MACHINE LEARNING IN KM3NET

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KM3NeT

Asterics
Astronomy ESFRI & Research Infrastructure Cluster

Obelics

UNIVERSITY OF CAMBRIDGE

LAPP

THIRD ASTERICS – OBELICS WORKSHOP

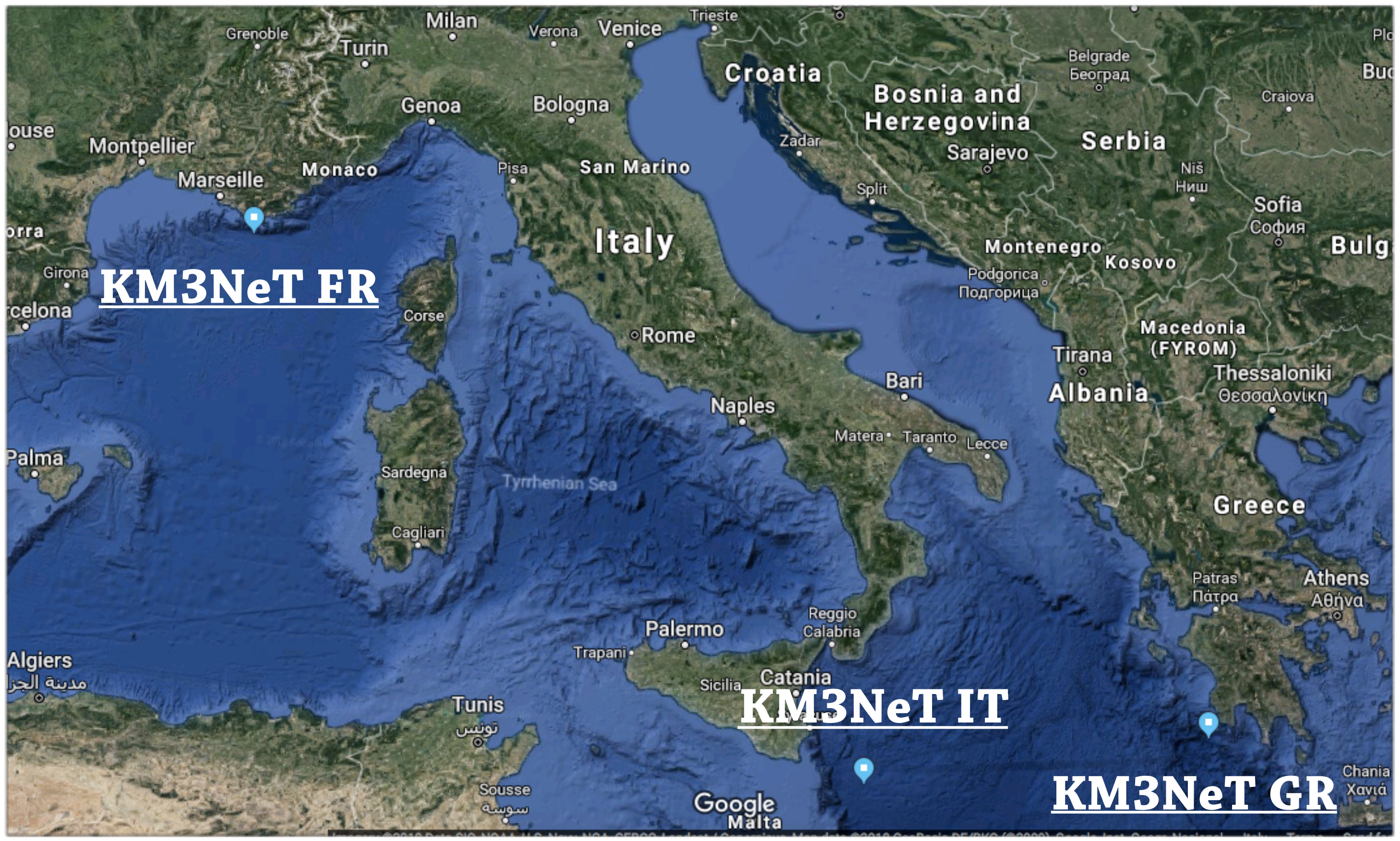
New paths in data analysis and open data provision in Astronomy and Astroparticle Physics

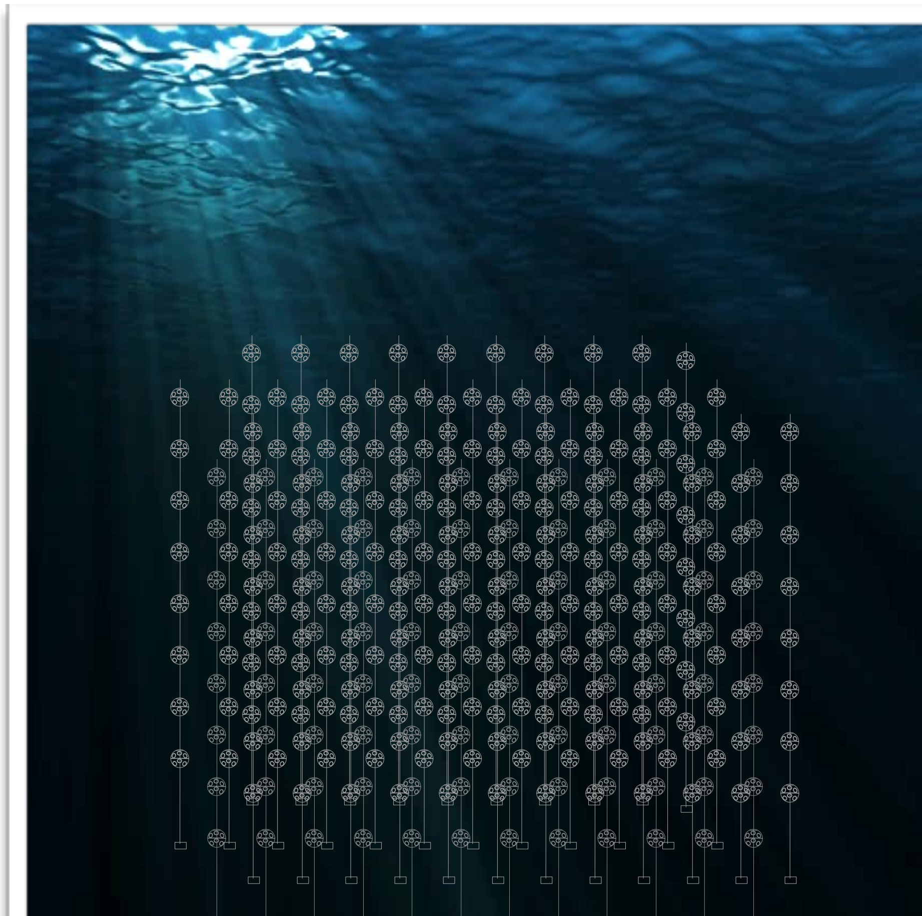
23- 26 OCTOBER 2018

POSTDOC CENTRE @ EDDINGTON
105 EDDINGTON PLACE
CAMBRIDGE
CB3 1AS

ASTERICS is a project supported by the European Commission Framework Programme Horizon 2020 Research and Innovation action under grant agreement n. 653477

KM3NeT Infrastructure





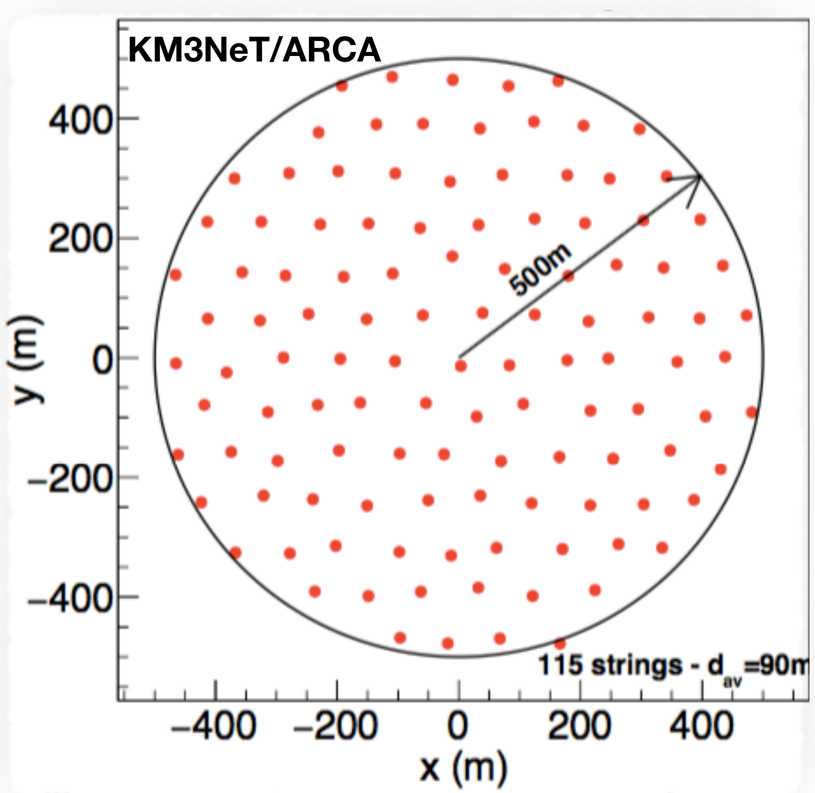
Looking at neutrinos from below, ie. look towards the centre of the Milky Way
Detector deployed deep under water

KM3NeT Experiment

KM3NeT-ARCA

Astroparticle Research with Cosmics in the Abyss

2 "building blocks" of **115** Detection Units
700m in height.
DOMs spaced **90**m in X-Y, **36**m in Z

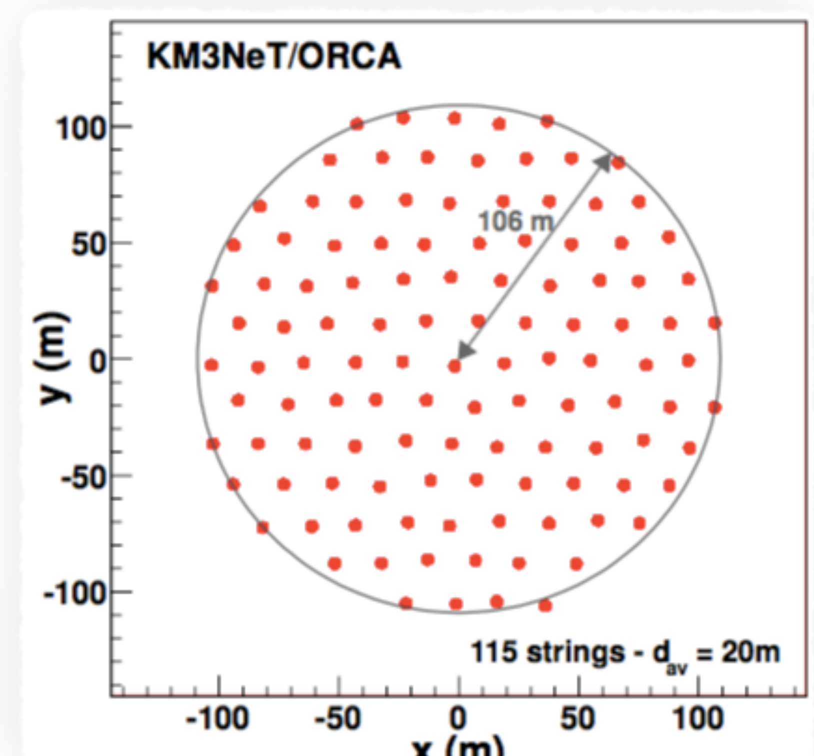


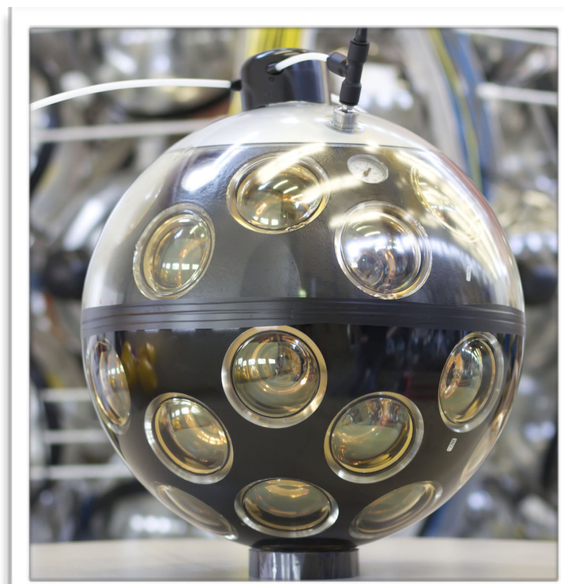
KM3NeT-ORCA

Oscillation Research with Cosmics in the Abyss

Low energy neutrino detection - Neutrino mass hierarchy

1 "building block" of **115** Detection Units:
200 m in height.
DOMs spaced **20**m in X-Y, **9**m in Z





