How far removed are you?

Scalable Privacy-Preserving Estimation of Social Path Length with Social PaL

N. Asokan

joint work with Marcin Nagy, Thanh Bui, Emiliano De Cristofaro, Ahmad-Reza Sadeghi, Jörg Ott

Aalto University

UNIVERSITY OF HELSINKI

Problem

How can you find if you have common friends with someone (nearby)?

… in a privacy-preserving way

Applications

- Intuitive means for specifying access control
  - Ride sharing
  - Tethering Internet access
  - ...
- Information
  - Friend radar
- ...

Requirements

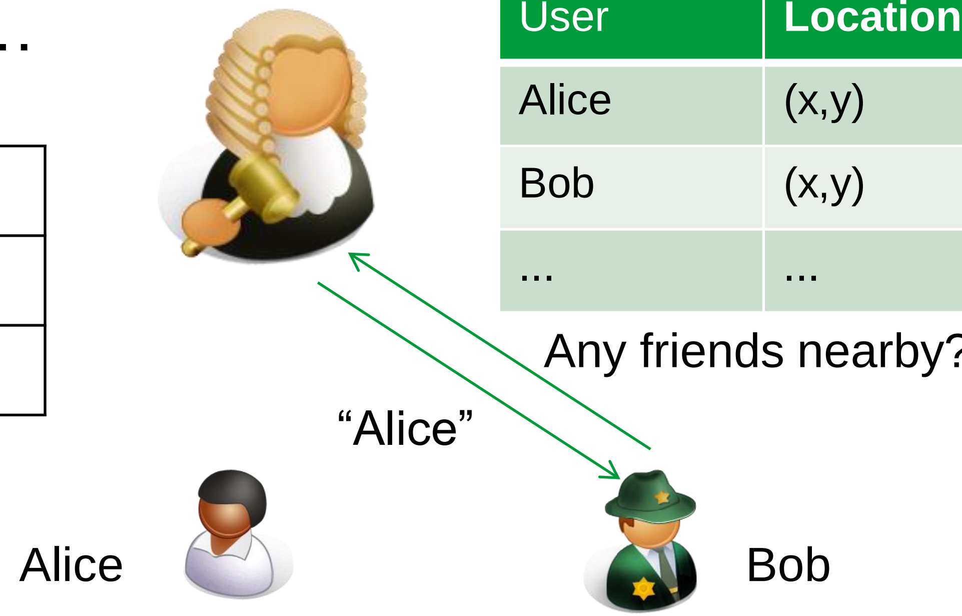
- **privacy**:
  - no more info. to participants than about common friends
  - no additional info. to anybody else (e.g., “trusted server”)
- **authenticity**:
  - no false claims of friendship
- **efficiency**:
  - applicable for mobile usage
  - minimize expensive crypto operations

