Abstract

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Event triggering and deep learning for particle identification in KM3NeT

Neutrino astronomy experiments like KM3NeT allow to survey the Universe leveraging the properties of neutrinos of being electrically neutral and weakly interacting particles, making them a suitable messenger. Observing neutrino emission in association with electromagnetic radiation allows evaluating models for the acceleration of particles occurring in high energy sources such as Supernovae or Active Galactic Nuclei. This is the main goal of the ARCA project in KM3NeT. In addition, KM3NeT has a program for lower energy neutrinos called ORCA, aimed at distinguishing between the scenarios of "normal hierarchy" and "inverted hierarchy" for neutrino mass eigenstates.

The KM3NeT Collaboration is currently building a network of three Cherenkov telescopes in the Mediterranean sea, in deep water off the coasts of Capopassero, Italy; Toulon, France, and Pylos, Greece. The water overburden shields the detectors from down-going charged particles produced by the interactions of cosmic rays in the atmosphere, while up-going neutrinos that cross the Earth are the target of the observation. Cosmic rays are a background to the KM3NeT signal, usually discarded by directional information. Nevertheless, they provide a reliable reference to calibrate the detector and work out its effective operating parameters, namely direction and energy of the incoming particles.

Estimation of tracking capabilities is directly connected to the evaluation of the ability of the experiment to detect astrophysical point-like sources, i.e. its discovery potential. Being able to distinguish among the three neutrino flavours, or between neutrinos and muons, as well as estimating the neutrino direction and energy, are the main goals of such experiments. Trigger and reconstruction algorithms are designed to separate

the signal from background and to provide an estimation for the above mentioned quantities, respectively.

This work describes an innovative approach, based on the application of Deep Learning models, to perform event classification and interaction parameters estimation. KM3NeT simulated events are used as input data to train Neural Network models, capable of classifying the neutrino events based on their shape and the time distribution of the signal hits produced in the detector. In particular, triggered events are fed into Convolutional Neural Network models specifically designed to accomplish 4 different tasks, namely: "up-going" and "down-going" neutrinos classification; ν_μCC and ν_eCC interactions classification; energy and direction estimations of simulated neutrinos. The Convolutional Neural Network models have been implemented using the Keras deep learning framework, a high-level neural networks API designed for easy and fast prototyping which runs seamlessly on CPU and GPU[1].

Since the selection criteria for the events affect the quality of the reconstruction, a preliminary study on the trigger conditions has been conducted to ensure the purity of the selected events.

The developed Deep Learning models have been tested on a dataset consisting of $258,879$ ν_μCC and ν_eCC simulated events, achieving an accuracy of 93.3% for the up-going/down-going classification and 92.8% for the ν_μCC/ν_eCC classification. For the estimation of the neutrino energy and the cosine of the zenith angle of the neutrino direction, the obtained mean squared errors are 0.22 and 0.03, respectively.

The performance of the Neural Network models for energy and direction estimations, as well as up-going/down-going classification have been compared to those calculated by the official reconstruction algorithm currently in use in the KM3NeT reconstruction software pipeline. In this case, only ν_μCC events have been used since the considered reconstruction algorithm, namely `JGandalf`, is based on the assumption of a track-like event shape. The results obtained with the two different approaches are comparable. Nevertheless, the capability of the Neural Networks of performing these estimations directly from raw data constitutes a promising approach in terms of computational times and resources required.

[1]Graphical Processing Unit.