

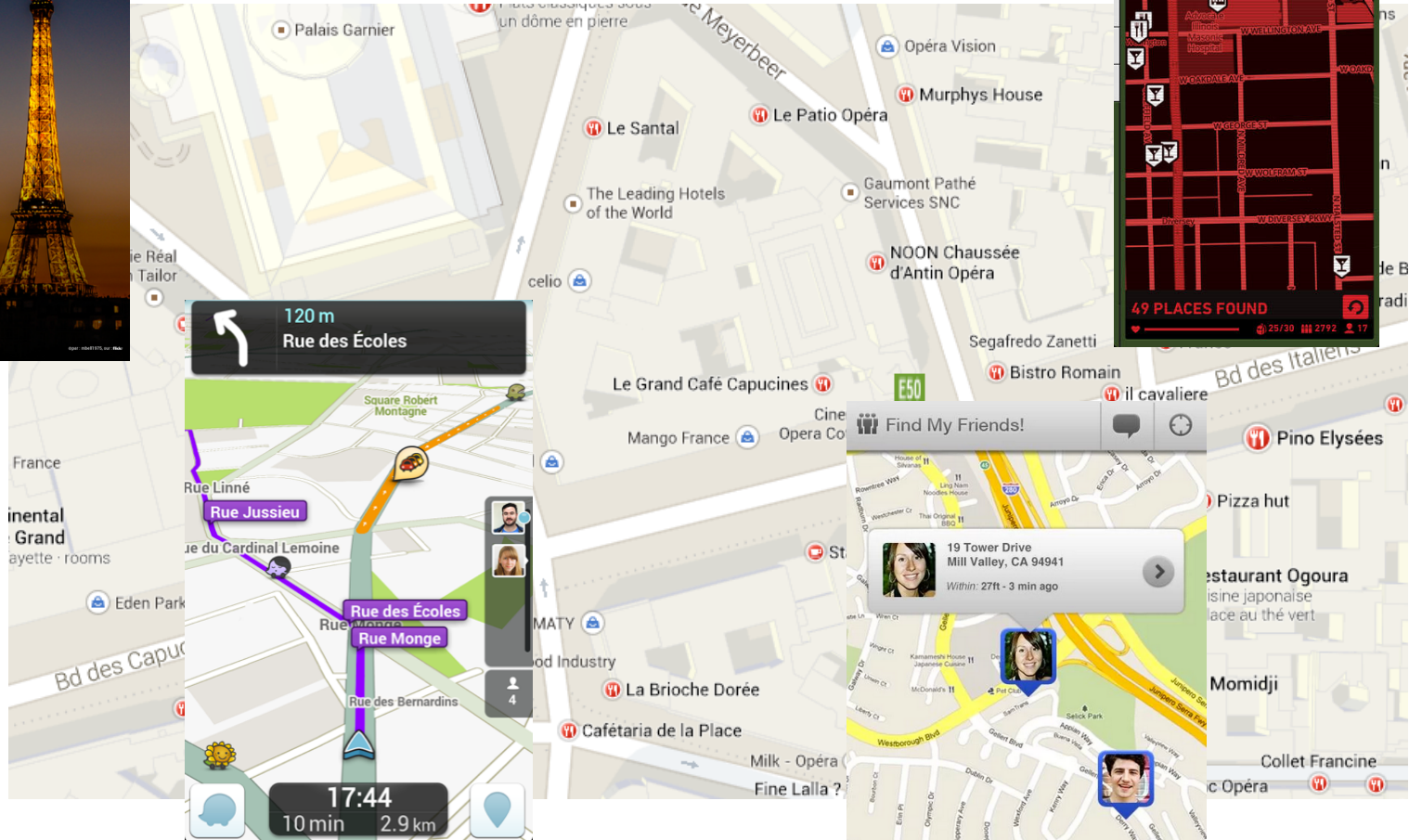
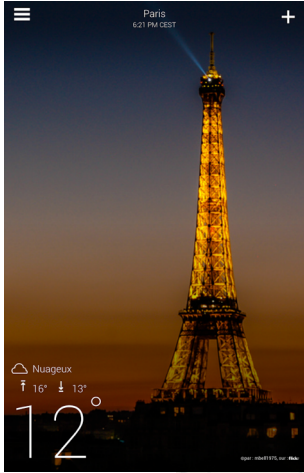


Differentially Private Location Privacy in Practice

Vincent Primault
Sonia Ben Mokhtar
Cédric Lauradoux
Lionel Brunie

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Location-based services





PLEASE ROB ME

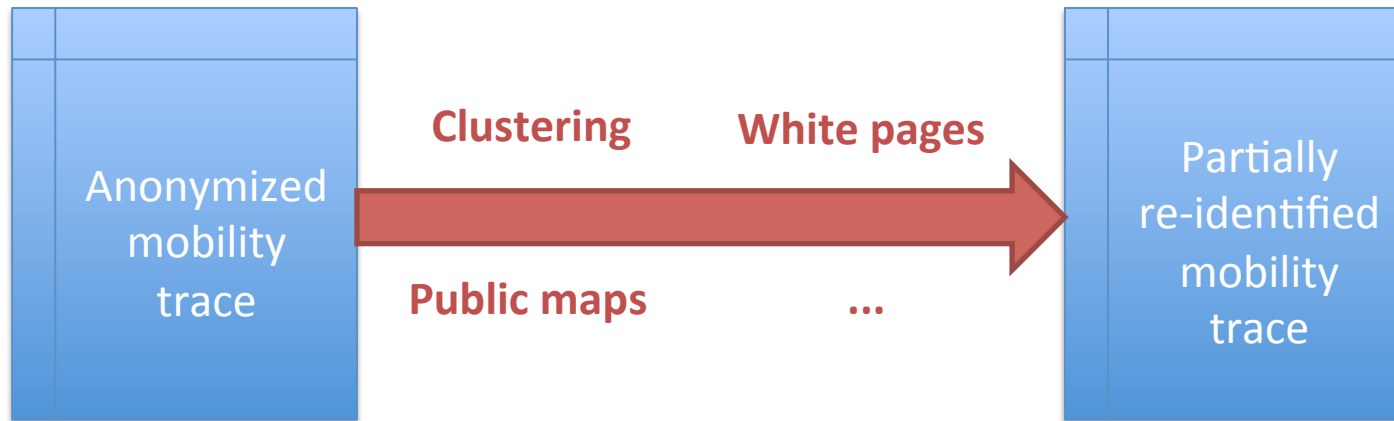


**Raising awareness
about over-sharing**

Check out our [guest blog post](#) on the CDT website.



