ENHANCED CLASSIFICATION AND RECONSTRUCTION OF SINGLE-LINE EVENTS IN THE ANTARES NEUTRINO TELESCOPE USING DEEP NEURAL NETWORKS ENDOWED WITH TRANSFER LEARNING

Juan García Méndez[a,b,*], Salva Ardid[a,c] and Miguel Ardid[a,c]
On behalf of the ANTARES collaboration

[a] Universitat Politècnica de València, Research Institute for Integrated Management of Coastal Areas
[b] Universitat Politècnica de València, PhD in Design, Manufacture and Management of Industrial Projects
[c] Universitat Politècnica de València, Department of Applied Physics
[*] E-mail: jgarmen@upvnet.upv.es

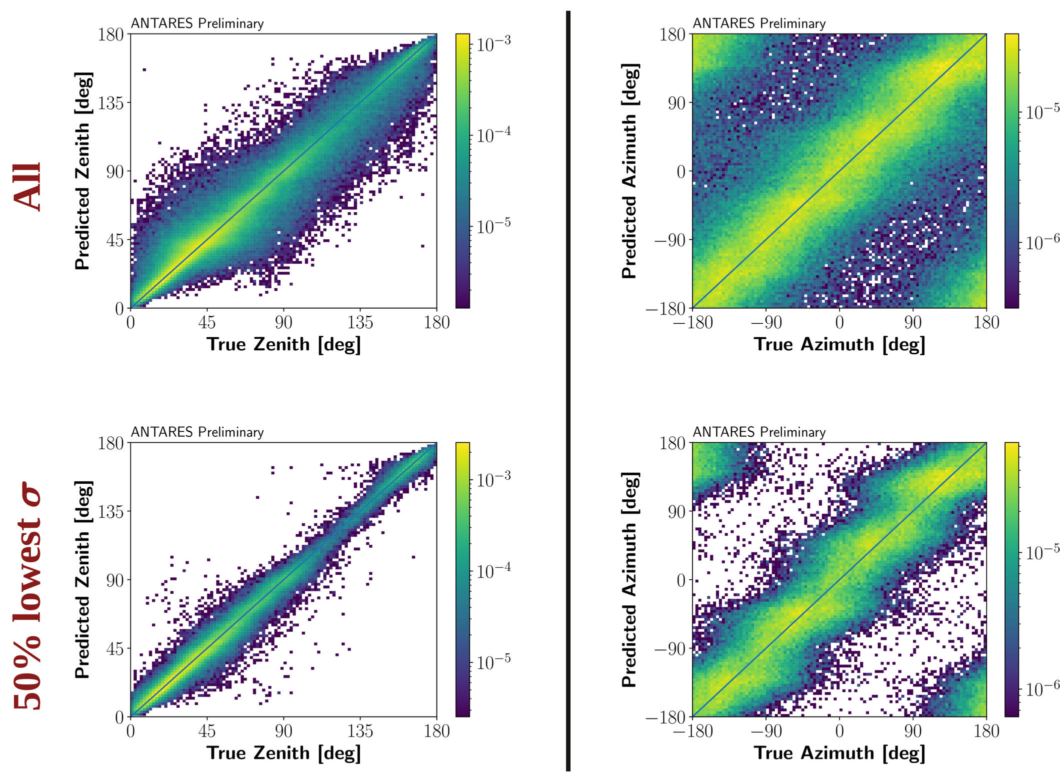
Introduction

ANTARES was the first deep-sea neutrino telescope [1]. It consisted of 12 vertical lines containing 25 storeys per line and 3 Optical Modules (OMs) per storey. It detected Cherenkov light induced by secondary particles from neutrino interactions. Current physics analyses in the low energy range of ANTARES ($\lesssim$ 150 GeV) are performed with reconstructed parameters from a standard χ^2-like fit [2], which is not able to reconstruct the azimuthal angle (ϕ) for single-line (SL) events. These events have useful information only in one line of the detector. Low energy studies in neutrino telescopes are important for some physics analyses: oscillations, dark matter (DM) indirect searches, etc.
In this contribution:

- We propose a deep learning method to improve the reconstruction performance of the zenithal angle (θ) for SL events and a first estimation of ϕ, to be applied to charged current muon-(anti)neutrino interactions [3].
- We also develop a machine learning technique to reconstruct the energy of these events, which is very challenging due to the physical processes involved.
- From previous trained networks, we use Transfer Learning to classify ANTARES SL events into tracks or showers.

