中山大學 物理与天文学院
SUN YAT-SEN UNIVERSITY SCHOOL OF PHYSICS AND ASTRONOMY

Application of Machine Learning in Astrophysics and astrophysical experiment

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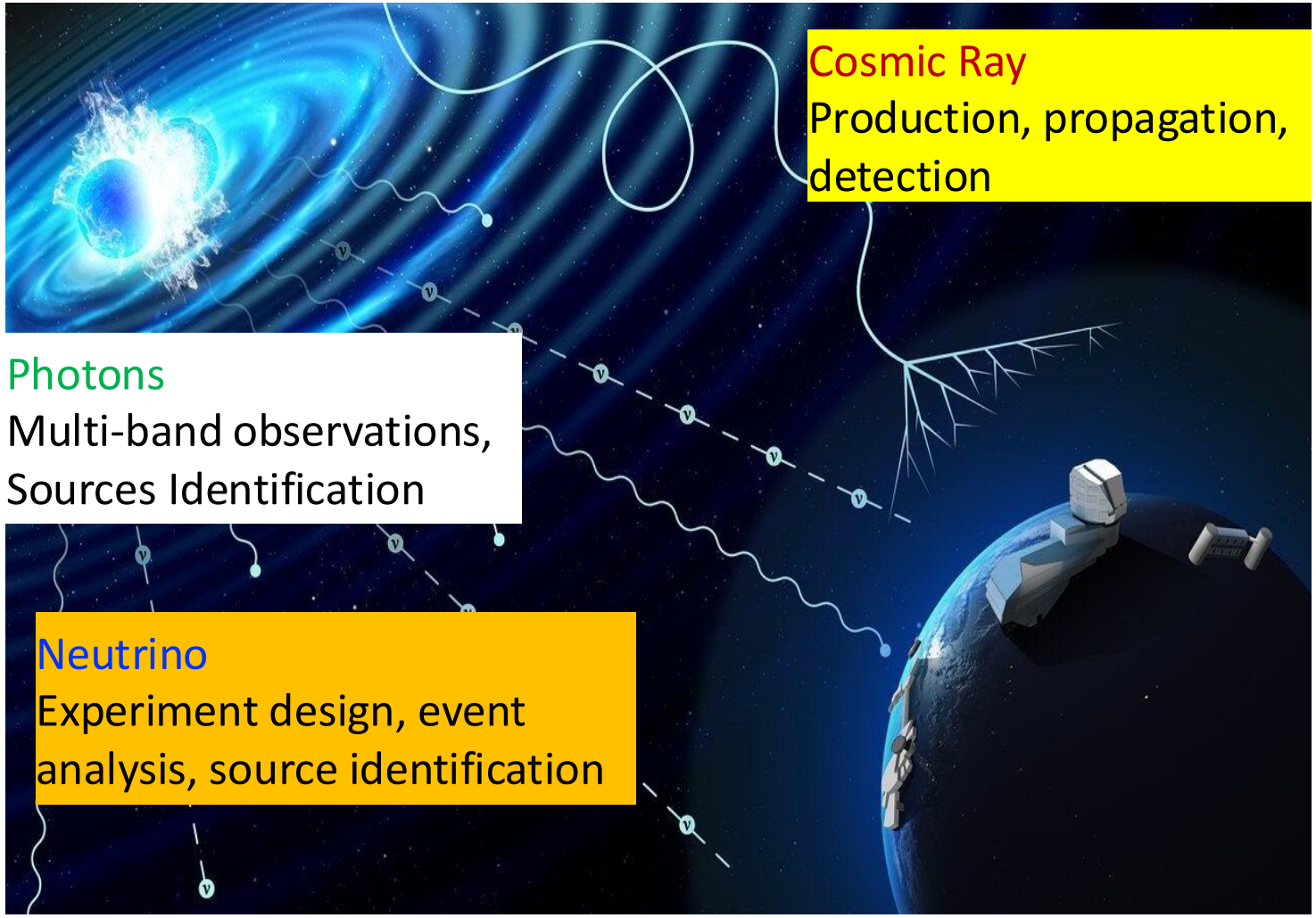
The 2nd SMASH workshop, 22th November 2026

Mon.Not.Roy.Astron.Soc. 523 (2023) 3, 4120-4135
Astrophys.J. 957 (2023) 2, 72
Eur. Phys. J. C 86, 1135 (2026)

SMASH
machine learning for science and humanities postdoctoral program

The Multimessenger & Multiwavelength Era

Searching for the origin of high-energy neutrinos



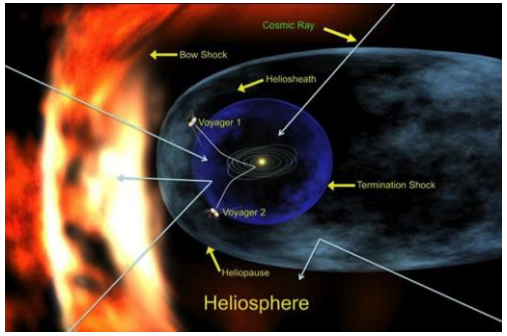
Heavy computational bottlenecks in simulations

High-dimensional non-linear parameter spaces

Massive data streams

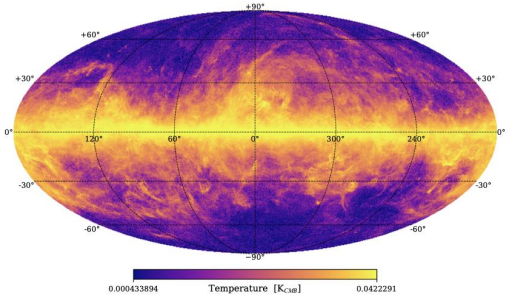
Severe background contamination

Research Roadmap



I Cosmic ray physics

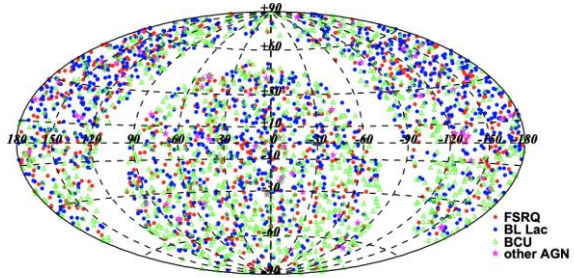
CRs undergo diffusion, energy changes, and solar modulation before they arrive at Earth.



