CS573 Data Privacy and Security

Location Privacy

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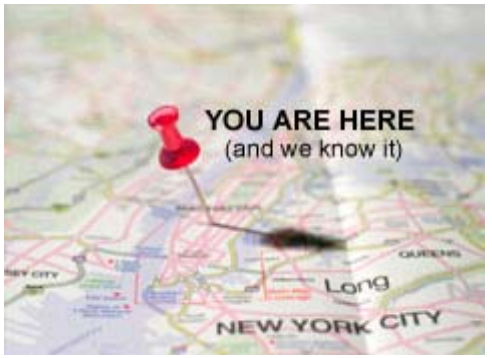
Outline

- What is Location Privacy

- Basic Techniques
  - Private Information Retrieval
  - Probabilistic Approach
    - Stationary
    - Temporal



What is Location Privacy

- Location Based Services (LBS)
  - Yelp, Google+, facebook, Instagram, Twitter…
  - Restaurant check-in, finding the nearest gas station, navigation, tourist city guide, …
- Location Sharing
  - Find Friends, Find my iphone, …
- Location Based Social Networks
  - Foursqure, Swarm

- Risks?
  - Give your location data for the service

Location Privacy

- Risks
  - Give your location traces to Google, Apple or other service providers
  - Enable malicious apps to know your locations
    - http://www.cnbc.com/2016/08/01/pokemon-go-and-other-apps-are-putting-your-privacy-at-risk.html
  - Sharing in Facebook, but available throughout internet
  - Locations may be leaked to other attackers through network
  - Physical danger, e.g. http://pleaserobme.com/
- User's choices
  - Use LBS, give up privacy
  - Or preserve privacy, give up the LBS
  - Can we achieve the two goals: utility and privacy?

Features of Location Privacy

- Vs. Standard Differential Privacy
  - Differential Privacy: the outputs are similar whether a user opts in or out
  - For LBS, only one user
- Data Type
  - Standard Differential Privacy: tuples in Database
  - Location Privacy: where a user is
- Location data is only two-dimensional
  - Or at most three-dimensional

Techniques

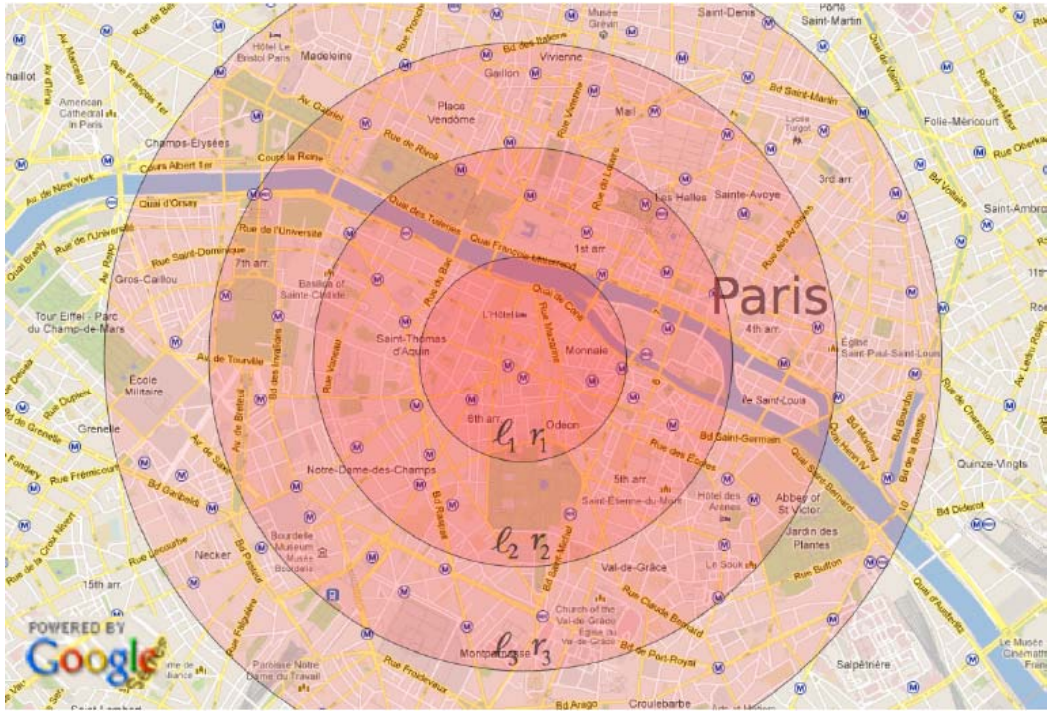
- Encryption-based Techniques
  - Private Information Retrieval
- Probabilistic Techniques
  - Location obfuscation, location cloaking
  - Location generalization
- Continuous Protection
  - Temporal correlations

Private Information Retrieval (PIR)

- Allow user to query database while hiding the identity of the data-items she is querying.
  - What is the nearest restaurant to me?
  - Send a query to the server
  - Get a restaurant from the server
- Computational PIR
  - Homomorphic encryption
- Intensive Computational Cost

Probabilistic Techniques

- Spatial Cloaking/Location Generalization
  - Instead of sending the exact location to the service providers, a user can send a “general area”.



