FWXMACHINA

Nanosecond machine learning with boosted decision trees for high energy physics





Tae Min Hong

- Paper JINST 16 P08016 (2021)
- Info http://fwx.pitt.edu
- Code http://gitlab.com/PittHongGroup/fwX

PIKIMO 2021

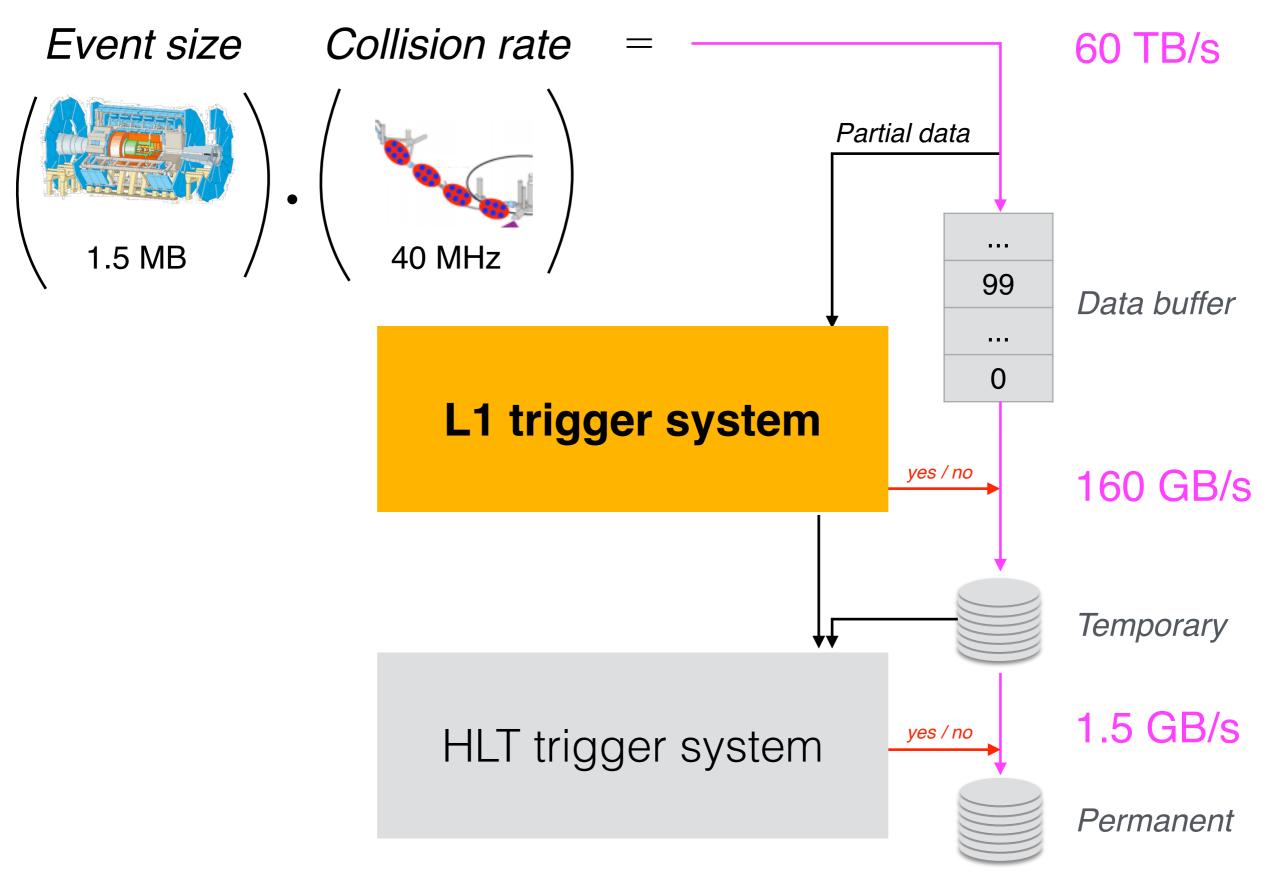
December 4, 2021

https://indico.cern.ch/event/1091676/

Machine learning at <u>L1 trigger</u>









BDT design

- Algorithm structure
- Firmware design

Results

- VBF Higgs vs. multijet
- (Electrons vs. photons)

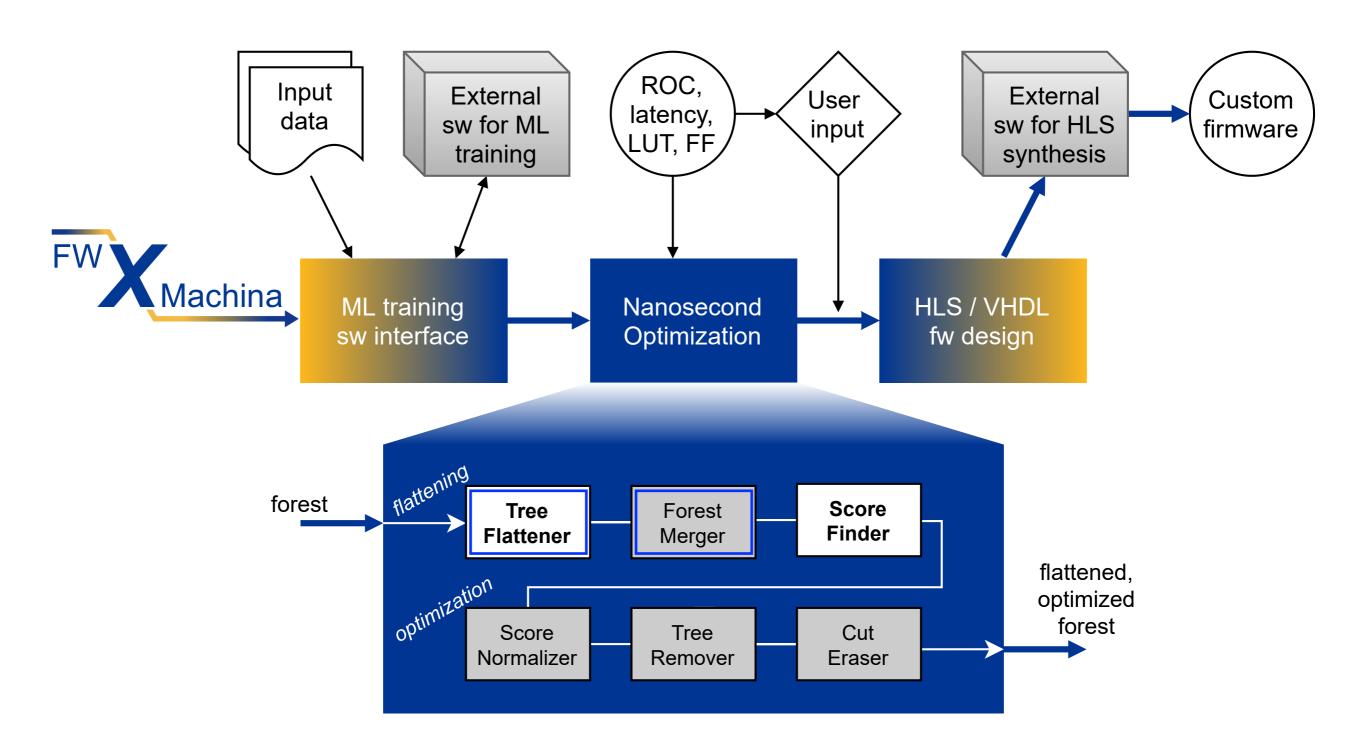
Comparisons

- vs. hls4ml's BDT
- vs. hls4ml's neural network

JINST 16 P08016 (2021)

