Particle reconstruction for dual-readout calorimeter using deep learning

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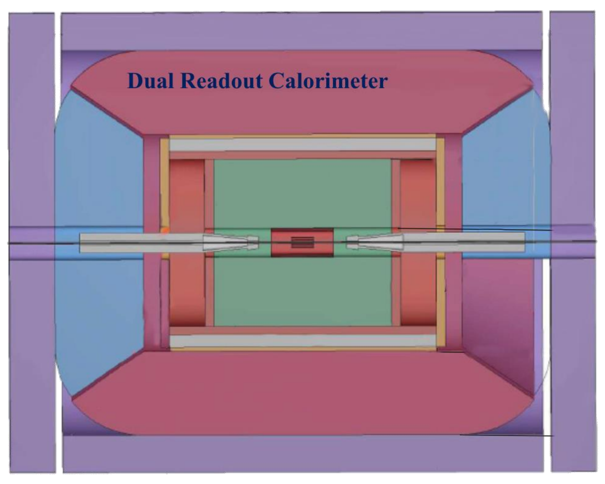
on behalf of the Korean Dual-readout Calorimeter Team

Introduction

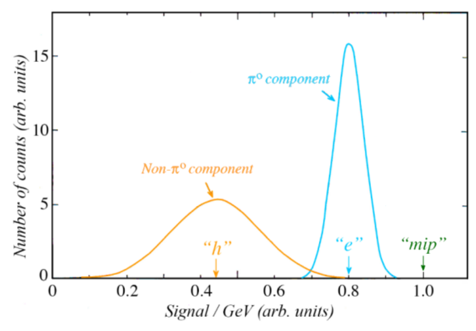
- Dual-readout calorimeters utilize two readouts from scintillation and Cerenkov fibers to measure energy, yielding high hadronic energy resolution.
- It can reconstruct the energy, position and have intrinsic particle identification capabilities distinguishing between electromagnetic and hadronic shower.
- We explore deep learning algorithms to optimize particle reconstruction across the calorimeter and to extend the identification of particle types.



Schematic layout of the IDEA detector[1]

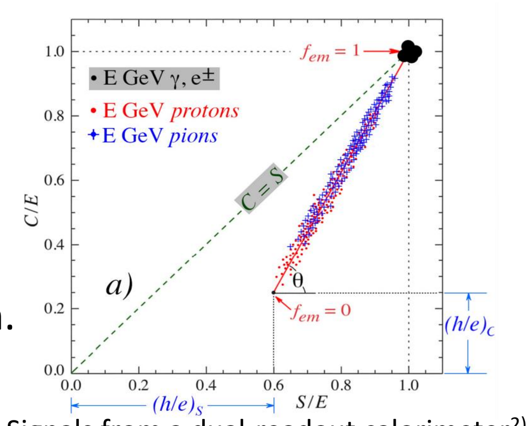
Dual-readout calorimeter

- Ratio of hadronic component and EM component(h/e) is differed by material.
  - Scintillation fibers react to both EM and hadronic particle, Cerenkov fiber reacts to EM particle only.
  - Scintillation part $(h/e)_S$ larger than Cerenkov part $(h/e)_C$.

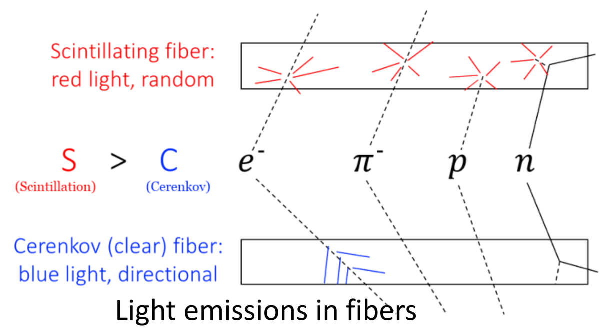


Distribution of shower components

- EM shower fraction(f_{em}) is directly measured by scintillation and Cerenkov responses.
  - Intrinsic capability of particle identification using f_{em}=1 for EM shower, f_{em}<1 for hadron shower.
  - Hadronic energy can be measured with better resolution.



