

# AtlantTIC

Research Center for  
Information & Communication Technologies



ÉCOLE POLYTECHNIQUE  
FÉDÉRALE DE LAUSANNE

# Rethinking Location Privacy for Unknown Mobility Behaviors

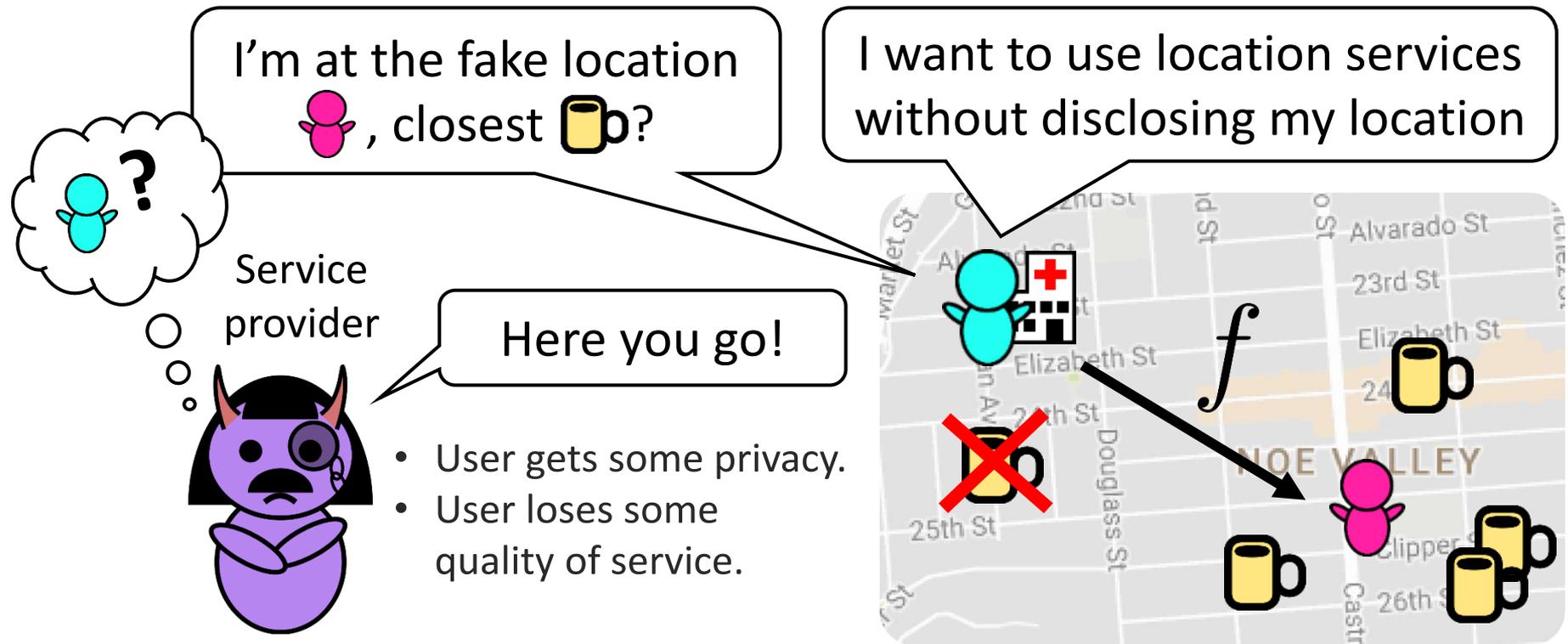
*Simon Oya (UVigo)*

*Carmela Troncoso (EPFL)*

*Fernando Pérez-González (UVigo)*

# Motivation: Obfuscation-based Location Privacy

- Location information is sensitive.
- Location Privacy-Protection Mechanisms (LPPMs)  $f(\text{pink}| \text{cyan})$



# LPPM Design Notions: Metrics and Mobility Models

## Quality Loss

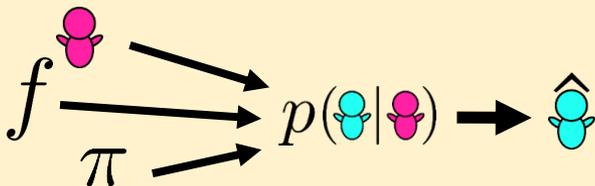
- Example: **Average Loss**

$$\bar{Q}(f, \pi) = E\{d_Q(\text{cyan}, \text{pink})\}$$

Euclidean, Hamming, semantic, ...

## Privacy

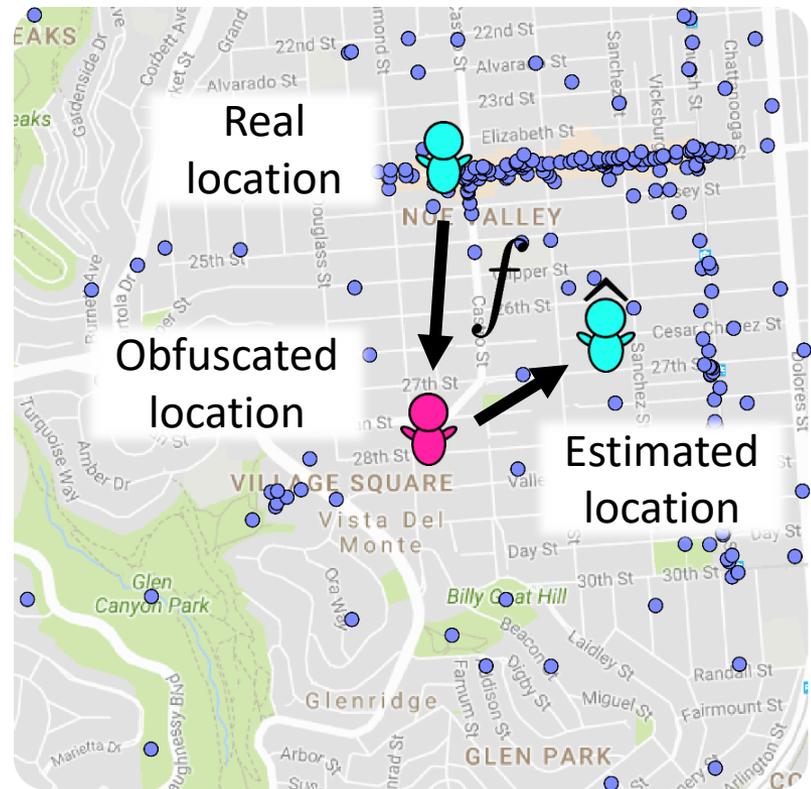
- Example: **Average Adversary Error**



Adversary's estimation of the real location

$$P_{AE}(f, \pi) = E\{d_P(\text{cyan}, \hat{\text{cyan}})\}$$

Euclidean, Hamming, semantic, ...

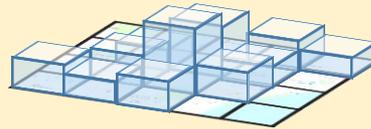


Shokri, Reza, et al. "Quantifying location privacy." *Security and privacy (sp), 2011 ieee symposium on*. IEEE, 2011.

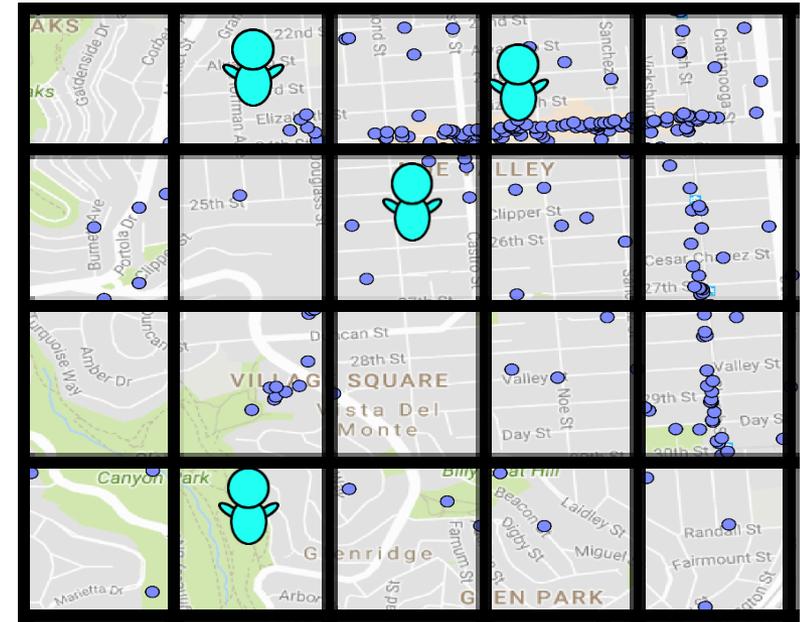
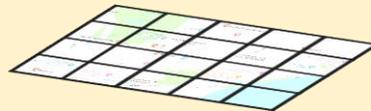
# LPPM Design Notions: Metrics and Mobility Models

## Sporadic

- Independent location reports.
- Adequate for infrequent usage (e.g., checking the weather)



## Non-Sporadic

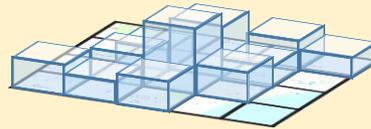


- Model how the user moves in the map.
- Typical computational constraints: discrete models.

