

Machine Learning Techniques for Triggering and Event Classification in Collider Experiments



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Trend in Calorimetry

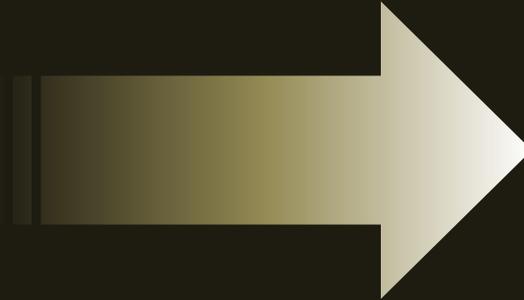
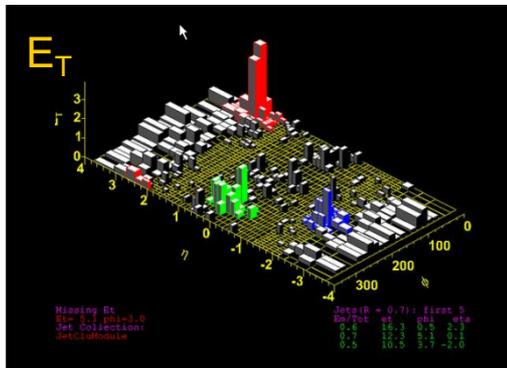


Tower geometry

Energy is integrated over large volumes into single channels

Readout typically with high resolution

Individual particles in a hadronic jet not resolved

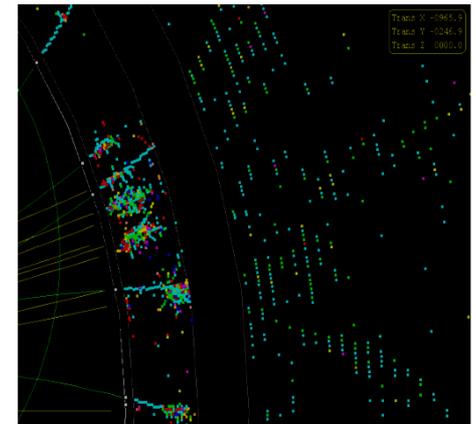
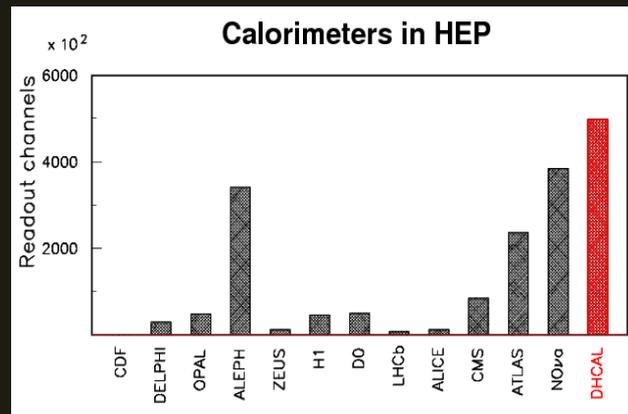


Imaging calorimetry

Large number of calorimeter readout channels ($\sim 10^7$)

Option to minimize resolution on individual channels

Particles in a jet are measured individually



Entirely tracking detector system.

Particle Flow Algorithms (PFAs)

Particles in jets	Fraction of energy	Measured with	Resolution [σ^2]
Charged	65 %	Tracker	Negligible
Photons	25 %	ECAL with 15%/√E	$0.07^2 E_{\text{jet}}$
Neutral Hadrons	10 %	ECAL + HCAL with 50%/√E	$0.16^2 E_{\text{jet}}$
Confusion	If goal is to achieve a resolution of 30%/√E →		$\leq 0.24^2 E_{\text{jet}}$

