



Edge-exchangeable graphs and sparsity

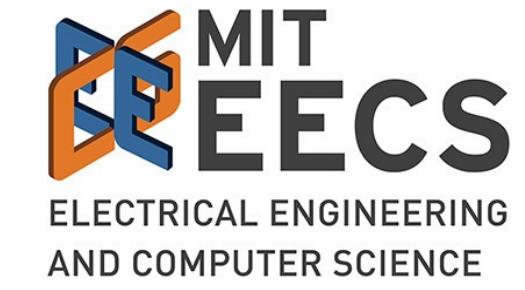
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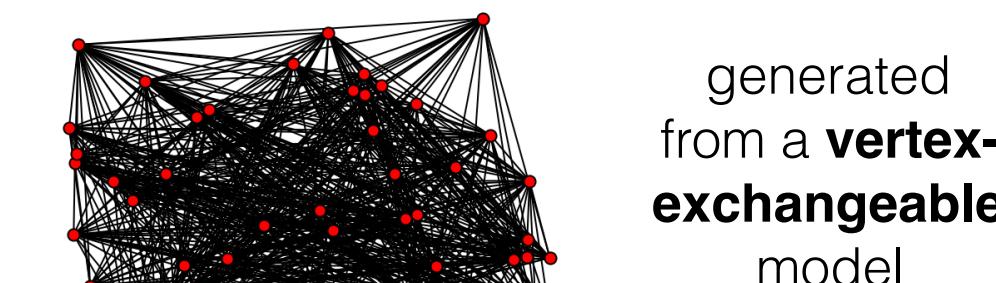


Motivation

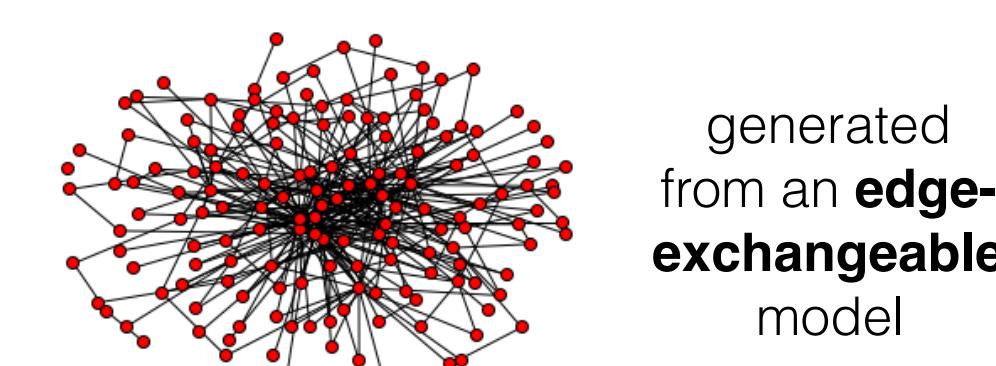
- The traditional notion of exchangeability for random graphs is *vertex exchangeability*.
- Vertex-exchangeable graphs are dense or empty almost surely.
- But most real-world graphs are *sparse*.
- We introduce the alternative notion of **edge exchangeability**, and show that a wide class of edge-exchangeable models can produce sparse graphs.

Projective graph sequences: We consider graph sequences G_1, G_2, G_3, \dots , where at each step of the sequence, we only add vertices and edges to the graph (instead of deleting edges).

Dense graph sequence:
 $[\#edges(G_n)] = \Omega([\#vertices(G_n)]^2)$
(quadratic growth)



