Progress on 5D Calorimetry and Particle Flow

Roman Pöschl

All credit goes to the persons who do the studies, all faults are mine

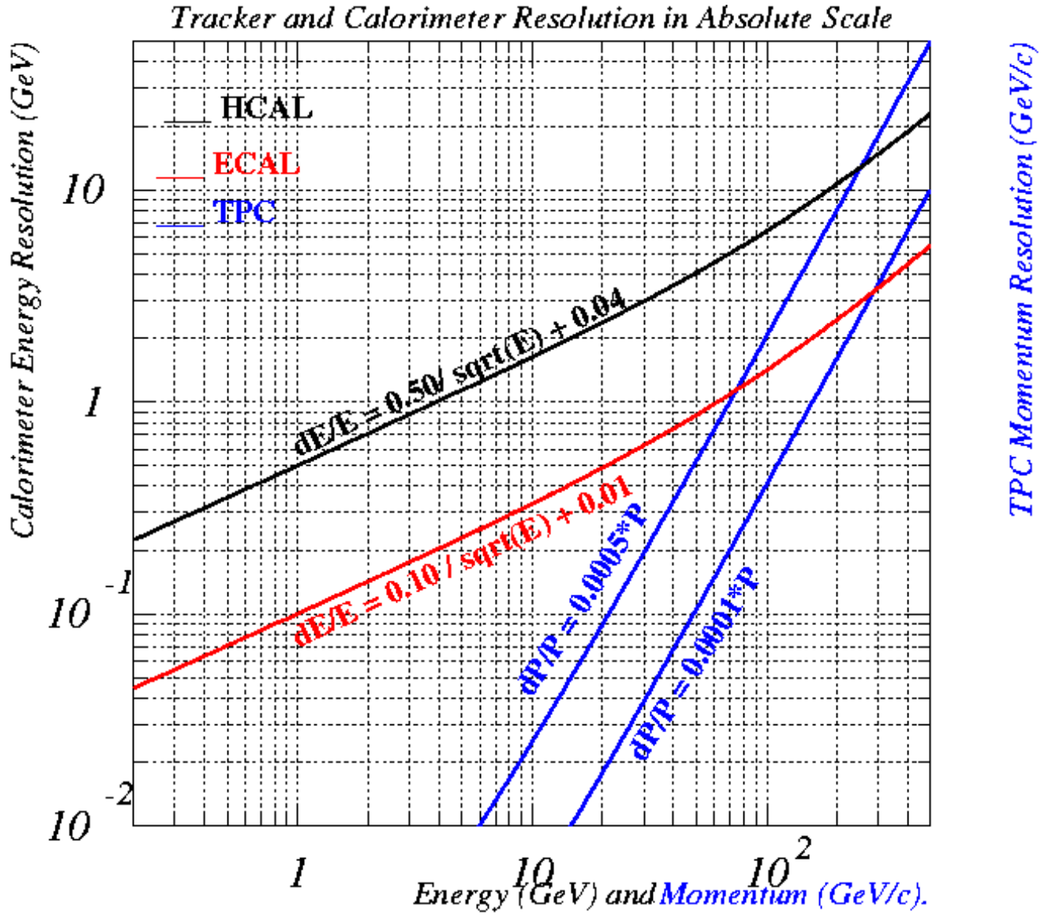
On behalf of the groups in the French-German CALO5D project

LCWS 2026 – KEK November 2026

This work was funded by the French-German ANR-DFG project CALO5D under the Grant Agreement ANR-23-CE31-0023.

Jet Energy Resolution

Final state contains high energetic jets from e.g. Z,W decays
Need to reconstruct the jet energy to the utmost precision !
Goal is around dE_{jet}/E_{jet} *- 3-4%* (e.g. 2x better than ALEPH)



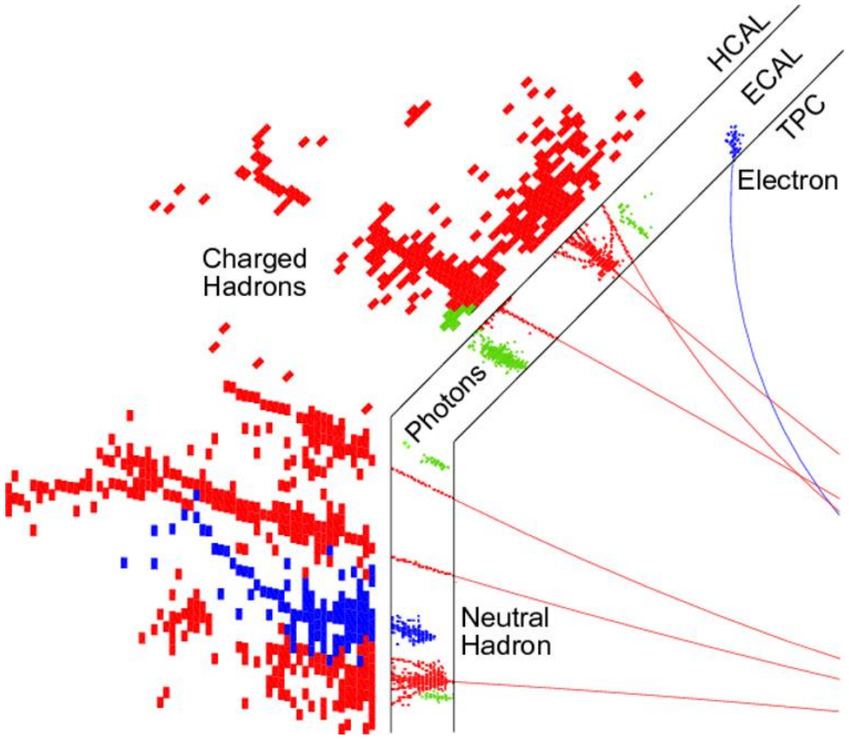
Jet energy carried by …

- Charged particles ($e^{\pm}$, $h^{\pm}$,$\mu^{\pm}$**):** 65%
  Most precise measurement by Tracker
  Up to 100 GeV
- Photons: 25%
  Measurement by Electromagnetic Calorimeter (ECAL)
- Neutral Hadrons: 10%
  Measurement by Hadronic Calorimeter (HCAL) and ECAL

$$\sigma_{Jet} = \sqrt{\sigma^2_{Track} + \sigma^2_{Had.} + \sigma^2_{elm.} + \sigma^2_{Confusion}}$$

Confusion Term

- Base measurement as much as possible on measurement of charged particles in tracking devices
- Separate of signals by charged and neutral particles in calorimeter



- Complicated topology by (hadronic) showers
- Overlap between showers compromises correct assignment of calo hits

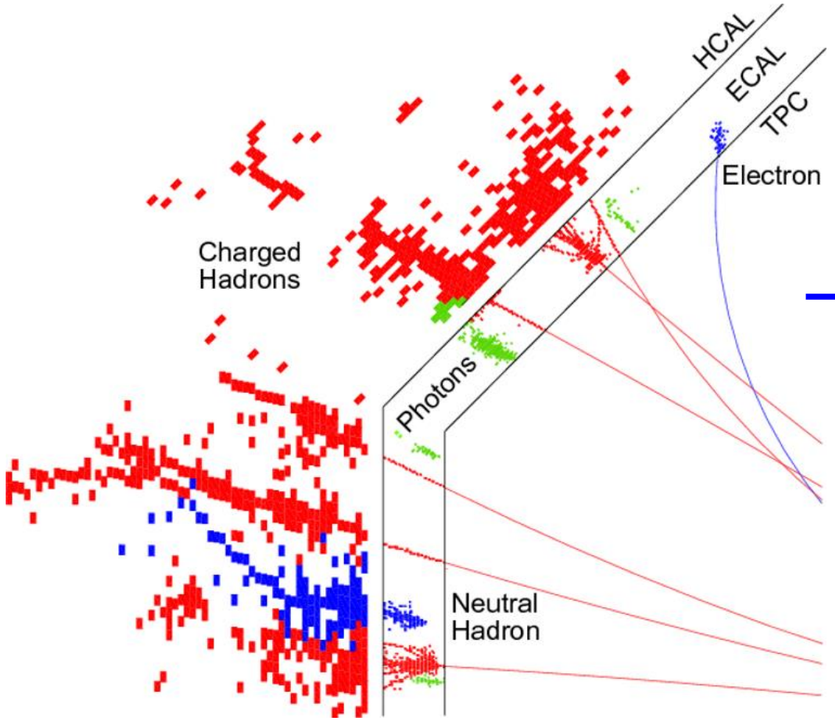
⇒ Confusion Term

Need to minimize the confusion term as much as possible !!!

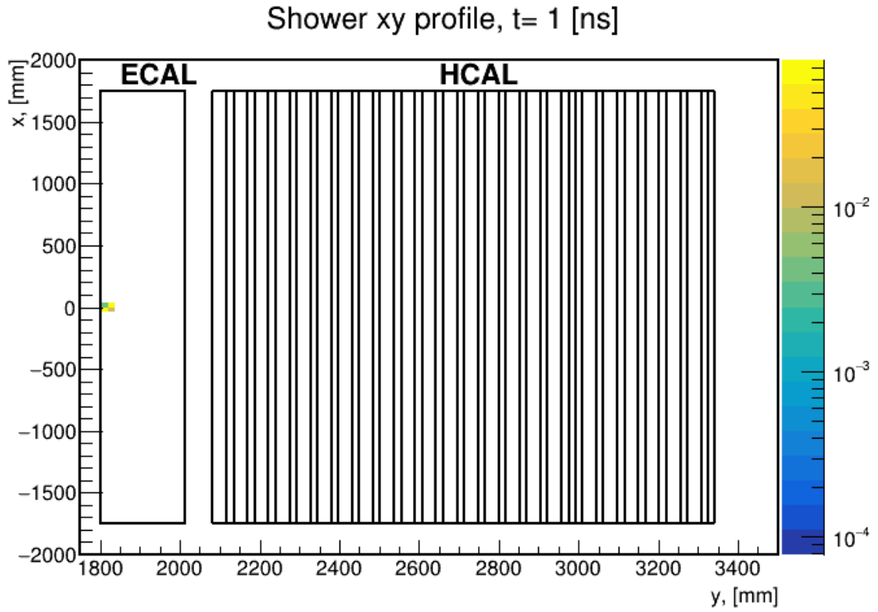
References for development of PFA concept and first comparisons between LEP results and prospects at TESLA/ILC:

J.C. Brient and H.Videau, arXiv:hep-ex/0202004 [hep-ex].
V.L. Morgunov, Proceedings, 10th International Conference, CALOR 2002, Pasadena, USA, March 25-29, 2002, pp. 70--84.

Event Reconstruction



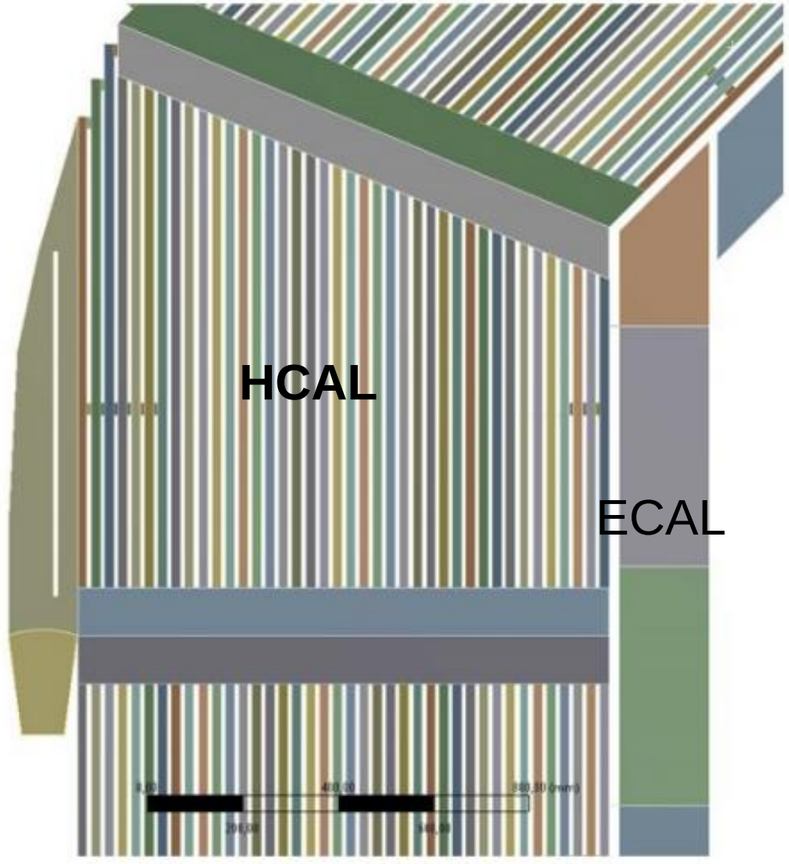
From static pictures to movies



Y. Padniuk, Master student
Technical University of Kiyv

- Optimisation of Particle Flow Algorithms with help of Machine Learning Techniques
- Can precise timing help for particle flow?
- Need find answers now since a visible improvement would trigger intensive R&D
  - ANR-DFG project CALO5D

