

Constraining below-threshold radio source counts with machine learning

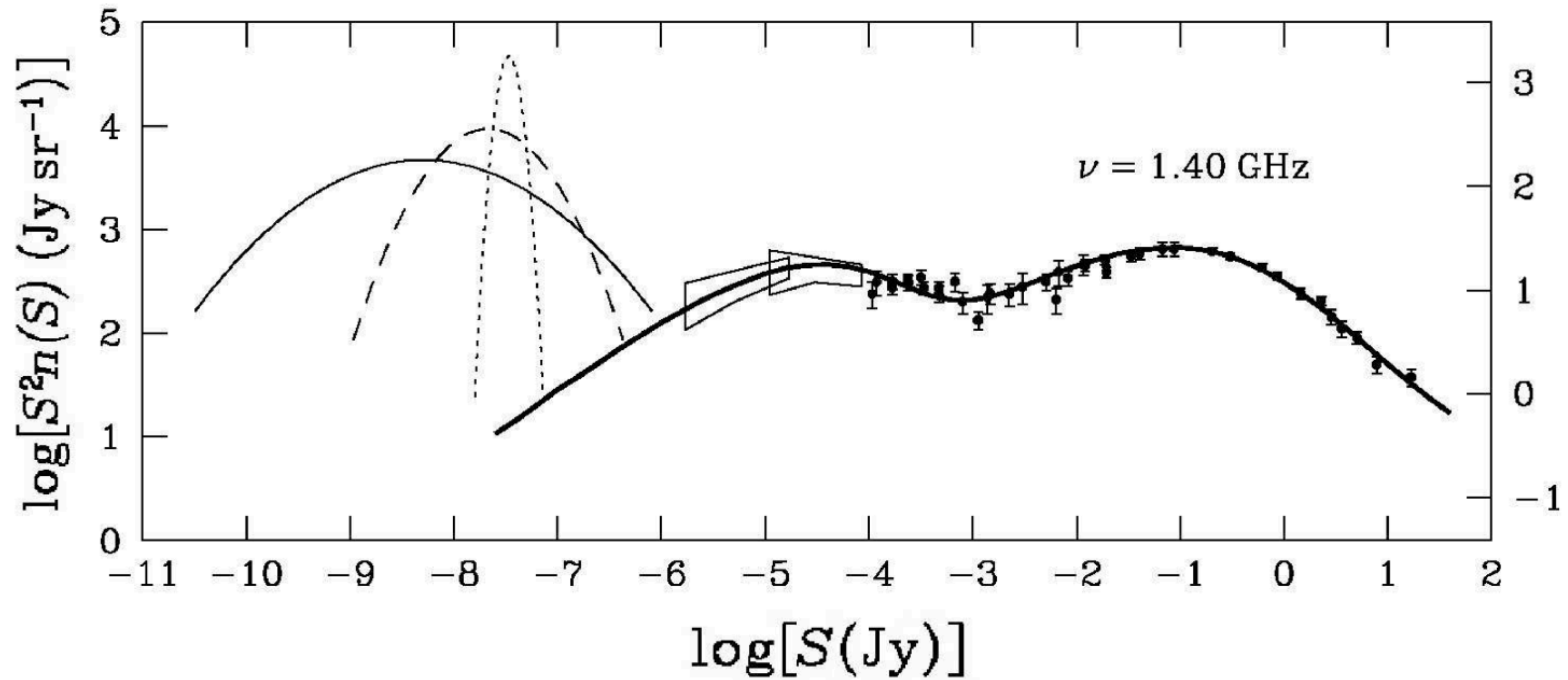
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(University of Turin and INFN, Turin)



hosts
Radio
Synchrotron
Background

Barolo, 16/06/2022

Source counts



Possible new source population

- dark matter decays and annihilations
- ultracompact halos
- dark stars in the early universe
- supernovae of massive population III stars
- dense nuggets of quarks
- primordial blackholes

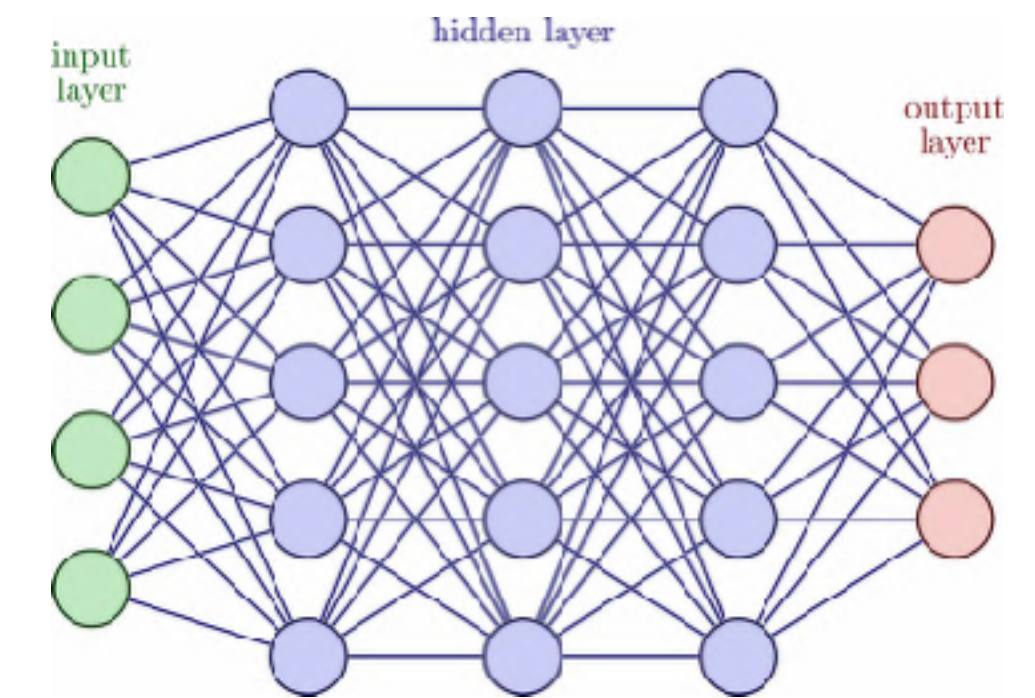
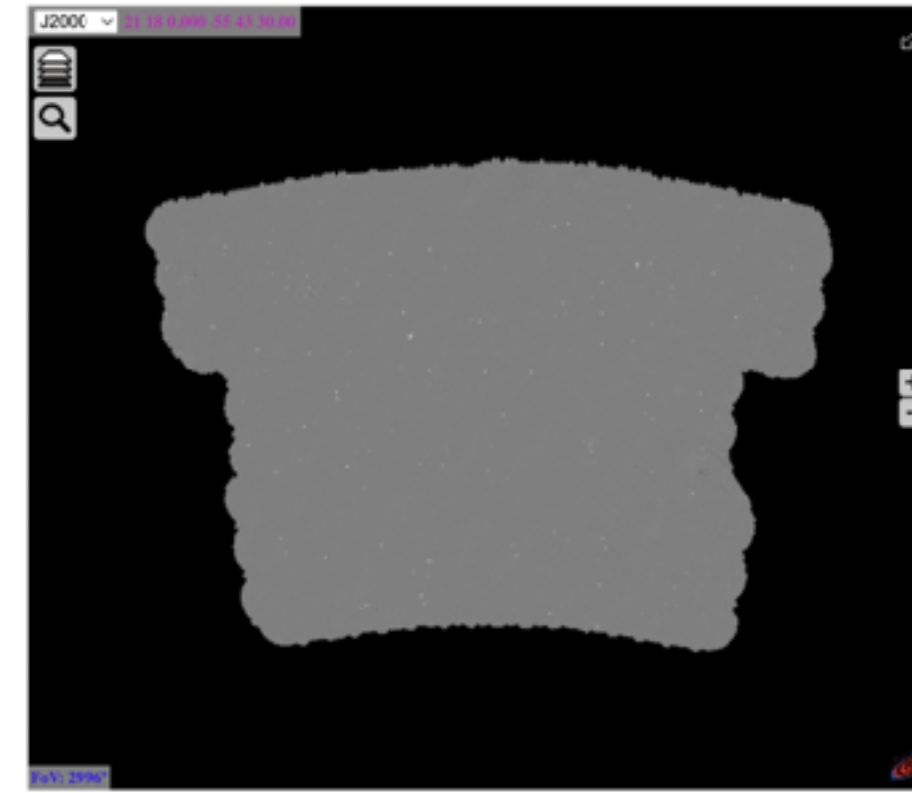
Our final goal

Use a Convolutional Neural Network (CNN)

to extract the source counts at low flux (between 10^{-5} and 10^{-7} Jy)

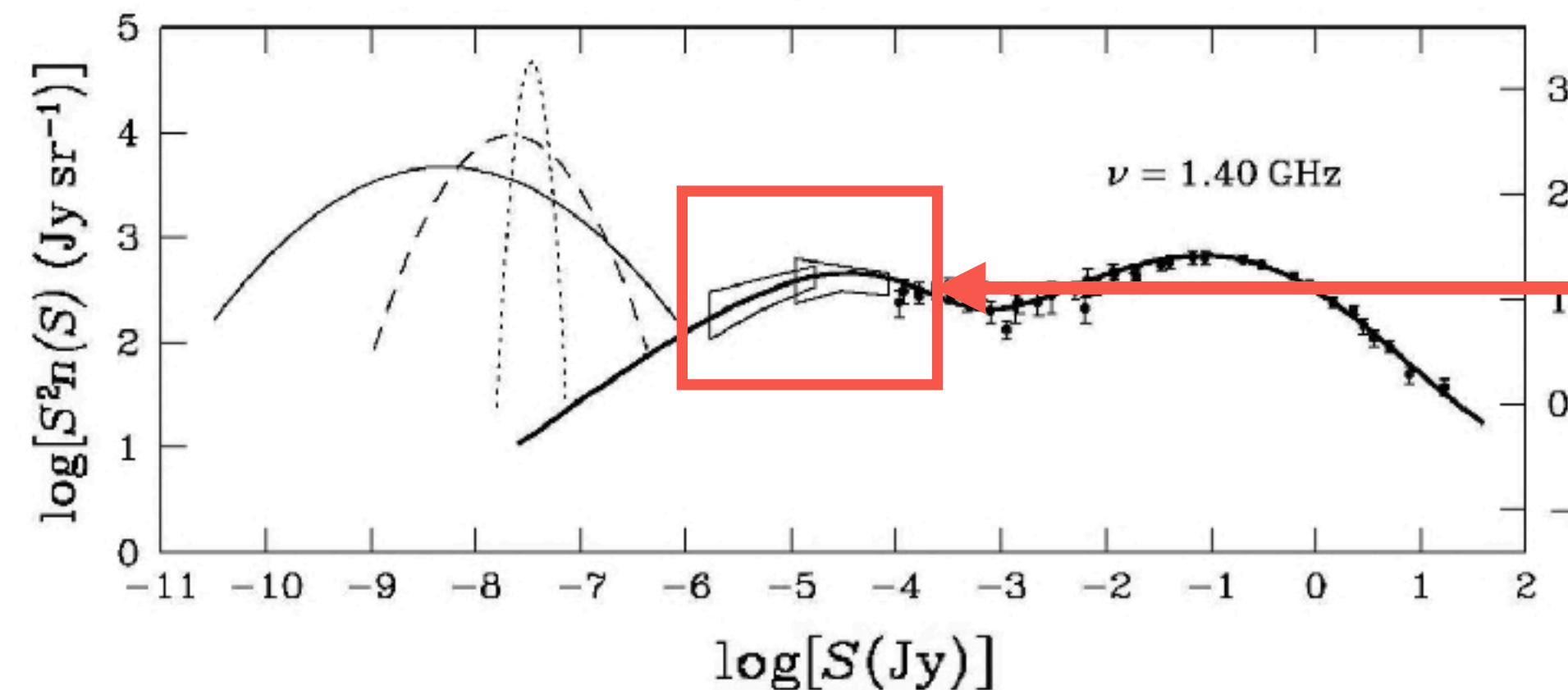
from the Evolutionary Map of the Universe (EMU) radio survey

EMU 940 MHz Pilot Survey



Can CNN “see through” noise and artefacts?

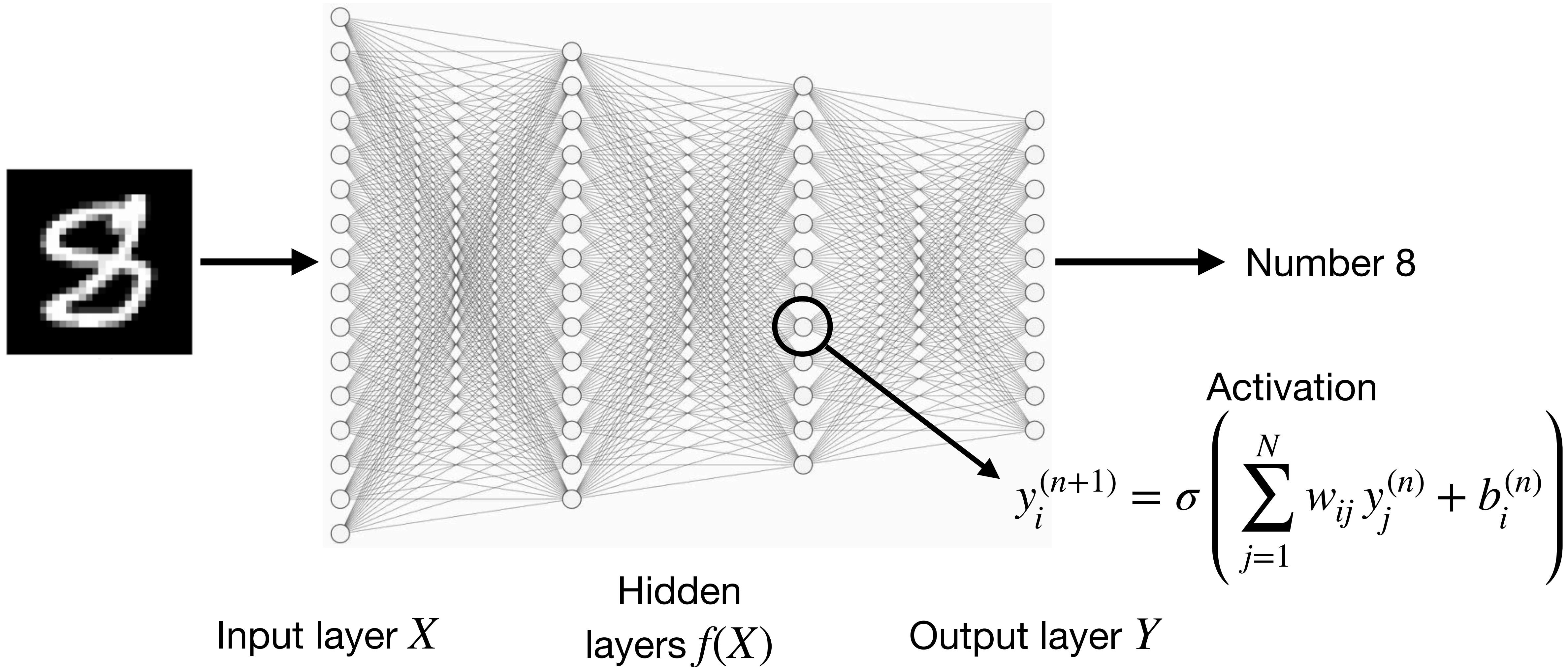
Can CNN correct for incompleteness, Eddington bias, resolution bias?



