

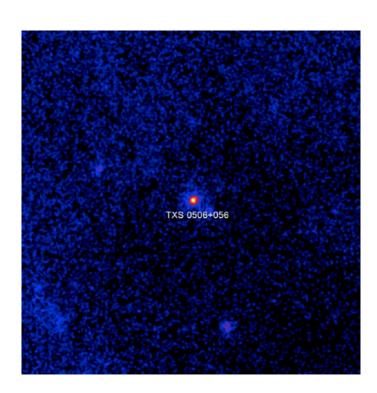
Recent Publications (2024–2025)

- ☑ Sahakyan, N., Bégué, D., Casotto, A., Dereli-Bégué, H., Vardanyan, V., Khachatryan, M., Giommi, P., Pe'er, A., Modeling Blazar Broadband Emission with Convolutional Neural Networks. III. Proton Synchrotron and Hybrid Models, The Astrophysical Journal, 990, 222 (2025), DOI: 10.3847/1538-4357/adf734S
- ☑ Harutyunyan, G., Sahakyan, N., Bégué, D., Modelling of the Time-Resolved Spectral Energy Distribution of Blazar OJ 287 from 2008 to 2023: A Comprehensive Multi-Epoch Study, Monthly Notices of the Royal Astronomical Society, 540, 582–593 (2025), DOI: 10.1093/mnras/staf713
- ☑Sahakyan, N., Vardanyan, V., Giommi, P., Bégué, D., Israyelyan, D., Harutyunyan, G., Manvelyan, M., Khachatryan, M., Dereli-Bégué, H., Gasparyan, S., Markarian Multiwavelength Data Center (MMDC): A Tool for Retrieving and Modeling Multitemporal, Multiwavelength, and Multimessenger Data from Blazar Observations, The Astronomical Journal, 168, 289 (2024), DOI: 10.3847/1538-3881/ad8231.
- ☑ Sahakyan, N., AI in the Cosmos, arXiv e-prints, arXiv:2412.10093 (2024), IJMPD, in press, DOI: 10.48550/arXiv.2412.10093
- Mohana A, K., Gupta, A. C., Fan, J., Sahakyan, N., Raiteri, C. M., Cui, L., Lähteenmäki, A., Gurwell, M., Tornikoski, M., Villata, M., Modeling the Multiwavelength Emission of 3C 279 during the 14 yr Fermi-LAT Era, The Astrophysical Journal, 989, 125 (2025), DOI: 10.3847/1538-4357/adec77



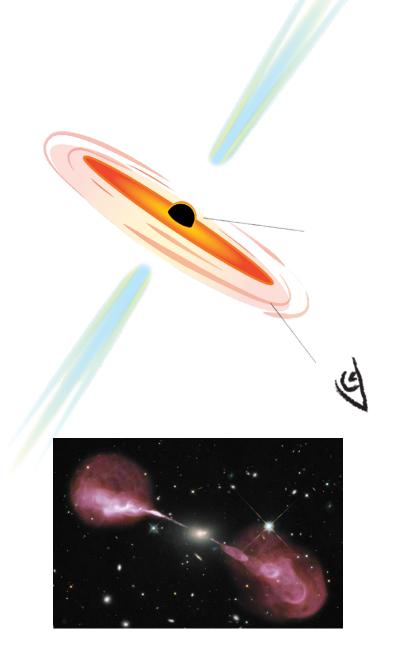
Blazars: Powerful and Rare Objects

The common model for blazar emission is that these sources are quasars in which a relativistic jet is pointing at the observer or very close to the observer's line of sight.



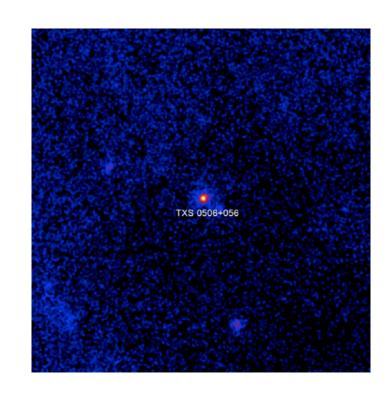
Blazars are rare objects. Even when combining data from multiple surveys, only about 6,000 sources exhibit blazar-like features among an estimated 100 to 200 billion galaxies.

Why blazars are interesting?



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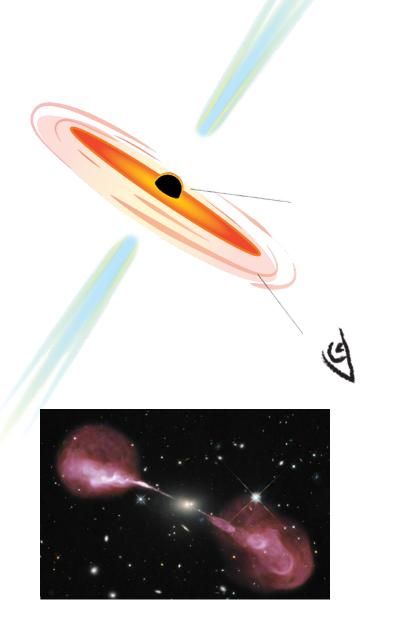


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- \circ High powers: most powerful "non-explosive" sources in the Universe ($\sim 10^{49} \, \text{erg/s}$)
- O Relativistic jets: emission is strongly Doppler amplified
- The powerful jets of blazars are powered by accretion onto supermassive black holes
- Fast variability/small emitting region; $R \le c t_{\text{var}}/(1+z)$
- \bigcirc Broadband emission: from radio to VHE γ -ray
- O Blazar emission is often highly polarized, in the radio, optical, and X-ray bands
- O Dominant sources in HE γ -ray sky: $\sim 55\%$ of 4FGL-DR3 sources are blazars.
- O Blazars are important sources in MM astronomy, being linked to VHE neutrinos



1963 First quasar (3C 273) Birth of blazar observations (1970s-1990s) 2025 Multimessenger monitoring

X UV/Opt



1963 First quasar (3C 273)

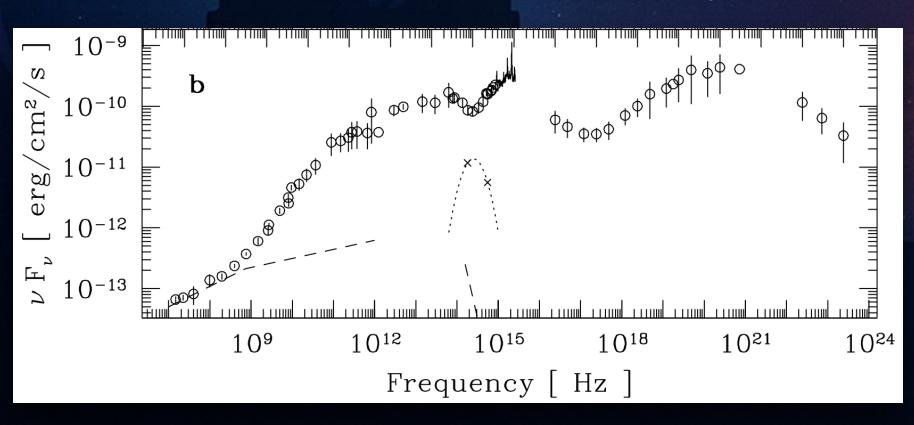




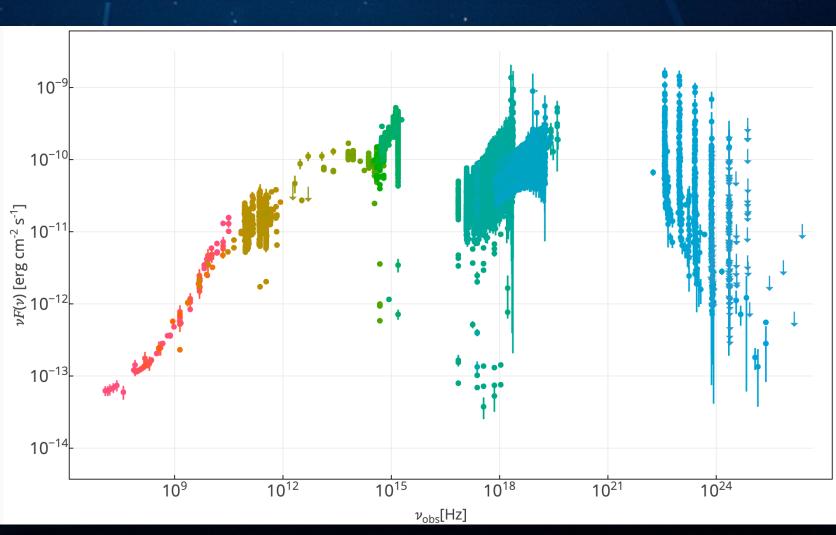








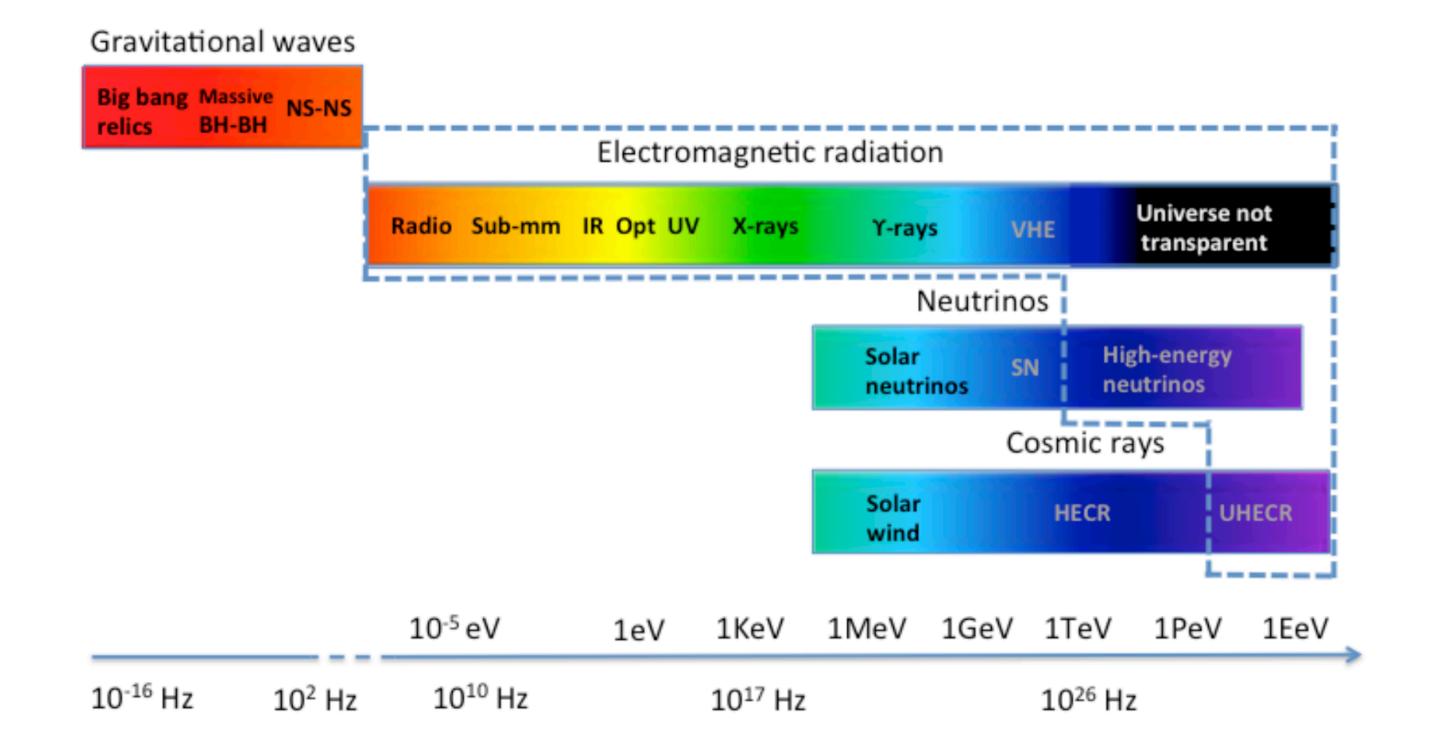




Our knowledge of the Universe relies on four cosmic messengers:

- Gravitational waves
- Photons
- Cosmic rays
- Neutrinos

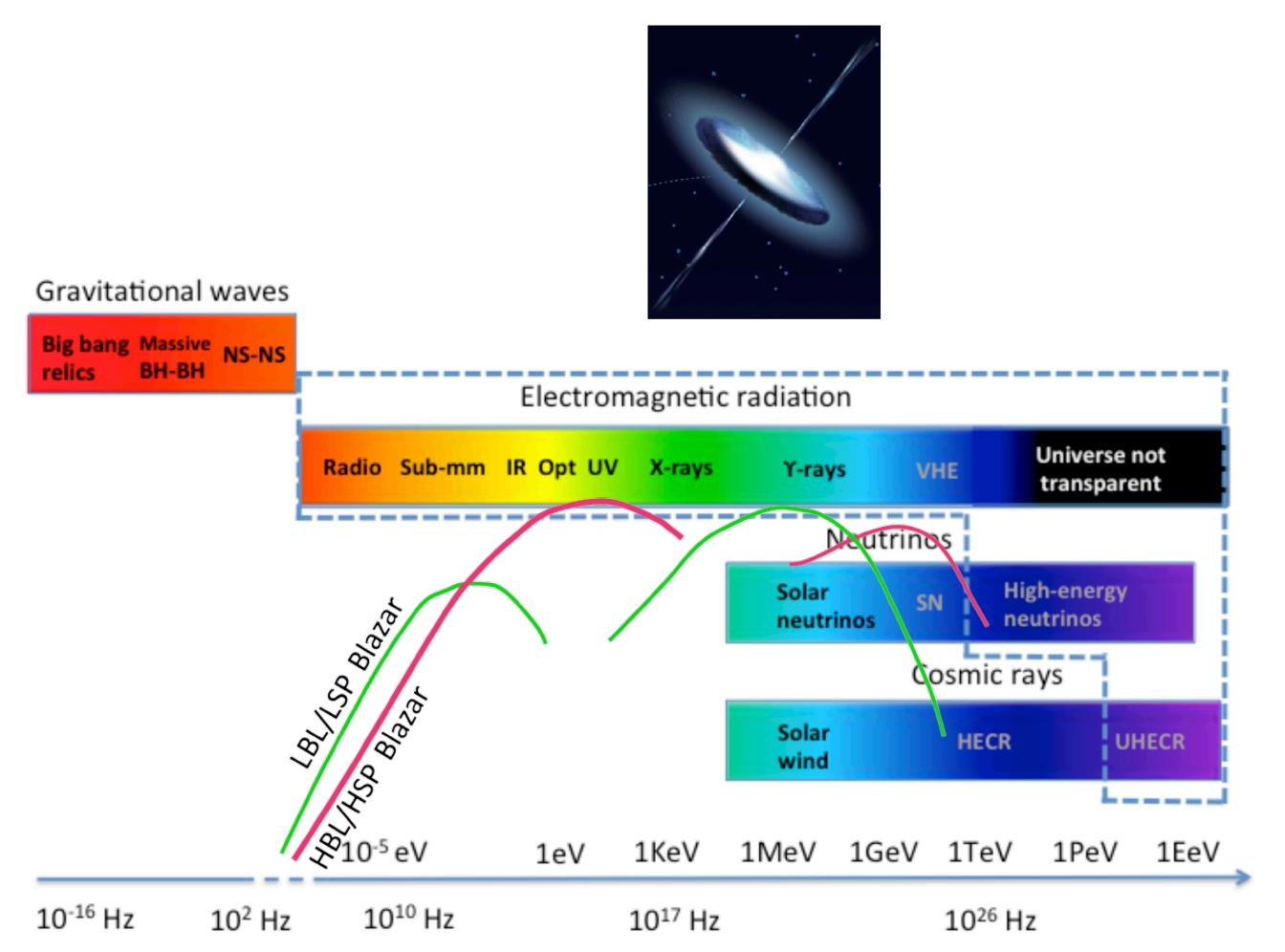
The information from these messengers spans a vast range of energies and frequencies, covering 50 orders of magnitude



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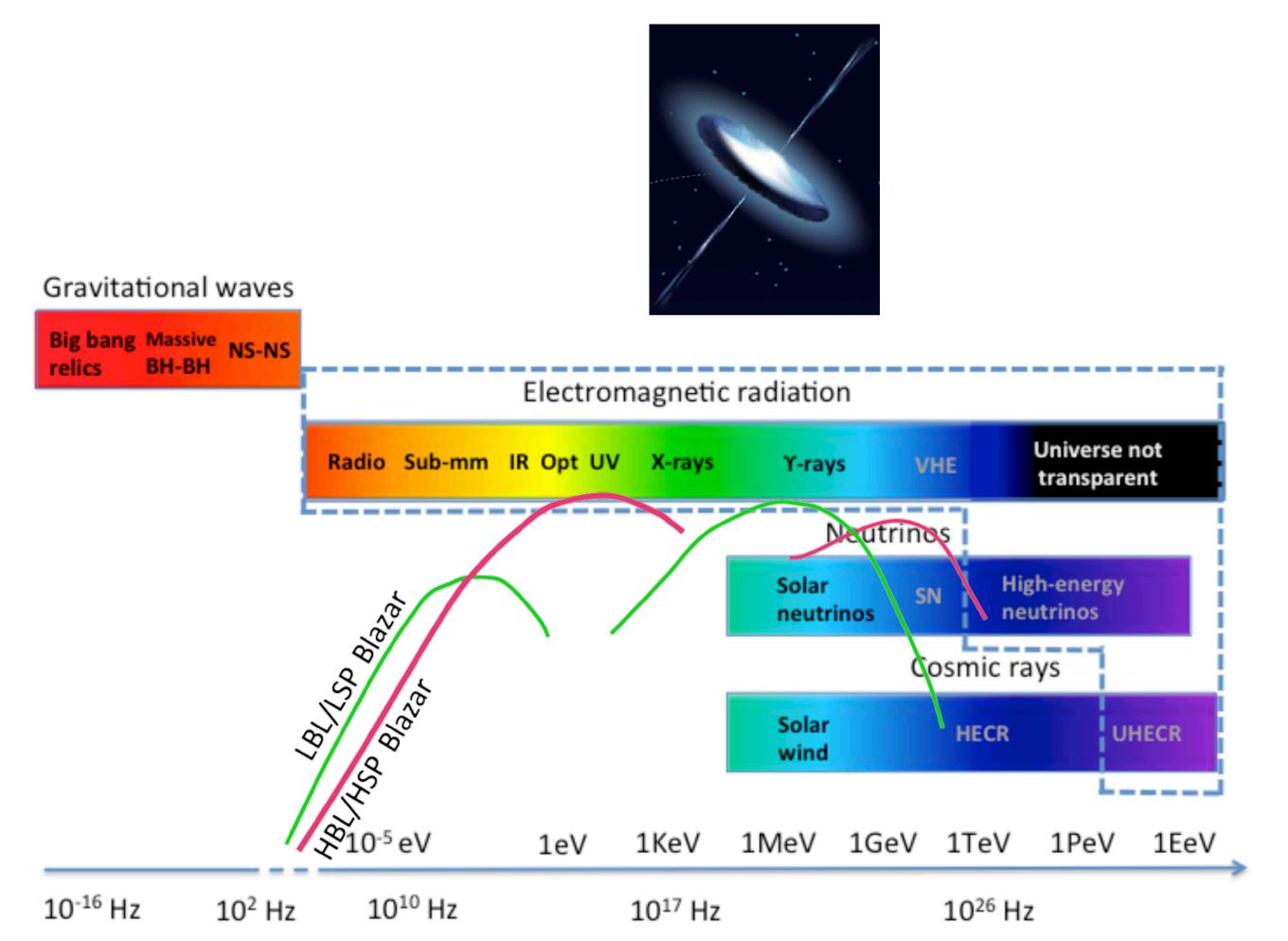
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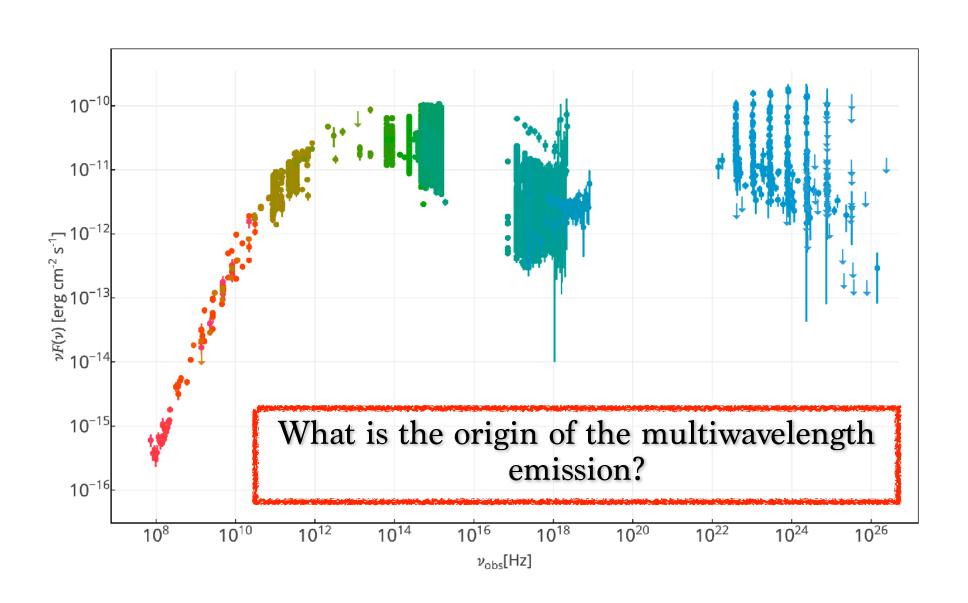
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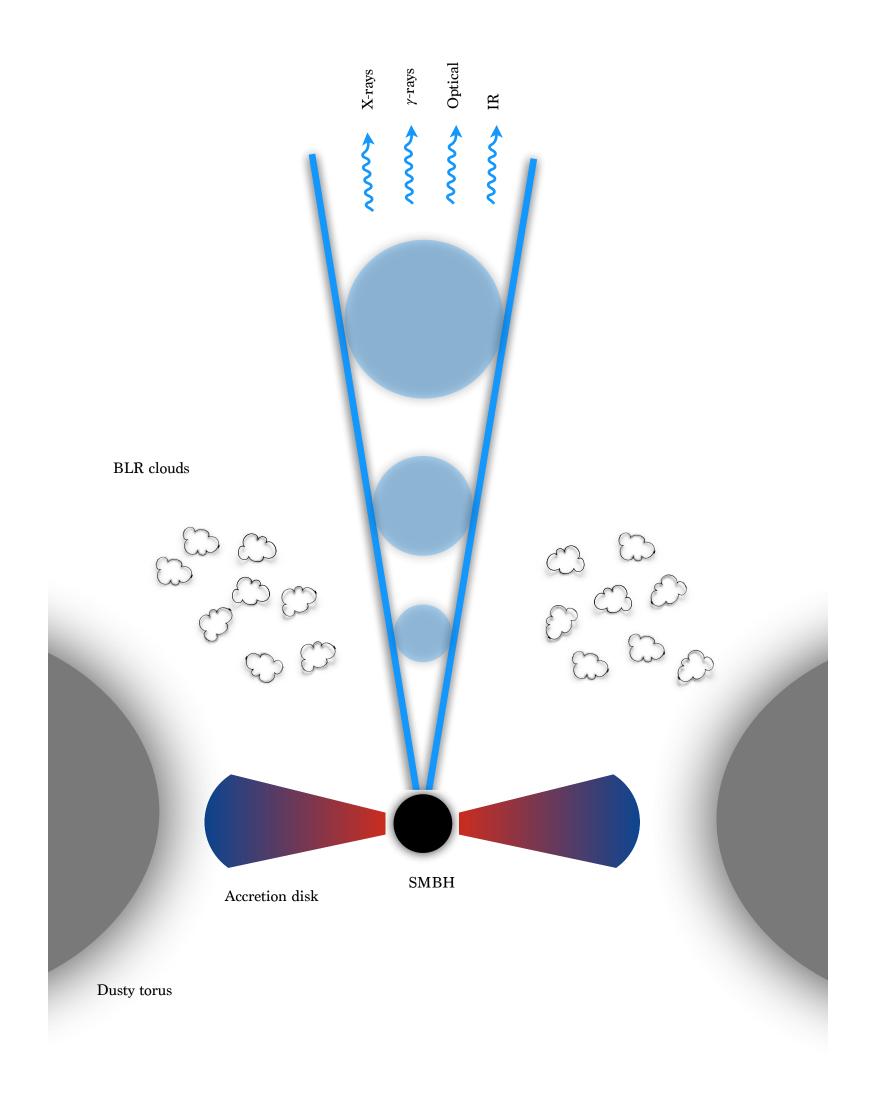
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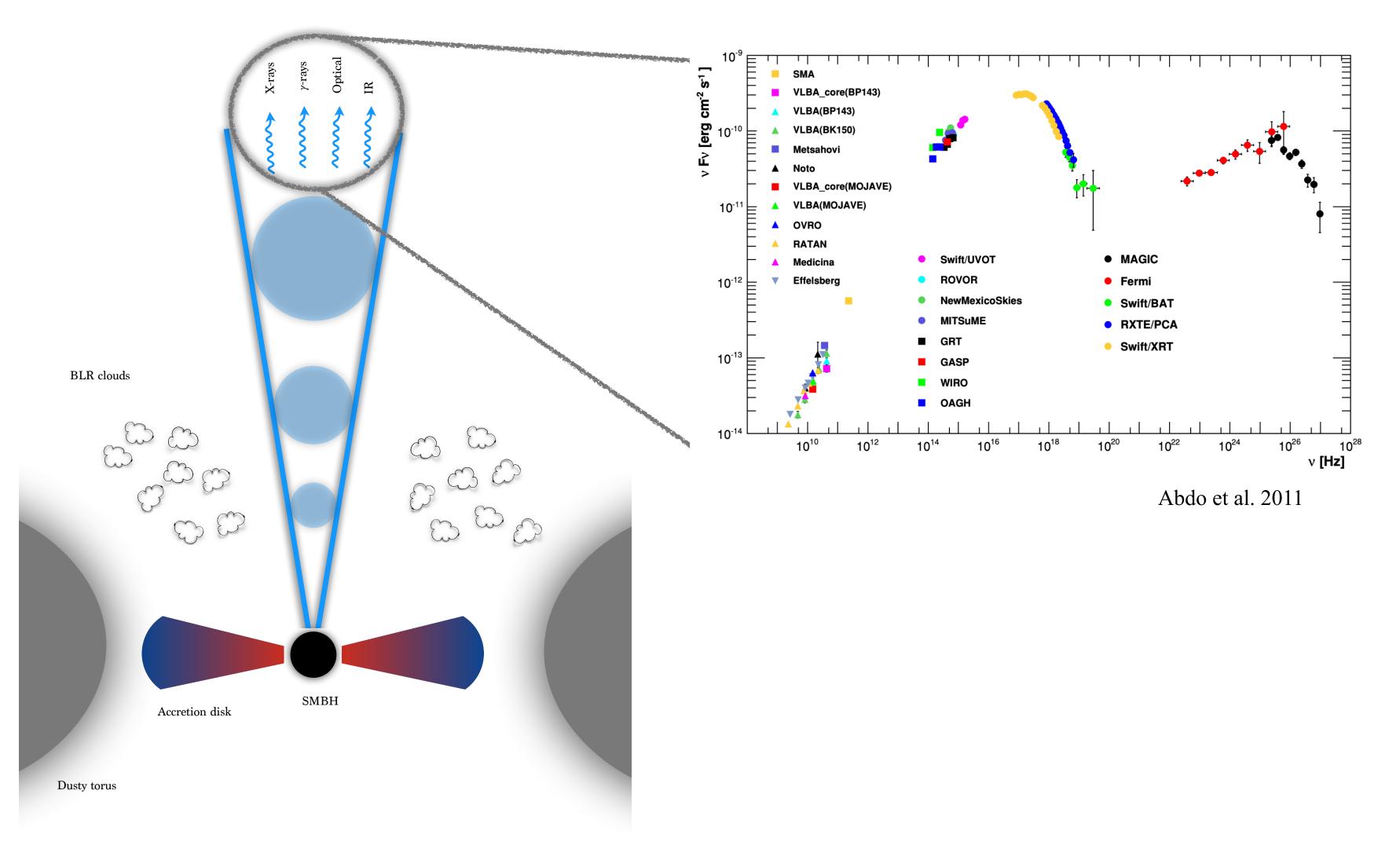
Blazar emissions can be investigated by detecting photons with energies ranging from radio to HE and VHE y-rays.



