ESORICS 2020

PGLP: Customizable and Rigorous Location Privacy through Policy Graph

Yang Cao[1] , Yonghui Xiao[2], Shun Takagi[1] , Li Xiong[2] , Masatoshi Yoshikawa[1], Yilin Shen[3], Jinfei Liu[2], Hongxia Jin[3], and Xiaofeng Xu[2]

[1] Kyoto University, [2] Emory University, [3] Samsung Research America

Outline

- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

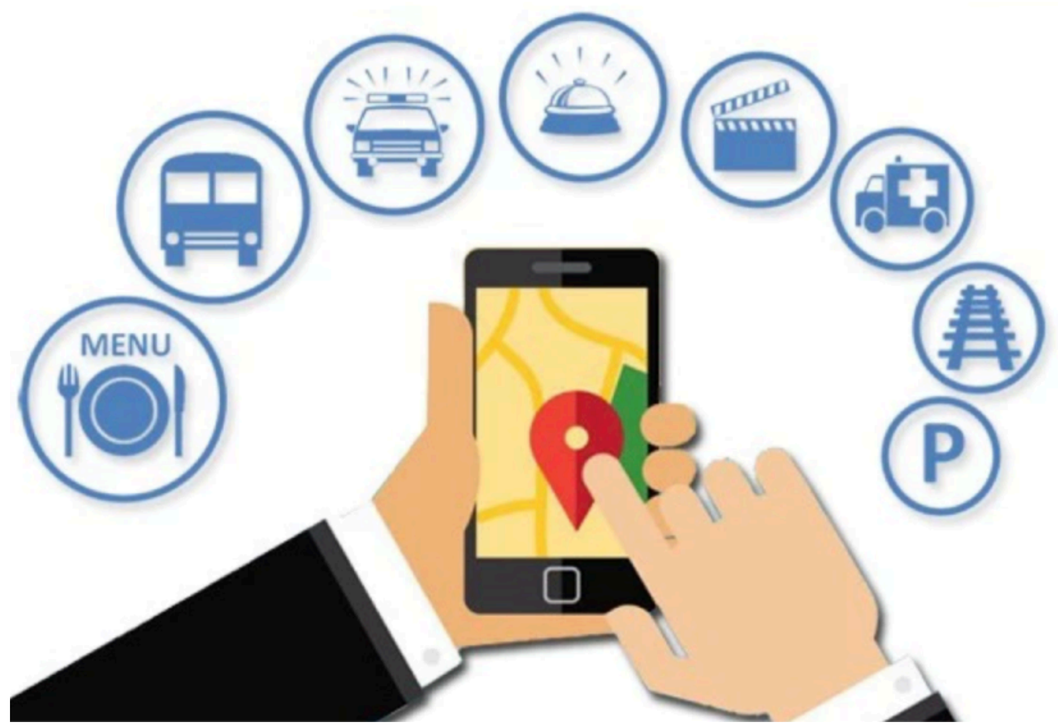
Outline

- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

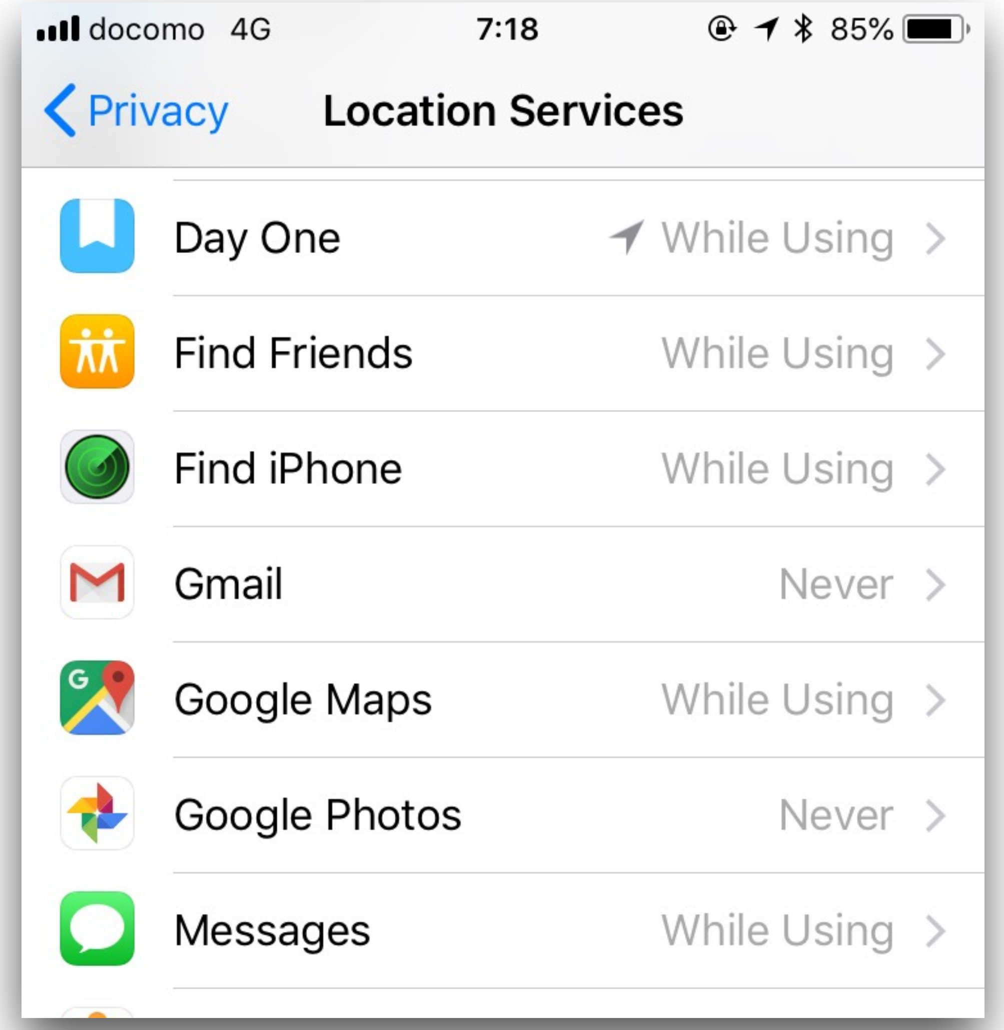
Motivation

Location data: valuable but sensitive

- Useful in our daily life for Location-based Service (LBS)



