Covert Communication in a Dark P2P Network

A major new version of Freenet

Ian Clarke and Oskar Sandberg

The Freenet Project

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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 next version of Freenet will be based on this philosophy, a so called dark network.

Overview of "Peer to Peer" networks

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- 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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- Advantage: Globally scalable with the right routing algorithm
- Disadvantage: Vulnerable to “harvesting”, ie. people you don’t know can easily discover whether you are part of the network

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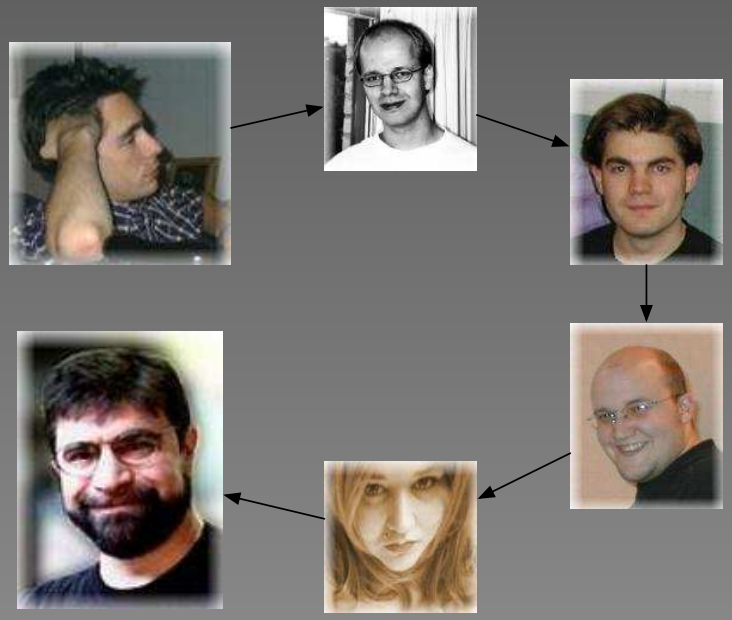
- Examples: Waste
- Advantage: Only your trusted friends know you are part of the network
- Disadvantage: Networks are disconnected and small, they typically don't scale well

The Small World Phenomenon



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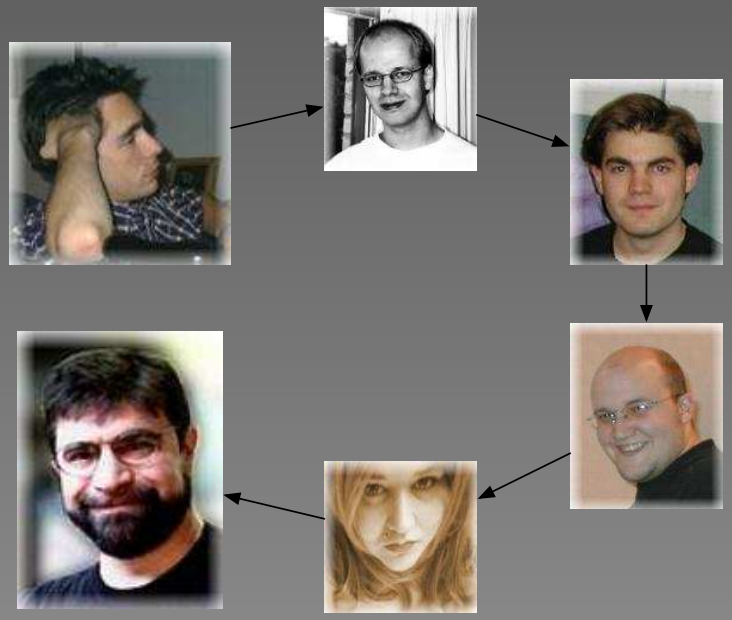

