Adversarial Classification Under Differential Privacy

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Kevin Ashton Describes "the Internet of Things"

The innovator weighs in on what human life will be like a century from now

By Arik Gabbai

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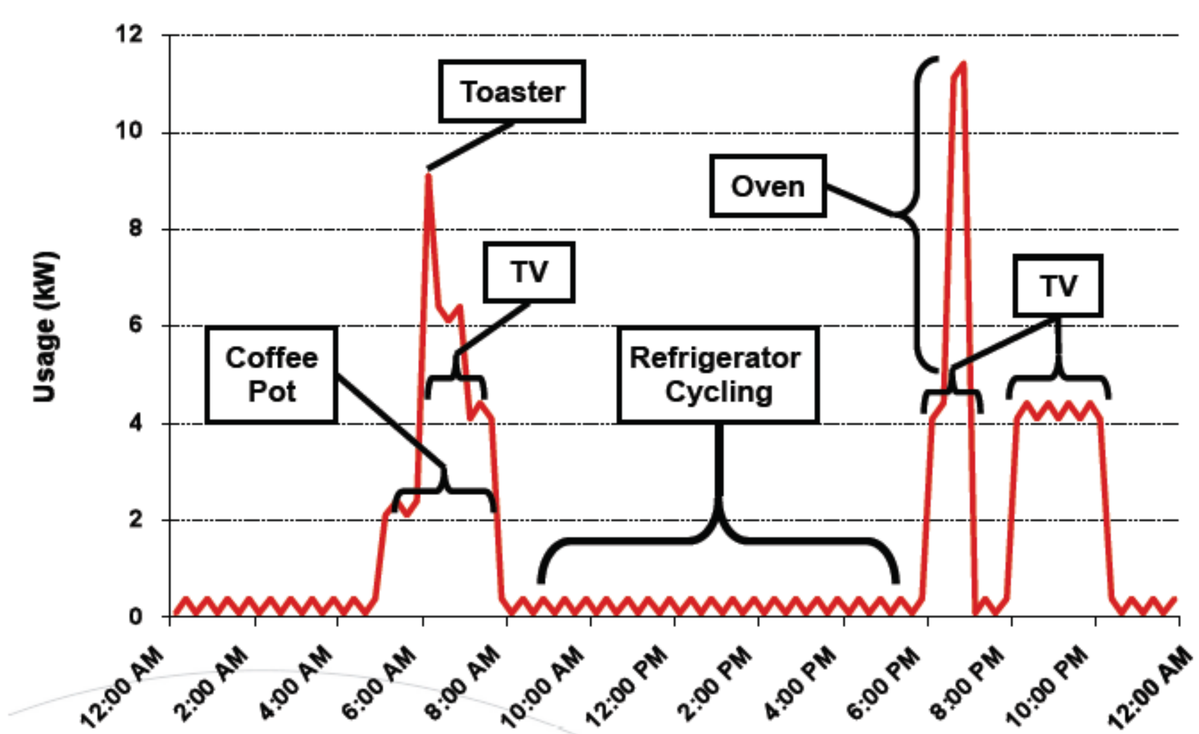
- 20th Century: computers were brains without senses—-they only knew what we told them.
- More info in the world than what people can type on keyboard
- 21st century: computers sense things, e.g., GPS we take for granted in our phones

Kevin Ashton (British entrepreneur) coined the term IoT in 1999.

New Privacy Concerns

Top car companies have disclosed their users' movements to third parties without consent (Nissan). A Ford exec has said: "We know everyone who breaks the law, we know when you're doing it. We have GPS in your car, so we know what you're doing." (Ford retracted the comments.)



In Addition to Privacy, There is Another Problem: Data Trustworthiness

Schneier on Security

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Waze Data Poisoning

People who don't want Waze routing cars through their neighborhoods are feeding it false data.

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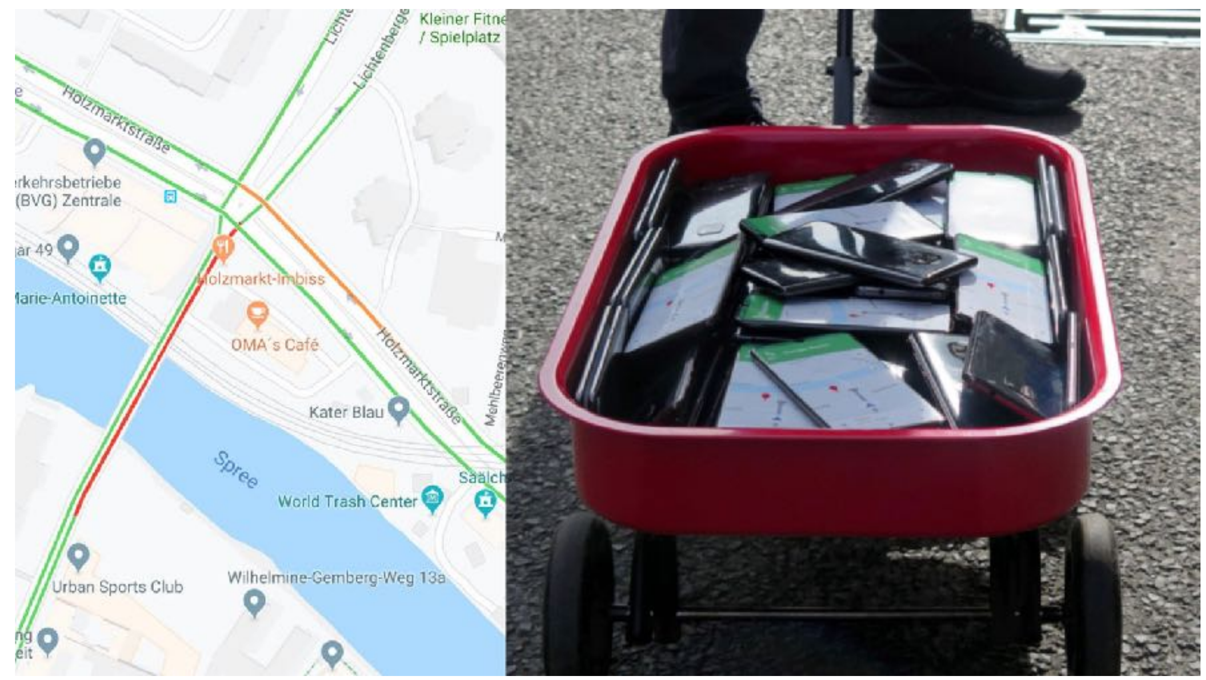
An Artist Used 99 Phones to Fake a Google Maps Traffic Jam

With his "Google Maps Hack," artist Simon Weckert draws attention to the systems we take for granted—and how we let them shape us.



Sections | The Washington Post — Democracy Dies in Darkness | Try 1 month for $1 | Sign in

