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Finding New Physics without learning about it: Anomaly Detection as a tool for Searches at Colliders

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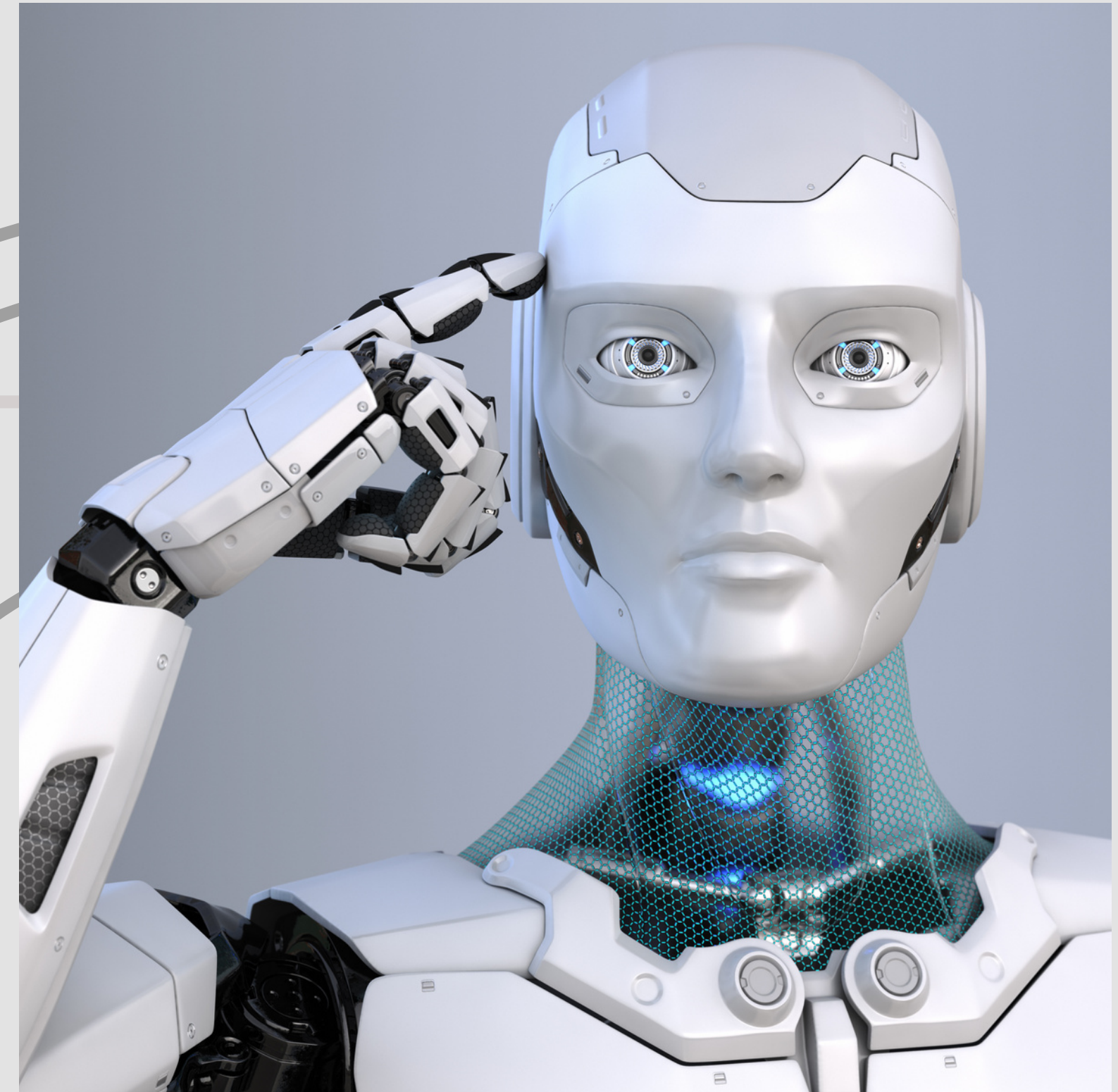
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Why to use machine learning

Machine learning can identify rare and unexpected events or anomalies in the data, which could indicate the presence of new and unknown phenomena. Anomalies might be signs of undiscovered particles or interactions. It was used python with tensorflow and pytorch to implement the machine learning algorithms.



Dataset

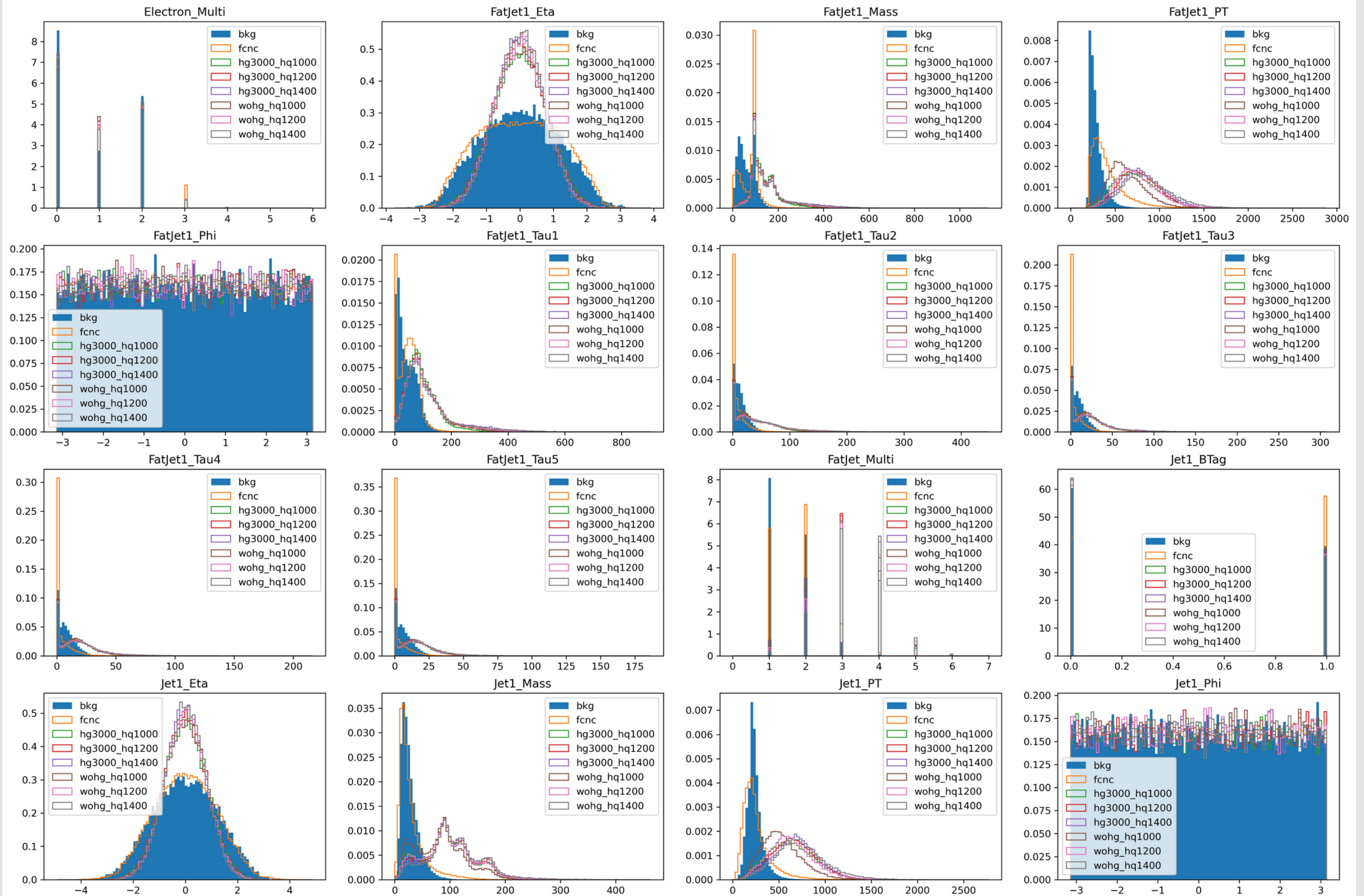
Background:

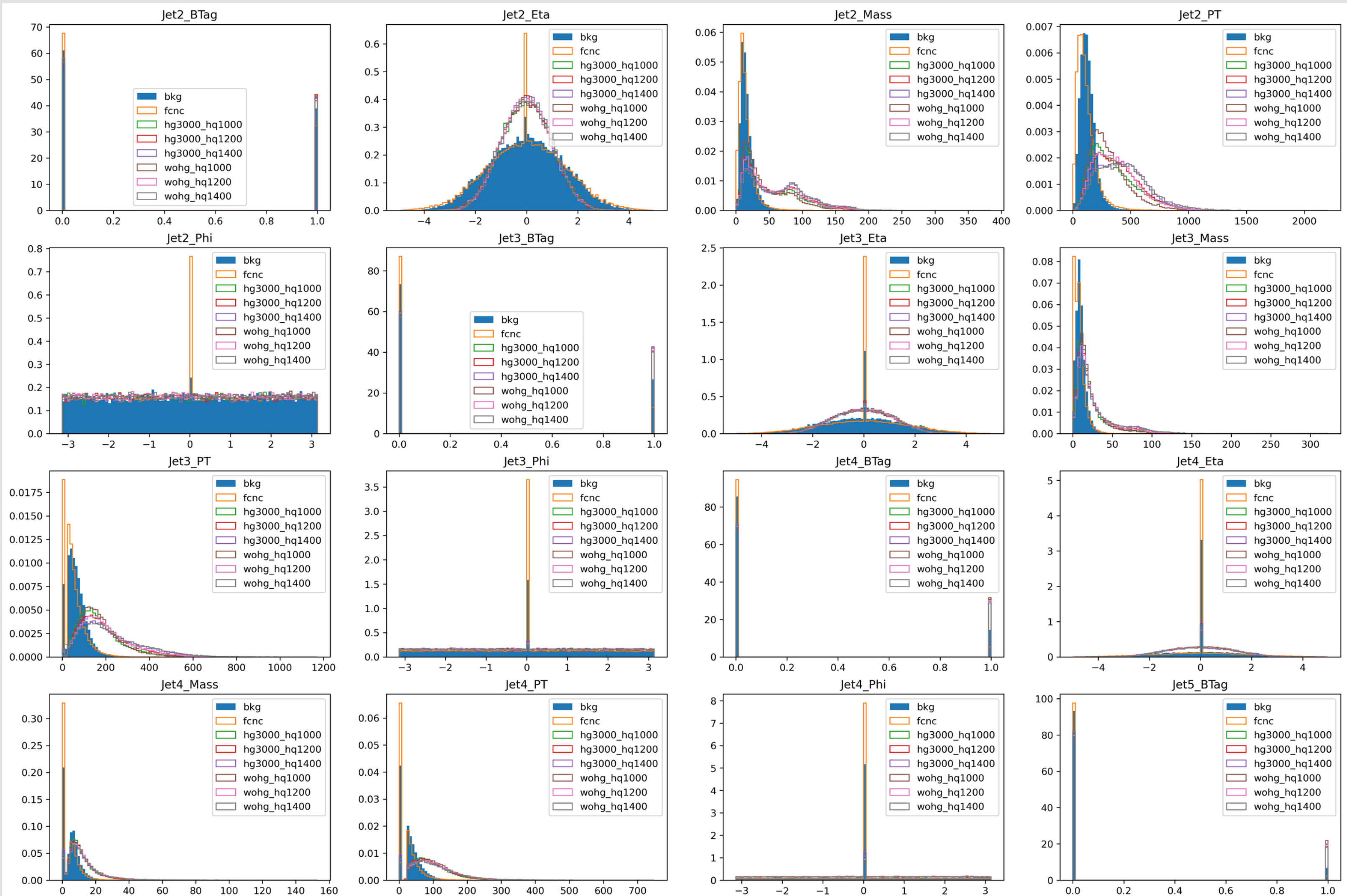
- Zj
- $t\bar{t}b\bar{b}$
- $Zb\bar{b}$
- WW
- WZ
- ZZ

