Denoise of Astronomical Image with Deep Learning

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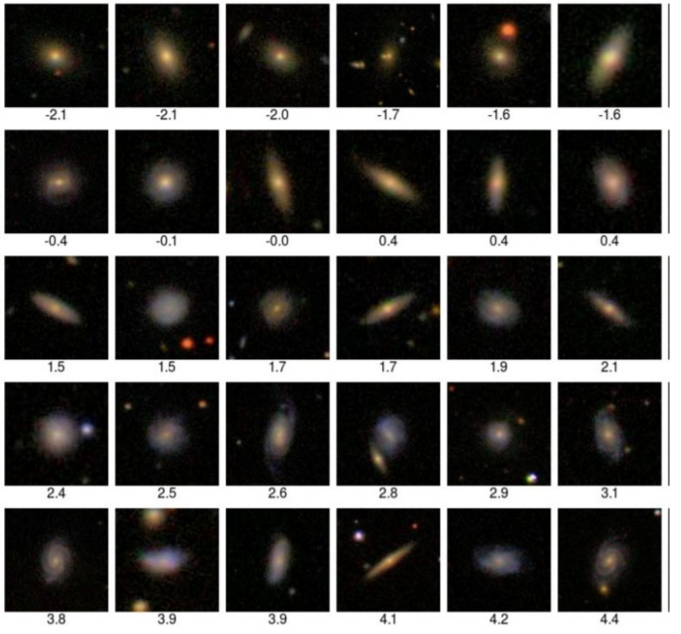
Introduction

- Examples of Deep Learning in astronomy
  - H. Dominguez Sanchez et al.
    - Galaxy morphology classification using Deep Convolutional Neural Network

Question	Meaning	P_{thr}	TPR	Prec.	Acc.
		0.2	0.97	0.91	
Q1	Disk/Features	0.5	0.95	0.96	0.98
		0.8	0.90	0.99	
		0.2	1.00	0.67	
Q2	Edge-on	0.5	0.99	0.83	0.97
		0.8	0.92	0.95	
		0.2	0.93	0.48	
Q3	Bar sign	0.5	0.79	0.80	0.97
		0.8	0.58	0.92	
		0.2	0.98	0.54	
Q6	Merger signature	0.5	0.96	0.82	0.97
		0.8	0.90	0.97	

