

PRESTO: A Python package for automated privacy mechanism selection and optimization

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DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

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Submitted: 01 January 1970

Published: unpublished

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Summary

PRESTO (Privacy REcommendation and SecuriTy Optimization) is a Python-based toolkit that automates the selection of differential-privacy mechanisms (Dwork & Roth, 2014) to balance data utility and privacy loss. By integrating descriptive and inferential statistics, Bayesian optimization, and data-similarity metrics, PRESTO analyzes arbitrary datasets—numerical, categorical, or structured—and recommends the optimal privacy algorithm and ϵ -parameter setting. Its modular design supports CPU/GPU execution, streaming and batch data, and extensibility for new algorithms and utility metrics. PRESTO's automated multi-objective optimization delivers application-specific, data-driven recommendations with quantified uncertainty, empowering both experts and non-experts to integrate privacy-preserving methods seamlessly into their workflows.

Statement of Need

As data collection proliferates across healthcare, finance, IoT, and beyond, safeguarding individual privacy without handicapping downstream analytics has become critical. Existing differential-privacy tools often require deep theoretical knowledge, manual tuning of privacy parameters, and trial-and-error to discover the right trade-off between noise injection and data utility. This steep adoption barrier impedes widespread deployment of privacy-preserving analytics in industrial and research settings. There is a pressing need for an intuitive, automated solution that can—given any dataset—identify the most suitable privacy mechanism and its optimal ϵ , quantify the remaining utility, and provide confidence intervals on its recommendations. PRESTO fills this gap, reducing the technical burden and accelerating safe, compliant data analysis.

State of the Field

A variety of packages from industry and academia—such as IBM's Diffprivlib (Holohan et al., 2019), Google's PyDP (Wilson et al., 2020), Facebook's Opacus (Yousefpour et al., 2021), LDP-Pure (Cormode et al., 2021), SmartNoise (Gaboridi et al., 2025), PETINA—offer implementations of noise-based DP mechanisms (Laplace, Gaussian, Exponential) (Dwork & Lei, 2009), local-DP protocols (Randomized Response, RAPPOR) (Erlingsson et al., 2014), and gradient perturbation for machine learning. However, they typically expose raw APIs, leaving users responsible for selecting and tuning algorithms, and provide limited guidance on choosing ϵ . Recent research has explored automatic hyperparameter tuning via cross-validation or surrogate modeling, but these approaches rarely integrate multi-objective optimization or deliver quantitative uncertainty measures.

PRESTO advances the state of the art by unifying statistical dataset analysis, Bayesian optimization, and data-similarity metrics into a single recommendation engine. It implements a broad suite of privacy mechanisms—including both batch and streaming algorithms—and automates their selection based on data characteristics and user-specified privacy-utility trade-offs, while providing 95% confidence intervals on its recommendations. Crucially, PRESTO is built on a modular architecture, enabling users to plug in new privacy algorithms or custom utility metrics at any time without modifying core logic. This extensibility ensures that PRESTO can evolve alongside emerging research and domain-specific needs, making it uniquely adaptable compared to existing static libraries.

Methodology

1. Dataset Profiling

- Compute descriptive (mean, variance, skewness, kurtosis) and, for categorical data, domain-size and frequency distributions.

2. Mechanism Library

- Maintain a dictionary of privacy functions (`get_noise_generators()`), each mapping $(data, \epsilon) \rightarrow \text{privatized_data}$.

3. Bayesian Optimization of ϵ

- For each mechanism, define:

$$f(\epsilon) = -\text{RMSE}(\text{data}, \text{mechanism}_\epsilon(\text{data}))$$

- Maximize this over:

$$\epsilon \in [\epsilon_{\min}, \epsilon_{\max}]$$

using Gaussian-process Bayesian optimization.

4. Confidence & Reliability

- Compute a 95% confidence interval on RMSE at the optimal ϵ^* , then define:

$$\text{Reliability} = \frac{1}{\text{Mean RMSE} \times \text{CI Width}}$$

5. Similarity Assessment

- Measure distributional similarity via Kolmogorov–Smirnov, Jensen–Shannon, Pearson correlation.

6. Multi-Objective Ranking

- Recommend top mechanisms on **max similarity**, **max reliability**, and **max privacy** axes.

Experiments

We evaluated PRESTO's effectiveness across diverse domains and data types, demonstrating its automated mechanism selection and optimization capabilities.

