Large Scale Private Learning via Low-rank Reparametrization

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Background

Differential privacy:

p[A(D) = t] tFor all D, D' that differ in one person's value, If A = ϵ -differentially private randomized algorithm, then:

$$\sup_t \Big| \log \frac{p(A(D) = t)}{p(A(D') = t)} \Big| \le \epsilon$$

The image is from https://www.ece.rutgers.edu/~asarwate/nips201 7/NIPS17_DPML_Tutorial.pdf

Deep learning with differential privacy: DP-SGD

- 1. Clip the gradients of individual samples for sensitivity control.
- 2. Add noise coordinate-wisely to the gradient.

Challenges of Applying DP-SGD in Large Models



A Reparametrization approach



Why Does Our Approach Work?

- Gradients are of low-stable rank.
 - Low-rank gradient carriers.



- How to generate proper L, R?
 - The principal components of the historical updates.
 - For linear regression, the current gradient stays exactly in the subspace spanned by historical updates.
 - For deep models, most energy of the current gradient also lives in such subspace.

RGP on Downstream Tasks of BERT

• Experiment architecture: the BERT_{base} model, 110M parameters