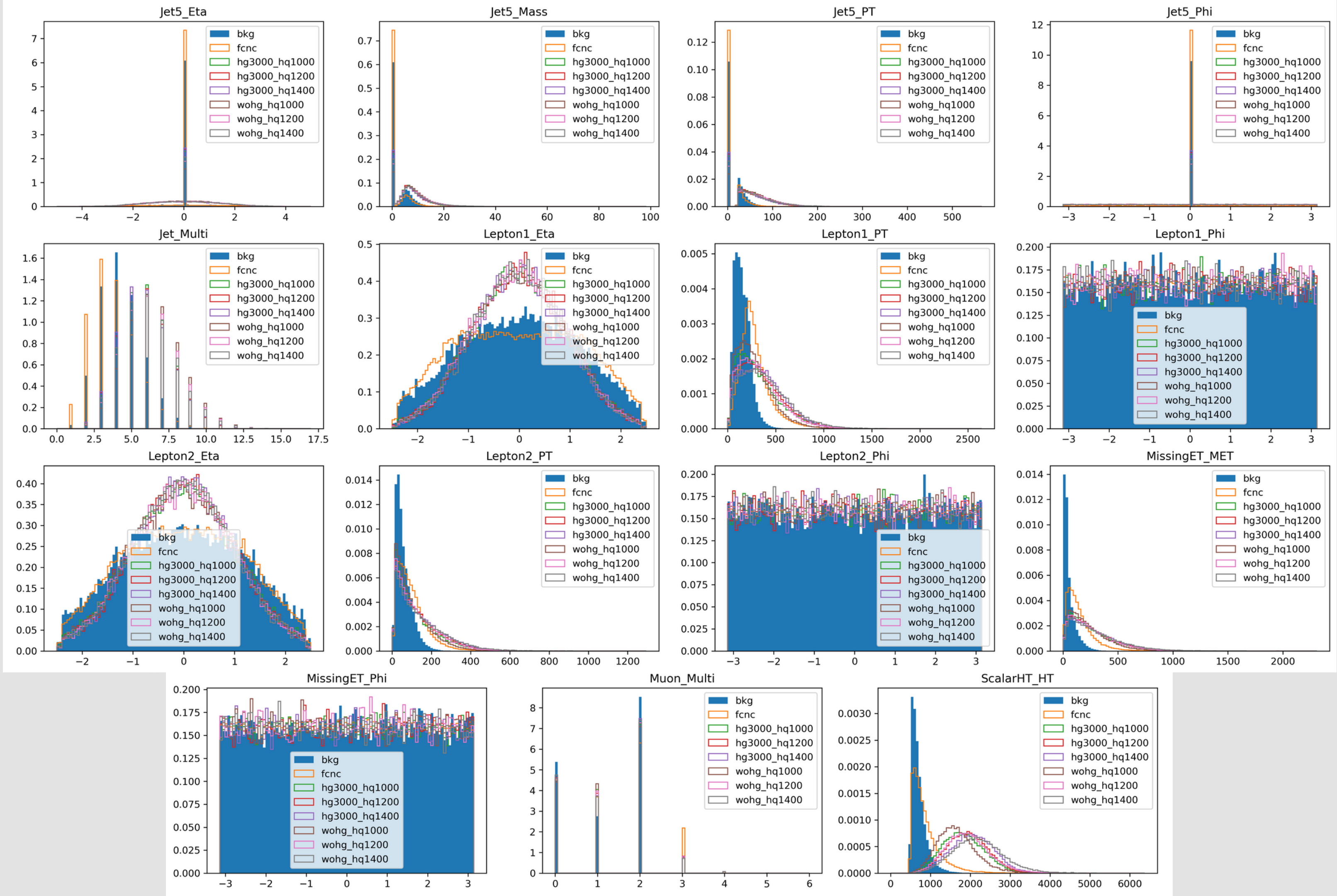
Signals:

- Standard-Model gluon (wohg)
- BSM 3TeV heavy gluon (hg3000)
- Flavour Changing Neutral Current (fcnc)









Used Algorithms

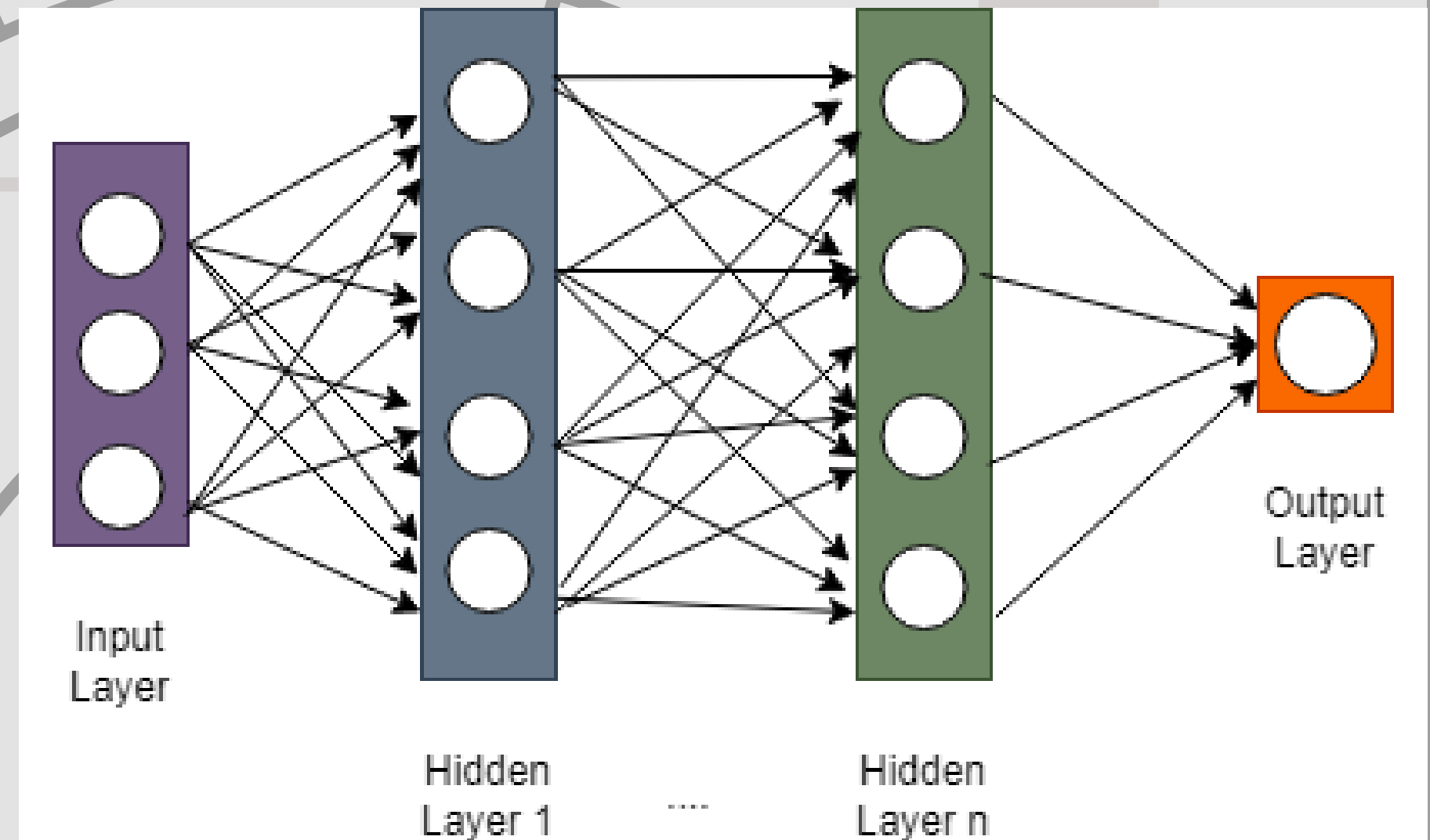
DNN (general)

DNN is a structure stores a value following the expression:

$$a = f \left(\sum_{i=1}^n (w_i \cdot x_i) + b \right)$$

- f is the activation function
- w is the weight
- x is the input value
- b is the bias term

The final layer stores the output. During train, the parameters are adjusted so the error between the output and the reality is minimized.



Used Algorithms

DNN (implemented)

Input size = 43

Loss function: Binary cross entropy

Structure:

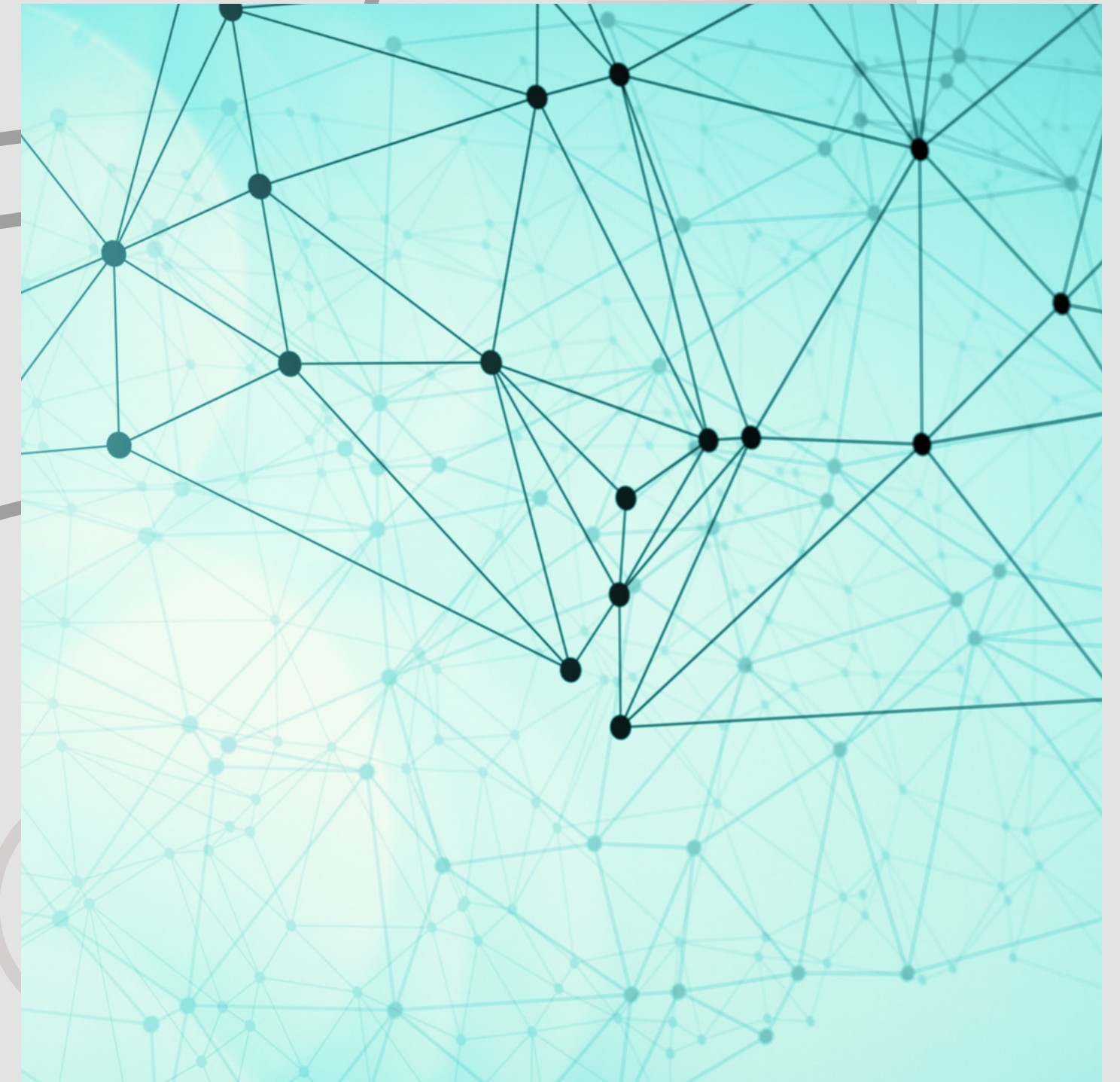
Input->128->128->output (1)

