CNN-Based Hadron Energy Regression for the ILD SiW-ECAL and AHCAL System

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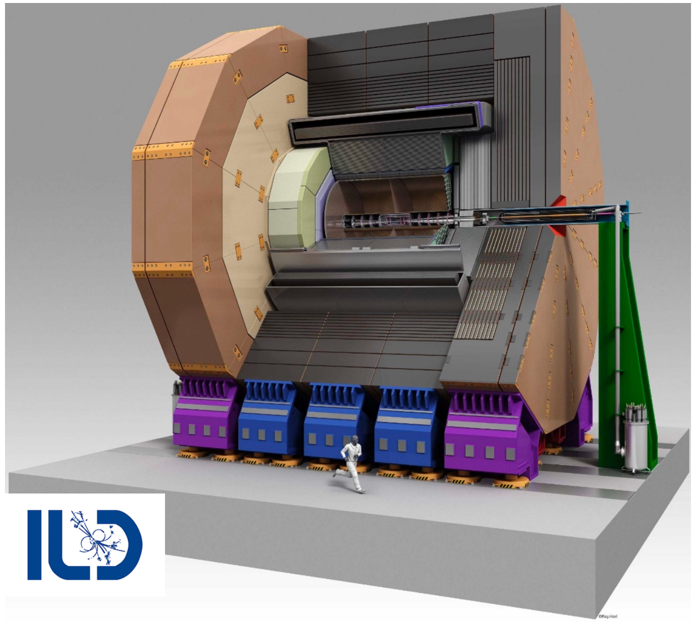
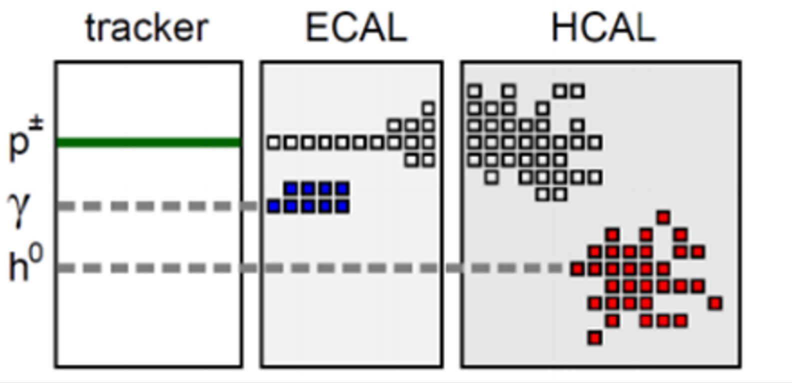
Why Calorimeter Energy Reconstruction Matters?

- Future Higgs factories rely on detectors to measure the energies of final-state particles.
- These particles are combined into jets, and jet energy resolution is a key physics performance target.
- Pandora Particle-Flow Algorithm (PFA):
  - $\sigma^2_{\mathrm{jet}} = \sigma^2_{\mathrm{p}^\pm,\,\mathrm{tracker}} + \boldsymbol{\sigma^2_{\gamma,\,ECAL}} + \boldsymbol{\sigma^2_{\mathrm{h}^0,\,HCAL}} + \sigma^2_{\mathrm{confusion}}$
    - σ_{ECAL}, σ_{HCAL}: key ingredients and limiting factors
- An essential metric for detector R&D
  - Detector design optimization
  - Technology comparison

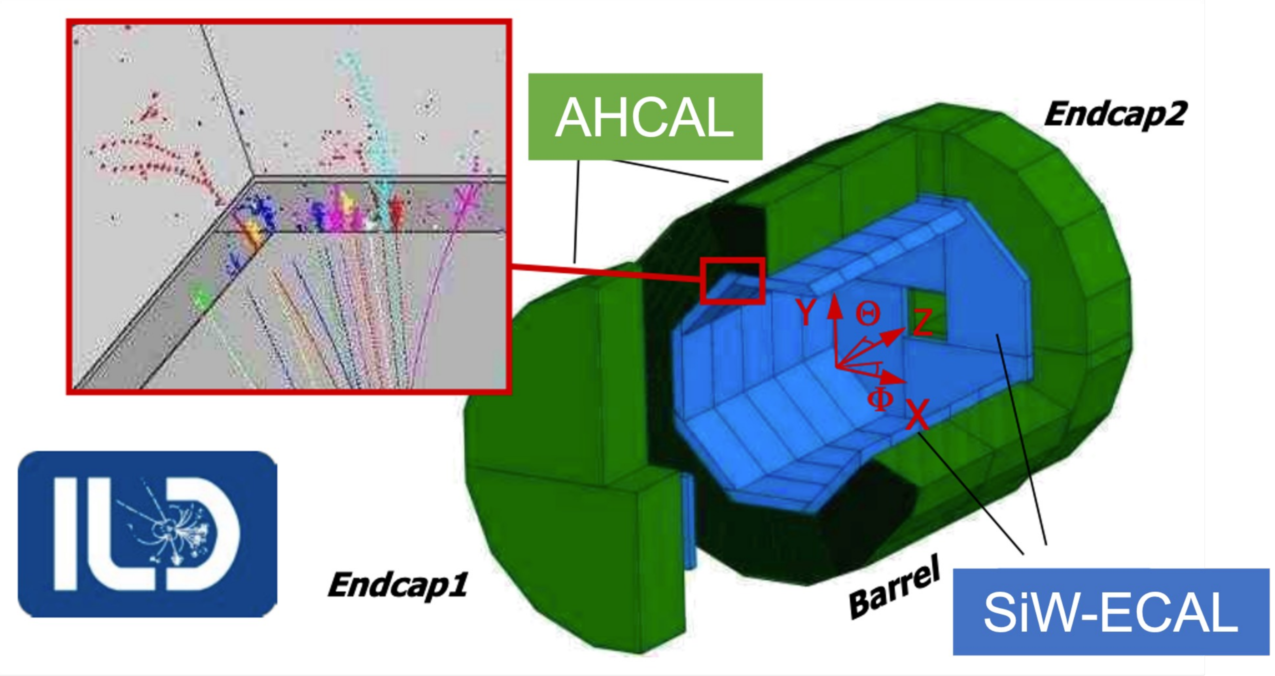




Pandora PFA: arXiv:0907.3577

ILD Calorimeter system

	Active material	Absorber	Cell size	#. Layers	Length	Type
SiW-ECAL	Silicon	Tungsten	0.5×0.5 cm^2	30 in 20 cm	~ $1\lambda_I$	Non-Compensation
AHCAL	Scintillator	Steel	3×3 cm^2	48 in 1 m	~ $5\lambda_I$	Non-Compensation



- Detector overview:
  - Combined SiW-ECAL + AHCAL system in ILD
  - High-granularity imaging calorimeter
- **Goal:** study hadron energy reconstruction in the realistic combined system (In PFA calorimeter design, ~55% particles interact in the ECAL)

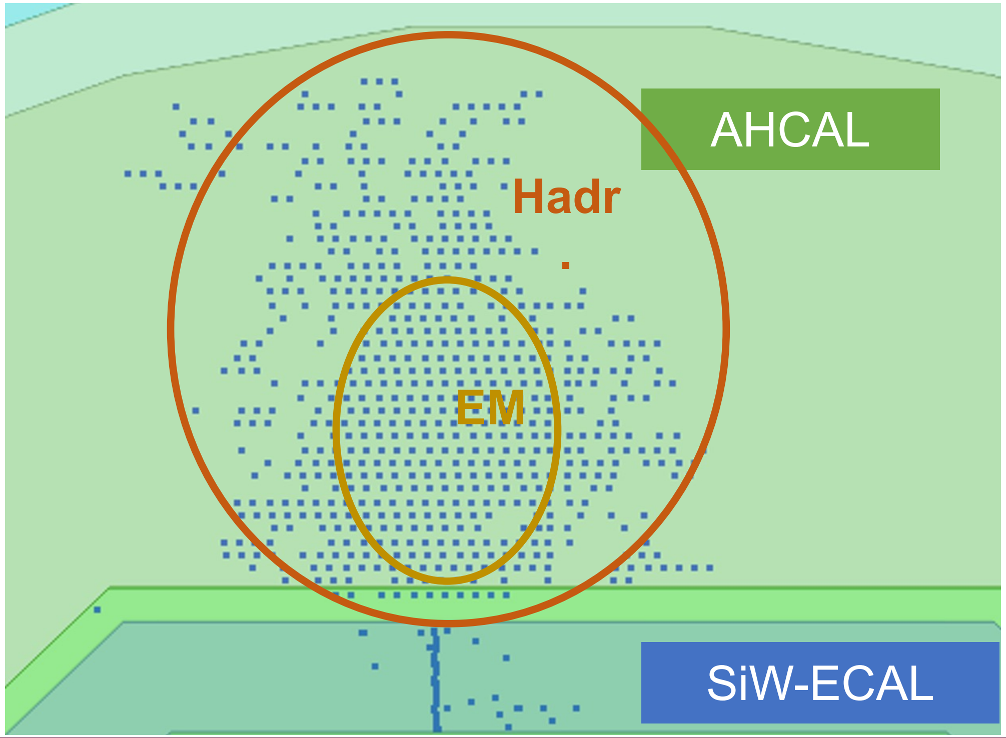
Challenges in Hadronic Energy Reconstruction

- 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 hadronic energy resolution

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



Samples preparation

Single-particle simulation → **Hits Digi & Reco** → **Particle energy reconstruction** → **Performance comparison**

Calorimeters	SiW-ECAL and AHCAL				
Incident position	ECAL surface				
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

Reco-level calorimeter hit observables

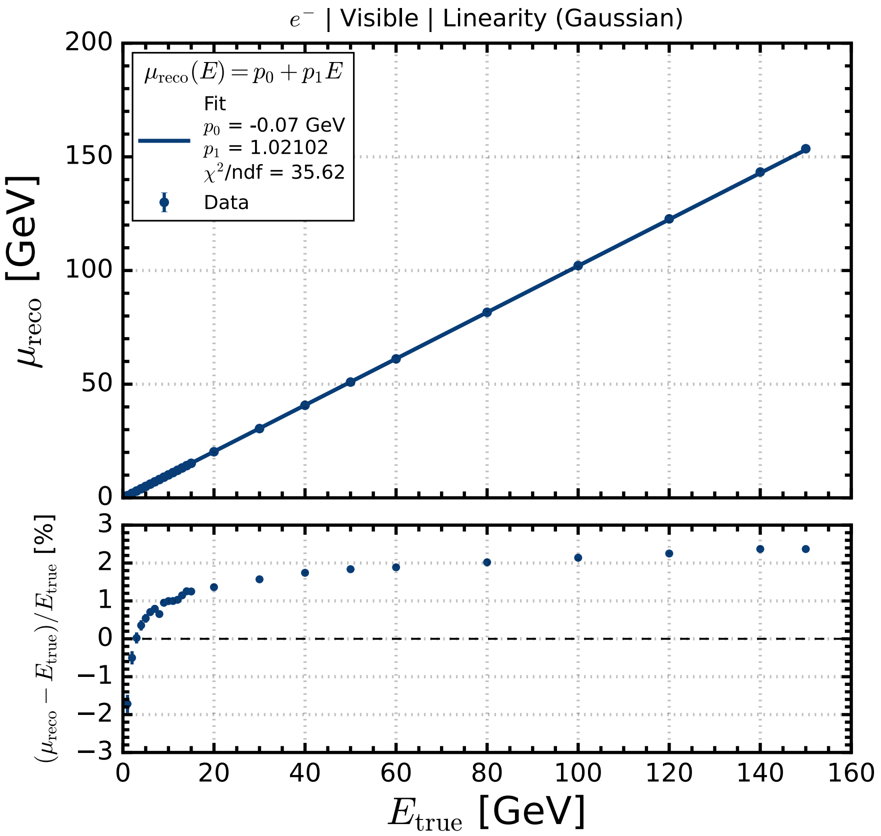
Single-particle simulation → Hits Digi & Reco → Particle energy reconstruction → Performance comparison

