Modeling of blazar emission: multiwavelength and multimessenger fit powered by Convolutional Neural Network

N. Sahakyan & D. Bégué

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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Why blazars are interesting ?

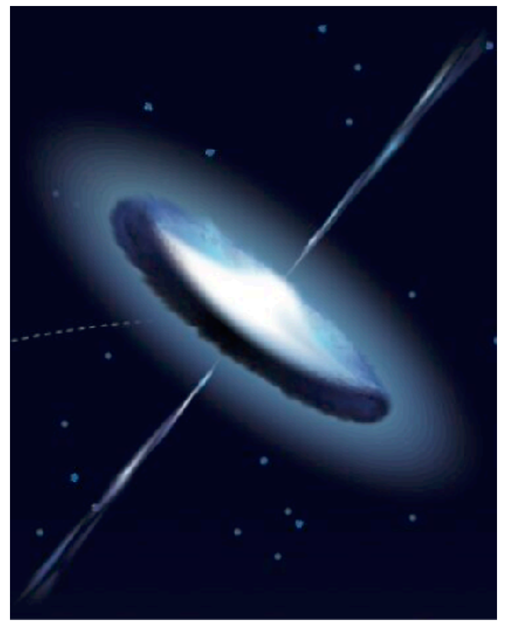
- High powers: most powerful "non-explosive" sources in the Universe ($\sim 10^{49}$ erg/s)
- Relativistic jets: emission is strongly Doppler amplified
- The powerful jets of blazars are powered by accretion onto supermassive black holes
- Fast variability/small emitting region; $R \leq c\, t_{\rm var}/(1+z)$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

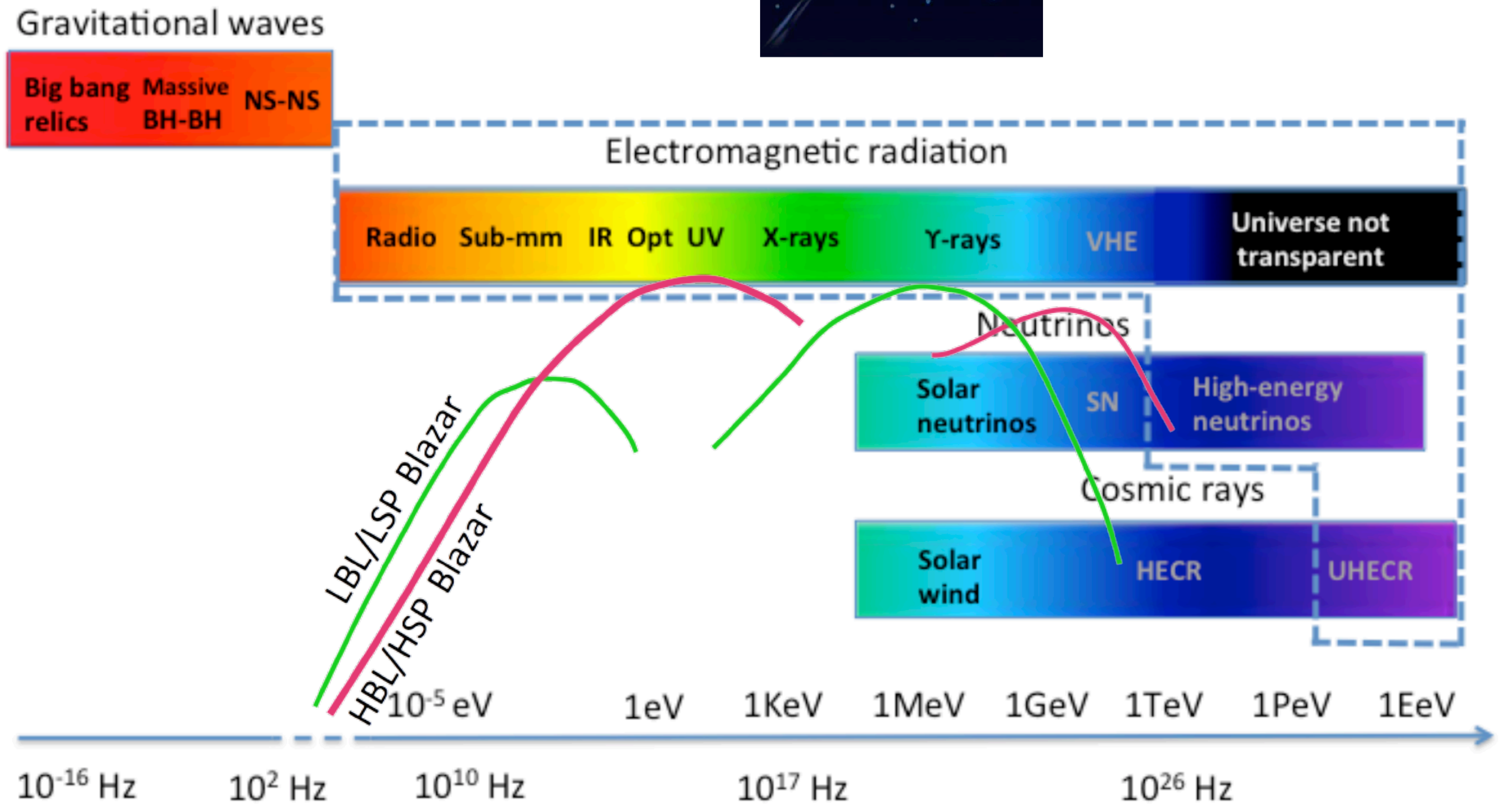
Astrophysical Messengers

Our knowledge of the Universe relies on four cosmic messengers:

- [ ] Gravitational waves
- [x] 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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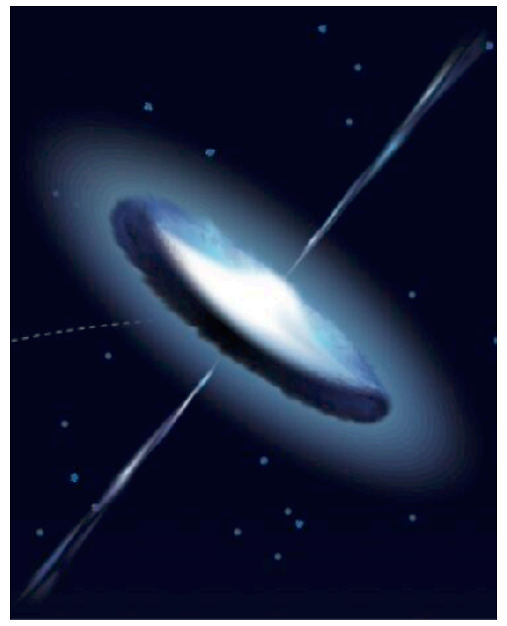
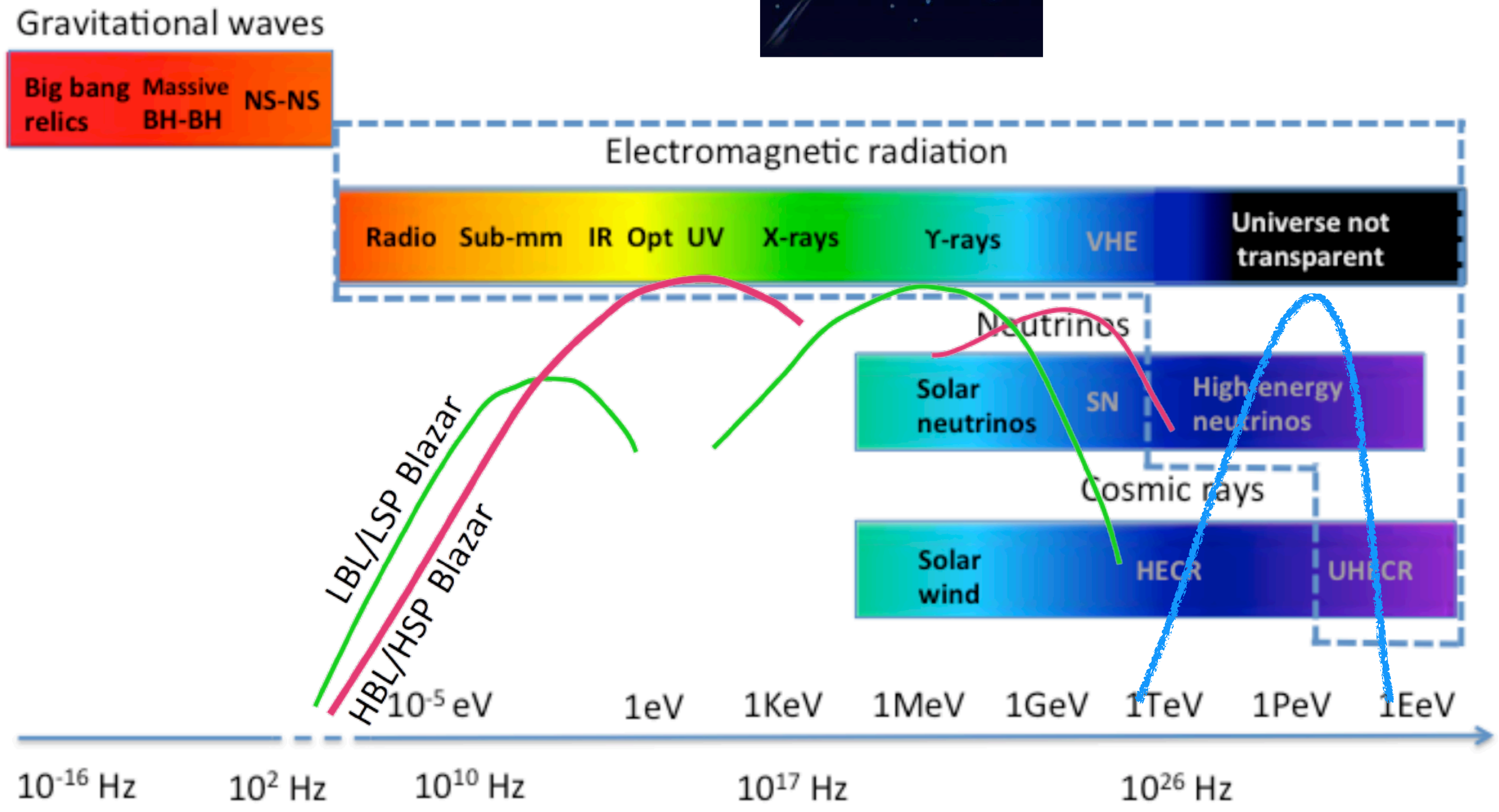
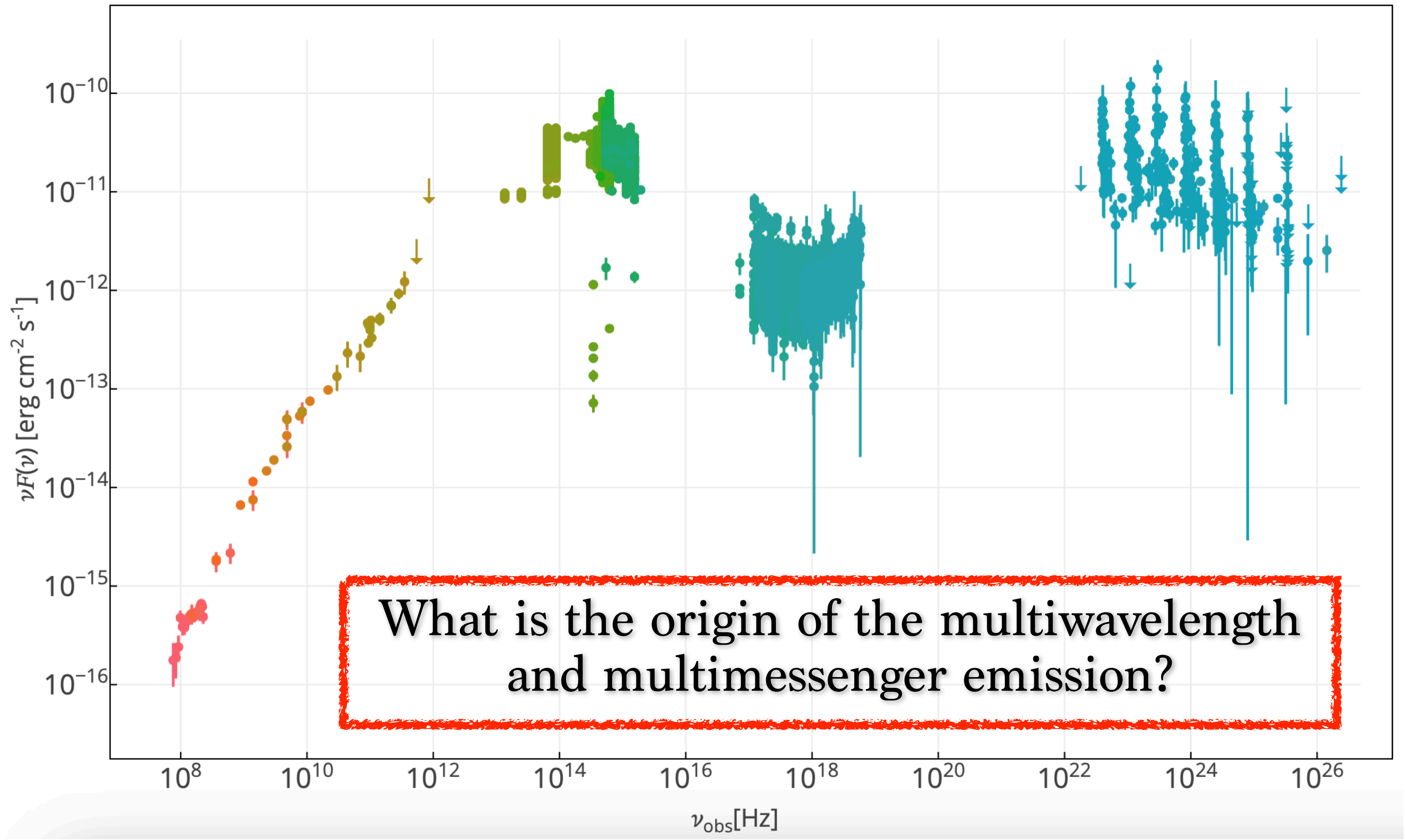


Blazar emissions can be investigated by detecting photons with energies ranging from radio to HE and VHE γ-rays.

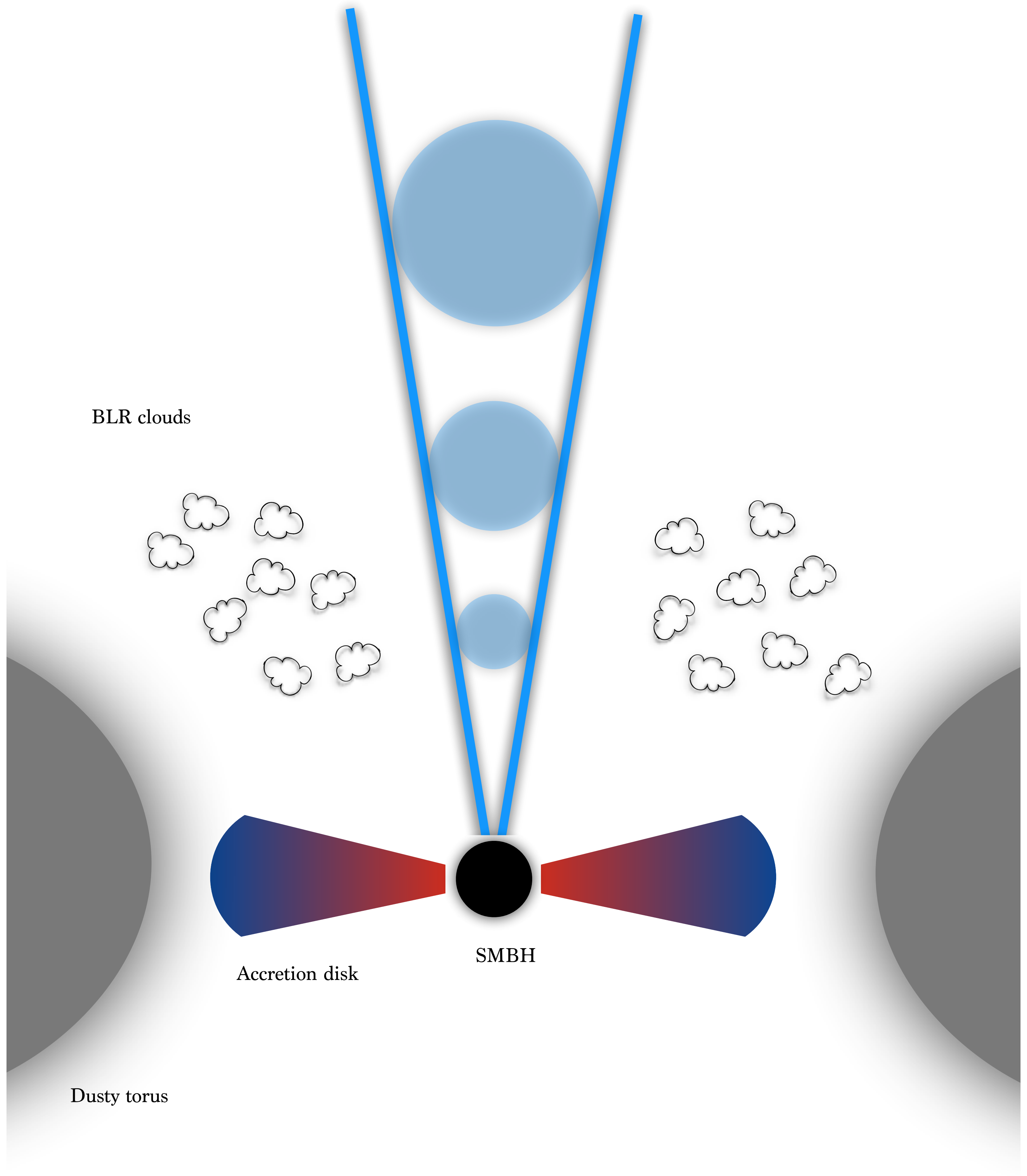
Blazars are associated with VHE neutrinos.





Origin of MW and MM Emission: Protons

The double hump structure of the blazar broadband SED: the low-energy component usually peaks between far infrared and X-rays, while the high-energy (HE) component is observed between X-rays and very high-energy (VHE) γ-rays.



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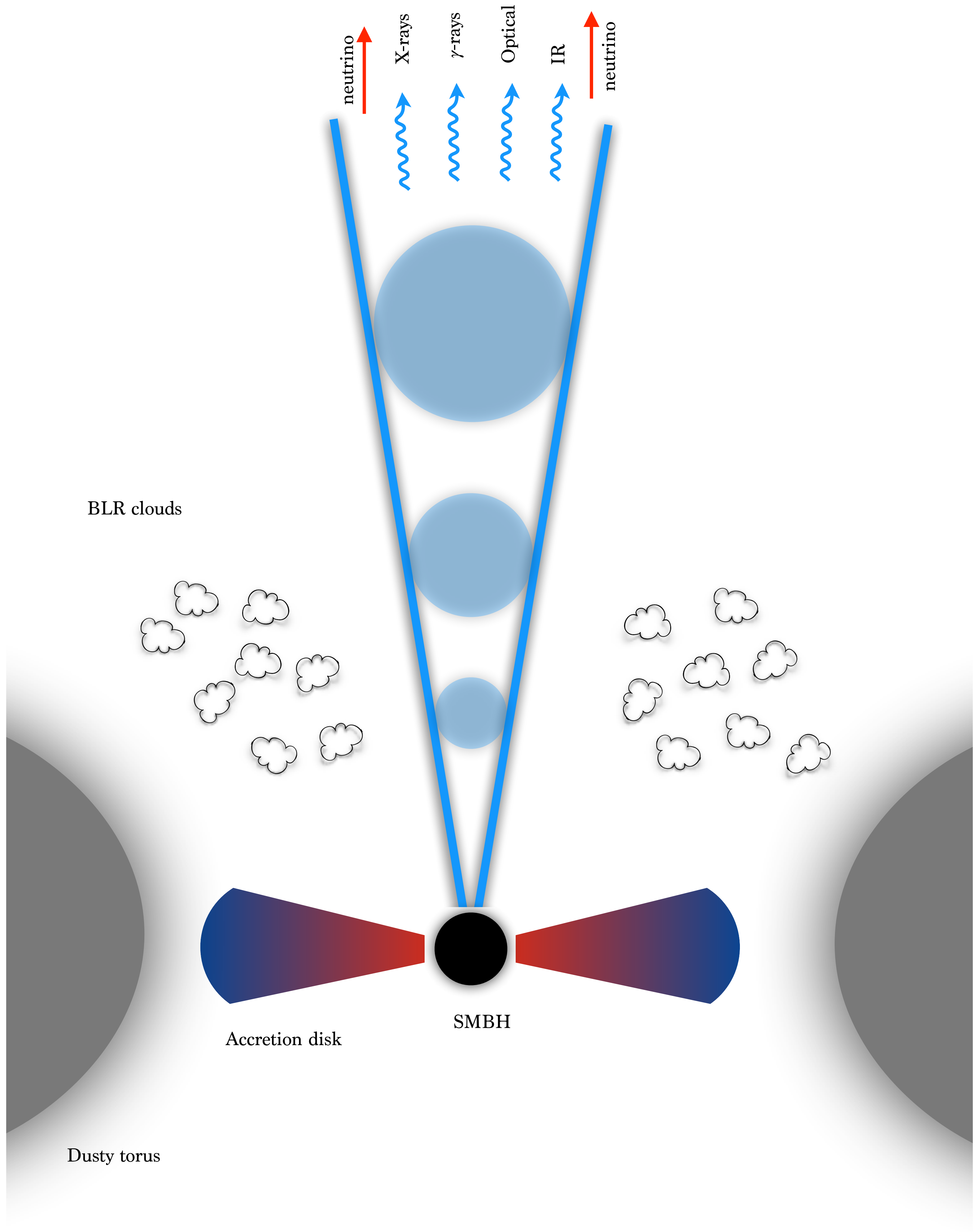

