Search for ultra-high energy photons using the Telescope Array Surface Detector array

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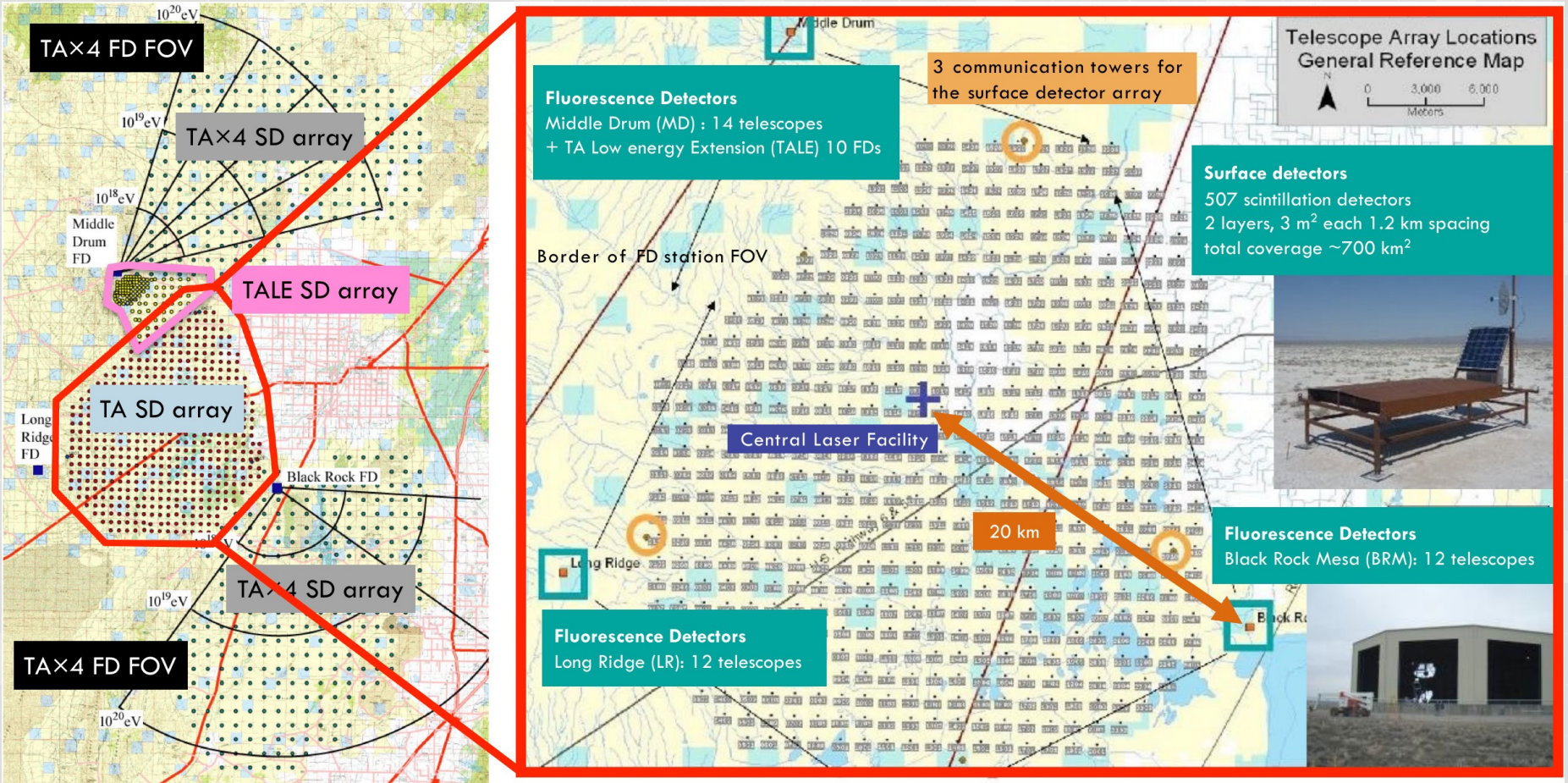
Telescope Array Experiment



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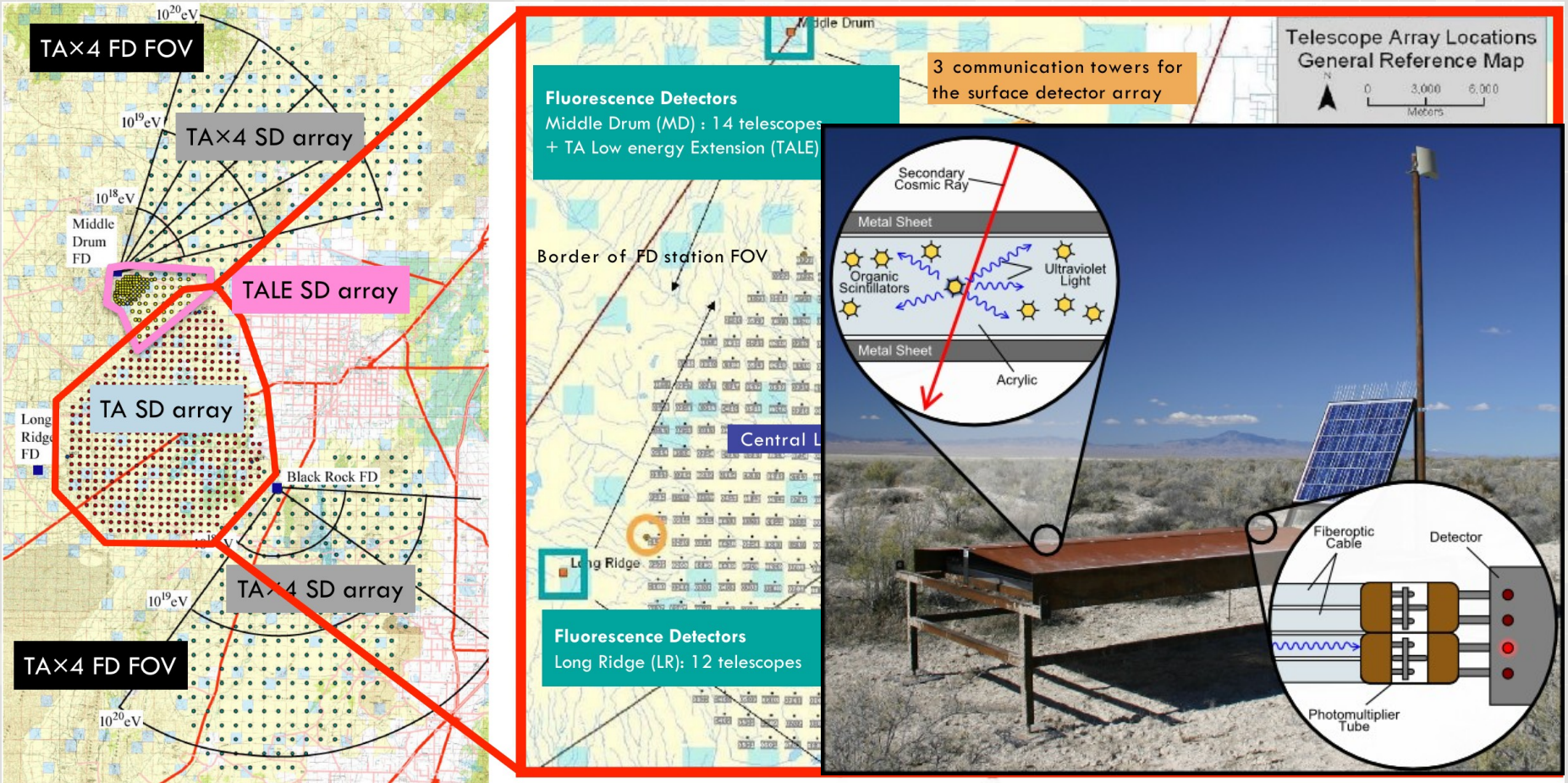


