Shower Separation in Five Dimensions using Machine Learning Techniques.

Jack Rolph, Gregor Kasieczka and Erika Garutti
University of Hamburg

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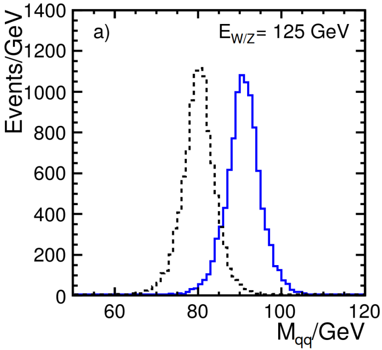
The need for sophisticated hadron shower clustering.

- **Future linear collider** required to **distinguish hadronic decays of W and Z bosons**;
- **Pandora Particle Flow** is current state-of-the-art for W-Z **jet energy resolution** ($\sigma_E/E = 3.8\%$);
- Pandora PFA [4] relies upon **sophisticated clustering for particle showers in highly granular calorimeters.**
- Machine Learning is **a rapidly developing science**, with **many state-of-the-art applications in clustering.**
- Can **machine learning** be used to aid in **PFA clustering**?
- Does a **calorimeter with temporal information** aid in clustering?



Reconstructed invariant mass distributions for the hadronic system in simulated $ZZ \to d\bar{d}\nu\bar{\nu}$ and $W^+W^- \to u\bar{d}\mu^-\bar{\nu}$ [4]

1

[1] M.A. Thomson. "Particle flow calorimetry and the PandoraPFA algorithm". In: (2009).

Goals.

Predict the fraction of energy belonging to two simultaneous hadronic showers observed in a highly granular calorimeter prototype, cell by cell, using existing state-of-the art machine learning methods.

- State of the art machine learning uses **graph networks** to achieve separation.
- Several options for neural shower separation:
  - **Standard Convolutional Neutral Network**;
  - **Dynamic Graph Convolutional Neutral Network** (DGCNN)[1]
  - **GravNet**[2] ;
- Is **time a useful variable** for **hadronic shower clustering**?
- What is the **effect of time resolution** on **network performance**?

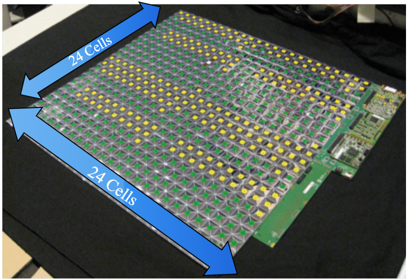
[1] Yue Wang et al. *Dynamic Graph CNN for Learning on Point Clouds.* 2018. arXiv: 1801.07829.

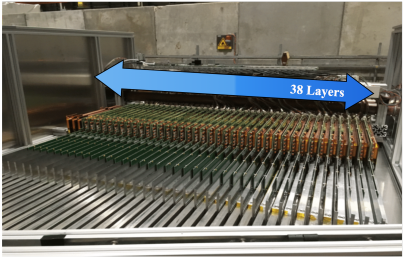
[2] Shah Rukh et al Qasim. "Learning representations of irregular particle-detector geometry with distance-weighted graph networks". In: (2019). ISSN: 1434-6052.

CALICE AHCAL Design

Detector Statistics:

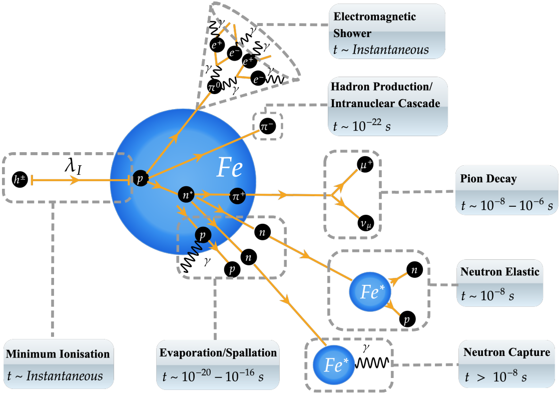
- Dimensions: 72 cm $\times$ 72 cm $\times$ 75 cm
- Sampling Calorimeter: 3mm
- Absorber: 17mm, steel
- Utilizes SiPM-on-Tile Technology.
- Depth: $\sim$ 4 λ_I over 38 Layers
- Cell Dimensions: $3 \times 3\text{cm}^2$;
- Total Channels: 21,888.

