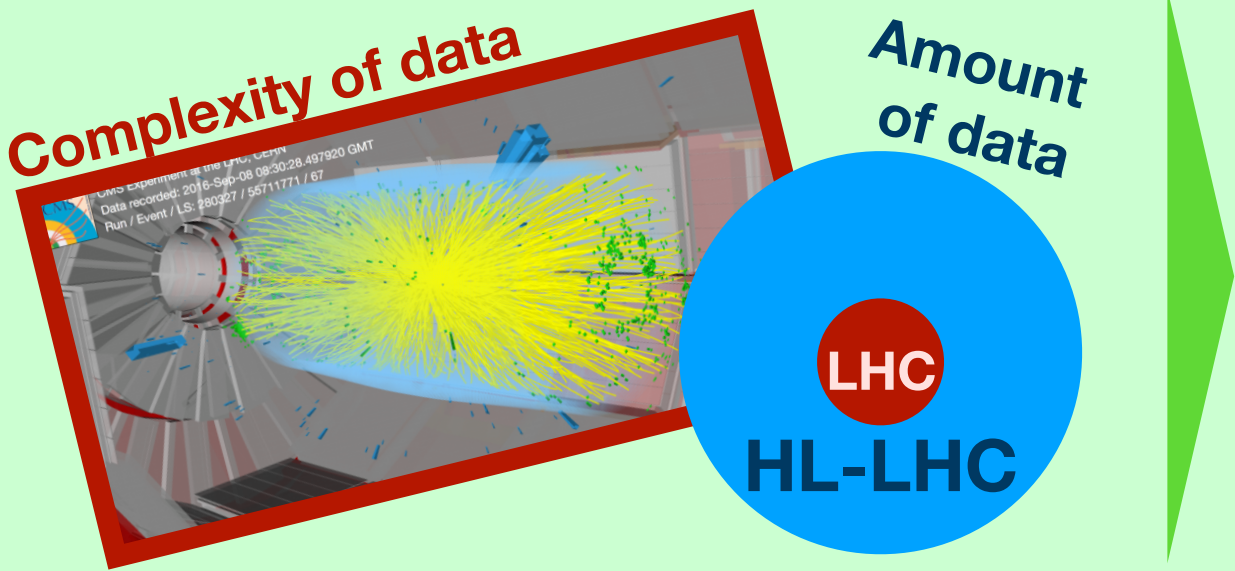


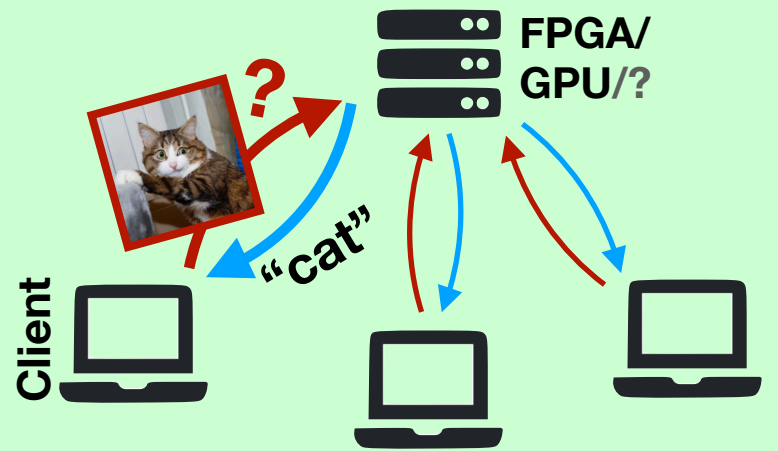
Accelerated Machine Learning as a Service for Particle Physics Computing

