

Networks Structure and Dynamics

11. Internet topology metrology

Maximilien Danisch, Marwan Ghanem, Lionel Tabourier

LIP6 – CNRS and Sorbonne Université

`first_name.last_name@lip6.fr`

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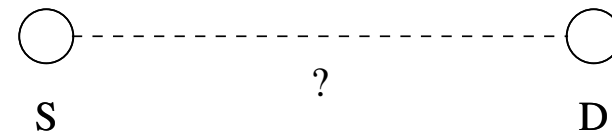
- 1 Introduction: traceroute measurement
- 2 Metrology
 - Influence of sources and destinations
 - Bias on degree

Outline

- 1 Introduction: traceroute measurement
- 2 Metrology
 - Influence of sources and destinations
 - Bias on degree

Topology of the internet

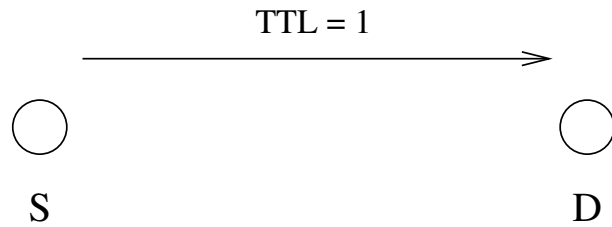
Measurement: exploration using `traceroute`



Principle: packets with same destination and increasing TTL

Topology of the internet

Measurement: exploration using `traceroute`



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Principle: packets with same destination and increasing TTL

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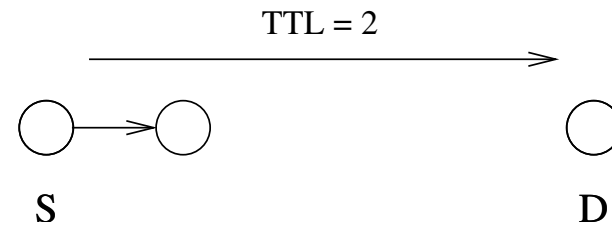
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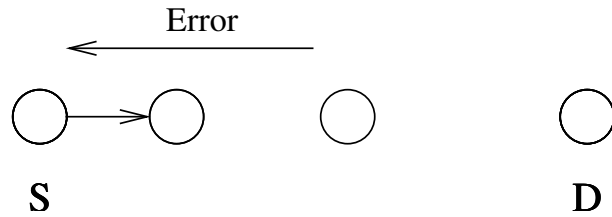
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Principle: packets with same destination and increasing TTL

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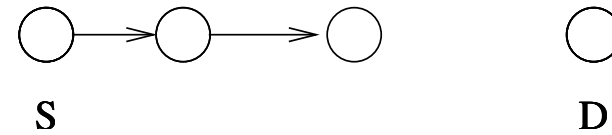
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Principle: packets with same destination and increasing TTL

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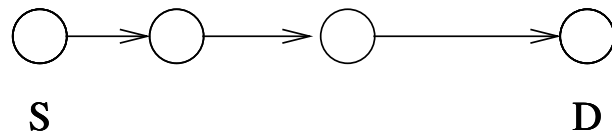
Measurement: exploration using `traceroute`



Principle: packets with same destination and increasing TTL

Topology of the internet

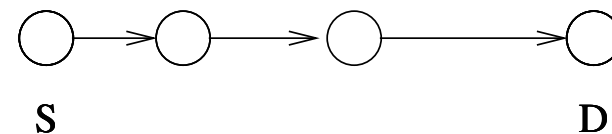
Measurement: exploration using `traceroute`



Principle: packets with same destination and increasing TTL

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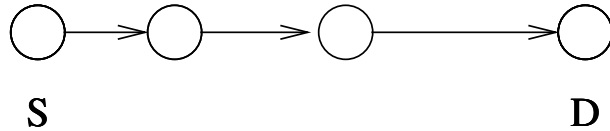
Measurement: exploration using `traceroute`



If no answer: *
ICMP filtered for various reasons:
Rate limiting
Time exceeded
...

