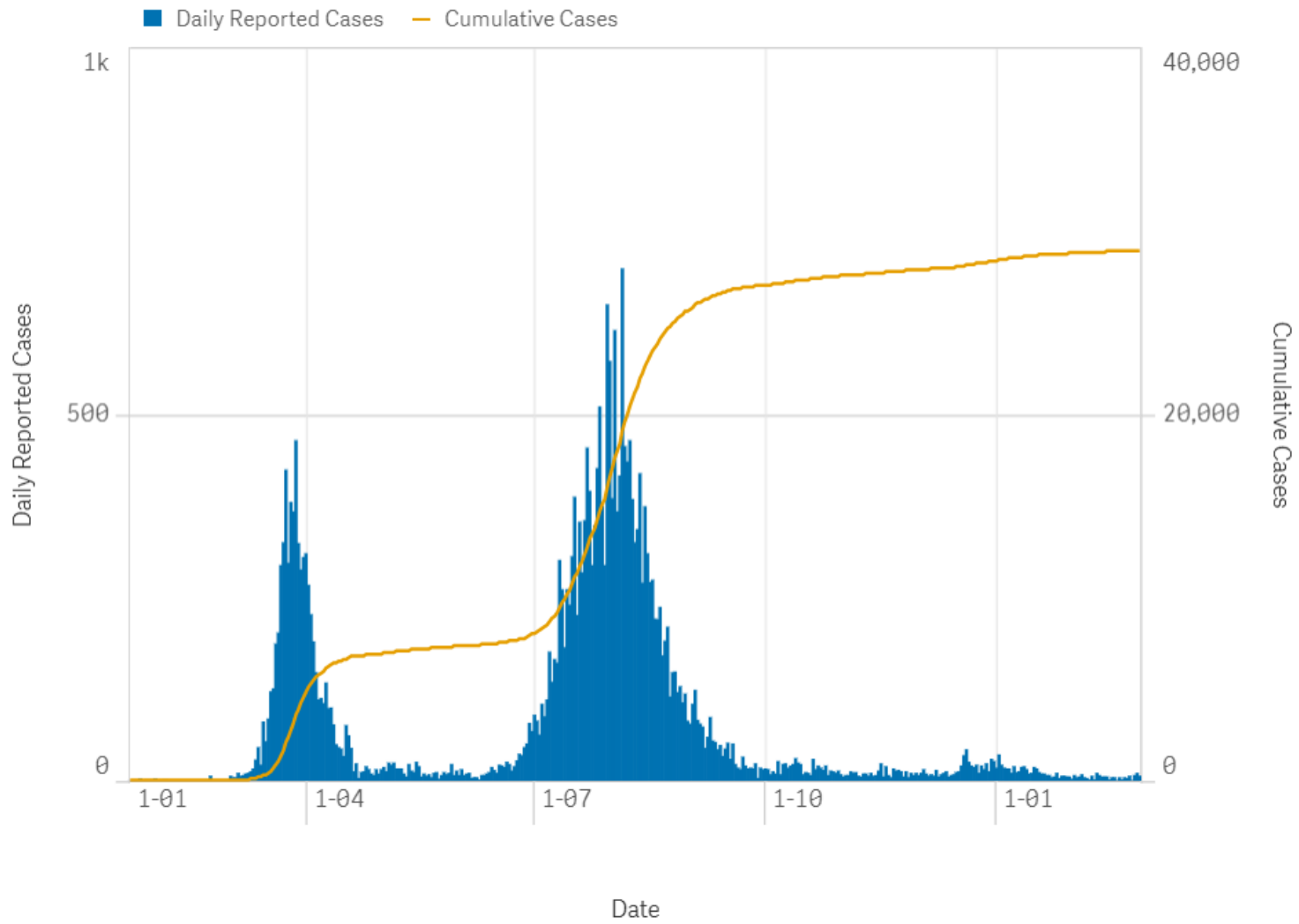