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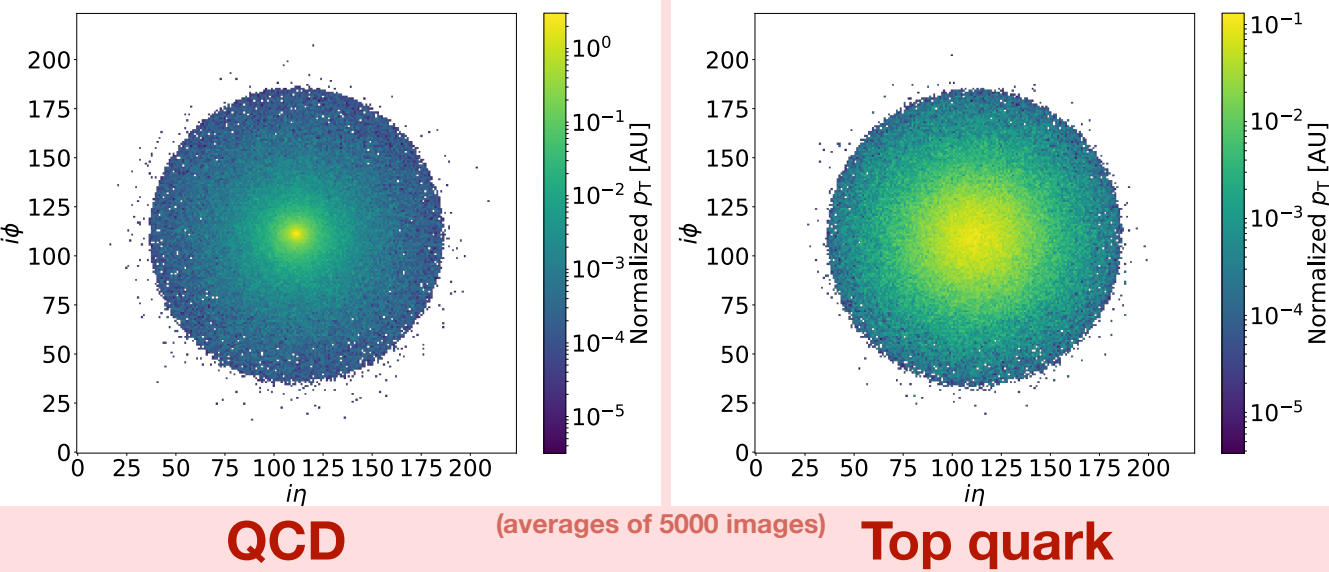
1: Fermi National Accelerator Laboratory, 2: University of California San Diego, 3: Massachusetts Institute of Technology, 4: CERN, 5: Microsoft, 6: University of Washington, 7: University of Illinois Chicago
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- Amount and complexity of high-energy physics data increases dramatically from 2025 onward
- Traditional algorithms will require too much CPU time
- Machine learning can solve **combinatorially-scaling** problems in **constant time**, but must be fast enough

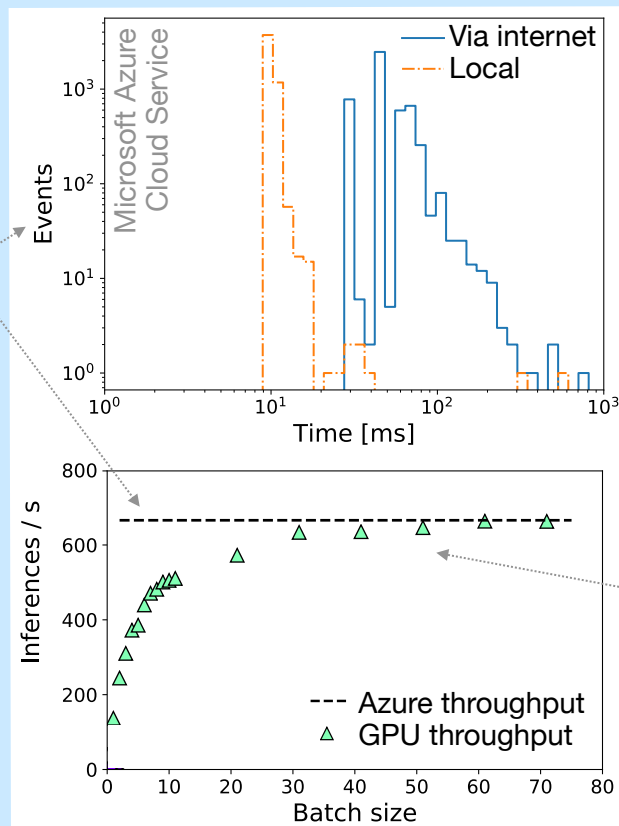
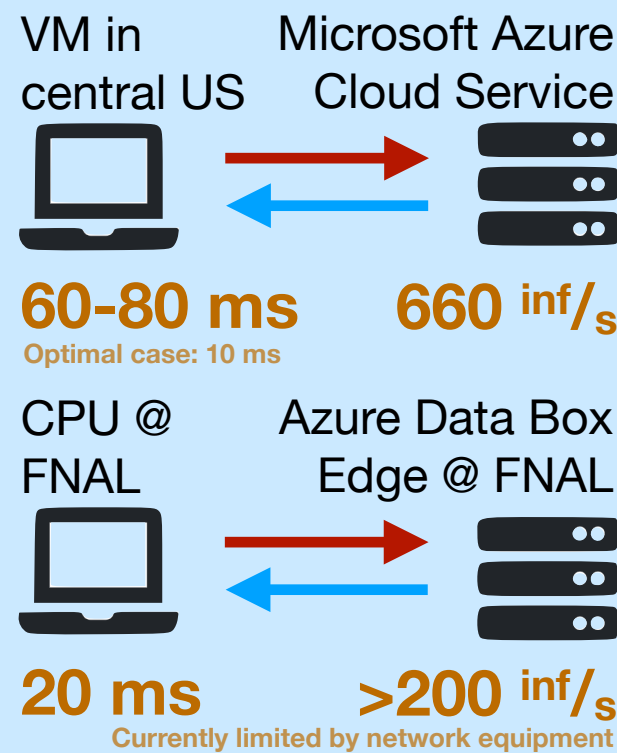


