Search for optimal deep neural network architecture for gamma ray search at KASCADE

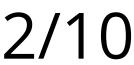
Authors: N. Petrov, M. Kuznetsov, I. Plokhikh, V. Sotnikov, M. Tsobenko



Motivation

- Gamma astronomy enters PeV era
 - LHAASO detected PeV gammas¹.
 - Tibet detected diffuse sub-PeV gammas²
- KASCADE exposure comparable with LHAASO one at PeV energies \rightarrow should contain gamma-rays in dataset
- Using DL with modern architectures³

1. Cao, Z. et al (2021). Ultrahigh-energy photons up to 1.4 petaelectronvolts from 12 γ-ray Galactic sources. Nature, 594(7861), 33–36.



^{2.} Amenomori, M. et al (2021). First Detection of sub-PeV Diffuse Gamma Rays from the Galactic Disk: Evidence for Ubiquitous Galactic Cosmic Rays beyond PeV Energies. Physical Review Letters, 126(14).

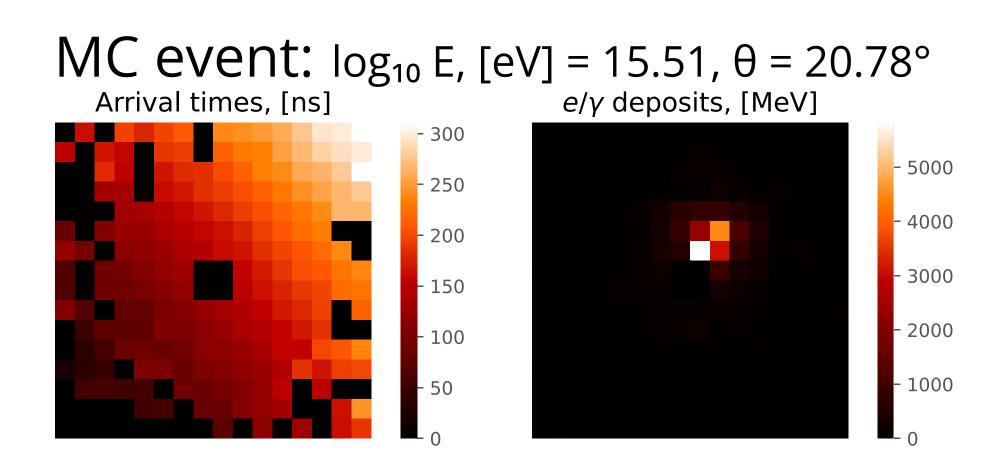
^{3.} Jin, C. et al (2020). Classifying cosmic-ray proton and light groups in LHAASO-KM2A experiment with graph neural network *. Chinese Physics C, 44(6), 065002.

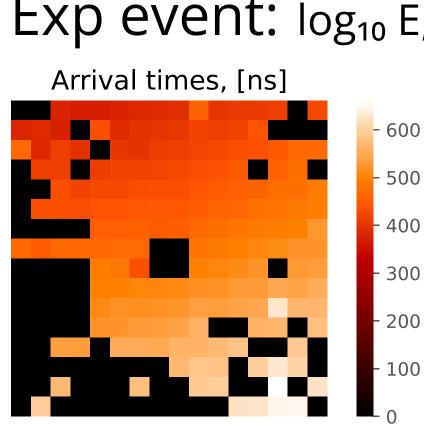
Data description

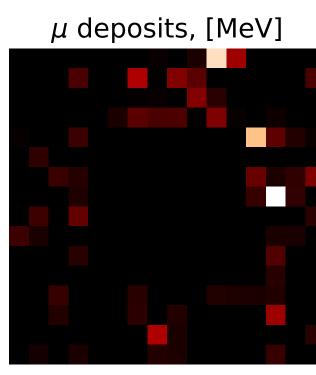
Event structure:

- 3 arrays, 16x16 shape
 - arrival times, [ns]
 - e/y energy deposits, [MeV]
 - µ energy deposits, [MeV]
- reconstructed features
 - energy, zenith and azimuth angles of the primary particle
 - shower core position
 - electron and muon numbers
 - shower shape parameter

* Data are taken from KCDC: A.Haungs et al; Eur. Phys. J. C (2018) 78:741; "The KASCADE Cosmic ray Data Centre KCDC: granting open access to astroparticle physics research data"; (doi: <u>10.1140/epjc/s10052-018-6221-2</u>)







