



# P.E.Ts: Trajectory privacy

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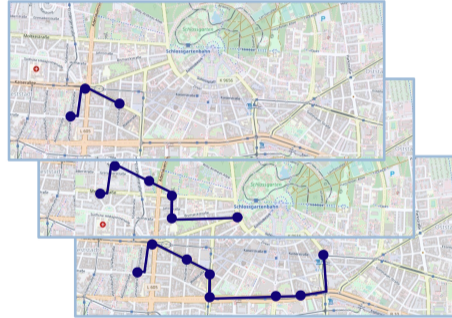
The background consists of two large, overlapping geometric shapes. A teal-colored shape is in the upper-left corner, and a light gray shape is in the lower-left corner. The rest of the background is white. The text is centered in the white area.

# Mechanism Achieving Differential Privacy

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**Figure 8:** Static context



**Figure 9:** Dynamic or streaming

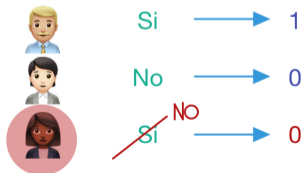
# Algorithms Achieving Differential Privacy

## $\ell_1$ -sensitivity

The  $\ell_1$ -sensitivity of a function  $f: \mathbb{N}^{|\mathcal{X}|} \rightarrow \mathbb{R}^n$  is:

$$\Delta(f) := \max_{\|D, D'\|_1=1} \|f(D) - f(D')\|_1$$

Antecedentes  
penales??



$$\Delta f = 1$$

# Algorithms Achieving Differential Privacy

## Laplace Mechanism



### Laplace Mechanism

Given any function  $f: \mathbb{N}^{|\mathcal{X}|} \rightarrow \mathbb{R}^n$  the Laplace mechanism is defined as:

$$ML(D, f(\cdot), \epsilon) = f(D) + (Y_1, \dots, Y_n)$$

where  $Y_i$  are i.i.d. random variables drawn from  $Lap(\frac{\Delta f}{\epsilon})$ .

Antecedentes  
penales??



Si → 1

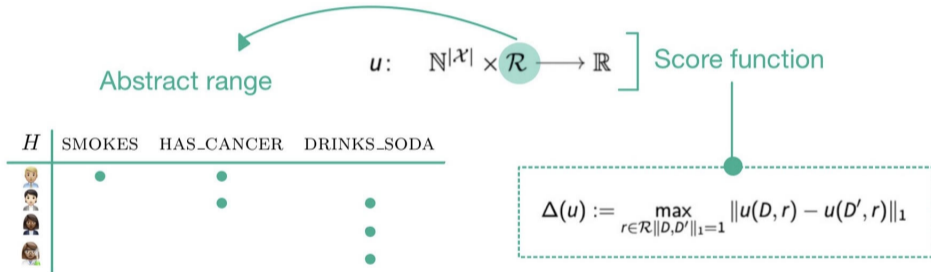
No → 0

Si → 1

$$\left. \begin{array}{l} \text{Si} \rightarrow 1 \\ \text{No} \rightarrow 0 \\ \text{Si} \rightarrow 1 \end{array} \right\} \xrightarrow{f} 2 + \text{dado} = 1$$

# Algorithms Achieving Differential Privacy

## Exponential Mechanism



$M_E(D, u, \mathcal{R})$  selects and outputs an element  $r \in \mathcal{R}$  with probability proportional to  $\exp\left(\frac{\epsilon u(D, r)}{2\Delta(u)}\right) \cdot 2u$

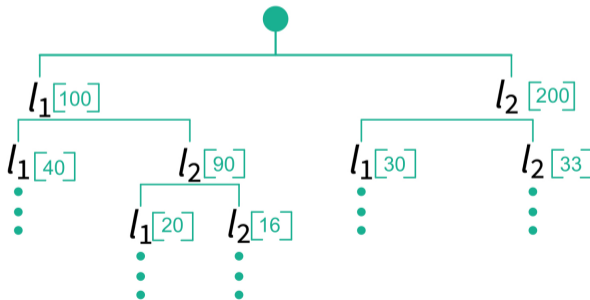
# Mechanism Achieving Differential Privacy

