Private Adaptive Optimization with Side Information

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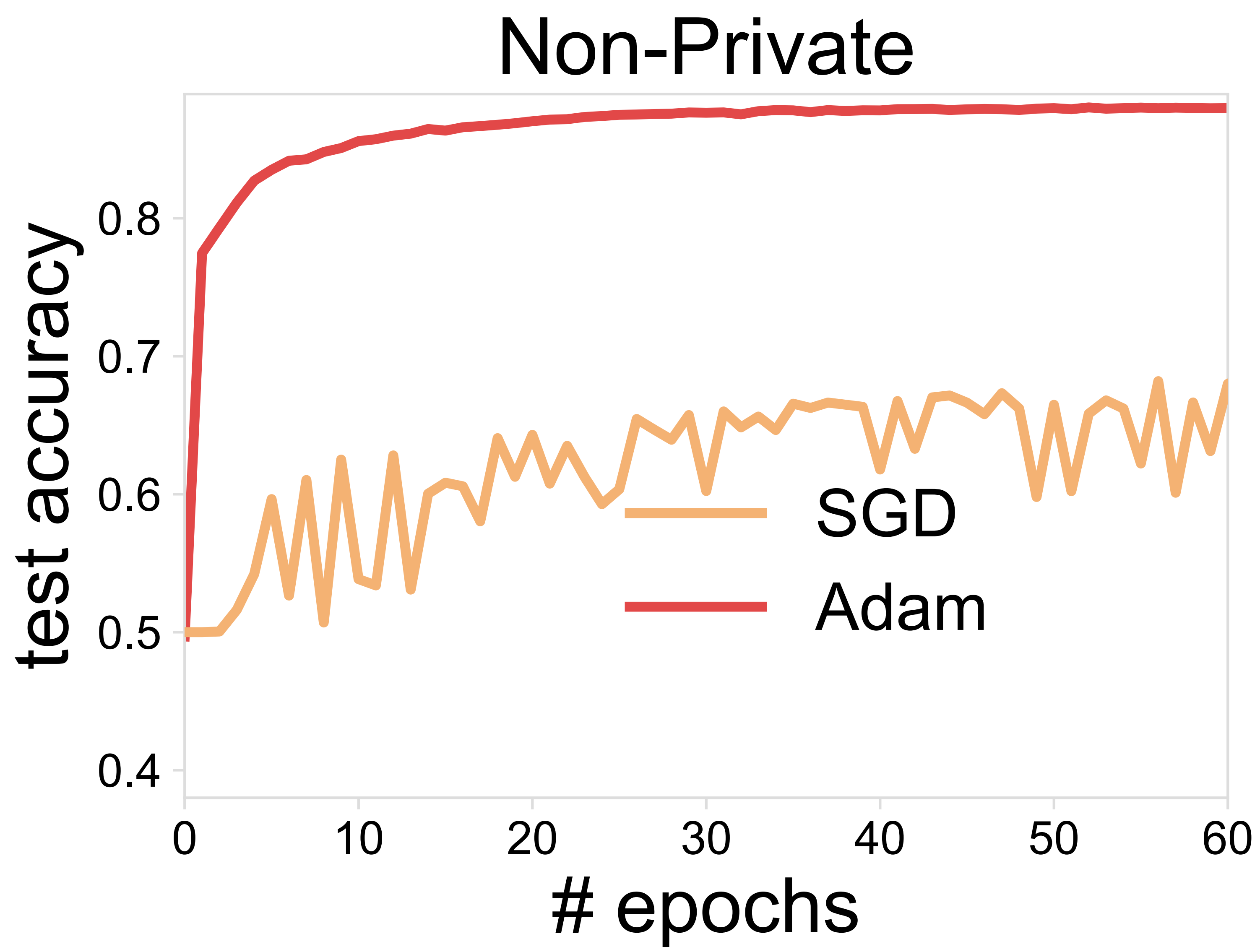
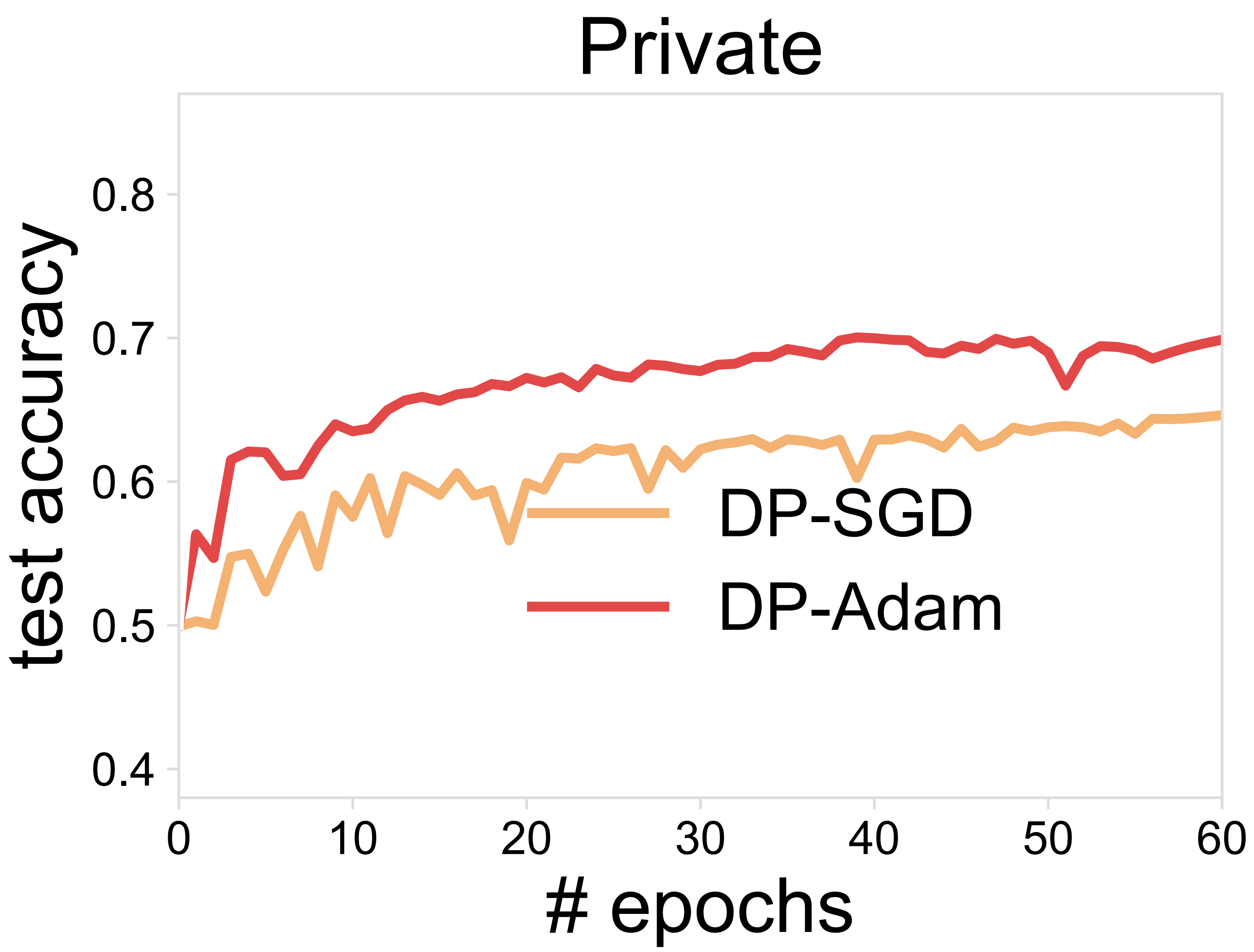
Motivation