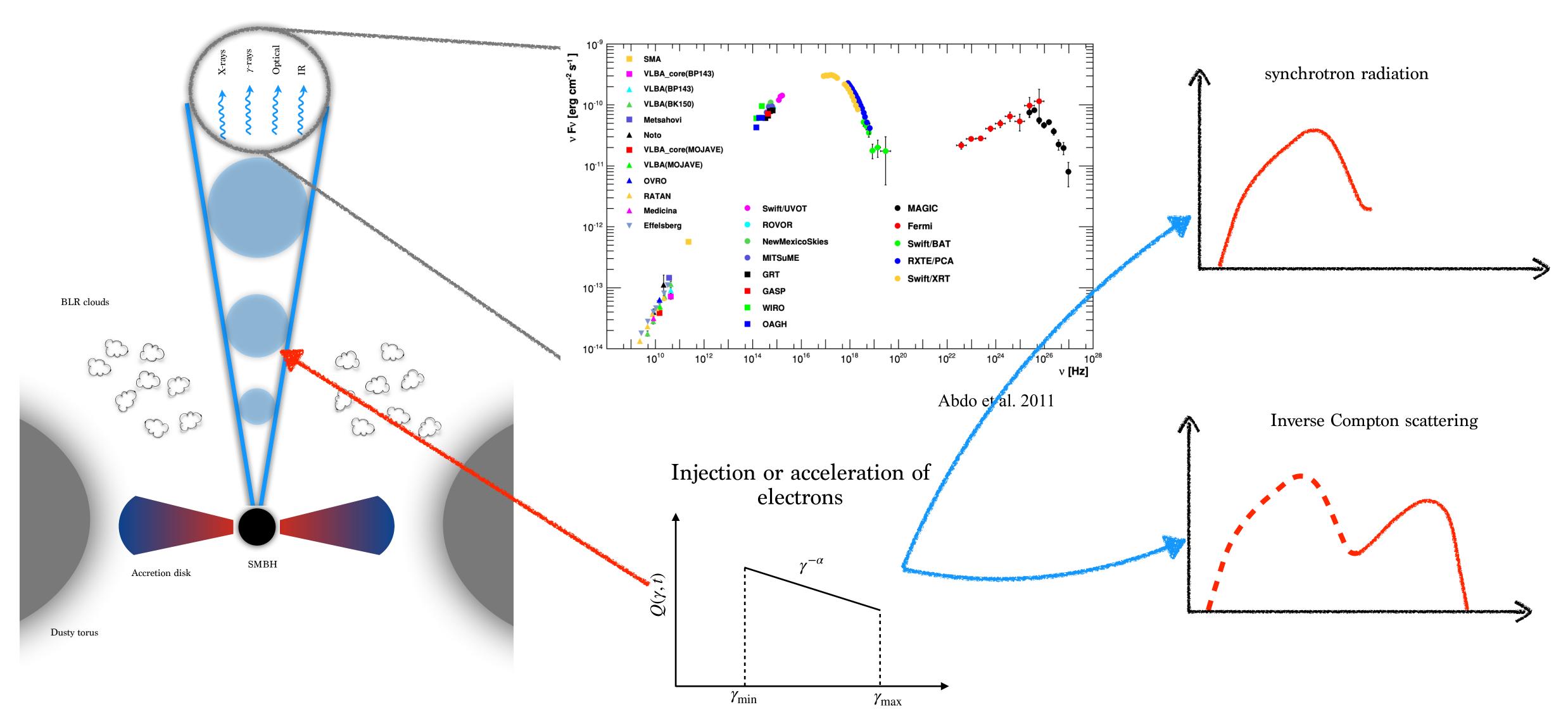
Origin of Multiwavelength Emission: Leptons



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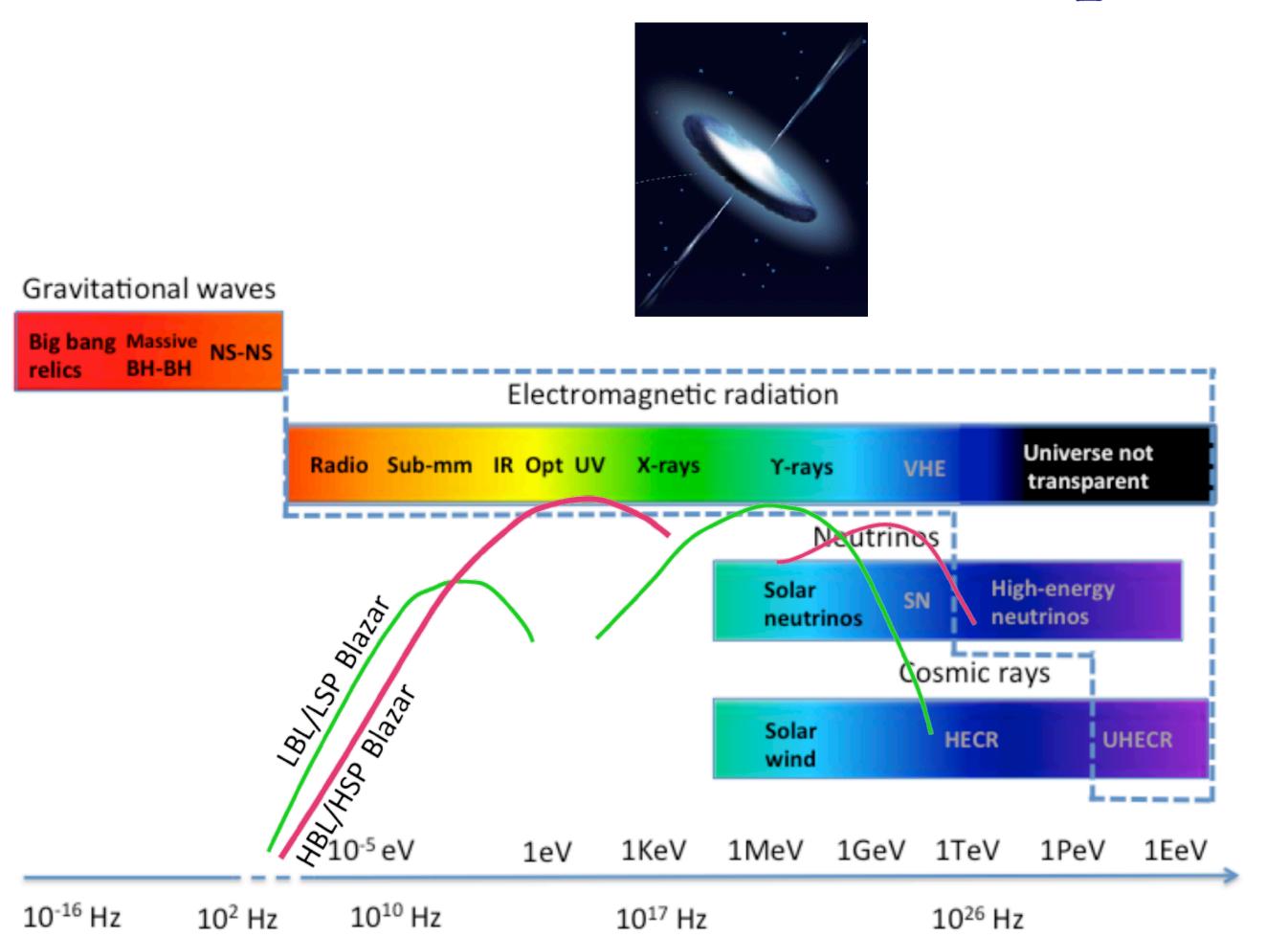
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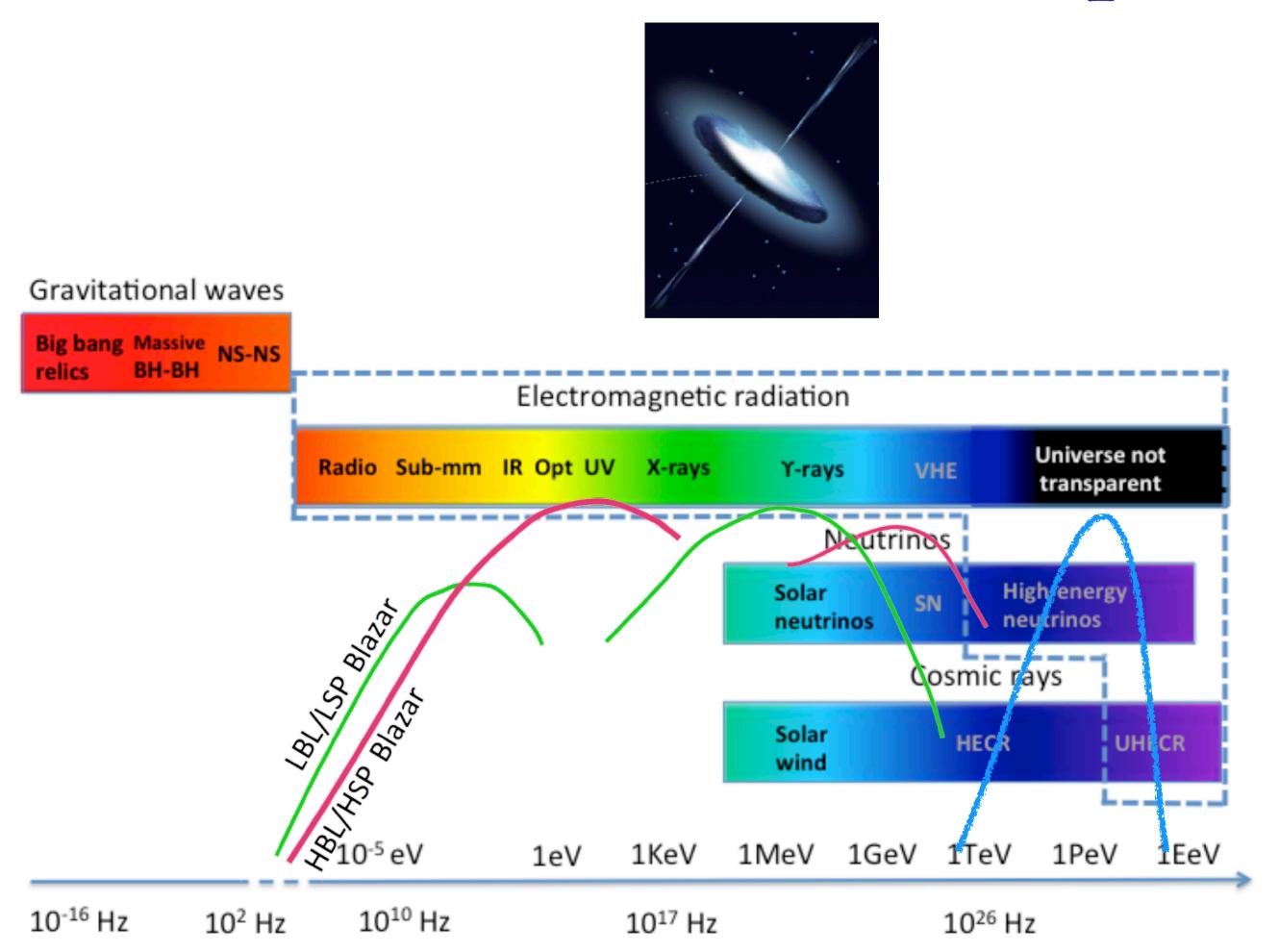
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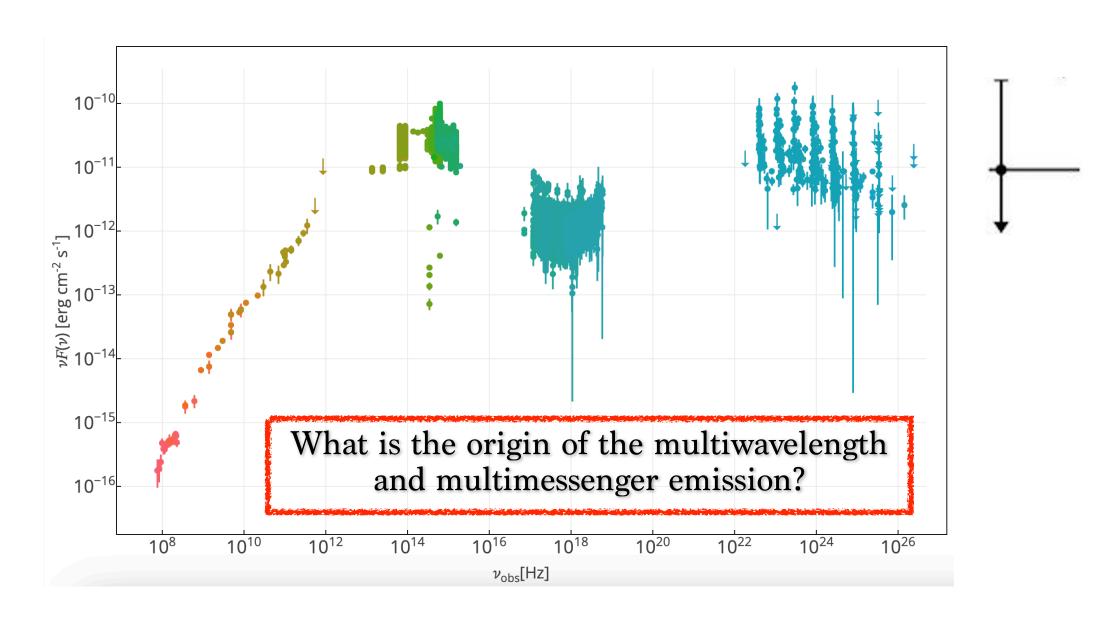
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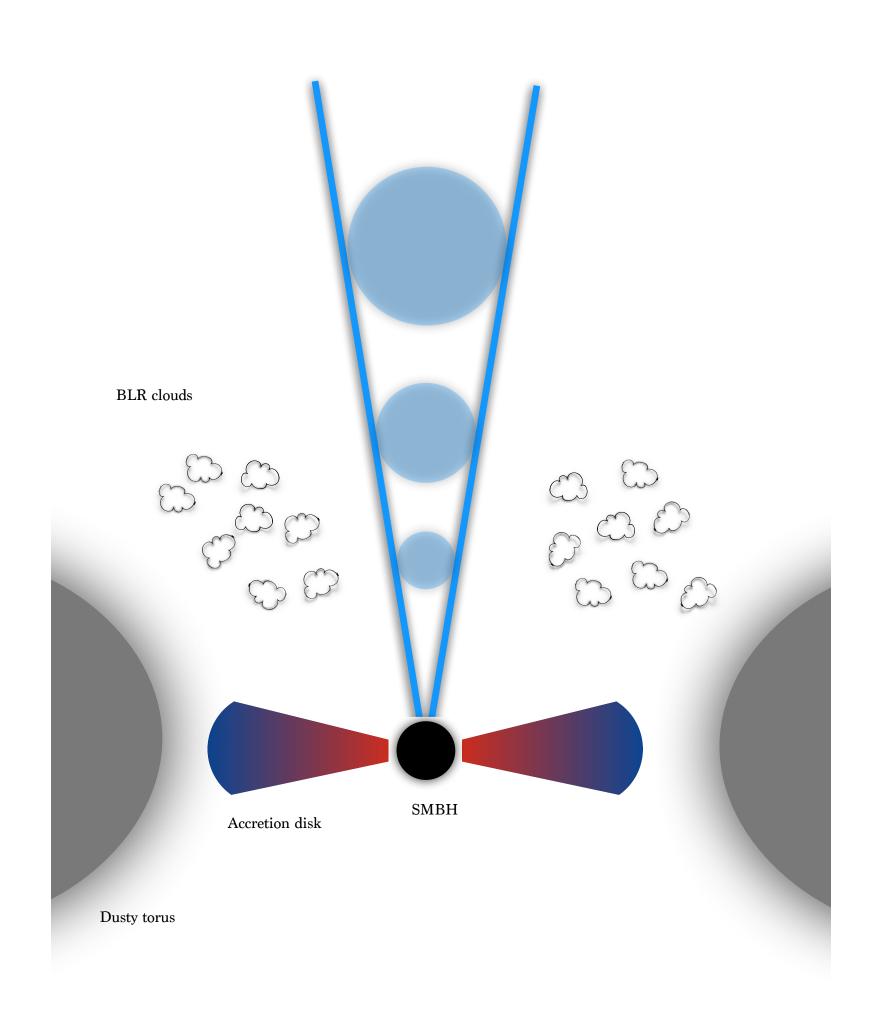
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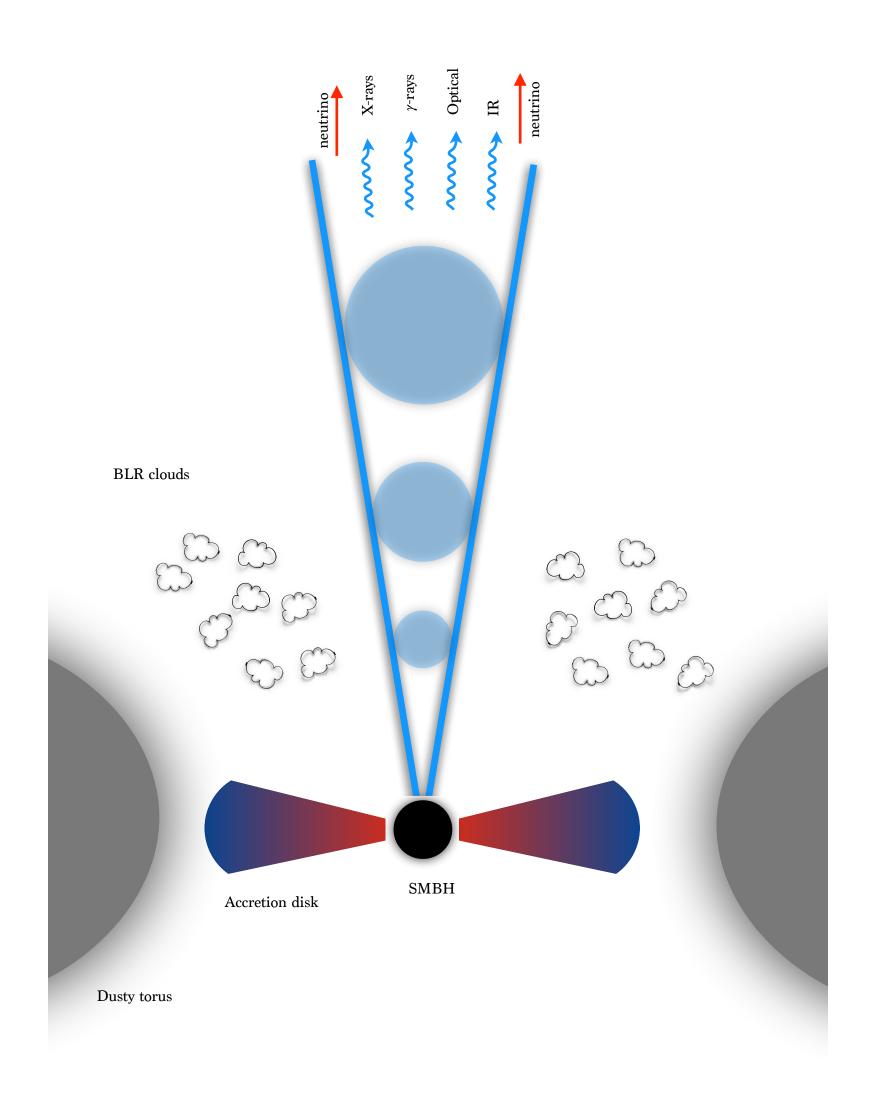


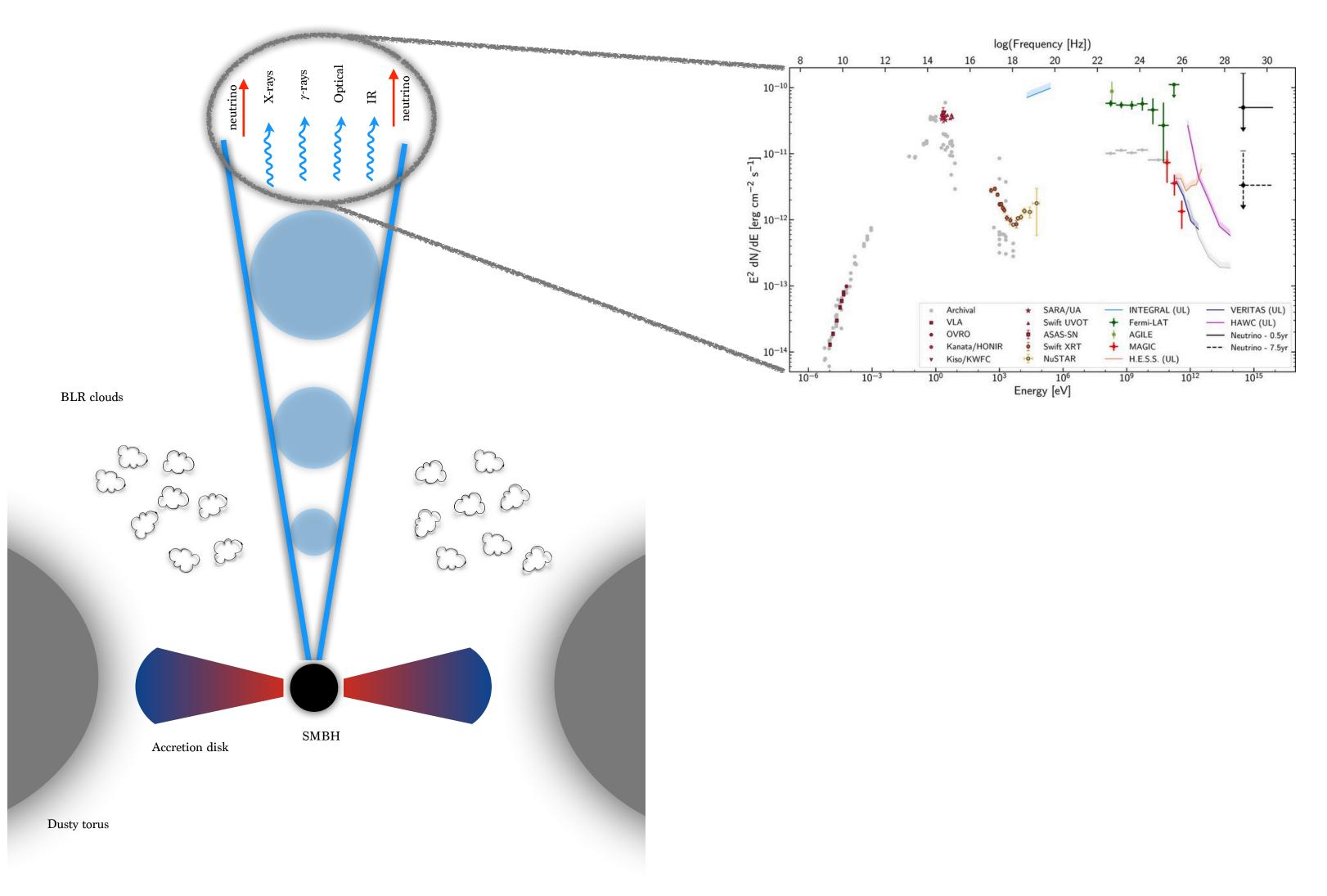
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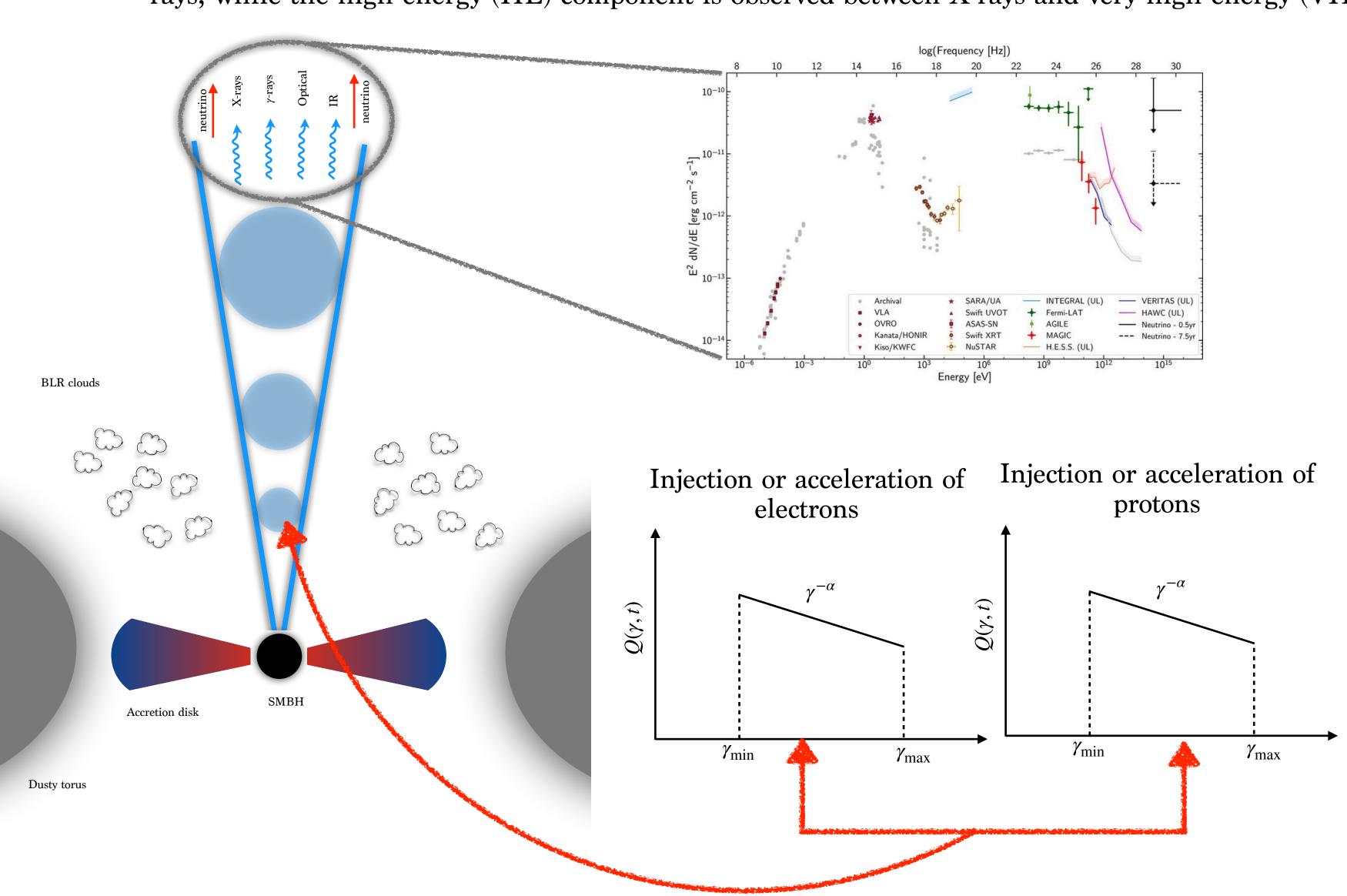
Blazars are associated with VHE neutrinos.