ILD concept and highly granular calorimeters

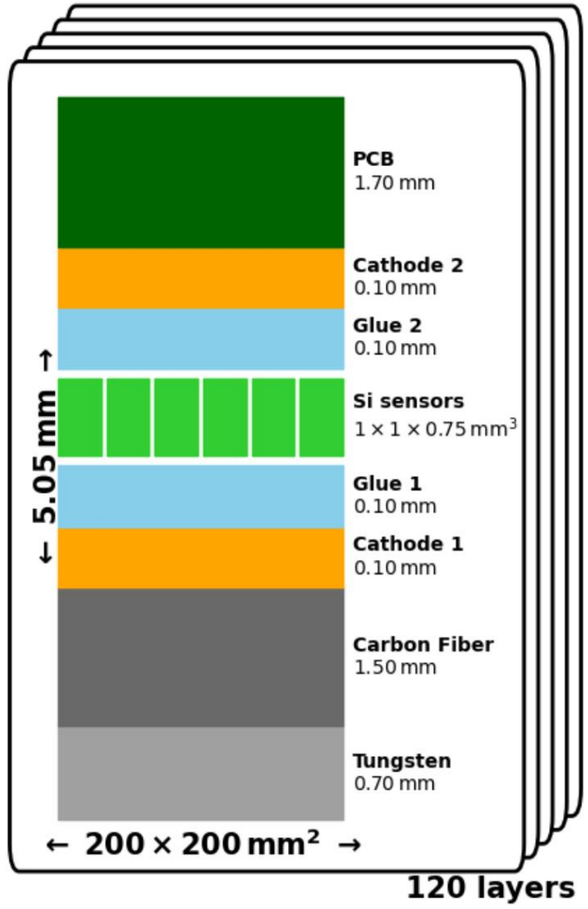


- ILD are particle flow detectors
  - Implies goal to measure every particle of hadronic final state
  - Key components for PFA are highly granular calorimeters

- Calorimeter options in ILD
  - Silicon-Tungsten Ecal
    - 26-30/40 layers
    - Cell size 5.5x5.5mm^2, layer depth 0.6-1.6 X_0
  - Scintillator-Tungsten Ecal
    - 30 layers
    - Strip size 5x45 mm^2, layer depth 0.7 X_0
  - Analogue Hcal
    - 48/44 layers
    - Scintillating tiles: 30x30mm^2, layer depth 0.11λ_I
    - Absorber stainless steel
  - Semi-Digital Hcal
    - 48 layers
    - GRPC: 10x10mm^2, layer depth 0.12 λ_I
    - Absorber stainless steel

SiW ECAL Optimisation Study

Ultraflexible Geometry



Multi Layer Percepton

Samples

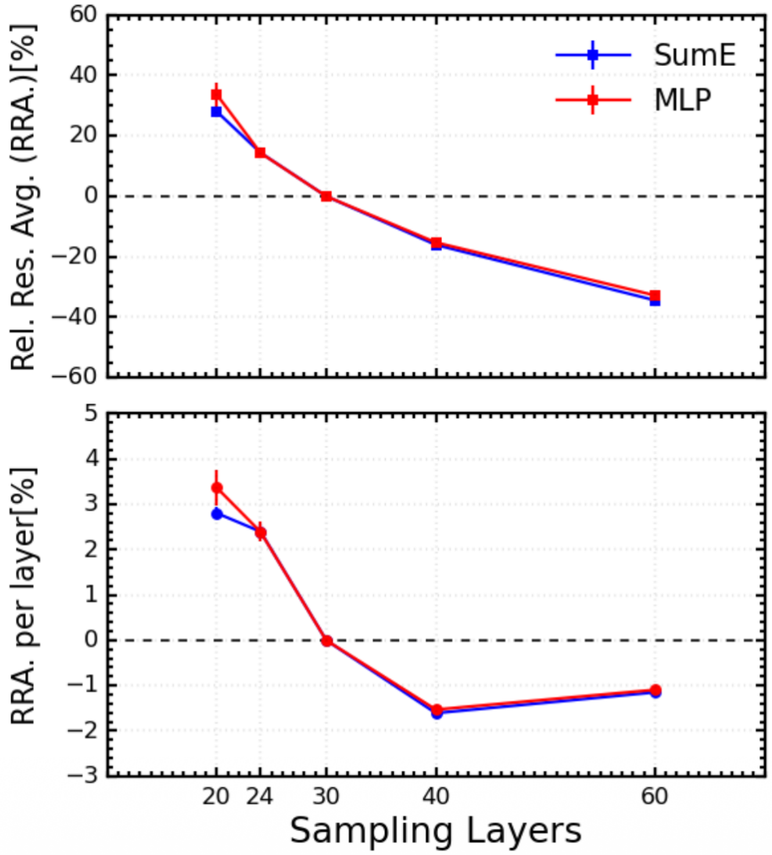
- Train & Validate samples
  - uniformed energy ranging: 0-70 GeV
  - 1M for training, 0.2M for validate
- Test samples
  - Discrete energy: 0.1,0.25,.....60 GeV
- Input Features: 152
  - E_i and N_i from each layer
  - E_{sum} and N_{sum}
  - E_i/E_{sum} ,N_i/N_{sum} and E_i/N_i

Model Setup

- Activation function: PReLU(Parametric Recitified Linear Unit)
- Loss function: Huber
- Layers: [256,128,64]
- Learning rate: warm up + cos
- Batch size:4096
- Epochs: 100+ early stop(patience=10)

Photons between 0-70 GeV (0-60 GeV) for training (testing)

Number of Sampling Layers



Yukun Shi, Vincent Boudry: 2604.27853

Jet Energy Resolution

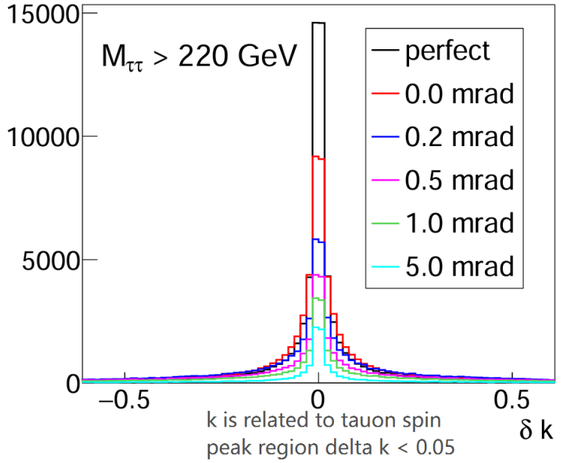
$$\sigma_{jet} = \sqrt{\sigma^2_{track} + \sigma^2_{elm.} + \sigma^2_{had.} + \sigma^2_{confusion}}$$

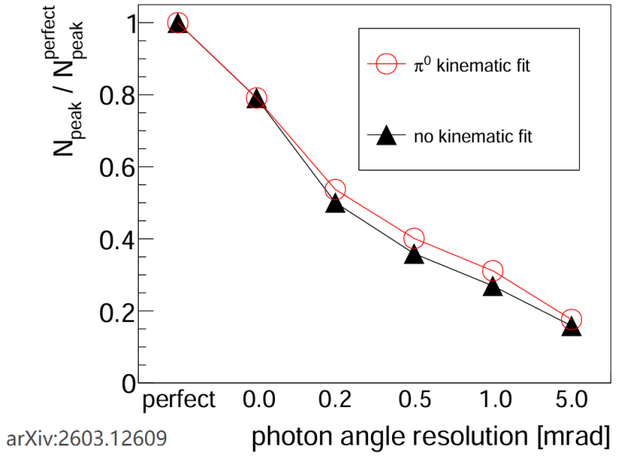
π^0 Reconstruction

- Neutral pions are reconstructed through $\pi^0 \rightarrow \gamma\gamma$.
- The reconstructed π^0 direction and energy depend directly on the two photon directions.
- In a π^0 kinematic fit,

$$M^2_{\pi 0} = 2E_{\gamma 1} E_{\gamma 2} (1-\cos \theta_{12})$$

- Better photon position reconstruction ⇒better π^0 direction reconstruction.

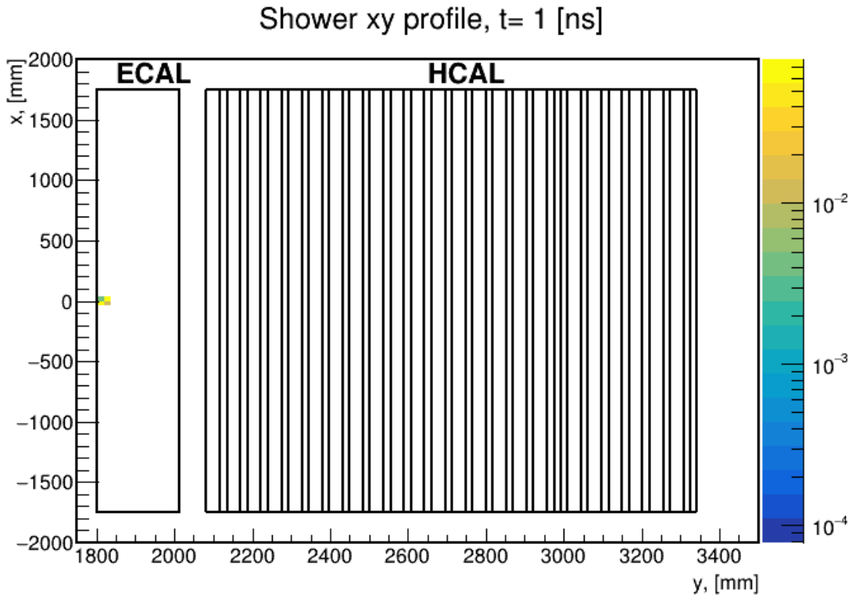




arXiv:2603.12609

- Precision timing calorimetry opens new opportunities
  - E.g. combining the starting hit with the shower barycenter

π^0 Reconstruction - Strategy

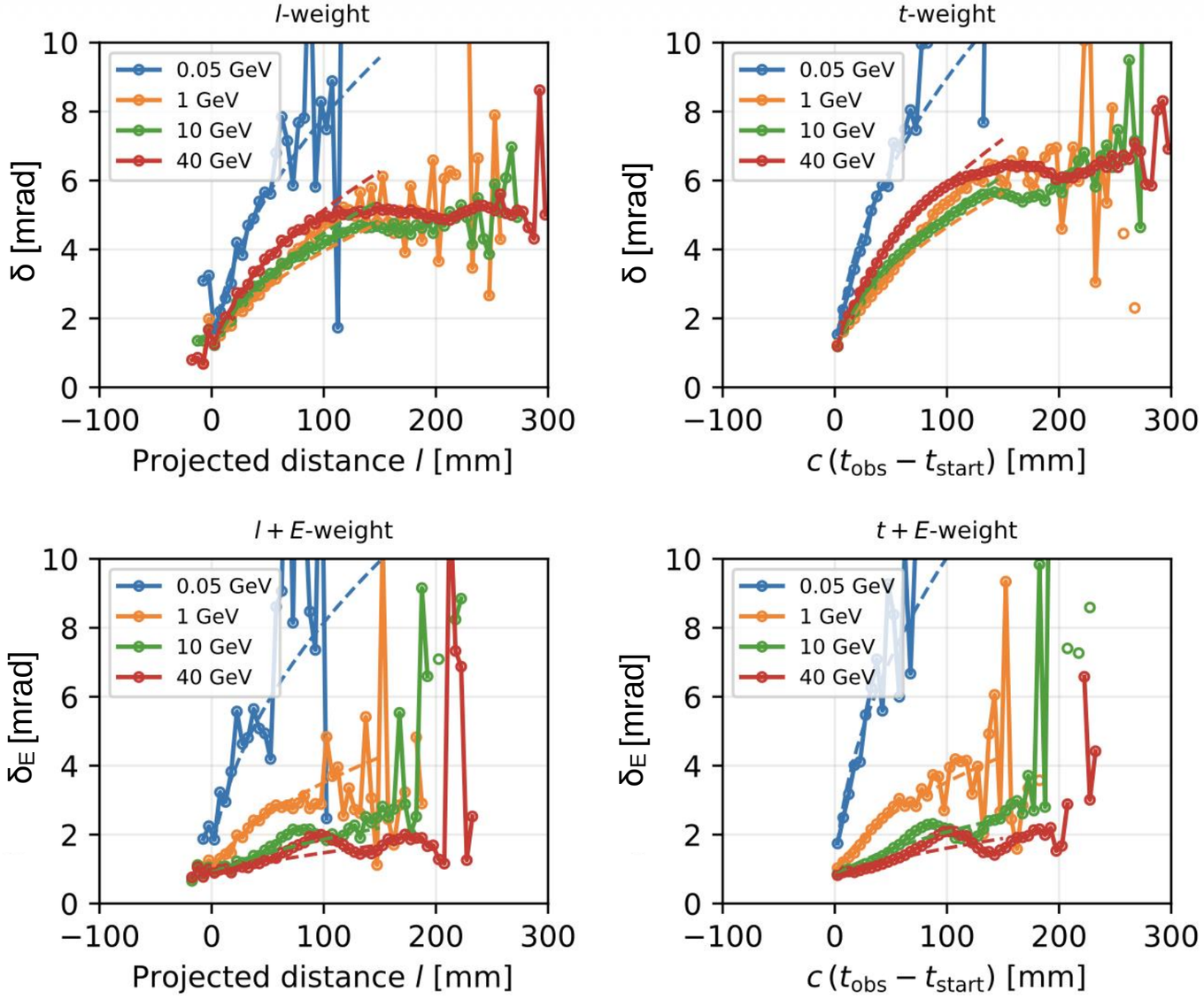


For illustration purposes only

- Find the shower starting hit of an individual photon
- Select high-quality hits with geometric and timing-based selections.
- Parameterize the hit-angle resolution.
- Reconstruct the photon angular position with an hit angle resolution-based weighted average.
- Optimize the hyperparameters for each method
- The study is optimised for a time resolution of 10 ps/cell

Hao Liang, Vincent Boudry, Henri Videau

π^0 Reconstruction – Hit Weights



- Determine hit-level angular distance δ_i to the predicted shower axis
- Alternatively: $\delta_{E,i} = \delta_i \frac{E_i}{\tilde{E}}$ with $\tilde{E} = \sqrt{(\sum E_i^2)/n}$
- Build in each bin of x (with x = l or x = t)*

