Privacy in Practice: The Feasibility of Differential Privacy for Telemetry Analysis

Tyler Kurpanek
tkurpane@ucsd.edu

Christopher Lum
cslum@ucsd.edu

Bradley Nathanson
bnathanson@ucsd.edu

Trey Scheid
tscheid@ucsd.edu

Mentor:
Yu-Xiang Wang
yuxiangw@ucsd.edu

UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Introduction

Research Question: How effective is differential privacy when it is applied in *practice*?

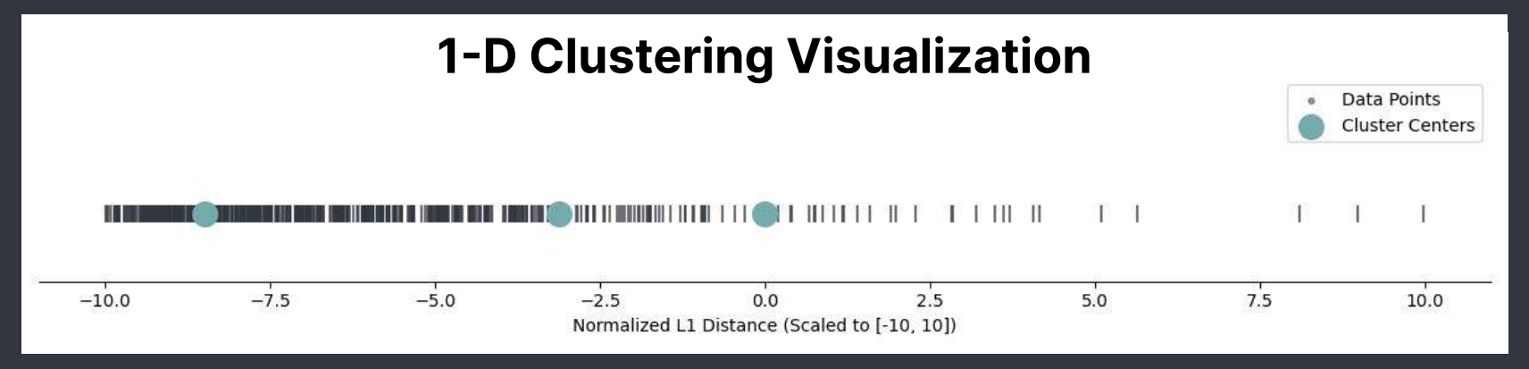
We replicated 4 papers implementing Differential Privacy (DP) in order to assess the utility lost from adding noise.

Privacy of user data is guaranteed by adding randomness into algorithms to ensure that results match the data patterns yet are indistinguishable between datasets with and without a specific datum.

Telemetry data is diagnostic information collected by devices such as CPUs or OSes. This data can paint a vibrant picture of a user given appropriate analysis.

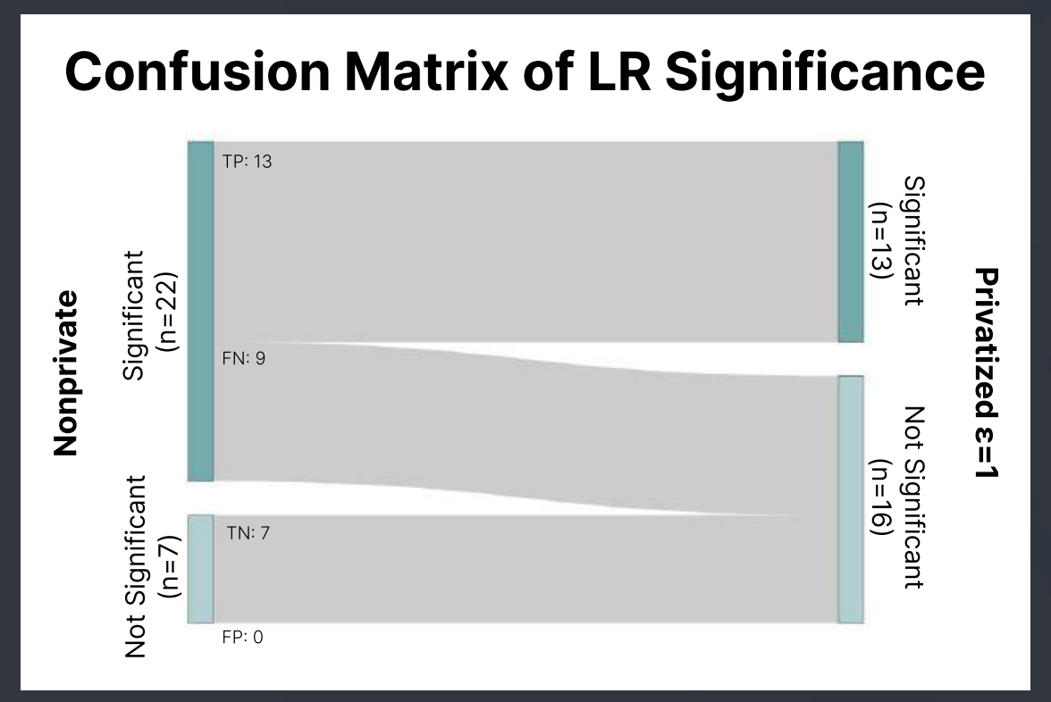
Methods	Description	Non-Private	Private
Conditional Probabilities	Probability of uncorrected error based on number of corrected errors	Histogram creation for event occurrence	Laplace Mechanism
Log. Regression Coefficient Test	Do corrected errors cause uncorrected errors? Testing 29 different errors	Wald test on logistic regression coefficient	Noisy Gradient Descent during LR training
Lasso Regression	Find features which best predict pack power usage	Coordinate Descent & Frank-Wolfe	Noisy Frank-Wolfe (Exponential Mechanism)
K-Means Clustering	Cluster devices based on usage counts	K-Means via Lloyd's algorithm	Noisy mean computation during centroid updates