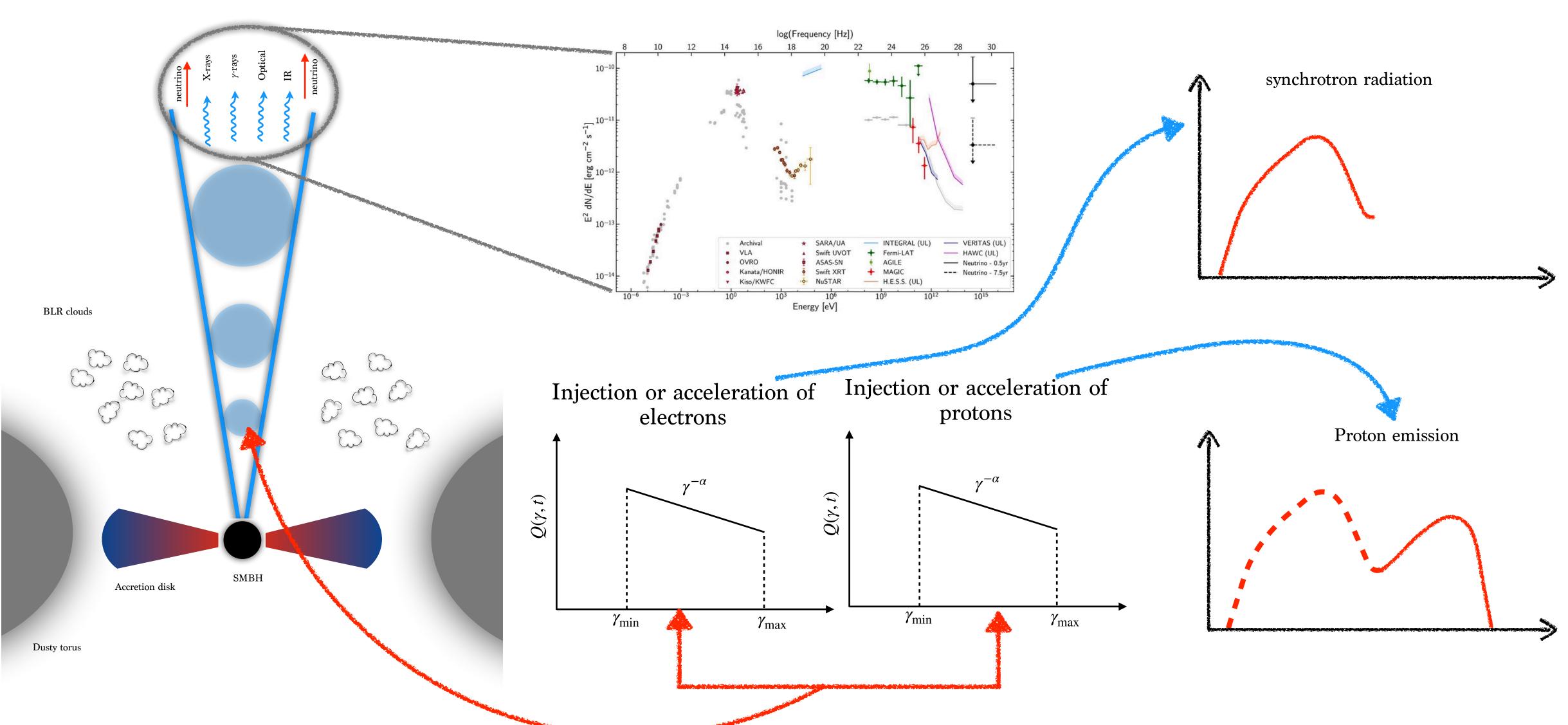


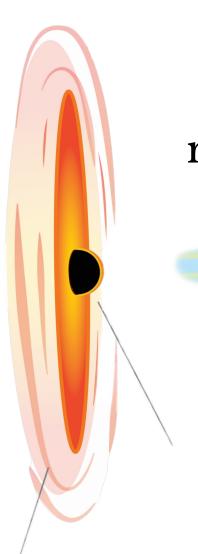




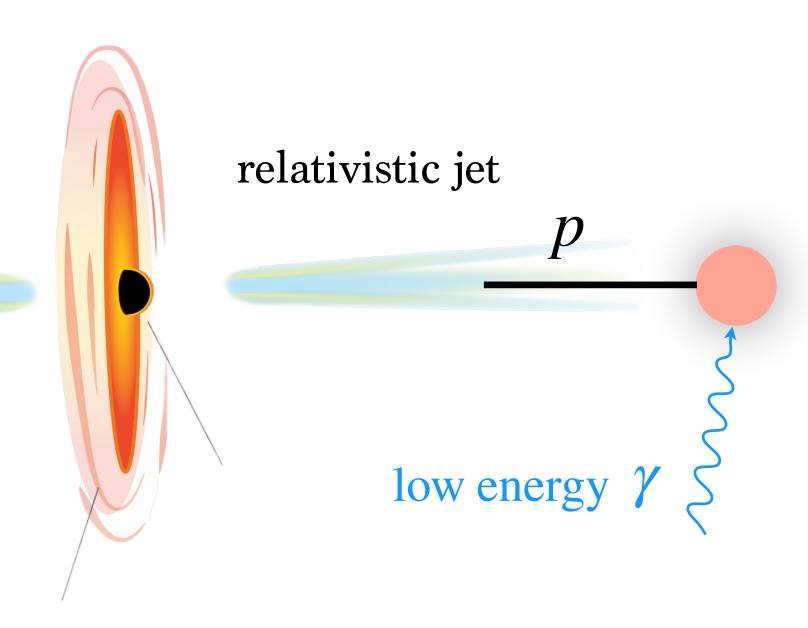


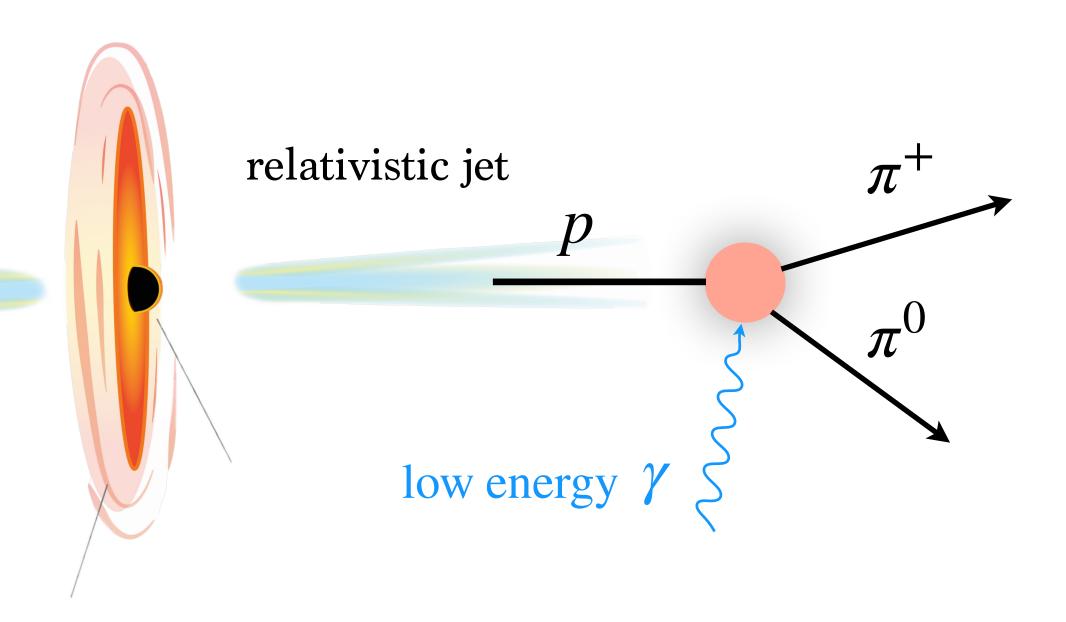


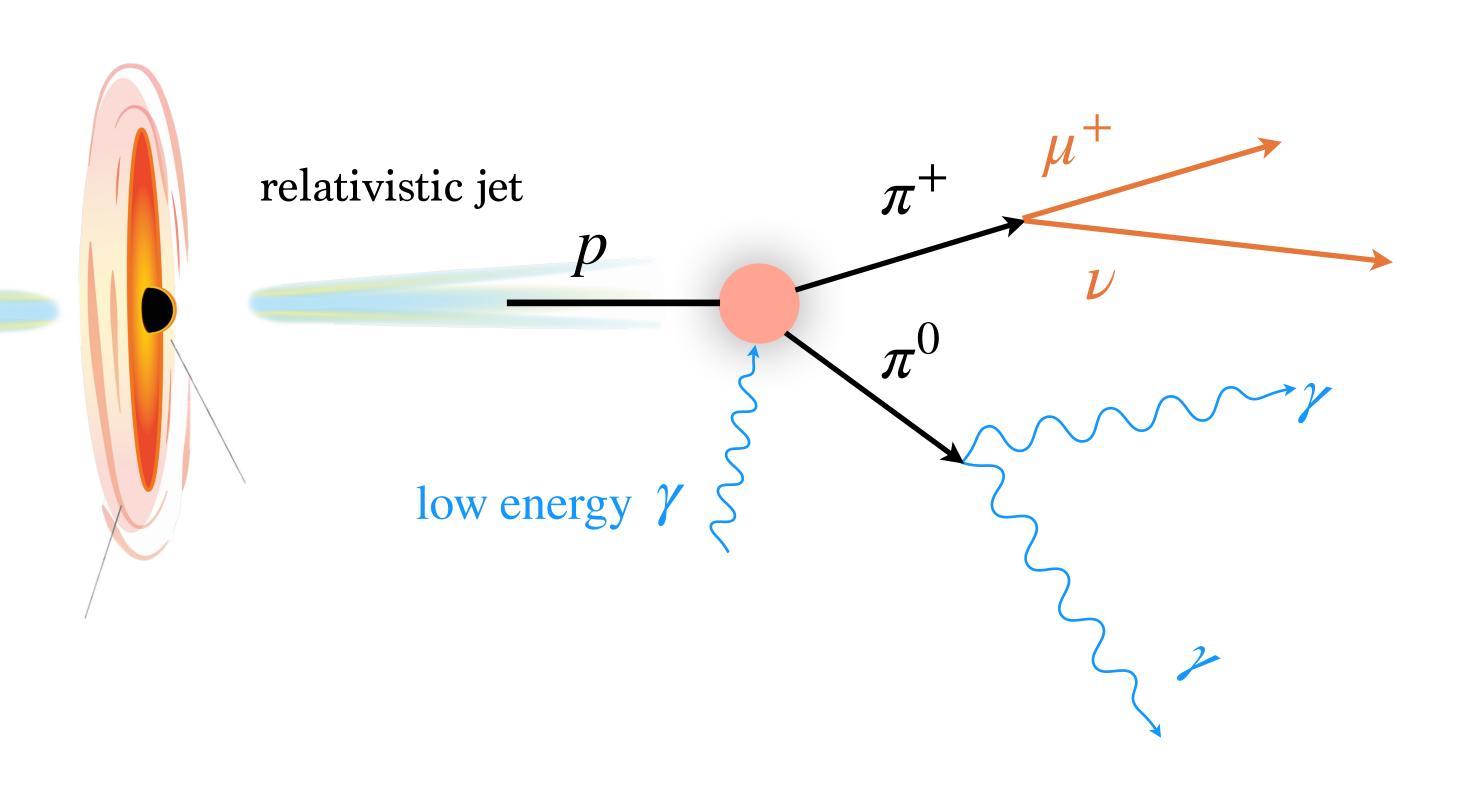


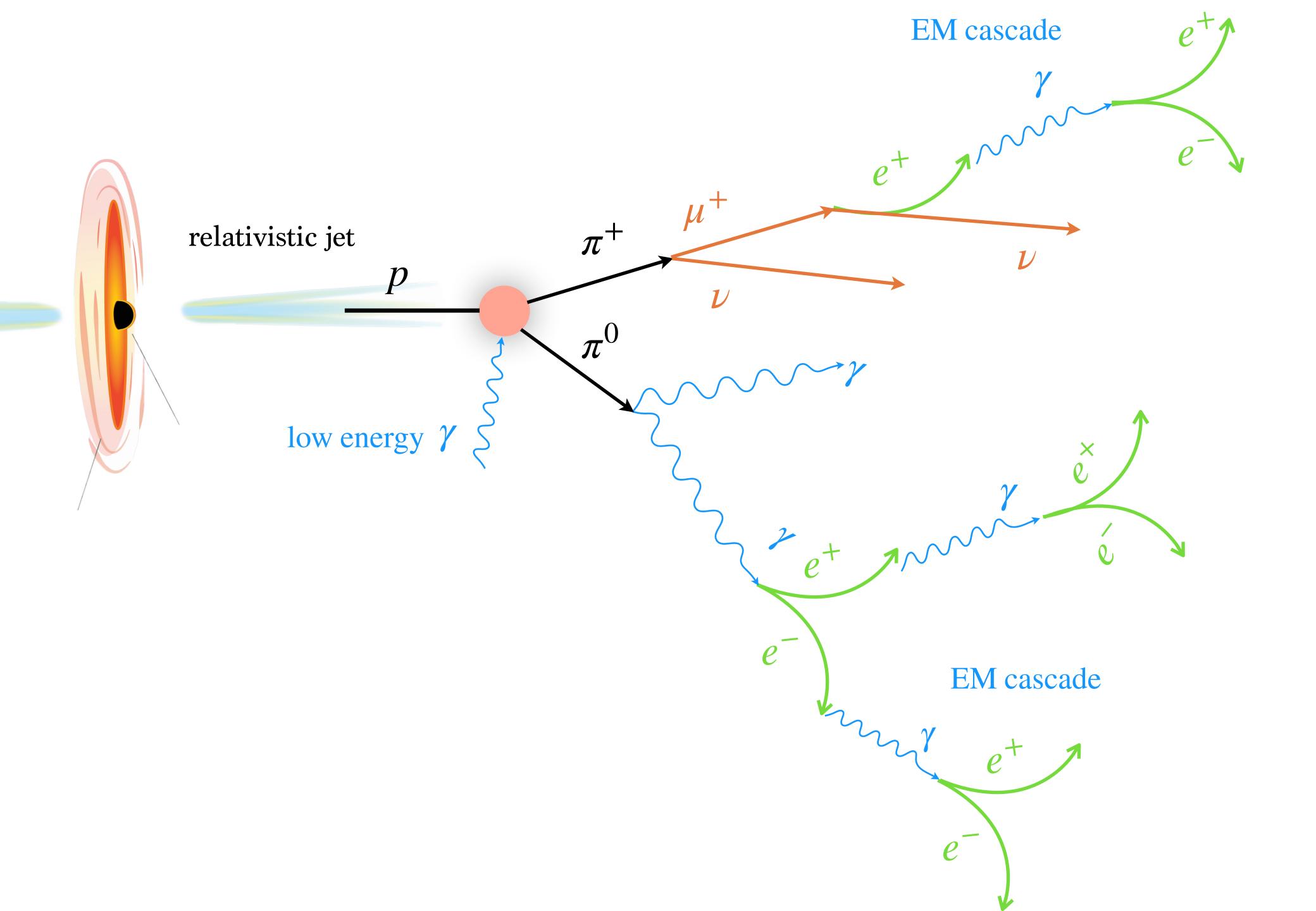


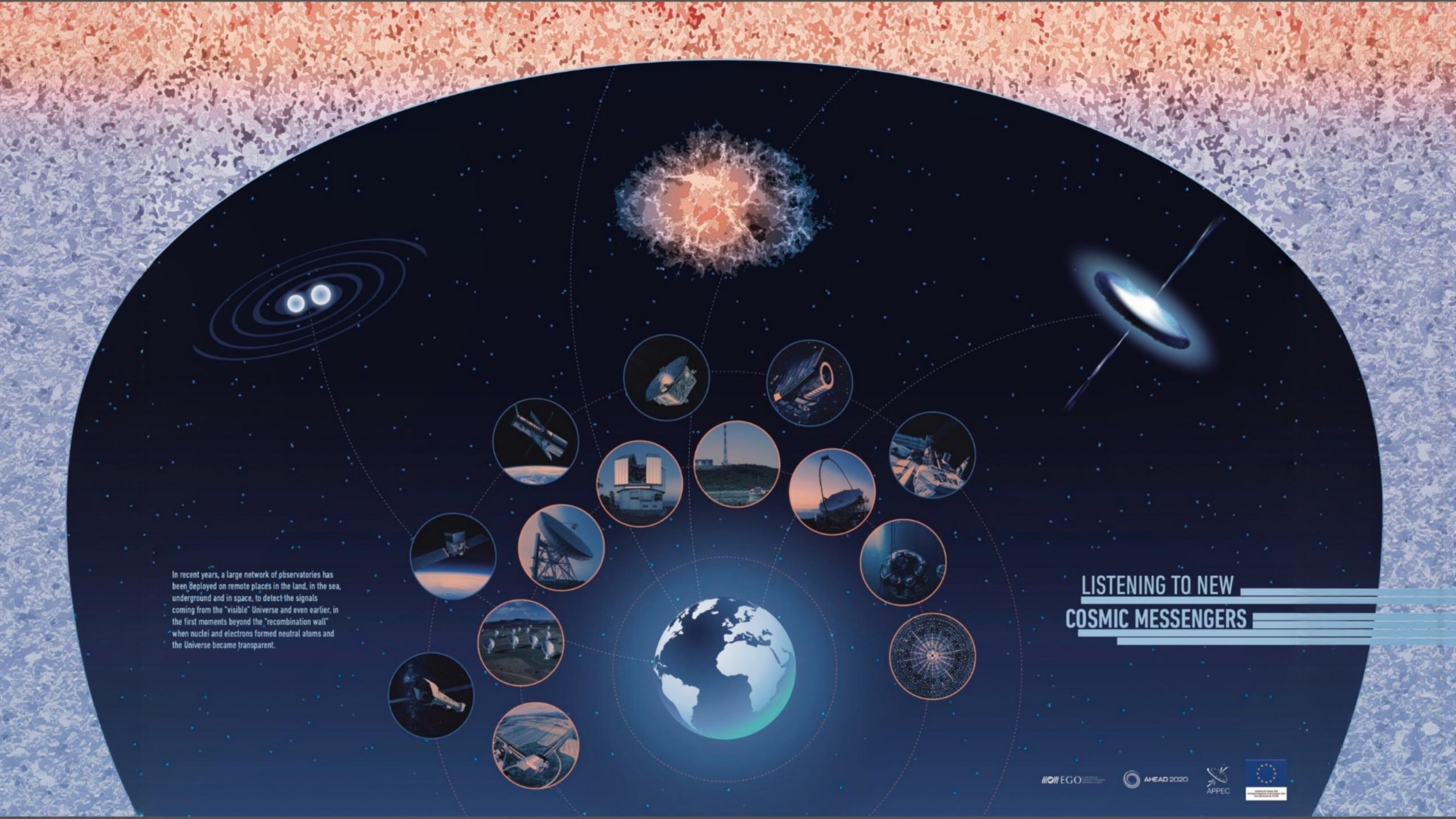
relativistic jet



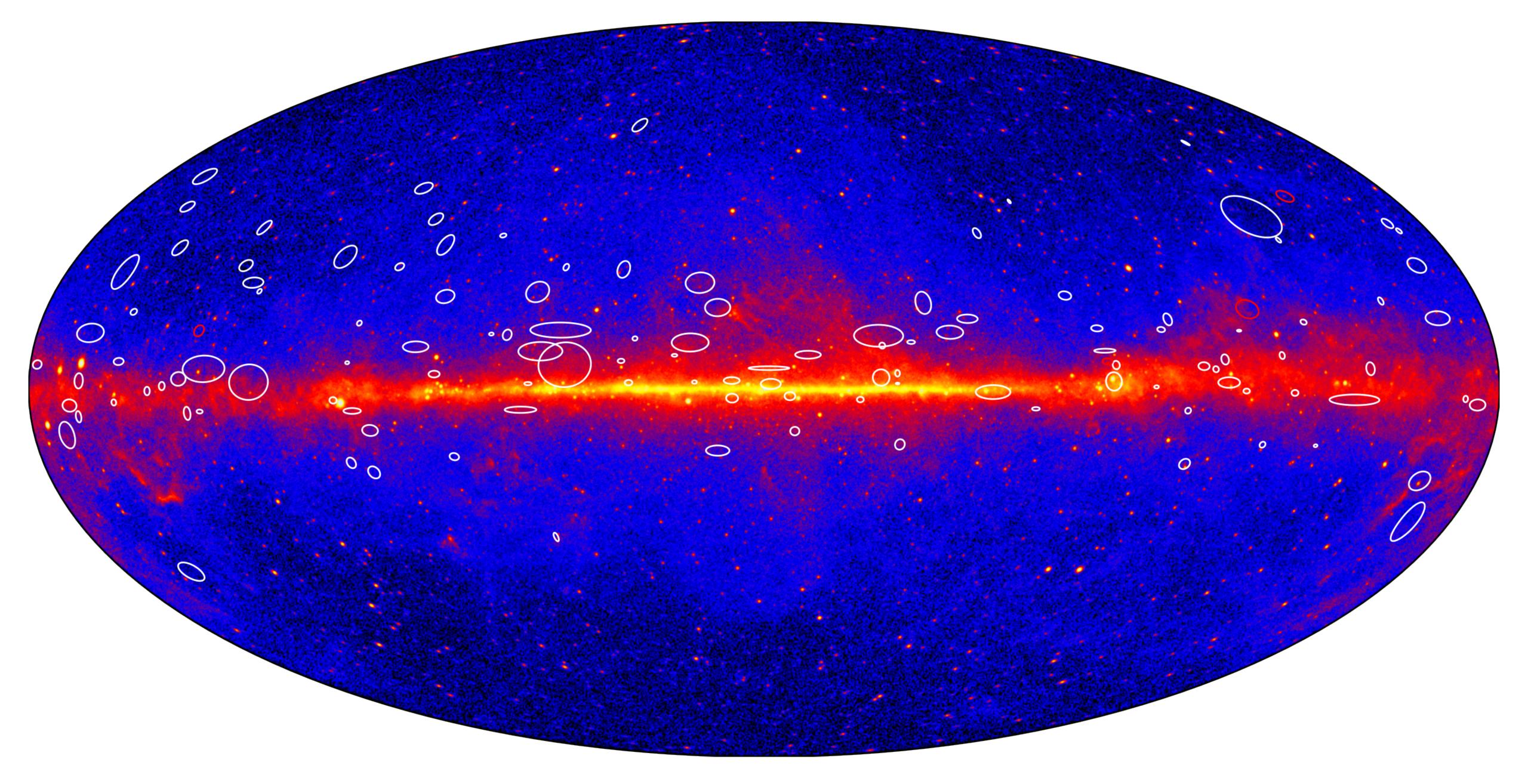




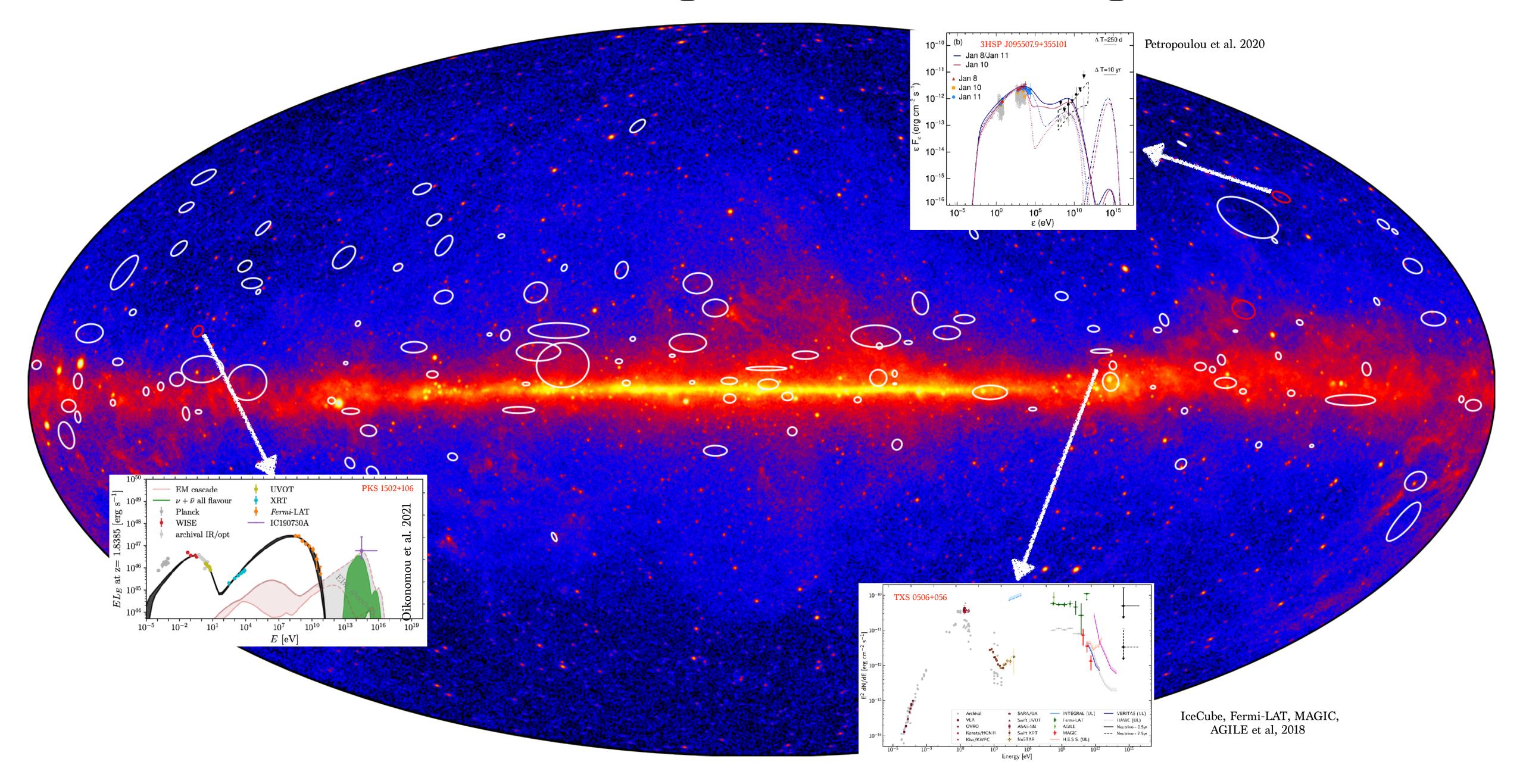


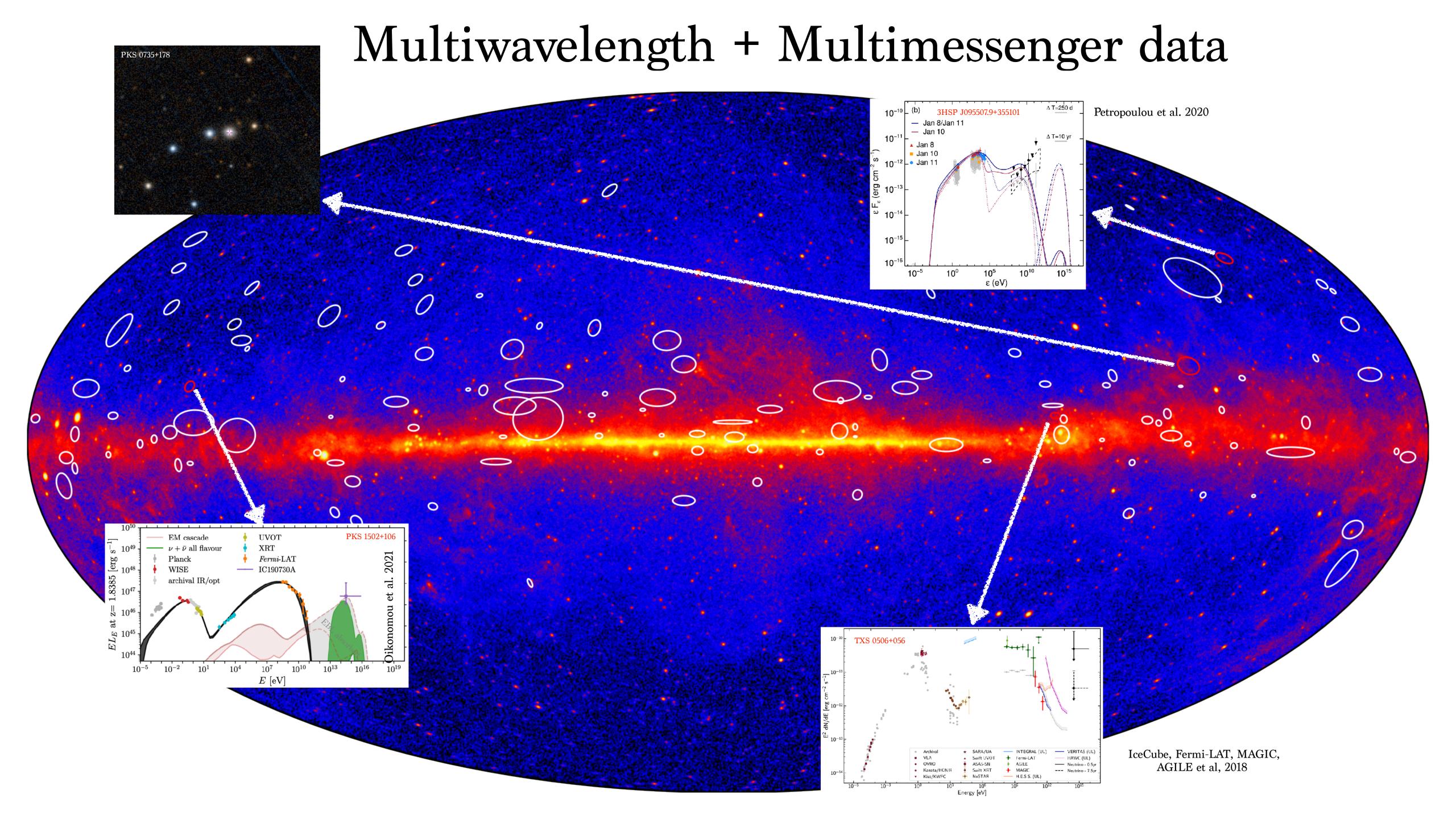


Multiwavelength + Multimessenger data

