

# Deeply Learning from Neutrino Interactions with the KM3NeT neutrino telescope

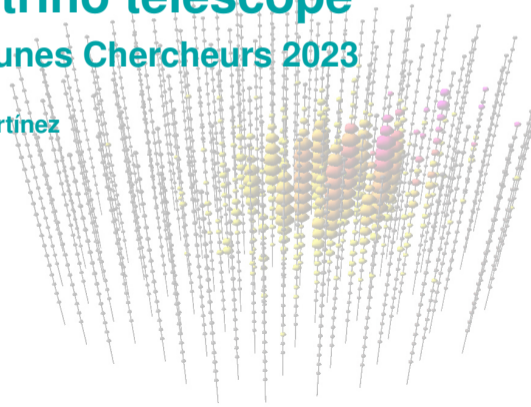
Journées de Rencontre des Jeunes Chercheurs 2023

Santiago Peña Martínez

APC - KM3NeT

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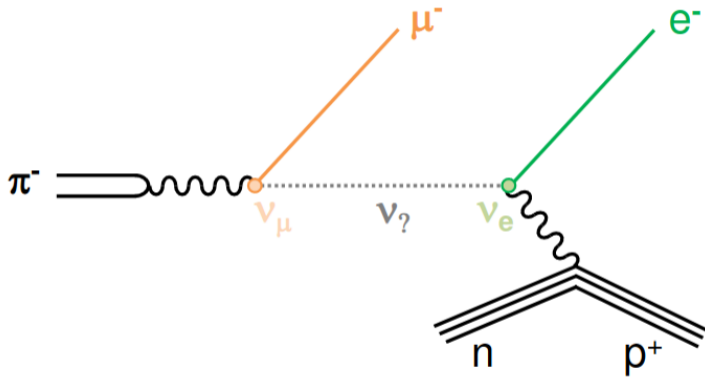
October 27, 2023



- Neutrino oscillations and Neutrino Mass Ordering
- About KM3NeT
- Motivation
- Neural Network for combined energy estimate
- Graph Neural Networks

