# An overview of Machine Learning techniques in KM3NeT

Neutrino Physics and Machine Learning
ETH Zurich

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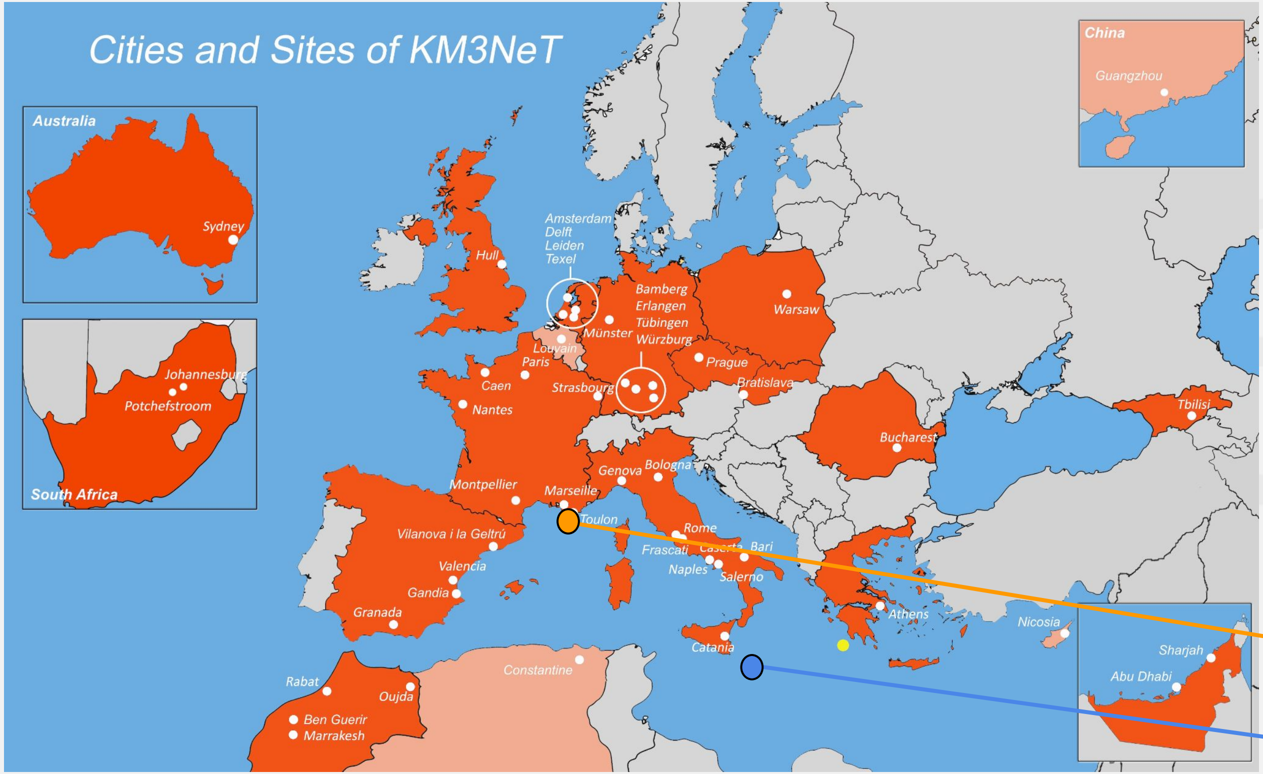
- KM3NeT/ARCA and KM3NeT/ORCA
- Summary of machine learning projects in KM3NeT
- Results of Machine Learning techniques applied in KM3NeT

# KM3NeT




- International collaboration with
  - ~250 members
  - 45 partner institutes
  - Over 14 countries.
- Two detectors in different sites: KM3NeT/ORCA and KM3NeT/ARCA:
  - Same technology
  - Same data processing
  - Same software and common dataformats.
  - Different size and granularity.

KM3NeT/ORCA

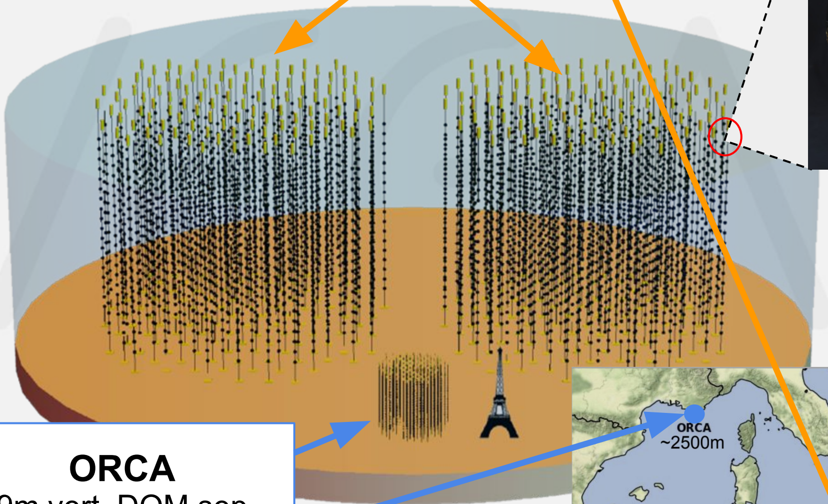
KM3NeT/ARCA

# KM3NeT - ARCA and ORCA

- **KM3NeT/ORCA:**
  - ➢ Low energies (~few GeV to hundreds of GeVs)
  - ➢ Fundamental neutrino property studies (mainly)
  - ➢ **Full ORCA**: 115 DUs, 18 DOMs per DU
  - ➢ **Current ORCA**: 23 DUs deployed
- **KM3NeT/ARCA:**
  - ➢ High energies (sub-TeV to few PeV)
  - ➢ Astrophysical studies (mainly)
  - ➢ **Full ARCA**: 230 DUs, 18 DOMs per DU
  - ➢ **Current ARCA**: 28 DUs deployed

