Deep neural networks for single-line event direction reconstruction in ANTARES

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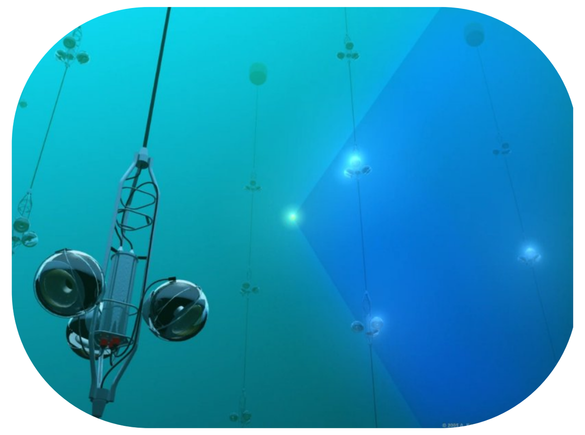
ANTARES in a nutshell



First large undersea neutrino telescope [1]:

- 12 vertical lines forming a 3D array of photo-sensors
- 25 floors per line
- 3 Optical Modules (OMs) per floor

It detects Cherenkov light induced by secondary particles from neutrino interactions

Problems

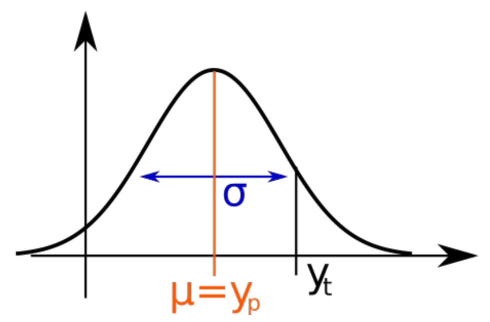
- The event reconstruction and background discrimination is challenging, specially for low-energy single-line events.
- Azimuth angle reconstruction is missing with classical approaches (BBfit) [2].
- The low-energy range is interesting for dark matter searches and other studies.

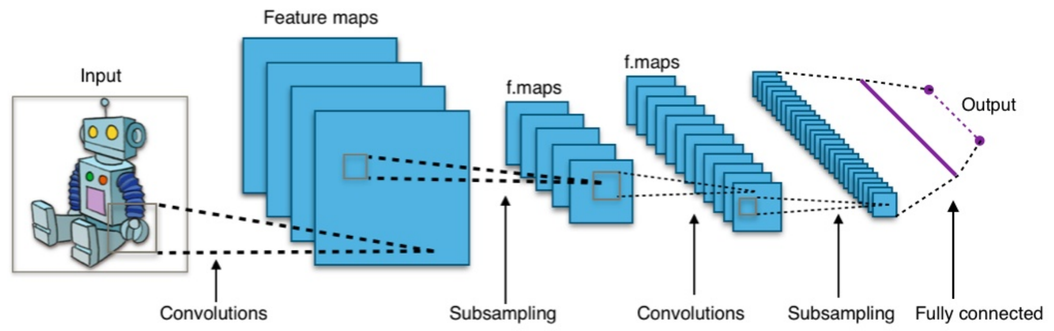
Solution

We present a method based on deep learning aimed to improve the direction reconstruction of low-energy single-line events [3]. It makes a full prediction of the neutrino direction.

Neural Network approach

We combined Deep Convolutional Networks (DCNs) [4] with Mixture Density Networks (MDNs) [5].





- MDNs allow to predict not only the direction angles but also their uncertainty.
- DCNs extract the important features.

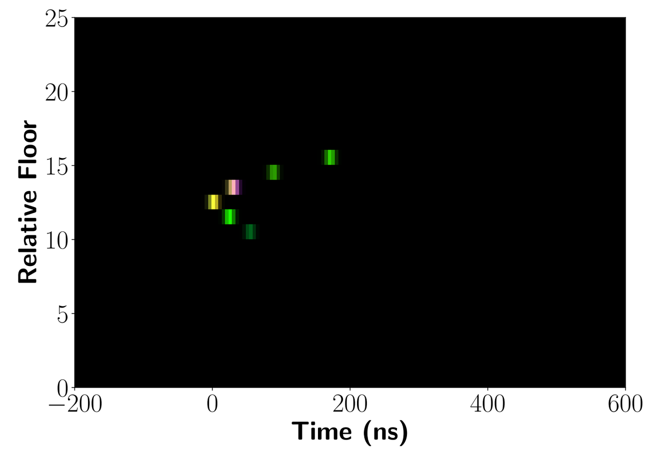
The network was trained with Monte Carlo simulations [6] of track-like events: (anti)muon-neutrino interactions:

