

Scaling limit of the Erdős-Rényi random graph and associated random walk

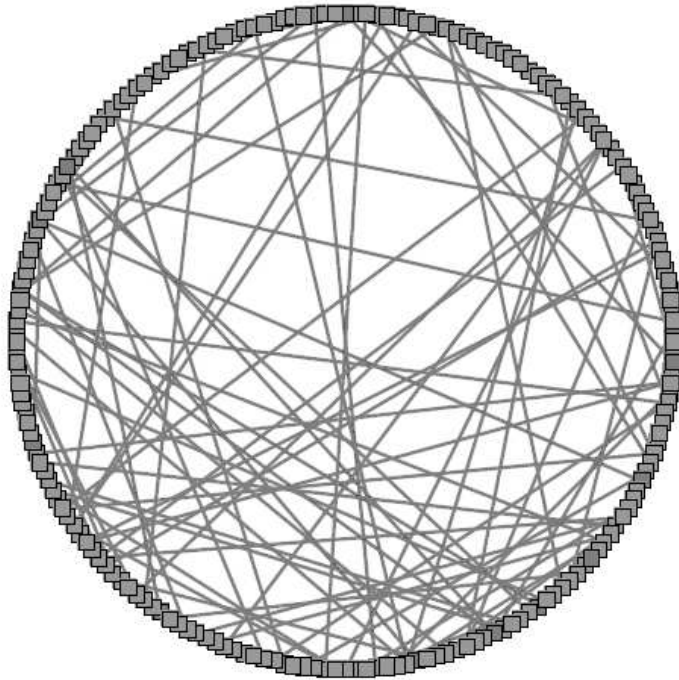
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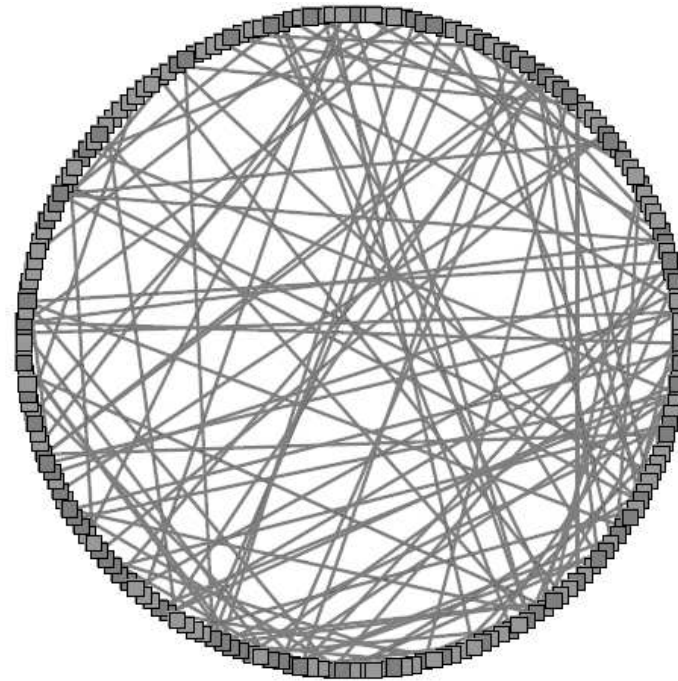
ERDŐS-RÉNYI RANDOM GRAPH

$G(n, p)$ is obtained via bond percolation with parameter p on the complete graph with n vertices. Often it is convenient to parameterise $p = c/n$.

