

Federico Testagrossa
(DESY Zeuthen)

Accelerating multi-messenger modeling of blazars with neural networks

Based on the work with:

Despina Karavola, Stamatis Stathopoulos, Chengchao Yuan,
Walter Winter, Maria Petropoulou, Georgios Vasiloupoulos



DAAD

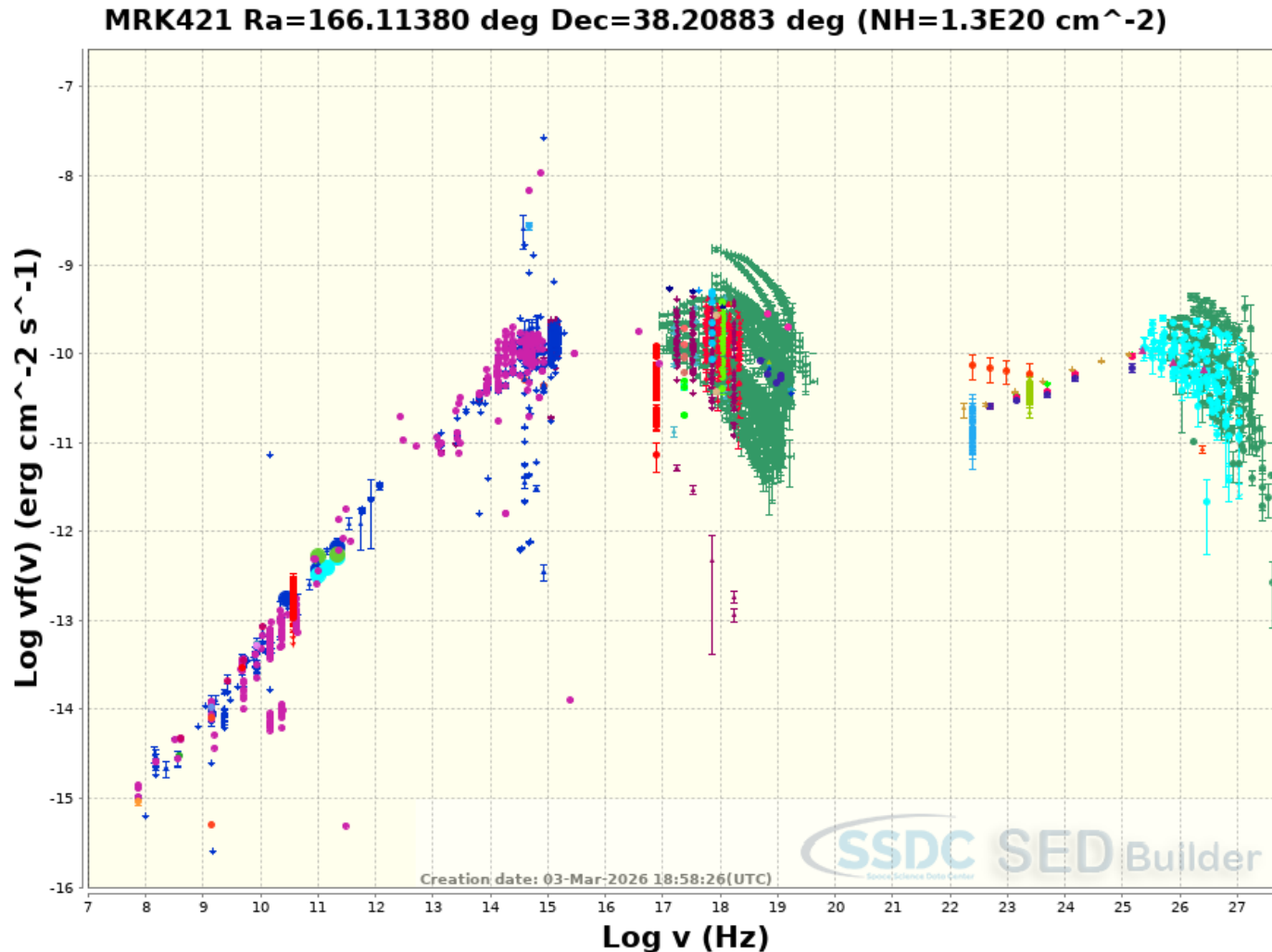
Deutscher Akademischer Austausch Dienst

IKYDA

HELMHOLTZ



Multiwavelength picture of blazars



Lots of multiwavelength data

- What is producing this radiation?
- Are the data in different bands correlated?
 - Variability?

Numerical modeling

Radiation comes from particles accelerated interacting and losing energy in one or more zones of the source

Make some assumptions and solve the transport equation

$$\partial_t n_i(E, t) = Q_i(E, t) - \partial_E [\dot{E}(E, t) n_i(E, t)] - k(E, t) n_i(E, t)$$

System of coupled PDEs (one for each particle species) → Numerical codes!