Signals from a dual-readout calorimeter[2]

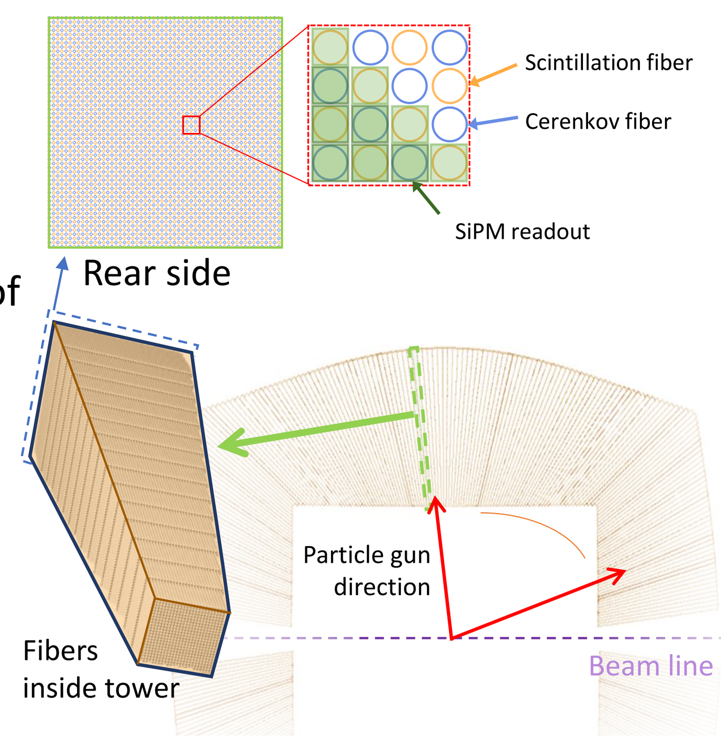


Light emissions in fibers

- $f_{em} = \frac{(h/e)_C-(C/S)(h/e)_S}{(C/S)[1-(h/e)_S]-[1-(h/e)_C]}$
- $S = E[f_{em}+\frac{1}{(e/h)_S}(1-f_{em})]$
- $C = E[f_{em}+\frac{1}{(e/h)_C}(1-f_{em})]$
- $\cot\theta = \frac{1-(h/e)_S}{1-(h/e)_C} = \chi$
- $E = \frac{S-\chi C}{1-\chi}$

Simulation Setup

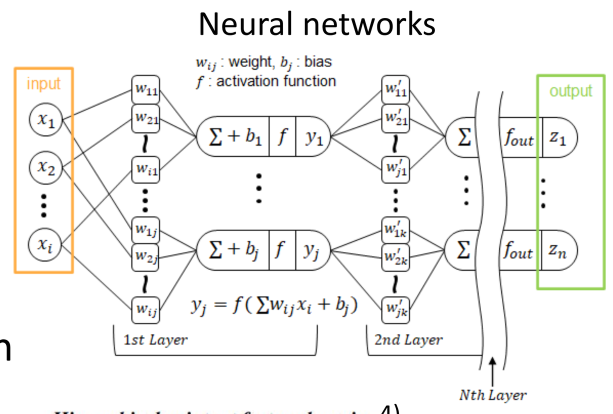
- Projective wedge geometry of dual-readout calorimeter.
  - Array of scintillation and Cerenkov fibers are implanted in copper towers.
  - SiPM readouts count optical photon at end of each fiber.
- GEANT4 for calorimeter and shower simulation.
  - Particle gun simulated at center of calorimeter.
  - e^-, gamma, π^+, π^0 are generated with energy between 10-100 GeV.
  - Incident direction cover region of 3.4°×80° ($\Delta\phi$: 0.06, $\Delta\theta$:1.4) on barrel and endcap.