Epochs: 100

Learning rate: 0.01

Implemented technics:

Early Stopping (10 epochs)

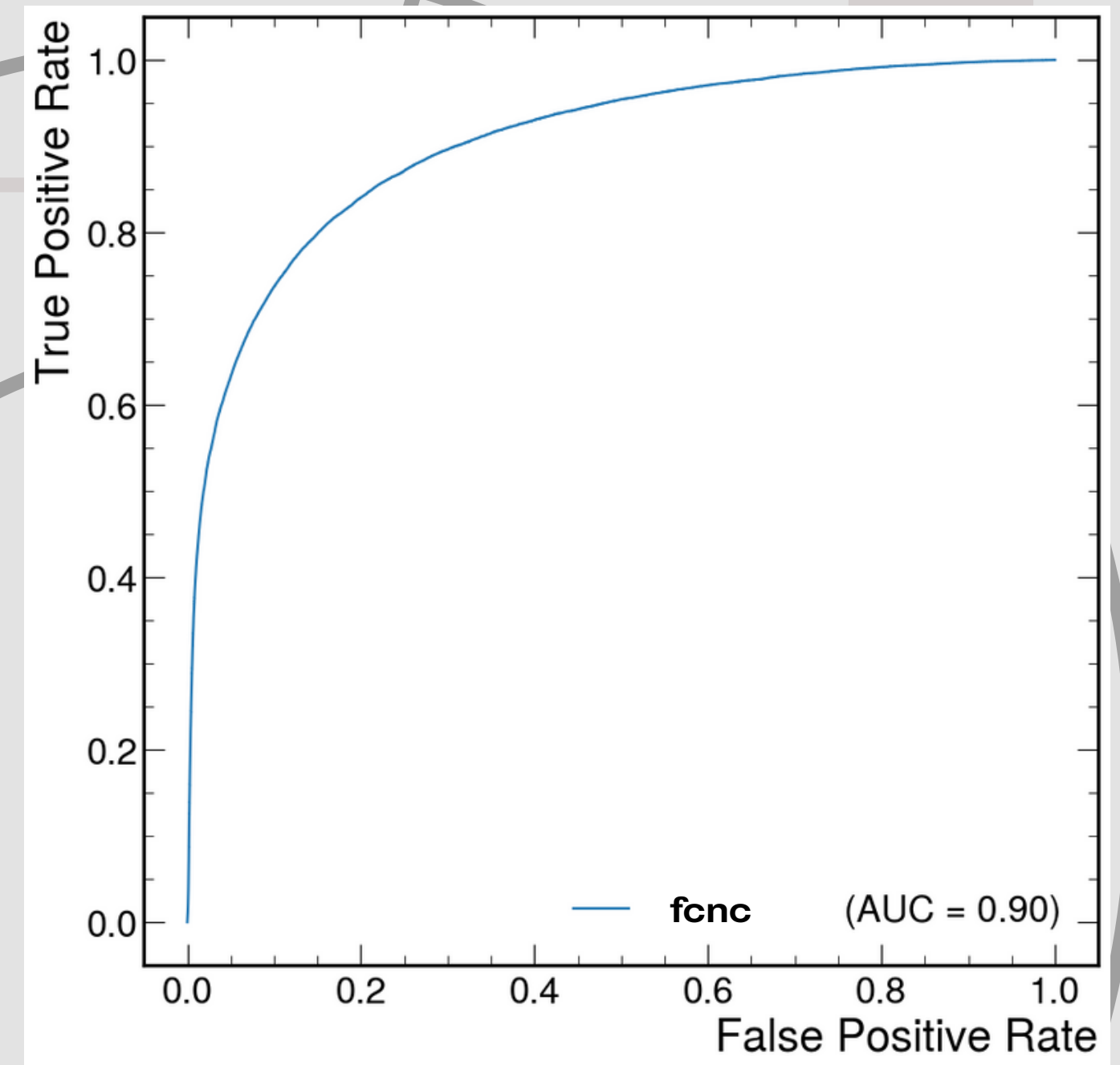
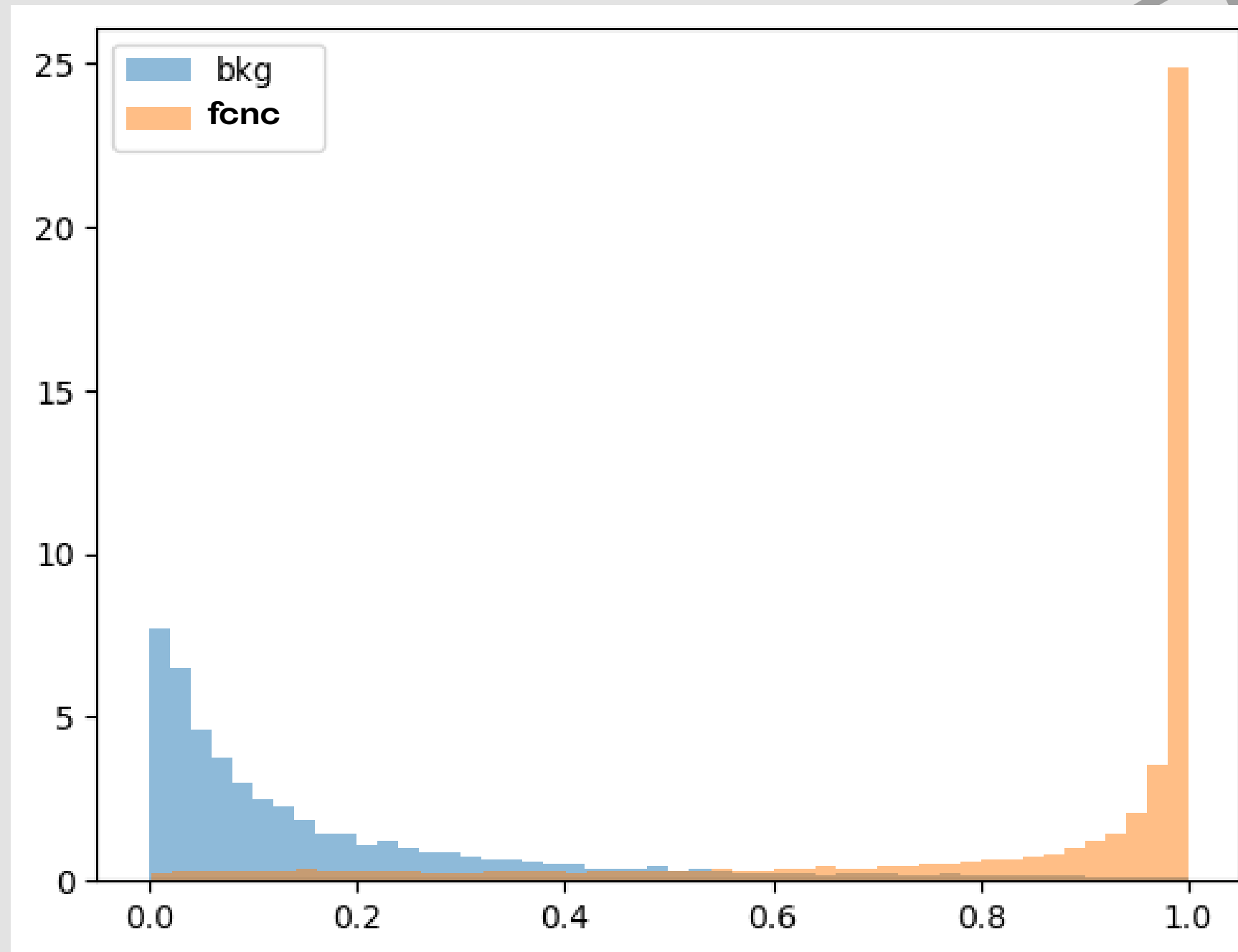


Used Algorithms

DNN (results)

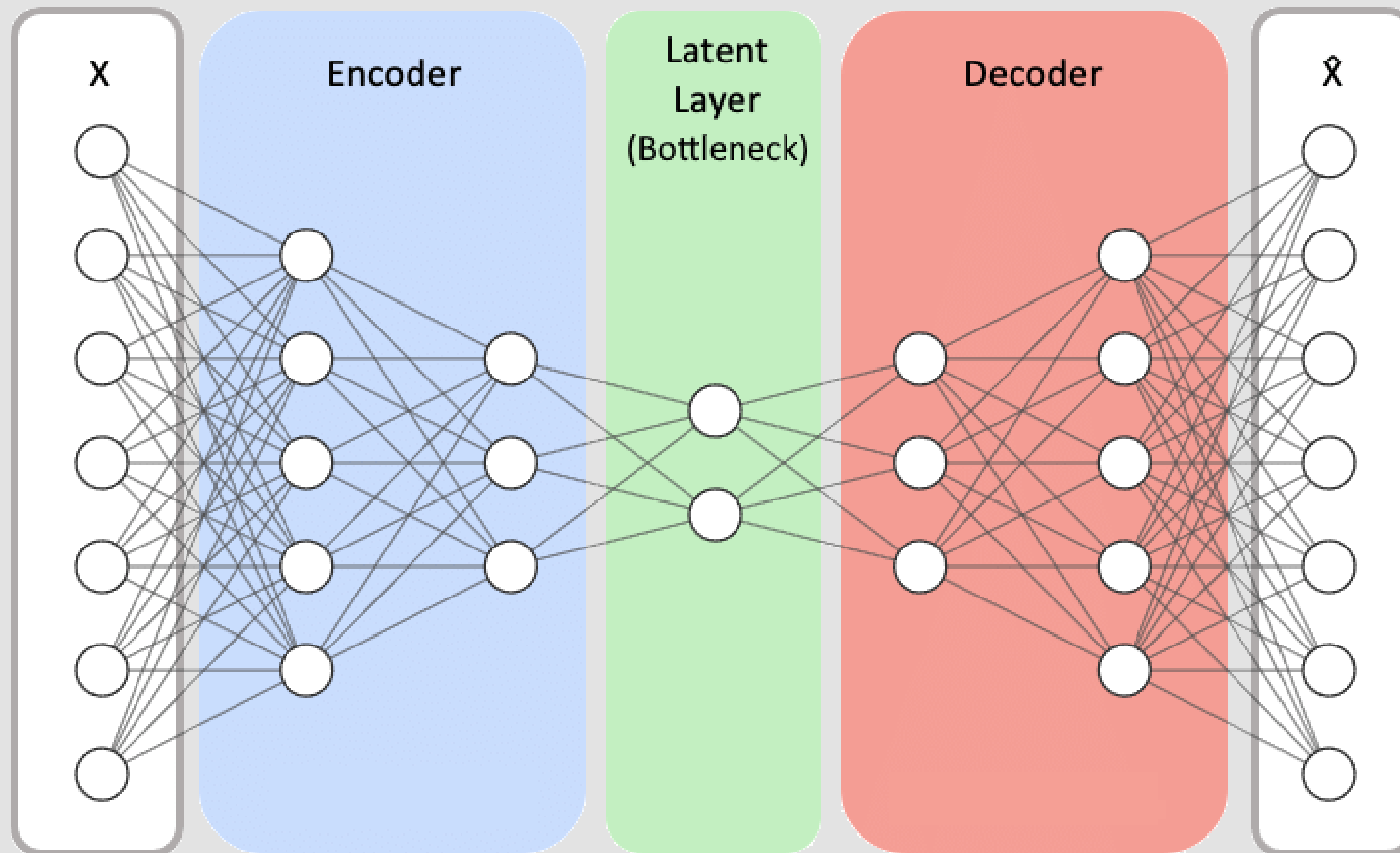
Classification

ROC curve



Used Algorithms

AE (general)