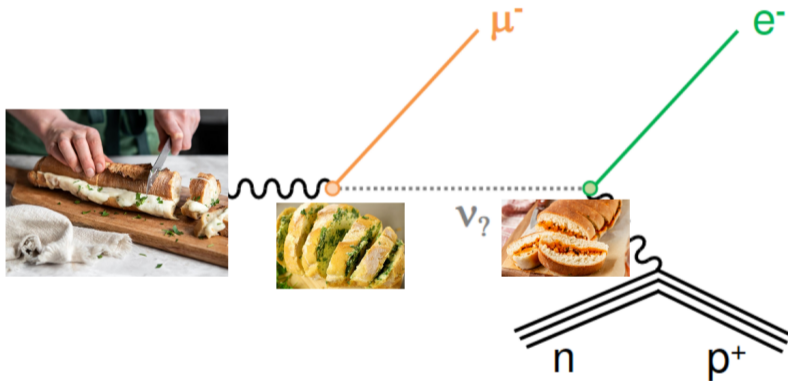


# Neutrino oscillations in a nutshell

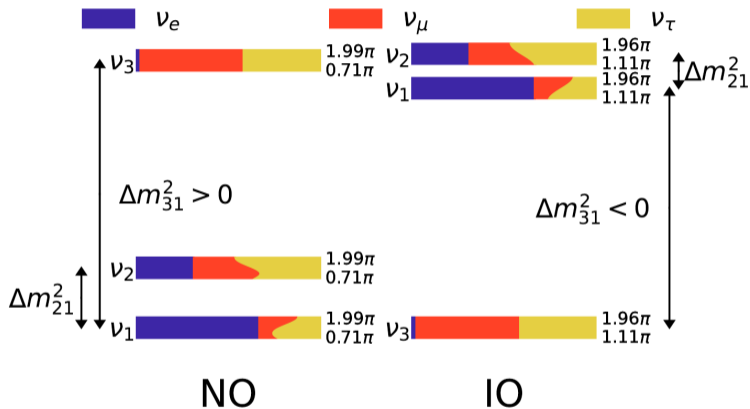


Credits J. Coelho

# Neutrino Préfou oscillations in a nutshell

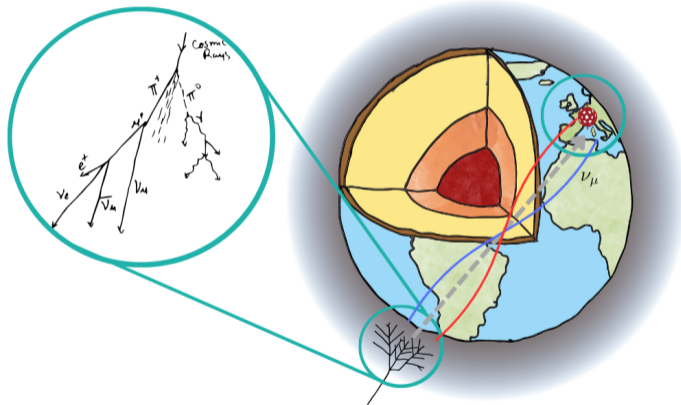


# Neutrino mass ordering (NMO)

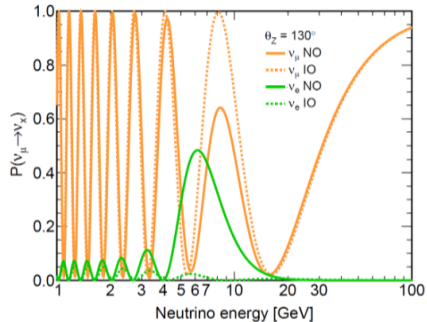
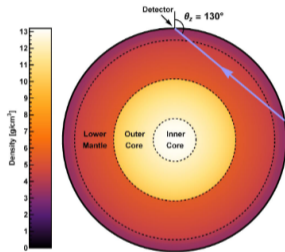


<https://globalfit.astroparticles.es/2018/07/03/neutrino-mass-ordering/>

# Atmospheric neutrinos production



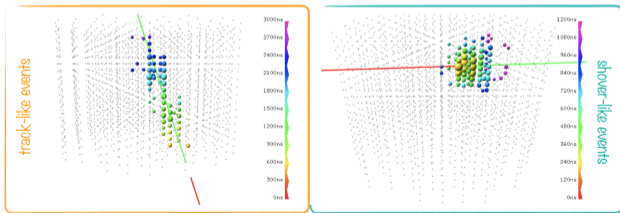
# Measuring $\nu$ mass ordering using matter effects



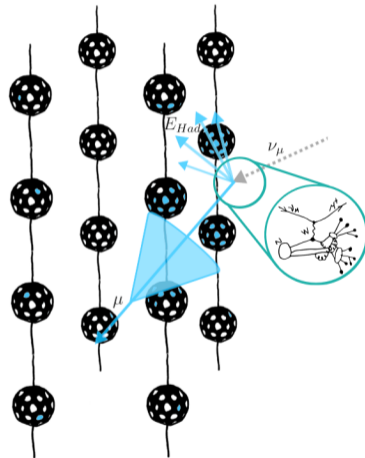
Credits J. Coelho

Neutrino telescope using a large sea water volume as detection volume:

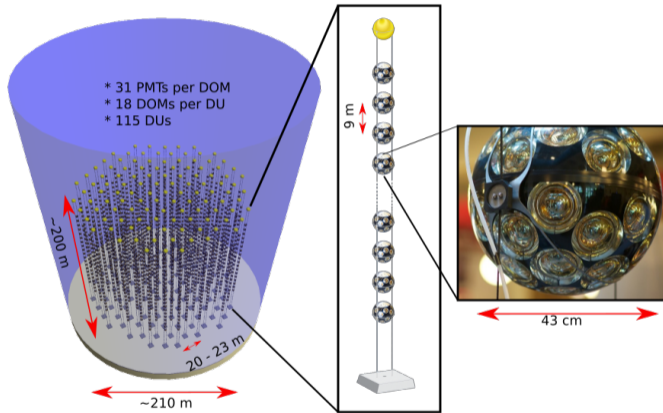
- Neutrino interaction in water produces charged secondary particles which induce Cherenkov radiation.
- Detector composed of large array of photosensors.
- Designed to have two construction sites with different physics goals but same technology.



J. Phys. G: Nucl. Part. Phys. 43 084001 (2016)







PMT: Photomultiplier Tube, DOM: Digital Optical Module, DU: Detection Unit (string of DOMs)

## ORCA

Study  $\nu$  properties, determine the Neutrino Mass Ordering (NMO) and measure oscillation parameters.

## Status

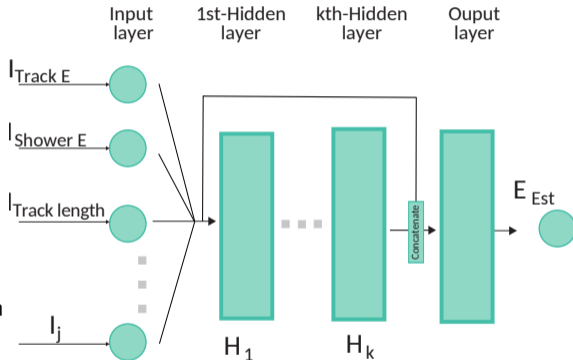
ORCA site currently has 18 working DUs, expected to have 28 by the end of the year.

The work presented here is done for the detector with 6 DUs → **ORCA6**.

**Using Deep Neural Networks (DNN) for a  
combined energy estimate**

# Problem and motivation

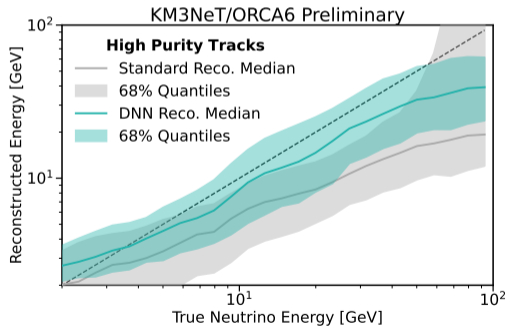
- Currently the collaboration uses physics based energy reconstructions.
- Information about triggered hits are shared in all reconstructions.
- Reconstructions provide auxiliary variables (Direction, vertex position, Cherenkov variables, etc...).
- A Neural Network can use all this information to estimate an optimal combination having the true energy as target.



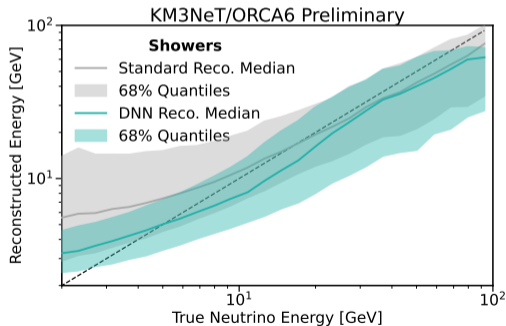


# DNN energy resolutions

- Energy reconstructions given by the DNN show less bias than the standard reconstructions for track and shower-like events.

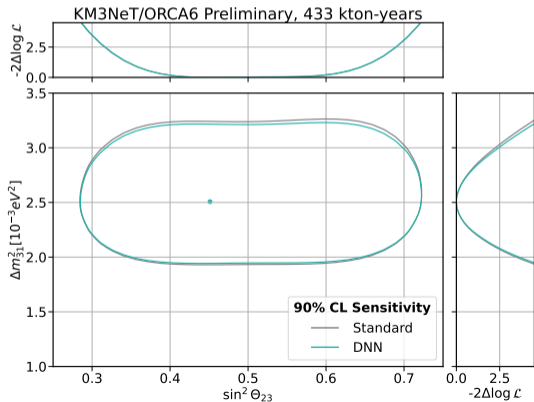


- Energies around the oscillation ranges 5-20 GeV show improved resolution for the DNN. This energy range is relevant for oscillations analysis.

