Power-efficient Deep Learning Workshop Introduction

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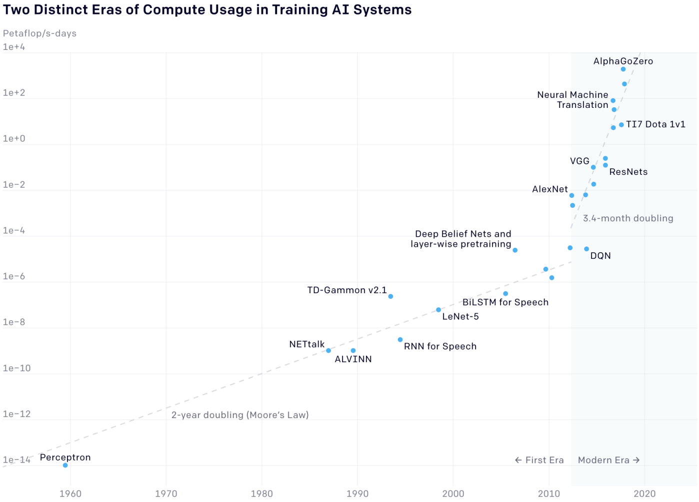
Workshop Introduction
November, 17th 2021

AI and Compute



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Low bitwidth approaches

- Originally from [7] - BinaryConnect
- Weights and I/O in [15, 5] - XNOR-nets $++$
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Bio-inspired energy efficiency

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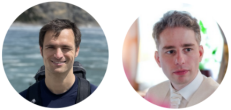

Power meters and Hardwares

Power measurements

- [4, 10, 2] uses **RAPL** and **nvidia-smi** specific performance counters,
- [16, 10] proposes a layer by layer energy measurements comparing Mobilenets [18] to standard Inception-V3 on a ARM Cortex-A57,
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statistical learning	sequential learning
signal-processing based	math / stats / game theory based

- a sequence of deterministic (or i.i.d.) **inputs** $z_1, \ldots, z_T \in \mathcal{Z}$,
- a set of **weak learners** $g \in \mathcal{G}$,
- a **loss** function $\ell(\cdot, \cdot) : \mathcal{G} \times \mathcal{Z} \to \mathbb{R}_+$.

$\boxed{\text{Goal}}$ Find a sequence of distributions such that:

$$\sum_{t=1}^{T} \mathbb{E}_{g' \sim \tilde{\rho}_t} \ell(g', z_t) - \inf_{g \in \mathcal{G}} \left\{ \sum_{t=1}^{T} \ell(g, z_t) + \lambda \text{pen}(g) \right\}$$

is minimum, where pen(g) measure the **'complexity'** of the decision $g \in \mathcal{G}$.

- $z = (x, y)$, $x \in \mathcal{X}$ input space of images, time series, network,
- $\mathcal{G} := \{g_{\mathbf{w}} : \mathcal{X} \to \mathcal{Y}, \mathbf{w} \in \mathcal{W}\}$, where $\mathbf{w}$ are the weights of a given standard or XNOR-nets architecture. For XNOR-nets convolutions are approximated by bitwise operations:

$$x_k = \left(\mathbf{w}_k^{\mathrm{bin}} \bigoplus \mathrm{sign} \circ \mathrm{BNorm}\left(x_{k-1}\right)\right) \bigodot \mathbf{w}_k^{\mathrm{scale}},$$

- the **cross-entropy** loss function $\ell(\hat{y}, y)$.

