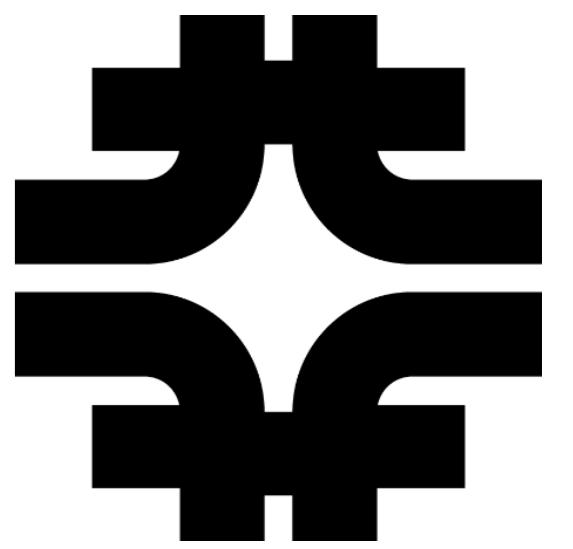


Deployment of inference as a service at the US CMS Tier-2 data centers

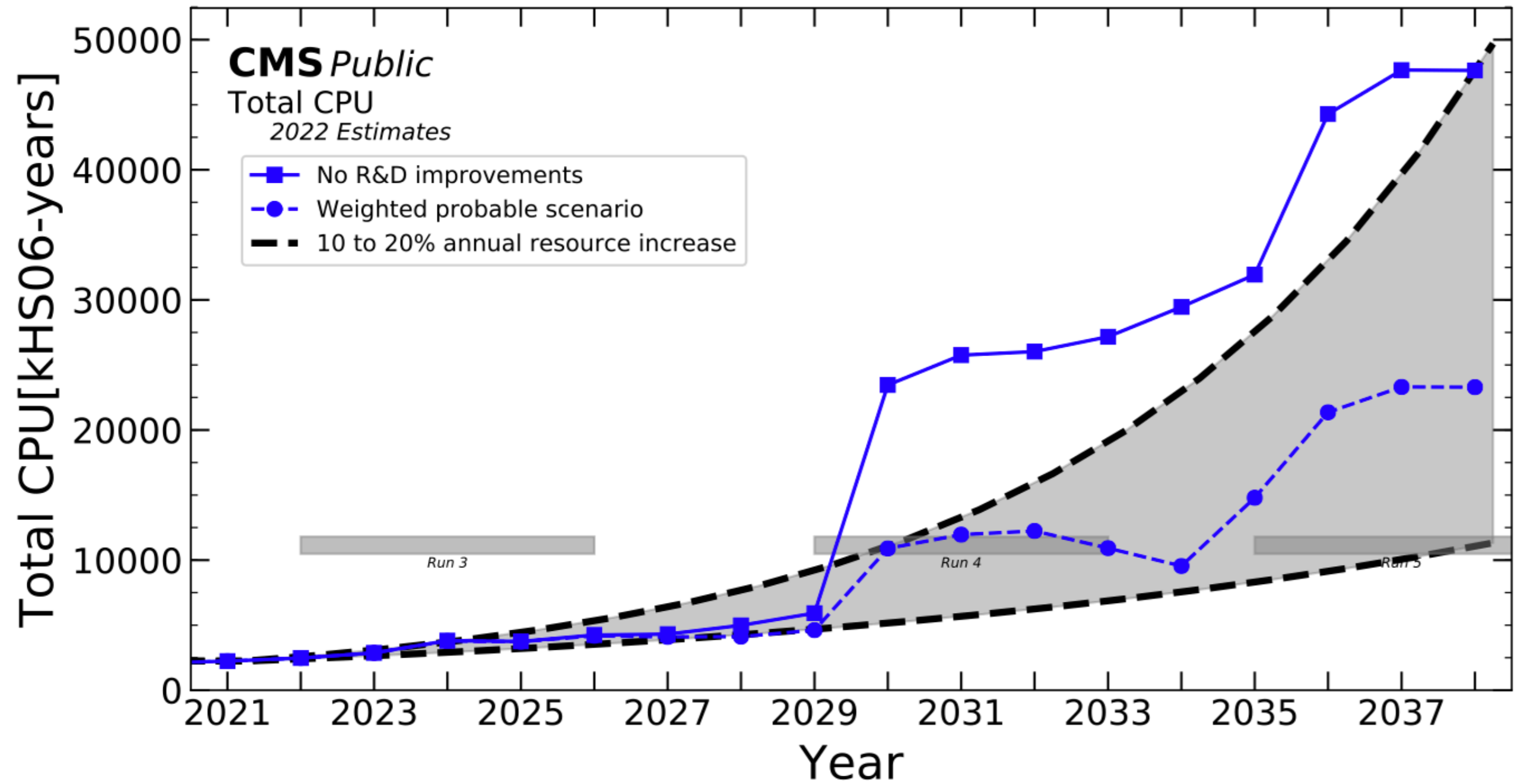


Burt Holzman, **Kevin Pedro**, Nhan Tran (FNAL); Philip Coleman Harris, Noah Paladino (MIT); Ethan Colbert, Dmitry Kondratyev, Miaoyuan Liu, Garyfallia Paspalaki, Stefan Piperov, Jan-Frederik Schulte, Yao Yao (Purdue); Javier Duarte (UCSD); Philip Chang, Kelci Ann Mohrman (UF); Yongbin Feng (TTU)
on behalf of the CMS Collaboration