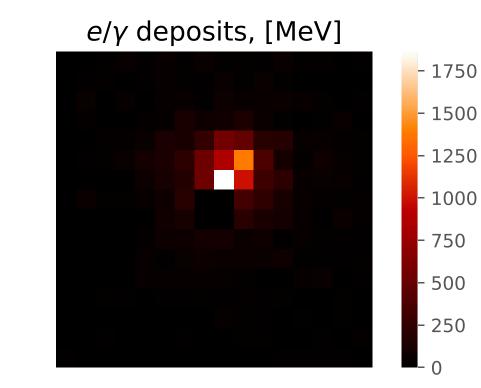
Exp event: log₁₀ E, [eV] = 15.45, θ = 19.37°

600

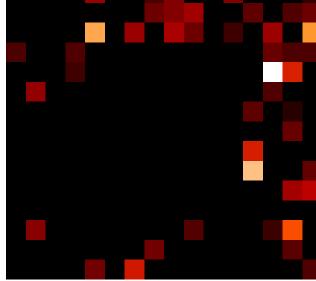
400

300

100

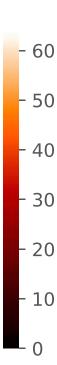


 μ deposits, [MeV]



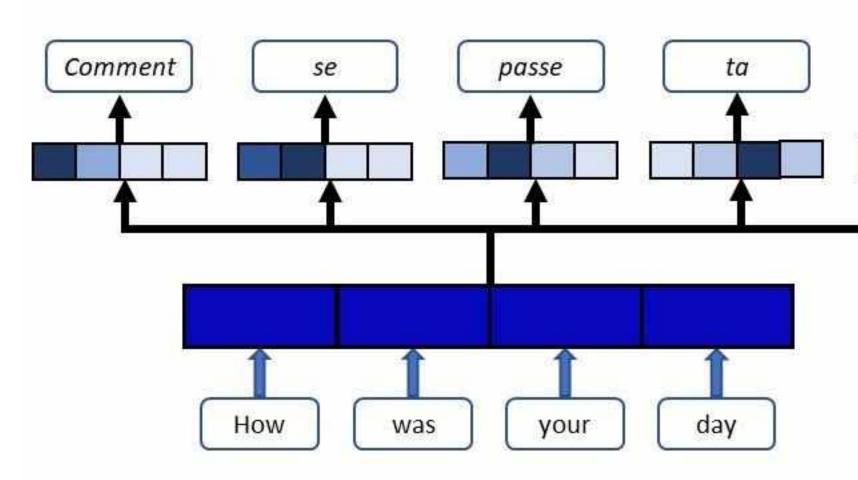






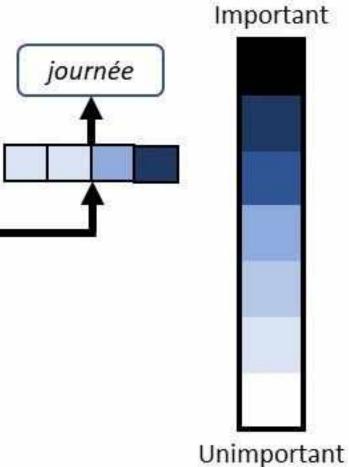
Self-attention network (self-att)

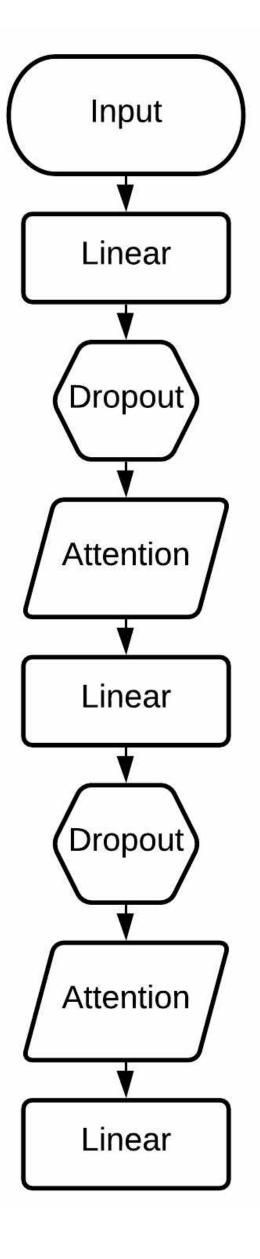
Uses revolutionary attention mechanism¹.