**ARCA**
36m vert. DOM sep.
90m hor. DU sep.
1 Gton detector

**DOM**
31x3” PMTs

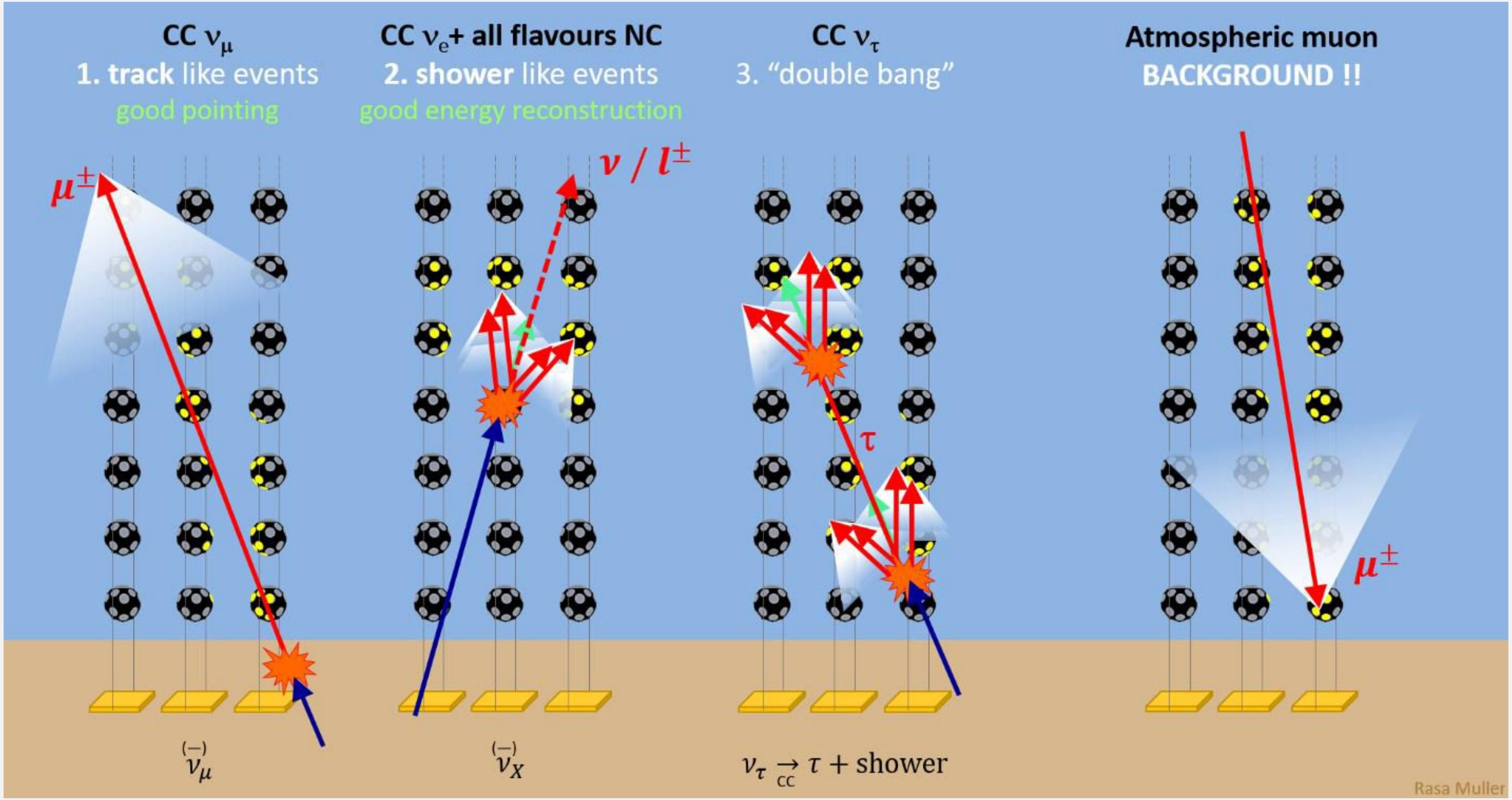



**ORCA**
9m vert. DOM sep
20m hor. DU sep
7 Mton detector

*DU: Detection Unit. String of 18 DOMs.*

*DOM: Digital Optical Module.*

# KM3NeT - Detection principle. Event topology



# Deep Learning Projects in KM3NeT

CNNs:

- Event reconstruction for KM3NeT/ORCA using convolutional neural networks (M. Moser, KM3NeT)
- Event Classification and Energy Reconstruction for ANTARES using Convolutional Neural Networks (N. Geißelbrecht, ANTARES)
- Deep learning reconstruction in ANTARES (J. García-Méndez et al., ANTARES)
- Dark matter search towards the Sun using Machine Learning reconstructions of single-line events in ANTARES (J. García-Méndez et al., ANTARES)

Fully-connected NNs:

- Deep Neural Networks for combined neutrino energy estimate with KM3NeT/ORCA6 (S. Peña Martínez, KM3NeT)

Transformers/Foundation models:

- Transformer based classification and reconstruction in KM3NeT/ORCA (I. Mozun, KM3NeT)
- Preliminary studies of foundation models in KM3NeT (M. Eff, KM3NeT)

# Deep Learning Projects in KM3NeT

GNNs:

- Development of detector calibration and graph neural network-based selection and reconstruction algorithms for the measurement of oscillation parameters with KM3NeT/ORCA (D. Guderian, KM3NeT)
- Data reconstruction and classification with graph neural networks in KM3NeT/ARCA6-8 (F. Filippini et al., KM3NeT)
- Cosmic ray composition measurement using Graph Neural Networks for KM3NeT/ORCA (S. Reck, KM3NeT)
- Optimisation of energy regression with sample weights for GNNs in KM3NeT/ORCA (B.Setter, KM3NeT)
- Tau neutrino identification with Graph Neural Networks in KM3NeT/ORCA (L. Hennig, KM3NeT)
- Energy reconstruction in ARCA21 using GNNs (E. Tragia, P. Gkotsis, E. Drakopoulou, KM3NeT)
- Particle ID classification, energy, direction and interaction vertex position reconstruction in KM3NeT/ORCA using Dynedge (J. Prado, KM3NeT)
- Neutrino Selection using GNNs for ARCA28 (A. Veutro, KM3NeT)
- Neutrino Direction reconstruction using GNNs for ARCA21 (M.R. Musone, KM3NeT)

And several different ML-based projects being already part of physics analyses (BDTs, RFs…):

