Predicting galaxy spectra from images with hybrid convolutional neural networks

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Abstract

Galaxies can be described by features of their optical spectra such as oxygen emission lines, or morphological features such as spiral arms. Although spectroscopy provides a rich description of the physical processes that govern galaxy evolution, spectroscopic data are observationally expensive to obtain. For the first time, we are able to robustly predict galaxy spectra from broad-band imaging.

We present a powerful new approach using a hybrid convolutional neural network (CNN) with deconvolution instead of batch normalization; this hybrid CNN outperforms other models in our tests. The learned mapping between galaxy images and spectra will be transformative for future wide-field imaging surveys, such as with the Vera C. Rubin Observatory and *Nancy Grace Roman Space Telescope*, by multiplying the scientific returns for spectroscopically-limited galaxy samples.

Context

Galaxies are shaped by the physics of their stars, gas, dust, central supermassive black hole, and dark matter. These physical processes leave imprints on galaxies' appearances, which can be captured in telescope imaging; similarly, they are manifest in galaxies' spectral features revealed by spectroscopic observations. Both perspectives are critical for understanding how galaxies grow and evolve (e.g., Figure 1). While modern telescopes can obtain deep imaging for large numbers of galaxies at once, spectroscopy at scale is prohibitively costly. We present a novel method for obtaining estimates of the spectra solely from image cutouts.

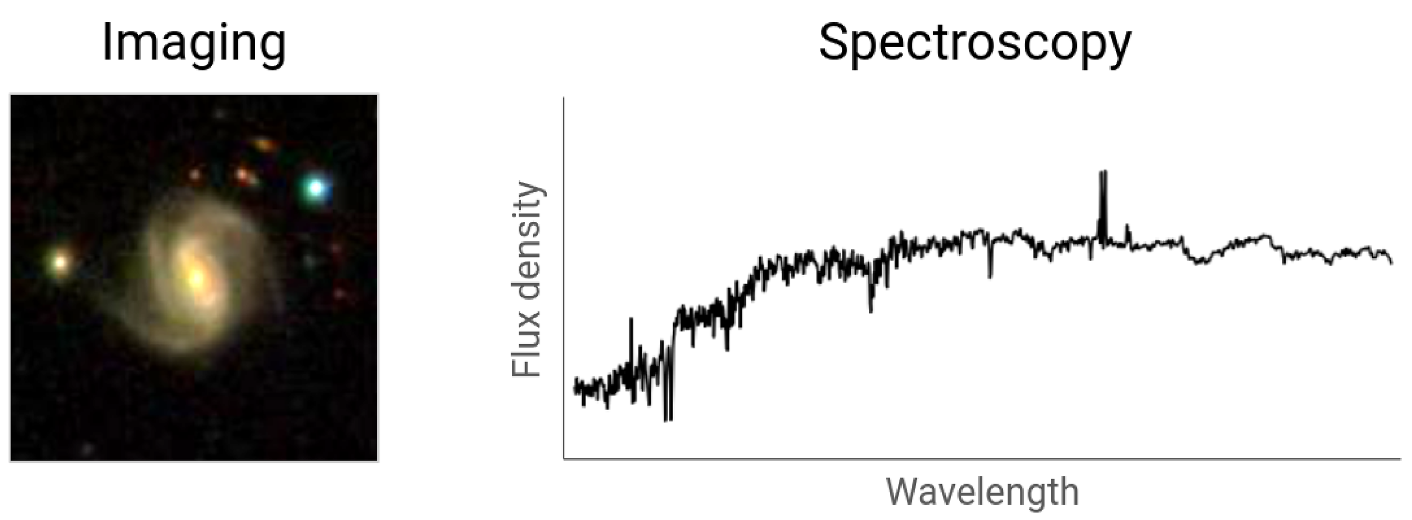

Figure 1: Two views of the same galaxy: a multi-channel (color) image and an optical-wavelength spectrum.

