Coprocessors for ML Algorithm Inference: SONIC Features and Performance Updates

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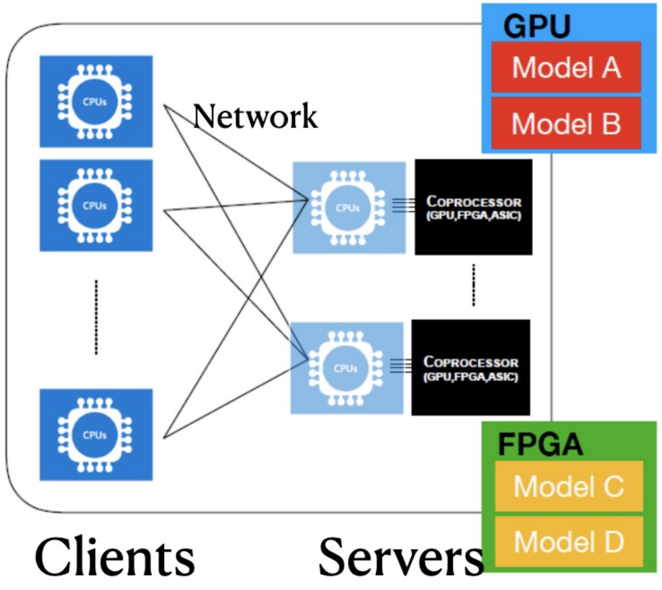

IML Monthly Meeting

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Context

Traditional Inference

- ML algorithm inference rarely optimized on CPU
- Simple approach = get a computer with a GPU/FPGA/ASIC and perform “direct” inference
  - 1-to-1 correspondence of CPU to coprocessor
  - “Problems”:
    - **Limited** (often non-optimal) usage of co-processors
    - Can also be **expensive**

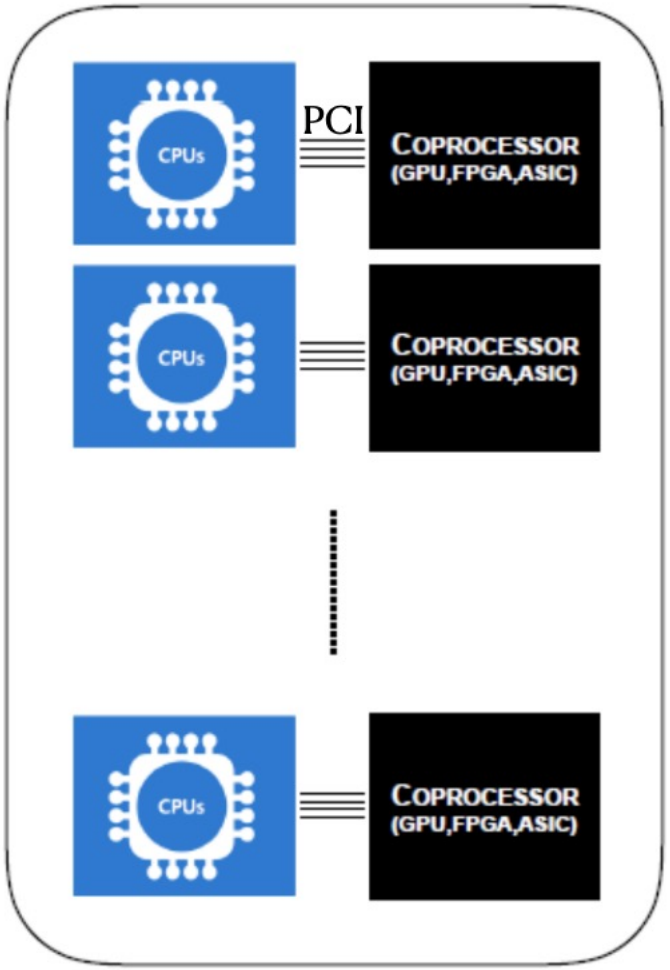
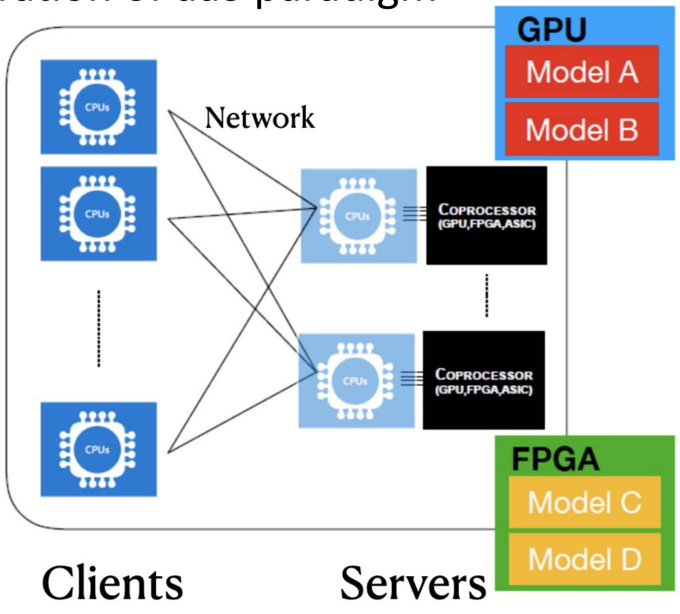


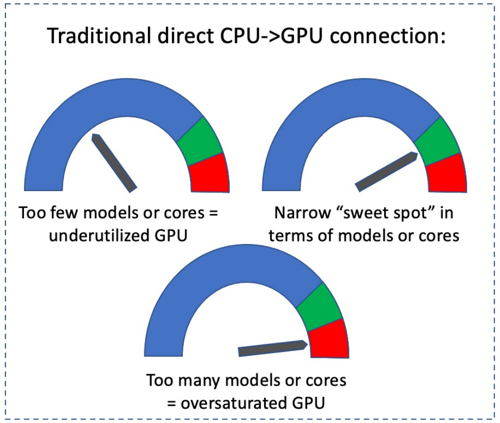
Illustration of “direct” co-processor paradigm