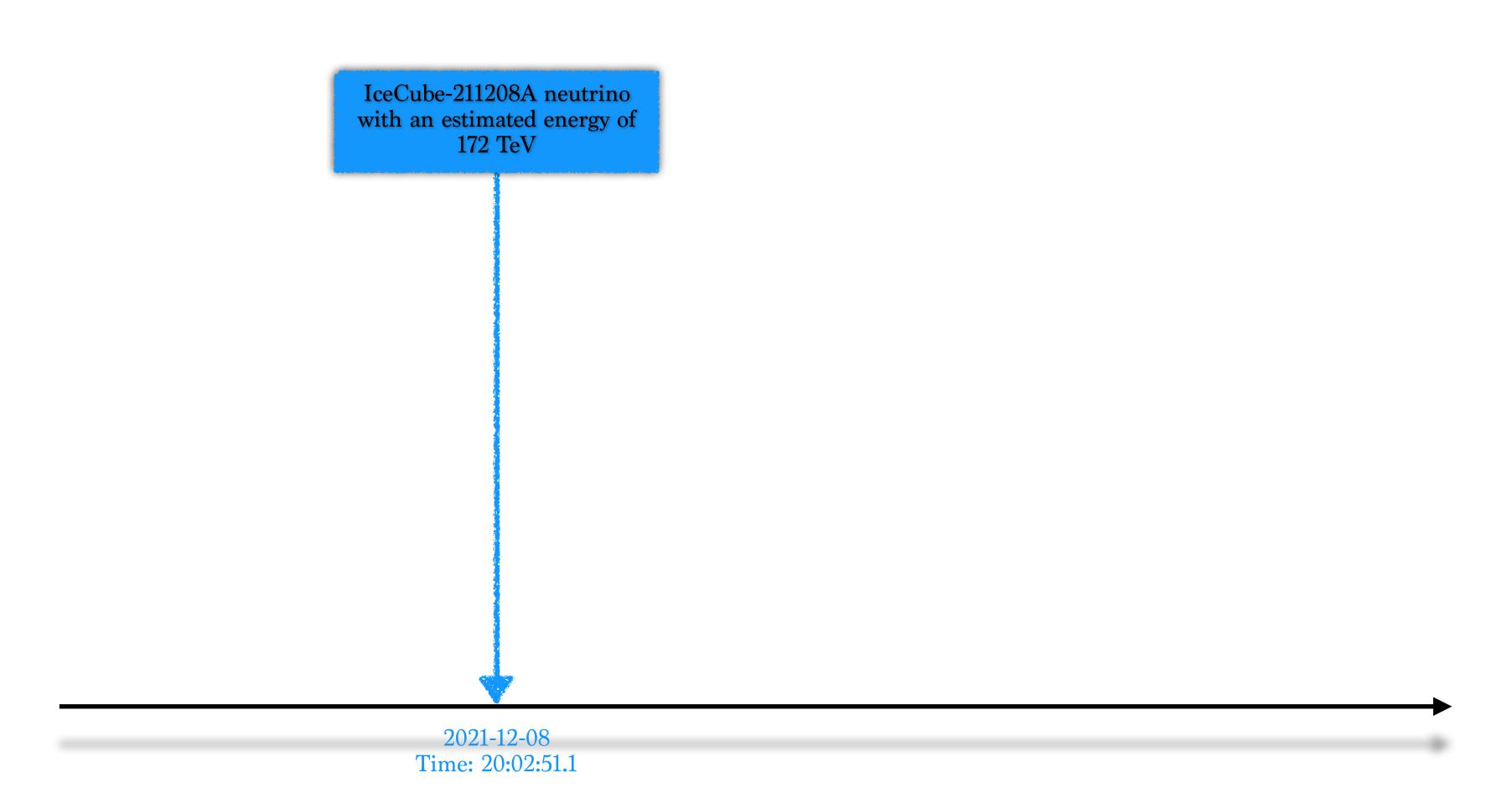


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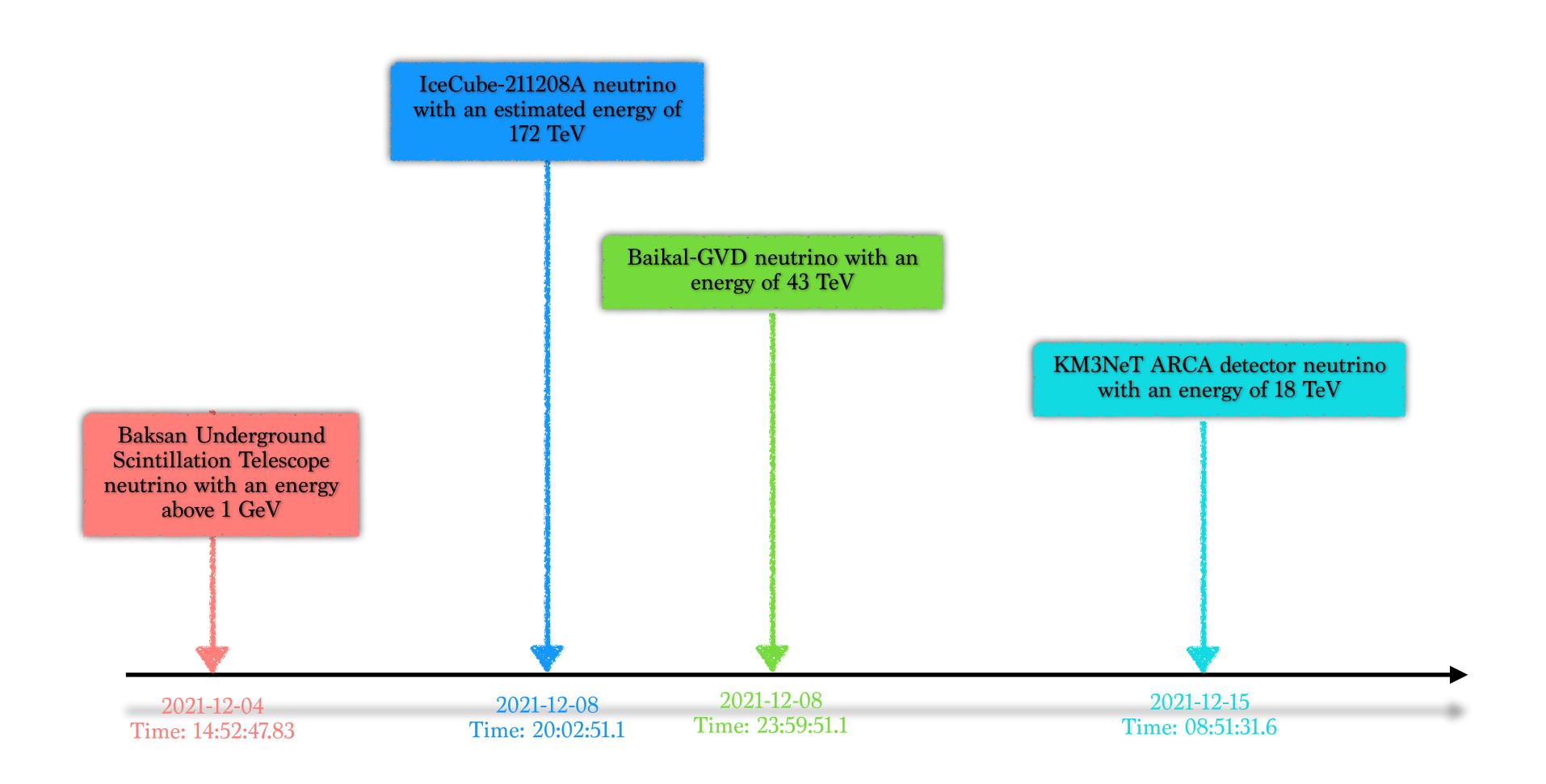




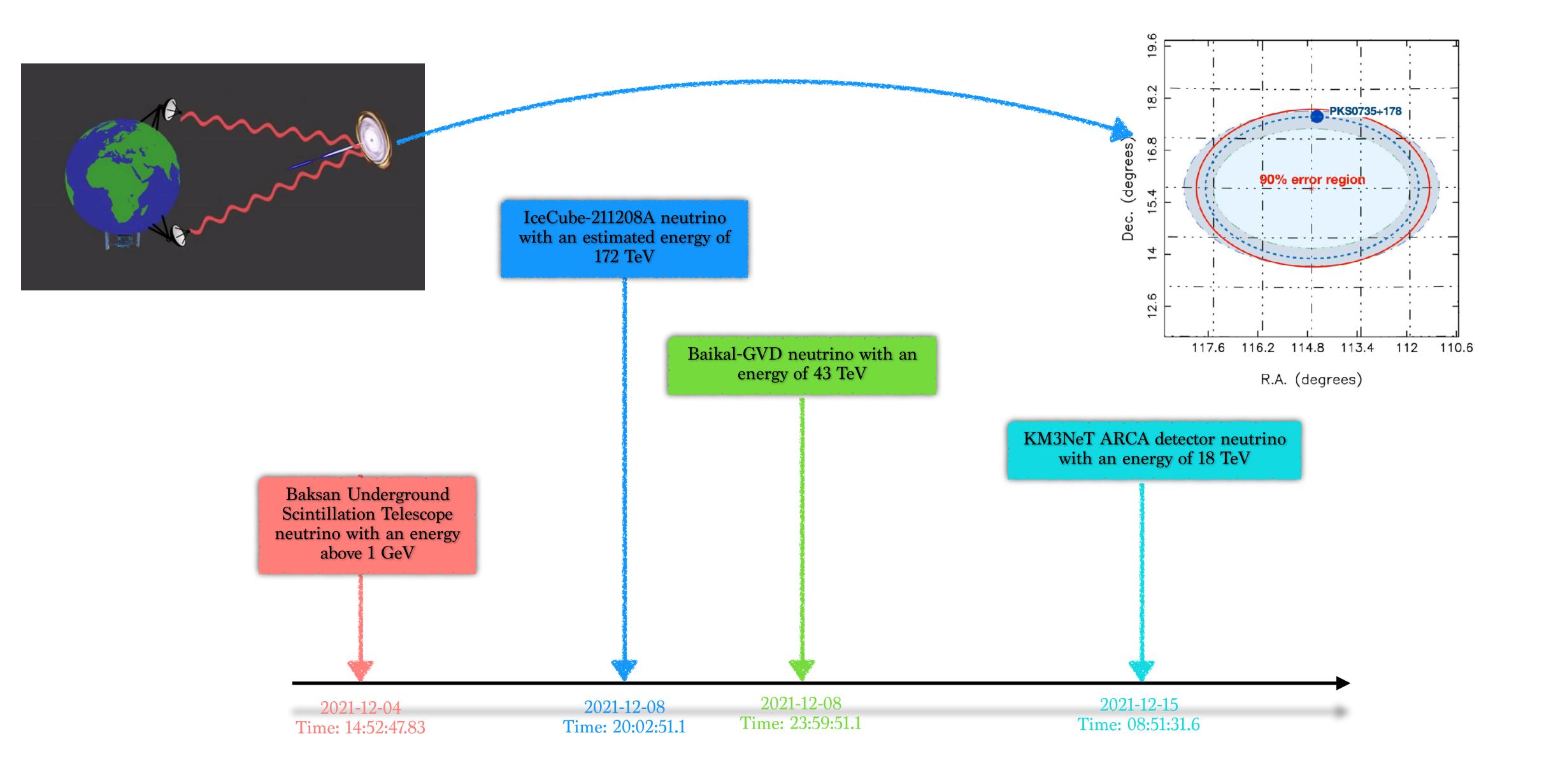
Neutrinos from PKS 0735+178



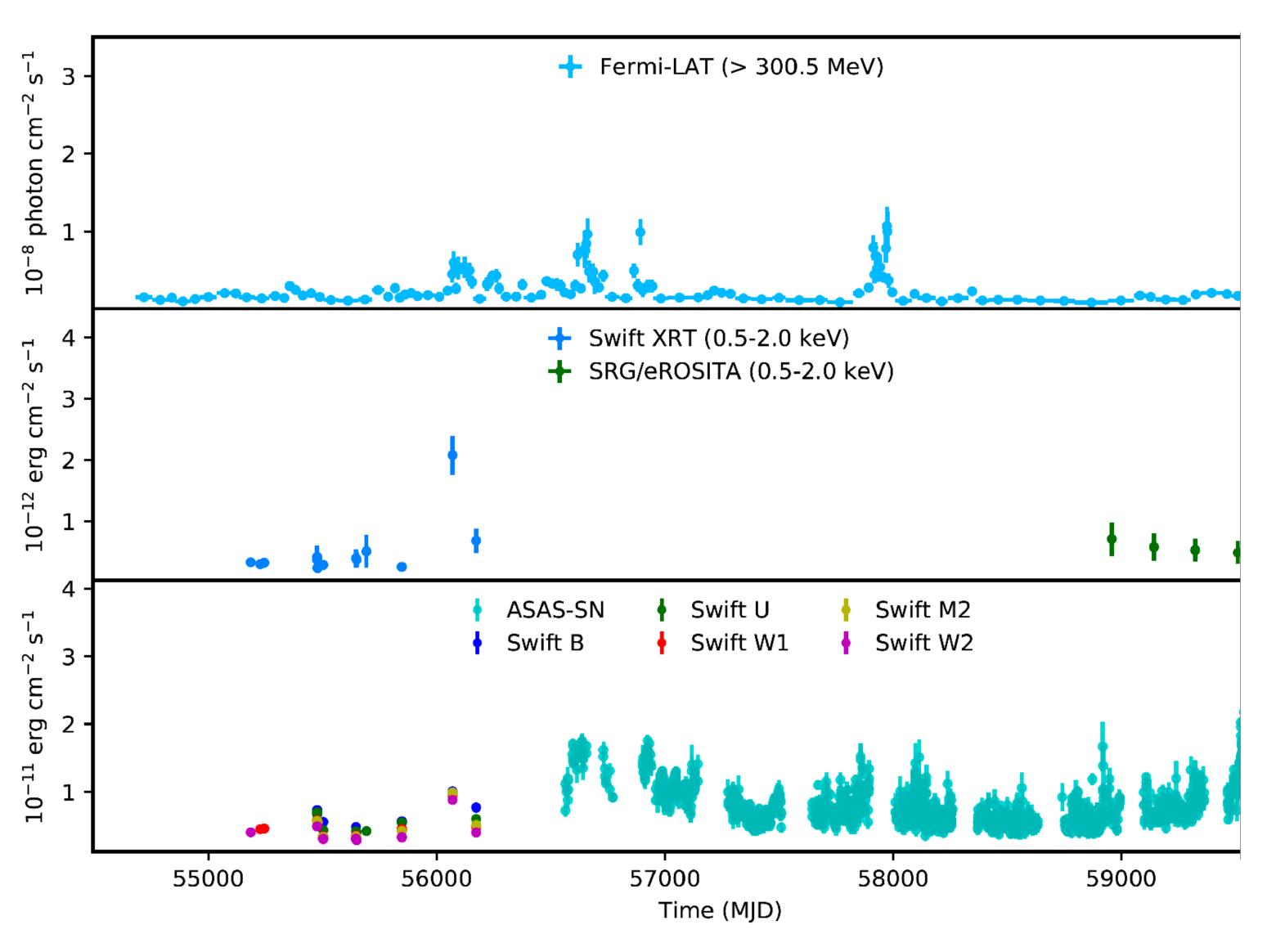
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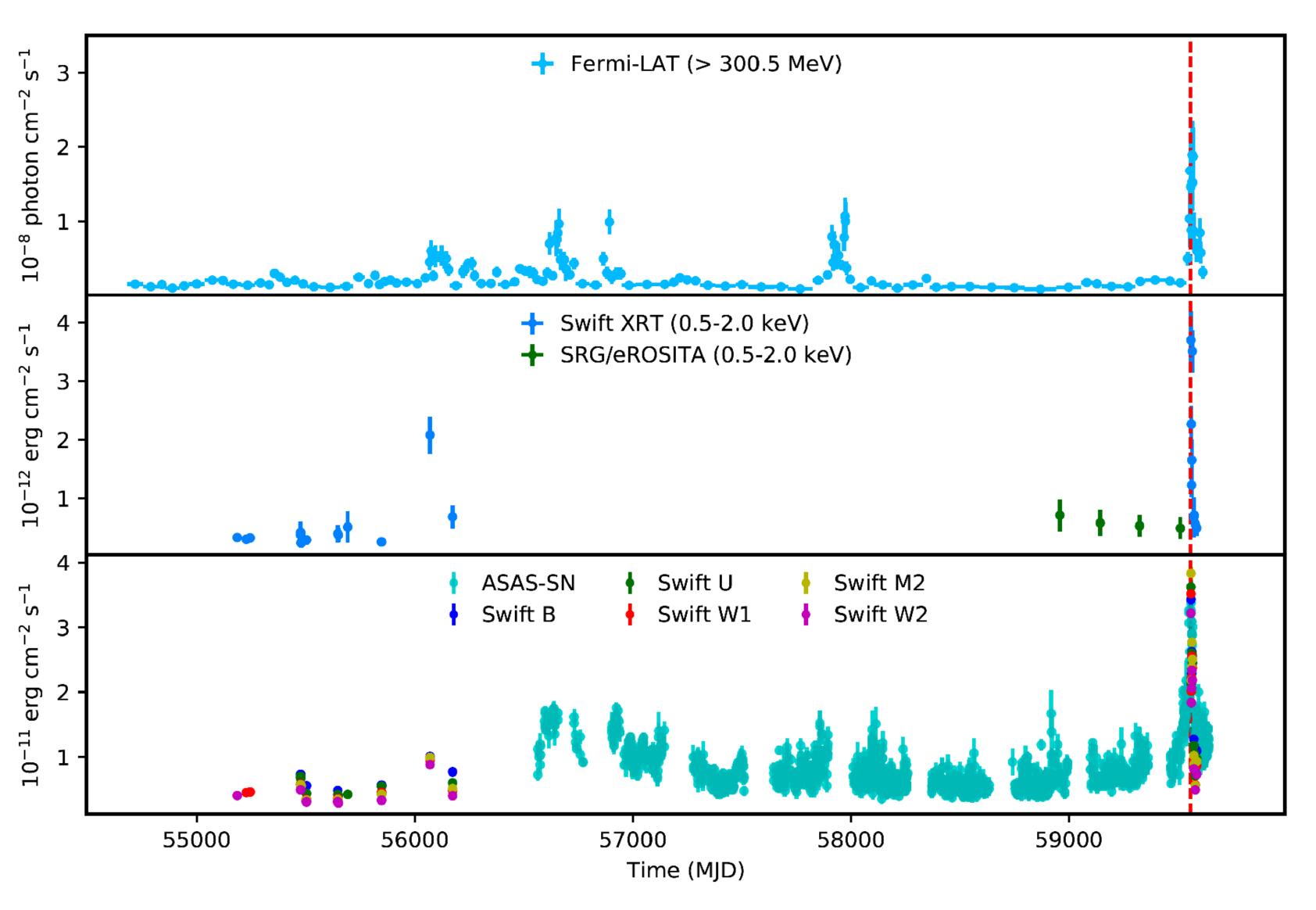


MW lightcurve of PKS 0735+178



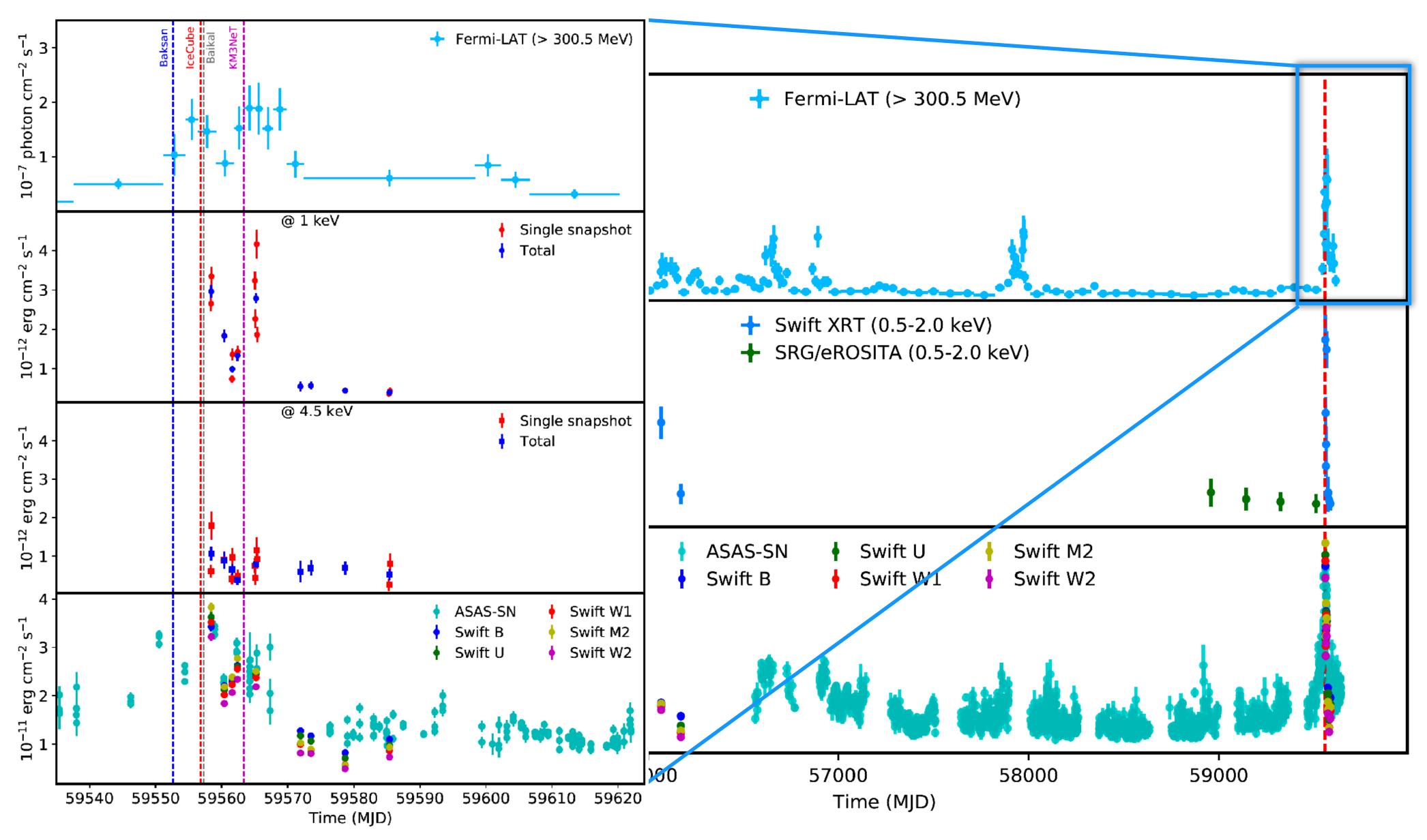
Sahakyan, Giommi, Padovani, et al., MNRAS, 2023

