Private Adaptive Optimization with Side Information

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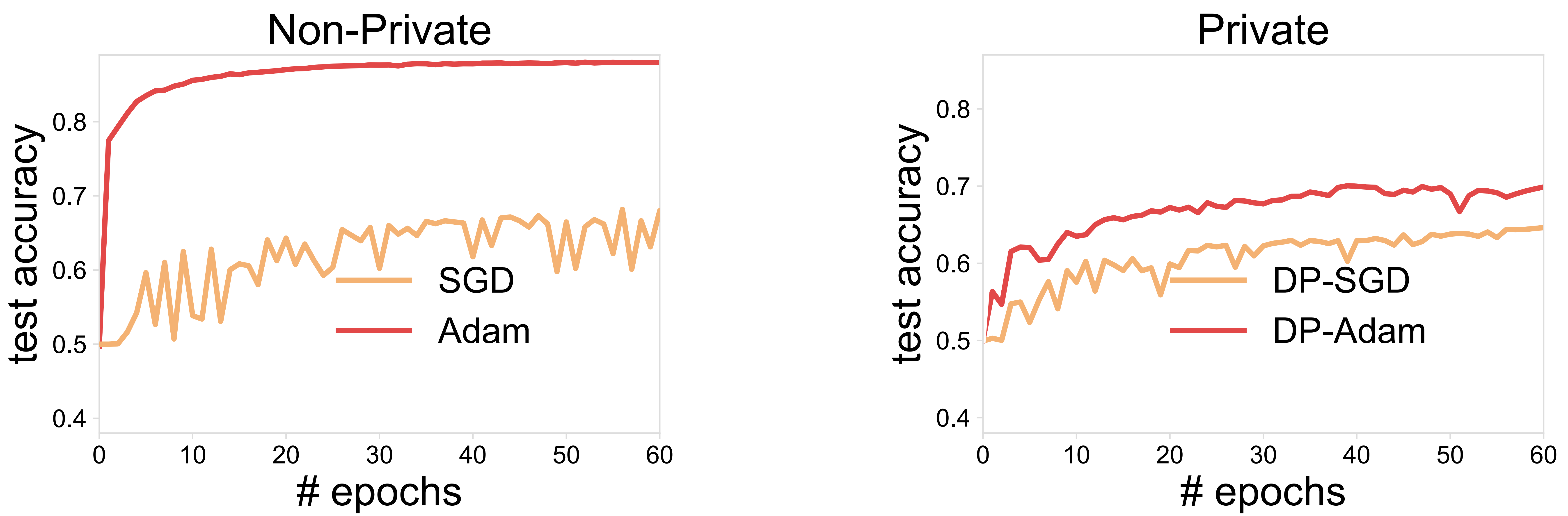

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$$m^t \leftarrow \beta_1 m^t + (1-\beta_1)\tilde{g}^t,\ v^t \leftarrow \beta_2 v^t + (1-\beta_2)\left(\tilde{g}^t\right)^2$$