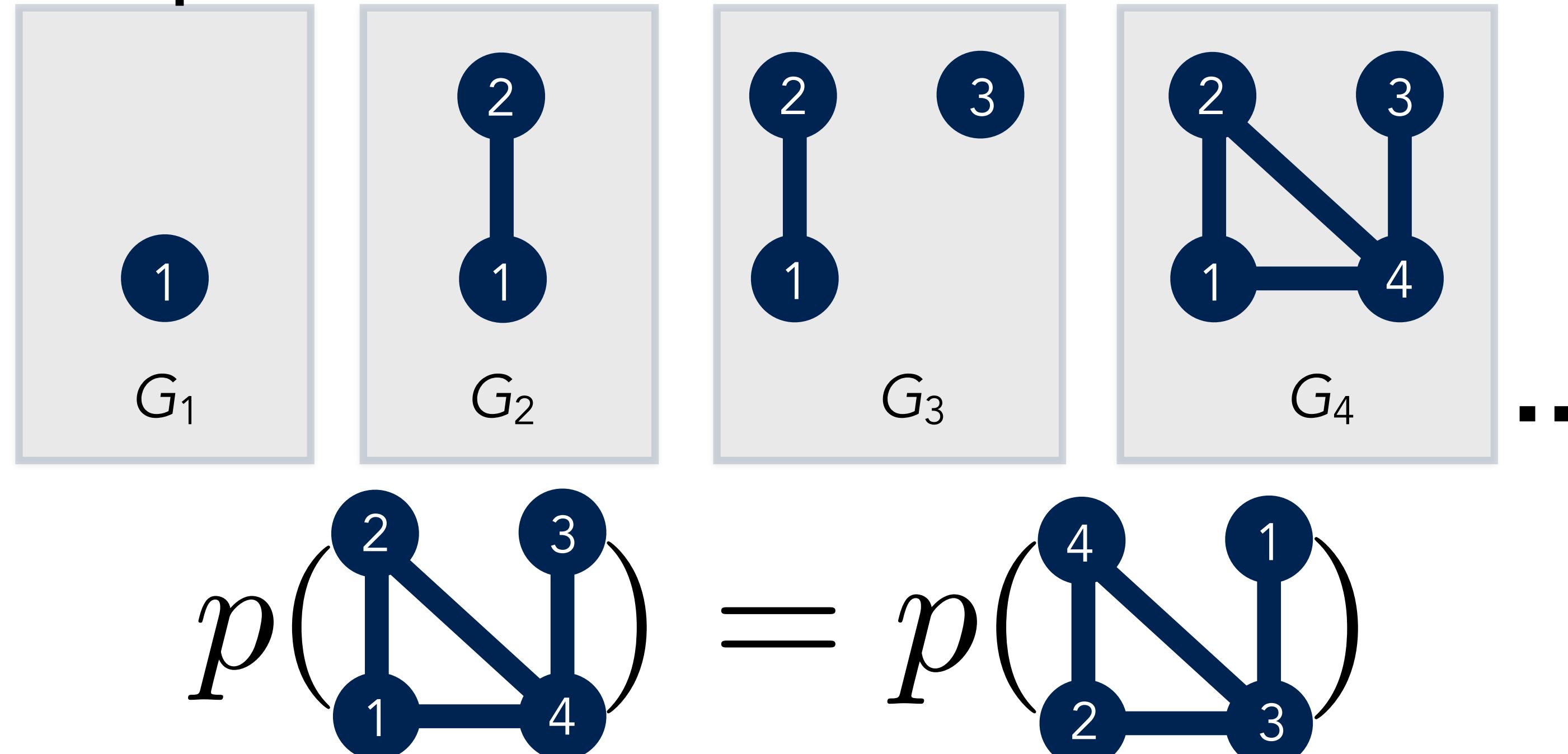
Sparse graph sequence
 $[\#edges(G_n)] = o([\#vertices(G_n)]^2)$
(sub-quadratic growth)



Vertex exchangeability

In vertex exchangeability, a new vertex joins the graph sequence at each step, is labeled with that step number, and instantiates all edges with *existing* vertices.

example realization:



Vertex exchangeability means that the distribution of any step in the random graph sequence is invariant to permutations of the vertex labels. Examples: Erdős–Rényi, stochastic block model

The Aldous-Hoover theorem implies that **vertex-exchangeable graphs are dense or empty with probability 1**, graphon $f : [0, 1]^2 \rightarrow [0, 1]$

