Routing in the Internet and Navigability of Scale-Free Networks

Dmitri Krioukov CAIDA/UCSD

dima@caida.org

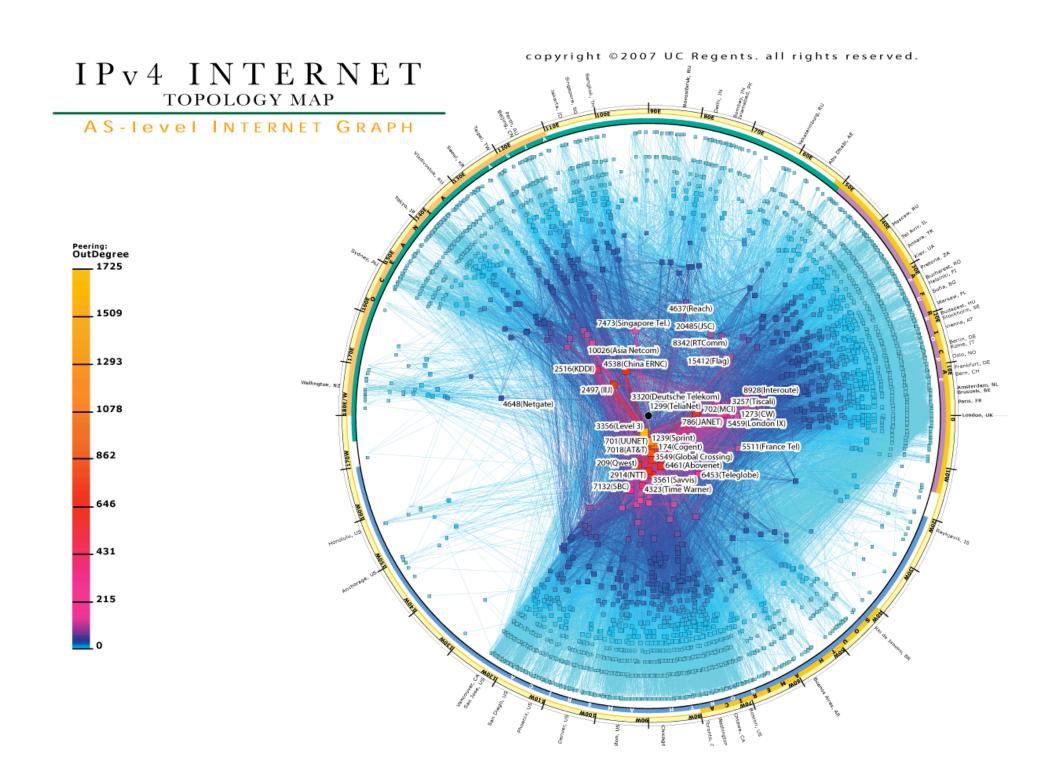
F. Papadopoulos, M. Boguñá, A. Vahdat

Science or engineering?

- **Network science vs. network engineering
- # Computer science vs computer engineering
- # Study existing networks vs. designing new ones
- We cannot really *design* truly large-scale systems (e.g., Internet)
 - We can design their building blocks (e.g., IP)
 - But we cannot fully control their large-scale behavior
 - Since they acquire some elements of self-organization, or self-evolving (self-*) behavior beyond our control
- Let us study existing large-scale networks and try to use what we learn in designing new ones
 - Discover "nature-designed" efficient mechanisms that we can reuse (or respect) in our future designs

Internet

- - IP/TCP, routing protocols
 - Routers
 - Per-ISP router-level topologies
- ★ Macroscopic view ("non-design")
 - Global AS-level topology is a cumulative result of local, decentralized, and rather complex interactions between AS pairs
 - Surprisingly, in 1999, it was found to look completely differently than engineers had thought
 - It is not a grid, tree, or classical random graph
 - It shares all the main features of topologies of other complex networks
 - scale-free (power-law) node degree distributions $(P(k) \sim k^{-\gamma}, \gamma \in [2,3])$
 - strong clustering (large numbers of 3-cycles)
- The big problem is that "design" has now to deal with "non-design"
 - Routing protocols have to find and promptly update paths to all destinations in the Internet



Routing practice

- # Global (DFZ) routing tables
 - 300,000 prefix entries (and growing)
 - 30,000 ASs (and growing)
- **■** Routing overhead/convergence
 - BGP updates
 - 2 per second on average
 - 7000 per second peak rate
 - Convergence after a single event can take up to tens of minutes
- **♯** Problems with design?
 - Yes and no

Routing theory

- There can be no routing algorithm with the number of messages per topology change scaling better than linearly with the network size in the worst case
- **■** Small-world networks are this worst case
- **♯** *Is there any workaround?*
- # If topology updates/convergence is so expensive, then may be we can route without them, i.e., without global knowledge of the network topology?
- # Let us look at the existing systems

Milgram's experiments

- Settings: random people were asked to forward a letter to a random individual by passing it to their friends who they thought would maximize the probability of letter moving "closer" to the destination
- **■** Results: surprisingly many letters (30%) reached the destination by making only ~6 hops on average
- **#** Conclusion:
 - People do not know the global topology of the human acquaintance network
 - But they can still find (short) paths through it

Navigability of complex networks

- In many (if not all) existing complex networks, nodes communicate without any global knowledge of network topologies
- **■** How is this possible???

