# Asymptotic Spectral Analysis of Random Graphs — Towards Complex Networks —

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Exploring a quantum probabilistic approach to network science

Bedlewo, August 6-12, 2007

#### I. Graph Spectrum

**Definition.** A graph is a pair G = (V, E), where V is the set of vertices and E the set of edges. For  $x, y \in V$  we write  $x \sim y$  (adjacent) if they are connected by an edge.

 $\star$  In this talk we focus on *finite graphs* with  $|V| = n < \infty$  and their limit as  $n \to \infty$ .

**Definition.** The *adjacency matrix*  $A = (A_{ij})_{i,j \in V}$  is defined by  $A_{ij} = \begin{cases} 1, i \sim j, \\ 0, \text{ otherwise.} \end{cases}$ 

- The characteristic polynomial of G :  $\varphi_G(x) = \det(xE A)$
- The spectrum of G: eigenvalues of A, say,  $\lambda_1, \ldots, \lambda_n$
- The spectral distribution of G:

$$\mu_G(dx) = \frac{1}{n} \sum_{k=1}^n \delta(x - \lambda_k) dx$$

• The moment sequence:

$$M_m(\mu_G) = \int_{-\infty}^{+\infty} x^m \mu_G(dx) = \frac{1}{n} \sum_{k=1}^n \lambda_k^m = \frac{1}{n} \operatorname{Tr} A^m$$

\* The graph spectrum is not enough to characterize a graph (up to isomorphisms), but contains valuable information about graph geometry (cf. algebraic graph theory).

## **II.** Random Graphs

Let  $V = \{0, 1, \dots, n-1\}$  be a fixed set of vertices (|V| = n).

 $\mathcal{G} = \{G; G \text{ is a graph whose vertex set is } V\}, \qquad |\mathcal{G}| = 2^{\binom{n}{2}}.$ 

Given a probability measure P,  $(\mathcal{G}, P)$  is called a *random graph*.

- The adjacency matrix  $A = A_G$  of  $G \in \mathcal{G} \implies$  random matrix
- The spectral distribution  $\mu = \mu_G$  of  $G \in \mathcal{G} \implies$  random distribution

Main objectives are:

• The *mean spectral distribution* of a random graph:

$$\mu = \mathbf{E}(\mu_G) = \sum_{G \in \mathcal{G}} P(\{G\}) \mu_G$$

• The moment sequence:

$$M_m(\mu) = \int_{-\infty}^{+\infty} x^m \mu(dx) = \frac{1}{n} \mathbf{E}(\text{Tr } A^m), \qquad m = 1, 2, \dots$$

• The asymptotic behaviour as  $n \to \infty$  (with some scaling balance)

A typical example:  $\mathcal{G}(n,p)$  the *Erdős–Rényi random graph* 

$$\begin{split} V &= \{0, 1, 2, \dots, n-1\}, \qquad 0$$

For example,  $\mathcal{G}(3,p)$ 



The mean spectral distribution:

$$\mu_{3,p} = p^3 \nu_3 + 3p^2 (1-p)\nu_2 + 3p(1-p)^2 \nu_1 + (1-p)^3 \nu_0$$

# **III.** Why Random Graphs?

Models of *real world networks* in our life (technological, social, biological, etc.)

#### Epoch-making papers:

- [1] D. J. Watts and S. H. Strogatz: Collective dynamics of 'small-world' networks, Nature 393 (1998), 440–442. ⇒ small world model (short distance between vertices)
- [2] A.-L. Barabási and R. Albert: Emergence of scaling in random networks, Science 286 (1999), 509–512. → scale-free model (power law of the degree distribution)
- Both models are suitable for computer simulation.
- But mathematical analysis remains open (seems very difficult).
- In particular, *spectral analysis of real world networks* is an interesting topic
- Also interesting for testing the recently developed techniques of quantum probability  $\implies$  My challenging theme

#### My Strategy:

- 1. Study Erdős–Rényi randoms (1960)
  - Original purpose was to prove existence of a graph having certain properties.
  - Referred to often as a first step toward real world networks, however, not realistic.
  - The explicit form of the asymptotic spectral distribution is still unknown.
- 2. Modify the WS-model and BA-model with the idea of random graphs and derive mathematically rigorous results.
- 3. Spectral analysis of the WS-model and BA-model and go further.

