SONIC

Coprocessors as a service for deep learning inference in high energy physics

arXiv:2007.10359

arXiv:2010.08556

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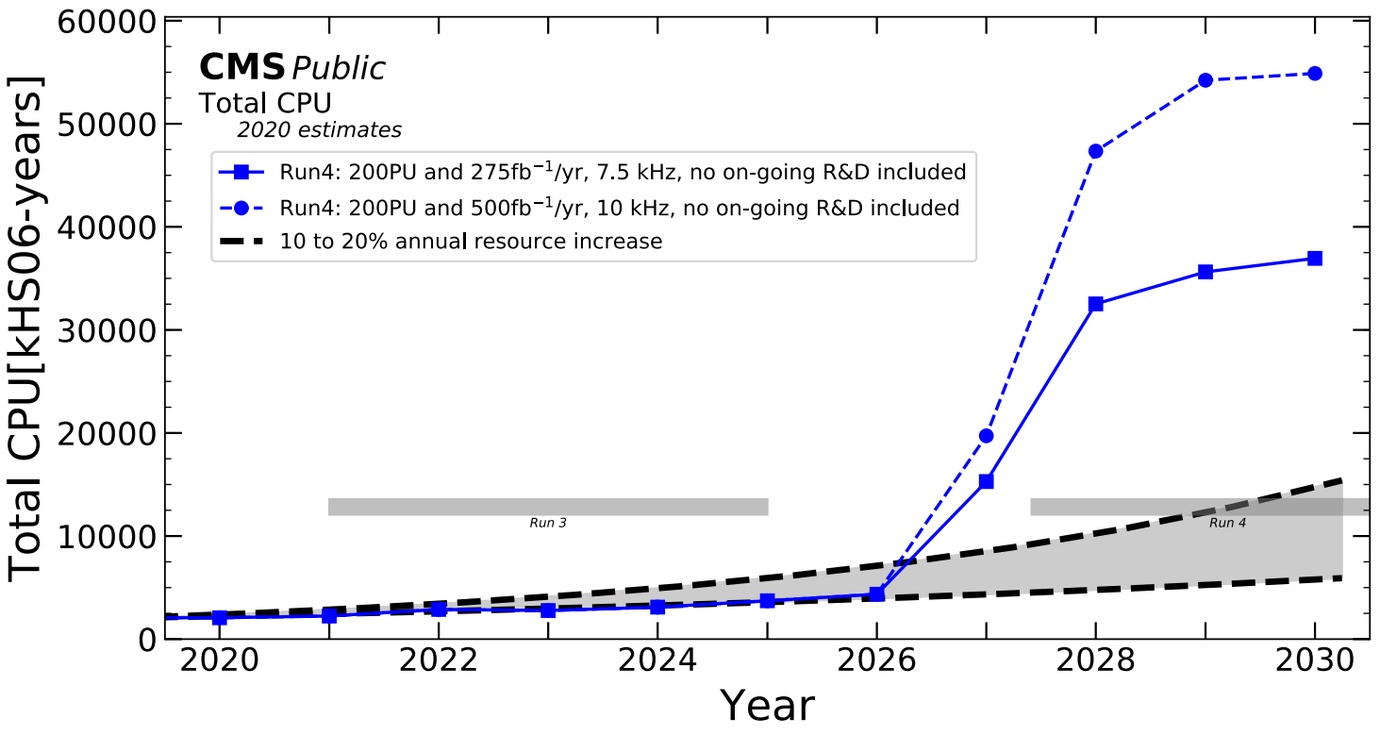
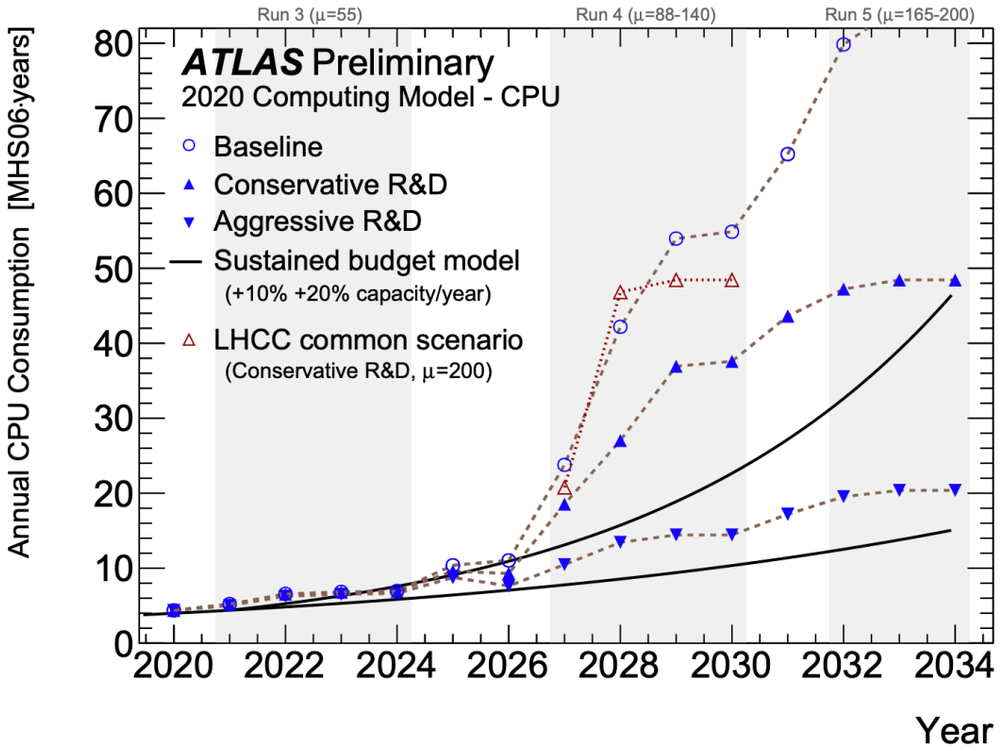
Introduction

- Computing projections for high energy physics (HEP) greatly outpace CPU growth, interest in ML rapidly increasing

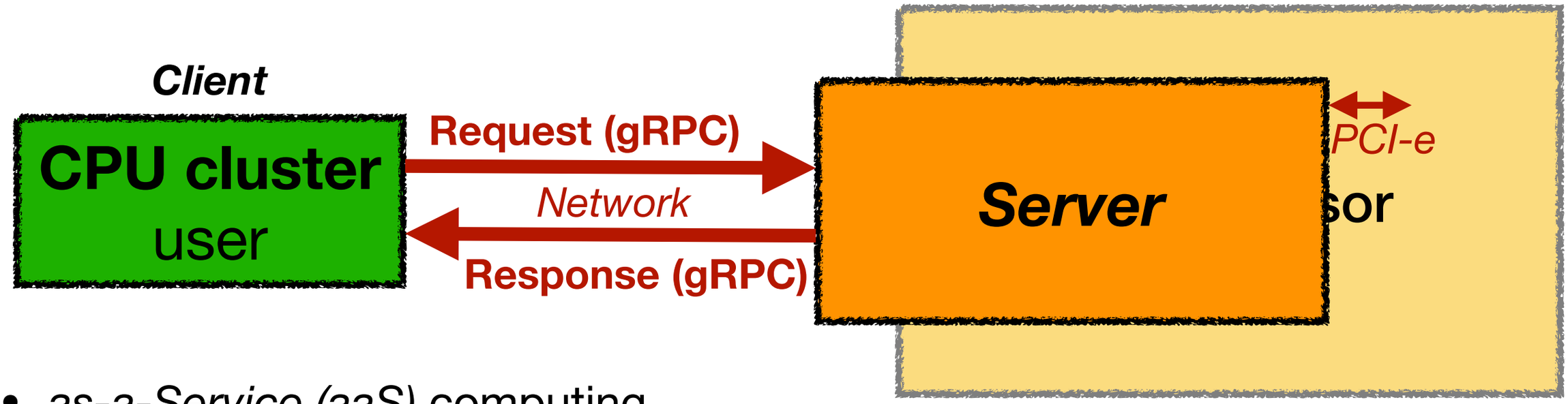




- **Coprocessors (GPU, FPGA, …) offer possible solution → as-a-Service (aaS) computing**
- Speedups at large:
  - Batch size and/or complexity

as-a-Service Computing

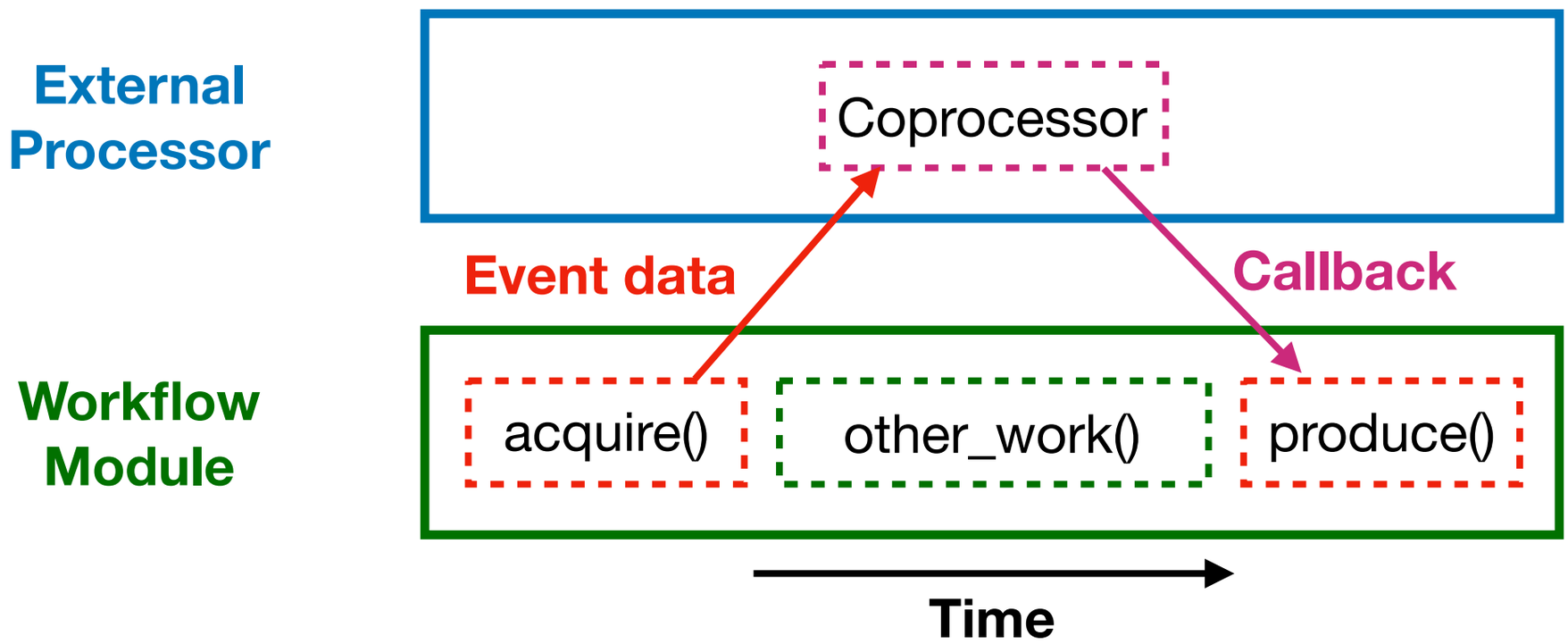
- As a user, I just want my workflow to run quickly



- *as-a-Service (aaS)* computing
  - Client communicates with server CPU, server CPU communicates with coprocessor
- Many existing tools available from industry, cloud
  - *Details in the backup*

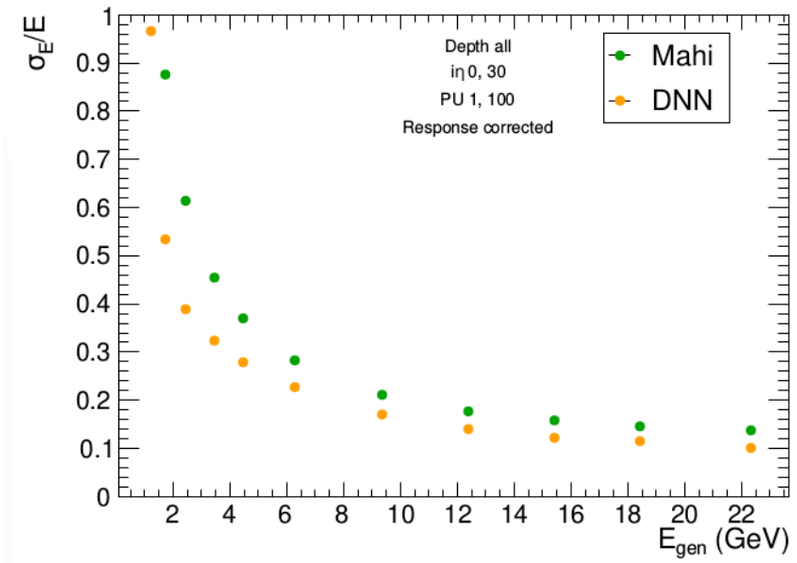
SONIC Framework

- Services for Optimized Network Inference on Coprocessors (SONIC)
- Integration of as-a-service requests into HEP workflows
  - Works with any accelerator
  - Requests are asynchronous, non-blocking