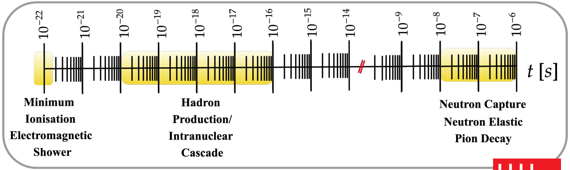




Why we measure time.

- Hadron showers involve **many different energy-deposition processes**.
  - **EM fraction** near **instantaneous**;
  - **Hadronic fraction slower**;
- **Late time development** correlated with **hadronic fraction**.
- **Shower development** of an **EM-process dominated shower completely different** to **hadronic-process dominated**.
- **Does this help clustering**?

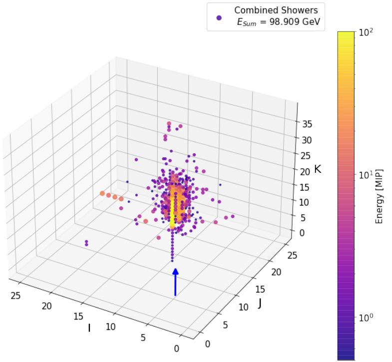




Simulation Information: Summary.

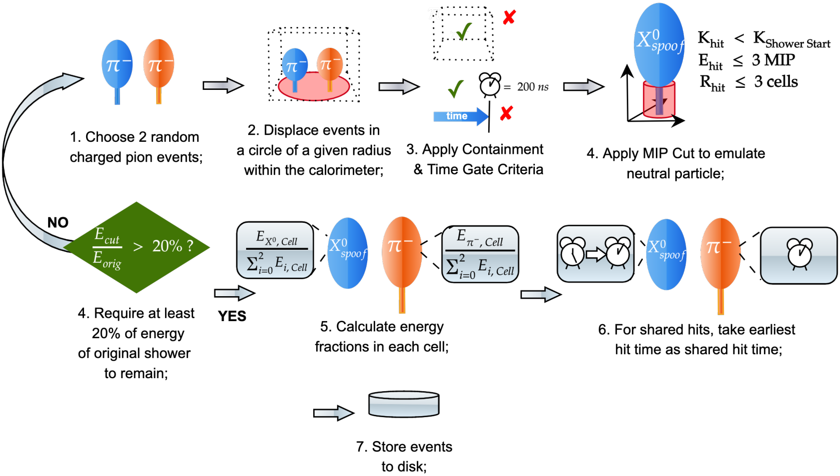
Simulation of π^- hadronic showers **using Geant4** in the AHCAL were used:

- Physics list: **QGSB_BERT_HP**
- **full detector simulation** (inc. SiPM saturation/noise thresholds etc.)
- Based on **June 2018 CALICE Testbeam** taken at SPS;
- **Actual data also used to validate**;
- Simulated particle energies: **10-80 GeV in steps of 5 GeV + 90 GeV, 120 GeV**
- **No neutral data; this must currently be spoofed.**

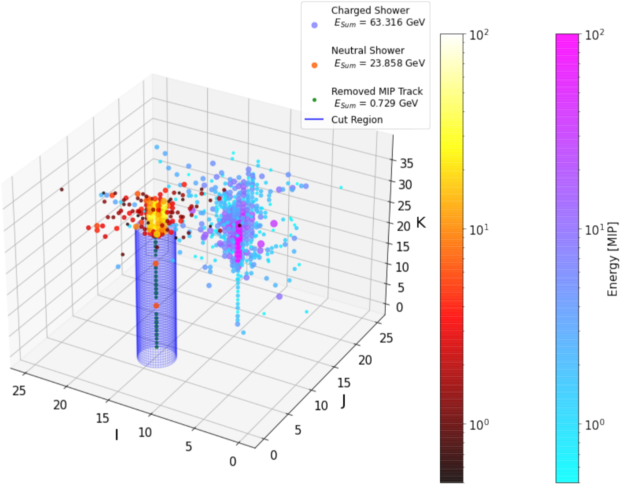


Example event display of a 80 GeV negative pion detected by the AHCAL

Simulation: Multi-shower Augmentation Algorithm.



