Muon bundle reconstruction with KM3NeT/ORCA using graph convolutional networks

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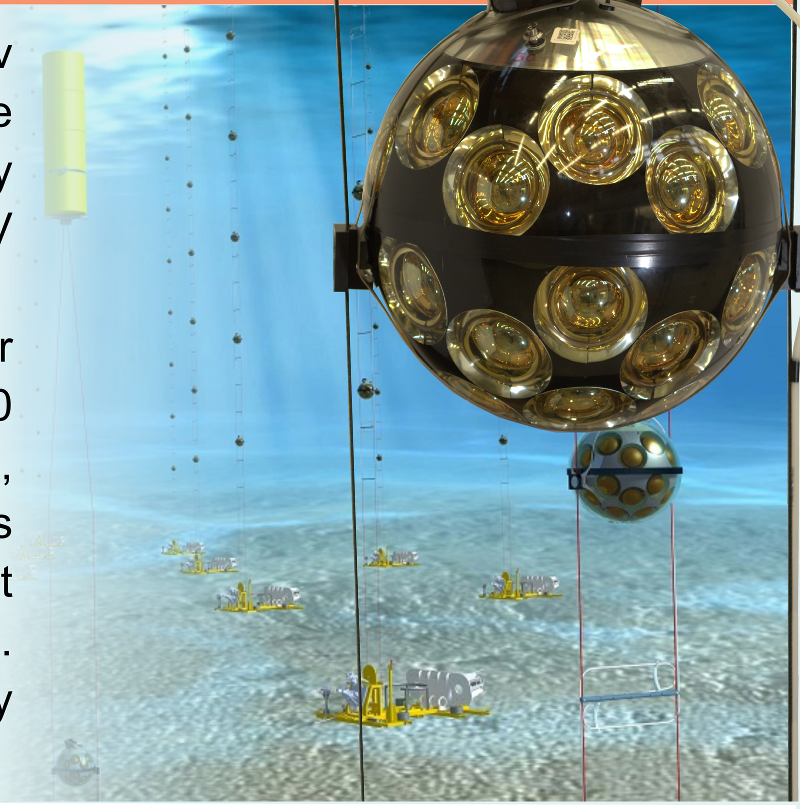
Summary

Convolutional graph neural networks are a promising alternative to image-based convolutional architectures. Since they operate on the more general structure of graphs, the hit information of KM3NeT events can be used as an input without any loss of information.
The **reconstruction of atmospheric muons** is the first application of graph neural networks in KM3NeT, and the first application of neural networks on KM3NeT measured data in general. The method shows excellent agreement to the classical approach for the zenith reconstruction. Novel reconstructions for the **muon multiplicity** and the **diameter** of atmospheric muon bundles are also presented, which allow for the indirect study of cosmic ray particles.

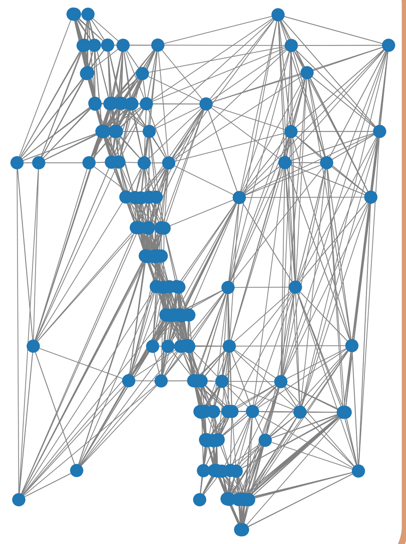
KM3NeT/ORCA [1] is a water Cherenkov detector currently under construction in the Mediterranean sea. Its primary goal is to study neutrino properties by detecting GeV neutrinos.
For this purpose, 7 mega-tons of sea water will be instrumented with a 3D-array of 2070 glass spheres, each housing 31 3" PMTs, arranged on 115 strings. As charged particles travel through the detector, they can emit Cherenkov light, which is detected by PMTs. This work uses data from the partially completed four-line detector.