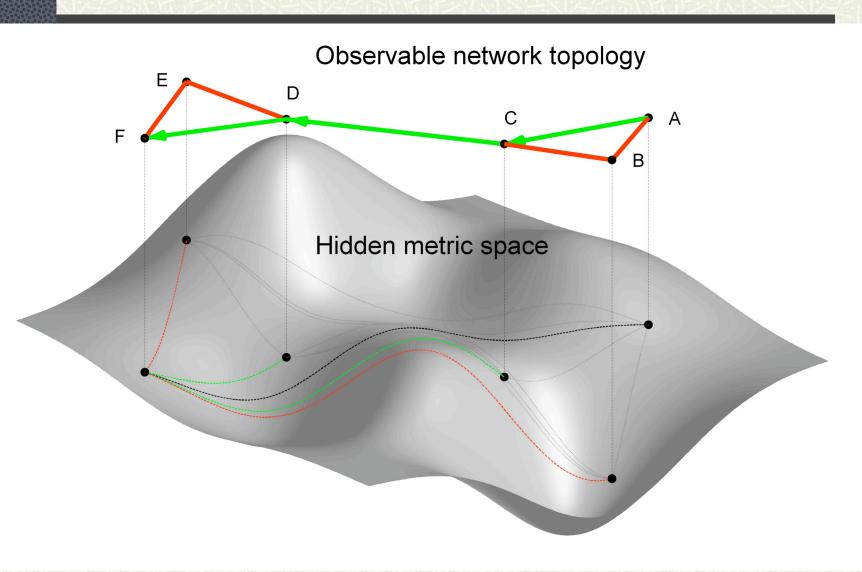
Hidden metric space explanation

- **■** All nodes exist in a metric space
- **■** Distance in this space abstract node similarities
- Network consists of links that exist with probability that decreases with the hidden distance
- More similar/close nodes are more likely to be connected
- **★** The result is that all nodes exist in "two places at once":
 - a network
 - a hidden metric space
- So that there are two distances between each pair of nodes
 - the length of shortest path between them in the network
 - hidden distance

Greedy routing (Kleinberg)

★ To reach a destination, each node forwards information to the one of its neighbors that is closest to the destination in the hidden space

Hidden space visualized



Questions raised by the approach

- **■** What is the hidden space?
- **■** What are the node positions in it?
- **■** What is the connection probability?
- **#** How efficient is the greedy routing process?
 - How often greedy-routing paths get stuck at nodes that do not have any neighbors closer to the destination than themselves
 - How closely greedy-routing paths follow the shortest paths in the network
- ₩ What topologies are navigable, i.e., congruent w.r.t. greedy routing, i.e., make it efficient?

Hidden spaces are metric spaces

- **■** Using the simplest metric space (a circle), we show that
 - the triangle inequality in hidden spaces
 - transitivity of being similar/closeexplains
 - strong clustering in real networks
 - transitivity of being connected
- It also explains their self-similarity

Self-similarity of complex networks (existing knowledge)

- **■** Self-similarity w.r.t. rescaling (of distances, time, etc.)
 - Fluctuations at phase transitions
 - Fractals
- # Fractal dimension
 - Box covering procedures
- **#** Complex networks
 - Degree distributions are self-similar
 - Some networks are self-similar w.r.t. box covering
 - But no distance rescaling since these networks are small worlds

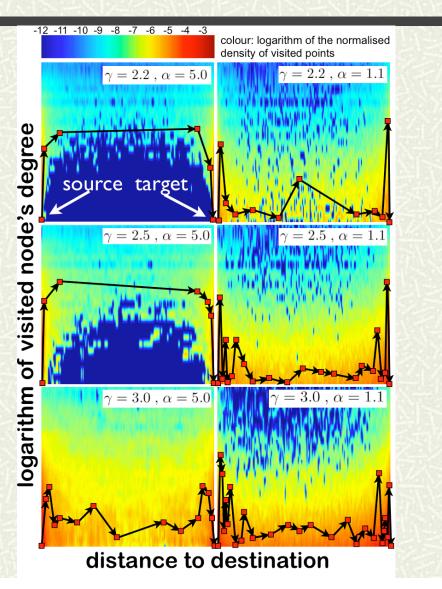
Self-similarity of complex networks (new perspective)

- If complex networks are embedded in hidden metric spaces, then distance rescaling in "large-world" hidden spaces is equivalent to degree renormalization
- ₩ W.r.t. this degree renormalization, all of the following are self-similar in real networks and modeled networks with metric spaces underneath
 - degree distribution
 - degree correlations
 - clustering
- Only degree distributions are self-similar in maximally random networks with degree distribution of real or modeled networks
- Evidence that metric spaces do underlie real networks which are self-similar w.r.t. hidden distance rescaling

