Reconstruction of Gamma events by Deep learning

Results of integrating conditional variables via the Condition Batch Norm method in **γ**-PhysNet

- IN2P3 Machine Learning Workshop (Caen, 2025)

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Introduction – Research field and organizations

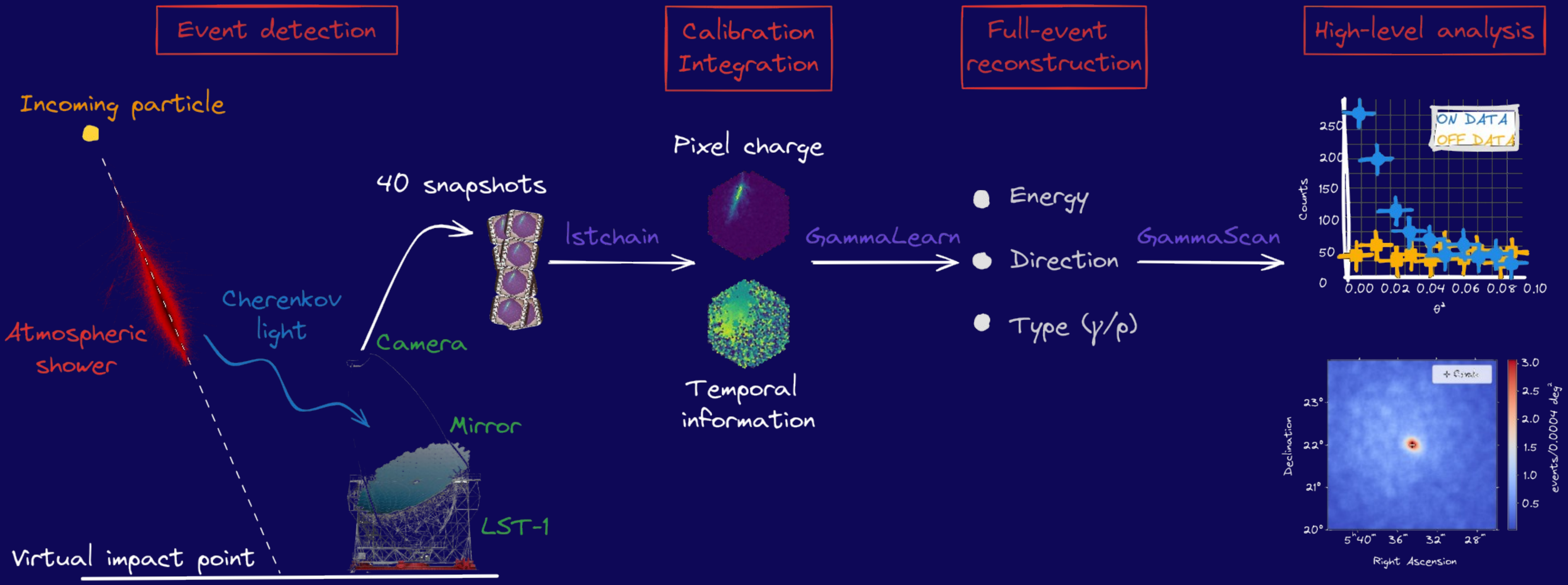
Gamma-ray astronomy
Observing universe at the very high energy ranges (>0.1 MeV)

CTAO collaboration
Next-generation ground-based observatory for gamma-ray astronomy
First operational Large-Sized Telescope (LST)

Gammalearn project
Collaboration between LAPP (CNRS) and LISTIC (Univ. Savoie Mont-Blanc)
Develop Deep Learning solutions for Imaging Atmospheric Cherenkov Telescopes data analysis.


Source : ctao.org

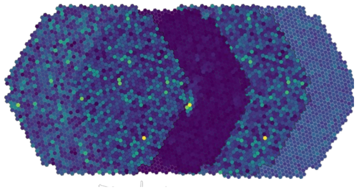
Introduction – Reconstruction procedure



Source : Michaël Dell'Aiera et al. (2024)

Introduction – Dataset description

Dataset used for experiments



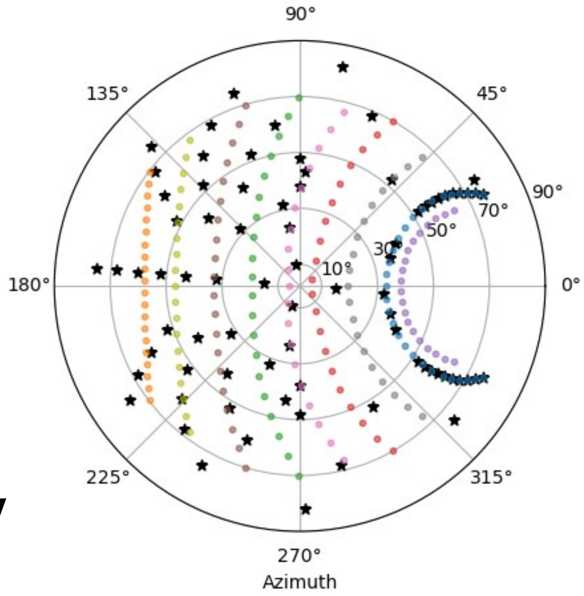
Bank of simulated (Monte Carlo) images with labels

