POET: Training Neural Networks on Tiny Devices with Integrated Rematerialization and Paging

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https://github.com/ShishirPatil/poet

Slides are borrowed from the author
Model Personalization Adapts Models by Training on User Data to Improve Accuracy

Privacy, no internet access

- + energy consumed by bulk data transmission can significantly reduce battery life
Model Fine-tuning – Train on Edge

**Key Challenge:** Limited memory for DNN training!

**Pros:**
+ guarantees user’s privacy as all data stays on their device
+ enables offline device operation

**Cons:**
- cannot train modern DNNs on edge devices
Memory optimization techniques

• Pruning
  • They do not reduce the size of activations.
  • Accuracy trade-off

• Quantization
  • poor hardware support for quantized operations under 8 bits
  • Accuracy trade-off

• Rematerialization

• Paging
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Value preserving
Reduce activation
Insight

- Paging is very energy-intensive
- Rematerializing might consume lower energy
- Paging might be quicker.
  - Paging can be done in parallel with the compute. DMA technique
- This is because, on edge devices, it is common practice to turn-off components that are not utilized (e.g., SD card, DMA, etc.)

- For example,
  - piecewise(cheap-to-compute but memory-intensive) \(\rightarrow\) recompute
  - conv, matmul(compute-intensive) \(\rightarrow\) paging
Rematerialization & Paging in DNN training

- **Sublinear & Revolve**
  - Strong assumption that models have uniform compute requirements. Heuristic so not optimal

- **Capuchin**
  - Paging as default. Rematerialization only when paging is not possible

- **Checkmate**
  - Optimal but static graph
  - Not energy-aware
  - No paging

- **POFO**
  - Not energy-aware
  - Assumes paging is asynchronous (e.g., CUDA) but this is not universally true for the edge devices we evaluate.
## Comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>General Graphs</th>
<th>Compute Aware</th>
<th>Memory Aware</th>
<th>Power Aware</th>
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<tbody>
<tr>
<td>Checkpoint all (PyTorch)</td>
<td>✓</td>
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<td>Griewank &amp; Walther (2000)</td>
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<td>Chen et al. (2016) $\sqrt{n}$</td>
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<td>Chen et al. (2016) greedy</td>
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<td>Checkmate (Jain et al., 2020)</td>
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<td>POFO (Beaumont et al., 2021)</td>
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<td>✓</td>
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<td>DTR (Kirisame et al., 2021)</td>
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<tr>
<td>POET (ours)</td>
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</table>
How to reduce the memory and energy requirements of ML training for modern DNN architectures within the constraints of edge devices?
Computational graph

Network Configuration

input

fullc-forward

sigmoid-forward

fullc-forward

softmax-forward
Computational graph

Gradient Calculation Graph

- input
- fullc-forward
- sigmoid-forward
- fullc-forward
- softmax-forward
- log-loss
- input-grad
- fullc-backward
- sigmoid-backward
- fullc-backward
- softmax-backward
- label
Training is Memory Intensive since Activation from Forward Pass Need to be Stored for Backpropagation
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Forward Pass

Backward Pass

RAM used

Peak RAM

Time

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Rematerialization and Paging: Two Techniques to Reduce Memory Consumption

Rematerialization:
Free early & recompute
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Forward Pass

A → B → C → D → E

Backward Pass

\(\uparrow A \uparrow B \uparrow C \uparrow D \uparrow E\)

RAM used

Peak RAM (no rematerialization nor paging)

Available RAM

Peak RAM

Paging:
Page-out to secondary storage and page-in Just-in-Time!
POET: Private Optimal Energy Training

{ML model, memory and runtime constraints}
POET: Private Optimal Energy Training

Accurate cost profile of ML operators on target edge platform
POET: Private Optimal Energy Training

Incorporate memory and runtime constraints into a Mixed Integer Linear Program (MILP) formulation.

POET solver

\[
\text{min } \text{total energy usage} \\
\text{s.t. memory constraint} \\
\text{s.t. runtime constraint}
\]
POET: Private Optimal Energy Training

POET finds a provably optimal solution through integrated rematerialization and paging.
Result: POET lowers energy consumption and allows training large models previously not possible!
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POET’s integrated Rematerialization and Paging enables training with much smaller memory budgets which was previously not possible!
• POET enables training SOTA DNN models locally on memory-constrained edge devices.
• POET’s fine grained profiling results in accurate cost profiles.
• POET’s MILP formulation finds the optimal training schedule through integrated *rematerialization* and *paging*.