GPU-accelerated machine learning inference for offline reconstruction and analysis workflows in neutrino experiments

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Accelerating Physics with ML @MIT

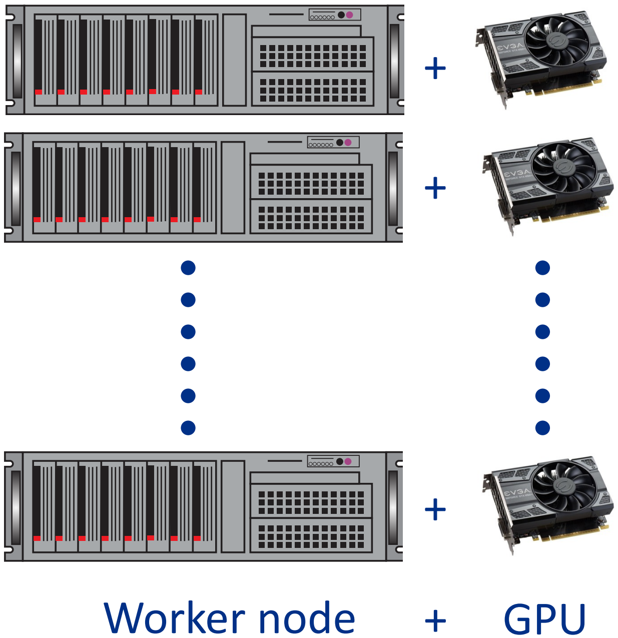
Jan 30, 2023

Introduction

- Machine learning applications, especially those employing deep neural nets (DNNs) have proven to be effective analysis tools in LArTPC-based neutrino experiments
- As a consequence, their use has become more common in offline reconstruction chains
- DNN training has its own computing challenges
  - But happens ~once/year and outside of compute infrastructure
- **Inference** happens on billions of events many times a year
  - Massive datasets of statistically independent events
  - Unique challenge across HEP
  - Slow on CPUs

Naïve solution: deploy GPUs on every worker node

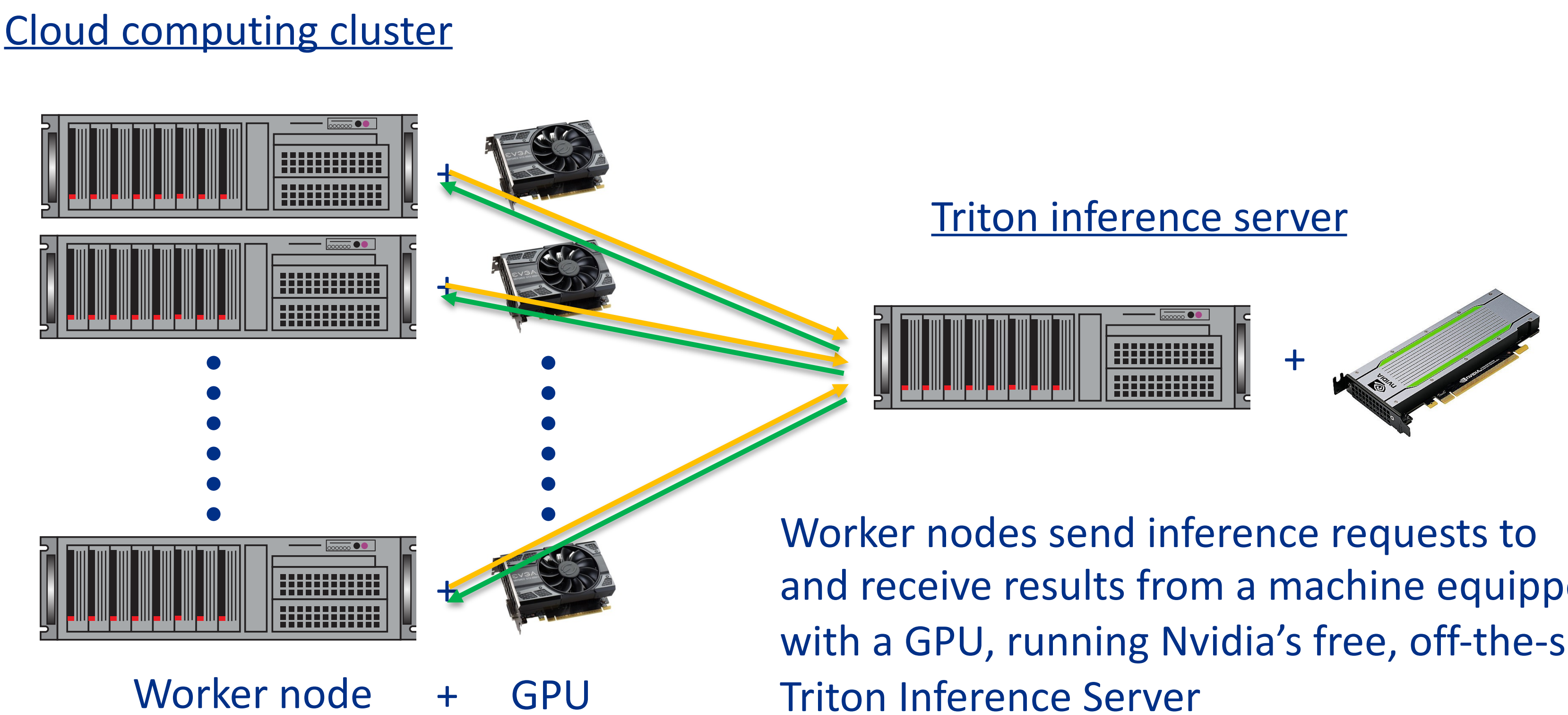
Cloud computing cluster



Assuming a moderately sized cluster with 100 nodes:

- Even with low to mid-range "gamer-class" GPUs, easily cost $20k-30k
- Increased hardware and software maintenance
- Increased power and cooling requirements
- Inefficient use of GPU resources
- Less flexible and more costly to upgrade or replace

Alternative: GPU as a Service (GPUaaS)



Worker nodes send inference requests to and receive results from a machine equipped with a GPU, running Nvidia's free, off-the-shelf Triton Inference Server

GPUaaS @FNAL

- **SONIC**: Services for Optimized Network Inference on Coprocessors (GPUs, FPGAs, TPUs, …)
  - C++ code running on CPU to convert data format and send the inference request to Triton.
  - DNN inference is handled completed by the Triton server on GPU.
- **Triton**: Inference server from Nvidia to use GPUs as a service
- Pioneering work by LHC experimentalists with Microsoft Research to demonstrate a proof-of-concept for providing FPGA-accelerated inference as a service for LHC experiments:

Original Article | Published: 14 October 2019

FPGA-Accelerated Machine Learning Inference as a Service for Particle Physics Computing

Javier Duarte, Philip Harris, Scott Hauck, Burt Holzman, Shih-Chieh Hsu, Sergo Jindariani, Suffian Khan, Benjamin Kreis, Brian Lee, Mia Liu, Vladimir Lončar, Jennifer Ngadiuba, Kevin Pedro, Brandon Perez, Maurizio Pierini, Dylan Rankin, Nhan Tran, Matthew Trahms, Aristeidis Tsaris, Colin Versteeg, Ted W. Way, Dustin Werran & Zhenbin Wu

Computing and Software for Big Science **3**, Article number: 13 (2019) | Cite this article

