

Elastic distinguishability metrics for Location Privacy

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joint work with

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Privacy for LBS

- Goal: limit semantic inference
- (not anonymity)
- Reasonable utility for LBS



Obfuscation

Mechanism

$$x \rightarrow \mathcal{M} \rightarrow z$$

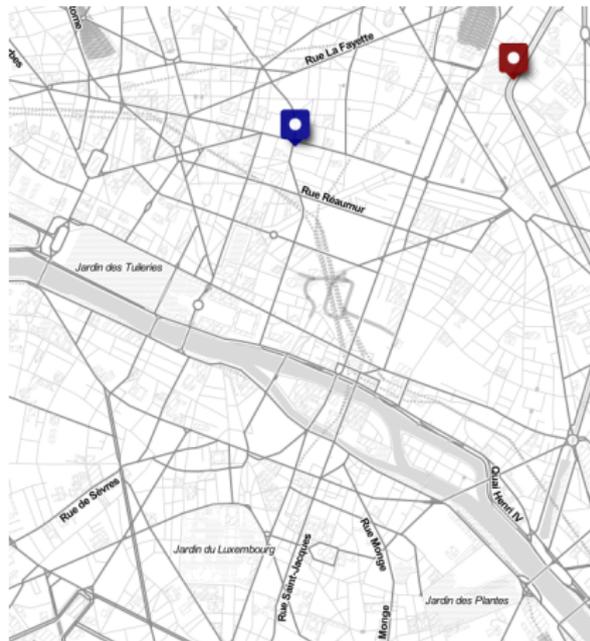


[Chatzikokolakis et. al: Broadening the Scope of Differential Privacy Using Metrics. PETS'13]

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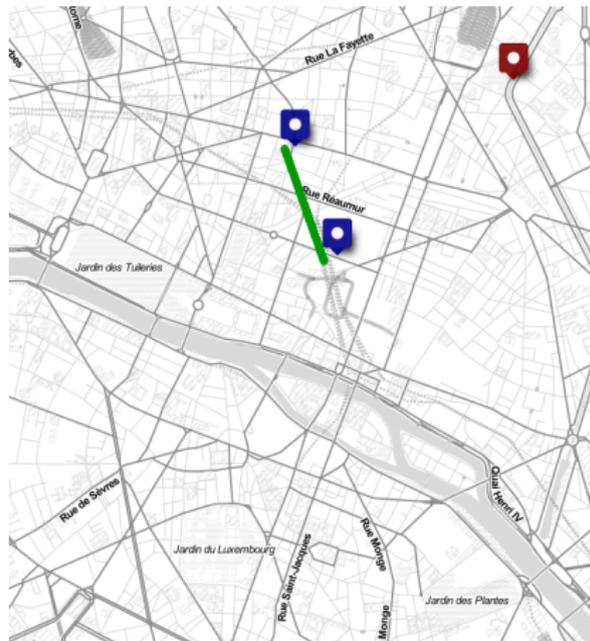


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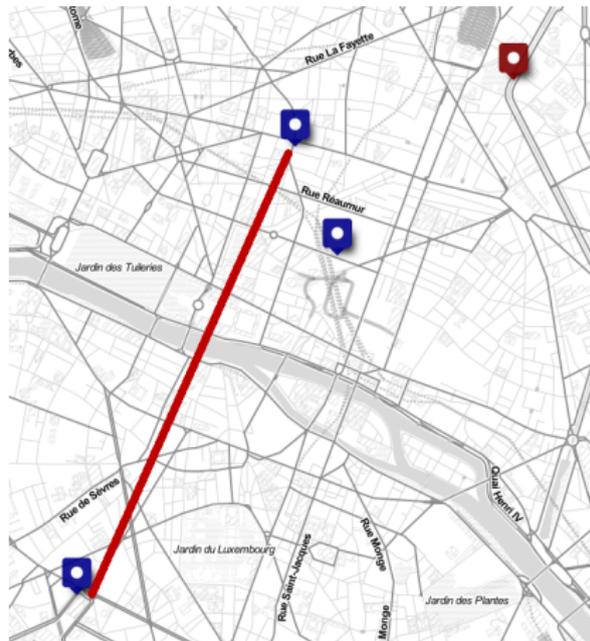