e.g. $n = 200, c = 0.8$



$n = 200, c = 1.2$

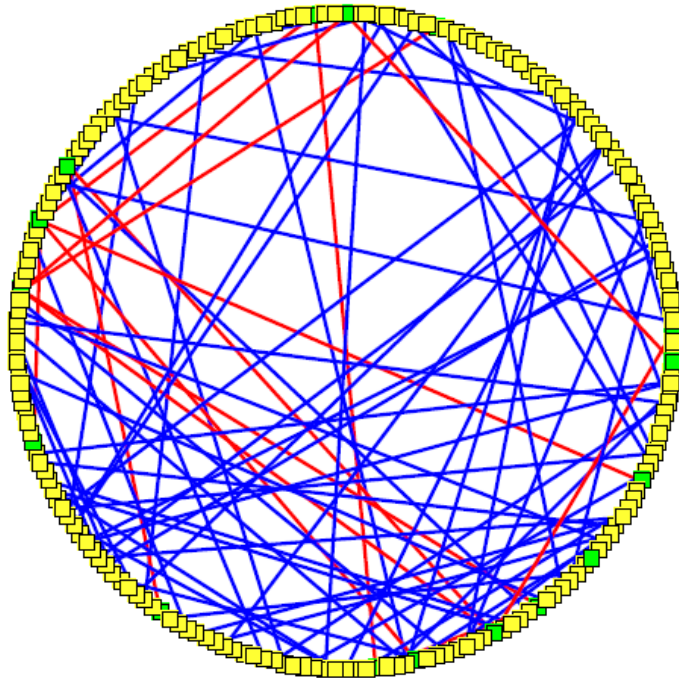


Pictures produced by Christina Goldschmidt.

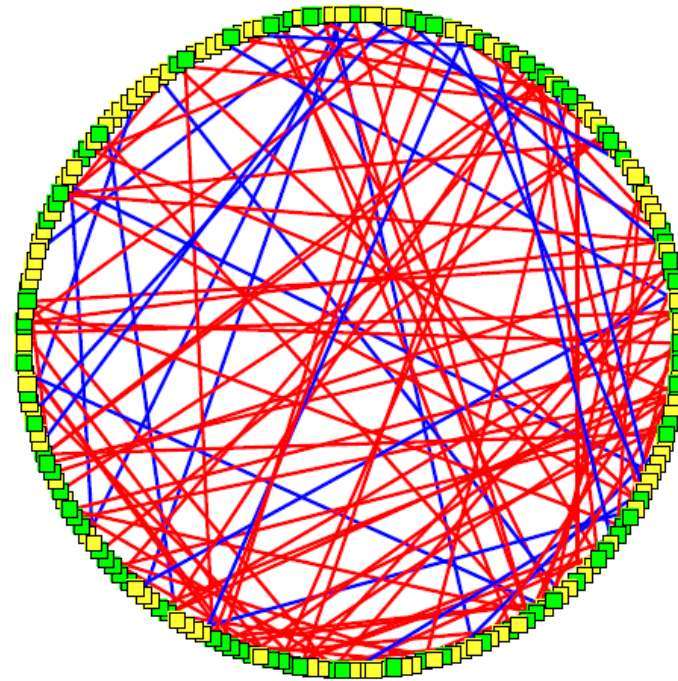
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PHASE TRANSITION

For $c > 1$, the largest connected component \mathcal{C}_1^n has $\Theta(n)$ vertices, and diameter of $\Theta(\ln n)$.

For $c < 1$, \mathcal{C}_1^n has $\Theta(\ln n)$ vertices.

Branching process intuition: A particular vertex, v say, has

$$\text{Bin}(n - 1, c/n) \approx \text{Po}(c)$$

neighbours. Iterating this, those vertices within a graph distance k of v are approximately the first k generations of a $\text{Po}(c)$ branching process (for k not too big).

SCALING LIMIT AT CRITICALITY

[Aldous] In the critical case, when $p = n^{-1}$, the largest connected component has size $\Theta(n^{2/3})$. Moreover, \mathcal{C}_1^n also has a $\Theta(1)$ surplus.

NB. The surplus of a component is equal to $\#E - (\#V - 1)$, which is the number of edges more than a spanning tree it has.

[Addario-Berry, Broutin, Goldschmidt] Considering the largest connected component as a metric space,

$$n^{-1/3}\mathcal{C}_1^n \rightarrow \mathcal{M}_1,$$

where \mathcal{M}_1 is a random metric space.