Not in paper

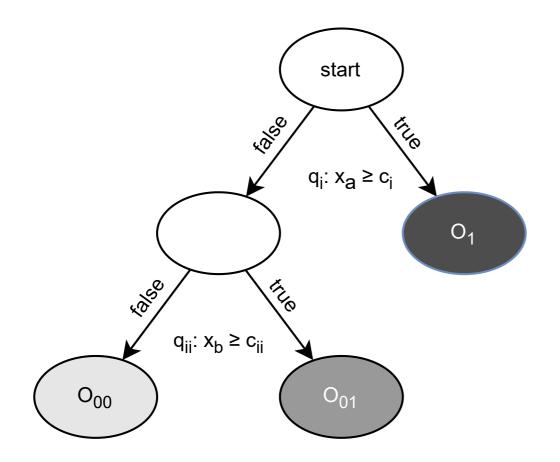




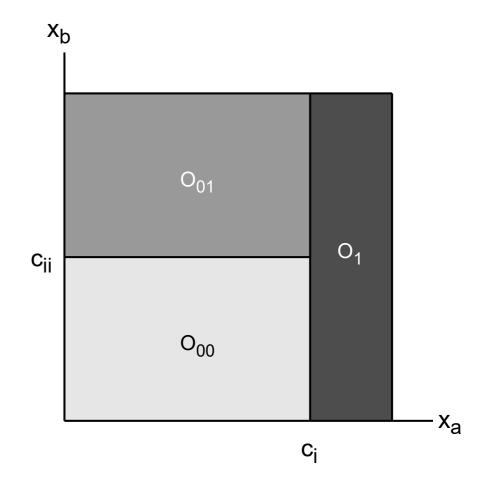
I will focus on the first two steps



Conventional tree structure



2d plane: x_a vs. x_b



Normal decision tree

Recursive in the number of depths

Firmware

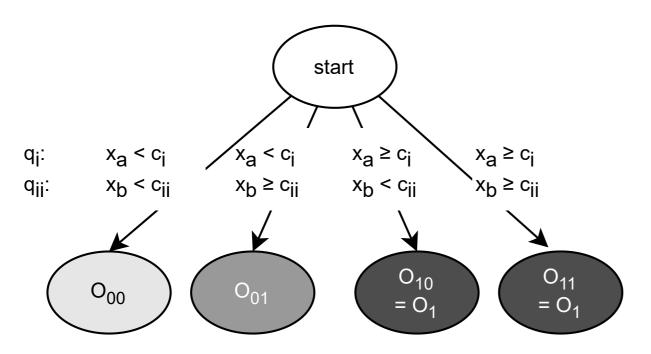
Not our design

TM Hong

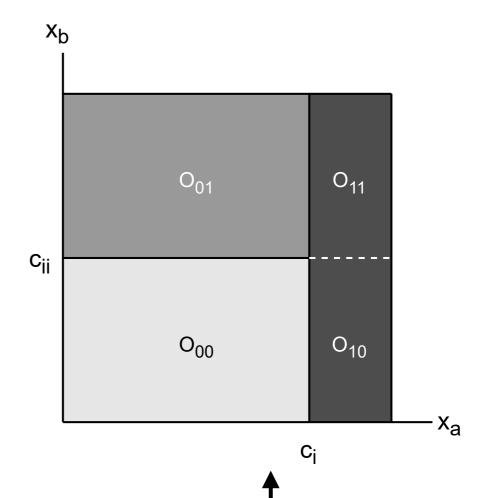
Flattened decision tree







2d plane: x_a vs. x_b



Flattened decision tree

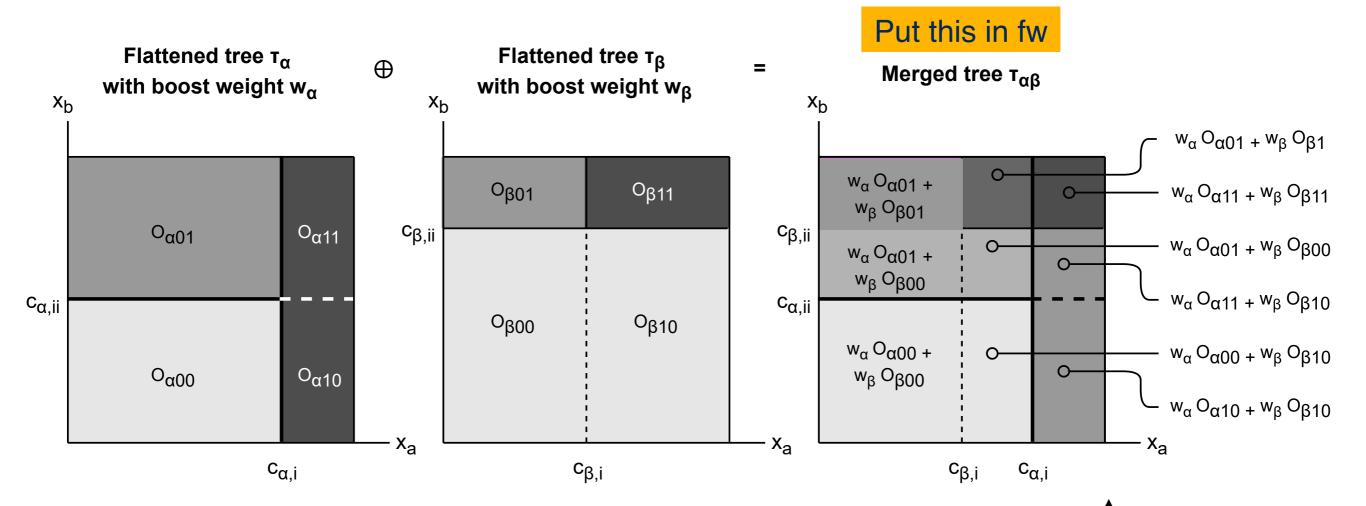
Axes are independent → Bin search problem on a grid

Firmware

Our design

Pre-merge the forest





Pre-merging trees

- Pre-processed in software before implementation in firmware
- No impact on physics performance

Firmware

Our look-up table design

Motivation: VBF Higgs vs. multijet





Same production, two decays

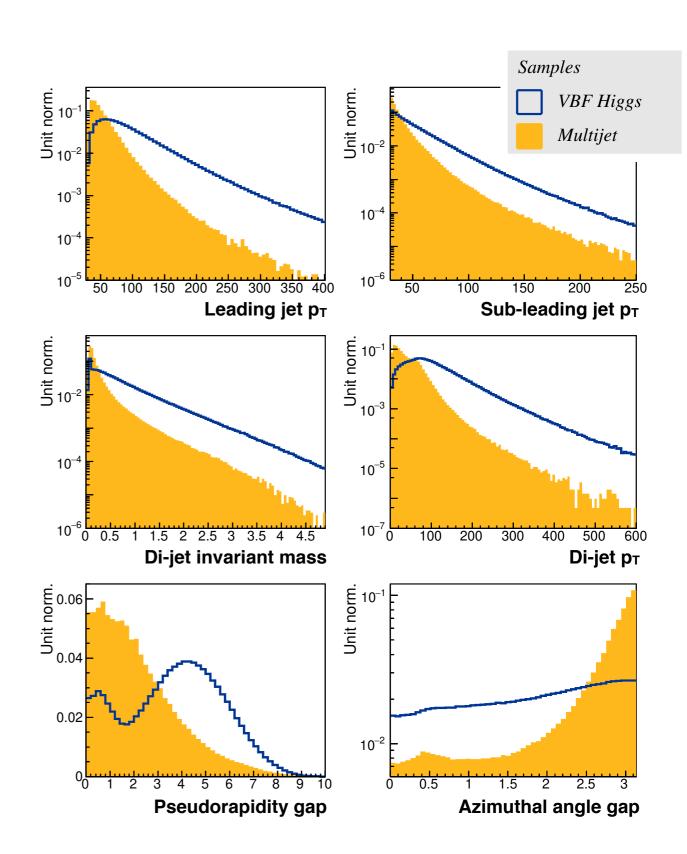
- H → vvvv, "invisible"
- H → bbbb, thru pseudoscalars