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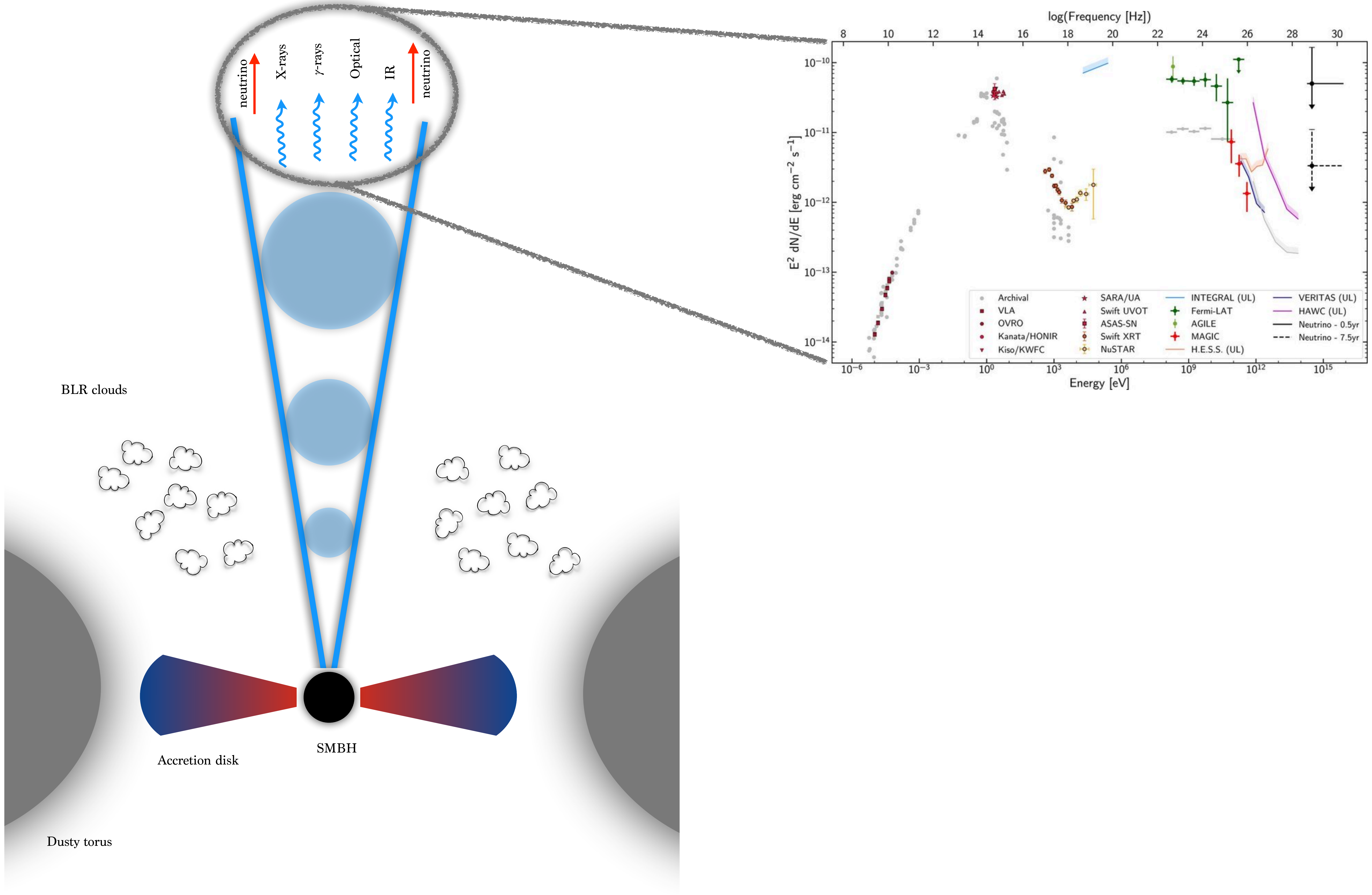

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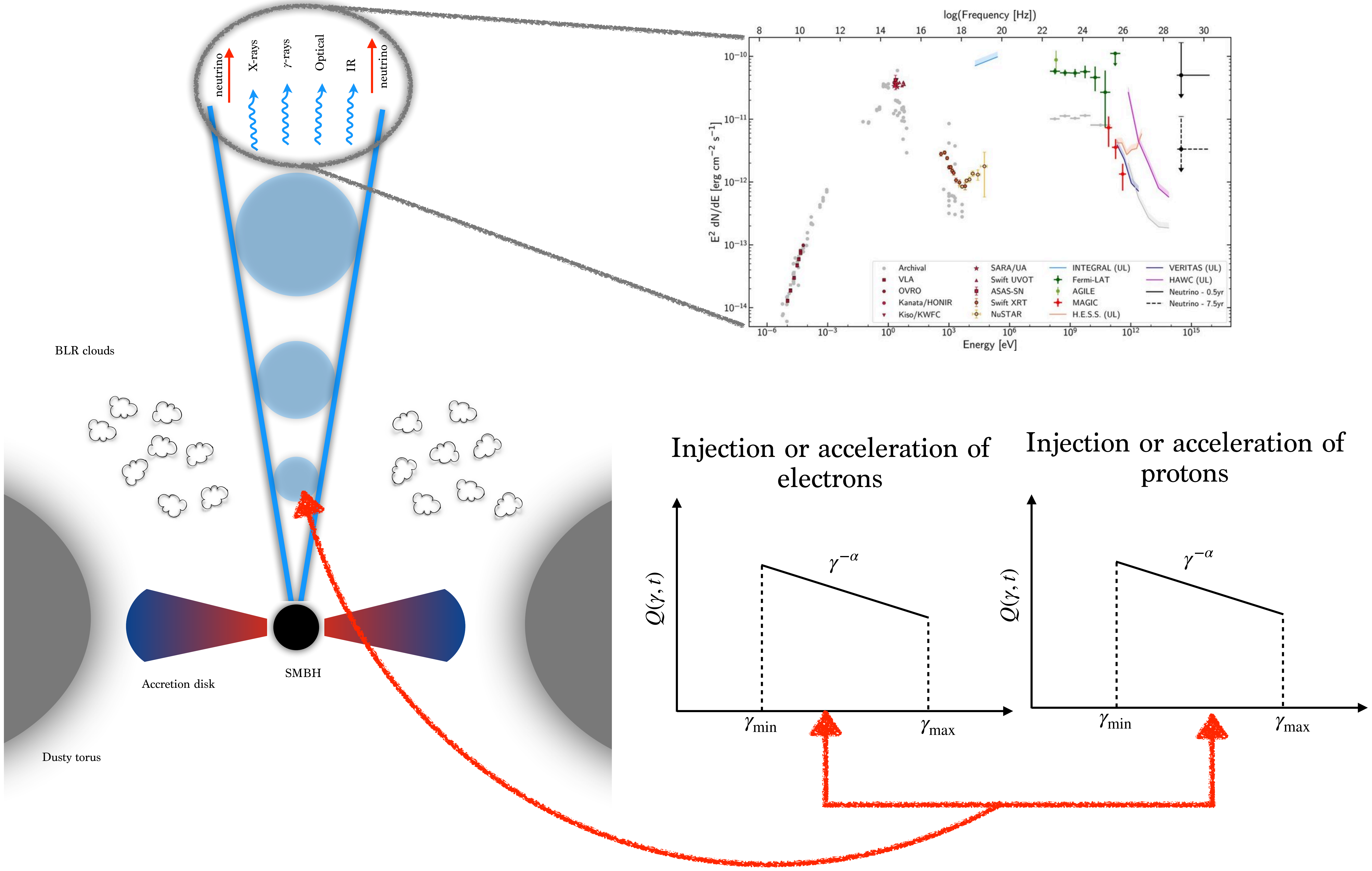

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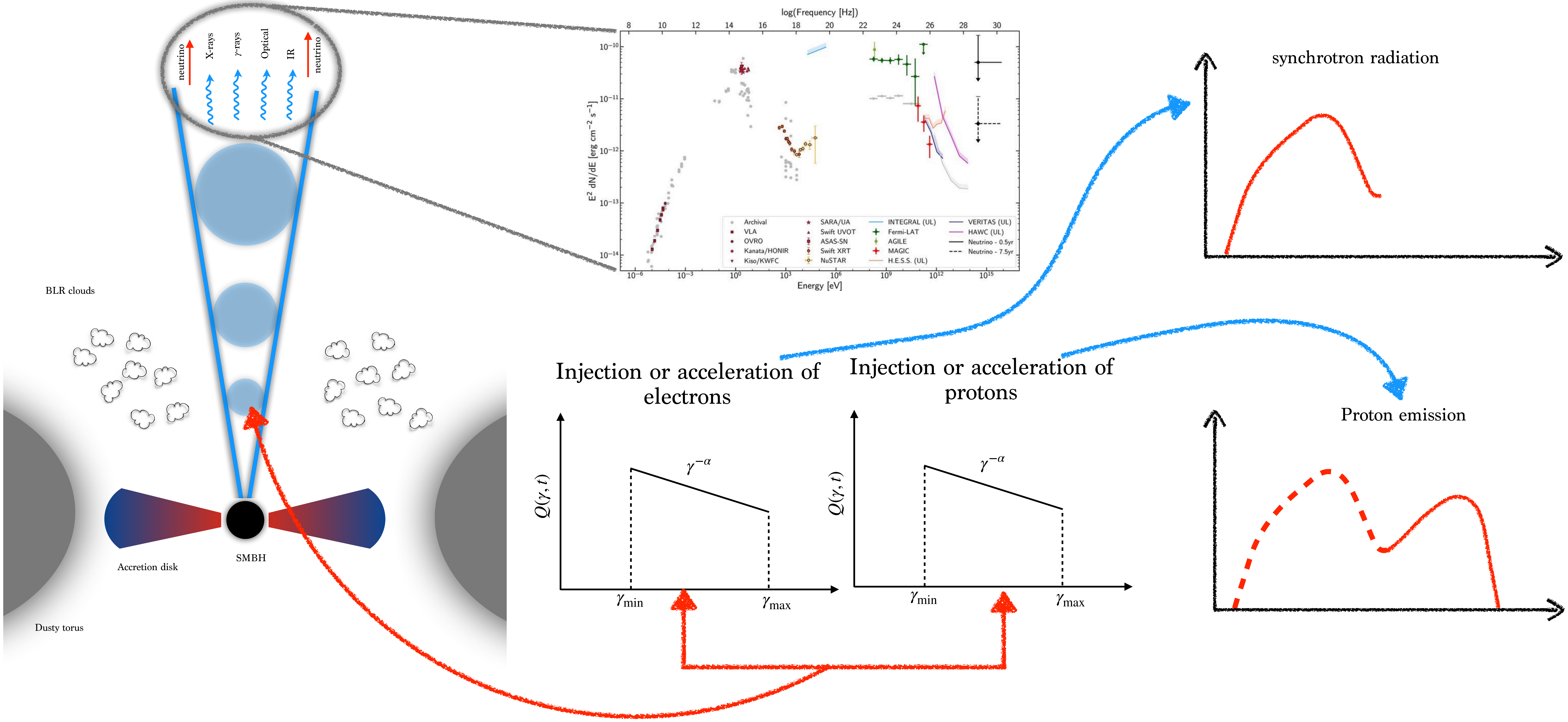
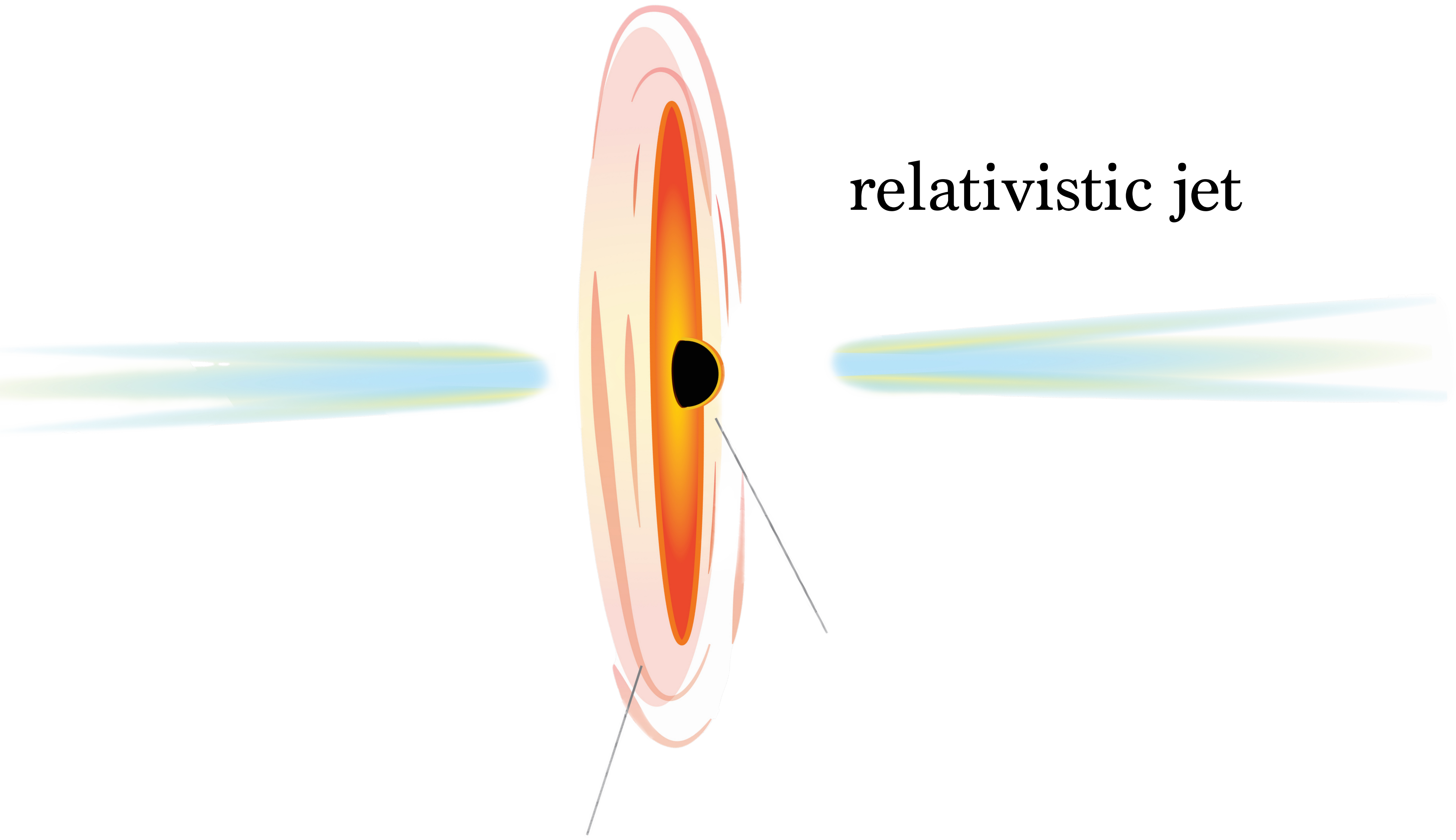
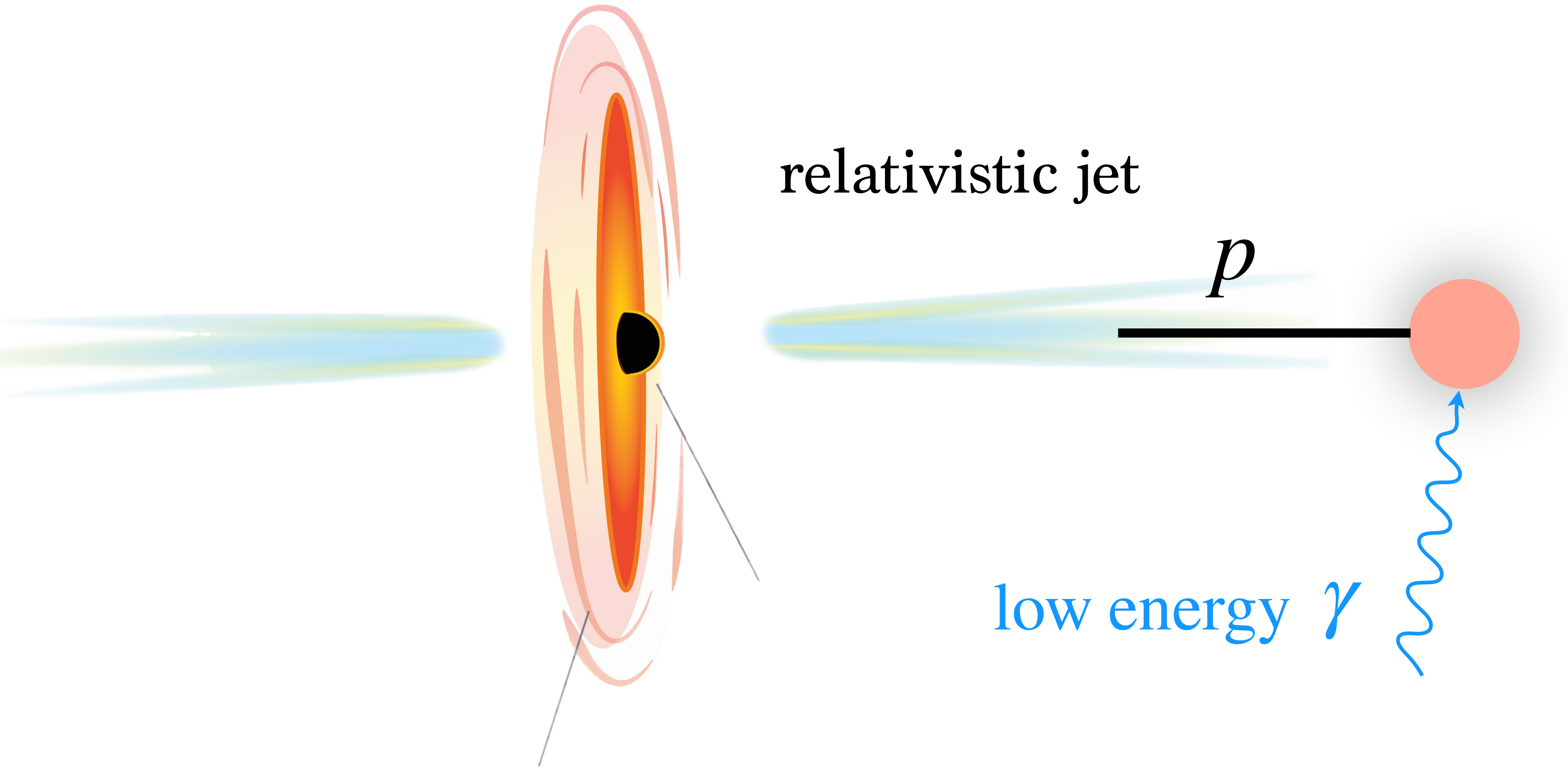
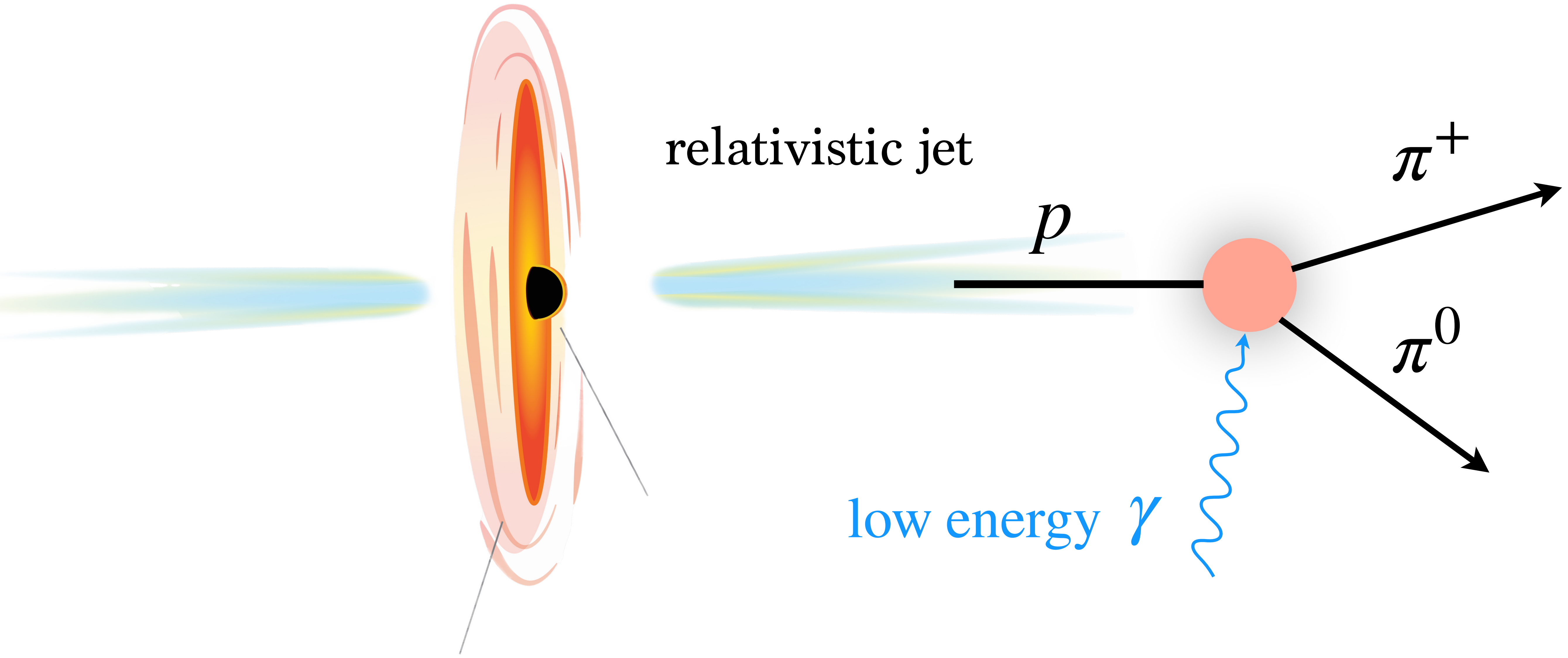
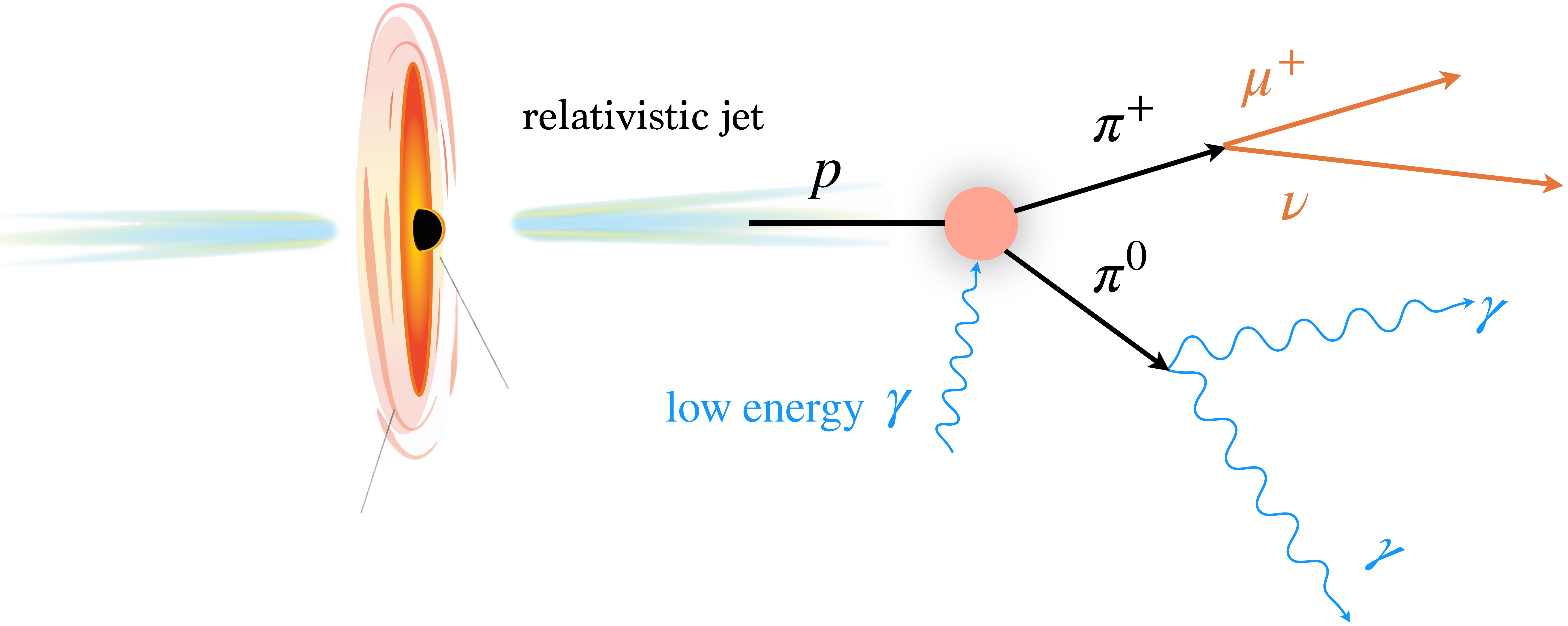