RANDOM WALK ON CRITICAL RANDOM GRAPH

For each fixed realisation of \mathcal{C}_1^n , we can define a corresponding discrete time simple random walk

$$\left(X_t^{\mathcal{C}_1^n} \right)_{t \geq 0}.$$

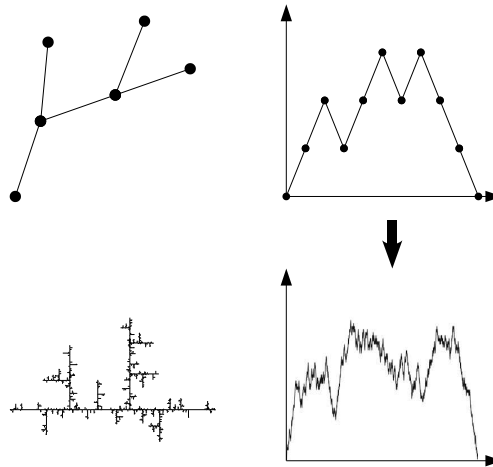
Given the results of the previous slide, an obvious next step is to determine how this process should be rescaled to yield a diffusion on the metric space scaling limit \mathcal{M}_1 (if indeed it can be).

Plan:

- Description of metric space scaling limit \mathcal{M}_1 .
- Random walk scaling limit.
- Asymptotic properties of random walks.

SCALING RANDOM TREES

n -vertex ordered graph tree, $T_n \leftrightarrow$ contour process,
rescaled by $n^{-1/2}$ in space and $(2n - 2)^{-1}$ in time



CRT, $\mathcal{T} \leftarrow$ normalised Brownian excursion

Examples:

- Conditioned finite variance branching processes [Aldous].
- Combinatorial random trees [Aldous].
- Connections with critical percolation clusters in high dimensions [Hara/Slade].

CONDITIONING \mathcal{C}_1^n ON ITS SIZE

For $m \in \mathbb{N}$, can construct $\mathcal{C}_1^n | \{\#\mathcal{C}_1^n = m\}$ as follows: first, choose an m -vertex random labelled tree T_m^p according to

$$\mathbf{P}(T_m^p = T) \propto (1 - p)^{-a(T)},$$

where $a(T)$ is the number of extra edges ‘permitted’ by T . Then, add extra edges independently with probability p to form G_m^p .

If G is a connected graph with depth-first tree T and surplus s ,

$$\begin{aligned} \mathbf{P}(G_m^p = G) &\propto (1 - p)^{-a(T)} p^s (1 - p)^{a(T) - s} = (p/(1 - p))^s \\ &\propto p^{m-1+s} (1 - p)^{\binom{m}{2} - m + 1 - s} = \mathbf{P}(G(m, p) = G). \end{aligned}$$

Finally, observe $\mathcal{C}_1^n | \{\#\mathcal{C}_1^n = m\} \sim G(m, p) | \{G(m, p) \text{ connected}\}$.

TILTING VIA THE EXCURSION AREA

In the discrete setting, the ‘permitted’ extra edges correspond to lattice points under the depth-first walk of the graph tree; the total number of them is (nearly) the area below this function.

In the continuous setting, an analogous construction of \mathcal{M}_1 is possible: first, choose a random excursion \tilde{e} according to the tilted measure

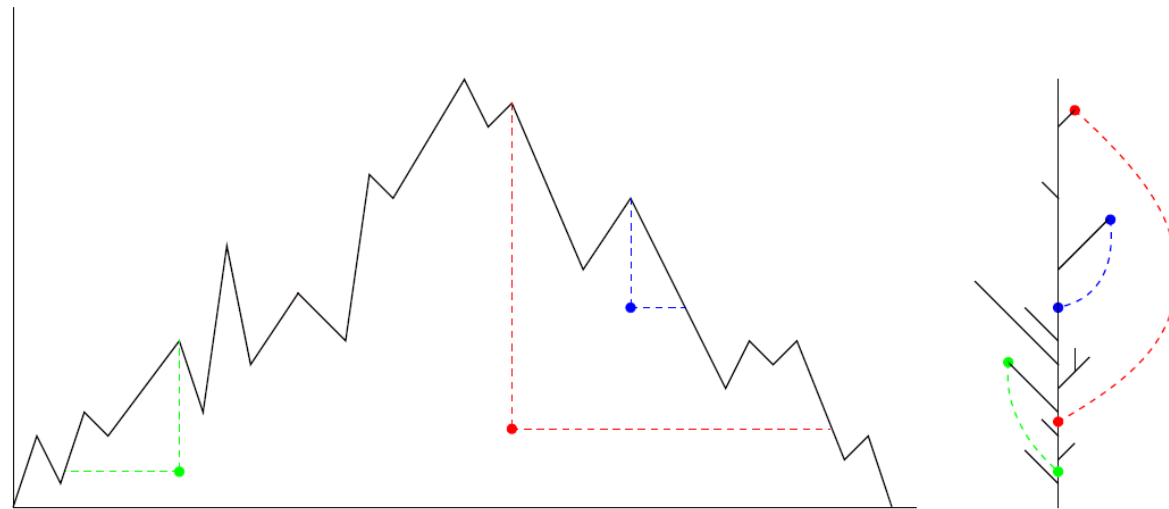
$$\mathbf{P}(\tilde{e} \in df) \propto \mathbf{P}(e \in df) \exp\left(\int_0^1 f(t) dt\right),$$

