Convolutional Neural Network and Soprano: computing numerically expensive models in the blink of an eye.

Damien Bégué

Bar Ilan University

With

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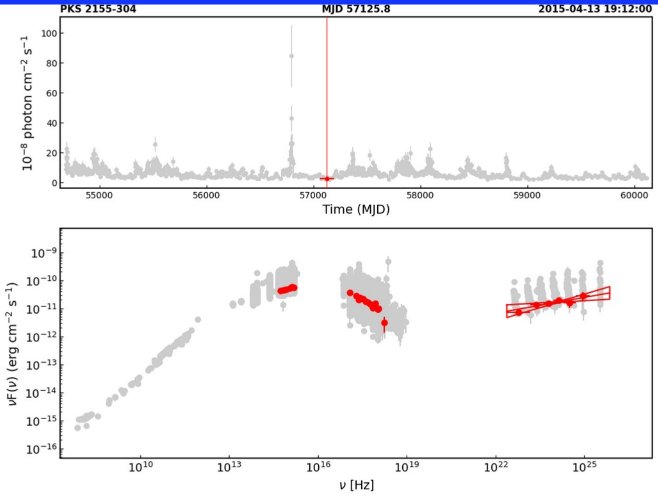
Paris, 21st-23rd of February 2024

Bar-Ilan University
אוניברסיטת בר־אילן

Goal



PKS 2155-304
MJD 57125.8
2015-04-13 19:12:00
10^{-8} photon cm^{-2} s^{-1}
Time (MJD)
$\nu F(\nu)$ (erg cm^{-2} s^{-1})
ν [Hz]

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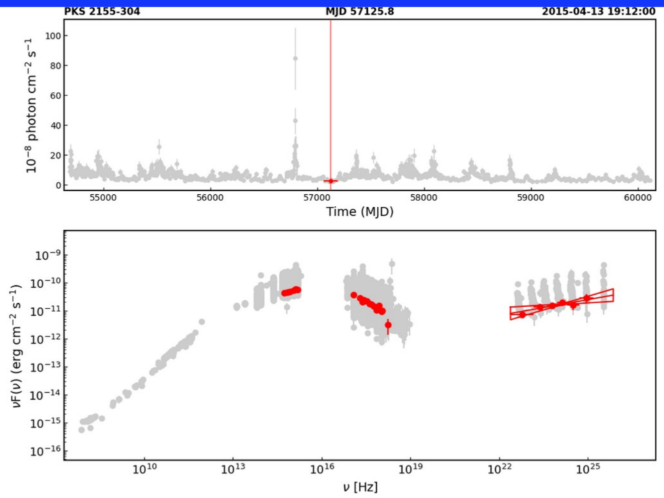

Your favorite model
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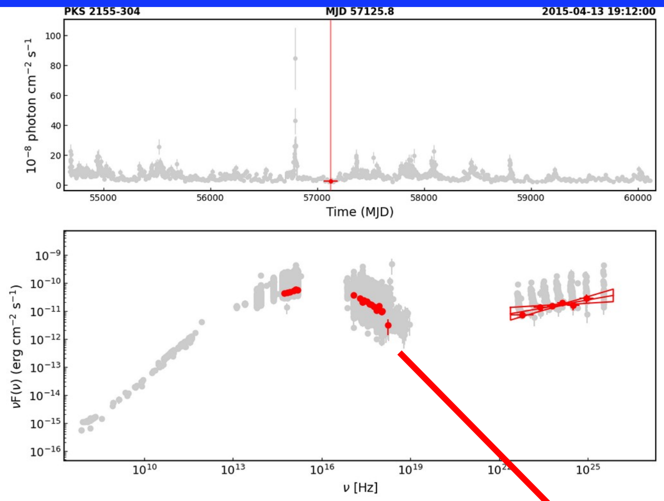

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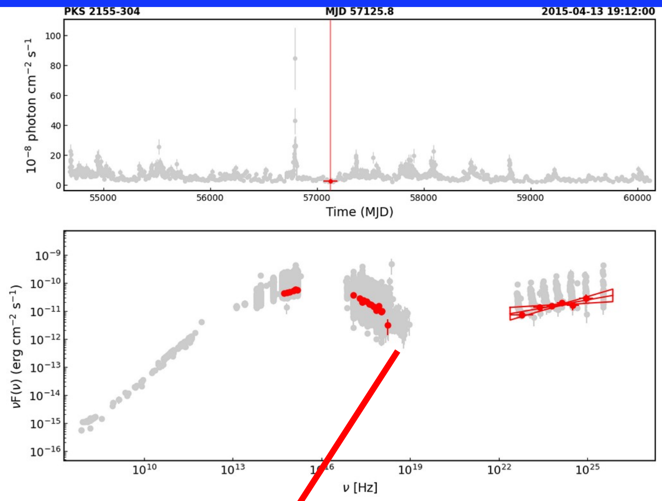

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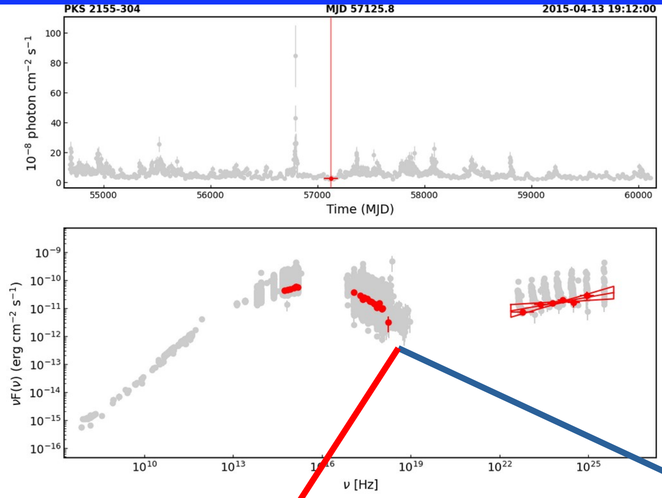

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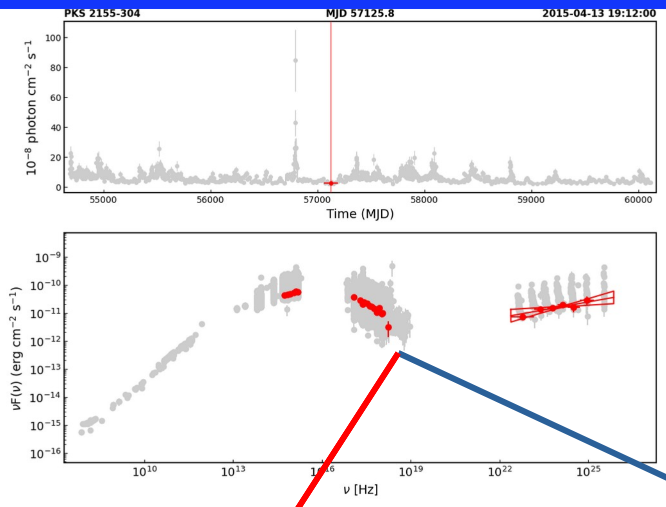

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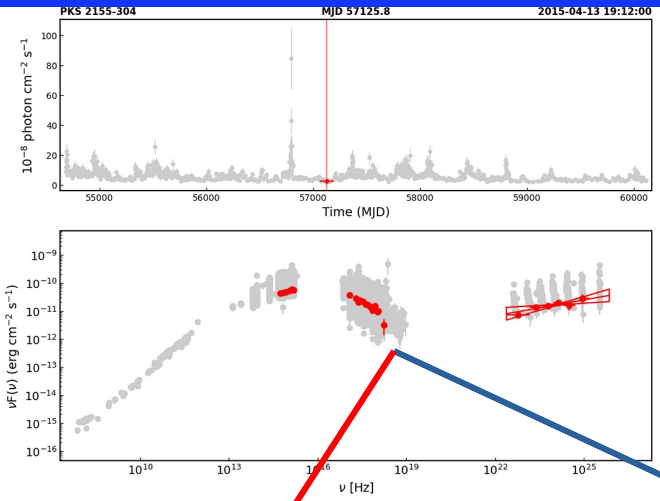

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4. My talk is about what happens at the intersection of
physics/numerical modeling and data.

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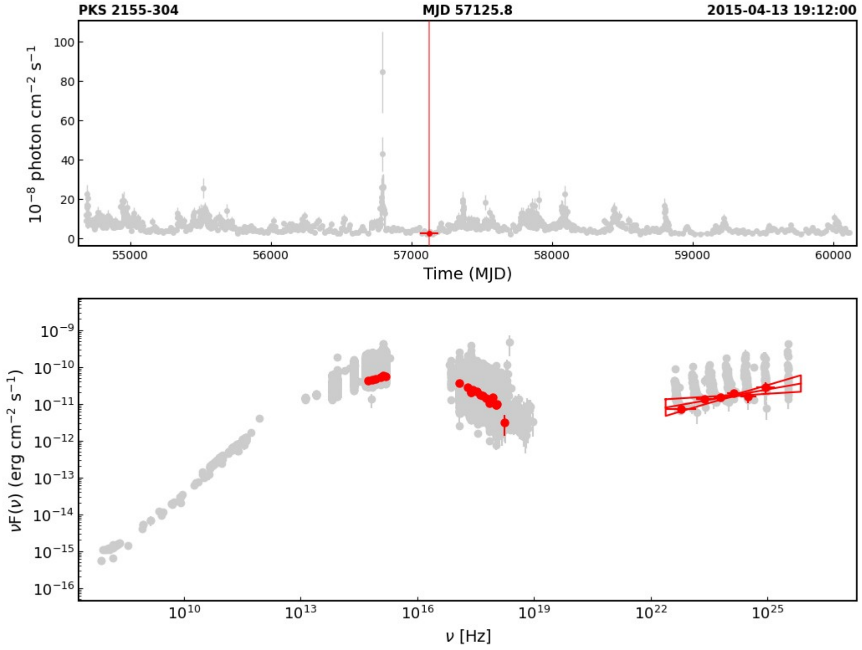

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But that computation needs to be done only once !

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  - Smaller impact of curse of dimensionality,
  - Sample can be non-equidistant.

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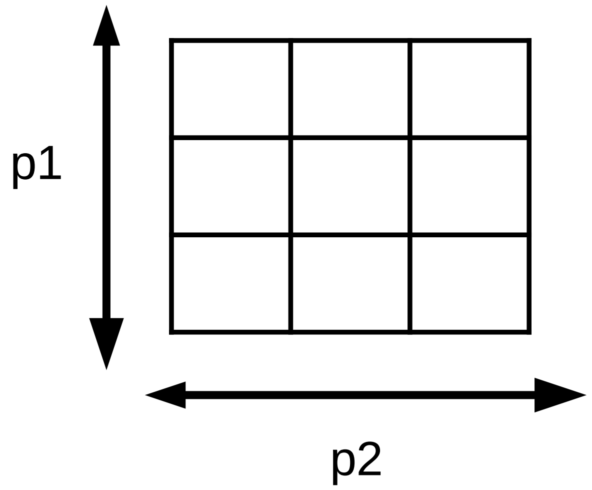
<ins>“Square parameter space”</ins>



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<u>Table model/parameter scan:</u>

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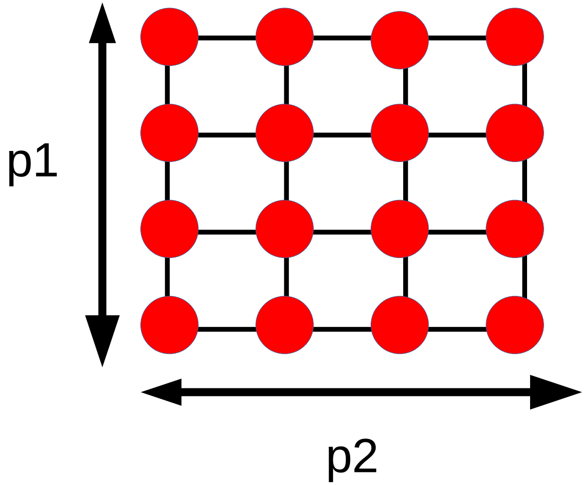

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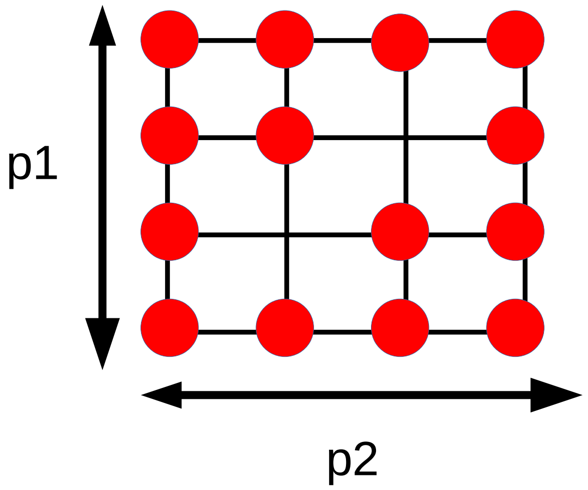

