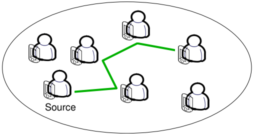
Searching a Needle in (Linear) Opportunistic Networks



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and Jussi Kangasharju‡

Aalto University, Finland †
University of Helsinki, Finland ‡

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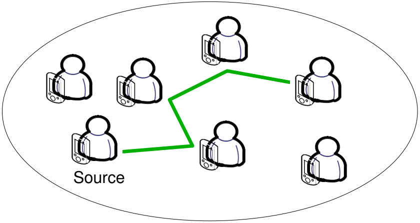
Outline

1. **Motivation**: searching content in opportunistic networks
2. **Searching a specific content**
3. **General search with partial answers**
4. **Conclusions**

1. Motivation

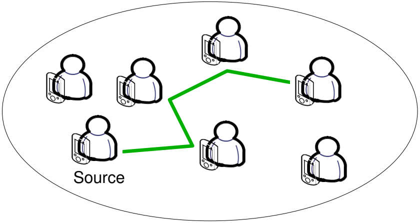
Searching content in opportunistic networks



Scenario

- Opportunistic networking with mobile nodes

Searching content in opportunistic networks



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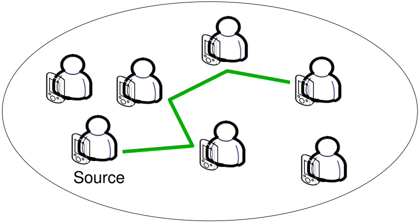

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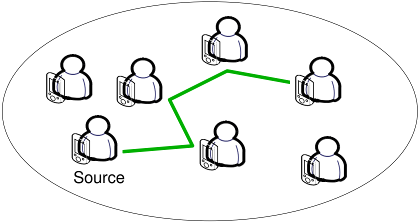

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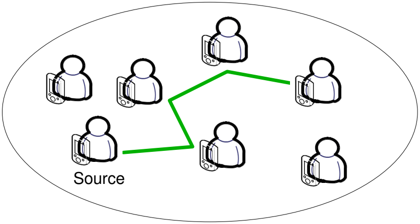

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Dynamic distributed decision making problem with partial information!

Model: Linear Network

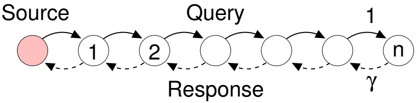

Figure 1: Query travels to right and a possible response to left.

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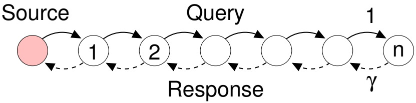

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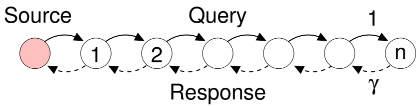

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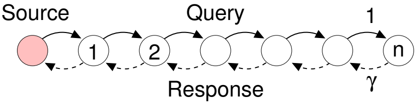

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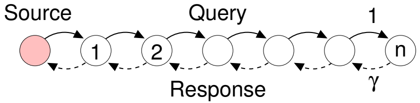

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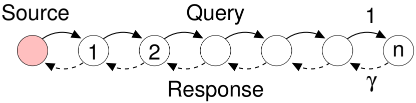

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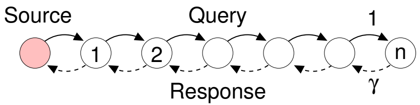
The net gain is $\boxed{\text{“value of content” - “transmission costs”}}$

2. Searching Specific Content

Searching specific content



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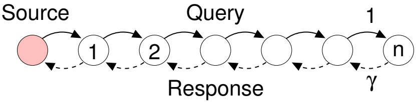

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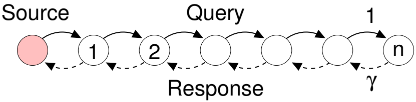

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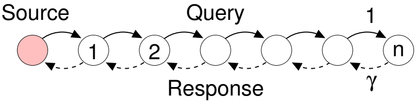

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$$\boxed{n^* = \left\lceil \frac{\log(2e/p)}{\log(1-p)} \right\rceil} \qquad (p > 2e) \qquad (1)$$

- p = availability of the content (value normalized to 1)
- e = unit transmission cost

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- Idea: *learn p* as the search progresses!

