

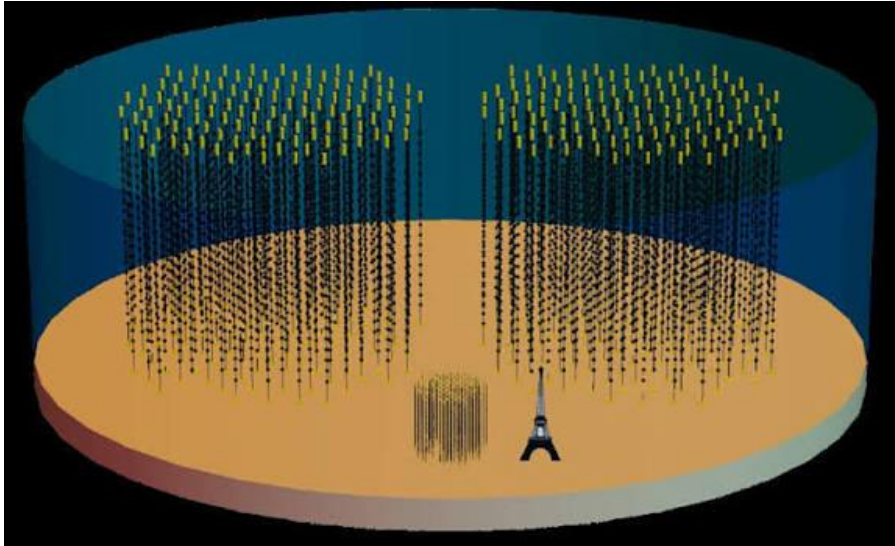
# Neutrino Oscillations and Machine Learning in KM3NeT

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From Monte Carlo simulation to event selection and classification

# KM3NeT: the ORCA and ARCA experiments

A deep-sea neutrino telescope.



## Detector concept

Neutrinos are detected from the traces they leave. Using photomultipliers at the bottom of the ocean, we can detect neutrinos from the Cherenkov radiation muons emit, or from hadronic showers caused by an interaction.

## Two complementary detectors

**ORCA:** optimized for lower-energy atmospheric neutrinos and oscillation studies.

**ARCA:** optimized for higher-energy astrophysical neutrino searches.

For our study, we will use **ORCA**, the smaller detector, to study lower energy physics and better analyze the flavor and oscillation of our parameters. Our data is coming from **ORCA10**, that being ORCA when it had 10 lines of detectors.

# Neutrino Oscillations

A small recap on why neutrinos oscillate.

$$i \frac{d}{dt} |\nu(t)\rangle_m = H |\nu(t)\rangle_m \implies |\nu_i(t)\rangle_m = |\nu_i(0)\rangle_m e^{-iE_i t} \quad \text{Free neutrinos have mass states (i = 1, 2, 3)}$$

