ASTROPHYSICAL SPECTRAL FITTING: USING DEEP LEARNING

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PROBLEM STATEMENT

Data received From Astrophysical sources

Contains Important Information

What kind of data we

- Spectrum
- Energy vs Flux

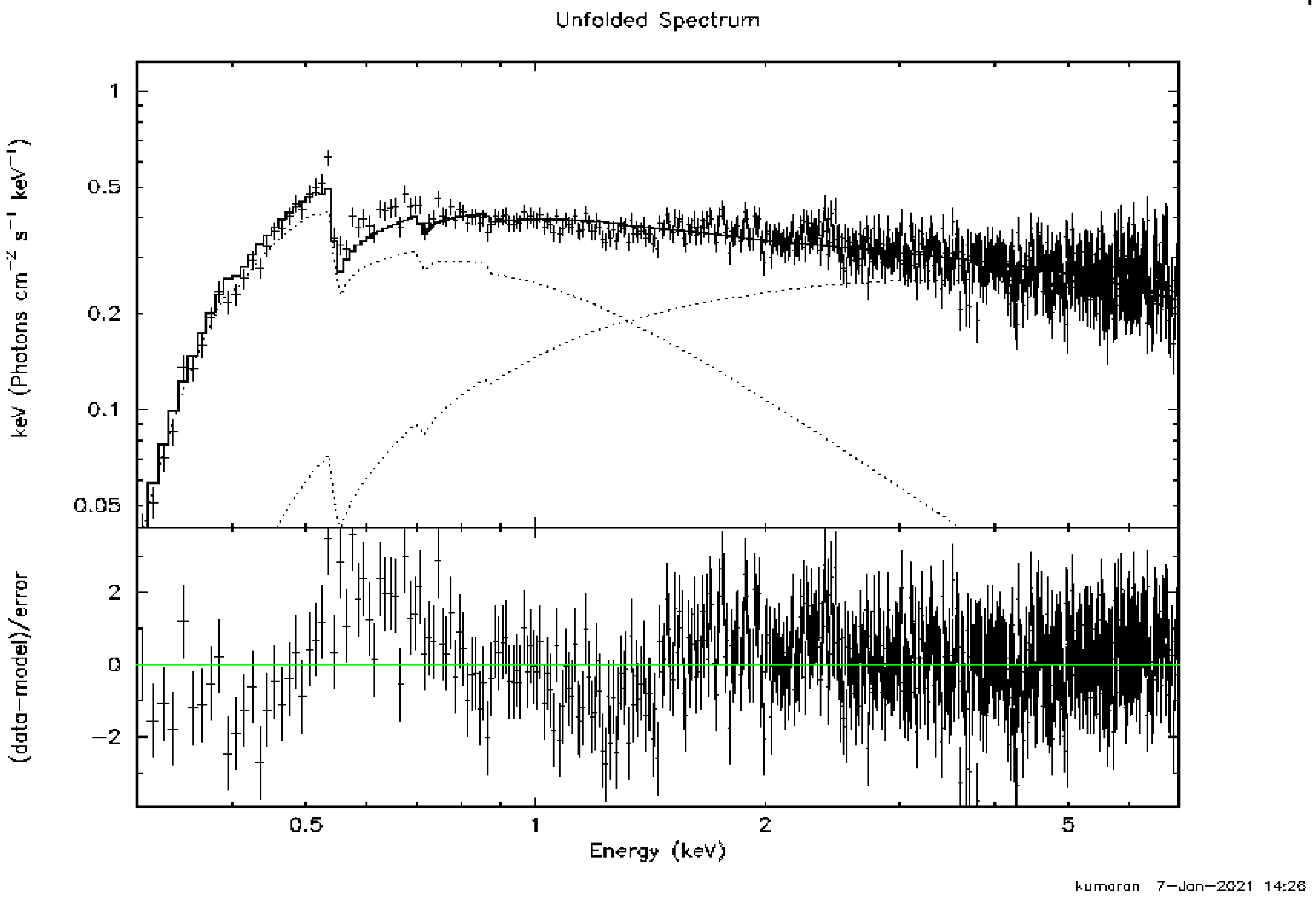
What kind of information

- Source properties
- Type of phenomenon
- Medium properties
- Deep Learning

Deep Learning

- Regression to fit a theocratical model on observed spectrum
- Estimate parameters

PROBLEM EXAMPLE

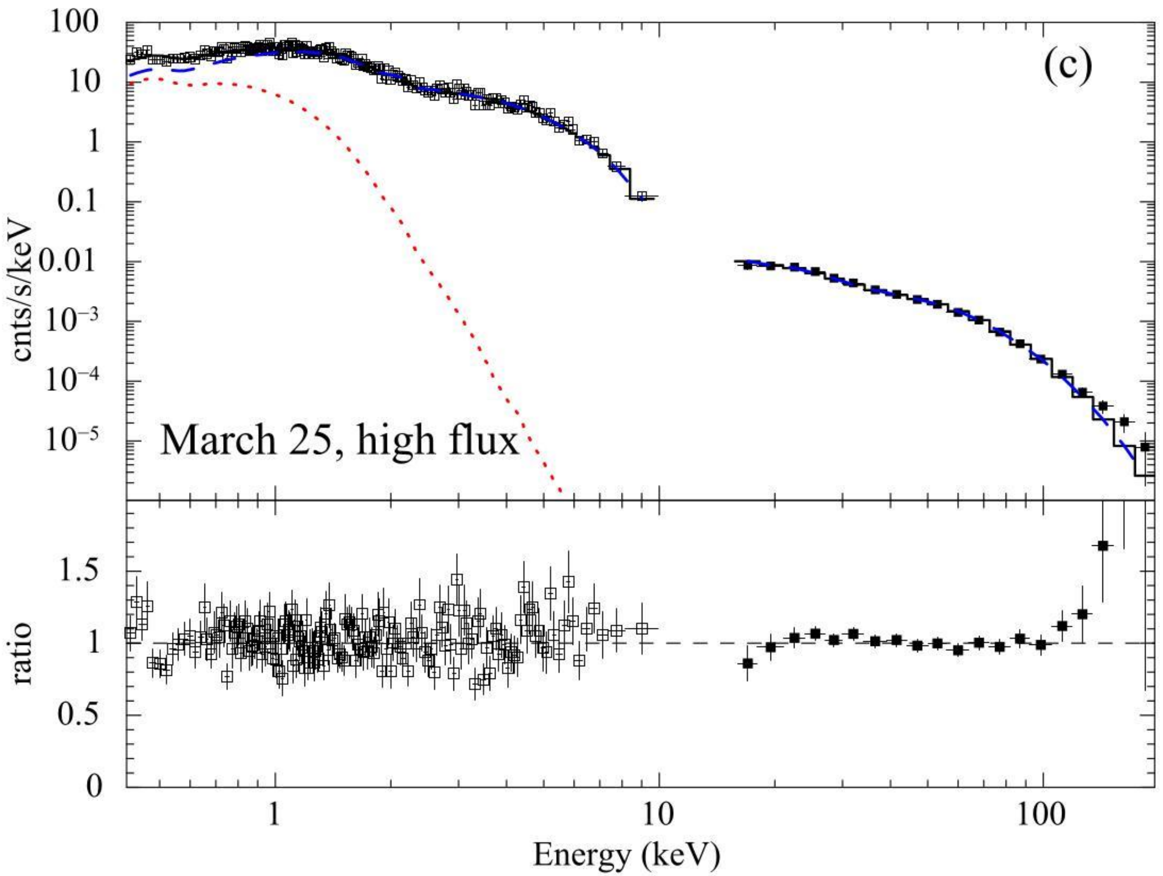


X-ray spectra from x-ray binary MAXI J1820+070. Obtained from SWIFT/XRT
Energy band – 0.3-7.0keV