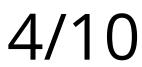


Attention principle schema

1. <u>Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).</u>

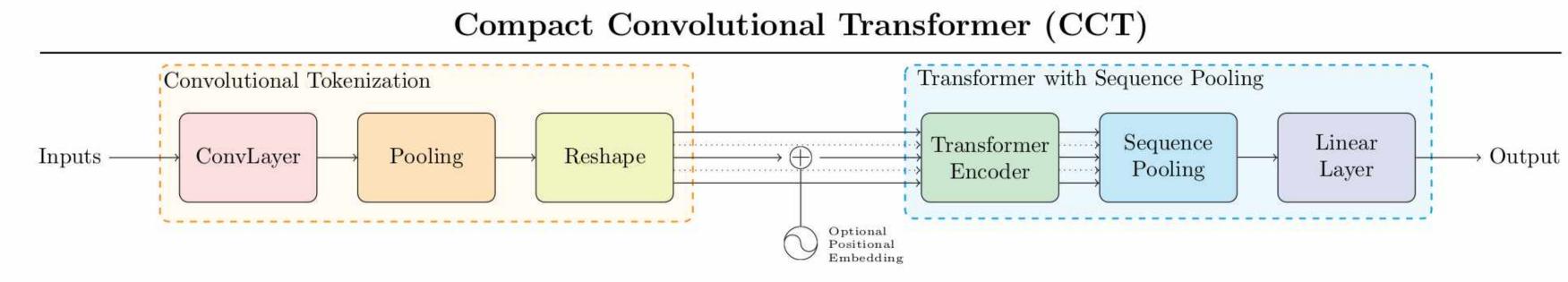




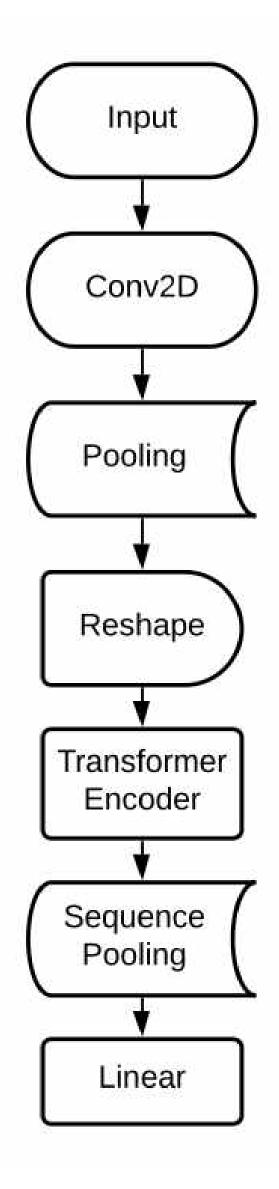


Compact Convolutional Transformer (CCT)

- Combines convolutions and attention mechanism.
- Outperforms Convolutional networks in classification tasks¹.



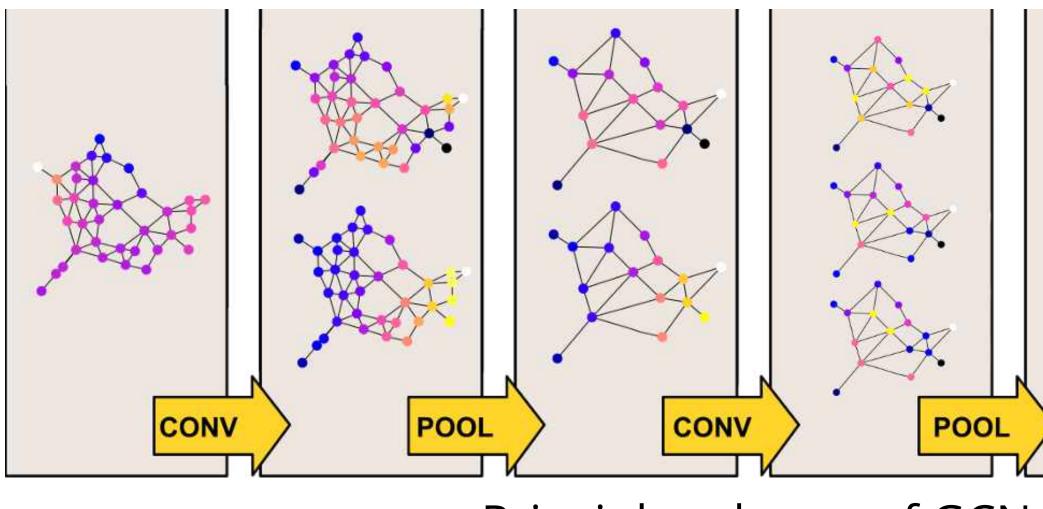
1. Hassani, A., Walton, S., Shah, N., Abuduweili, A., Li, J., & Shi, H. (2021). Escaping the Big Data Paradigm with Compact Transformers. arXiv.