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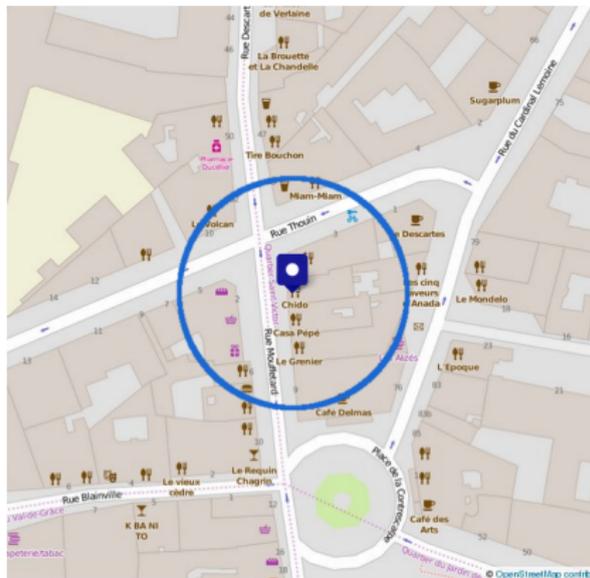
Geo Indistinguishability

$$d_{\mathcal{X}}(x, x') = \epsilon d_E(x, x')$$

- Space is privacy
- ϵ tunes how much

Requirement

I want to be indistinguishable from a certain amount of space.



[Andrés et al: Geo-indistinguishability: differential privacy for location-based systems. CCS'13]