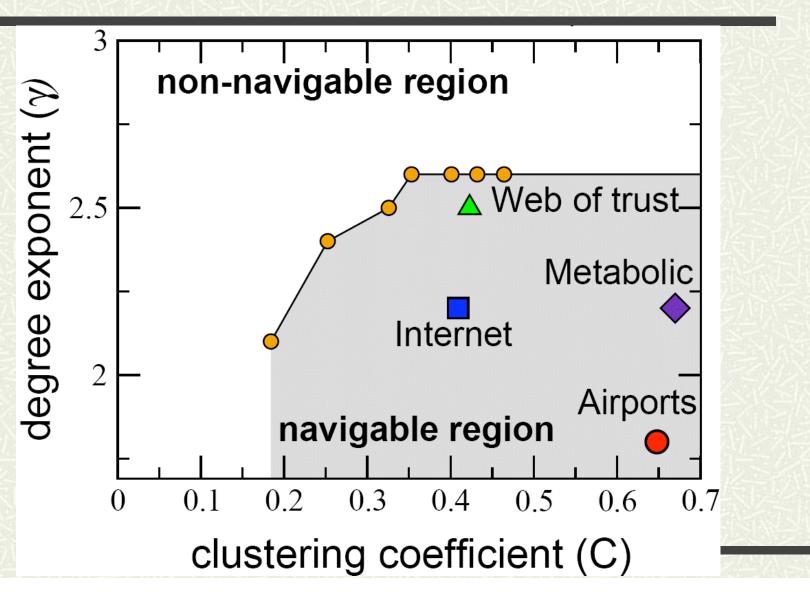
Navigability mechanisms

- **■** More navigable networks are networks with
 - more heterogeneous node degree distributions
 - more hubs
 - stronger clustering
 - stronger influence of hidden distances on links
 - stronger congruency between hidden geometries and observed topologies
 - stronger congruency between greedy and shortest paths
- **♯** Greedy routing paths follow navigable path pattern

Navigable path pattern



Real networks are navigable



Hidden geometries

■ What hidden geometries are maximally congruent with the navigability mechanisms of the observed complex network topologies?

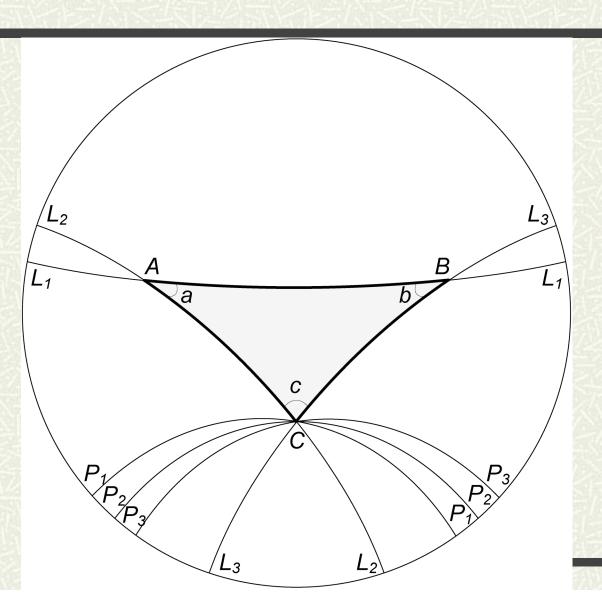
Hidden metric spaces are hyperbolic

- ➡ Network nodes can often be hierarchically classified
 - Community structure (social and biological networks)
 - Customer-provider hierarchies (Internet)
 - Hierarchies of overlapping balls/sets (all networks)
 - The mapping between balls in R^d B(x,r) and points $\alpha = (x,r)$ in H^{d+1} satisfies
 - If $|\alpha \alpha'| \le C$, then there exist k(C) s.t. $k^{-1} \le r/r' \le k$ and $|x x'| \le k r$
 - If $|x-x'| \le k r$ and $k^{-1} \le r/r' \le k$, then there exist C(k) s.t. $|\alpha \alpha'| \le C$
- **■** Hierarchies are (approximately) trees
- **■** Trees embed isometrically in hyperbolic spaces