In this talk I will report preliminary consideration and some results:

- (i) Propose a model based on WS-model and ER-random graphs
- (ii) Combinatorial formula for the asymptotic spectral distributions

## **IV.** Our Model



Our model

 $\{X_{ij}; i, j \in V, i \neq j\}$ : independent random variables with values in  $\{0, 1\}$  $A = (A_{ij})$  with  $A_{ij} = \frac{1}{2}(X_{ij} + X_{ji})$ : adjacency matrix of a "weighted" graph (network)



Moreover, "geometric location" is taken into account.

E.g., near vertices are connected at a large probability and remote ones at a small probability Fix a subset  $R \subset \{(i, j) \in V \times V; i \neq j\}$ Let 0 and <math>0 < p' < 1. Define a random variable  $X_{ij}$  by (i) If  $(i, j) \in R$ , set  $P(X_{ij} = 1) = p$  and  $P(X_{ij} = 0) = 1 - p$ . (ii) If  $(i, j) \notin R$ , set  $P(X_{ij} = 1) = p'$  and  $P(X_{ij} = 0) = 1 - p'$ . Then  $A_{ij} = \frac{1}{2}(X_{ij} + X_{ji})$  has 3 different distributions according to the location of i and j.



Thus, our model  $\mathcal{G}(n, R; p, p')$  contains:

(i) grade of connection, i.e.,  $A_{ij} = 1$  (tight),  $A_{ij} = 1/2$  (loose),  $A_{ij} = 0$  (none).

(ii) probability of connection depends on location of vertices,  $A_{ij} \sim \alpha, \beta, \gamma$ .

**V.** Some general results on  $\mathcal{G}(n, R; p, p')$ 

We assume "symmetry" in order that all vertices i are "statistically equivalent."

For any  $i_0 \in V$  there exists a permutation  $\sigma$  on V such that  $\sigma(i_0) = 0$  and for all  $i, j \in V$ , the distributions of  $A_{ij}$  and  $A_{\sigma(i)\sigma(j)}$  coincide. (This is a condition on R.)

Mean degree of  $\mathcal{G}(n,R;p,p')$ 

$$\bar{d}(\mathcal{G}(n,R;p,p')) = \frac{1}{n} \sum_{i \in V} \mathbf{E}(\deg_G(i)) = \frac{1}{n} \sum_{i \in V} \sum_{j \neq i} \mathbf{E}(A_{ij})$$
$$= \sum_{j \neq 0} \mathbf{E}(A_{0j}) = pR_2 + \frac{p+p'}{2}R_1 + p'R_0,$$

where  $R_0 + R_1 + R_2 = n - 1$  and

$$R_{2} = |\{j \in V; (0, j) \in R \cap R^{t}\}|, \quad R_{0} = |\{j \in V; j \neq 0, (0, j) \notin R \cup R^{t}\}|, R_{1} = |\{j \in V; (0, j) \in R \cup R^{t} \text{ but } \notin R \cap R^{t}\}|.$$

Sparse limit (Poisson limit):  $n \to \infty$  and  $\bar{d} \to \text{constant}$ .

E.g., in case of  $R=\{(i,i+1)\,;\,i\in V\}$  , we take

$$n \to \infty, \qquad p' \to 0, \qquad np' \to \lambda \text{ (constant)}$$

Mean spectral distribution of  $\mathcal{G}(n, R; p, p')$  is characterized by the moment sequence:

$$M_m = \sum_{\mathcal{L} \in \Lambda_m(\{\alpha, \beta, \gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L}) t(\mathcal{L}; n) \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \alpha}} \alpha_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \beta}} \beta_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \gamma}} \gamma_{\kappa(e)},$$

where  $\alpha_{\kappa}$ ,  $\beta_{\kappa}$ ,  $\gamma_{\kappa}$  are the  $\kappa$ -th moments of the distributions  $\alpha, \beta, \gamma$ , respectively. Namely,

$$\alpha_{\kappa} = p^2 + \frac{2p(1-p)}{2^{\kappa}}, \quad \beta_{\kappa} = pp' + \frac{p+p'-2pp'}{2^{\kappa}}, \quad \gamma_{\kappa} = p'^2 + \frac{2p'(1-p')}{2^{\kappa}}.$$