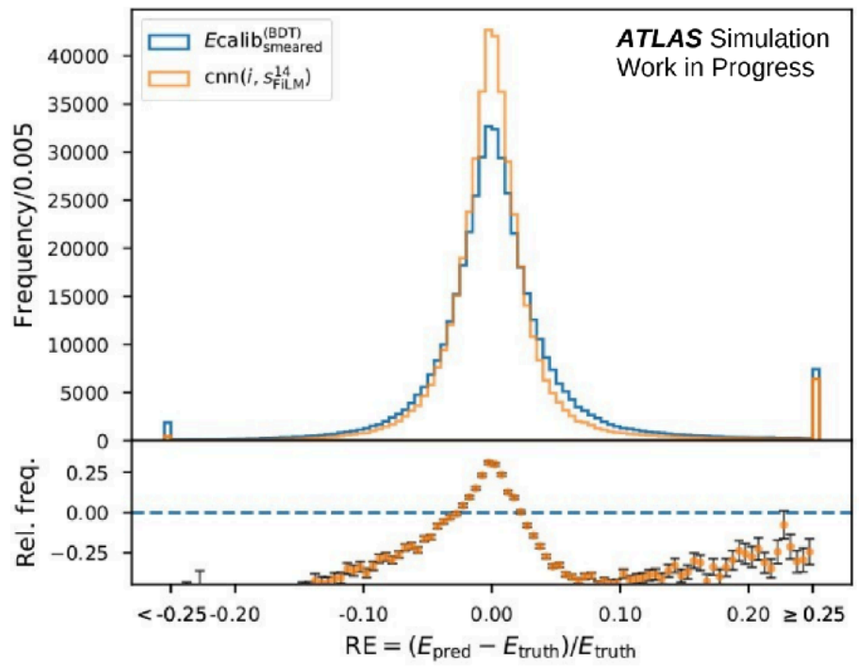
Benchmarks

FACILE



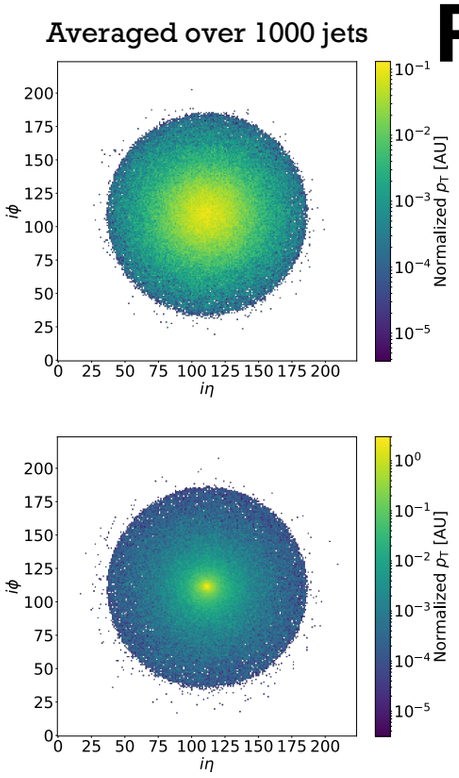
Calorimeter energy regression

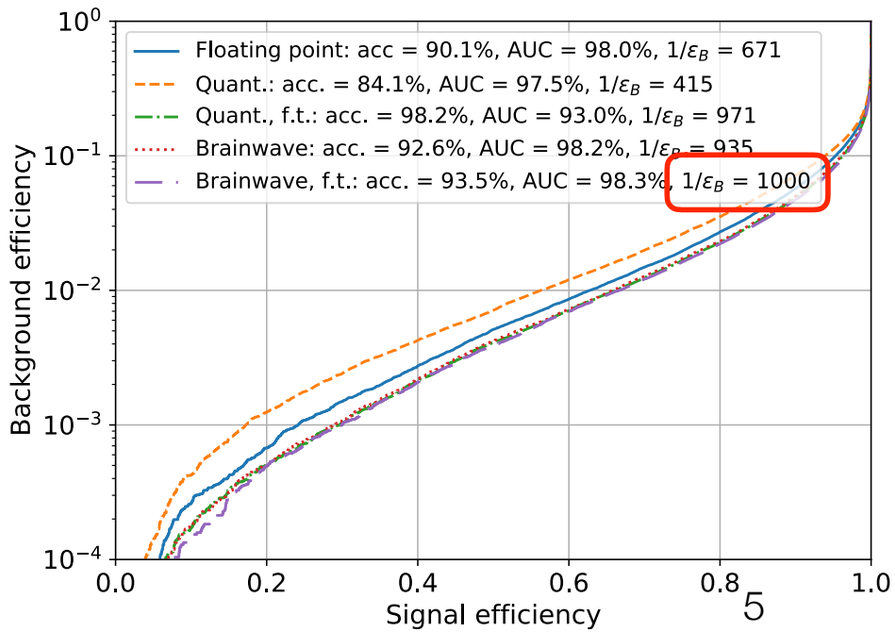
DeepCalo



Cluster energy regression

ResNet top quark image classification

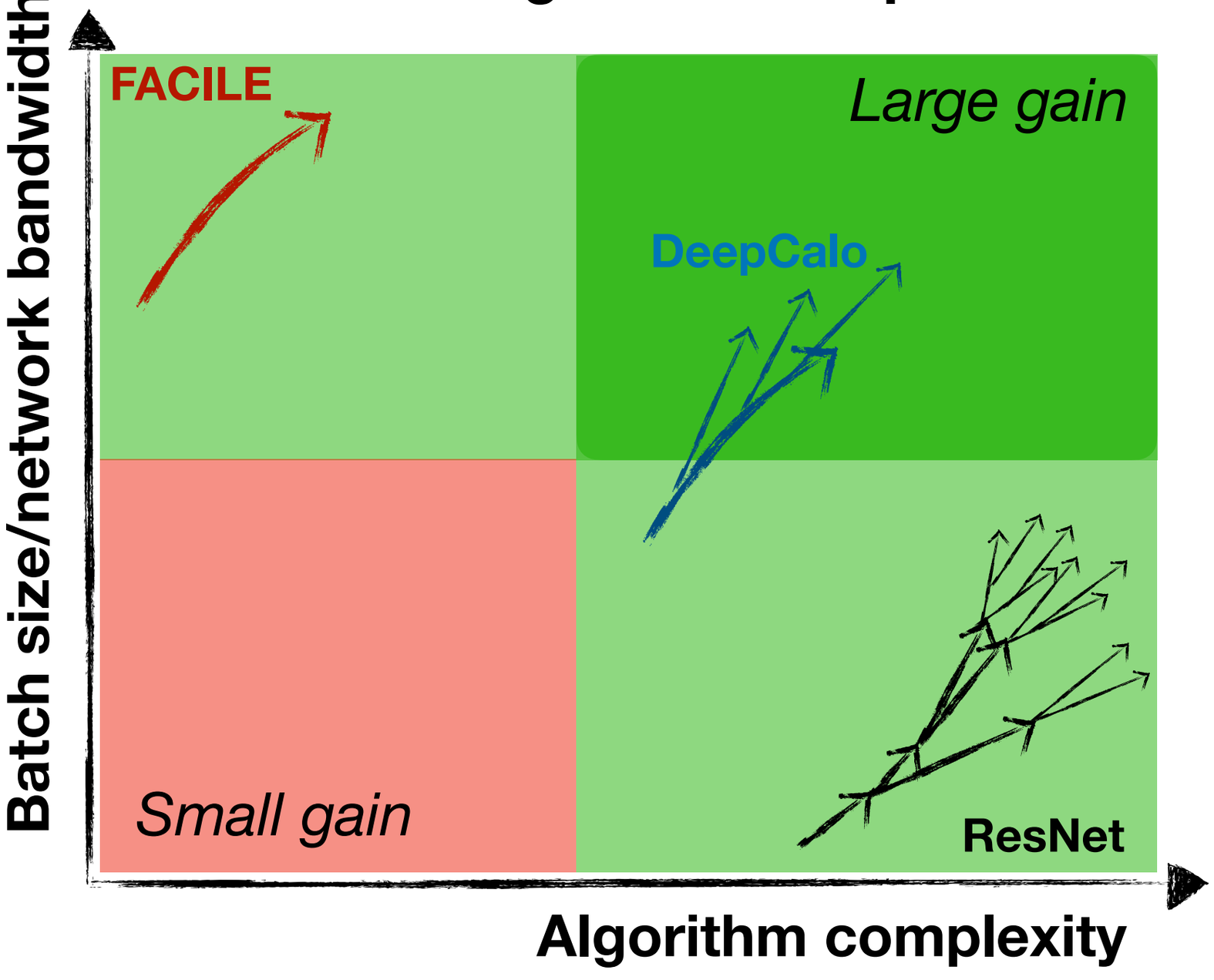




- **FACILE** *(batch 16000)* — **2k parameters**
- **DeepCalo** *(batch 10)* — **2M parameters**
- **ResNet** *(batch 10)* — **10M parameters**

Gains

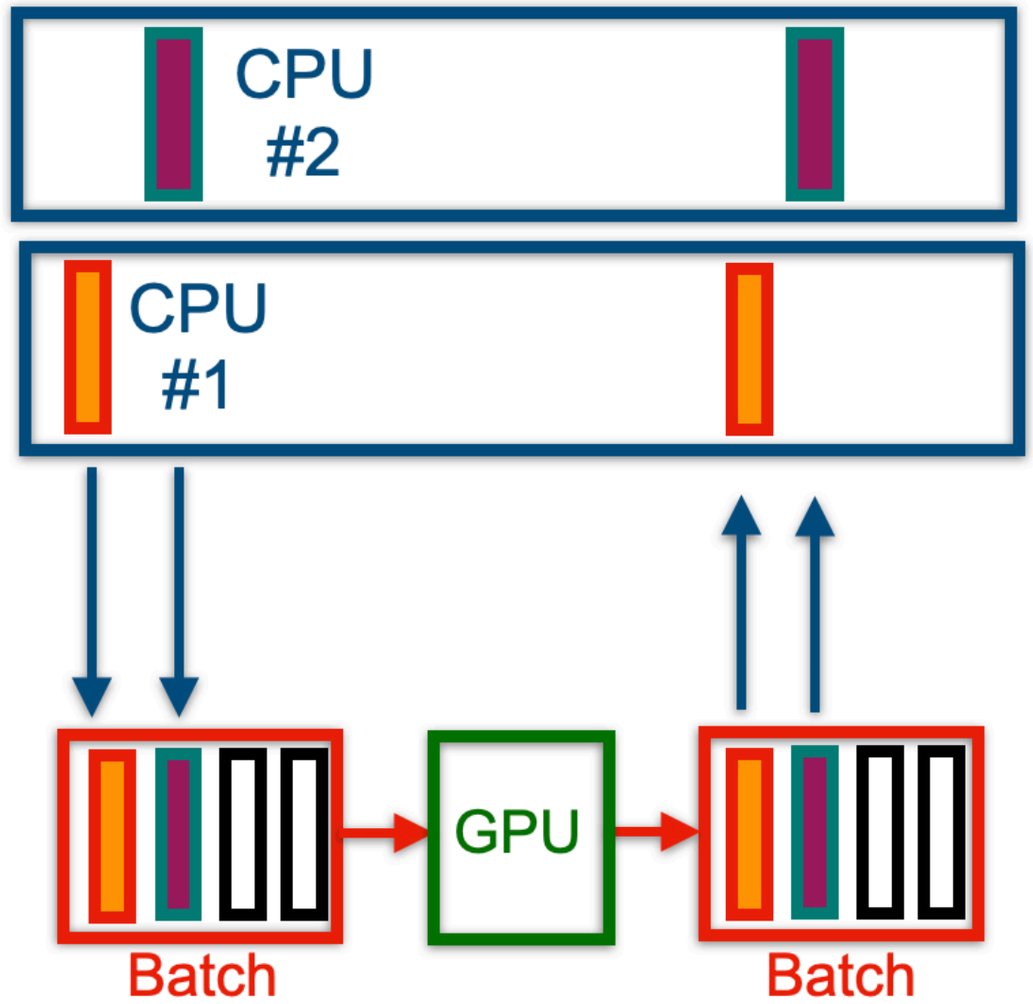
Where do we gain from coprocessors?