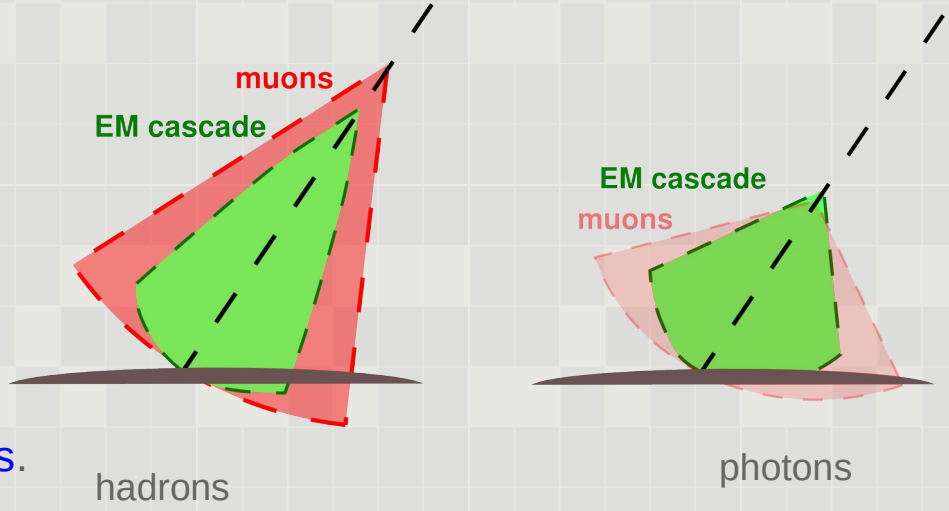
Search for EeV photons: motivation

The ultra-high-energy photons may be produced by GZK-process or in the interactions which includes new physics.

Observations of EeV photons would provide the strongest high energy test of quantum electrodynamics, including the test of the Lorentz invariance.

The expected flux if low, so the exposure should be as big as possible

- Surface detectors operate more than 95% of time.
- To get the best separation of photon- and hadron-induced air showers, we employ Neural Networks.



Approach

1. Train a neural network to distinguish photon- and hadron-induced air-showers.
   - Use Monte-Carlo simulated photon- and proton-induced events for training.

2. Find optimal classification threshold.
   - Optimize on MC by requiring best sensitivity to photon flux in case of the null hypothesis, i.e., no photons in the data.

3. Verify the applicability to real data analysis.

4. Set limits on the photon flux by analyzing the data.

TA SD data set and Monte-Carlo simulations

- Data collected by TA surface detector for the 14 years:
  2008-05-11 – 2022-05-10

- Full Monte-Carlo simulations for 14 years of TA SD operation time
  - Protons:
    - CORSIKA: QGSJET-II-04, SIBYLL, EPOS + FLUKA.
    - Monte-Carlo spectrum reproduces the observed one
  - Photons
    - QGSJET-II-04 + FLUKA
    - E^{-1} spectrum

- For training of the neural network: equal-efficiency mixture of proton- and photon-induced events

Event selection procedure

- We use the same quality requirements for both data and Monte Carlo events
  - 7 of more stations are triggered
  - core distance to array boundary is larger than 1200 m
  - χ^2 /d.o.f. < 5 for the joint fit of the shower front and lateral distribution function
  - $\theta < 55^o$
  - exclude the events time correlated with the lightnings registered by National Lightning Detection Network (10 min window)
- For each event we estimate E_γ using the photon Monte-Carlo
- Number of the events after cuts:
  - 42979 events with $E_\gamma > 10^{18.5}$ eV
  - 14046 events with $E_\gamma > 10^{19.0}$ eV

Neural network architecture

Spatial detector bundle
(geometrical features):

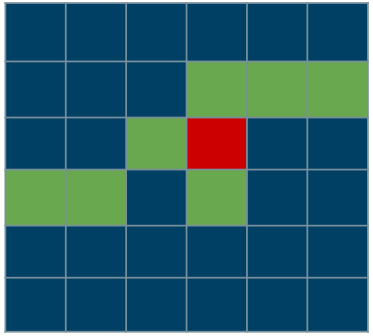
- 6 x 6 detector tiles are processed via convolutions

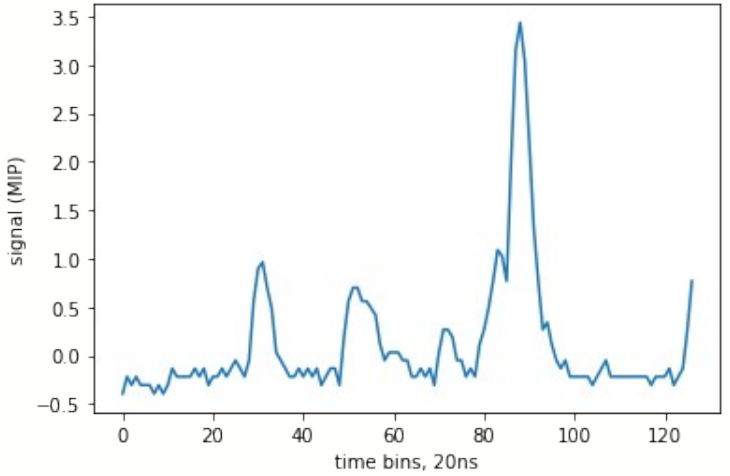
Temporal detector bundle:
(overall structure)

- Waveforms are encoded via combination of convolutions and recurrent layers
- Time-ordered detector activations are processed by recurrent layers

Making predictions:

- All obtained features are concatenated, including **reconstructed parameters**, and passed through dense layers.