Current approach: Using a trusted server

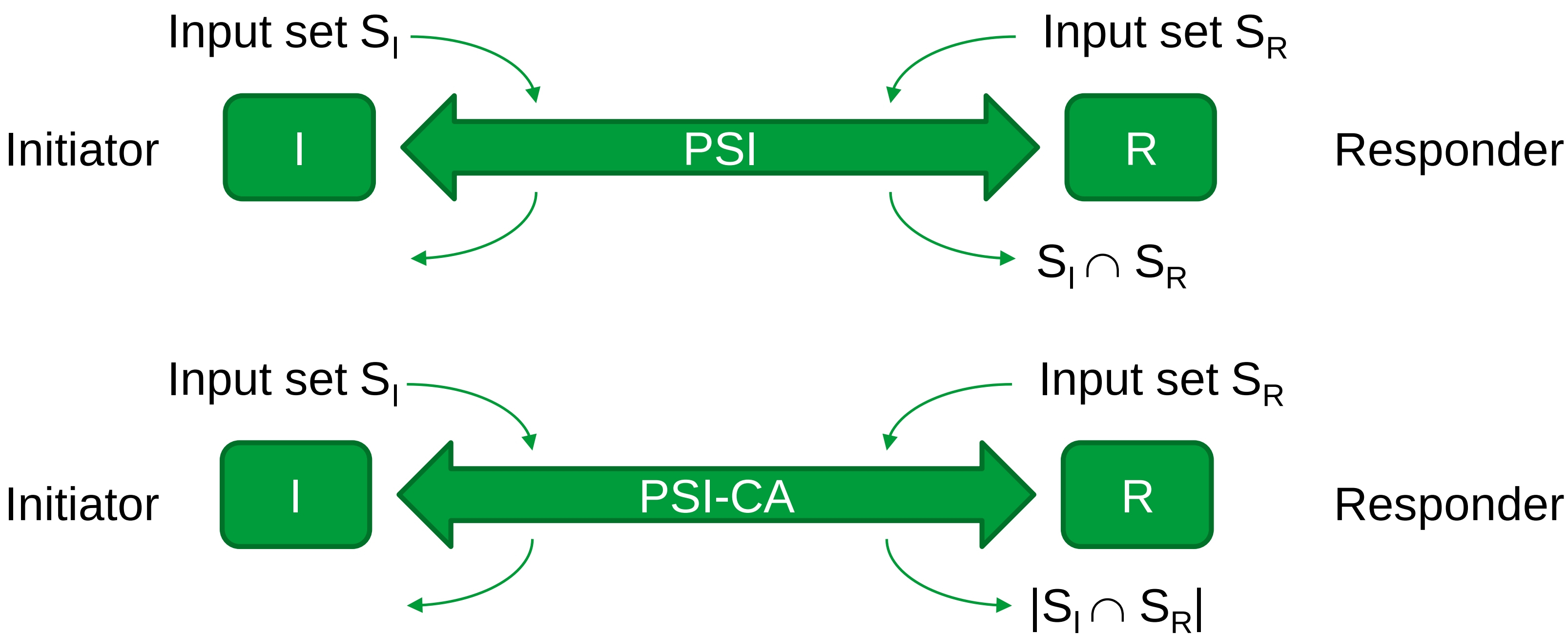
- FourSquare, Tencent, …

Privacy	×
Authenticity	√
Efficiency	√

User	Location
Alice	(x,y)
Bob	(x,y)
…	…



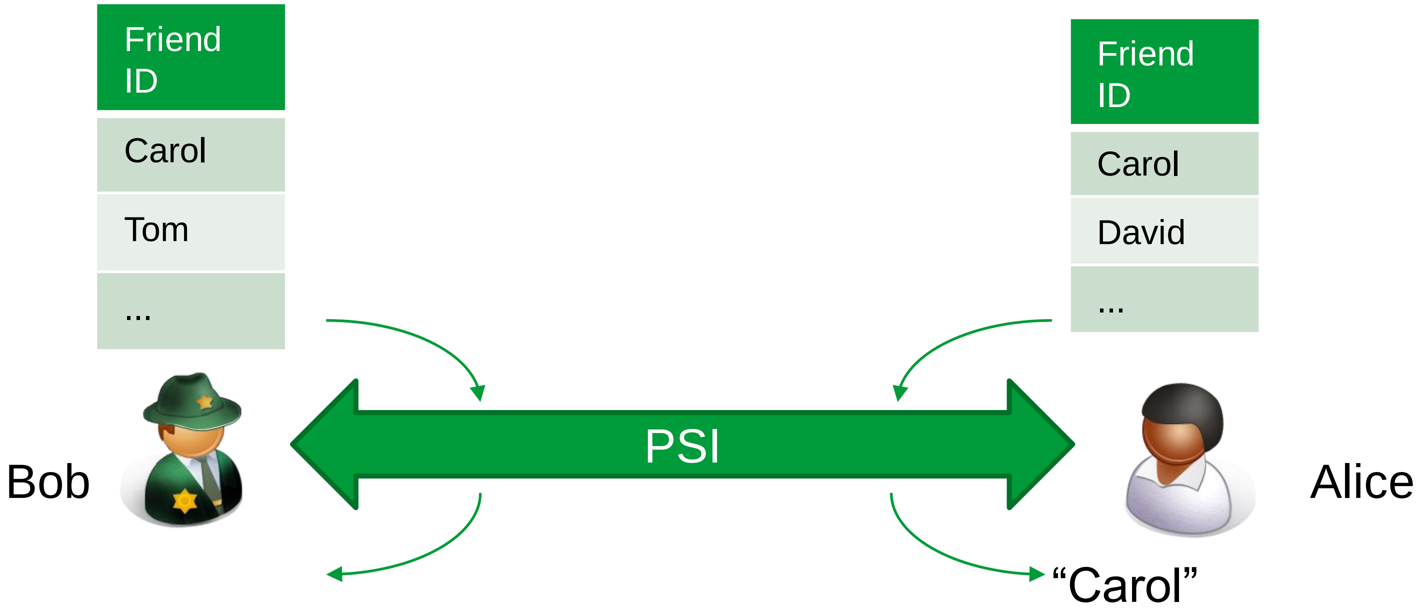
Alternative: Private Set Intersection Protocols



Secure in the honest-but-curious model
$O(|S_I|+|S_R|)$ modular exponentiations

[De Cristofaro et al, FC'10, Asiacrypt '10, CANS'12]

Finding Common Friends using PSI naively



Privacy	?
Authenticity	×
Efficiency	×

Approach

- Make use of widely deployed online social networks
  - user authentication, social graph
- But don't cede even more information to them

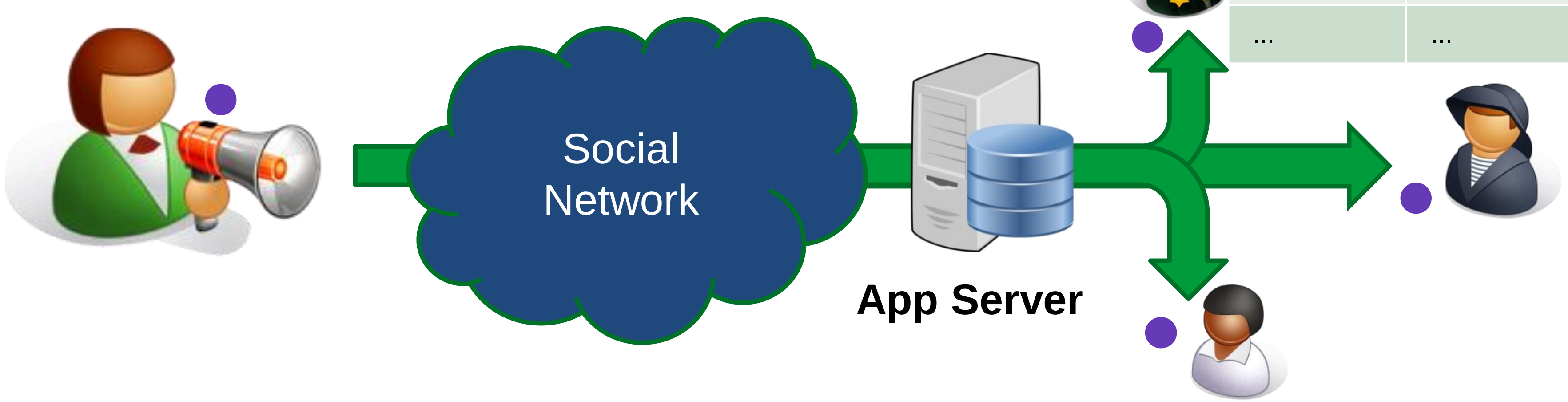
Aalto University

UNIVERSITY OF HELSINKI

Finding Common Friends using PSI with capabilities

1. Distribute (short-lived) bearer capability to friends

User	Capability
Carol	
Tom	
...	...



2. Private Set Intersection on capability sets to find common friends

Privacy	√
Authenticity	√
Efficiency	×

Aalto University

UNIVERSITY OF HELSINKI

Can we build a fast "PSI"?