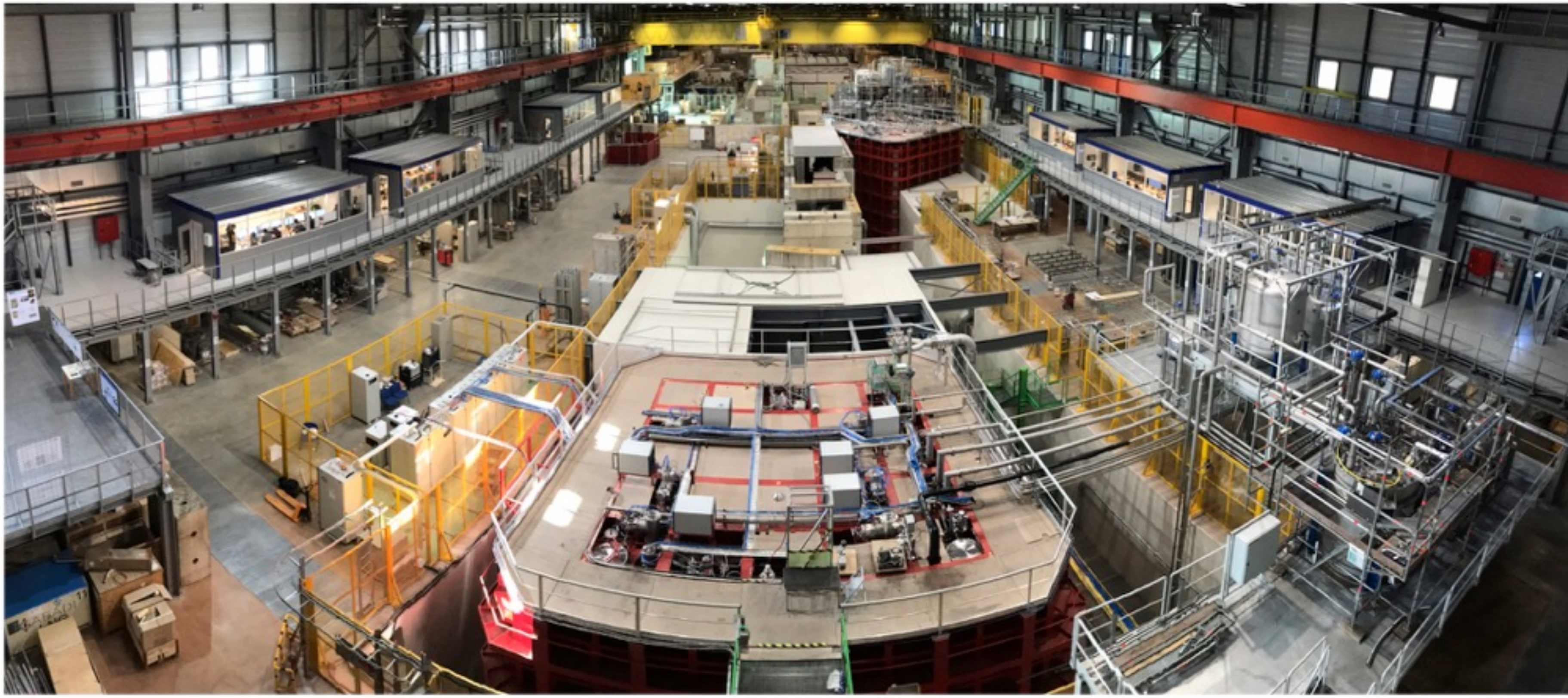
NVIDIA

- First developed for CMS; now expanding to DUNE, ATLAS, astro…

GPUaaS for DUNE

- Wang M, Yang T, Flechas MA, Harris P, Hawks B, Holzman B, Knoepfel K, Krupa J, Pedro K and Tran N (2021) **GPU-Accelerated Machine Learning Inference as a Service for Computing in Neutrino Experiments**. Front. Big Data 3:604083.
  - First demonstration of a big reduction in ML inference time for the ProtoDUNE experiement using GPUaaS.
  - Focusing on GPU saturation.
- Cai T, Herner K, Yang T, Wang M, Flechas MA, Harris P, Holzman B, Pedro K, Tran N (2023) **Accelerating Machine Learning Inference with GPUs in ProtoDUNE Data Processing.** arXiv:2301.04633.
  - A large-scale ProtoDUNE data production using GPUaaS.
  - Focusing on network saturation.

Detector Activation - start: Sept. 21, 2018



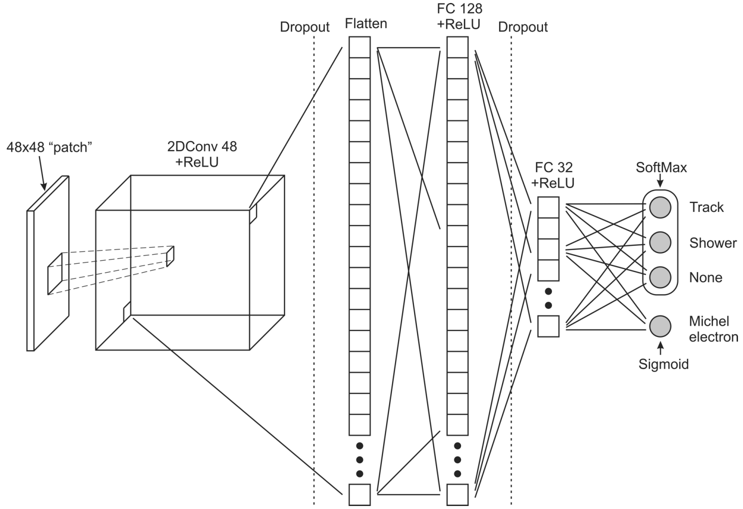
ProtoDUNE SP ~1kt LAr-TPC at CERN

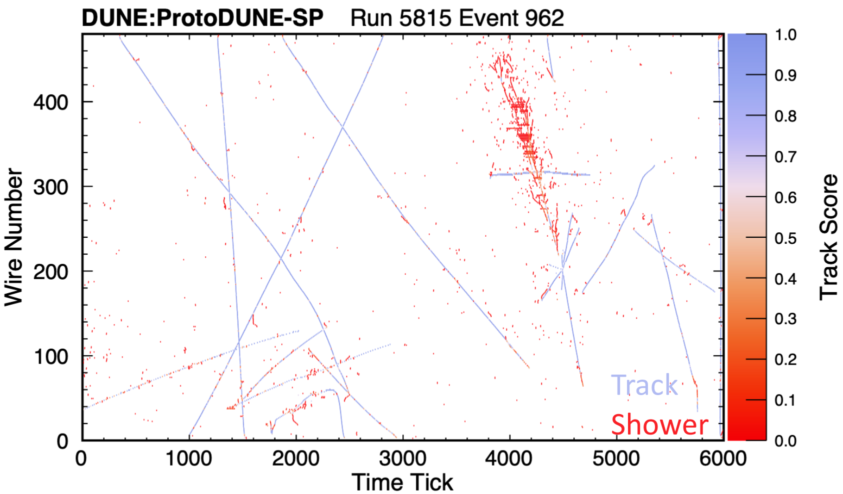
One of the two prototypes for DUNE far detector

arXiv:2007.06722: **First results on ProtoDUNE-SP liquid argon time projection chamber performance from a beam test at the CERN Neutrino Platform**

EmTrkMichelId CNN

Eur. Phys. J. C 82, 903 (2022)