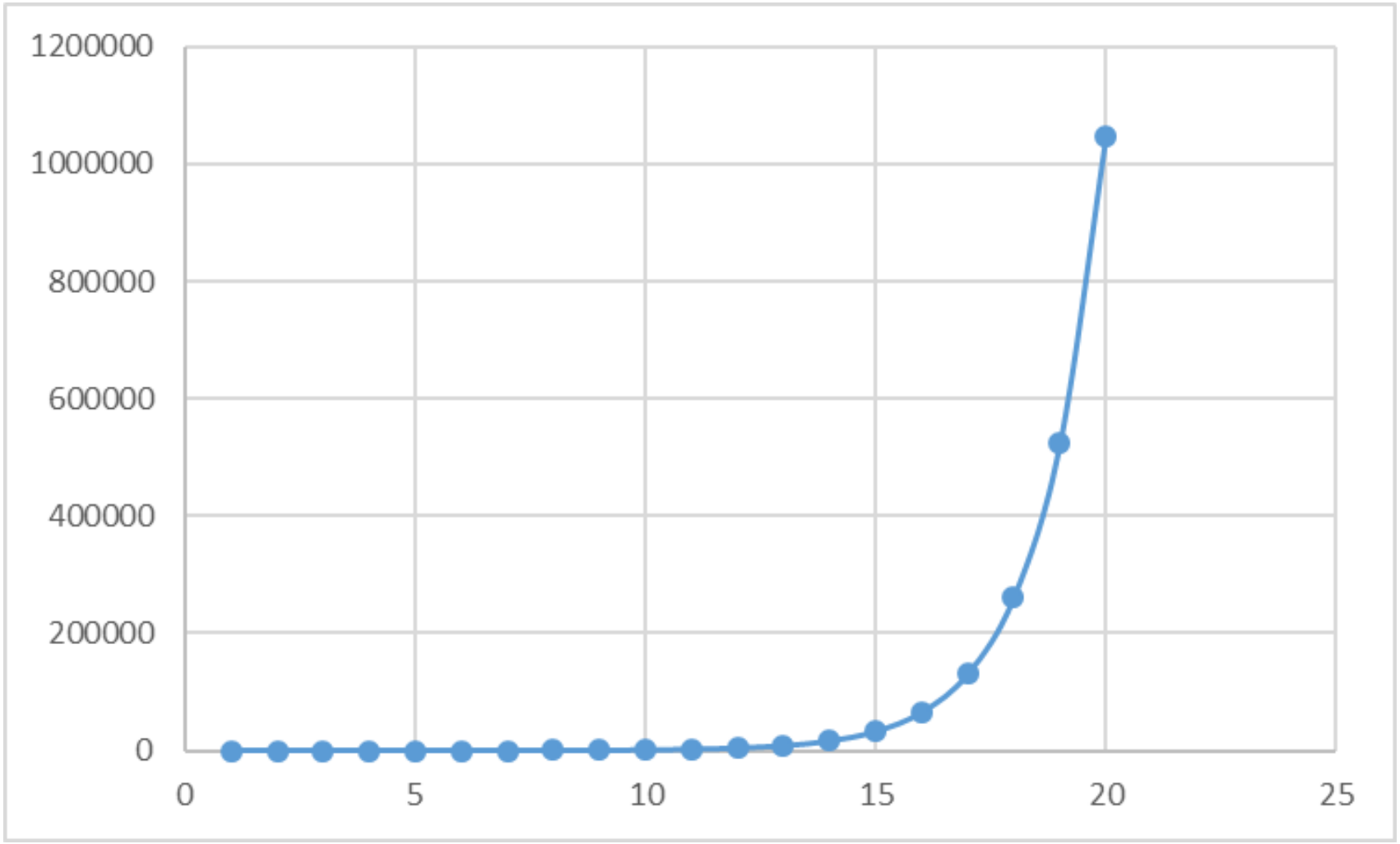


