GNN applications in KM3NeT-ARCA

A. Capone[a,b], S. Celli[a,b], I. Di Palma[a,b], A. Domi[f], E. Drakopoulou[e], S. Gagliardini[a,b], P. Gkotsis[e], M. Mastrodicasa[a,b], P. Migliozzi[d], Maria Rosaria Musone[c,d], B. Spisso[d], E. Tragia[e], E. Tzamariudaki[e], Alessandro Veutro[a,b]

on behalf of the KM3NeT Collaboration

[a]Sapienza Università di Roma, [b]INFN-Sezione di Roma,
[c]Università degli studi della Campania"L.V." , [d]INFN-Sezione di Napoli
[e]NCSR Demokritos, [f] Erlangen Centre for Astroparticle Physics of Friedrich-Alexander-Universität

ABSTRACT

The KM3NeT next generation deep-sea neutrino telescopes are currently under construction in the Mediterranean Sea. Two water-Cherenkov neutrino detectors, ARCA and ORCA, are located in two different sites, south-est of Portopalo di Capo Passero (Italy) and close to Toulon (France), respectively. The KM3NeT/ARCA telescope, a cubic kilometer volume detector, is optimised for the detection of high-energy astrophysical neutrinos in the TeV-PeV range. Once completed, the detector will consist of 230 Detection Units, each housing 18 Optical Modules. In order to search for neutrino signals, a high background rejection power is needed and deep learning techniques provide promising methods for achieving this result. The flexibility of the so-called Graph Neural Networks (GNNs) suits perfectly the topology of a complex detector such as KM3NeT. This contribution will be focused on two interesting applications of GNNs: discrimination of signal events from the background, mainly composed of atmospheric induced events, and energy and direction event reconstruction.

WHY GNNs?

A set of objects, and the connections between them, can be naturally expressed as a **graph**. Graph Neural Networks (**GNNs**) are a class of deep learning methods designed to perform inference on data described by graphs. While a Random Decision Forest or a Boost Decision Tree require a very good knowledge of the variables to consider during the classification, GNNs do not, which means that GNNs and standard reconstruction algorithms are independent and they can run in parallel. Contrary to what happen with a Convolutional Neural Network, GNNs do not require rigid pre-chosen spatial and temporal bins to model the detector. This makes GNNs perfectly suitable in the context of a spatially dynamic, moving and rotating detector such as KM3NeT [1].

In this work, 3 possible applications of GNNs have been explored (**neutrino classification, direction and energy reconstruction**) and 2 different network architectures have been taken into account: **OrcaNet** (based on ParticleNet [2]) and **GraphNeT DynEdge** [3].

OrcaNet

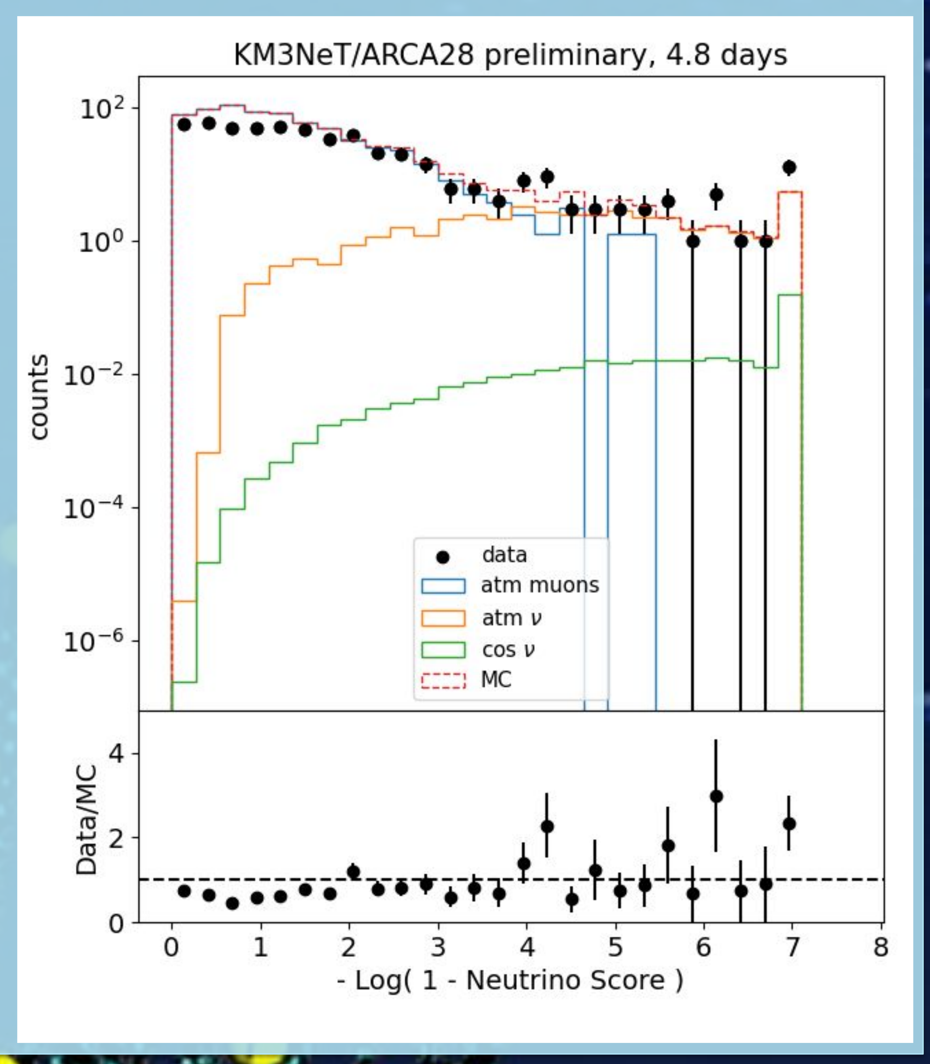
GraphNeT
Deep Learning for Neutrino Telescopes

