Finanziato dall'Unione europea NextGenerationEU
Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
ICSC Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing

Anomaly Detection in Time Series from Fermi ACD Data Analysis with ML techniques

Andrea Adelfio for WP3 (INFN Perugia)

Scientific Rationale

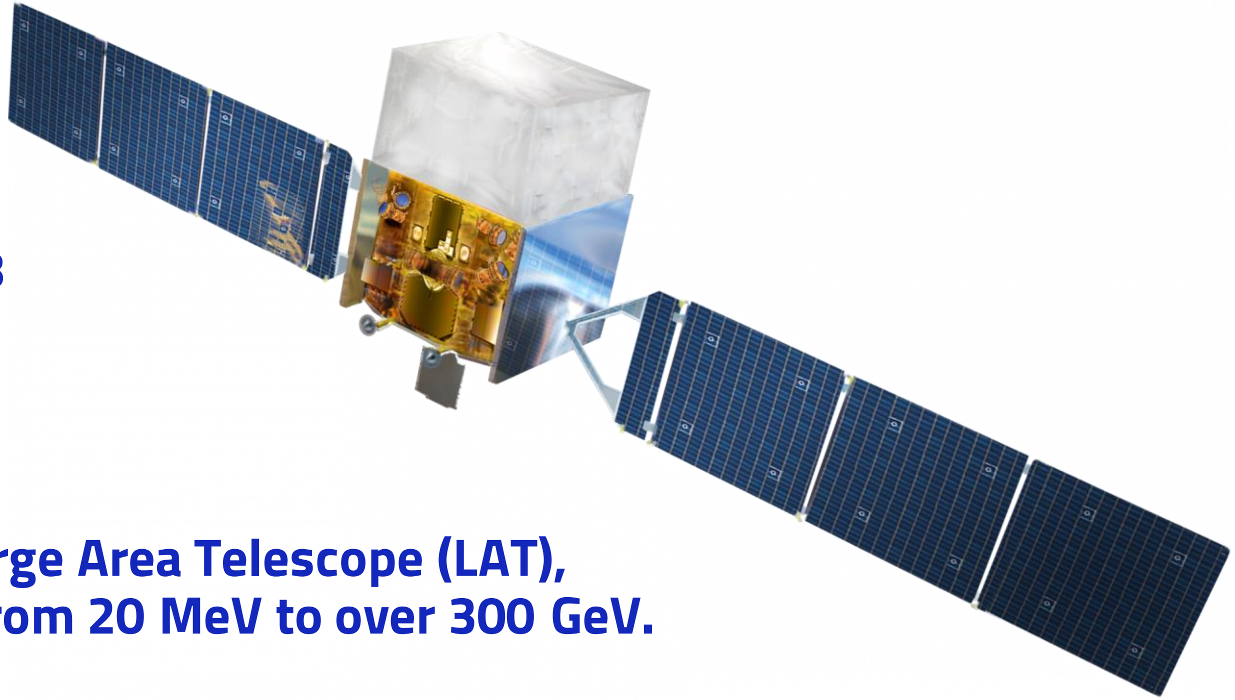
- To develop an Anomaly Detection algorithms using astrophysical data and machine learning techniques;

- Use of Astrophysical data from the Anti-Coincidence Detector (ACD) on board of the Fermi satellite;

- Use of Machine Learning techniques to have a baseline prediction of the signal background;

- In collaboration with Intesa Sanpaolo to work on banking time series.

Fermi satellite and ACD



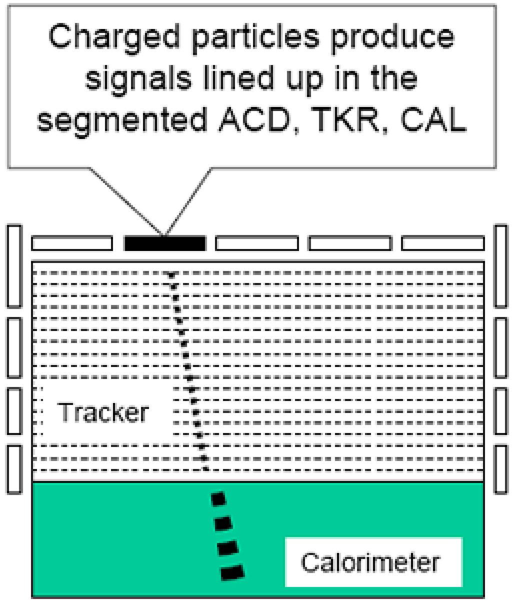
The Fermi Gamma-ray Space Telescope
is a space observatory launched by NASA in 2008
to study high-energy gamma rays.

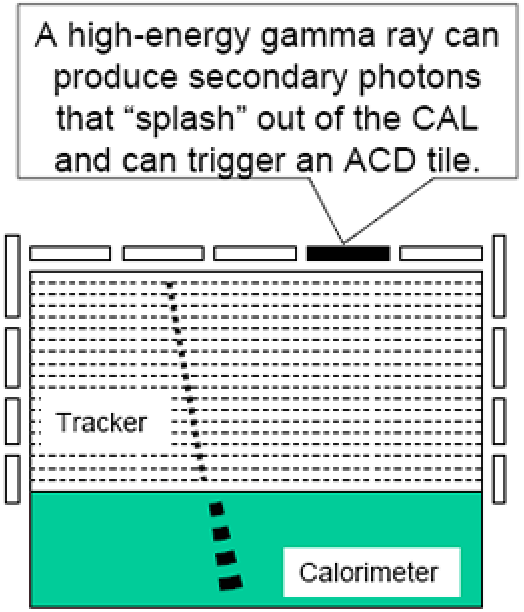
The primary instrument on board Fermi is the Large Area Telescope (LAT),
which detects gamma rays in the energy range from 20 MeV to over 300 GeV.

The Gamma-ray Burst Monitor (GBM), designed to observe gamma-ray bursts
in the energy range from 8 keV to 40 MeV.

Fermi satellite and ACD

The LAT instrument is surrounded by its Anti-Coincidence Detector (ACD), used to filter out unwanted signals, such as cosmic rays, that can mimic gamma-ray signatures.





The ACD consists of an array of plastic scintillator tiles, which emit light when traversed by charged particles. By detecting these particles, the ACD helps identify and reject events caused by charged particles, allowing the LAT to focus on gamma-ray signals.

Data

The dataset that is being used is 52 days long, from the 2023-12-05 to 2024-02-02.

It consists of two Fermi data products, all with a time resolution of 1 second:

-Weekly Spacecraft data (from Fermi FTP), which contains all the parameters describing the spatial configuration of the satellite, with other parameters such as the geomagnetic flux description along the orbit;

-Photons counts for each face of the ACD system;

-Solar Activity from the Geostationary Operational Environmental Satellite (GOES) Network.

Spacecraft Data

START (seconds) -> Mission Elapsed Time of start of interval

STOP (seconds) -> Mission Elapsed Time of end of interval

SC_POSITION (meters) -> Three element array giving the position (x, y, z) of spacecraft in inertial (ECI) coordinates at START

SC_VELOCITY -> Three element array giving the spacecraft velocity in the same coordinate frame as SC_POSITION at START

LAT_GEO -> ground point latitude

LON_GEO -> ground point longitude

RAD_GEO -> spacecraft altitude

RA_ZENITH -> RA of zenith direction at START

DEC_ZENITH -> Dec of zenith direction at START

Spacecraft Data

B_MCILWAIN -> McIlwain B parameter, magnitude of the magnetic field at START

L_MCILWAIN -> McIlwain L parameter, distance/shell value at START
'https://www.spenvis.oma.be/help/background/magfield/bl.html'

GEOMAG_LAT -> invariant geomagnetic latitude

LAMBDA -> effective geomagnetic latitude (signed to indic

IN_SAA -> whether spacecraft was in SAA

Spacecraft Data

LAT_MODE -> Spacecraft GNC mode, where the 3 nominal modes are 3(inertial point), 4 (Maneuver) and 5 (zenithpoint/survey). Other modes include 1 and 2 (capture and sunpoint - rarely used) and 6 and 7 (reentry modes).

LAT_CONFIG -> Flag for the configuration of the LAT (1 = nominal science configuration, 0 = not recommended for analysis)

DATA_QUAL -> Signed integer value indicating the quality of the LAT data

LIVETIME -> Accumulated livetime of the LAT during the interval from START to STOP

Spacecraft Data

QSJ_1 -> First component of SC attitude quaternion

QSJ_2 -> Second component of SC attitude quaternion

QSJ_3 -> Third component of SC attitude quaternion

QSJ_4 -> Fourth component of SC attitude quaternion

Spacecraft Data

RA_SUN -> RA of Sun

DEC_SUN -> DEC of Sun

Photons Counts Data

The dataset contains the counts of photons in each face of the ACD. Based on the three axes of the cube (X,Y,Z) we call the faces:

-top (Z)

-Xpos (X+)

-Xneg (X-)

-Ypos (Y+)

-Yneg (Y-)

Photons Counts Data

- -top (Z)
- -Xpos (X+)
- -Xneg (X-)
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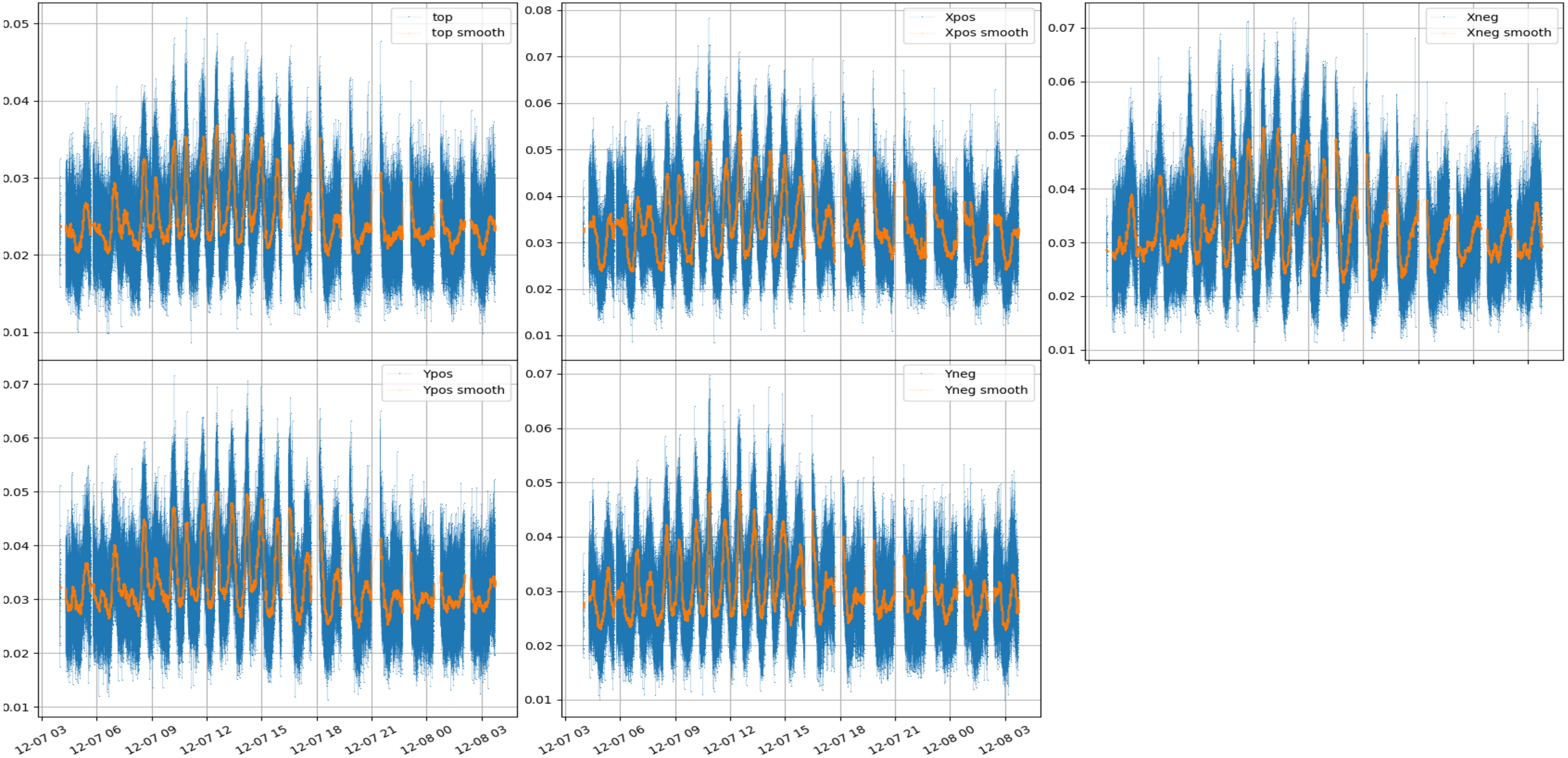