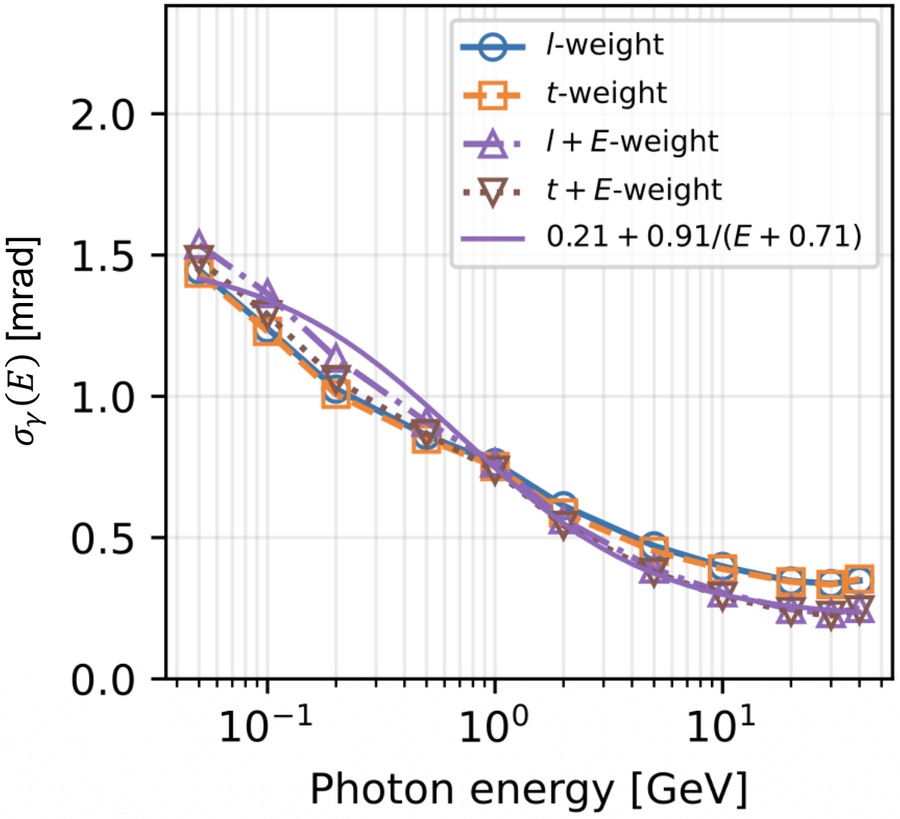
  $\delta = \sqrt{(\sum \delta_i^2)/n}$ and $\delta_E = \sqrt{(\sum \delta_{E,i}^2)/n}$
- Parameterise: $\sigma_E = \sqrt{a + bx}$ and $\sigma_E = \sqrt{\alpha + \beta x}$
- Build weight: $w(x) = 1/\sigma_\delta^2(x)$ and $w_E(x) = 1/\sigma_{\delta_E}^2(x)$
  - Detailed weights in backup

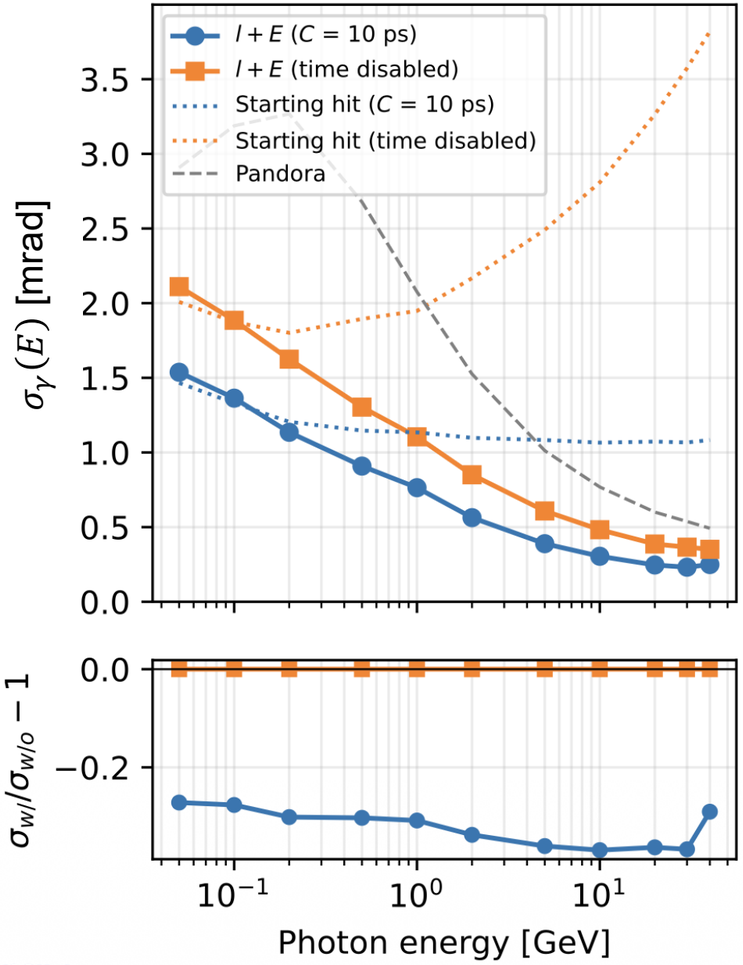
*Exact definitions of l and t, see backup

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π^0 Reconstruction – Photon Angular Resolution

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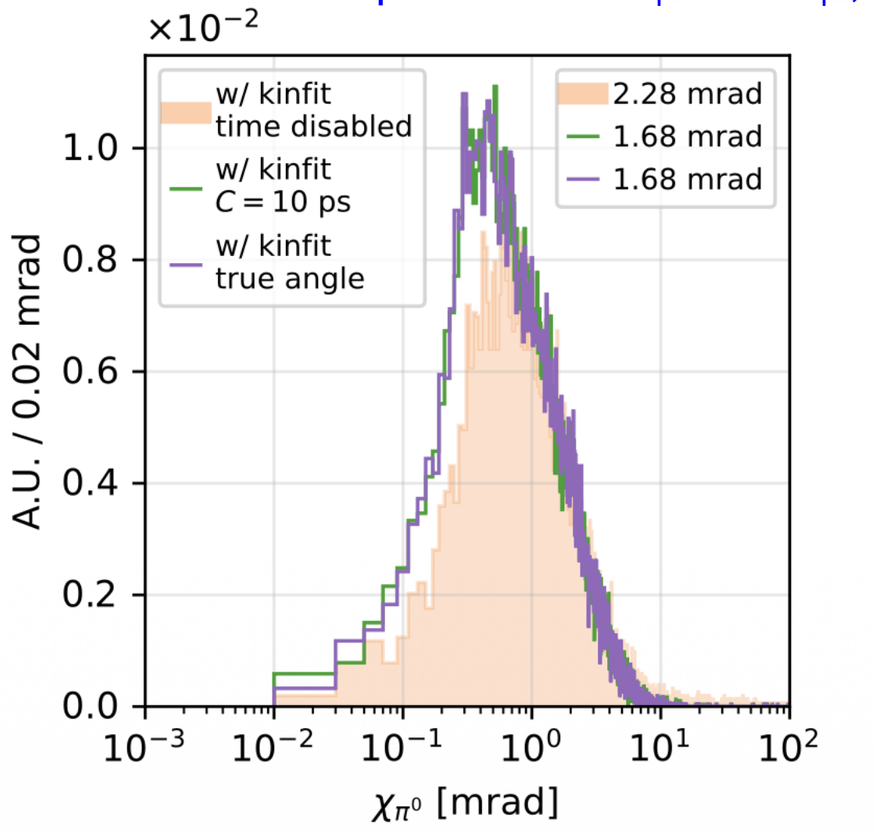


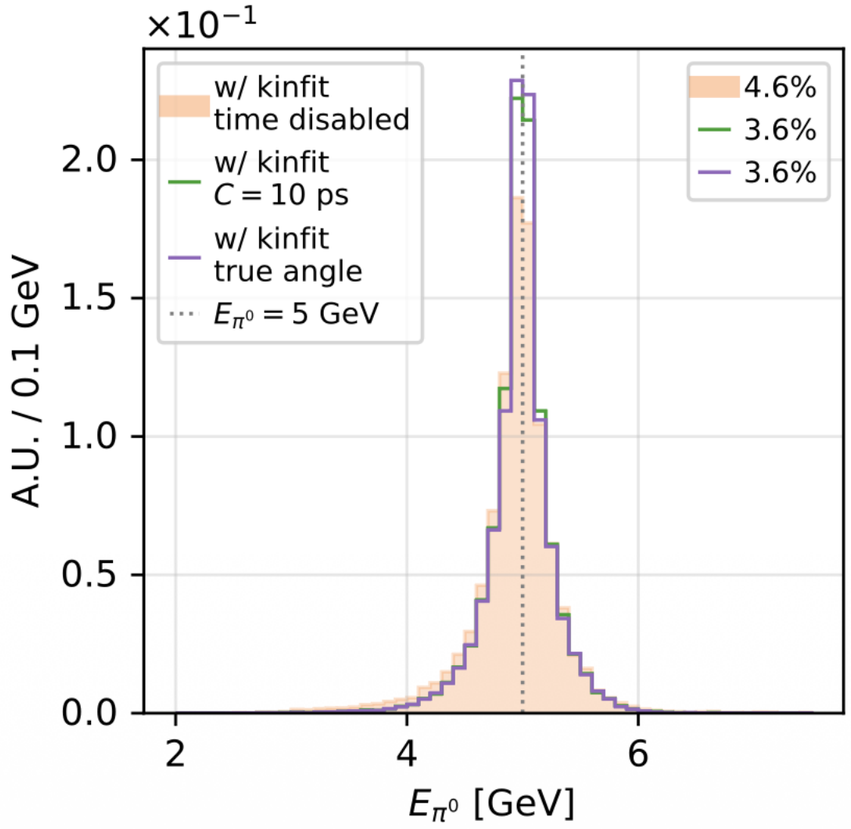


- Resolution improves monotonically with photon energy.
- Full weighting beats seed-only at higher energy; Pandora is worse, especially at low energy.

π^0 Reconstruction – Kinematic Reconstruction

- 5 GeV π^0 sample at 10 ps.
- Event preselection: two photons reaching the calorimeter; at least one reconstructed cluster per photon; leading cluster for each photon kept.
- Kinematic fit with free parameters $E_{\gamma 1}$ and $E_{\gamma 2}$, constrained by the nominal π^0 mass





- Timing clearly seems to improve pion reconstruction
- Work in progress and we work on the minimal requirements on time resolution,
  - N.B.: at the moment 25 ps at cell level seems to be needed (see backup)

Hao Liang, Vincent Boudry, Henri Videau

Jet Energy Resolution

$$\sigma_{jet} = \sqrt{\sigma^2_{track} + \sigma^2_{elm.} + \sigma^2_{had.} + \sigma^2_{confusion}}$$

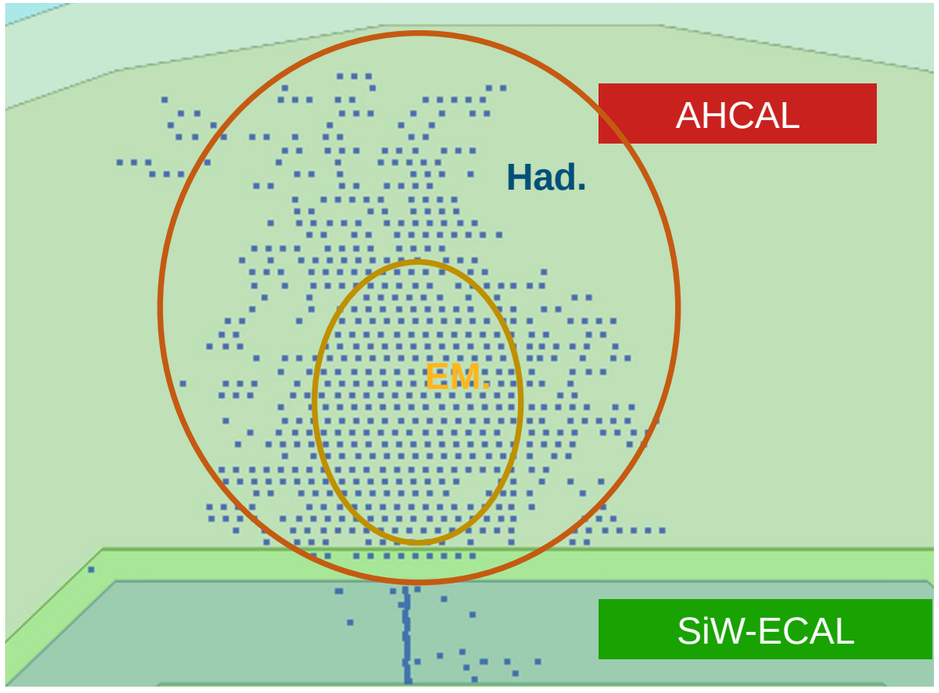
Challenges in Hadronic Calorimetry

- Hadron showers contain:
  - Electromagnetic(EM) components ($\pi^0 \rightarrow \gamma\gamma$)
  - Hadronic components
- The EM fraction fluctuates significantly event by event

- However, Non-compensating calorimeters:
  - Different response to EM and hadronic components ($e/h \neq 1$)

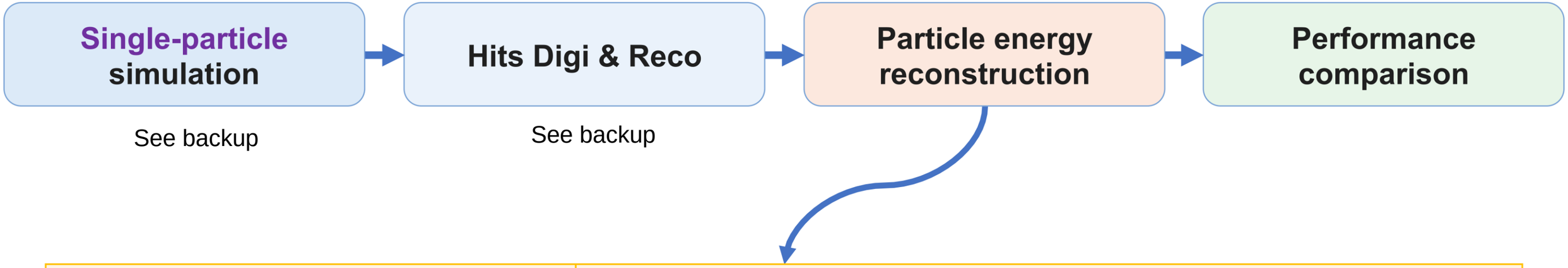
- Therefore, large variations in detector response, which degraded the hadron energy resolution

