Memory Efficient EBM Training

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Abstract

To be completed...

1 Introduction

Definition 1 (Top-k)**.** *For $x \in \mathbb{R}^d$, denote $\mathcal{S}$ as the size-k set of $i \in [d]$ with largest k magnitude $|x_i|$. The **Top-**k compressor is defined as $\mathcal{C}(x)_i = x_i$, if $i \in \mathcal{S}$; $\mathcal{C}(x)_i = 0$ otherwise.*

Definition 2 (Block-Sign)**.** *For $x \in \mathbb{R}^d$, define M blocks indexed by $\mathcal{B}_i$, $i = 1, ..., M$, with $d_i := |\mathcal{B}_i|$. The **Block-Sign** compressor is defined as $\mathcal{C}(x) = [sign(x_{\mathcal{B}_1})\frac{\|x_{\mathcal{B}_1}\|_1}{d_1}, ..., sign(x_{\mathcal{B}_M})\frac{\|x_{\mathcal{B}_M}\|_1}{d_M}]$.*

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2 Distributed and Private EBM Training

Algorithm 1: Distributed and private EBM

Input: Total number of iterations T, number of MCMC transitions K and of samples M, sequence of global learning rate $\{\eta_t\}_{t>0}$, sequence of MCMC stepsizes $\gamma_{k\,k>0}$, initial value θ_0, MCMC initialization $\{z_0^m\}_{m=1}^M$. Set of selected devices $\mathcal{D}^t$.

Output: Vector of fitted parameters θ_{T+1}.

Data: $\{x_i^p\}_{i=1}^{n_p}$, n_p number of observations on device p. $n = \sum_{p=1}^P n_p$ total.

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for $t = 1$ *to* T **do**

`/* Happening on distributed devices */`

for *For device* $p \in \mathcal{D}^t$ **do**

Draw M negative samples $\{z_K^{p,m}\}_{m=1}^M$ `// local langevin diffusion`

for $k = 1$ *to* K **do**

$$
z_k^{p,m} = z_{k-1}^{p,m} + \gamma_k/2\nabla_z f_{\theta_t}(z_{k-1}^{p,m})^{p,m} + \sqrt{\gamma_k}\mathsf{B}_k^p \ ,
$$

where B_k^p denotes the Brownian motion (Gaussian noise).

Assign $\{z_t^{p,m}\}_{m=1}^M \leftarrow \{z_K^{p,m}\}_{m=1}^M$.

Sample M positive observations $\{x_i^p\}_{i=1}^M$ from the empirical data distribution.

Compute the gradient of the empirical log-EBM `// local - and + gradients`

$$
\delta^p = \frac{1}{M}\sum_{i=1}^M \nabla_\theta f_{\theta_t}\left(x_i^p\right) - \frac{1}{M}\sum_{m=1}^M \nabla_\theta f_{\theta_t}\left(z_K^{p,m}\right)
$$

Use black box compression operators

$$
\Delta^p = \mathcal{C}(\delta^p)
$$

Devices broadcast Δ^p to Server

`/* Happening on the central server */`

Aggregation of devices gradients: $\nabla \log p(\theta_t) \approx \frac{1}{|\mathcal{D}^t|}\sum_{p=1}^{|\mathcal{D}^t|}\Delta^p$.

Update the vector of global parameters of the EBM: $\theta_{t+1} = \theta_t + \eta_t \nabla \log p(\theta_t)$

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3 Conclusion

A Appendix