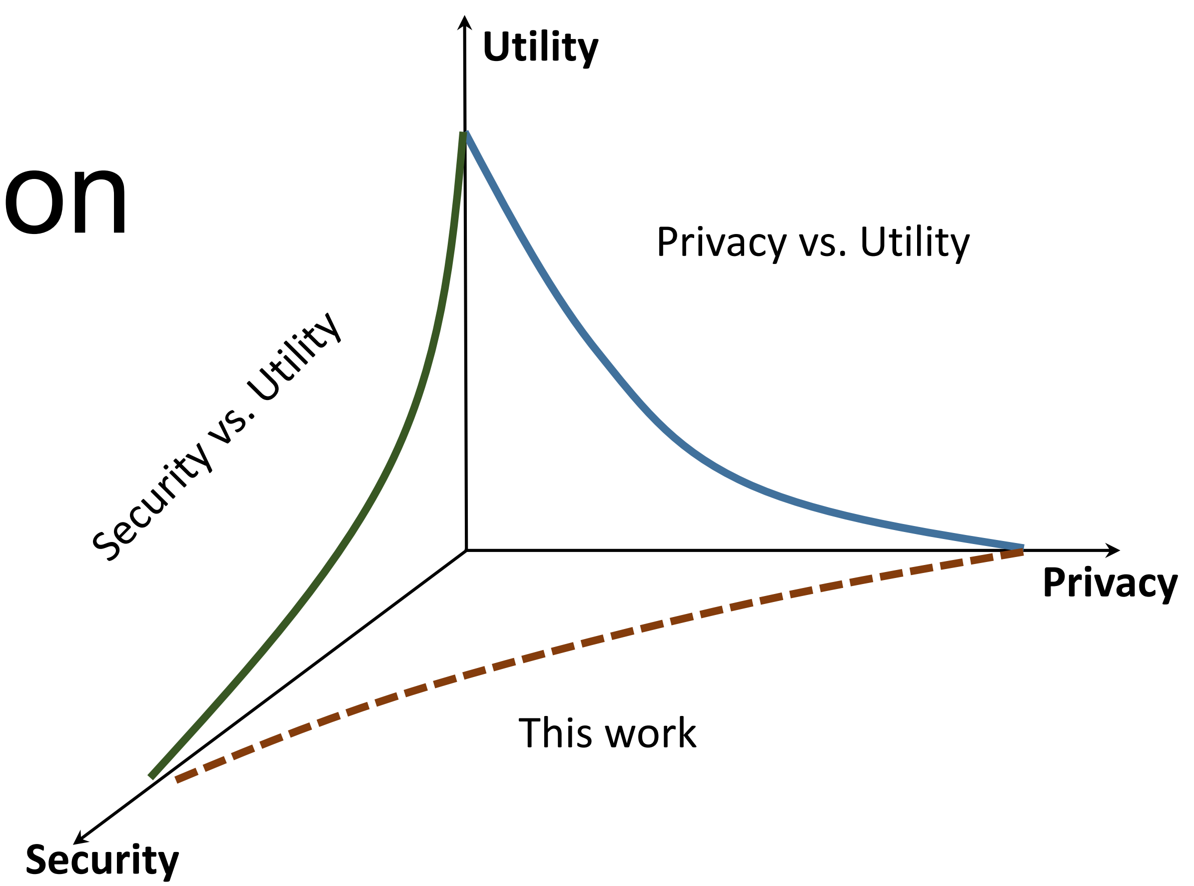
WorldViews

Israeli soldiers using Waze attacked by Palestinians after taking wrong route

By Ruth Eglash

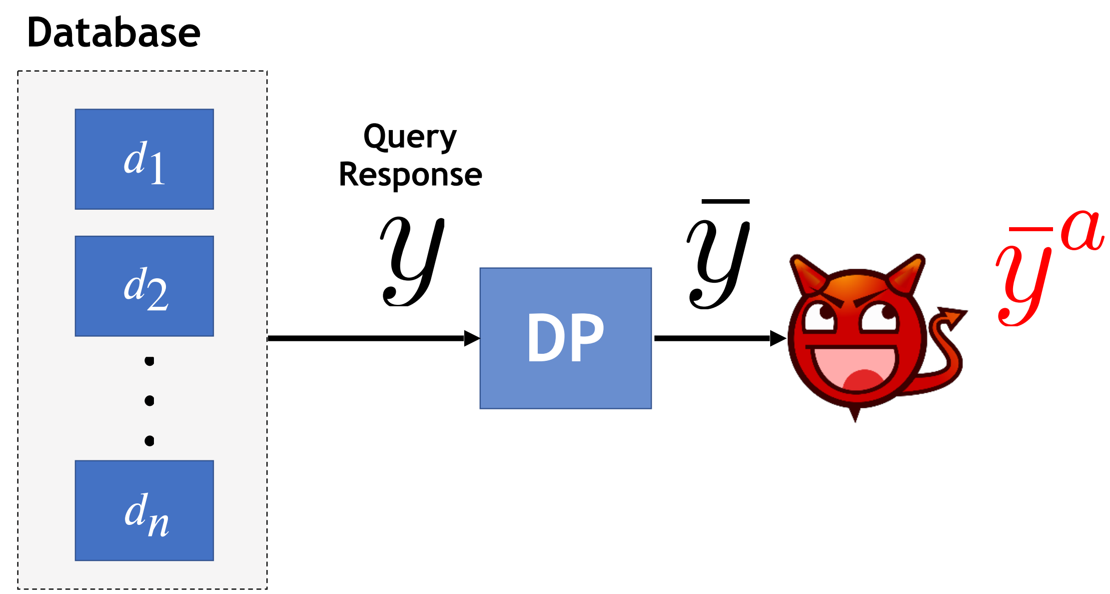
We Need to Provide 3 Properties

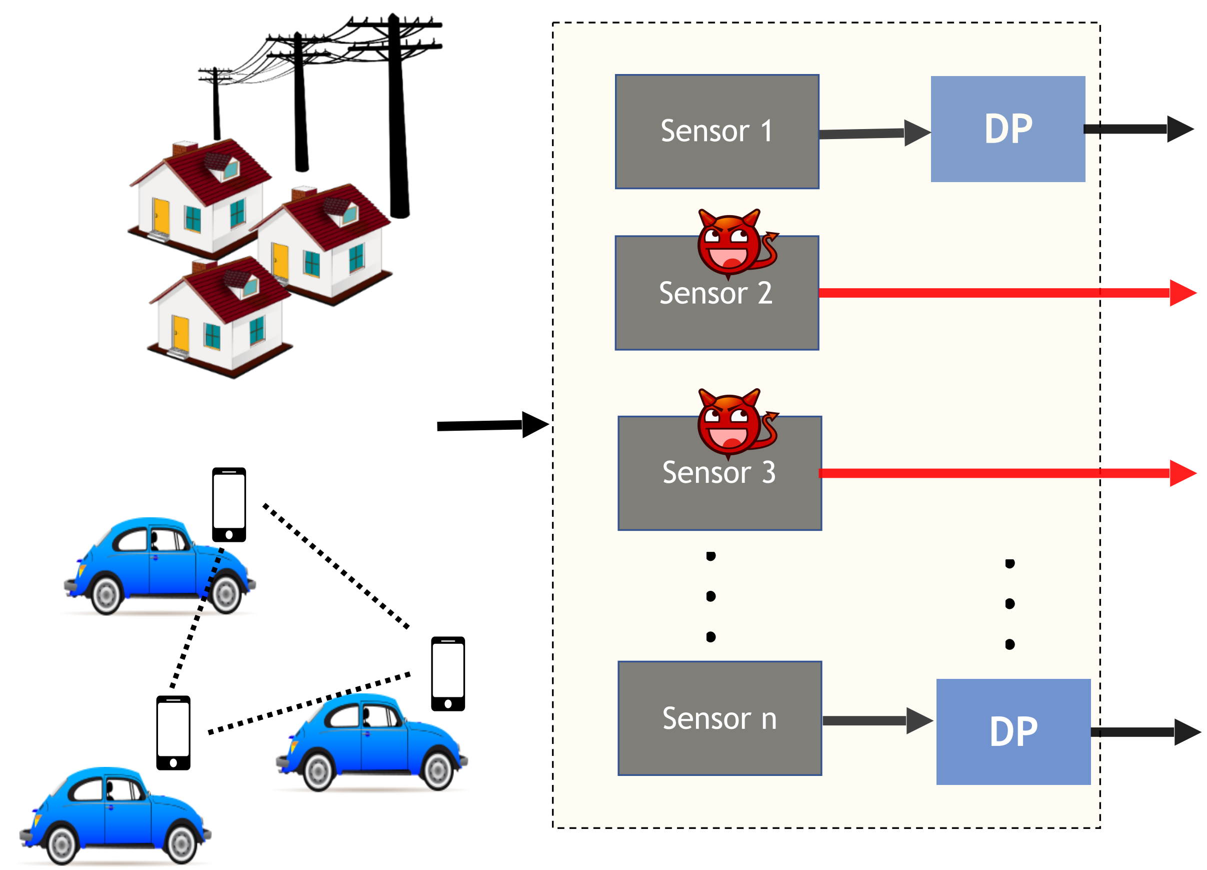
1. Classical Utility
   - Usable Statistics
   - Reason for data collection
2. Privacy
   - Protect consumer data
3. Security
   - Trustworthy data
   - Detect data poisoning
   - Different from classical utility because this is an adversarial setting



New Adversary Model

- Consumer data protected by Differential Privacy (DP)
- Classical adversary in DP is curious
  - Our adversary is different: data poisoning by hiding their attacks in DP noise
- Global and local DP





Adversary Goals

- Intelligently poison the data in a way that is hard to detect (hide attack in DP noise)
- Achieve maximum damage to the utility of the system (deviate estimate as much as possible)

Classical DP

$$\bar{\boldsymbol{Y}} \leftarrow \mathcal{M}(D)$$

$$\bar{\boldsymbol{Y}} \sim f_0$$

Attack

$$\boldsymbol{Y^a} \text{ instead of } \bar{\boldsymbol{Y}}$$

Attack Goals:
Multi-criteria Optimization

$$\max_{f_a} E[\mathbf{Y}^a]$$

$$s.t.$$

$$D_{KL}(f_a \| f_0) \leq \gamma$$

$$f_a \in \mathcal{F}$$

Functional Optimization Problem

- We have to find a probability distribution
  - A probability density function f_a
- Among all possible continuous functions as long as

$$\int_{r \in \Omega} f_a(r) dr = 1$$

- What is the shape of f_a ?