1 DOM = 31 PMTs

KM3NeT IT

2 ARCA Detection Units

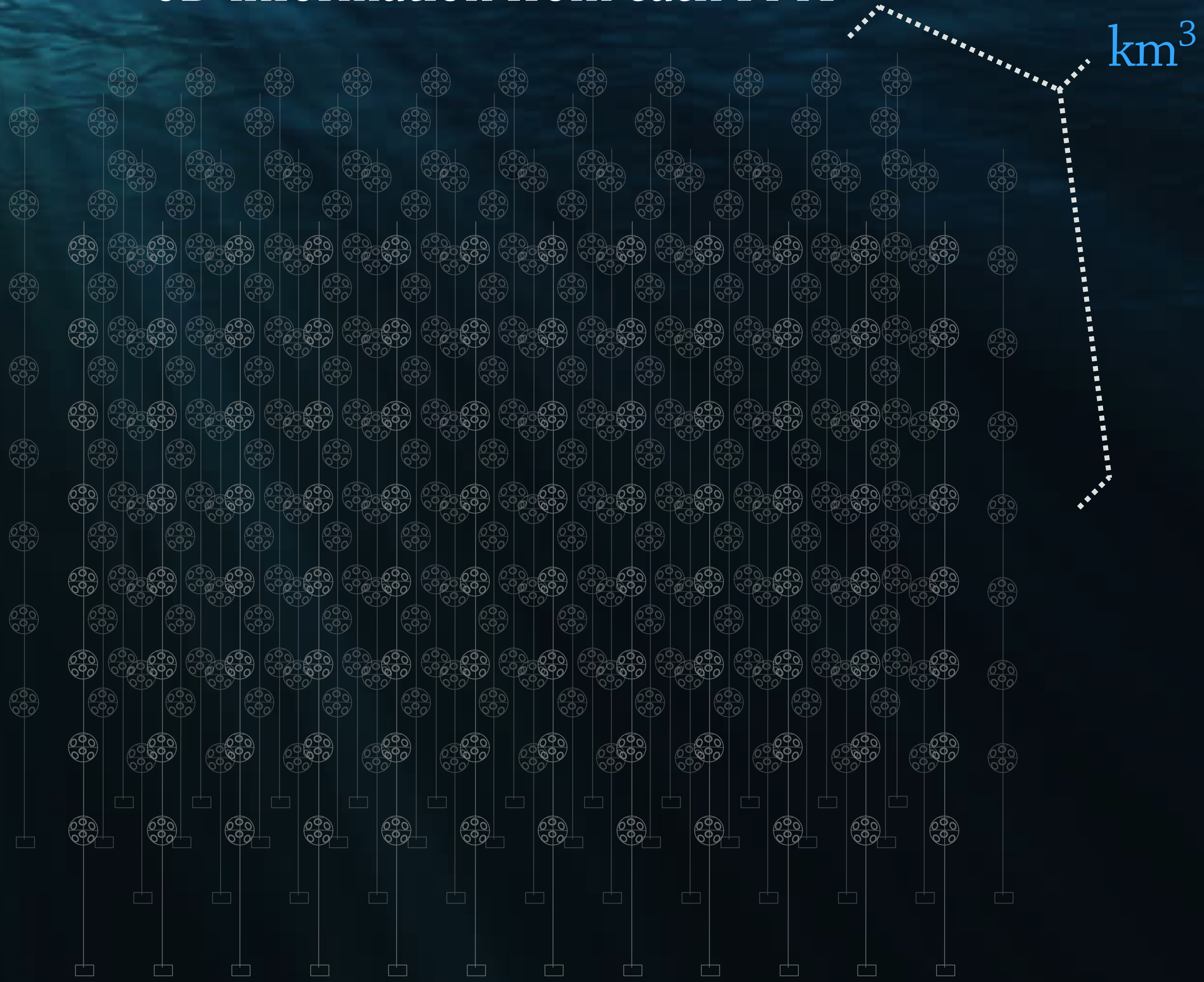
current status

KM3NeT FR

2 ORCA Detection Units

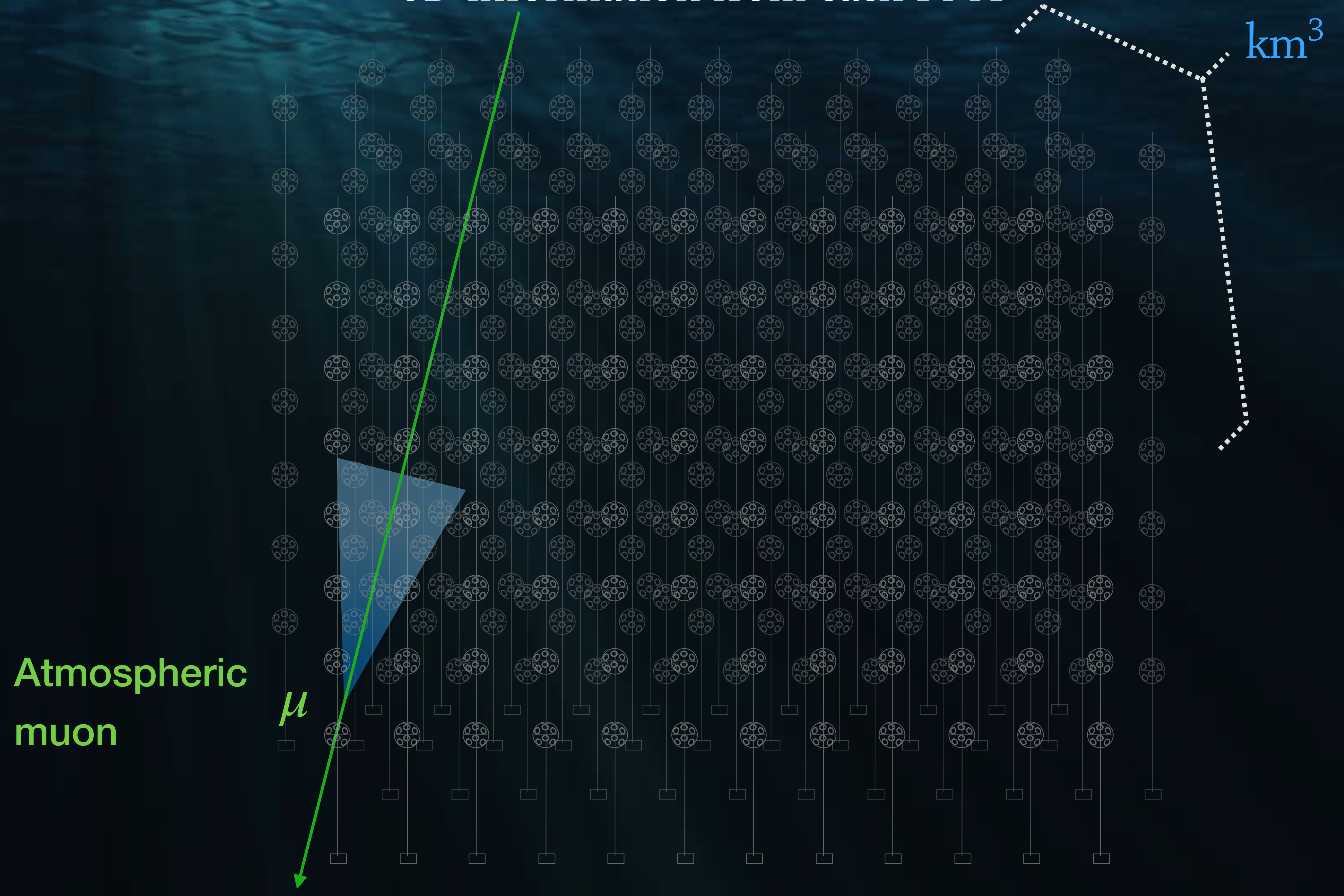
KM3NeT events

6D information from each PMT



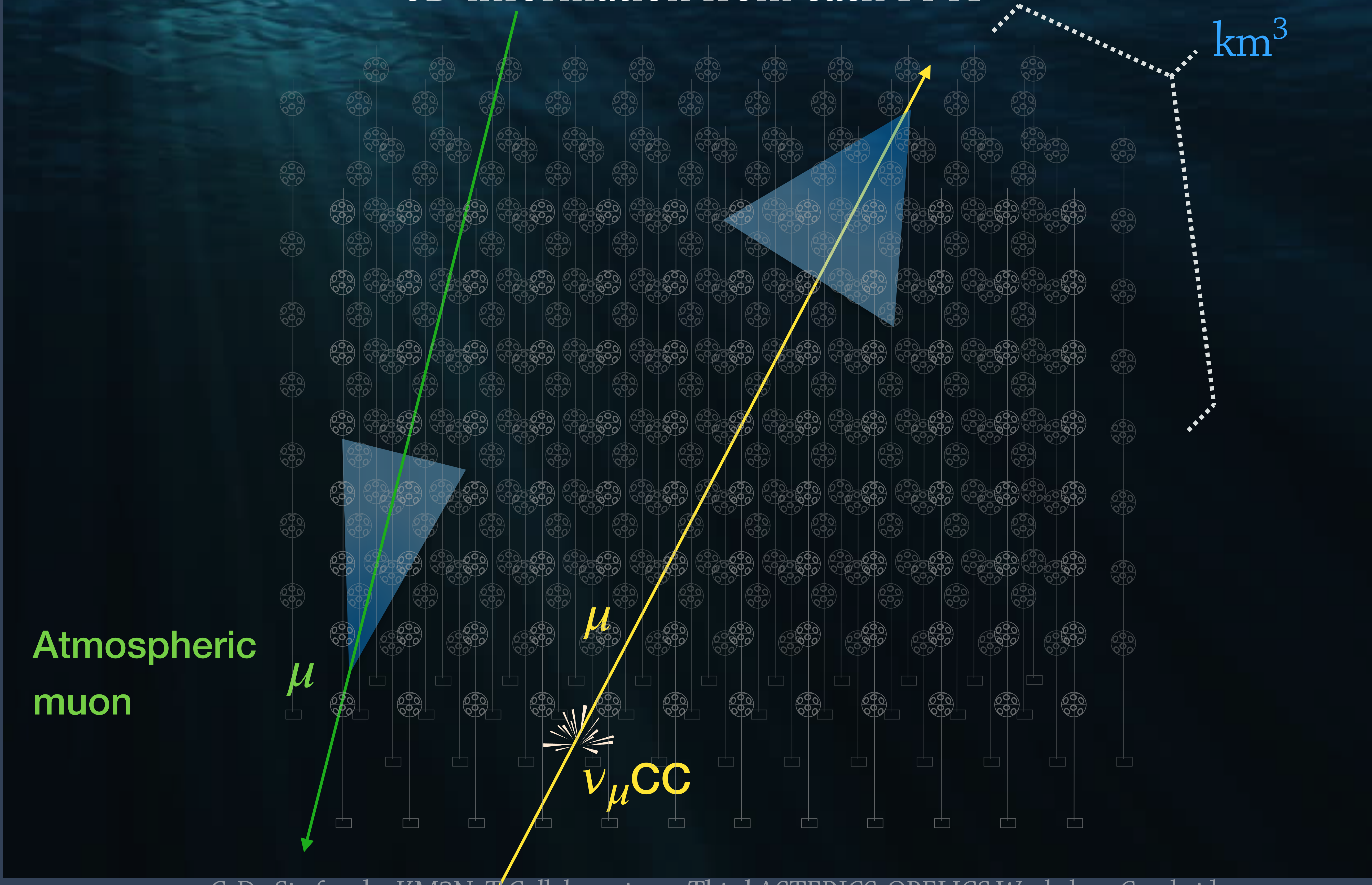
KM3NeT events

6D information from each PMT



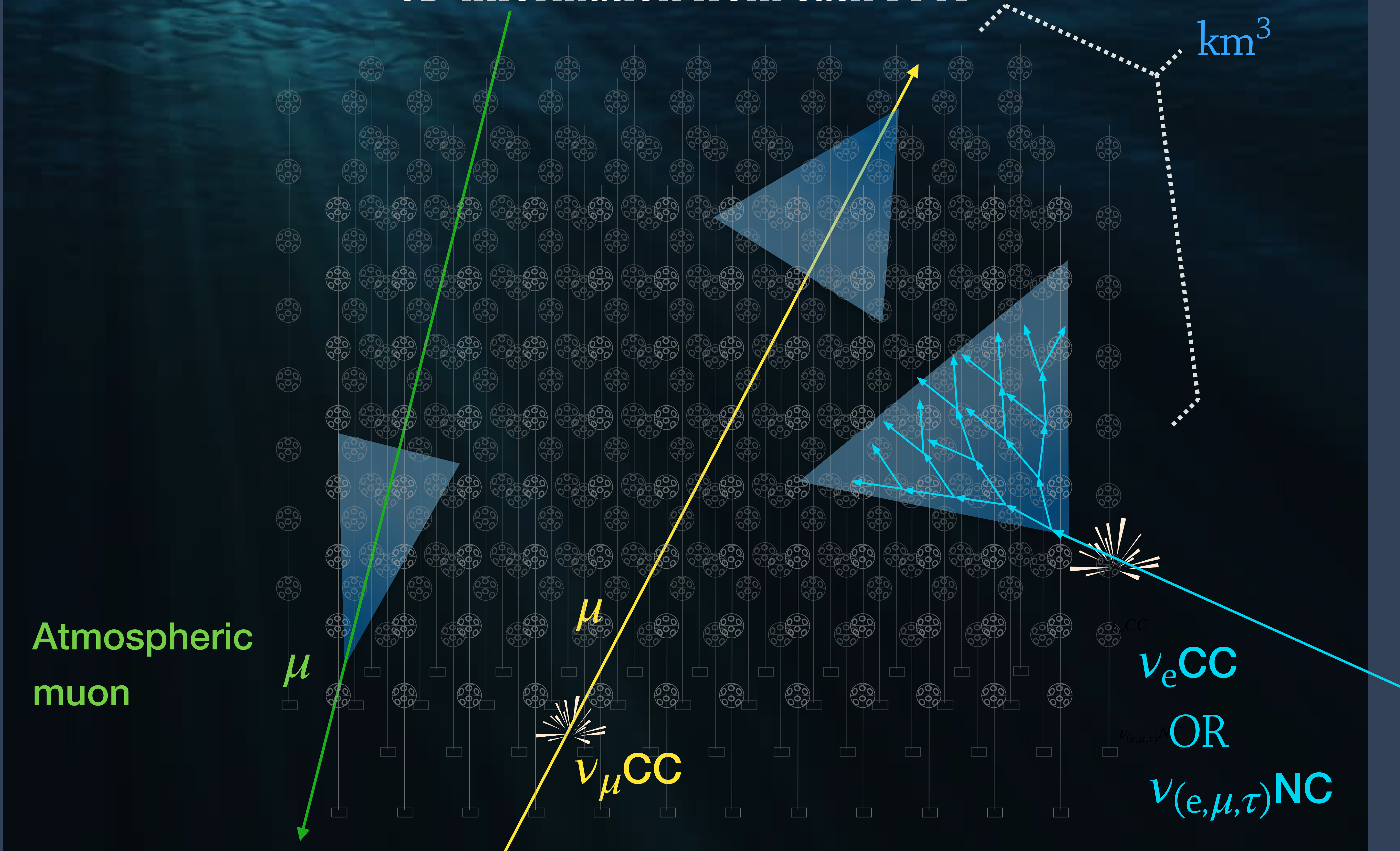
KM3NeT events

6D information from each PMT



KM3NeT events

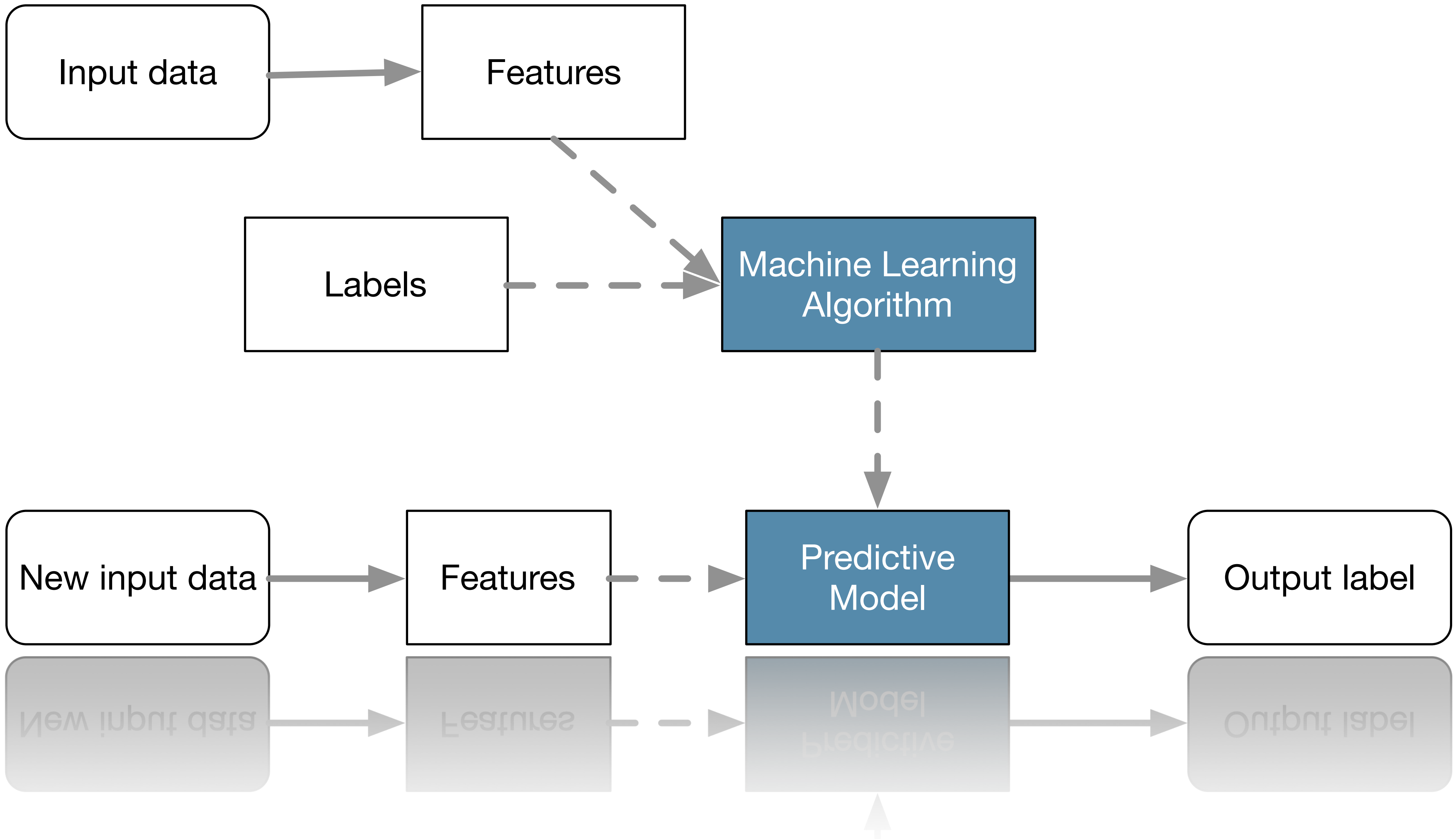
6D information from each PMT



STUDYING NEUTRINO INTERACTIONS WITH DEEP LEARNING

EXTRACT INFORMATION FROM RAW DATA - NO RECONSTRUCTION REQUIRED

Machine Learning: Learning from examples



Categorical labels:
Classification

Continuous labels:
Regression

(Some) Existing Machine Learning Applications for KM3NeT

- MVA in Point-Source Analysis (Credits A. Trovato)
    - Random Forest for 3-class Prediction (Source, Atm ν, Atm μ)
- High Energy Starting Muons (Credits K. Pikounis)
    - Boosted Decision Trees for 2-class Prediction (Signal, Background)
- EReNN: Energy Reconstruction with Neural Networks (Credits E. Drakopoulou, et al.)
    - Multi-Layer Perceptron for Energy Reconstruction
- Shallow and Deep Learning Applications in KM3NeT (Credits S. Geißelsöder et al.)
    - Multiple applications of Machine and Deep Learning Models in Supervised and Unsupervised Learning settings

- **Deep Learning applications for ARCA** (C. De Sio - **me**)
- **Deep Learning in ORCA with OrcaNet** (M. Moser et al. - **ECAP**)

DESCRIBED IN THIS PRESENTATION

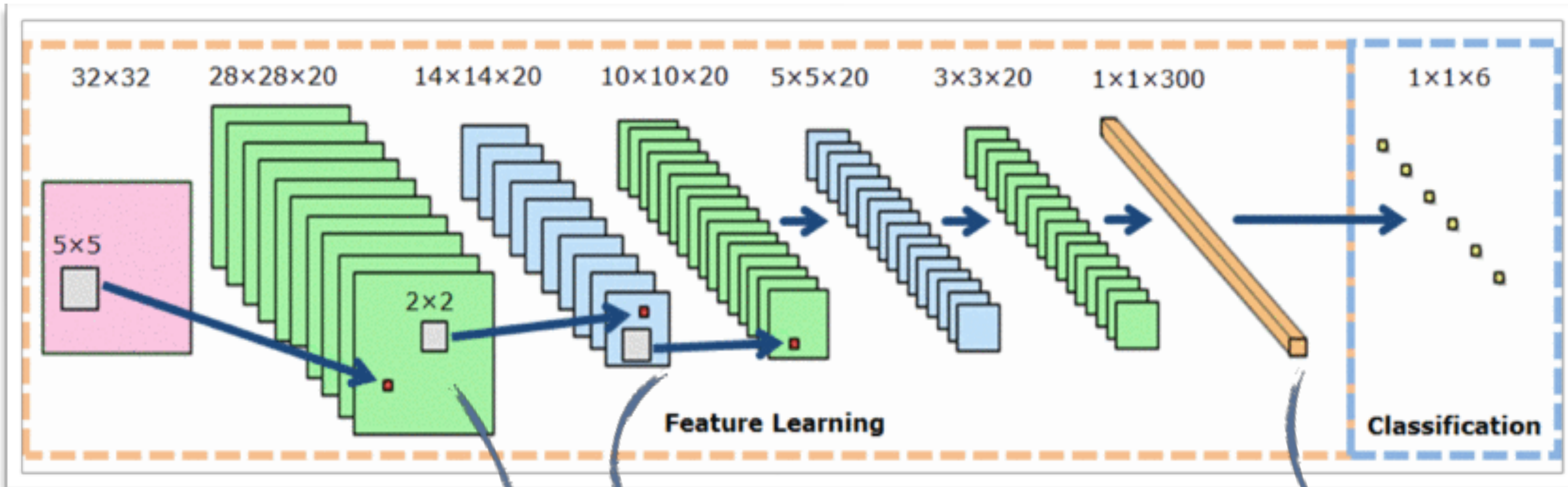
Deep Learning Applications for KM3NeT-ARCA

Four learning tasks:

1) Up-going/Down-going particle Classification
2) $\nu_\mu CC \, / \, \nu_e CC$ interaction Classification
3) Particle Energy Estimation
4) Particle Direction Estimation (Z component)

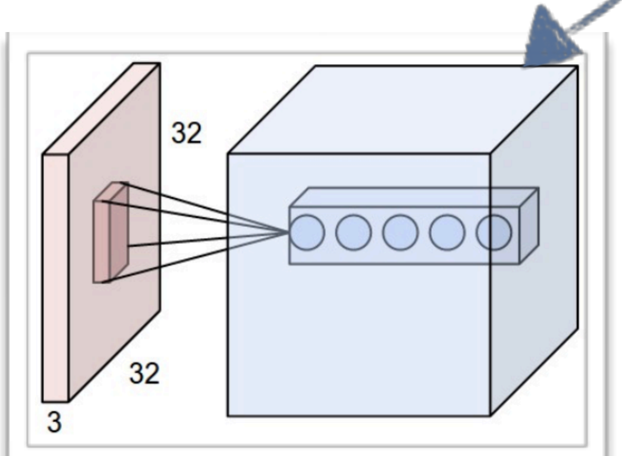
- Using **triggered hits** and times as input data
- Convolutional Neural Network models have been **designed** for each task