- Why are classic PSIs slow?
  - Designed to work even when input sets are enumerable
    - i.e., elements are predictable
  - Naive hash-each-element approach fast, but insecure for enumerable input sets
- However, bearer capabilities are random
  - Hash-each-element approach is safe
  - Still O(n) communication complexity

- **Idea: use a Bloom Filter to represent input set**

Aalto University

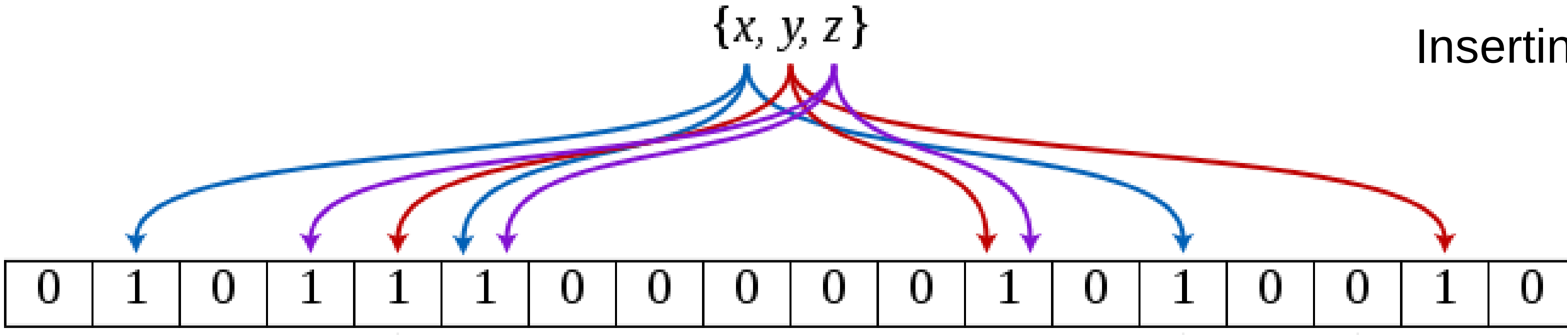
UNIVERSITY OF HELSINKI

What is a Bloom Filter?

Efficient data structure for testing set membership

Map each element to k positions in a bit vector

Inserting



No false negatives; false positives possible

Source: Wikipedia

Bloom Filter PSI Protocol

Initiator I **Responder R**

Challenges

Insecure channel

Secure channel establishment

Man-in-the-middle

Channel binding

insert elements into BF — BF → *check each element for presence in BF*

False positives

False positives removal e.g., challenge-response

Privacy	√
Authenticity	√
Efficiency	√

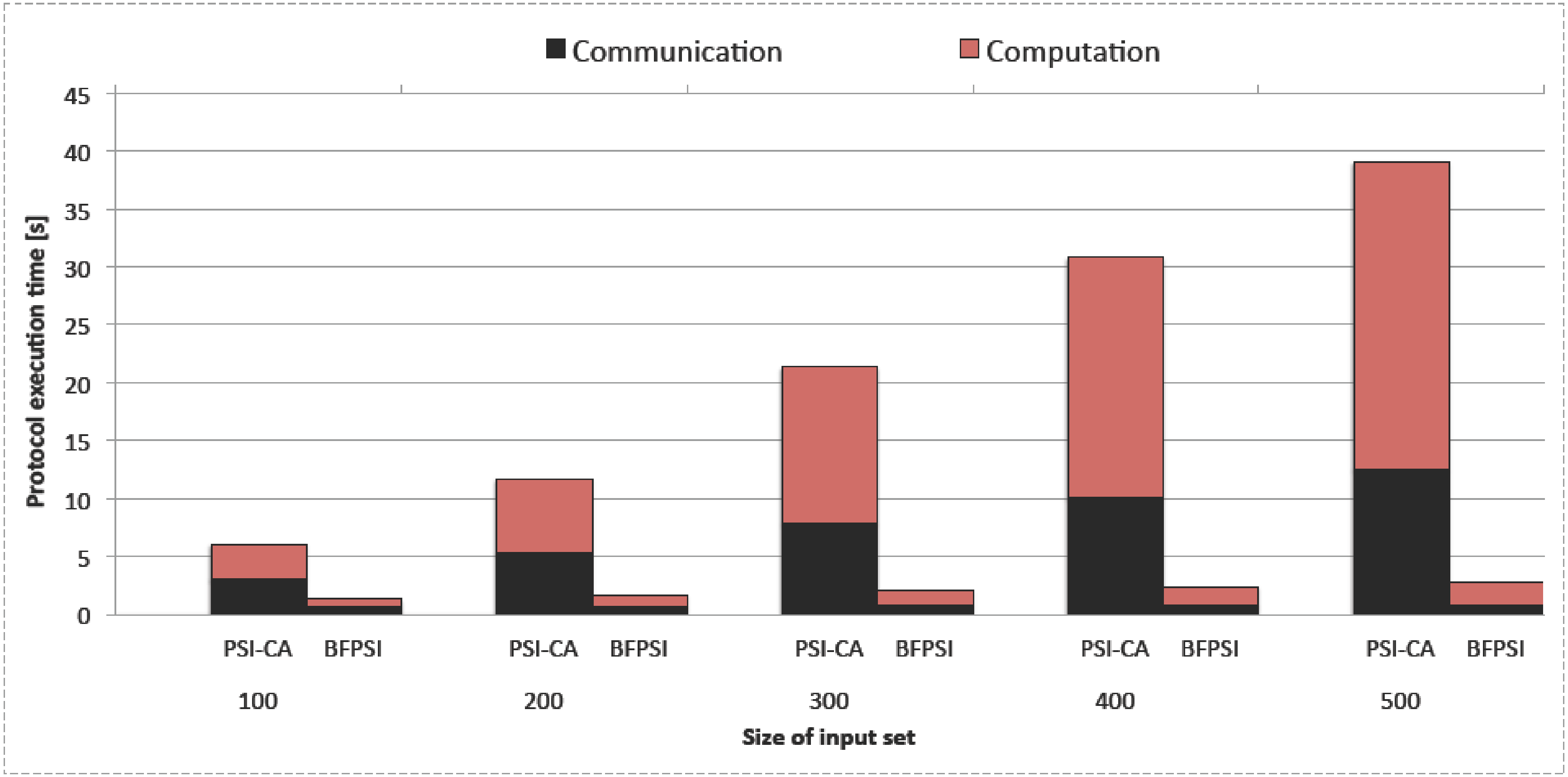
Not a replacement for PSI in general!

