MU5IN075
Network Analysis and Mining
14. Structure of the Internet

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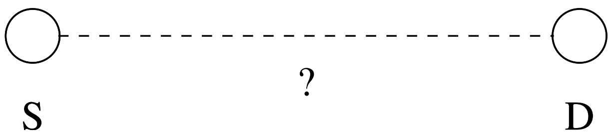
Outline

Topology of the internet

Measurement: exploration using `traceroute`



Principle: packets with same destination and increasing TTL

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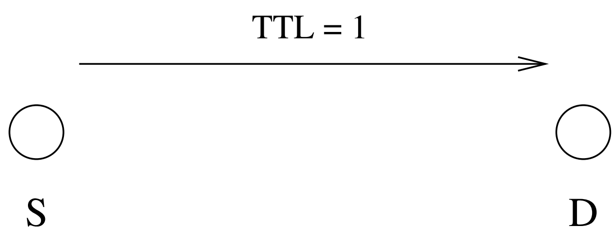

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Introduction: traceroute measurement
Metrology
Correcting the bias

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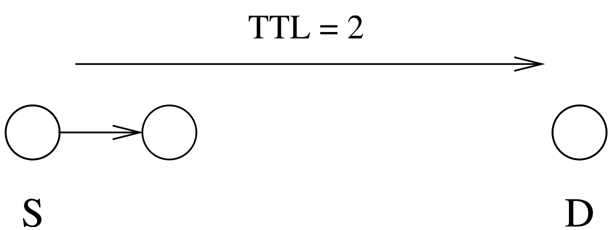

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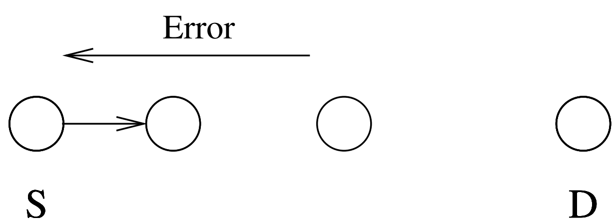

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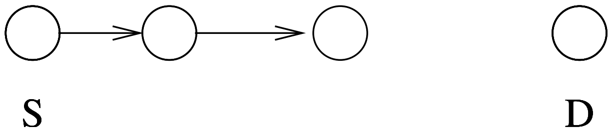

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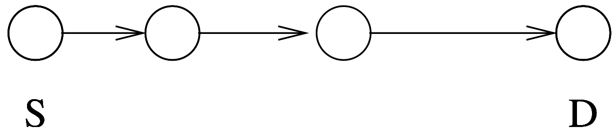

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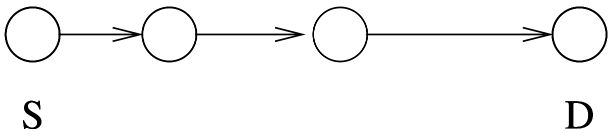

If no answer: *

ICMP filtered for various reasons: *rate limiting, time exceeded,*
...

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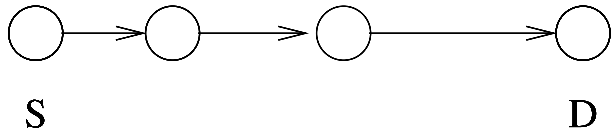

Remark:
one router = several IP addresses
answers with the IP address that sends the packet
$\Rightarrow$ simplified description of the process

Measurement bias

> *A very general but largely ignored fact about Internet-related measurements is that what we can measure in an Internet-like environment is typically not the same as what we really want to measure (or what we think we actually measure)*

Mathematics and the internet: A source of enormous confusion and great potential - *W. Willinger et al., Notices of the AMS, 2009*

example: traceroute measurement from source S to target T

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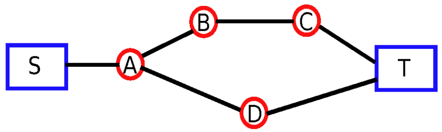

Problematic

Information collection

Practically, a few sources, a lot of destinations

- we know that we don't see everything...
- how to get a meaningful view? ($\rightarrow$ evaluate bias)

Measured property: the degree distribution

Degree distribution of the Internet:
we know it is heterogeneous, close to a power-law

On routes and multicast trees in the Internet - *Pansiot and Grad, 1998*
On power-law relationships of the internet topology - *Faloutsos, Faloutsos and Faloutsos, 1999*

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Surprising degree distribution observed → bias?

How to procede?

- Experimental: measure from a large number of sources
- Also calls for theoretical studies

Lecture goal
understand and analyze research results
topic: IP maps of the Internet

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Outline

Volume of information

On the Marginal Utility of Network Topology Measurements - *Barford, Bestavros, Byers, Crovella, 2001*

General idea of the article

- Use data from measurements (rather than simulations)
- Evaluate number of nodes/links seen vs number of sources/destinations → unit of the information volume

When using more sources and destinations...

