Denoising simulated Roman grism images for faint, high-redshift quasars with U-Net model

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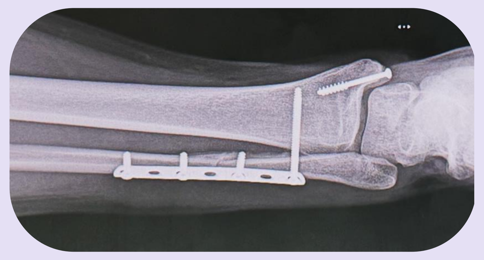

Figure 9. Unfortunately, I am unable to attend the poster session due to injury, but please reach out!

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Why study faint, high-redshift quasars?

- Reionization: probing into redshift of z > 6 provides insight on the first galaxies that ionized the universe.
- Early black holes: high-redshift quasars give hints to early universe active galactic nuclei formation and evolution. [1]
- Galaxy dynamics: observations of early universe quasars challenge our understanding of early galaxy formation and evolution.

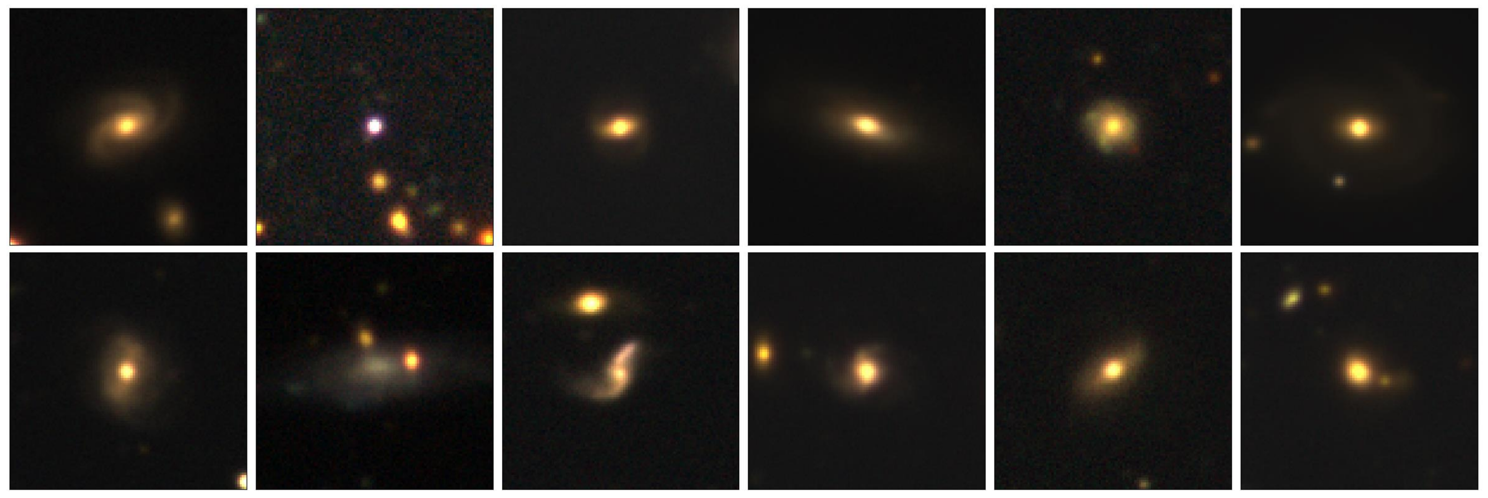

Figure 1. Active galactic nuclei sources in low redshift (z < 5) in I, R, G bands.

Why Roman Grism?

- Grism (grating + prism) on-board Roman allows for slitless multi-object spectroscopy
- Designed to maximize (1,1) efficiency
- In grism images, photon noise (from zodiacal + thermal background) drown out high redshift, faint sources (J-band magnitude greater than ~25) (Fig. 2)
- Noiseless Roman grism images simulated with ESpRESSO [2]