Photons Counts Data

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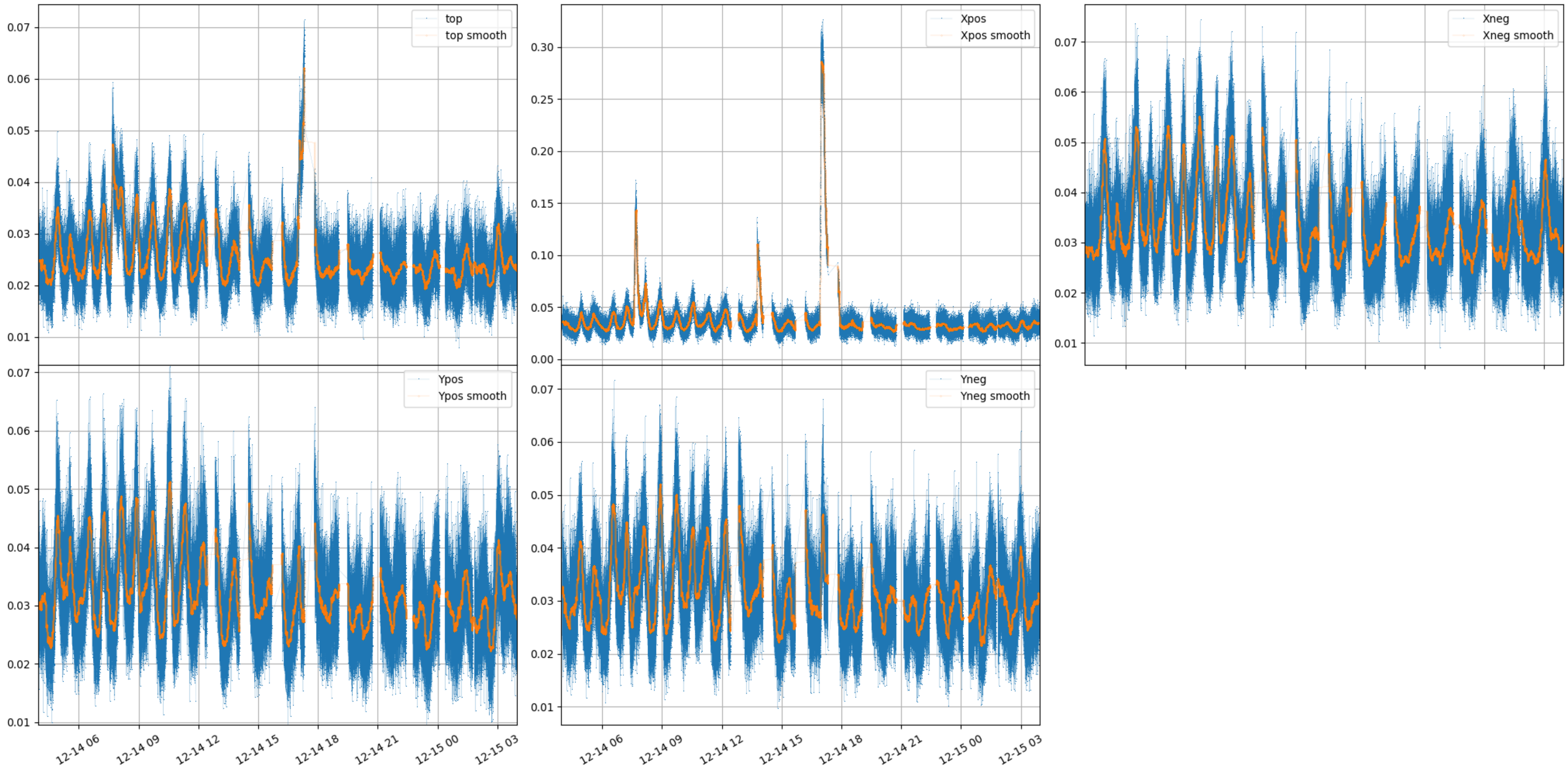
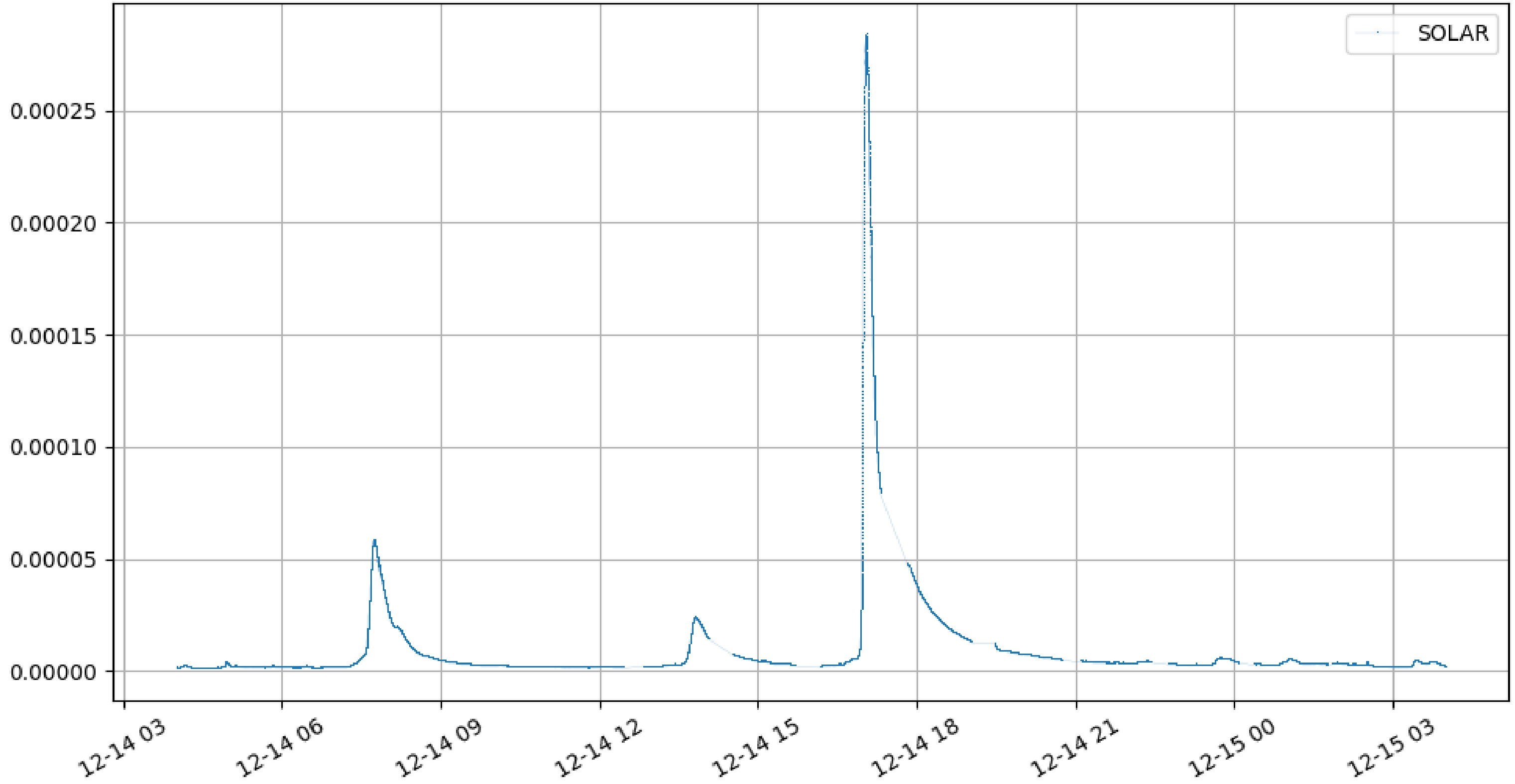


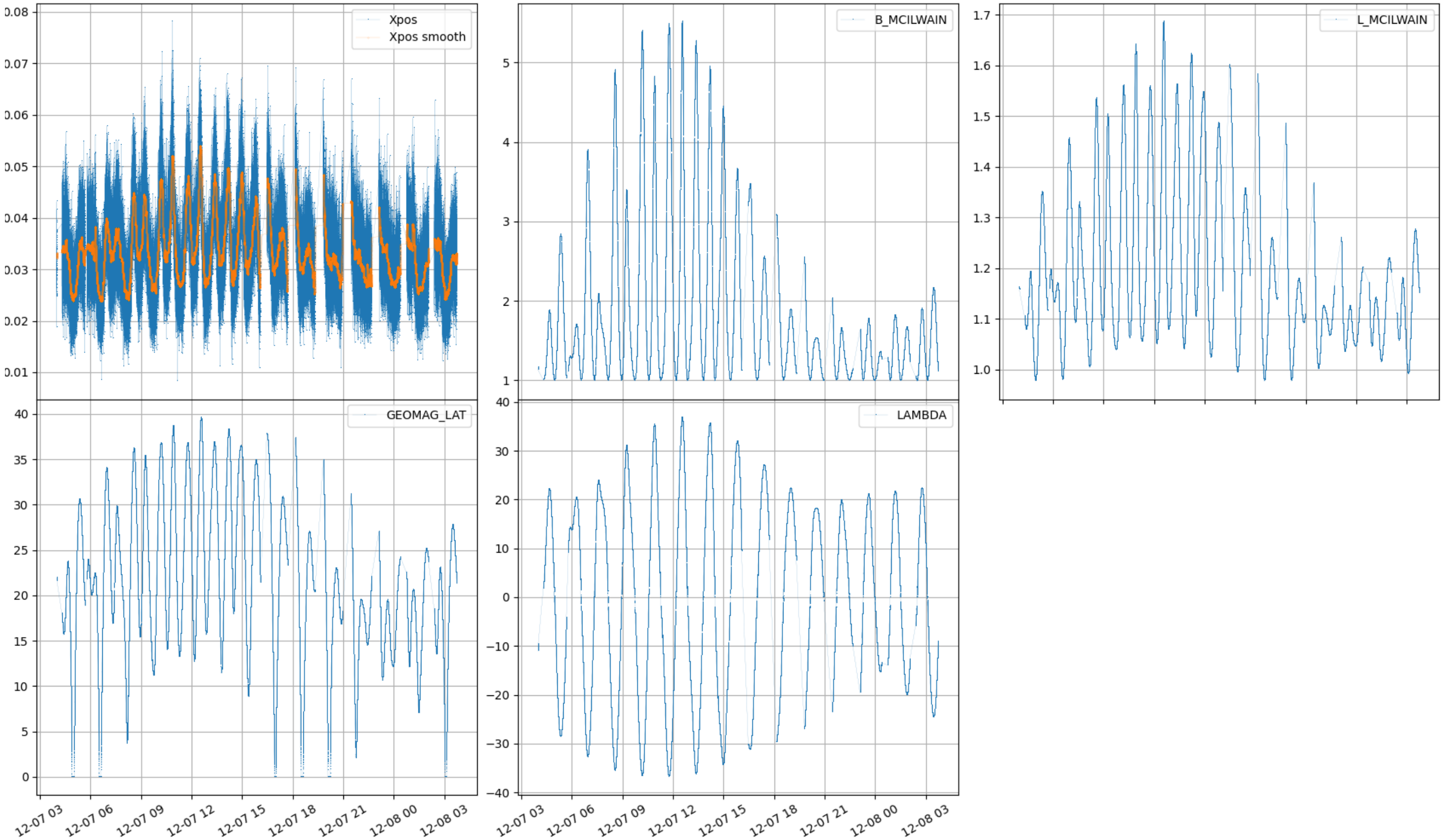
Solar Activity Data

It contains the counts of photons coming from the Sun.