Solution: Variational Methods

- Variational methods are a useful tool to find the shape of functions or the structure of matrices
- They replace the function or matrix optimization problem with a parameterized perturbation of the function or matrix
- We can then optimize with respect to the parameter to find the "shape" of the function/ matrix
- The Lagrange multipliers give us the final parameters of the function

Solution

Maximize

$$\int_{r\in\Omega} r f_a(r)dr$$

Subject to:

$$\int_{r\in\Omega} f_a(r)\ln\left(\frac{f_a(r)}{f_0(r)}\right)dr \leq \gamma.$$

$$\int_{r\in\Omega} f_a(r)dr = 1.$$

Auxiliary Function

$$q(r,\alpha) = f_a^*(r) + \alpha p(r).$$

Lagrangian:

$$L(\alpha) = \int_{r\in\Omega} rq(r,\alpha)dr + \kappa_1\left(\int_{r\in\Omega} q(r,\alpha)\ln\frac{q(r,\alpha)}{f_0(r)}dr - \gamma\right) + \kappa_2\left(\int_{r\in\Omega} q(r,\alpha)dr - 1\right)$$

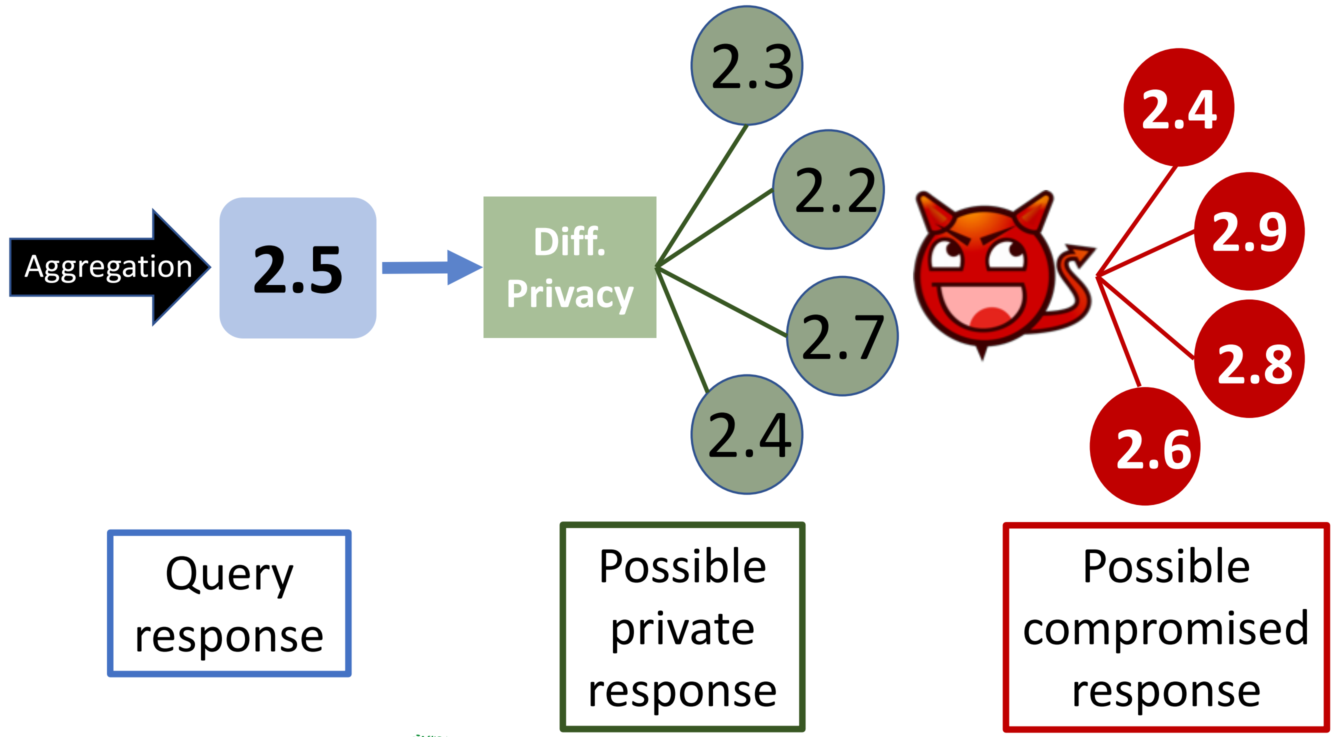
Solution:

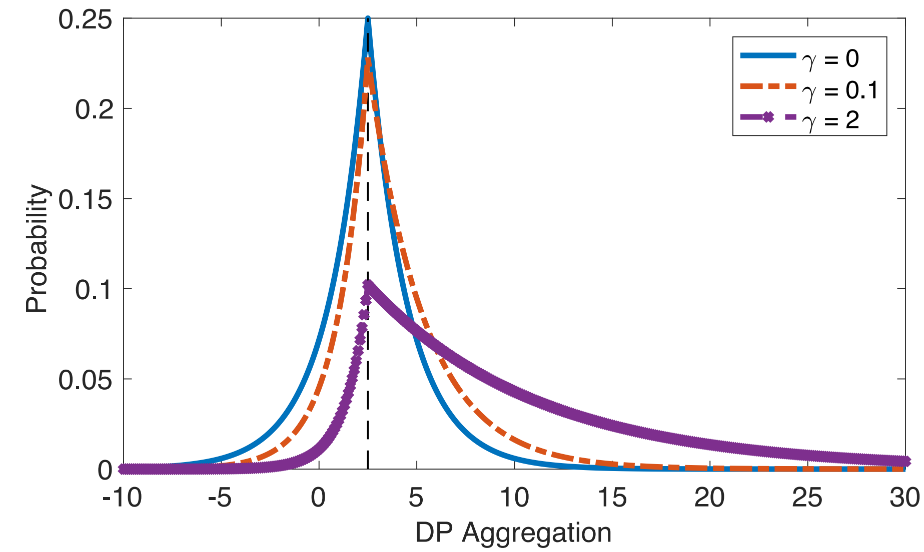
$$f_a^*(y) = \frac{f_0(y)e^{\frac{y}{\kappa_1}}}{\int f_0(r)e^{\frac{r}{\kappa_1}}dr}, \text{where } \kappa_1 \text{ is the solution to } D_{KL}(f_a^*\|f_0) = \gamma.$$

