5-D calorimeter design issues with an integrated online/offline AI/ML approach

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ML4FE Workshop, University of Hawaii
May 20, 2025

Introduction: Motivation for this discussion

Many (most?) physics analyses are using data from detectors designed and constructed quite some time ago.

Analyses take the recorded data and, beyond traditional selection-based approaches, apply AI/ML techniques to enhance purity of samples, reduce limits on searches etc.

(The same is true for analysis of simulated data from proposed designs for future detectors for e.g. FCCee, ILC, CLIC, C3,…)

It is therefore relevant to question whether a proposed design is optimal for application of AI/ML techniques. Also as consideration is being given to onboard intelligence it is time to take a look at an integrated online/offline AI/ML approach.

Disclaimer:

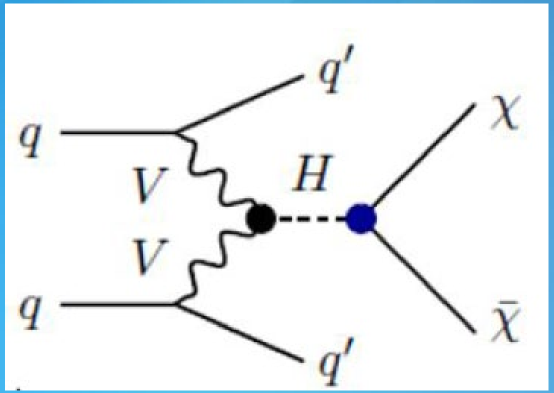
My interest in AI/ML for use in analysis using calorimeter data stems from an ATLAS analysis and consideration of calorimeter systems for future Higgs Factory detectors.

This work has mainly focused on calorimeter design with respect to offline data analysis using AI/ML.

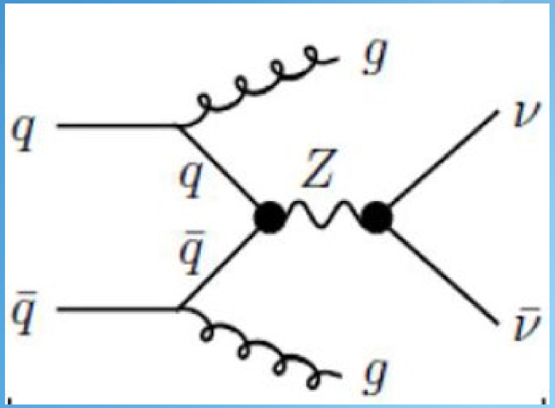
More recently (from conversations within ECFA DRD6/CALICE) aspects of online AI/ML have also appeared worth considering and the potential for a more integrated approach to both online and offline calorimeter systems design – hence this talk!

An example of an analysis using an ML approach to improving a search for new physics.

VBF Higgs to Invisible Analysis Using ML on Calorimeter energy deposition patterns



Identified as Signal



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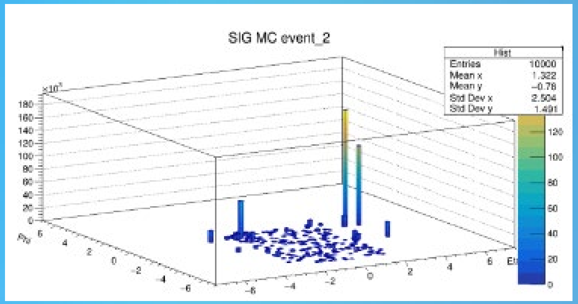
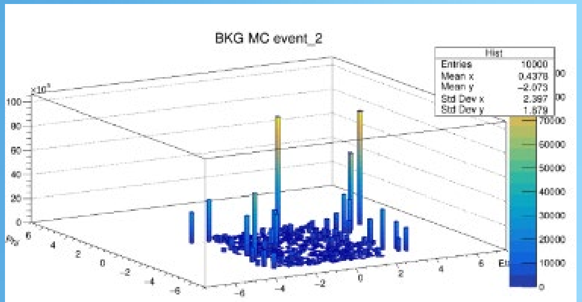
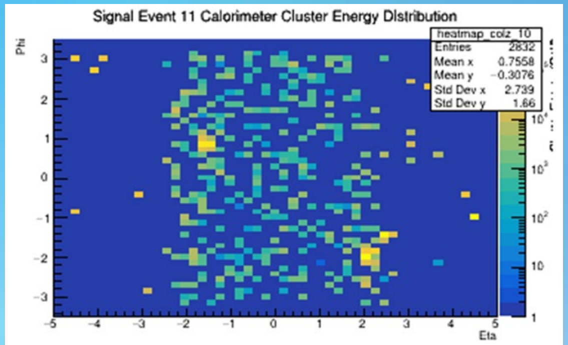
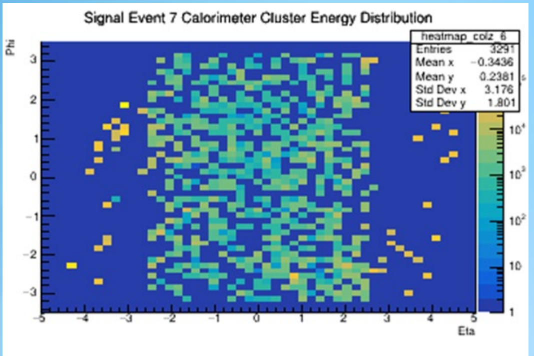