“Common Friends”: Nagy et al, ACSAC 2013

Aalto University

UNIVERSITY OF HELSINKI

Comparison: execution time



average of 30 runs

Two challenges with Common Friends

- Bootstrapping is a problem
- Limited to social paths of length 2

Bootstrapping the system

- Only participating users upload capabilities

The system can only find common friends who are participating in the system

Fixing bootstrapping: Ersatz profiles

Assumption:

1. App server may query Social Network for list of friends of a participating user

Have App server create replacements for missing profiles

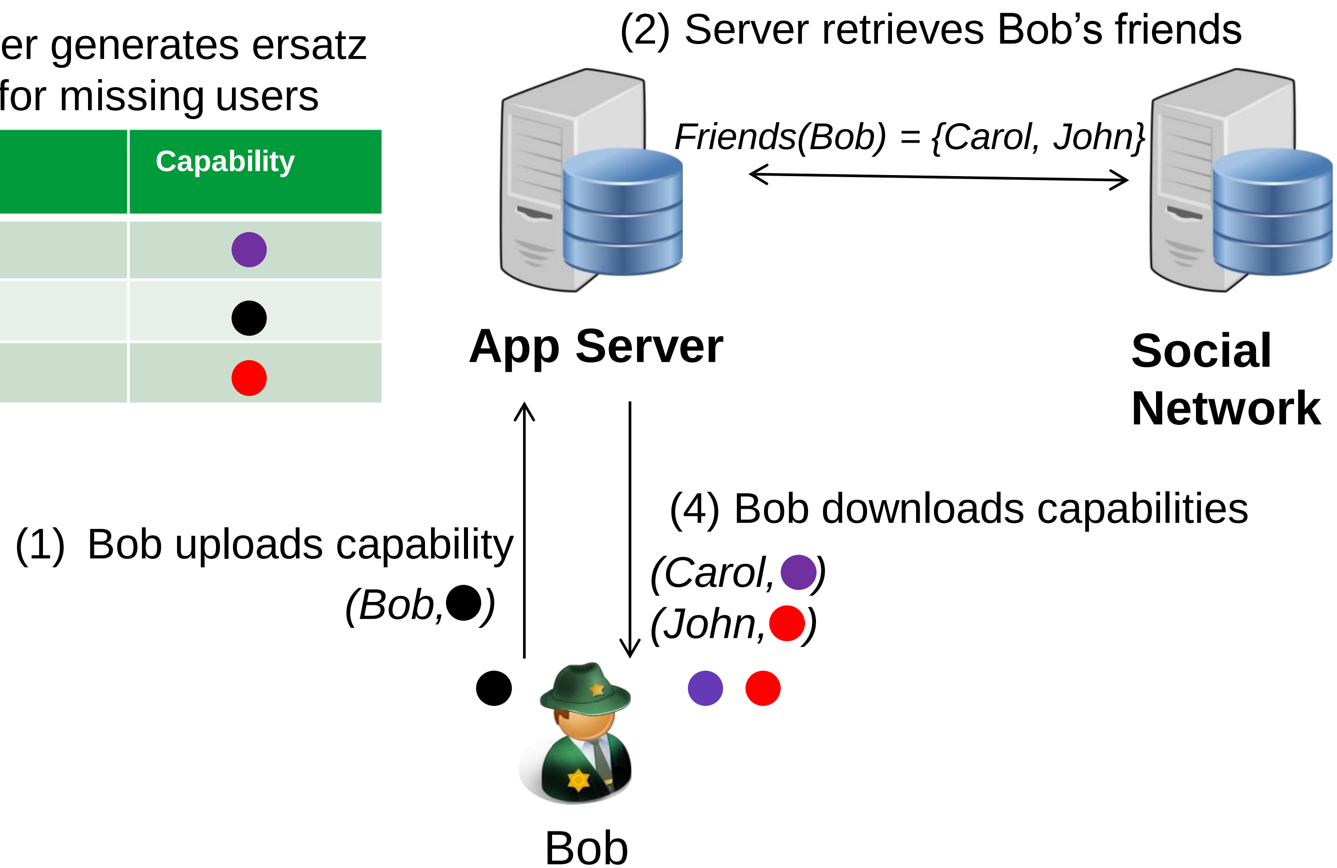
1. Identify friends of participating users
2. Create/maintain capabilities for those missing

Ersatz profile = Social Network identity + server generated capability

Fixing bootstrapping: Ersatz profiles

(3) Server generates ersatz profiles for missing users

User	Capability
Carol	
Bob	
John	



Fixing bootstrapping: Ersatz profiles

User	Capability
Carol	
John	
Bob	
Alice	

App Server

Friend ID
Carol John

Friend ID
John

With ersatz profiles all common friends are always discovered

Finding lengths of longer social paths

How can you find your social graph “distance” to someone (nearby)?

… in a privacy-preserving way

Social PaL: Social Path Length Finder

More applications

- Intuitive means for specifying access control
  - Ride sharing
  - Tethering Internet access
  - ...
- Information
  - Friend radar
- Routing in “dense” ad-hoc environment
- Place familiarity estimation
- ...