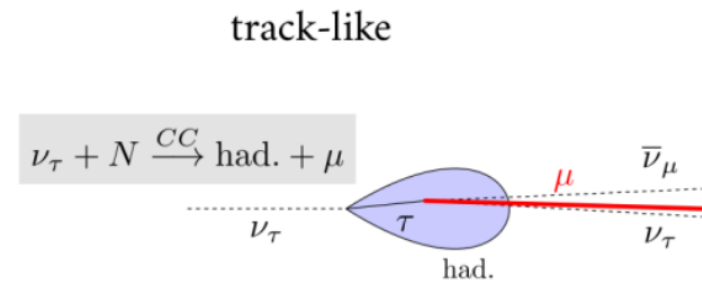
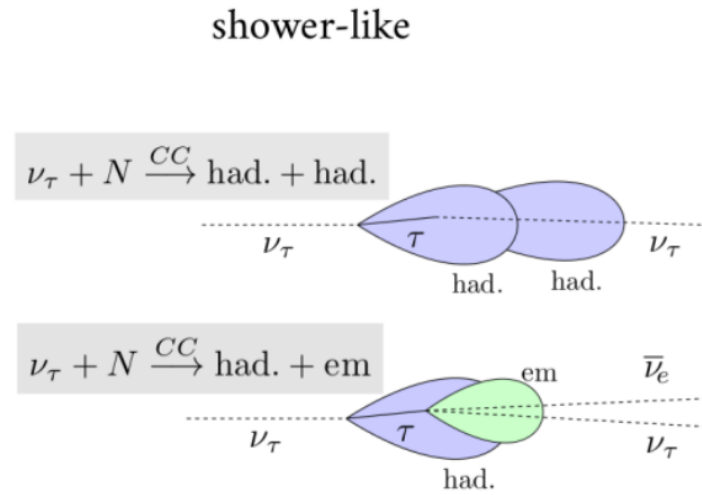
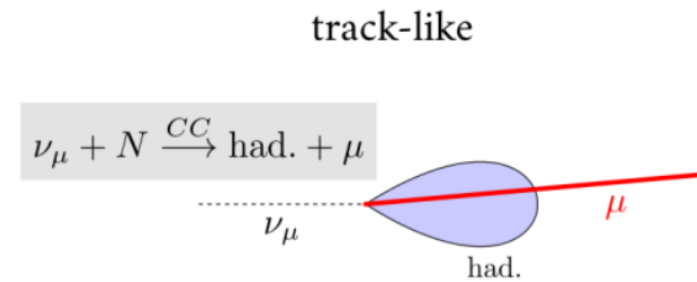
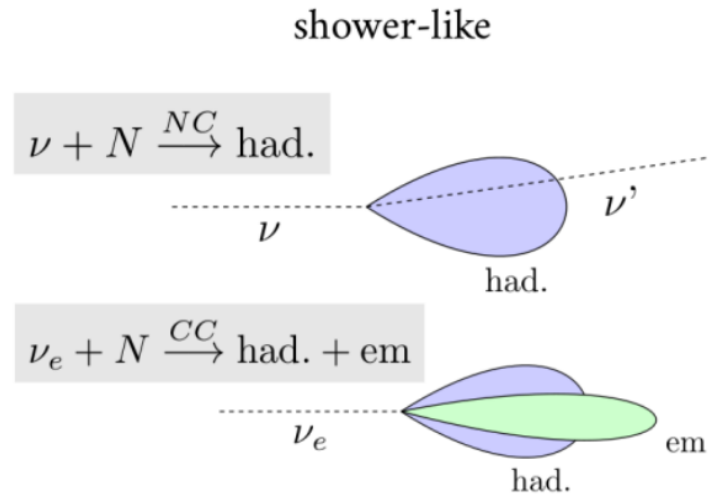
## The PMNS Matrix

$$U_{\text{PMNS}} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & c_{23} & s_{23} \\ 0 & -s_{23} & c_{23} \end{pmatrix} \begin{pmatrix} c_{13} & 0 & s_{13}e^{-i\delta_{\text{CP}}} \\ 0 & 1 & 0 \\ -s_{13}e^{i\delta_{\text{CP}}} & 0 & c_{13} \end{pmatrix} \begin{pmatrix} c_{12} & s_{12} & 0 \\ -s_{12} & c_{12} & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\text{Where } c_{ij} \equiv \cos \theta_{ij}, \quad s_{ij} \equiv \sin \theta_{ij}. \quad \begin{pmatrix} \nu_e \\ \nu_\mu \\ \nu_\tau \end{pmatrix} = U_{\text{PMNS}}^* \begin{pmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{pmatrix}$$

# Topology of events

Different event topologies indicate which type of particles we have witnessed interacting



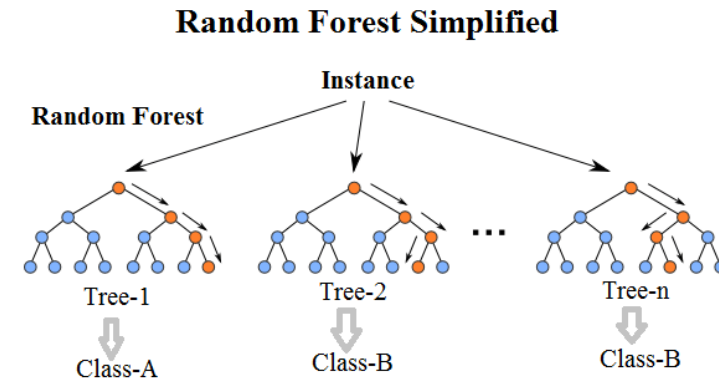
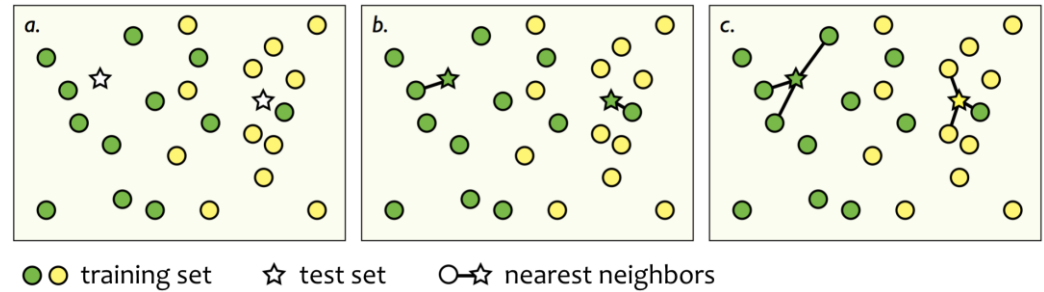
# Machine learning in neutrino physics

Classification and regression algorithms are trained using ORCA and ARCA data.

