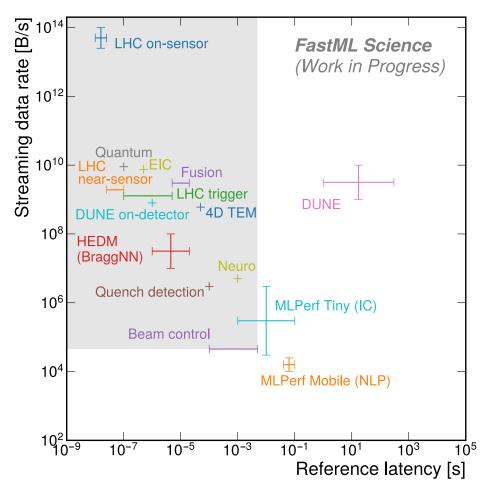
#### FastML Science Benchmarks: Accelerating Real-Time Scientific Edge ML

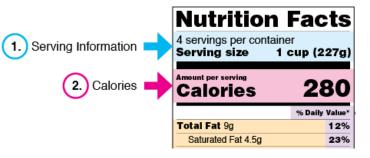


Aim to provide datasets, objectives, constraints, a reference solution, and metrics for each task.

• Current material on github.

Eager to scale this effort to incorporate new scientific domains and new kinds of technical challenges.

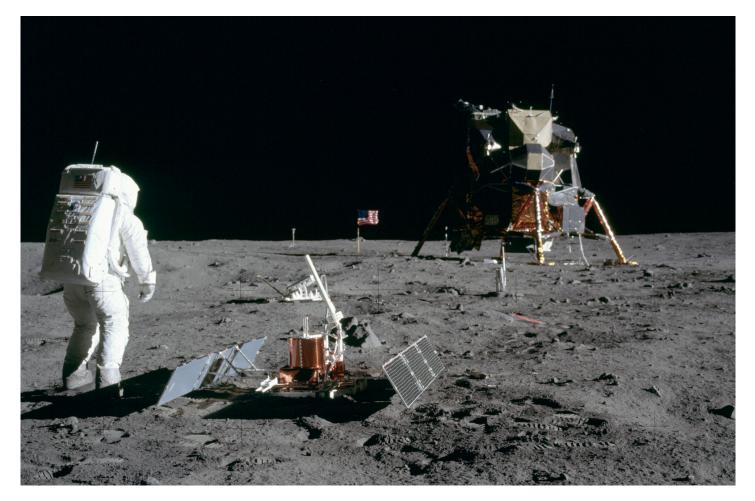
- How to effectively curate these tasks?
  - Aim to highlight the unique challenges.
  - "Representative" versus "cutting-edge"?
- "Nutrition facts" summary for each task?



**莽** Fermilab

#### Grand challenges, moonshots

# Benchmarks are great but not super glamorous, instead... Capture people's imagination of what's possible from the science side





## Grand challenges, moonshots

# **Scientific Grand Challenges** spur innovation

LHC: all sub-detectors analyzing data at 40 MHz

DUNE: expansive (non-)accelerator v program (solar, supernova, proton decay, ββ decay)

Accelerator controls with adaptive online agents and digital twin

Science:

- · Quantum,
- · Magnet development,
- Fusion,
- · Neuroscience,
- · Nuclear,
- Material sciences, etc.

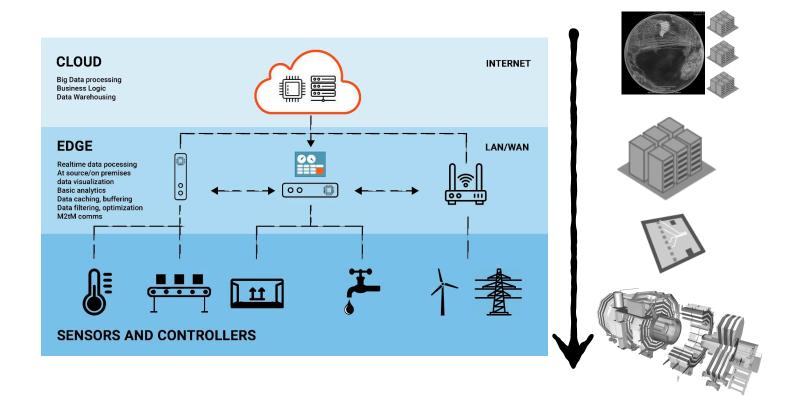
Industry: Internet-of-Things, AVs, manufacturing