Strategy

- Train on Multijet vs. VBF H → vvvv
- Apply to Multijet vs. VBF H → bbbb

Why

- Can trigger on VBF Higgs → anything
- Does it work? Yes, next slide



Results

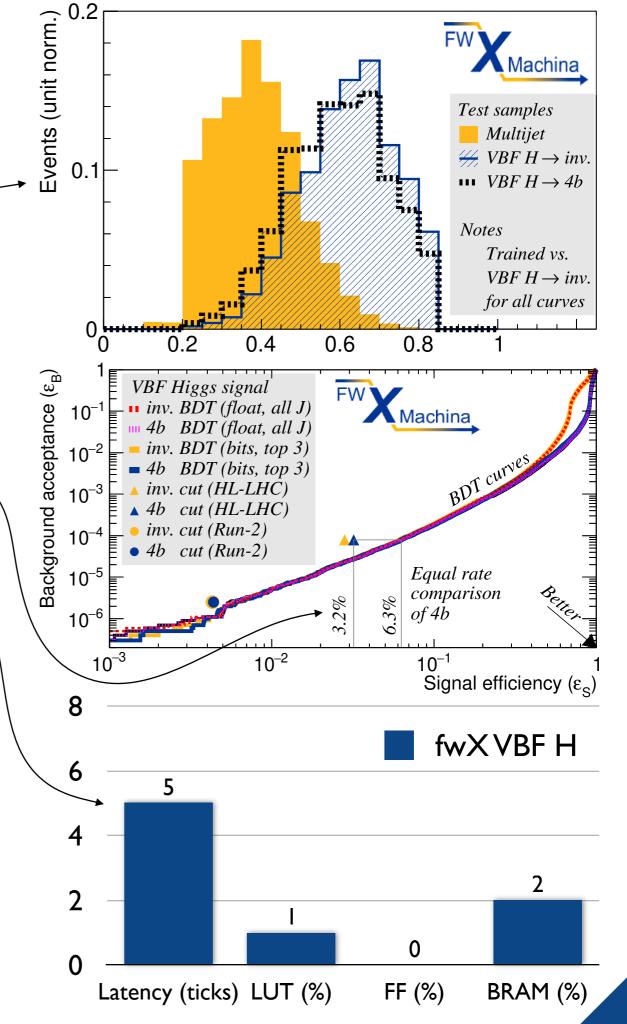
It works!