# LPPM Design Notions: Metrics and Mobility Models

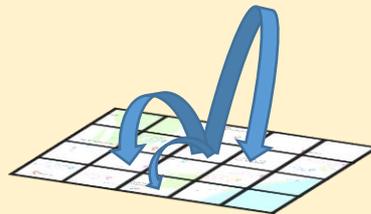
## Sporadic

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- Adequate for infrequent usage (e.g., checking the weather)



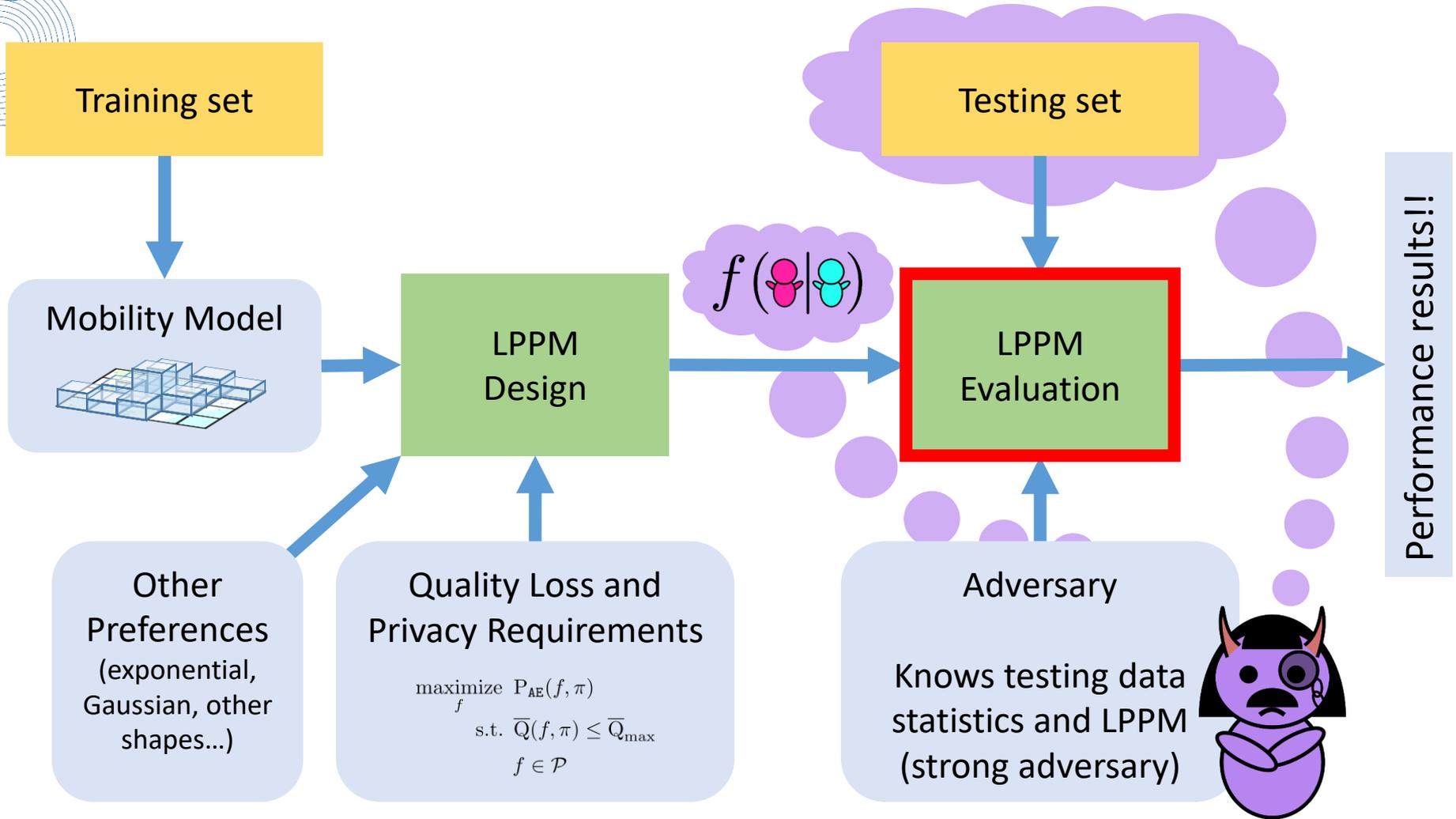
## Markov

- Dependent locations
- Adequate for continuous usage (e.g., live location sharing)



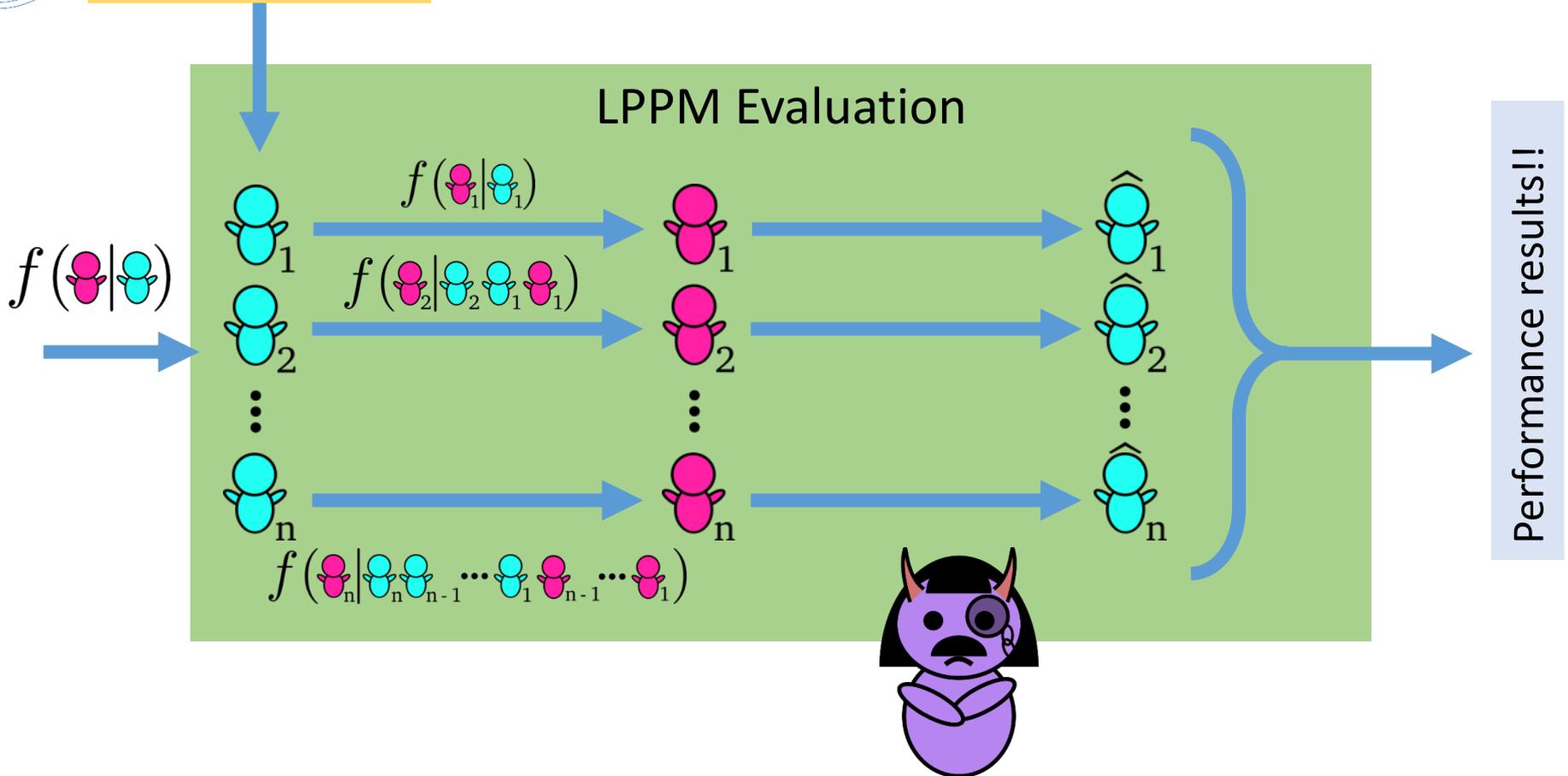
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# LPPM Design and Evaluation Framework