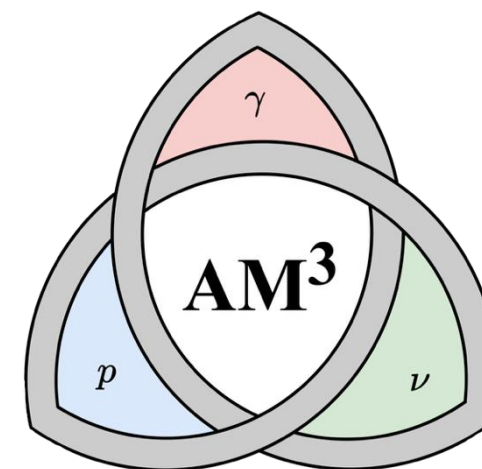


[Stathopoulos et al. (2023)]

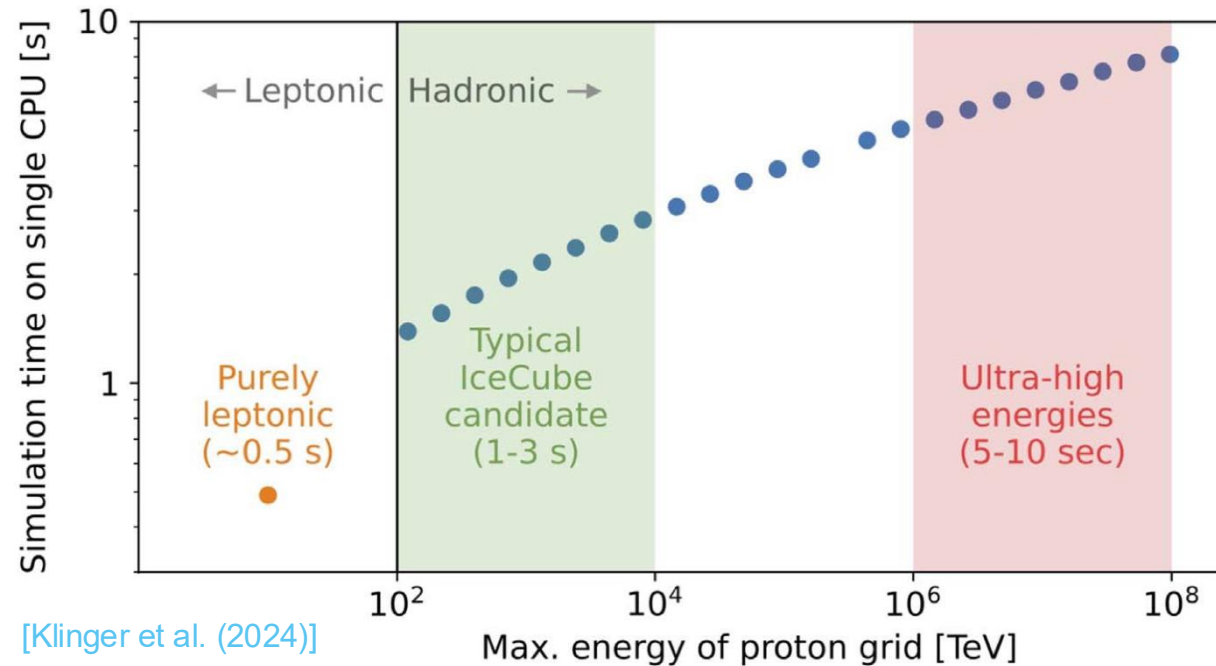
Github

[Klinger et al. (2024)]

Website



AM^3 – Astrophysical Multimessenger modeling



Single-zone leptonic (6 parameters)
Single-zone hadronic (10 parameters)
+ more if external photon fields are included

$10^5 - 10^6$ evaluations needed to fit a source → computationally expensive!

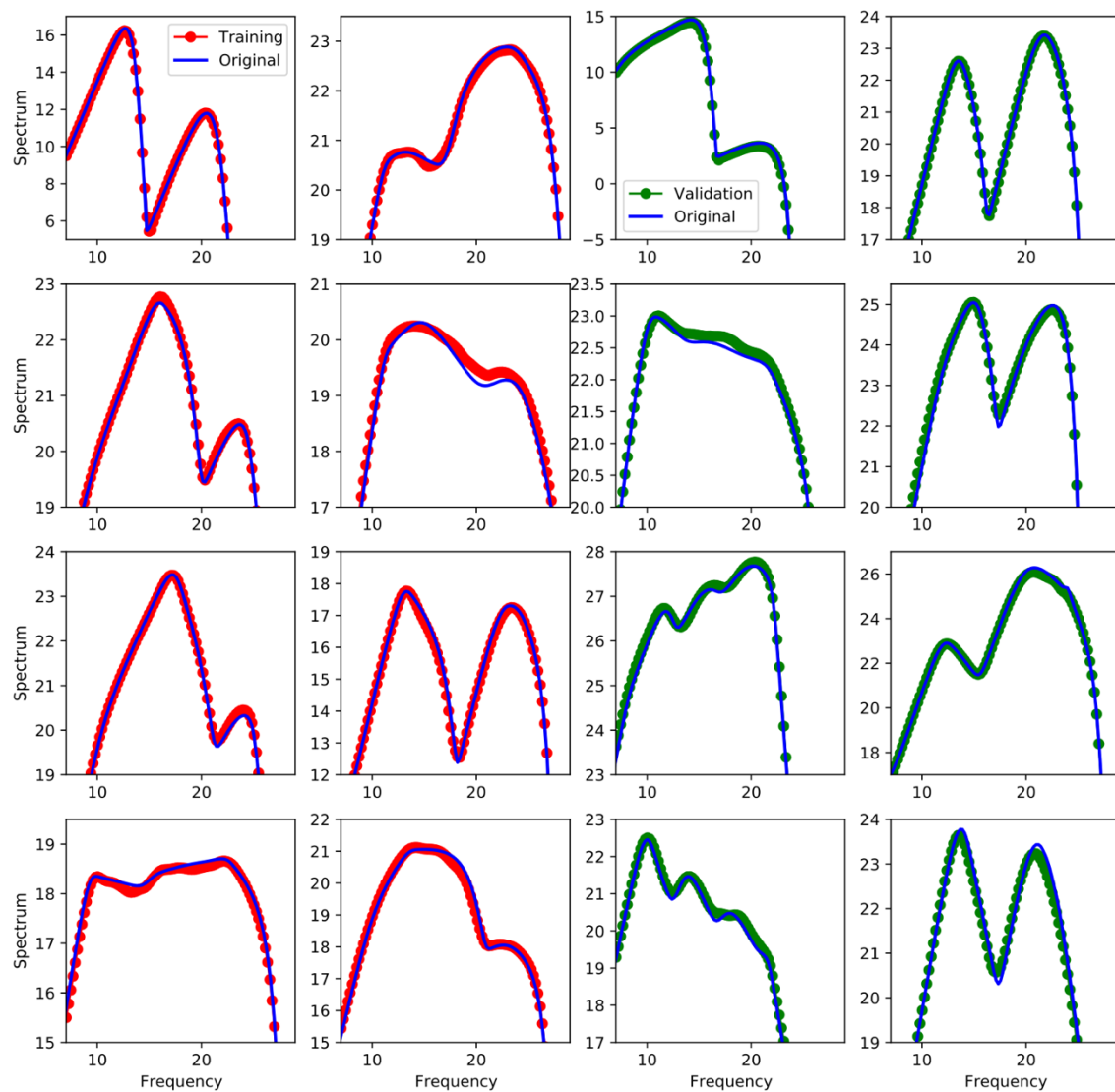
Can we evaluate models faster than that?