Deep Learning with Graph Neural Networks

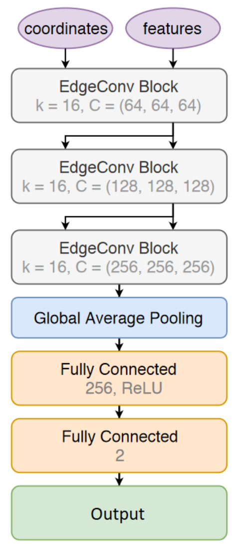
Input: hit information represented as graph

- Photon signals (hits) of events are recorded; for each hit, we have the following coordinates: 3D position in the detector, time, pointing direction of the photomultiplier
- Represent each hit with a node in a graph. The features of each node are the coordinates specified above
- This way, the network has access to the full information of each event
- 20M + 5M events simulated for training + plotting using MUPAGE [2]



Training: Graph neural network

- Model is based on ParticleNet [3], using the tensorflow framework
- At the heart of this architecture is the Edge Convolutional layer; similar to convolutional operations on images, a kernel network is convolved over the graph
- Custom open-source implementation of the EdgeConv was developed [4]
- ~5 days of training on a Nvidia GTX1080ti GPU with CUDA 10



layout of the network [2]

Output:

The output of the network is a (log-) normal distribution. The loss that is minimized during training is the negative log-likelihood of the true value given this distribution.

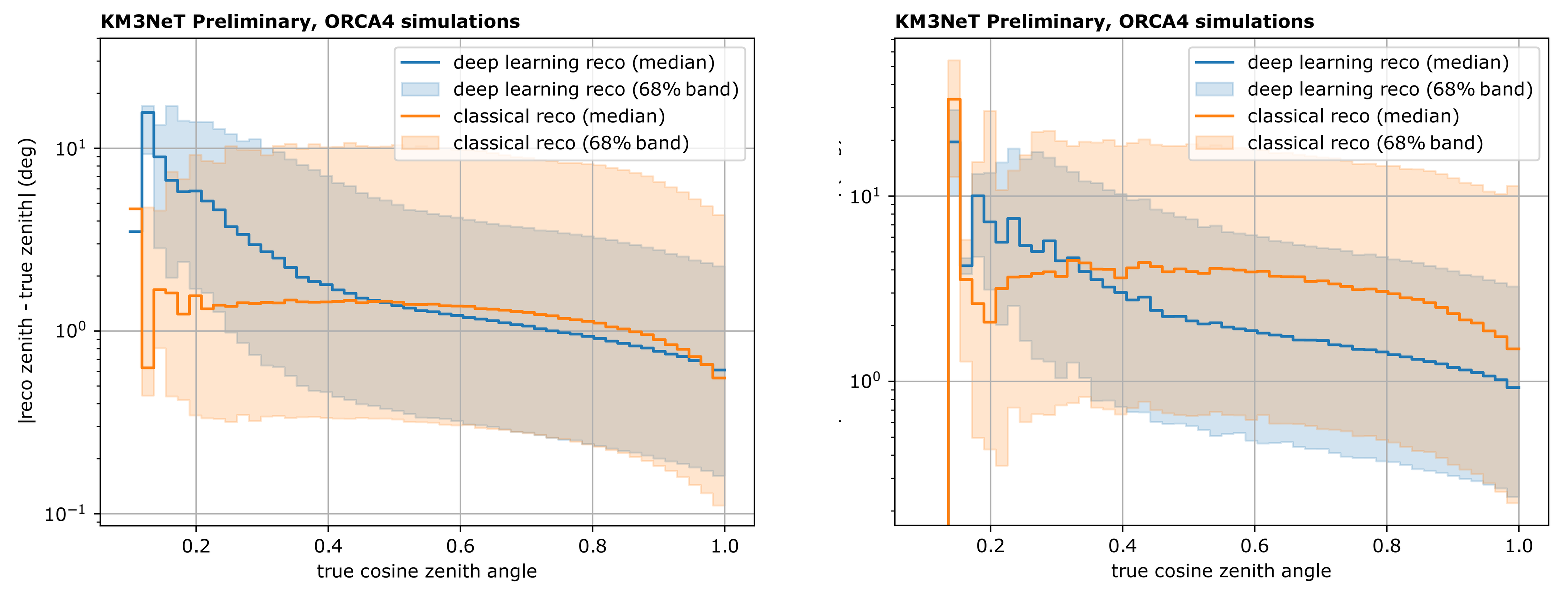
Last layer has two neurons for each reconstructed observable:

mu	- Linear activation - Estimator for the observable
sigma	- Exponential activation - Estimator for the uncertainty