II All-Sky Diffuse Maps

Planck × Fermi-LAT all-sky maps

To study the physical connection between various bands



III Blazar SED & Neutrino origin

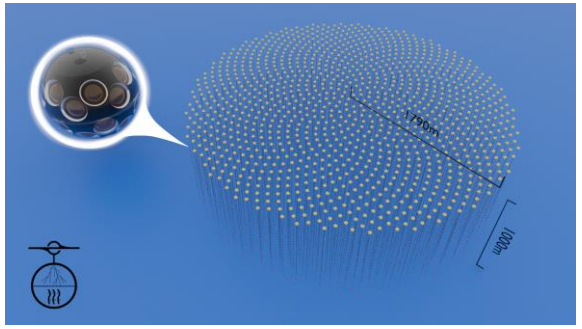
Synchrotron + IC double-hump shape

IceCube sky-map source association

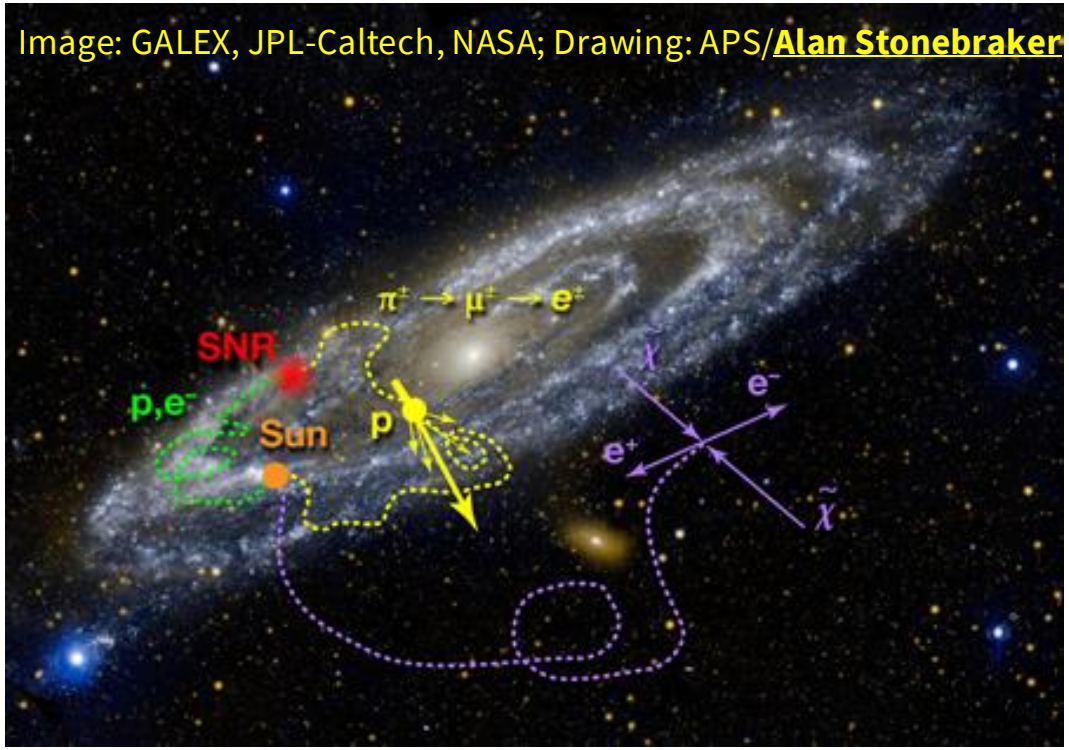
IV High-energy astroparticle experiment

LHAASO gamma-ray data

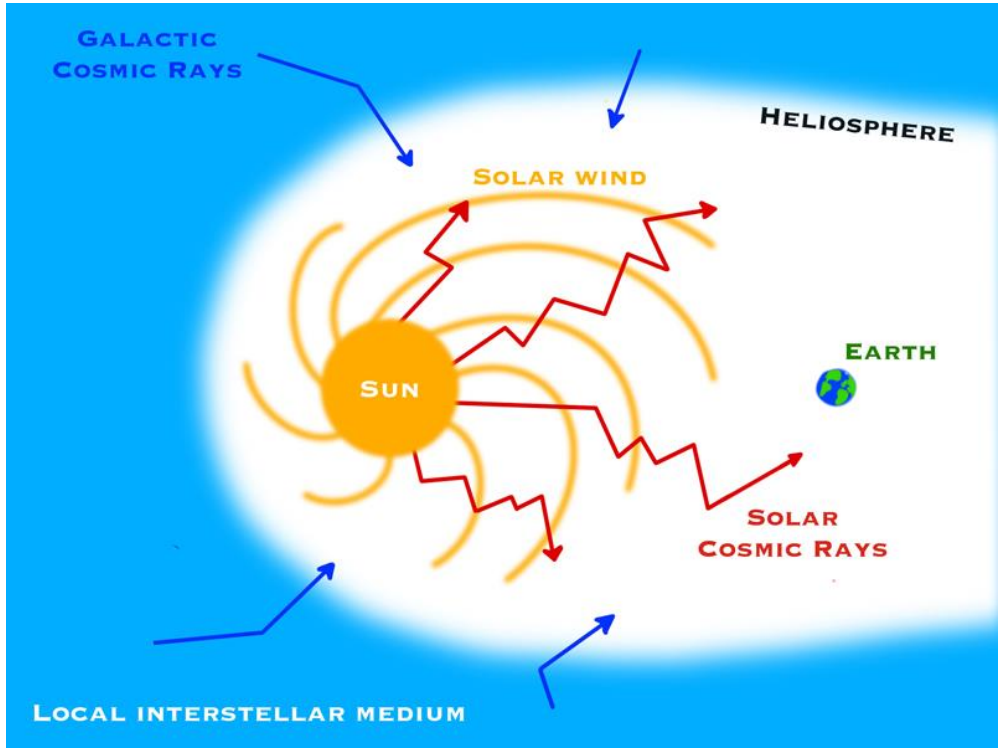
NEON design and event analysis



Part I: Neural Surrogates for CR Transport & Solar Modulation



Propagation

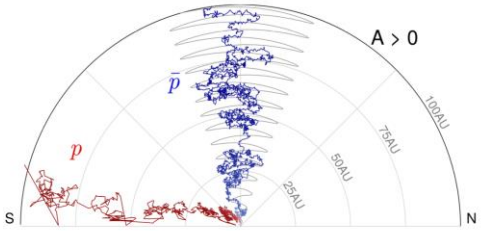


Solar Modulation

GALPROP

Precision data now available

- AMS-02: 10+ years monthly p & $\bar{p}$ fluxes (May 2011 – Dec 2022)
- Voyager 1 & 2: local interstellar spectra (LIS) beyond the heliopause
- B/C ratio: Galactic propagation constraints



HELPROP

PropMat: encoder-decoder surrogate for linear energy transition

$$\frac{\partial f}{\partial t} = \nabla \cdot (\mathbf{K}\nabla \mathrm{f}) - \mathbf{V_{sw}} \cdot \nabla \mathrm{f} + \frac{1}{3}(\nabla \cdot \mathbf{V_{sw}}) \frac{\partial \mathrm{f}}{\partial \mathrm{lnp}}$$

$$\psi_{\mathrm{TOA}} = M(\theta)\, \psi_{\mathrm{LIS}}$$

$$\psi_{\mathrm{TOA}} = M_H(\theta_H)\, M_G(\theta_G)\, \psi_{\mathrm{inj}}$$

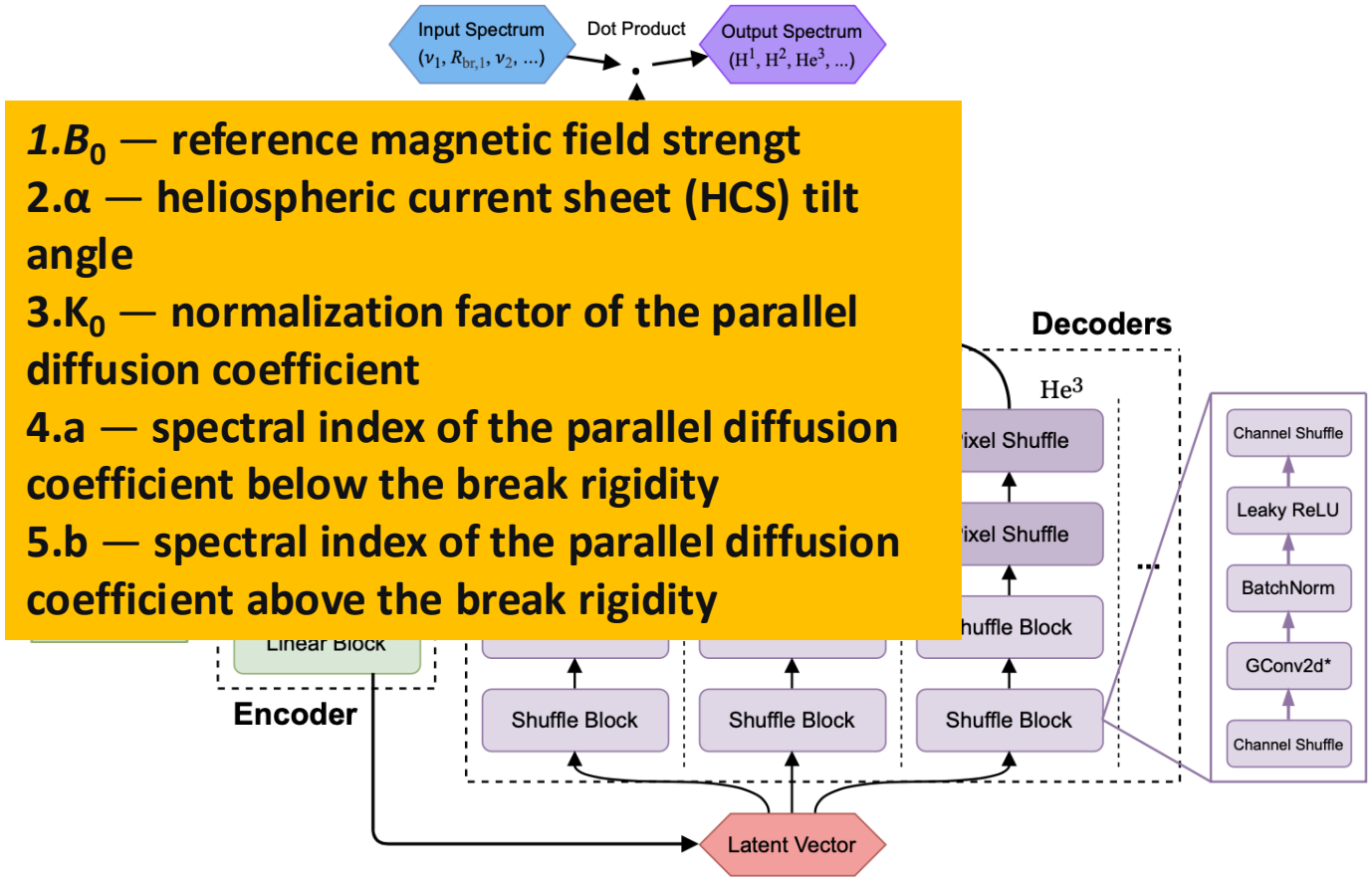
The computational wall

Single HELPROP run: tens of minutes per parameter set

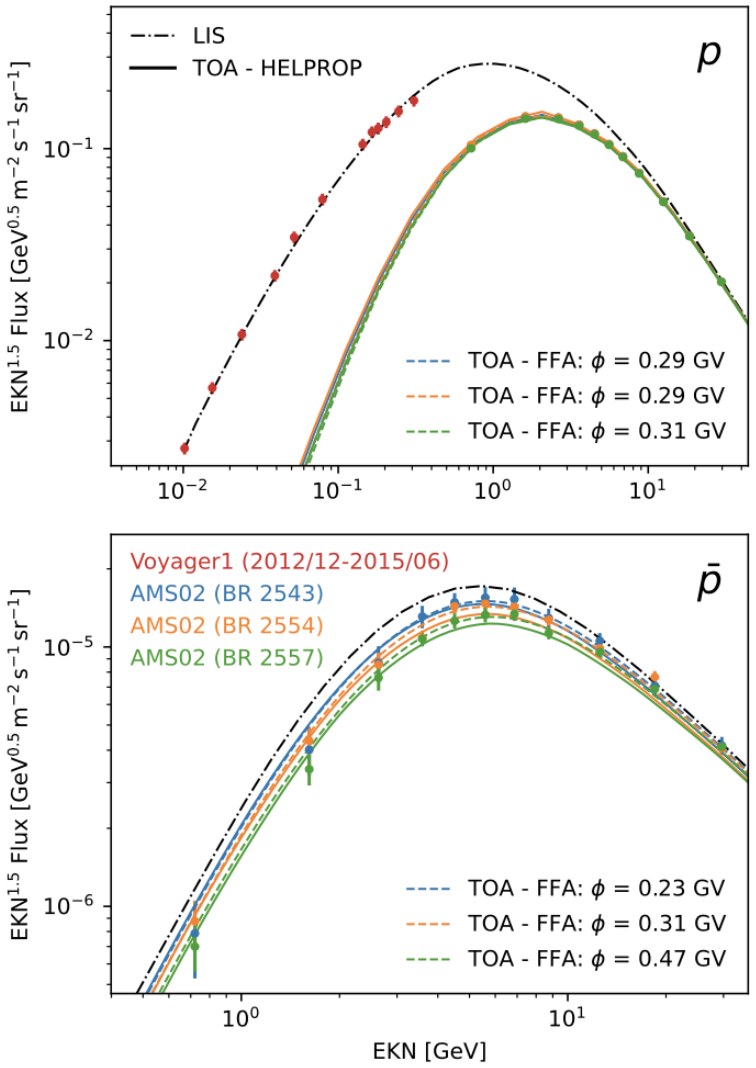
MCMC dimensionality: 5 free modulation params × 103 Bartels rotations ≈ 500+ parameters