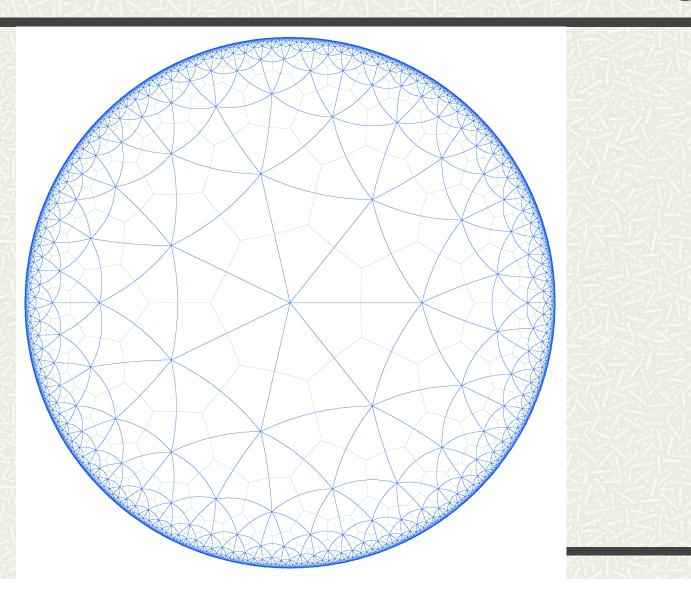
Hyperbolic geometry

■ Geometry in which through a point not belonging to a line passes not one but infinitely many lines parallel to the given line

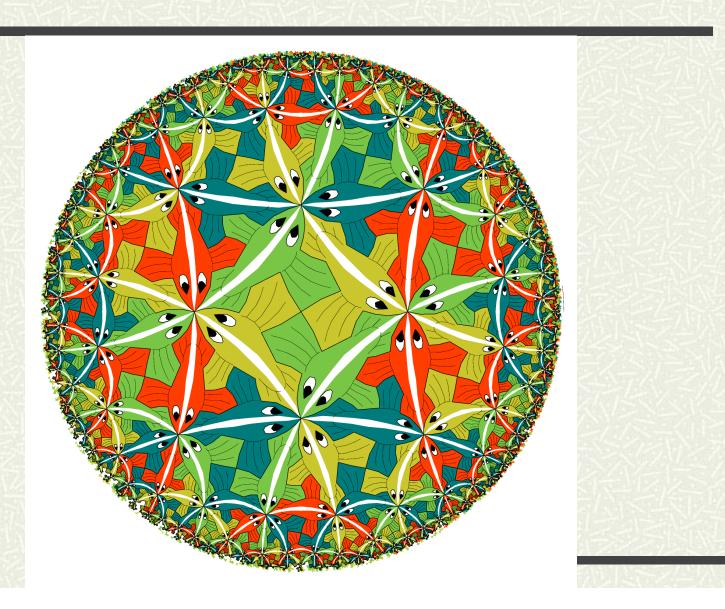
Poincaré disc model



Tessellation and tree embedding



Tessellation art



Geometry properties

Property	Euclid.	Spherical	Hyperbolic
Curvature	0	1	-1
Parallel lines	1	0	∞
Triangles are	normal	thick	thin
Shape of triangles			
Sum of angles	π	$>\pi$	$<\pi$
Circle length	$2\pi R$	$2\pi \sin R$	$2\pi \sinh R$
Disc area	$2\pi R^2/2$	$2\pi(1-\cos R)$	$2\pi(\cosh R - 1)$

Main hyperbolic property

 \blacksquare The volume of balls and surface of spheres grow with their radius r as

ear

where $\alpha = (-K)^{1/2}(d-1)$, K is the curvature and d is the dimension of the hyperbolic space

 \blacksquare The numbers of nodes in a tree within or at r hops from the root grow as

 b^r

where b is the tree branching factor

The metric structures of hyperbolic spaces and trees are essentially the same $(\alpha = \ln b)$

Hidden space in our model

- Hyperbolic disc of radius R, where $N = \kappa e^{R/2}$, N is the number of nodes in the network and κ controls its average degree
 - Average degree is fixed (by κ) to the same value (~6, like in many real networks) for all modeled networks

Node distribution

 \blacksquare Number of nodes n(r) located at distance r from the disc center is

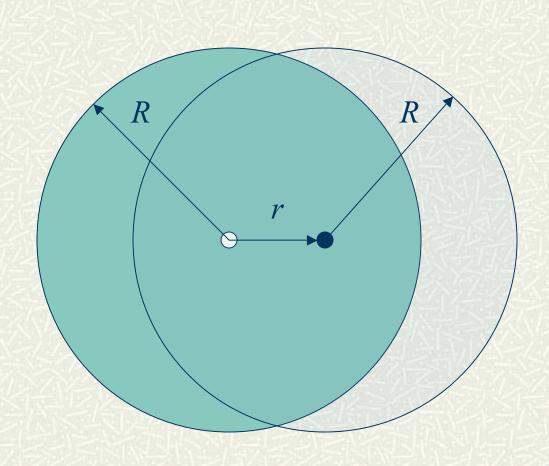
$$n(r) \sim e^{\alpha r}$$

where $\alpha = 1$ corresponds to the uniform node distribution in the hyperbolic plane of curvature -1

Connection probability

 \blacksquare Connected each two nodes if the distance between them is less than or equal to R