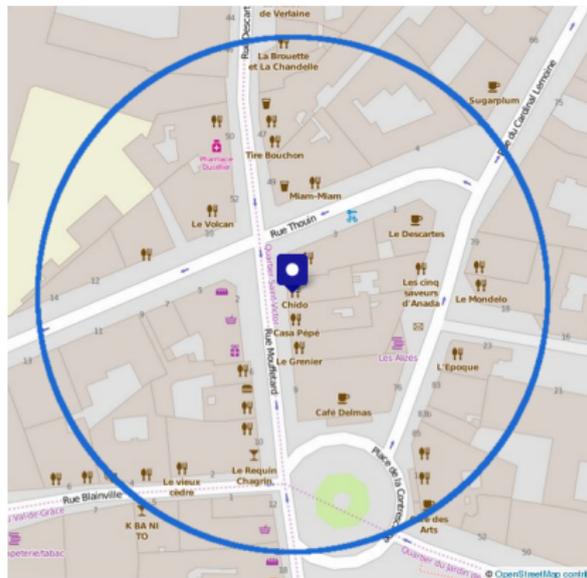
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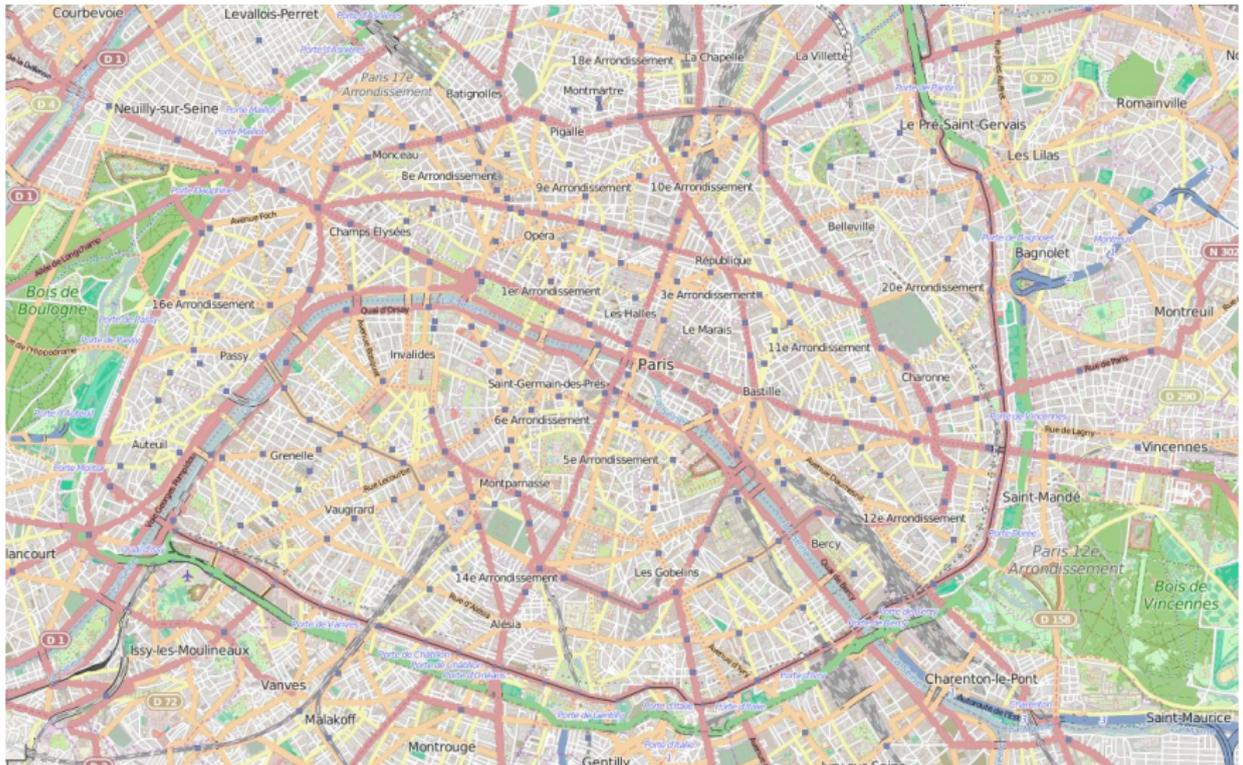
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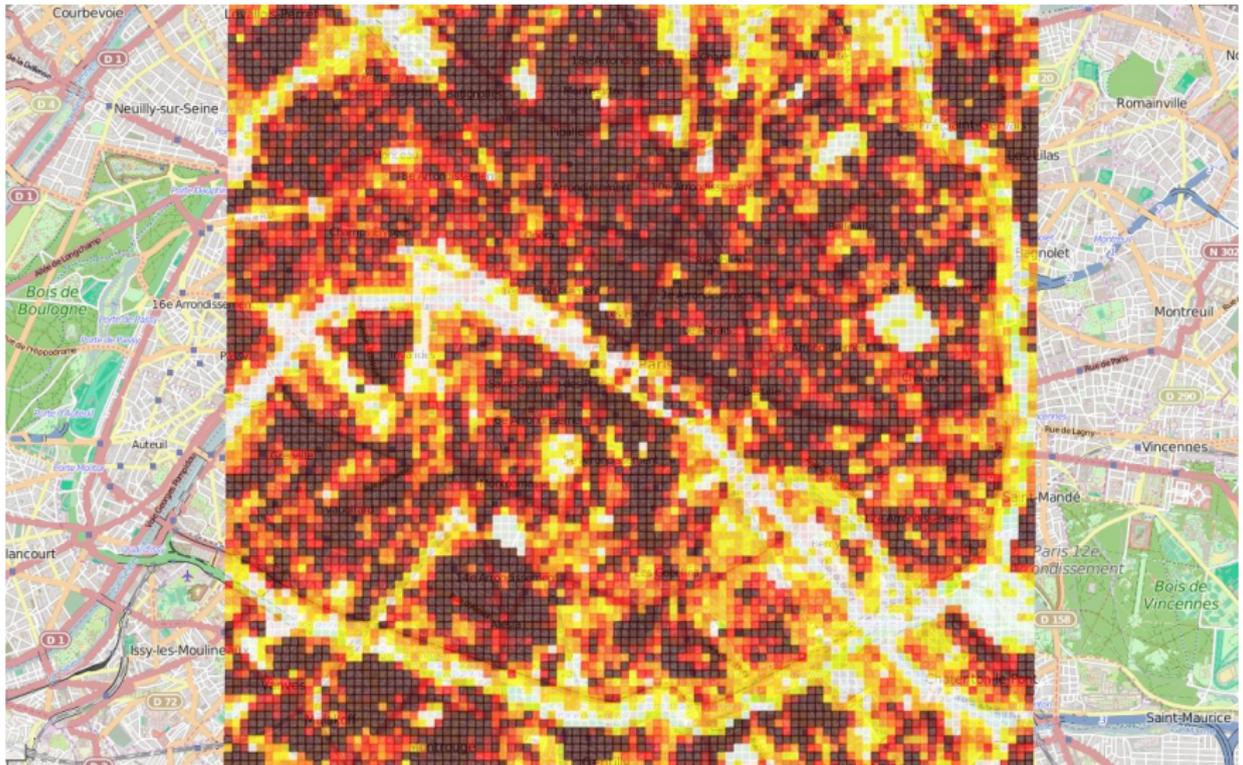