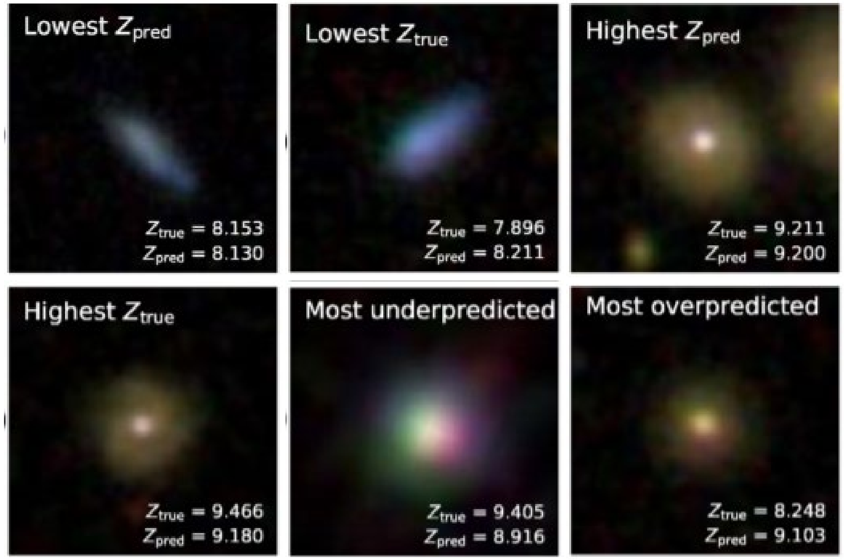
Morphology classification

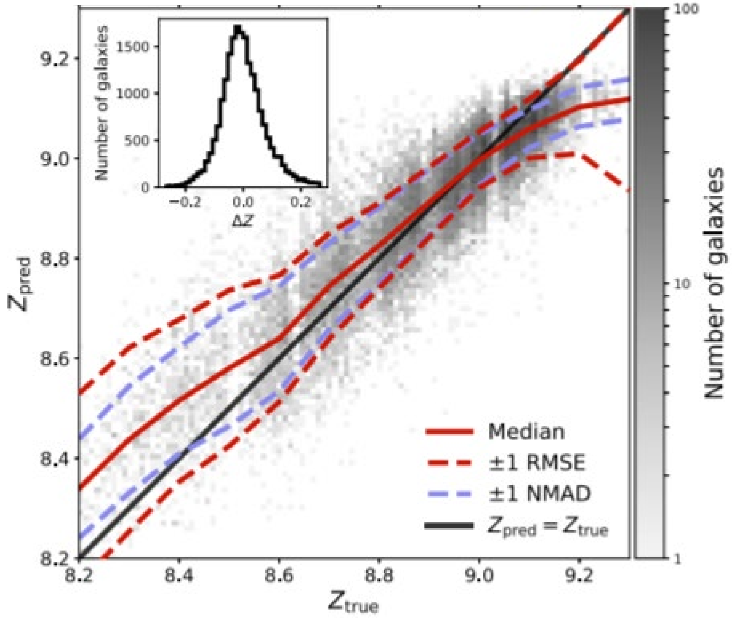


T-Type classification

Introduction

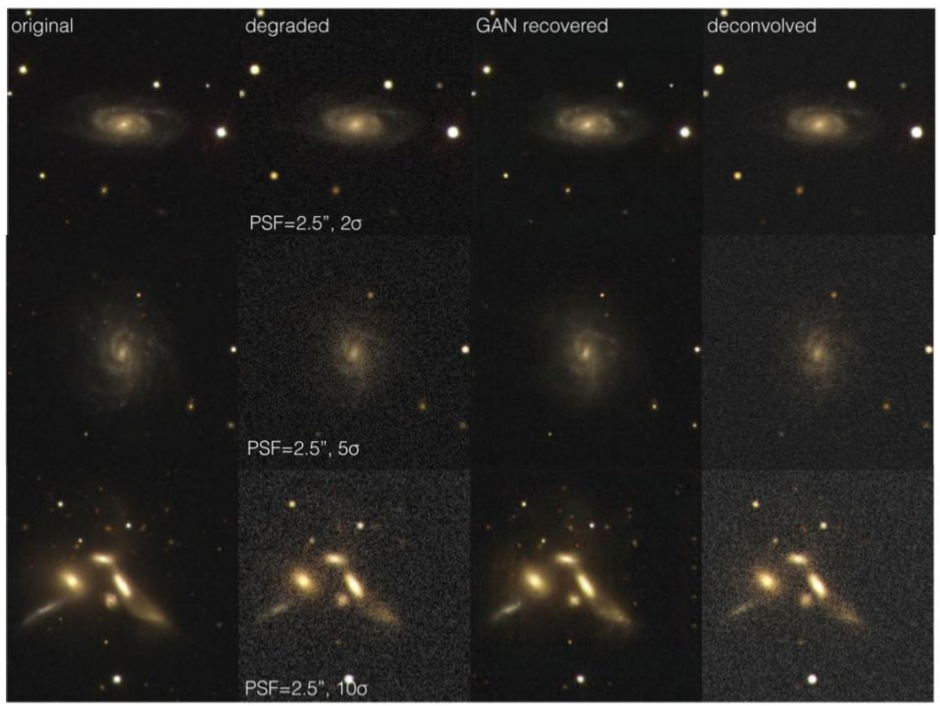
- Examples of Deep Learning in astronomy
  - John F. Wu and Steven Boada
    - Predict galaxy metallicity from three-color images



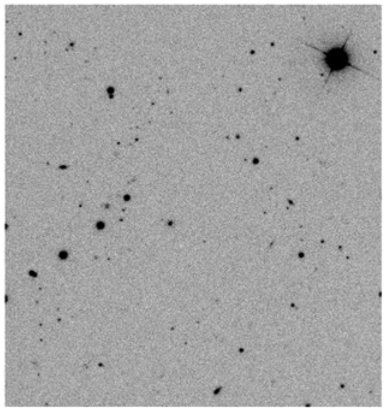


Introduction

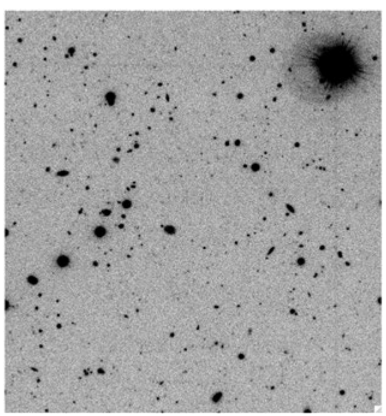
- Examples of Deep Learning in astronomy
  - Kevin Schawinski et al.
    - Degraded galaxy images and restored them using GAN