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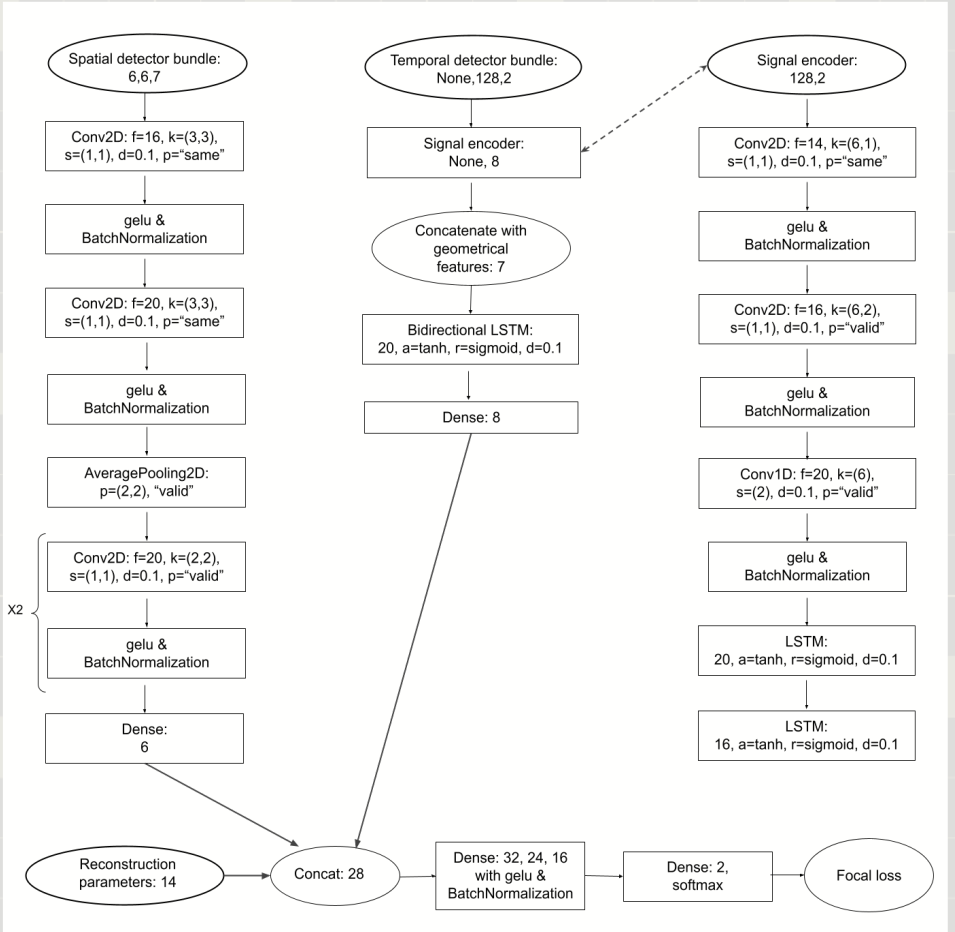


Reconstructed parameters used by the NN classifier

1. Zenith angle, θ;
2. Signal density at 800 m from the shower core, S_{800};
3. Linsley front curvature parameter, a;
4. Area-over-peak (AoP) of the signal at 1200 m;

Pierre Auger Collaboration, Phys.Rev.Lett. 100 (2008) 211101

5. AoP LDF slope parameter;
6. Number of detectors hit;
7. N. of detectors excluded from the fit of the shower front;
8. $\chi^2/d.o.f.$;
9. $S_b = \sum S_i \times r_i^b$ parameter for $b = 2.5, 3.0, 3.5, 4.0$ and $b = 4.5$;

Ros, Supanitsky, Medina-Tanco et al. Astropart.Phys. 47 (2013) 10

10. The sum of signals of all detectors of the event;
11. Asymmetry of signal at upper and lower layers of detectors;
12. Total n. of peaks within all FADC traces;
13. N. of peaks for the detector with the largest signal;

14-15. N. of peaks present in the upper layer and not in lower (and vice versa);

Model dependence

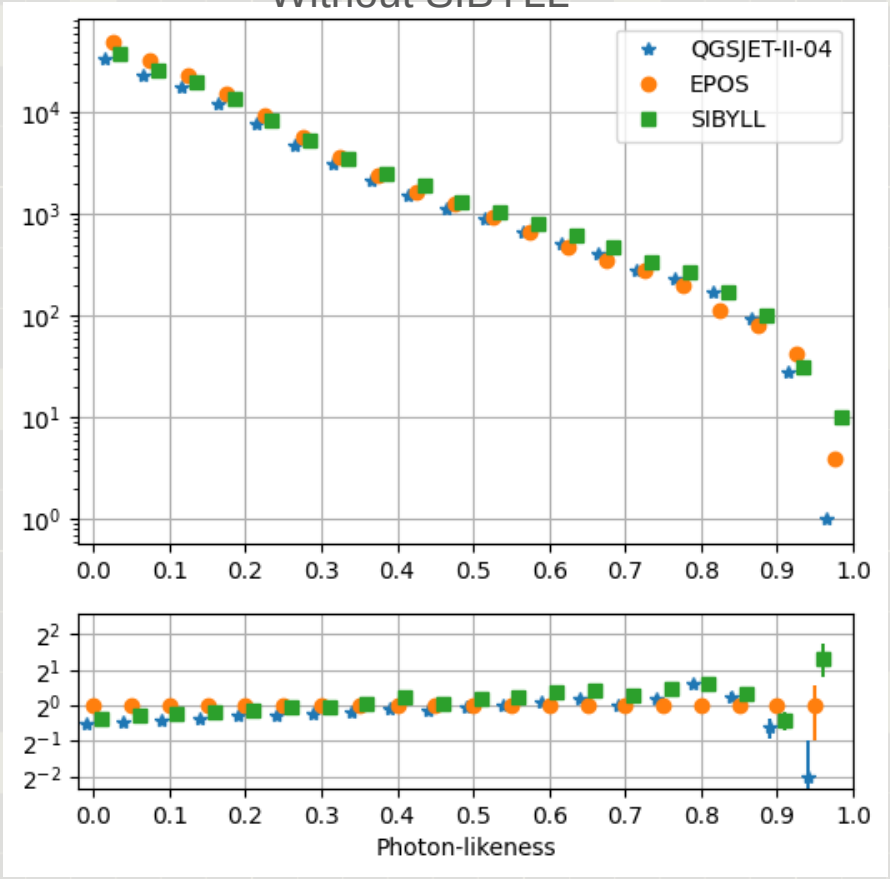
1) Select one of the hadronic models (SIBYLL);

2) Do not use it for training;