[1] S. Adrián-Martínez et al., *Letter of Intent for KM3NeT 2.0*, J.Phys. **G43** (2016), no. 8 084001, [arXiv:1601.0745]
[2] G. Carminati, et al., *Atmospheric muons from parametric formulas: a fast generator for neutrino telescopes (mupage)* (2008) [arXiv:0802.0562v2]
[3] H. Qu, L. Gouskos, ParticleNet: Jet Tagging via Particle Clouds, Phys. Rev. D 101, 056019 (2020), [arXiv:1902.08570]
[4] https://github.com/StefReck/MEdgeConv
[5] D. Heck, et al., *CORSIKA: A Monte Carlo code to simulate extensive air showers*, FZKA-6019 (1998)
[6] K. Gaisser, T. Stanev, S. Tilav, *Cosmic Ray Energy Spectrum from Measurements of Air Showers*, Front.Phys. 8 (2013) 748

Reconstruction: zenith angle

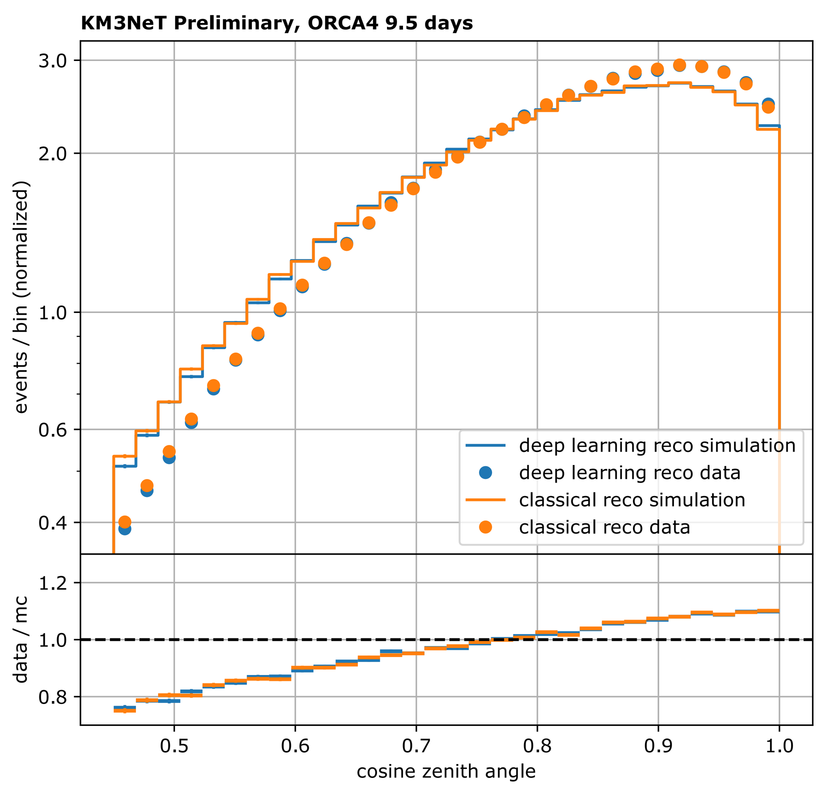
- Overall: similar performance to classical single-track reco described in [1]
- Significant improvement for multi-muon events



Absolute difference between reconstructed and true zenith angle of atmospheric muons plotted over the true zenith angle. Shown are the median and the 68% band for the classical (orange) and the deep learning approach (blue). Since it was trained on the expected distribution, the deep learning reconstruction is biased for true cosine zeniths below 0.5, leading to an increase in the error. Most atmospheric muons are not in that region. ***Left****: all events* ***Right****: only events with 2 or more muons*

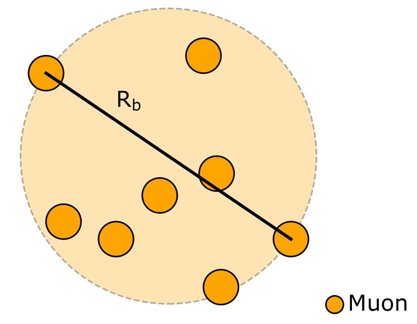
- Excellent agreement between classical and deep learning approach on both data and simulations for single muon events

Data-MC comparison of the reconstructed zenith angle for the classical approach (orange) and deep learning (blue). A cut is used on the classical reco quality in order to remove noise and multi-muon events. Each curve is normalized to have an integral of one.