Performance

- Efficiency: 2x better vs. HL-LHC ATLAS
- Latency : 16 ns = 5 clock ticks

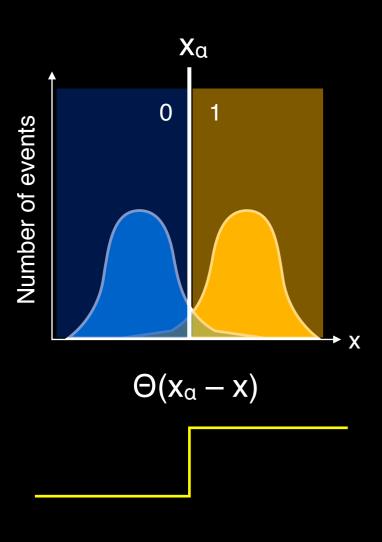
Details

Validation: Eff. matches ATLAS Run-2 paper

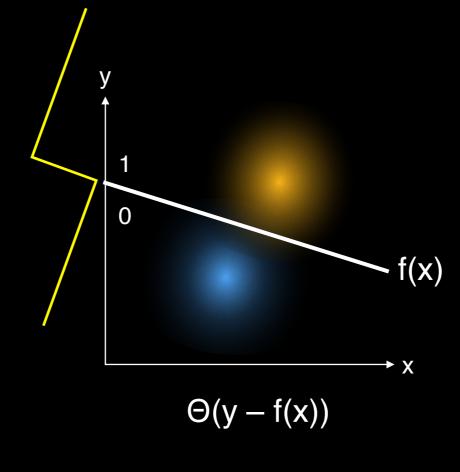


BDT vs. neural networks

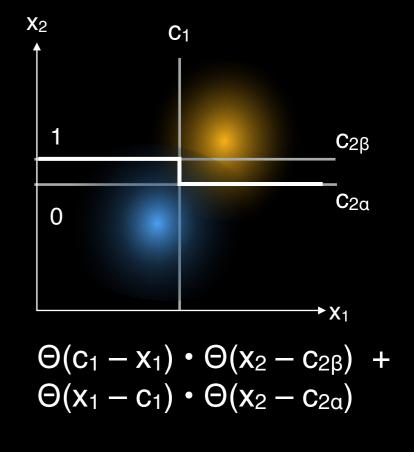
Step function for 1d



Neural network 2d

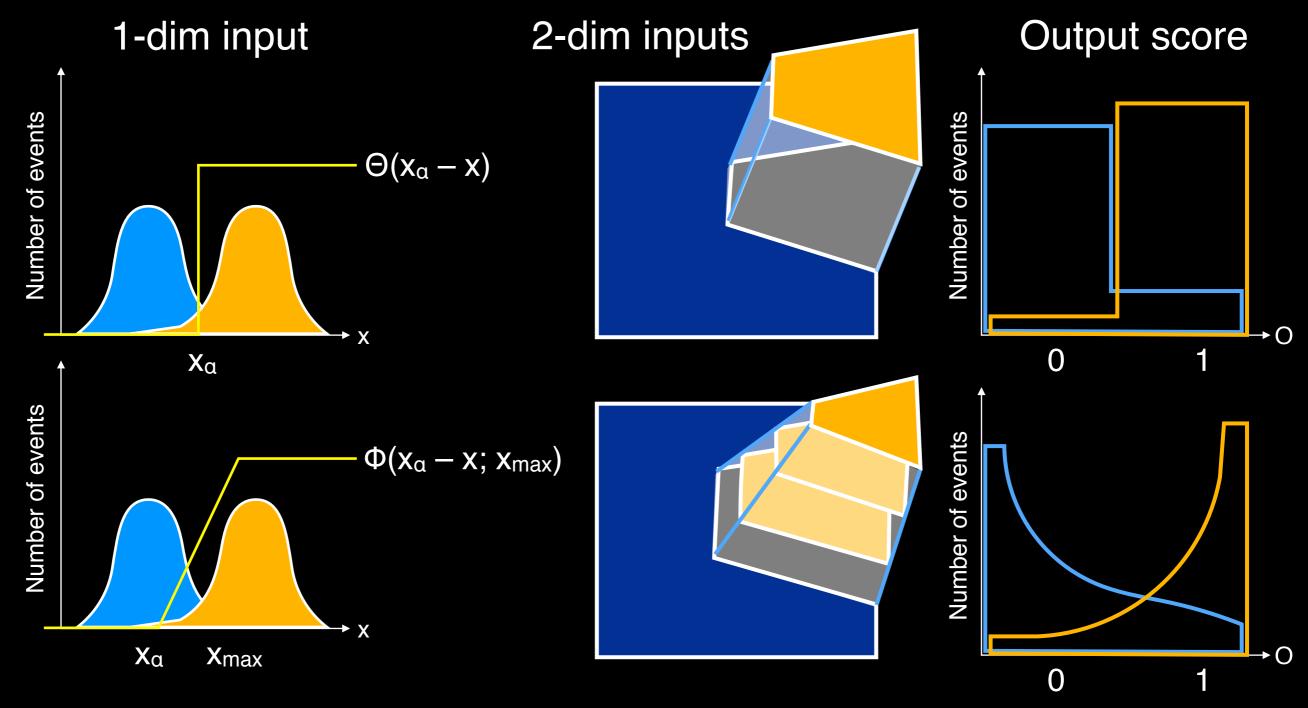


Decision tree 2d



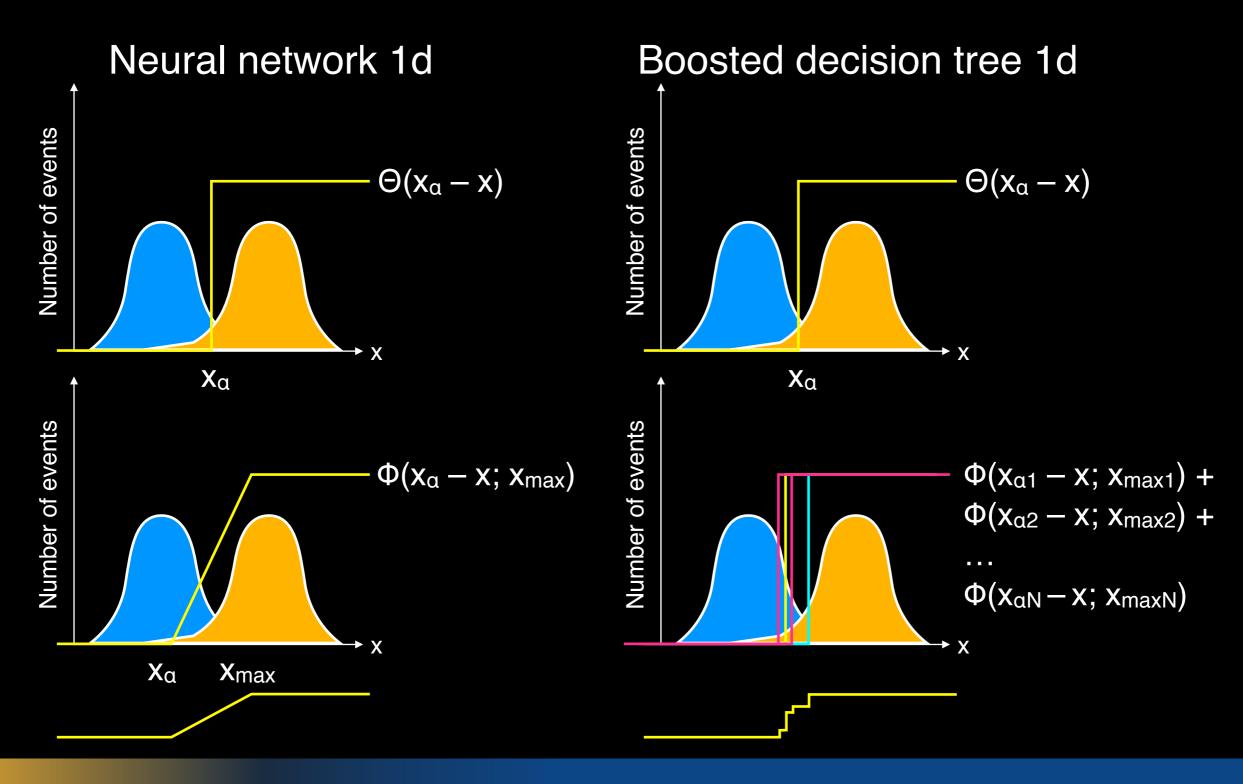
Activation function for NN

Fuzzy boundary using a turn-on function



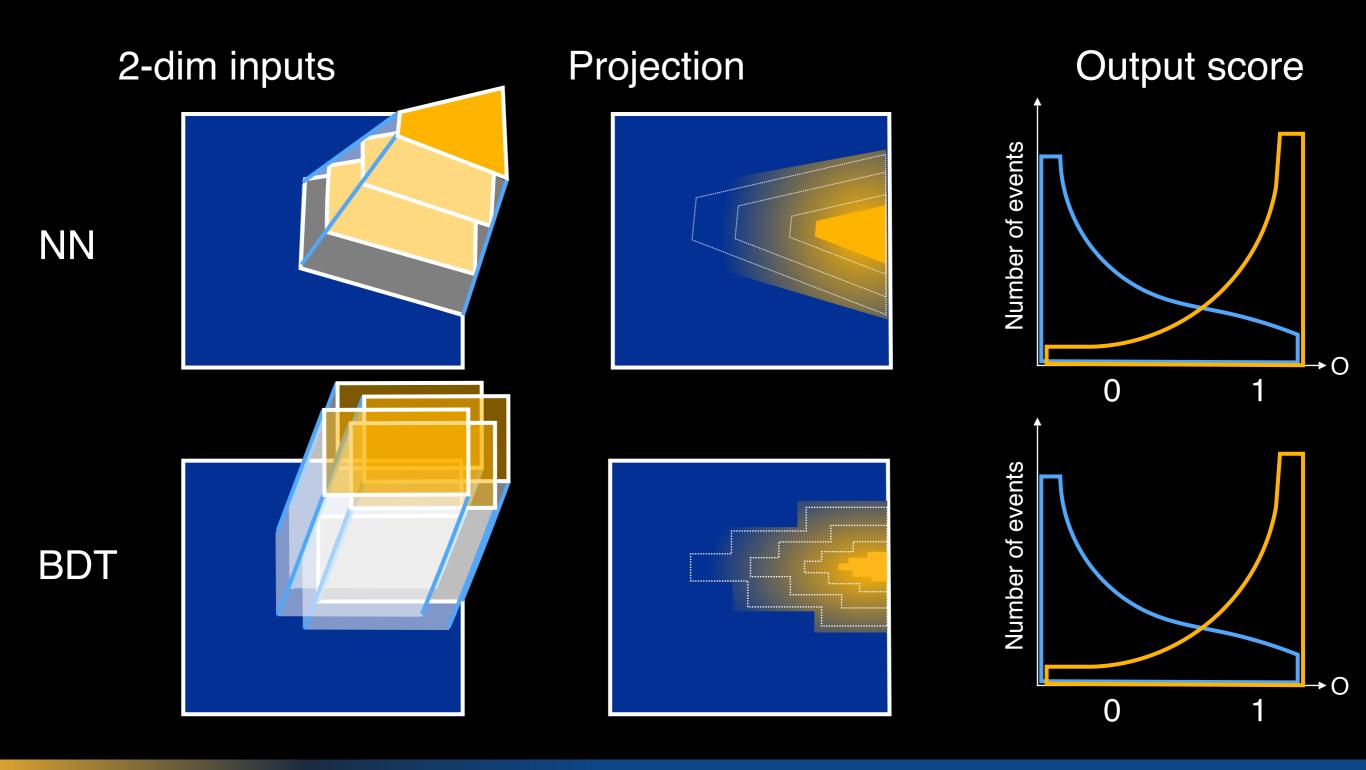


Forest of decision trees





Fuzzy boundaries





Data format

We encode in N-bit integers
 E.g., ap_int(3) means 0 - 7 range

Advantages

Represent variety of precision, e.g., p_T from GeV-TeV vs. φ from 0-2 π

Subtleties

Transformation adds 1-bit ambiguity

$$c_{\text{int}} = f(c_{\text{float}}) = \left[\frac{c_{\text{float}} - c_{\text{min}}}{c_{\text{max}} - c_{\text{min}}} \cdot \left(2^N - 1 \right) \right]$$

Equal up to one bit because of floor

$$f(x_1 + x_2) = f(x_1) + f(x_2)$$

Firmware adds the pre-evaluated f(x)

hls4ml encodes in fixed pt

E.g., ap_fixed(5,2) means

00.000 00.001 00.002 00.003 00.004 00.005 00.006

Advantages

More familiar to physicists who use floating / fixed values

Subtleties

Need to use "quantized aware training" to reduce the number of bits



fwX BDT vs. hls4ml BDT

Setup

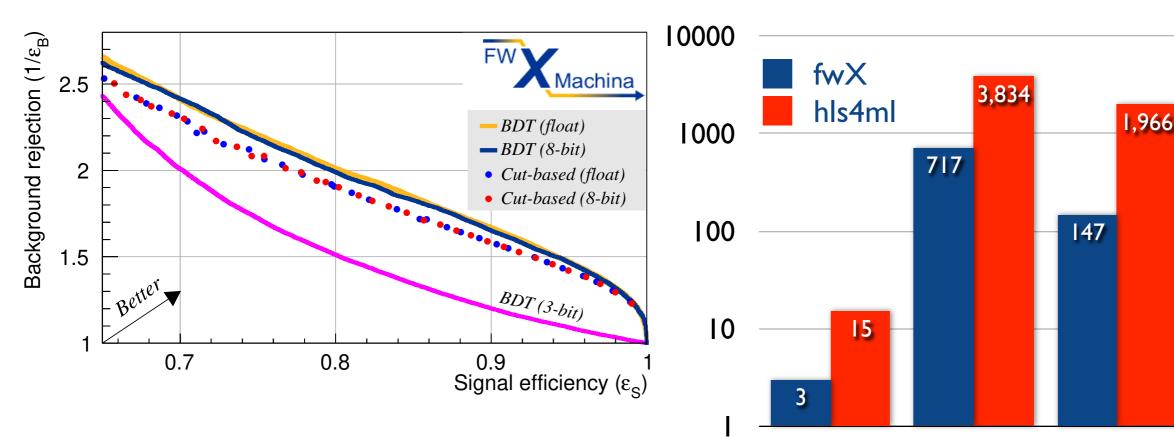
- Details in paper, same as possible
- Public datasets of e vs. γ
- ROC is same bec. use same BDT

Comparison

Latency (ticks)

LUT

- Lower latency
- Lower LUT, FF
- Higher BRAM (but 0.1% of avail.)





