Particle ID with Dual Readout calorimeter

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On behalf of the IDEA detector concept group

Introduction

Case study: particle identification in the IDEA dual-readout calorimeter (DRC)

- leverage modern machine learning methods based on differentiable deep neural networks
- study performance using only standalone DRC information
- helps in optimizing the detector and design of the readout electronics

Task studied:

- Single particle classification with CNN and PointNet
- Classification of τ-decays and separation from QCD jets based on Graph Neural Networks (DGCNN)
- Bayesian-DGCNN for confidence estimation of NN predictions
- (on-going) DGCNN-based identification secondary particles inside tau decays

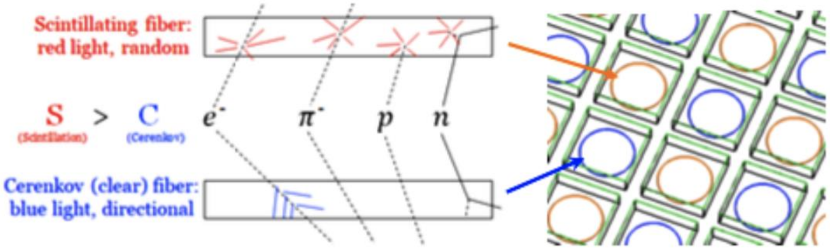
DRC Principle

- The major difficulty of measuring energy of hadronic showers comes from the fluctuation of EM fraction of a shower, f_em

- Correct shower energy reconstructed by implementing two different channels with different h/e response in a calorimeter

$$S = E[f_{em} + (h/e)_s(1 - f_{em})]$$
$$C = E[f_{em} + (h/e)_c(1 - f_{em})]$$

$$E = \frac{S - \chi C}{1 - \chi} \qquad \chi = \frac{1 - (h/e)_S}{1 - (h/e)_C}$$

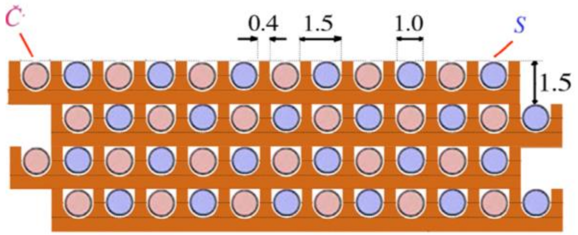


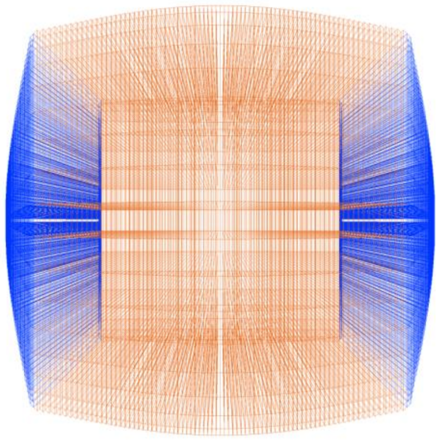
different patterns of S vs C light from different particles, combined with the fine segmentation provided by the fibres can be exploited in particle identification

IDEA DRC Simulation

Geant4 simulation of calorimeter geometry:

- Longitudinally unsegmented fiber-sampling calorimeter
- Includes B field and solenoid material in front of the calorimeter
- Fiber-sampling calorimeter: Cu absorber - 1 mm fibers
- A total of 130M fibers, providing excellent granularity and lateral shape sensitivity: $\Delta\theta, \Delta\phi = \sim 0.035°$