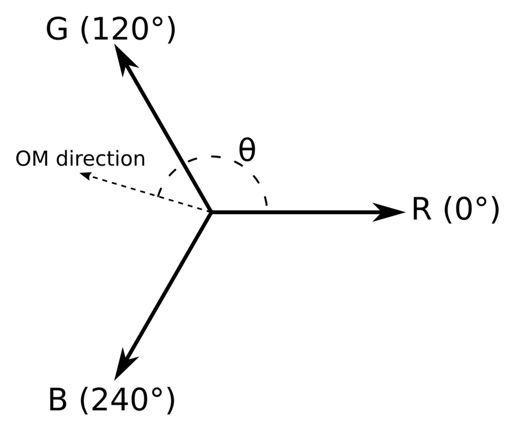
- Training set (60%)
- Validation set (20%), to avoid over-fitting through Early Stopping
- Test set (20%), to evaluate the generality of the results

Input (25,161,3)	Convolution 2D + ReLU Filters 16, Kernel 2x10	Max Pooling 2D Kernel 2x2	Convolution 2D + ReLU Filters 32, Kernel 2x10	Max Pooling 2D Kernel 2x2
Flatten + DropOut (0.2)	Max Pooling 2D Kernel 2x2	Convolution 2D + ReLU Filters 128, Kernel 2x10	Max Pooling 2D Kernel 2x2	Convolution 2D + ReLU Filters 64, Kernel 2x10
Dense + ReLU + Batch Normalization. Size 128	Dense + ReLU + Batch Normalization. Size 128	Dense + ReLU + Batch Normalization. Size 32	Dense + ReLU + Batch Normalization. Size 32	(Scaled) tanh: μ output ELU+1: σ output

From data to images

Two-dimensional images are created (floor x time) using the hits information. Images are then centered based on the reference hit.





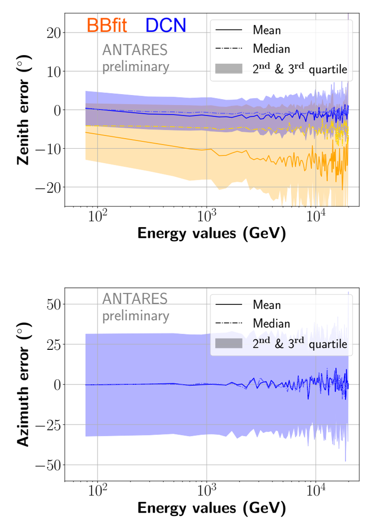
The RGB colors of the pixels are obtained by weighting the angle of the OM with the voltage amplitude of the hit.