Radiative models can be highly nonlinear and hard/impossible to predict analytically
→ can a neural network “understand” them better?

The idea:

- Create a large dataset of simulations
- Use it as training/validation data for a neural network
- The neural network quickly predicts the outcome of the simulations without solving the equations

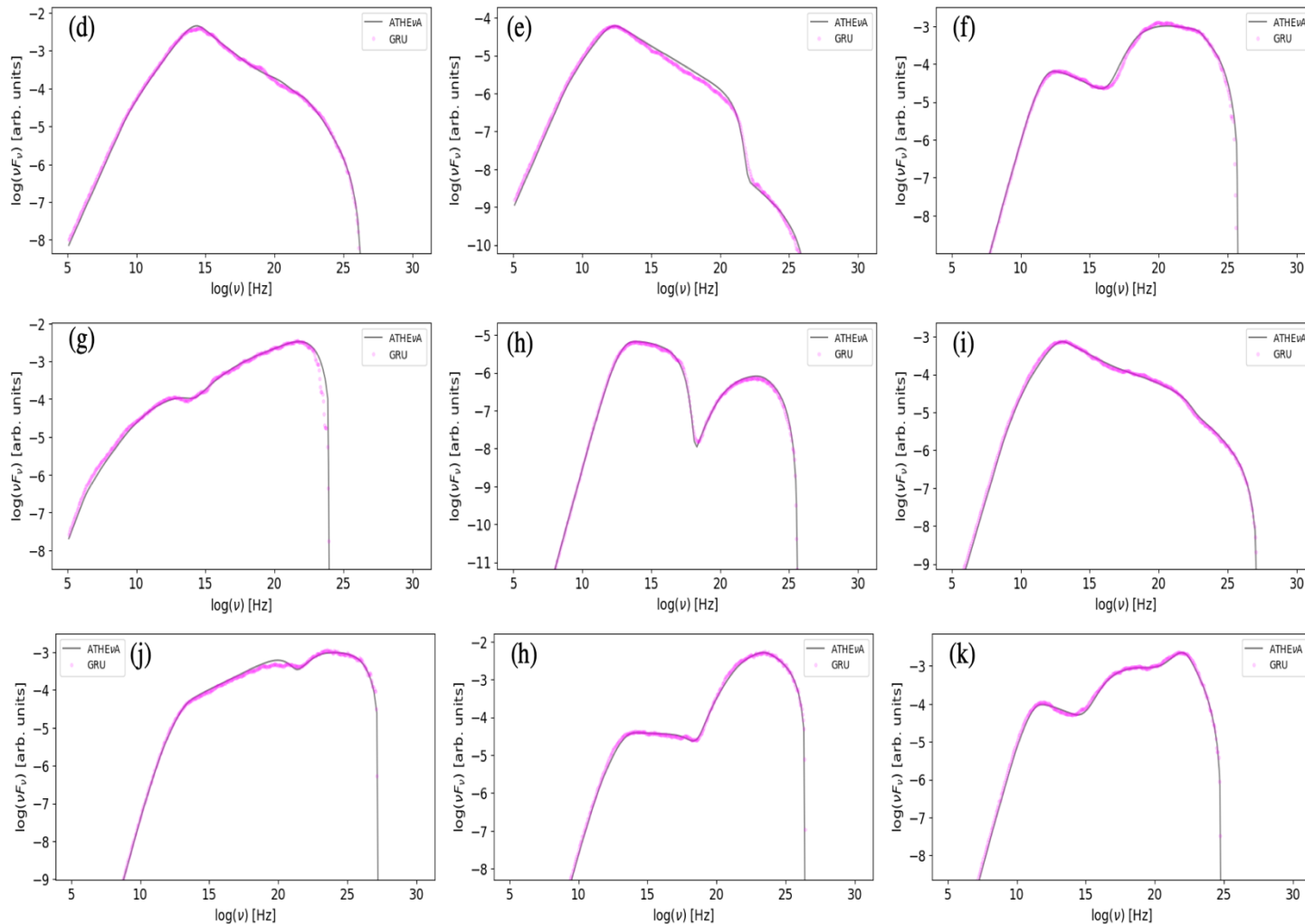
CNN (Convolutional Neural Networks)



First attempts with CNNs, using code SOPRANO
→ multiple upgrades in the last years,
check out <https://www.mmdc.am>

[Bégué et al. (2024), Sahakyan et al. (2024)] (leptonic)
[Sahakyan et al. (2025)] (hadronic)

RNN (Recursive Neural Networks)



Good choice for anything involving sequences:
SEDs are sequences in energy!

