FPGAs as a Service to Accelerate Machine Learning Inference

LPC Topic of the Week
April 15, 2019

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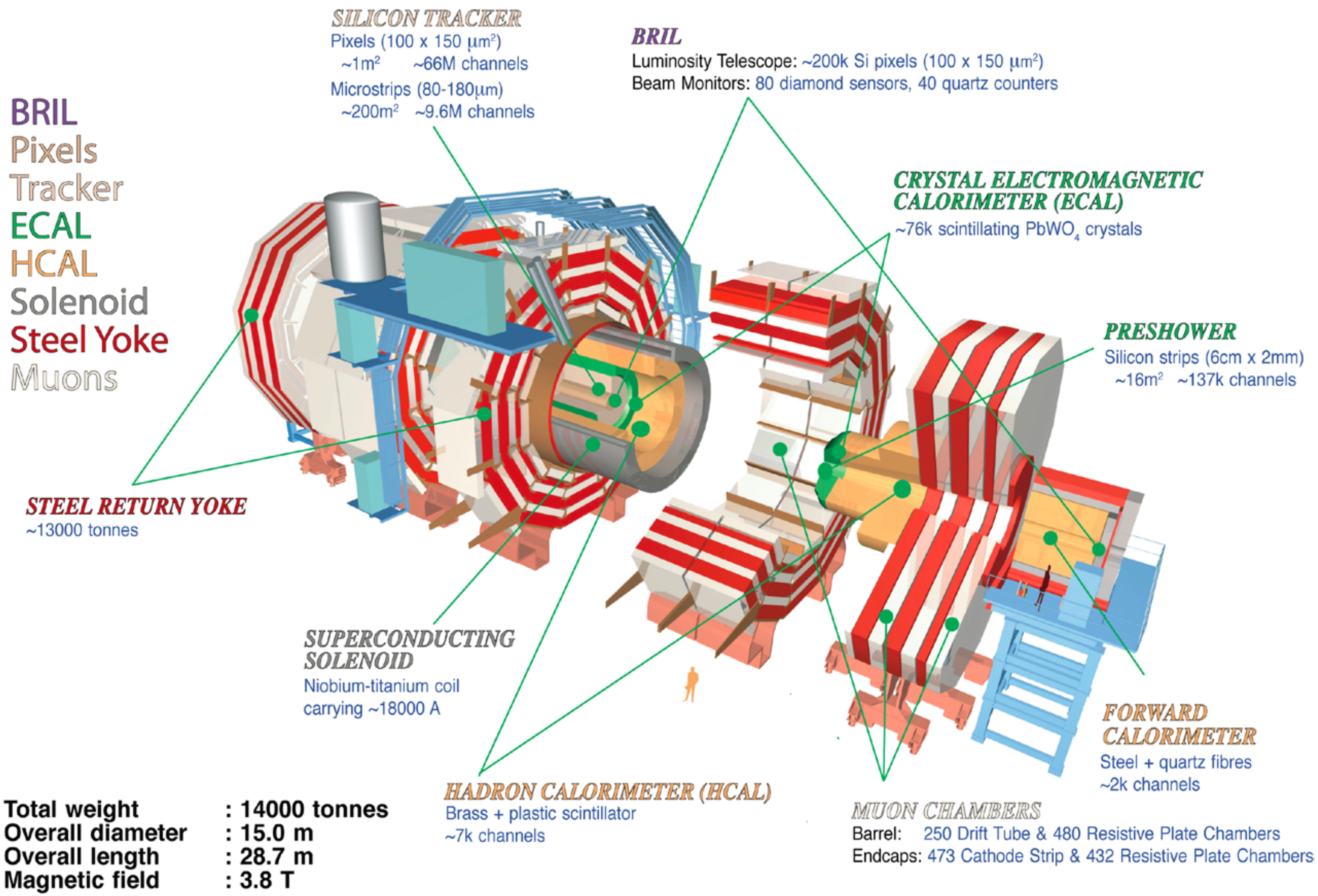
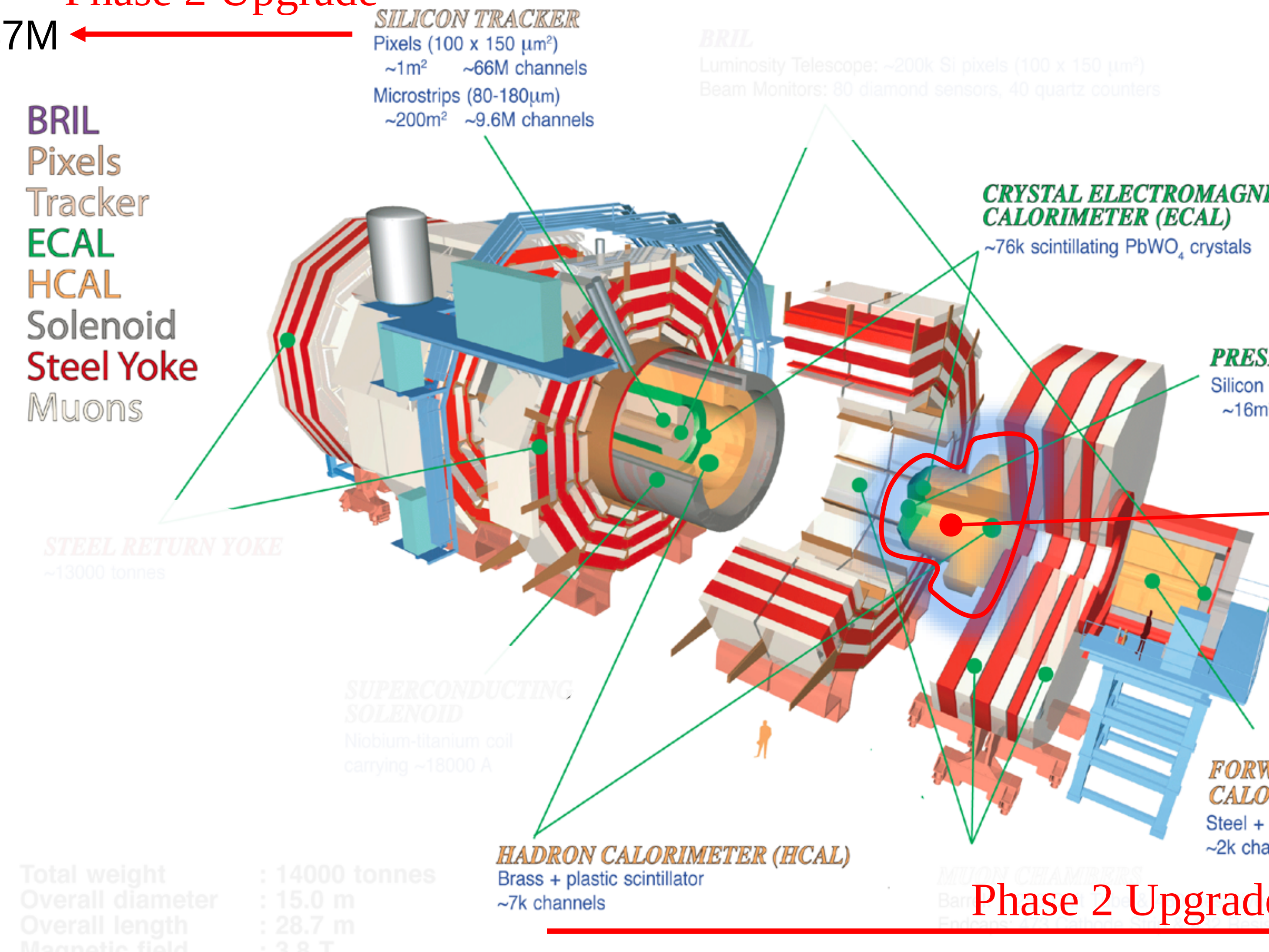
The CMS Detector: Phase 0



The CMS Detector: Phase 2

Phase 2 Upgrade

1947M



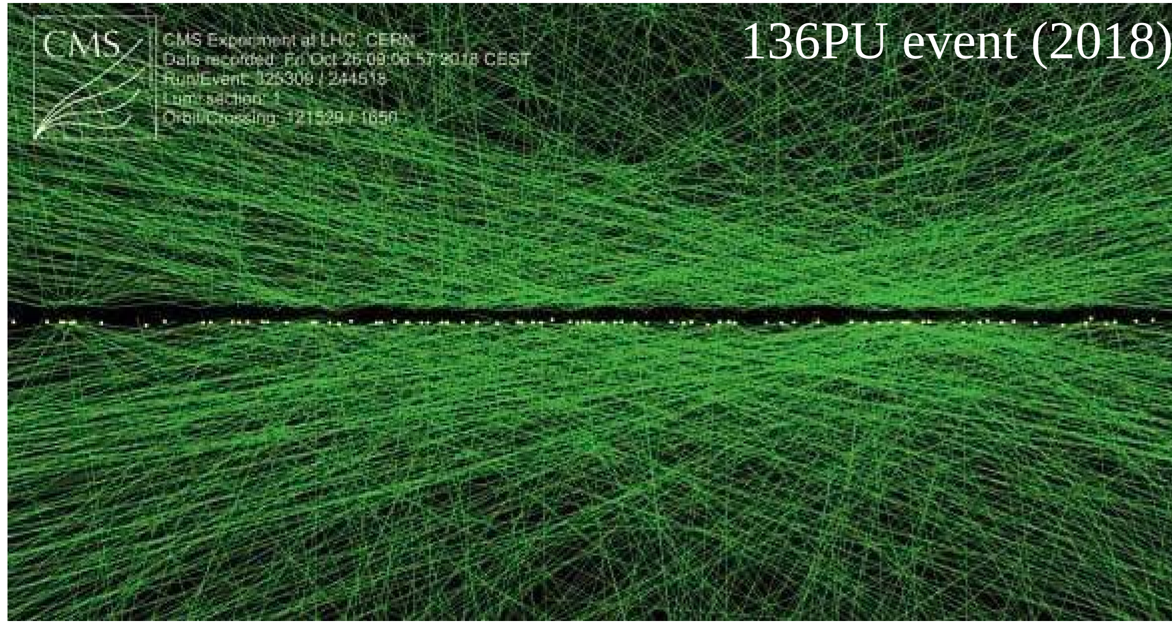
High Granularity Calorimeter (HGCal)
Silicon, scintillator
~6M channels

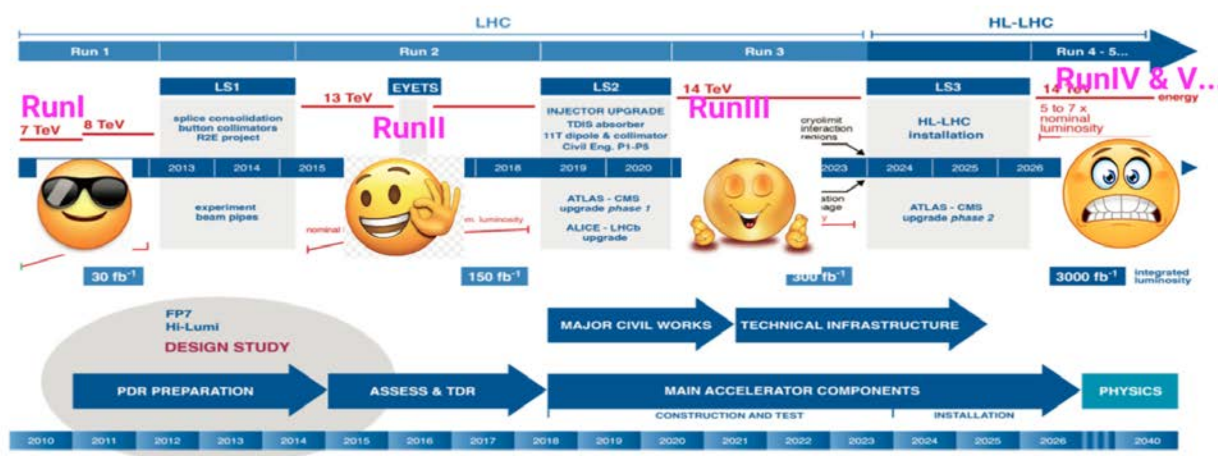
Phase 2 Upgrade

CMS Computing Challenges

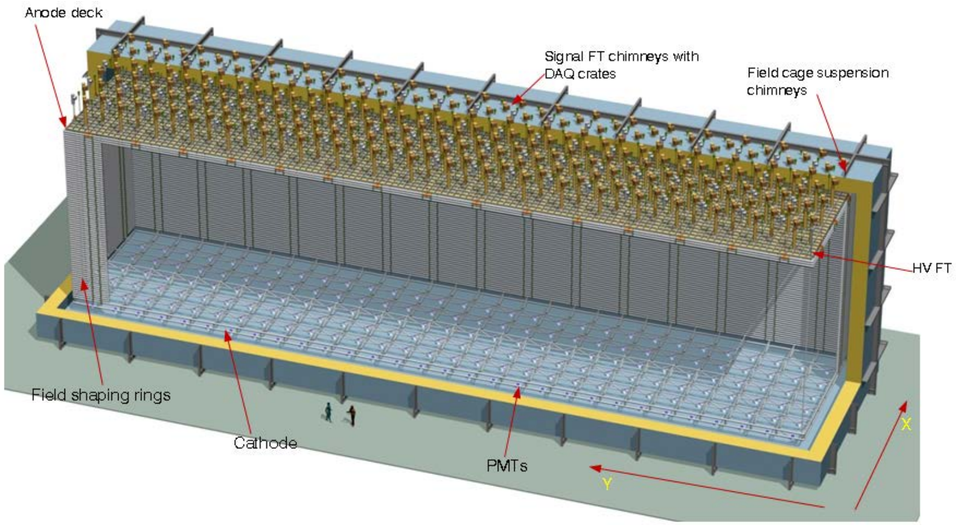
Energy frontier: HL-LHC

- 10× data vs. Run 2/3
  → exabytes
- 200PU
  (vs. ~30PU in Run 2)
- CMS:
  - 15× increase in pixel channels
  - 65× increase in calorimeter channels
  - (similar for ATLAS)



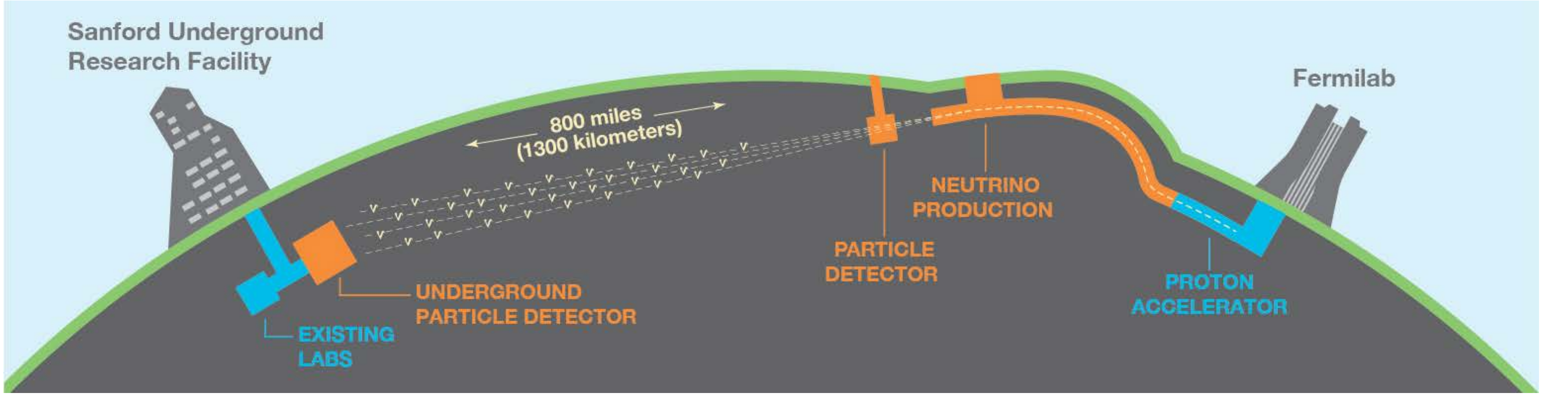


Neutrino Computing Challenges



Intensity frontier: DUNE

- Largest liquid argon detector ever designed
- ~1M channels, 1 ms integration time w/ MHz sampling
  → 30+ petabytes/year



➢ CPU needs for particle physics will increase by *more than an order of magnitude* in the next decade

How Bad Is It?