Location privacy threats



Only 4 points are sufficient to uniquely identify you! [1]

[1] De Montjoye et al. **Unique in the Crowd: The privacy bounds of human mobility.** *Scientific reports*, 2013.

[2] Golle et al. **On the Anonymity of Home/Work Location Pairs.** *Pervasive'09*.

Can a protection mechanism
efficiently protect
points of interest of a user?

Outline

- Introduction
- **About points of interest**
- Protection mechanisms
- Experimental settings
- Evaluation metrics & results
- Sum-up

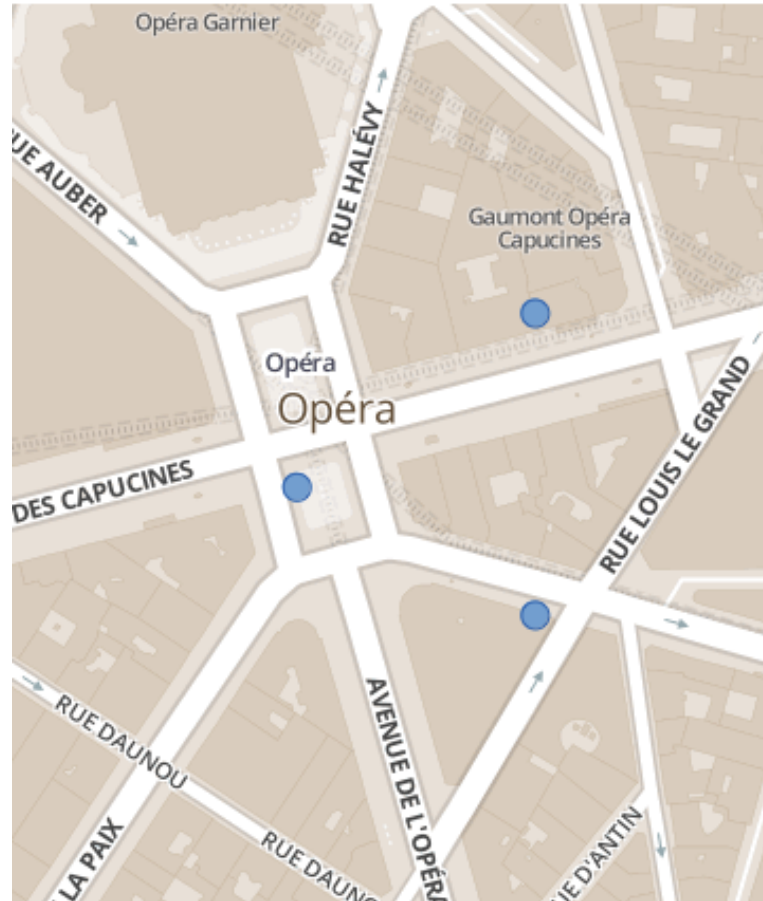
A mobility trace



Areas of interest



Points of interest



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Location-privacy protection mechanisms

