Sparse random graphs with exchangeable point processes

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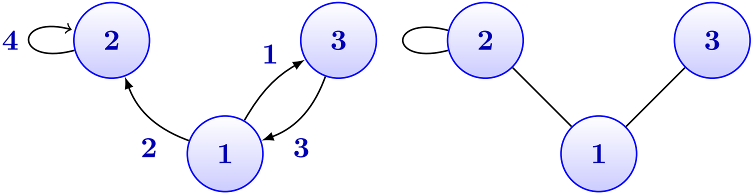
Joint work with Emily Fox (U. Washington)

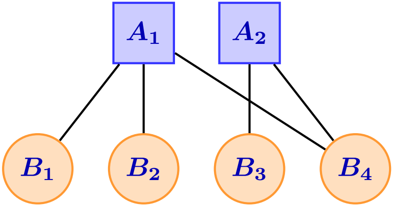
Outline

Introduction



- Multi-edges directed graphs
  - Emails
  - Citations
  - WWW
- Simple graphs
  - Social network
  - Protein-protein interaction

Introduction



- Bipartite graphs
  - Scientists authoring papers
  - Readers reading books
  - Internet users posting messages on forums
  - Customers buying items

Introduction

- Build a statistical model of the network to
  - Find interpretable structure in the network
  - Predict missing edges
  - Predict connections of new nodes

Introduction

- Properties of real world networks
  - Sparsity

$$\text{Dense graph: } n_e = \Theta(n^2)$$
$$\text{Sparse graph: } n_e = o(n^2)$$

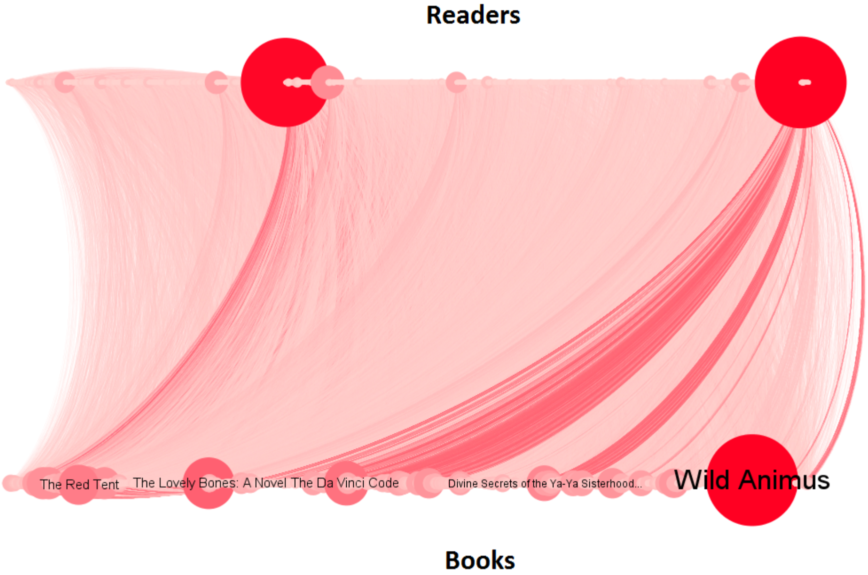
    with n_e the number of edges and n the number of nodes

  - Power-law degree distributions

[Newman, 2009, Clauset et al., 2009]

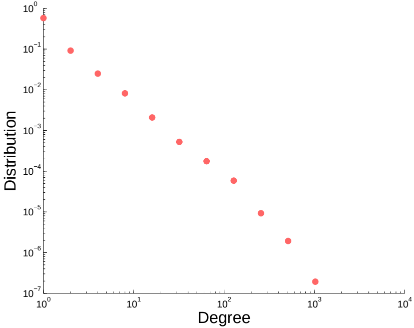
Book-crossing community network

5 000 readers, 36 000 books, 50 000 edges

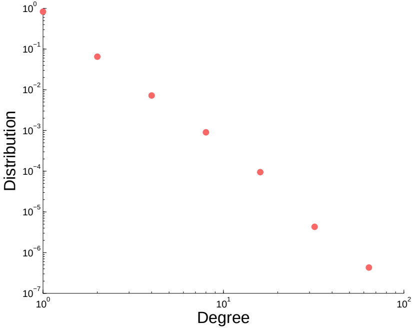


Book-crossing community network

Degree distributions on log-log scale



(a) Readers

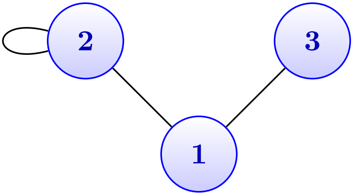


(b) Books

Outline

Introduction

- Statistical network modeling
- Probabilistic symmetry: exchangeability
- Ordering of the nodes is irrelevant