Direction and energy reconstruction

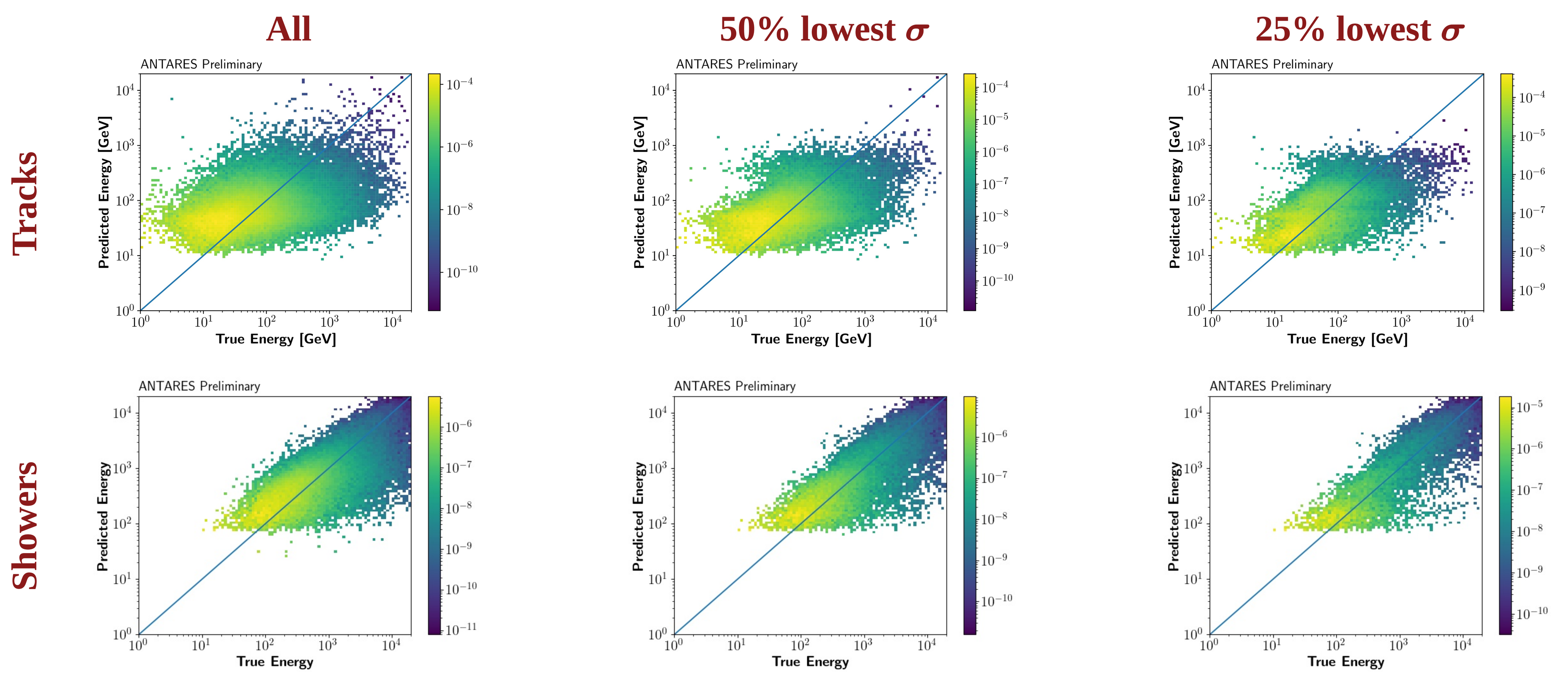
The direction is reconstructed in terms of the zenithal (θ) and the azimuthal (ϕ) angles that fully determine the track direction of the neutrinos. The architecture of a Deep Convolutional Network (DCN) is combined with the predictions of a Mixture Density Network (MDN) [4] to achieve this goal. MDNs allow to estimate an error estimation (σ) for each angle.



Evaluation of the technique shows an improvement for the zenithal angle compared to the traditional method, as the mean angular error is reduced from 15.5º to 7.5º. Furthermore, in the azimuthal angle we move from total ignorance to a mean error of ~40°, which is considered as a success due to the physical limitation of not having valuable information from other detector lines, while a single line has 120º resolution.

