Routing in The Dark

Scalable Searches in Dark P2P Networks

Ian Clarke and Oskar Sandberg

The Freenet Project

Introduction

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- But when individual users come under attack, decentralisation is not enough.
- Future networks may need to limit connections to trusted friends.
- The big question is: Can such networks be useful?

Overview of “Peer to Peer” networks

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- Information is spread across many inter-connected computers
- Users want to find information
- Some are centralised (eg. Napster), some are semi- centralised (eg. Kazaa), others are distributed (eg. Freenet)

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- Disadvantage: Vulnerable to “harvesting”, ie. people you don’t know can easily discover whether you are part of the network

Dark or “Friend to Friend” P2P Networks

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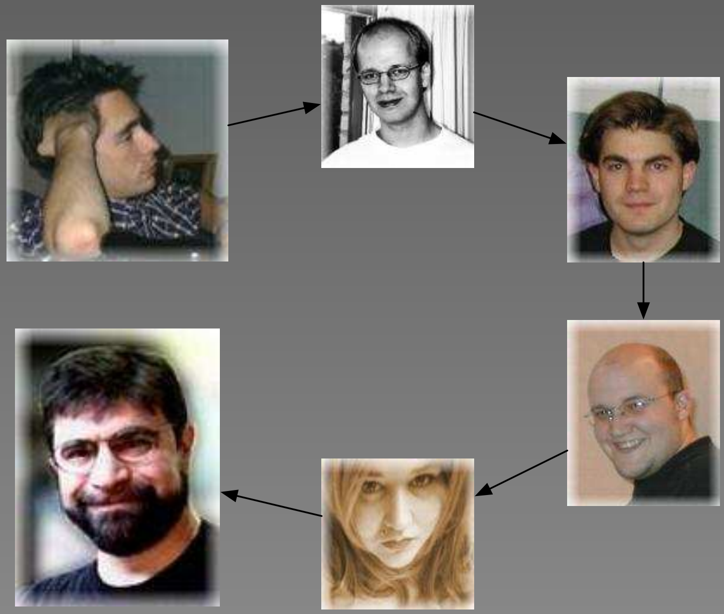
- Examples: Waste
- Advantage: Only your trusted friends know you are part of the network
- Disadvantage: Networks are disconnected and small, they typically don’t scale well

The Small World Phenomenon



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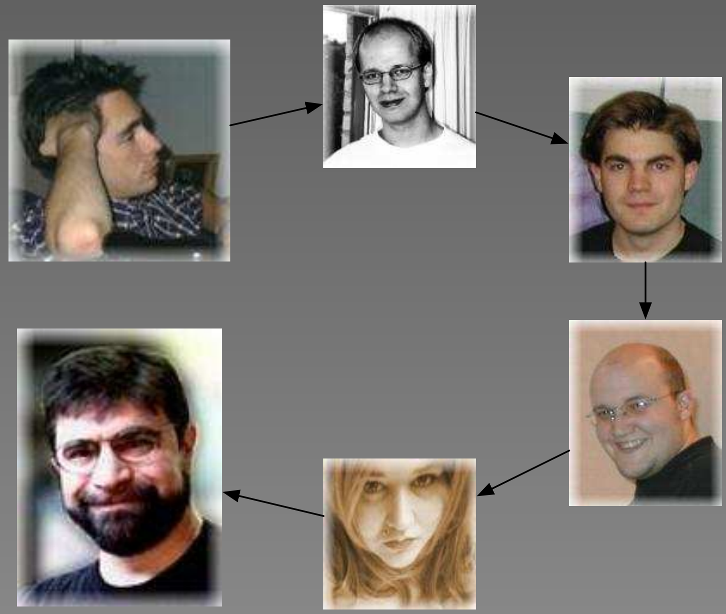