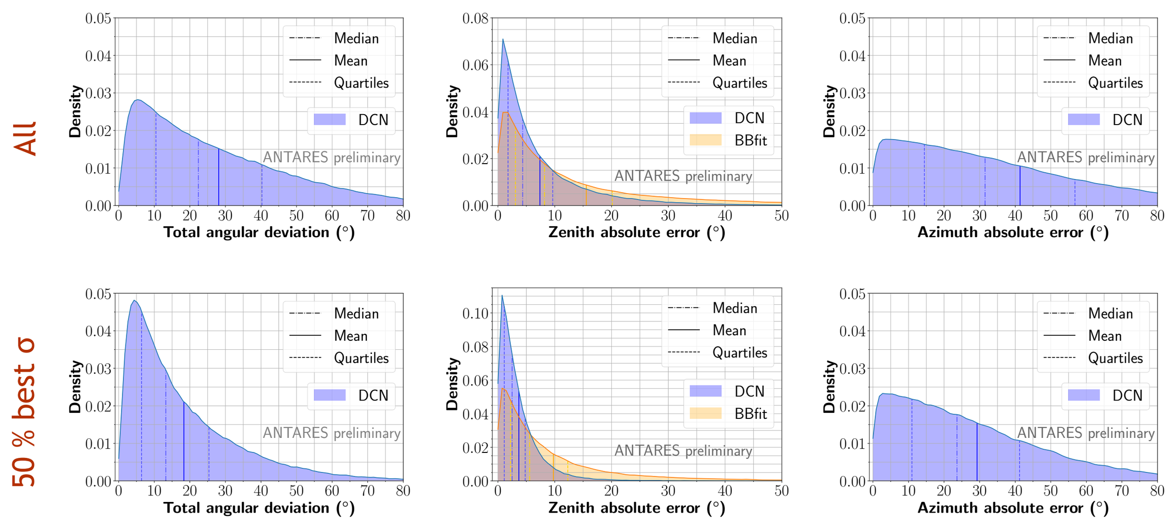
Results

DCN outperforms classical reconstruction methods

Absolute error	BBfit		DCN		DCN (50% lowest σ)	
	Mean	Median	Mean	Median	Mean	Median
Zenith	15.5°	8.5°	7.4°	4.4°	3.7°	2.5°
Azimuth	-	-	41.4°	31.5°	29.3°	23.6°
Total	-	-	28.1°	22.4°	18.3°	13.2°

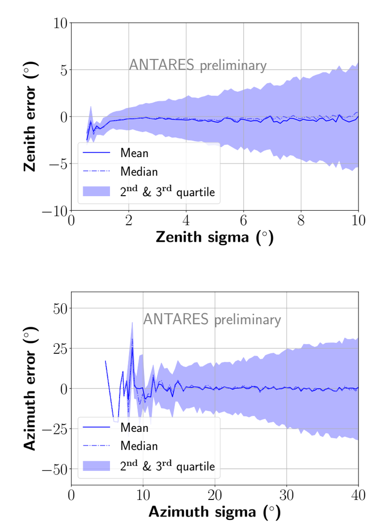
Error vs energy

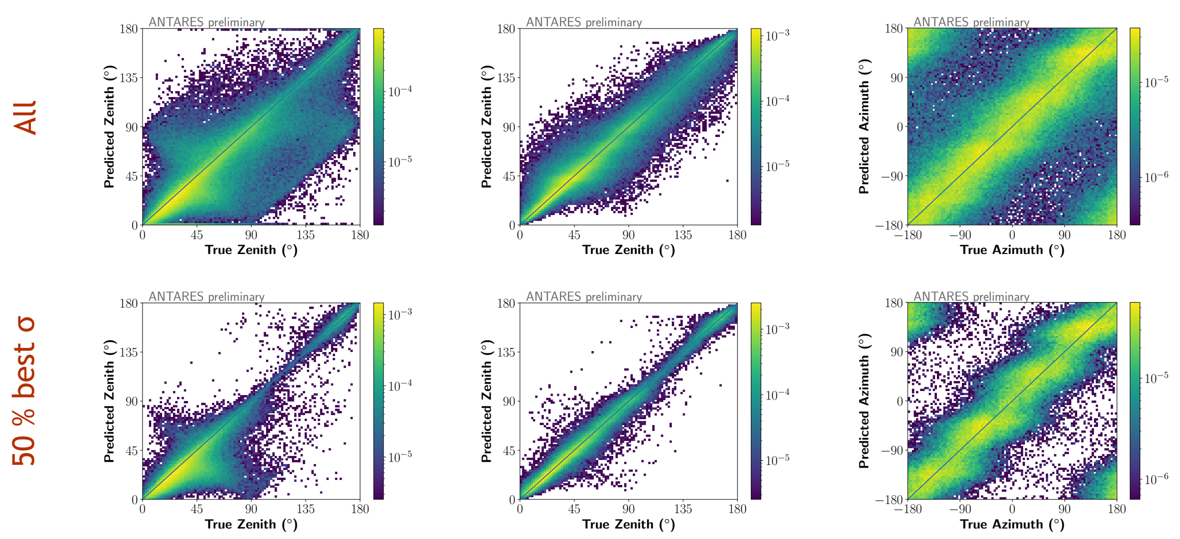




Our predictions are unbiased against the energy of the neutrino

Error vs sigma





Moreover, our uncertainty parameter behaves as expected for a standard deviation value.