71 **Energy Consumption Analysis (Dataset: Hourly Energy Usage, 168 points)**

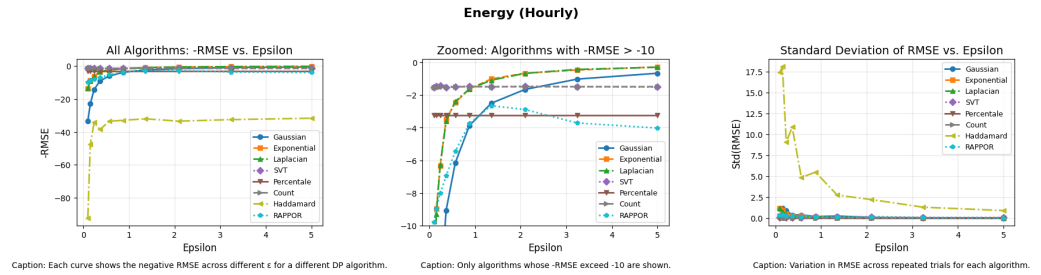


Figure 1: Privacy loss (epsilon) vs utility (RMSE) for selected/preferred privacy algorithms

72 **Top-3 Recommendations:**

- 73 ■ **DP_Laplace:** $\epsilon = 3.6277$, mean_rmse=0.3817, ci_width=0.0279, reliability=93.90
- 74 ■ **DP_Exponential:** $\epsilon = 3.6300$, mean_rmse=0.3835, ci_width=0.0416, reliability=62.68
- 75 ■ **DP_Gaussian:** $\epsilon = 4.1687$, mean_rmse=0.8326, ci_width=0.0525, reliability=22.88

76 **Medical Measurements Analysis (Dataset: Heart Rate Monitoring, 1440 points)**

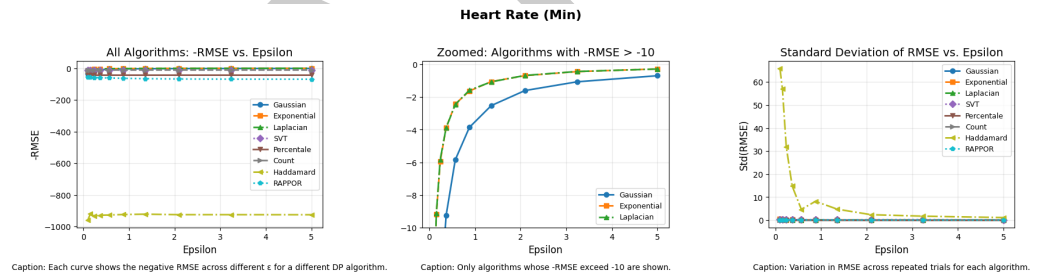


Figure 2: Privacy loss (epsilon) vs utility (RMSE) for selected/preferred privacy algorithms

78 **Top-3 Recommendations:**

- 79 ■ **DP_Laplace:** $\epsilon = 3.6254$, mean_rmse=0.3901, ci_width=0.0054, reliability=474.71
- 80 ■ **DP_Exponential:** $\epsilon = 3.6319$, mean_rmse=0.3916, ci_width=0.0051, reliability=500.71
- 81 ■ **DP_Gaussian:** $\epsilon = 5.0000$, mean_rmse=0.6824, ci_width=0.0047, reliability=311.79

83 Financial Transaction Analysis (Dataset: Log-Normal Payment Data, 10,000 84 points)

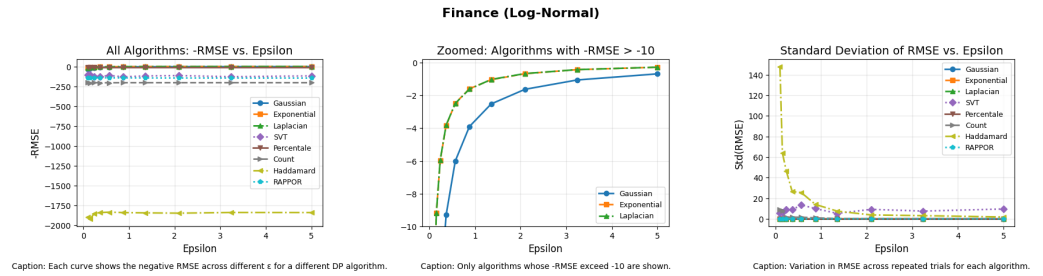


Figure 3: Privacy loss (epsilon) vs utility (RMSE) for selected/preferred privacy algorithms

85 Top-3 Recommendations:

- 86 ■ **DP_Laplace:** $\epsilon = 4.1687$, mean_rmse=0.3461, ci_width=0.0340, reliability=84.98
- 87 ■ **DP_Exponential:** $\epsilon = 3.6296$, mean_rmse=0.3864, ci_width=0.0453, reliability=57.13
- 88 ■ **DP_Gaussian:** $\epsilon = 4.1690$, mean_rmse=0.8270, ci_width=0.0560, reliability=21.59