Introduction



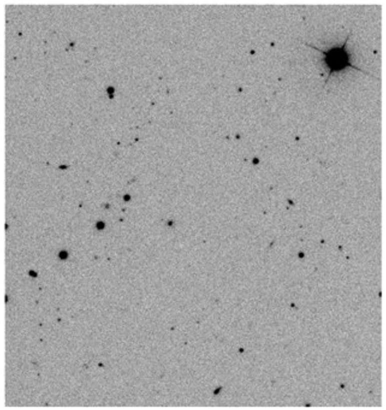
Single pass data



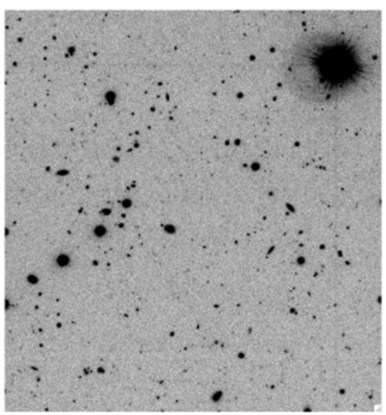
28 images stacked

- Image Stacking
  - Averaging pixel values of multiple pictures taken of a specific area
  - Pros
    - computationally inexpensive
    - can get higher signal-to-noise ratio ($\sqrt{N}$ times better)
      - For SDSS Stripe 82 data, we can see ~2 magnitude fainter objects compared to single pass data
    - true value(error < 0.02 mag for SDSS data)

Introduction



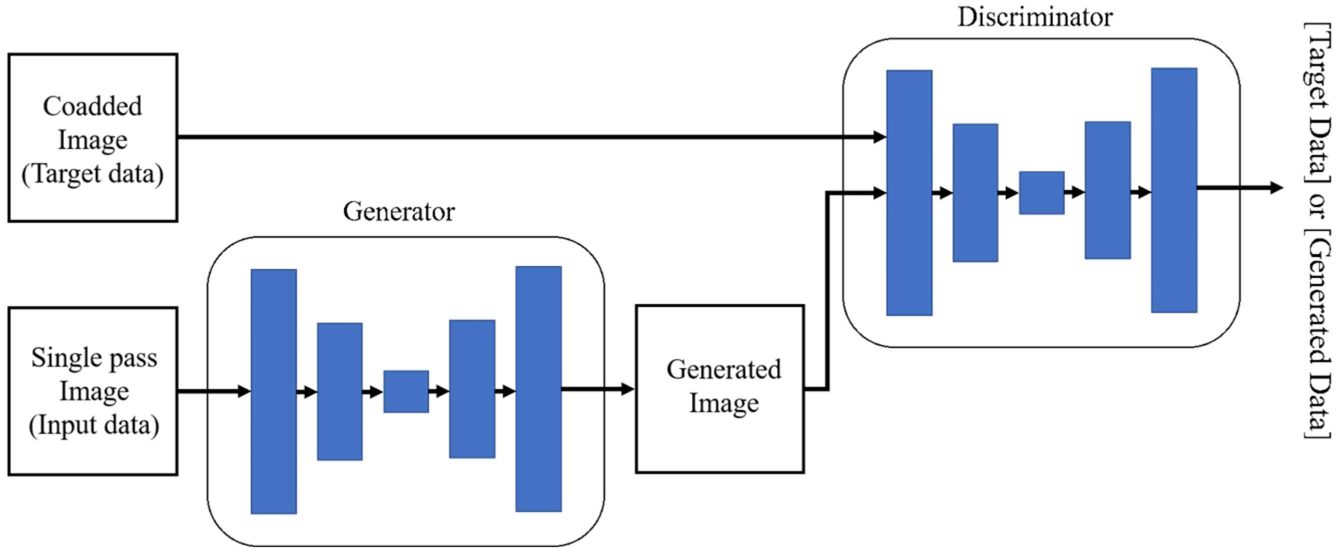
Single pass data



28 images stacked

- Image Stacking
  - Averaging pixel values of multiple pictures taken of a specific area
  - Pros
  - Cons
    - complicated Point Spread Function
    - object with fast proper motion can be vanished
    - takes long time to observe repeatedly