Static Context

Noisy counts

Clustering

Perturbing semantic trajectories



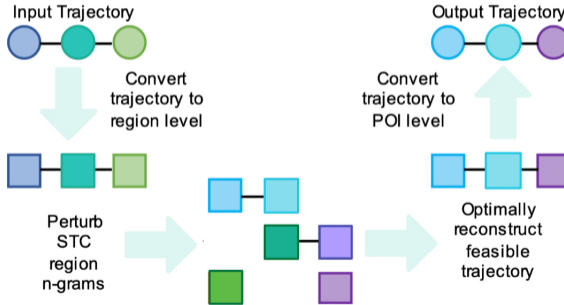
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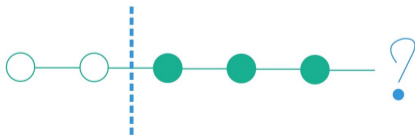


# Mechanism Achieving Differential Privacy

## Discrete-time Markov process of order $l$

Given a sequence of random variables  $X_1, X_2, X_3, \dots$ . We say that they follow a Markov process of order  $l$  iff probability of moving to the next state depends only on the  $l$  previous states :

$$\Pr(X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \Pr(X_{n+1} = x \mid X_{n-l} = x_{n-l}, \dots, X_n = x_n)$$



# Mechanism Achieving Differential Privacy

## Synthetic Data



| Mechanisms            | <i>n</i> -grams        | DPT  | DP-STAR                             |
|-----------------------|------------------------|--|-------------------------------------|
| Time variable         | ✗                      | ✗  | ✗                                   |
| Prefix tree           | ✓                      | ✓  | ✗                                   |
| Neighboring databases | $D_1 = D_2 \cup \{T\}$ | $D_1 = D_2 \cup \{PT\}$                    | $D_1 = D_2 \cup \{T\}$              |
| Main mechanism        | Laplacian mechanism    | Laplacian mechanism                        | Laplacian and exponential mechanism |
| Sensitivity bound     | $l_{max}$ truncation   | Normalization by #transitions in <i>PT</i> | Normalization by $ T $              |
| Markov process        | order $n - 1$          | order $l < k$                              | order 1                             |

# Mechanism Achieving Differential Privacy

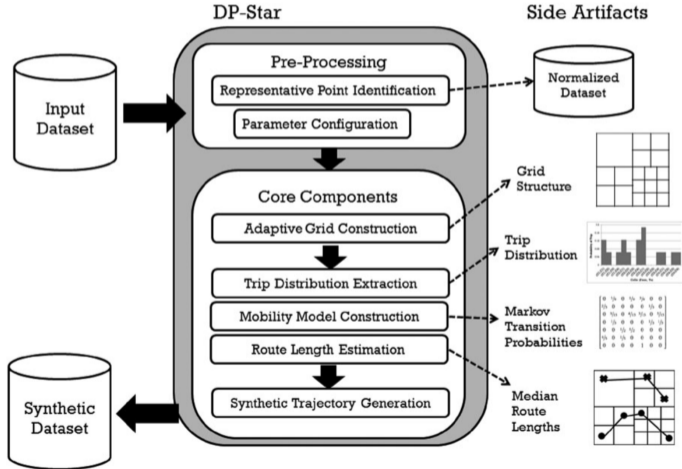
## Synthetic Data



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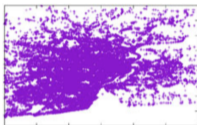
# Mechanism Achieving Differential Privacy

## Synthetic Data

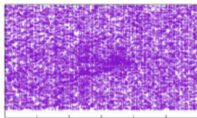


# Mechanism Achieving Differential Privacy

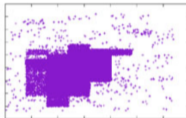
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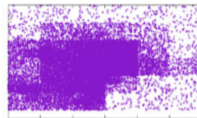
(a) Original distribution



(b) DPT



(c) ngram



(d) DP-Star

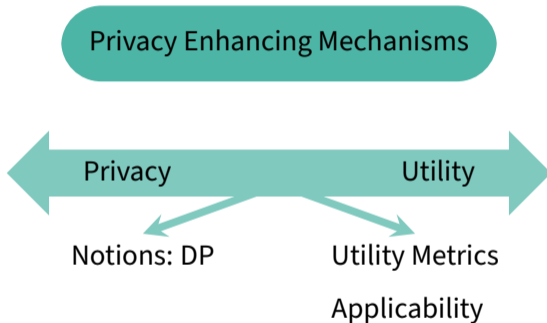
$T = \langle l_1, \dots, l_n \rangle$  where each  $l_i$  is a location

TIME?

