

Probabilistic models for ecological networks

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Outline

- 1 Introduction, why probabilistic models for networks ?
- 2 Stochastic Block Model for classical networks
- 3 Latent Block Model for bipartite networks
- 4 Some possible extensions

Network data



Networks can account for

- Food web,
- Co-existence networks,
- Host-parasite interactions,
- Plant-pollinator interactions,
- ...

Networks may be or not bipartite: Interactions between nodes belonging to the same or to different functional group(s).

Terminology

A network consists in:

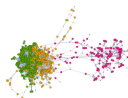
- nodes/vertices which represent individuals / species which may interact or not,
- links/edges/connections which stand for an interaction between a pair of nodes / dyad.

A network may be

- directed / oriented (e.g. food web...),
- symmetric / undirected (e.g. coexistence network),
- with or without loops.

This distinction only makes sense for simple networks (not bipartite).

Available data and goal



Available data:

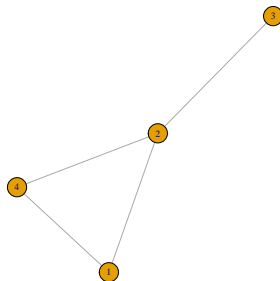
- the network provided as:
 - an adjacency matrix (for simple network) or an incidence matrix (for bipartite network),
 - a list of pair of nodes / dyads which are linked.
- some additional covariates on nodes, dyads which can account for sampling effort.

Goal:

- Unraveling / describing / modeling the network topology.
- Discovering particular structure of interaction between some subsets of nodes.
- Understanding network heterogeneity.
- Not inferring the network !

Network representation and adjacency matrix

$$X = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{pmatrix}$$



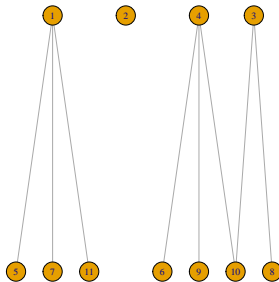
- n rows and n columns,
- symmetric or not.

Bipartite network and incidence matrix

$$X = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 \end{pmatrix}$$

- n rows and m columns, rectangular matrix.
- corresponding adjacency matrix $(n + m) \times (n + m)$:

$$\begin{pmatrix} 0 & X \\ X^T & 0 \end{pmatrix}$$



Some common traits studied on networks

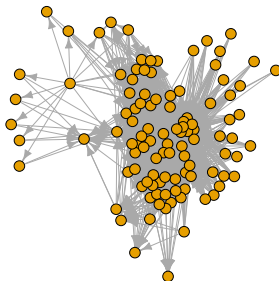
- Degree distribution, can be viewed as a measure of heterogeneity,
- Nestedness: a network is said to be nested when its nodes that have the smallest degree, are connected to nodes with the highest degree, [Rodríguez-Gironés & Santamaria \(2006\)](#)
- Betweenness centrality: for a node, numbers of shortest paths between any pair of nodes passing through this node. [Freeman \(1979\)](#)
- Modularity: is a measure for a given partition of its tendency of favoring intra-connection over inter-connection. \Rightarrow Finding the best partition with respect to modularity criterion. [Clauset, Newman & Moore \(2004\)](#)

All this criterion shall be adapted to:

- directed network,
- bipartite network.

[R packages: igraph, sna, vegan.](#)

Example Chilean food web

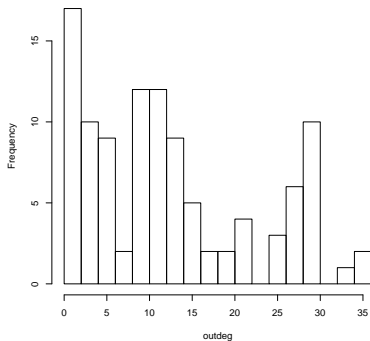


- $n = 106$ species / nodes,
- density of edges: 12.1%.