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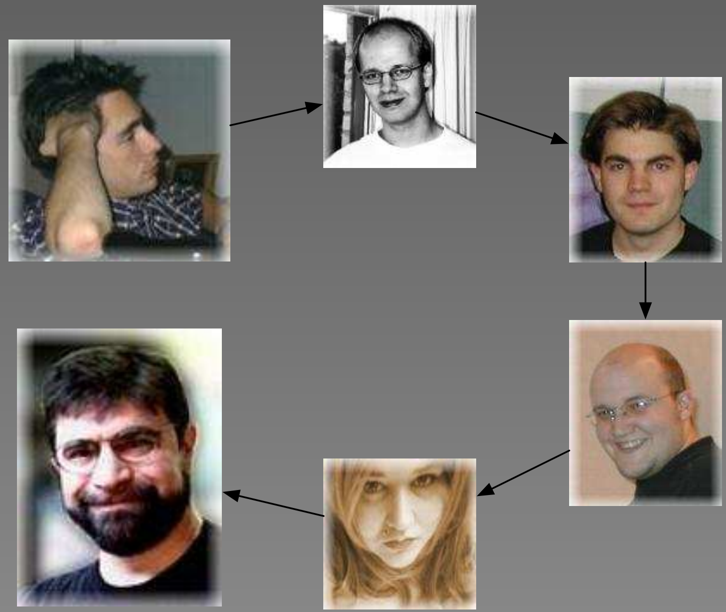

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- Short paths may exist but they may not be easy to find

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- This is called “Greedy Routing”
- Freenet and “Distributed Hash Tables” rely on this principal to find data in a scalable decentralised manner

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- If people can route in a social network, then it should be possible for computers.
- Jon Kleinberg explained in 2000 how small world networks can be navigable.

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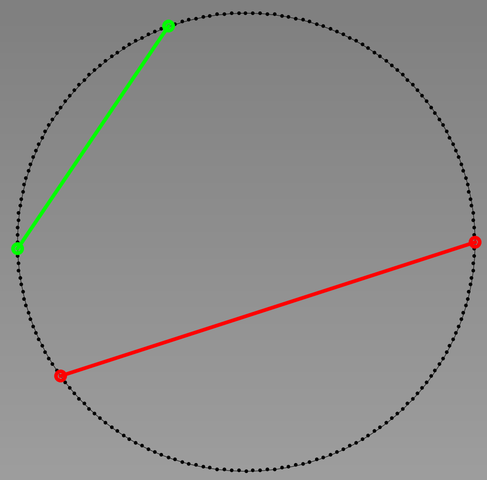