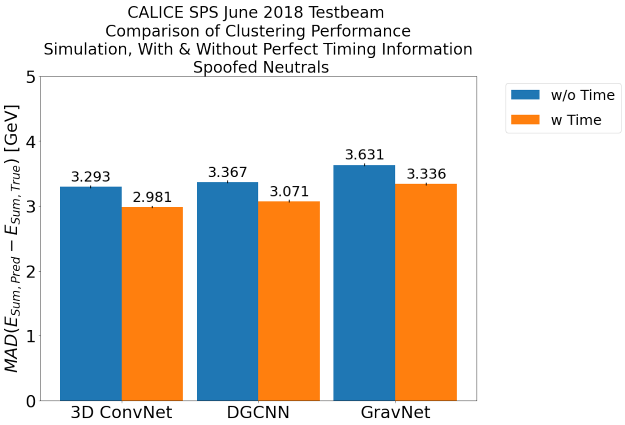
Simulation: Example Combined Shower Event.



The Experiment.

- **Train** a series of **shower separation networks**, **with** and **without time** as an input variable. using **perfect simulated time resolution**;
  - Is there an **improvement** in **energy resolution**?
  - Can it be applied to **actual data**?
- Obtain **samples** of hadronic **shower pairs** with **decreasing time resolution** from 0ns to 2ns;
  - **At what resolution** does does the **improvement** in clustering **due to time cease**?

Results: Network Validation on Simulation.

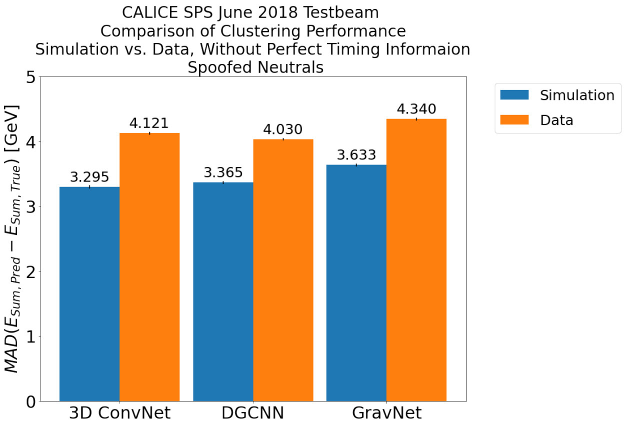


$$\mathrm{MAD}(X) = \mathrm{Median}\left(|X_i - \mathrm{Median}(X)|\right) \quad (1)$$

What one learns:

- Performance measured by: **difference between true/predicted shower energies.**
- **Energy resolution always improves with time.**
- **Improvement around 300 MeV;**
- **GravNet performs worst overall** on simulation;
- **3D ConvNet performs best overall** on simulation;

Results: Network Validation on Data - A First Ever Study!

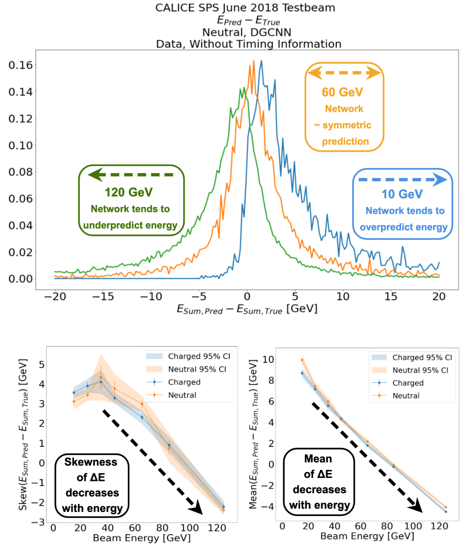


$$\mathrm{MAD}(X) = \mathrm{Median}\left(|X_i - \mathrm{Median}(X)|\right) \tag{2}$$