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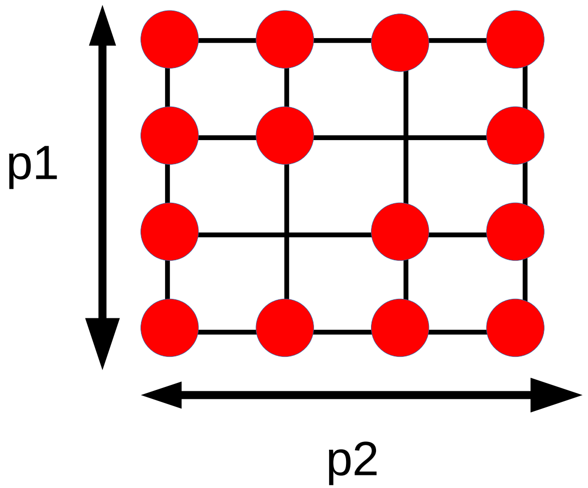

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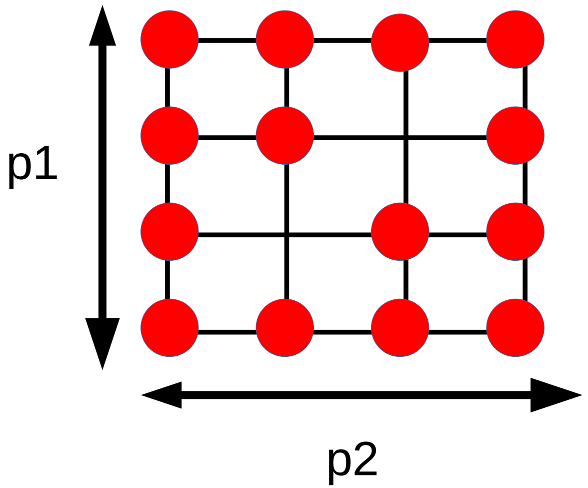

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→ Latin hypercube sampling

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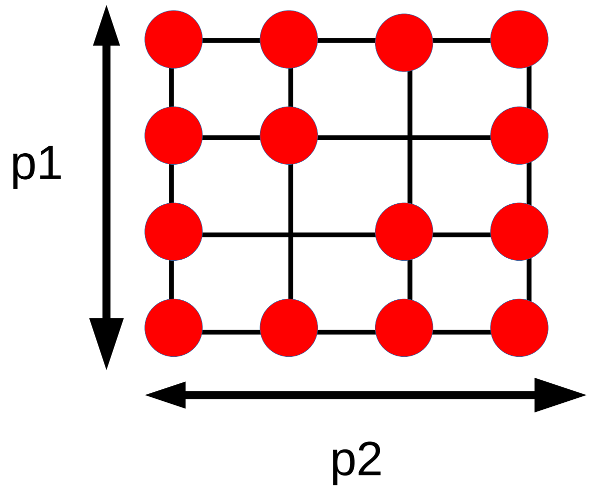

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3) test the neural network with smaller training set
   - Smaller sample, faster training,

FNC is the synthesis of decades of experience with jobs schedulers

PBS + Grid Engine + Accelerator

ALTAIR

Scalable
- From 1 job to 20 million jobs in queue

Small, Quick
- Small memory footprint
- Speed: clocked up to 70k+ tasks/second

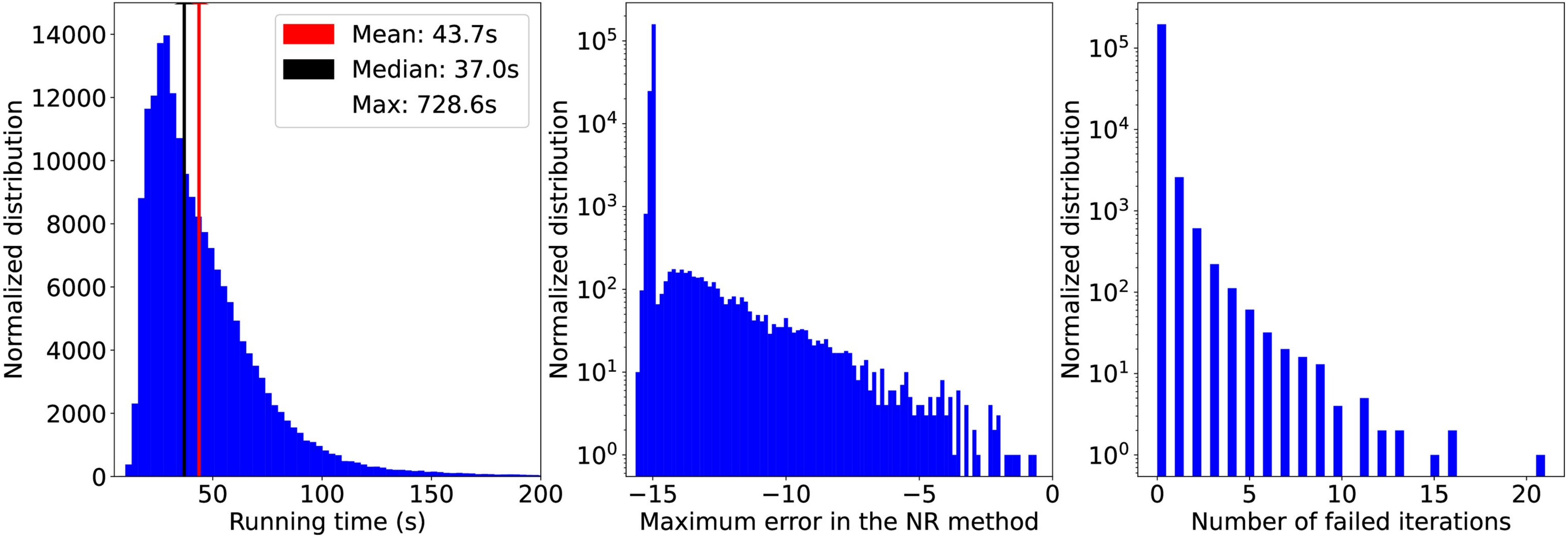
Feature Rich
- Full-cycle scheduler
- Cost-driven job placement
- Workload analysis (via simulation)
- Prediction of job duration + job size
- PMIx support (evolution of MPI)
- SAGA (storage-aware scheduling)
- Rapid Scaling in cloud

Contact: casotto@altair.com

Use of monitoring data

Metadata for SSC model:

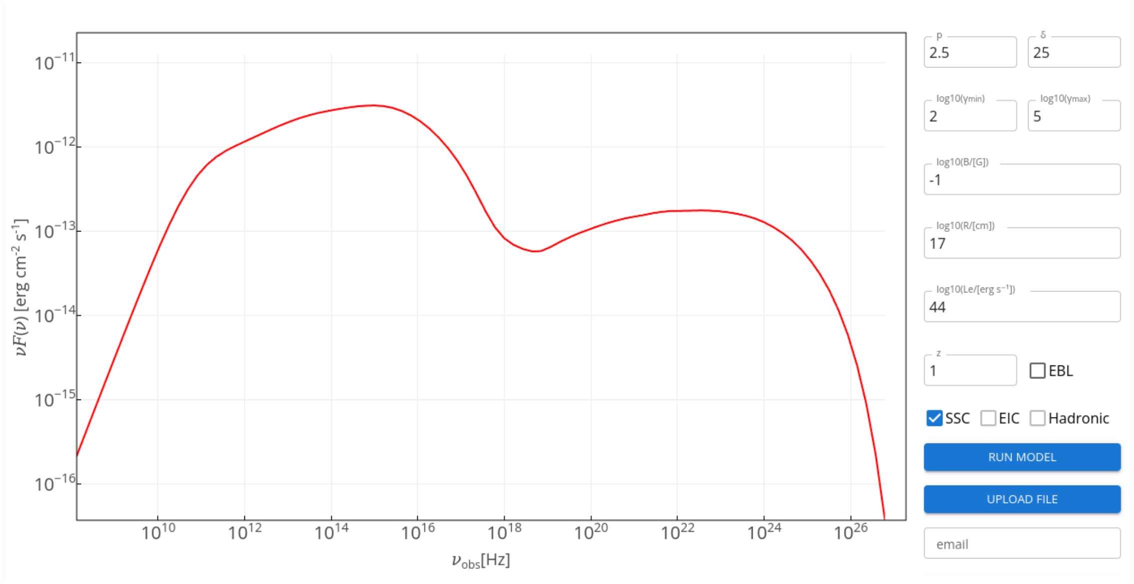
$2x10^5$ spectra



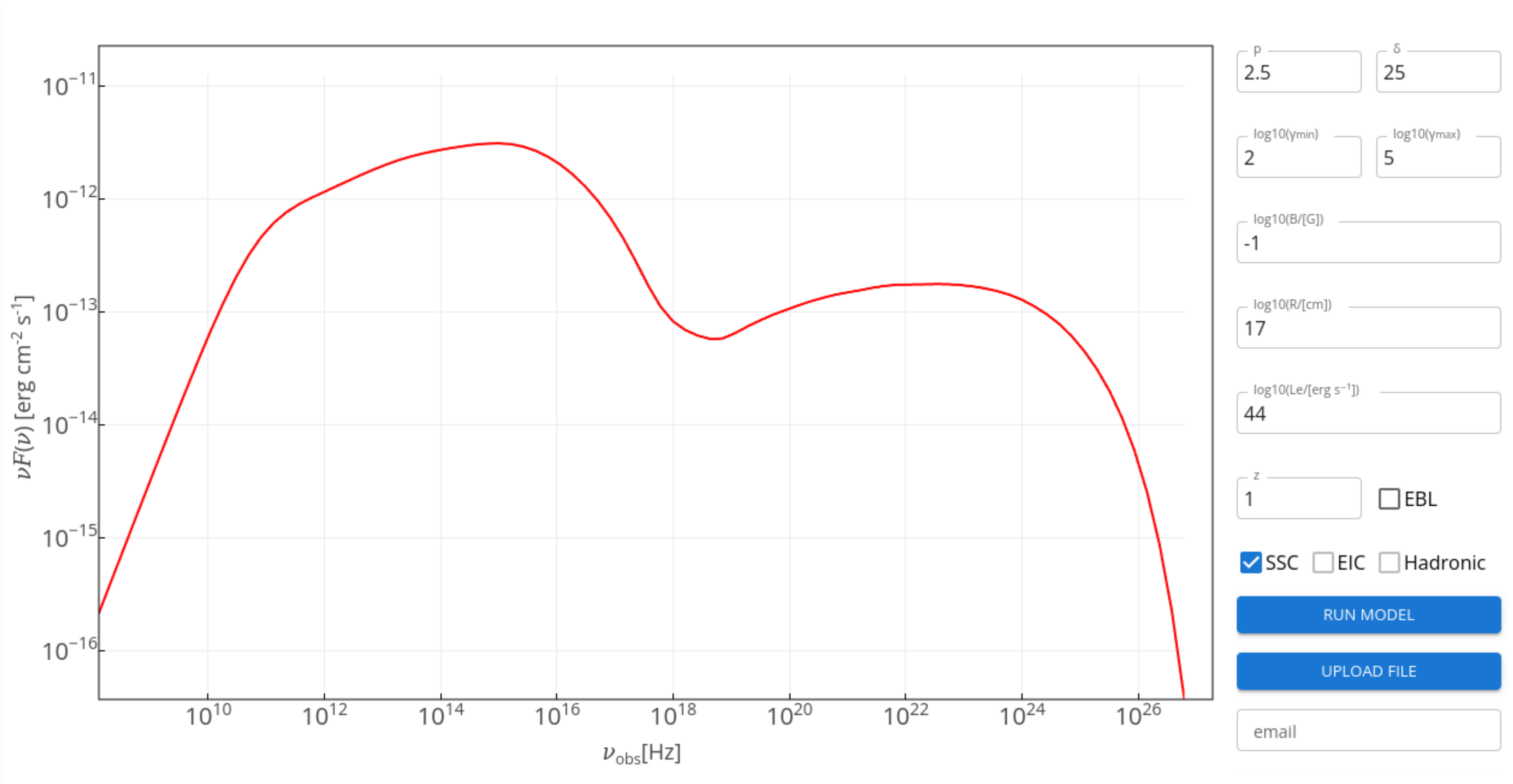
Building the neural network

P1
P2
P3
P4
P5
P6
...

f(P1, P2, P3 ...)