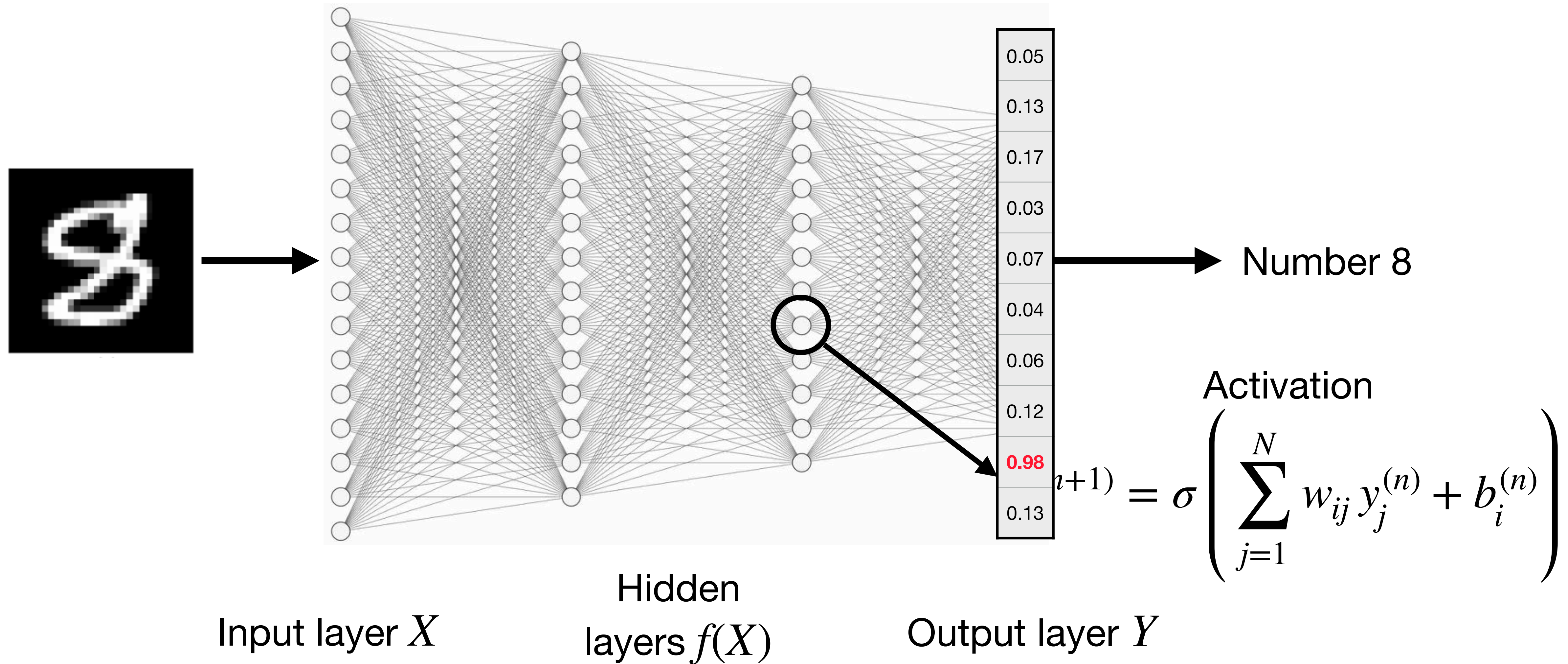
Obtained with P(D) method

Neural Networks

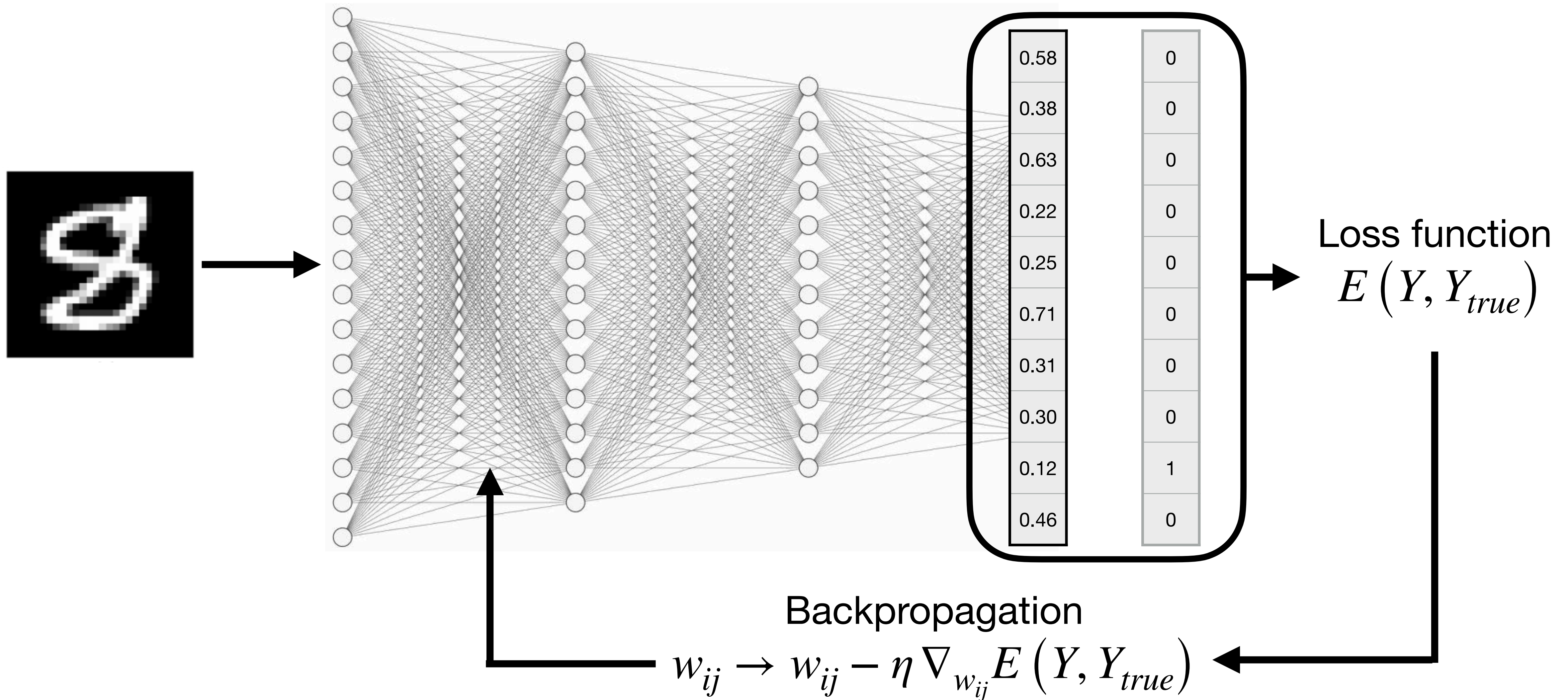
Neural Networks



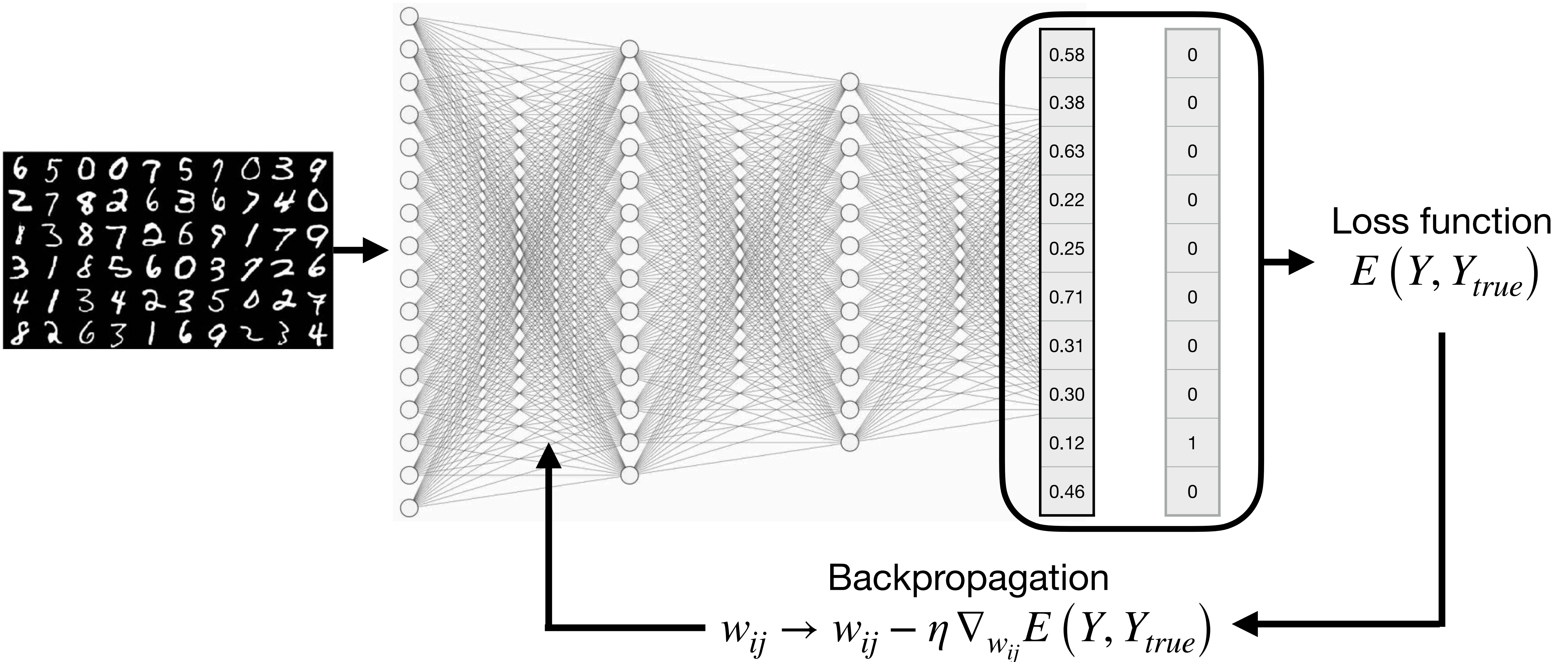
Neural Networks



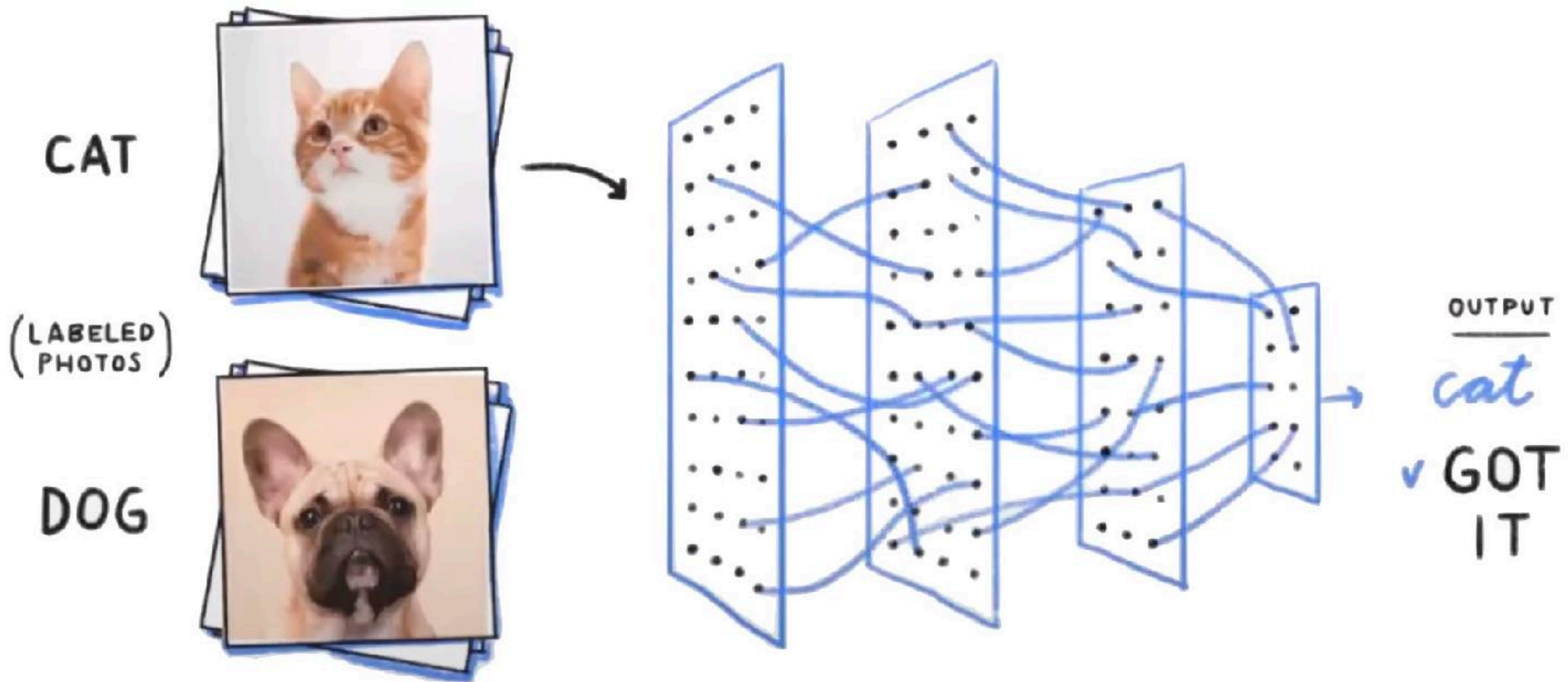
Neural Networks



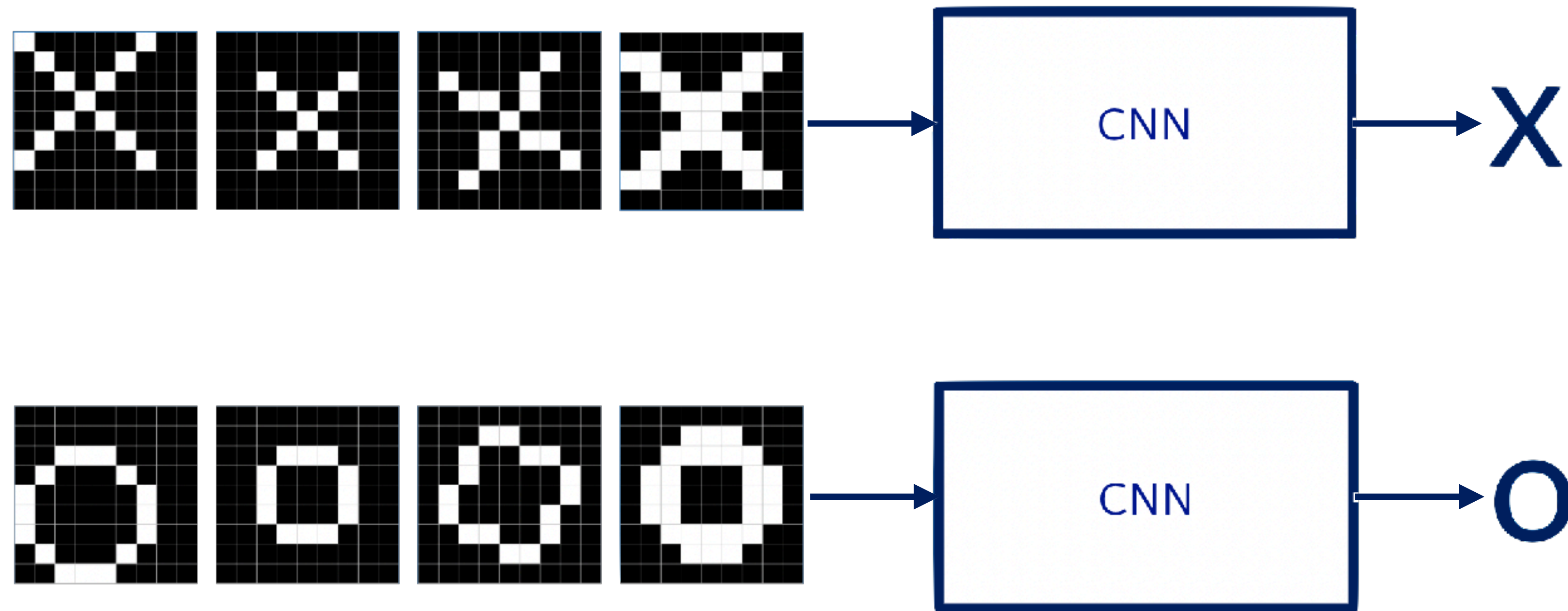
Neural Networks



Convolutional Neural Networks



Convolutional Neural Networks



Example taken from <https://e2eml.school/blog.html>

Convolution layer

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1



1	-1	-1
-1	1	-1
-1	-1	1



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1



1	-1	1
-1	1	-1
1	-1	1



0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	0.55	0.55	-0.77	0.55	0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

