IoT Benchmarks

Mark Charlebois
Director Engineering
Qualcomm Technologies Inc
Overview

• IoT Devices
• AI for IoT
• AI On Microcontrollers
• Benchmarks
• Open Issues
• Summary
IoT Devices
Resource-Constrained Computers

- **Cortex M0**: 50 DMIPS, 32 KB
- **Cortex M4**: 200 DMIPS, 128 KB
- **Cortex A7/M7**: 850 DMIPS, 384 KB
- **Raspberry Pi Zero**: 1250 DMIPS, 512 MB
- **Raspberry Pi 3**: 11,000 DMIPS, 1 GB
- **Smartphone (2016 Samsung)**: 50,000 DMIPS, 4 GB

Source sample text
Device Categories

EEMBC Device Categories

• Ultra-Low Power and Internet of Things
• Heterogeneous Compute
• Single-core Processor Performance
• Multi-core Processor Performance
• Phone and Tablet

https://www.eembc.org/products
AI for IoT
Running a Model on IoT Platform

Model Optimization and Retraining (Manual)

FP32 Model (TF, PyTorch, etc) → Customized Model (TF, PyTorch, etc)

Model Export/Conversion/Compilation (Framework or SDK Tools)

IoT Runtime (TFLite, ARM NN, SNPE, etc) → Fully compiled model(s)

Device HW

CPU  GPU  NPU
AI on Microcontrollers
TFLite on Microcontrollers

- C++ API, with runtime that fits in 16KB on a Cortex M3
- Uses standard TensorFlow Lite FlatBuffer schema
- Pre-generated project files for popular embedded development platforms, such as Arduino, Keil, and Mbed
- Optimizations for several embedded platforms
- Sample code demonstrating spoken hotword detection
- [https://www.tensorflow.org/lite/microcontrollers/overview](https://www.tensorflow.org/lite/microcontrollers/overview)
ARM NN / CMSIS NN for ARM Microcontrollers

https://github.com/ARM-software/ML-examples

• ARM NN
  • To support the Machine Intelligence Initiative by Linaro, Arm has donated Arm NN, our open-source network machine learning (ML) software.

• CMSIS NN
  • A library of kernels optimized for running neural networks on Cortex-M (and Cortex-A) processor cores.
  • Provides: Convolution, Activation, Fully-connected, Pooling, Softmax, and support Functions
  • https://github.com/ARM-software/CMSIS_5
Benchmarks
Mobile Benchmarks

- Android Benchmarks (Play Store)
  - AIMark (Ludashi)
  - AlBenchmark (Uses NNAPI)
  - AITuTu
  - Neuralscope
  - MLBench

- Consortiums
  - MLPerf
  - AIIA

- Mobile benchmarks use NNAPI, TFLite, and/or Vendor SDK
  - e.g. https://developer.qualcomm.com/software/qualcomm-neural-processing-sdk
Models Used in Mobile Benchmarks


- **Object Classification**
  - MobileNet-V1 (16.9 MB / 4.3 MB Quantized)
  - MobileNet-V2 (14.0 MB / 3.6 MB Quantized)
  - Inception-V3 (95.3 MB / 24.1 MB Quantized)
  - ResNet-50 (102.2 MB / 25.7 MB Quantized)
  - Resnet34 (AIMark - ~83 MB)

- **Object Segmentation**
  - DeepLab-V3 (8.5 MB)

- **Object Detection**
  - MobileNet-SSD (27.3 MB / 6.9 MB Quantized)
MLMark from EMBC

https://github.com/eembc/mlmark

• The targets provided are:
  • Tensorflow (tensorflow) - Only fp32 and concurrency of 1, can use GPU
  • Intel OpenVINO (openvino_ubuntu) - Intel CPUs, GPUs, Movidius Neural Compute Sticks, HDDLr and FPGA.
  • TensorRT Nano (tensorrt) - TensorRT, cuDNN and Cuda for the Jetson Nano platform.
  • ArmNN (armnn_ubuntu) - ArmNN + ACL on CPU (A5 and A7), Mali GPUs. (SSDMobileNet is not supported.)