Convolutional Deep Networks (CNN): Main Ingredients



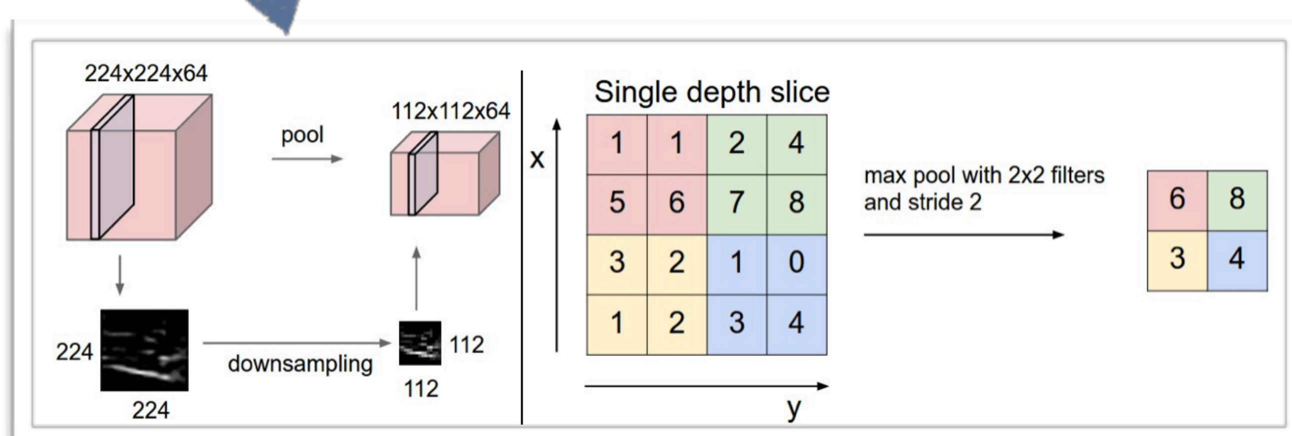
source: bit.ly/cnn-ingredients

Convolutional Layer



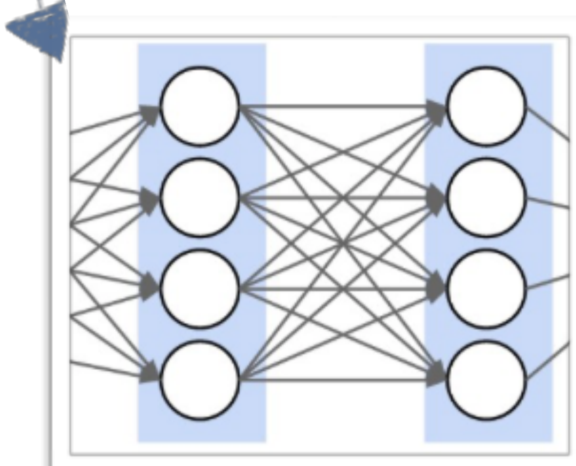
Local Feature Maps Learning

Pooling Layer



Downscaling and Space Invariant Features Learning

Dense Layer

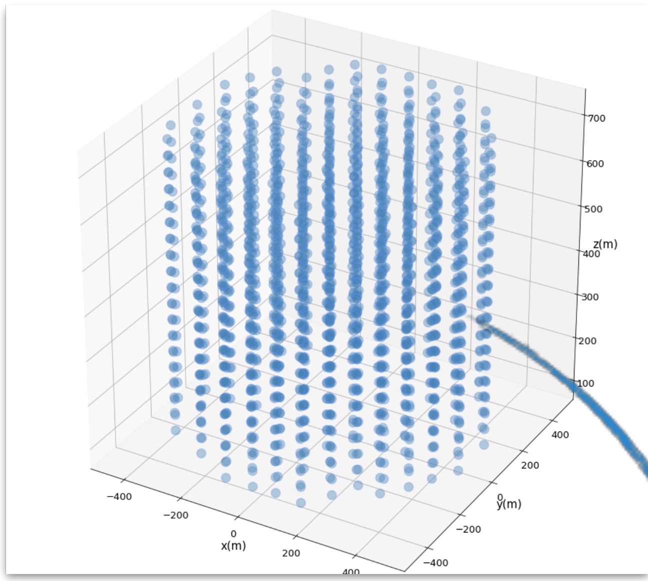


Global Feature Learning & Prediction

DATA PREPARATION

PREPARE DATA TO BE FED INTO NEURAL NETWORKS

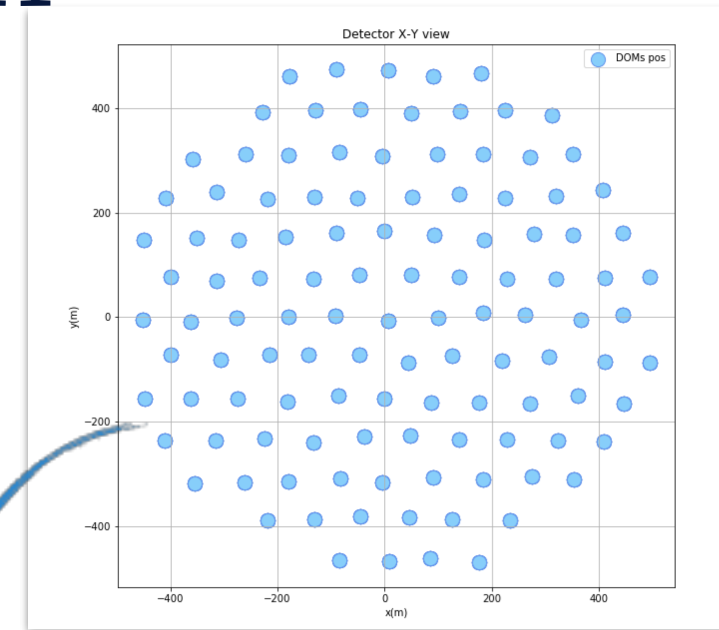
Space regularisation

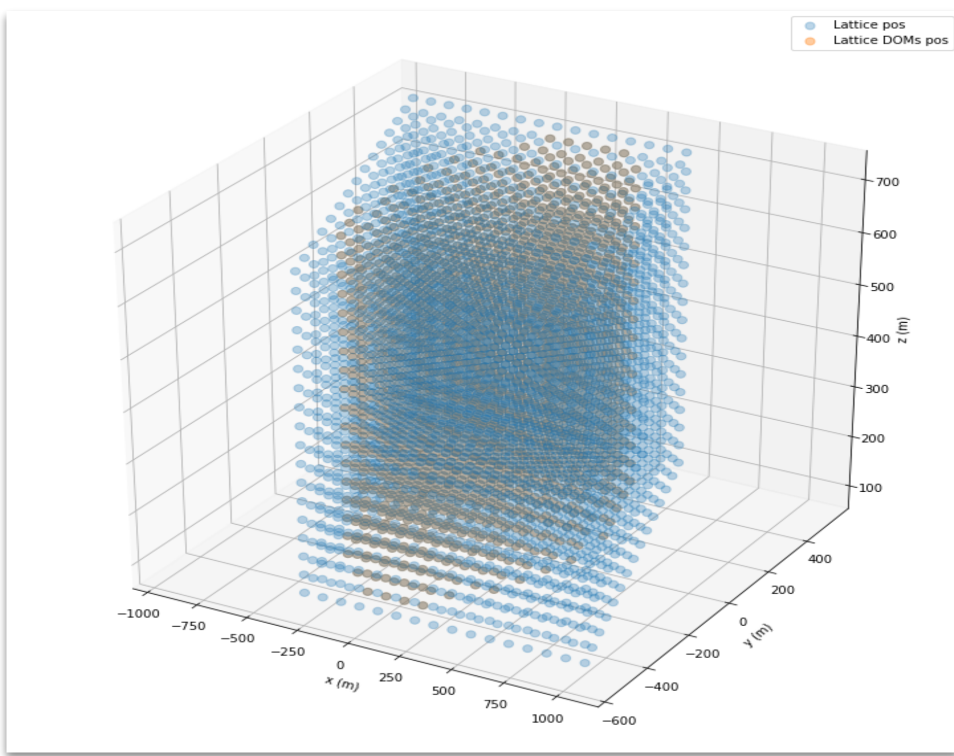


Regularised Detector Structure*

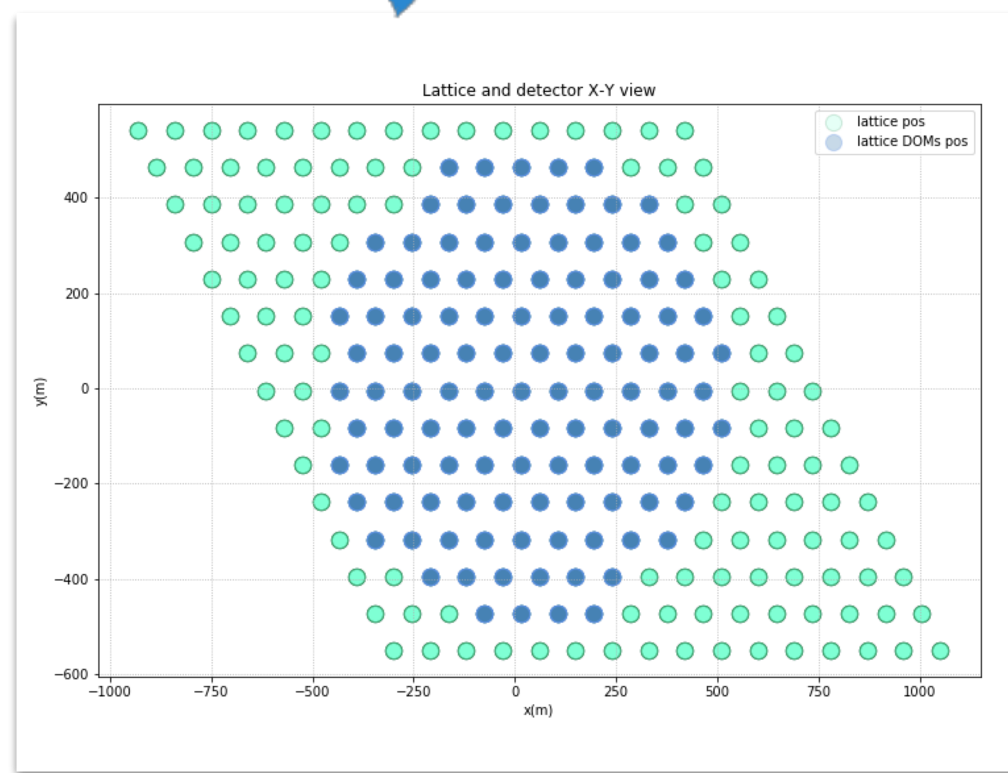
- **exactly** 90m spaced in (X,Y)
- **exactly** 36m spaced in Z

Regularised detector contained in **Lattice**





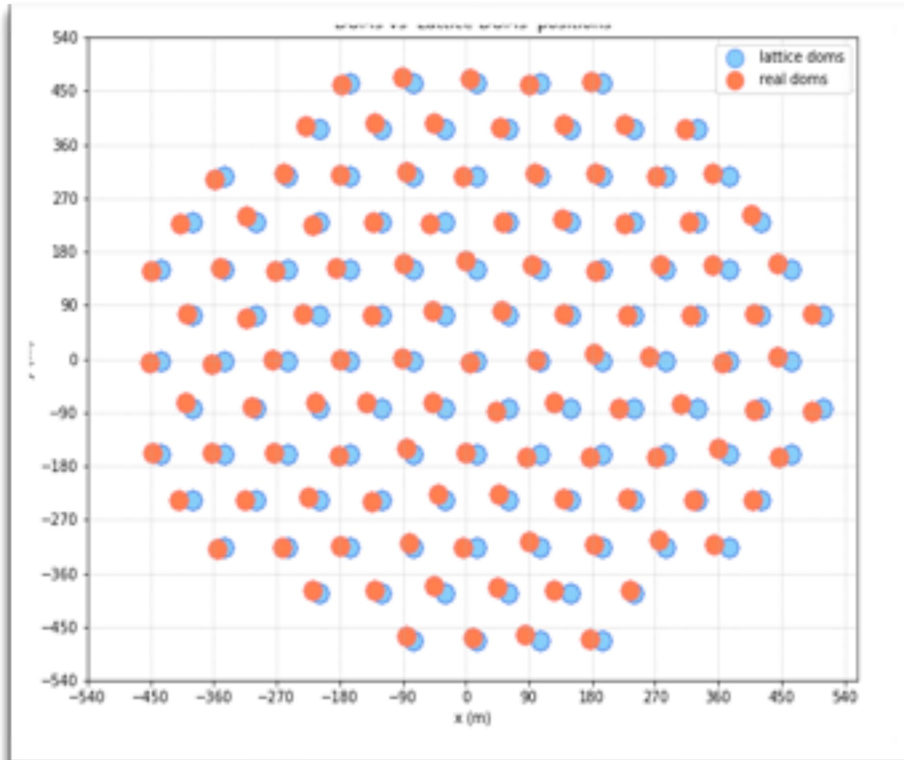
Regularised Detector XYZ-view



Regularised Detector XY-view

*Deviation from regularised structure can be introduced later as a next-order correction

Event Definition



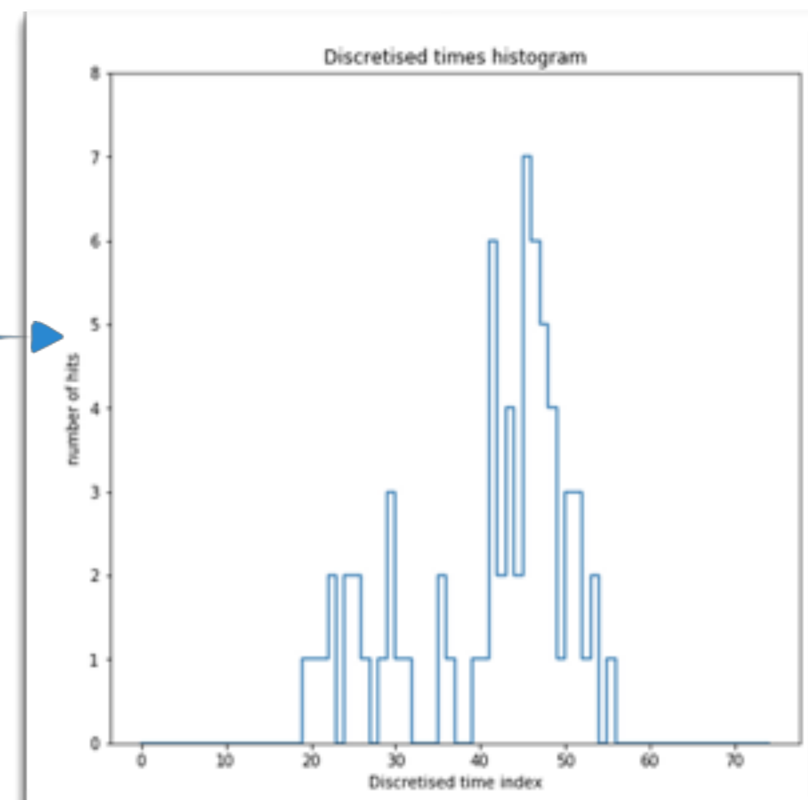
Lattice DOMs vs Real DOMs Positions

Reducing (useless and time consuming) sparsity in data

- Transforming DOM IDs into Lattice DOM IDs
  - a single DOM ID is mapped to an index in the [16x15x18] Lattice

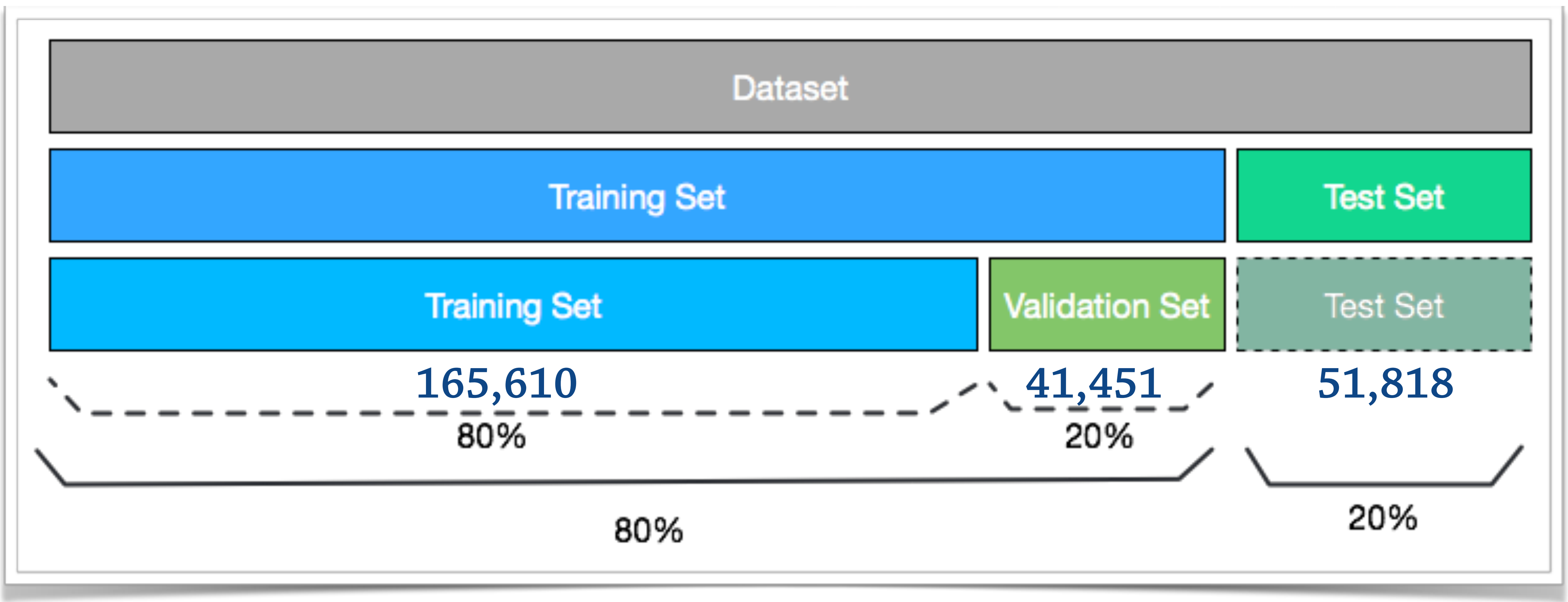
Event in the Regularised Detector:

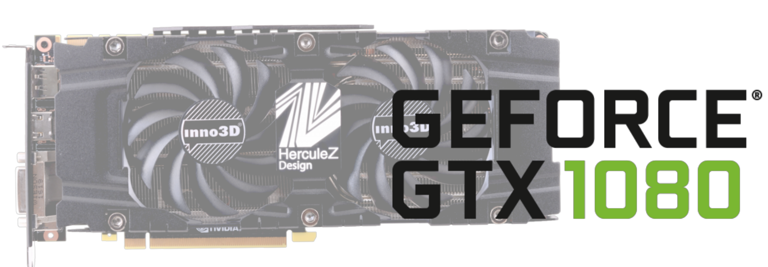
1. Times are discretized, with a fixed number of steps (i.e. n_Time_steps=75) ~12 ns/bin
2. A collection of **hits** over time
   - Event mapped to a 4D structure (tensor) of shape [75x16x15x18]
   - [discrete_time_index, x_index, y_index, z_index]



Dataset

258,879 total events (samples) arranged from 100 $\nu_e CC$ + 100 $\nu_\mu CC$ files



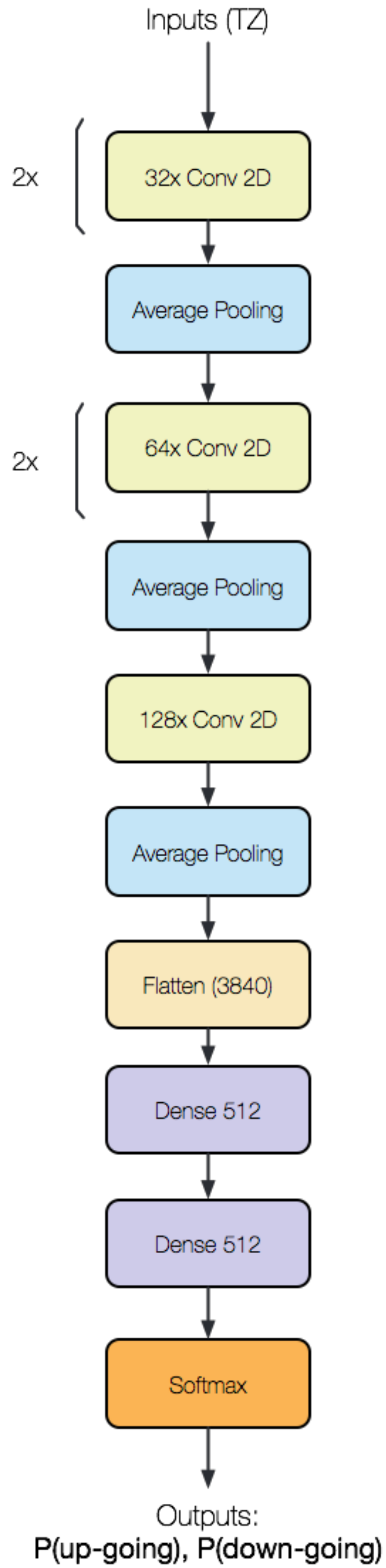


scikit learn + TensorFlow + Keras

LEARNING TASK 1. UP-GOING/DOWN-GOING NEUTRINO CLASSIFICATION

CLASSIFY UP-GOING AND DOWN-GOING NEUTRINOS ACCORDING TO THEIR Z-COORDINATE EVOLUTION OVER TIME

Model architecture and Input Data



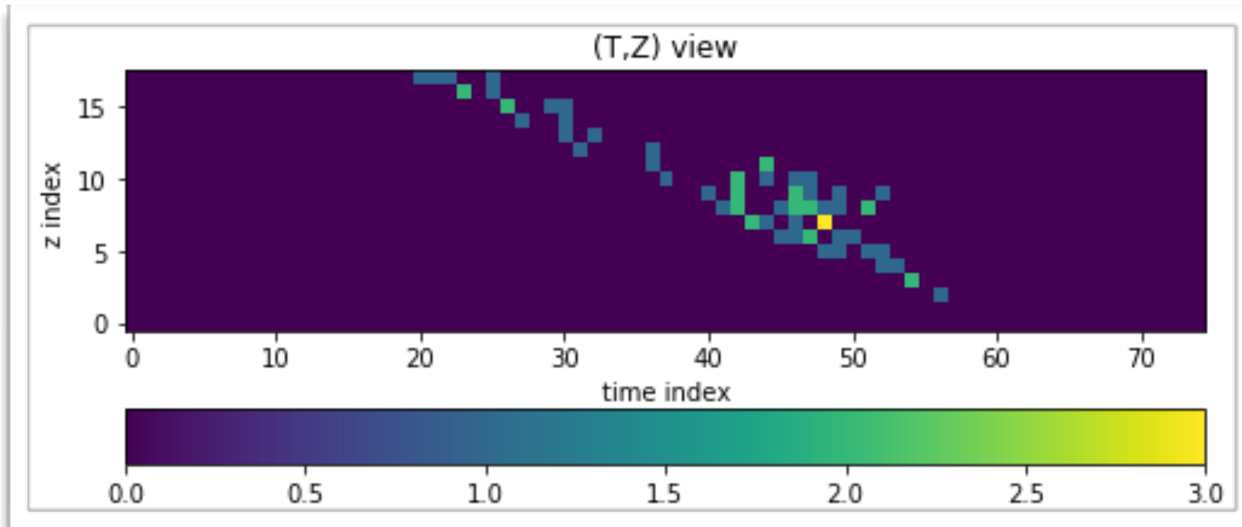
Labels

$$y: \begin{cases} \cos(\theta_z) > 0 : \text{“up-going"} \\ \cos(\theta_z) \leq 0 : \text{“down-going”} \end{cases}$$

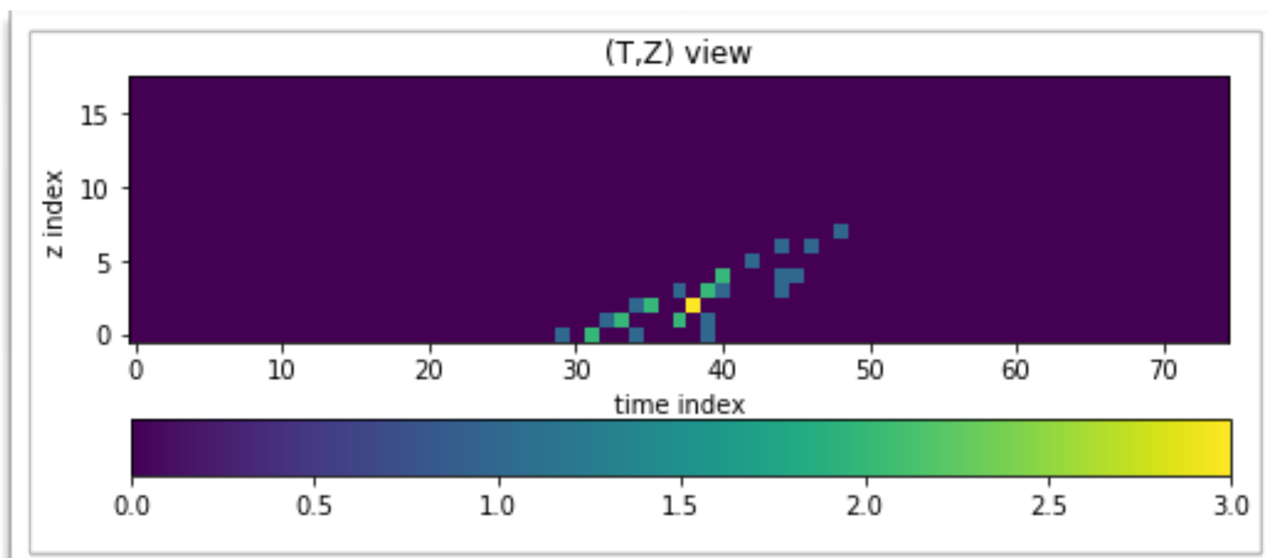
Input tensors reshaped to:

(T,Z): [n_samples, 75, 18]

Input array summed over X and Y axes



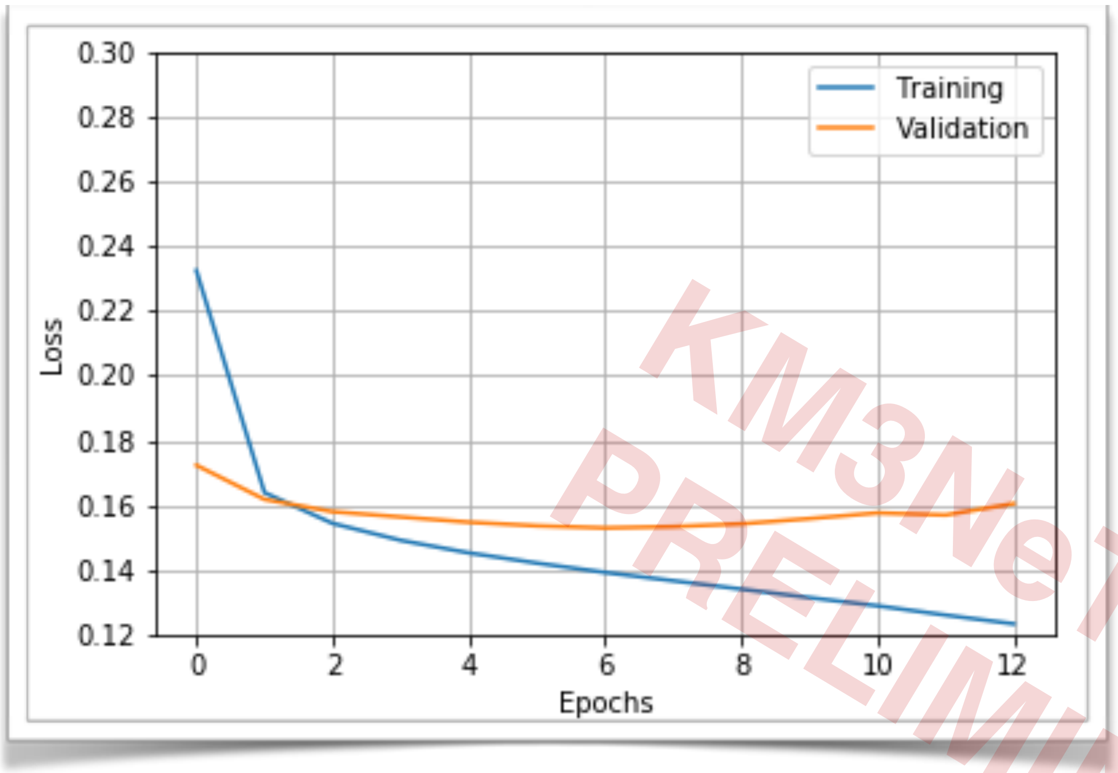
Down-going

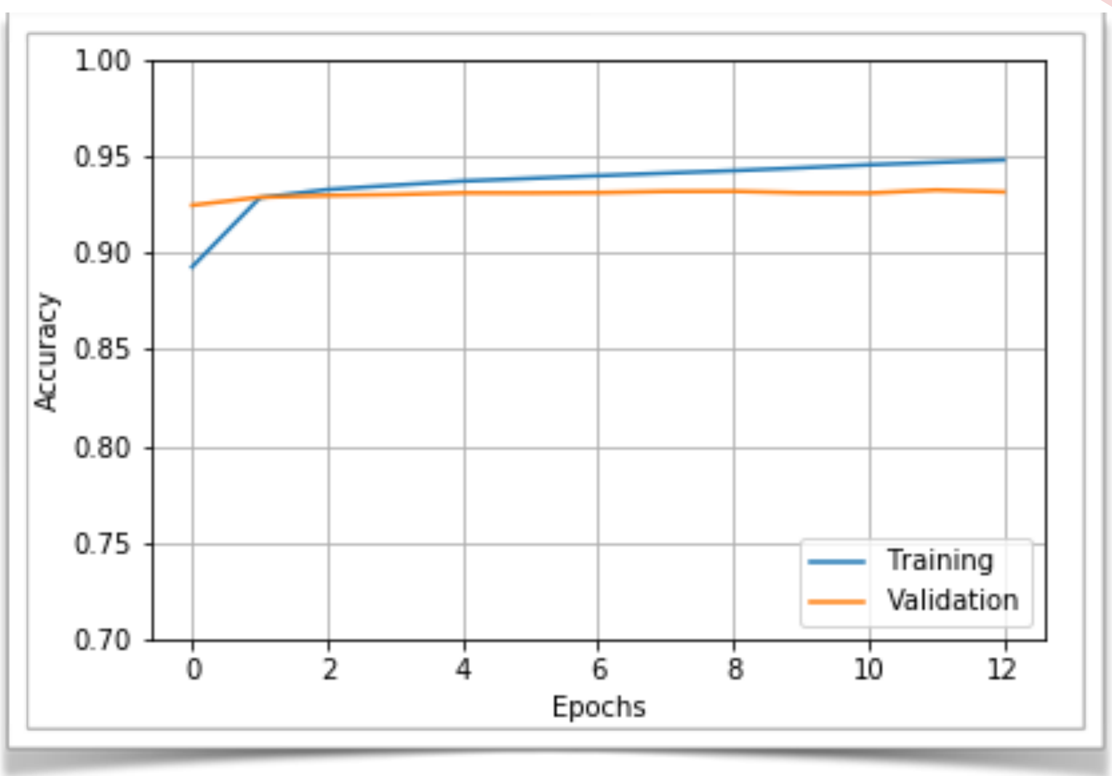


Up-going

Classification results

Training history

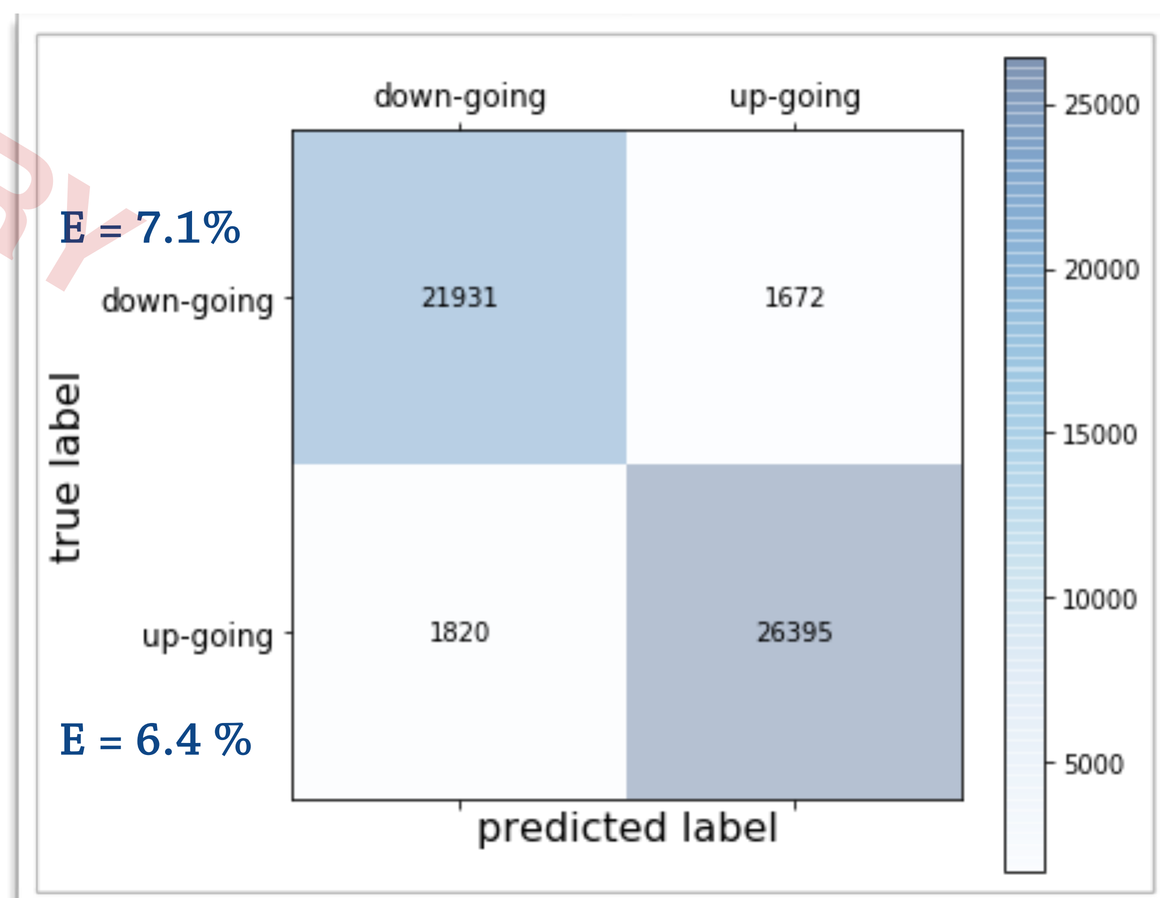




Classification accuracy (on test data)

93.3 %

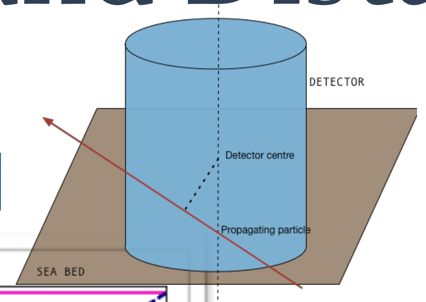
Confusion matrix (on test data)



Energy and Distance dependency

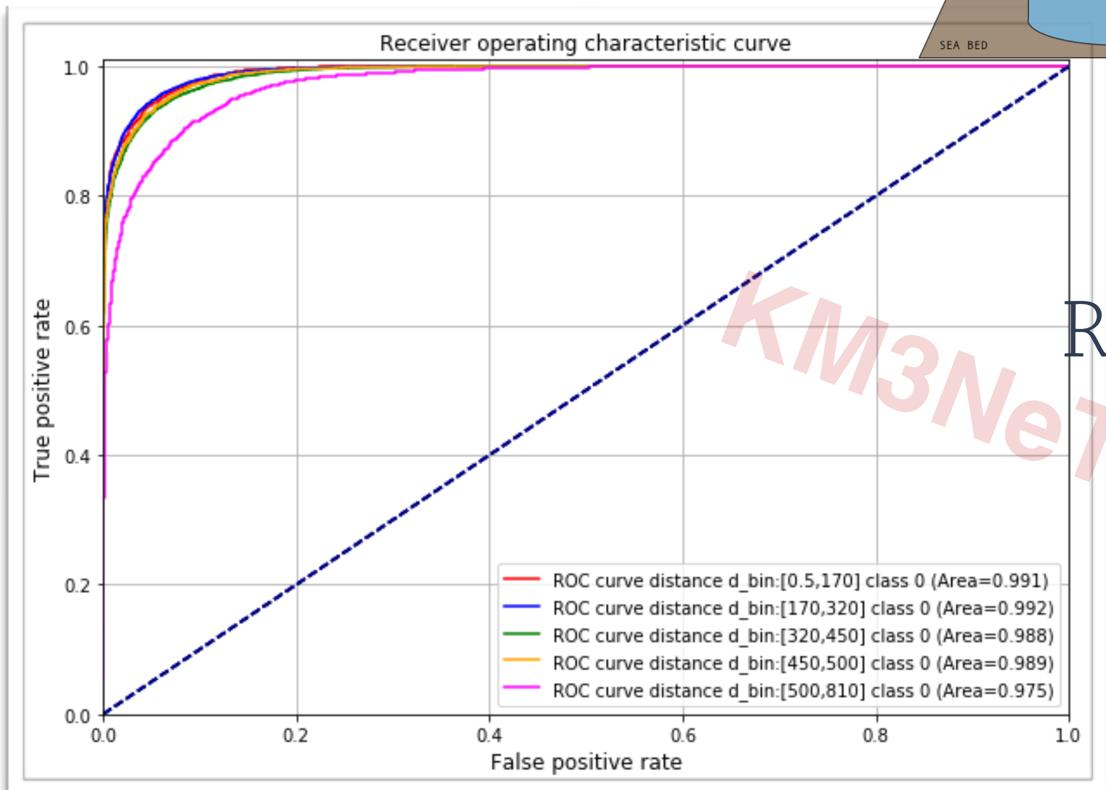
Distance bins (m)

[0.5, 170, 320, 450, 500, 810]

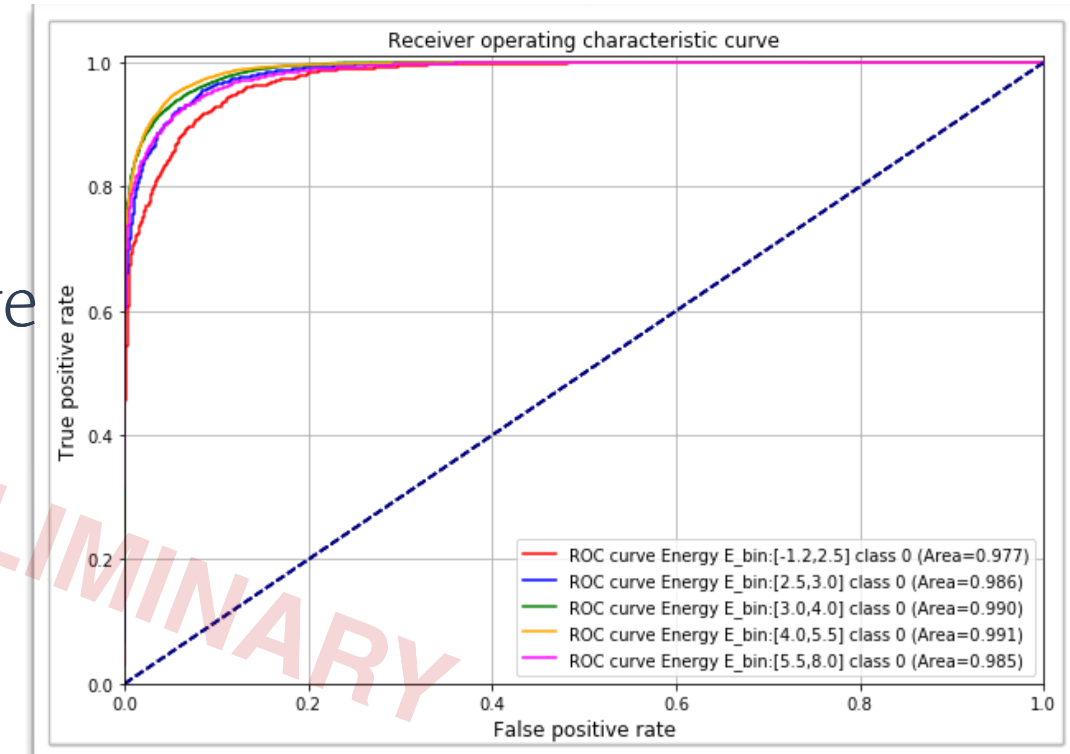


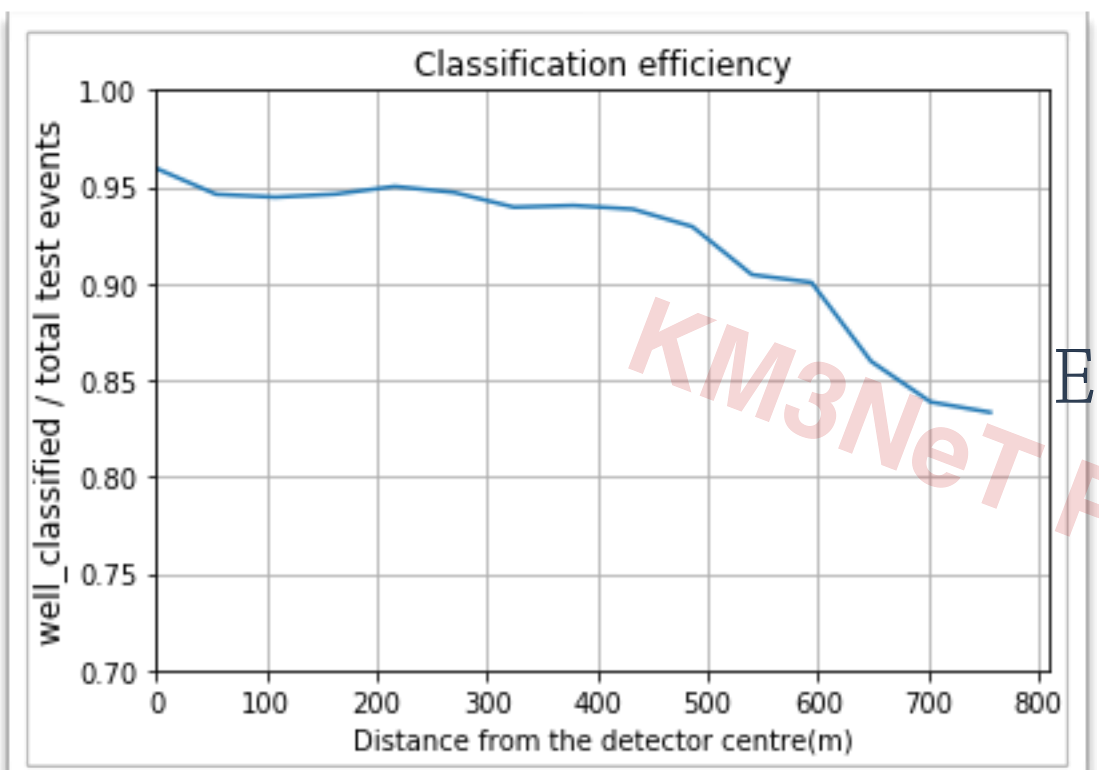
Energy bins (Log(E)) [GeV]

[-1.2, 2.5, 3.0, 4.0,5.5, 8.0]