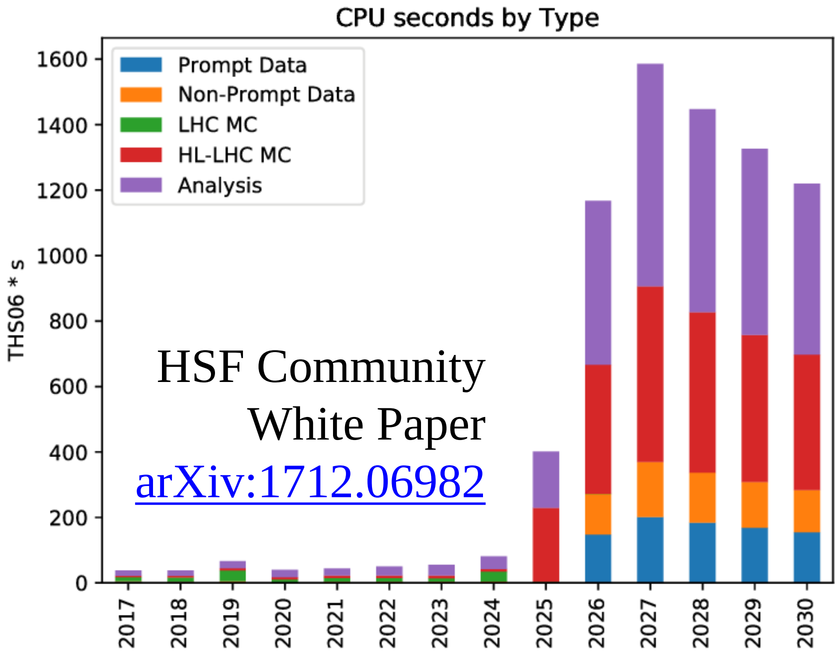
- CMS does extensive resource projections for HL-LHC
- Expected needs for 2027 (HL-LHC startup):
  - 1,400,000 CPU cores
  - 2.2 exabytes disk, 3 exabytes tape
- Usually project 20%/year “technology improvement” from Moore’s law

➢ Still a shortfall of 2–5×

- More realistic: 10%/year

➢ Shortfall of **4–10×**

- Try to *thrive*, not just survive

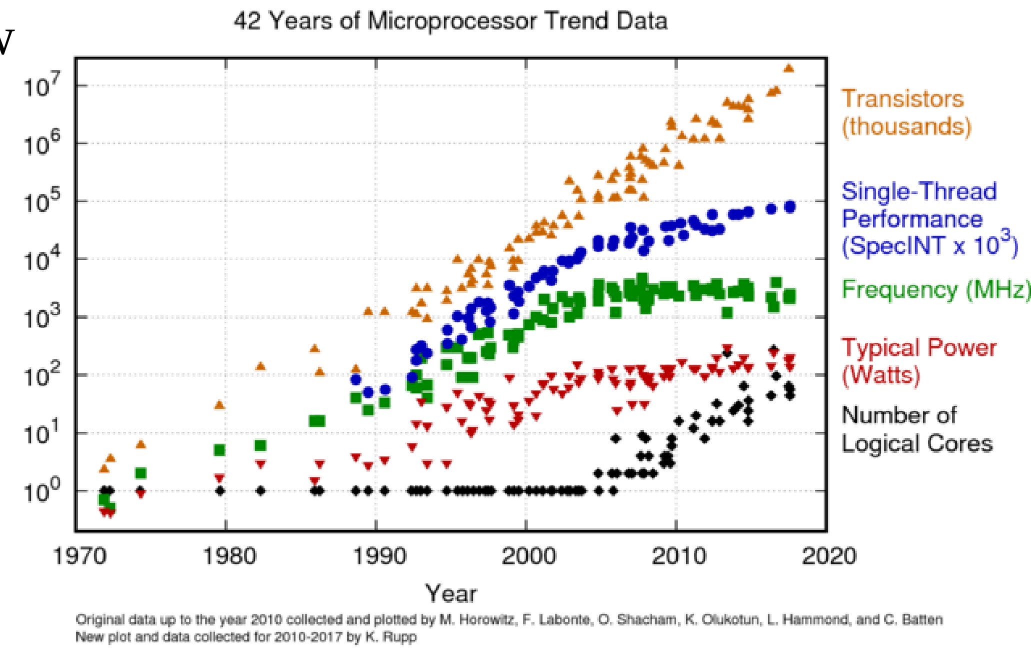


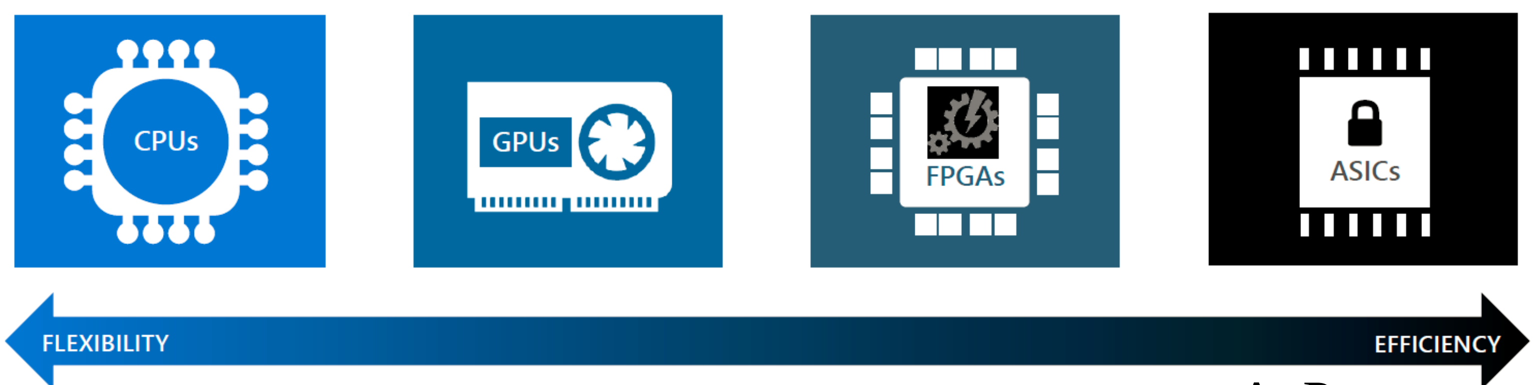
HSF Community White Paper
arXiv:1712.06982

More at CMSOfflineComputingResults

The Computing Landscape

- Transistor counts continue to grow
- Clock speed and single-thread performance have stagnated
  - ➢ *No longer expect* **traditional CPUs** to keep up with demands from particle physics
  - ➢ **Coprocessors**: *specialized hardware* attached to CPU, dedicated to *specific tasks*





A. Putnam

Development for Coprocessors

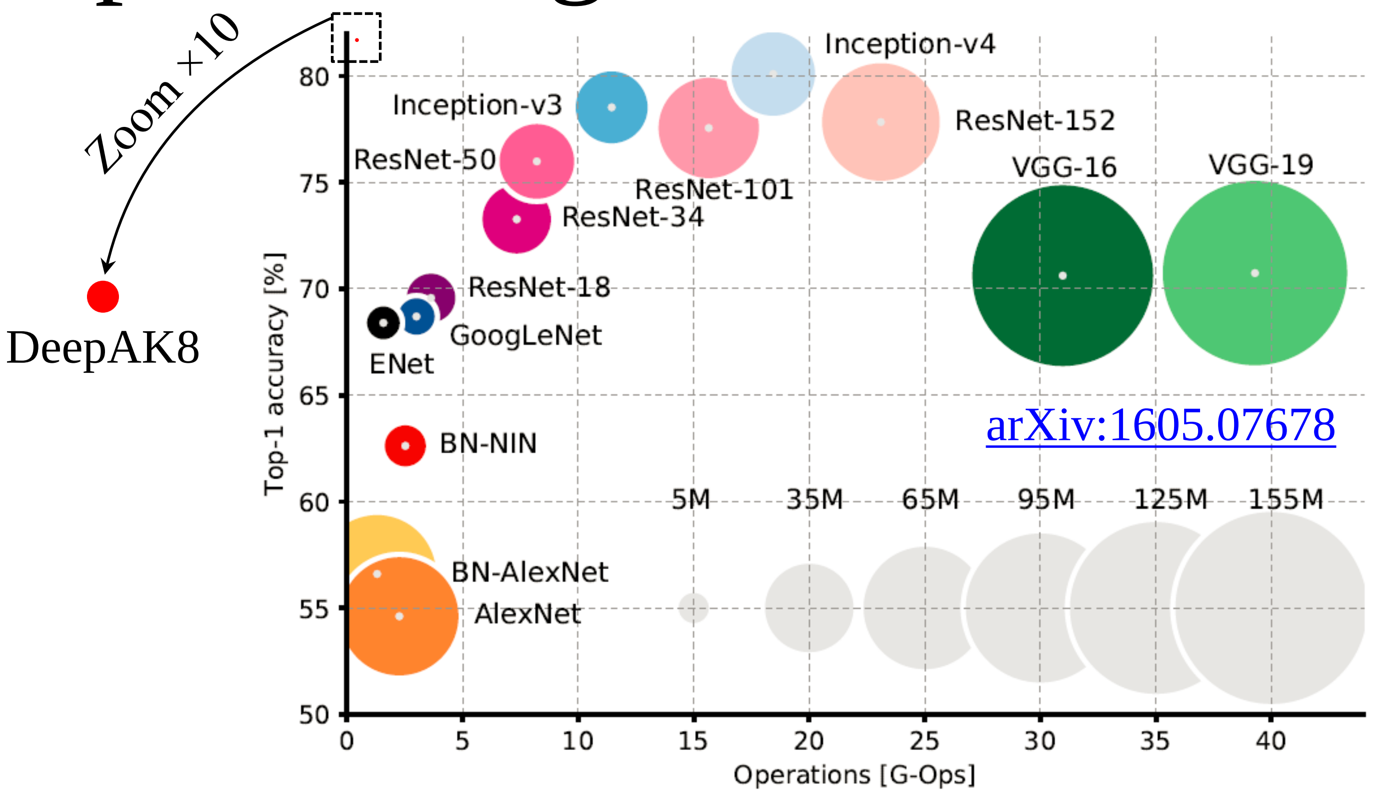
- Large speed improvement from hardware accelerated coprocessors
  - Architectures and tools are geared toward **machine learning**

Option 1	**Option 2**
re-write physics algorithms for new hardware	**re-cast physics problem as machine learning problem**
Language: OpenCL, OpenMP, HLS, CUDA, …?	Language: C++, Python (TensorFlow, PyTorch,…)
Hardware: FPGA, GPU	Hardware: FPGA, GPU, ASIC

Why (Deep) Machine Learning?

- Common *language* for solving problems: simulation, reconstruction, analysis!
- Can be universally expressed on optimized computing hardware (follow industry trends)

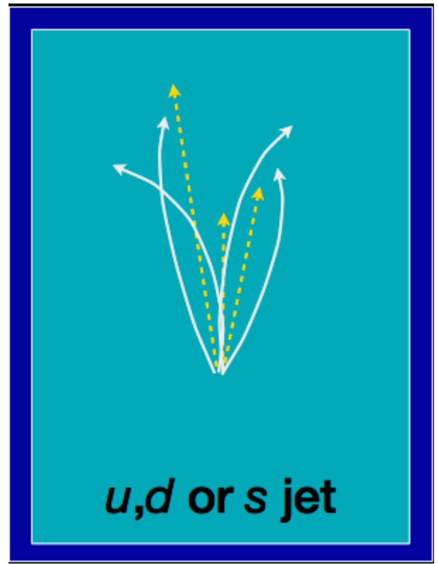
Deep Learning in Science and Industry

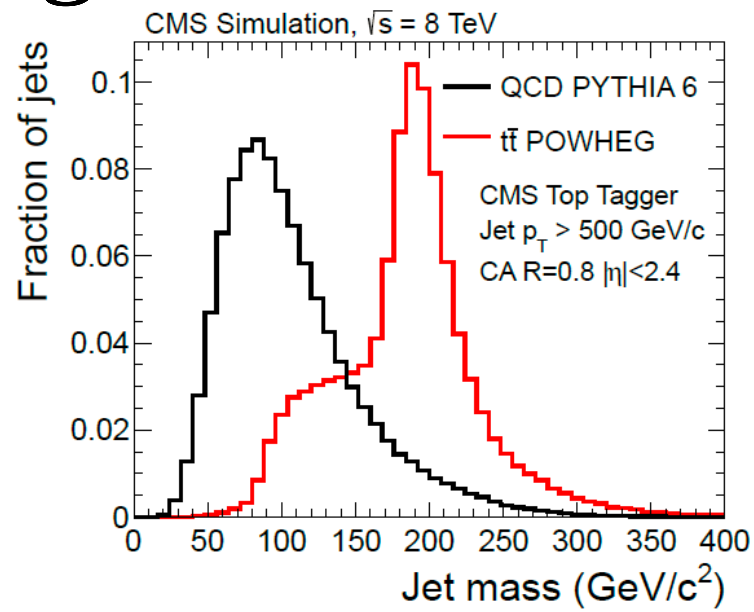


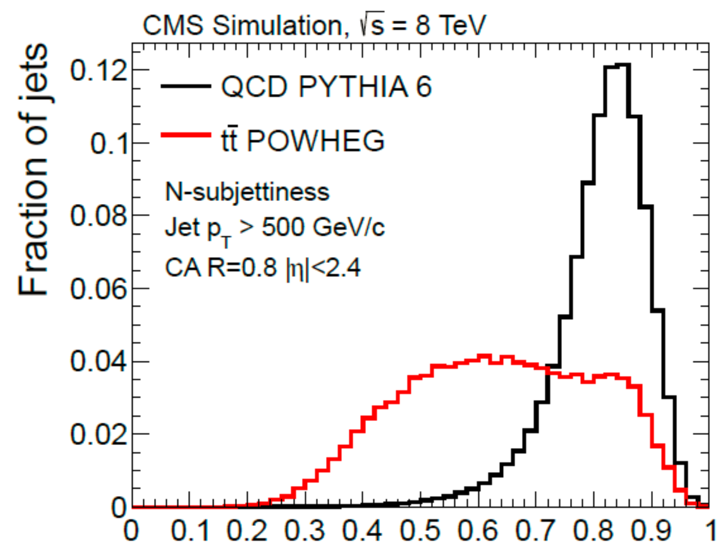
[arXiv:1605.07678](https://arxiv.org/abs/1605.07678)

