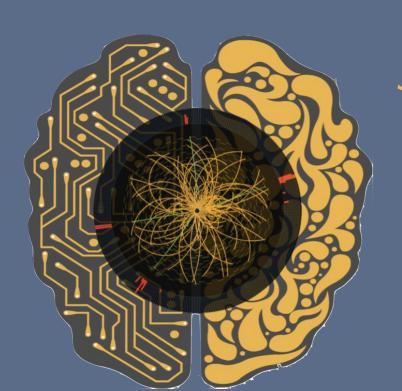
# UC San Diego

# Low-latency machine learning inference on FPGAs



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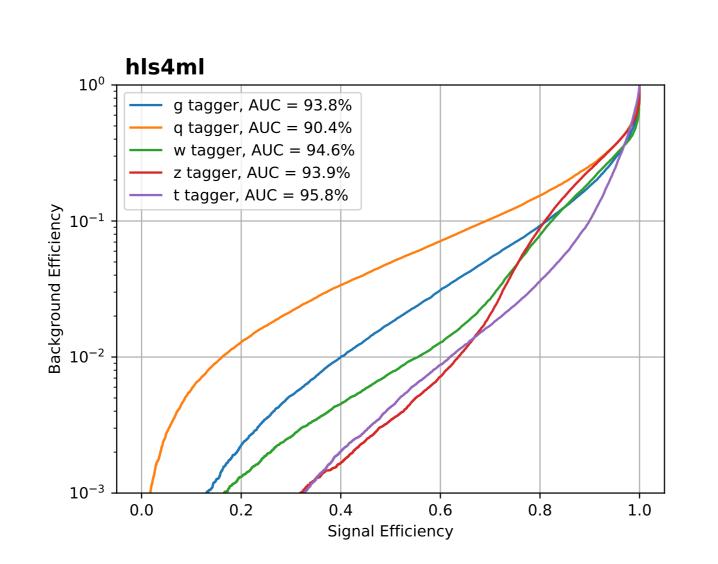
### Introduction

# Compute Latency 1 ns 1 µs 1 ms 1 kHz 1 MB/evt Offline

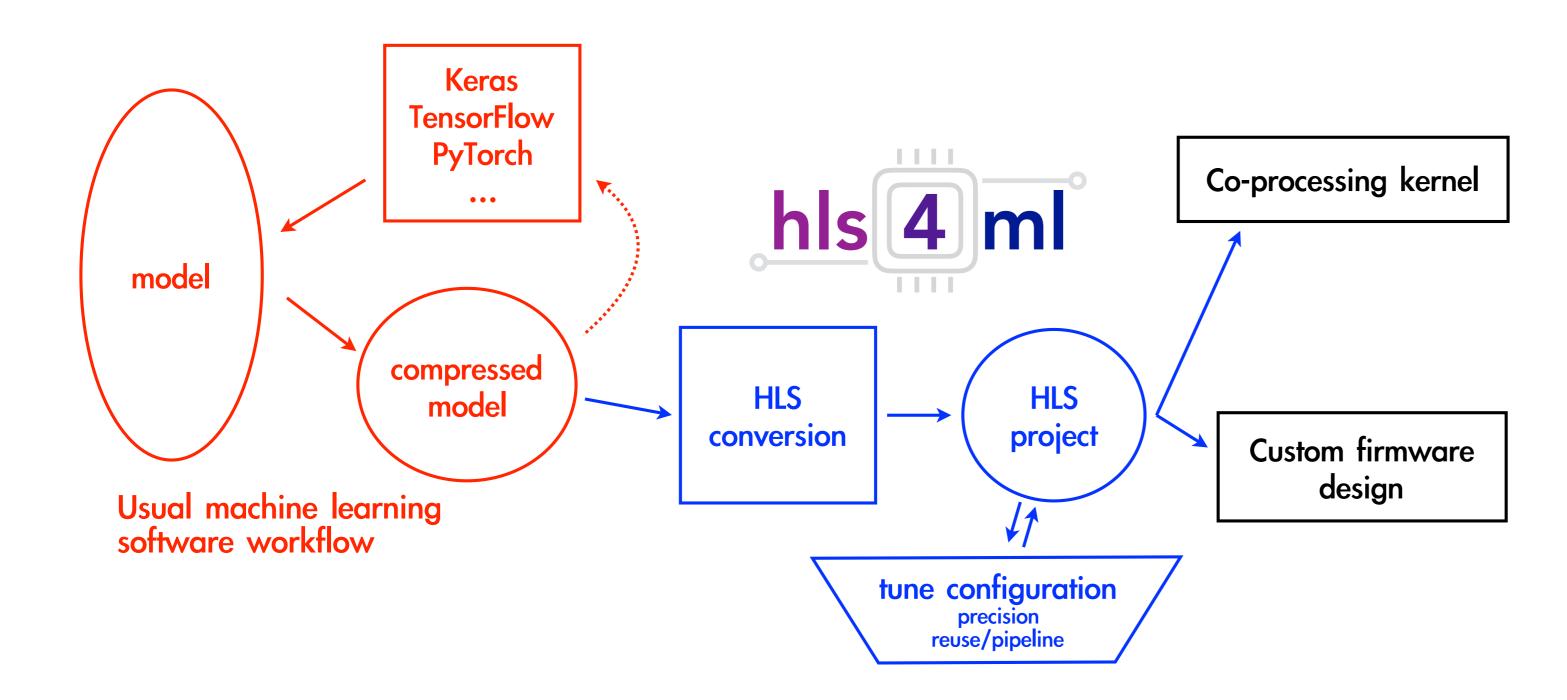
- ► Machine learning (ML) use case in particle physics: first stage of real-time data processing and filtering in field programmable gate arrays (FPGAs)
- ightharpoonup CERN LHC requirements: high input data rates ightharpoonup TB/s, ightharpoonup fixed algorithm latency, constrained FPGA resources
- ► Compiler based on high-level synthesis (HLS) called hls4ml to rapidly prototype ML models in FPGAs