Introduction

- Statistical network modeling
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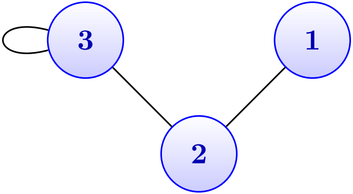
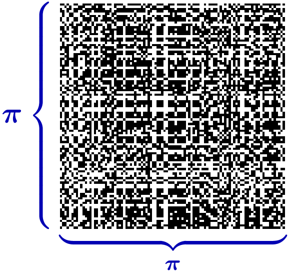


Introduction

- Graphs usually represented by a discrete structure
- Adjacency matrix $X_{ij} \in \{0, 1\}, (i, j) \in \mathbb{N}^2$
- Joint exchangeability

$$(X_{ij}) \overset{d}{=} (X_{\pi(i)\pi(j)})$$

for any permutation π of $\mathbb{N}$



Introduction

- Aldous-Hoover representation theorem

$$(X_{ij}) = (F(U_i, U_j, U_{\{ij\}}))$$

where U_i,$U_{\{ij\}}$ are uniform random variables and F is a random function from $[0,1]^3$ to $\{0,1\}$
- Several network models fit in this framework (e.g. stochastic blockmodel, infinite relational model, etc.)

[Hoover, 1979, Aldous, 1981, Lloyd et al., 2012]

Introduction

- Corollary of A-H theorem

  Exchangeable random graphs are either empty or dense

- To quote the survey paper of Orbanz and Roy

  "the theory [...] clarifies the limitations of exchangeable models. It shows, for example, that most Bayesian models of network data are inherently misspecified"

- Give up exchangeability for sparsity? e.g. preferential attachment model

[Barabási and Albert, 1999, Orbanz and Roy, 2015]

Outline

Point process representation

- Representation of a graph as a (marked) point process over $\mathbb{R}_+^2$
- Representation theorem by Kallenberg for jointly exchangeable point processes on the plane
- Construction based on a completely random measure
- Properties of the model
  - Exchangeability
  - Sparsity
  - Power-law degree distributions (with exponential cut-off)
  - Interpretable parameters and hyperparameters
  - Reinforced urn process construction
- Posterior characterization
- Scalable inference

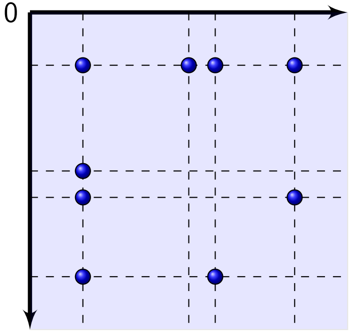
[Kallenberg, 2005, Caron and Fox, 2014]

Point process representation

- Undirected graph represented as a point process on $\mathbb{R}_+^2$

$$Z = \sum_{i,j} z_{ij} \delta_{(\theta_i, \theta_j)}$$

with $\theta_i \in \mathbb{R}$, $z_{ij} \in \{0, 1\}$ with $z_{ij} = z_{ji}$



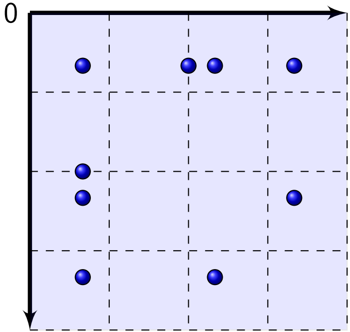
Point process representation

Joint exchangeability

Let $A_i = [h(i-1), hi]$ for $i \in \mathbb{N}$ then

$$(Z(A_i \times A_j)) \overset{d}{=} (Z(A_{\pi(i)} \times A_{\pi(j)}))$$

for any permutation π of $\mathbb{N}$ and any $h > 0$



Point process representation

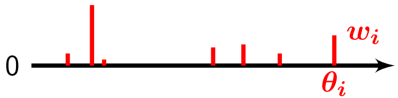
- Kallenberg derived a de Finetti style representation theorem for jointly and separately exchangeable point processes on the plane
- Representation via random transformations of unit rate Poisson processes and uniform variables
- Continuous-time equivalent of Aldous-Hoover for binary variables
- Our construction will fit into this framework