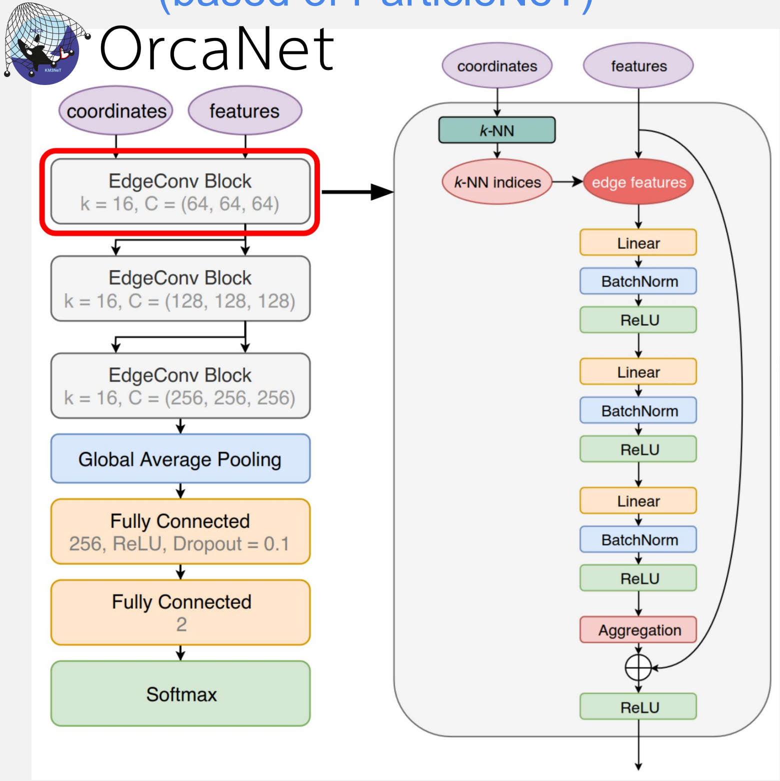
- ParamPID: t/s, nu/noise and nu/mu classifier with XGBoost (A. Lazo & L. Maderer, KM3NeT)
- CR composition measurement: Atm. muon bundle reconstruction using RFs (P. Kalaczynski, KM3NeT)
- BoostTauID: identify GeV tau neutrinos in ORCA with XGBoost/ParamPID (N.Geißelbrecht, KM3NeT)

# Deep Learning data preprocessing in KM3NeT

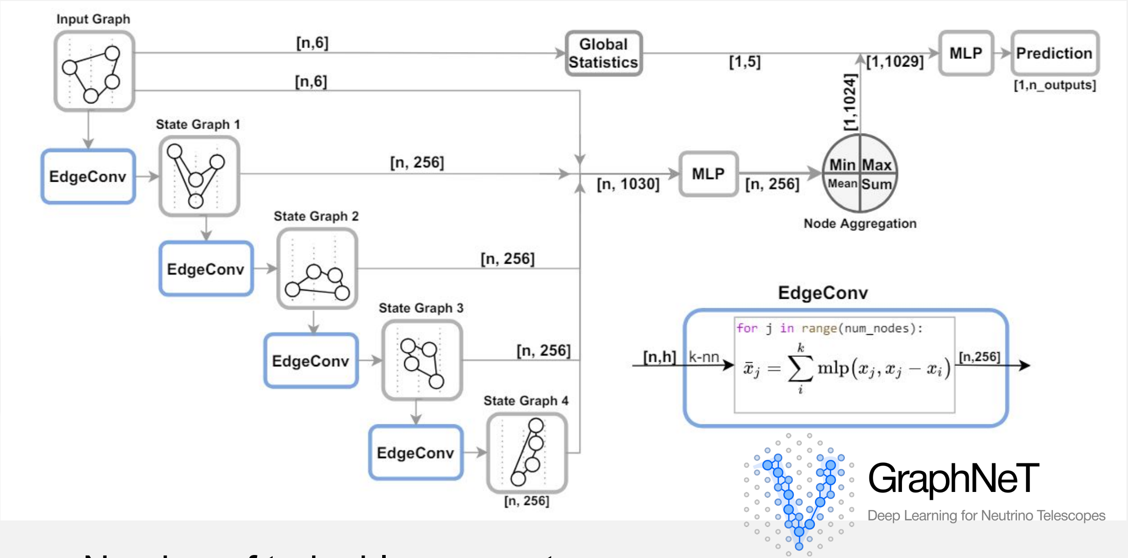
- **OrcaSong** is a project for preprocessing raw KM3NeT/ORCA or KM3NeT/ARCA data for the use of neural networks (maintained by Lukas Hennig).
  - ➢ Produces list of nodes, each representing info about a hit in the detector for graph networks.
  - ➢ Produces n-dimensional images for convolutional networks.
- **GraphNeT 2.0** is a common framework for DL projects with a modular pipeline to build your own experiment data converter.
  - ➢ KM3NeT classes already implemented - waiting for review.
  - ➢ Very easy to include your model there. Very well documented software [GraphNeT instructions].

# Graph Neural Networks in KM3NeT

## OrcaNeT (based of ParticleNeT)




## GraphNeT-Dynedge




- Number of trainable parameters:
  - ➢ Dynedge: ~1.6M
  - ➢ ParticleNeT: ~370k

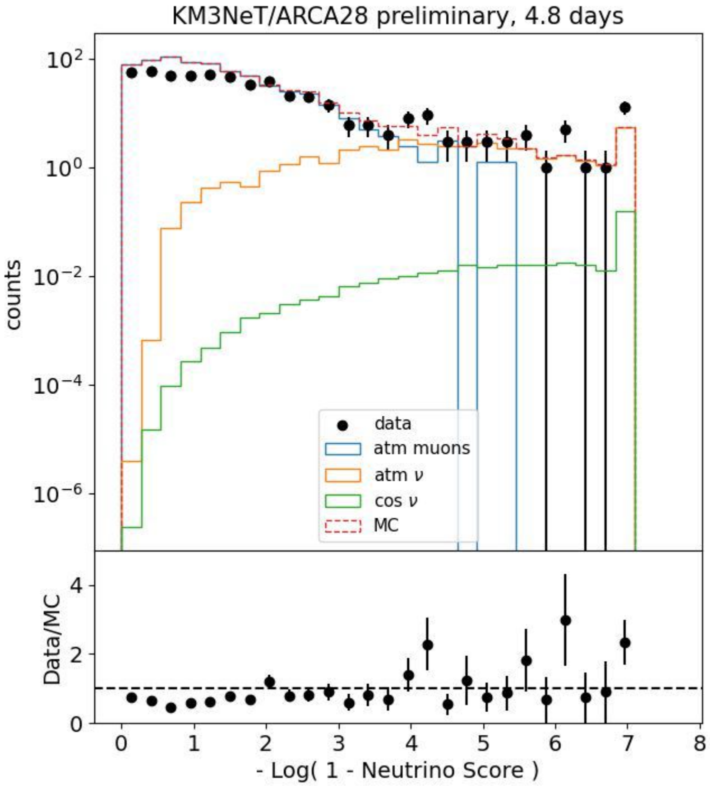
[OrcaNeT software documentation here]
[ParticleNet model documentation here]
[Graphnet-Dynedge model documentation here]