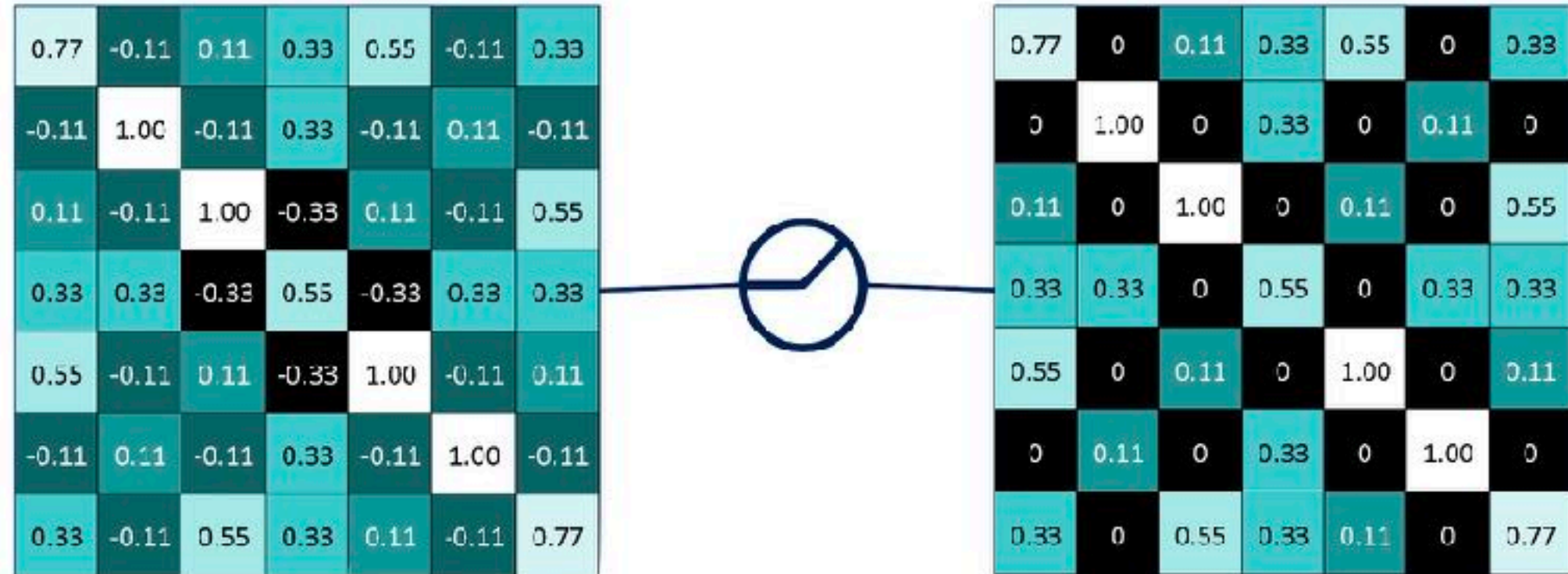


-1	-1	1
-1	1	-1
1	-1	-1

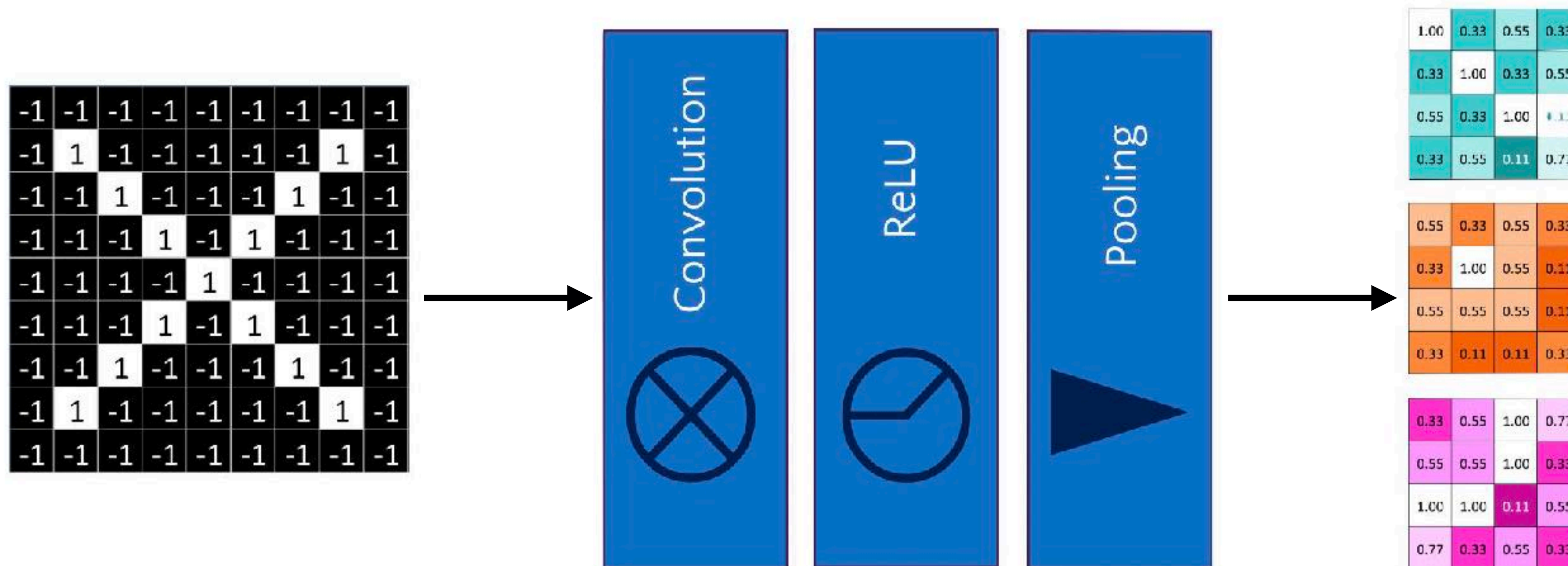
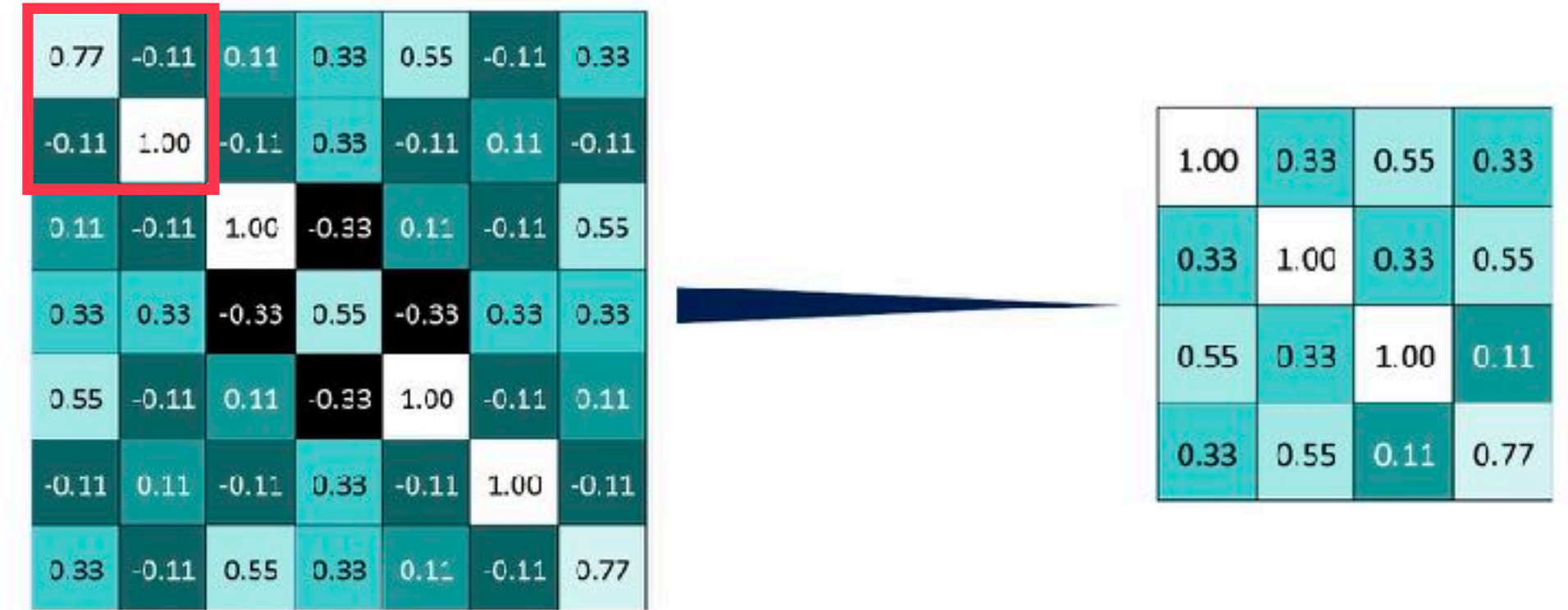


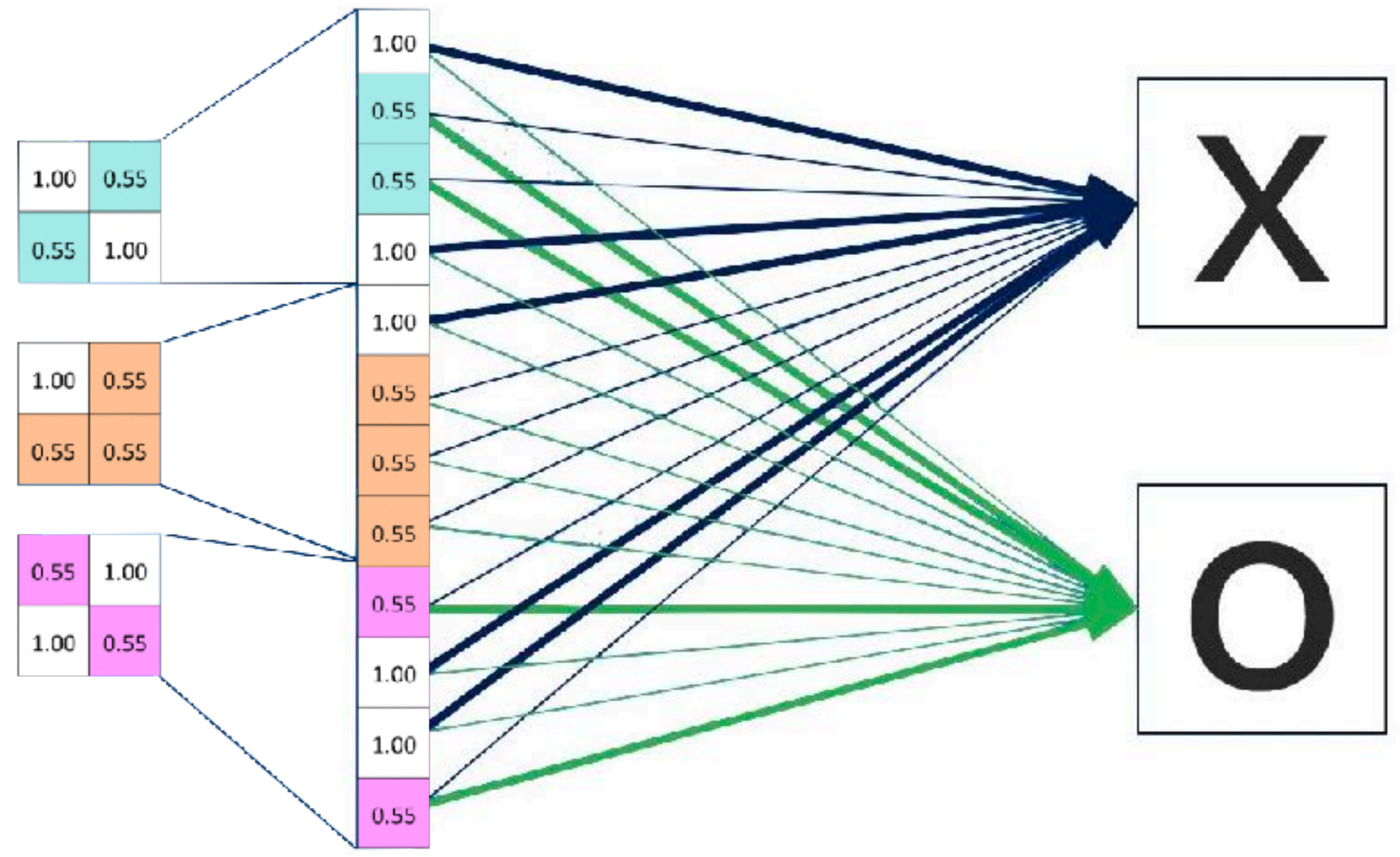
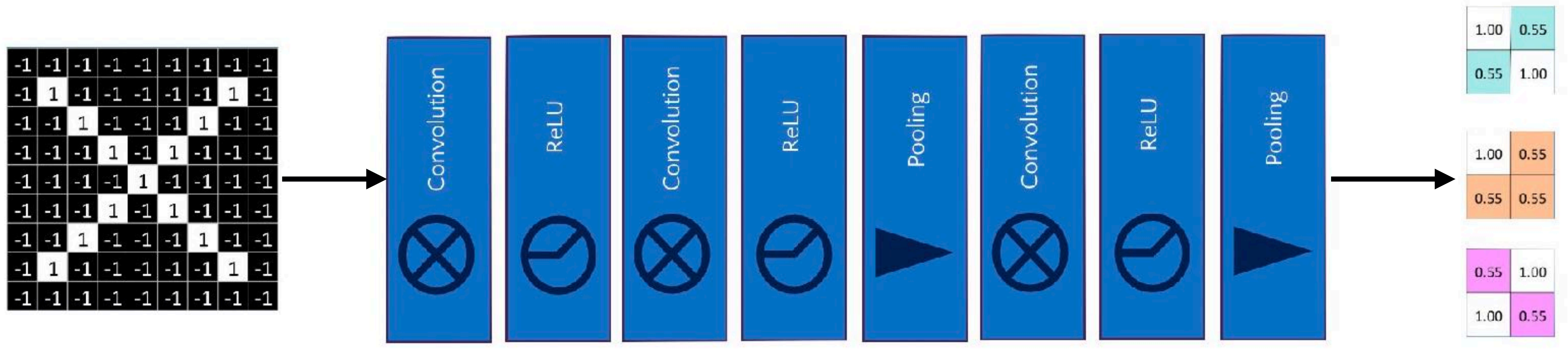
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