COVID-19 outbreak

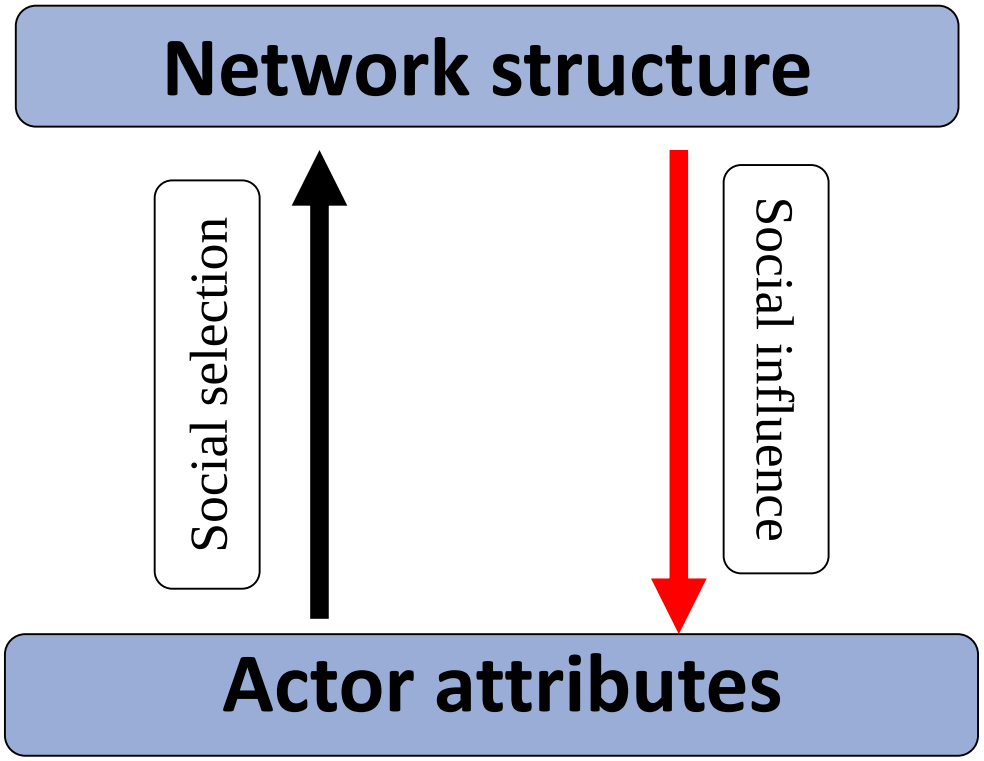
Source: Department of Health, States & Territories Report 27/2/2021



If everyone has 1 unique close contact…



Social dynamics



Network structure influences actor attributes at the same time as actors shape the structure of their behaviour (smoking behaviour, friendship)

MPNet: ERGMs and ALAAM

SIENA: stochastic actor-oriented models (SAOM)

Social influence
(Robins et al., 2001)

Questions: What explains emergence of outcomes of individuals?

- *Individual outcome self-organization*

  Attribute variables tend to be associated in particular ways

- *Network-level explanation*

  "Network position" can explain individual outcomes

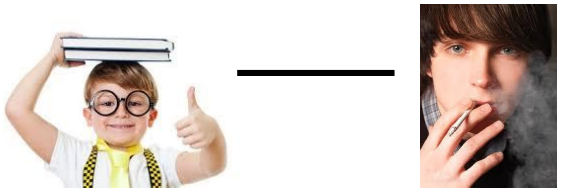
  dyadic social influence (contagion effect) – when people are influenced by their direct network connections

  generalised social influence – when people are influenced by their position in the network

Social influence

- SI models can:
  - Predict a binary variable from other individual level variables (logistic regression!)
- BUT ALSO…..
  - Network ties of varying configurations

  - Attributes of alters & network ties



  - Spatial
    - Optimise study

ALAAMs and ERGMs

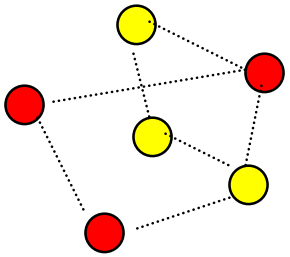
Auto-logistic models

- ALAAM is a node-based model
- Predicting behaviour
- Social influence
- Number of data points is the number of actors:
  - n

- ERGM is a tie-based model
- Predicting ties
- Social selection
- Number of data points is the number of possible ties:
  - $n(n\text{-}1)$

Snijders et al (2006) SAOM can do both simultaneously
But only with longitudinal data

ALAAMs



Here we regard the network as **fixed**, and treat the states of nodes (eg attitude, belief, behaviour) as (binary) variables

The node state variables are ***not*** assumed independent

Some potential effects (e.g. tendency for the state of an actor to depend on the state of a network partner) are assumed to be ***common*** across the system

The result is a ***model*** that can be estimated from an observation on the network and node state variables (and any covariates)