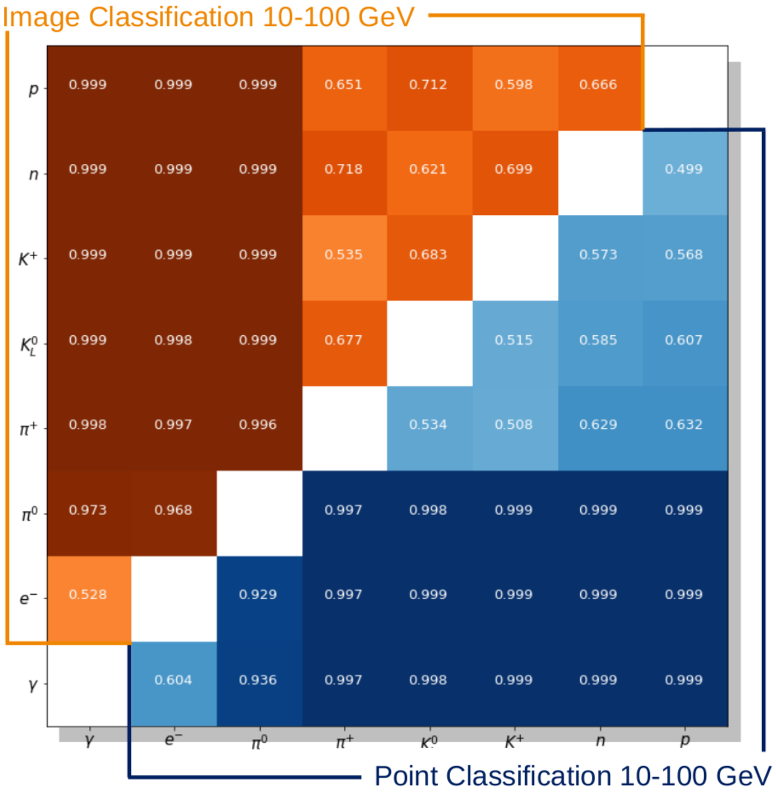
SiPM simulation :

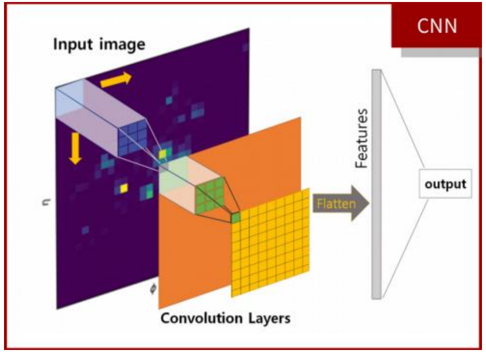
- SiPM simulation library [link] is developed (SimSiPM)
- Parameterized inputs from the datasheet
  (Dark counts, afterpulses, crosstalk, saturation, noise, …)
- Each fiber read out by a dedicated SiPM

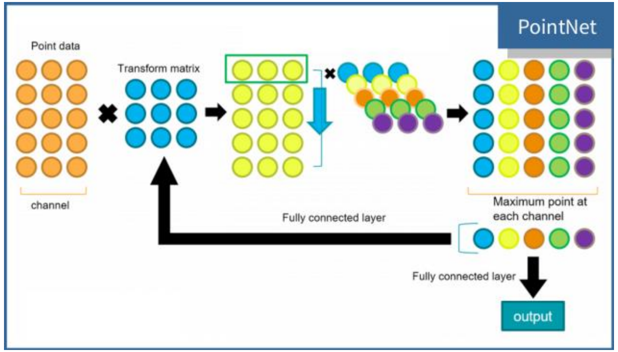
Particle identification

Image-based (CNN) vs Point-Cloud based (PointNet):

- Particle gun simulations with uniform energy distribution (10GeV<E<100GeV)
- Calorimeter standalone identification (no tracker, no magnetic field applied)
- AUC of of binary classification between rows and columns
    - Excellent pi0 identification against EM and had. particles