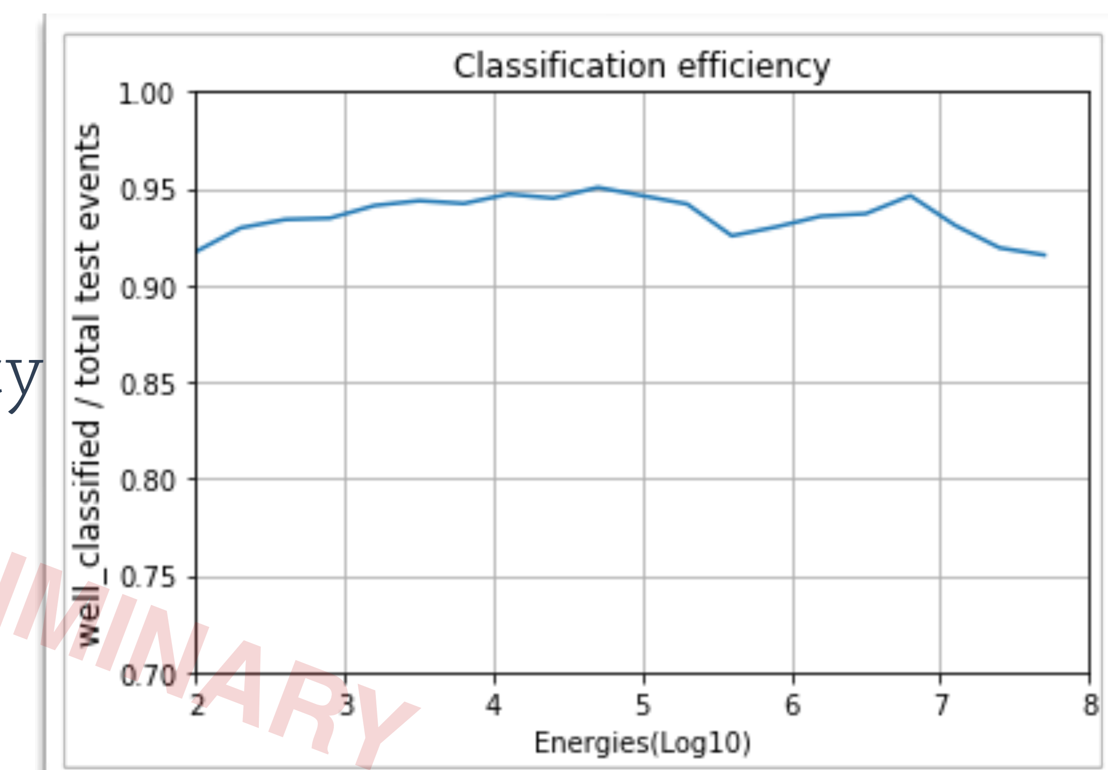


ROC curve





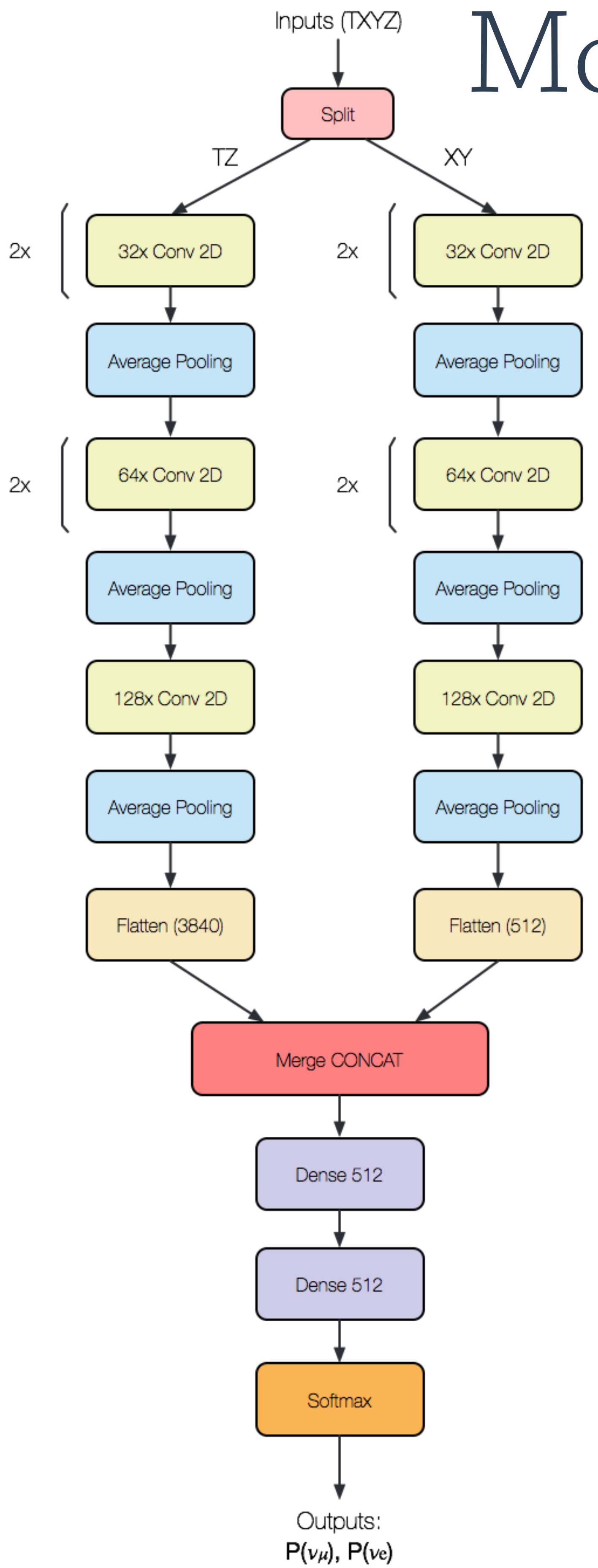
Efficiency



LEARNING TASK 2. $\nu_\mu \mathrm{CC} / \nu_\mathrm{e} \mathrm{CC}$ INTERACTION CLASSIFICATION

CLASSIFY $\nu_\mu CC$ / $\nu_e CC$ INTERACTIONS BASED ON THE SHAPE OF THE EVENTS AND THE EVOLUTION OF POSITIONS OVER TIME

Model architecture and Input Data



CNN model with parallel branches analysing (T,Z) and (X,Y) evolution separately, merged to extract common features

2 Input tensors of shapes:

(T,Z): [n_samples, discrete_time_index, z_index]

(X,Y): [n_samples, x_index, y_index]

Labels

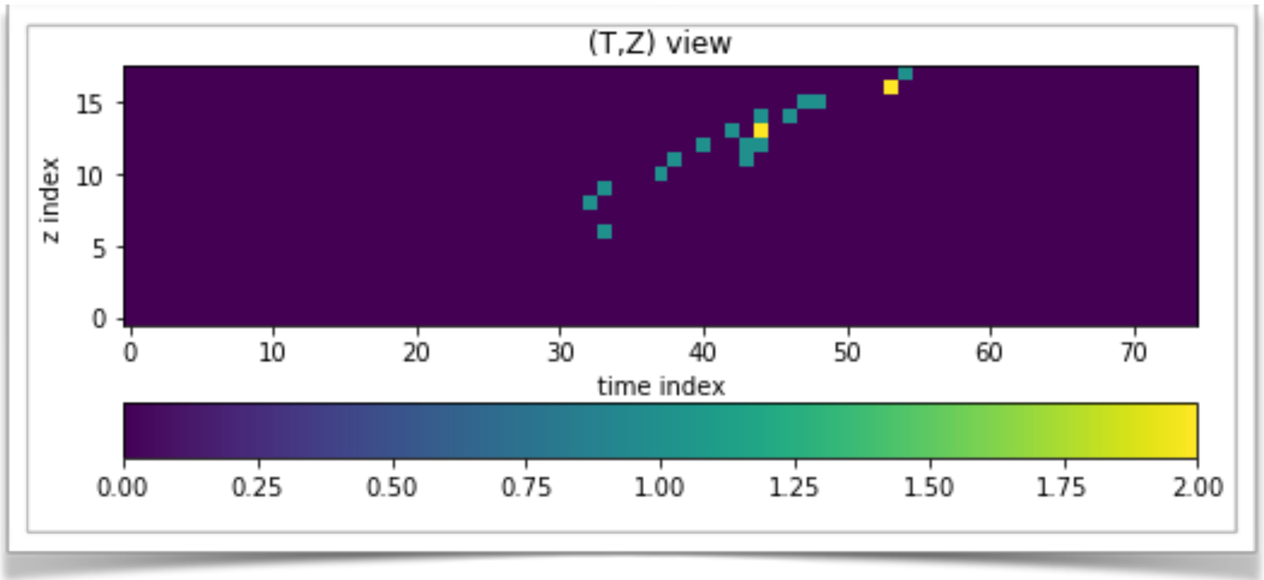
$$y = \begin{cases} 0: & \nu_\mu CC \\ 1: & \nu_e CC \end{cases}$$

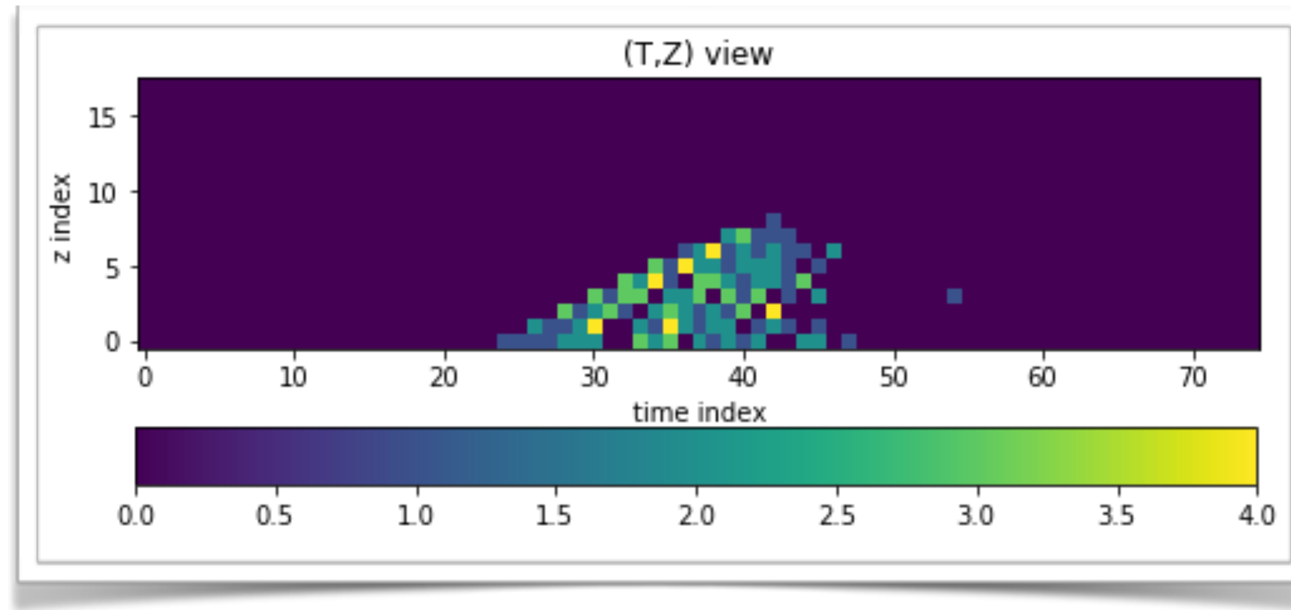
Multiple Views of Events

ν_μCC

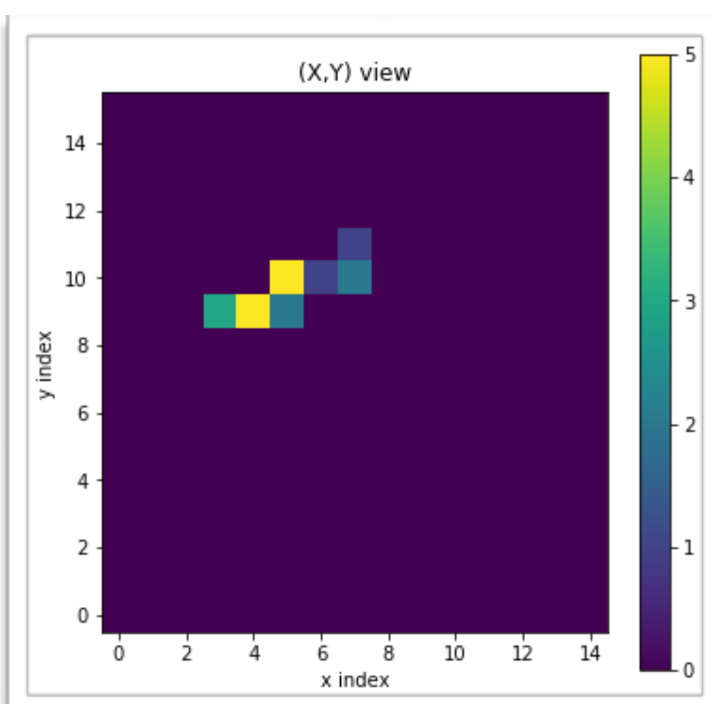
TZ View

ν_eCC

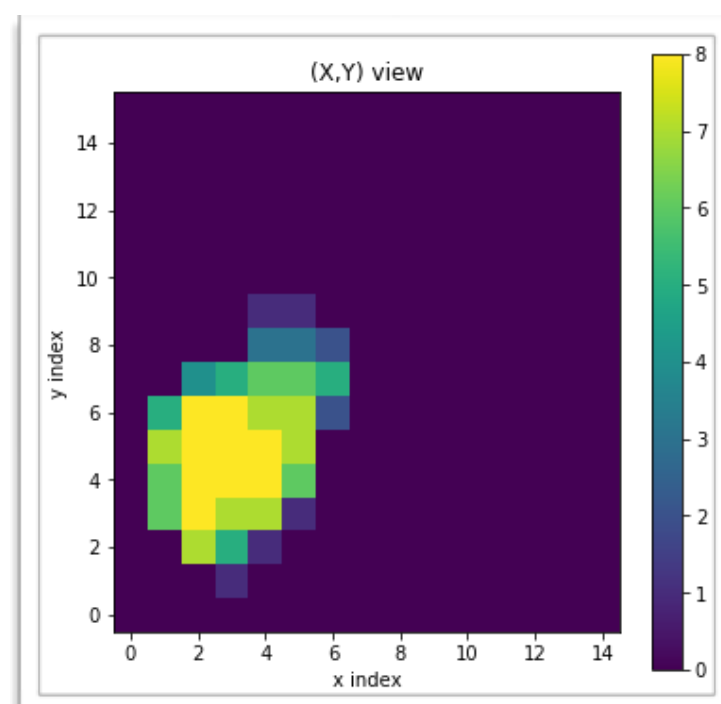




600 GeV



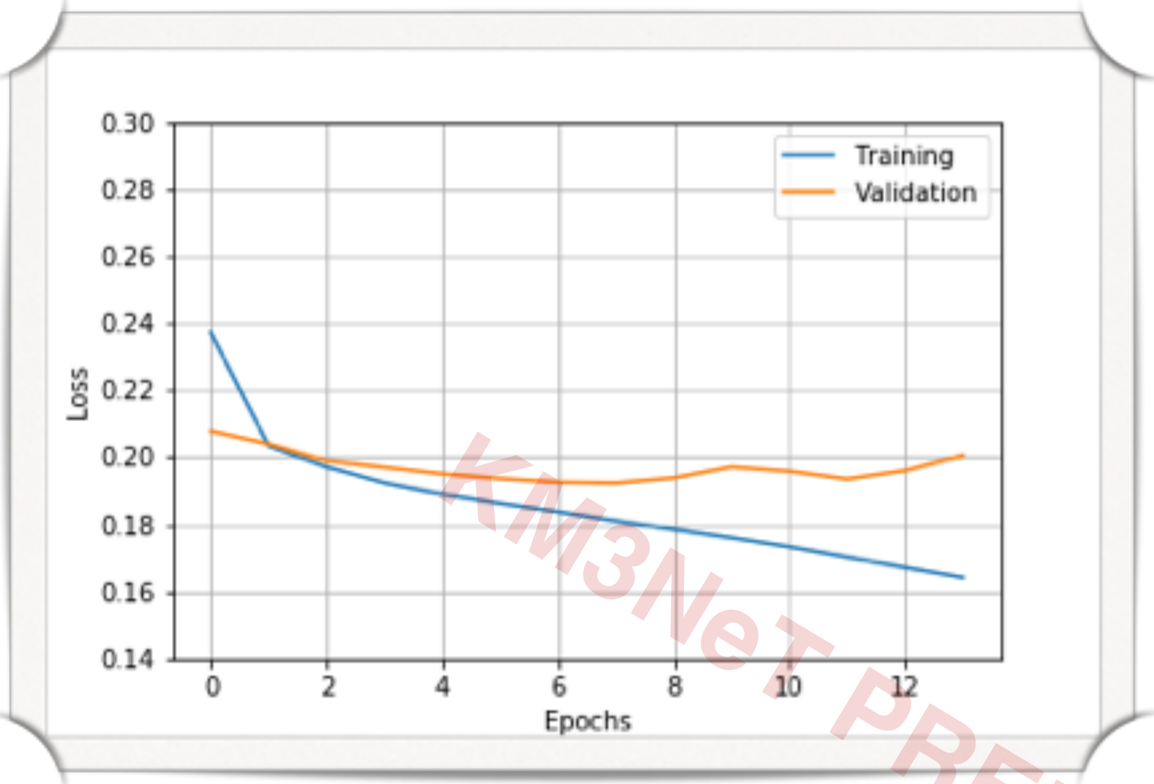
XY View

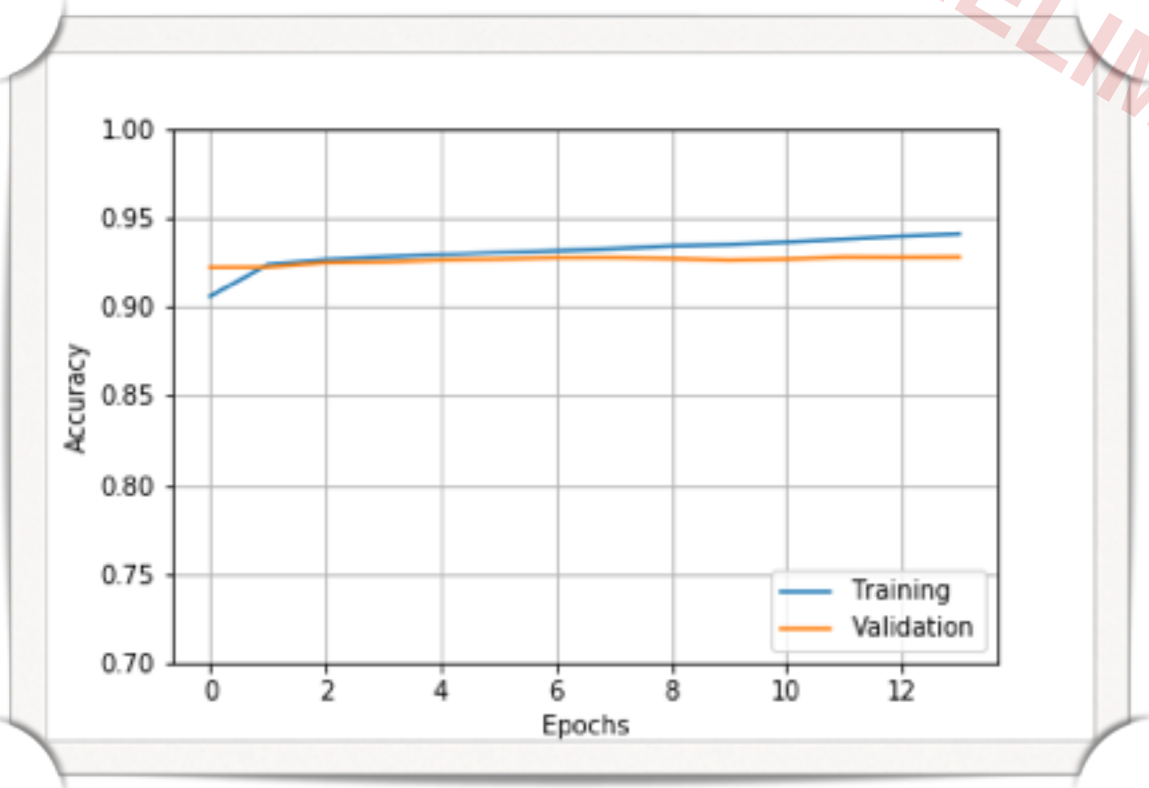


2.5 TeV

Classification results

Training history

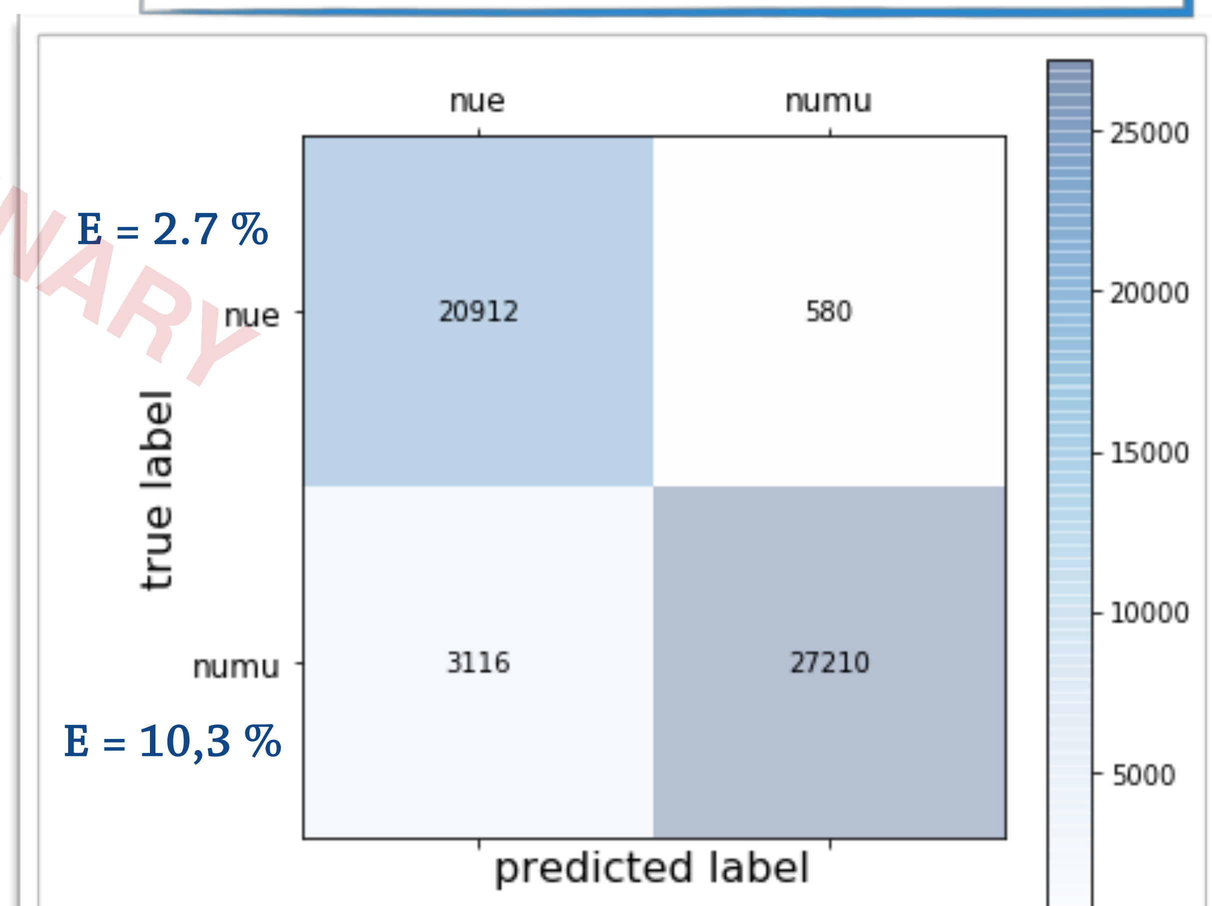




Classification accuracy (on test data)