Pseudonymity
Mix-zones

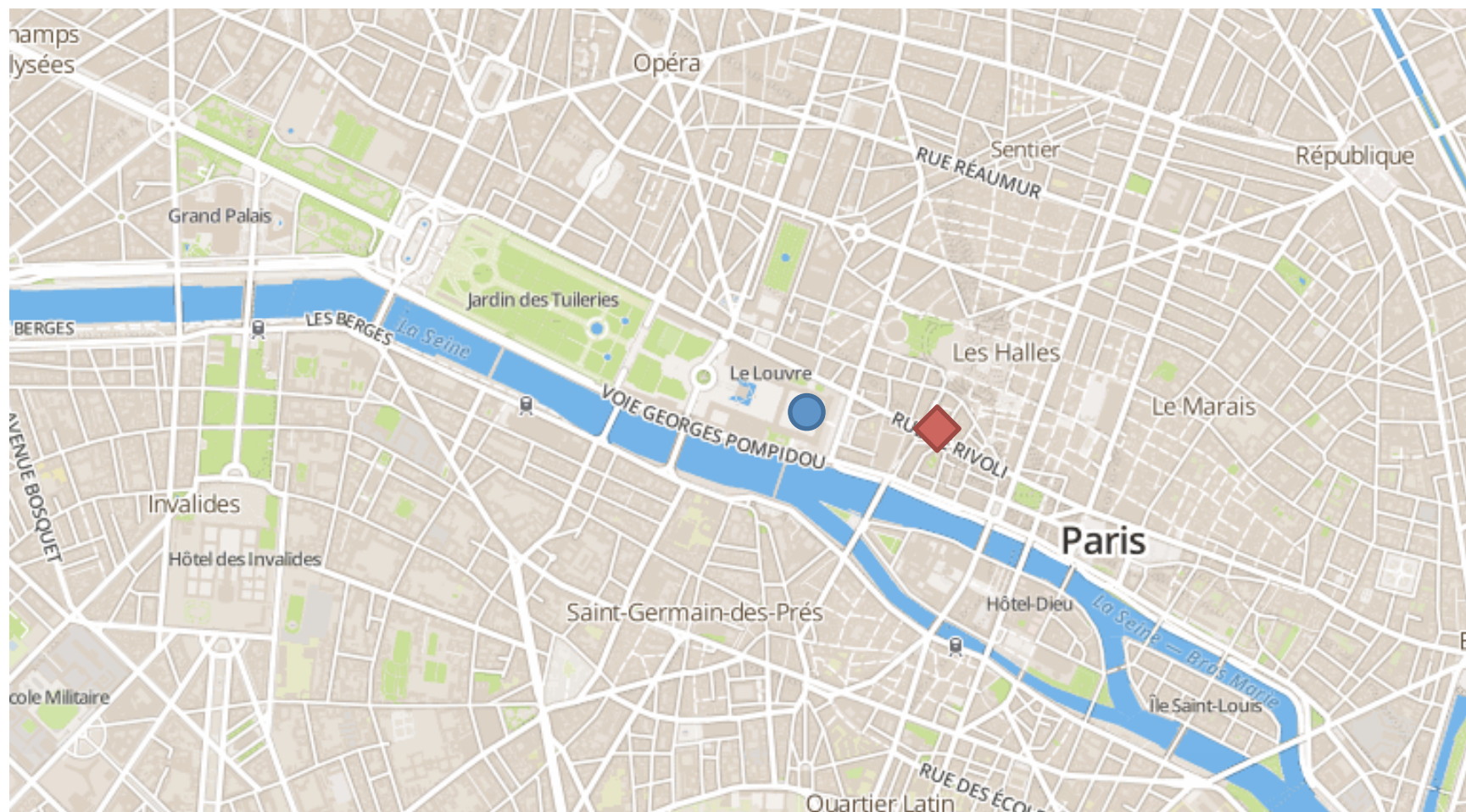
Spatial cloaking
k-anonymity

Noise-based
solutions

Cryptographic
protocols

Geo-indistinguishability

● Real location ◆ Reported location



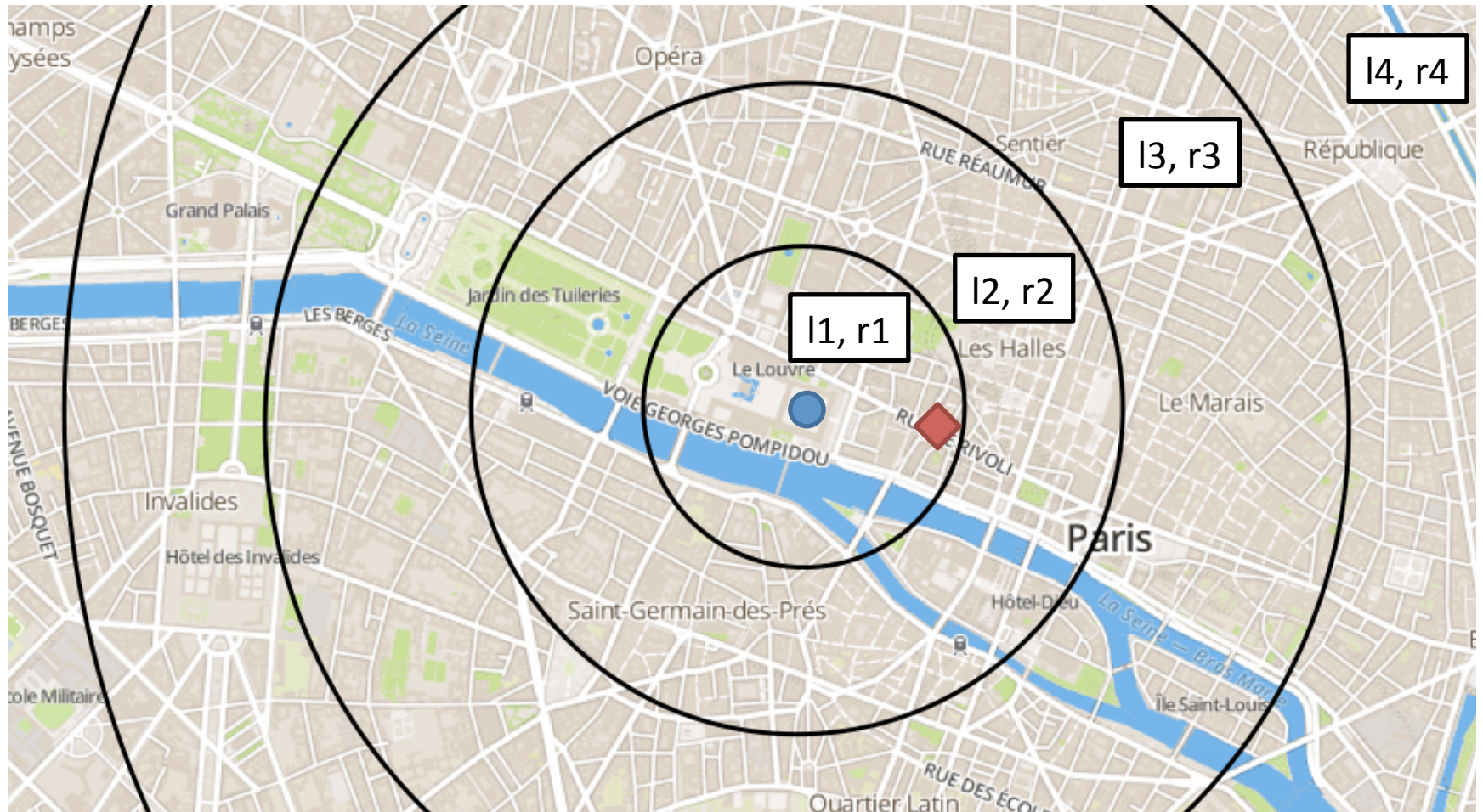
[3] Andrés et al. **Geo-indistinguishability: Differential privacy for Location-based Systems.** *CCS'13*.