- ResNet-50: 25M parameters, 7B operations
- Largest network currently used by CMS:
  - DeepAK8, 500K parameters, 15M operations
- Newer approaches w/ larger networks in development…

Top Tagging



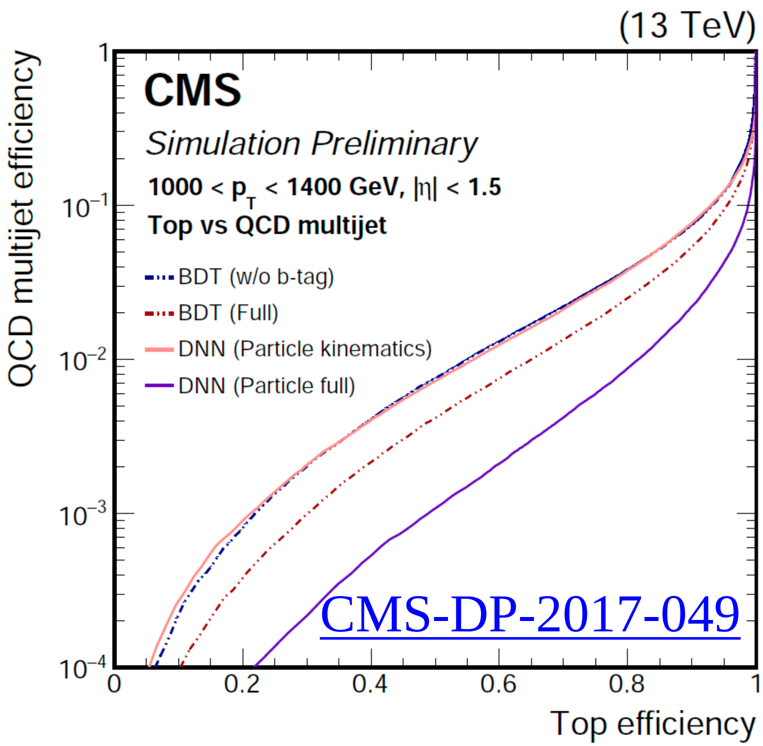




- High p_T top quarks are boosted: form a single large-radius jet with substructure
- Top tagging started as simple cuts on high-level variables (right)
- Now advanced to particle-level deep neural networks (next slide)
- (Can also do Higgs tagging, W/Z tagging, etc.)

CMS-PAS-JME-17-003

Top Tagging with Deep Learning

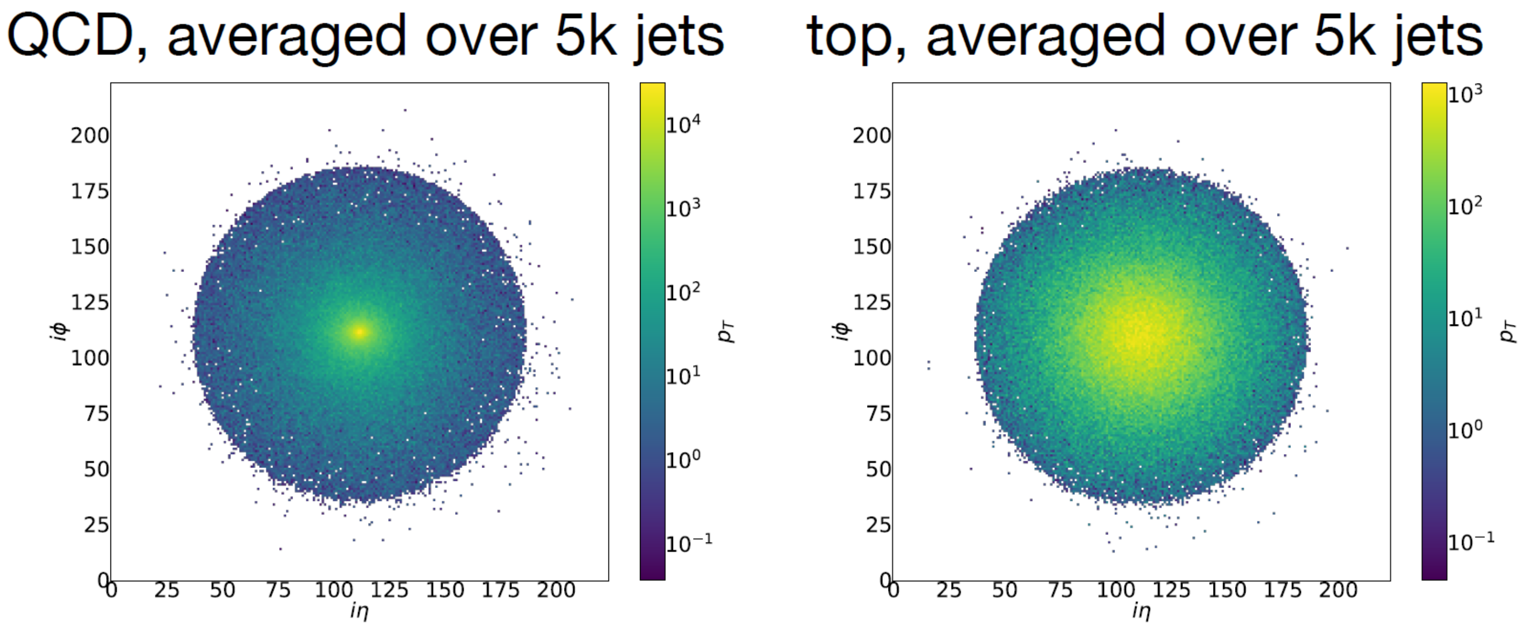


- DNNs outperform simpler ML algorithms (such as BDTs)
- Many approaches now developed
  - Some use much larger networks than DeepAK8: Particle cloud, ResNet-like
- Metrics: AUC, accuracy, $1/\varepsilon_B$ @ ε_S=30%

Approach	AUC	Acc.	1/eB (@ eS=0.3)	Contact	Comments
LoLa	0.980	0.928	680	GK / Simon Leiss	Preliminary number, based on LoLa
LBN	0.981	0.931	863	Marcel Rieger	Preliminary number
CNN	0.981	0.93	780	David Shih	Model from *Pulling Out All the Tops with Computer Vision and Deep Learning (1803.00107)*
P-CNN (1D CNN)	0.980	0.930	782	Huilin Qu, Loukas Gouskos	Preliminary, use kinematic info only (https://indico.physics.lbl.gov/indico/event/546/contributions/1270/)
6-body N-subjettiness (+mass and pT) NN	0.979	0.922	856	Karl Nordstrom	Based on 1807.04769 (*Reports of My Demise Are Greatly Exaggerated: N-subjettiness Taggers Take On Jet Images*)
8-body N-subjettiness (+mass and pT) NN	0.980	0.928	795	Karl Nordstrom	Based on 1807.04769 (*Reports of My Demise Are Greatly Exaggerated: N-subjettiness Taggers Take On Jet Images*)
Linear EFPs	0.980	0.932	380	Patrick Komiske, Eric Metodiev	d<= 7, chi <= 3 EFPs with FLD. Based on 1712.07124: *Energy Flow Polynomials: A complete linear basis for jet substructure.*
Particle Flow Network (PFN)	0.982	0.932	888	Patrick Komiske, Eric Metodiev	Median over ten trainings. Based on Table 5 in 1810.05165: *Energy Flow Networks: Deep Sets for Particle Jets.*
Energy Flow Network (EFN)	0.979	0.927	619	Patrick Komiske, Eric Metodiev	Median over ten trainings. Based on Table 5 in 1810.05165: *Energy Flow Networks: Deep Sets for Particle Jets.*
2D CNN [ResNeXt50]	0.984	0.936	1086	Huilin Qu, Loukas Gouskos	Preliminary from indico.cern.ch/event/745718/contributions/3202526
DGCNN	0.984	0.937	1160	Huilin Qu, Loukas Gouskos	Preliminary from indico.cern.ch/event/745718/contributions/3202526

G. Kasieczka

Top Tagging with Images



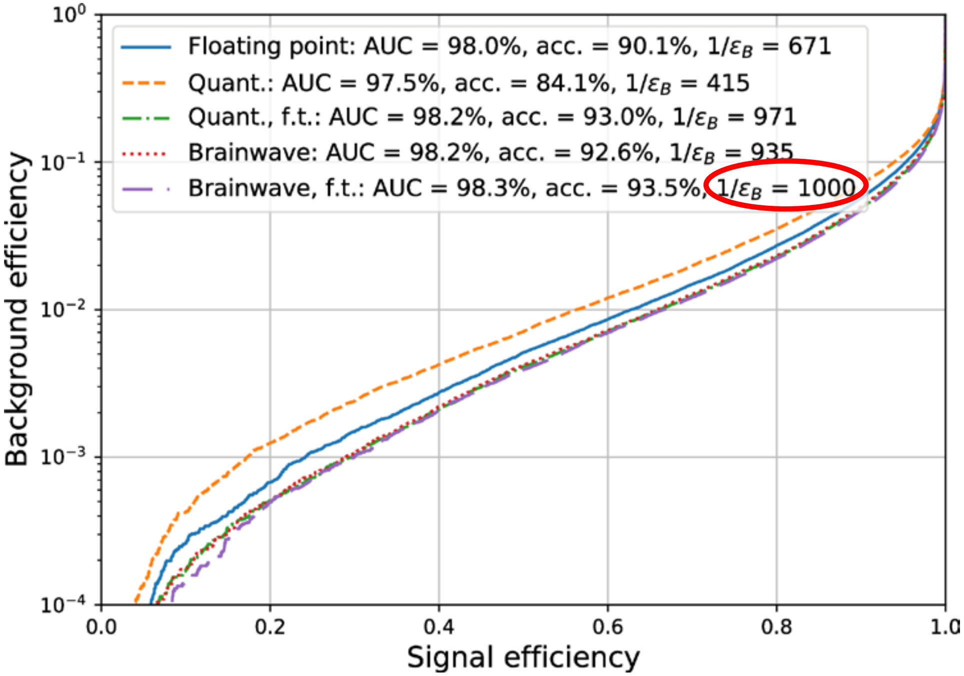
- Deep learning in industry focuses on image recognition
- Jets are not images, but can pretend in order to test industry networks
- Convert jets into images using constituent p_T, η, φ: 224x224 pixels
- Standardized top quark tagging dataset is publicly available: https://goo.gl/XGYju3

Top Tagging with ResNet-50

- Retrain ResNet-50 on publicly available top quark tagging dataset

  → New set of weights, optimized for physics

  - Add custom classifier layers to interpret features from ResNet-50

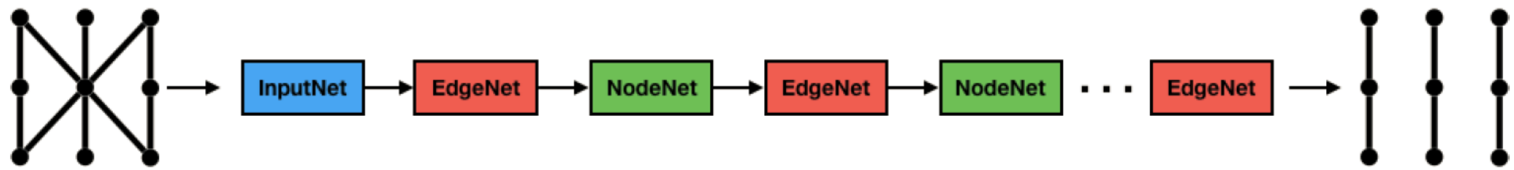


- ResNet-50 model that runs on FPGAs is "quantized"

  - Tune weights to achieve similar performance

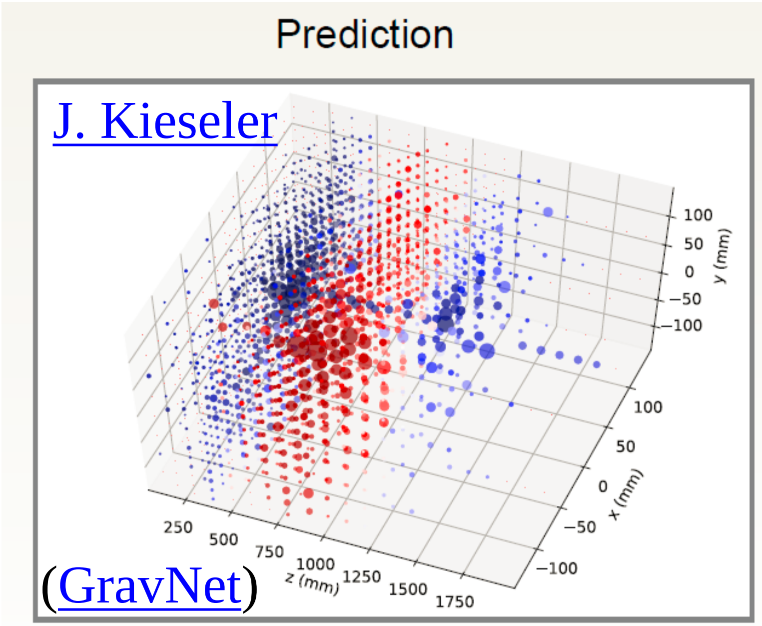
➤ State-of-the-art results vs. other leading algorithms

