Космические лучи ультравысоких энергий

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Космические лучи ультравысоких энергий

план

Многокомпонентный (multimessenger) подход

Интерпретация экспериментальных данных

Ultra-High Energy Neutrino Fluxes and Their Constraints

connection to γ and cosmic rays



Cosmic ray, photon and neutrino fluxes are connected in well-defined way. If we know one of them we can estimate other ones:

$$E_{\gamma} \simeq E_{\nu}$$

Kalashev, Kuzmin, Semikoz, Sigl 2002

expected contributions

Unresolved sources

mainly BL Lacs, also FSRQs, misaligned AGNs,

star forming galaxies

 86^{+16}_{-14} % of γ ray flux above 50GeV by blazars. *Fermi LAT 2016*



BL Lacs give main contribution to high energy part of diffuse gamma-ray flux

Neronov, Semikoz 2012

M. Di Mauro et al 2013

expected contributions

• Unresolved sources

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• Ultra-high energy cosmic rays

may saturate flux above few 100 GeV (constraints on protondominated models)

minimal flux is not negligible



Processes contributing to EM cascade:



expected contributions

Unresolved sources

mainly BL Lacs, also FSRQs, misaligned AGNs,

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may saturate flux above few 100 GeV (constraints on protondominated models)

minimal flux is not negligible

Neutrino sources

may saturate flux above 10 GeV

sources opaque to 1–100 GeV γ rays are preferable

contribution of star forming galaxies is limited

no ν correlation with Fermi BL Lacs was found (27% or less between around 10 TeV and 2 PeV), *IceCube 2016*





K. Bechtol et al 2017

With single scenario we try to explain

- Ultra-high energy cosmic ray flux
- UHECR mass composition
- Observed neutrino flux in IceCube
- Satisfy diffuse gamma-ray limit

Model constraints.

Composition

- Mass composition below 0.2 EeV by CASCADE-Grande
- Limits on 4 element fractions above 0.6 EeV by Auger



W. D. Apel et al. [KASCADE-Grande Collaboration], Astropart. Phys. 47, 54 (2013). A. Aab et al. [Pierre Auger Collaboration], Phys. Rev. D 90, no. 12, 122006 (2014)

Model constraints.

Composition

- Mass composition below 0.2 EeV by CASCADE-Grande
- Limits on 4 element fractions above 0.6 EeV by Auger



- Proton fraction 40-60% for 0.7 < E/EeV < 7
- Above 7 EeV
 - proton fraction decreases
 - intermediate elements fraction increases
- Fe fraction is limited by 15-20% for 0.7<E/EeV<20
- Galactic component ends around 0.7 EeV (escape model)

Model summary

Acceleration close to the SMBH:

- shock acceleration in accretion shocks [Kazanas, Ellison 1986]
- acceleration in regular fields close to the SMBH [Blandford 1976]

Energy spectrum after acceleration:

$$j_{inj}(E) \propto E^{-\alpha} \exp[-E/(ZE_{max})]$$

Attenuation:

- zone I photohadronic interactions of nuclei
- zone II interactions with gas
- propagation via intergalactic space after escaping the source

Zonel

Photo-hadronic interactions

- Thermal emission from dust surrounding the SMBH main source of attenuation
- Model parameters:

T - radiation temperature

 $\tau_0^{p\gamma} = R_{int}/R_{esc}$ - interaction depth for protons with $E_0 = 10 \, EeV$ $R_{esc} \propto (E/Z)^{\delta_{p\gamma}}$ - escape rate (neutrons escape freely)

• Modelled using kinetic equations in one dimension with rates multiplied by the escape times.

Zone II

Interactions with gas

• Model parameters:

 $\tau_0^{pp} = R_{int}/R_{esc}$ - interaction depth for protons with $E_0 = 10$ EeV $R_{esc} \propto (E/Z)^{\delta_{pp}}$ - escape rate (neutrons escape freely)

• Modelled with Monte Carlo using QGSJET-II-04 in leaky-box approximation

Observable spectra calculation

- Use output from zone II as effective source spectrum
- Calculate total diffuse flux from a distribution of sources taking into account propagation effects with code by O.K., Kido 2014:
 - interactions with EBL
 - redshift
- Model parameters:
 - source distribution (or evolution)
 - EBL spectrum

