



Differential Privacy of Populations in Routing Games

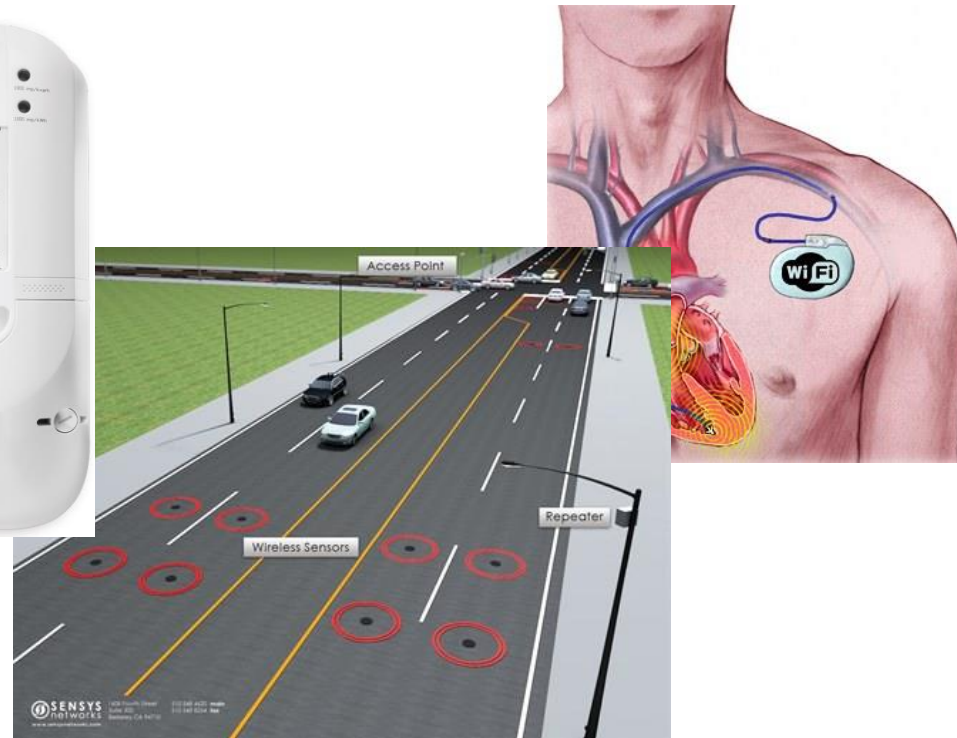
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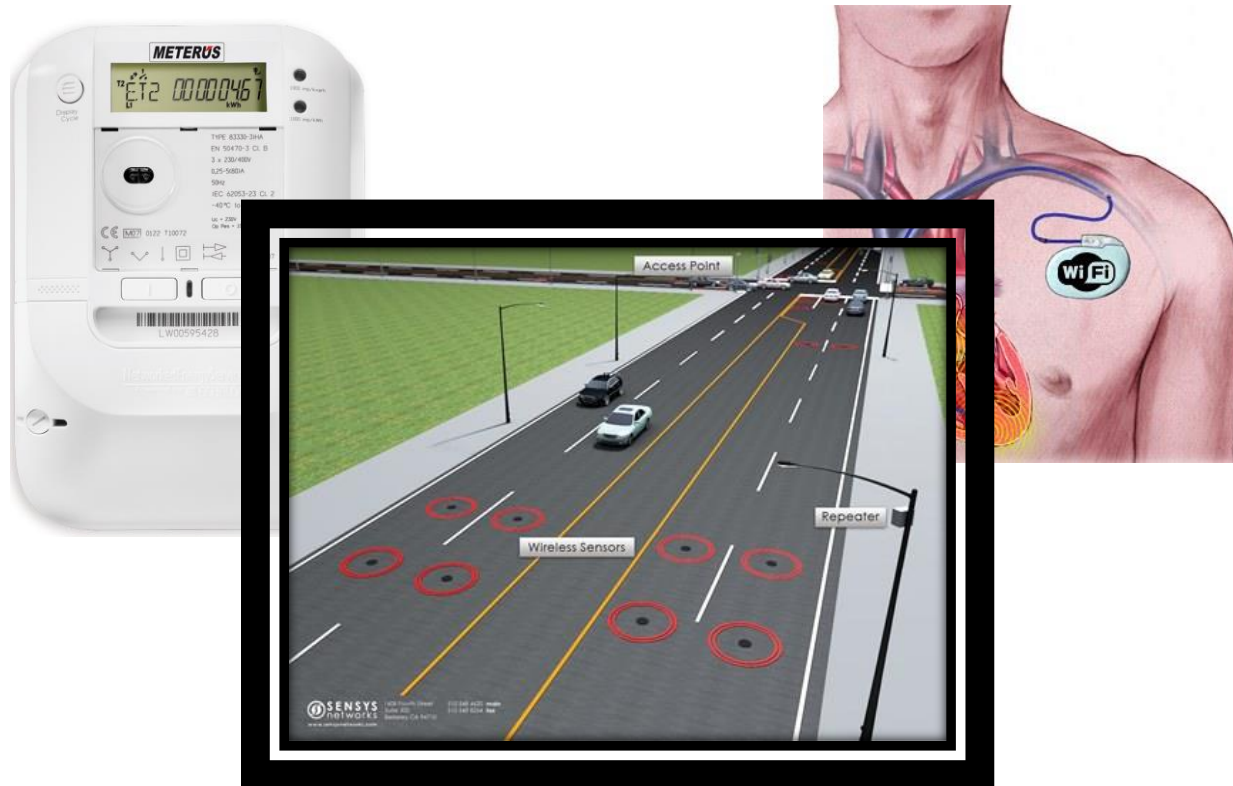
Privacy in Human Cyber-Physical Systems