CNN-based approach for the full ILD ECAL + HCAL system (realistic detector setup)



Xin Xia

Energy Reconstruction Methods



Visible (baseline)	$E = \sum_{all_hits} E_{hit}$
CNN w/o time	**(E, x, y, z)**
CNN w. time	**(E, T, x, y, z)**

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Irregular Calorimeter Grid → CNN Input

CNN input requirements:

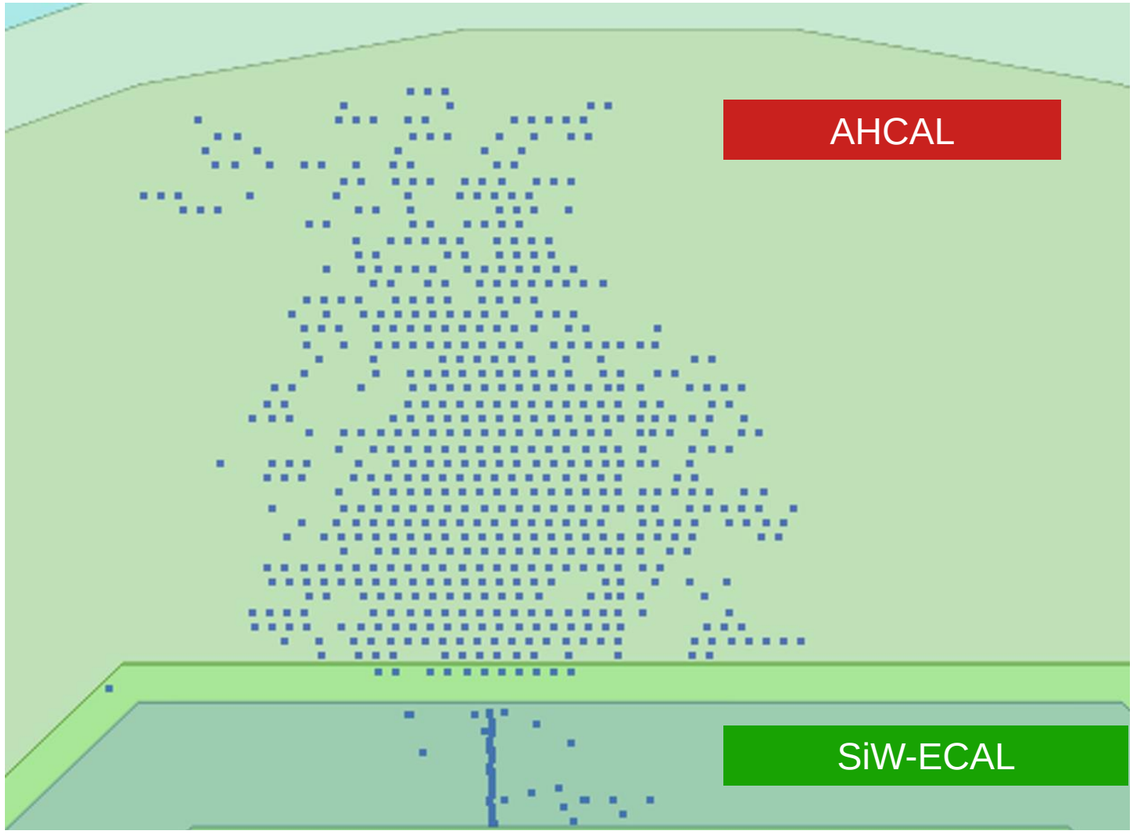
- Regular grid format
- Operate within a fixed spatial window

However, Detector reality: calorimeter data are irregular

- Discrete hits with non-uniform geometry
- Different granularity in ECAL and HCAL

Therefore, calorimeter hits need a structured representation for CNN input

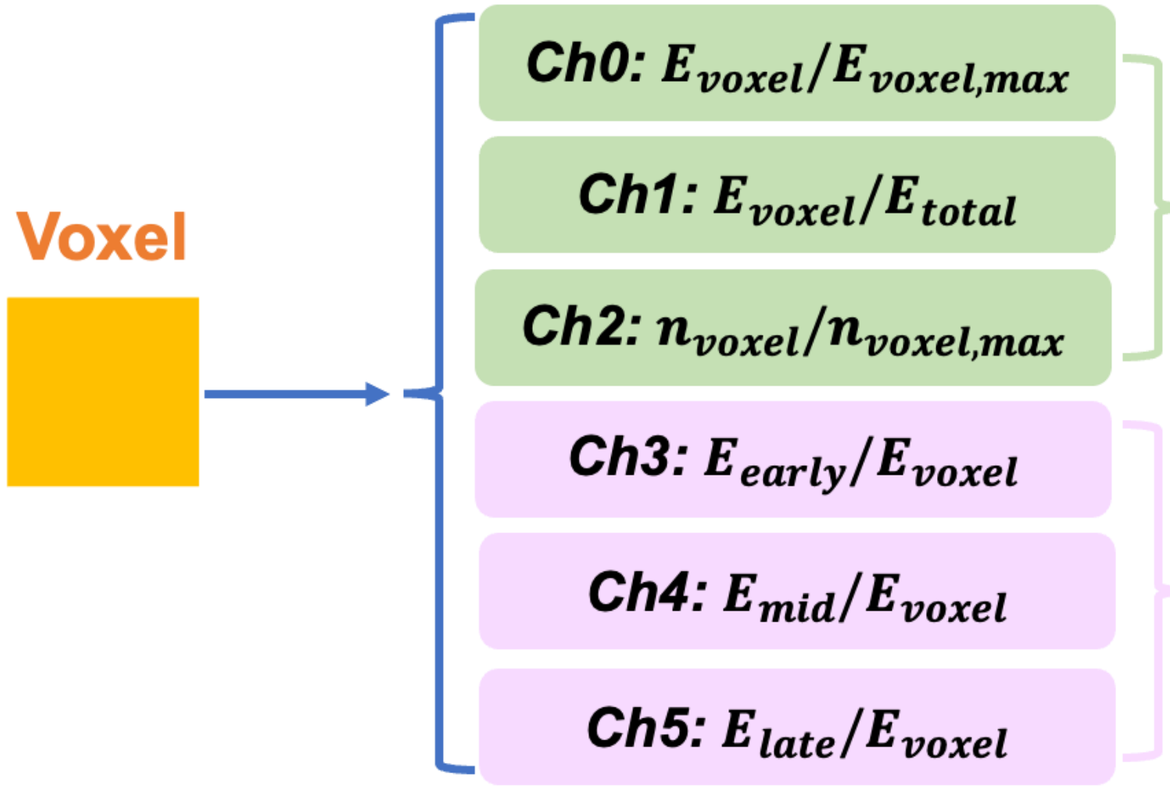
- Voxelization
- Details on Voxelisation, see backup



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Voxel Information with Time

For CNN w. timing information:



Spatial-energy structure

- *Where and how much energy is deposited*

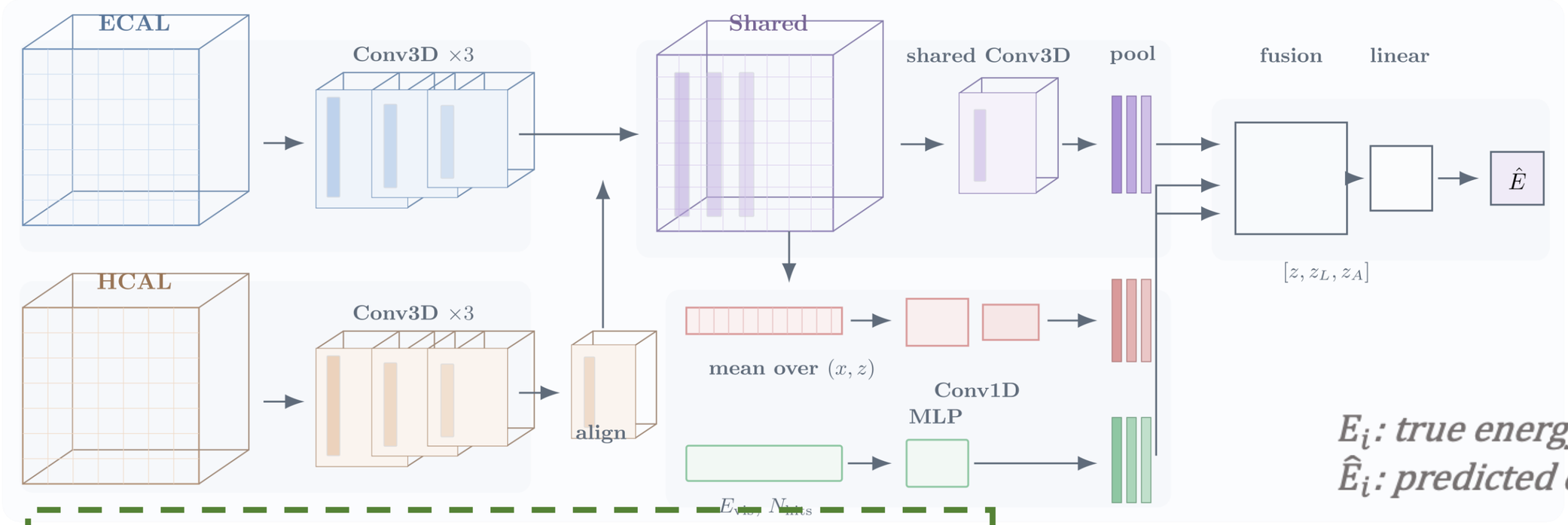
Spatial-time-category structure

- *How the energy is distributed in time*
- *Use perfect time for upper-bound study*

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Dual Branch CNN Model

- Calorimeter-aware design, balance and exploit the complementary information from the two calorimeters.



E_i: *true energy*
$\hat{E}_i$: *predicted energy*

Inputs:

- Voxelized shower images from **ECAL** and **HCAL**
- Global features: E_{dep}, N_{Hits}

Optimization objective:

- $Loss = 0.5\, r^2$
- $r = \begin{cases} (\hat{E}_i - E_i)/E_i, E_i \geq 0.7\ GeV \\ \hat{E}_i - E_i, E_i < 0.7\ GeV \end{cases}$

- Details on training, see backup

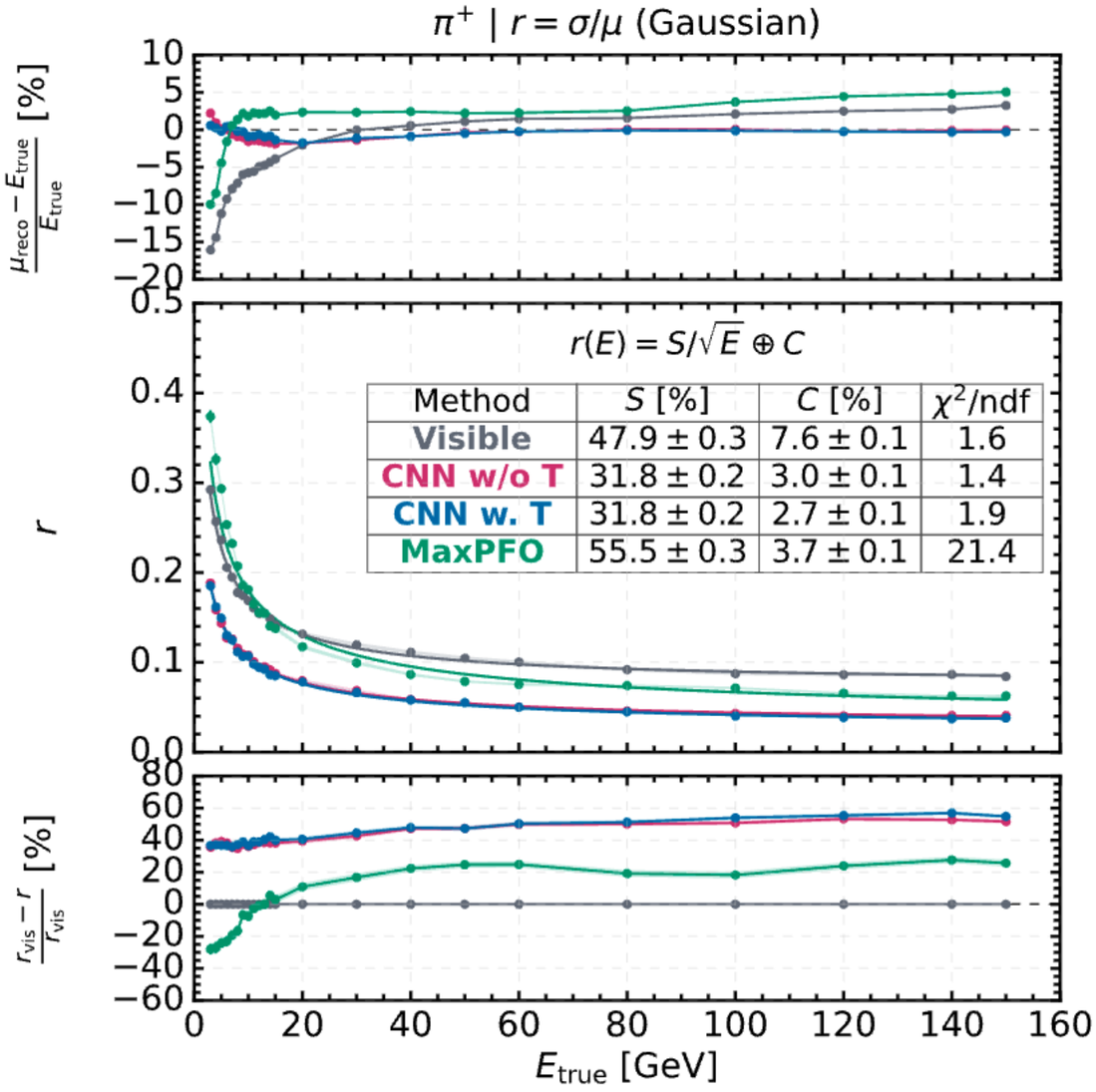
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Energy distributions of π^+ - CNN vs. Baseline

- CNN significantly outperforms visible-energy baseline in both linearity and resolution. (40% - 60% improvement in resolution)
- The dominant gain comes from the spatial-energy shower structure.
- Timing only provides a modest additional improvement over the no-time CNN.