Dataset for the Neural Network

From the data, we can observe that some parameters have a significant influence on the number of photons observed:



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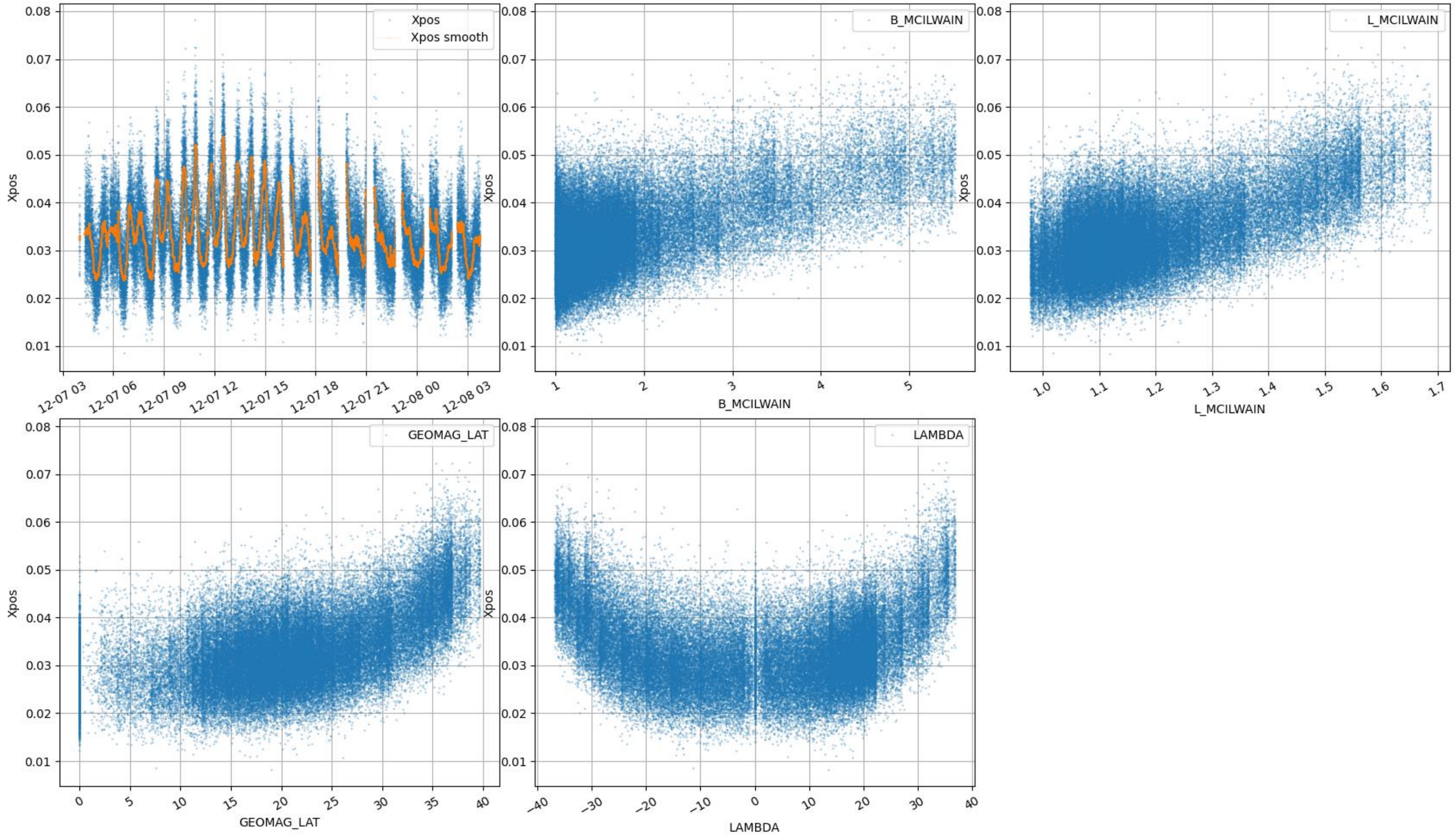

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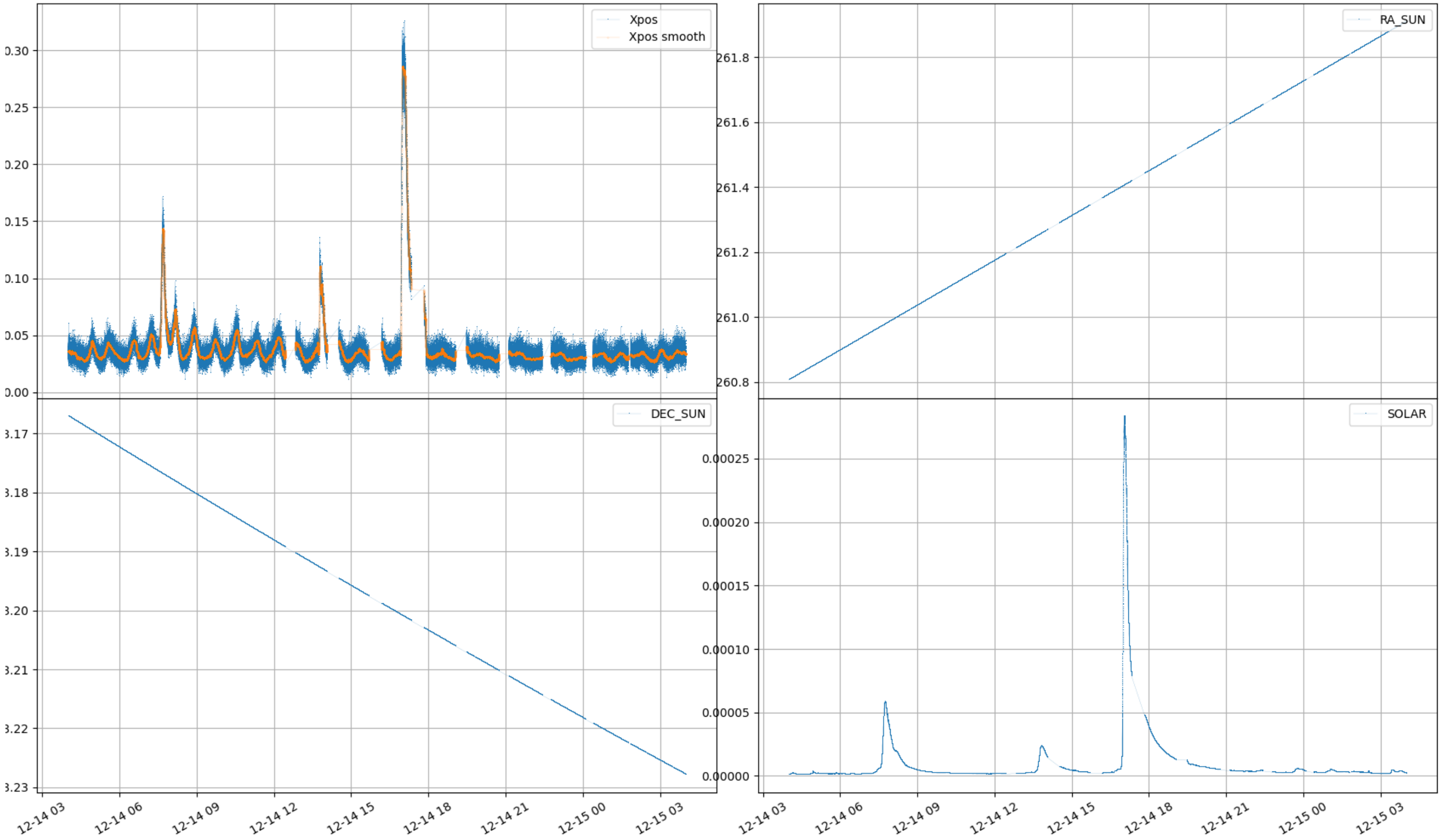

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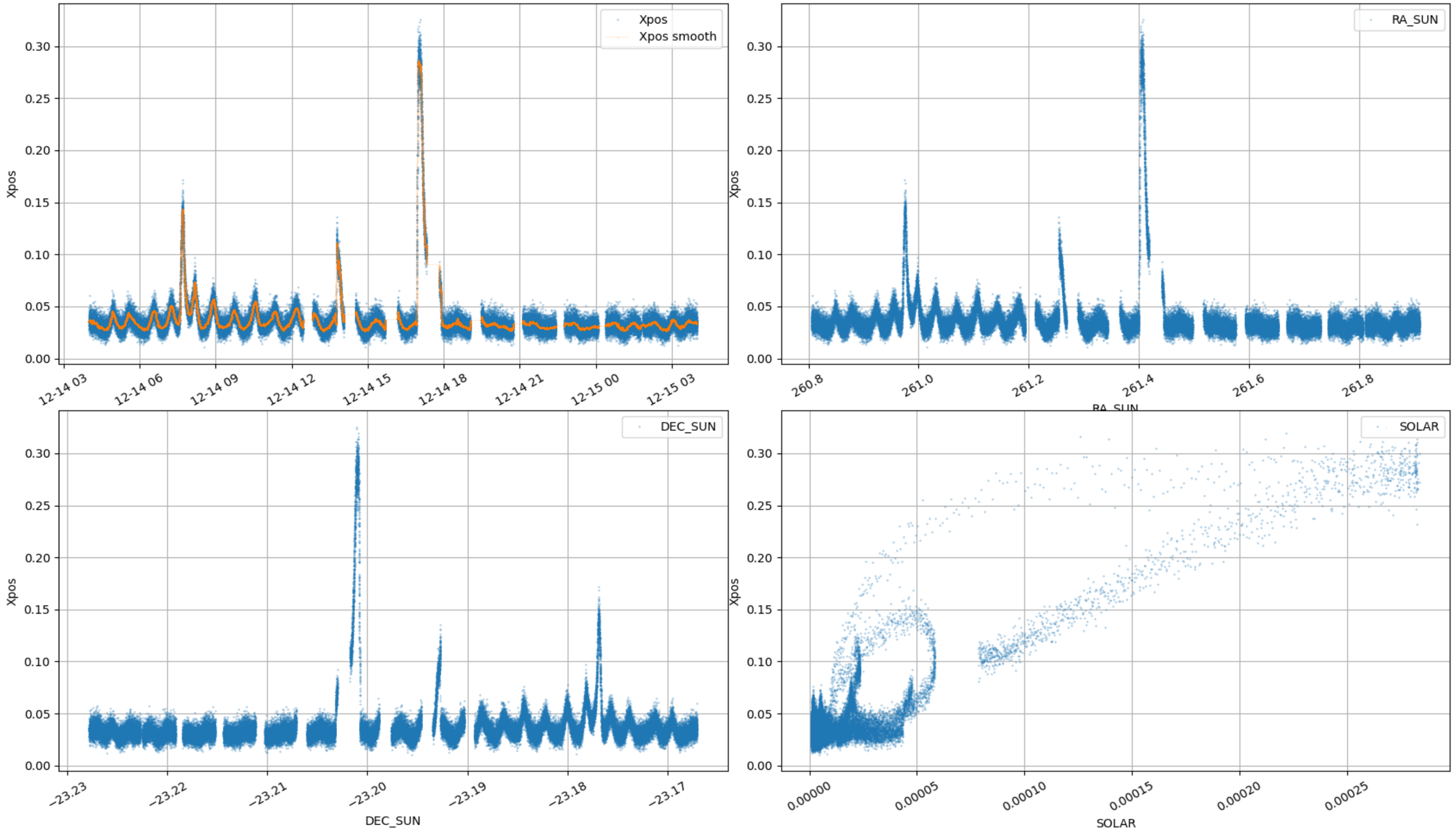
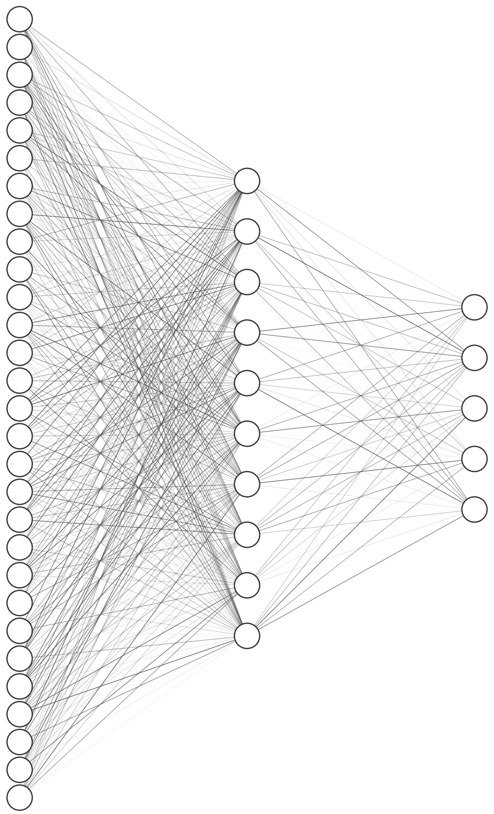


Dataset for the Neural Network

It is divided in 29 input parameters (Spacecraft + Solar Activity) and 5 outputs containing the signals of the five ACD faces.



