Evaluating the energy impact of device and workload parameters for DNN inference on edge

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Motivation

- Deployment of large DNN models
- Edge Computing
  - Examples - Jetson lineup
  - Scarcity of resources and energy
- Large parameter space to optimize

Introduction

- Sustainable DNN workload deployments on the Edge
- Study the impact of **hardware** parameters
  - CPU frequency
  - GPU frequency

Device Specifications and Workloads

Specification	Jetson Nano	Jetson Xavier NX
CPU	4-core ARM A57	8-core Nvidia Carmel
CPU Freq. range	102 MHz – 1.48 GHz	115 MHz – 1.9 GHz
CPU Freq. step	100 MHz (15 steps)	77 MHz (25 steps)
GPU	Nvidia Maxwell	NVIDIA Volta
CUDA Cores	128	384
Tensor Cores		48
Memory	4 GB LPDDR4	8 GB LPDDR4
GPU Freq. range	76 MHz – 921 MHz	114 MHz – 1.1 GHz
GPU Freq. steps	77 MHz (count 12)	90 MHz (count 15)
Throughput	472 GFLOPs	21 TOPs
Power Modes	5W, 10W	10W, 15W
Libraries	CUDA 10.2 + cuDNN 8.2.1	CUDA 10.2 + cuDNN 8.0.0

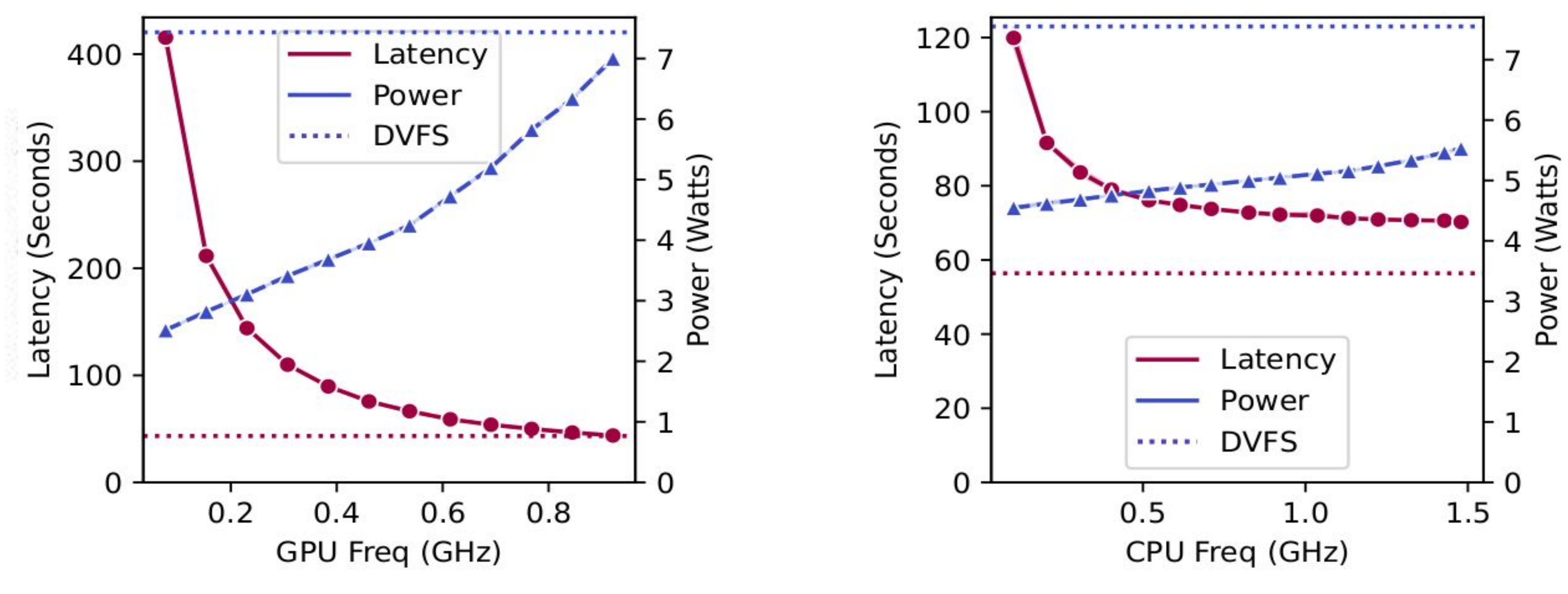
Model	Layers	Params	Ops (GFLOPs)	Batch Size	Input
AlexNet	8	61M	0.727	4, 8, 16, 32, 64	Tensor (3,224,224)
ResNet-18	18	11M	2	4, 8, 16, 32, 64	Tensor (3,224,224)
MobileNet-V2	53	3.4M	0.57	4, 8, 12	Tensor (3,224,224)
YOLOv4-Tiny	29	6.1M	6.9	4, 8, 16, 32, 64	Tensor (3,416,416)
BERT-Tiny	4	4.4M	0.0353	4, 8, 16, 32, 64	String (512 words, 1.1kb)
DistilBERT	6	43.2M	4.3	4, 8, 16	String (512 words, 1.1kb)

