## Weighted distances in scale-free random graph models

Komjáthy Júlia

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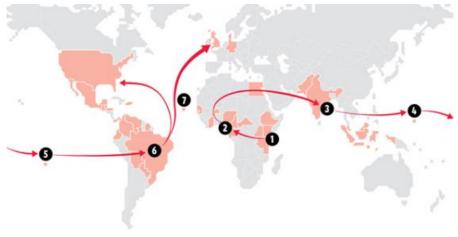
# Information diffusion

#### Information diffusion Includes

### Viruses



# Viruses



The spread of the Zika virus

## Online viruses

#### Wannacry ransomware attack, May 2017



from Kasperski lab daily

# Memes



# Memes



# Viral videos



# Search Interest

#### Search intensity of Gangnam style

from knowyourmeme.com

# Models

We need models!

# The scale-free property

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$$\mathbb{P}(\mathsf{deg}(v) = x) \asymp \frac{C}{x^{\tau}}$$

$$\log \mathbb{P}(\deg(v) = x) \asymp \log C - \tau \log x$$

log(proportion of degree x vertices) vs log x is a straight line.

## Power laws

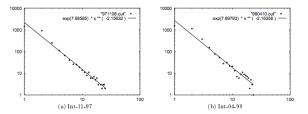
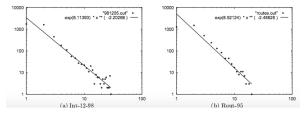


Figure 5: The outdegree plots: Log-log plot of frequency  $f_d$  versus the outdegree d.

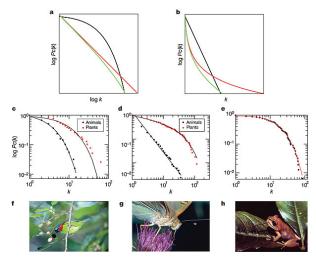


Degree distribution of the router level internet network

from Faloutsos, Faloutsos, Faloutsos. 1999

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## Power laws



Degree distribution of ecological networks

from Montoya, Pimm, Polé. Nature 2006

#### Power laws

Note:  $\tau \in (2,3)$  often!

When  $\tau \in (2,3)$  then  $\mathbb{V}ar_n[\deg(v)] \to \infty$  and  $\mathbb{E}_n[\deg(v)] < \infty$ .



# Configuration model

# The configuration model

Matches the degree sequence of the network you would like to model.

[Configuration model simulator by Robert Fitzner]

[Configuration model with power law degrees by Robert Fitzner]

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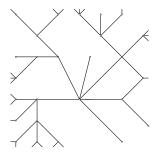
Edge weight = time/cost of transmission through the edge The spreading time between two vertices u, v= the weighted distance:

$$d_{\sigma}(u,v)$$

How does  $d_{\sigma}(u, v)$  behave in terms of the degrees and the distribution  $\sigma$ ?

# Local weak convergence

Local neighborhoods look like random trees with size biased degrees.



## Preliminaries

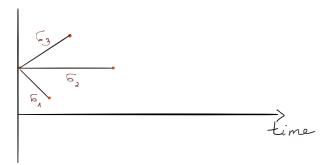
Initial stage of the spreading in the graph looks like a random tree with

- power law degrees, tail exponent  $\alpha := \tau 2 \in (0, 1)$
- each edge has an i.i.d 'length' or 'weight'
- called age-dependent branching process

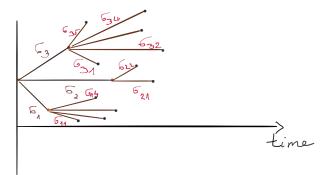
In an *age-dependent* branching process  $BP(X, \sigma)$ • root is born at time 0,



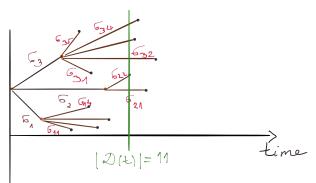
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Explosive vs conservative

When is a branching process  $BP(X, \sigma)$  explosive?