ReLU

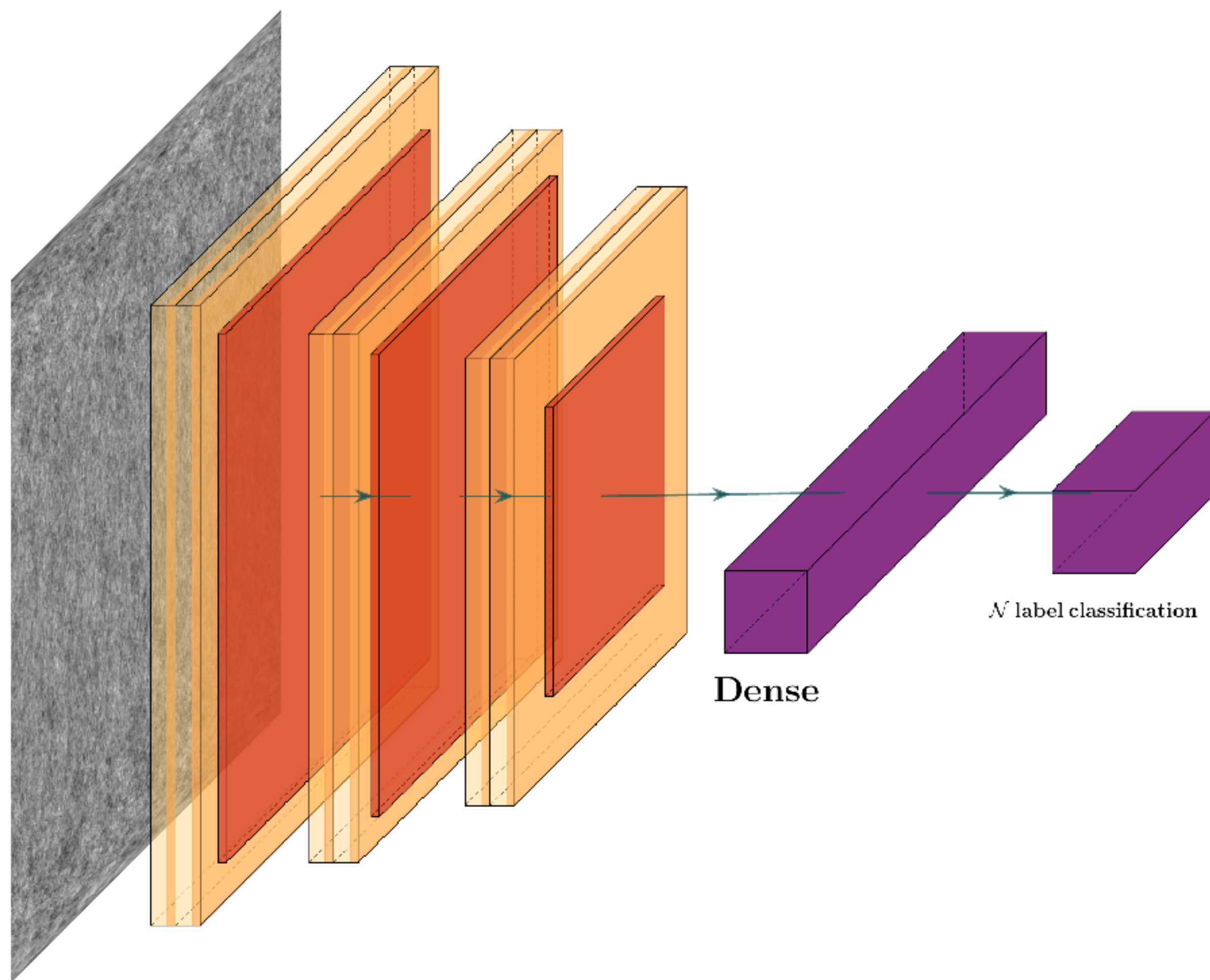


Max pooling

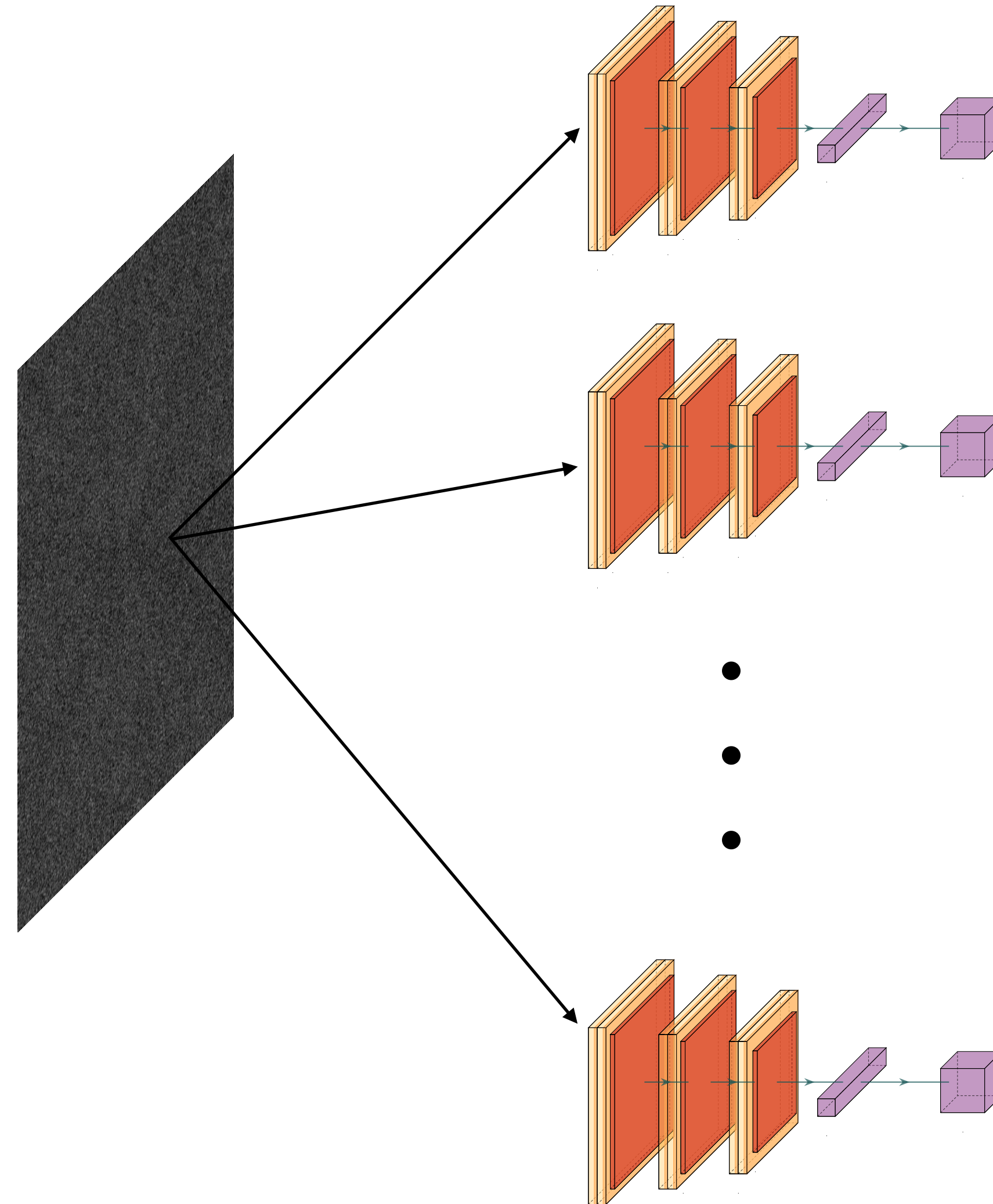




CNN architecture (1st attempt)



CNN architecture (2nd attempt)



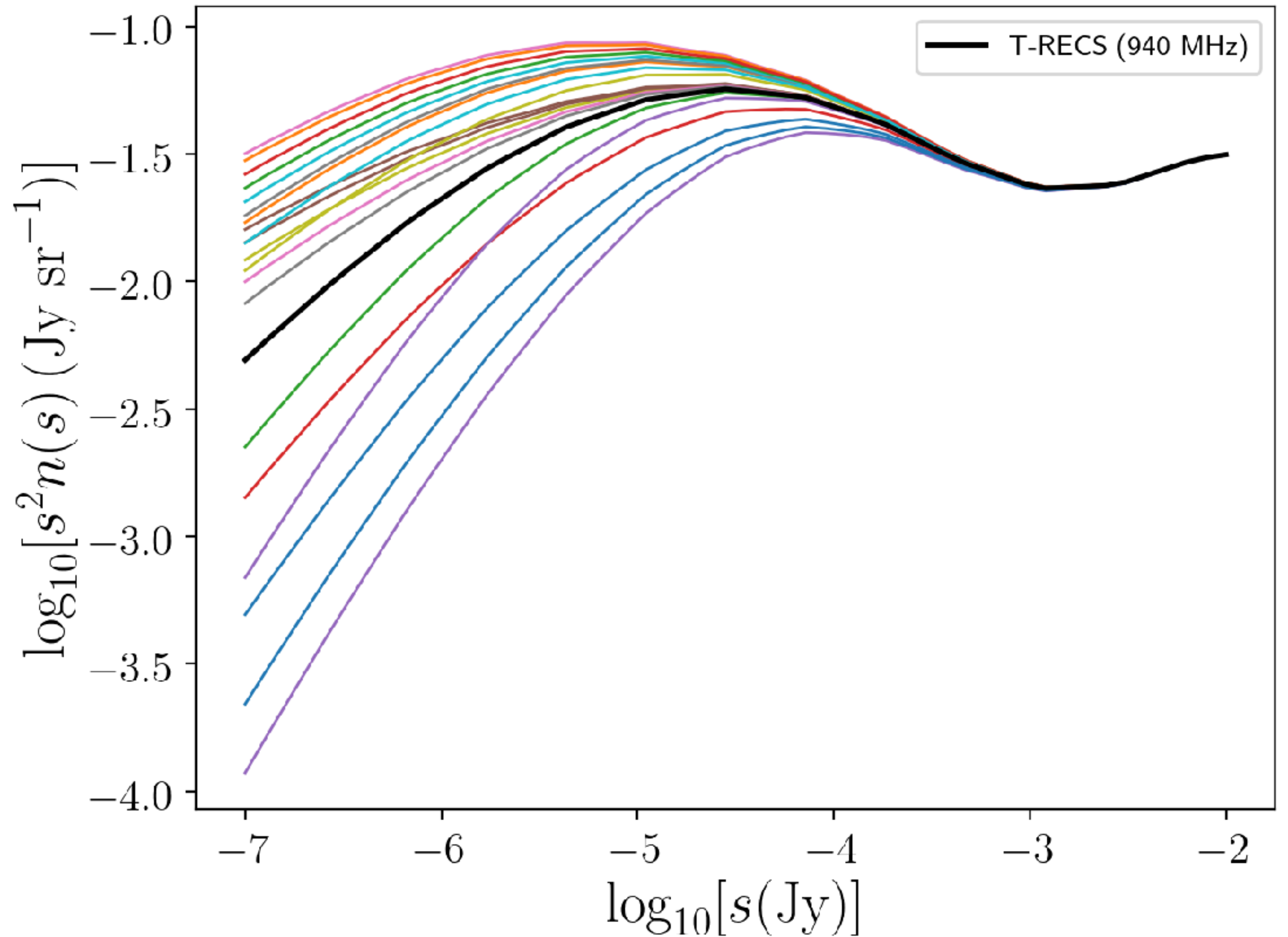
Training and testing

Our pipeline

1. Create training set
 - A. Start from T-RECS simulated catalogue of AGN and SFG (Bonaldi et al., 2019, MNRAS, 482, 2)
 - B. Modify number of sources as a function of flux $N(s)$
 - C. Create images of the sky with ASKAPsoft (Yandasoft) (Guzman J., et al., 2019, ascl:1912.003)
2. Train CNN to extract $N(s)$ from images
3. Test CNN