- Most time-consuming module in the reco chain.
  - Input of 48x48 pixel patch
  - A single convolutional layer containing 48 5x5 pixel filters
  - Two dense layers and two dropout layers
  - Output split into two branches
    - Track/Shower/None
    - Michel electron
- ~11.9M parameters
- Each event has ~55k patches
- Image size: 4.1 Gb/event

ProtoDUNE reco chain	CPU time/event
Non-ML module	110s
ML module (EmTrkMichelId)	220s
Total	330s

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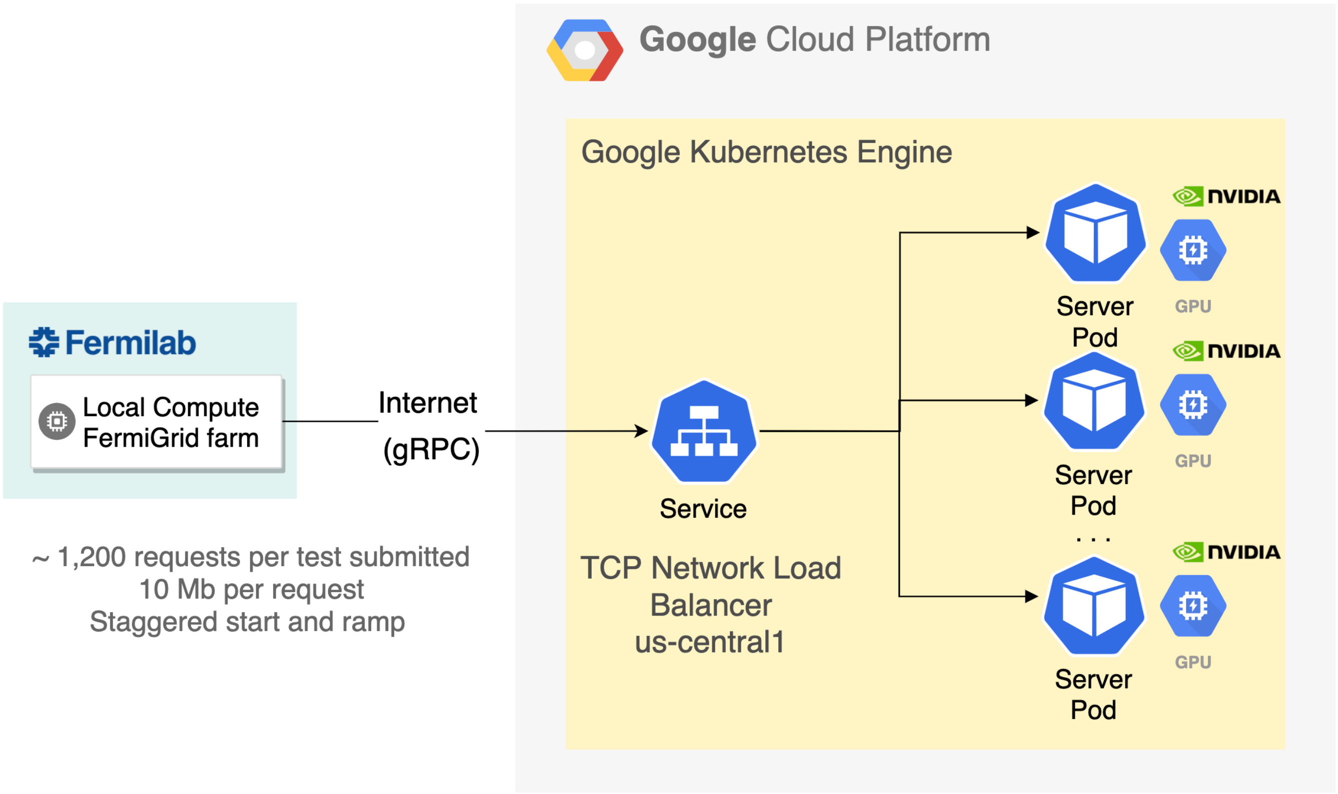
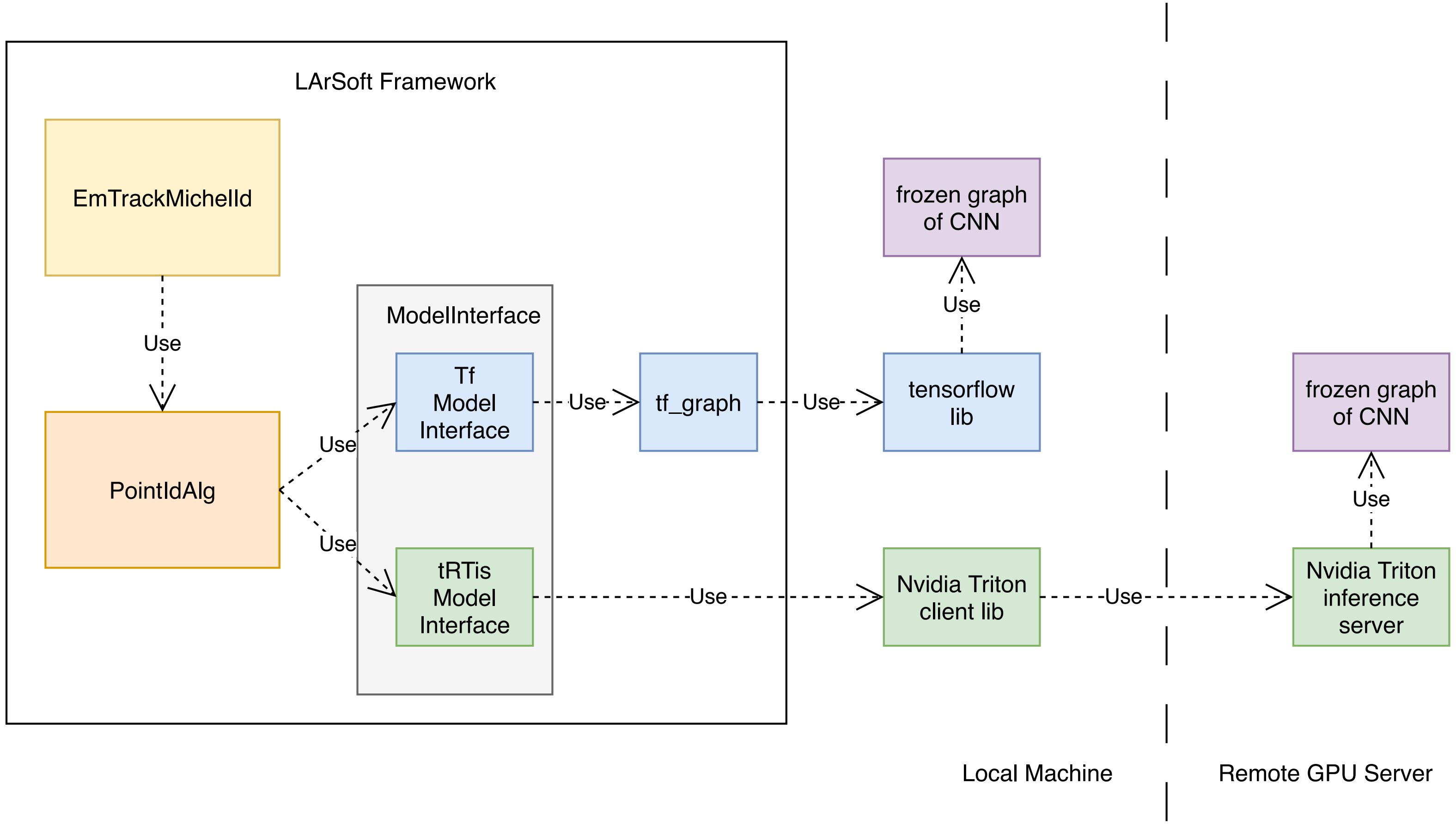
GPUaaS for ProtoDUNE

- Use the K8s Triton inference server attached with 4 Nvidia T4 GPUs on the Google Cloud.
- gRPC: open-source remote procedure call (RPC) system developed by Google.
- Goal is to demonstrate the improvement in inference time when using GPU as a service.



