

DP-Adam: Correcting DP Bias in Adam's Second Moment Estimation



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Abstract

We observe that the traditional use of DP with the Adam optimizer introduces a bias in the second moment estimation, due to the addition of independent noise in the gradient computation. This bias leads to a different scaling for low variance parameter updates, that is inconsistent with the behavior of non-private Adam, and Adam's sign descent interpretation. Empirically, correcting the bias introduced by DP noise significantly improves the optimization performance of DP-Adam.

The Adam Update under Differential Privacy

Interpretation of Adam as Sign Descent

- Adam maintains exponential moving average for estimating $\mathbb{E}[g_t]$ and $\mathbb{E}[g_t^2]$: the vector of first and second moment of updates to each parameter during training.
- Previous evidence supports the hypothesis: Adam may derive its empirical performance from being a smoothed out version of sign descent.

Using Adam with Differential Privacy

- Existing DP approaches using Adam substitutes mini-batch gradient g_t with privatized \tilde{g}_t to preserve privacy.
- $g_n = \nabla f(\theta_t, x_n)$ is the gradient for sample n; B, C, σ are batch size, maximum L2-norm clipping value and noise multiplier,

$$\overline{g}_t = (1/B) \sum_{n \in B} g_n / \max(1, ||g_n||_2 / C),$$

$$\widetilde{g}_t = \overline{g}_t + (1/B) z_t, \ z_t \sim \mathcal{N}(0, \sigma^2 C^2 \mathbb{I}^d).$$

DP Noise Shifts Second Moment Estimates

The independent DP noise has no impact on the first moment in expectation,

$$\mathbb{E}[m_t^p] = \mathbb{E}\left[(1 - \beta_1) \sum_{\tau=1}^t \beta_1^{t-\tau} \tilde{g}_\tau \right] = (1 - \beta_1) \sum_{\tau=1}^t \beta_1^{t-\tau} \left(\mathbb{E}[\overline{g}_\tau] + \frac{1}{\underline{B}} \mathbb{E}[z_\tau] \right) = \mathbb{E}[m_t^c].$$

 v_t^p is a biased estimate of the second moment of the mini-batch clipped gradient \bar{g}_t ,

$$\mathbb{E}[v_t^p] = \mathbb{E}\left[(1 - \beta_2) \sum_{\tau=1}^t \beta_2^{t-\tau} \tilde{g}_\tau^2 \right] = \underbrace{(1 - \beta_2) \sum_{\tau=1}^t \beta_2^{t-\tau} \mathbb{E}[\overline{g}_\tau^2]}_{\mathbb{E}[v_t^c]} + \underbrace{(1 - \beta_2^t) \left(\frac{\sigma C}{B}\right)^2}_{\Phi}.$$

When $|\mathbb{E}[\bar{g}_t]|_i \approx \sqrt{\mathbb{E}[\bar{g}_t^2]_i}$, the Adam update becomes $\pm \frac{|\mathbb{E}[\bar{g}_t]|_i}{\sqrt{\mathbb{E}[\bar{g}_t^2]_i + \Phi}}$ instead of ± 1 .

Correcting for DP noise in DP-Adam

We correct for this bias by changing the Adam update Δ_t as:

$$\Delta_t = \eta \cdot \hat{m}_t / \sqrt{\max \left(\hat{v}_t - (\sigma C/B)^2, \gamma'\right)}.$$

It enables a sign descent interpretation for DP-Adam closely follows Adam, except that the variance is compared to Φ instead of $\mathbf{0}$:

For each parameter i,

- If $|\mathbb{E}[\bar{g}_t]|_i \approx 0$:
 - If $\operatorname{Var}\left[\overline{g}_{t}\right]_{i}\gg\Phi$, then $\Delta_{t}\approx0$.
 - If $Var[\overline{g}_t]_i \lesssim \Phi$, the γ' parameter ensures $\Delta_t \approx 0$.
- If $|\mathbb{E}[\bar{g}_t]|_i \gg 0$, then our correction restores the smoothed sign descent behavior of DP-Adam:
 - If $\operatorname{Var}\left[\overline{g}_{t}\right]_{i}\gg\Phi$, $|\mathbb{E}[\overline{g}_{t}]|_{i}\approx\sqrt{\mathbb{E}[\overline{g}_{t}^{2}]_{i}}$, and $\Delta_{t}\approx\pm1$.
 - If $Var[\overline{g}_t]_i \lesssim \Phi$, $\Delta_t \in [0,1]$, performing a smooth (variance scaled) version of sign descent.