MW lightcurve of PKS 0735+178



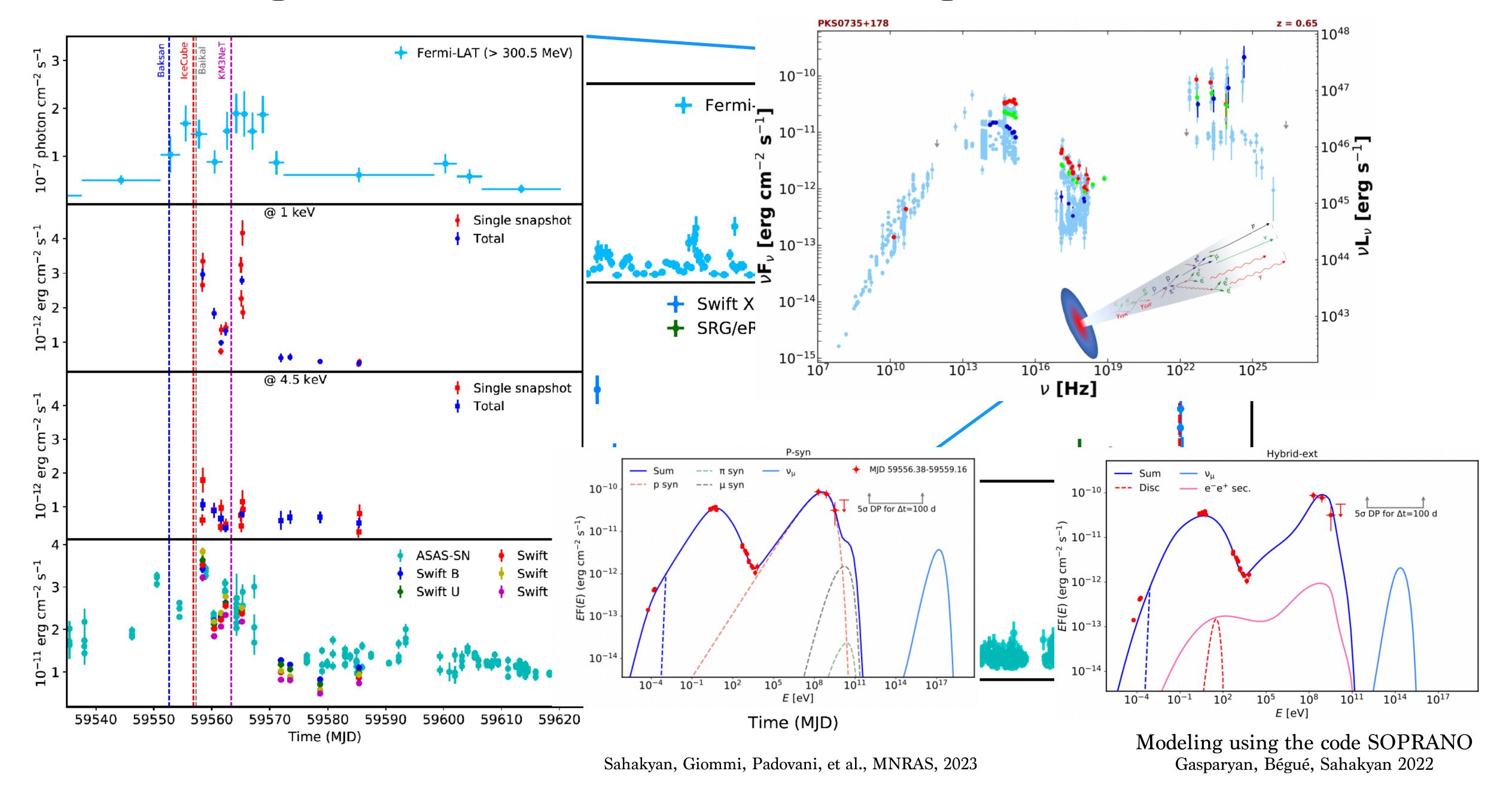
Sahakyan, Giommi, Padovani, et al., MNRAS, 2023

MW lightcurve of PKS 0735+178 and origin of the emission

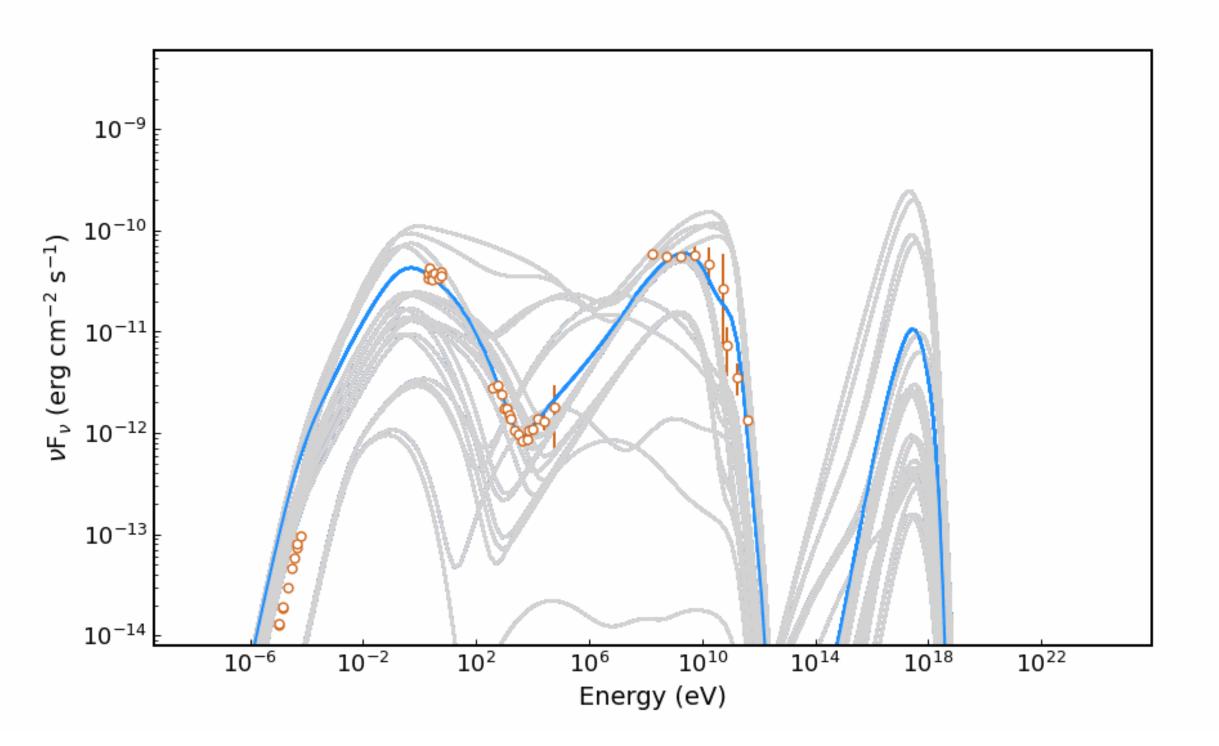


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Computational Challenges and ML-based Solutions



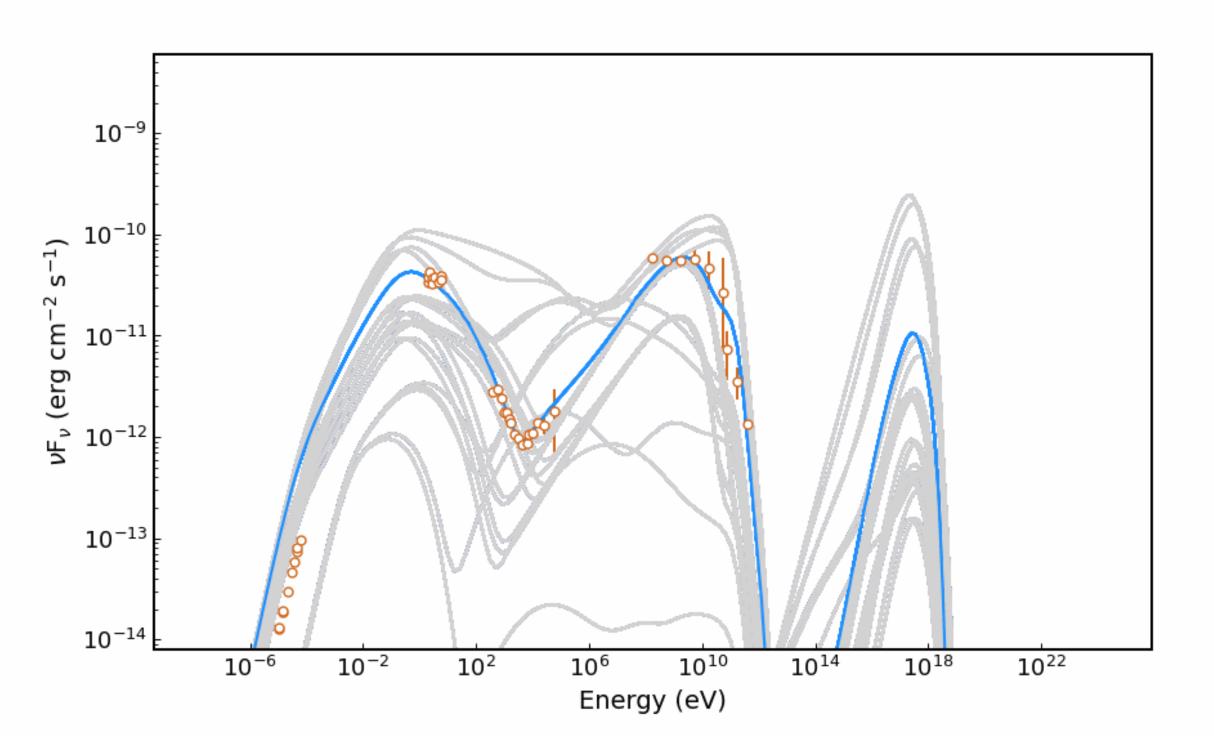
Traditional Modeling:

- Frequent likelihood evaluations, making computations time-consuming.
- O Models computed for each dataset, resulting in redundant and costly computations.
- O For Bayesian fitting, models must be evaluated 10⁴-10⁵times.

Computation Time Estimates (8 cores):

- \bigcirc SSC / EIC model: ~30 sec \rightarrow 3.5 35 days
- O Hadronic model: $\sim 90 \text{ sec} \rightarrow 10 100 \text{ days}$

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Machine Learning for Accelerated Model computations:

- Efficient: avoids exhaustive parameter space exploration.
- Reusable across different datasets after training.
- Several orders-of-magnitude faster evaluations.

References:

- M Bégué, Sahakyan et al., ApJ, 963, 71 (2024)
- M Sahakyan, Bégué et al., ApJ, 971, 70 (2024)
- Mac Sahakyan, Bégué et al., ApJ, 990, 222 (2025)

Parameter	Units	Symbol	Minimum	Maximum	Type of distribution
Doppler boost	_	δ	3.5	100	Linear
Blob radius	\mathbf{cm}	\mathbf{R}	$10^{14.5}$	10^{18}	Logarithmic
Minimum electron injection Lorentz factor	-	$\gamma_{\rm e,min}$	$10^{1.5}$	10^5	Logarithmic
Maximum electron injection Lorentz factor	-	$\gamma_{ m e,max}$	10^{2}	10^{8}	Logarithmic
Maximum proton injection Lorentz factor	-	$\gamma_{ m p,max}$	10^{3}	10^{11}	Logarithmic
Injection index electrons	-	p_e	1.7	5	Linear
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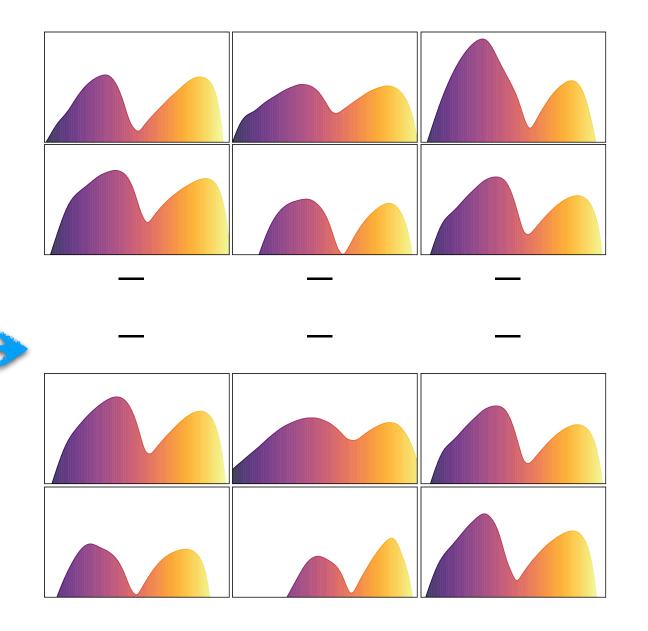
Gasparyan, Bégué, Sahakyan 2022



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Gasparyan, Bégué, Sahakyan 2022

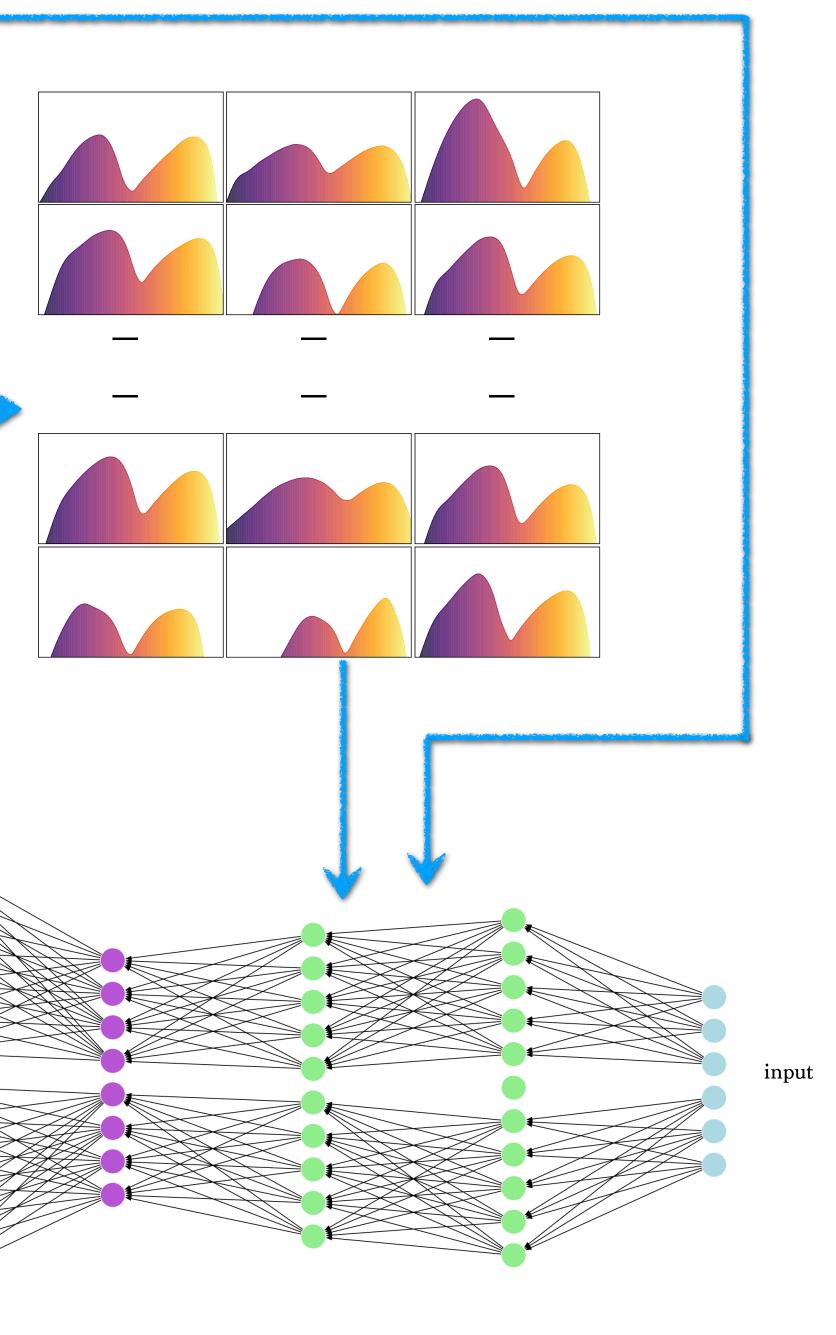




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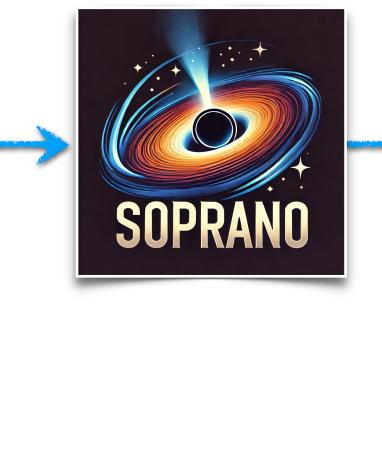
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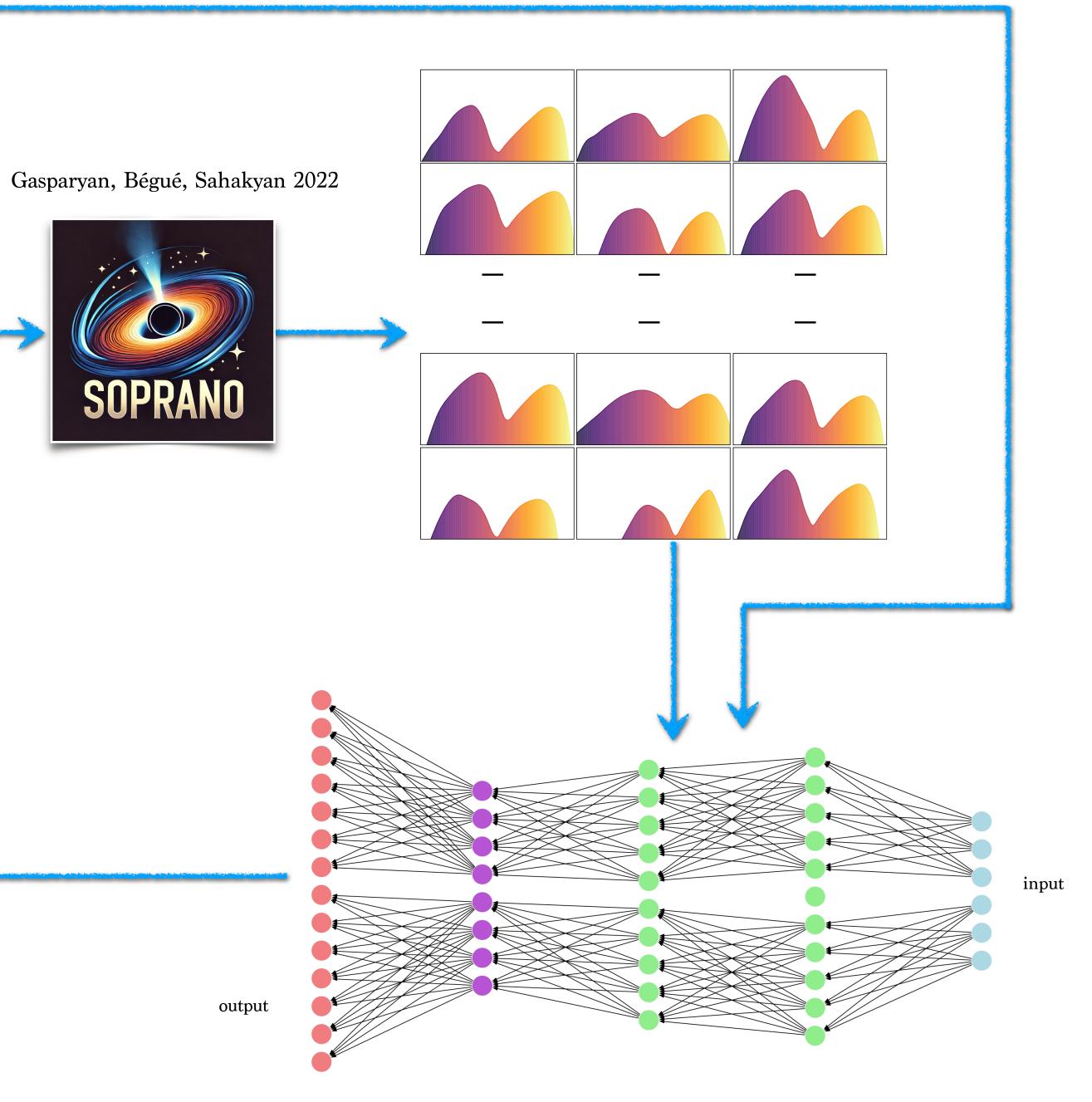


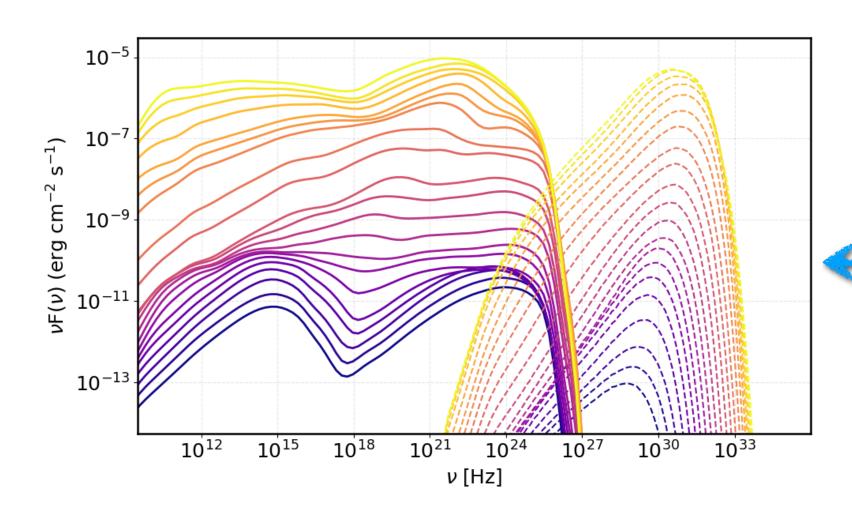
output

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output





Convolutional Neural Network

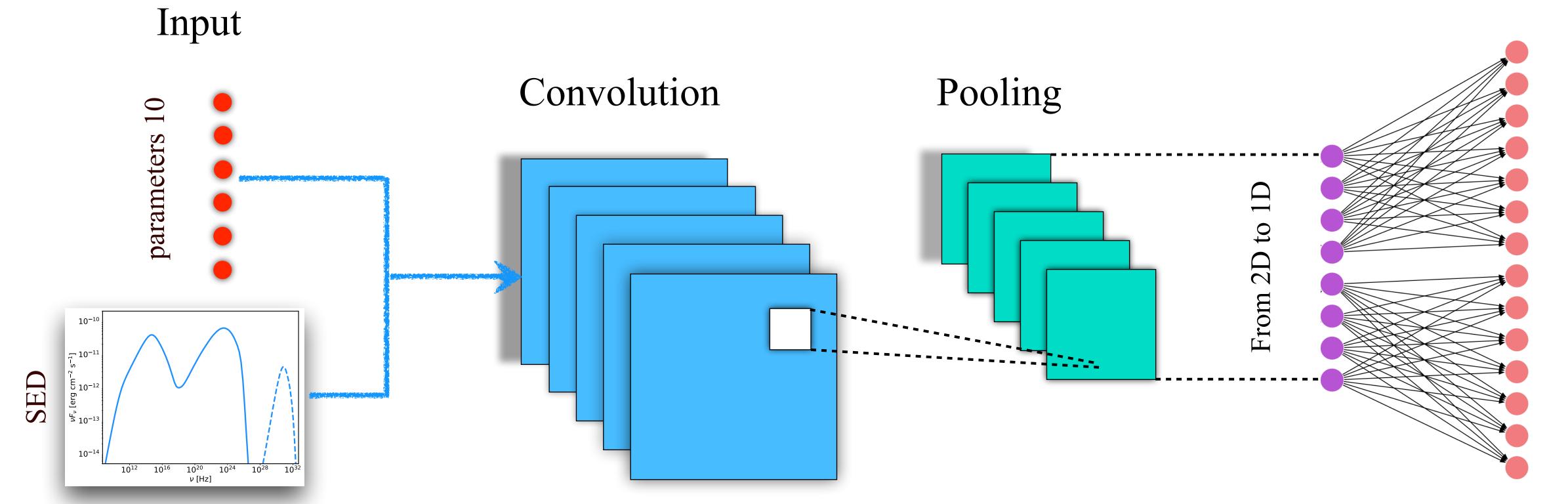
Why CNN?

