FastML Science Benchmarks: Accelerating Real-Time Scientific Machine Learning

Javier Duarte[3], Nhan Tran[1], Ben Hawks[1], Christian Herwig[1],
Jules Muhizi[1,2], Shvetank Prakash[2], Vijay Janapa Reddi[2]

ML Challenge
December 15th, 2022

[1]Fermi National Research Laboratory
[2]Harvard University
[3]UC San Diego

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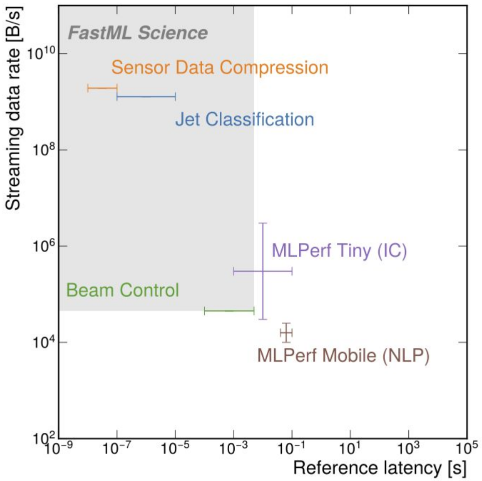
Machine Learning!

- Rise of ML as a data processing framework for large data
- DNNs have proven to be versatile at complex problems
- Scientific domain latency budget a **much** smaller than industry



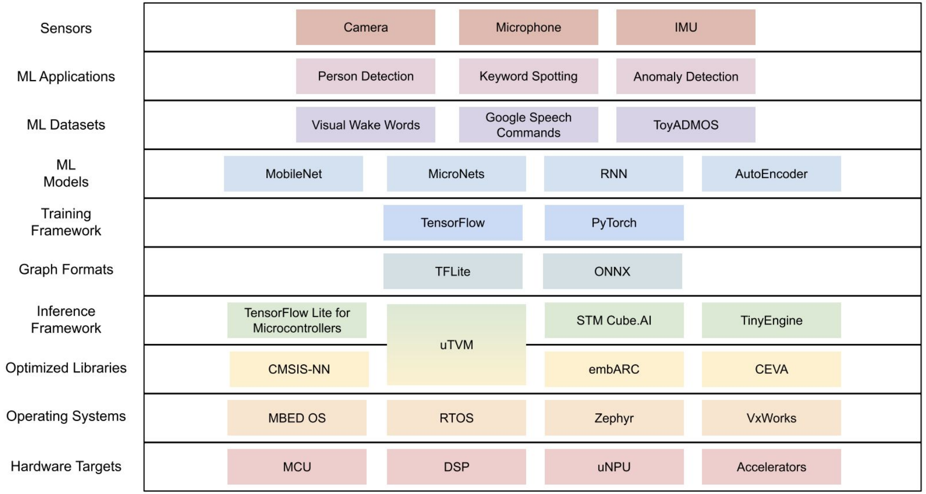
ML
Commons

06.16.2021 — San Francisco, CA

MLPerf Tiny Inference Benchmark

Use Case	Dataset (Input Size)	Model (TFLite Model Size)	Quality Target (Metric)
Keyword Spotting	Speech Commands (49x10)	DS-CNN (52.5 KB)	90% (Top-1)
Visual Wake Words	VWW Dataset (96x96)	MobileNetV1 (325 KB)	80% (Top-1)
Image Classification	CIFAR10 (32x32)	ResNet (96 KB)	85% (Top-1)
Anomaly Detection	ToyADMOS (5*128)	FC-AutoEncoder (270 KB)	.85 (AUC)

Table 1: MLPerf Tiny v0.5 Inference Benchmarks.