ALAAMs

$$\Pr(\mathbf{Y}=\mathbf{y}\mid\mathbf{X}=\mathbf{x})=\frac{1}{\kappa}\exp\left\{\sum_{Q}\lambda_{Q}z_{Q}\left(\mathbf{y}\right)+\sum_{R}\lambda_{R}z_{R}\left(\mathbf{x},\mathbf{y}\right)\right\}$$

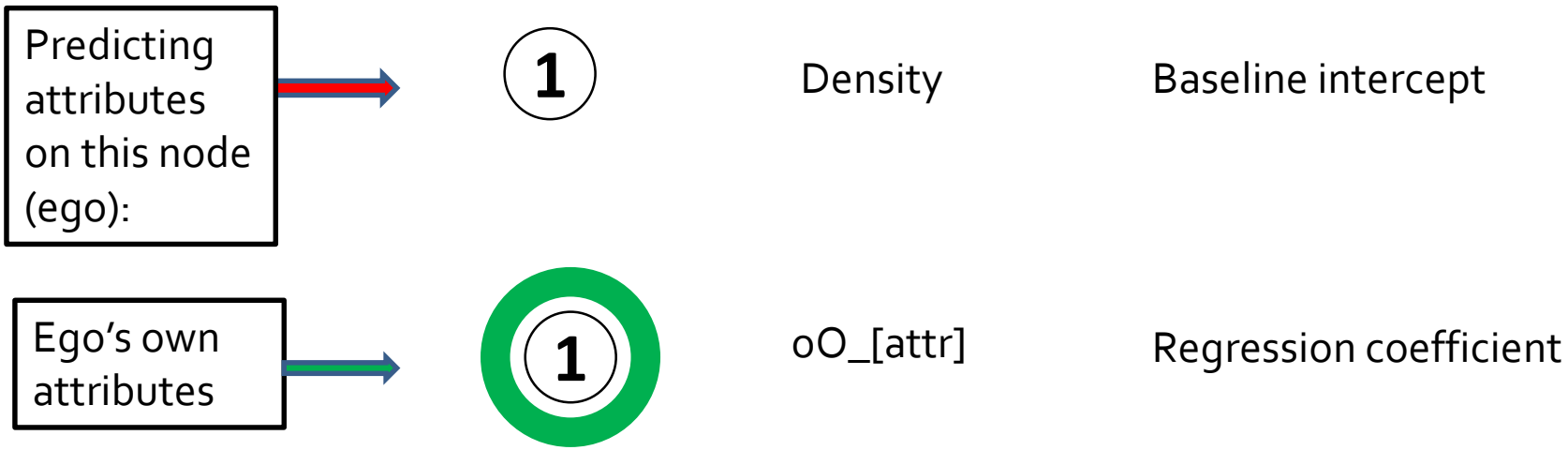
where

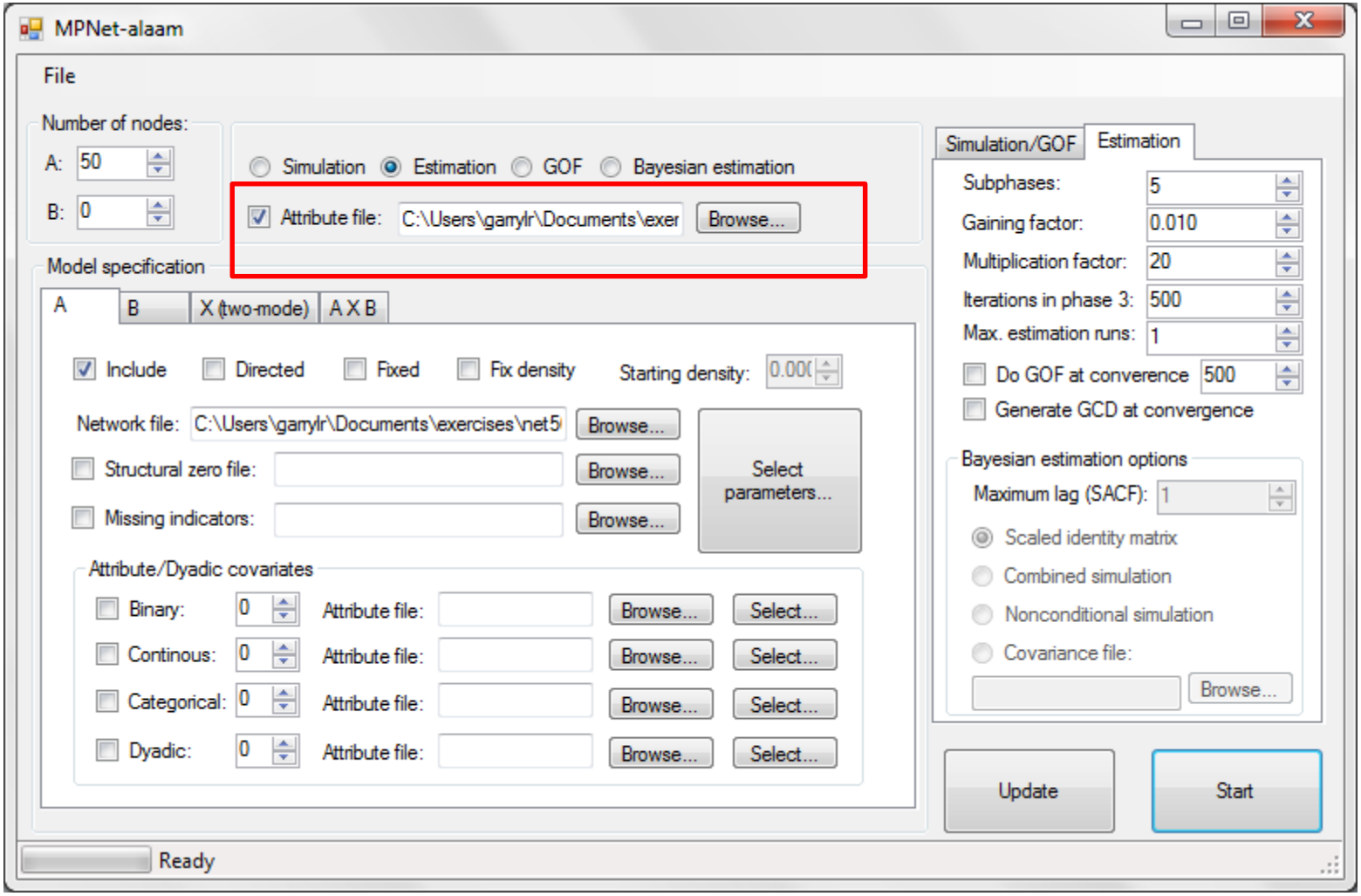
- $X = [X(i, j)]$ is a matrix of network tie variables, with realisations $x = [x(i,j)]$
- $Y = [Y(i)]$ is a vector of binary node attribute variables, with realisations $y = [y(i)]$
- $z_Q(y)$ and $z_R(x, y)$ are a network-attribute statistic (consistent with assumed dependence)
- λ is a corresponding parameter
- $\kappa(\theta) = \sum_{\mathbf{y}}\exp\{\sum\lambda z(y,x)\}$ is a normalising quantity

A model for the distribution of attributes, conditional on the observed network structure and other covariates.

ALAAM/Logistic regression configurations

Simple configurations:




MPNet-alaam
File
Number of nodes:
A: 50
B: 0
Simulation
Estimation
GOF
Bayesian estimation
Attribute file:
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Browse...
Model specification
A
B
X (two-mode)
A X B
Include
Directed
Fixed
Fix density
Starting density:
Network file:
C:\Users\garrylr\Documents\exercises\net5
Structural zero file:
Missing indicators:
Select parameters...
Attribute/Dyadic covariates
Binary:
Continous:
Categorical:
Dyadic:
Attribute file:
Select...
Simulation/GOF
Estimation
Subphases: 5
Gaining factor: 0.010
Multiplication factor: 20
Iterations in phase 3: 500
Max. estimation runs: 1
Do GOF at converence 500
Generate GCD at convergence
Bayesian estimation options
Maximum lag (SACF): 1
Scaled identity matrix
Combined simulation
Nonconditional simulation
Covariance file:
Update
Start
Ready

Characterising dependence: some possible assumptions

$Y(i)$ and $Y(j)$ are conditionally independent unless:

Distance 0

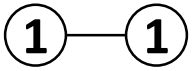
$\mathbf{D_0}$: *i and j are the same node*

