

ERGMs

A discrete random vector \mathbf{Z} belongs to the exponential family

$$P_{\theta}(\mathbf{Z}=\mathbf{z}) = \exp\{\underbrace{\theta^T \mathbf{g}(\mathbf{z})}_{\text{param.}} - \underbrace{\psi(\theta)}_{\text{sufficient stat}}\}$$

In ERGMs \mathbf{Y} random adj. matrix

$$P_{\theta}(\mathbf{Y}=\mathbf{y}) = \frac{1}{K} \exp\left(\sum_H \theta_H g_H(\mathbf{y})\right) \quad g_H(\mathbf{y}) = \begin{cases} 1 & \text{if config. } H \text{ occurs in } \mathbf{y} \\ 0 & \text{otherwise} \end{cases}$$

|
configurations

| Nonzero implies
edges in H are
dependent.

Ex: $Y_{ij} \perp\!\!\!\perp Y_{i'j'}$ so $\theta_H = 0 \quad \forall |H| \geq 3$ (ER model)

So $g_H(\mathbf{y}) = g_{ij}(\mathbf{y}) = y_{ij}$, $P_{\theta}(\mathbf{Y}=\mathbf{y}) = \frac{1}{K} \exp\left\{\sum_{i,j} \theta_{ij} y_{ij}\right\}$

Model is equivalent $p_{ij} = \text{logit}^{-1}(\theta_{ij})$

Assume homogeneity then $P_{\theta}(\mathbf{Y}=\mathbf{y}) = \frac{1}{K} \exp\{\theta L(\mathbf{y})\}$

$L(\mathbf{y}) = N_e$ literally a ERGM

Ex: Suppose $Y_{ij} \not\perp\!\!\!\perp Y_{ik} \quad \forall k \neq j$. for all $k \neq j$.

Inspires a Markov Random Graph Model

$$P_{\theta}(Y=y) = \frac{1}{K} \exp \left\{ \sum_{k=1}^{Nv-1} \theta_k S_k(y) + \theta_z T(y) \right\}$$

$$S_1(y) = N_e, \dots, S_k(y) = \# k\text{-stars} \quad 2 \leq k \leq Nv-1$$

$$T(y) = \# \text{ triangles}$$

Other Extensions

- functions of stars, degree distributions, and k -triangles
- non markovian conditional dependence
- Correlates for edge/vertex attributes

Use ML for θ and LR testing

- use pseudo likelihood for computational issues
- model degeneracy a major concern
 - tons of collinearity in star counts
 - Two solutions: empty/full graphs

↳ Lots of use of MGFs + Graphons

- Current state of the art involves MCMC or Robins/Monroe as a way to estimate θ .
- Some initial work on goodness of fit with these MCMC replicates.

Ways to account for collinearity

$$P_{\theta, \rho}(y|x=x) \sim \frac{1}{K(\theta, \rho)} \exp \left(\underbrace{\theta_1 S(y)}_{N_L} + \underbrace{\theta_2 AKT_\lambda(y)}_{\substack{\text{alternating} \\ k\text{-star}}} + \underbrace{\beta^T g(y, x)}_{\text{vertex attributes}} \right)$$

$$AKT_\lambda(y) = 3I_1 + \sum (-1)^{k+1} \frac{I_k(y)}{\lambda^{k-1}}$$

"removes" collinearity

$$g(y, x) = \sum_{i,j} y_{ij} h(x_i, x_j)$$