5.5

BRAM

FF

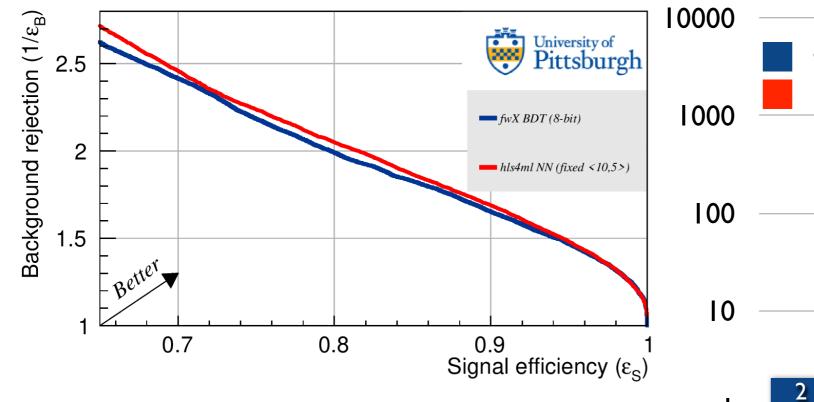
fwX BDT vs. <u>hls4ml neural network</u>

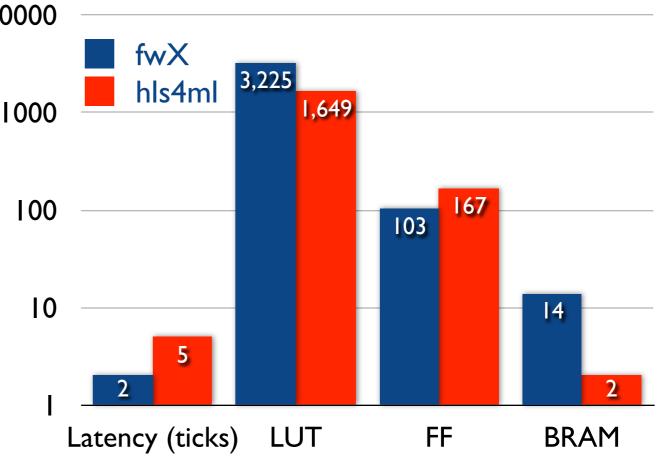
Setup

- Details <u>not</u> in paper
- Using 200 MHz clock here
- Chose NN architecture to match ROC performance of BDT

Comparison

- Lower latency
- Comparable LUT, FF
- Higher BRAM (but 0.3% of avail.)





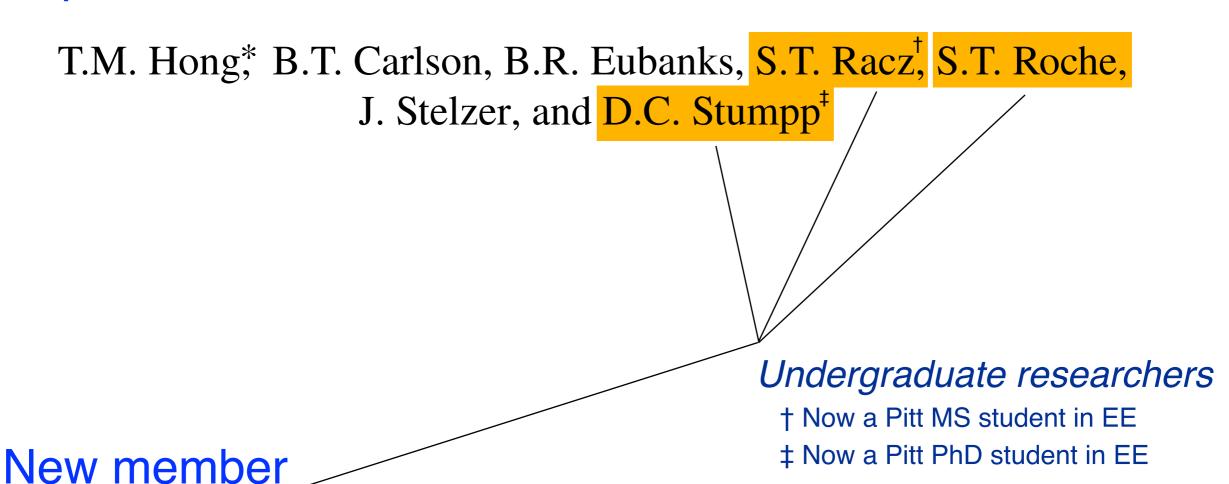


Thank you to my collaborators





Paper authors



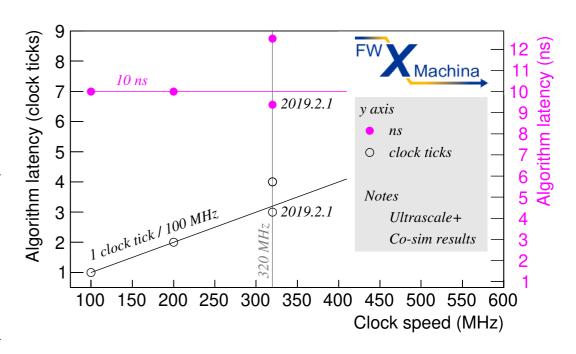
A. Rodic (did the comparison with hls4ml's neural network)

Back up

Benchmark firmware perform'ce



Parameter	Value	Comments	
FPGA setup			
Chip family	Xilinx Virtex Ultrascale+		
Chip model	xcvu9p-flga2104-2L-e		
Vivado version	2019.2.1		
Synthesis type	C-Synthesis		
HLS or RTL	HLS		
HLS interface pragma	None		
Clock speed	$320\mathrm{MHz}$	Clock period is 3.125 ns	
ML training configuration			
ML training method	Boosted decision tree	Binary classification	
Boost method	Adaptive	AdaBoost with yes/no leaf	
No. of event types to classify	2	Signal vs. background	
No. of input variables	4		
No. of trees used for training	100		
Maximum tree depth	4		
Nanosecond Optimization configuration			
Bin Engine type	BIT SHIFT BIN ENGINE (BSBE)		
No. of bits for input variables	8 bits for each		
No. of bits for cut thresholds	8 bits for each		
No. of bits for BDT output score	8 bits		
No. of trees after merging	10	Tree Merger via ordered lis	
No. of final trees	10, none removed	Tree Remover by truncation	
No. of bins	26132	Cut Eraser not used	
FPGA cost			
Latency	3 clock ticks	9.375 ns	
Interval	1 clock tick	3.125 ns	
Look up tables	1903 out of 1182240	< 0.2% of available	
Flip flops	138 out of 2364480	< 0.01% of available	
Block RAM	8 out of 4320	< 0.2% of available	
Ultra RAM	0 out of 960	-	
Digital signal processors	0 out of 6840	-	