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Privacy Mass from OpenStreetMap

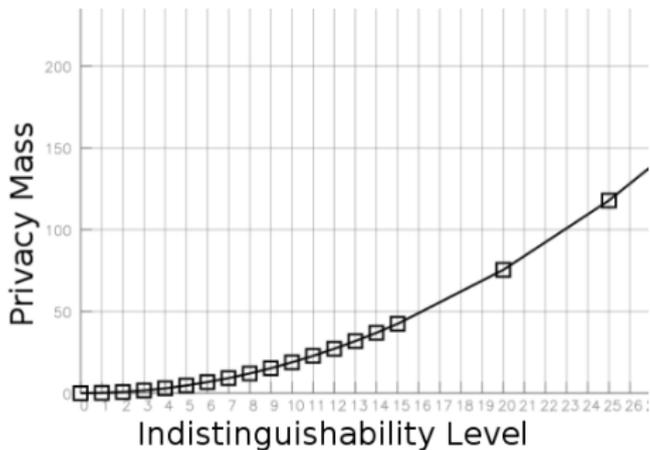


Privacy Mass from OpenStreetMap



Privacy Requirement

I want to be indistinguishable from a certain amount of *privacy mass*.

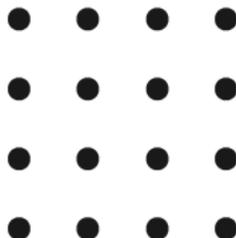


$$req(l) = mass$$

Building an Elastic Metric

Graph-based algo:

- start with a disconnected graph
- iterate over all nodes
 - ▶ compute `mass`
 - ▶ add an edge with $l = req^{-1}(\text{mass})$
- we stop at l^\top

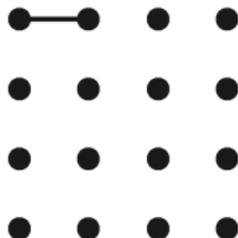


$$d_x(x, x') = \text{shortest-path}(x, x')$$

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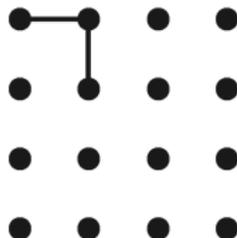


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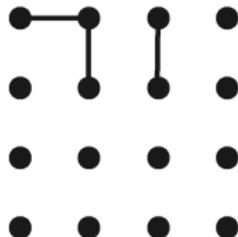


