PORTABILITY AND PERFORMANCE IN EMBEDDED DEEP NEURAL NETWORKS: CAN WE HAVE BOTH?

Cormac Brick
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INTEL® MOVIDIUS™ VPU TECHNOLOGY ENABLES POWER-EFFICIENT IMAGE PROCESSING, CV, AND DEEP LEARNING INFERENCE IN EDGE DEVICES
INTEL® Movidius™ VPU Technology ENABLES POWER-EFFICIENT IMAGE PROCESSING, CV, AND DEEP LEARNING INFERENCE IN EDGE DEVICES.
THE QUESTION:

Can we have neural networks that are fast and portable?
THE QUESTION:

Can we have neural networks that are fast and portable without losing any accuracy?
OVERVIEW

- Selecting a fast network
- Making a fast network faster in a portable way
- Network portability: Ecosystems including ONNX
WHAT IS A FAST NETWORK?

Classical approach, look at:

• Number of FLOPS
• Number of parameters
WHAT IS A FAST NETWORK?

Classical approach, look at:
1. Number of flops

Ref[1]
WHAT IS A FAST NETWORK?

Classical approach, look at:
1. Number of FLOPS
2. Number of parameters
WHAT IS A FAST NETWORK?

Classical approach, look at:
1. Number of FLOPS
2. Number of parameters

On Embedded platforms, dataflow is a key determinant of performance, so we should also consider:
3. Activation heap size
   \[\Rightarrow \text{Keep activations in local mem/cache}\]
4. FLOPs/param/layer
   \[\Rightarrow \text{Avoid being DDR bound on weight fetch}\]
ACTIVATION HEAP SIZE

DenseNet

Resnet 50

Long lifetime data – larger heap

Limited lifetime data – smaller heap
ACTIVATION HEAP SIZE – WHAT IF ONLY 1MB L1 MEM?

DenseNet

Resnet 50

Long lifetime data – larger heap

Limited lifetime data – smaller heap
AVERAGE OPS/BYTE ON COMMON VISION NETWORKS

Average OPs/Byte for Network - Higher Better - Log Scale
OVERVIEW

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• Network portability: Ecosystems including ONNX
# Refining a Fast Model to Make It Faster

<table>
<thead>
<tr>
<th>Technique</th>
<th>What are we reducing?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prune Networks</td>
<td>OPs, heapSize, #params</td>
</tr>
<tr>
<td>Use 8 bits for activation and weights</td>
<td>OPs</td>
</tr>
<tr>
<td>Use &lt;8 bits for weights / codebook</td>
<td>Parameter bytes</td>
</tr>
<tr>
<td>Sparsify</td>
<td>ModelSize, OPs</td>
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<tr>
<td>Split 3x3 Conv in to DW separable Conv</td>
<td>OPs</td>
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<tr>
<td>Use &lt;8 bits for activations</td>
<td>heapSize, OPS</td>
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Model Pruning

- Very effective when transfer learning to simpler domains
- Consider pruning to multiples of 8/16 channels. Many hardware implementations have this type of restriction
Fine Grained Pruning for Sparsity
- Good benefit by reducing deployment model size
- Less Weight bandwidth on platforms supporting compression
Reducing Precision of Weights (4b / 2b / 1b)

- Reduce precision
- Benefits over a range of platforms:
  - Save bandwidth on platforms that directly support low precision weights
  - Save a little less bandwidth on platforms that just support compression
  - Can still work on all platforms
INTERSECTION OF PORTABILITY AND MODEL REFINEMENT

- Enhancing portability of 8 bits
  - Dynamic range of activations introduces some risks when determining scale factor
  - Some layers can require higher precision