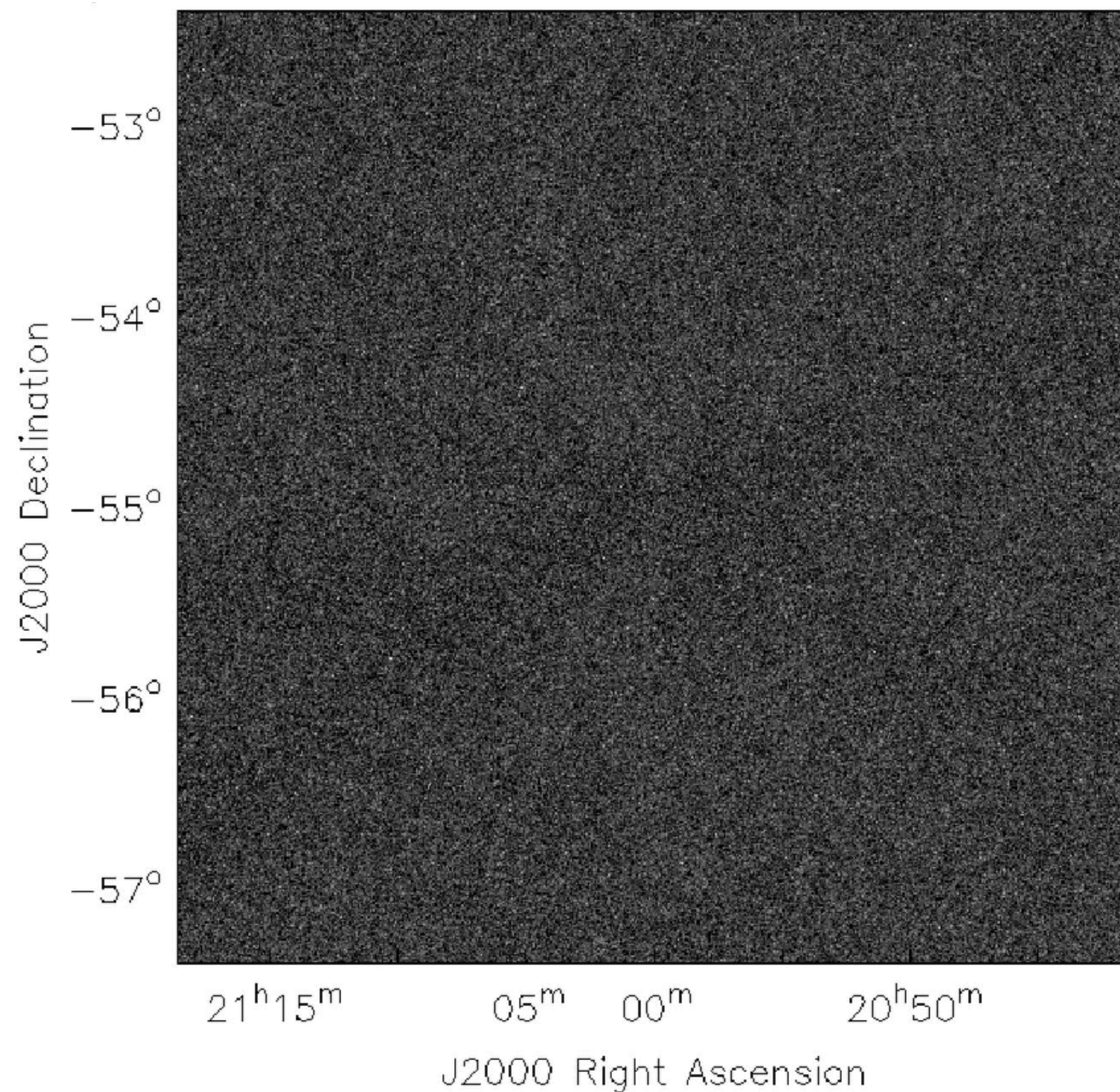
Training set

$$n(s) = \left(1 + \frac{s_0}{s}\right)^\alpha n_{T-RECS}(s)$$

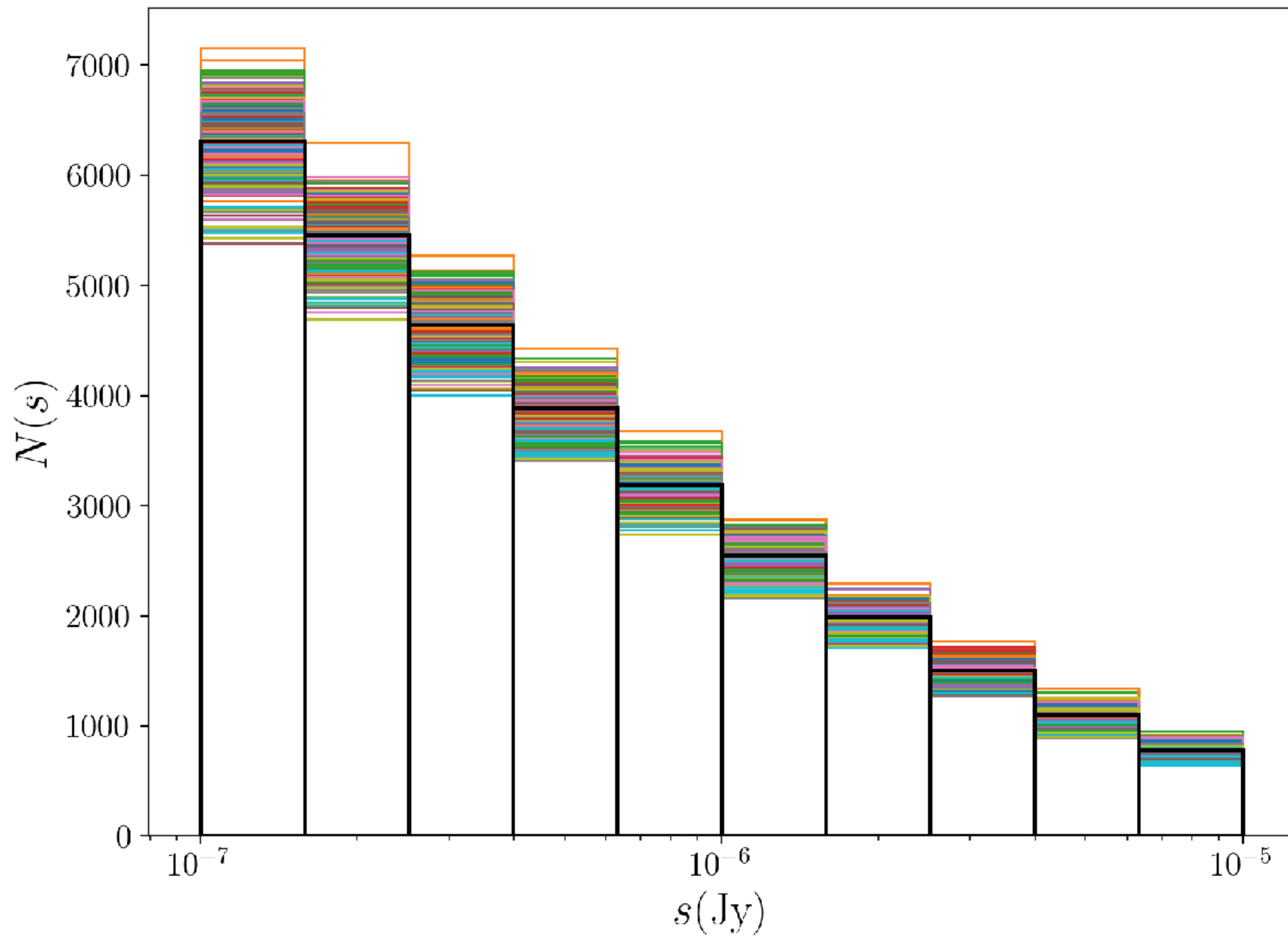


Training set

- 21 images
 - 25 deg², 2560x2560 pixels
- 400 sub-images for each image
 - 128x128 pixels
- Total 8400 sub-images
 - 6048 training
 - 1512 validation
 - 840 testing



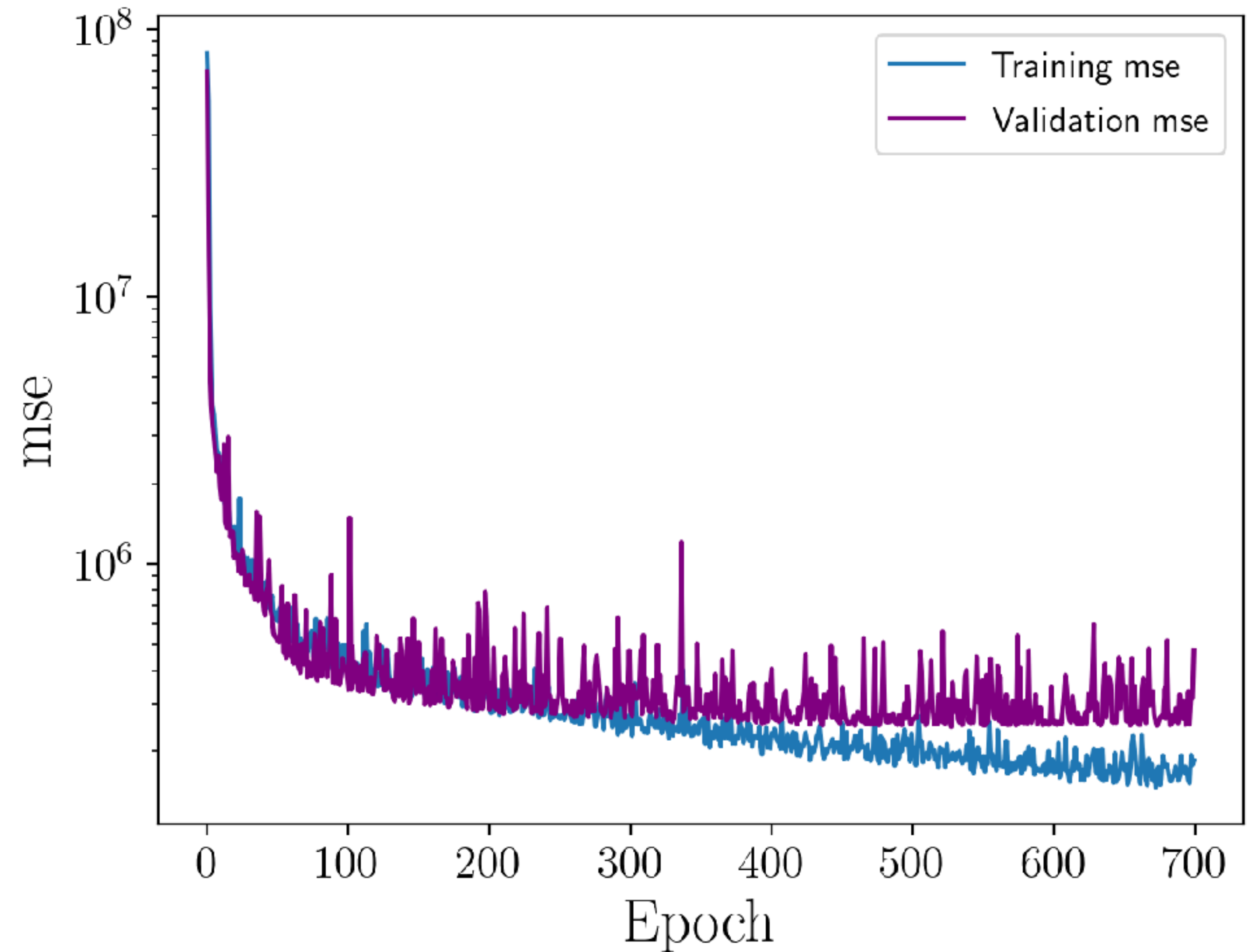
One image



Train with sky model images

- No telescope effects
- Loss function

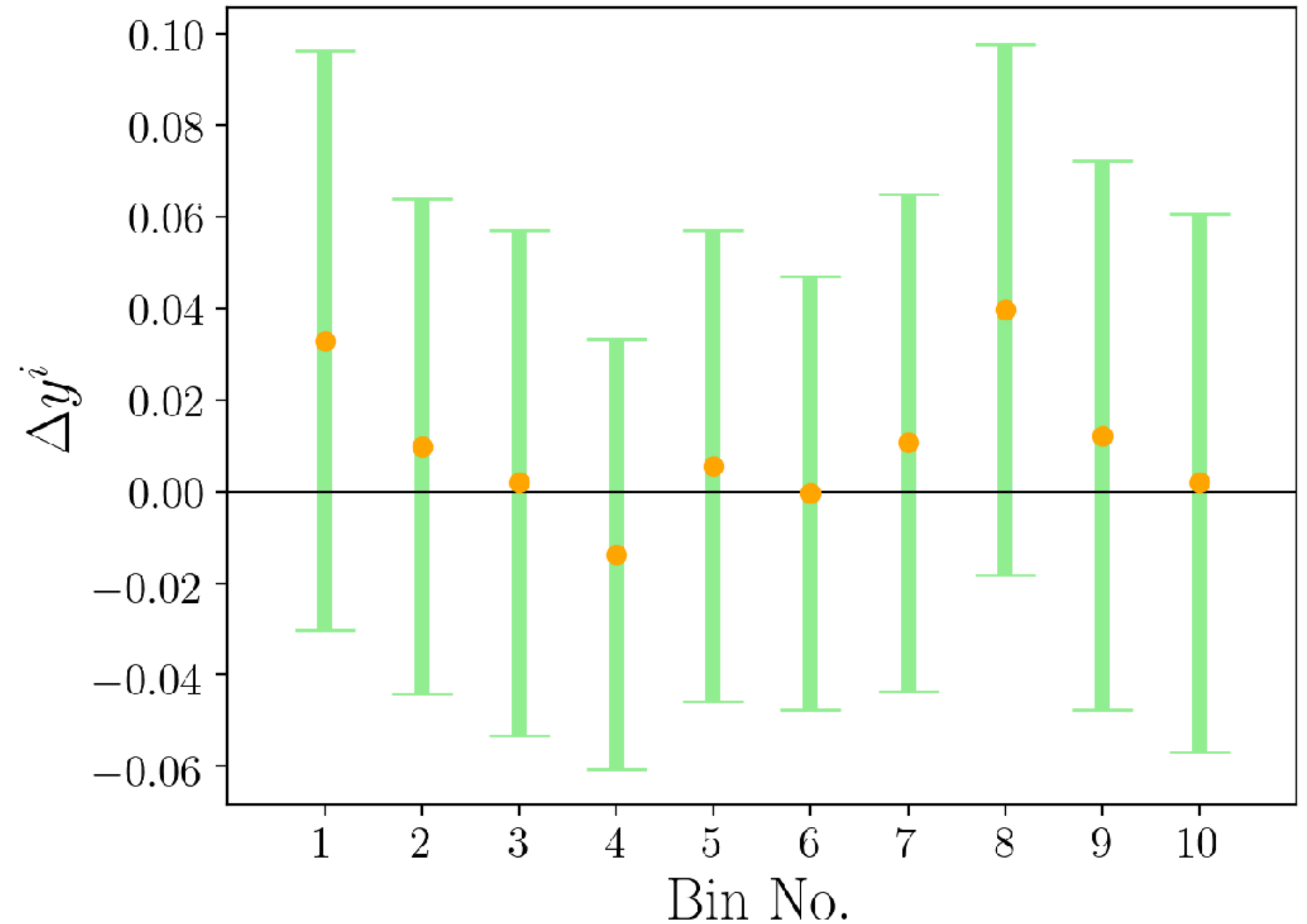
$$mse = \frac{1}{N_{labels}} \sum_{i=1}^{N_{labels}} \left(y_{true}^i - y_{prediction}^i \right)^2$$

