Generate Source Galaxy Images from Strong Gravitational Lens Images

(Computer Vision, Generative Modeling, Astrophysics)

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Abstract

Gravitational pull bends the light on distant galaxies, which causes them to appear lensed. Using Convolutional Neural Networks, U-Net, and Means Squared Error with Structural Similarity Index, we were able to generate un-lensed images of these galaxies.i.e. Undoing effect of gravitational lensing and generating source image . Also, we are able to predict lensing parameters of the strong gravitational lensed which caused this distortion.

Introduction

We will be investigating a generative modeling problem to convert a gravitational lens[1] image into the galaxy that it represents. Here, a picture of one galaxy in front with another behind it. Because light bends due to gravity, the second galaxy's image gets distorted, so it looks like it makes a circle around the first galaxy. We are interested in developing an algorithm to undo this visual effect so that we can detect other possible unidentified gravitational lenses. i.e. generating images of the source galaxy.

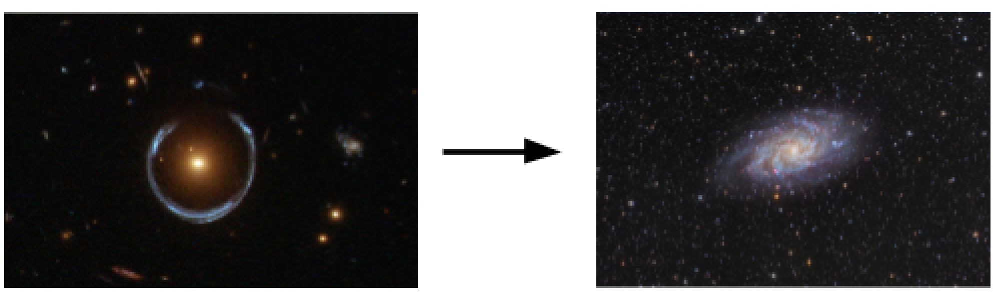


Figure 1: A simple illustration of what we want our model to achieve. The lens in the left image should be converted to a galaxy such as the spiral on the right.

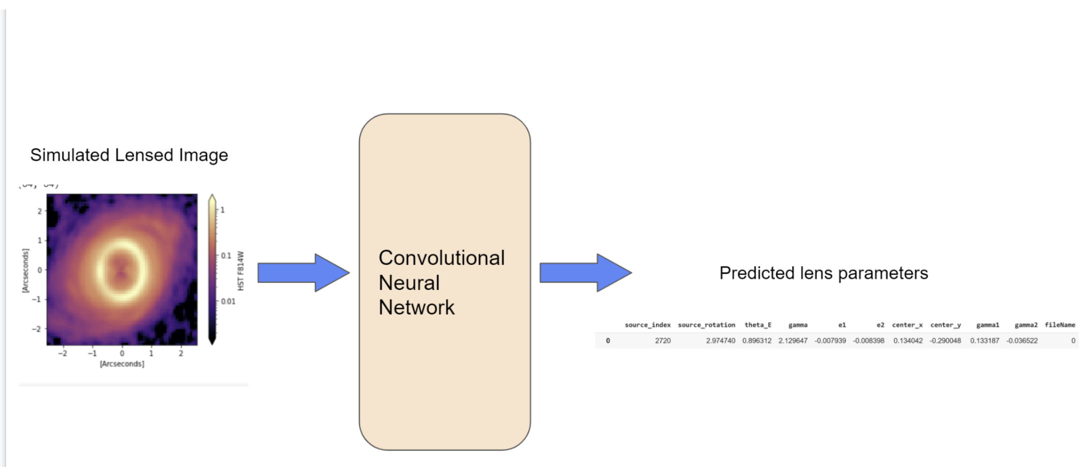
Dataset

As not many images of strong gravitational lenses are available, So we decided to simulate data using the Cosmos dataset[2].Cosmos dataset has 60K galaxy images. We used redshift properties to filter out galaxies to use for our project(Details appendix). After filtering galaxies, we used Lenstronomy[3] and randomly generated lens parameters to simulate lensed images of the source galaxies. We also used rotation data augmentation[4] to generate more simulated data. Our dataset is made up of generated lensed images and its source real galaxy pairs. Images of these galaxies can be lensed or un-lensed 64x64 grayscale images. They have been distributed into test, validation, and training datasets based on galaxy distinct source id to avoid data leak between the sets. The lensed images are used to predict the lensing parameters of gravitational lens for a galaxy. The un-lensed images are the correct depiction of the same galaxy used to predict the non lensed galaxy given the lensed image.