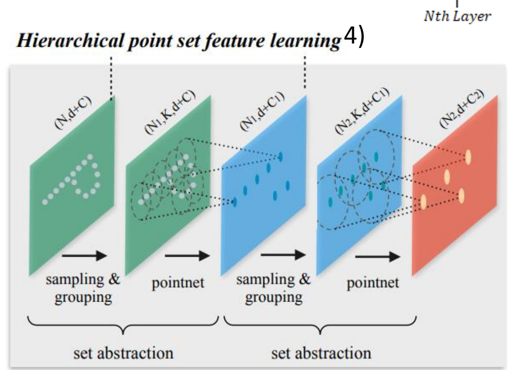


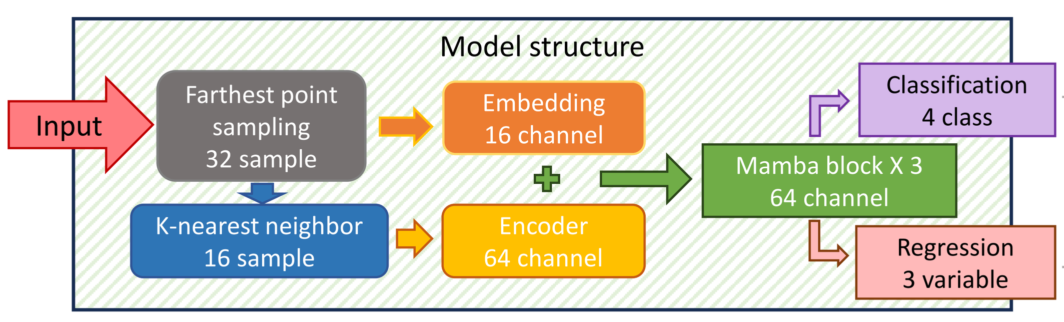
Dual readout Calorimeter (cross-section)

Deep learning model

- One of ML methods, which are based on neural networks
  - In each layer, weighted sum of inputs and bias are passed through subsequent layer.
  - Neural networks model can fit arbitrary dataset to necessary output.
- PointMamba[3] model is applied for particle reconstruction
  - Based on selective state space model.
  - Point cloud processing model is proposed for 3d shape classification and segmentation.
  - Set abstraction of sampling and grouping extracts hierarchical features from point cloud.



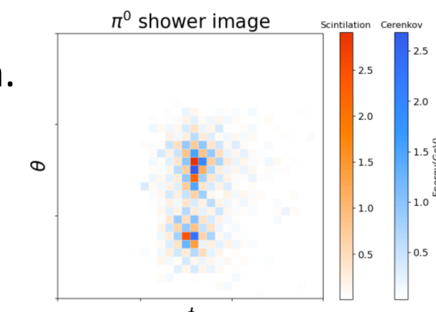


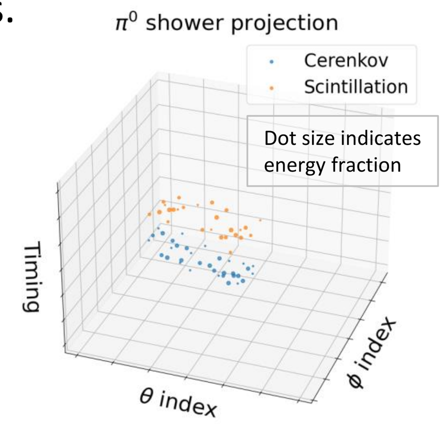


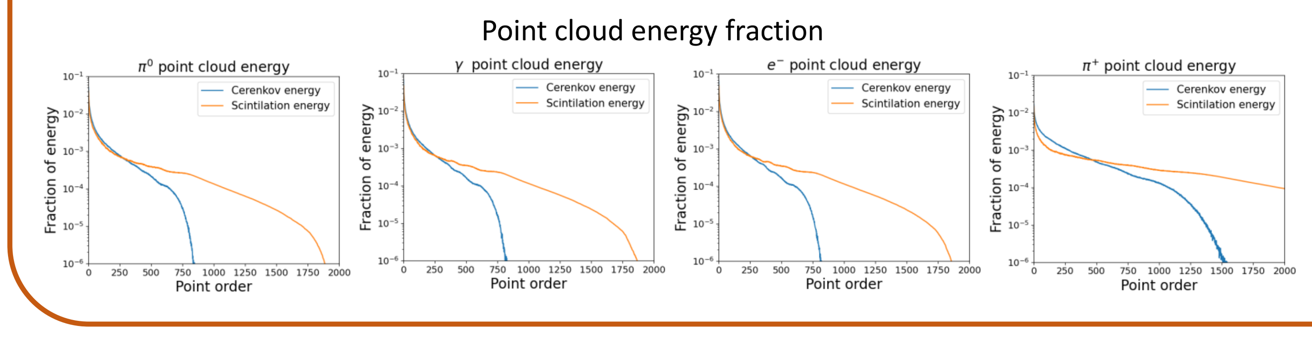
- Multi-task learning improves generalization and regularization.