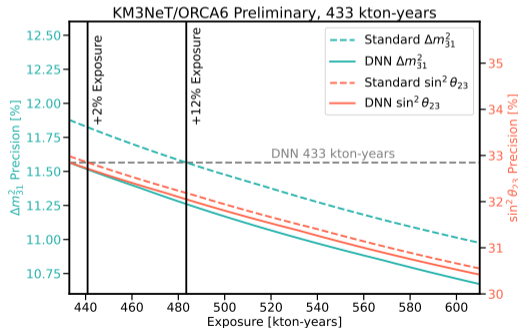


# Sensitivity to oscillation parameters

- Energy reconstructions given by the DNN show less bias than the standard reconstructions for track and shower-like events.



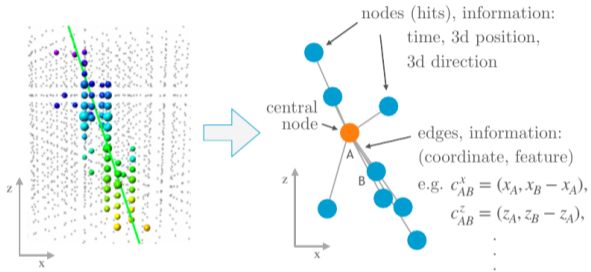
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# Graph Neural Networks (GNN) in KM3NeT

# About Graph Neural Networks

- Event of neutrino going through the detector can be represented as a graph composed of nodes and edges.
- Graph given to the network as an input fully encodes the information of the event.
- Already used in KM3NeT for different tasks:
  - Signal vs noise classification
  - Track vs shower topology classification
  - Energy regression
  - Direction regression



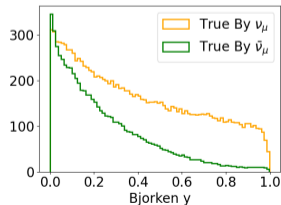
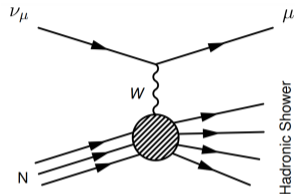
From: Development of detector calibration and graph neural network-based selection and reconstruction algorithms for the measurement of oscillation parameters with KM3NeT/ORCA, Daniel Guderian, PhD Thesis

# Inelasticity of a neutrino interaction

Inelasticity is given by the variable called Björken  $y$ , defined as the fraction of the lepton's energy transferred to the nucleon rest frame:

$$y = 1 - E'/E = E_{Sh}/E_{Tot}$$

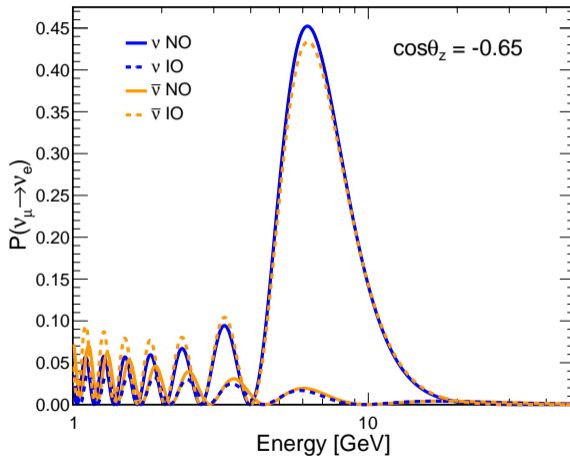
For neutrinos interacting with matter, the distribution of Björken  $y$  is different for  $\nu$  and  $\bar{\nu}$ .





