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Maximally random graph ensembles

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The **probability**,  $P(\mathbb{A})$ , for a  $N \times N$  adjacency matrix  $\mathbb{A} = \{a_{ij}\} \in [0, 1]^{\binom{N}{2}}$  that maximizes the **entropy** subjected to the  $L$  **constraints** ( $l = 1, 2, \dots, L$ )

$$S(\{\mathbb{A}\}) = - \sum_{\mathbb{A}} P(\mathbb{A}) \ln P(\mathbb{A}) \quad \bar{F}_l = \sum_{\mathbb{A}} F_l(\mathbb{A}) P(\mathbb{A})$$

is ( $\alpha_l$  being the  $l$ -th Lagrange multiplier)

$$P(\mathbb{A}) \propto \exp \left( - \sum_{l=1}^L \alpha_l F_l(\mathbb{A}) \right) .$$

Phys. Rev. E 68, 026112 (2003)

Phys. Rev. E 86, 026120 (2012)



Example 1: fixing the expected number of edges

$$\bar{F}_1 = \sum_{i=1}^N \sum_{j=i+1}^N a_{ij} = M$$

yields the Bernoulli random graph ensemble

$$P(\mathbb{A}) = \prod_{i=1}^N \prod_{j=i+1}^N p^{a_{ij}} (1-p)^{1-a_{ij}} \quad \text{with} \quad p = \frac{1}{e^{\alpha_1} + 1}.$$

Example 2: fixing the expected degree sequence

$$\bar{F}_l = \sum_{j=1}^N a_{lj} = k_l$$

for  $l = 1, \dots, N$  yields the soft configuration model

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Redefining  $\kappa_l = \sqrt{\langle \kappa \rangle N} e^{\alpha_l}$  for  $l = 1, \dots, N$  yields the Chung-Lu model

$$p_{ij} = \frac{1}{1 + \frac{\langle \kappa \rangle N}{\kappa_i \kappa_j}} \simeq \frac{\kappa_i \kappa_j}{\langle \kappa \rangle N}.$$

Studying the conditions for which  $p_{ij}$  can be factorised informs us on the degree-degree correlations observed in real networks.