Privacy Analysis

The privacy guarantee holds following the post-processing property of DP, and composition over training iterations.

Algorithm: DP-Adam (with corrected DP bias in second moment estimation)

Output: Model parameters θ Input: Data $D=\{x_i\}_{i=1}^N$, η , σ , B, C, β_1 , β_2 , γ' , ϵ -DP, δ -DP Initialize θ_0 randomly; initialize moment estimates $m_0=0, v_0=0$;

Total number of steps $T = f(\epsilon\text{-DP}, \delta\text{-DP}, B, N, \sigma)$; for $t = 1 \dots, T$ do

Take a random batch with sampling probability B/N; $\tilde{g}_t = \frac{1}{B} \left(\sum_i g_i / \max\left(1, \frac{\|g_i\|_2}{C}\right) + z_t \right), \ z_t \sim \mathcal{N}\left(0, \sigma^2 C^2 \mathbb{I}^d\right)$;

 $m_{t} \leftarrow \beta_{1} \cdot m_{t-1} + (1 - \beta_{1}) \cdot \tilde{g}_{t}, \ \hat{m}_{t} \leftarrow m_{t} / (1 - \beta_{1}^{t});$ $v_{t} \leftarrow \beta_{2} \cdot v_{t-1} + (1 - \beta_{2}) \cdot \tilde{g}_{t}^{2}, \ \hat{v}_{t} \leftarrow v_{t} / (1 - \beta_{2}^{t});$ $\theta_{t} \leftarrow \theta_{t-1} - \eta \cdot \hat{m}_{t} / \sqrt{\max\left(\hat{v}_{t} - (\sigma C / B)^{2}, \gamma'\right)}$ end

The Empirical Effect of Correcting for DP Noise

Performance of Uncorrected, Corrected DP-Adam and DP-SGD

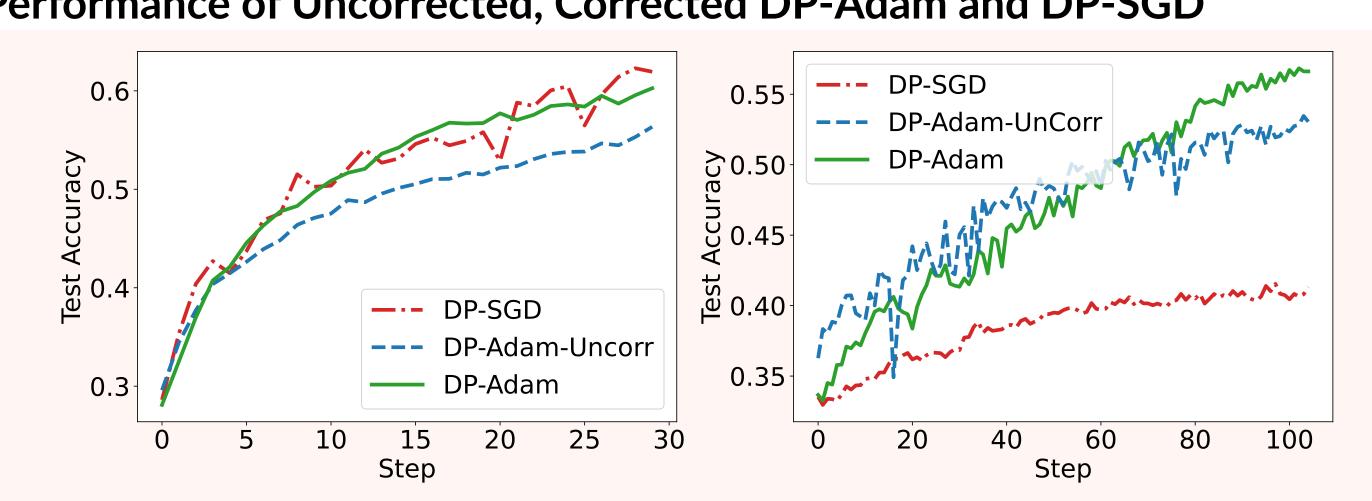


Figure 1. Comparing the performance of DP-Adam, DP-Adam-Uncorr and DP-SGD on **Left:** CIFAR10 and **Right:** SNLI. Tested under training-from-scratch setting. η , γ (or γ') are tuned at a coarse granularity for $\epsilon \approx 7$.