# Problem and motivation

- NMO effects are visible when looking at  $\nu$  and  $\bar{\nu}$
- But the KM3NeT detector cannot distinguish  $\nu$  from  $\bar{\nu}$  so far.
- Björken  $y$  distributions can help make this distinction.
- Information of the inelasticity can be retrieved from the track and shower components.
- A Graph Neural Networks may have enough power to reconstruct the Björken  $y$ .



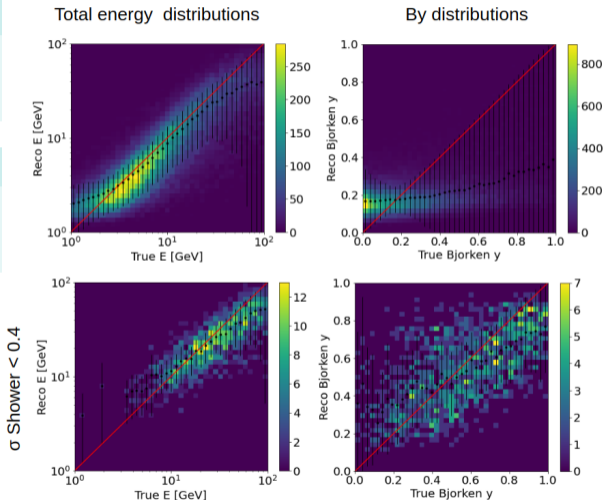
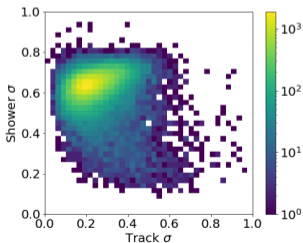
# Total energy estimation

Upper row: Without quality cut

Total E reco of the event is slightly underestimated.  
Björken  $y$  is mostly reconstructed at a fixed value.

Lower row: With cut  $\sigma_{Sh} < 0.4$

Total E reco continues be correlated. Björken  $y$  has a wide range of estimated values.





# Conclusions

Additional information can be extracted when considering track and a shower component of events.

## DNN for energy reconstruction

- Hits contain additional information.
- Shows to improve oscillation parameter estimation.
- Gain in sensitivity is limited by systematic uncertainties.

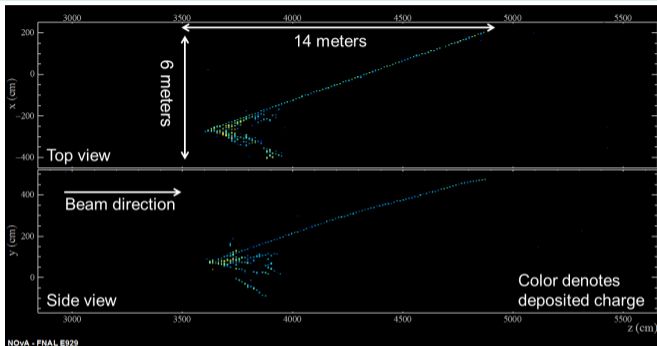
## GNN for Björken $y$ reconstruction

- GNN can reconstruct the energy of the full event.
- Björken  $y$  mostly reconstructed at a fixed value.
- Certain events are correctly reconstructed, this can be exploited.

Both tasks are expected to improve performance with bigger detector size.

**Backup slides**

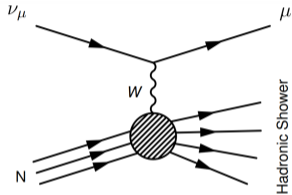
## $\nu$ event is composed of track and shower



Event display from the NO $\nu$ A experiment. Taken from: <https://nusoft.fnal.gov/nova/public/neutrinos/zoomed-notes.png>

Reconstruction methods used at the moment do not include information about both components.