89 IoT Sensor Analysis (Dataset: Temperature Time-Series, 168 points)

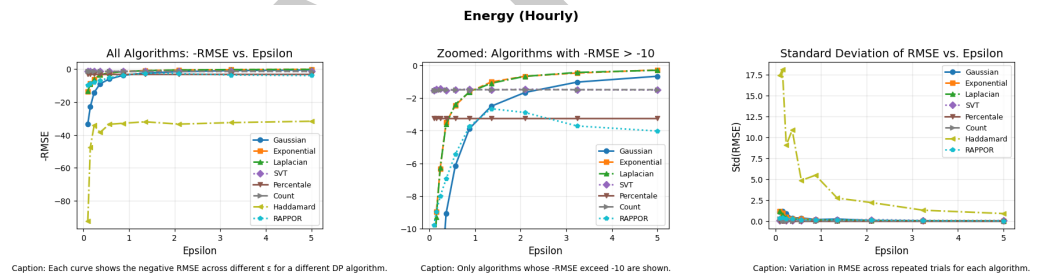


Figure 4: Privacy loss (epsilon) vs utility (RMSE) for selected/preferred privacy algorithms

90 Top-3 Recommendations:

- 91 ■ **DP_Laplace:** $\epsilon = 3.6296$, mean_rmse=0.3846, ci_width=0.0126, reliability=206.36
- 92 ■ **DP_Exponential:** $\epsilon = 3.6296$, mean_rmse=0.3883, ci_width=0.0187, reliability=137.72
- 93 ■ **DP_Gaussian:** $\epsilon = 3.6296$, mean_rmse=0.9459, ci_width=0.0334, reliability=31.65

95 Fixed Privacy Budget Analysis ($\epsilon = 1$)

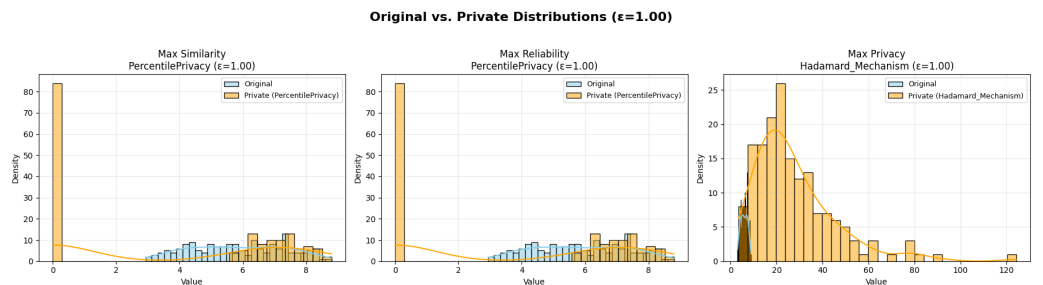


Figure 5: The best algorithm for a given epsilon

- 96 ■ Best by Similarity: {'algorithm': 'PercentilePrivacy', 'score': np.float32(0.9841)}
- 97 ■ Best by Reliability: {'algorithm': 'PercentilePrivacy', 'score': inf}
- 98 ■ Best by Privacy: {'algorithm': 'Hadamard_Mechanism', 'score': 71.6581}

99 Machine Learning Integration: Privacy-Preserving Neural Network Training

- 100 ■ Baseline Accuracy (no privacy): 93.00%
- 101 ■ DP Accuracy with 'PercentilePrivacy': 94.00%