What one learns:

- Performance measured by: **difference between true/predicted shower energies.**
- **Time information in data not sufficiently calibrated for validation on neural network.**
- **Data** experiences around **700 MeV worse** performance than in **simulation.**
- **Distributions available in backup slides.**

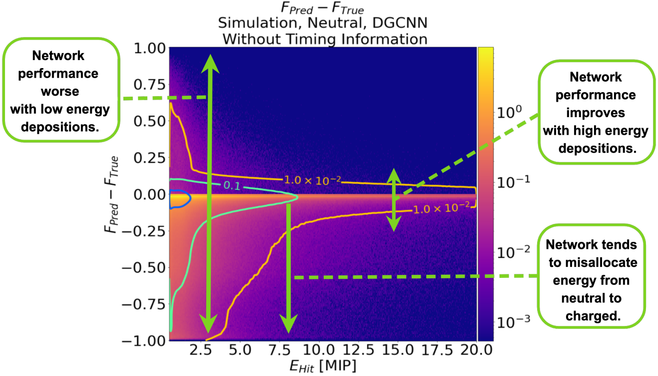
Results: Network Validation on Data, ΔE distributions.



What one learns:

- Algorithm learns energy range of hadron shower data.
- Over-predicts at the low-end of energy range;
- Under-predicts at the high-end of energy range;

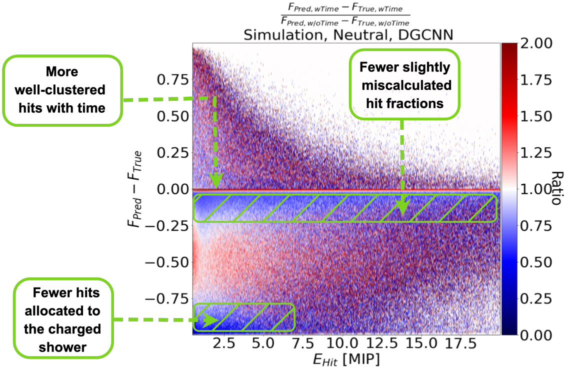
Results: Performance Vs Hit Energy, E_{hit}.



What one learns:

- **Neutral shower fractions** tend to be **under-predicted**.
- **Performance improves** with **hit energy**;

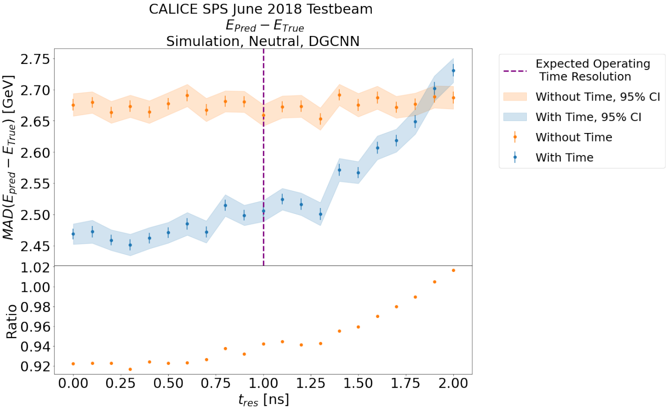
Results: Performance Vs Hit Energy, E_{hit}



What one learns:

- Time improves slight deviations from truth at all energies;
- Time improves mis-allocated hits to charged shower at low energies.

Results: Increasing Time Resolution.



What one learns:

- Reduction in performance degrades well above desired operating resolution of 1 nanosecond.