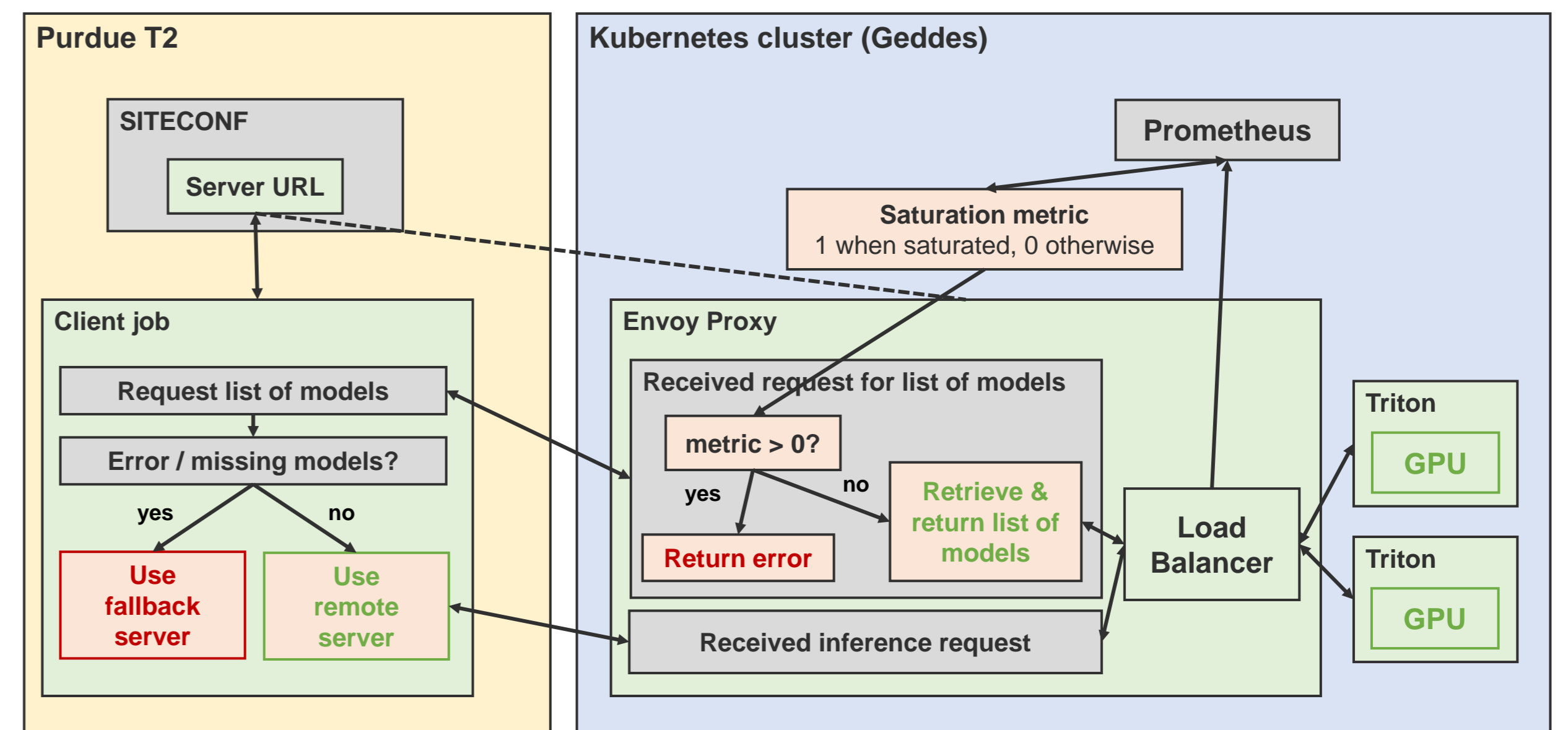
Computing Demands

- Large computing demands for HL-LHC, but CPU performance increases expected to be limited [1]



Architecture at Purdue T2

- Server discovery through official site configuration
- Prevent connections to saturated servers based on queue latency
- Load balancing via Envoy Proxy
- Autoscaling via KEDA (Kubernetes Event-Driven Autoscaling)
- Configuration bundled into Helm chart to deploy at other T2 sites



Coprocessors

- Recent performance improvements in coprocessors rather than CPUs
- Tradeoffs between flexibility and efficiency