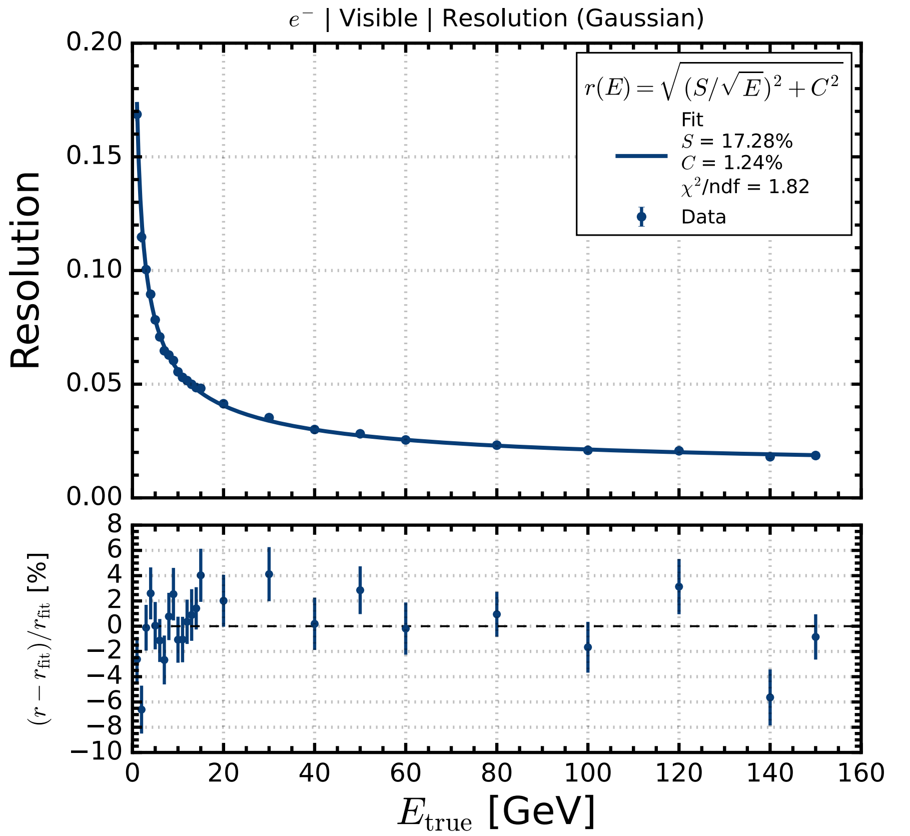
X, Y, Z	Reconstructed hit position in detector coordinates
E	Calibrated reconstructed hit energy with 0.5 MIP threshold
T	Earliest contribution within the integration window, relative to the generator-level production time of the incident particle

Detector response and reconstruction work properly

At EM scale (electrons), evaluating the reconstruction performance

- Summing of all the visible hits
- Linearity: within 2.5%; Resolution: S=17.3%, C=1.2%





Reconstruction Methods

Single-particle simulation → Hits Digi & Reco → Particle energy reconstruction → Performance comparison

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

Irregular calorimeter data → CNN input ?

CNN input requirements:

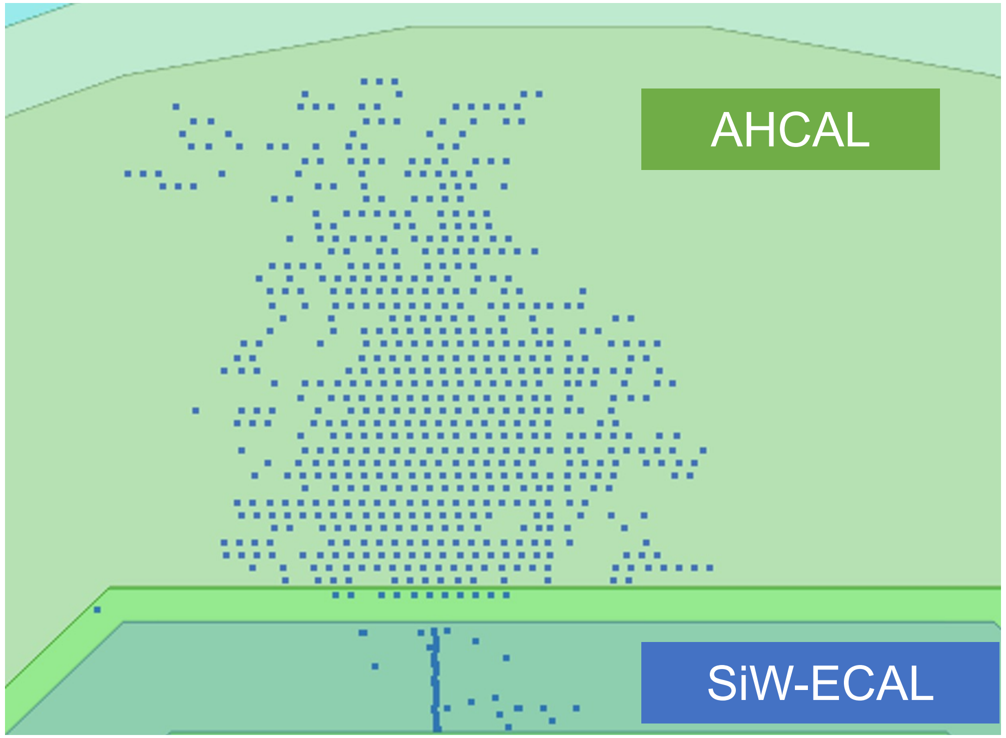
- Regular grid format
- Operate within a fixed spatial window

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

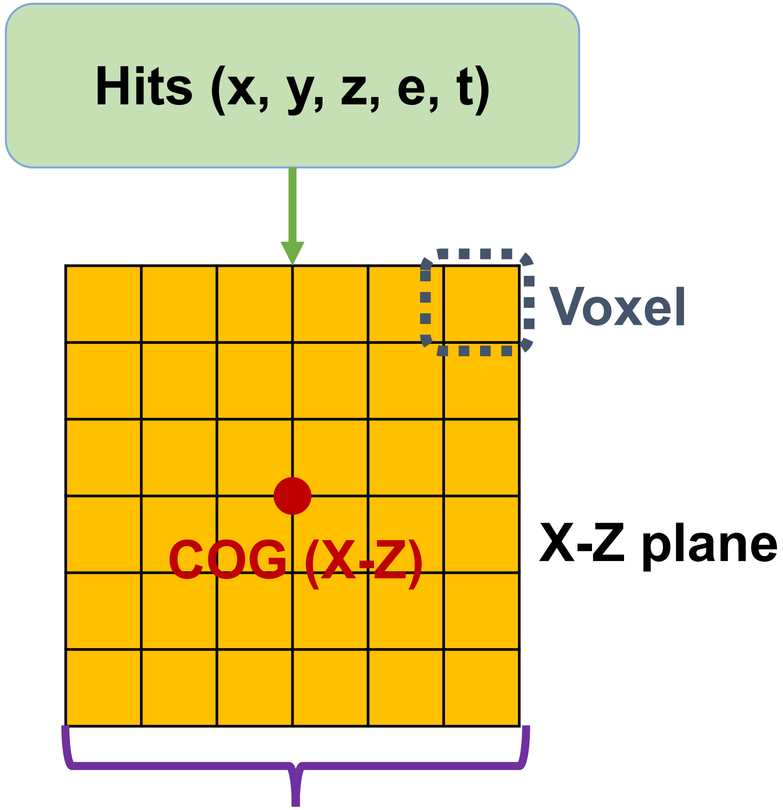


How to perform voxelization?

- Voxelization:
  - Transform shower hits to calorimeter images

💡 Detector-aware representation

  - Transverse plane: 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

What information is encoded into the voxel?

	(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:

Voxel

Ch0: $E_{voxel}/E_{voxel,max}$

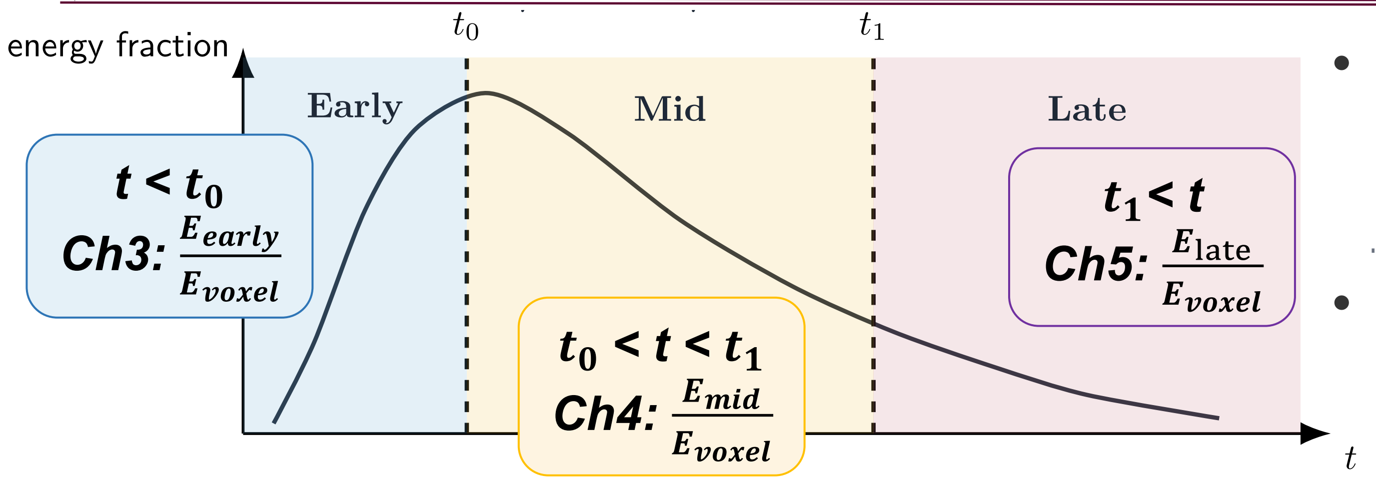
Ch1: E_{voxel}/E_{total}

Ch2: $n_{voxel}/n_{voxel,max}$

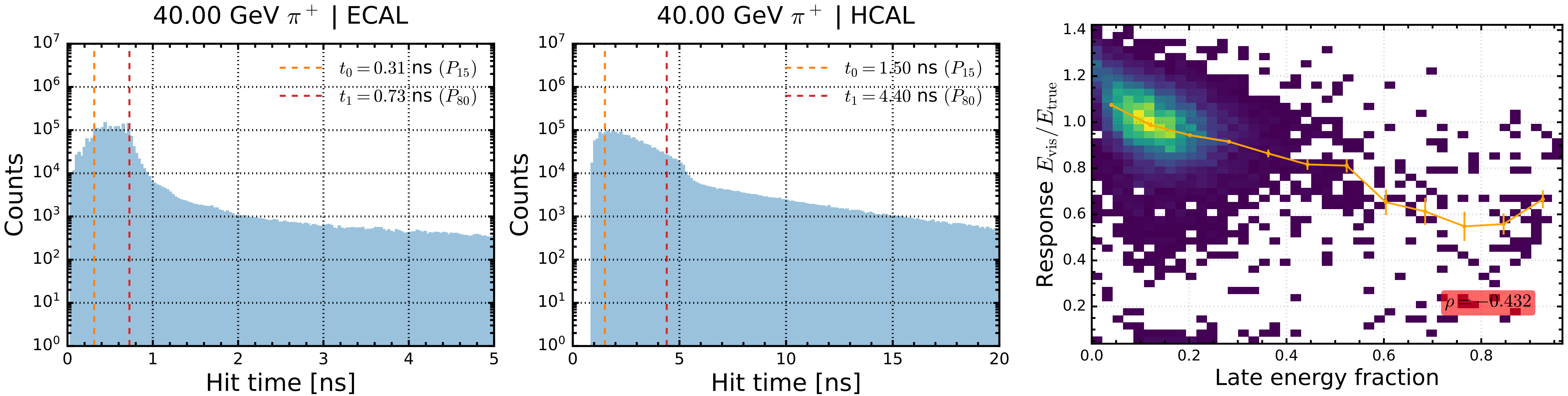
Spatial-energy structure

- ***Where and how much energy is deposited***

How to implement 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.



What information is encoded into the voxel?

For CNN w. timing information:

Voxel

- ***Ch0:*** $E_{voxel}/E_{voxel,max}$
- ***Ch1:*** E_{voxel}/E_{total}
- ***Ch2:*** $n_{voxel}/n_{voxel,max}$
- ***Ch3:*** E_{early}/E_{voxel}
- ***Ch4:*** E_{mid}/E_{voxel}
- ***Ch5:*** E_{late}/E_{voxel}

Spatial-energy structure

- *Where and how much energy is deposited*

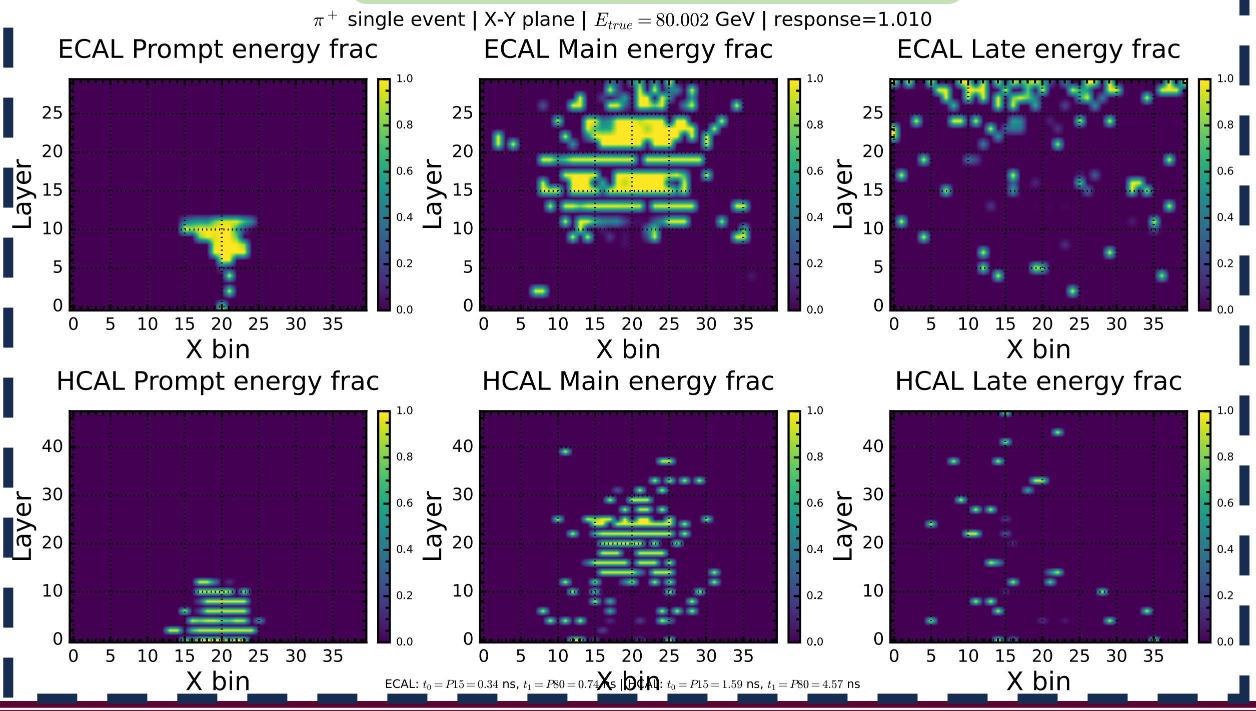
Spatial-time-category structure

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

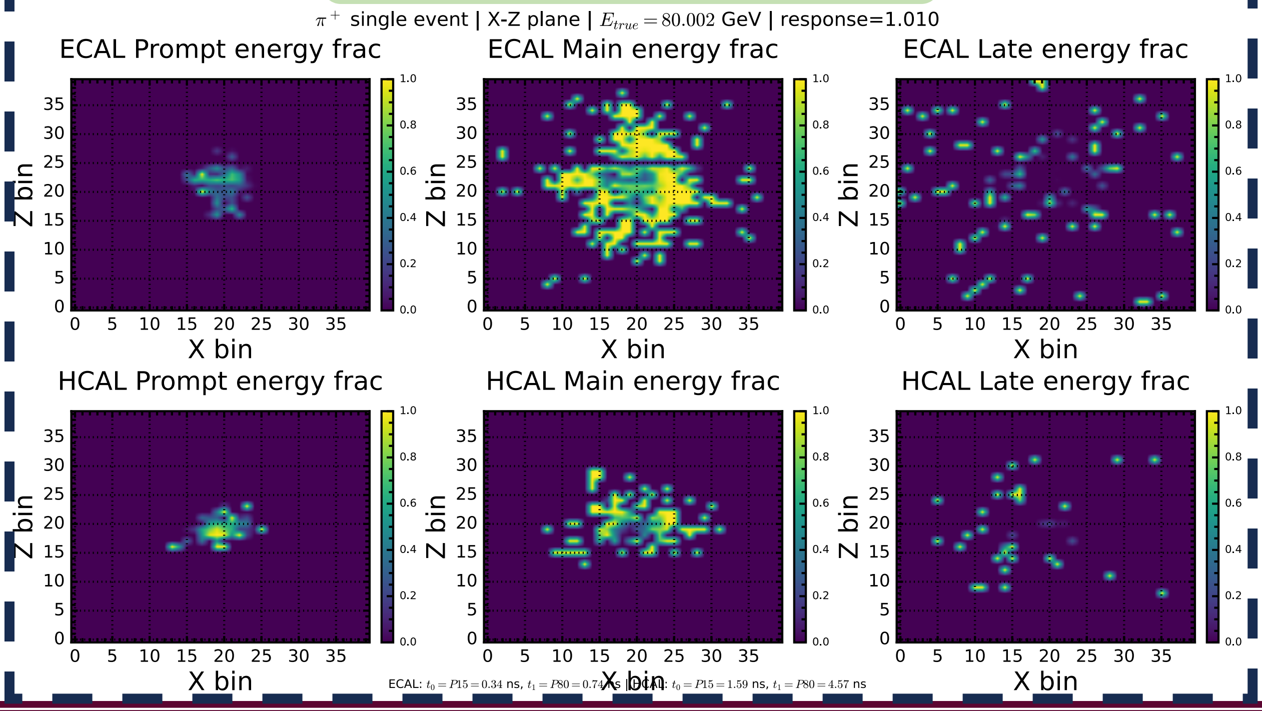
Time-Separated Spatial Patterns

- Temporal structure of the shower is converted into a set of time-resolved spatial and energy maps *(combine time with spatial-energy structure)*.
- The model can learn where different time components tend to appear and how they are distributed across the ECAL and HCAL.

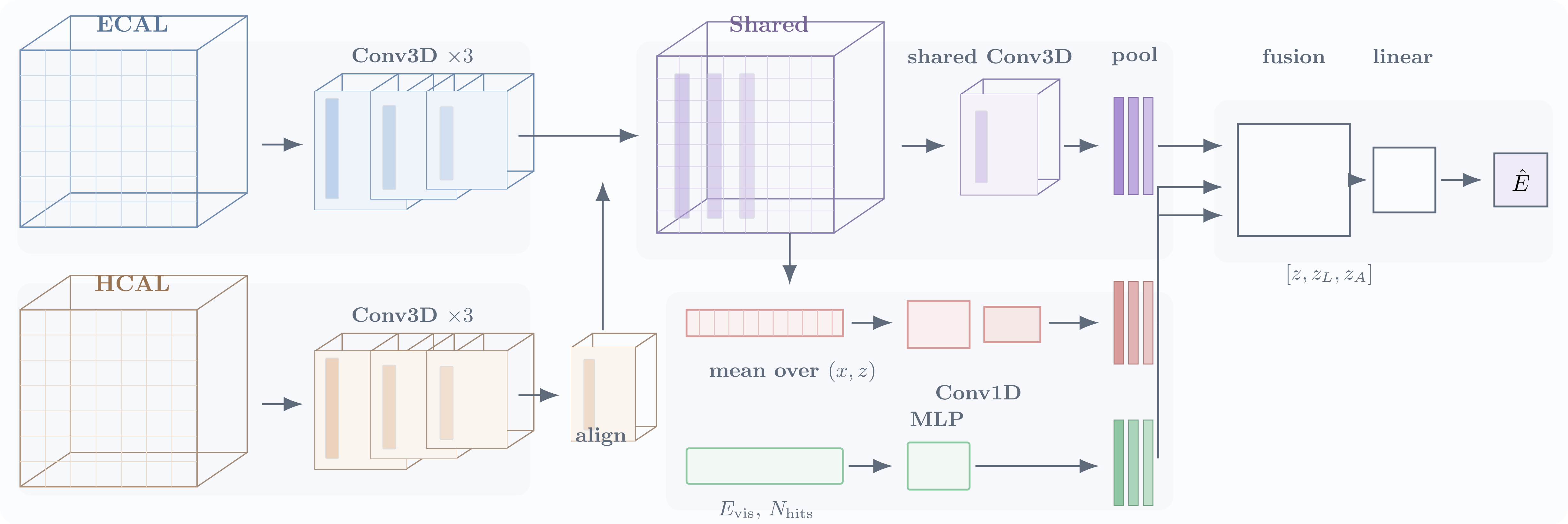
Longitudinal



Transverse



Dual-branch CNN model



Inputs:

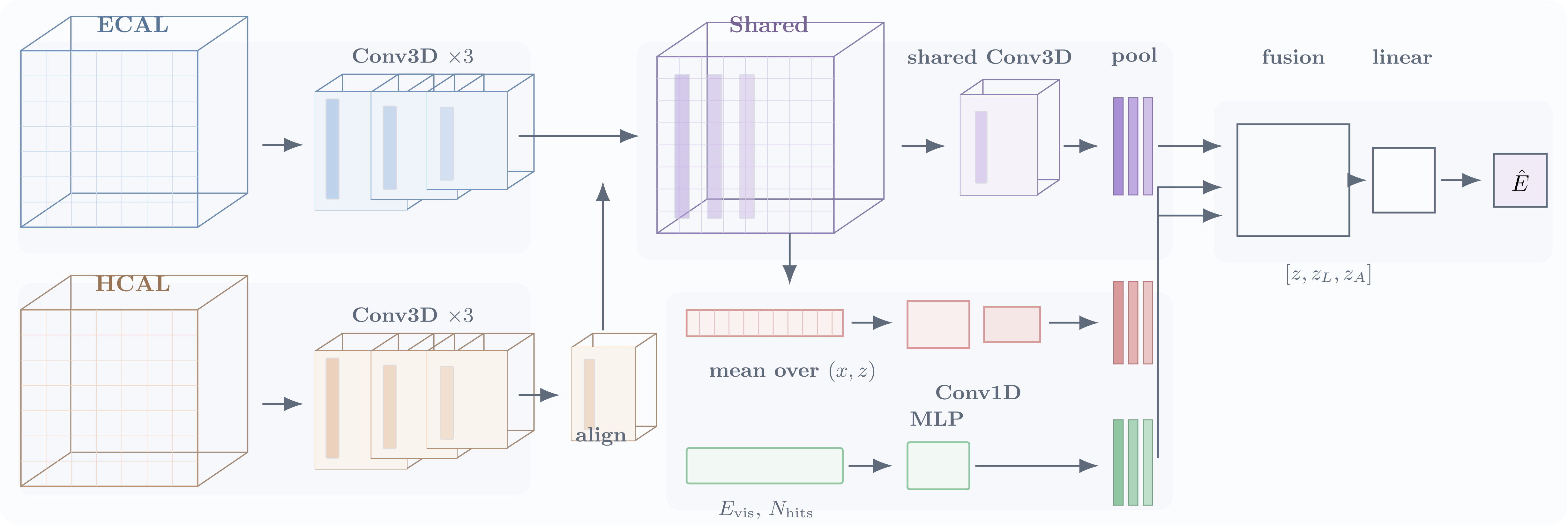
- Voxelized shower images from **ECAL** and **HCAL**
- Global features: $E_{\text{dep}}, N_{\text{Hits}}$

Optimization objective:

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

Dual-branch CNN model

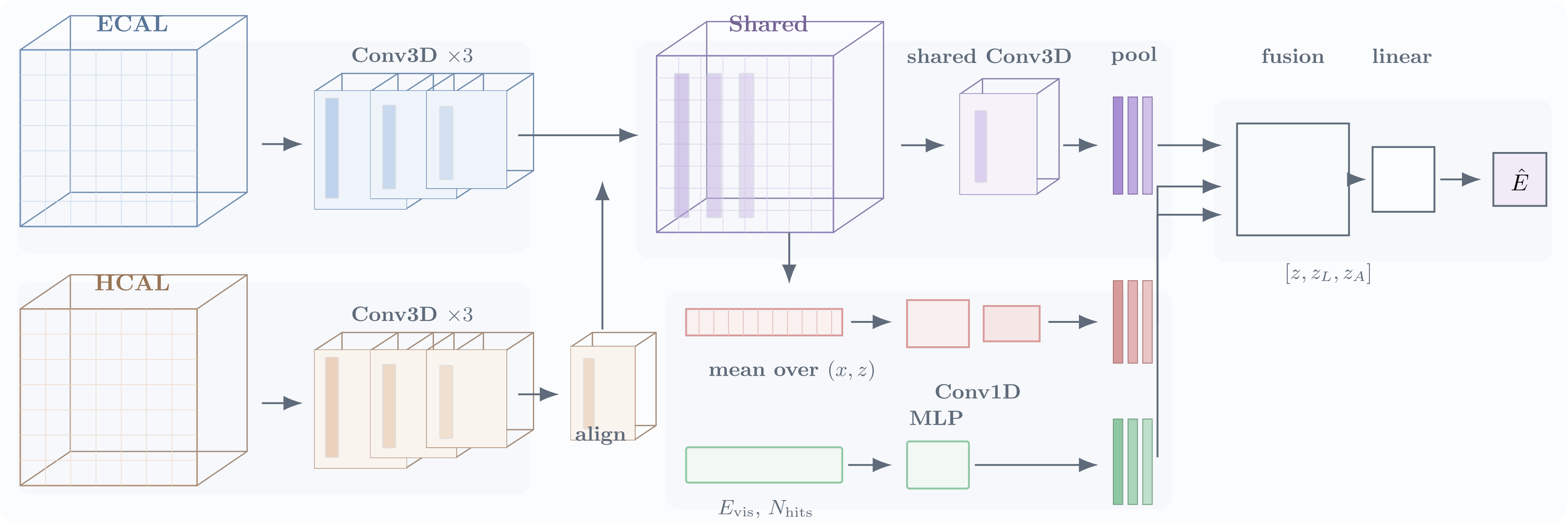
Calorimeter-aware design, balance and exploit the complementary information from the two calorimeters.



What physical information can CNN potentially learn?

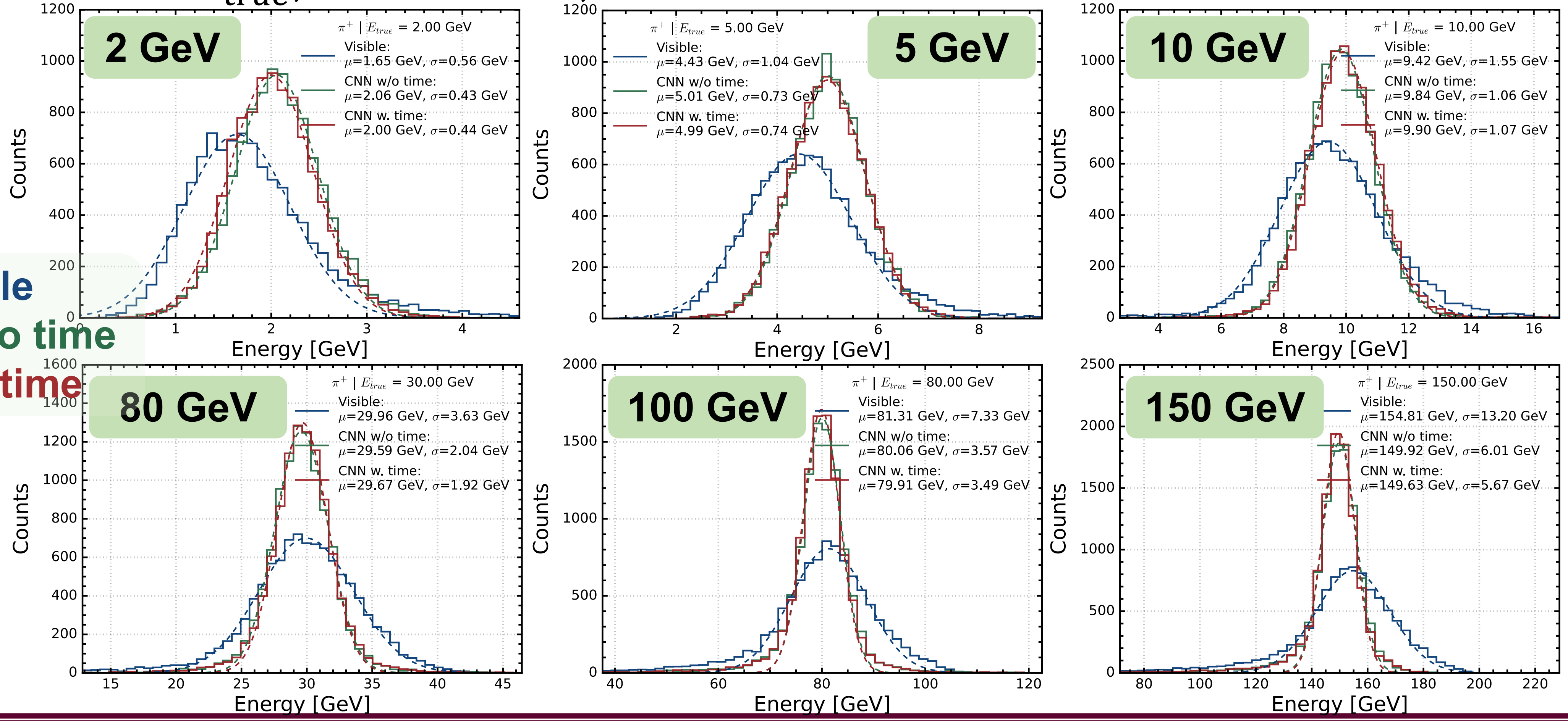
Potentially Learned features:

- ECAL/HCAL energy sharing
- Shower start and depth
- Longitudinal spread
- Local density and topology
- Leakage tendency
- Electromagnetic vs non-electromagnetic mixture