 $\Lambda_m(\{\alpha,\beta,\gamma\}) \ni \mathcal{L} = (\mathcal{V},\mathcal{E},o,\nu,\kappa) \text{ is a } \{\alpha,\beta,\gamma\}\text{-labeled rooted graph of size } m \text{, i.e.,}$ 

- (L1) a connected graph  $(\mathcal{V}, \mathcal{E})$  with  $2 \leq |\mathcal{V}| \leq m$ ;
- (L2) a distinguished vertex  $o \in \mathcal{V}$  which is called the root;
- (L3) a map  $\nu : \mathcal{E} \to {\alpha, \beta, \gamma};$
- (L4) a map  $\kappa : \mathcal{E} \to \{1, 2, \dots, m\}$  such that  $\sum_{e \in \mathcal{E}} \kappa(e) = m$ .

 $u(\mathcal{L})$ : the number of unicursal walks in  $\mathcal{L}$ 

 $t(\mathcal{L}; n)$ : the number of A-admissible embeddings, i.e., injections  $\varphi : \mathcal{V} \to \{0, 1, \dots, n-1\}$ such that  $\varphi(o) = 0$  and for every  $\{v, v'\} \in \mathcal{E}$ ,  $\nu(\{v, v'\})$  coincides with the distribution of  $A_{\varphi(v)\varphi(v')}$ .

#### *Outline of proof:*

(1) By definition and symmetry assumption,

$$M_m = \frac{1}{n} \mathbf{E}(\operatorname{Tr} A^m) = \mathbf{E}\langle \delta_0, A^m \delta_0 \rangle = \sum_{[i] \in \mathcal{W}(V,m)} \mathbf{E}(A_{0i_1} A_{i_1 i_2} \cdots A_{i_{m-1} 0}),$$

$$\mathcal{W}(V,m) = \{ [i] : 0 \neq i_1 \neq \cdots \neq i_{m-1} \neq 0, \ i_k \in V \}.$$

(2) Let G[i] be the underlying graph and for  $e=\{j,j'\}\in E(G[i])$  we define

$$\nu(e) = \text{the distribution of } A_{jj'} = A_{j'j},$$
  

$$\kappa(e) = |\{0 \le s \le m - 1; \{i_s, i_{s+1}\} = \{j, j'\}\}|.$$

(3) By independence of  $\{A_{jj'}; 0 \le j < j' \le n-1\}$ ,

$$M_m = \sum_{[i]} \mathbf{E} \left( \prod_{j < j'} A_{jj'}^{\kappa(j,j')} \right) = \sum_{[i]} \prod_{j < j'} \mathbf{E} (A_{jj'}^{\kappa(j,j')}) = \sum_{[i] \in \mathcal{W}(V,m)} \prod_{e \in E(G[i])} M_{\kappa(e)}(\nu(e))$$

(4) Setting  $\mathcal{L}[i] = (G[i], 0, \nu, \kappa)$ ,

$$M_{m} = \sum_{\mathcal{L} \in \Lambda_{m}(\{\alpha,\beta,\gamma\})} |\{[i] \in \mathcal{W}(V,m); \mathcal{L}[i] \cong \mathcal{L}\}| \prod_{e \in E(\mathcal{L})} M_{\kappa(e)}(\nu(e))$$
$$= \sum_{\mathcal{L} \in \Lambda_{m}(\{\alpha,\beta,\gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1}u(\mathcal{L})t(\mathcal{L};n) \prod_{\substack{e \in E(\mathcal{L})\\\nu(e) = \alpha}} \alpha_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L})\\\nu(e) = \beta}} \beta_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L})\\\nu(e) = \gamma}} \gamma_{\kappa(e)}.$$

**VI.** Model I:  $R = \{(i, i+1); i \in V\}$ 

• Note that the distribution  $\alpha$  does not appear since  $R\cap R^t=\emptyset.$  Hence,

$$M_m(n, p, p') = \sum_{\mathcal{L} \in \Lambda_m(\{\beta, \gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L}) t(\mathcal{L}; n) \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \beta}} \beta_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \gamma}} \gamma_{\kappa(e)}$$

• By our definition, an  $\beta$ -edge corresponds to an edge  $\{i, i \pm 1\} \in R \cup R^t$ .