Generative Adversarial Network



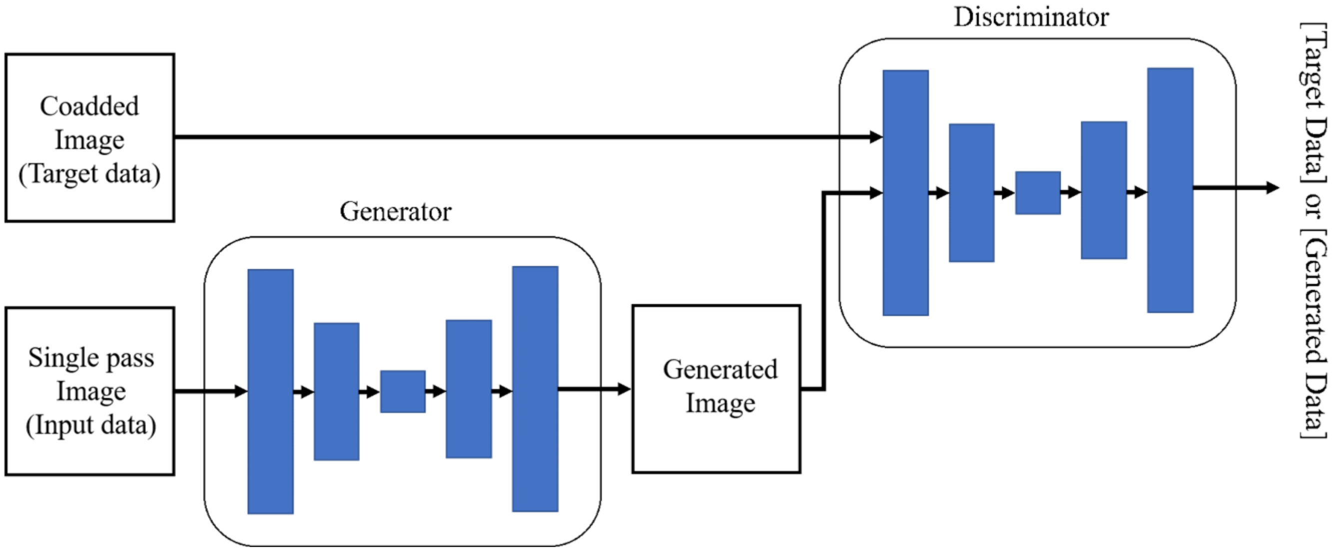
GENERATOR

- Trained to generate image that has similar probability distribution of target data

DISCRIMINATOR

- Trained to discriminate difference between probability distribution of target image and generated image

