On the Utility Gain of Iterative Bayesian Update for Locally Differentially Private Mechanisms

Héber H. Arcolezi, Selene Cerna, and Catuscia Palamidessi

Inria and École Polytechnique (IPP), Palaiseau, France
{heber.hwang-arcolezi,selene-leya.cerna-nahuis,catuscia.palamidessi}@inria.fr

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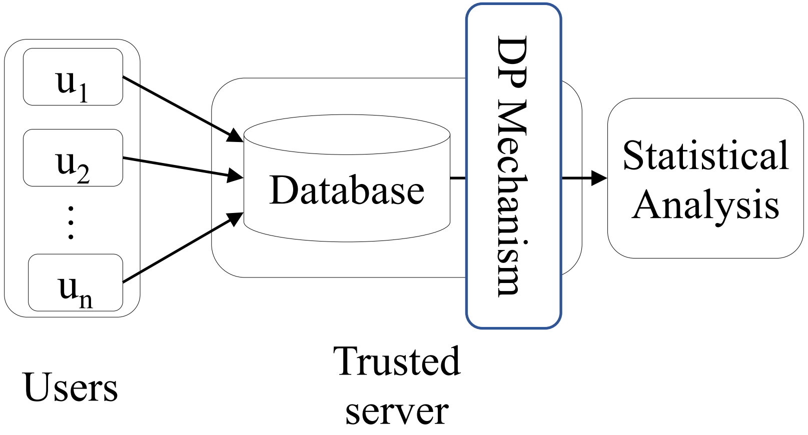
Context

Differential Privacy (DP) [Dwork et al, 2006]

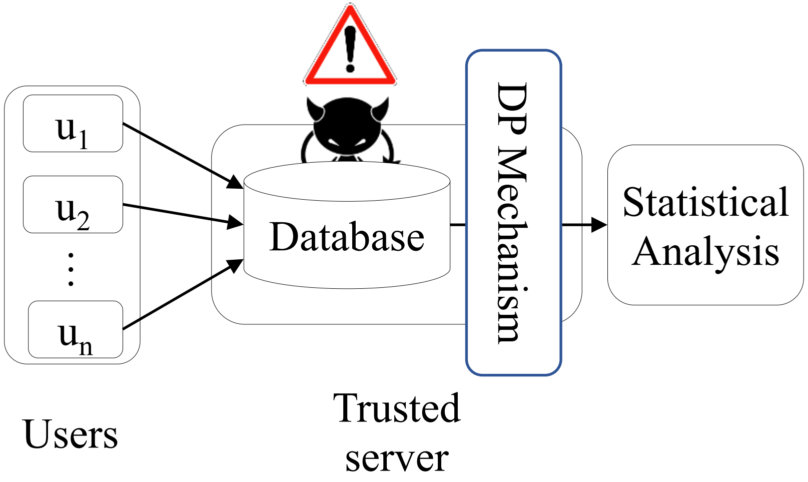


Centralized DP:

✓ High utility.

✗ Need to trust the server.

Differential Privacy (DP) [Dwork et al, 2006]



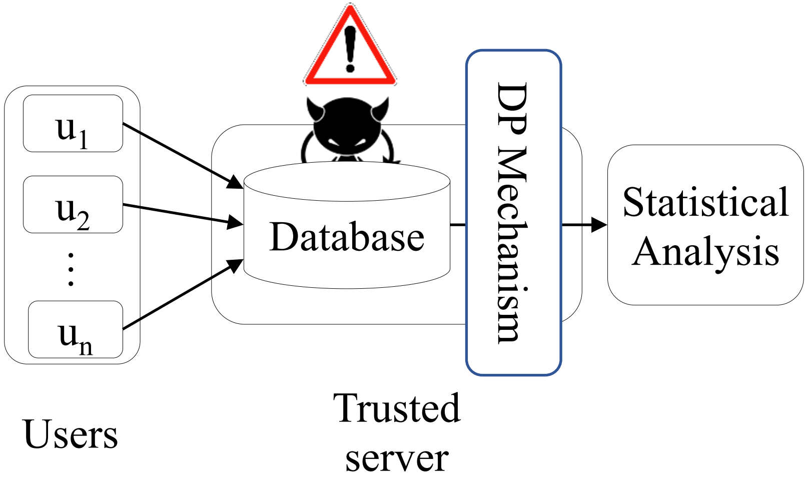
Centralized DP:

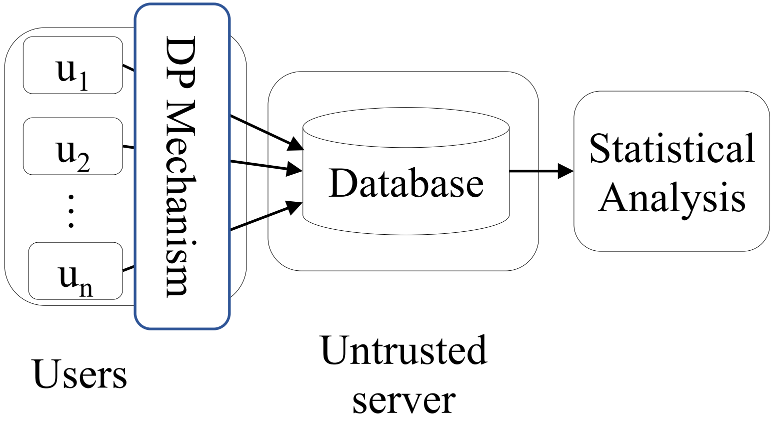
✓ High utility.

✗ Need to trust the server.

✗✗ **Data breaches, data misuse, etc.**

Differential Privacy (DP) [Dwork et al, 2006; Duchi et al, 2013]





Centralized DP:

✓ High utility.

✗ Need to trust the server.

✗✗ **Data breaches, data misuse, etc.**

Local DP (LDP):

✓ No need to trust the server.

✗ Low utility.

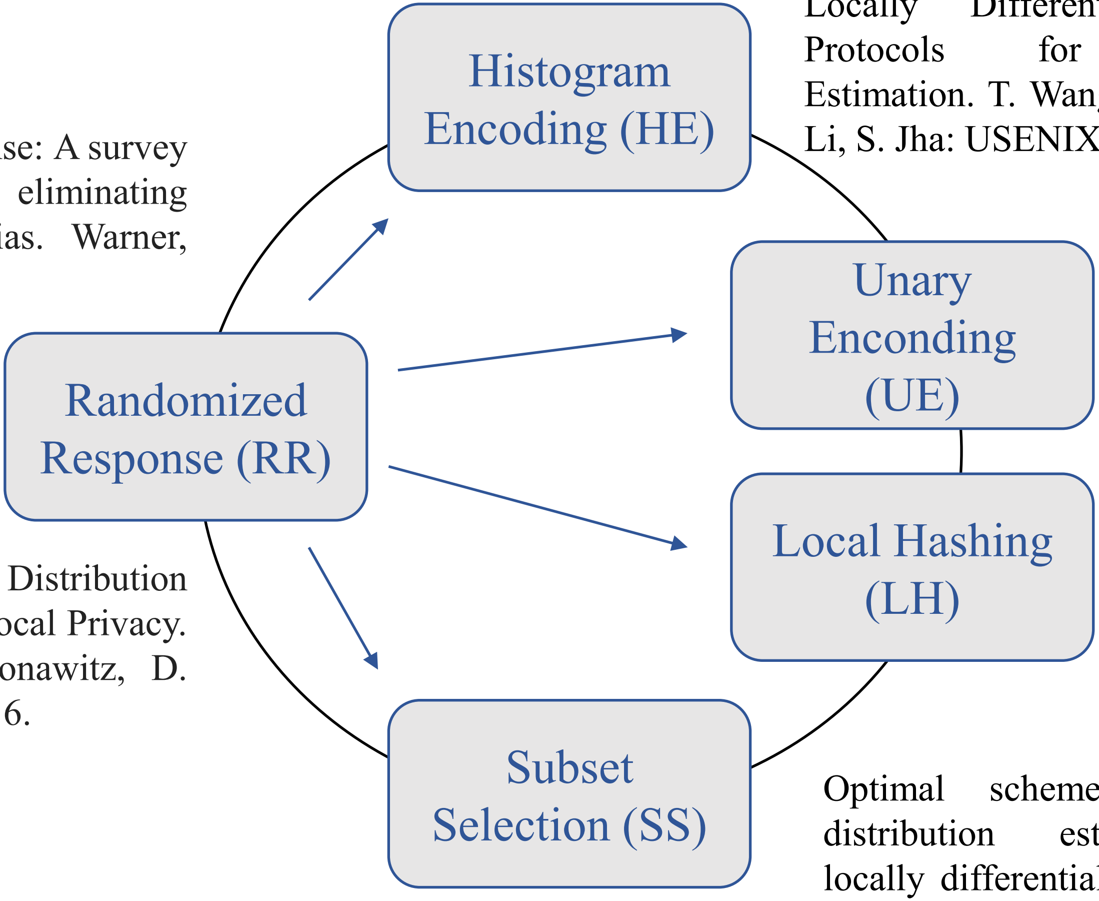
Key Differences Between Central and Local DP

- Central DP concerns any two neighboring datasets;
  - Let f be the mean query on database D: $\tilde{\mu} = f(D) + \text{Lap}({}^{s}/_{\epsilon})$.
- Local DP concerns any two values;
  - Let the user's value x lies in range [-1, 1]: $y = x + \text{Lap}({}^{2}/_{\epsilon})$;
  - The server aggregates LDP data to estimate mean: $\tilde{\mu} = \frac{1}{n}\sum_{i=1}^{n} y_i$.
- As a result, **the amount of noise is different** (each sample);
- Two lines of research to improve the privacy-utility trade-off:
  1. Design new LDP mechanisms;
  2. Improve the estimation at the server side.