Potentially Learned features:

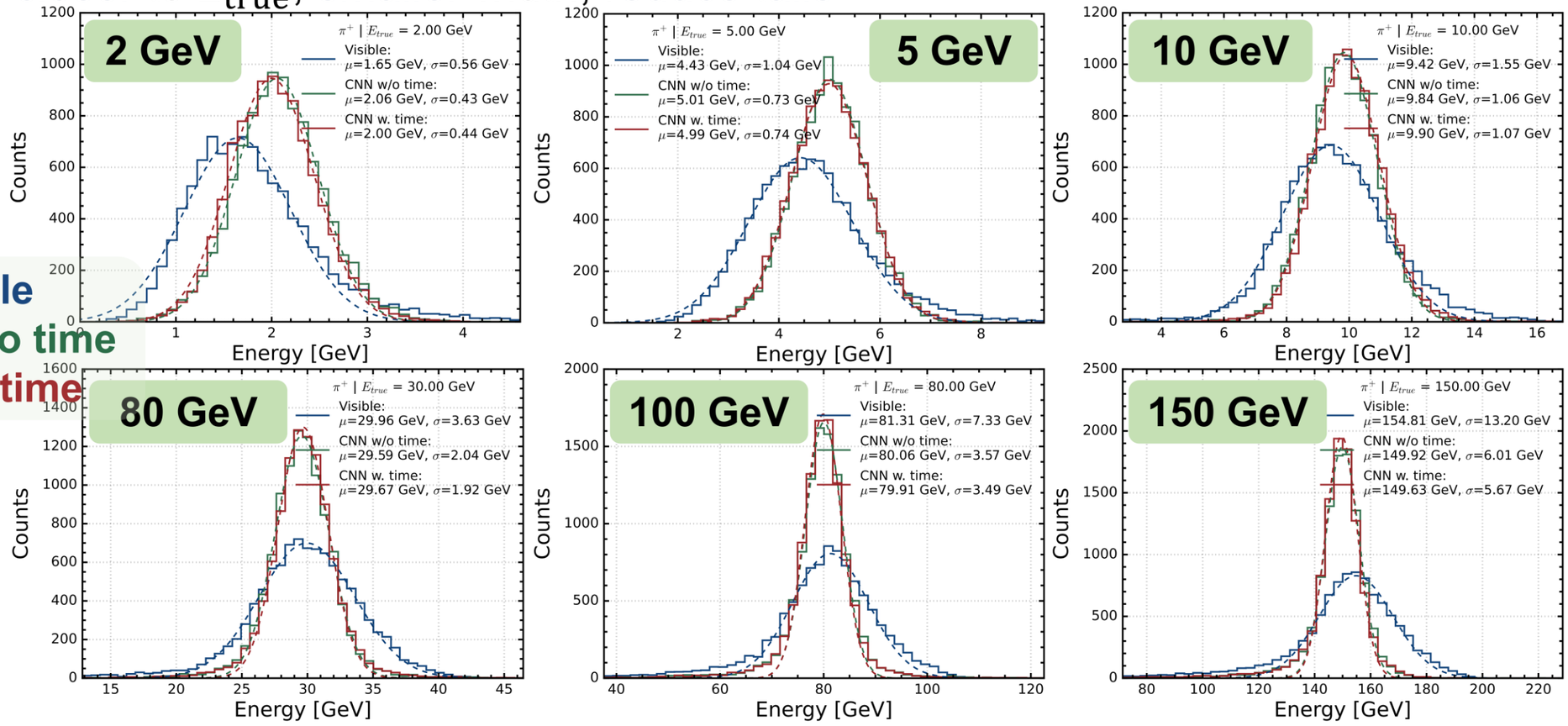
- ECAL/HCAL energy sharing
- `Local density and topology
- Shower start and depth • Leakage tendency
- Longitudinal spread • Electromagnetic vs non-electromagnetic mixture
- prompt / main / late spatial-time patterns (only for CNN w. time information)



Energy distributions of π^+ - CNN vs. Baseline

- Metric: Gaussian fit to the reconstructed energy distribution
- CNN shows better performance:
  - mean closer to E_{true}; smaller width; reduce tails

Blue: visible
Green: CNN w/o time
Red: CNN w. time



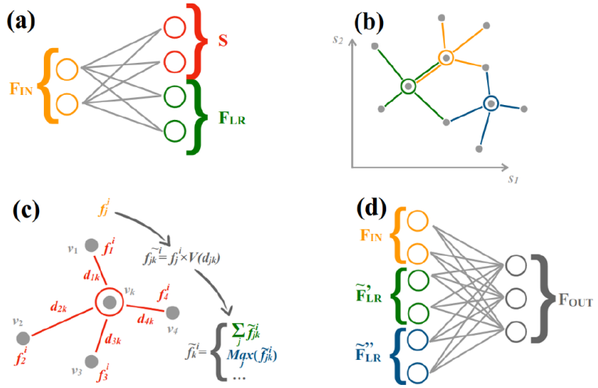
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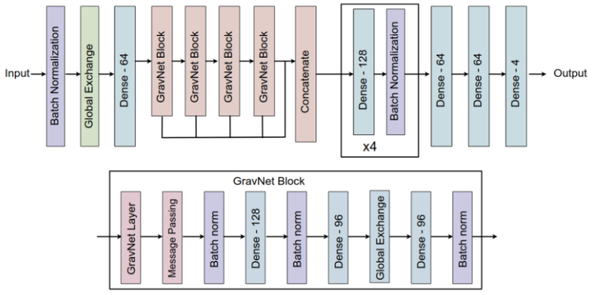
Jet Energy Resolution

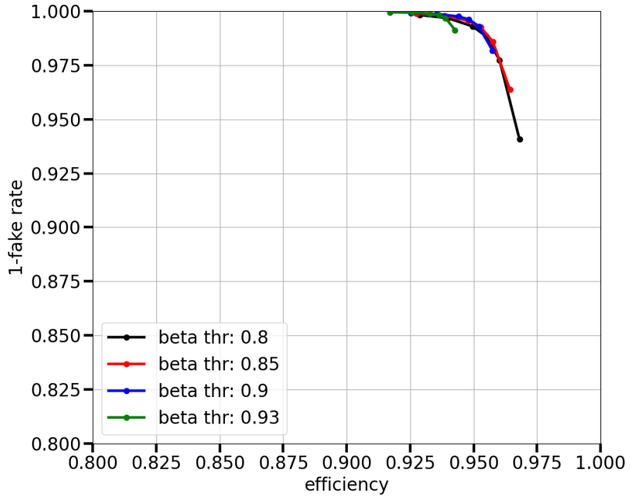
$$\sigma_{jet} = \sqrt{\sigma^2_{track} + \sigma^2_{elm.} + \sigma^2_{had.} + \sigma^2_{confusion}}$$

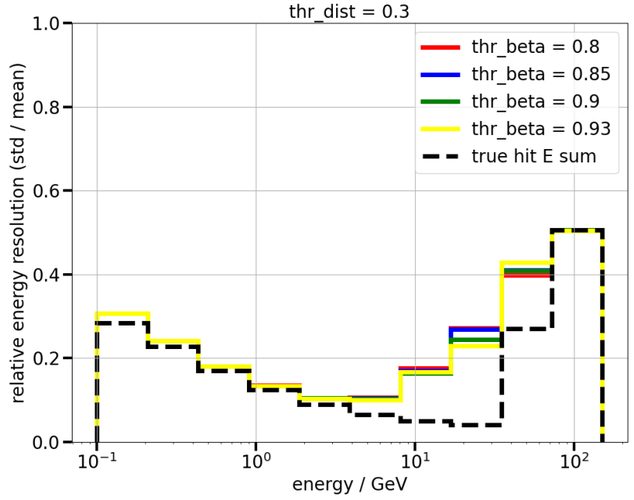
GravNet + Object Condensation

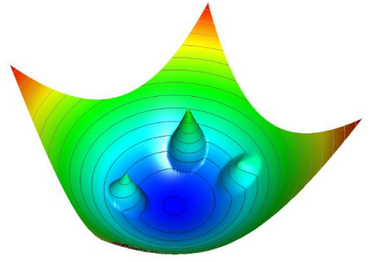
- Using GNN GravNet with Object Condensation (additional clustering loss component to create one representative condensation point per PFO) for MLPF, easy to add timing information
- End-to-end reconstruction: from calo hits + tracks in one network to predicted particles with energy, position and PID
- Implemented for ILD MC data, large production available
- Stable model training + inference, but overall results so far not as performant as expected → work in progress!
- So far only small impact of timing visible











Katharina Schäuble, Uli Einhaus

Summary and Outlook

- CALO5D investigates all (calorimetric) aspects of jet energy resolution with highly granular calorimeters
  - Explore potential of applying machine learning based algorithms
  - Explore the potential of timing
  - Carries out detector optimisation studies

- Machine learning improves hadronic energy resolution by a lot; 50% statistical term -> ~30%
  - Limited effect of timing
  - Everything looks a bit nicer

- Timing seems to help for photon angular reconstruction
  - Needs however excellent time resolution (~10ps)

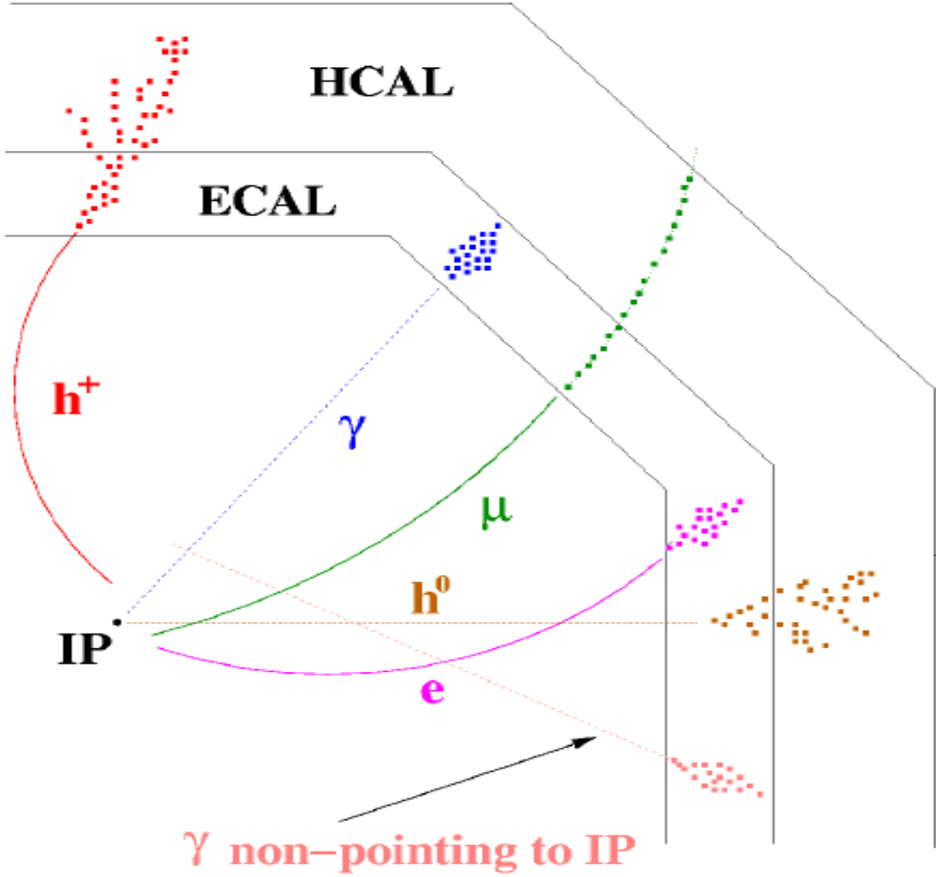
- Jet energy resolution
  - No clear improvement by DGCNN reconstruction
  - DGCNN results seem to be “cleaner” than Pandora, better behaviour in tails
  - Timing brings results in agreement with Pandora everywhere
  - Still big gap to “perfect PFA”
  - Exploration of alternatives such as GravNet with Attention

Backup

Particle Flow Calorimetry

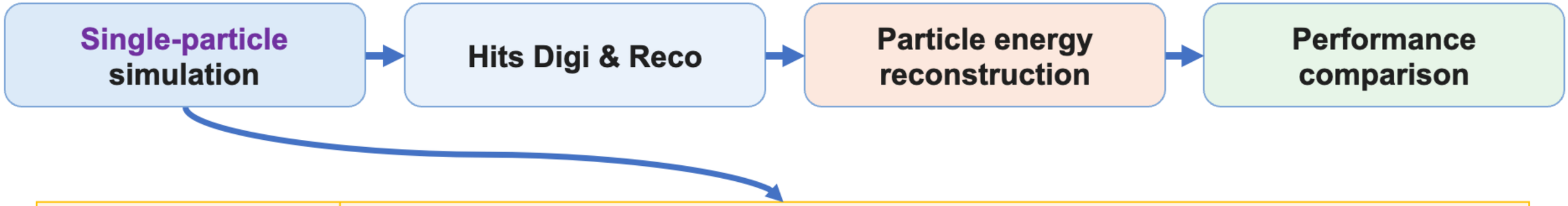
Jet energy measurement by measurement of **individual particles**
Maximal exploitation of precise tracking measurement