Training dataset

Protons
Gamma diffuse

Testing dataset

Gamma diffuse



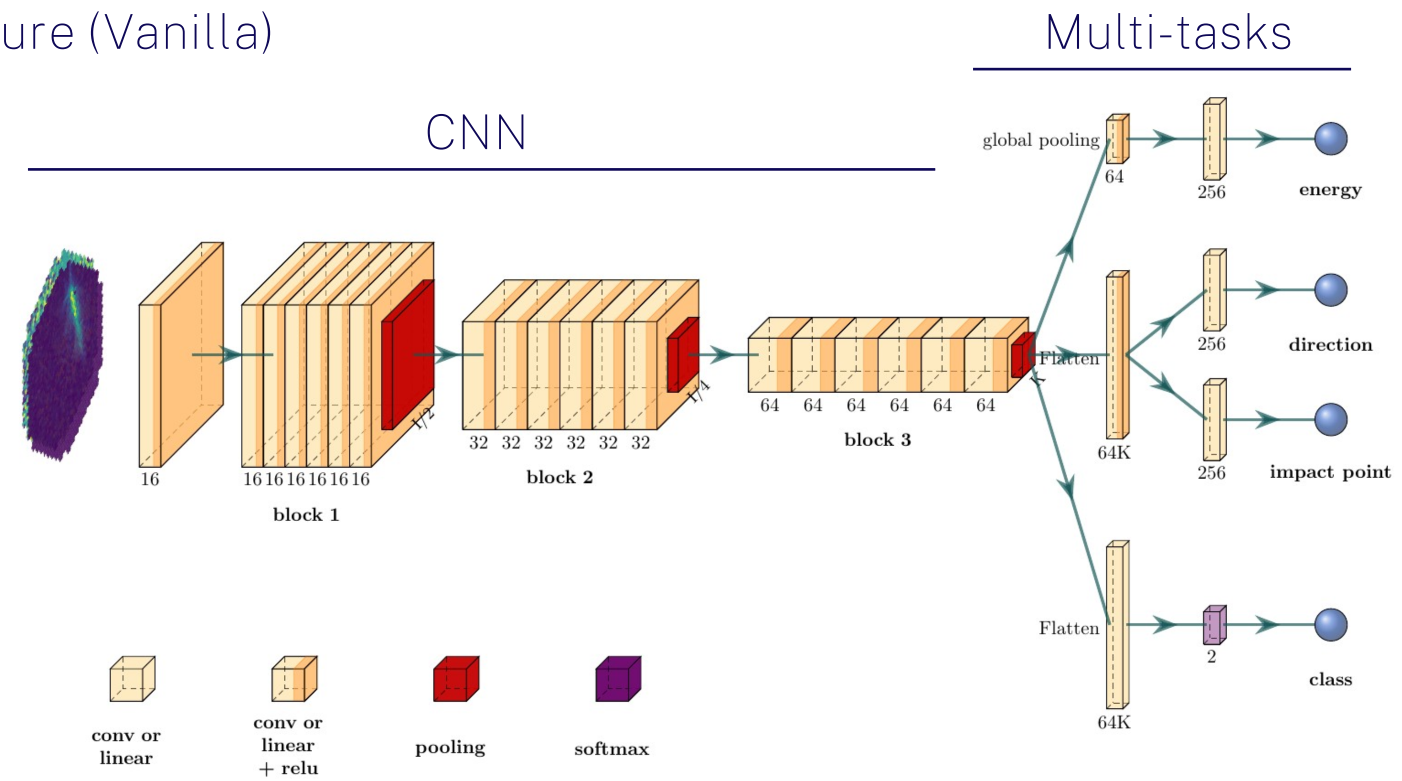
Source : cta-observatory.github.io

Research question – Model architecture

The γ-PhysNet architecture (Vanilla)

- One network for all tasks
- Better performances than Hillas+RF
- Less computational time and memory consumption

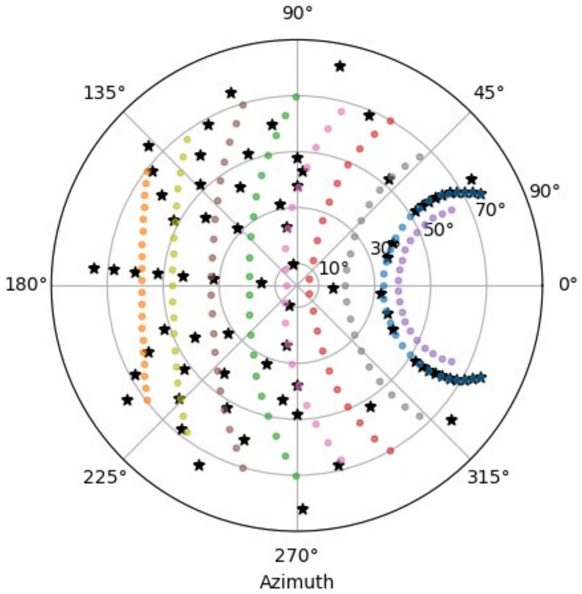
Current architecture does not benefit from observation conditions (NSB, pointings…).



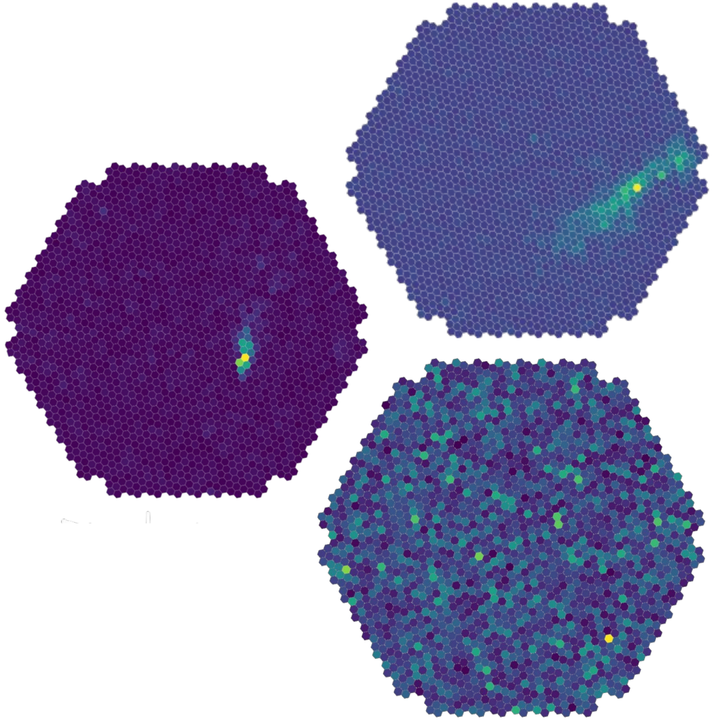
Sources : Michaël Jacquemont et al. (2020), Michaël Dell'Aiera et al. (2024)