Social Path Length

Definition:

minimum number of hops in social graph between two users

Additional requirements

- **Privacy:**
  - Two users can’t learn more than by gathering information using standard social network interfaces available to them
- **Functional:**
  - Maximize number of paths discovered between two users
  - Determine exact path length between two users

22

Capabilities as path length proofs

Intuition:

1. Capability distributed to friends used as friendship proof
2. Use hash chains to generate **higher order capabilities**

From capability c generate ith order capability:

$$h^i(c) = c^i$$

1. Distribute c^i to contacts i+1 hops away
2. Recipient includes c^i, c^{i+1}, …, c^n in input to PSI

Aalto University

UNIVERSITY OF HELSINKI

Social PaL graph building

Social PaL only learns friend lists of actual users

- users explicitly authorize Social PaL

If relationships in the social network are reciprocal

- Partial view of friend lists of ersatz profiles possible

Social PaL capability distribution

John

Bob — Carol — Steve — Thomas — Alice

App Server

Carol
John:
Anon: 1

Bob

1. Friends' capabilities returned **with identities**
2. Higher order capabilities returned **w/o identities**

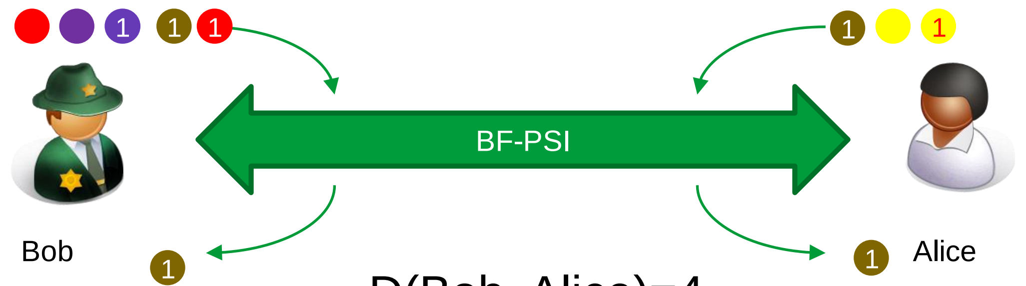
Aalto University

UNIVERSITY OF HELSINKI

Social PaL path length discovery

Friend ID	
Carol	1
Anon	1
John	1

2 + 2 = 4



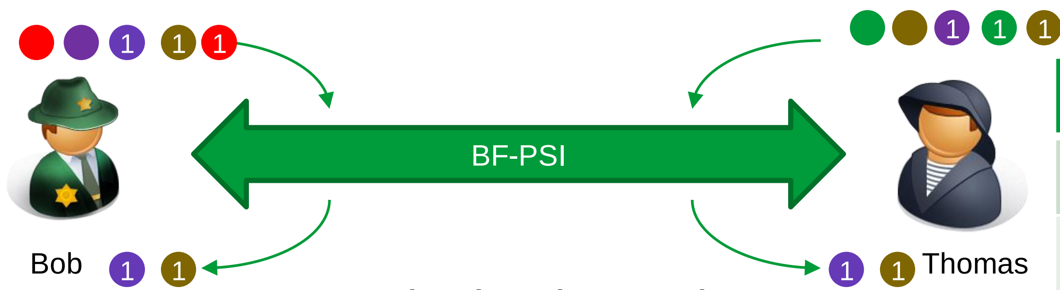
D(Bob, Alice)=4

Friend ID	
Thomas	1
Anon	1

2 + 2 = 4

Friend ID	
Carol	1
Anon	1
John	1

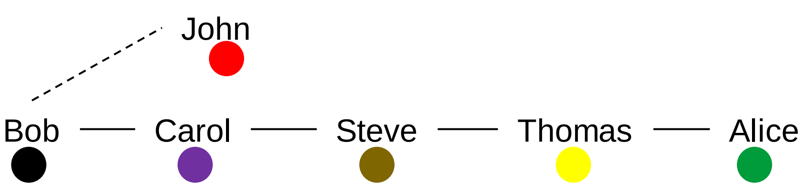
2 + 2 = 4
1 + 2 = 3



D(Bob, Thomas)=3

Friend ID	
Alice	1
Steve	1
Anon	1

2 + 2 = 4
1 + 2 = 3



Aalto University

UNIVERSITY OF HELSINKI

Coverage of social path discovery

- *Theorem*: If Social PaL discovers a path between A and B, then both A and B can determine its exact length.
- **Coverage:** probability that A & B will discover a k-hop path that exists between them in the social network

Aalto University

UNIVERSITY OF HELSINKI

Dataset for estimating coverage

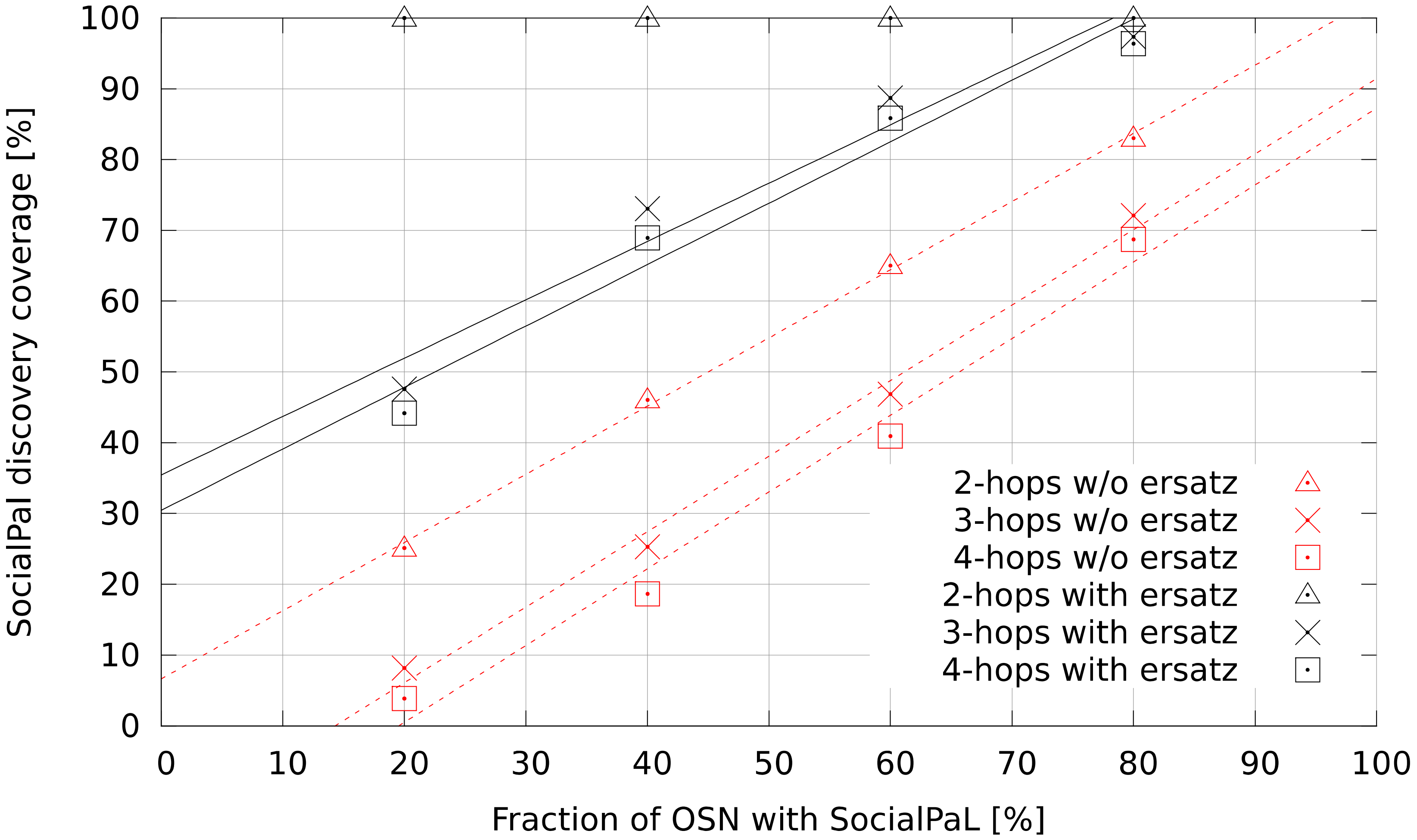
- Social Filter dataset
  - By Sirivanos et al
  - Derived from dataset by Gjoka et al (UC Irvine)
  - 500 000 users; 30 connections on average

