Percolation Phase Transitions on Dynamically Grown Graphs

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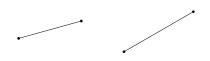
Background

Dynamically grown graphs and percolation

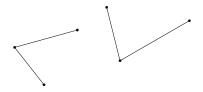
Start with a graph with n vertices and 0 edges

Add edges randomly every 1/n units of time

We'll work in the limit as $n \to \infty$







Percolation

A giant component is a cluster that takes up a finite fraction of the graph

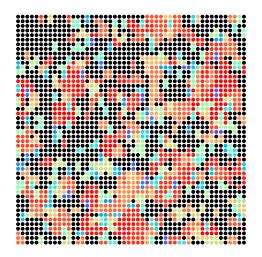
Percolation is when a giant component first emerges (call this time t_c)

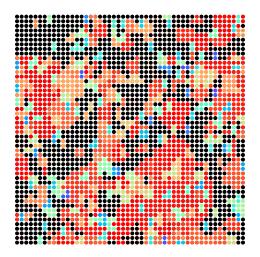
Percolation

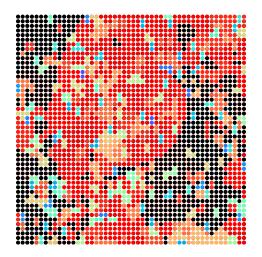
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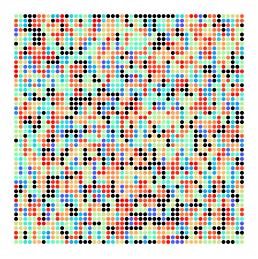
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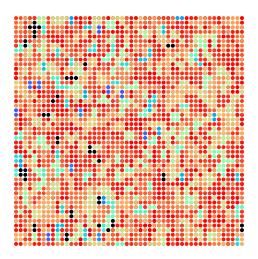
This emergence has lots of different behaviors

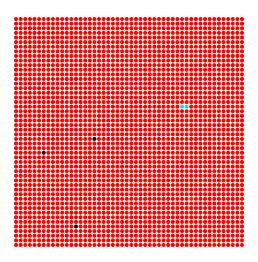












Explosive Percolation

Explosive Percolation is a sudden, seemingly discontinuous emergence of the giant component

Basic Results

Continuous phase transition and scaling behavior

Continuous phase transition

Achlioptas rule: select two edges at random, then choose one of them to keep via some rule based on the cluster sizes of the edges' vertices

Achlioptas (2009): claimed to have found a discontinuous emergence of a giant component based on simulations

Continuous phase transition

Riordan and Warnke (2012)

 ℓ -vertex rule: choose ℓ vertices i.i.d., and you're only required to add an edge if all ℓ of them are in distinct clusters (generalizes Achlioptas processes)

All ℓ -vertex rules have a continuous phase transition

Continuous phase transition

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All ℓ -vertex rules have a continuous phase transition

Proof by contradiction...

Scaling behavior

Because of the continuous phase transition, the distribution of vertices belonging to a cluster of size s follows a power law

$$s^{1-\tau}f(s\delta^{1/\sigma})$$

where $\delta = t - t_c$ and f is a scaling function.

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where $\delta = t - t_c$ and f is a scaling function.

Noticing scaling behavior in rules with explosive percolation was motivation for proving their continuity

Critical Exponents

Hi

Our Results

Pick two finite groups of i.i.d. vertices

Follow a deterministic method to choose a representative vertex from each group (can be a different rule for each group)

Add an edge between the two representatives

Erdős Rényi: Both groups are size 1, so this is the same as sampling edges randomly

Correspondence with Erdős Rényi random graph

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Correspondence with Erdős Rényi random graph

da Costa: both groups are of size *m*, and pick the vertex with the smallest cluster size from each group

Consider

$$1 - \langle 1 \rangle_{\phi} = 1 - \sum_{s \text{ finite}} \phi(s),$$

where $\phi(s) = \mathbb{P}(\text{representative has cluster size } s)$

Under certain regularity conditions, this quantity is $\sim \delta^{F(\beta)}$ need to define \sim

