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

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

then plug in private gradients to any adaptive optimization methods

\[
m^t \leftarrow \beta_1 m^t + (1 - \beta_1) \tilde{g}^t, \quad v^t \leftarrow \beta_2 v^t + (1 - \beta_2) (\tilde{g}^t)^2
\]

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

estimates can be very noisy!
**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

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

A encodes how predictive each coordinate is

preconditioning *before* privatizing the gradients
AdaDPS: Private Adaptive Optimization with Side Information

Convergence:

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

reduced DP noise when the gradients are sparse

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

\(A\) encodes how predictive each coordinate is

preconditioning \textit{before} privatizing the gradients
Empirical Results

centralized training
sample-level DP

federated learning
client-level DP

Private

StackOverflow, private

![Graph showing test accuracy over epochs and communication rounds for different methods in centralized and federated learning scenarios.]
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](https://arxiv.org/abs/2202.05963)
Code:        [github.com/litian96/AdaDPS](https://github.com/litian96/AdaDPS)