Semi-supervised net

Utilities:

File compression

Denoising

Specific learning (such as AD)

Used Algorithms

AE (implemented)

Input size = 43

Loss function: Mean square error

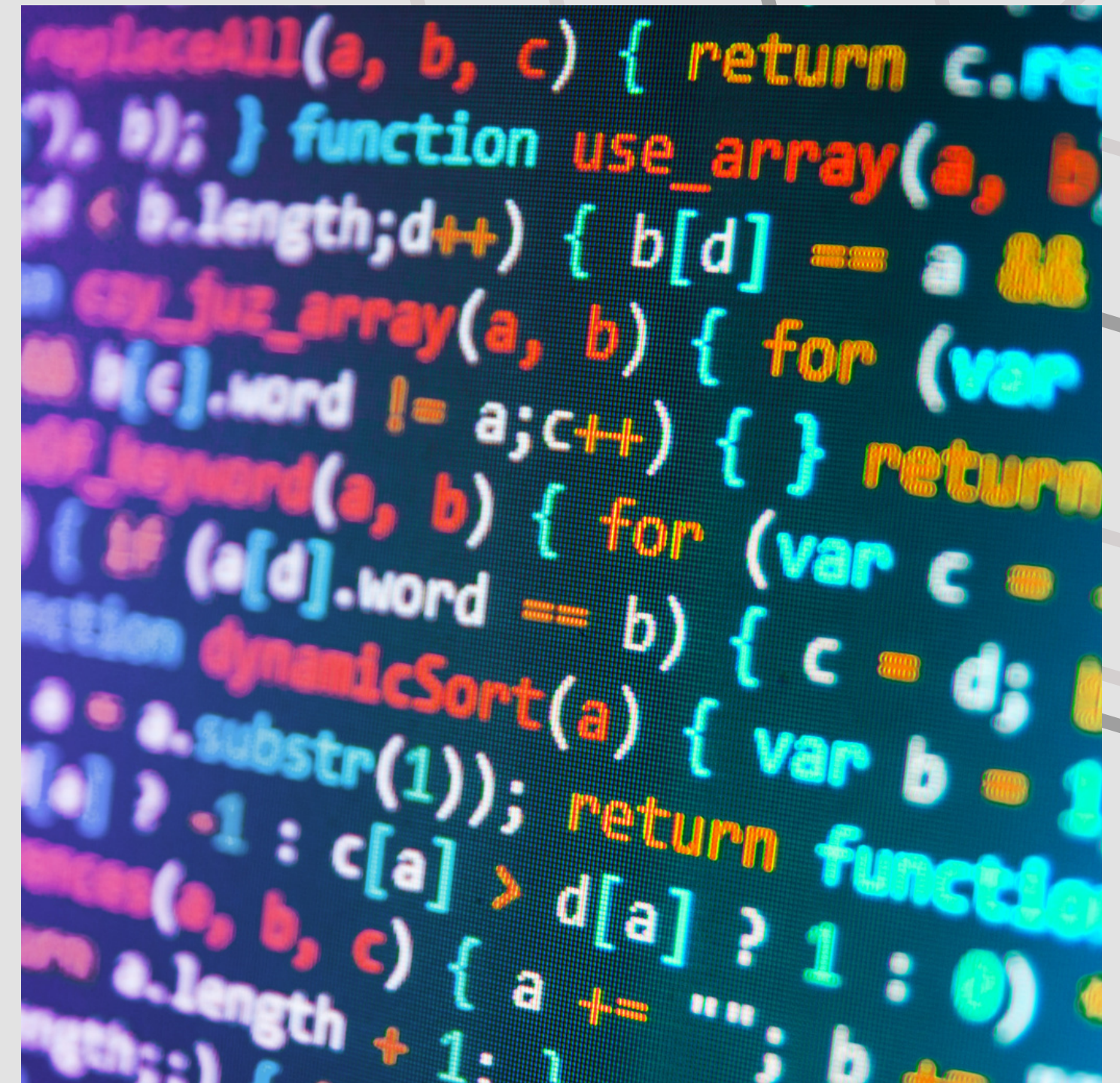
Structure:

Input->32->16->8->16->32->output

Learning rate: 0.01

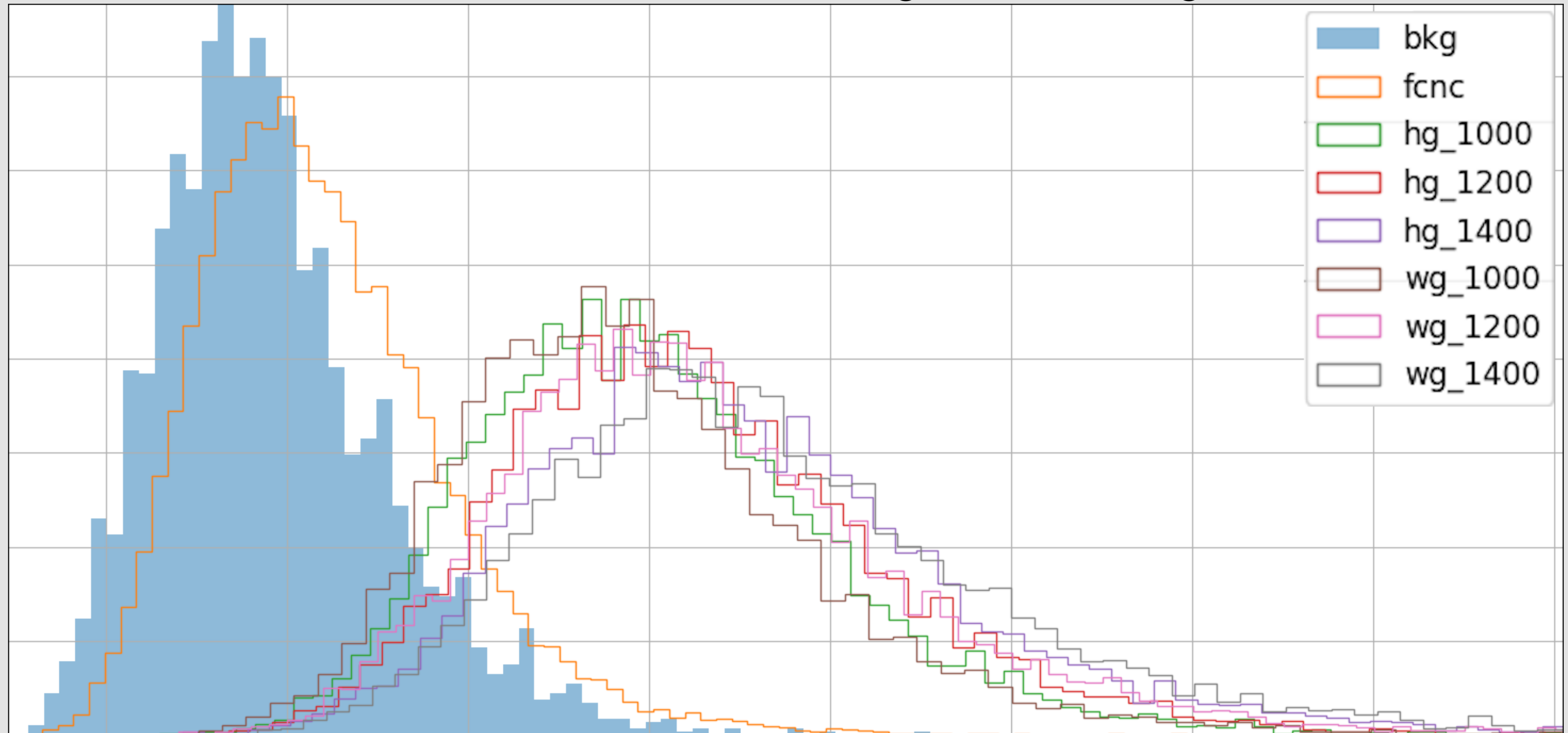
Implemented technics:

Early Stopping (10 epochs)