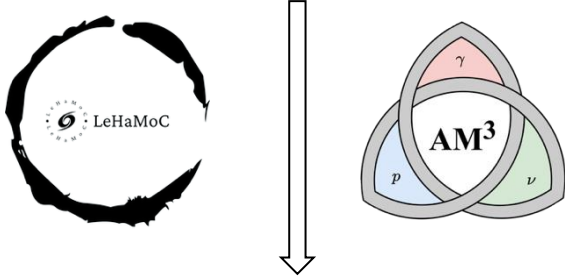
Tzavellas et al (2024):

- Dataset of 10k SSC simulations (ATHEvA)
- Different architectures → best with GRUs

[Tzavellas et al. (2024)]

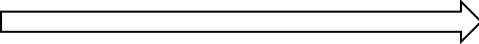
This work

Sample **500k**
combinations of
input parameters
(leptohadronic
one-zone models
with no external
photon field)



Large dataset
of leptohadronic
simulations
(3k CPU hrs)

Training (GRU)
Separately for AM^3 and LeHaMoC



Surrogate model
predicts simulation output of the
numerical codes – radiation density
(for this specific model)

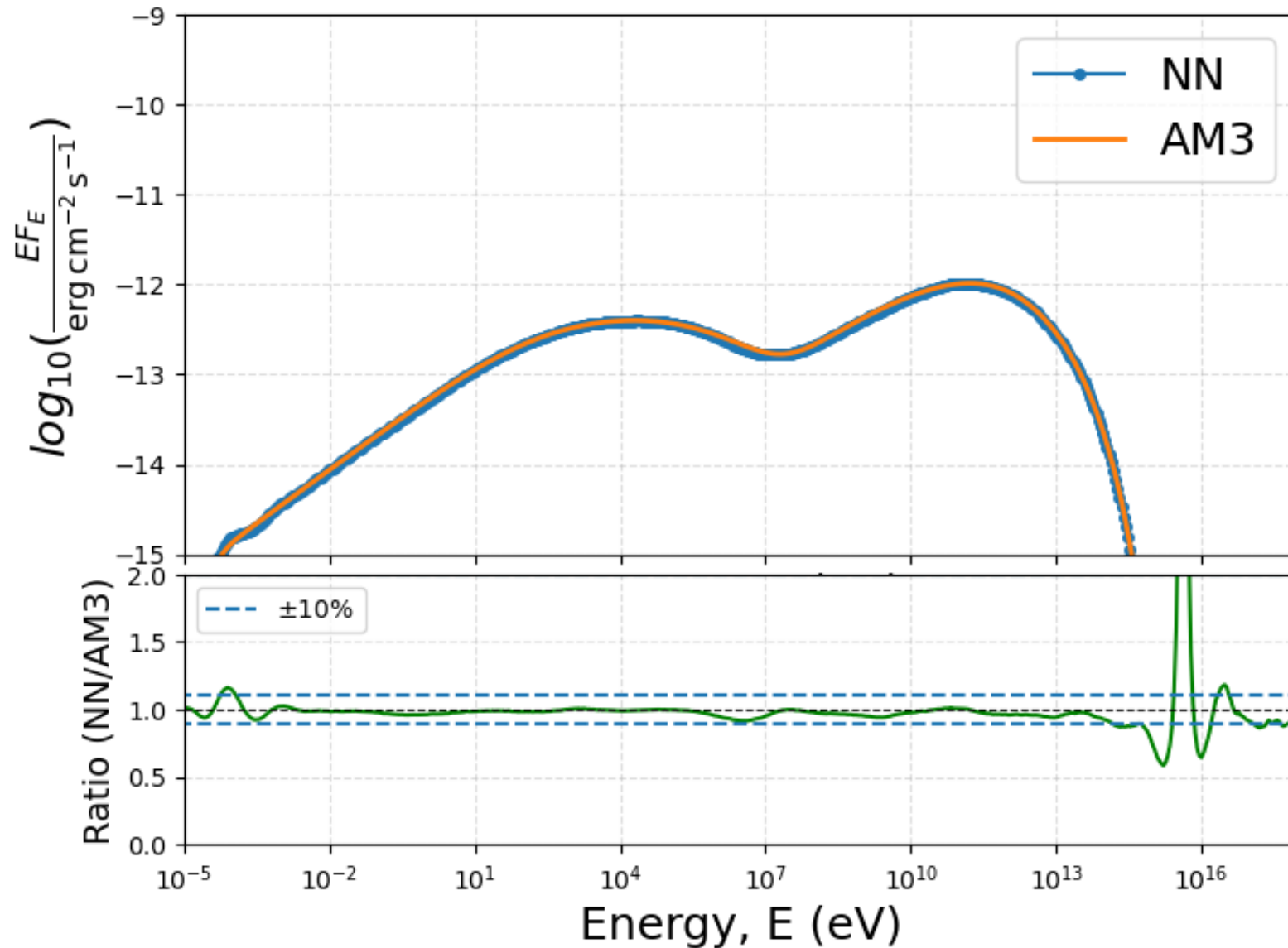
Table 1. Input parameter ranges used for the generation of training and validation datasets. The parameters are intended in the blob rest frame. $U[\cdot \cdot \cdot]$ stands for a uniform distribution.