Geo-indistinguishability

Level of privacy l_i within r_i proportional to an ϵ

● Real location

◆ Reported location



[3] Andrés et al. **Geo-indistinguishability: Differential privacy for Location-based Systems.** *CCS'13*.

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Two different data sets

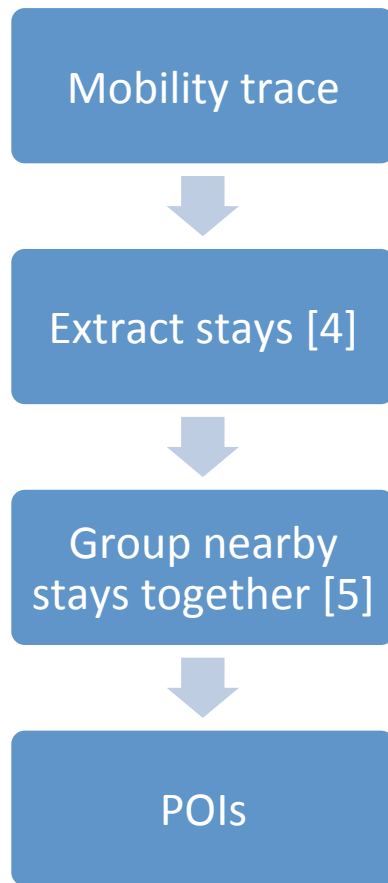
San Francisco cabs
In the SF Bay Area
1 month in 2009
536 taxis
11 millions points

Geolife
Around Beijing
4 years (2007-2011)
182 users
25 millions points



Reduced Geolife
Around Beijing
1 continuous month
61 users
5 millions points

POIs extraction algorithm



Time-ordered list of locations

1 hour

?

Centroids of areas where a user has spent at least ***minTime*** within a ***maxDistance*** radius

Stays within $\frac{3}{4}$ *maxDistance* where a user passed through at least ***minPts*** times

2 times

A set of important places for a user

[4] Hariharan et al. **Project Lachesis: parsing and modeling location histories.** *GIScience'04.*

[5] Zhou et al. **Discovering Personal Gazetteers: An Interactive Clustering Approach.** *GIS'04.*

Playing with distance threshold

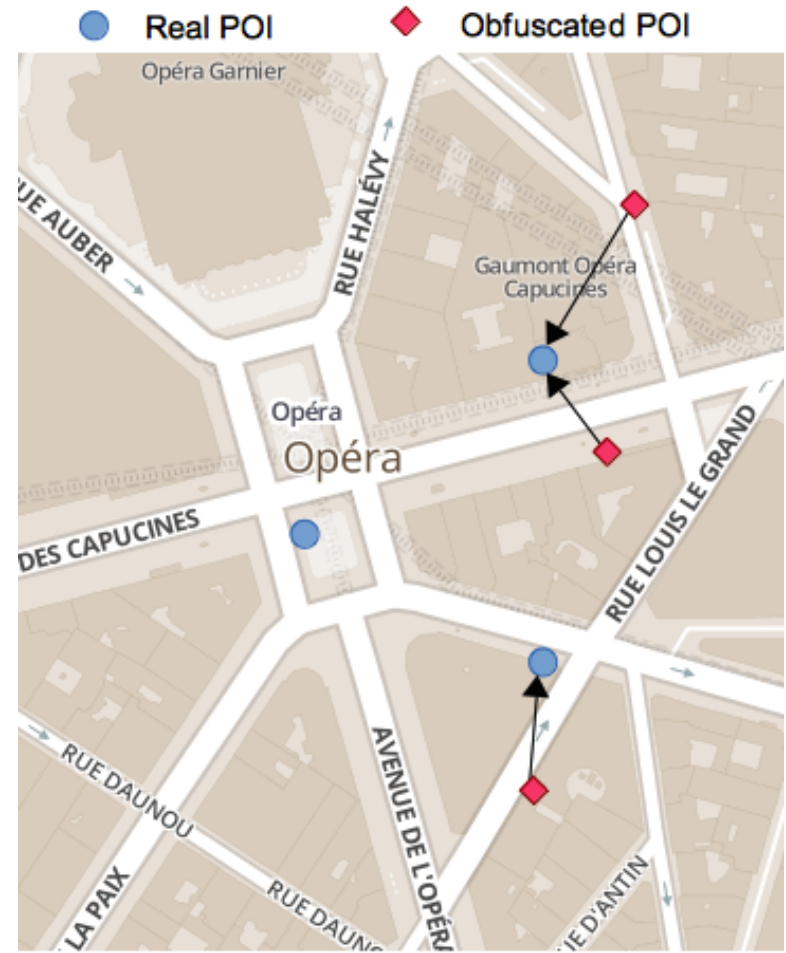
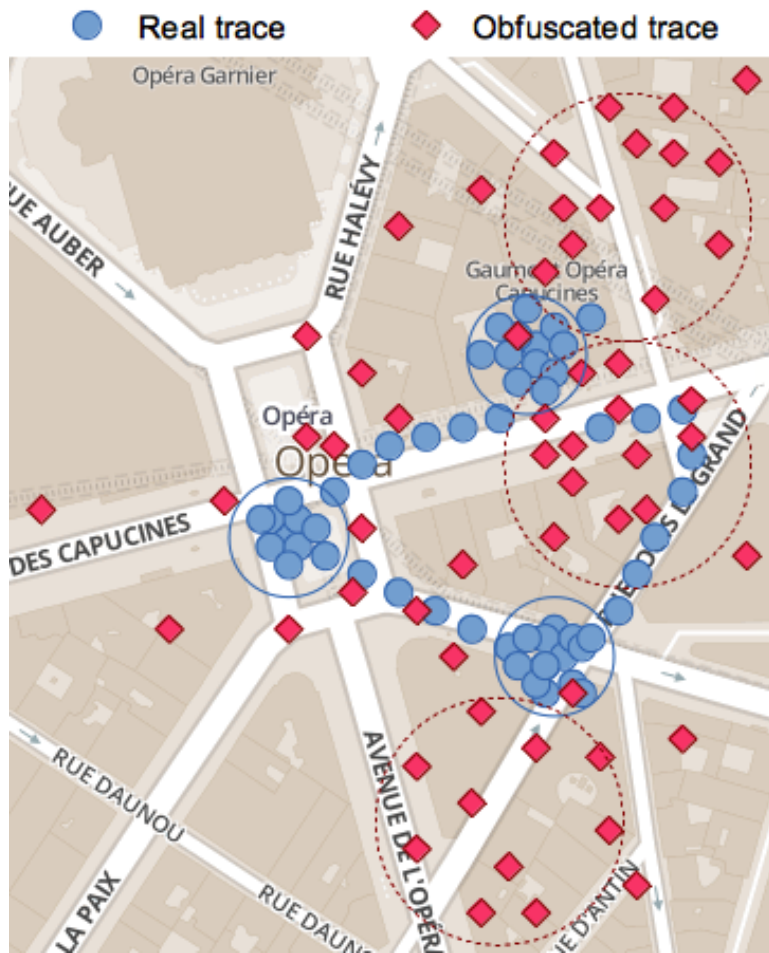
	SF cabs	Geolife
<i>Unobfuscated</i>	<i>250 m</i>	<i>250 m</i>
Weak privacy	700 m	600 m
Medium privacy	1000 m	1200 m
Strong privacy	2000 m	2500 m