HOW WE CURRENTLY DO IT

- Based on the suspected model
  - Need to find parameters for that model
- Use **XSPEC** tool For model fitting
  - Grid search
  - Chi-sq minimization
  - ML estimate
- Problems
  - Slow technique
  - Fine hand-tuning of parameter required
  - Local Maxima problem

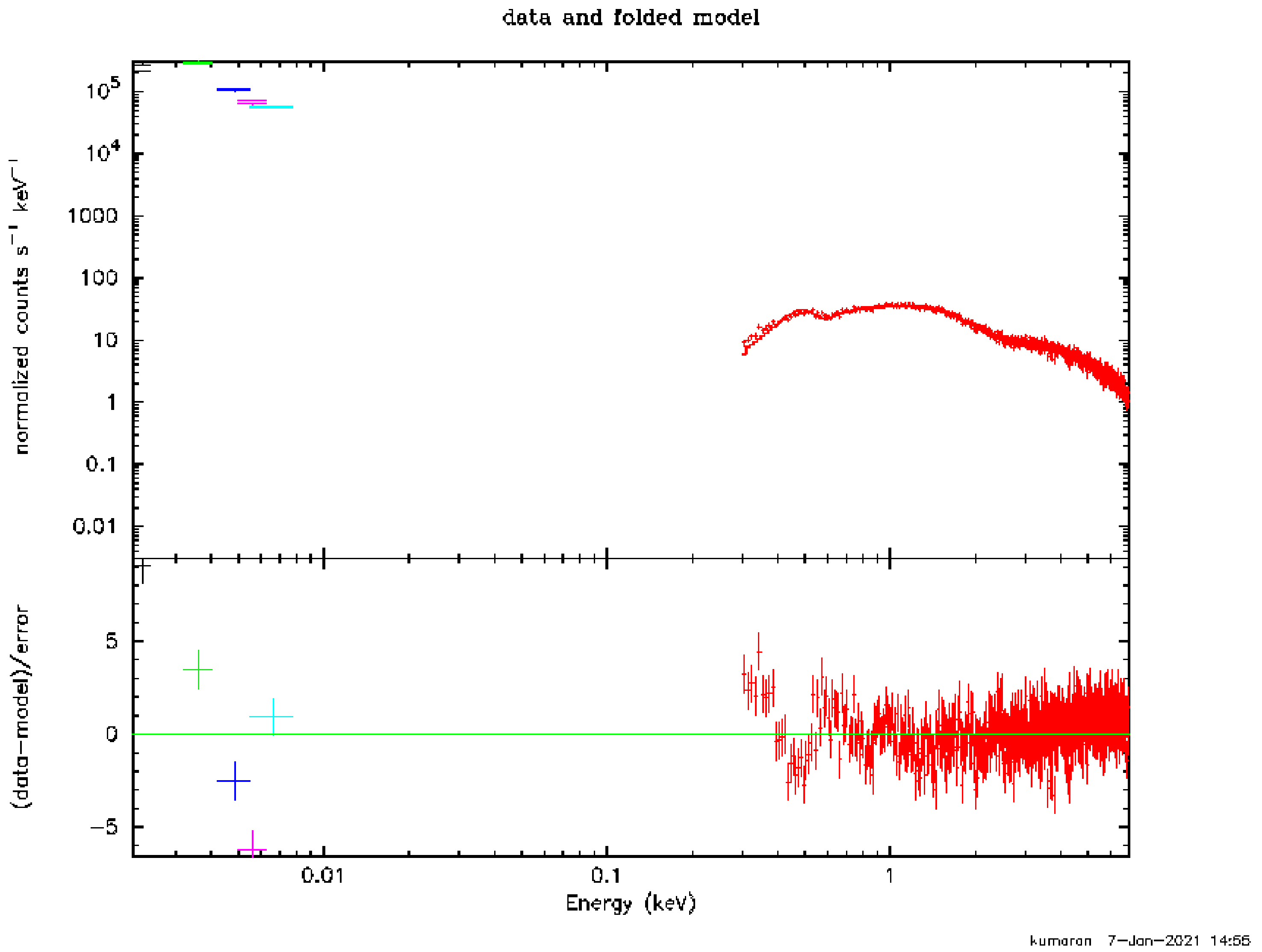
MOTIVATION



X-ray spectra from x-ray binary MAXI J1820+070. Obtained from two satellites MAXI/GSC and SWIFT/BAT
Credit - Shidatsu et al.

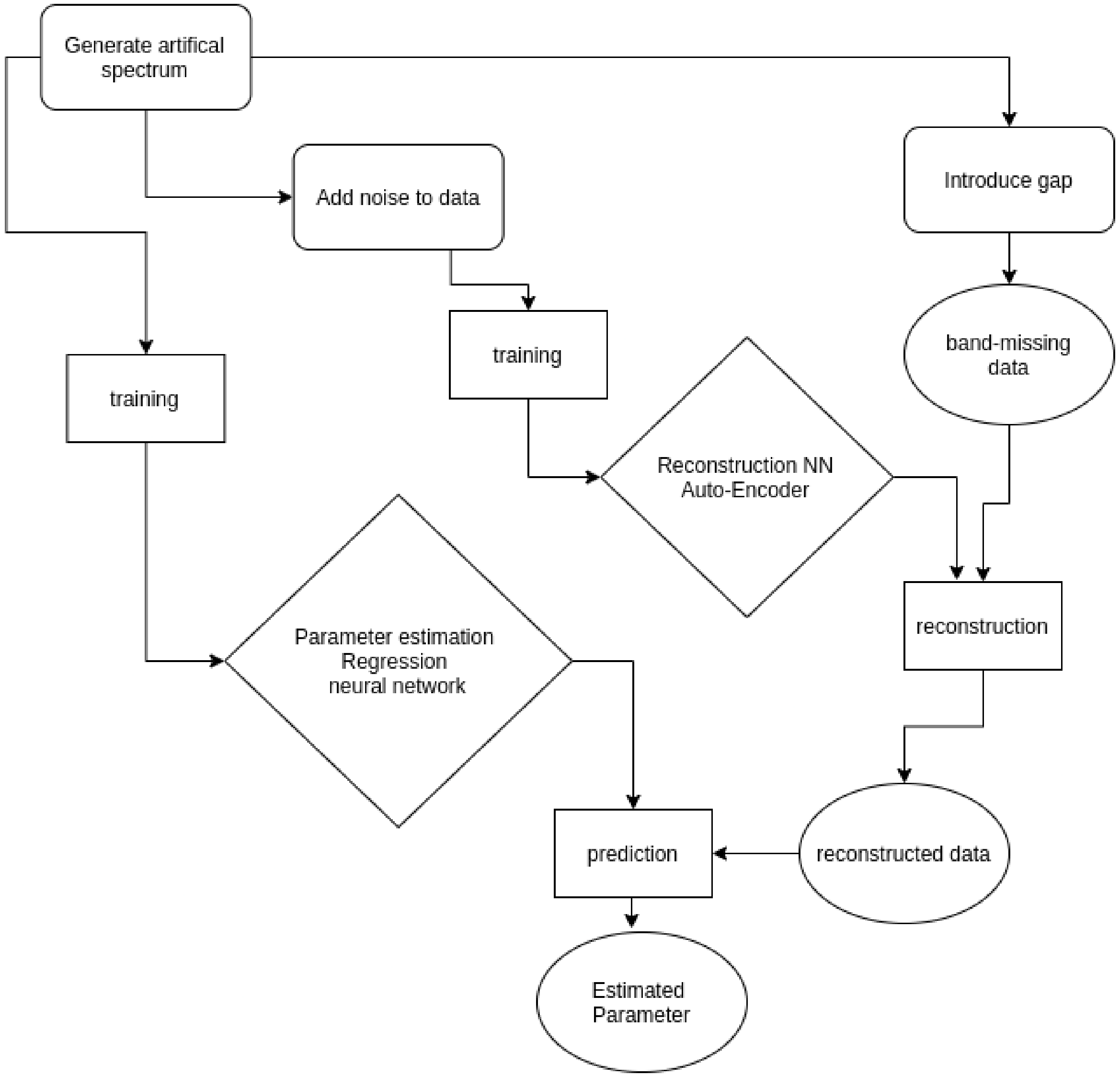
- Broad- Band Spectral Fitting
  - Data is not available in all bands
  - Simultaneous fitting is required
  - Fit separate Model to each band
    - Doesn't make sense
    - Source is same
  - Interpolation is needed
  - Common techniques lacks
    - Information distribution information