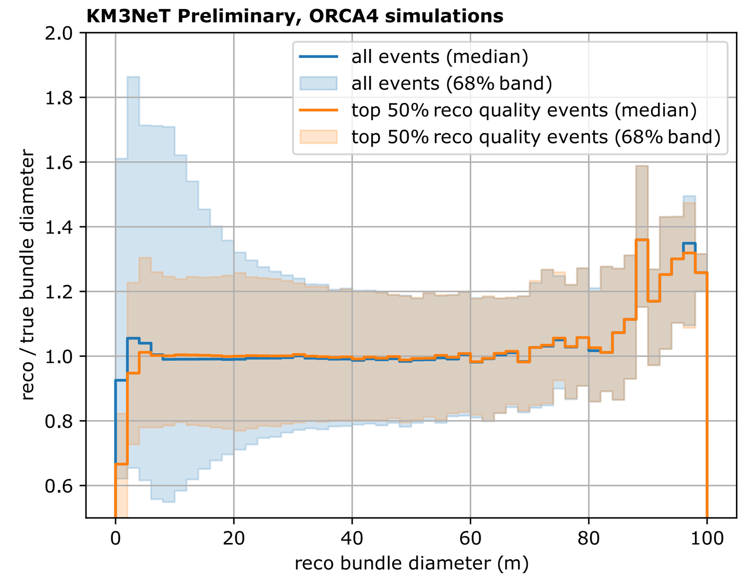


Reconstruction: Muon bundle diameter

When multiple muons travel through the detector at the same time, a characteristic observable of the bundle is the lateral spread of the muons. For the first time in KM3NeT, a reconstruction for the diameter of a muon bundle was developed.



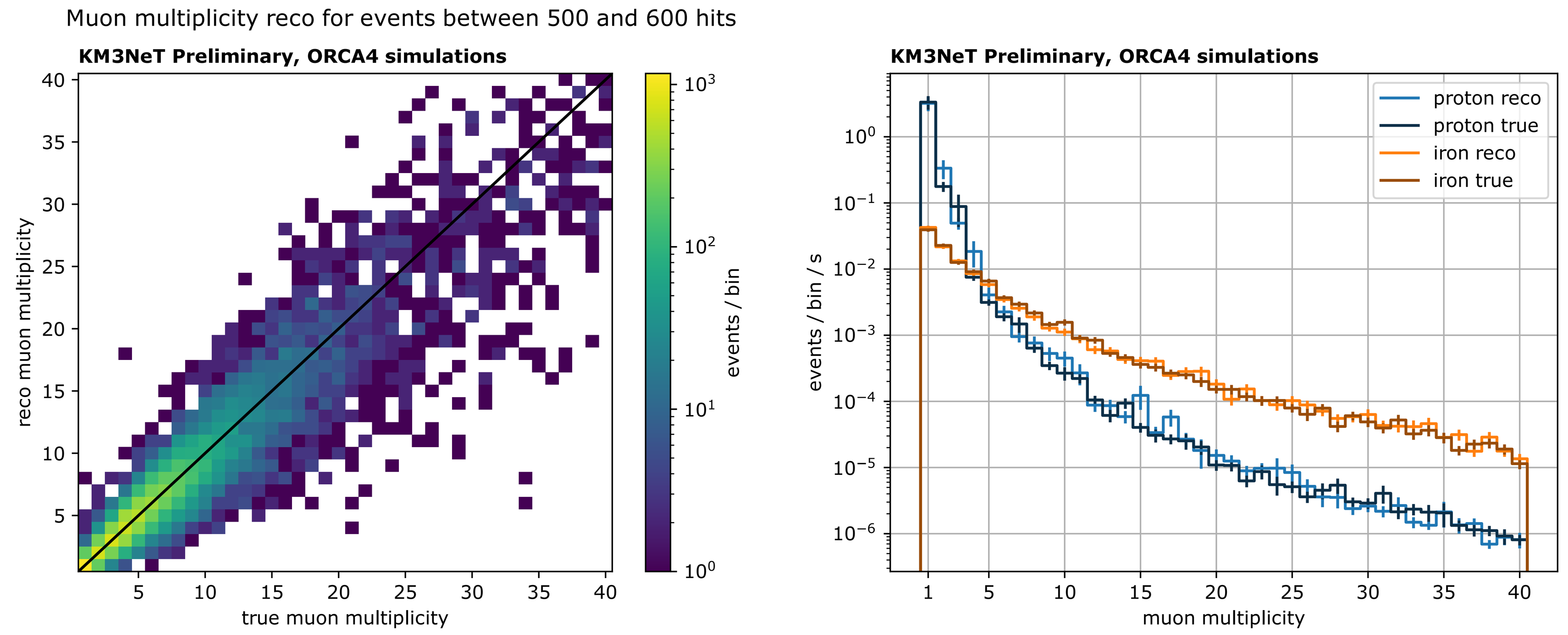
Scheme showing the bundle diameter R_b, here defined as the maximum distance between any pair of muons. The orange circles are the position of muons in the shower plane at the detector.