Sparsity regret bound

XNOR-Nets case

Theorem (L. Chee and Gay, 2021)

Considering inputs $\{(x_t, y_t), t = 1, \ldots, T\}$, *the decision space* $\mathcal{G}$, *and cross-entropy loss, there exists a* ***sequence of distributions*** $(\tilde{\rho}_t)_{t=1}^T$ *on* $\mathcal{G}$ *such that:*

$$\sum_{t=1}^{T} \mathbb{E}_{g' \sim \tilde{\rho}_t} \ell(y_t, g'(x_t)) \leq \inf_{\mathbf{w} \in \mathcal{W}_{\mathrm{XNOR}}} \left\{ \sum_{t=1}^{T} \ell(y_t, g_{\mathbf{w}}(x_t)) + pen(g_{\mathbf{w}}) \right\} + \Delta_T,$$

where $\Delta_T > 0$ *is defined in [13] and* $pen(g_{\mathbf{w}})$ *measure the complexity of the network as follows:*

$$pen(g_{\mathbf{w}}) = 4 \sum_{\mathbf{w} \in \{\mathbf{w}^{\mathrm{real}}, \mathbf{w}^{\mathrm{scale}}\}} \|\mathbf{w}\|_0 \log\left(1 + \frac{\|\mathbf{w}\|_1}{\tau \|\mathbf{w}\|_0}\right) + p_{\mathrm{bin}} \log 2$$

Accept-Reject algorithm

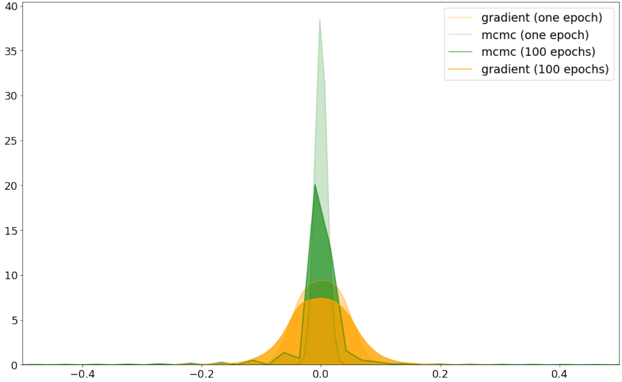
Pseudo-code

init. $\lambda > 0$, sparsity prior π, $k = 1$.

1. Draw $\hat{\mathbf{w}}_1$ from π.
2. **Repeat** for $k = 1, \dots, K$:
   - Generate a proposal $\tilde{\mathbf{w}} \sim \tilde{p}_{\hat{\mathbf{w}}_k, \sigma}$, where $\tilde{p}$ has mean $\hat{\mathbf{w}}_k$.
   - Compute:
   $$\rho_j(\tilde{\mathbf{w}}, \hat{\mathbf{w}}_k) = \frac{\exp\{-\lambda \ell(\tilde{\mathbf{w}}, B_j)\}\, \pi(\tilde{\mathbf{w}})}{\exp\{-\lambda \ell(\hat{\mathbf{w}}_k, B_j)\}\, \pi(\hat{\mathbf{w}}_k)}.$$
   - Update
   $$\hat{\mathbf{w}}_{k+1} = \begin{cases} \tilde{\mathbf{w}} & \text{with proba } \rho_j(\tilde{\mathbf{w}}, \hat{\mathbf{w}}_k) \\ \hat{\mathbf{w}}_k & \text{otherwise.} \end{cases}$$

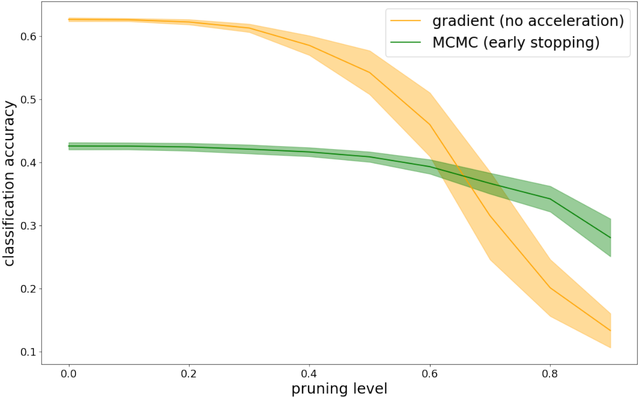
Weight distributions

SGD vs MCMC



Robustness to pruning

SGD vs MCMC



Future works

- Structural sparsity and more specific priors,
- Asynchronous and decentralized algorithms,
- Forward accelerations,
- Extensions to non-diff losses and other divergences, link with MTS problem,
- Workshop page see - the dedicated page -

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