# Galaxy Image Translation with Semi-supervised Noise-reconstructed Generative Adversarial Networks

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## Abstract

We propose a two-way image translation model using Generative Adversarial Networks (GANs) that exploits both paired and unpaired images in a semi-supervised manner, and introduce a noise emulating module that is able to learn and reconstruct noise characterized by high-frequency features. By experimenting on multi-band galaxy images from the Sloan Digital Sky Survey (SDSS) and the Canada France Hawaii Telescope Legacy Survey (CFHT), we show that our method recovers global and local properties effectively and outperforms benchmark image translation models. To our best knowledge, this work is the first attempt to apply semi-supervised methods and noise reconstruction techniques in astrophysical studies.

## Introduction

Astronomical images obtained from different sky surveys usually have diverse instrumental and observational effects. We aim to develop a Deep Leaning approach for translating galaxy images with different survey properties. This is a potentially useful way to extract salient information concerned for science studies, and a way to simulate unobserved images for certain surveys.

**Challenges**

- For domain translation, it is preferable to use paired data (i.e., images from two surveys containing the same objects), with one image serving as the ground truth for its counterpart in a supervised manner. However, due to limited overlapping sky coverage, we are usually lack of paired data to train large-scale neural networks, whereas there is sufficient unpaired data to use.
- Background noise is an essential part for reconstructing realistic images, but it is hard to learn and preserve due to its high-frequency nature.

**Contributions**

- We develop a two-way translation model for galaxy images. Our semi-supervised training scheme makes use of not only the unpaired data representative of the distribution of the full dataset, but also the paired data that ensures precise calibration of the target domain.
- Unlike other studies that focus on removing noise from images, we attempt to preserve noise information from real images and reconstruct noise in image translation. This is achieved by adversarially training noise emulating modules and discriminators that are designed to concentrate on high-frequency features.

## Method & Data

**Networks and training (see Figures 1, 2 for details)**

- Assumption: the noise and non-noise parts are separable at the pixel level.
- The training consists of two steps. We conduct noise reconstruction in Step 1 and domain translation in Step 2.

**Data**

- Images from two sky surveys — the Sloan Digital Sky Survey (SDSS) and the Canada France Hawaii Telescope (CFHT).
- 2557 paired training images; 2500 paired test images; 513014 (SDSS) + 125036 (CFHT) unpaired training images.
- Each image consists of five passbands (u, g, r, i, z); has a galaxy at the center.
- Image size: 64 × 64 pixels (SDSS); 136 × 136 pixels (CFHT).

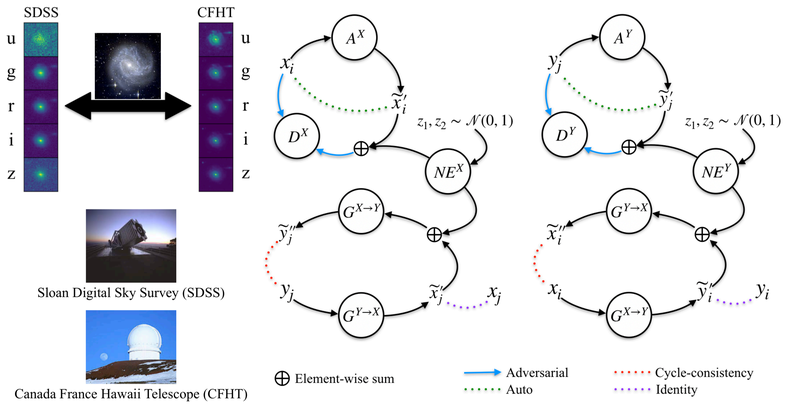


**Figure 1. Left:** Galaxy images from two surveys covering five photometric passbands (u, g, r, i, z). **Right:** Framework of our two-step training scheme. ***Step 1*** — (i) update the Autoencoders $A^X$, $A^Y$ with the original images $x$, $y$ from the two domains $X$, $Y$ respectively, which are used for reconstructing the non-noise image components; (ii) adversarially update the Noise Emulators $NE^X$, $NE^Y$ and the Discriminators $D^X$, $D^Y$ while keeping $A^X$, $A^Y$ (thus the regenerated non-noise components) fixed and taking the Gaussian random seeds $z_1$, $z_2$ as inputs to $NE^X$, $NE^Y$ to produce noise. $z_1$ controls the noise amplitude while $z_2$ controls the 2D noise map. ***Step 2*** — update the Generators $G^{X\to Y}$, $G^{Y\to X}$ for translating the non-noise components, added with noise produced by the trained $NE^X$, $NE^Y$.