# Explosion of BPs

Theorem (Amini, Devroye, Griffith, Olver & K) Assume for x large enough and some  $\varepsilon > 0$ 

$$rac{1}{x^{arepsilon}} > \mathbb{P}(X > x) > rac{1}{x^{1-arepsilon}}.$$
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The branching process  $BP(X, \sigma)$  is explosive if and only if for some K > 0

$$\int_{K}^{\infty} F_{\sigma}^{(-1)} \left( e^{-e^{z}} \right) dz < \infty$$
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where  $F_{\sigma}^{(-1)}$  is the inverse of the distribution function  $F_{\sigma}(x) = \mathbb{P}(\sigma \leq x)$ .

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#### Corollary

If a distribution  $\sigma$  explodes for one X satisfying (PL) then it explodes for all X satisfying (PL) (including all power laws  $\tau \in (2,3)$ ).

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Examples

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Boundary case: F<sub>σ</sub>(t) = exp{-exp{1/t<sup>β</sup>}}. Explosive for β < 1, conservative for β ≥ 1.</li>

# Back to the configuration model

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$$d_{\sigma}(u,v) \stackrel{d}{\longrightarrow} V^{(1)} + V^{(2)}$$

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This was first shown for  $\sigma \sim \mathrm{Exp}(1)$  by Bhamidi, Hofstad, Hooghiemstra.

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$$\frac{d_{\sigma}(u,v)}{2\sum\limits_{k=1}^{\log\log n/|\log(\tau-2)|}} \xrightarrow{\mathbb{P}} 1.$$

Gives back the main term for  $\sigma \equiv 1$ .

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## When $\tau > 3$

# $\tau \in (2,3)$

Dichotomy: bounded average distance for explosive weight distributions, non-bounded average distance for conservative weight distributions

Theorem (Bhamidi, Hofstad, Hooghiemstra)

Universally, for all  $\sigma$  that have a density,

$$d_{\sigma}(u,v) = \frac{1}{\lambda} \log n + tight,$$

where  $\lambda$  is the Malthusian parameter (exponential growth rate) of BP( $D^*, \sigma$ ).

# A model with geometry

## Scale-free percolation (SFP)

- Vertex set is  $\mathbf{Z}^d$ , collection of vertex-weights  $(W_z)_{z \in \mathbf{Z}^d}$ .
- nearest neighbor edges are present
- Conditionally on  $(W_z)_{z \in \mathbb{Z}^d}$ , edges are present independently. With  $\alpha > d$ ,  $\lambda > 0$ ,

$$\mathbb{P}((x,y) \; \textit{open}) = 1 - \expig( - \lambda \mathit{W}_x \mathit{W}_y / \|x-y\|^lpha ig)$$

• add i.i.d. edge-weights  $\sigma$  to all open edges.

### Theorem (Deijfen, Hofstad)

Consider SFP with  $\alpha > d$ , and  $\gamma := \alpha(\tau - 1)/d > 1$ . Then the degree distribution satisfies

$$\mathbb{P}(D_0 > x) = \ell(x)/x^{\gamma}$$

for some slowly varying function  $\ell(x)$ .

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# Scale free percolation

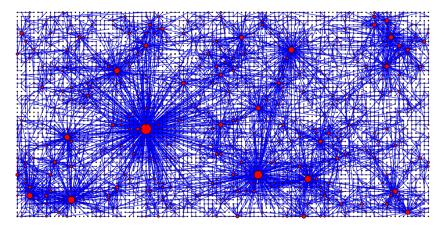


Figure: Scale free percolation with  $\alpha=3.9, \tau=1.95, \lambda=0.1.$  Simulation by B. Lodewijks

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## Weighted distances for SFP