GPU/FPGA aaS	***Gain w.r.t. CPU***
2 ms (GPU) 0.2 ms (FPGA)	**8x (GPU)** **80x (FPGA)**
0.1 ms (GPU) in progress (FPGA)	**750x**
1-2 ms (GPU/FPGA)	**500x**

Dynamic Batching

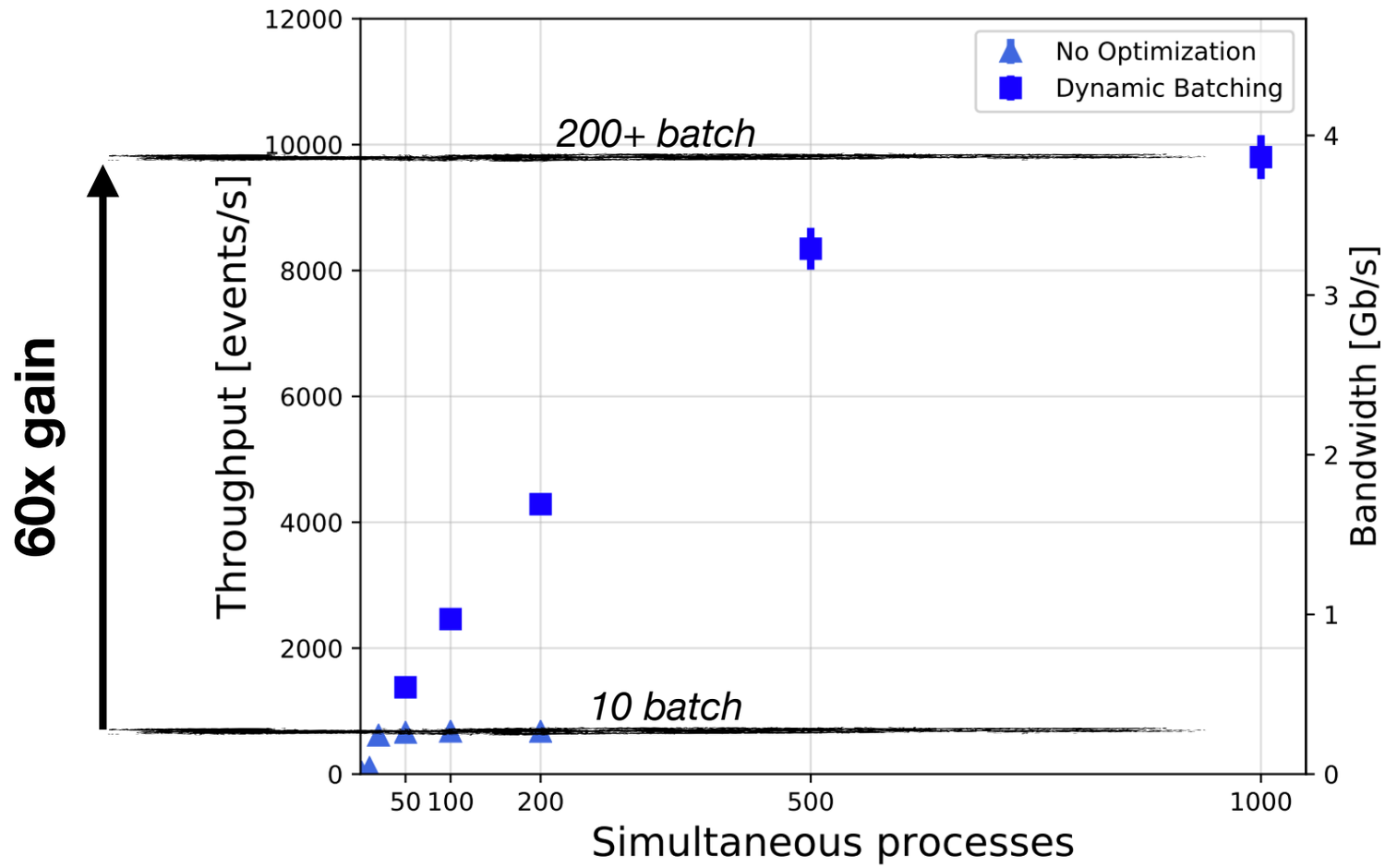
- Allows server to wait for requests to build up
- Most beneficial for small-batch algorithms
- Can extend event-by-event processing to multi-event processing
  - Transparent to user
- Single-line change to server configuration




```
dynamic_batching {
  preferred_batch_size: [ 100 ]
}
```

Can also specify max wait time

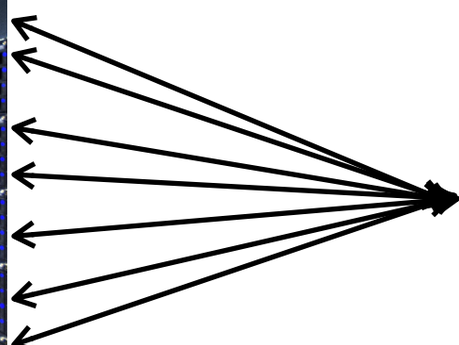
Dynamic Batching



- 60x throughput gain in this case
  - 10k events/s for 1M weight model
  - ~1000 simultaneous clients to saturate single GPU

Scalability

High Level Trigger (HLT) emulation



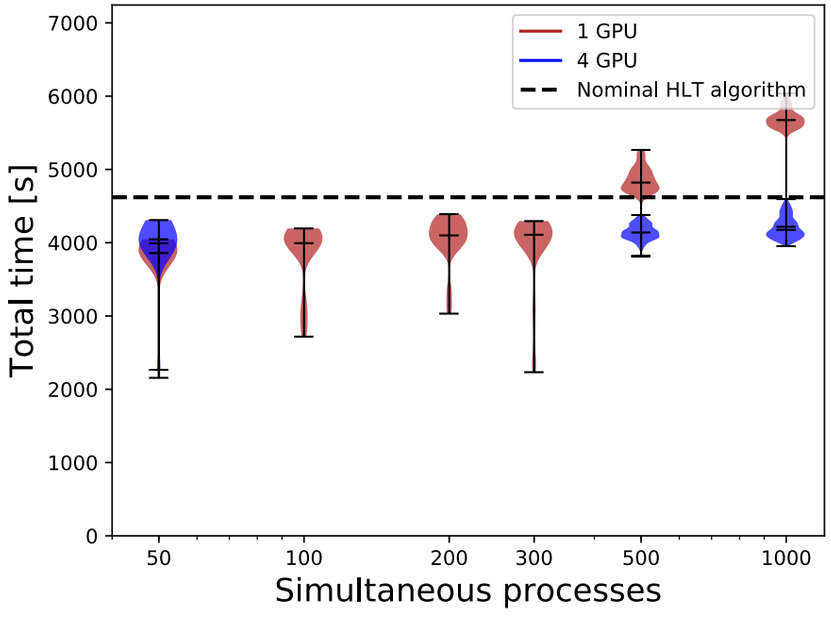
Server with GPUs/FPGAs

On-site server

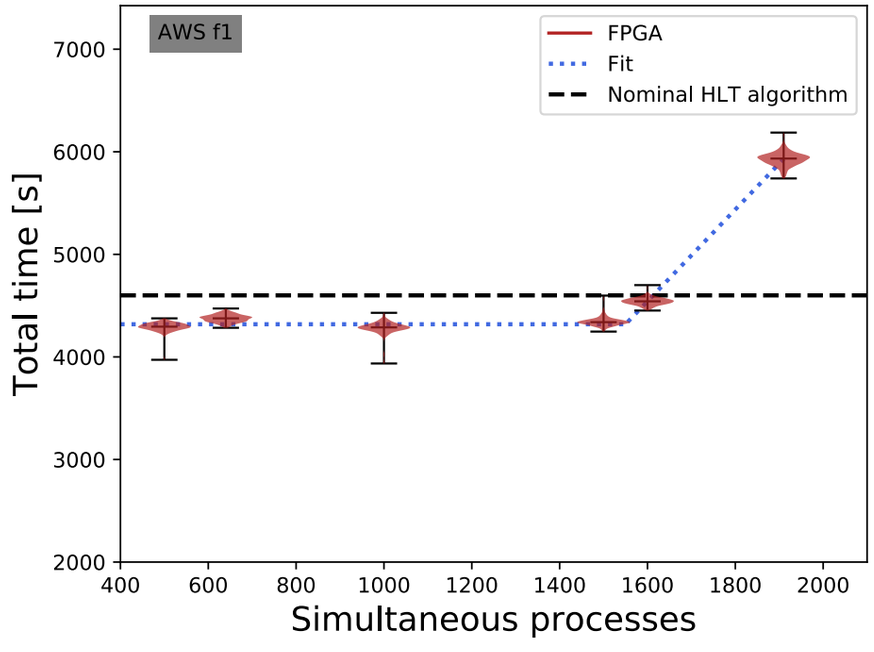
- Used **FACILE** in CMS HLT workflow to test as-a-service model in realistic computing environment
- Use of cloud resources allows at-scale test

- **10% reduction in computing time operating as-a-service**
  - → Maximal achievable reduction for this single algorithm
- No increase in latency until 300/1500 clients (GPU/FPGA)
  - FPGA limited by 25 Gbps network (Alveo U250 capable of serving 3300 clients)

V100 GPU

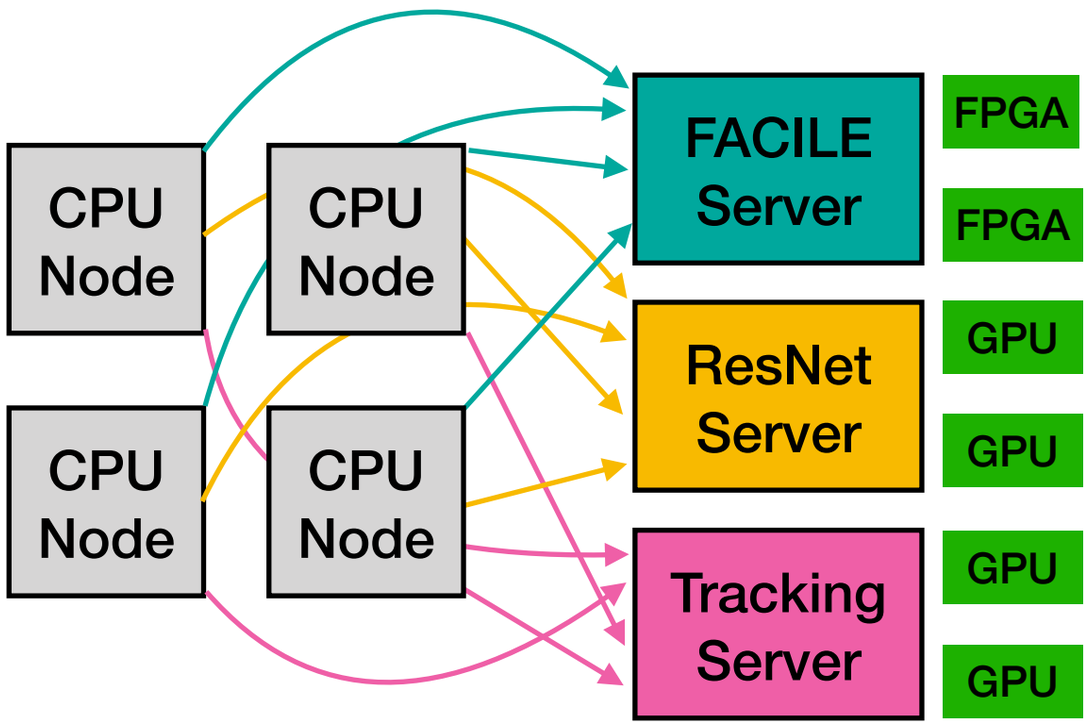


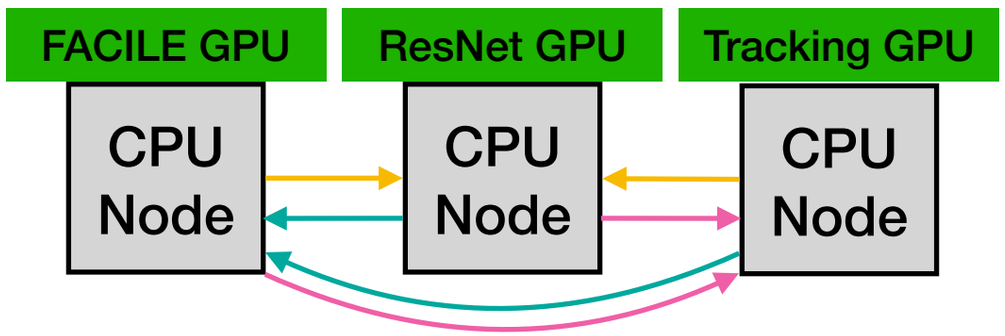
AWS f1 FPGA (VU9P)

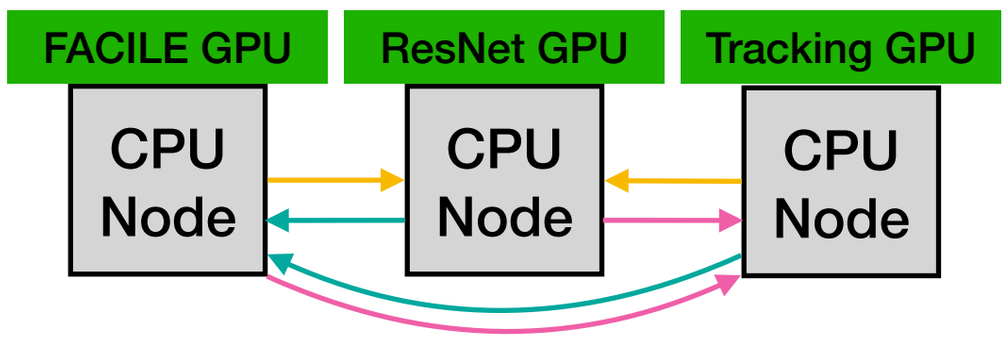


Summary

- As-a-service computing has many existing tools that we can leverage to address HEP computing challenges
    - Very cohesive with ML usage, extremely simple for end user
- Papers detailing GPUaaS (2007.10359), FPGAaaS (2010.08556)
- Work is enabling heterogeneous systems for real-time processing
- Many more possibilities for improvement