MOTIVATION



X-ray spectra from x-ray binary MAXI J1820+070. Obtained from two satellites SWIFT/UVOT and SWIFT/XRT

WORKFLOW


Generate artifical spectrum
Add noise to data
Introduce gap
training
band-missing data
training
Reconstruction NN Auto-Encoder
Parameter estimation Regression neural network
reconstruction
prediction
reconstructed data
Estimated Parameter

DATA GENERATION

SOXS: Simulated Observations of X-ray Sources

SOXS is a software suite which creates simulated X-ray observations of astrophysical sources

$$s = n * (E(1+z))^{-\alpha}$$

- Source Model
  - Powerlaw
- Parameters
  - Z , redshift
    - [0.1 , 2.5] 1000 Normal distribution
  - Alpha ,Photon index
    - [0.5 , 2.5] Normal distribution
  - Norm (n) = 1e-7 (fixed)
- Energy range 0.3-7.0keV
- Energy bins = 128
- Output Vector
  - 128 dimension vector
- No of Spectrum generated – 10000
- Normalized data

REGRESSION MODEL – TRAINING DATA

Outputs obtained corresponding to 128 input energy channels from the power law model

10,000 such output datasets are artificially generated

2 parameters for power law model for each instance

Log normalization done for input data

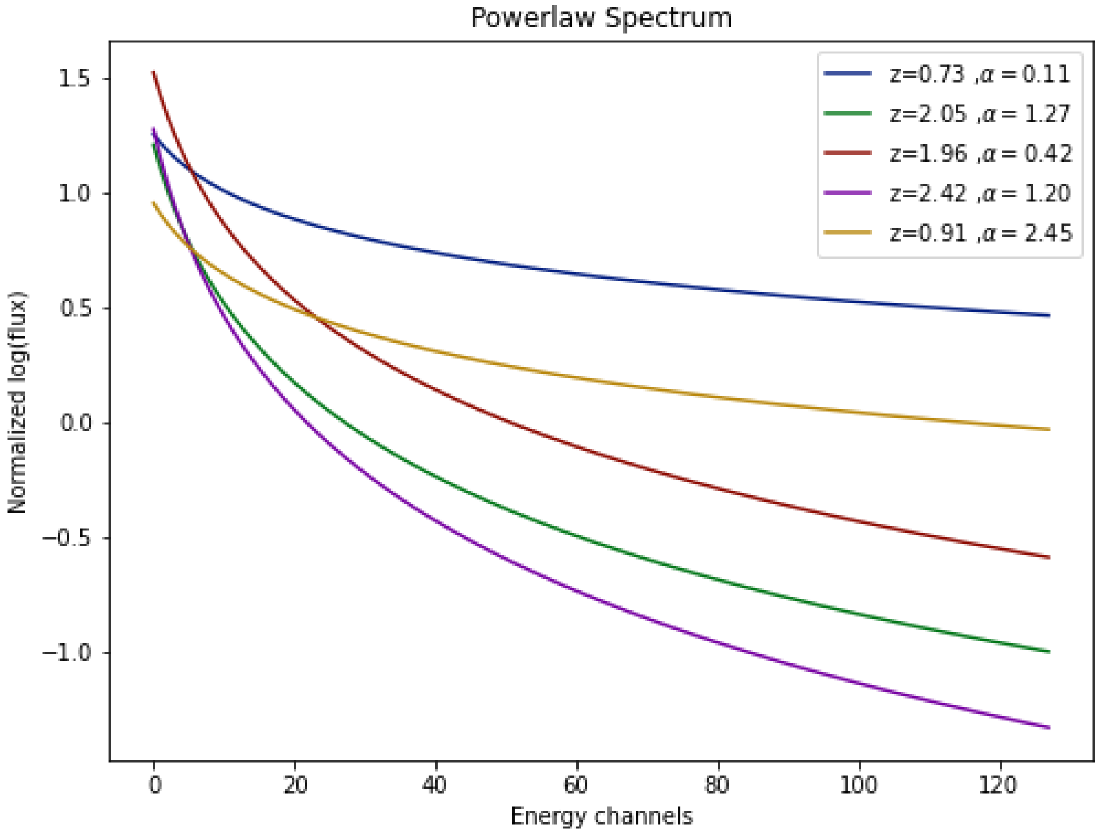


Table 3.1: Data Overview

Input data vector length	128
Target data vector length	2
Number of instances	10000

Table 3.2: Architecture tuning (Loss function: MSE)

Architecture	Training error (MSE)	Testing error (MSE)
128-64-64-32-32-2	3.56e-05	3.48e-05
128-64-64-64-64-2	1.29	1.285
128-32-32-32-32-2	2.581	2.578
128-64-64-2	3.12e-4	3.124e-4
128-32-32-2	1.29	1.294
128-64-32-2	6.34e-4	6.33e-4

Table 3.3: Architecture tuning (Loss function: MAE)

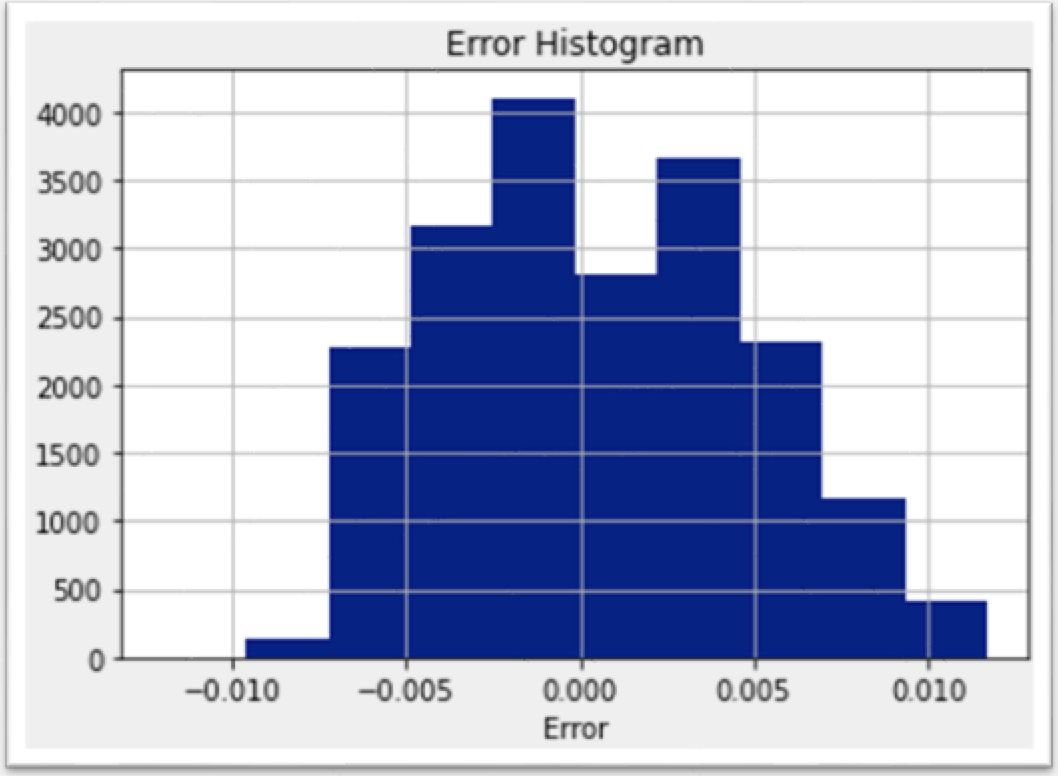
Architecture	Training error (MSE)	Testing error (MSE)
128-64-64-32-32-2	1.29	1.28
128-64-64-64-64-2	9.55e-4	9.77e-4
128-32-32-32-32-2	1.29	1.30
128-64-64-2	9.68e-4	9.58e-4
128-32-32-2	1.42e-4	1.40e-4
128-64-32-2	2.58	2.584

