Nanosecond machine learning with BDT for high energy physics

Abstract: We present a novel implementation of classification using boosted decision trees (BDT) on field programmable gate arrays (FPGA). Two example problems are presented, in the binary classification of electrons vs. photons and in the selection of vector boson fusion-produced Higgs bosons vs. the rejection of the multijet processes. The firmware implementation of binary classification requiring 100 training trees with a maximum depth of 4 using four input variables gives a latency value of about 10ns. Implementations of machine learning algorithms such as BDT will enable the level-1 trigger systems of the Run 4 LHC to be more sensitive to new physics. The work is described in [2104.03408].

Introduction

- ATLAS and CMS have FPGA based L1 trigger systems reduce rate: 40MHz → 100 kHz, latency of μs [1,2]
- Lots of effort to evolve "simple" algorithms, e.g., di-jet mass to ML algorithms: BDT, NN [3,4]
- fwX: implement a new set of ML tools to prepare a BDT for firmware implementation
- The fwX workflow shown in Fig. 1 starts by training a BDT using software, such as TMVA

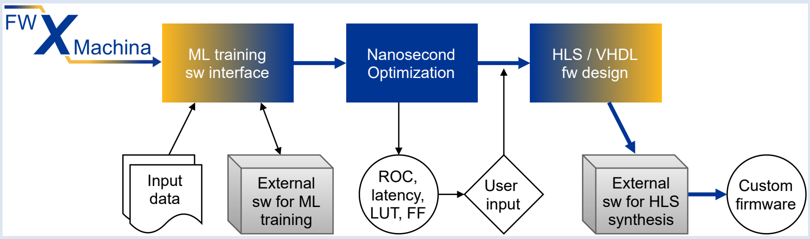


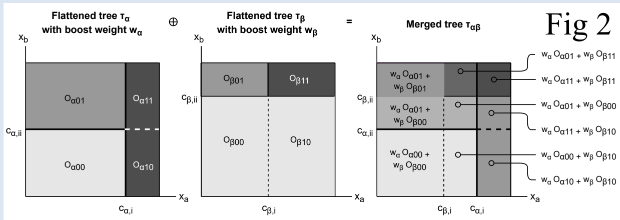
Figure 1: The work flow for training a BDT using external software, which is then passed to the nanosecond optimization component of fwX in preparation for firmware implementation

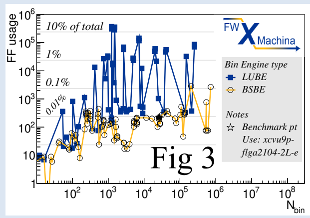
Firmware optimization

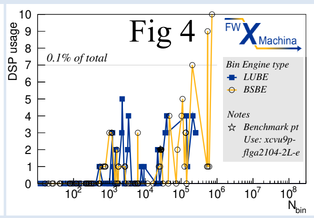
- Fixed bit precision is used to represent input variables
- The tree is first "flattened" as shown in Fig. 2
- Bin engines are used to identify the appropriate weight
- BSBE: Bin engine by bit shift, LUBE: Bin engine by look-up table

Resource utilization

- Evaluate resource cost vs: N_{var}, tree depth, bin engine, and N_{bits}
- Problem: e/γ separation, using public dataset provided in [5]
- **Latency**: as low as 10ns
- **Resource** (LUT, FF, DSP, BRAM) costs can be a few % and scale with the number of bins in the BDT as shown in Fig. 3 & 4







VBF Higgs trigger: a sample physics case

Dataset & training

- Goal: VBF Higgs vs. multi-jet bkg
- Signal: VBF H→inv. (POWHEG)
- Background: Multijet (Pythia)
- Test: VBF H→aa→4b
- Detector smearing & pileup done using DELPHES [6], with μ = 50.

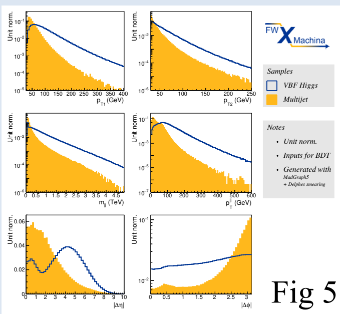


Fig 5: input variables for BDT

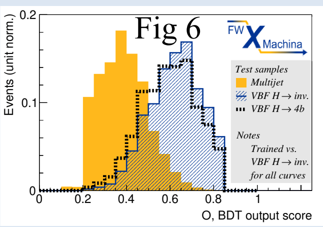


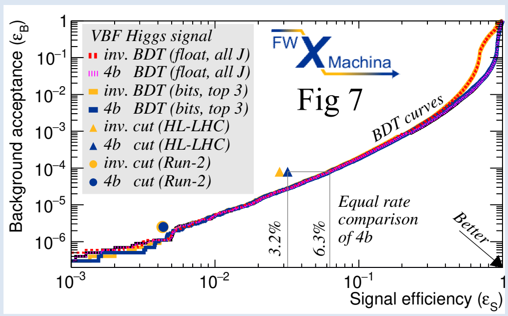
Fig 6: BDT distribution for signal and background. Test sample with hadronic b-jets shows that the training is robust for a variety of Higgs decay modes

Results

- Table 1: after optimization of BDT, few % cost and latency
- BDT can improve cut based performance by 2x (Fig. 7)
- Equivalent performance for firmware vs. software BDT (Fig. 7)

	Opt	Non-opt
N_{var}	5	7
$N_{bit\text{-}var}$	8	12
N_{bin}	40k	1M
Latency	5 ticks	6 ticks
LUT	1%	1.5%
Flip	~0	~0
BRAM	2%	30%
DSP	0	~0

Table 1



References

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[5] M. Michela et al., Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multilayer Calorimeters, Phys. Rev. Lett. 120, 042003 (2018).
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