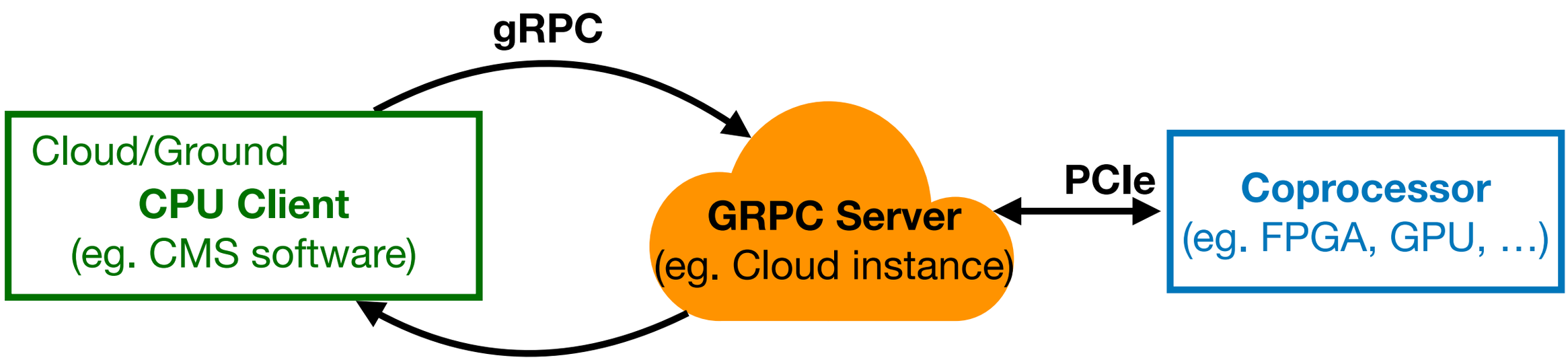




BACKUP

Setup

- For fast inference we focus on gRPC protocol
  - Open source remote procedure call (RPC) system developed by Google



1. Formats inputs
2. Sends asynchronous, non-blocking gRPC call
3. Interprets response

1. Initializes model on coprocessor
2. Receives and schedules inference request
3. Sends inference request to accelerator
4. Outputs and send results
5. Monitors network/device utilization

1. Runs the inference

Tools (backup)

Use NVidia triton inference server for GPU + Customized GCP Kubernetes

Wrote our own FPGA gRPC inference server

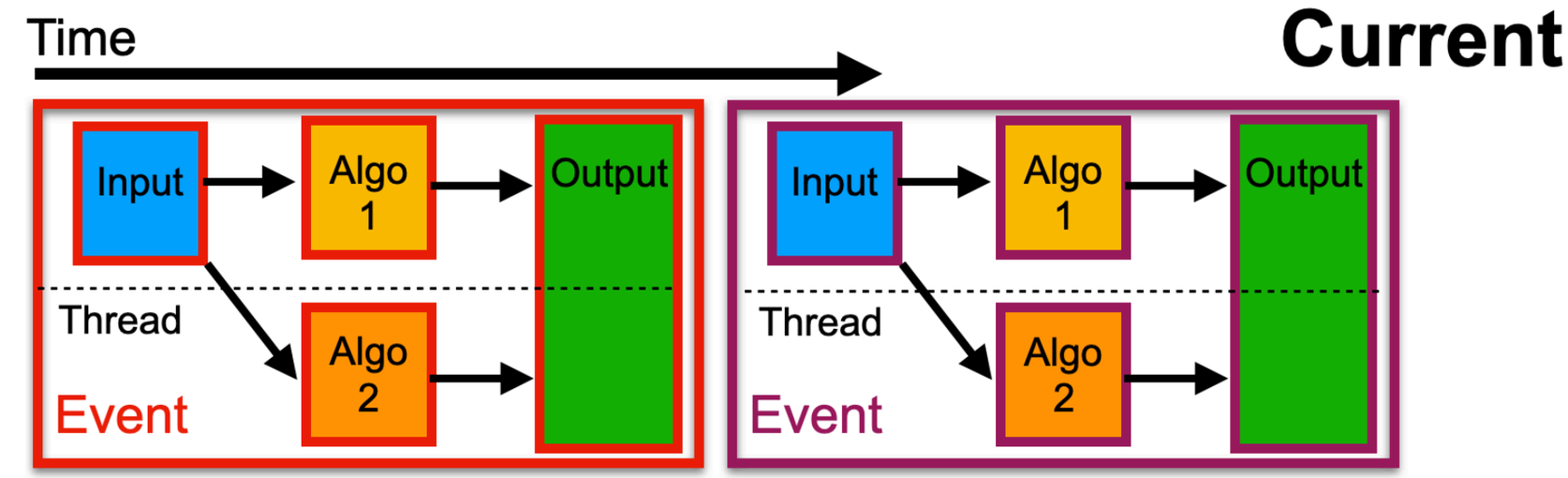
As-a-service Computing

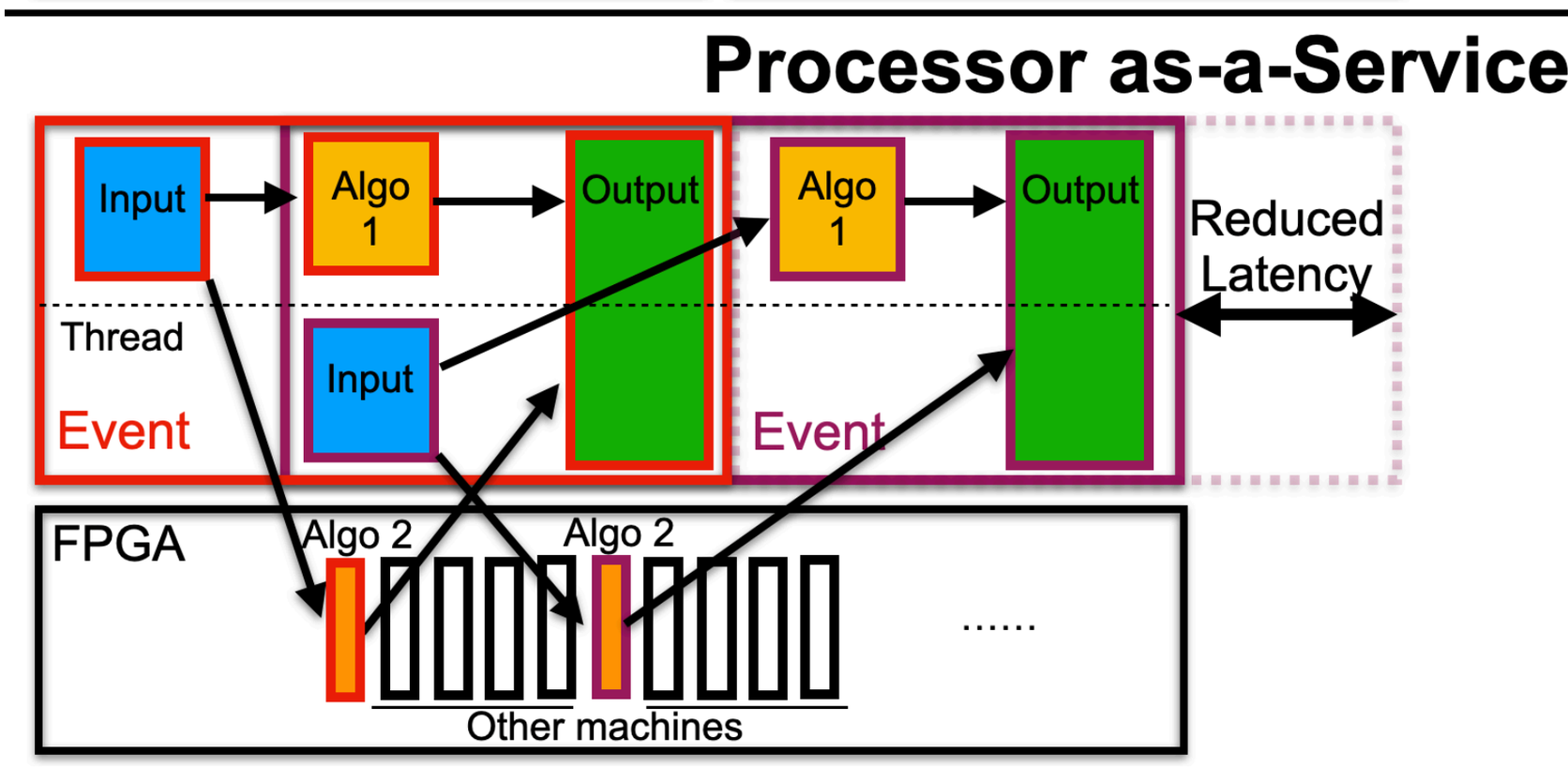
- Can provide large speed up w.r.t traditional computing model

- In principle, as-a-service can be used for any algorithm

- Simply send all inputs to server, server returns outputs

- Just need server able to accept requests and communicate with GPU or FPGA

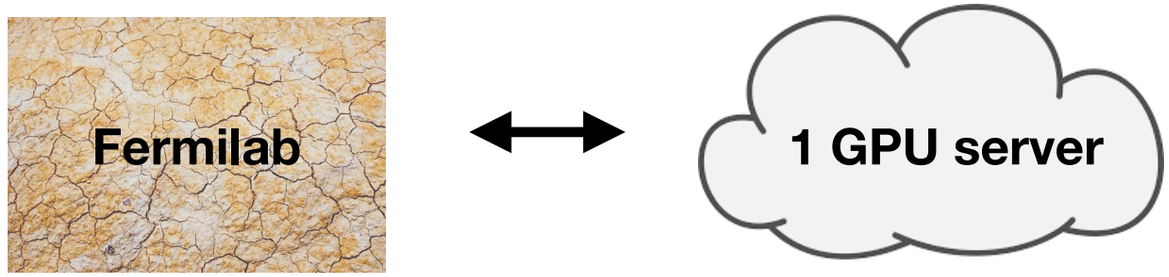




1 GPU Server

Google Cloud Platform

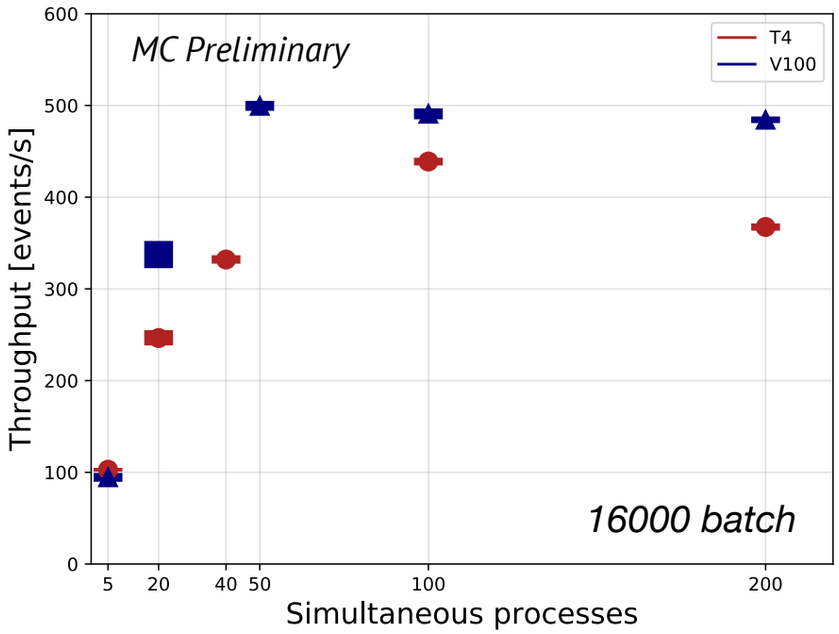
- Inference performed in CMS workflow
- Larger models saturate with fewer clients, lower throughput
- Range of performance for GPUs