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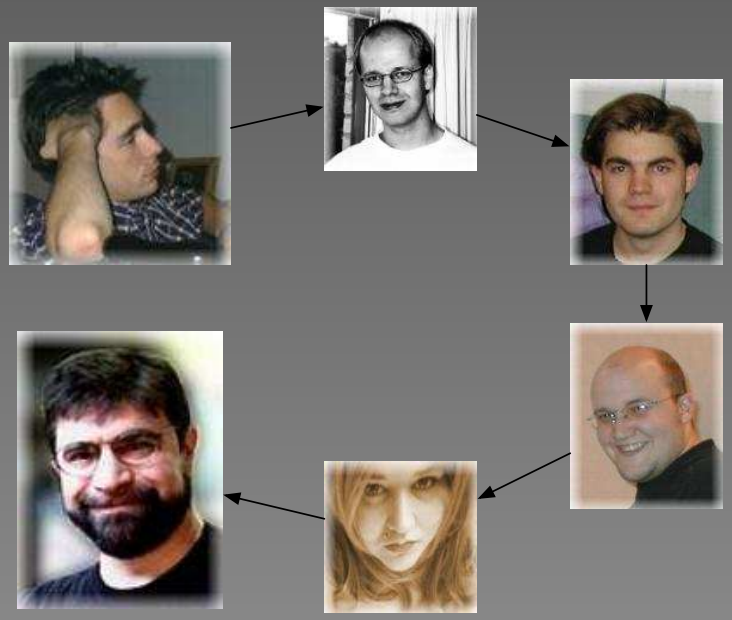

- In "Small world" networks short paths exist between any two peers
- People tend to form this type of network (as shown by Milgram experiment)
- Short paths may exist but they may not be easy to find

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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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- Just like on the Internet, we need a way to route through the network.
- 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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- In this case a simple *greedy routing* algorithm performs in $O(\log^2 n)$ steps.
- 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.

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- 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.

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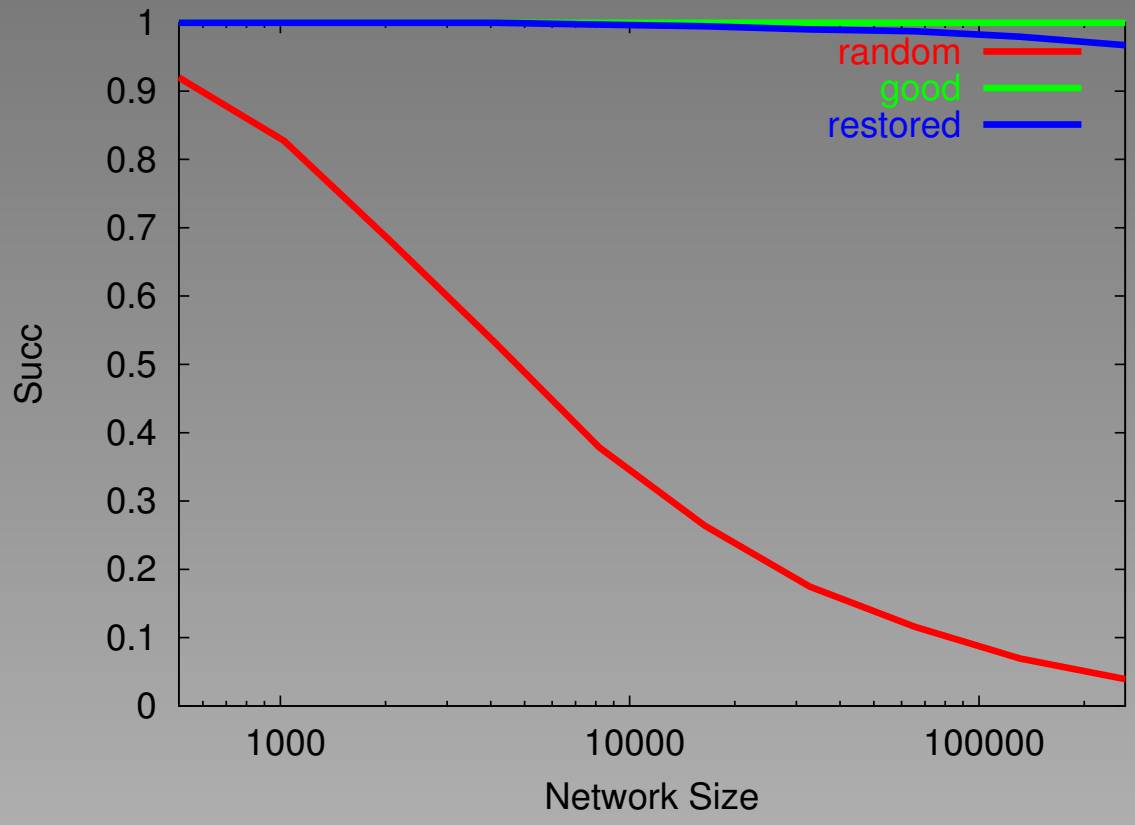