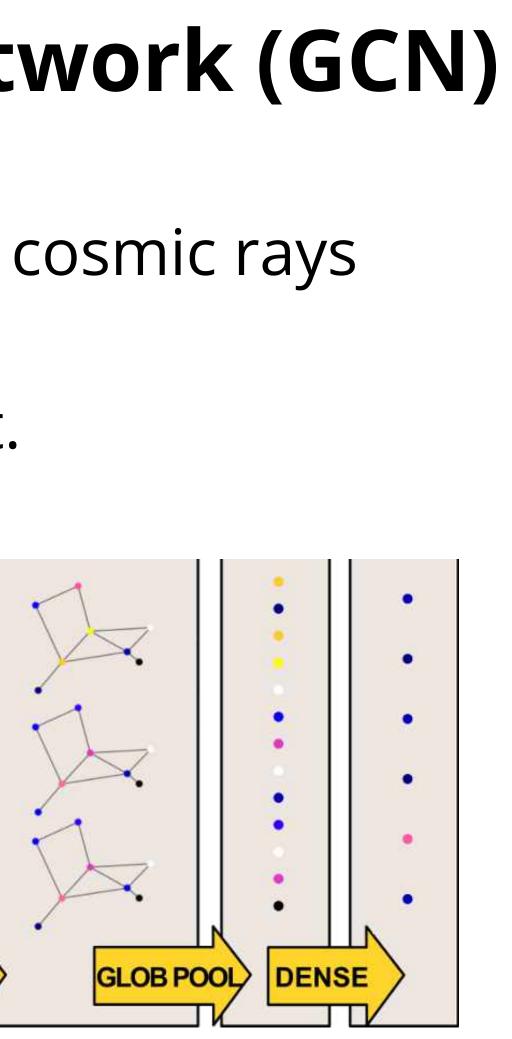
Graph Convolutional Network (GCN)

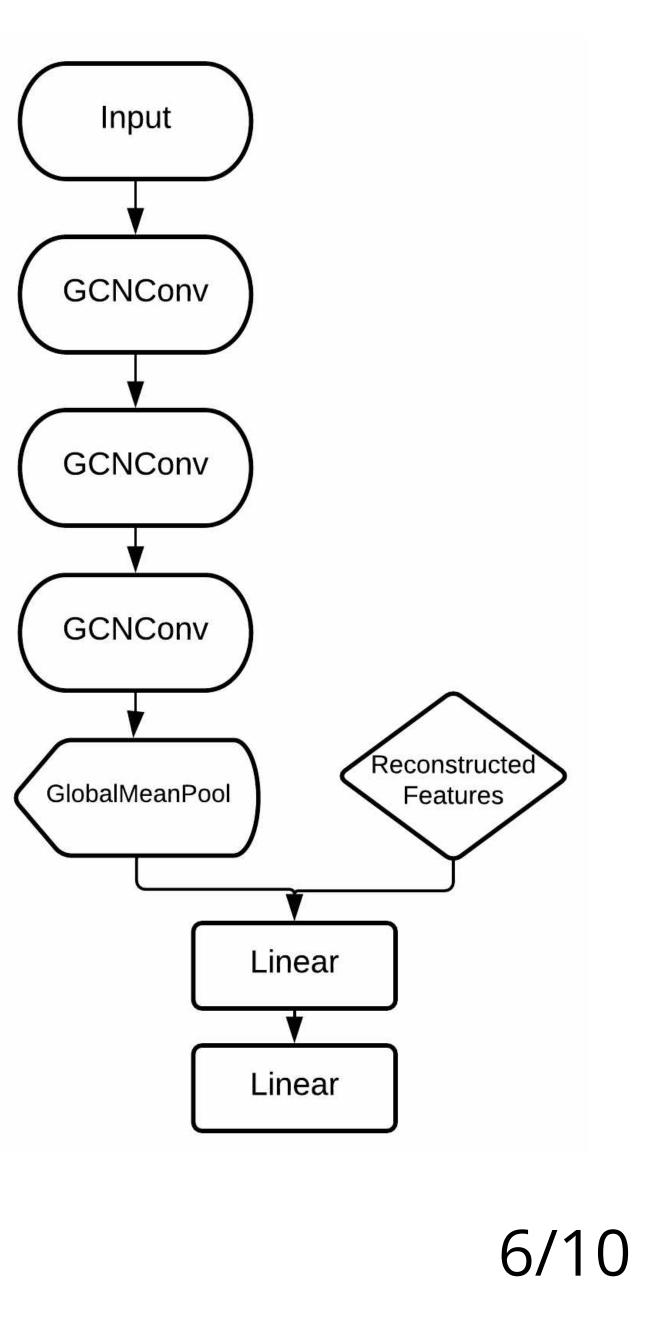
- Successfully used for classifying cosmic rays at LHAASO¹.
- Takes irregularities into account.