→ ...does it increase the volume of information?
→ ...does it decrease the bias?

Volume of information

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Data

Two datasets

- 8 sources
- 1277 destinations
- 1 traceroute every 30 minutes
- approximately 7 months

- 12 sources
- $>$ 300 000 destinations
- same measurement method
- duration unknown

Data

Remark about the benefit of repeating measurements

Because of load-balancing, ...
→ repeating give more information (and more noise too...)

Methodology

Assess the number of nodes seen as a function of

- the number of sources
- the number of destinations

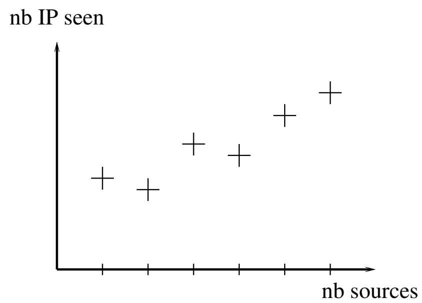
s sources, d destinations → $s \times d$ combination of values

A lot of possibilities...

→ how to choose?

Methodology

What do we want?



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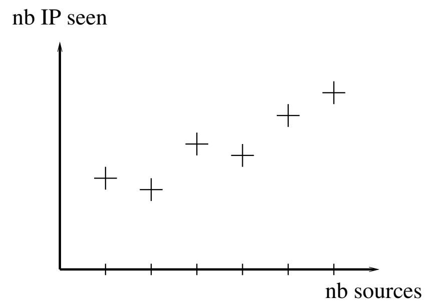
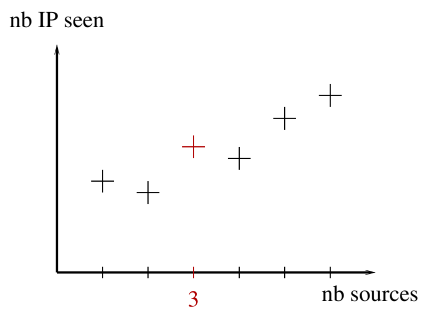


same thing with destinations

Problem



Number of IPs seen with 3 sources: which 3 sources?

Looking for a strategy which maximizes the IPs seen

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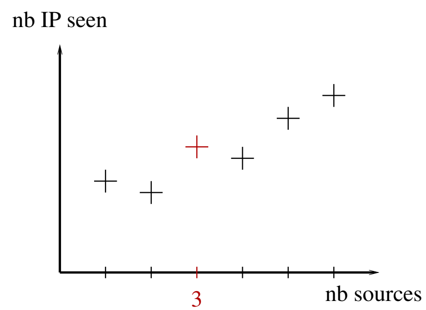

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Example

One source → set of IPs seen

Example

s_1 : $\{a, b, c, d, e\}$ | s_4 : $\{g, h\}$
s_2 : $\{a, b, c, d, f\}$ | s_5 : $\{i, j, k\}$
s_3 : $\{a, b\}$ | s_6 : $\{a, d\}$

$s_1 + s_3 + s_6 \rightarrow$ 5 IPs
$s_1 + s_4 + s_5 \rightarrow$ 10 IPs

Depends on how complementary the sources are
→ no obvious choice

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At each step: add the source which adds most information

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2 sources: $s_1 s_5$

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4 sources: $s_1 s_5 s_4 s_2$

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Motivation: close to "best" case, without testing all combinations

Complexity of this processing

Complexity of the union of two sets

Complexity of step 2

compute $n-1$ unions
(supposing that all sets approximately of the same size for simplicity)

Complexity of step i

compute $n-(i-1)$ unions

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$\rightarrow$ proportional to size of the smallest
(at least, it depends on the implementation)

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$\rightarrow (n - i + 1) \times k$

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so, from step $i = 2$ to step $i = n$
$\rightarrow k((n-1) + (n-2) + \ldots + 2 + 1) = \frac{kn(n-1)}{2}$

total: $\mathcal{O}(kn^2)$
long if large number of sources (n)

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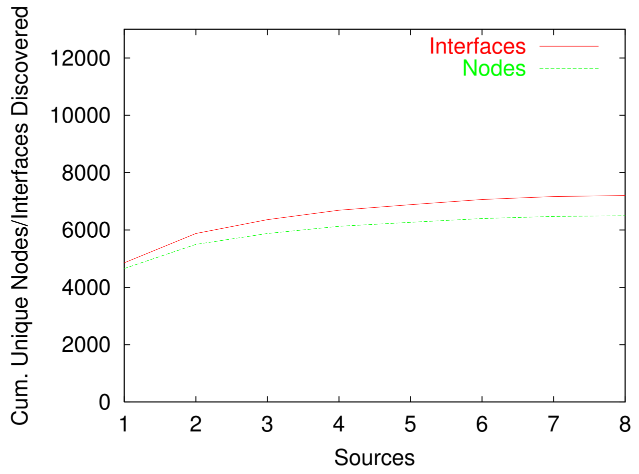