Observable spectra

Hadronic interactions only

total EG total Gal

> 2-45-16 17-28

29-56

10¹⁸

Auger

10²⁰

Injection power-low $\alpha = 1.8$ 10⁵ 10^{4} **KASCADE** Grande Maximal energy $E_{max} = 3 \text{ EeV}$ 10^{3} E² F(E) [eV/cm²/s/sr] Evolution: BL Lac, Fermi LAT 10² IceCube EBL model: Inoue et al. 2012 ν 10^{1} Interaction depth $\tau_0^{pp} = 0.035$ 10⁰ 10^{-1} Diffusion: 10^{-2} 10¹² 10¹⁴ 10¹⁰ 10¹⁶ $\delta_{Ap} = 0.5$ (Kraichnan turbulence) E [eV] 80 900 without $A\gamma$ 70 850 QGSJetII-4 OGS.JetII-4 interactions we failed 60 800 RMS(X_{max}) [g/cm²] X_{max} [g/cm²] 50 750 to fit $E(X_{max})$ and 700 $RMS(X_{max})$ 30 650 simultaneously 20 600 10 10¹⁸ 10¹⁹ 10¹⁷ 10²⁰ 550 10¹⁸ 10¹⁹ 10²⁰ 10^{17} E [eV] E [eV]

Observable spectra calculation

Photo-hadronic and hadronic interactions

 10^{5} total EG Injection power-low $\alpha = 1.5$ total Gal 10^{4} **KASCADE** Gran 5 - 1617-28 Maximal energy $E_{max} = 6 \text{ EeV}$ 10³ 29-56 E² F(E) [eV/cm²/s/sr] Fermi LAT 10² Auger Evolution: AGN with $LogL_{x} = 43.5$ IceCube 10^{1} Photon temperature T = 850 K10⁰ Interaction depth $\tau_0^{pp} = 0.035$ 10^{-1} Interaction depth $\tau_0^{p\gamma} = 0.29$ 10^{-2} 10¹⁸ 10²⁰ 10¹⁰ 10¹² 10¹⁴ 10¹⁶ E [eV] Diffusion: 900 80 850 70 $\delta_{Ap} = 0.5$ 800 60 RMS(X_{max}) [g/cm²] X_{max} [g/cm²] 750 50 $\delta_{A\gamma} = 0.77$ 700 40 650 30 600 20

10¹⁹

E [eV]

10 └─ 10¹⁷

10¹⁸

E [eV]

10¹⁹

10²⁰

10²⁰

550

10¹⁷

10¹⁸

Conclusion

We demonstrated the toy scenario explaining astrophysical neutrino flux above 200 TeV along with UHECR cosmic ray spectrum and mass composition. The predicted contribution to the EGRB is of order 30%

Beyond This Model

- Correlation of IceCube neutrino arrival directions with central parsec-scale regions of radio-bright blazars was found at 4.1σ level. A.V.Plavin et al 2020
- Can we also explain radio waves? (work in progress)





radio waves produced by synchrotron emitting electrons originated in pp interactions along with ν in parsec-scale relativistic jet propagating through circum-nuclear medium of the AGN

Telescope Array Surface Detector





- 507 SD's, 3 m² each
- ▶ 680 *km*² area
- operating since May 2008

Largest UHECR statistics in the Northern Hemisphere

Outline

With ML-based reconstruction we will

- recover UHE primary energy and direction
- study mass composition
- search for UHE photons

O. Kalashev et al, PoS ICRC2019 (2020) 304 TA Collaboration,, J.Phys.Conf.Ser. 1525 (2020) 1, 012001 D. Ivanov et al, Mach.Learn.Sci.Tech. 2 (2021) 1, 015006 TA Collaboration, PoS ICRC2021 (2021) 384 TA Collaboration, PoS ICRC2021 (2021) 864

O. Kalashev et al, arXiv:2112.02072

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Sample event



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standard parametric approach

$$f(r) = \left(\frac{r}{R_m}\right)^{-1.2} \left(1 + \frac{r}{R_m}\right)^{-(\eta - 1.2)} \left(1 + \frac{r^2}{R_1^2}\right)^{-0.6}$$

 $R_m = 90.0 \text{ m}, R_1 = 1000 \text{ m}, R_L = 30 \text{ m}, \eta = 3.97 - 1.79 (\sec(\theta) - 1),$ $r = \sqrt{(x_{\text{core}} - x)^2 + (y_{\text{core}} - y)^2},$

Timing

$$t_r = t_o + t_{plane} + a \times (1 + r/R_L)^{1.5} LDF(r)^{-0.5}$$

 $LDF(r) = f(r)/f(800 \text{ m}) \quad S(r) = S_{800} \times LDF(r)$

Free parameters:

$$x_{core}, y_{core}, \theta, \phi, S_{800}, t_0, a$$

Observables:

 t_r - detector time

 $S_r\,$ - detector integral signal

standard parametric approach



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Machine learning approach

Purpose (ideally): recover primary particle properties (arrival direction, energy, mass, ...) as function of observables.