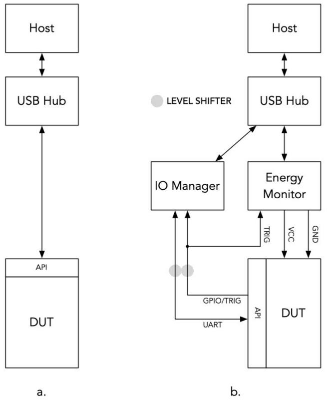


Figure 3: The two configuration modes of the benchmark framework for (a.) latency and accuracy measurement, or (b.) energy measurement.

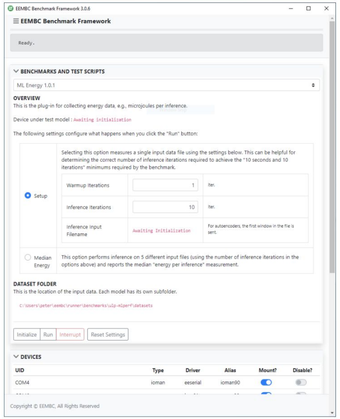


Figure 4: The graphical user interface (GUI) for the benchmark runner.

Key Challenges

How do we design a generally applicable ML benchmark using specific **scientific** applications?

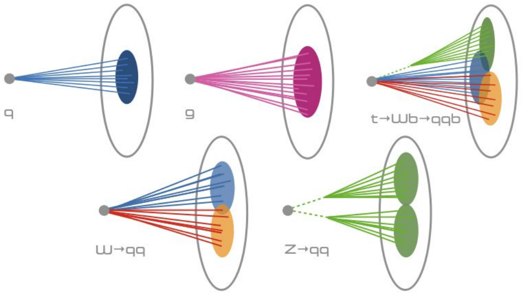
How can we design benchmark tasks to satisfy challenging **system-level** requirements while maintaining commonality?

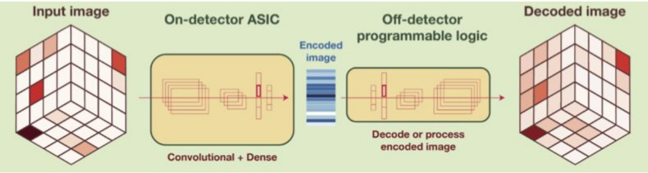
FastML Science Benchmarks

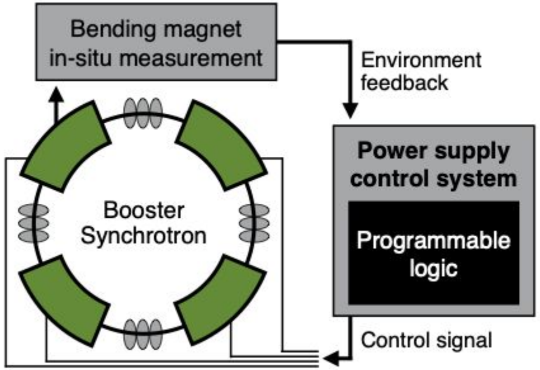
Supervised learning for rare physics event classification

Unsupervised compression of sensor data

Reinforcement learning for accelerator beam control







Agenda

- Existing Works
- Benchmark Design Philosophy
- Benchmark
    - Supervised Learning for Physics event triggering
    - Unsupervised learning for lossy compression of sensor data
    - Reinforcement learning for accelerator beam control