• If  $\mathcal{L} = (\mathcal{V}, \mathcal{E}, o, \nu, \kappa) \in \Lambda_m(\{\beta, \gamma\})$  contains a  $\beta$ -cycle or a  $\beta$ -branch, there is no A-admissible embedding (for a large n).



• The sum is taken over

$$\Lambda_m^*(\{\beta,\gamma\}) = \left\{ \mathcal{L} \in \Lambda_m(\{\beta,\gamma\}); \begin{array}{l} \text{(i) contains no } \beta\text{-cycles}; \\ \text{(ii) contains no } \beta\text{-branches} \end{array} \right\}.$$

In other words, in  $\mathcal{L} \in \Lambda_m^*(\{\beta, \gamma\})$  every  $\beta$ -edge appears only as a linear segment ( $\beta$ -segment).

**VII.** Model I in the Sparse Limit  $(n \to \infty, p' \to 0, np' \to \lambda)$ 

Mean degree:  $\lim \overline{d}(\mathcal{G}_I(n, p, p')) = \lim \{p + (n-2)p'\} = p + \lambda$ 

Moments of  $\beta$  and  $\gamma$ :  $\lim \beta_{\kappa} = \frac{p}{2^{\kappa}}$ ,  $\lim n\gamma_{\kappa} = \frac{2\lambda}{2^{\kappa}}$ .

Our target:

$$\lim M_m(n, p, p') = \lim \sum_{\mathcal{L} \in \Lambda_m^*(\{\beta, \gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L}) t(\mathcal{L}; n) \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \beta}} \beta_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \gamma}} \gamma_{\kappa(e)}.$$

First a few moments:

$$\lim M_1(n, p, p') = 0,$$
  

$$\lim M_2(n, p, p') = \frac{p}{2} + \frac{\lambda}{2},$$
  

$$\lim M_3(n, p, p') = 0,$$
  

$$\lim M_4(n, p, p') = \frac{p}{8} + \frac{\lambda}{8} + \frac{p^2}{4} + p\lambda + \frac{\lambda^2}{2}.$$

THEOREM 1. Let  $M_m = M_m(n, p, p')$  be the *m*-th moment of the mean spectral distribution of  $\mathcal{G}_I(n, p, p')$ . Then, in the sparse limit

$$\lim M_m = \begin{cases} 0, & \text{if } m \text{ is odd,} \\ \sum_{\mathcal{L} \in \Lambda_m^{**}(\{\beta,\gamma\})} |\operatorname{Aut} \left(\mathcal{L}\right)|^{-1} u(\mathcal{L}) \, 2^{|\mathcal{E}_{\gamma}| + 1 - b(\mathcal{L}) - m} \, p^{|\mathcal{E}_{\beta}|} (2\lambda)^{|\mathcal{E}_{\gamma}|}, & \text{if } m \text{ is even.} \end{cases}$$

Outline of Proof. (0) Start with

$$\lim M_m(n, p, p') = \lim \sum_{\mathcal{L} \in \Lambda_m^*(\{\beta, \gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L}) t(\mathcal{L}; n) \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \beta}} \beta_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \gamma}} \gamma_{\kappa(e)}.$$

(1) Let  $\tilde{\mathcal{L}} = (\tilde{\mathcal{V}}, \tilde{\mathcal{E}})$  be a connected graph obtained from  $\mathcal{L}$  by  $\beta$ -edge contraction. (2) Let  $b(\mathcal{L})$  be the number of isolated vertices of  $(\mathcal{V}, \mathcal{E}_{\beta})$ .

$$2^{|\tilde{\mathcal{V}}|-b(\mathcal{L})} (n-2m^2)^{|\tilde{\mathcal{V}}|-1} \le |t(\mathcal{L};n)| \le 2^{|\tilde{\mathcal{V}}|-b(\mathcal{L})} n^{|\tilde{\mathcal{V}}|-1}.$$

(3) For any connected graph G = (V, E) we have  $|V| \le |E| + 1$ . Moreover, the equality holds if and only if G is a tree.