Maximum exploitation of precise tracking measurement

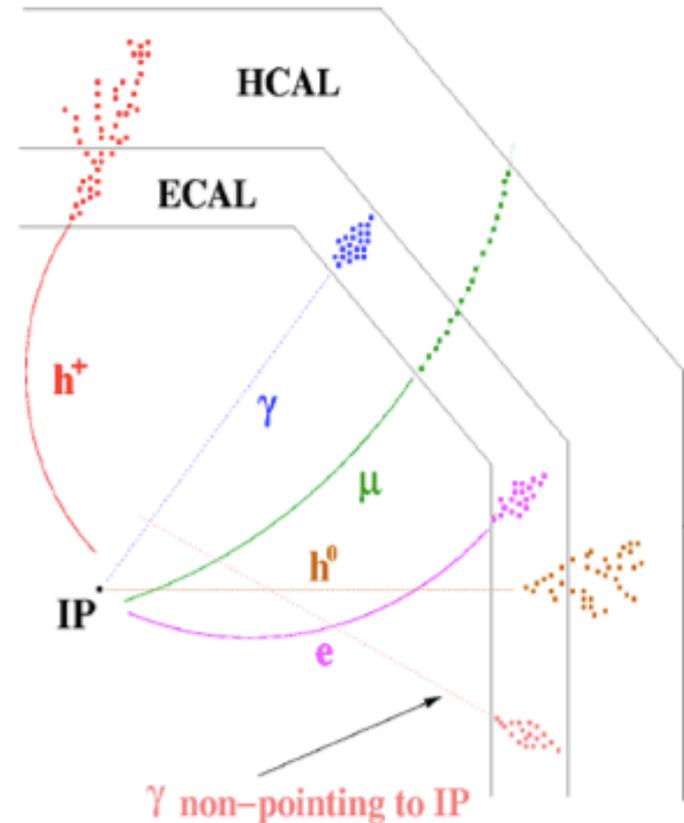
- Large radius and length to separate the particles
- Large magnetic field for high precision momentum measurement
- “no” material in front of calorimeters (stay inside coil)
- Small Moliere radius of calorimeters to minimize shower overlap
- High granularity of calorimeters to separate overlapping showers

Emphasis on tracking capabilities of calorimeters



High lateral and longitudinal segmentation

Attempt to measure the energy/momentum of each particle with the detector subsystem providing the best resolution



High Segmentation Calorimeter Prototypes

- **Si-W ECAL**

Silicon pixels
10x10x0.5 mm³
Tungsten absorber

- **Sc ECAL**

scintillator strips with SiPM readout
45x5x3 mm³
Tungsten absorber



- **Analogue HCAL**

scintillator tiles with SiPM readout
30x30x5 mm³
Steel or tungsten absorber

- **Semi-digital HCAL**

GRPCs (microMegas)
10x10x1.2 mm³
Steel absorber

- **Digital HCAL**

RPCs (GEMs)
10x10x1.15 mm³
Steel or tungsten absorber



See E. Sicking's talk for an overview.

Near Future Implementation

The CMS HGCal Upgrade

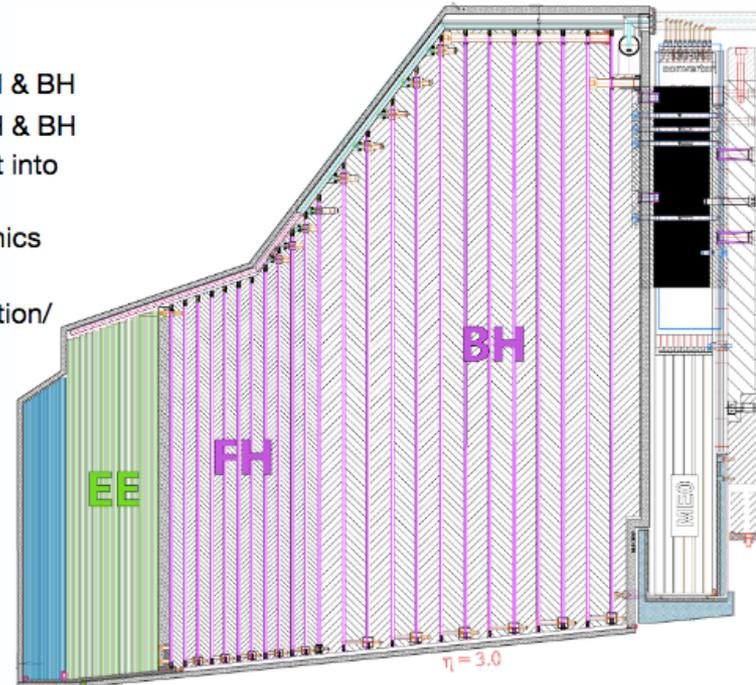


Key facts:

- ▶ **High granularity throughout the calorimeter**
- ▶ **Hexagonal silicon sensors** in EE and high-radiation FH & BH
- ▶ **Scintillating tiles** with SiPM readout in low-radiation FH & BH
- ▶ Sensors with W/Cu backing plate and readout PCB built into **modules**
- ▶ Modules will be mounted on cooling plates with electronics and absorbers to make up **cassettes**
- ▶ Goal is **~50 ps timing** on cell level for vertex reconstruction/pile-up rejection

Key parameters:

- ▶ HGCal covers $1.5 < \eta < 3$
- ▶ **Full system maintained at -30°C**
- ▶ **~ 600 m² of silicon**
- ▶ **~ 500 m² of scintillators**
- ▶ **~ 6M silicon channels, ~0.5 and ~1 cm² cell-size**
- ▶ Power at end of life **~120 kW** of which **~20%** is sensor leakage current



Endcap Electromagnetic calorimeter (EE): Si, Cu & CuW & Pb absorbers, 28 layers, $25 X_0$ & $\sim 1.3 \lambda$

Front Hadronic calorimeter (FH): Si & scintillator, steel absorbers, 12 layers, $\sim 3.5 \lambda$

Backing Hadronic calorimeter (BH): Si & scintillator, steel absorbers, 12 layers, $\sim 5 \lambda$

Multivariate Analysis Techniques for High Segmentation Calorimeters

High lateral and longitudinal segmentation allows an excessive number of topological event variables.

In addition to simple addition of energy deposits in the calorimeter stack (+ a number of software compensation techniques), these topological variables can be utilized to reconstruct the energy of a given event by multivariate regression.

Requires a deep understanding of the detector and of the topological event variables together with their dependence on the particle type and energy.

Toolkit for Multivariate Data Analysis (TMVA) with ROOT¹

TMVA enables the training, testing, evaluation and application of many regression and classification methods:

An MLP (multilayer perceptron or artificial neural networks) is a simulated collection of inter-connected neurons, with each neuron producing a certain response at a given set of input signals. By applying an external signal to some input neurons the network is put into a defined state that can be measured from the response of one or several output neurons. One can therefore view the neural network as a mapping from a space of input variables onto a one-dimensional or multi-dimensional space of output variables.

The BDTG (boosted decision/regression trees) is a binary tree structured classifier/regressor. Repeated left/right decisions are taken on one single variable at a time until a stop criterion is fulfilled. The phase space is split this way into many regions. Each output node represents a specific value of the target variable. The boosting of a regression tree extends this concept from one tree to several trees, which form a forest.

The LD (linear discriminant analysis), FDA (functional discriminant analysis), SVM (support vector machines), ...

There are also other tools like Theano, ScikitLearn and Keras.

¹ A. Hoecker, et.al., *TMVA - Toolkit for Multivariate Data Analysis*, PoS ACAT 040 (2007), arXiv:physics/0703039

MVA Implementation

A toy hadron calorimeter response was simulated with Geant4:
1x1 cm² scintillators with