Existing Works

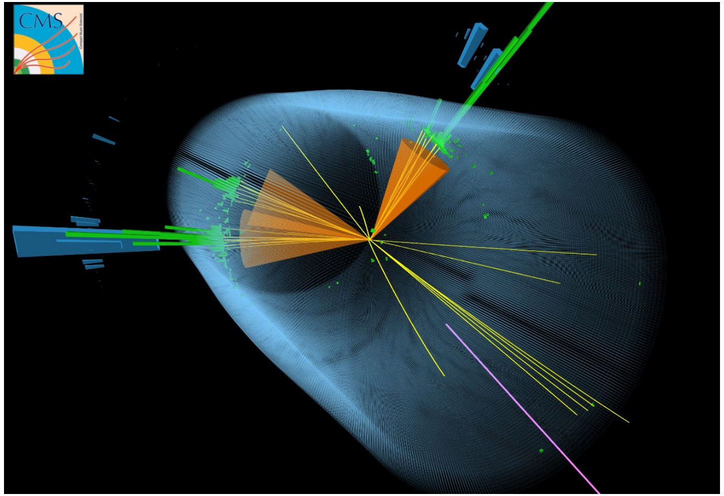
	Formalized Benchmark	Scientific Workload(s)	Edge Computing	Real-Time Constraints
FastML Science Benchmarks (this work)	✓	✓	✓	✓
SciMLBench (Thiyagalingam et al., 2021)	✓	✓	✓	×
LHC New Physics Dataset (Govorkova et al., 2021)	×	✓	✓	✓
MLPerf HPC (Farrell et al., 2021)	✓	✓	×	×
BenchCounil AIBench HPC (BenchCouncil, 2018)	✓	✓	×	×
MLCommons Science (MLCommons, 2020)	✓	✓	×	×
ITU Modulation Classification (ITU, 2021)	×	×	✓	✓

Benchmark Design Philosophy

- Applicatications are for the extreme edge
- Contrasting features between tasks
  - Quantization specification
  - Task specific performance metric
  - System level constraints on each benchmark
    - Latency
    - Power & Area

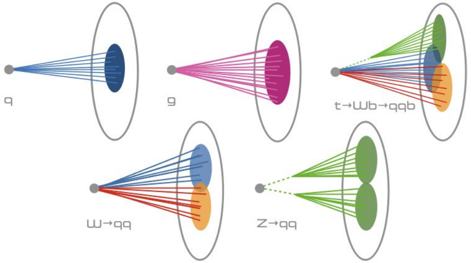
Jet Classification

- CMS experiment observes ~ 40MHz collision rate
- Data rates must be reduced by **triggering***
- Custom FPGA platforms in use as triggers at μs latency



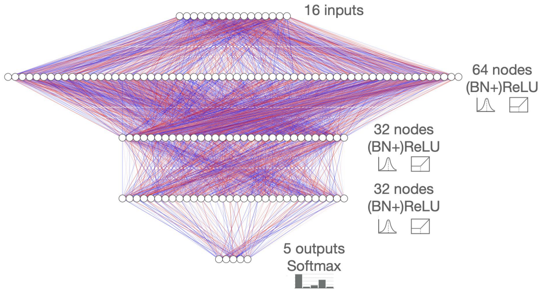
*triggering: real-time filtering
to save only certain events

Supervised Learning: Jet Classification

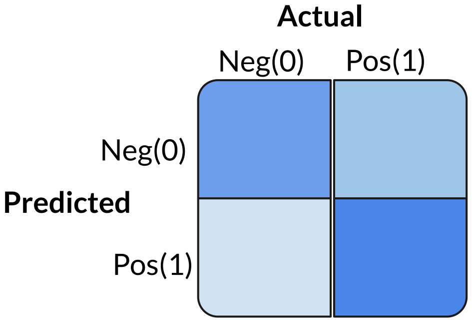


- Trigger only **interesting** events
- Jet tagging as supervised learning
- Baseline platform: Xilinx FPGAs within custom electronics