# Graph Neural Networks in ARCA (ARCA28*)

## Neutrino Classification with ORCANeT

- Network trained to distinguish between atmospheric muons and neutrinos (cosmic and atmospheric)
- Efficiency requiring neutrino score >0.99996:
  - ➢ Muon contamination below 20%
  - ➢ Expected cosmic neutrino rate around 1.8 per month
- Real time performance. Average time to process an event:
  - ➢ 230 ms if running on CPU
  - ➢ 140 ms if running on GPU

[Credit A. Veutro]

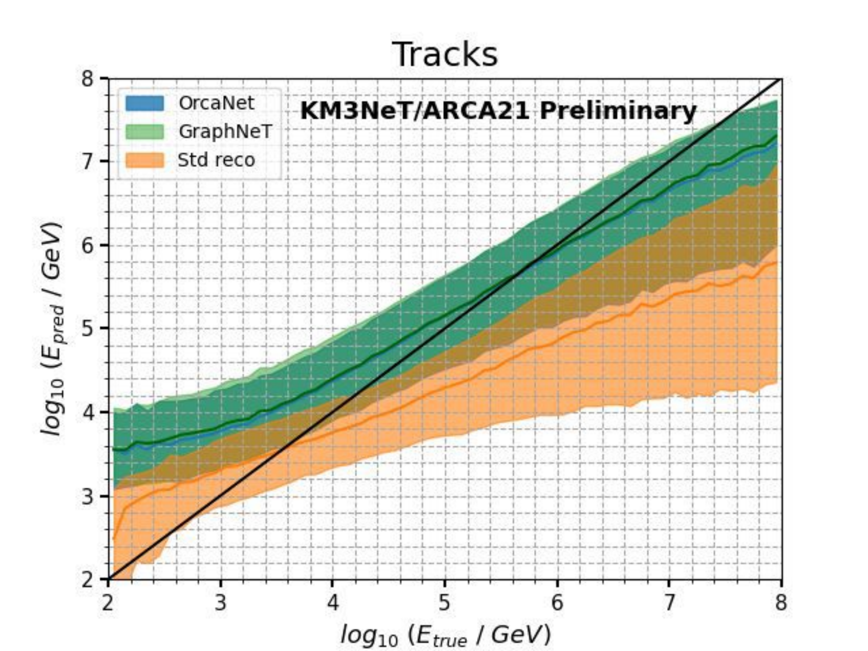



(*) ORCA(N) or ARCA(N) with N accounting for the number of working DUs

# Graph Neural Networks in ARCA (ARCA21)

## Tracks Energy reco with ORCANeT and Dynedge

- **ORCANeT** and **Dynedge** trained on the same dataset, using the same loss function, on the reconstruction of the **true energy of the neutrino**.
- Each PMT hit is a node with features: position, PMT-direction, time and Time over Threshold.
- Node connected to k=16 nearest neighbours.
- Cut on the uncertainty provided by the GNN or on the maximum likelihood of the standard reconstruction.
- **Similar performance of Dynedge and ORCANeT.**



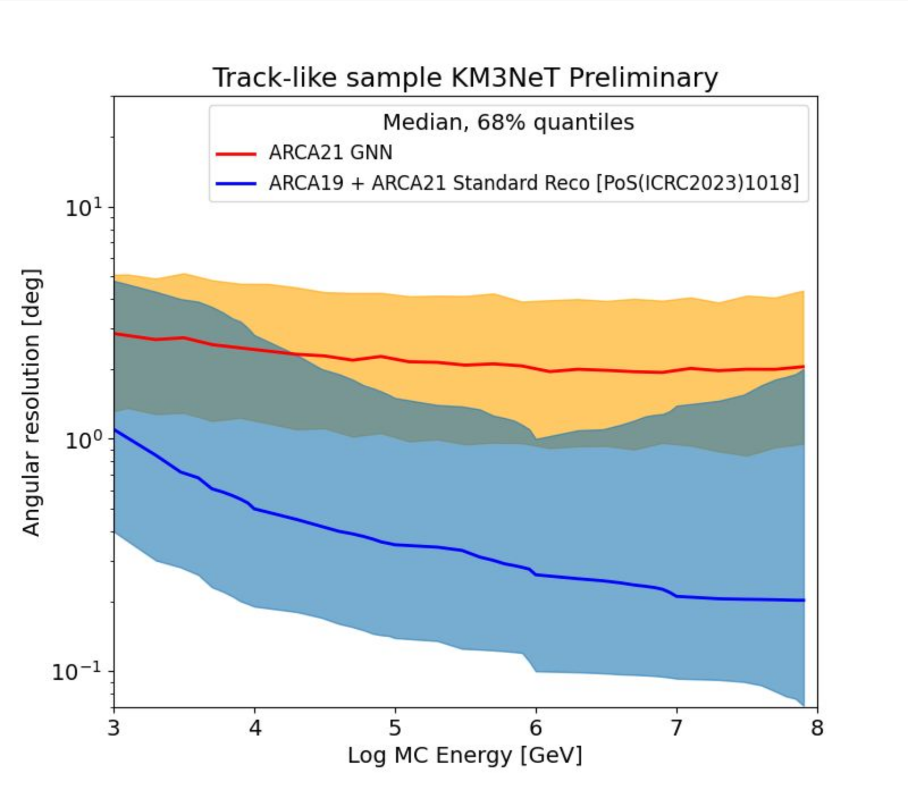

[Credit
E. Tragia &
P. Gkotsis]

# Graph Neural Networks in ARCA (ARCA21)

[Credit M. R. Musone]