The background features a diagonal split between a teal upper-left section and a light gray lower-right section, with a white central area where the text is located.

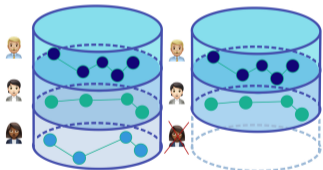
# Mechanisms Analysis

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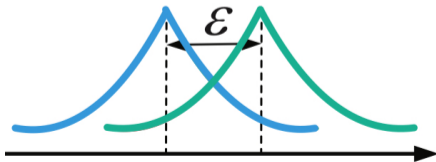
# Mechanisms Analysis

## Privacy Analysis



Privacy Loss (by observing  $r$ )

$$\mathcal{L}_{M(D)||M(D')}^r = \ln \left( \frac{\mathbb{P}(M(D) = r)}{\mathbb{P}(M(D') = r)} \right) \leq \epsilon$$





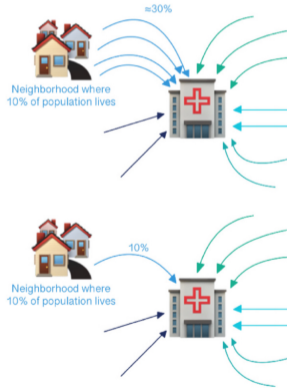
# Mechanisms Analysis

## Limitations on Differential Privacy



Correlation

### Bayesian inference



Infinity streaming

REBELIEF

# Mechanisms Analysis

## Limitations on Differential Privacy

- $$\mathcal{P}(r|_{X_1=x_1}) = \sum_{y \in \mathcal{Y}} \mathcal{P}(r|_{x_1, y}) \cdot \mathcal{P}(y|_{x_1})$$

$X_1, X_2$  independent  $\Rightarrow \mathcal{P}(y|_{x_1}) = \mathcal{P}(y)$

$$\begin{aligned} \mathcal{P}(r|_{X_1=x_1}) \cdot \sum_{y \in \mathcal{Y}} \mathcal{P}(r|_{x_1, y}) \cdot \mathcal{P}(y) &\leq \\ &\leq \sum_{y \in \mathcal{Y}} e^{\epsilon} \mathcal{P}(r|_{\tilde{x}_1, y}) \cdot \mathcal{P}(y) \leq \\ &\leq e^{\epsilon} \mathcal{P}(r|_{\tilde{x}_1}). \end{aligned}$$

- $$\mathcal{P}(r|_{X_1=x_1}) = \sum_{y \in \mathcal{Y}} \mathcal{P}(r|_{x_1, y}) \cdot \mathcal{P}(y|_{x_1})$$

$\mathcal{P}(X_1=X_2) = 0.9$  ] correlation !!

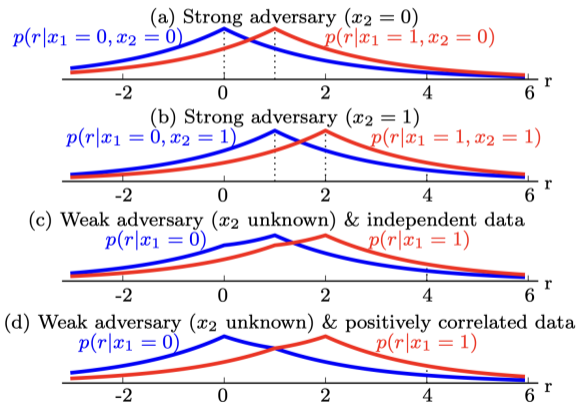
$$\begin{aligned} \mathcal{P}(r|_{X_1=x_1}) \cdot \sum_{y \in \mathcal{Y}} \mathcal{P}(r|_{x_1, y}) \cdot \mathcal{P}(y|_{x_1}) &\approx \\ &\approx 0.8 \cdot \mathcal{P}(r|_{x_1, x_1}) + \mu_{\tilde{x}_0} \end{aligned}$$

$$\mathcal{P}(r|_{X_1=\tilde{x}_1}) \approx 0.8 \mathcal{P}(r|_{\tilde{x}_1, \tilde{x}_1}) + \tilde{\mu}_{\tilde{x}_0}$$