Code is available at github.com/jwuphysics/predicting-spectra-from-images

Method

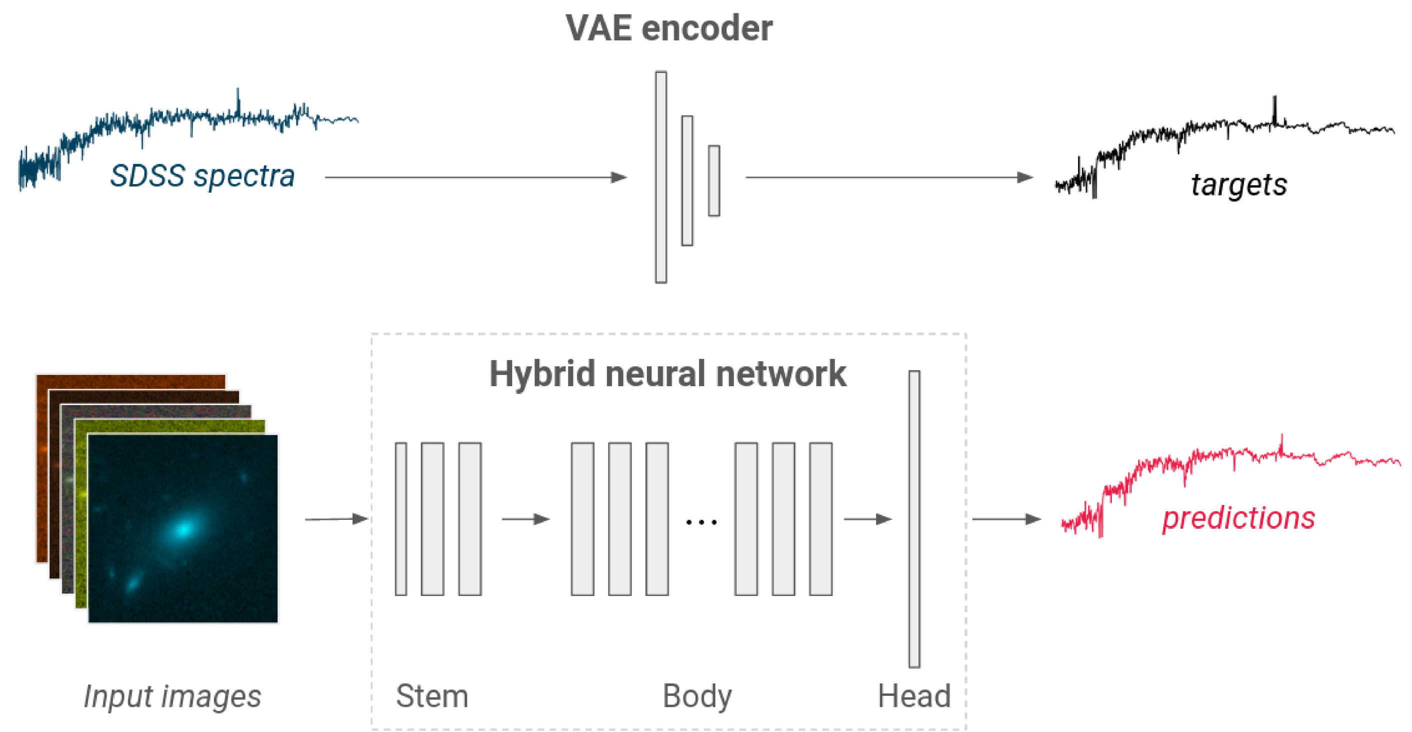

Figure 2: A schematic of our method. A pretrained VAE maps SDSS spectra to six latent variables, which we use as training labels (*upper*). We optimize a CNN to estimate the latent variables from images (*lower*).

In this work, we introduce a novel method for predicting galaxy spectra directly from images (see Figure 2). We represent galaxy spectra from the Sloan Digital Sky Survey (SDSS) using six physically meaningful latent variables learned by a variational autoencoder (VAE; Portillo et al. 2020). We optimize a CNN to predict these latent variables from Pan-STARRS galaxy image cutouts. We find that network deconvolution (Ye et al. 2020) encourages a CNN to efficiently represent galaxy image features, and that deconvolution is most powerful when used in lieu of batch normalization only the first layers of a CNN (Figure 3).