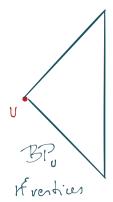
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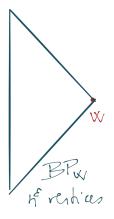
Consider SFP with  $\alpha > d, \gamma = \alpha(\tau - 1)/d \in (1, 2)$  and conservative edge-weights  $\sigma$ . Fix an arbitrary unit vector <u>e</u>. Then, as  $m \to \infty$ ,

$$\frac{\operatorname{d}_{\sigma}(0, \lfloor \underline{m\underline{e}} \rfloor)}{2\sum\limits_{k=1}^{\lfloor \log \log m/|\log(\gamma-1)| \rfloor} F_{\sigma}^{(-1)}\left(\exp(-\frac{1}{(\gamma-1)^{k}})\right)} \stackrel{\mathbb{P}}{\longrightarrow} 1.$$

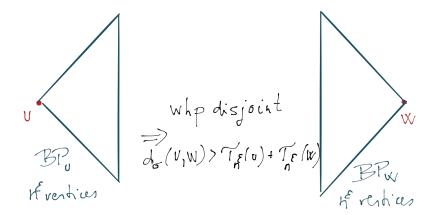


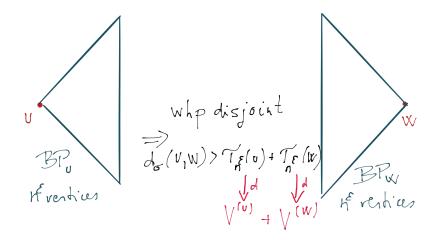


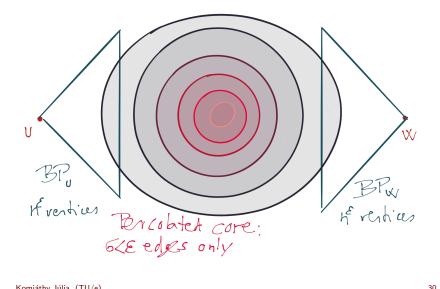


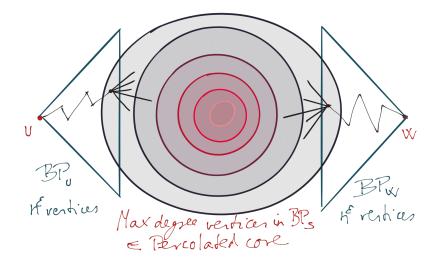


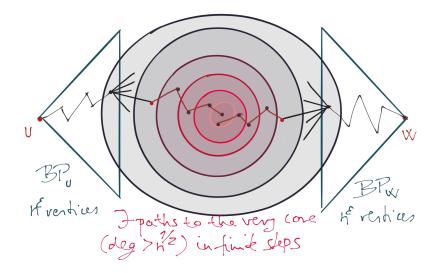
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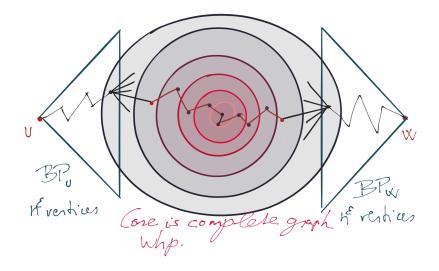


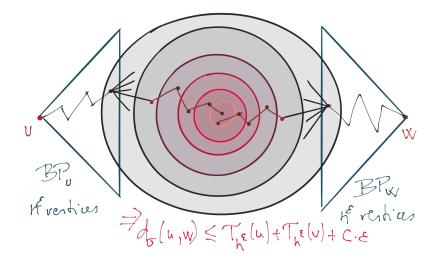






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# Proof for conservative edge-weights

## Step 1: Coupling

Couple the initial stages of the spreading by two independent BPs, one started at u, one at v, until generation  $M_n$  for some small  $M_n = o(\log n)$ .

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### Step 2: Degree-dependent percolation

Percolate the whole graph: independently, for each edge e,

$$1\!\!1_{e \text{ is kept}} = 1\!\!1_{\sigma_e \leq \operatorname{tr}(d_1, d_2)}$$

*e* connects vertices with degrees  $d_1$ ,  $d_2$ ,  $tr(d_1, d_2)$  some well-chosen threshold function.