NEUTRINO CLASSIFICATION with OrcaNet

In order to search for neutrino signal, a high background rejection power is needed. This goal can be achieved by training the network to distinguish between atmospheric muons and neutrinos (cosmic and atmospheric). The resulting classifier will assign to each event a **neutrino score**, which is the probability of being a neutrino.

Efficiency:
By requiring neutrino score > 0.99996 we achieve:
- a muon contamination below 20%
- an expected cosmic neutrino rate around 1.8 per month.

Real-time performance:
GNN classifier has been running in the real-time framework [4] since June 2023 and the average time required to process a single event of the stream is:
- **230 ms** if running on **CPU**
- **140 ms** if running on **GPU**



DIRECTION RECONSTRUCTION with OrcaNet

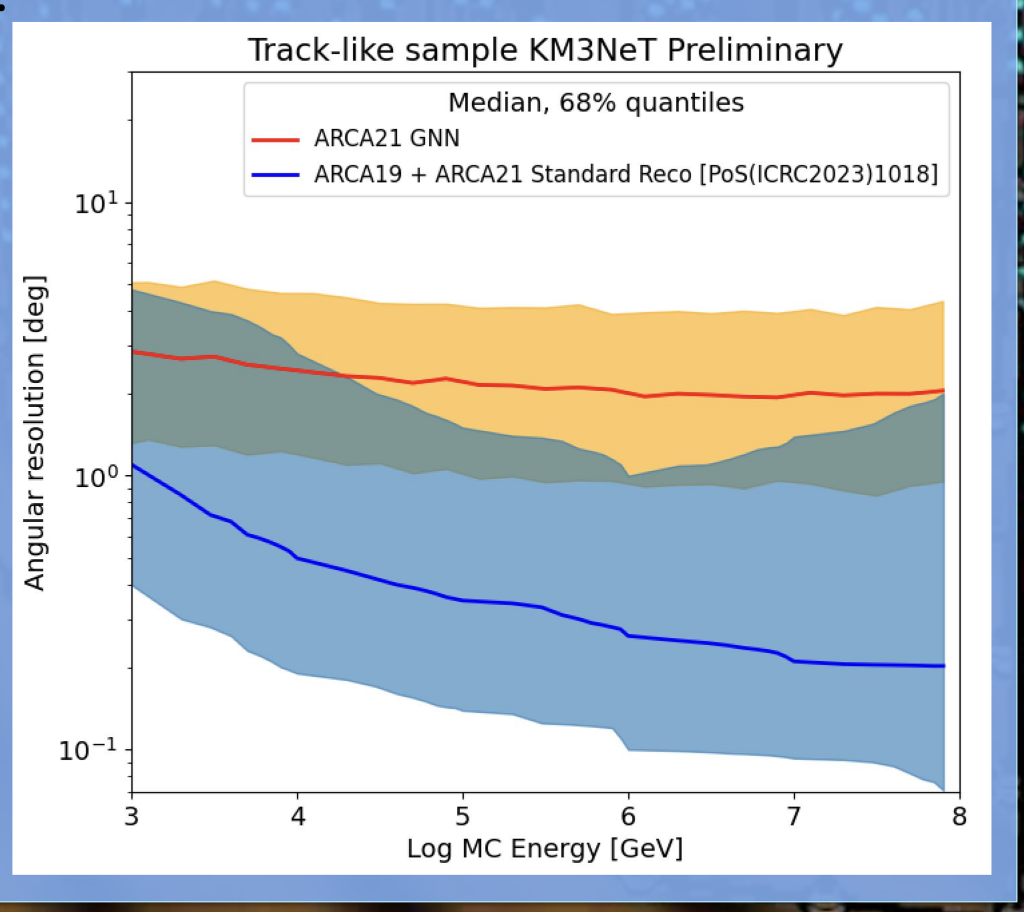
The reconstruction of **neutrino direction** is performed by GNN composed of 3 Edge Convolutional blocks followed by a fully-connected layer and 3 parallel layer one for each component of the neutrino direction: CosX, CosY and CosZ.