## Direction reconstruction with ORCANeT

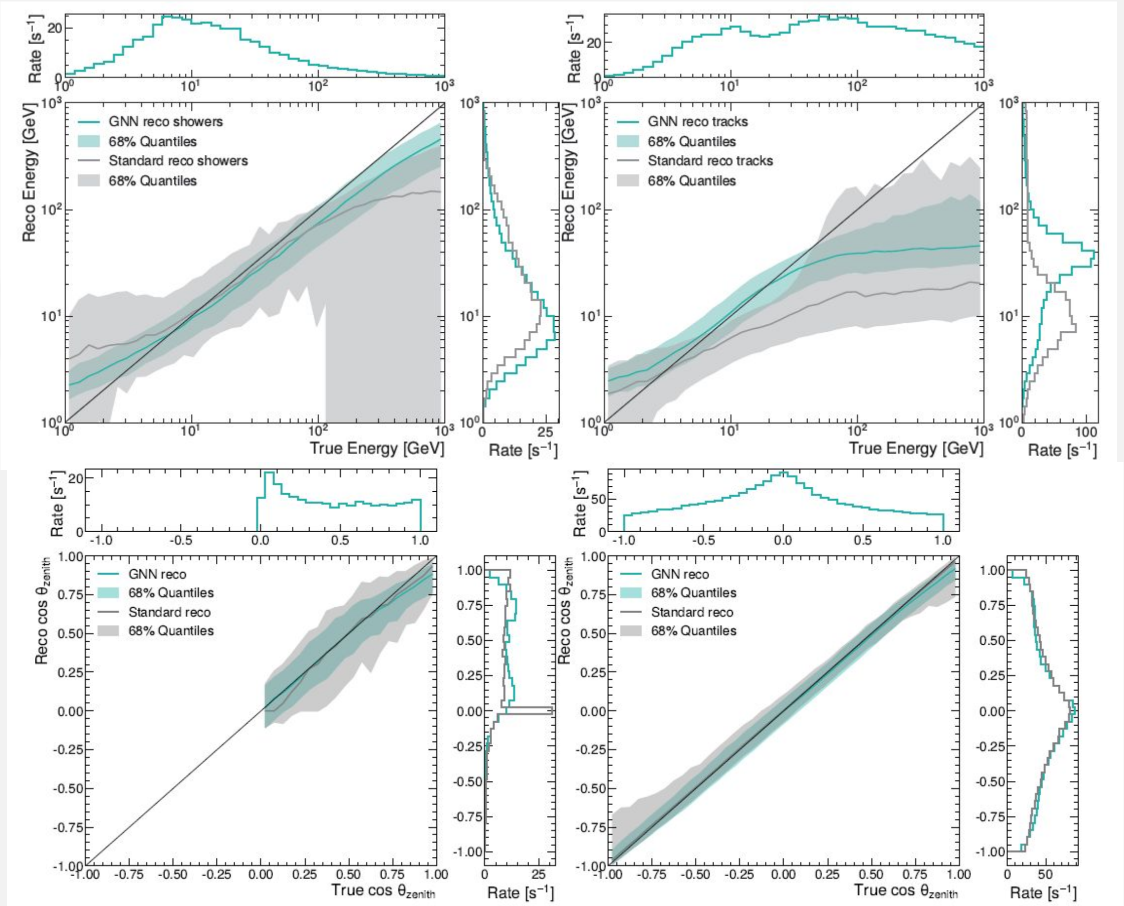
- Direction reconstruction for track-like events.
- Each node corresponds to a PMT with features position, direction, and time connected with its k=16 nearest neighbours.
- Quality cut applied to both algorithms so that 42% of the events survive.
- **GNN does not improve for the moment** the performance of the **standard likelihood reconstruction**.
- **Work in progress flag** as the GNN performance can be improved by using larger number of neighbours.



# Graph Neural Networks in ORCA (ORCA6)

## Multiple tasks with ORCANeT

- **Work in progress!**
- GNN trained for:
  - ➢ Signal/noise classif.
  - ➢ Track/shower classif.
  - ➢ Energy Regression
  - ➢ Direction Regression
  - ➢ Inelasticity Regression (Björken-y)
- **Very good results** found for **energy** and **direction regression**. The GNN struggles with classification tasks.
- Studying feasibility of Björken-y reconstruction. Difficult task

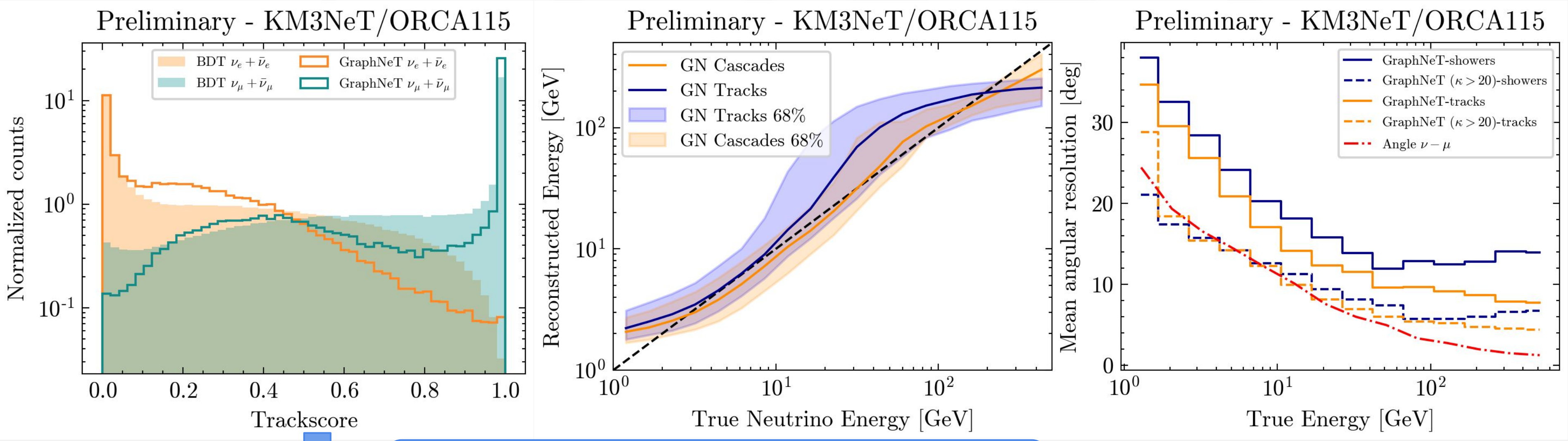



[Credit S. Peña Martínez]

# Graph Neural Networks in ORCA (ORCA115)

Multiple tasks with GraphNeT-Dynedge

- GNN trained for:
  - ➢ Track/Shower Classification.
  - ➢ Energy, Direction and Vertex position reconstruction.
- First training using GraphNeT dedicated software.
- Preliminary results but **very promising in both classification and regression problems.**




Comparison of Dynedge and XGBoost based BDT with standard cuts applied to the BDT sample and not for GraphNeT.