We checked the robustness of our results using 5-fold cross-validation

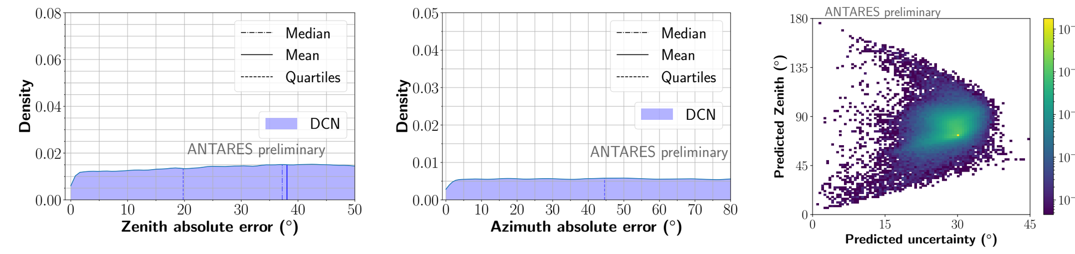
Mean Absolute error — Randomized

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Zenith	7.4°	7.4°	7.4°	7.4°	7.4°
Azimuth	41.5°	41.3°	41.6°	41.4°	41.3°
Total	28.2°	28.1°	28.4°	28.1°	28.1°

Mean Absolute error — Date-sorted

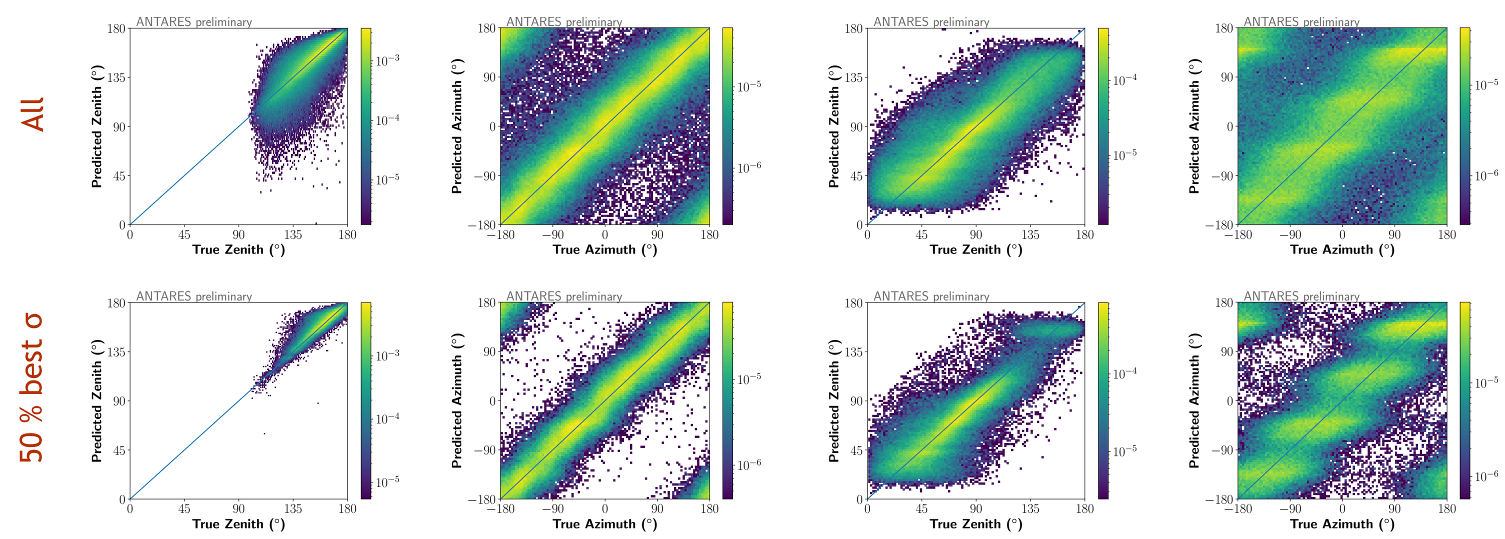
	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Zenith	8.1°	7.6°	7.4°	7.5°	6.9°
Azimuth	44.4°	42.2°	41.4°	41.7°	39.7°
Total	30.0°	28.7°	28.4°	29.1°	26.3°

