

# Search for optimal deep neural network architecture for gamma detection at KASCADE

**Speaker:**

Margarita Tsobenko

**Co-authors:**

P. Bezyazeev, S. Golovachev, D. Kostunin, V. Lenok,  
I. Plokhikh, N. Petrov, D. Reutsky, V. Sotnikov,  
V. Tokareva, O. Shchegolev

# Motivation

- Gamma astronomy enters PeV era
- LHAASO detected PeV gammas<sup>1</sup>. Tibet detected diffuse sub-PeV gammas<sup>2</sup>
- KASCADE exposure comparable with LHAASO one at PeV energies => should contain gamma-rays in dataset
- Using DL with modern architectures<sup>3</sup>

1. [Zhen Cao et al. "Ultra-high-energy photons up to 1.4 petaelectronvolts from 12  \$\gamma\$ -ray Galactic sources". In: 2021](#)

2. [M. Amenomori et al. "First Detection of sub-PeV Diffuse Gamma Rays from the Galactic Disk: Evidence for Ubiquitous Galactic Cosmic Rays beyond PeV Energies". In: 2021](#)

3. [Chao Jin et al. "Classifying cosmic-ray proton and light groups in LHAASO-KM2A experiment with graph neural network". In: 2019](#)

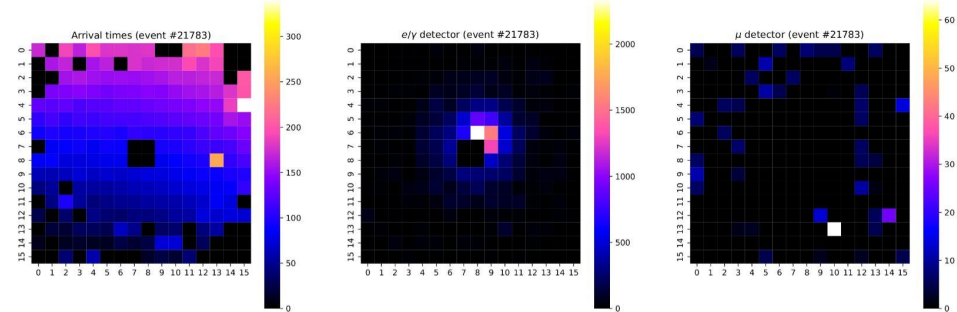
# Data description

Each event consists of the following components:

- 3 arrays (16x16 shape):
  - arrival times per station (ns)
  - e/ $\gamma$  energy deposit per station (MeV)
  - muon energy deposit per station (MeV)

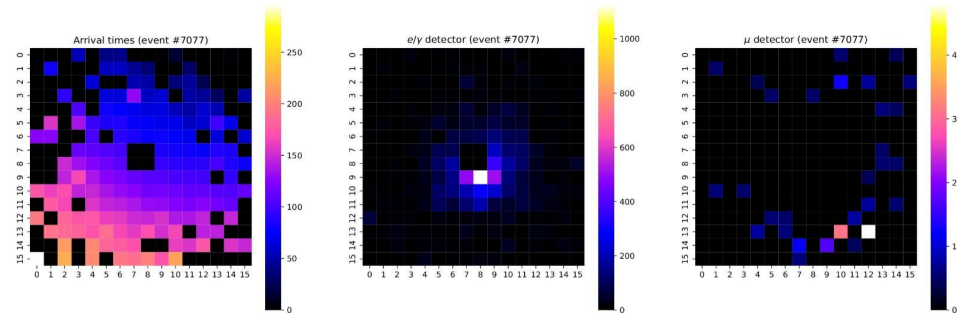
- Reconstructed features:
  - energy of the primary particle
  - arrival direction
  - number of electrons and muons
  - shower age

## *Simulated event*



$\lg E$  [eV] = 15.25,  $\theta = 15.96^\circ$ , Core distance = 17.91 m

## *Real event*

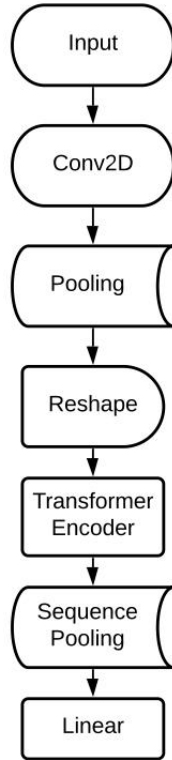


$\lg E$  [eV] = 15.10,  $\theta = 14.98^\circ$ , Core distance = 15.04 m

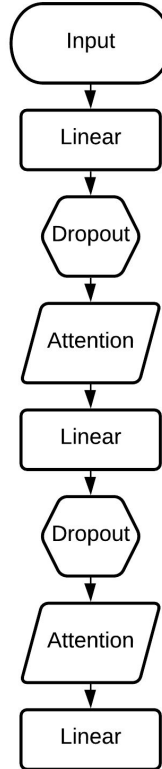
Data and Simulations are taken from KCDC  
A.Haungs et al; Eur. Phys. J. C (2018) 78:741;  
“The KASCADE Cosmic ray Data Centre KCDC: granting open access to  
astroparticle physics research data”;  
(doi: 10.1140/epjc/s10052-018-6221-2)