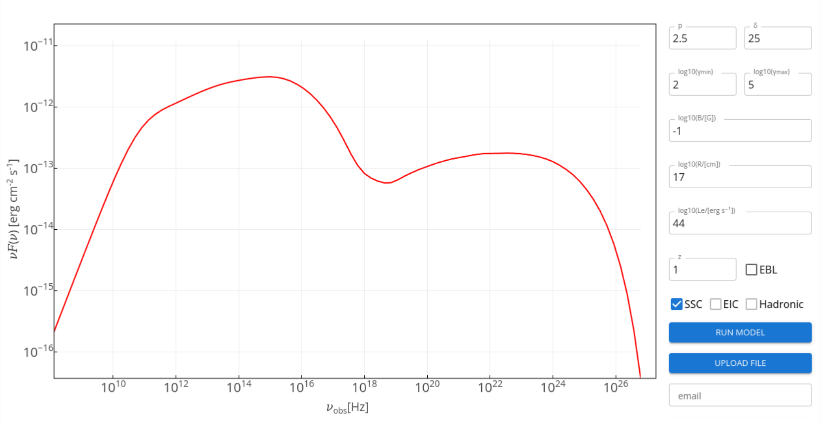


Data preprocessing



Data preprocessing

Step 1: log the data



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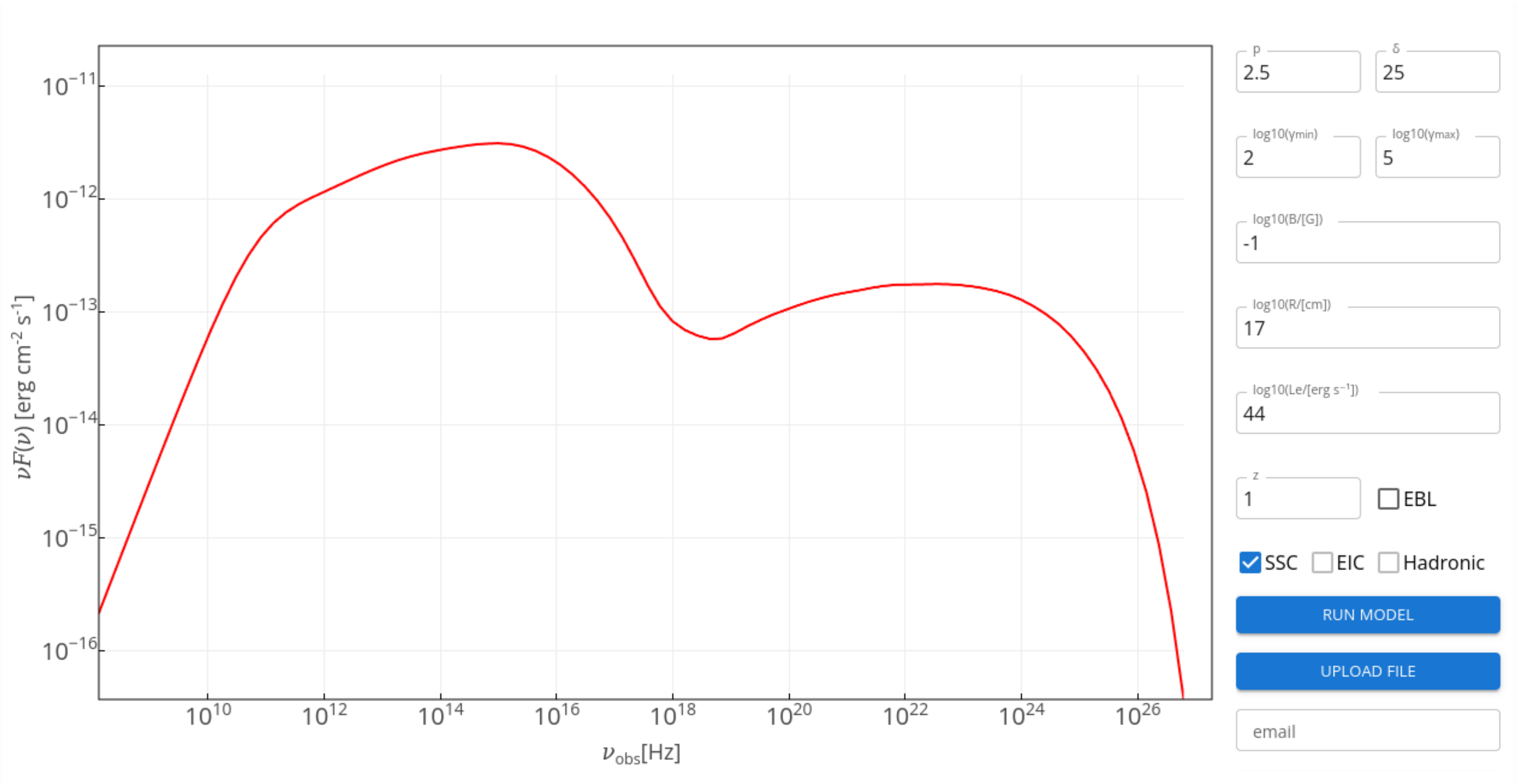

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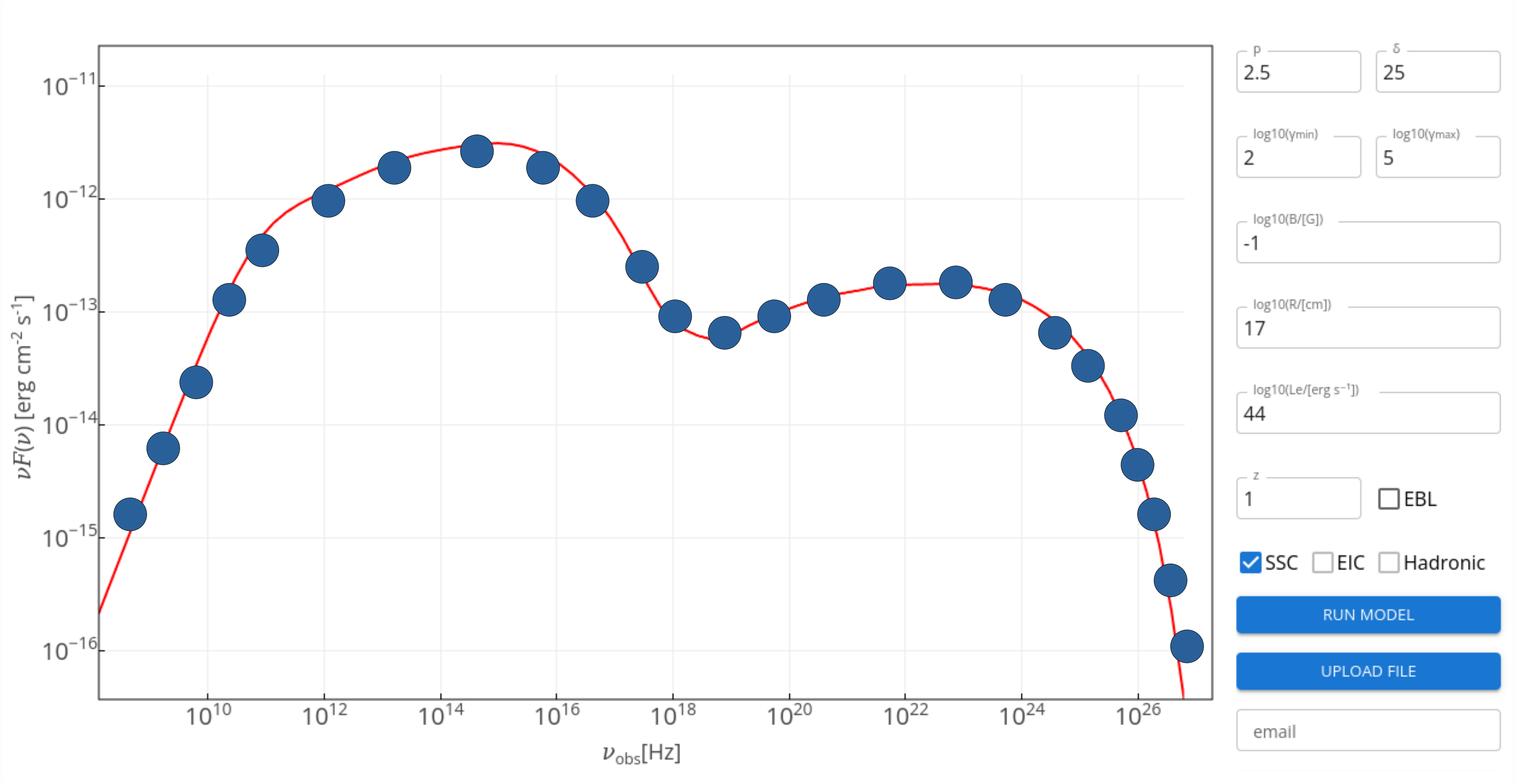

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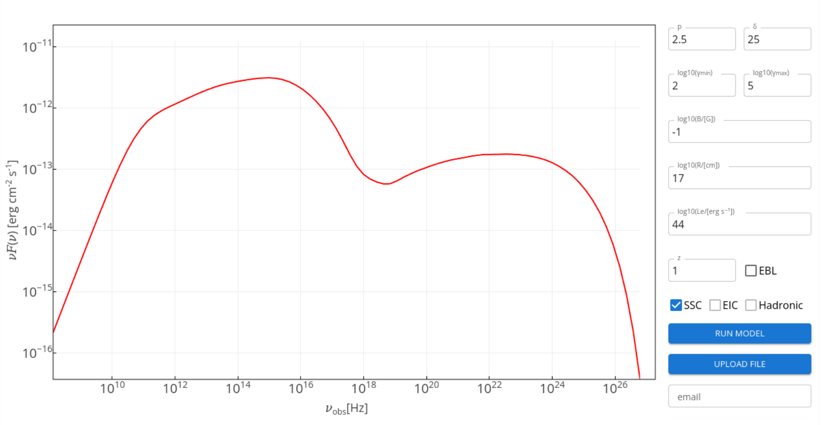
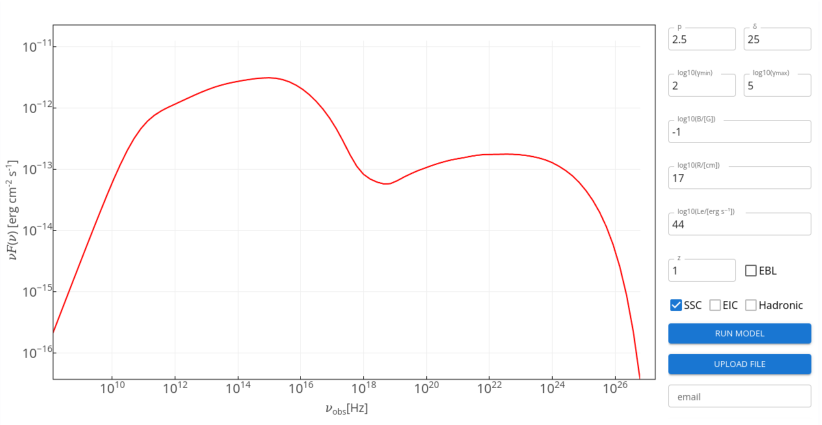


Step 1: log the data

Step 2: remove the mean

Data preprocessing



Step 1: log the data
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(Step 3: detrend)

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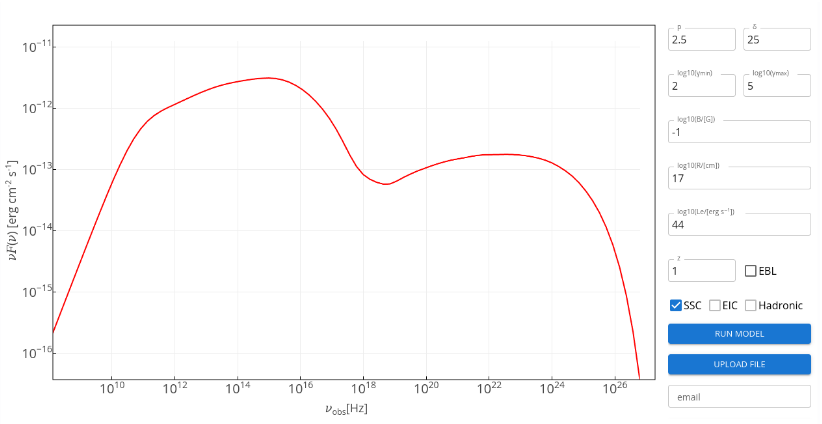

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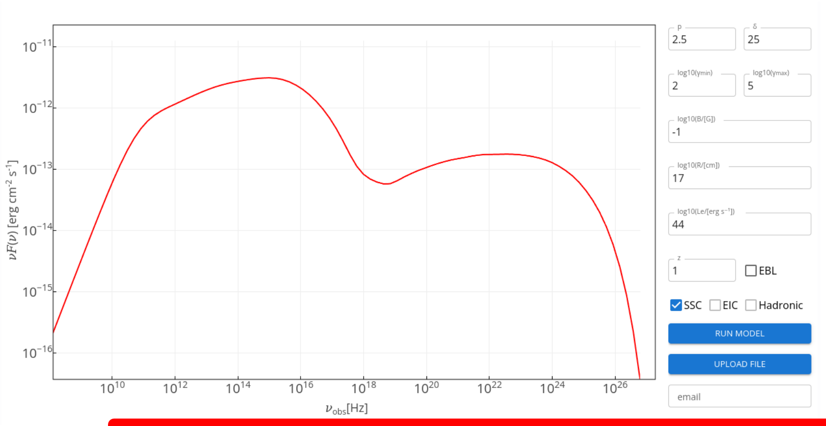

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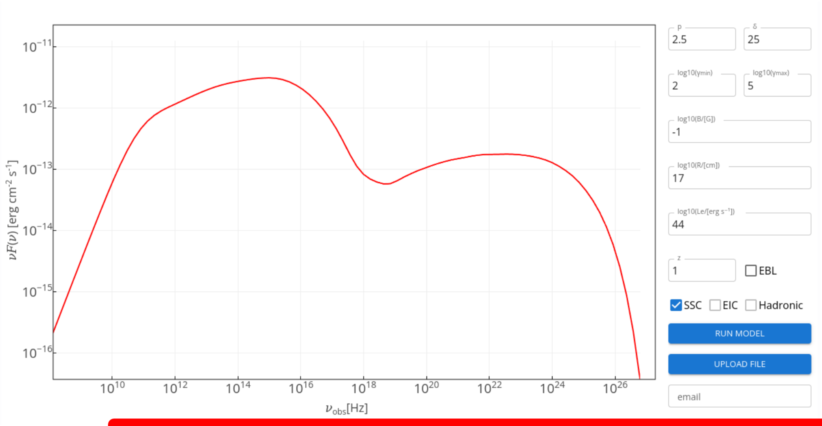

