Multi-objective optimization for the CMS High Granularity Calorimeter Level 1 trigger

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on behalf of CMS collaboration

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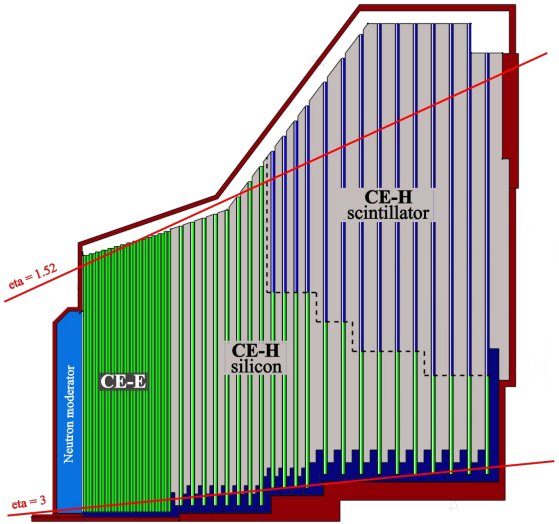
Context

HGCal

CMS new endcap calorimeter for high luminosity LHC



Electromagnetic shower classification @ L1T

Trigger Primitives Generation
energy → cluster → cluster shape variables

→ Central L1 trigger
Machine Learning

ML model constraints:

- FPGA = quantized inputs → number of bits optimization
  - ↘ bits = ↘ TPG resource usage
  - ↘ TPG-L1 links needed
- limited resources → constrained model size

Methodology

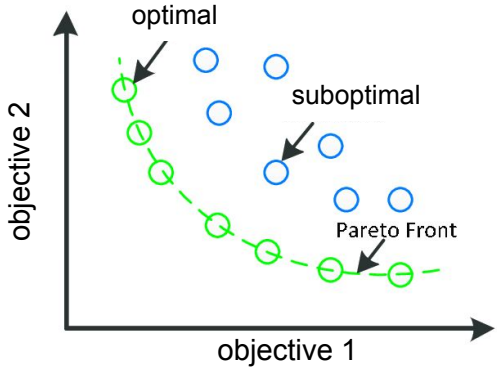
Classification electrons vs pions/jets/PU

- ↗ discrimination power
- ↗ fewer bits
- ↗ smaller models (BDT splits)

} 3 obj.

Parameters:

- number of bits for each input
- model complexity parameters



Genetic Algorithm (NSGA-II)

Quantize the 16 inputs (0-12 bits)
Initialize population (100 individuals)

train models

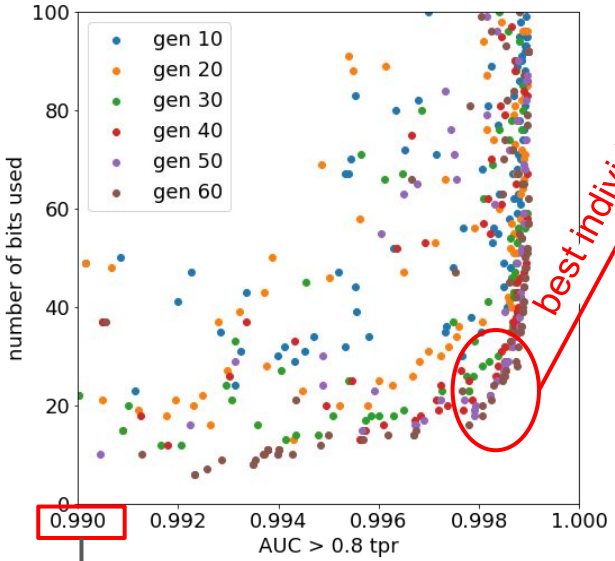
Score (3 objective functions) and select optimal individuals

Reproduction (crossover + mutation) → new generation

repeat until convergence

Results

Convergence towards Pareto front



Focus on the high AUC region

best individuals

	vee	1st lay	hbm	1stH_1	sho lgth	Emx_4R	Emx_5	core lgth	rev ebm1	vzz	meanz	abseta	vpp	ebm1	EoT	vrr	boost rounds	max depth	eta	n_kept	bits	splits	eff
61	0	0	1	1	0	0	2	1	0	1	0	0	5	7	9	7	188	2	0.1	9	34	559	99.86
96	0	1	0	1	1	0	2	1	2	0	0	0	4	4	9	7	199	2	0.1	10	32	586	99.85
91	0	0	1	2	0	0	2	1	2	2	2	0	4	1	9	7	158	2	0.1	11	33	468	99.84
34	0	1	0	1	1	0	2	1	2	0	0	1	4	4	10	7	145	2	0.1	11	34	428	99.84
74	0	0	1	0	0	0	2	1	0	6	0	6	1	7	0	3	154	2	0.1	8	27	461	99.84
55	0	0	0	0	0	0	1	1	0	6	4	3	0	2	2	6	154	2	0.1	8	25	445	99.84
57	1	0	1	1	0	0	2	1	1	5	0	0	6	1	1	3	187	2	0.1	11	23	559	99.83
64	0	0	0	1	0	0	1	1	0	0	4	3	0	2	0	5	187	2	0.1	7	17	534	99.83
21	0	1	1	0	6	0	0	1	0	0	4	3	7	1	0	7	93	2	0.1	9	31	267	99.82

features bits | model params | objectives

- some inputs need more bits
- some inputs are more efficient to reduce model size
- some inputs can be dropped
- there is a trade-of between number of bits and model size

Conclusions

- Classification with constraints → MOO techniques
- Find optimal feature set and bit distribution
- Method can also be used with hardware resources on FPGA as objective function