Learning strategy

Learning Search Strategy

- *At every step i, update our estimate on $\hat{p}_i$*
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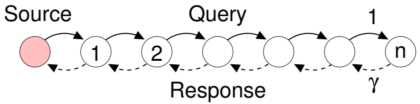
$$\boxed{n^* = \left\lceil \frac{1}{2e} \right\rceil - 2} \qquad (e < 0.25) \tag{3}$$

Search strategies with a general γ



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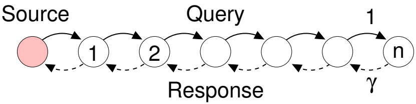

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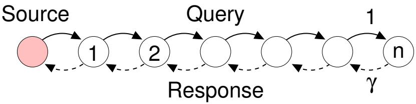

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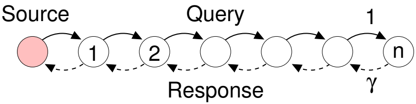

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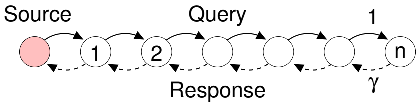

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  - See details in the paper

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- Searching specific content:
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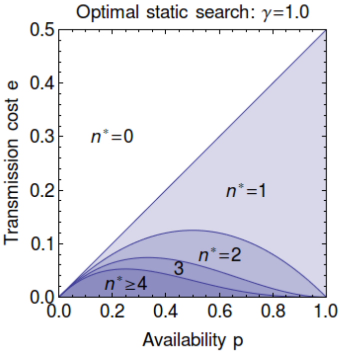
- Unit transmission cost e is a free parameter

Example #1: Static strategy



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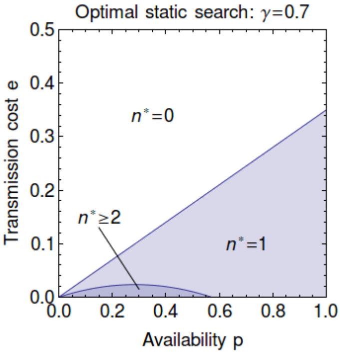

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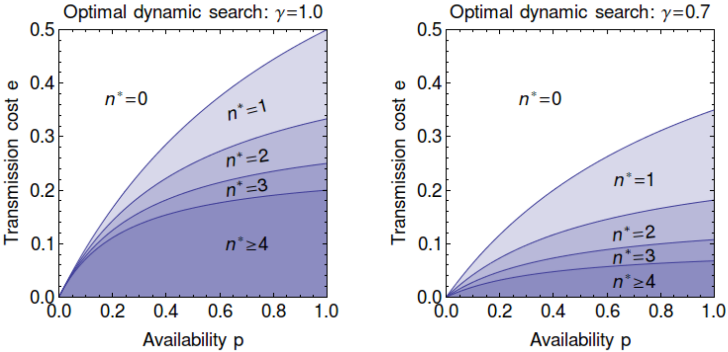

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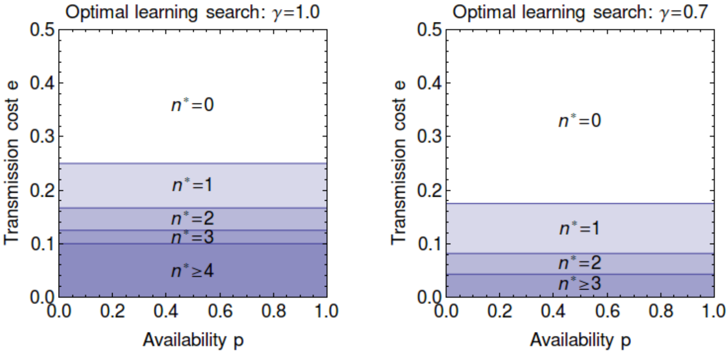

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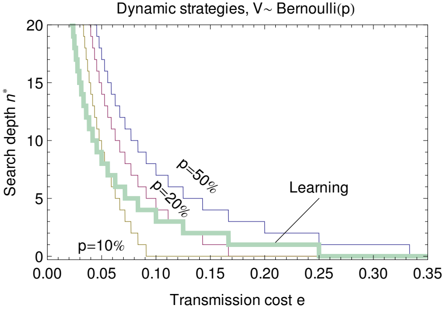

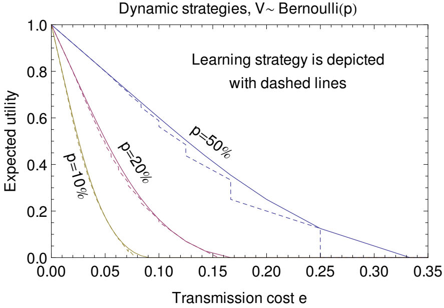

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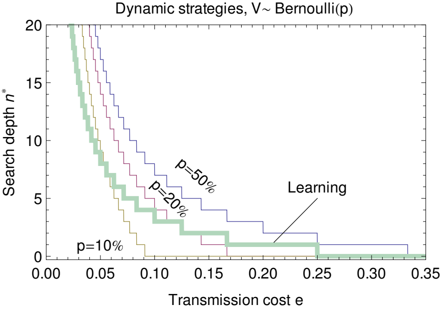