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Any different treatment is producing oscillations in the resulting spectrum

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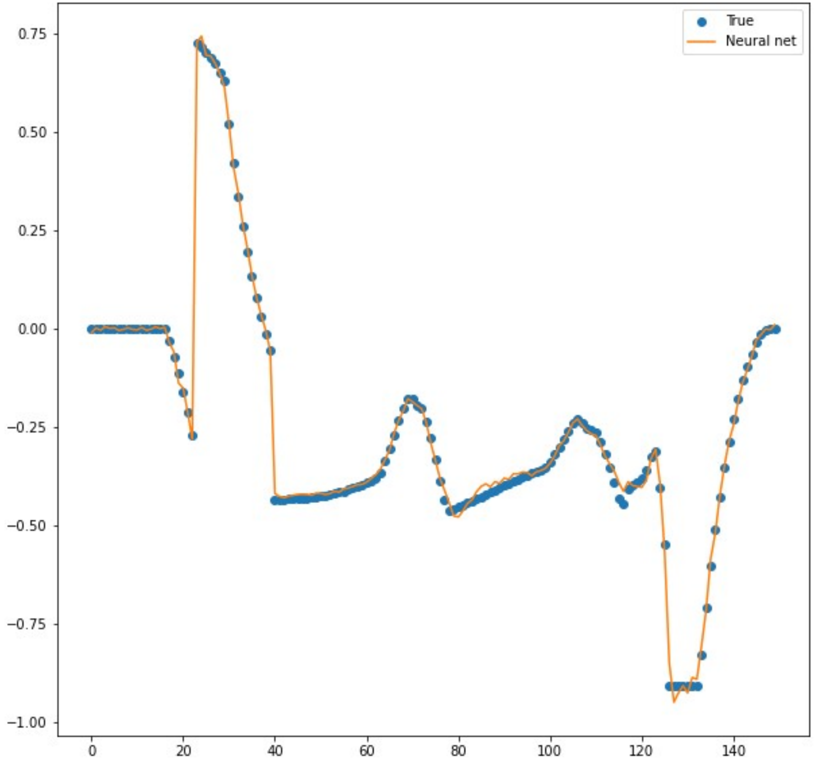

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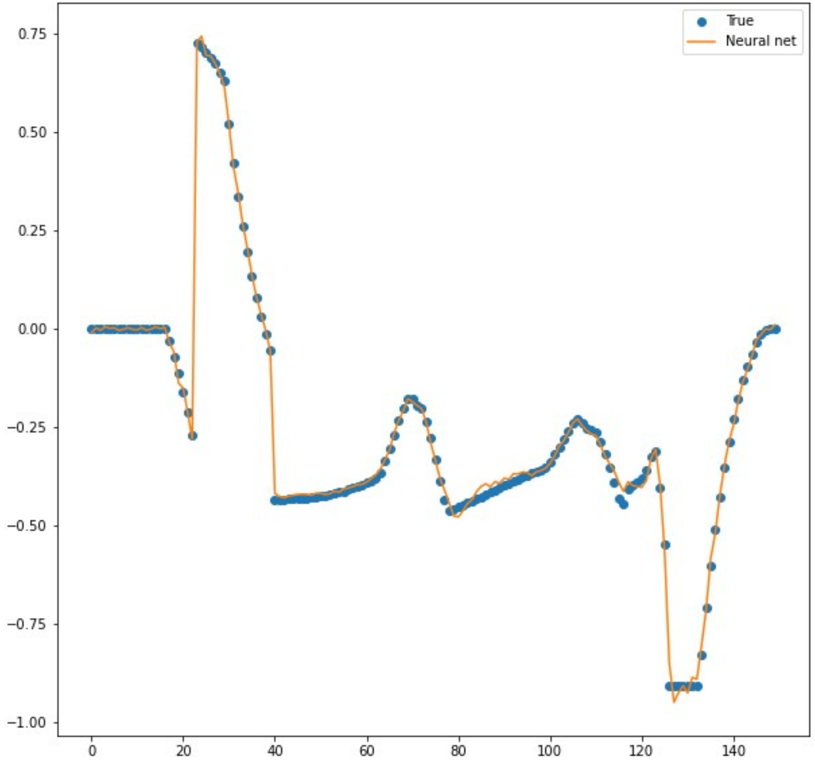

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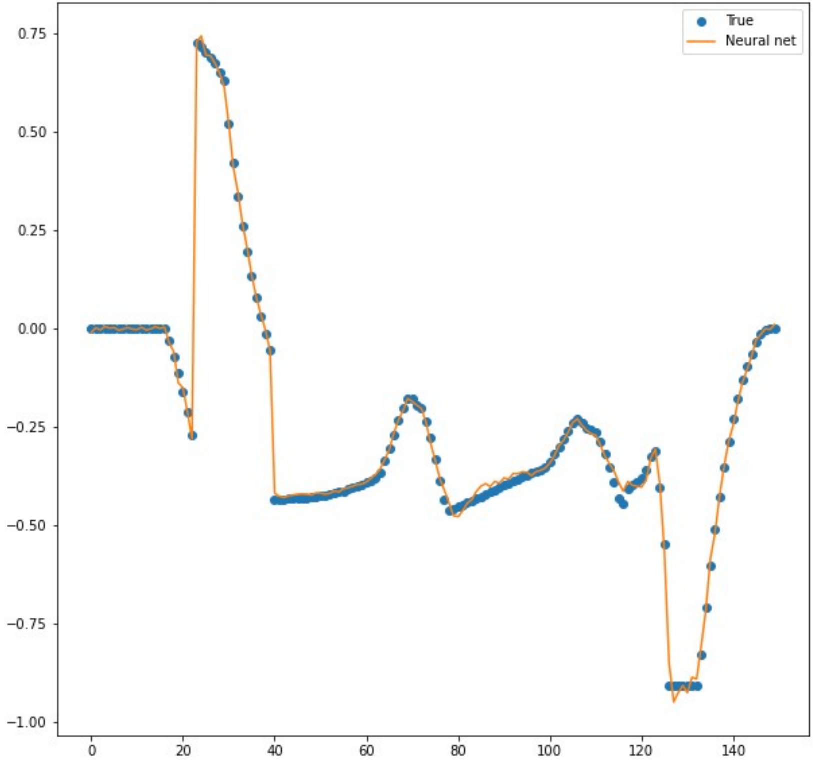

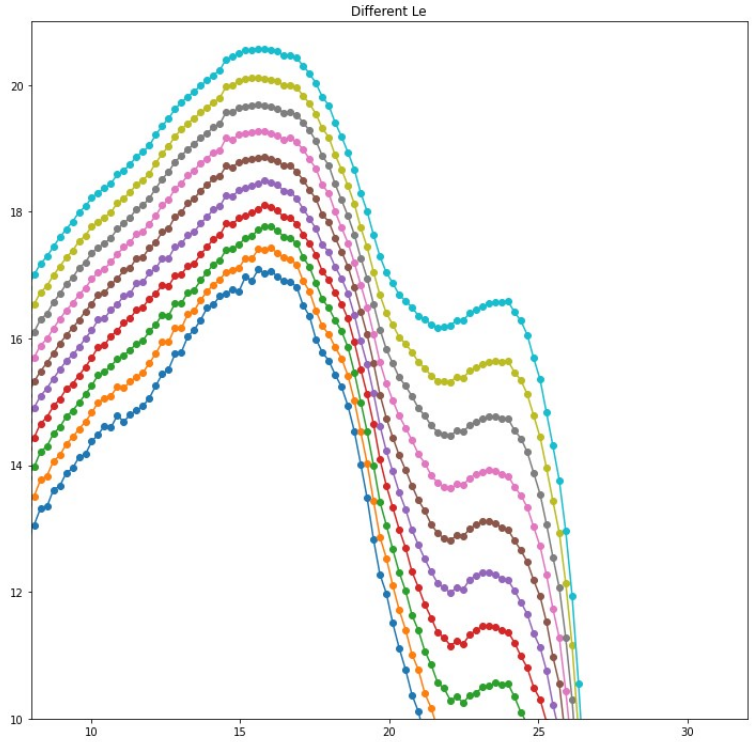

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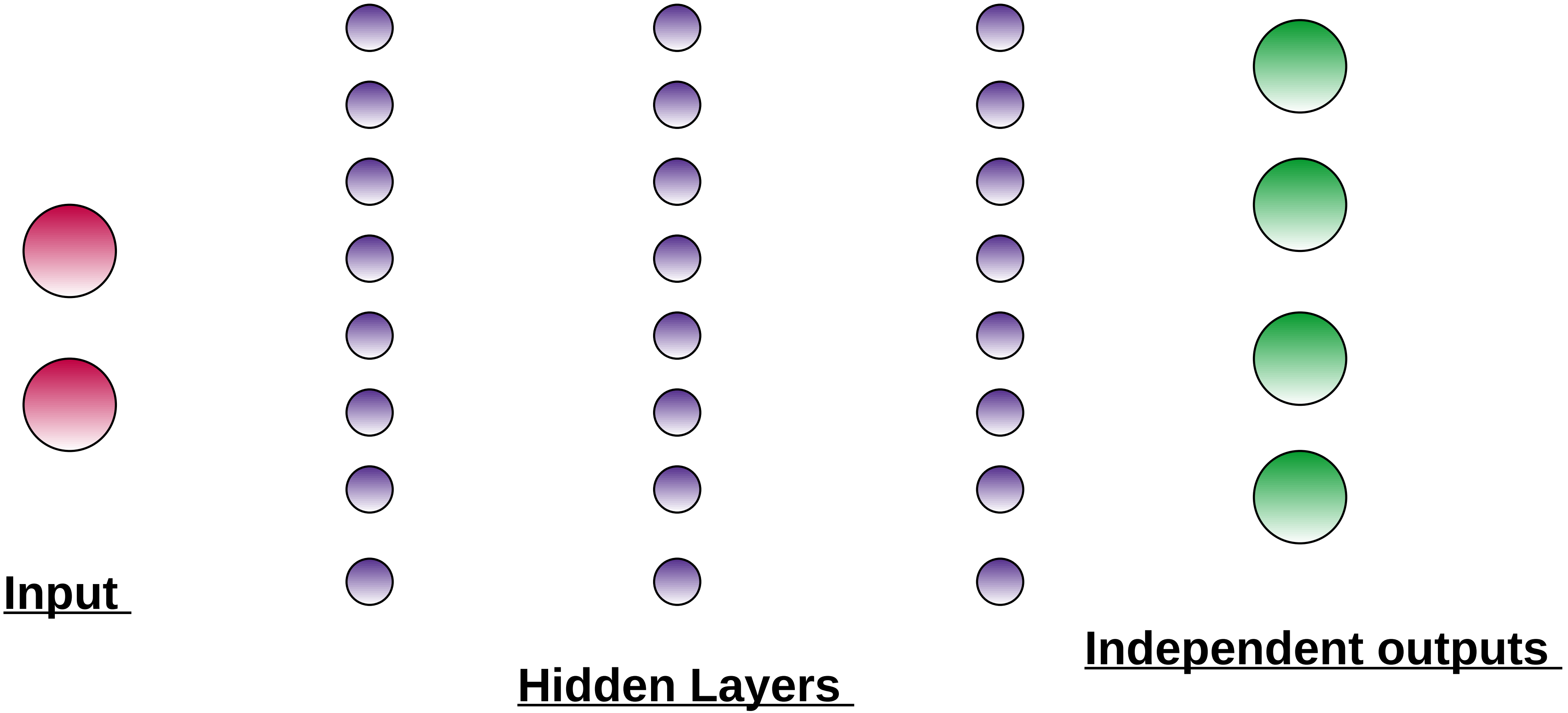
The neural network