Research question – Image acquisition conditions

Image acquisition covers heterogeneous observation conditions :
- Noise Signal Background (NSB) variations : (moonlight, weather ...)
- Changes in the telescope pointing



Source : cta-observatory.github.io

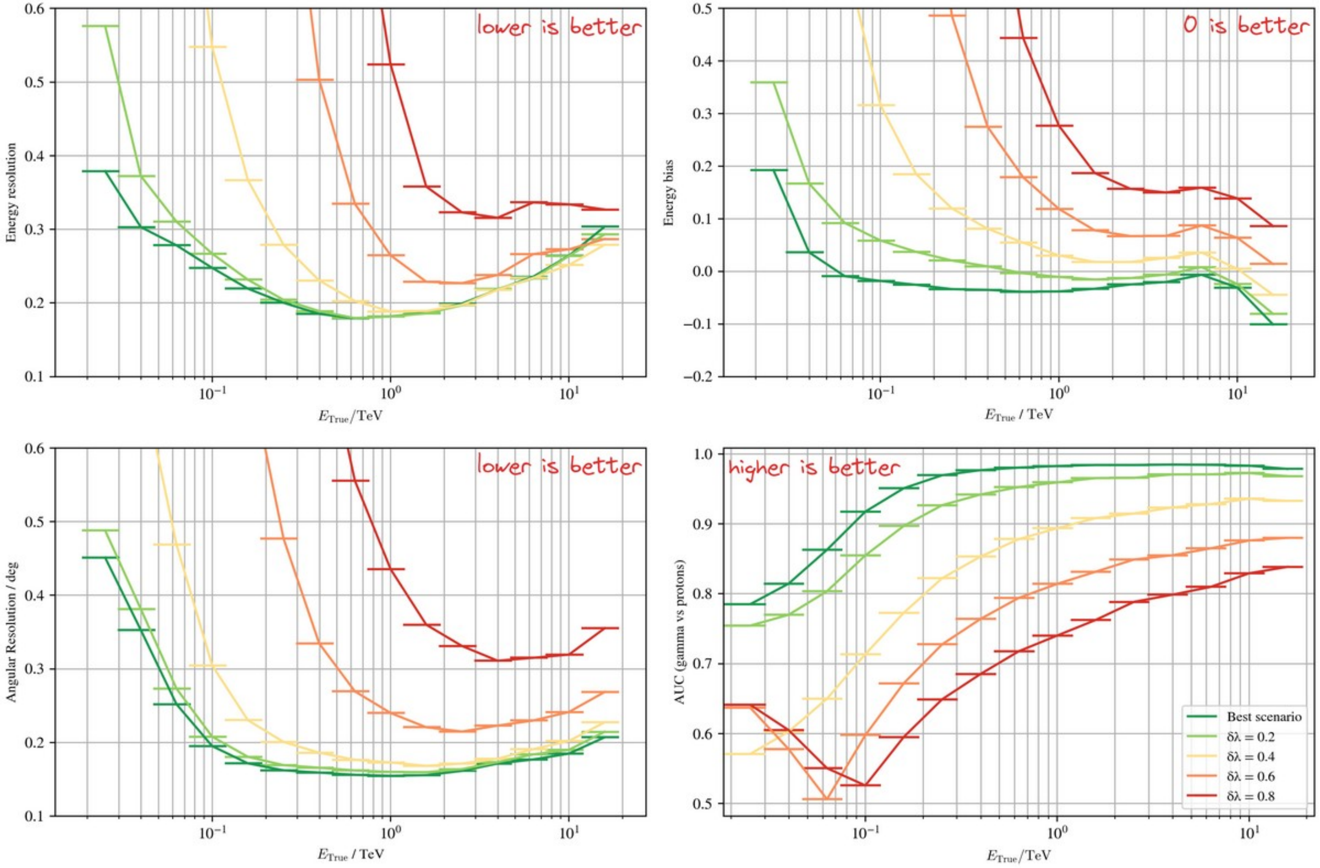


Different noise levels on images

Research question – Influence of observation conditions

- Model performances are negatively impacted by increasing noise level

- Model performances are impacted by pointing variations



Source : *Michaël Dell'Aiera et al. (2024)*

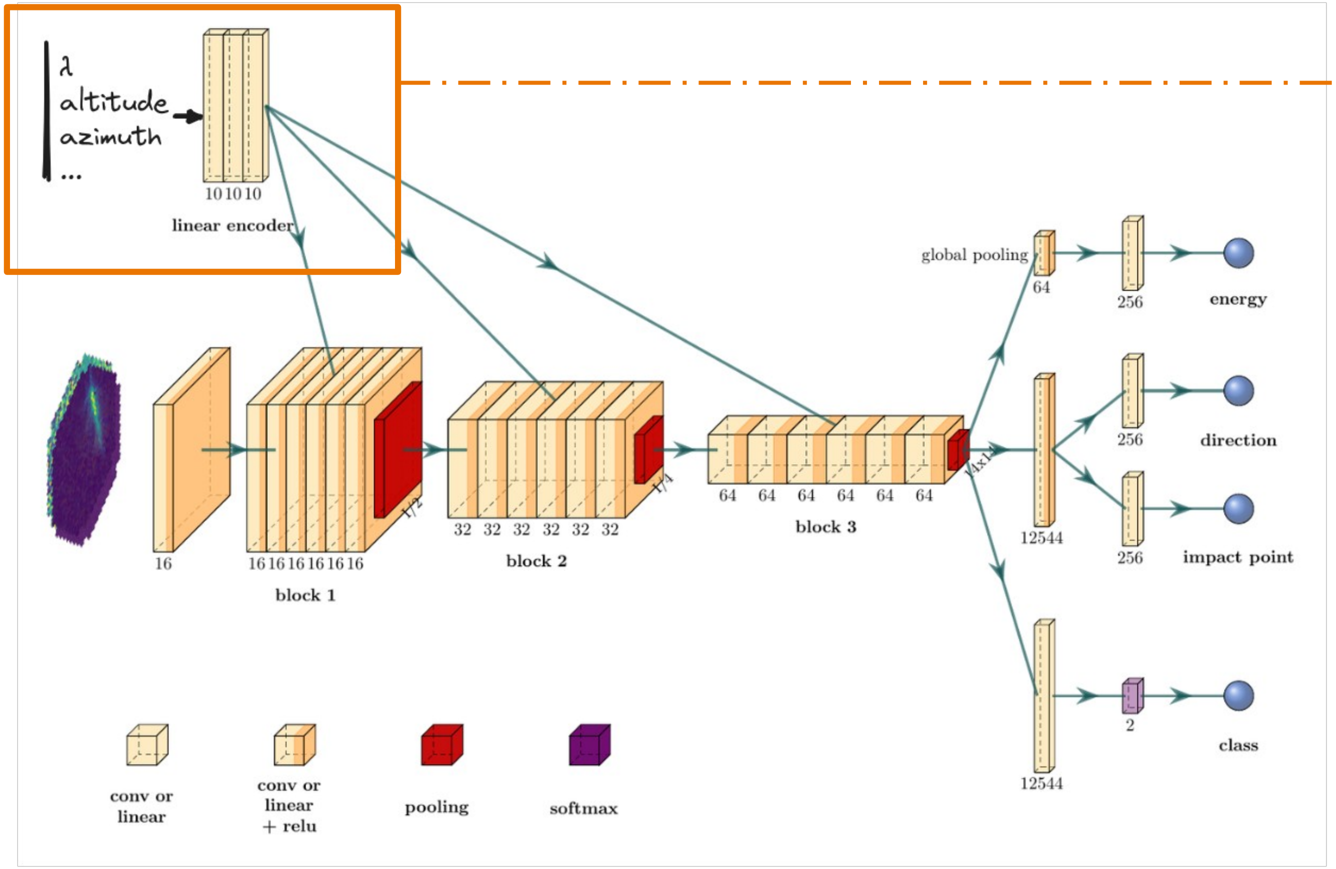
Research question

Hypothesis
Explicitly include noise level rate and telescope pointing (altitude and azimuth) in the model’s layers could improve model performances to better reconstruct events.

Question
Does the inclusion of additional variables (NSB, altitude and azimuth) increase model performances?

Test
Study a multi-modal method called the Conditional Batch Norm with NSB and/or pointing direction as conditional variables.

Methodology – Architecture description



Source : Michaël Dell'Aiera et al. (2024)

CBN method