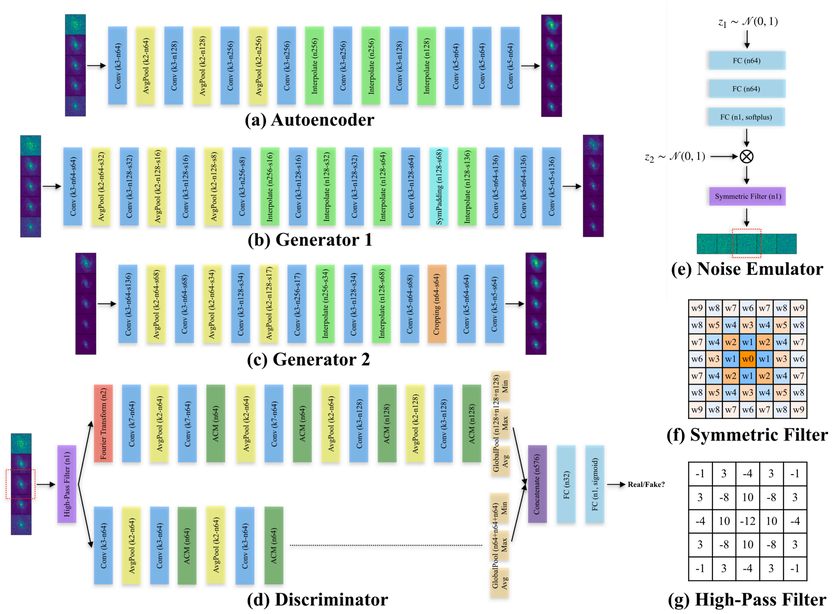


**Figure 2. (a)** Architecture of the Autoencoders. **(b)** Architecture of the Generator translating SDSS images to non-noise CFHT images. **(c)** Architecture of the Generator translating CFHT images to non-noise SDSS images. The size of each output feature map or image is specified. **(d)** Architecture of the Discriminators for each of the five passbands. **(e)** Architecture of the Noise Emulators for each passband. **(f)** The 7×7 zero-bias symmetric filter applied in the Noise Emulators for introducing short-scale correlations. **(g)** The high-pass filter applied in the Discriminators for extracting high-frequency features.

## Results

- The images generated by our method show good quality in visual comparison with the real images, in contrast to other variant cases.
- We evaluate the reconstruction of global galaxy shapes and local fluctuation patterns with metrics defined using flux distributions and 2D Fourier maps, verifying the necessity to use paired images in training and introduce noise reconstruction techniques.

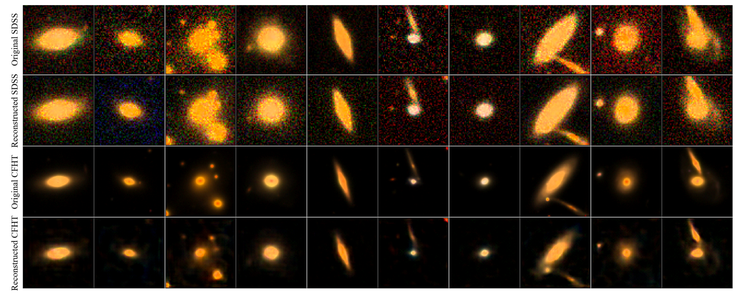


**Figure 3.** Examples of images generated by our method in comparison with their real counterparts shown in the RGB format.

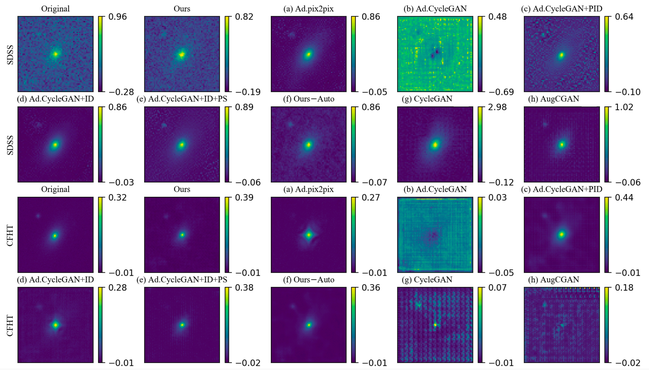


**Figure 4.** The z-band images of a galaxy obtained in variant cases.

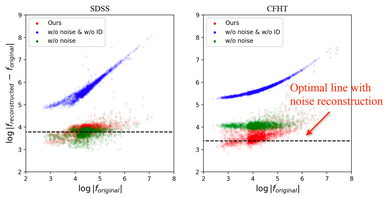


**Figure 5.** Global shape reconstruction evaluated on spatial flux distributions using r-band images.

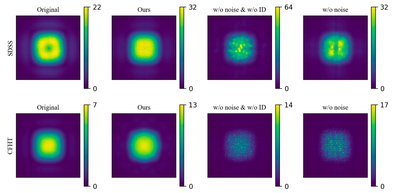


**Figure 6.** Local fluctuation patterns displayed by stacked 2D Fourier maps using r-band images.

## Conclusions

We develop a semi-supervised noise-reconstructed GAN approach to making image-to-image translation between two sky surveys. As displayed by our experimental results, this method is able to recover galaxy shapes and noise properties, and has promises for various science applications.

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