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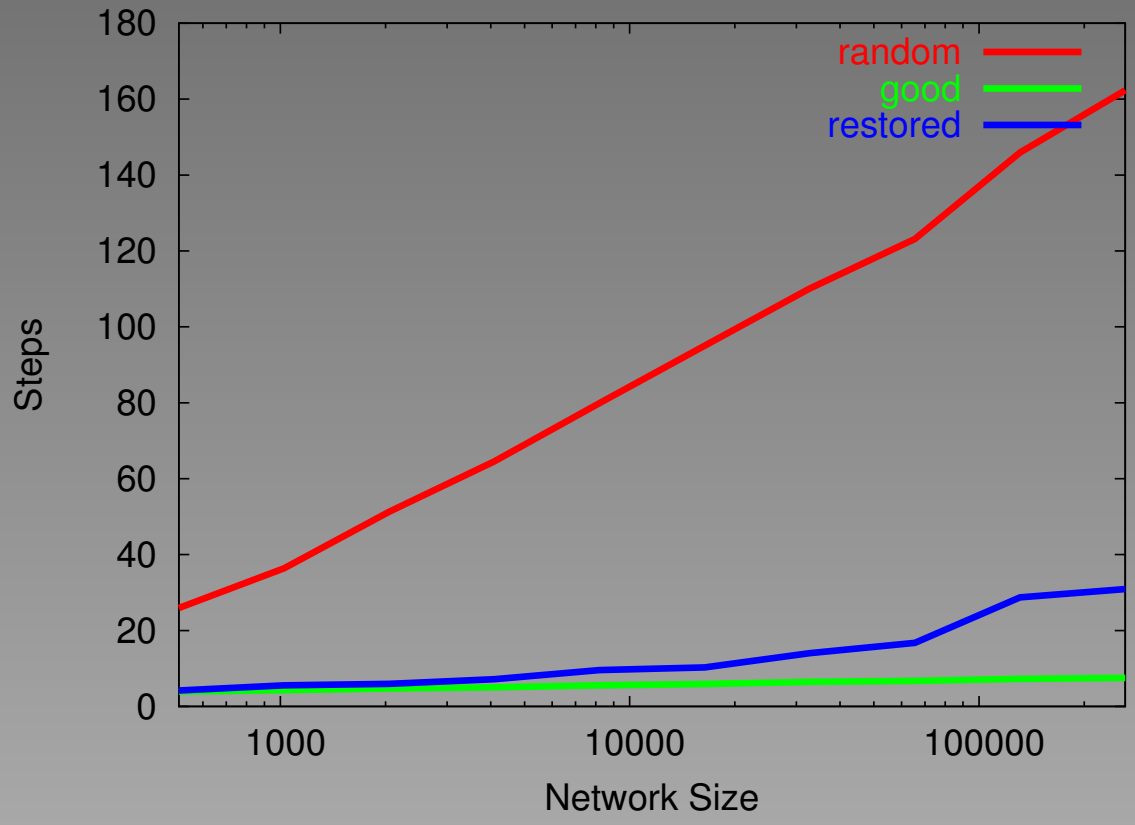

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- We borrowed some data from orkut.com. 2196 people were spidered, starting with Ian.

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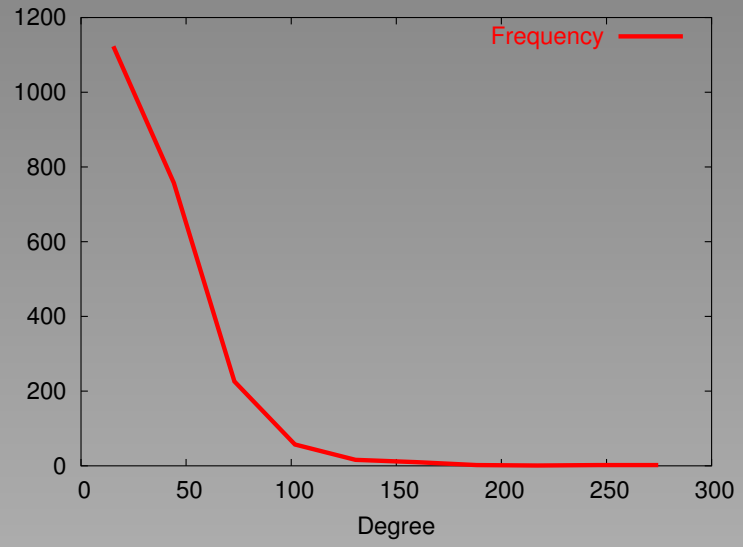
- The degree distribution is approximately Power-Law:



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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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  - Ensuring ease of use
  - Storing data

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- Manipulation of other node's identities

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- What about NATs and firewalls
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  - Would require third- party for negotiation

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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/*.