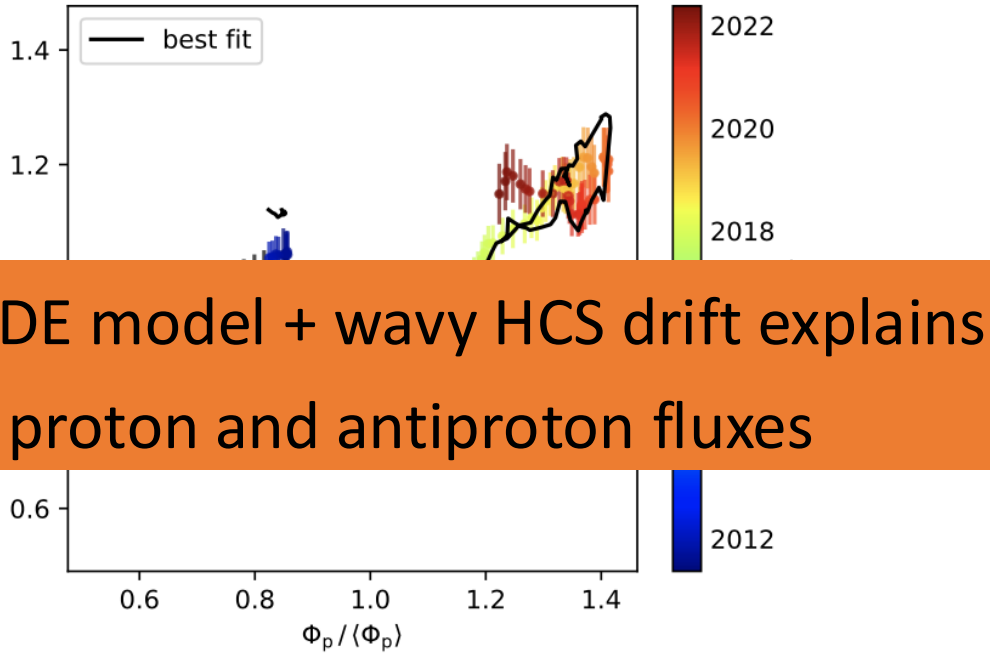
10+ years monthly AMS-02 data
→ MCMC requires ~10^6 evaluations
→ Years of CPU time — infeasible

1.B_0 — reference magnetic field strengt
2.α — heliospheric current sheet (HCS) tilt angle
3.K_0 — normalization factor of the parallel diffusion coefficient
4.a — spectral index of the parallel diffusion coefficient below the break rigidity
5.b — spectral index of the parallel diffusion coefficient above the break rigidity



Deciphering Charge-Dependent Drift in Solar Minima



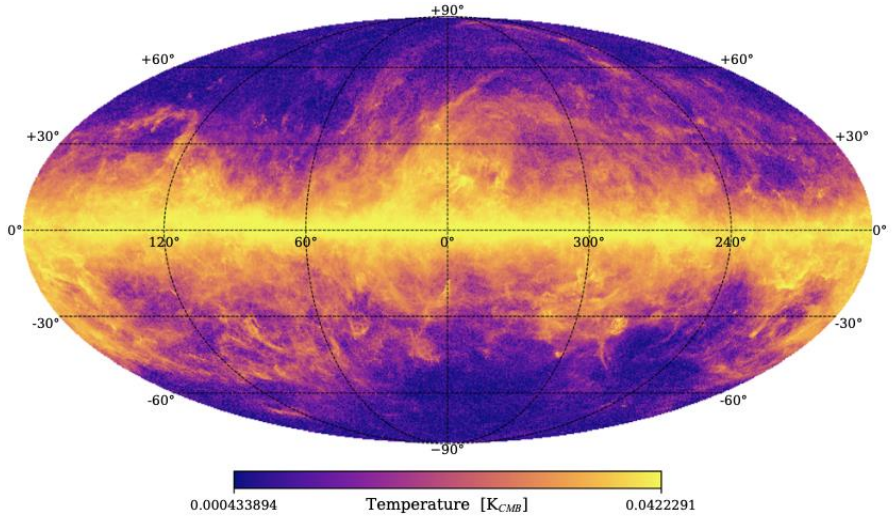


Praker SDE model + wavy HCS drift explains AMS-02 proton and antiproton fluxes

The fitted magnetic field and HCS tilt track independent observations during the solar quiet period. The charge-dependent drift dynamics are correctly captured.

Part II: Cross-Wavelength Data-Driven Modeling of GDE

Cosmic rays, neutrinos, and photons are intrinsically coupled through gas, magnetic fields, and radiation fields. However, for high-energy gamma-ray and neutrino experiment, the templates are lack.



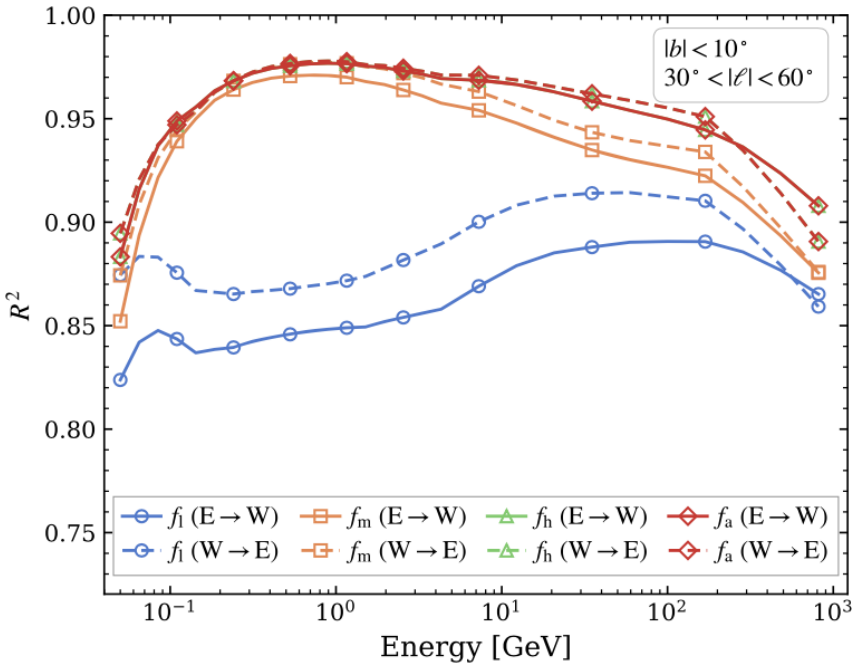
Physics-based templates (e.g., GALPROP) require extensive parameterization, leading to degeneracies and limited predictive power — especially at high energies.

Question: Can multi-frequency microwave data directly predict gamma-ray intensity?

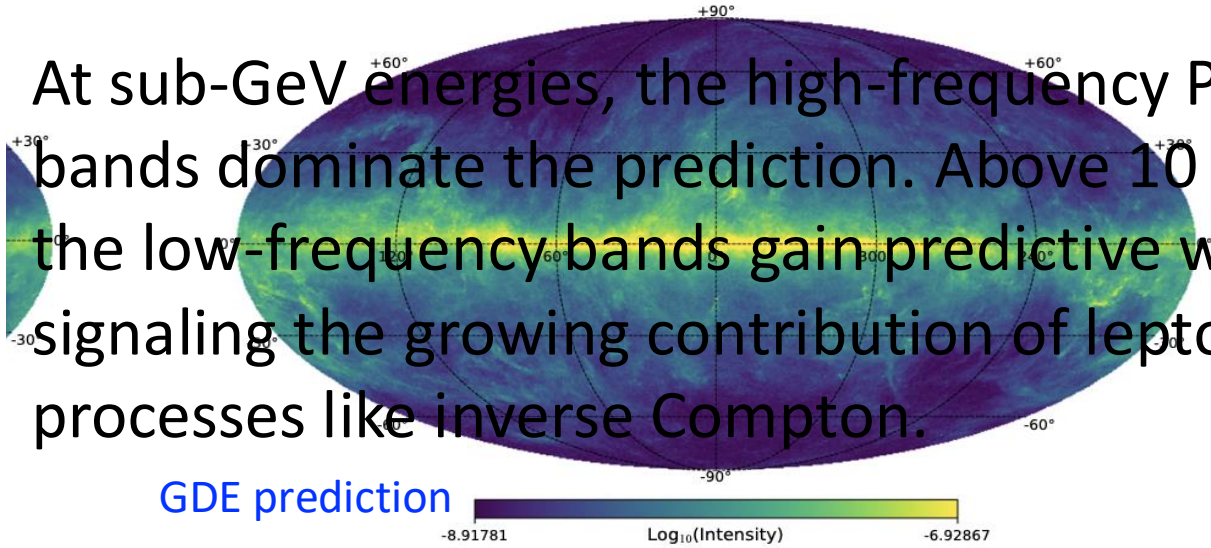
Mapping Planck Microwave Bands to Fermi-LAT Gamma Rays

Using 9 multi-frequency full-sky maps (30–857 GHz) from the Planck satellite (tracing synchrotron, spinning dust, and thermal dust) as Interstellar Medium (ISM) predictors.