- large radius and length
  - → to separate the particles
- large magnetic field
  - → to sweep out charged tracks
- “no” material in front of calorimeters
  - → stay inside coil
- small Molière radius of calorimeters
  - → to minimize shower overlap
- **high granularity of calorimeters**
  - → to separate overlapping showers



Particle flow as privileged solution for experimental challenges
=> Highly granular calorimeters!!!
Emphasis on tracking capabilities of calorimeters

Samples Preparation using ILD Software



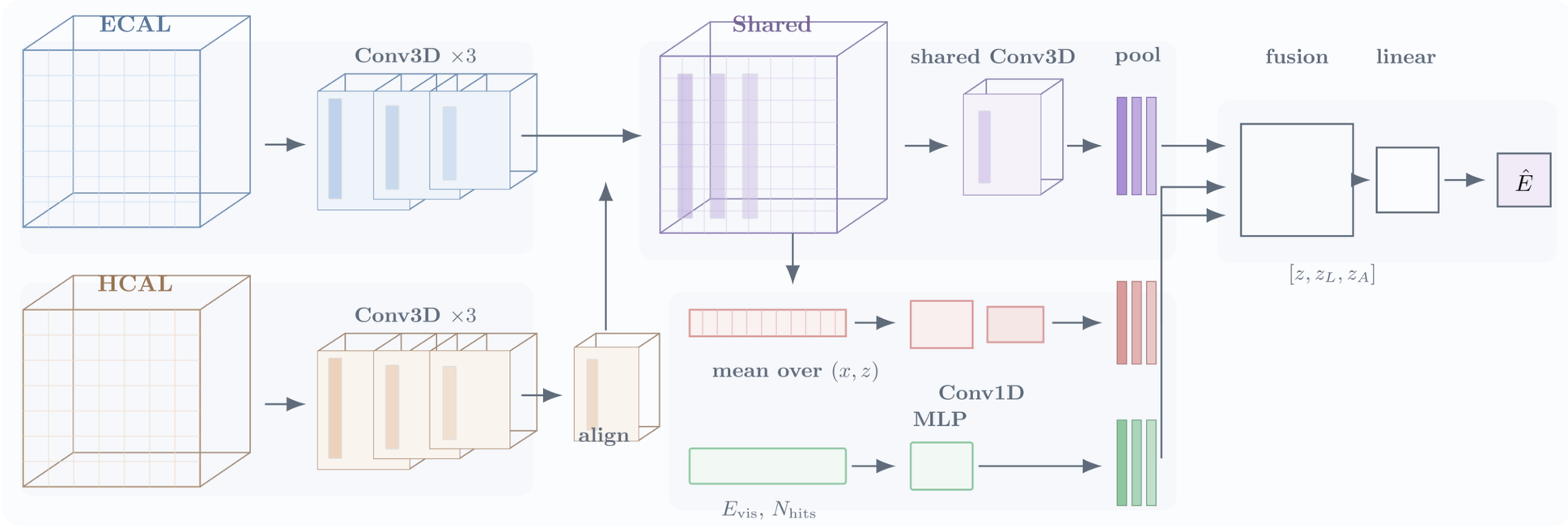
Calorimeters	SiW-ECAL and AHCAL				
Incident position	ECAL surface (with position smear in X-Z plane to avoid cracks)				
Incident angle	Perpendicular along the y-axis				
Particle	π^+		e^-	K^-	K_L^0
Energy	0.2 GeV – 200 GeV (1k uniform E points)	3-150 GeV	3-150 GeV	3-150 GeV	3-150 GeV
Num. of events	1M	230k	230k	230k	230k
Used for	Train & Validation	Evaluation	Evaluation	Evaluation	Evaluation

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What Could the Model Learn?

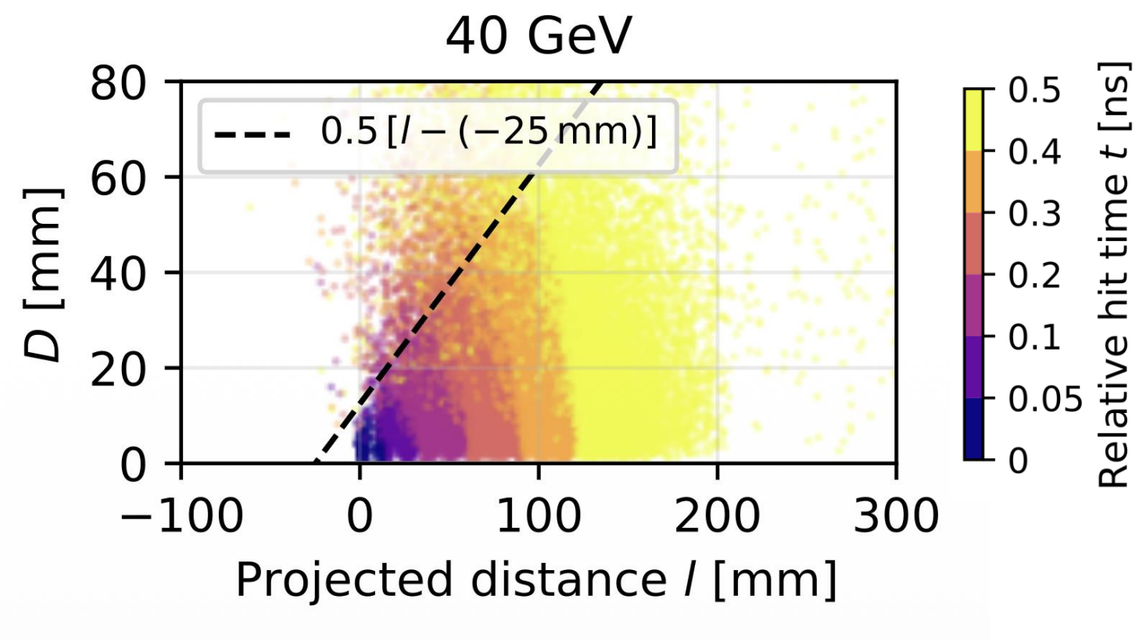
Potentially Learned features:

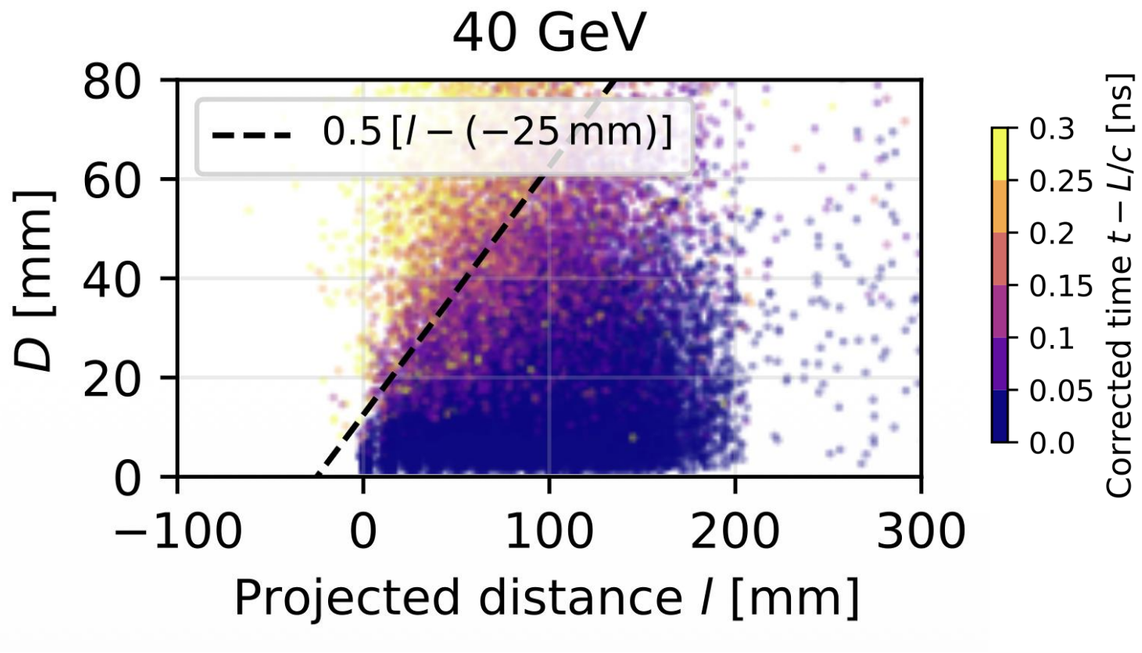
- ECAL/HCAL energy sharing
- Shower start and depth
- Longitudinal spread
- Local density and topology
- Leakage tendency
- Electromagnetic vs non-electromagnetic mixture
- *prompt / main / late spatial-time patterns (only for CNN w. time information)*



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π^0 Reconstruction – Hit Selection





- Longitudinal window:
  - −25 mm <l <200 mm with
  - $l = (\mathbf{r} - \mathbf{r_{start}})\hat{\mathbf{r}}$
- Cone cut:
  - $d \leq k_c\ (l - l_0)$
- Select a fraction $f_{earliest}$ of the earliest hits using
  - $t = t_{obs} - t_{start}$
  - => keeps hits closer the shower start
- *D = Distance to extrpolated momentum vector*
- t_{obs} *observed hit time.*
- k_c, $f_{earliest}$ tunable parameters.

- Select a fraction f_{fast} of fast hits using t_c.
  - These are preferentially closer to the photon axis.

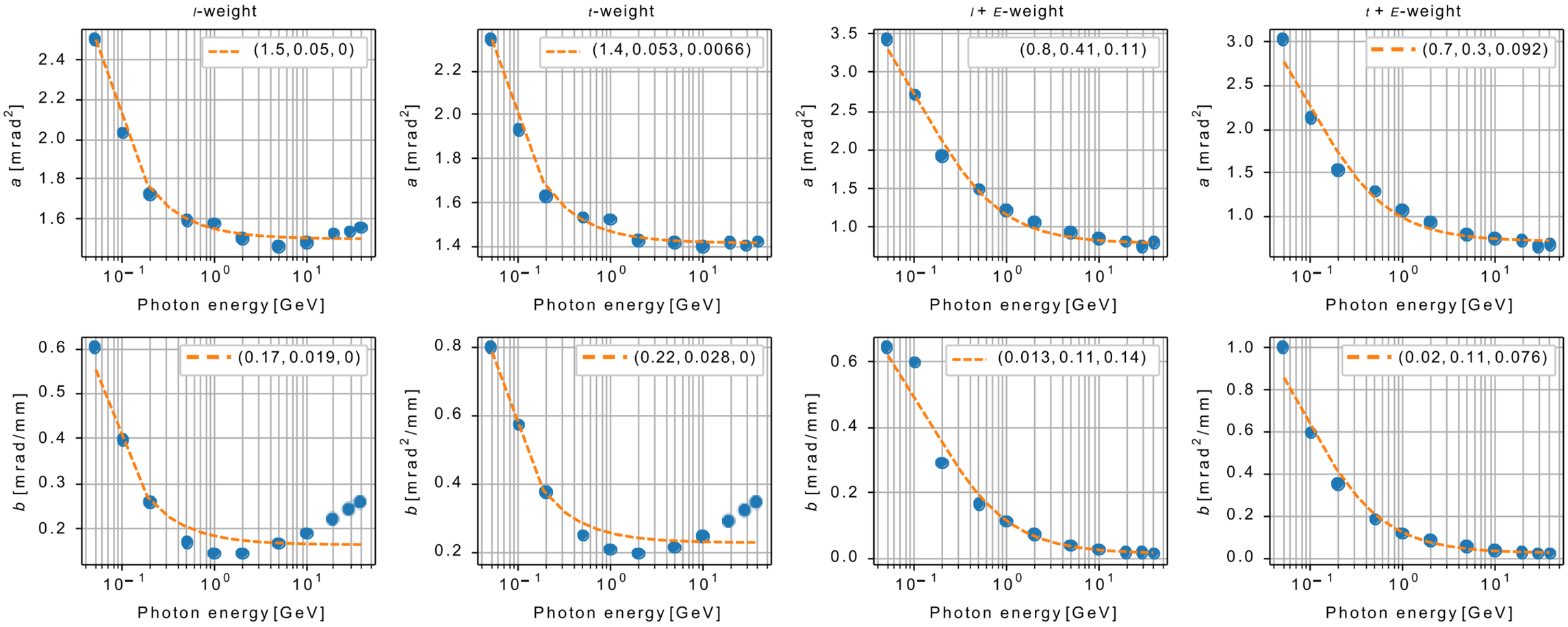
Definitions:

$t_c = t_{obs} - L/c$

L: distance from the interaction point to the hit.

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Weights for photon direction reconstruction

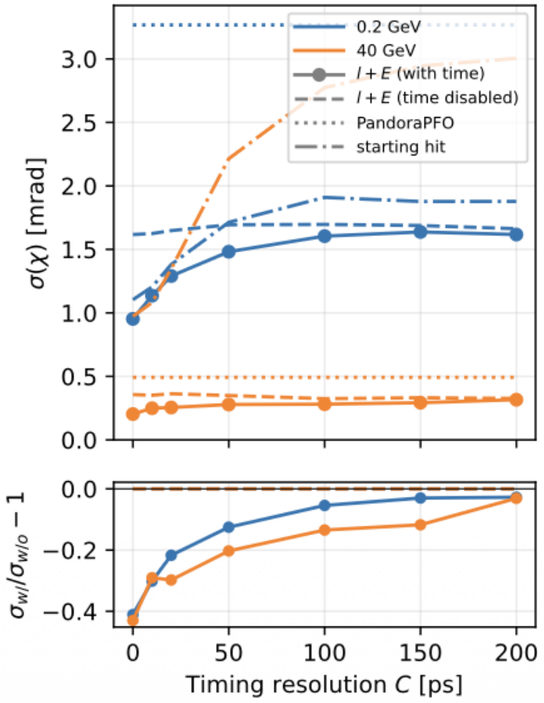


$$a \text{ or } b = a' + \frac{b'}{c' + E}, \qquad c' > 0$$

(or α and β)

Dependence of Timing Resolution

- We scale the constant and stochastic terms with the same factor.
- The hyperparameters are optimized for each timing resolution.