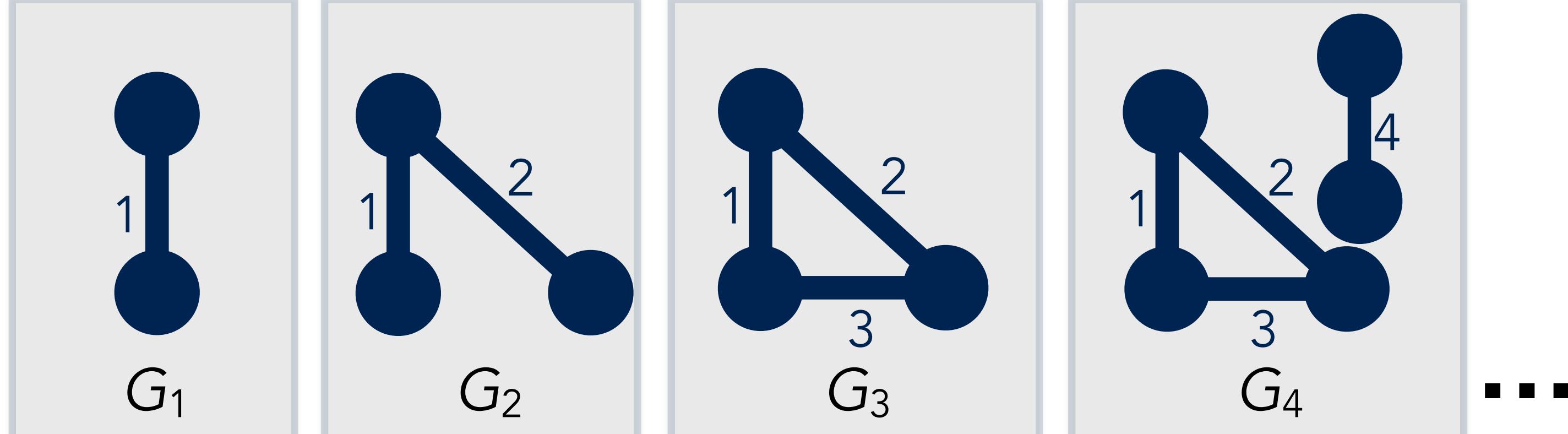
$$\mathbb{E}([\#edges(G_n)]) = \mathbb{E} \left(\binom{n}{2} \frac{1}{2} \int_0^1 \int_0^1 f(x, y) dx dy \right) \sim c \cdot n^2 = c \cdot [\#vertices(G_n)]^2$$

so we need something else that can give us sparse graphs.

Edge exchangeability

In edge exchangeability, a new edge joins the graph sequence at each step, is labeled with that step number, and instantiates any new vertices in that edge along the way.

example realization:



Sparsity results

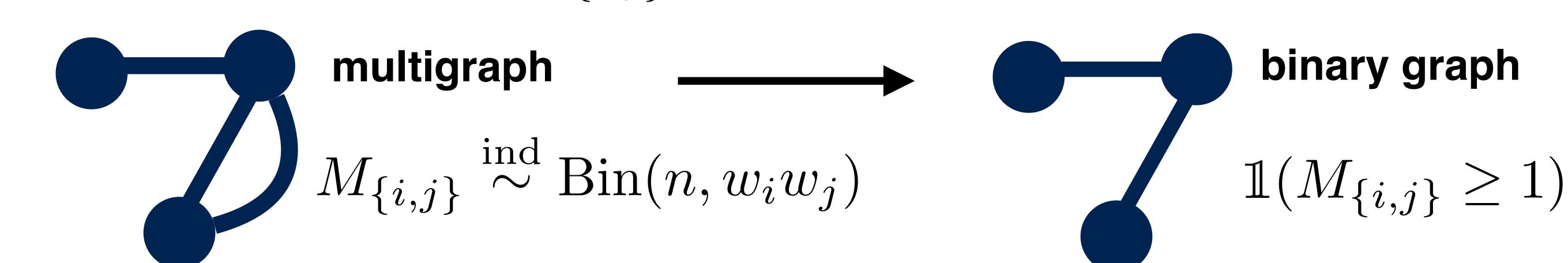
Consider a graph frequency model with edge frequencies $w_{\{i,j\}} = w_i w_j$ and $(w_i) \sim \text{Poisson Point Process}(\nu)$, and the rate measure ν has **power law tails**:

$$\int_x^1 \nu(dw) \xrightarrow{x \rightarrow 0} x^{-a} \ell(x^{-1}) \quad \forall c > 0, \ell(cx)/\ell(x) \xrightarrow{x \rightarrow \infty} 1$$

ν is **regularly varying** with exponent a

$\ell : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is **slowly varying**

Generate a multigraph $M_{\{i,j\}}$ and also construct binary graph:



Theorem. Suppose the rate measure ν is regularly varying with exponent a . Let $\ell : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ be a slowly varying function.

of instantiated vertices: $\Theta(n^a \ell(n))$ a.s.

Multigraph # of edges: $\Theta(n)$ a.s.