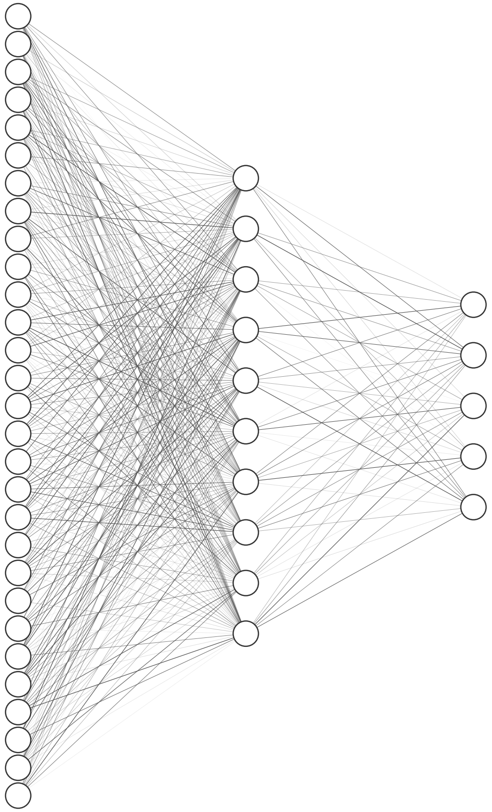
Feed Forward Neural Network

We use a Feed Forward Neural Network to find the best model that fits the background signal.

We started some preliminary analysis to understand the best structure to train the NN model.

The base structure is a dense hidden layer with N nodes.

It has been considered the use of a Batch Normalization Layer and a Dropout Layer adjacent to the hidden layer.



Loss function is the mean absolute error:

$$\mathrm{MAE}(z, y) = \frac{1}{n}\sum_{i=1}^{n} | y_i - z_i |$$

Feed Forward Neural Network

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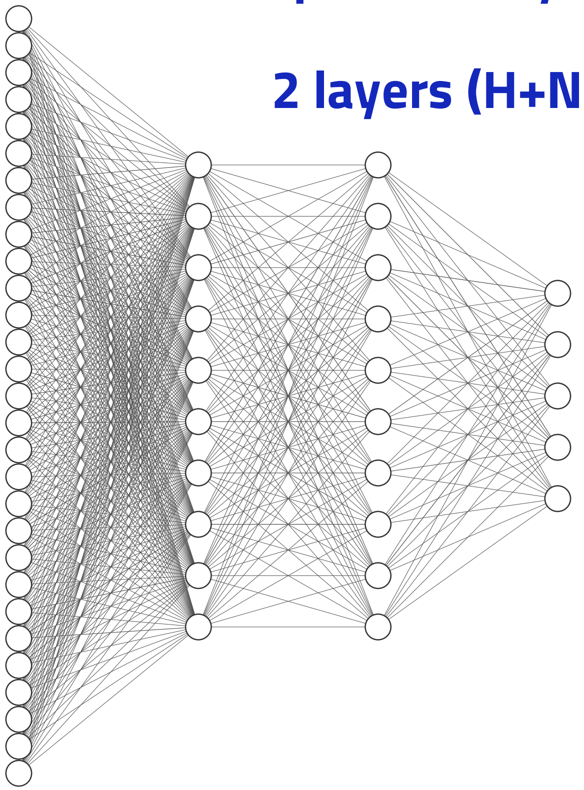
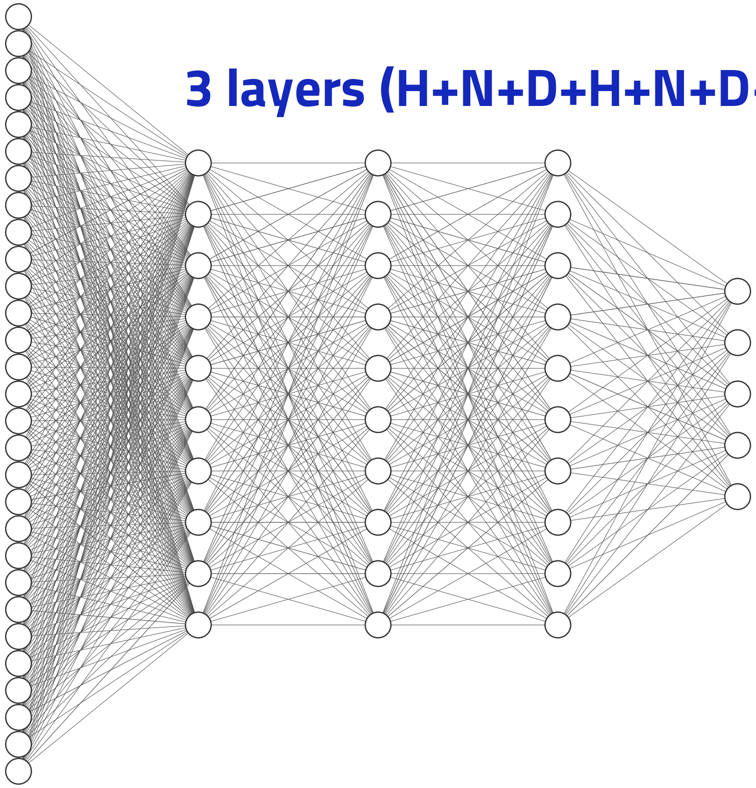
2 layers (H+N+D+H+N+D)

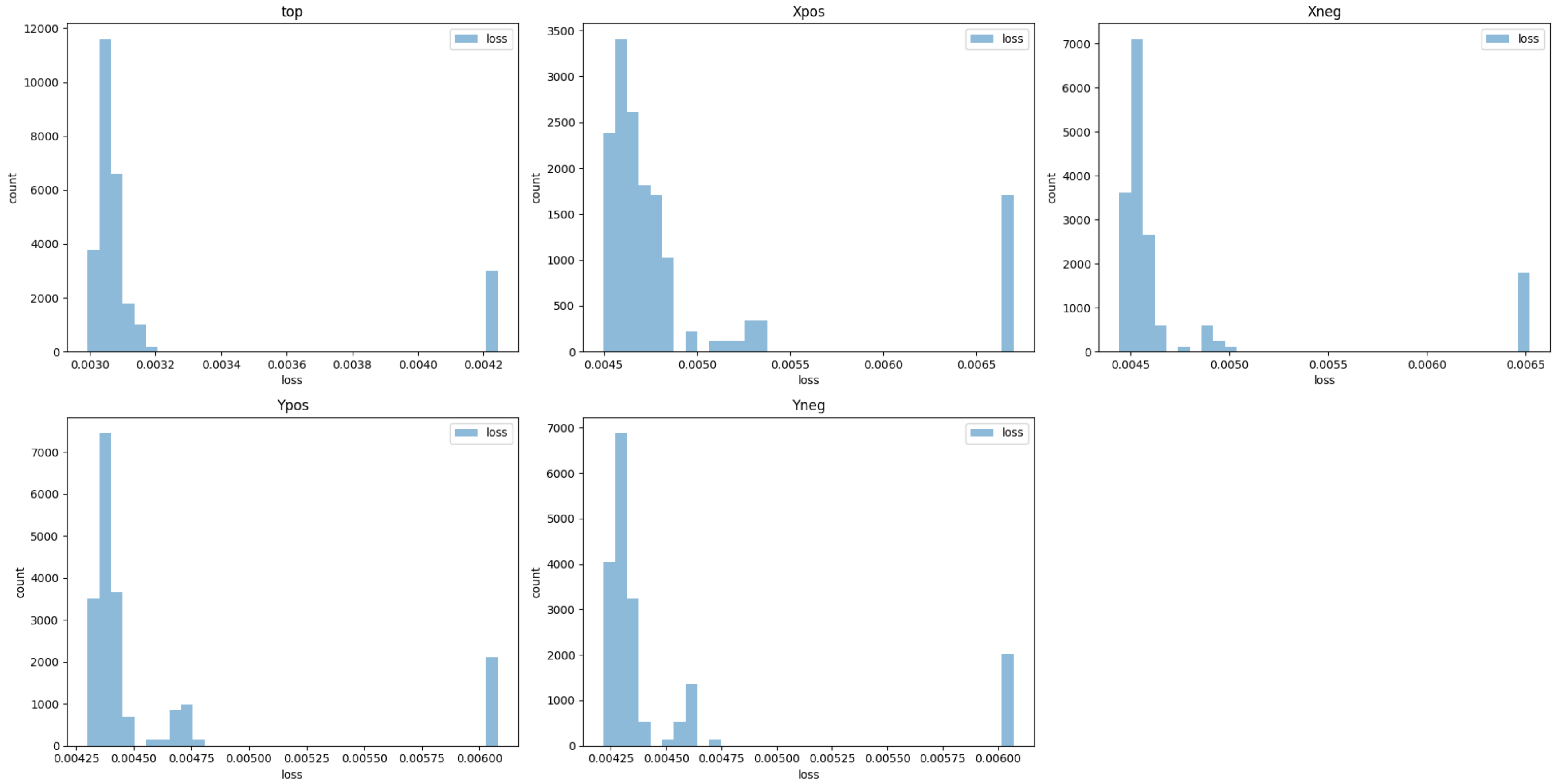


3 layers (H+N+D+H+N+D+H+N+D)



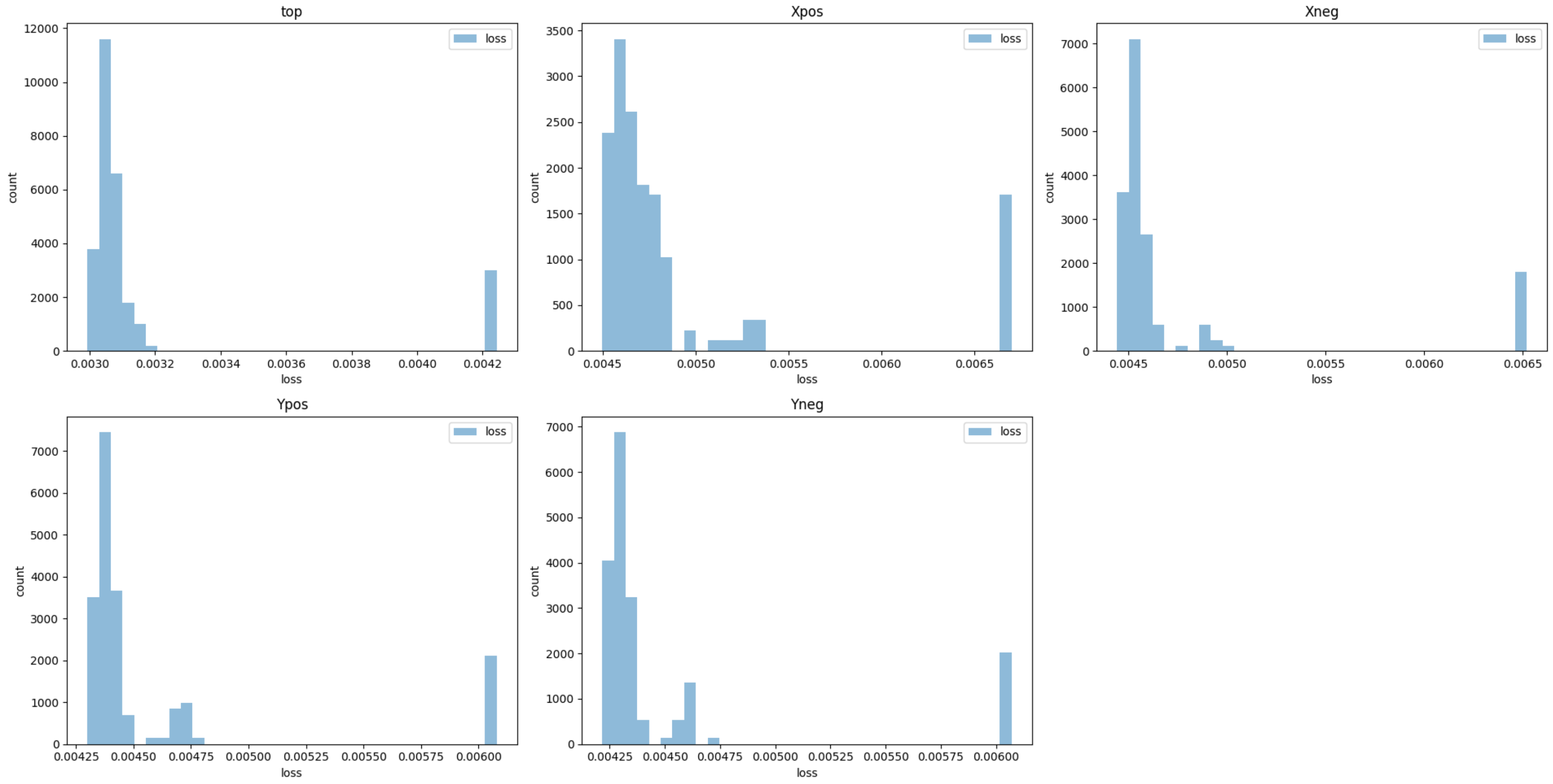
NN Training and results

Each combination of these layers has been trained for 60 epochs.