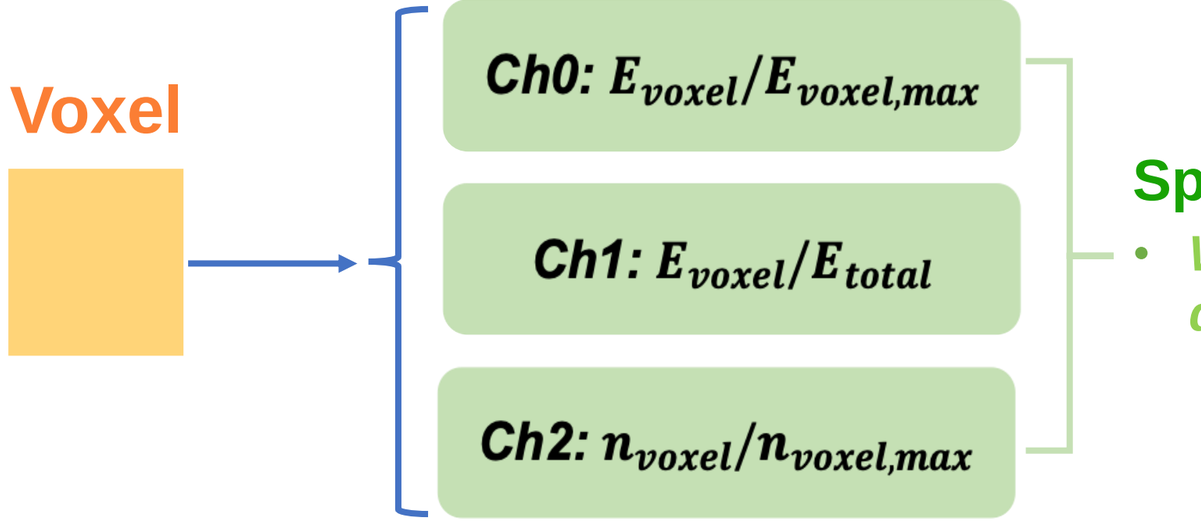


Performance degrades as the timing resolution worsens, and the gain from timing is largest at low photon energy. Timing becomes especially useful below about 25 ps.

Voxel Information?

	(x, y, z)	E	t
EM component	Narrow, compact, shorter	Higher density	Prompt
Hadronic component	Broader, longer	Lower, spread out	Delayed components

For CNN w/o timing information:



Spatial-energy structure

- *Where and how much energy is deposited*

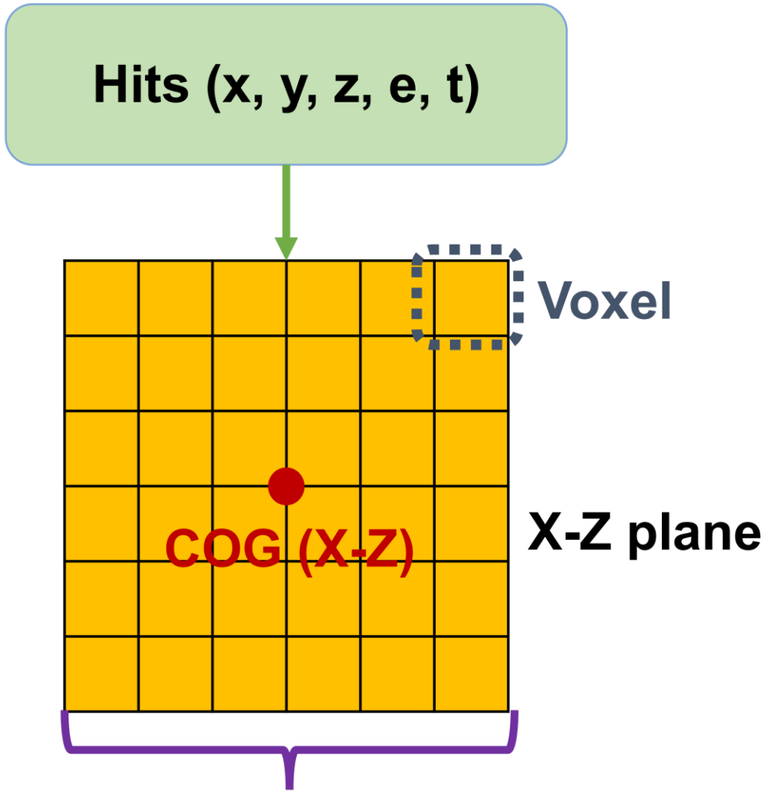
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How to perform Voxelisation

- Voxelization:
  - Transform shower hits to calorimeter images

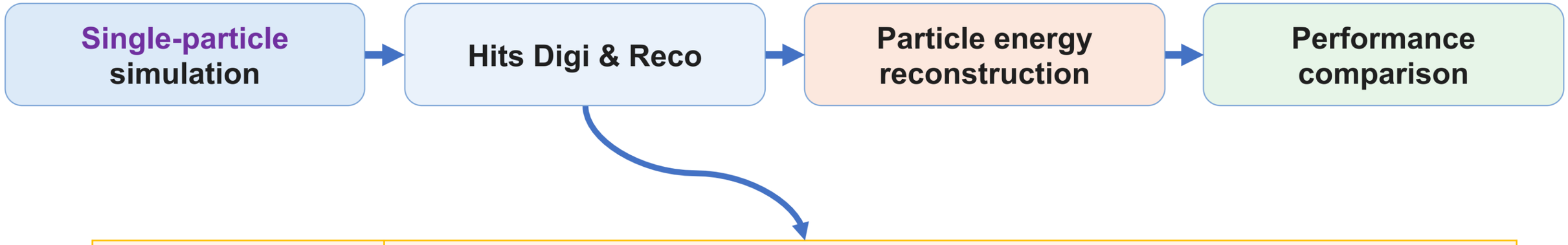
💡 Detector-aware representation

  - Transverse plane (X-Z): local windows centered on the shower COG
  - Longitudinal direction: native detector segmentation retained
  - Preserve different granularity and geometry



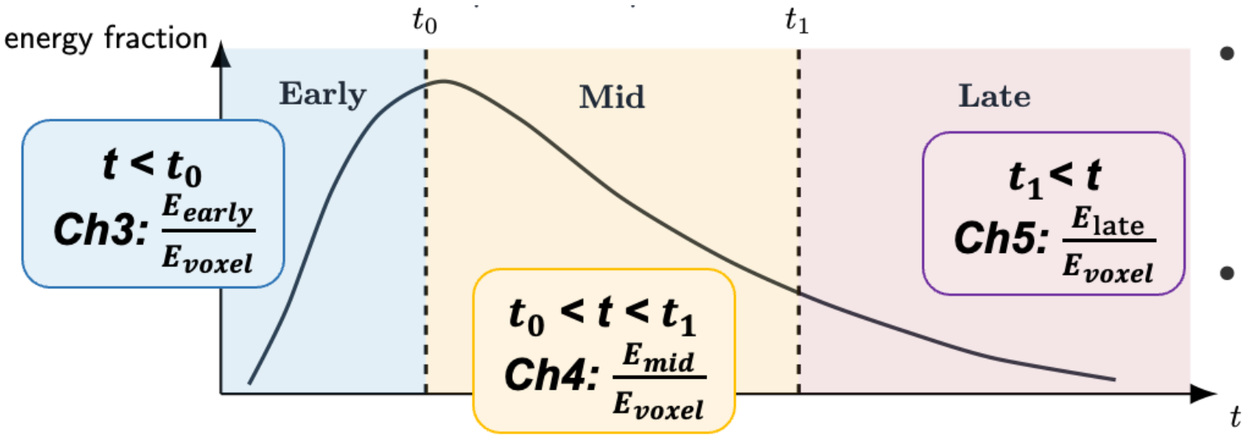
	Bins (mm^2)	Windows (mm^2)
ECAL	5×5	200×200
HCAL	30×30	1200×1200

Reco Level Hit Observables

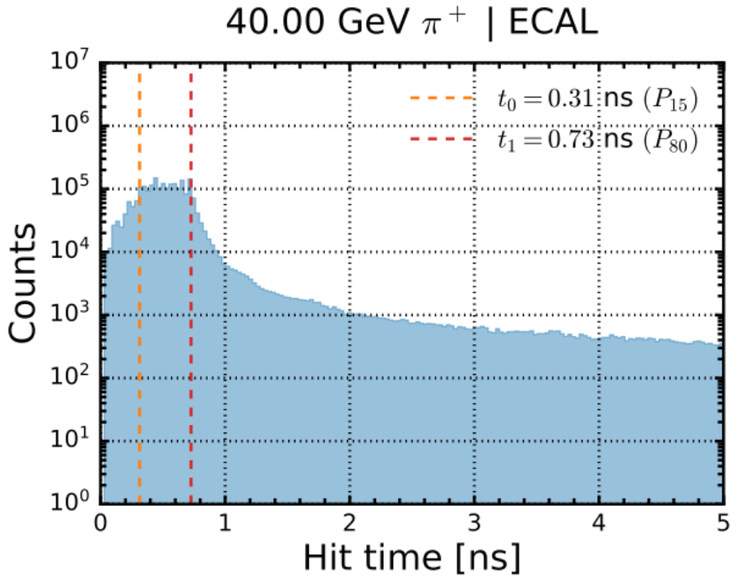


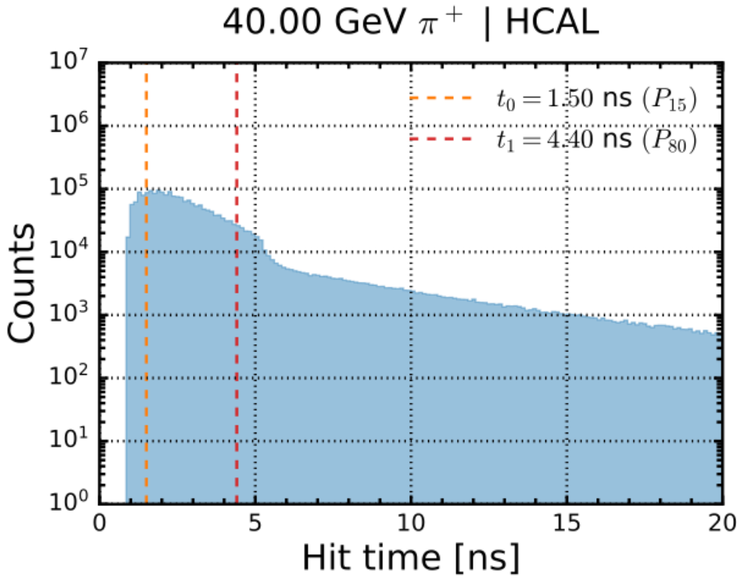
X, Y, Z	Reconstructed hit position in detector coordinates
E	Calibrated reconstructed hit energy with 0.5 MIP threshold
T	Earliest contribution within the integration window, relative to the generator-level production time of the incident particle

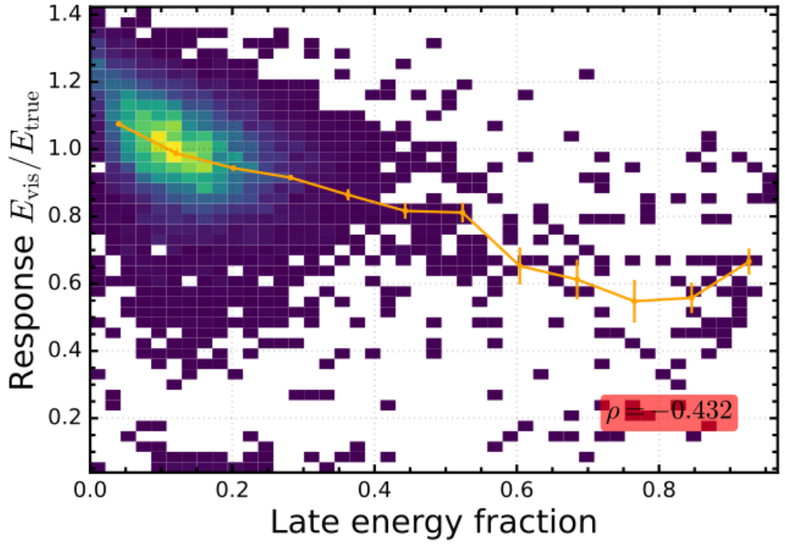
Adding Time



- Timing is encoded through threshold-defined shower components.
  - Choice: $t_0 = t_{P_{15}}$, $t_1 = t_{P_{80}}$
- Prompt/main/late energy fractions show correlations with the visible calorimeter response.