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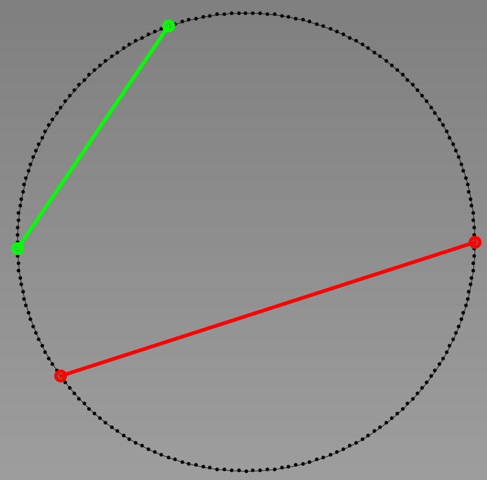
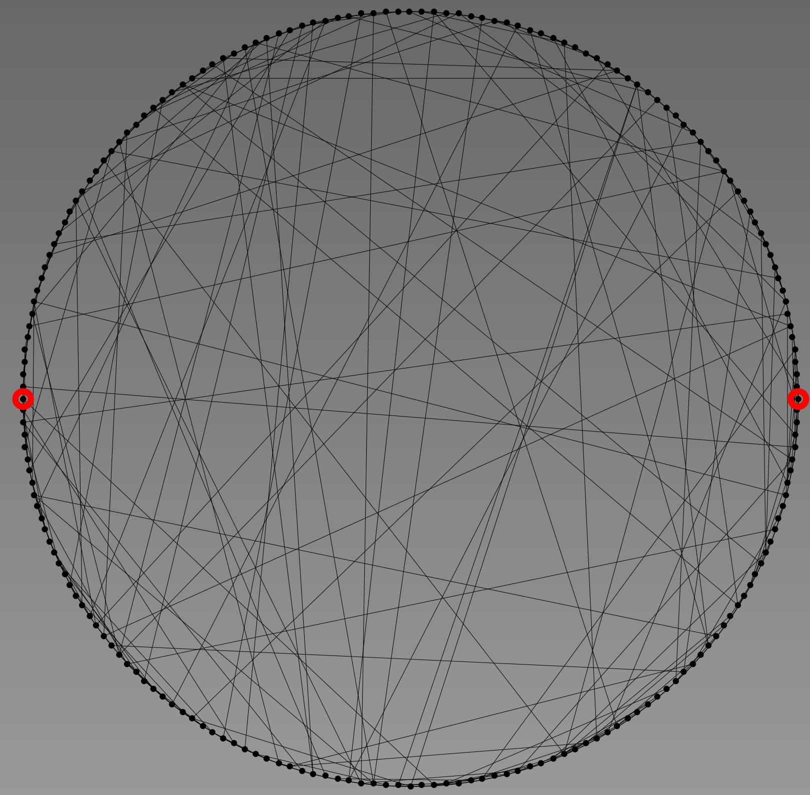


- In this case a simple *greedy routing* algorithm performs in $O(\log^2 n)$ steps.

Kleinbergs Result, cont.



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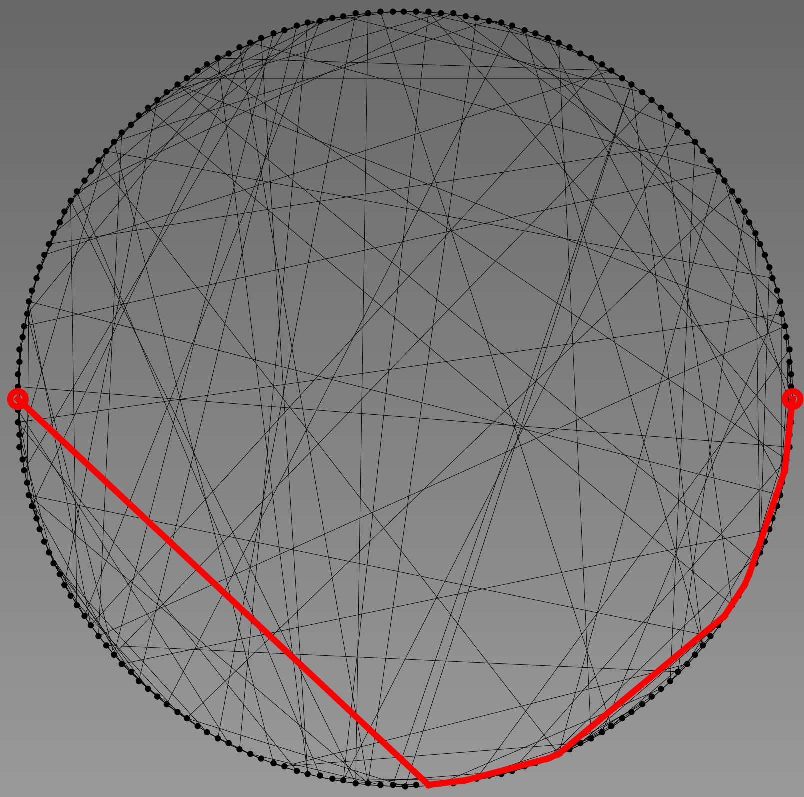

