

INTRODUCTION

Privacy model: Local differential privacy (LDP) protects individual's privacy without relying on a trusted third party.

Contribution: `Multi-freq-ldpy` implements state-of-the-art LDP protocols [1-6] for frequency (or **histogram**) estimation of **single**, **multidimensional**, and/or **longitudinal** data.



\$ pip install multi-freq-ldpy

license MIT



MODULES (TASKS COVERED)

Single Frequency Estimation

LDP protocols for a single attribute:

- **General Randomized Response (GRR)**: a.k.a. k -RR or direct encoding [1];
- **Unary Encoding (UE)**: Symmetric UE [4] & Optimal UE [1];
- **Local Hashing (LH)**: Binary LH & Optimal LH [1];
- **Subset Selection (SS)** [2].

Multidimensional Frequency Estimation

Solutions for multiple $d \geq 2$ attributes:

- **Splitting (SPL)**: Sanitizes each attribute with ϵ/d -LDP;
- **Random Sampling (SMP)**: Sanitizes a single (random) attribute with ϵ -LDP;
- **Random Sampling Plus Fake Data (RS+FD)** [3]: SMP plus random fake data for all $d - 1$ non-sampled attributes.

Longitudinal Frequency Estimation

LDP protocols for multiple collections:

- **Google's RAPPOR** [4];
- **Microsoft's d BitFlipPM** [5];
- **Longitudinal UE (L-UE)** [6] and **Longitudinal GRR (L-GRR)** [6].

Longitudinal & Multidimensional Frequency Estimation

Combining solutions for multiple attributes and LDP protocols for multiple collections:

- **SPL solution with Longitudinal protocols**;
- **SMP solution with Longitudinal protocols** [6];

USAGE EXAMPLE (LONGITUDINAL FREQUENCY ESTIMATION)

Importing functions and numpy package.

```
# Multi-Freq-LDPy functions for L-SUE (RAPPOR [4]) protocol
from multi_freq_ldpy.long_freq_est.L_SUE import L_SUE_Client, L_SUE_Aggregator
```

```
# NumPy library
import numpy as np
```

Setting parameters and generating synthetic dataset for simulation.

```
# Parameters for simulation
eps_perm = 2 # longitudinal privacy
eps_1 = 0.5 * eps_perm # first report privacy
n = int(1e6) # number of users
k = 5 # attribute's domain size
```

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

One essentially needs 2 lines of code to simulate the LDP data collection pipeline.

```
# Simulation of data collection
reports = [L_SUE_Client(user_data, k, eps_perm, eps_1) for user_data in dataset]
```

```
# Simulation of server-side aggregation
est_freq = L_SUE_Aggregator(reports, eps_perm, eps_1)
>>> array([0.199, 0.201, 0.200, 0.198, 0.202])
```

RESULTS & PERFORMANCE (LONGITUDINAL FREQUENCY ESTIMATION)

Setup of Experiments

Local machine:

- Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz, 16GB RAM, Windows 11.

Dataset:

- $n = 10^4$ users, $k = 5$ values, Uniform distribution.

Privacy guarantees:

- $\epsilon_\infty = [0.5, 1, \dots, 4.5, 5]$ and $\epsilon_1 = 0.5 \cdot \epsilon_\infty$.

iterations:

- 50 (as LDP protocols are randomized).

LDP Protocols

RAPPOR [4]

d BitFlipPM [5]

L-GRR [6]

L-OSUE [6]

L-OUE [6]

L-SOUE [6]

Execution Time (s)