- Adaptive optimizers (e.g., Adam, AdaGrad, RMSProp) are useful for a variety of ML tasks
- However, performance may degrade significantly when trained with differential privacy (DP), especially when the model dimension is large





How to effectively adapt to the geometry of gradients under DP?

directly plug in private gradients to estimate the statistics ?

first privatize the gradients

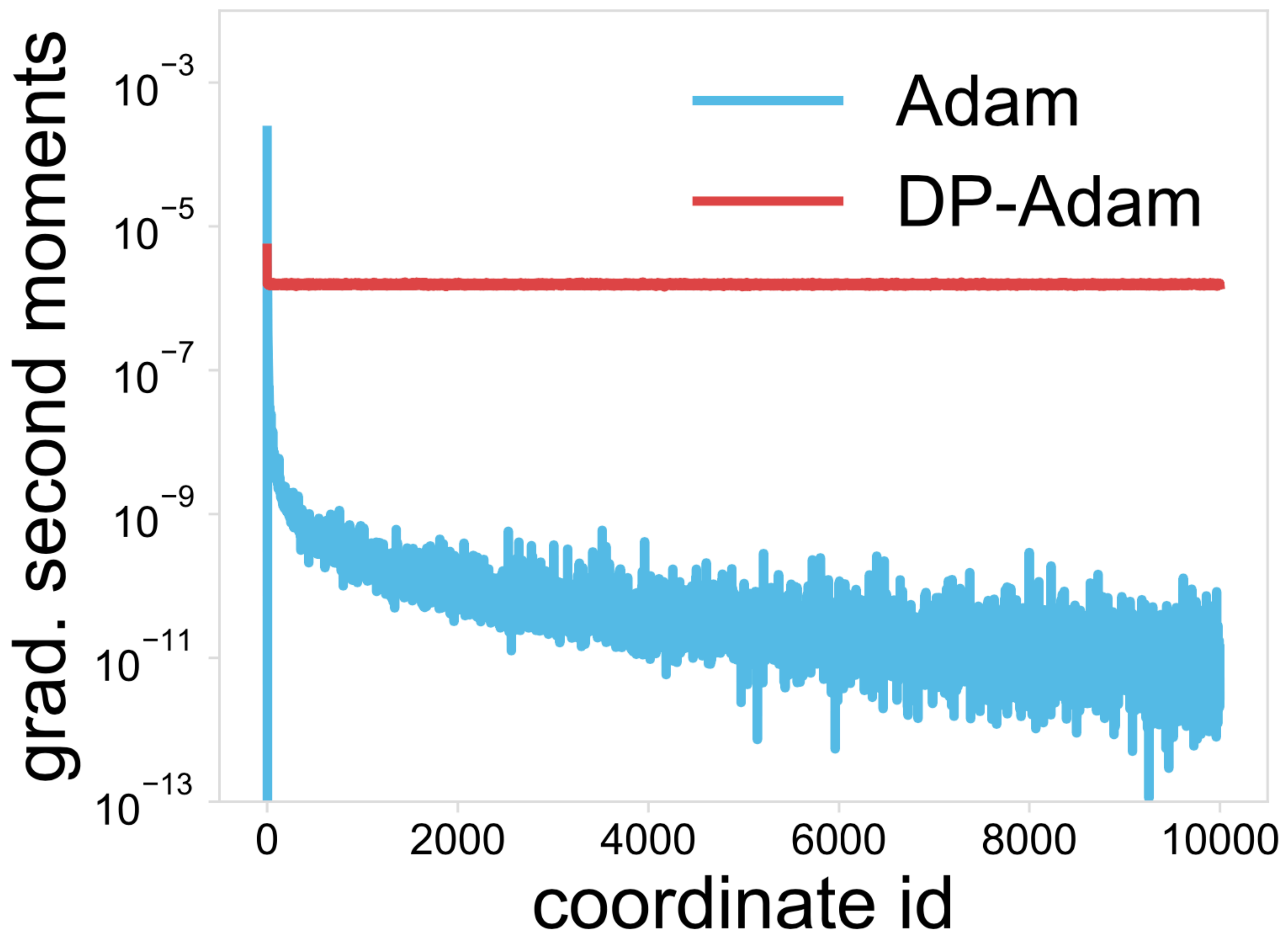
$$\tilde{g}^t \leftarrow \frac{1}{|B|}\left(\sum_{i \in B} \text{clip}\left(g^{i,t}, C\right) + \mathcal{N}\left(0, \sigma^2 C^2\right)\right)$$

then plug in private gradients to any adaptive optimization methods

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

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

estimates can be very noisy!