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

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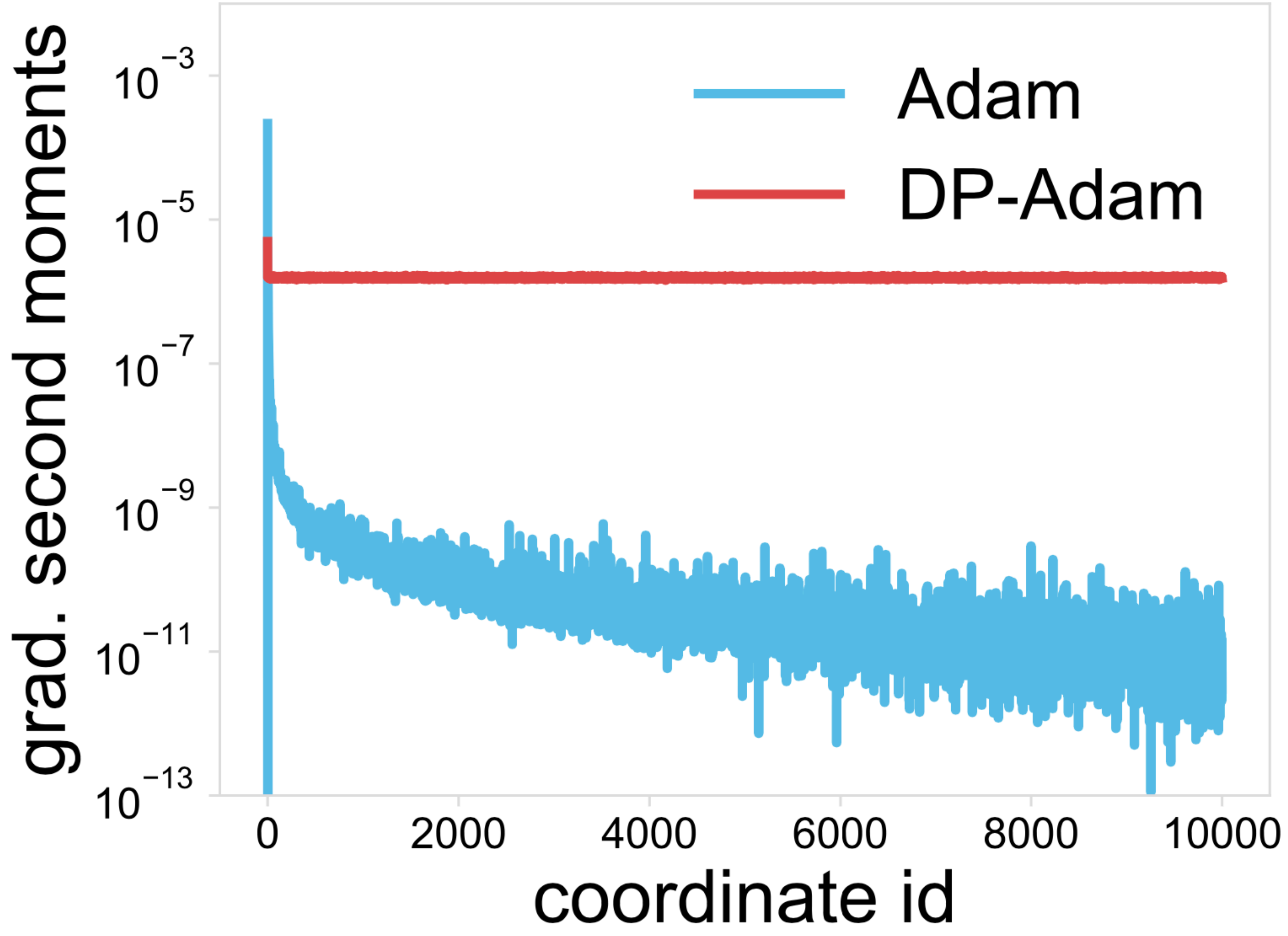
estimates can be very noisy!



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With public data

Estimate gradient statistics on public data at each iteration

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Convergence:

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

reduced DP noise when the gradients are sparse

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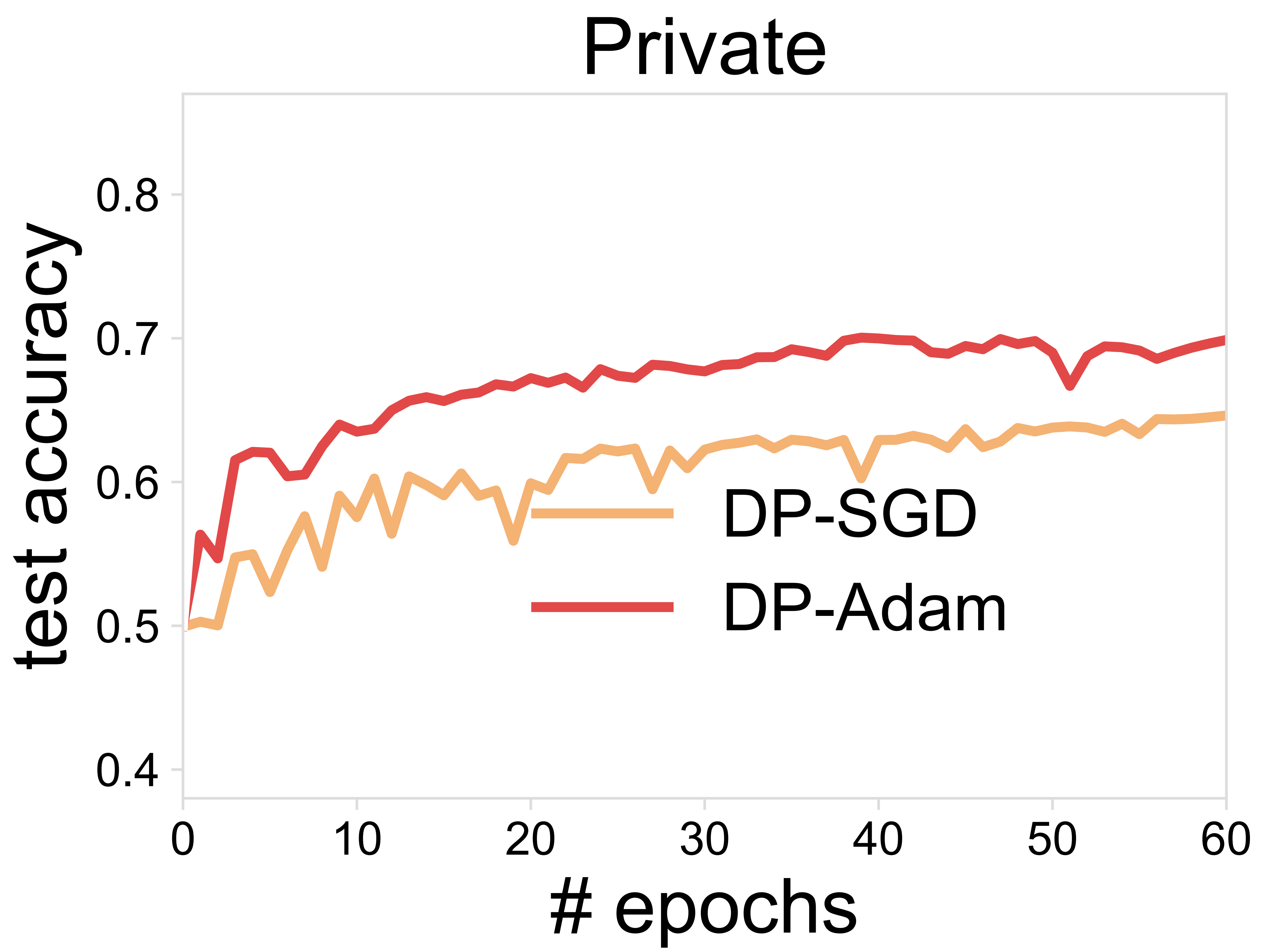