State-of-the-Art LDP Distribution Estimation Mechanisms

Randomized response: A survey technique for eliminating evasive answer bias. Warner, S.L. JASA 1965.

Discrete Distribution Estimation under Local Privacy. P. Kairouz, K. Bonawitz, D. Ramage, ICML 2016.



Randomized Response (RR)

Histogram Encoding (HE)

Unary Enconding (UE)

Local Hashing (LH)

Subset Selection (SS)

Locally Differentially Private Protocols for Frequency Estimation. T. Wang, J. Blocki, N. Li, S. Jha: USENIX Security 2017.

RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response. Ú. Erlingsson, V. Pihur, A. Korolova, CCS 2014.

Locally Differentially Private Protocols for Frequency Estimation. T. Wang, J. Blocki, N. Li, S. Jha: USENIX Security 2017.

Optimal schemes for discrete distribution estimation under locally differential privacy. M. Ye, A. Barg: IEEE TIT 2018.

Post-Processing Distribution Estimator for LDP Mechanisms

Paper	**Estimator**	**Post-Processing**	**LDP Mechanisms Evaluated**
Discrete Distribution Estimation under Local Privacy (ICML 2016)	Matrix Inversion (MI)	• Re-normalization • Projection onto the probability simplex	• Generalized RR (GRR) • Symmetric UE (SUE)
Locally Differentially Private Frequency Estimation with Consistency (NDSS 2020)	MI	• 10 techniques (e.g., enforcing only non-negativity, re-normalization, ...)	• Optimal LH (OLH)
Generalized iterative bayesian update and applications to mechanisms for privacy protection (Euro S&P 2020)	Iterative Bayesian Update (IBU)	• Generic IBU for personalized LDP	• GRR • SUE
Reconstruction of the distribution of sensitive data under free-will privacy (arXiv 2022)			
Our (DBSec 2023)	MI vs IBU	• MI re-normalization	• 7 one-time (*e.g.*, GRR, SUE, ...) • 7 longitudinal (*e.g.*, RAPPOR)

Outline

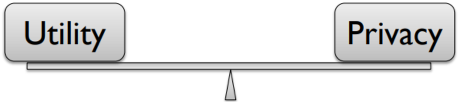
1. Context
2. **Background & Problem Statement**
3. Experimental Results
4. Conclusion & Perspectives

LDP: Formal Definition & Properties [Duchi et al, 2013]

Def (ϵ-LDP). A randomized mechanism $\mathcal{M}$ satisfies ϵ-LDP, where $\epsilon \geq 0$, if for **any two inputs** $v, v' \in \text{Domain}(\mathcal{M})$ and for **any output** $z \in \text{Range}(\mathcal{M})$:

$$\frac{\Pr[\mathcal{M}(v) = z]}{\Pr[\mathcal{M}(v') = z]} \leq e^{\epsilon}$$

Privacy Loss



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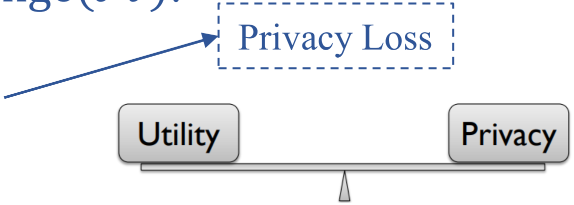

Def (Pure ϵ-LDP) [Wang et al, 2017]. An ϵ-LDP mechanism $\mathcal{M}$ is pure if there are two probability parameters $0 < q^* < p^* < 1$ such that for all $v \neq v' \in \text{Domain}(\mathcal{M})$:

$$\Pr[\mathcal{M}(v) \in \{z | v \in S(z)\}] = p^*,$$
$$\Pr[\mathcal{M}(v') \in \{z | v \in S(z)\}] = q^*,$$

where $S(z)$ is the set of items that z 'supports'.

LDP Distribution Estimation: MI and IBU

$\mathbf{f}$: Original distribution $\tilde{\mathbf{f}}$: Observed distribution

Matrix Inversion (MI)

$$\hat{\mathbf{f}} = \frac{\tilde{\mathbf{f}} - nq^*}{n(p^* - q^*)} = \tilde{\mathbf{f}} A_{vz}^{-1}$$

Iterative Bayesian Update (IBU)

$$\hat{\mathbf{f}}^{t+1} = \tilde{\mathbf{f}} \cdot \frac{\hat{\mathbf{f}}^{t} * A_{vz}}{\hat{\mathbf{f}}^{t} \cdot A_{vz}}$$

Channel matrix (probability of obtaining z given v):

$$A_{vz} = \begin{bmatrix} p^* & \cdots & q^* \\ \vdots & \ddots & \vdots \\ q^* & \cdots & p^* \end{bmatrix}$$

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1. Context
2. **Background & Problem Statement**
   i. **One-Time Distribution Estimation;**
   ii. Longitudinal Distribution Estimation.
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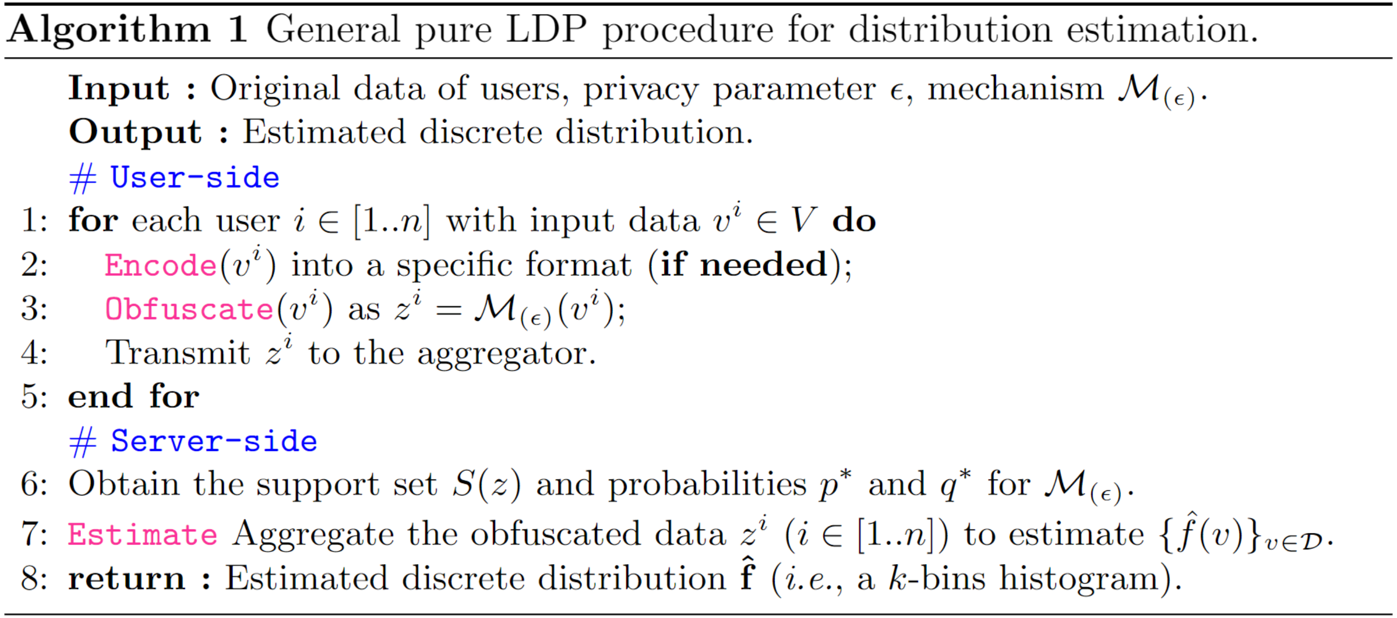
Problem Statement #1: One-Time Distribution Estimation



Algorithm 1 General pure LDP procedure for distribution estimation.