#### Grand challenges, moonshots

## Grand challenges are multi-scale problems:

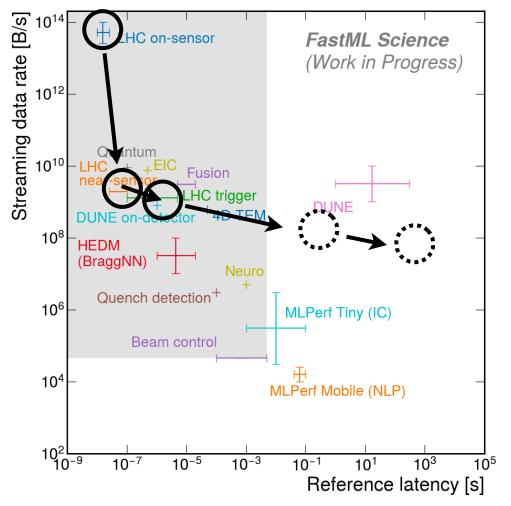
Real-time processing, control, reconstruction, simulation, analysis → Edge AI, Efficient AI, Foundation models, Digital Twins, Robustness, UQ





# Scientific Grand Challenge = Σ<sub>1...N</sub> {benchmarks}<sub>i</sub>

Compile benchmarks as a critical path to grand challenges



# Example Moonshot: analyze all data from LHC

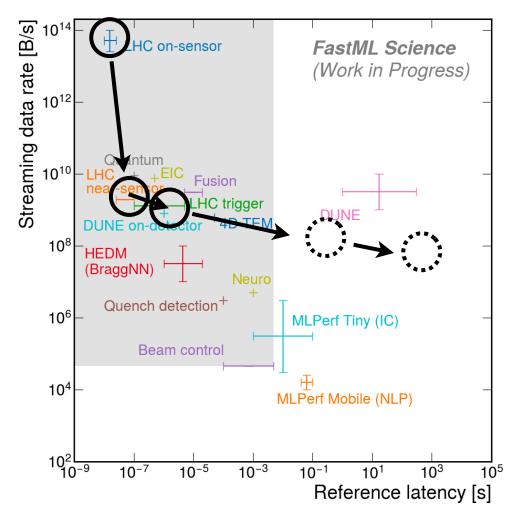
#### **Benchmarks:**

- Read out pixel detector at 40 MHz with full fidelity, e.g. smart pixels
- Enable real-time streaming processing (40 MHz scouting), e.g. dark machines
- Offline tracking at 200 PU with same performance as 60 PU with 10x speedup/event, e.g. ExaTrkX challenge
- Accelerate fast simulations by 100x with same fidelity as full simulation, e.g. Calo Challenge
- Enable automized calibrations (no more re-reconstruction), .e.g ??