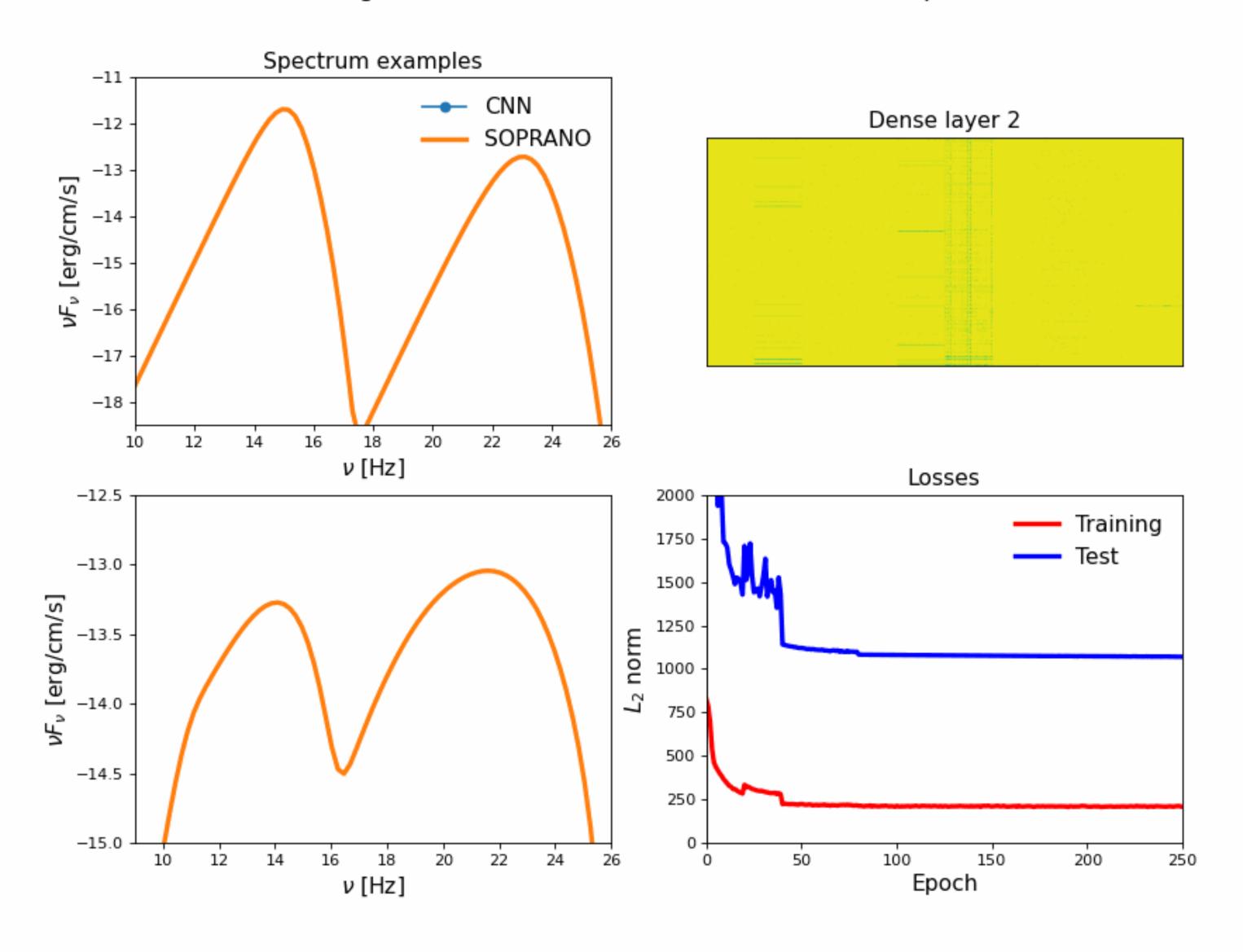
- Structured Data Handling: Ideal for 1D structured inputs like spectra and time-series.
- O Pattern Recognition: Detects local emission features
- O Parameter Scalability: Scales well with complex, high-dimensional inputs.

Architecture Overview

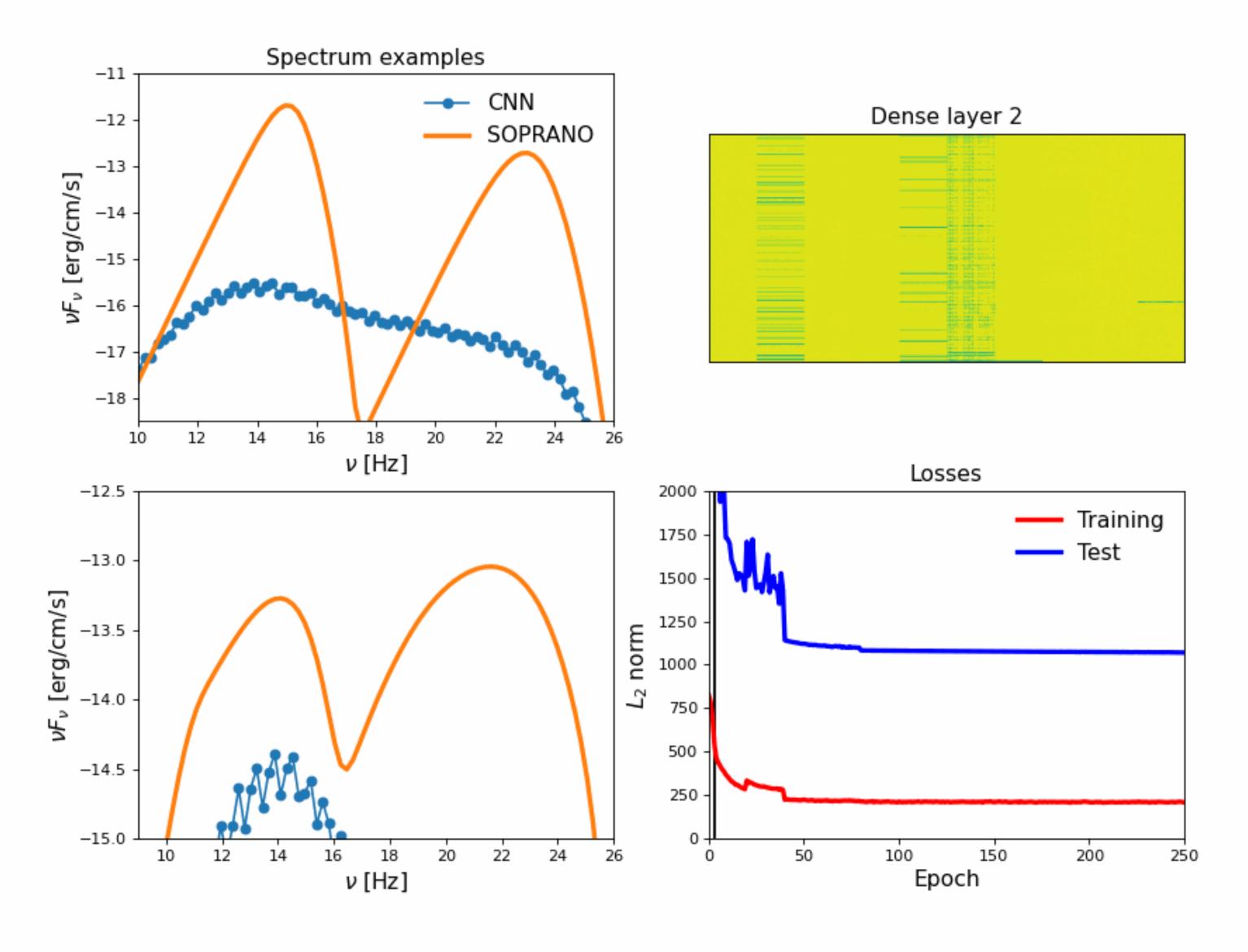
- Input: 10 physical parameters
- \bigcirc Dense → 5×Conv1D → MaxPool → Flatten → Dense
- Output: 150 independent observables

Output

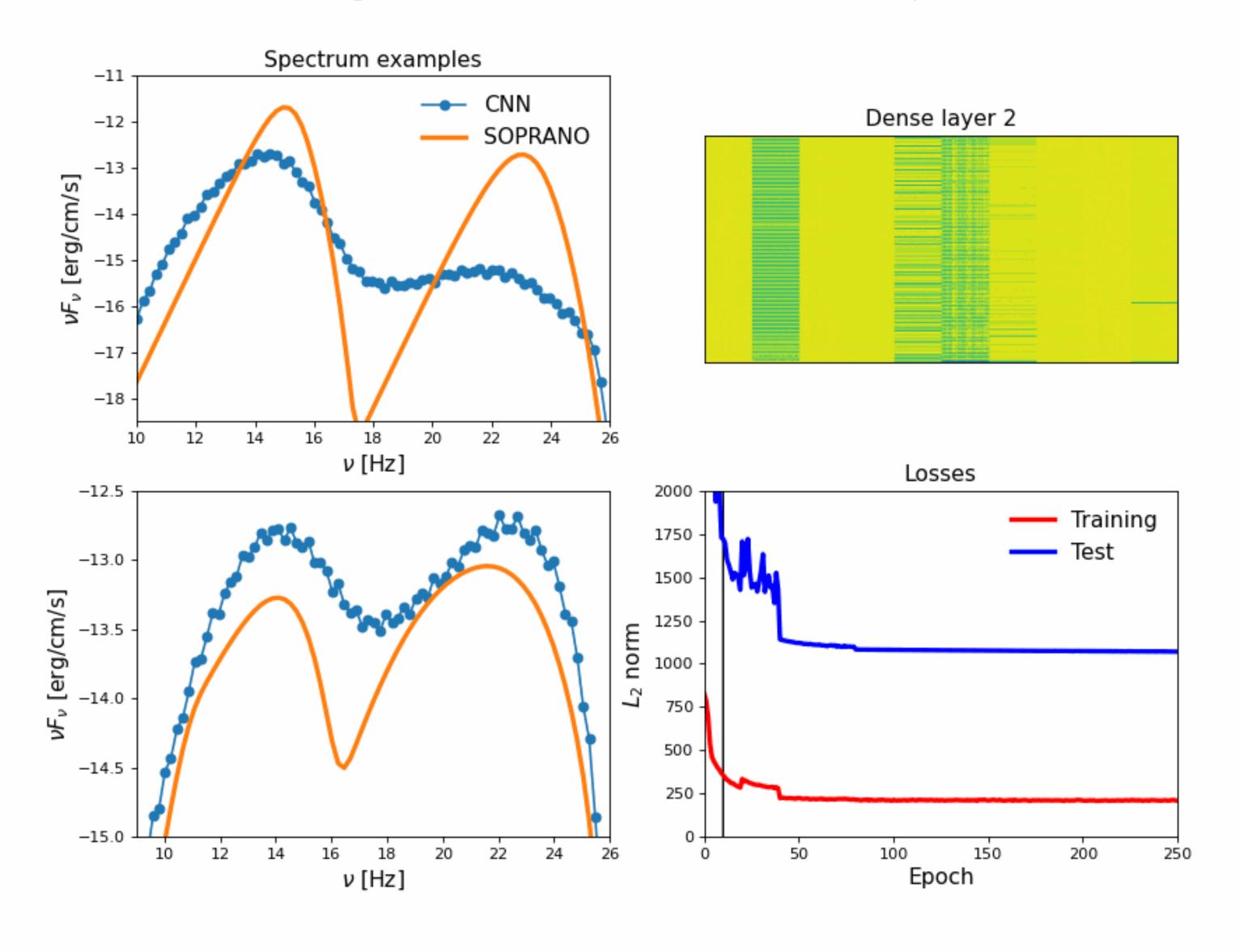




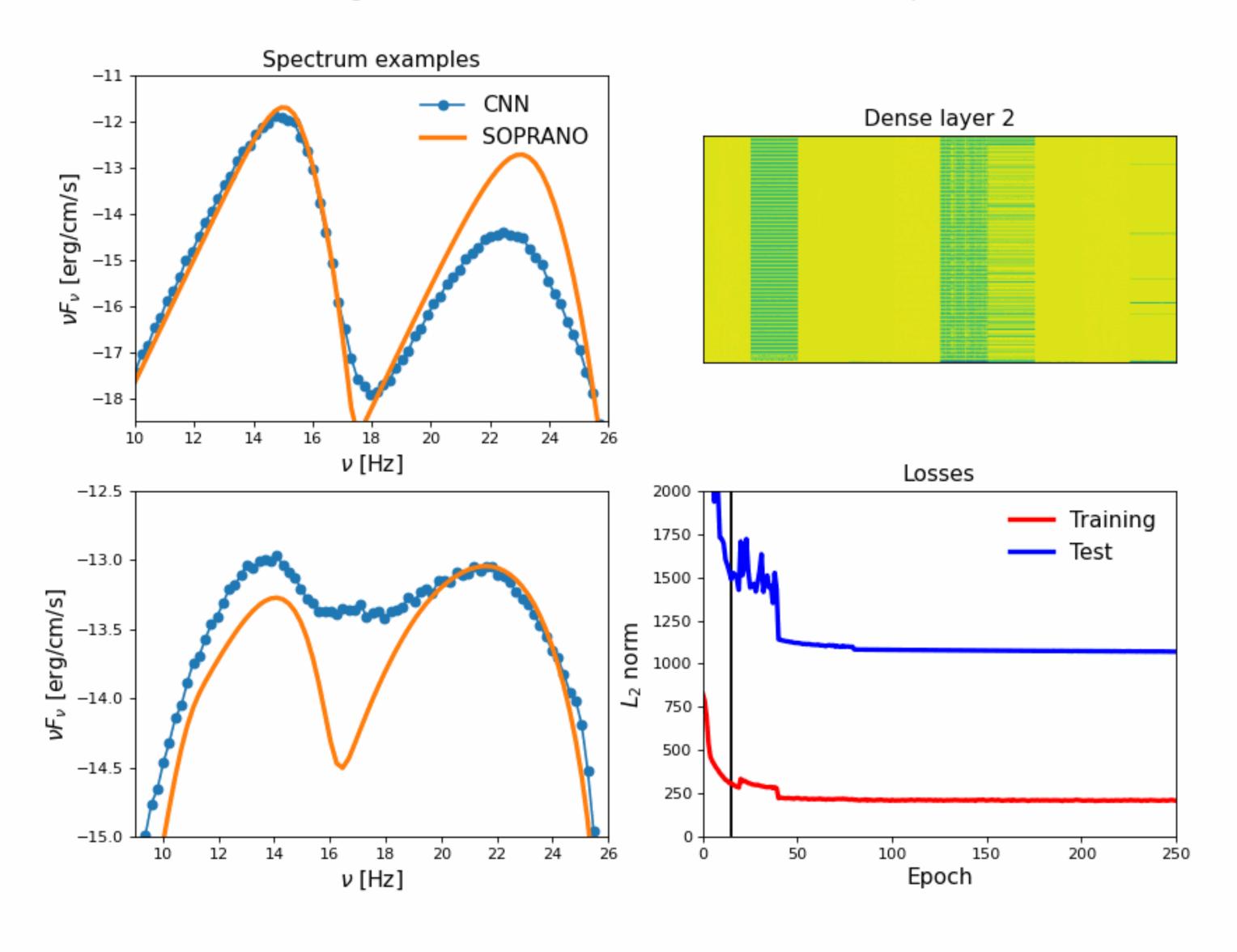
from D. Bégué (https://www.youtube.com/watch?v=L3KxgWYghHE)



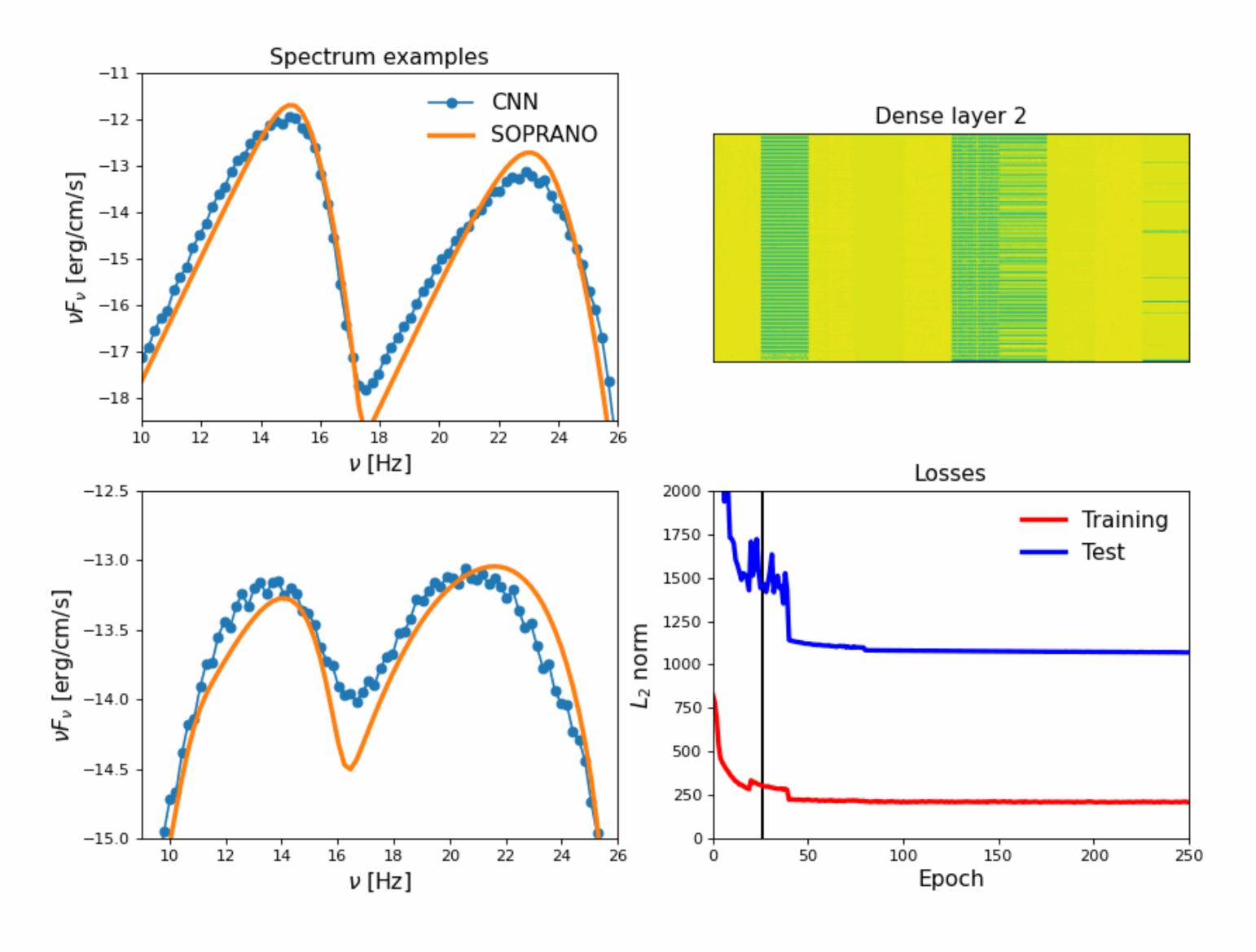
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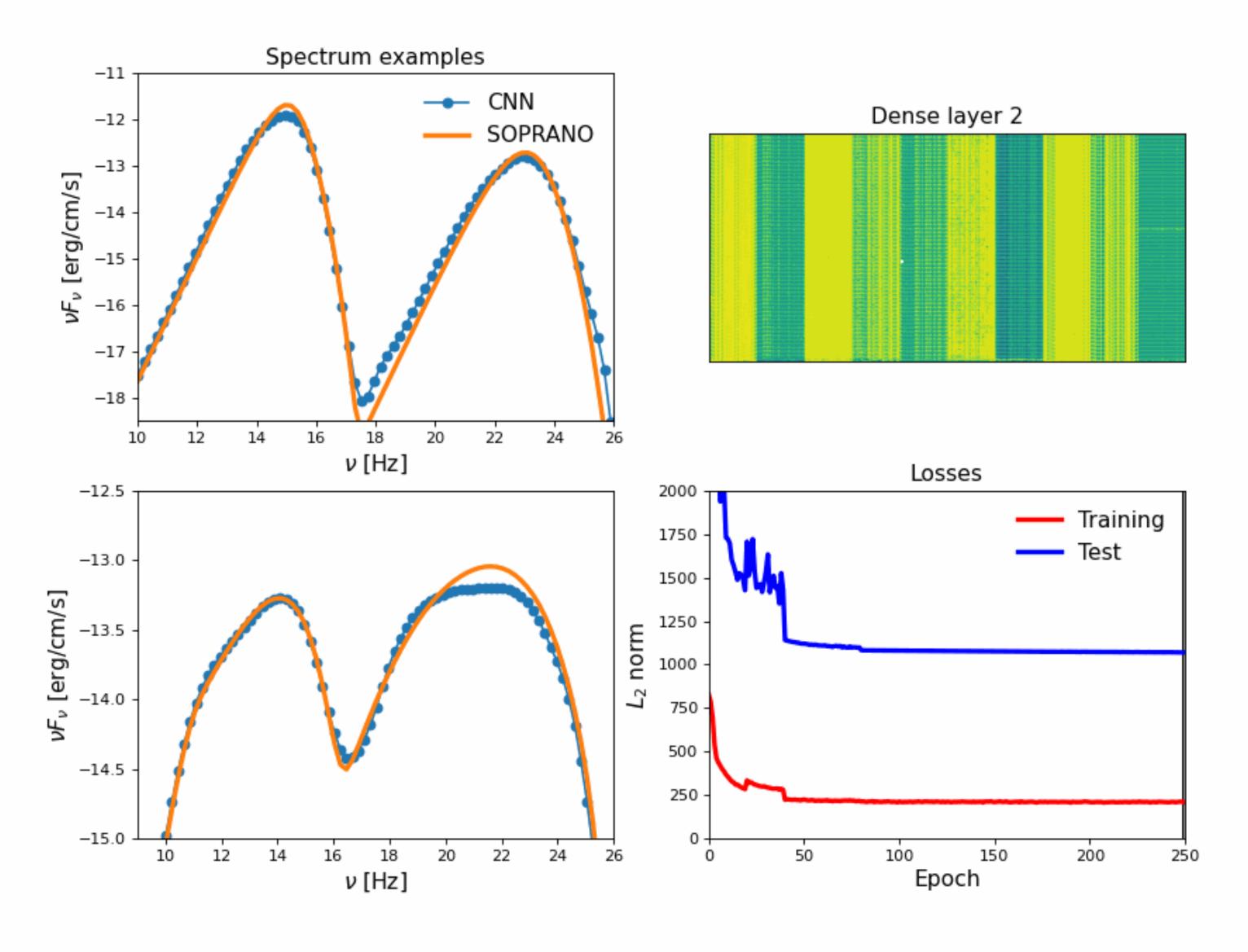
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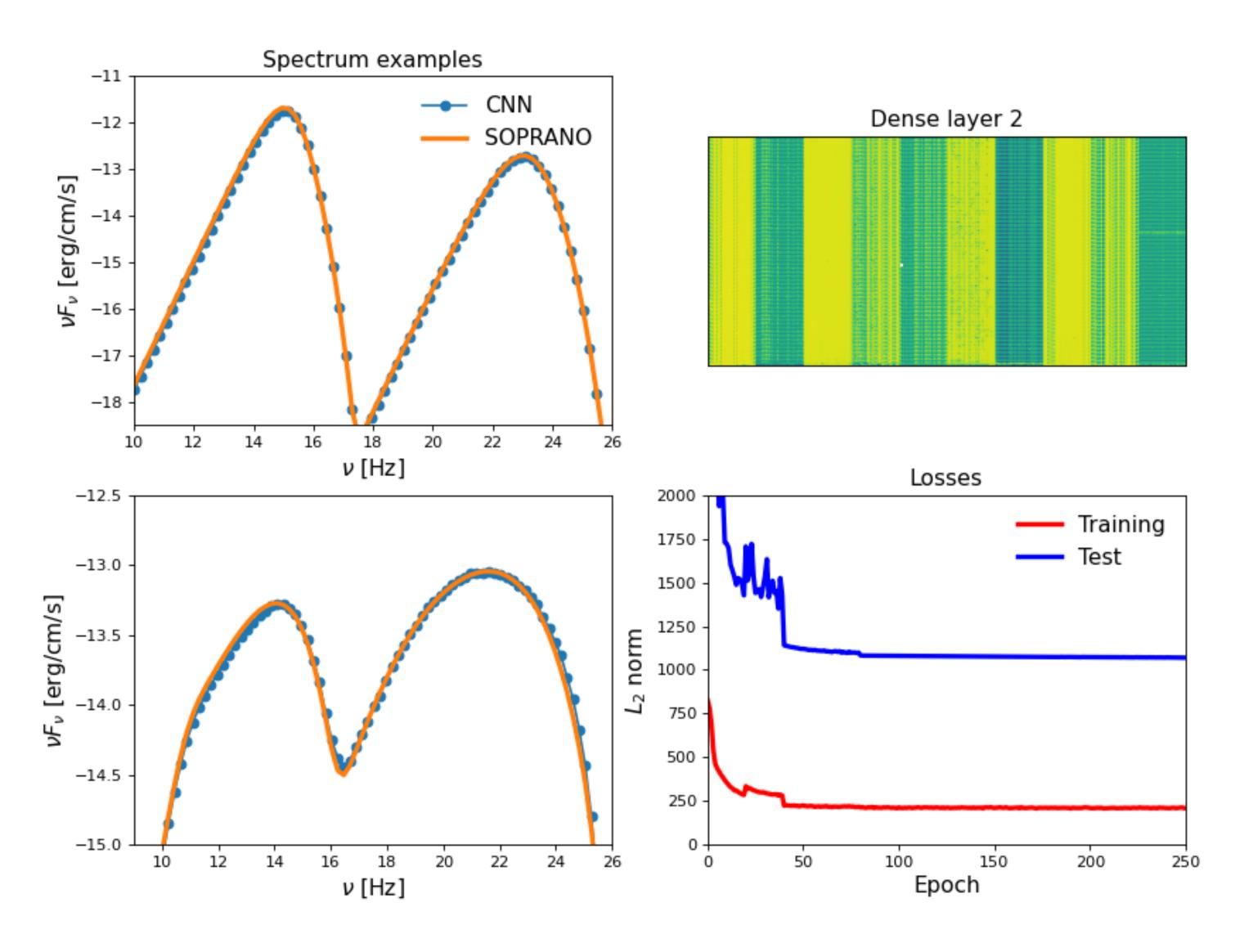


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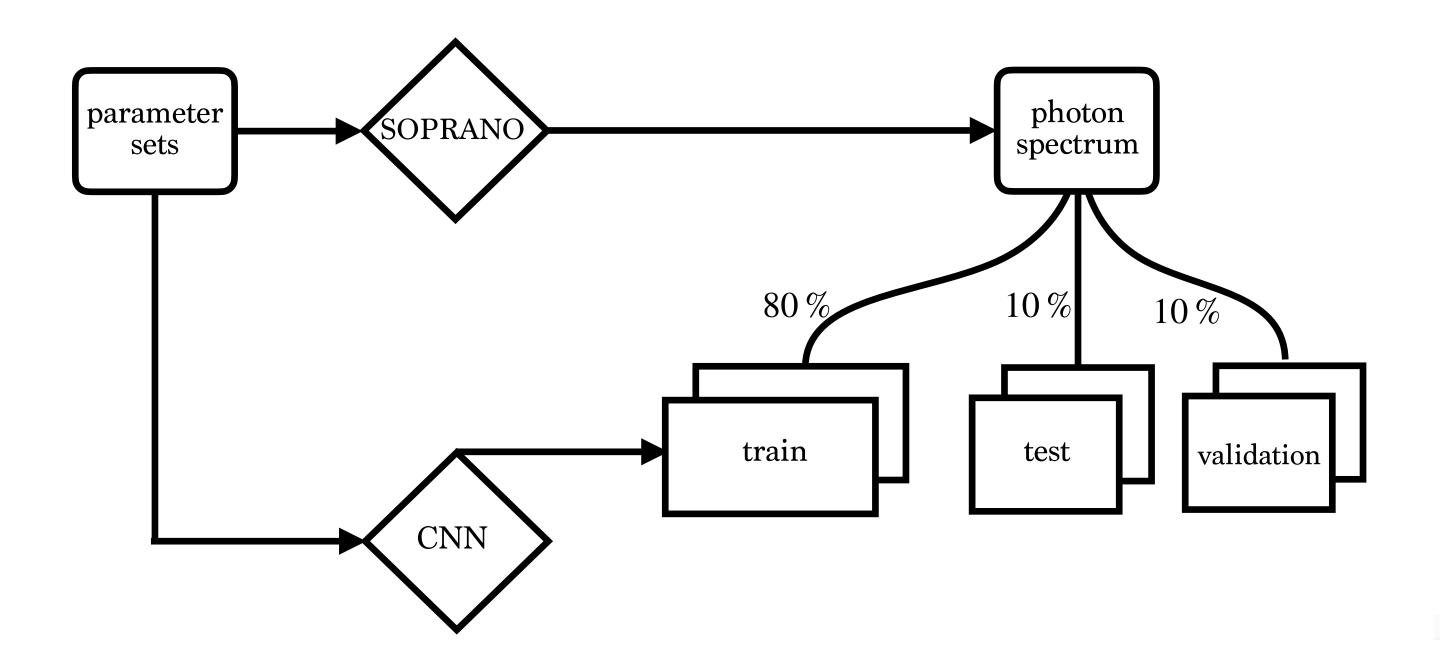
Training of the SSC model. Full database

