Solving Inverse Problems for Spectral Energy Distributions with Deep Generative Networks

National Technical University of Athens

European University Cyprus

Agapi Rissaki[1] Orestis Pavlou[2] Dimitris Fotakis[1] Vicky Papadopoulou[2] Andreas Efstathiou[2]

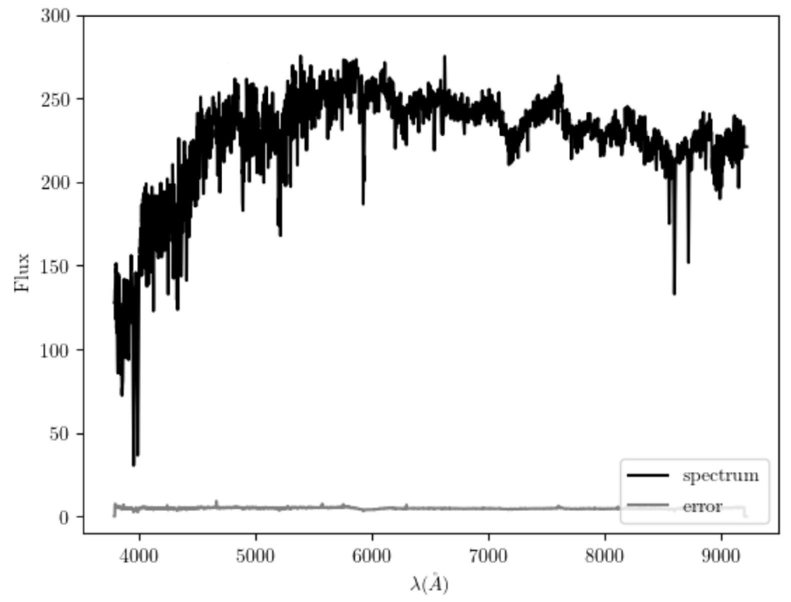
1: National Technical University of Athens
2: European University Cyprus

What is this about?

Task

❖ Spectral Energy Distributions (SEDs) :
- Energy measurements of astronomical objects, for different wavelengths
- Useful to discover properties and evolution of astronomical objects
- Noise/Interference/Expensive Measurement Procedure => erroneous/incomplete samples

❖ Goal:
- Correct/Enhance SEDs via Deep Learning => generalization + robustness
- Idea: Deep Generative Model as Structural Prior
- Properties such as high-frequency and irregularity of SEDs => potential challenge for deep learning



https://www.astroml.org/

3-Step Approach

1) Preprocessing step -> create a complete dataset, *iterative PCA*
2) Train a Deep Generative Model
3) Test-time Reconstruction from incoming *noisy*/incomplete samples

The Method

Formulation

Given (noisy) linear measurements y (m-dimensional) , via a known procedure A
Goal to reconstruct x* (d-dimensional)

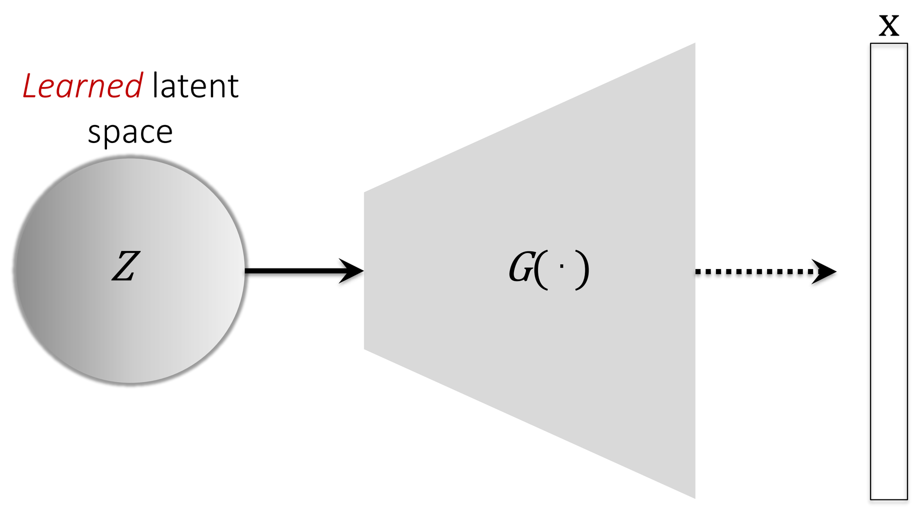
$$y = Ax^* + \eta$$

=> Compressed Sensing (d>>m)