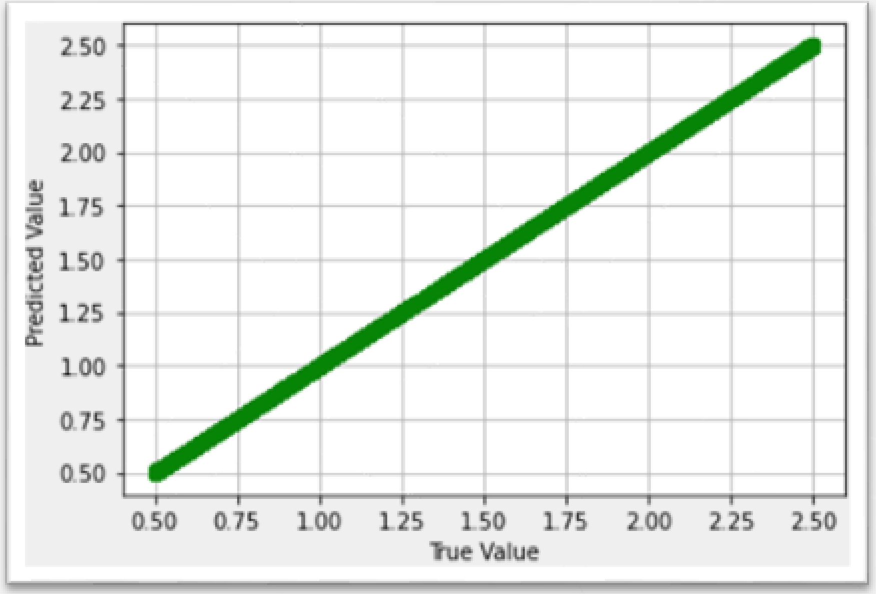
REGRESSION MODEL TRAINING

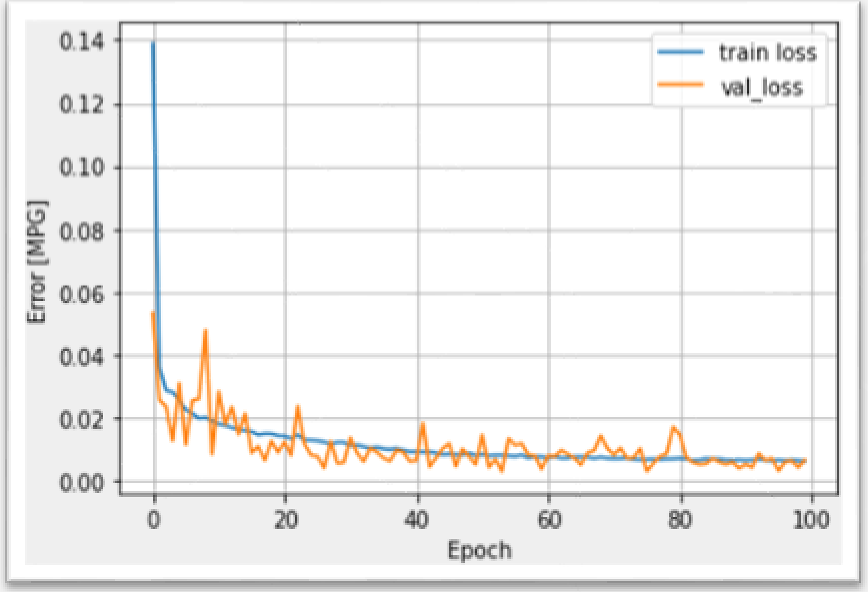
- Train – test split : 80-20%
- Train – validation split : 80-20%
- ADAM Optimizer with a learning rate of 0.001
- ReLu Activated Layers
- Architecture tuning done
- Loss functions : MAE and MSE
- Testing and Training errors calculated using MSE

FINAL REGRESSION NETWORK

- Architecture : 128-64-64-32-32-2
- ReLu activated layers
- Total trainable parameters : 15,618
- ADAM Optimizer with learning rate of 0.001
- MSE Loss function