Simulation for estimating coverage

1. Test set: randomly choose x% of users
   - x = 20, 40, 60, 80 (represents fraction using Social Pal)
2. Pick 50k pairs randomly from “test set” w/ k-hop path
   - k = 2, 3, 4
3. Compute fraction for which Social PaL discovers path

Repeat steps 1-3 ten times; average results

Coverage: Social Filter dataset



Datasets for estimating coverage

- Social Filter dataset
  - By Sirivanos et al
  - Derived from dataset by Gjoka et al (UC Irvine)
  - 500 000 users; 30 connections on average
  - Sampling did not preserve node degree

Dataset for estimating coverage

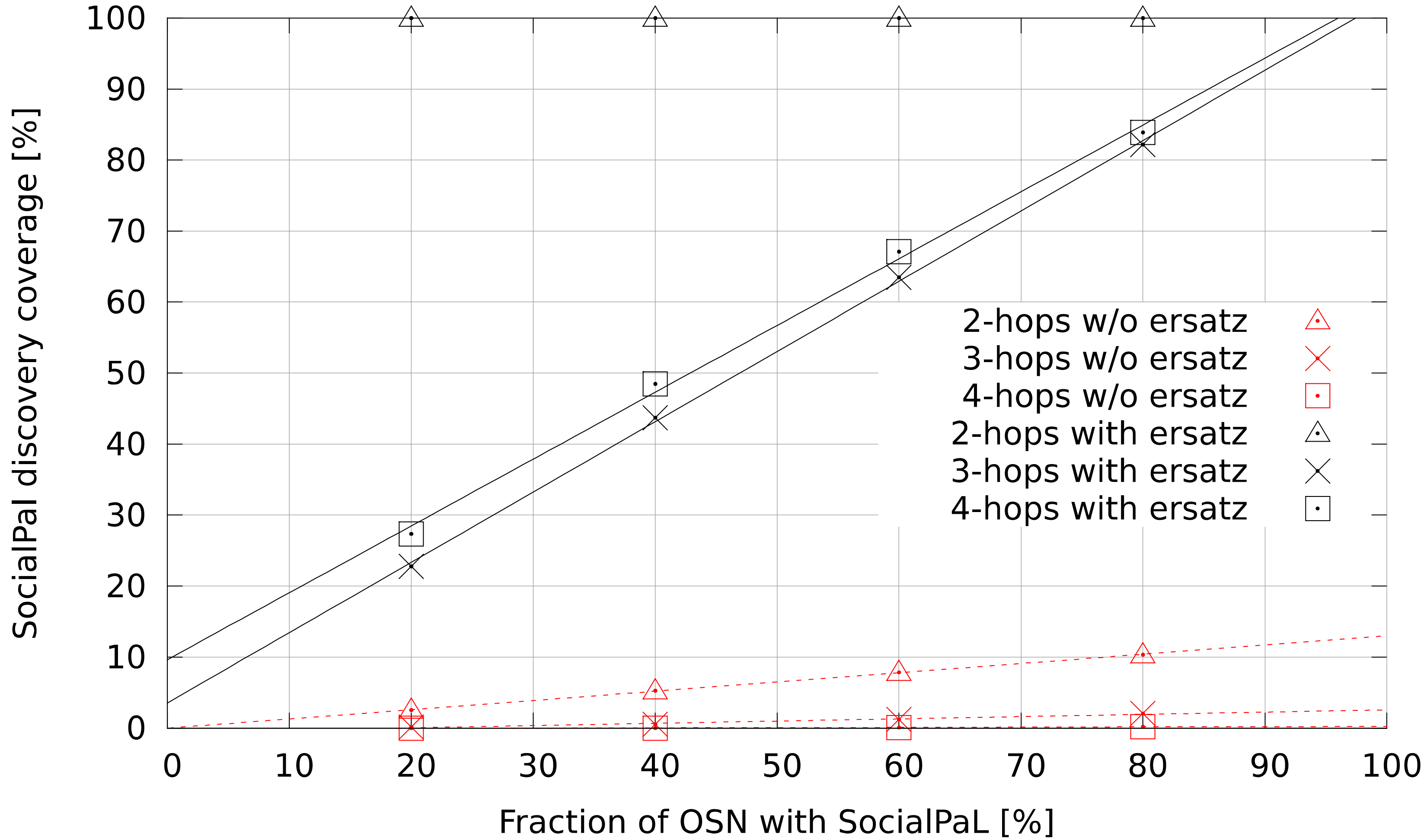
- MHRW dataset
  - Sampled using Metropolis Hastings random walk
  - 95 700 “sampled users”, 175 connections on average
  - 72.2 million “outside users”
  - among sampled users: 3 connections on average
- From Gjoka et al (Infocom 2010)