Uber 食べログ YAHOO! JAPAN

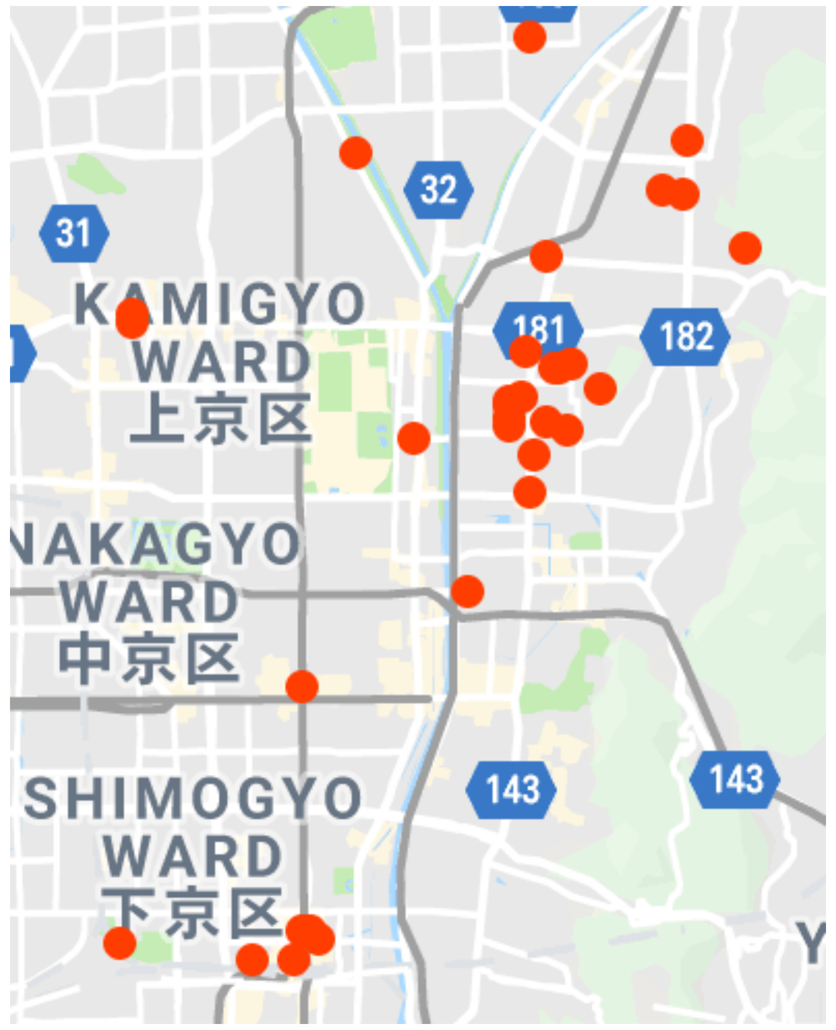


- Fundamental in research areas IoT, Crowdsourcing, Smart City..

Motivation

Location data: valuable but sensitive

- risky for an individual
  - reveal many sensitive info: identification, home, office, lifestyle, hobbies…



Google Map “frequently visited locations”

- risky for companies who utilize user location data


BBC

CNBC

TECH

Europe's huge privacy fines against Marriott and British Airways are a warning for Google and Facebook

Motivation

How to Protect Location Privacy

- general **idea**: add **uncertainty** to the true location

true loc.

Location
Privacy
Protection
Mechanis

noisy loc.

"what is weather tomorrow near my location?"

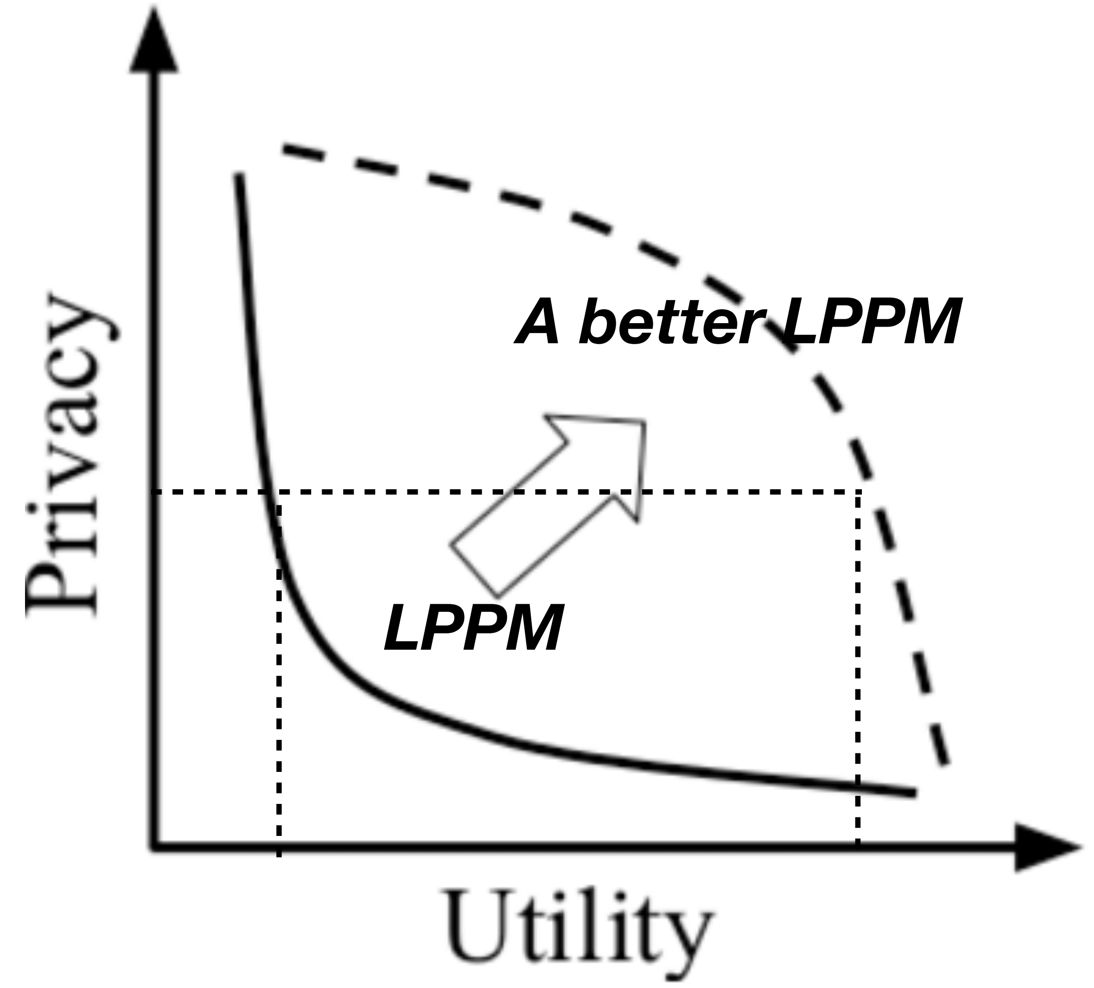
My location = Kyoto University — *better utility*