+noise, pileup

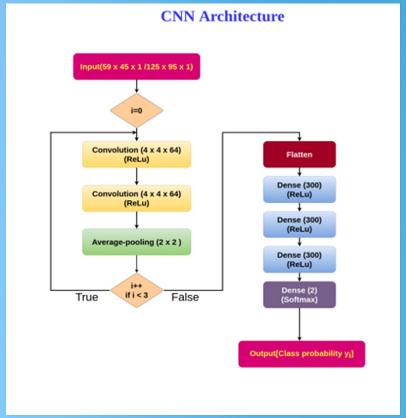


JHEP

Published for SISSA by Springer

Received: February 17, 2022
Accepted: June 24, 2022
Published: August 8, 2022

Search for invisible Higgs-boson decays in events with vector-boson fusion signatures using 139 fb^{-1} of proton-proton data recorded by the ATLAS experiment



Observed	Expected	$+1\sigma$	-1σ	$+2\sigma$	-2σ
0.145	0.103	0.144	0.075	0.196	0.055

Table 9. Observed and expected limits on $\mathcal{B}_{\text{inv}}$ for a Higgs boson with a mass of 125 GeV calculated at the 95% CL for a 139 fb^{-1} data set. The $\pm1\sigma$ and $\pm2\sigma$ variations of the expected limit are also shown.

- Applying ML to existing ATLAS Cal data

Issues raised:

- CNN efficiency vs. Threshold(s)
- Using ML to “see through” noise
- Implications for electronics design

Detector (calorimeter) design and AI/ML

There are (at least) two approaches related to detector design and AI/ML:

1) Using AI/ML to achieve an optimal design for e.g. best calorimeter energy resolution, shower position resolution.

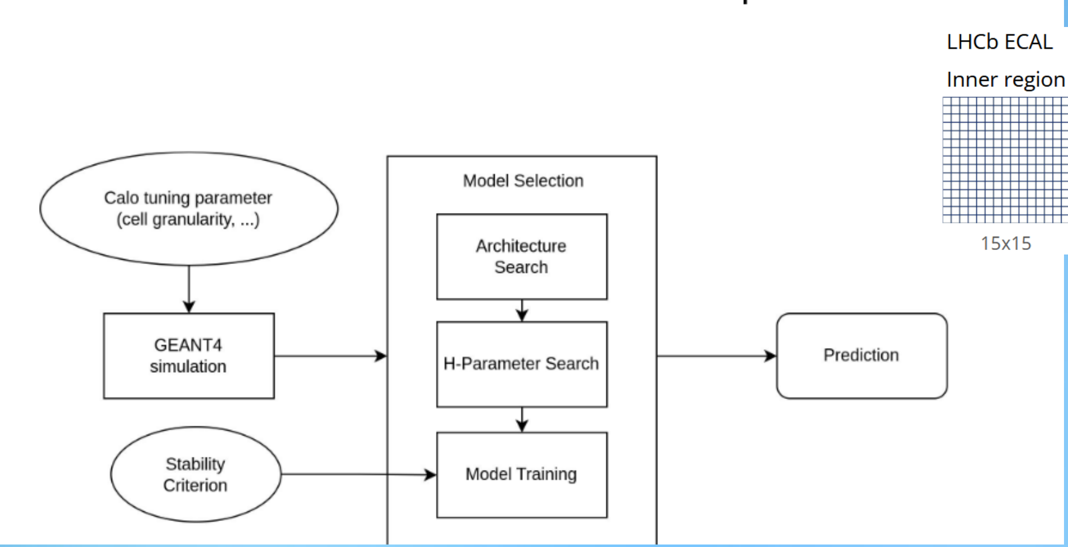
2) Asking whether a detector design is optimal for the application of AI/ML online and in the offline analysis of the data output.

