NA-DPVI AISTATS 2025 Rebuttle

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1 Introduction

$(\boldsymbol{x}_i)_{i=1}^N \leftarrow$ data;
$(\epsilon, \delta) \leftarrow$ DP privacy level;
$C \leftarrow$ clipping threshold;
$T \leftarrow$ training iterations;
$\lambda \leftarrow$ learning rate;
$\kappa \leftarrow$ Poisson sampling rate;
$\boldsymbol{\phi}_0 \leftarrow$ initial values for $\boldsymbol{\phi}$;
$d \leftarrow \dim(\phi_0)$
$\sigma_{\mathrm{DP}} \leftarrow$ RDP-Accountant$(\epsilon, \delta, T, \kappa)$;

Algorithm 1 DPVI

```
for t = 1, ..., T − 1 do
    g_{t+1} ← Σ_{i∈B_{t+1}} clip(∇_φ ℓ(φ_t; x_i), C);
    Sample η_{t+1} ~ N(0, I_d);
    g̃_{t+1} ← g_{t+1} + σ_DP C η_{t+1}
    φ_{t+1} ← φ_t − λ g̃;
end for
return T = (φ_t)_{t=0}^T, g̃ = (g̃_t)_{t=1}^T;
```

for $t = 1, \ldots, T-1$ **do**
  $\boldsymbol{g}_{t+1} \leftarrow \sum_{i \in \mathcal{B}_{t+1}} \mathrm{clip}\left(\nabla_{\boldsymbol{\phi}} \ell(\boldsymbol{\phi}_t; \boldsymbol{x}_i), C\right)$;
  Sample $\boldsymbol{\eta}_{t+1} \sim \mathcal{N}(0, \mathbf{I}_d)$;
  $\widetilde{\boldsymbol{g}}_{t+1} \leftarrow \boldsymbol{g}_{t+1} + \sigma_{\mathrm{DP}} C \boldsymbol{\eta}_{t+1}$
  $\boldsymbol{\phi}_{t+1} \leftarrow \boldsymbol{\phi}_t - \lambda \widetilde{\boldsymbol{g}}$;
end for
return $\mathcal{T} = (\boldsymbol{\phi}_t)_{t=0}^T, \widetilde{\boldsymbol{g}} = (\widetilde{\boldsymbol{g}}_t)_{t=1}^T$;

Algorithm 2 NA-DPVI

$M \leftarrow$ number of samples;
$\boldsymbol{\mu}_{\boldsymbol{\phi}^*} \leftarrow \boldsymbol{\phi}^*$ prior distribution mean;
$\Sigma_{\boldsymbol{\phi}^*} \leftarrow \boldsymbol{\phi}^*$ prior distribution covariance matrix;
$\boldsymbol{\mu}_{\mathbf{A}} \leftarrow \mathbf{A}$ entries prior distribution mean;
$\Sigma_{\mathbf{A}} \leftarrow \mathbf{A}$ entries prior distribution covariance matrix;
$\boldsymbol{\mu}_{\Sigma_{\mathrm{sub}}} \leftarrow \Sigma_{\mathrm{sub}}$ entries prior distribution mean;
$\Sigma_{\Sigma_{\mathrm{sub}}} \leftarrow \Sigma_{\mathrm{sub}}$ entries prior distribution covariance matrix;
$\mathcal{T}, \widetilde{\boldsymbol{g}} \leftarrow$ DPVI;
model-definition $\widetilde{\boldsymbol{g}} \mid \mathcal{T}, \boldsymbol{\phi}^*, \mathbf{A}, \Sigma_{\mathrm{sub}}$
  $\boldsymbol{\phi}^* \sim \mathcal{N}(\boldsymbol{\mu}_{\boldsymbol{\phi}^*}, \Sigma_{\boldsymbol{\phi}^*})$;
  $\mathbf{A} \sim \mathcal{N}(\boldsymbol{\mu}_{\mathbf{A}}, \Sigma_{\mathbf{A}})$;
  $\Sigma_{\mathrm{sub}} \sim \mathcal{N}(\boldsymbol{\mu}_{\Sigma_{\mathrm{sub}}}, \Sigma_{\Sigma_{\mathrm{sub}}})$;
  $\widetilde{\boldsymbol{g}}_{t+1} \mid \boldsymbol{\phi}_t, \mathbf{A}, \boldsymbol{\phi}^*, \Sigma_{\mathrm{sub}} \sim \mathcal{N}\left(\kappa \mathbf{A}\left(\boldsymbol{\phi}_t - \boldsymbol{\phi}^*\right), \sigma_{\mathrm{DP}}^2 C^2 \mathbf{I}_d + \Sigma_{\mathrm{sub}}\right)$;
end model-definition
Sample $(\boldsymbol{\phi}_i^*, \mathbf{A}_i, \Sigma_{\mathrm{sub},i})_{i=1}^M \sim \boldsymbol{\phi}^*, \mathbf{A}, \Sigma_{\mathrm{sub}} \mid \widetilde{\boldsymbol{g}}, \mathcal{T}$; ▷ using any approximate inference method.
return $\widetilde{p}(\boldsymbol{\theta} \mid \mathcal{T}) = \frac{1}{M} \sum_{i=1}^M q_{\mathrm{VI}}(\boldsymbol{\theta}; \boldsymbol{\phi}_i^*)$;