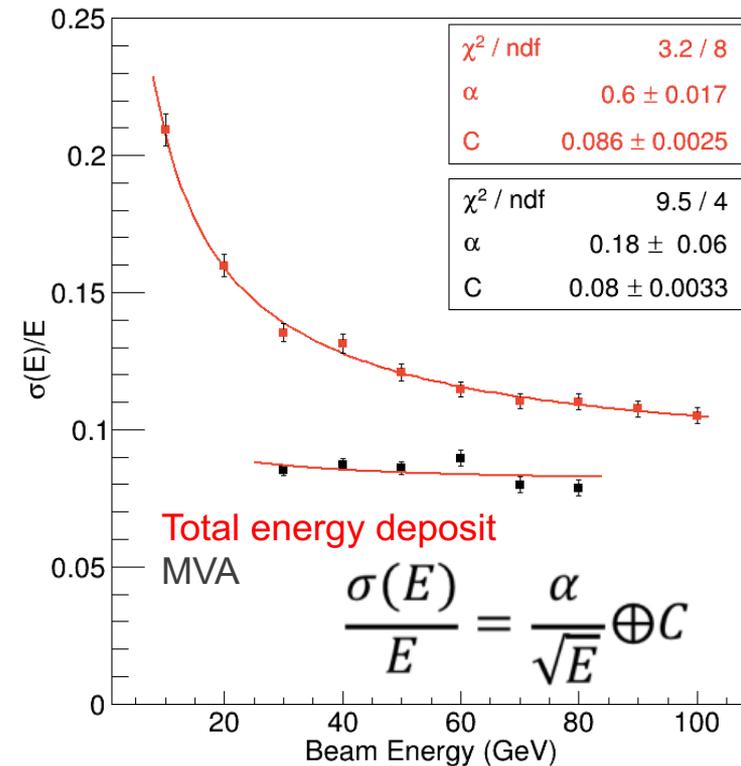
10.5 mm W
2 mm Steel
5 mm Scintillator (active layer, measures energy deposits)
5 mm G10
2 mm Steel

Stack of 50 layers, 1 m x 1 m
15 % fluctuation is added to MIP signal.

Total number of MIPs: Conventional variable to obtain the energy resolution

Number of active tiles in the layer with maximum energy deposit: To demonstrate the performance of MVAs with non-linear variables

Compactness index: The sum of the responses of the tiles in the interaction region inversely weighted by their distances to the tile with maximum energy deposit



- 70 % improvement in the hadronic energy resolution!
- Minimal dependence on the energy (not intrinsic, due to the decorrelation before the implementation of the MVA).
- Event variables and MVA methods not yet optimized.
- Overall, limited by the constant term (which is defined by the imposed MIP signal fluctuations).

MVA Implementation - 2

A toy EM calorimeter response was simulated with Geant4:

1x1 cm² Si with

3.5 mm W

525 um Si (active layer, measures energy deposits)