Input

Independent outputs

The neural network



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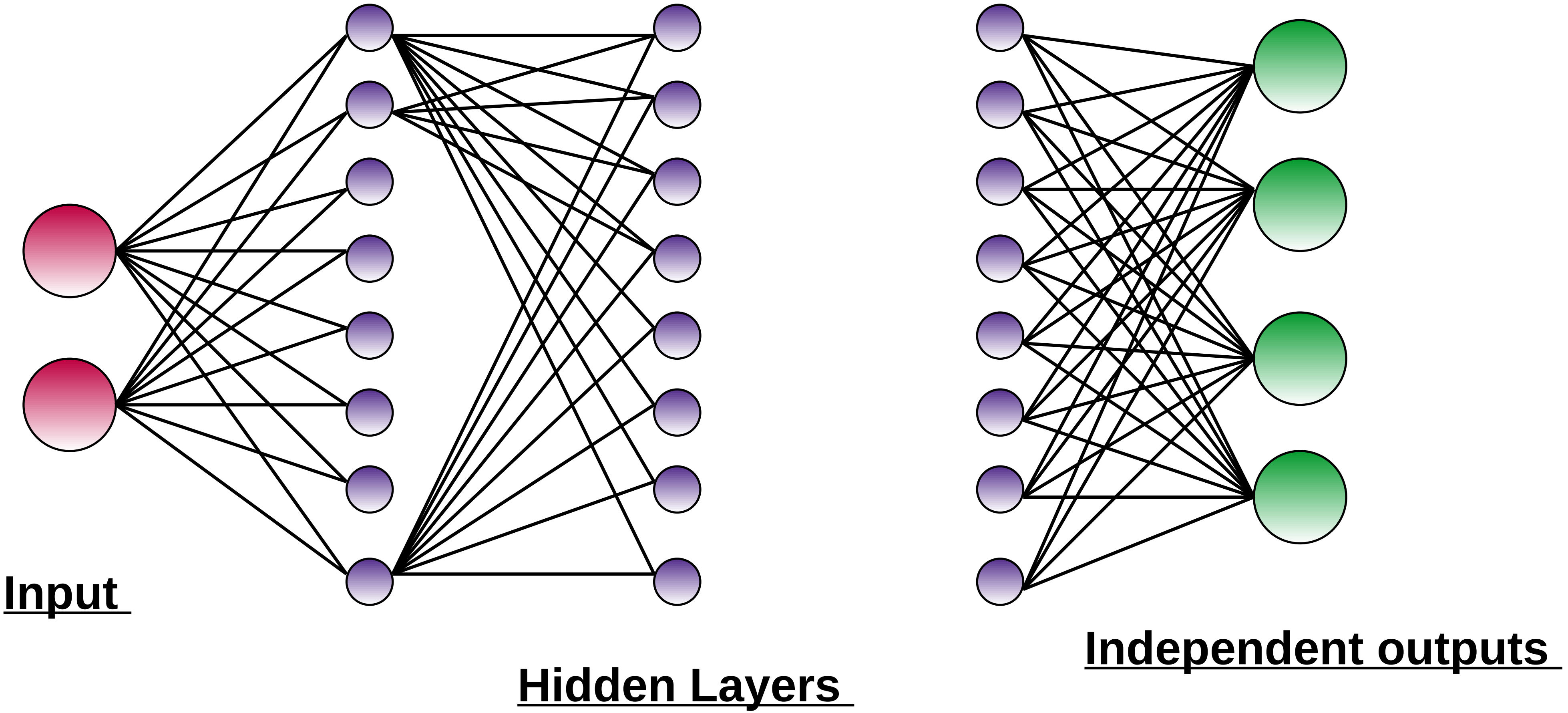

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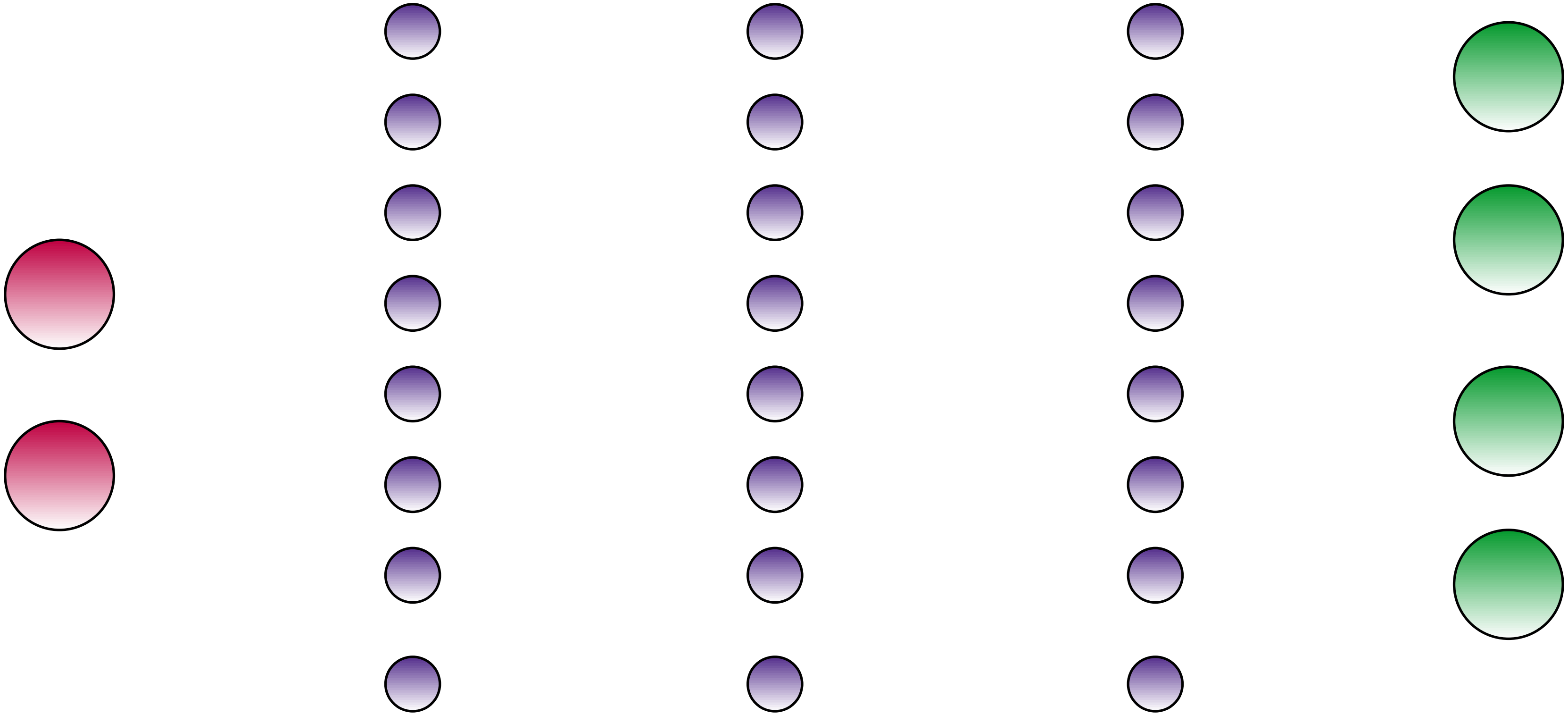
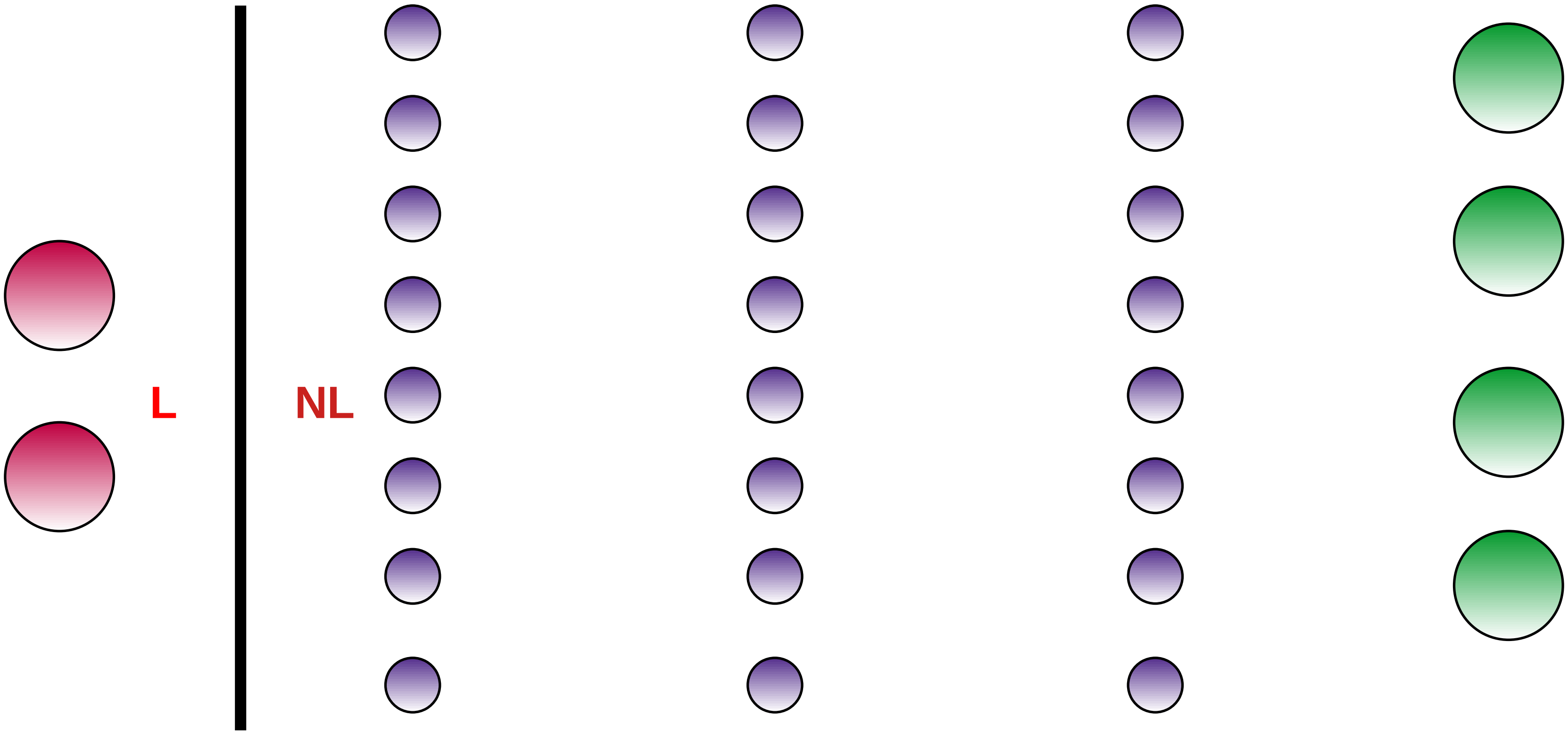


i

The neural network



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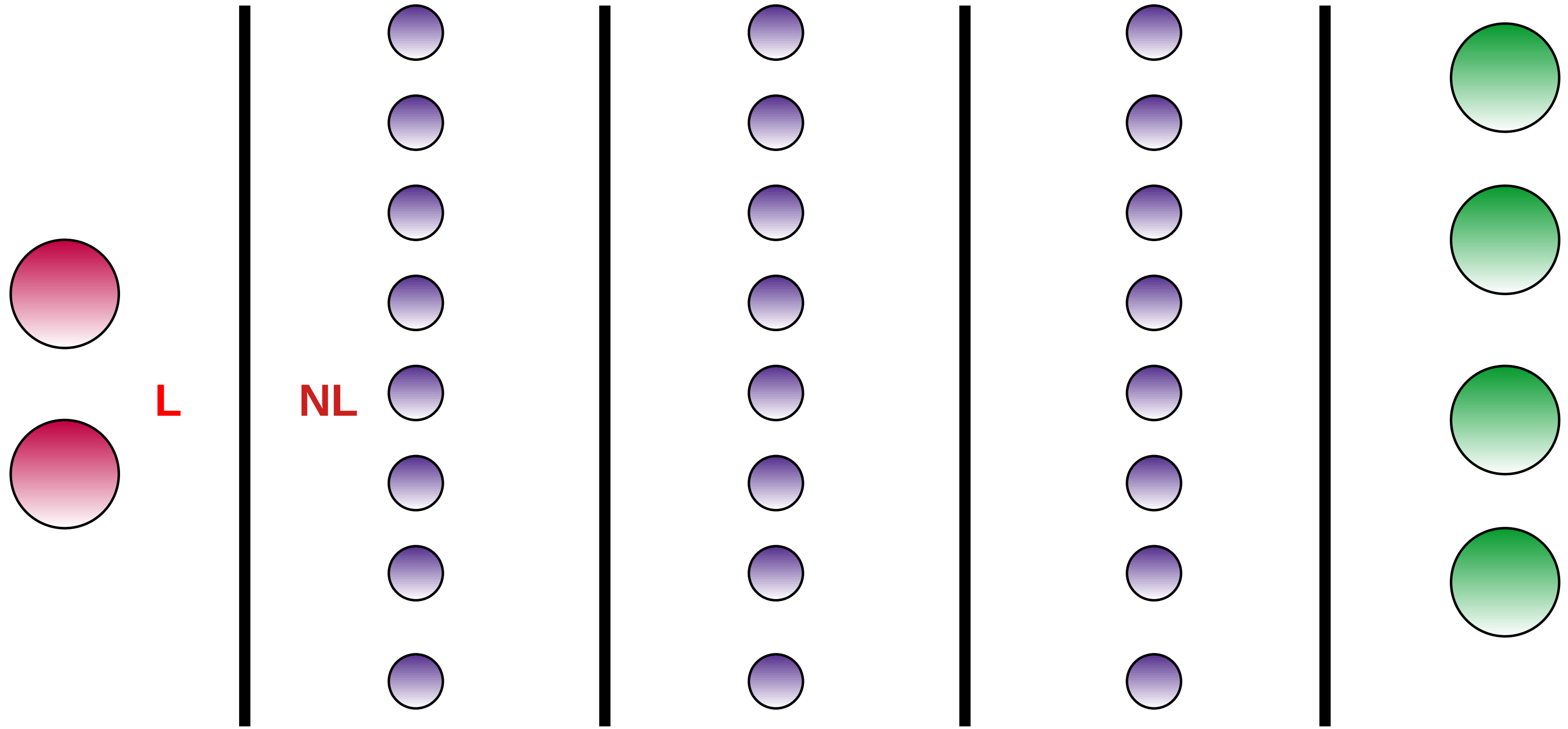

i   l1 = NL(L(i))   l2 = NL(L(l1))   l3 = NL(L(l2))   o = NL(L(l3))

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- Too large: risk of over fitting
- Too small: results are not accurate

Many options: padding, offset, size ...