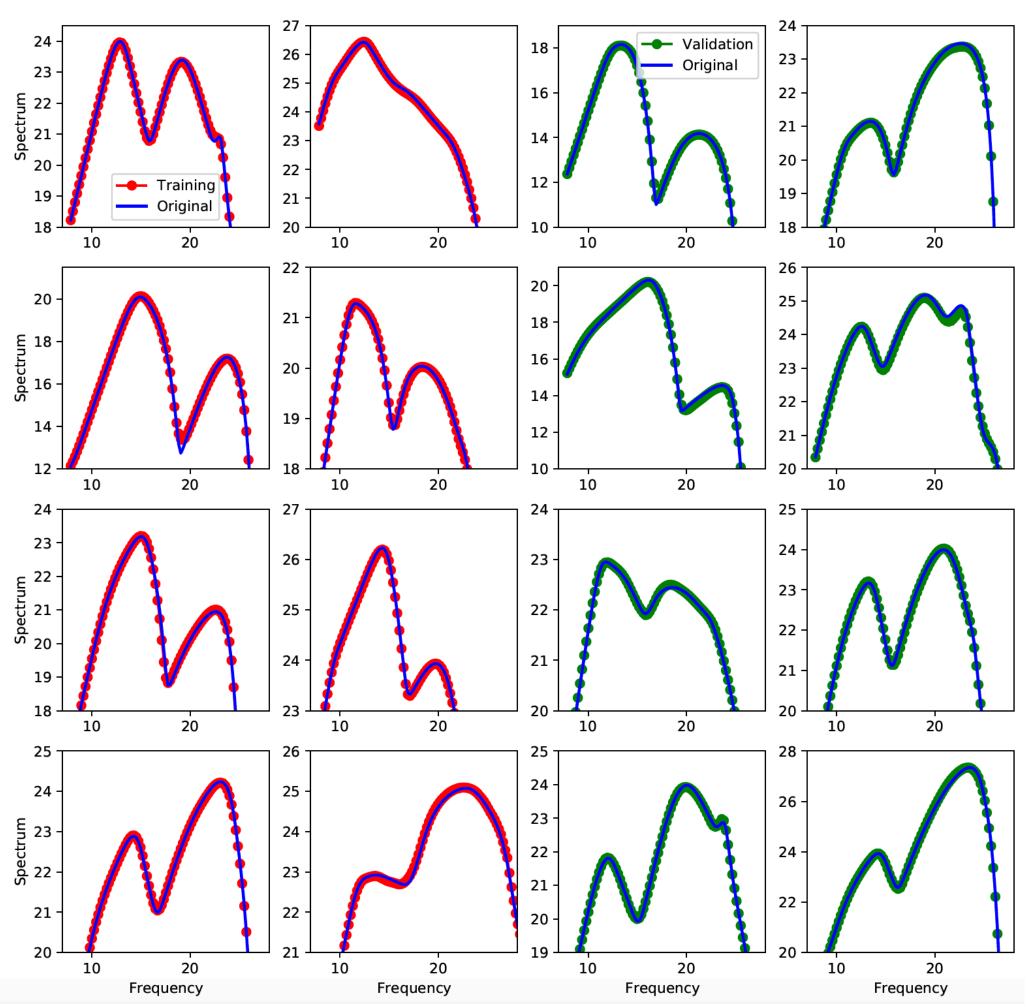


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Training CNN Surrogates for Hadronic Blazar Models

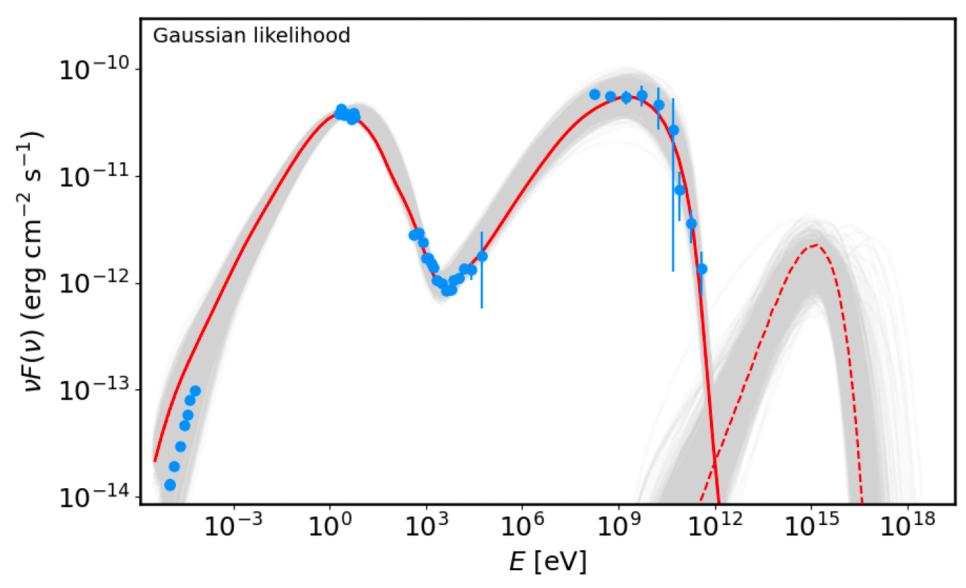
- O CNN trained on 7 million spectra generated using the SOPRANO code.
- O Training spans 10-dimensional parameter space with broad, physically motivated ranges.





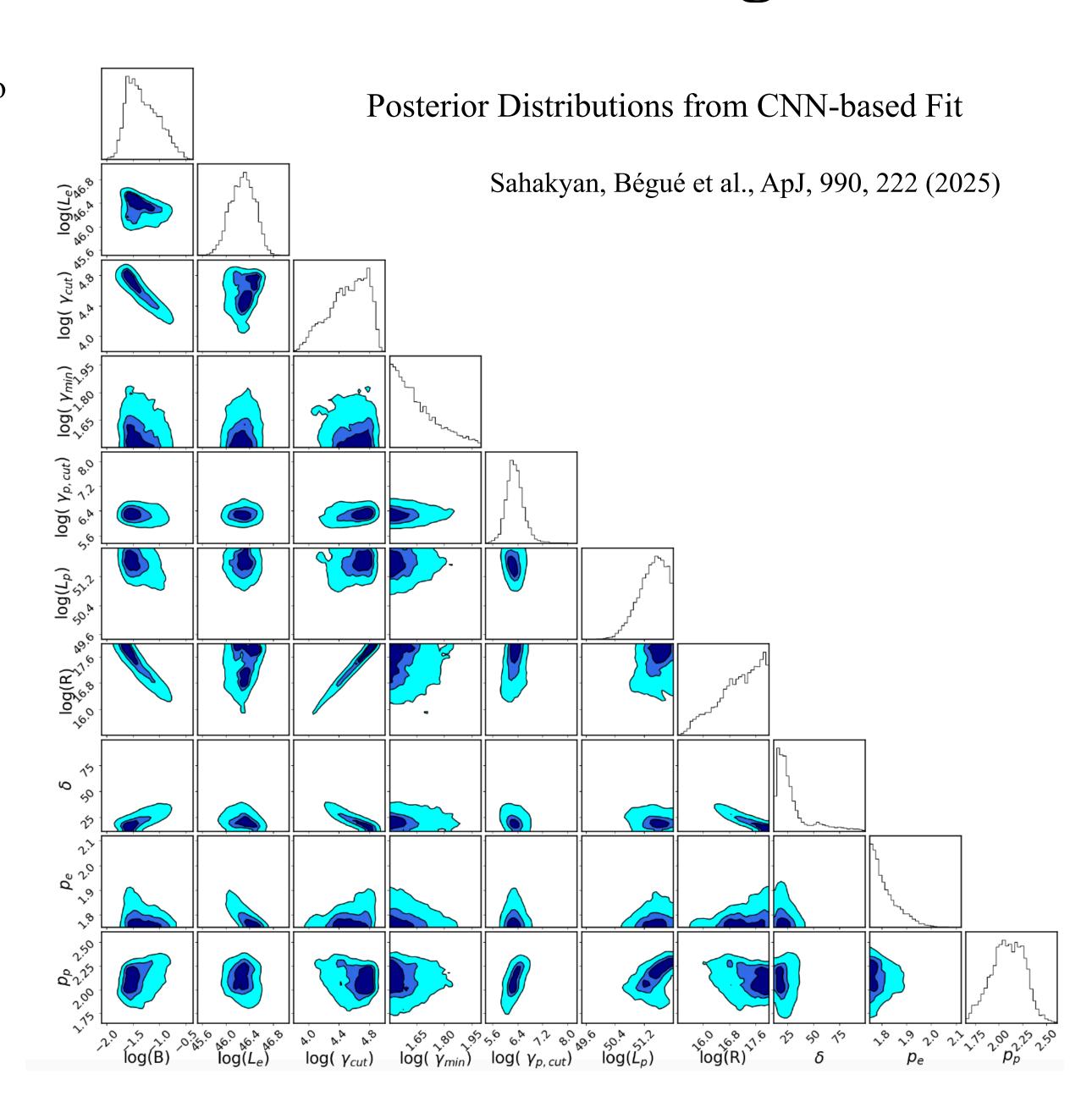
Parameter Estimation in hadronic Modeling

Modeling the SED of TXS 0506+056 during the IceCube-170922A neutrino event using a convolutional neural network trained on hadronic models.



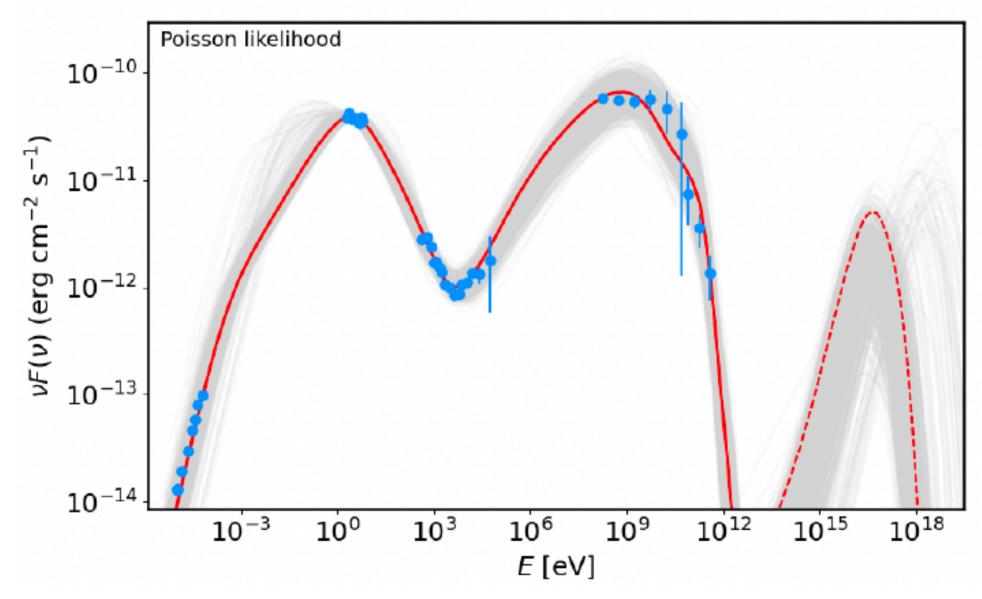
Model parameters for TXS 0506+059

Parameter	Value	Parameter	Value
p_e	1.77	p_p	2.03
$\log_{10}(\gamma_{ m e,max})$	4.76	$\log_{10}(\gamma_{ m e,min})$	1.52
$\log_{10}(\gamma_{ m p,max})$	6.37	δ	15.49
$\log_{10}(B[ext{G}])$	-1.52	$\log_{10}(R[ext{cm}])$	17.76
$\log_{10}(L_{ m e}[{ m erg/s}])$	46.50	$\log_{10}(L_{ m p}[{ m erg/s}])$	51.18



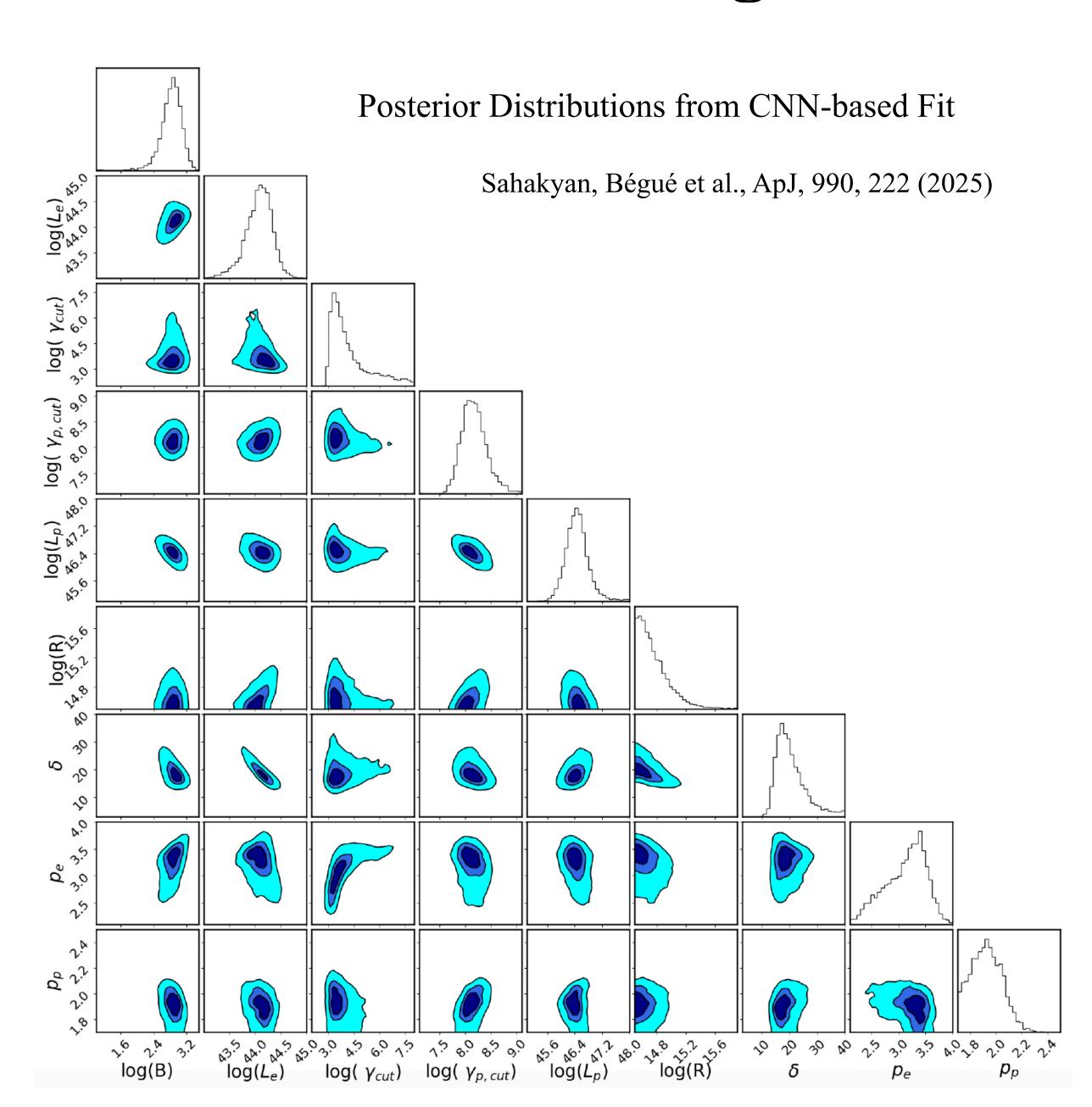
Parameter Estimation in hadronic Modeling

Modeling the SED of TXS 0506+056 during the IceCube-170922A neutrino event using a convolutional neural network trained on hadronic models.



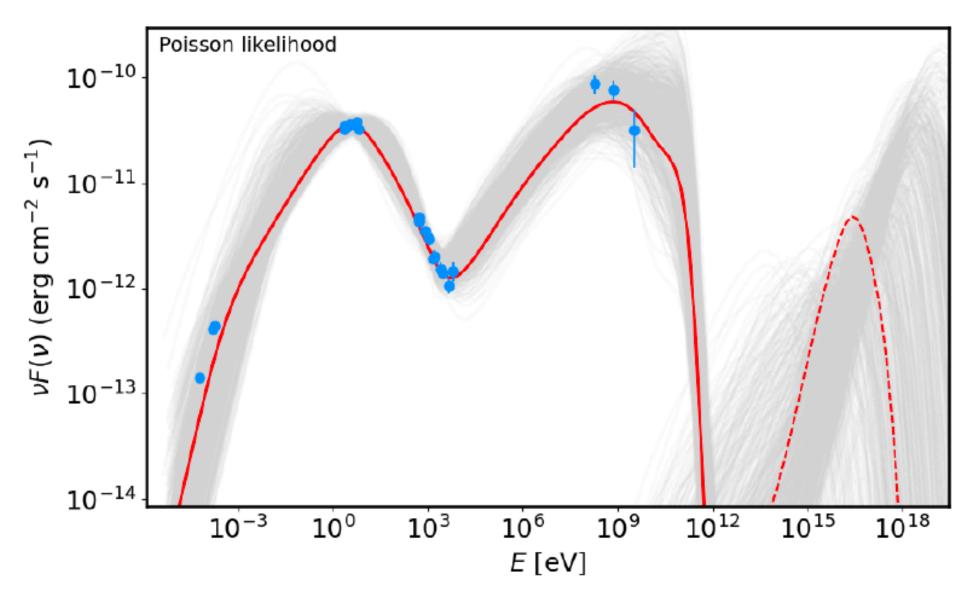
Model parameters for TXS 0506+059

Parameter	Value	Parameter	Value
p_e	2.87	p_p	2.00
$\log_{10}(\gamma_{ m e,max})$	3.25	$\log_{10}(\gamma_{ m e,min})$	2.00
$\log_{10}(\gamma_{ m p,max})$	8.00	δ	23.18
$\log_{10}(B[ext{G}])$	2.73	$\log_{10}(R[ext{cm}])$	14.53
$\log_{10}(L_{ m e}[{ m erg/s}])$	43.99	$\log_{10}(L_{ m p}[{ m erg/s}])$	46.69



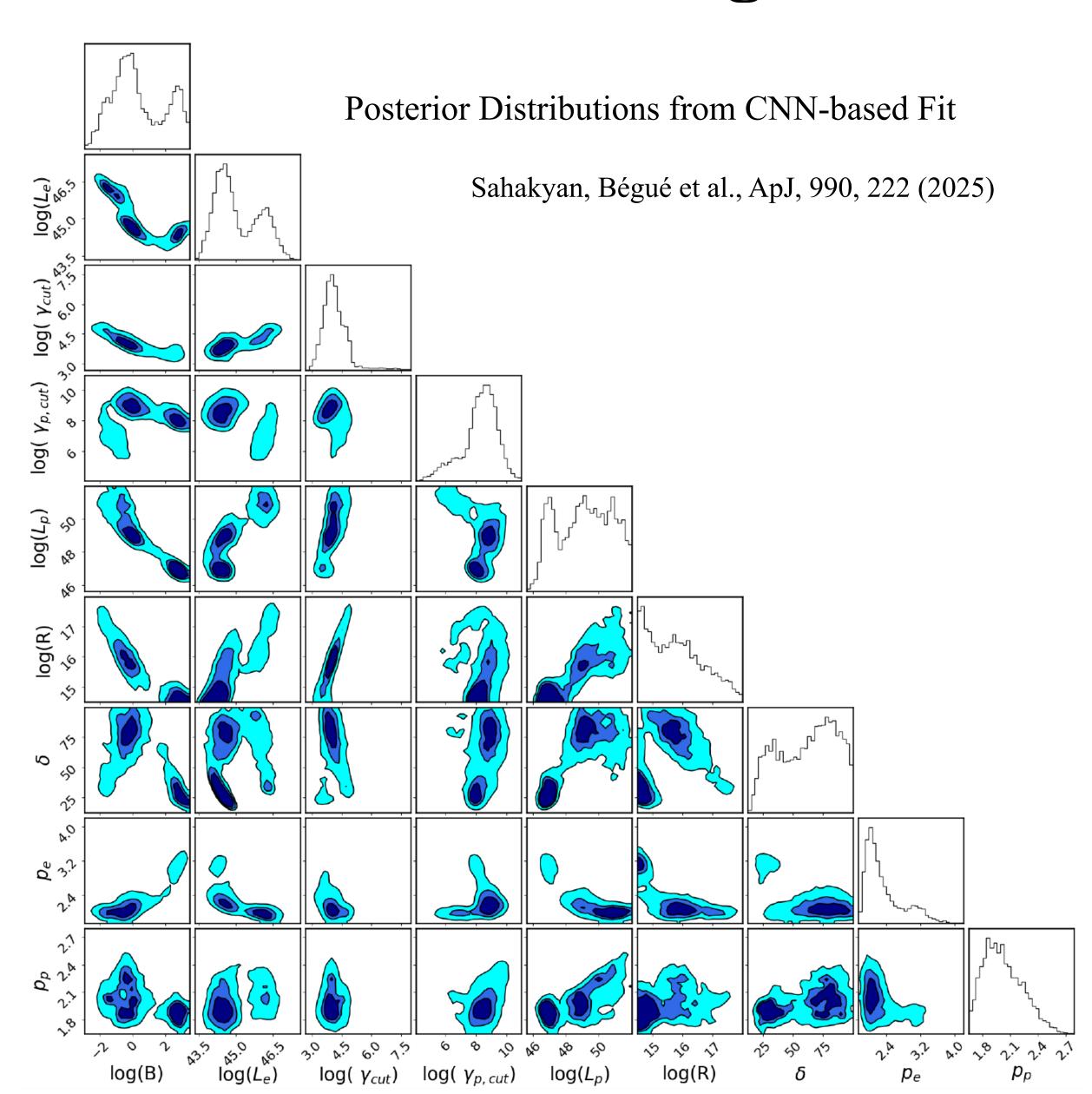
Parameter Estimation in hadronic Modeling

Modeling the SED of PKS 0735+178 during the IceCube-211208A neutrino event using a convolutional neural network trained on hadronic models.



Model parameters for PKS 0735+178

Parameter	Value	Parameter	Value
p_e	2.62	p_p	1.87
$\log_{10}(\gamma_{ m e,max})$	3.10	$\log_{10}(\gamma_{ m e,min})$	2.00
$\log_{10}(\gamma_{ m p,max})$	7.95	δ	26.00
$\log_{10}(B[ext{G}])$	2.88	$\log_{10}(R[ext{cm}])$	14.55
$\log_{10}(L_{ m e}[{ m erg/s}])$	44.61	$\log_{10}(L_{ m p}[{ m erg/s}])$	46.91



Markarian Multiwavelength Data Center

THE ASTRONOMICAL JOURNAL

OPEN ACCESS

Markarian Multiwavelength Data Center (MMDC): A Tool for Retrieving and Modeling Multitemporal, Multiwavelength, and Multimessenger Data from Blazar Observations

N. Sahakyan, V. Vardanyan, P. Giommi, D. Bégué, D. Israyelyan, G. Harutyunyan, M.

M. Khachatryan, H. Dereli-Bégué, and S. Gasparyan

Published 2024 November 28 • © 2024. The Author(s). Published by the American Astronom

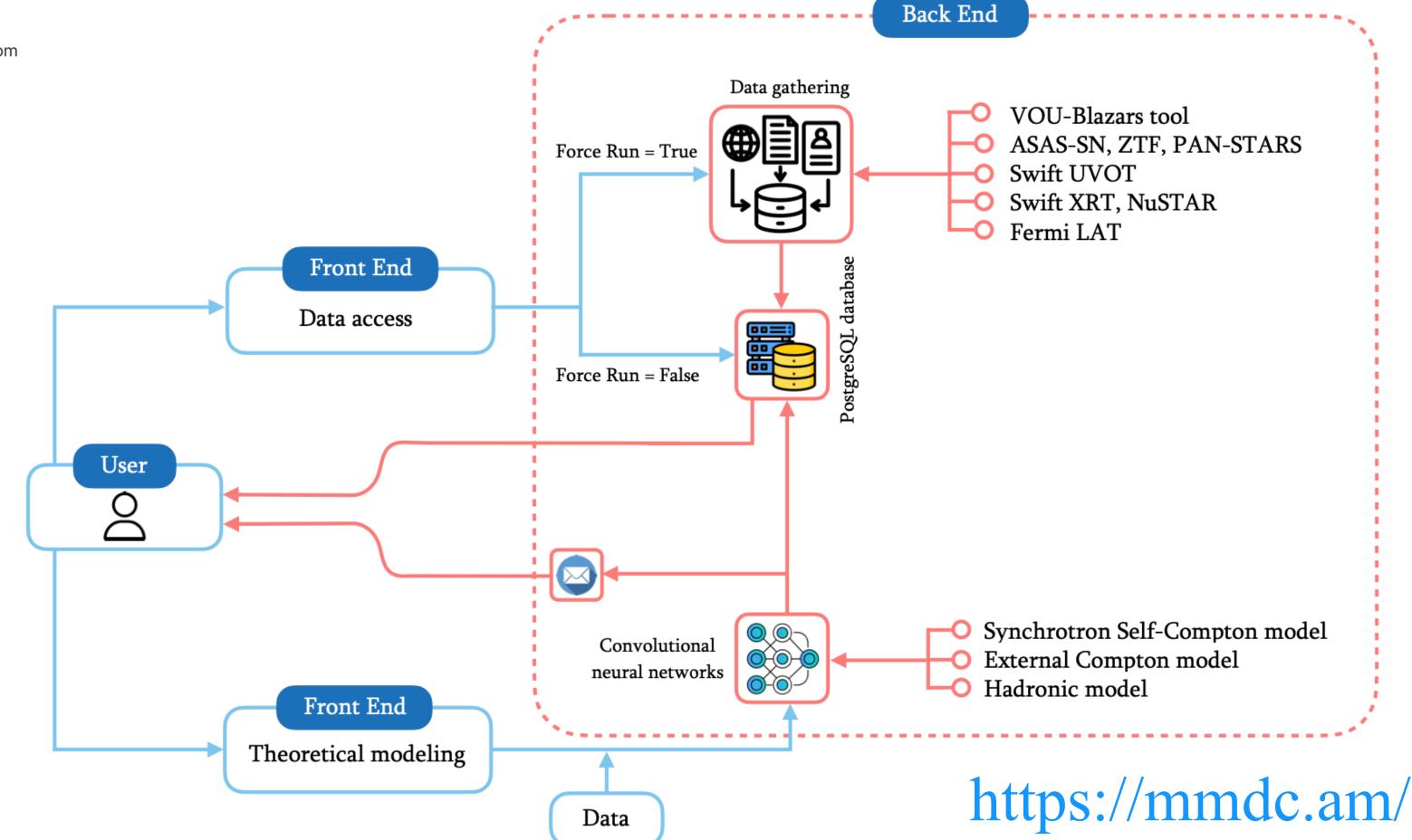
The Astronomical Journal, Volume 168, Number 6