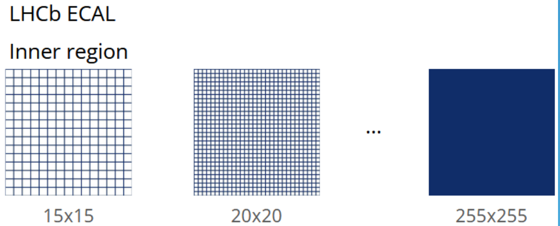
It is not *a priori* clear that 1) would lead directly to the desired outcome in 2), but perhaps studies using 1) could have a second stage leading to 2)?

Using AI/ML for optimizing detector design – an example

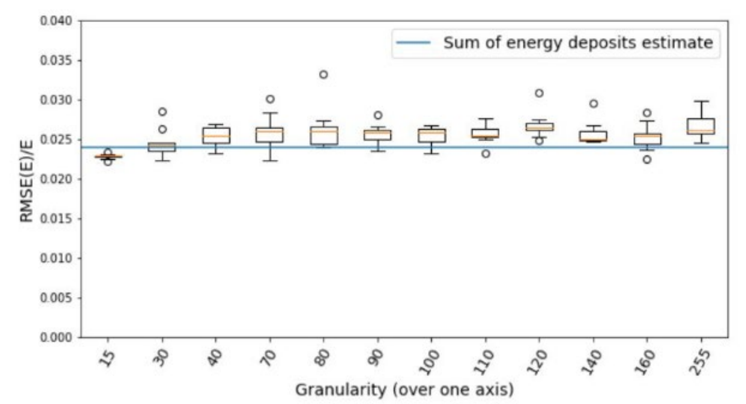
MODE
Machine-learning Optimized Design of Experiments

Automated ML for Calo Optimization

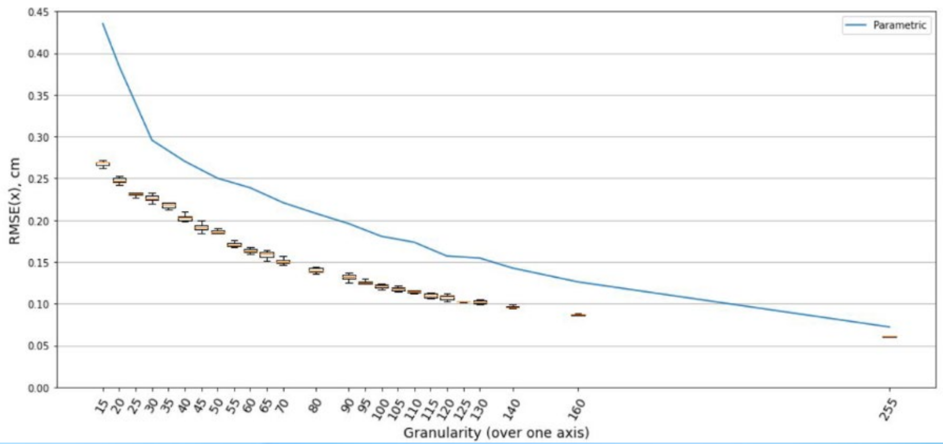




Results: Energy Reconstruction



Results: Position Reconstruction



4th MODE Workshop, 23 September 2024
Alexey Boldyrev, Fedor Ratnikov, Andrey Shevelev

Calorimeter design parameters/features that could influence the performance of an AI/ML analysis