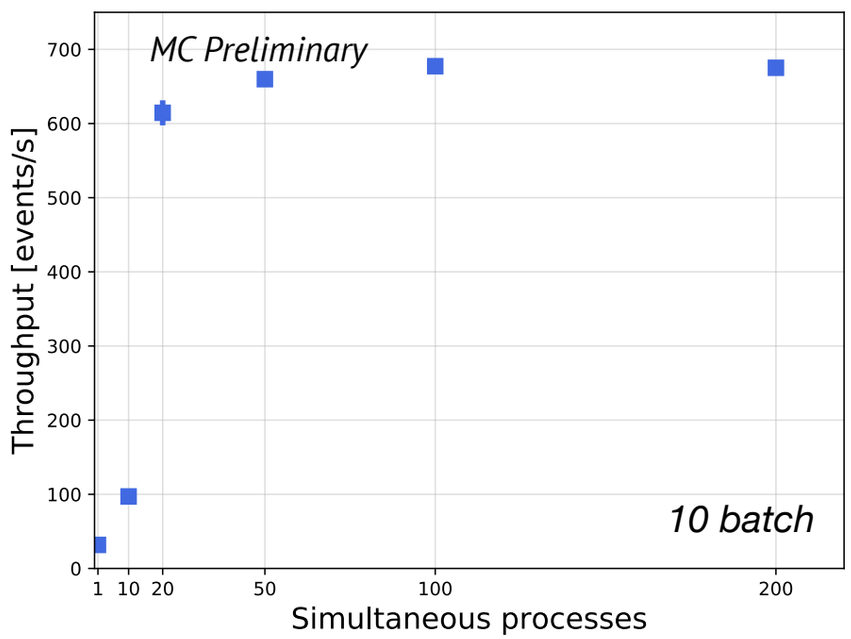


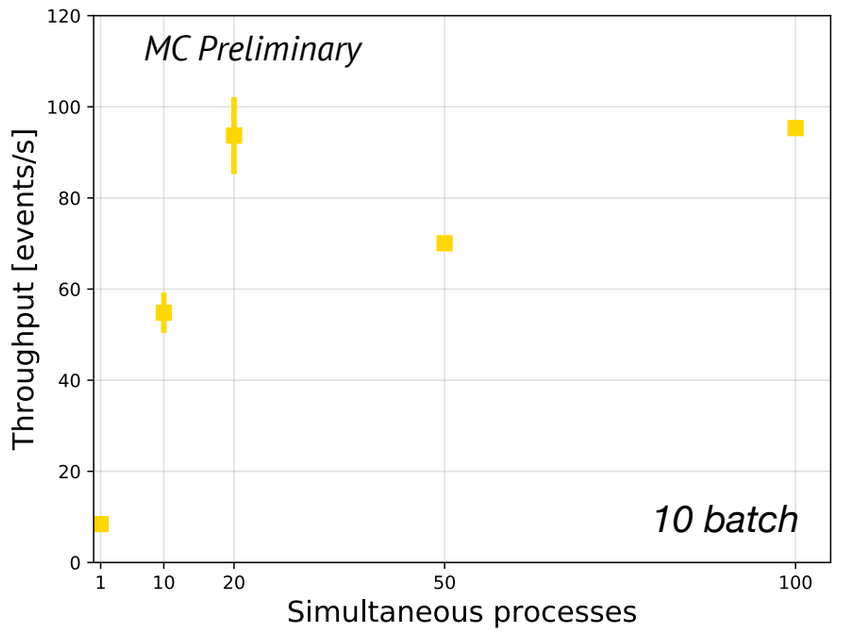
FACILE

DeepCalo

ResNet







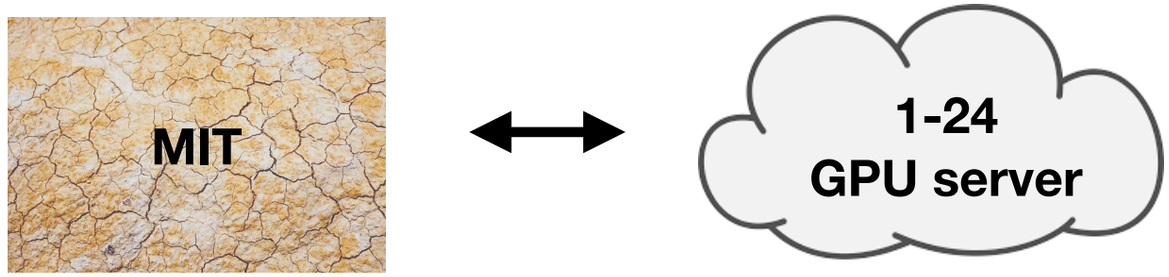
Multi-GPU Server

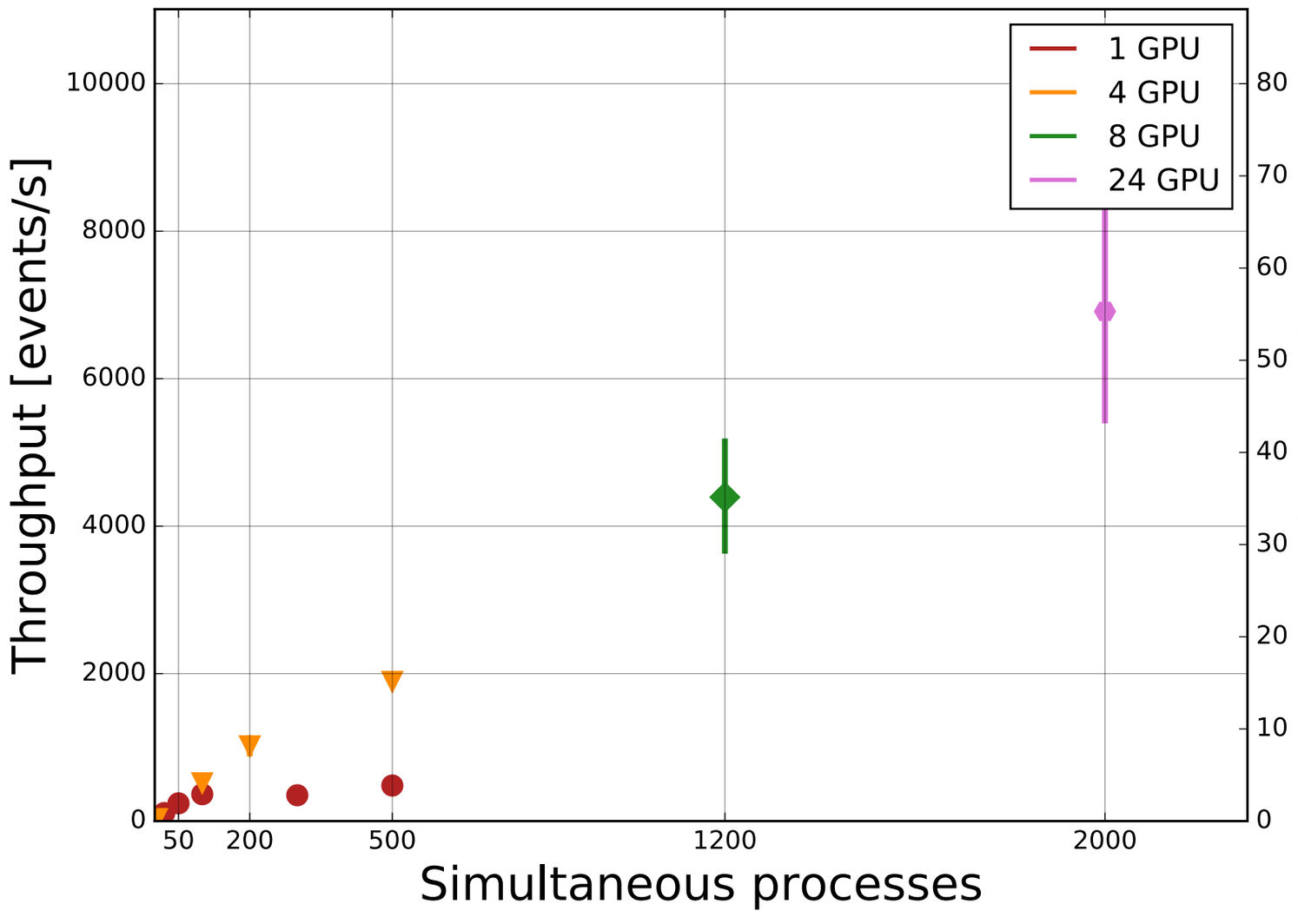
Google Cloud Platform

- High bandwidth, long distance (MIT and Google Cloud US-central)

- Linear scaling with # of GPUs

- Throughput saturates at ~60 Gbps (8000 events/s)

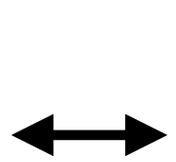




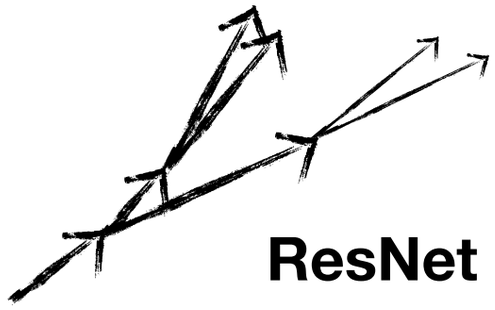
FACILE

FPGA Server

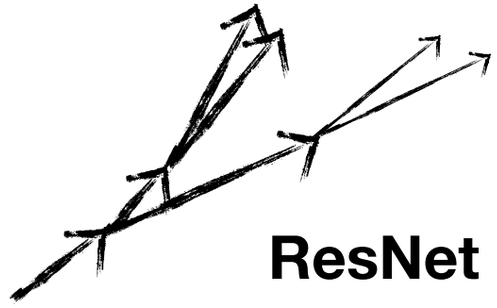
- With small **FACILE** network, major speedup w.r.t. GPU (500 evt/s)
  - Limitation from CPU
- For larger **ResNet**, comparable or slightly better throughput w.r.t GPU