Generative Adversarial Network



GENERATOR

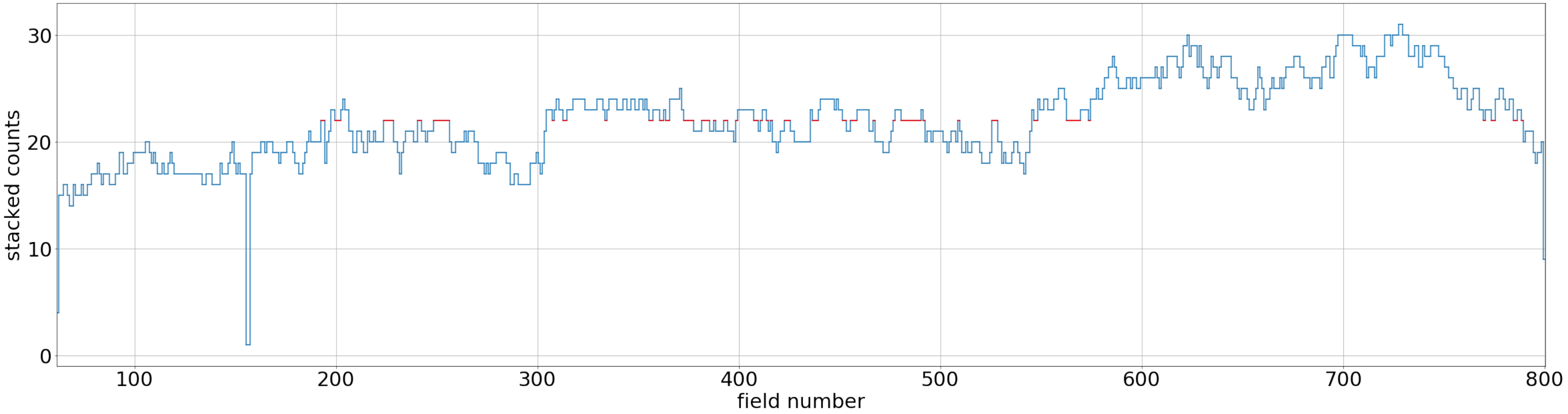
$$G(input) \sim target$$

DISCRIMINATOR

$$D(target) = 1$$
$$D\big(G(input)\big) = 0$$

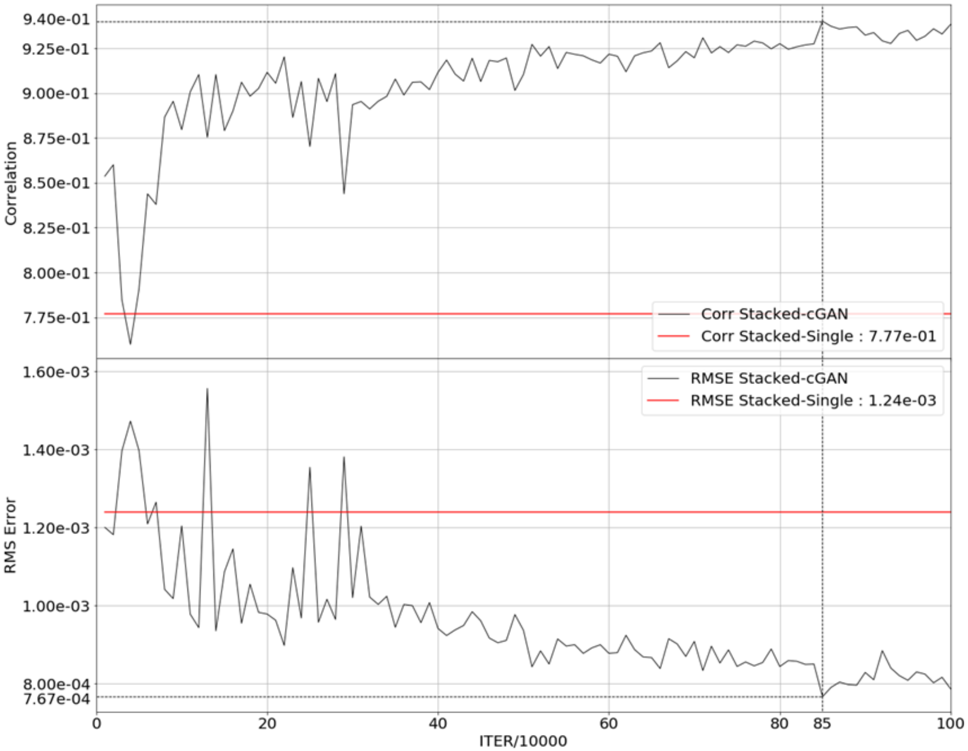
$$D(target) = D\big(G(input)\big) = 0.5$$

Training Samples



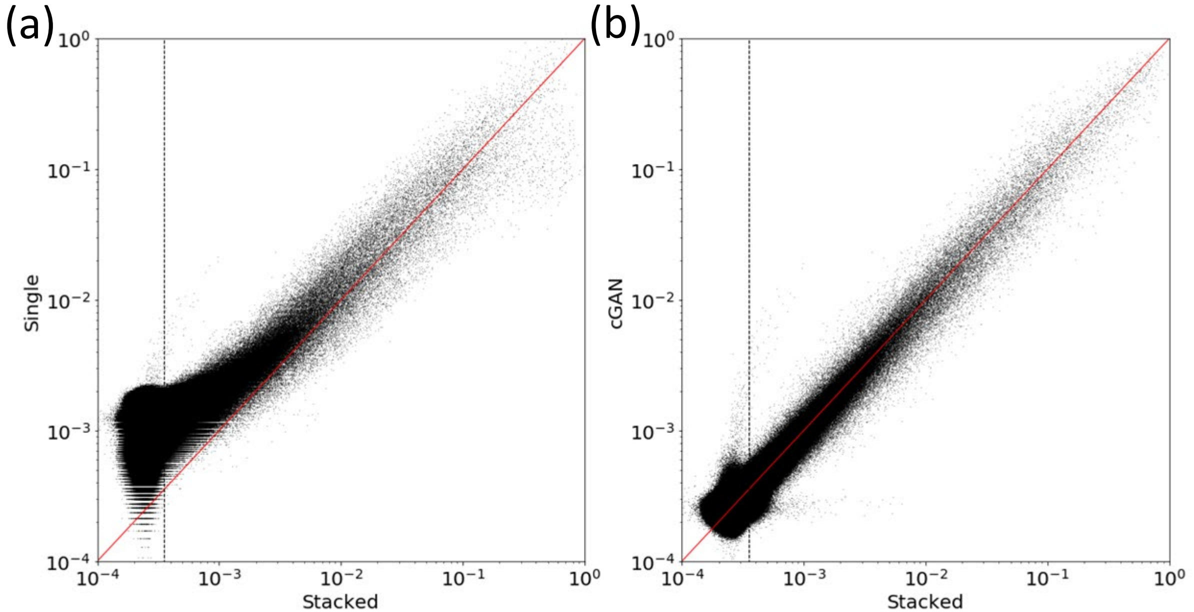
- SDSS stripe 82 r-band camcol2 data
  - Stacked with only 22 individual images
  - Single pass data -> 92 fields
- Cut into 128x128 pixel size with 28 pixels overlapping
- 17930 pairs of image(14234 for training, 3696 for test)

Training Progress



- First, the accuracy of generated data is in the form of differences of pixel values
  - Correlation coefficient of pixel values between GAN-generated and stacked image increased from 7.77×10^{-1} to 9.40×10^{-1}
  - RMS error of pixel values decreased from 1.24×10^{-3} to 7.67×10^{-4}