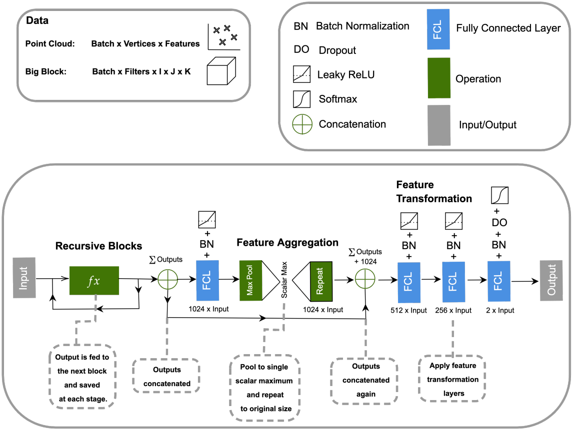
Conclusion.

- An **efficient multi-shower data augmentation tool** was developed;
- **Small improvement** in **clustering performance** of around **300 MeV** was observed using **perfect time resolution.**
- **Improvement due to time** is **due to minor error-correction** and **correctly otherwise misallocated hits**
- **Networks can be applied to data**, but perform with **700 MeV worse resolution than simulation**;
- **Improvement due to time is no longer useful** after $\sim$ **1.5 ns time resolution**;

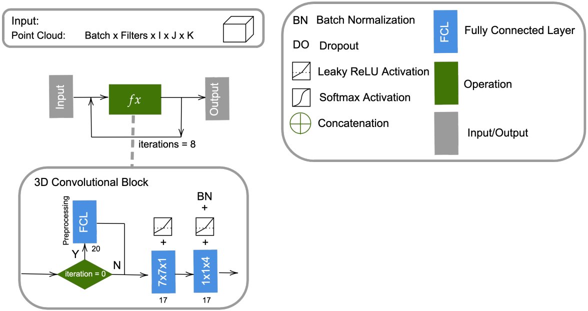
Outline

> Backup

Network: Underlying Architecture

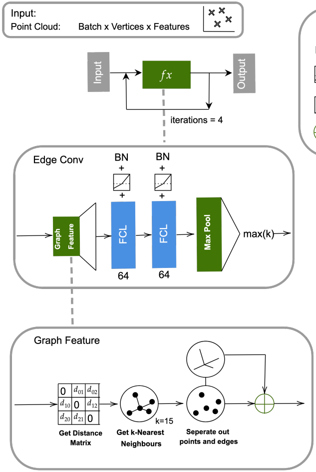


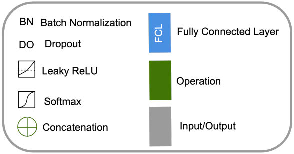
Network: Standard Convolutional Block



Convolutional block architecture. Complete network has 991,679 learnable weights

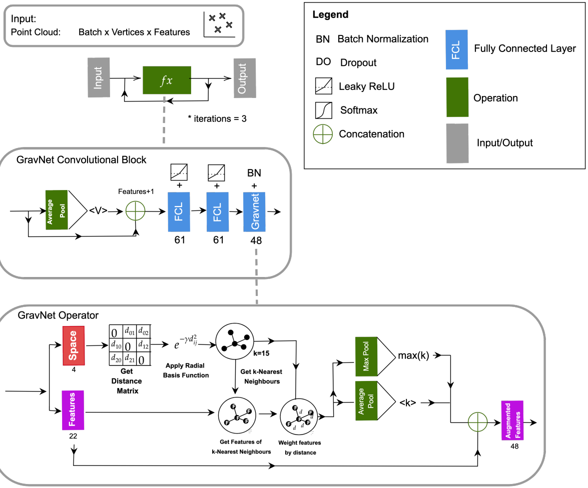
Network: Dynamic Graph Convolutional Block





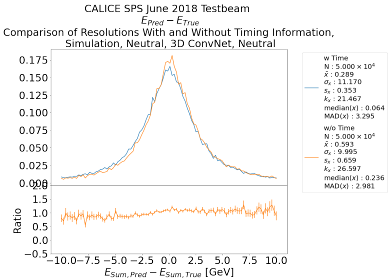
Dynamic Graph Convolutional block architecture. Complete network has 977,024 learnable weights.