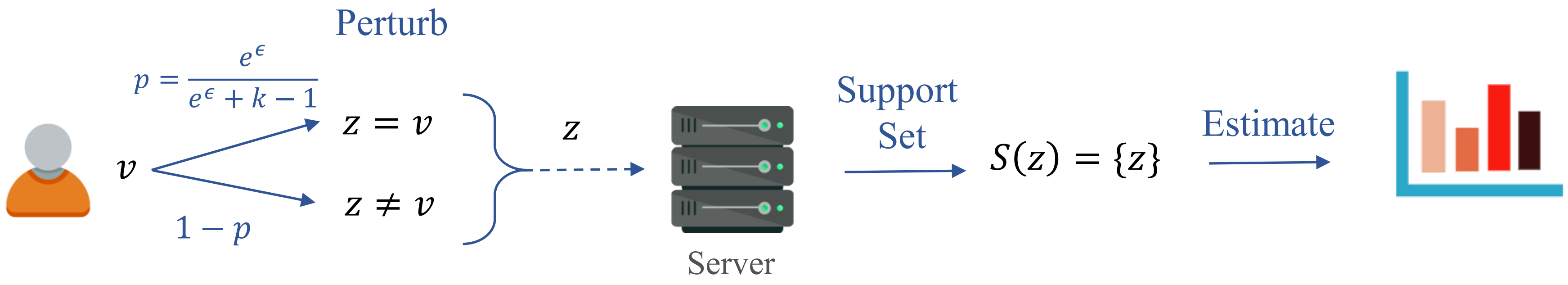
```
Input : Original data of users, privacy parameter $\epsilon$, mechanism $\mathcal{M}_{(\epsilon)}$.
Output : Estimated discrete distribution.
# User-side
for each user $i \in [1..n]$ with input data $v^i \in V$ do
    Encode($v^i$) into a specific format (if needed);
    Obfuscate($v^i$) as $z^i = \mathcal{M}_{(\epsilon)}(v^i)$;
    Transmit $z^i$ to the aggregator.
end for
# Server-side
Obtain the support set $S(z)$ and probabilities $p^*$ and $q^*$ for $\mathcal{M}_{(\epsilon)}$.
Estimate Aggregate the obfuscated data $z^i$ ($i \in [1..n]$) to estimate $\{\hat{f}(v)\}_{v \in \mathcal{D}}$.
return : Estimated discrete distribution $\hat{\mathbf{f}}$ (i.e., a $k$-bins histogram).
```

$\mathbf{f}$: Original distribution $\hat{\mathbf{f}}$: Estimated distribution

MSE$(\mathbf{f}, \hat{\mathbf{f}})$ ⇄ MAE$(\mathbf{f}, \hat{\mathbf{f}})$

One-Time LDP Distribution Estimation Mechanisms

Generalized Randomized Response (GRR)



Perturb

$p = \frac{e^{\epsilon}}{e^{\epsilon} + k - 1}$

v

$1 - p$

$z = v$

$z \neq v$

z

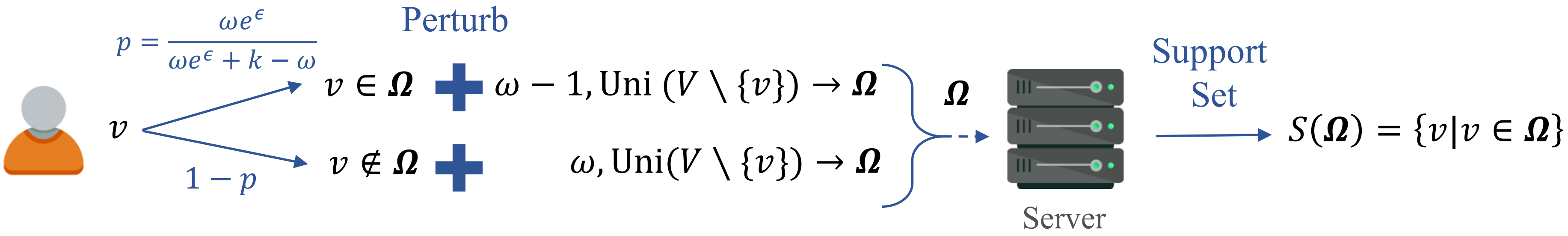
Server

Support Set

$S(z) = \{z\}$

Estimate

Subset Selection (SS)



Perturb

$p = \frac{\omega e^{\epsilon}}{\omega e^{\epsilon} + k - \omega}$

v

$1 - p$

$v \in \boldsymbol{\Omega}$ + $\omega - 1, \text{Uni}\ (V \setminus \{v\}) \rightarrow \boldsymbol{\Omega}$

$v \notin \boldsymbol{\Omega}$ + $\omega, \text{Uni}(V \setminus \{v\}) \rightarrow \boldsymbol{\Omega}$

$\boldsymbol{\Omega}$

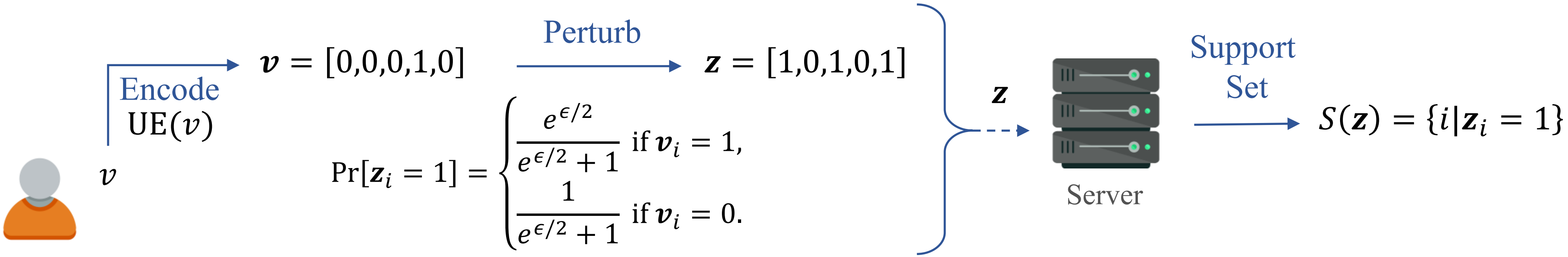
Server

Support Set

$S(\boldsymbol{\Omega}) = \{v | v \in \boldsymbol{\Omega}\}$

One-Time LDP Distribution Estimation Mechanisms

Symmetric Unary Encoding (SUE)



v

Encode

$\mathrm{UE}(v)$

$\boldsymbol{v} = [0,0,0,1,0]$ $\xrightarrow{\text{Perturb}}$ $\boldsymbol{z} = [1,0,1,0,1]$

$$\Pr[\boldsymbol{z}_i = 1] = \begin{cases} \dfrac{e^{\epsilon/2}}{e^{\epsilon/2}+1} & \text{if } \boldsymbol{v}_i = 1, \\ \dfrac{1}{e^{\epsilon/2}+1} & \text{if } \boldsymbol{v}_i = 0. \end{cases}$$

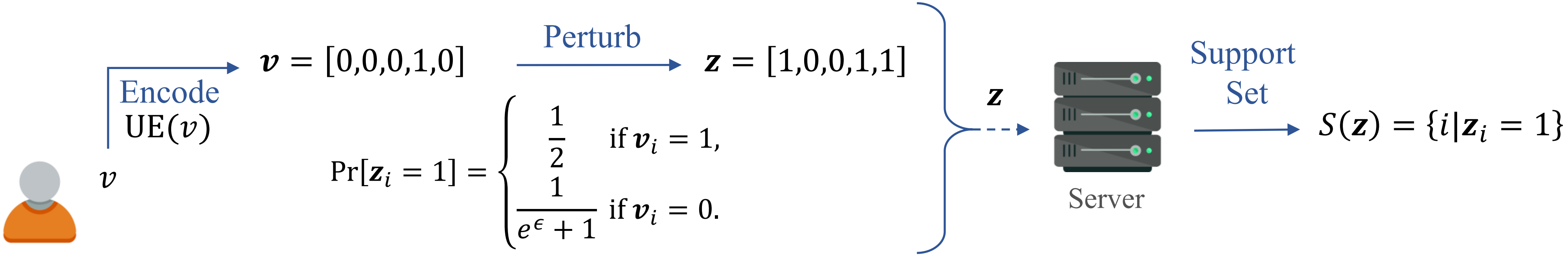
$\boldsymbol{z}$

Server

Support Set

$S(\boldsymbol{z}) = \{i \mid \boldsymbol{z}_i = 1\}$

Optimized Unary Encoding (OUE)



v

Encode

$\mathrm{UE}(v)$

$\boldsymbol{v} = [0,0,0,1,0]$ $\xrightarrow{\text{Perturb}}$ $\boldsymbol{z} = [1,0,0,1,1]$

$$\Pr[\boldsymbol{z}_i = 1] = \begin{cases} \dfrac{1}{2} & \text{if } \boldsymbol{v}_i = 1, \\ \dfrac{1}{e^{\epsilon}+1} & \text{if } \boldsymbol{v}_i = 0. \end{cases}$$

$\boldsymbol{z}$

Server

Support Set

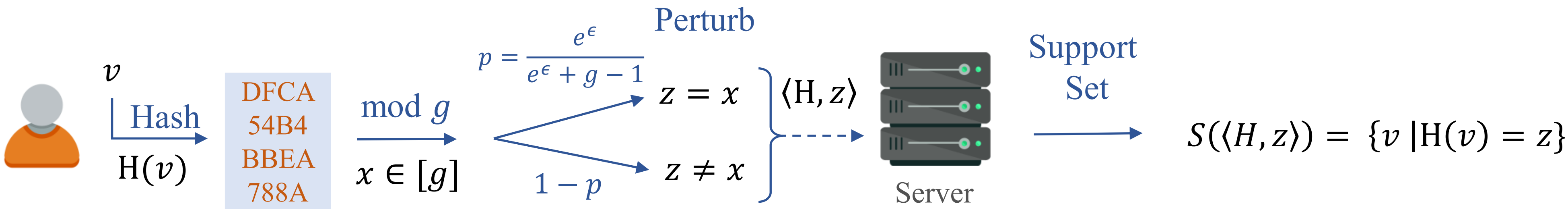
$S(\boldsymbol{z}) = \{i \mid \boldsymbol{z}_i = 1\}$

One-Time LDP Distribution Estimation Mechanisms

Local Hashing (LH)