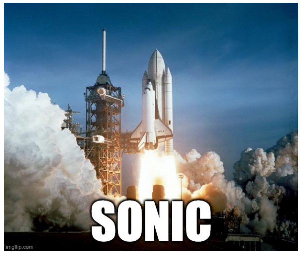
GPUaaS for LArSoft: νSONIC



- LArSoft: common framework for LArTPC reconstruction
- Interface added to communicate with the remote Triton inference server.

Processing time using SONIC

	CPU time/event	SONIC
Non-ML module	110s	110s
ML module (EmTrkMichelId)	220s	12s
Total	330s	122s



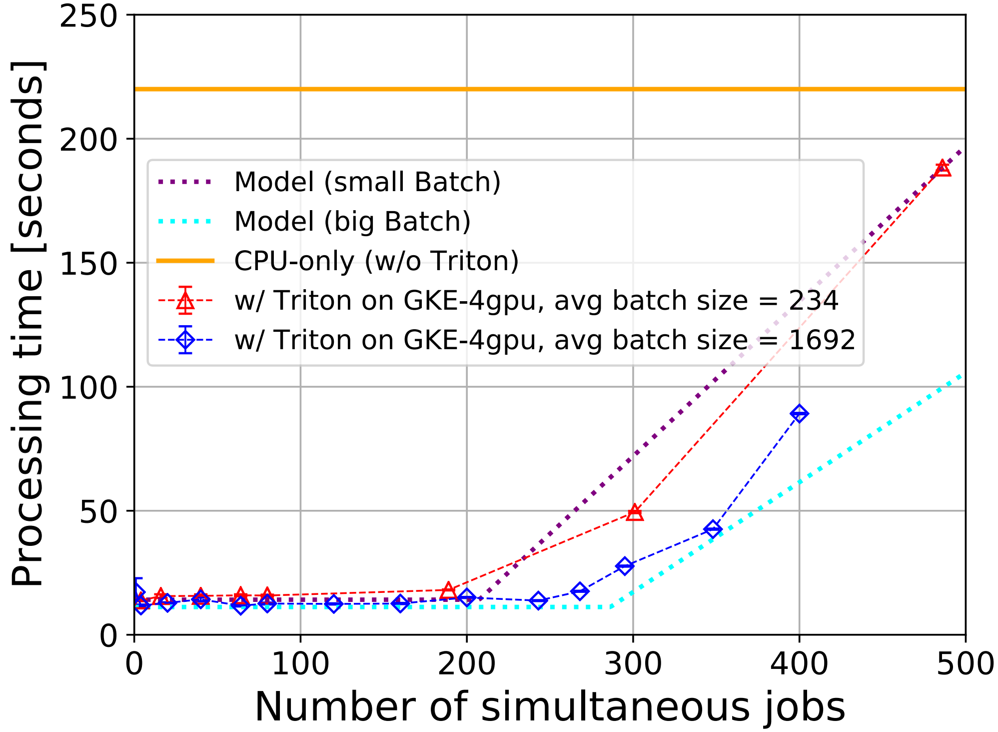
- 18x reduction in processing time for EmTrkMichelId module when using SONIC!

Break down of SONIC time

- We studied two batch sizes
  - Batch size 235, number of batches per event = 235
  - Batch size 1693, number of batches per event = 32
  - Big batch is preferred as it increases the inference speed and reduces latency.

- The total ML processing time using SONIC is ~12 s/event
  = 7s (ML model preprocessing on CPU)
  + 1.9s (Bandwidth latency @ 2Gbps)
  + 0.4s (Travel latency to GCP in Iowa)
  + 2.7s (GPU inference time)

Data and Time scaling model



- Processing time is a constant up to 190 (270) processes for small (big) batch size.
- Optimal ratio of CPU processes to a single GPU is **68:1**.
  - Ratio determined by the CPU time for non-ML module and the SONIC time for ML module.

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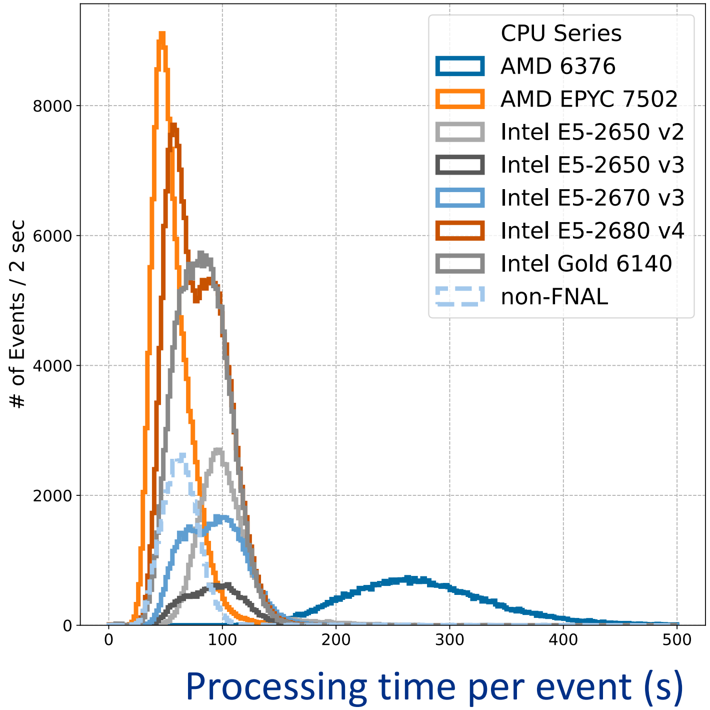
Large-scale ProtoDUNE processing

- In 2022, 7.2 M ProtoDUNE real data events were reprocessed with an improved EmTrkMichelId model
  - 6.4 M events processed through the SONIC infrastructure (GPU as a service).
  - 800 k events processed with CPU-only for comparison.
  - The workflow only consists of one ML algorithm.
  - A good demonstration of scalability of the GPUaaS method.
  - Cloud credits for this study were provided by Internet2 managed Exploring Cloud to accelerate Science (NSF grant PHY-190444).