11.15

94.96

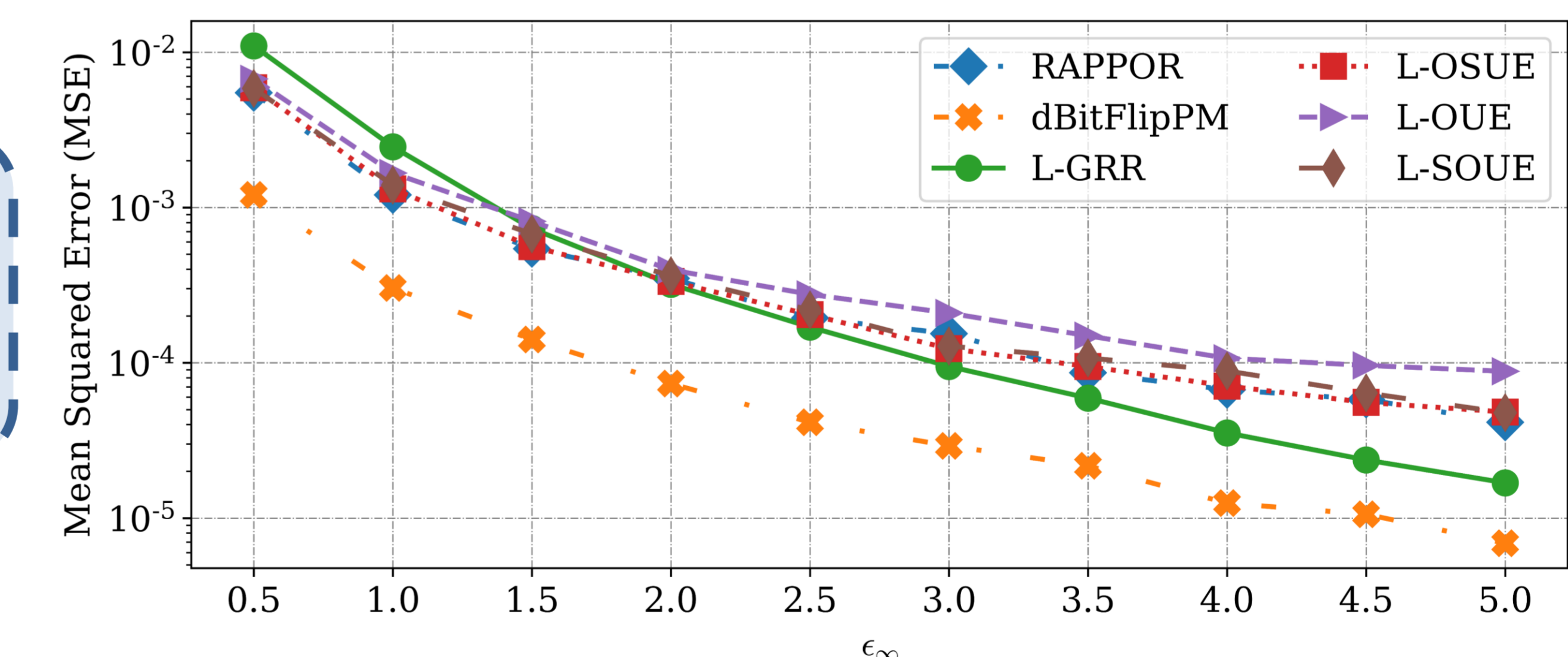
82.30

10.20

10.75

11.64

Easy-to-use and fast execution toolkit to benchmark state-of-the-art LDP protocols.



CONTACT

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ARTIFACT



SCAN ME

REFERENCES

[1] Wang T, Blocki J, Li N, Jha S. Locally differentially private protocols for frequency estimation. In: USENIX Security, 2017.

[2] Wang S, et al. Mutual information optimally local private discrete distribution estimation. In: arXiv:1607.08025, 2016.

[3] Arcolezif HH, et al. Random sampling plus fake data: Multidimensional frequency estimates with local differential privacy. In: CIKM, 2021.

[4] Erlingsson Ú, Pihur V, Korolova A. RAPPOR: Randomized aggregatable privacy-preserving ordinal response. In: CCS, 2014.

[5] Ding B, Kulkarni J, Yekhanin S. Collecting telemetry data privately. In: NIPS, 2017.

[6] Arcolezif HH, et al. Improving the utility of locally differentially private protocols for longitudinal and multidimensional frequency estimates. In: Digital Communications and Networks, 2022.