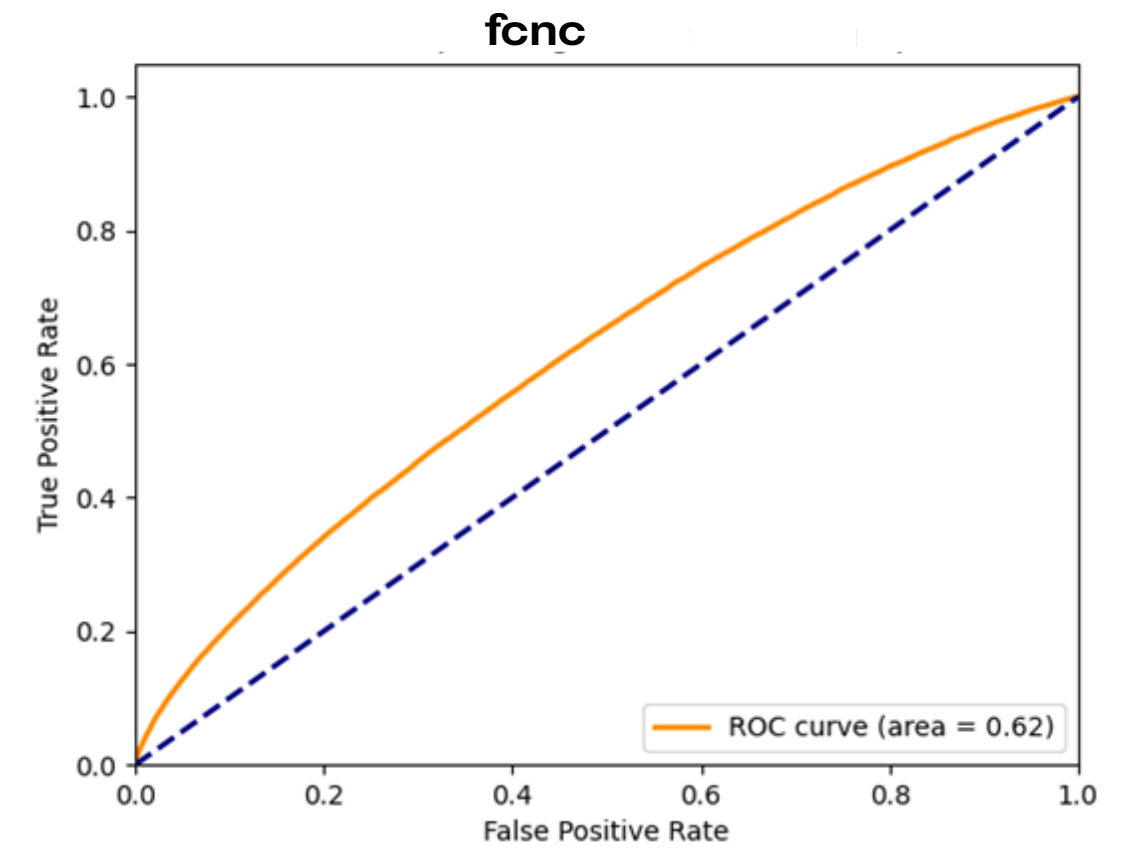
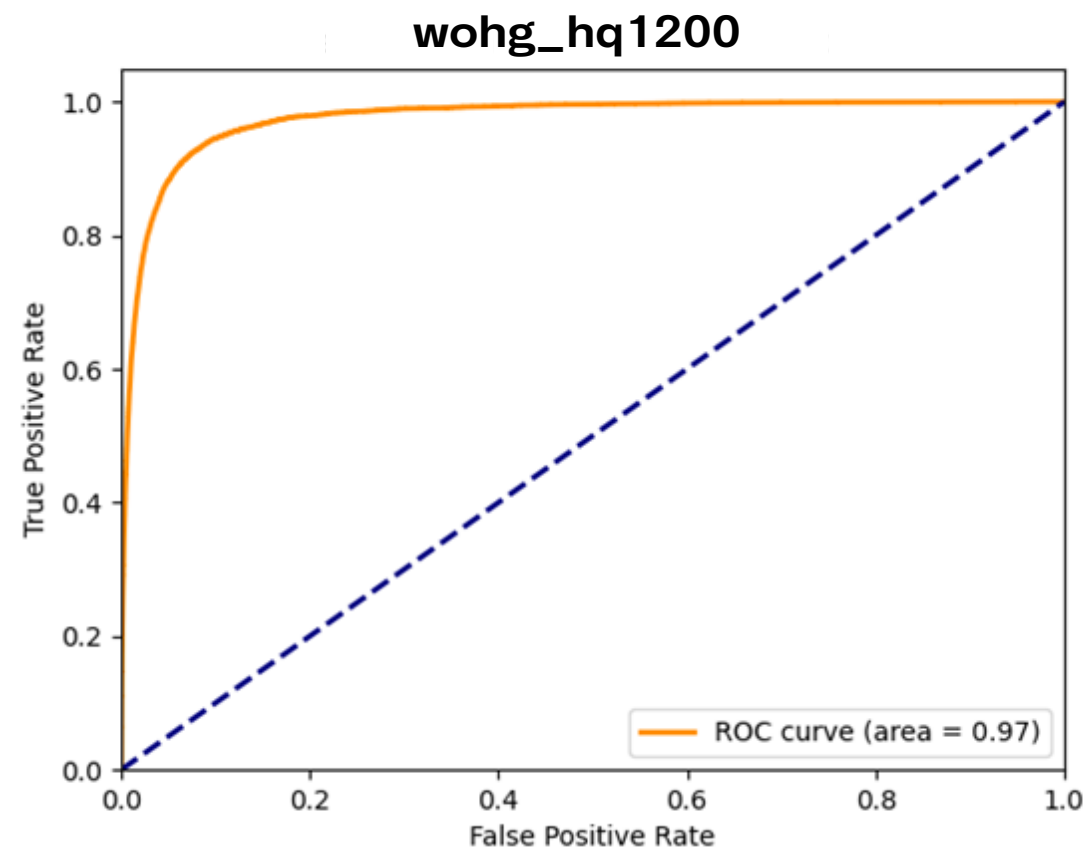
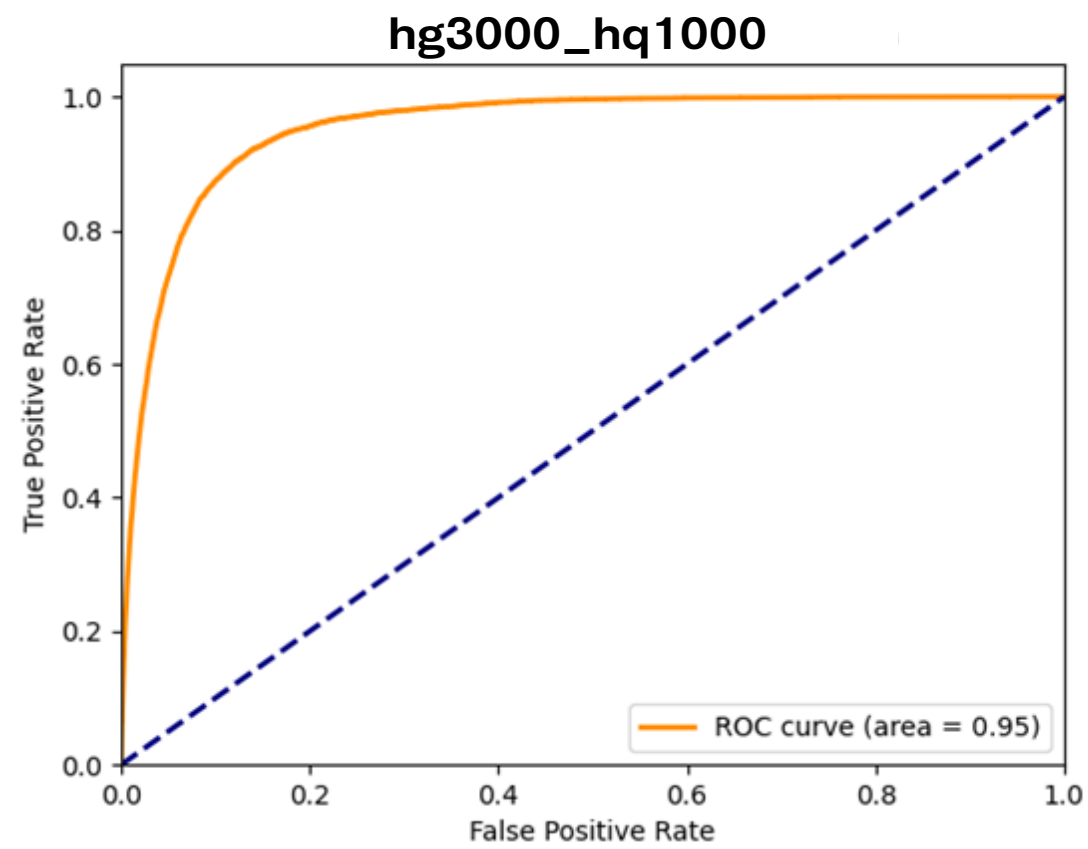


AE (results)

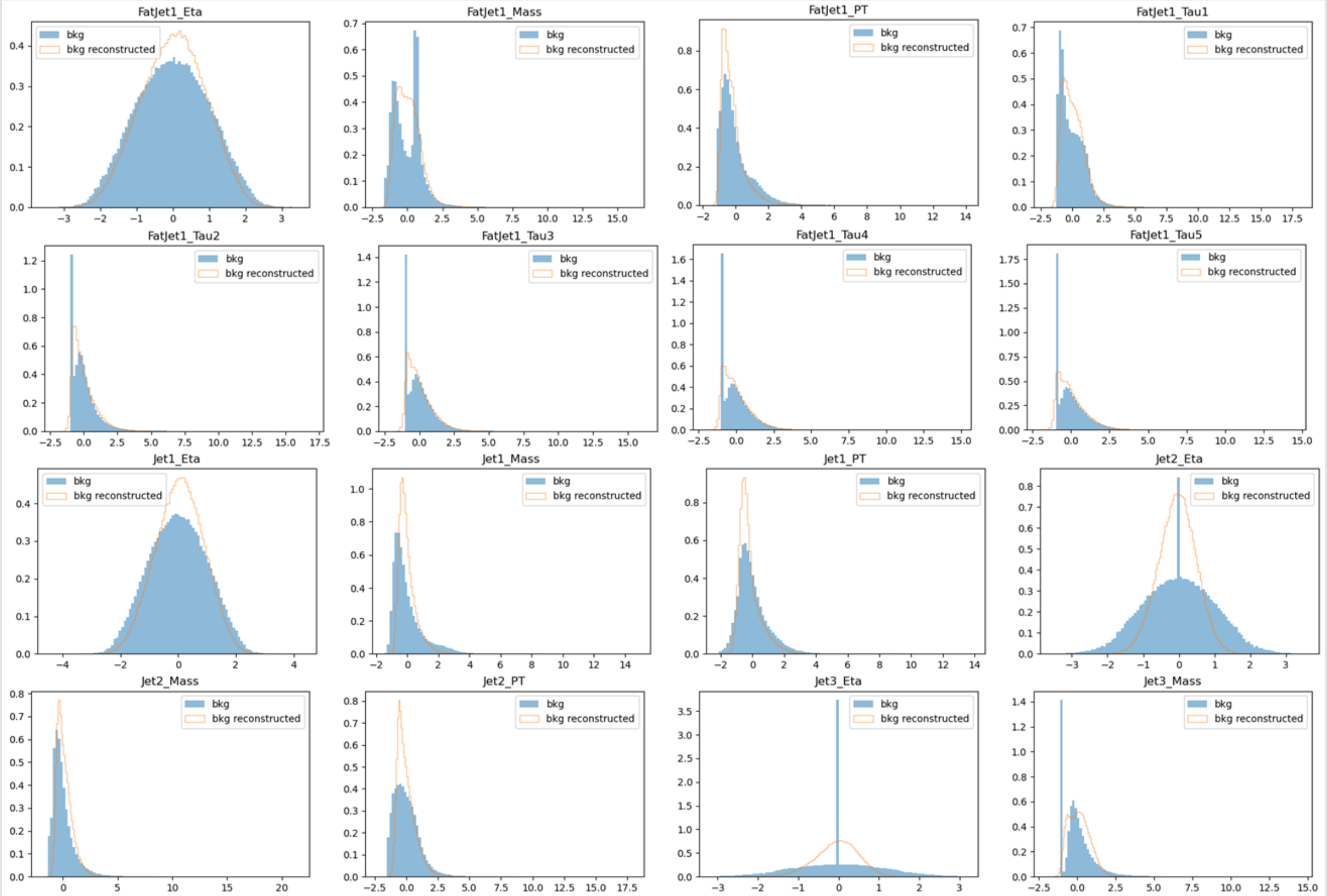
Reconstruction loss background vs signal



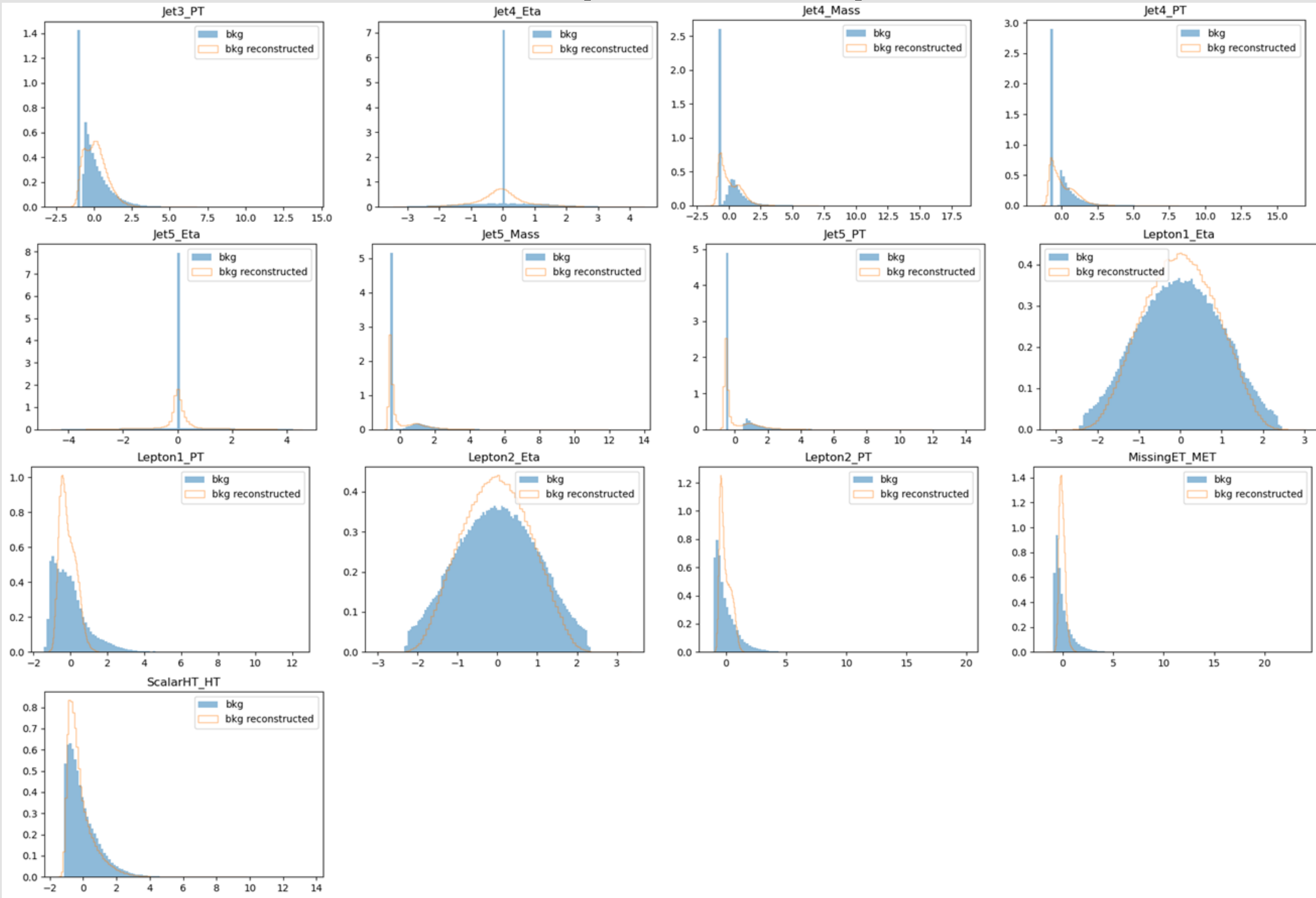
AE (results)