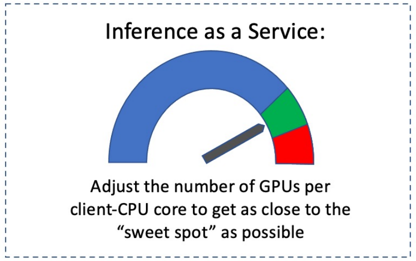
Inference as a Service (aaS)

- Alternative: treat co-processor as distinct server
- Here, CPUs act as clients, preprocessing data for inference and making calls to server
- **Advantages:**
  - CMSSW no longer needs to handle ML framework, just preprocessing and I/O (*can use otherwise unsupported frameworks*, like PyTorch)
  - Take advantage of industry efforts; simple support available for different co-processors with no need to rewrite models
  - One co-processor can service many CPUs – *optimize computational load*
  - Server can provide access to multiple types of co-processor – choose best one on per-model basis
  - Can access remote GPUs (only way to do this)!
  - ***Portable, Simple, Containerizable, and Flexible***

Illustration of aaS paradigm



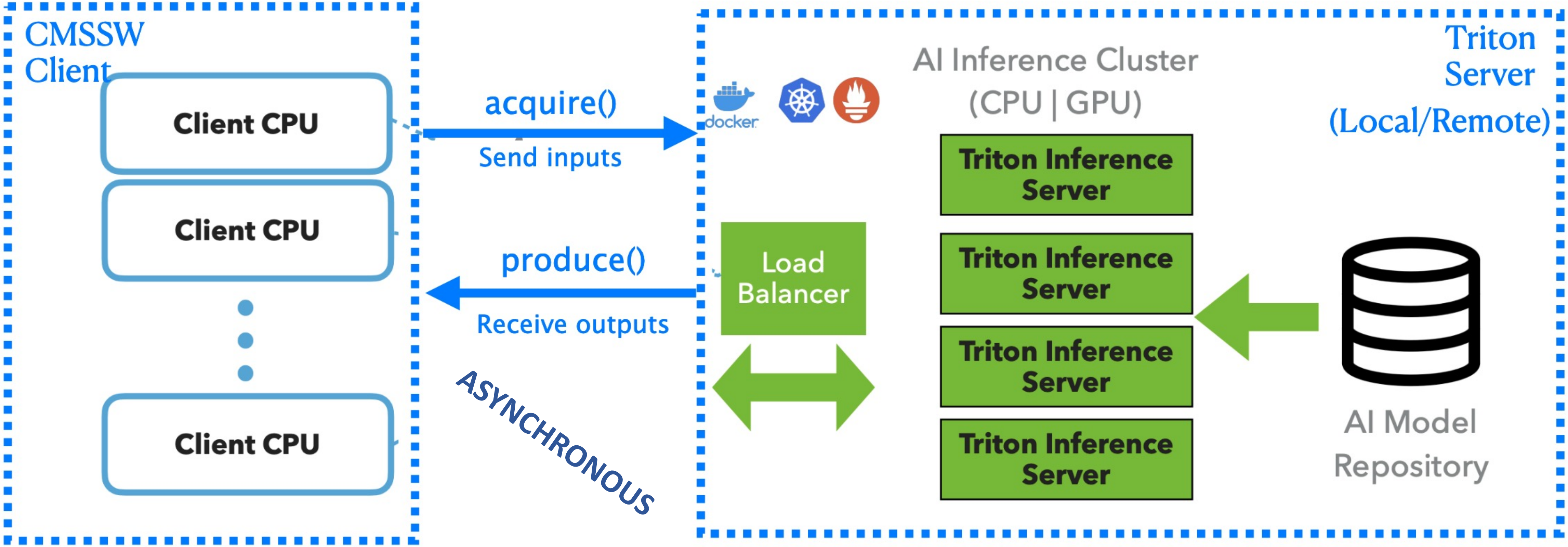




Taking advantage of industry efforts

- **For GPUS**, we can use the NVIDIA Triton Inference Server (more documentation & github)
  - Supports Tensorflow, TensorRT, ONNX, and PyTorch, XGBoost, Scikit Learn (BDT) models + Custom backends
- **In CMSSW**: runs through SONIC (Services for Optimized Network Inference on Coprocessors)
  - Main code in SonicCore and SonicTriton
  - Can make **asynchronous inferences requests**
  - If GPU resource not available, automatically spins up **fallback server on CPU**

SONIC Visualized



- Use acquire() and produce() functions to send/receive information to/from server
  - See example of use for DeepMET algorithm (and model file PRs)