Preliminary Results

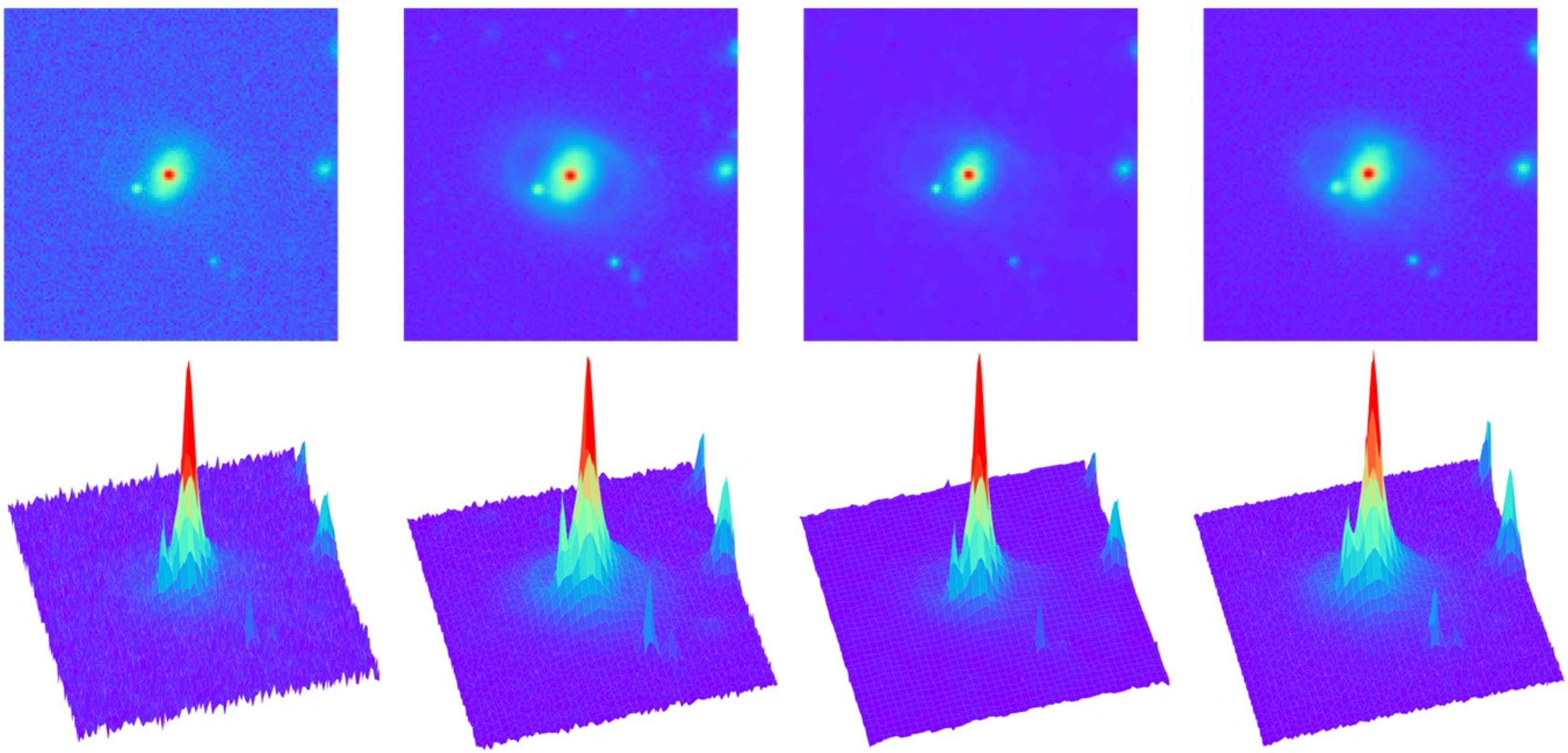


- Pixel values comparing of all test images between
  - (a) single and stacked image data and
  - (b) cGAN-generated and stacked image data.
- Black dashed line is to distinguish between signal and sky background.
- Points deviating from the red diagonal line present pixels with lower signal-to-noise ratios.