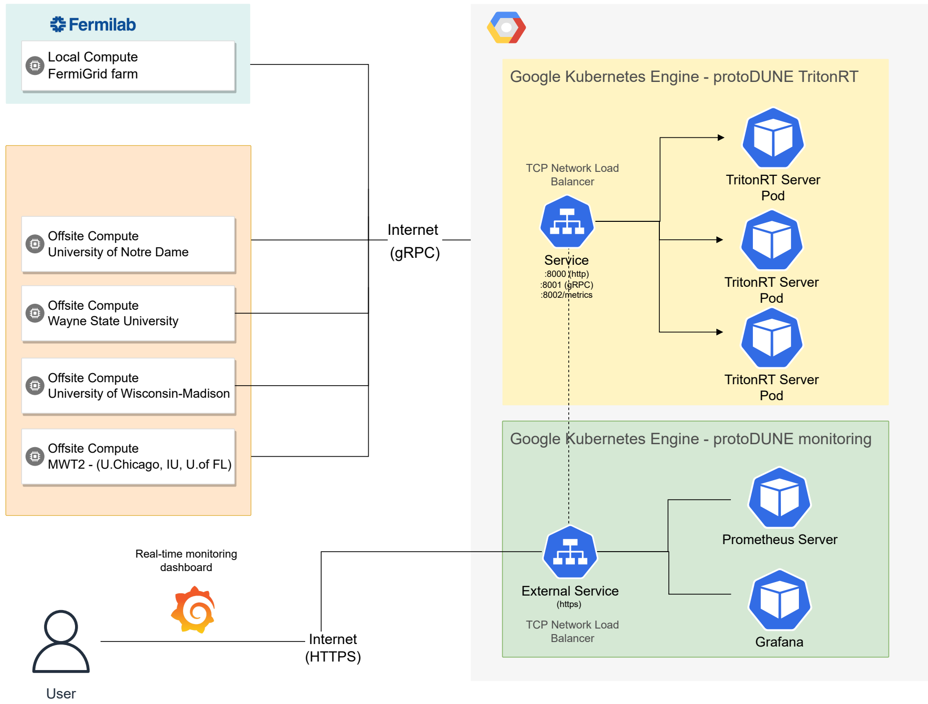
CPU-only results



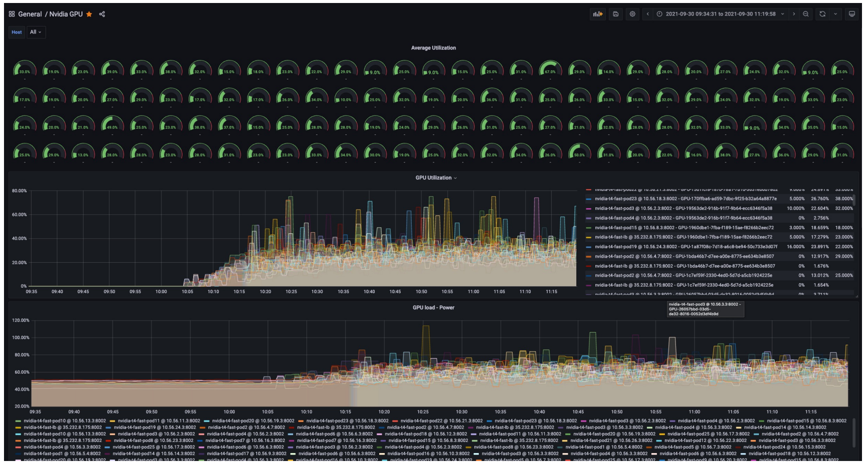
- Processing time per event for CPU-only jobs.
- Compared with the 2021 study:
  - Same types of CPUs were used.
  - Tensorflow version in LArSoft (C++) changed from 1.12.0 to 2.3.1

- Oldest CPUs (AMD 6376) still take a long time to process an event (~250 s/event, comparable to the 2021 study).
- News CPUs are much faster
  - Newer version of Tensorflow takes advantage of the instruction set

GPUaaS setup

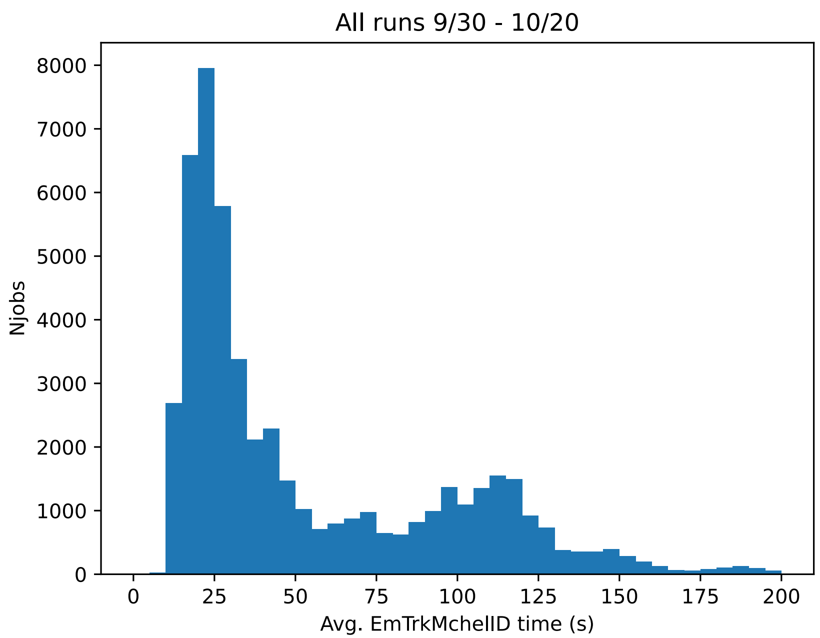


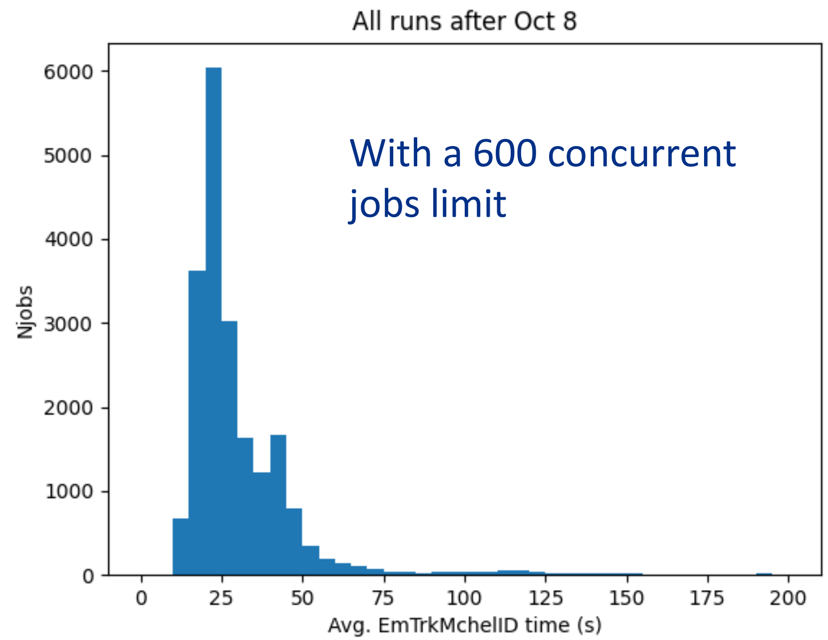
A real-time monitoring view of a 100-GPU cluster run



- Used a 100-GPU cluster running Nvidia Triton Inference Server.
- One significant improvement: the deployment of metrics and monitoring through Triton's built-in metrics endpoint.