92.8 %

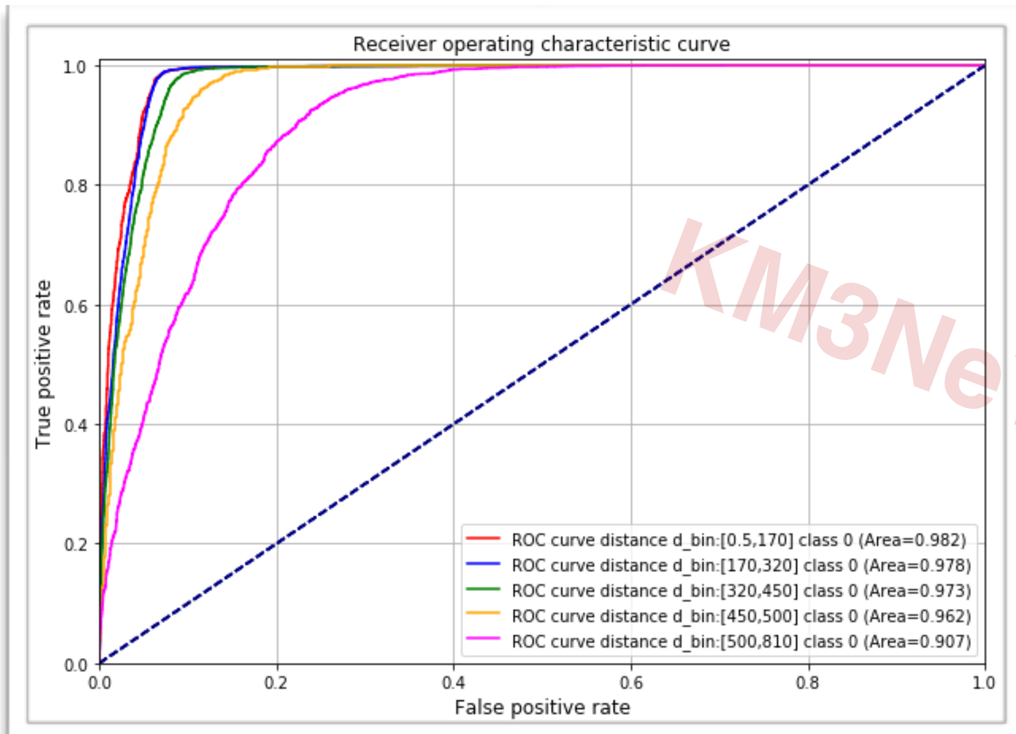
Confusion matrix (on test data)



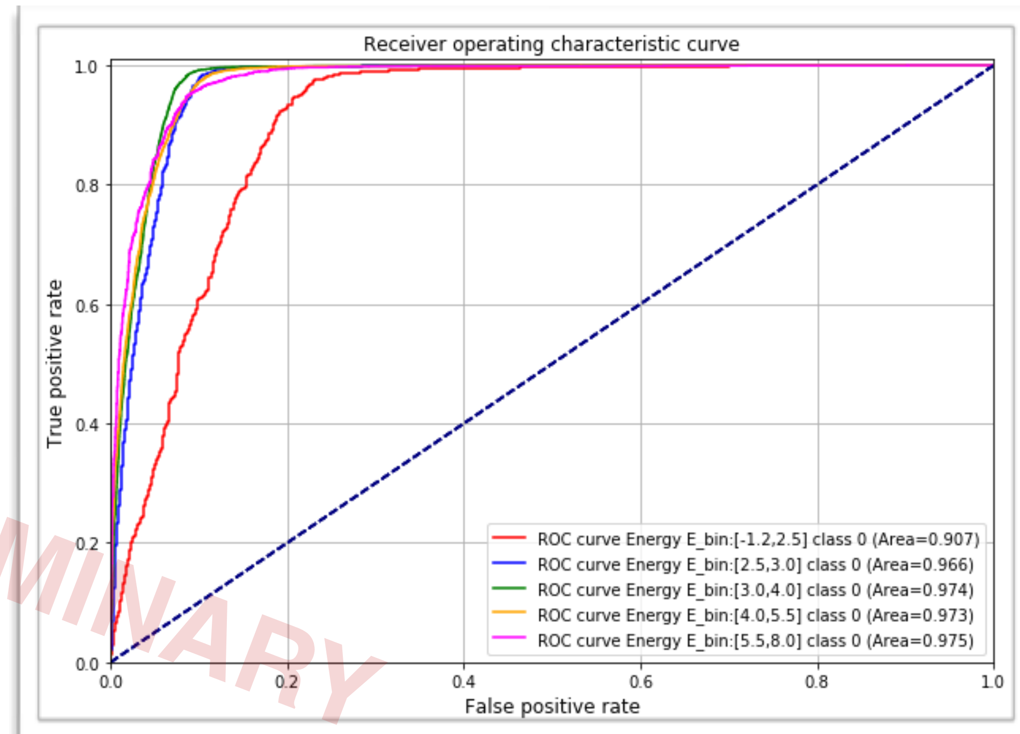
Energy and Distance dependency

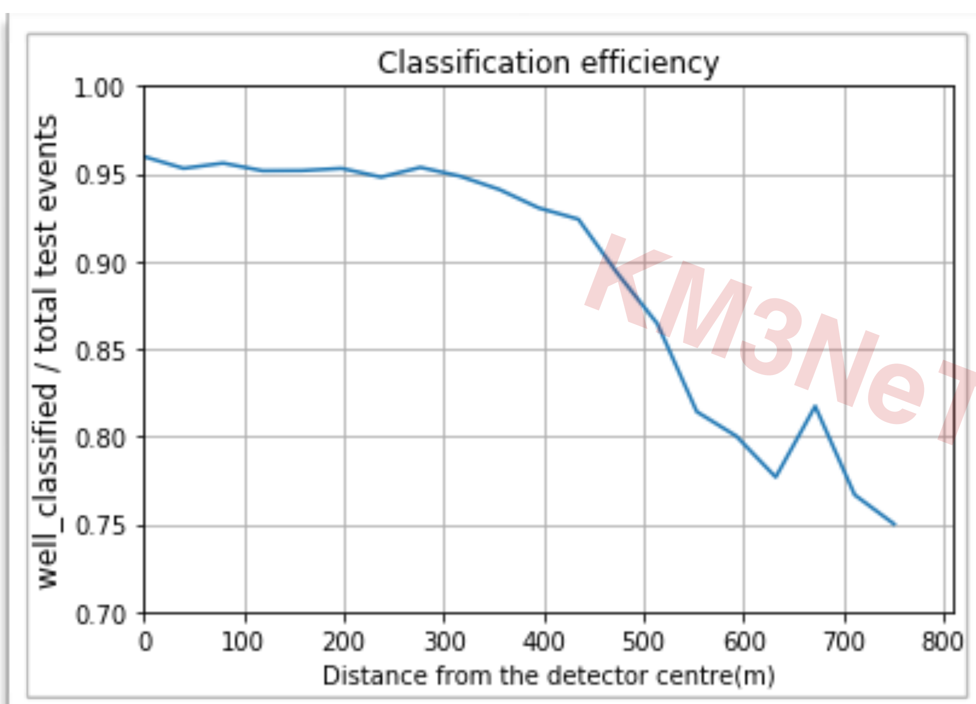
Distance bins (m)
[0.5, 170, 320, 450, 500, 810]

Energy bins (Log(E)) [GeV]
[-1.2, 2.5, 3.0, 4.0,5.5, 8.0]

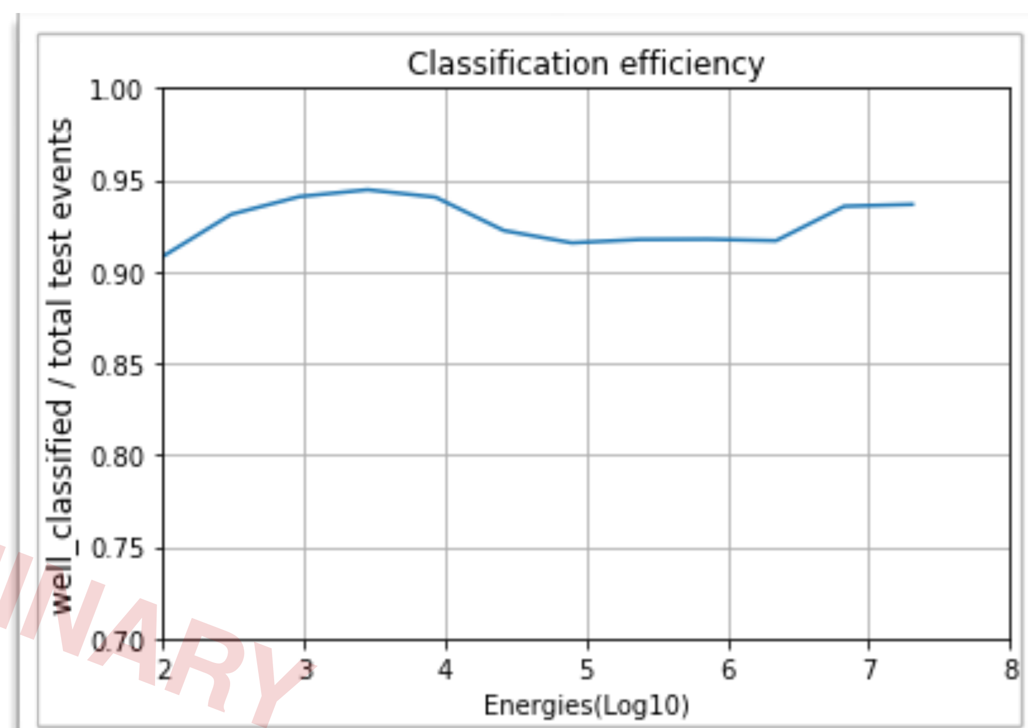


ROC curve





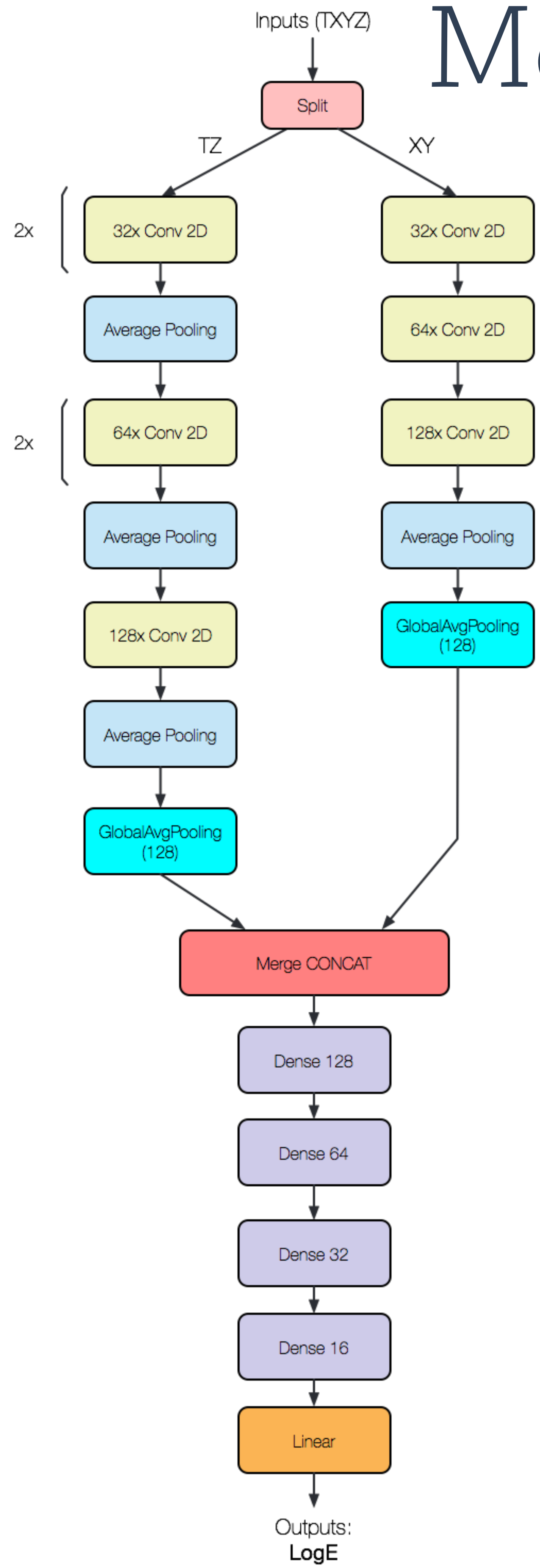
Efficiency



LEARNING TASK 3. PARTICLE ENERGY ESTIMATION

REGRESSION MODEL TO ESTIMATE NEUTRINO ENERGY (GEV)

Model architecture and Input Data



CNN model with parallel branches analysing (T,Z) and (X,Y) evolution separately, merged to extract common features, fed into multiple fully connected layers

2 Input tensors of shapes:

(T,Z): [n_samples, discrete_time_index, z_index]

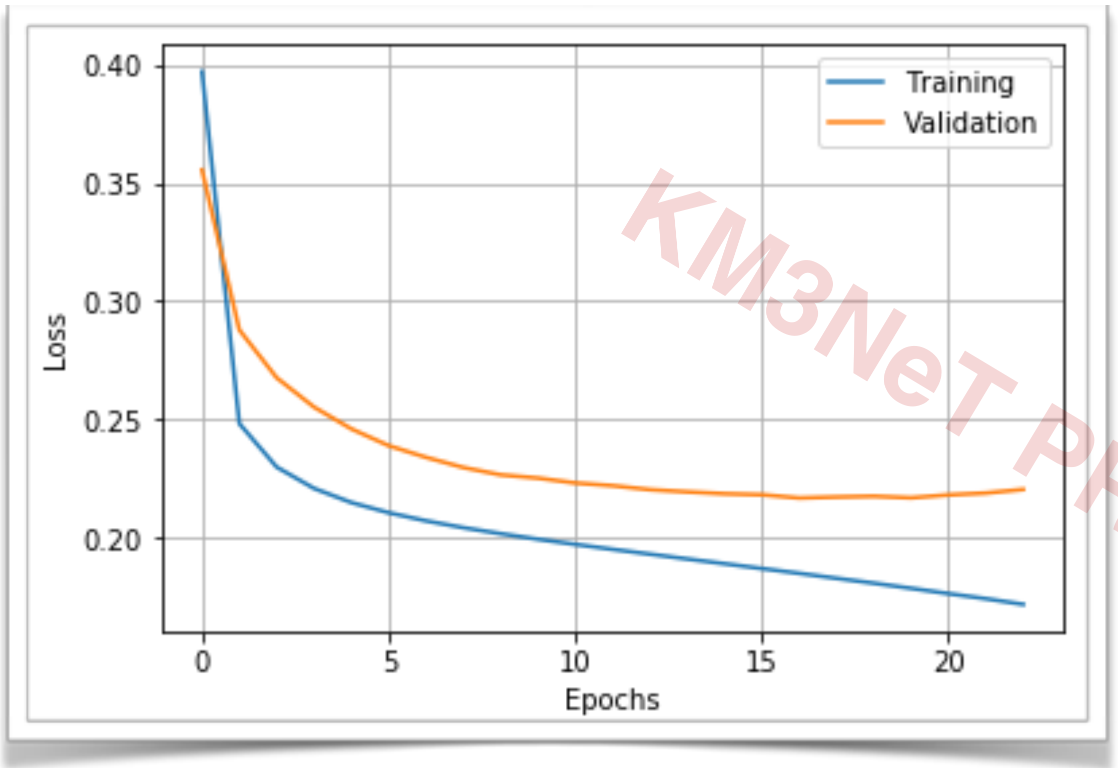
(X,Y): [n_samples, x_index, y_index]

Labels:

Energy: MC truth

Results

Training history



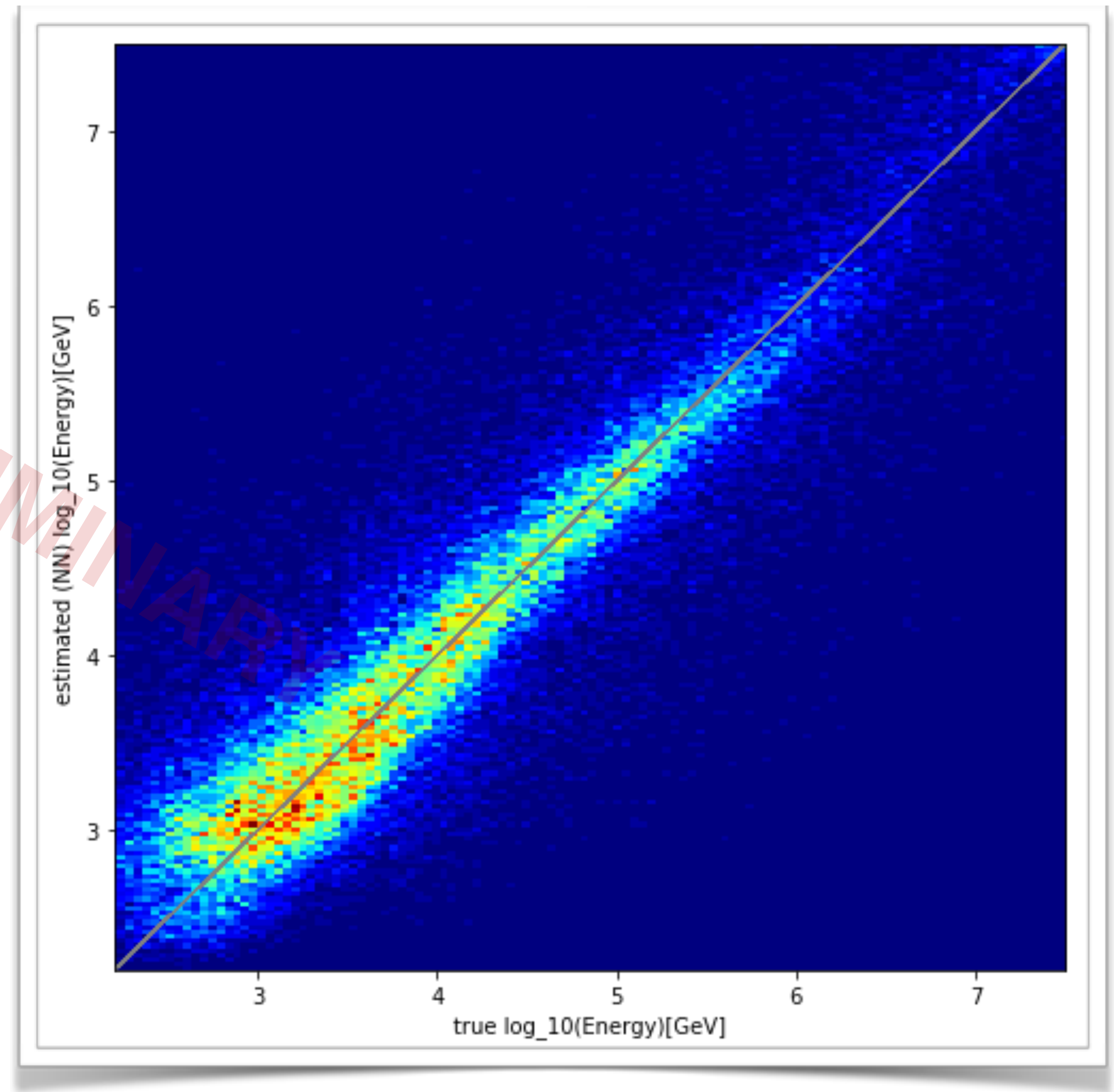
Mean Squared Error (on test data)

0.22

r^2 score (on test data)