My location = Kyoto City. — *better privacy*

- general **research goal**: better tradeoff between privacy and utility

Location Privacy Model

Privacy Definition: metrics of privacy	**LPPM:** achieve a privacy metrics with high utility



Motivation

Existing Location Privacy Definitions

extended from K-anonymity

- location k-anonymity, [MobiSys03].
- mix zone, [PerCom03].
- The New Casper [VLDB06].
- maximum arrival boundary [TKDE12].

extended from Differential Privacy (DP)

- Geo-Indistinguishability [CCS13].
- δ-location set privacy [CCS15].

Motivation

Existing Location Privacy Definitions are Not Sufficient

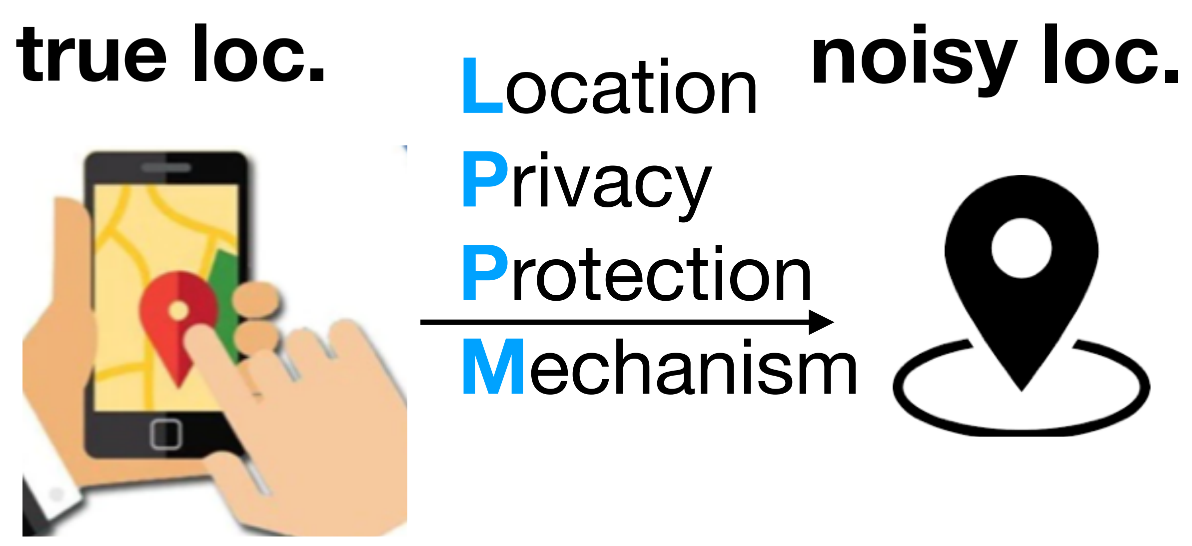
- K-anonymity based Location privacy is not rigorous
    - L-diversity argue K-anonymity has flaws
    - T-closeness say: L-diversity has flaws
    - ….
- Existing DP-based location privacy is not customizable
    - Only use one parameter ε to control the privacy-utility trade-off.
    - However, different LBS may have different requirements on privacy or utility.

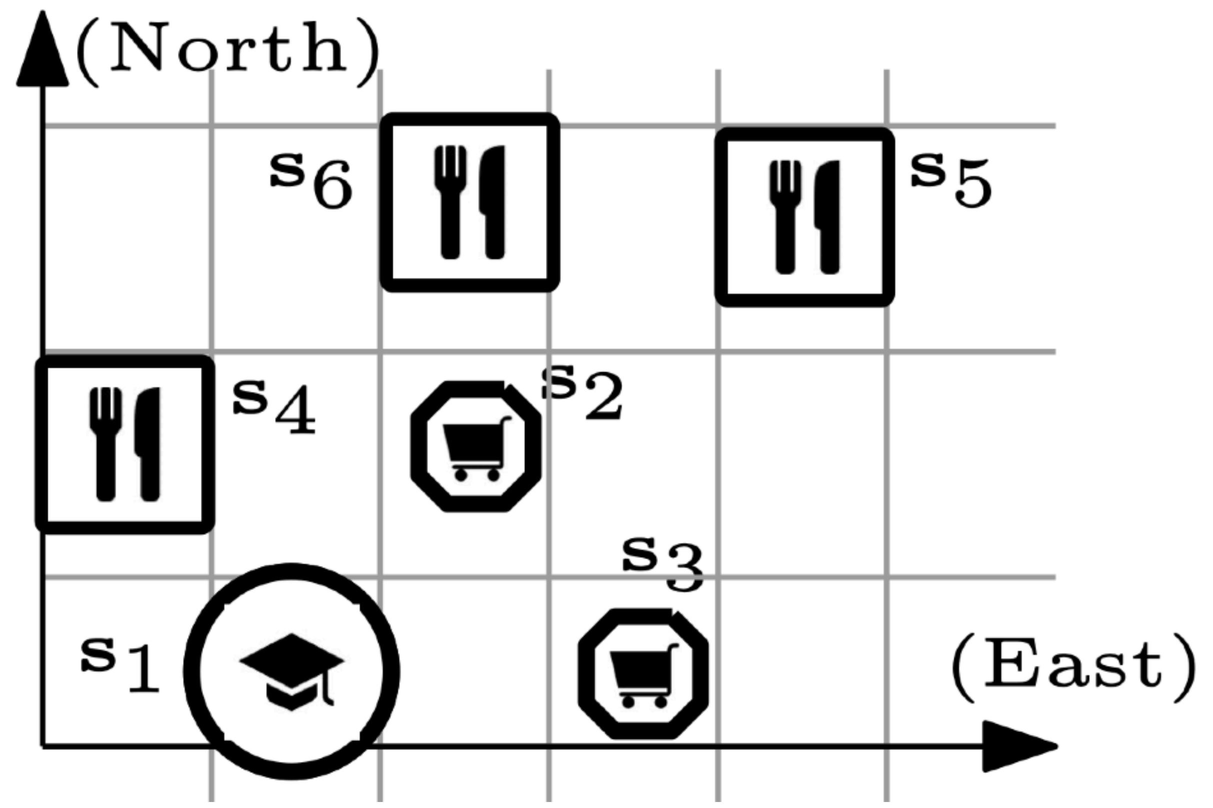
$$\frac{\Pr(M(l) = o)}{\Pr(M(l') = o)} \leq e^{\epsilon \cdot d(l,l')}$$