↑ distance = 2 !!  
↓ not neighboring  
↓  $\not\approx \epsilon$

# Mechanisms Analysis

## Limitations on Differential Privacy



# Mechanisms Analysis

## Classification of Utility Metrics



### Utility metrics

- ▶ **Total preservation of data**
  - ▶ *Location preservation, number of suppressed points, ...*
- ▶ **Close preservation of data**
  - ▶ *Use of similarity measures, preservation range query, discernability...*
- ▶ **Preservation of semantic information**
  - ▶ *Most visited places, frequent sequential patterns, trajectory length preservation...*
  - ▶ *Query error distortion function:*

$$\text{error}(q) = \frac{|q(D) - q(D')|}{\max\{q(D), b\}}.$$

- ▶ **Assurance of realism**
  - ▶ *Reachability, geo-spatial consistency...*

# Mechanisms Analysis

## Classification of Utility Metrics

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# Mechanisms Analysis

## Similarity Measures

|   | Euclidean distance | Hausdorff & Fréchet | DTW | TWED | LCSS | EDR |
|---|--------------------|---------------------|-----|------|------|-----|
| Can compare different lengths                   | X                  | ✓                   | ✓   | ✓    | ✓    | ✓   |
| Considers time & allows for local time shifting | X                  | X                   | ✓   | ✓    | ✓    | ✓   |
| Is robust to noise                              | X                  | X                   | X   | X    | ✓    | ✓   |
| Is a metric                                     | ✓                  | ✓                   | X   | ✓    | X    | X   |

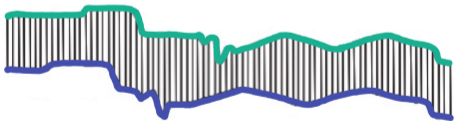
**Table 3:** DTW: Dynamic time warping, TWED: Time warping edit distance, LCSS: Longest common subsequence, EDR: Edit distance on real sequences

# Mechanisms Analysis

## Euclidean distance

|   | Euclidean distance |
|---|--------------------|
| Can compare different lengths                   | X                  |
| Considers time & allows for local time shifting | X                  |
| Is robust to noise                              | X                  |
| Is a metric                                     | ✓                  |

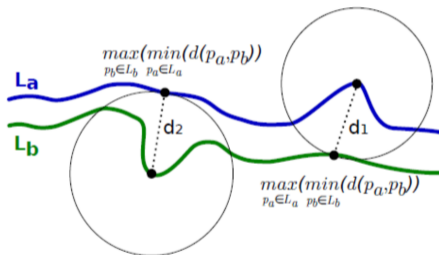
$$\text{Eu}(T, T') = \sqrt{\sum_{i=1}^n d((x_i, x'_i), (y_i, y'_i))^2}$$



# Mechanisms Analysis

## Hausdorff & Fréchet distances

|   | Hausdorff & Fréchet |
|---|---------------------|
| Can compare different lengths                   | ✓                   |
| Considers time & allows for local time shifting | ✗                   |
| Is robust to noise                              | ✗                   |
| Is a metric                                     | ✓                   |



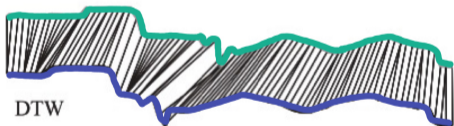
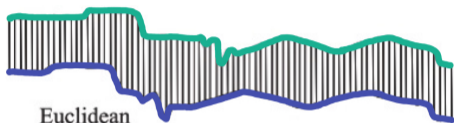


# Mechanisms Analysis

## Dynamic time warping (DTW) & variations

|   | DTW | TWED |
|---|-----|------|
| Can compare different lengths                   | ✓   | ✓    |
| Considers time & allows for local time shifting | ✓   | ✓    |
| Is robust to noise                              | ✗   | ✗    |
| Is a metric                                     | ✗   | ✓    |