Energy Distribution of π^+: CNN vs Baseline

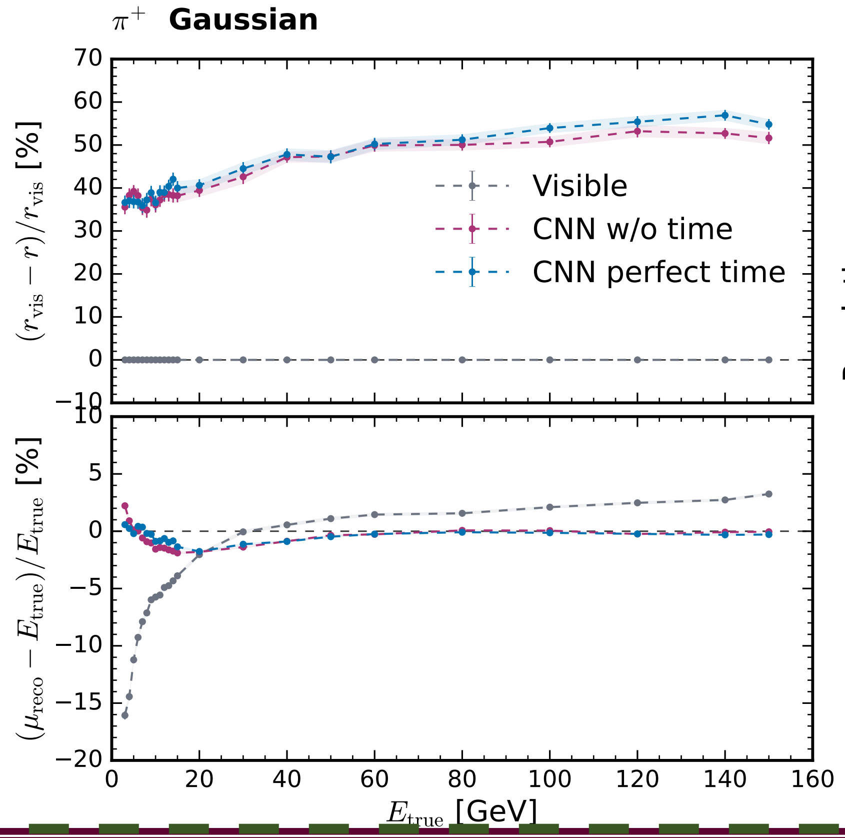
- Metric: Gaussian fit to the reconstructed energy distribution
- CNN shows better performance:
  - mean closer to E_{true}; smaller width; reduce tails

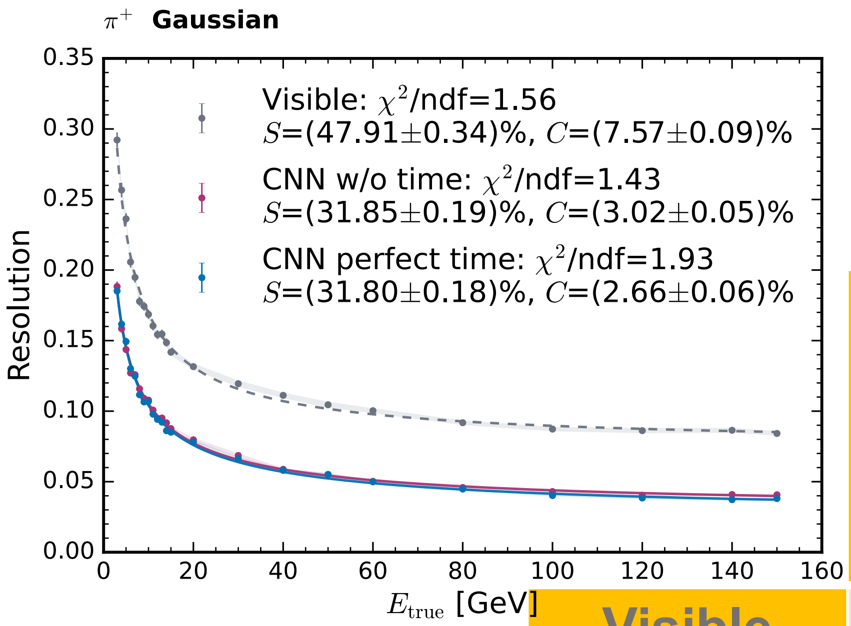


Blue: visible
Green: CNN w/o time
Red: CNN w. time

CNN Gain for π^+ over 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.

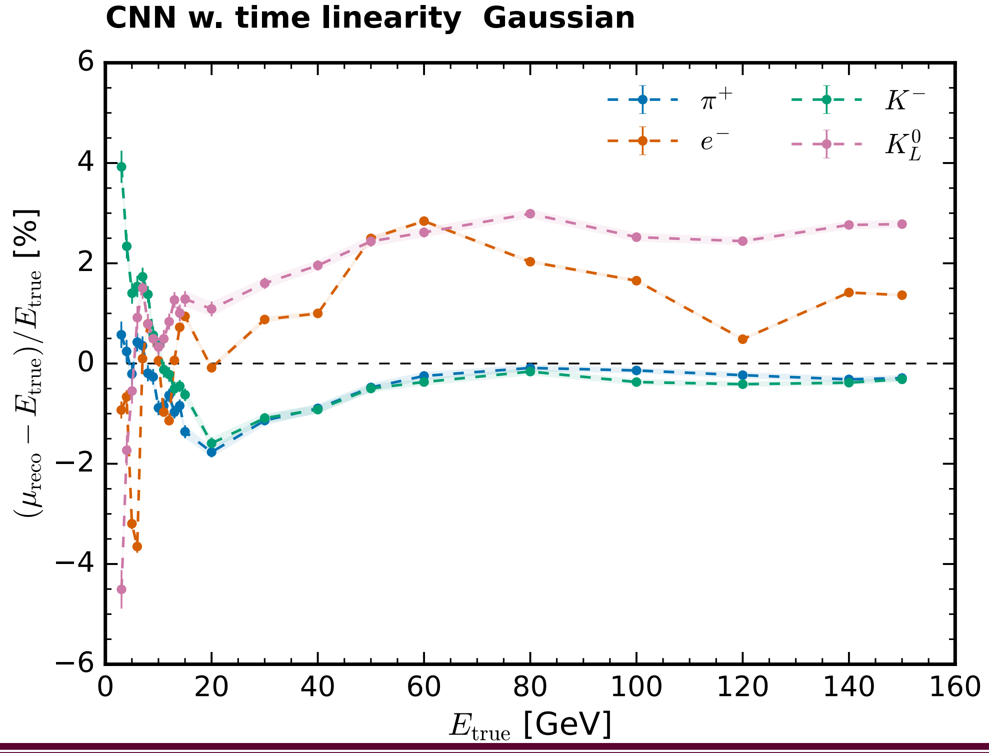


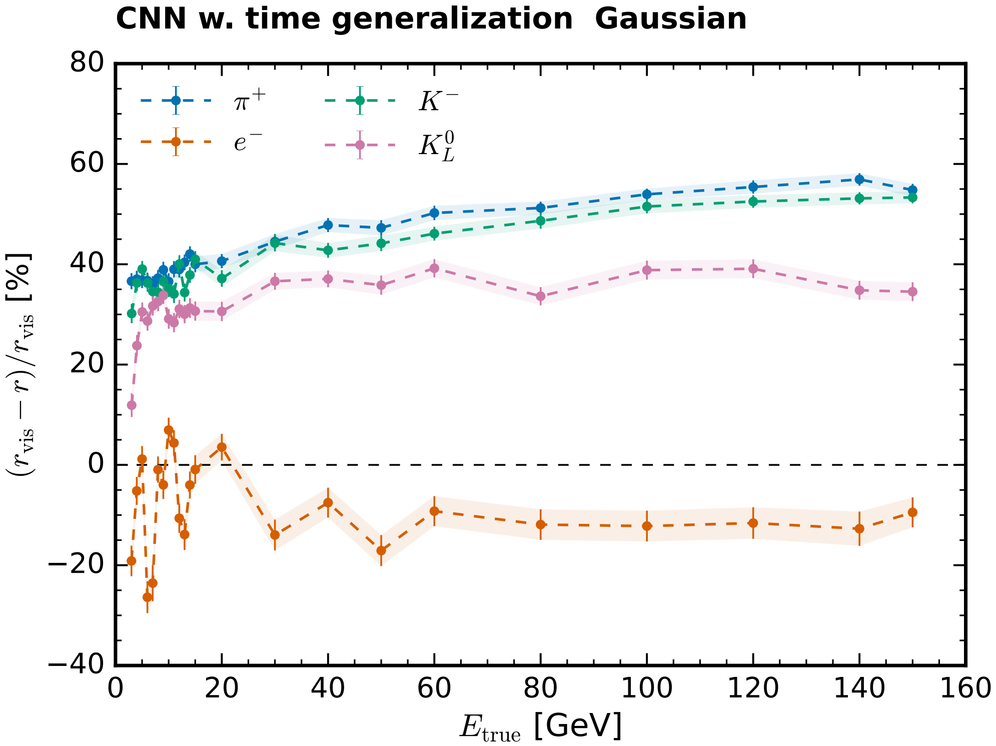


	Linearity	Resolution $r(E) = \sqrt{\left(\frac{S}{\sqrt{E}}\right)^2 + C^2}$	
		S	C
Visible	18%	47.7%	7.6%
CNN w/o T	3%	31.9%	3.0%
CNN w. T	2%	31.8%	2.7%

Generalization across particles

- The model trained on π^+ performs best on K^-, still improves K_L^0, 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.