- Heterogeneous computing:** make best use of each processor type

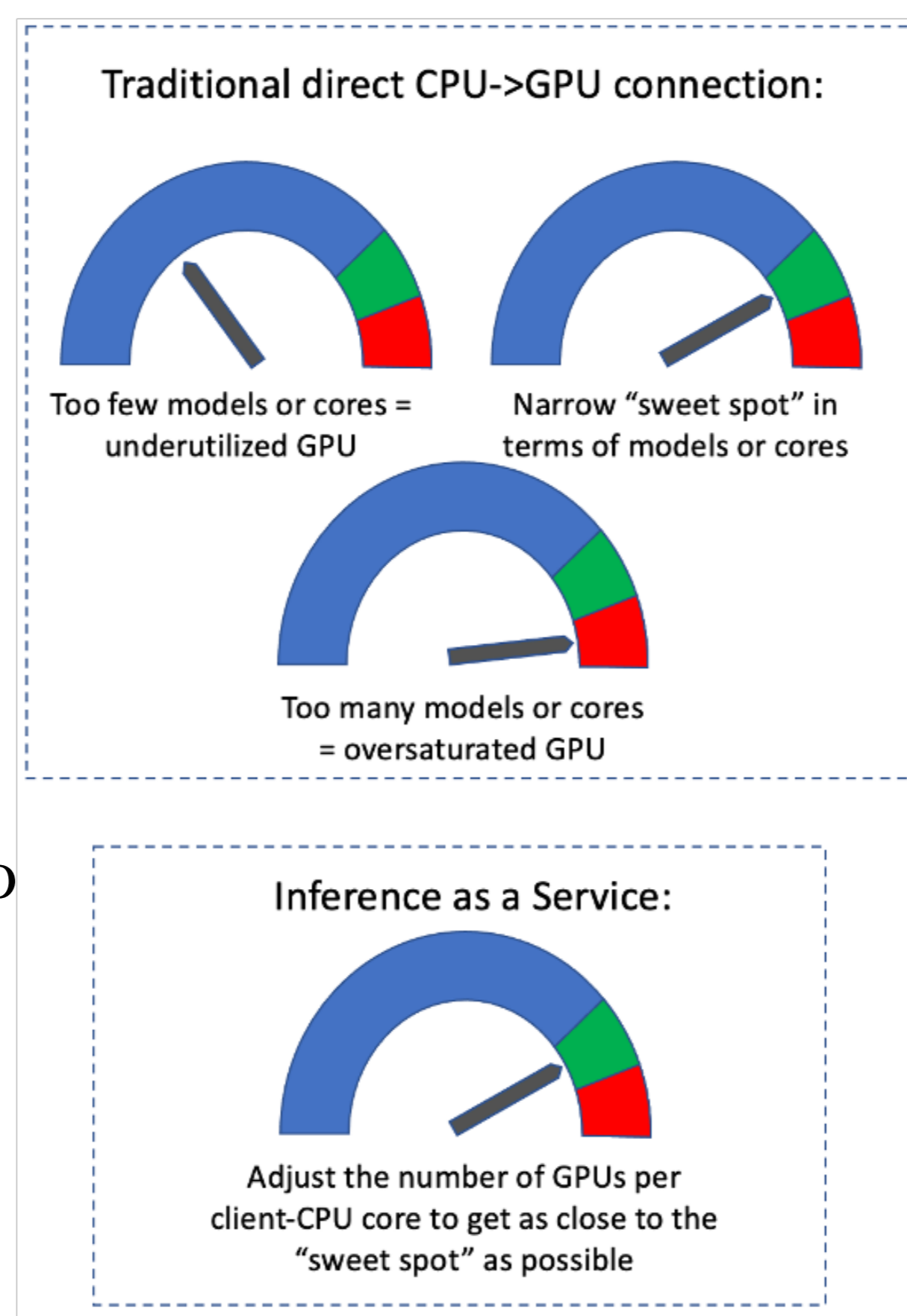
Inference as a Service

- SONIC:** Services for Optimized Network Inference on Coprocessors [2]
 - Design pattern for inference as a service in experiment software