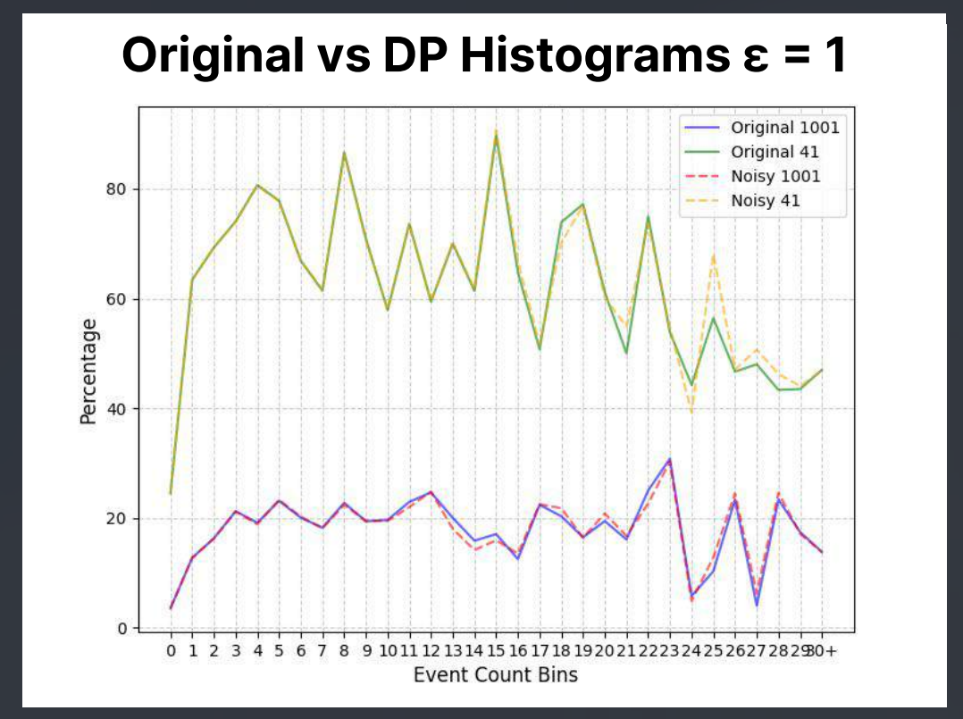
Results at Privacy ε = 1



DP-KMeans centroids are near lower L1 distances given the skewed distribution.

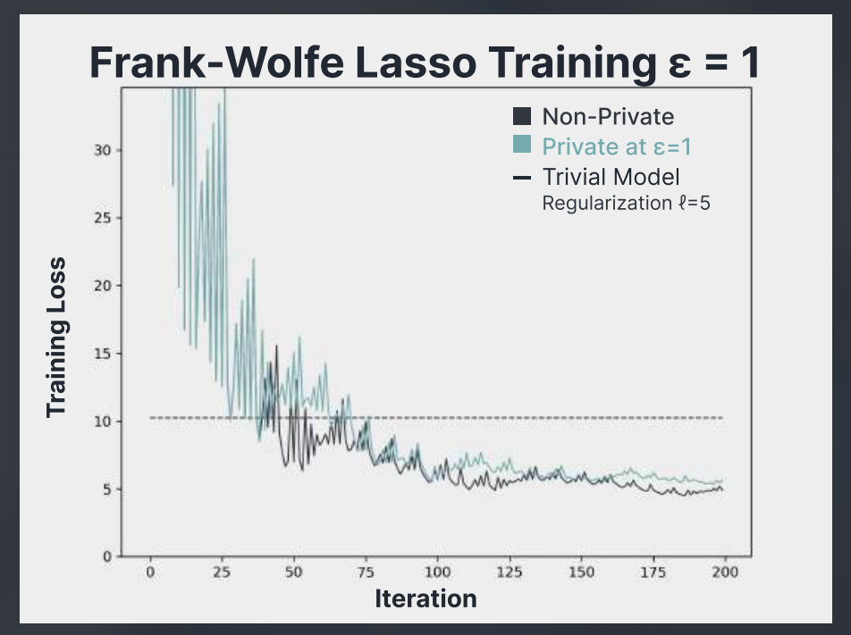
Private Wald test errantly found that 40% of cases that should've been significant were insignificant.