**‡** Fermilab

# Scientific Grand Challenge = Σ<sub>1...N</sub> {benchmarks}<sub>i</sub>

Compile benchmarks as a critical path to grand challenges



## Example Moonshot: neutrino physics Benchmarks:

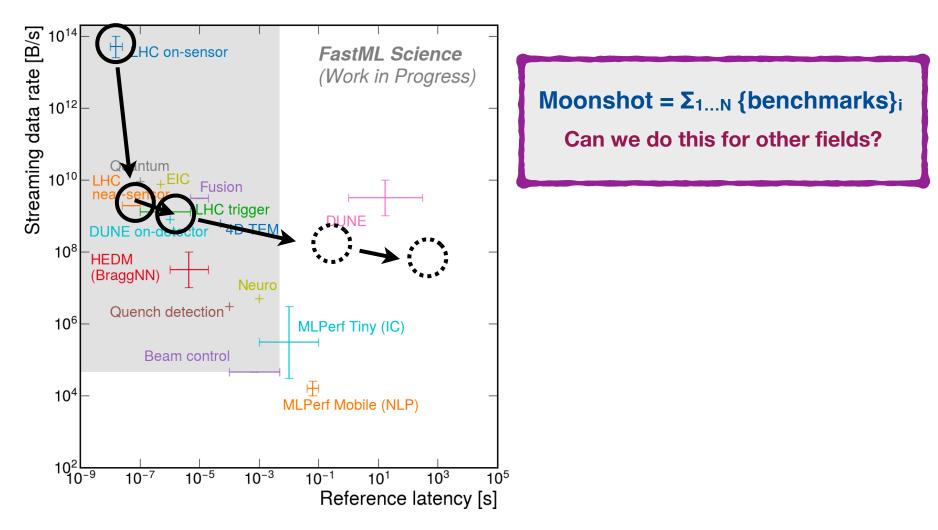
- Improve SuperNova Burst streaming signal acceptance by XX% with data reduction rate of YY
- Enable ZZ sensitivity to neutrinoless double beta decay with low energy reconstruction task A
- $\cdot$  Charge current reconstruction performance with resolution of  $\sigma$

•???



# Scientific Grand Challenge = Σ<sub>1...N</sub> {benchmarks}<sub>i</sub>

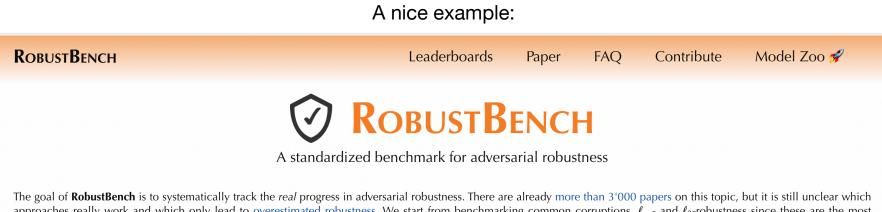
Compile benchmarks as a critical path to grand challenges





#### Another axis for benchmark metrics: Robustness and UQ

- What happens when the detector, environment, conditions change?
- Develop new benchmarks for robust science use-cases
  - harder to develop benchmarks



approaches really work and which only lead to overestimated robustness. We start from benchmarking common corruptions,  $\ell_{\infty}$ - and  $\ell_2$ -robustness since these are the most studied settings in the literature. We use AutoAttack, an ensemble of white-box and black-box attacks, to standardize the evaluation (for details see our paper) of the  $\ell_p$  robustness and CIFAR-10-C for the evaluation of robustness to common corruptions. Additionally, we open source the RobustBench library that contains models used for the leaderboard to facilitate their usage for downstream applications.

To prevent potential overadaptation of new defenses to AutoAttack, we also welcome external evaluations based on *adaptive attacks*, especially where AutoAttack flags a potential overestimation of robustness. For each model, we are interested in the best known robust accuracy and see AutoAttack and adaptive attacks as complementary.



## Vision

		Scientific Moonshots				
		Domain A		Domain N		
AI thrusts	AI - 1: Real-time	Benchmark 1A		Benchmark 1N		
	AI - 2: Control					
	AI - 3: Autonomous					
	AI - 4: Foundation					
	AI - 5: Generative	Benchmark 5A		Benchmark 5N		