AE (results)

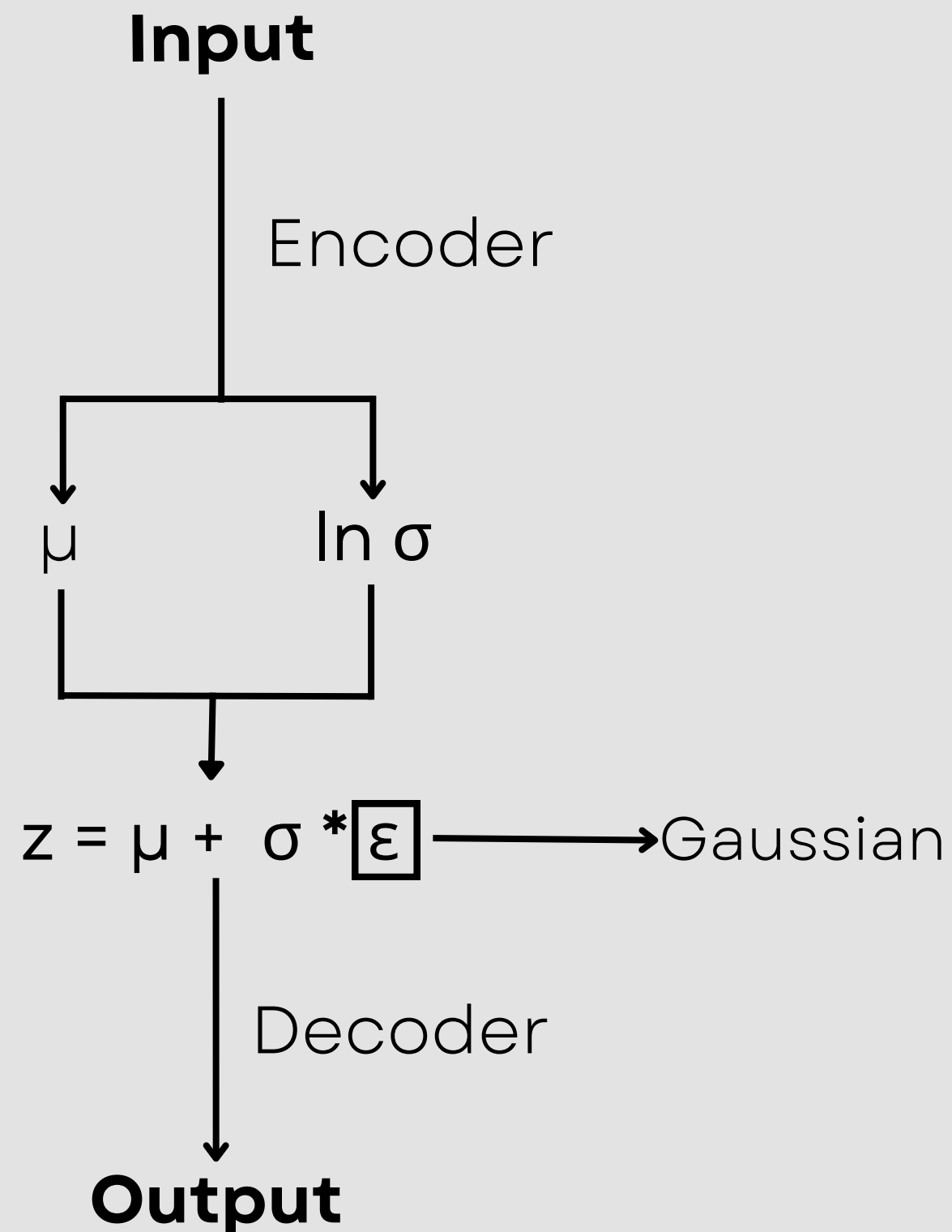


AE (results)



Used Algorithms

VAE (general)



Loss function:

$$L = \text{Recontruction loss} + \beta * \text{KL Divergence}$$

MSE/MAE/....

$$-\frac{1}{2} * (1 + \ln \sigma^2 - \mu^2 - \sigma^2)$$

Used Algorithms

VAE (implemented)

Structure: 32-16-8-16-32

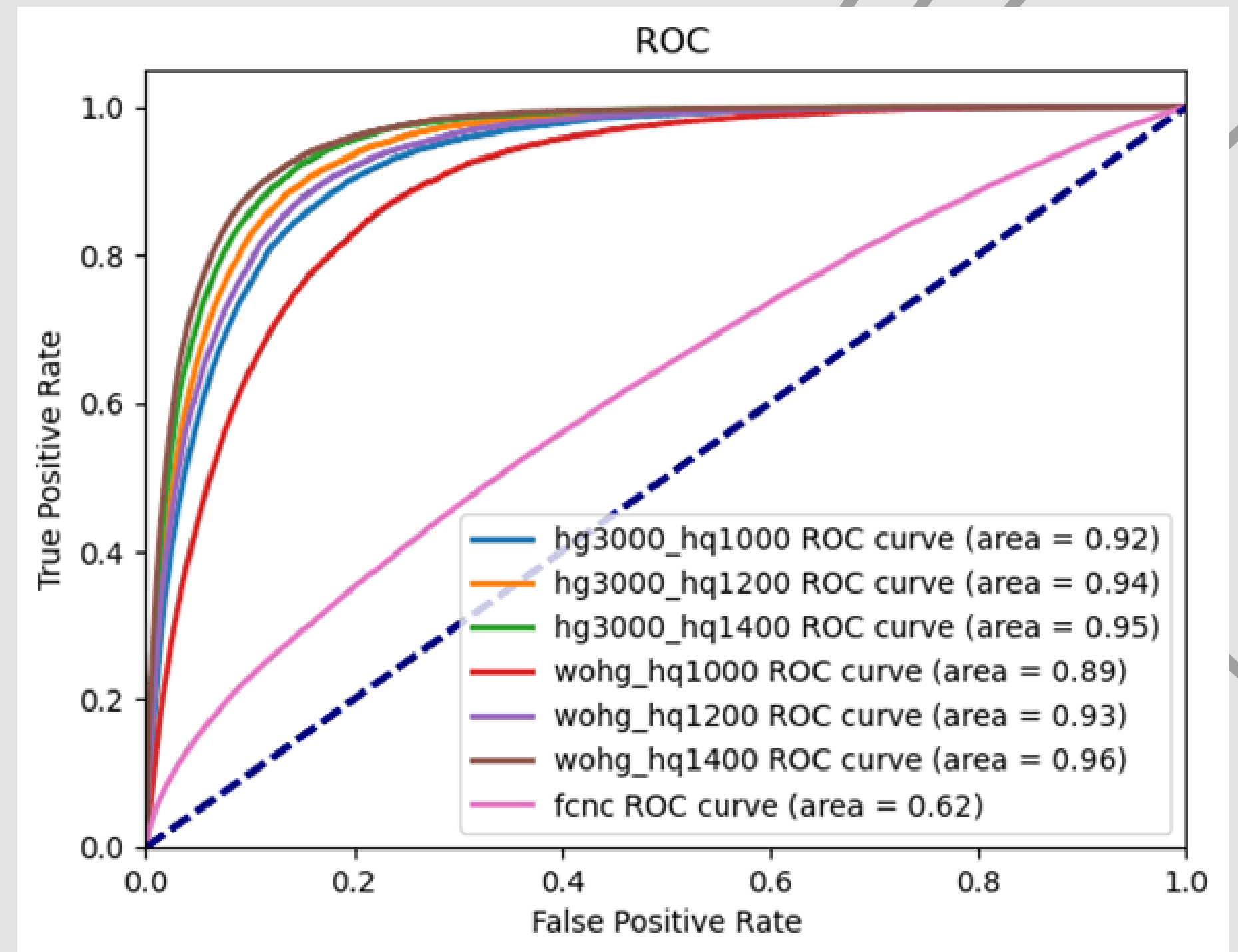
Loss function: Mean Absolute Error

Hiperparameters:

Learnig rate = 0.01

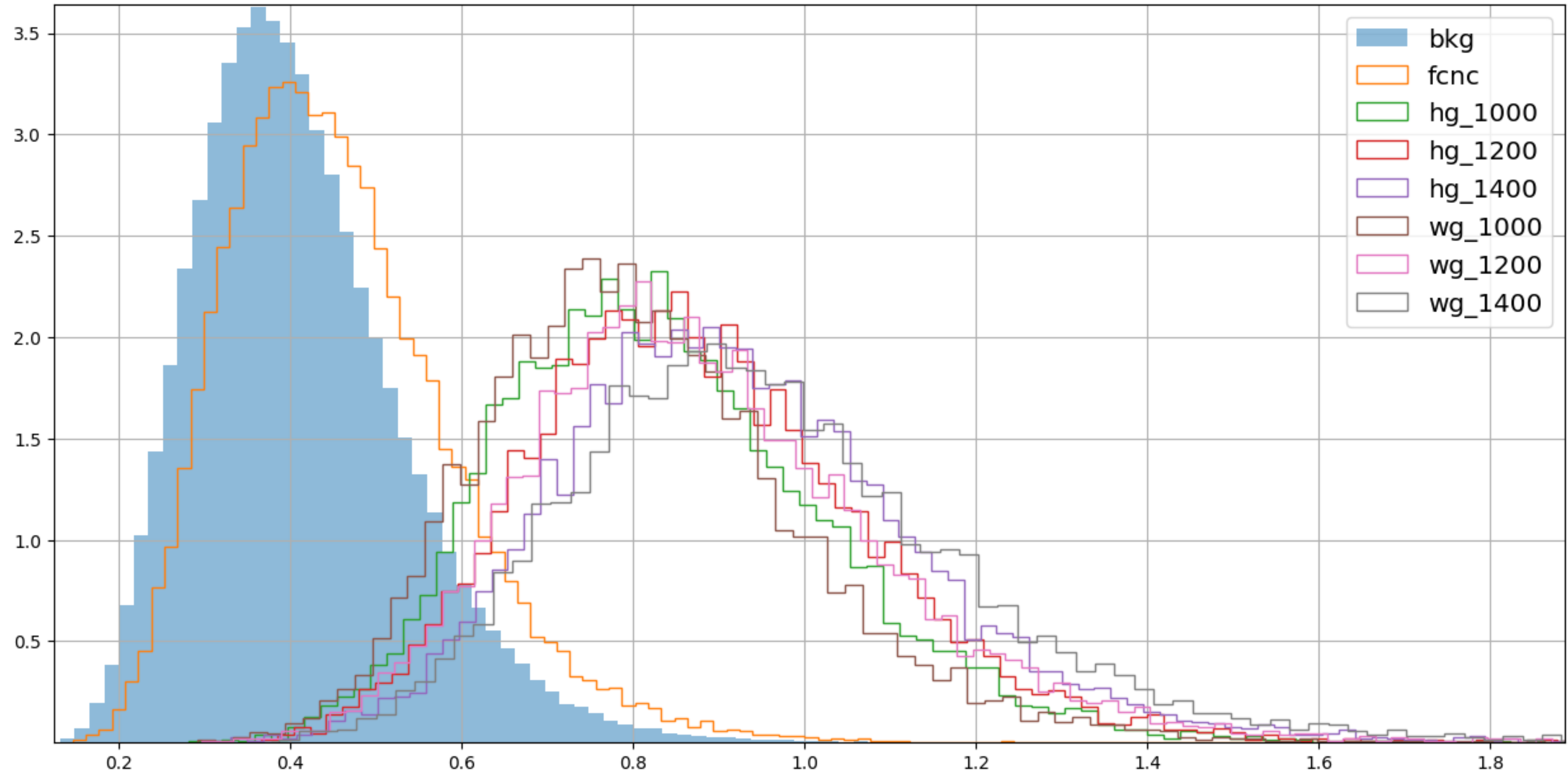
No. of epochs = 200

β = exponential growth until 0.5

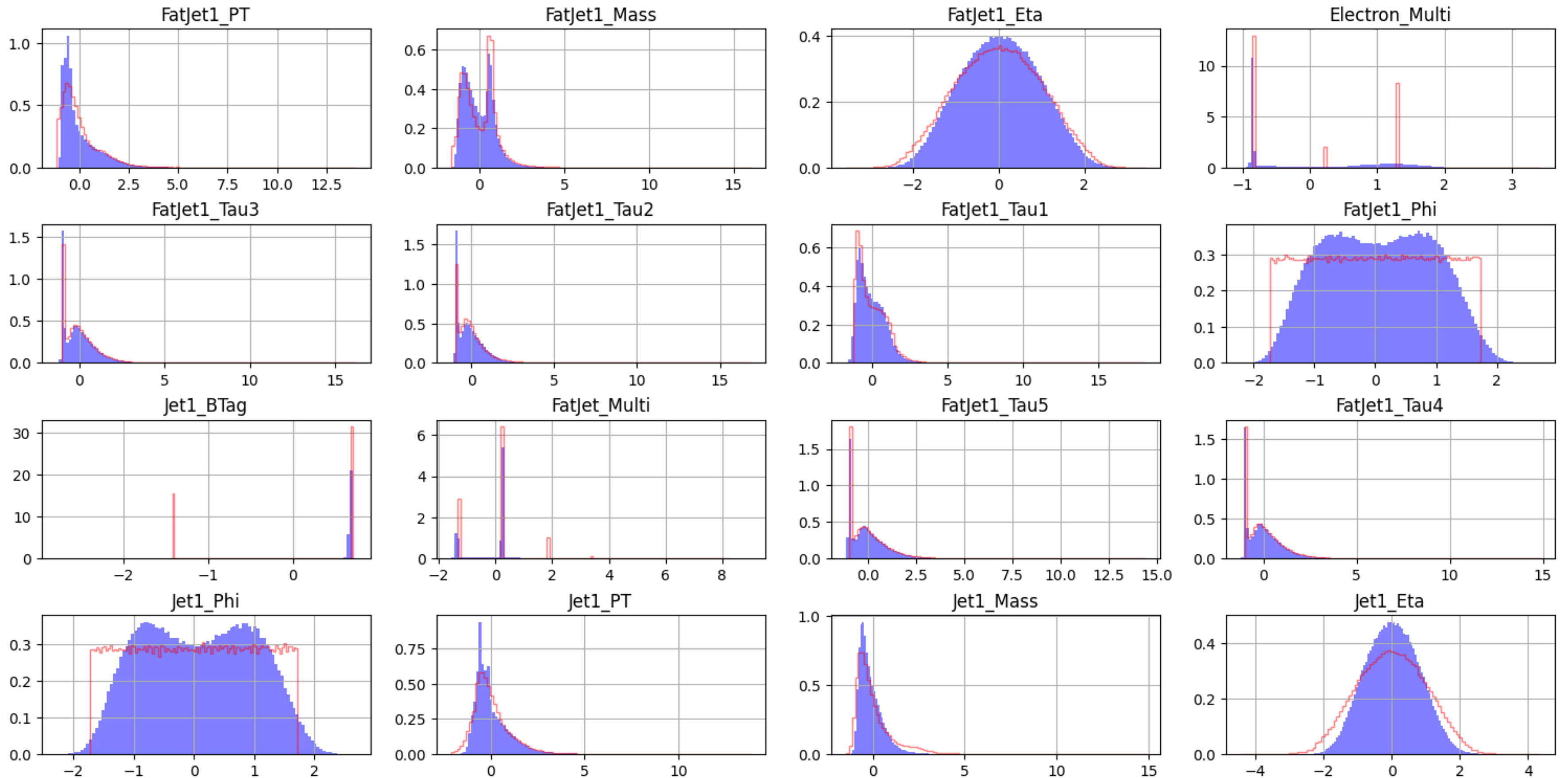


VAE (Loss background vs signal)

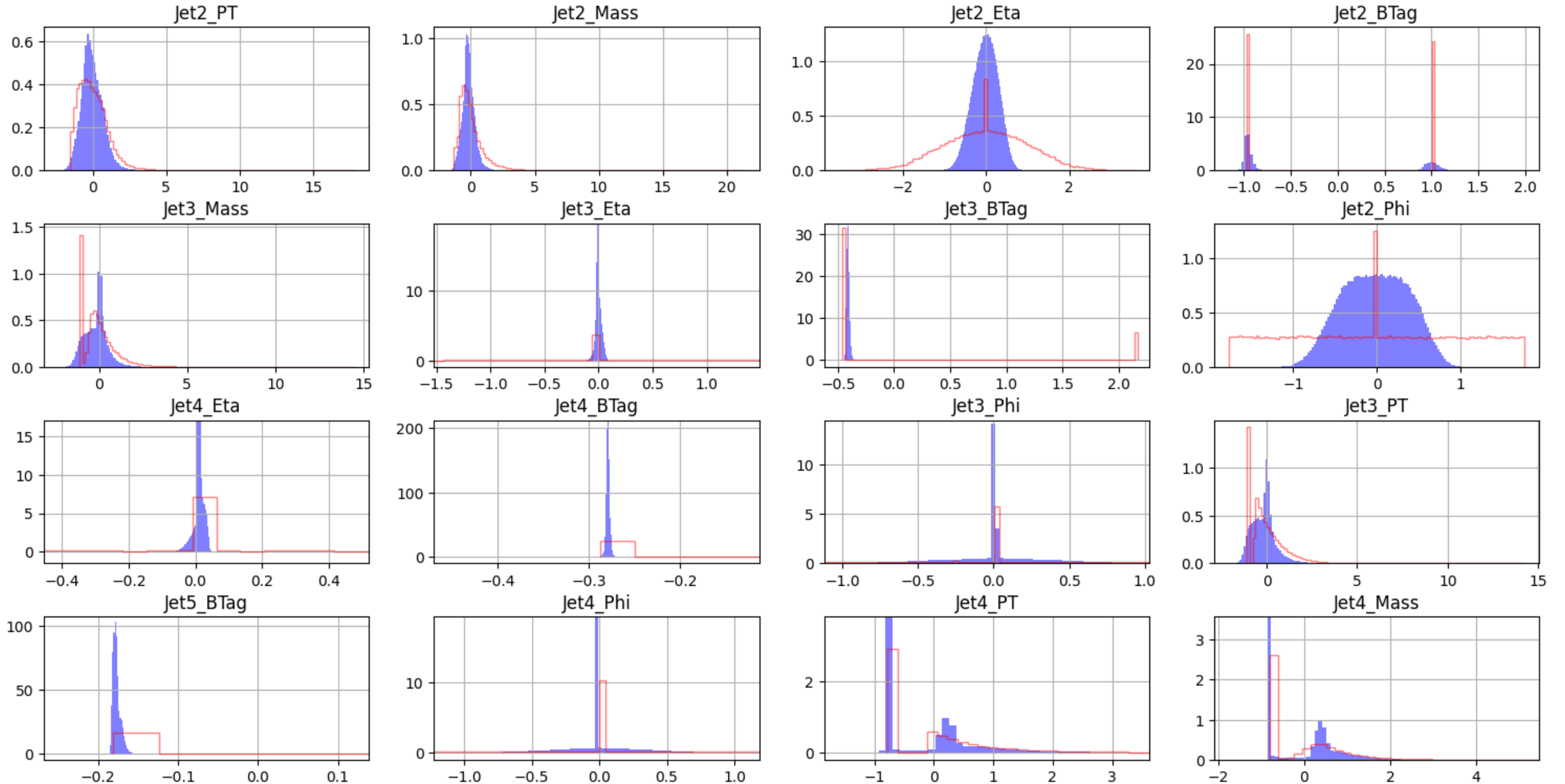
Reconstruction loss background vs signal



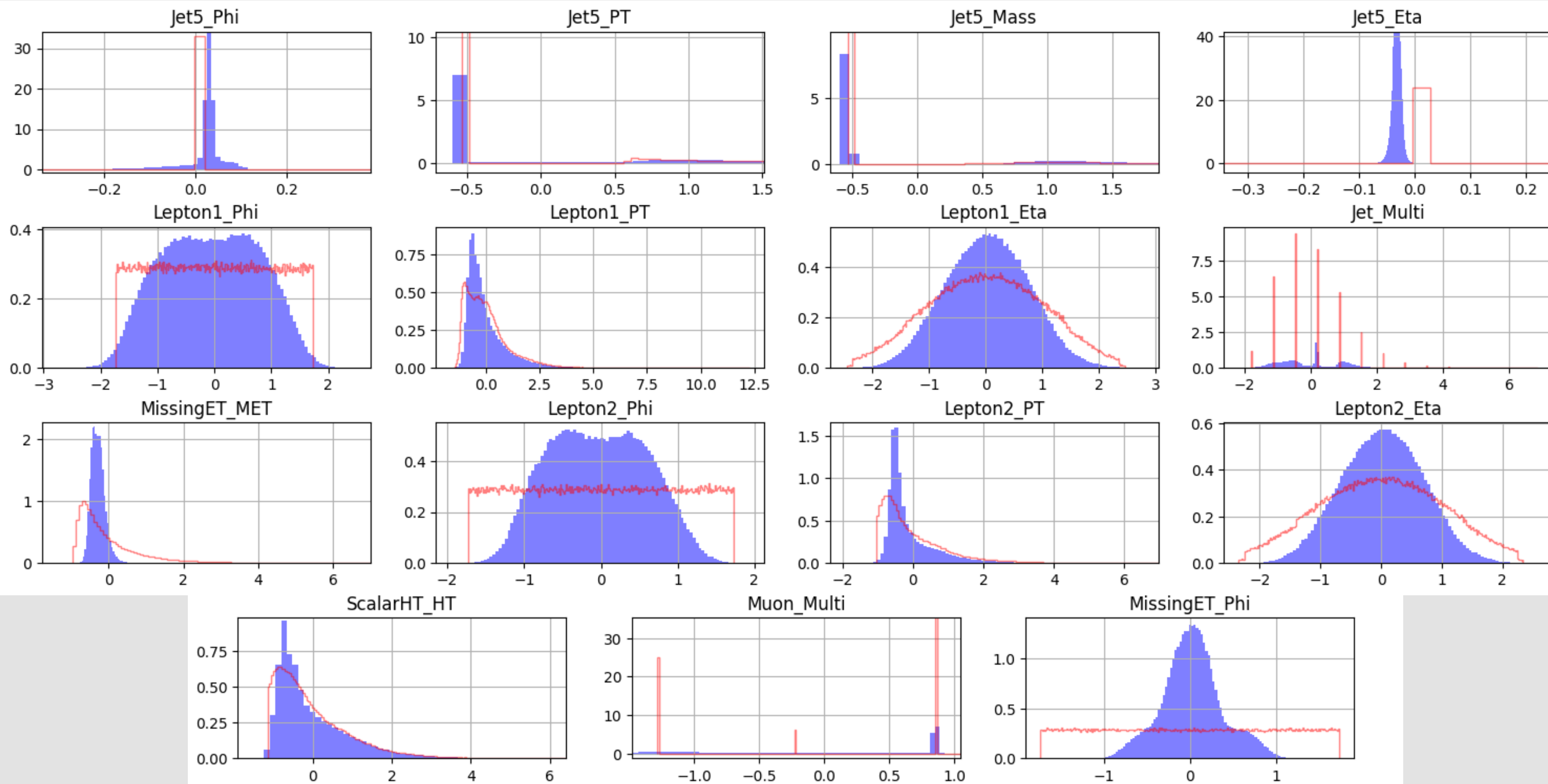
VAE (reconstructions)