### Case study

- Task: differentiate showers (or *jets*) produced in decays of heavy standard model particles (W and Z bosons and top quarks), from backgrounds consisting mainly of light quark- (u, d, c, s, b) and gluon-initiated jets
- ► Fully-connected neural network (NN) with 16 inputs and 3 hidden layers (64, 32, 32) to classify 5 categories of jets
- Performance quantified in a receiver operating characteristic (ROC) curve of signal efficiency versus misidentification rate for quark, gluon, W boson, Z boson, and top quark jets



### Design



Explore the FPGA design space through

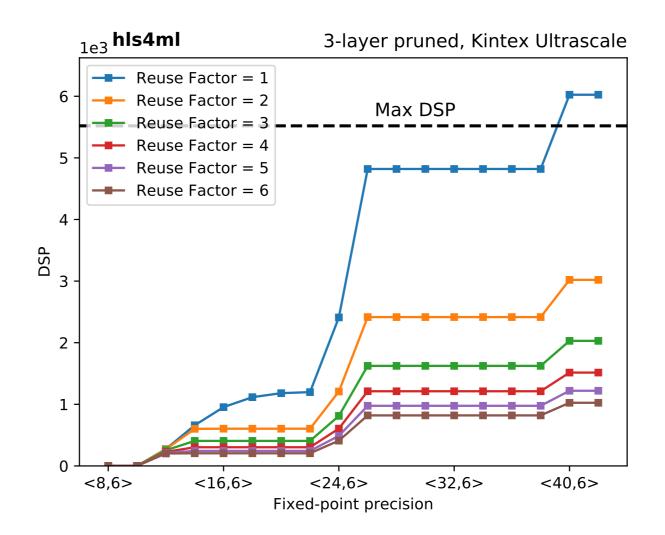
- **compression**, the three-hidden-layer model with 70% of the parameters removed using iterative retraining with  $L_1$  regularization and magnitude-based pruning
- **quantization**, the precision of the inputs, weights, and biases
- **parallelization**, the number of times a given multiplier is used for a layer computation, quantified by a *reuse factor*