Our principal work was to train classification and regression algorithms using the data at ORCA and ARCA.

We used two algorithms to classify between neutrinos and muons:

1. **Random Forest**
2. **K-nearest neighbours**



# The confusion matrix

A confusion matrix summarizes the model predictions against the true labels.

|        |          | Predicted |          |
|--------|----------|-----------|----------|
|        |          | Positive  | Negative |
| Actual | Positive | TP        | FN       |
|        | Negative | FP        | TN       |

TP / TN are correct predictions; FP / FN are the two types of classification errors.

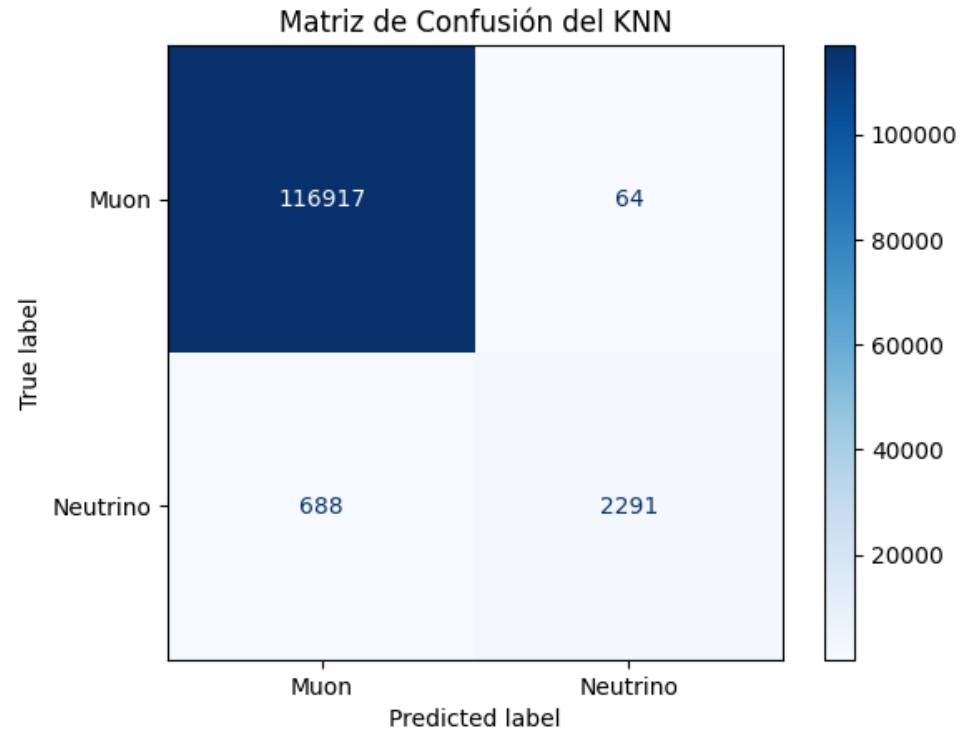
## How to read it

- Rows represent the true class.
- Columns represent the predicted class.
- Good classifiers concentrate events on the diagonal.
- Off-diagonal cells show the remaining confusion.

