

#### Why do we use stochastic network models?

#### According to the intro article assigned for this week (Lusher et al, 2007):

- To capture complex social phenomena that are the result of both regularities/interdependencies and "randomness"
- Make inferences as to whether certain network signatures will appear more often than we would expect by chance alone
- Distinguish between different social processes that may have similar results (e.g. is clustering due to homophily or structural balance?)
- Deterministic approaches are not always useful/parsimonious enough in the context of complex network data (e.g. network evolution over time)
- Better understanding of the way local social processes interact and combine to shape global network patterns.

### **Basics of the approach**

- Assume we have an observed network of size n.
- What are the mechanisms driving the formation of our network (e.g. reciprocity, transitivity)?
- Given those mechanisms, are some network configurations (e.g. mutual dyads, transitive triplets) more common than you would expect by chance?
- Include a parameter for each configuration in the model. Parameter values will help us identify a probability distribution for all graphs of size n. (e.g. if we have a high value for the reciprocity parameter, graphs that have a lot of mutual dyads will be more probable than ones that do not)
- Estimate the parameters: find the parameter values that best match the observed network. We do that using MCMC-MLE: Markov Chain Monte Carlo Maximum Likelihood Estimation techniques.
- Once we have our probability distribution, we can draw random graphs from it and compare any of their characteristics to those of our observed network.

### **Exponential Random Graph Models**

A class of stochastic models that share the following general form:

$$\Pr(Y = y) = \left(\frac{1}{k}\right) \exp\left\{\sum_{A} \eta_{A} g_{A}(y)\right\}$$

#### Where:

- Y is a network realization
- y is the observed network
- The summation is over all configurations A
- $\bullet$   $\eta_A$  is the parameter corresponding to configuration A
- $\mathbf{g}_A(y)$  is the network statistic corresponding to configuration A
- k is a normalizing factor calculated by summing up  $\exp\left\{\sum_{A}\eta_{A}\,g_{A}(y)\right\}$  over all possible network configurations

## **Simple Examples**

Note: Homogeneity assumption!

Edge only (Bernoulli random graph distributions):

$$\Pr(Y = y) = \left(\frac{1}{k}\right) \exp\left\{\sum_{i,j} \eta_{ij} y_{ij}\right\} = \left(\frac{1}{k}\right) \exp\left\{\theta \sum_{i,j} y_{ij}\right\}$$

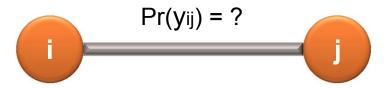
Edge and reciprocity:

$$\Pr(Y = y) = \left(\frac{1}{k}\right) \exp\left\{\theta \sum_{i,j} y_{ij} + \rho \sum_{i,j} y_{ij} y_{ji}\right\}$$

Where  $\theta$  is the density parameter and  $\rho$  is the reciprocity parameter.

Note that the two models are identical for symmetric networks.

### **Edge probability**



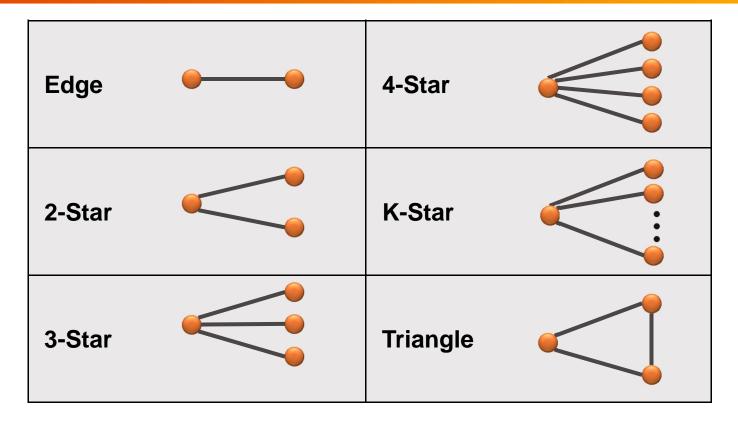
$$\Pr(y_{ij} = 1 | Y^{(ij)}) = \Pr(Y^+) / \{ \Pr(Y^+) + \Pr(Y^-) \}$$

Conditional log odds of a tie:

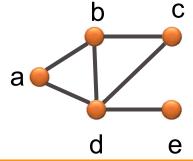
$$logit [Pr(y_{ij} = 1 | Y^{(ij)})] = \theta_1 \delta_1(y^{(ij)}) + \theta_2 \delta_2(y^{(ij)}) + \dots + \theta_k \delta_k(y^{(ij)})$$

Where  $\theta$  is the coefficient and  $\delta$  is a change statistic.

## **Network Configurations: Undirected Networks**



**Example:** 



Edge: 6

2-Star: 1+3+1+6+0=11 3-Star: 0+1+0+4+0=5

4-Star: 1 Triangle: 2

# **Network Configurations: Directed Networks**

	Arc	Reciprocity	
	Isolate	2-mixed-star	
	2-in-star	2-out-star	
•	K-in-star	K-out-star	
	Transitive triad	Cyclic triad	

#### **ERGM Software**

There are a number of tools that will allow you to estimate exponential random graph models. Two of the most commonly used ones are:

- ERGM package in R
  Maintained by David R. Hunter, Penn State University
  For more information visit: <u>Statnet.org</u>
- PNet software family
  Maintained by the MelNet center, Melbourne, Australia
  For more information visit: <a href="PNet by MelNet">PNet by MelNet</a>