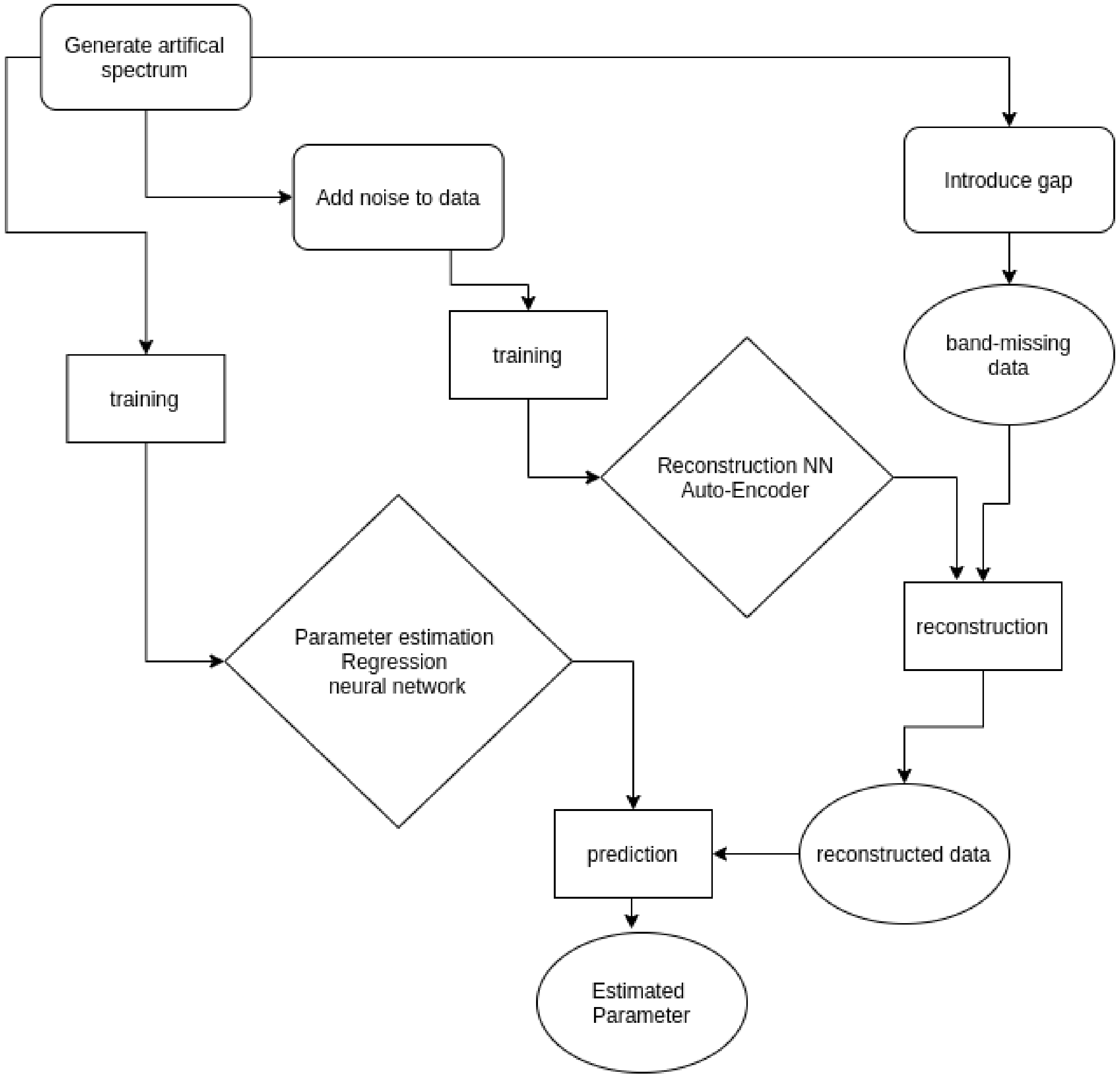






PREDICTION ON ACTUAL EXPECTED DATA

WORKFLOW


Generate artifical spectrum
Add noise to data
Introduce gap
training
training
band-missing data
Reconstruction NN Auto-Encoder
reconstruction
Parameter estimation Regression neural network
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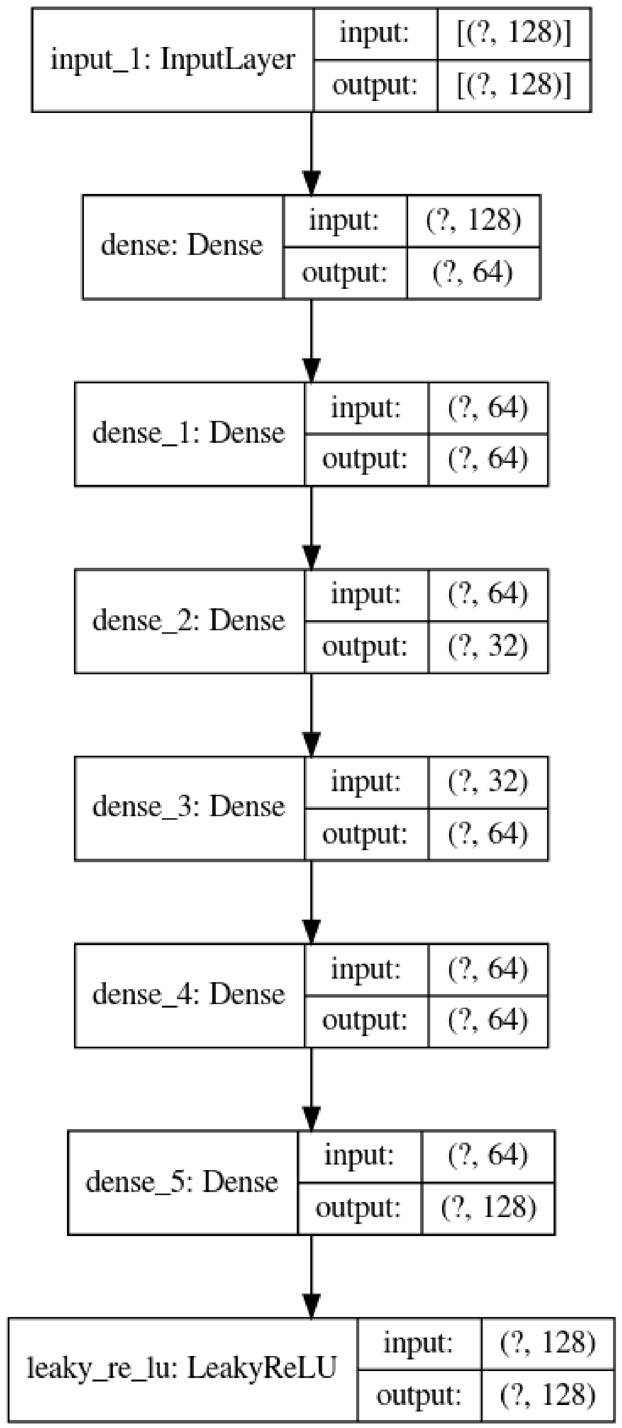
prediction
Estimated Parameter

AUTO-ENCODER

NETWORK STRUCTURE

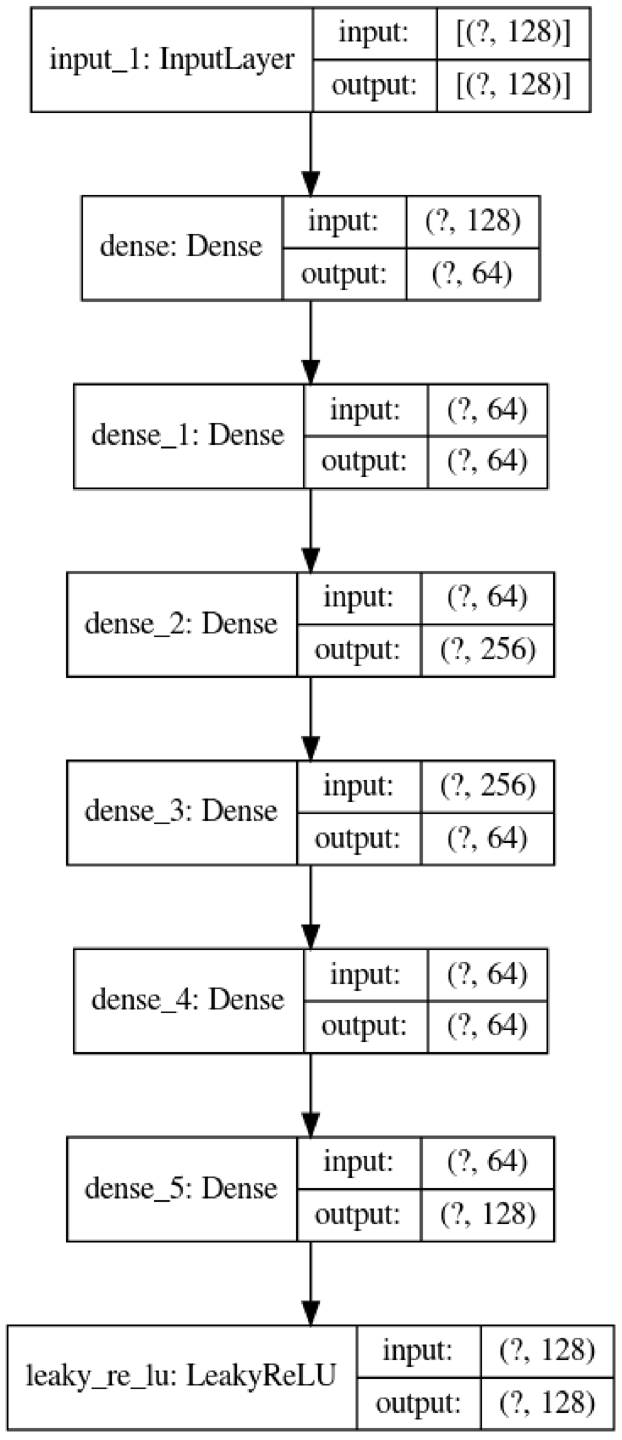
- ADAM Optimizer with learning rate of 0.001
- MSE loss function
- ReLu activated layers
- Training – validation split : 70-30%



DENOISING AUTO-ENCODER

NETWORK STRUCTURE

- ADAM Optimizer with learning rate of 0.001
- MSE loss function
- ReLu activated layers
- Training – validation split : 70-30%