Binary graph # of edges: $O(\min\{n^{(1+a)/2}, n^{3a/2} \ell(n)\} \ell(n^{1/2}))$ a.s.

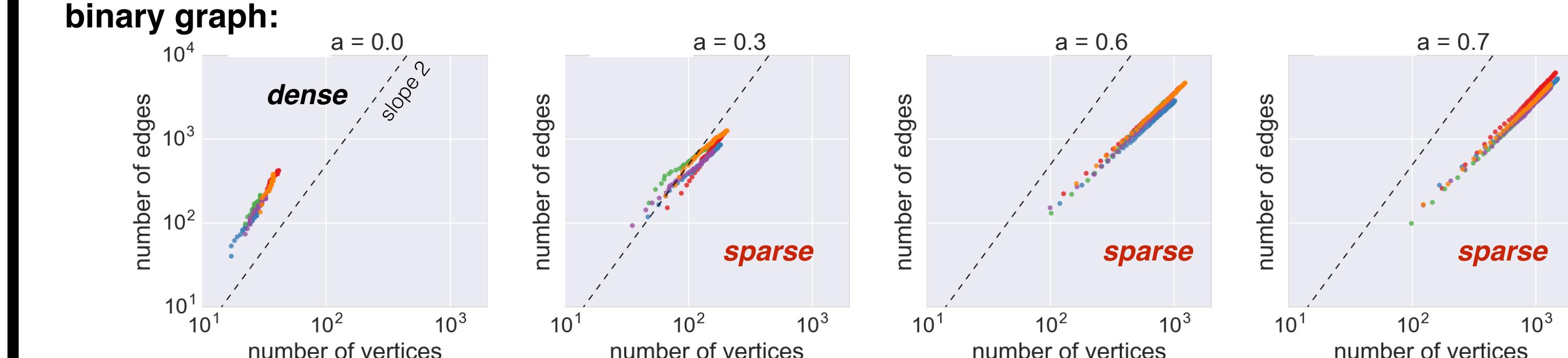
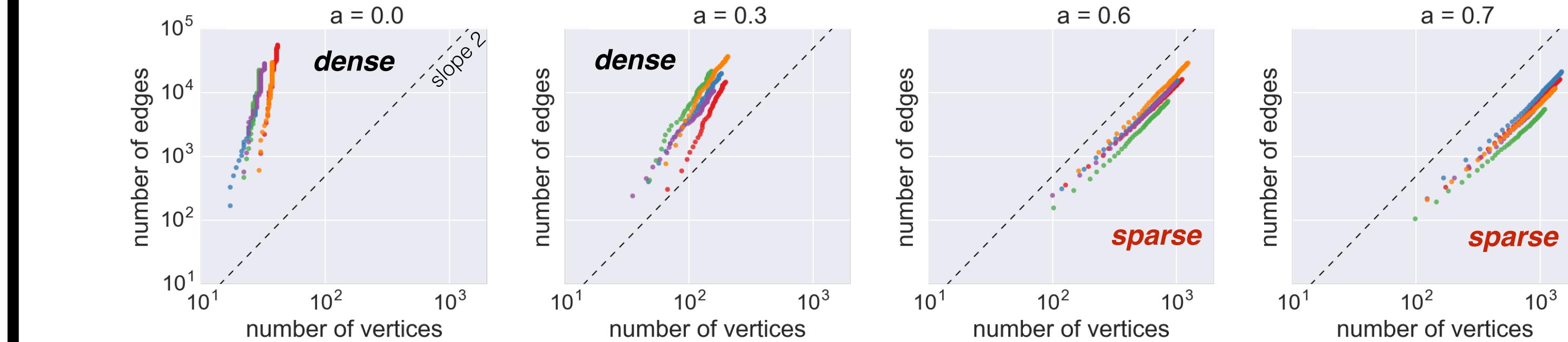
Thus, the multigraph is sparse when $1/2 < a < 1$; the binary graph is sparse when $0 < a < 1$, and dense otherwise.

Simulations

We generate the weights (w_i) from a Poisson point process with the **3-parameter beta process** rate measure:

$$\nu(dw) = \frac{\Gamma(1+b)}{\Gamma(1-a)\Gamma(a+b)} w^{-1-a} (1-w)^{a+b-1} dw$$

multigraph:
mass > 0
discount in $(0, 1)$
concentration > 0



Empirically, we get a range of dense and sparse behavior that agrees with the above theorem.

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