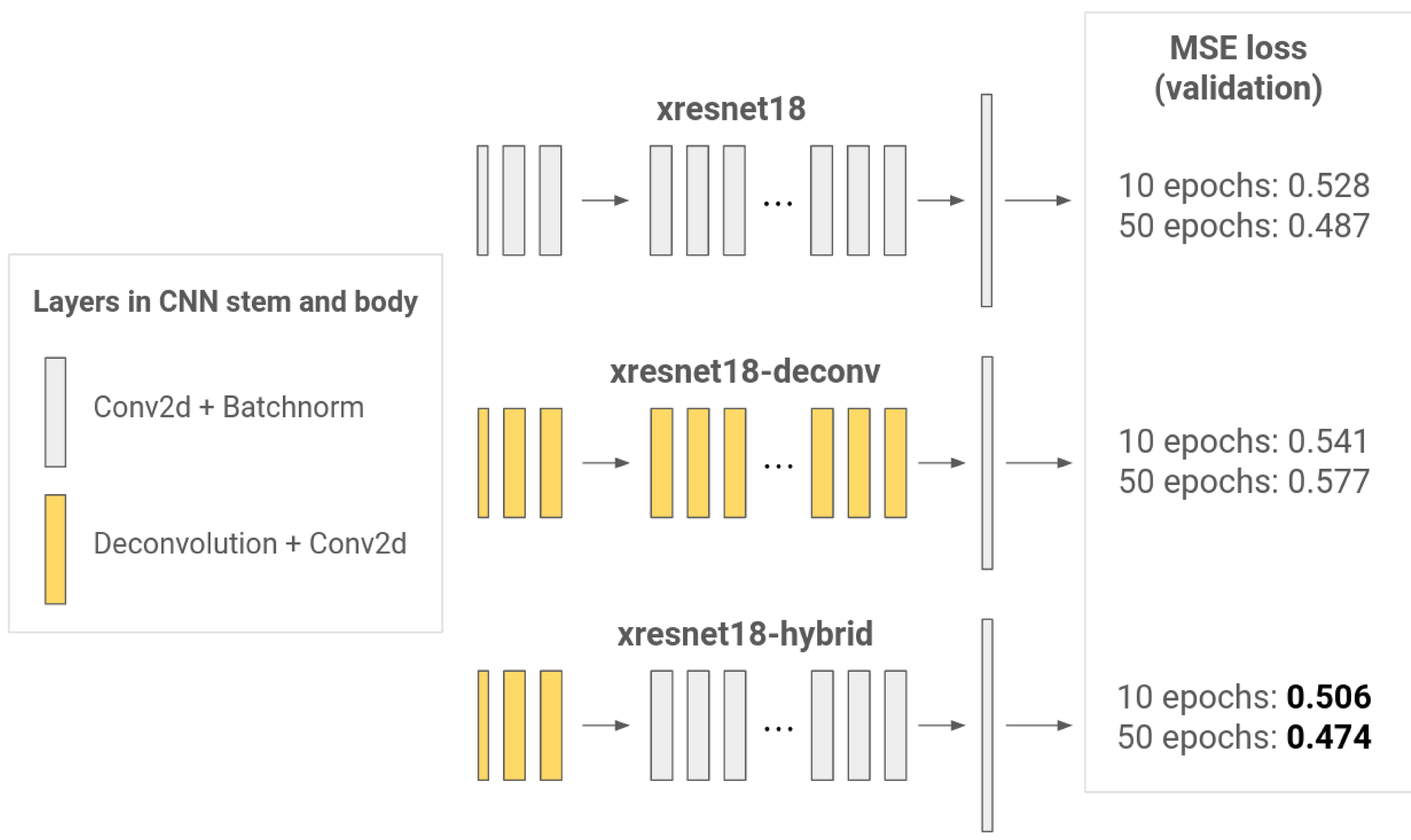

Figure 3: We replace batch normalization (batchnorm) with deconvolution in an 18-layer residual CNN ("xresnet18"). The CNN variant with deconvolution only in the early layers (the *stem*) performs the best according to MSE loss.