We must greatly increase the ***maxDistance*** threshold at highest privacy levels in order to retrieve an interesting number of POIs.

Outline

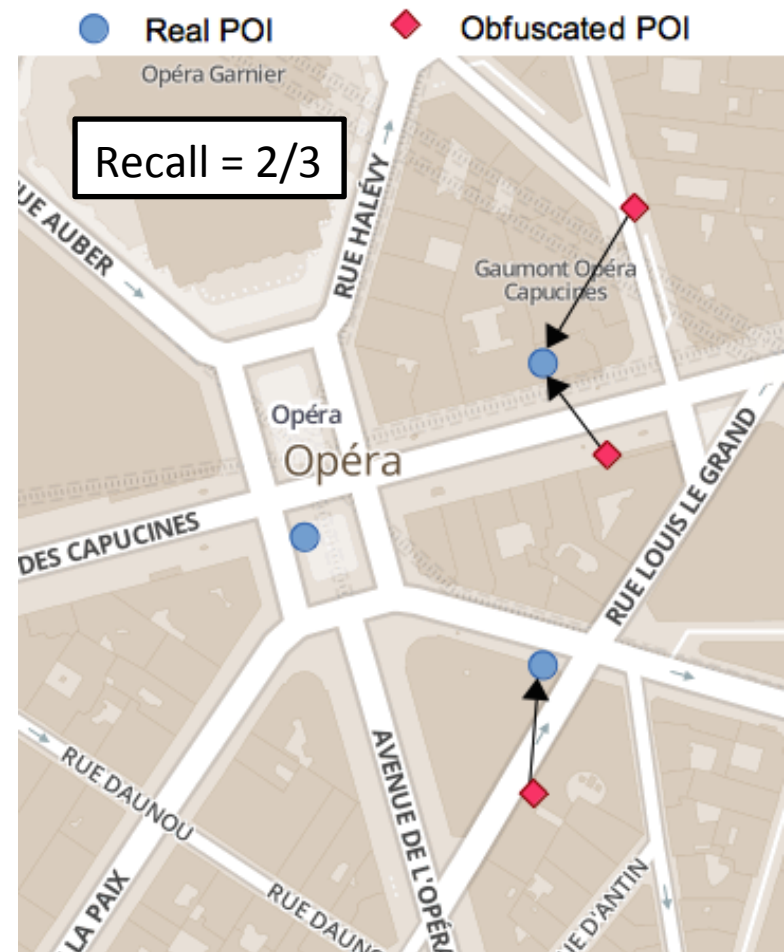
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Measuring privacy



Recall rate

Recall rate is the proportion of real POIs successfully retrieved.



Recall rate

	SF cabs	Geolife
Weak privacy	73 %	72 %
Medium privacy	72 %	71 %
Strong privacy	71 %	61 %

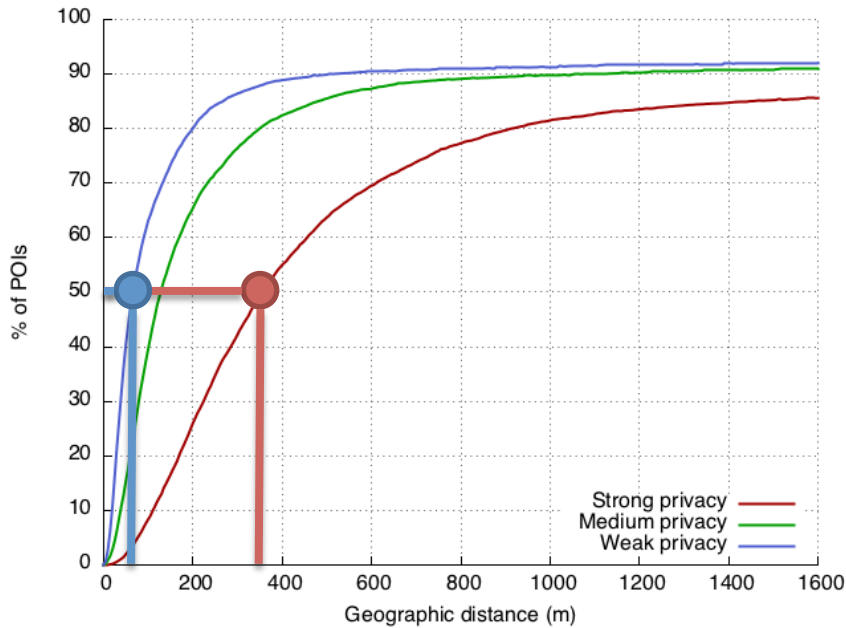
	SF cabs	Geolife
<i>Reference (unobfuscated)</i>	<i>1111 POIs (~ 2/user)</i>	<i>258 POIs (~ 4/user)</i>