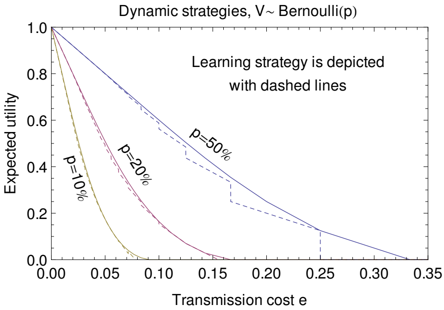

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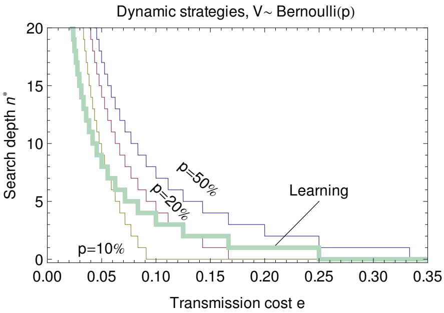

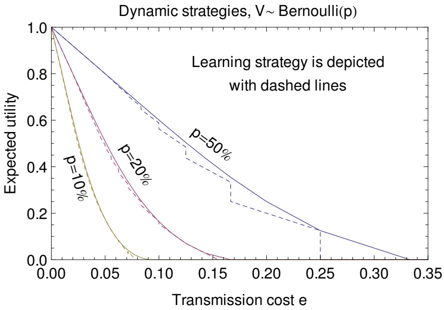

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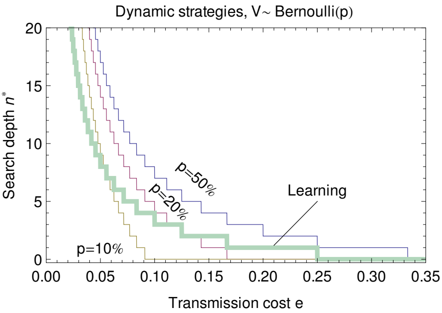

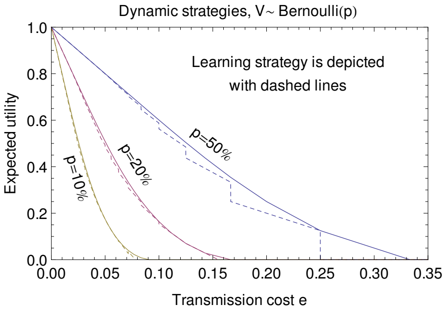

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  - Largest differences when *p* is high;
  - Short searches and no time to learn

3. General Search with Partial Answers

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$$w(m, n, d, b) = \max\{a_1, a_2, a_3, a_4\}$$

where a_j denotes the (expected) final utility with action j

1) stop the search
2) stop the search and send a response back
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Formally,

$$\begin{cases} a_1 = d - m \cdot e \\ a_2 = b - (m + n) \cdot e \\ a_3 = \mathrm{E}[w(m + 1, n + 1, d, \max\{b, V_{n+1}\})] \\ a_4 = \mathrm{E}[w(m + n + 1, n + 1, b, \max\{b, V_{n+1}\})] \end{cases}$$

Dynamic programming (cont.)

The optimal action in state z is given by

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    (no better response than already delivered is available)
  - Actions a_3 and a_4 can be excluded when n, m are large
    (even the best response would yield negative net gain)

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(Details in the paper)

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- *Search n nodes, and return the best answer.*

Dynamic-0

- *Search at most n nodes*
- *Stop immediately if the perfect answer is found*
- *Return the best answer, unless it has no value ($v = 0$)*

Example: $V_i \sim \mathrm{U}(0, 3)$

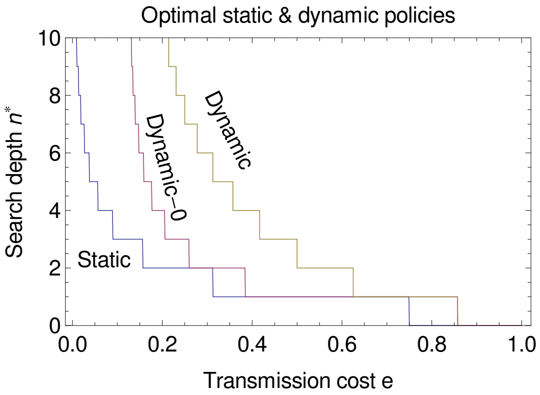

Figure 2: Optimal (max.) search depth with different strategies.

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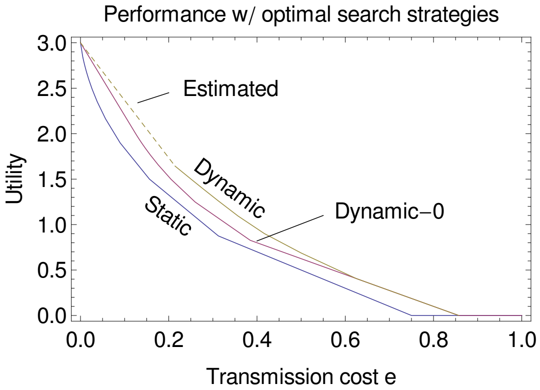

Figure 3: Performance (mean utility) with different strategies.

4. Conclusions

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- General case with dynamic programming
- Future work: concurrent searches, dynamic topology, . . .

Thanks!

http://www.netlab.tkk.fi/tutkimus/pdp/