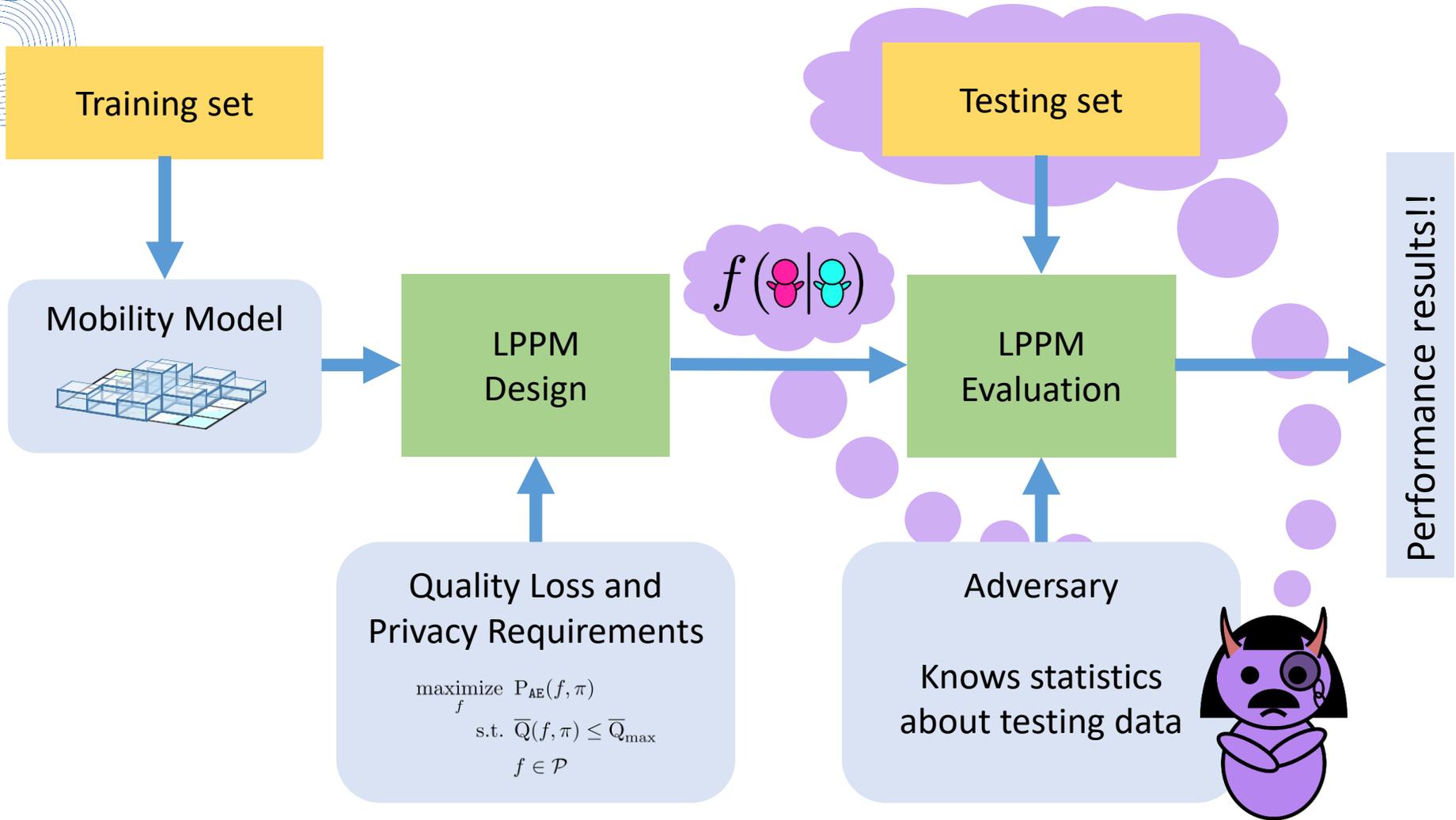


# LPPM Design and Evaluation Framework

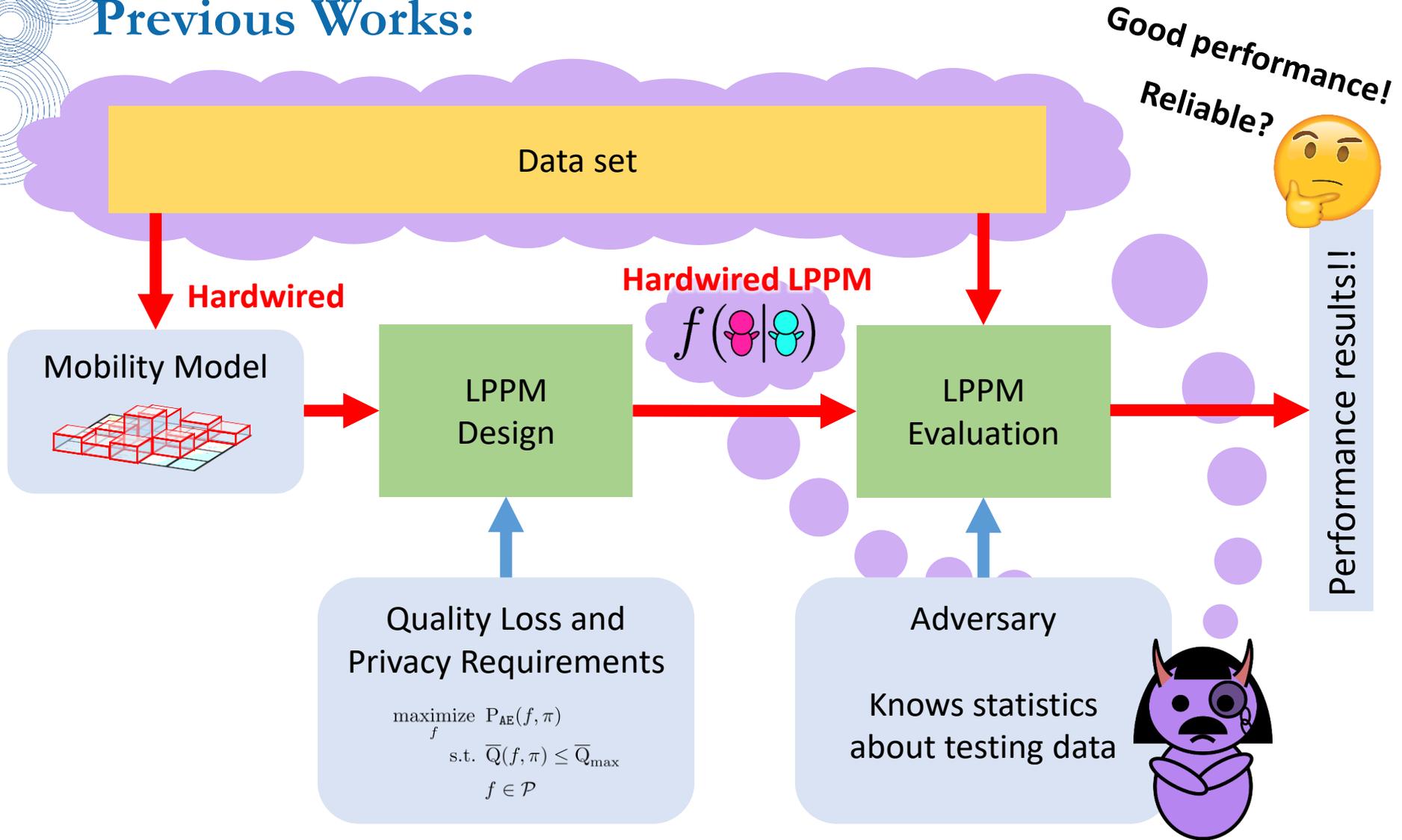
Testing set



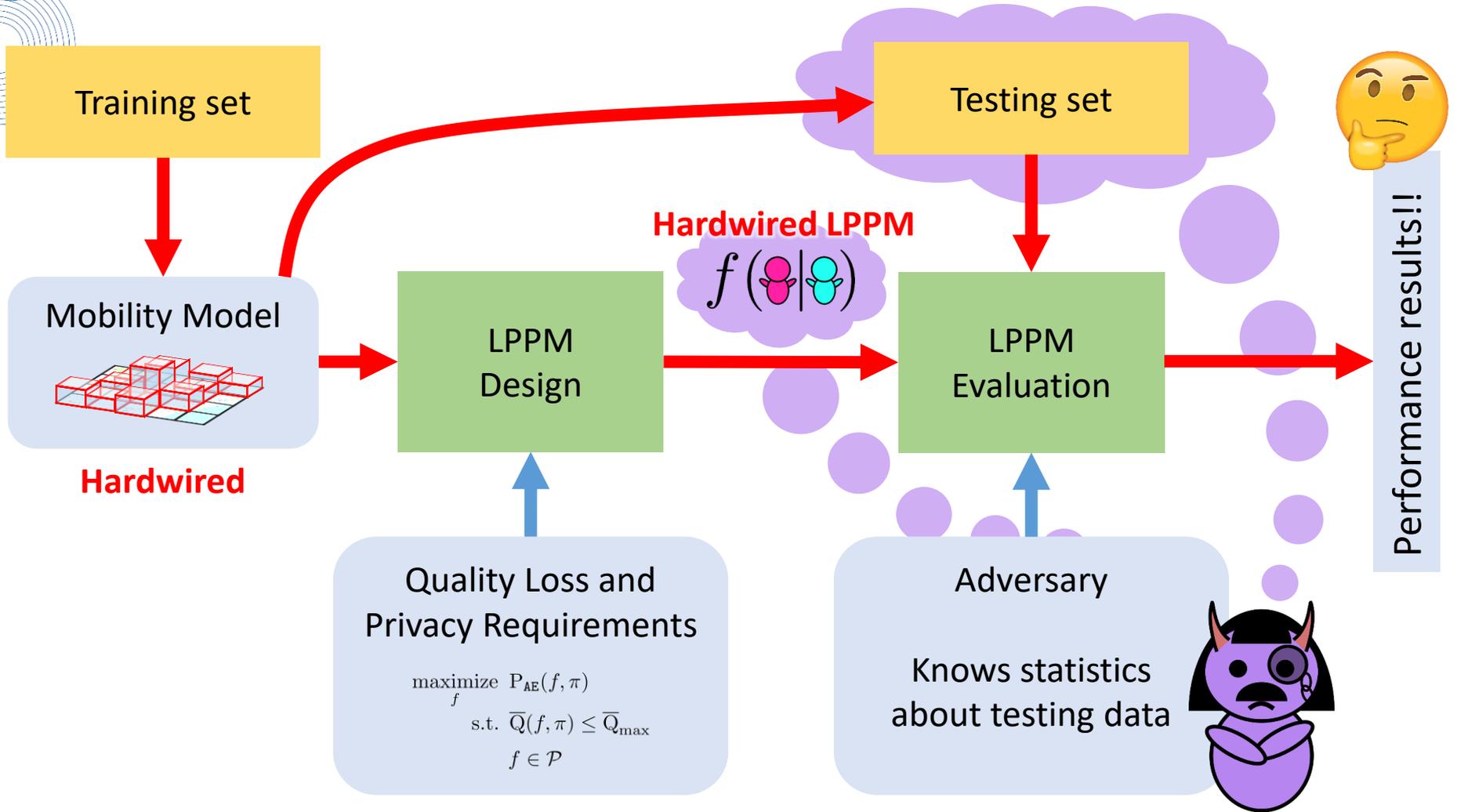
# Previous Works:



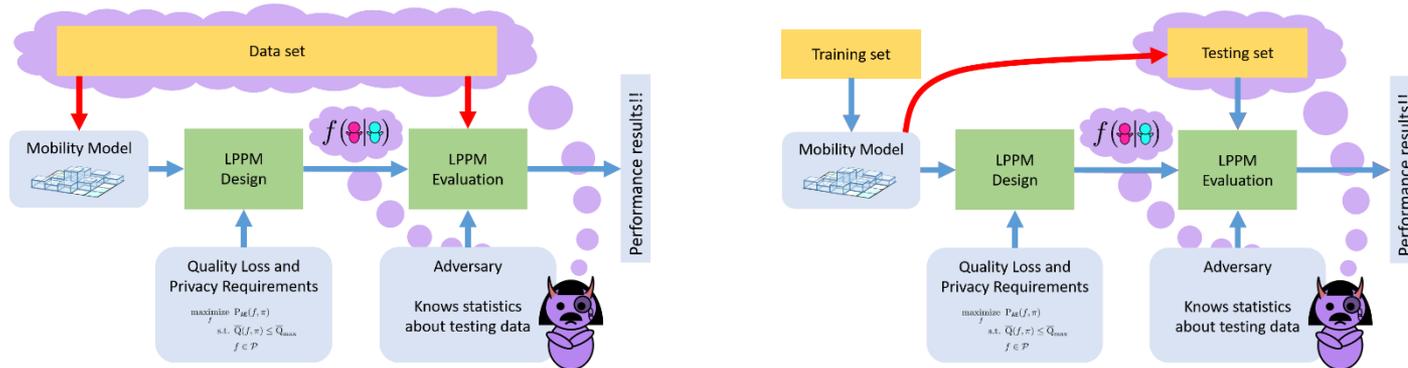
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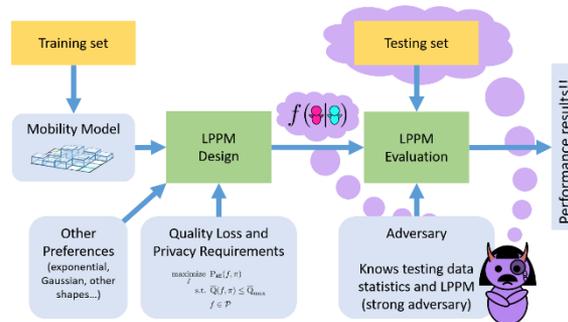
# Previous Works:



- In these frameworks, it makes sense to **hardwire** the training set into the LPPM:



- How do these LPPMs fare when we split training/testing data?



# Experiment: let's see what would happen "in practice"

- Data gathering:

For sporadic mobility:

Gowalla  
Brightkite

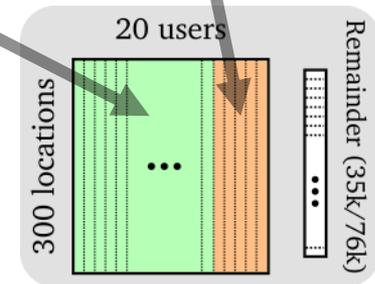
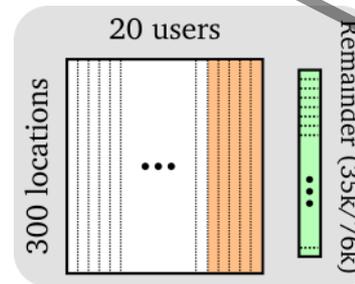
Pre-processing

Training set

Testing set

Scarce

Rich



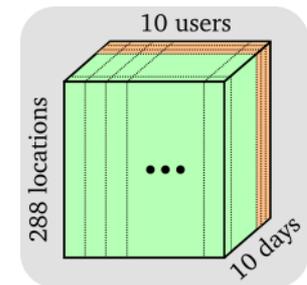
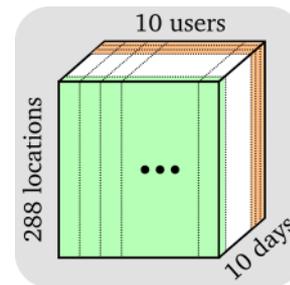
Non-sporadic mobility:

TaxiCab  
(dense cab location reports for 30 days)