NN Training and results

These histograms have been subdivided based on the number of layers.



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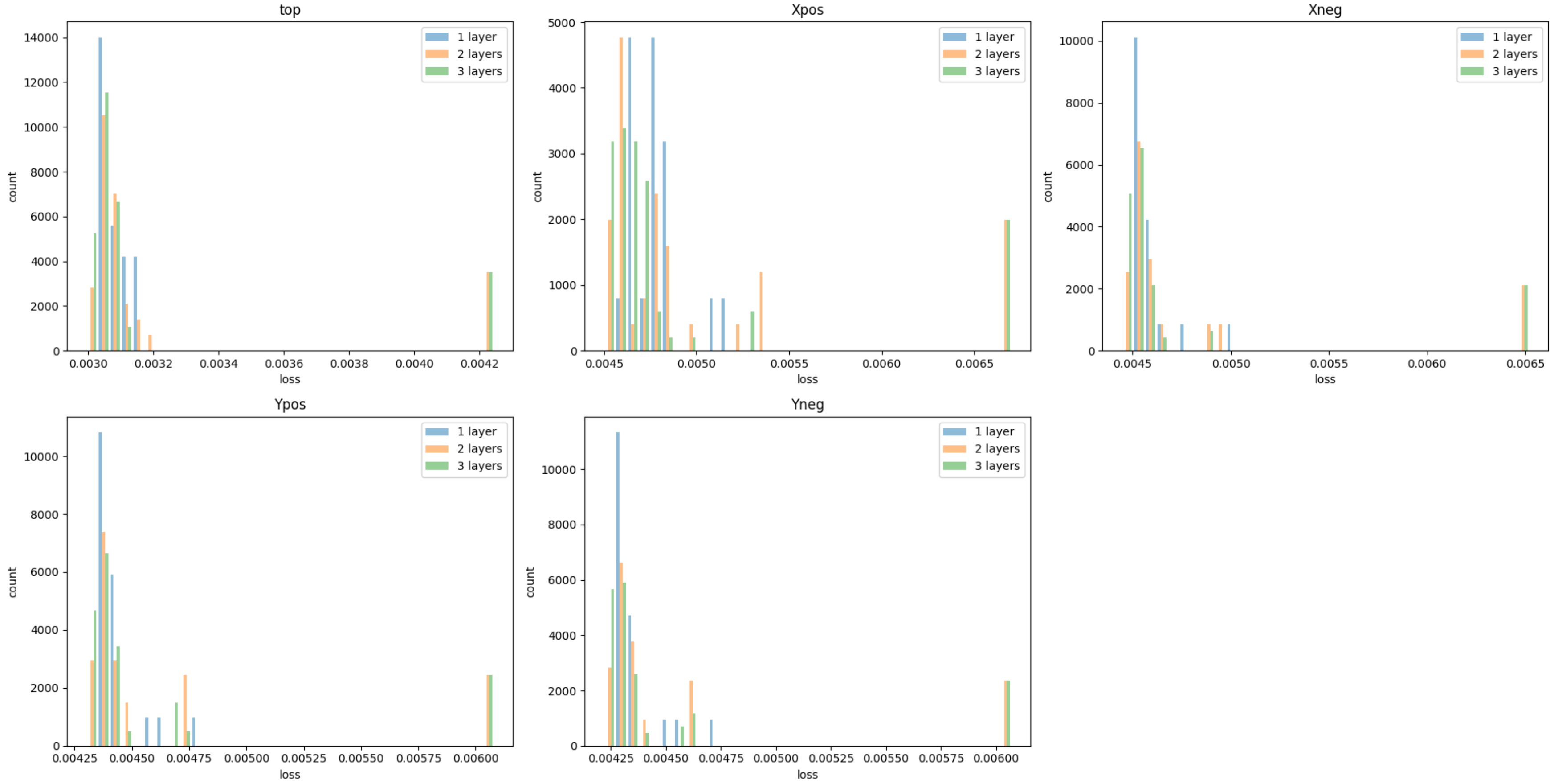

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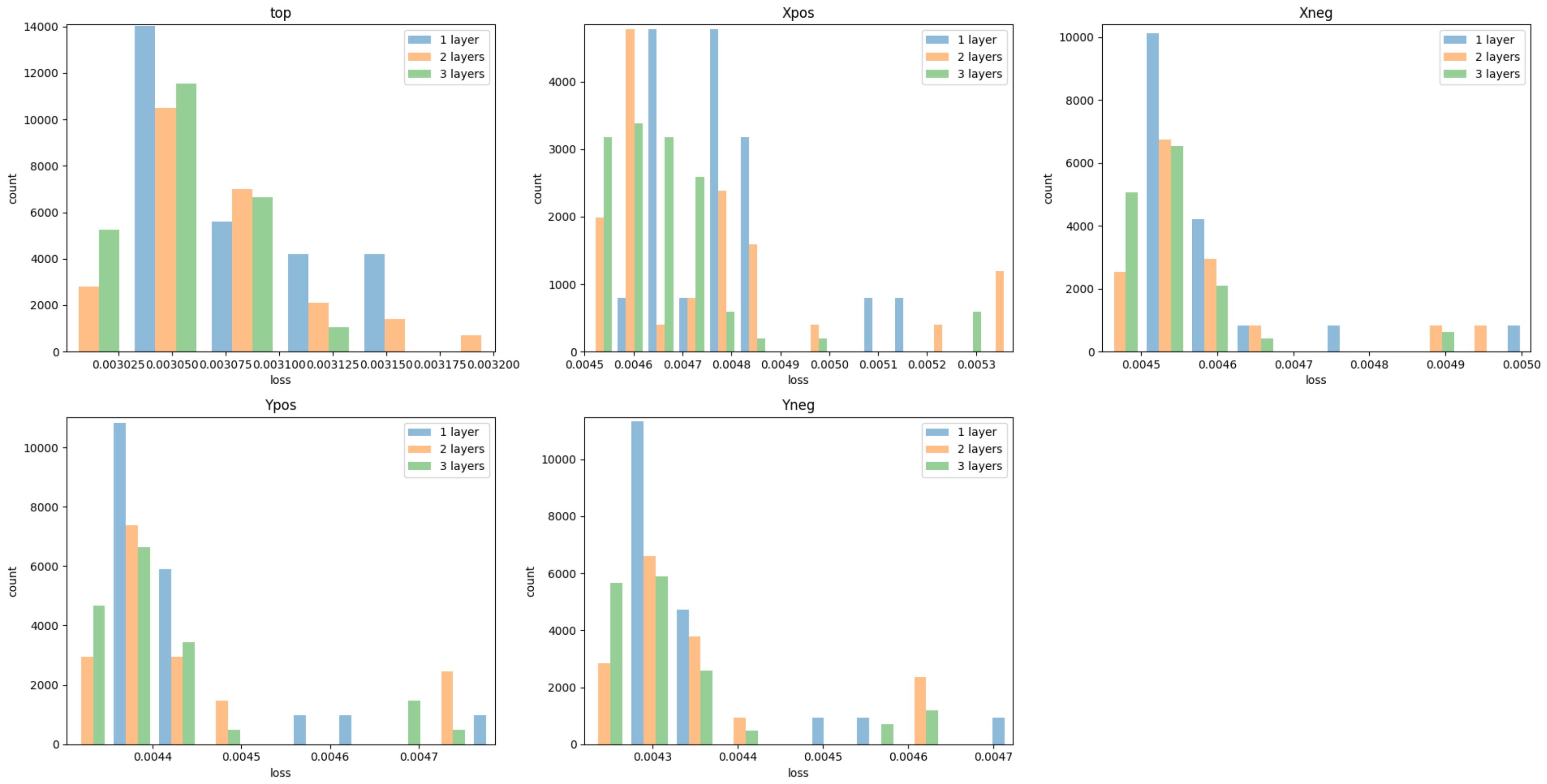
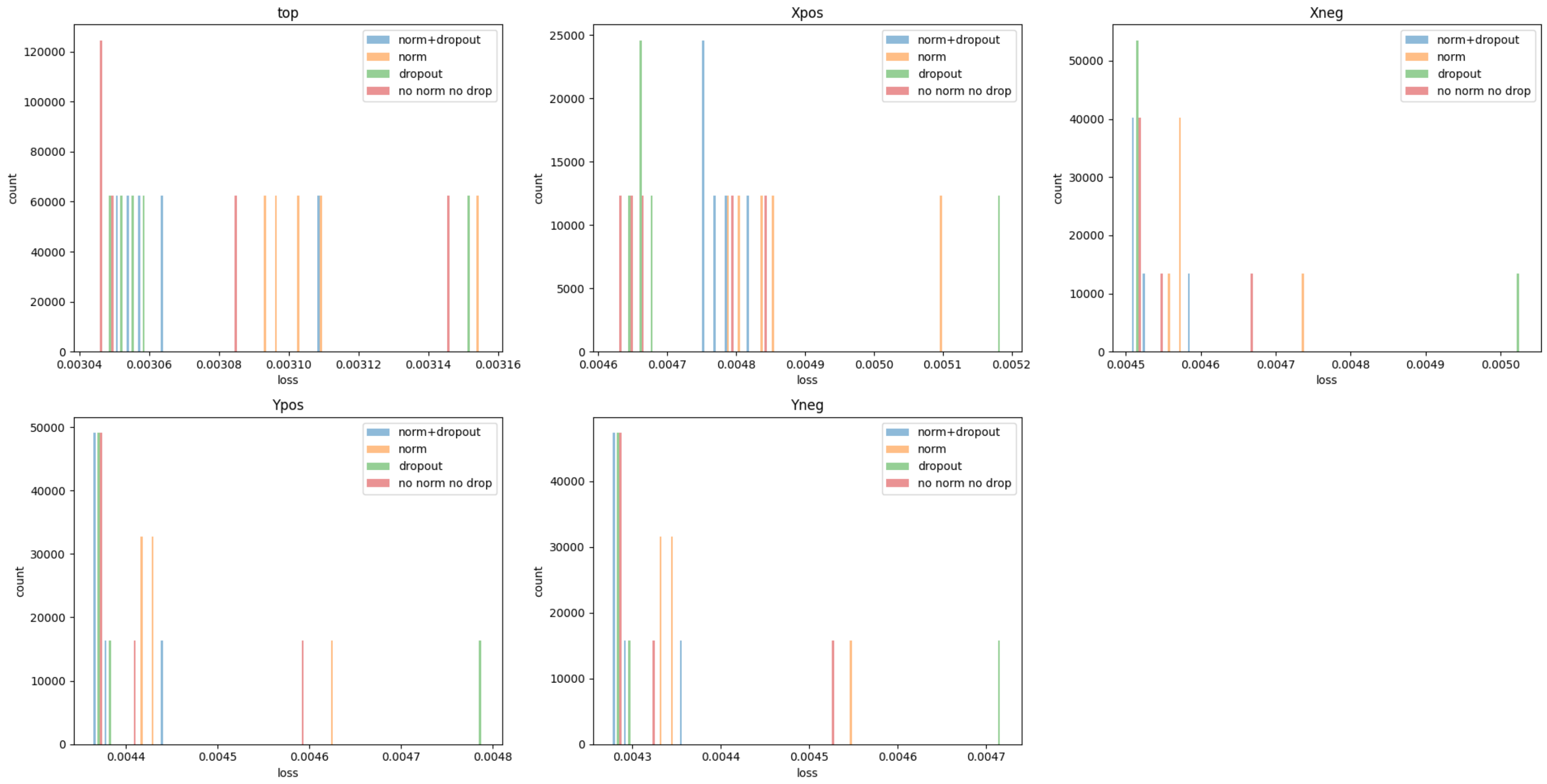