Tau identification Dataset

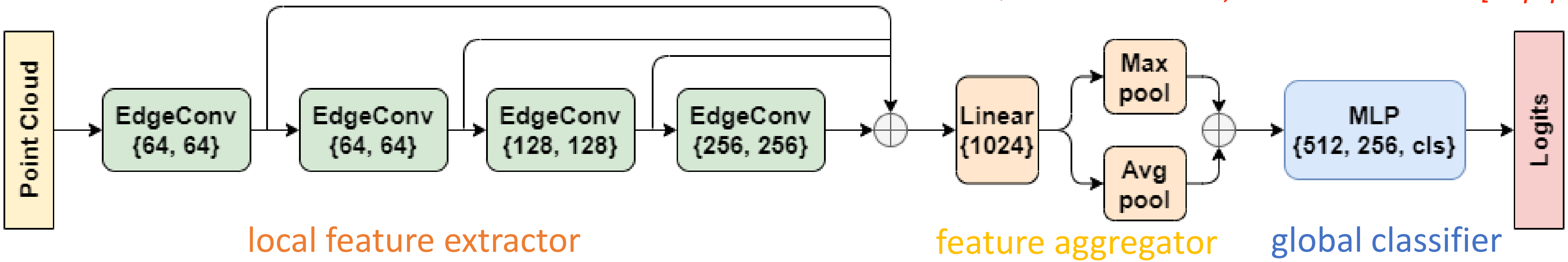
- Simulation of e^+e^- collisions around the Z pole (Pythia8)
- Simple geometrical clustering (K-means)
- No specific selection or fiducial volume applied
- Information available:
  - **Geometric**: Δθ and Δφ from cluster centroid
  - **Fiber Type**: one-hot encoding
  - **SiPM data**: Integral, Peak, Time of Arrival, Time over Threshold, Time of Peak

10000 clusters for each decay mode

Decay	Label 8-class
$\tau^- \to e^- \nu_e \nu_\tau$	0
$\tau^- \to \pi^- \nu_\tau$	1
$\tau^- \to \pi^0 \pi^- \nu_\tau$	2
$\tau^- \to \pi^0 \pi^0 \pi^- \nu_\tau$	3
$\tau^- \to \pi^- \pi^- \pi^+ \nu_\tau$	4
$\tau^- \to \pi^0 \pi^- \pi^- \pi^+ \nu_\tau$	5
$\tau^- \to \mu^- \nu_\mu \nu_\tau$	6
$Z \to q\bar{q} \to jet\, jet$	7