## But how do you predict the Björken $y$ ?



Björken  $y$  is a continuous value between 0 and 1 which is annoying from the point of view of a loss function. Regression loss functions work with unbounded continuous values.

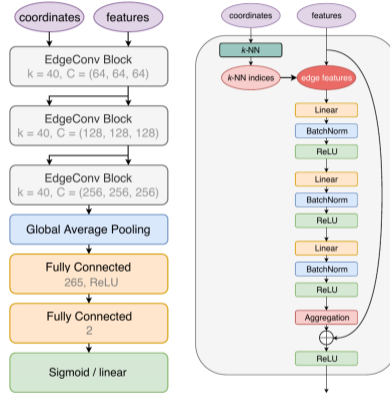
To try to solve this issue one can ask the network for two output neurons with their corresponding uncertainties:

- Energy of the track
- Energy of the shower

Train on  $\nu_{\mu}$  and  $\bar{\nu}_{\mu}$  charged current (CC) events, this allows to have shower and track in one event. Training done for events in the 0 — 100GeV range for simplicity to compensate the detector size.

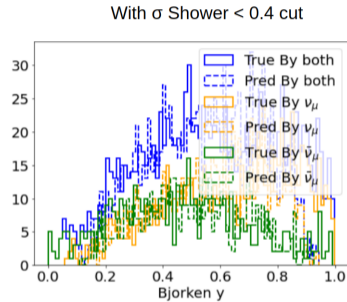
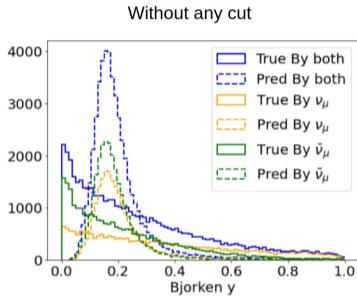
# Architecture of the network

- Nodes are passed through three edge convolution blocks.
- Afterwards the output is passed through a fully connected network.
- The output is subject to an activation function depending on the task.



From: Development of detector calibration and graph neural network-based selection and reconstruction algorithms for the measurement of oscillation parameters with KM3NeT/ORCA, Daniel Guderian, PhD Thesis

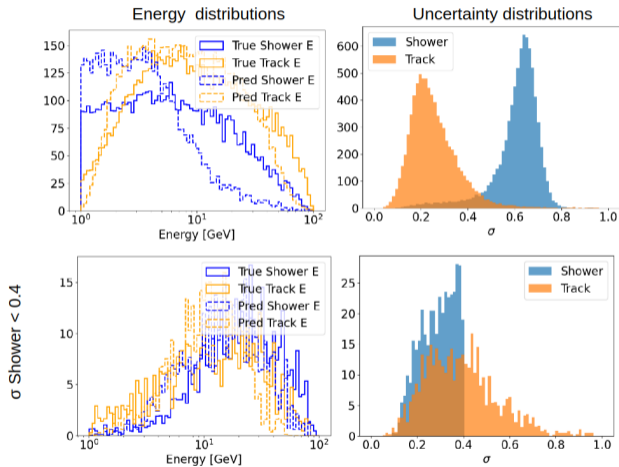
# Björken $y$ distributions



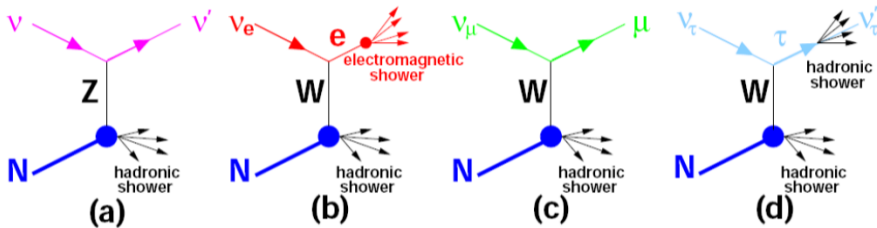
GNN reconstructs using the average of the Björken  $y$  distribution. The events with improved shower reconstruction have a high Björken  $y$ .