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Can express critical exponents in terms of β and $F(\beta)$

need to introduce γ_{ϕ} somewhere

For a two-choice rule with $1 - \langle 1 \rangle_{\phi} \sim \delta^{F(\beta)}$,

$$\gamma_{\phi} = F(\beta) - \beta + 1$$

$$\gamma_{P} = 2(F(\beta) - \beta) + 1$$

$$\frac{1}{\sigma} = 2F(\beta) - \beta + 1$$

$$\tau = \frac{\beta}{2F(\beta) - \beta + 1} + 2$$

da Costa (2015): if groups are size m and the rule selects the vertex with the smallest cluster size, then

$$\begin{split} \gamma_{\phi} &= 1 + (m-1)\beta \\ \gamma_{P} &= 1 + 2(m-1)\beta \\ \frac{1}{\sigma} &= 1 + (2m-1)\beta \\ \tau &= 2 + \frac{\beta}{1 + (2m-1)\beta} \end{split}$$

need to introduce S somewhere

Since $1-\langle 1\rangle_\phi$ is the probability that a vertex chosen by our rule is in an infinite cluster,

$$1 - \langle 1 \rangle_{\phi} = S^m \sim (\delta^{\beta})^m \sim \delta^{m\beta},$$

so
$$F(\beta) = m\beta$$

Plugging this into our earlier equations recovers da Costa's scaling relations

This is the da Costa rule with m = 1, so

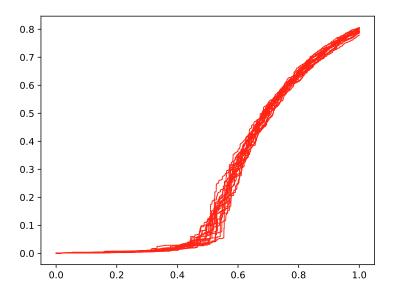
$$\begin{split} \gamma_{\phi} &= \gamma_{P} = 1 \\ &\frac{1}{\sigma} = \beta + 1 \\ &\tau = \frac{\beta}{\beta + 1} + 2 \end{split}$$

Much more is possible since Erdős Rényi is such a simple rule

Known result: $\beta = 1$, i.e. giant component grows linearly near t_c

This fixes
$$\gamma_P = 1$$
, $\frac{1}{\sigma} = 2$, $\tau = 5/2$

Erdős Rényi (n = 2500)

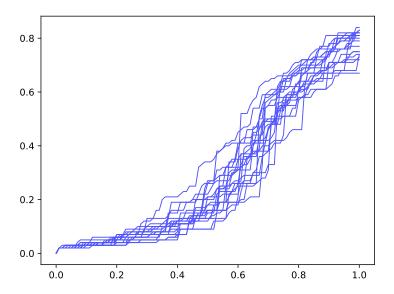


Scaling behavior occurs in region of order $\Theta(s^{-1/2})$ around t_c

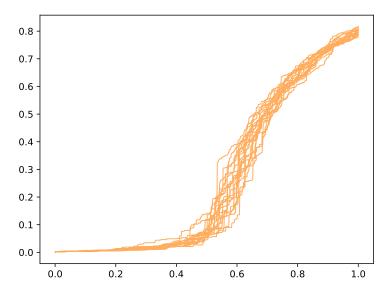
As $s \to \infty$, the scaling window shrinks

In particular, the region of linear giant component growth shrinks as $n \to \infty$

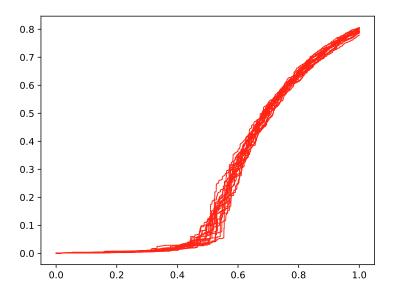
Erdős Rényi (n = 100)



Erdős Rényi (n = 1000)



Erdős Rényi (n = 2500)



Bounded Size Rules

Rules that are almost Erdős Rényi

Bounded Size Rules

A *bounded size rule* with size threshold K treats all clusters of size > K the same

Intuition: eventually there will be so few clusters of size $\leq K$ that it starts acting like Erdős Rényi

Bohman-Frieze

For each group of vertices, do the following:

- \triangleright Pick m+1 vertices
- ► If any of the first *m* vertices are isolated, pick one at random as the representative
- ▶ If not, pick the (m+1)-st vertex instead

Bounded size rule with size threshold K = 1

For any bounded size rule, $1 - \langle 1 \rangle_{\phi} \sim \delta^{\beta}$

Thus $F(\beta) = \beta$ (the same as Erdős Rényi!)

Same scaling relations as Erdős Rényi (with potentially different β)

$$\gamma_{\phi} = \gamma_{P} = 1$$

$$\frac{1}{\sigma} = \beta + 1$$

$$\tau = \frac{\beta}{\beta + 1} + 2$$

Need to finish up the presentation somehow