First and Second Moment Estimates of Clipped and Private Gradients

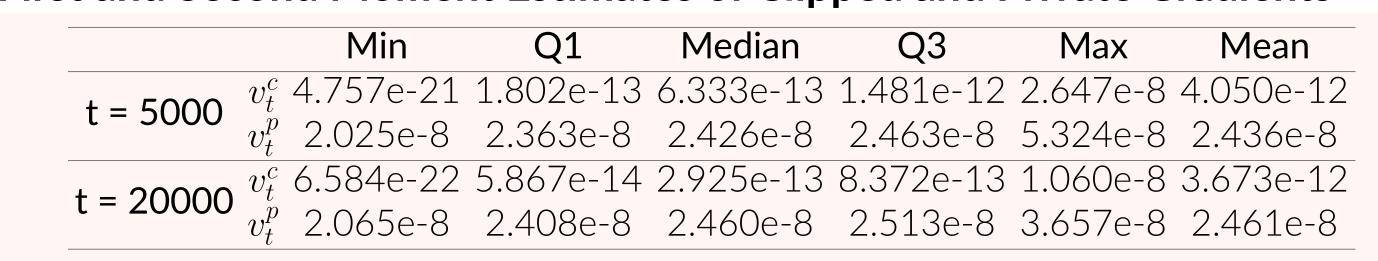


Table 1. Summary statistics of v_t^p with the SNLI dataset.

- Scale and spread of v_t^p is different from that of v_t^c , suggesting v_t^p largely affected by the DP noise,
- Φ dominates the size of $\mathrm{Var}\left[\overline{g}_{t}\right]$ (and hence v_{t}^{p}) thus making Δ_{t} smaller.

Correcting Second Moment with Different Values

• Correcting for a different value (of $\Phi' > \Phi$ or $\Phi' < \Phi$) does not provide a good estimate for $\mathrm{Var}\left[\overline{g}_t\right]$.

Effect of the Numerical Stability Constant

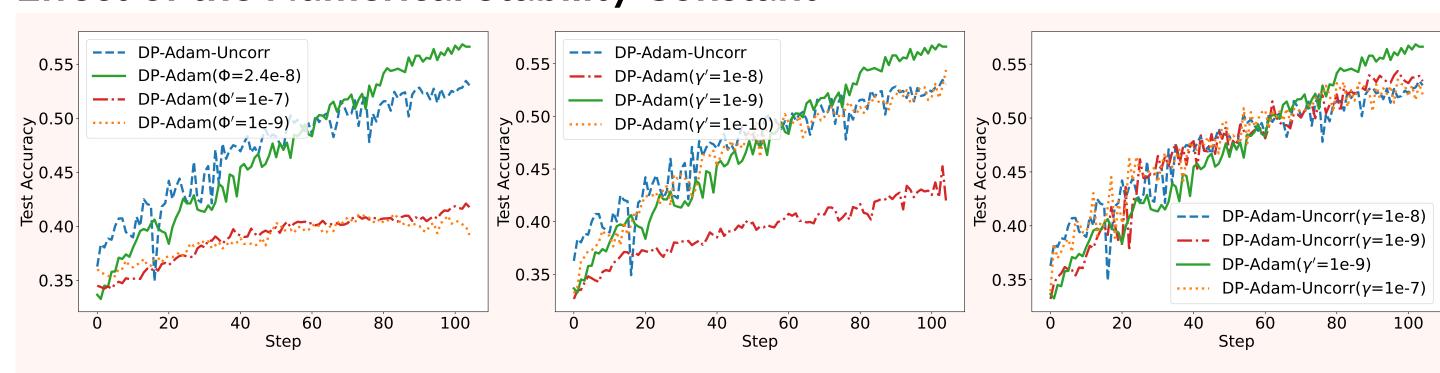


Figure 2. Compare the performance when **Left:** subtracting different (fake) values of Φ , **Middle:** tuning γ' in DP-Adam, **Right:** tuning γ in DP-Adam-Uncorr.

- γ' impacts the performance of DP-Adam: v_t^p are small, changing γ' avoids magnifying parameters with tiny estimates of v_t^c ,
- Tuning γ with DP-Adam-Uncorr does not lead to the same effect as correcting Φ in DP-Adam, and DP-Adam achieves higher accuracy.