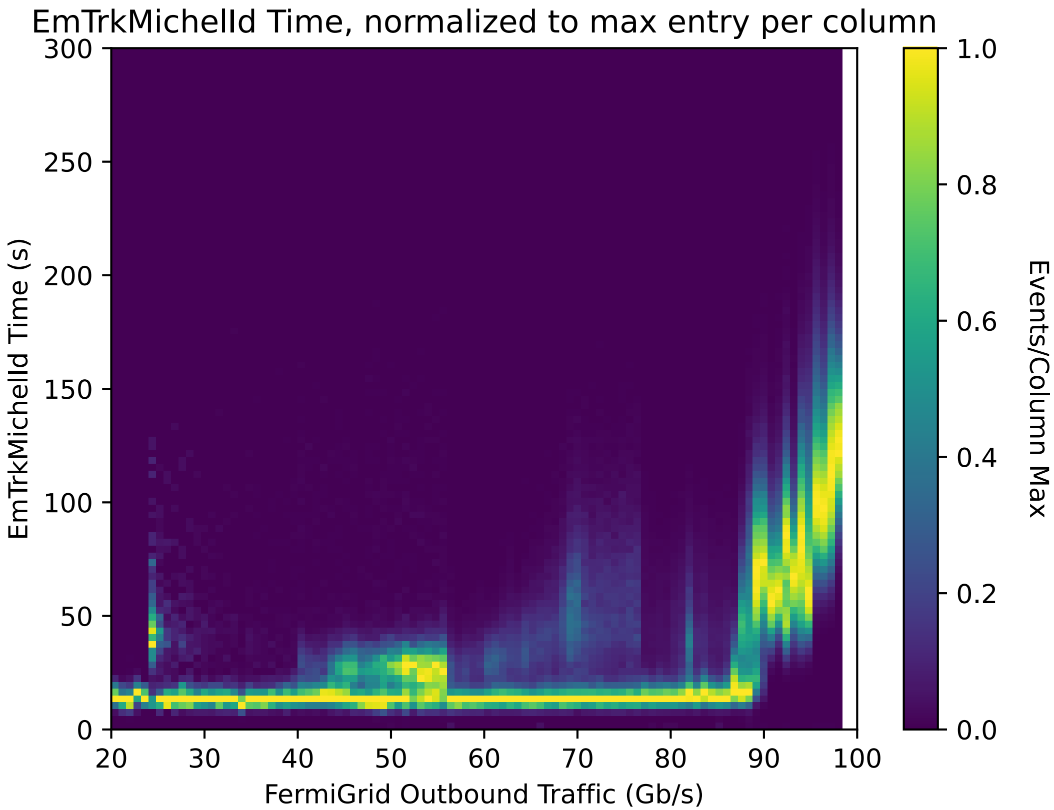
SONIC (GPUaaS) results





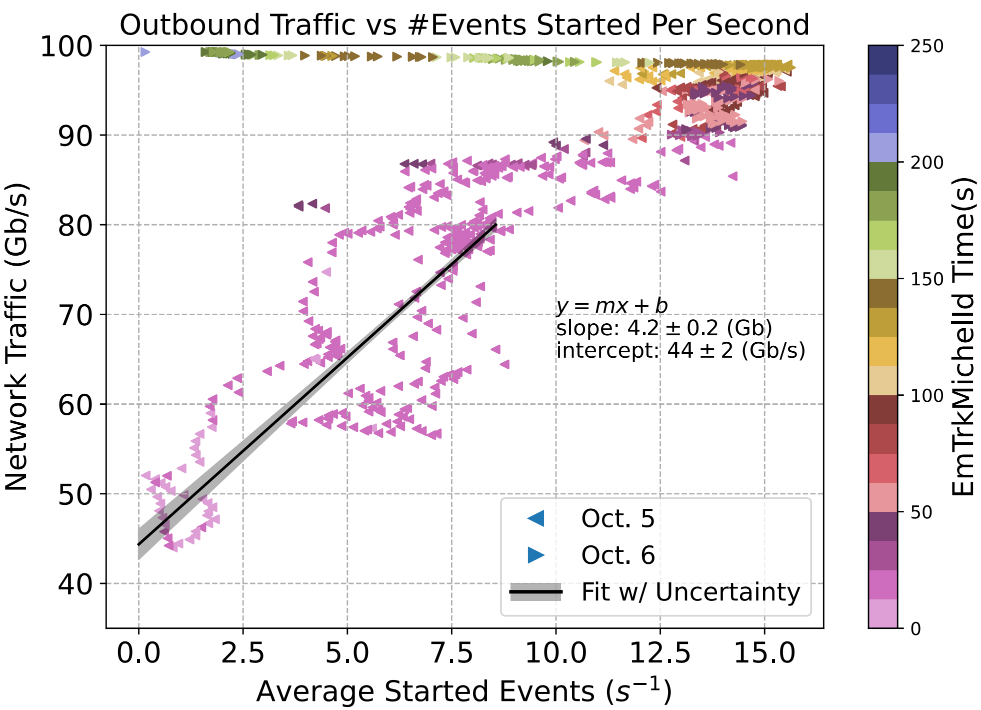
- Observed a double-peak structure.
- The first peak shows a much shorter processing time compared with CPU-only runs. But there is a second peak and a long tail.
- We saw evidence of network saturation. Since Oct 8, 2022, we imposed a 600 concurrent jobs limit, and we only saw the first peak since then.

Network saturation



- Fermigrid has a 100 Gb/s switch for outbound traffic.
- Processing time increases as the outbound traffic approaches 100 Gb/s.

Network saturation



- Average started events is a proxy for the number of concurrent jobs.
- Slope: size of data transfer per event (image size)
- Intercept: network traffic from non-ProtoDUNE jobs.

- To avoid network saturation, the maximum number of concurrent jobs should be:
  (100 Gb/s)/(4.1 Gb/event)×(25 s/event) ≈ 600

  Switch speed limit Image size GPU processing time

- This is consistent with the limit we imposed on Oct 8.

Discussions

- Despite of the network saturation in the first few days, most of the grid jobs finished successfully. The produced files are used by many physics analyses.
- Without network saturation, GPUaaS sped up the required processing time by more than a factor of two, even comparing to the fastest CPU runs.
- In a more typical workflow where we have both ML and non-ML algorithms, the outbound traffic is reduced, which allows for more concurrent jobs.
- Possible improvements:
  – Compress images before sending them to the inference server.
  – Take advantage of local GPUs if they are available on the worker nodes.

Conclusions

- SONIC accelerates ML inference for ProtoDUNE reconstruction
  - 18x speed up of the ML module
  - 2.7x speed up of full ProtoDUNE workflow
- Acceleration needs: 1 T4 GPU per ~68 CPU processes
- In the special case where one only runs ML algorithms, the network bandwidth could be a bottleneck to the maximum allowed concurrent jobs.

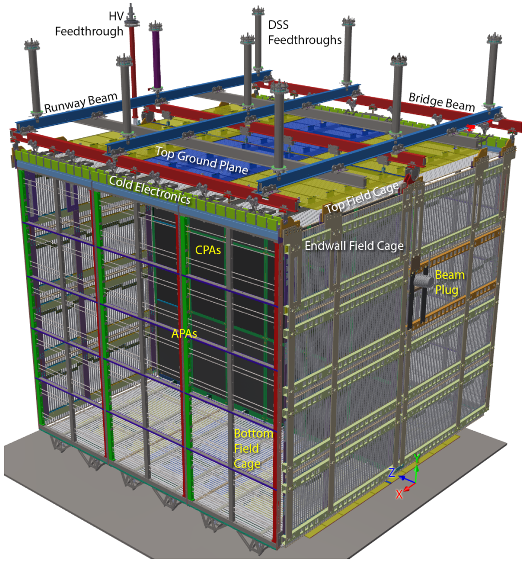
Thank you for your attention!