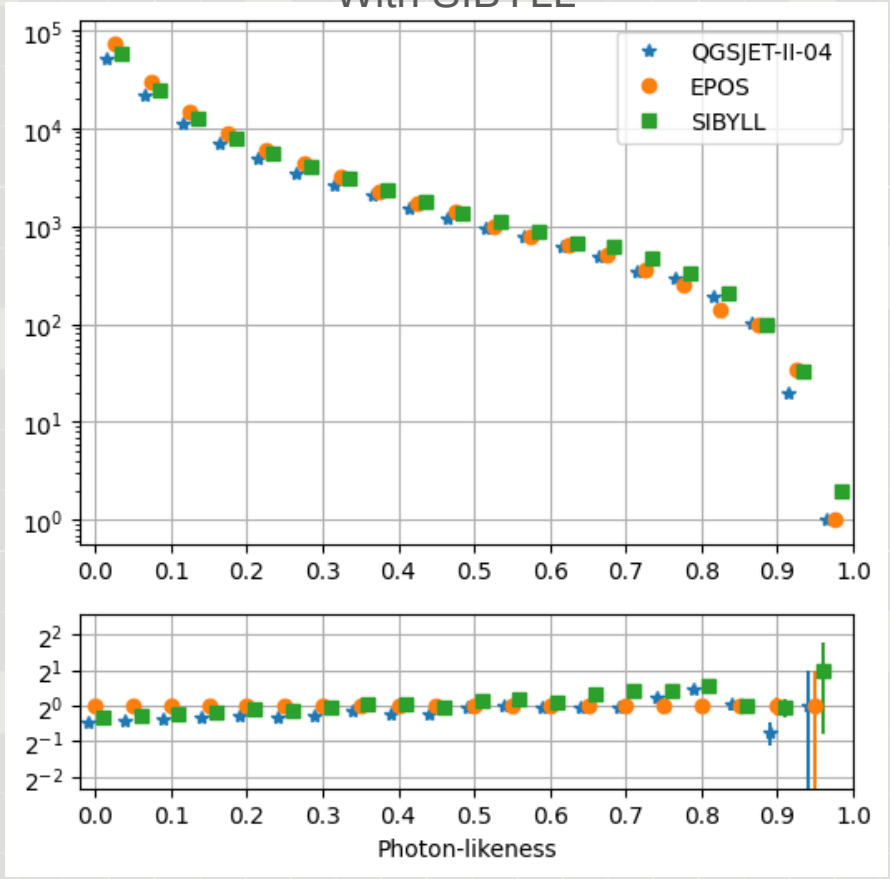
3) Compare neural network predictions for the hidden and other hadronic models.