relativistic jet

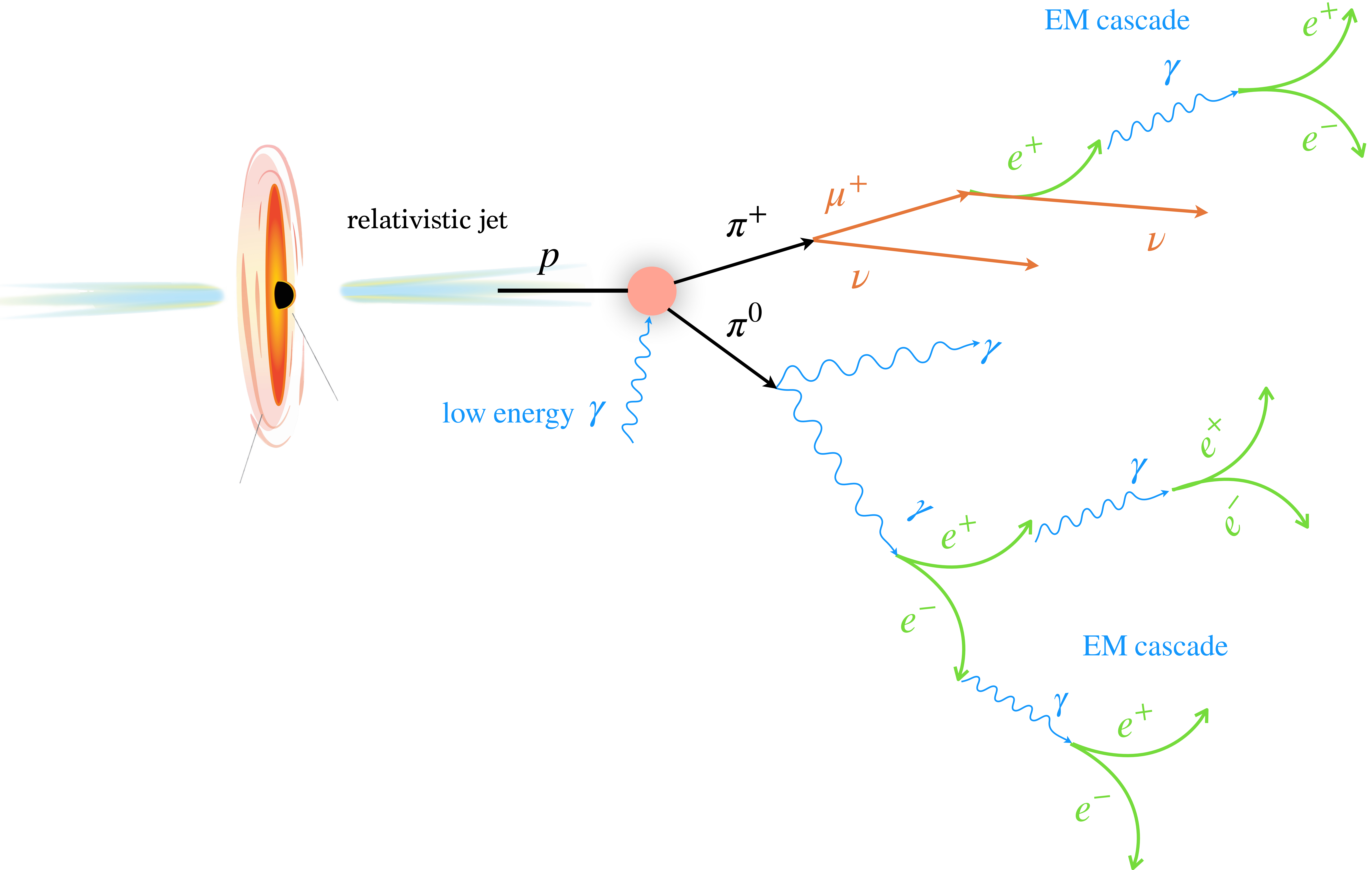

relativistic jet
p
low energy γ



relativistic jet
p
π^+
π^0
low energy γ



relativistic jet
p
π^+
μ^+
ν
π^0
γ
low energy γ
γ


EM cascade
relativistic jet
p
π^+
μ^+
ν
ν
e^+
γ
e^+
e^-
π^0
γ
low energy γ
γ
e^+
γ
e^+
e^-
e^-
EM cascade
γ
e^+
e^-

Neutrino Observations of Blazars

1. Key Observational Milestones

– IceCube-170922A / TXS 0506+056 (2017): A ~ 290TeV neutrino coincident with a GeV–TeV flare from TXS 0506+056 (z=0.336). Follow-ups by Fermi-LAT, MAGIC, Swift, and NuSTAR revealed multi-band enhancement; strong evidence for hadronic interactions.

– Archival TXS 0506+056 excess (2014–2015): Cluster of 13±5 neutrinos over ~ 110 days without γ-ray flare.

– Other candidates: PKS 1502+106, PKS 0735+178, PKS 1424–418, GB6 J1040+0617……

2. Significance

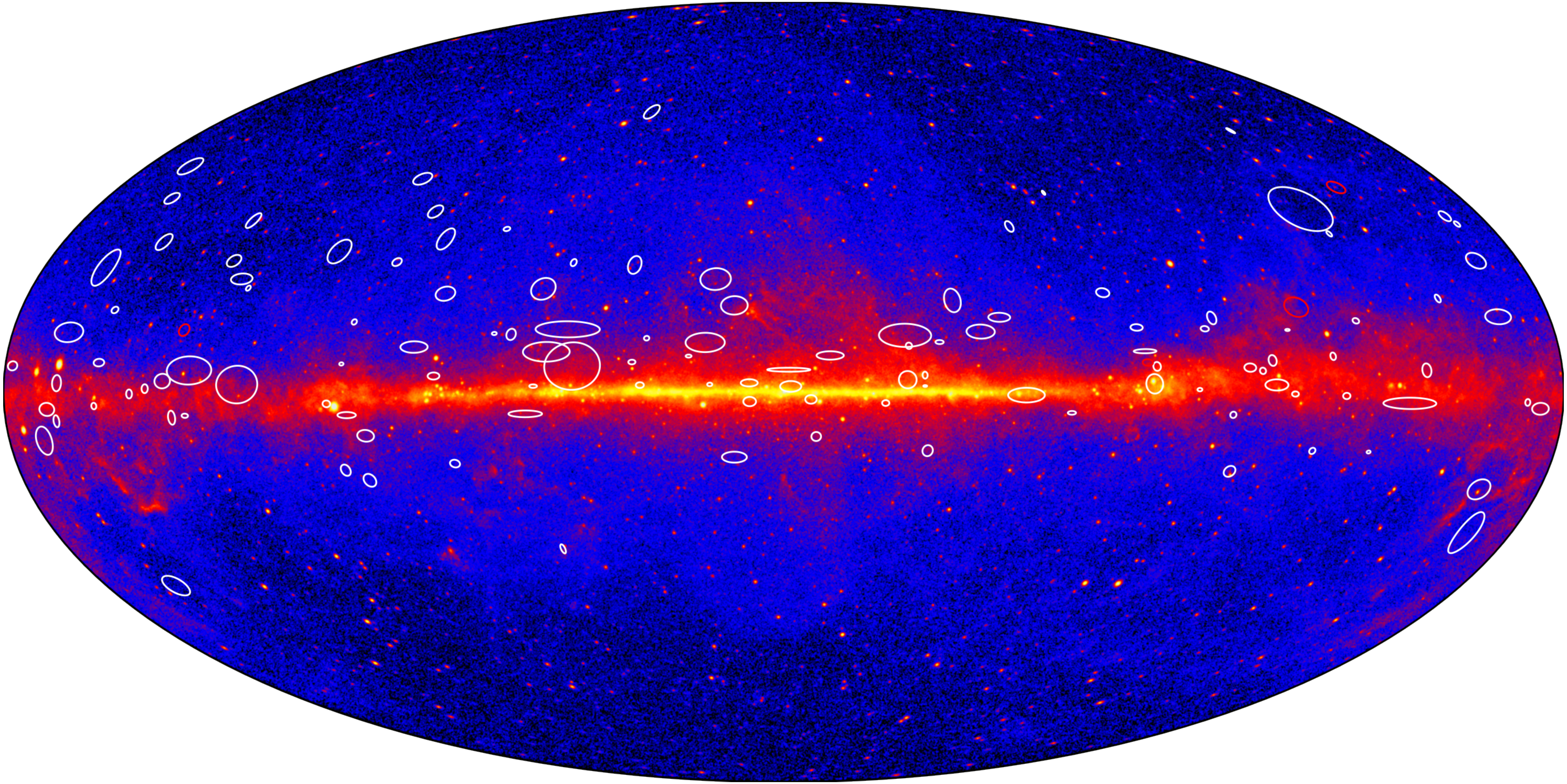
– Confirms hadronic acceleration in relativistic jets.

– Blazars as potential sources of high-energy cosmic neutrinos.

– Supports contribution of blazars to diffuse astrophysical neutrino background.

– Demonstrates the power of multimessenger astronomy: neutrinos + γ-rays + X-rays + optical.

Multiwavelength + Multimessenger data



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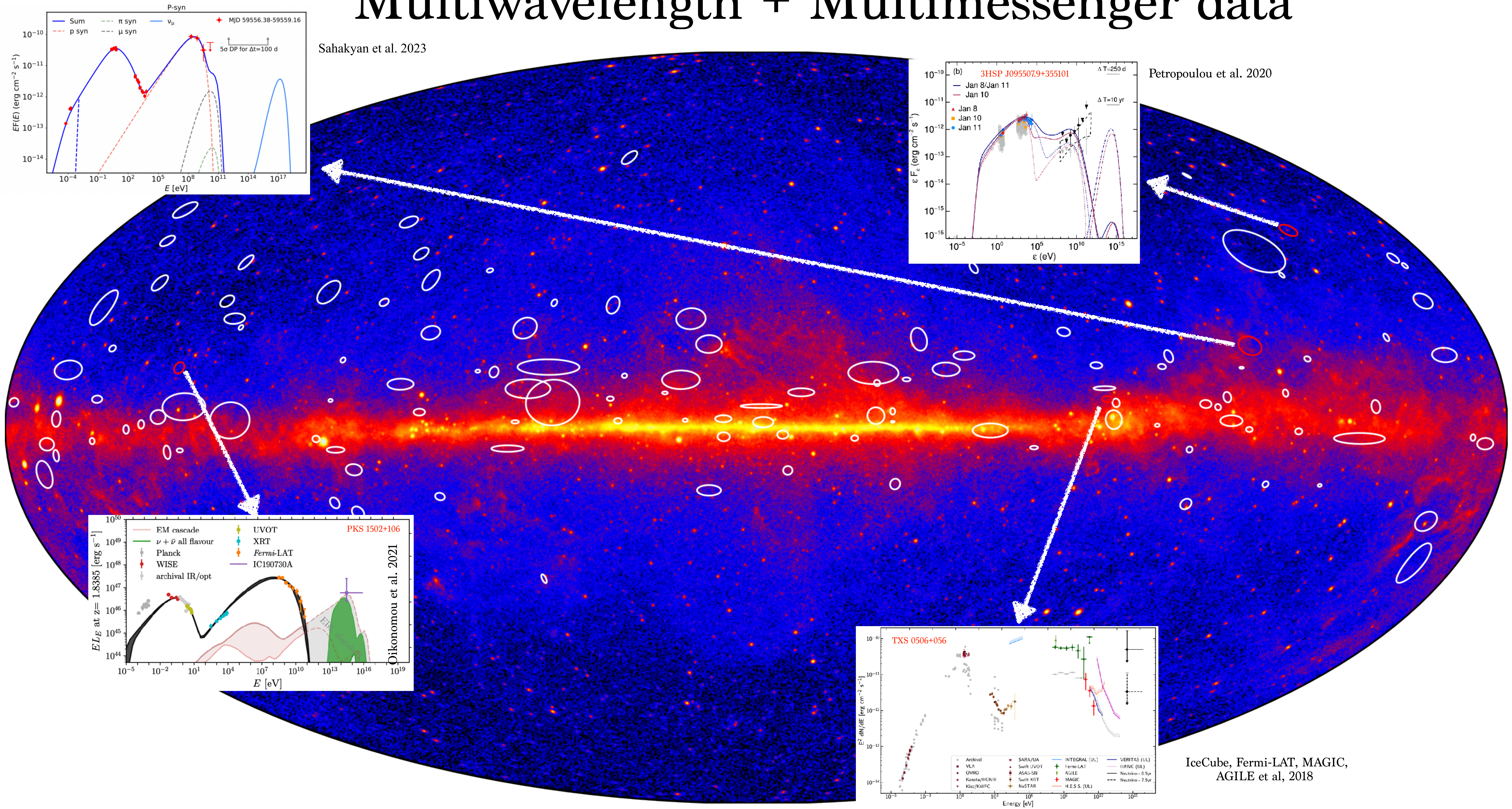
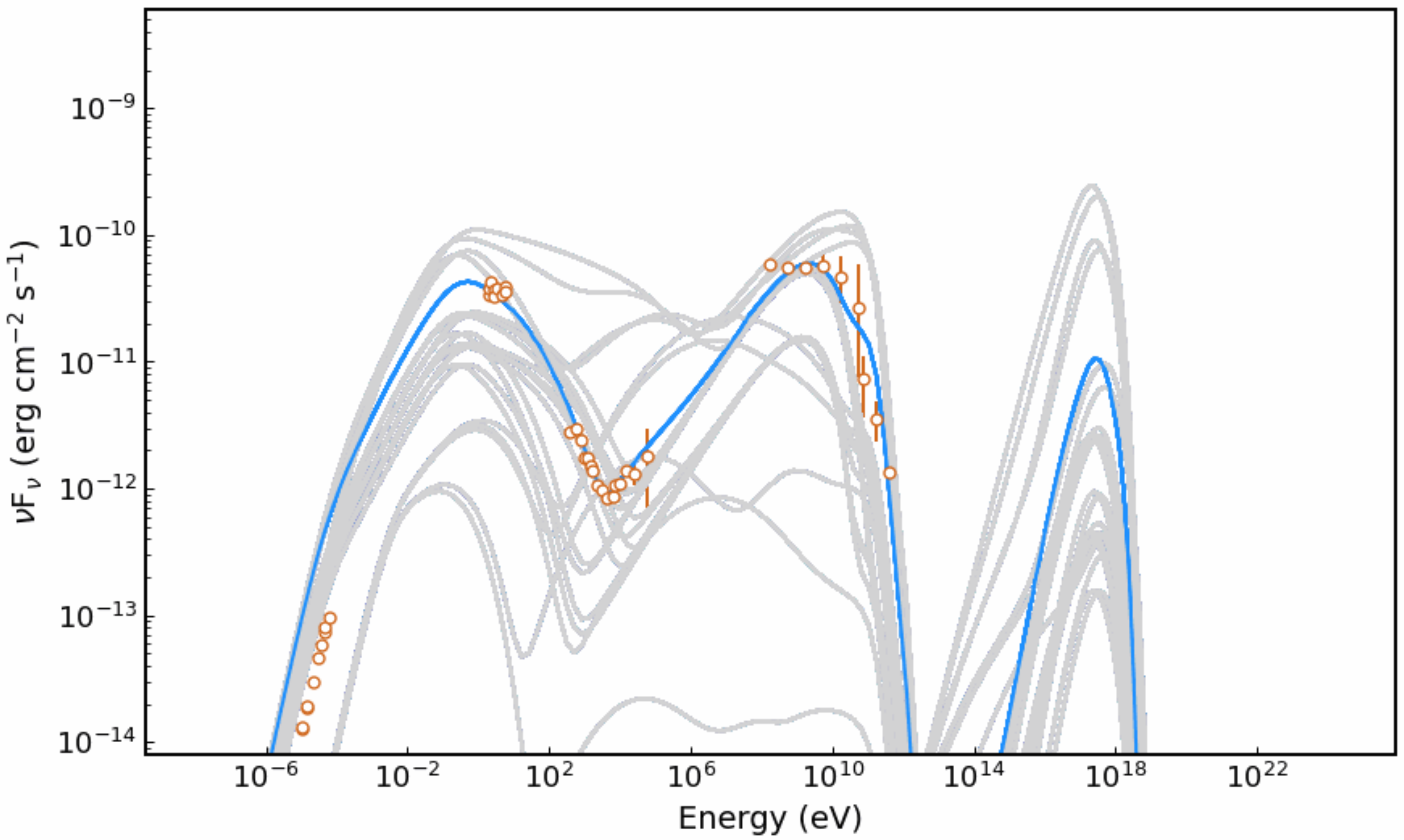


Computational Challenges and ML-based Solutions



Traditional Modeling :

- Frequent likelihood evaluations, making computations time-consuming.
- Models computed for each dataset, resulting in redundant and costly computations.
- For Bayesian fitting, models must be evaluated 10^4-10^5times.