Binary LH: $g = 2$

Optimal LH: $g = e^{\epsilon} + 1$



v

Hash

$\mathrm{H}(v)$

DFCA 54B4 BBEA 788A

mod g

$x \in [g]$

Perturb

$p = \frac{e^{\epsilon}}{e^{\epsilon} + g - 1}$

$1 - p$

$z = x$

$z \neq x$

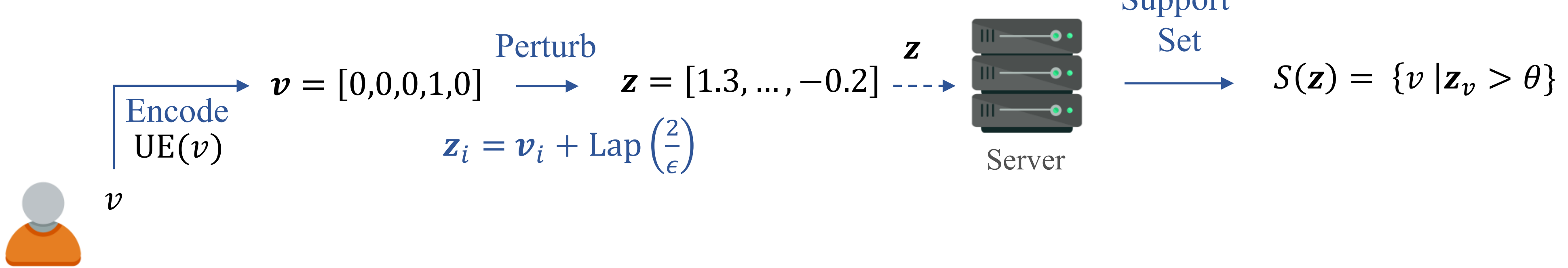
$\langle \mathrm{H}, z \rangle$

Server

Support Set

$S(\langle H, z \rangle) = \{v \mid \mathrm{H}(v) = z\}$

Thresholding w/ Histogram Encoding (THE)



v

Encode

$\mathrm{UE}(v)$

$\boldsymbol{v} = [0,0,0,1,0]$

Perturb

$\boldsymbol{z} = [1.3, \ldots, -0.2]$

$\boldsymbol{z}_i = \boldsymbol{v}_i + \mathrm{Lap}\left(\frac{2}{\epsilon}\right)$

$\boldsymbol{z}$

Server

Support Set

$S(\boldsymbol{z}) = \{v \mid \boldsymbol{z}_v > \theta\}$

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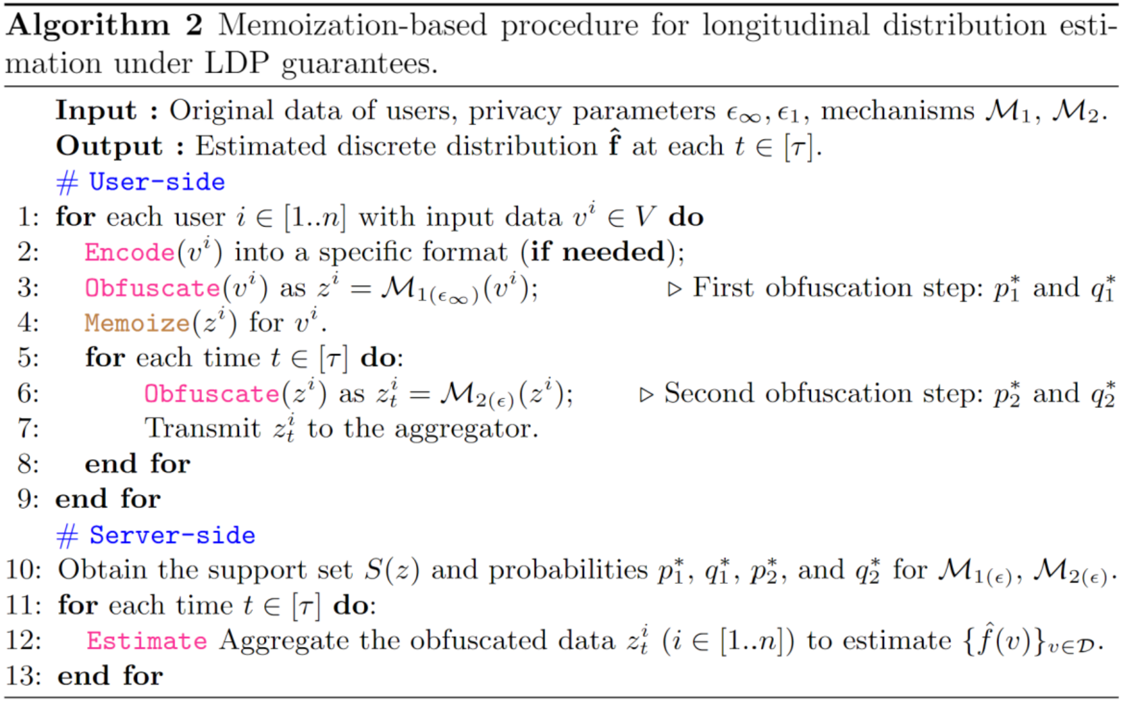
Problem Statement #2: Longitudinal Distribution Estimation



Algorithm 2 Memoization-based procedure for longitudinal distribution estimation under LDP guarantees.

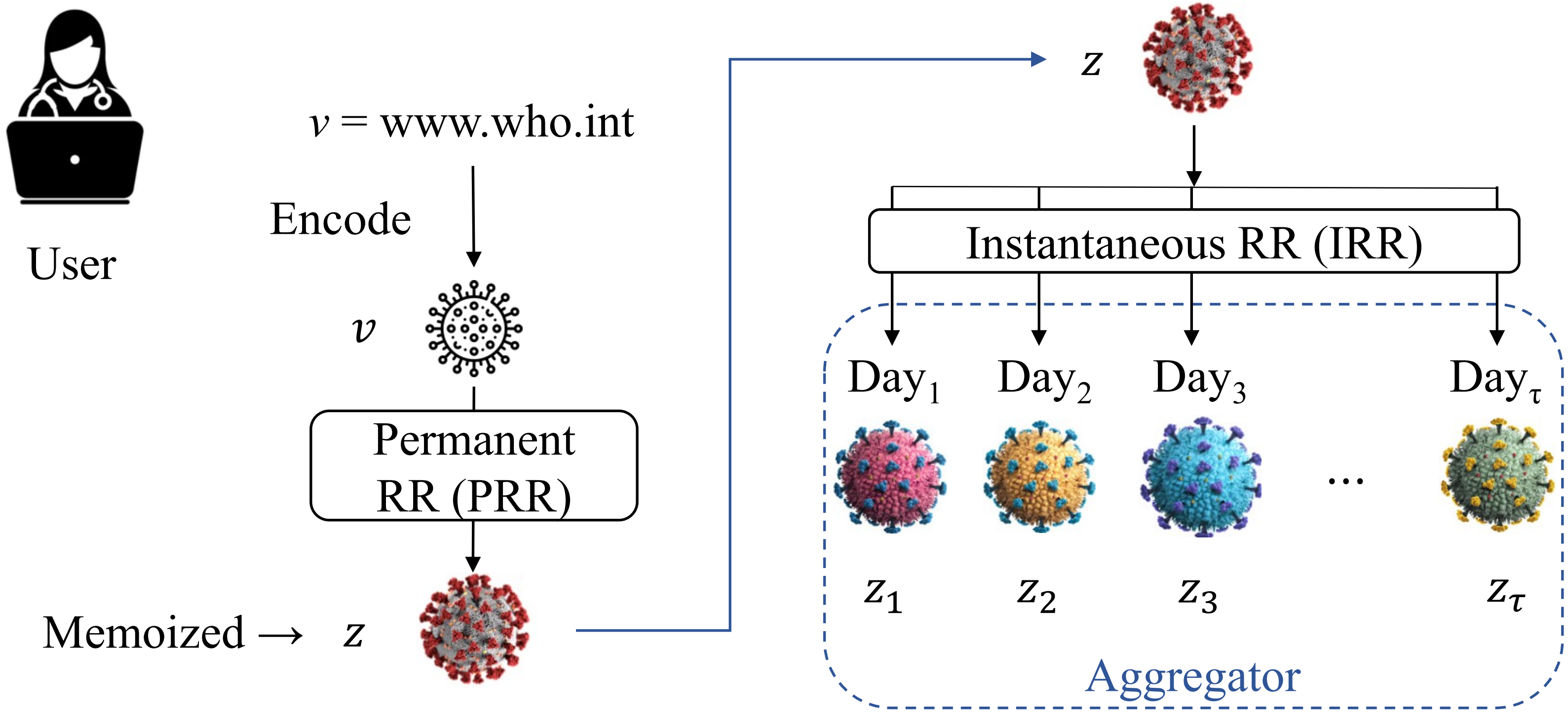
```
Input : Original data of users, privacy parameters $\epsilon_\infty, \epsilon_1$, mechanisms $\mathcal{M}_1$, $\mathcal{M}_2$.
Output : Estimated discrete distribution $\hat{\mathbf{f}}$ at each $t \in [\tau]$.
# User-side
for each user $i \in [1..n]$ with input data $v^i \in V$ do
    Encode($v^i$) into a specific format (if needed);
    Obfuscate($v^i$) as $z^i = \mathcal{M}_{1(\epsilon_\infty)}(v^i)$;        ▷ First obfuscation step: $p_1^*$ and $q_1^*$
    Memoize($z^i$) for $v^i$.
    for each time $t \in [\tau]$ do:
        Obfuscate($z^i$) as $z_t^i = \mathcal{M}_{2(\epsilon)}(z^i)$;        ▷ Second obfuscation step: $p_2^*$ and $q_2^*$
        Transmit $z_t^i$ to the aggregator.
    end for
end for
# Server-side
Obtain the support set $S(z)$ and probabilities $p_1^*$, $q_1^*$, $p_2^*$, and $q_2^*$ for $\mathcal{M}_{1(\epsilon)}$, $\mathcal{M}_{2(\epsilon)}$.
for each time $t \in [\tau]$ do:
    Estimate Aggregate the obfuscated data $z_t^i$ $(i \in [1..n])$ to estimate $\{\hat{f}(v)\}_{v \in \mathcal{D}}$.
end for
```