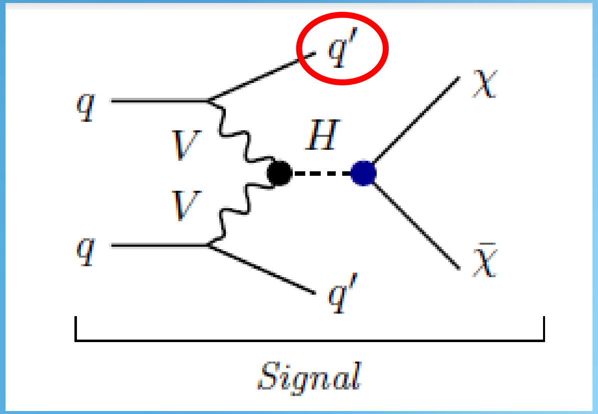
- Granularities: ECal, Hcal (50 µm x 50 µm ECal)
- Signal thresholds
- Timing – special layers?
- Tracking – special layers – to assist PFA?
- ECal/HCal separation, integrated design
- On-detector logic?
- Inter-layer communication?
- AI/ML in trigger – configuration, topological?
- DAQ – compression/noise suppression/preparation for offline AI/ML analysis

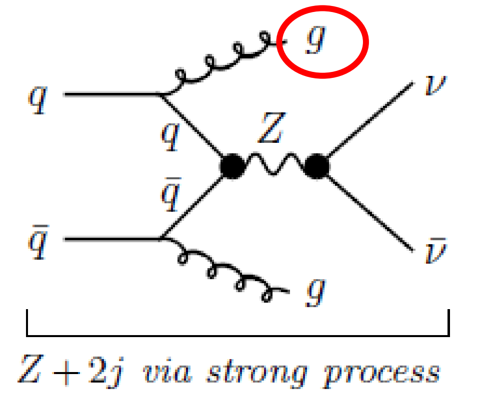
Granularity

- What level is useful vs. too much burden (confusion, GPU processing time,…) for ML pattern recognition?
- Should we always design for finest granularity we can afford (e.g. vs. installing other features such as timing) and then preprocess prior to ML use?
- Study trade-off in energy resolution between more granularity vs. less + ML
- Requirement for e.m. shower position, measurement, π^0 reconstruction, γ separation
- Do we need more granularity for jet substructure in an analysis? Does this help?
- What granularity would help with separating quark and gluon jets?
- Event pattern recognition, topological trigger, coarser granularity online

Motivation: can we use quark/gluon jet discrimination?

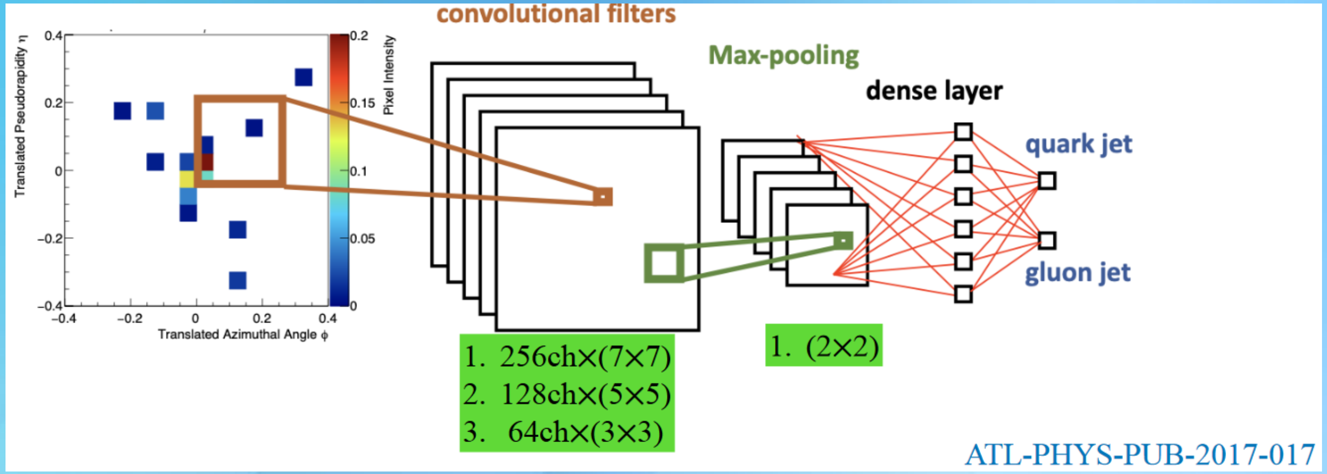
Application to Higgs to invisible analysis:





Leading quark jets

Leading gluon jets

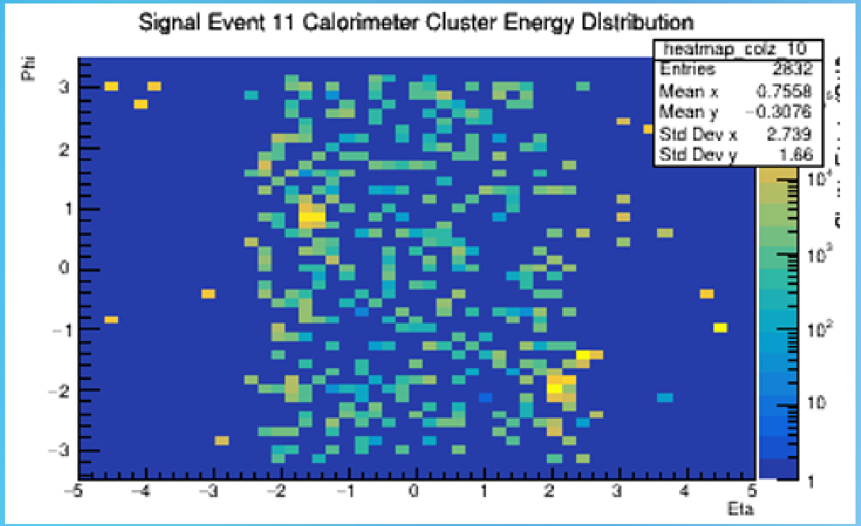


Improvement found using "Pointwise CNN" with η, φ directly into CNN rather than pixels -> track backwards to see how CNN is using the input.

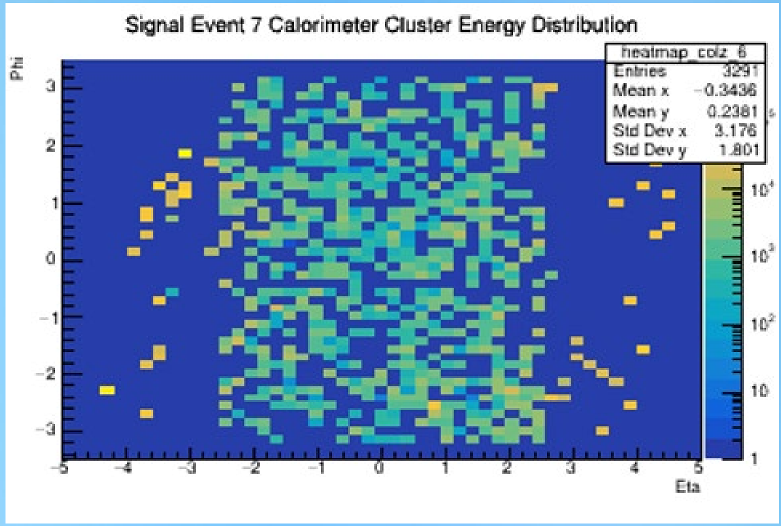
Used for VBS semi-leptonic

Calorimeter signal readout thresholds?

Some calorimeter energy deposition patterns allowing clear recognition of features



Some events have much noise/pile up etc.



- Need to test e.g. CNN efficiency vs. threshold(s): balance time vs. correct identification success
- Implications of ability of ML algorithms to “see/sort through” noise etc. for electronics design/noise specification criteria?

ML use for Particle Flow?