Average node degree at distance *r* from the disc center



Average node degree at distance *r* from the disc center

 \blacksquare For $\alpha = 1$, we obtain a terse but exact expression

$$k(r) = \delta \left\{ (\cosh R - 2)\pi + 2 \left(\cosh \chi \arccos \frac{\cosh r \cosh \chi - \cosh R}{\sinh r \sinh \chi} \right) \right.$$

$$+ \cosh R \arctan \frac{\cosh \chi - \cosh R \cosh r}{\sqrt{(\cosh r - \cosh R \cosh \chi) (\cosh (R + \chi) - \cosh r)}} \right\}$$

$$- \arctan \frac{8 (\cosh r - \cosh R \cosh \chi) \sqrt{(\cosh r - \cosh (R - \chi)) (\cosh (R + \chi) - \cosh r)}}{16 (\cosh r - \cosh R \cosh \chi) \cosh r - 8 \cosh^2 r + 4 (\cosh^2 R + \cosh^2 \chi + \cosh^2 \chi) - 1} \right\}$$

$$= \frac{10^3}{10^3}$$

$$\frac{k(r)}{10^2}$$

$$= \frac{10^3}{10^3}$$

$$\frac{10^3}{10^3}$$

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\blacksquare For other α :

where
$$\beta = \alpha \text{ if } \alpha \leq \frac{1}{2}$$

 $\beta = \frac{1}{2}$ otherwise

Node degree distribution

Is given by the combination of exponentials to yield a power law

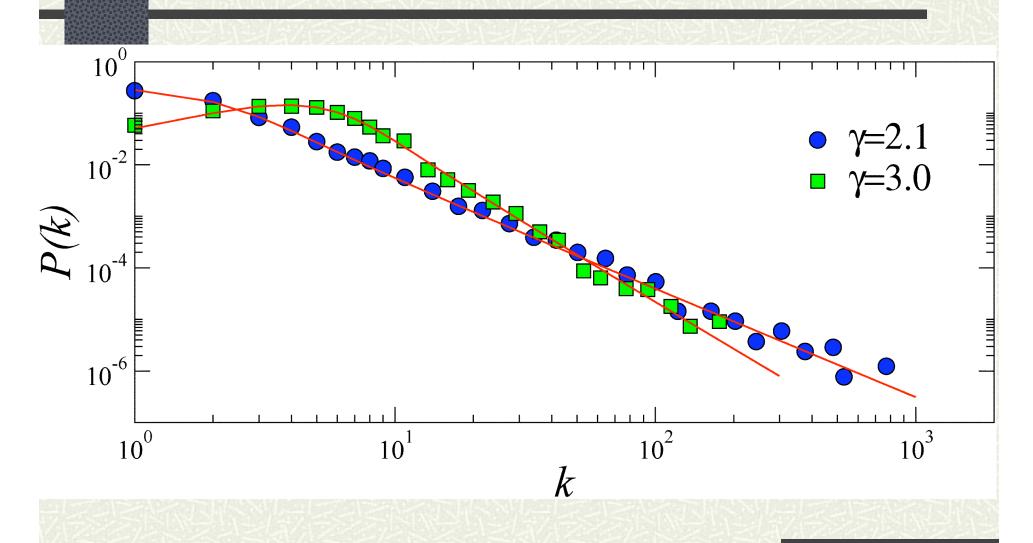
$$P(k) \sim k^{-\gamma}$$

where

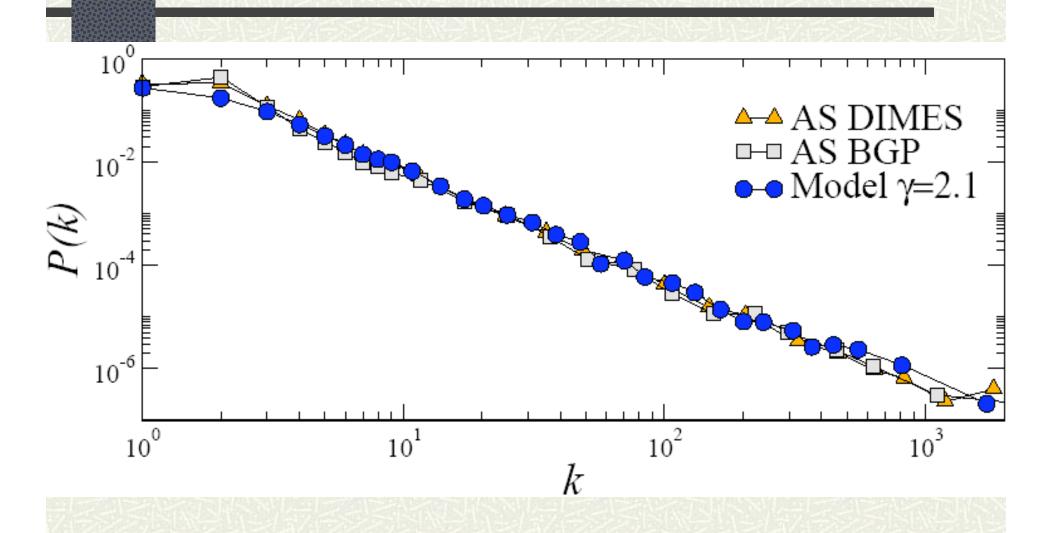
$$\gamma = 1 + \alpha/\beta =$$
 $2 \text{ if } \alpha \leq \frac{1}{2}; \text{ or}$
 $2 \alpha + 1 \text{ otherwise}$