$\mathbf{f}$: Original distribution $\hat{\mathbf{f}}$: Estimated distribution

$\mathrm{MSE}(\mathbf{f}, \hat{\mathbf{f}})$ $\mathrm{MAE}(\mathbf{f}, \hat{\mathbf{f}})$

Longitudinal LDP Distribution Estimation Mechanisms

Memoization-based solution [Erlingsson, Pihur, Korolova, 2014]:



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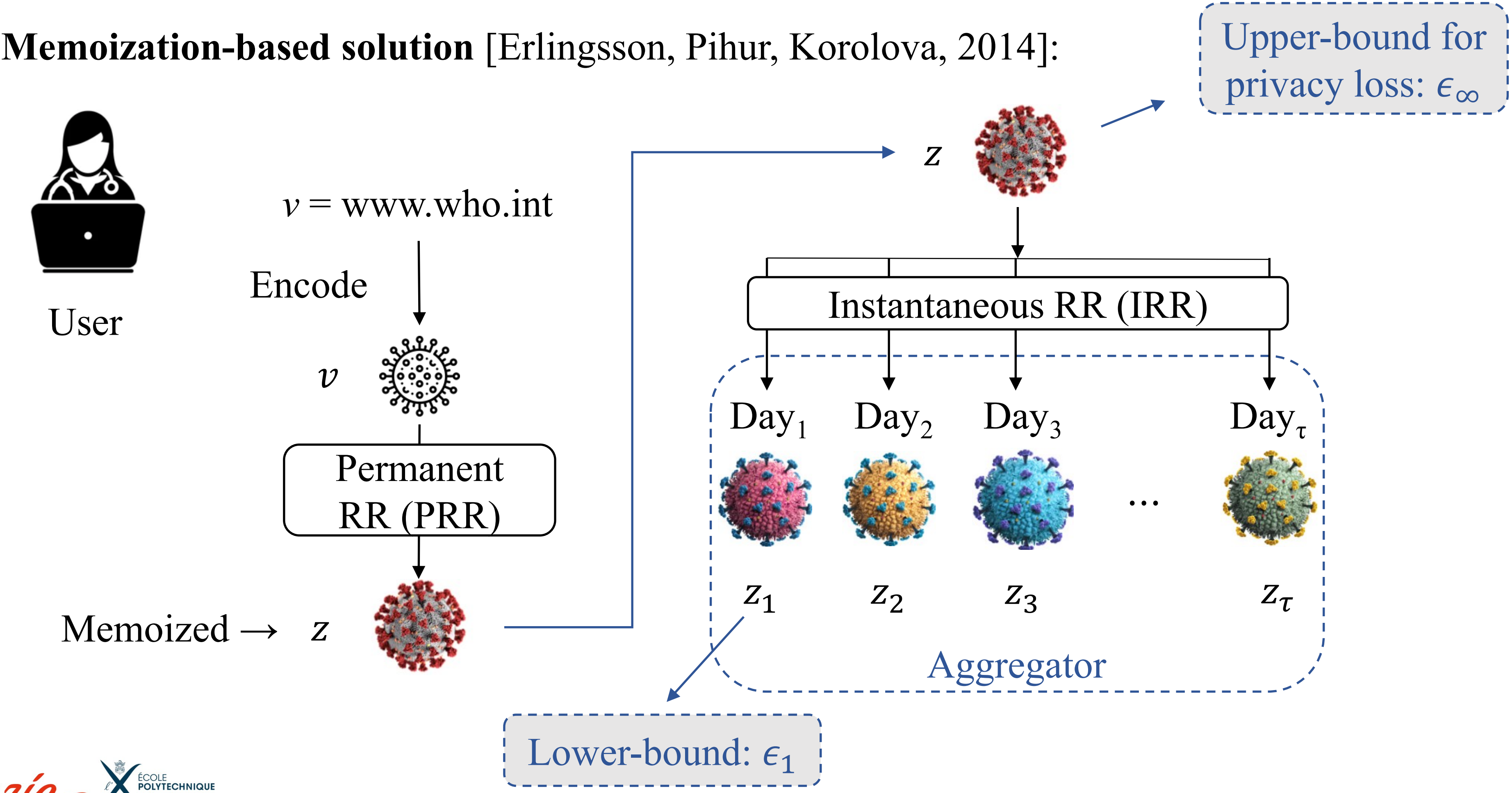


Upper-bound for privacy loss: ϵ_∞

User

v = www.who.int

Encode

v

Permanent RR (PRR)

Memoized → z

z

Instantaneous RR (IRR)

Day$_1$ Day$_2$ Day$_3$ … Day$_\tau$

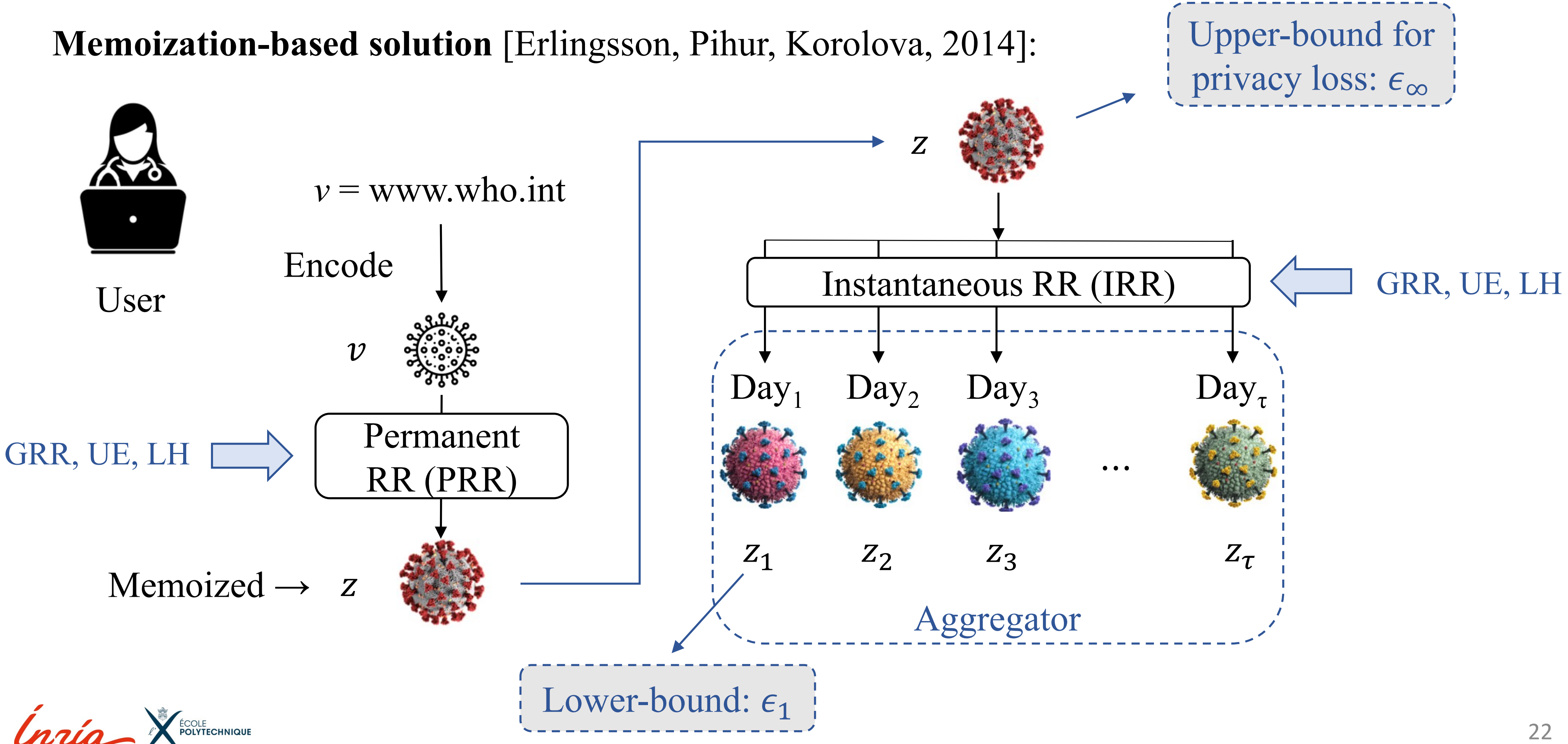
z_1 z_2 z_3 z_τ

Aggregator

Lower-bound: ϵ_1

Longitudinal LDP Distribution Estimation Mechanisms

Memoization-based solution [Erlingsson, Pihur, Korolova, 2014]:



User

v = www.who.int

Encode

v

GRR, UE, LH

Permanent RR (PRR)

Memoized → z

z

Upper-bound for privacy loss: ϵ_∞

Instantaneous RR (IRR)

GRR, UE, LH

Day_1 Day_2 Day_3 … Day_τ

z_1 z_2 z_3 z_τ

Aggregator

Lower-bound: ϵ_1

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Setting of Experiments

Six data distributions:

- Gaussian, Exponential, Uniform, Poisson, Triangular, Real.

Four domain size:

- $k \in \{2, 50, 100, 200\}$.

Two number of users:

- $n \in \{20000, 100000\}$.