Performance of the bundle diameter reconstruction on events with 2 or more muons. Blue shows all events, orange shows the best 50% of events according to the reconstructed sigma.
This cut removes events whose diameter is difficult to reconstruct, e.g. because the muons are too close together to be resolved, or because they are too far away from the instrumented volume of the detector.

Reconstruction: Muon multiplicity

The number of muons in an event is an important observable for indirectly studying cosmic rays. This deep learning approach is the first reconstruction of the muon multiplicity in KM3NeT. Despite being in an early stage of construction, the detector already provides separation power between iron and proton induced events.

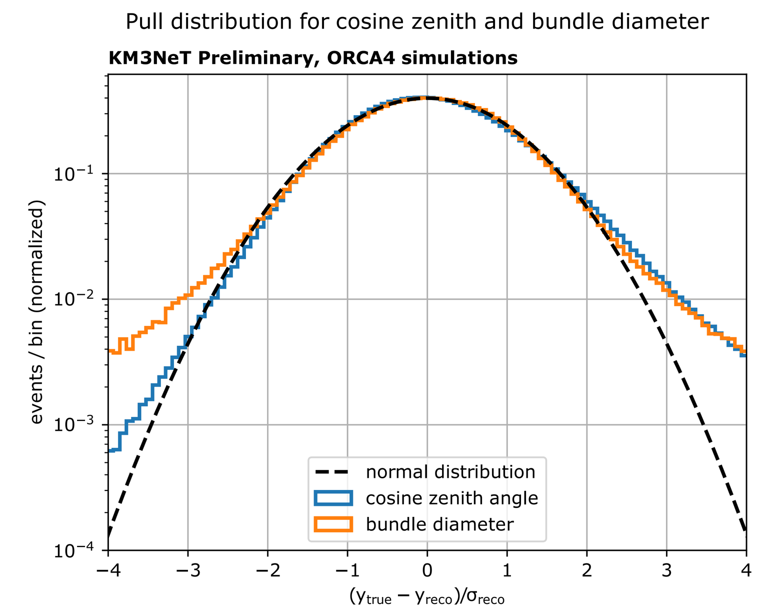


Reconstructed over true muon multiplicity. The multiplicity is in general correlated to the number of hits, since more muons produce more light on average. The plot only shows events with a comparable number of hits (between 500 and 600). Even in this particularly difficult case, the reconstruction is functional.

Reconstructed (light) and true (dark) muon multiplicity rates for events generated in a proton (blue) and iron (orange) induced atmospheric shower. Here, a set of Corsika [5] SIBYLL 2.3c simulations with the GST-3 [6] spectrum was used.

Uncertainty estimate

- The width of the reconstructed distributions, given by the paramter sigma, provides an event-by-event uncertainty estimate
- Can be used as an event selection, and to assert coverage



Pull distribution of the reconstructed zenith angle and bundle diameter. The dashed black line is the ideal normal distribution. The distributions match well for up to 2 sigma.

The Deep Learning efforts for ORCA have been combined into a tensorflow based, open-source neural network framework called OrcaNet :
https://github.com/KM3NeT/OrcaNet

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