 10 ns is independent of clock from 100-320 MHz

ATLAS-inspired cuts

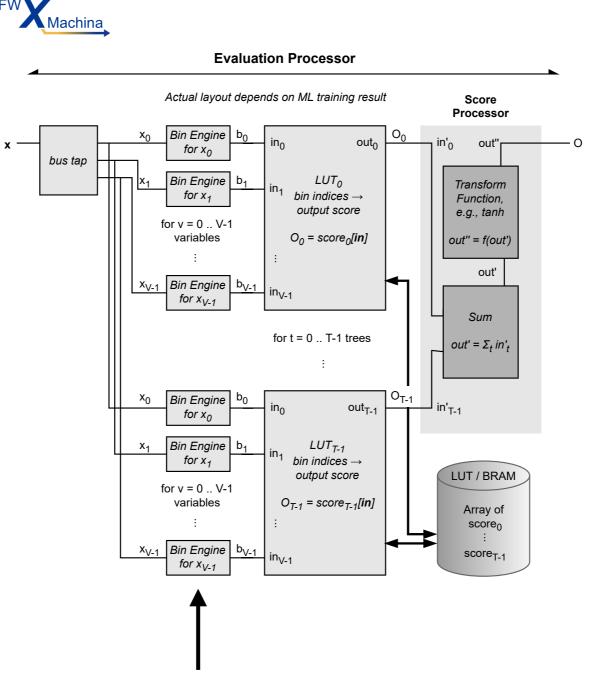


Table 9: List of input variables for the classification of the VBF Higgs boson vs. multijet process. Also given are the ATLAS-inspired cut-based offline thresholds for Run 2 [64] and HL-LHC [65]. For Run-2, differences arise with respect to the document when the m_{jj} threshold is quoted as 1100 GeV for L1 MJJ-500-NFF; we use the > 99% offline efficiency point, which is achieved around m_{jj} > 1300 GeV. for others the offline thresholds are used. For HL-LHC, the single-level scheme values are quoted. The performance of the cut-based approach using these values is compared the performance to the BDT result in figure 16. The non-optimized (non-opt) configuration includes the five variables from the optimized configuration.

Input	Description	ATLAS Run-2 offline	ATLAS HL-LHC offline	Used in BDT
variable		cut [64], see caption	cut [65], see caption	
p_{T1}	Leading jet $p_{\rm T}$	> 90 GeV	> 75 GeV	_
p_{T2}	Subleading jet $p_{\rm T}$	> 80 GeV	> 75 GeV	Optimized
$p_{\mathrm{T}12}$	$Sum p_{T1} + p_{T2}$	-	-	Optimized
$ \eta_1 $	Leading jet η	< 3.2	-	-
$ \eta_2 $	Subleading jet η	< 4.9	-	-
\prod_{η}	Product $\eta_1 \cdot \eta_2$	-	-	Optimized
$ \Delta \overset{\cdot}{\eta} $	Separation in $ \eta_2 - \eta_1 $	> 4.0	> 2.5	-
$ \Delta \phi $	Separation in $ \phi_2 - \phi_1 $	< 2.0	< 2.5	non-opt
$ \Delta R $	$\sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$	-	-	non-opt
m_{jj}	Dijet invariant mass	$> 1300\mathrm{GeV}$	_	Optimized
p_T^{jj}	Dijet p_{T}	-	-	Optimized

Data flow



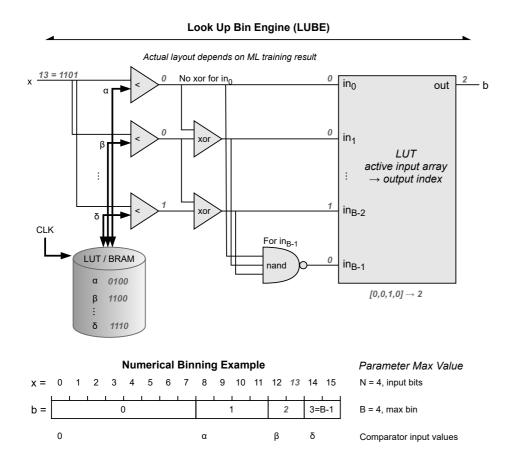


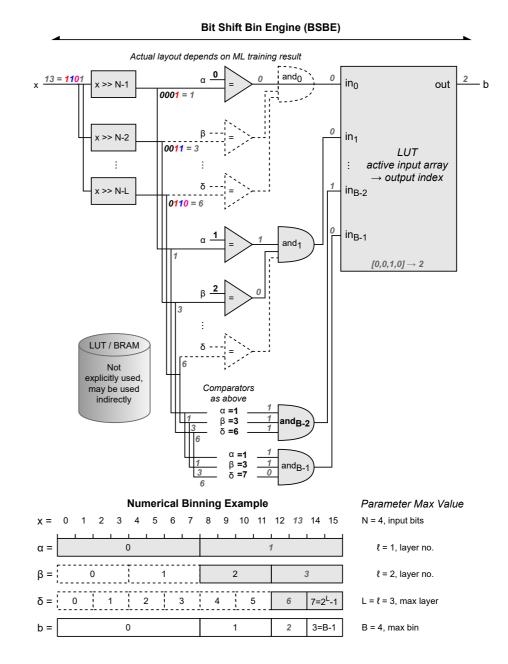
 Each variable is processed independently of each other

TM Hong

Firmware design: Bin Engines





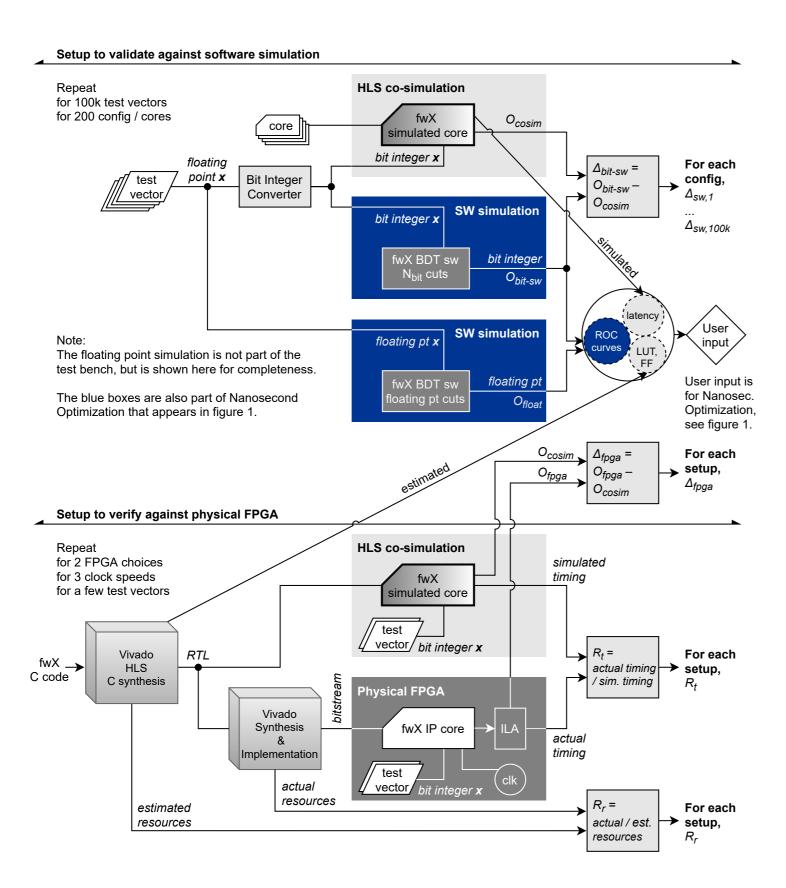


 Look up thresholds in memory, compare

- Bit shift to localize data
 - This is fast
- Use combinatoric logic as much as possible without multiplication. No explicit clocked operations.