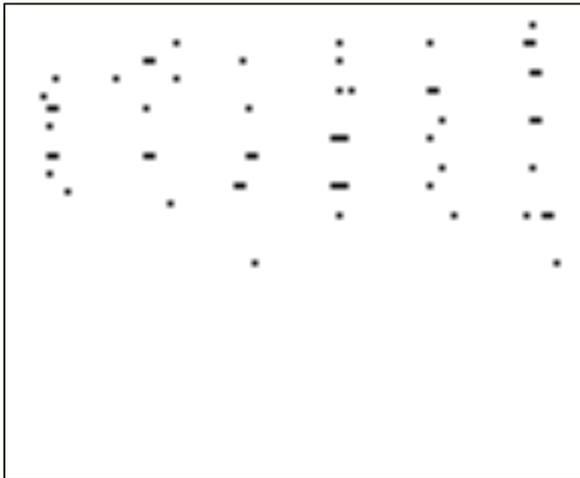
4 mm G10

Stack of 30 layers, 0.5 m x 0.5 m

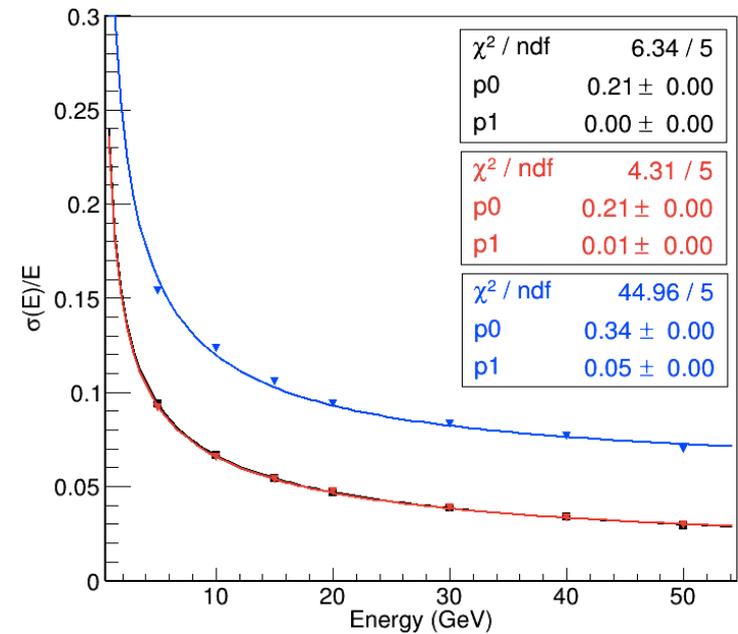
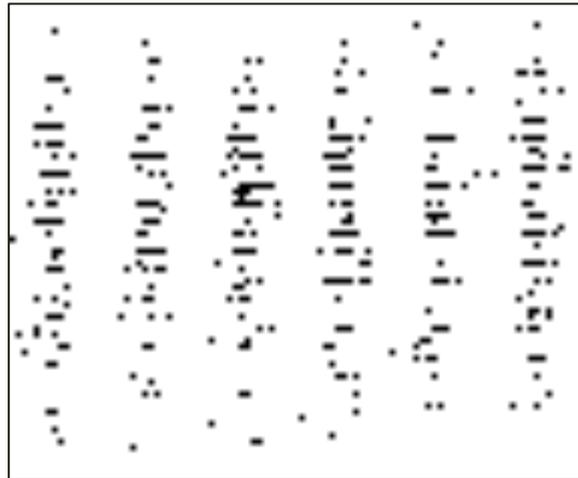
8 % fluctuation is added to MIP signal.