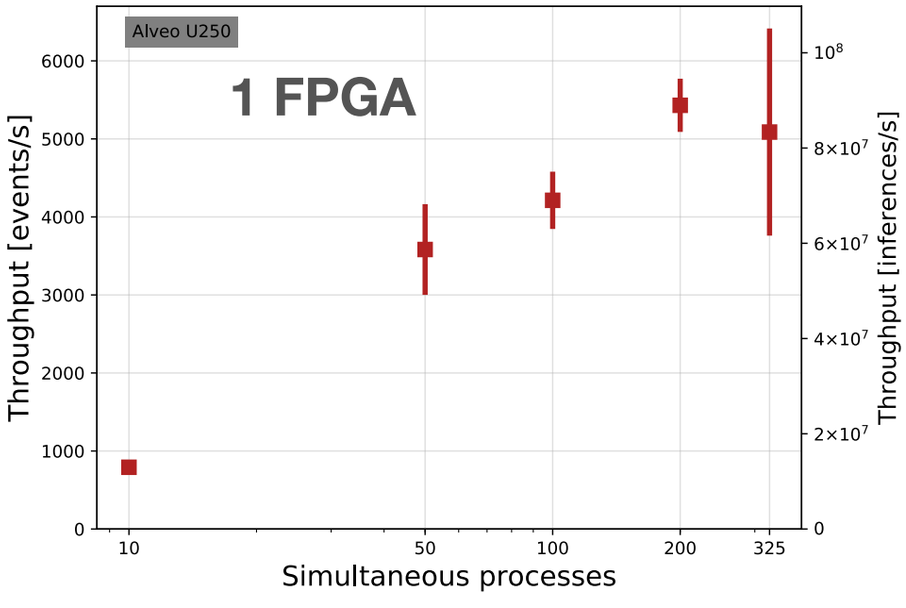
FACILE

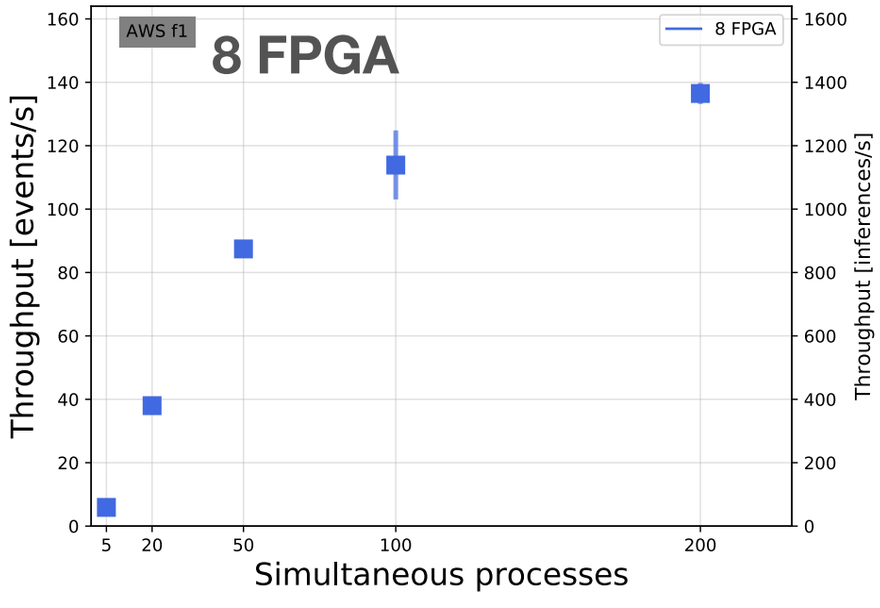


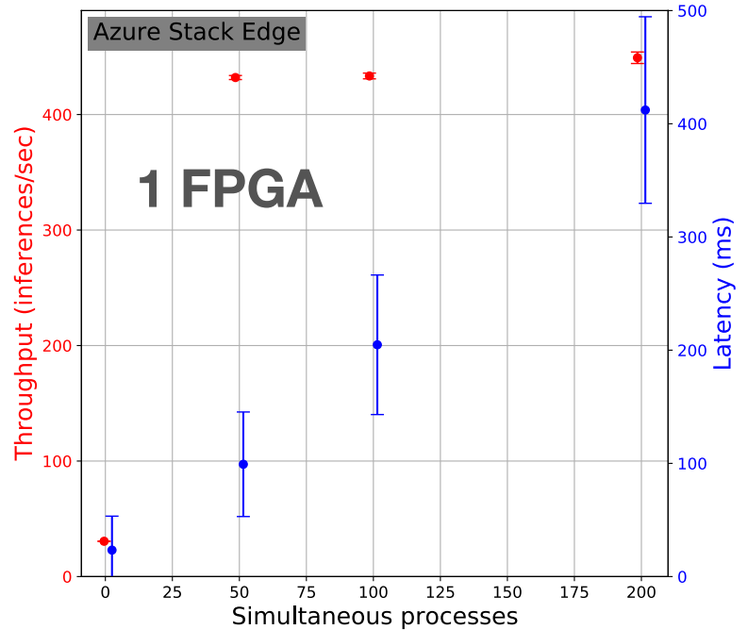
ResNet



ResNet

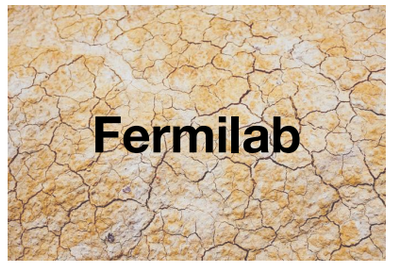


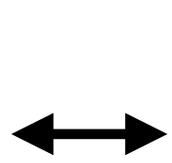


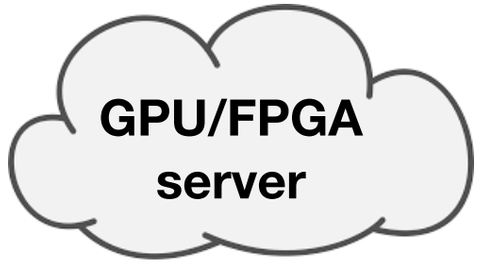


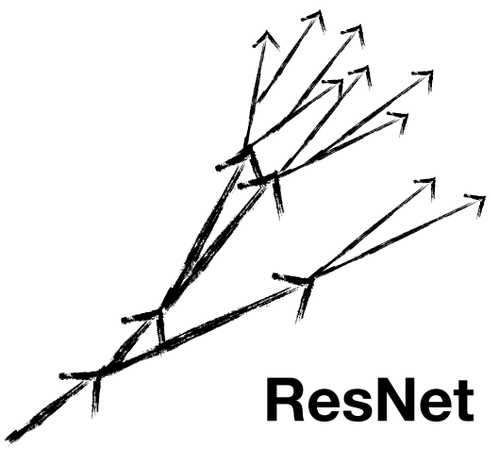
8 GPU/FPGA Server

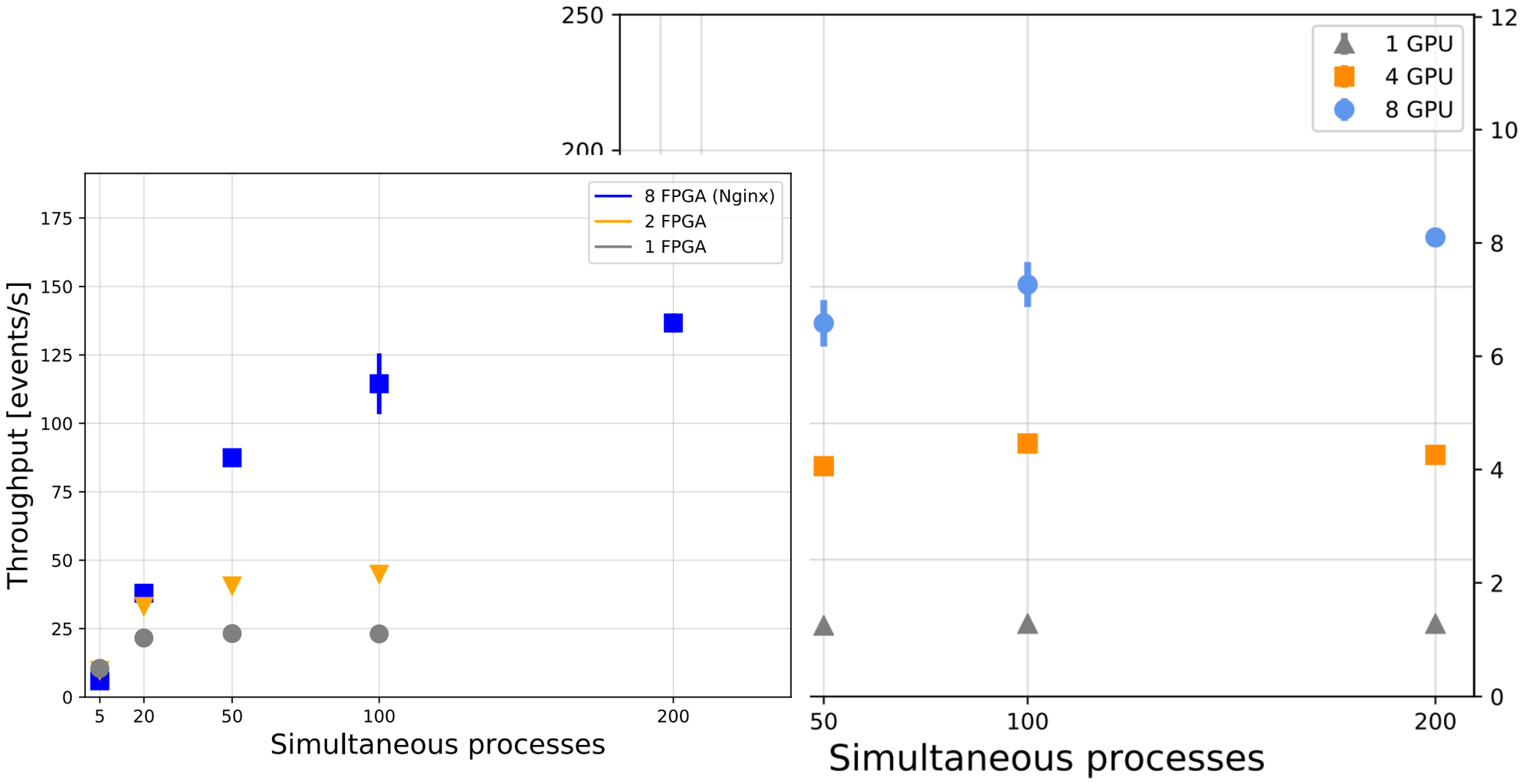
- Similar performance between GPU and FPGA
  - ~150 evt/s







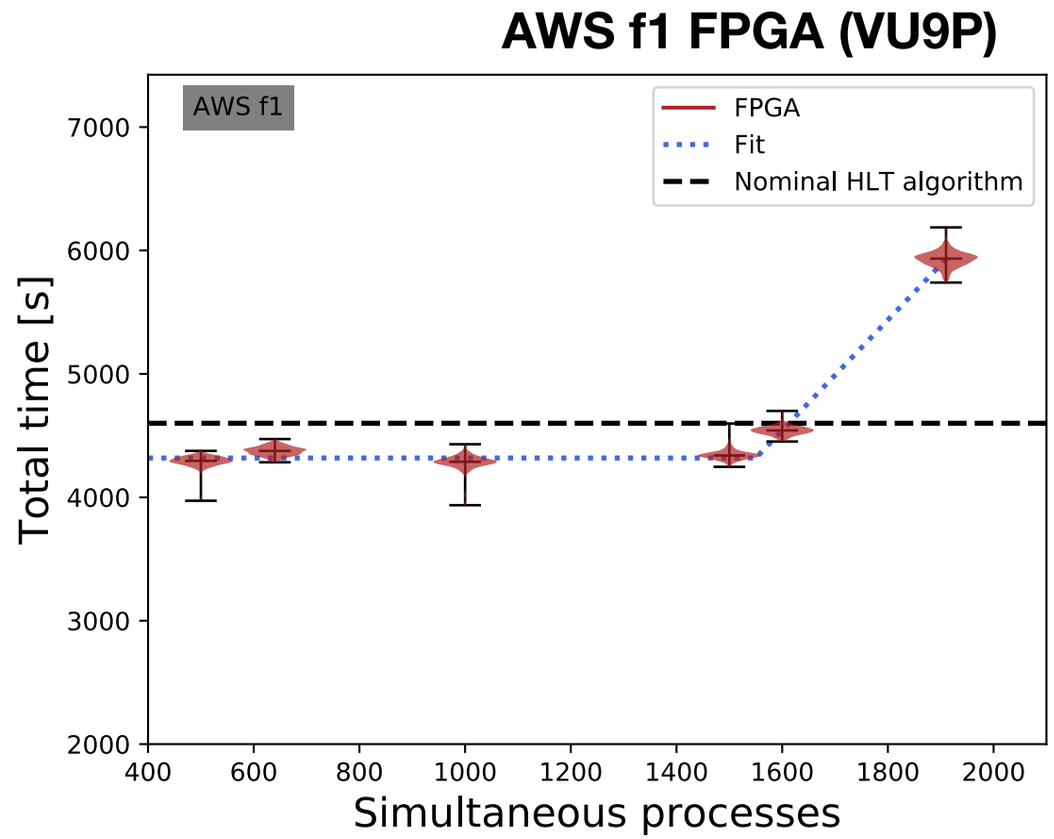




Coprocessor Scalability

- Factor of 5 improvement between of FPGA over GPU for HLT less than >10x shown earlier

- Running on AWS, network network bandwidth is limited to 25 Gbps

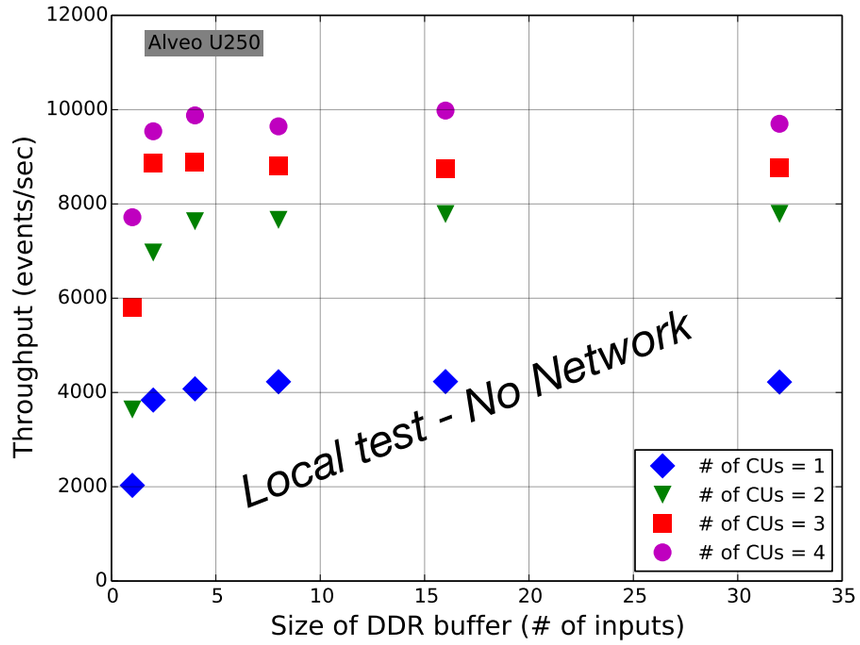


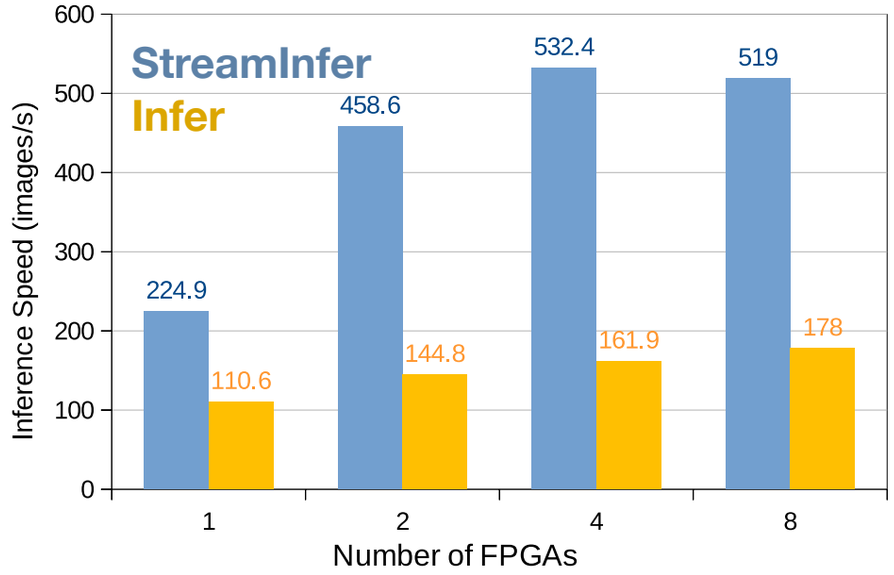
- Corresponds to a maximal throughput of ~2500 events/s