Adaptation of a standard Batch Normalization (BN) process by making the normalization parameters conditional on some auxiliary information (or context)

An MLP takes the condition (c) as input and outputs the specific values for the scaling (**γ**(c)) and shifting (**β**(c)) parameters.

$$(\gamma(c),\beta(c))=\mathrm{MLP}(c)$$

Source : Harm de Vries (2017)

Methodology – Experiments & ressources

	Experiment NSB only	Experiment Pointing only	Experiment NSB+pointing
Conditional variables	NSB	Altitude + Azimuth	NSB Altitude + Azimuth
Number of training images	1 874 137	3 398 707	3 398 707
Number of random seeds	5	5	5
Number of images per batch	256	256	256

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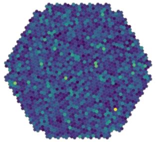
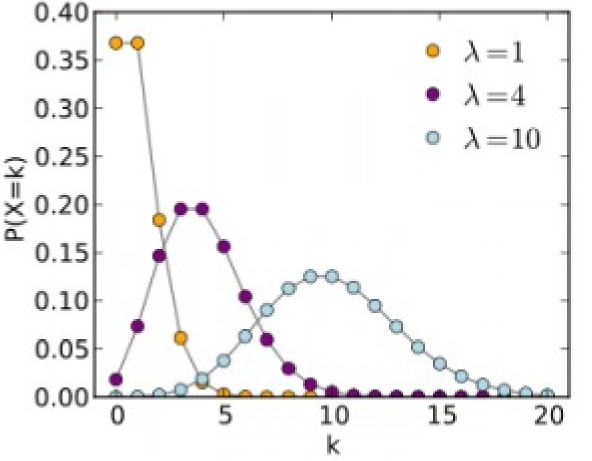
Computational resources

- 3 x GPUs Ampere A100 80GB
- 24 cpus
- 576 GB RAM memory

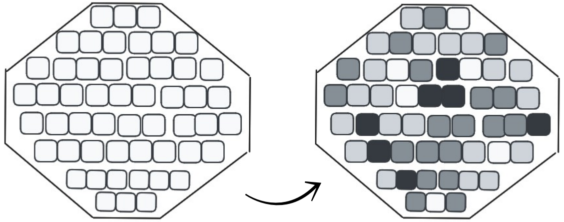
Results – Experiment NSB only



Training process



Add a noise sampled from a Poisson distribution to the pixel charges.



Non-transformed image

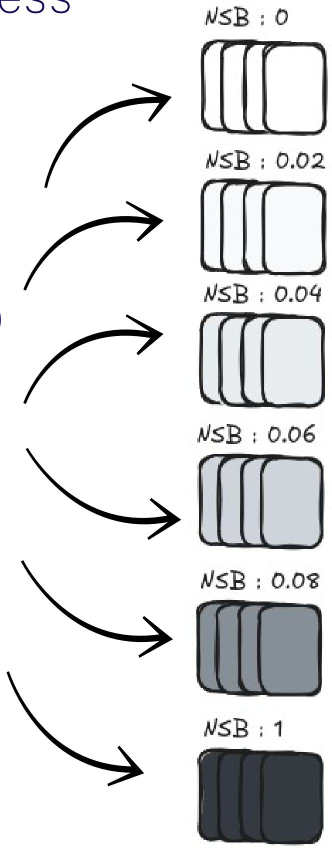
Image with noise augmentation

Testing process

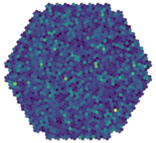
1 node (pointing)