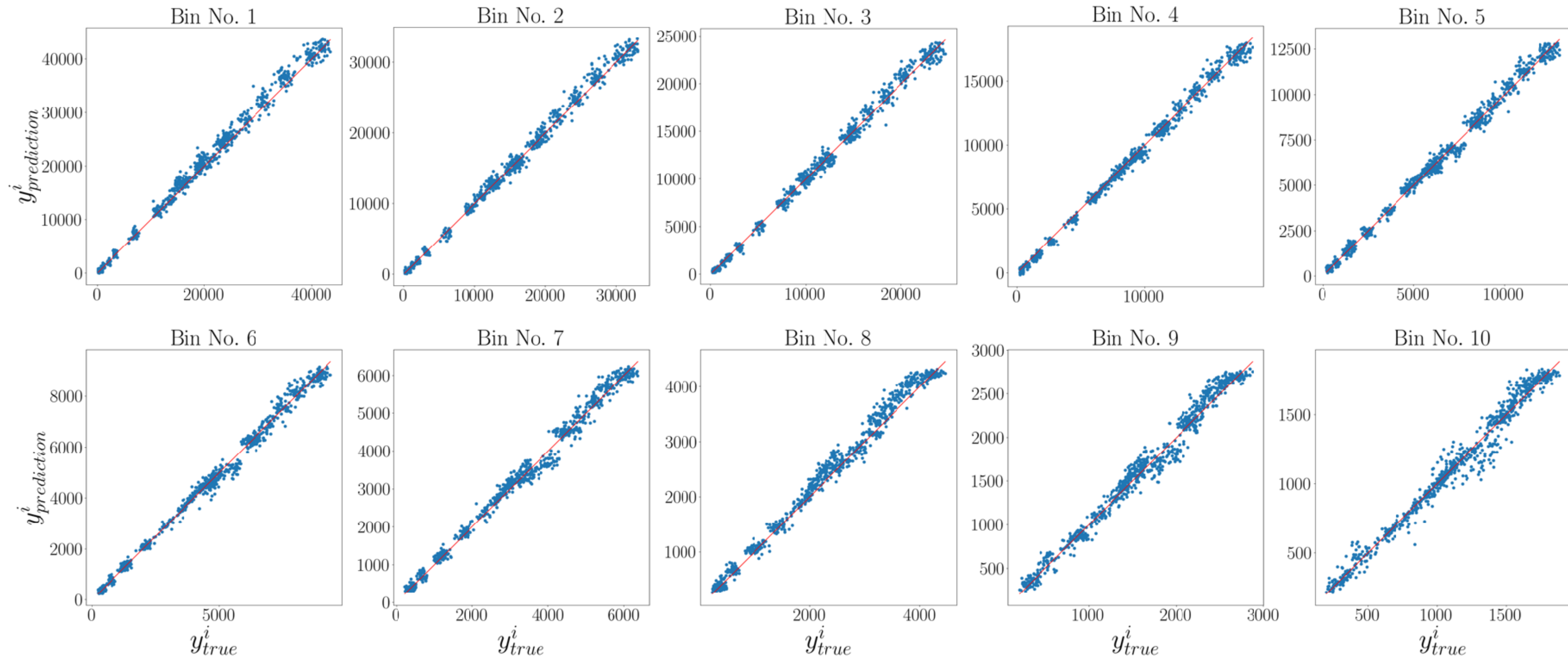


Train with sky model images

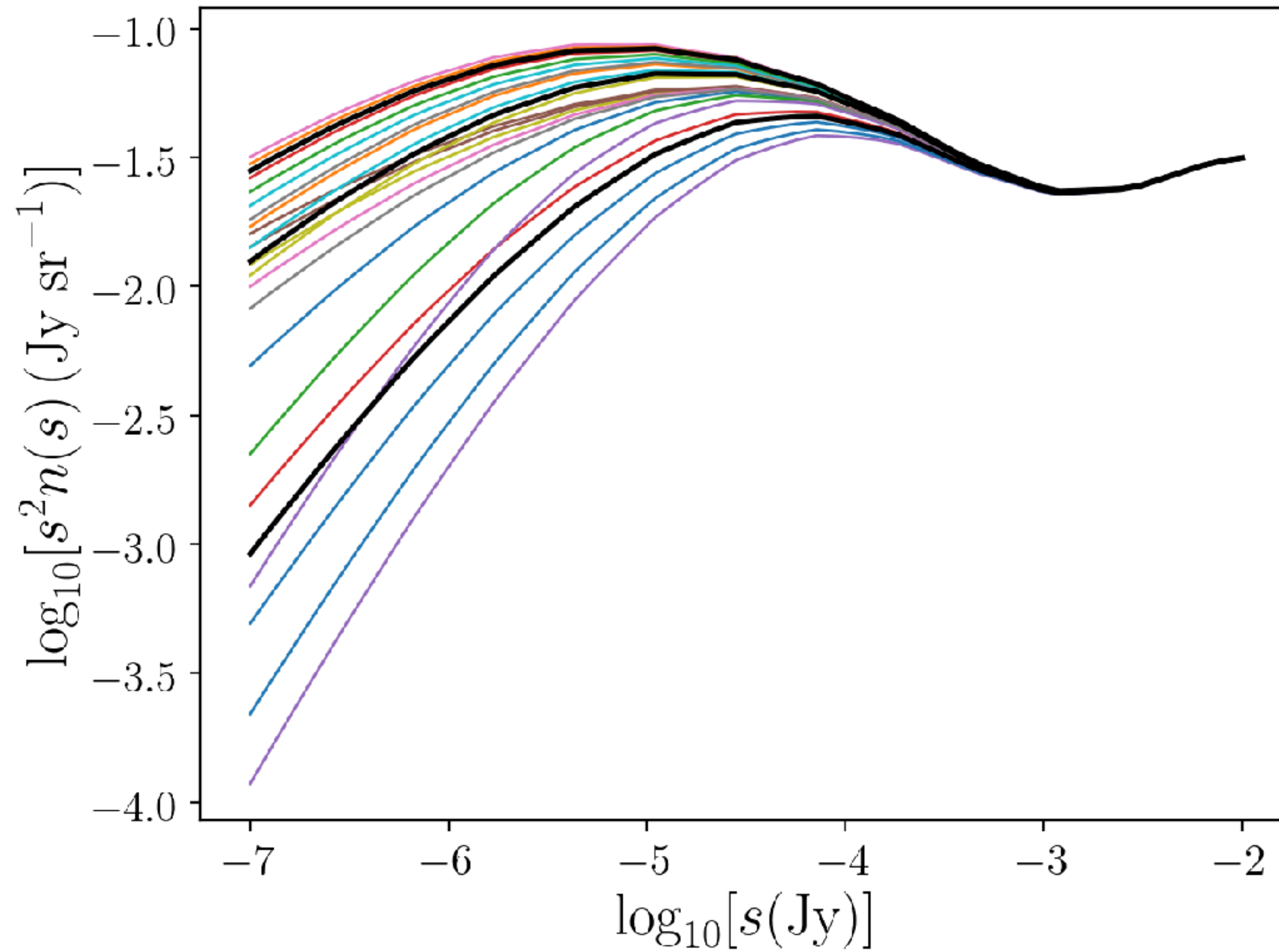
- Reconstruction residual

$$\Delta y^i = \frac{y_{prediction}^i - y_{true}^i}{\frac{1}{N_{labels}} \sum_{i=1}^{N_{labels}} y_{true}^i}$$

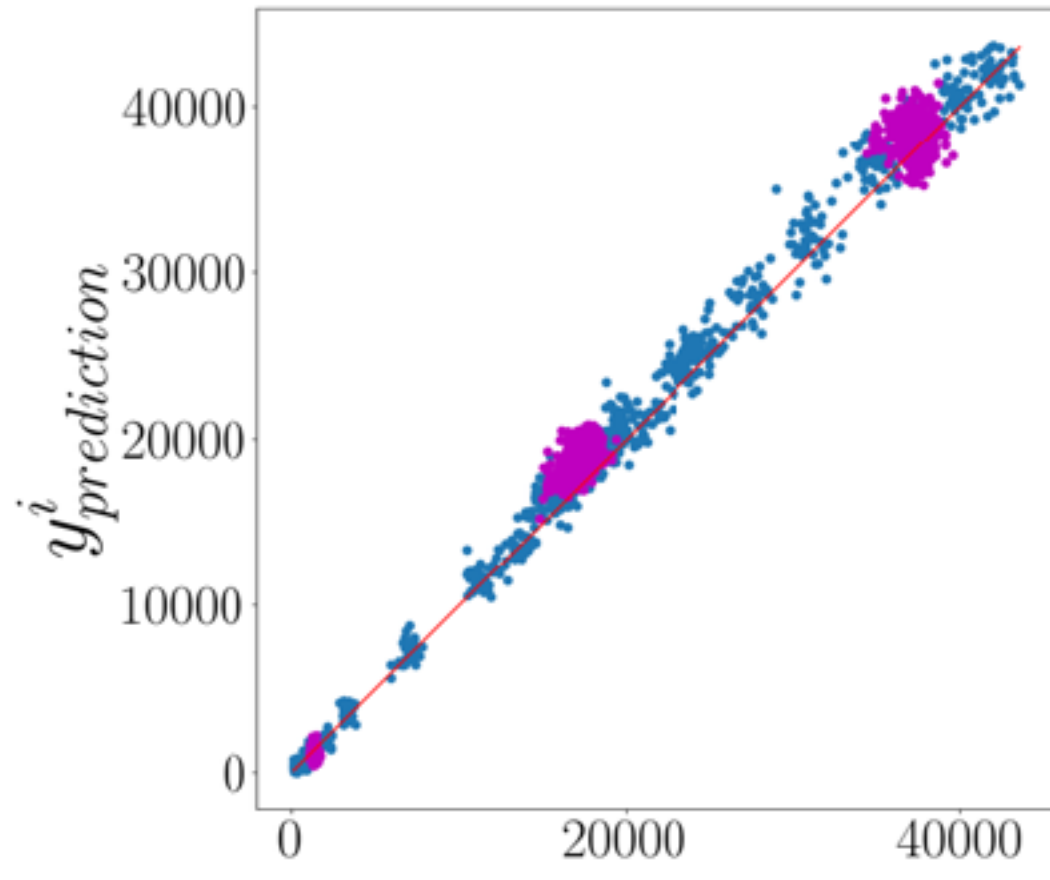




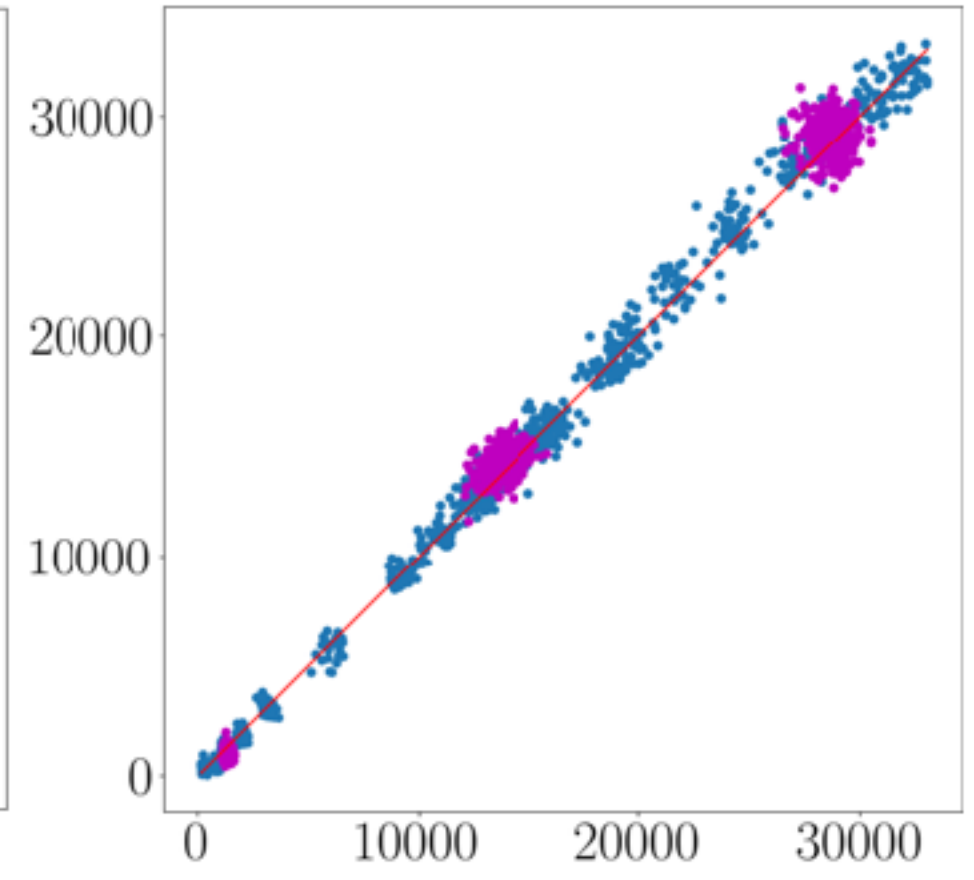
Test: same shape, different parameter values



