





The Structure of Sparse Random Bipartite Graphs

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Introduction

Random Bipartite
 Graphs

• First Results

Generating Functions

The Component

Structure

- We consider multigraphs with two types of labelled nodes.
 - Each labelled edge connects nodes of different types and is chosen uniformly at random.
- We concentrate on (relatively) sparse graphs.

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First Results

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Consider a random bipartite graph G, consisting of m nodes of each type and n edges.

Theorem 1. The probability, that G contains only tree and unicyclic components, provided that $n = \lfloor (1 - \varepsilon)m \rfloor$ and $\varepsilon \in (0, 1)$, equals

$$1 - \frac{(2\varepsilon^2 - 5\varepsilon + 5)(1 - \varepsilon)^3}{12(2 - \varepsilon)^2 \varepsilon^3} \frac{1}{m} + \mathcal{O}\left(\frac{1}{m^2}\right)$$

Theorem 2. Assume *m* equals *n*. The probability, that *G* contains only tree and unicyclic components, equals $\sqrt{2/3} + o(1)$.

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- Devroye and Morin showed 1 O(1/m) in 2001.
 - The analytic structure of generating functions for bipartite random graphs is more difficult than that of usual random graphs.
- Nevertheless the results look the same, cf. Janson et al. 1993. Thus, one can expect that most properties of random graphs have a counterpart in random bipartite graphs (birth of giant component etc.).

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- Asymptotic Analysis
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- The "critical" case

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Bipartite Trees

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- We use the generating functions t₁(x, y) and t₂(x, y) for bipartite rooted trees, where the root is contained in first respectively second subset of nodes.
- This generating functions are given by

 $t_1(x,y) = xe^{t_2(x,y)}, \quad t_2(x,y) = ye^{t_1(x,y)}.$

- Let $\tilde{t}(x, y)$ denote the generating function of unrooted bipartite trees.
- Furthermore, one can show:

 $\tilde{t}(x,y) = t_1(x,y) + t_2(x,y) - t_1(x,y)t_2(x,y)$

Cyclic Components

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- Of course, a cycle has to have an even number of nodes, say 2k, where k nodes are of type 1 and the other k nodes of type 2.
- A cyclic node of type 1 can be considered as the root of a rooted tree of type 1 and similarly, for type 2.



• The product of the generating functions of this trees is divided by 2k, to account for cyclic order and change of orientation.

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• Consequently the generating function of a connected graph with exactly one cycle is given by

$$c(x,y) = \sum_{k\geq 1} \frac{1}{2k} t_1(x,y)^k t_2(x,y)^k$$
$$= \frac{1}{2} \log \frac{1}{1 - t_1(x,y)t_2(x,y)}$$

Trees and Unicycles

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- Let $g^{\circ}(x, y)$ denote the generating function of bipartite graphs consisting only of tree and unicyclic components.
- Note that such a graph possesses exactly 2m n tree components.
- Hence, we get

$$g^{\circ}(x,y) = \frac{1}{(2m-n)!} \frac{\tilde{t}(x,y)^{2m-n}}{\sqrt{1-t_1(x,y)t_2(x,y)}}.$$

• We are interested in $[x^m y^m]g^{\circ}(x,y)$.

Asymptotic Analysis

$$[x^{m}y^{m}]g^{\circ}(x,y) = \frac{-(m!)^{2}}{4\pi(2m-n)!} \int_{|x|=x_{0}} \int_{|y|=y_{0}} \frac{\tilde{t}(x,y)^{2m-n}}{\sqrt{1-t_{1}(x,y)t_{2}(x,y)}} \frac{dx\,dy}{(xy)^{m+1}}$$

This is in fact an integral that can be asymptotically evaluated with help of a (double) saddle point method. It turns out, that if $n = (1 - \varepsilon)m$ and $\varepsilon \in (0, 1)$ is fixed, the saddle point is given by

$$x_0 = y_0 = \frac{n}{m}e^{-\frac{n}{m}} = (1-\varepsilon)e^{\varepsilon-1} < \frac{1}{e}.$$