Least-Favorable Laplace Attack

User ID	Data
User 1	0.5
User 2	0.3
User 3	0.7
User 4	1

Database





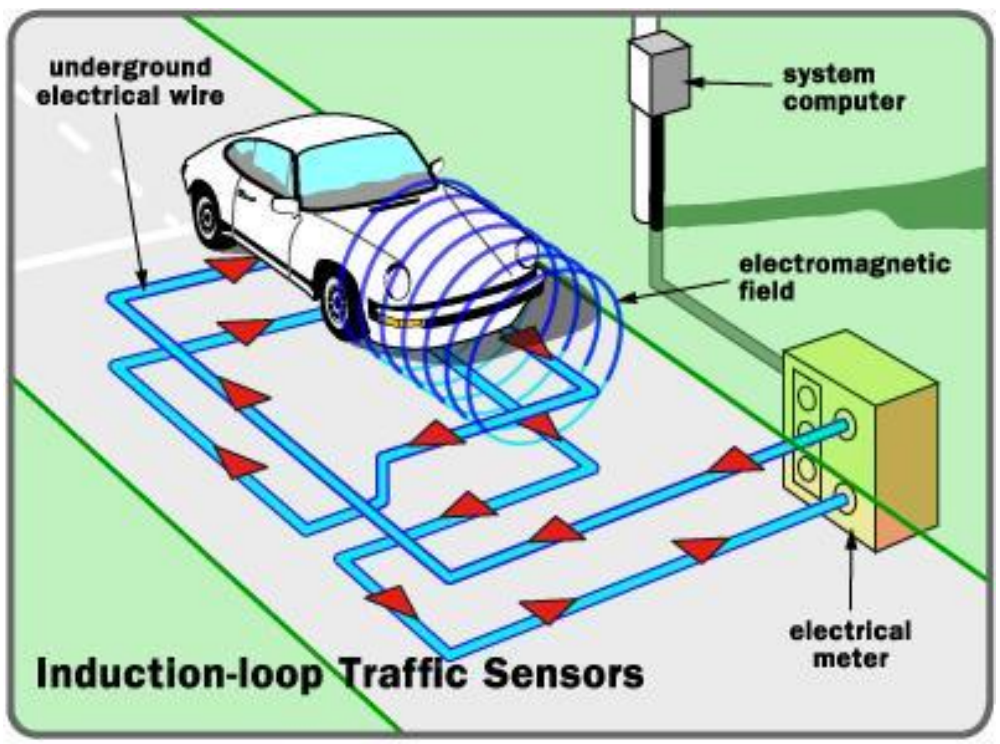
$$f_0(y) = \frac{1}{2b} e^{-|y-\theta|/b}$$

$$f_a^*(y) = \frac{\kappa_1^2 - b^2}{2b\kappa_1^2} e^{-\frac{|y-\theta|}{b} + \frac{(y-\theta)}{\kappa_1}}$$

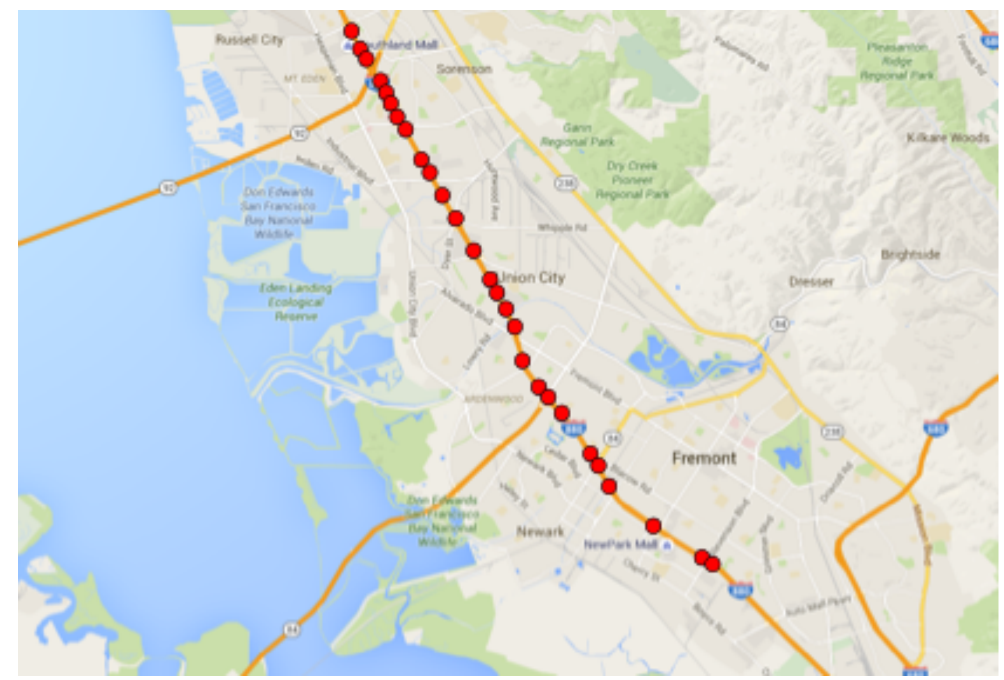
κ_1 is the solution to

$$\frac{2b^2}{\kappa_1^2 - b^2} + \ln\left(1 - \frac{b^2}{\kappa_1^2}\right) = \gamma$$