Location Obfuscation

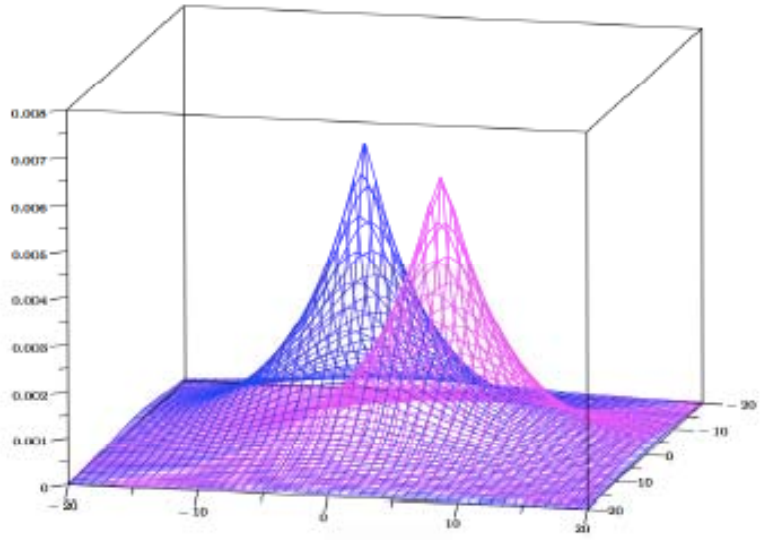
- Location Obfuscation
  - Instead of sending the exact location to the service providers, a user can send a “noisy” location.
  - Essentially, similar to spatial cloaking.
    - With the “general area”, a point can be randomly chosen to represent the “noisy” location.
    - The posterior probability of the “noisy” location will be the same as the “general area”. Can you prove it?

Probabilistic Techniques

- Privacy Guarantee
  - Uniform distribution in a circle
  - Uniform distribution in a polygon
  - Laplace distribution
  - Other distributions: 2D Gaussian distribution
- The trade-off between utility and privacy
  - What is the expected distance between the noisy location and the real location?
  - How much extra information does the noisy location give to attackers?
  - Can you derive the above distance function and the privacy function?

Geo-indistinguishability

- Geo-indistinguishability
  - A “differentially private” cloaking method
  - Based on the 2D Laplace distribution
  - Randomly draw a point from the distribution



Geo-indistinguishability

- Definition
  - Pr(z|x)<=e^{epsilon}*Pr(z|x')
  - Where x and x' are any two locations in a circle with a radius r, z is the noisy location
- Features
  - Location data: x and x' are two points on a map
  - Neighboring databases: any points in the circle
  - Protection: indistinguishability in the circle

Geo-indistinguishability

- Geo-indistinguishability
  - How to prove the privacy?

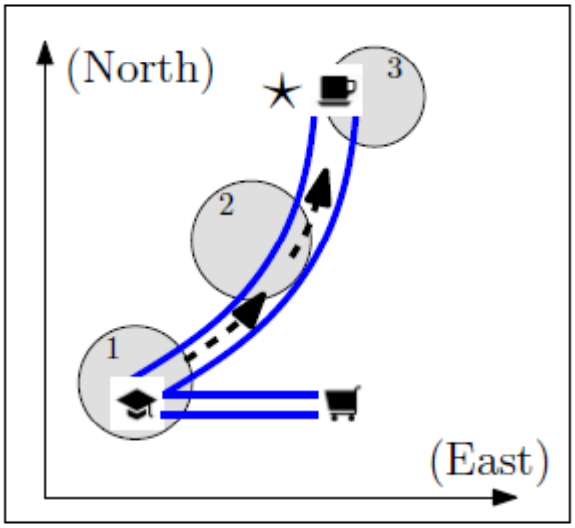
$$D_\epsilon(x_0)(x) = \frac{\epsilon^2}{2\pi} e^{-\epsilon\, d(x_0,x)}$$