Pre-processing

Scarce

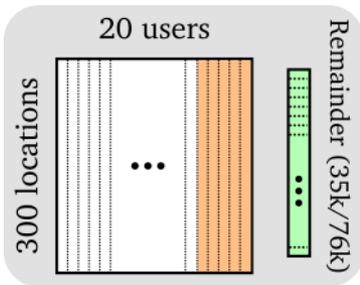
Rich



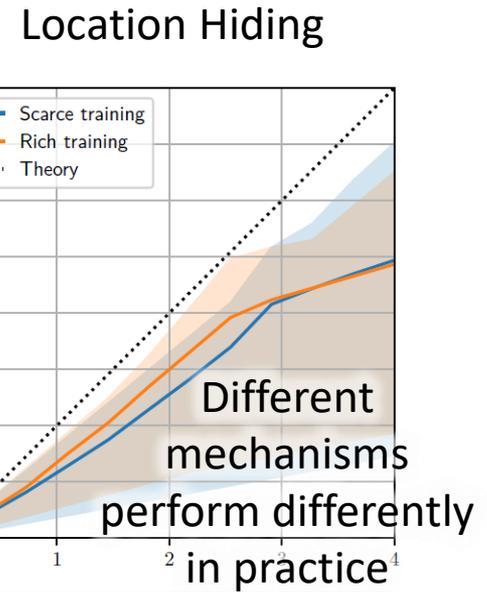
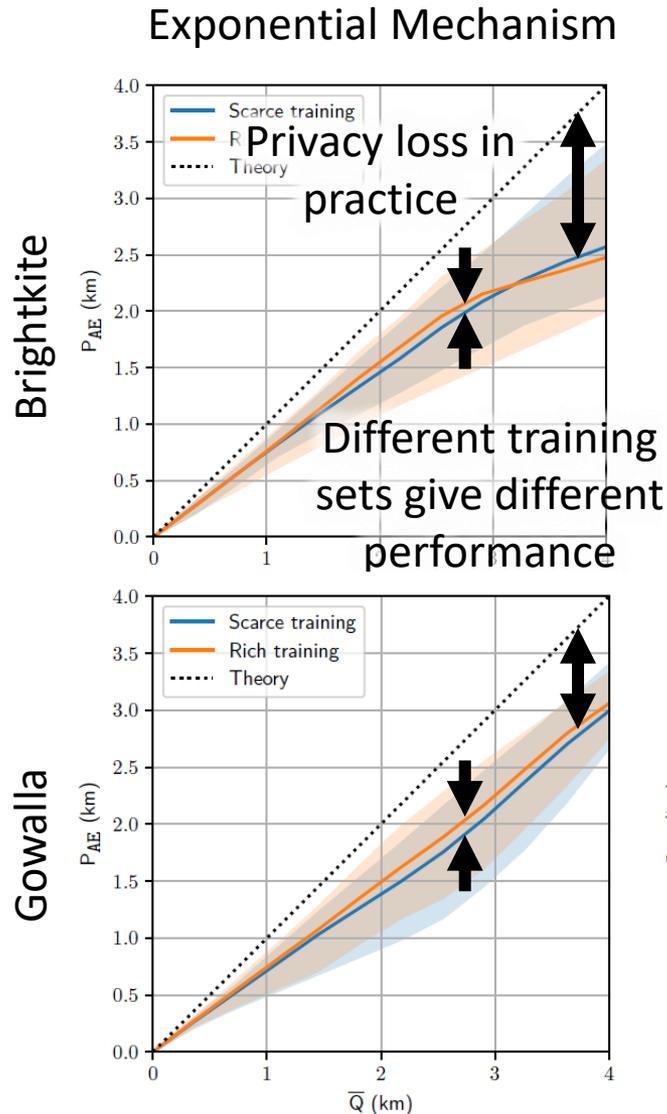
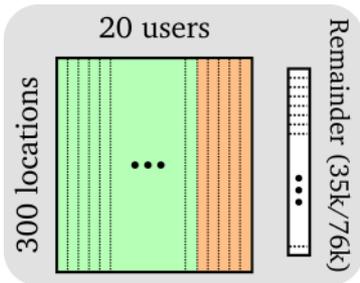
# Performance Results (sporadic case)

Datasets with sporadic reports (shuffled)

Scarce



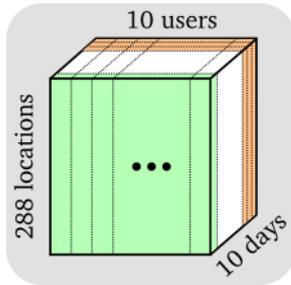
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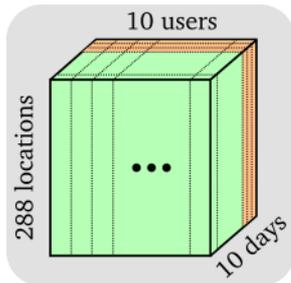
# Performance Results (non-sporadic case)

**TaxiCab**  
Dataset with  
continuous reports

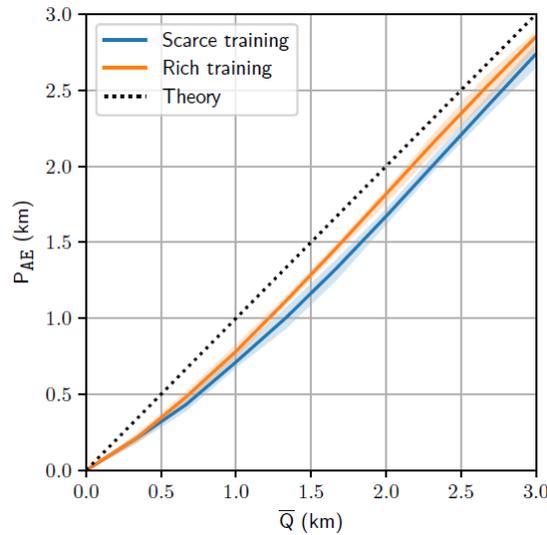
Scarce



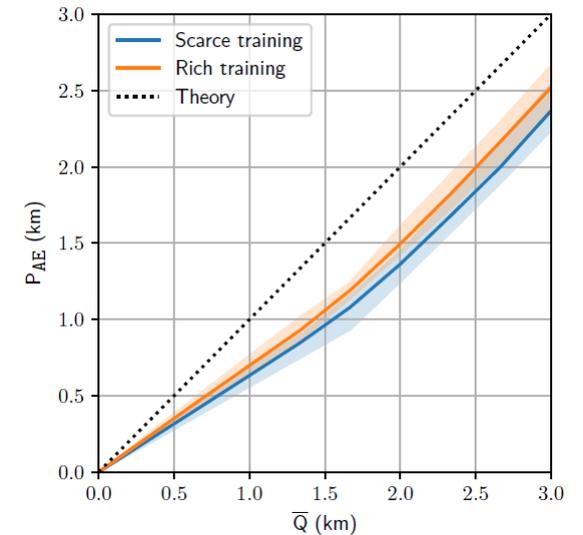
Rich



Exponential Mechanism



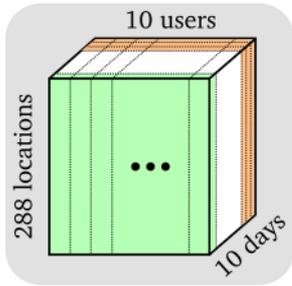
Location Hiding Mechanism



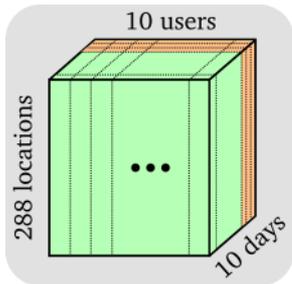
# Performance Results (non-sporadic case)

**TaxiCab**  
Dataset with  
continuous reports

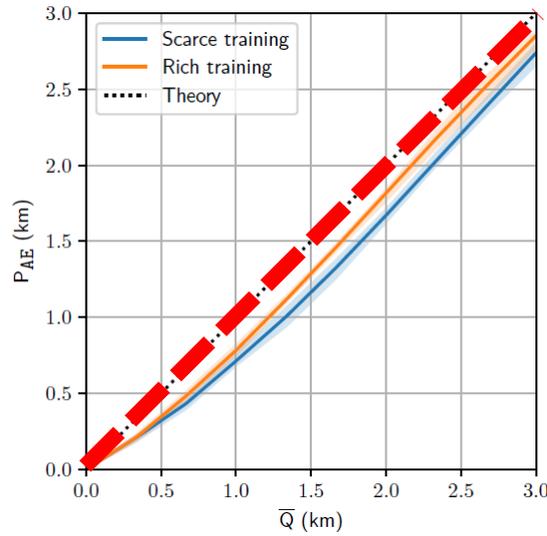
Scarce



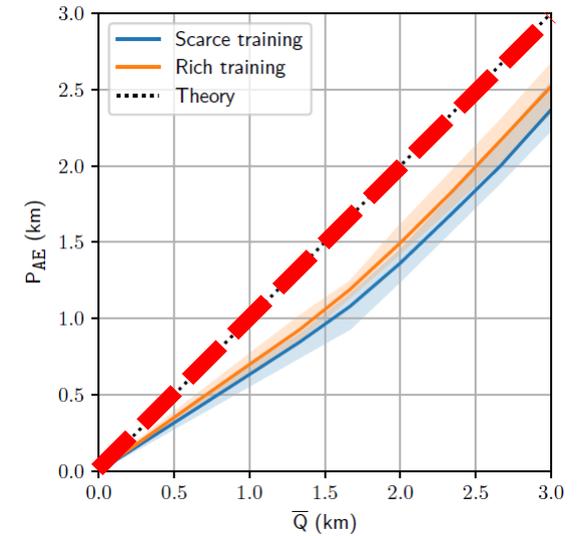
Rich



Exponential Mechanism



Location Hiding Mechanism

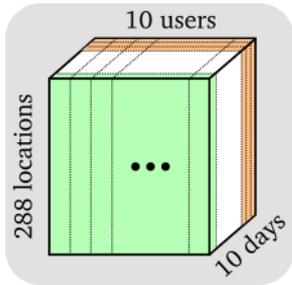


Same (optimal) performance in theory...