[Kallenberg, 1990, Kallenberg, 2005]

Completely random measures

- Nodes are embedded at some location $\theta_i \in \mathbb{R}_+$
- To each node is associated some sociability parameter w_i
- Homogeneous completely random measure on $\mathbb{R}_+$

$$W = \sum_{i=1}^{\infty} w_i \delta_{\theta_i} \quad W \sim \mathrm{CRM}(\rho, \lambda).$$



- Lévy measure $\nu(dw, d\theta) = \rho(dw)\lambda(d\theta)$ with λ the Lebesgue measure

[Kingman, 1967]

Completely random measures

- Lévy measure $\nu(dw, d\theta) = \rho(dw)\lambda(d\theta)$ with λ the Lebesgue measure
- ρ is a measure on $\mathbb{R}_+$ such that

$$\int_0^\infty (1 - e^{-w})\rho(dw) < \infty. \tag{1}$$

which implies that $W([0, T]) < \infty$ for any $T < \infty$.

$$\int_0^\infty \rho(dw) = \infty \Longrightarrow$$ Infinite number of jumps in any interval $[0, T]$

"Infinite activity CRM"

$$\int_0^\infty \rho(dw) < \infty \Longrightarrow$$ Finite number of jumps in any interval $[0, T]$

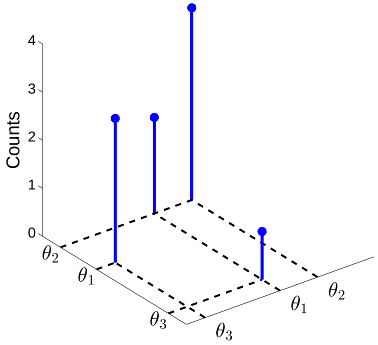
"Finite activity CRM"

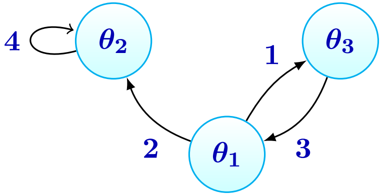
Model for multi-edges directed graphs

Multigraph represented by an atomic measure on $\mathbb{R}_+^2$

$$D = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} n_{ij} \delta_{(\theta_i, \theta_j)},$$

where n_{ij} counts the number of directed edges from node θ_i to node θ_j.

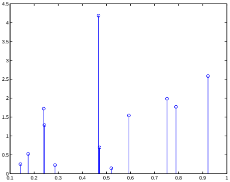




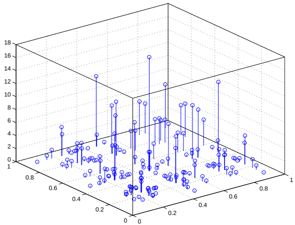
Model for multi-edges directed graphs

- Conditional Poisson process with intensity measure $\widetilde{\boldsymbol{W}} = \boldsymbol{W} \times \boldsymbol{W}$ on the product space $\mathbb{R}_+^{\mathbf{2}}$:

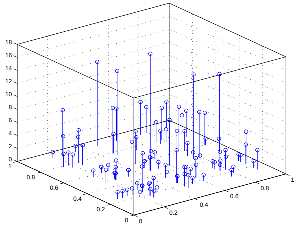
$$\boldsymbol{D} \mid \boldsymbol{W} \sim \text{PP}(\boldsymbol{W} \times \boldsymbol{W})$$



(c) CRM $\boldsymbol{W}$



(d) Intensity measure $\widetilde{\boldsymbol{W}}$



(e) Poisson process $\boldsymbol{D}$

Model for multi-edges directed graphs

- By construction, for any bounded intervals A and B of $\mathbb{R}_+$, $\widetilde{W}(A \times B) = W(A)W(B) < \infty$
- Finite number of counts over $A \times B \subset \mathbb{R}_+^2$

$$D(A \times B) < \infty$$

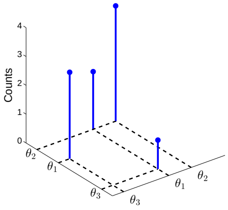
Model for undirected graphs

- Point process

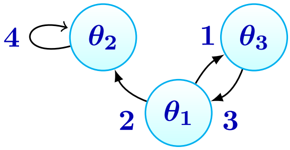
$$Z = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} z_{ij} \delta_{(\theta_i, \theta_j)},$$

with the convention $z_{ij} = z_{ji} \in \{0, 1\}$

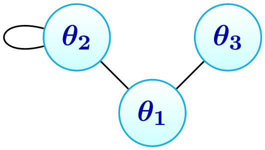
- Constructed from D by setting $z_{ij} = z_{ji} = 1$ if $n_{ij} + n_{ji} > 0$ and $z_{ij} = z_{ji} = 0$ otherwise