- * **Ubiquity** of sensing and actuation modalities.



Privacy in Human Cyber-Physical Systems

- * **Ubiquity** of sensing and actuation modalities.



Privacy

- * What conception of privacy are we using?



Privacy

- * What type of disclosure are we concerned with?
 - * **Identity** disclosure.
 - * **Attribute/inferential** disclosure.



Differential Privacy

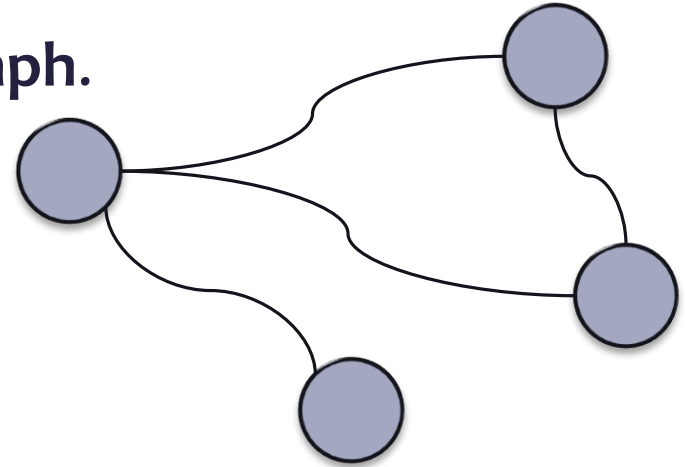
- * The “gold standard” for database privacy.
 - * Pros:
 - * Models arbitrary side information.
 - * Has “composition” theorems.
 - * Cons:
 - * Needs an aggregate of a large population.
 - * Often needs a noise source of a particular form.

Outline

- * Introduction to the Routing Game
- * Definitions of Differential Privacy for the Routing Game
- * Theoretical Results

The Routing Game

- * Represent the traffic network as a **graph**.
- * Traffic is abstracted as **flow**.
 - * Drivers are **non-atomic**.
- * Agents have fixed origins and destinations, and decide which **path** to take.
- * The cost of an edge **depends on the total flow** on that edge.



Definition of the Routing Game

Definition: The *routing game* is given by:

A directed graph $G = (V, E)$.

For each edge $e \in E$, edge cost functions $c_e: \mathbb{R}_+ \rightarrow \mathbb{R}_+$.

- These functions are assumed to be non-decreasing and Lipschitz continuous.

A finite set of origin-destination pairs $(o_i, d_i) \in V \times V$, indexed $i \in \{1, 2, \dots, I\}$.

A finite set of populations P_k , indexed $k \in \{1, 2, \dots, K\}$.

- A population is defined by a vector $\theta_k \in \mathbb{R}_+^I$.

Actions in the Routing Game

- * For each origin-destination pair (o_i, d_i) :
 - * Let \mathcal{P}_i denote the set of paths that connect o_i to d_i .
 - * Then, let:

$$\Delta^{\mathcal{P}_i} = \left\{ m \in \mathbb{R}_+^{|\mathcal{P}_i|} : \sum_{p \in \mathcal{P}_i} m_p = 1 \right\}$$

Actions in the Routing Game

- * Populations decide how to allocate mass for each origin-destination pair.
- * For each origin-destination pair (o_i, d_i) , the population k chooses how to allocate $(\theta_k)_i$ of flow among the paths connecting o_i to d_i .
- * **Actions:** $x_k \in \Delta^{\mathcal{P}_1} \times \Delta^{\mathcal{P}_2} \times \dots \times \Delta^{\mathcal{P}_I}$.
- * So: $(x_k)_i \in \Delta^{\mathcal{P}_i}$, and population k allocates a flow of $(\theta_k)_i ((x_k)_i)_p$ to $p \in \mathcal{P}_i$.