The Saddle Point Method

Lemma 1. f(x, y) and g(x, y) analytic functions in a ball around (0, 0) (+ technical assumptions):

$$[x^{m_1}y^{m_2}]g(x,y)f(x,y)^k = \frac{g(x_0,y_0)f(x_0,y_0)^k}{2\pi x_0^{m_1}y_0^{m_2}k\sqrt{\Delta}} \left(1 + \frac{h}{24\Delta^3}\frac{1}{k} + O\left(\frac{1}{k^2}\right)\right),$$

where x_0 and y_0 are uniquely defined by

$$\frac{m_1}{k} = \frac{x_0}{f(x_0, y_0)} \left[\frac{\partial}{\partial x} f(x, y) \right]_{(x_0, y_0)}$$
$$\frac{m_2}{k} = \frac{y_0}{f(x_0, y_0)} \left[\frac{\partial}{\partial y} f(x, y) \right]_{(x_0, y_0)}.$$

 $(m_1, m_2, \text{ and } k \text{ have to be of the same order of magnitude})$

Generally, let the cummulants κ_{ij} and $\overline{\kappa}_{ij}$ be

$$\kappa_{ij} = \left[\frac{\partial^i}{\partial u^i} \frac{\partial^j}{\partial v^j} \log f(x_0 e^u, y_0 e^v)\right]_{(0,0)}$$

$$\overline{\kappa}_{ij} = \left[\frac{\partial^i}{\partial u^i} \frac{\partial^j}{\partial v^j} \log g(x_0 e^u, y_0 e^v)\right]_{(0,0)}$$

Further let $\Delta = \kappa_{20}\kappa_{02} - \kappa_{11}^2$, then h is a constant depending on $\kappa_{02}, \kappa_{11}, \kappa_{20}, \kappa_{03}, \kappa_{12}, \kappa_{21}, \kappa_{30}, \overline{\kappa}_{01}, \overline{\kappa}_{10}, \overline{\kappa}_{02}, \overline{\kappa}_{11}$, and $\overline{\kappa}_{20}$.

The "critical" case

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- Here, we consider the special case $\varepsilon = 0$.
 - The proof of Theorem 2 follows the same idea.
- However, the saddle point $x_0 = y_0 = 1/e$ coalesces with the singularity of the denominator of

$$\frac{\tilde{t}(x,y)^{2m-n}}{\sqrt{1-t_1(x,y)t_2(x,y)}}$$

• We use the following series of $\#G^{\circ}_{m,m,m}$ and consider each summand separately,

$$(m!)^{2} \sum_{k \ge 0} \binom{2k}{k} \frac{1}{4^{k}} [x^{m}y^{m}] \tilde{t}(x,y)^{m} t_{1}(x,y)^{k} t_{2}(x,y)^{k}.$$

• Using Lagrange's Inversion Theorem, we get

$$[x^m y^m]\tilde{t}(x,y)^m t_1(x,y)^k t_2(x,y)^k = \frac{1}{m} [u^m y^m] f(u,y)^m l(u,y) h(u,y).$$

Hereby, we use the following functions:

$$f(u, y) = (u + ye^{u}(1 - u)) \exp(ye^{u}),$$

$$l(u, y) = u^{k} (ye^{u})^{k},$$

$$h(u, y) = u \frac{mu - mye^{u}u^{2} + ku + kye^{u} + ku^{2} - ku^{2}ye^{u}}{u (u + ye^{u}(1 - u))}.$$

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The saddle point now equals u₀ = 1, y₀ = 1/e.
We have to handle the integral

$$\int_{0}^{\infty} s e^{-\frac{2}{3}s^3 + \frac{2\zeta}{\sqrt[3]{m}}ks} dt \, ds.$$

This function is related to the Lommel function of second kind, that is a solution of the inhomogeneous Bessel differential equation

$$x^{2}\frac{d^{2}y}{dx^{2}} + x\frac{dy}{dx} + (x^{2} - \nu^{2})y = x^{\mu+1}.$$