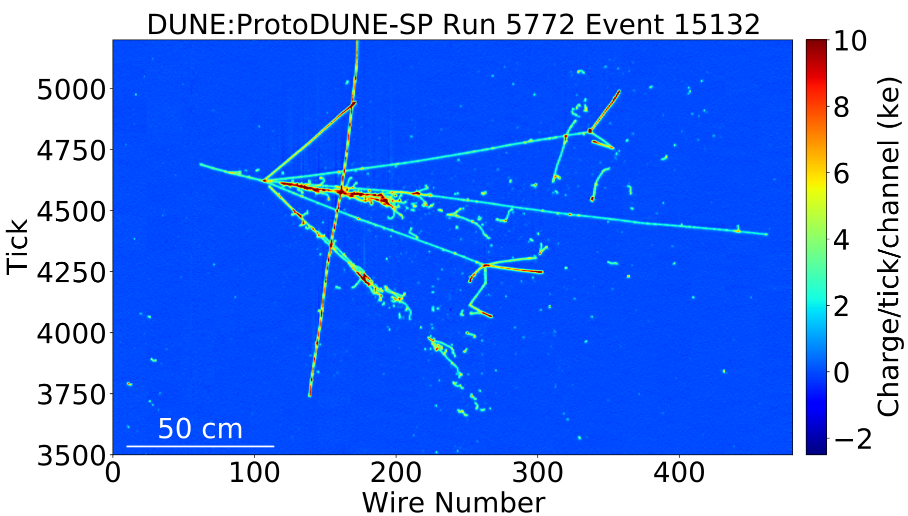
GPUaaS for CMS

- The CMS triton client is now officially integrated: SonicTriton
- Inference server “ailab01.fnal.gov” located at Fermilab FCC2:
  - server class machine (2 x 10-core Cascade Lake Xeon Silver CPUs)
  - running Nvidia Triton inference server (r19.10)
  - “Turing” architecture Tesla T4 GPU (2,560 CUDA + 320 Tensor cores, 16GB GDDR6) and FPGA-based accelerators
  - T4 is a lower power (and cost) GPU for inference. More powerful GPUs (e.g. V100) are available.
- arXiv:2007.10359: **GPU coprocessors as a service for deep learning inference in high energy physics**
- We have recently started applying GPUaaS to the LArTPC reconstruction using ProtoDUNE as an example.

Layer	Output Shape	# Parameters	
Conv2D	44 x 44 x 48	1248	5*5*48+48, 5x5 kernel, stride=1 ReLU activation
Dropout-1	44 x 44 x 48	0	
Flatten	92928	0	
Dense-1	128	1189491	92928*128+128
Dropout-2	128	0	
Dense-2	32	4128	128*32+32
Output “emtrk_none_out”	3	99	32*3+3 softmax activation
Output “michel_out”	1	33	32*1+1 sigmoid activation
Total Number of Parameters		11,900,420	

ProtoDUNE event reconstruction





A 6 GeV/c π^+

- Largest LArTPC ever built
  - 7.2 x 6.0 x 6.9 m^3
  - 15,360 channels
  - Wire spacing 5 mm
  - Readout window 3 ms
- Lots of activities in the TPC
  - Cosmic ray muons
  - Beam particles
- Reconstruction chain
  - Noise mitigation and deconvolution
  - Hit finder
  - Pandora pattern recognition
  - CNN EmTrkMichelId

GPUaaS for LArSoft

- The Triton client is now fully integrated in LArSoft
  - LArSoft: a common framework for LArTPC simulation and reconstruction, used by many experiments (MicroBooNE, SBN, DUNE/ProtoDUNE, etc.) – larsoft.org
  - TrtIS (Triton Inference Server) client libraries are available as a UPS product (trtis_clients)

```
mwts{mwang}1002% setup trtis_clients v19_11a -q e19:prof
mwts{mwang}1003% ups active
Active ups products:
gcc                  v8_2_0          -f Linux64bit+3.10-2.17                    -z /products
opencv               v4_2_0          -f Linux64bit+3.10-2.17 -q e19:p372        -z /products
protobuf             v3_11_2a        -f Linux64bit+3.10-2.17 -q e19             -z /products
python               v3_7_2          -f Linux64bit+3.10-2.17                    -z /products
sqlite               v3_26_00_00     -f Linux64bit+3.10-2.17                    -z /products
trtis_clients        v19_11a         -f Linux64bit+3.10-2.17 -q e19:prof        -z /products
ups                  v6_0_8          -f Linux64bit+3.10-2.17                    -z /products
```

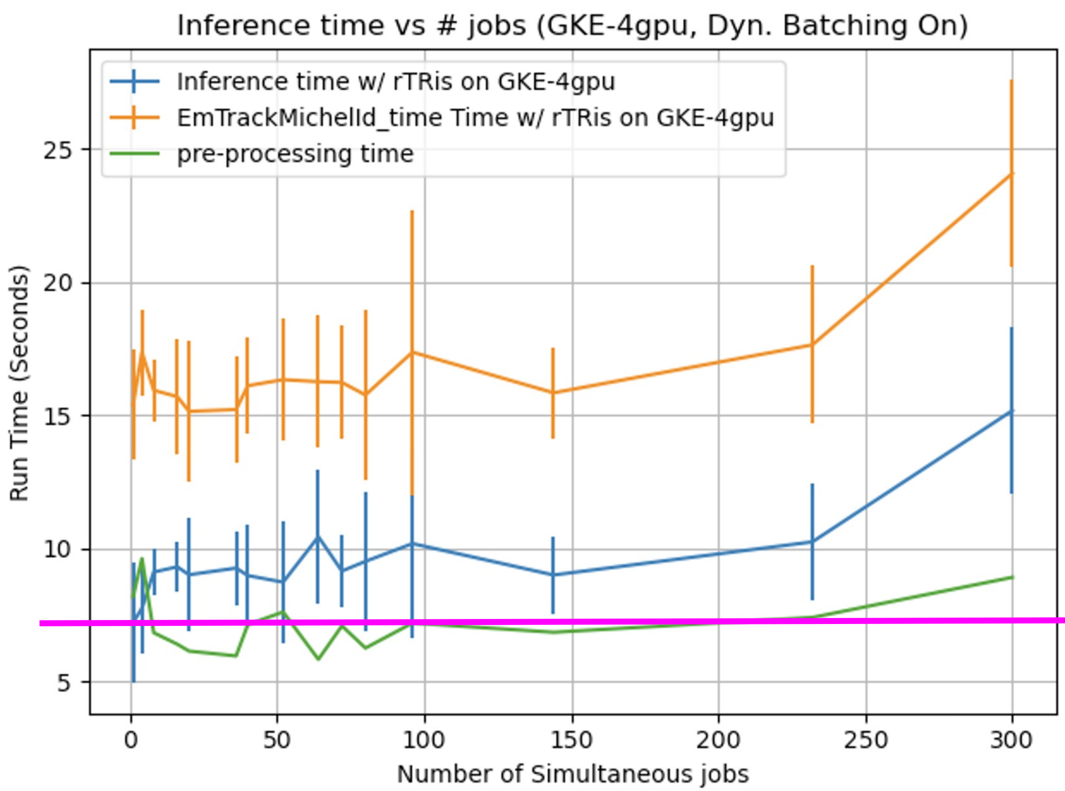
  - EmTrkMichelId is modified to include a new Tritis inference client Model Interface.
    - [PointIdAlgTrtis_tool.cc]()

Different configurations being studied

- Small batch vs large batch
  - Batch size 235, number of batches = 235
  - Batch size 1693, number of batches = 32
  - Small batches means more gRPC calls and longer latency
- Dynamic batching on the Triton server
  - Accumulate requests from multiple events, then process together
  - Massive gain in efficiency and throughput
  - Simple configuration: (docs)

```
dynamic_batching {
    preferred_batch_size: [ 4, 8 ]
    max_queue_delay_microseconds: 100}
```

Preprocessing time



Small batch

Preprocessing time should be constant and is around 7 seconds per event

- Preprocessing time: 7 s per event
  - Retrieve hit information, prepare patches, etc.