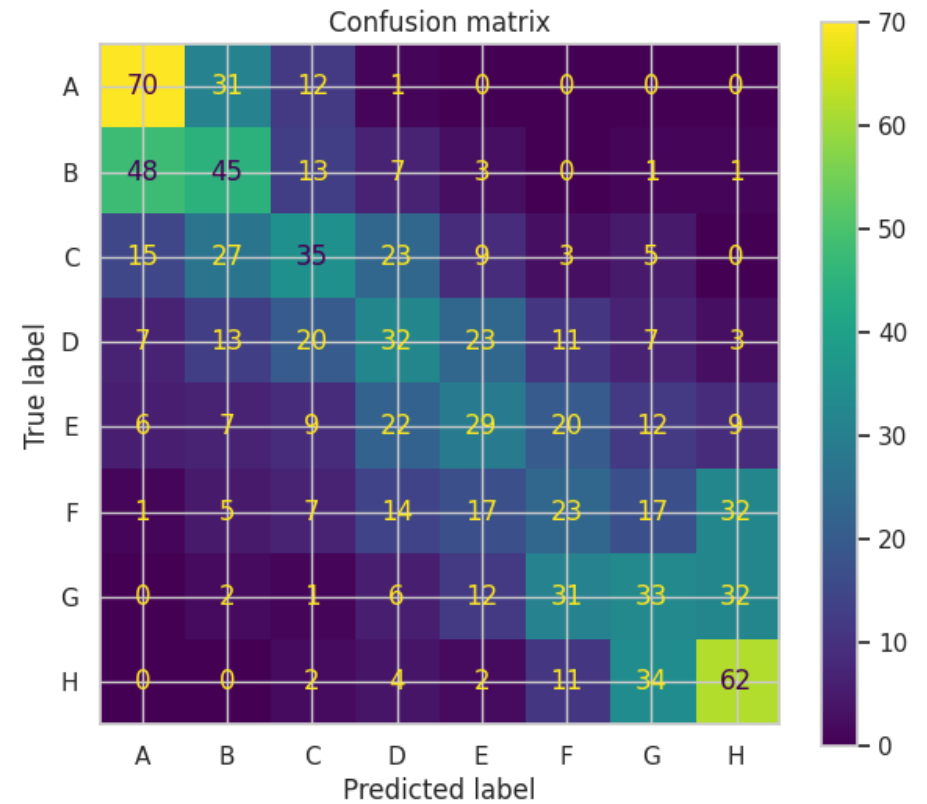


# And what about flavours?

The same validation idea can be applied to different classification tasks.



Task: Muon vs neutrino



Task two: Flavours

# Creating a model from a MC simulation

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## Parameters:

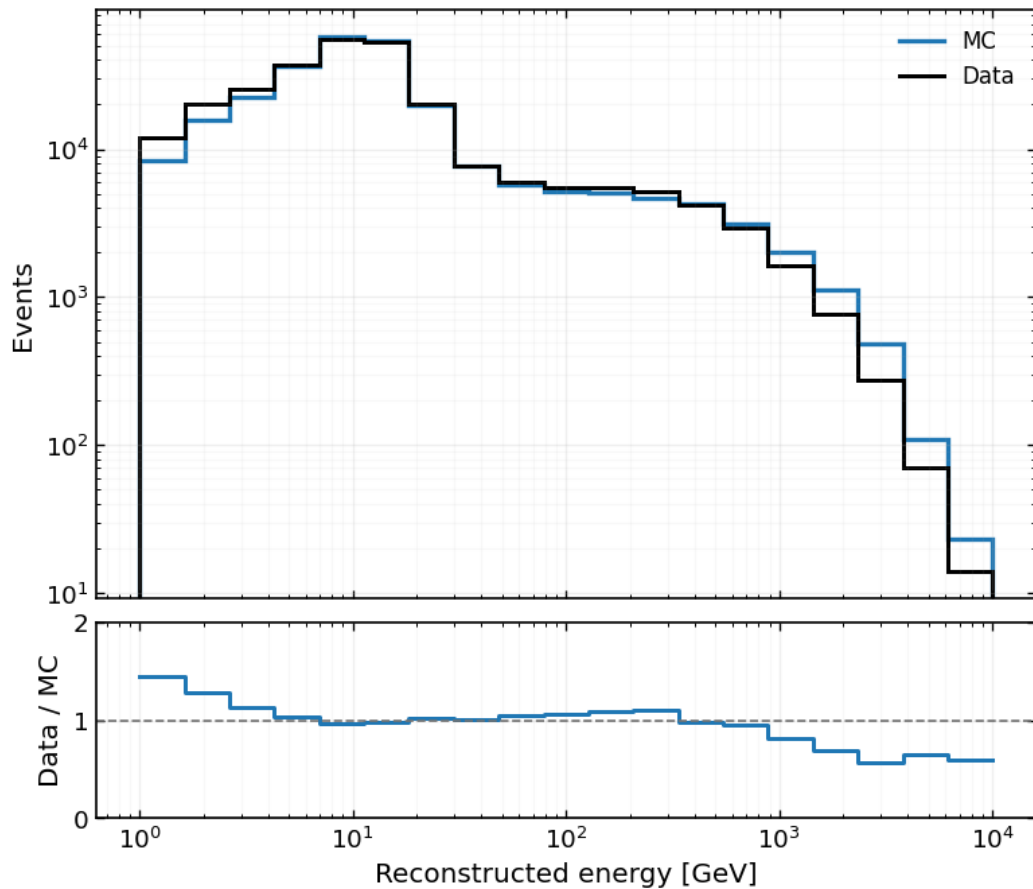
- Weight
- Weight (no oscillations)
- Energy
- $\cos(\theta)$
- Neutrino BDT
- Anti-Noise BDT
- Track BDT
- N° hits