Pure protons, model dependence: log(E)>17.45

Without SIBYLL

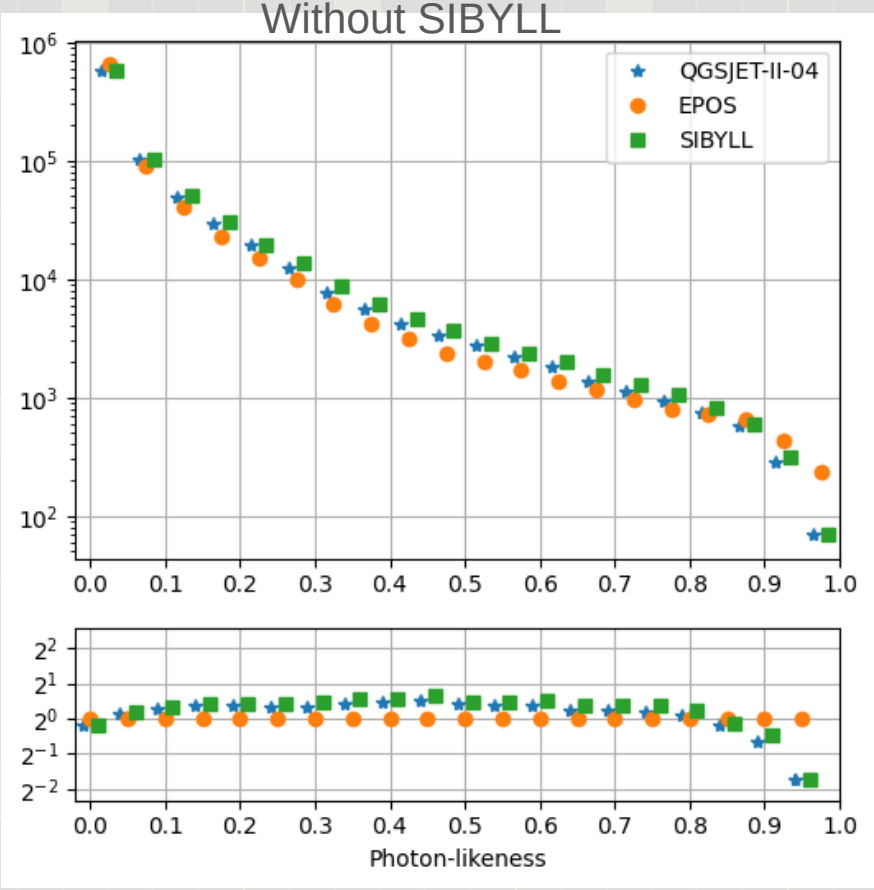


With SIBYLL

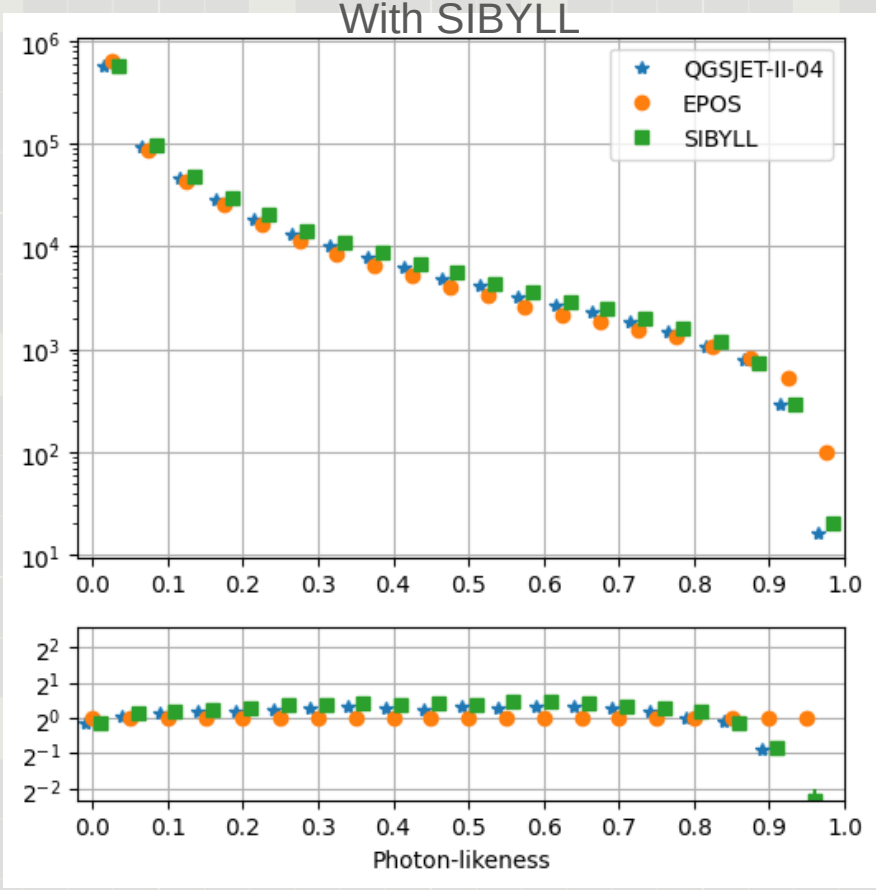


Pure protons, model dependence: log(E)>18.95

Without SIBYLL

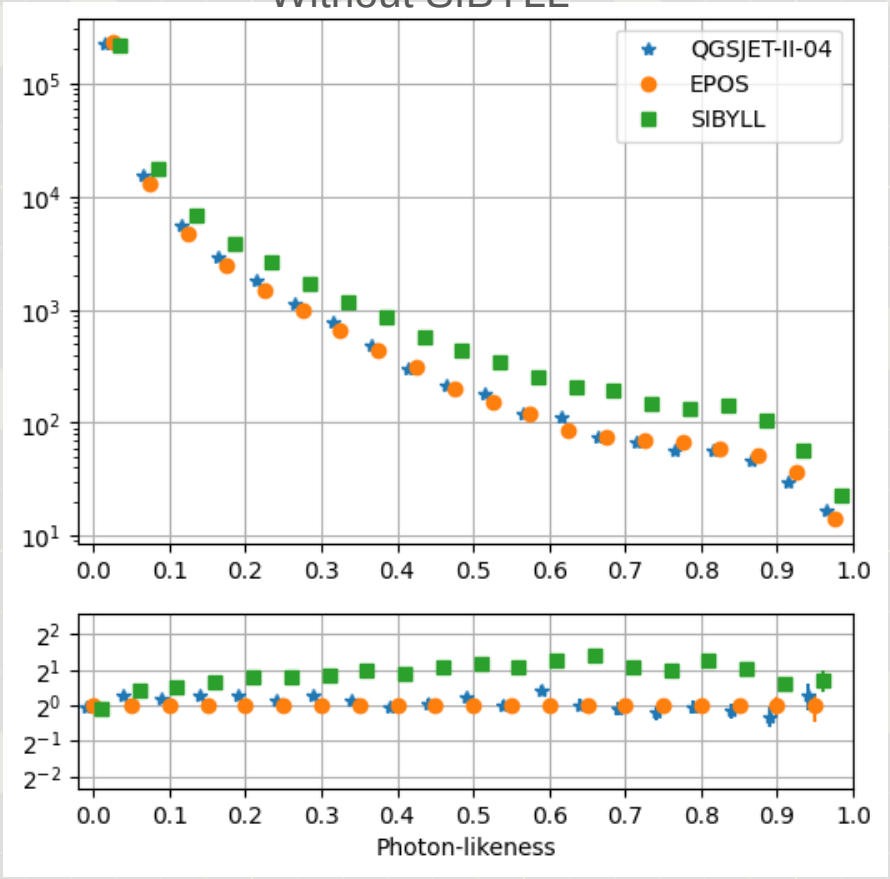


With SIBYLL

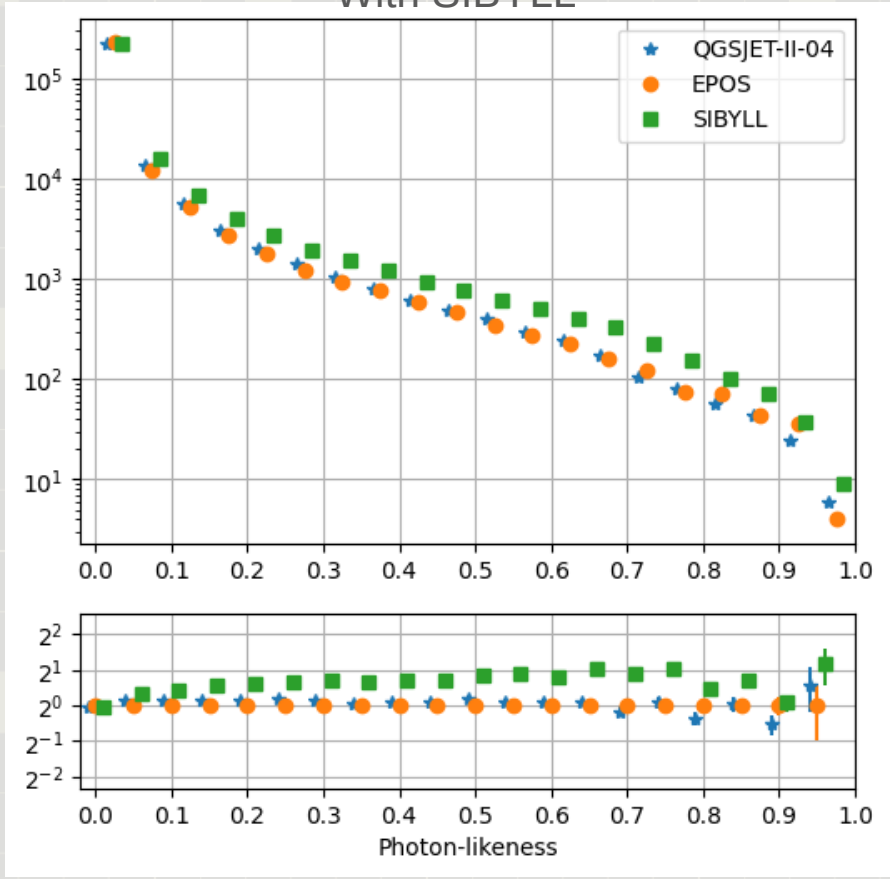


Pure protons, model dependence: log(E)>19.45

Without SIBYLL



With SIBYLL



Model dependence

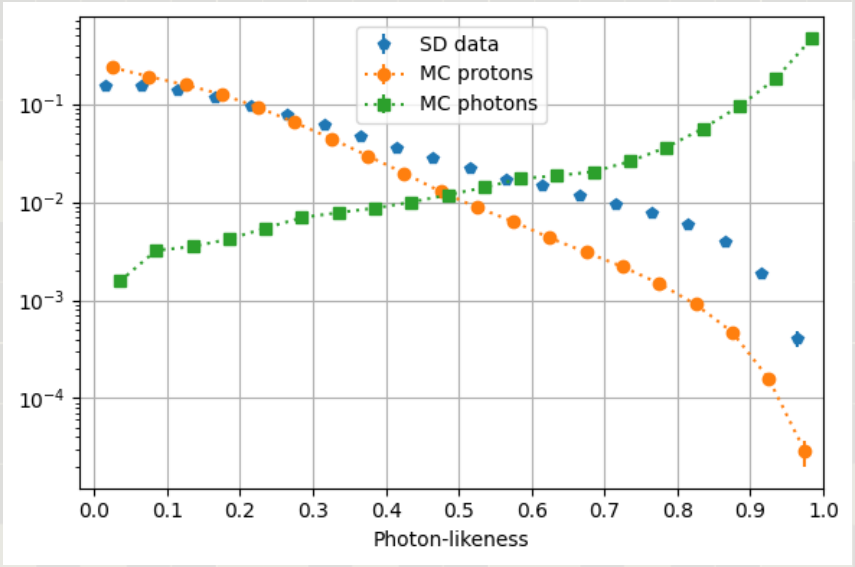
- No universal dependence on hadronic interaction model:
  - log(E)> 18.95: EPOS protons are more photon-like in the rightmost bin.
  - 19.45 sample: SIBYLL protons are more photon-like.
  - Small dependence on whether SIBYLL was used for training or not

None of hadronic interaction models is preferable. We use all models for training.