Communication latency

```
<des91.fnal.gov> ping 35.202.61.4
PING 35.202.61.4 (35.202.61.4) 56(84) bytes of data.
64 bytes from 35.202.61.4: icmp_seq=1 ttl=107 time=11.7 ms
64 bytes from 35.202.61.4: icmp_seq=2 ttl=107 time=11.7 ms
64 bytes from 35.202.61.4: icmp_seq=3 ttl=107 time=11.7 ms
64 bytes from 35.202.61.4: icmp_seq=4 ttl=107 time=11.7 ms
64 bytes from 35.202.61.4: icmp_seq=5 ttl=107 time=11.9 ms
```

Ping time is ~12ms.
Tests are run with large (~1693) and small batch size (~235)

For ~55k inferences per event this means:
~32 gRPC calls per event for large batch size
~235 gRPC calls per event for small batch size

Travel time (ΔT_{travel}) = 0.4 s for large batch and 2.6 s for small batch

Time on server vs. time on GPU

```
Concurrency: 20, 15933 infer/sec, latency 2476755 usec
Time elapsed
112

Concurrency: 20, 25333 infer/sec, latency 1538820 usec
Time elapsed
233

Inferences/Second vs. Client Average Batch Latency
Concurrency: 20, 17133 infer/sec, latency 2352441 usec
Time elapsed
123

Inferences/Second vs. Client Average Batch Latency
Concurrency: 20, 26666 infer/sec, latency 1491572 usec
Time elapsed
234
```

Perf Client tests show about ~20k inf/s +/- 2k (with larger errors)
For 55k inference per event, we expect time on GPU to be between **2.7+/-0.3s per event**

Total time = 12s
$\Delta T_{preproc}$ ~ 7s
ΔT_{SONIC} ~ 5s

Indicates that there is additional non-trivial latency between when the request arrives at the server (ping) and the time it spends on the GPU:

$\Delta T_{on\ GPU\ server}$ ~ 5.1s

ΔT_{travel} ~ 0.4s (large batch)
$\Delta T_{on\ GPU}$ ~ 2.7s

$\Delta T_{bandwidth}$ ~ 2s
One event:
48x48 image x 32b x 55,000 inferences = 3.9 Gigabits

Bandwidth = 2 Gbps
Bandwidth latency = 2s per event

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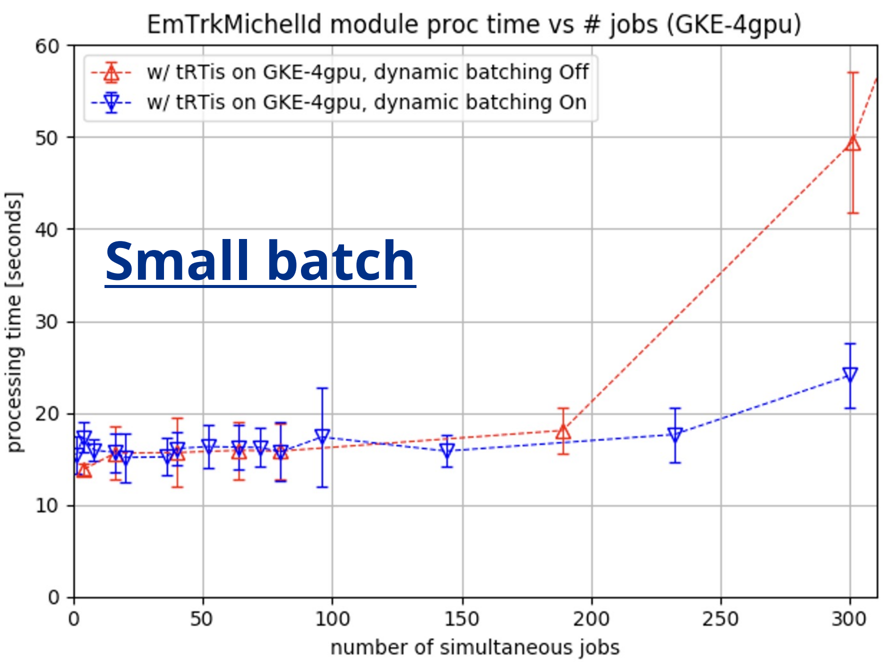
Processing time scaling

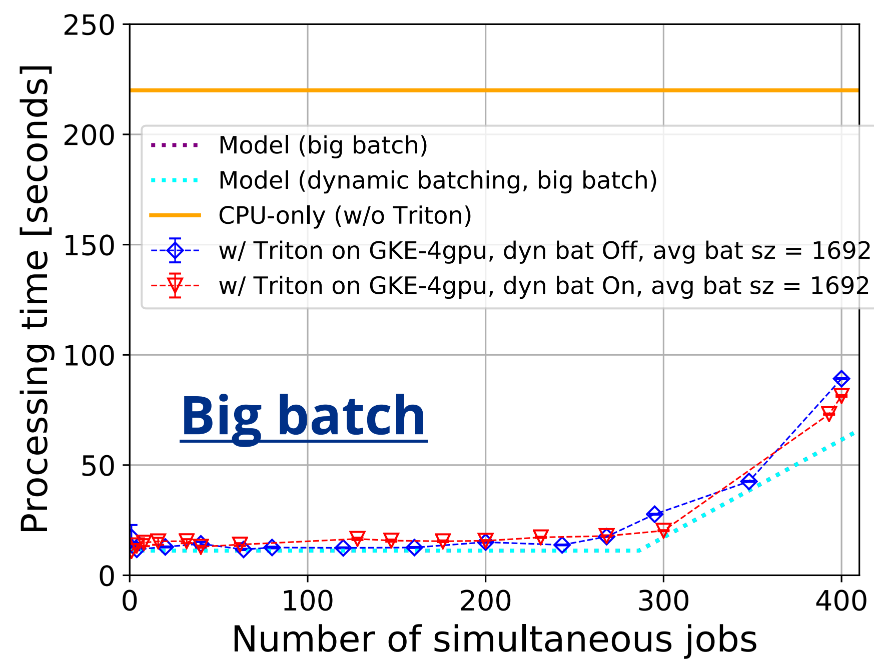
$$t_{\text{CPU}} = (1 - p) \times t_{\text{CPU}} + p \times t_{\text{CPU}}$$
$$t_{\text{ideal}} = (1 - p) \times t_{\text{CPU}} + t_{\text{GPU}} + t_{\text{latency}}$$

- p = fraction of parallelizable computations
- Ideal scenario: GPU not saturated, always available
  - Assume t_{GPU} small enough & CPU requests staggered enough
  - Blocking calls, CPU waits for GPU to finish
- GPU(s) can saturate if too many request sent: $\frac{N_{CPU}}{N_{GPU}} > \frac{t_{ideal}}{t_{GPU}}$
  → CPUs have to wait (effective t_{GPU} increases)

$$t_{SONIC} = (1-p)\times t_{CPU} + t_{GPU}\left[1 + max\left(0, \frac{N_{CPU}}{N_{GPU}} - \frac{t_{ideal}}{t_{GPU}}\right)\right] + t_{\text{latency}}$$

Dynamic batching





- Dynamic batching helps for small batch size but does not impact the case of big batch size
  - Does not seem to add any appreciable latency (or at least small on our time scales)

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