Geographic distance

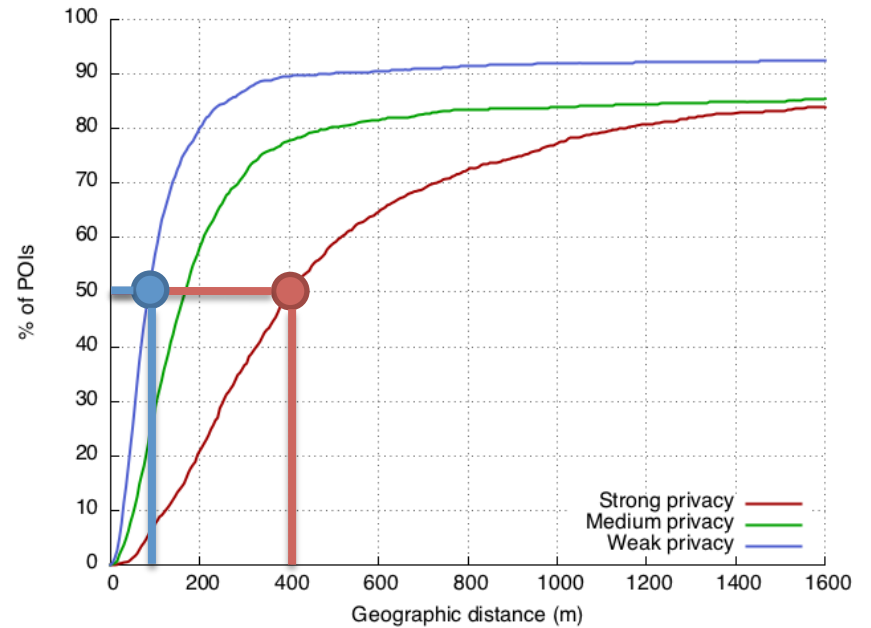
Geographic distance
between an obfuscated
POI and the nearest real
POI



Cumulative geographic distance



SF cabs



Geolife

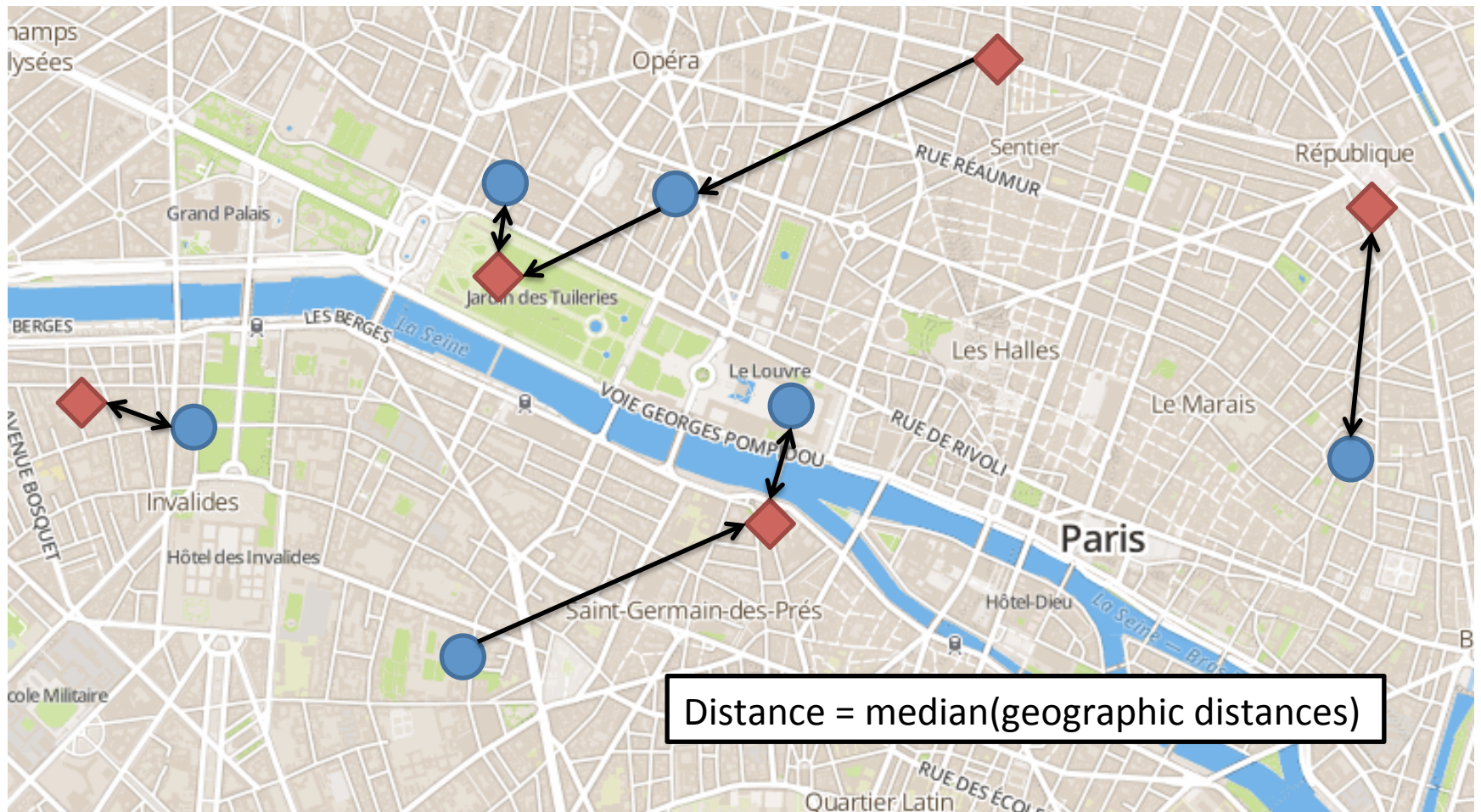
Re-identification rate

Scenario: I use a LBS without any protection and one day, I use a geo-indistinguishable mechanism.