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#### Step 3: High-deg vertices $\widetilde{u}, \widetilde{v}$

Find two vertices  $\tilde{u}$ ,  $\tilde{v}$  with high enough percolated degree  $\deg_p(\tilde{u}), \deg_p(\tilde{v}) > K_n = K_n(M_n)$  in the two BPs

$$1_e$$
 is kept  $= 1_{\sigma_e \leq \operatorname{tr}(d_1, d_2)}$ 

$$\mathbb{1}_{e \text{ is kept}} = \mathbb{1}_{\sigma_e \leq \operatorname{tr}(d_1, d_2)}$$

### Janson's argument

When  $\mathbb{P}(e \text{ is kept}) = p(d_1)p(d_2)$ , for some  $p(\cdot)$ , percolated graph can be looked at as a (new) configuration model

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Let c> 0,  $\eta<$  1, define

$$p(d) := \exp(-c(\log d)^{\eta})$$

#### Threshold function

Keep each edge independently with probability  $p(d_1)p(d_2)$ , i.e.,

$$\operatorname{tr}(d_1, d_2) := \mathcal{F}_{\sigma}^{(-1)}\left(\exp\left(-c(\log d_1)^\eta - c(\log d_2)^\eta
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Power law preserving  $\eta < 1$ 

For  $\eta < 1$ , the new degree distribution has the same power-law exponent  $\tau$ .

### Step 4: Layers

In the percolated subgraph, whp there is a nested layering starting with degree  $K_n$  with the property that a vertex in layer *i* is connected to at least one vertex in layer i + 1, and the degrees deg *v* in layer *i* is  $\approx K_n^{1/(\tau-2)^i}$ .

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#### Step 5: Combine

 $\widetilde{u}$ ,  $\widetilde{v}$  falls into layer 1. Thus whp

$$d_L(u,v) \leq d_L(u,\widetilde{u}) + d_L(v,\widetilde{v}) + 2\sum_{i=1}^{\# ext{ layers}} ext{tr}(\mathcal{K}_n^{1/( au-2)^i},\mathcal{K}_n^{1/( au-2)^{i+1}}).$$

$$d_L(u,v) \leq d_L(u,\widetilde{u}) + d_L(v,\widetilde{v}) + 2\sum_{i=1}^{\# \text{ layers}} \operatorname{tr}(\kappa_n^{1/(\tau-2)^i},\kappa_n^{1/(\tau-2)^{i+1}}).$$

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$$\operatorname{tr}(d_1, d_2) := F_{\sigma}^{(-1)}\left(\exp\left(-c(\log d_1)^{\eta} - c(\log d_2)^{\eta}\right)\right)$$

Step 6: Last term is

$$\frac{2}{\eta} \sum_{i=1}^{\eta \log \log n/|\log(\tau-2)|} F_{\sigma}^{-1}\left(\exp\{-(\tau-2)^{-i}\}\right).$$

 $\eta < 1$ , so summation boundary is fine, choose  $1/\eta < 1 + \varepsilon/3$ .

$$d_L(u,v) \leq d_L(u,\widetilde{u}) + d_L(v,\widetilde{v}) + 2(1+\varepsilon/3) \sum_{i=1}^{\log \log n/|\log(\tau-2)|} F_{\sigma}^{-1}\left(\exp\{-(\tau-2)^{-i}\}\right)$$

First two terms: If we choose  $\tilde{u}$  independently of the edge weights  $\sigma_{e}$ ,

$$d_L(u,\widetilde{u}) \stackrel{d}{\leq} \sum_{i=1}^{M_n} \sigma_i$$

Choose  $M_n \to \infty$  so that

$$\lim_{n \to \infty} \mathbb{P}\left(\sum_{i=1}^{M_n} \sigma_i \ge \varepsilon/3 \sum_{i=1}^{\log \log n/|\log(\tau-2)|} F_{\sigma}^{-1}\left(\exp\{-(\tau-2)^{-i}\}\right)\right) = 1$$

This is always possible,  $M_n$  (also) depends on the tail of  $\sigma$ .

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Thank you for the attention!