Direct observables in SD:

• Time series of the SD signals

Instruments:

- SD Monte-Carlo (EAS development and detector response)
- Artificial neural network (NN)
 - Can describe any continuous function of input data
 - Can be tuned using examples generated using Monte-Carlo

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Machine learning approach

Purpose (ideally): recover primary particle properties (arrival direction, energy, mass, ...) as function of observables. *In real life*:

- observables depend on unknown/random factors
- NN function defines optimal test statistic
- obtain corrections to parametric reconstruction
 Observables in SD:
 - Time series of the SD signals

Instruments:

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Method in nutshell

- Extract useful detector features using 1-D convolutions
- Treat detector network as a multichannel image using 2D convolution layers

M. Erdmann et al, Astropart.Phys. 97 (2018) 46-53

SD reconstruction NN architecture



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ML for Cosmic Ray Air Showers Workshop

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SD reconstruction NN architecture

x 6



- waveform encoder extracts useful features from readings of the two SD station layers
- the extracted features are passed to 2D-convolutional network along with <u>SD</u> station properties
- event features extracted by convolutional network are analysed along with <u>14</u> composition sensitive variables in the dense layer part of the model

D. Ivanov et al, Mach.Learn.Sci.Tech. 2 (2021) 1, 015006

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SD station features

Produced by standard reconstruction procedure

- Detector signal saturation flag
- If detector is excluded from geometry fit (affected by random muon)
- x relative to shower core
- y relative to shower core
- z detector position altitude relative to common level
- detector signal, MIP
- time of the plane front arrival
- time of the waveform relative to the plane front

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Event features

Produced by standard reconstruction procedure

Signal density at 800 m from the shower core, S_{800} ; Linsley front curvature parameter, *a*; Area-over-peak (AoP) of the signal at 1200 m;

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

AoP LDF slope parameter;

Number of detectors hit;

N. of detectors excluded from the fit of the shower front;

 $\chi^{2}/d.o.f.;$

 $S_b = \sum S_i \times r_i^b$ 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

The sum of signals of all detectors of the event;

Asymmetry of signal at upper and lower layers of detectors;

Total n. of peaks within all FADC traces;

N. of peaks for the detector with the largest signal;

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

Training the model

- Minimizing mean square error
- Adaptive learning rate (adadelta optimizer arxiv 1212.5701)
- Number of training samples ~ 10⁶ (100 GB data) do not fit into RAM). hdf container is used и generator API in keras
- Number of weights to learn 10⁵ 10⁶
- Regularization to avoid overfitting:
 - L2
 - dropout
 - noise layers
- Optimizing network architecture hyper-parameters (ray.tune & hyperopt)
- Hardware: NVIDIA GTX-2080 GPU
- Instruments: python, numpy, tensorflow, keras, h5py

EAS modelling

T. Abu-Zayyad et al. Astrophys. J., 768:L1, 2013

- MC: CORSIKA
- HE hadronic interactions: QGSJETII-03 and QGSJETII-04 (test set only)
- LE hadronic interactions: FLUKA
- EM processes: EGS4
- Detector response: GEANT4
- Event sampling:
 - Energy sampling E⁻¹
 - Mass composition: H, He, N, Fe (1:1:1:1)
 - Isotropic primary flux with zenith angles < 45 degrees
 - Standard energy spectrum reconstruction cuts applied

Reconstruction comparison

in presence of unavoidable uncertainty

Explained variance score

$$EV(y, \hat{y}) = 1 - \frac{Var(y - \hat{y})}{Var(y)}$$

- y true value of quantity being predicted (in our case, error of parametric reconstruction)
- \hat{y} -model estimate of $\,y\,$

How to see that model does job

in presence of unavoidable uncertainty

Explained variance score

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More visually: Compare error distribution in two approximations



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How to see that model does job

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Explained variance for directional vector reconstruction

 $(EV_X + EV_Y + EV_z)/3$



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Zenith angle reconstruction error distribution