Losses in the Routing Game

- * Suppose each population picks its action.
- * Then, the flow on edge e is:

$$\phi_e(x_1, \dots, x_K) = \sum_{k=1}^K \sum_{i=1}^I \sum_{\{p \in \mathcal{P}_i : e \in p\}} (\theta_k)_i ((x_k)_i)_p$$

- * The loss on path p is:

$$\ell_p(x_1, \dots, x_K) = \sum_{e \in p} c_e(\phi_e(x_1, \dots, x_K))$$

- * Let $\ell(x_1, \dots, x_K)$ denote the vector of all path losses.

Losses in the Routing Game

- * Finally, the cost for each population k is:

$$\sum_{i=1}^I \sum_{p \in \mathcal{P}_i} (\theta_k)_i ((x_k)_i)_p \ell_p(x_1, \dots, x_K)$$

- * More succinctly:

$$\langle x_k, \ell(x_1, \dots, x_K) \rangle_{\theta_k}$$

Observation Model

- * At each time t , populations observe a noisy version of the loss vector $\hat{\ell}^{(t)}$.

Assumption:

$$\hat{\ell}^{(t)} = \ell \left(x_1^{(t)}, x_2^{(t)}, \dots, x_K^{(t)} \right) + v_t$$

The v_t are independent across time and identically distributed according to a $N(0, \sigma^2)$ distribution.

Dynamics of the Routing Game

- * How do drivers decide **which path** to take?
 - * Based on their new observation and previous decision.

Routing Game Dynamics:

$$x_k^{(t+1)} = \operatorname{argmin}_{x_k \in \Delta^{\mathcal{P}_1} \times \Delta^{\mathcal{P}_2} \times \dots \times \Delta^{\mathcal{P}_I}} \langle x_k, \hat{\ell}^{(t)} \rangle_{\theta_k} + \frac{1}{\eta_k^{(t)}} D_{\psi_k} \left(x_k, x_k^{(t)} \right)$$

- * Here, D_{ψ} is the *Bregman divergence* of ψ :

$$D_{\psi}(x, y) = \psi(x) - \psi(y) - \langle \nabla \psi(y), x - y \rangle$$

Dynamics of the Routing Game

$$x_k^{(t+1)} = \underset{x_k \in \Delta^{\mathcal{P}_1} \times \Delta^{\mathcal{P}_2} \times \dots \times \Delta^{\mathcal{P}_I}}{\operatorname{argmin}} \langle x_k, \hat{\ell}^{(t)} \rangle_{\theta_k} + \frac{1}{\eta_k^{(t)}} D_{\psi_k} \left(x_k, x_k^{(t)} \right)$$

$\langle x_k, \hat{\ell}^{(t)} \rangle_{\theta_k}$: Minimize losses with respect to the most recent observed loss.

$D_{\psi_k} \left(x_k, x_k^{(t)} \right)$: Penalize large changes.

$\eta_k^{(t)}$: Learning rate for population k .

The Routing Game

* In our privacy framework:

θ : The origins and destinations.

$u = \psi_e \left(x_1^{(t)}, x_2^{(t)}, \dots, x_K^{(t)} \right)$: The flow on each edge.

$y = \hat{\ell}^{(t)}$: The observed congestion.

$$\theta \sim p_\theta$$

$$u \mid \theta \sim p_{u \mid \theta}$$

$$y \mid u, \theta \sim p_{y \mid u}$$

Differential Privacy

* Let $Y(\theta) : \theta \mapsto (\hat{\ell}^{(1)}, \hat{\ell}^{(2)}, \dots, \hat{\ell}^{(T)})$.

Definition:

Two population vectors θ and θ' are *adjacent* if there exists some k such that:

$$\|\theta_k - \theta'_k\|_\infty \leq c$$

$$\theta_{k'} = \theta'_{k'} \text{ for all } k' \neq k$$

Differential Privacy

Definition:

The routing game is (ϵ, δ) differentially private if, for any adjacent θ and θ' if for any measurable set B :

$$P(Y(\theta) \in B) \leq \exp(\epsilon) P(Y(\theta') \in B) + \delta$$

Differential Privacy

Theorem (Differential privacy of the routing game)

After T iterations, the mapping $\theta \mapsto (\hat{\ell}^{(1)}, \hat{\ell}^{(2)}, \dots, \hat{\ell}^{(T)})$ is (ϵ, δ) differentially private, where:

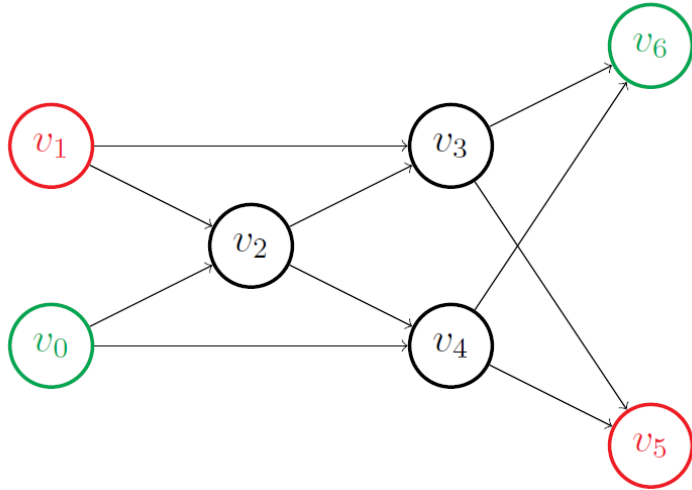
$$\epsilon = \sum_{t=1}^T \epsilon_t \quad \delta = \sum_{t=1}^T \exp\left(\sum_{t'=t+1}^T \epsilon_{t'}\right) \delta_t + \delta'$$

The constants ϵ_t , δ_t , and δ' are such that, for some a :

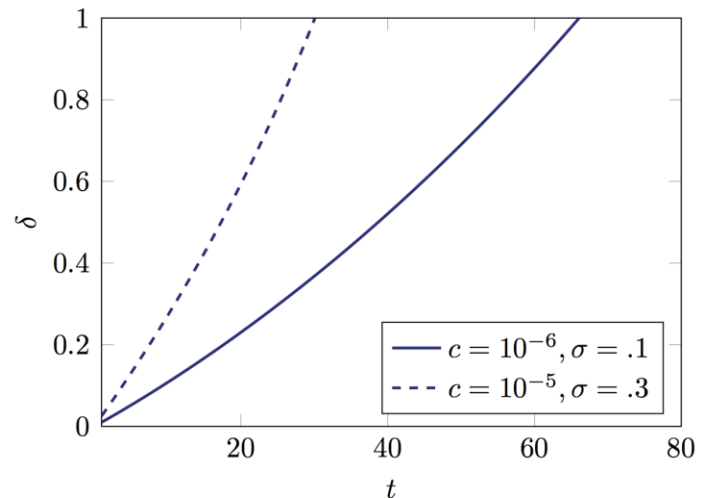
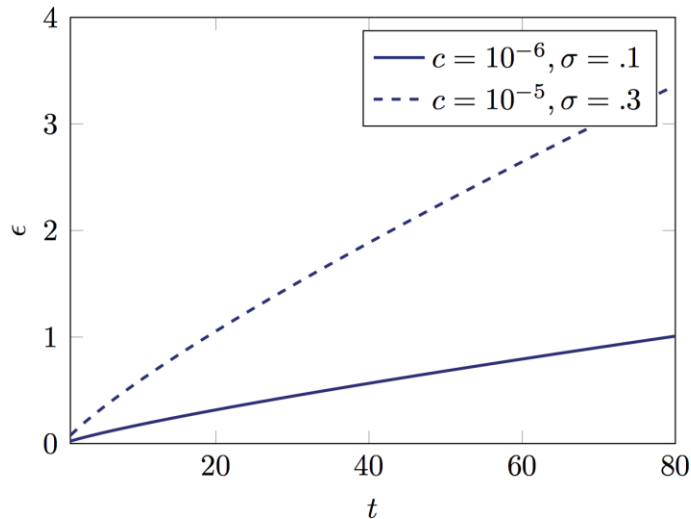
$$1 - \delta' = \left(1 - 2 \exp\left(-\frac{a^2}{2\sigma^2}\right)\right)^{T \sum_{i=1}^I |\mathcal{P}_i|}$$

$$\epsilon_t > \frac{cA_\ell A_x \left(2 \ln\left(\frac{1.25}{\delta_t}\right)\right)^{\frac{1}{2}}}{\sigma^2} \times \left[A_\Delta + \frac{A_\theta \max_k \left(\eta_k^{(t)}\right) \left(\sum_{i=1}^I |\mathcal{P}_i|\right)^{\frac{1}{2}} (M + a)}{\min_k \ell_{\psi_k}} \right]$$

Routing Game Example



$$\theta \mapsto (\hat{\ell}^{(1)}, \hat{\ell}^{(2)}, \dots, \hat{\ell}^{(T)})$$



Thanks!