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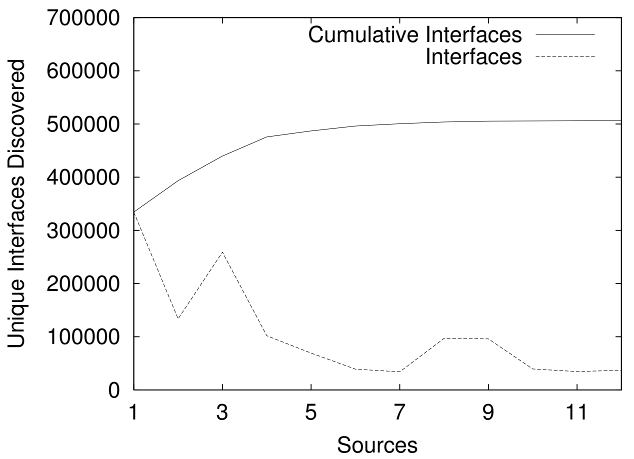

Observations

Convergence of the curve:
the last ones bring nearly no new information
$\rightarrow$ authors conclude marginal utility of source addition

to be discussed later...

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Destinations utility

In the ideal case, similar approach:
for every destination → set of IPs seen

but greedy strategy is expensive → random strategy

Random strategy

For one source, at each step:

- add randomly a destination

Compare curves for all sources

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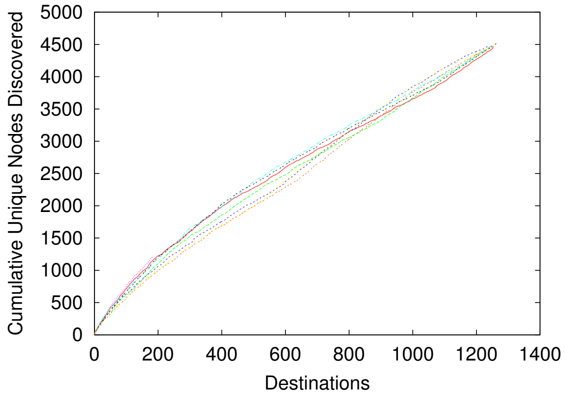

Observation: roughly linear increase
same benefit for all destinations

Comparison sources and destinations

→ relevant to increase number of destinations rather than number of sources

On the Marginal Utility of Network Topology Measurements - *Barford, Bestavros, Byers, Crovella, 2001*

We observe difference between curves
→ why such difference between sources and destinations?

while the intuition is
s sources, *d* destinations $\Longleftrightarrow$ *d* sources, *s* destinations

→ importance of the strategy used
greedy vs random

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Critical look at the study

In spite of its interest ...

Lack of information on
→ the disparity between sources
(one source only sees 184 nodes , > 4000 for the largest one)
→ influence of the strategy implemented

Q: is the choice of sources more important than their number?

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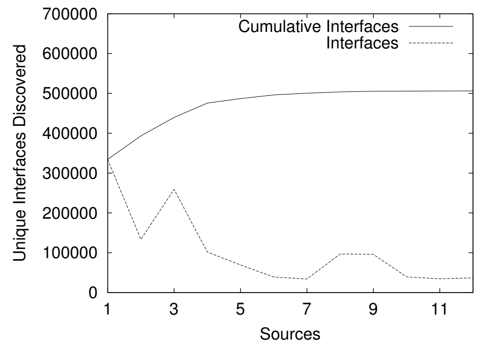

Last sources: bring few information
but the greedy strategy induces the shape of the curve
no obvious best strategy...

Datasets

To get a better understanding: compare different strategies

Ouédraogo, Magnien - *Computer Communications, 2011*

Data

- 11 sources
- 3 000 destinations
- 100 traceroutes per day
- $\sim$ 2 months

Difference between sources

Number of IPs seen per sources

Vary between:

- $\sim$ 16,500
- $\sim$ 26,500

$\rightarrow$ Every sources are not equivalent
(although more homogeneous than in *Barford et al.*)

Influence of sources and destinations

Three different strategies

- **greedy-max**:
  add the source which brings the most information
- **random**:
  add a random source
- **greedy-min**:
  add the source which brings the least information

Influence of sources and destinations

Greedy strategy $\neq$ maximum possible with k sources

Example

$s_1 : \{a, b, c, d, e\}$ $\quad$ $s_3 : \{a, c, d, g\}$
$s_2 : \{a, b, e, f\}$

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Representativeness of maximum? (close to “standard” case?)
Cost to compute the maximum?