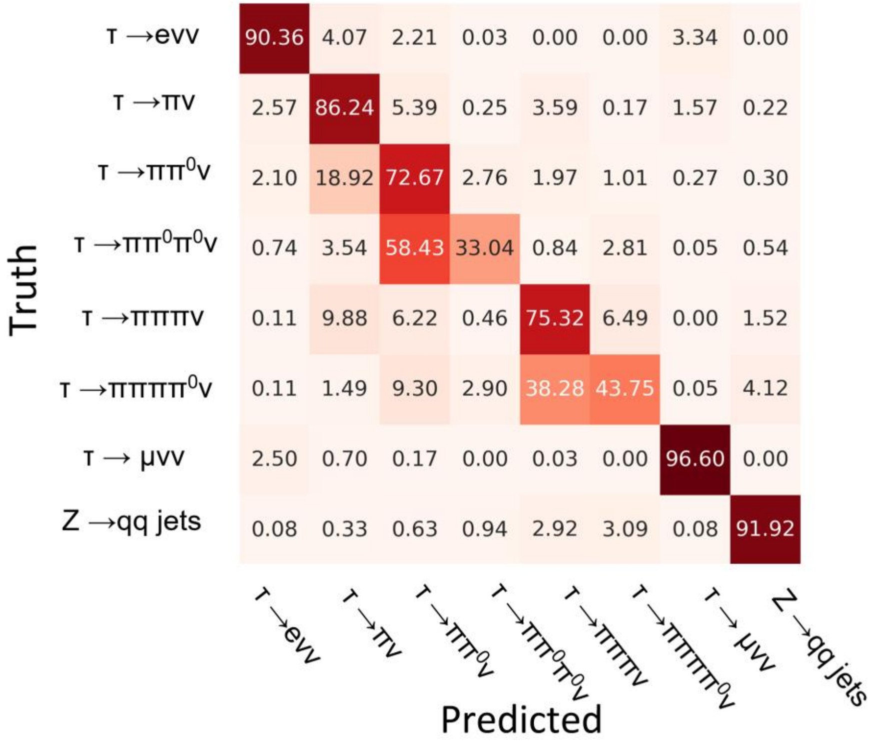
DGCNN

Y. Wang et al., arXiv:1801.07829 [cs.CV]
H. Qu and L. Gouskos, arXiv:1902.08570 [hep-ph]



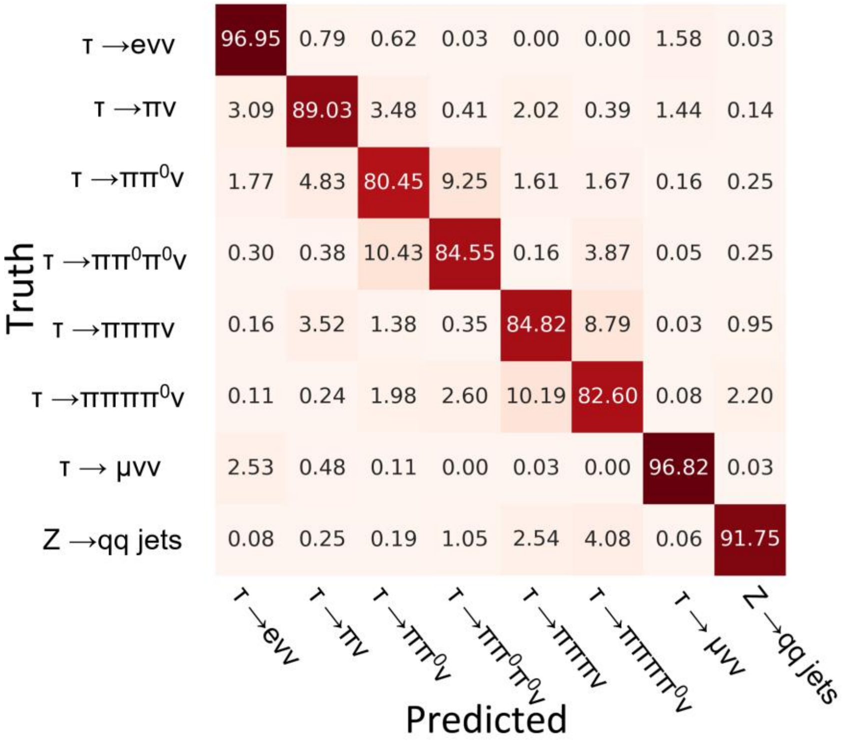
- flexible architecture optimized for point cloud inputs able to learn both local (trough the edge convolution) and global (through the feature aggregator) structures
- simplify inclusion of additional features
- Graph-based: k-nn graph dynamically updated in each layer
- #input fibers fixed, discarding those with lowest signals if more or adding zero valued vectors if fewer

Tau Decay Identification Performance



Truth \ Predicted	$\tau\to e\nu\nu$	$\tau\to\pi\nu$	$\tau\to\pi\pi^0\nu$	$\tau\to\pi\pi^0\pi^0\nu$	$\tau\to\pi\pi\pi\nu$	$\tau\to\pi\pi\pi\pi^0\nu$	$\tau\to\mu\nu\nu$	$Z\to qq$ jets
$\tau\to e\nu\nu$	90.36	4.07	2.21	0.03	0.00	0.00	3.34	0.00
$\tau\to\pi\nu$	2.57	86.24	5.39	0.25	3.59	0.17	1.57	0.22
$\tau\to\pi\pi^0\nu$	2.10	18.92	72.67	2.76	1.97	1.01	0.27	0.30
$\tau\to\pi\pi^0\pi^0\nu$	0.74	3.54	58.43	33.04	0.84	2.81	0.05	0.54
$\tau\to\pi\pi\pi\nu$	0.11	9.88	6.22	0.46	75.32	6.49	0.00	1.52
$\tau\to\pi\pi\pi\pi^0\nu$	0.11	1.49	9.30	2.90	38.28	43.75	0.05	4.12
$\tau\to\mu\nu\nu$	2.50	0.70	0.17	0.00	0.03	0.00	96.60	0.00
$Z\to qq$ jets	0.08	0.33	0.63	0.94	2.92	3.09	0.08	91.92