0.84

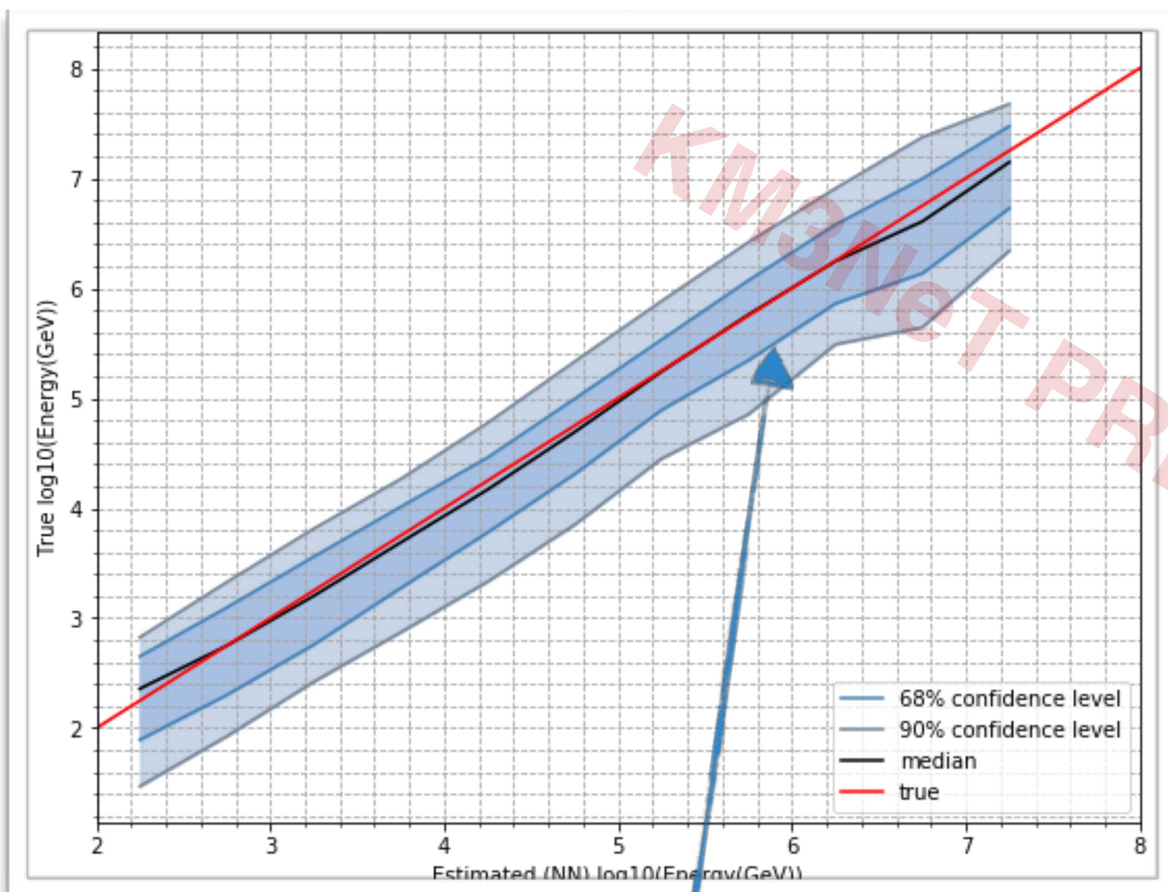
Estimated vs True Energy



test dataset ($\nu_\mu CC + \nu_e CC$ events)

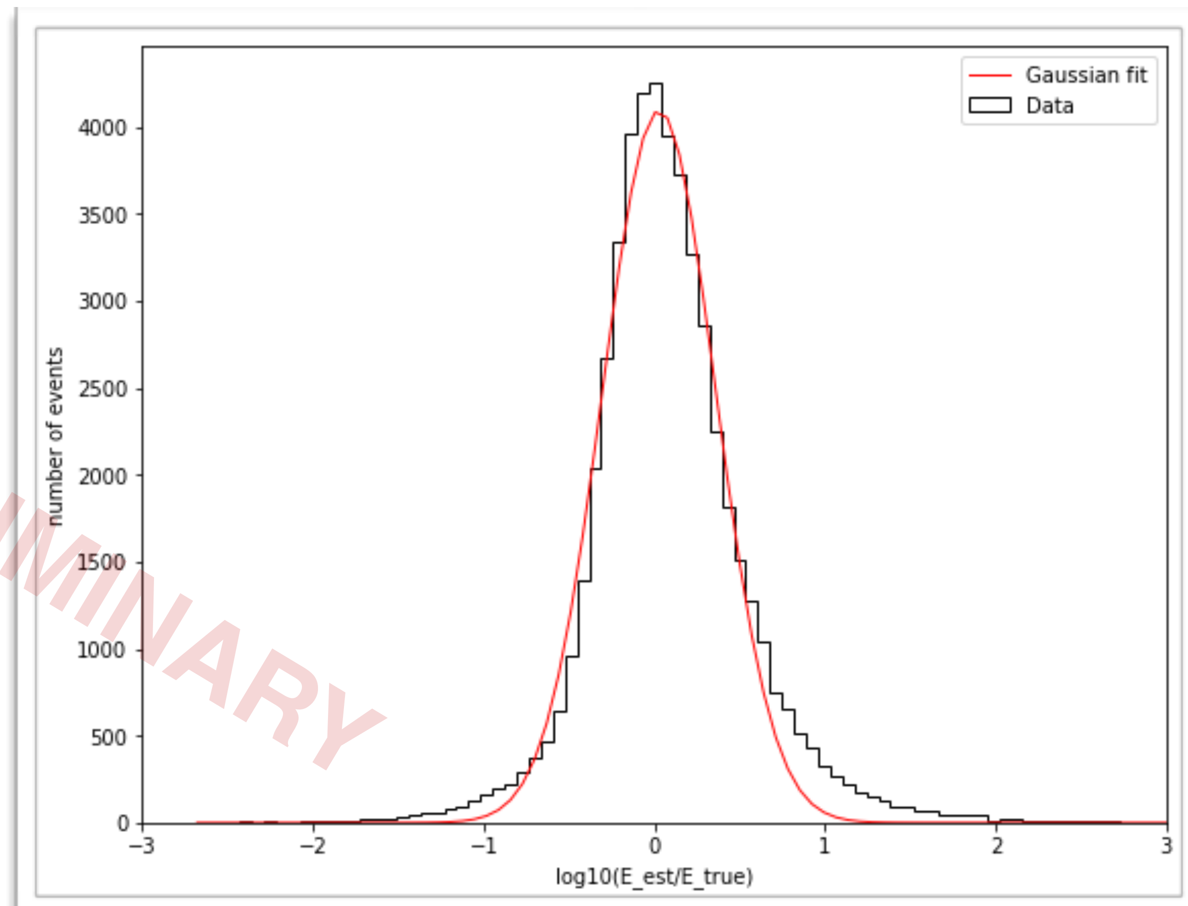
Results

True vs Neural Network Estimated Energy



lack of statistics at high energy

Energy resolution

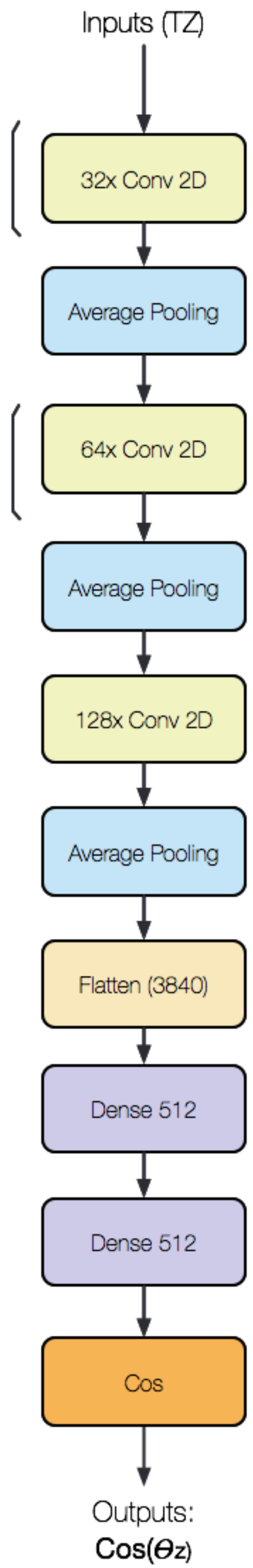


Gaussian fit w/ μ = 0.03, σ = 0.33

test dataset ($\nu_\mu CC + \nu_e CC$ events)

LEARNING TASK 4. DIRECTION ESTIMATION (Z)

REGRESSION MODEL TO ESTIMATE Z-COMPONENT OF THE NEUTRINO DIRECTION



Model architecture and Input Data

CNN model to analyse (T,Z) evolution and predict $\cos(\theta_z)$ value

Input tensor reshaped to :

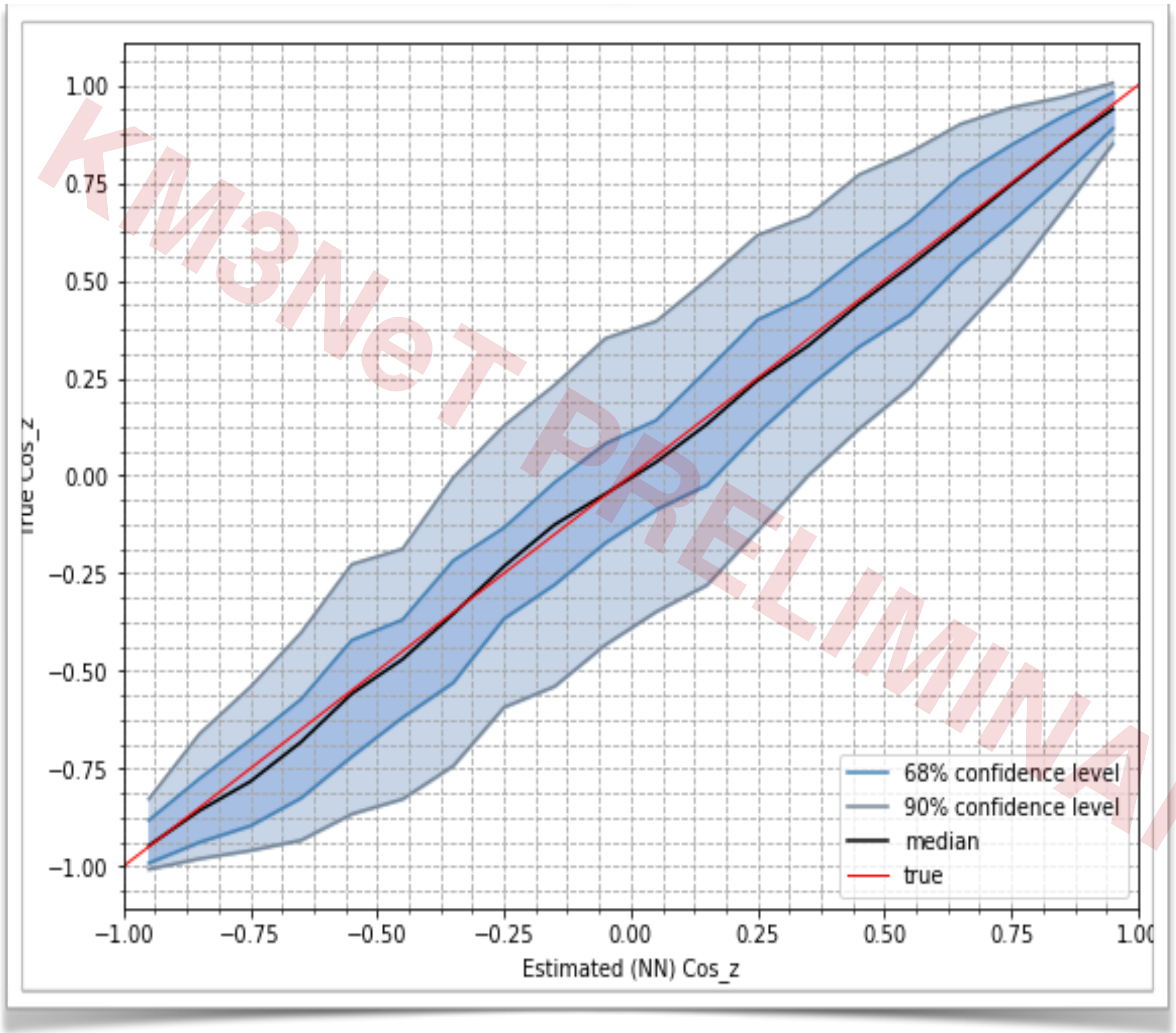
(T,Z): [n_samples, discrete_time_index, z_index]

Labels

$\cos(\theta_z)$: MC truth

Results

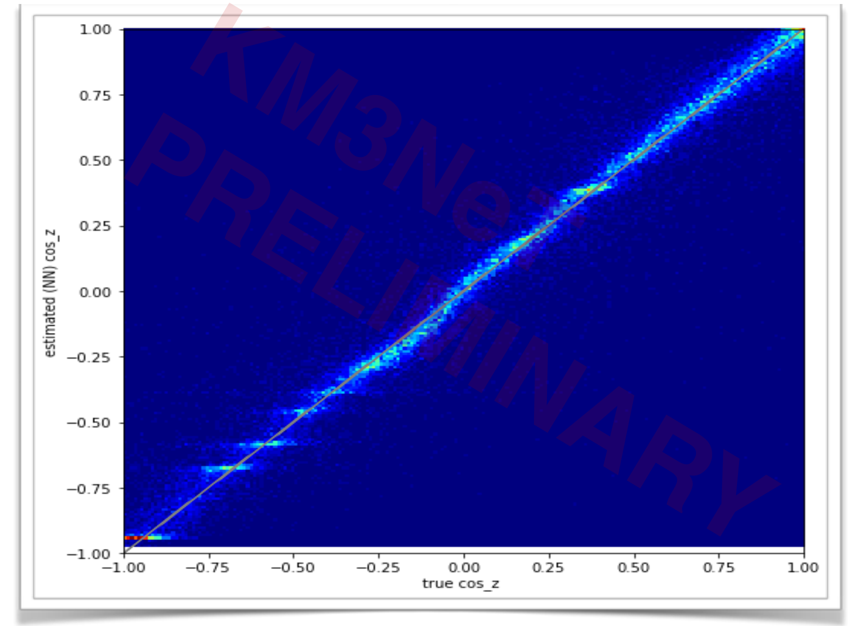
True vs NN Estimated direction (Z)



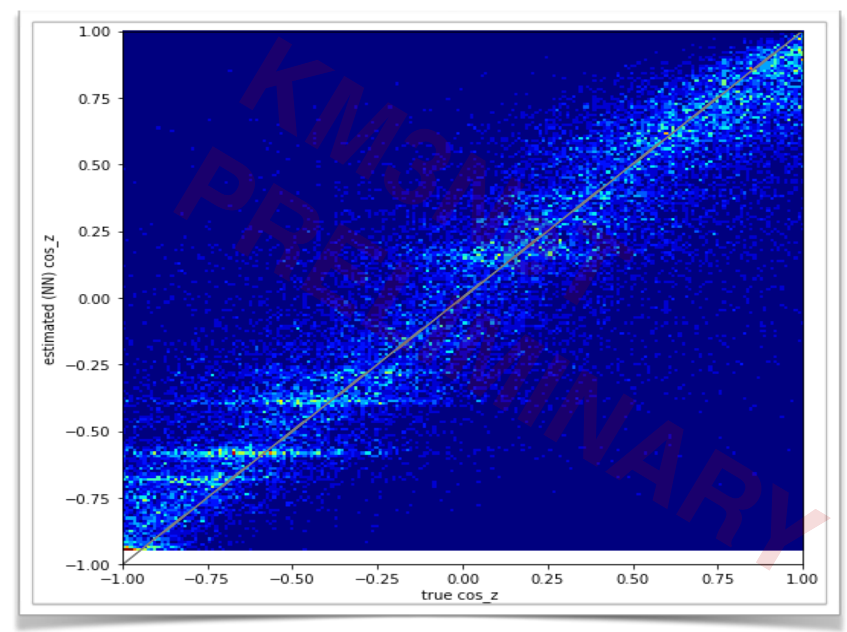
test dataset ($\nu_\mu CC + \nu_e CC$ events)

Mean Squared Error (on test data) **0.03**

$\nu_\mu CC$ vs. $\nu_e CC$



$\nu_\mu CC$



$\nu_e CC$

Muon neutrino event direction is better estimated w.r.t. electron neutrino direction

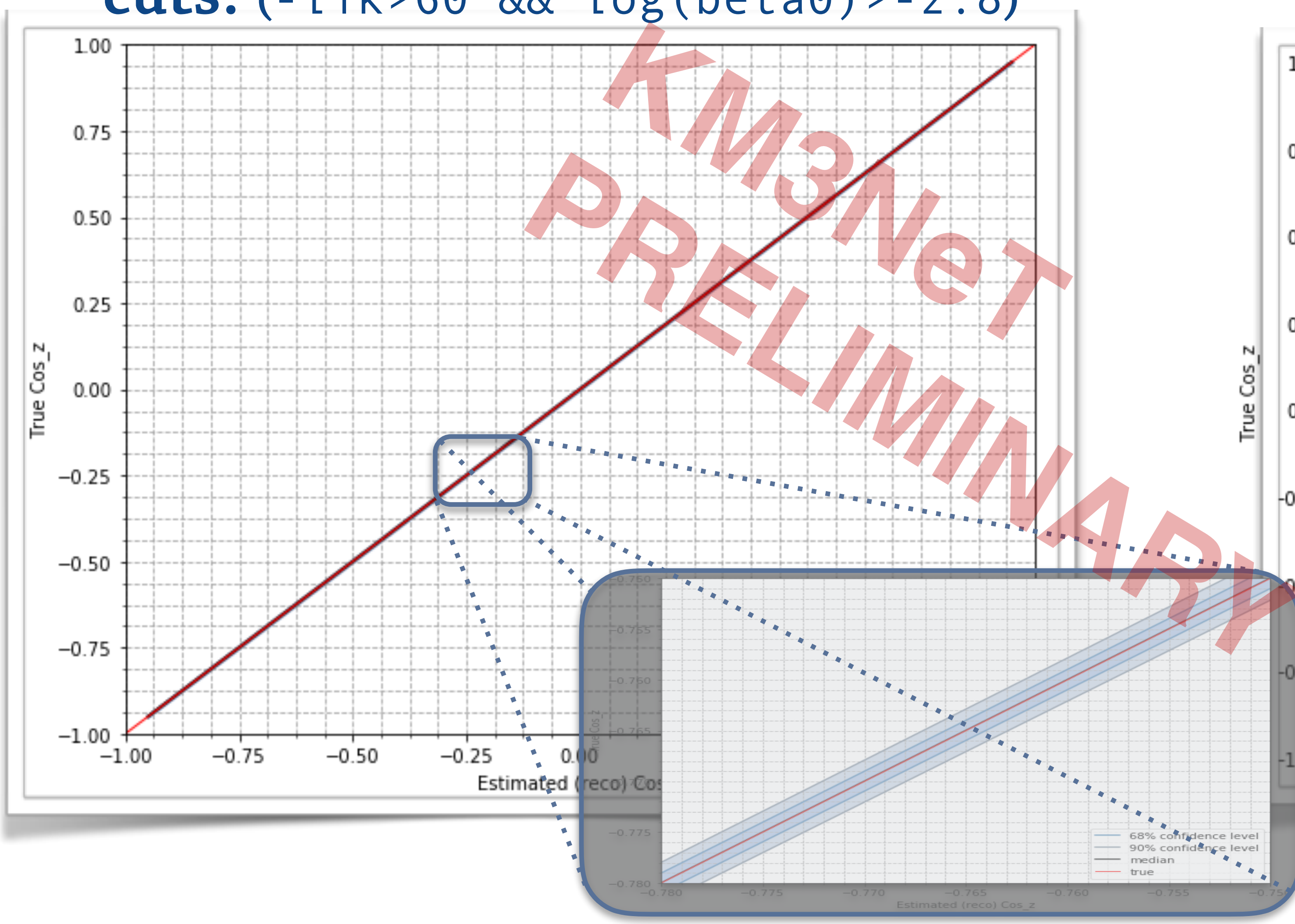
COMPARISON WITH THE KM3NET STANDARD RECONSTRUCTION ALGORITHM

PERFORMANCES COMPARISON ON $\nu_\mu CC$ EVENTS
TO COMPARE RESULTS WITH STANDARD TRACK RECONSTRUCTION ALGORITHM, WHEN APPLICABLE