Turn the digital response into images

5 GeV



50 GeV



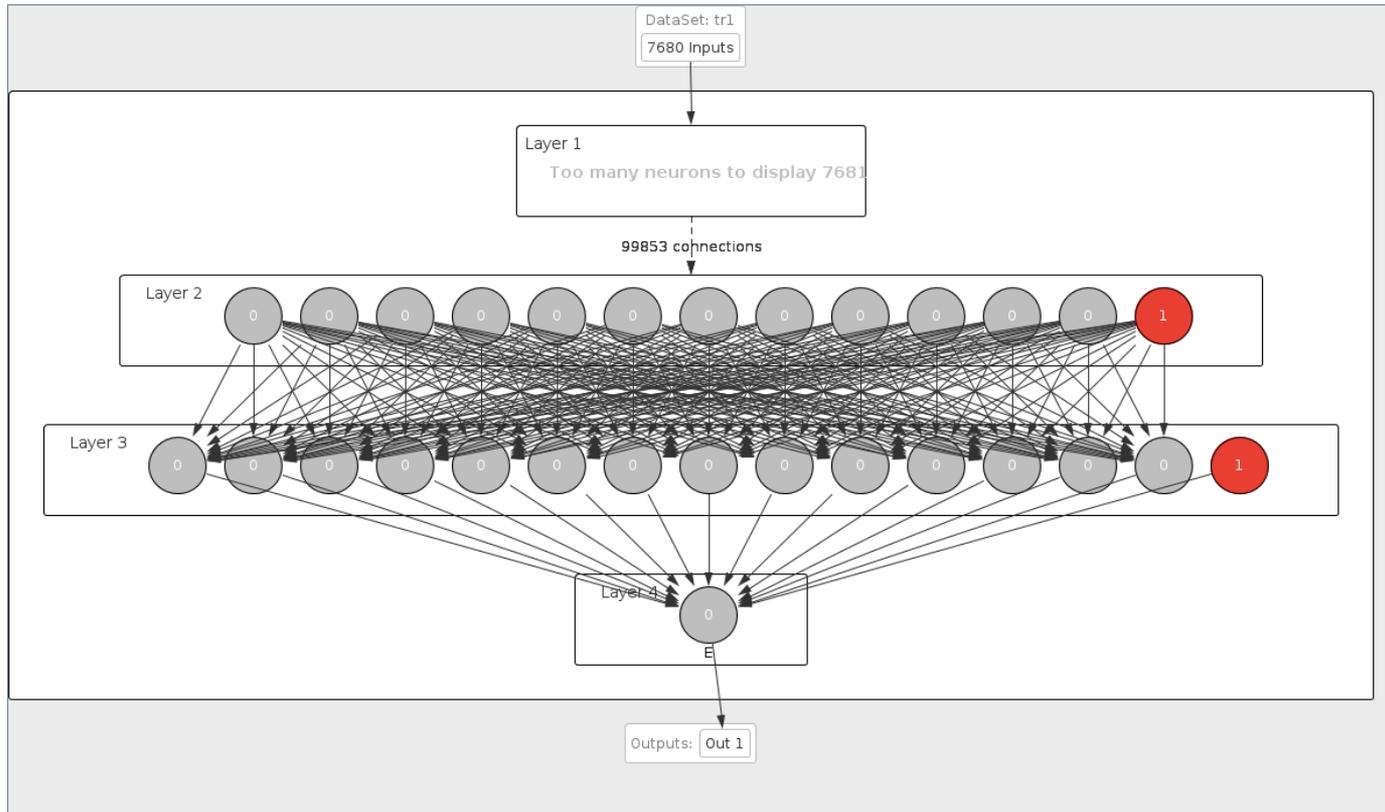
Full spectrum

Digitized with 8 bits

Digitized with 1 bit

MVA Implementation - 2

One can then do image recognition with multilayer perceptron.



Reconstruction probability of 5 GeV electrons:

E : 0.9996

E : 0.9966

E : 1

E : 1

E : 0.9487

E : 0.9995

E : 0.9862

E : 0.9914

E : 0.998

E : 1

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. .

TIPP??

TIPP??

Now, hardware that can do neural networks exists!

Neural Network Hardware

The Neuromorphic Computing Platform was developed by the Human Brain Project in order to simulate the human brain
(<https://www.humanbrainproject.eu/en/silicon-brains/neuromorphic-computing-platform/>)

BrainScaleS



SpiNNaker



Deployed in March 2016.

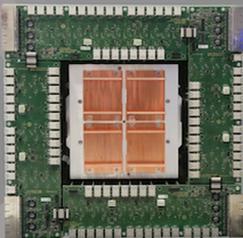
The BrainScaleS neuromorphic physical model system



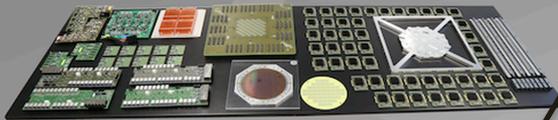
BrainScaleS



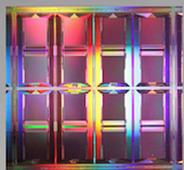
20 wafer modules
3.932.160 neurons
880.803.840 synapses



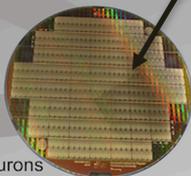
wafer module (50 cm x 50 cm)



components of a wafer module



48 reticles per wafer
196.608 neurons
44.040.192 synapses



(ø20 cm)

8 HICANN chips per reticle
(2 cm x 2 cm)



512 neurons
114.688 synapses per HICANN chip
(0.5 cm x 1 cm)

1 plastic synapse
(10 μm x 10 μm)



2 neurons
(150 μm x 20 μm)

March 2016



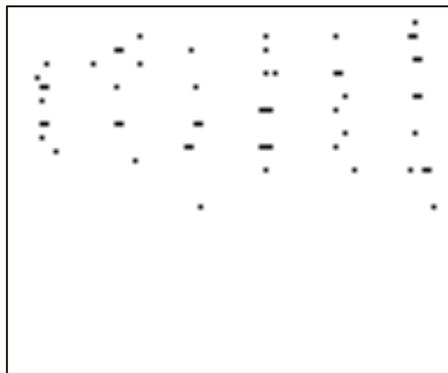
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HiCANN: High-Count Analogue Neural Network

Copy the analog data on the hardware and let the system evolve on this data.

