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Private Adaptive Optimization with Side Information

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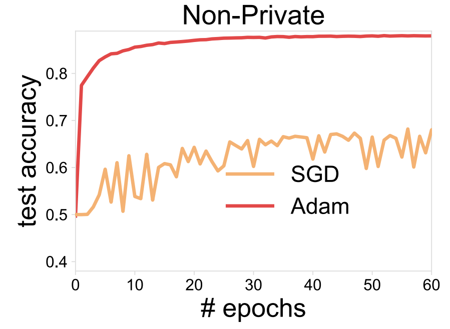
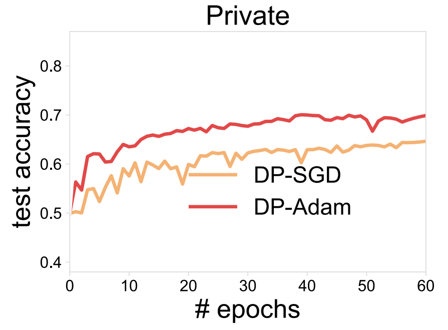
Motivation

✔ Adaptive optimizers (e.g., Adam, AdaGrad, RMSProp) are useful for a variety of ML tasks

✘ Performance may degrade significantly when trained with differential privacy (DP)





A baseline: directly plug in private gradients to estimate the statistics?

For example (vanilla DP-Adam)

1. first privatize the gradients

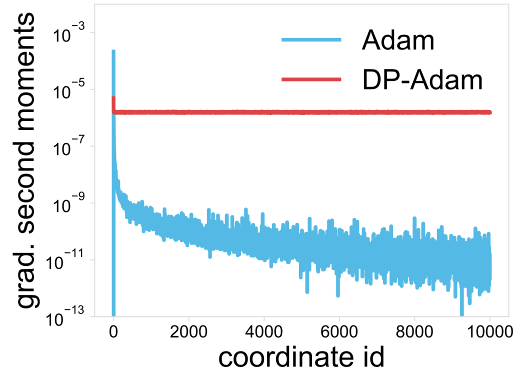
$$\tilde{g}^t \leftarrow \frac{1}{|B|}\left(\sum_{i\in B} \text{clip}\left(g^{i,t}, C\right) + \mathcal{N}\left(0, \sigma^2 C^2\right)\right)$$

2. then plug in private gradients to any adaptive optimization methods (e.g., Adam)

$$m^t \leftarrow \beta_1 m^t + (1-\beta_1)\tilde{g}^t,\; v^t \leftarrow \beta_2 v^t + (1-\beta_2)(\tilde{g}^t)^2$$

$$w^{t+1} \leftarrow w^t - \alpha \frac{m^t}{\sqrt{v^t}+\epsilon}$$

Estimates can be very noisy!



Insights

Use side Information to approximate the preconditioner

Estimate gradient statistics on small public data at each iteration

- obtained via 'opt-out' users or proxy data
- can be in-distribution or out-of-distribution

Non-sensitive common knowledge about the training data

- easy to obtain before training
- e.g., token frequencies in NLP

Useful for both private and non-private training

AdaDPS: Private Adaptive Optimization with Side Information

Option 1: With public data x_{pub}

1. get gradients on public data: $\hat{g}^t \leftarrow \frac{1}{|B|}\sum_{j\in B}\nabla f(x^j; w^t), x^j \in x_{\text{pub}}$
2. update preconditioner A^t with recurrence ϕ: $A^t \leftarrow \phi(A^{t-1}, \hat{g}^t)$

Option 2: Without public data

A^t estimated via heuristics (e.g., TF-IDF values or feature frequencies)

(optional) maintain a momentum buffer using $\tilde{g}^t$

Privatize preconditioned gradients (in the simplest form)

$$\tilde{g}^t \leftarrow \frac{1}{|B|}\left(\sum_{i\in B}\text{clip}\left(\frac{g^{i,t}}{A+\epsilon}, C\right) + \mathcal{N}\left(0, \sigma^2 C^2\right)\right)$$

A encodes how predictive each coordinate is / estimates of gradient geometry

- preconditioning *before* privatizing the gradients (instead of the other order)
- can cover a range of adaptive methods