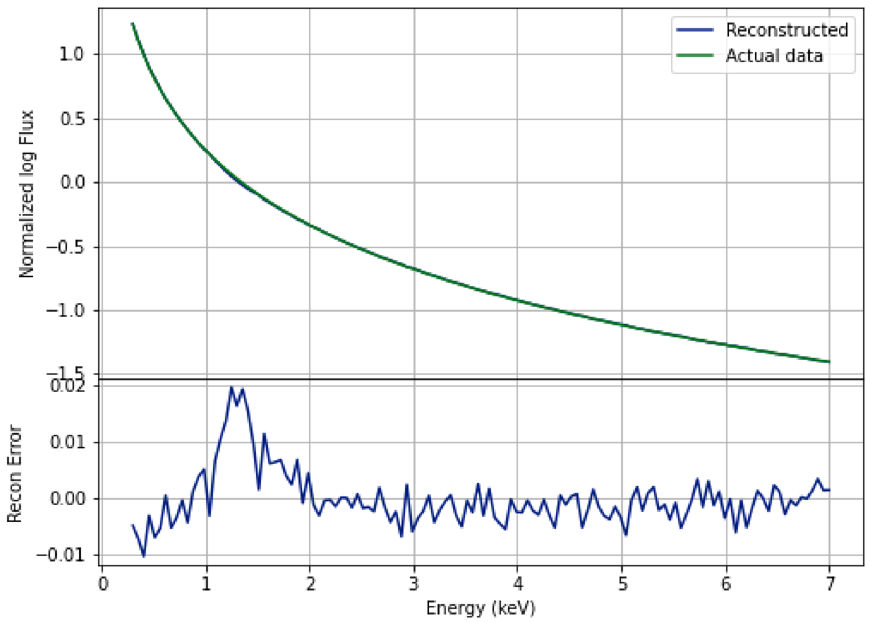
ENCODER

PERFORMANCE STUDY METHODOLOGY

- Original training and test data
  - Use encoder reconstructed output
  - Find training and testing loss
  - Predict the parameter on original test data and reconstructed test data
  - Find prediction loss
- Simulate gap in the data
- Fill this gap with random noise
- Find reconstruction loss
- Predict parameter on:
  - Full-band data
  - Missing data
  - Noise-filled data
  - Reconstructed data
  - Find prediction loss