Will my privacy be preserved or will the LBS be able to link my obfuscated trace with my original trace?

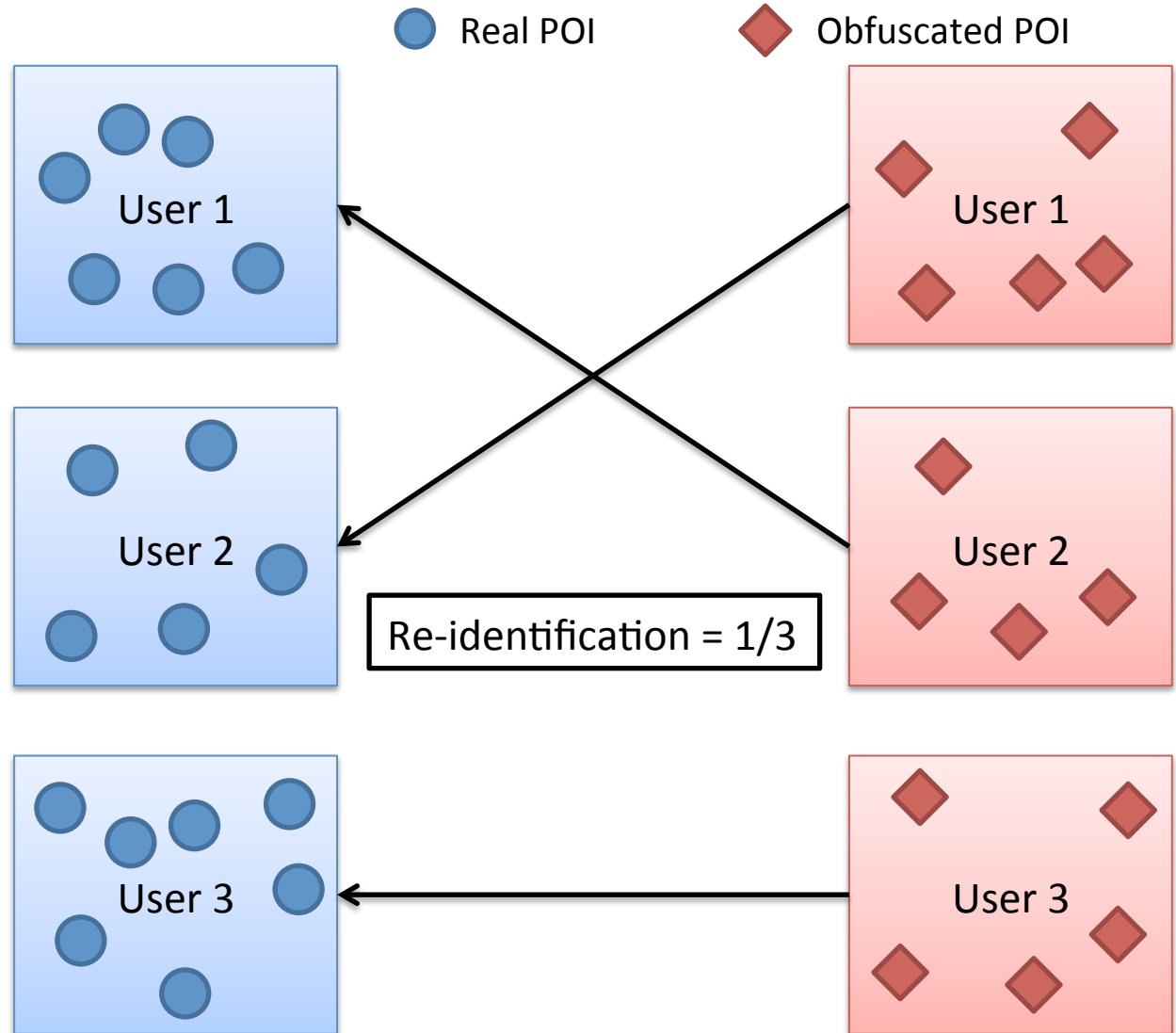
Re-identification rate

● Real POI ◆ Obfuscated POI



Re-identification rate

Associate to each set of obfuscated POIs the set of real POIs with which it has the minimal distance.



Re-identification rate

	SF cabs	Geolife
Strong privacy	6 %	63 %
Medium privacy	8 %	83 %
Weak privacy	10 %	90 %