Beyond Tagging

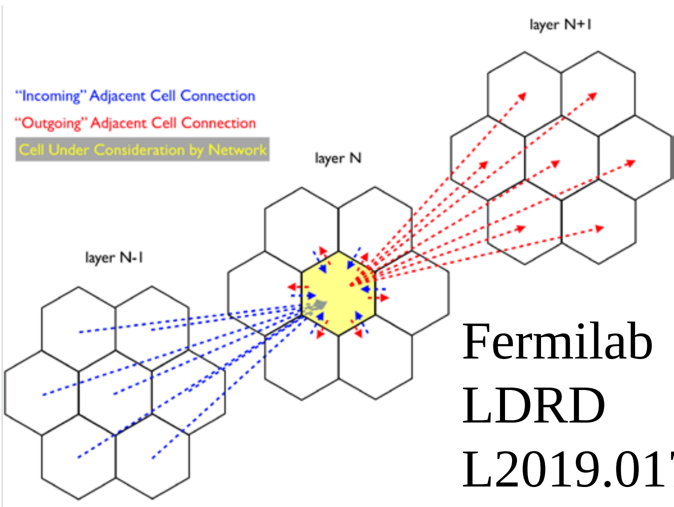


- R&D to use novel network architectures for tracking and clustering
- Optimal use of complex new detectors
- May be crucial for Phase 2

[HEP.TrkX](#)
Message Passing Neural Network
Graph-based ML for tracking

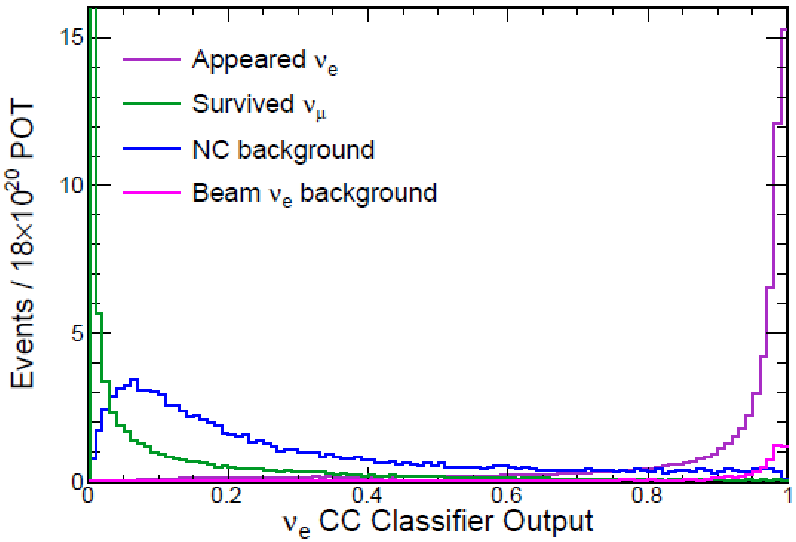


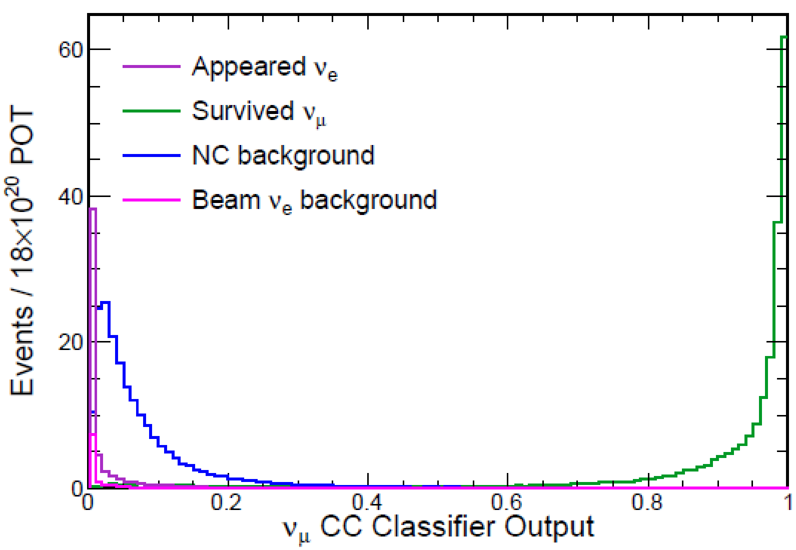
MPNN for HGCal
Exploit hexagonal cells & 3D structure



Fermilab LDRD L2019.017

NoVA: First Particle Physics CNN

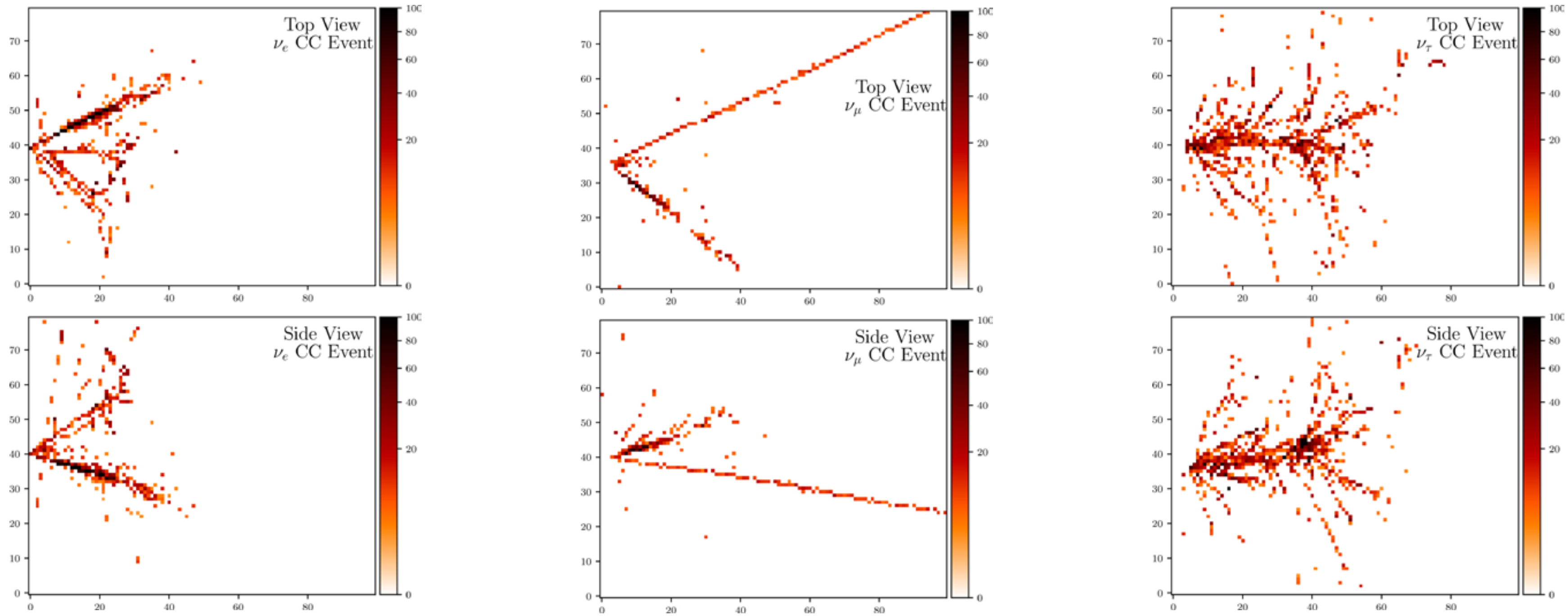




- NOvA was the first particle physics experiment to publish a result obtained using a CNN
- Achieved similar efficiency for ν_μ (58% vs. 57%), improvement for ν_e (49% vs. 35%) vs. existing algorithms (arXiv:1604.01444)
- Used to constrain oscillation parameters: (arXiv:1703.03328)

➢ Inverted mass hierarchy w/ θ_{23} in lower octant excluded at 93% CL for all δ_{CP} values

Neutrino Recognition with ResNet-50



- ResNet-50 can also classify neutrino events to reject cosmic ray backgrounds
- Use *transfer learning*: keep default featurizer weights, retrain classifier layers
- Events above selected w/ probability > 0.9 in different categories
- CNN inference already a large fraction of neutrino reconstruction time

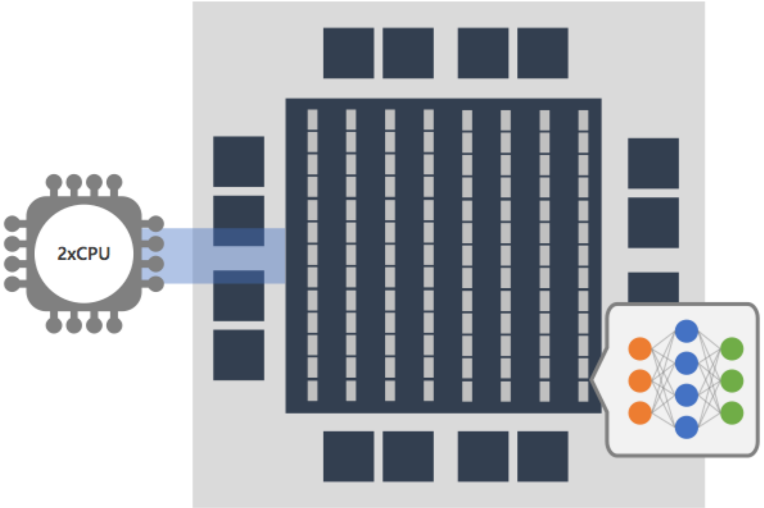
➢ Prime candidate for acceleration with coprocessors

Why Accelerate Inference?

- Training is viewed as "hard" part of machine learning
- But…
- DNN training happens ~once/year/algorithm
    - Cloud GPUs or new HPCs are good options
- Once DNN is in common use, inference will happens *billions* of times
    - MC production, analysis, prompt reconstruction, high level trigger…

➢ Training is done by developers, inference is done by everyone

Inference as a Service



- Inference as a service:
  - Minimize disruption to existing computing model
  - Minimize dependence on specific hardware
  - Avoid need for large input batches
    - Large batches are necessary to use GPUs efficiently
    - Not a good fit for most particle physics applications: prefer to load one (complex) event into memory, then run all algorithms on it
- Performance metrics:
  - Latency (time for a single request to complete)
  - Throughput (number of requests per unit time)

What are FPGAs?

- Field Programmable Gate Arrays
- "Programmable hardware":
  arrange gates to perform desired task
- Execute many instructions *in parallel* on input data: **spatial computing**
  - vs. CPUs, which execute instructions *in series*: **temporal computing**
- Can be *reconfigured* in 100ms–1s
- Ideal for deep networks: many operations, fixed model parameters
- ASICs (Application Specific Integrated Circuits) not configurable – require stable problem to solve

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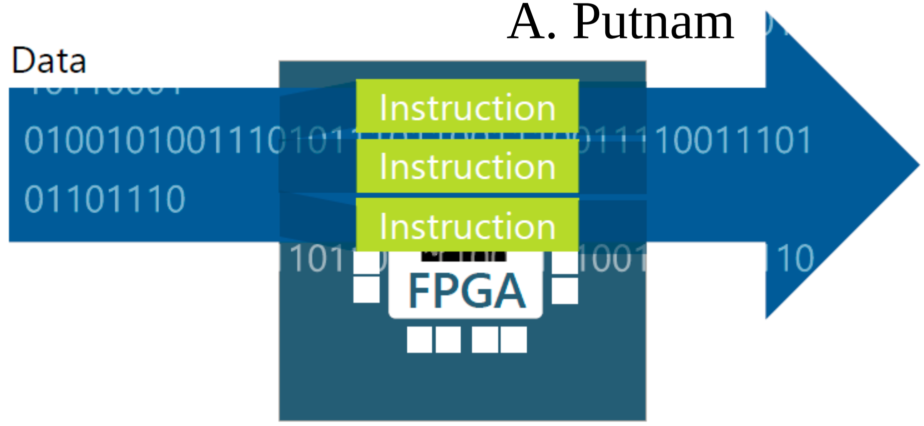
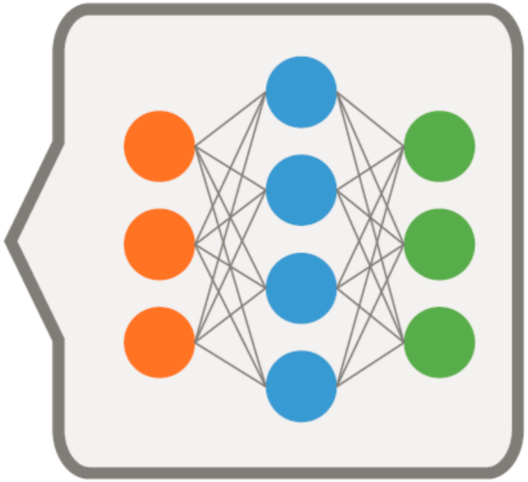
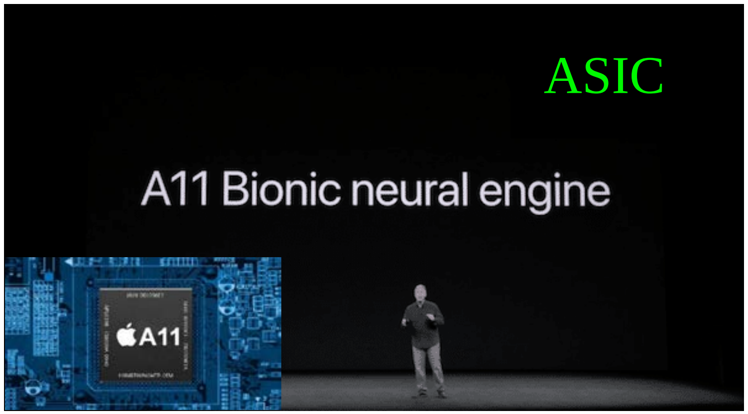