(4) 
$$\lim t(\mathcal{L}; n) \prod \gamma_{\kappa(e)} = 0$$
 unless  $\mathcal{L}$  belongs to  
 $\Lambda_m^{**}(\{\beta, \gamma\}) = \{\mathcal{L} \in \Lambda_m^*(\{\beta, \gamma\}); \tilde{\mathcal{L}} \text{ is a tree and } |\tilde{\mathcal{E}}| = |\mathcal{E}_{\gamma}| \iff \mathcal{L} \text{ is a tree}\} \}.$ 

# **VIII.** Model II: $R = \{(i, i \pm 1); i \in V\}$

Mean degree of  $\mathcal{G}_{II}(n, p, p')$ :

$$\bar{d}(\mathcal{G}_I(n,p,p')) = 2p + (n-3)p'.$$

Moment sequence of  $\mathcal{G}_{II}(n, p, p')$ :

$$M_m(n, p, p') = \sum_{\mathcal{L} \in \Lambda_m^*(\{\alpha, \gamma\})} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L}) t(\mathcal{L}; n) \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \alpha}} \alpha_{\kappa(e)} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \gamma}} \gamma_{\kappa(e)}.$$

In the sparse limit  $n \to \infty$ ,  $p' \to 0$ ,  $np' \to \lambda$ :

$$\lim \bar{d}(\mathcal{G}_I(n, p, p')) = 2p + \lambda, \qquad \lim \alpha_{\kappa} = p^2 + \frac{2p(1-p)}{2^{\kappa}}, \qquad \lim n\gamma_{\kappa} = \frac{2\lambda}{2^{\kappa}}.$$

THEOREM 2. Let  $M_m(n, p, p')$  be the *m*-th moment of the mean spectral distribution of  $\mathcal{G}_{II}(n, p, p')$ . Then, in the sparse limit

$$\lim M_m = \begin{cases} 0, & \text{if } m \text{ is odd,} \\ \sum_{\mathcal{L} \in \Lambda_m^{**}(\{\alpha, \gamma\})} |\operatorname{Aut} \left( \mathcal{L} \right)|^{-1} u(\mathcal{L}) \, 2^{|\mathcal{E}_{\gamma}| + 1 - b(\mathcal{L}) - m} \left( 2\lambda \right)^{|\mathcal{E}_{\gamma}|} \prod_{\substack{e \in E(\mathcal{L}) \\ \nu(e) = \alpha}} \left( (2^{\kappa(e)} - 2)p^2 + 2p \right), \\ & \text{if } m \text{ is even.} \end{cases}$$

## **IX.** The Erdős–Rényi Random Graph

**Definition.** Let  $n \ge 1$ ,  $0 . Let <math>\mathcal{G}(n,p)$  be the set of all graphs with vertex set  $V = \{0, 1, 2, \dots, n-1\}$  with probability  $P(\{G\})$  defined by

$$P(\{G\}) = p^{|E(G)|}(1-p)^{\binom{n}{2} - |E(G)|}, \qquad E(G) = \{\text{edges of } G\}.$$

Some statistics of  $\mathcal{G}(n,p)$ 

• The mean spectral distribution  $\mu_{n,p}$  — rather complicated!

• The mean degree: 
$$\bar{d}(\mathcal{G}(n,p)) = \frac{1}{n} \sum_{i \in V} \mathbf{E}(\deg_G(i)) = (n-1)p$$

• The mean number of edges: 
$$\mathbf{E}(|E(G)|) = \frac{n}{2}M_2 = \frac{n(n-1)}{2}p$$

• The mean number of triangles: 
$$\mathbf{E}(|\triangle(G)|) = \frac{n}{6}M_3 = \frac{n(n-1)(n-2)}{6}p^3$$

Problem: Find  $\lim \mu_{n,p}$  in the sparse limit

$$n \to \infty$$
,  $p \to 0$ ,  $np \to \lambda$  (constant).