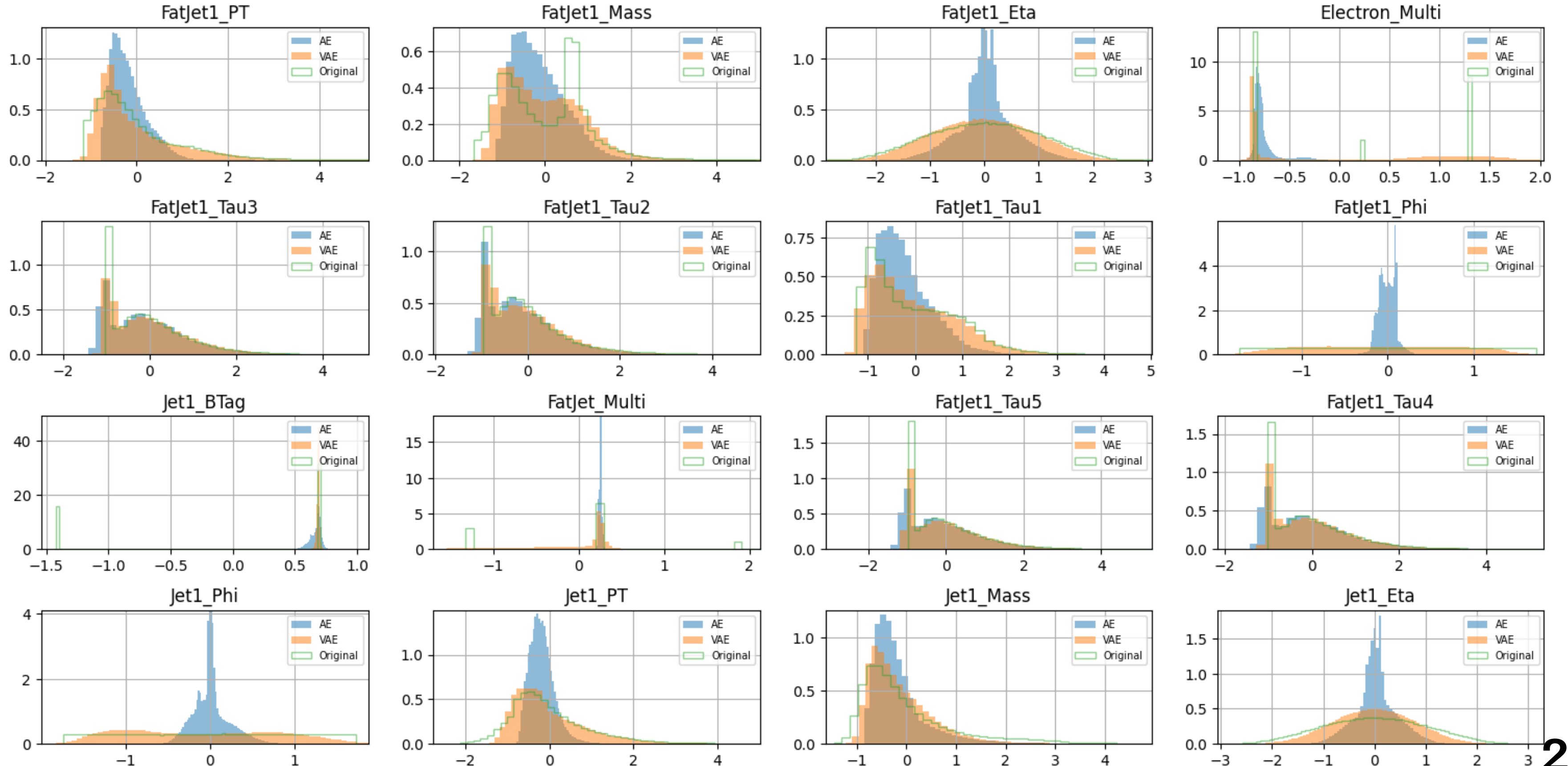
VAE (reconstructions)



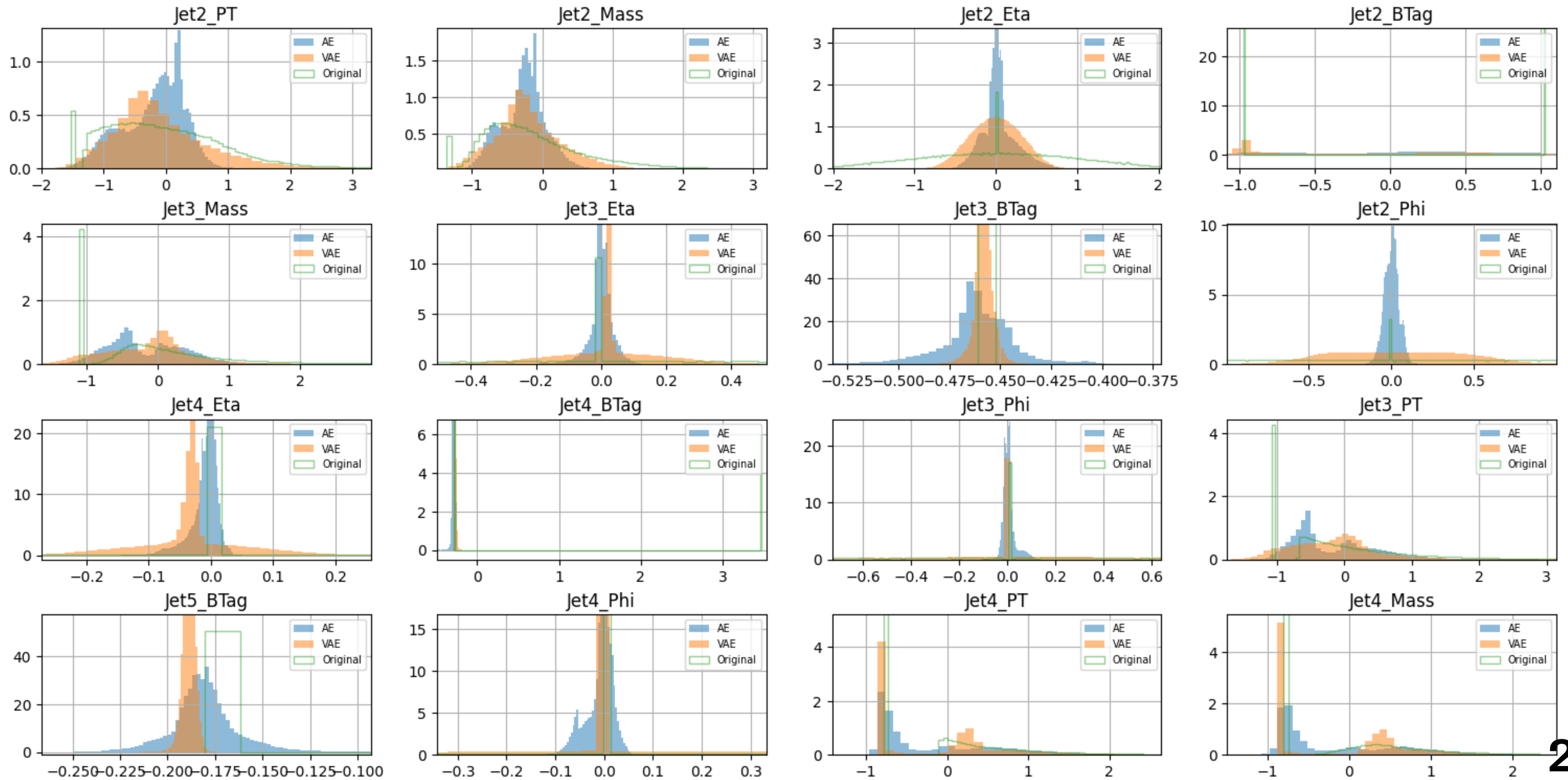
VAE (reconstructions)



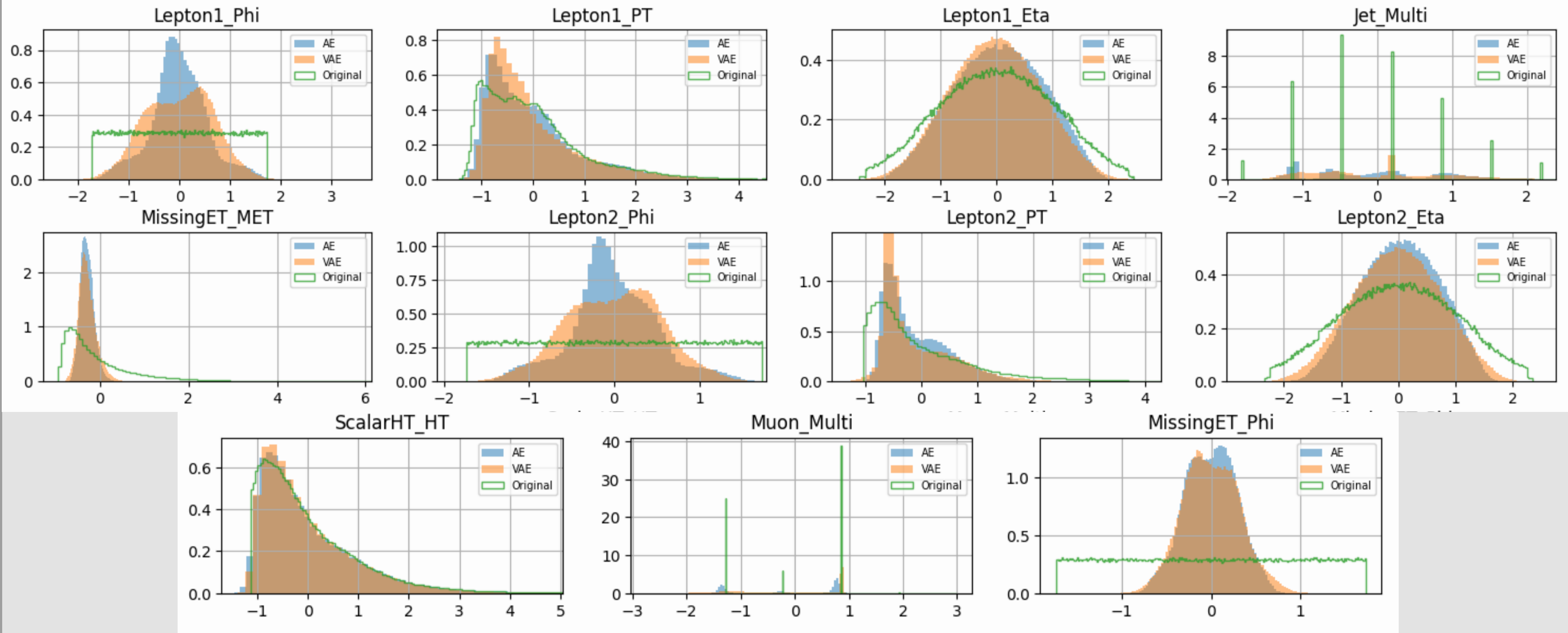
AE vs VAE (reconstructions)



AE vs VAE (reconstructions)



AE vs VAE (reconstructions)



Future Steps

- Regularization methods such as L1 and L2
- Reduce LR on plateau method
- Dropout layers to avoid overfitting
- Longer training
- More appropriate optimizer and loss function
- Find correlations between features



Conclusion

Though AE got better AUC's, VAE made better background reconstructions. Both algorithms had good performance for AD, showing that the capability of machine learning to find new physics.