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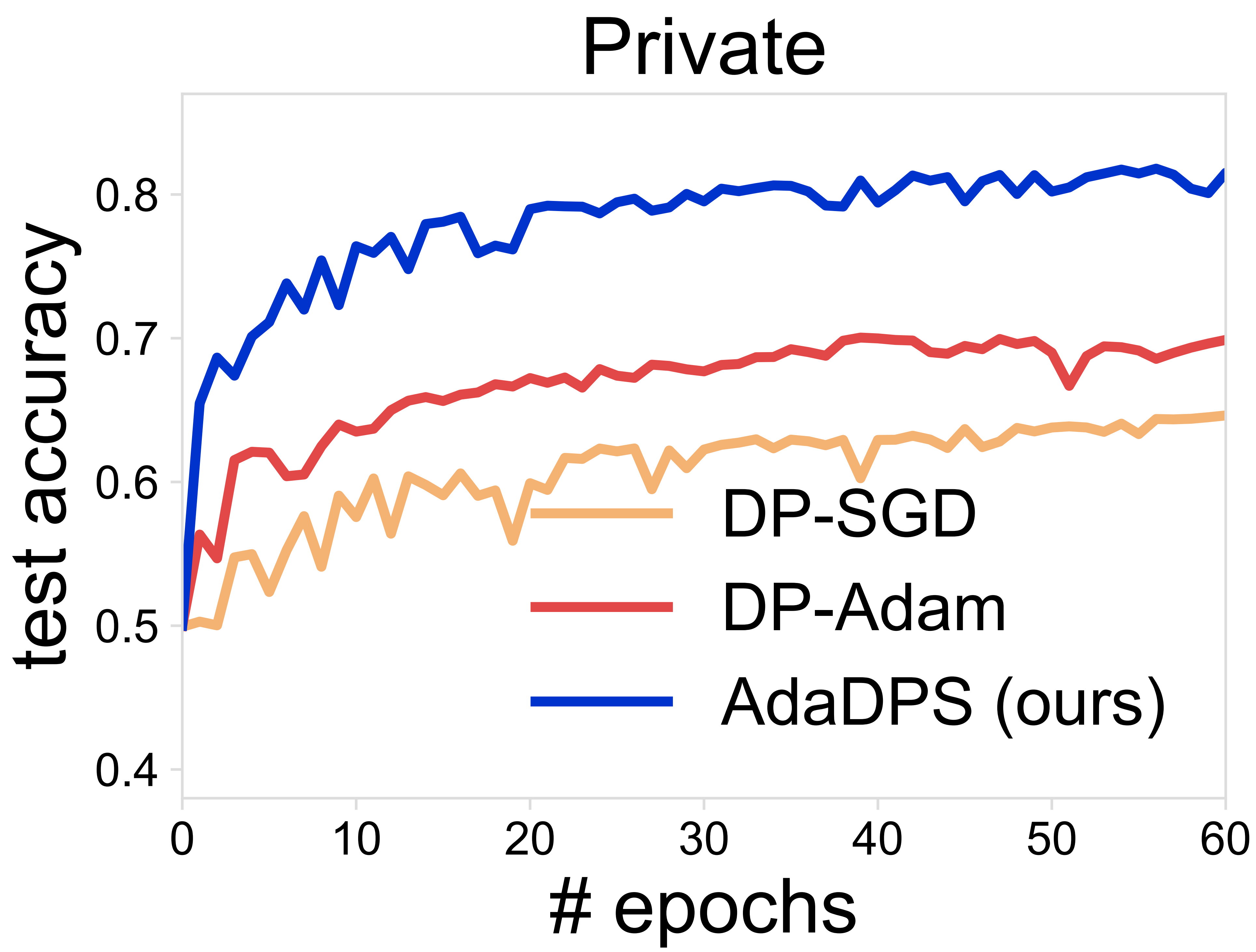