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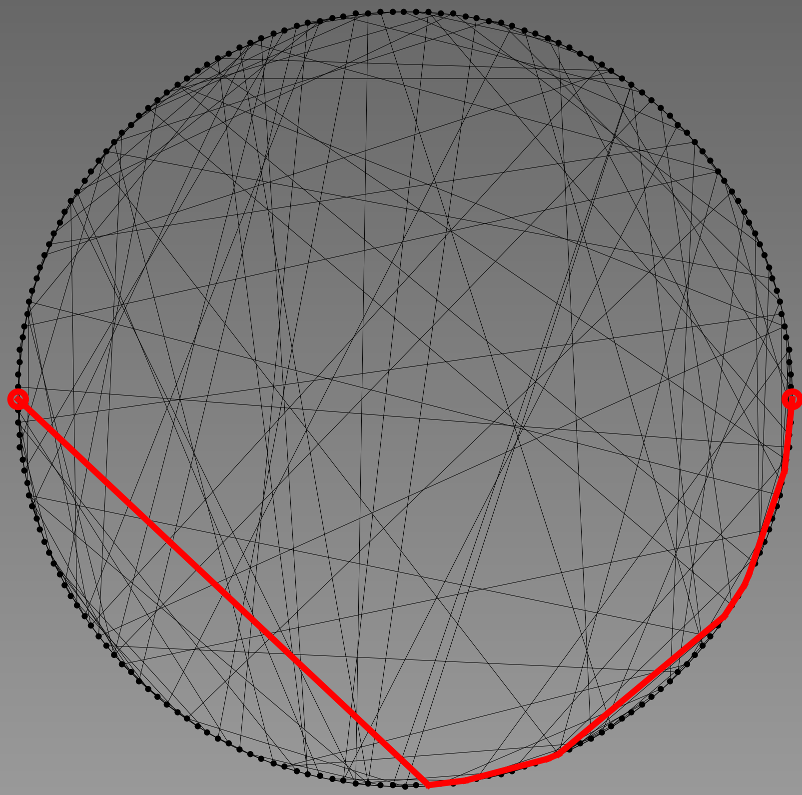

But in a social network, how do we see if one person is closer to the destination than another?

Application, cont.

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- One cannot, in practice, expect a computer to route based on such things.
- Instead, we let the network tell us!

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- Then greedy route with respect to these numerical identities.

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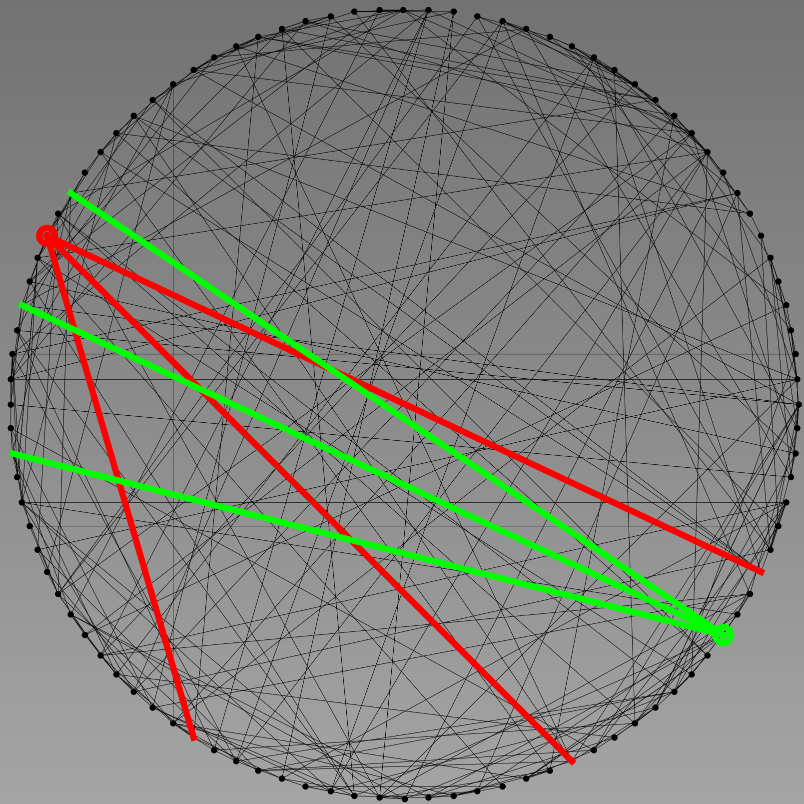
- They then switch positions with other nodes, so as to minimize the product of the edge distances.