- Solutions:
  - Train with RELU6: \( y = \min(\max(x, 0), 6) \)
  - Train with Batch Norm, by default keeps \( \sigma=1 \)
<table>
<thead>
<tr>
<th>(PyTorch) ResNet50</th>
<th>#Param bytes (Non Zero)</th>
<th>TOPs</th>
<th>Accuracy @Top1</th>
<th>Ops/Paramter Byte (higher better)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>25.5M</td>
<td>7.66</td>
<td>76.01%</td>
<td>300</td>
</tr>
<tr>
<td>Fine-grained (80% sparse)</td>
<td>5.1M (5x)</td>
<td>7.66</td>
<td>75.68%</td>
<td>1502</td>
</tr>
<tr>
<td>Coarse-grained Pruning</td>
<td>17.2M</td>
<td>3.82 (2x)</td>
<td>74.87%</td>
<td>222</td>
</tr>
<tr>
<td>Hybrid: Coarse then Fine (73% sparse thin)</td>
<td>6.9M</td>
<td>3.82</td>
<td>74.32%</td>
<td>554</td>
</tr>
<tr>
<td>Hybrid + 4b weights</td>
<td>3.5M</td>
<td>3.82</td>
<td>73.81%</td>
<td>1107</td>
</tr>
</tbody>
</table>

⇒ Pruning, sparsity and low precision are compatible and portable
⇒ 0.3%-2.2% accuracy loss, gap reducing over time
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⇒ Pruning, sparsity and low precision are compatible and portable
⇒ 0.3%-2.2% accuracy loss, gap reducing over time

Learn more by visiting Intel Movidius Team Members in Poster Session Starting at 12pm Today

“Low-precision Sparse Thin Network for Fast Inference on Edge Devices”
### INTERSECTION OF PORTABILITY AND MODEL REFINEMENT

#### SUMMARY

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<th>Technique</th>
<th>Portability</th>
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<tr>
<td>Prune Networks</td>
<td>Good, benefit varies</td>
</tr>
<tr>
<td>Use 8 bits for activation and weights</td>
<td>Good, when used with care</td>
</tr>
<tr>
<td>Use &lt;8 bits for weights / codebook</td>
<td>Good, benefit varies</td>
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<td>Sparsify</td>
<td>Good, benefit varies</td>
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<td>Split 3x3 Conv in to DW separable Conv</td>
<td>Varies</td>
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<td>Poor</td>
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OVERVIEW

• Selecting a fast network

• Making a fast network faster in a portable way

• Network portability: Ecosystems including ONNX
PORTABLE NETWORK ECOSYSTEMS

• Deploying Model on Multiple Targets
  • OS Specific frameworks
    • DirectML
    • AndroidNN API
    • CoreML
  • Network interchange:
    • ONNX
PORTABILITY: ONNX GOALS

Provide a standard way to represent models so that:

- Serialized models are interoperable between frameworks
- Have a common target for optimization for different backends
ONNX - OVERVIEW
ONNX: OPEN ECOSYSTEM FOR AI MODELS

High level API & Framework Frontends

ONNX

Hardware Vendor Libraries & Devices

ML HW
GPU
CPU
FPGA
DSP

Caffe2
mxnet
Chainer
PaddlePaddle
Cognitive Toolkit
PyTorch
INTEL OPENVINO

Delivers computer vision and deep learning capabilities from edge to cloud.

Agnostic, complementary to major frameworks.

High performance, high efficiency for the edge.

Cross-platform flexibility.

Open source: coming soon.
• Select network carefully considering dataflow implications

• Optimize networks using portable techniques, specifically:
  • Pruning, 8 bit activations, low precision weights, sparsity

• ONNX has strong momentum as ecosystem for portable models
RESOURCES

• Useful Resources:
  • Intel Nervana AI Academy
  • http://www.arxiv-sanity.com/
  • https://github.com/NervanaSystems/distiller

• References:
  • [1] Learning Transferable Architectures for Scalable Image Recognition,
  • [2] MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,
    https://arxiv.org/abs/1704.04861
  • [3] To prune, or not to prune: exploring the efficacy of pruning for model compression,
    https://arxiv.org/abs/1710.01878
  • [4] Learning both weights and connections for efficient neural networks,
    https://arxiv.org/abs/1506.02626
  • [5] Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference,
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