Influence of sources and destinations

Other strategies

- Random max $\rightarrow$ max over 1000 random orders
- Random min $\rightarrow$ min over 1000 random orders
- Random $\rightarrow$ average over 1000 random orders

Influence of sources and destinations

Example

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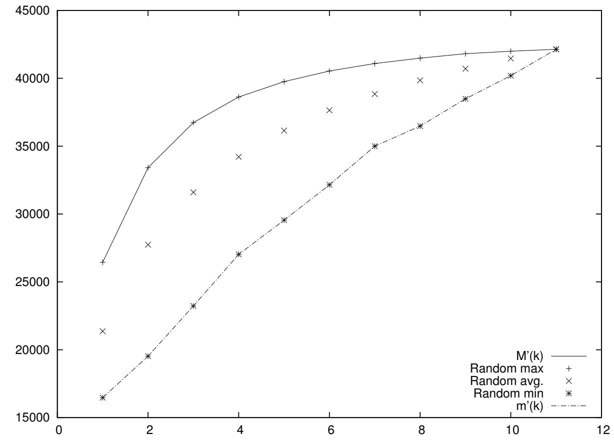
random 1	s_3	s_4	s_6	s_5	s_2	s_1
	2	4	6	7	10	11
random 2	s_5	s_6	s_2	s_4	s_3	s_1
	3	3	7	9	10	11
random min	2	3	6	7	10	11
random max	3	4	7	9	10	11
random average	2.5	3.5	6.5	8	10	11

Results (number of IPs seen)



Influence of sources
rk: M′ is greedy-max, m’ is greedy-min

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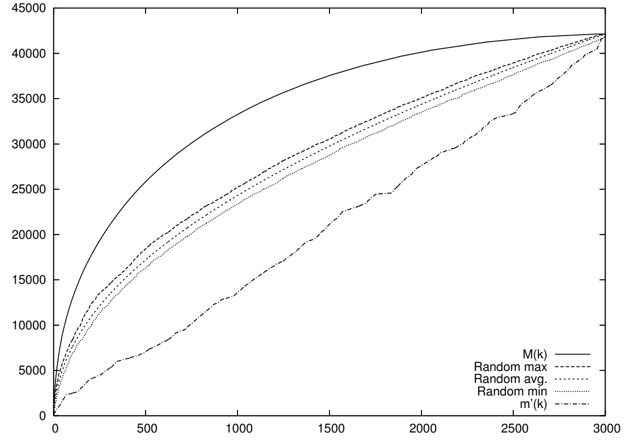

Influence of destinations

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Observations

- Every curves ends at point n
  because every node discovered
- Random max (min) = Greedy max (min) for sources only
  because few sources
- Greedy max (averaged)
  similar qualitative behaviors for sources and destinations
- In practice, larger variability with sources
  because few sources

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Conclusion

Utility decreases, but not null
→ choice of sources might be more important than number

Ouédraogo, Magnien - *Computer Communications, 2011*

Exploration bias

Sampling Biases in IP Topology Measurements - *Lakhina, Byers, Crovella, Xie, 2003*

Principle of the article: simulation-based

- Generate artificial graphs → topology
- Simulate traceroutes → measure
- Observe and analyze results

Explore the explicative dimension of modelling

Introduction: traceroute measurement
Metrology
Correcting the bias
Influence of sources and destinations
Bias on degree

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30/54

Implementation - graph models

Basic graph models

- Erdős-Rényi
- Fixed degree distribution → configuration model

Implementation – traceroute simulation

How to simulate traceroute?
. . . several possibilities

Usual choice

- route = shortest path (not true but default choice)

Shortest path

- One/every shortest paths?
- If one, which one?

Implementation – traceroute simulation

How to simulate traceroute?
. . . several possibilities

Usual choice

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The authors' choice

Give a weight to each link ($\rightarrow$ weighted graph)
$1 + \epsilon$, with a random $\epsilon \ll 1$

Length of a path: sum of the weights of the links
$\rightarrow$every paths have different weights

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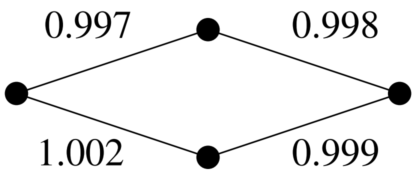
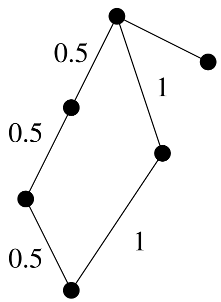