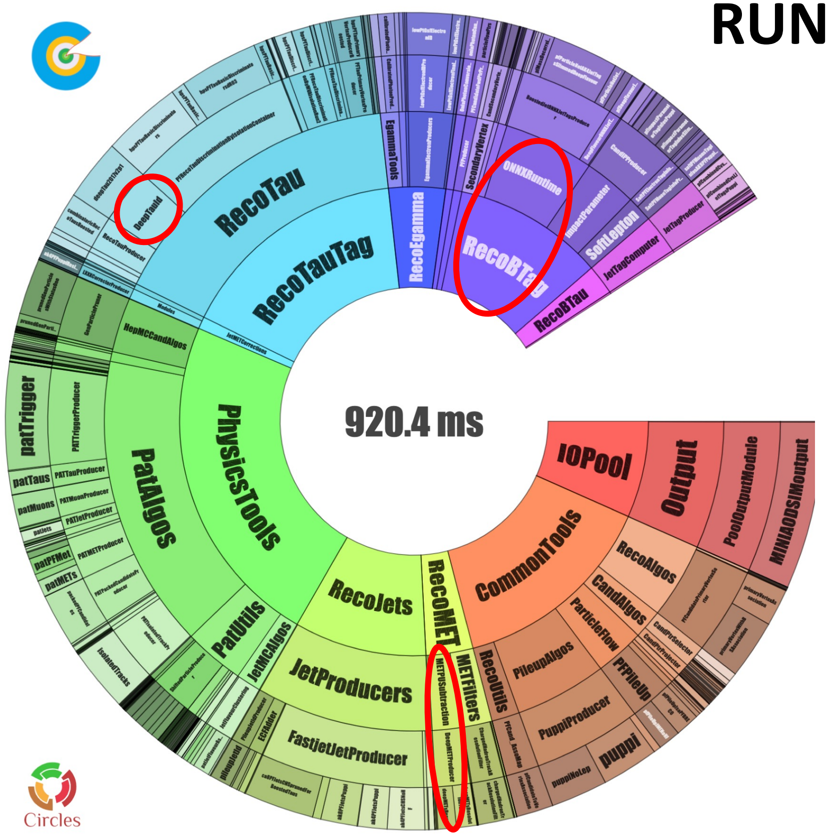
Workflow Demonstrator
– or –
The Benefits of SONIC

MiniAOD Demonstrator

- We made a MiniAOD demonstrator includes SONICized versions of the algorithms circled on the right
  - **ParticleNet** – ONNX model for jet tagging (AK4, AK8 flavor, AK8 MassRegression, and mass) decorrelator
    - See presentation and paper
  - **DeepMET** – TF MET calculation
    - See internal twiki, Yongbin's thesis
  - **DeepTau** – TF model with CNN for tau ID
    - CADI, approval talk, also these older slides
- These account for ~9% of total miniAOD production latency*
  - This was all run on a **ttbar dataset**
- Presentations from the fall:
  - O&C
  - S&C Blueprint

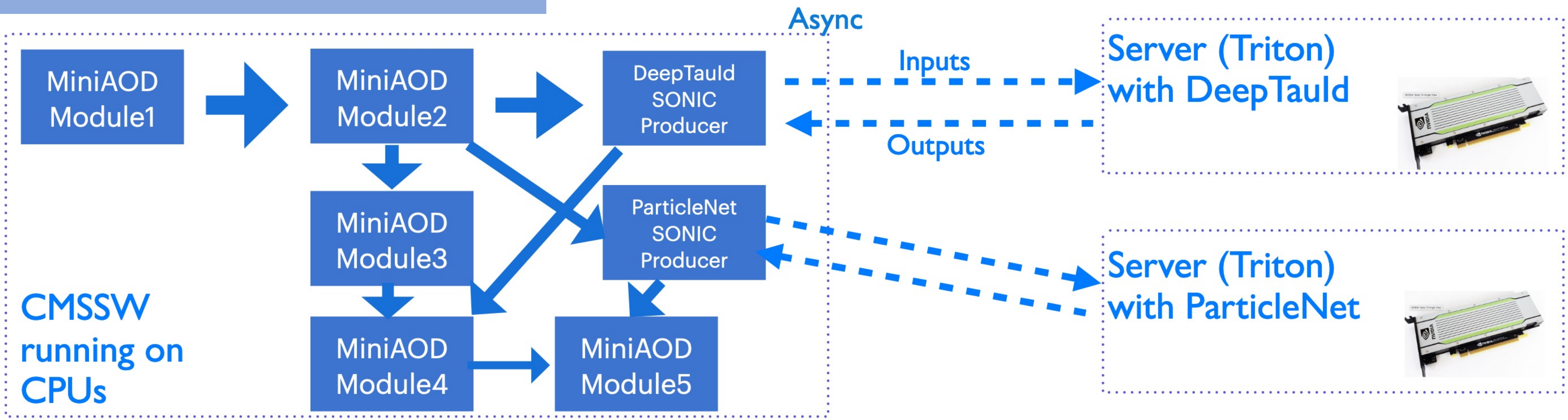
	Time(ms)	Fraction(%)
Total	920.4	100
ParticleNet	43.4	4.7
DeepTau	22.3	2.4
DeepMET	14.0	1.5
Sum	89.7	8.6

RUN 2



*11-12% for Run 3 miniAOD

Explicit Workflow



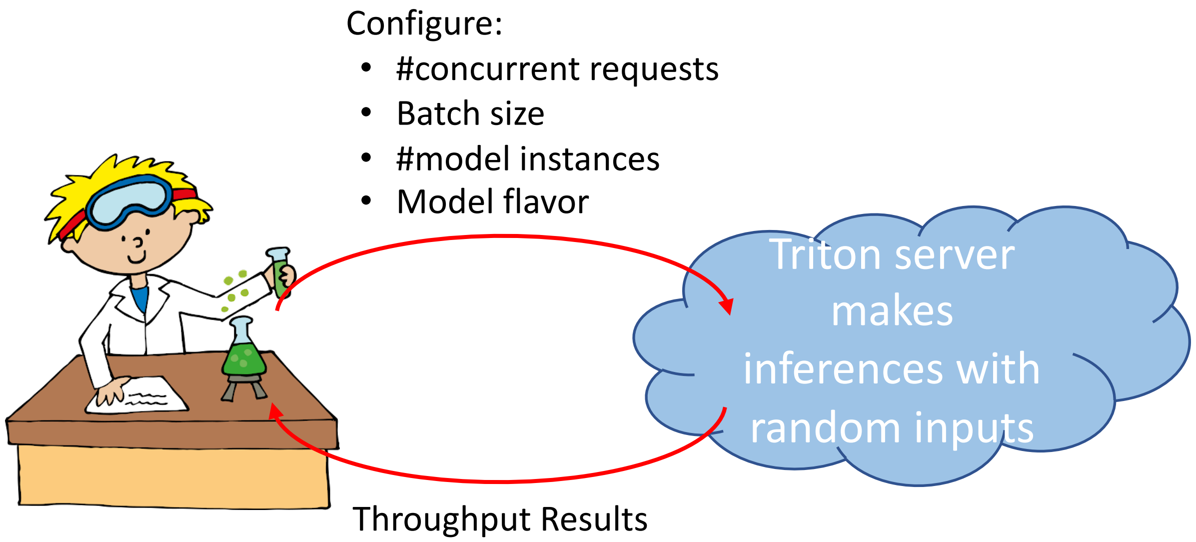
- Servers load the model files (PRs: DeepTau, DeepMET, ParticleNet)
- Three SONIC Producers to do the pre/post-processing and handle the IOs for model inferences (PRs: DeepTau, DeepMET, ParticleNet)
  - We validated object by object that the output between the regular workflow and SONIC producers are identical (up to the numerical precision)