Copy the digital data on the hardware, configure the neural network and run.



The SpiNNaker neuromorphic many core system



SpiNNaker

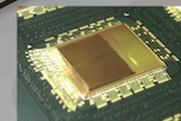


System with 5x5 crates
500,000 cores,
460M neurons, 460B synapses

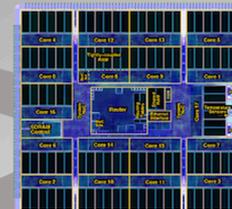
Crate with 24 boards
20,000 cores,
18M neurons, 18B synapses



Board with 48 chips
864 cores,
750k neurons, 750M synapses



Chip with 18 cores
16k neurons, 16M synapses



Core
1k neurons, 1M synapses

info@neuromorphic.eu

April 2016



Started exploring these systems very recently.

ID	Status	Platform	Code	Submitted on	Submitted by
92032	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:59:01	Burak Bilki
92031	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:54:56	Burak Bilki
92030	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:52:18	Burak Bilki
92029	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:50:58	Burak Bilki
92028	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:48:58	Burak Bilki
92027	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:40:48	Burak Bilki
92026	finished	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:34:11	Burak Bilki
92025	error	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:22:33	Burak Bilki
92024	finished	BrainScaleS	import pyhmf as pynn from pymarocco import PyMaroc...	2017-05-19 16:15:34	Burak Bilki
92023	error	BrainScaleS	import numpy as np from pyhalbe import HICANN imp...	2017-05-19 16:04:15	Burak Bilki
92022	error	BrainScaleS	import numpy as np from pyhalbe import HICANN imp...	2017-05-19 15:51:24	Burak Bilki

There are still some issues in the systems.

Extensive user support is available.

NB(0) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(1) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(2) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(3) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(4) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(5) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(6) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
NB(7) top bottom	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31

```
9899 [0x7fe0a34c7700] INFO marocco.routing.SynapseRouting null - calc synapse driver requirements for hicann HICANNGlobal(HICANNOnWafer(Enum(367)), Wafer(33))
9984 [0x7fe0a34c7700] INFO marocco.parameter.HICANNParameters null - Configuring neuron parameters
9984 [0x7fe0a34c7700] DEBUG marocco.parameter.HICANNParameters null - configuring analog parameters for NeuronOnWafer(NeuronOnHICANN(Enum(0)), HICANNOnWafer(Enum(367)))
```

Summary

High segmentation detectors offer numerous topological event variables as a result of the unprecedented spatial detail of the interactions.

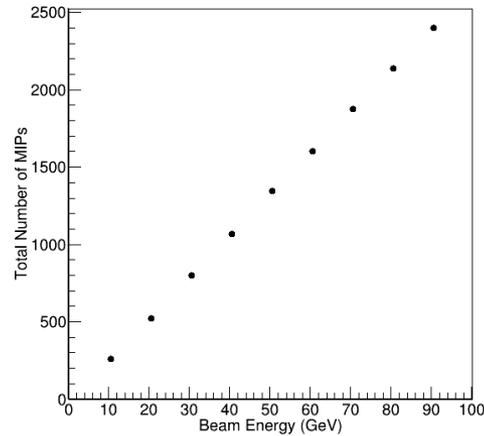
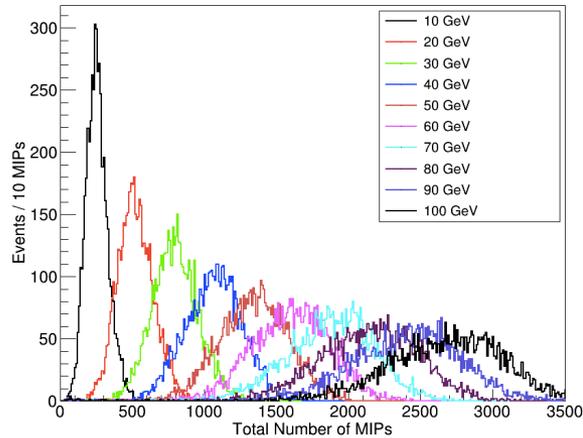
Software multivariate regression techniques can be used to estimate many event parameters for calorimetry: Interaction layer, electromagnetic energy fraction, total energy, ...