Topology of the internet

Measurement: exploration using `traceroute`

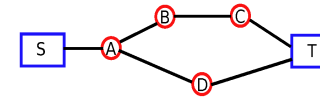


Remark:
one router = several IP addresses
answers with the IP address that sends the packet
⇒ **simplified description of the process**

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.



Problematic

Information collection

A few sources, a lot of destinations:

- We know that we don't see everything
- How to get a meaningful view? (→ evaluate **bias**)

Measured property

The degree distribution, we discussed this property a lot...
Degree distribution of the Internet: heterogeneous, even a **power-law**

Pansiot, Grad - 1998

Faloutsos, Faloutsos, Faloutsos - 1999

Surprising degree distribution observed → **bias?**

How to procede?

- Measure from a large number of sources
- Call to theoretical and experimental studies

Lecture goal: understand and comment research papers

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Outline

- 1 Introduction: traceroute measurement
- 2 **Metrology**
 - Influence of sources and destinations
 - Bias on degree

Volume of information

Barford, Bestavros, Byers, Crovella - *On the Marginal Utility of Network Topology Measurements, 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](#)

Interest of using more sources and destinations

- Does it increase the volume of information?
- Does it decrease the bias?

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

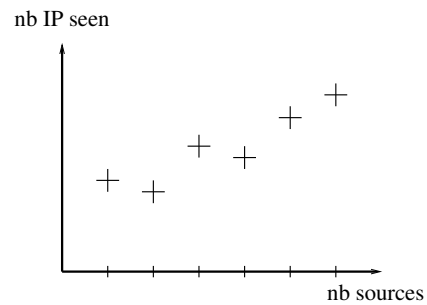
s sources, d destinations → $s \times d$ possible parameter values

A lot of possibilities. ...

Interpretation?

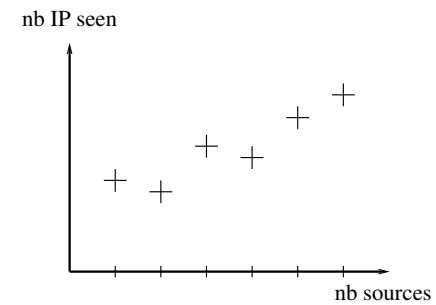
Methodology

What do we want?



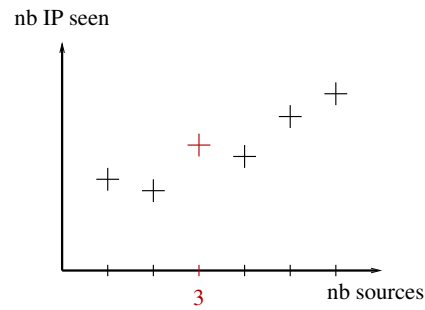
Methodology

What do we want?



same thing with **destinations**

Problem



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

Example

One source → **set** of IPs seen

Example

$s_1 : \{a, b, c, d, e\}$

$s_2 : \{a, b, c, d, f\}$

$s_3 : \{a, b\}$

$s_4 : \{g, h\}$

$s_5 : \{i, j, k\}$

$s_6 : \{a, d\}$

$s_1 + s_3 + s_6 \rightarrow 5 \text{ IP}$

$s_1 + s_4 + s_5 \rightarrow 10 \text{ IP}$

Depends on how complementary the sources are
no obvious choice

Example

One source → **set** of IPs seen

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Greedy strategy

At each step: add the source which **adds most information**

Example

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1 source: s_1

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2 sources: $s_1 s_5$

Greedy strategy

At each step: add the source which **adds most information**

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

3 sources: $s_1 s_5 s_4$

Greedy strategy

At each step: add the source which **adds most information**

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

4 sources: $s_1 s_5 s_4 s_2$

Greedy strategy

At each step: add the source which **adds most information**

Example

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

5 sources: $s_1 s_5 s_4 s_2 s_3$

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Greedy strategy

At each step: add the source which **adds most information**

Example

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

6 sources: $s_1 s_5 s_4 s_2 s_3 s_6$

14/51

Greedy strategy

At each step: add the source which **adds most information**

Example

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

sources: $s_1 s_5 s_4 s_2 s_3 s_6$

Motivation: close to “best” case, without testing all combinations

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Complexity

Complexity of the union of two sets

Complexity of step 2

compute $n - 1$ unions

Complexity of step i

compute $n - (i - 1)$ unions

15/51

Complexity

Complexity of the union of two sets

proportional to size of the smallest
(minimum, depends on the implementation)