• Cluster coefficient:  $\mathbf{E}(|\triangle(G)|)/|\{\text{all possible triangles}\}| = p^3 \rightarrow 0$  (not realistic!)

Moment sequence of  $\mu_{n,p}$  (=mean spectral distribution of  $\mathcal{G}(n,p)$ )

$$M_m(\mu_{n,p}) = \frac{1}{n} \mathbf{E}(\operatorname{Tr} A^m) = \frac{1}{n} \sum_{i \in V} \mathbf{E}((A^m)_{ii}) = \mathbf{E}((A^m)_{00})$$
$$= \sum_{\mathcal{L} \in \Lambda_m} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L})(n-1)(n-2) \cdots (n-(|V(\mathcal{L})|-1)) p^{|E(\mathcal{L})|},$$

where  $\Lambda_m$  is the collection of all labeled graphs  $\mathcal{L} = (\mathcal{V}, \mathcal{E}, o, \kappa)$ , where

- (i)  $(\mathcal{V}, \mathcal{E})$  is a connected graph with  $2 \leq |\mathcal{V}| \leq m$ ,
- (ii)  $o \in V$  is a distinguished vertex,

(iii) 
$$\kappa : \mathcal{E} \to \{1, 2, ...\}$$
 such that  $\sum_{e \in \mathcal{E}} \kappa(e) = m$ .

First few moments of  $\mu_{n,p}$ 

$$M_{1}(\mu_{n,p}) = 0, \qquad M_{2}(\mu_{n,p}) = (n-1)p, \qquad M_{3}(\mu_{n,p}) = (n-1)(n-2)p^{3}$$

$$M_{4}(\mu_{n,p}) = (n-1)p + 2(n-1)(n-2)p^{2} + (n-1)(n-2)(n-3)p^{4}$$

$$M_{5}(\mu_{n,p}) = 5(n-1)(n-2)p^{3} + 5(n-1)(n-2)(n-3)p^{4} + (n-1)(n-2)(n-3)(n-4)p^{5}$$

#### THEOREM 3.

$$M_m \equiv \lim M_m(\mu_{n,p}) = \begin{cases} 0, & m \text{ is odd}, \\ \sum_{\mathcal{L} \in \Lambda_m^{**}} |\operatorname{Aut} (\mathcal{L})|^{-1} u(\mathcal{L}) \lambda^{|E(\mathcal{L})|}, & m \text{ is even}, \end{cases}$$

where  $\Lambda_m^{**}$  is the collection of all labeled graphs  $\mathcal{L} = (\mathcal{V}, \mathcal{E}, o, \kappa)$ , where

(i) 
$$(\mathcal{V}, \mathcal{E})$$
 is a *tree* with  $2 \leq |\mathcal{V}| \leq m$ ,

(ii)  $o \in V$  is a distinguished vertex,

(iii) 
$$\kappa : \mathcal{E} \to \{1, 2, \dots\}$$
 such that  $\sum_{e \in \mathcal{E}} \kappa(e) = m$ .

*Outline of Proof:* (1)

$$M_m(\mu_{n,p}) = \sum_{\mathcal{L}\in\Lambda_m} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L})(n-1)(n-2)\cdots(n-(|V(\mathcal{L})|-1)) p^{|E(\mathcal{L})|}$$
$$\sim \sum_{\mathcal{L}\in\Lambda_m} |\operatorname{Aut}(\mathcal{L})|^{-1} u(\mathcal{L})n^{|V(\mathcal{L})|-1-|E(\mathcal{L})|}(np)^{|E(\mathcal{L})|}.$$
 (\*)

- (2) If  $\mathcal{L}$  is not a tree, then  $|V(\mathcal{L})| \leq |E(\mathcal{L})|$  and (\*) vanishes.
- (3) If  $\mathcal{L}$  is a tree, then  $|V(\mathcal{L})| = |E(\mathcal{L})| + 1$  and we get the result.
- Cf. Bauer–Golinelli (2001), Dorogovtsev–Goltsev–Mendes–Samukhin (2003)