AdaDPS: Private Adaptive Optimization with Side Information

With public data

Estimate gradient statistics on public data at each iteration

- obtained via 'opt-out' users or proxy data

Without public data

Non-sensitive common knowledge about the training data

- e.g., token frequencies in NLP

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

A encodes how predictive each coordinate is

preconditioning *before* privatizing the gradients

AdaDPS: Private Adaptive Optimization with Side Information

Convergence:

(informal) rate: $O\left(\frac{1}{\sqrt{T}}\right) + O\left(\frac{1}{\sqrt{T}} \boxed{\mathbb{E}\left[\|\mathcal{N}\|_A^2\right]}\right)$

reduced DP noise when the gradients are sparse

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

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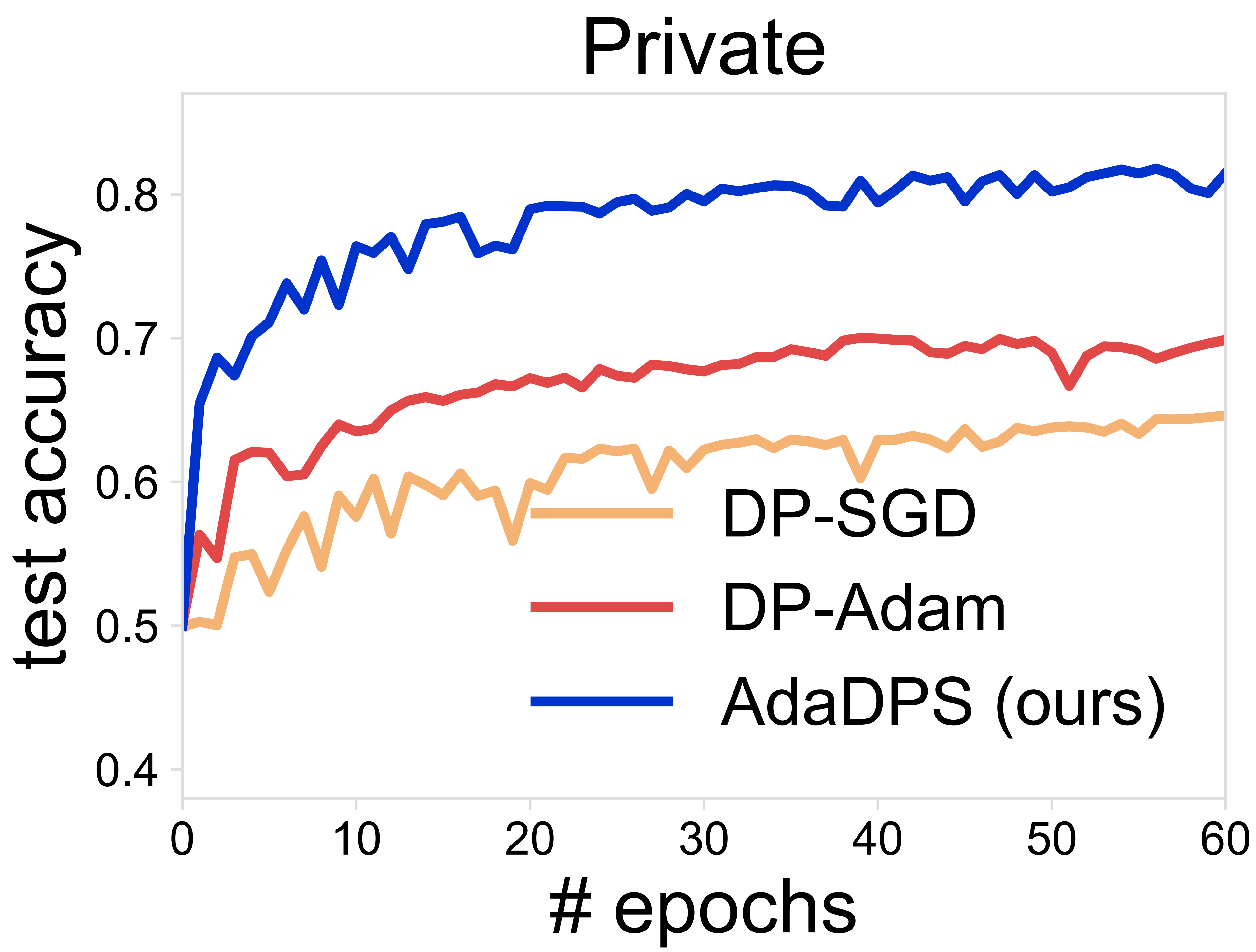
Empirical Results