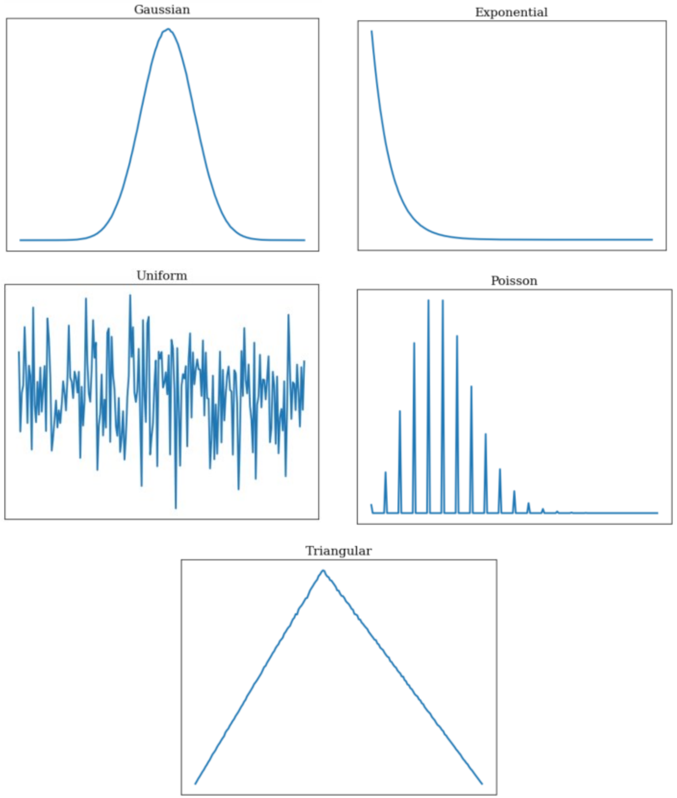
Fourteen LDP mechanisms:

- One-time: GRR, SS, SUE, OUE, BLH, OLH, THE.
- Longitudinal: L-GRR, four L-UE, two L-LH.

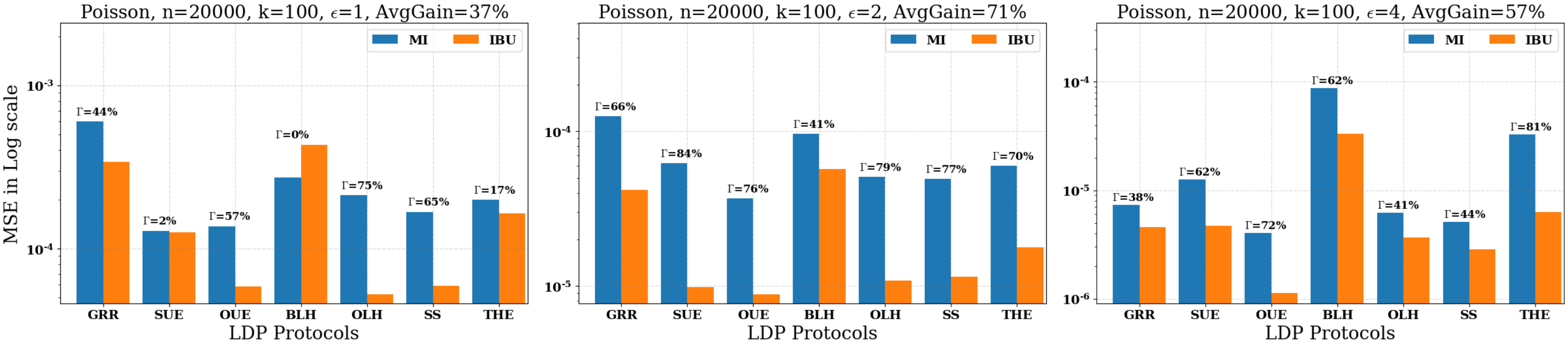
Two utility metrics:

- MSE and MAE. ⇨ IBU utility gain

$$\Gamma(\%) = 100 \cdot \max\left(\frac{\text{Metric}_{\text{MI}} - \text{Metric}_{\text{IBU}}}{\text{Metric}_{\text{MI}}}, 0\right)$$



Instance of IBU Utility Gain: One-Time LDP Mechanisms



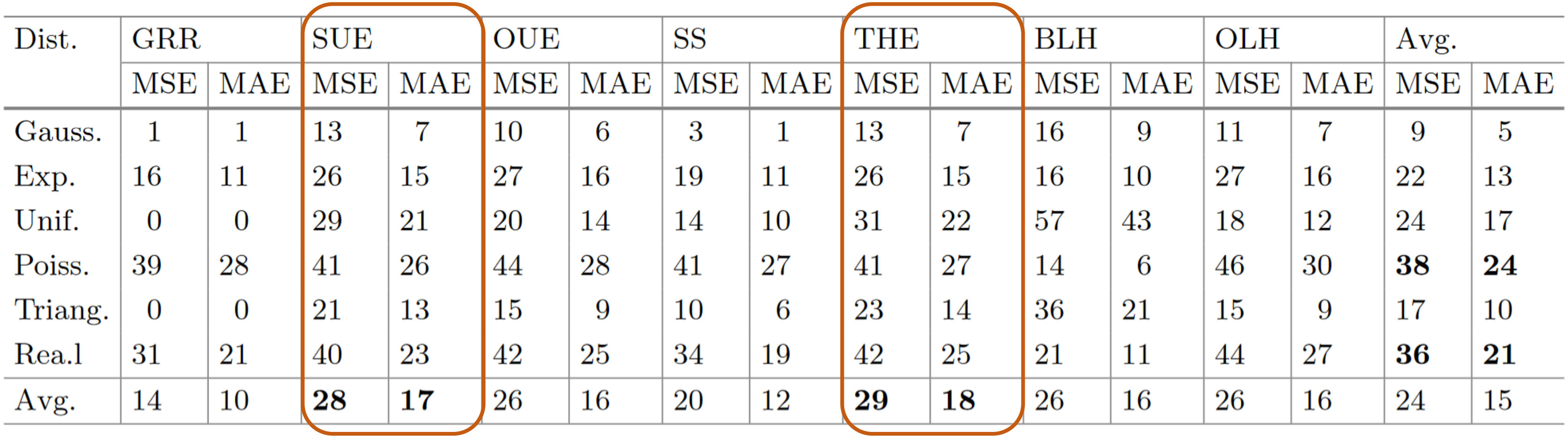
Poisson, n=20000, k=100, ϵ=1, AvgGain=37%

Poisson, n=20000, k=100, ϵ=2, AvgGain=71%

Poisson, n=20000, k=100, ϵ=4, AvgGain=57%

Summary of IBU Utility Gain: One-Time LDP Mechanisms

Averaged IBU gain in % considering all experimented k, n, ϵ.

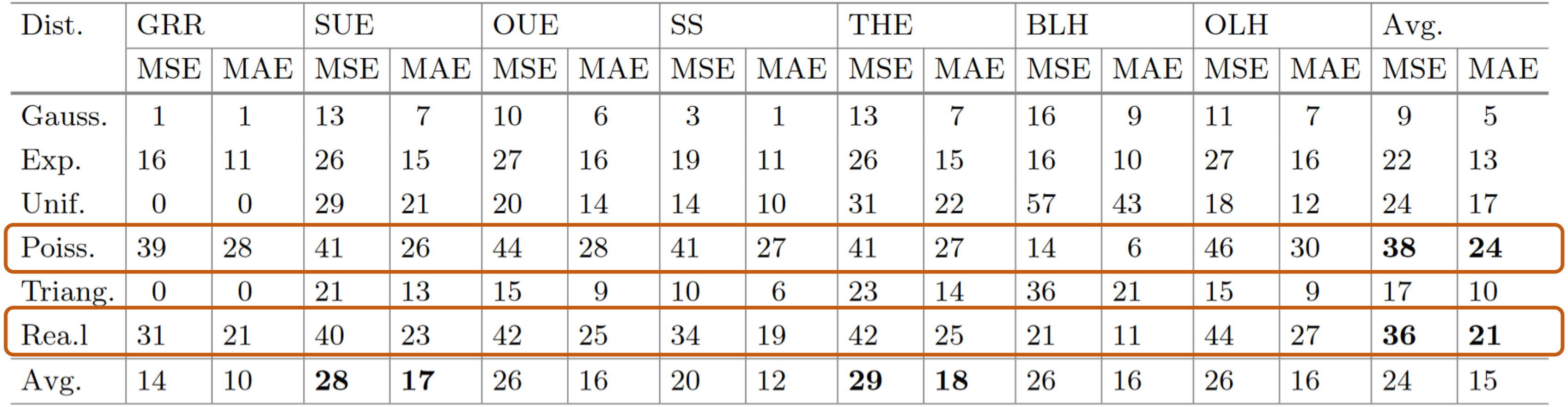


Dist.	GRR		SUE		OUE		SS		THE		BLH		OLH		Avg.	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Gauss.	1	1	13	7	10	6	3	1	13	7	16	9	11	7	9	5
Exp.	16	11	26	15	27	16	19	11	26	15	16	10	27	16	22	13
Unif.	0	0	29	21	20	14	14	10	31	22	57	43	18	12	24	17
Poiss.	39	28	41	26	44	28	41	27	41	27	14	6	46	30	**38**	**24**
Triang.	0	0	21	13	15	9	10	6	23	14	36	21	15	9	17	10
Rea.l	31	21	40	23	42	25	34	19	42	25	21	11	44	27	**36**	**21**
Avg.	14	10	**28**	**17**	26	16	20	12	**29**	**18**	26	16	26	16	24	15