Approach

We broke our problem down into two steps. First, predict the lensing parameters: Einstein radius (theta_E), Exponent of the lens's power-law mass distribution (gamma), Ellipticity components of the lens (e1,e2), Location of the lens in the image (center_x,center_y), in arcseconds, External shear components (gamma1,gamma2) of lensed image. Second, U-net generates the unlensed source galaxy image from its lensed pair image.

Architecture Part 1



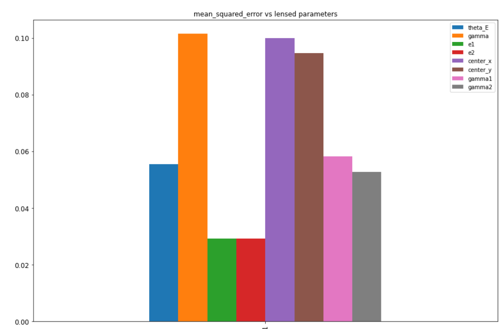
After we preprocessed our images, we used our training dataset in a convolutional neural network with three blocks, using the corresponding lensing parameters as the output of the last layer, which produced our model for part 1. In each block, we applied 2D Convolution, Max Pooling, and Batch Normalization, and a Relu activation function. Finally, we flattened the layers and passed the input into two dense layers, one Relu and the other a Linear function. We assigned all 8 parameters to be predicted as our labels in each dataset, then ran the function on all the images in the datasets. It is able to predict the lensing parameters with good metrics across all three datasets.

Hyperparameters of Part 1: We tuned the learning rate for Adam, number of layers for our CNN, mini batch size, and epochs.

Part 1 Results & Analysis

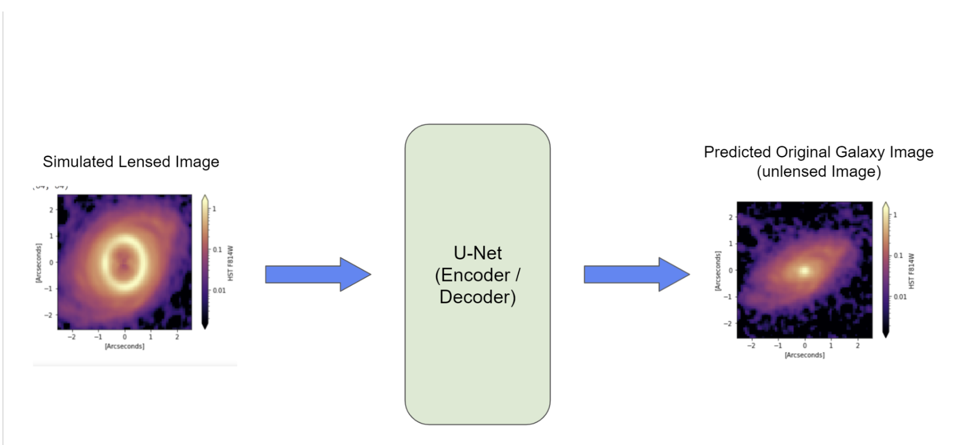
Metric Mean_squared_error Output per Lensed Parameter Class Test Set:

theta_E	gamma	e1	e2	center_x	center_y	gamma1	gamma2
0.0699	0.116535	0.029133	0.02902	0.106336	0.110213	0.064819	0.056223



This shows that theta_E (Einstein's radius) is easier to predict than lensed center coordinates and gamma, but harder than the lens ellipticity components (e1, e2).

Architecture Part 2



In part 2, we converted a lensed image to an un-lensed source galaxy image. For this we used our U-net encoder decoder network and image similarity for our error/loss function.

U-Net Experiments and hyperparameter tuning

We started a simple U-Net with multiple Conv2D, max pooling, transpose convolution layers, and linear activation for the last layer with MSE loss and Adam optimizer. After that, we added more hidden blocks in U-Net that improved its performance. Then we experimented with different activation functions: relu, elu, etc. Relu gave us better results for intermediate layers. Then we added dropouts which did not improve results much so removed it. Also, adding batch normalization helped U-Net. Still it was not generating better images for spiral galaxies from manual error analysis, so we decided to use different image similarity loss functions. All these different models are in an experiment notebook.