E > 10 EeV

E > 57 EeV

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Proton Monte Carlo event set, QGSJETII-03 hadronic interaction model

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Angular distance between true and reconstructed arrival direction



Proton Monte Carlo event set, QGSJETII-03 hadronic interaction model

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Angular resolution dependence on energy



QGSJETII-03

QGSJETII-04

Proton and iron Monte Carlo event sets

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Angular resolution dependence on the number of detector stations triggered



QGSJETII-03



Proton and iron Monte Carlo event sets

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Energy reconstruction

Energy reconstruction error distribution



Both bias and variance decreased

Systematic uncertainty due to hadronic model choice is comparable

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Energy reconstruction

 $\sigma(LogE - LogE_{MC})$



proton Monte Carlo event set

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Conclusions

Energy reconstruction

- + log(E) resolution relative improvement is about 20%
- systematic bias due to uncertainty in the hadronic interaction model (or primary particle mass) is comparable

Arrival direction reconstruction

- + 20-25% improvement in angular resolution
- + we don't see any systematic bias due to uncertainty in the hadronic interaction model

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- Mass composition study

Mass reconstruction on event by event basis:

- Classic regression task or classification task for N nuclei
- With p,He,N,Fe nuclei and NN described above we get accuracy ~ 35% (25% is random model result)

Mass reconstruction on event by event basis:

- Classic regression task or classification task for N nuclei
- With p,He,N,Fe nuclei and NN described above we get accuracy ~ 35% (25% is random model result)
- Showers initiated by different nuclei are similar and highly stochastic. Primary particle mass mainly affects the expectation of the first interaction point depth (random quantity)
- with given observables there is no way to reconstruct primary particle mass on event by event basis

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Aim: estimate mass composition for a set of events:

- Train NN to reconstruct primary particle
- Use NN-classifier output as "optimal" composition sensitive observable

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How to recover composition from model predictions: - apply classifier to each individual event and count fractions - correct fractions using model confusion matrix (linear model)

 y_{pr} - predicted fractions of nuclei in control set

 y_{true} - true fractions of nuclei in control set

$$y_{corrected} = C^{-1} y_{pr}$$

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 $y_{pr} = C y_{true}$

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 $y_{pr} = Cy_{true}$ y_{true} - true fractions of nuclei in control set

$$y_{corrected} = C^{-1} y_{pr}$$

- Problems: strong dependence of C^{-1} on control dataset
 - negative predictions

Aim: estimate mass composition for a set of events:

- Train NN to reconstruct primary particle
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How to recover composition from model predictions: - apply classifier to each individual event and count fractions - correct fractions using model confusion matrix (linear model) - use some nonlinear model

Input: $E(p_A), Var(p_A)$ - average predicted "probabilities" for class Aand their variance for A = p, He, N, Fe

Output: y_{true} - true fractions of nuclei

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10 000 ensembles of events, consisting of 5 000 samples each used for training/validation

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Aim: estimate mass composition for a set of events:

- Train NN to reconstruct primary particle
- Use NN-classifier output as "optimal" composition sensitive observable

How to recover composition from model predictions: - apply classifier to each individual event and count fractions - use model normalised confusion matrix (linear model) - use nonlinear model (another neural network 'converter')

Final result accuracy strongly depend on classifier accuracy

- try to enhance classifier

Enhanced classifier

Uses

Reconstruction parameters

+

•Spatial detectors data (without waveforms)

+

•Waveforms from the detector with largest signal

 Temporal detector data (waveforms only)

~35K trainable params





Classifier accuracy (4 components): 40.2%

Separate block performance:

| | temporal | reconstruction | spatial detector | most active |
|----------|-----------------|----------------|------------------|-------------|
| | detector bundle | parameters | bundle | detector |
| accuracy | 39.5% | 33.8% | 32.9% | 31.0% |

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Mass fraction calculation for two random compositions





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Separate block performance:

| | temporal | reconstruction | spatial detector | most active |
|----------|-----------------|----------------|------------------|-------------|
| | detector bundle | parameters | bundle | detector |
| accuracy | 39.5% | 33.8% | 32.9% | 31.0% |

Mass fraction calculation accuracy (4 components)

| Average absolute error | | proton | helium | nitrogen | iron |
|------------------------|------------|--------|--------|----------|------|
| | classifier | 0.10 | 0.11 | 0.11 | 0.09 |
| based on 2000 test | confusion | 0.06 | 0.14 | 0.12 | 0.04 |
| ensembles | converter | 0.03 | 0.07 | 0.06 | 0.02 |