Mechanisms w/ highest IBU gain: SUE and THE

Summary of IBU Utility Gain: One-Time LDP Mechanisms

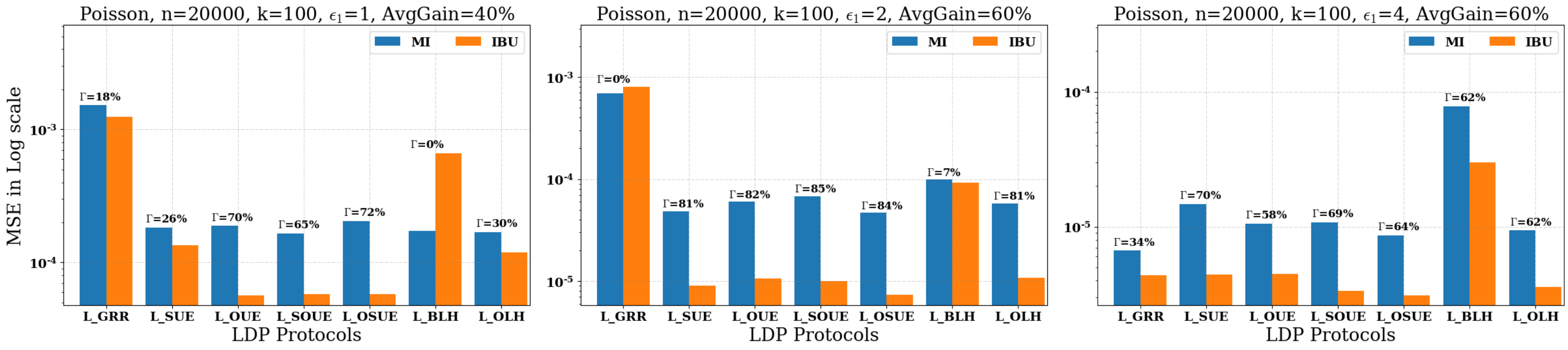
Averaged IBU gain in % considering all experimented k, n, ϵ.



Dist.	GRR		SUE		OUE		SS		THE		BLH		OLH		Avg.	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Gauss.	1	1	13	7	10	6	3	1	13	7	16	9	11	7	9	5
Exp.	16	11	26	15	27	16	19	11	26	15	16	10	27	16	22	13
Unif.	0	0	29	21	20	14	14	10	31	22	57	43	18	12	24	17
Poiss.	39	28	41	26	44	28	41	27	41	27	14	6	46	30	**38**	**24**
Triang.	0	0	21	13	15	9	10	6	23	14	36	21	15	9	17	10
Rea.l	31	21	40	23	42	25	34	19	42	25	21	11	44	27	**36**	**21**
Avg.	14	10	**28**	**17**	26	16	20	12	**29**	**18**	26	16	26	16	24	15

Distributions w/ highest IBU gain: Poisson and real

Instance of IBU Utility Gain for Longitudinal LDP Mechanisms



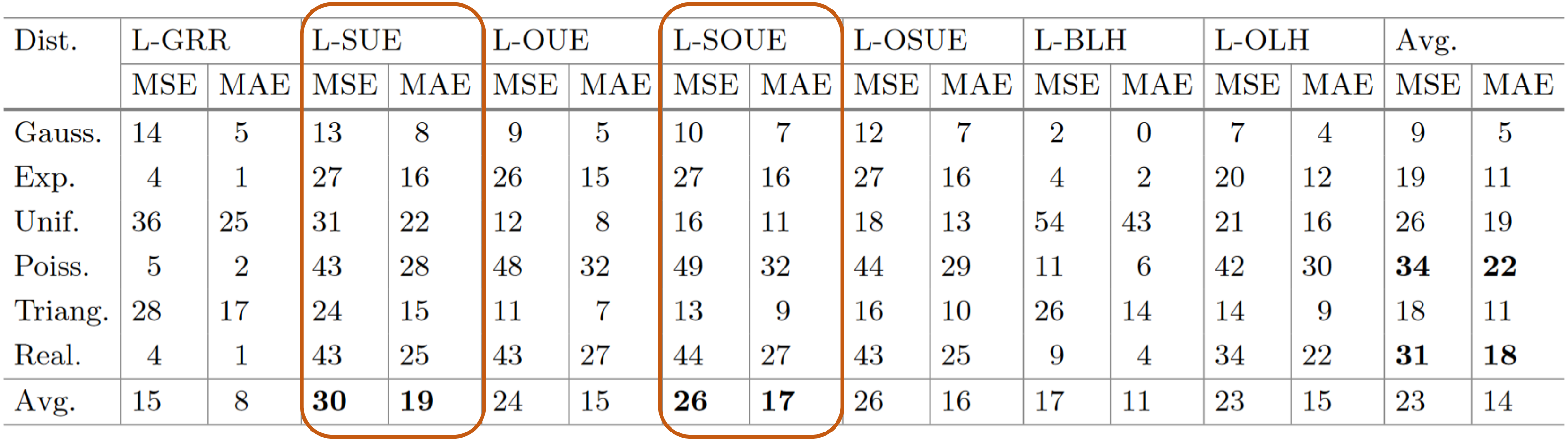
Poisson, n=20000, k=100, ϵ_1=1, AvgGain=40%

Poisson, n=20000, k=100, ϵ_1=2, AvgGain=60%

Poisson, n=20000, k=100, ϵ_1=4, AvgGain=60%

Summary of IBU Utility Gain: Longitudinal LDP Mechanisms

Averaged IBU gain in % considering all experimented k, n, ϵ.



Dist.	L-GRR		L-SUE		L-OUE		L-SOUE		L-OSUE		L-BLH		L-OLH		Avg.	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Gauss.	14	5	13	8	9	5	10	7	12	7	2	0	7	4	9	5
Exp.	4	1	27	16	26	15	27	16	27	16	4	2	20	12	19	11
Unif.	36	25	31	22	12	8	16	11	18	13	54	43	21	16	26	19
Poiss.	5	2	43	28	48	32	49	32	44	29	11	6	42	30	**34**	**22**
Triang.	28	17	24	15	11	7	13	9	16	10	26	14	14	9	18	11
Real.	4	1	43	25	43	27	44	27	43	25	9	4	34	22	**31**	**18**
Avg.	15	8	**30**	**19**	24	15	**26**	**17**	26	16	17	11	23	15	23	14

Mechanisms w/ highest IBU gain: L-SUE and L-SOUE

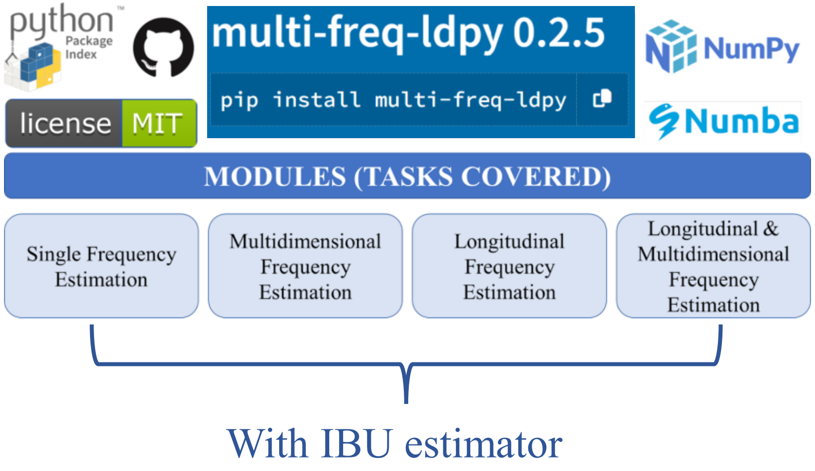
Summary of IBU Utility Gain: Longitudinal LDP Mechanisms

Averaged IBU gain in % considering all experimented k, n, ϵ.

Dist.	L-GRR		L-SUE		L-OUE		L-SOUE		L-OSUE		L-BLH		L-OLH		Avg.	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Gauss.	14	5	13	8	9	5	10	7	12	7	2	0	7	4	9	5
Exp.	4	1	27	16	26	15	27	16	27	16	4	2	20	12	19	11
Unif.	36	25	31	22	12	8	16	11	18	13	54	43	21	16	26	19
Poiss.	5	2	43	28	48	32	49	32	44	29	11	6	42	30	**34**	**22**
Triang.	28	17	24	15	11	7	13	9	16	10	26	14	14	9	18	11
Real.	4	1	43	25	43	27	44	27	43	25	9	4	34	22	**31**	**18**
Avg.	15	8	**30**	**19**	24	15	**26**	**17**	26	16	17	11	23	15	23	14

Distributions w/ highest IBU gain: Poisson and real

IBU Implementation into Multi-Freq-LDPy [Arcolezi et al, 2022]



multi-freq-ldpy 0.2.5

```
pip install multi-freq-ldpy
```

MODULES (TASKS COVERED)

- Single Frequency Estimation
- Multidimensional Frequency Estimation
- Longitudinal Frequency Estimation
- Longitudinal & Multidimensional Frequency Estimation