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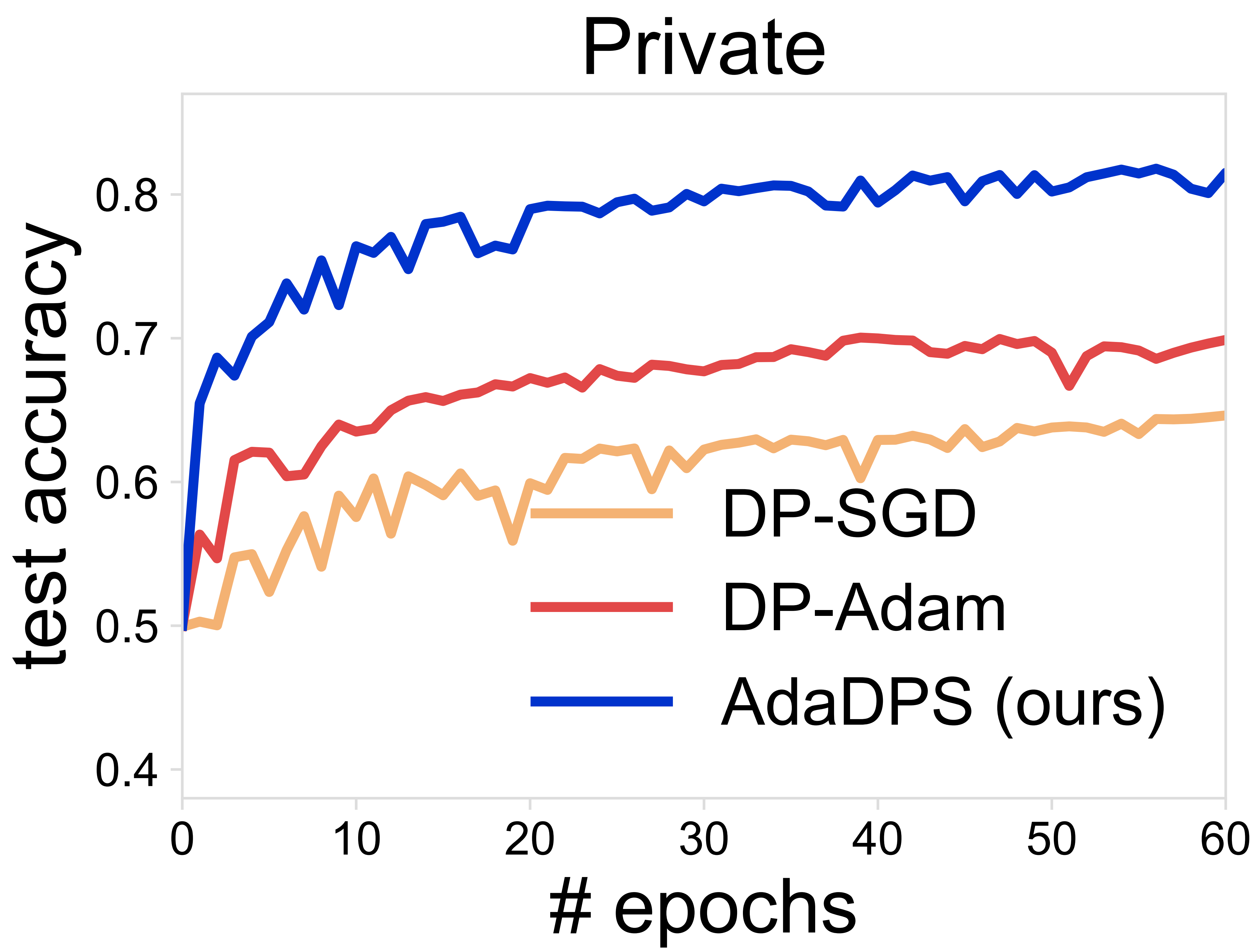