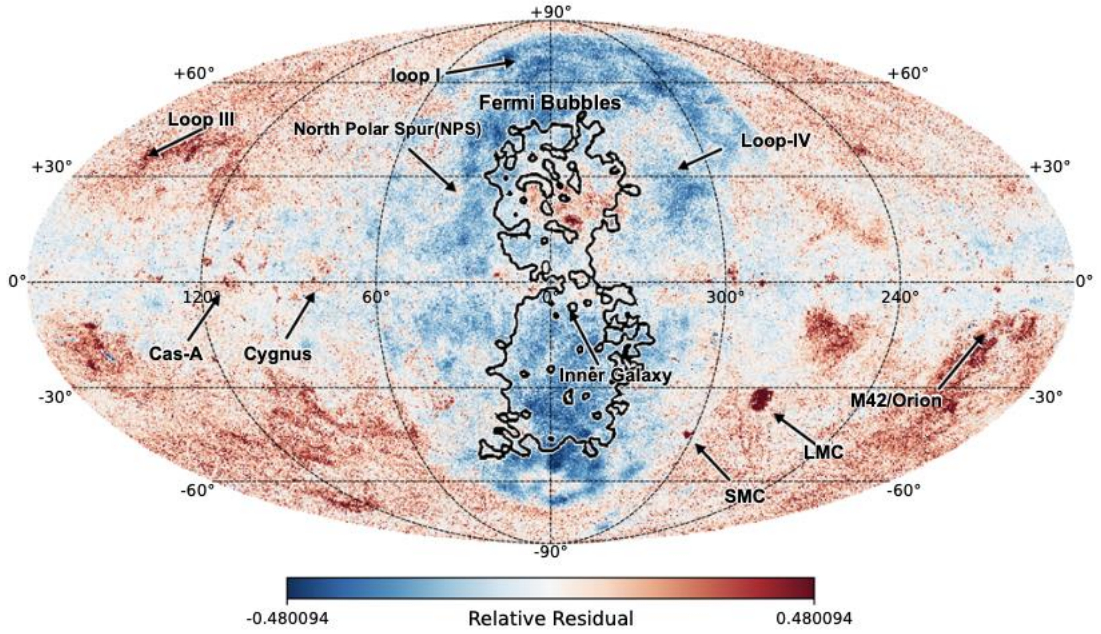
Supervised non-linear mapping (Random Forest & KNN) to reconstruct 28 Fermi-LAT γ-ray sky maps $R^2 > 0.95$



At sub-GeV energies, the high-frequency Planck bands dominate the prediction. Above 10 GeV, the low-frequency bands gain predictive weight, signaling the growing contribution of leptonic processes like inverse Compton.



Physical Interpretability & Residual Anomaly Diagnostics

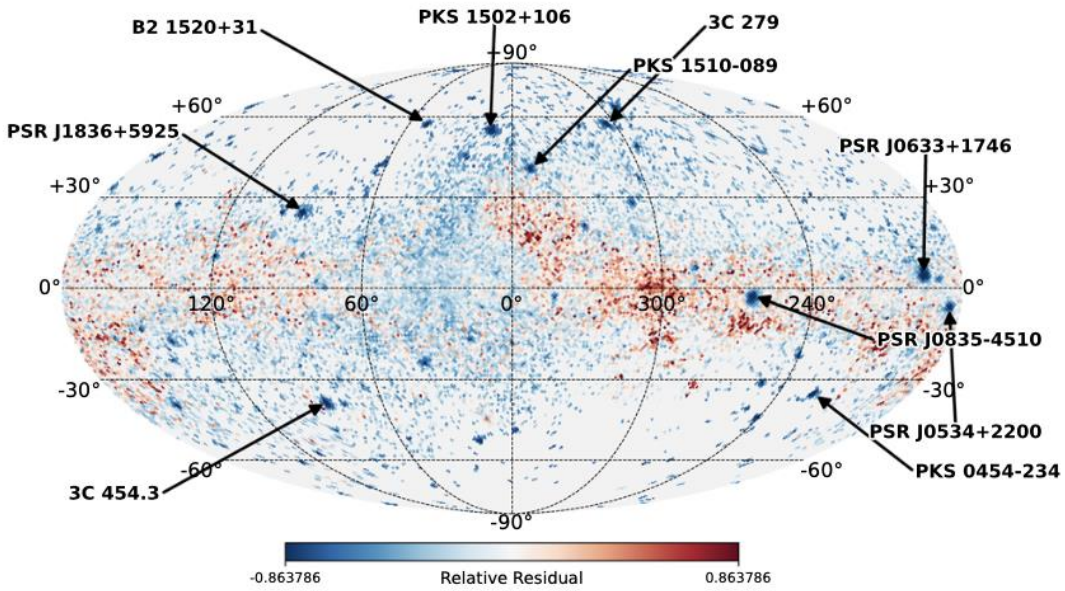


Positive Residuals (Prediction Over-Model)

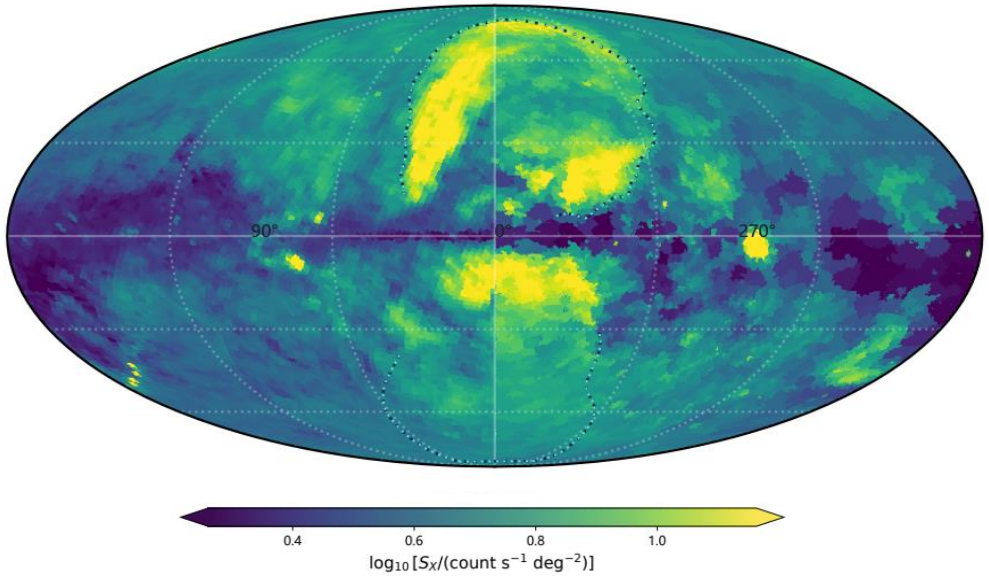
- LMC/SMC
- Orion & Gum Nebula
- Gas-and-dust maps miss these regions

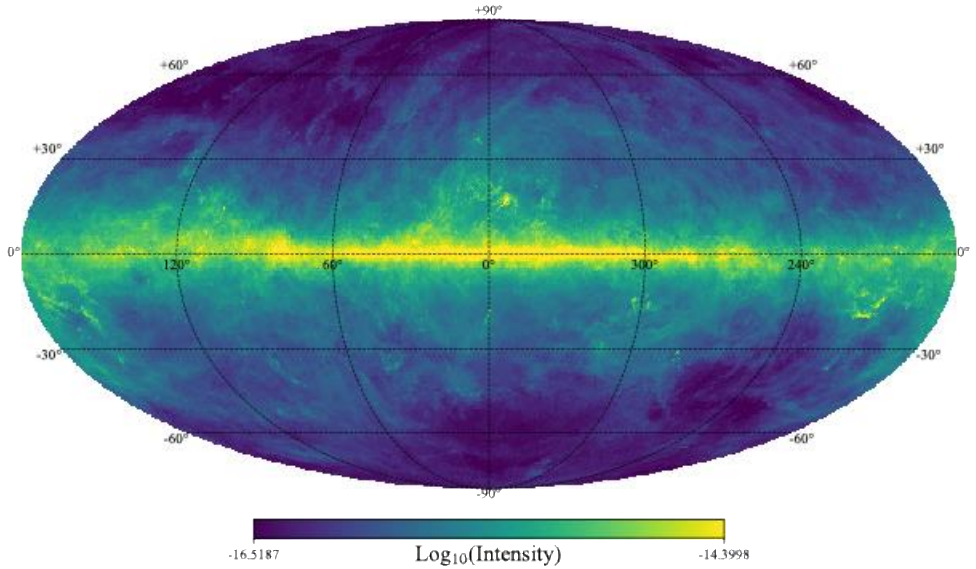
Negative Residuals (Prediction Under-Model)