where e is the normalised Brownian excursion.

Define $\tilde{\mathcal{T}} := \mathcal{T}_{\tilde{e}}$.

POINT PROCESS DESCRIBING CONNECTIONS

Let \mathcal{P} be a unit intensity Poisson process on the plane. Points of \mathcal{P} that lie below the excursion \tilde{e} describe pairs of vertices to 'glue' together.



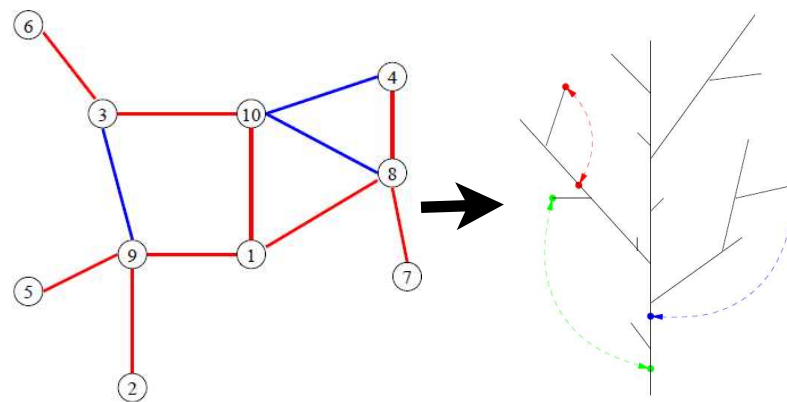
Picture produced by Christina Goldschmidt.

A point at (t, x) identifies the vertex v at height $\tilde{e}(t)$ with the vertex at distance x along the path from the root to v .

CRITICAL RANDOM GRAPH SCALING LIMIT

[Addario-Berry, Broutin, Goldschmidt]

The random metric space scaling limit \mathcal{M}_1 of the rescaled largest connected component of the critical random graph $n^{-1/3}\mathcal{C}_1^n$ is defined, up to a random scaling factor Z_1 , by gluing of pairs of vertices of $\tilde{\mathcal{T}}$ according to \mathcal{P} .



Pictures produced by Christina Goldschmidt.

SCALING LIMIT FOR RANDOM WALKS ON GALTON-WATSON TREES

Let $(T_n)_{n \geq 1}$ be a family of Galton-Watson trees such that:

- T_n - has critical (mean 1), finite variance offspring distribution.
- is conditioned to have n vertices.

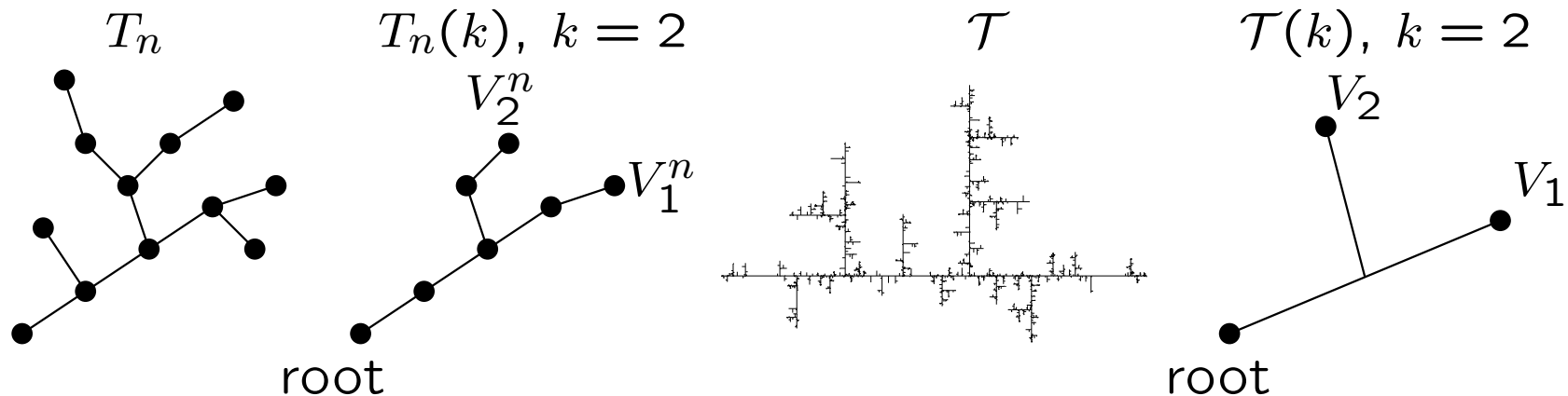
We can randomly isometrically embed all the graph trees $(T_n)_{n \geq 1}$ and the continuum random tree \mathcal{T} into a common metric space, E say, so that