Production testbeds

- Workflow can be deployed in a variety of computing contexts
  - **Google Cloud**: Triton server on cloud VM, with client-side CPUs also in cloud. *Effectively, use cloud as a scalable, temporary tier 2*
  - **Current Tier 2** (Purdue): 2 T4s available – client CPUs at Purdue (can also use cloud GPUs)
  - **HPC computing cluster** (NTU - NCHC): Many GPUs available – client CPUs in Taiwan (can also use cloud GPUs)
- NOTE: Can use CPUs at one site to communicate with GPUs at another site

Optimization: understanding our models

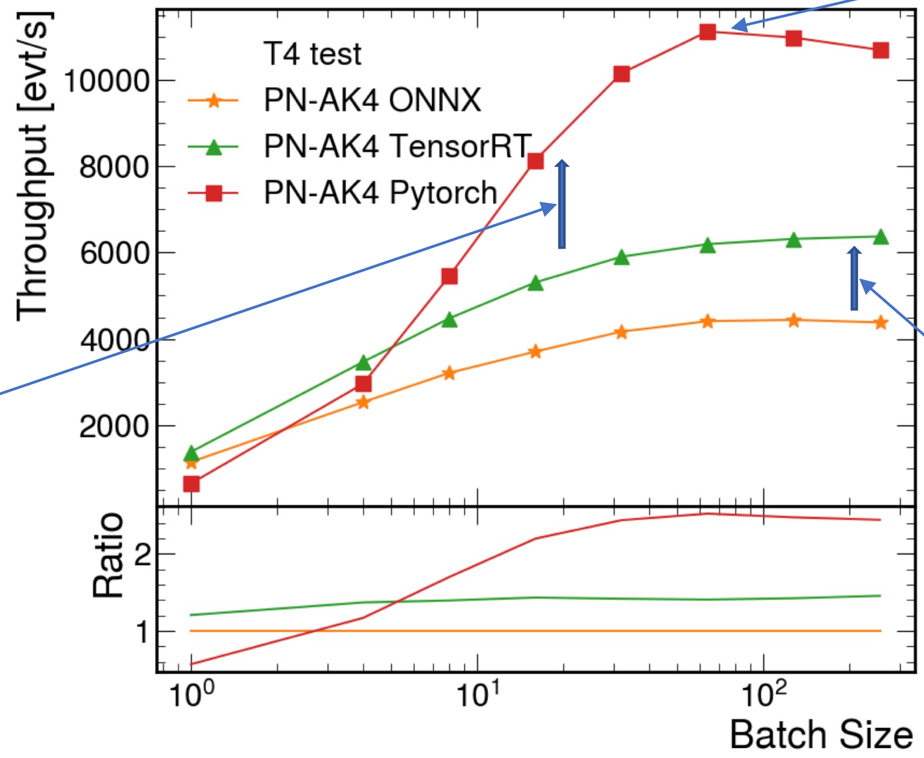
- In the IaaS paradigm, GPU server is wholly separate from client side
  - Triton provides a variety of native **tools to explore model performance**
- Using these tools, we can explore different model configurations to achieve peak throughput



Optimization: perf_client examples

- Tests performed with a Triton server on 1 NVIDIA T4 GPU
  - Single model is loaded into server, and triton’s perf_client feeds in random inputs to determine throughputs
  - Examples of what we can learn:
    - Expected throughputs
    - Optimal configuration
    - “Best” version of model if multiple available

Peak expected performance at batch size ~60 jets



PyTorch preferred at higher batch size (number of jets inferenced at once)

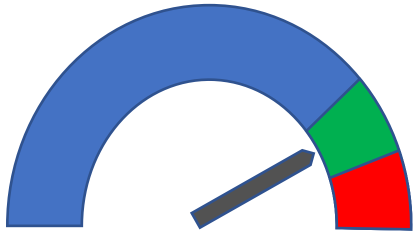
TRT* outperforms bare ONNX

*TRT=TensorRT. An NVIDIA-specific algorithm to optimize performance on NVIDIA GPUs