$i = j$

Logistic regression model

Distance 1

$\mathbf{D_1}$: *i* is directly connected to *j*

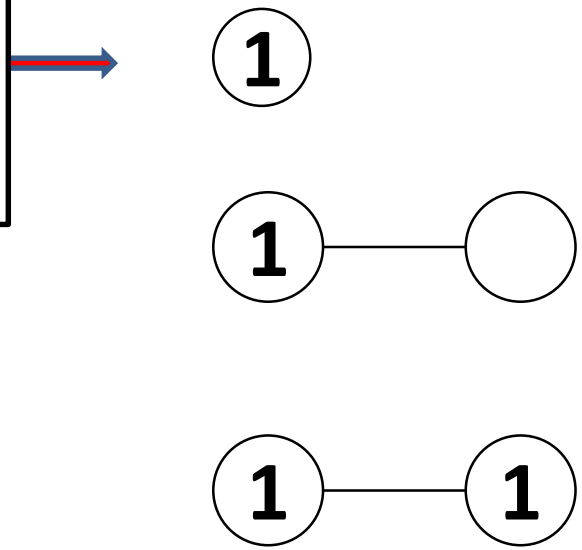


Autologistic regression – the model used here (Besag, 1974)

ALAAM configurations

Simple configurations:

Predicting attributes on this node (ego):



Density

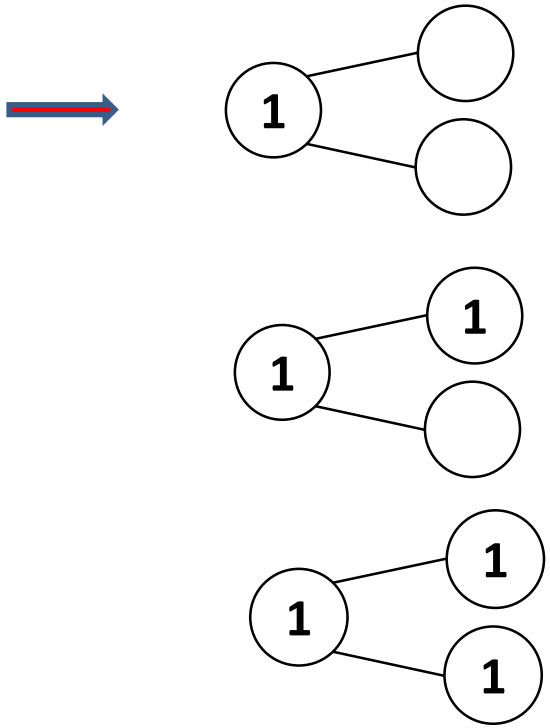
Activity (Having partners, whether they have the attribute or not)

Contagion (Having partners with the attribute)

ALAAM configurations

Star configurations:

Predicting attributes on this node (ego):



Ego-2star (Having many partners, irrespective of their attribute status)

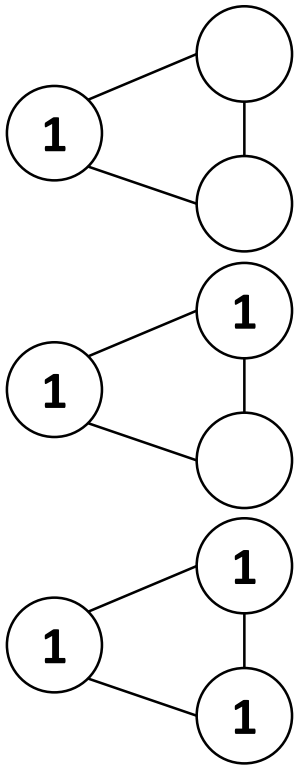
Alter-2star1 (Having partners, with a mix of attributes)

Alter-2star2 (Having many partners with the attribute)

ALAAM configurations

Triangle configurations:

Predicting attributes on this node (ego):