  - Consistent with HLT saturation at 1500 processes

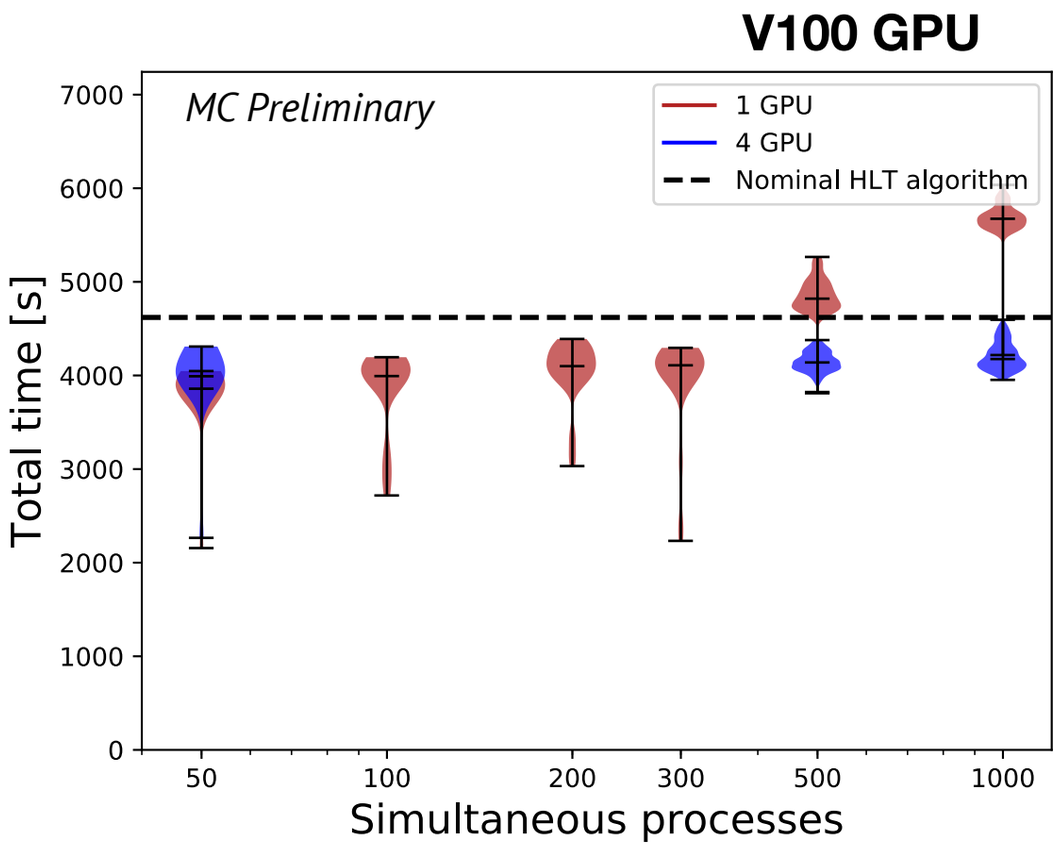
FPGA Server Design

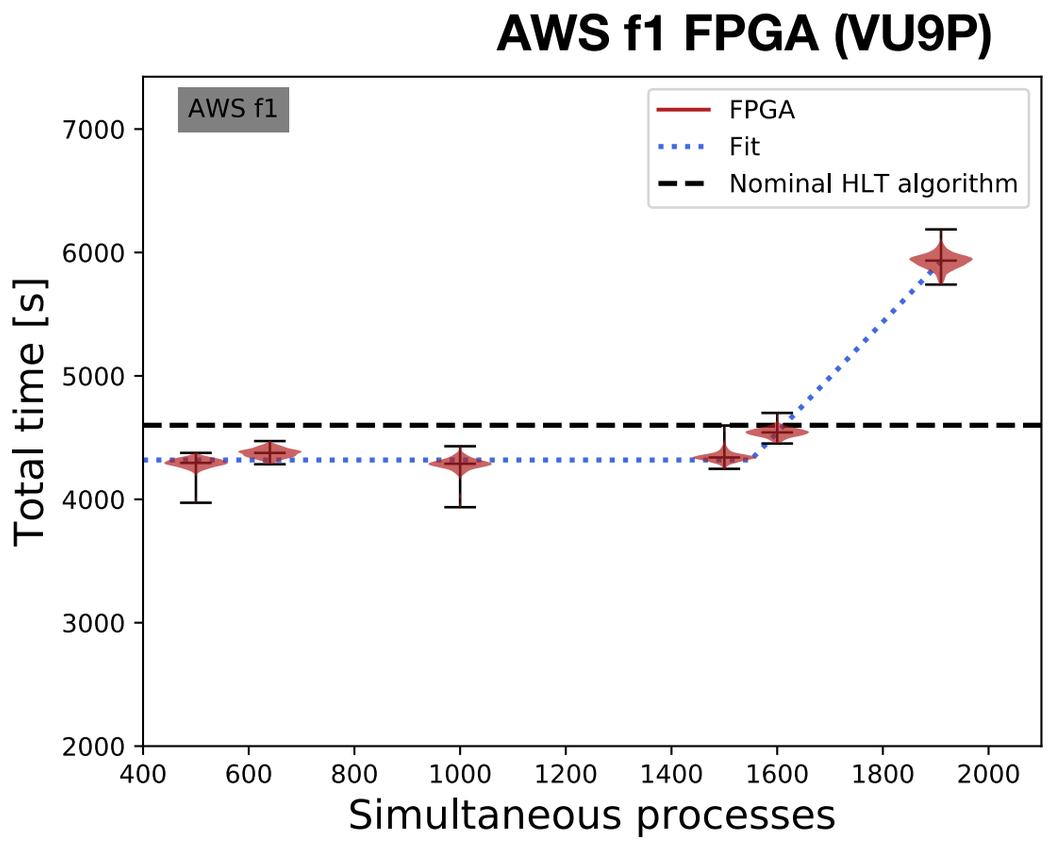
- Same workflow developed for FPGA coprocessors
  - gRPC base (Triton calls), same config as for running on GPU
  - **FACILE:** hls4ml (Alveo U250 & AWS f1)
  - **DeepCalo:** hls4ml (ongoing work)
  - **ResNet:** Xilinx ML Suite (AWS f1)
  - **ResNet:** Microsoft Azure ML Studio (Azure Stack Edge)
- Many design settings to optimize





Coprocessor Scalability



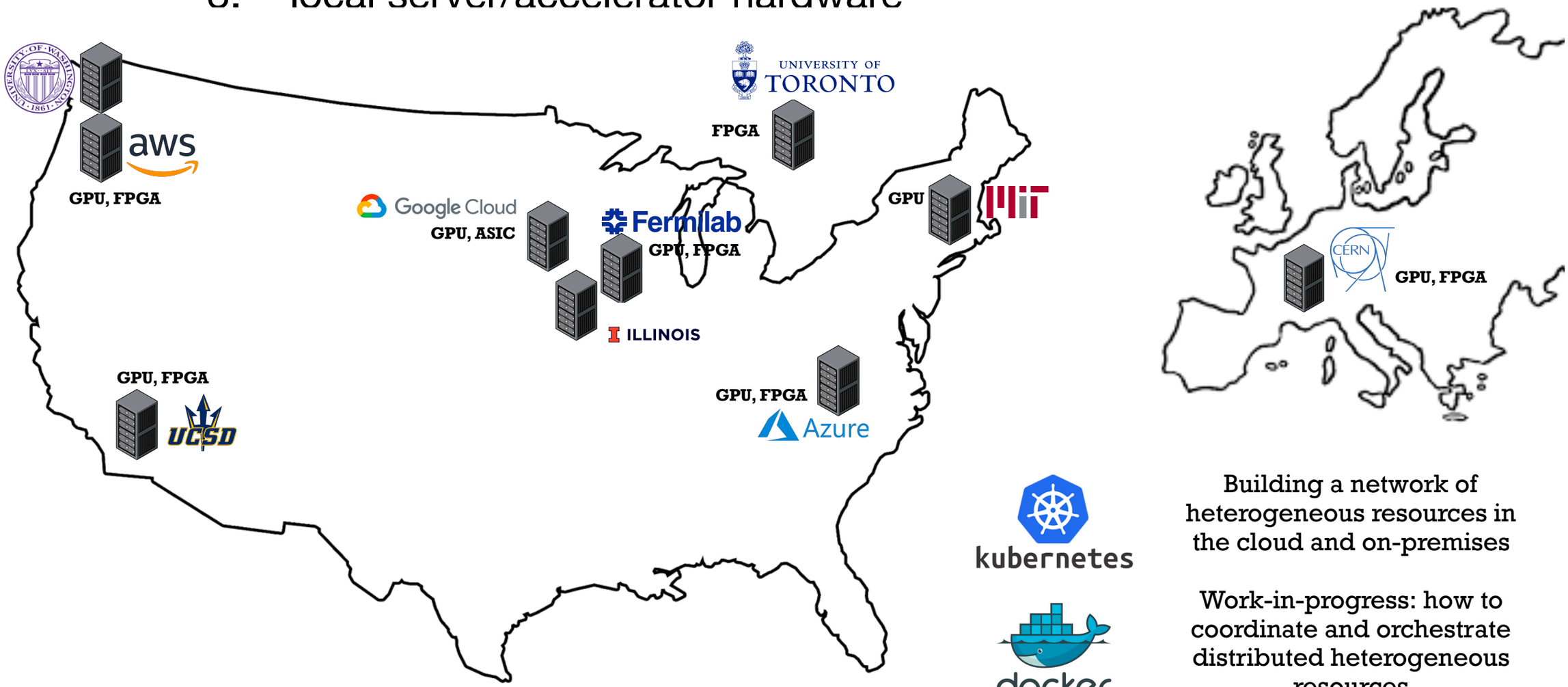


- **10% reduction in computing time operating as-a-service**
  - Consistent with fraction of time spent on HCAL local reco w.r.t total HLT time
  - → Maximal achievable reduction for this single algorithm
- No increase in latency until 300/1500 clients (GPU/FPGA)
  - Single device can service 300/1500 HLT instances

Tools

Our tools for prototyping CMS reconstruction as-a-service

1. Google Cloud/Amazon Web Services/Microsoft Azure
2. T2/T3 clusters
3. local server/accelerator hardware



kubernetes

docker

Building a network of heterogeneous resources in the cloud and on-premises

Work-in-progress: how to coordinate and orchestrate distributed heterogeneous resources

We have a wide network of resources, and perform at-scale tests with many different client-servers configurations, with servers both remote and on-site

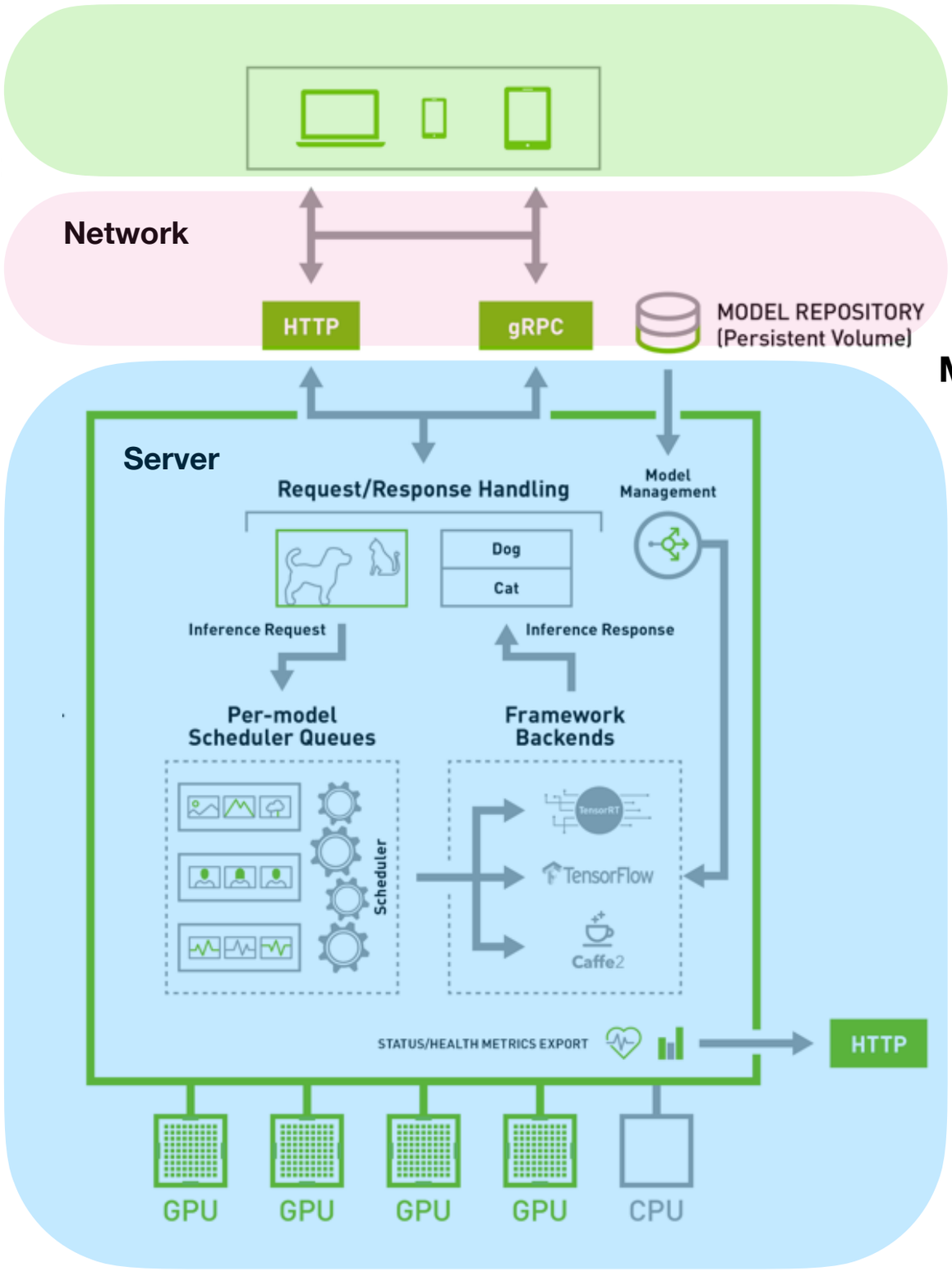
Triton Inference Server

Client sends request over network

Server receives request

Server queues and schedules request

The number of connected GPUs/FPGAs is scaleable; each has an instance of each model