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15/51

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 $\rightarrow (n - 1) \times k$ if all sets are of size k

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15/51

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Complexity of step i

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

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Complexity

At step i

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

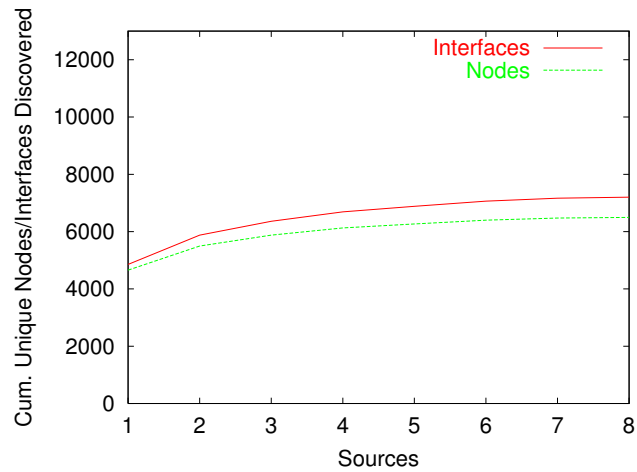
$$k((n - 1) + (n - 2) + \dots + 2 + 1) = \frac{kn(n-1)}{2}$$

$$\mathcal{O}(kn^2)$$

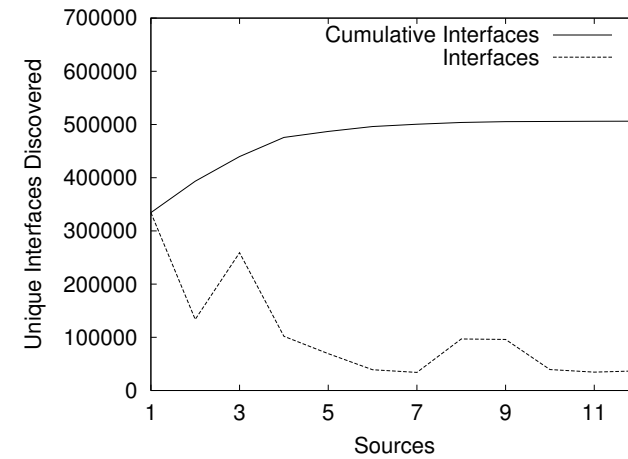
long if large number of sources (n)

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Results



Results



Observations

Convergence of the curve:
the last ones bring nearly no new information
→ authors conclude **marginal utility** of source addition

to be discussed later...

Destinations utility

In the ideal case, inverse approach:
Every destination → set of IPs seen
Greedy strategy is expensive → **random strategy**

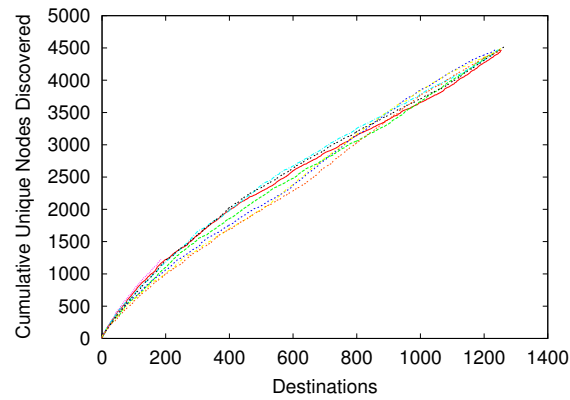
For one source

At each step:

- add randomly a destination

Compare curves for all sources

Results



Observation: roughly linear increase
similar benefit for all destinations

Comparison sources and destinations

Difference between curves

→ Why such difference between sources and destinations?