Construction of a neural network

To be specified:

1) The number of layers
   - Too many: strong risk of over fitting
   - Too few: results are not accurate
2) The type of layers:
   - Fully connected (linear)

The size of the linear layers:
- Too large: risk of over fitting
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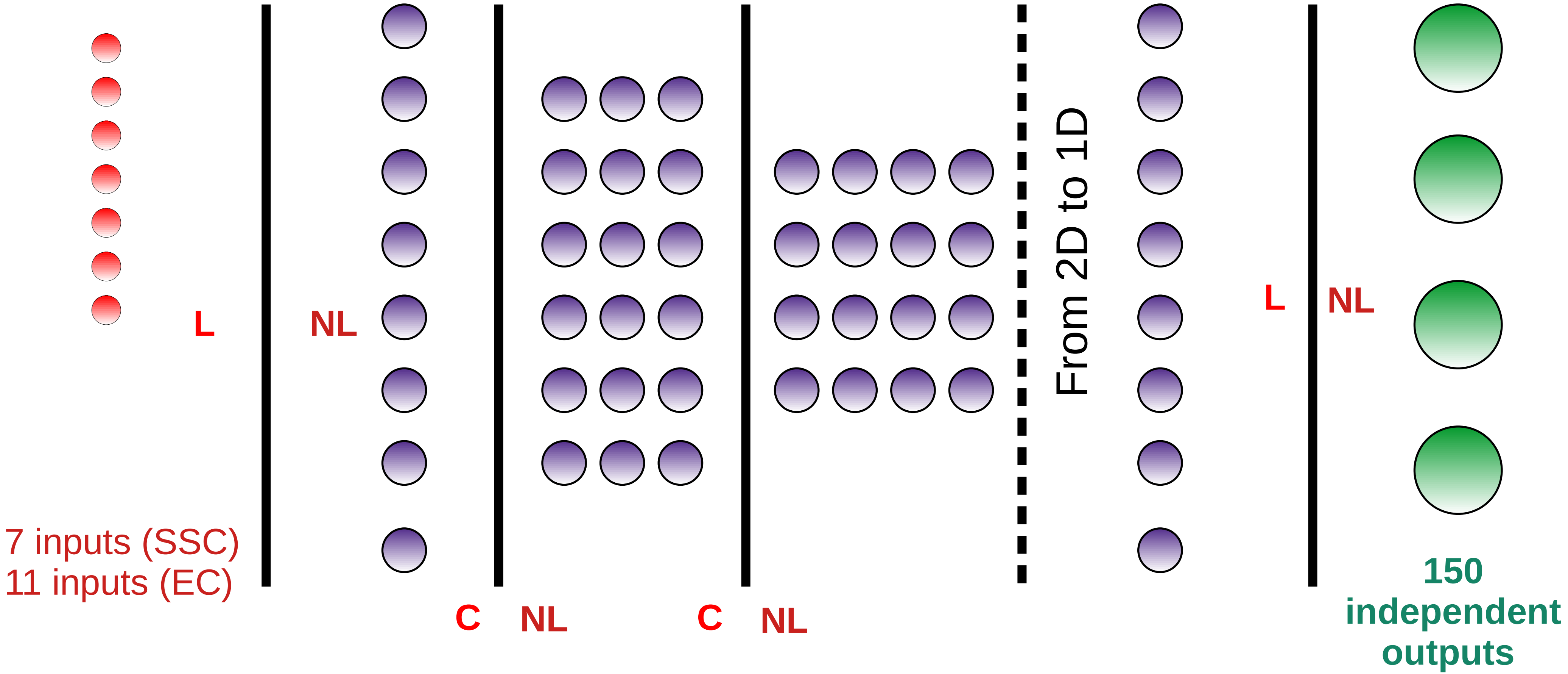
   - Convolutional layers (filter)

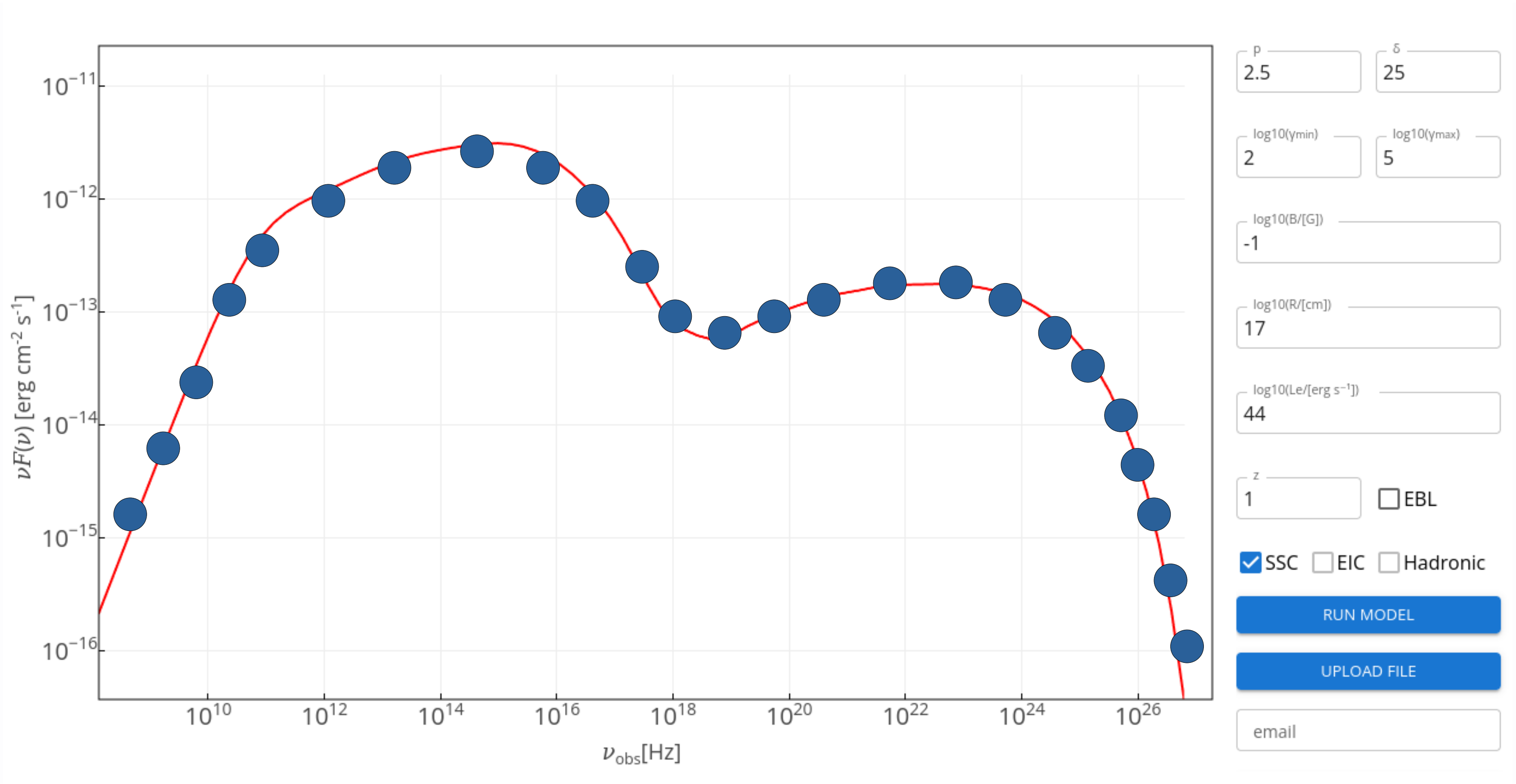
Many options: padding, offset, size ...

3) The type of activation layer (non-linearity):
   - ReLu
   - atan

The neural network we are using



How to produce dependent ouputs?



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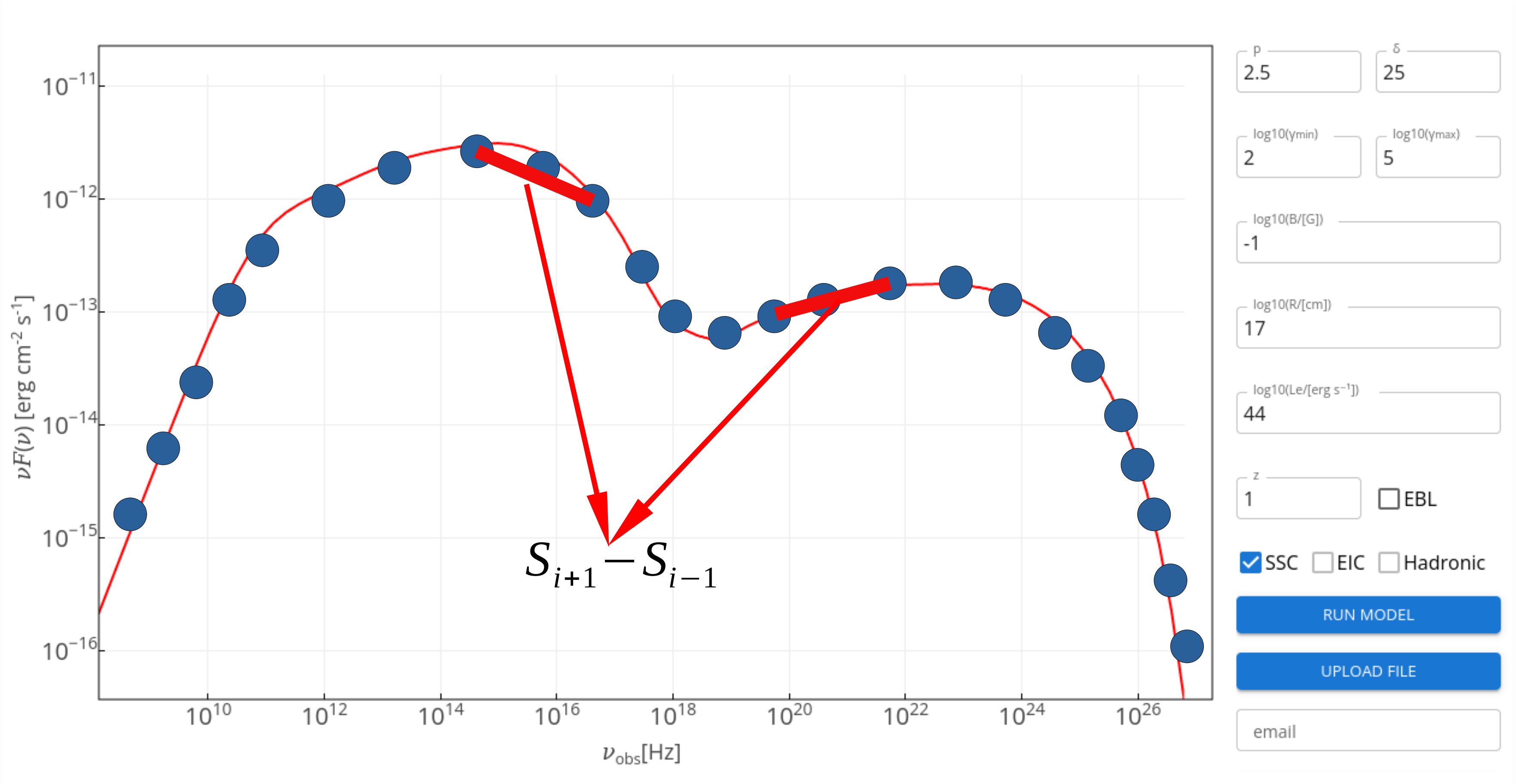