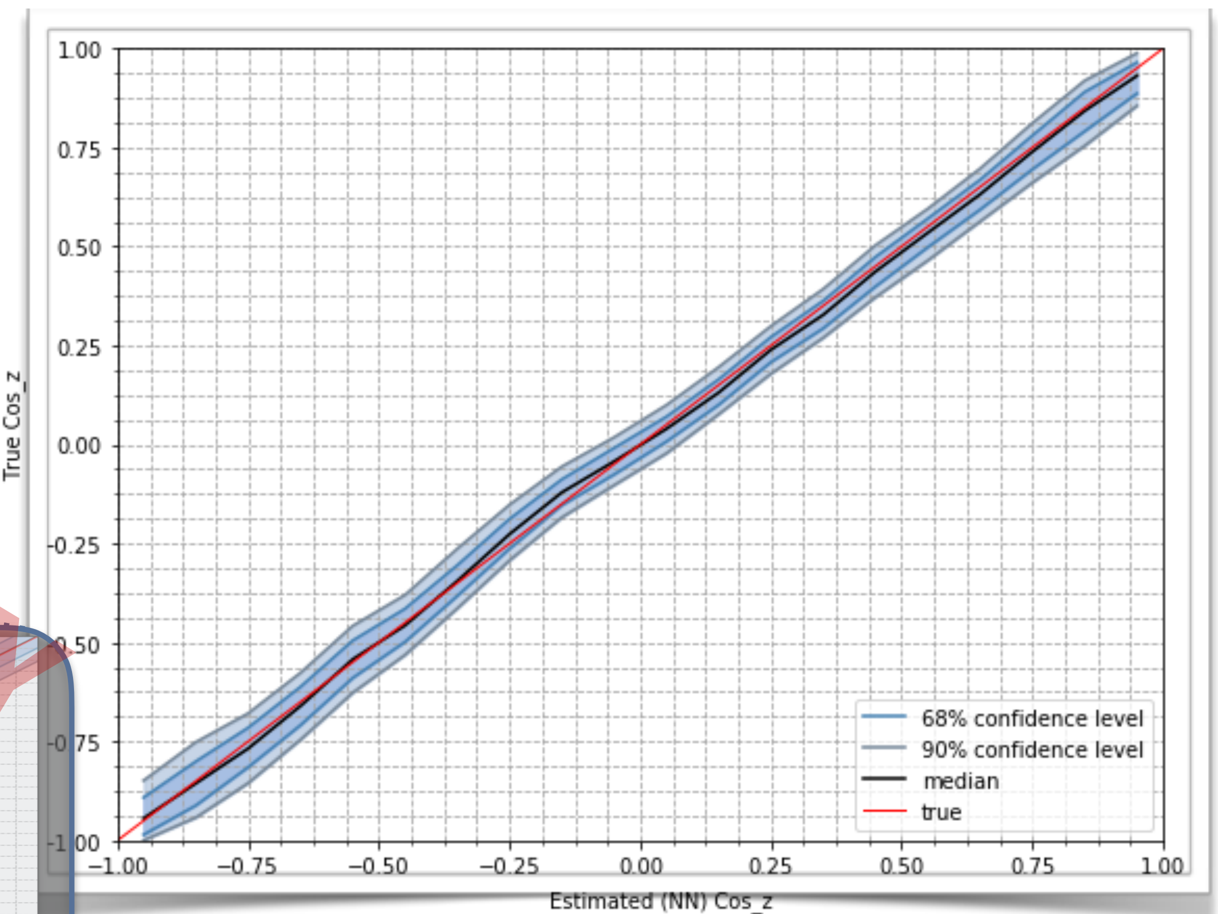
Direction estimation (Z)

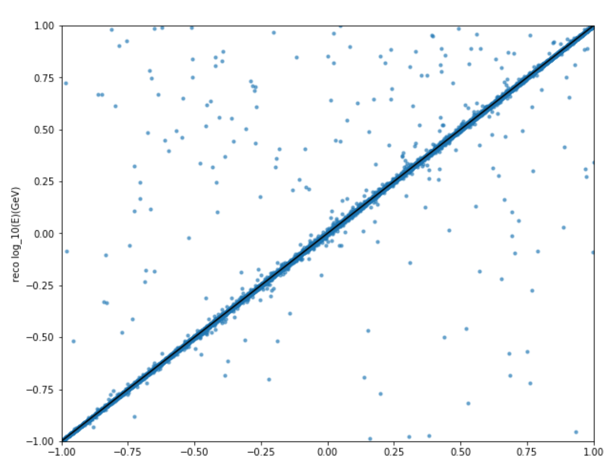
True vs Std. Reco. Est. direction (Z)

cuts: `(-lik>60 && log(beta0)>-2.8)`

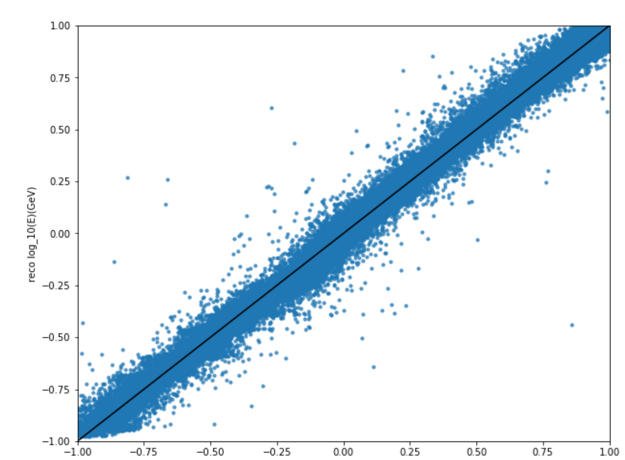


True vs CNN Est. direction (Z) on **the same** $\nu_{\mu}CC$ events





Estimated vs true
Neutrino direction (Z)
scatter plots



Comparison on Up-going/Down-going classification

- apply "labels" to reconstructed events:
  - $\cos(\theta_z) > 0$: "up-going"
  - $\cos(\theta_z) <= 0$: "down-going"
- Compare predictions

Accuracy on up-going/down-going classification

KM3NeT standard reconstruction
(-lik>60 && log(beta0)>-2.8)

Classification Accuracy

0.998

CNN regression running test on $\nu_\mu CC$ events only

Classification Accuracy

0.987

only $\nu_\mu CC$ events (selecting well reconstructed events) with quality cuts

Deep Learning Applications for KM3NeT-ORCA

Aim:

Multipurpose classification and regression studies in ORCA

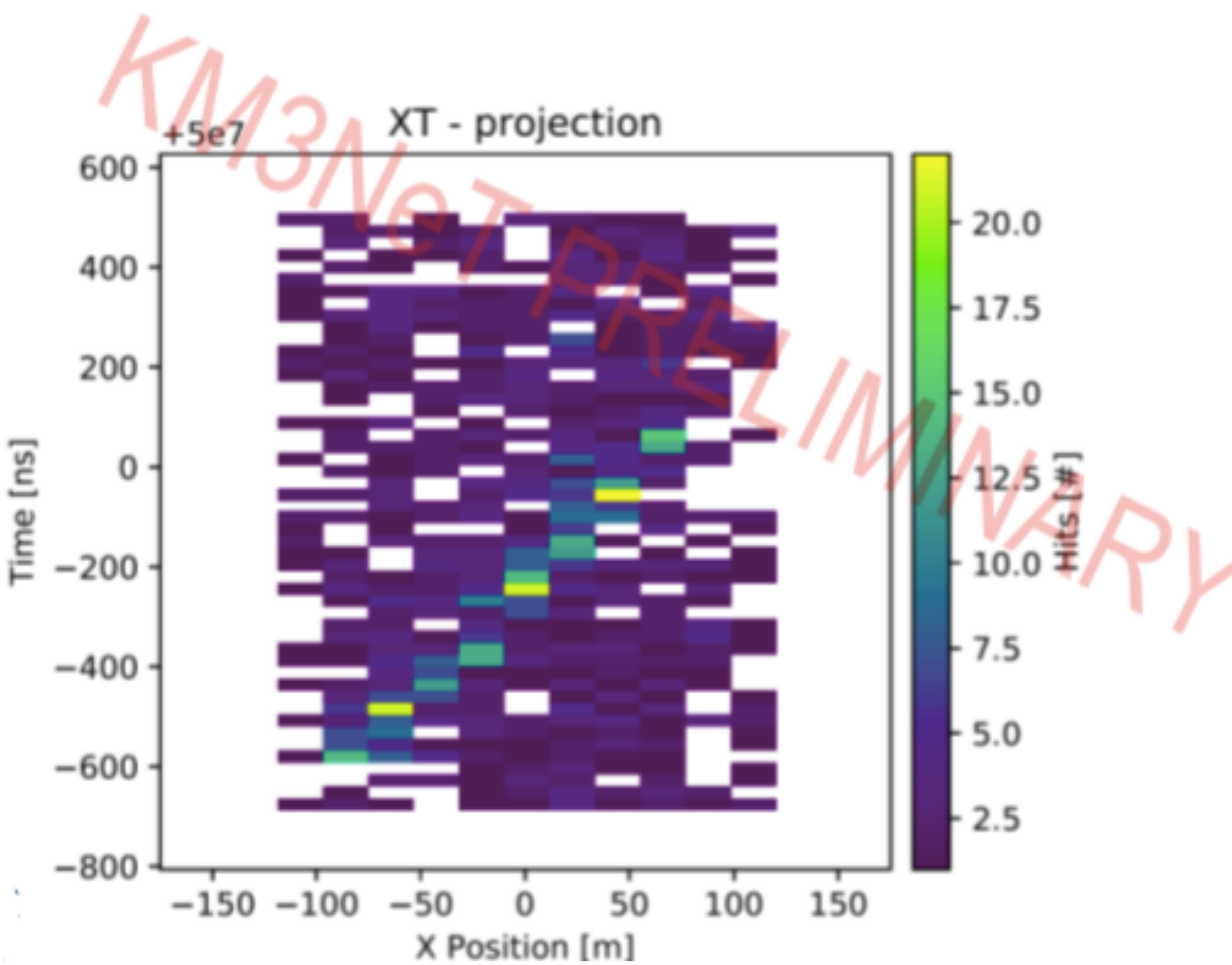
Task:

Reconstruct energy and direction, track-shower composition, PID

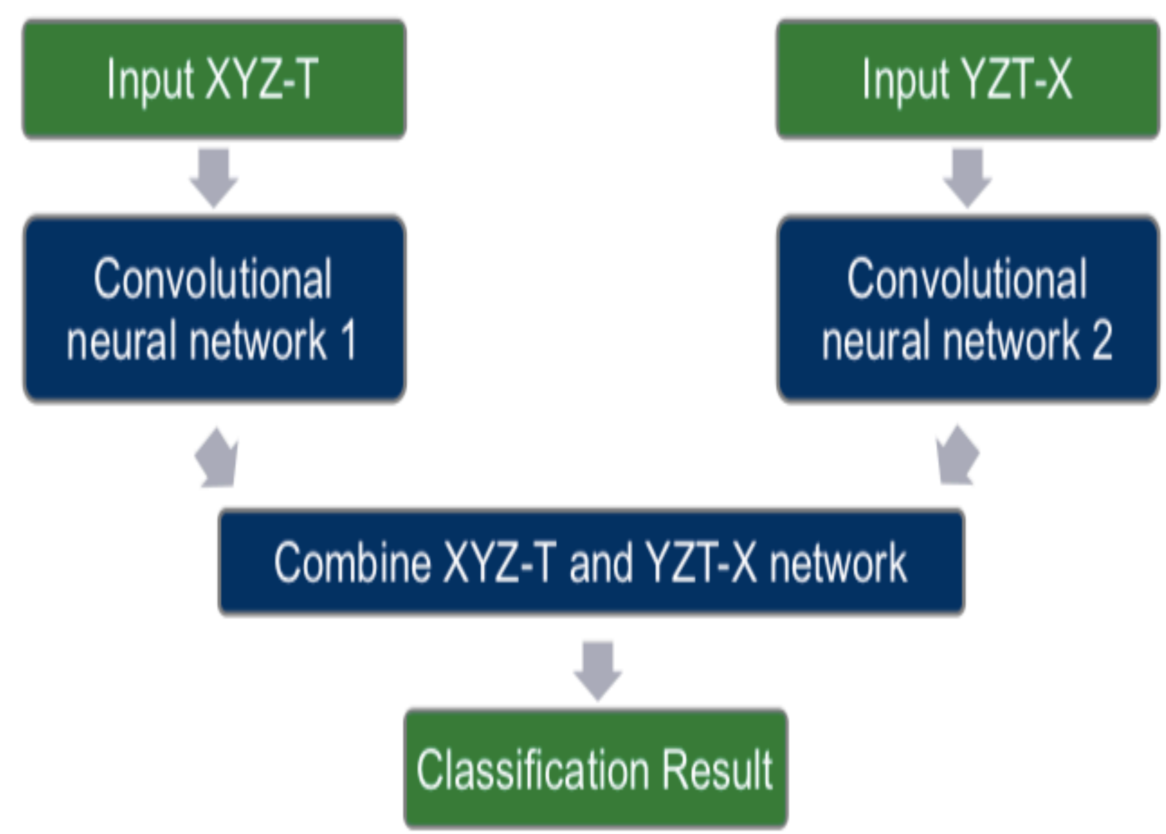
- Developed a Deep Learning track-shower classifier called OrcaNet, based on Convolutional Neural Networks

Deep Learning for ORCA with OrcaNet

- 6D information (XYZ, T, azimuth, zenith) projected to 4D subspace (neglect PMT direction)
- Time binning: 60 bins (~10 ns/bin)
- Space binning: 11x13x18
- 4 week training on HPC GPU Cluster (4xGTX 1080)



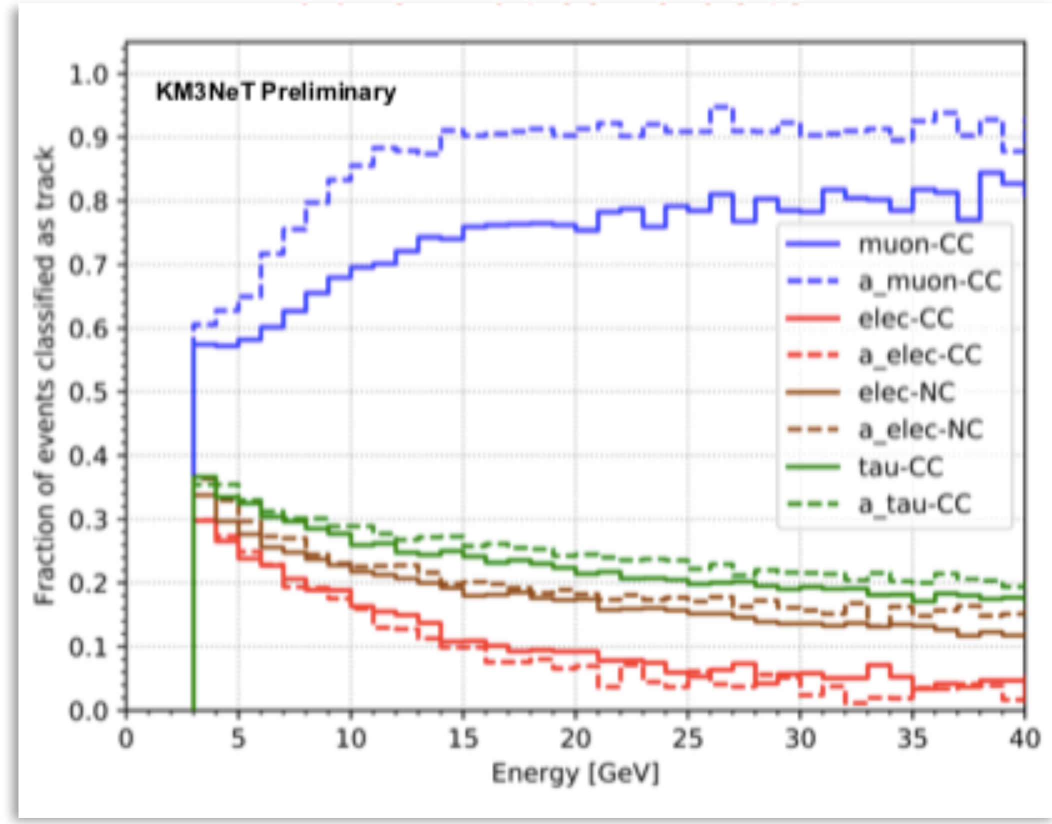
XY view of a ν_μ CC event



CNN model architecture

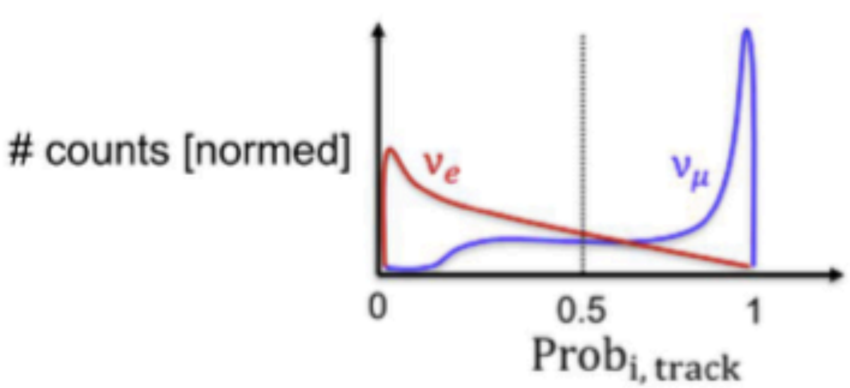
Results

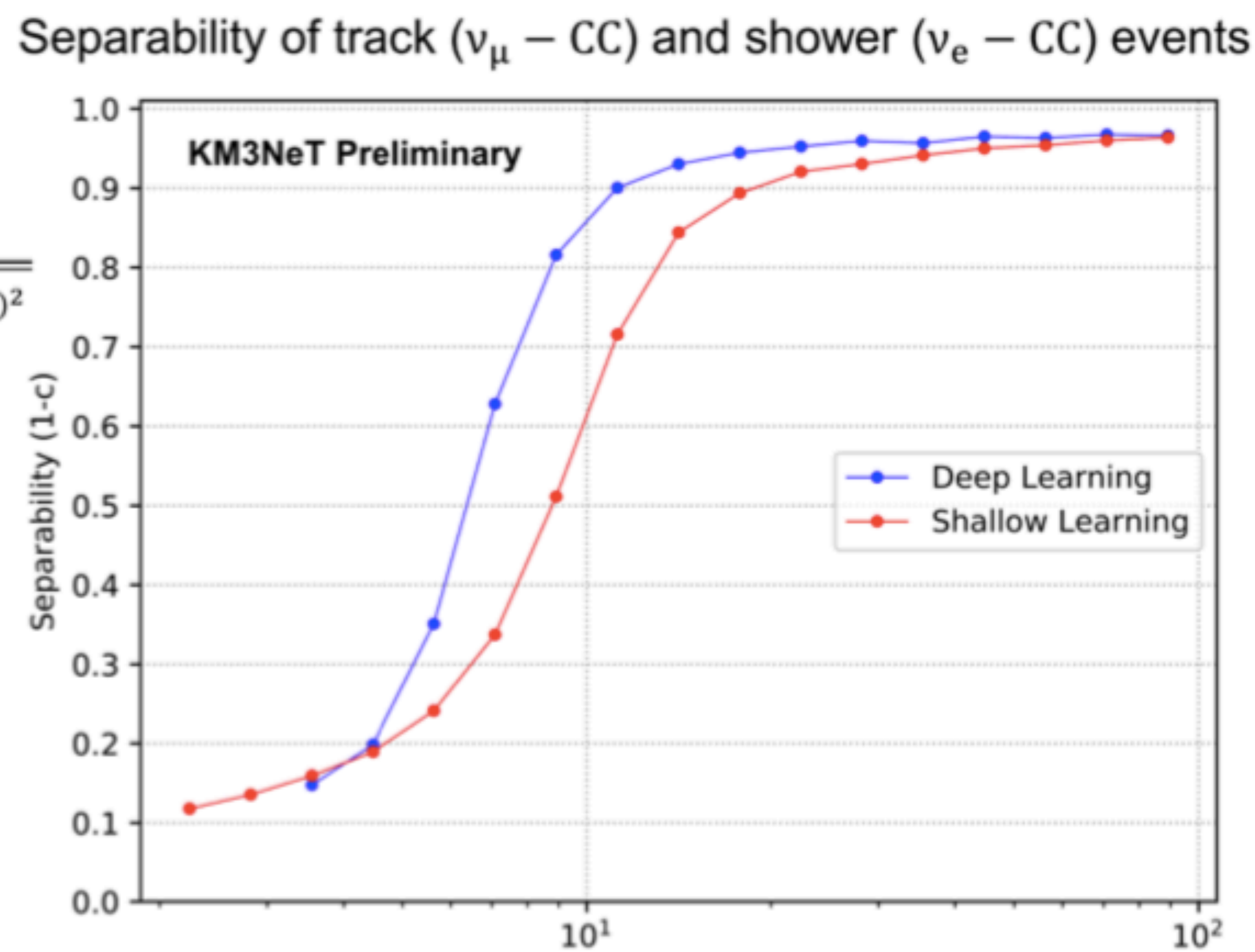
Track/shower event classification
No reconstruction output used



CNN **outperforms** RDF with human-selected features

$$S(E) = 1 - c = 1 - \frac{\sum_i P^{\nu_\mu}_{i,\,\mathrm{track}}(E) \cdot P^{\nu_e}_{i,\,\mathrm{track}}(E)}{\sqrt{\sum_i (P^{\nu_\mu}_{i,\,\mathrm{track}}(E))^2 \cdot \sum_i (P^{\nu_e}_{i,\,\mathrm{track}}(E))^2}}$$





Conclusions and outlook

- ML Results are promising in these **first iterations**:
  - ML provides **stable estimations,** comparable and in some cases better than KM3NeT standard reconstruction
  - ML does not depend on any reconstruction algorithm: **independent** event study directly from **raw data**
- Room for improvement and a lot of work to do (detailed detector description, complete reconstruction, complete flavour identification) – More results coming soon!
- KM3NeT expects to produce a DL toolset for CNN applications in ASTERICS (H2020) WP 3 - Possibly portable to other event-based experiments, to be added to ASTERICS repository
- KM3NeT INFN groups to contribute with ML algorithms in Task 3.4 of ESCAPE (proposal)

Thanks a lot for your kind attention

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