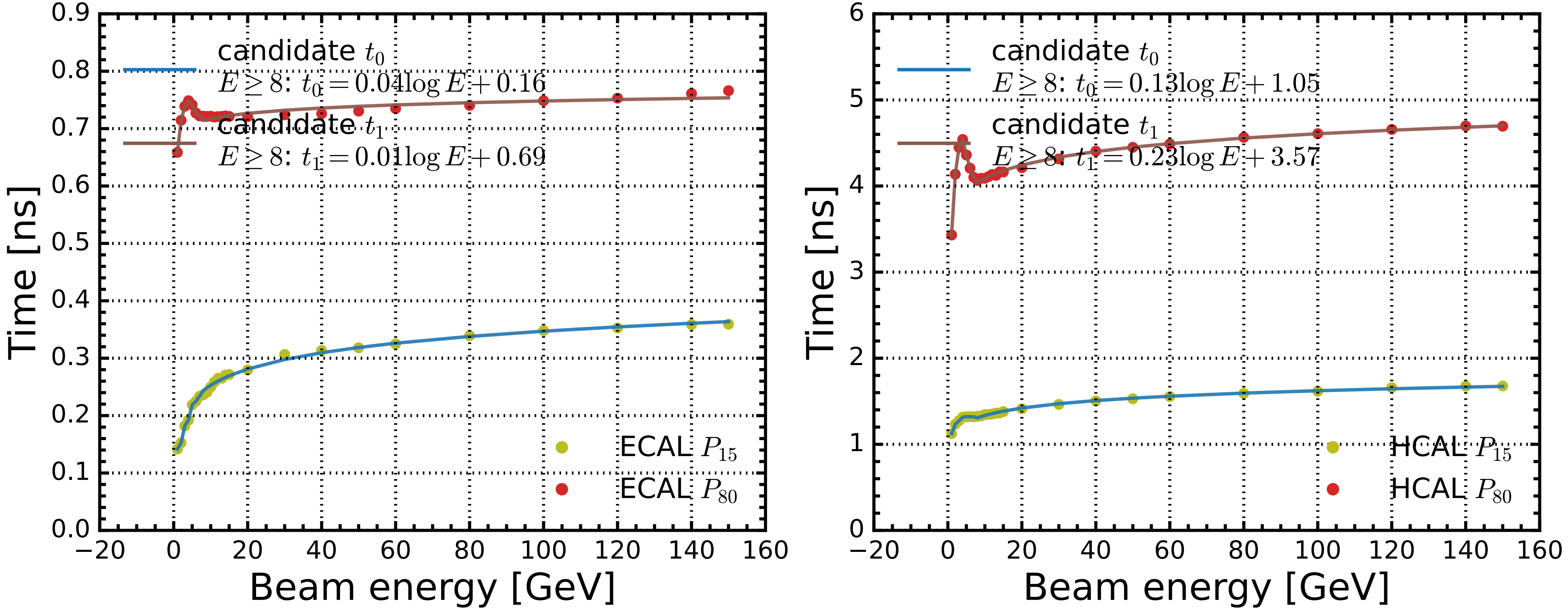
Summary

- A CNN-based energy regression model has been developed for the ILD SiW-ECAL + AHCAL system.
- For single-particle π^+, the CNN provides around 50% improvement over visible-energy baselines from 3 GeV to 150 GeV.
    - Linearity at 2% level and a Gaussian-fit resolution of about $31.8\%/\sqrt{E} \oplus 2.7\%$.
- The model remains effective even for showers with a reduced electromagnetic component. The generalization behavior supports that the network learns genuine hadronic shower features.
- Timing carries some additional information, especially in the late component, but the current bin-based timing encoding provides only a modest extra gain; the dominant improvement comes from the spatial-energy shower structure.

Thanks!

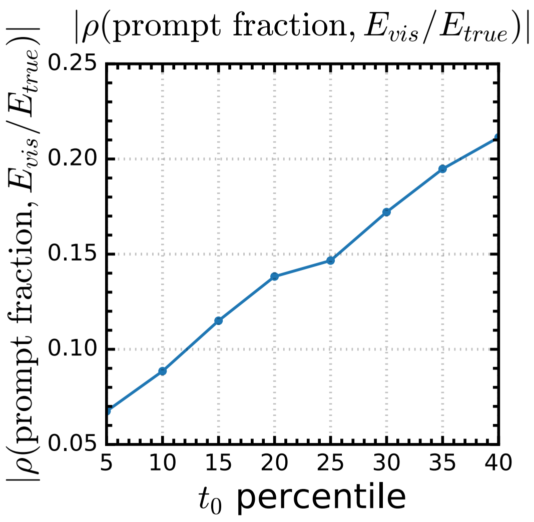
Backup

t0/t1

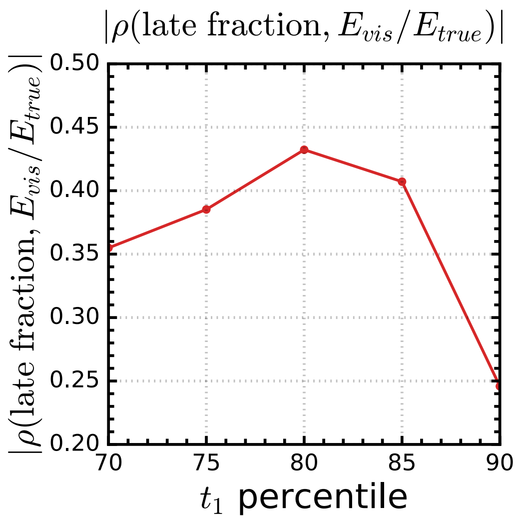


candidate t_0
$E \geq 8$: $t_0 = 0.04 \log E + 0.16$
candidate t_1
$E \geq 8$: $t_1 = 0.01 \log E + 0.69$
ECAL P_{15}
ECAL P_{80}
Time [ns]
Beam energy [GeV]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
−20
0
20
40
60
80
100
120
140
160
candidate t_0
$E \geq 8$: $t_0 = 0.13 \log E + 1.05$
candidate t_1
$E \geq 8$: $t_1 = 0.23 \log E + 3.57$
HCAL P_{15}
HCAL P_{80}
Time [ns]
Beam energy [GeV]
0
1
2
3
4
5
6
−20
0
20
40
60
80
100
120
140
160

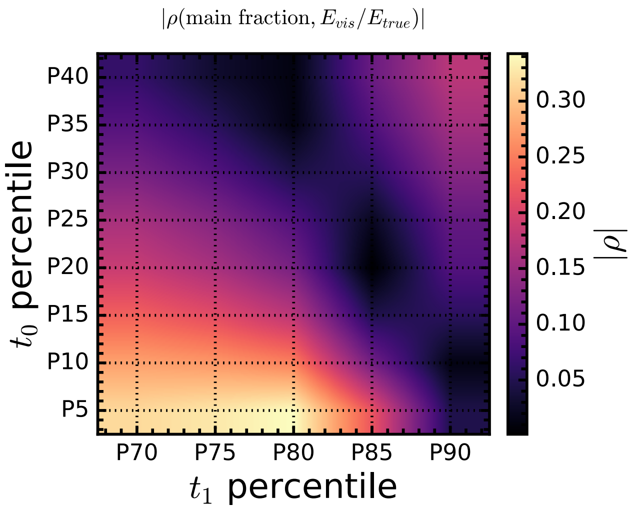
t0/t1



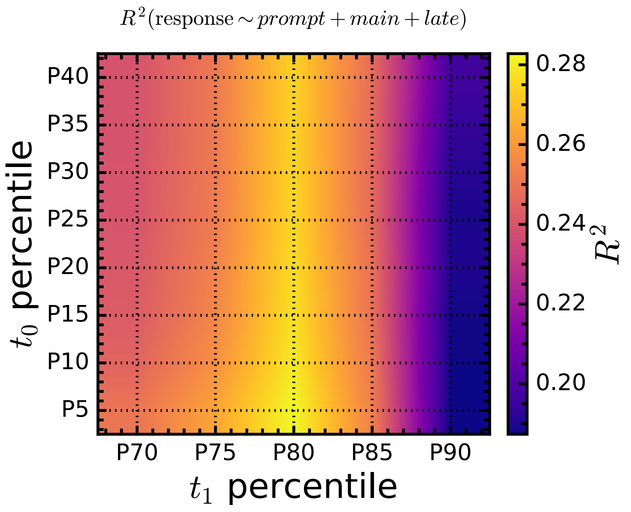
$|\rho(\text{prompt fraction}, E_{vis}/E_{true})|$
t_0 percentile



$|\rho(\text{late fraction}, E_{vis}/E_{true})|$
t_1 percentile

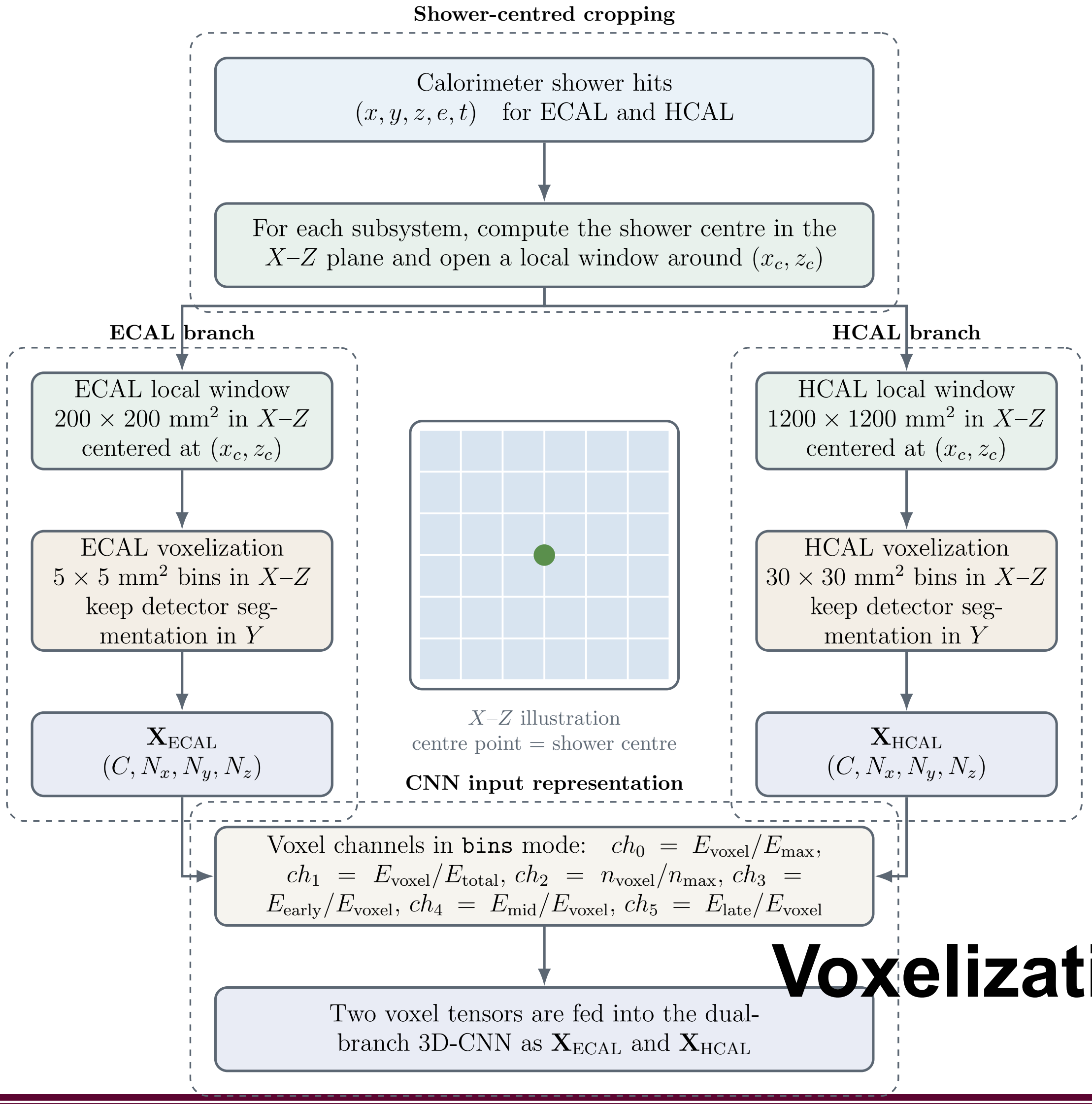


$|\rho(\text{main fraction}, E_{vis}/E_{true})|$
t_0 percentile
t_1 percentile
$|\rho|$