Computation Time Estimates (8 cores) :

- SSC / EIC model: ~30 sec → 3.5 – 35 days
- Hadronic model: ~90 sec → 10 –100 days

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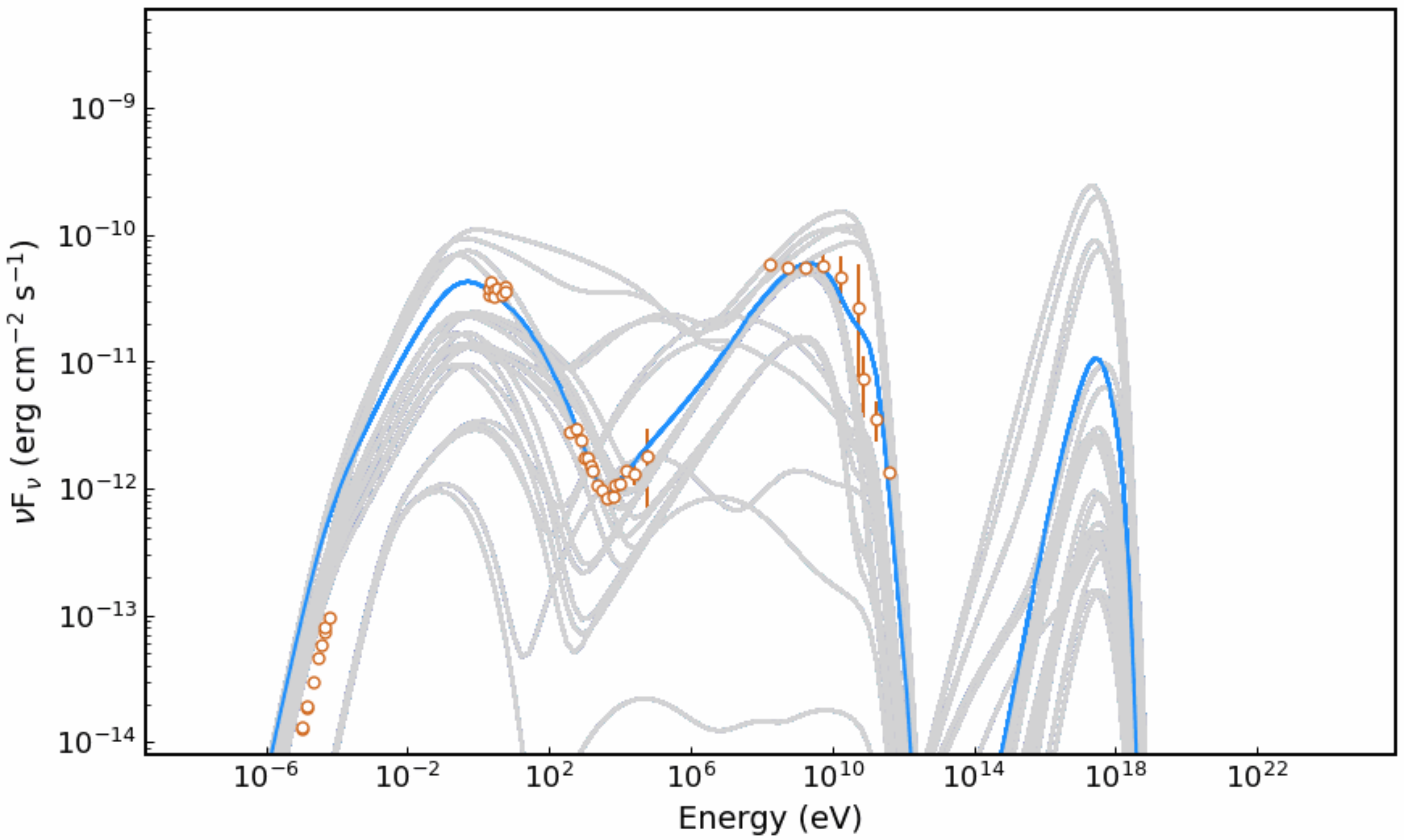

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Machine Learning for Accelerated Model computations:

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

References :

- ☑ Bégué, Sahakyan et al., ApJ, 963, 71 (2024)
- ☑ Sahakyan, Bégué et al., ApJ, 971, 70 (2024)
- ☑ 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	cm	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	-	$\gamma_{\rm e,max}$	10^{2}	10^{8}	Logarithmic
Maximum proton injection Lorentz factor	-	$\gamma_{\rm p,max}$	10^{3}	10^{11}	Logarithmic
Injection index electrons	-	p_e	1.7	5	Linear
Injection index protons	-	p_p	1.6	3.5	Linear
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Gasparyan, Bégué, Sahakyan 2022

SOPRANO

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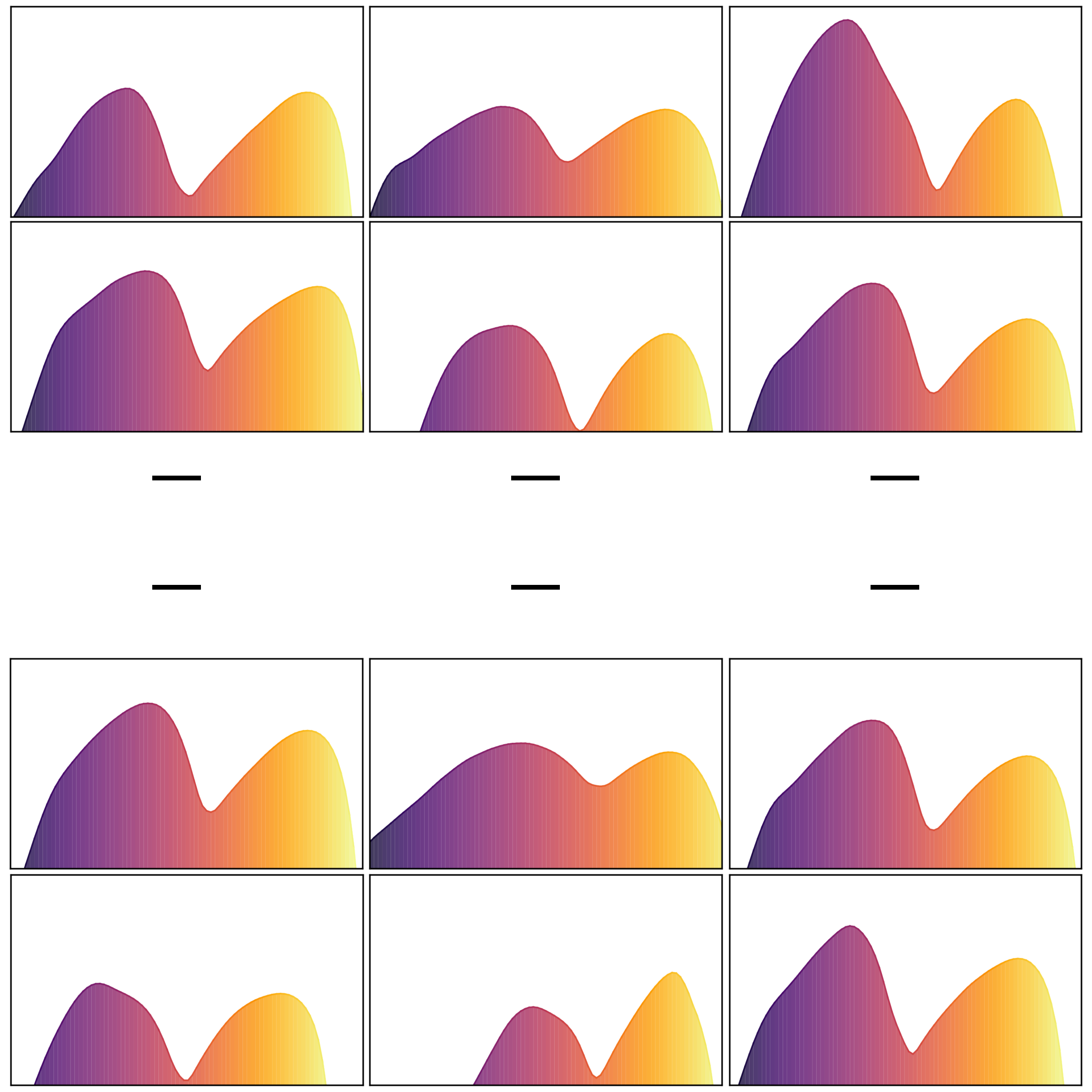

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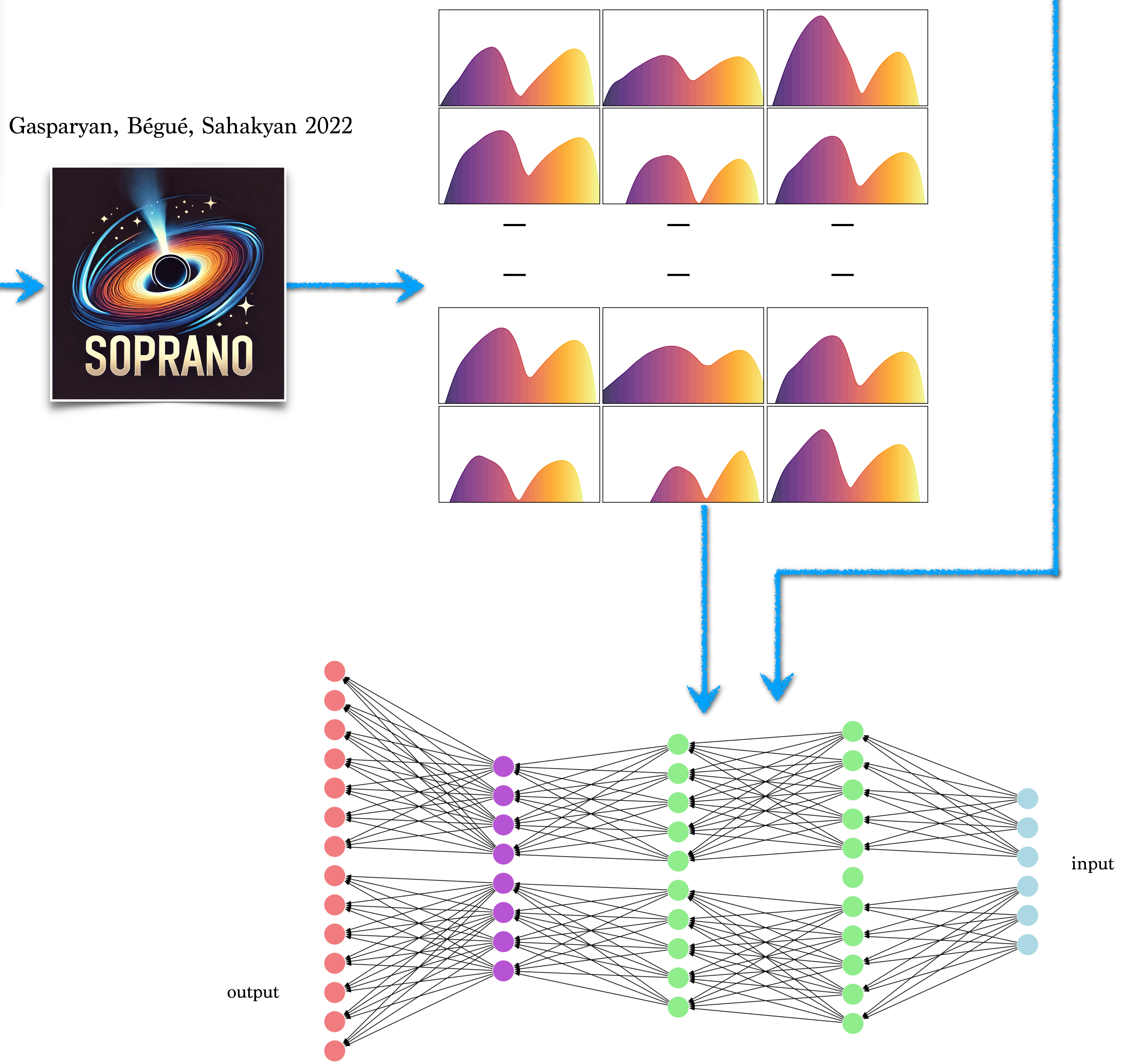

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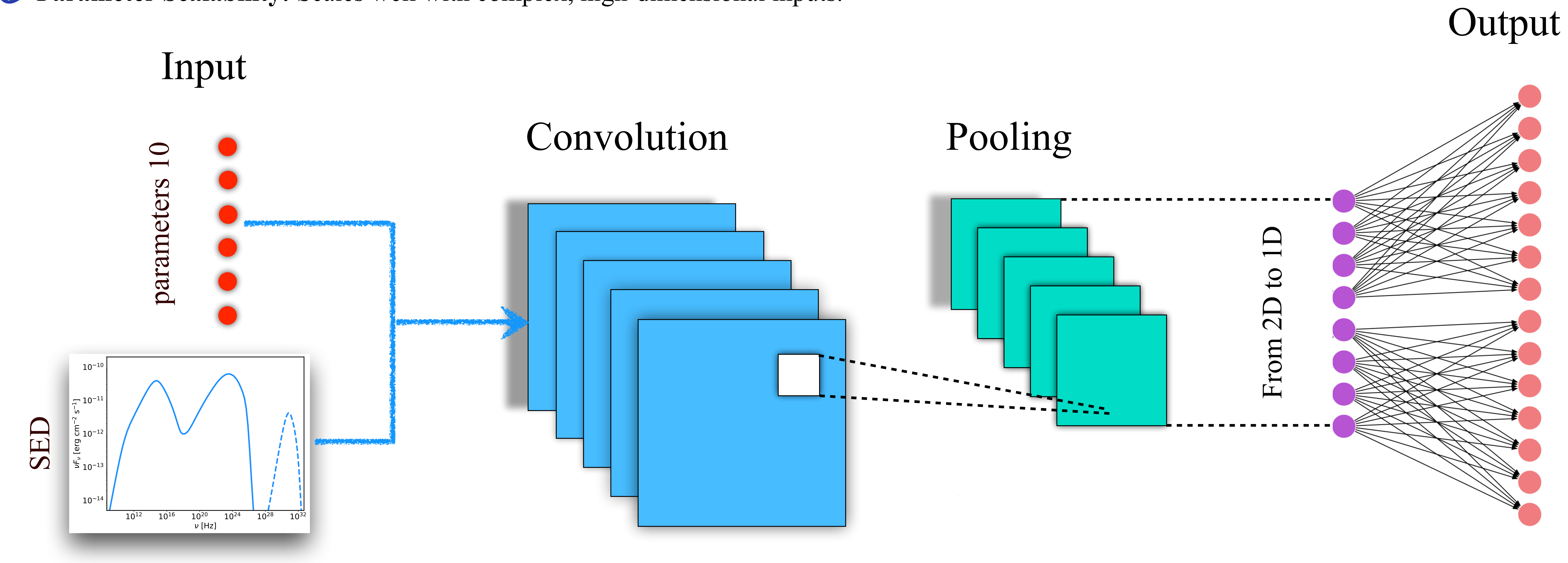
Convolutional Neural Network

Why CNN?

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

Architecture Overview

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



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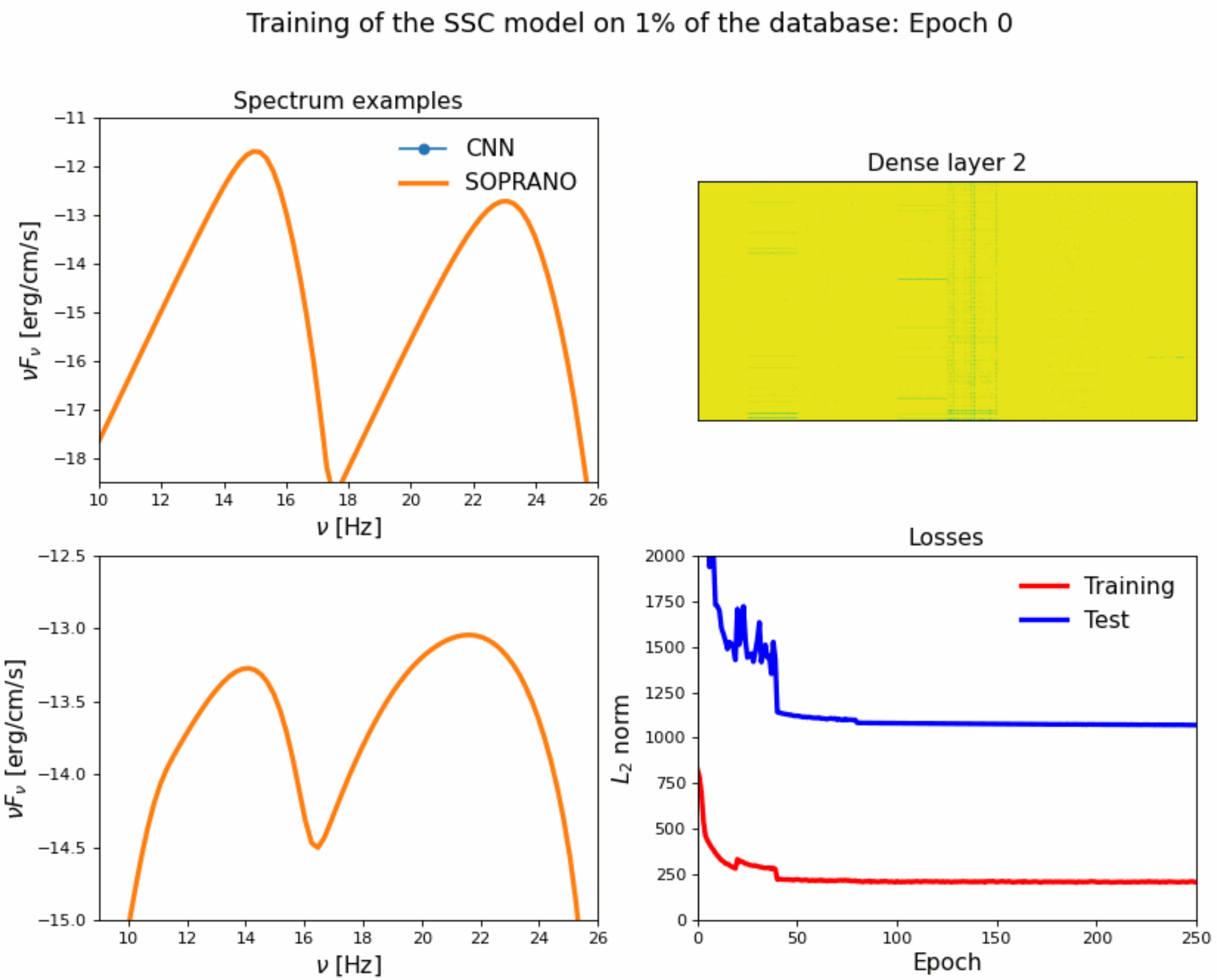

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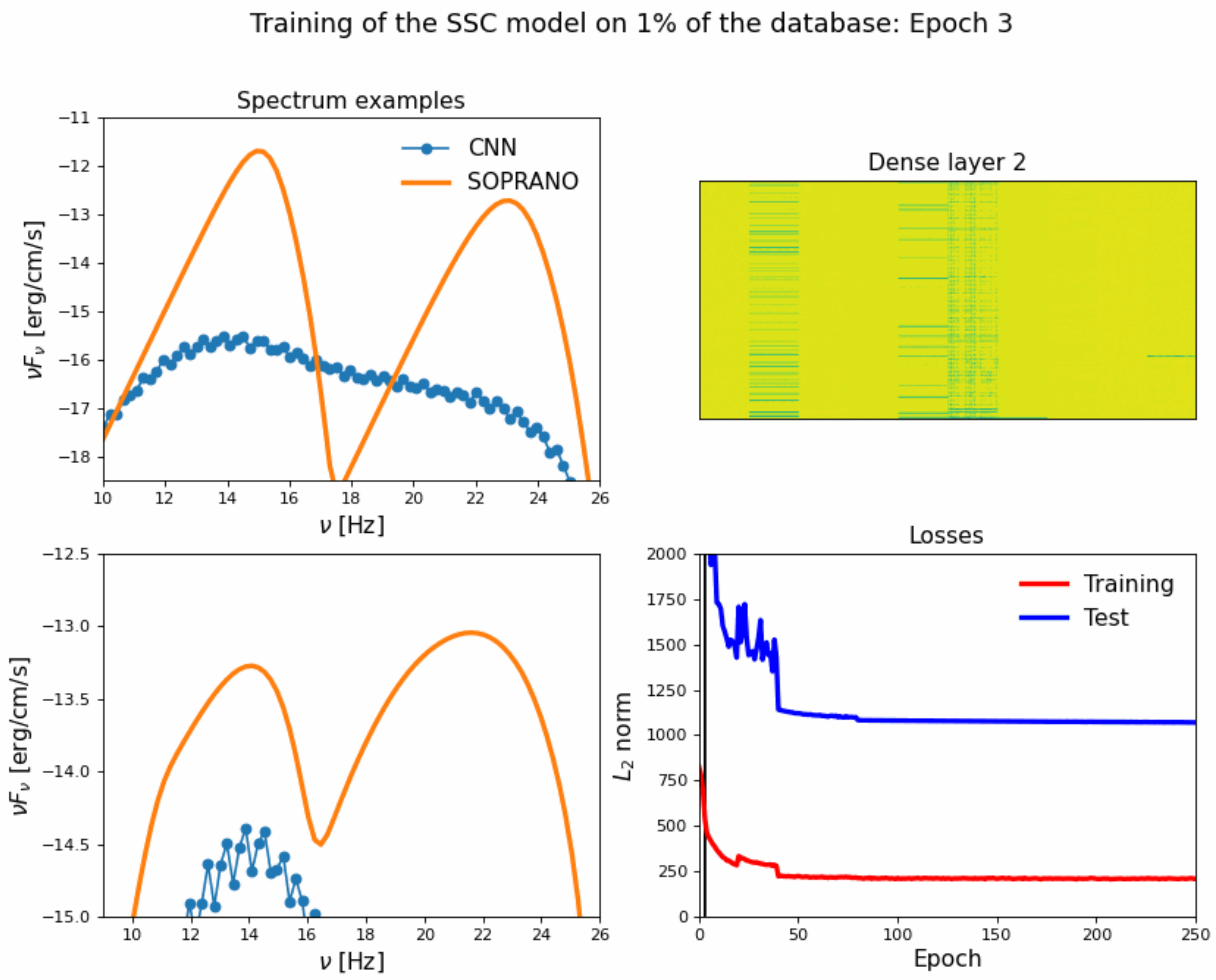