6 noise levels

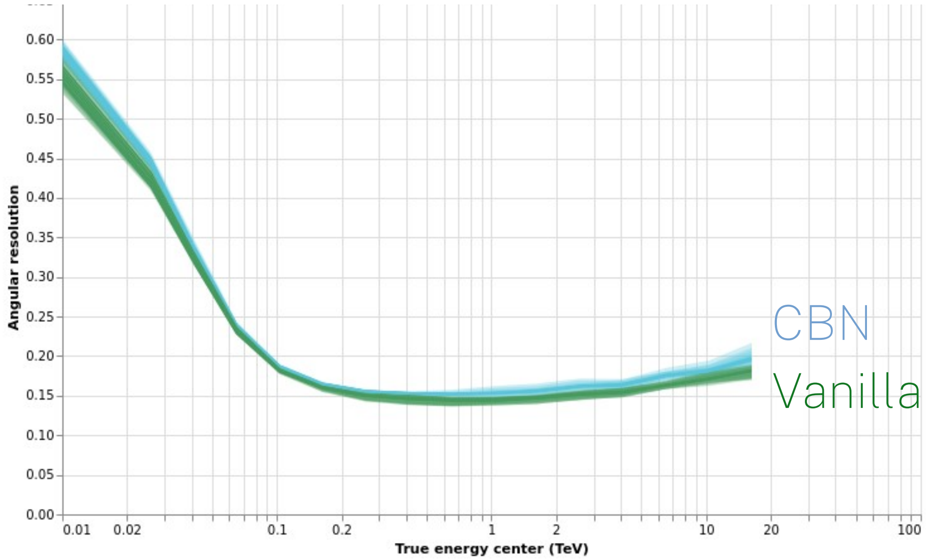
= 6 experiments



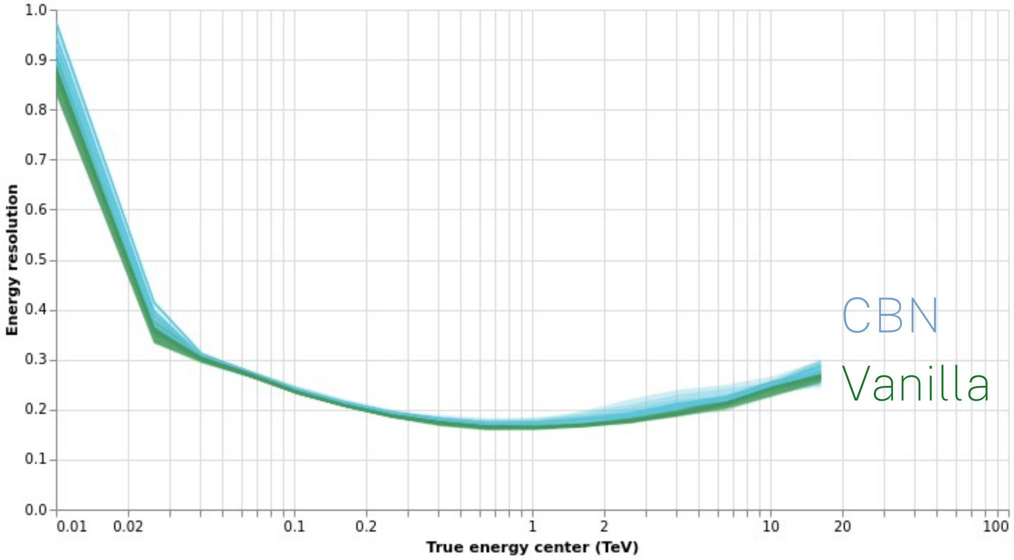
Results – Experiment NSB only



Angular resolution vs True energy center

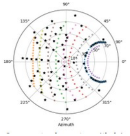


Energy resolution vs True energy center

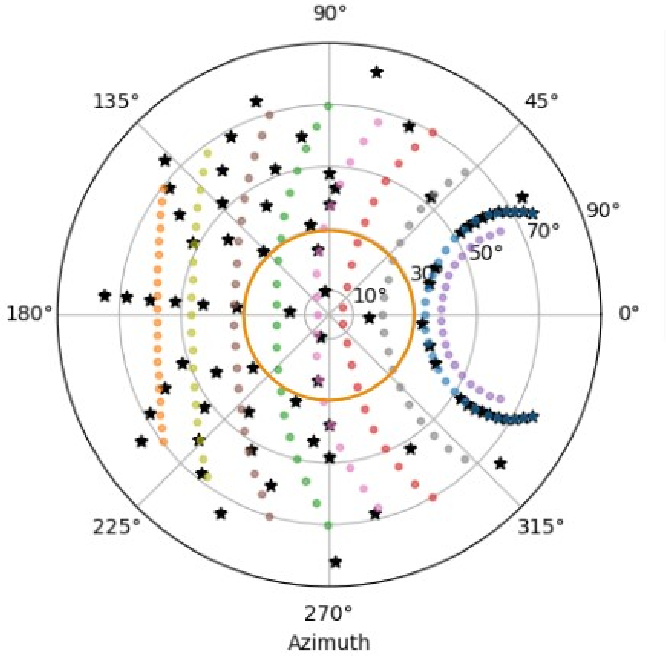


CBN and Vanilla architectures provide very similar results for the 6 noise levels studied.