• The TensorFlow based workloads selected are:
  • ResNet-50 v1.0 (resnet50)
  • MobileNet v1.0 224x224 (mobilenet)
  • SSDMobileNet v1.0 300x300 (ssdmobilenet)

• "Commercial MLMARK License" from EEMBC is required for Licensee to disclose, reference, or publish test results generated by MLMARK ... (This does not include academic research.)
MLMark from EMBC

Scoring

• **Throughput (fps)**
  - throughput = \( X \text{ iterations} \times Y \text{ batch sizes} / \text{total time} \).

• **Latency**
  - Time it takes to process a single input for a single iteration
  - Use 95th percentile of all iterations in ms
  - latency mode forces a batch size one and a concurrency of one.

• **Accuracy**
  - For Resnet and MobileNet: Top-1 and Top-N accuracy
  - For SSD its IOU (Intersection over Union) mAP (Mean Average Precision)
  - All floating-point results are reported with three significant figures (not fixed decimal points).
MLPerf


• Rules:
  • System and framework must be available
  • Benchmark implementations must be shared (open source)
  • Replicability is mandatory

• Scenarios
  • Single Stream and Multi-stream

• Divisions
  • Open and Closed

• Reporting Framework
  • Must integrate “loadgen” with the runtime

• Audits
  • Still under discussion
MLPerf

Models

• Vision
  • Resnet50-v1.5
  • MobileNets-v1 224
  • SSD-ResNet34
  • SSD-MobileNets-v1

• Language
  • GMNT

• fp32 and some TF quantized models available
• Can used quantization tools on the networks, no re-training
• Quantized Accuracy must be within within 1% of fp32 models
Artificial Intelligence Industry Alliance (AIIA) AlBench

https://github.com/AIIABenchmark/AIIA-DNN-benchmark

• AlBench supports several deep learning frameworks (SNPE, HIAI, TENGINE and TFLite)

• Object_Classification
  • Mobilenetv2 / Resnet101 / VGG16 / Inceptionv3

• Object Detection
  • ssd_mobilenetv1 / ssd_mobilenetv2 / ssd_vgg16

• Image_Super_Resolution
  • Vdsr (Used for enlarging an image)

• Image_Segmentation
  • fcn

• Face_Recognition
  • VGG16 (~528 MB)
Open Issues
Lots of Open Issues

• Active research areas to prune, transform, re-train and optimize models
  • Benchmarks need an apples to apples comparison
  • Are the techniques used open or closed? What is allowed? Auditability and reproducibility
  • Quantized models vs fp models
  • Runtimes vs compiled models

• What is important to measure?
  • TOPS? TOPS/Watt? TOPS/$? TOPS/sqmm?
    • Even if TOPS are high, does YOUR model meet KPIs? FPS/Watt?
  • Accuracy? Accuracy/speed?
  • How do you measure power used?

• Device Categories
  • Many fp32 models (and even many quantized models) are too big for constrained devices
Testing Models vs Use Cases

• Today’s Benchmarks are Model Based
  • Model manipulation techniques must be “available” and useable for benchmarks
  • What manipulations are allowed? Re-training? Preprocessing, post processing?
  • Auditability and reproducibility
  • Typically PyTorch or TensorFlow models…. ONNX?

• Use cases
  • Object detection
  • Face detection
  • Hot word detection
  • How do you handle scoring for accuracy vs speed tradeoffs? Weighting different tests/models?

• Current Approach Ignores Platform Capabilities
  • Pre-processing capabilities of device
  • Concurrency of multiple networks
Summary

- Existing Benchmarks, don’t address the range of IoT devices doing AI
- The models relevant for IoT may be different
- Quantized models are important for IoT, and improving/maintaining quantized accuracy
- TOPS/Watt or FPS/Watt more relevant than TOPS in many cases
- Too much customization of models doesn’t produce meaningful benchmarks
- The device’s concurrent capabilities may outweigh single model performance
Thank you

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