Software image recognition techniques can be utilized (mostly) for digital detector systems.

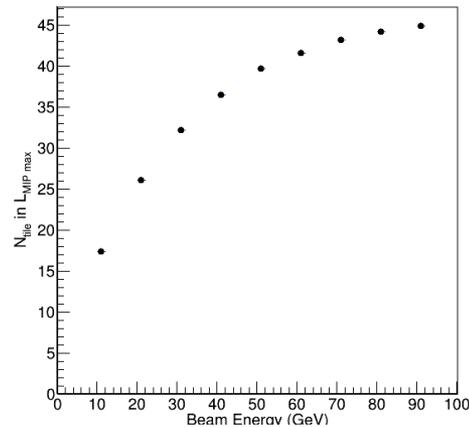
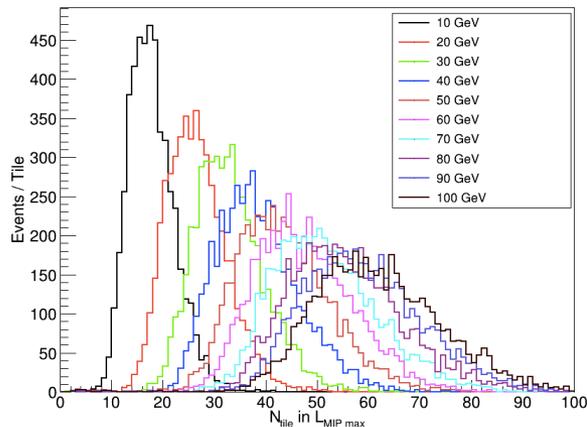
Hardware neural network implementation opens a door to unexplored territory. It is also likely to have many online implementations e.g. triggering, event classification, anomaly detection, ...

Backup

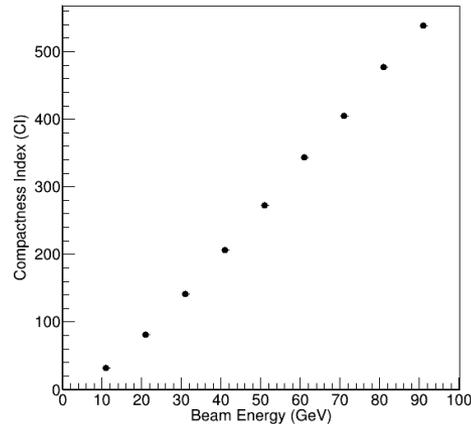
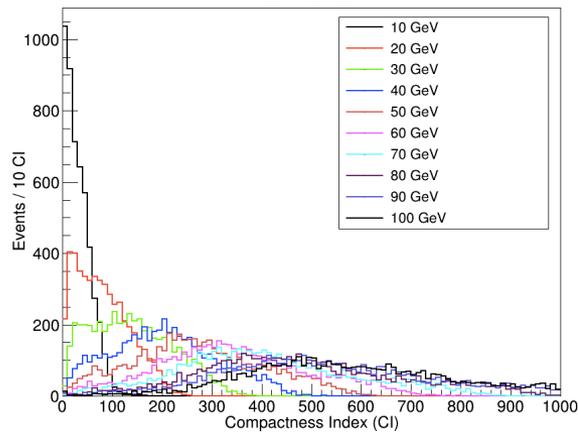
Event Variables for Energy Reconstruction



Total number of MIPs:
Conventional variable to
obtain the energy
resolution



Number of active tiles in
the layer with maximum
energy deposit: To
demonstrate the
performance of MVAs
with non-linear variables



Compactness index: The
sum of the responses of
the tiles in the interaction
region inversely weighted
by their distances to the
tile with maximum energy
deposit