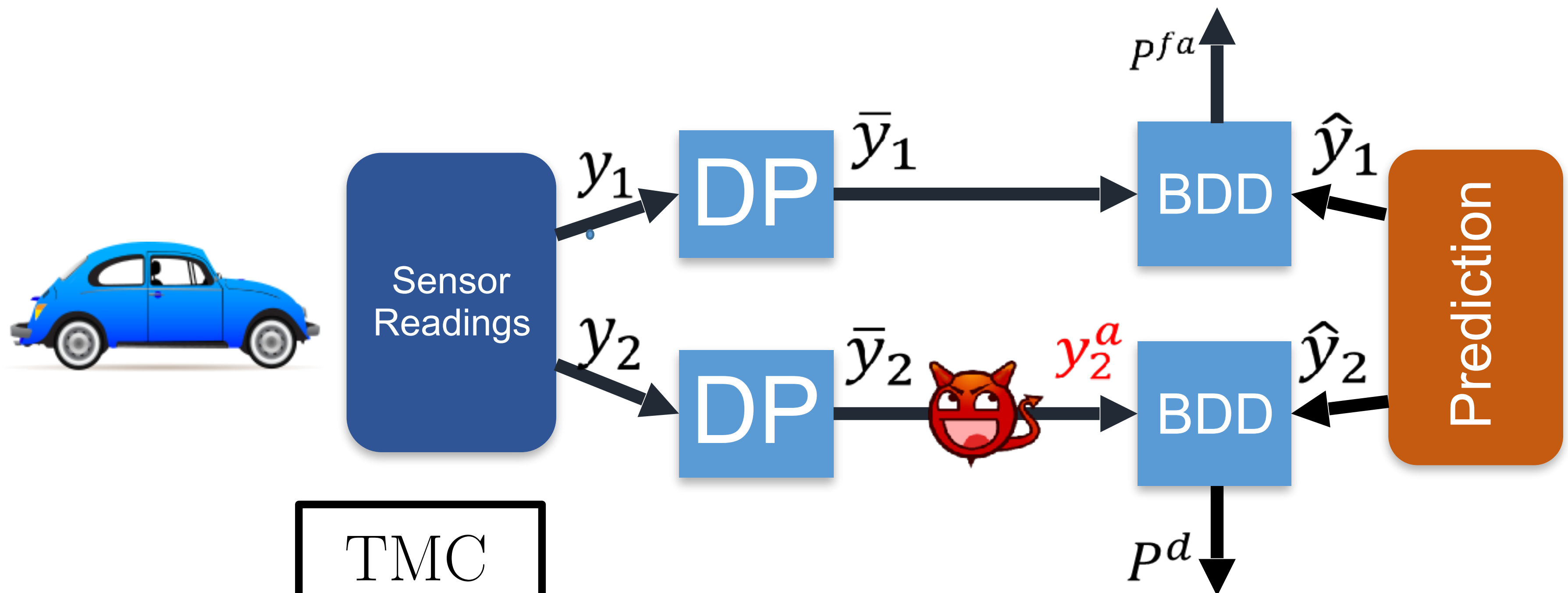
Example: Traffic Flow Estimation

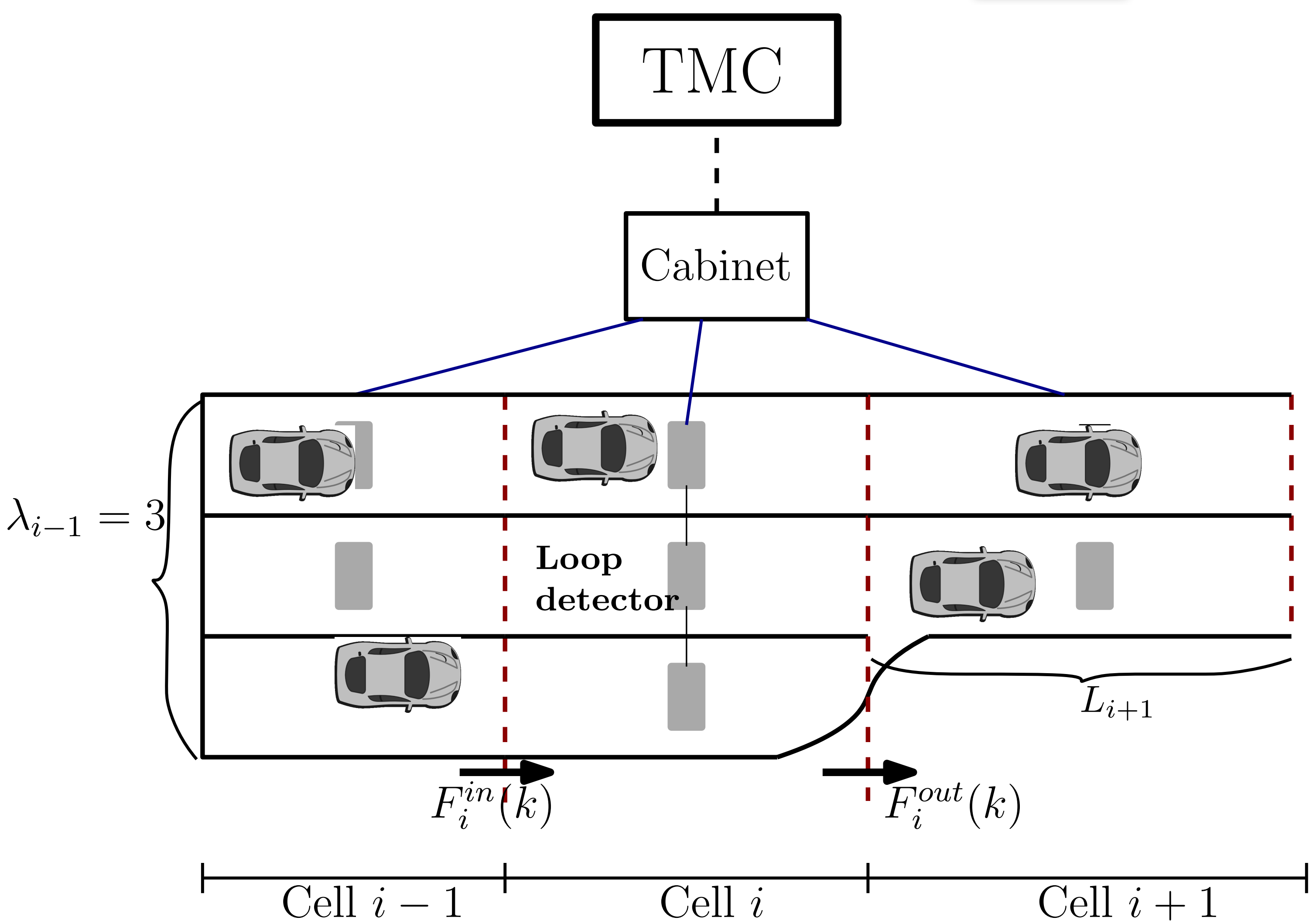


We use loop detection data from California



Classical Bad Data Detection in Traffic Flow Estimation

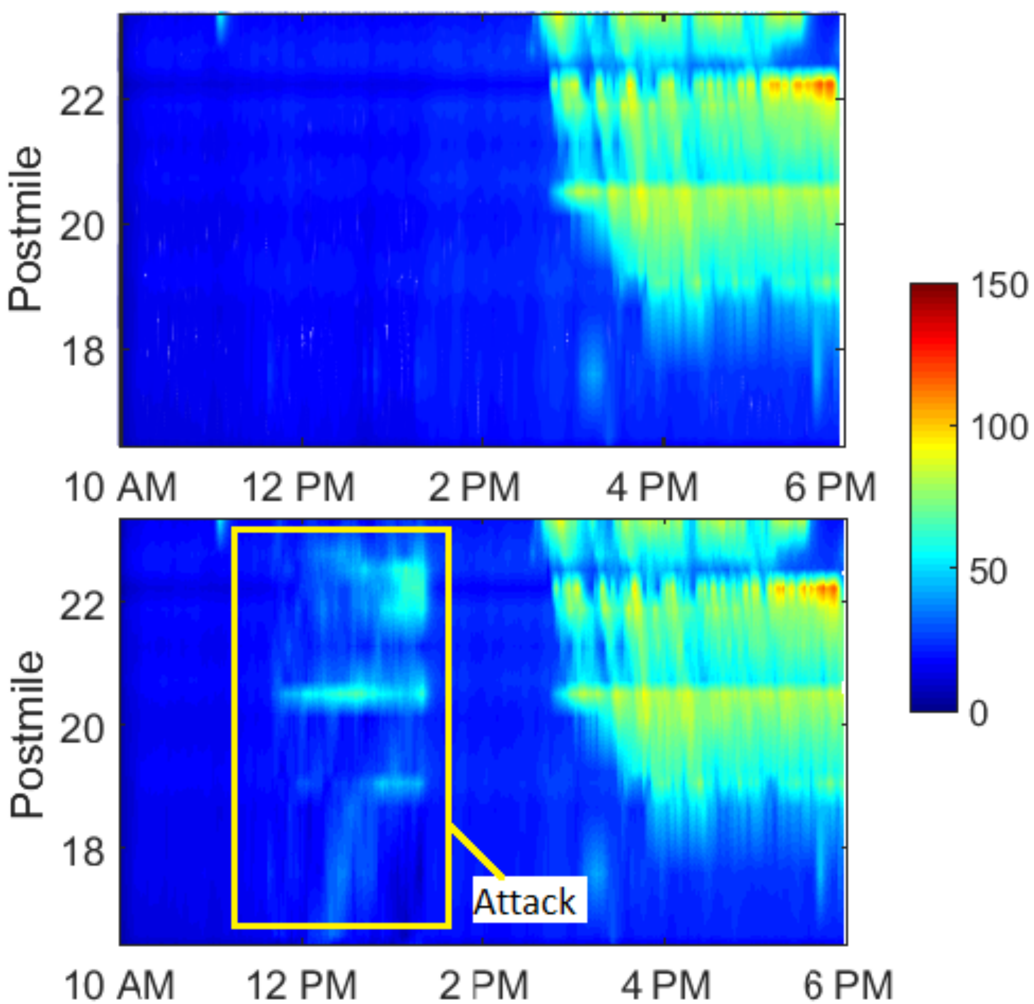




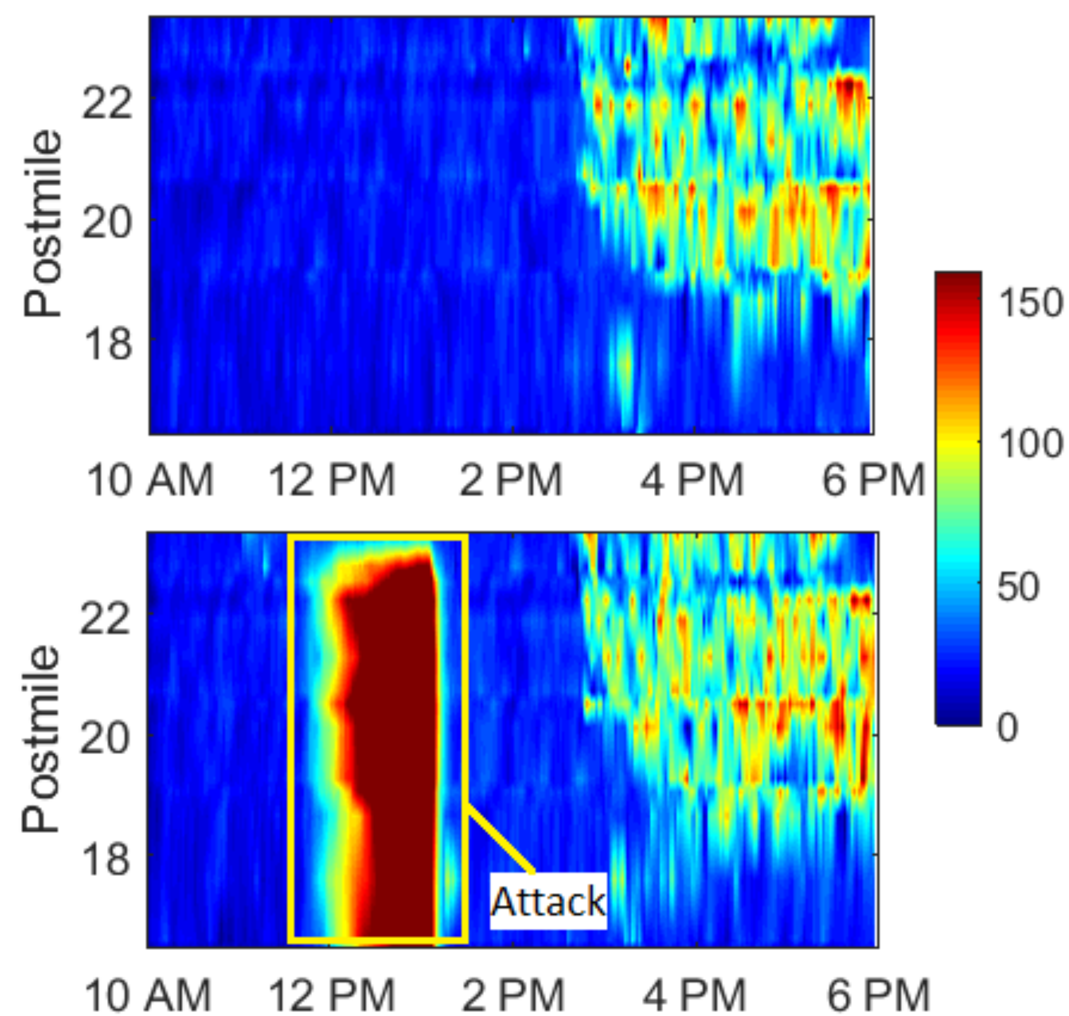
$$\hat{y}_i(k+1) = \hat{y}_i(k) + \frac{\mathcal{T}}{l_i}\left(\frac{l_{i-1}}{l_i}F_i^{in}(k) - F_i^{out}(k)\right) + Q_i(y_i(k) - \hat{y}_i(k))$$