- Loop I & North Polar Spur
- Fermi Bubbles



Application: more work is on-going





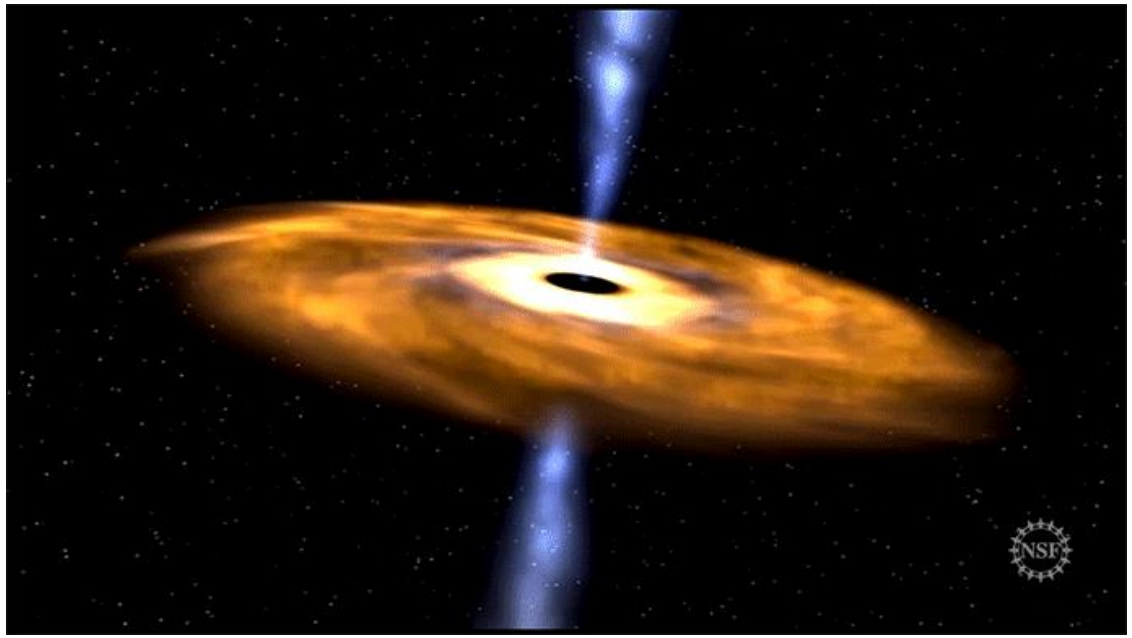
Generate neutrino sky map

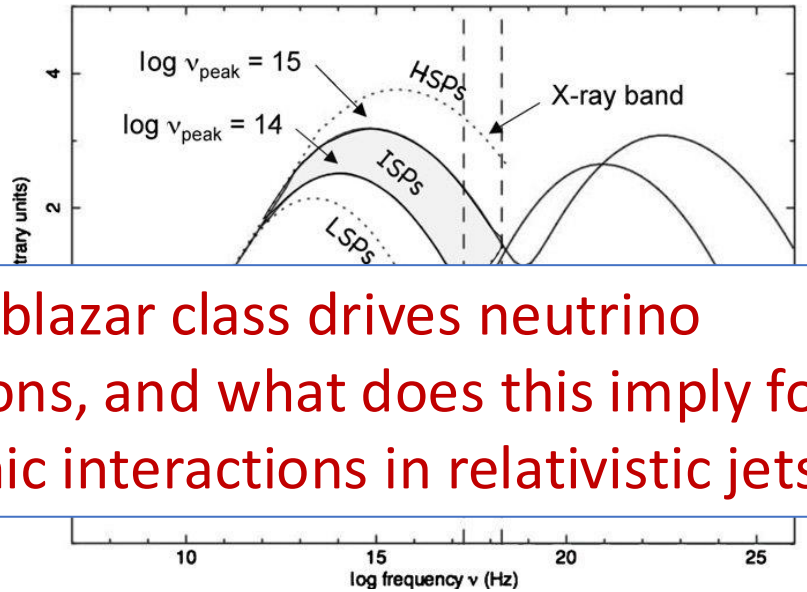


Predict X-ray sky map of eROSITA

A data-driven ML approach can map Planck microwave foregrounds to the Fermi-LAT gamma-ray sky, physically interpretable. Will incorporate additional radio and Hα surveys.

Part III: Hybrid Deep Learning for Blazars and neutrinos

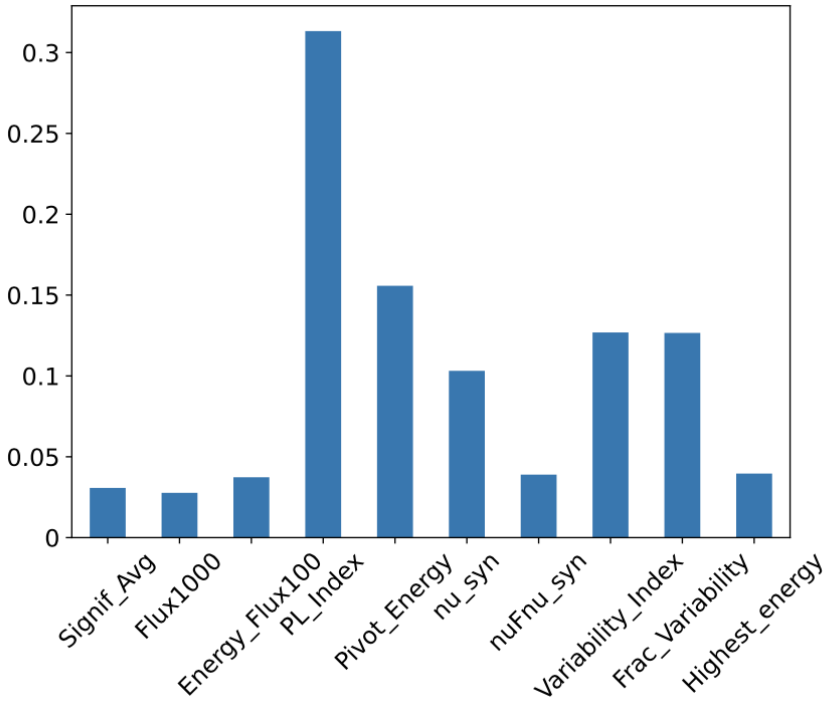


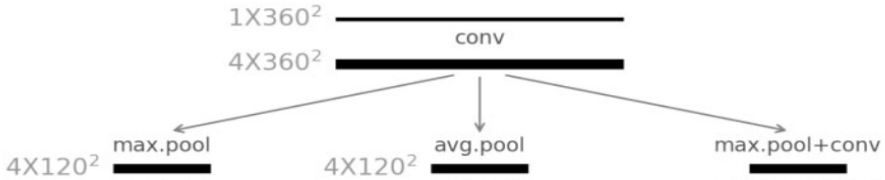


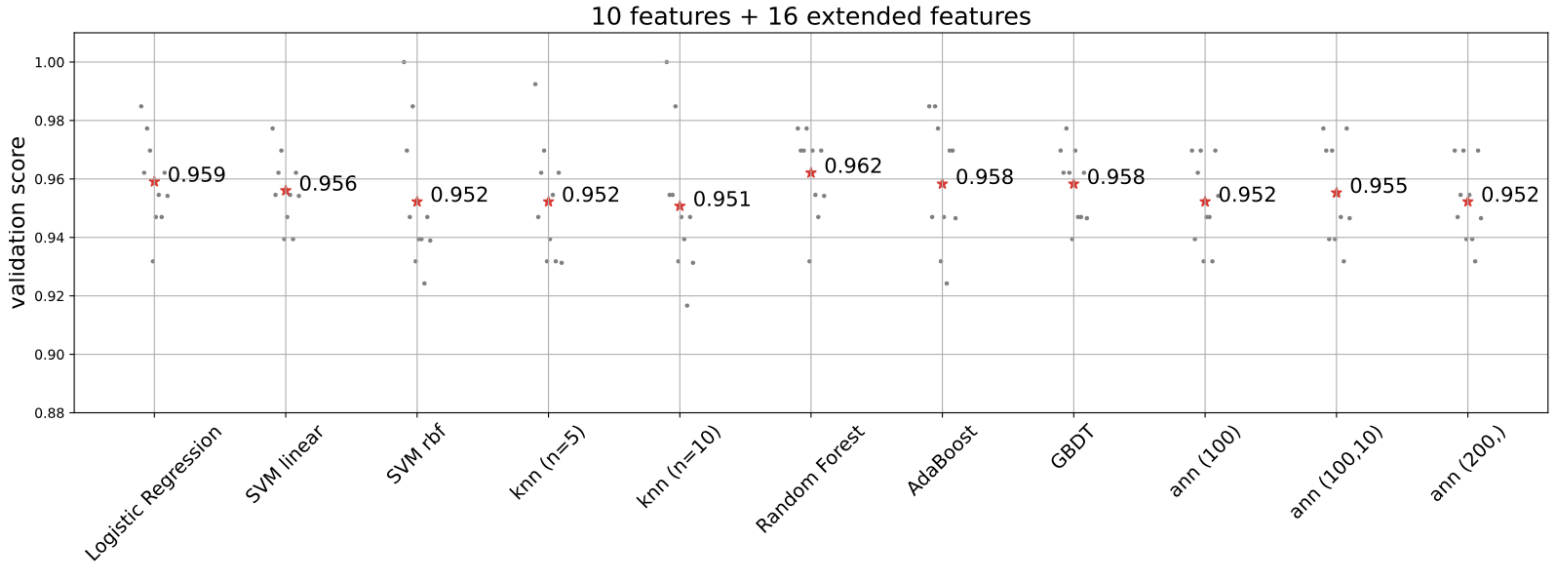
Which blazar class drives neutrino emissions, and what does this imply for hadronic interactions in relativistic jets?

- Blazars represent ~62% of all Fermi-LAT gamma-ray sources
- Historically divided into FSRQs (Flat-Spectrum Radio Quasars) and BLLs (BL Lacertae objects)
- ~38% of blazars in 4LAC remain classified as Blazars of Uncertain Type (BCUs)
- Since the TXS 0506+056 breakthrough (3.5σ association with IceCube-170922A), blazars are primary candidates for high-energy cosmic rays and neutrinos.

Hybrid Model Architecture: 2D-SED CNN + 11-Classifier ML Ensemble







Combining deep Convolutional Neural Networks (extracting continuous spectral shapes from 2D Spectral Energy Distributions) with 11 traditional ML algorithms (processing high-dimensional discrete photometric features).

Achieving an unprecedented classification accuracy of >96%, substantially outperforming single-algorithm benchmarks.

The BCU Census & Neutrino Associations

HESE/EHE ID	Source name	Blazar type	SED type	z
37	4FGL J1117.0+2013	BLL	HSP	0.139
8	4FGL J1159.3−2142	FSRQ	LSP	0.927
40	4FGL J1018.3−3124	FSRQ	LSP	0.794
40	4FGL J1023.9−3236	FSRQ	LSP	1.568
87	4FGL J1316.1−3338	FSRQ	LSP	1.210
EHE 170922	4FGL J0509.4+0542	BLL	ISP	0.336

The HESE and EHE neutrinos associated with known-type blazars.