ENCODER

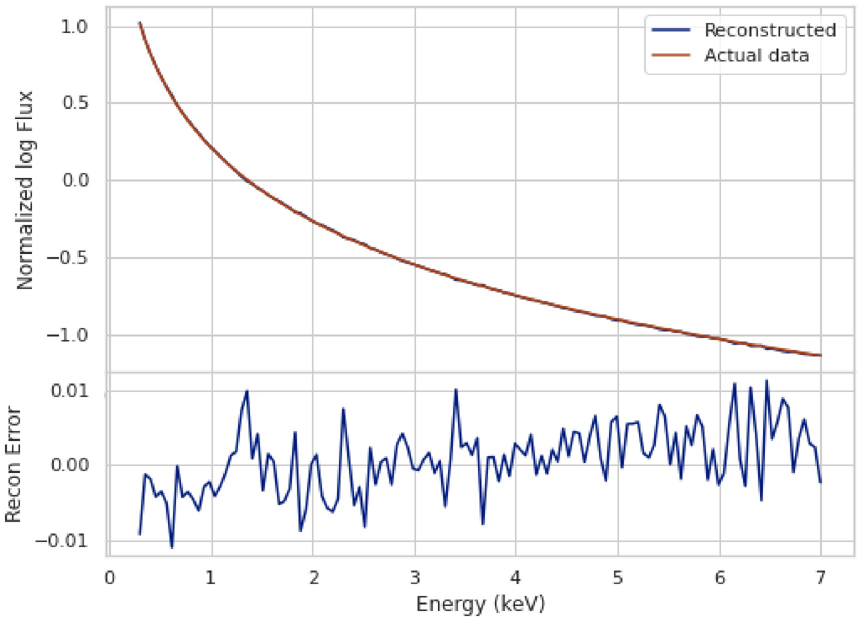
RECONSTRUCTION PERFORMANCE ON FULL-BAND DATA



Auto-Encoder

Reconstruction LOSSES

- On reconstructed data
  - Training - 1.2022e-05
  - Testing - 1.1786e-05



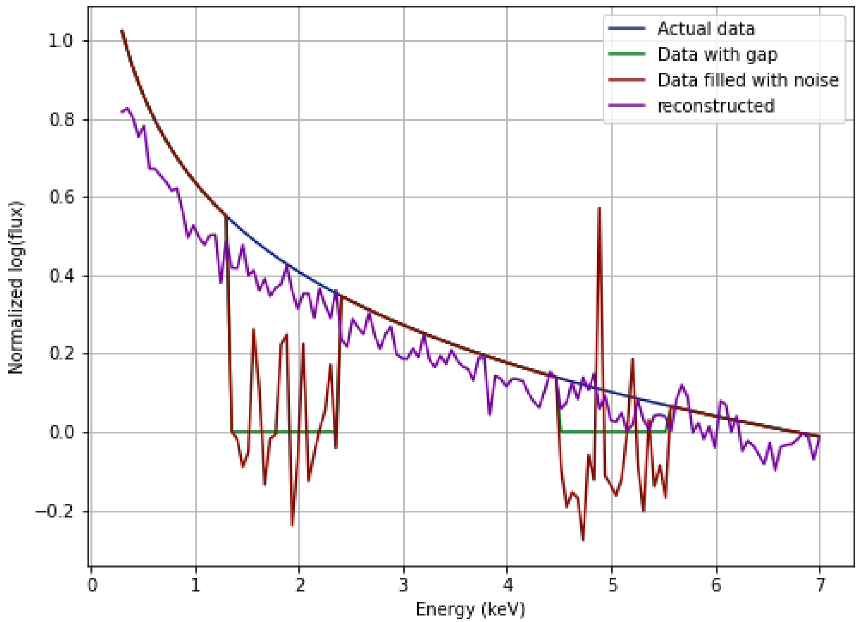
Denoising Auto-Encoder

Denoising Auto-Encoder
Reconstruction LOSSES

- On reconstructed data
  - Training – 0.000637
  - Testing – 0.000650

ENCODER

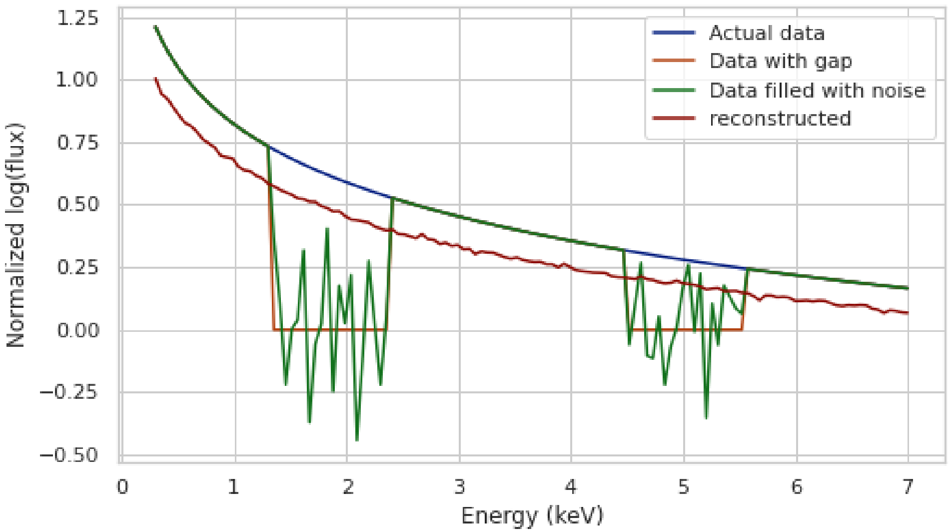
RECONSTRUCTION PERFORMANCE ON MISSING-BAND DATA



Auto-Encoder

Reconstruction LOSSES

- On reconstructed data
  - Training - 0.0224
  - Testing - 0.03268



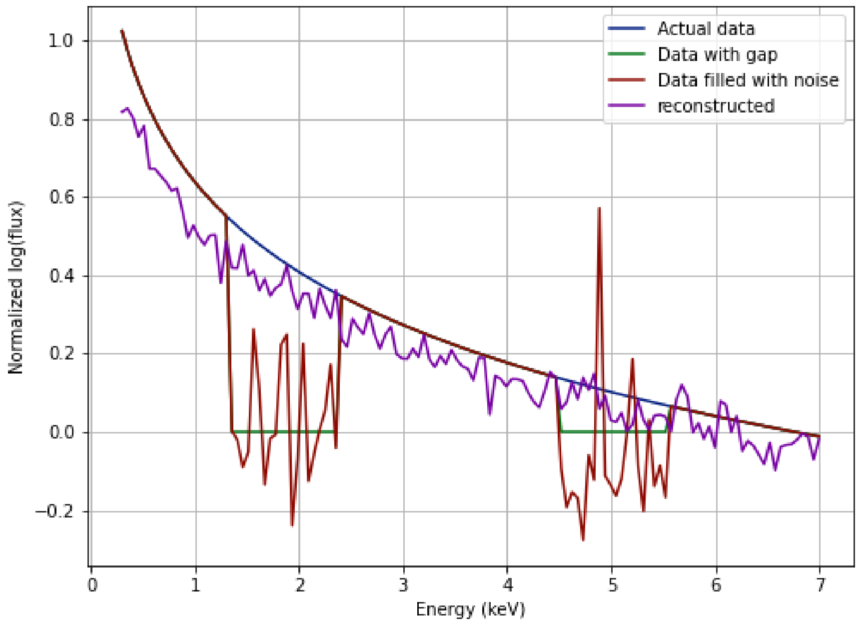
Denoising Auto-Encoder

Reconstruction LOSSES

- On reconstructed data
  - Training – 0.02024
  - Testing – 0.0244

ENCODER

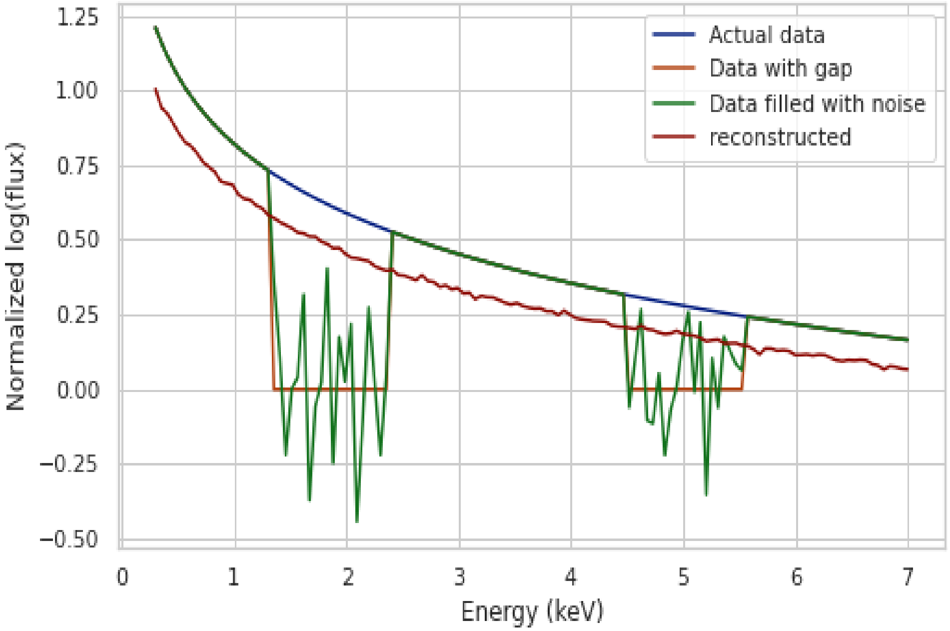
PARAMETER PREDICTION PERFORMANCE ON MISSING-BAND RECONSTRUCTED DATA



Auto-Encoder

Parameter estimation LOSSES
- On Missing data
  - Testing – 3.23

Parameter estimation LOSSES
- On reconstructed data
  - Test dataset– 3.18

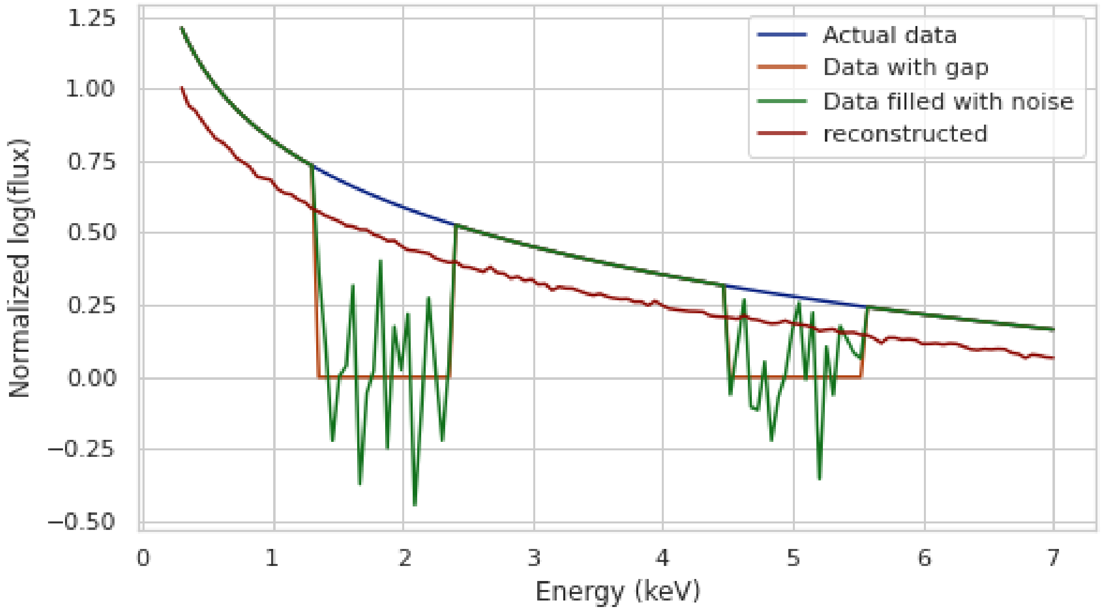


Denoising Auto-Encoder

Parameter estimation LOSSES
- On Missing data
  - Testing – 3.23

Parameter estimation LOSSES
- On reconstructed data
  - Test dataset– 0.392

MAKING DAE BETTER

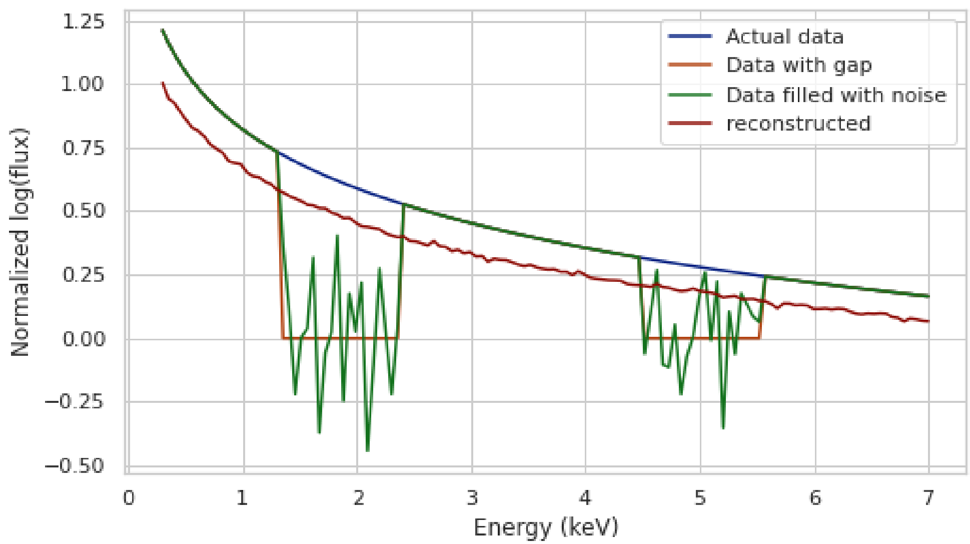


IMPROVING RECONSTRUCTION

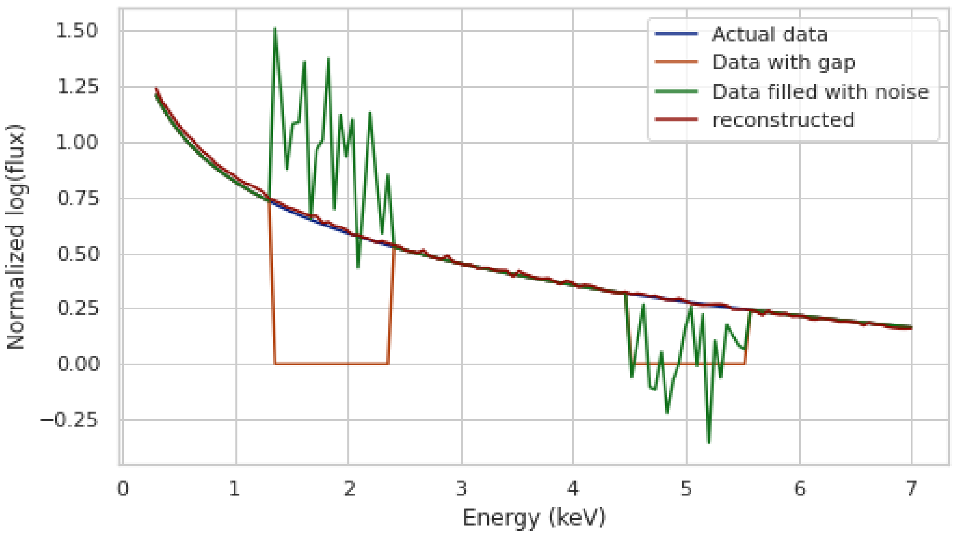
- Reconstruct data from band-missing data
- In the missing region of the band-missing data add the generated data