(a) D



(b) Integer-valued directed graph



(c) Undirected graph

Model for undirected graphs

- Hierarchical model

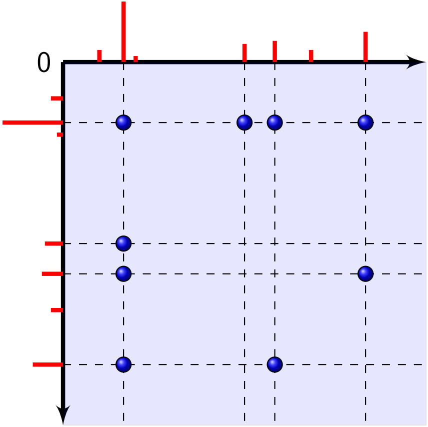
$$\begin{aligned} W &= \sum_{i=1}^{\infty} w_i \delta_{\theta_i} & W &\sim \text{CRM}(\rho, \lambda) \\ D &= \sum_{ij} n_{ij} \delta_{(\theta_i, \theta_j)} & D &\sim \text{PP}\left(W \times W\right) \\ Z &= \sum_{ij} \min(n_{ij} + n_{ji}, 1) \delta_{(\theta_i, \theta_j)} & & \end{aligned}$$

Model for undirected graphs

- Equivalent direct formulation for $i \leq j$

$$\Pr(z_{ij} = 1 \mid w) = \begin{cases} 1 - \exp(-2w_i w_j) & i \neq j \\ 1 - \exp(-w_i^2) & i = j \end{cases}$$

and $z_{ji} = z_{ij}$



Outline

Properties: Exchangeability

Exchangeability

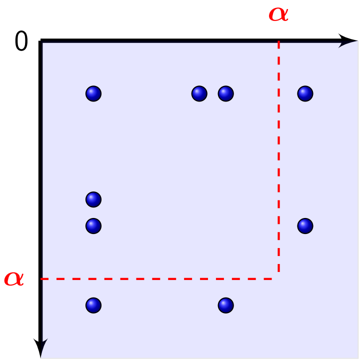
Let $h > 0$ and $A_i = [h(i-1), hi]$, $i \in \mathbb{N}$. By construction,

$$(Z(A_i \times A_j)) \stackrel{d}{=} (Z(A_{\pi(i)} \times A_{\pi(j)}))$$

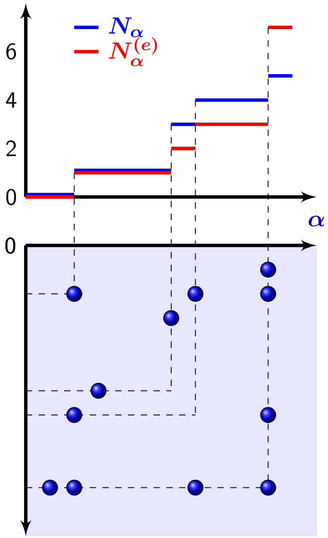
for any permutation π of $\mathbb{N}$.

Properties: Sparsity

- $W(\mathbb{R}_+) = \infty$, so infinite number of edges on $\mathbb{R}_+^2$
- Restrictions D_α and Z_α of D and Z, respectively, to the box $[0, \alpha]^2$.
- N_α number of nodes, and $N_\alpha^{(e)}$ number of edges



Properties: Sparsity



Properties: Sparsity

Definition

(Regular variation) Let $W \sim \mathrm{CRM}(\rho, \lambda)$. The (infinite-activity) CRM is said to be *regularly varying* if the tail Lévy intensity verifies

$$\int_x^\infty \rho(dw) \overset{x \downarrow 0}{\sim} \ell(1/x) x^{-\sigma}$$

for $\sigma \in (0, 1)$ where ℓ is a slowly varying function satisfying $\lim_{t\to\infty} \ell(at)/\ell(t) = 1$ for any $a > 0$.