Results – Experiment Pointings only

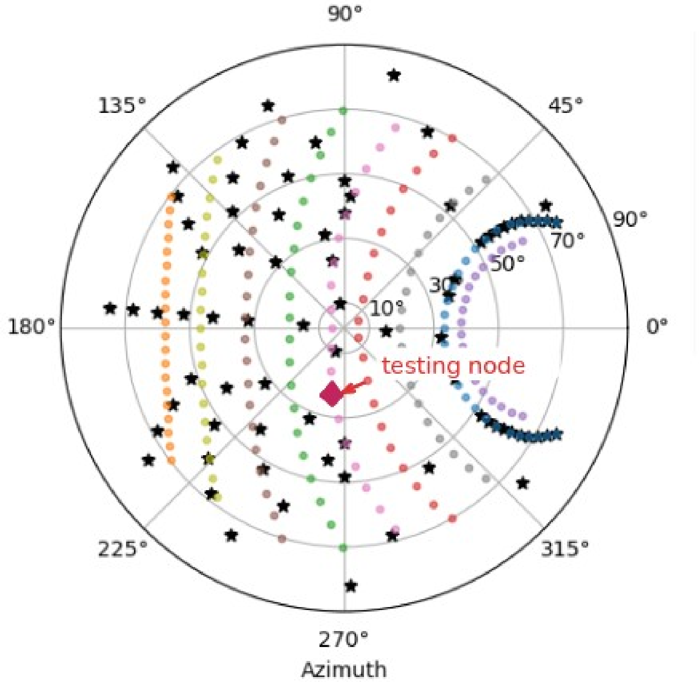


Training stage

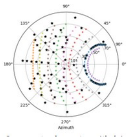


28 pointings = 3 398 707 files = 431 GB

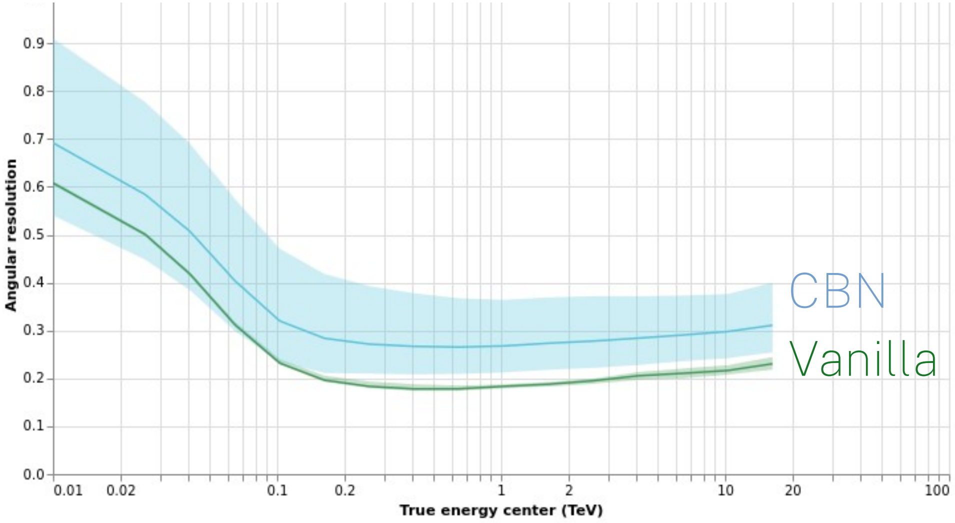
Testing stage



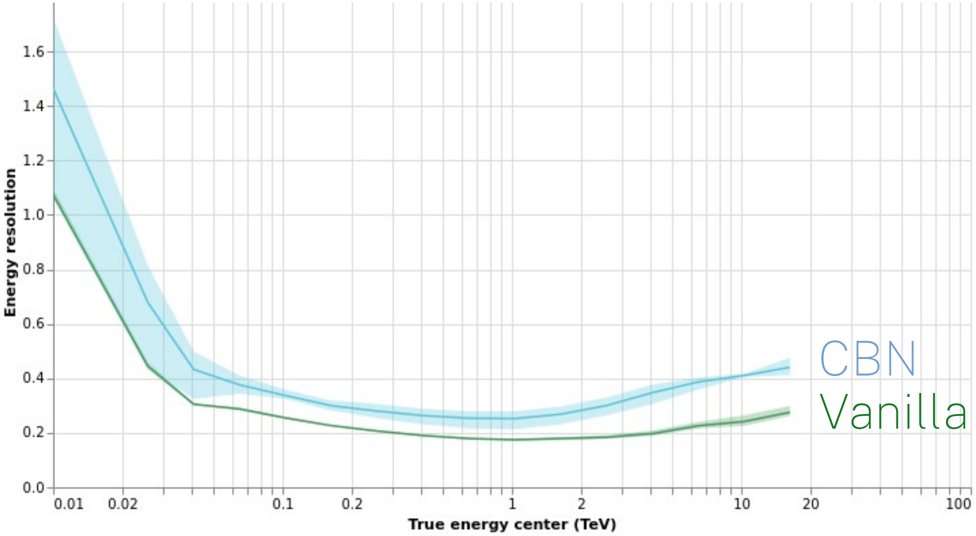
Results – Experiment Pointing only



Angular resolution vs True energy center



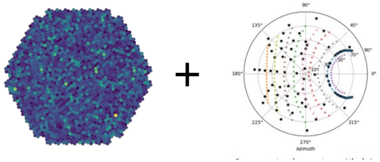
Energy resolution vs True energy center



Vanilla architecture have a lower angular and energy resolutions at nearly all the energy levels

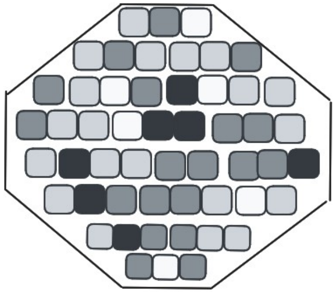
CBN depicts higher variability across the different seeds