The Attack Can Hide in DP Noise and Cause a Larger Impact

Without DP the attack is limited



With DP, the attacker can lie more without detection



Can we do better?

Defense Against Adversarial (Adaptive) Distributions

- Player 1 designs classifier **D** $\in \mathcal{S}$ minimize **Φ(D,A)** (e.g., Pr[Miss Detection] Subject to fix false alarms)
  - Player 1 makes the first move
- Player 2 (attacker) has multiple strategies **A**$\in \mathcal{F}$
  - Makes the move after observing the move of the classifier
- Player 1 wants provable performance guarantees:

- Once it selects **D**^{o} by minimizing **Φ,** it wants proof that no matter what the attacker does, **Φ<m, i.e.**

.

$$\forall A \in \mathcal{F}: \quad \Phi(D^o, A) \leq m$$

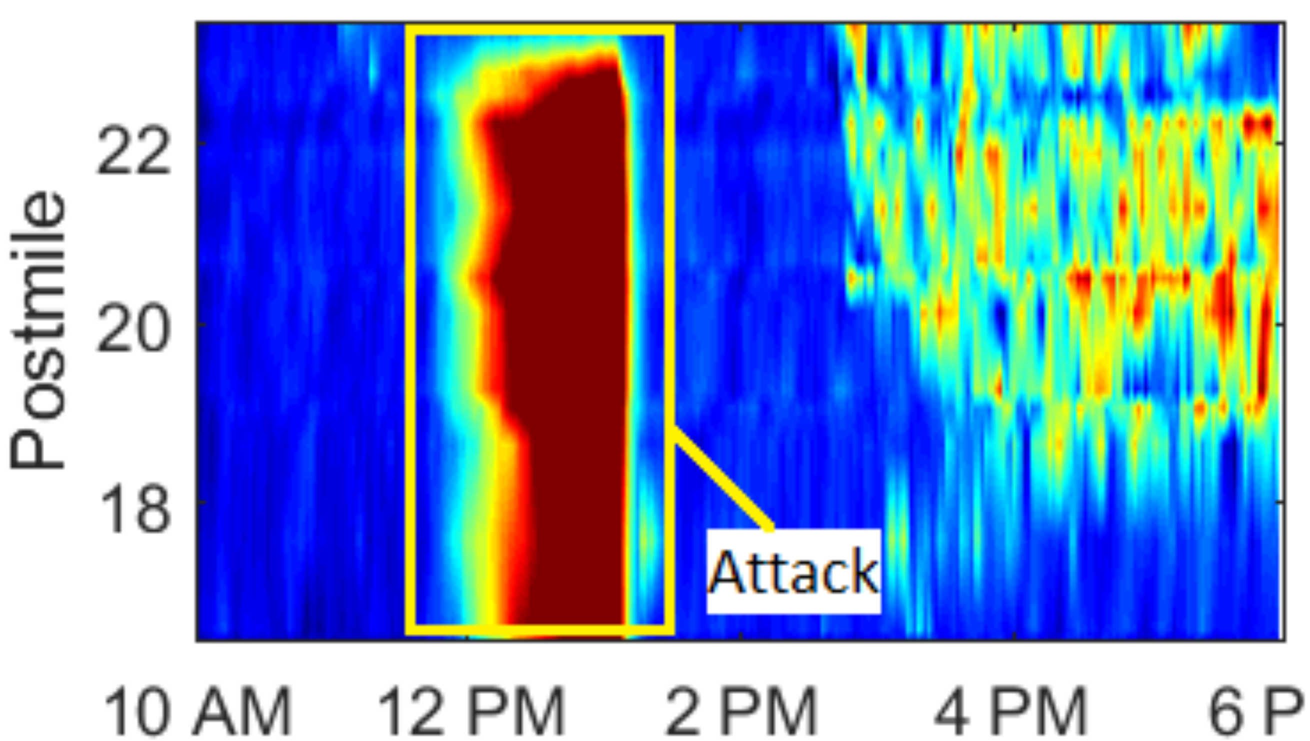
Defense in Traffic Case

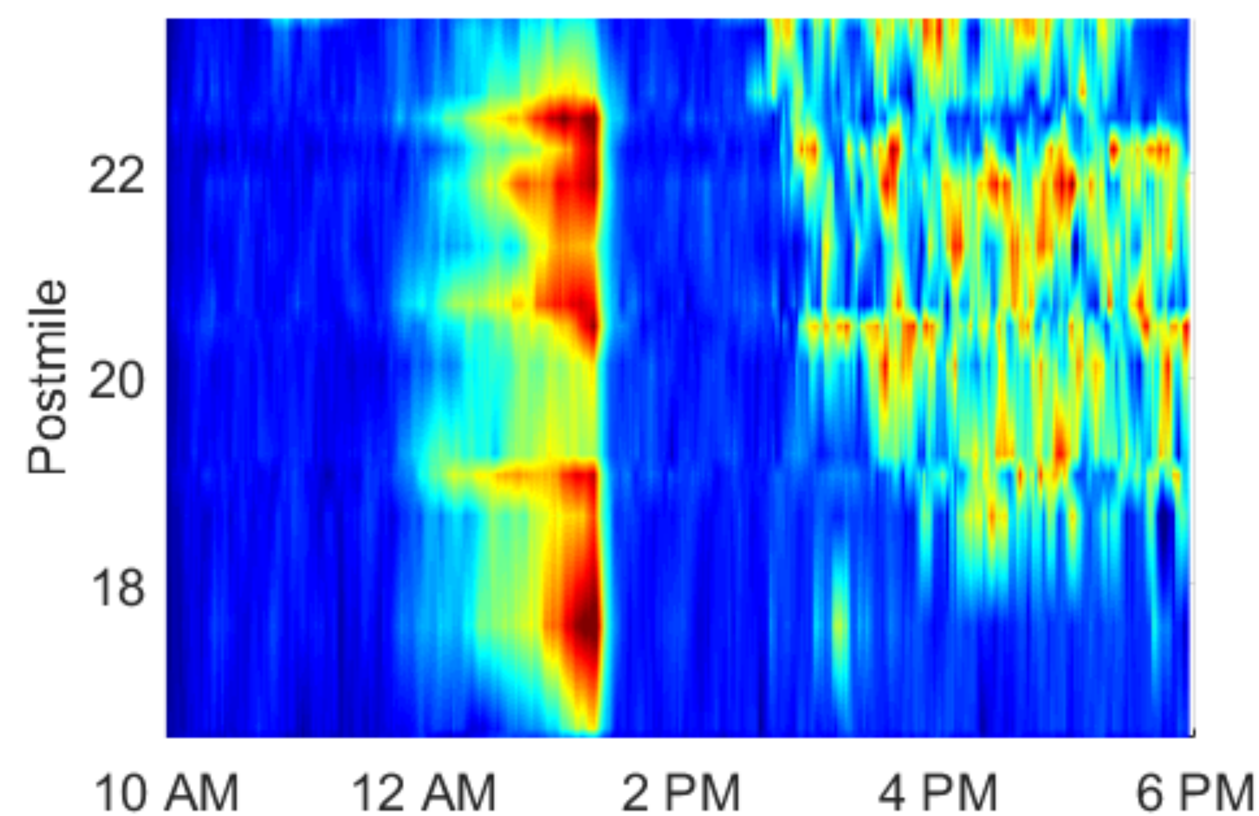
Proposed new defense as game between attacker and defender:

$$\min_{D \in \mathcal{S}} \max_{A \in \mathcal{F}} \Phi(D, A) = \max_{A \in \mathcal{F}} \min_{D \in \mathcal{S}} \Phi(D, A)$$