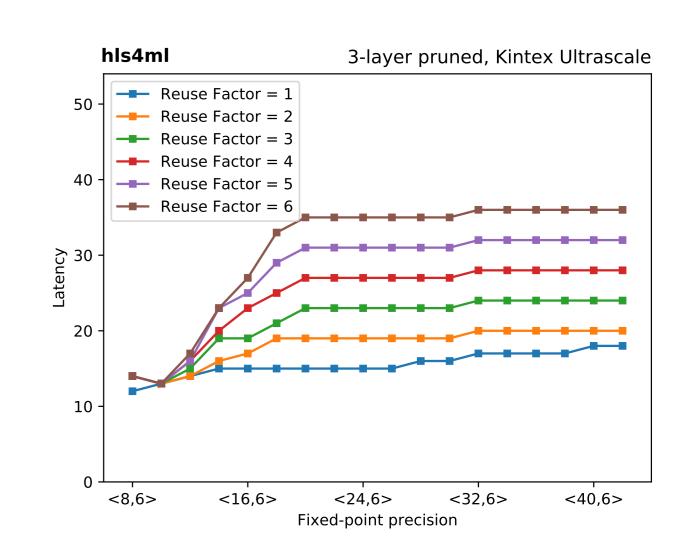
With these handles, monitor

- resources: digital signal processors (DSPs), block random access memory (BRAM), flip-flops (FFs), and lookup tables (LUTs)
- ► latency: time it takes to compute the full network
- initiation interval (II): time before a new set of inputs can be accepted

### **Implementation**

- ► First evaluate NN with fixed point precision: <16,6> fixed-point precision reproduces the ROC curve performance
- ► DSP usage in the compressed 3-hidden-layer model increases as a function of the network precision and decreases for larger reuse factors
- ► Latency increases from 10 to 35 clock cycles (50 to 175 ns) for larger reuse factors
- ► Results based on Xilinx Kintex Ultrascale FPGA part number xcku115-flvb2104-2-i, 200 MHz clock frequency, Vivado HLS 2017.2





### Recent developments

To enhance the flexibility of hls4ml, several new developments include

- extension to allow for significantly larger dense networks in terms of the number of neurons per layer
- Inclusion of zero-suppression for weights stored in on-chip memory or BRAM, reducing the use of on-chip logic registers
- addition of binary and ternary matrix multiplication

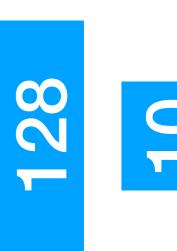
To demonstrate the new developments, several versions of a large dense network to classify handwritten MNIST digits are benchmarked

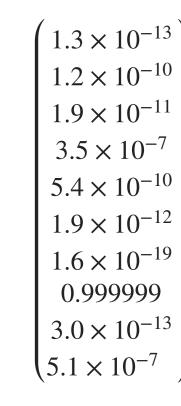












Model	11	Accuracy	Latency	DSP	BRAM	FF	LUT
MNIST dense	128	0.97	$2.6~\mu \mathrm{s}$	21%	45%	12%	33%
MNIST binary dense	128	0.93	$2.6~\mu \mathrm{s}$	0%	33%	7%	39%
MNIST ternary dense	128	0.95	$2.6~\mu \mathrm{s}$	0%	33%	7%	40%
MNIST dense, 95% pruned	128	0.96	$2.8~\mu s$	1%	34%	13%	164%
MNIST dense	4096	0.97	$68.1~\mu$ s	1%	66%	27%	83%
MNIST dense, 95% pruned	4096	0.96	82.1 $\mu$ s	0%	34%	9%	25%

## Summary

- ► hls4ml: compiler based on HLS for porting fully-connected NNs to an FPGA from conventional training frameworks such as Keras and PyTorch
- ► Focus on real-time event reconstruction and filtering at the LHC in FPGAs, with many other applications to real-time detector systems in the physical sciences
- ▶ Implemented a dense 3-hidden-layer NN in a Xilinx Kintex Ultrascale using roughly 10% of the available DSPs and latency of approximately 75–150 ns with a clock frequency of 200 MHz
- Extend the capabilities and flexibility of hls4ml to allow larger NN architectures for applications with latency constraints of approximately 1–100  $\mu$ s