Event ID	Source name	Blazar type	SED type
134139_35473338	4FGL J1702.2+2642	BLL	LSP
133331_47828126	4FGL J1523.2+0533	BLL	LSP
132792_60166398	4FGL J1045.3+2751	BLL	HSP
136556_43687362	4FGL J0733.8+0455	FSRQ	LSP
135363_69917294	4FGL J2219.2+1806	FSRQ	LSP
133609_37927131	4FGL J1103.0+1157	FSRQ	ISP
133331_47828126	4FGL J1512.2+0202	FSRQ	LSP
132910_57145925	4FGL J1504.4+1029	FSRQ	LSP

The GOLD and BRONZE neutrino alerts associated with known-type blazars.

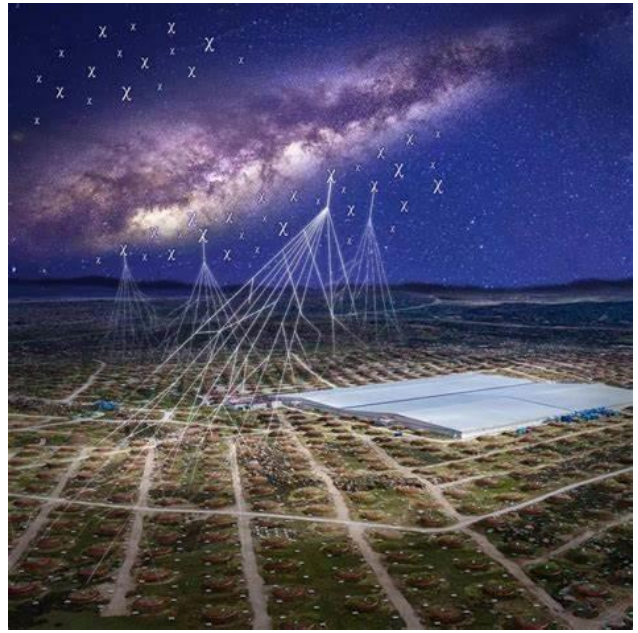
- Delivering robust classifications for 406 BCUs, 361 BLL and 45 FSRQ
- Cross-correlating classified samples with IceCube HESE/Alert neutrino tracks: demonstrating significant neutrino clustering around Low-Synchrotron-Peaked (LSP) blazars, providing data-driven constraints for hadronic photopion interactions.

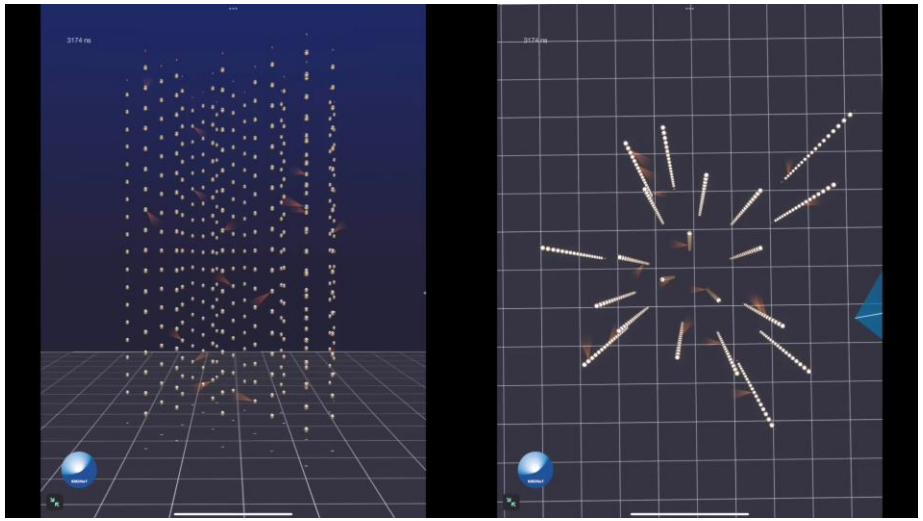
Part IV: High-energy astroparticle detection

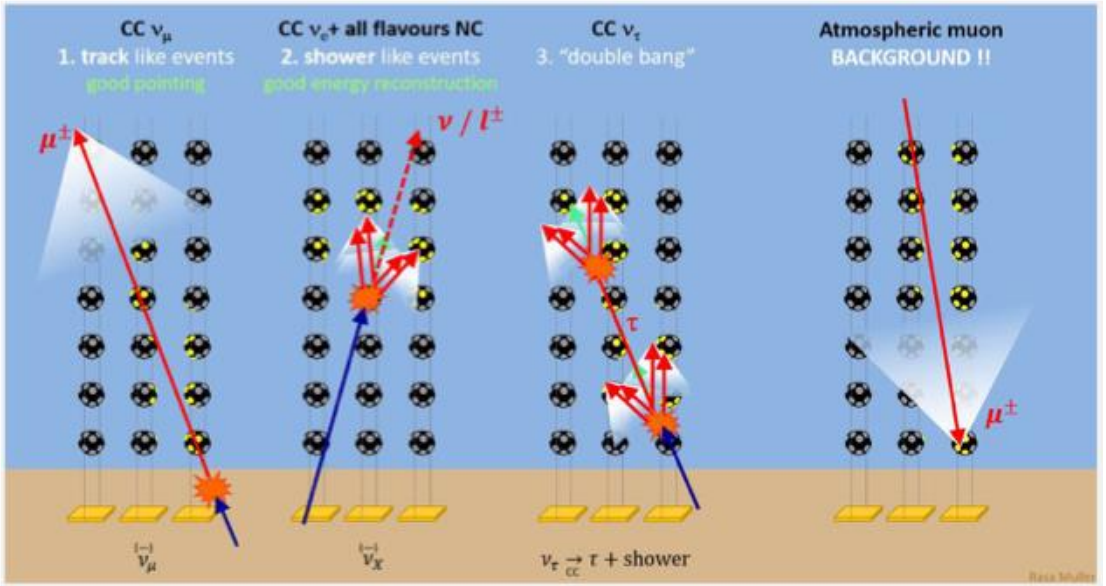
HE cosmic-ray, gamma-ray and neutrino experiment

- Challenge: background discrimination, event-type distinguish, rigidity, angular and energy reconstruction
- Benefits: faster, better, real-time online processing

GNNs are natural choice of machine learning paradigm for problems with irregular geometry.









NOBELPRISET I FYSIK 2026
THE NOBEL PRIZE IN PHYSICS 2026

KUNGL. VETENSKAPS-AKADEMIEN
THE ROYAL SWEDISH ACADEMY OF SCIENCES



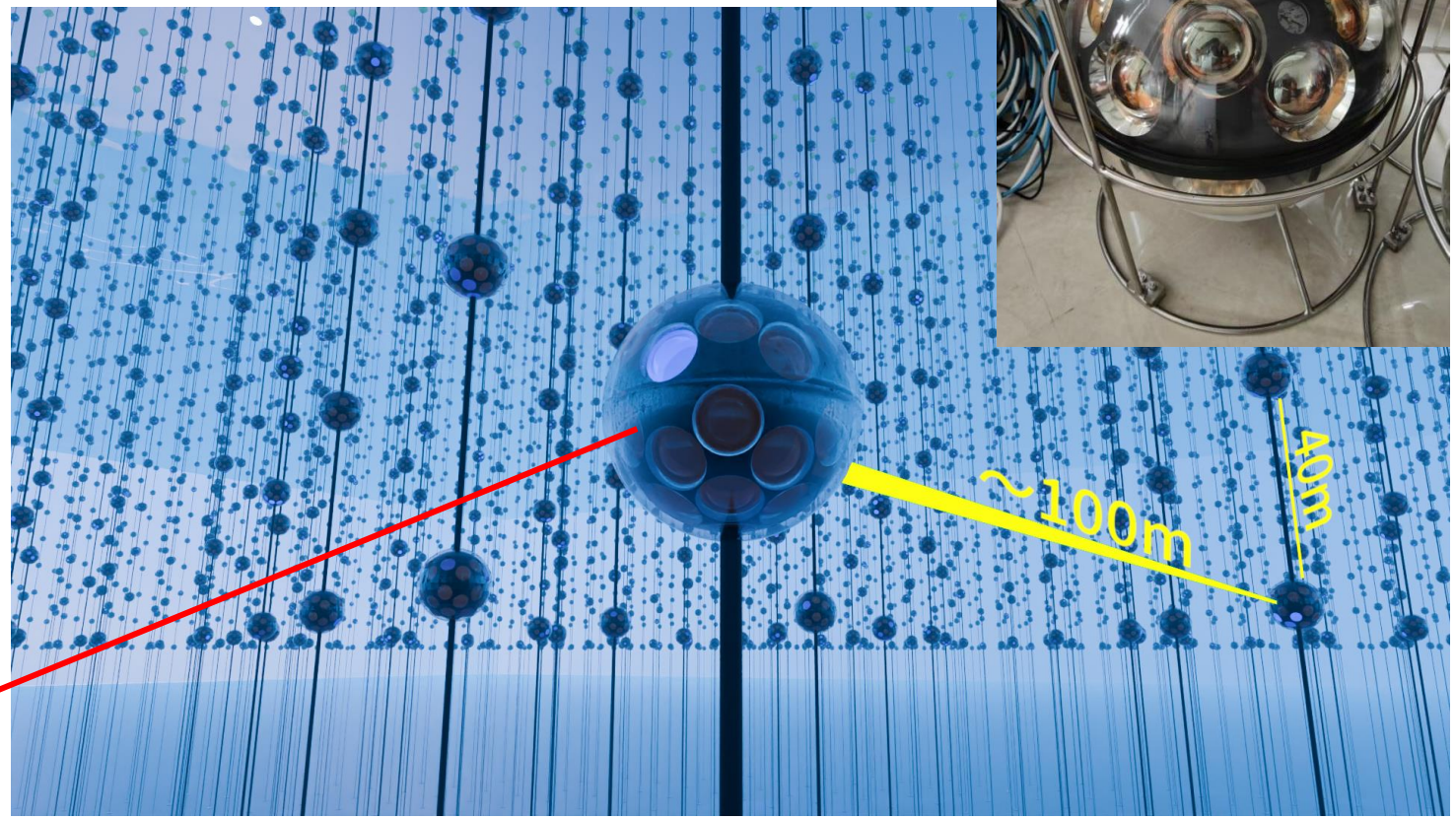
A world-wide network of neutrino telescopes is now planned.