# Maximally random graph ensembles

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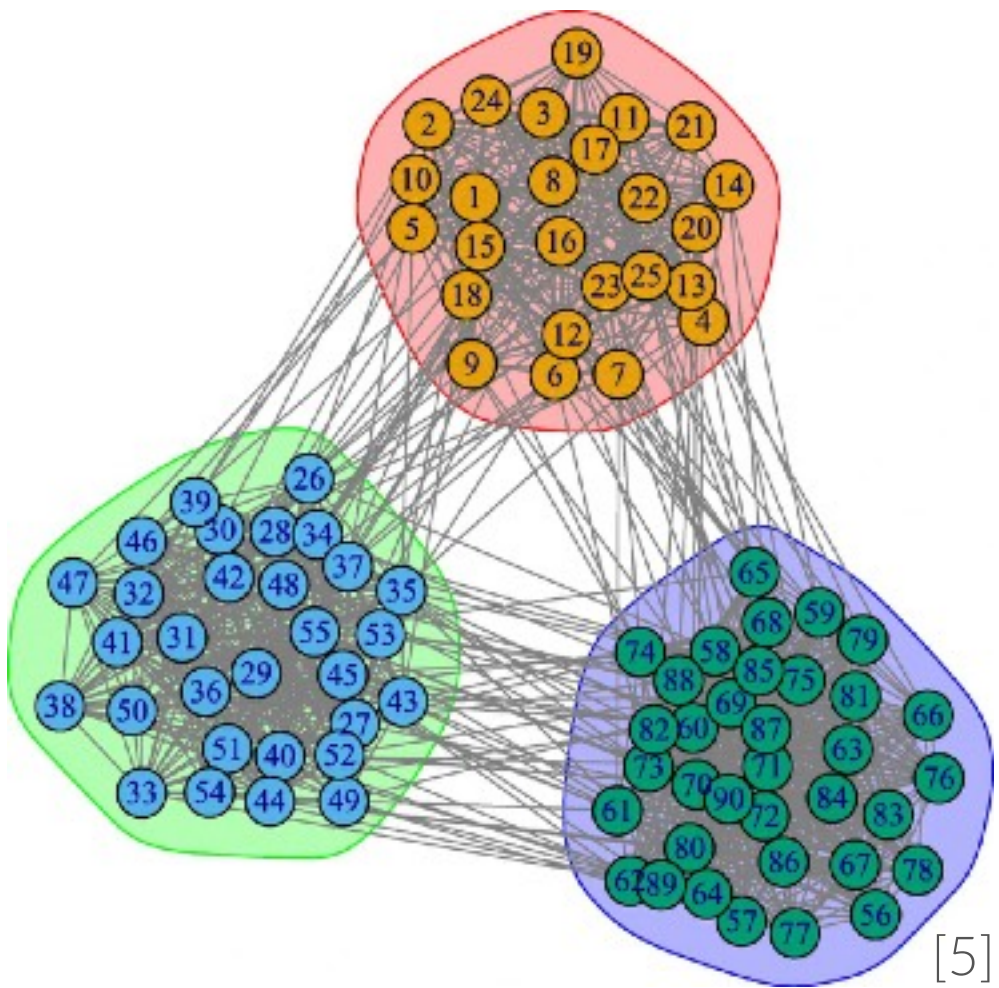
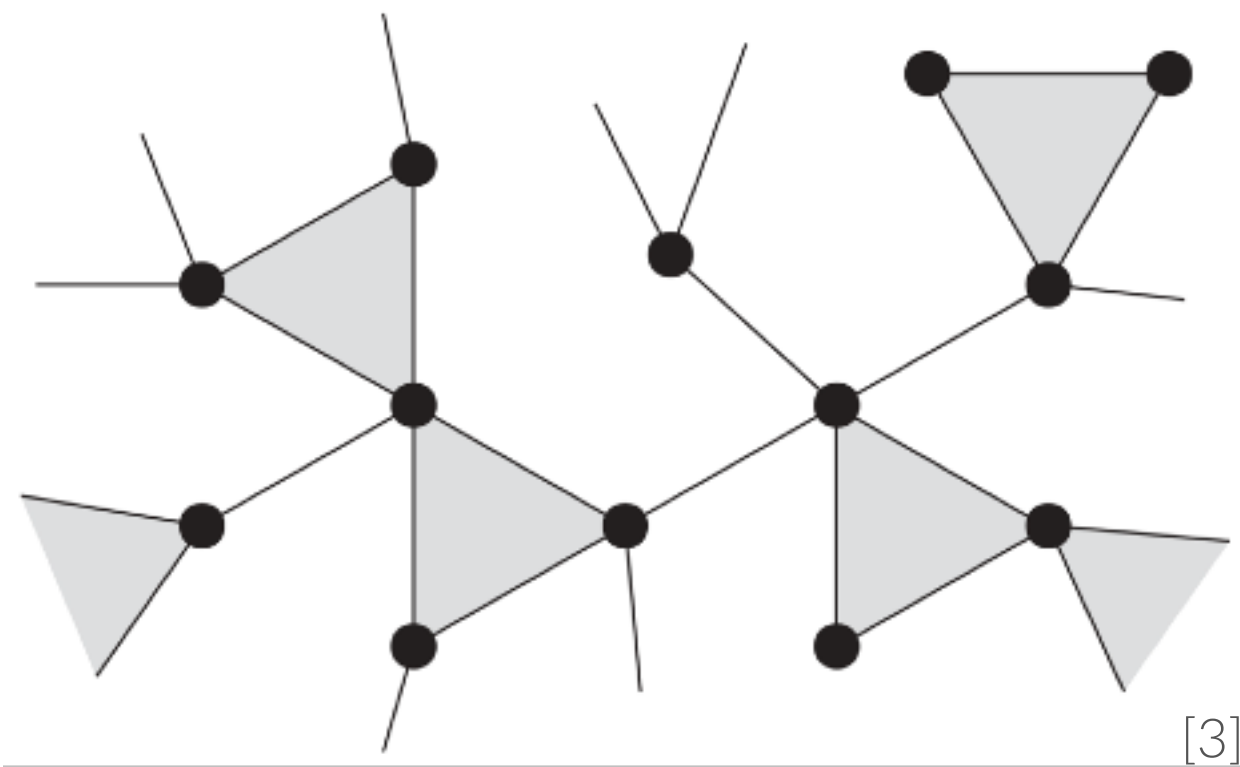
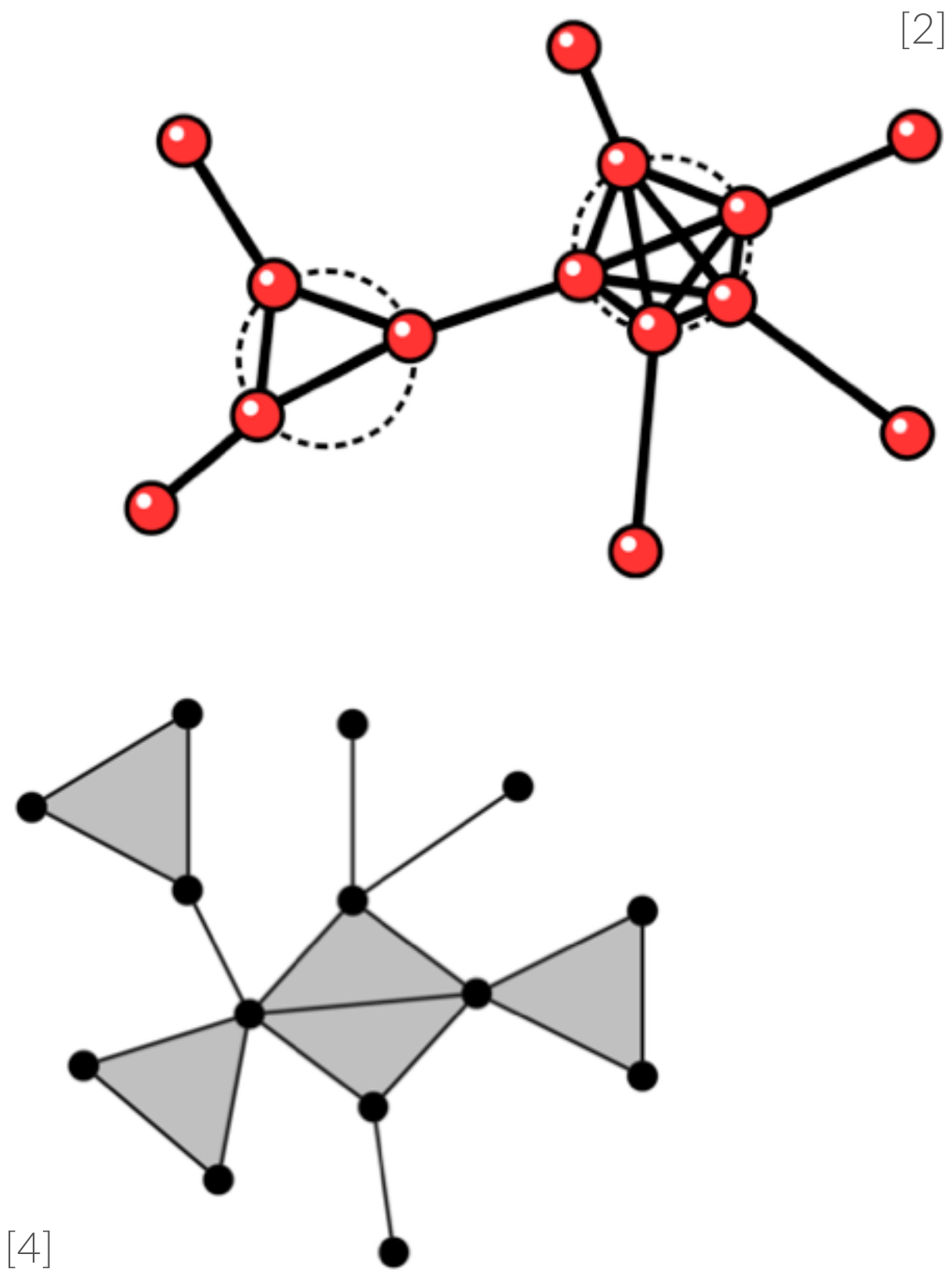
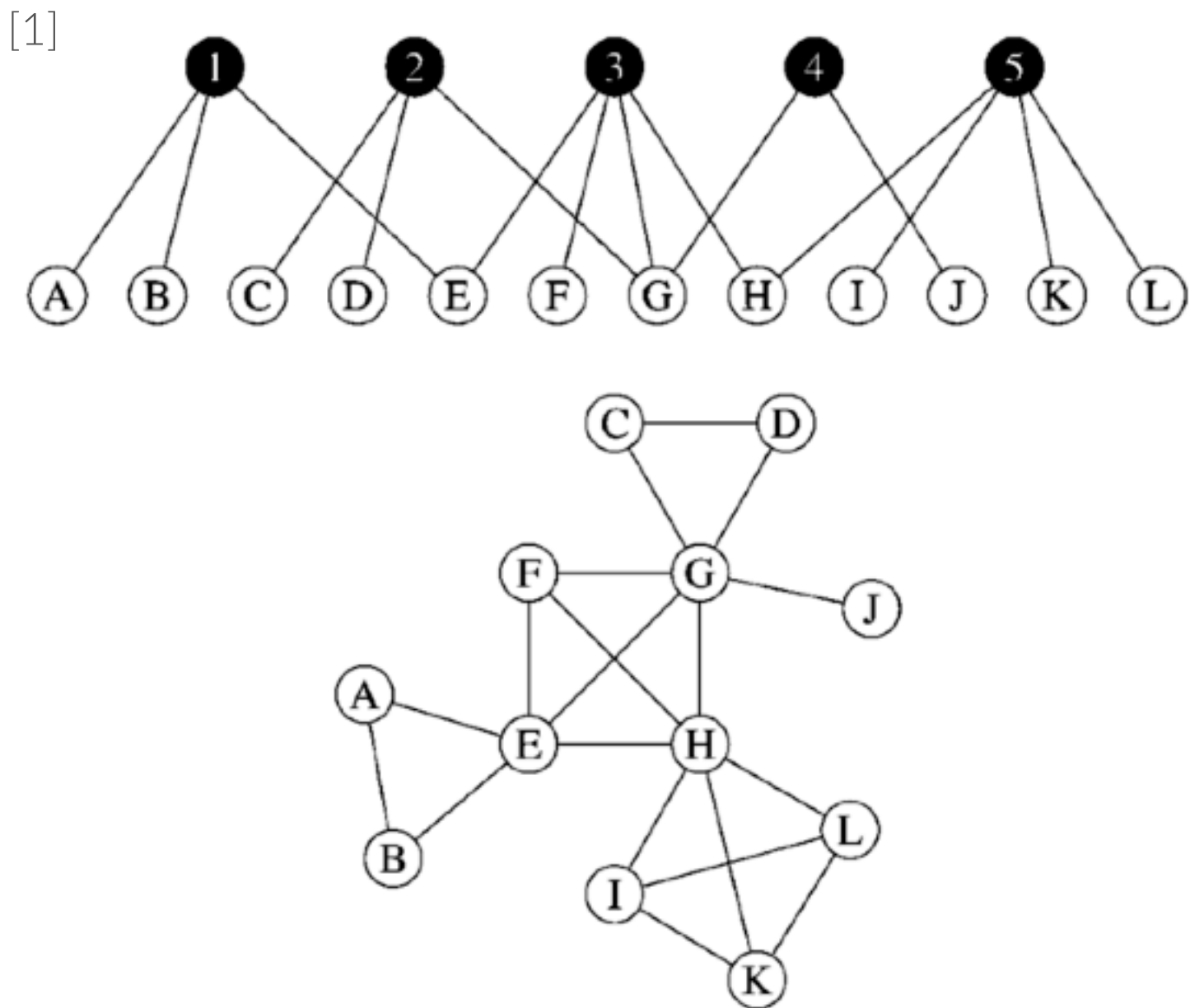
Studying the conditions for which  $p_{ij}$  can be **factorised** informs us on the degree-degree correlations observed in real networks.

# Modeling clustering

Tricky because clustering consists in **three-node interactions** while our mathematical tools rely on **pairwise interactions** either explicitly or implicitly.

Straightforward inclusion of triangles to the maximally random graph ensemble formalism yields **unwanted behavior** (ex.: triangle agglutination in the Strauss model [6]).

- Most models therefore assume
- ▷ an **underlying tree-like** structure
  - ▷ that the networks are **dense**



[1] Phys. Rev. E 68, 026121 (2003)  
[2] Phys. Rev. E 80, 036107 (2009)  
[3] Phys. Rev. Lett. 103, 058701 (2009)  
[4] Phys. Rev. E 82, 066118 (2010)  
[5] Appl. Netw. Sci. 4, 122 (2019)  
[6] Phys. Rev. E 72, 026136 (2005)