NN Training and results

The same have histograms have been plotted only for models with 1 layer



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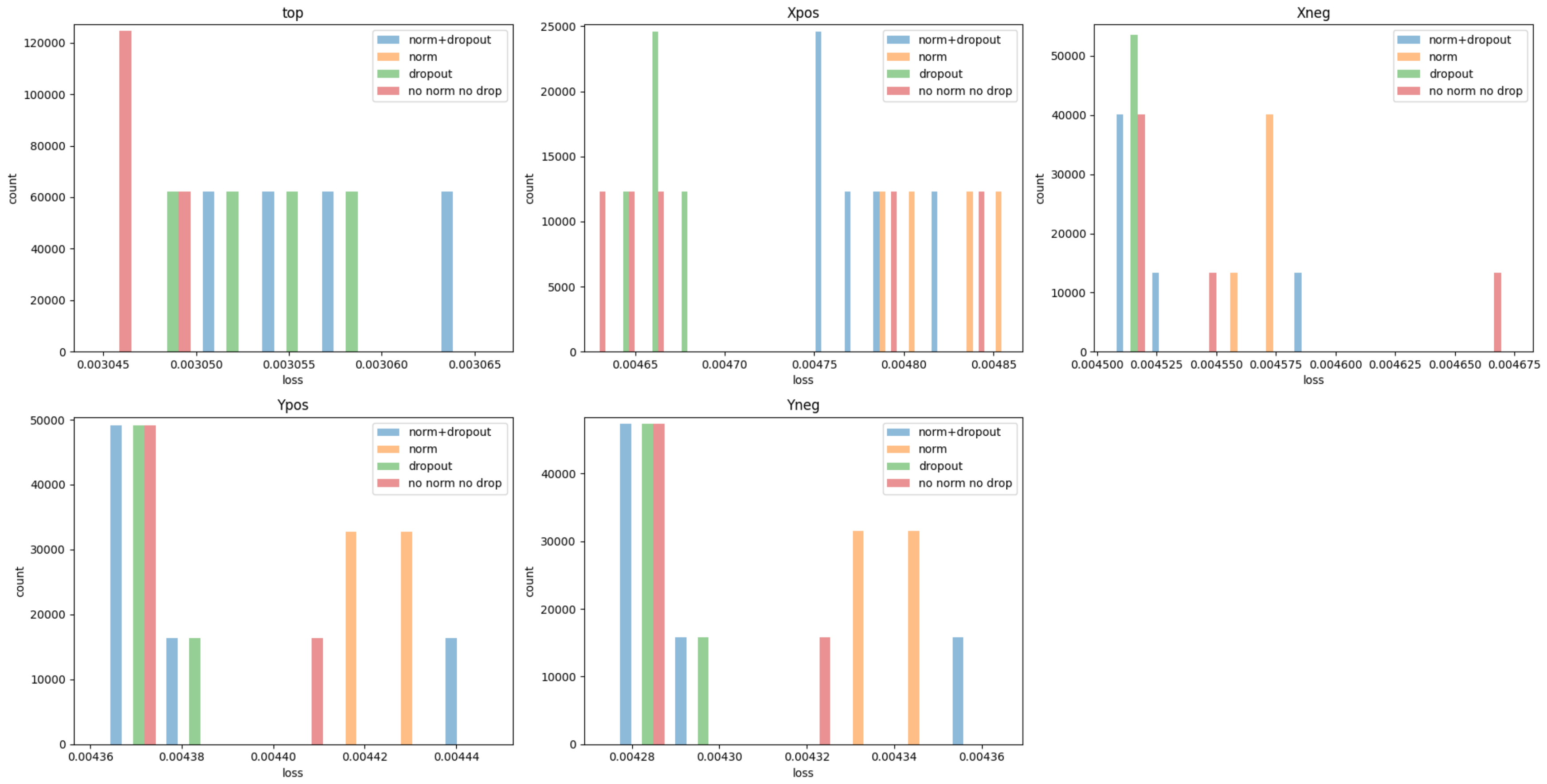
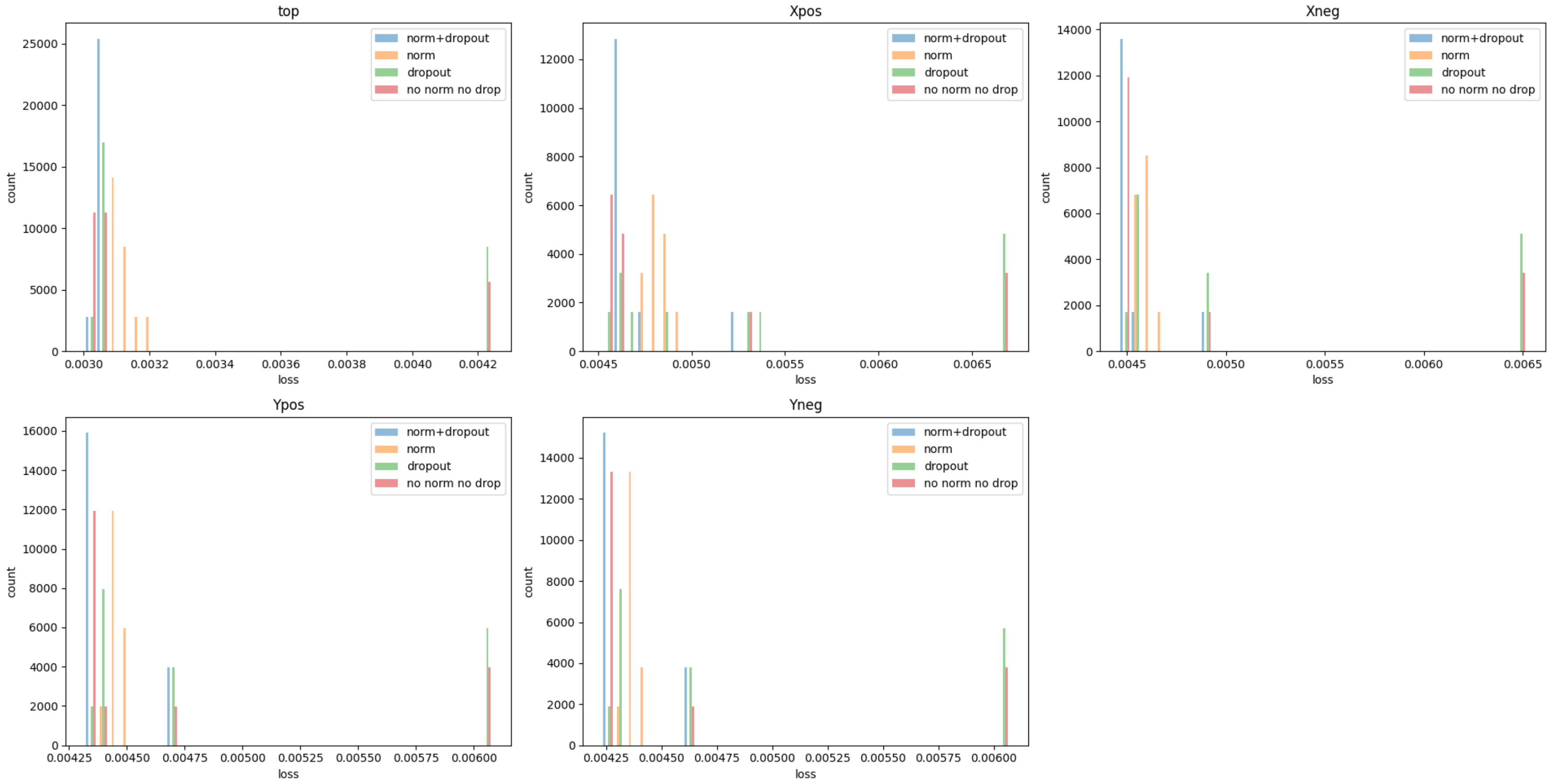


NN Training and results

The same have histograms have been plotted only for models with 2 layer



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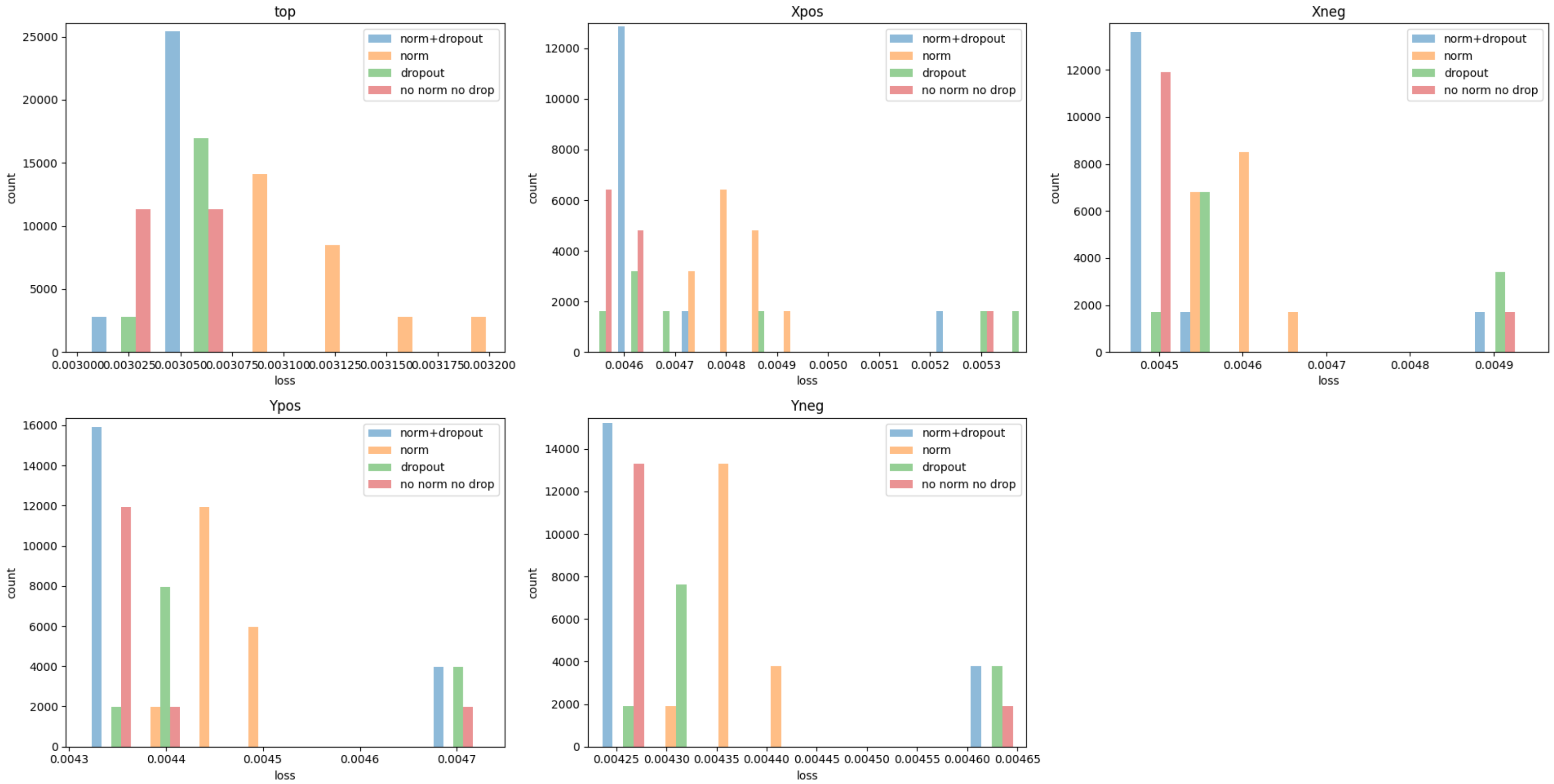
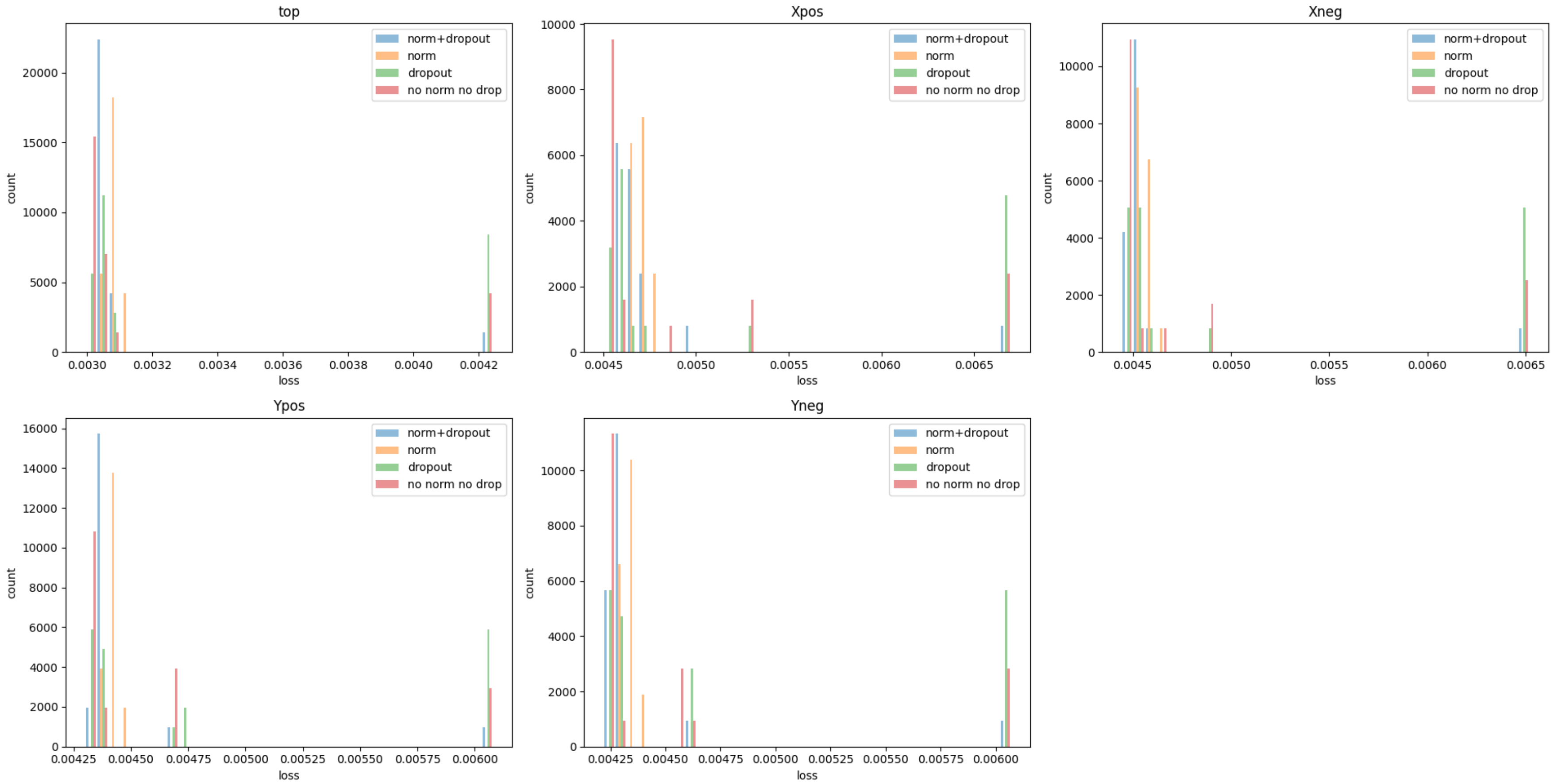