The networks are trained with Monte Carlo (MC) simulations of track-like and shower-like events [5]. Same approach was also applied to the reconstruction of the closest point of the track to the detector and interaction vertex of showers. (Only tracks shown above)

A combination of Neural Networks (NNs) and a Principal Component Analasys (PCA) [6] worked best for energy reconstruction. Activations of all layers from the zenith and the closest point (interaction vertex) networks are taken to perform a PCA. The most relevant subset of obtained components are used as the inputs of a feed-forward NN to infer the muon energy for tracks and neutrino energy for showers.

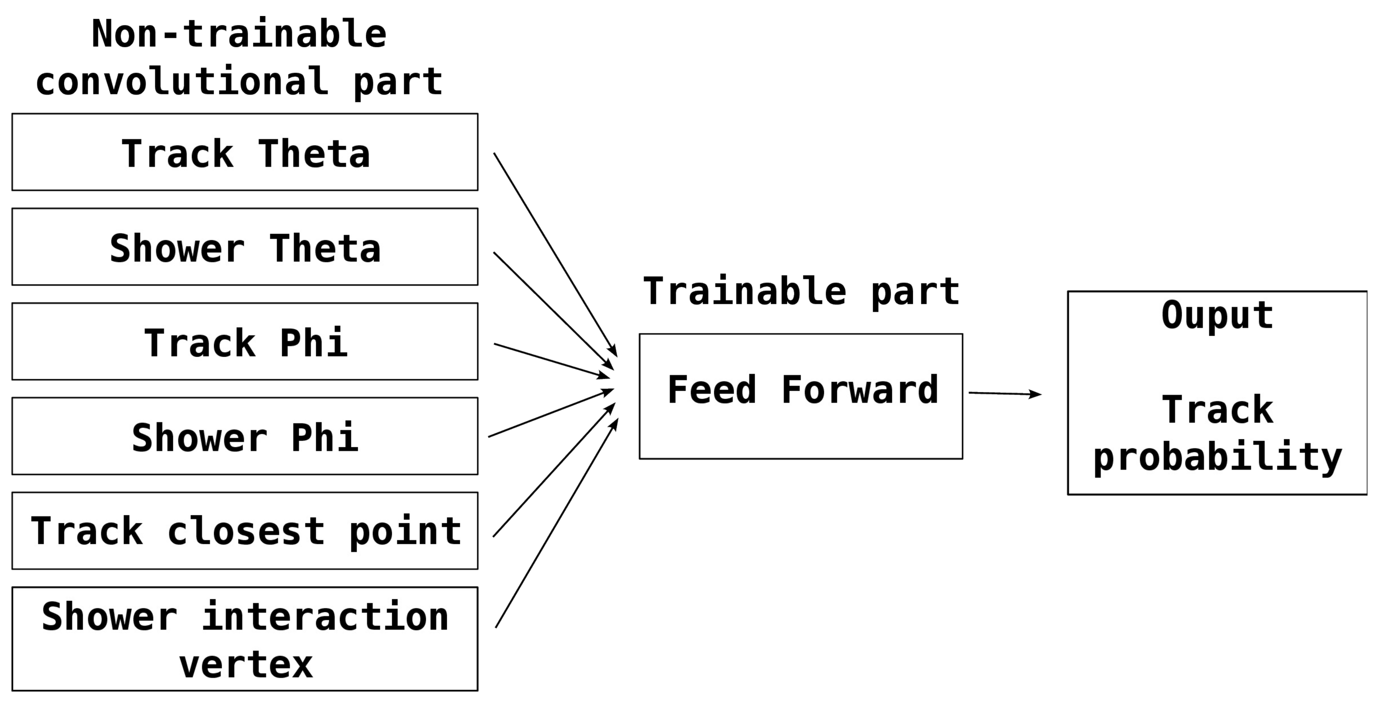


Same MC simulations are used as in the direction reconstruction. To achieve these results, a pre-selection on data must be applied to work with the most suitable events based on direction and closest point or interaction vertex reconstructions.