Example challenge

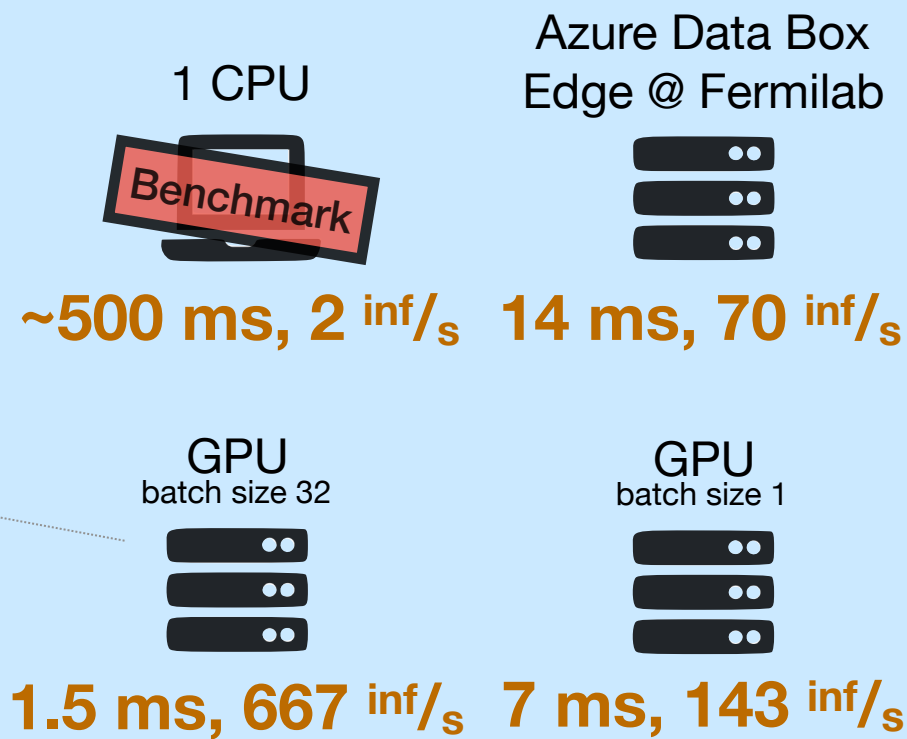
Separate "**top quarks**" (interesting!) from "**QCD jets**" (uninteresting)

- Inputs 224x224 'single-color' images in a ResNet50 architecture
- Pixels are energy collections in the CMS electromagnetic calorimeter crystals

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Local



Results

An **FPGA-aaS** reaches the same throughput as a **locally connected GPU**, the former by having many CPUs access it and the latter by setting a high batch size

- What NN architectures are suitable for our physics problems **and** IaaS?
- How scalable are these solutions to HL-LHC data volumes?

