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

- Information is spread across many interconnected computers
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- Users want to find information
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- Information is spread across many interconnected computers
- Users want to find information
- Some are centralised (e.g., Napster), some are semi-centralised (e.g., Kazaa), others are distributed (e.g., Freenet)
The Small World Phenomenon

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- 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
Navigable Small World Networks

- Concept of similarity or “closeness” between peers
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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
Light P2P Networks

- Examples: Gnutella, Freenet, Distributed Hash Tables
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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
Dark or “Friend to Friend” P2P Networks

- Peers only communicate directly with “trusted” peers
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- Examples: Waste
Dark or “Friend to Friend” P2P Networks

- Peers only communicate directly with “trusted” peers
- Examples: Waste
- Advantage: Only your trusted friends know you are part of the network
Application

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- A Darknet is, essentially, a social network of peoples trusted relationships.
- 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.
Kleinberg’s Result

- The possibility of routing efficiently depends on the proportion of connections that have different lengths with respect to the “position” of the nodes.
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- If the positions are in a ring, the proportion of connections with a certain length should be inverse to the length:

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

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

Is Alice closer to Harry than Bob?
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- In real life, people presumably use a large number of factors to decide this. Where do they live? What are their jobs? What are their interests?
- One cannot, in practice, expect a computer to route based on such things.
- Instead, we let the network tell us!
Application, cont.

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- We can assign numerical identities placing nodes in a circle, and do it in such a way that this is fulfilled.
- Then greedy route with respect to these numerical identities.
The Method

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The Method

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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:
An advantageous switch of position:
The Method, cont.

Some notes:
The Method, cont.

Some notes:

- Switching is essential!
The Method, cont.

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

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- Two nodes are chosen in some random fashion, and attempt to switch.
- They calculate $\ell_b$ as the product of all the lengths of their current connections. Then they calculate $\ell_a$ as the product of what all their respective connection lengths would be after they switched.
- If $\ell_b > \ell_a$ they switch. Otherwise they switch with probability $\ell_b / \ell_a$. 
The Algorithm, cont.

Let $d(z)$ give the degree (number of connections) of a node $z$, and let $e_i(z)$ and $e'_i(z)$ be distance of $z$'s $i$-th connection before and after a switch occurs. Let nodes $x$ and $y$ be the ones attempting to switch. Calculate:

$$p = \frac{\ell(a)}{\ell(b)} = \frac{\prod_{i=1}^{d(x)} e_i(x) \prod_{i=1}^{d(y)} e_i(y)}{\prod_{i=1}^{d(x)} e'_i(x) \prod_{i=1}^{d(y)} e'_i(y)}$$

$x$ and $y$ will complete the switch with probability $\min(1, p)$. Otherwise we leave the network as it is.
The Algorithm, cont.

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• Because there is a greater chance of moving to positions with shorter connection distances, it will tend to minimize the product of the distances.
• Because the probability of making a switch is never zero, it cannot get stuck in a bad configuration (a local minima).
The Algorithm, cont.

- How do nodes choose each other to attempt to switch?
The Algorithm, cont.

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- Any method will work in theory, but some will work better than others. Only switching with neighbors does not seem to work in practice.
The Algorithm, cont.

- How do nodes choose each other to attempt to switch?
- Any method will work in theory, but some will work better than others. Only switching with neighbors does not seem to work in practice.
- Our current method is to do a short random walk starting at one of the nodes and terminating at the other.
Simulations

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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:
Simulations, cont.

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Simulations, cont.

The average length of the successful routes:
Simulations, cont.

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Results

- Simulated networks are only so interesting, what about the real world?
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- We borrowed some data from orkut.com. 2196 people were spidered, starting with Ian.
Results, cont.

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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.

<table>
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<tr>
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Results, cont.

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<tr>
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<td>0.72</td>
<td>43.85</td>
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# Results

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.
Practical Concerns

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- Key concerns:
  - Preventing malicious behaviour
  - Ensuring ease of use
  - Storing data
Preventing Malicious Behaviour

Threats:

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Preventing Malicious Behaviour

Threats:

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- Manipulation of other node’s identities
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  - Email
  - Phone
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- What about NATs and firewalls
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  - Would require third-party for negotiation
Storing Data

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  • Both peers route towards the same random identity
  • When paths cross a connection is established
Conclusion

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- There is still much work to do on the theory.
  - Can other models work better?
  - Can we find better selection functions for switching?
- It needs to be tested on more data.
Conclusion, cont.

- We have learned the hard way that practice is more difficult than theory.
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People who are interested can join the discussion at http://freenetproject.org/.
Long Live the Darknet!