Properties: Sparsity

Assume $\rho \neq 0$ and $\mathbb{E}[W([0,1])] < \infty$.

Theorem

Let N_α be the number of nodes and $N_\alpha^{(e)}$ the number of edges in the undirected graph restriction, Z_α. Then

$$N_\alpha^{(e)} = \begin{cases} \Theta\left(N_\alpha^2\right) & \text{if } W \text{ is finite-activity} \\ o\left(N_\alpha^2\right) & \text{if } W \text{ is infinite-activity} \\ O\left(N_\alpha^{2/(1+\sigma)}\right) & \text{if } W \text{ is regularly varying}^1 \text{ with } \sigma \in (0,1) \end{cases}$$

almost surely as $\alpha \to \infty$.

[1] with $\lim_{t\to\infty} \ell(t) > 0$

Outline

Generalized Gamma Process

- Lévy intensity
$$\frac{1}{\Gamma(1-\sigma)} w^{-1-\sigma} e^{-\tau w}$$
with $\sigma \in (-\infty, 0]$ and $\tau > 0$
or $\sigma \in (0, 1)$ and $\tau \geq 0$
- Special cases:
  - Gamma process ($\sigma = 0$)
  - Stable process ($\tau = 0, \sigma \in (0, 1)$)
  - Inverse Gaussian process ($\sigma = 1/2, \tau > 0$)
- Infinite activity for $\sigma \geq 0$
- Regularly varying for $\sigma \in (0, 1)$
- Exact sampling of the graph via an urn process
- Power-law degree distribution

[Brix, 1999, Lijoi et al., 2007]

Generalized Gamma Process

Sparsity

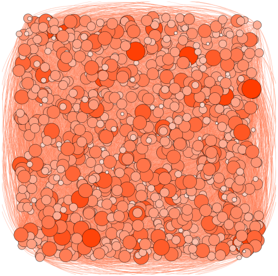
Theorem

Let N_α *be the number of nodes and* $N_\alpha^{(e)}$ *the number of edges in the undirected graph restriction,* Z_α*. Then*

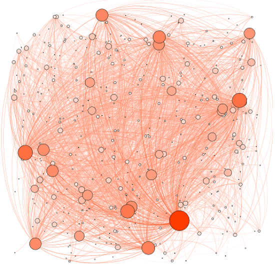
$$N_\alpha^{(e)} = \begin{cases} \Theta\left(N_\alpha^2\right) & \text{if } \sigma < 0 \\ o\left(N_\alpha^2\right) & \text{if } \sigma \in [0,1), \tau > 0 \\ O\left(N_\alpha^{2/(1+\sigma)}\right) & \text{if } \sigma \in (0,1), \tau > 0 \end{cases}$$

almost surely as $\alpha \to \infty$*. That is, the underlying graph is sparse if* $\sigma \geq 0$ *and dense otherwise.*

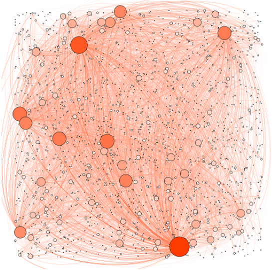
Particular cases: Generalized Gamma Process



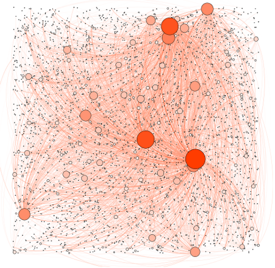
Erdös-Rényi $\boldsymbol{G(1000, 0.05)}$



Gamma Process

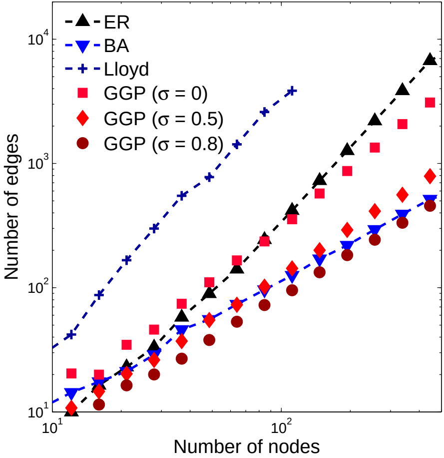


GGP ($\boldsymbol{\sigma = 0.5}$)



GGP ($\boldsymbol{\sigma = 0.8}$)