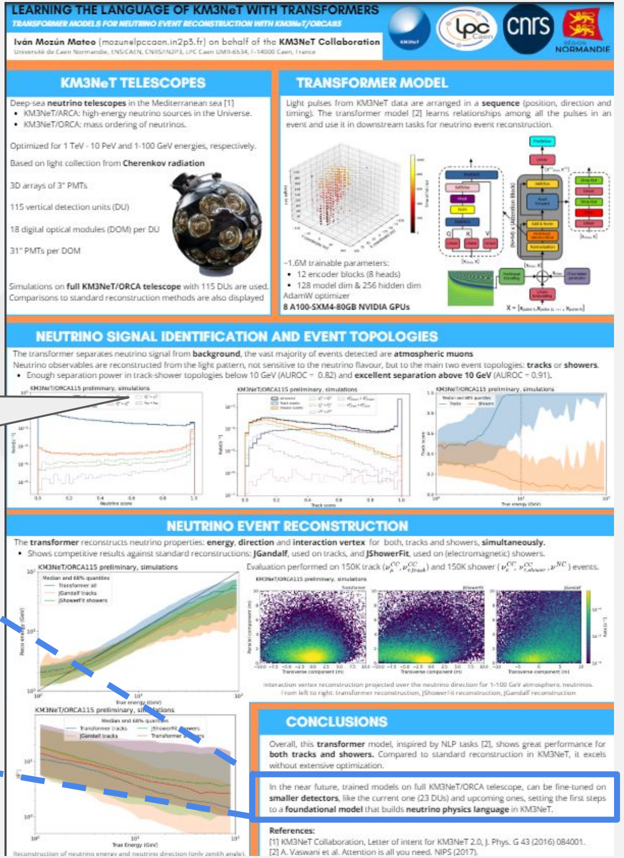
[Credit J. Prado]

# Transformers in KM3NeT

- **Work in progress - Very promising results!**
- Transformer model inspired in Natural Language Processing tasks arranges light pulses in a sequence and learns relationships among them to then perform different tasks.
- Transformer model trained for:
  - ➢ Neutrino/atmospheric muon classification.
  - ➢ Track/shower classification.
  - ➢ Energy Regression.
  - ➢ Direction Regression.
  - ➢ Interaction vertex position regression.
- *“In the near future, trained models on the full KM3NeT/ORCA telescope can be fine-tuned on smaller detectors, setting the first steps to a foundation model that builds neutrino physics language in KM3NeT.”*

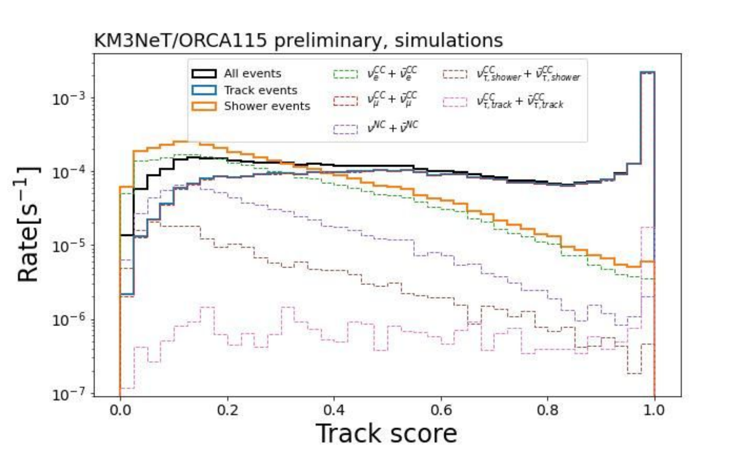
**Check me out in the NPML poster session!**

[NPML contribution 6 ]




[Credit I. Mozún]

# Transformers in ORCA (ORCA115)

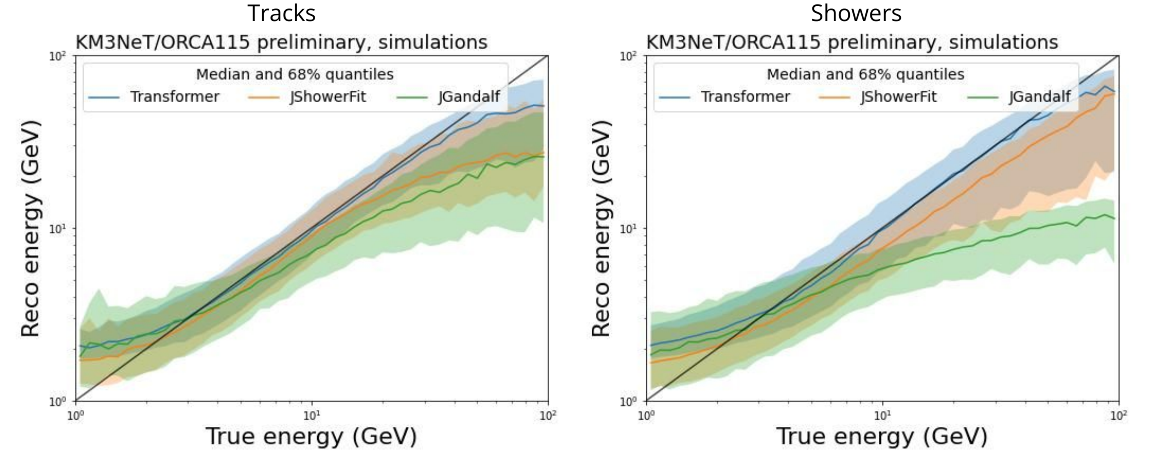



## Track-Shower classification with Transformers

- **Good** Track/Shower topology **separation below 10 GeV** (AUROC=0.82).
- **Great** Track/Shower topology **separation between 10-100 GeV** (AUROC = 0.91).