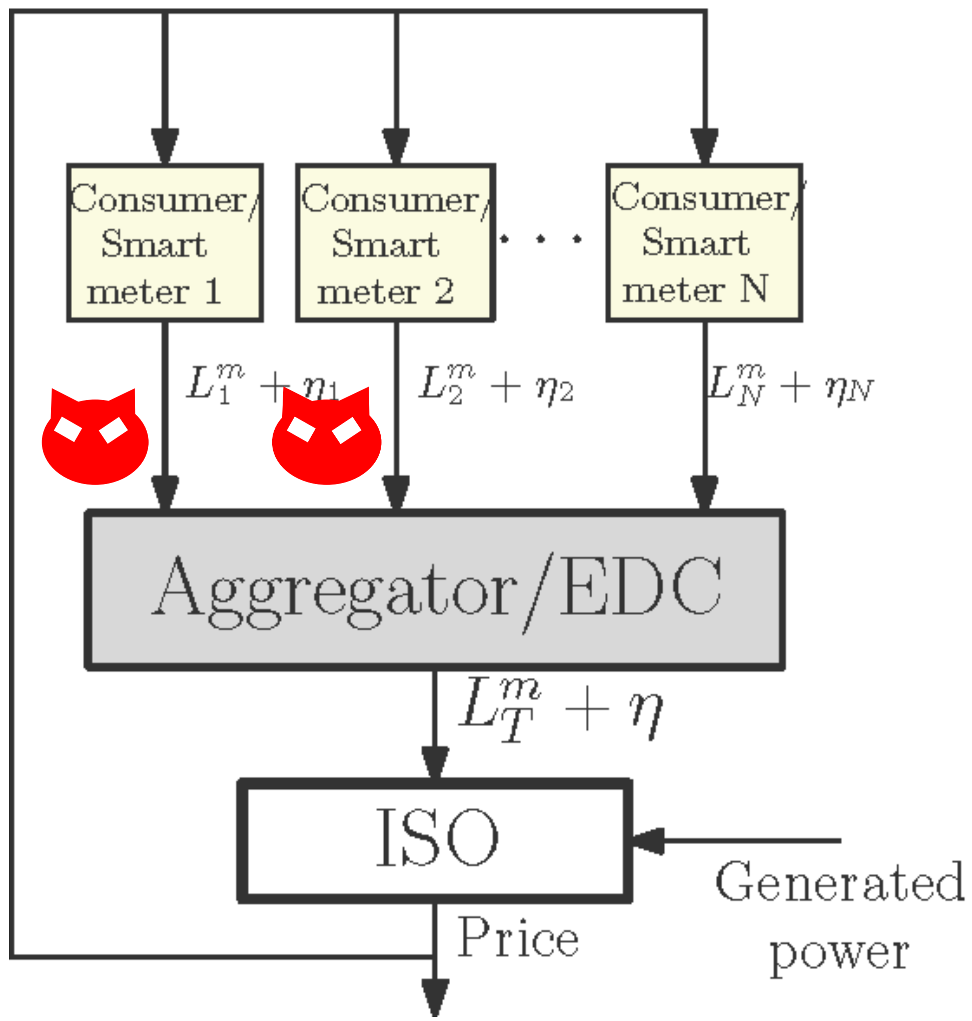
$$\forall D, \forall A, \quad \Phi(D^*, A) \leq \Phi(D^*, A^*) \leq \Phi(D, A^*)$$

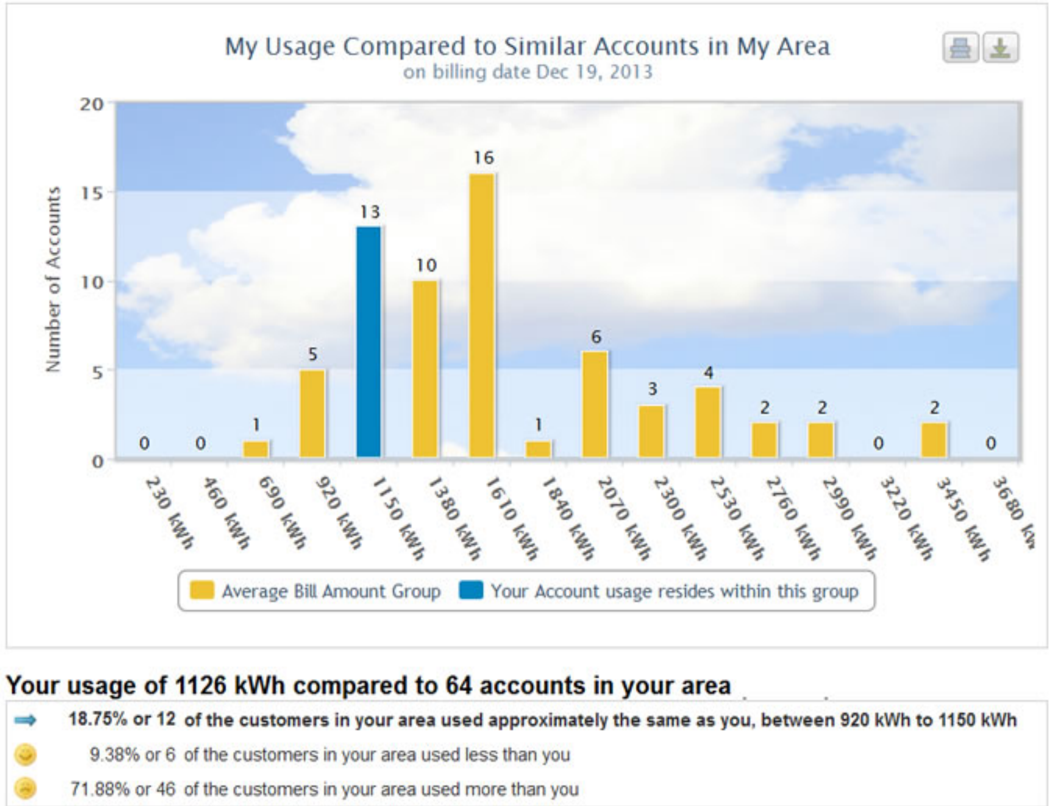
- With classical defense
- With our defense