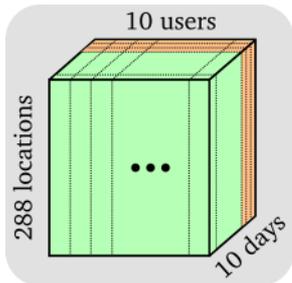
# Performance Results (non-sporadic case)

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Dataset with  
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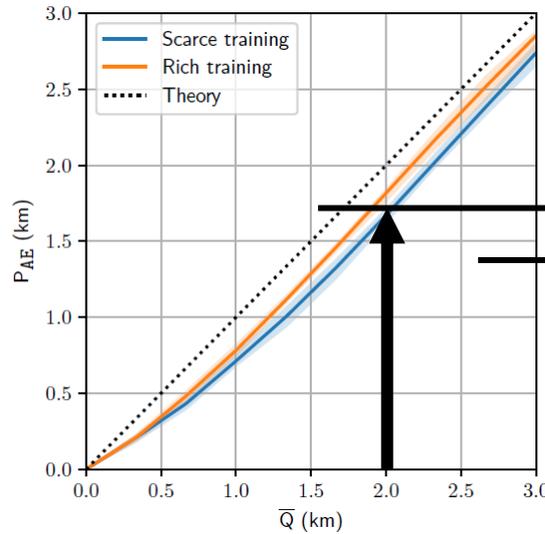
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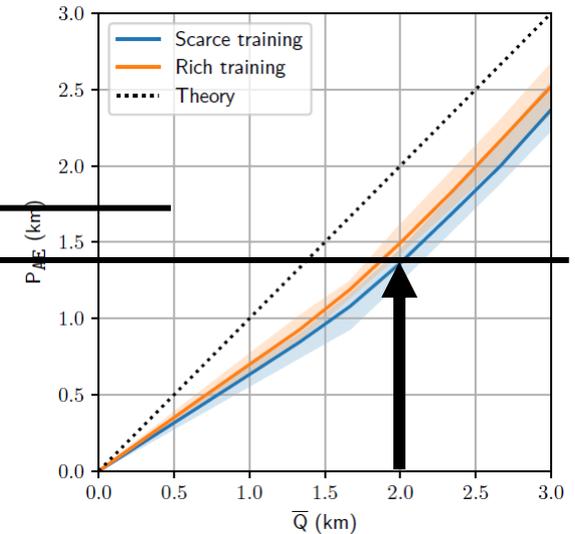
Rich



Exponential Mechanism



Location Hiding Mechanism



Same (optimal) performance in theory...  
but different performance in practice

# Let's think about it...

- **Hardwired** LPPMs will be useful when user behavior (in practice) is captured by the training data.

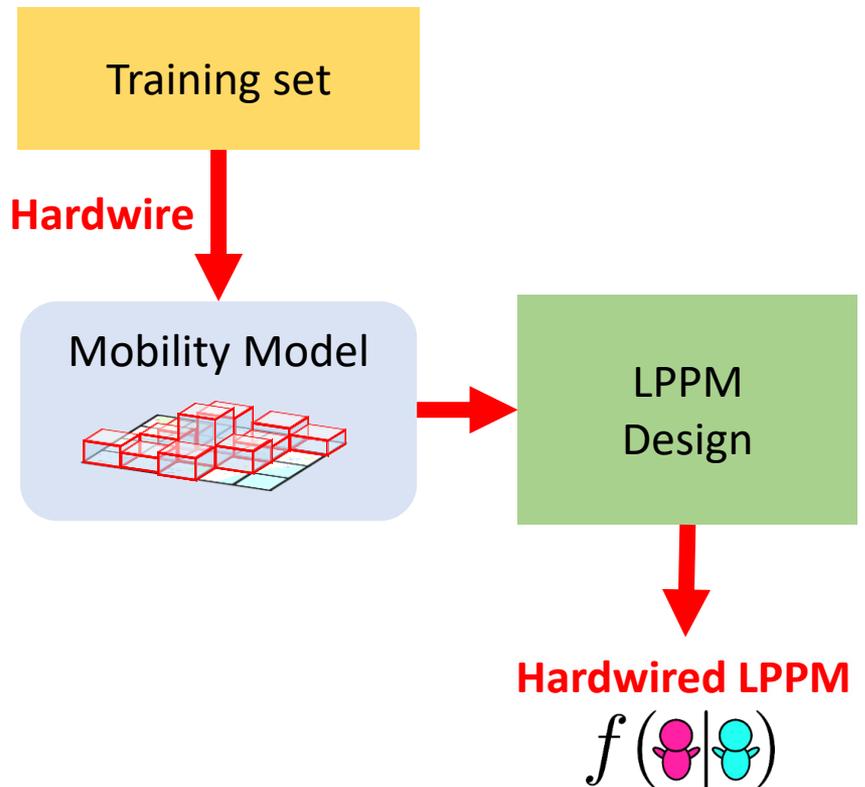


- They will NOT perform well when:

Unknown Behavior

- Insufficient data
- Deprecated data
- Non-representative data
- Unexpected change in user behavior
- ...

- What can we do in all of these cases?



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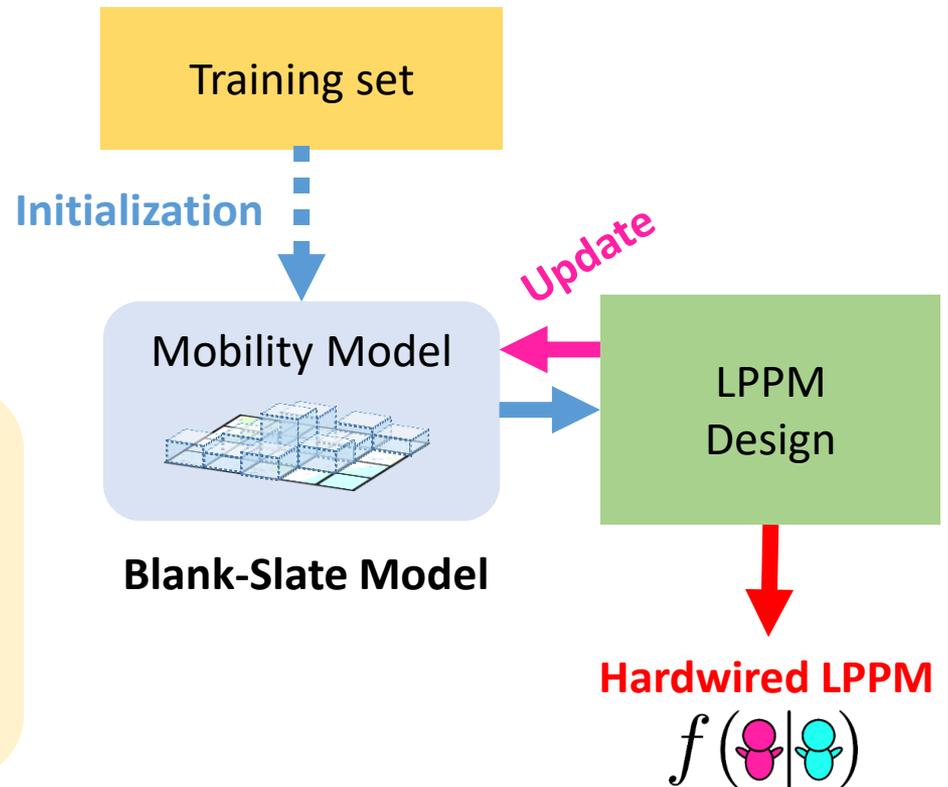


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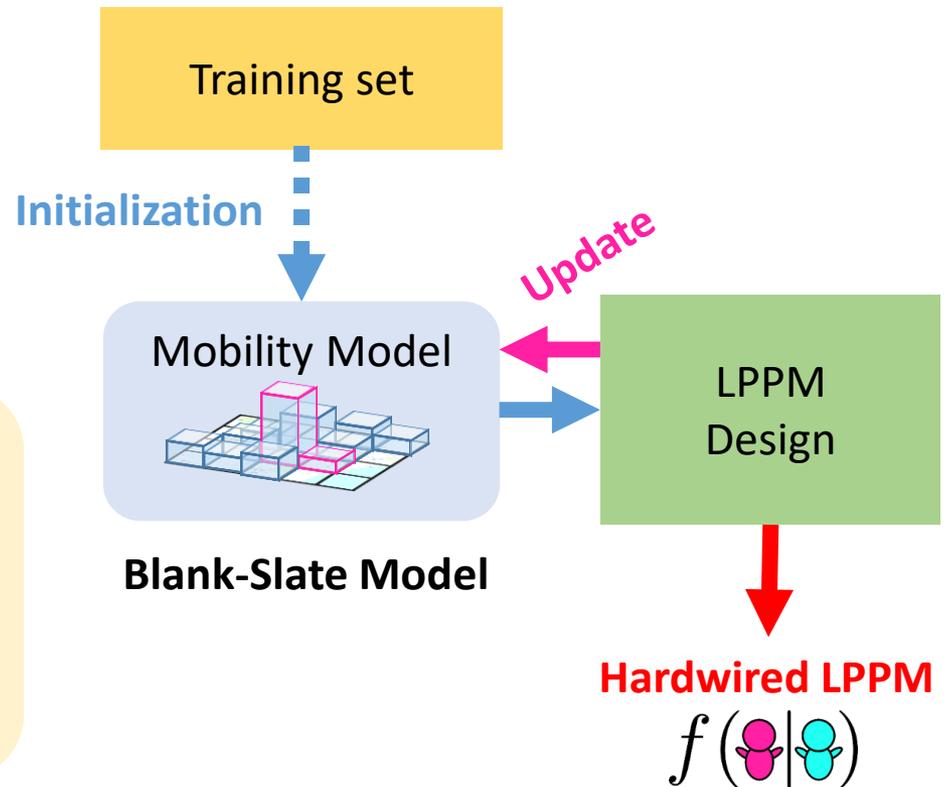