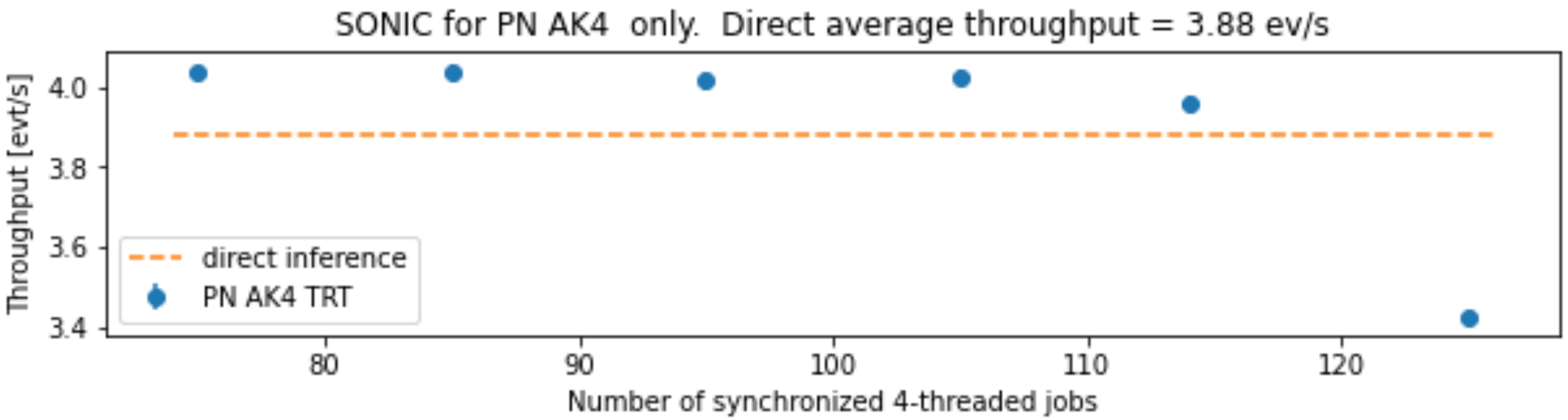
Optimization: saturation scan examples

- We also want to know how many client-side jobs a single GPU can handle
  - Allows us to reach the GPU-per-CPU “sweet spot”
  - Also allows us to calculate how many GPUs we need

Inference as a Service:



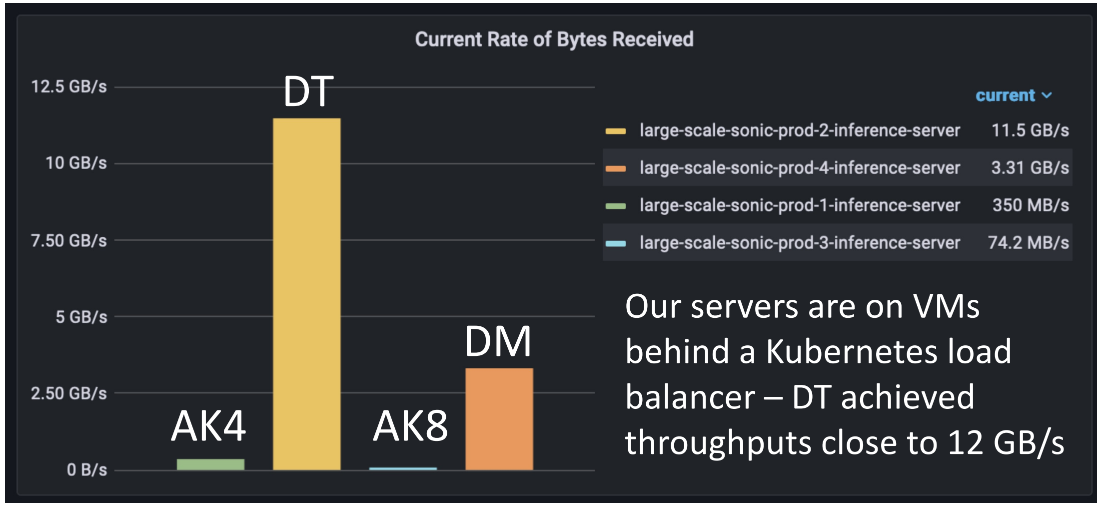
Adjust the number of GPUs per client-CPU core to get as close to the “sweet spot” as possible

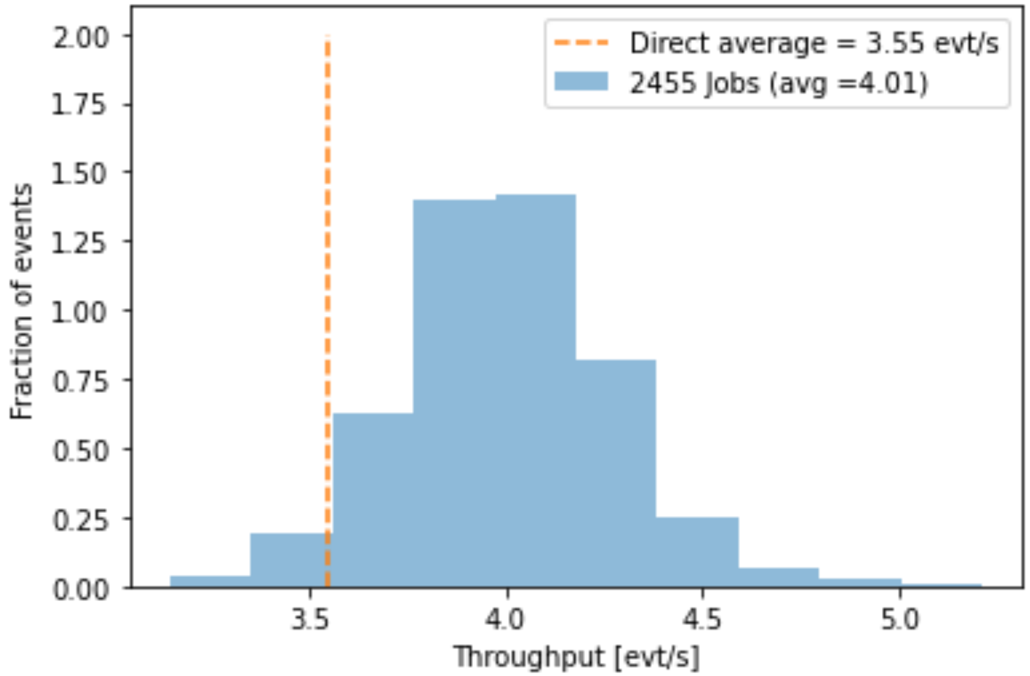


Results for TRT-ized version of PN-AK4. 1 GPU can handle about 115 simultaneous 4-threaded jobs, but for server setup, might want to use ~105 jobs to be safe