Parameter	Symbol [unit]	Range
Source radius	$\log_{10} R$ [cm]	$U[14, 18]$
Magnetic field strength	$\log_{10} B$ [G]	$U[-2, 2]$
Electron injection luminosity	$\log_{10} L_e$ [erg s $^{-1}$]	$U[39, 46]$
Electron minimum Lorentz factor	$\log_{10} \gamma_{e,\min}$	$U[0.1, 4]$
Electron maximum Lorentz factor	$\log_{10} \gamma_{e,\max}$	$U[\log_{10} \gamma_{e,\min} + 1, \min(9, \log_{10} \gamma_{e,H})]^\dagger$
Electron power-law slope	p_e	$U[1, 3]$
Proton injection luminosity	$\log_{10} L_p$ [erg s $^{-1}$]	$U[39, 48]$
Proton minimum Lorentz factor	$\log_{10} \gamma_{p,\min}$	$U[0.1, 4]$
Proton maximum Lorentz factor	$\log_{10} \gamma_{p,\max}$	$U[\log_{10} \gamma_{p,\min} + 1, \min(9, \log_{10} \gamma_{p,H})]^\dagger$
Proton power-law slope	p_p	$U[1, 3]$

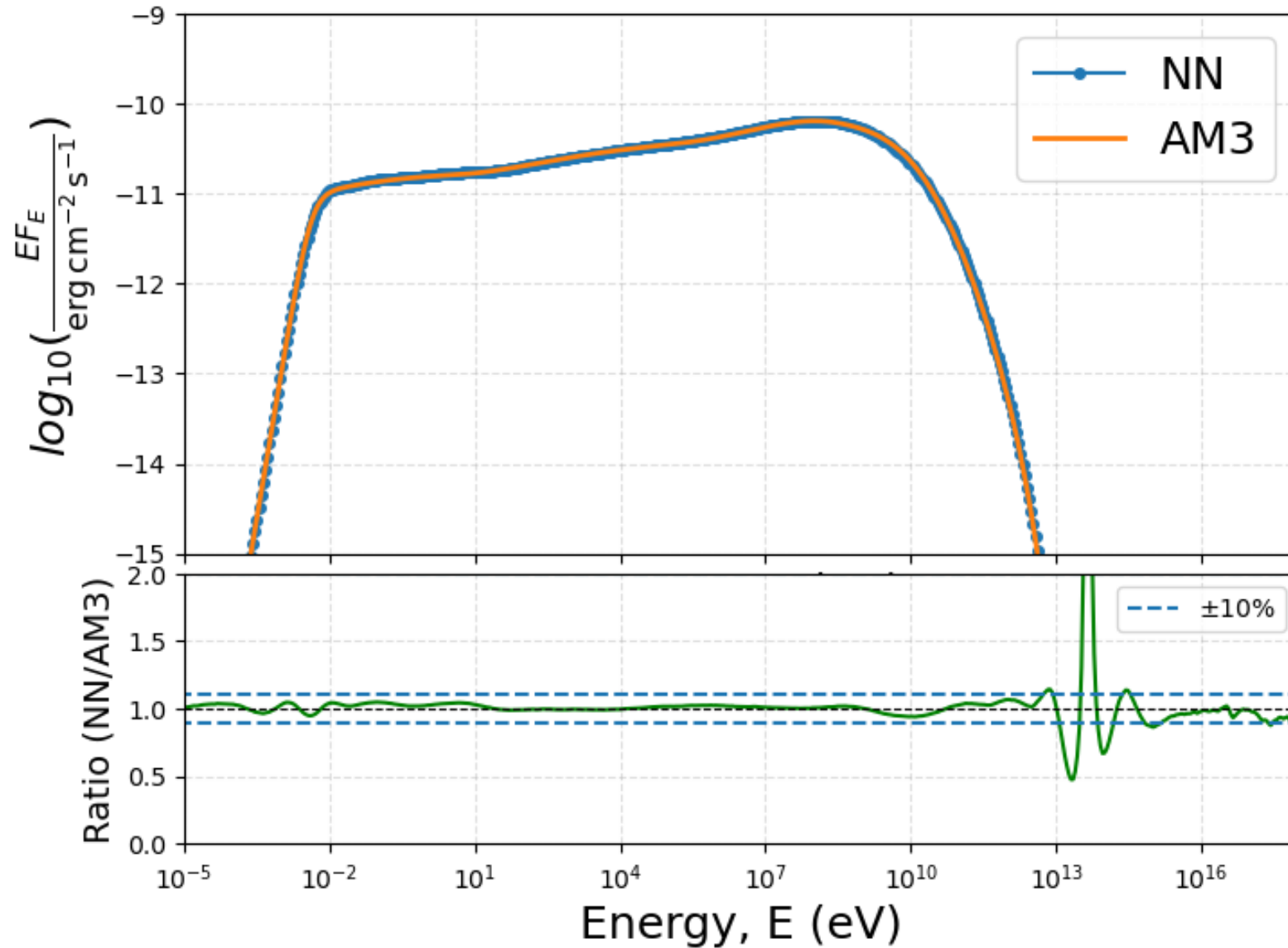
† The symbol $\gamma_{i,H}$ indicates the Hillas-limited Lorentz factor of particle species i , which is defined as $\gamma_{i,H} = eBR/m_i c^2$ (Hillas 1984).