Average absolute error dependence on energy (with 'converter' model)

| energy bin, log scale | 18–18.25 | 18.25–18.5 | 18.5 - 18.75 | 18.75 - 19 | > 19 |
|--------------------------|----------|------------|--------------|------------|-------|
| averaged MAE | 0.072 | 0.053 | 0.048 | 0.043 | 0.038 |

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Mass composition study Systematic uncertainty

Predictions on mono-composition data simulated using QGSJET-II 04 hadronic interaction model



averaged predictions of the classifier



'converter' predictions

| primary particle | proton | helium | nitrogen | iron | averaged |
|------------------|--------|--------|----------|------|----------|
| reconstruction | 0.53 | 0.68 | 1.00 | 0.20 | 0.60 |
| error | | | | | |

Method application is limited by systematics

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Conclusions

Energy reconstruction

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Arrival direction reconstruction

+ 20-25% improvement in angular resolution

+ we don't see any systematic bias due to uncertainty in the hadronic interaction model

Mass composition study

- + Accuracy 7% (for p-He-N-Fe mixtures)
- Method application is limited by systematics

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Photon-induced showers:

- develop deeper in the atmosphere \Rightarrow arrive younger
- contain less muons \Rightarrow SD waveforms are less compressed

We use the neural-network classifier trained on both the

- time-resolved waveforms
- and derived features: front curvature, Area-over-peak, number of FADC signal peaks, \u03c8²/d.o.f., S_b

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• The p- γ classifier is trained with two Monte-Carlo sets:

- \blacktriangleright γ -induced events (Signal)
- proton-induced events (Background)
- The output of the classifier for each event is a number ξ ∈ [0 : 1]: 1 − pure signal (γ), 0 − pure background (p).
- We call "photon-candidates" events with $\xi > \xi_{cut}$.
- The optimal value of ξ_{cut} is obtained by the requirement of the strongest sensitivity in case null-hypothesis is valid, i.e. all events are protons.



False positive errors have stronger effect on sensitivity than false negative

We adjust sample weights: $w_p/w_\gamma \simeq 10$

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Data collected by TA surface detector for the 11 years: 2008-05-11 – 2019-05-10

p and γ Monte-Carlo sets with CORSIKA and dethinning

Stokes et al, Astropart.Phys.35:759,2012

Cuts for both data and MC:

- 7 or more detectors triggered
- core distance to array boundary is larger than 1200m
- $\chi^2/d.o.f. < 5$
- θ < 55°
- \blacktriangleright $E_{\gamma} > 10^{19.0} \text{ eV}$ (E_{γ} is estimated with photon Monte-Carlo)
 - or $E_{\gamma} > 10^{18.5}$ eV for training Monte-Carlo sets

11327 events after cuts

MC set is split into 3 parts: (I) 80% of events, for training the classifier, (II) for testing and cut optimization, (III) for exposure estimate.

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| <i>E</i> ₀ , eV | 10 ^{19.0} | 10 ^{19.5} | 10 ^{20.0} |
|----------------------------|---------------------|---------------------|--------------------|
| γ candidates | 16 2 | 111 | 5 0 |
| <u></u> | 6.72 | 5.14 | 3.09 |
| A _{eff} | 3428 | 5546 | 7875 |
| $ F_{\gamma} <$ | $2.0 	imes 10^{-3}$ | $9.3 	imes 10^{-4}$ | $3.9	imes10^{-4}$ |

95% CL Limits: Gelmini et al. 2008, GZK p 1.00000 Hooper et al. 2011, GZK p ŗ 2011. GZ ∓ Yakutsk_⊥ ່ _{ວ່}0.10000 Integral γ flux, km⁻² SI 000100 km⁻² SI Γ**Α** 9ν Pierre Auger hybrid TA 9yr TA 11vr Pierre Auger SD 0.00010 10¹⁸ 10¹⁹ 10²⁰ E_γ, eV

Terrestrial Gamma-Ray Flashes candidate events are time correlated with the lightnings registered by National Lightning Detection Network.