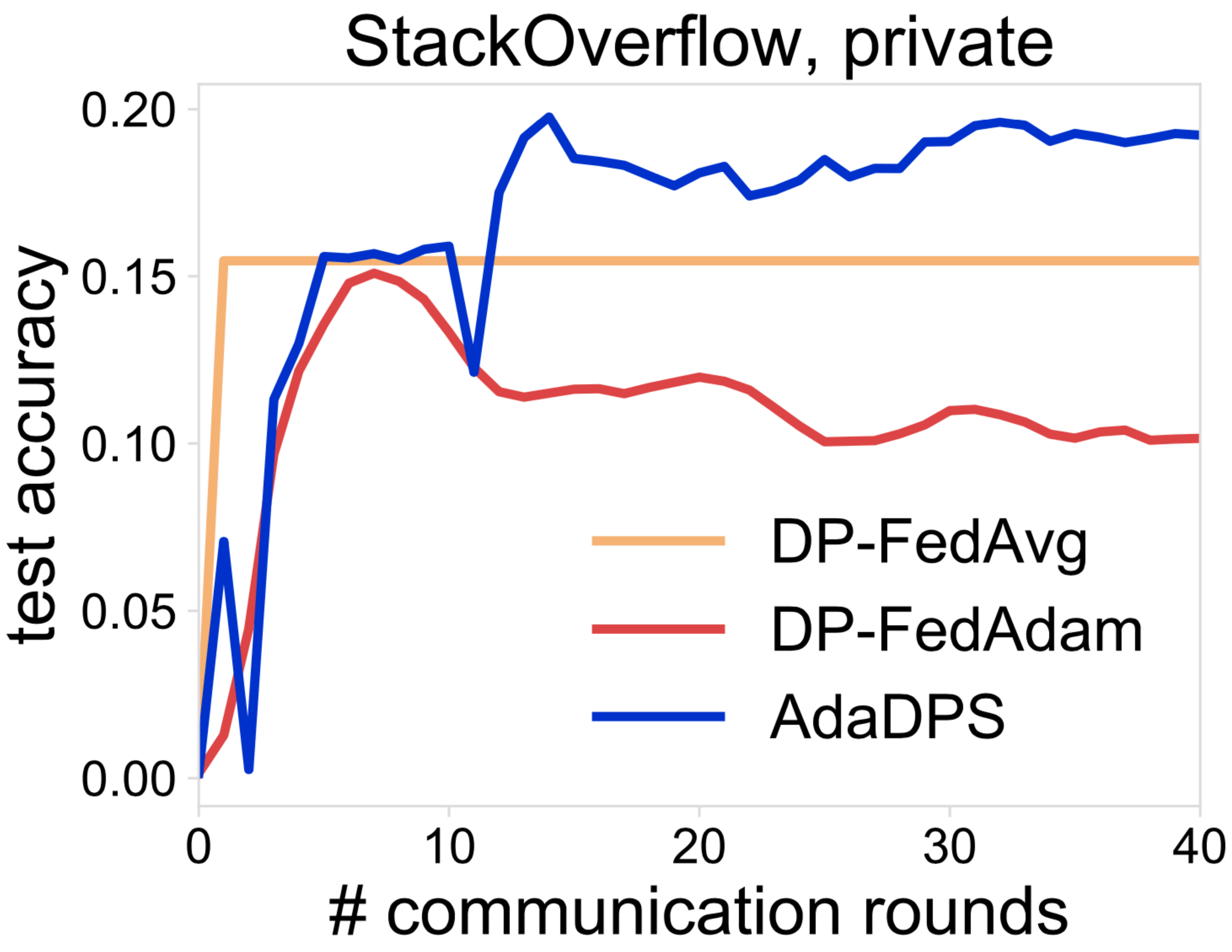
centralized training

sample-level DP



federated learning

client-level DP



Future Works

- Exploring other approaches of reducing noise (e.g., with tree aggregation)
- Generalizing our approach without public data to arbitrary neural networks

Full paper: *arxiv.org/abs/2202.05963*

Code: *github.com/litian96/AdaDPS*