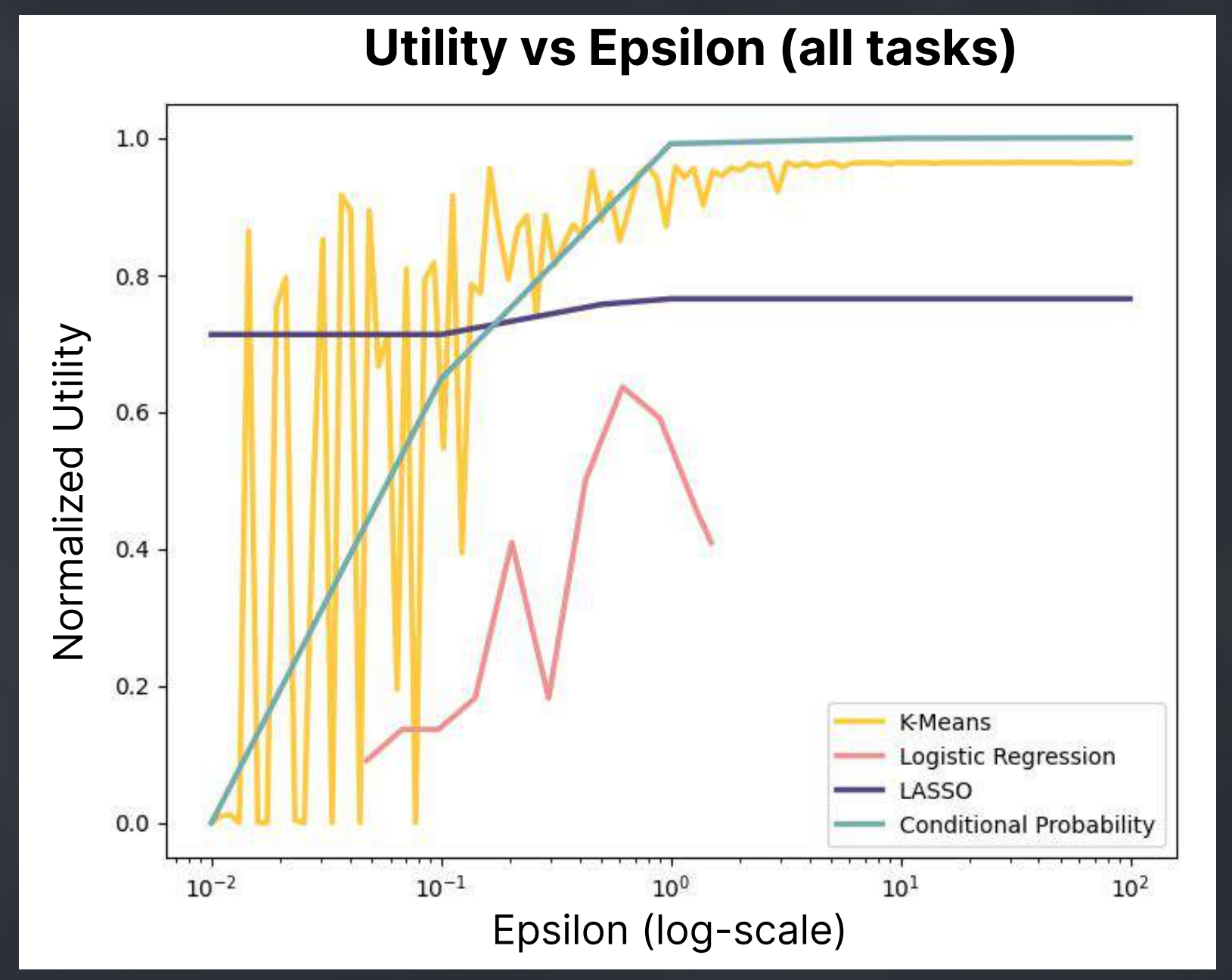




Corrected error (19) counts vs the uncorrected error (41 & 1001) percents with and without noise.

Privatized Lasso reaches near optimal performance for small max iterations K=200, not as competitive for large K.





Normalized utility is a range from 0-1 of the accuracy of each model, relative to a baseline (non-private model)

Epsilon determines the trade-off between utility and privacy

Discussion

Epsilon of 1 is generally considered to be **highly private**. In our tests, high privacy results in somewhat unusable and highly-incorrect analyses. Further, for some methods such as DP-GD, compute scales linearly with epsilon making meta-analysis more costly for higher values of epsilon.

Epsilon of 10 or more is typically considered very poor, however interpreting is vague. For most tasks utility is usable (near the non-private baseline) only at large epsilon.

Adding noise using python can be simple, scaling and tracking budgets requires following theorems from research.

Key Takeaways

- Even with large amounts of data, **strong privacy** guarantees ε<0.1 suffer from grave **utility loss**
- Privately selecting *hyperparameters* either requires vast domain knowledge or taking from the privacy budget
- Practical application of DP may require loosening which agents are protected against
- *Epsilon* is a poor quantification of privacy for *non-expert practitioners*