Intuition:

s sources, d destinations \iff d sources, s destinations

→ Importance of the strategy used
greedy vs random

Comparison sources and destinations

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Critical look

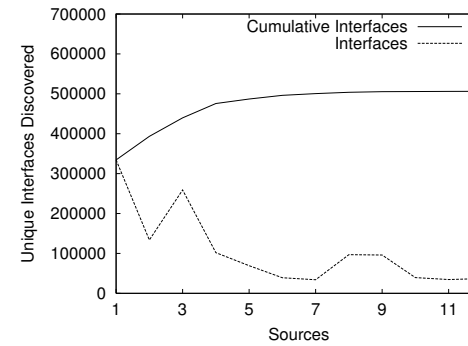
Interesting study, but...

Lack of details on

- **disparity** between sources
(one source only sees 184 nodes , > 4000 for the largest one)
- influence of the **strategy**

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

Critical look



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

Datasets

To get a better understanding: **compare different strategies**

Quédraogo, Magnien - *Computer Communications*, 2011

Data

- 11 sources
- 3 000 destinations
- 100 traceroutes per day
- ~ 2 months

Difference between sources

Number of IPs seen per sources

Vary between:

- ~ 16,500
- ~ 26,500

→ Every sources are **not equivalent**

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

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Influence of sources and destinations

Greedy strategy \neq maximum possible with k sources

Example

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

$s_3 : \{a, c, d, g\}$

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Influence of sources and destinations

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Example

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

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1 sources : s_1

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Influence of sources and destinations

Greedy strategy \neq maximum possible with k sources

Example

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

$s_3 : \{a, c, d, g\}$

2 sources : $s_1 s_2$

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Influence of sources and destinations

Greedy strategy \neq maximum possible with k sources

Example

$s_1 : \{a, b, c, d, e\}$

$s_2 : \{a, b, e, f\}$

$s_3 : \{a, c, d, g\}$

3 sources : $s_1 s_2 s_3$

Influence of sources and destinations

Greedy strategy \neq maximum possible with k sources

Example

$s_1 : \{a, b, c, d, e\}$

$s_2 : \{a, b, e, f\}$

$s_3 : \{a, c, d, g\}$

3 sources : $s_1 s_2 s_3$

$s_2 + s_3 : 7$ IP

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

Influence of sources and destinations

Other strategies

- Max \rightarrow max over 1000 random orders
- Min \rightarrow min over 1000 random orders
- Random \rightarrow average over 1000 random orders

Influence of sources and destinations

Example

$s_1 : \{a, b, c, d, e\}$

$s_2 : \{a, b, c, d, f\}$

$s_3 : \{a, b\}$

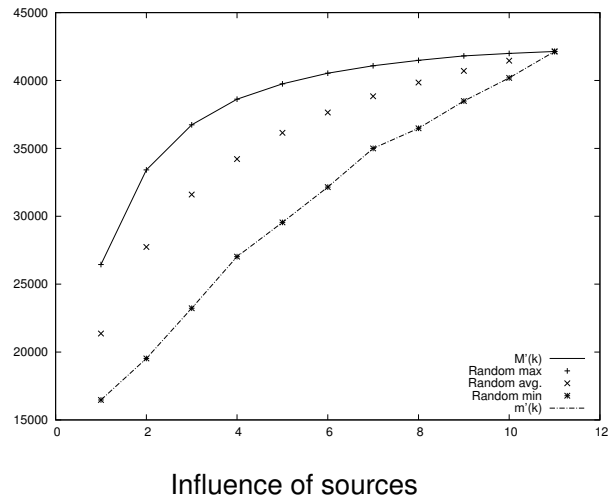
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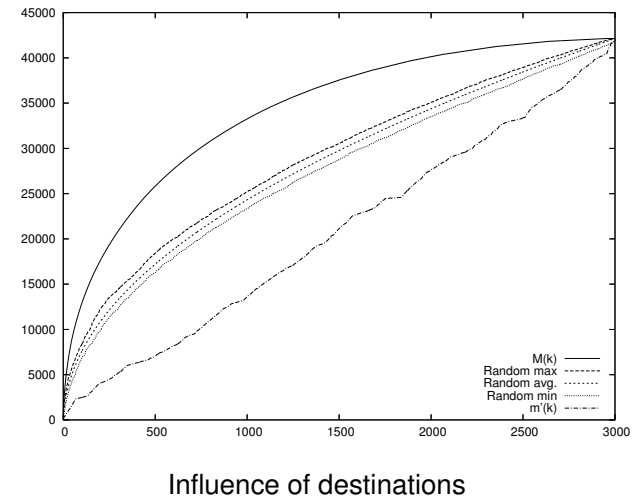
	s_3	s_4	s_6	s_5	s_2	s_1
	2	4	6	7	10	11
	<hr/>					
	s_5	s_6	s_2	s_4	s_3	s_1
	3	3	7	9	10	11
	<hr/>					
Min	2	3	6	7	10	11
Max	3	4	7	9	10	11
Average	2.5	3.5	6.5	8	10	11