coordinates only: test acc. 73.7%



Truth \ Predicted	$\tau\to e\nu\nu$	$\tau\to\pi\nu$	$\tau\to\pi\pi^0\nu$	$\tau\to\pi\pi^0\pi^0\nu$	$\tau\to\pi\pi\pi\nu$	$\tau\to\pi\pi\pi\pi^0\nu$	$\tau\to\mu\nu\nu$	$Z\to qq$ jets
$\tau\to e\nu\nu$	96.95	0.79	0.62	0.03	0.00	0.00	1.58	0.03
$\tau\to\pi\nu$	3.09	89.03	3.48	0.41	2.02	0.39	1.44	0.14
$\tau\to\pi\pi^0\nu$	1.77	4.83	80.45	9.25	1.61	1.67	0.16	0.25
$\tau\to\pi\pi^0\pi^0\nu$	0.30	0.38	10.43	84.55	0.16	3.87	0.05	0.25
$\tau\to\pi\pi\pi\nu$	0.16	3.52	1.38	0.35	84.82	8.79	0.03	0.95
$\tau\to\pi\pi\pi\pi^0\nu$	0.11	0.24	1.98	2.60	10.19	82.60	0.08	2.20
$\tau\to\mu\nu\nu$	2.53	0.48	0.11	0.00	0.03	0.00	96.82	0.03
$Z\to qq$ jets	0.08	0.25	0.19	1.05	2.54	4.08	0.06	91.75

coordinates + fiber type: test acc. 88.3%

Tau Decay Identification Performance

adding SiPM information:

- Test accuracy between 88% e 91% depending on what features are used
- Temporal information is most informative

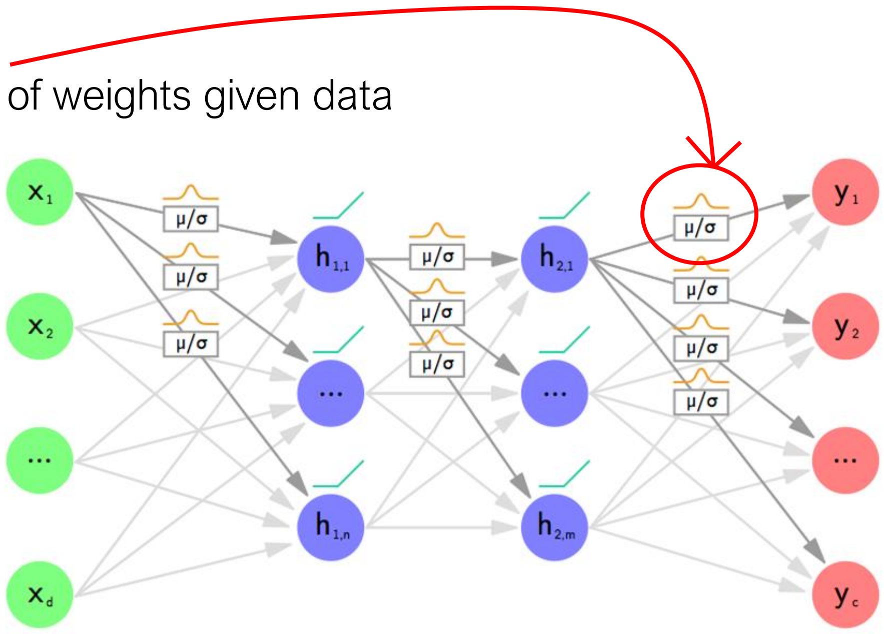
All SiPM information: test acc. ≈ 91%

Truth \ Predicted	$\tau \to e\nu\nu$	$\tau \to \pi\nu$	$\tau \to \pi\pi^0\nu$	$\tau \to \pi\pi^0\pi^0\nu$	$\tau \to \pi\pi\pi\nu$	$\tau \to \pi\pi\pi\pi^0\nu$	$\tau \to \mu\nu\nu$	$Z \to qq$ jets
$\tau \to e\nu\nu$	98.81	0.26	0.79	0.00	0.00	0.00	0.13	0.00
$\tau \to \pi\nu$	2.07	90.69	3.75	0.91	1.94	0.13	0.26	0.26
$\tau \to \pi\pi^0\nu$	1.03	1.41	89.46	6.04	0.26	1.16	0.00	0.64
$\tau \to \pi\pi^0\pi^0\nu$	0.26	0.26	9.85	88.24	0.13	0.90	0.13	0.26
$\tau \to \pi\pi\pi\nu$	0.13	3.70	1.79	0.38	86.61	5.99	0.13	1.28
$\tau \to \pi\pi\pi\pi^0\nu$	0.13	0.38	1.78	3.18	5.46	87.67	0.00	1.40
$\tau \to \mu\nu\nu$	0.79	0.53	0.00	0.00	0.00	0.00	98.55	0.13
$Z \to qq$ jets	0.00	0.28	0.41	1.24	1.24	1.93	0.00	94.90