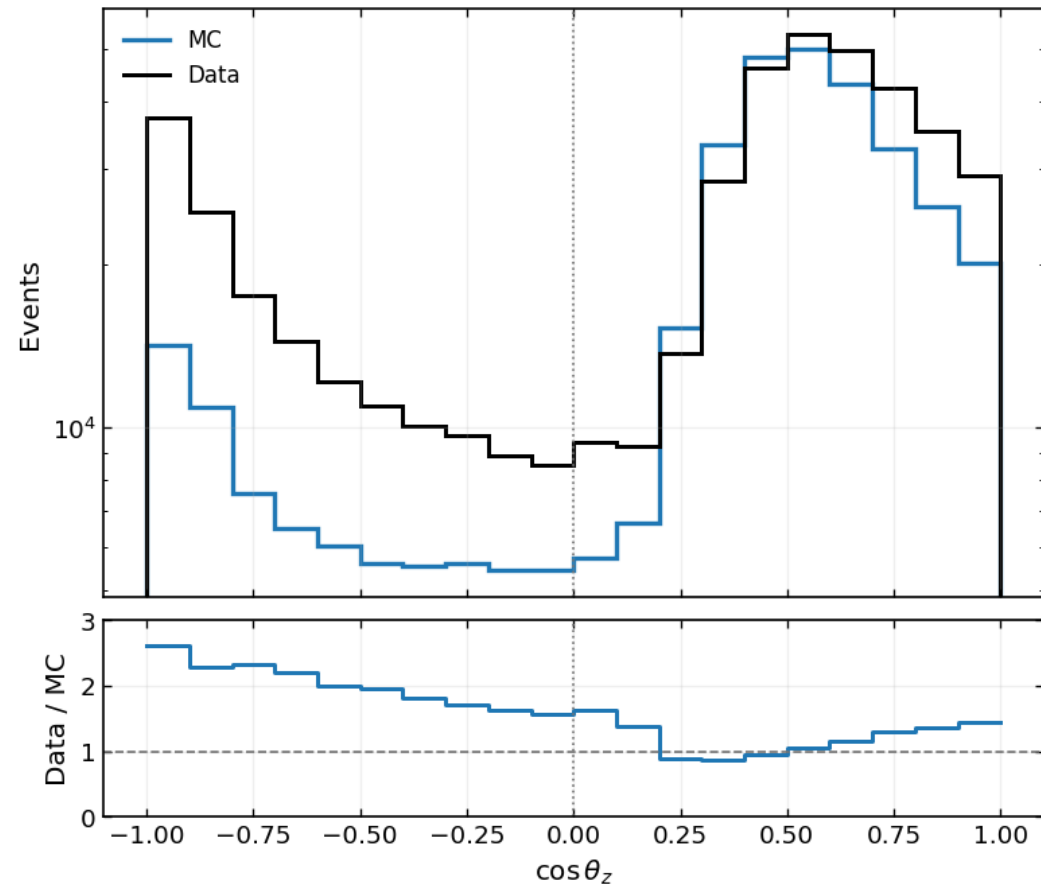
# Comparing the data

How well does raw data correspond to the simulated Monte Carlo?