- Build on industry technologies: gRPC, Nvidia Triton inference server

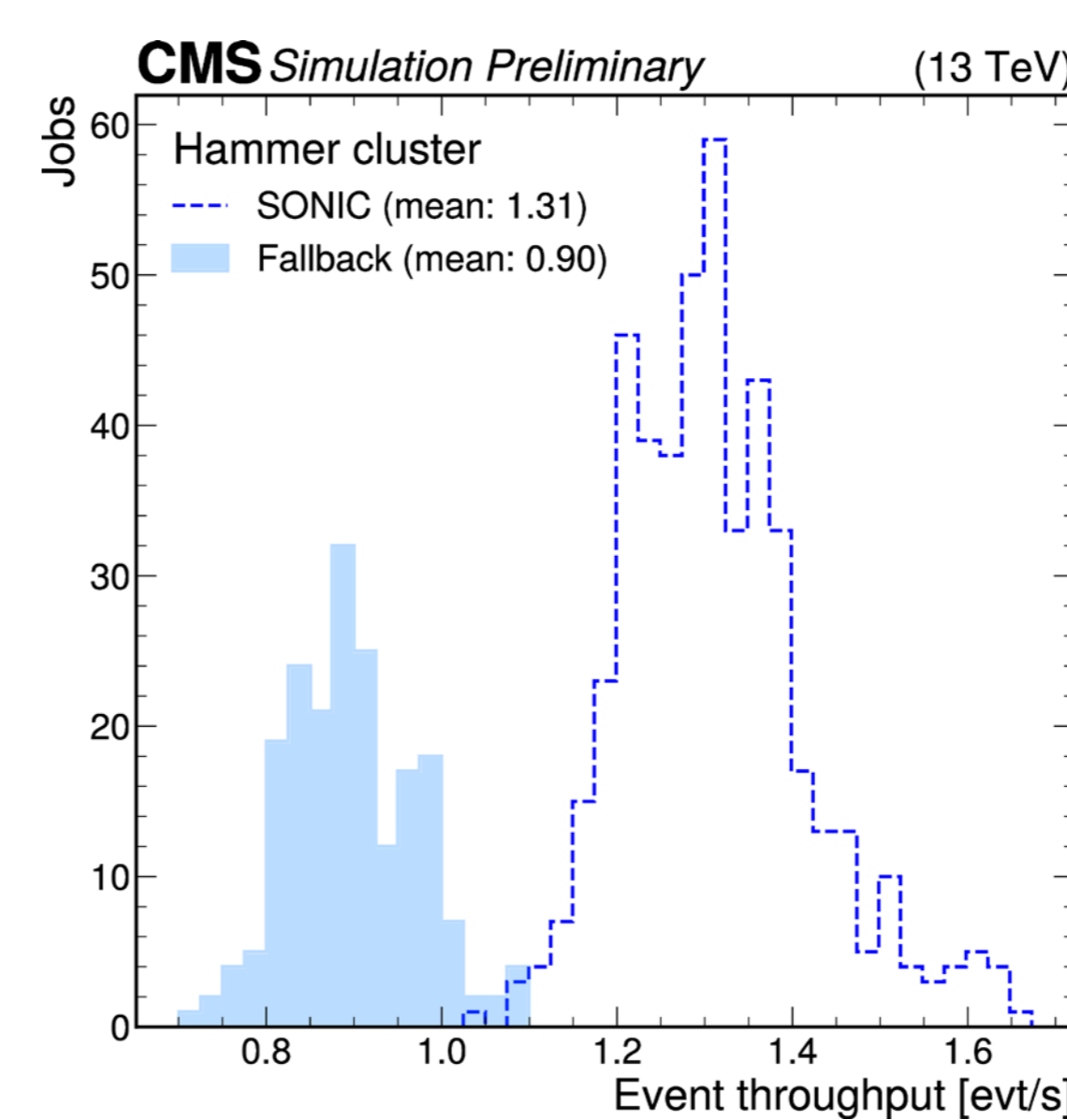
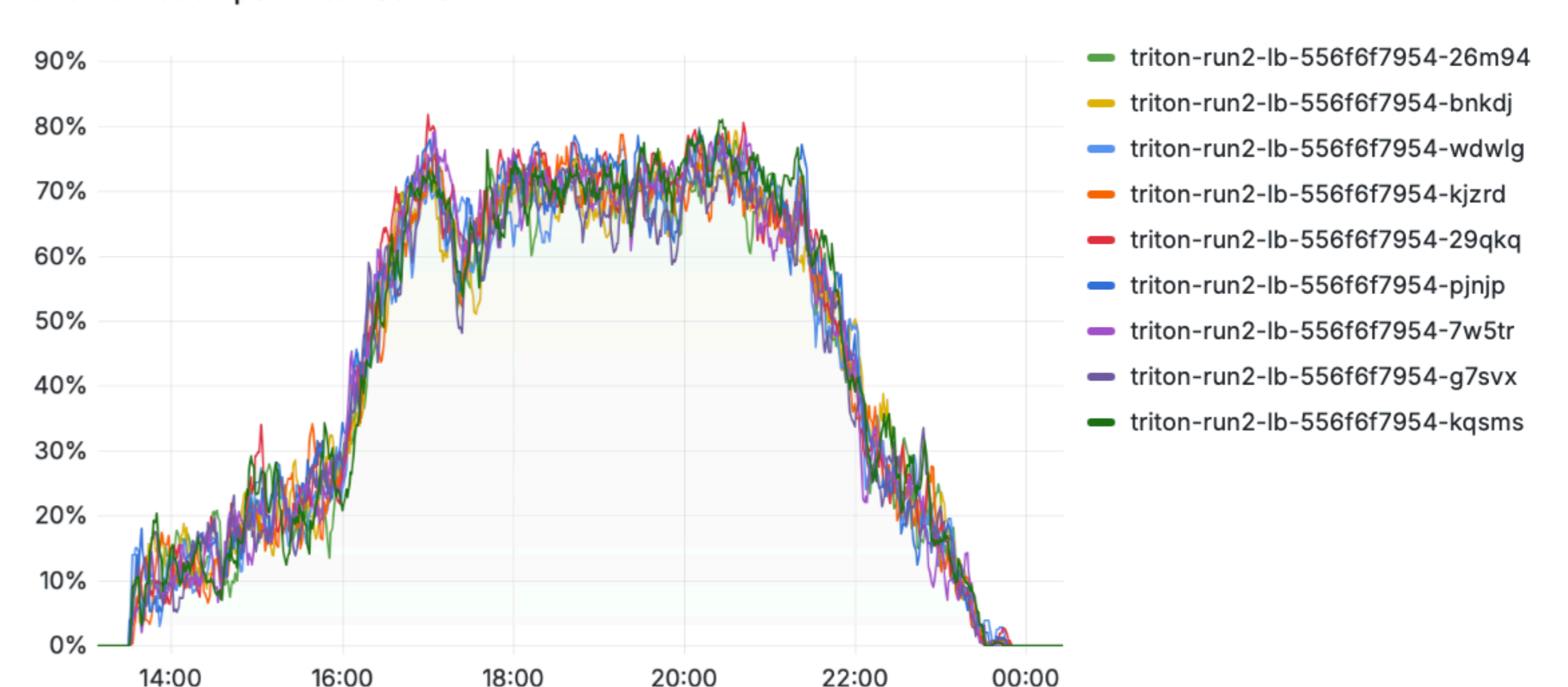
- Advantages:

- Isolation:** factorize ML frameworks out of experiment software
- Simplicity:** client code only handles input/output conversions
- Flexibility:** CPU-GPU ratios can be adjusted dynamically
- Efficiency:** optimize CPU-GPU ratios to ensure full usage (minimizes cost)
- Portability:** use CPU, GPU, FPGA, etc. with no client-side code changes
- Accessibility:** use remote coprocessors if none available locally



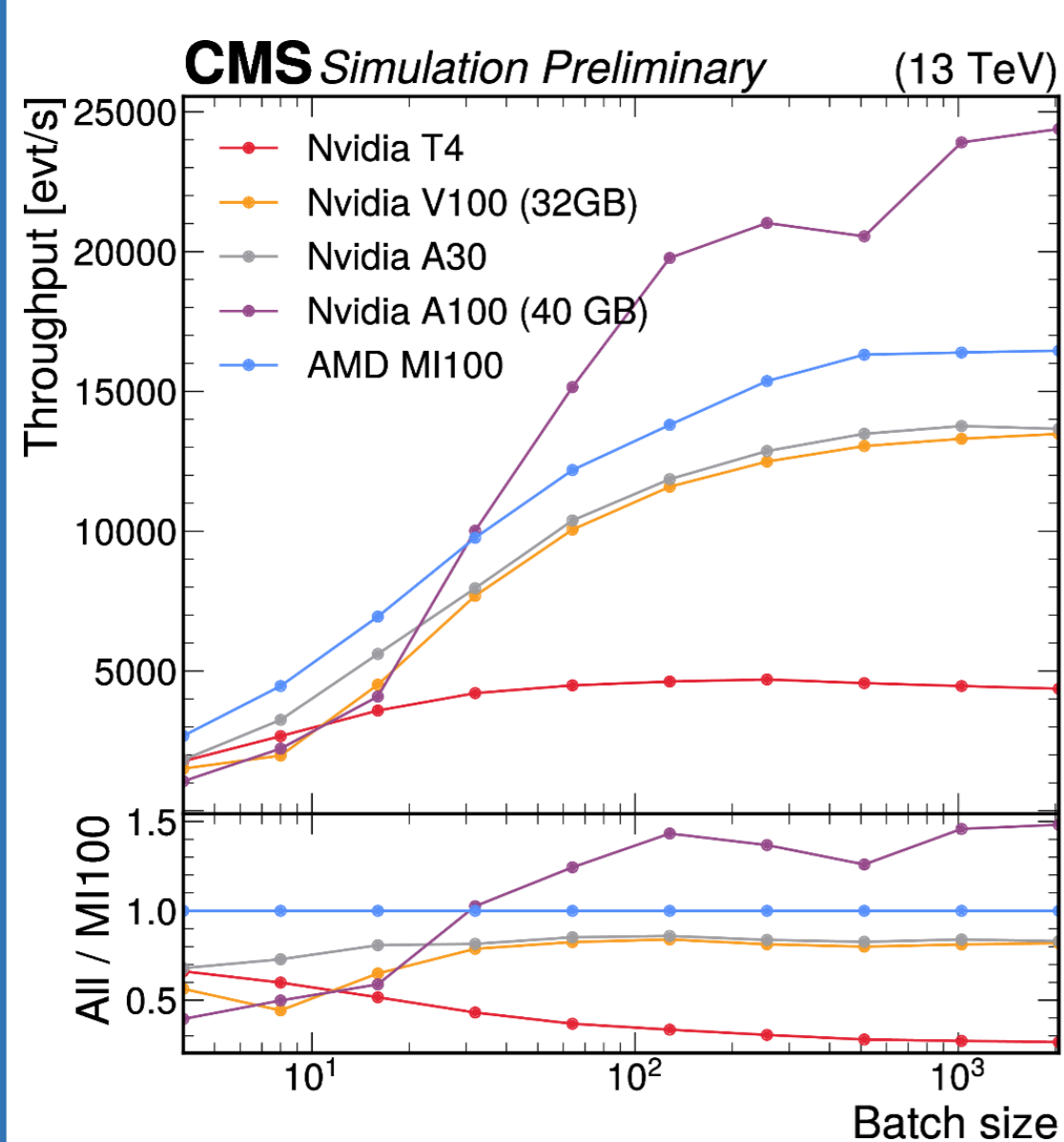
Scaling and Load Balancing

GPU utilization per Triton server



- Production-like “continuous flow” of jobs (via CRAB): 1000 jobs in batches of 50, every 10 min
- New load balancer distributes load *per request*: consistent and uniform load across GPUs for hours
- 45%** speedup in Run 2 miniAOD workflow when offloading ML inference to GPUs vs. falling back to CPU-only processing
 - Depends on CPU properties