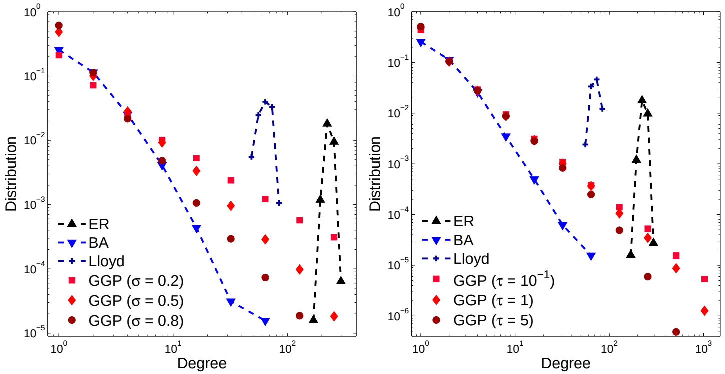
Particular cases: Generalized Gamma Process



Particular cases: Generalized Gamma Process

Power-law degree distributions

- Power-law like behavior providing a heavy-tailed degree distribution
- Higher power-law exponents for larger σ
- The parameter τ tunes the exponential cut-off in the tails.



Particular cases: Generalized Gamma Process

Outline

Posterior characterization

Conditional distribution of $\boldsymbol{W_\alpha}$ given $\boldsymbol{D_\alpha}$.

Theorem

Let $(\theta_1,\ldots,\theta_{N_\alpha})$, $N_\alpha \geq 0,$ *be the set of support points of* D_α *such that* $D_\alpha = \sum_{1\leq i,j\leq N_\alpha} n_{ij}\delta_{(\theta_i,\theta_j)}$. *Let* $m_i = \sum_{j=1}^{N_\alpha}(n_{ij}+n_{ji}) > 0$ *for* $i=1,\ldots,N_\alpha$. *The conditional distribution of* W_α *given* D_α *is equivalent to the distribution of*

$$w_* \sum_{i=1}^{\infty} \widetilde{P}_i \delta_{\widetilde{\theta}_i} + \sum_{i=1}^{N_\alpha} w_i \delta_{\theta_i}$$

where $\widetilde{\theta}_i \sim \mathrm{Unif}([0,\alpha])$, *and* $(\widetilde{P}_i)|w_* \sim \mathrm{PK}(\rho|w_*)$ *are from a Poisson-Kingman distribution . The weights* $(w_1,\ldots,w_{N_\alpha},w_*)$ *are jointly dependent conditional on* D_α, *with* $p(w_1,\ldots,w_{N_\alpha},w_*|D_\alpha) \propto$

$$\left[\prod_{i=1}^{N_\alpha} {w_i}^{m_i}\right] e^{-\left(\sum_{i=1}^{N_\alpha} w_i + w_*\right)^2} \left[\prod_{i=1}^{N_\alpha} \rho(w_i)\right] \times g_\alpha^*(w_*)$$

where g_α^* *is the probability density function of the random variable* $W_\alpha^* = W_\alpha([0,\alpha])$.

[Prünster, 2002, James, 2002, James et al., 2009]

Posterior inference for undirected graphs

- Let $\phi = (\alpha, \sigma, \tau)$ with flat priors
- We want to approximate

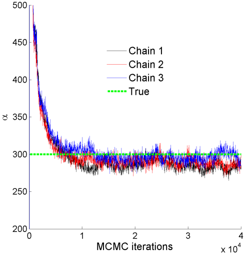
$$p(w_1, \dots, w_{N_\alpha}, w_*, \phi | (z_{ij})_{1 \leq i,j \leq N_\alpha})$$

- Latent count variables $\overline{n}_{ij} = n_{ij} + n_{ji}$
- Markov chain Monte Carlo sampler
  1. Update the weights $(w_1, \dots, w_{N_\alpha})$ given the rest using an Hamiltonian Monte Carlo update
  2. Update the total mass w_* and hyperparameters $\phi = (\alpha, \sigma, \tau)$ given the rest using a Metropolis-Hastings update
  3. Update the latent counts $(\overline{n}_{ij})$ given the rest from a truncated Poisson distribution

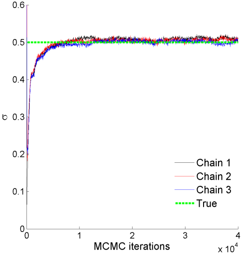
Outline

Simulated data

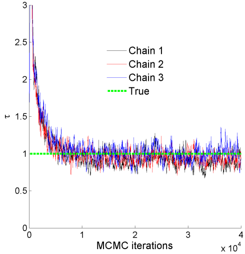
- Simulation of a GGP graph with $\boldsymbol{\alpha = 300, \sigma = 1/2, \tau = 1}$
- 13,995 nodes and 76,605 edges
- MCMC sampler with 3 chains and 40,000 iterations
- Takes 10min on a standard desktop with Matlab