NN Training and results

The same have histograms have been plotted only for models with 3 layer



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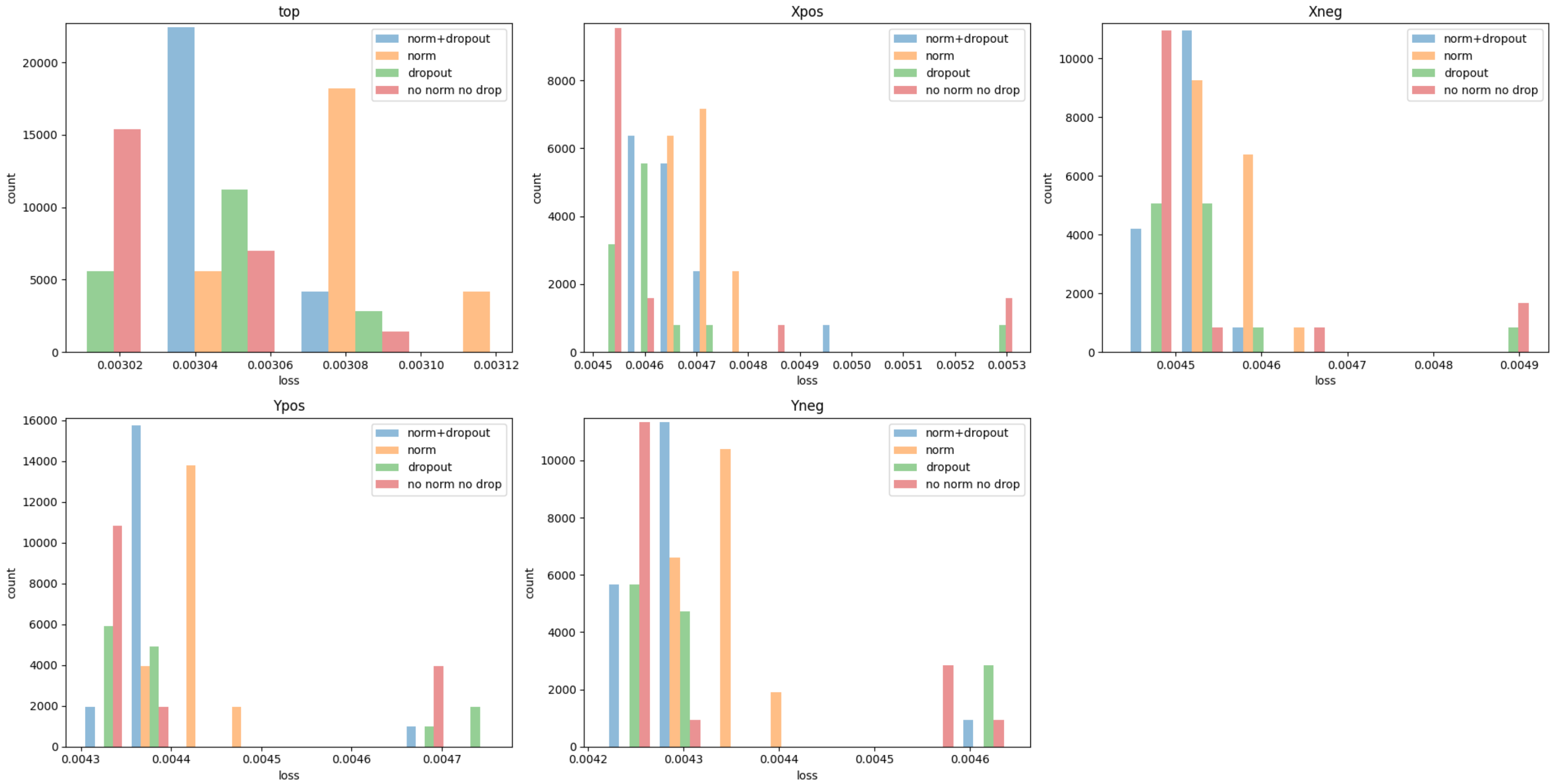


NN Training and results

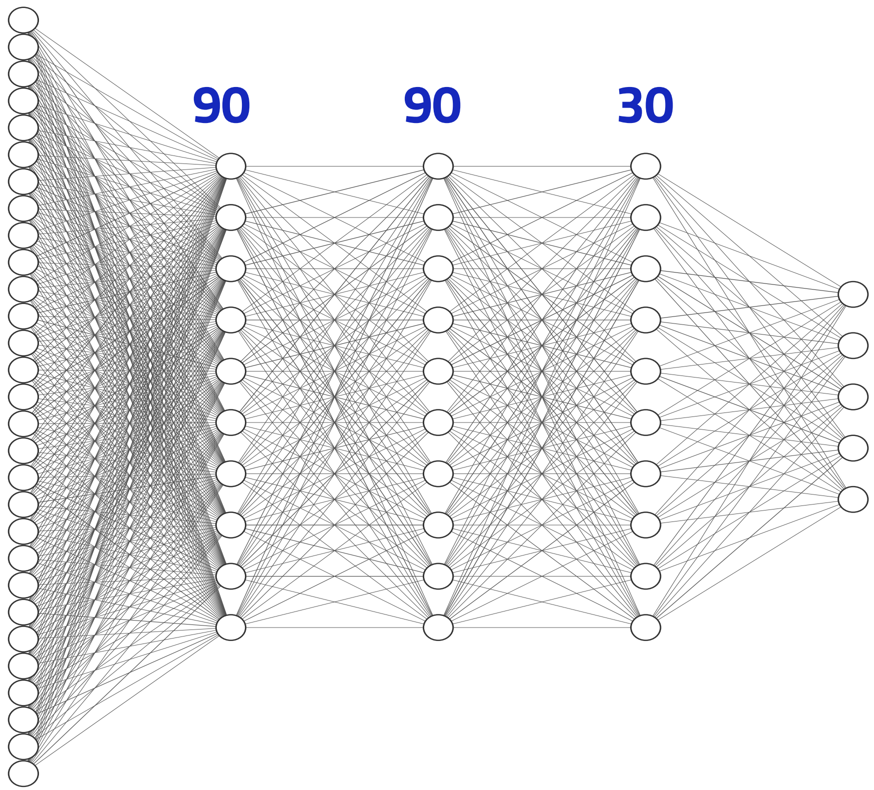
The best models appear to be the three layers models without Normalization and without Dropout.

[5 rows x 17 columns]

	model_id	units_1	units_2	units_3	norm	drop	...	loss_type	top	Xpos	Xneg	Ypos	Yneg
92	92	50	90	70	0	0	...	mae	0.002998	0.004502	0.004454	0.004312	0.004225
96	96	50	90	90	0	0	...	mae	0.003004	0.004509	0.004462	0.004321	0.004232
108	108	90	50	50	0	0	...	mae	0.002993	0.004507	0.004442	0.004300	0.004217
124	124	90	90	30	0	0	...	mae	0.003024	0.004504	0.004466	0.004317	0.004229
132	132	90	90	70	0	0	...	mae	0.002998	0.004499	0.004454	0.004312	0.004224

NN Training and results

The best models appear to be the three layers models without Normalization and without Dropout. In particular, the best model has this structure:



NN Training and results

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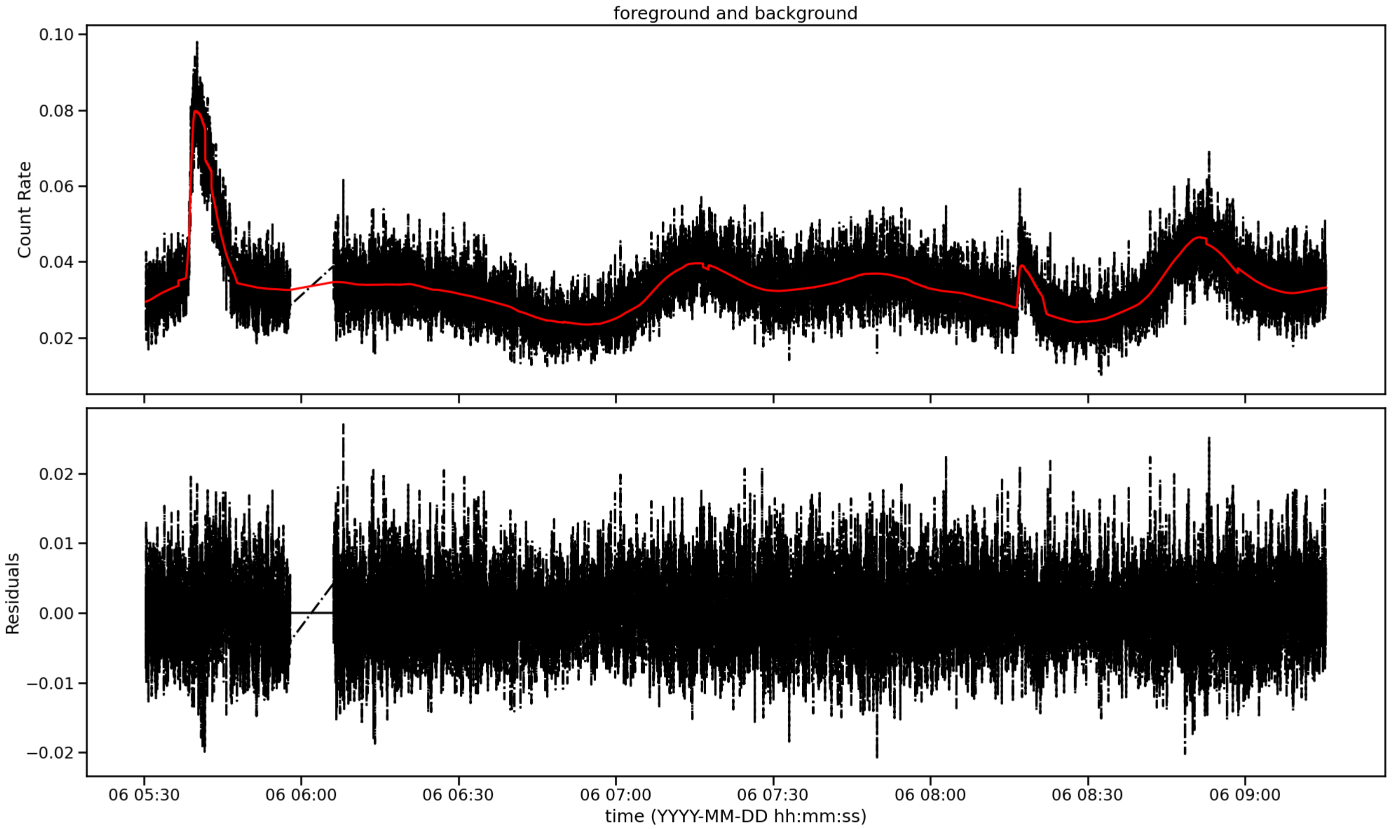
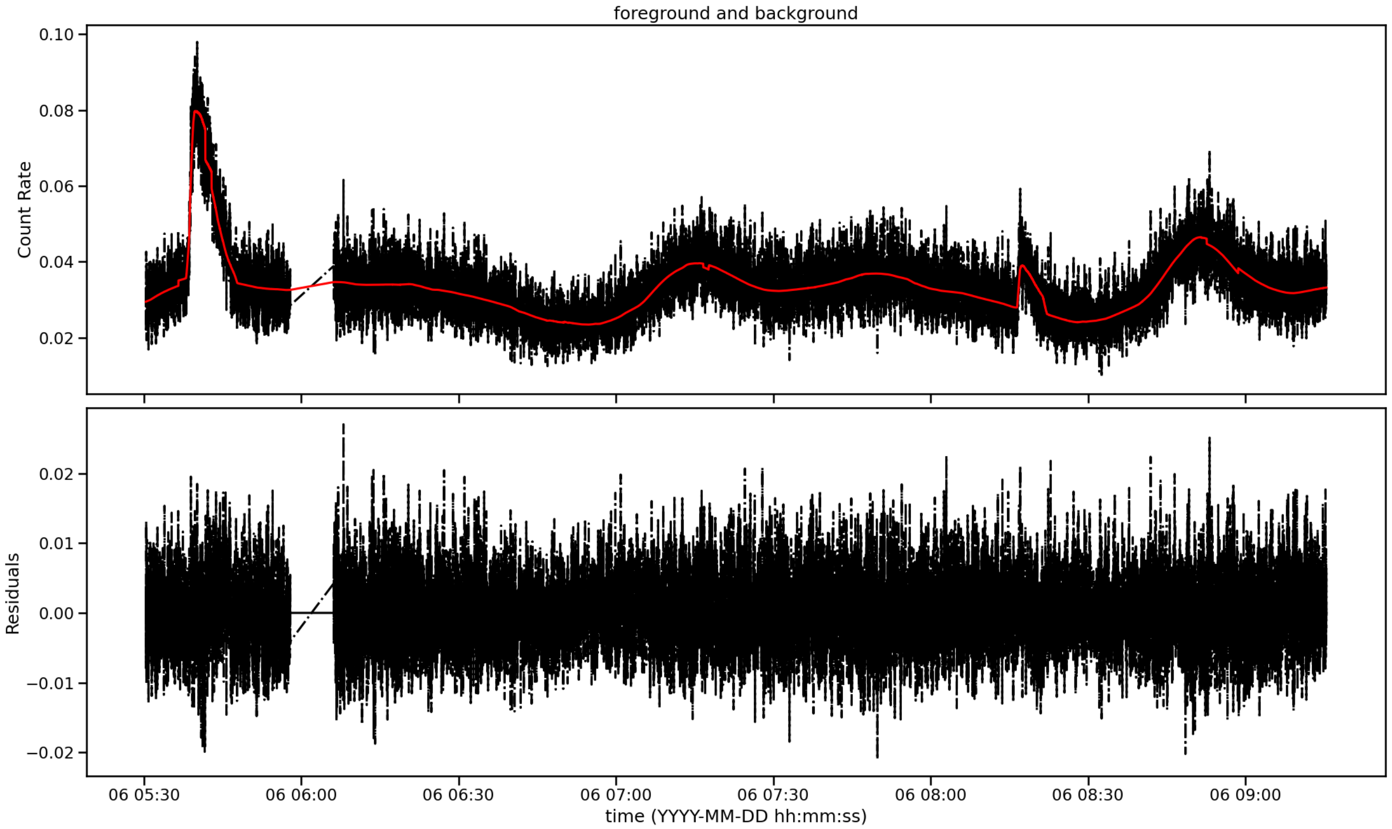


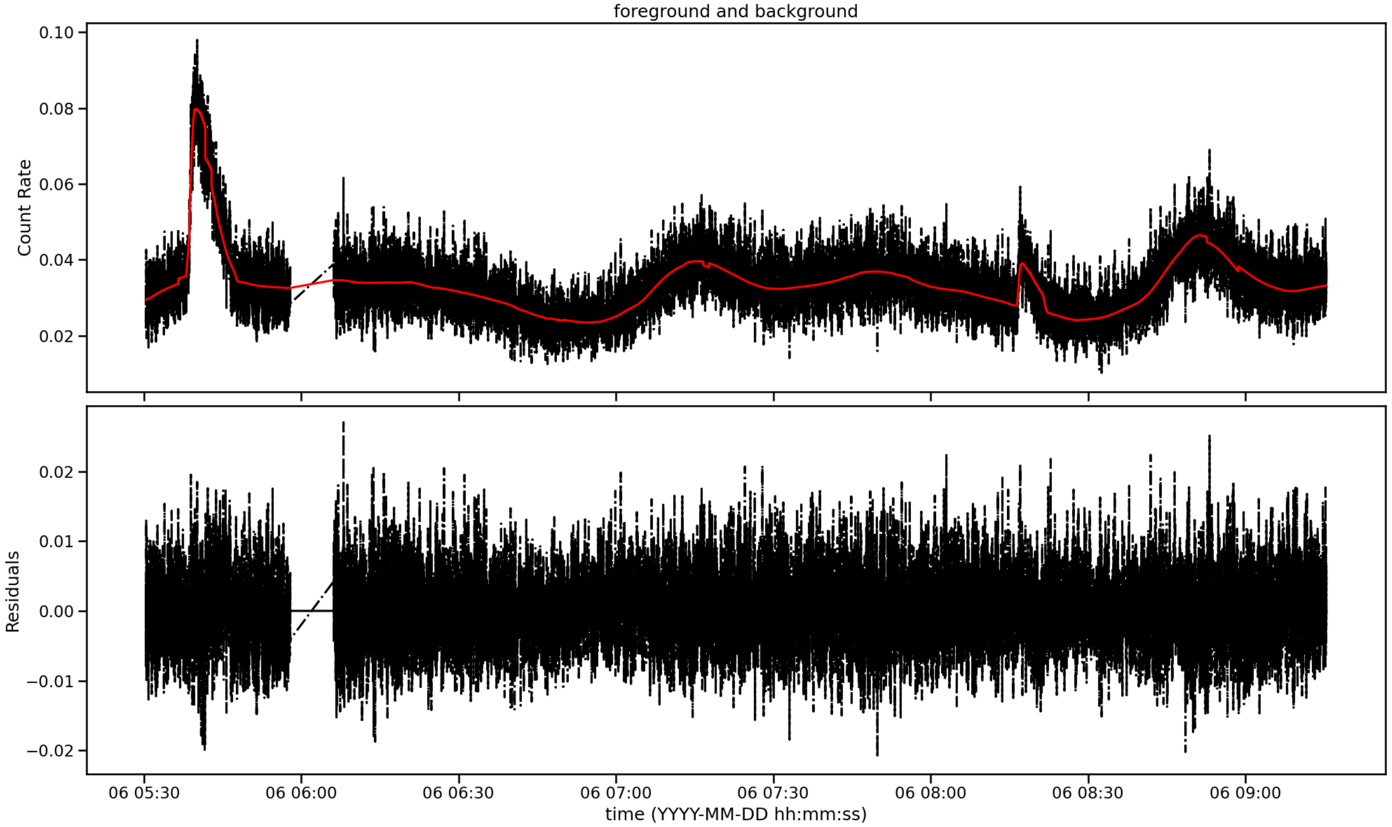
Next Steps

We will continue this type of analysis with more data (a few more months) and more complicated models, such as Recurrent Neural Networks.



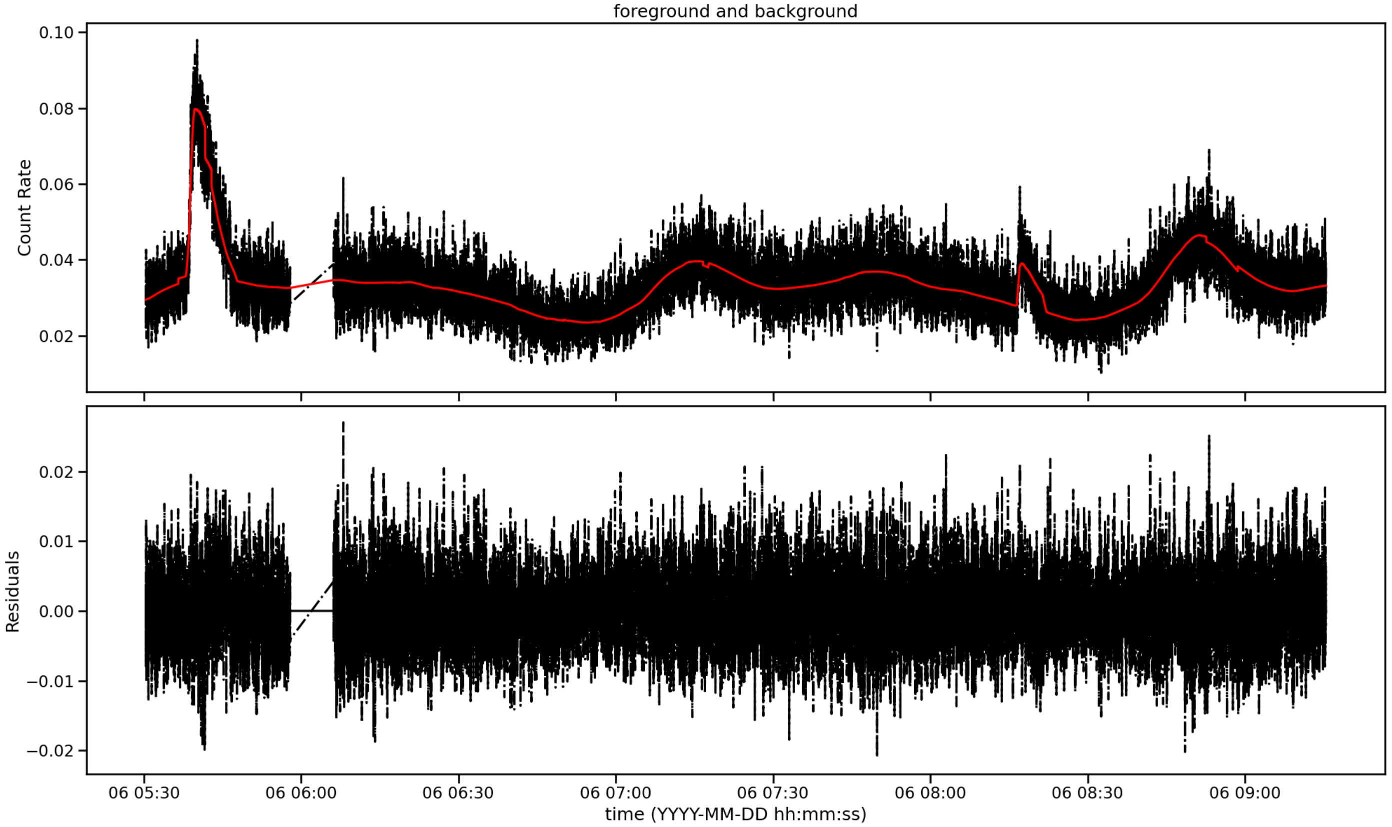
Next Steps

Also, the addition of new input parameters, such as a description of the flux of cosmic rays, could help to better assess the background signal.



Next Steps

Finally, we will implement a trigger algorithm, called Poisson-FOCuS, to automate the identification of significant anomalies



Thank you