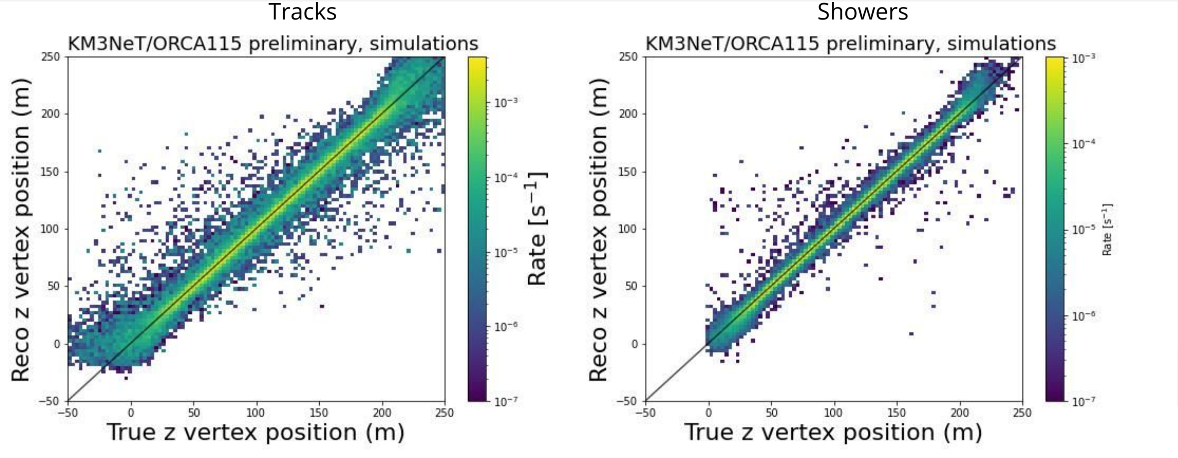
## Energy reconstruction with Transformers

- Transformer trained on both track and shower simultaneously for energy, direction and vertex position reconstruction, and evaluated on a sample of 150k tracks and 150k showers.




[Credit I. Mozún]

# Transformers in ORCA (ORCA115)

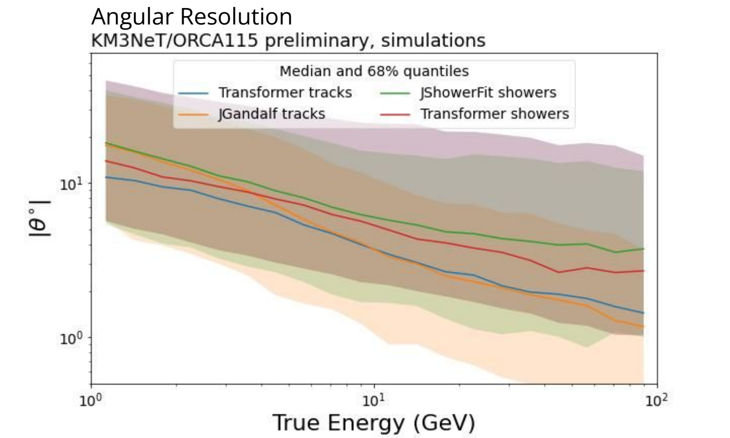



## Vertex position reconstruction with Transformers

- Better performance on showers than on tracks.
- Considering training on entry point on the detector instead of in interaction vertex position (future).

## Direction reconstruction with Transformers

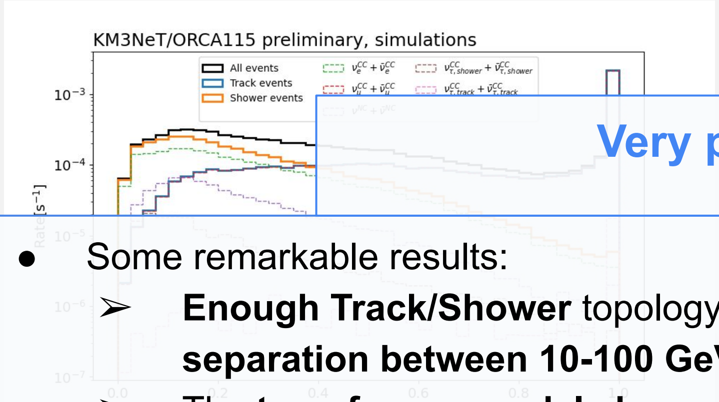
- Angular resolution better than 10 degrees for neutrino energies over 10 GeV.
- **Demonstrated strong capabilities** in energy, direction and vertex position reconstruction.

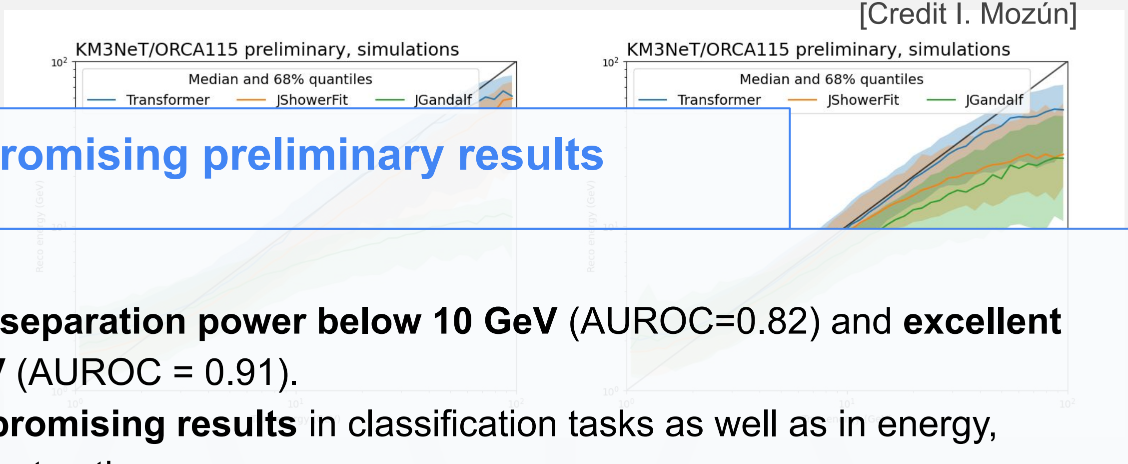



[Credit I. Mozún]