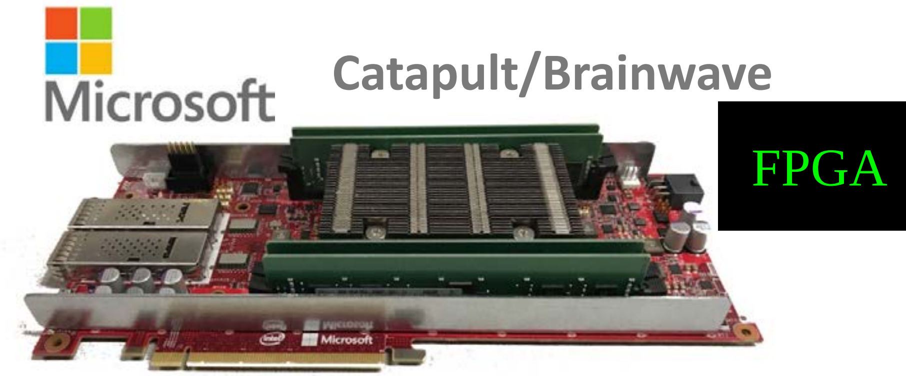
FPGA: spatial compute

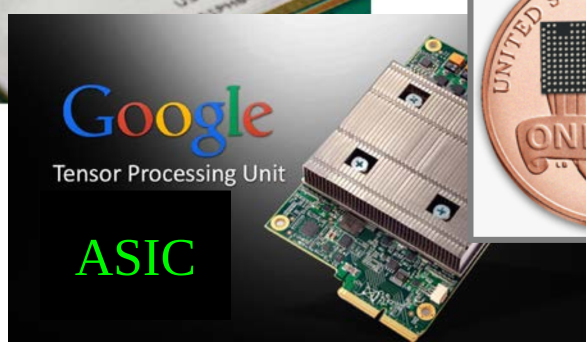


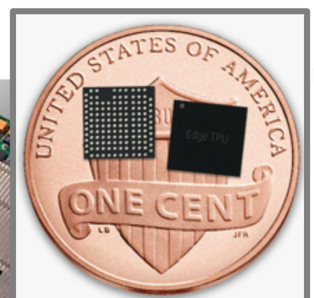
Coprocessors: An Industry Trend

Specialized coprocessor hardware for machine learning inference



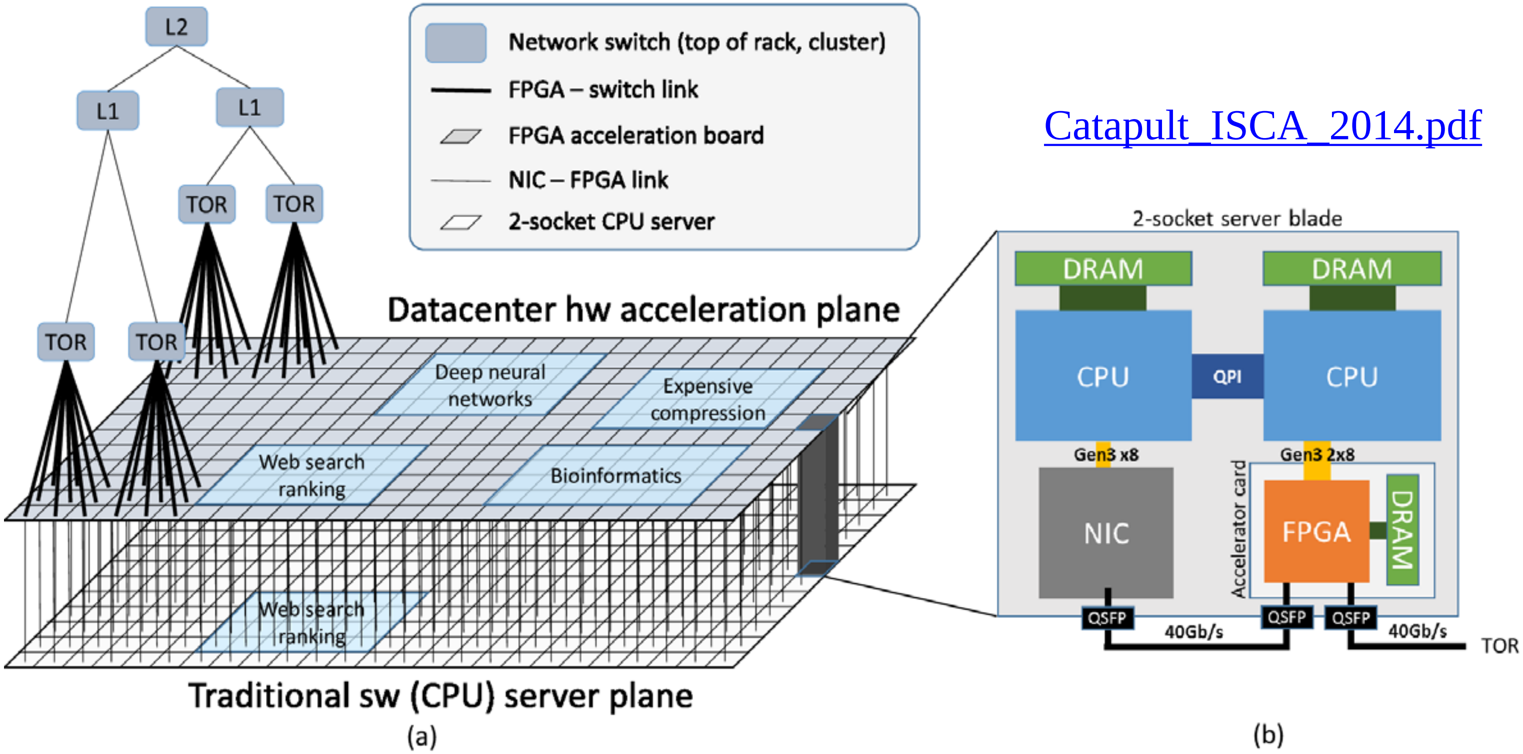






Microsoft Brainwave

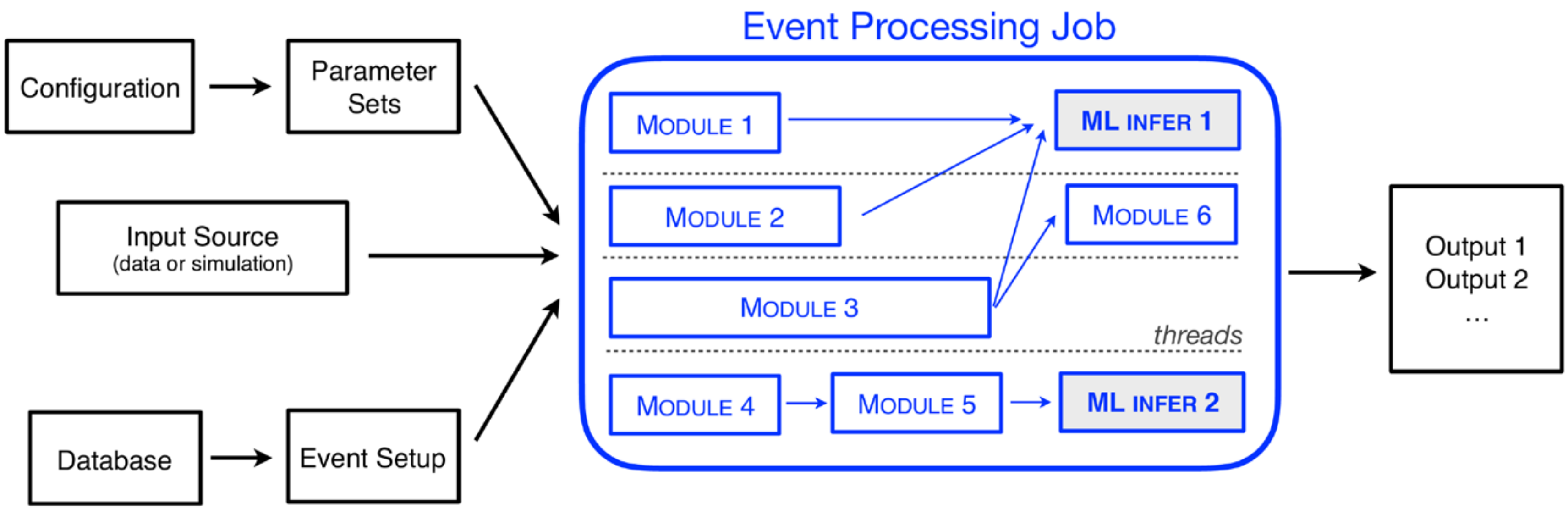
[Catapult_ISCA_2014.pdf]



- Provides a full service at scale (more than just a single co-processor)
- Multi-FPGA/CPU fabric accelerates *both* **computing** and **network**
- Weight retuning available: retrain supported networks to optimize for a different problem

Brainwave supports:
- ResNet50
- ResNet152
- DenseNet121
- VGGNet16

Particle Physics Computing Model

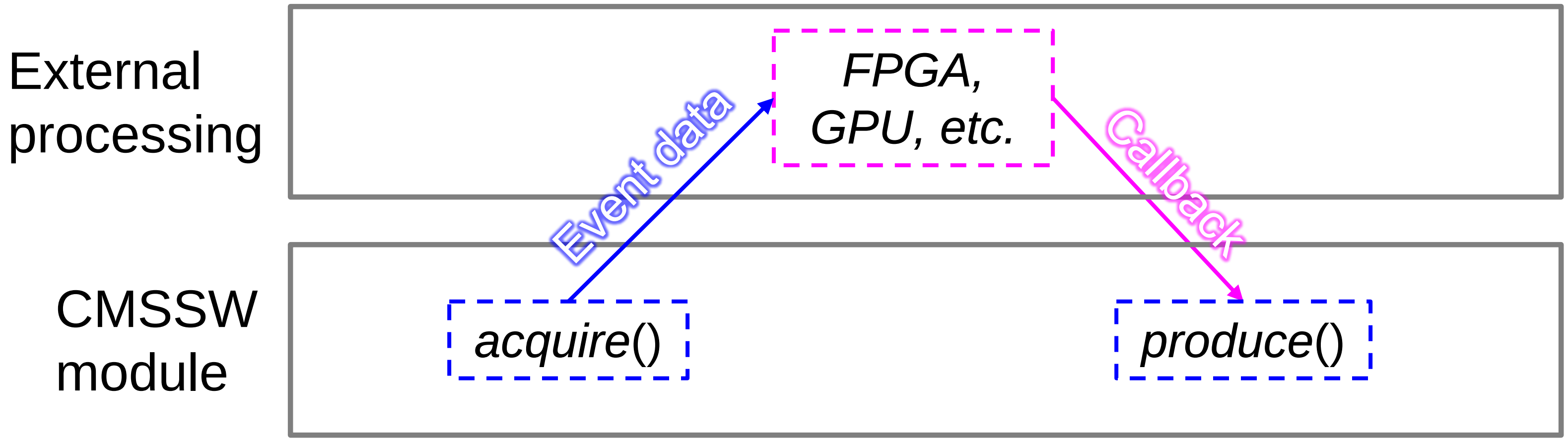


- Event-based processing
  - o Events are very complex with hundreds of products
  - o Load one event into memory, then execute all algorithms on it

➢ Most applications not a good fit for large batches, which are required for best GPU performance

Accessing Heterogeneous Resources

- New CMSSW feature called ExternalWork:
  - Asynchronous task-based processing



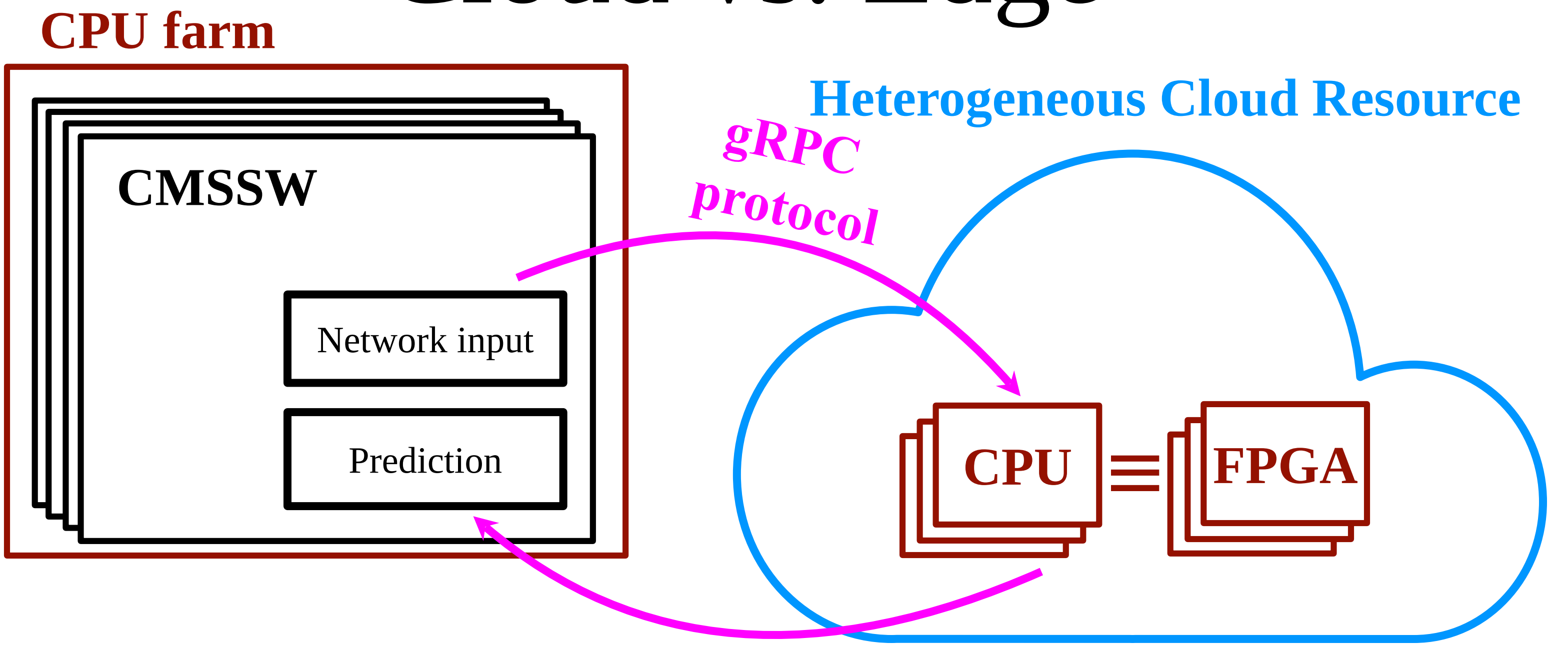
  - Non-blocking: schedule other tasks while waiting for external processing
- Can be used with GPUs, FPGAs, cloud, …
  - Even other software running on CPU that wants to schedule its own tasks

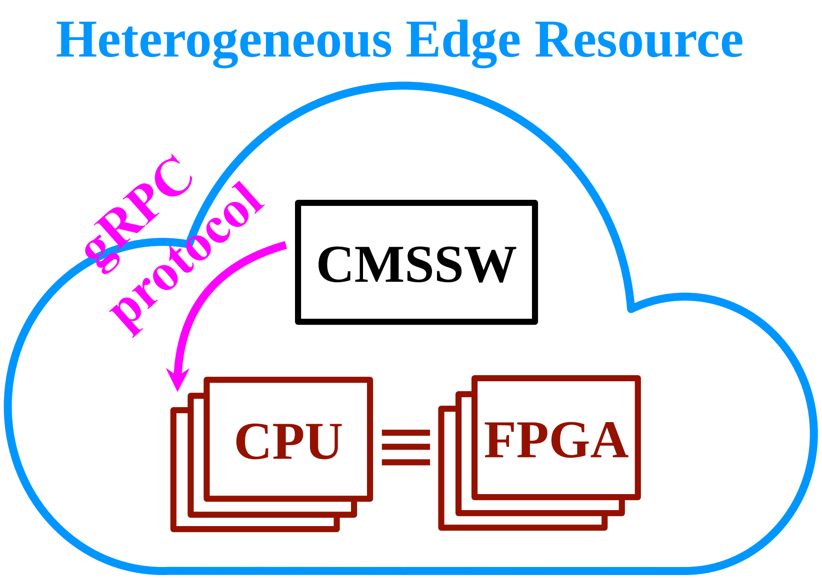
➢ Now demonstrated to work with Microsoft Brainwave!