Simulation for estimating coverage

1. Test set: randomly choose x% of "sampled users"
   – x = 20, 40, 60, 80 (represents fraction using Social Pal)
2. Pick 50k pairs randomly from "test set" w/ k-hop path
   – k = 2, 3, 4
3. Compute fraction for which Social PaL discovers path

Repeat steps 1-3 ten times; average results

Coverage: MHRW dataset (random walk)



X-axis shows fraction of sampled users
Sampled users: 957 000
Outside users: 72.2 million

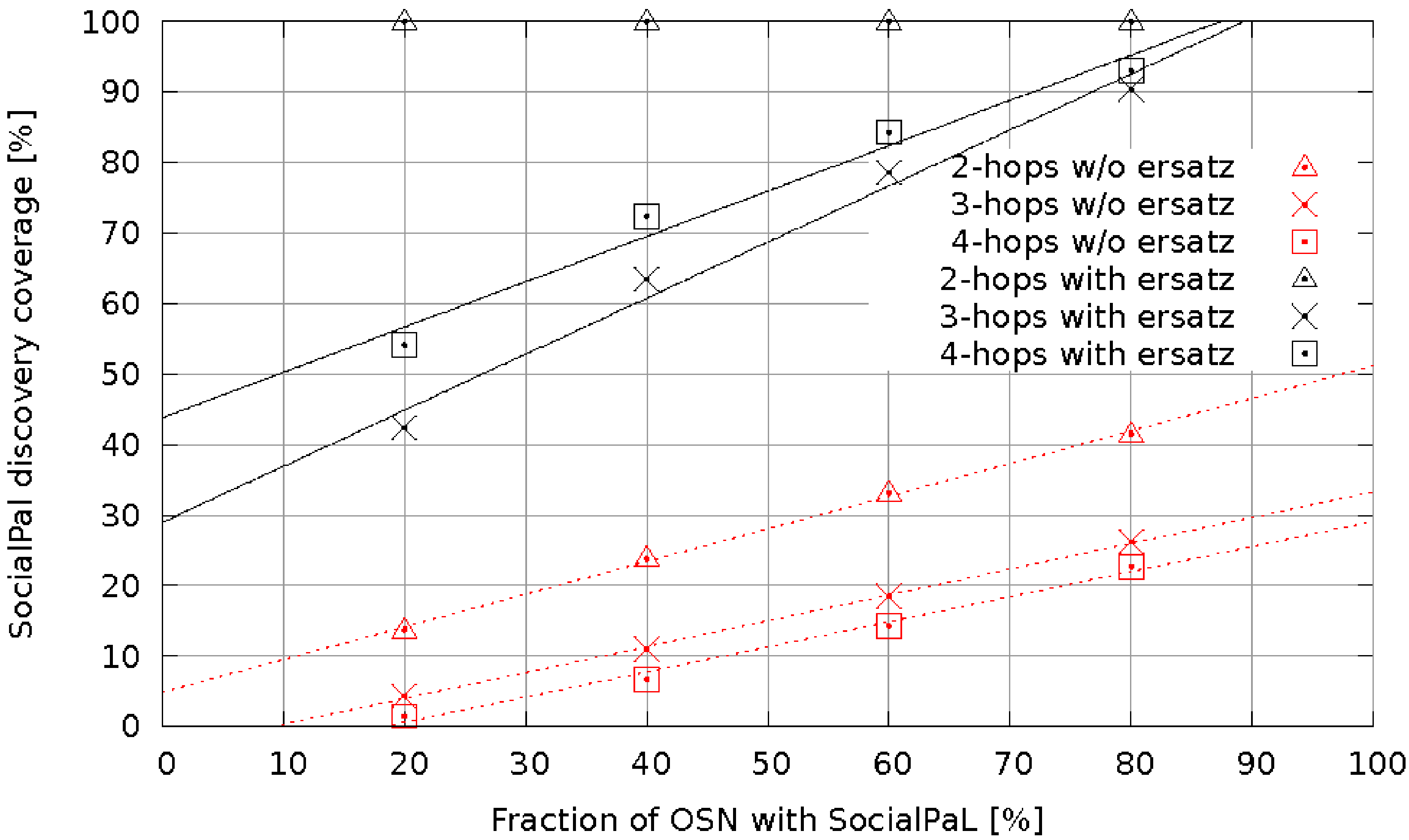
Aalto University

UNIVERSITY OF HELSINKI

Dataset for estimating coverage

- BFS dataset
  - Sampled using breadth-first search
  - 2.2 million sampled users, 310 connections on average
  - among sampled users: 53 connections on average
- Also from Gjoka et al (Infocom 2010)