Baseline Model



Metrics

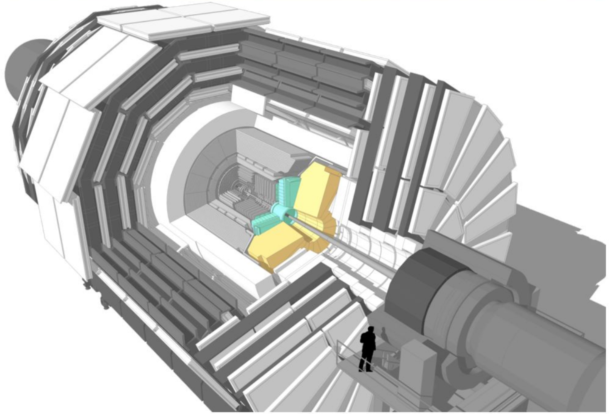


Constraints

Input precision	Pipeline interval	Real-time latency
16b	150ns	1 μs

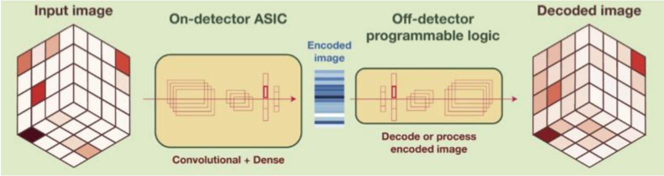
Sensor Data Compression

- High Granularity Calorimeter imaging detector produces large data
- Big data challenge posed by need to compression large for decision making
- Generalizable task to on-detector sensor data compression

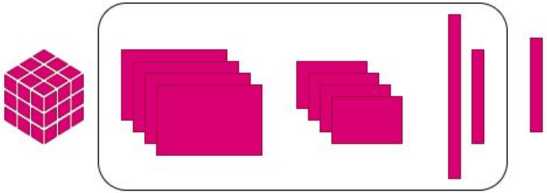


Unsupervised Learning: Irregular Sensor Data Compression

- Compress data for downstream processing
- Unsupervised data compression
- Reference platform: ASIC compresses sensor data



Baseline Model



Metrics

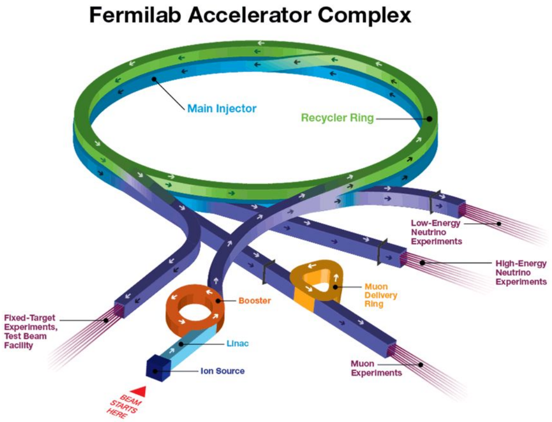
Similarity score using magnitude and distance of sensor data output

Constraints

Input precision	Pipeline interval	Real-time latency
9b	25ns	100 ns

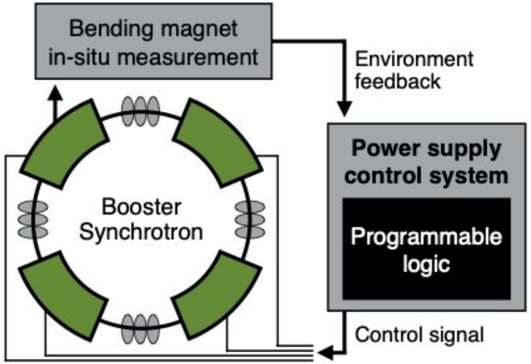
Beam Control

- Intense particle beam control is useful in general scientific work (optics, cancer therapy …etc)
- Precise control key to operation at DOE facilities
- Control systems problem:
  - Fermilab booster synchrotron: drive particle beam intensity and reduce beam intensity loss

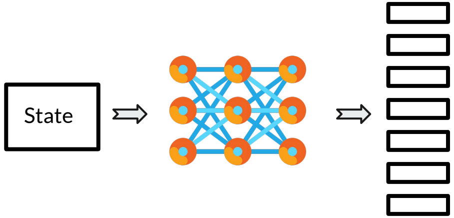


Reinforcement Learning: Beam Control

- Proton beam control critical to physics experiment
- Controls: reduce beam intensity loss
- Benchmark platform: Arria10 SoC