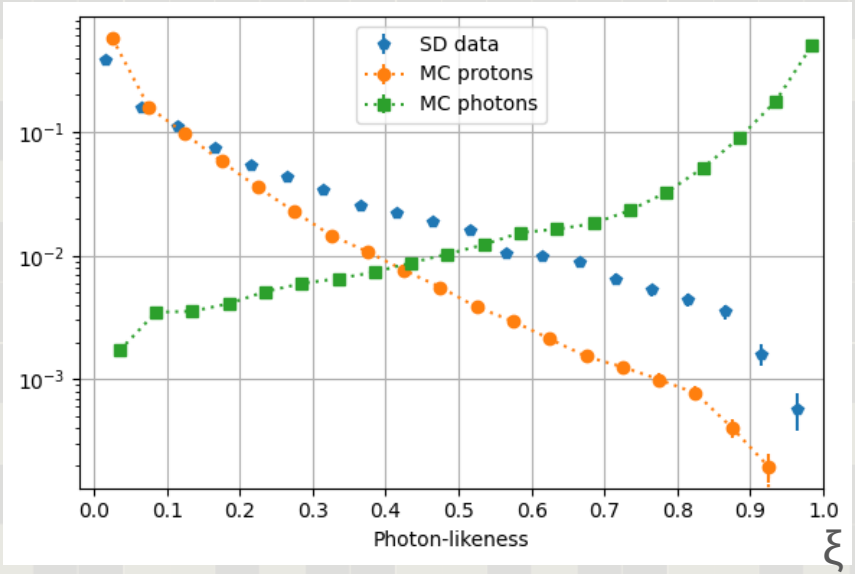
Data and Monte-Carlo comparison for photon-likeness

MC unavoidably differs from experimental data due to assumptions in the modeling.

Erec > 10^{18} eV



Erec > 10^{19} eV

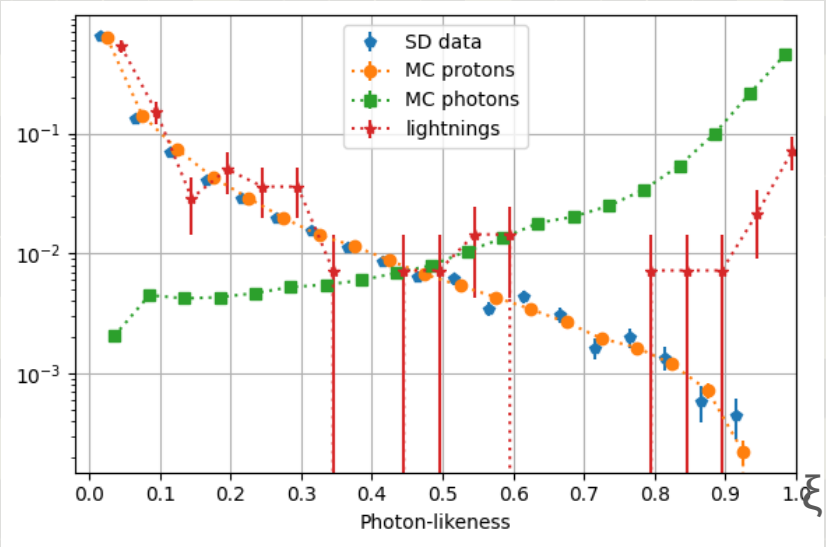


Fine-training on experimental data

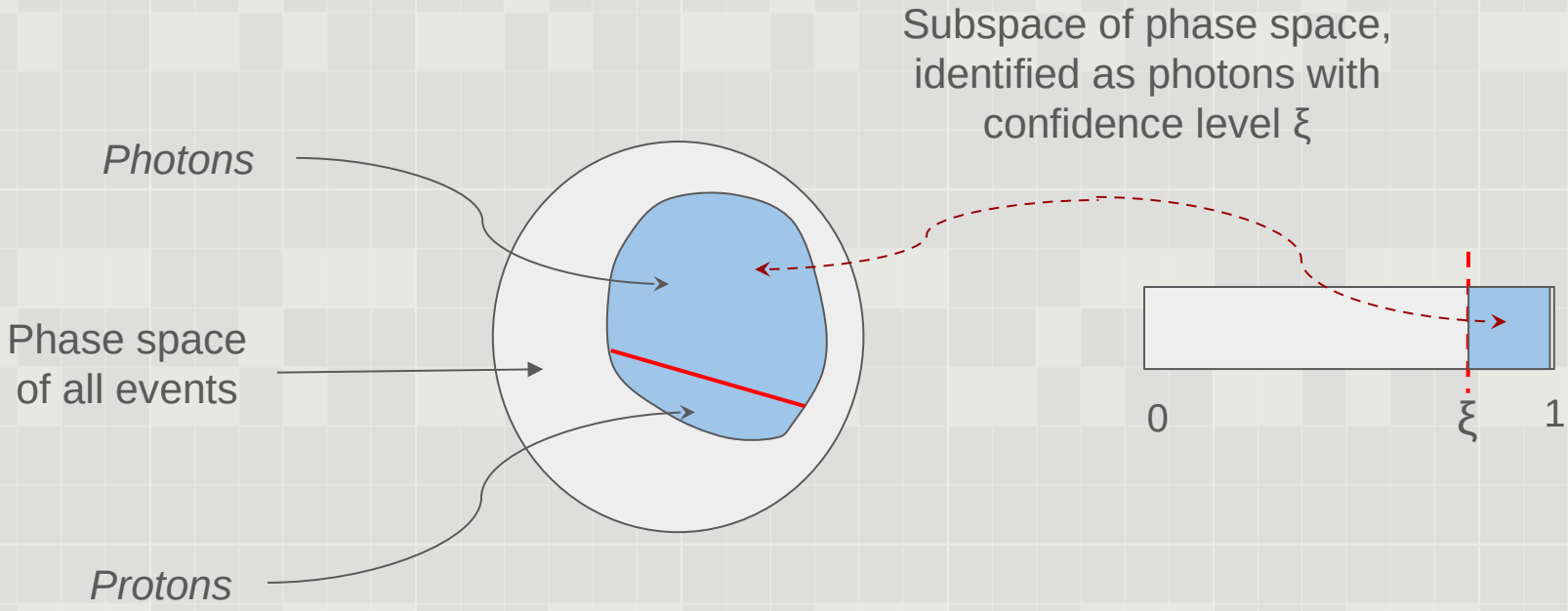
One can inform neural network on how actual experimental data looks like:

1. Train NN on MC data
2. Apply NN to experimental data
3. Select events that are classified as protons with high confidence ($\xi < 0.2$)
4. Include these protons to the training data set
5. Fine-train NN on the resulting mix