102 Multi-Objective Optimization: Pareto Front Analysis

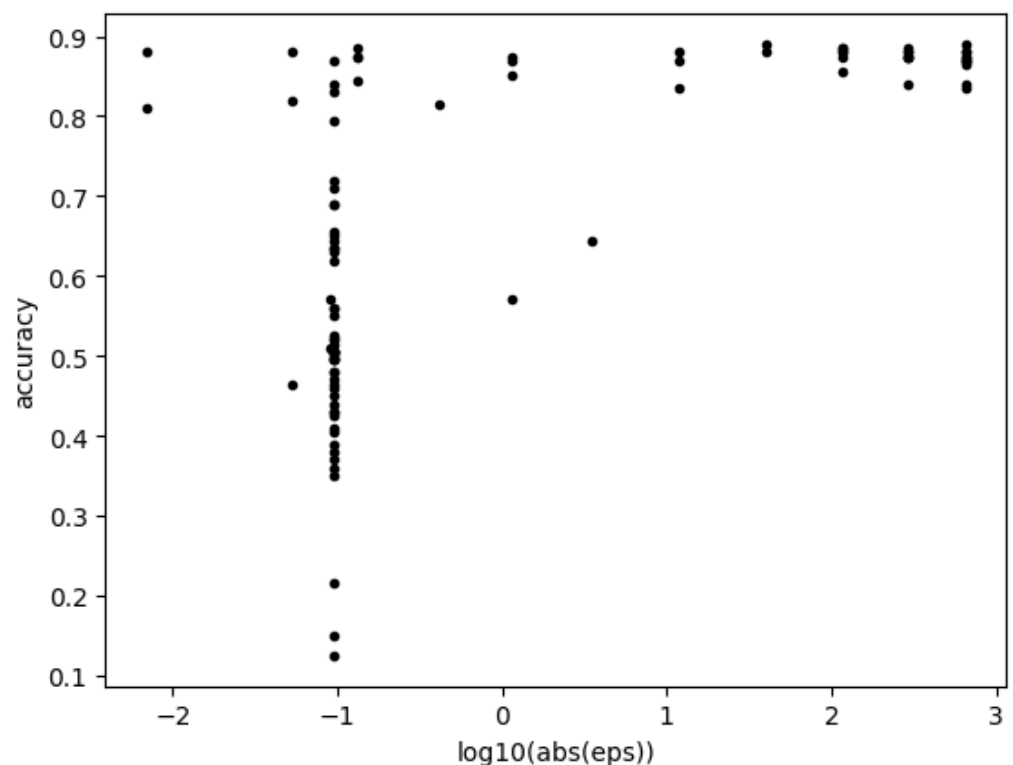


Figure 6: Pareto front for privacy budget vs accuracy

103 Conclusion

104 PRESTO delivers a data-driven, automated, and extensible framework for differential-privacy
 105 mechanism selection and tuning. By profiling statistical properties, optimizing ϵ via Bayesian
 106 methods, and quantifying both utility and uncertainty, PRESTO guides users to the privacy
 107 solution best suited for their data. Its modular design allows seamless integration of new
 108 algorithms and metrics, positioning PRESTO as a flexible platform for both practitioners and
 109 researchers aiming to embed privacy guarantees in diverse analytical workflows.

110 Acknowledgements

111 This manuscript has been co-authored by UT-Battelle, LLC under Contract No. DE-AC05-
 112 00OR22725 with the U.S. Department of Energy. The United States Government retains
 113 and the publisher, by accepting the article for publication, acknowledges that the United

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118 (<http://energy.gov/downloads/doe-public-access-plan>). This material is based upon work
119 supported by the U.S. Department of Energy, Office of Science, Office of Advanced Scientific
120 Computing Research under Contract No. DE-AC05-00OR22725. This research is sponsored by
121 the Artificial Intelligence Initiative as part of the LDRD-SEED Program, at ORNL, managed
122 by UT-Battelle, LLC and DOE ASCR Program.

123 References

- 124 Cormode, G., Maddock, S., & Maple, C. (2021). Frequency estimation under local differential
125 privacy [experiments, analysis and benchmarks]. *Proceedings of the VLDB Endowment*,
126 14, 2046–2058.
- 127 Dwork, C., & Lei, J. (2009). Differential Privacy and Robust Statistics. *Proceedings of the*
128 *41st Annual ACM Symposium on Theory of Computing*, 371–380.
- 129 Dwork, C., & Roth, A. (2014). The Algorithmic Foundations of Differential Privacy. *Founda-*
130 *tions and Trends in Theoretical Computer Science*, 9(3–4), 211–407. [https://doi.org/10.](https://doi.org/10.1561/04000000042)
131 [1561/04000000042](https://doi.org/10.1561/04000000042)
- 132 Erlingsson, Úlfar, Pihur, V., & Korolova, A. (2014). RAPPOR: Randomized Aggregatable
133 Privacy-Preserving Ordinal Response. *Proceedings of the 2014 ACM SIGSAC Conference*
134 *on Computer and Communications Security*, 1054–1067.
- 135 Gaboardi, M., Hay, M., & Vadhan, S. (2025). *OpenDP: The OpenDP Library* (Version 0.13.0).
136 <https://github.com/opendp/opendp>
- 137 Holohan, N., Braghin, S., Aonghusa, P. M., & Levacher, K. (2019). Diffprivlib: The IBM
138 Differential Privacy Library. *arXiv Preprint*. <https://arxiv.org/abs/1907.02444>
- 139 Wilson, R. J., Zhang, C. Y., Lam, W., Desfontaines, D., Simmons-Marengo, D., & Gipson, B.
140 (2020). *Google Differential Privacy Library*. <https://github.com/google/differential-privacy>
- 141 Yousefpour, A., Shilov, I., Sablayrolles, A., Testuggine, D., Prasad, K., Malek, M., Nguyen,
142 J., Ghosh, S., Bharadwaj, A., Zhao, J., Cormode, G., & Mironov, I. (2021). Opacus:
143 User-friendly differential privacy library in PyTorch. *arXiv Preprint arXiv:2109.12298*.