# Models Overview

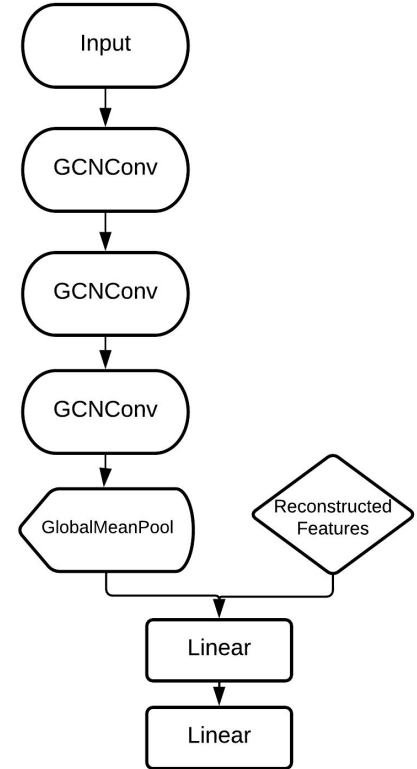
## Compact Convolutional Transformer



## Self-Attention Network



## Graph Convolutional Network



# Basic differences

## Compact Convolutional Transformer

Input:  
two-channel image

2D Convolutions,  
Attention, Pooling

Partially spatially invariant

## Self-Attention Network

Input:  
one-dimensional array

Attention

Spatially non-invariant

## Graph Convolutional Network

Input:  
graph with real  
distances between  
detector stations

Graph Convolutions

Spatially non-invariant

# Implementation details

## Compact Convolutional Transformer

Reconstructed  
features are not used

Arrival time is not used

Number of  
parameters: 30531

## Self-Attention Network

Reconstructed  
features are not used

Arrival time is not used

Number of  
parameters: 30183

## Graph Convolutional Network

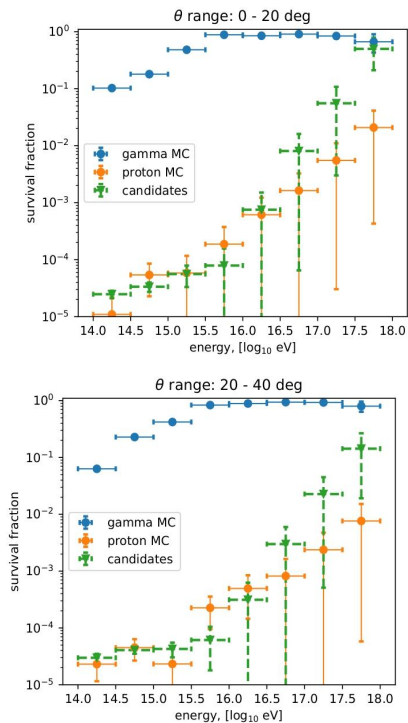
Reconstructed  
features are used

Arrival time is used

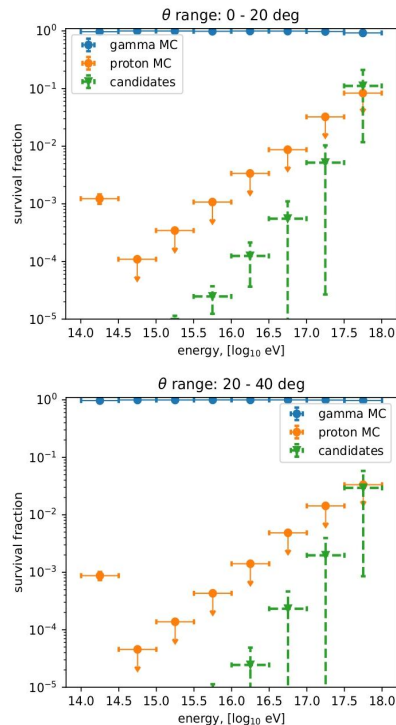
Number of  
parameters: 2952

# Intermediate Results

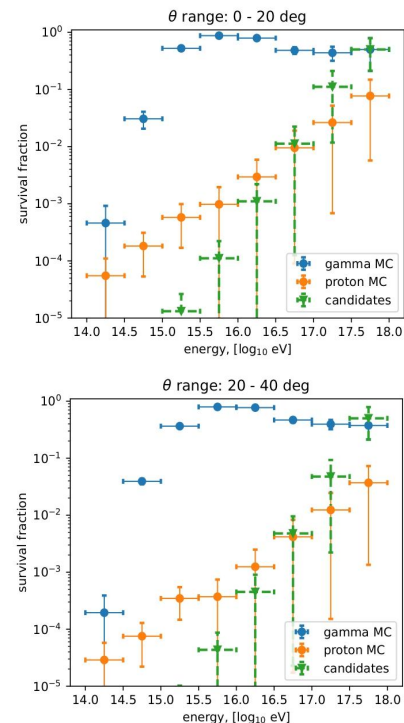
## Compact Convolutional Transformer



## Self-Attention Network



## Graph Convolutional Network



All networks are trained with QGSJet-II.04 protons, photons are mixed from different models

# Conclusion

- We are testing different architectures for gamma search at KASCADE
- We use semi-blind approach (80% of data are hidden until classifier is finalized)
- Compact Convolutional transformer satisfactorily describes data
- We need more Monte-Carlo events for network evaluation (especially for Self-Attention network)
- GNN has order of magnitude less trainable parameters

# Future plans

- Improve the quality of models (try new optimization techniques, improve architectures)
- Conduct an ablation study (how number of high-energy events in training set affects performance)
- Use more simulated data