Computation of the shortest weighted path

Remark: BFS not suited for weighted networks



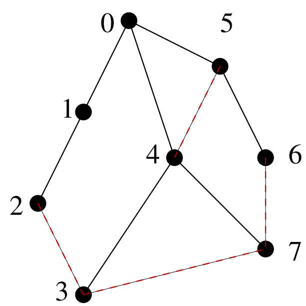
shortest paths from one node in weighted graph (weights>0)
$\rightarrow$ Dijkstra algorithm (not detailed here)

Our choice: restricted BFS

- no weight
- distances computed with a BFS
- storage of the output of the BFS $\rightarrow$ table of fathers

Value i: father of i
Value root: root itself

0	0	1	4	0	0	5	4
0	1	2	3	4	5	6	7



Restiction to destinations

Table initialized at -1

For each destination `d` : (here : `d` = 3, 4, 6, 1)

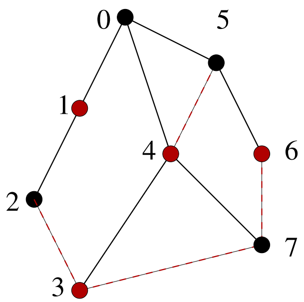
- While `AR[d] == -1`
  - AR[d] = A[d]
  - d = A[d]

A

0	0	1	4	0	0	5	4
0	1	2	3	4	5	6	7

AR

0	0	-1	4	0	0	5	-1
0	1	2	3	4	5	6	7



Degree computation

Degree of a node in the BFS tree using table of fathers:

Degree computation

Degree of a node in the BFS tree using table of fathers:
- number of times it appears +1
- except for the **root** : number of times -1

0	0	-1	4	0	0	5	-1
0	1	2	3	4	5	6	7

(boxes with -1: nodes which are not in the BFS tree)

Several sources

Several sources:
$\rightarrow$ one BFS per source

How to compute the degree of the nodes?
mark links as present or absent

Connectedness

Problem if the graph is not connected...

Several solutions

- choose sources and destinations in the same connected component
- use only connected graphs
- ...

No ideal solution

Introduction: traceroute measurement
Metrology
Correcting the bias
Influence of sources and destinations
Bias on degree

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Connectedness

Problem if the graph is not connected...

Authors' choice:

Restrict to the largest connected component

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Simulations

Two cases under study:

Erdős-Rényi graphs (homogeneous degree)

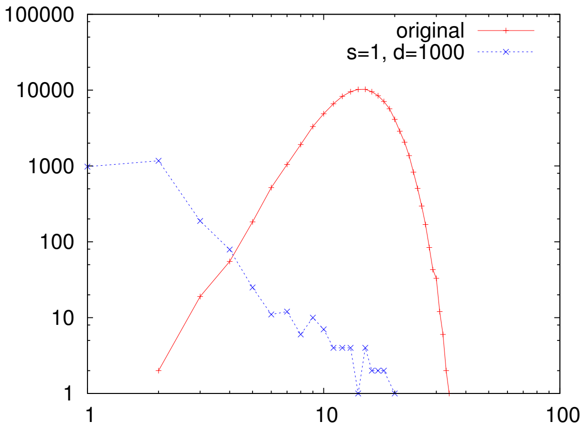
- $n = 100\,000$
- $m = 750\,000$ ($d^{\circ}(G) = 15$)
- sources: 1, 5, 10
- destinations: 1000, chosen randomly

Fixed degree distribution (heterogeneous degree)

- $n \sim 100\,000$
- $m \sim 190\,000$
- power-law, $\alpha \sim 2.1$

Results

Erdős-Rényi graphs



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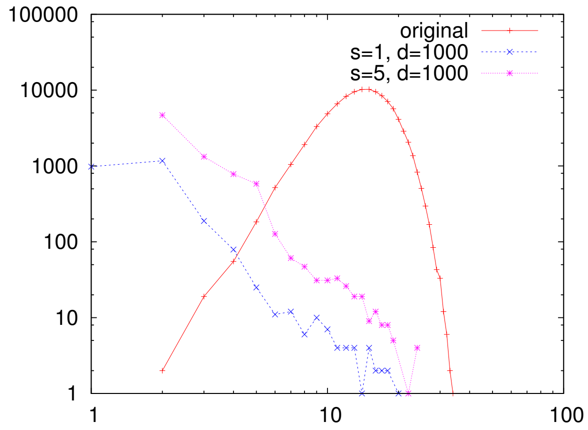