Baseline Model



Metrics

Difference in target and measured beam intensities

Constraints

Input precision	Pipeline interval	Real-time latency
32b	5ms	5ms

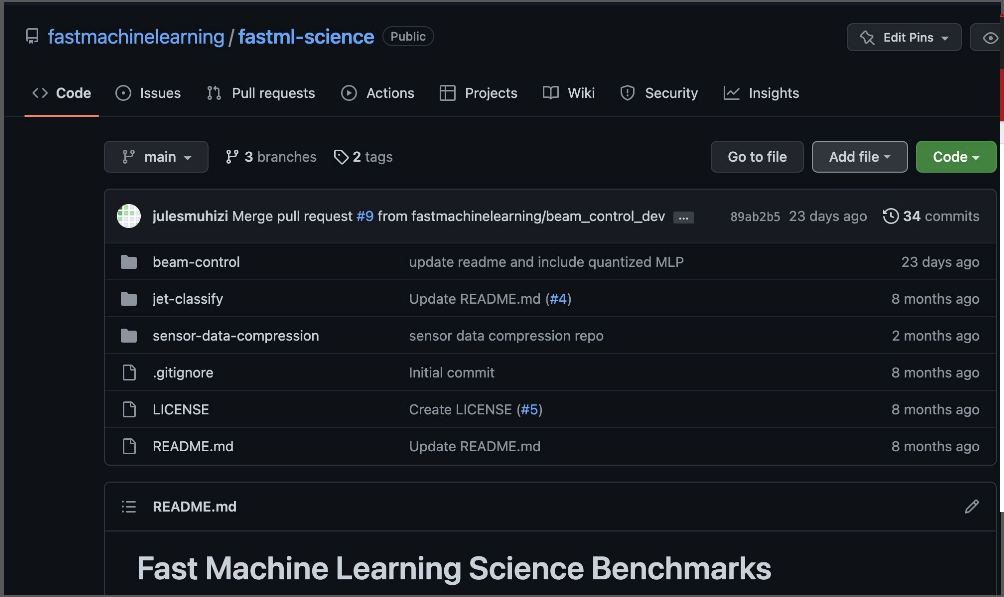
Review Key Challenges

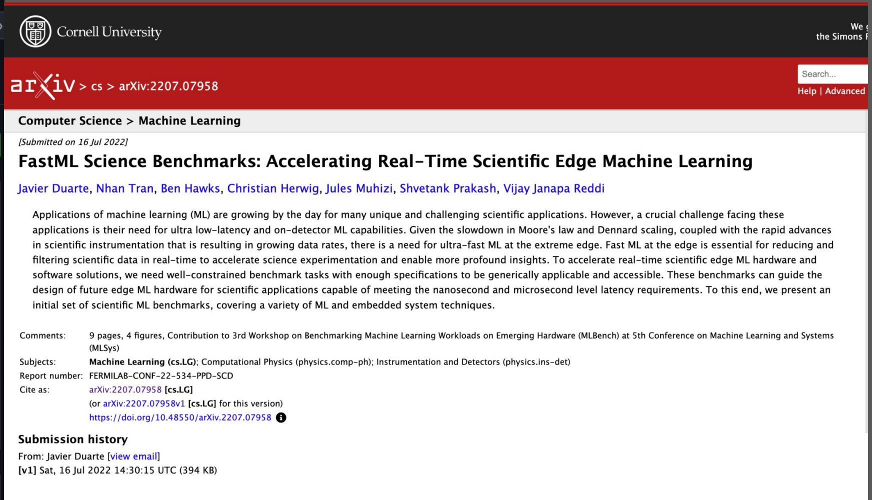
- How do we design a generally applicable ML benchmark using specific **scientific** applications?
    - Abstract away scientific complexity where applicable
    - Allow for new additions from scientific domain experts
    -
- How can we design benchmark tasks to satisfy challenging **system-level** scientific while maintaining commonality?
    - Features such as quantization are innate to data at the edge
    - We vary our platforms from ASIC to FPGA
    - Take inspiration from MLPerf Tiny™ to standardize platforms

Outlook

- Dennard scaling and Moore’s will become more and more apparent
- Edge computing and processing exceedingly crucial
- Motivate other science domain experts to bring more applications

Visit the repo and checkout the paper!





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