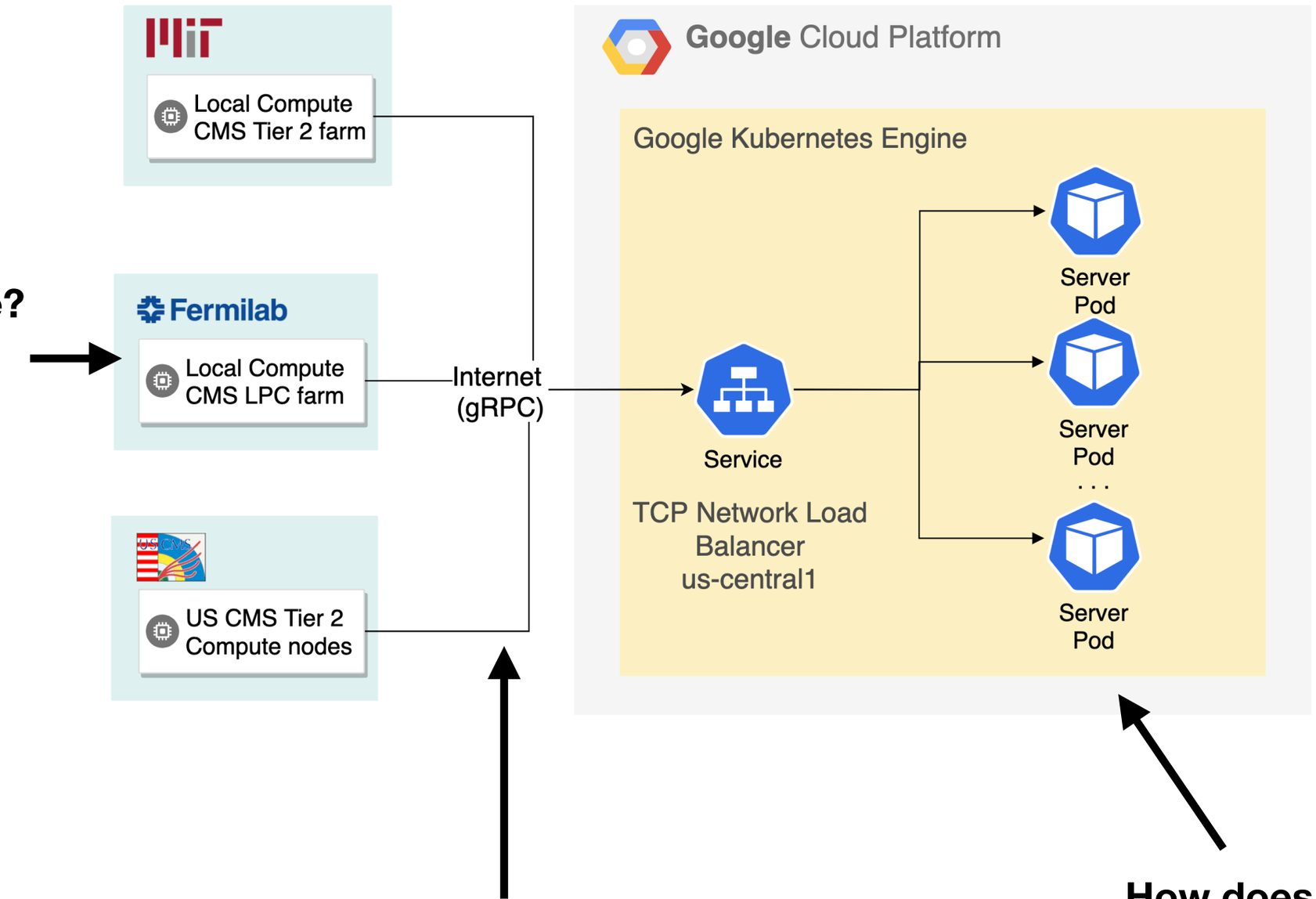
Models are stored in local repository

Many model formats (TensorFlow, Pytorch, TensorRT, …)

Output monitoring information

Scalability

A client-server schematic

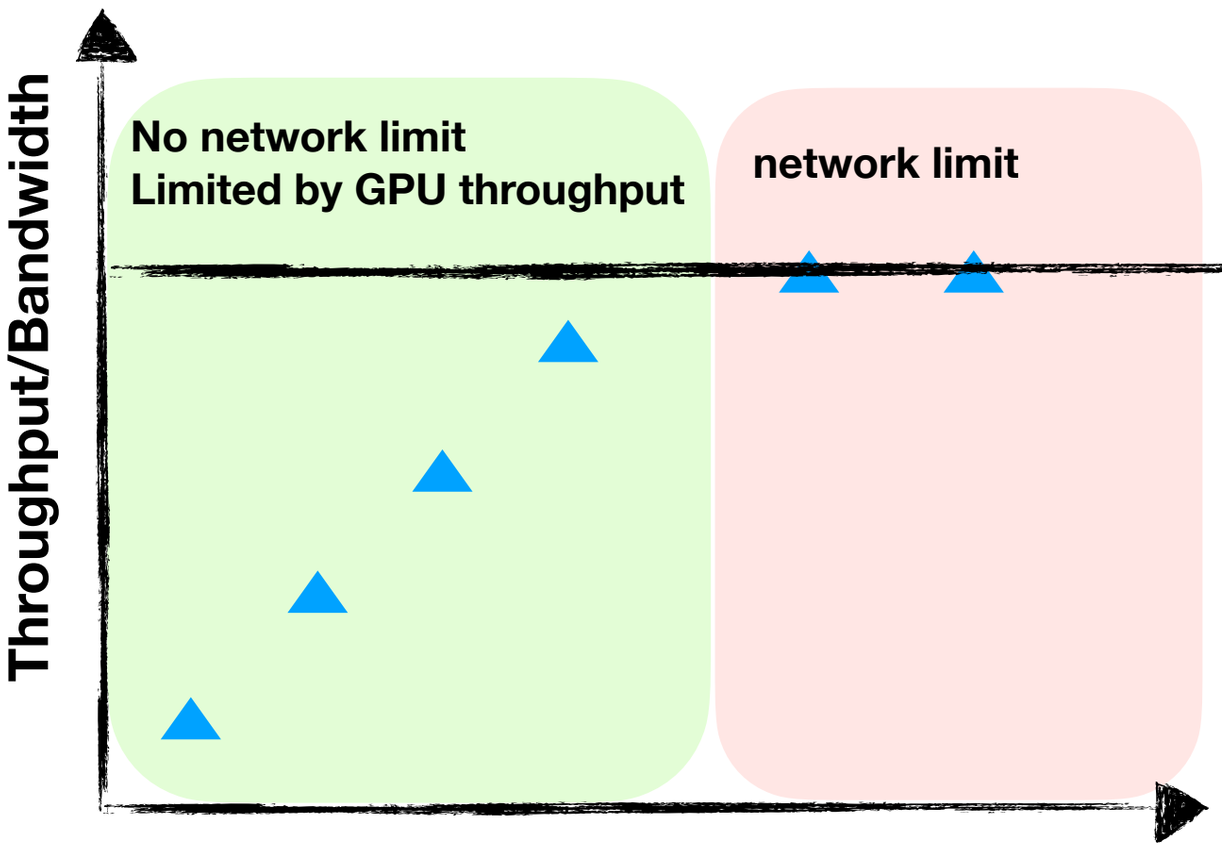


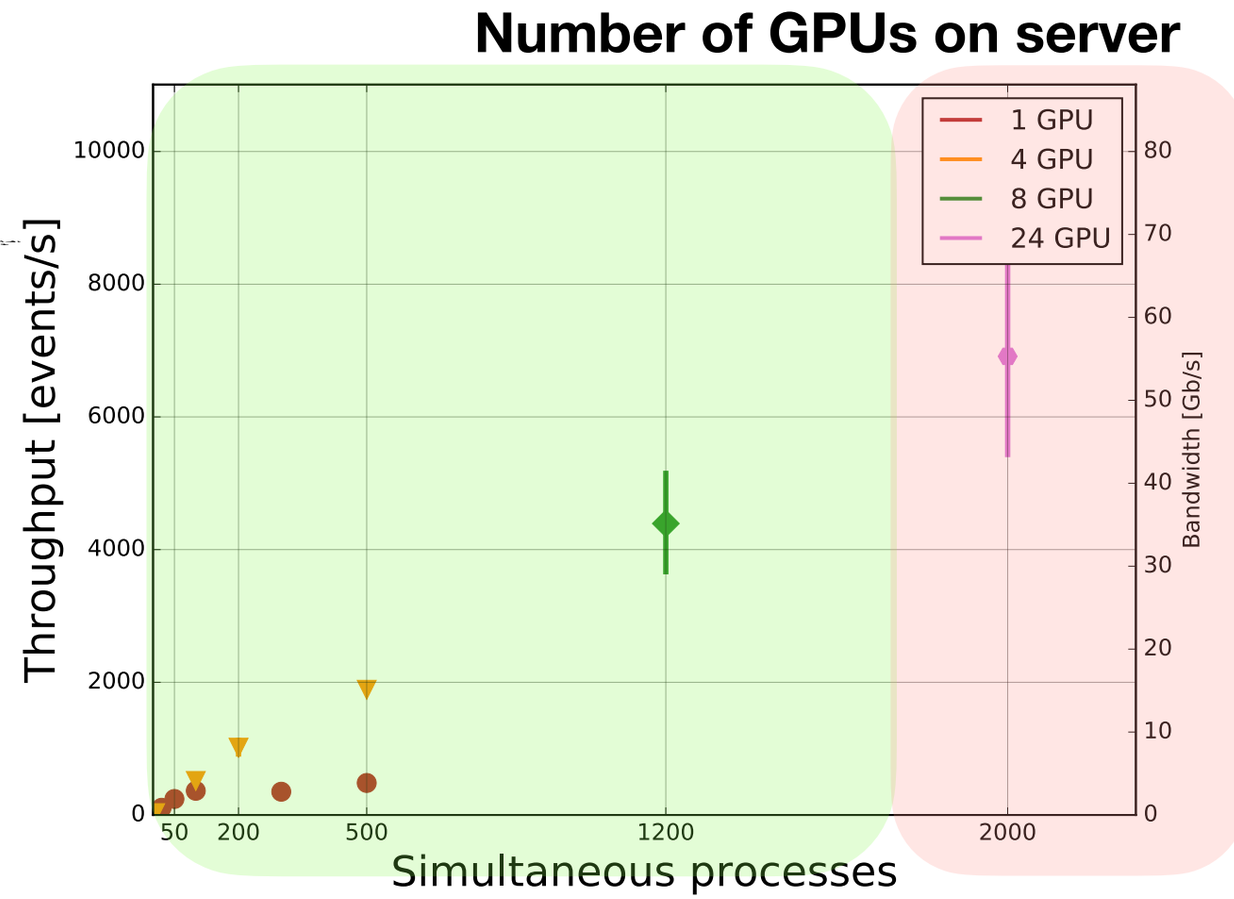
How many clients can a GPU service? What is the throughput?

What is the network limit? How reliable is it?

How does the throughput scale with server size?

Network Limit





- Server-on-site: no bandwidth limit found
- Remote server: egress limit at 70 Gb/s for MIT T2
  - Exceeds needs for use cases considered