Results



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Results



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Observations

- Every curves ends at point n
- Random max (min) = Greedy max (min) for sources only
- Greedy max (averaged)
- In practice, larger variability with sources

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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 decrease, but not null
Choice of sources might be more important than number

Exploration bias

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

Principle of the article: simulation-based

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

Explore the explicative dimension of modelling

Implementation - graph models

Basic graph models

- Erdős-Rényi
- Fixed degree distribution → configuration model

Implementation – traceroute simulation

How to simulate traceroute?
...several possibilities

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?

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The authors' choice

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

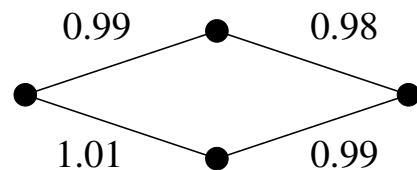
Length of a path: **sum of the weights** of the links
→ Every paths have different weights

34/51

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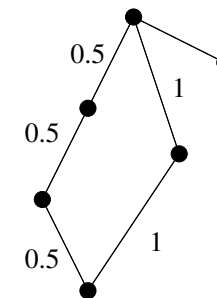
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Computation of the shortest weighted path

BFS **not suited** for weighted networks



shortest paths from one node in weighted graph (weights>0)
→ **Dijkstra** algorithm (not detailed here)

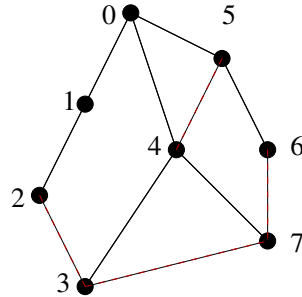
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Our choice: restricted BFS

No weight
Distances computed with a BFS
Storage of the output of the BFS → table

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

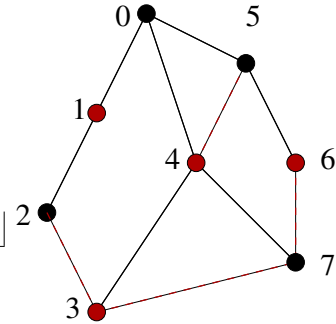
Table initialized at -1

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:

Degree computation

Degree of a node in the BFS tree:

- 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:
→ 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

Connectedness

Problem if the graph is not connected...

Authors' choice:

Restrict to the largest connected component

Simulations

Two cases under study:

Erdős-Rényi graphs (homogeneous degree)

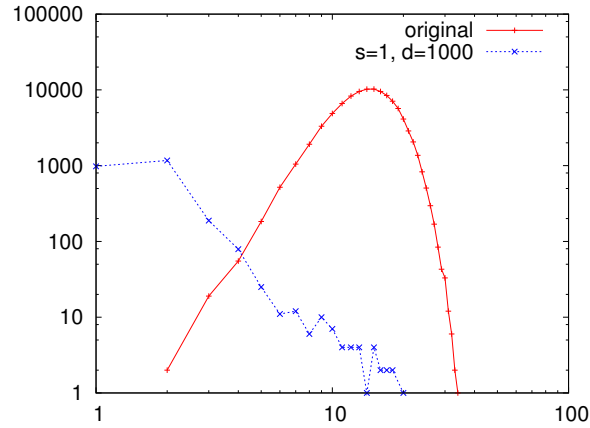
- $n = 100\,000$
- $m = 750\,000$ ($d^\circ(G) = 15$)
- sources: 1, 5, 10
- destinations: 1000, chosen randomly