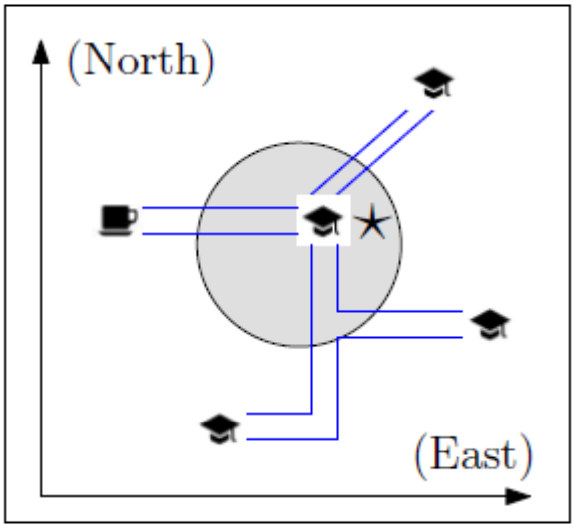
  - How much differential privacy can it provide?

- Open question:
  - Can you come up with a better sampling algorithm than the paper (Geo-indistinguishability ,CCS13)

Continuous Approach

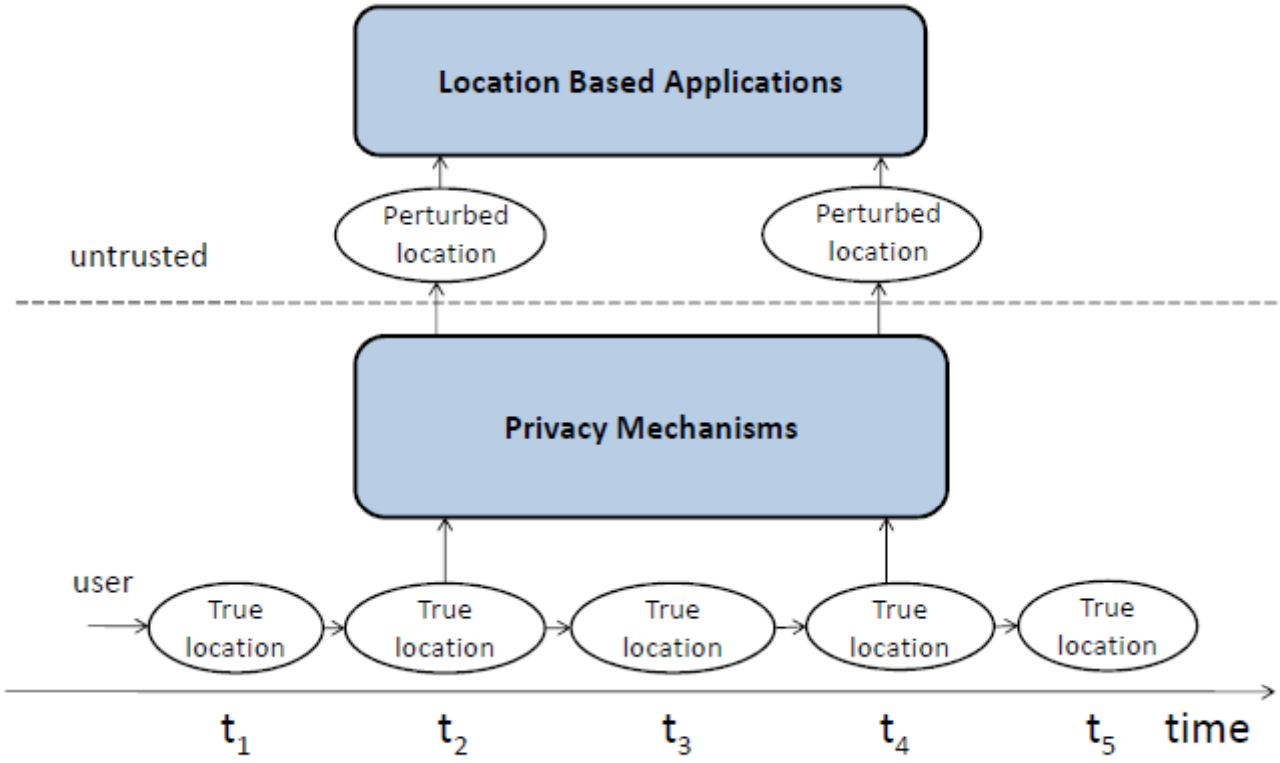
- Potential problems of the cloaking algorithms at stationary timestamps.
  - Not private in a period of time.
  - Examples:





Continuous Approach

- Location Release over time

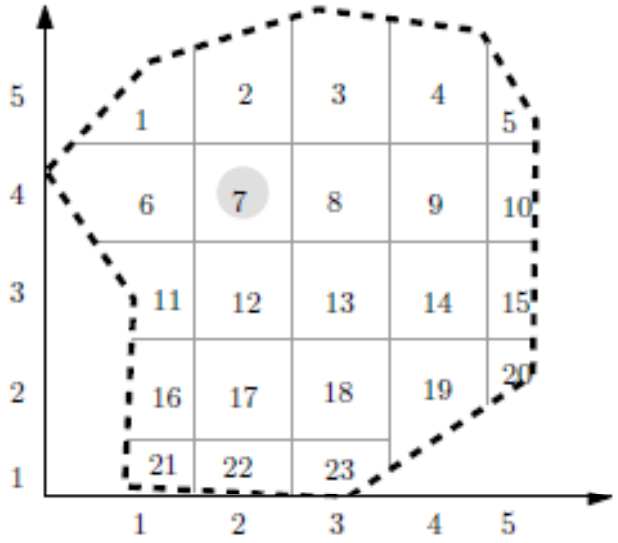


Continuous Approach

- Temporal Correlations
  - Road network
  - Moving patterns of a user
  - Example:
    - Given that Alice is at MSC building now, she may go to Starbucks with probability 0.3, DUC with probability 0.3, and library with probability 0.4.
- How to describe such correlations?
  - A common method is to use Markov model

Markov Model

- Markov Model
  - Coordinate System



$$\mathbf{u} = \mathbf{s}_7 = [\ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 1\ \ 0\ \ \cdots\ \ 0\ ]$$

$$\mathbf{x} = [2,4]^T \ \textit{with}\ \mathbf{x}[1] = 2\ \textit{and}\ \mathbf{x}[2] = 4$$

Markov Model

- Markov Model
  - Transition Matrix
    - A matrix M denotes the probabilities that a user moves from one location to another
  - M_{i,j} is the probability of moving from location i to location j.
    - M_{i,j} is the element of ith row and jth column.

Markov Model

- Markov Model
  - Emission Probability
    - Given the real location i, what is the probability distribution of the noisy locations?

$$Pr(\mathbf{z}_t | \mathbf{u}_t^* = \mathbf{s}_i)$$

  - Inference and Evolution

$$\mathbf{p}_t^+[i] = Pr(\mathbf{x}_t = \mathbf{s}_i | \mathbf{z}_t) = \frac{Pr(\mathbf{z}_t | \mathbf{x}_t = \mathbf{s}_i)\mathbf{p}_t^-[i]}{\sum_j Pr(\mathbf{z}_t | \mathbf{x}_t = \mathbf{s}_j)\mathbf{p}_t^-[j]}$$

Markov Model

- Derive the possible locations at current timestamp
  - Bayesian inference using the previously released locations.
  - A set of possible locations can be generated.
- Only protect the true location within this set of possible locations.
  - Recall the definition of “neighboring databases”
  - What is the new neighboring databases here?

Extended Differential Privacy

Definition (Differential Privacy)

At any timestamp t, a randomized mechanism $\mathcal{A}$ satisfies ϵ-differential privacy on δ-location set if, for any output $\mathbf{z}_t$ and any two locations $\mathbf{x}_1$ and $\mathbf{x}_2$ in δ-location set, the following holds:

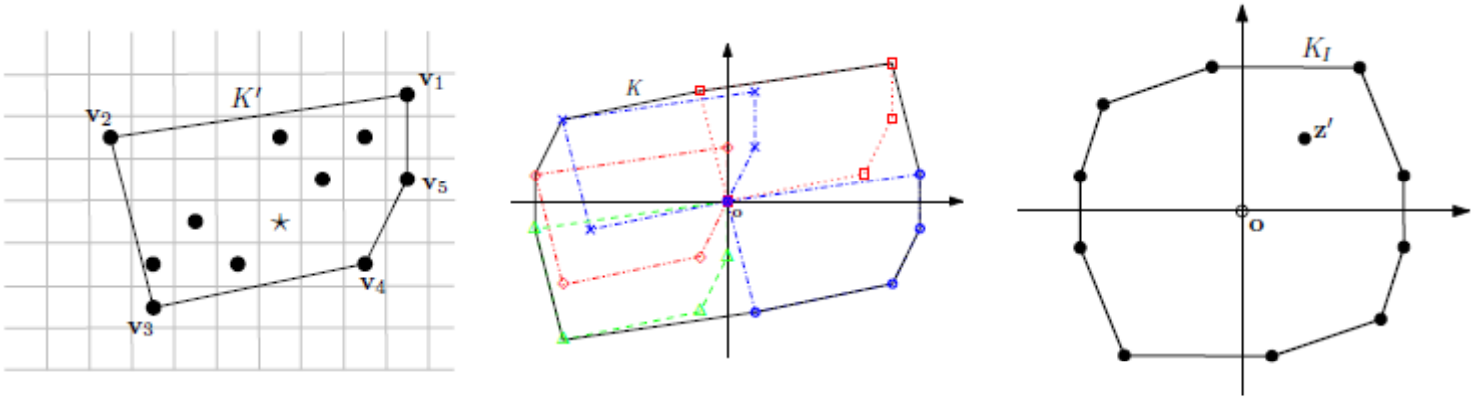
$$\frac{Pr(\mathcal{A}(\mathbf{x}_1) = \mathbf{z}_t)}{Pr(\mathcal{A}(\mathbf{x}_2) = \mathbf{z}_t)} \leq e^{\epsilon}$$