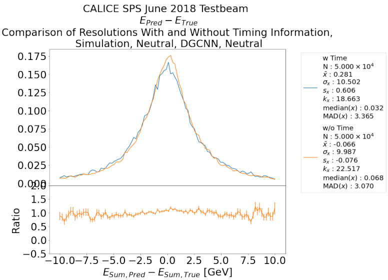
Network: GravNet Block

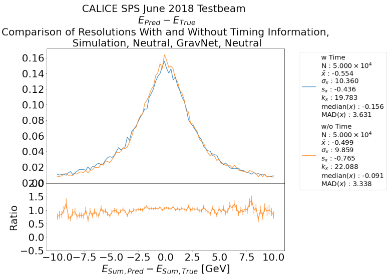


GravNet Convolutional block architecture. Complete network has 980,042 learnable weights.

Results: E_{sum} Reco. Performance (Simulation).



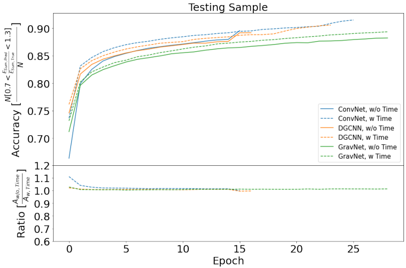




Results: Accuracy Curves.

What one learns:

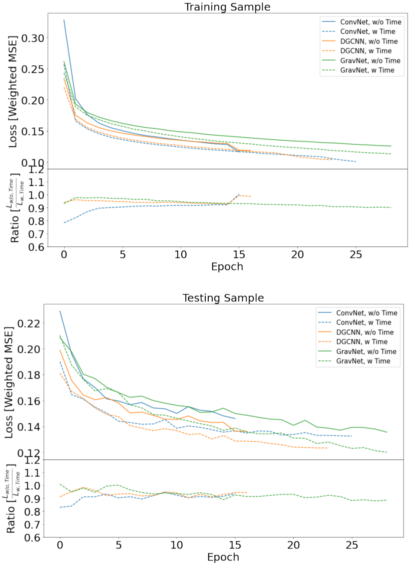
- Accuracy **always improves with time.**
- **'Kink' at 15 epochs** in loss curve due to **overcompensating step function** applied to **learning rate** due to **gradient explosion**;
- **Still attempting to find solution.**
- Training still in progress as a result.
- **As above with accuracy, see backup.**



Results: Loss Curves.

What one learns:

- Loss **always improves with time.**
- **'Kink' at 15 epochs** in loss curve due to **overcompensating step function** applied to **learning rate** due to **gradient explosion**;
- **Still attempting to find solution.**
- Training still in progress as a result.
- **As above with accuracy, see backup.**



Network: Figures of Merit and Hyperparameters.

Figures of merit:

- Loss Function:

$$L = \sum_k \frac{\sum_i \sqrt{E_i t_{ik}} \left(p_{ik} - t_{ik}\right)^2}{\sum_i \sqrt{E_i t_{ik}}} \quad (3)$$

Mean-square error, weighted with the square-root of the true cell energy.

- Accuracy Function:

$$A = \frac{N_{Events}(0.7 < \frac{E_{pred}}{E_{true}} \leq 1.3)}{N_{Events}} \quad (4)$$

Ratio of number of charged particles with 70%-130% of their true, reconstructed energy predicted to all charged particle

$E \longrightarrow$ Ground Truth Energy [MIP];
$t \longrightarrow$ Ground Truth Energy Fraction;
$p \longrightarrow$ Predicted Energy Fraction;
$i \longrightarrow$ Cell Energy Index;
$k \longrightarrow$ Shower Index;

Hyperparameters:

In machine learning, a hyperparameter is a parameter whose value is used to control the learning process. By contrast, the values of other parameters (typically node weights) are derived via training. [2]

All figures of merit and choice of hyperparameters used were defined in the reference paper [3].