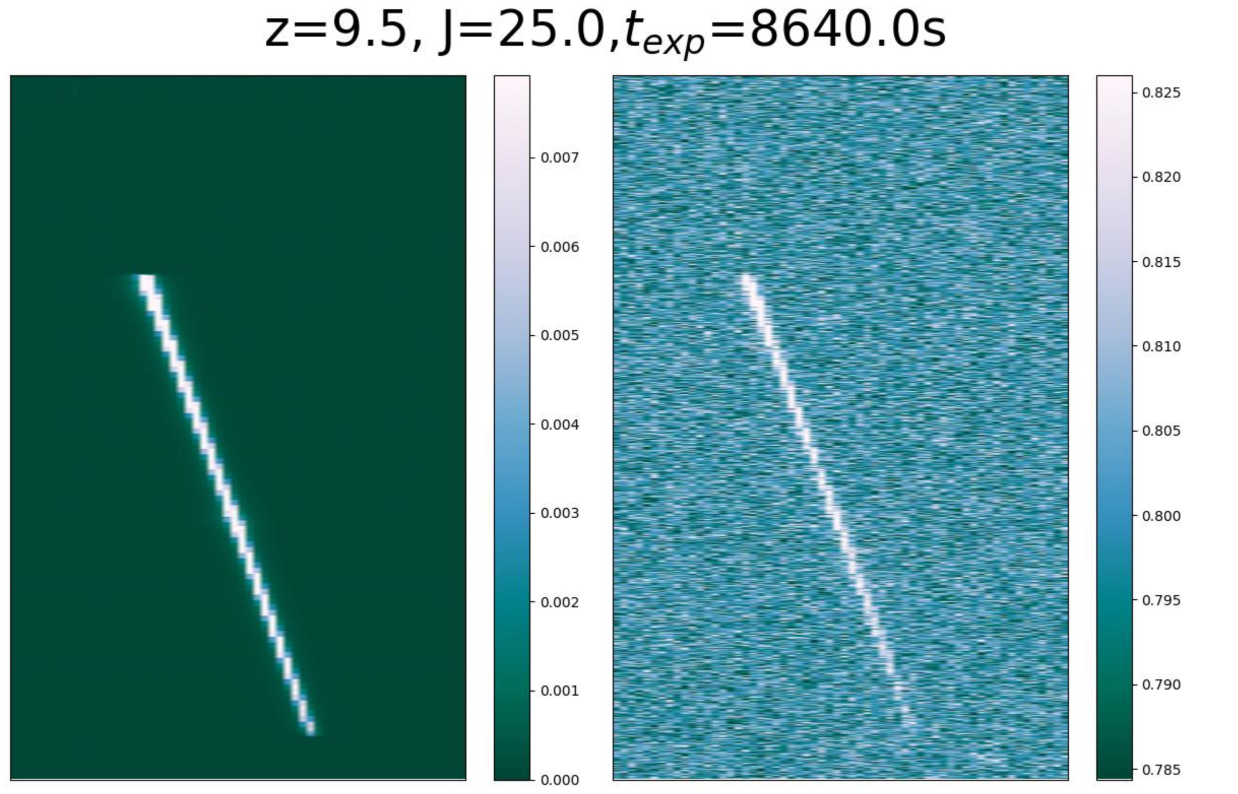

Figure 2. Example simulated grism trace before and after adding Gaussian and Poisson noise according to expected photon noise, for a source of z = 9.5, J = 25.0, and exposure time of 8640 seconds.

Denoising with U-Net

- Trained probabilistic diffusion model with U-Net-backed reverse process (denoising) in this work [3][4]
- U-Net features symmetric convolutional and up-convolutional blocks (Fig. 4)

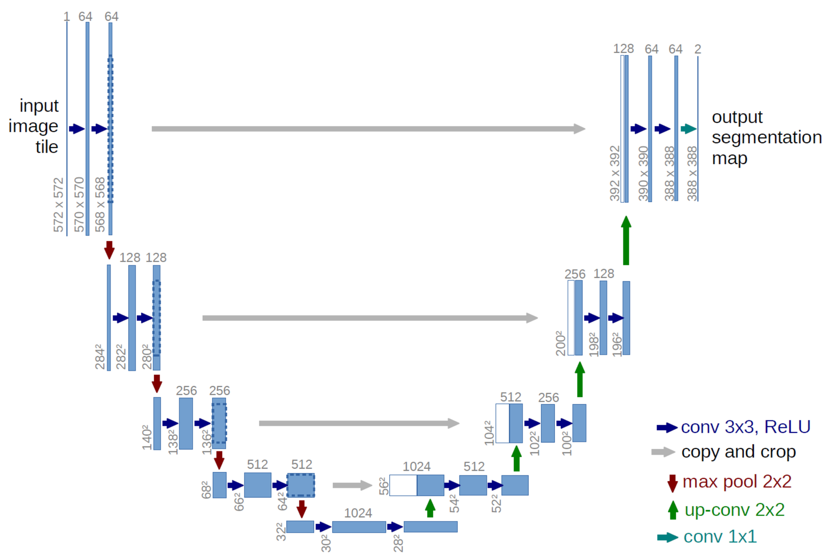

Figure 4. Example U-Net architecture with the same number of convolutional blocks as this work. [2]