#NobelPrize

THE NOBEL PRIZE

Neutrino Observatory in the Nanhai (NEON)







Coverage: 10 km^3

Depth: 1700 and 3500 meters

1200 strings, 6.6 million PMTs

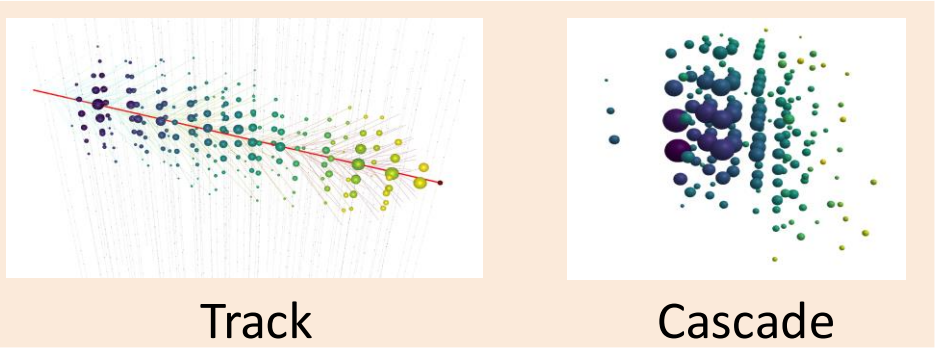


Model architecture

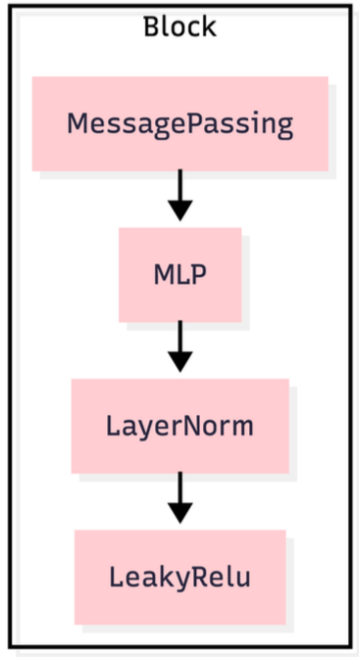
HIERARCHICAL GNN

3D spatial-temporal point cloud

(position, time, charge per PMT)