Fixed degree distribution (heterogeneous)

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

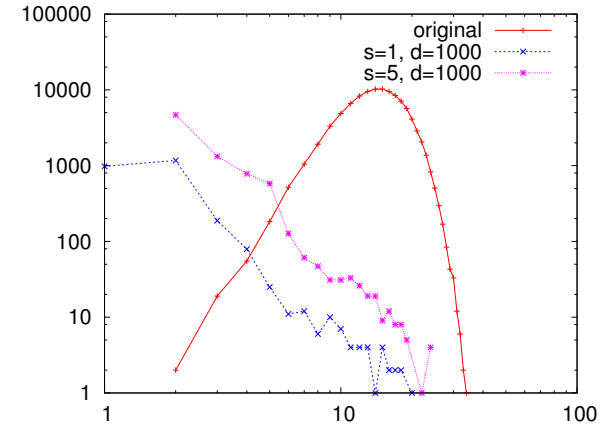
Results

Erdős-Rényi graphs



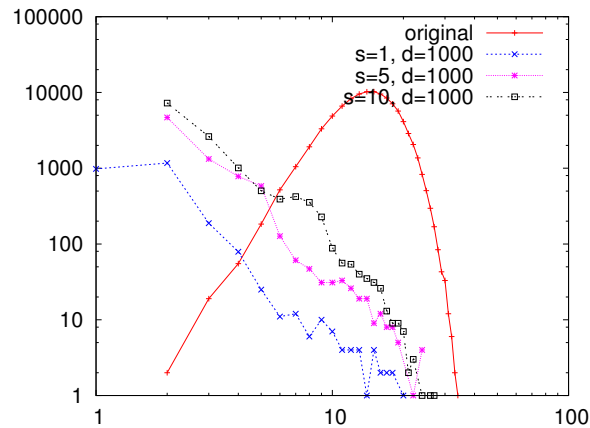
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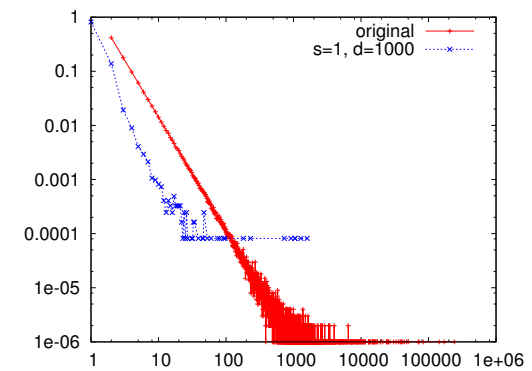
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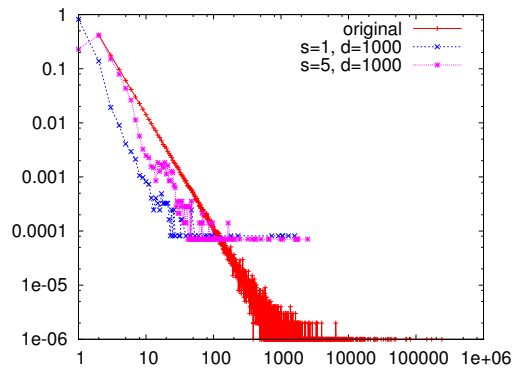
Graphs with fixed heterogeneous degree



Remark: notice the 1/N floor

Results

Graphs with fixed heterogeneous degree

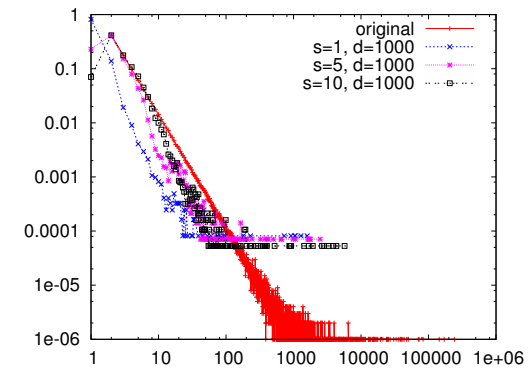


Remark: notice the $1/N$ floor

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Results

Graphs with fixed heterogeneous degree



Remark: notice the $1/N$ floor

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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 ~ 30
→ impossible to conclude on heterogeneity

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homogeneous appears as **heterogeneous**
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slope, max degree, ...