Preliminary Results

- Test galaxy images

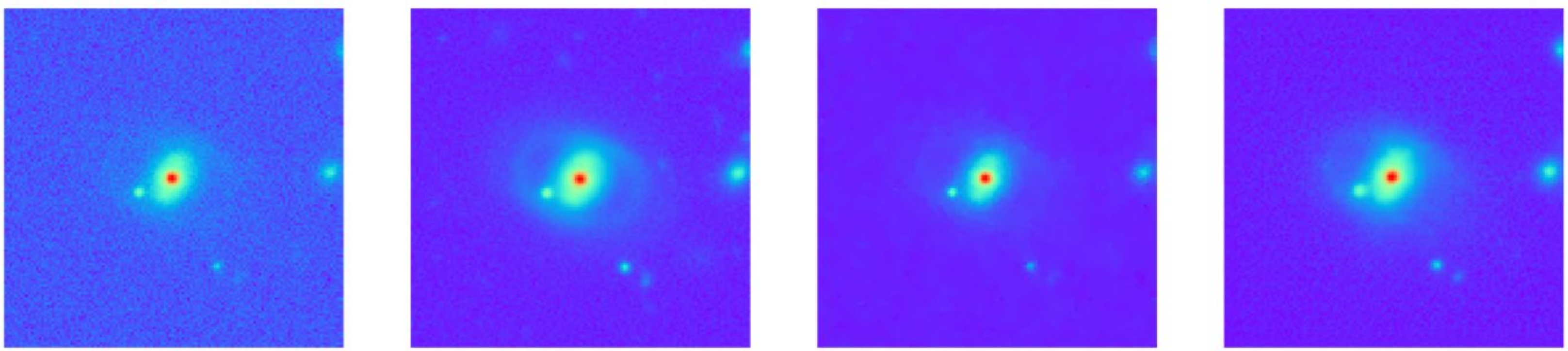
Single | Stacked | Total Variation De-noising | GAN generated