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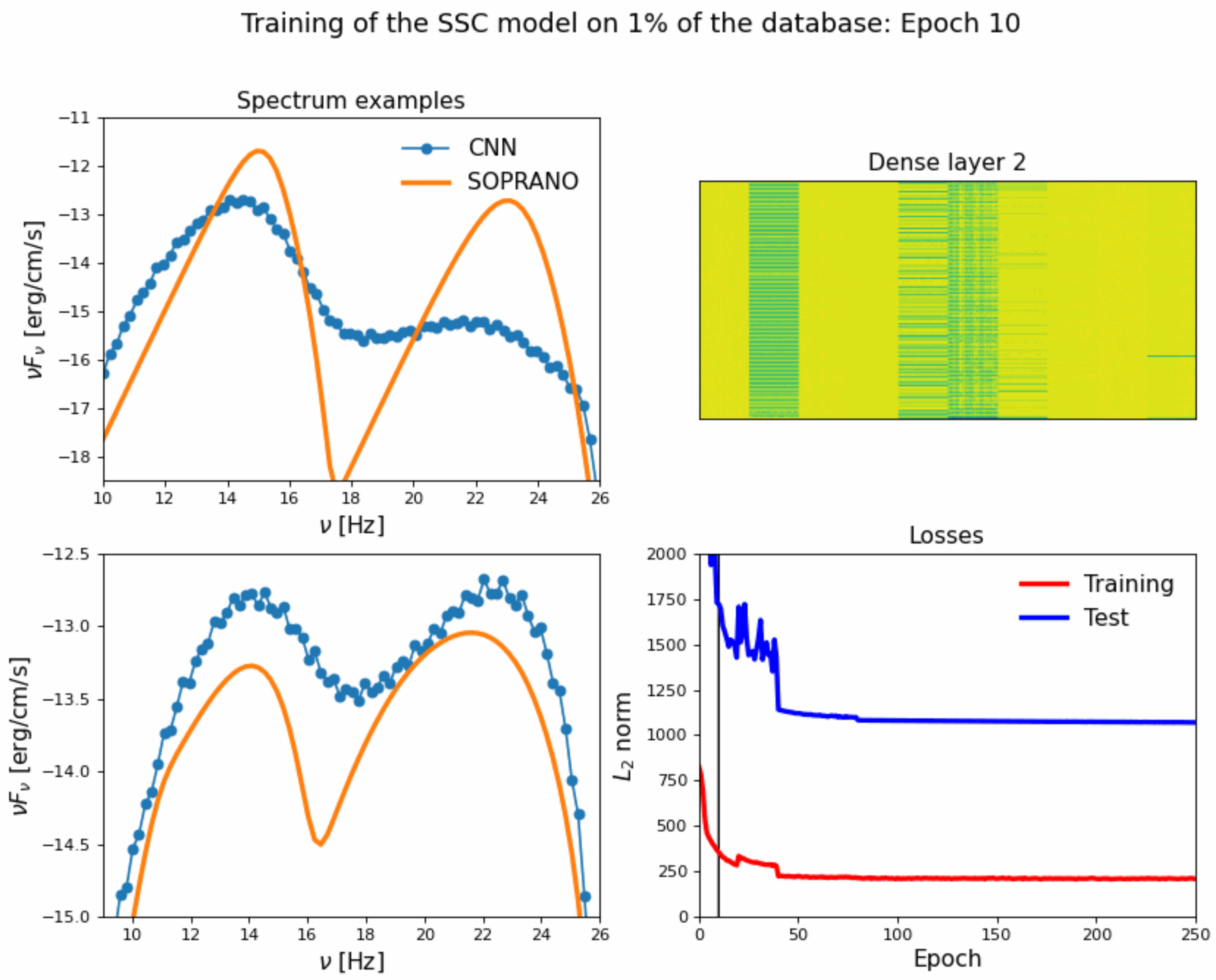

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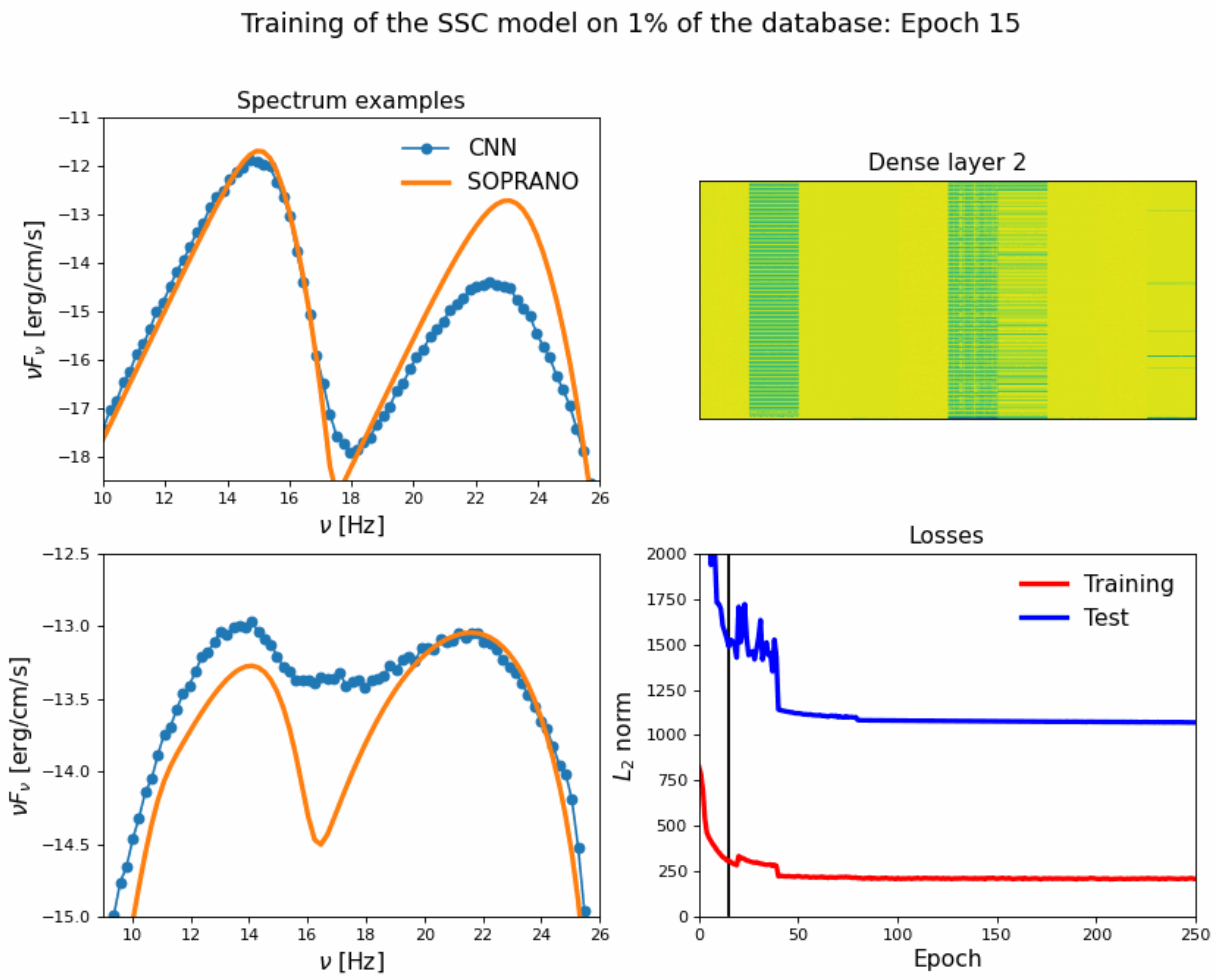

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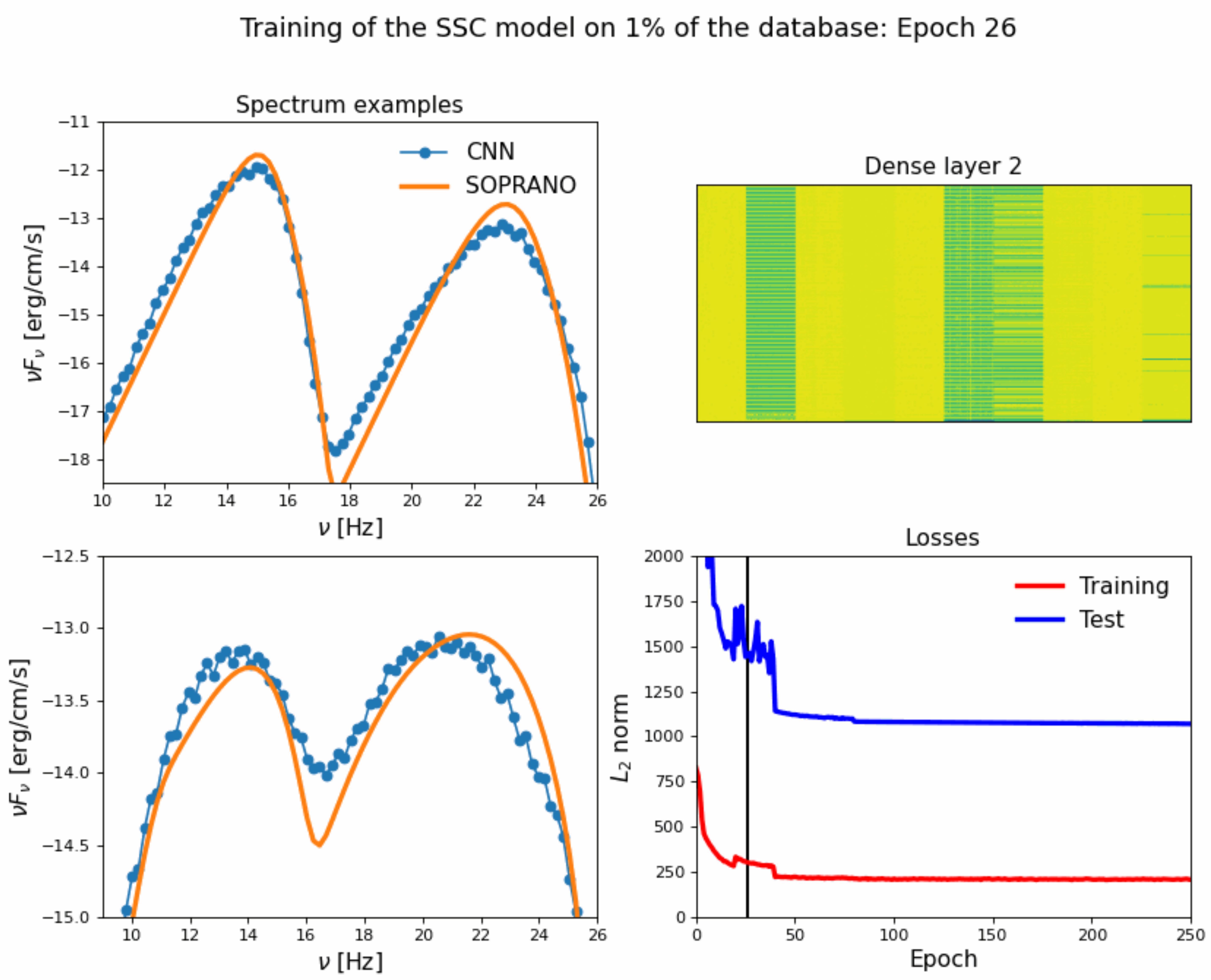

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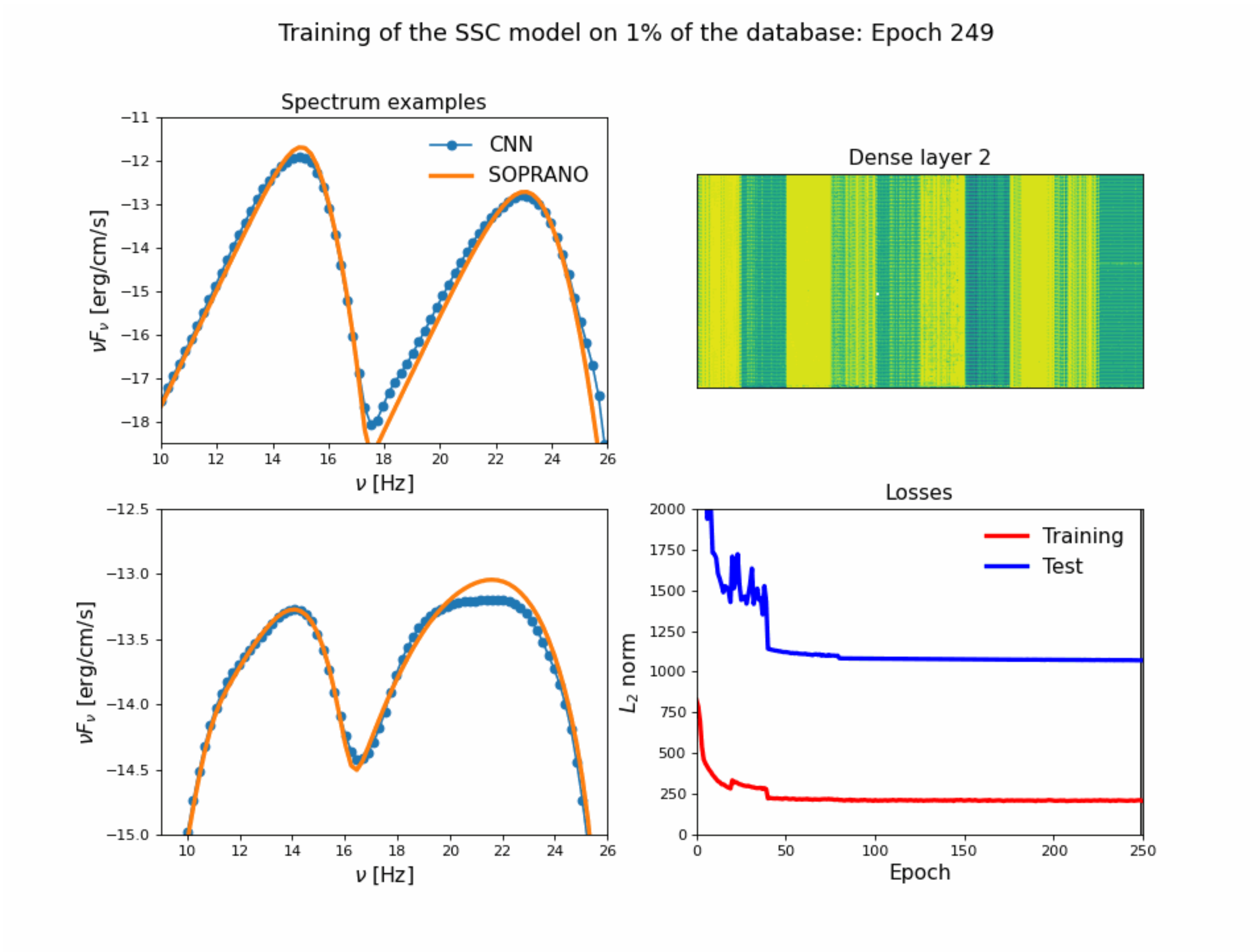

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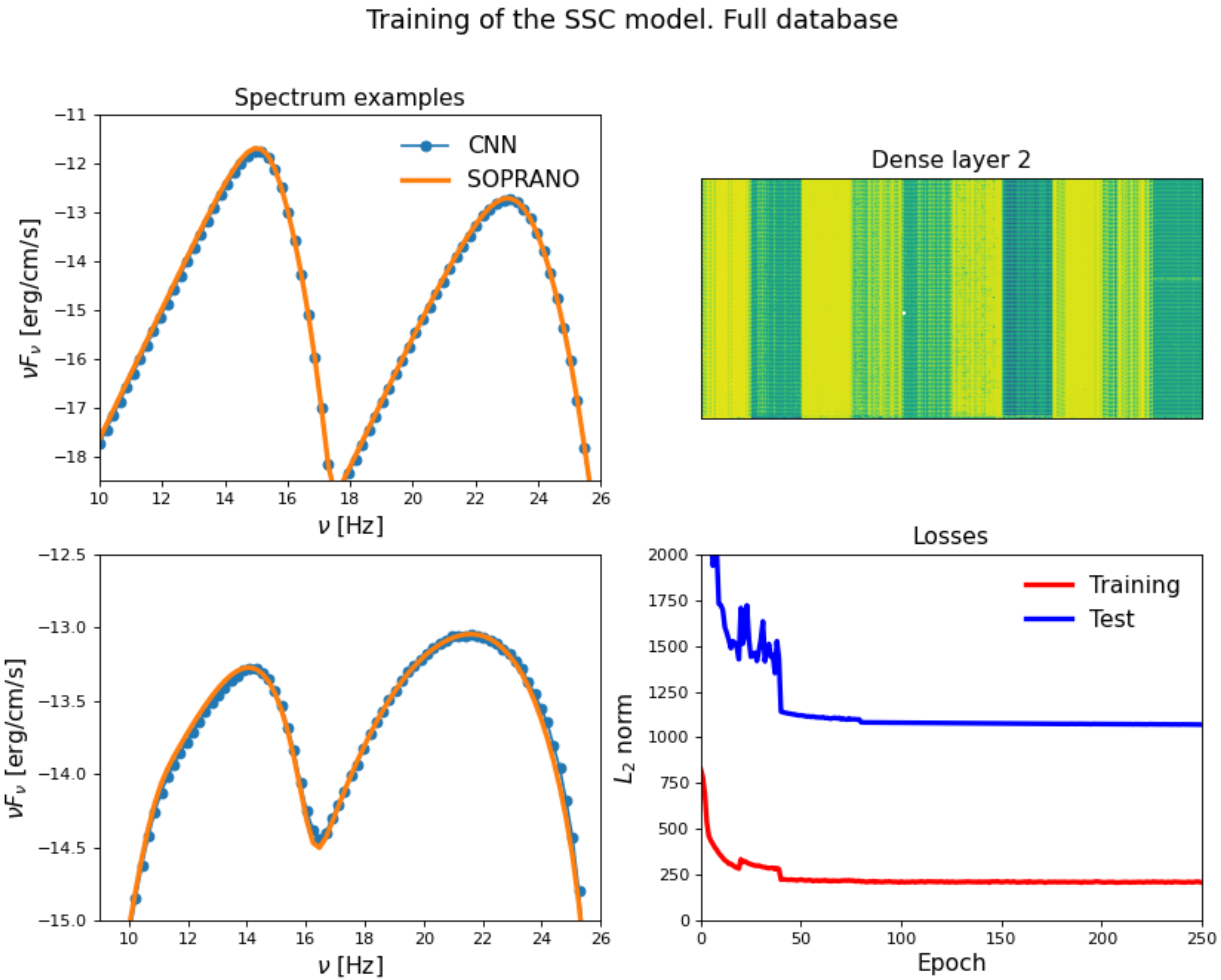

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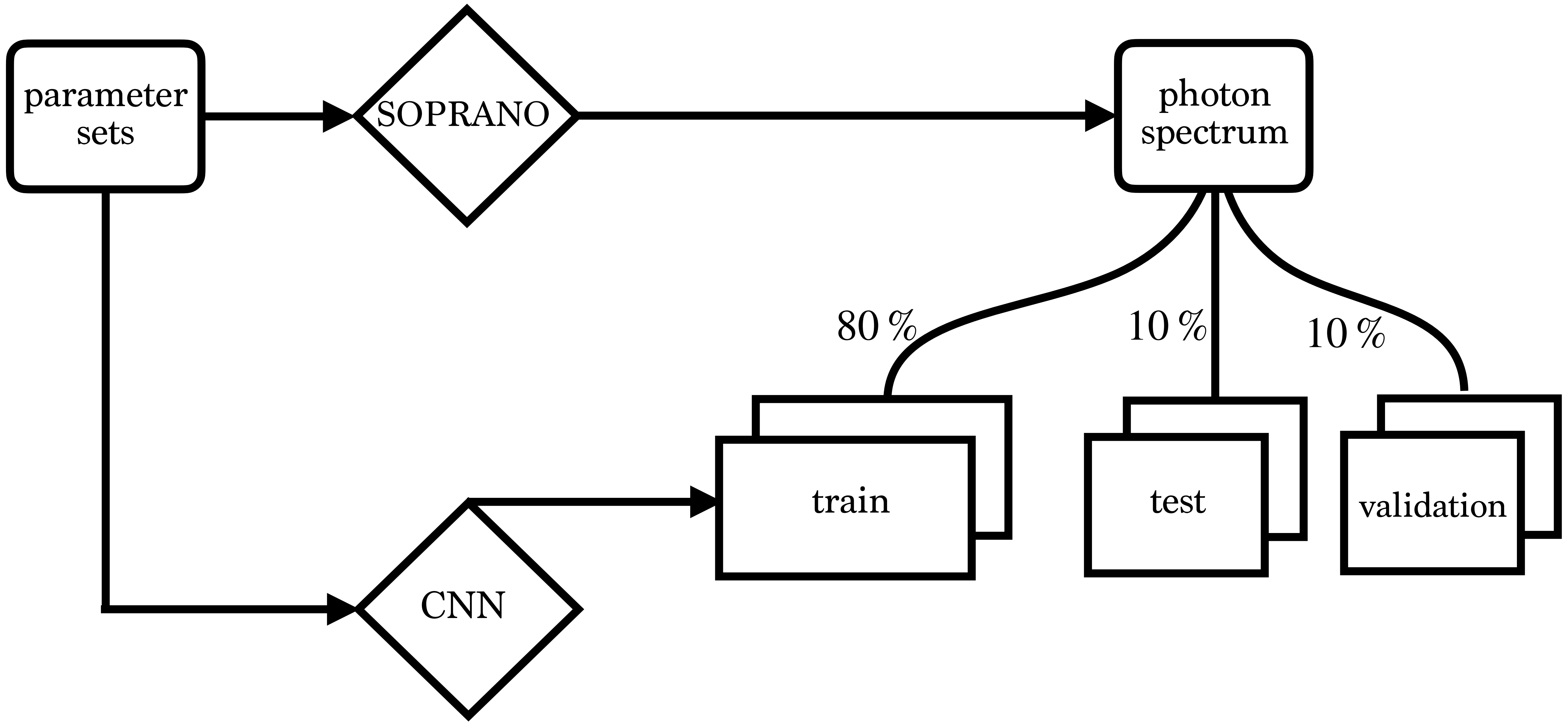
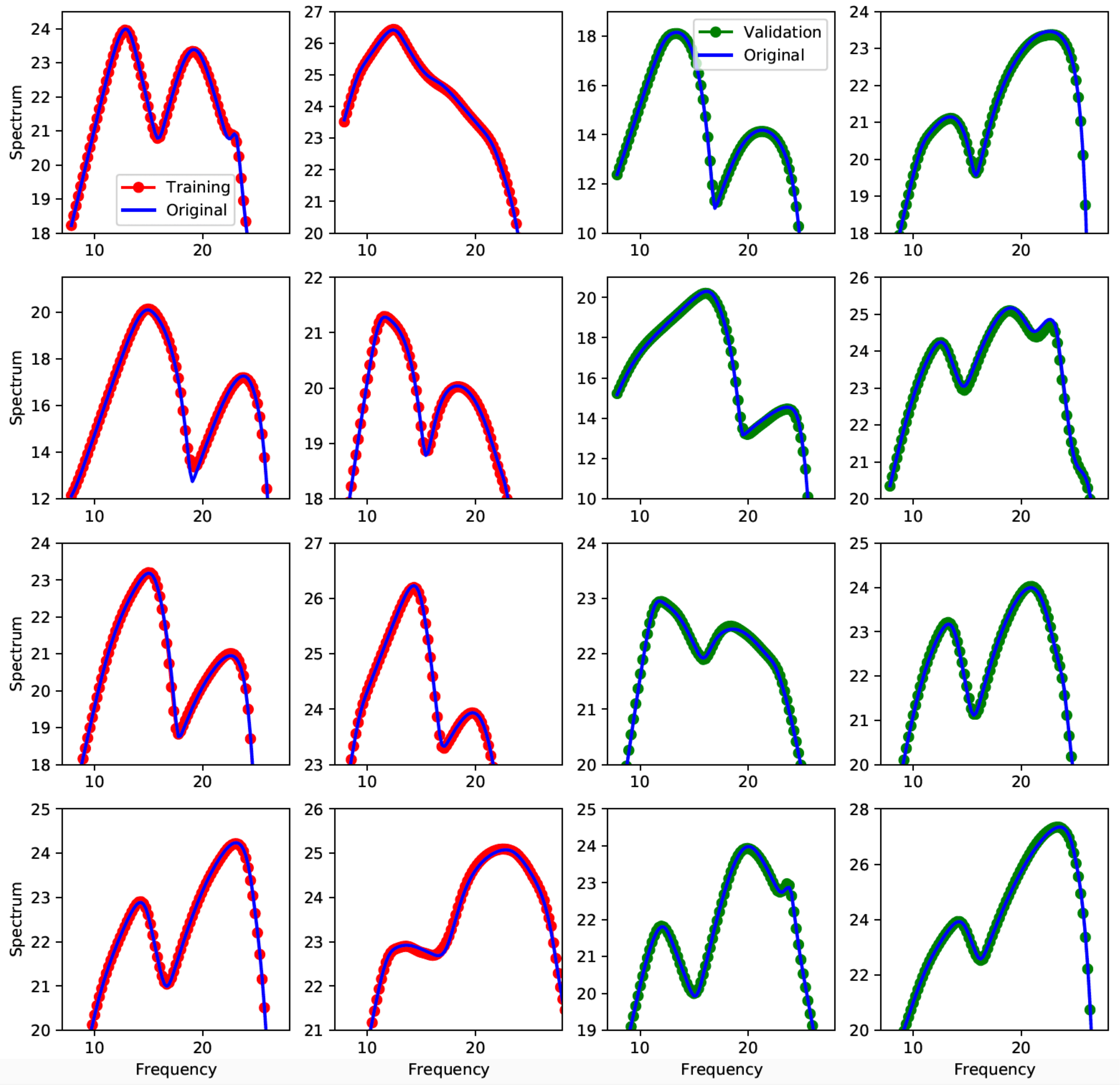
Training CNN Surrogates for Hadronic Blazar Models