Motivation

Different LBS, Different Utility Requirement

- City-level weather forecast
  - Query: which city is the user in?
  - High utility when the noisy location is in the same city of the true location.
- Location-based advertising
  - Query: what kind of loc. (shopping mall/restaurant) is the user in?
  - High utility when the noisy location has the same category of the true location.
- Location-based Social Network
  - Query: where is my nearest friend?
  - High utility when the distance between two noisy locations is similar to the distance between the true locations.





Outline

- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

Our Solution

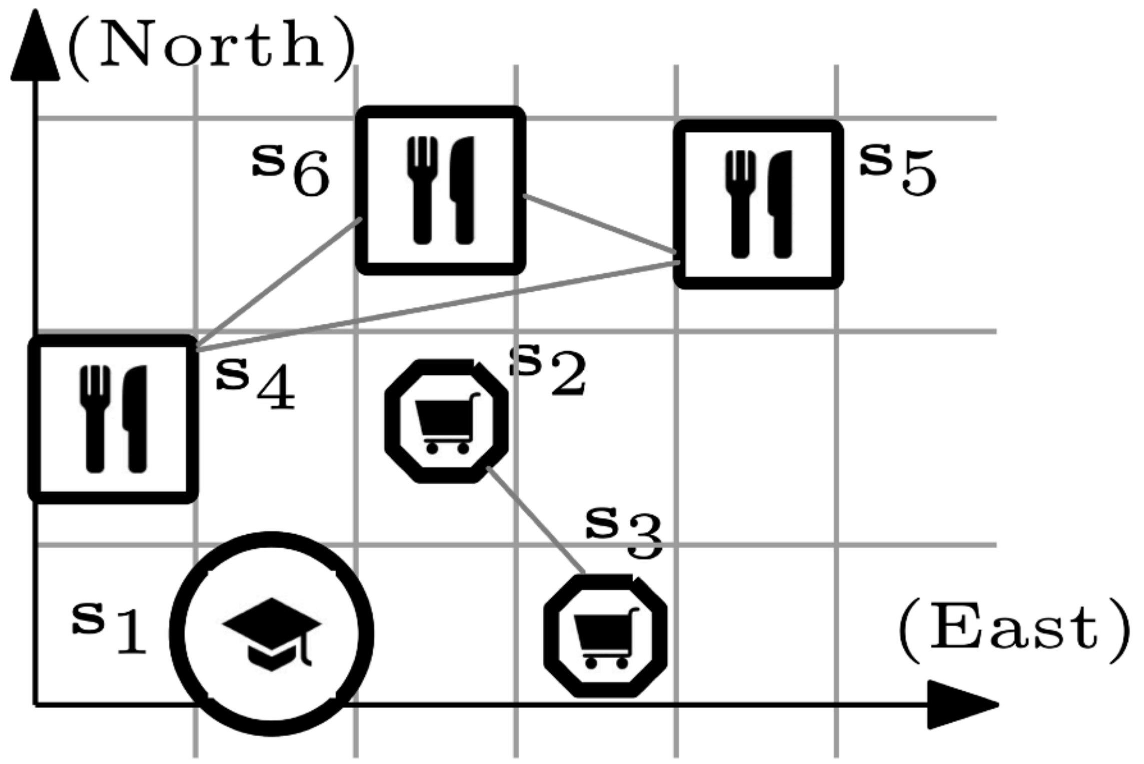
Intuitions for a Customizable and Rigorous Location Privacy

- Inspired by Blowfish Privacy [SIGMOD14], the privacy-utility Tradeoff can be fine-tuned by “*Privacy Policies*”:
    - **secrets**: what are the secrets that we need to protect?
    - **constraints**: what does the adversary know?
- However, Blowfish Privacy cannot be directly applied in location privacy.
    - Location privacy: single user, point query on single record (location).
    - Statistical privacy: multiple users, aggregate query on a database.
- How to formalize Location Privacy Policy and how to achieve it?