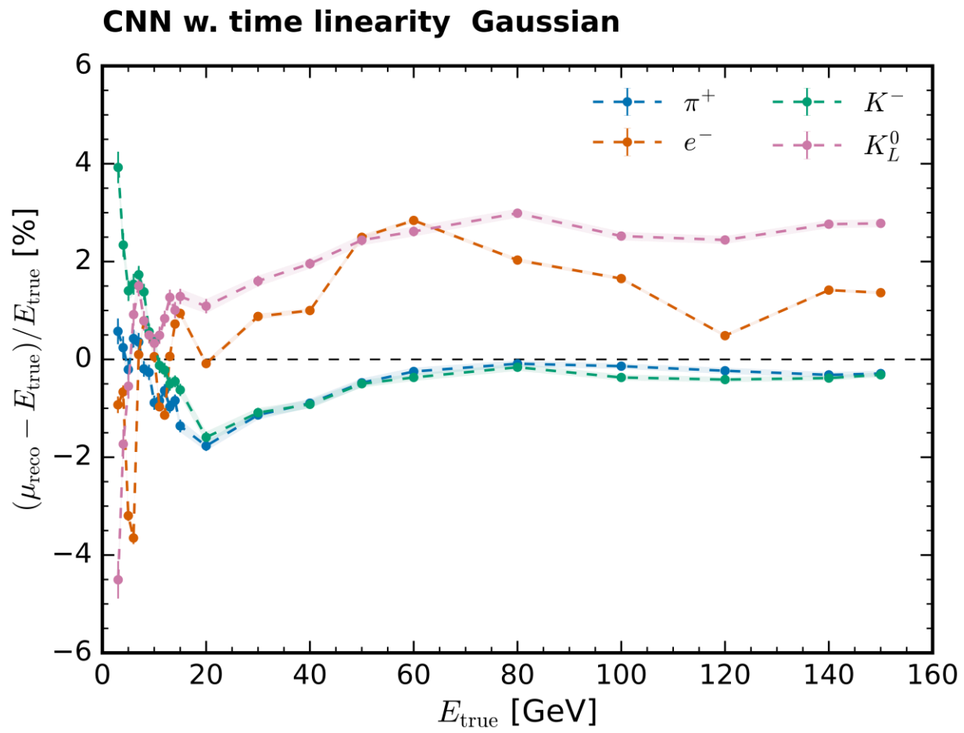


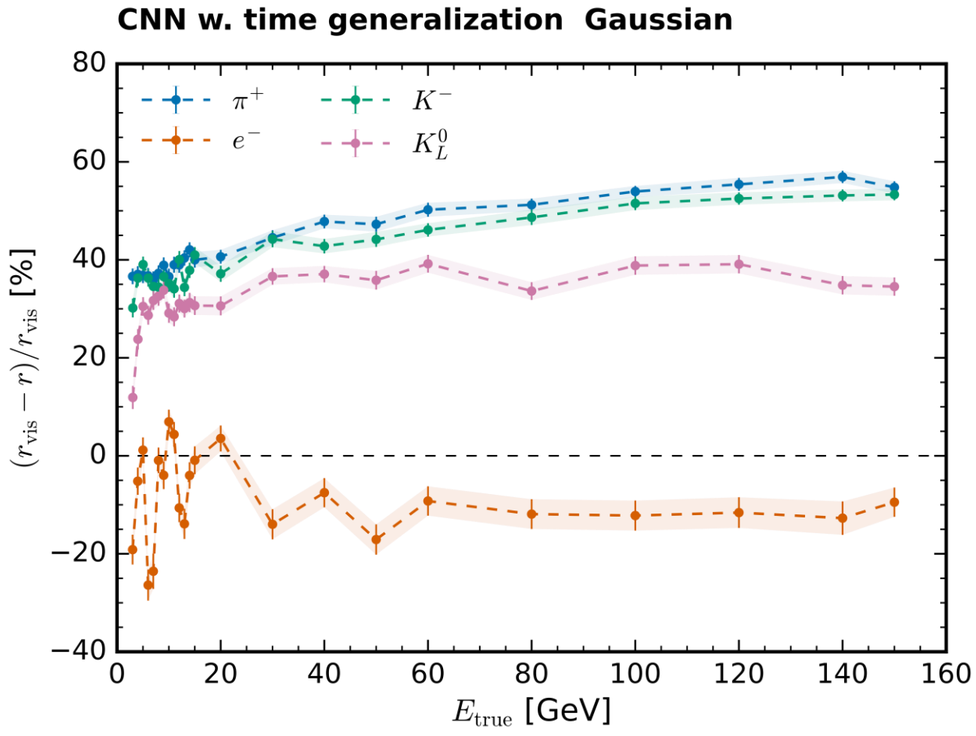


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Energy distributions of π^+ - CNN vs. Baseline

- The model trained on π^+ performs best on K^-, still improves K^0_L, and shows a slight degradation for e^-.
- This indicates that the model has learned genuine hadronic shower features relevant for energy reconstruction and shows robustness to kaon-induced showers which have lower EM component.





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Study of Jet Energy Resolution - Premises

Motivation and Study Object

PandoraPFA

- 3–4% JER @ 100 GeV
- optimised for ILD

Bottlenecks:

- ecal/hcal energy resolution
- confusion

NN + timing → better JER?

- Z→qq(u,d,s) @40,91,200,350,500 GeV
- ILD reco

Method

NN architecture

- Dynamic Graph CNN -like
- Input: hit + track features
- Output: E_{CM} regression

Hit input features

Position	x, y, z, ρ, r, θ, layer,
Calo type	is_{ecal}, is_{hcal}, is_{barrel}, is_{endcap},
Energy	E_{hit},
Time	t, t - r/c

Track input features

Position	x, y, z, ρ, r, θ
Momentum	p_x, p_y, p_z, p_T, p

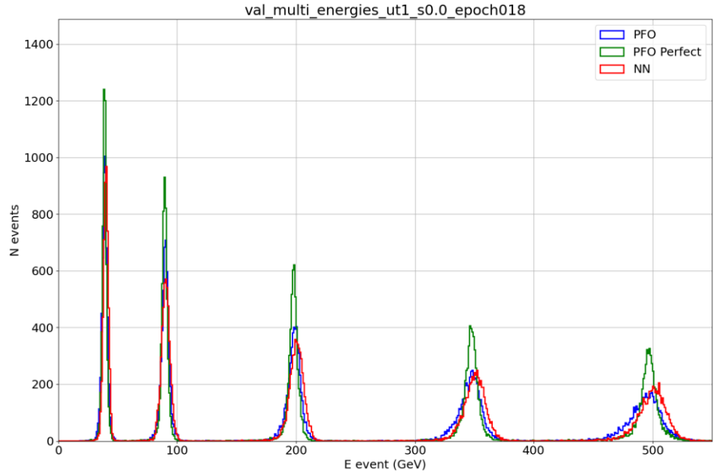
Training

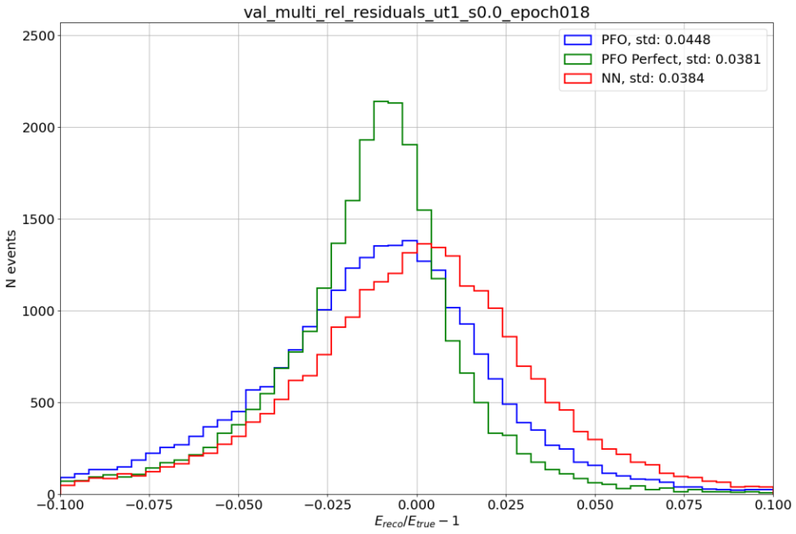
- Target: generator level E_{CM}
- 25k/25k events train/test
- w/ and w/o timing

Bohdan Dudar

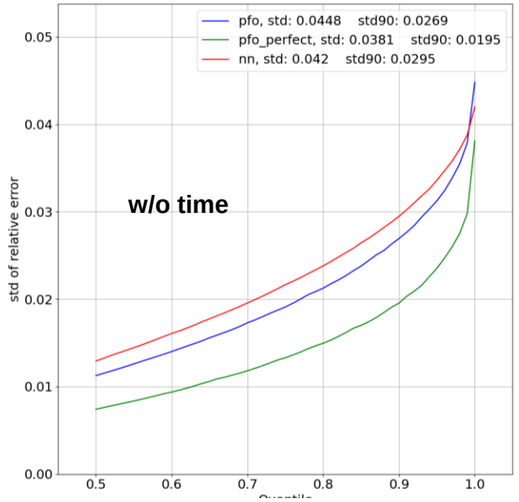
Study of Jet Energy Resolution - Results

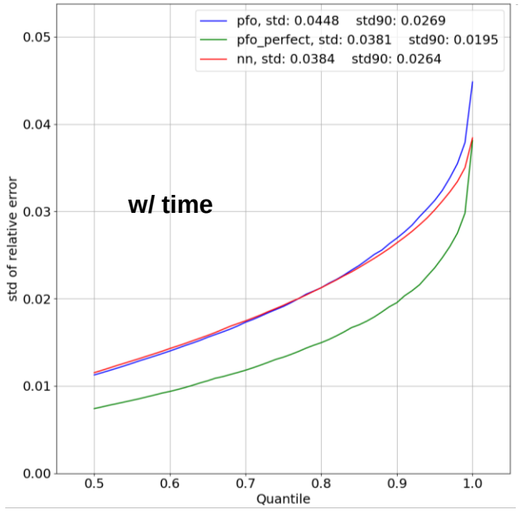
E_{CM} resolution is close to Pandora



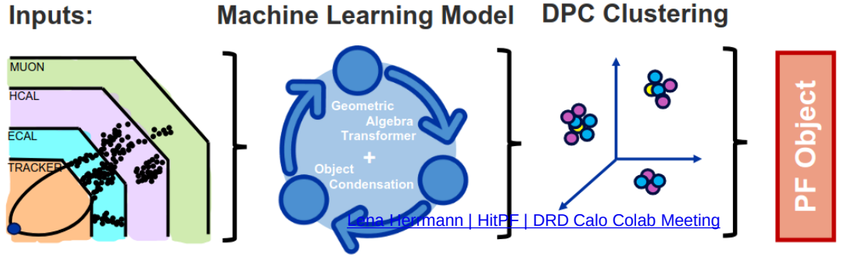


Timing effect is visible but more validation is needed for conclusions





Outlook: Trying with HitPF



- *HitPF outputs particle objects* (end-to-end reconstruction, not only E_{CM} regression)
- *HitPF has better E_{CM} resolution than Pandora* with Z→qq(u,d,s)@91GeV and CLD reco

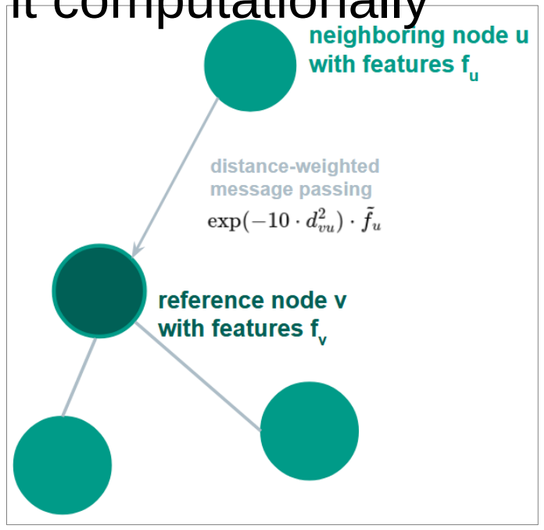
Bohdan Dudar

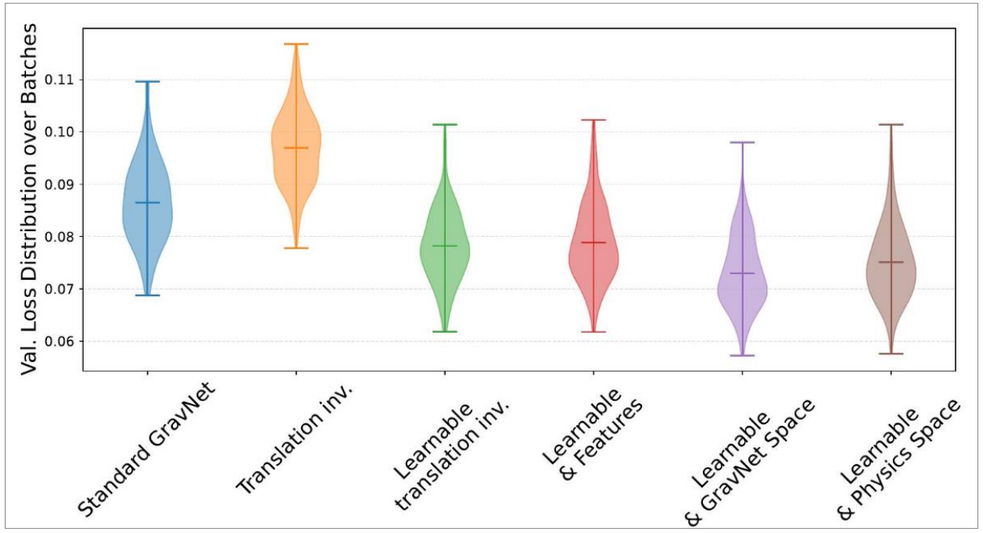
Further Improvement – GravNet with Attention

- Cooperation with KIT-ETP: work on more mathematical-technical improvements of the neural networks
- Example: adapt the message passing between nodes via learnable weights and depending on different reference spaces
- See the impact on validation loss, use to optimise the network while still keeping it computationally compact

Distance-weighted message passing $\exp(-10 \cdot d_{vu}^2) \cdot \tilde{f}_u$

- 'Standard' $\tilde{f}_u = f_u$
- Translation equivariant $\tilde{f}_u = f_u - f_v$
- Learnable parameter $\tilde{f}_u = f_u - \text{sigmoid}(a) \cdot f_v$
- Depending on features $\tilde{f}_u = f_u - \text{sigmoid}(a \cdot f_v) \cdot f_v$ (vector)
- Depending on GravNet space $\tilde{f}_u = f_u - \text{sigmoid}(A \cdot s_v) \cdot f_v$
- Depending of physical space $\tilde{f}_u = f_u - \text{sigmoid}(A \cdot x_v) \cdot f_v$ (matrix)





Katharina Schäuble,
Uli Einhaus