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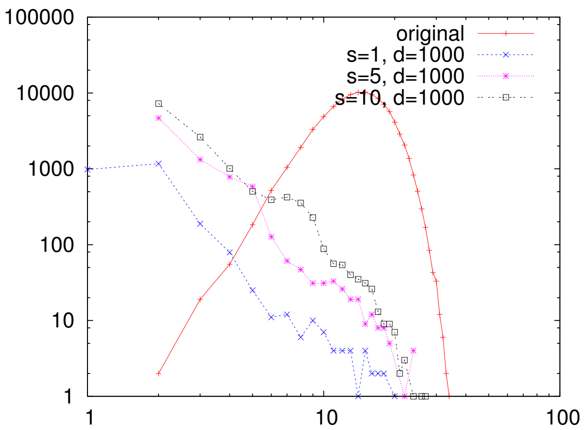
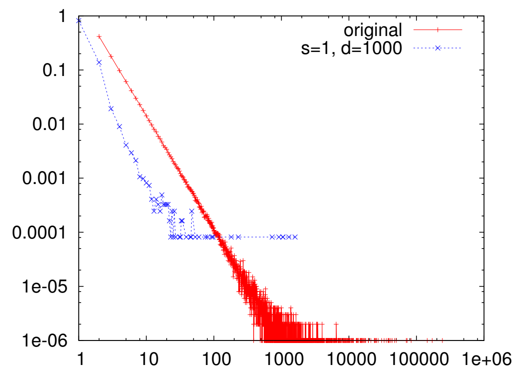


Results

Graphs with fixed heterogeneous degree



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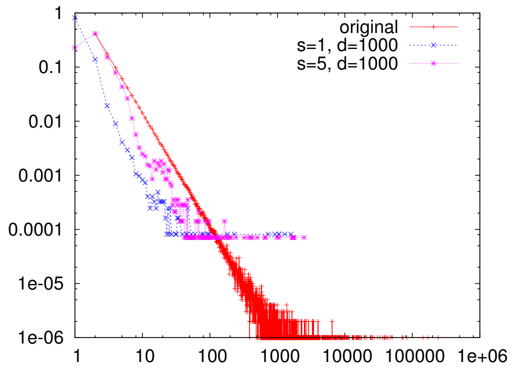

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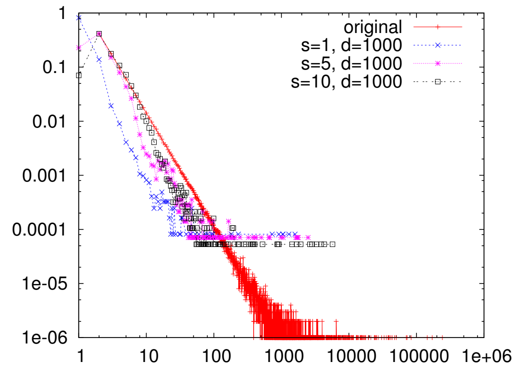
Graphs with fixed heterogeneous degree



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Observations

- Distribution observed $\neq$ real distribution
- Erdős-Rényi: qualitative difference
  homogeneous appears as heterogeneous
- Graphs with fixed degree: quantitative difference
  slope, max degree, . . .

Warning:
ER graphs: Maximum degree observed $\sim$ 30
$\rightarrow$power-law models are not reliable at this scale

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Conclusion of the study

Observing heterogeneous distrib $\not\Rightarrow$ Real heterogeneous distrib

No conclusion on the real distribution

Discussion (1/2)

Important result

- From a theoretical point of view
- Need to be careful about conclusions in practice

What conclusions can we draw from this?

Observed distribution heterogeneous

$\rightarrow$ is the real distribution homogeneous?
$\rightarrow$ is the real distribution heterogeneous?

Discussion (2/2)

Case of ER graphs

Maximal degree observed:

Discussion (2/2)

Case of ER graphs

Maximal degree observed:
close to average degree of the graph.

Experimentally, maximum degree observed > 1000
$\rightarrow$ ER graph with average degree $\simeq$ 1000? not realistic

Discussion (2/2)

Case of ER graphs

Maximal degree observed:
close to average degree of the graph.

Experimentally, maximum degree observed > 1000
$\rightarrow$ ER graph with average degree $\simeq$ 1000? not realistic

$\rightarrow$real distribution probably heterogeneous. . .
need more work

Causes of the bias: first hypothesis

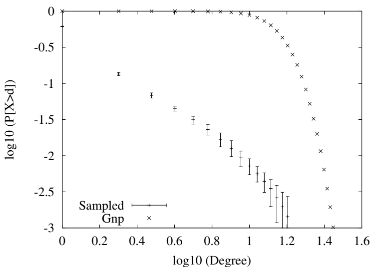
Hyp: Bias in the node sample?