SONIC in CMSSW

- **S**ervices for **O**ptimized **N**etwork **I**nference on **C**oprocessors
  - Convert experimental data into neural network input
  - Send neural network input to coprocessor using communication protocol
  - Use ExternalWork mechanism for asynchronous requests
- Currently supports:
  - gRPC communication protocol
    - Callback interface for C++ API in development
      → wait for return in lightweight std::thread
  - TensorFlow w/ inputs sent as TensorProto (protobuf)
- Tested w/ Microsoft Brainwave service (cloud FPGAs)
- gRPC [SonicCMS]() repository on GitHub

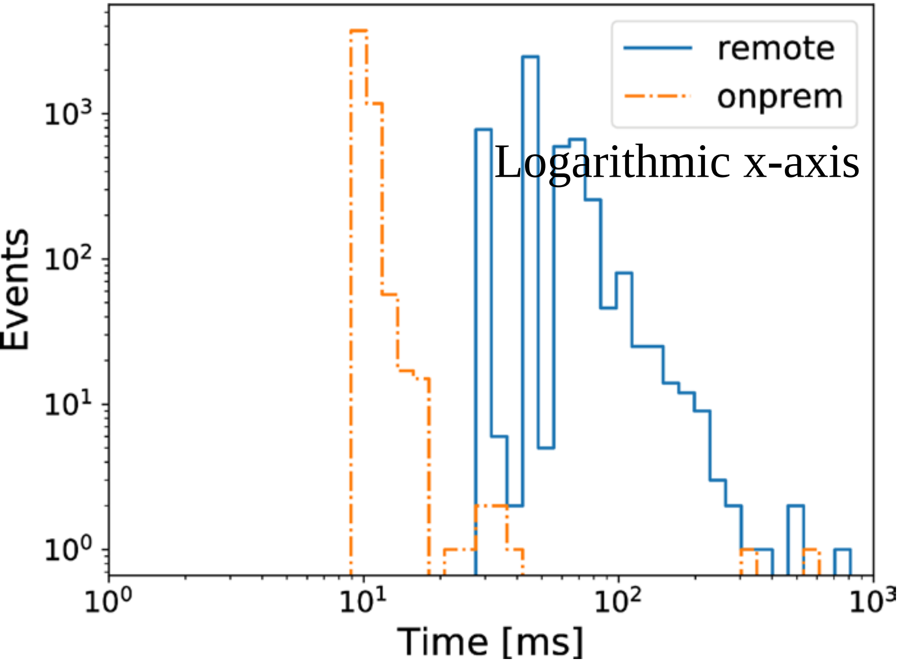
Cloud vs. Edge

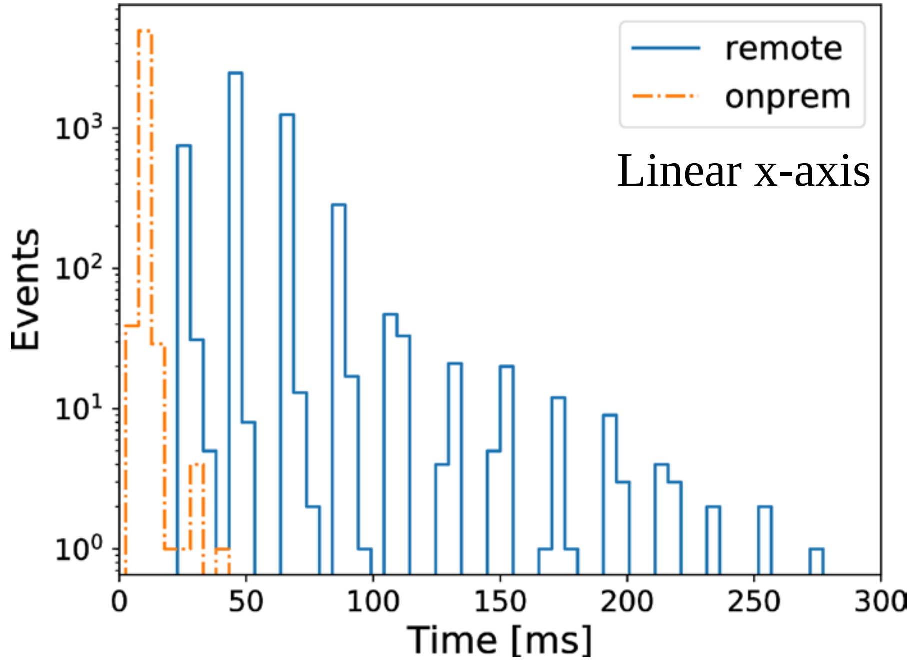




- Cloud service has latency
- Run CMSSW on Azure cloud machine → simulate local installation of FPGAs (“on-prem” or “edge”)
- Provides test of ultimate performance
- Use gRPC protocol either way

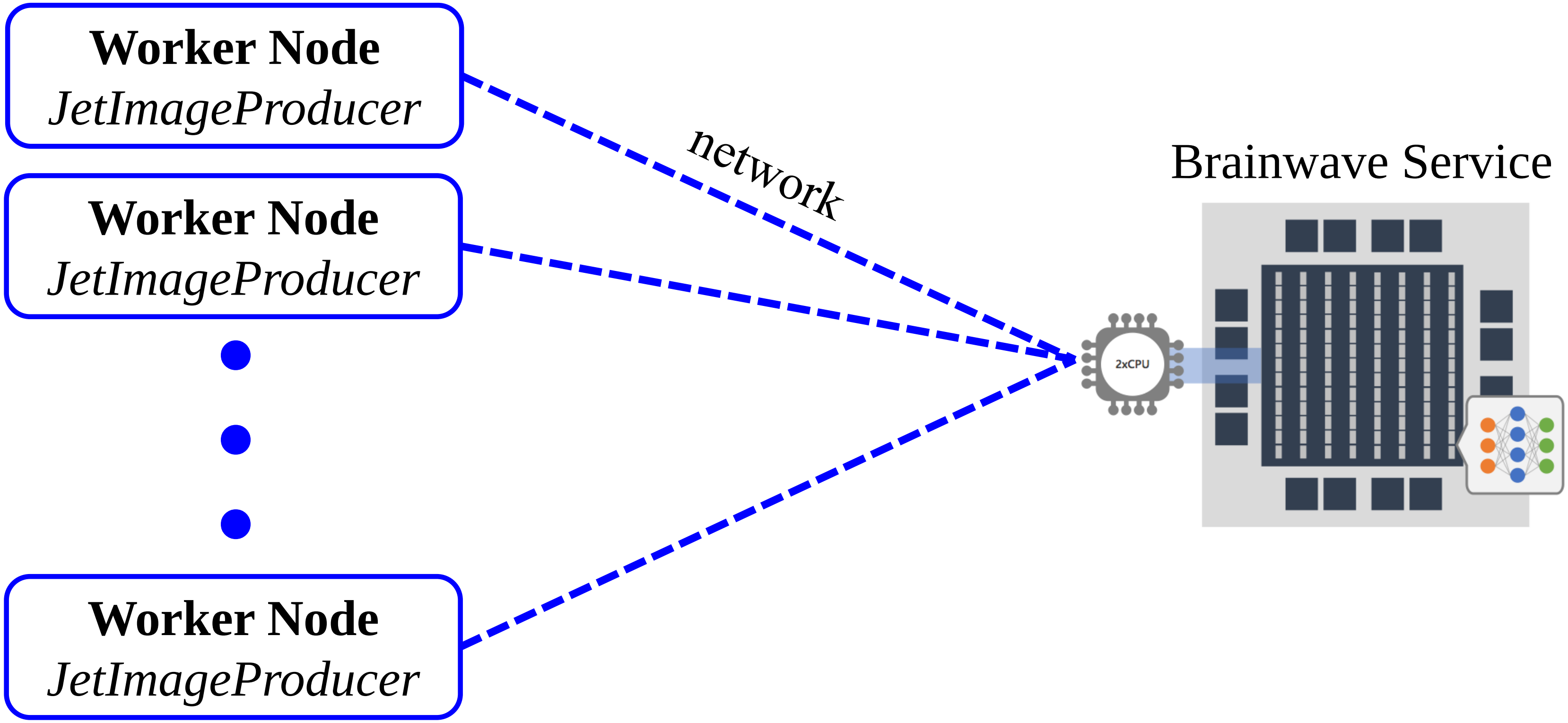
SONIC Latency





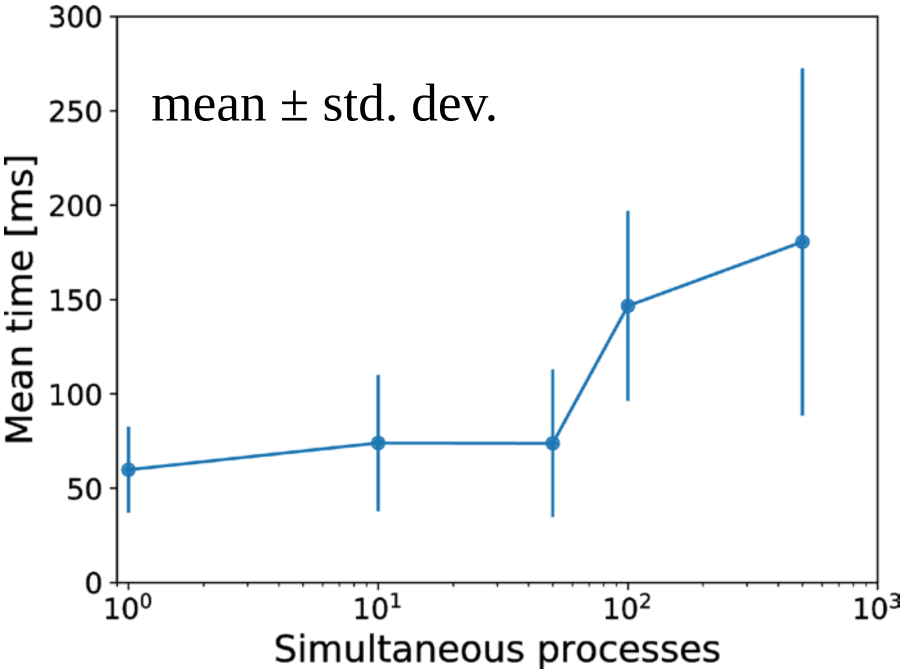
- Remote: cmslpc @ FNAL to Azure (VA), ‹time› = 60 ms
    - Highly dependent on network conditions
- On-prem: run CMSSW on Azure VM, ‹time› = 10 ms
    - FPGA: 1.8 ms for inference
    - Remaining time used for classifying and I/O

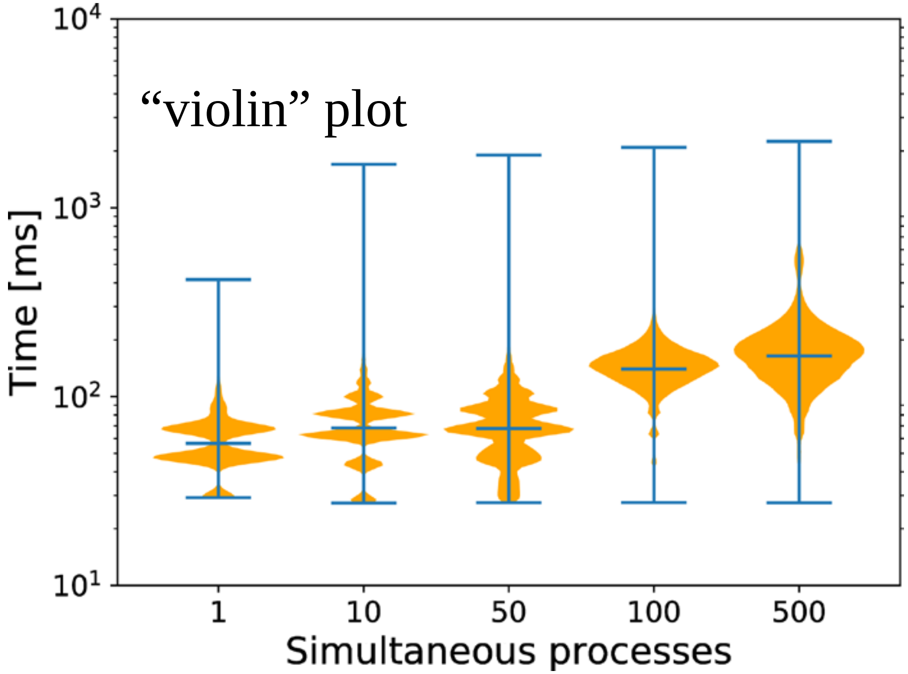
Scaling Tests



- Run N simultaneous processes, all sending requests to 1 BrainWave service
- Processes only run JetImageProducer from SONIC → "worst case" scenario
  - Standard reconstruction process would have many non-SONIC modules
- FPGA performs inference serially (1 image at a time)

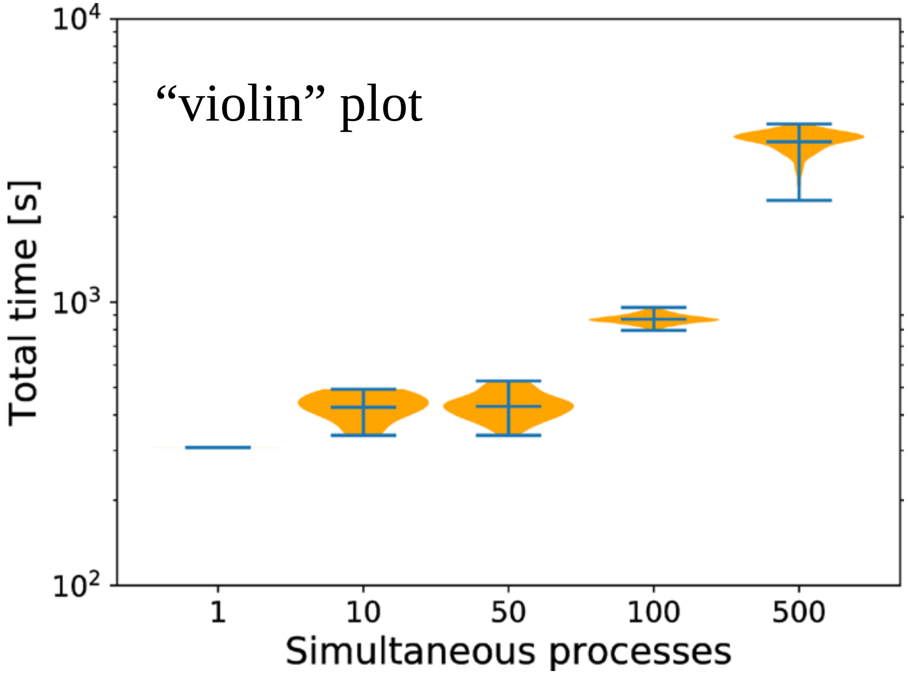
SONIC Latency: Scaling

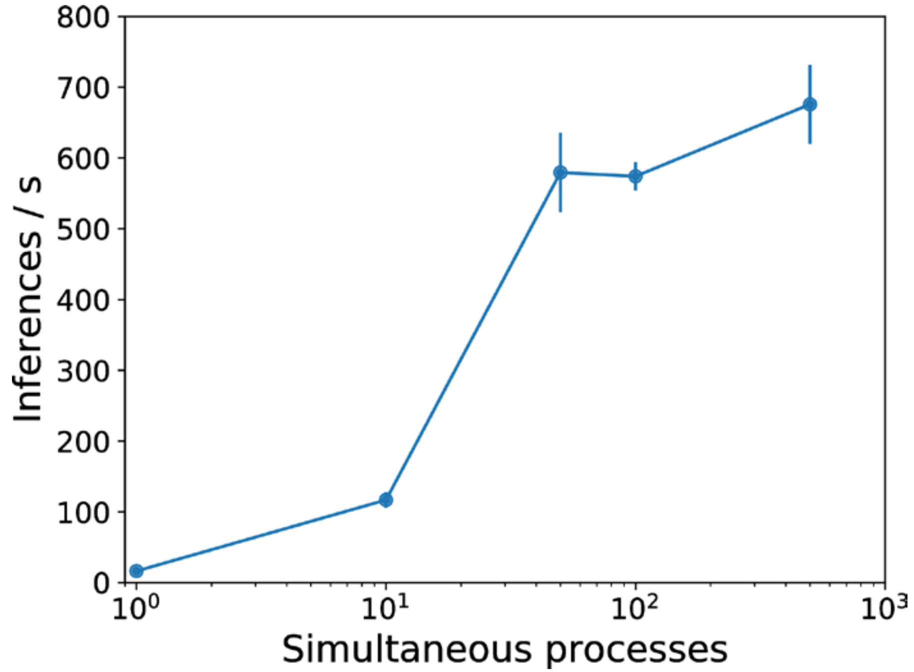




- Tests: N = 1, 10, 50, 100, 500
- Only moderate increases in mean, standard deviation, and long tail for latency
  - Fairly stable up to N = 50