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Number of Cycles

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Application

Suppose that $\varepsilon \in (0, 1)$ is fixed and that $n = \lfloor (1 - \varepsilon)m \rfloor$. Then a labelled random bipartite multigraph with $2 \times m$ vertices and n edges satisfies the following properties:

• The number of unicyclic components with cycle length 2k has in limit a Poisson distribution $Po(\lambda_k)$ with parameter

$$\lambda_k = \frac{1}{2k} \left(1 - \varepsilon \right)^{2k},$$

and the number of unicyclic components has in limit a Poisson distribution $Po(\lambda)$, too, with parameter

$$\lambda = -\frac{1}{2}\log\left(1 - (1 - \varepsilon)^2\right).$$

Trees with fixed size

• Denote the number of tree components with k vertices by t_k . Mean and variance of this random variable are asymptotically equal to

$$m\mu = 2m \frac{k^{k-2}(1-\varepsilon)^{k-1}e^{k(\varepsilon-1)}}{k!},$$

respectively

$$m\sigma^2 = m\mu - \frac{2me^{2k(\varepsilon-1)}k^{2k-4}(1-\varepsilon)^{2k-3}(k^2\varepsilon^2 + k^2\varepsilon - 4k\varepsilon + 2)}{(k!)^2}$$

Furthermore t_k satisfies a central limit theorem of the form

$$\frac{t_k - \mu}{\sigma} \to N(0, 1).$$

Nodes in all cyclic Components

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• Furthermore, the expected value of the number of nodes in unicyclic components is asymptotically given by

$$\frac{(1-\varepsilon)^2}{\varepsilon \left(1-(1-\varepsilon)^2\right)},$$

and its variance by

$$\frac{(1-\varepsilon)^2(\varepsilon^2-3\varepsilon+4)}{\varepsilon^2\left(1-(1-\varepsilon)^2\right)^2}.$$

Remarks

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Because of Theorem 1, it is sufficient to consider graphs that contain tree and unicylic components only. Recall the corresponding generating function

$$g^{\circ}(x,y) = \frac{\tilde{t}(x,y)^{2m-n}}{(2m-n)!} \exp(c(x,y)),$$

where c(x, y) denotes the generating function of an unicyclic component.

• Similar results hold for "usual" random graphs too.

Proof: Step 1

Introduce a "new" Variable w to mark the Parameter of interest:

• Number of cycles

$$g_1^{\circ}(x, y, w) = \frac{\tilde{t}(x, y)^{2m-n}}{(2m-n)!} \exp(wc(x, y))$$

• Trees possessing k nodes

$$g_2^{\circ}(x, y, w) = \frac{\left(\tilde{t}(x, y) + (w - 1)\tilde{t}_k(x, y)\right)^{2m - n}}{(2m - n)!} \exp(c(x, y))$$

• Nodes in all cyclic Components

$$g_3^{\circ}(x, y, w) = \frac{\tilde{t}(x, y)^{2m-n}}{(2m-n)!} \exp(c(\boldsymbol{w}x, \boldsymbol{w}y))$$

Proof: Step 2

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Calculate the l-th factorial Moment

$$\mathcal{M}_{l} = \frac{\left[x^{m}y^{m}\right] \left[\frac{\partial^{l}}{\partial w^{l}}g^{\circ}(x, y, w)\right]_{w=1}}{\left[x^{m}y^{m}\right]g_{t}^{\circ}(x, y, 1)},$$

or the characteristic function

$$\phi(s) = \frac{[x^m y^m] g^{\circ}(x, y, e^{is})}{[x^m y^m] g^{\circ}_t(x, y, 1)}$$

The calculation itself is again performed using the saddle point method.

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Cuckoo Hashing

- Hash table data structure introduced by Pagh and Rodler in 2001.
- Offers constant worst case search time.
- Uses two tables and two different hash functions h_1 and h_2 , both determine a unique position in each table.
- Resolve conflicts by rearranging keys.
- Algorithm can be modelled by a random bipartite graph.

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