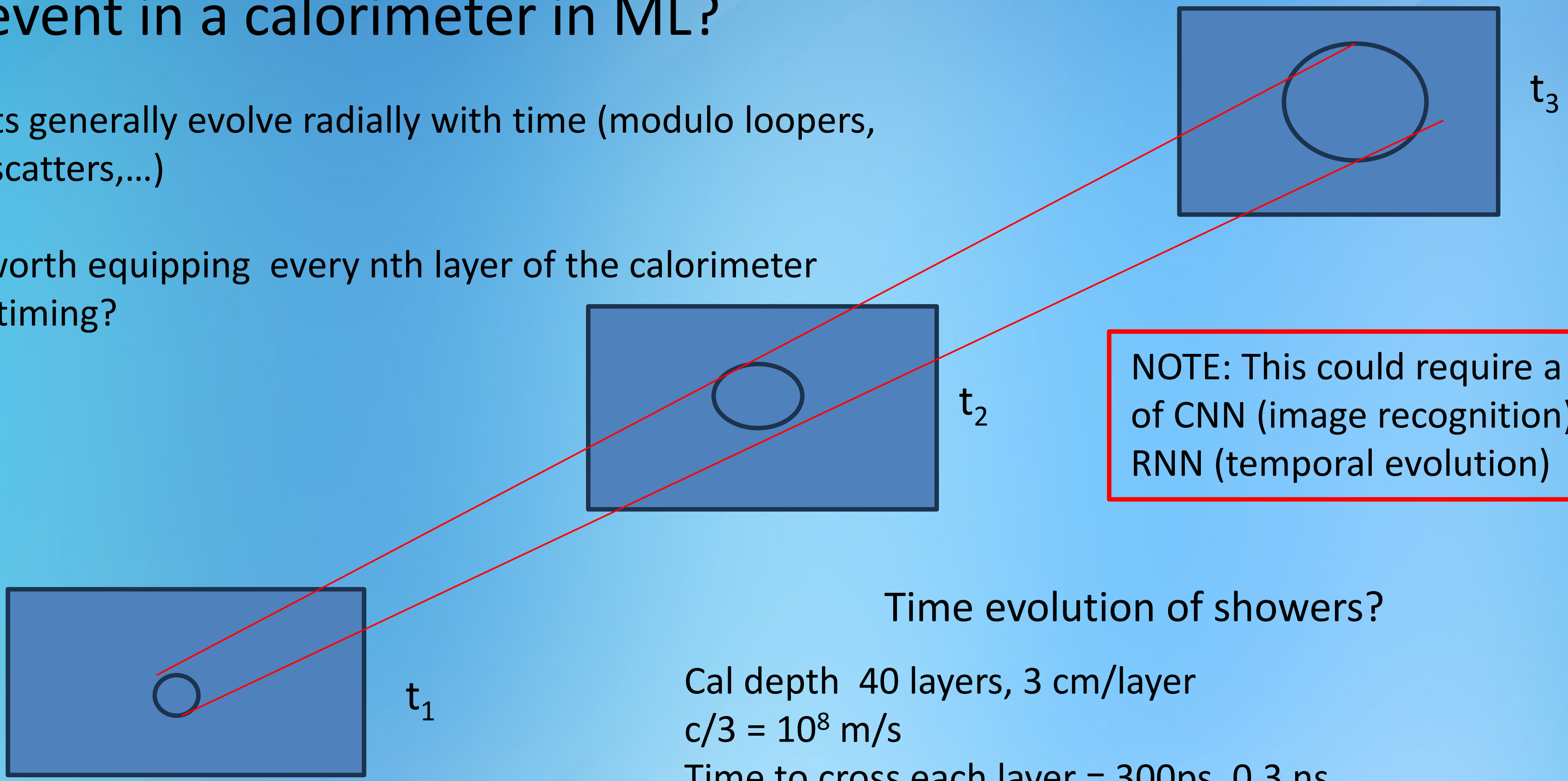
(Motivated by communication from Frank Simon – "CALO5D" project with ML building on software compensation with Pandora.)

- Track following through calorimeter layers
- Track-cluster association ("local" ML?)
- ML recognition of neutral energy clusters?
- Use of time ordered energy depositions to make correct cluster-to-cluster associations?
- How to build software compensation into ML?
- Should we consider implementing a "reduced" version of a "PFA"/triggering online?
- How to integrate tracking and calorimeter data for online PFA?

How to effectively include the time evolution of an event in a calorimeter in ML?

- Events generally evolve radially with time (modulo loopers, backscatters,…)

- Is it worth equipping every nth layer of the calorimeter with timing?



NOTE: This could require a mixture of CNN (image recognition) and RNN (temporal evolution)

Time evolution of showers?

Cal depth 40 layers, 3 cm/layer
$c/3 = 10^8$ m/s
Time to cross each layer = 300ps, 0.3 ns
~1ns for 3 layers
⇒ Instrument every 4th layer with O(1ns) timing?