The Method, cont.

An advantageous switch of position:



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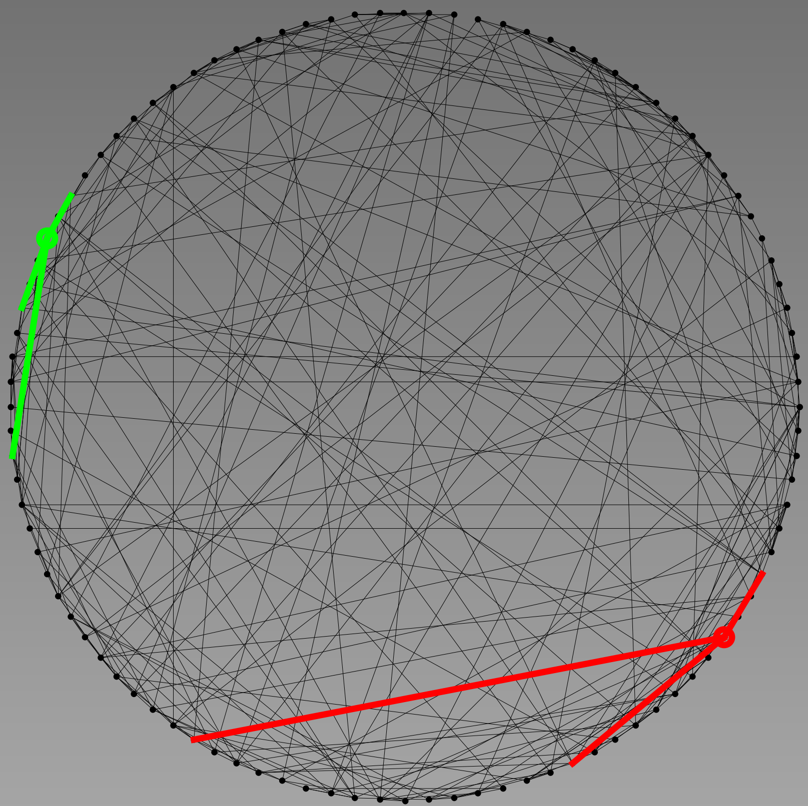

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- Because this is an ongoing process as the network grows (and shrinks) it will be difficult to keep permanent positions.

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- Random walk search: “random”.
- Greedy routing in Kleinberg’s model with identities as when it was constructed: “good”.
- Greedy routing in Kleinberg’s model with identities assigned according to our algorithm (2000 iterations per node): “restored”.

Simulations, cont.

The proportion of queries that succeeded within $(\log_2 n)^2$ steps, where n is the network size:

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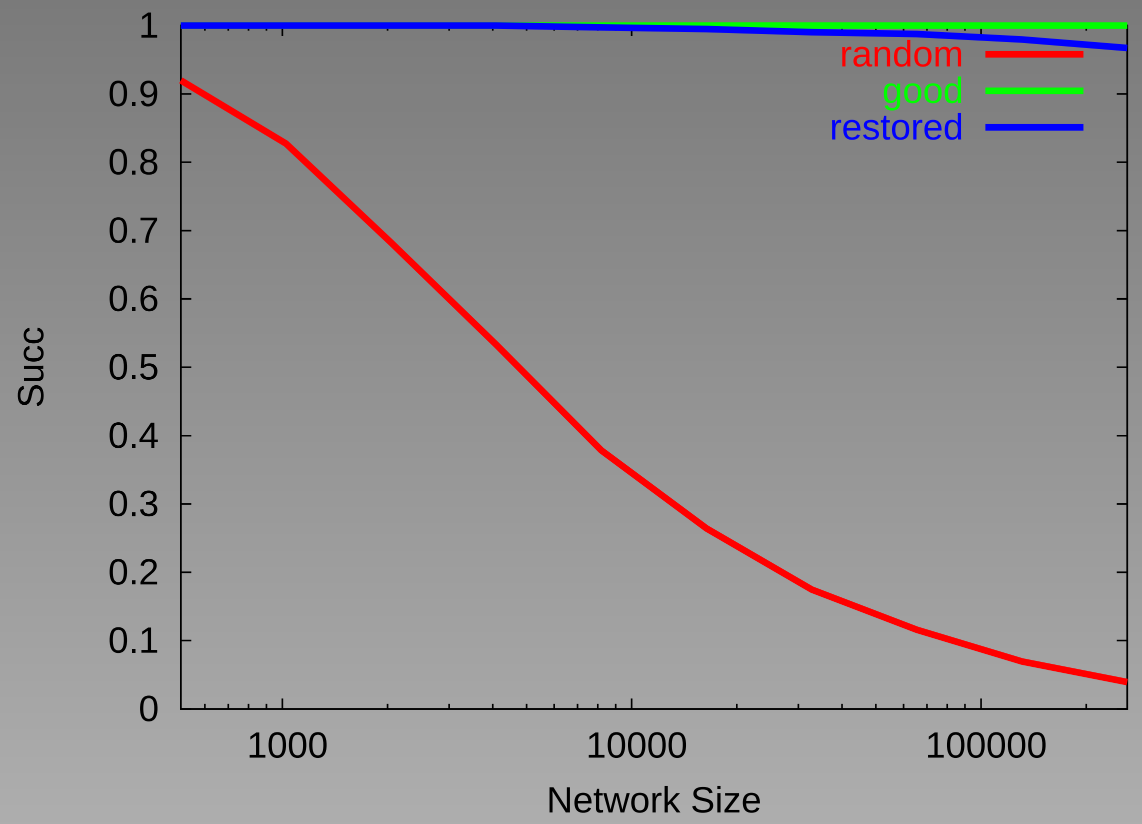

Simulations, cont.

The average length of the successful routes:

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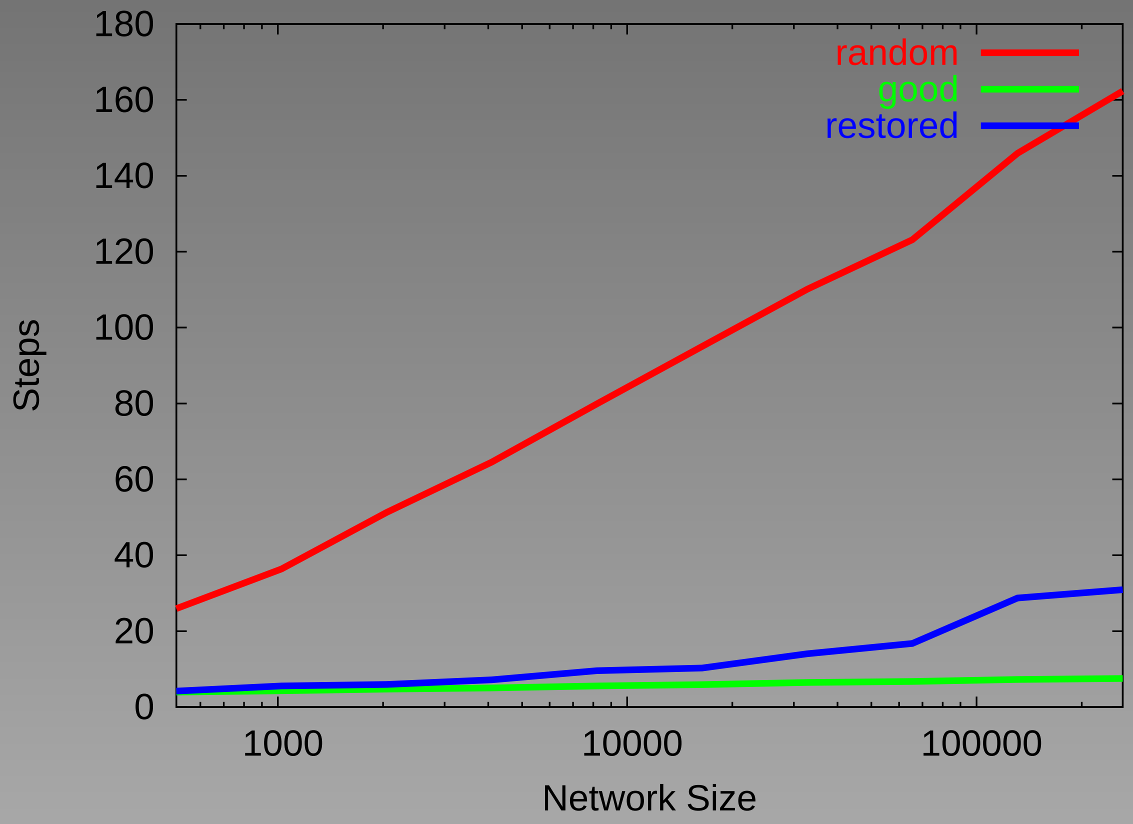

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- We borrowed some data from orkut.com. 2196 people were spidered, starting with Ian.

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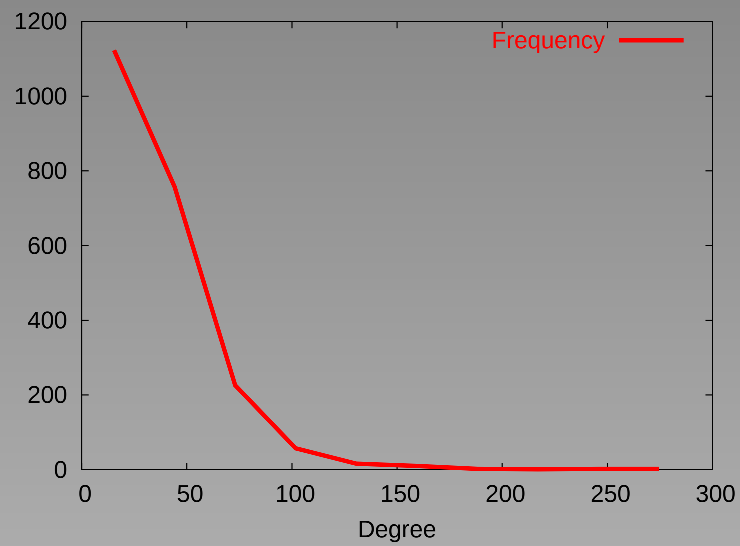
- It contains mostly American techies and programmers. Some are probably in this room. (No Brazilians...)
- The degree distribution is approximately Power-Law:



Results, cont.

Searching the Orkut dataset, for a maximum of $\log_2(n)^2$ steps.

	Success Rate	Mean Steps
Random Search		
Our Algorithm		

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Clipping degree at 40 connections. (24.2 connections per person.)

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Our algorithm takes advantage of there being people who have many connections, but it does not depend on them.

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  - Can other models work better?
  - Can we find better selection functions for switching?
  - It needs to be tested on more data.

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People who are interested can join the discussion at *http://freenetproject.org/*.

Long Live the Darknet!