The uniform node distribution in the plane $(\alpha = 1)$ yields $\gamma = 3$

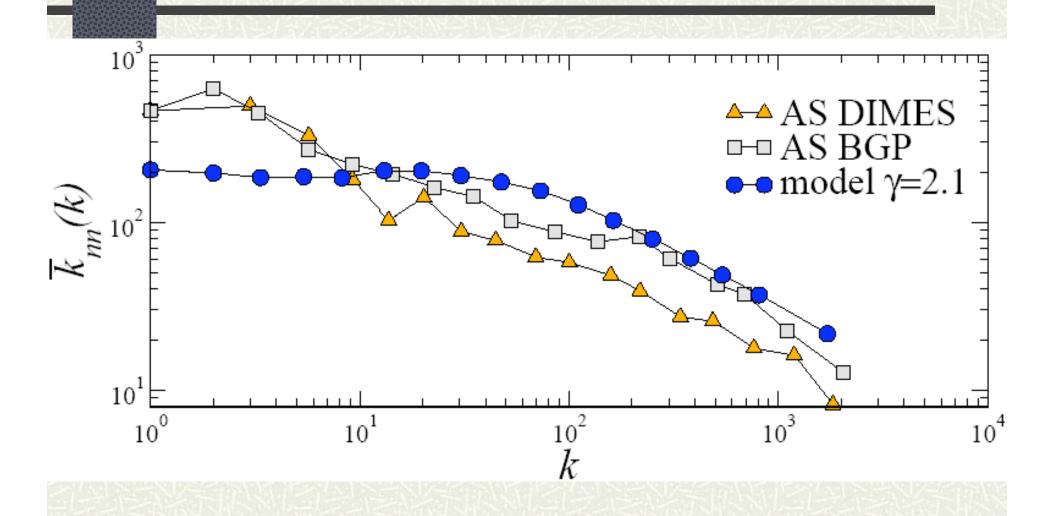
Node degree distribution: theory vs. simulations



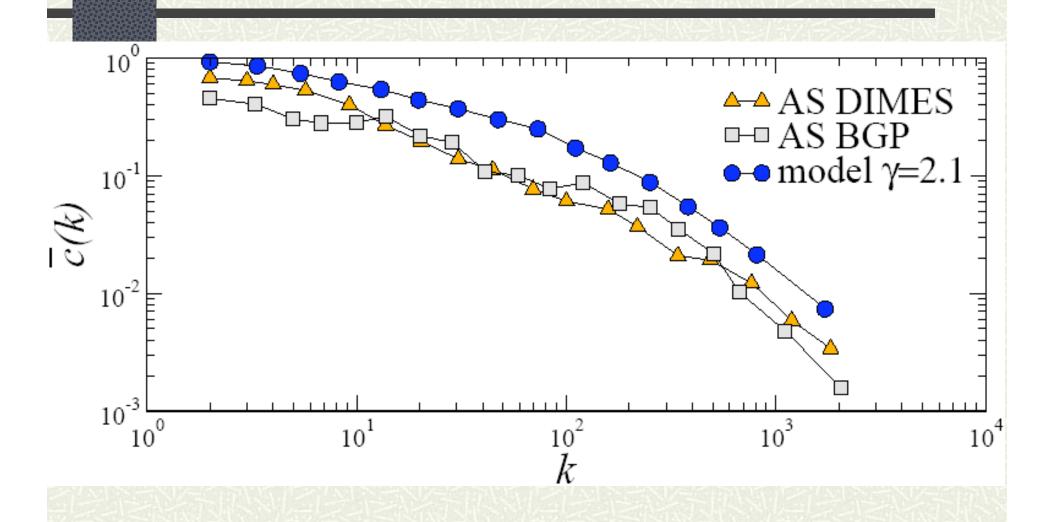
Node degree distribution: model vs. Internet