- U-Net is commonly used ML architecture for image segmentation and iterative image denoising
- Forward process gradually adds noise. In reverse process, U-Net model learns to iteratively subtract noise to retrieve underlying signal. (Fig. 5)

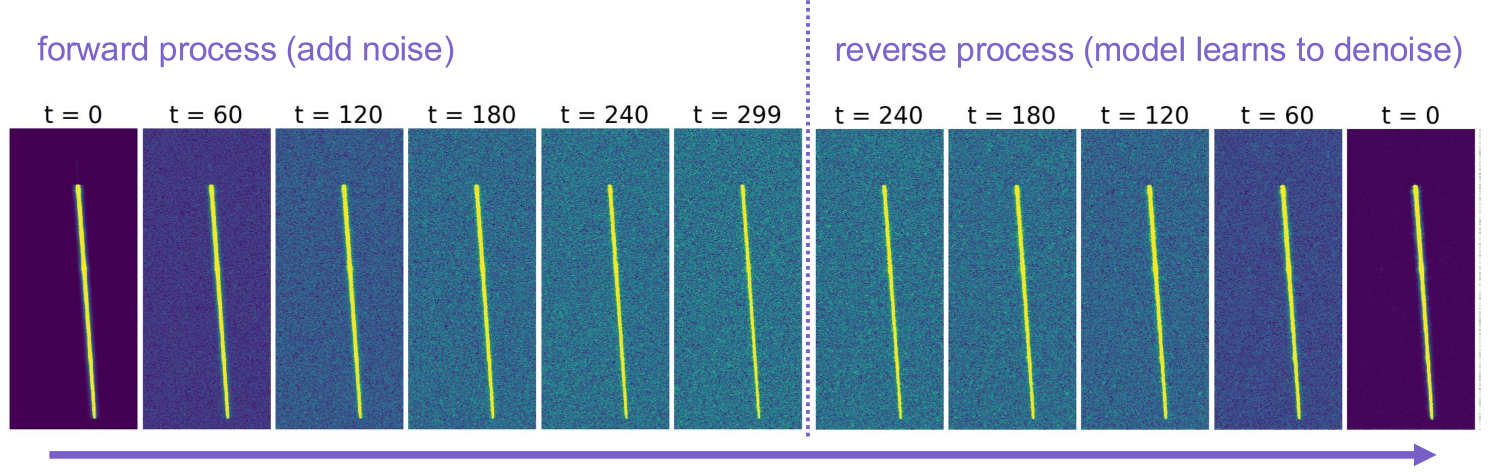

Figure 5. Example denoising process of simulated source with z = 9.5 and J = 25 showing the forward (iterative noise addition) and reverse (iterative denoising) process used to train the denoising model.