Uncertainty in the classification

- Neural networks based on **point values estimates** for weights suffer of **overconfidence** when analyzing new data **especially in regions without examples** in the training set

- **Bayesian inference**: estimate posterior distribution of weights given data
  → inducing an infinite **ensemble of models**

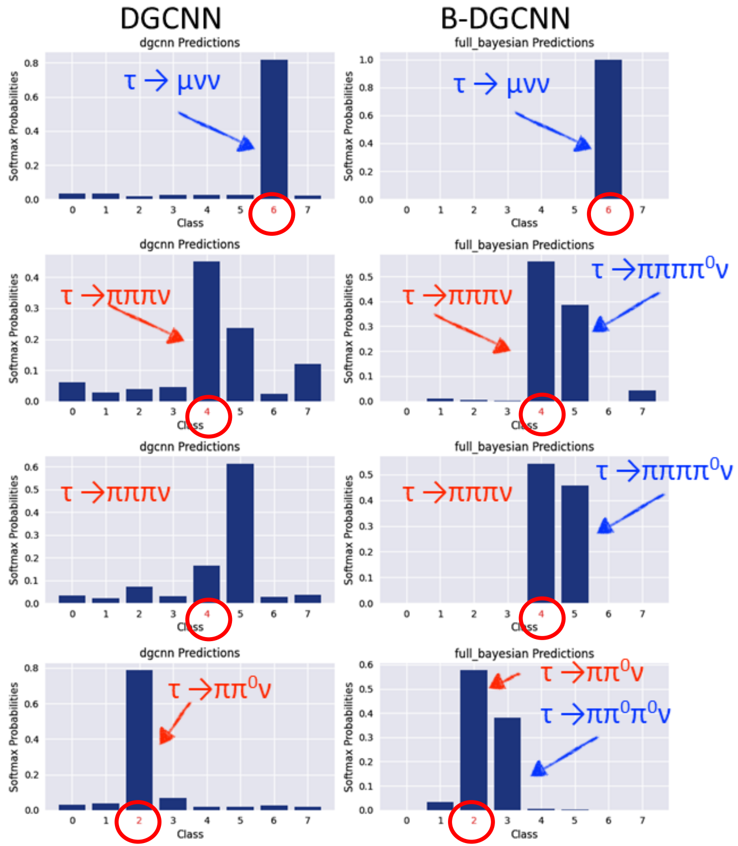


- Confidence of predictions can be estimated sampling multiple weight's configurations