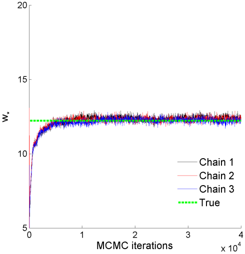
(a) $\boldsymbol{\alpha}$



(b) $\boldsymbol{\sigma}$

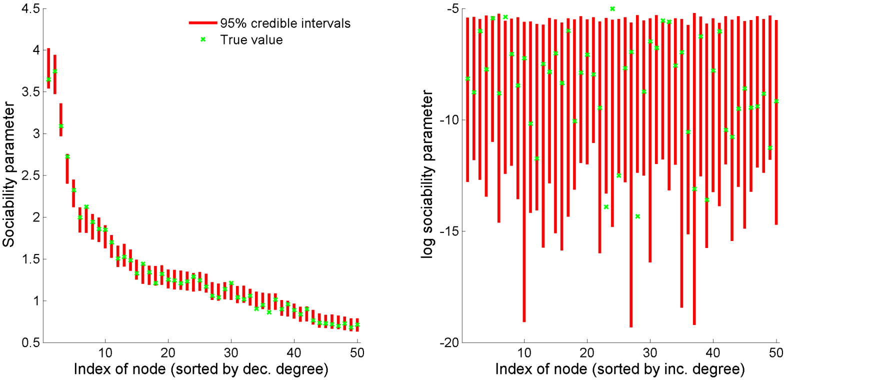


(c) $\boldsymbol{\tau}$



(d) $\boldsymbol{w_*}$

Simulated data

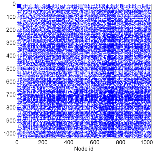


(a) 50 nodes with highest degree (b) 50 nodes with lowest degree

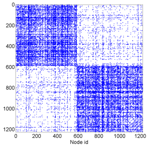
Figure: 95 % posterior intervals of (a) the sociability parameters w_i of the 50 nodes with highest degree and (b) the log-sociability parameter $\log w_i$ of the 50 nodes with lowest degree. True values are represented by a green star.

Real network data

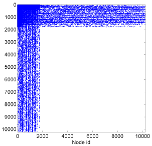
- Assessing the sparsity of the network
- We aim at reporting $\mathbf{Pr(\boldsymbol{\sigma} \geq 0|\boldsymbol{z})}$ based on a set of observed connections $(\boldsymbol{z})$
- 12 different networks
- $\sim \mathbf{1,000 - 300,000}$ nodes and $\mathbf{10,000 - 1,000,000}$ edges