Aspects of Integrated Online/Offline AI/ML

Online aspects to consider: Triggering, DAQ, Monitoring, Calibration, Preparation for Offline

- Individual subsystems/combined subsystems (e.g. for PFA)

- Preserving online ML structures for the offline?

- Online ML output as input seeds to offline ML?

- DAQ as reduction/organizing stage for offline ML?

- Online anomaly detection – fed to offline for extended ML-based analysis

Topological ML-based/assisted trigger system?

- Study efficiency of ML/topological pattern trigger system vs. traditional trigger menu plus cut-based analysis for physics process identification/separation.

- Readout of neighboring layer data (local sub-patterns) – fast readout/high data rates? *

- Multiple (parallel) ML triggers for recognition of different topologies?

- How to best organize calorimeter data for input to ML style trigger logic?
  Is this the same question as for ML data analysis offline – probably not…

- What are the implications for calorimeter design? Cost effectiveness vs. complexity.

* ECFA DRD7:

Project 7.1c: WADAPT (Wireless Allowing Data and Power Transmission)

This project aims to develop wireless technology based on a millimeter wave (mmw) transceiver IC as well as on Free Space Optics to connect neighboring detector layers, providing increased data rates, high power efficiency and high density of data links, with the aim of reducing mass and power consumption.

Use of online ML in Monitoring, Calibration, Fault finding, Data Quality Assurance

While we are considering the use of ML online for calorimeter systems we should ask whether other/all aspects of calorimeter operation could benefit from ML.

ML could be used for:

- flagging dead/intermittent/noisy channels (comparing with known history)
- deciding when a recalibration is needed (maybe in coordination with history of online ML-reconstructed objects?)
- tracking/reporting data quality
- reducing the need for extensive data reprocessing – leading to long analysis delays
- checking for expected symmetries (e.g. phi symmetry, forward/backward,…)
- suggesting/deciding when certain tasks are needed (e.g. charge injection to check FE electronics, laser pulsing for SiPM, PMTs, crystals,…)

Conclusions, questions

Fundamental question – is a detector design and the data it produces optimal for analysis using AI/ML techniques online and/or offline?

Attention so far given to use of AI/ML for calorimeter system design (e.g. ECFA DRD6/CALICE) but not much consideration of ***online ML***.

Given the long interval between an initial calorimeter system design and its implementation and use, and the rapid evolution and use of AI/ML, how should we project expected functionalities and their relation to future physics requirements and calorimeter systems design?

Additional slides

Electromagnetic/Hadronic Calorimetry Division?

- Many hadron showers start in the ECal (typically 1λ)

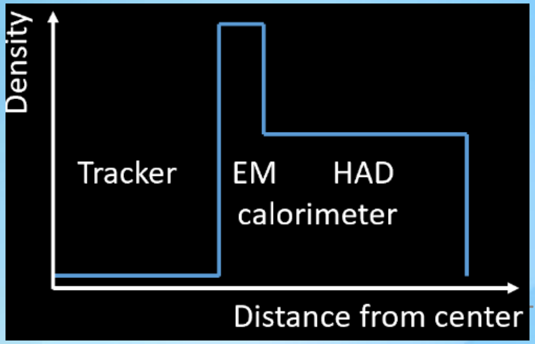
- If a MAPS ECal is used with very fine structure (50 μm x 50 μm pixels?) how would say a CNN handle the abrupt change to e.g. a 3 cm x 3cm tile size HCal?

- Would some precision tracking layers in the HCal help?
 (not just for PFA, but for cluster building)

- Maybe some layers of e.g. smaller tiles at the front of the HCal?

(3) Is there a better density profile than the dichotomic one we have used in collider experiments for six decades?

T. Dorigo, DRD6 Meeting Nov 1 2024



A thinner/cheaper Calorimeter – with ML estimate of Shower Tails

- For a detector with HCal inside solenoid an extra cm. in radius is ~+$1M
  -> motivation for a compact design

- Given the variability of hadron shower energy deposition patterns can we train an ML algorithm to estimate the energy "lost" in the tail of a shower?

- Need a study with main HCal and a "backing HCal" to verify efficiency of a shower tail energy estimator.

- Compare with estimate using muon system as tail-catcher.