Demonstration: Scale tests

- Optimization can be performed with just a few GPUs per algorithm of interest
- For a demonstration of how this scales up, we can deploy ~100 GPUs to service thousands of CPU nodes, all in the cloud

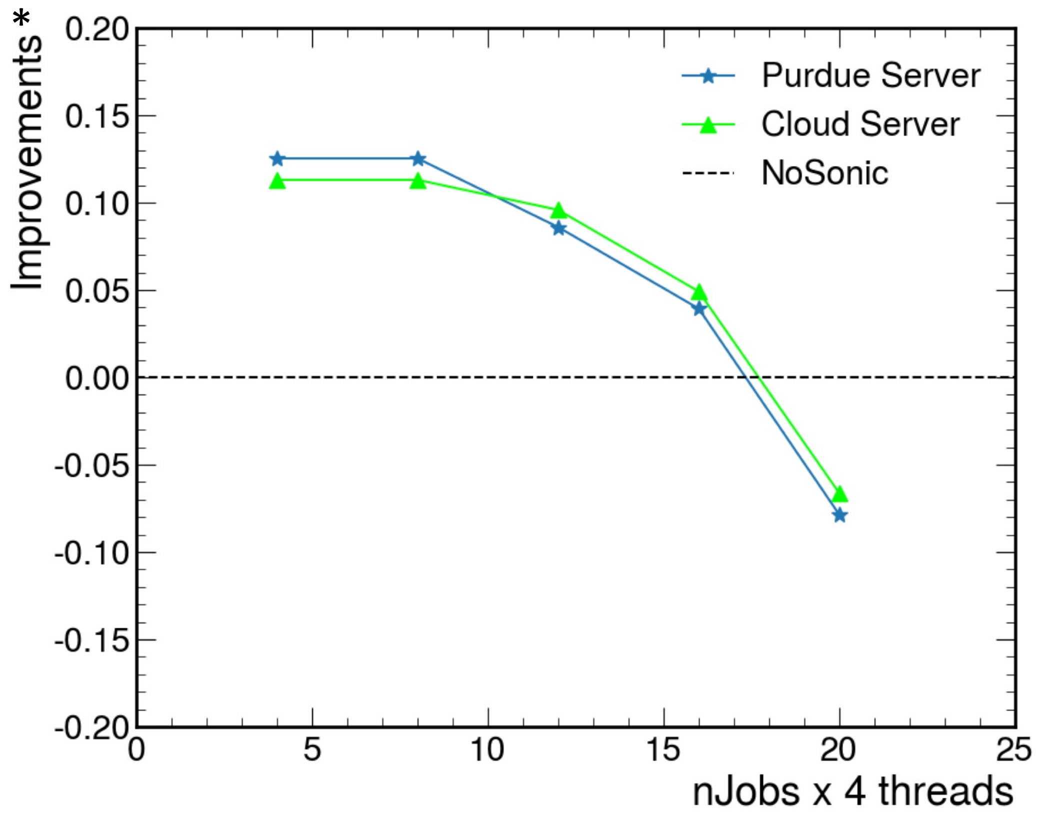




Here, we ran with 10,000 CPU cores and ~100 GPUs, achieving expected speed-up in processing. **NOTE:** with direct inference (say 32-to-1 CPU to GPU ratio), this would take ~300 GPUS

Demonstration: Server location robustness

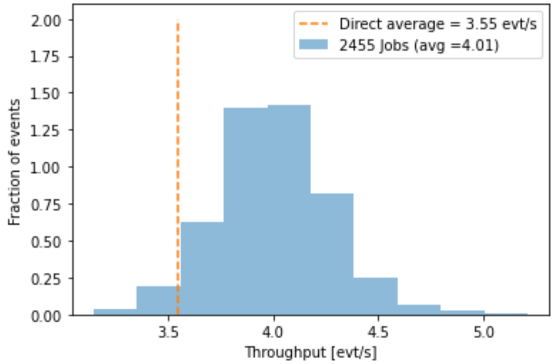
- Comparing the throughputs between one server at Purdue and one server in Google Cloud VM
  - CMSSW jobs running at Purdue T2 (Run-3) workflow
  - Similar results between Purdue server and GCP server

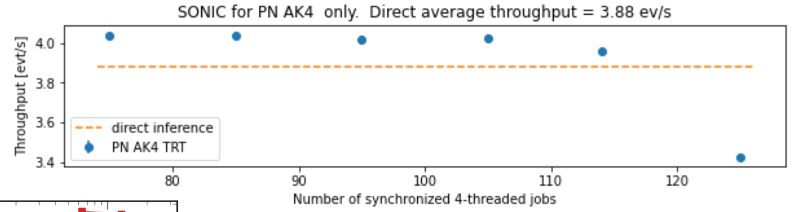


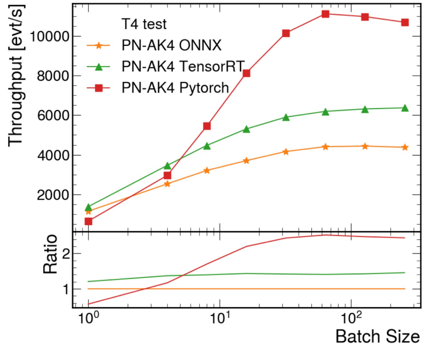
*Improvements = fractional increase in throughput relative to CPU-only inference