TA collaboration, JGR Atmospheres (2020)

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Observable spectra

K. Fang, K. Murase 2018



Appendix

Observable spectra calculation

Source Distribution

Option I. Using luminosities in X-rays for AGN

Hasinger et al. Astron. Astrophys. 441, 417 (2005)

| | $\int (1+z)^m$ | ! | for $z < z$ | | |
|------------------|---|----------------------|---------------|-------------|---|
| $\rho(z) =$ | $\left\{ \left(1+z_c\right)^n \right\}$ | n | for $z_c <$ | $z < z_d$, | $\log L = 45-46$ |
| | $\left(\left(1+z_c\right)^n\right)$ | $n^{n}10^{k(z-z_d)}$ | for $z > z$ | d, | $(10g H_x - 10 - 10)$ $(10g H_x - 10)$ (|
| $\log L_{\rm x}$ | 42.5 | 43.5 | 44.5 | 45.5 | log |
| m | 4.0 ± 0.7 | 3.4 ± 0.5 | 5.0 ± 0.2 | 7.1 ± 1.0 | 0 42-43 |
| $z_{ m c}$ | 0.7 | 1.2 | 1.7 | 1.7 | |
| $z_{ m d}$ | 0.7 | 1.2 | 2.7 | 2.7 | 0 5 10 |
| k | -0.32 | -0.32 | -0.43 | -0.43 | t (Gy) |

Observable spectra calculation

Source Distribution

Option II. Using γ -ray Luminosity-Dependent Density Evolution for FR I / BL Lac sources

M.Di Mauro et al. 2014 ApJ 786 129

$$N_{c}(z) \propto \int_{L_{\gamma}^{max}}^{L_{\gamma}^{max}} \rho(z, L_{\gamma}) L_{\gamma} dL_{\gamma} \qquad \rho(z, L_{\gamma}) = \rho(L_{\gamma}) e(z, L_{\gamma})$$

$$\rho(L_{\gamma}) = \frac{A}{\log(10)L_{\gamma}} \left[\left(\frac{L_{\gamma}}{L_{c}} \right)^{\gamma_{1}} + \left(\frac{L_{\gamma}}{L_{c}} \right)^{\gamma_{2}} \right]^{-1} \qquad \text{Peaks at low redshift:}$$

$$z < 1$$

$$e(z, L_{\gamma}) = \left[\left(\frac{1+z}{1+z_{c}(L_{\gamma})} \right)^{p_{1}} + \left(\frac{1+z}{1+z_{c}(L_{\gamma})} \right)^{p_{2}} \right]^{-1}$$

Surface Detectors



Problem: how to better take absent/not functioning detectors

- The event may occur close to detector network boundary
- Part of detectors may be turned off

Problem: how to better take absent/not functioning detectors

- The event may occur close to detector network boundary
- Part of detectors may be turned off

Dropout, the regularisation method in NN, simulate this situation

- Dealing with absent/not working detectors:
- Dropout, the regularisation method in NN

Srivastava et. al JMLR 15 (2014)





- In training mode neurons are switched off with probability p
- For p=0.5 we train simultaneously 2^n thinned neural networks
- In prediction mode neurons are on but their output weights are multiplied by *p* (we average predictions of thinned nets)

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- Weights are corrected using fraction of working detectors
- In training mode part of the detectors may be switched off as in conventional dropout
Cuts applied on MC samples.

- 1. Each event must include at least 5 counters.
- •2. The reconstructed primary zenith angle must be less than 45° .
- 3. The reconstructed event core must be more than 1200 m from edge of the array.
- 4. Both the timing and lateral distribution fits must have χ 2/degree of freedom value less than 4.
- 5. The angular uncertainty estimated by the timing fit must be less than 5° .
- 6. The fractional uncertainty in S(800) estimated by the lateral distribution fit must be less than 25%.

Search for UHE photons

• Geometric exposure for $\theta \in (0^\circ, 55^\circ)$: **13221 km² sr yr**

Effective exposure is estimated using photon MC assuming E⁻² primary spectrum

| E ₀ | quality cuts | $\xi > \xi_{cut}$ | A _{eff} km ² sr yr |
|--------------------|--------------|-------------------|--|
| 10 ^{19.0} | 43.7% | 59.4% | 3428 |
| 10 ^{19.5} | 52.0% | 80.7% | 5546 |
| 10 ^{20.0} | 64.3% | 92.7% | 7875 |

Efficiency of photon candidate selection ($\xi > \xi_{cut}$) has substantially grown compared to the previous analysis with BDT classifier – 16.2%, 37.2% and 52.3% for $\log_{10} E_0 = 19.0, 19.5$ and 20.0, correspondingly.

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