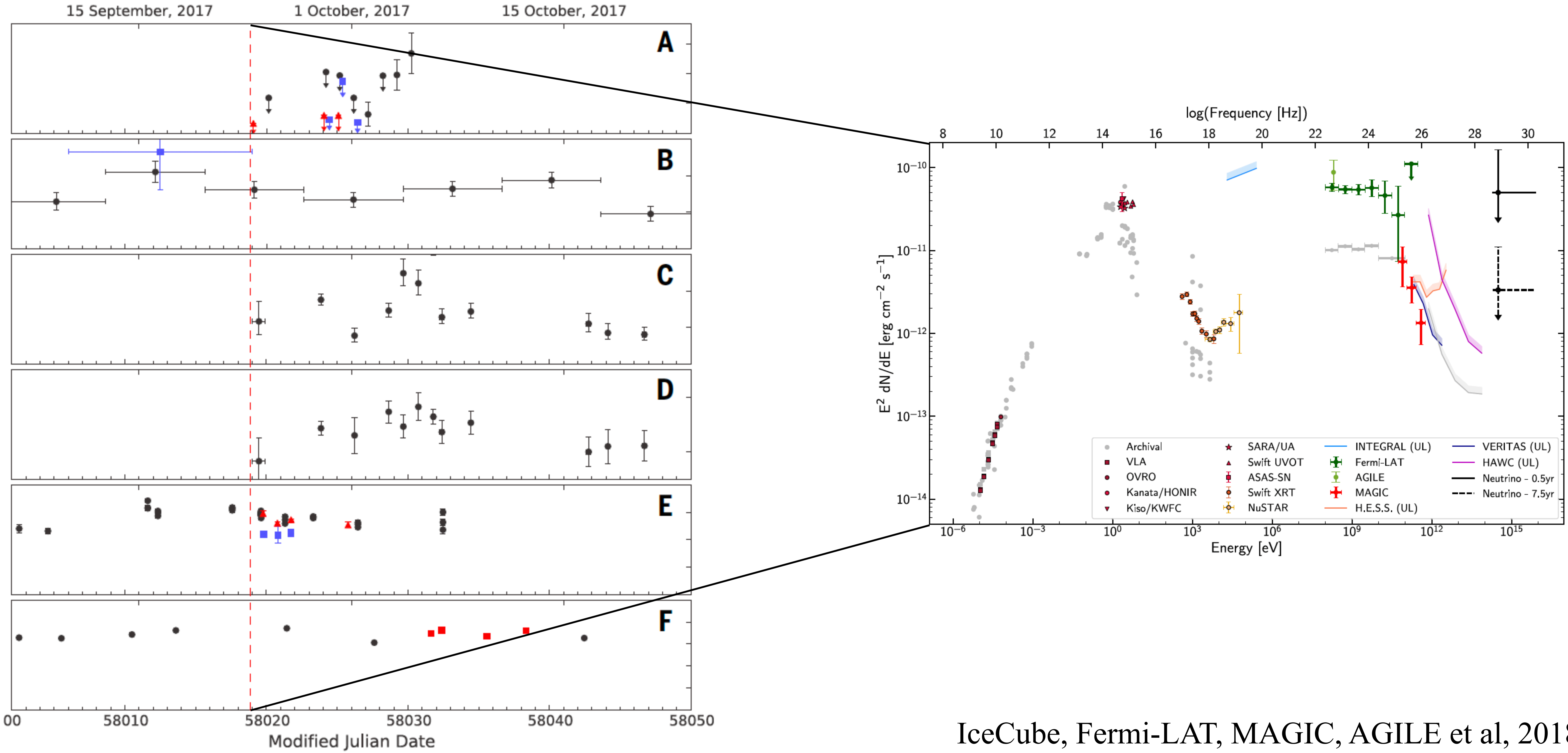
- CNN trained on 7 million spectra generated using the SOPRANO code.
- Training spans 10-dimensional parameter space with broad, physically motivated ranges.





Sahakyan, Bégué et al., ApJ, 990, 222 (2025)

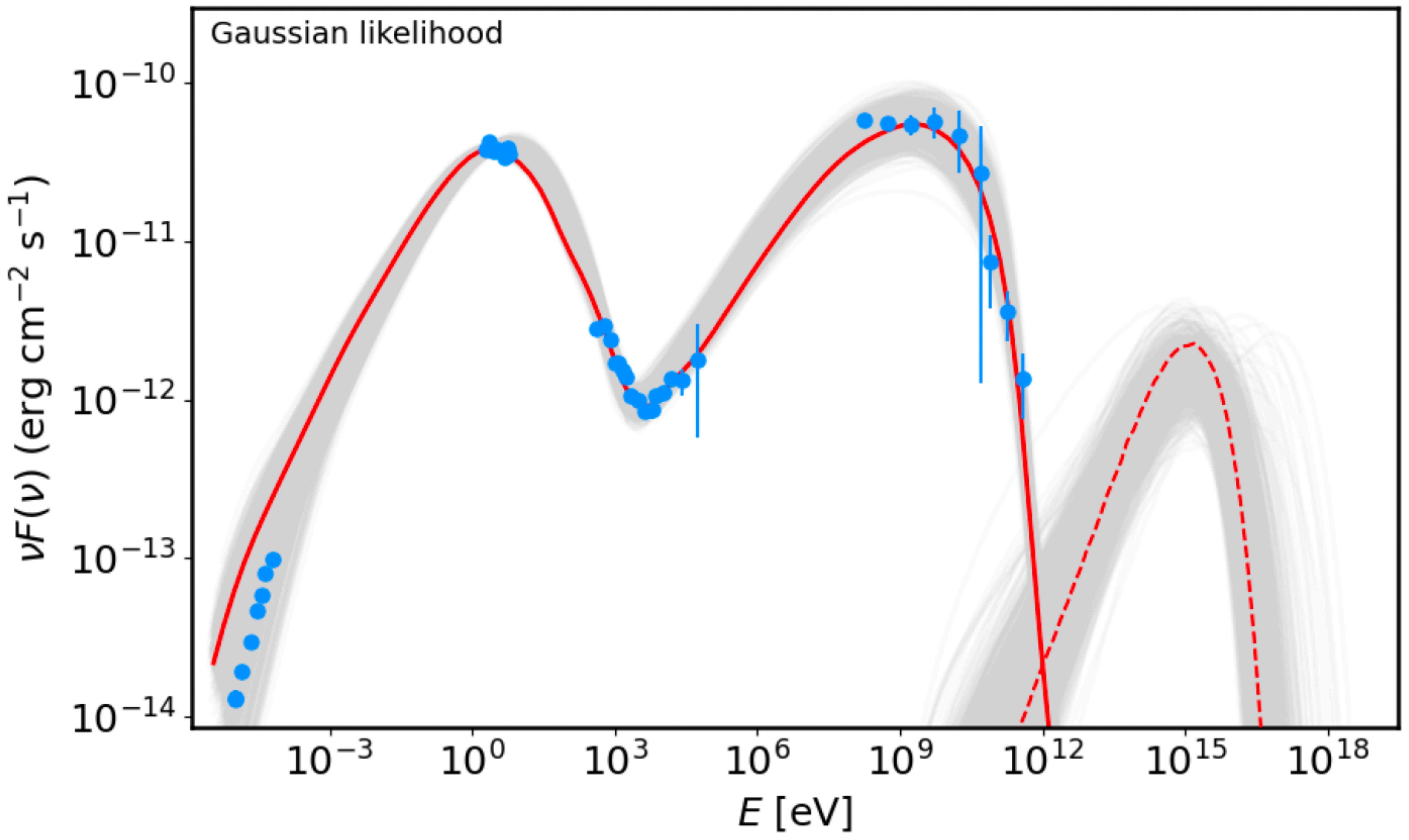
IceCube-170922A— TXS 0506+059



IceCube, Fermi-LAT, MAGIC, AGILE et al, 2018

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.

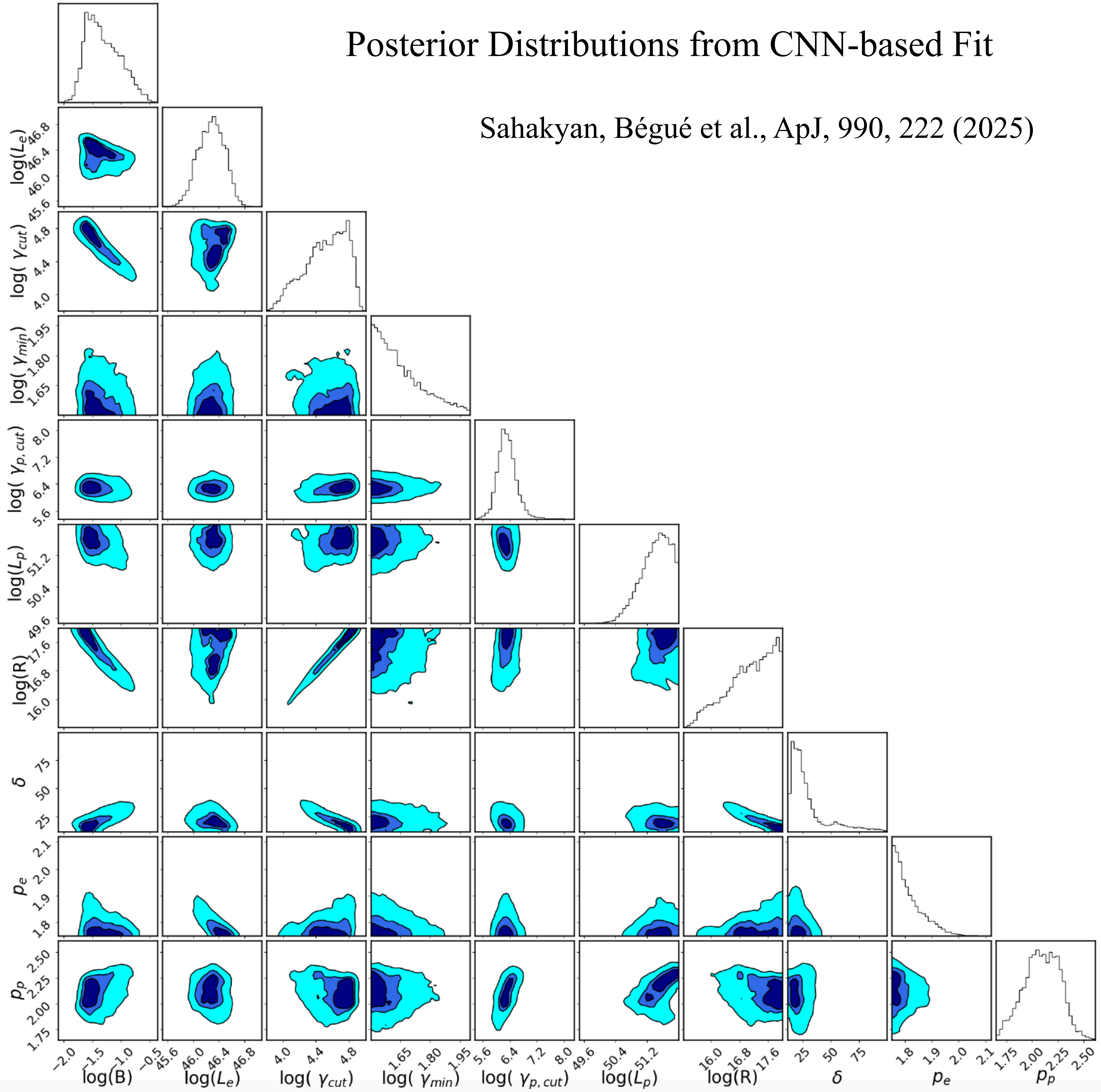


Model parameters for TXS 0506+059

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

Posterior Distributions from CNN-based Fit

Sahakyan, Bégué et al., ApJ, 990, 222 (2025)



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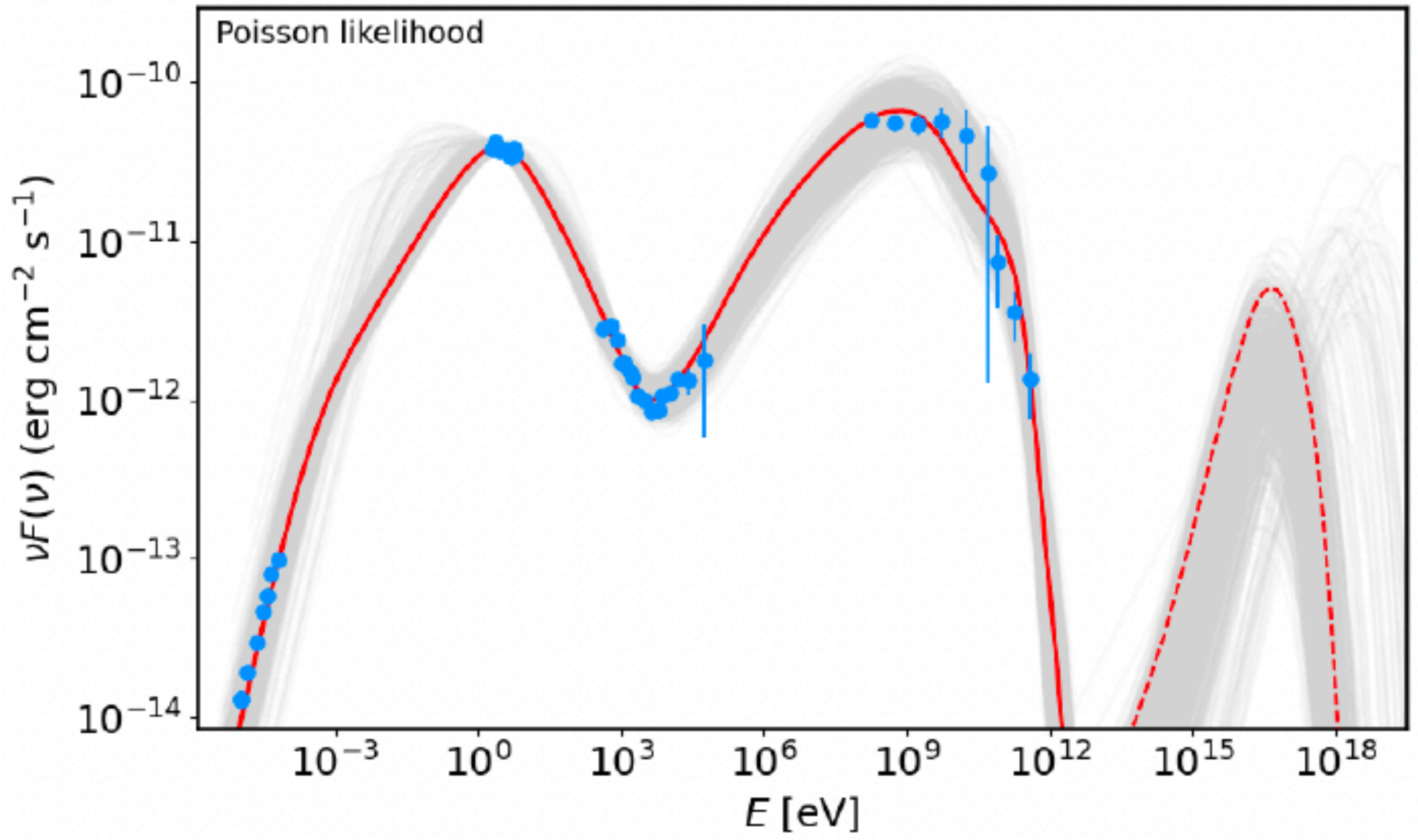
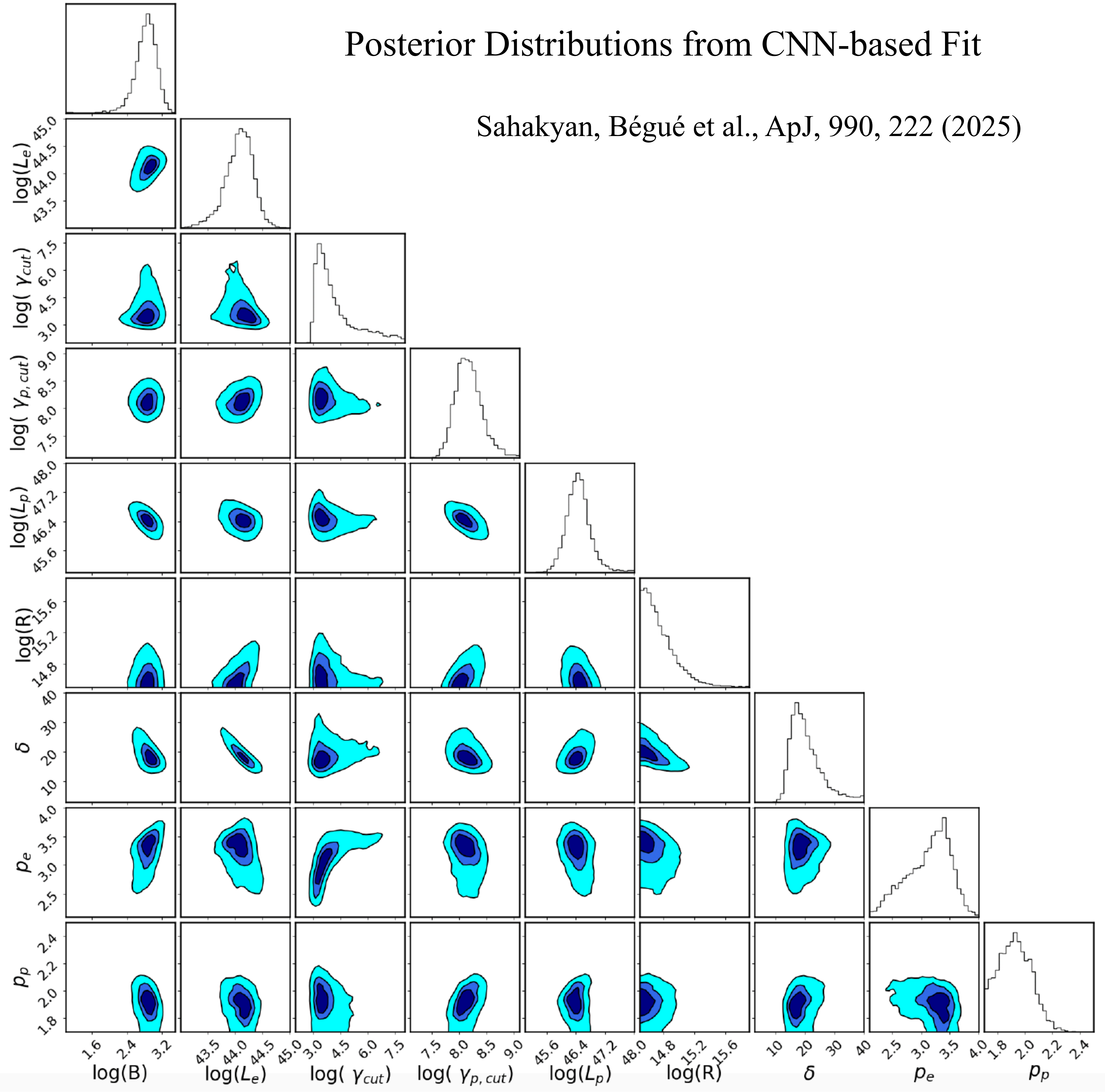