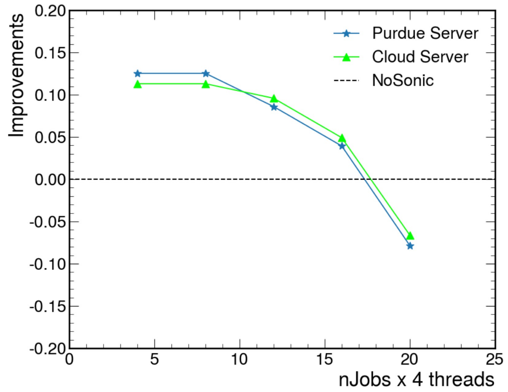
SONIC: Summary of benefits

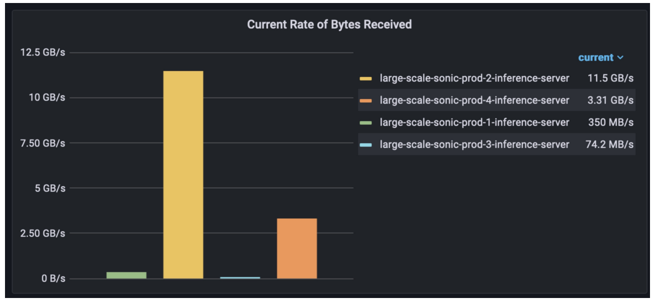
- Why use SONIC?
  - **Increase throughput**
    - GPUs enable acceleration of ML algorithms
  - **Optimize GPU-to-CPU ratio**
    - Save money if looking to buy GPUs or increase utilization of current resources
  - **Flexibility of algorithm design + optimization**
    - Not restricted to currently supported frameworks in CMSSW
    - Can tweak deployment parameters to optimize inference rates and use e.g. TRT
  - **Not restricted to local GPUs**
    - You just need access to a GPU, you don't need to buy one necessarily
  - **Bandwidth limitations not yet seen in realistic deployments**
    - We got up to 12 GB/s of data transfer for deepTau in our scale tests









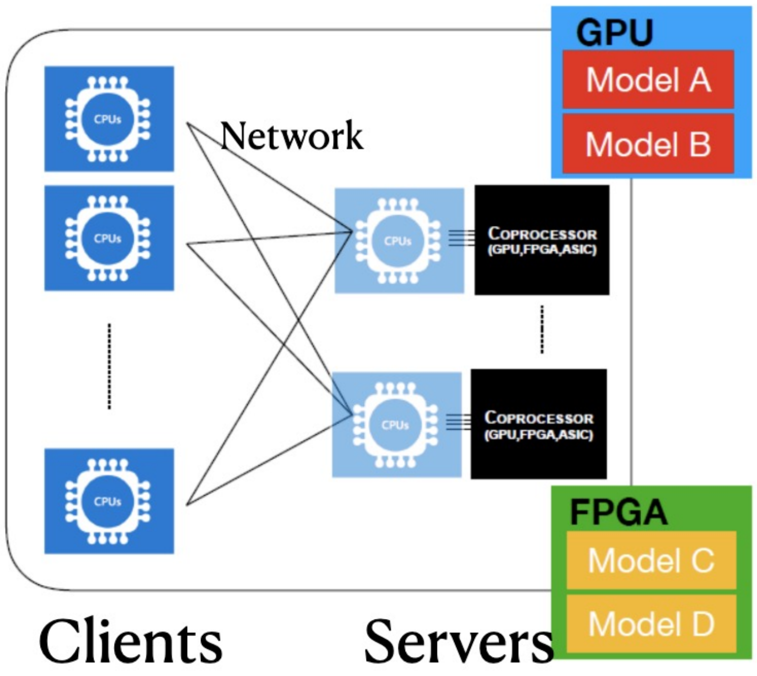


Looking Forward

GPU server deployment

- On our to-do list: create resource allocation framework
  - Assign GPUs to jobs
  - Automated way to spin up GPU-based servers
  - Ensure that we don't saturate GPU resources

Want to make this as easy as possible for users



Additional Projects

- Beyond data processing, SONIC could be **useful for analysis** groups
  - Let's say you have a complex ML algorithm but no GPU
  - Perhaps in the future, you could deploy a server on some collaboration-wide shared GPU resources and run using that
  - "**PySONIC**" framework under development
- Implementing some additional Triton features, such as "**ragged batching**"
  - E.g. Currently have to zero-pad tensors for ParticleNet, increasing network demands and latency
  - "Ragged batching" makes zero-padding unnecessary
- New demonstrator algorithms under development (only possible with SONIC for now)
  - **ECAL Dynamic Reduction Network** regression – PyTorch Geometric based algorithm [S. Rothman]
  - **SPVCNN** algorithm to use depth information in HCAL clusterizing
- Algorithms in the pipeline
  - MLPF
  - Tracking as a service (ExaTrk or ACTS)

Summary

- Coprocessors, such as GPUs are becoming increasingly important
  - But they can be expensive and not widely available
- SONIC is a powerful tool to optimize coprocessor utilization and availability
  - Already demonstrated to deliver expected throughput increases at large scale for MiniAOD reprocessing
- Physics case for SONIC: we can deploy models in any format supported by Triton and even make custom backends
  - More flexibility than what is currently in CMSSW!
- Working on robustness studies and developing ease-of-use tools