Also, the formulation models realistic inverse problems *e.g.*, denoising, inpainting, super-resolution

The Generative Network

Generative Latent Optimization aka GLO



Optimizing the parameters of G along with the *latent space* to reconstruct the training data , with a simple reconstruction loss L and backpropagation:

$$\min_G \frac{1}{N} \sum_{i=1}^{N} \min_{z_i \in \mathcal{Z}} [\mathcal{L}(G(z_i), x_i)]$$

To impose *structure in latent space* during training, project the *latent codes* onto the *unit sphere.*

Reconstruction Methods

Estimate a latent code by minimizing the *measurement error* (backpropagation) =>
corresponds to a signal in the domain of G that *approximately agrees with the measurements*

$$\hat{z} = \arg\min_{z \in \mathcal{Z}} \frac{1}{m} ||AG(z) - y||_2^2 \qquad \hat{z} = \arg\min_{z \in \mathcal{Z}} \frac{1}{m} ||AG(z) - y||_2^2 + \lambda ||z||_2^2$$

(**a**) Explicit projection onto the unit sphere

(**b**) Implicit regularization with extra regularization term

The Setup

Data

❖ Sloan Digital Sky Survey or SDSS Corrected Spectra dataset by the astroML library
- SEDs of *4000 galaxies*, moved to restframe
- Preprocessed with *iterative PCA*
- Resampled to 1000 wavelengths (3000 - 8000Å)

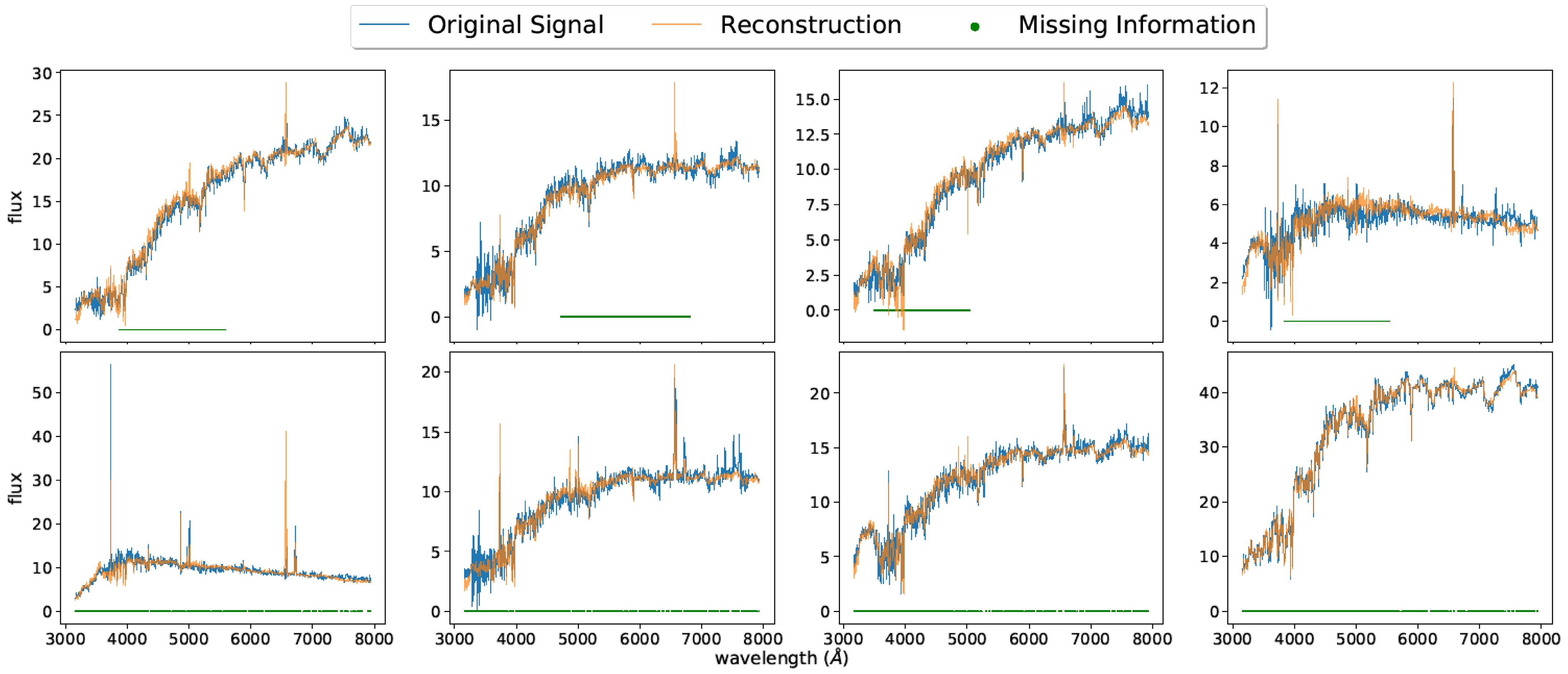
❖ The original dataset consists of innately incomplete and/or corrupted SEDs => lack of ground truth