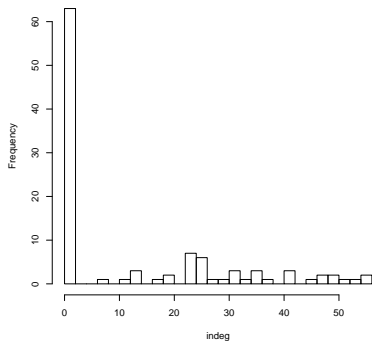
Kéfi, Miele, Wieters, Navarrete & Berlow (2016)

Degree distribution

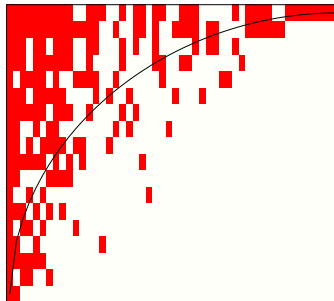
Histogram of outdeg



Histogram of indeg

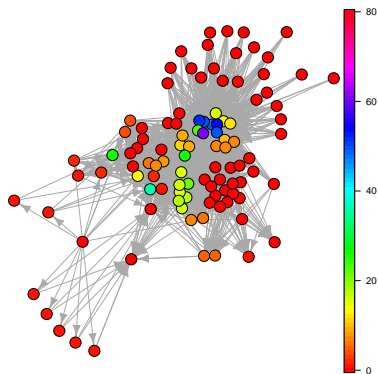


Nestedness



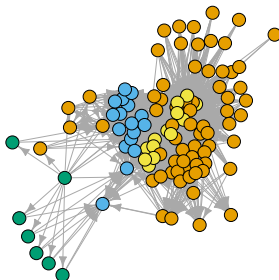
- more generally used on incidence matrices,
- significance of the nestedness index computed by random permutations of the matrix,
- this food web is found to be nested.

Betweenness



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.000	0.000	0.000	6.604	6.929	59.570

Modularity



	1	2	3	4
	69	17	7	13

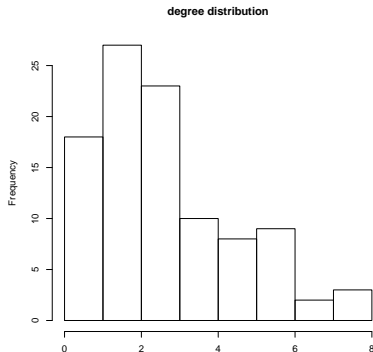
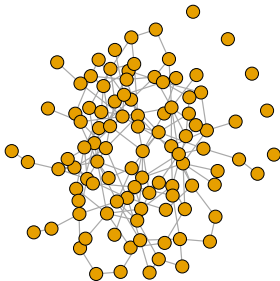
- very low modularity.

A first random graph model for network: Null model

Erdős-Rényi (1959) Model for n nodes

$$\forall 1 \leq i, j \leq n, \quad X_{ij} \stackrel{i.i.d.}{\sim} b(p),$$

where b is the Bernoulli distribution and $p \in [0, 1]$ a probability for a link to exist.



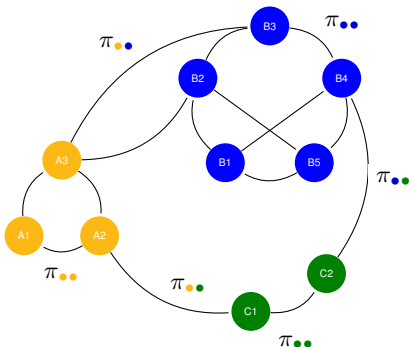
Limitations of an ER graph to describe real networks

- Degree distribution too concentrated, no high degree nodes,
- all nodes are equivalent (no nestedness...),
- no modularity.