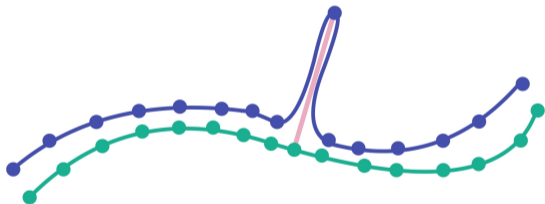
TWED: Time warping edit distance



# Mechanisms Analysis

## Longest common subsequence (LCSS)

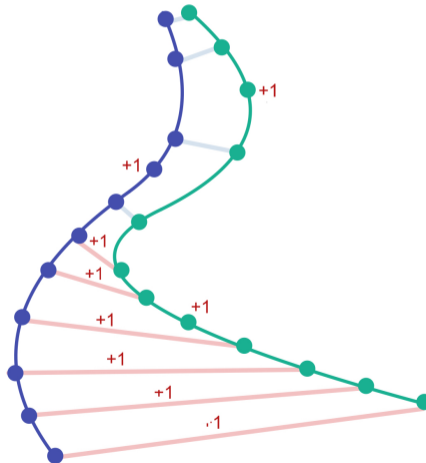
|   | LCSS |
|---|------|
| Can compare different lengths                   | ✓    |
| Considers time & allows for local time shifting | ✓    |
| Is robust to noise                              | ✓    |
| Is a metric                                     | ✗    |



# Mechanisms Analysis

Edit distance on real sequences (EDR)

|   | EDR |
|---|-----|
| Can compare different lengths                   | ✓   |
| Considers time & allows for local time shifting | ✓   |
| Is robust to noise                              | ✓   |
| Is a metric                                     | ✗   |

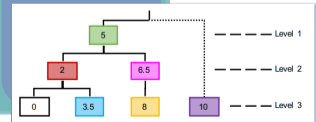
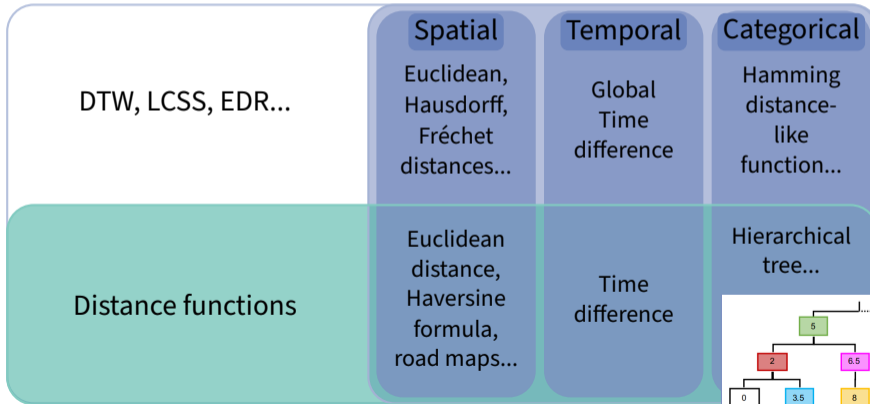


# Mechanisms Analysis

## Similarity Measures Divisions

Dimension-wise

Point-wise



# Mechanisms Analysis

## Limitations on Utility

### Inherent properties of trajectory data

Sparseness

*leads to*  
Unavoidable data lost  
&  
high sensitivities

High dimensionality

### Problems of current proposals

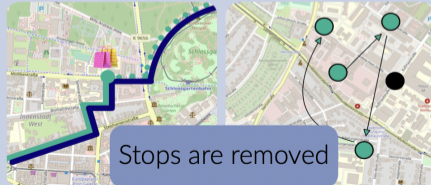
Impossible trajectories

Small universe of locations

Utility metrics are not representative

Weird trajectory patterns

Ignoring the temporal dimension



Stops are removed

The background features a diagonal split between a teal color in the upper-left and a light gray color in the lower-right, with a white area in the center where the text is located.

## Conclusions and Future Research

# Conclusions and Future Research