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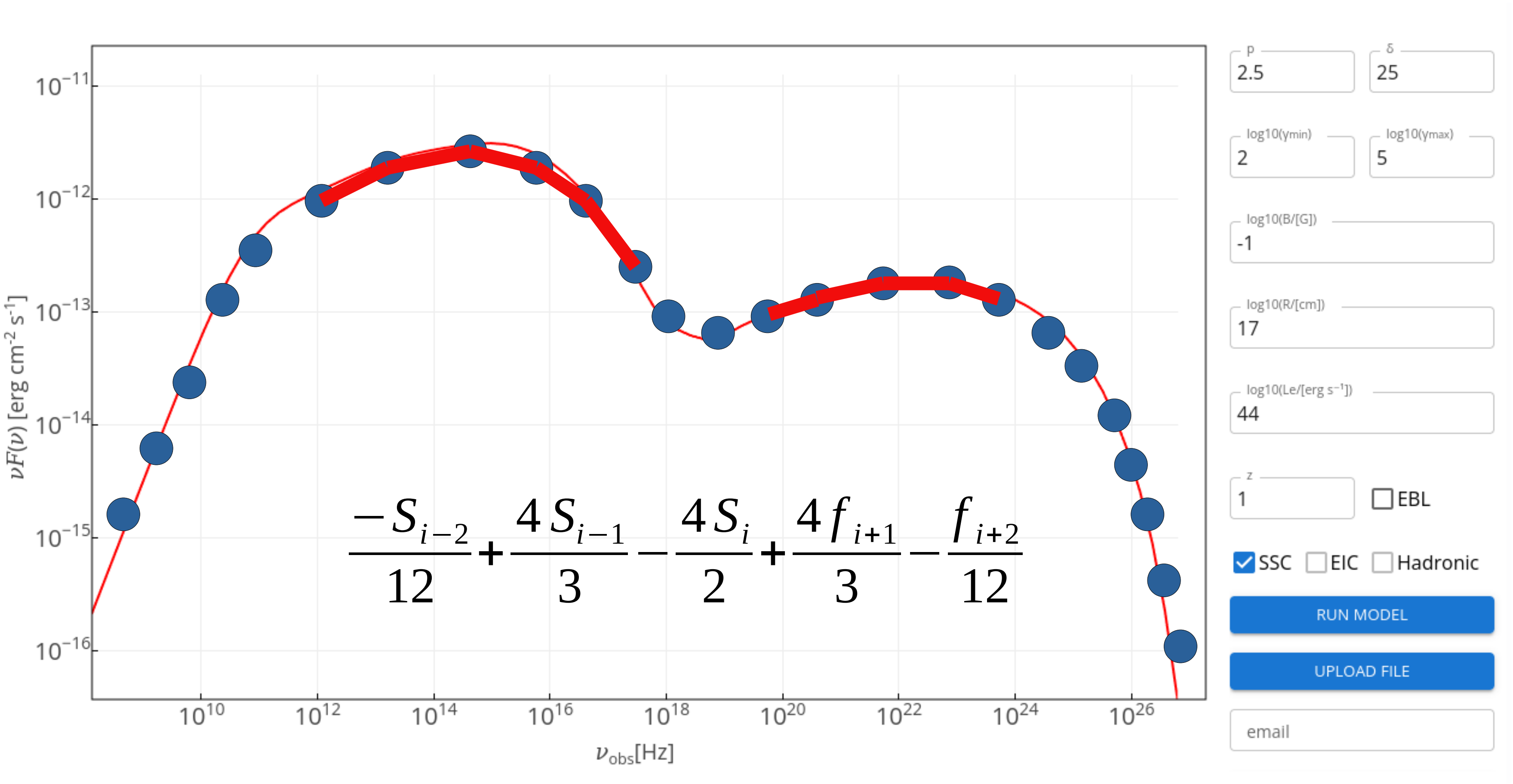

$$\frac{-S_{i-2}}{12}+\frac{4\,S_{i-1}}{3}-\frac{4\,S_i}{2}+\frac{4\,f_{i+1}}{3}-\frac{f_{i+2}}{12}$$

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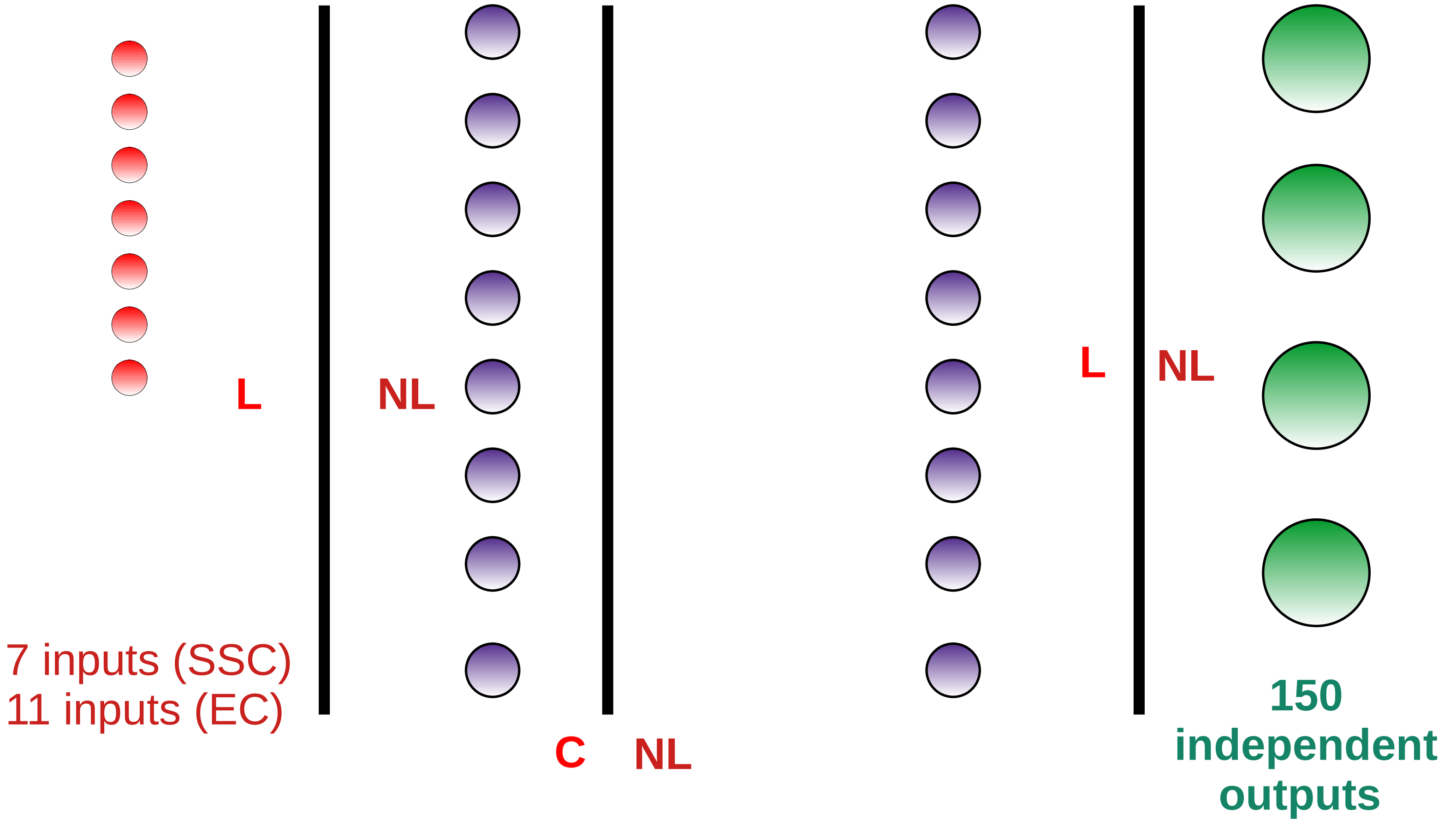

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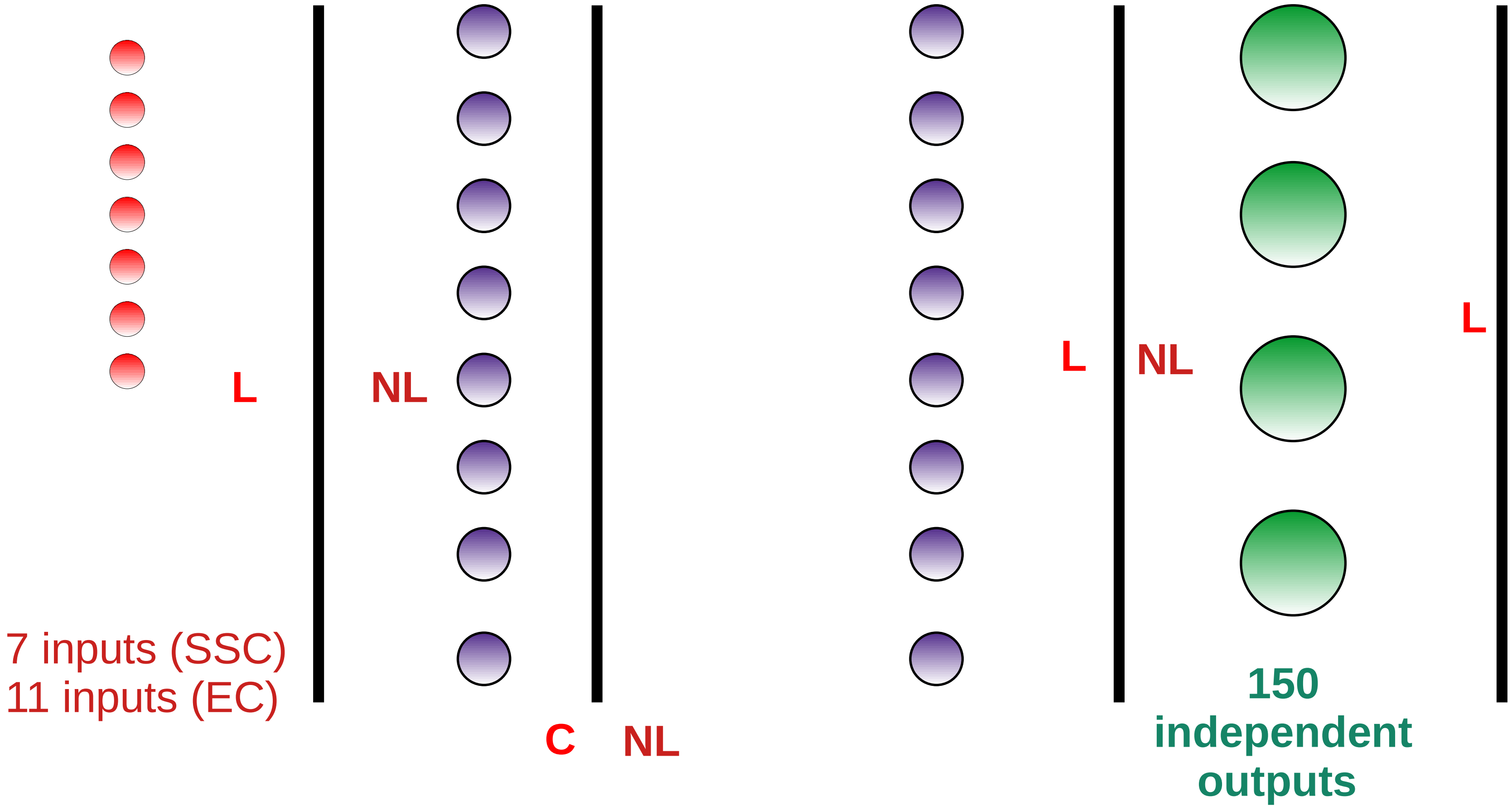

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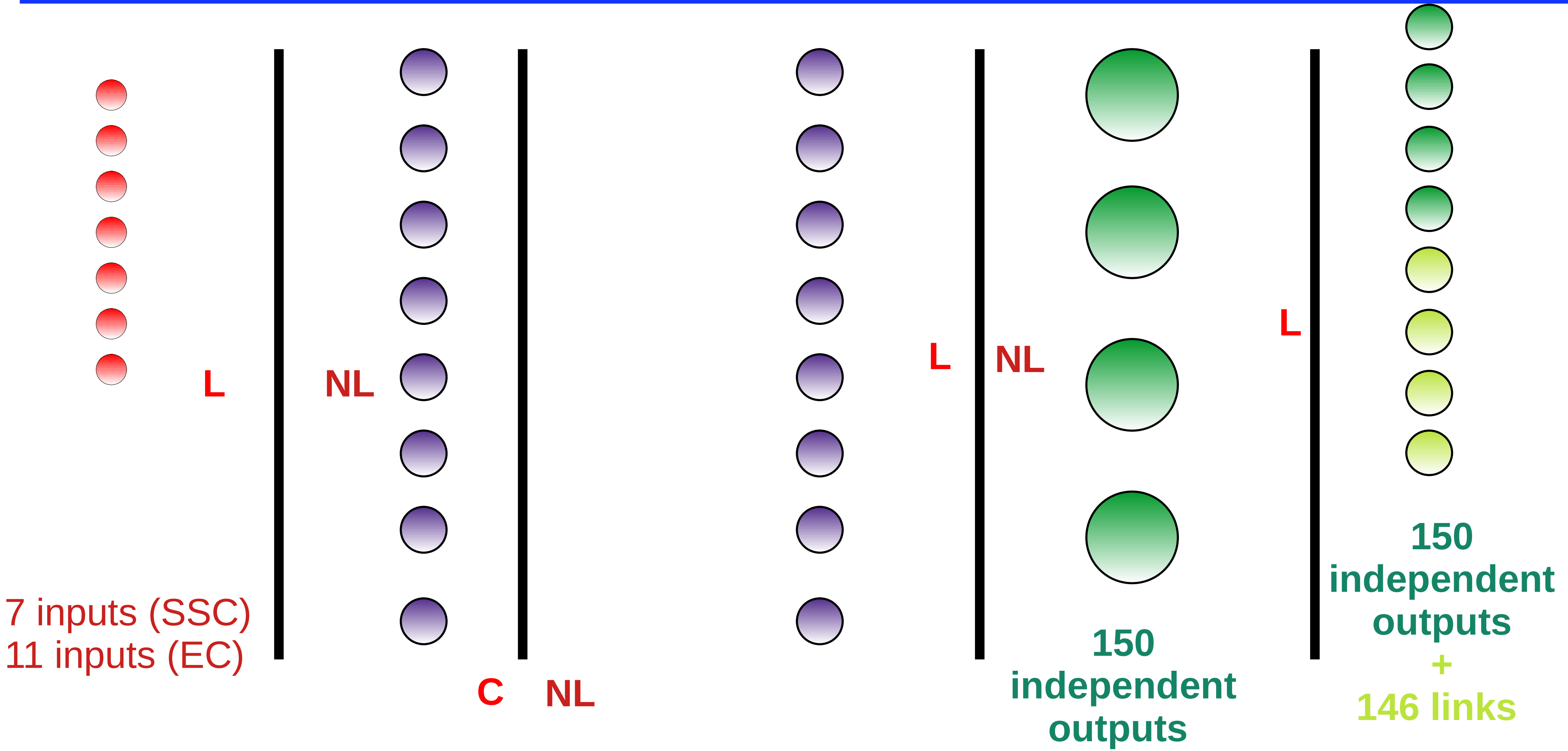