Our Solution : PGLP

Location Policy Graphs

- How to formalize these polices? — Location Privacy Policy Graph
  - Nodes: the user's possible locations.
  - Edges: the two connected locations need to be indistinguishable to the adversary



- The right policy is a good fit for "Location-based advertising"
  - High utility if the noisy location has the same category of the true location.
  - Policy: "*allowing the app to access the semantic category (e.g., a restaurant or a shop) of a user's location but ensuring indistinguishability among locations with the same category*"

Our Solution : PGLP

Definition

- **key idea**: only satisfy the indistinguishability defined in the given policy graph.
- Location Policy Graph:

Definition 3 (Location Policy Graph). *A location policy graph is an undirected graph $\mathcal{G} = (\mathcal{S}, \mathcal{E})$ where $\mathcal{S}$ denotes all the locations (nodes) and $\mathcal{E}$ represents indistinguishability (edges) between these locations.*

- Policy Graph-based Location Privacy:

Definition 6 ($\{\epsilon, \mathcal{G}\}$-Location Privacy). *A randomized algorithm $\mathcal{A}$ satisfies $\{\epsilon, \mathcal{G}\}$-location privacy iff for all $\boldsymbol{z} \subseteq Range(\mathcal{A})$ and for all pairs of neighbors $\boldsymbol{s}$ and $\boldsymbol{s}'$ in $\mathcal{G}$, we have $\frac{\Pr(\mathcal{A}(\boldsymbol{s})=\boldsymbol{z})}{\Pr(\mathcal{A}(\boldsymbol{s}')=\boldsymbol{z})} \leq e^{\epsilon}$.*

Our Solution : PGLP

Definition

- PGLP is a generalization of DP-based location privacy definitions.
  - it reduces to Geo-Indistinguishability [CCS13] and δ-location set privacy [CCS15] under different configuration of the policy graph.

Theorem 1. *An algorithm satisfying $\{\epsilon, \mathcal{G}_1\}$-location privacy also achieves ϵ-Geo-Indistinguishability.*

Theorem 2. *An algorithm satisfying $\{\epsilon, \mathcal{G}_2\}$-location privacy also achieves δ-Location Set privacy.*

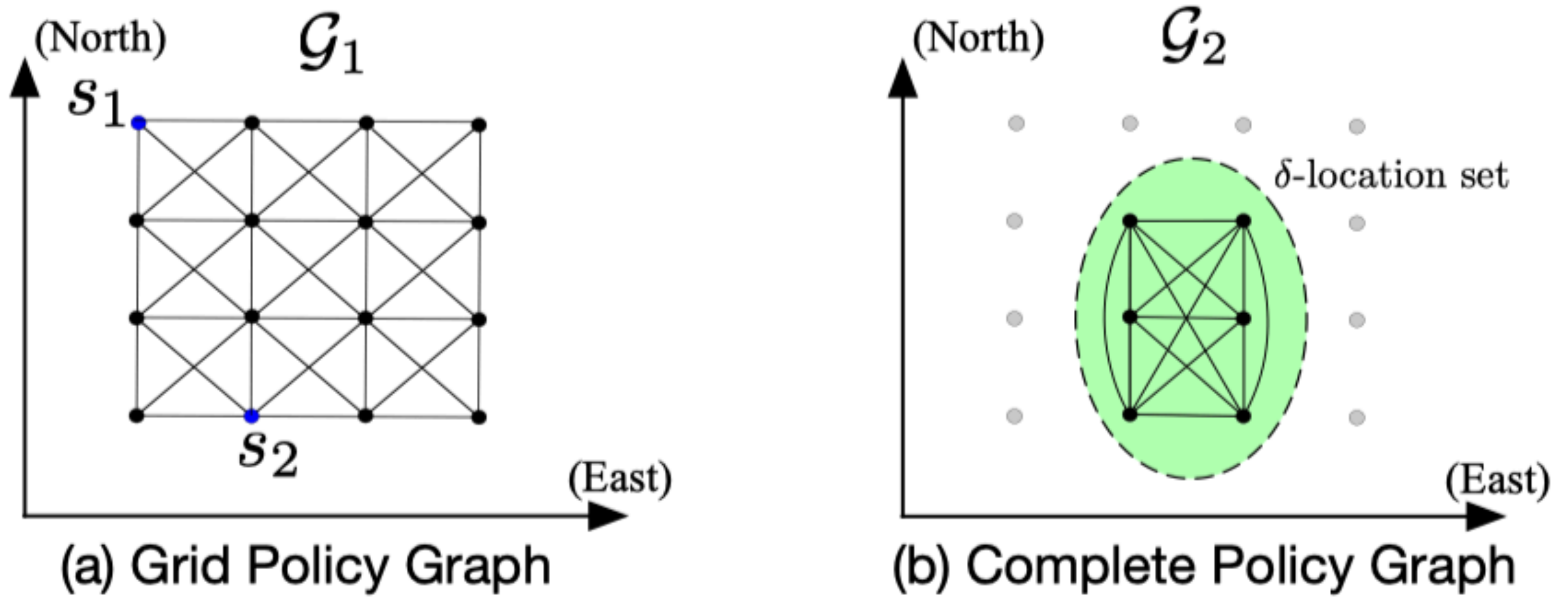


Fig. 2: Two examples of location policy graphs.

Our Solution : PGLP

Mechanisms

- **key idea**: calibrate the sensitivity w.r.t. a given policy graph.

Algorithm 1 Policy-based Laplace Mechanism (P-LM)

Require: ϵ, $\mathcal{G}$, the user's true location $\mathbf{s}$.

1: Calculate $S_f^{\mathcal{G}} = sup||\big(f(\mathbf{s}) - f(\mathbf{s}')\big)/d_{\mathcal{G}}(\mathbf{s}, \mathbf{s}')||_1$ for all $\mathbf{s}' \in \mathcal{N}^{\infty}(\mathbf{s})$;

2: Perturb location $\mathbf{z}' = f(\mathbf{s}) + [Lap(S_f^{\mathcal{G}}/\epsilon), Lap(S_f^{\mathcal{G}}/\epsilon)]^T$;

3: **return** a location $\mathbf{z} \in \mathcal{S}$ that is closest to $\mathbf{z}'$ on the map.

Algorithm 2 Policy-based Planar Isotropic Mechanism (P-PIM)

Require: ϵ, $\mathcal{G}$, the user's true location $\mathbf{s}$.

1: Calculate $K(\mathcal{G}) = Conv||\big(f(\mathbf{s}) - f(\mathbf{s}')\big)/d_{\mathcal{G}}(\mathbf{s}, \mathbf{s}')||_1$ for all $\mathbf{s}' \in \mathcal{N}^{\infty}(\mathbf{s})$;

2: $\mathbf{z}' = f(\mathbf{s}) + Y$ where Y is two-dimension noise drawn by Eq.(1) with sensitivity hull $K(\mathcal{G})$;

3: **return** a location $\mathbf{z} \in \mathcal{S}$ that is closest to $\mathbf{z}'$ on the map.

