Evaluating Differentially Private Machine Learning In Practice

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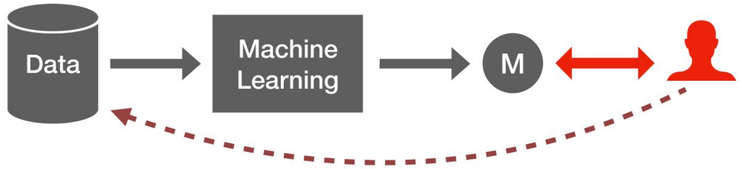
Privacy Concerns in Machine Learning

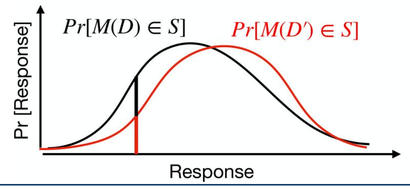


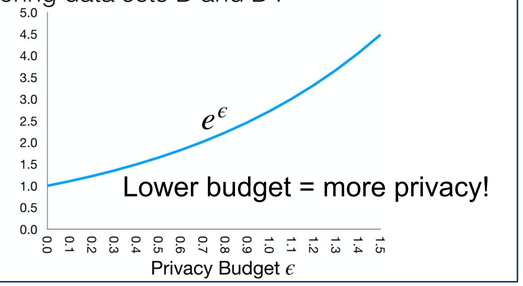
What can be inferred about the training data?

Solution: Differential Privacy

A randomized function M is ϵ-**differentially private** if it produces similar response over both neighboring data sets D and D':

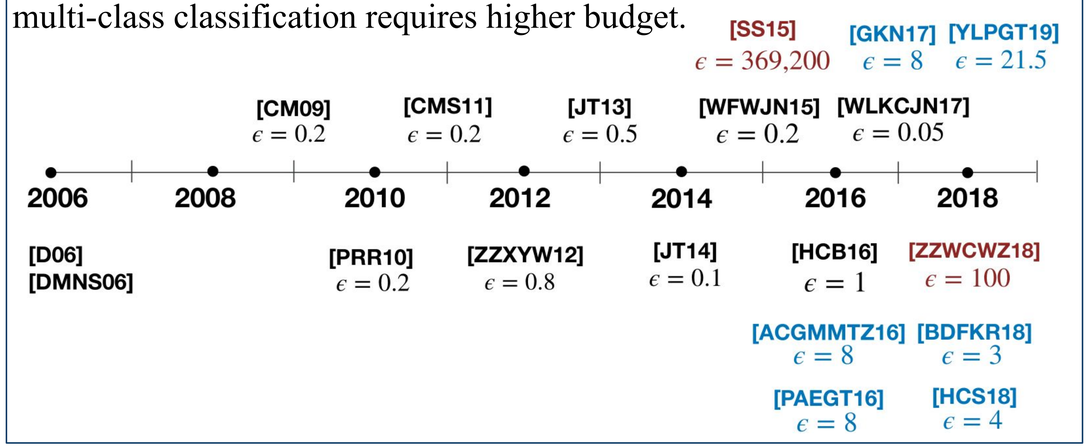
$$\frac{Pr[M(D) \in S]}{Pr[M(D') \in S]} \leq e^{\epsilon}$$



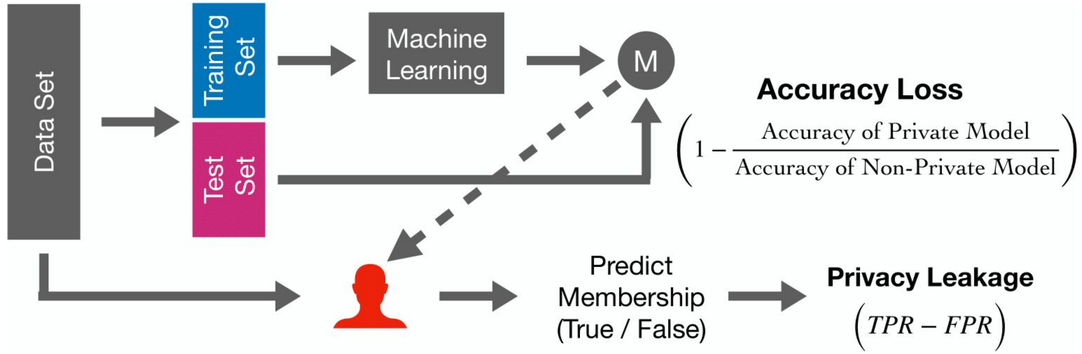


Existing Differentially Private ML Implementations

While private ERM algorithms for binary classification tasks can be achieved with low privacy budget, complex tasks such as deep learning for multi-class classification requires higher budget.