#### Alternative expression of $M_m$

THEOREM 4. The sparse limit of the 2m-th moment of mean spectral distribution of the Erdős–Rényi random graph  $\mathcal{G}(n, p)$  is given by

$$M_{2m} = \sum_{\vartheta \in \mathcal{P}_{\mathrm{T}}(2m)} \lambda^{|\vartheta|}$$

Outline of Proof: (1)

$$M_{2m}(\mu_{n,p}) = \mathbf{E}((A^{2m})_{00}) = \sum_{[i] \in \mathcal{W}(V,2m)} \mathbf{E}(A_{0i_1}A_{i_0i_1}\cdots A_{i_{2m-1}0}) = \sum_{[i] \in \mathcal{W}(V,2m)} p^{|E(G[i])|}$$

(2) In the limit, we need only consider

$$[i]: 0 \equiv i_0 \neq i_1 \neq i_2 \neq \cdots \neq i_{2m-1} \neq i_{2m} \equiv 0, \qquad i_k \in V,$$

such that G[i] is a tree (by Theorem 3).

(3) For a such  $[i] \in \mathcal{W}(V, 2m)$  we associate a partition  $\vartheta = \vartheta[i]$  of  $\{1, 2, \ldots, 2m\}$ . The set of such partitions is denoted by  $\mathcal{P}_{\mathrm{T}}(2m)$ .

(4) For  $\vartheta=\vartheta[i]$  we have  $|E(G[i])|=|\vartheta|$  and

$$M_{2m} = \lim \sum_{\vartheta \in \mathcal{P}_{\mathrm{T}}(2m)} \sum_{\substack{[i] \in \mathcal{W}(V, 2m)\\ \vartheta[i] = \vartheta}} p^{|\vartheta|} = \lim \sum_{\vartheta \in \mathcal{P}_{\mathrm{T}}(2m)} (n-1)(n-2) \cdots (n-|\vartheta|) p^{|\vartheta|}.$$

What is  $\mathcal{P}_{\mathrm{T}}(2m)$ ?

Every partition in P<sub>T</sub>(2m) is obtained from a non-crossing pair partition of {1, 2, ..., 2m}.
Given ϑ ∈ P<sub>NCP</sub>(2m), (i) two or more blocks can be joined if their depth = 1; (ii) two or more blocks can be joined if their depth are the same and the upper blocks are already joined.

• Let  $\mathcal{P}_{\text{TNC}}(2m)$  be the set of all non-crossing partitions of  $\{1, 2, \ldots, 2m\}$  such that each block consists of even number of points. Then  $\mathcal{P}_{\text{TNC}}(2m) \subset \mathcal{P}_{\text{T}}(2m)$ 

Non-crossing approximation

$$M_{2m} = \sum_{\vartheta \in \mathcal{P}_{\mathrm{T}}(2m)} \lambda^{|\vartheta|} \ge \sum_{\vartheta \in \mathcal{P}_{\mathrm{TNC}}(2m)} \lambda^{|\vartheta|} = M_{2m}(\pi_{\lambda/2} \boxplus \pi_{\lambda/2}^{\vee})$$

where  $\pi_{\lambda/2}$  be the free Poisson distribution with parameter  $\lambda/2$  and  $\pi_{\lambda/2}^{\vee}$  its reflection (Bożejko, the free moment–cumulant calculus)

Asymptotics for large  $\lambda$ 

$$M_{2m} = \sum_{\vartheta \in \mathcal{P}_{\mathrm{T}}(2m)} \lambda^{|\vartheta|} = |\mathcal{P}_{\mathrm{NCP}}(2m)| \lambda^{m} + O(\lambda^{m-1}).$$

explaining the Erdős-Rényi random graphs behave like a tree.

# Summary

- 1. We proposed two models of real world complex networks. Motivated by Erdős–Rényi random graph + Watts-Strogatz small world model.
- 2. We derived combinatorial formulas for the spectral distribution in the sparse limit.
- 3. We examined a similar question for the Erdős-Rényi random graph.
- 4. Analytic study of the limit distribution is left open (a challenging problem for quantum probabilistic method).

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