- **Batch Size**: 20 events
- **Total** $N_{\textbf{epochs}}$: 20
- **Training Size**: 2×10^5 Events
- **Test Size**: 2×10^4 Events (10 % of Training Size)
- **Validation Size**: 5×10^4 Events (25 % of Training Size)
- **Optimizer**: ADAM
- **Learning Rate**: $3 - 1 \times 10^{-4}$, varies by network
- **Scheduler**: Exponential Decay, Factor = 0.99 + Step Function if Training Loss Increases, Factor = 0.75
- **GPU**: Nvidia P100

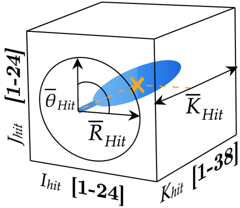
1

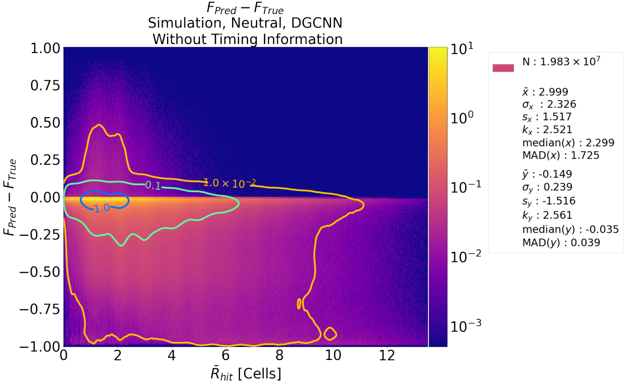
[1] *Hyperparameter (machine learning)*. In: *Wikipedia*. Page Version ID: 984957886. Oct. 23, . (Visited on 01/18/2021).

Results: Performance Vs Hit Radius, $\bar{R}_{hit}$.

What one learns:

- **Neutral shower fractions** tend to be **under-predicted.**
- **Over-prediction close to the shower core.**
- **Performance worsens slightly** with **distance from the hadron shower core;**



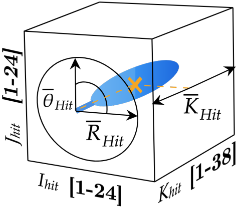


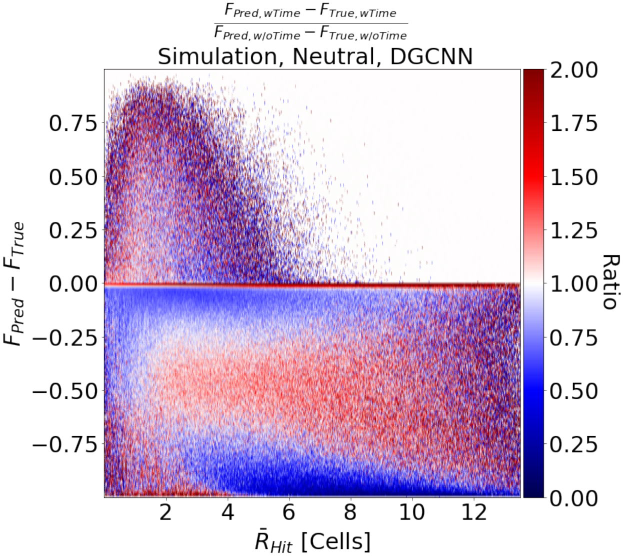
Results: Performance Vs Hit Time, $\bar{t}_{hit}$.

What one learns:

Time improves:

- slight deviations from truth close to shower core;
- mis-allocated hits further from shower core.

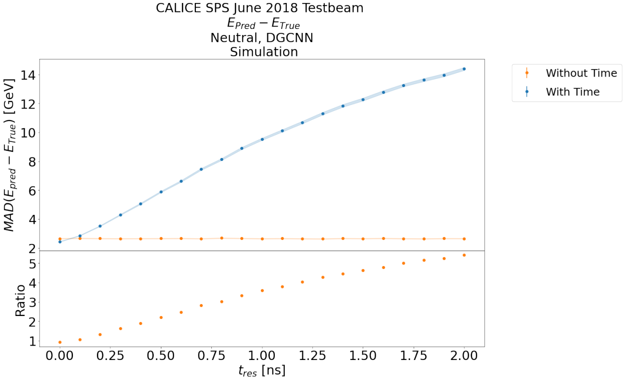




Results: Increasing Time Resolution.