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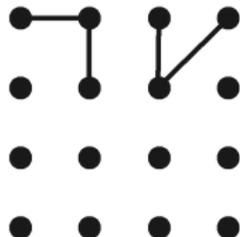


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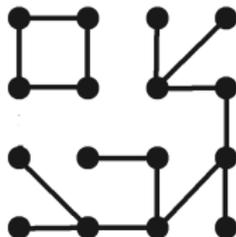


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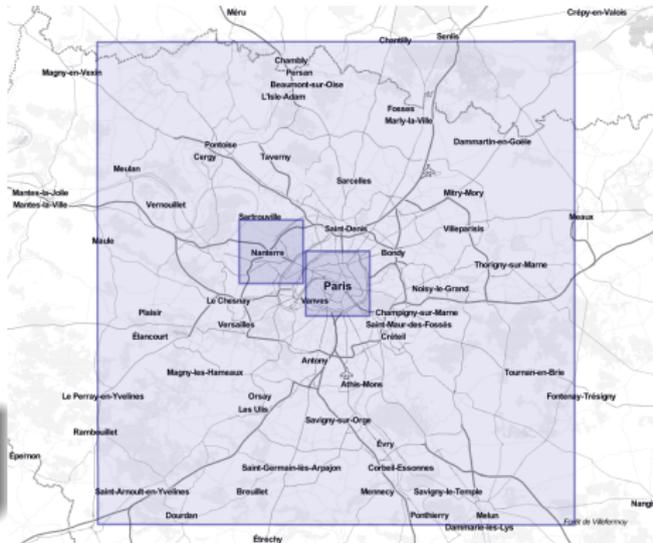
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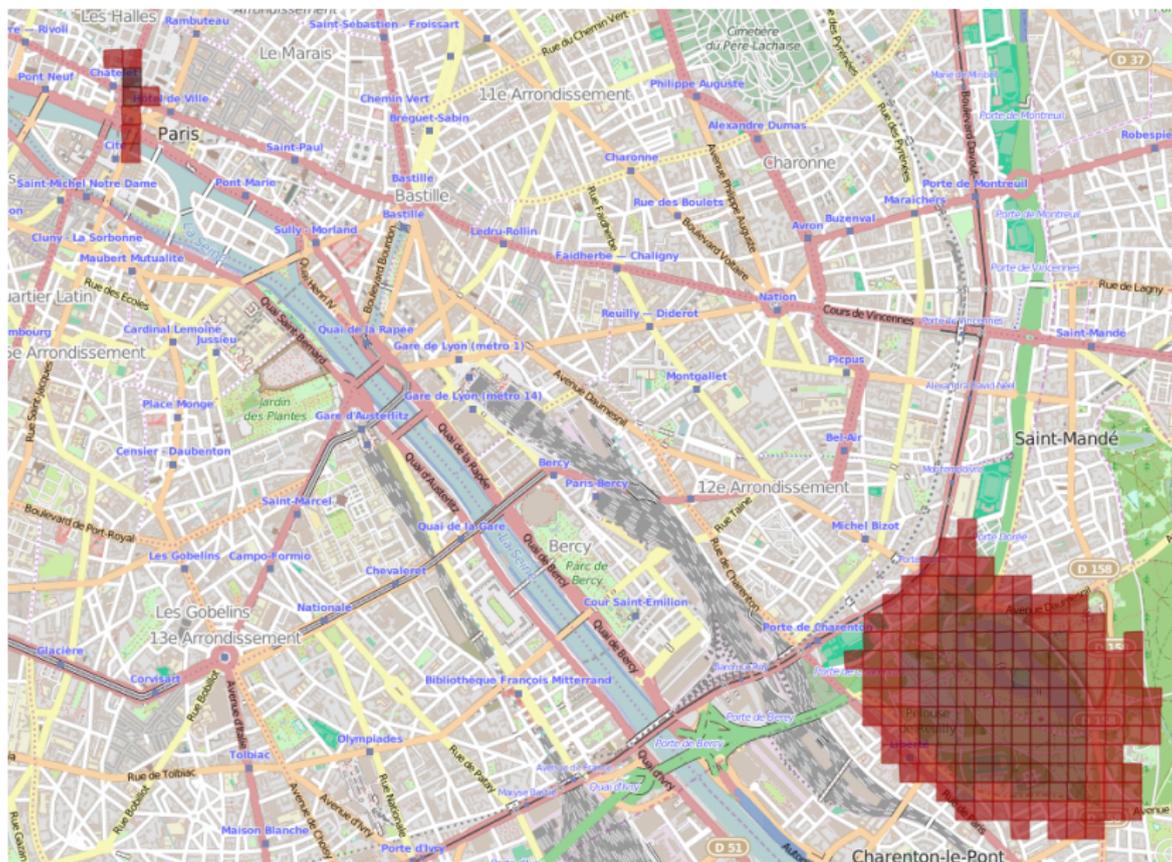
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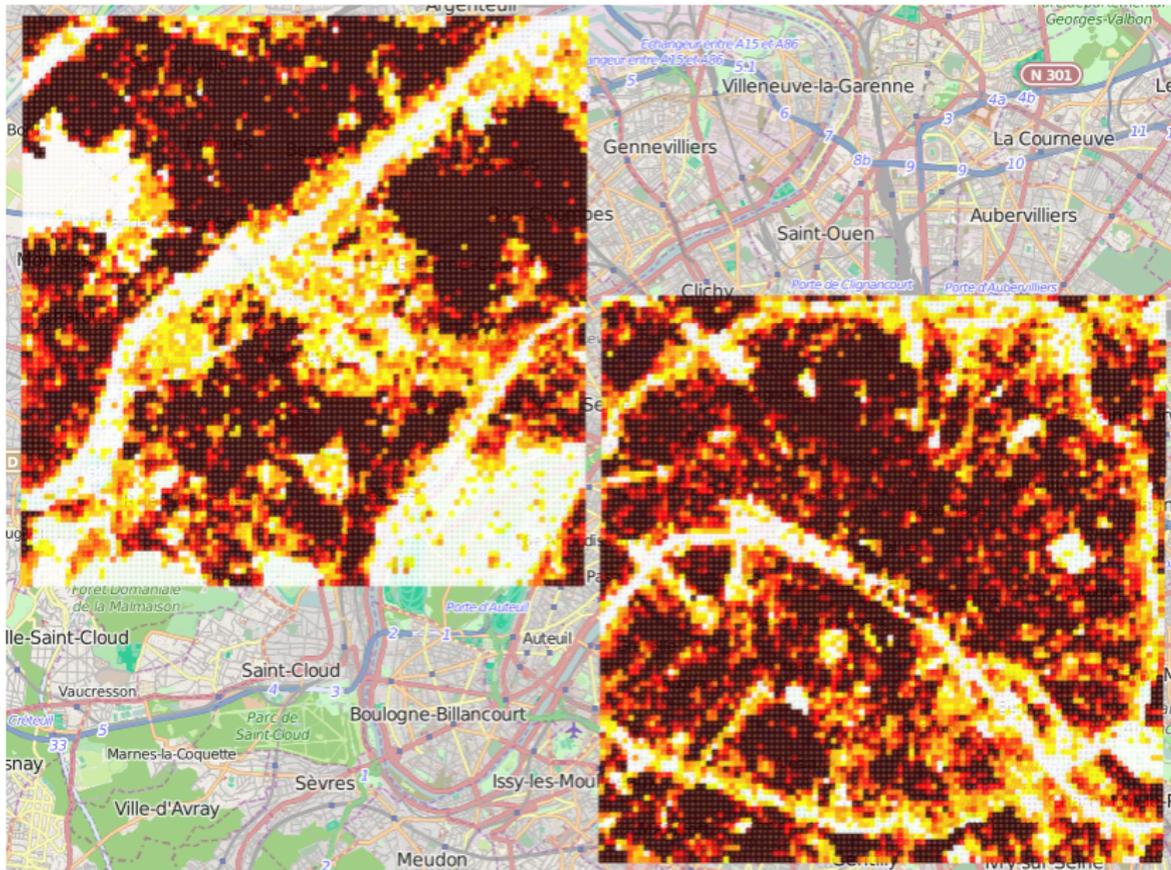
Elastic Mechanism

