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Self-similarity of complex networks & hidden metric spaces

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Self-similarity of complex networks?

scale-free degree distributions
$$P(k) \sim k^{-\gamma}$$
 scale invariant property $f(\lambda v) = \lambda^r f(v)$

box-covering renormalization procedures

some systems (WWW, biological networks) have degree distributions that remain invariant and have finite "fractal" dimension

C. Song, S. Havlin, H. A. Makse, Nature 433, 392-395 (2005); Nature Physics 2, 275-281 (2006)

Where is geometry?



Self-similarity and scale invariance of complex networks are still not well defined in a proper geometrical sense

Lack of a metric structure

except lengths of shortest paths

small world property

geometric length scale transformations?



Networks embedded in metric spaces	
maybe "hidden"	
(as variations of hidden variables)	M. Boguñá and R. Pastor-Satorras, Phys. Rev. E 68 , 036112 (2003). G. Caldarelli, A. Capocci, P. D. L. Rios, and M. A. Muñoz, Phys. Rev. Lett. 89 , 258702 (2002).

- Geography as an obvious geometrical embedding: airport networks, urban networks...
- Hidden metric spaces: WWW (similarity between pages induced by content), social networks (closeness in social space)...

...how to identify these hidden metric spaces...



- Some real scale-free networks are self-similar (degree distribution, degree-degree correlations, and clustering) with respect to a simple degree-thresholding renormalization procedure (purely topological)
- A class of hidden variable models with underlying metric spaces are able to accurately reproduce the observed self-similarity properties

We conjecture that hidden geometries underlying some real networks are a plausible explanation for their observed self-similar topologies



degree-thresholding renormalization procedure



 $k_{i} / < k_{i} (k_{T}) >$

Hierarchy of nested subgraphs



Topological properties of the subgraphs 10^{0} as a function of The inner degree Rescaled by the average 10⁻² 10⁻¹ $>\overline{k}_{nn}$ inner degree $\langle \vec{k} \rangle$ BGP map of the Internet at 10^{0} the AS level SF with exponent 2.1 randomized N=17446 10 10⁻¹ 10⁻² < k > = 4.68PGP social web of trust SF with exponent 2.5 N=57243



Average nearest neighbors degree

(also U.S. airports network)



$\overline{c}(k, |k_T)$ K.K Internet BGP map 10^{-2} 10^{-2} 10⁻¹ 10² 10-1 10¹ $|<k(k_{\pi})>$ 10⁰ • 100 $\begin{array}{c} \bullet \rightarrow k_T = 5 \\ \bullet \rightarrow k_T = 10 \\ \bullet \rightarrow k_T = 20 \\ \bullet \rightarrow k_T = 50 \\ \bullet \rightarrow k_T = 100 \end{array}$ $C(k_i | k_T)$ 10 PGP network 10⁻³ 10-3 10² 10-1 100 ′10⁻¹ 10⁰ 10



Degree dependent clustering coefficient



A random model like the CM will produce self-similar networks regarding the degree distribution and degreedegree correlations, if the degree distribution of the complete graph is SF....

the key point is to reproduce self-similar clustering





Therefore, we focus on clustering as a potential connection between the observed topologies and hidden geometries.



• A class of hidden variable models with underlying metric spaces are able to accurately reproduce the observed self-similarity properties



$$r\left(\frac{d}{d_c}\right)$$

Nodes that are close to ech other are more likely to be connected

To control the degree distribution, the characteristic $d_c(\kappa)$ distance depends on the expected degree, and so $\rho(\kappa) \approx P(k)$

$$d_c(\kappa,\kappa') \propto (\kappa\kappa')^{1/D}$$









10³

10³

103



FIG. 1: Degree distribution P(k), average nearest neighbours' degree $\bar{k}_{nn}(k)$, and degree-dependent clustering coefficient $\bar{c}(k)$ generated by our model with $\gamma = 2.1$ and $\alpha = 2$ compared to the same metrics for the real Internet map as seen by BGP data and the DIMES project.

FIG. 2: Degree distribution P(k), average nearest neighbours' degree $\bar{k}_{nn}(k)$, and degree-dependent clustering coefficient $\bar{c}(k)$ generated by our model with $\gamma = 1.6$, $\alpha = 5$ and a cut-off at $k_c = 180$ compared to the same metrics for the real US airport network.





- $\rho(\kappa)$ controls the degree distribution, SF
- independently, lpha controls the level of clustering , strong clustering
- given α , the parameter $\mu = \left(\frac{\gamma 2}{\gamma 1}\right)^2 \frac{(\alpha 1) < k >}{2\delta \kappa_0^2}$ controls the average degree
- if $1 < \alpha < 2, 2 < \gamma < 3$, small-world!!! but underlying metric space!

$$p(d, \kappa | \kappa') = \frac{2}{\kappa'} \rho(\kappa) \left(1 + \frac{d}{\mu \kappa \kappa'} \right)^{-\alpha} \qquad \boxed{\text{D=1}}$$

$$p(d|\kappa') \sim d^{-\alpha} \text{ when } \alpha < \gamma - 1 \qquad \boxed{d(\kappa')} = \int x p(x|\kappa') dx$$

$$N, R \to \infty \longrightarrow 0$$

$$p(d|\kappa') \sim d^{1-\gamma} \text{ when } \alpha > \gamma - 1$$



Nodes in the complete graph can be represented such that higher degree nodes are closer to the center of the S¹ ring



Initial graph



A subgraph is formed by all nodes and their connections inside a circle of radius r







Subgraph



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Self-similarity of the S¹ model

$$\rho(\kappa) = (\gamma - 1) \frac{\kappa_0^{\gamma - 1}}{\kappa^{\gamma}} \qquad N = \delta 2\pi R$$
$$r(\theta, \kappa; \theta', \kappa') = \left(1 + \frac{d(\theta, \theta')}{\mu \kappa \kappa'}\right)^{-\alpha},$$
$$\mu = \left(\frac{\gamma - 2}{\gamma - 1}\right)^2 \frac{(\alpha - 1) < k >}{2\delta \kappa_0^2}$$





In particular, clustering spectrum and clustering...

$$\bar{c}(\kappa|\kappa_T) = f(\kappa/\kappa_T), \quad \bar{c}(k_i|k_T) \approx f(k_i/k_T^{3-\gamma}) = \tilde{f}[k_i/\langle k_i(k_T)\rangle],$$
$$\bar{c}(\kappa_T) = \int_{\kappa_T} d\kappa \rho(\kappa|\kappa_T) \bar{c}(\kappa|\kappa_T), \quad \text{Independent of } \kappa_T$$











In summary

hidden geometries underlying the observed topologies of some complex networks appear to provide a simple a natural explanation of their degree-renormalization self-similarity real networks could be, after all, embedded in metric spaces

Future work

- fractality, C. Song, S. Havlin, H. A. Makse, Nature 433, 392-395 (2005); Nature Physics 2, 275-281 (2006). K.I. Goh, G. Salvi, B. Kahng, and D. Kim, PRL 96, 018701 (2006); J.S. Kim, K.I. Goh, B. Kahng, and D. Kim, New J. Phys 9, 177 (2007);
- k-core self-similarity, J. I. Alvarez-Hamelin, L. Dall'Asta, A. Barrat and A. Vespignani, Networks and Heterogeneous Media, 3, 395-411 (2008).



THANK YOU for your attention

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