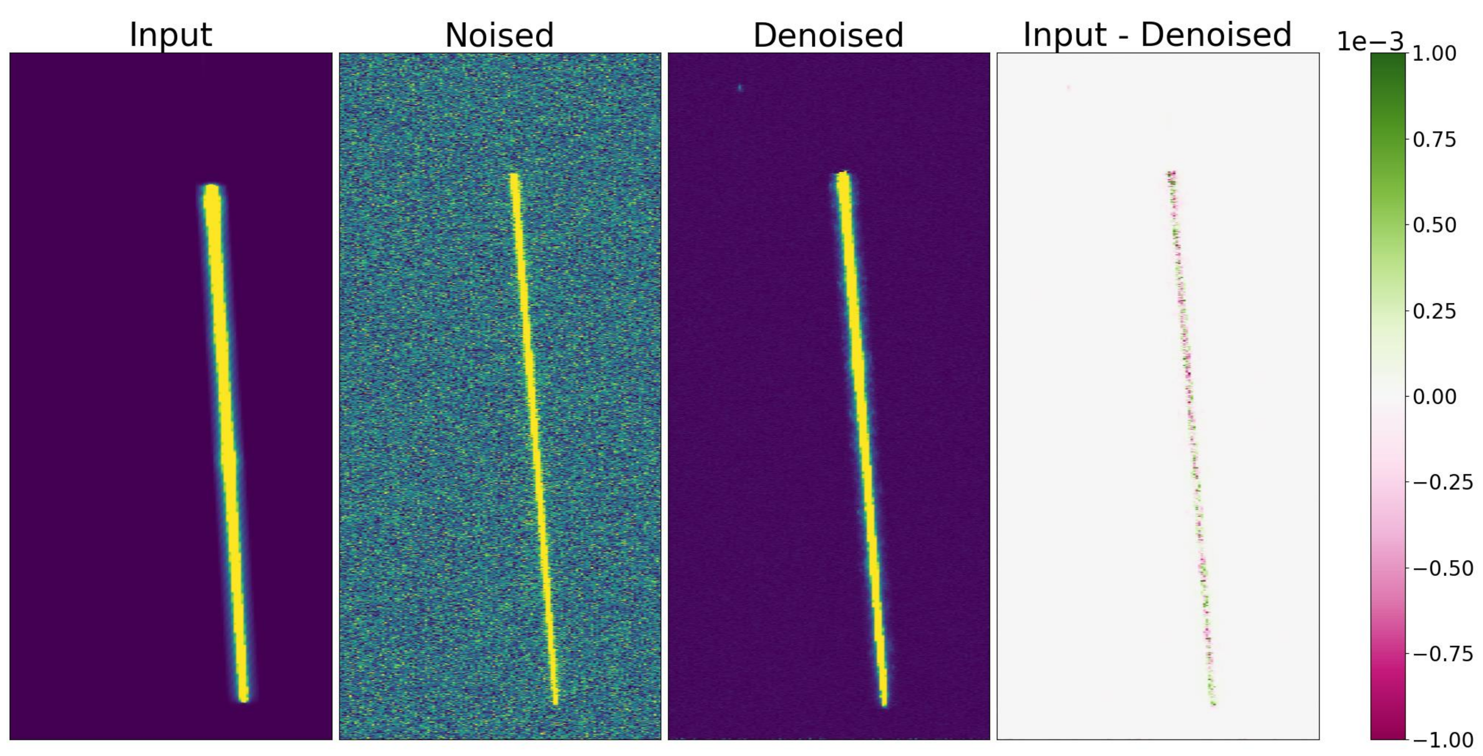

Figure 6. Simulated source with z = 9.5 and J = 25, the panels respectively show the input noiseless trace, the noise-added trace, the ML-denoised trace, and finally, the difference between the input and denoised images.

Findings and Evaluation

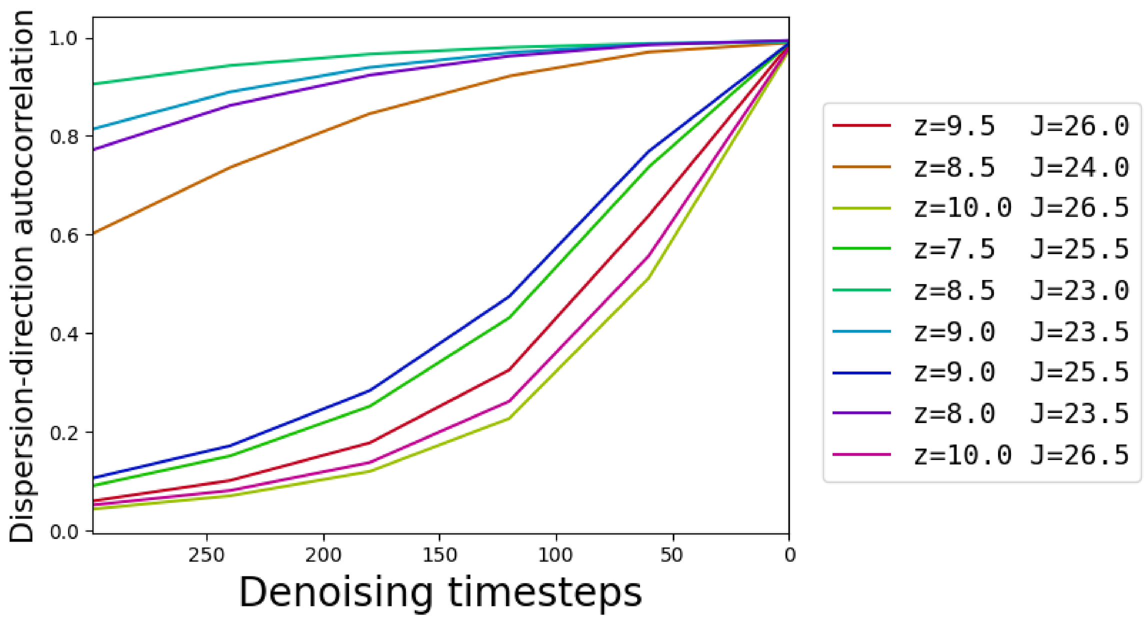

Figure 7. Pixel-level Pearson autocorrelation coefficient in the dispersion direction of the trace for selected sources over denoising timesteps. A Pearson autocorrelation coefficient closer to +1.0 means that neighboring pixels are positively linearly correlated with one another.