[Testagrossa et al. (2025)]

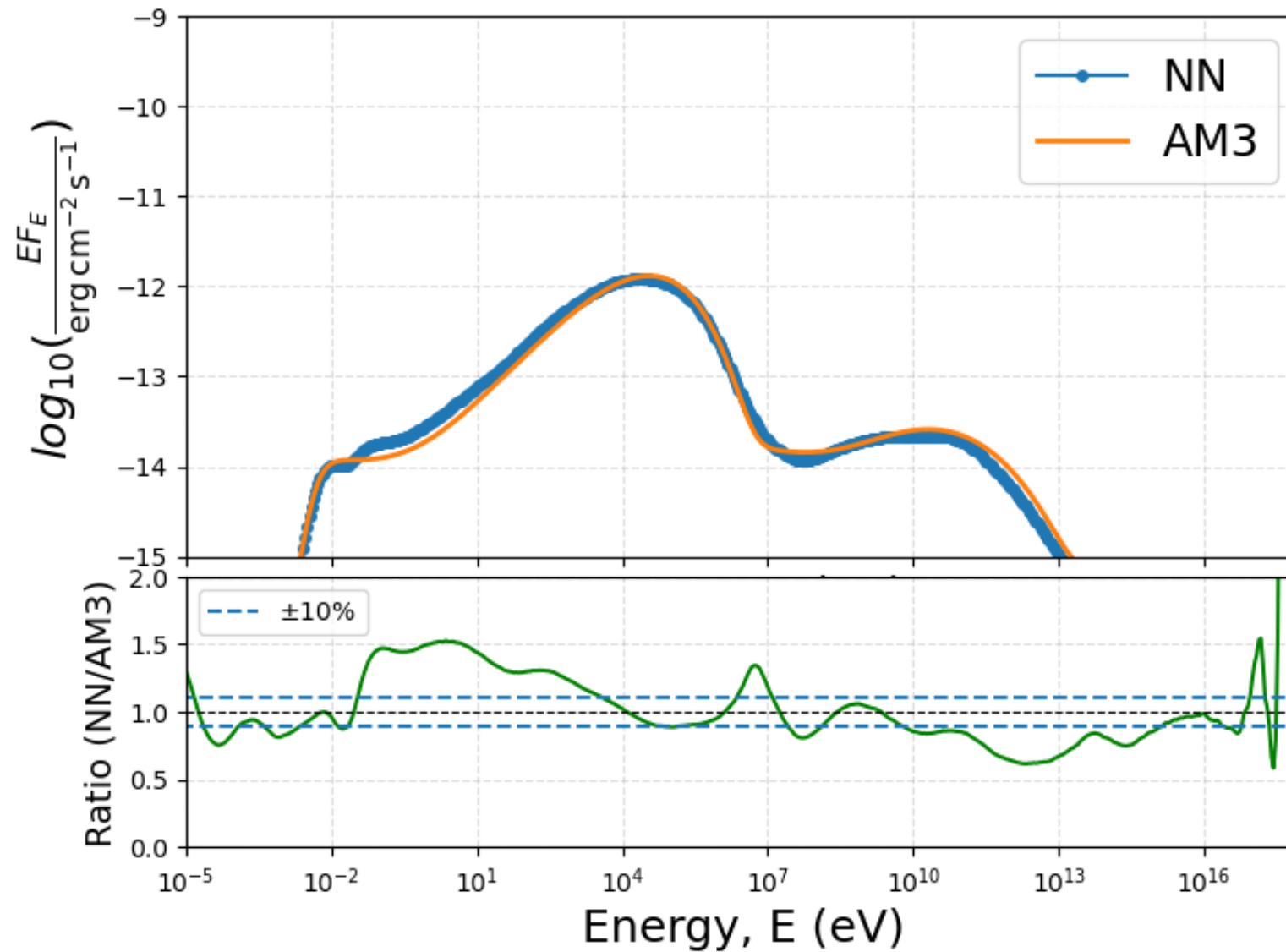
Training on AM^3 - some results



Training on AM^3 - some results

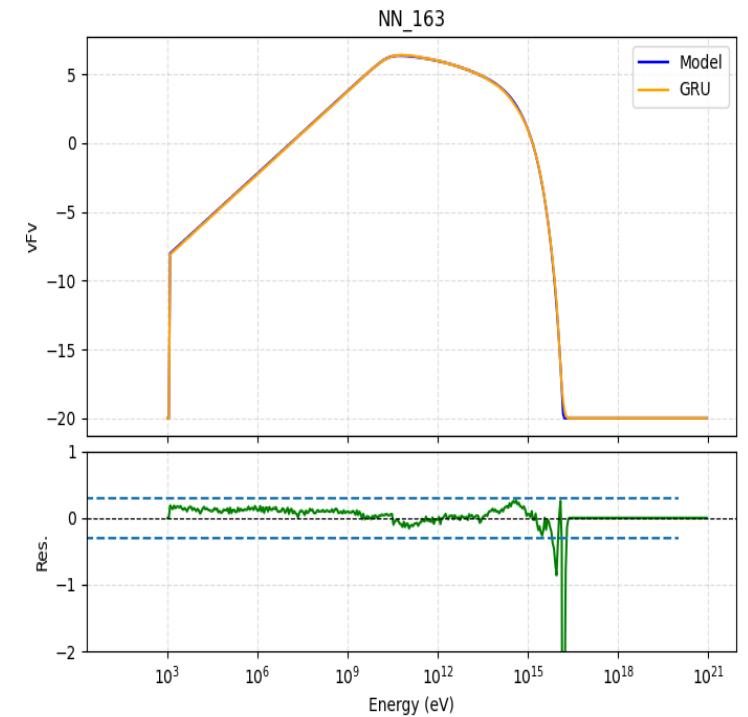
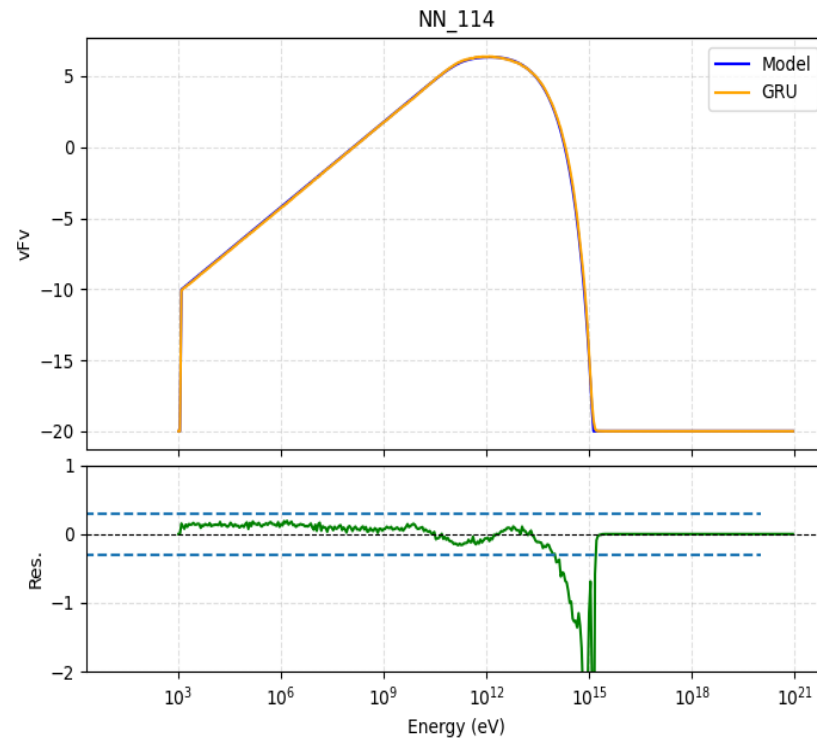