For each node: compare the degree observed to its real degree

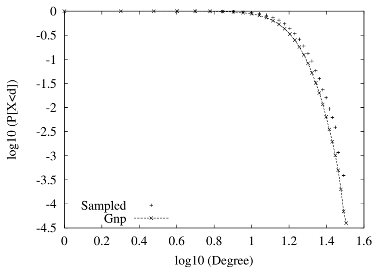
Causes of the bias: first hypothesis

Hyp: Bias in the node sample?

observed deg vs original deg



real deg vs original deg



With 1 source

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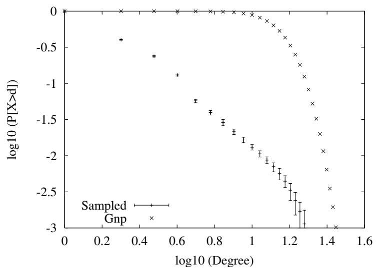

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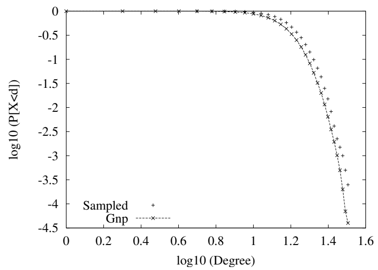

With 5 sources

Causes of the bias: first hypothesis

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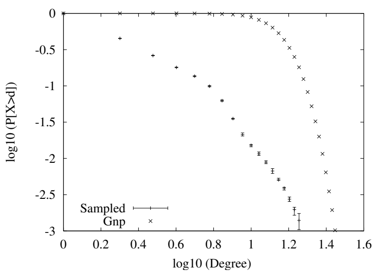

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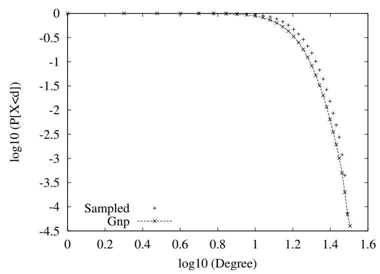
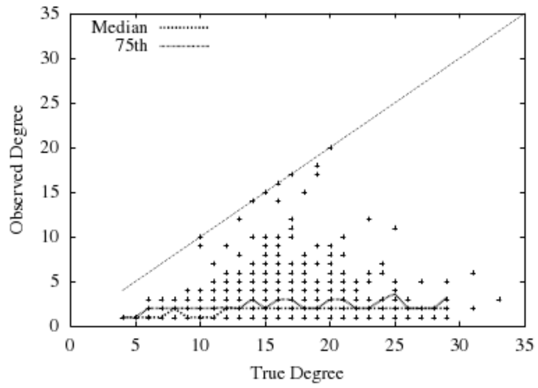


With 10 sources
Nodes are chosen without bias on the degree

Causes of the bias: second hypothesis

Hyp: Bias in the link sample?

degree observed vs true degree
With 1 source



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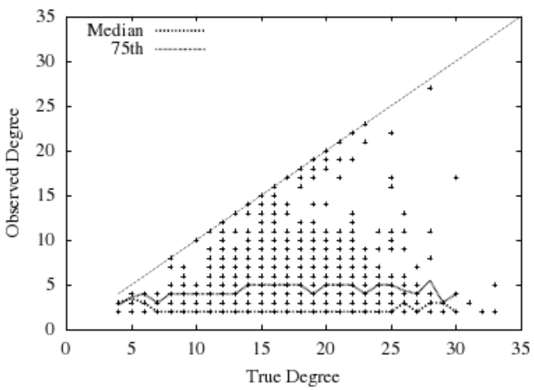

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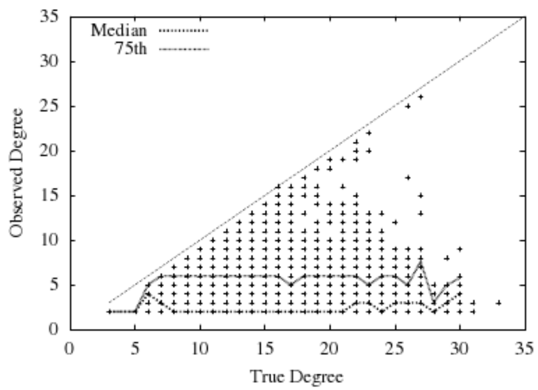
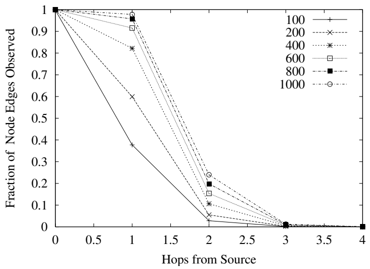