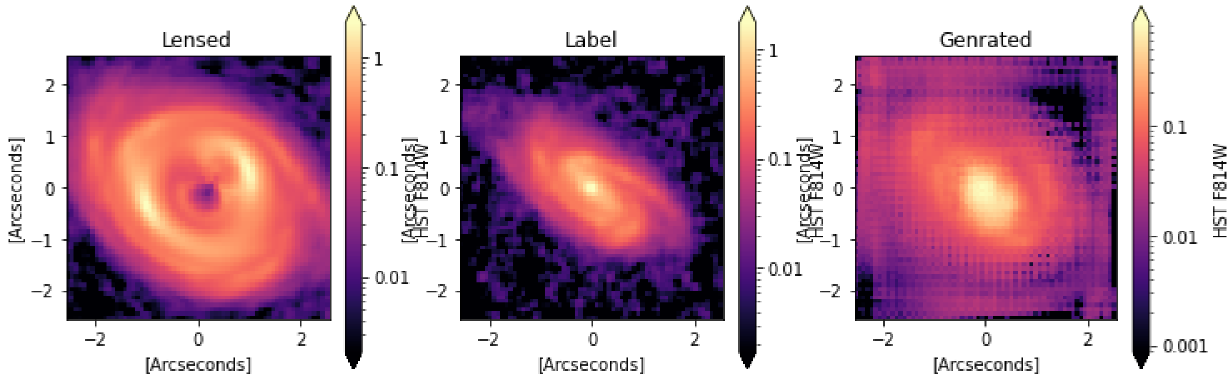


Figure 2: Initial Model

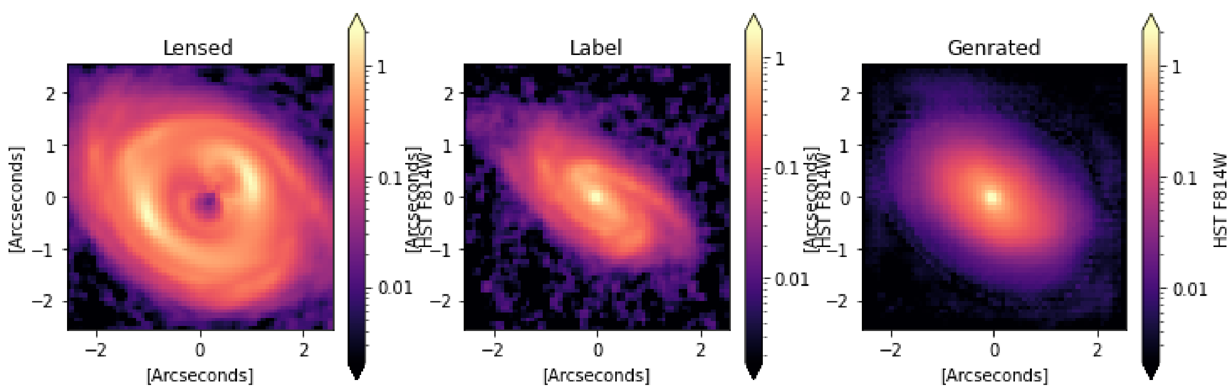


Figure 3: Intermediate model with mse generating correct shapes

Metrics and Custom Loss functions :

We experimented with image structural similarity SSIM index[5], Peak signal to noise ratio (PSNR)[6], and mean squared error (MSE) as loss functions. SSIM gave us better results. We further improved our results by writing a custom loss function which is a combination of SSIM and MSE.

```
tf.reduce_mean(tf.math.squared_difference(y_true, y_pred))+ 1 -
tf.reduce_mean(tf.image.ssim(y_true, y_pred, 1.0))
```

This loss function is generating better results for spiral galaxies as well.

val_mse: 0.0023 - val_ssim_loss: 0.0468 - val_psnr_loss: 30.6308. Loss curves.

U-Net Results on Test Set Improved Model: more results[7]

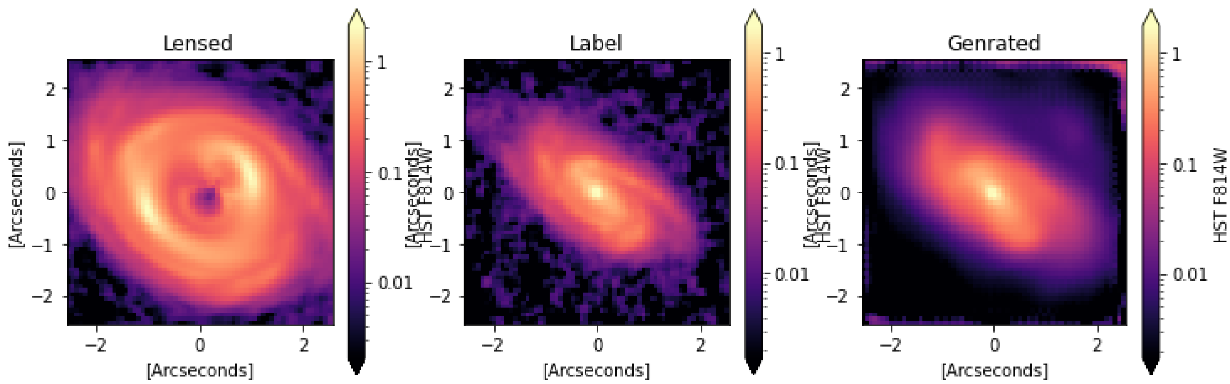


Figure 4: Improved model with custom loss function generating patterns as well

Insights and Future work:

We tried to generate a source from our trained model for original strong gravitational lensed images from the internet as well, but we need more preprocessing and noise removal for that data. We will also try gaussian noise removal as well as augmenting more data (Data based approach). We will also experiment with RGB images and continue to refine our models for both parts. So we can get closer to predict how these source galaxies actually look like. Also,we will make simulated data publicly available.