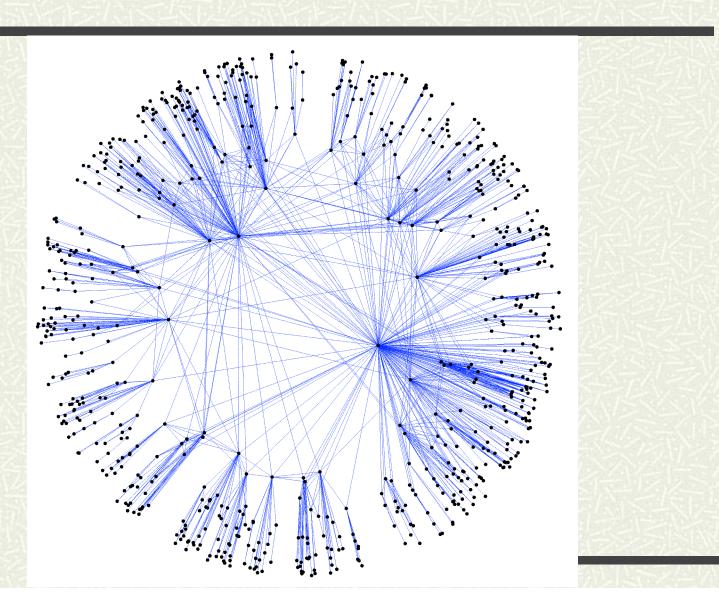
Degree correlations: model vs. Internet



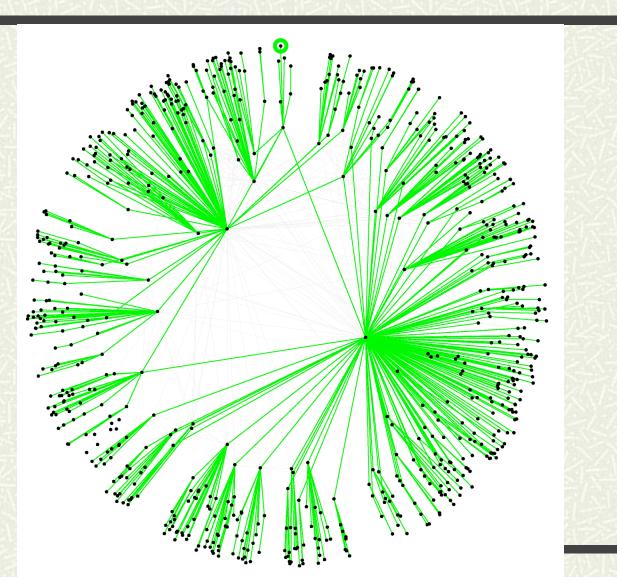
Clustering: model vs. Internet



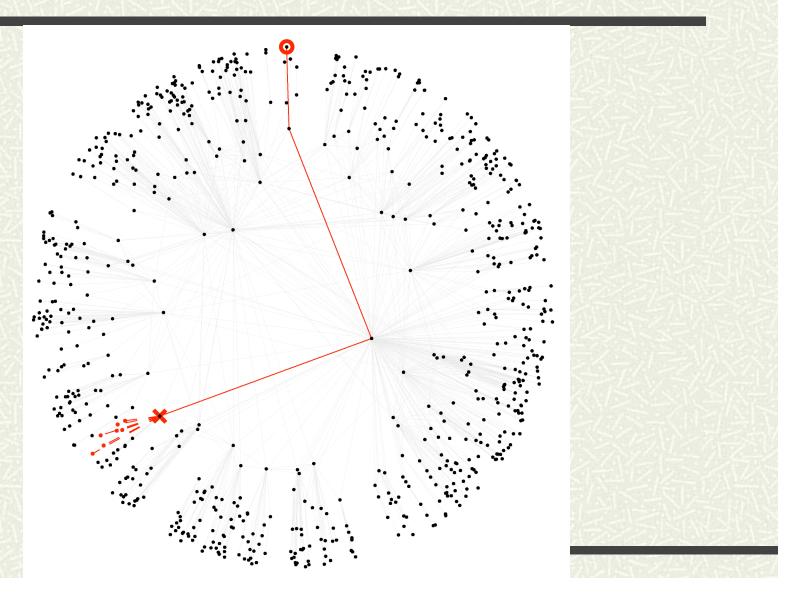
Visualization of a modeled network



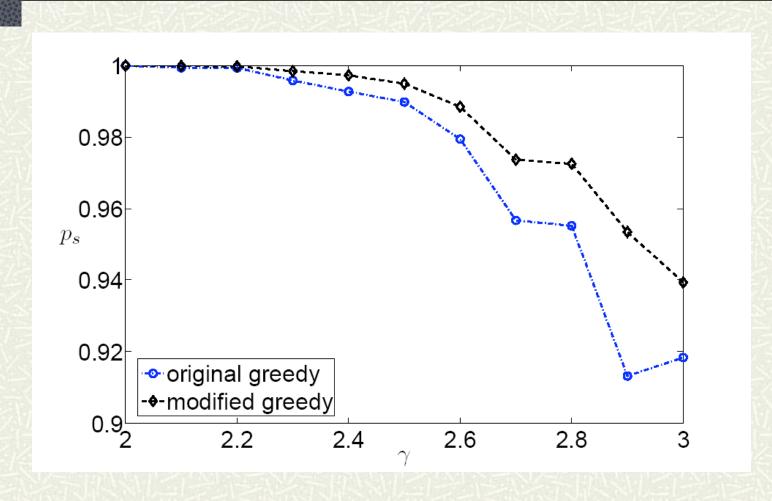
Successful greedy paths



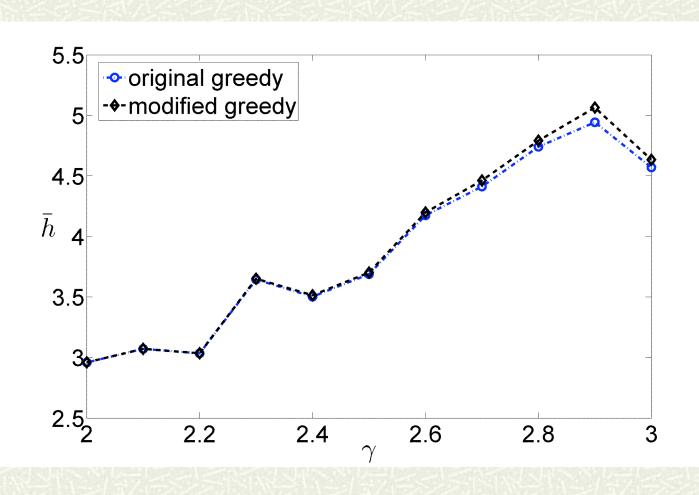
Unsuccessful greedy paths



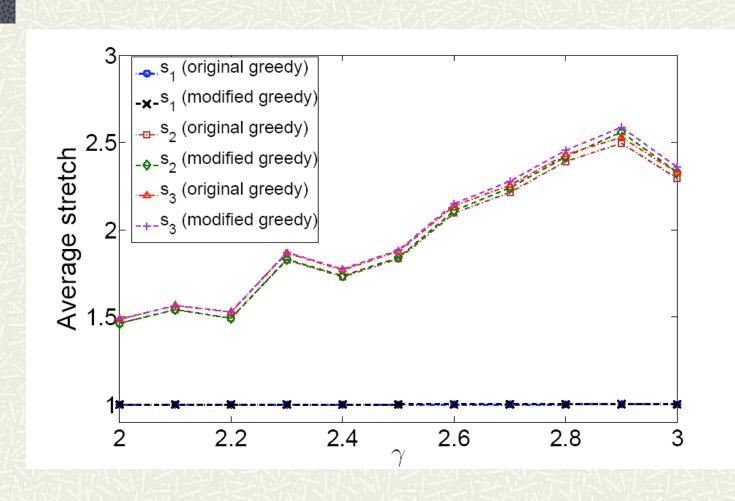
Percentage of successful paths



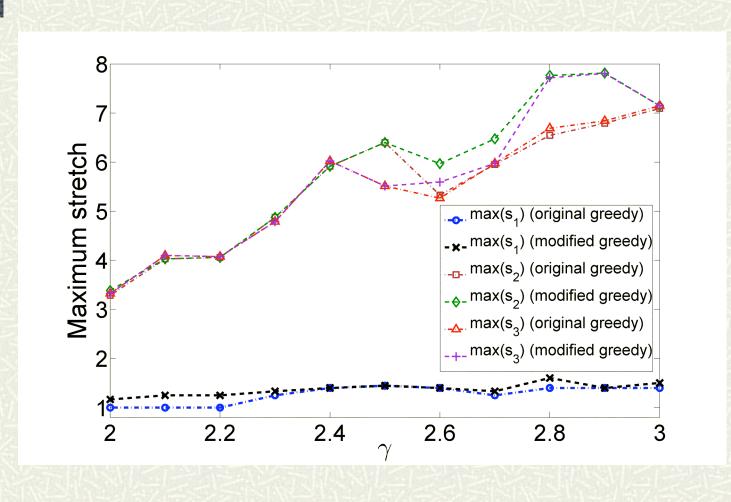
Average length of successful paths



Multiplicative average stretch



Multiplicative maximum stretch



Robustness of greedy routing w.r.t. network dynamics

- ★ As network topology changes, the greedy routing efficiency characteristics deteriorate very slowly
- **■** For example, for $\gamma \le 2.5$, removal of up to 10% of the links from the topology degrades the percentage of successful path by less than 1%

In summary

- **■** Scale-free networks are congruent w.r.t. hidden hyperbolic geometries
 - Greedy paths follow shortest paths that approximately follow shortest hidden paths, i.e., geodesics in the hyperbolic space
- ☐ This congruency is robust w.r.t. network dynamics/evolution
 - There are many shortest paths between the same source and destination that satisfy the above properties
 - If some of them go away, others remain available, and greedy routing still finds them

Conclusion

- ➡ Hidden hyperbolic metric spaces explain, simultaneously, the two main topological characteristics of complex networks
 - scale-free degree distributions
 - strong clustering
- Greedy routing mechanism in these settings may offer virtually infinitely scalable routing algorithms for future communication networks
 - Zero communication costs (no routing updates!)
 - Constant routing table sizes (coordinates in the space)
 - No stretch (all paths are shortest, stretch=1)

Problems to solve

- **♯** Find the exact structure of hidden metric spaces underlying real networks
- # Find the coordinates of nodes in them