Graph node is composed of each PMT hit and is connected with its k = 16 nearest neighbors. Position, direction and time are features used in the training .

The **training** was performed with **900k events** of ARCA21 equally divided among **numuCC** and **anumuCC,** while the validation and inference data-set were composed by 10% of events.

Selection events:
Quality cut are applied for GNN sample. The 40% of events survived after cut.
The result for standard likelihood reconstruction takes into account a different event sample, more details can be found in [5].

GNN performances could improve by using a larger number of nearest neighbors.



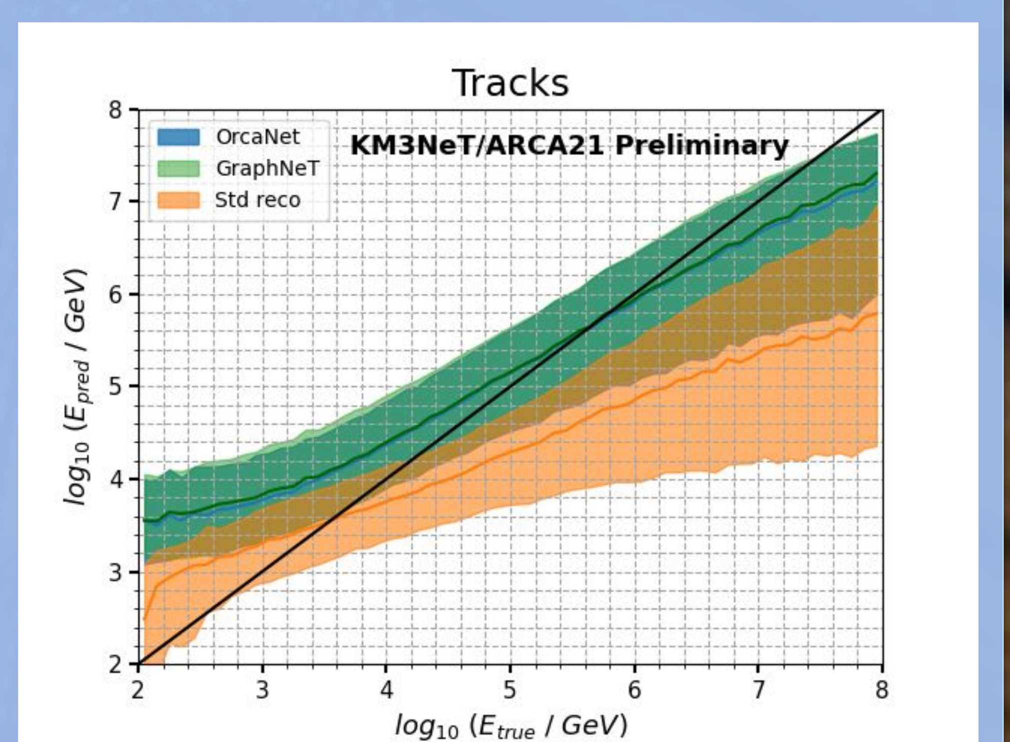
TRACK ENERGY RECONSTRUCTION with OrcaNet/GraphNeT

Energy reconstruction of tracks is carried out on both the **OrcaNet** and **GraphNeT DynEdge** architectures. The same MC event sample, as well as the same loss function, is used for both GNNs. For each event, the GNN returns an energy prediction, as well as an uncertainty estimate for that prediction.

Graph representation:
- Each PMT hit is one graph node with features: position, time, direction, ToT.
- Each graph node is connected with its k = 16 nearest neighbors, measured by Euclidean distance.

Appropriate **quality criteria** have been applied to both the GNNs (uncertainty cut) and the standard maximum likelihood reconstruction to ensure the reconstruction quality. Both GNN architectures are shown to have similar performances.

Event sample:
- Training: 672160 events
- Validation: 133025 events
- Inference: 172484 events



The logarithm of the reconstructed energy with respect to the logarithm of the MC neutrino energy

CONTACTS

gkotsis@inp.demokritos.gr
mrmusone@km3net.de
alessandro.veutro@roma1.infn.it
etragia@km3net.de

REFERENCES

[1] S. Adrian-Martinez et al. [KM3NeT], J. Phys. G 43 (2016) 8, 084001;
[2] Q. Huilin and L. Gouskos, Phys. Rev. D 101, 056019 (2020);
[3] R. Abbasi et al, JINST 17 P11003 (2022)
[4] M. Mastrodicasa et al. [KM3NeT], PoS TAUP2023 (2024), 273;
[5] Muller, R. et al. [KM3NeT]. PoS(ICRC2023)1018.

NEUTRINO 2024