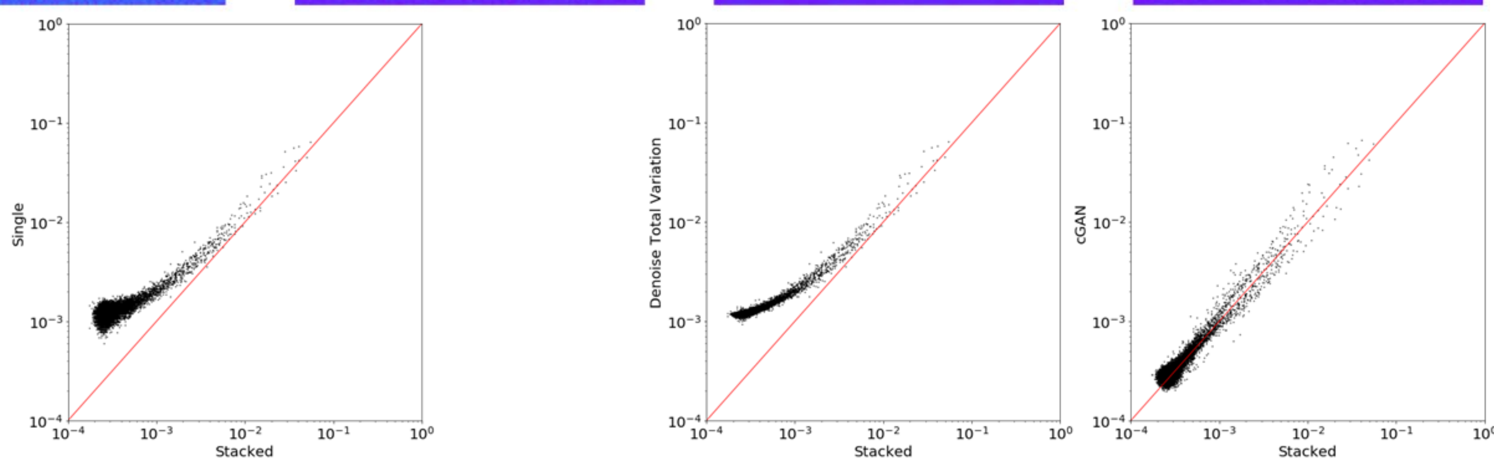


Preliminary Results

- Test galaxy images

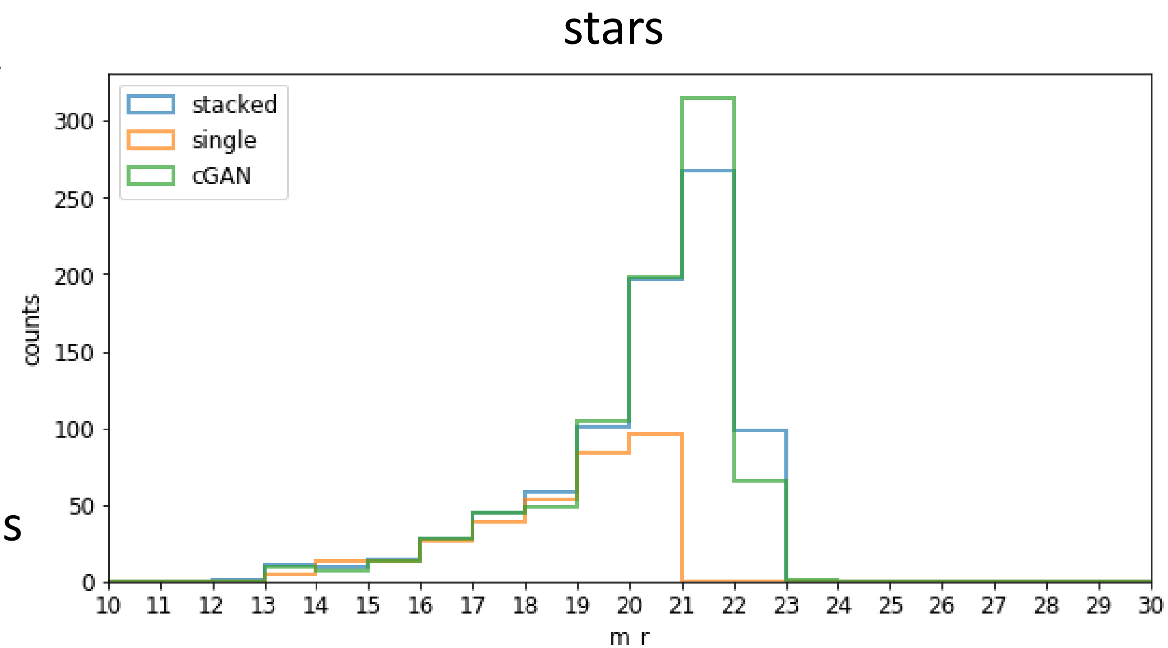
Single	Stacked	Total Variation De-noising	GAN generated

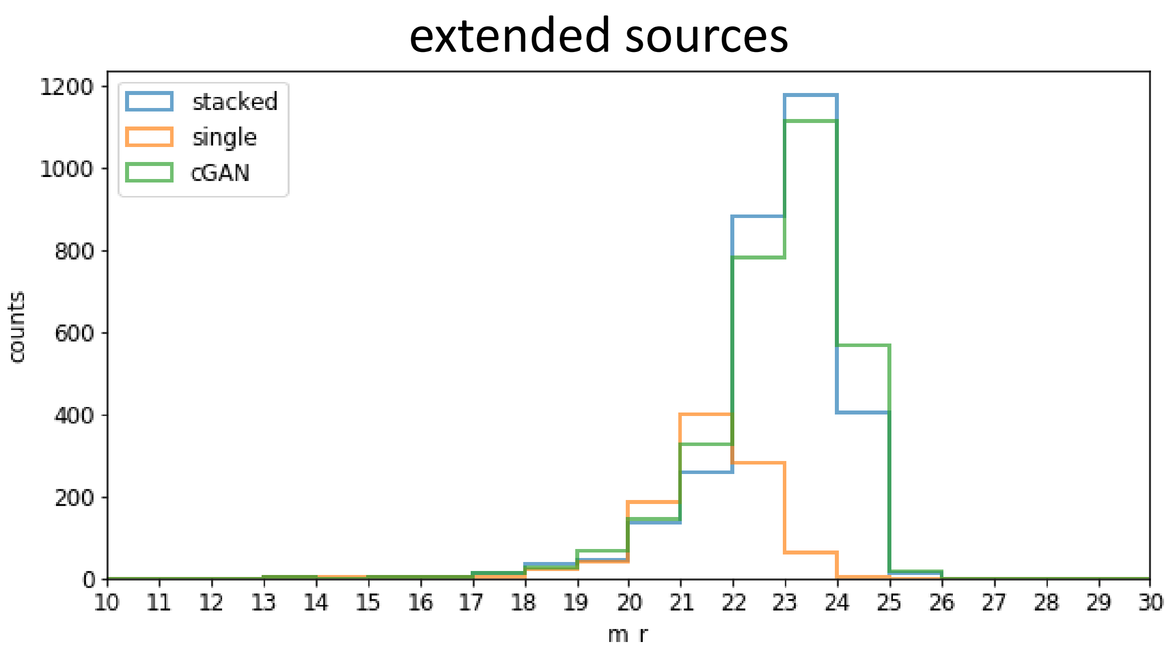




Preliminary Results

- Photometry
  - magnitude distributions in the r-band for the three samples images of 0.0708 deg^2.





Summary

- Deep learning can generate data with more information from data with less information

- As a part of that, we reproduced stacked image from single pass data using Deep Learning GAN

- It can lower the completeness limit in the apparent magnitude as much as that of the stacked sample

- But more precise photometry is needed