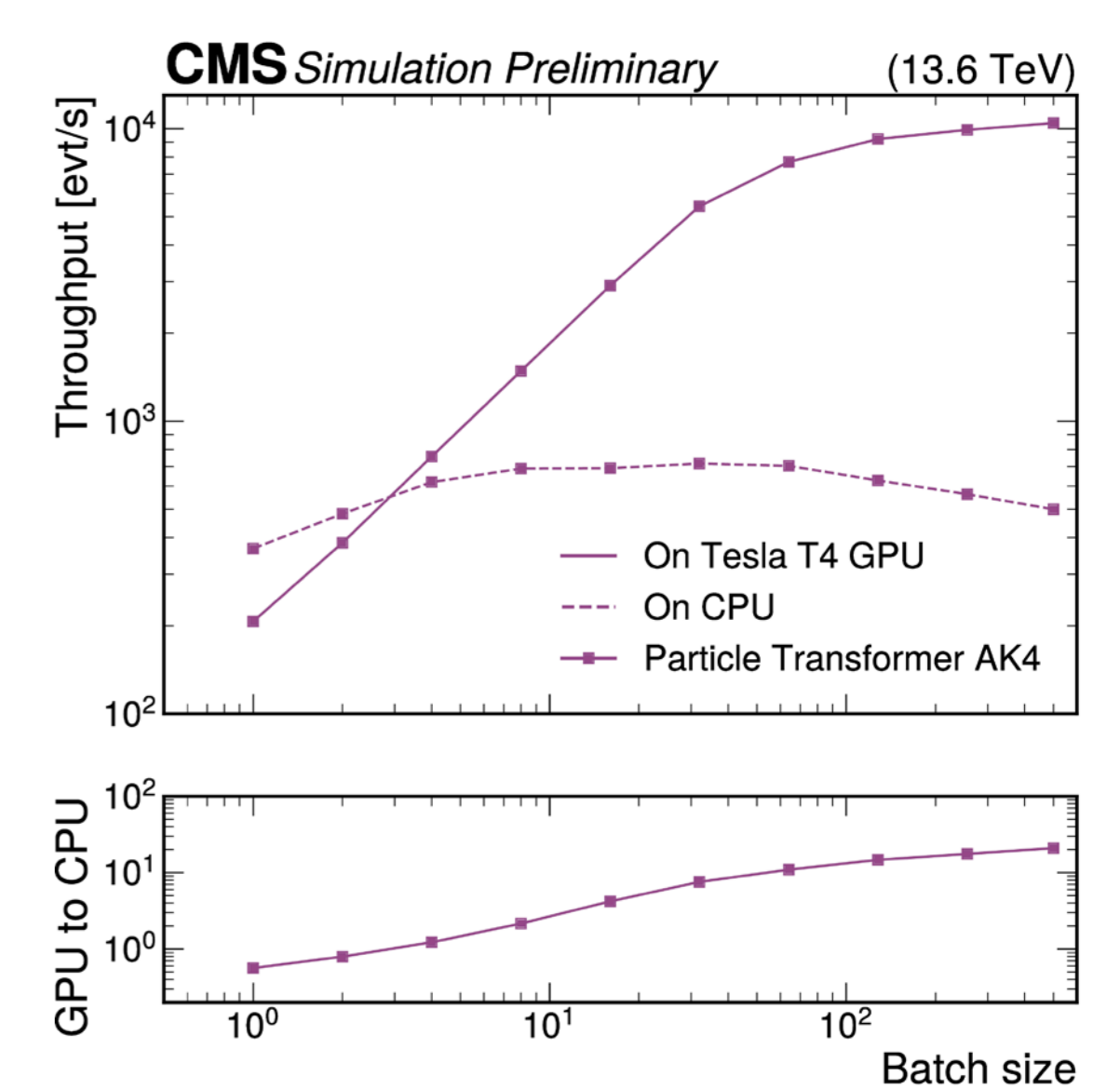
AMD GPUs



- First demonstration of non-Nvidia GPU usage, using important CMS ParticleNet [3] algorithm
- AMD MI100 has superior throughput to several existing GPU types (even A100s at smaller batch sizes)
- AMD GPUs can be accessed through the Triton server using a custom backend: dedicated instructions loaded by server via Python (or compiled into shared library)

Run 3: Transformers

- CMS Run 3 miniAOD processing now includes Particle Transformer (ParT) [4], successor to ParticleNet
- Factor 10 speedup demonstrates advantages of batching
 - Dynamic batching (combining requests from different threads/jobs) only possible via SONIC/Triton!
- Overall miniAOD workflow speedup: **33%** w/ ParT on GPU through SONIC



References

- [1] [CMS-NOTE-2022-008](#) [3] [PRD 101 \(2020\) 056019](#)
[2] [CSBS 8 \(2024\) 17](#) [4] [PMLR 162 \(2022\) 18281](#)