$$\left(n^{-1/2} X_{\lfloor tn^{3/2} \rfloor}^{T_n} \right)_{t \geq 0} \rightarrow \left(X_t^{\mathcal{T}} \right)_{t \geq 0},$$

in distribution in $D(\mathbb{R}_+, E)$.

PROOF IDEA

Let $T_n(k)$ be minimal sub-tree of T_n spanning root and k uniform random vertices.



Similarly, given T and μ^T , let $\mathcal{T}(k)$ be minimal sub-tree of T spanning root and k μ^T -random vertices.

Step 1: Show processes on graph subtrees converge for each k .

Step 2: Show these are close to processes of interest as $k \rightarrow \infty$.

INTUITION FOR TIME SCALING FACTOR

For a simple random walk on a graph tree T , an elementary calculation yields the commute time identity

$$\mathbf{E}_x \tau_y + \mathbf{E}_y \tau_x = 2 \#E(T) d_T(x, y).$$

(In fact, with resistance distance this holds for all graphs).

In particular, we might reasonably expect that

$$\begin{aligned} \text{time scaling} &= \text{mass scaling} \times \text{distance scaling} \\ &= n \times n^{1/2} \\ &= n^{3/2}. \end{aligned}$$

ADAPTING TO RANDOM GRAPHS

Essentially the same argument works:

- select subgraphs consisting of a finite number of line segments.
- prove convergence on these.
- show these are close to processes of interest.

For the largest component of the critical random graph, the time scaling becomes

$$\begin{aligned}\text{time scaling} &= \text{mass scaling} \times \text{distance scaling} \\ &= n^{2/3} \times n^{1/3} \\ &= n.\end{aligned}$$

NB. This has been seen before in the mixing time of the random walk [Nachmias/Peres].

SCALING LIMIT FOR RANDOM WALKS ON CRITICAL RANDOM GRAPHS

Let \mathcal{C}_1^n be the largest component of random graph at criticality window, $p = n^{-1}$, then

$$\left(n^{-1/3} X_{\lfloor tn \rfloor}^{\mathcal{C}_1^n} \right)_{t \geq 0} \rightarrow \left(X_t^{\mathcal{M}_1} \right)_{t \geq 0},$$

in distribution in both a quenched (for almost-every environment) and annealed (averaged over environments) sense.

SOME COROLLARIES

Convergence of maximum commute time:

$$N^{-1} \max_{x,y \in \mathcal{C}_1^n} (\mathbf{E}_x \tau_y + \mathbf{E}_y \tau_x) \rightarrow 2Z_1 \text{diam}_R \mathcal{M}_1,$$

in distribution.

Convergence of mixing times: for fixed $\varepsilon > 0$,

$$N^{-1} t_{\text{mix}}(\mathcal{C}_1^n) \rightarrow t_{\text{mix}}(\mathcal{M}_1),$$

in distribution, where

$$t_{\text{mix}}(\mathcal{C}_1^n) := \inf \left\{ t : \frac{1}{2} \sum_{x \in \mathcal{C}_1^n} |\mathbf{P}_\rho(X_t^{\mathcal{C}_1^n} = x) - \pi^n(x)| \leq \varepsilon \right\}.$$