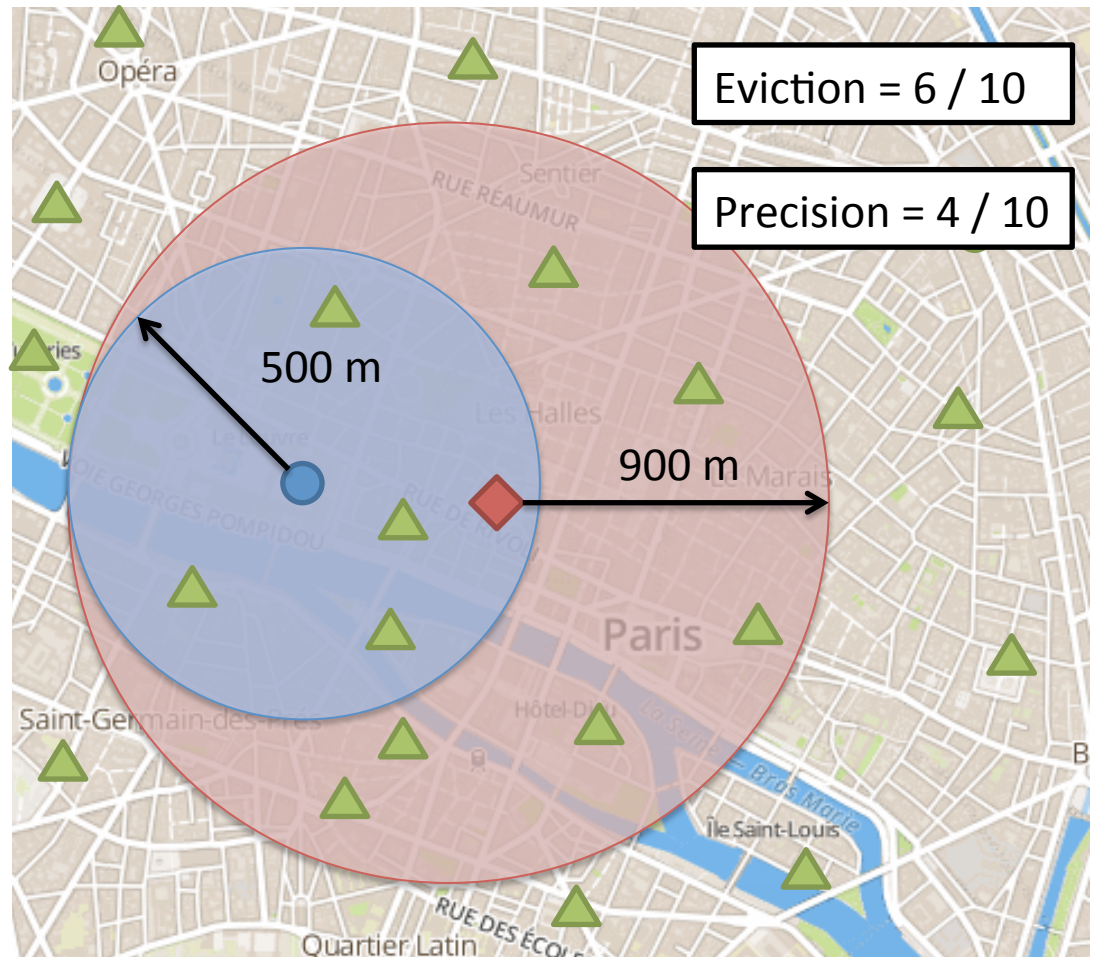
- Few unique patterns in SF cabs data set, drivers are likely to have a similar behavior.
- Mobility patterns can be captured in Geolife and act like a fingerprint.

Measuring precision

▲ Restaurant ● Real location ◆ Reported location

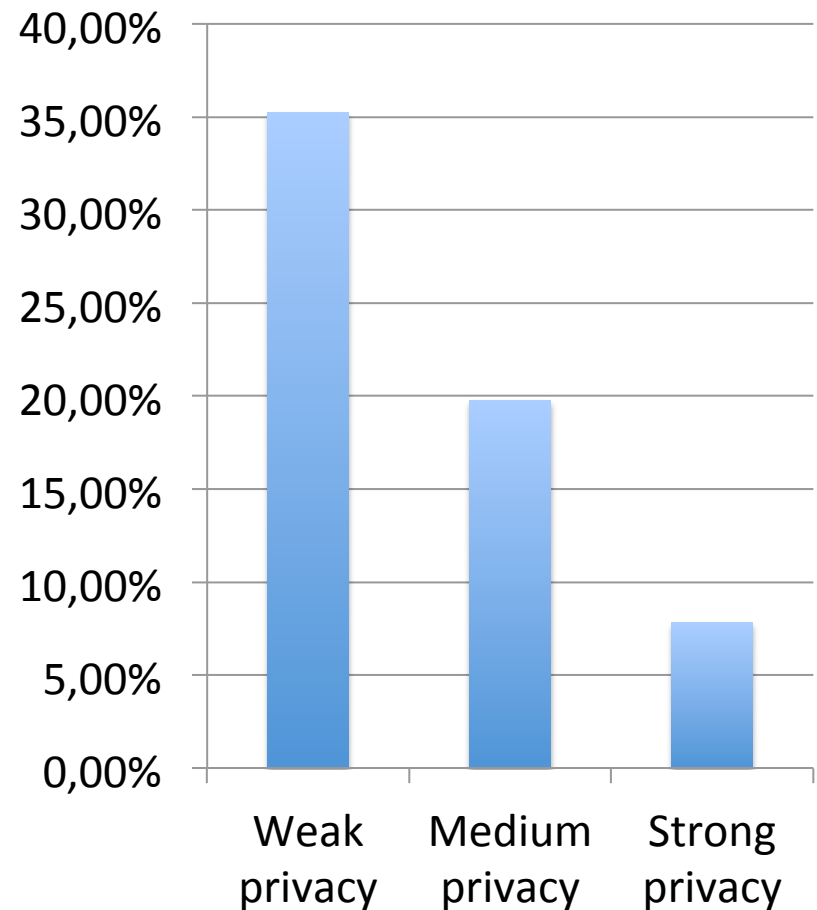
Eviction rate is the ratio between the number of useless results and the total number of results.

Precision is 1 minus the eviction rate.



Precision of results when querying LBS

- 100 points sampled from the SF cabs dataset
- Use a "*find restaurants 500 meters around me*" query against OpenStreetMap data



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Conclusion

- Protection mechanisms improve privacy...
 - but still allow to infer a large quantity of sensitive information (> 60 %)
 - at the cost of degraded performance
- Difficult to achieve a trade-off between precision, utility and performance

Future work

- Study the exact impact of the temporal component
- Investigate if dynamically adapting the privacy parameter can help
- Propose counter-measures w.r.t. our framework and related work

Questions?