Citation N. Sahakyan et al 2024 AJ 168 289

DOI 10.3847/1538-3881/ad8231

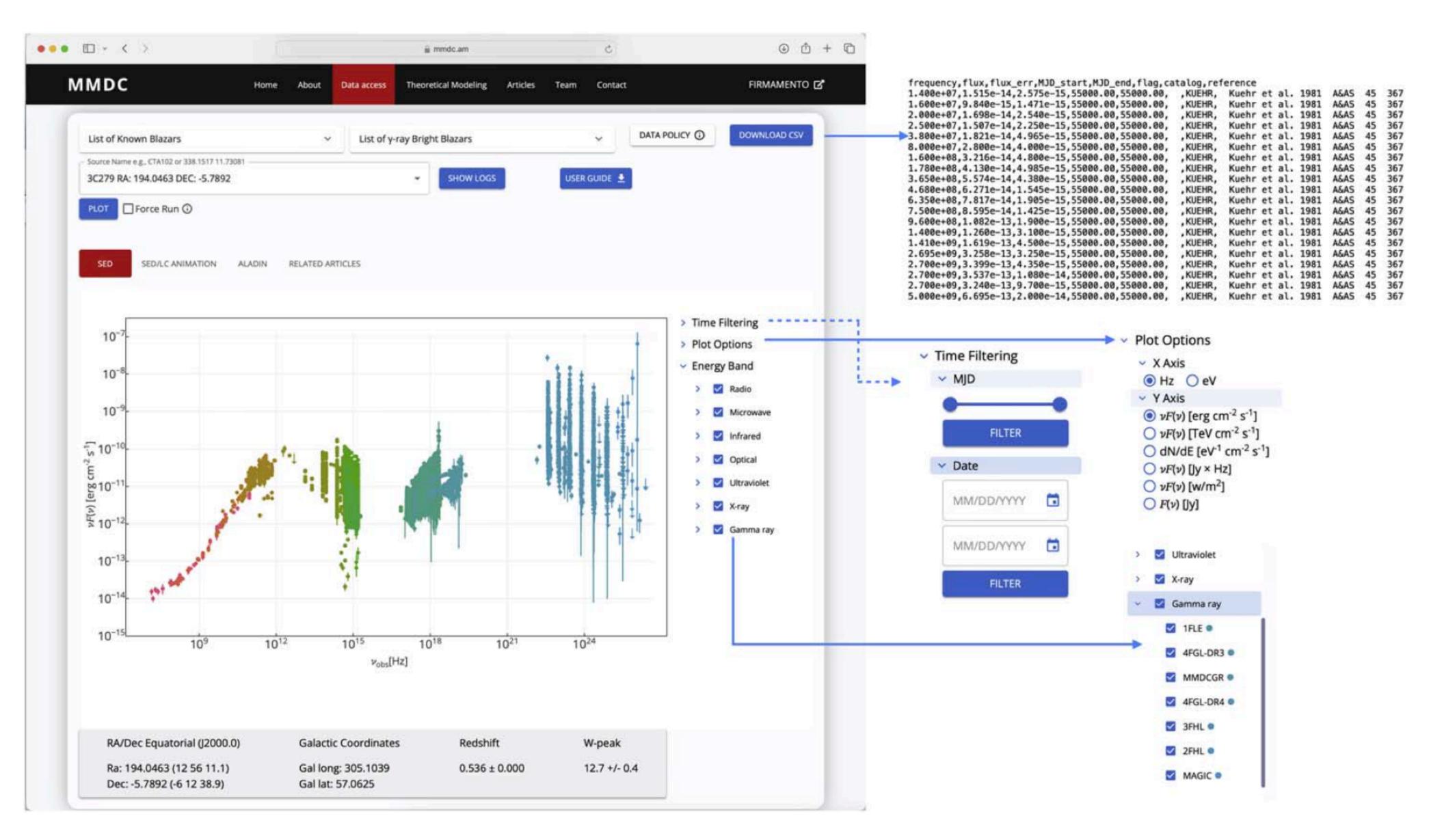






Sahakyan et al., 2024, ApJ, 168, 289, 2024

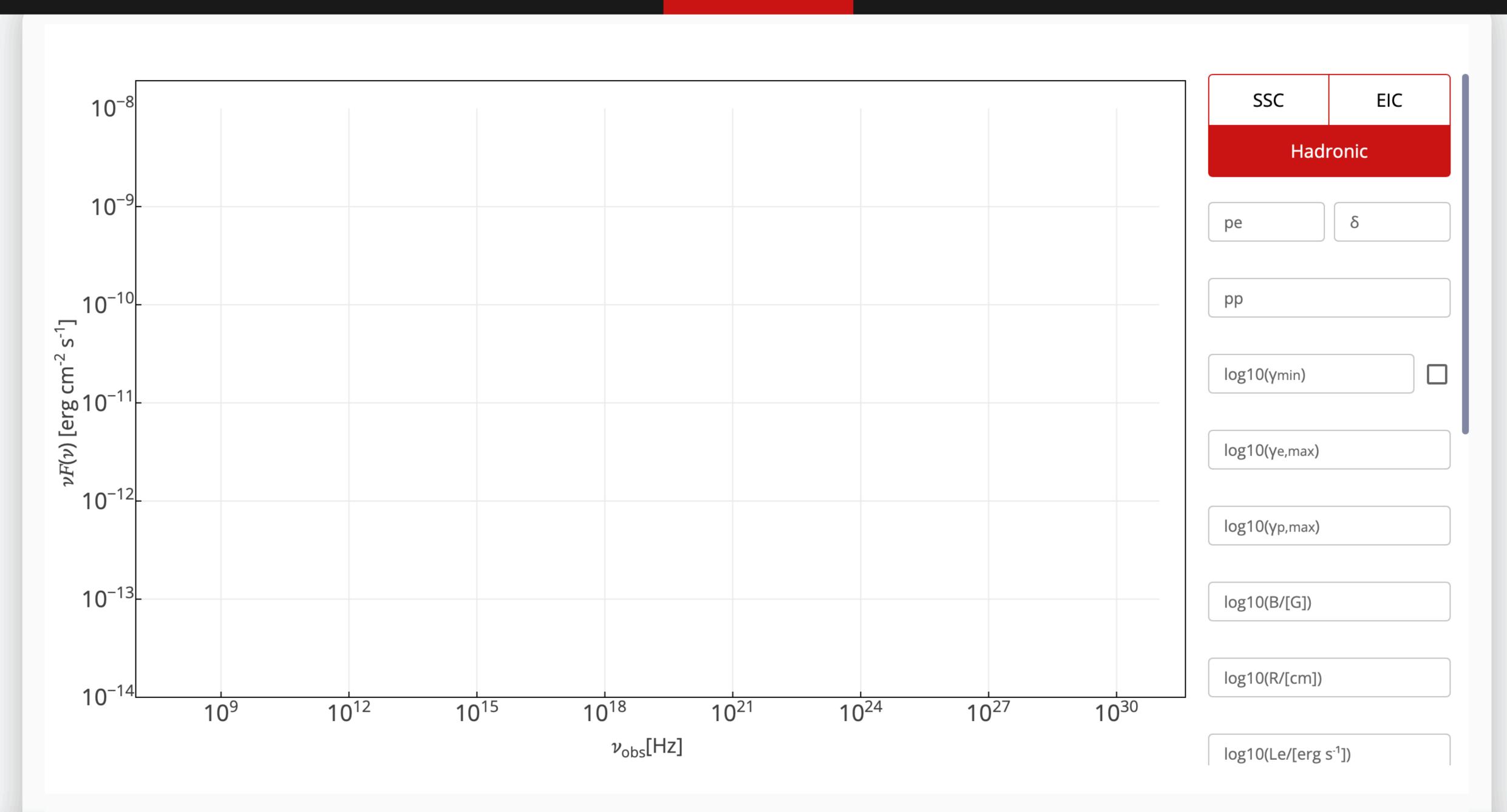
Data access

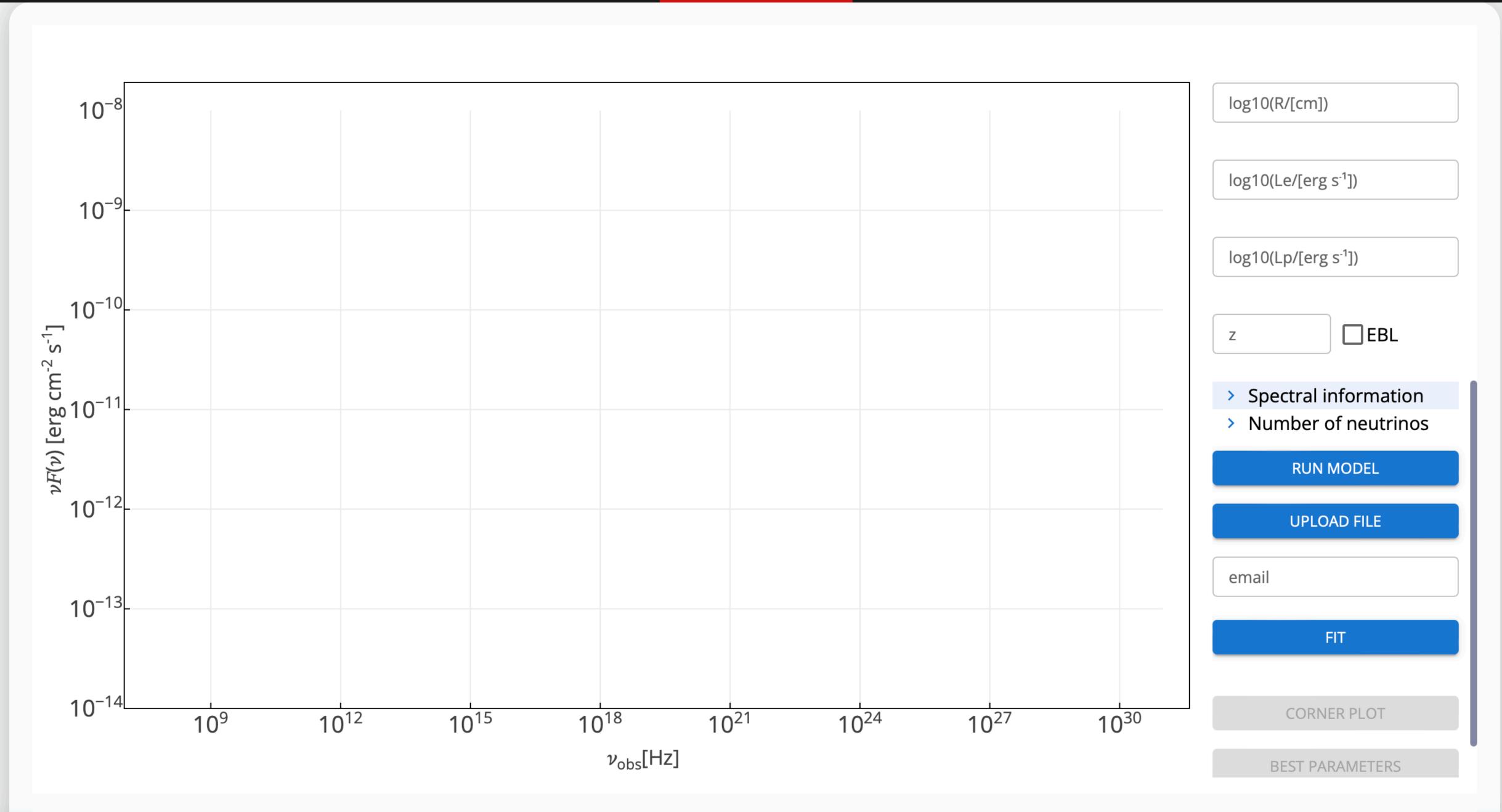


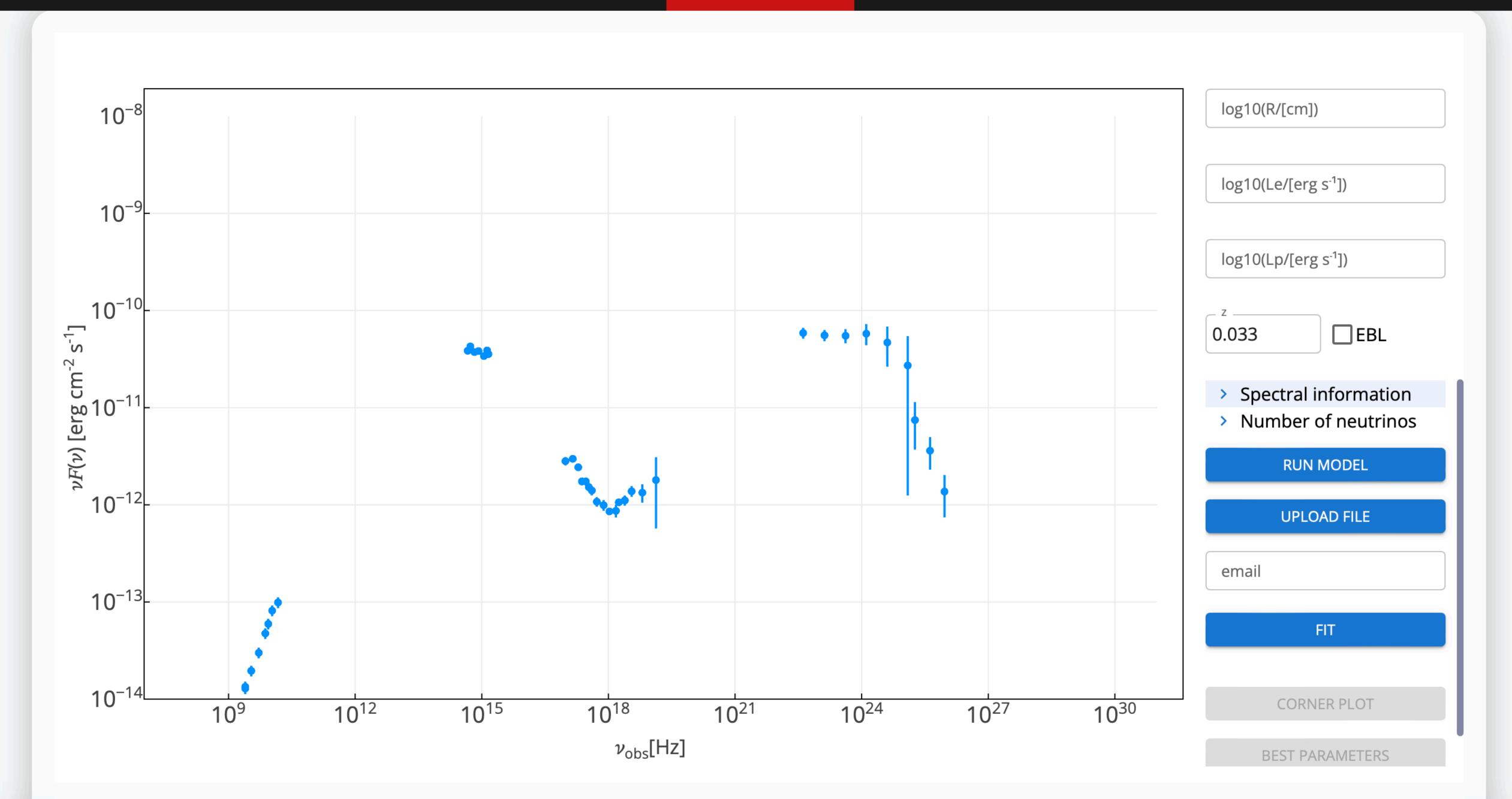
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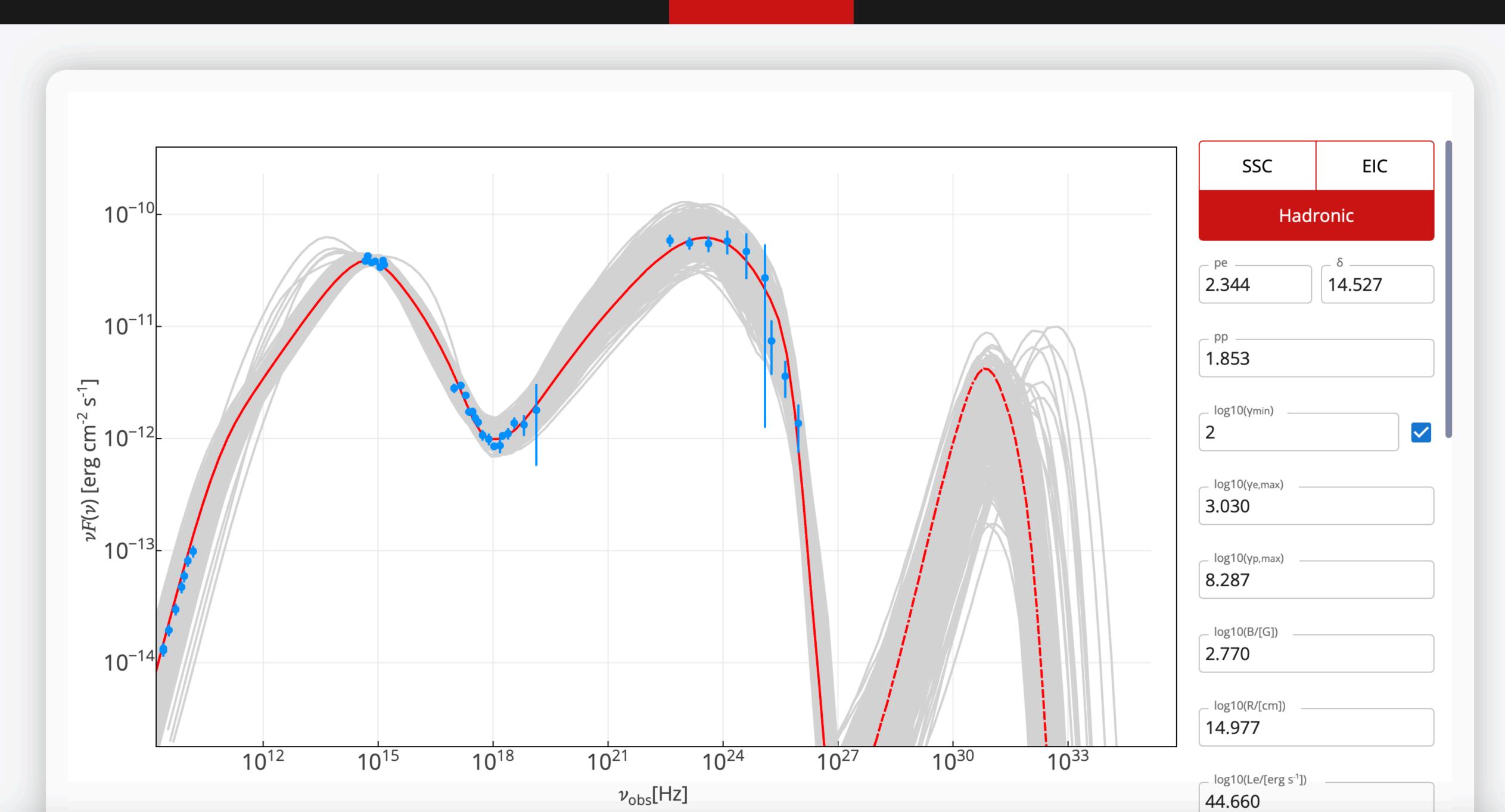




MMDC

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FIRMAMENTO



Rapid Multimessenger data Fitting

Key Result

- ✓ CNN-based training for hadronic & lepto-hadronic models
- ✓ Achieves full multimessenger data fit in \approx 3 minutes
- ✓ No one else can currently fit, let alone this fast

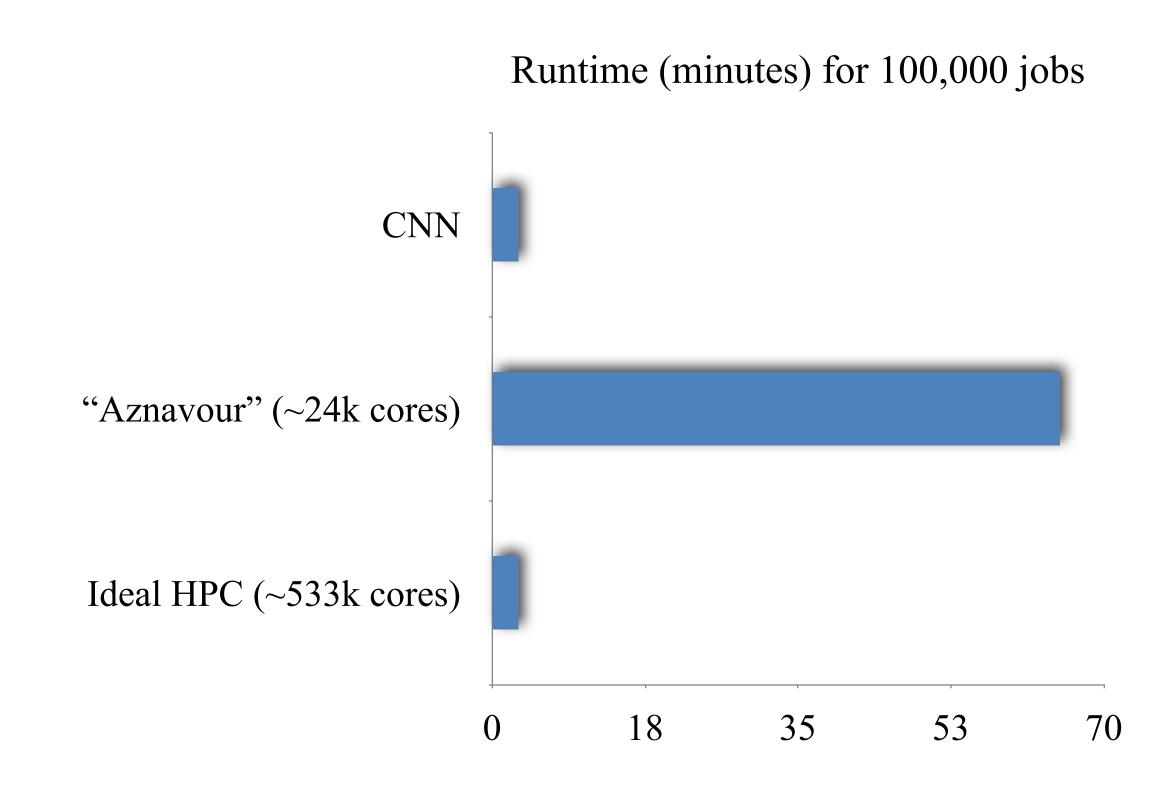
Traditional HPC Requirement for a single fit

- One job: $8 \text{ cores} \times 2 \text{ min} = 16 \text{ core-minutes}$
- 100,000 jobs = 1.6 million core-minutes
- To finish in 3 min: \geq 533,000 cores
- "Aznavour" Supercomputer resources (24,480 cores):

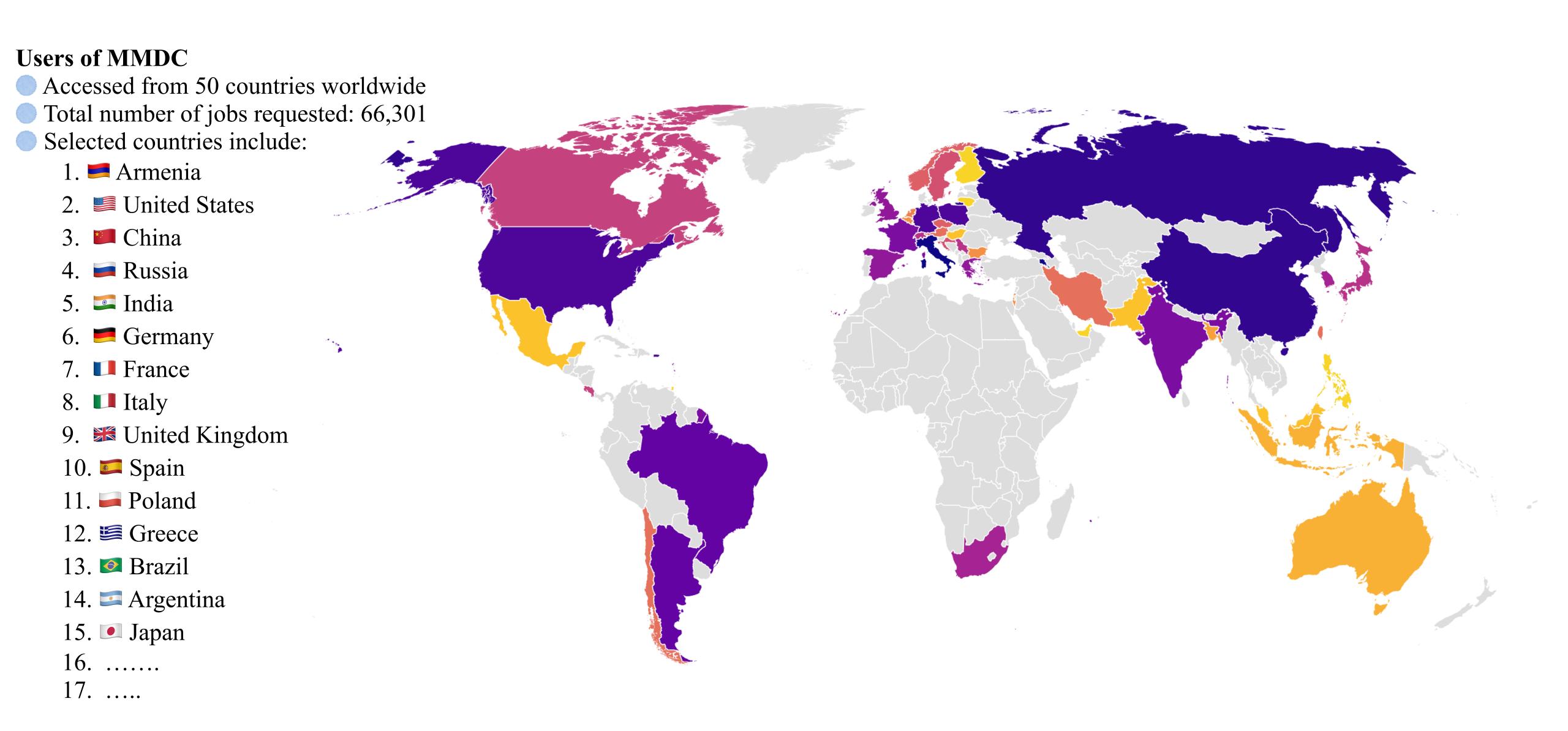
Runtime ≈65 min

CNN Approach

Train once → inference is instantaneous



Markarian Multiwavelength Data Center (MMDC): a platform for building and analyzing multiwavelength SEDs.







AstroGenesis will make the simple simpler and complex possible