Training

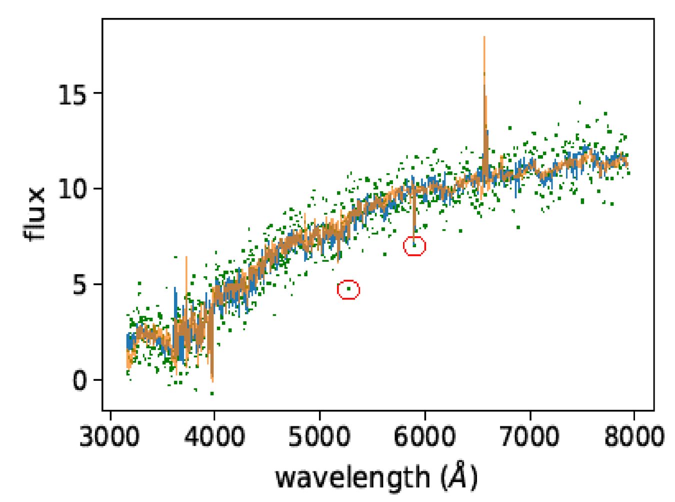
❖ Training setup:
- Architecture: 7-layer feed-forward network with leakyReLU activations, 50-dim latent space
- Optimization: Adam, 10000 epochs, batches of 64 SEDs
- Learning rate: 0.1 for the network - 0.01 for the latent codes
- Reconstruction loss: Mean Squared Error (MSE)

❖ Reconstruction setup similar to training, *limited to 1000 epochs*.

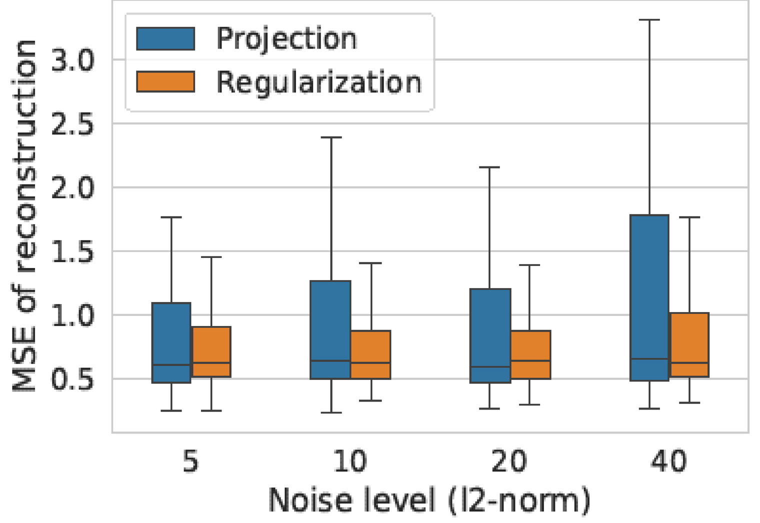
Some Preliminary Results



➢ Reconstruction for 40% missing information
(TOP) Inpainting: measurements are missing in a continuous window
(BOTTOM) Super-resolution: randomly selected measurements are missing



➢ Reconstruction from noisy signal
Denoising: removing added noise drawn by a normal distribution



➢ MSE of reconstruction for 100 randomly selected SEDs on:

(LEFT) Inpainting, for different levels of missing information (%) => displays generalization capability

(RIGHT) Denoising, for different levels of added noise (l2-norm) => regularization appears more flexible