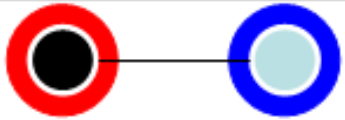


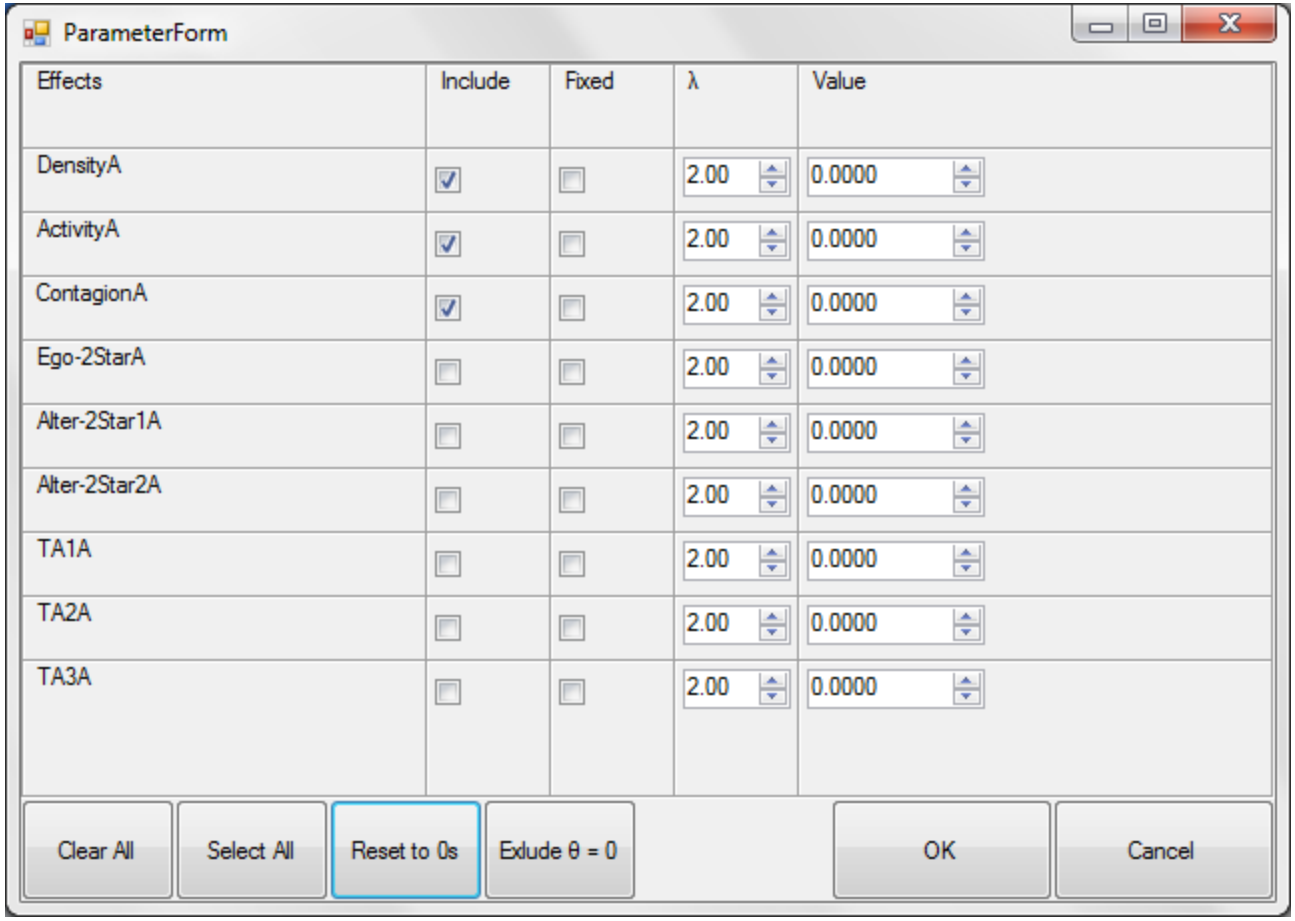
TA1 (Being in closed structures, irrespective of the attribute status of partners)

TA2 (Being in closed structures with mixed attribute status of partners)

TA3 (Being in closed structures with actors with the attribute)

Attribute covariates

Parameters for Binary Attributes			
oOb		o_Ob	
Parameters for Continuous Attributes			
oOc		o_Oc	
Parameters for Categorical Attributes			
oO_Osame		oO_Odiff	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Value
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ActivityA
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ContagionA
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Ego-2StarA
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Alter-2Star1A
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Alter-2Star2A
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TA1A
2.00
0.0000
TA2A
2.00
0.0000
TA3A
2.00
0.0000
Clear All
Select All
Reset to 0s
Exlude θ = 0
OK
Cancel