Experimental Setup

- Power readings for each device are polled at 100ms intervals
  - Overhead for 100 ms < 0.5%; Overhead for more frequent polling (10 ms or 1 ms) > 2%
- PyTorch for all the workloads except for YOLOv4 (OpenCV)
- Implemented a separate thread to poll the I2C interface for continuous power readings
- Each experiment on a given model
  - One out of x CPU+GPU Freq combinations
  - Fixed workload - 3200 inferences inputs
  - 10 reruns; variance was less than 5%

Evaluation

Frequency Sweeps - Jetson Nano

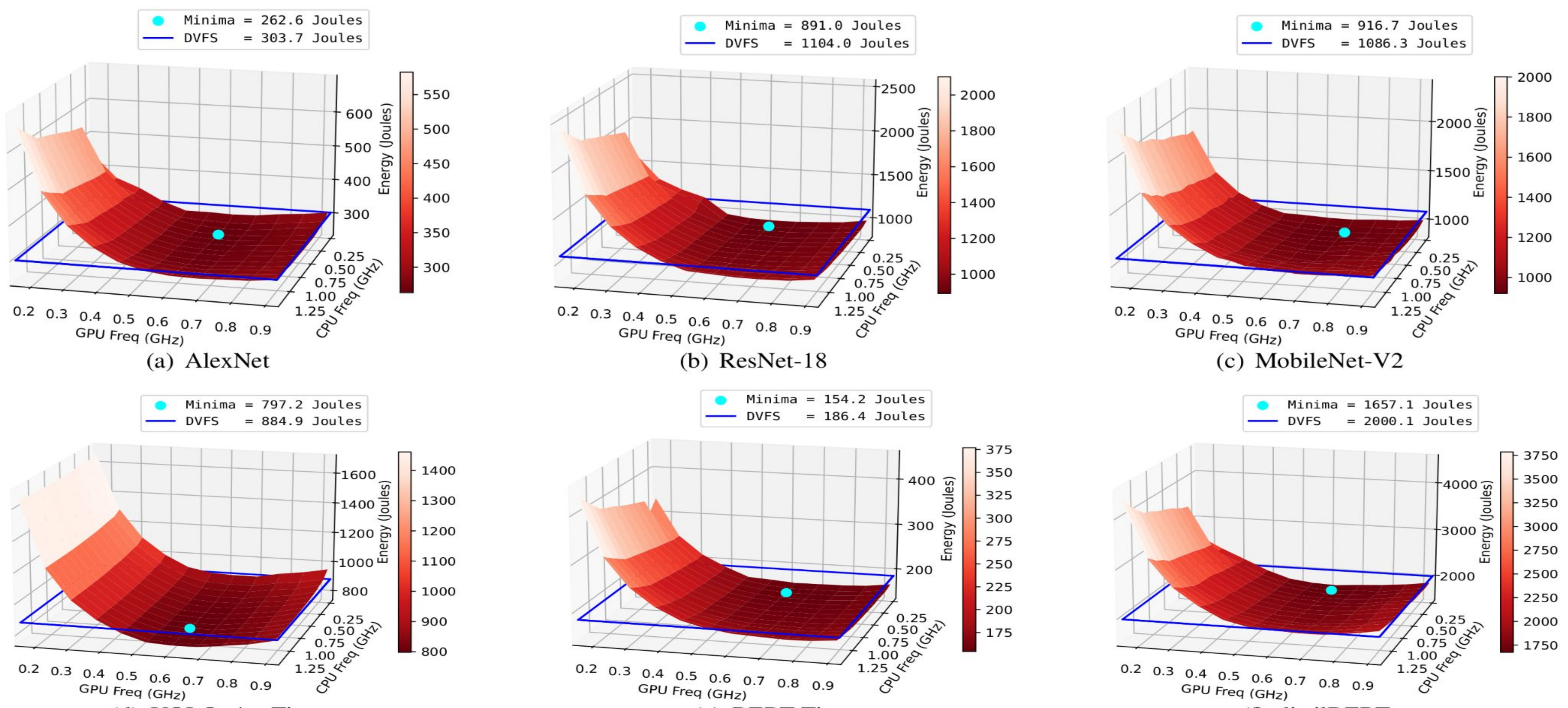


(a) Changing GPU frequency (b) Changing CPU frequency

- DVFS Governor
  - CPU Default - "schedutil"
  - GPU Default - "nvhost_podgov"
  - Highest freq - CPU 89%; GPU 83%
  - Other governors < 1% variation

Monotonic relation with freq | **Impact of CPU Freq < GPU Freq**

Energy usage trends on Jetson Nano

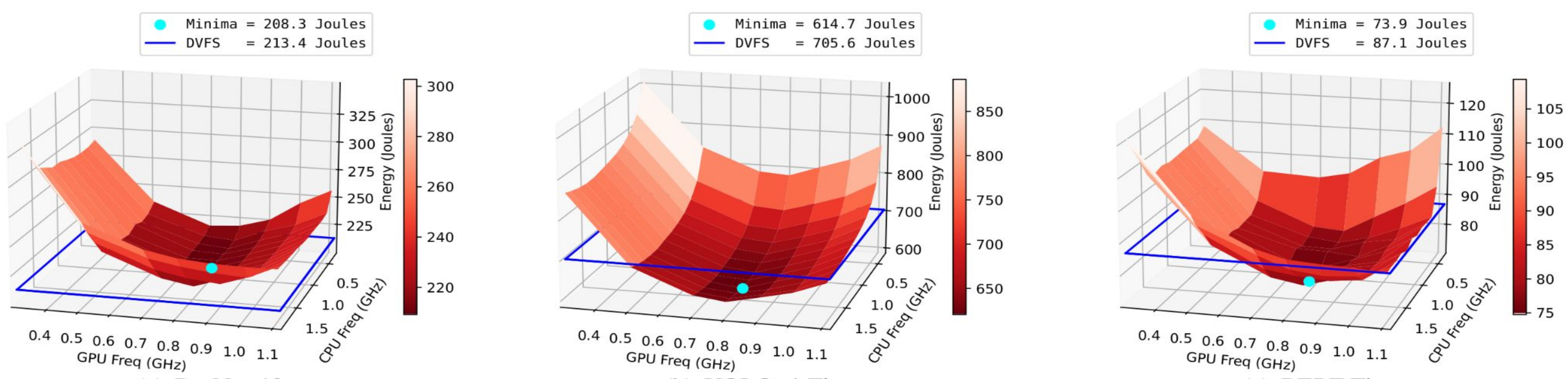


(a) AlexNet (b) ResNet-18 (c) MobileNet-V2 (d) YOLOv4 - Tiny (e) BERT-Tiny (f) distilBERT

Minima consumes 13%, 19%, 15%, 9%, 17% lower energy than DVFS

GPU Freq substantially impacts Energy but non-monotonic

Energy Usage Trends on Xavier NX



(a) ResNet-18 (b) YOLOv4-Tiny (c) BERT-Tiny

Minima consumes 2%, 13%, 15% lower energy than DVFS

Non-monotonic behaviour of CPU Freq is more prominent

Conclusion

- Selecting optimal freqs gives upto 19% saving in energy for Jetson Nano
- Selecting optimal freqs gives upto 15% savings in energy for Xavier NX
- Energy Consumption of Xavier NX is significantly lower between 2x and 4x as compared to Nano

Future Work

- Study the impact of **workload** parameters
  - Batch Size
  - Number of layers
- Develop a joint workload parameter optimization strategy for optimal energy configuration

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