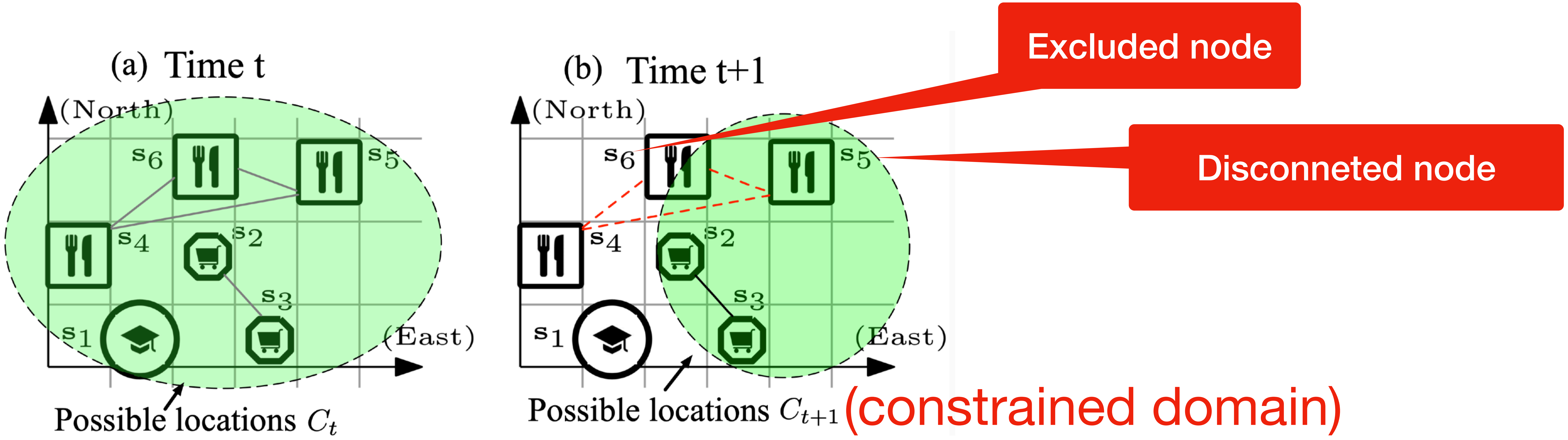
Outline

- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

PGLP for Continuous Release

Challenges

- The user possible location set may change over time.



- Location Exposure under constrained domain:
  If the user is at s5, the attacker may be able to figure out her true loc.

- Not all of the disconnected node will lead to Location Exposure, which also depends on the mechanism.

PGLP for Continuous Release

Countermeasure: Risk Detection and Policy Repair algorithm

- Detect Isolated Node in a policy graph

  Isolated Node: the disconnected node that causes location exposure.

- Repair a policy graph with high utility.

  Key idea: add an edge to protect the isolated node.

Algorithm 3 Finding Isolated Node

Require: $\mathcal{G}$, $\mathcal{C}$, disconnected node $\mathbf{s}_i \in \mathcal{C}$.

$\Delta f^{\mathcal{G}} = \bigvee_{\overline{\mathbf{s}_j\mathbf{s}_k} \in \mathcal{E}^{\mathcal{C}}} (f(\mathbf{s}_j) - f(\mathbf{s}_k))$;

$K(\mathcal{G}^{\mathcal{C}}) \leftarrow Conv(\Delta f^{\mathcal{G}})$;

for all $\mathbf{s}_j \in \mathcal{C}, \mathbf{s}_j \neq \mathbf{s}_i$ **do**

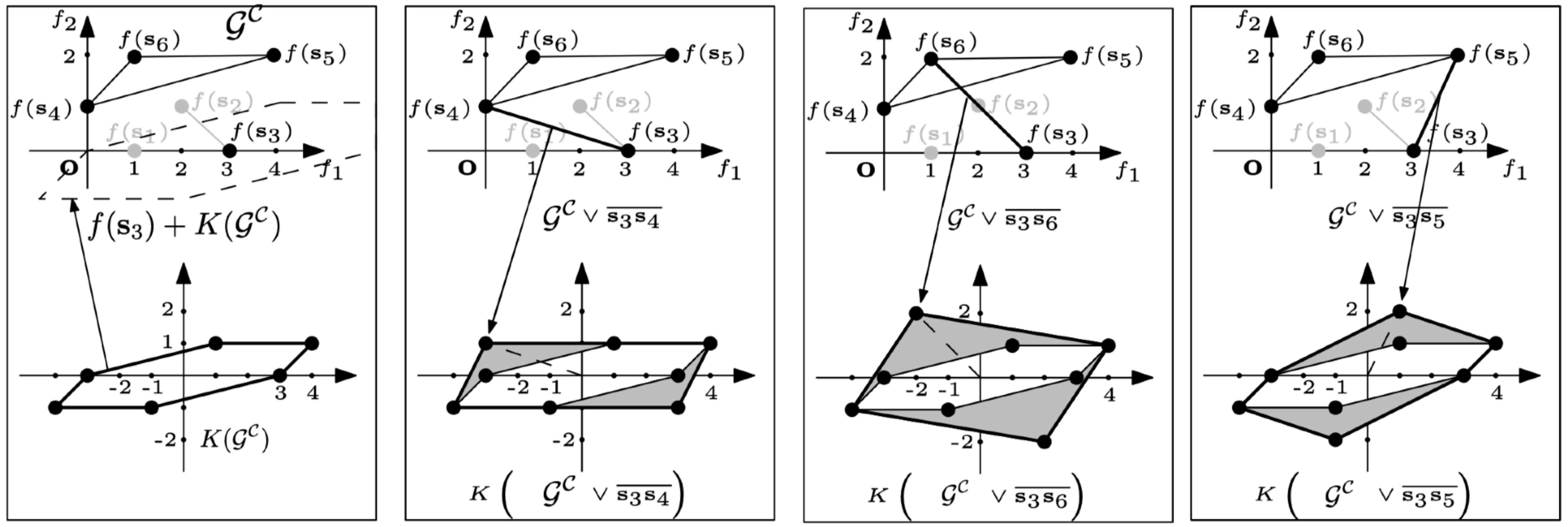
    if $Conv(\Delta f^{\mathcal{G}}, f(\mathbf{s}_j) - f(\mathbf{s}_i)) == K(\mathcal{G}^{\mathcal{C}})$ **then**

        return false

    end if

end for

return true



(a) (b) (c) (d)

See our paper for more details.