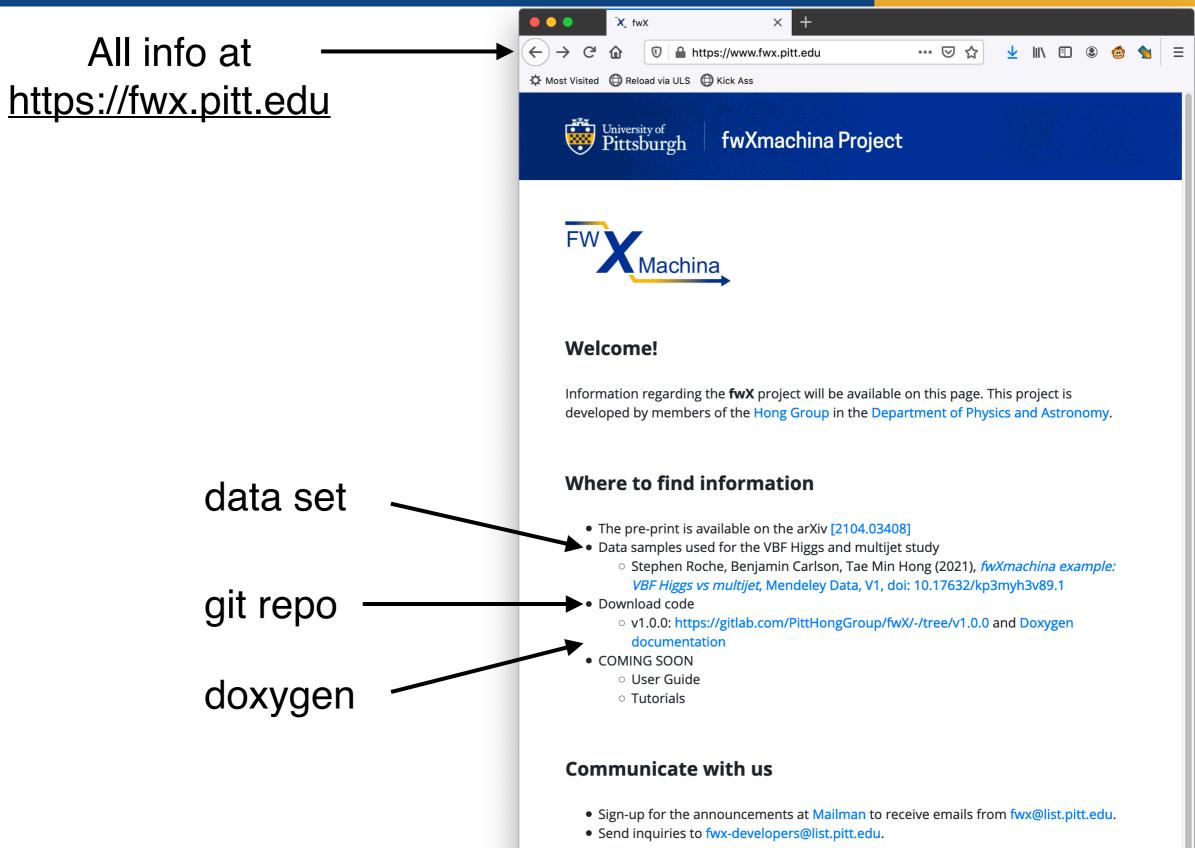
Test bench



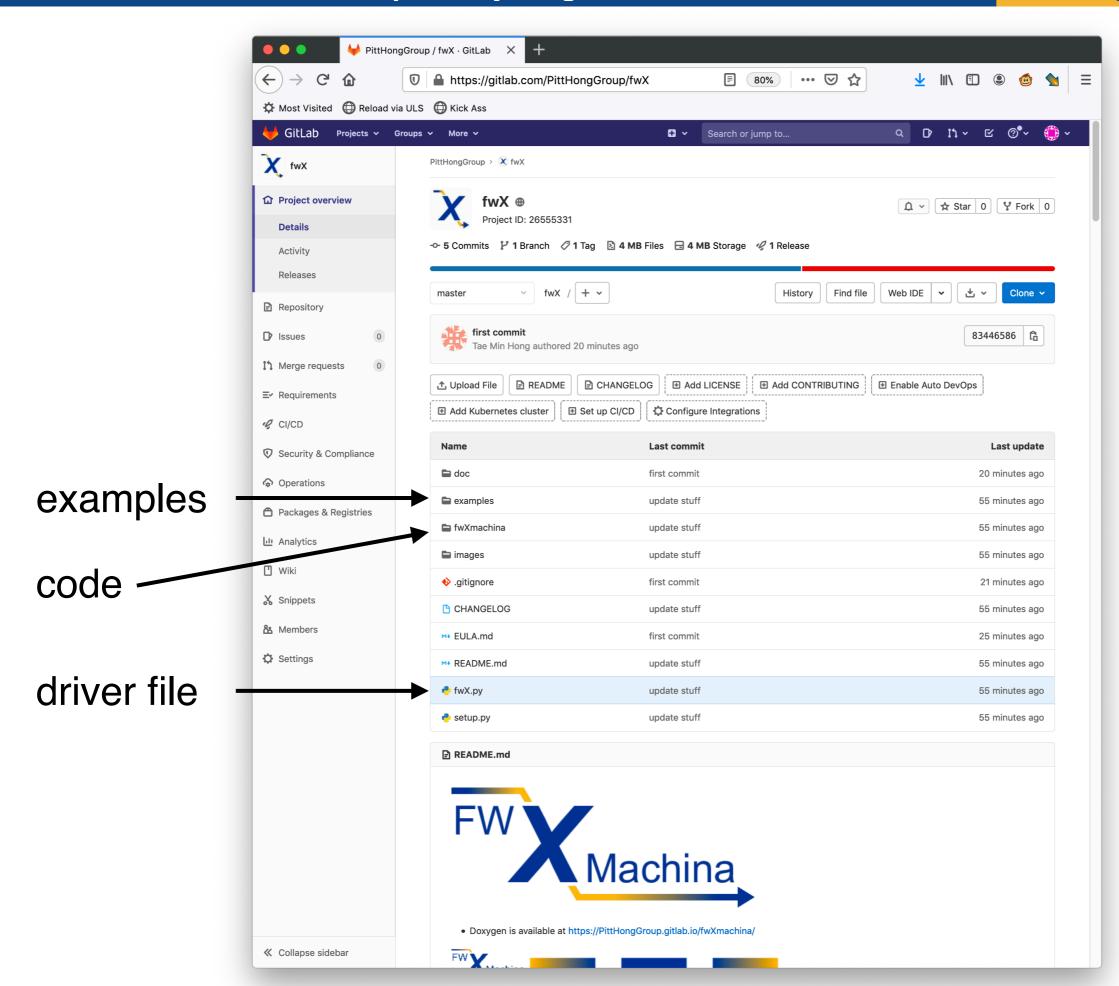


 No difference seen wrt software implementation

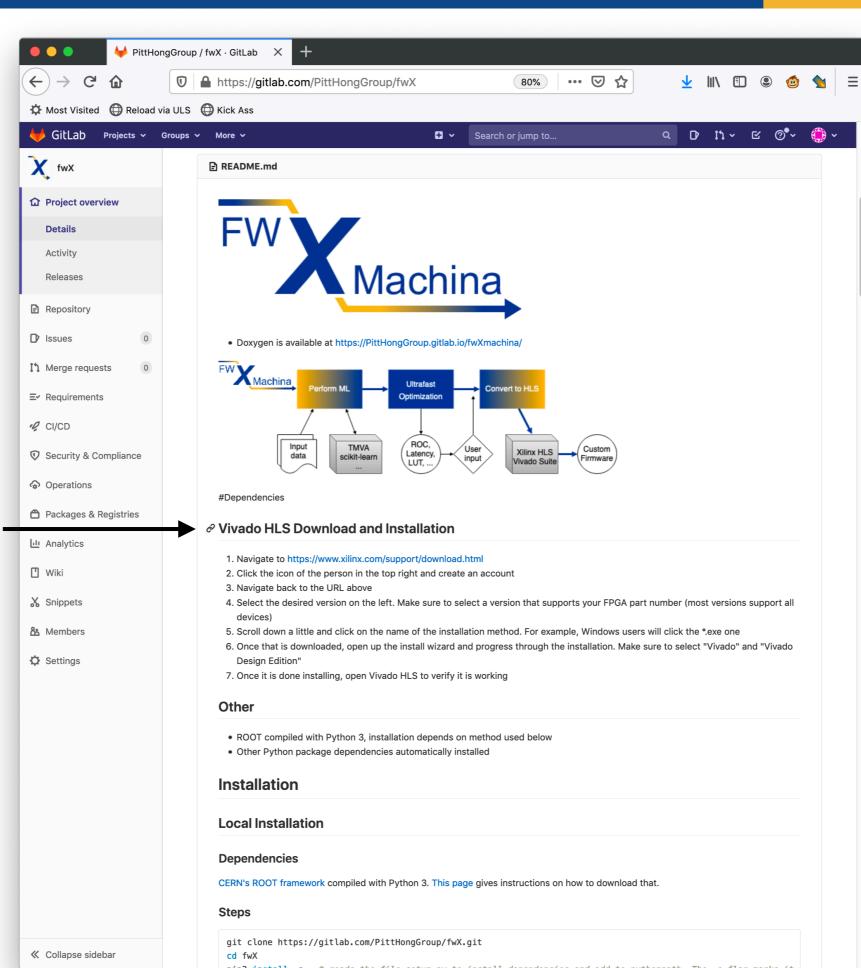






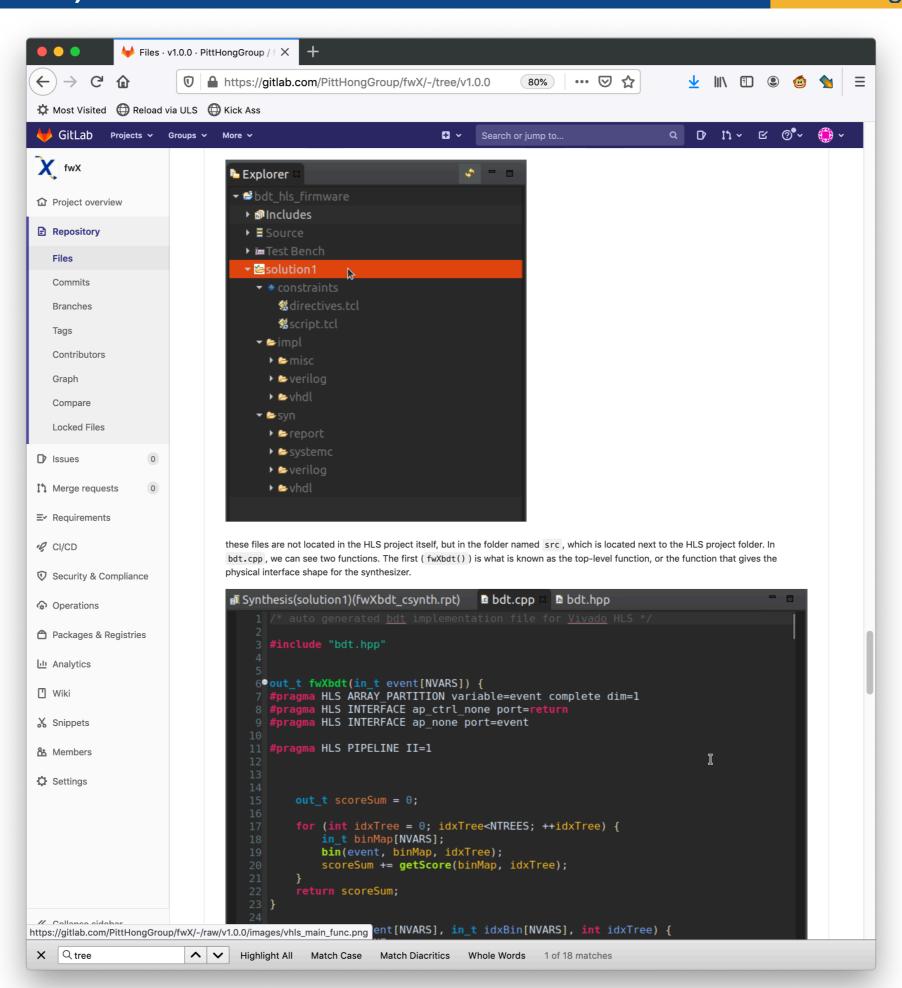




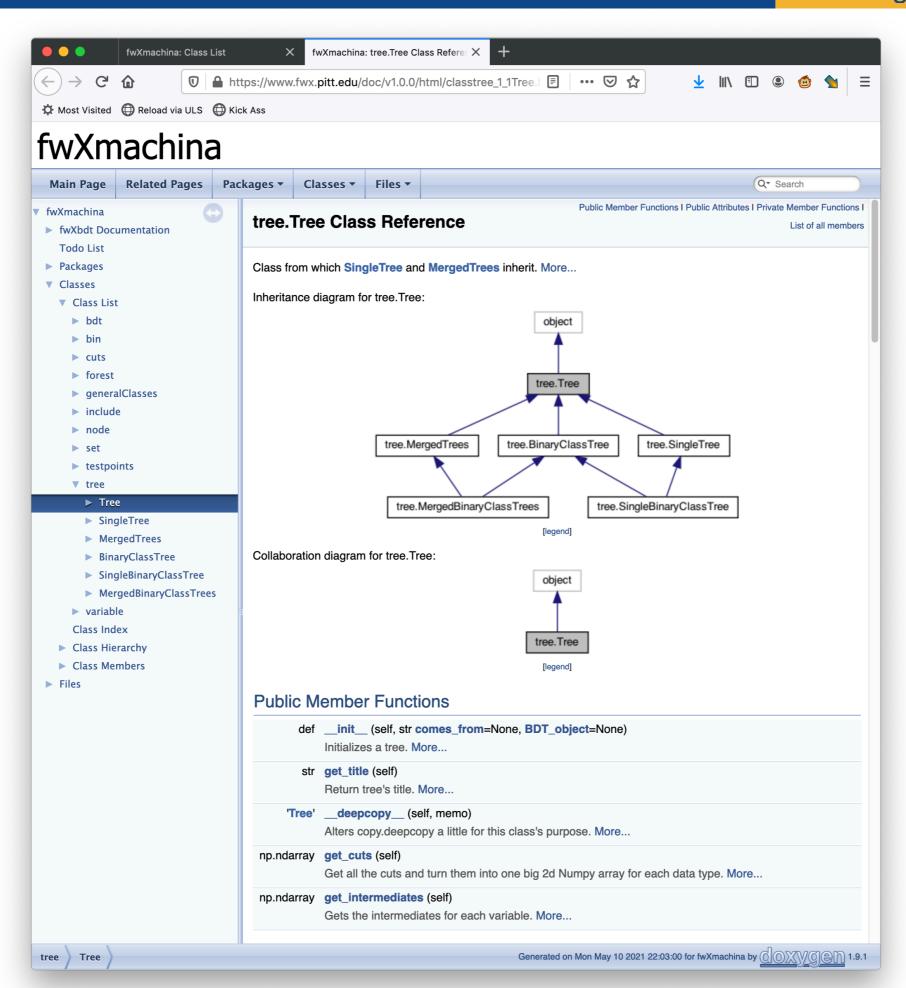


install









vs. hls4ml's BDT

Parameter	FWXMACHINA	hls4ml/Conifer			
ML training setup					
Training software	TMVA	TMVA			
Physics problem	electron vs. photon	electron vs. photon			
Training samples	from ref. [56]	from ref. [56]			
No. of event classes	2	2			
No. of training trees	100	100			
Max. depth	4	4			
No. of input variables	4	4			
Other TMVA parameters	TMVA defaults TMVA defaults				
Nanosec. Optimization	Flattened & merged to 10	N/A			
	final trees, without TREE				
	Remover or Cut Eraser				
FPGA and firmware setup					
Chip family	Xilinx Virtex Ultrascale+	Xilinx Virtex Ultrascale+			
Chip model	xcvu9p-flga2104-2L-e	xcvu9p-flga2104-2L-e			
Vivado HLS version	2019.2	2019.2			
Clock speed, period	$320{\rm MHz},3.125{\rm ns}$	$320{\rm MHz},3.125{\rm ns}$			
Precision	$ap_int\langle 8 \rangle$	ap_ufixed $\langle 10, 5 \rangle$			
BIN ENGINE	BSBE	N/A			
FPGA cost					
Actual timing values and resource usage by RTL synthesis and implementation					
Latency	3 clock ticks, 9.375 ns	15 clock ticks, 46.875 ns			
Interval	1 clock ticks, 3.125 ns	1 clock tick, 3.125 ns			
LUT	717, 0.06% of total	3834, 0.3% of total			
FF	147, < 0.01% of total	1966, < 0.1% of total			
BRAM 18k	5.5, 0.1% of total	0			
URAM	0	0			
DSP	2,0.03% of total	0			