Point cloud format

- Point cloud is efficient for sparse data with geometric information.
  - Position of reconstructed hit and its energy value became point component.
  - Timing(depth) information from waveform is used as additional channel.
- 5 channels(ϕ, θ, Timing, Scintillation and Cerenkov energy) inputs.
  - Maximum 1024 points are utilized for data efficiency.

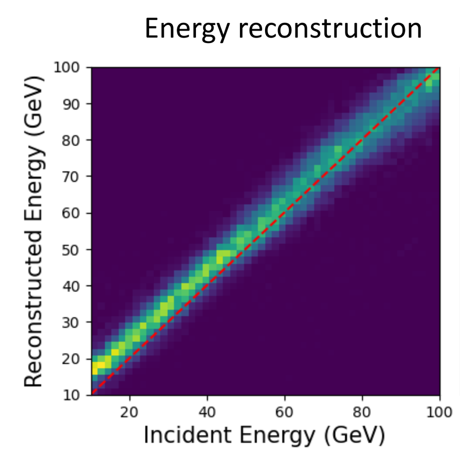


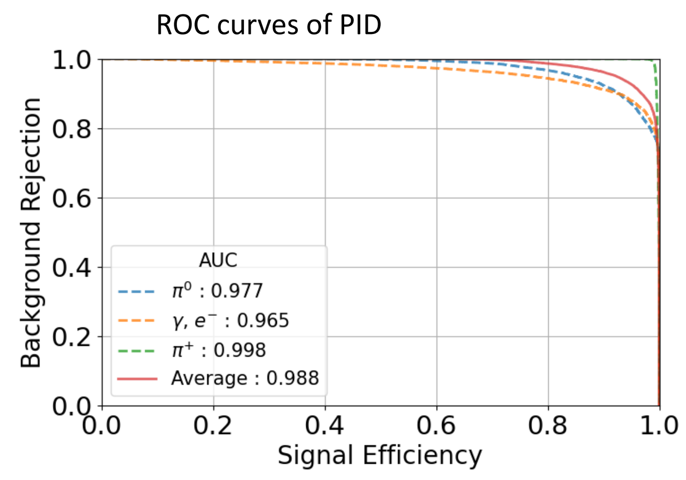


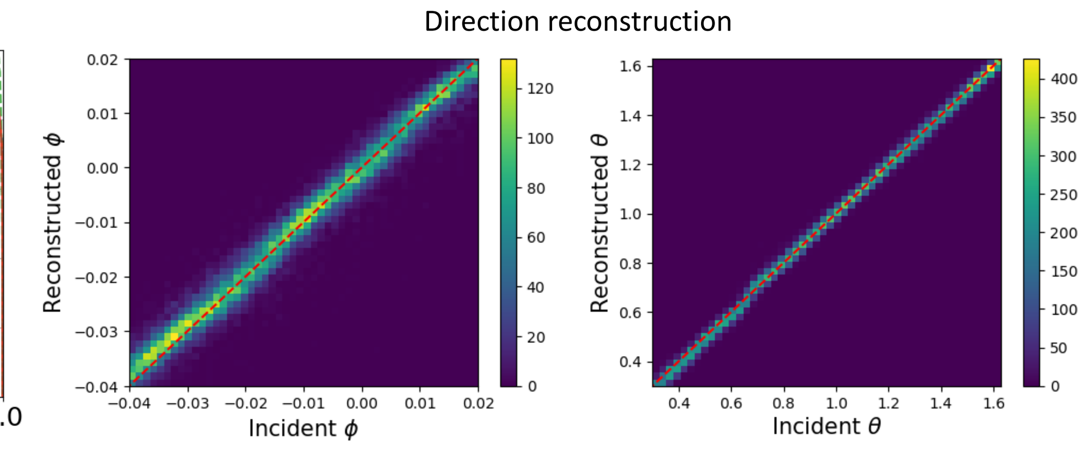


Particle reconstruction

- Model is trained to predict incident energy and direction of shower in addition to particle identification.
  - gamma and e^- showers are considered as same type.
- Model distinguishes different types of showers.
- Reconstructed ϕ, θ directions of shower follow linear fit with incident direction.