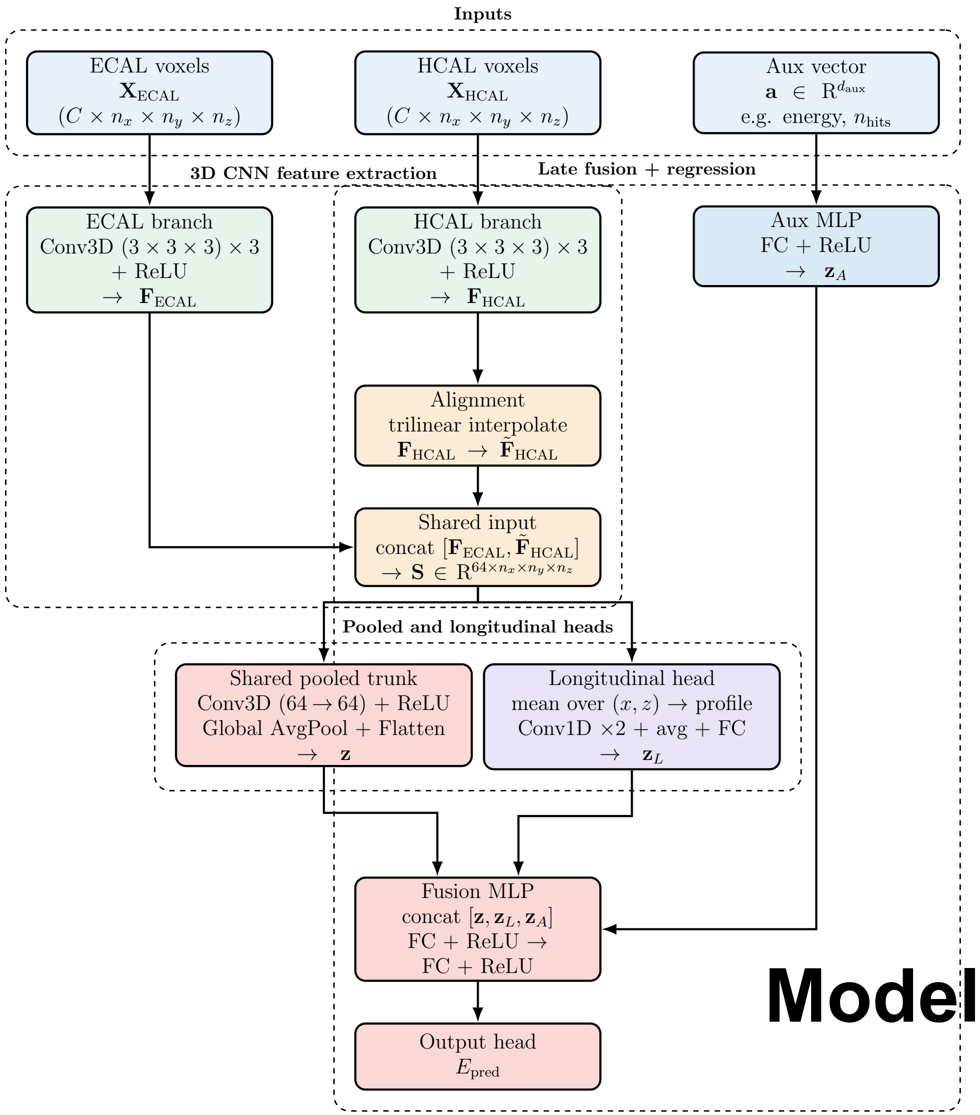


$R^2(\text{response} \sim prompt + main + late)$
t_0 percentile
t_1 percentile
R^2

Voxelization strategy and model



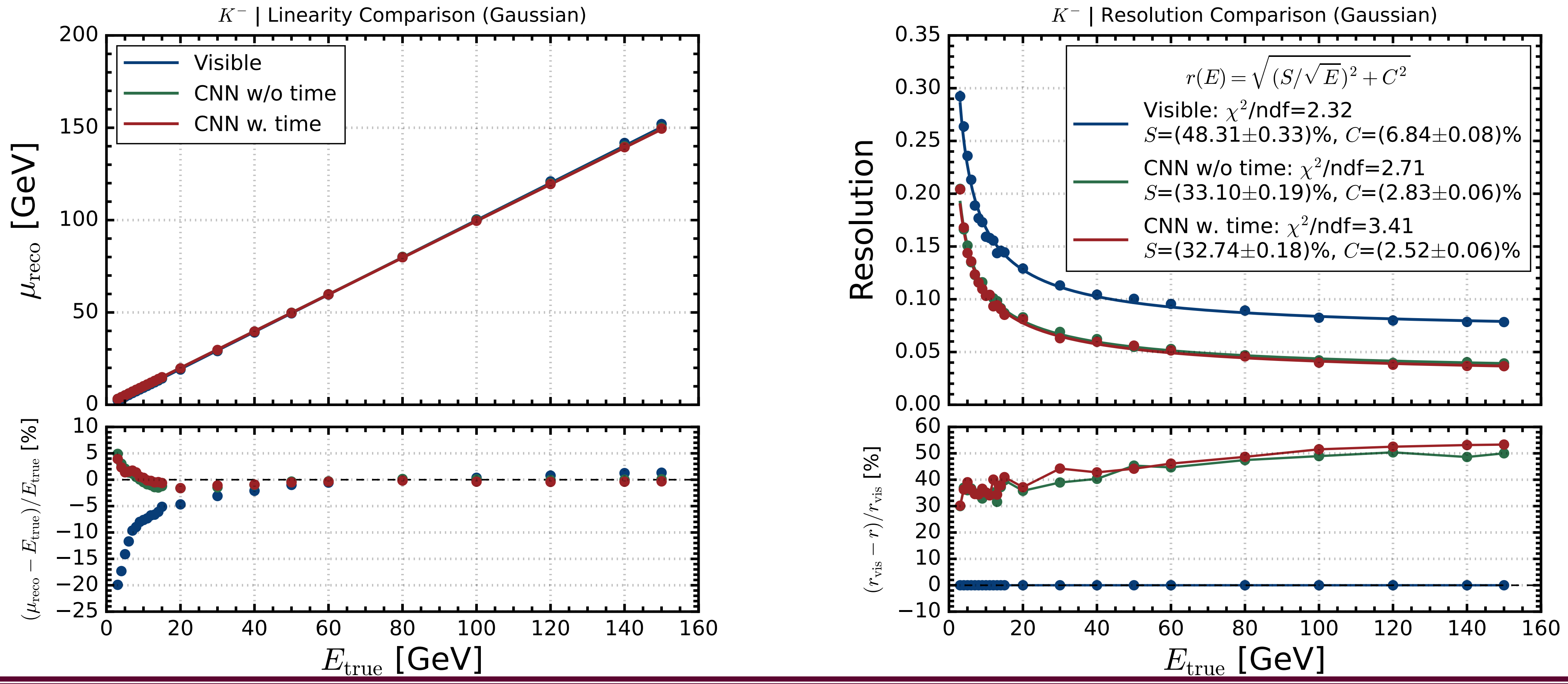
Voxelization



Model

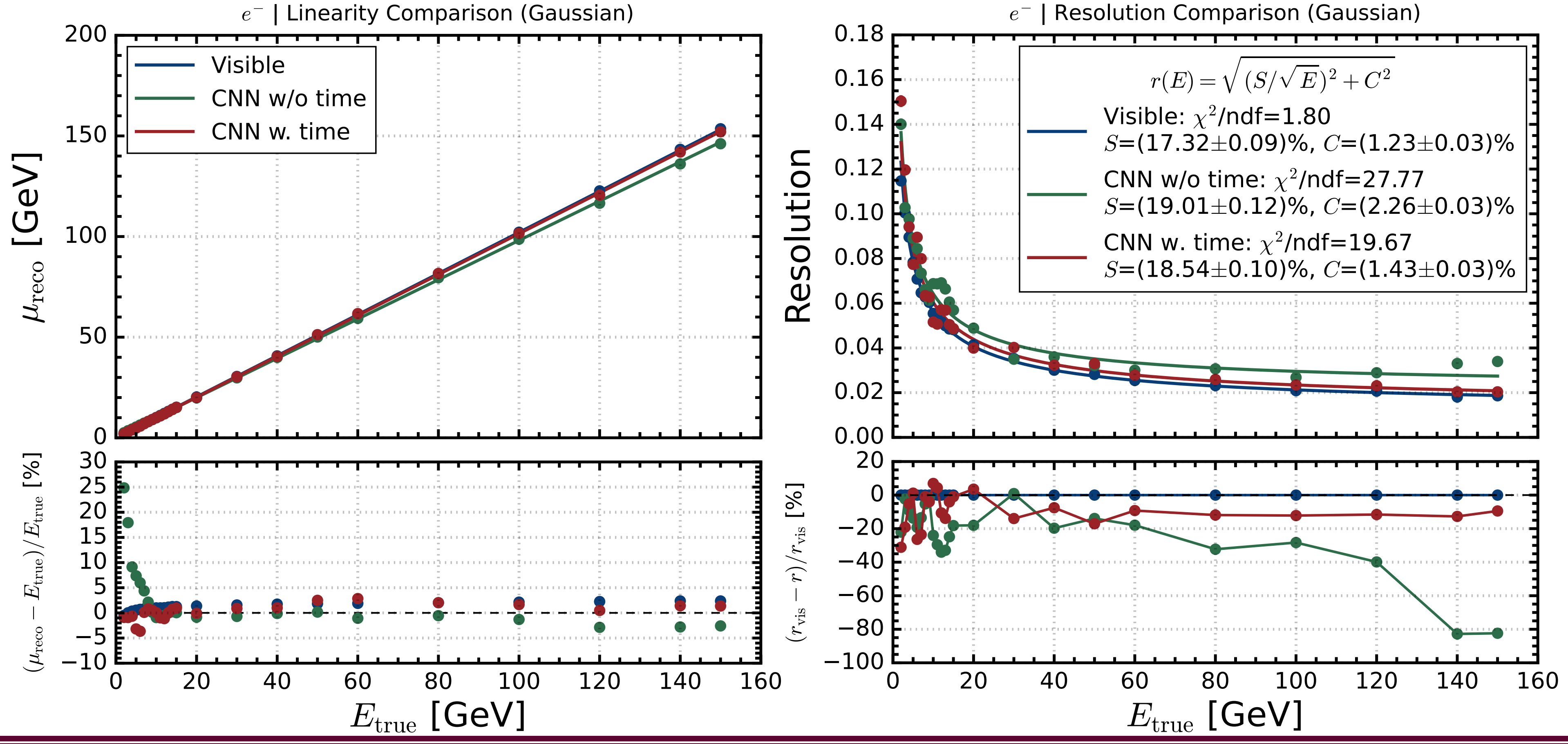
Transfer to K^- (Model trained on π^+)

- The model generalizes well to K^-, which is the most similar to π^+ among the tested particles.
- The performance remains strong:
  - linearity at the few-% level and clear resolution improvement over the visible baseline.