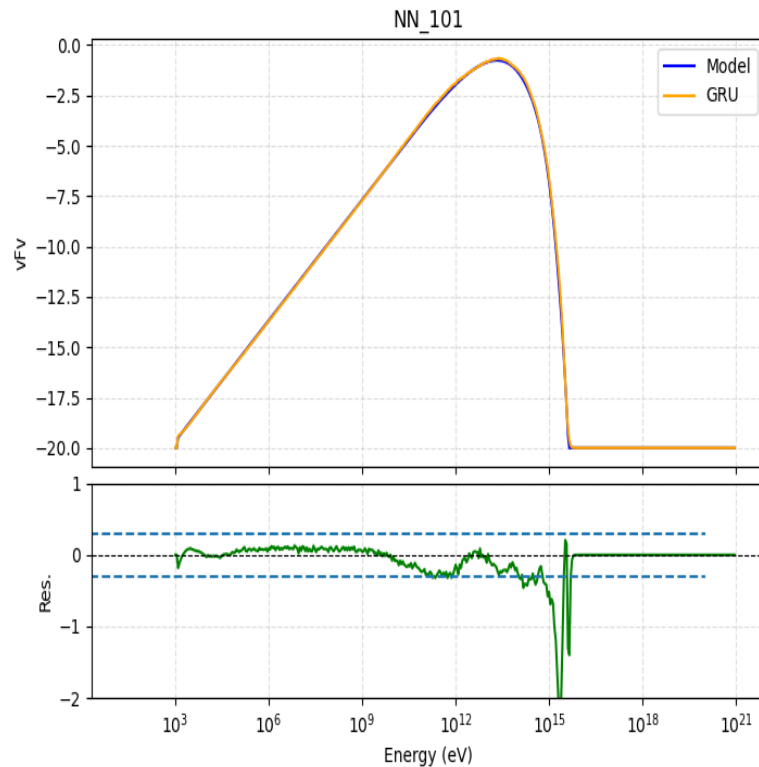


Training on AM^3 - some results



Training on neutrinos

Another NN trained on neutrino simulations → successful training, with similar performances