PGLP for Continuous Release

An end-to-end Location Trace release framework

- Pipelines the *calculation of constrained domains*, *isolated node detection*, *policy graph repair*, and *private location release mechanism*.
- Utilizing HMM model (assume transition and initial probabilities are known)

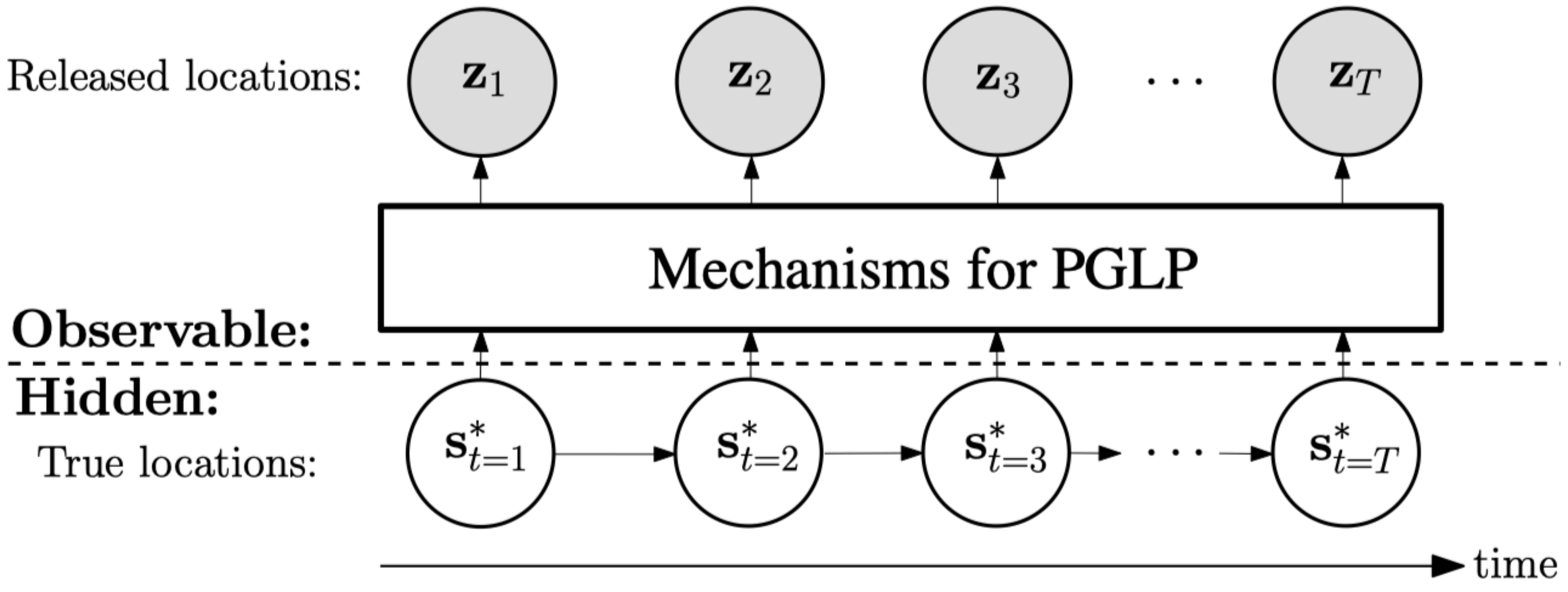


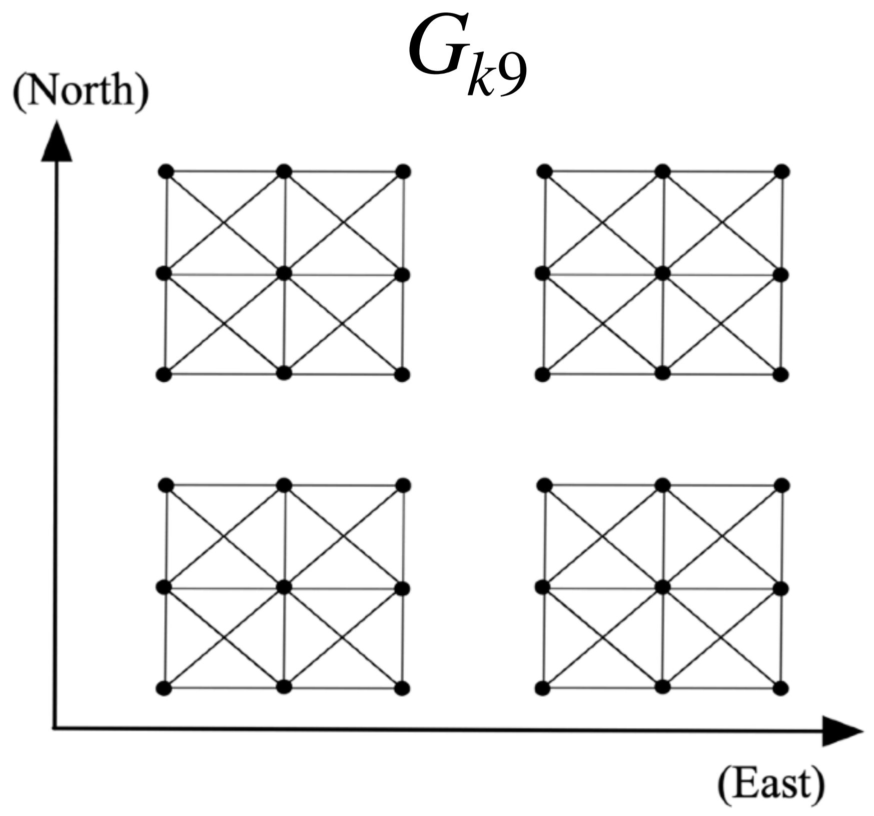
Fig. 5: Private location trace release via HMM.