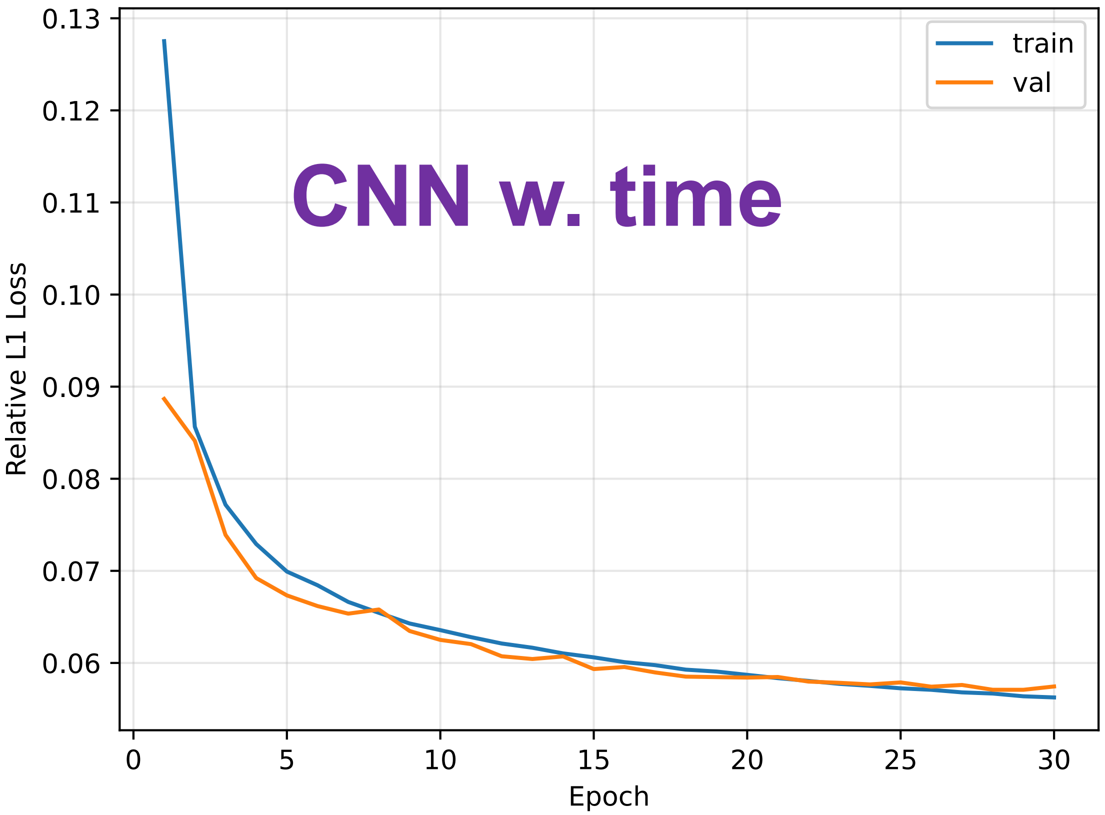


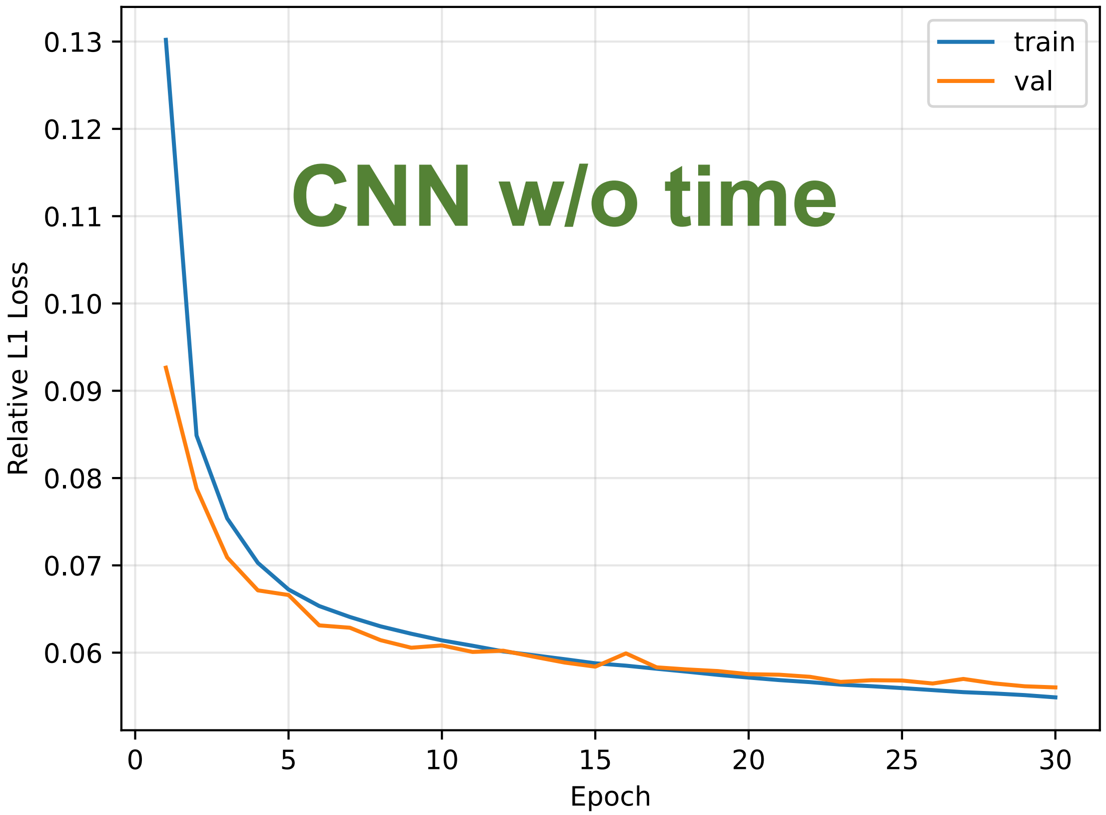
Transfer to e^- (Model trained on π^+)

- The model trained on hadronic showers does not provide gain for e^-.
- This is physically expected, since electromagnetic showers have a very different spatial development and much smaller event-by-event response fluctuations than hadronic showers.

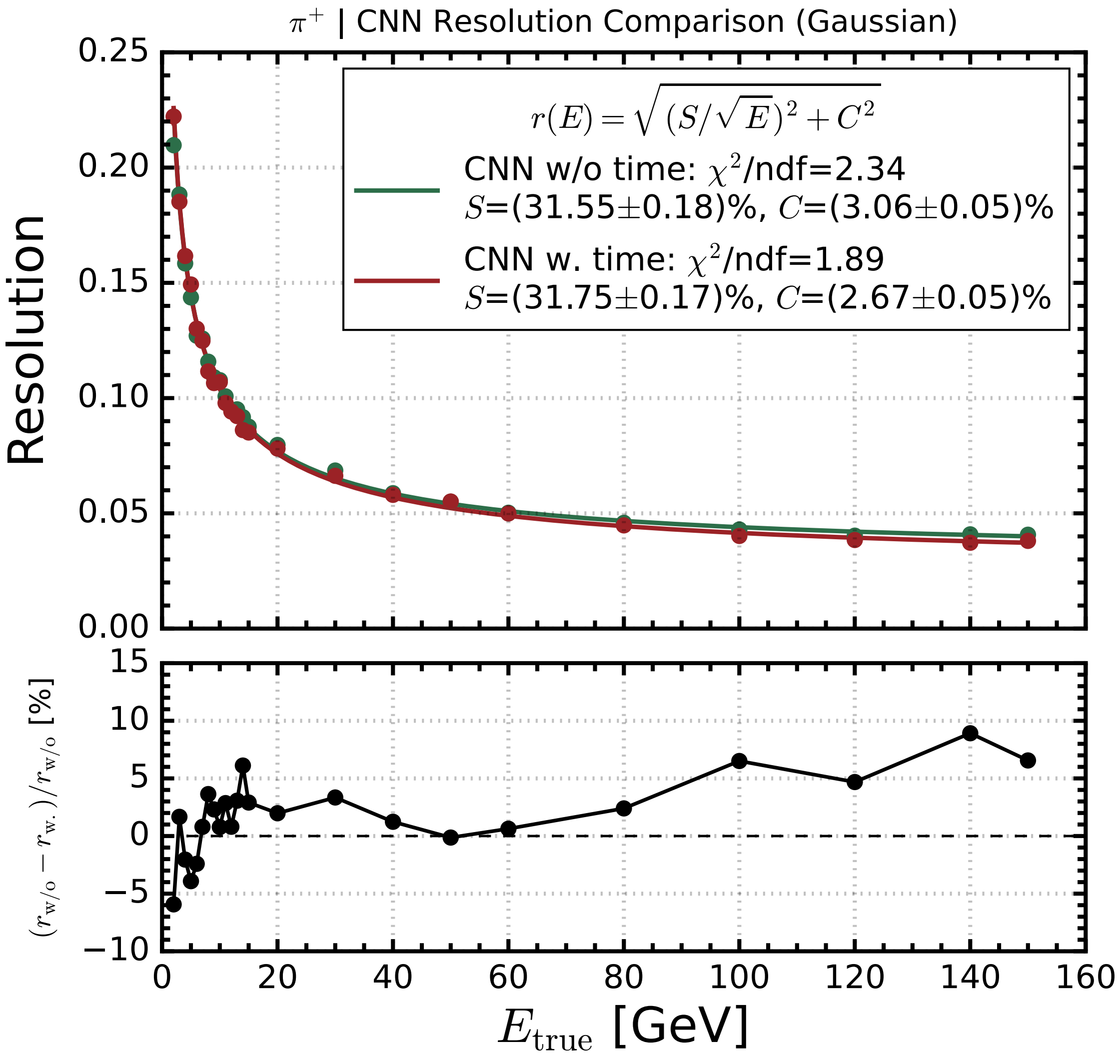


Loss curve


CNN w. time
train
val
Relative L1 Loss
Epoch
0.13
0.12
0.11
0.10
0.09
0.08
0.07
0.06
0
5
10
15
20
25
30


CNN w/o time
train
val
Relative L1 Loss
Epoch
0.13
0.12
0.11
0.10
0.09
0.08
0.07
0.06
0
5
10
15
20
25
30

Time gain


π^+ | CNN Resolution Comparison (Gaussian)
$r(E) = \sqrt{(S/\sqrt{E})^2 + C^2}$
CNN w/o time: χ^2/ndf=2.34
S=(31.55±0.18)%, C=(3.06±0.05)%
CNN w. time: χ^2/ndf=1.89
S=(31.75±0.17)%, C=(2.67±0.05)%
Resolution
$(r_{w/o} - r_{w.})/r_{w/o}$ [%]
E_{true} [GeV]