Model parameters for TXS 0506+059

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



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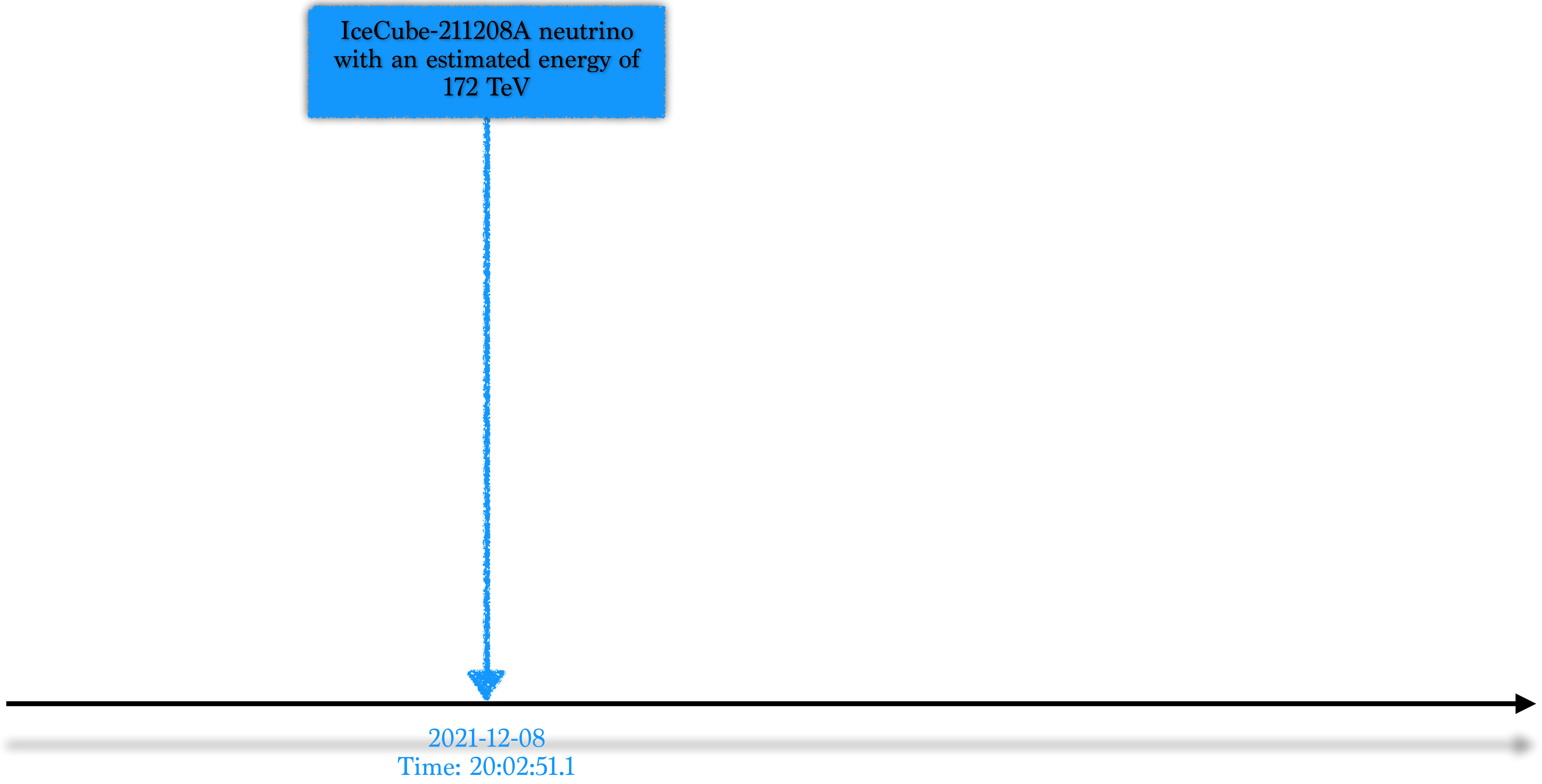
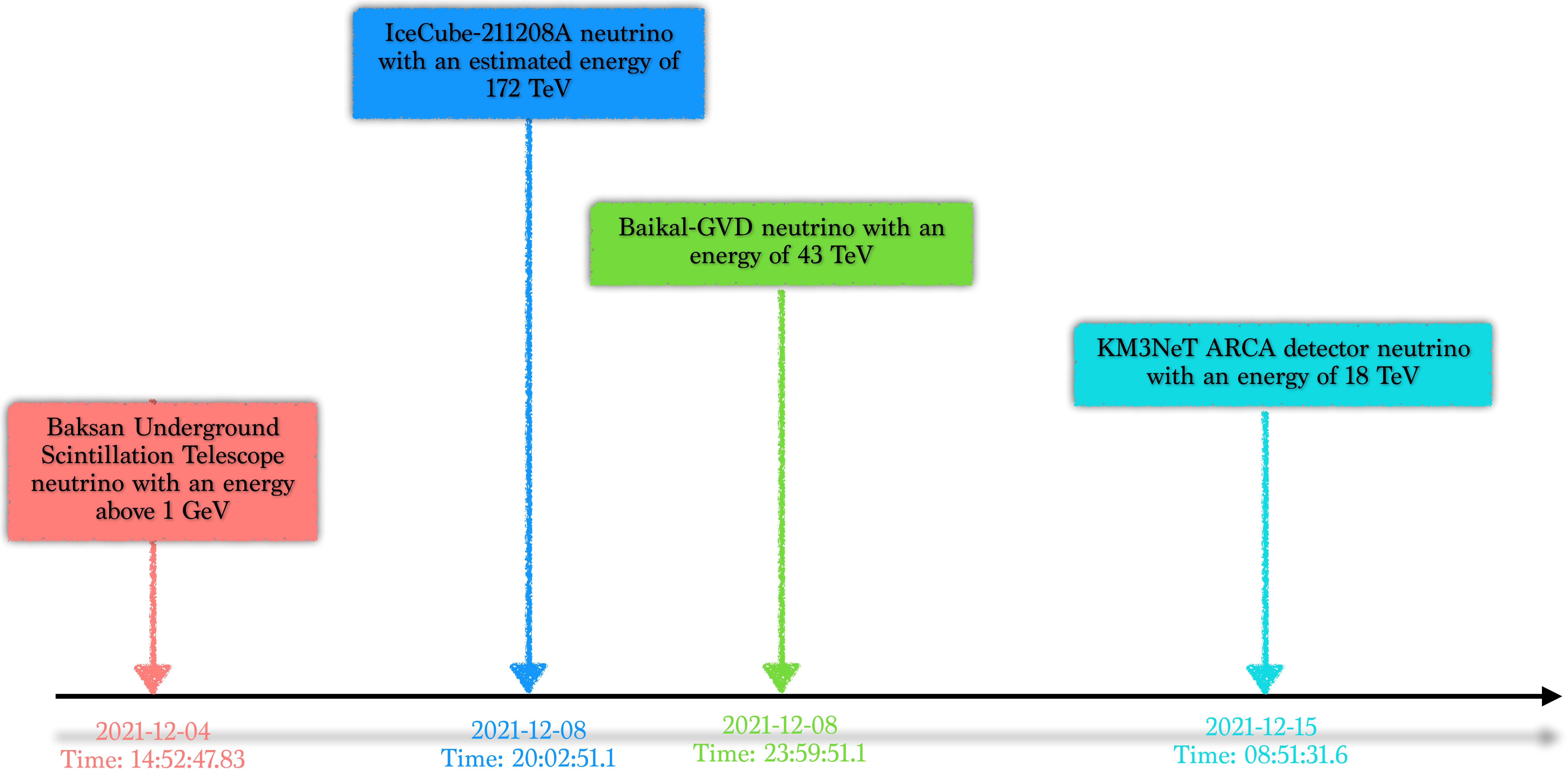
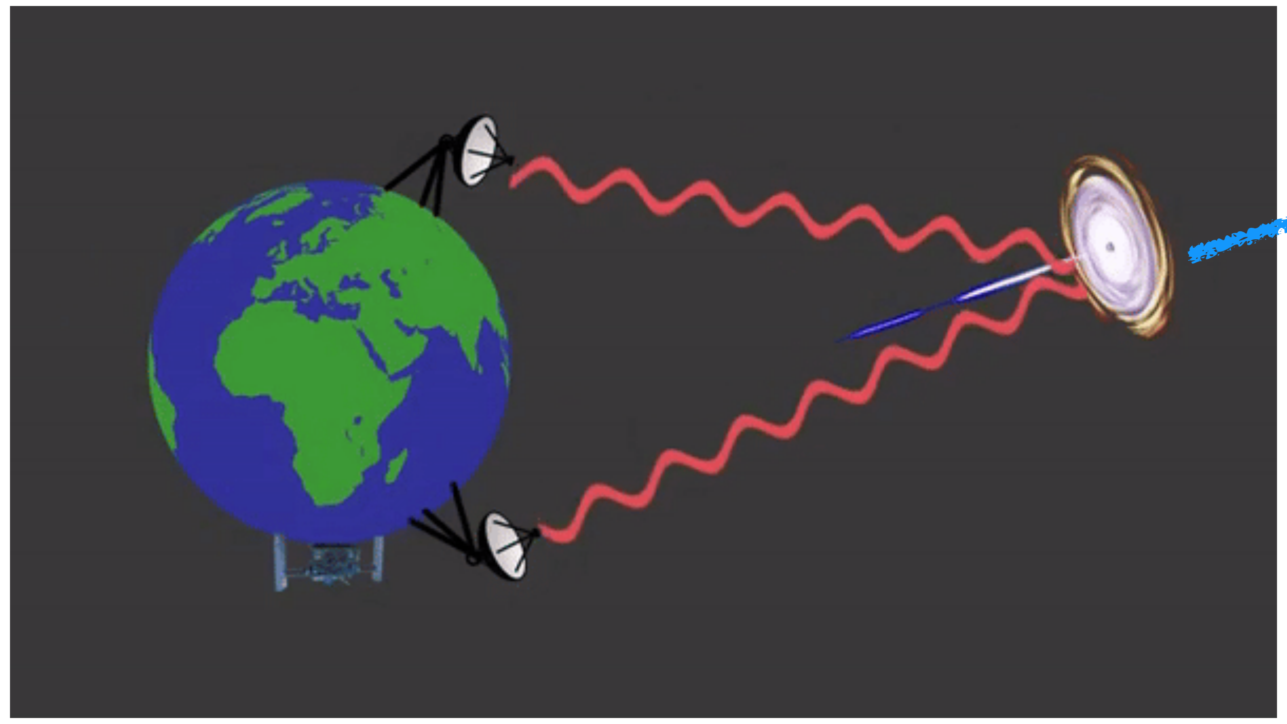
Neutrinos from PKS 0735+178