Track vs shower classifier

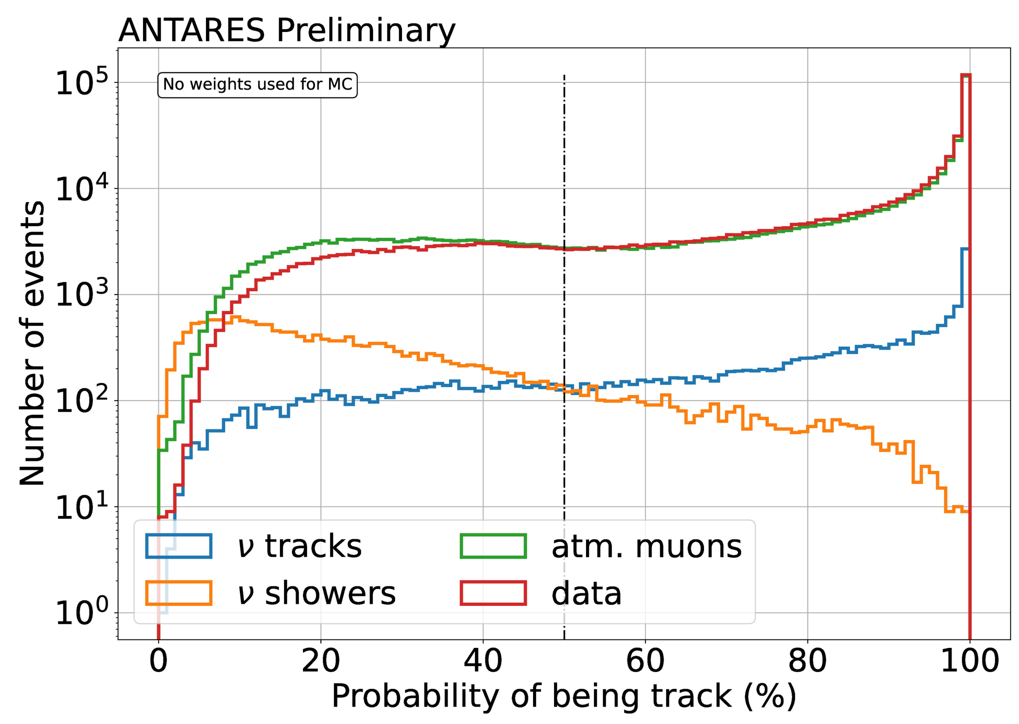
Transfer Learning is a machine learning technique where a model trained on one task is reused for a different, but related task. In neural networks, it involves taking a pre-trained model and fine-tuning it for a specific task with limited data, such as classifying specific types of objects [7].

We used this approach to train a classifier for SL events. We used the pre-trained convolutional part of the previous networks and connected them to a simple trainable feedforward network. The performance with Transfer Learning was better than training a whole new network.



Performance

- Accuracy: ~80%
- Recall: ~75% for tracks and ~86% for showers
- Precision: ~84% for tracks and ~77% for showers



Conclusions

- We enhanced the reconstructions of SL events in ANTARES and create a new classifier that takes advantage of the benefits of transfer learning.
- We applied this new reconstruction methodology to physics analyses, such as the search of dark matter candidates (WIMPs) in the Sun (see poster #399).
- We expect to improve the flux sensitivities in the WIMP mass range where the SL events are already dominant ($\lesssim$ 150 GeV) when the method is applied to the full ANTARES dataset.

References

[1] ANTARES collaboration, Nucl. Instrum. Meth. A 656 (2011) 11
[2] ANTARES collaboration, Astroparticle Physics 34(9) (2011) 652
[3] J. García-Méndez et al, JINST 16 (2021) C09018
[4] C. M. Bishop, NCRG/94/004 (1994)
[5] ANTARES collaboration, Journal of Cosmology and Astroparticle Physics 2021(01) (2021) 64
[6] F. Kherif and A. Latypova, Academic Press (2020) 209
[7] J. Yosinski et al. Advances in Neural Information Processing Systems 27 (2014) 3320

The authors acknowledge the financial support of Generalitat Valenciana Gen-T Program (ref. CIDEGENT/2019/043), Ministerio de Ciencia e Innovación/European Union (FEDER): Programa Estatal de Generación de Conocimiento (ref. PID2021-124591NB-C42), and "European Union NextGenerationEU/PRTR" Programa de Planes Complementarios I+D+I (ref. ASFAE/2022/014). The authors also acknowledge the computer resources at Artemisa, funded by the European Union ERDF and Comunitat Valenciana.