Intuition

the released location $\mathbf{z}_t$ (observed by the adversary) will not help an adversary to differentiate any instances in δ-location set.

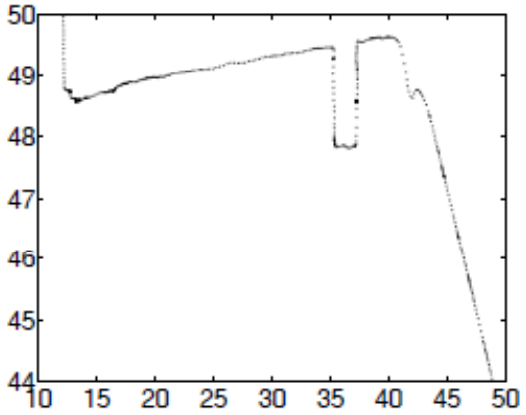
Probability Design

- Design a distribution on the set of possible locations.

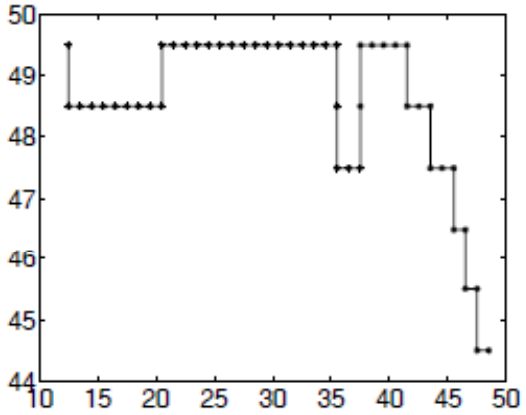


Continuous Released Locations

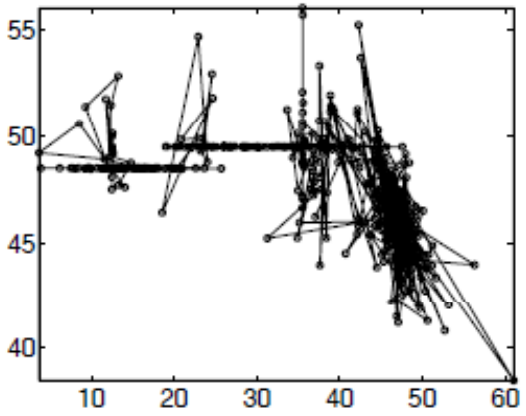
- Example: Released “Noisy” Locations



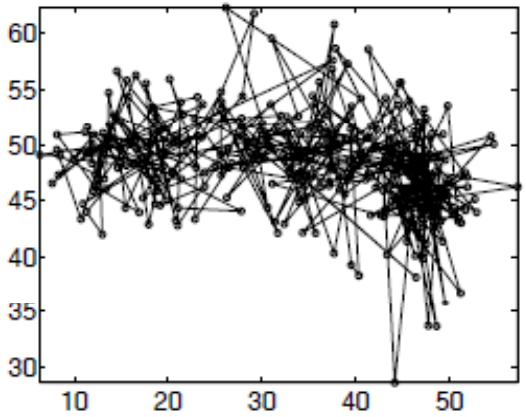
Original trace in map coordinate



Original trace in state coordinate



PIM released trace



LM released trace

References

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- Protecting Locations with Differential Privacy under Temporal Correlations, CCS, 2015
- Quantifying Location Privacy, IEEE SP 2011
- In-Network Trajectory Privacy Preservation, ACM Computing Surveys (CSUR) 2015