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Stochastic Block Model



Stochastic Block Model

Let n nodes divided into

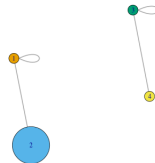
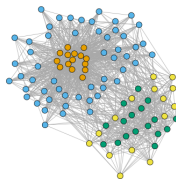
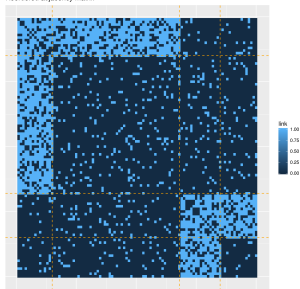
- $\mathcal{Q} = \{\bullet, \bullet, \bullet\}$ classes
- $\alpha_{\bullet} = \mathbb{P}(i \in \bullet), \bullet \in \mathcal{Q}, i = 1, \dots, n$
- $\pi_{\bullet\bullet} = \mathbb{P}(i \leftrightarrow j | i \in \bullet, j \in \bullet)$

$$Z_i = \mathbf{1}_{\{i \in \bullet\}} \sim^{\text{iid}} \mathcal{M}(1, \alpha), \quad \forall \bullet \in \mathcal{Q},$$

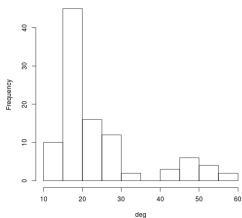
$$X_{ij} | \{i \in \bullet, j \in \bullet\} \sim^{\text{ind}} \mathcal{B}(\pi_{\bullet\bullet})$$

Some remarkable structure generated with SBM : networks with hubs

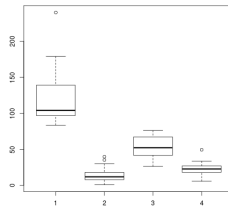
Reordered adjacency matrix



Histogram of degrees

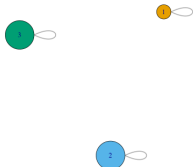
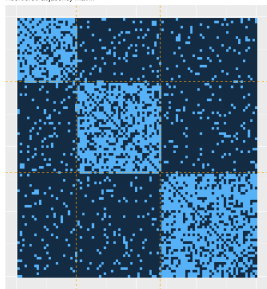


Betweenness by block

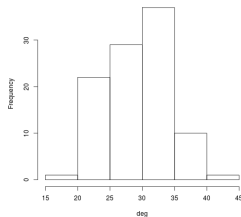


Some remarkable structure generated with SBM : community network

Reordered adjacency matrix

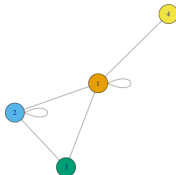
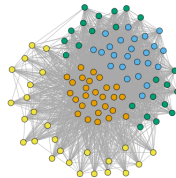
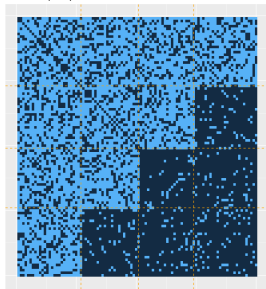


Histogram of degrees

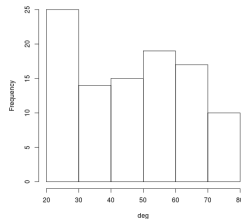


Some remarkable structure generated with SBM : nestedness

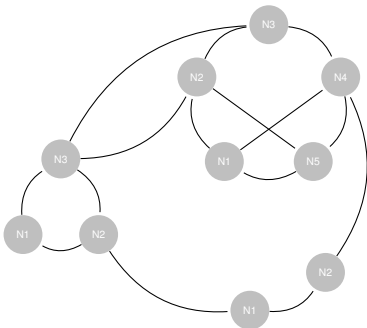
Reordered adjacency matrix



Histogram of degrees



Statistical inference



Stochastic Block Model

Let n nodes divided into

- $\mathcal{Q} = \{\bullet, \bullet, \bullet\}$, $\text{card}(\mathcal{Q})$ known
- $\alpha_{\bullet} = ?$,
- $\pi_{\bullet} = ?$



Nowicki, Snijders, JASA, 2001

Estimation and prediction for stochastic blockstructures.

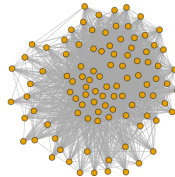
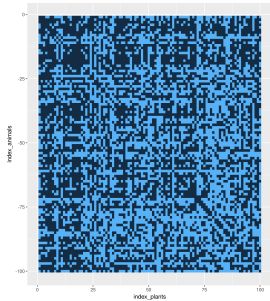


Daudin, Picard, Robin, Statistics and Computing, 2008

A mixture model for random graphs.

