AI on the Edge: Characterizing AI-based IoT Applications using Specialized Edge Architectures

Qianlin Liang
qliang@cs.umass.edu

Prashant Shenoy
shenoy@cs.umass.edu

David Irwin
irwin@ecs.umass.edu
Computing infrastructure that is positioned between endpoint device and cloud.
EDGE-BASED AI WORKLOADS

An emerging class of edge workloads:

- Running deep learning inference on edge
- Computationally intensive
COMPUTING PARADIGMS FOR IOT APPLICATIONS

Cloud Server → Cloud Accelerator → Edge Server → Edge Accelerator

IoT Devices → Device Accelerator
1) What are the price, performance, and energy benefits offered by edge hardware accelerators?
2) How should modern IoT applications exploit the distributed processing capabilities of specialized edge nodes and the cloud by using various types of split processing?
3) How suitable are edge accelerators for supporting concurrent edge applications from multiple tenants?
SPECIALIZED EDGE ACCELERATORS

- **Intel NCS2**
  - Power: 1-2 W
  - Memory: 512 MB
  - Price: $99
  - Accelerate computer vision workloads

- **Google EdgeTPU**
  - Power: 0.5-2 W
  - Memory: 8 MB
  - Price: $75
  - Accelerate 8-bit quantized models

- **Nvidia Jetson Nano**
  - Power: 5-10 W
  - Memory: 4 GB
  - Price: $99
  - Accelerate any GPU workloads

- **Nvidia Jetson TX2**
  - Power: 7.5-15 W
  - Memory: 8 GB
  - Price: $399
  - Accelerate any GPU workloads
METHODOLOGY

To ensure a fair comparison across hardware platforms, we run the same model on all platforms and subject it to the same inference workload.

**Workloads**

- MobileNet V2 (Image classification)
- Inception V4 (Image classification)
- SSD MobileNet V1 (Object detection)
- SSD MobileNet V2 (Object detection)
- cnn-trad-fpool3 (Keyword spotting)

**Platforms**

- AWS p3.2xlarge (Server-class)
- Nvidia Tesla V100 GPU (Server-class)
- Raspberry Pi 3 B+ (Edge-class)
- Intel NCS 2 (Accelerator)
- Google EdgeTPU (Accelerator)
- Nvidia Jetson Nano/TX2 (Accelerator)
Edge accelerators can achieve cloud CPU level throughput. Some of them can even outperform cloud CPU.

Edge accelerators exhibit very low power consumption compared to cloud CPU and cloud GPU, which consume 131.26W and 111.66W respectively.
Edge accelerators have lower normalized power consumption than cloud CPU.

Edge accelerators have 10-100X higher throughput per dollar than cloud CPU and GPU.
How should IoT applications exploit distributed and split processing capabilities offered at various tiers?
Splitting the model at layer 10 yields nearly 8x network saving over using lossless compression for a not-split model.

We cannot achieve any network bandwidth saving without splitting at the last 4 layers in this case.
Model compression yield different level of network bandwidth saving depending on the threshold.

Model compression can also improve inference latency when the threshold is small.
Consider a scenario where the inputs are not random but skewed towards the common case (e.g. surveillance camera). The compressed model is well-trained for frequently occurring inputs.

3x – 4x latency reduction

More latency reduction when network latency is high
CONCURRENCY AND MULTI-TENANCY

• For VPN, Nano and TX2, the degree of concurrency is bounded by device memory.

• For Nano and TX2, memory are shared between host RAM and GPU. More RAM used by host process, less memory can be allocated by GPU.

• For EdgeTPU, the degree of concurrency is unbounded as it automatically performs model swapping on-demand. However, this also result in switch overhead at run time if multiple models are loaded.
CONCLUSIONS

1. Edge accelerators show promising performance
   - Higher throughput per watt
   - Higher throughput per dollar

2. Spiting processing paradigm with specialized edge accelerators can achieve considerable benefit
   - Model splitting for bandwidth saving and running large model
   - Model compression for both bandwidth saving and latency deduction

3. The degree of concurrency depends on the device memory, model size, framework software overheads, and system optimizations.
Thank you!!