$E_\gamma > 10^{19.0}$



Finding optimal classification threshold



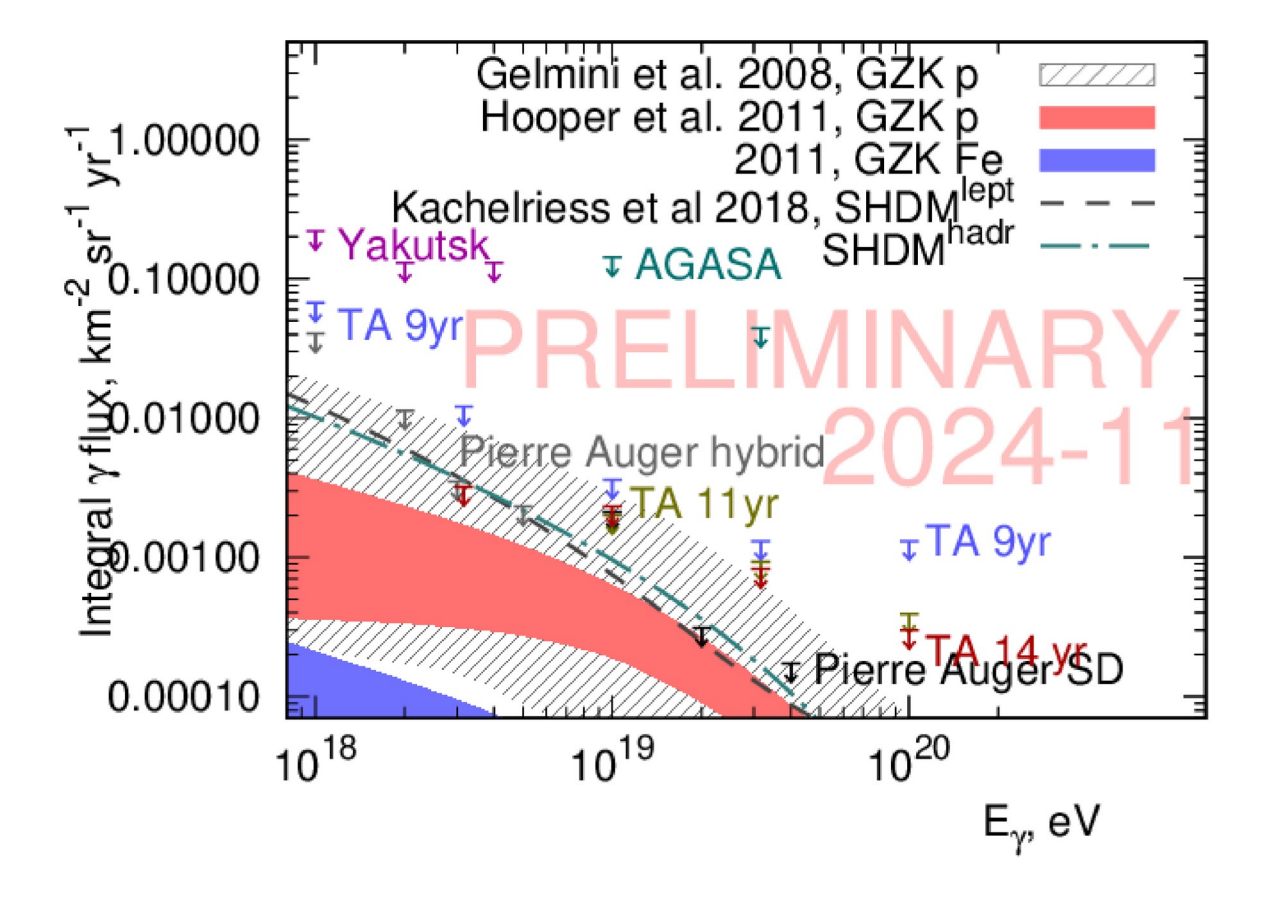
Minimize merit function :

$$L^{95} = \frac{M\left(\sigma^{95}\left(n_{\text{cand}}(\xi)\right)\right)}{S(\xi)}, \quad S(\xi) = \frac{n_\gamma(\xi)}{n_\gamma^0}$$

Results

Energy	Metric	ξ-cut efficiency	Effective exposure, km^2 sr yr	Number of photon candidates	Flux limit, km^{-2} sr^{-1} yr^{-1}
$\log(E_\gamma) > 18.5$	13.3	0.25	979.2	0	3.2×10^{-3}
$\log(E_\gamma) > 19.0$	8.2	0.46	3576	3	2.3×10^{-3}
$\log(E_\gamma) > 19.5$	5.1	0.64	6300	1	8.2×10^{-4}
$\log(E_\gamma) > 20.0$	4.0	0.91	10440	0	3.0×10^{-4}

Results


Gelmini et al. 2008, GZK p
Hooper et al. 2011, GZK p
2011, GZK Fe
Kachelriess et al 2018, SHDM lept
SHDM hadr
Yakutsk
AGASA
TA 9yr
PRELIMINARY
2024-11
Pierre Auger hybrid
TA 11yr
TA 9yr
TA 14 yr
Pierre Auger SD
Integral γ flux, km-2 sr-1 yr-1
1.00000
0.10000
0.01000
0.00100
0.00010
10^18
10^19
10^20
Eγ, eV

Conclusions

- A neural network classifier is developed and trained on the photon-induced and proton-induced Monte-Carlo event sets
  - The input data includes both the time-dependent waveform signals at each SD station and event-level composition-sensitive parameters.
- A classifier is fine-trained using the data events which are not photons with high confidence.
- The limits on the ultra-high-energy photon flux are established based on 14 years of TA SD data.
- The events associated with TGFs are excluded from the data set, otherwise they are classified as photon-induced.

Thank you for attention!

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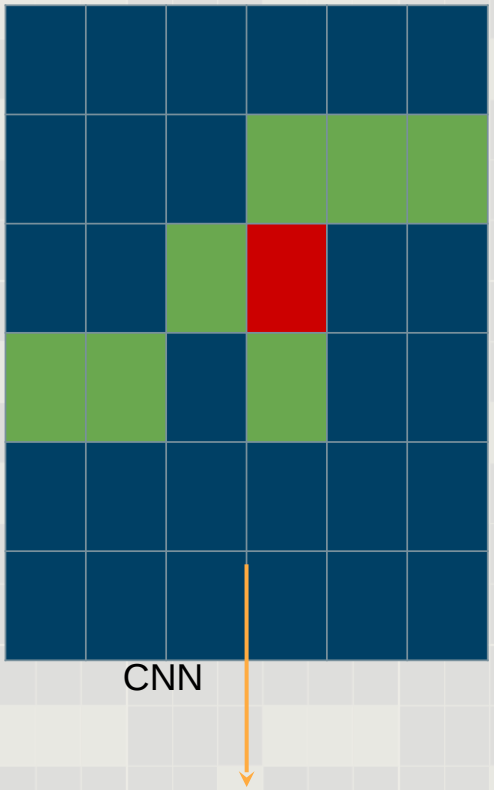
Backup slides