Bias sources

Link visibility as a function of their distance to the source

10,000 nodes



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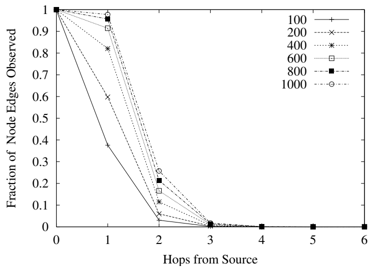

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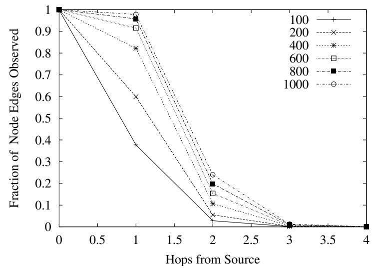

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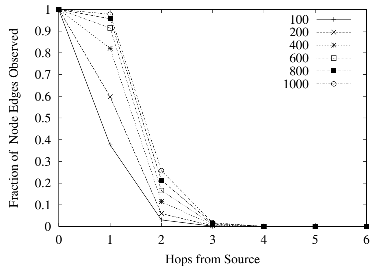


The further an edge is from the source,
the less are its chances to be seen

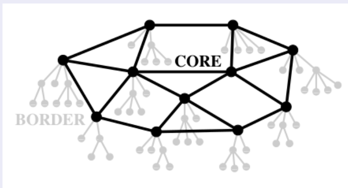
Outline

How to make an unbiased measurement?

Rigorous Measurement of the Internet Degree Distribution - *Latapy et al., 2017*

Core routers vs. border routers

- core: non-trivial routing
- border: routing in a tree

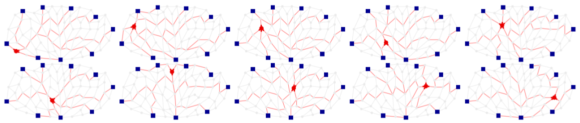


→ focus on core routers degree distribution

Uniform sampling of core routers: protocol

Measurement protocol basis

- 700 sources (PlanetLab monitors)
- 3 million destinations (IP addresses)
- UDP ping from all monitors to all destinations on unallocated port



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- one of target interfaces sends back error message
  ⇒ one interface address of the router
- enough monitors ⇒ all core interfaces = router core-degree

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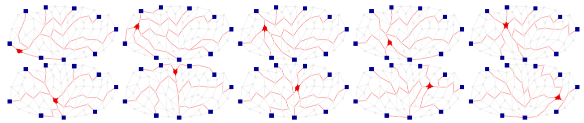

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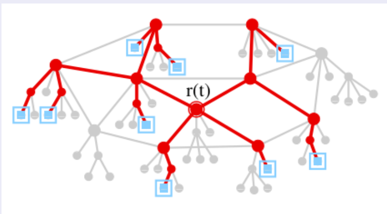
Unbiased core degree distribution

Nodes filtering

- core nodes: all interfaces in the core are seen
- border nodes: monitors only detect the interface towards the core



→ 5600 interfaces of reliable core routers

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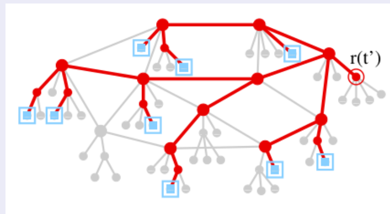

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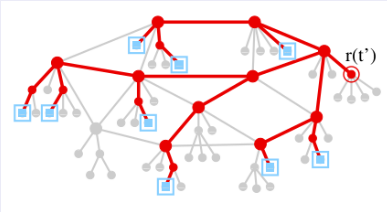


$\rightarrow$ 5600 interfaces of reliable core routers

Unbiased core degree distribution

During all measurements, we register the interfaces of a reliable router that send an error message

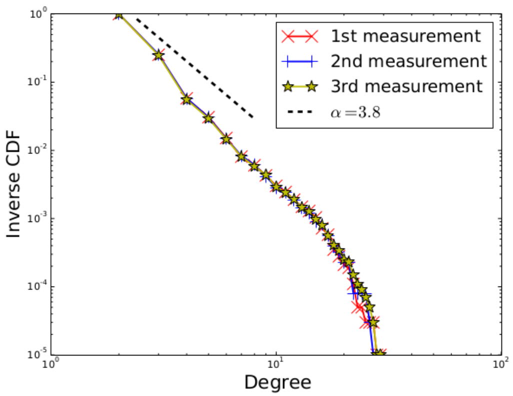
From the observed to the real distribution

Other biases to eliminate:

1. Discard border interfaces of core routers
2. Correct probability distribution as the probability to sample a router is proportional to its number of interfaces
   - router core-degree k: probability observed p'_k
   - real degree distribution $p_k \propto \frac{p'_k}{k}$

After all that...

(Core) degree distribution of core routers



Heterogeneous, but not a power-law