Convergence Analysis

1. With public data, convex case, RMSProp updates

$$\underbrace{\frac{G}{\sqrt{T}}\sum_{j=1}^{d}\mathbb{E}\left[A_j^T\right]}_{\text{standard RMSProp rate}} + \underbrace{\frac{\alpha}{\sqrt{T}}\max_{t\in[T]}\mathbb{E}\left[\|\mathcal{N}\|^2_{A^t}\right]}_{\text{DP noise (subsampled Gaussian mechanism)}}$$

reduced DP noise when the gradients are sparse

2. Without public data, fixed preconditioner A, convex case, RMSProp updates

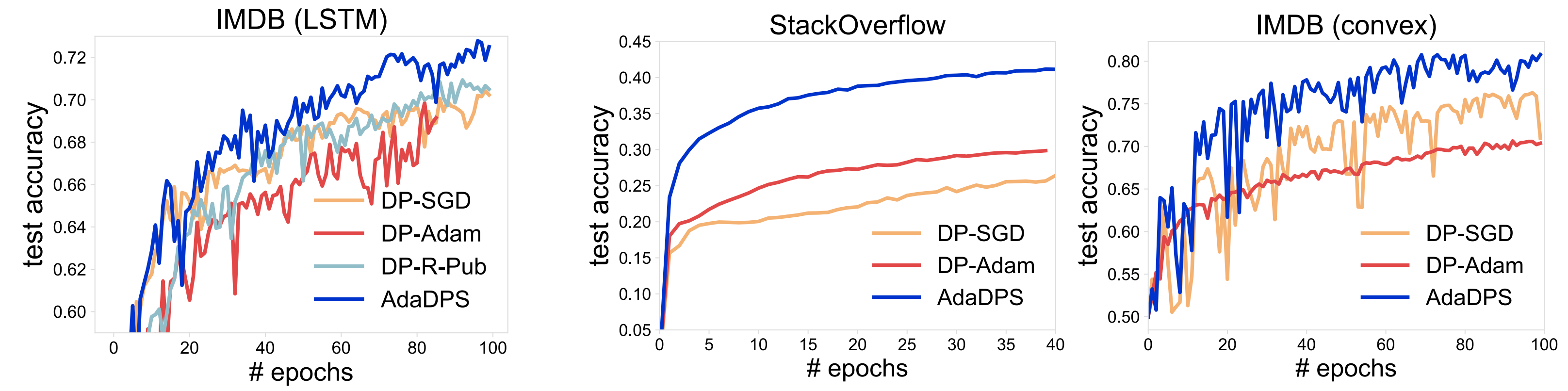
$$\frac{\alpha R+1}{\sqrt{T}}\sum_{j=1}^{d}A_j + \frac{\alpha}{\sqrt{T}}\mathbb{E}\left[\|\mathcal{N}\|^2_A\right], R := \max_{j,t}\frac{\mathbb{E}[(g_j^t)^2]}{A_j^2}$$

One practical choice: feature frequencies for generalized linear models: $A_j = \mathbb{E}[|x_j|] + \epsilon$

Evaluation

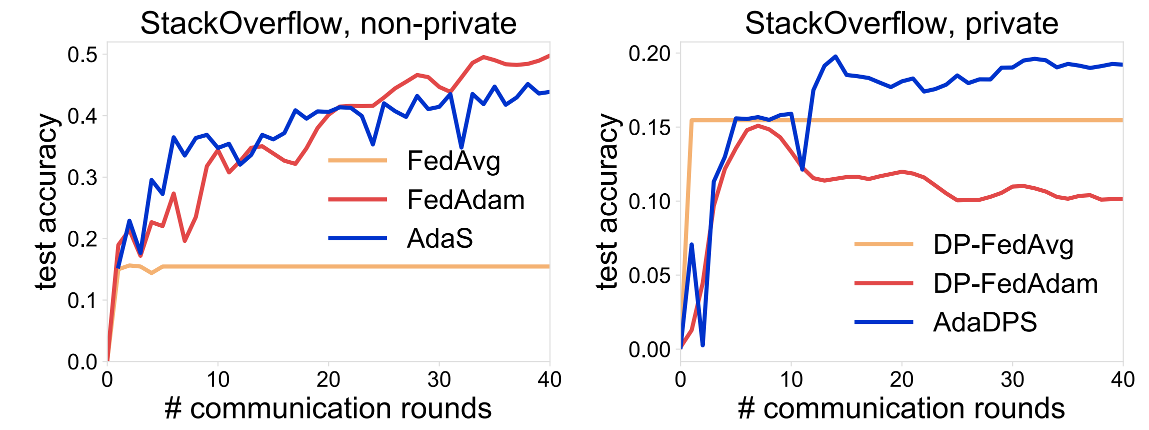
centralized training: sample-level DP

With public data | Without public data



In both convex and non-convex cases, AdaDPS outperforms the baselines significantly.

federated learning: client-level DP



We apply AdaDPS on the client side at each local update in federated optimization. It improves over baselines of vanilla DP-FedAvg and DP-FedAdam.

See paper for all results on all datasets, comparisons with additional recent baselines, results of using OOD data as public data, the effect of public data size, etc.

Future Work

- Exploring other approaches of reducing noise (e.g., with tree aggregation) in the context of adaptive optimization
- Generalizing our approach without public data to arbitrary neural network models

Code: https://github.com/litian96/AdaDPS
ArXiv: https://arxiv.org/abs/2202.05963

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