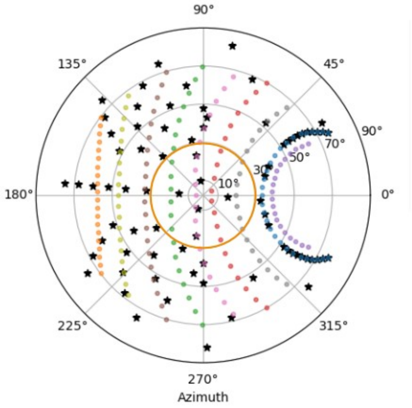
Results – Experiment NSB + Pointing



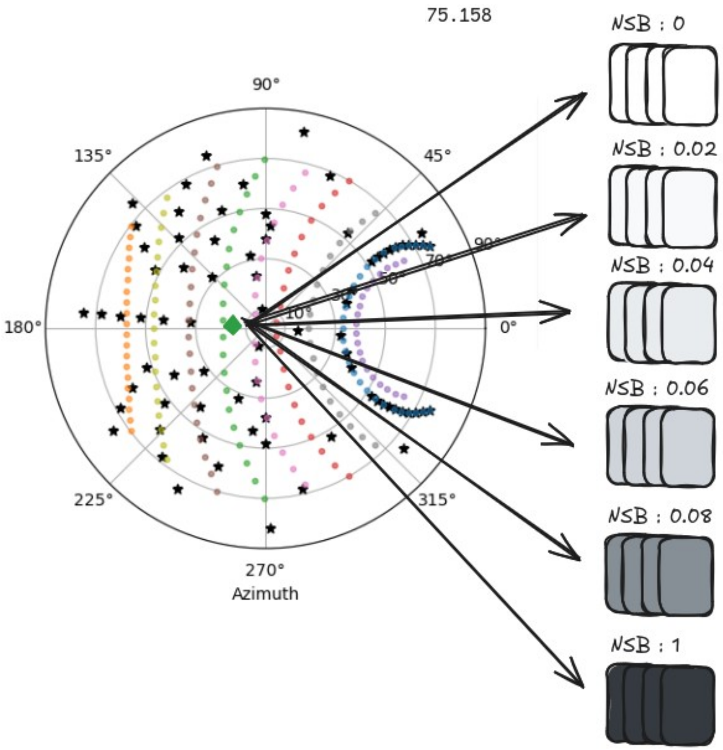
Training stage

Combination of multiple pointings AND noise augmentation

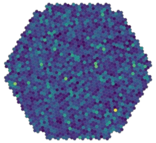




Testing stage



Results – Experiment NSB + Pointings



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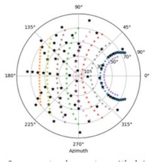
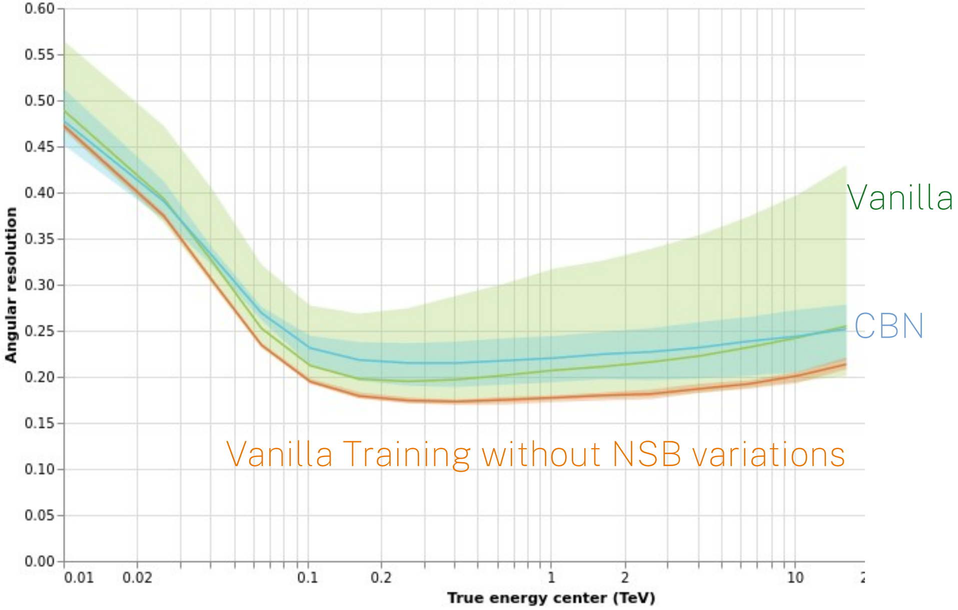
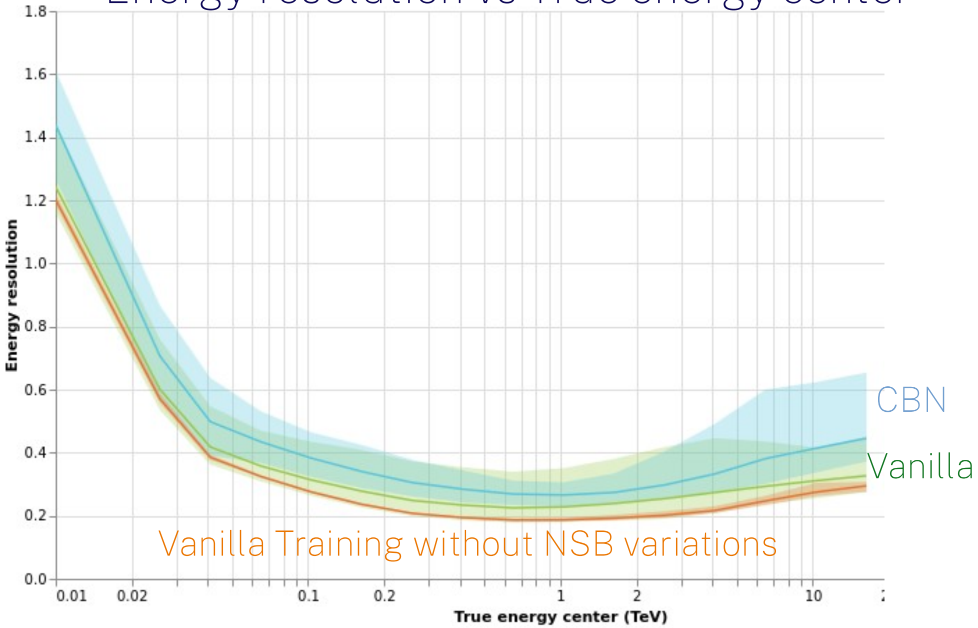


NOISE=0

Angular resolution vs True energy center

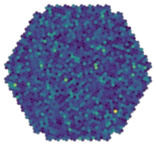
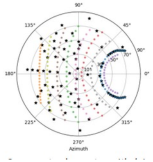