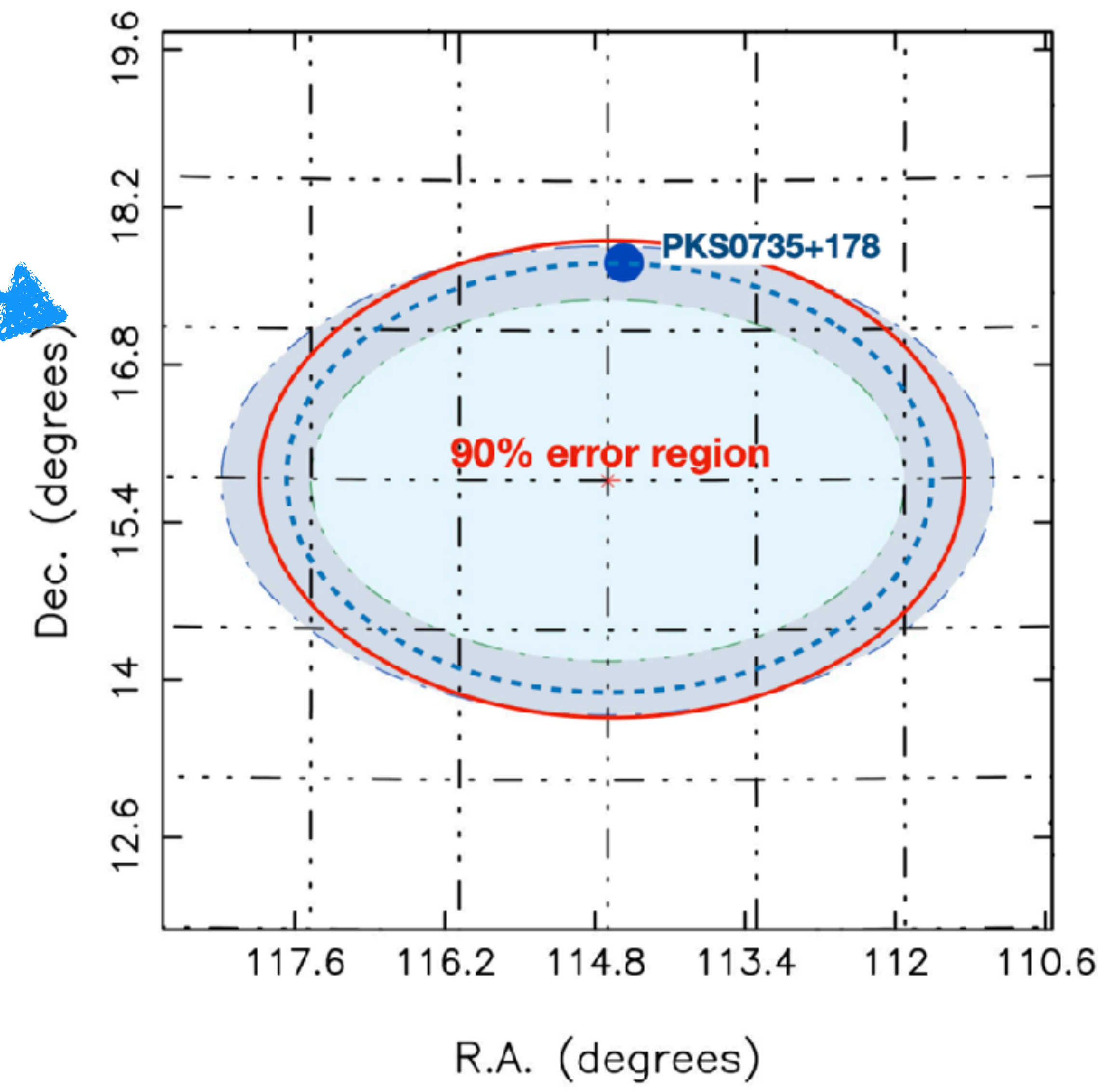


Neutrinos from PKS 0735+178



Neutrinos from PKS 0735+178





IceCube-211208A neutrino with an estimated energy of 172 TeV

Baikal-GVD neutrino with an energy of 43 TeV

KM3NeT ARCA detector neutrino with an energy of 18 TeV

Baksan Underground Scintillation Telescope neutrino with an energy above 1 GeV

2021-12-04
Time: 14:52:47.83

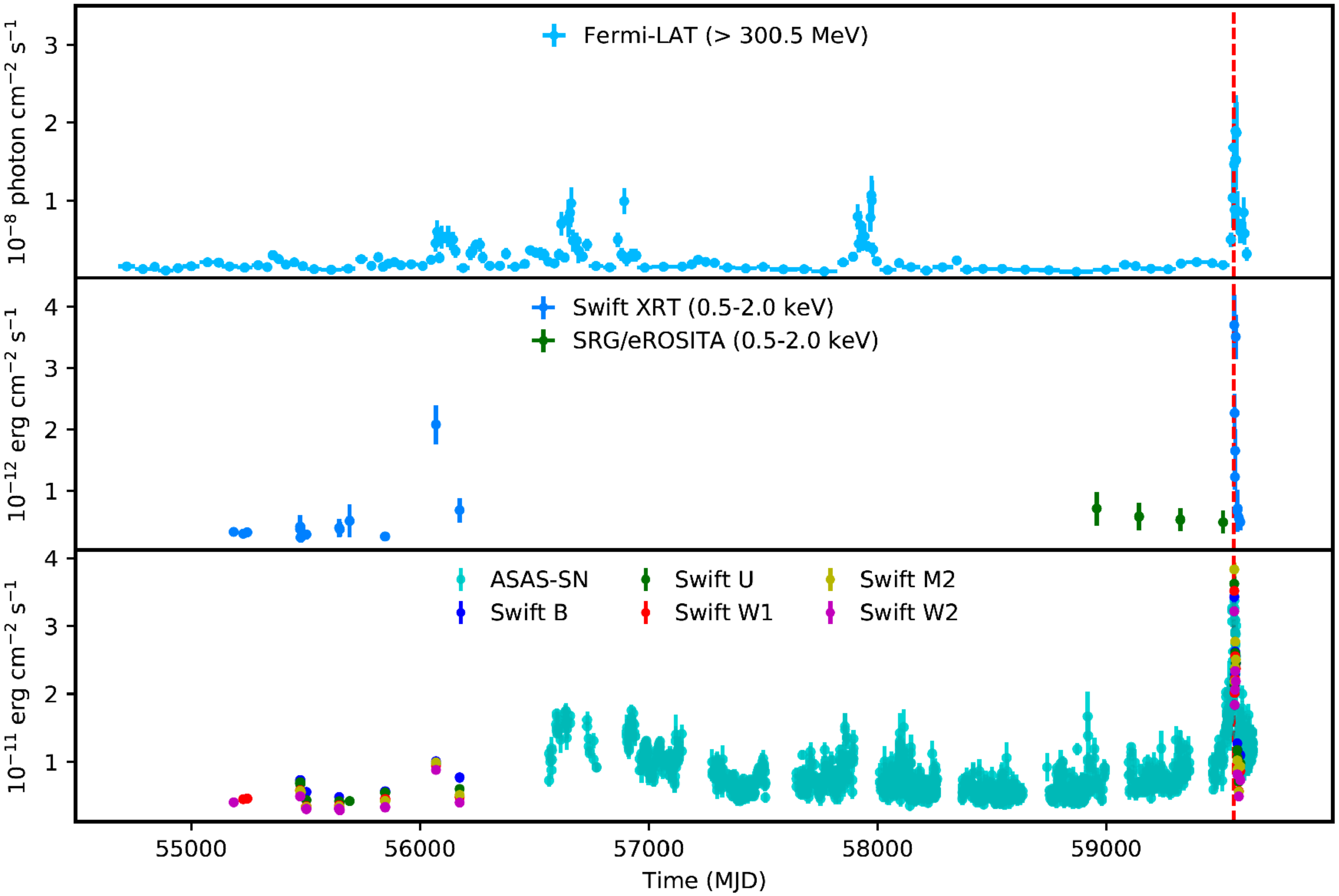
2021-12-08
Time: 20:02:51.1

2021-12-08
Time: 23:59:51.1

2021-12-15
Time: 08:51:31.6

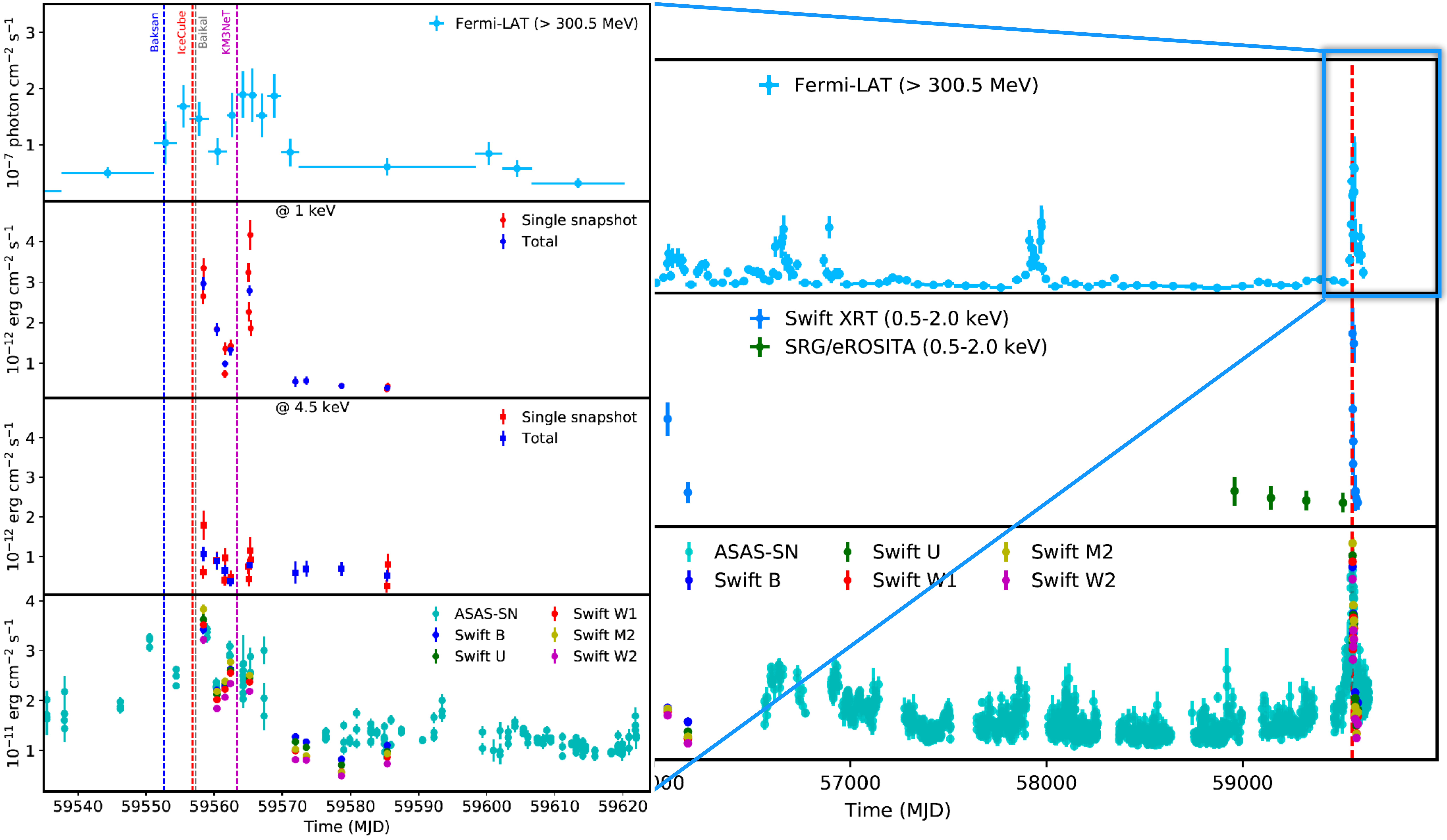
Sahakyan, Giommi, et al., MNRAS, 2023

MW lightcurve of PKS 0735+178



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

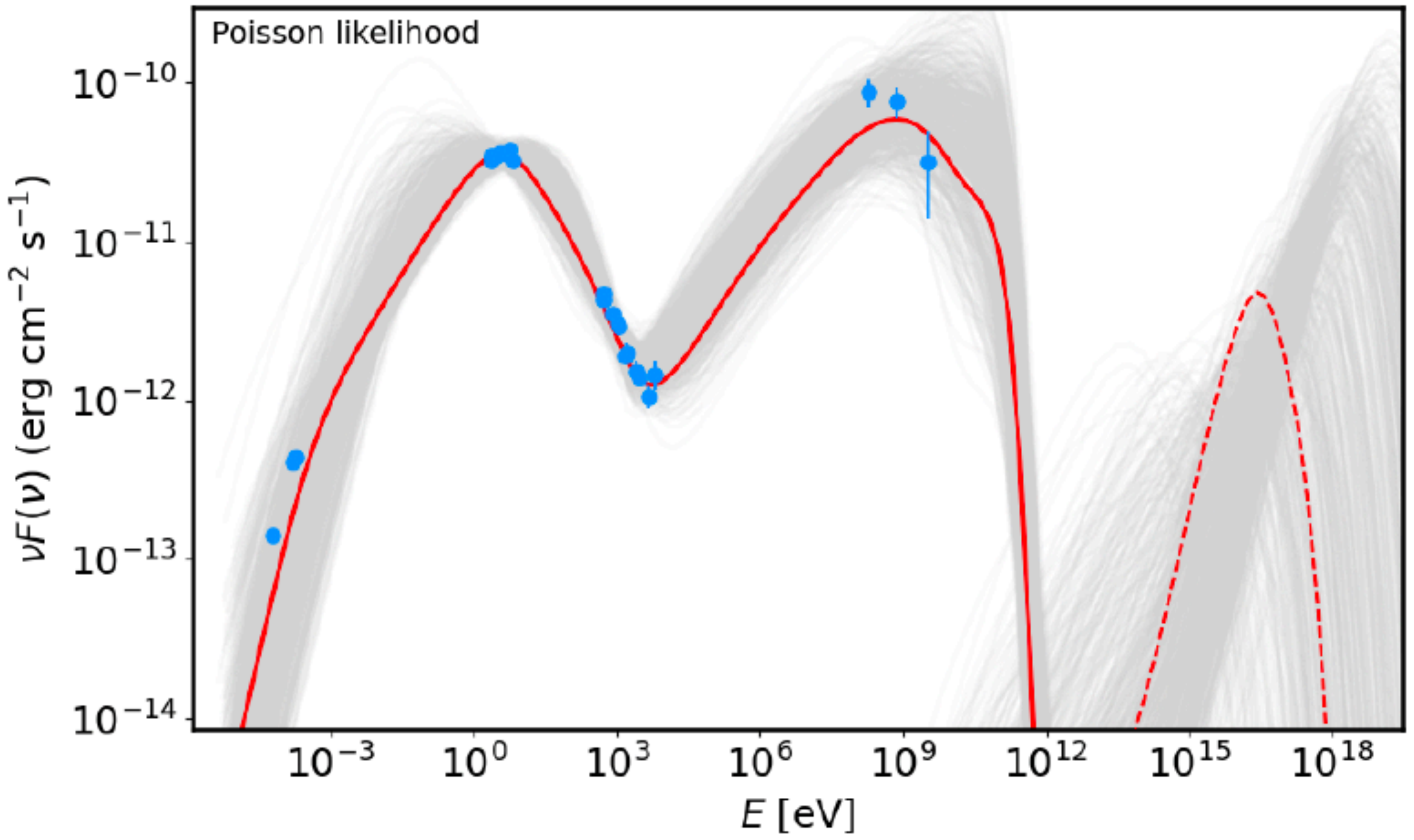
MW lightcurve of PKS 0735+178 and origin of the emission



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

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.

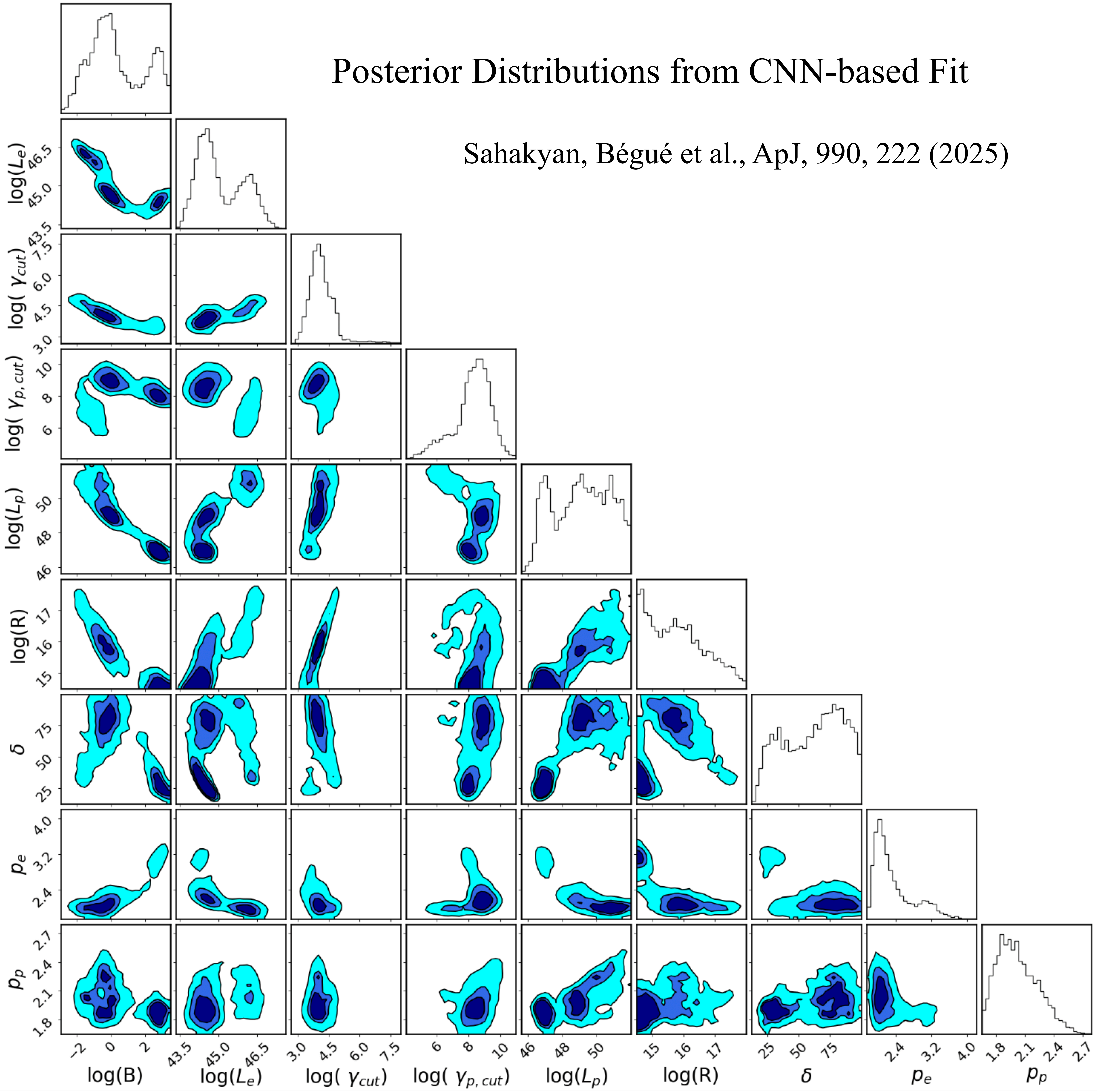


Model parameters for PKS 0735+178

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

Posterior Distributions from CNN-based Fit

Sahakyan, Bégué et al., ApJ, 990, 222 (2025)

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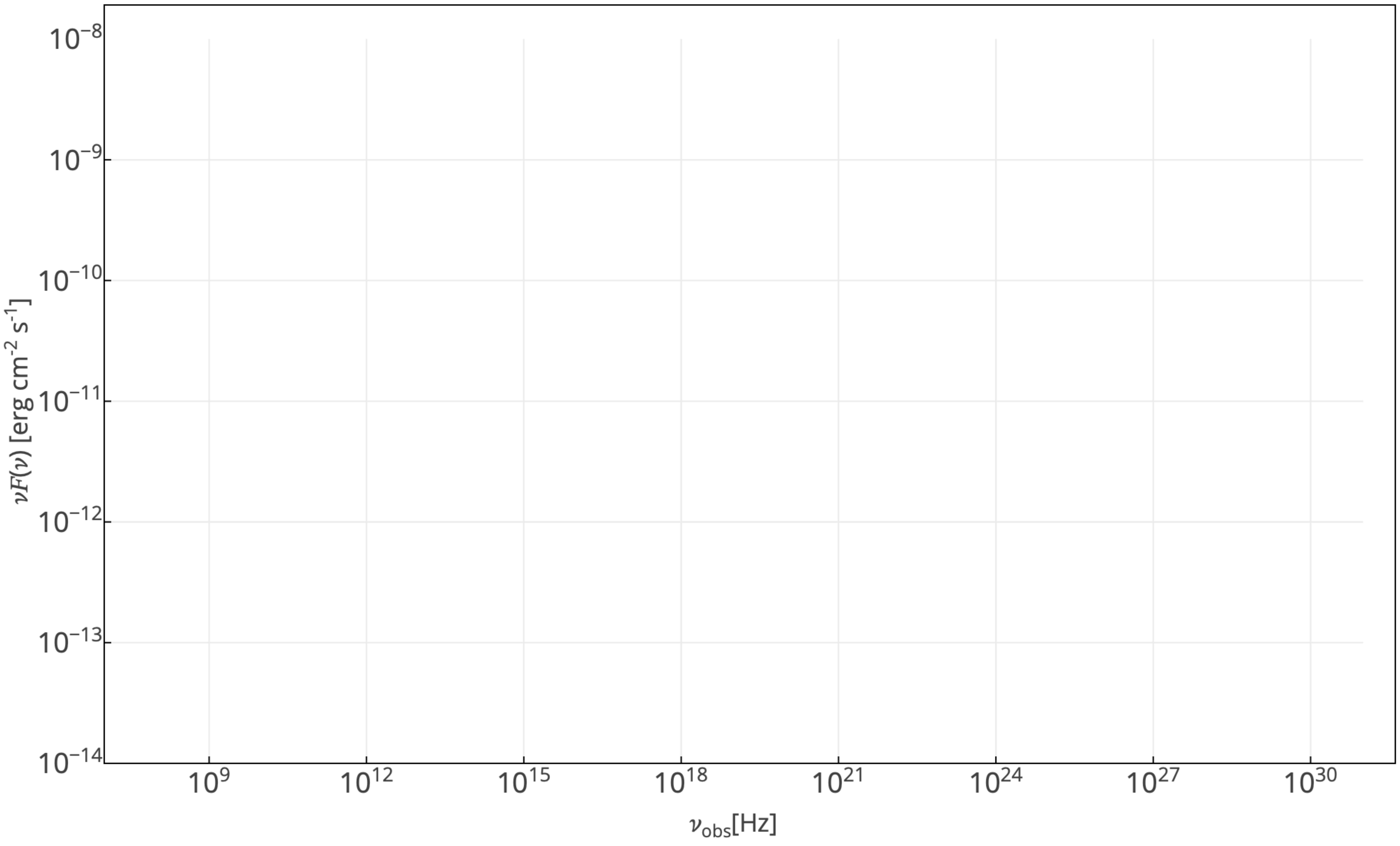

SSC | EIC

Hadronic

pe | δ

pp

log10(γmin)

log10(γe,max)

log10(γp,max)

log10(B/[G])

log10(R/[cm])

log10(Le/[erg s^{-1}])

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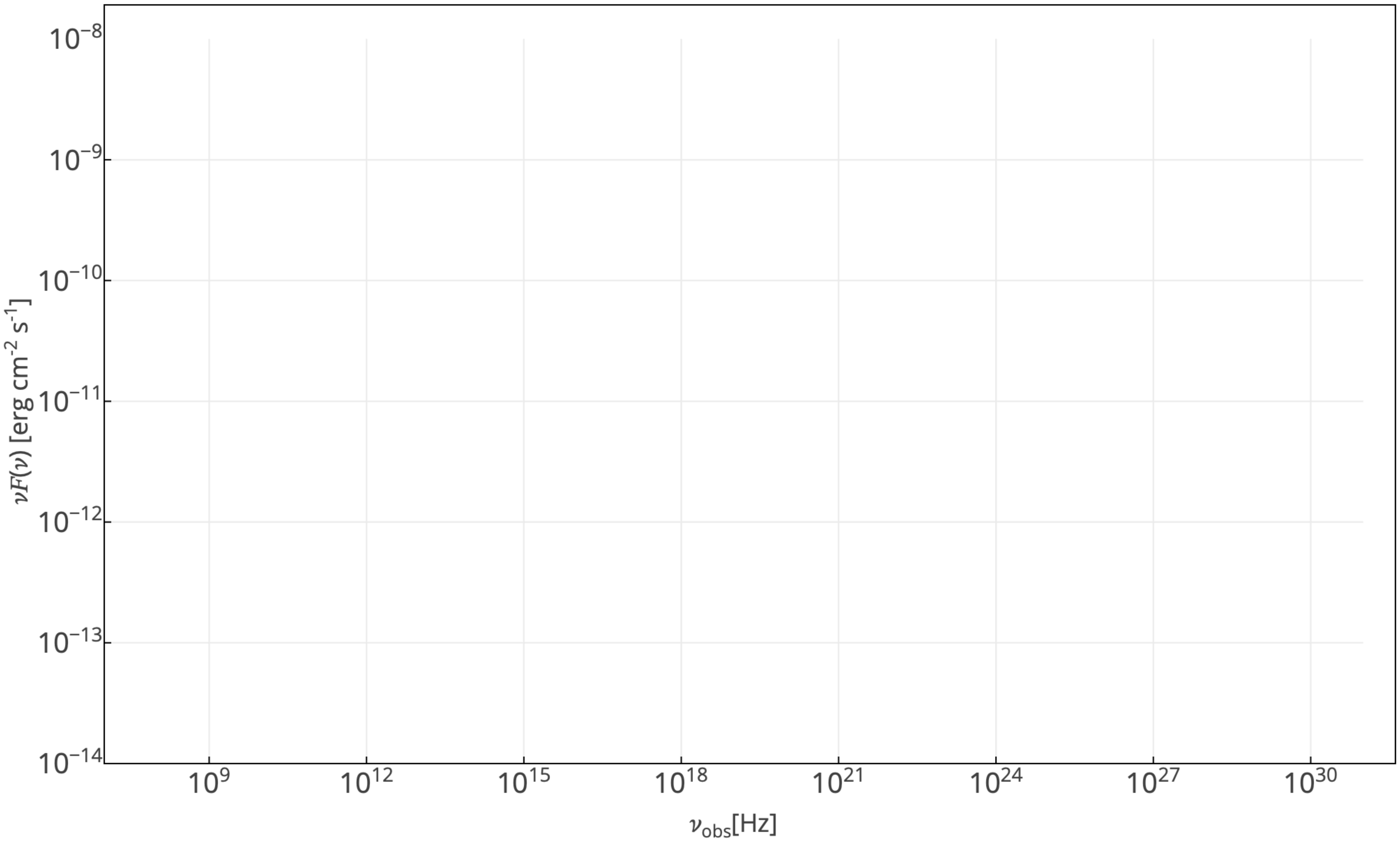

log10(R/[cm])

log10(Le/[erg s^{-1}])

log10(Lp/[erg s^{-1}])

z

EBL

› Spectral information

› Number of neutrinos

RUN MODEL

UPLOAD FILE

email

FIT

CORNER PLOT

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Home
About
Data access
Theoretical Modeling
Articles
Team
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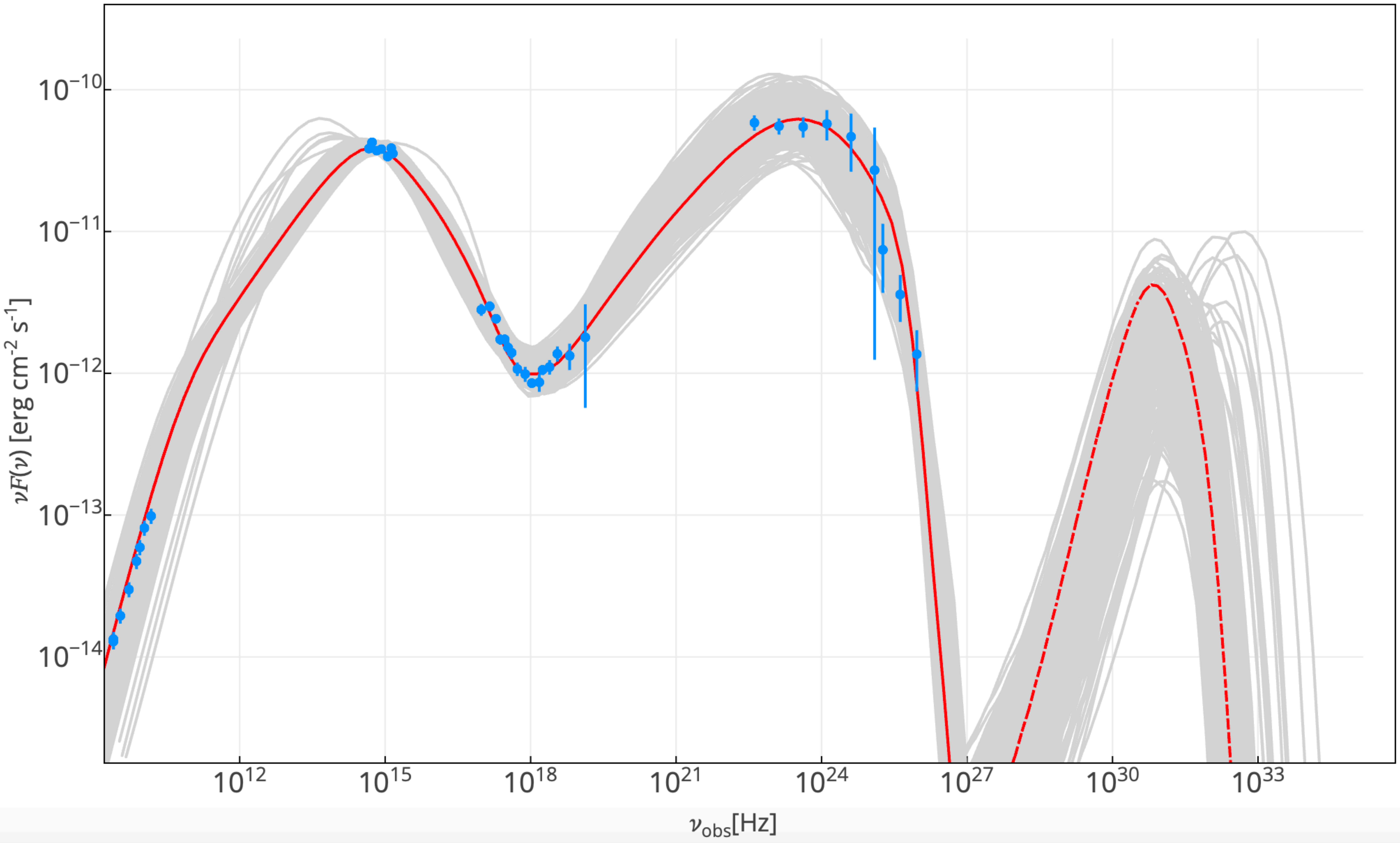
$\nu F(\nu)$ [erg cm^{-2} s^{-1}]
10^{-8}
10^{-9}
10^{-10}
10^{-11}
10^{-12}
10^{-13}
10^{-14}
10^{9}
10^{12}
10^{15}
10^{18}
10^{21}
10^{24}
10^{27}
10^{30}
ν_{obs}[Hz]
log10(R/[cm])
log10(Le/[erg s^{-1}])
log10(Lp/[erg s^{-1}])
z
0.033
EBL
Spectral information
Number of neutrinos
RUN MODEL
UPLOAD FILE
email
FIT
CORNER PLOT
BEST PARAMETERS



SSC | EIC

Hadronic

pe: 2.344

δ: 14.527

pp: 1.853

log10(γmin): 2

log10(γe,max): 3.030

log10(γp,max): 8.287

log10(B/[G]): 2.770

log10(R/[cm]): 14.977

log10(Le/[erg s^{-1}]): 44.660

Conclusions

- ✓ Traditional models of blazar emission—SSC, EIC, and hadronic—have significantly advanced. However, full parameter space exploration remained computationally expensive, especially when accounting for particle injection and cooling.
- ✓ We developed machine learning surrogates for each model class using convolutional neural networks. These accurately reproduce the spectra across wide parameter ranges. The hadronic model—previously requiring extensive computational resources for full parameter inference—can now be explored within minutes.
- ✓ This enables fast, scalable, and statistically robust modeling of blazar emission, including during multimessenger events.
- ✓ The growing volume and quality of multiwavelength and multimessenger data from modern observatories, when combined with machine learning, are poised to significantly enhance our understanding of blazar physics.