With IBU estimator

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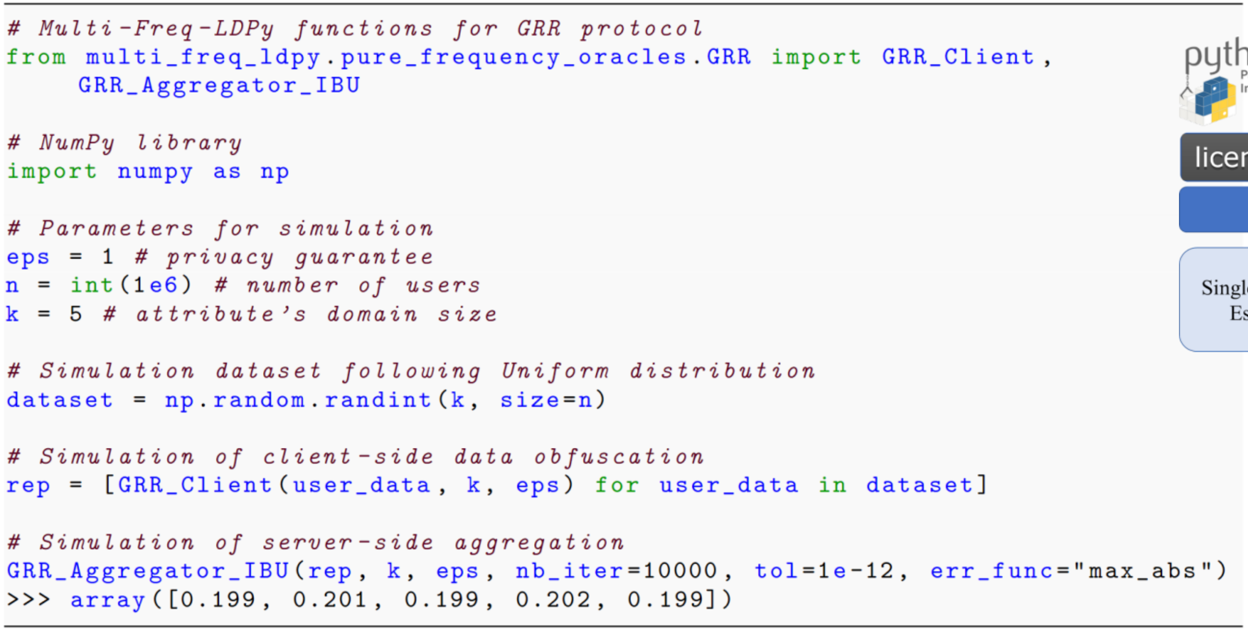
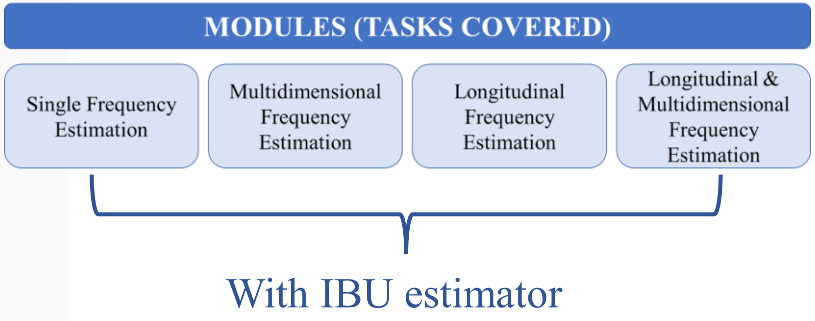


```
# Multi-Freq-LDPy functions for GRR protocol
from multi_freq_ldpy.pure_frequency_oracles.GRR import GRR_Client,
     GRR_Aggregator_IBU

# NumPy library
import numpy as np

# Parameters for simulation
eps = 1 # privacy guarantee
n = int(1e6) # number of users
k = 5 # attribute's domain size

# Simulation dataset following Uniform distribution
dataset = np.random.randint(k, size=n)

# Simulation of client-side data obfuscation
rep = [GRR_Client(user_data, k, eps) for user_data in dataset]

# Simulation of server-side aggregation
GRR_Aggregator_IBU(rep, k, eps, nb_iter=10000, tol=1e-12, err_func="max_abs")
>>> array([0.199, 0.201, 0.199, 0.202, 0.199])
```



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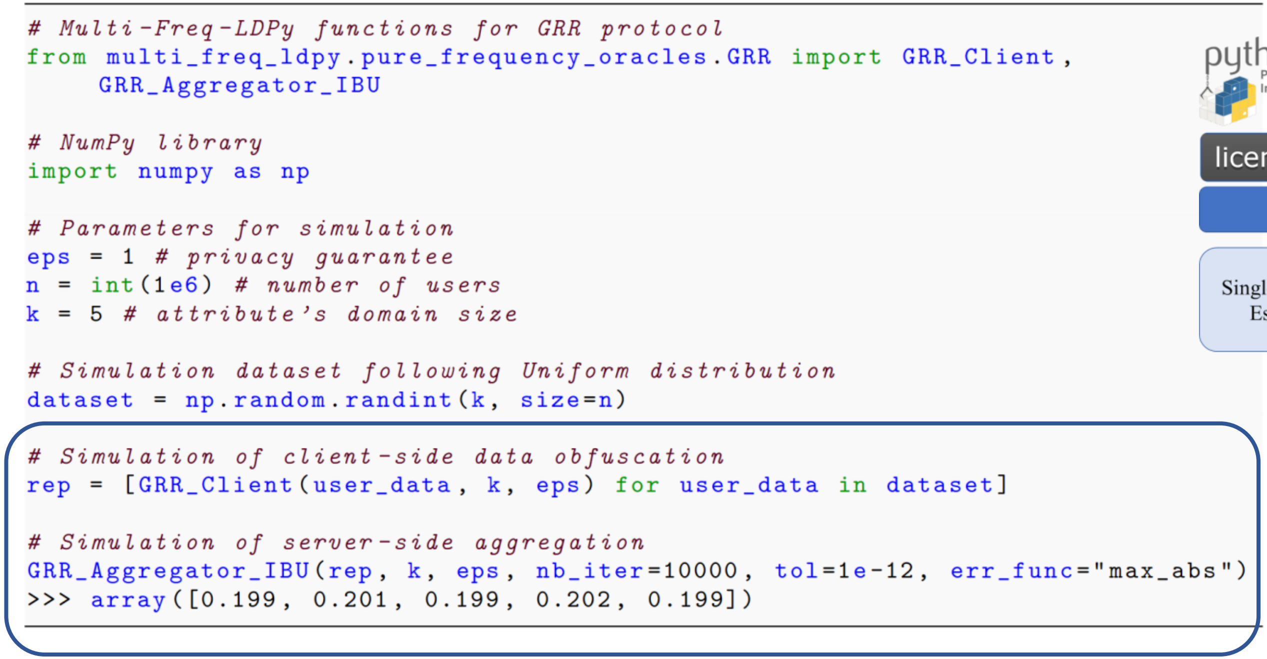

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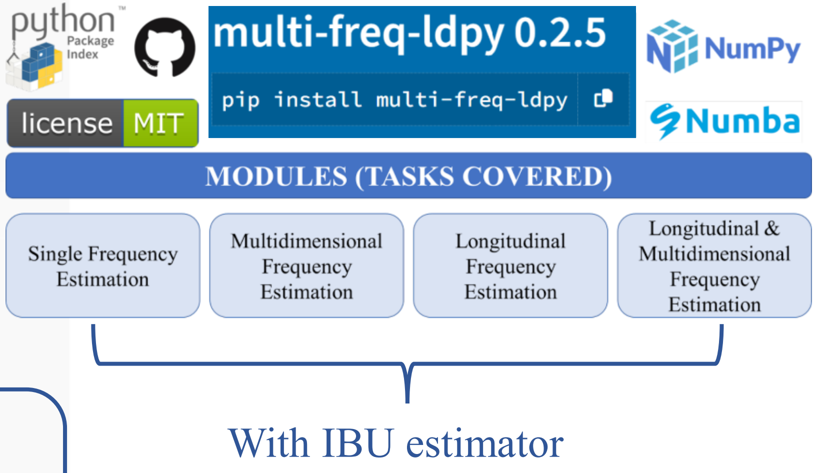

MODULES (TASKS COVERED)

Single Frequency Estimation

Multidimensional Frequency Estimation

Longitudinal Frequency Estimation

Longitudinal & Multidimensional Frequency Estimation

With IBU estimator

Essentially just 2 lines of code to simulate the LDP data collection pipeline with IBU estimation

Outline

1. Context
2. Background & Problem Statement
3. Experimental Results
4. **Conclusion & Perspectives**

Takeaway Messages

Conclusions:

- We benchmarked IBU against MI in several contexts for 14 LDP mechanisms;
- IBU can significantly improve the utility of LDP distribution estimation;
- We implemented IBU into multi-freq-ldpy.

Takeaway Messages

Conclusions:

- We benchmarked IBU against MI in several contexts for 14 LDP mechanisms;
- IBU can significantly improve the utility of LDP distribution estimation;
- We implemented IBU into multi-freq-ldpy.

Perspectives:

- Investigate IBU for "non-pure" LDP mechanisms;
- Consider different initialization and stopping criteria for IBU;
- IBU for high-dimensional data (*i.e.*, $k \gg 200$);
- Implement Generalized IBU (GIBU) into multi-freq-ldpy.

On the Utility Gain of Iterative Bayesian Update for Locally Differentially Private Mechanisms

Héber H. Arcolezi, Selene Cerna, and Catuscia Palamidessi

Inria and École Polytechnique (IPP), Palaiseau, France

PAPER

ARTIFACT

CONTACT

🌐 hharcolezi.github.io ✉ heber.hwang-arcolezi@inria.fr 🐦 @hharcolezi