- Do reconstruction on this data
- Estimate parameters
- Repeat this process again

ENCODER

PARAMETER PREDICTION PERFORMANCE ON MISSING-BAND RECONSTRUCTED DATA



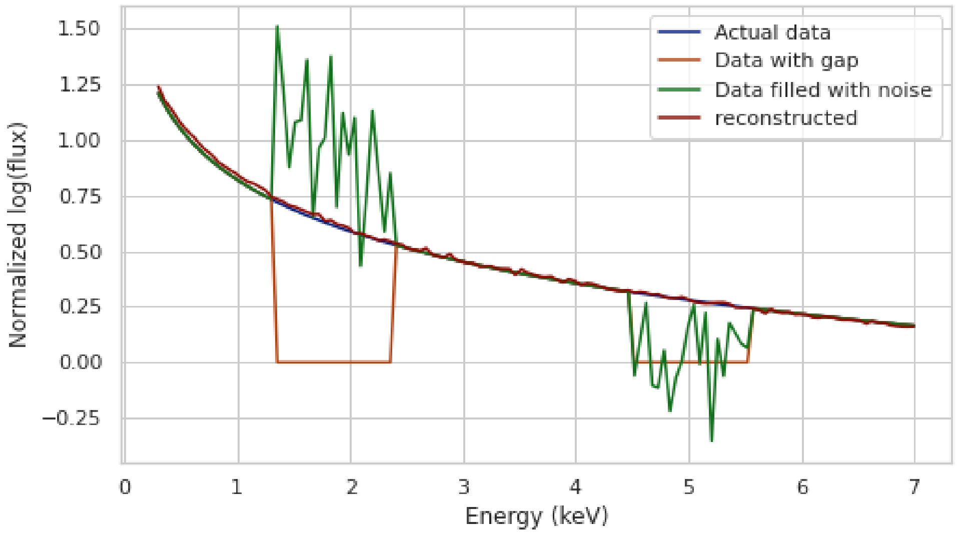
Parameter estimation LOSSES
- On reconstructed data
    - Testing – 0.3924



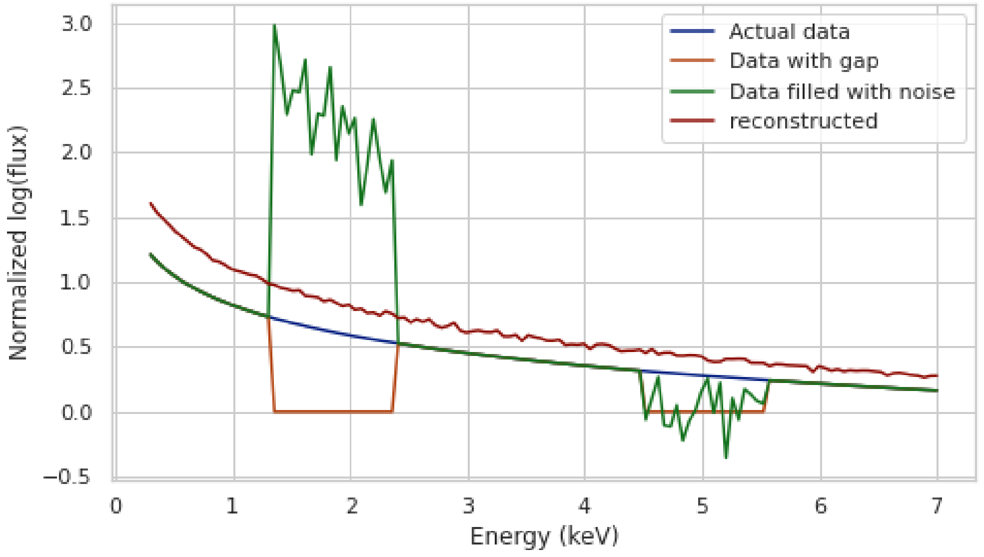
Parameter estimation LOSSES
- On reconstructed data
    - Testing – 0.1474

ENCODER

PARAMETER PREDICTION PERFORMANCE ON MISSING-BAND RECONSTRUCTED DATA



Parameter estimation LOSSES
- On reconstructed data
    - Testing – 0.1474



Parameter estimation LOSSES
- On reconstructed data
    - Testing – 0.6819

CONCLUSION

AND FUTURE WORK SCOPE

1. Regression Neural network (Fully connected network) is designed for parameter estimation
2. Denoising Auto encoder successfully reconstructed data in the missing band.
3. DAE clearly shown much better performance on faithful reconstruction than simple autoencoder.
4. Performance improvement is achieved by using 2 phase of reconstruction

FUTURE SCOPE

1. Generalize the whole workflow for other models
2. Try other generative models
3. Create a software package to incorporate XSPEC model fitting algorithm

REFERENCES

1. Badr, W., 2019. Auto-Encoder: What Is It? And What Is It Used For?(Part 1). *Towards Data Science. Online: https://towardsdatascience. com/auto-encoder-whatis-it-and-what-is-it-used-for-part-1-3e5c6f017726 (Zugriff: 22.02. 2020)*.
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