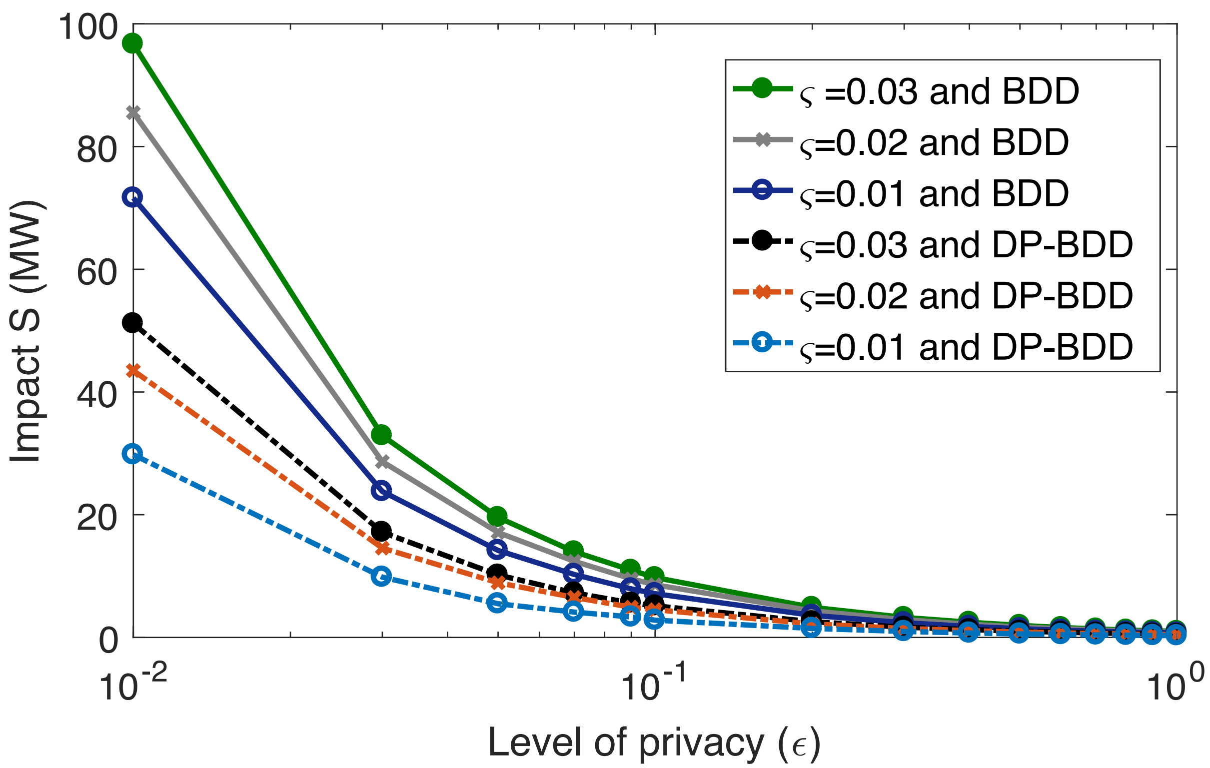




Another Example: Sharing Electricity Consumption







Conclusions

- Growing number of applications where we need to provide utility, privacy, and security
  - In particular, adversarial classification under differential privacy
- Various possible extensions
  - Different quantification of privacy loss (e.g., Rényi DP)
  - Adversary models (noiseless privacy), etc.
- Related work on DP and adversarial ML
  - Certified robustness

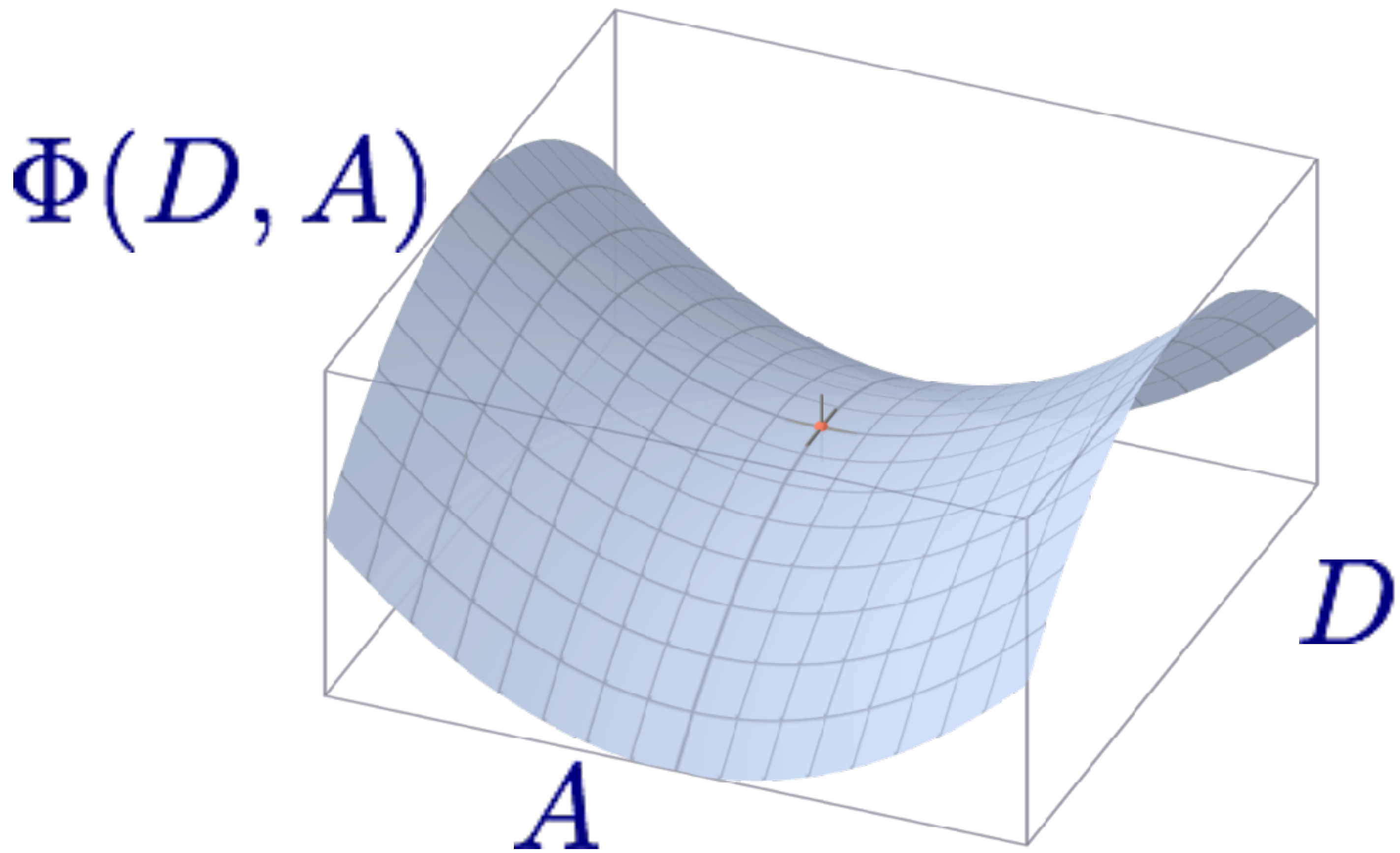
Strategic Adversary + Defender

- Player 1 designs classifier **D** $\in$ S minimizing **Φ(D,A)** (e.g., Pr[Error])
  - Defender makes the first move
- Player 2 (attacker) has multiple strategies **A**$\in$ F
  - Attacker makes the move after observing the move of the classifier
- Player 1 wants provable performance guarantees:
  - Once it selects **D**^{o} by minimizing **Φ,** it wants proof that no matter what the attacker does, **Φ<m, i.e.**

$$\forall A \in \mathcal{F} : \quad \Phi(D^o, A) \leq m$$

Strategy: Solve maximin and Show Solution is equal to minimax

– For any finite, zero sum-game:
– Minimax = Maximin = Nash Equilibrium (saddle point)



$$\min_{D \in \mathcal{S}} \max_{A \in \mathcal{F}} \Phi(D, A) = \max_{A \in \mathcal{F}} \min_{D \in \mathcal{S}} \Phi(D, A)$$

$$\forall D, \forall A, \quad \Phi(D^*, A) \leq \Phi(D^*, A^*) \leq \Phi(D, A^*)$$

Sequential Hypothesis Testing

- Sequence of random variables $X_1, X_2, \ldots$
  - Honest sensors have $X_1, X_2, \ldots, X_i$ distributed as $f_0(X_1, X_2, \ldots, X_i)$ (Defined by DP)
  - Tampered sensor has $X_1, X_2, \ldots, X_i$ distributed as $f_1(X_1, X_2, \ldots, X_i)$ (note that f_1 is unknown)
- Collect enough samples i until we have enough information to make a decision!
  - $D=(N,d_N)$ where N=stopping time, d_N=decision

$$\mathcal{S}_{a,b} = \{(N, d_N) : \mathbb{P}_0[d_N = 1] \leq a \text{ and } \mathbb{P}_1[d_N = 0] \leq b\}$$

Sequential Probability Ratio Test (SPRT)

$$\min_{D \in \mathcal{S}_{a,b}} \mathbb{E}_1[N]$$

The solution of this problem is the SPRT:

$$S_n = \ln \frac{f_1(x_1, ..., x_n)}{f_0(x_1, ...x_n)}$$

$$N = \inf_n S_n \in [L, U] \qquad d_N = \begin{cases} 1 & \text{if } S_N \geq U \\ 0 & \text{if } S_N \leq L, \end{cases}$$

$$U \approx \ln \frac{1-b}{a}$$

$$L \approx \ln \frac{b}{1-a}$$