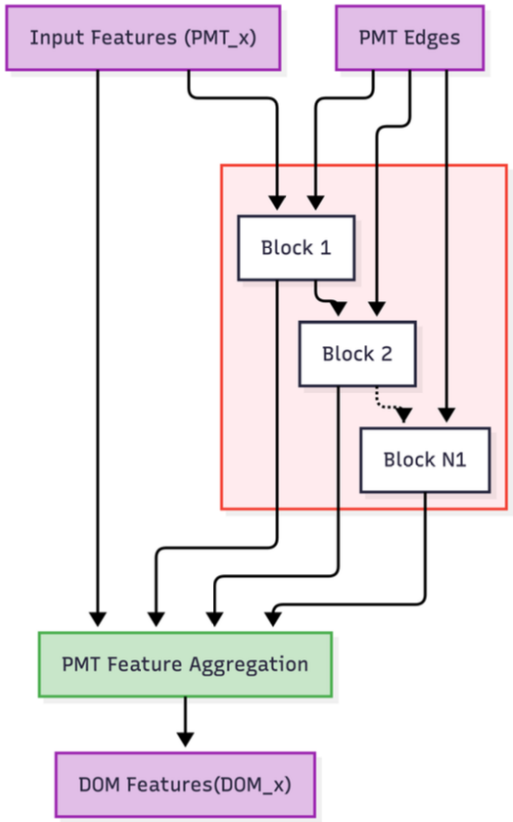


Track Cascade



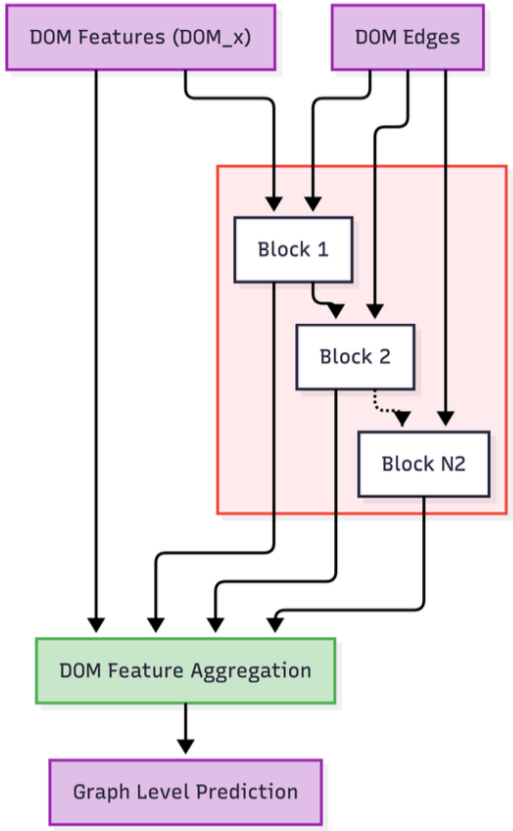
Stage 1 · intra-DOM

PMT correlations

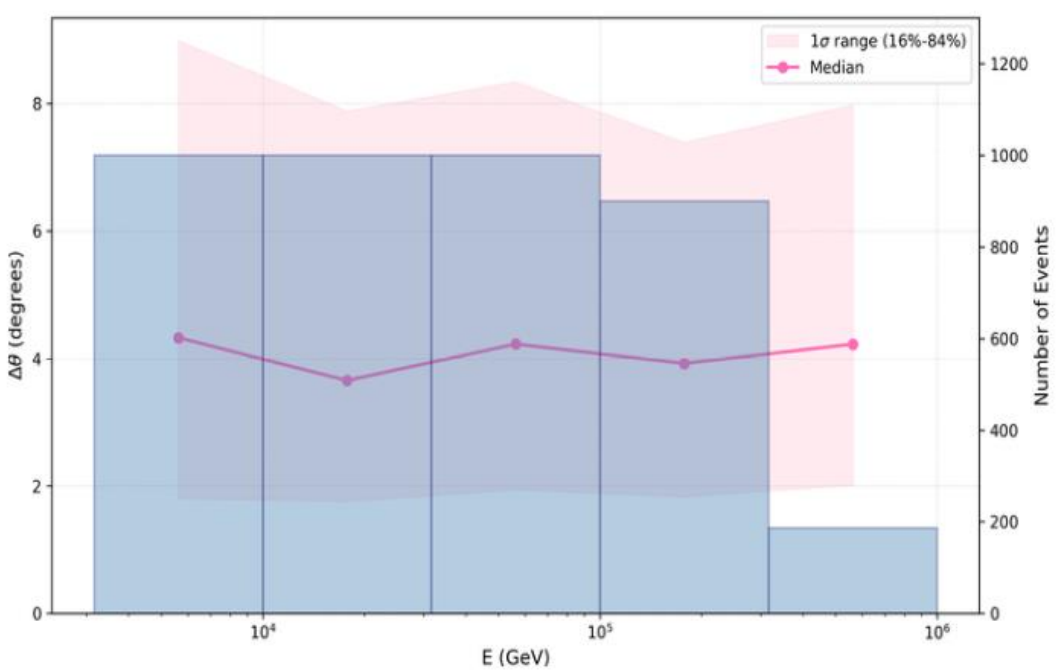


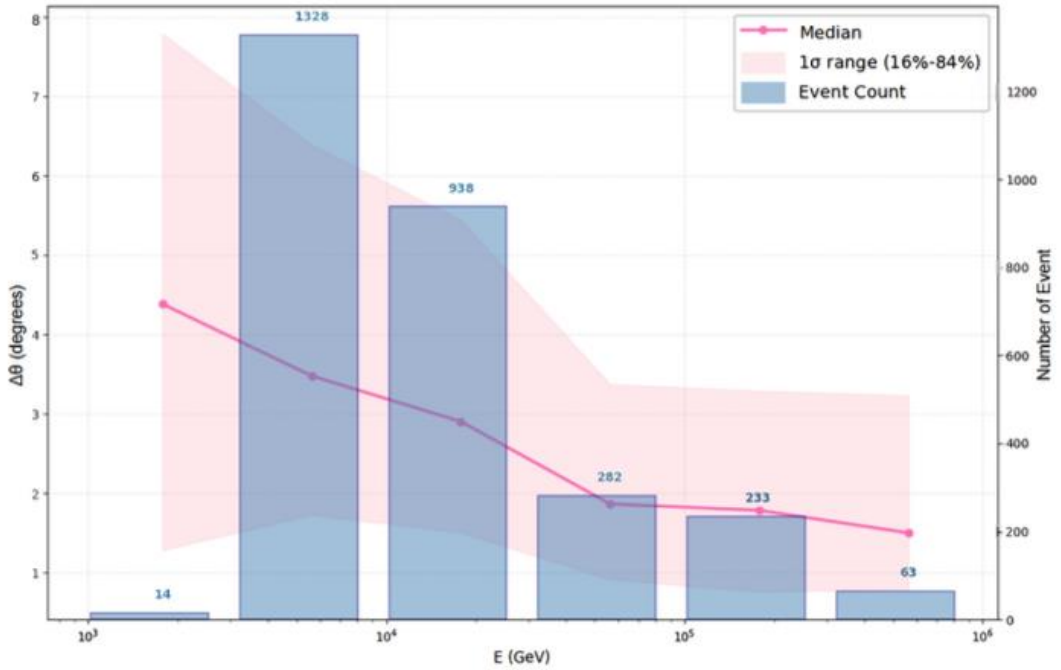
Stage 2 · inter-DOM

shower topology across DOMs



Comparison between traditional and GNN method

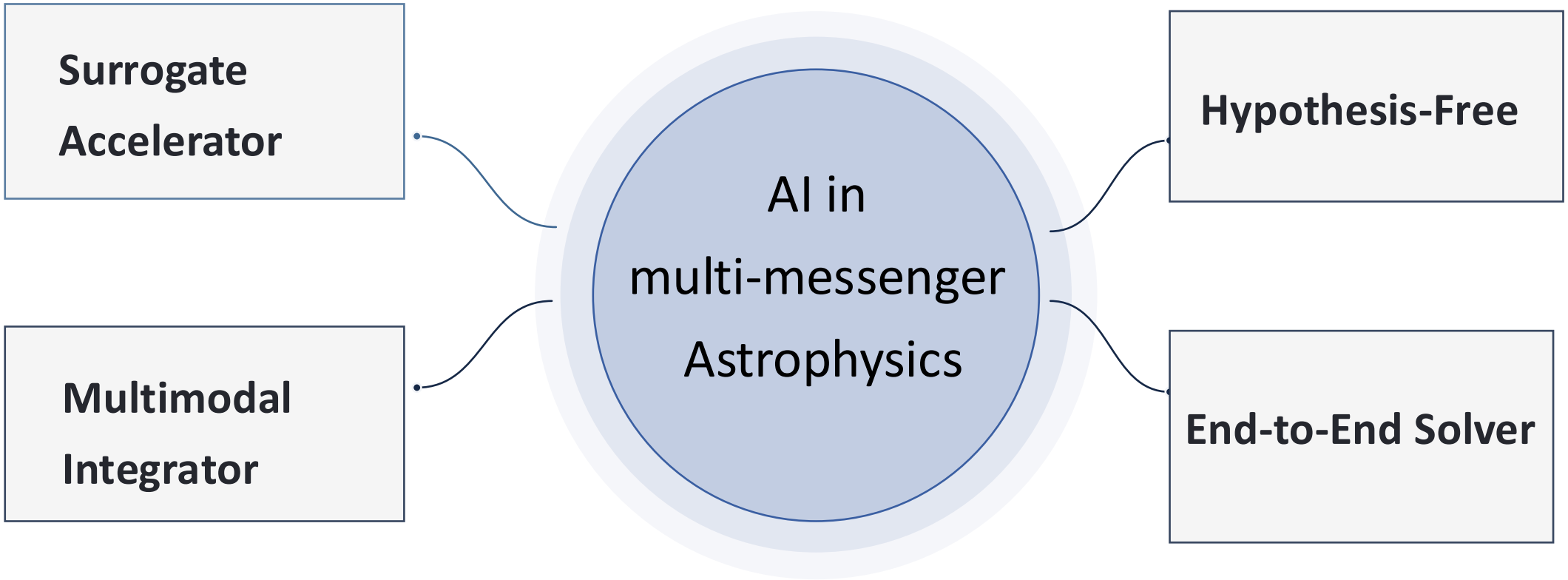




Median angular resolution at 30 TeV (GNN), 1.8° vs. ~4° for MLE

Energy resolution across 40–300 TeV is ~20%

Summary and Future Perspectives



Take home message

- **Ultra-Low-Latency Edge AI for Next-Gen Detectors (NEON, LHAASO)**
  - **On-Detector Hardware Acceleration:** Quantizing and pruning GNN to embed them directly into **FPGA/ASIC electronics**.
  - **Real-Time Trigger & Filtering:** Achieving ms-level noise rejection against deep-sea ^{40}K backgrounds and atmospheric muons at the front-end.
  - **Sub-Minute Multi-Messenger Alerts:** Triggering automated, low-latency target-of-opportunity (ToO) pointing commands across global observatories.
- **Astroparticle Foundation Models & Multimodal Self-Supervised Learning**
  - **Unified Representation:** Pre-training foundation models on massive, uncurated, heterogeneous streams.
  - **Zero-Shot Anomaly Detection:** Moving beyond supervised classification toward identifying unexpected physical phenomena
  - **Physics-Informed Differentiable Simulators:** Integrating differentiable forward models (Geant4/CORSIKA surrogates) directly into the optimization loop

A base with a favorable environment and superior testing conditions has been planned for the future sea trials.



National Marine Comprehensive Field Zhuhai

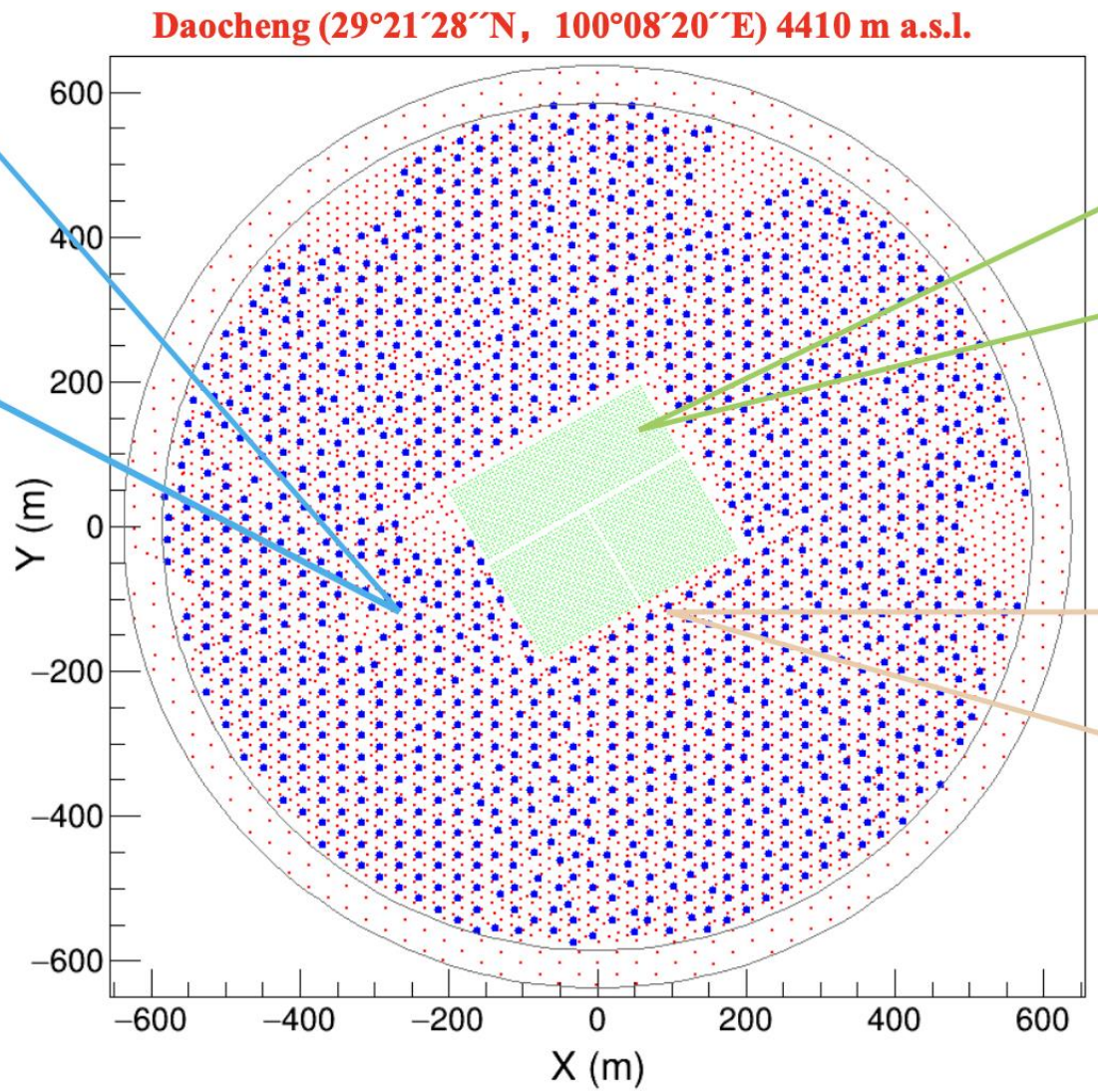
Further efforts are ongoing.

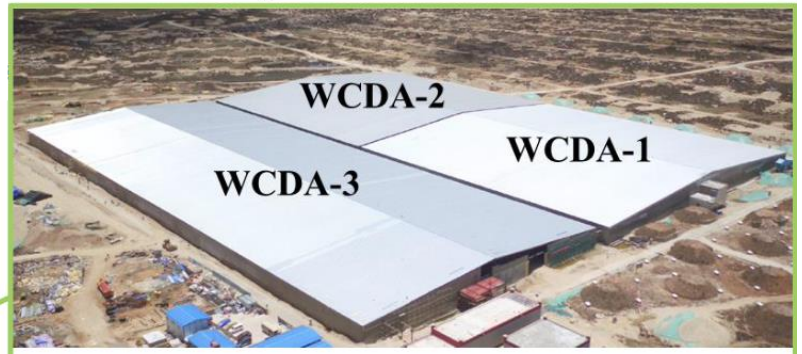
Thank you!

LHAASO experiment



KM2A: (1.3 km^2)
Electromagnetic Particle Detectors (ED)
Muon Detectors (MD)





WCDA: (78,000 m^2)
Water Cherenkov Detector Array



WFCTA: (18)
Wide-Field Air Cherenkov Telescope Array