Energy resolution vs True energy center



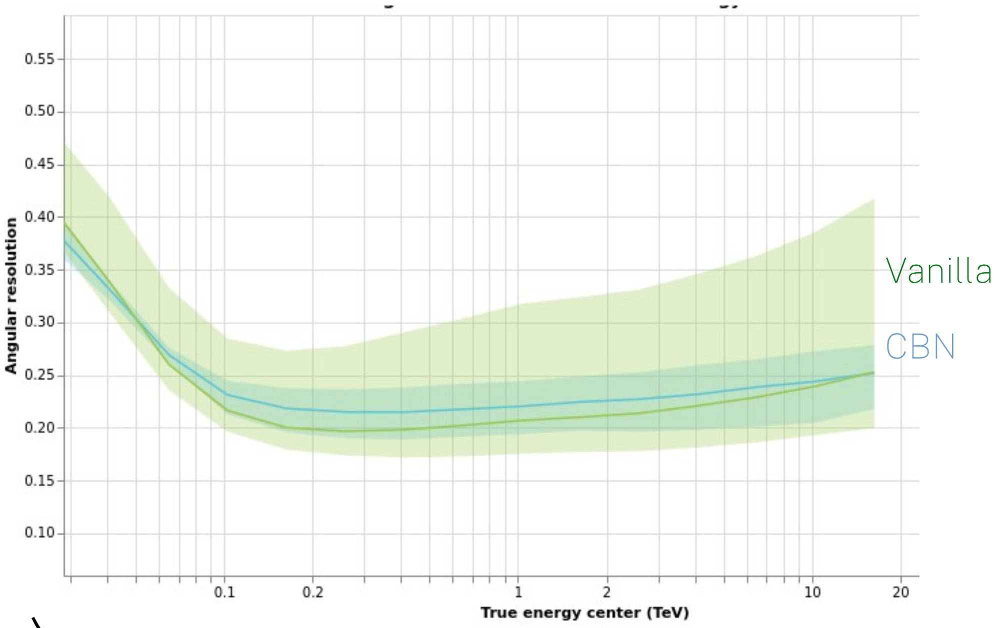
- Increase of variability for Vanilla but best seed is similar to Vanilla training without NSB variations
- CBN's best seed is higher than Vanilla best seed for angular and energy resolutions

Results – Experiment NSB + Pointings

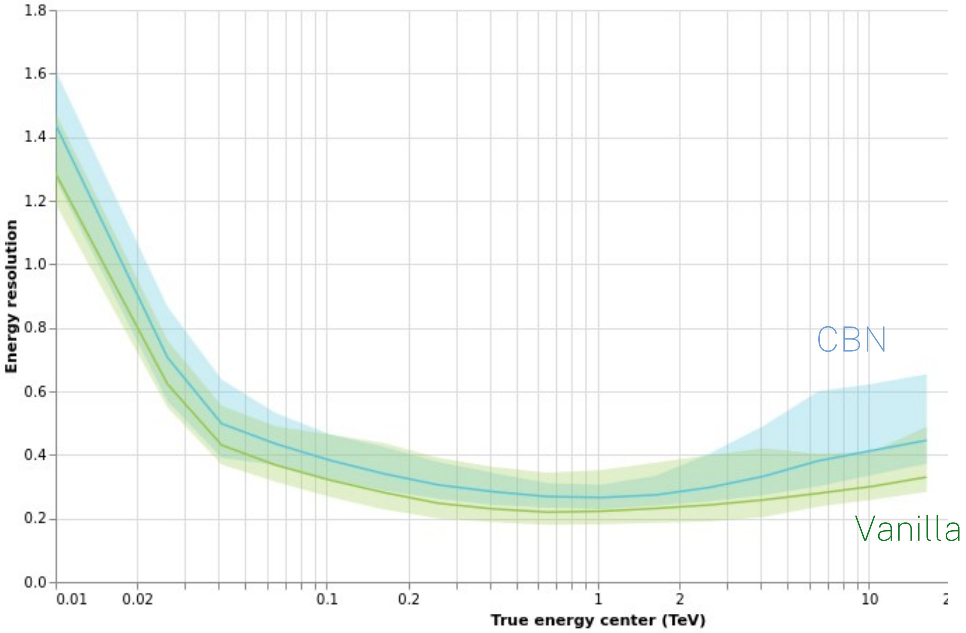
 + 

NOISE=1

Angular resolution vs True energy center



Energy resolution vs True energy center



- Increase of variability for angular resolution for Vanilla
- Vanilla still has the best seed for angular and energy resolutions compared to CBN.

Conclusion & Perspectives

- CBN architecture does not significantly improve energy and angular resolutions
- Reducing model robustness to different acquisition conditions
- More complexity in the architecture and in the training and inference phases.

Do not change the architecture but increase training dataset size

- Increase performances
- Simplify the use of model in production phases

Try new multi-modal methods (mid-level information fusion, late information fusion…)
Sources : Li et al. (2024), Guarrassi et al. (2025)

References

Dell'Aiera, M. (2024). From simulations to real data, on the relevance of deep learning models and domain adaptation: Application to astrophysics with CTAO and LST-1 (Doctoral dissertation, Université Savoie Mont Blanc). Retrieved from https://theses.hal.science/tel-05031312

Vries, H. de, Strub, F., Mary, J., Larochelle, H., Pietquin, O., & Courville, A. C. (2017). Modulating early visual processing by language. Advances in Neural Information Processing Systems 30. Retrieved from https://arxiv.org/abs/1707.00683

Li, Y., Daho, M. E. H., Conze, P.-H., Zeghlache, R., Boité, H. L., Tadayoni, R., … Quellec, G. (2024). A review of deep learning-based information fusion techniques for multimodal medical image classification. Retrieved from https://arxiv.org/abs/2404.15022

Guarrasi, V., Aksu, F., Caruso, C. M., Di Feola, F., Rofena, A., Ruffini, F., & Soda, P. (2025). A systematic review of intermediate fusion in multimodal deep learning for biomedical applications. Image and Vision Computing, 158, 105509. doi:10.1016/j.imavis.2025.105509

Jacquemont, M., Vuillaume, T., Benoit, A., Maurin, G., & Lambert, P. (2021a). Multi-Task Architecture with Attention for Imaging Atmospheric Cherenkov Telescope Data Analysis. Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2021) - Volume 5: VISAPP, 534–544. doi:10.5220/0010297405340544

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https://www.ctao.org/for-scientists/library/acknowledgments/
and here: https://purl.org/gammalearn/acknowledgements