Network predictions derived from background noise



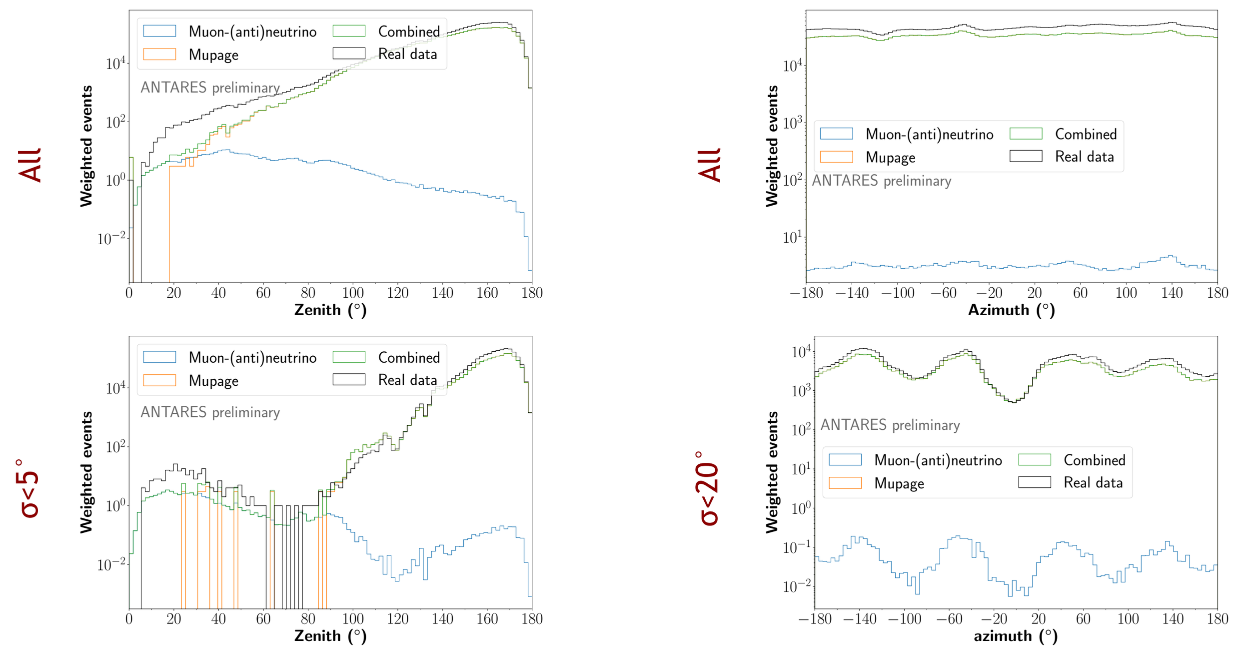
As expected the network is not able to predict the direction using background noise and the predicted uncertainty is high.

Reconstructing other types of simulated events



Accurate predictions for their direction and uncertainty, despite these events were not explicitly trained.

Comparing with real data



Good agreement between real data and simulations, especially when cutoffs based on quality parameters were applied.

Conclusion

- We clearly outperform classical reconstruction methods for single-line events.
- An azimuth prediction is made, which was previously missing.
- The method is robust and ready to be applied in physics analyses.

References:

[1] ANTARES collaboration, Nucl. Instrum. Meth. A 656 (2011) 11 [arXiv:1104.1607]
[2] ANTARES collaboration, Astropart. Phys. 34 (2011) 652 [arXiv:1105.4116].
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[4] J. Gu et al., Pattern Recognition 77 (2018) 354.
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[6] ANTARES collaboration, JCAP 01 (2021) 064 [arXiv:2010.06621].

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