Backup

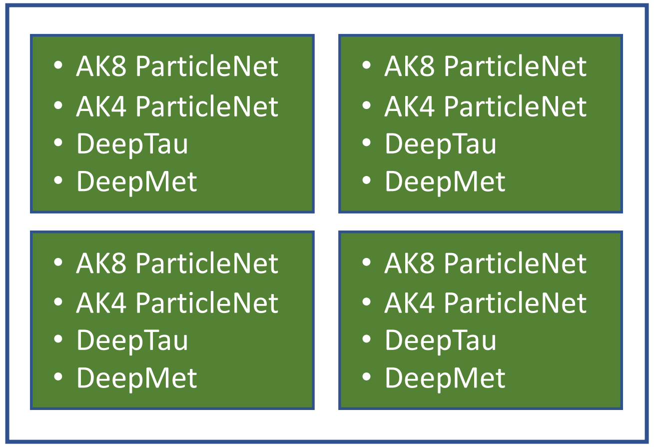
SONIC: Some Current Features

- Currently available:
  - **TritonService**: tracks available servers and models
  - **Local fallback server**: will automatically start a server on local GPU or on CPU if model not on remote server
  - **Shared memory**: can speed up inference on local servers – for CPU uses memory-backed temporary file system and for GPU uses CUDA to copy directly to GPU memory
  - **I/O compression**: Use some CPU resources to compress I/O to use less bandwidth
  - **SSL Authentication support**
  - CMSSW ProcessModifier "**enableSonicTriton**" turns on SONIC features
    - Also "**allSonicTriton**" to enable full workflow

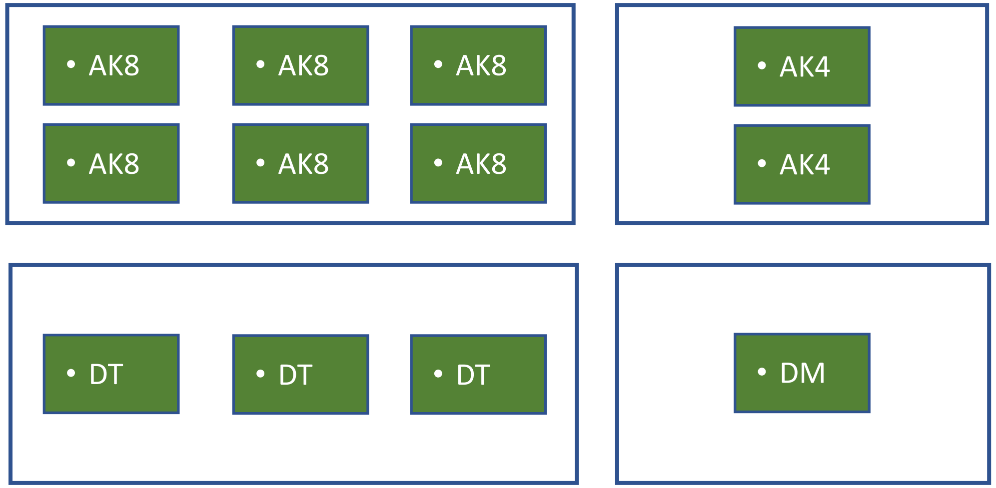
- Still to come:
  - **Client-side ragged batching** – use of different size inputs vectors within the same batch; in contact with NVIDIA now (3x speed up when ragged batching is used in direct CPU inference for ParticleNet jet tagging)

Optimization: server deployment

- We can **choose how to distribute our models** over GPUs
  - Difficult option to probe in perf_client
- Main options:
  - Load every model onto every GPU
  - Load models onto separate GPUs and run with multiple servers
  - Use different combinations of models on GPUs
- In practice, we often see slightly better performance with split models
  - ~3% fewer GPUs needed
  - This is likely sample dependent (most R&D here used ttbar samples)



One IP address

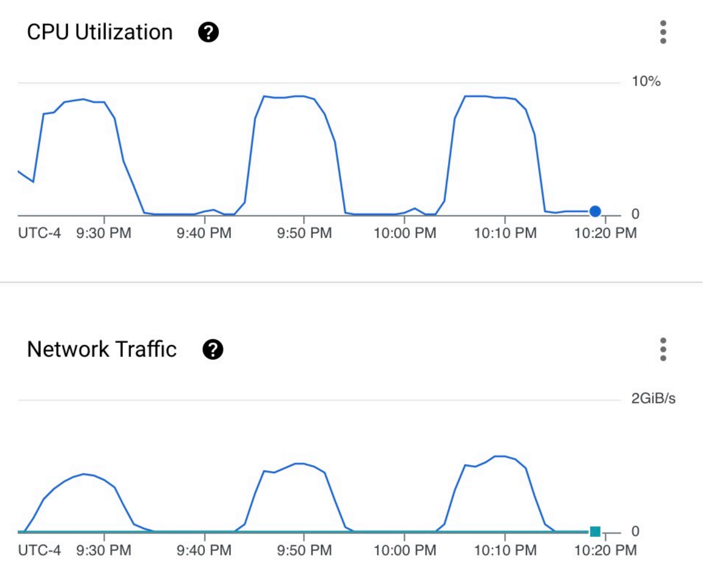


4 IP addresses in this example

Note: How many server-side CPUs do we need?

- Disclaimer: in our Google Cloud VMs, we give each GPU 24 CPU cores
  - **HOWEVER:** this is because allowed bandwidth in Google Cloud is somewhat restricted based on the number of CPUs in a VM
- Triton doesn't actually use all of these cores
  - We can monitor the actual CPU utilization at the saturation point, as below

Model	CPU utilization percent (24 cores available)	Cores used per GPU
PN AK4 TRT	4.8%	1.15
PN AK8 TRT (all 3 models)	8.4%	2.02
DeepTau TRT	8.93%	2.14
DeepMET	17.48%	4.19
ALL Models on 1 GPU (saturation at ~32 4-threaded jobs)*	16.09%	3.86



76 jobs/GPU 90 jobs/GPU 100 jobs/GPU

Example of bandwidth and CPU utilization monitoring in 2-GPU VM servicing DeepTau for runs with various numbers of synchronized jobs

***In this simplified scenario, 128 client-side cores are serviced by 1 GPU with 4 server-side CPUs**