Warning:

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Conclusion of the study

Observing heterogeneous distrib \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

- Real distribution homogeneous?
- 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.

- Practically, maximum degree observed > 1000
- random graph with **average degree = 1000**?
- **real distribution probably heterogeneous...**
- Need more studies

Sources of the bias

Hyp: Bias in the node sample?

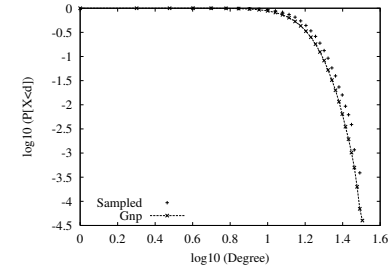
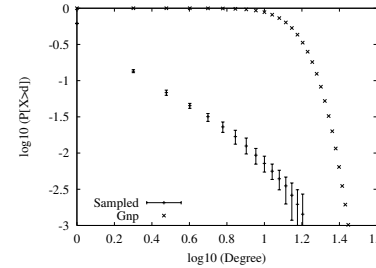
For each node: compare the degree **observed** to its **real** degree

Sources of the bias

Hyp: Bias in the node sample?

observed deg vs original deg

real deg vs original deg



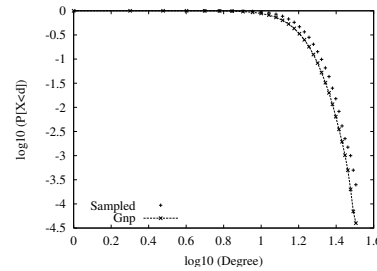
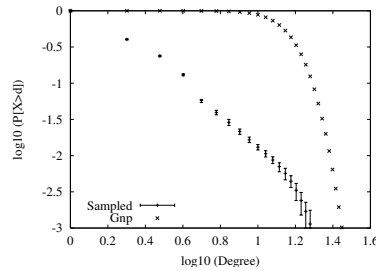
With 1 source

Sources of the bias

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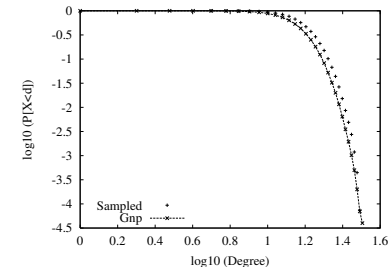
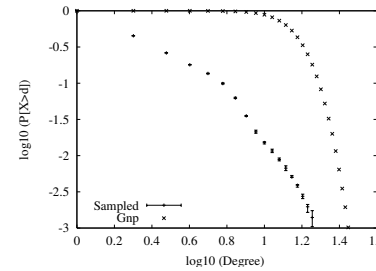
With 5 sources

Sources of the bias

Hyp: Bias in the node sample?