Coverage: Breadth-first search dataset



Aalto University

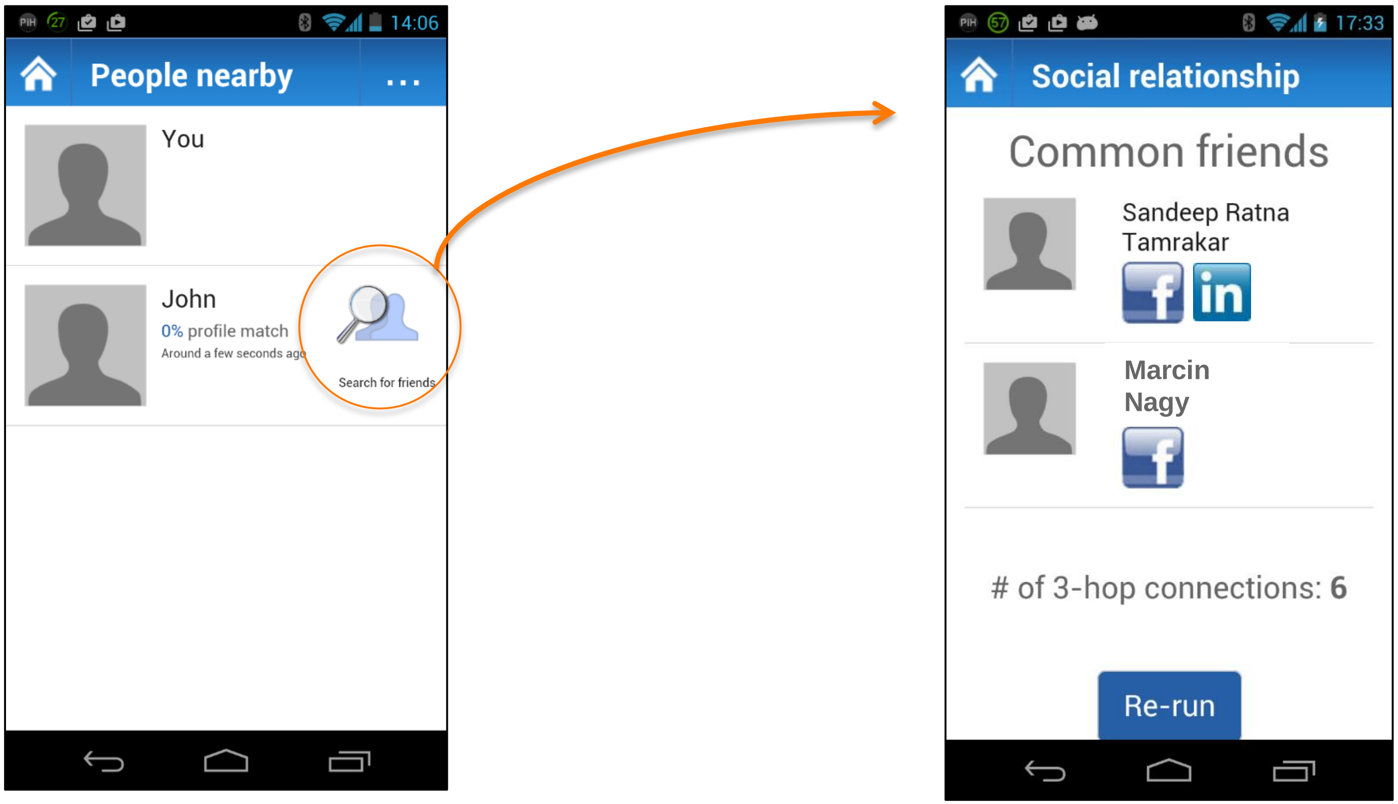
X-axis shows fraction of sampled users
Sampled users: 2,2 million
Total users: 93,8 million

UNIVERSITY OF HELSINKI

Coverage analysis summary

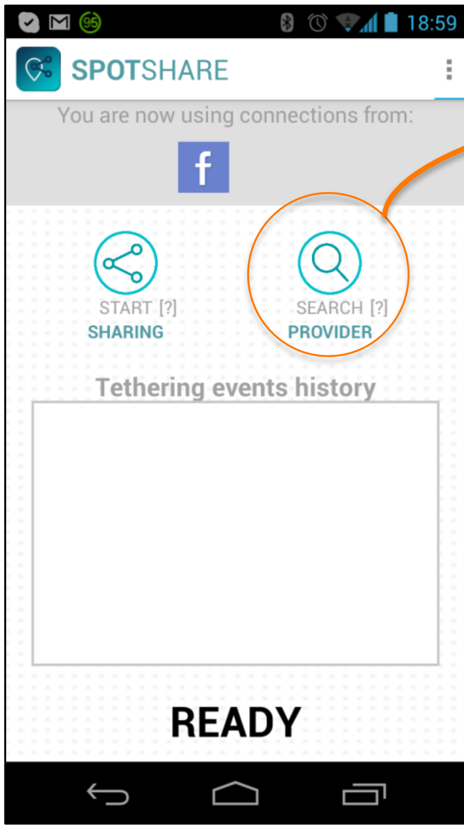
- Use of ersatz profiles significantly increases coverage
  - Always 100 % coverage for 2-hop paths (detects all)
  - Only 20% users with Social PaL: coverage > 40%
    - Except for MHRW dataset
  - 80% users with Social PaL: coverage > 80%, always
- Coverage is better in datasets with higher connectivity
  - BFS dataset ~ Social Network in regions with high penetration
- 4-hop paths more readily discovered than 3-hop paths!

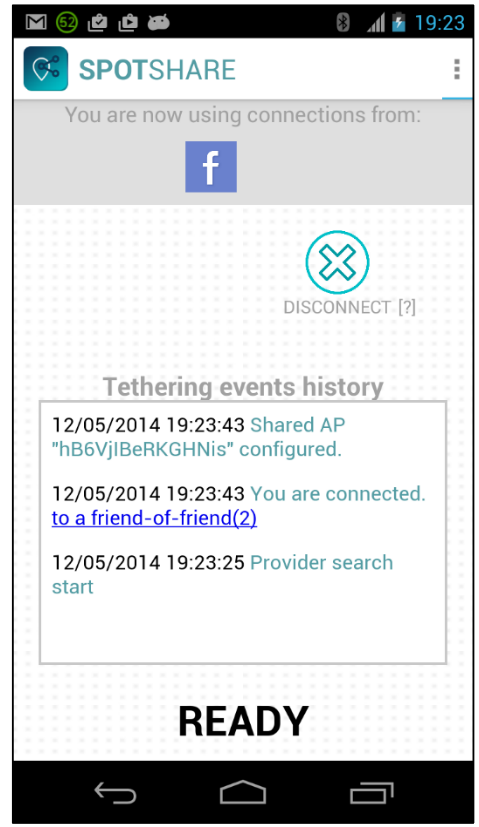
Example App: nearbyPeople



[nearbyPeople]

Example App: SpotShare





SpotShare
(Google Play)

Summary

- Privacy-preserving, scalable protocols for finding
  - common friends
  - lengths of social paths
- Used in two applications (available for download)
  - Easy-to-use tethering (“SpotShare”)
  - Friend radar (“nearbyPeople”)
- Source code available for research use
- More info at https://se-sy.org/projects/pet/