# GNN Reconstructed energy distributions



# $\nu$ interaction topologies



Summary of Deep Inelastic Scattering (DIS) neutrino event topologies in neutrino telescopes: (a) flavour-insensitive NC, (b)  $\nu_e$  CC, (c)  $\nu_\mu$  CC, (d)  $\nu_\tau$  CC.

Taken from: A. Trovato. "Development of reconstruction algorithms for large volume neutrino telescopes and their application to the KM3NeT detector". PhD thesis. Università degli Studi di Catania, Scuola Superiore di Catania, 2010

## ARCA

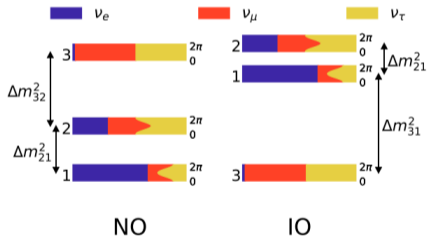
Discover/Observe high-energy neutrino sources in the universe.



From: <https://indico.cern.ch/event/855372/contributions/4454016/>

## ORCA

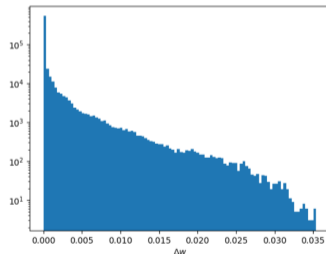
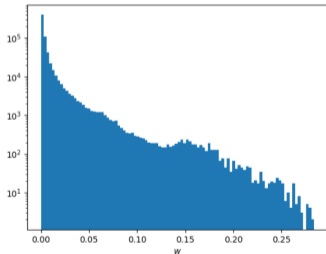
Study  $\nu$  properties, determine the Neutrino Mass Ordering (NMO) and measure oscillation parameters.



From: <https://doi.org/10.3389/fspas.2018.00036>

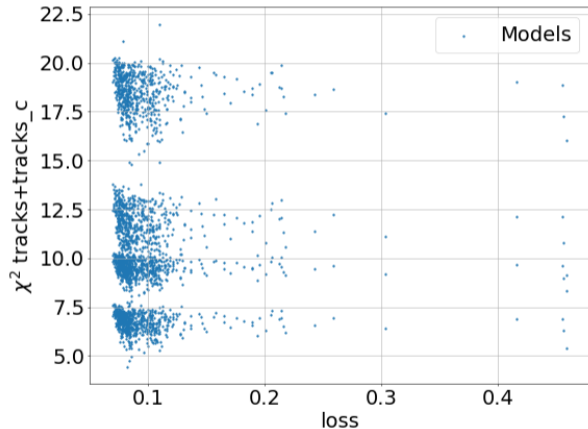
# Using oscillation weights for training: Defining weight

- We want the network to be right specially for events sensitive to oscillation effects.
- Define the weights for training as  $w = \Delta w * k + w(\Delta m_{31} = 2.5e - 3, \sin^2(\theta_{23}) = 0.5)$ , where  $\Delta w = |w(\Delta m_{31} = 2.5e - 3, \sin^2(\theta_{23}) = 0.5) - w(\Delta m_{31} = 2e - 3, \sin^2(\theta_{23}) = 0.6)|$  and  $k$  is a hyperparameter which controls the importance of the difference in the oscillation weights.



# HPO doing the right thing?

- Short answer, no.
- The apparent best model selected is not the one with the best sensitivity possible.
- So far it is still the best option.
- Phase space of hyperparameters has a very complicated shape.
- Longer warm-up for bayesian algorithm allows to better explore the phase space.





# Hyperparameter optimization methodology

- Train many models.
- Compute log likelihood ratio for different oscillation parameter combinations.
- Select the best in terms of sensitivity.
- Go to contours and compare with JEnergy contours.