Simulated vs real event counts in Energy



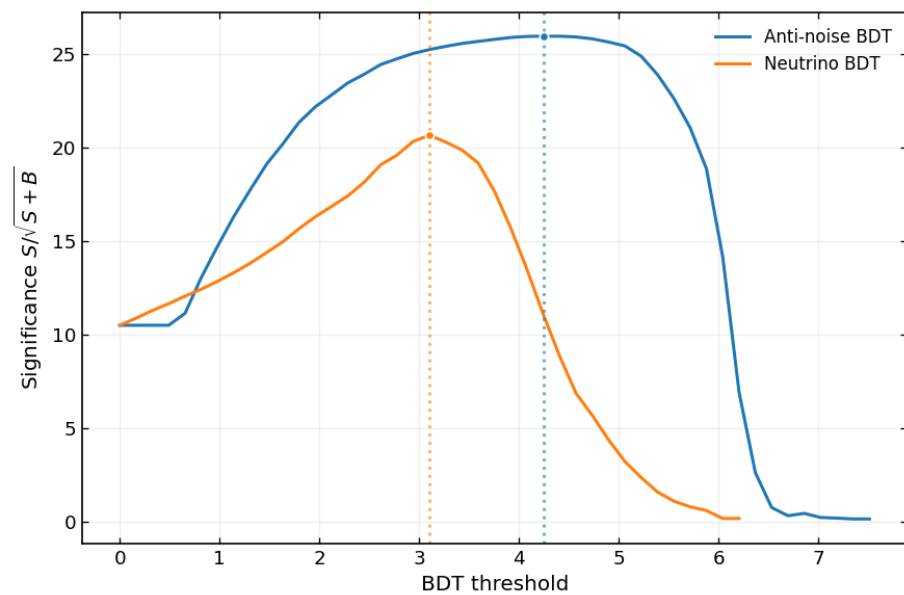
Simulated vs real event counts in  $\cos\theta$



# Signal cutting

Event selection removes dominant backgrounds before the oscillation comparison.

In order to discern between the different types of detection, and most importantly remove noise and contribution from atmospheric muons, we must cut some parameters at certain thresholds.