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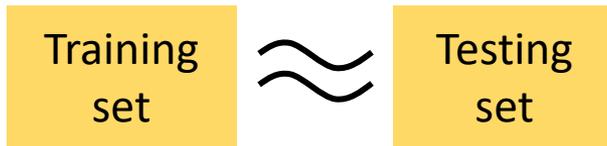
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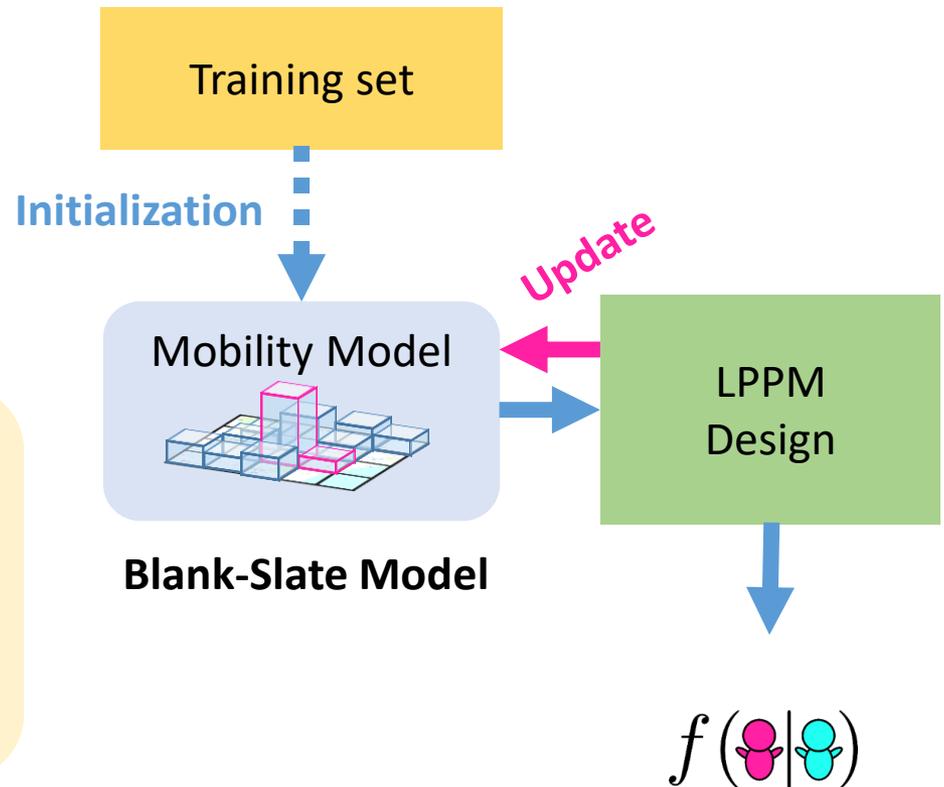


- They will NOT perform well when:

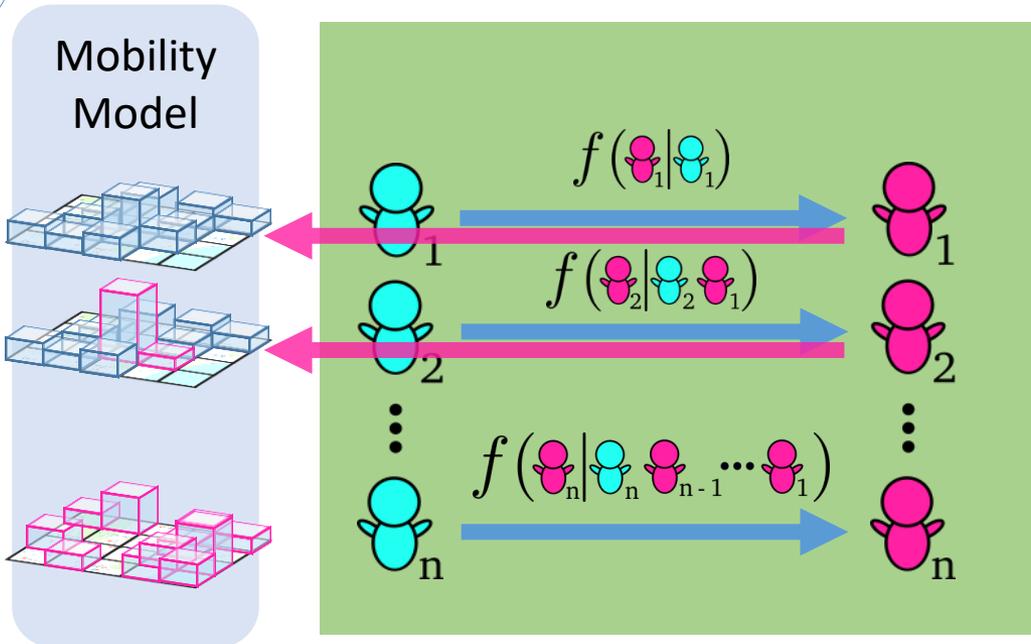
Unknown Behavior

- Insufficient data
- Deprecated data
- Non-representative data
- Unexpected change in user behavior
- ...

- What can we do in all of these cases?



# Writing in the blank-slate using the reported locations



[In the paper]  
MLE of the mobility profile  
in **sporadic** models

$$\left. \begin{array}{l}
 \text{robot}_1 \quad f(\text{robot}_1 | \text{robot}_1) \\
 \text{robot}_2 \quad f(\text{robot}_2 | \text{robot}_2, \text{robot}_1) \\
 \vdots \\
 \text{robot}_n \quad f(\text{robot}_n | \text{robot}_n, \text{robot}_{n-1}, \dots, \text{robot}_1)
 \end{array} \right\} \Pr(\text{robot})$$

Iterative algorithm

Profile Estimation-Based  
(PEB) LPPMs

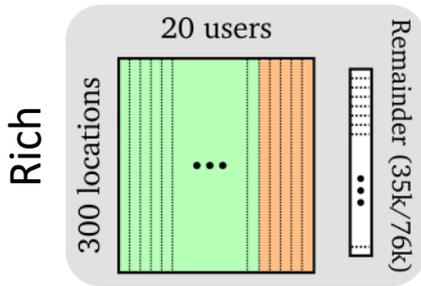
Result: an LPPM that can be written as:

$$f(\text{robot}_n | \text{robot}_n, \text{robot}_{n-1}, \dots, \text{robot}_1)$$

- We can evaluate them against a worst-case adversary.
- Will do better in sporadic settings.