- full Bayesian implementation of DGCNN based on BayesByBackprop

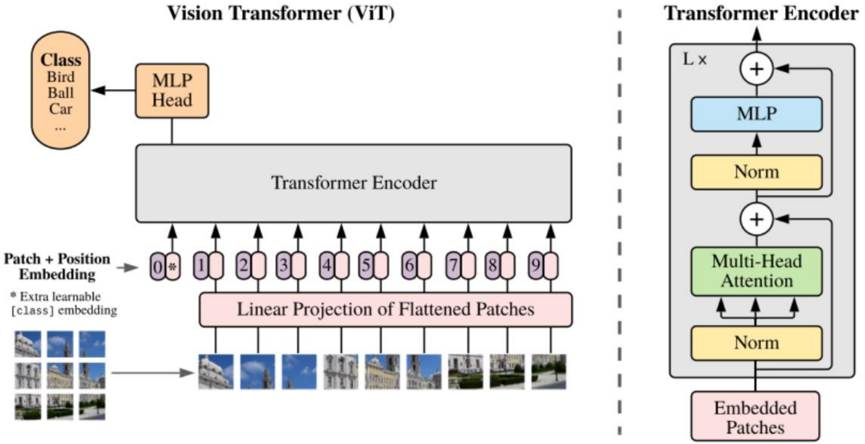
Bayes-DGCNN Predictions

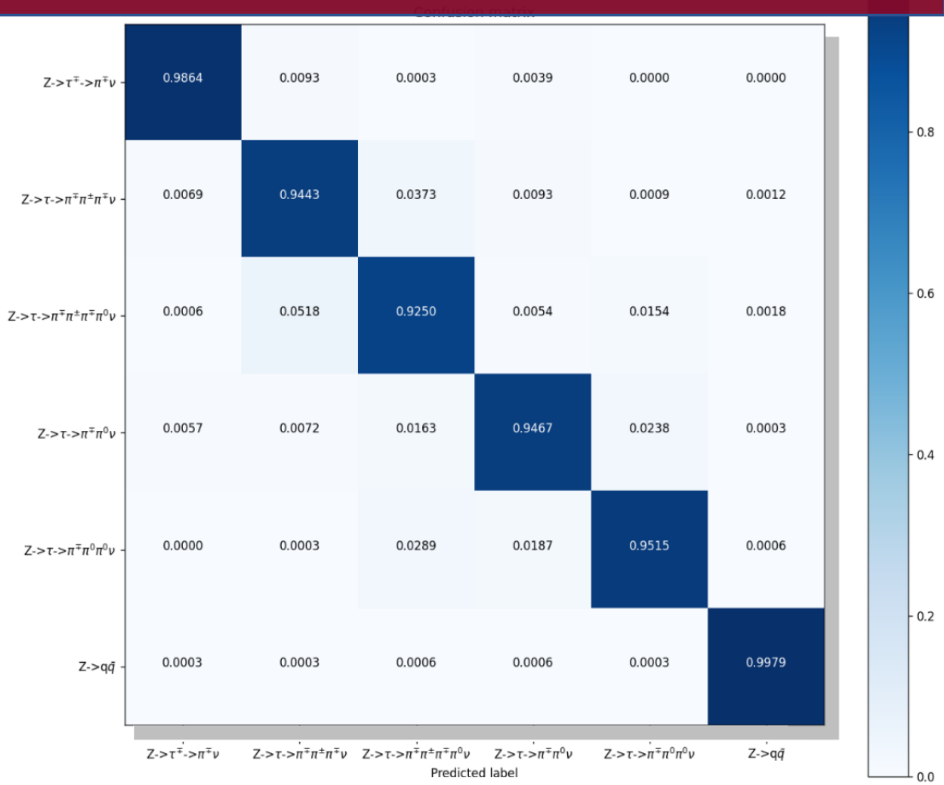
- Uncertainty in prediction of random events evaluated by:
  - DGCNN: Softmax values
  - Bayes-DGCNN: voting
- Class probabilities are better aligned with physics expectations
- Same performance as point estimate DGCNN in terms of average accuracy



Tau identification with Transformers

- State of the art image-based technique
- Extract 256x256 images around 0.5 rad x 0.5 rad for each cluster, aggregating small number of fibers
- Uses flattened image patches (64x64 pixels)

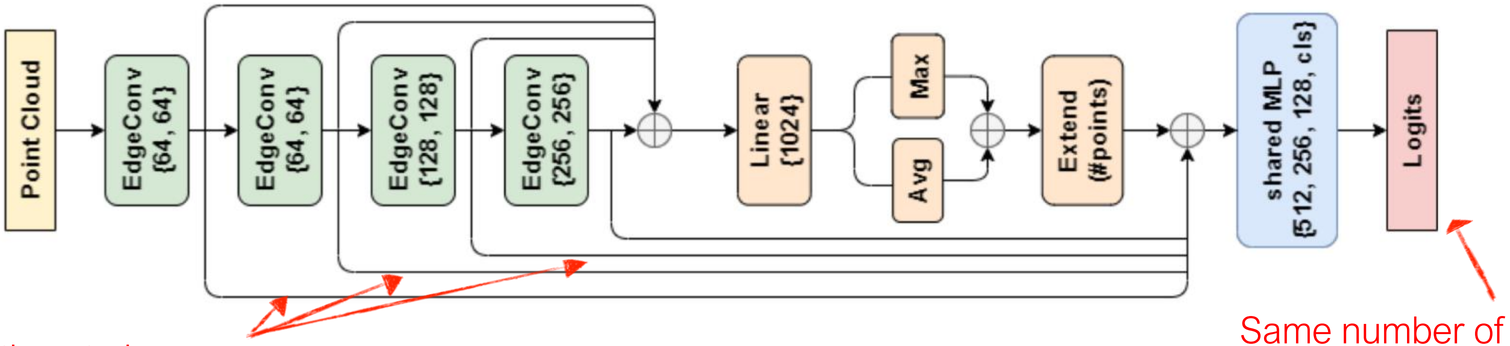




does not include SiPM emulation
95% acc.