Significance on different graphs for different thresholds

## Final signal cut

$\cos \theta$  **< 0**

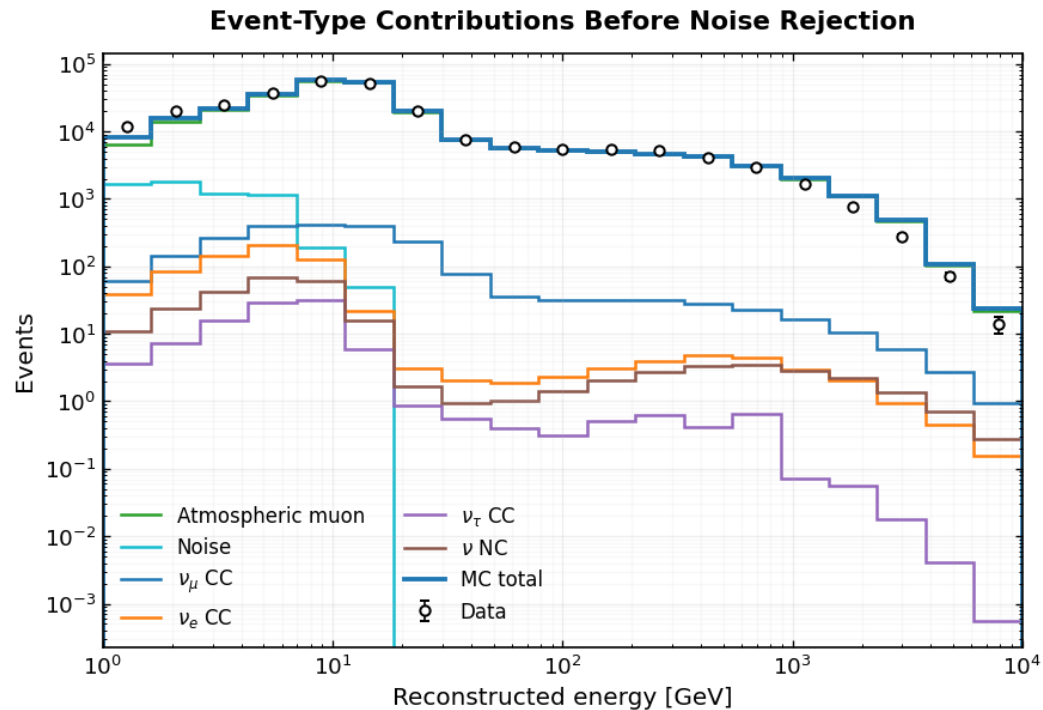
Neutrino BDT **> 3,1**

Noise BDT **> 4,2**

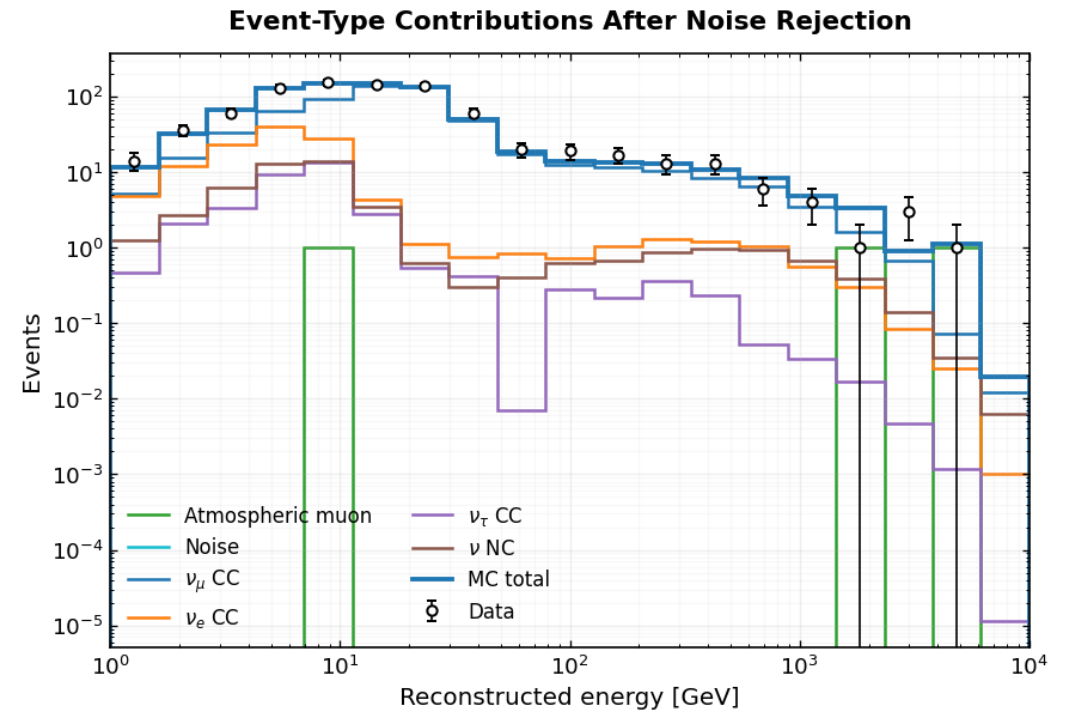
These thresholds are chosen by maximising the significance, in order to reduce noise and atmospheric muon contamination while keeping the neutrino signal.

# Signal cutting: event-type contributions

The cut changes the mixture of event types and suppresses the background-dominated regions.

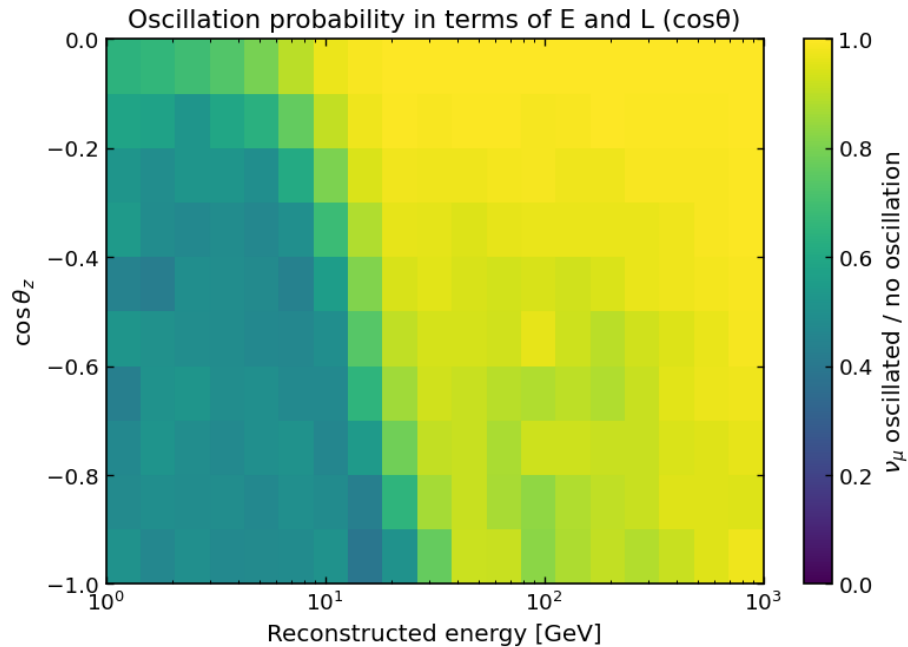


Most of our hits are atmospheric muons, and below  $\sim 10$  GeV, noise is really predominant. We must set thresholds in our data taking to ensure they aren't as significant.



With our cut, noise has been able to be completely removed, and atmospheric muons have essentially been wiped. However, we also have many less hits.