# Experimental Results. Sporadic Case

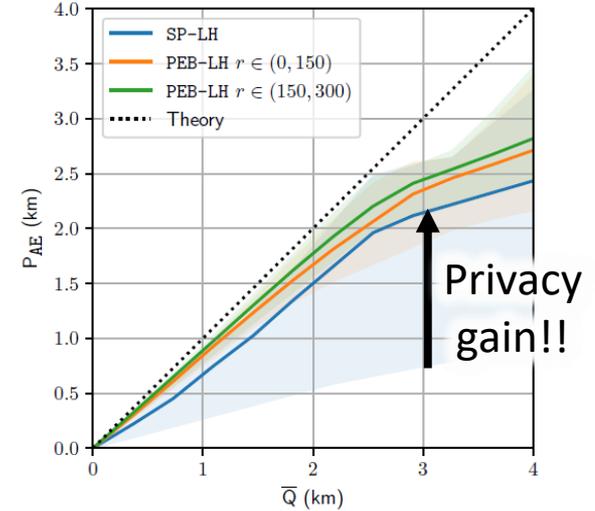
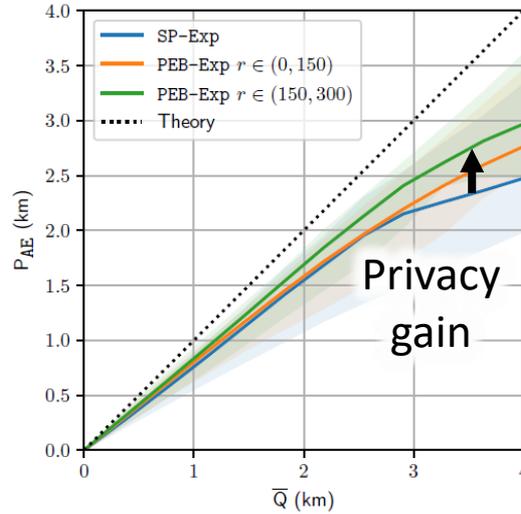
Datasets with sporadic reports (shuffled)



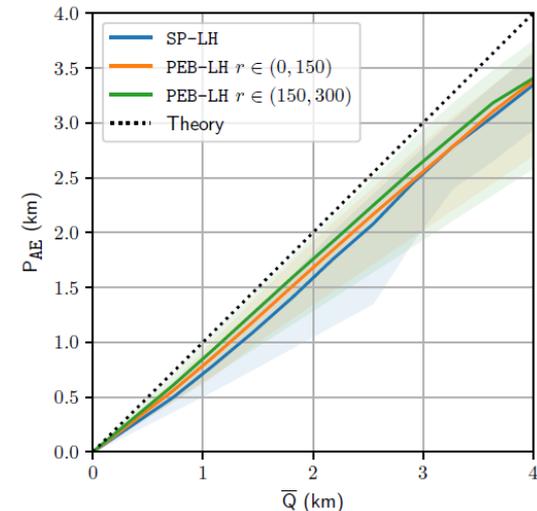
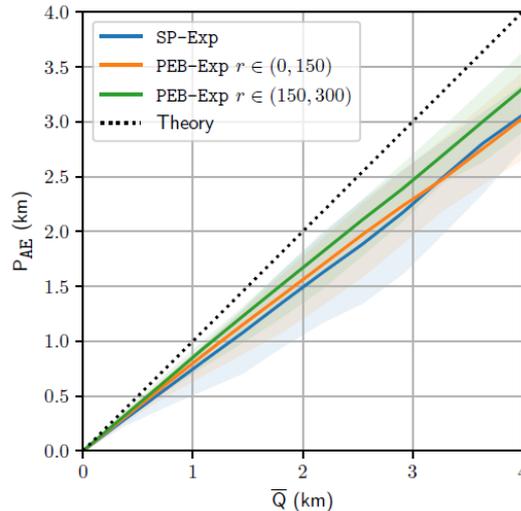
## Exponential Mechanism

## Location Hiding

Brightkite



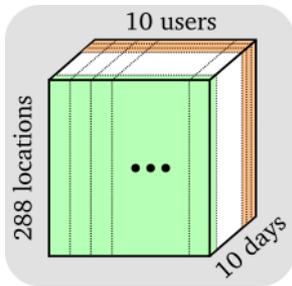
Gowalla



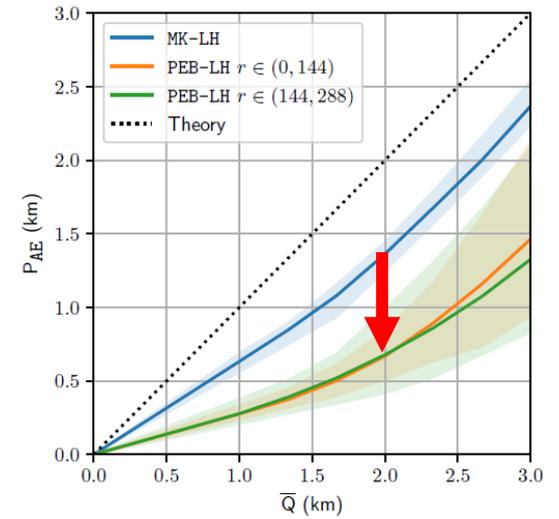
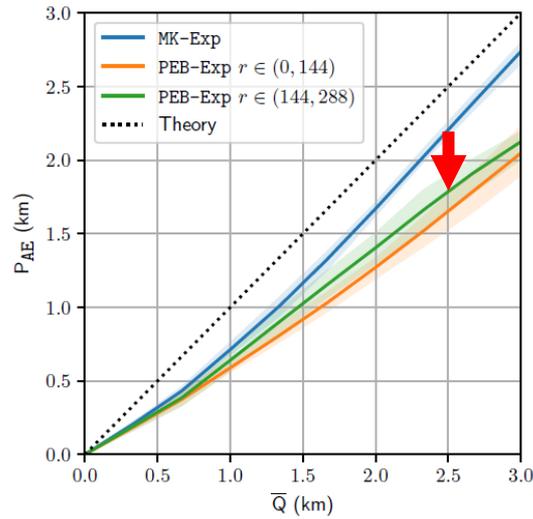
# Experimental Results. Non-Sporadic Case.

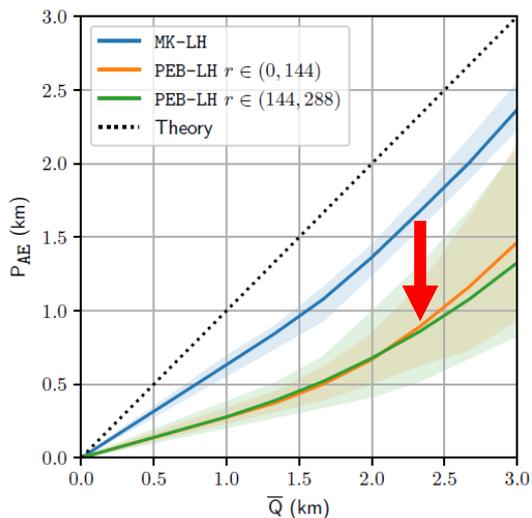
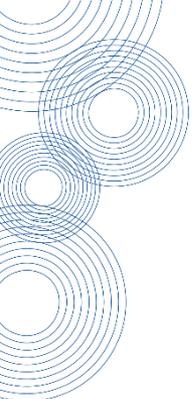
Dataset with continuous reports

Scarce



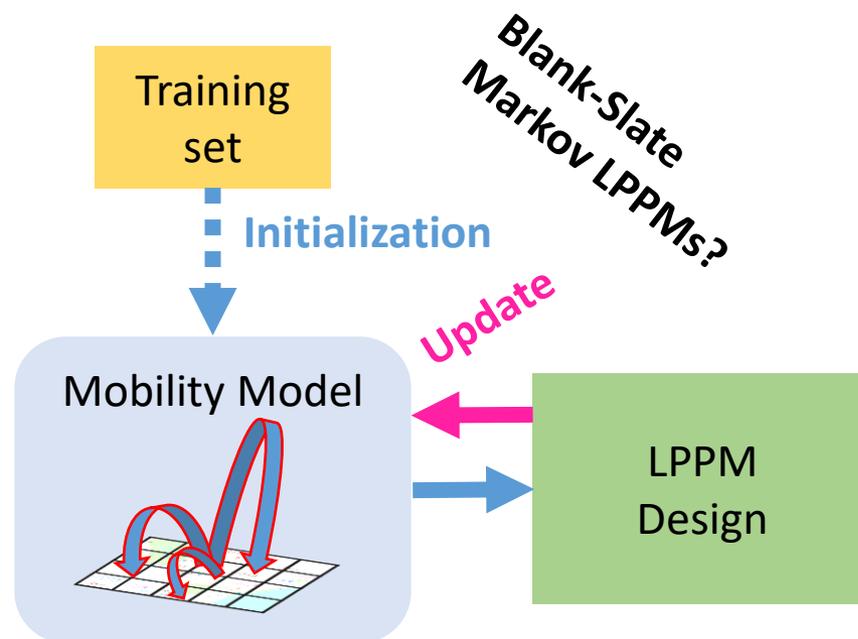
TaxiCab





- However, current Markov LPPMs do not account for differences in train/test.

- Hardwired Markov-based LPPMs encode road restrictions.
- Sporadic PEB-LPPMs do not!
- This explains their difference in performance.



# Summary

To build PETs with strong privacy guarantees in practice, we have to embrace that training data cannot always capture user behavior.

Training set



Testing set

- Current proposals **hardwire** training data into the LPPMs.
- We propose **blank-slate** models that improve the performance in sporadic scenarios.

## Future Work

- Blank-slate Markov models
- Evaluate LPPMs with more data sets
- Develop other techniques to improve performance in practice...

**Thank you!!** [simonoya@gts.uvigo.es](mailto:simonoya@gts.uvigo.es)