**‡** Fermilab



#### FastML Science Benchmarks: Accelerating Real-Time Scientific Edge ML

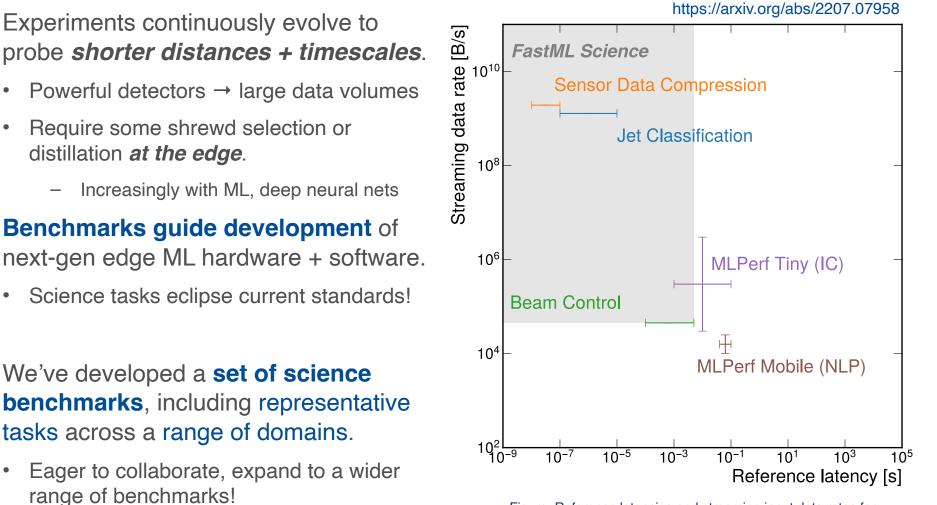
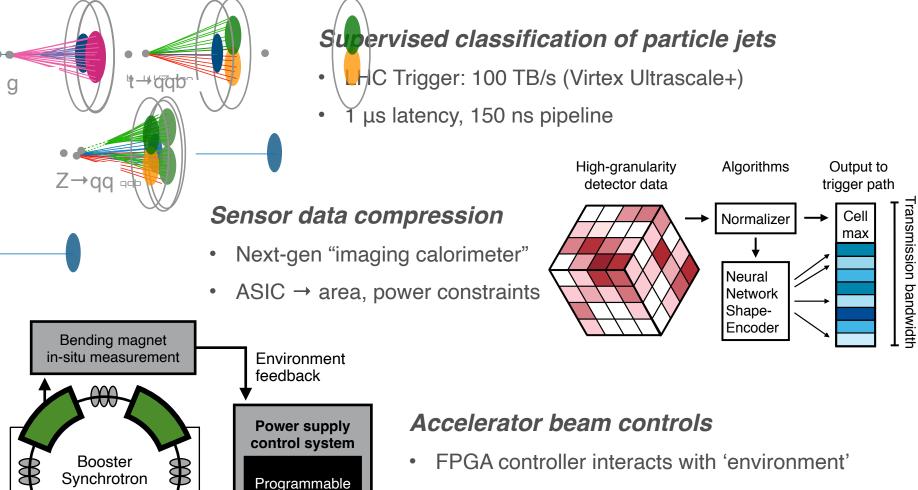


Figure: Reference latencies and streaming input data rates for common industry benchmarks and FastML Science.



## marks: Accelerating Real-Time Scientific Edge ML



- Reinforcement learning
- Inputs from 50 devices across accel. complex.



logic

Control signal

## FastML Science Benchmarks: Accelerating Real-Time Scientific Edge ML

Benchmark task	Data representation	ML type	Latency	Throughput	Target platform	Material status? (Data/model/
LHC Sensor	image	unsupervised	10-100ns	1-10 TBps	ASIC	
LHC Trigger	Point cloud	supervised	0.1-100us	1-10 TBps	FPGA	
Neutrino	Image/spectral	unsupervised	1s - 5 min	1-50 GBps	ASIC / GPU(?)	
Accelerator control	spectral	control	1ms	100 kBps	FPGA	
4D TEM	image	unsupervised	50us	1 GBps	FPGA	
Qubit readout	RF spectral	supervised	0.1-1ns	50 GBps	FPGA	
Fusion	image	supervised	5-20us	1-10 GBps	FPGA	
Neuro	spectral	unsupervised	1ms	5 MBps	ASIC (?)	

. .

Fermilab

(And many more...)

What is the most impactful set of material to highlight?

• Power budget, number of operations, ...