# Why do we measure in L/E?



We find a clear diagonal line separating the region where neutrinos will start to oscillate.

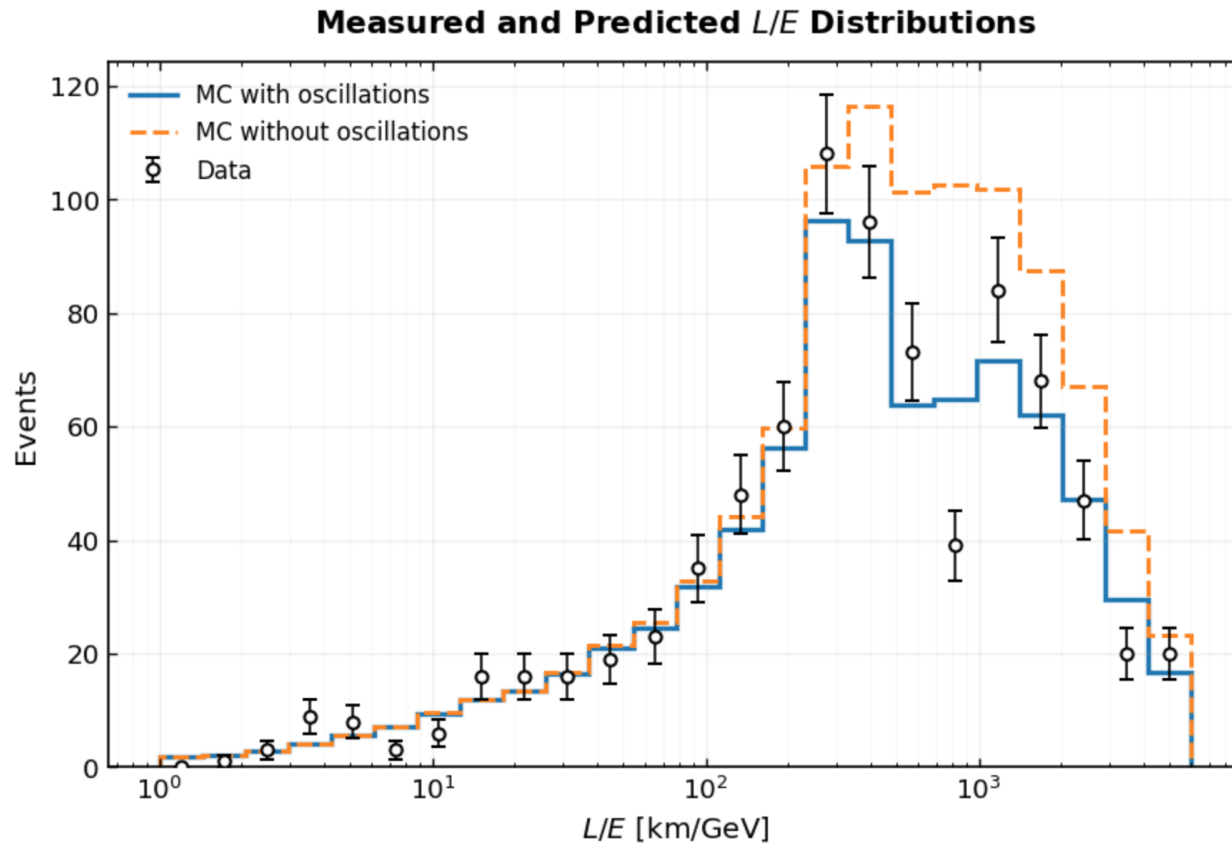
## Core idea

The oscillation probability evolves in a term proportional to  $L/E$  (see below). Atmospheric neutrinos arrive with different path lengths  $L$  and energies  $E$ , so  $L/E$  is the natural variable for the disappearance pattern.

$$P(\nu_i \rightarrow \nu_j) \propto \sin^2\left(\frac{\Delta m_{ij}^2 L}{2E}\right)$$

# Comparing our data: does it fit the simulation?

The L/E distribution is compared with oscillated and non-oscillated MC predictions.



## $\chi^2$ comparison

MC with oscillations

$$\chi^2 = 1,85$$

MC without oscillations

$$\chi^2 = 7,64$$

$$\chi^2 = \frac{\sum_i (n_i^{\text{data}} - n_i^{\text{model}})^2}{n_i^{\text{data}}}$$

Lower  $\chi^2$  indicates better agreement between the data and the model

# Thank you for listening

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Questions?