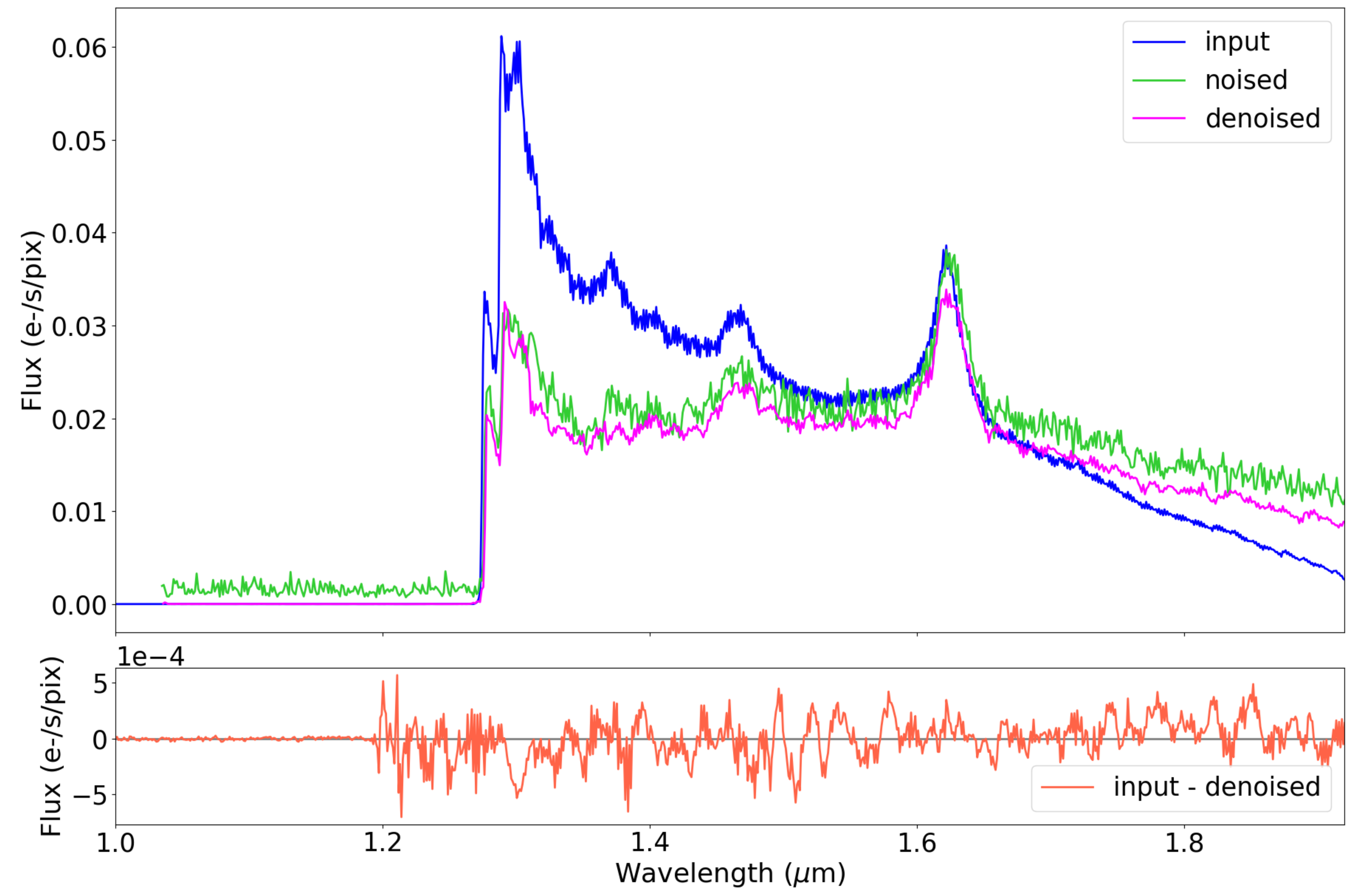

Figure 8. *Top*: Optimally extracted spectra from input, noised, and denoised grism images. *Bottom*: Optimally extracted spectra from the subtracted image between the input and the denoised images. [5]

Conclusions

- Trained U-Net that can recover spectral features in input noiseless data from noised image >1 magnitude deeper
- Future work: recovery of faint post-Lyman break features in 2D trace; addition of correct response function in spectra.

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