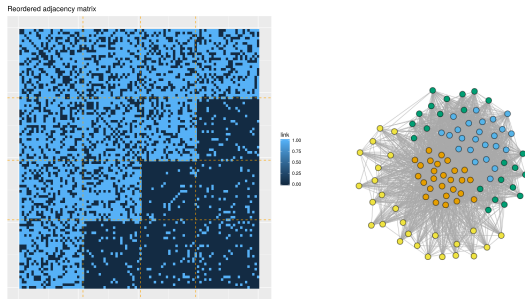
Statistical inference

From....



Statistical inference

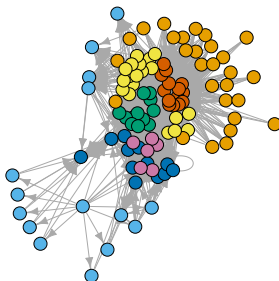
... to



Statistician job

- Find the clusters
- Find the number of clusters
- Theoretical and practical constraints

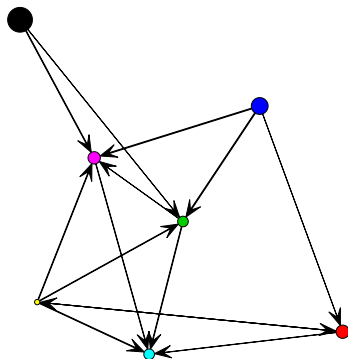
Application to the Chilean food web



- 7 groups/blocks/clusters found,

■	1	2	3	4	5	6	7
	28	15	12	19	12	14	6

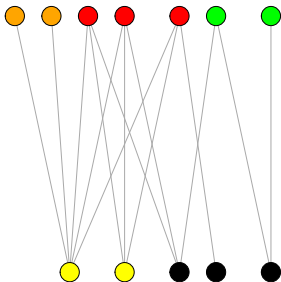
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Latent Block Model



Latent Block Model

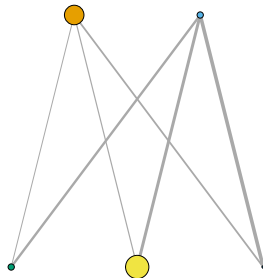
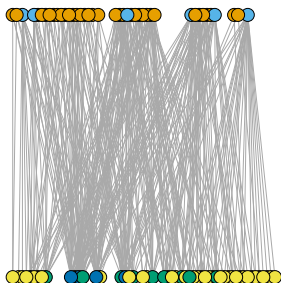
- n row nodes $\mathcal{Q}_1 = \{\bullet, \circ, \bullet\}$ classes
- $\alpha_\bullet = \mathbb{P}(i \in \bullet), \bullet \in \mathcal{Q}_1, i = 1, \dots, n$
- m column nodes $\mathcal{Q}_2 = \{\bullet, \bullet\}$ classes
- $\beta_\bullet = \mathbb{P}(j \in \bullet), \bullet \in \mathcal{Q}_2, j = 1, \dots, m$
- $\pi_{\bullet\bullet} = \mathbb{P}(i \leftrightarrow j | i \in \bullet, j \in \bullet)$

$$Z_i = \mathbf{1}_{\{i \in \bullet\}} \sim^{\text{iid}} \mathcal{M}(1, \alpha), \quad \forall \bullet \in \mathcal{Q}_1,$$

$$W_j = \mathbf{1}_{\{j \in \bullet\}} \sim^{\text{iid}} \mathcal{M}(1, \beta), \quad \forall \bullet \in \mathcal{Q}_2,$$

$$X_{ij} \mid \{i \in \bullet, j \in \bullet\} \sim^{\text{ind}} \mathcal{B}(\pi_{\bullet\bullet})$$

LBM for ant-plant data



- 2 blocks found over the 41 ant species,
- 3 blocks found over the 51 plant species.

Blüthgen, Stork & Fiedler (2004)

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- Valued edges: abundance count, weighted interactions...
- multiple interactions between nodes,
- multipartite networks: plants, pollinator, seed dispersers, ants...
- Taking into account sampling conditions (through covarites...).