Results

Our results suggest that network deconvolution promotes efficient optimization. We propose that deconvolution layers in the stem allows encourages the model to represent galaxy images sparsely with independent low-level features, while traditional batchnorm layers throughout the rest of the CNN permits it to learn redundant features necessary for expressing physical symmetries in the data.

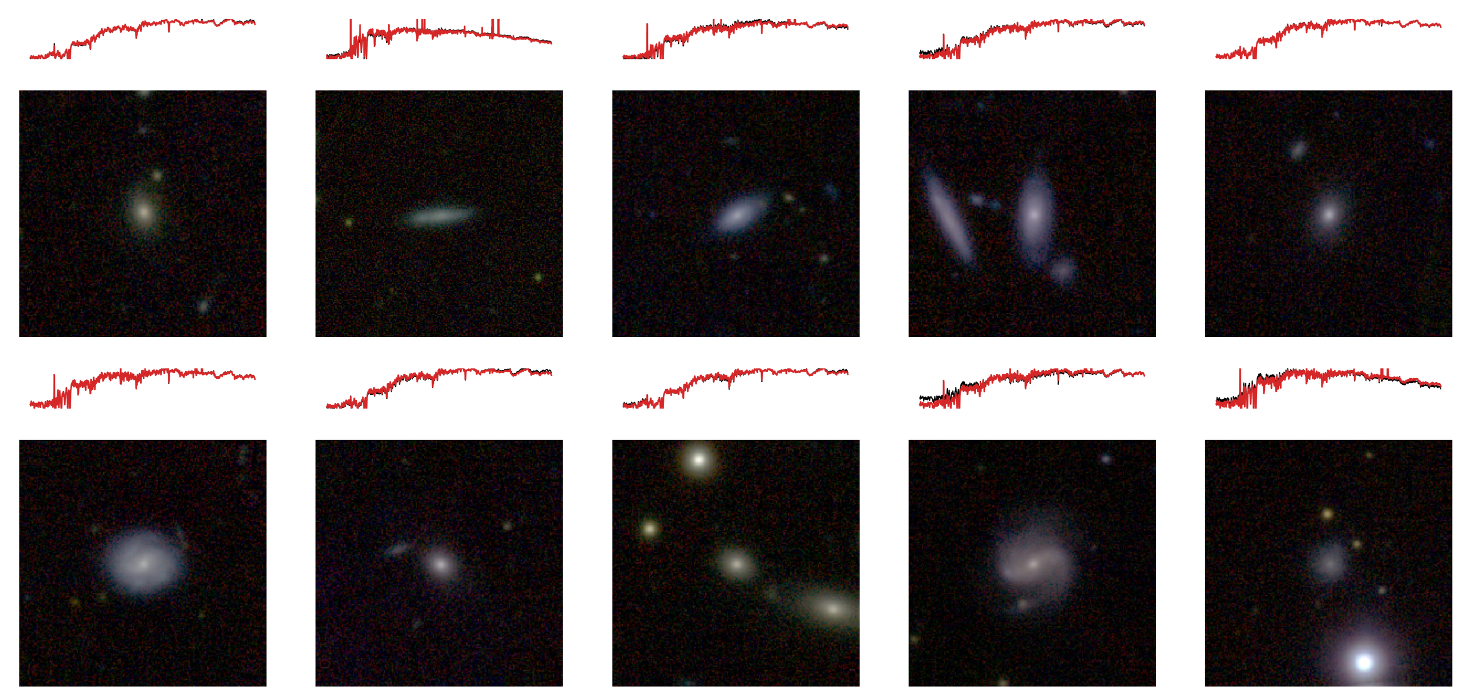

Figure 4: Random examples of Pan-STARRS *grizy* (five-channel) image inputs and reconstructed spectrum outputs. Labels and predictions are shown in black and red, respectively (after being decoded into SDSS spectra by the VAE).

The robust mapping between galaxy images and spectra (Figure 4) allows us to estimate image-based priors on the spectrum. Alternatively, we can seek out aberrant galaxies that depart from the learned mapping in order to understand the physics behind such failure modes. Finally, our method can be used to select galaxies of interest for targeted spectral follow-up observations, which will be valuable in the coming era of wide-field galaxy imaging surveys.

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References

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