Object detection (on going)

- DGCNN and dual-readout calorimeter high granularity can also be exploited for object (particle) detection inside taus and jets
- a proto-step for a particle flow algorithm for taus and jets
- train the DGCNN to predict the label associated with each fiber

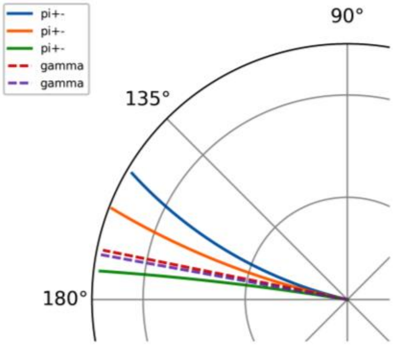


skip connections to increase sensitivity to multiscale features

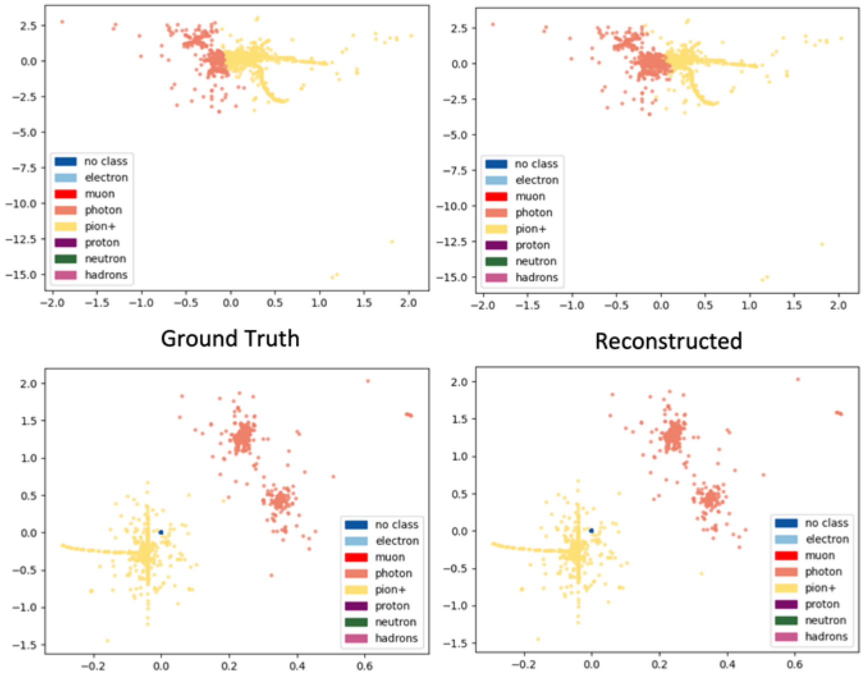
Same number of inputs and outputs

Object detection (on going)

- identify the particle associated to the larger energy deposit in each fiber
- label each fiber by extrapolating MC truth particles from production to the DRC into the IDEA magnetic field



Example: segmentation of two $\tau \rightarrow \pi\pi^0\nu_\tau$ events



Summary

- Very good performances in particle identification obtained by leveraging geometrical deep learning models using standalone dual readout calorimeter of the IDEA concept detector
- Results based on full GEANT4 simulation of the IDEA detector geometry including B field, solenoid material effects, and parametric simulation of SiPM readout
- Up to 91% average identification accuracy for an 8-class classification of QCD jets and leptonic and hadronic tau decay modes
- Developed a Bayesian-DGCNN for robust estimation of model prediction and uncertainties with comparable performances as the conventional DGCNN
- On-going: identification of secondary particles inside tau decays and QCD jets for proto particle-flow
- Extension the developed techniques with the use of the whole IDEA detector will follow soon …