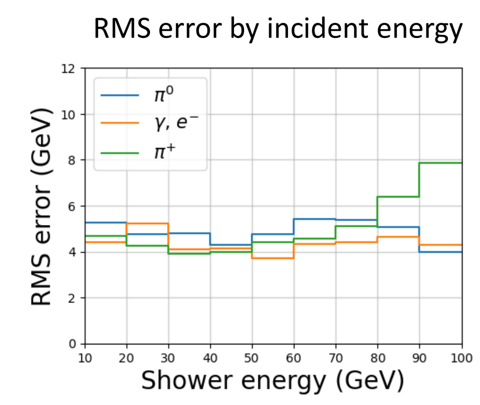


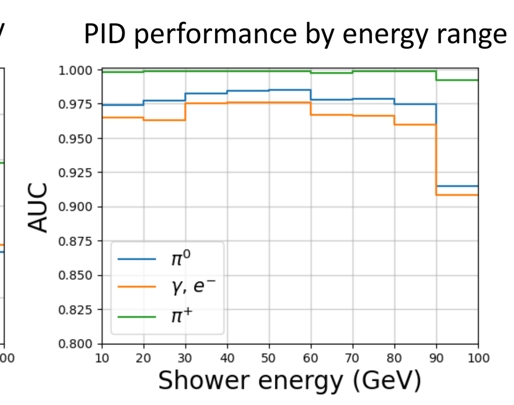


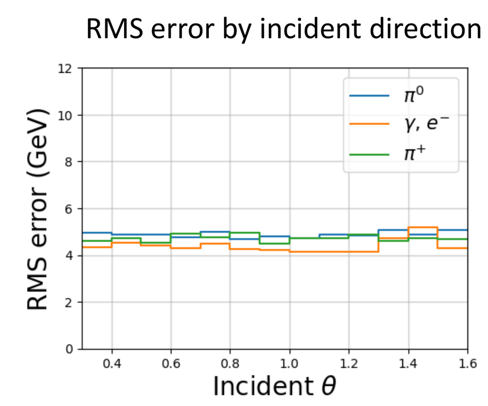


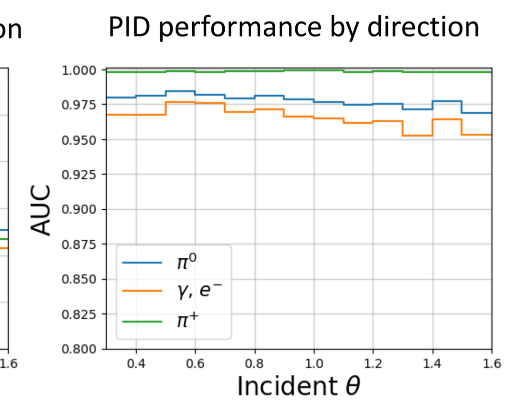
Performances by particles

- Error of π^+ energy reconstruction increase at higher energy due to leakages.
- PID performances for e^-, gamma and π^0 are drop at 90-100 GeV.
  - Opening angle of π^0 decay is getting very narrow over 80 GeV.
- Particle reconstruction performances are compared at $\Delta\theta$:1.4(0.25 - 1.63)
- Energy reconstruction errors stay under 5 GeV at different θ.
- PID performances increase by θ at endcap but decreased at barrel.









Summary

- Deep learning implementation has been studied to extended particle identification.
- Dual-readout calorimeters need geometrically efficient data format which is point cloud of energy deposits.
- Point cloud based model have capability of particle identification and reconstruction.
- Particle identification performance don't decrease on multi-task learning.

References

1) Abada, A., Abbrescia, M., AbdusSalam, S.S. et al. (2019) Eur. Phys. J. Spec. Top. 228, 261–623
2) Lee, S., Livan, M. and Wigmans, R. (2018) Nuclear Instruments and Methods A 882, 148-157
3) Dingkang Liang, Xin Zhou et al., arXiv:2402.10739
4) Charles R. Qi et al. (2017) Advances in neural information processing systems 30

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