# Transformers in ORCA (ORCA115)

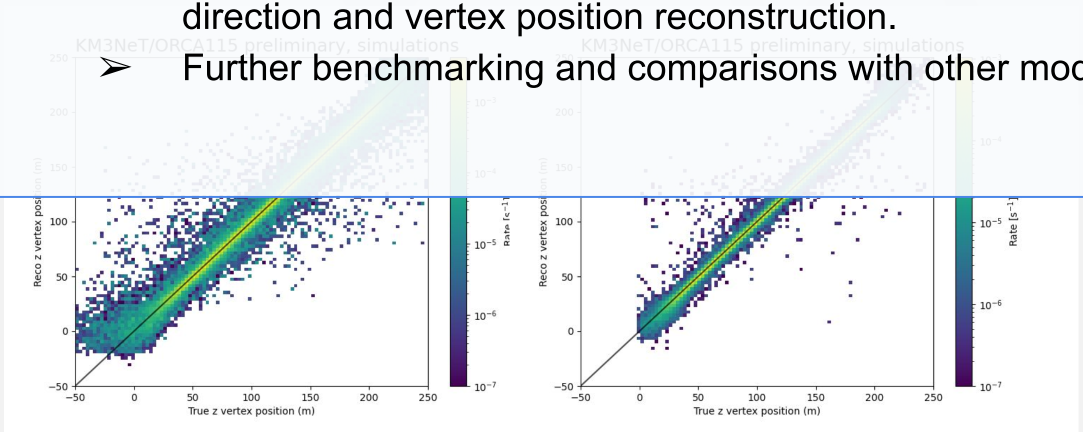
[Credit I. Mozún]

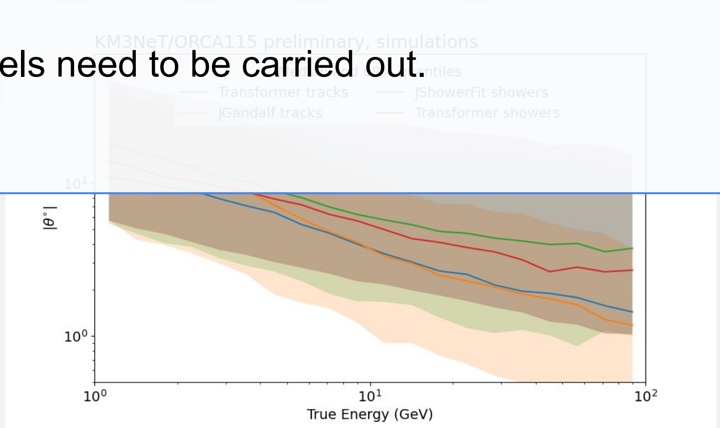



**Very promising preliminary results**

- Some remarkable results:
  - ➢ **Enough Track/Shower** topology **separation power below 10 GeV** (AUROC=0.82) and **excellent separation between 10-100 GeV** (AUROC = 0.91).
  - ➢ The **transformer model shows promising results** in classification tasks as well as in energy, direction and vertex position reconstruction.
  - ➢ Further benchmarking and comparisons with other models need to be carried out.



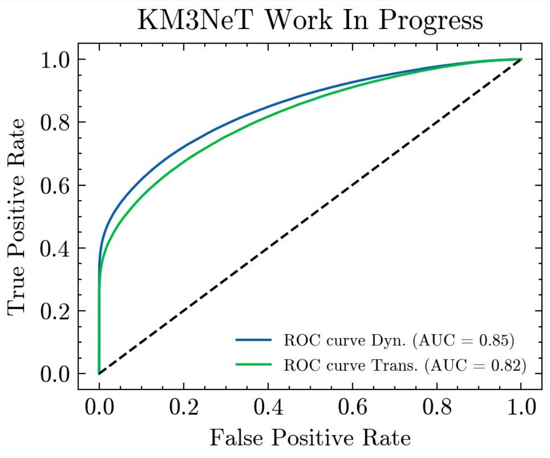
# Dynedge - Transformers (ORCA115)

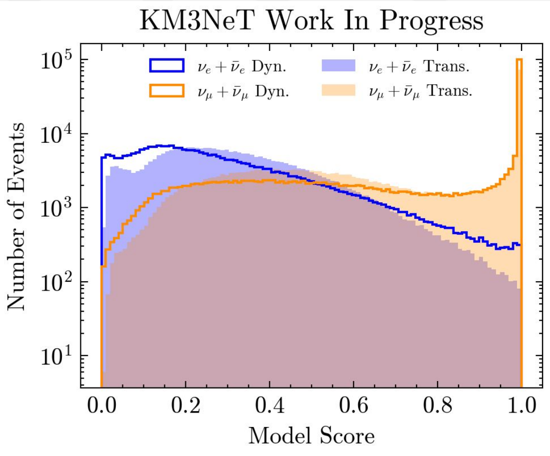
Track-shower classifier with
GraphNeT-Dynedge and Transformers

- Transformer and Dynedge models embedded in GraphNeT-KM3NeT software facilitating model comparison with benchmarked databases.
- Transformer and Dynedge trained on events of each taken from the same dataset and both are **predicting on the exact same events**.

| | Trans. | Dyn. |
|---|---|---|
| Train time per epoch | 15mins | 30mins |
| Total number of epochs | 30 | 28 |
| Events used for the training per topology | 2.4M | 2.2M |
| Model trainable parameters | 1.6M | 1.4M |
| Time for inference | 5.8ms | 3.1ms |

GPUs used: - Tesla V100-SXM2-32GB for Dynedge training and both inference.
- 8xA100-SXM4-80GB NVIDIA for Transformer model.




[Credit I. Mozún & J. Prado]

# Closing remarks

- Machine learning is a **very active field in KM3NeT**:
  - ➢ Significant efforts have been made to test different deep learning algorithms. Classification and reconstruction tasks performed by **GNNs** and **Transformer**-based models have shown **promising results** in both KM3NeT/ORCA and KM3NeT/ARCA
  - ➢ Two different contributions at NPML.
  - ➢ Four KM3NeT members participated in the 4th GraphNeT workshop.
- There is still **a long way to go**:
  - ➢ Common framework for benchmarking and easy reproducibility.
  - ➢ Further comparisons of the performance of different models, as well as with the likelihood based methods.
  - ➢ Tests for robustness.
  - ➢ Investigate the impact of systematics.
- We are trying **not to reinvent the wheel**. Use tuned models that have already been proven to work on similar problems.

# Thank you!

# Backup slides

# Appendix - Standard KM3NeT reconstructions

- The standard reconstruction methods for tracks and showers in KM3neT are called **JGandalf** and **Jshowerfit**, respectively.
- The way the methods reconstructs:
  - ➢ In both methods, based on the PMTs hits distribution, a first estimation of the quantity to reconstruct is performed.
  - ➢ Then, following different PDFs a sample of hypothesis is performed.
  - ➢ Finally, the likelihood of all the hypothesis is evaluated and the ones with a maximum value of the likelihood are stored as the best reconstruction.

# Appendix - Transformer Architecture