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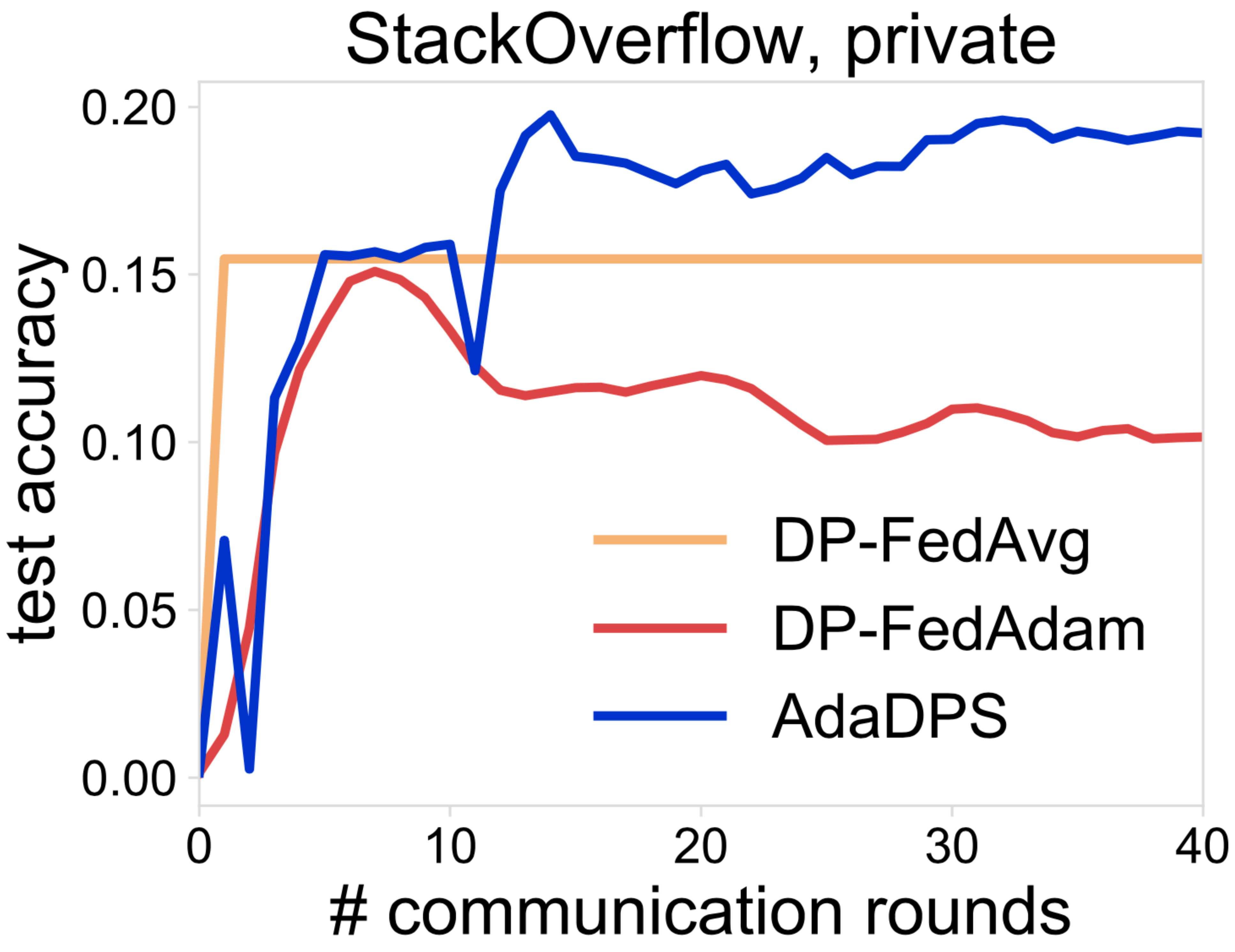

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Full paper: *arxiv.org/abs/2202.05963*

Code: *github.com/litian96/AdaDPS*