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Several trainings:
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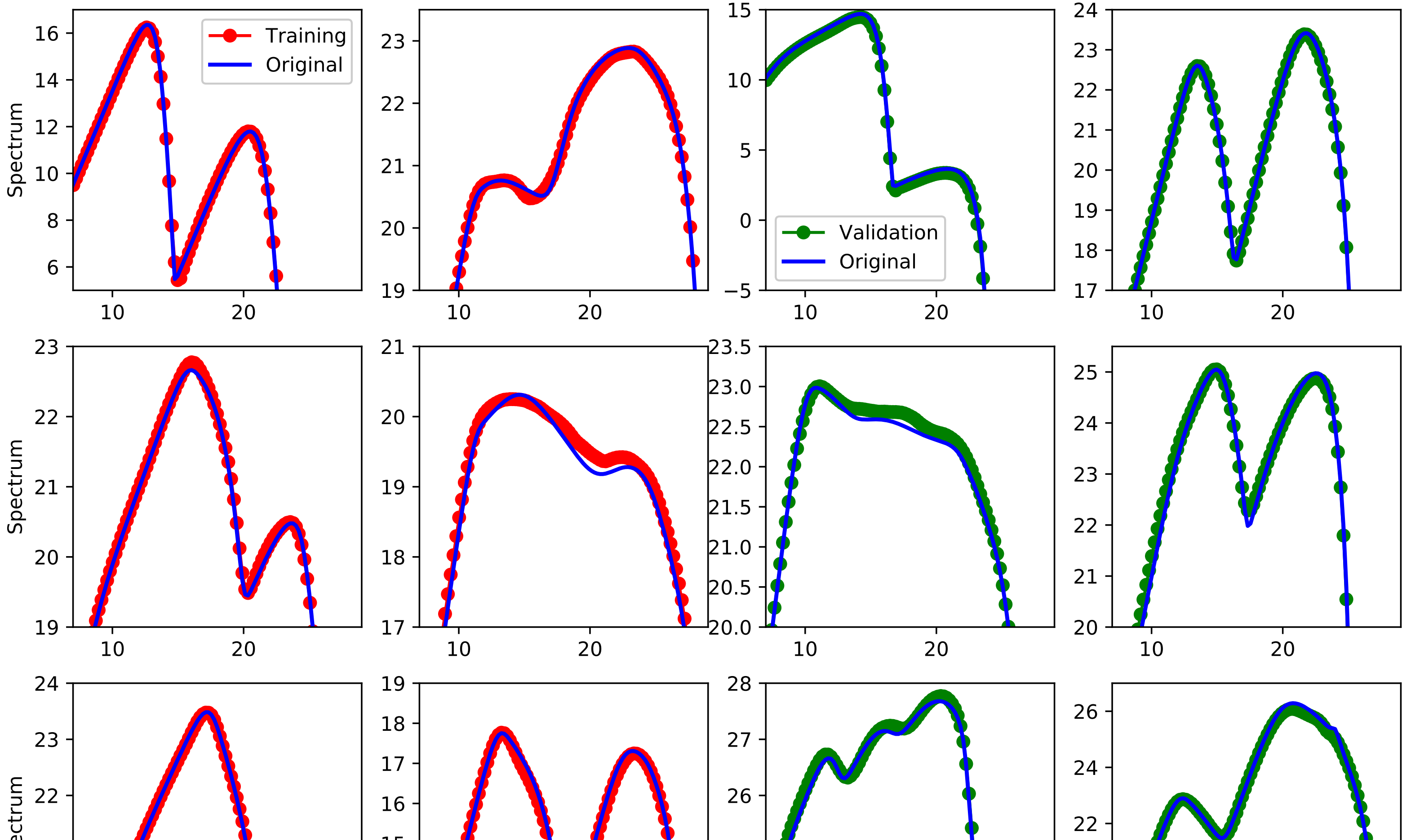
Large compute load. Done on 4 A100 GPUs,
2 training setup at a time per GPUs

Final result



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As of today, we have two models: synchrotron self-Compton and external Compton.

So much effort .... for what ?

We have a black box which compute a spectrum from a parameter set in ~1 ms.

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Perspectives

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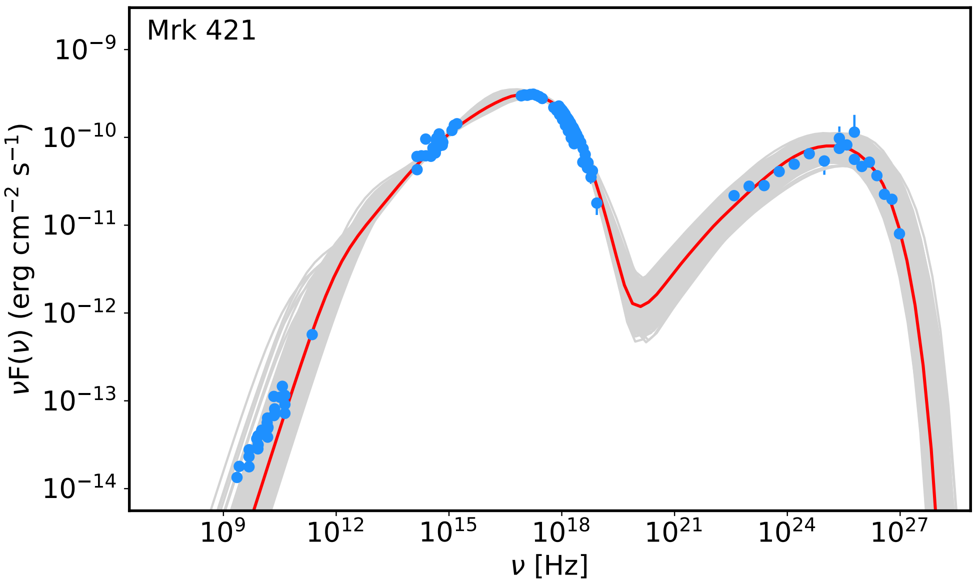
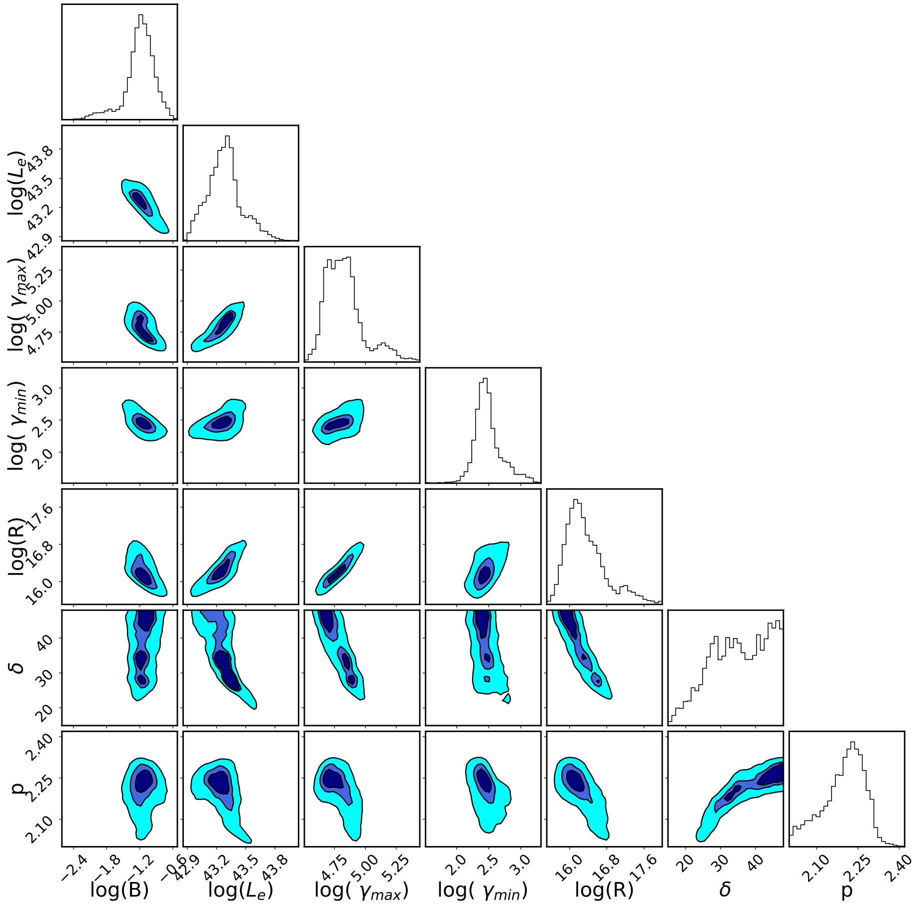
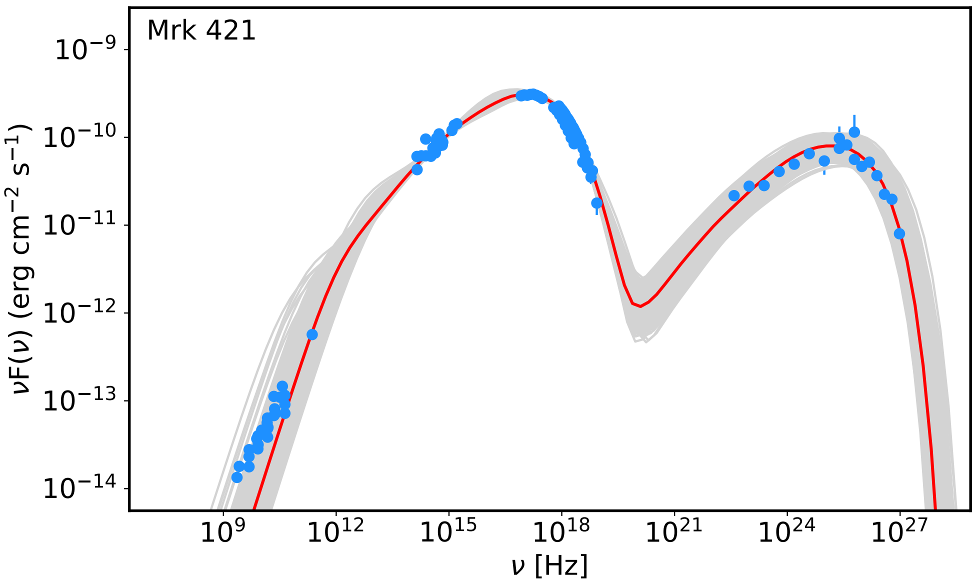
5) New type of CNN to derive the posterior distribution directly from the data (remove entirely the fit procedure).
   - Requires many fit results to train the network.... will be feasible when we will have done many many fits.

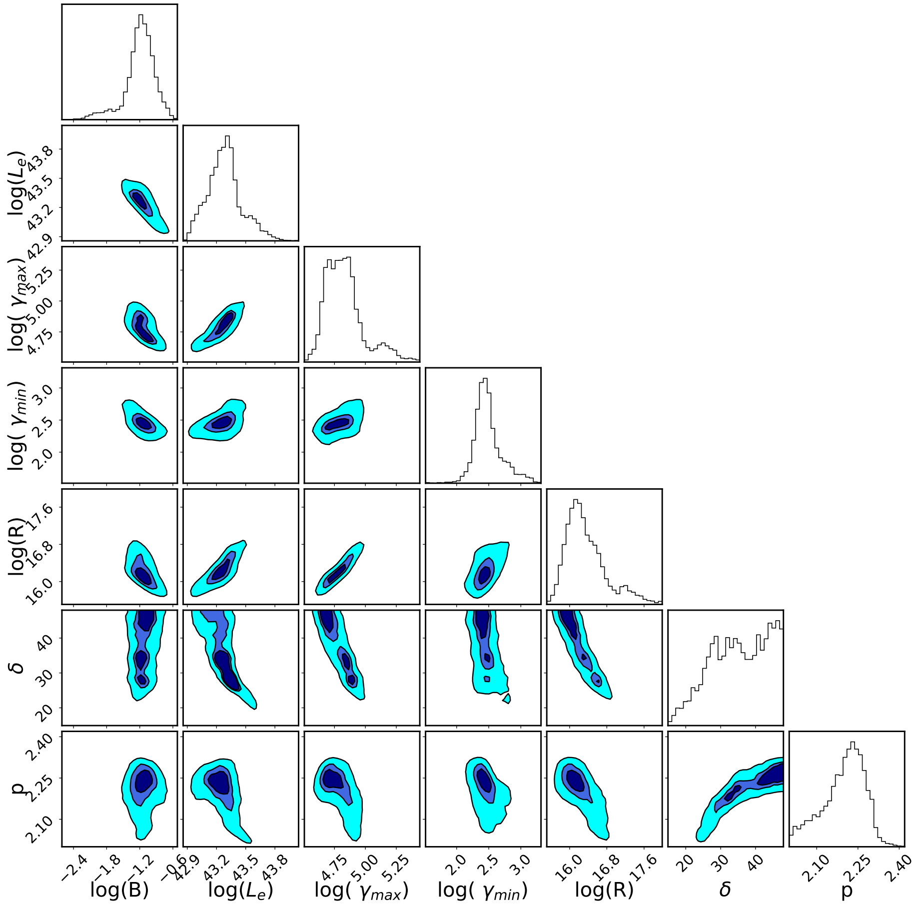




See Husne's and Narek's talks

Thank you





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