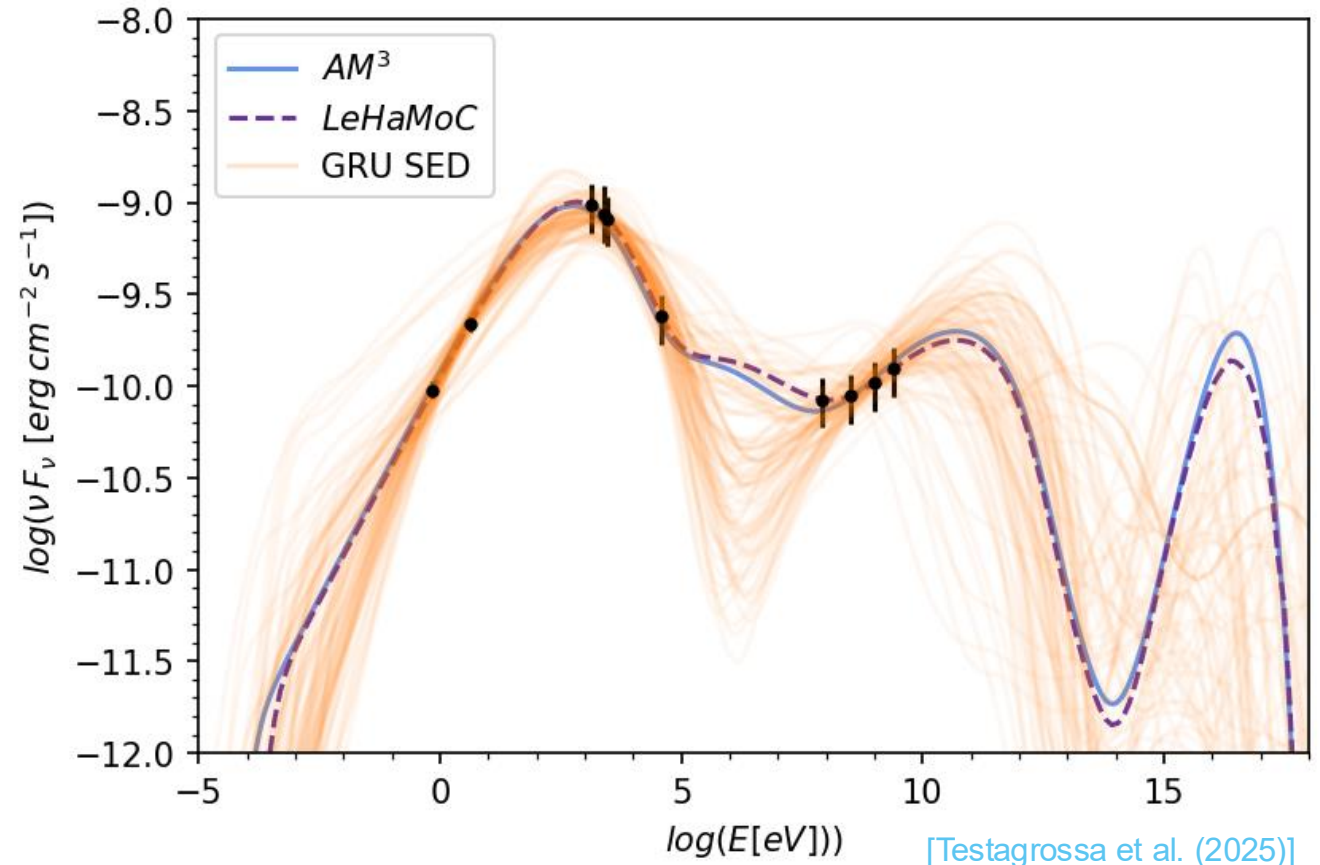


AM^3 surrogate model and MCMC fitting

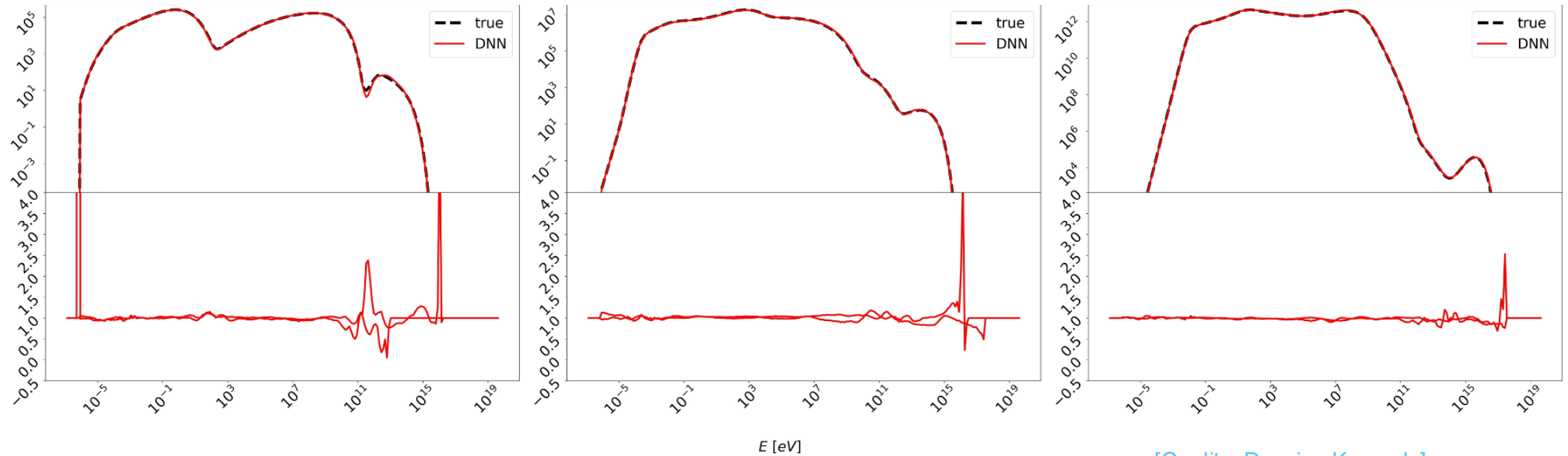
Surrogate model evaluates in ~ 1 ms

Running an MCMC fit (emcee) with 24 walkers and 50k steps takes ~ 1 hour on a laptop!

Tested on fake data
→ retrieved best fit + alternative solutions



Training on LeHaMoC



[Credits: [Despina Karavola](#)]

The same neural network successfully trained on LeHaMoC simulations, with similar performances

Summary and Conclusions

- A neural network trained on a large sample of numerical simulations can accurately predict the outcome of radiative codes in ms time (Combine with MCMC allows for efficient Bayesian analysis)
- This work: RNN (GRU), successfully trained on 2 codes (AM3 and LeHaMoC)
[Testagrossa et al, in preparation]
- Single-zone leptohadronic (working on implementing external photon field...)
- Training with this NN is fast (1 hour on laptop) and flexible (worked with photons/neutrinos, and with different codes)
→ contact me if you're interested in trying this training on your code! @federico.testagrossa@desy.de
(...or wait until we make everything open source, by the end of my PhD)

Thank you!