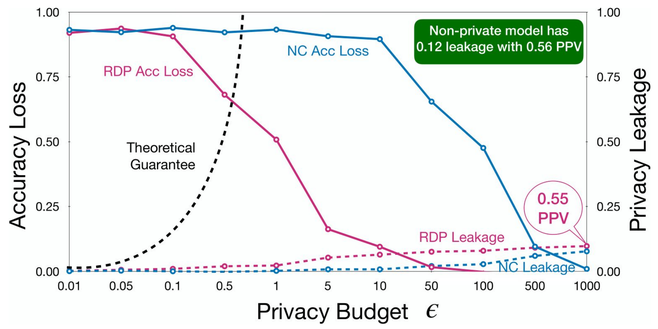


Experimental Setup: Evaluating Accuracy Loss and Privacy Leakage

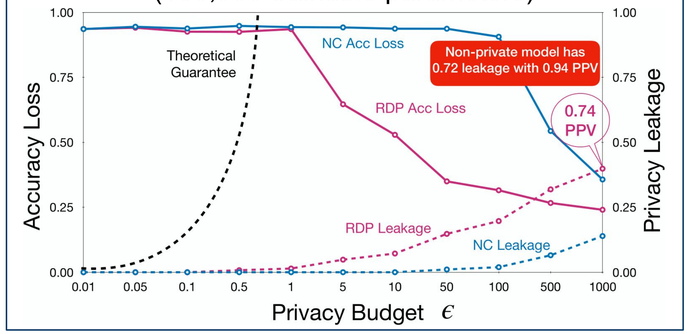


Privacy-Utility Comparison of Models trained with DP

Results for Logistic Regression (5,000 trainable parameters)

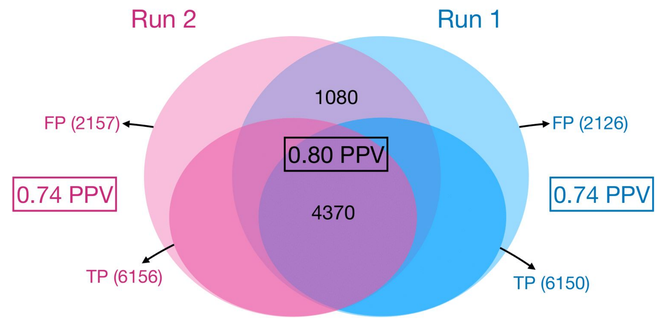


Results for Neural Network (103,936 trainable parameters)



Analyzing Multiple Runs of Neural Network trained with RDP ($\epsilon = 1000$)

Membership Predictions across Two Runs



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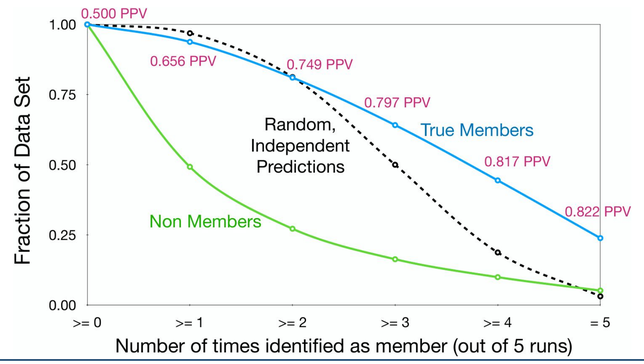

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Link to Code: https://github.com/bargavj/EvaluatingDPML

Conclusion: Privacy doesn't come for free.
For a fixed privacy budget, improving composition increases model utility but at the cost of privacy leakage.