What one learns:

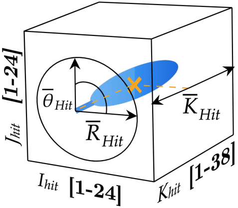
- Reduction in performance degrades well above theoretical operating resolution of 1 nanosecond.
- Graph networks sensitive to time resolution
- ConvNet result suggests clustering in only space is sufficient.

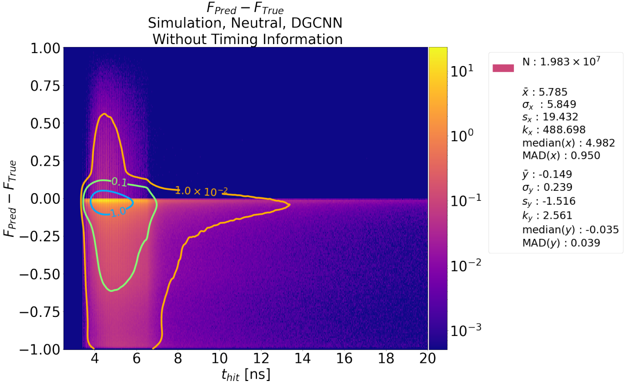


Results: Performance Vs Hit Time, $\bar{t}_{hit}$.

What one learns:

- Neutral shower fractions tend to be **under-predicted**.
- Interestingly, **late hits are clustered better than earlier hits - unexpected.**

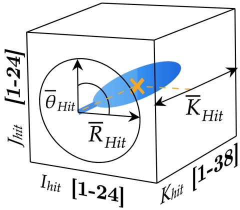


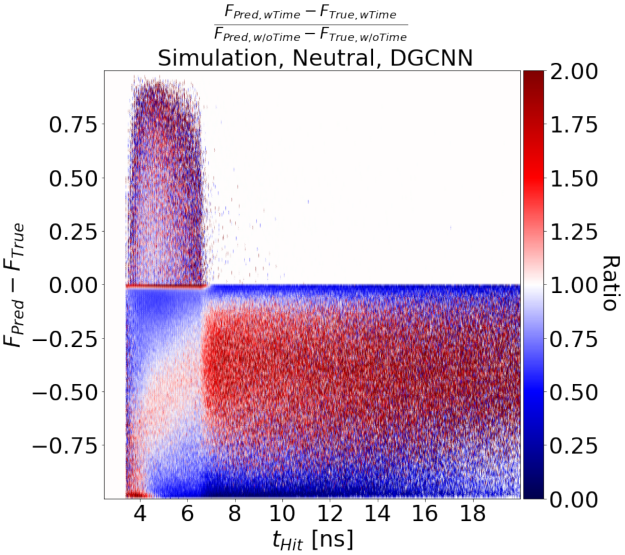


What one learns:

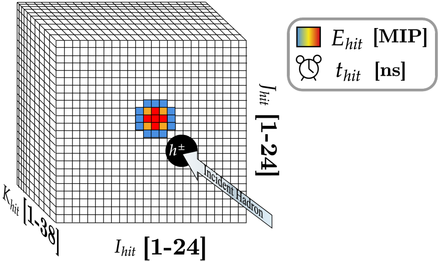
Time improves:

- slight deviations from truth at all energies;
- mis-allocated hits to charged shower at low energies.





Detector Observables.



$E_{sum} = \sum_{i=0}^{N} E_{hit}$ [MIP]

$N_{hits} = dim\left(\overrightarrow{E_{hit}}\right)$

$CoG = \frac{\sum_{i=0}^{N_{Hits}} E_{Hit,\,i}\, x_{ik}}{\sum_{i=1}^{N_{Hits}} E_{Hit,i}}$ [Cells]

	0.5	0.5	0.5	
0.5	1.0	2.0	1.0	0.5
0.5	2.0	6.0	2.0	0.5
0.5	1.0	2.0	1.0	0.5
	0.5	0.5	0.5	

24 MIP

	1	1	1	
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
	1	1	1	

20