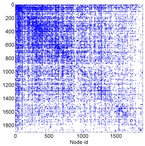
(a) facebook107



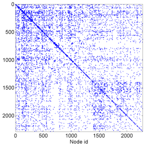
(b) polblogs



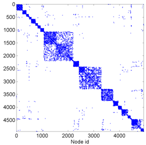
(c) USairport



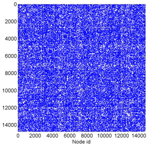
(d) UCirvine



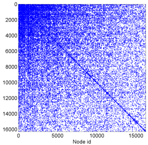
(e) yeast



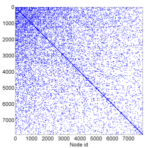
(f) USpower



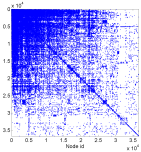
(g) IMDB



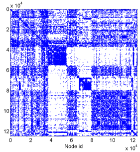
(h) cond-mat1



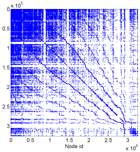
(i) cond-mat2



(j) enron



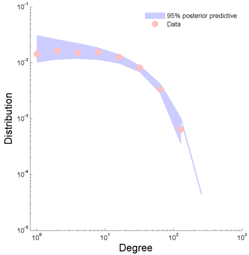
(k) internet



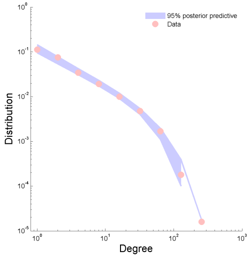
(l) www

Real network data

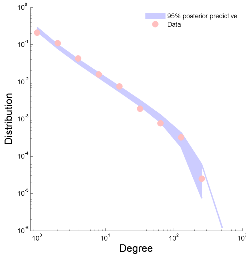
Name	Nb nodes	Nb edges	Time (min)	$\mathbf{Pr(\sigma > 0 \mid z)}$	99% CI $\boldsymbol{\sigma}$
facebook107	1,034	26,749	1	0.00	$[\mathbf{-1.06, -0.82}]$
polblogs	1,224	16,715	1	0.00	$[\mathbf{-0.35, -0.20}]$
USairport	1,574	17,215	1	1.00	$[\ \mathbf{0.10,\ 0.18}]$
UCirvine	1,899	13,838	1	0.00	$[\mathbf{-0.14, -0.02}]$
yeast	2,284	6,646	1	0.28	$[\mathbf{-0.09, 0.05}]$
USpower	4,941	6,594	1	0.00	$[\mathbf{-4.84, -3.19}]$
IMDB	14,752	38,369	2	0.00	$[\mathbf{-0.24, -0.17}]$
cond-mat1	16,264	47,594	2	0.00	$[\mathbf{-0.95, -0.84}]$
cond-mat2	7,883	8,586	1	0.00	$[\mathbf{-0.18, -0.02}]$
Enron	36,692	183,831	7	1.00	$[\ \mathbf{0.20,\ 0.22}]$
internet	124,651	193,620	15	0.00	$[\mathbf{-0.20, -0.17}]$
www	325,729	1,090,108	132	1.00	$[\mathbf{0.26, 0.30}]$



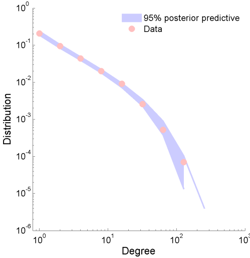
(a) facebook107



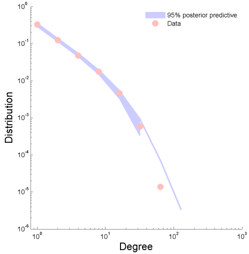
(b) polblogs



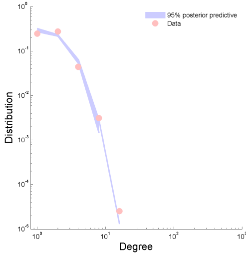
(c) USairport



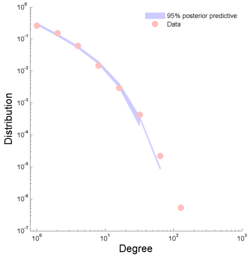
(d) UCirvine



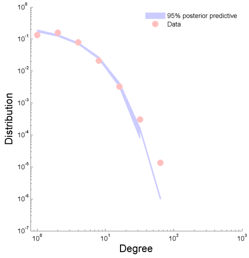
(e) yeast



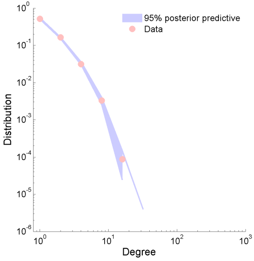
(f) USpower



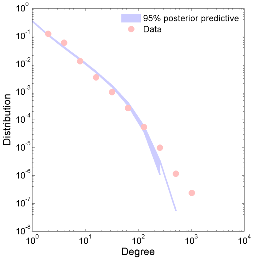
(g) IMDB



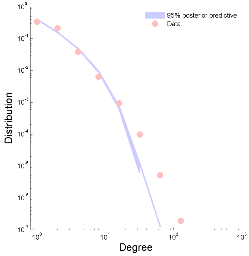
(h) cond-mat1



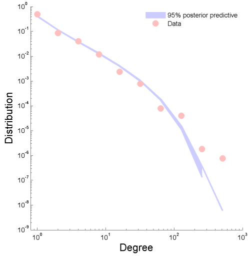
(i) cond-mat2



(j) enron



(k) internet



(l) www

Conclusion

- Statistical network models
- Build on exchangeable random measures
- Sparsity and power-law properties
- Scalable inference
- Similar construction for bipartite graphs
- Extensions to more structured models: low-rank, block-model, covariates, dynamic networks,etc
- Matlab code available

  http://www.stats.ox.ac.uk/~caron/code/bnpgraph/

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