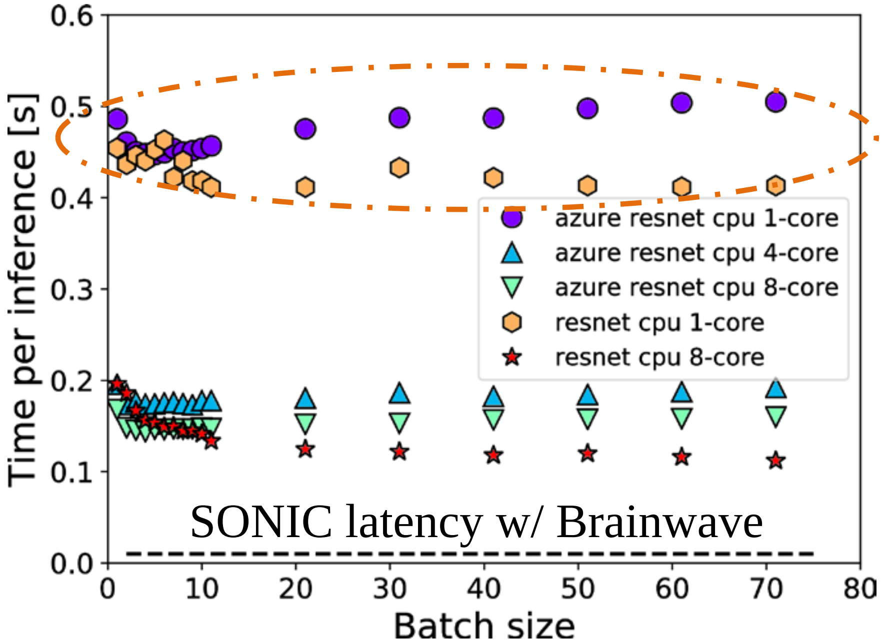
SONIC Throughput

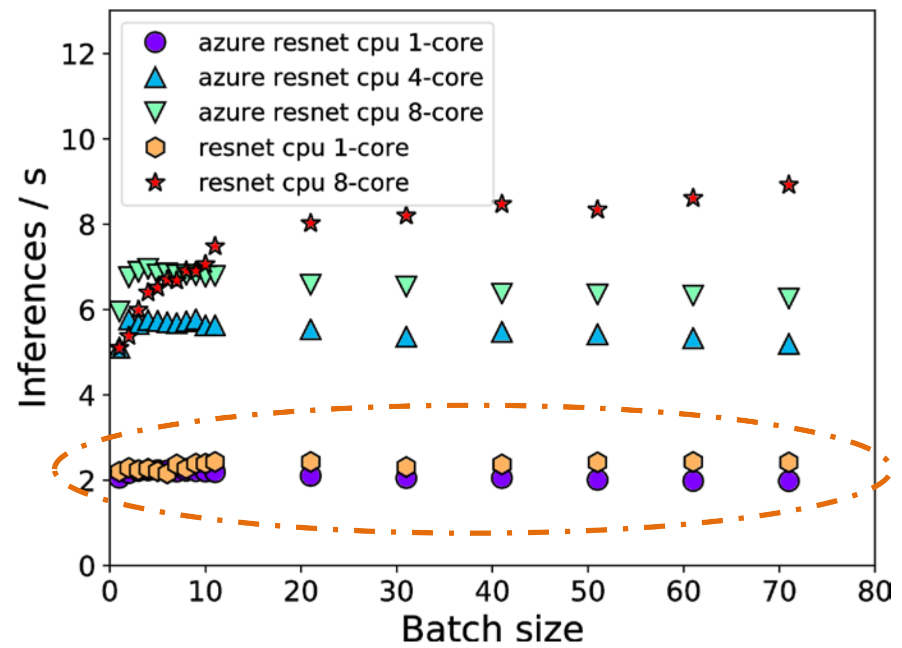




- Each process evaluates 5000 jet images in series
- Remarkably consistent total time for each process to complete
  - o Brainwave load balancer works well
- Compute inferences per second as $(5000 \cdot N)/(\text{total time})$
- N = 50 ~fully occupies FPGA:
  - o Throughput up to 600 inferences per second (max ~650)

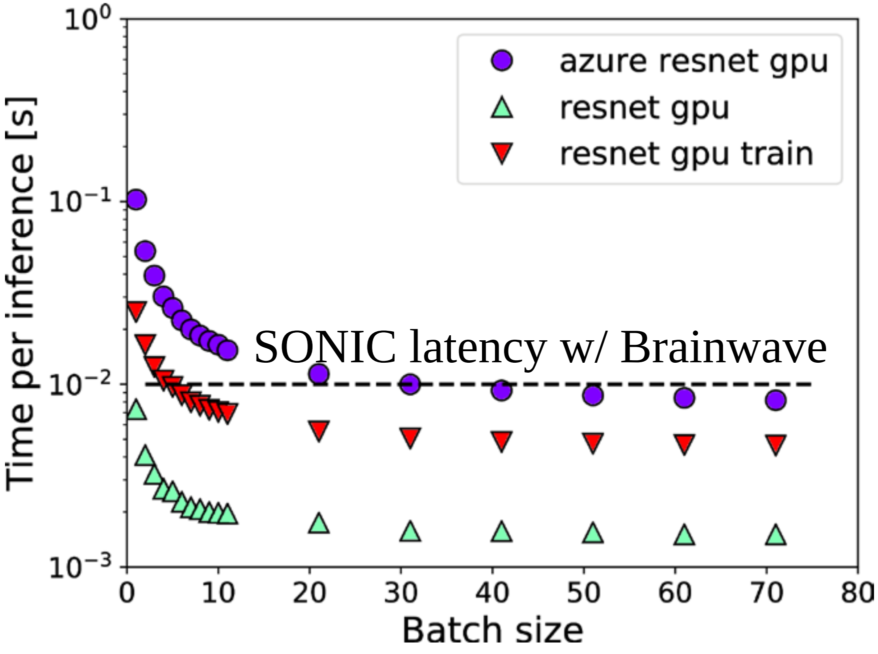
CPU Performance

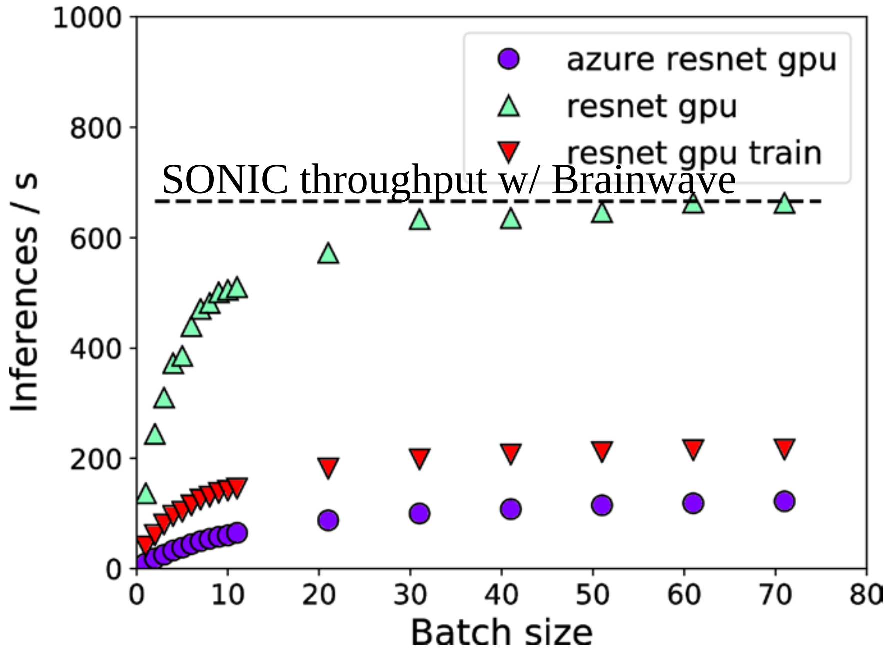




- Above plots use i7 3.6 GHz, TensorFlow v1.10
- Local test with CMSSW on cluster @ FNAL:
  - Xeon 2.6 GHz, TensorFlow v1.06
  - 5 min to import Brainwave version of ResNet-50
  - 1.75 sec/inference subsequently

GPU Performance





- Above plots use NVidia GTX 1080, TensorFlow v1.10
- GPU directly connected to CPU via PCIe
- TF built-in version of ResNet-50 performs better on GPU than quantized version used in Brainwave

Performance Comparisons

Type	Note	Latency [ms]	Throughput [img/s]
CPU*	Xeon 2.6 GHz	1750	0.6
	i7 3.6 GHz	500	2
GPU**	batch = 1	7	143
	batch = 32	1.5	667
Brainwave	remote	60	660
	on-prem	10 (1.8 on FPGA)	660

- *CPU performance depends on:
  - clock speed, TensorFlow version, # threads (=1 here)
- **GPU caveats:
  - Directly connected to CPU via PCIe – not a service
  - Performance depends on batch size & optimization of ResNet-50 network
- SONIC achieves:
  - ➢ 175× (30×) on-prem (remote) improvement in latency vs. CMSSW CPU!
  - ➢ Competitive throughput vs. GPU, w/ single-image batch as a service!

Summary

- Particle physics experiments face extreme computing challenges
  - More data, more complex detectors, more pileup
- Growing interest in machine learning for reconstruction and analysis
  - As networks get larger, inference takes longer
- FPGAs are a promising option to accelerate neural network inference
  - Can achieve order of magnitude improvement in latency over CPU
  - Comparable throughput to GPU, without batching
    - ➢ Better fit for event-based computing model
- SONIC infrastructure developed and tested
  - Compatible with any service that uses gRPC and TensorFlow

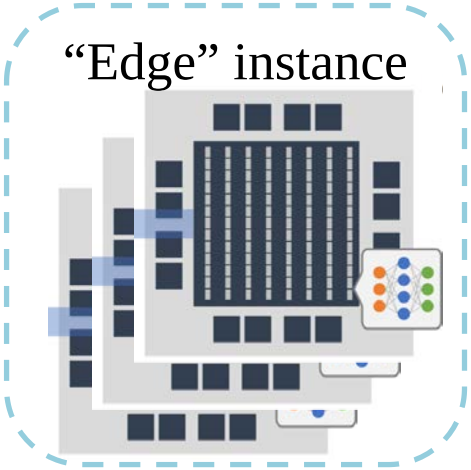
➢ **Paper with these results in preparation**

- Thanks to Microsoft for lots of help and advice!
  - Azure Machine Learning, Bing, Project Brainwave teams
  - Doug Burger, Eric Chung, Jeremy Fowers, Kalin Ovtcharov, Andrew Putnam

Continuing Work

- **Continue to translate particle physics algorithms into machine learning**
  - Easier to accelerate inference w/ commercial coprocessors
- **Develop tools for generic model translation**
  - E.g. graph NNs used for HEP.TrkX and other projects
- **Explore broad offering of potential hardware**
  - Google TPUs, Xilinx ML suite on AWS, Intel OpenVINO, …
- **Continue to build infrastructure and study scalability/cost**
  - Adapt SONIC to handle other protocols, other network architectures and ML libraries, other experiments (e.g. neutrinos)