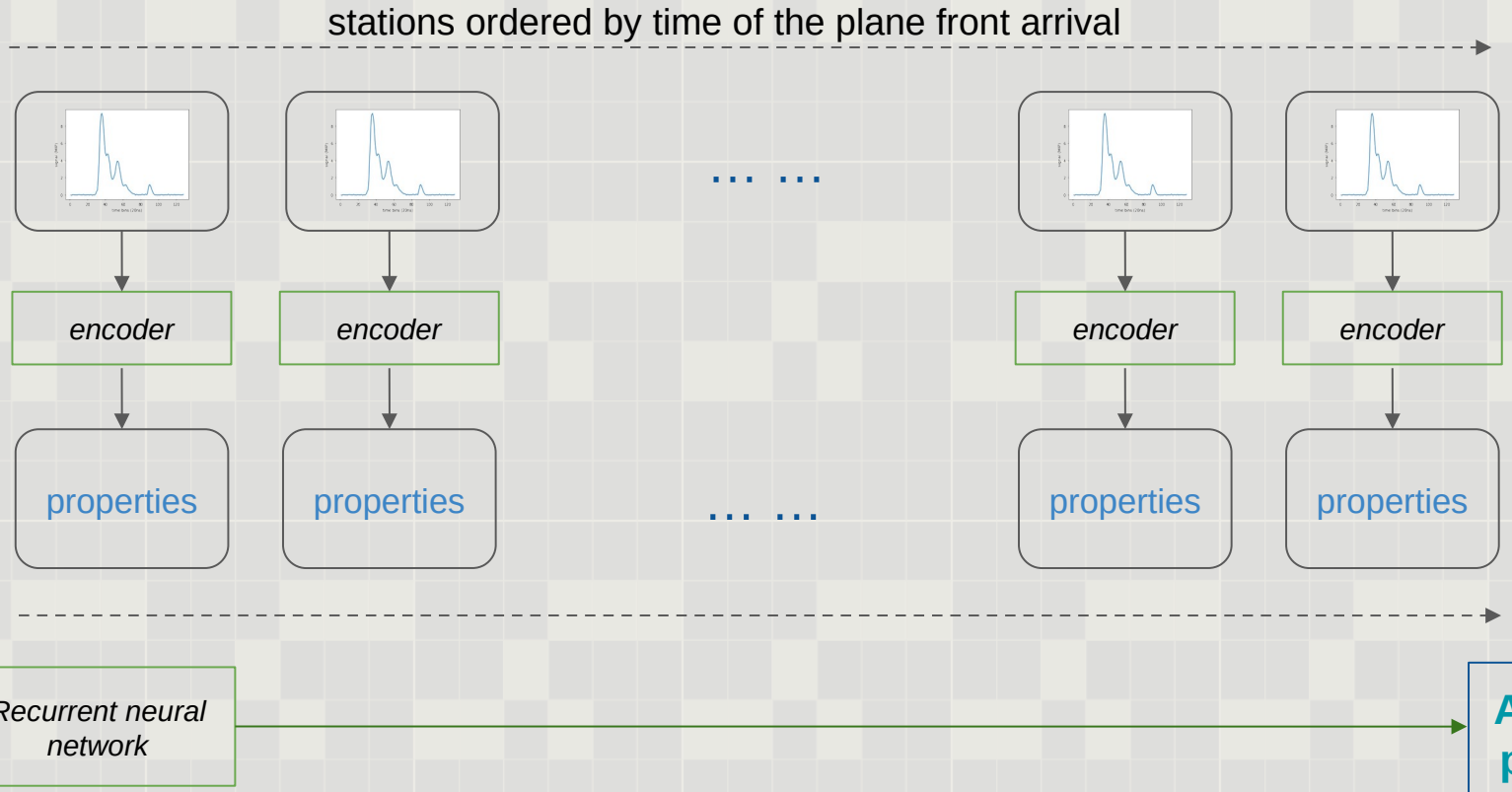
Stations bundle

- x, y, and z coordinates of the station
- Station’s total signal
- Time of the plane front arrival
- Difference in time between the start of the recorded signal and the wavefront arrival
- Masks:
  - Was triggered?
  - Was saturated?
  - Was excluded from the geometry fit?

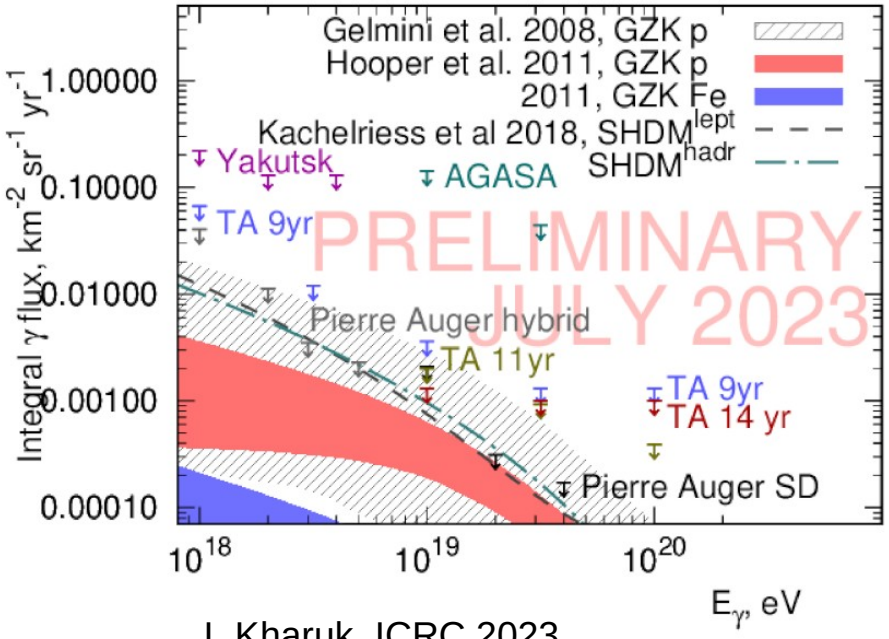


Spatial station features

Temporal detector bundle



Comparison with the ICRC 2023 result



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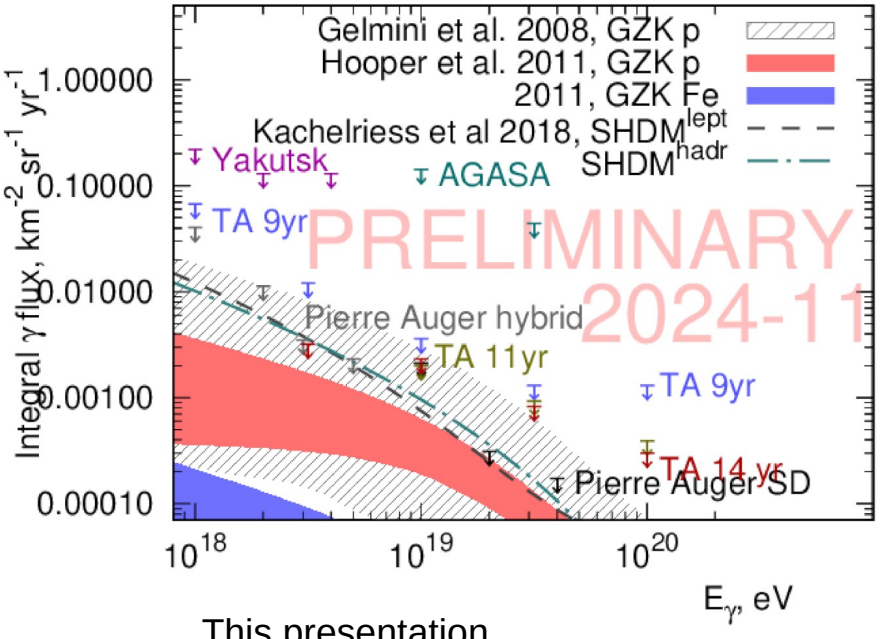

This presentation