Principle schema of GCN

1. Jin, C. et al (2020). Classifying cosmic-ray proton and light groups in LHAASO-KM2A experiment with graph neural network *. Chinese Physics C, 44(6), 065002.





Models comparison

Self-att

 $e/\gamma + \mu$ deposits,

flatten to 1x512

Peculiarities Attention

Spatial invariance

Input

Number of parameters:

Non-invariant

30 183

CCT

GCN

 $e/y + \mu$ deposits, as an image 2x16x16

a graph: $e/y + \mu$ deposits as nodes; edges btw stations + reconstructed features

2D convolutions, Attention, Pooling

Graph Convolutions

Partially invariant

Non-invariant

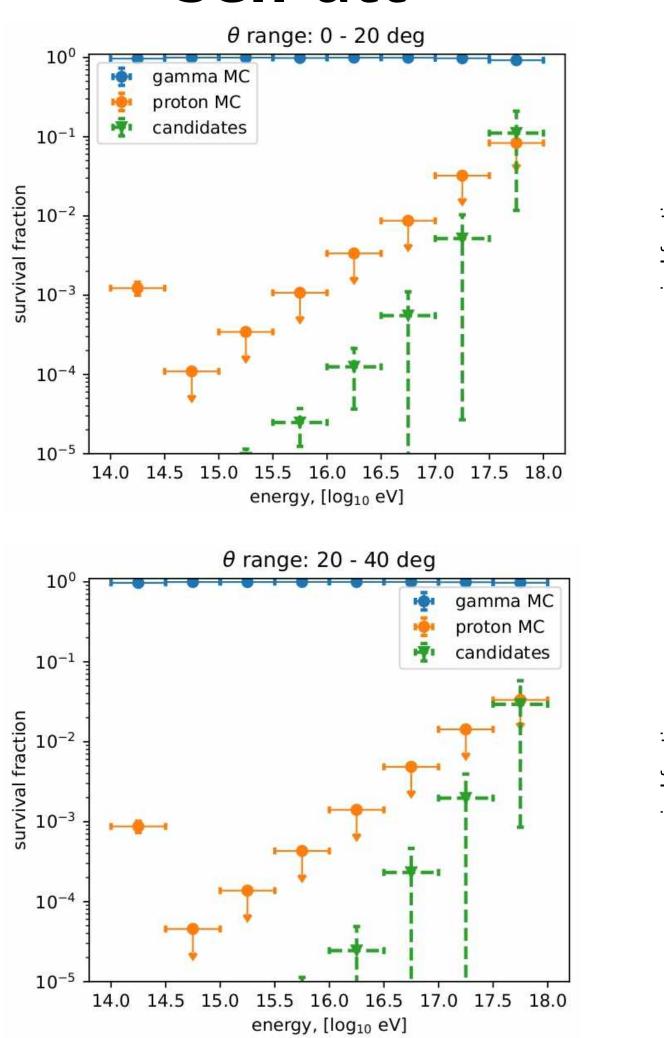
30 531

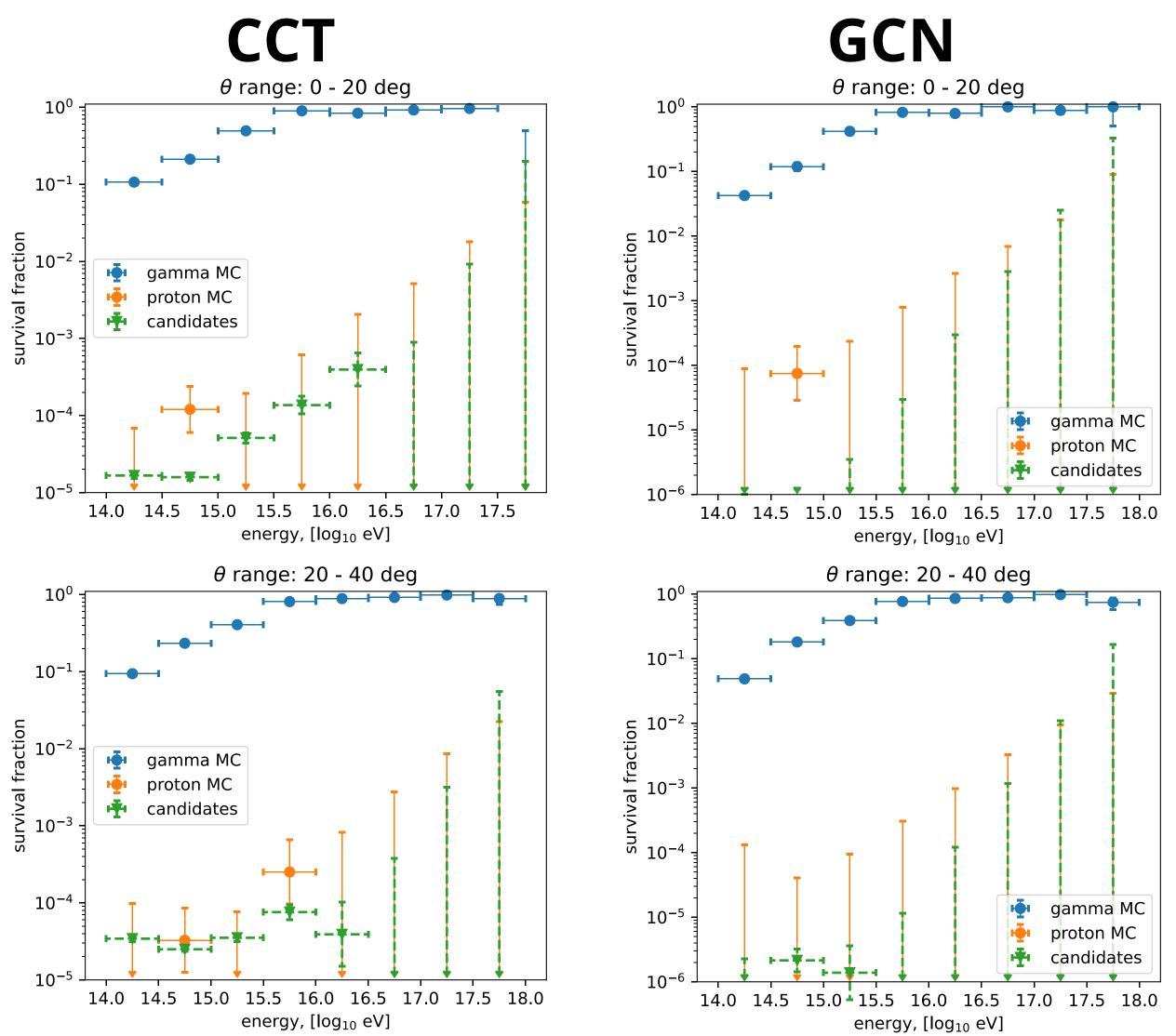
29 520

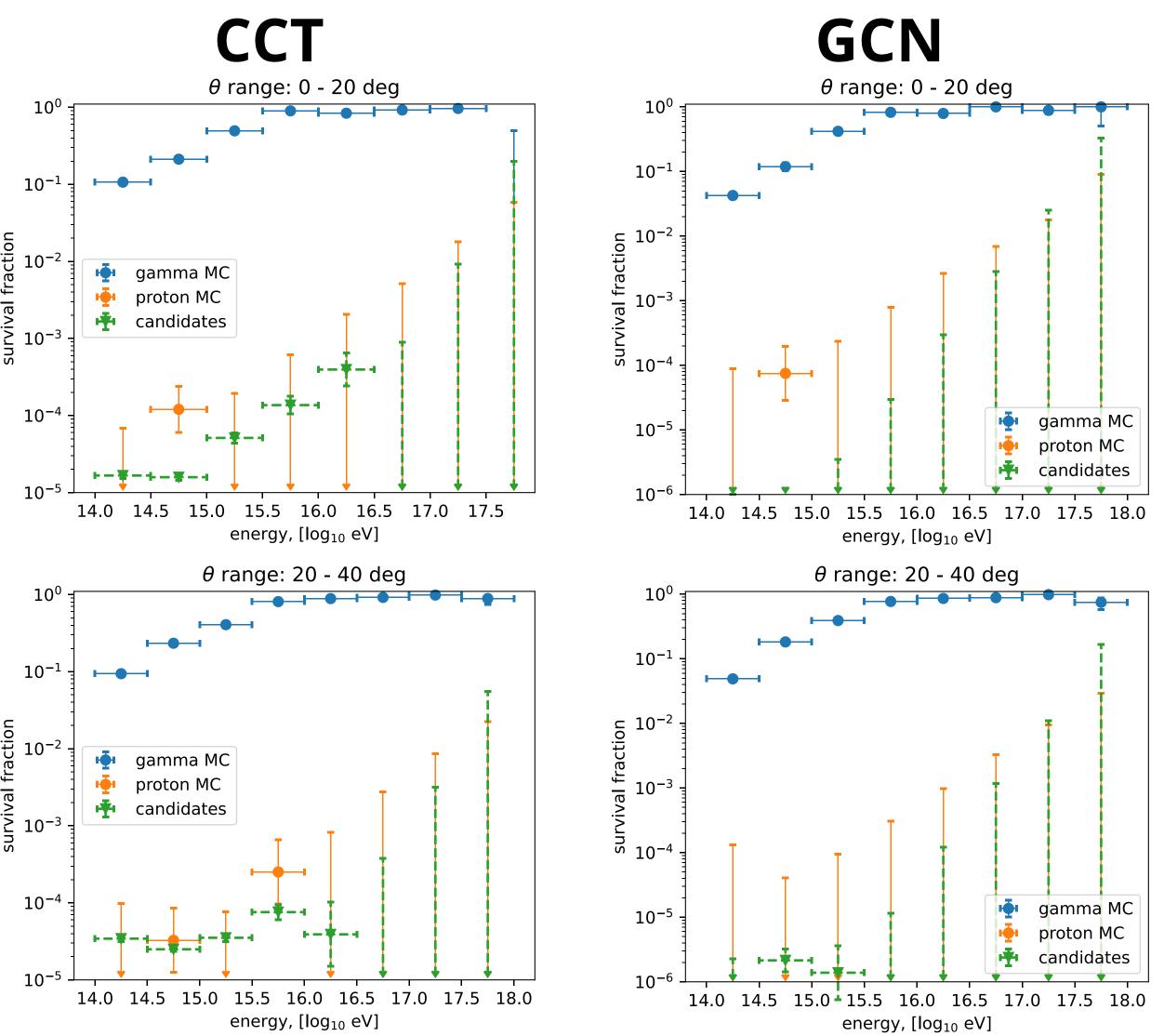


Preliminary results

Self-att









Conclusion

- We've developed a pipeline for gammas search at KASCADE data
- We've tested different architectures for gammas search at KASCADE
- We need more MC simulations

Future plans

- Improve a quality of the models
- Conduct an ablation study
- Use more MC simulations

Models has a good agreement btw experimental data and simulations



Acknowledgments

This work was supported by the Russian Science Foundation (RSF)

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Backup slides

Data details

MC Dataset structure

γ: QGS + EPOS + Sibyll ~90 000 events

p: QGS ~600 000 events

Experiment dataset

Unblind: 20%

~400 000 000 events in total