Elastic Mechanism = Elastic Metric + Exponential Mechanism

Elastic Mechanism



Elastic Mechanism



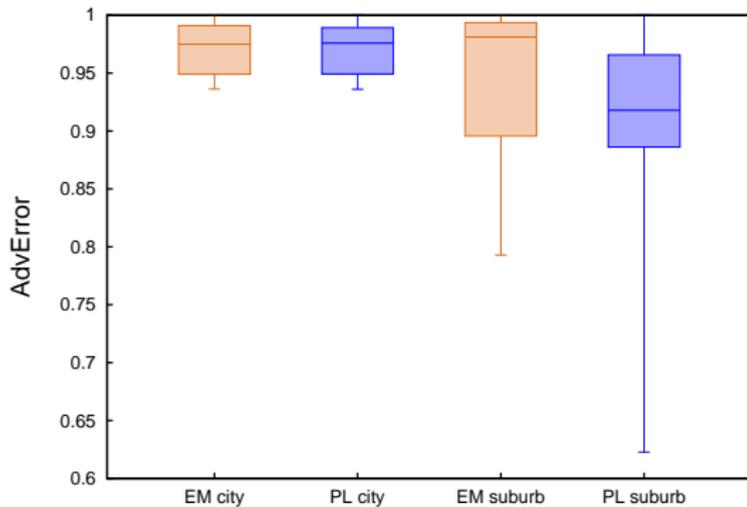
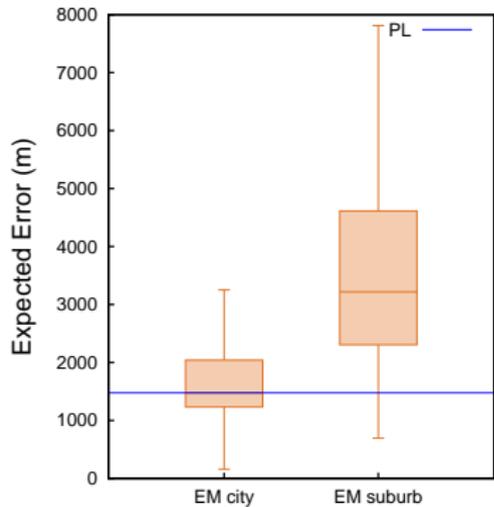
Evaluation

- EM vs PL
- City (Paris) vs Suburb (Nanterre)
- Fixed Utility as Expected Error
- Compare Privacy as Adversarial Error
- Gowalla and Brightkite datasets



[Shokri, Theodorakopoulos, Boudec, Hubaux. Quantifying location privacy. S&P'11]

Evaluation



Conclusion & Future

- Geoid is simple and efficient (Location Guard)
- Too rigid!

Contributions:

- Elastic metric with privacy mass requirement
- Scalable algorithm

Future Work:

- Include in privacy mass ideas from k-anonymity
- Lightweight version for Location Guard

Thanks



Don't miss Location Guard tomorrow



Fences

- linear growth of epsilon
- fences for recurrent places
- achieve “better privacy” consuming less ϵ

$$d_F(x, x') = \begin{cases} d_x(x, x') & x, x' \notin F \\ 0 & x, x' \in F \\ \infty & o.w. \end{cases}$$