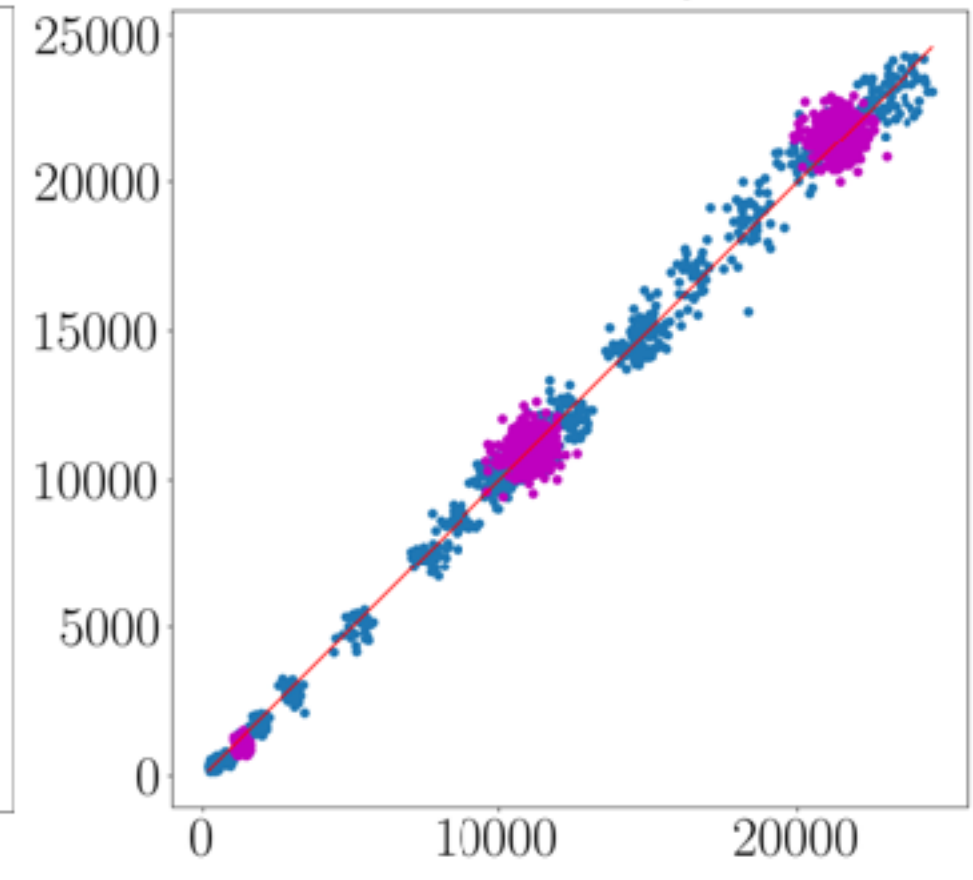
Bin No. 1



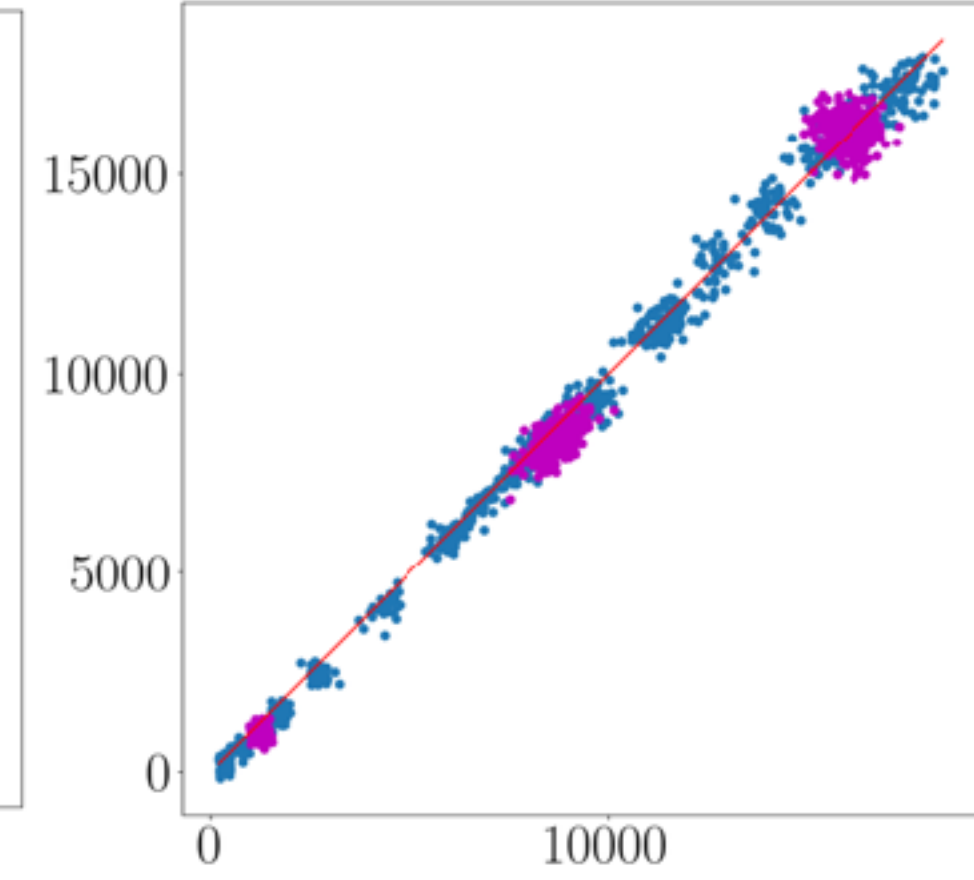
Bin No. 2



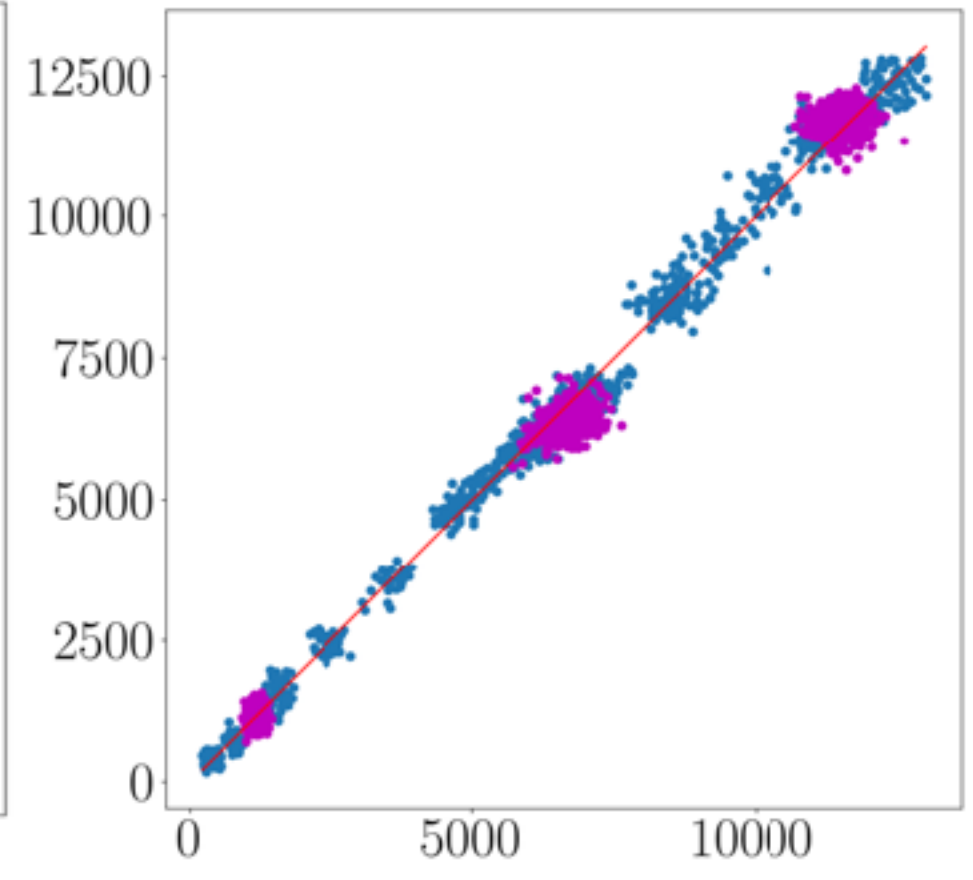
Bin No. 3



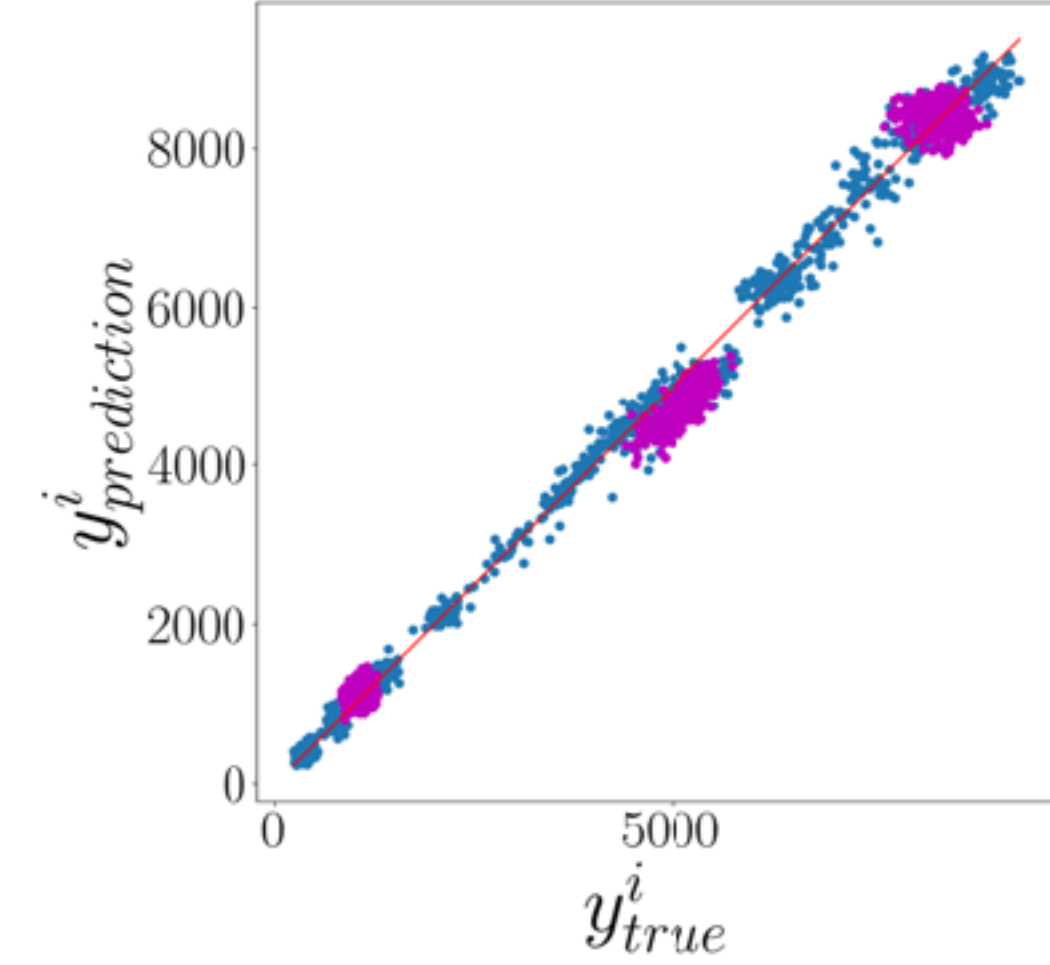
Bin No. 4



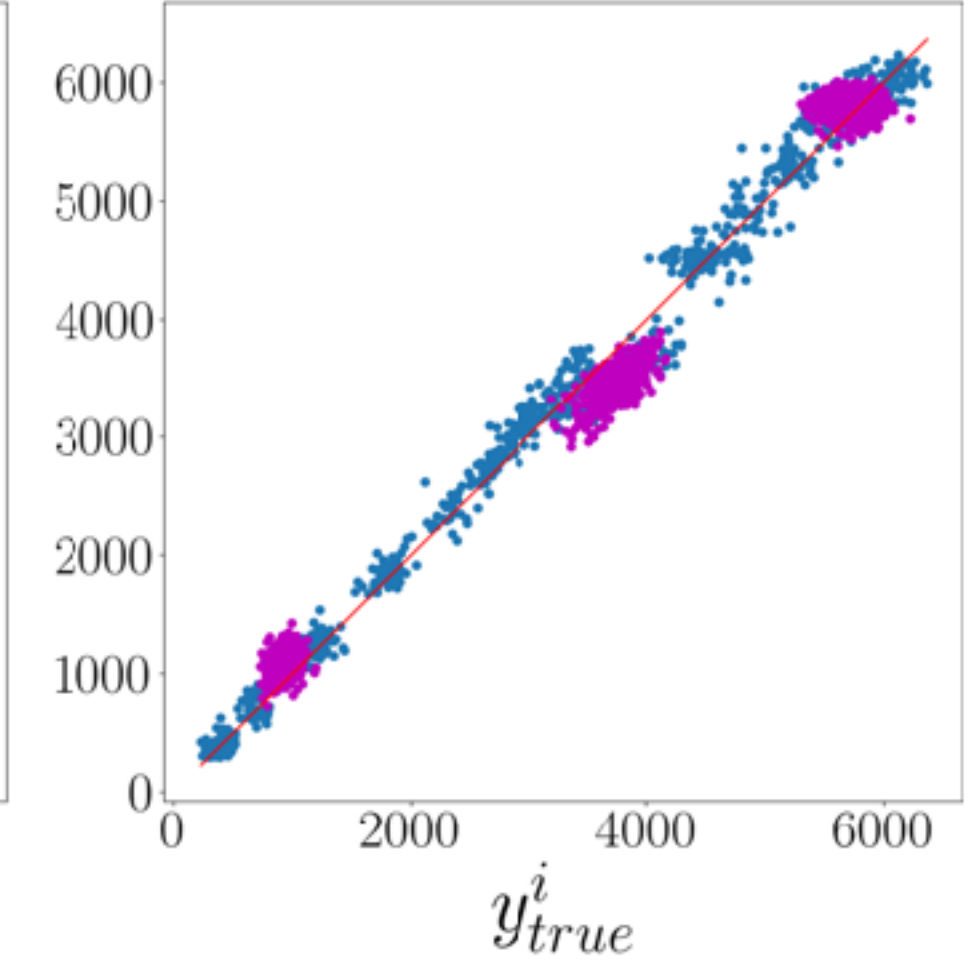
Bin No. 5



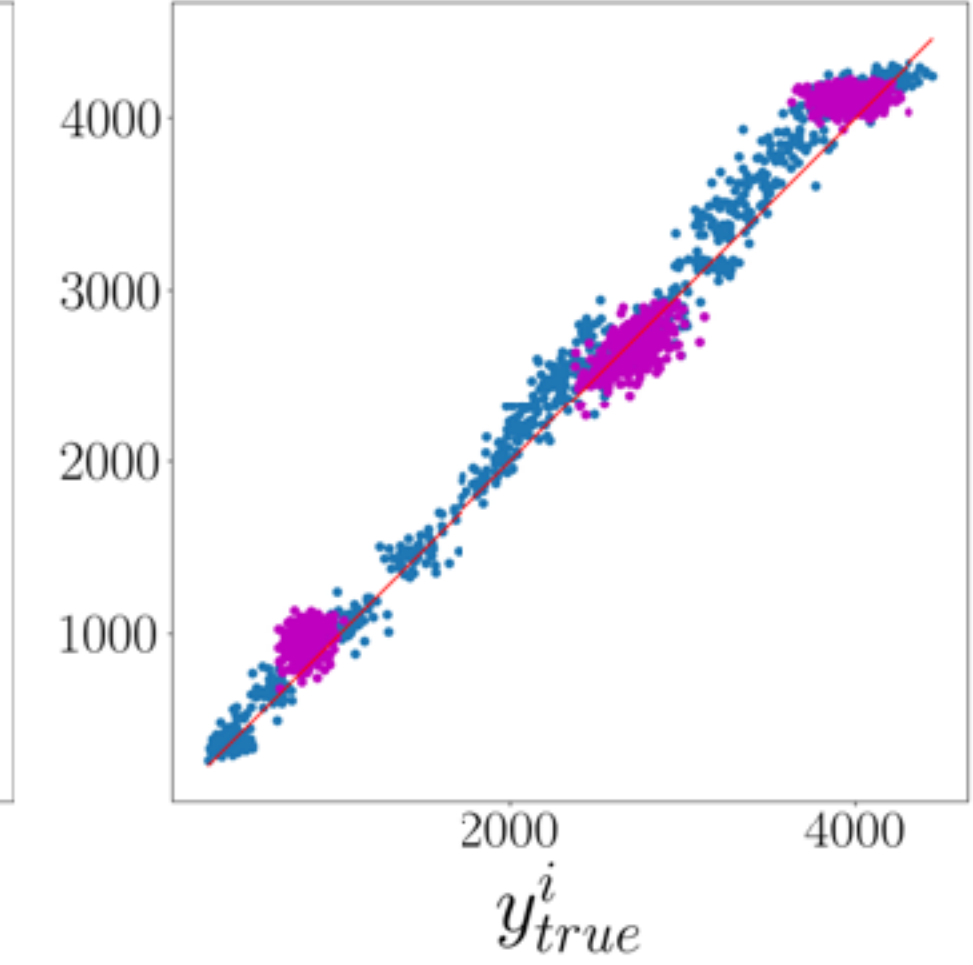
Bin No. 6



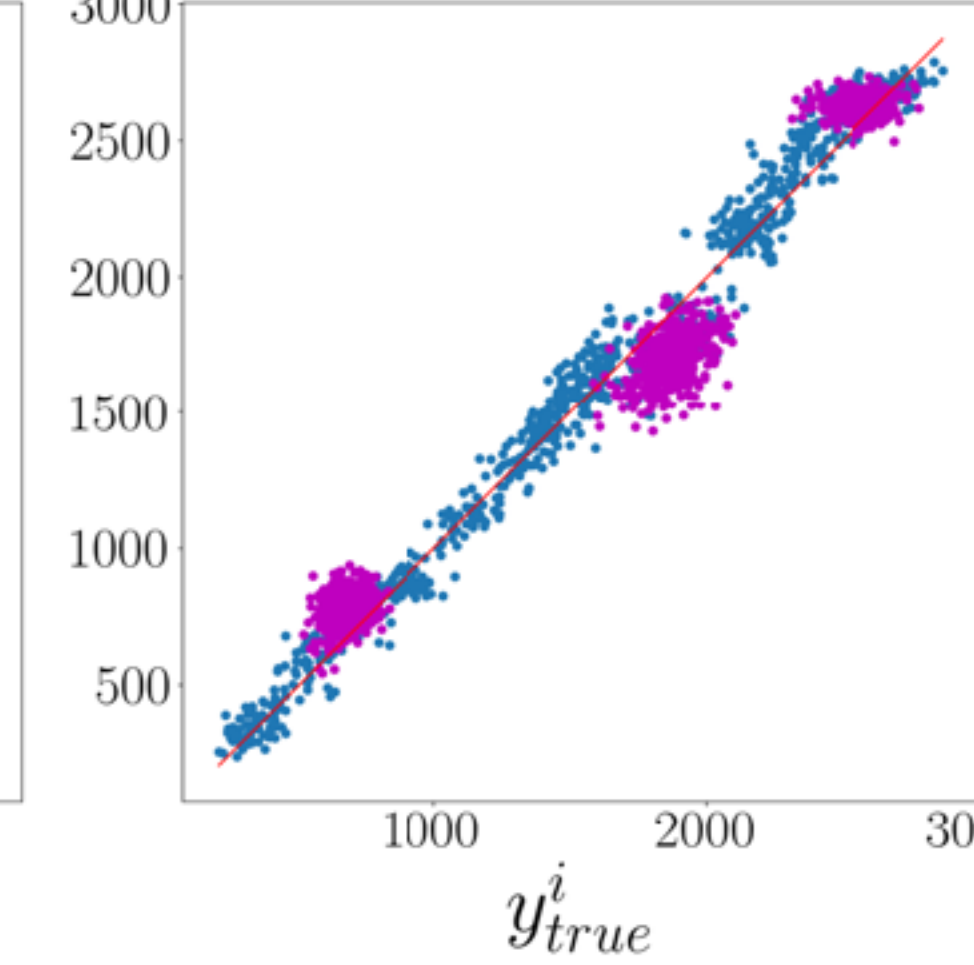
Bin No. 7



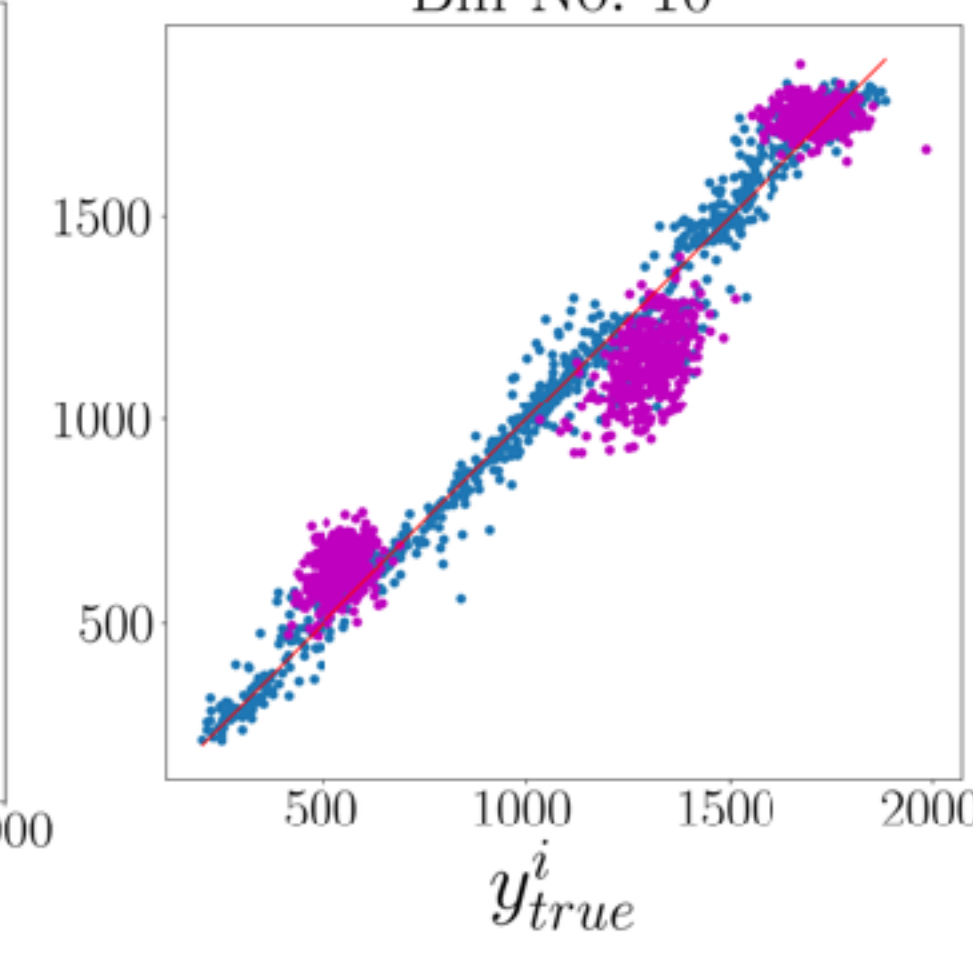
Bin No. 8



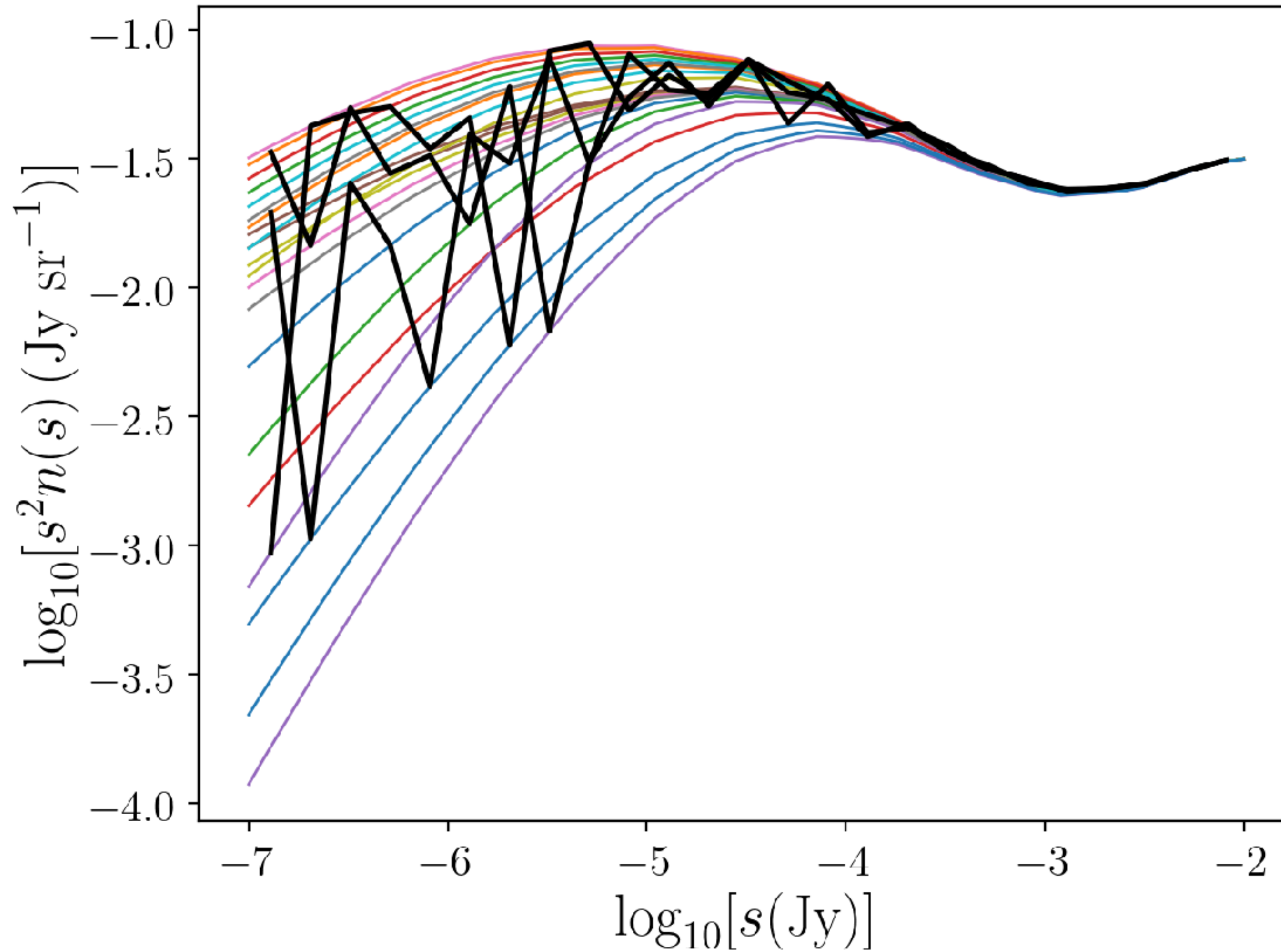
Bin No. 9

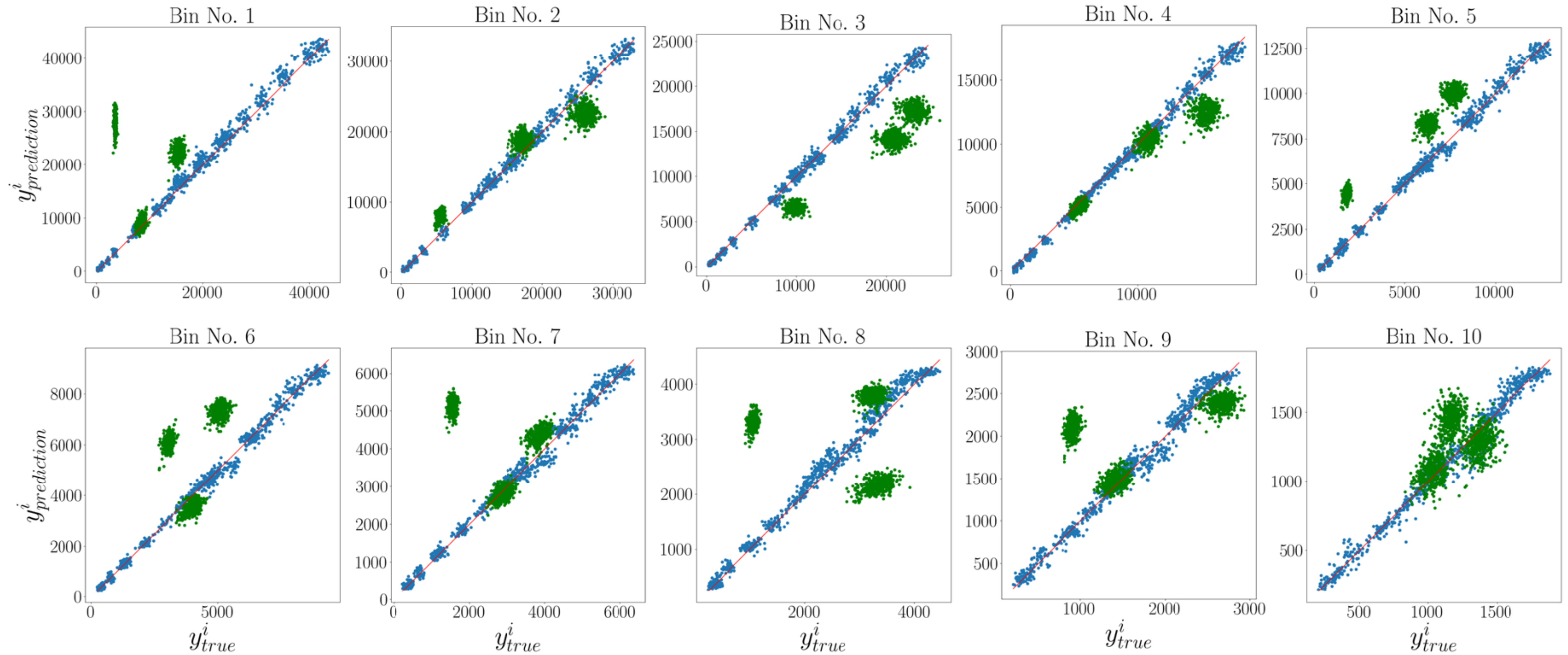


Bin No. 10



Test: same shape, different parameters





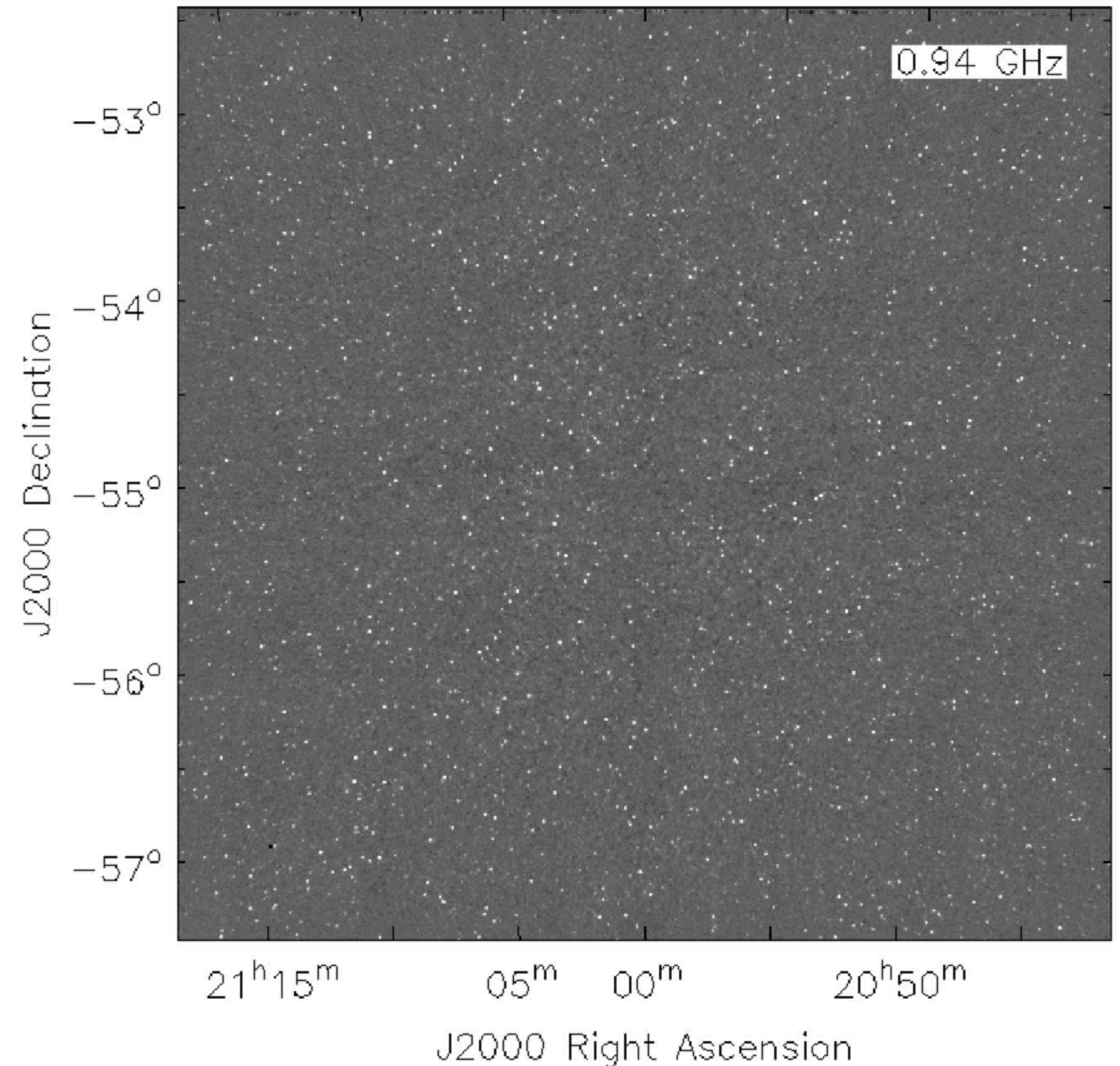
How to decorrelate the bins?

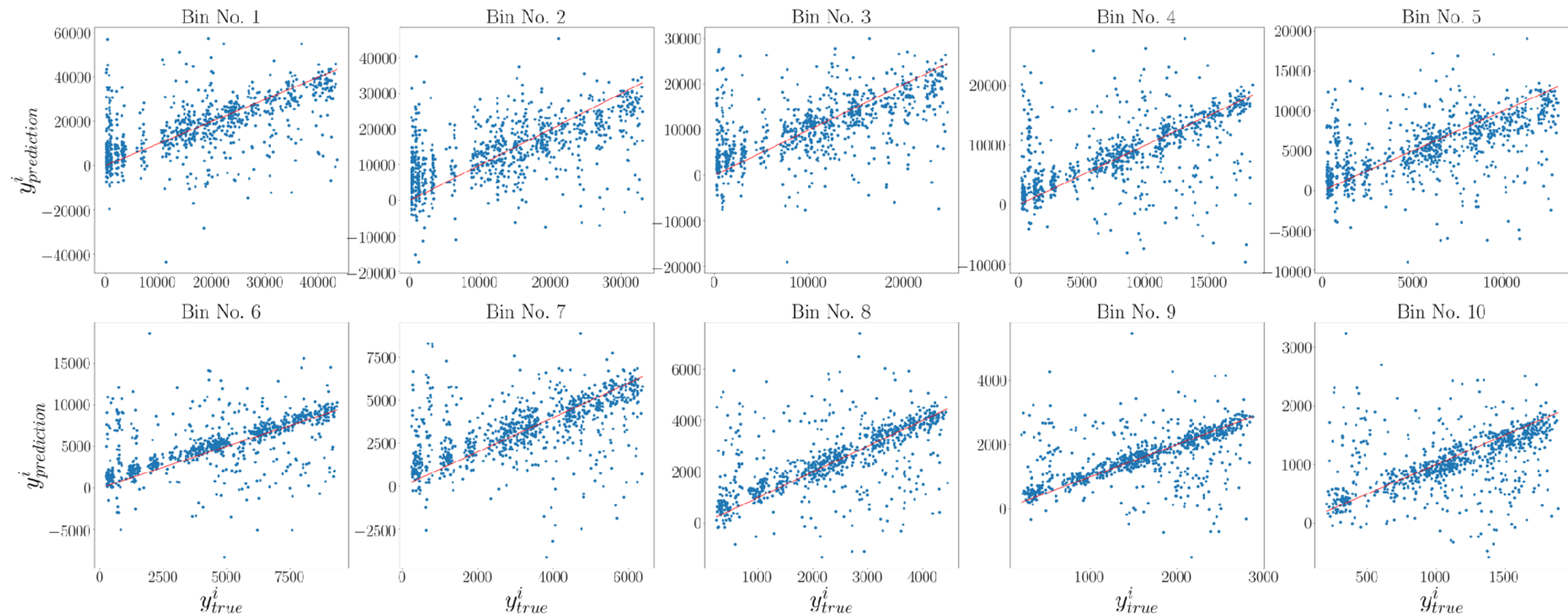
- Network learns the functional shape of $N(s)$
- Even training one separate network for each bin does not solve the problem
- What we'll try next:
 - Train with different functional shapes
 - Denser training data in each bin



Train with restored images

- Simulation of visibilities starting from sky model with ASKAPsoft
- CLEAN image
- Images include
 - noise
 - convolution with PSF gives side lobes





Avenues to improvement

- Find better ASKAPsoft parameters to improve cleaning
- Data pre-processing
 - Normalization and stretching
 - Data augmentation
- Give network auxiliary information (eg. total brightness)
- CNN hyperparameters
- CNN architecture

Thank you!