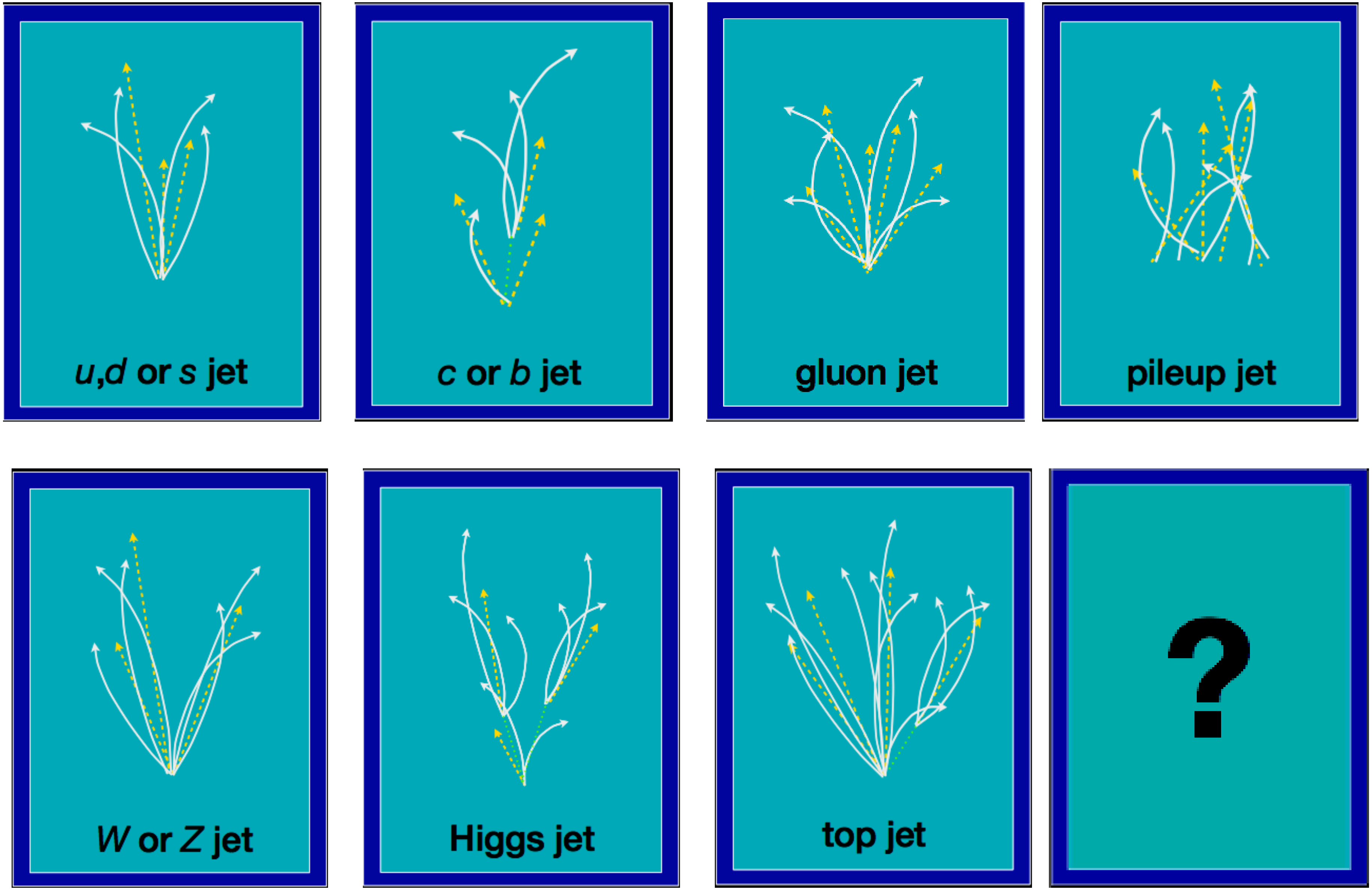
A Vision of the Future



- A single FPGA can support many CPUs → cost-effective
  - SONIC throughput results indicate 1 FPGA for 100–1000 CPUs running realistic processes (many algorithms, only some ML inferences)
- Install small “edge” instances at T1s and T2s
  - Can also install a dedicated instance for CMS HLT farm at CERN

Backup

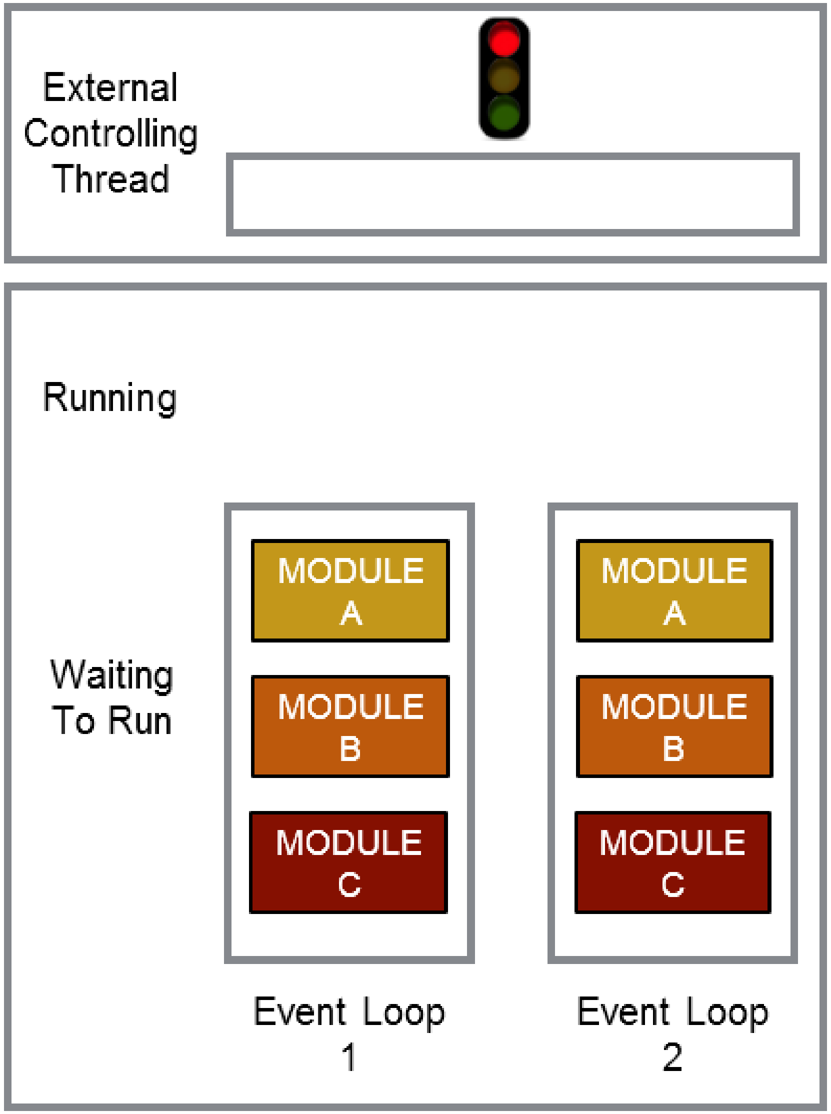
Jet Substructure



External Work in CMSSW (1)

Setup:

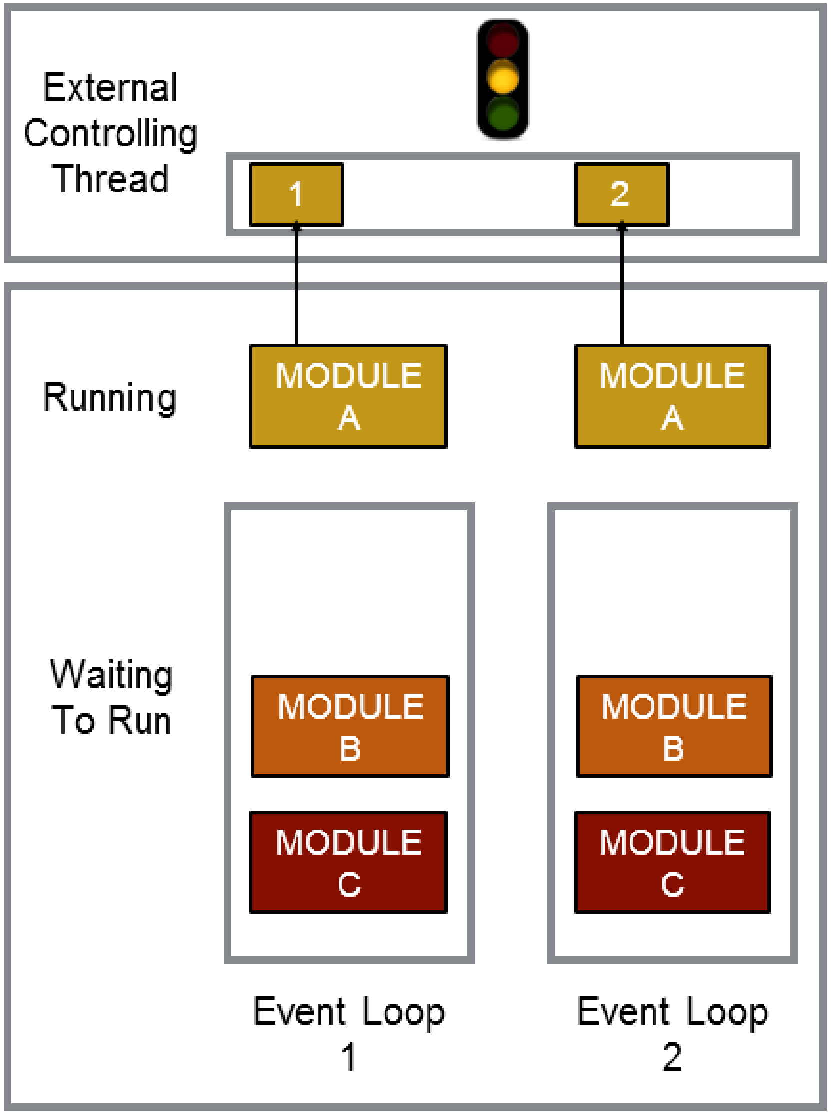
- TBB controls running modules
- Concurrent processing of multiple events
- Separate helper thread to control external
- Can wait until enough work is buffered before running external process



External Work in CMSSW (2)

Acquire:

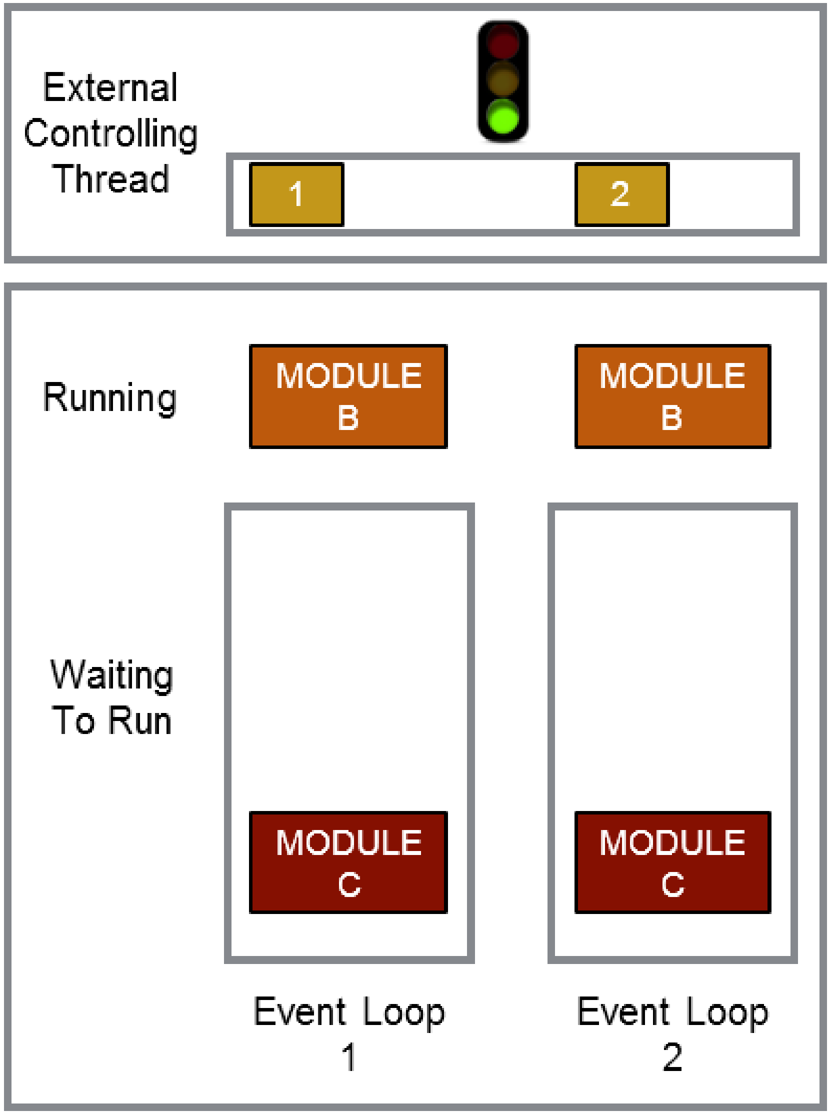
- Module *acquire*() method called
- Pulls data from event
- Copies data to buffer
- Buffer includes callback to start next phase of module running



External Work in CMSSW (3)

Work starts:

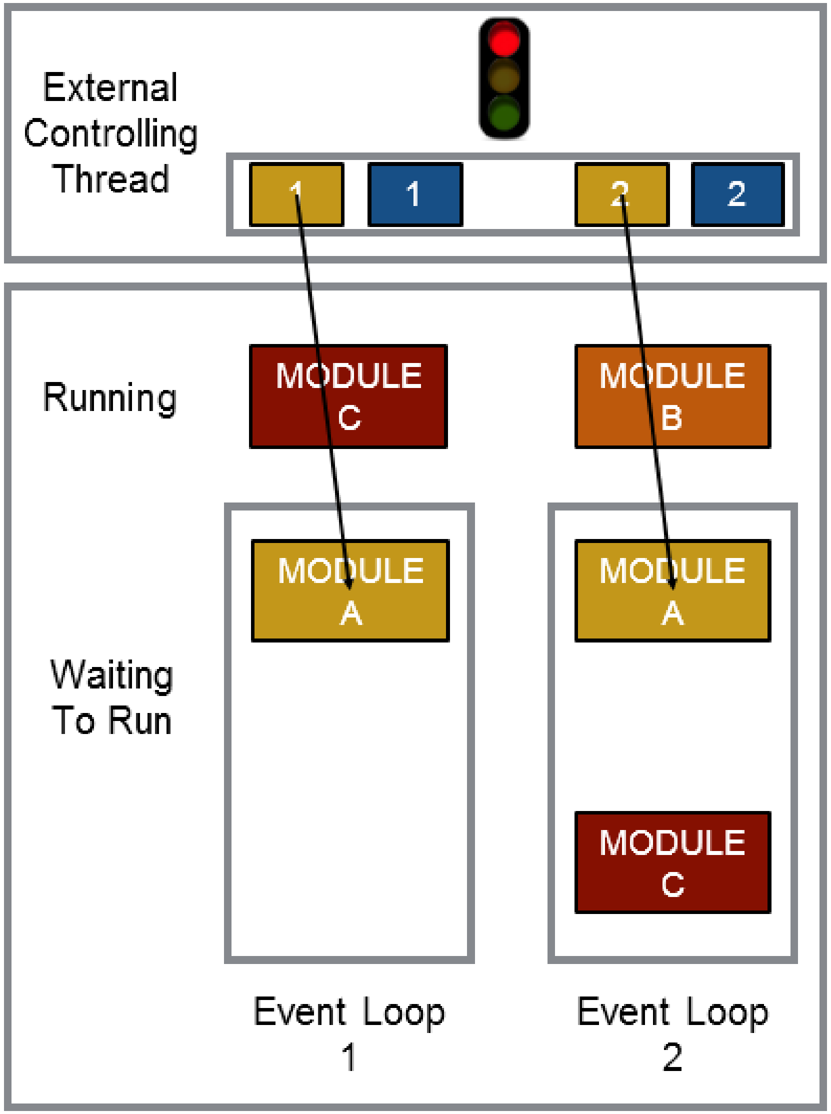
- External process runs
- Data pulled from buffer
- Next waiting modules can run (concurrently)



External Work in CMSSW (4)

Work finishes:

- Results copied to buffer
- Callback puts module back into queue



External Work in CMSSW (5)

Produce:

- Module *produce*() method is called
- Pulls results from buffer
- Data used to create objects to put into event