observed deg vs original deg

real deg vs original deg

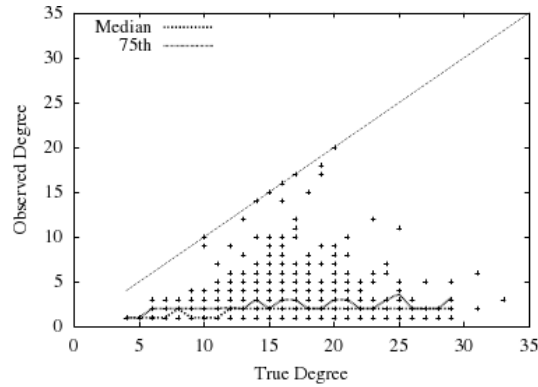


With 10 sources

Nodes are chosen **without bias** on the degree

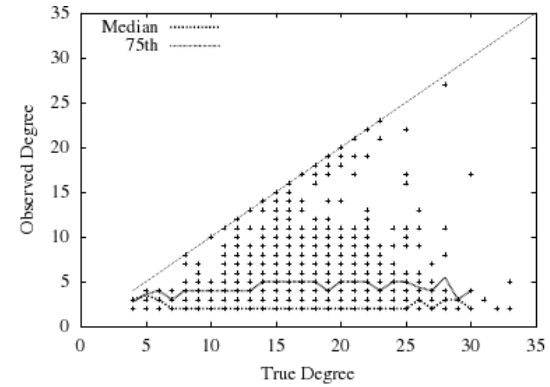
Bias sources

Hyp: Bias in the link sample?
degree observed vs original degree
With 1 source



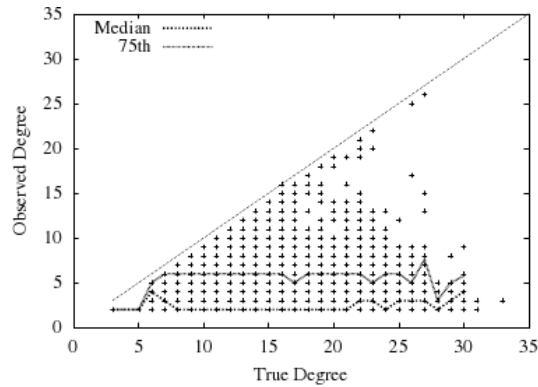
Bias sources

Hyp: Bias in the link sample?
degree observed vs original degree
With 5 sources



Bias sources

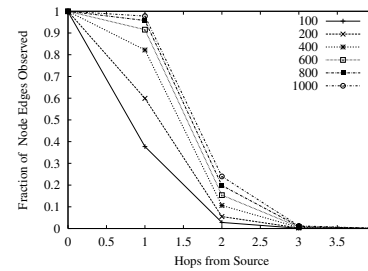
Hyp: Bias in the link sample?
degree observed vs original degree
With 10 sources



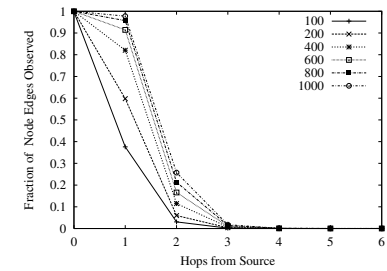
Bias sources

Link visibility as a function of their distance to the source

10,000 nodes



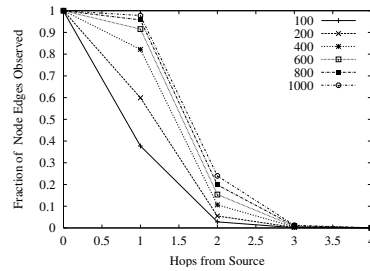
1,000,000 nodes



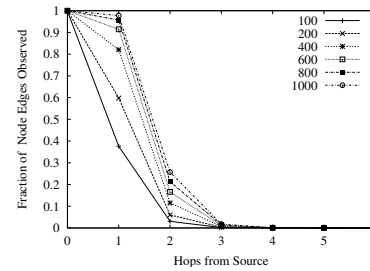
Bias sources

Link visibility as a function of their distance to the source

10,000 nodes



1,000,000 nodes



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

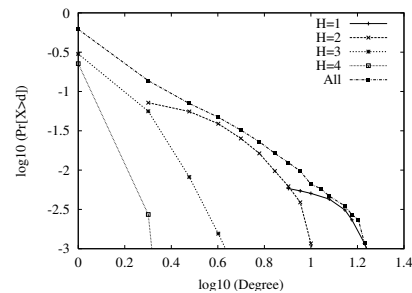
Given sample → bias?

Given a sample (but **not the original graph**),
can we know if there is some **bias**?

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Given a sample (but **not the original graph**),
can we know if there is some **bias**?

Measure the probability to observe both
degree d *and* distance h



The most distant are the nodes, the weaker is the degree