Outline

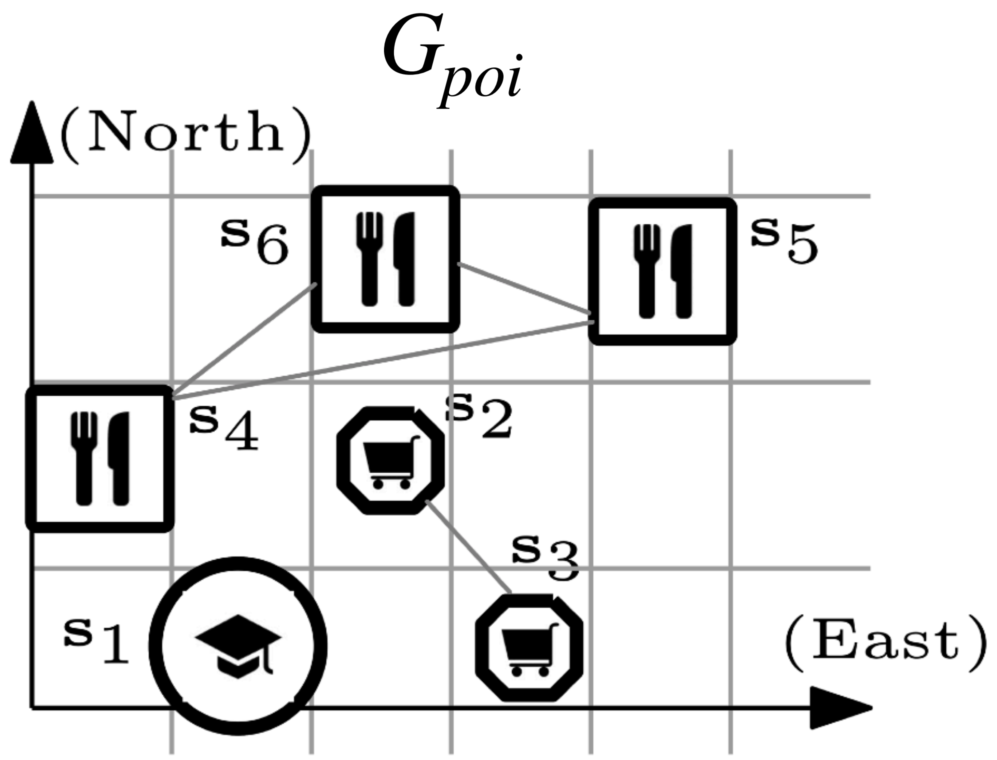
- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

Experiments

- How different location policy graphs affect the privacy-utility tradeoffs?
- Settings:
  - Two types of location policy graphs:
    - “block-graph": G_{k9}, G_{k16}, G_{k25} suitable for weather apps
    - “category-graph”: G_{poi} suitable for location-based advertising



  - Three types of Utilities
    - E_{eu} : Euclidean distance between noisy and true locations. suitable for weather apps
    - E_r : L0 distance between range queries on noisy and true locations, like “whether the released location is in the same region with the true location”
    - E_{poi} : L0 distance between category queries on noisy and true locations, like “whether the released location is the same category with the true location”. suitable for location-based advertising



Experiments

E_{eu}, E_r, E_{poi} the lower the better.

Verified that we can flexibly design suitable policy w.r.t. the desired utility & privacy.

- Observations: G_{k9} is best for E_{eu} and E_r ; G_{poi} is the best for E_{poi}.

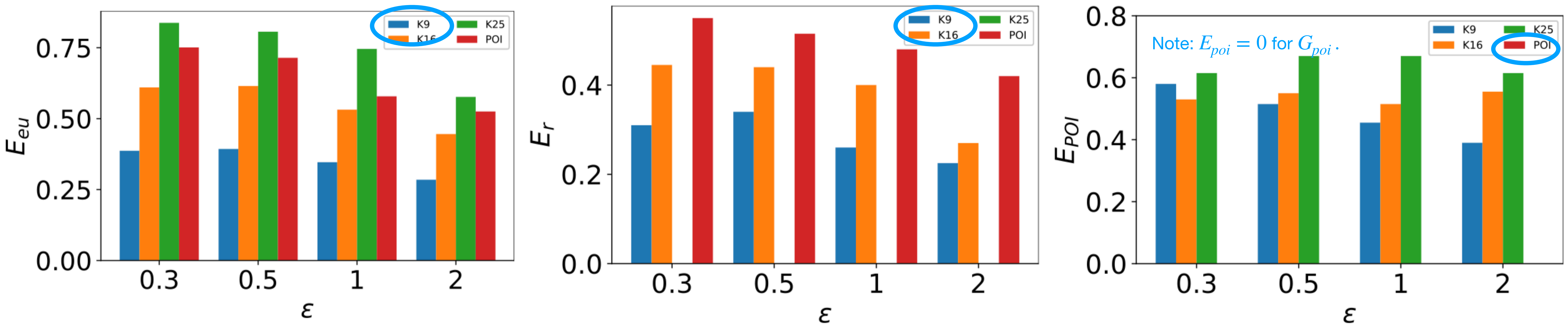


Fig. 7: Utility of different policy graphs.

(check the paper for more experimental results)

Outline

- Motivation
  — why we need a customizable and rigorous location privacy model.
- Our Solution: Policy Graph based Location Privacy (PGLP)
  — a flexible interface for location privacy to tune privacy-utility tradeoffs.
- PGLP for Location Trace Release
  — challenges and countermeasures when using PGLP continuously.
- Experiments
- Conclusion & Future work

Conclusion & Future Work

- Takeaway
  - PGLP provides a rich interface for privacy-utility tradeoff in location privacy.
- Future directions
  - Design advanced mechanisms for PGLP
  - Design optimal policy graphs for location-based applications, such as spatial crowdsourcing.