Contributions

Git Repository : Generate-Source-Galaxy-Images-from-Strong-Gravitational-Lens-Images
Data : lensingData

Acknowledgements

We would like to thank our mentor Mr. Jelle Aalbers,Kavli Postdoctoral Fellow at Stanford University, domain expert in astrophysics for the idea, helping us set up our data, providing guidance and advice to build our models, and giving feedback on our test results.

References:

[1] https://en.wikipedia.org/wiki/Strong_gravitational_lensing

[2] COSMOS real galaxy dataset

[3] https://github.com/sibirrer/lenstronomy

[5] Structural Similarity (SSIM)

[6] Peak Signal to Noise Ratio (PSNR)

https://kipac.stanford.edu/

https://arxiv.org/abs/2002.01479

http://spiff.rit.edu/classes/phys240/lectures/grav_lens/grav_lens.html

https://arxiv.org/pdf/1511.08861.pdf

https://naokishibuya.medium.com/up-sampling-with-transposed-convolution-9ae4f2df52d0

https://up42.com/blog/tech/image-similarity-measures

https://towardsdatascience.com/understanding-semantic-segmentation-with-unet-6be4f42d4b47

https://towardsdatascience.com/nucleus-segmentation-using-u-net-eceb14a9ced4

https://www.tensorflow.org/tutorials/images/

https://hubblesite.org/resource-gallery/images

Related work on Part 1:

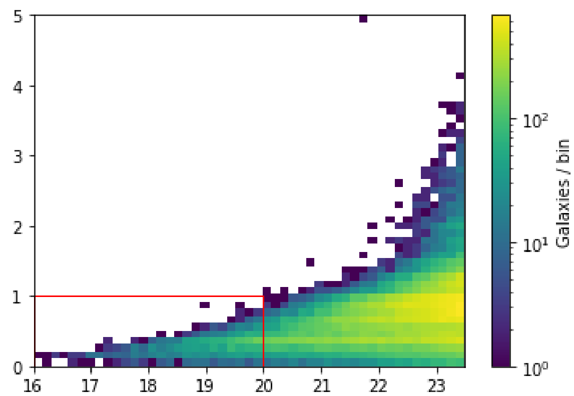
https://www.nature.com/articles/nature23463

Appendix

Preprocessing

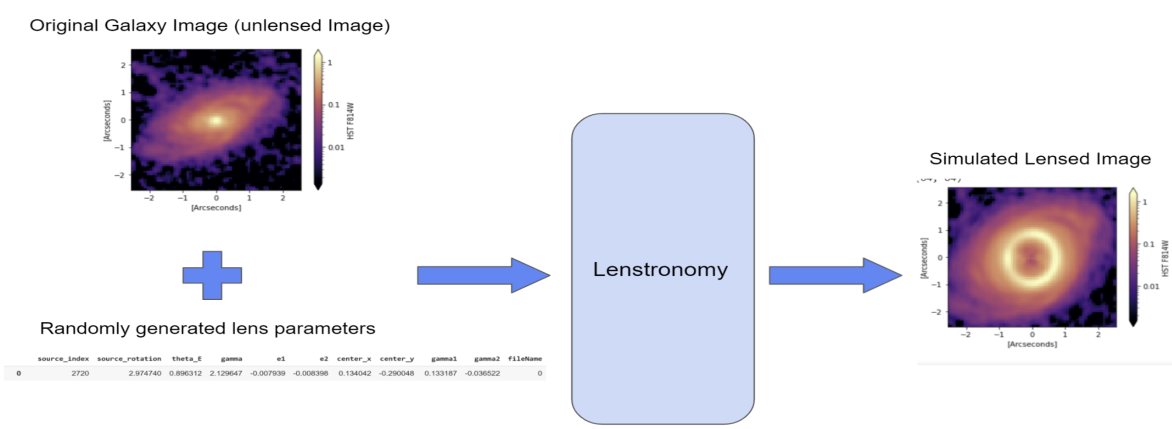
The COSMOS catalog contains many images. Some of these are 'bad' in various ways:

- Some contain only a point source. This isn't very interesting to reconstruct.
- Some have a very poor signal/noise, perhaps because the galaxy is far away (high redshift) or very faint (high magnitude).
- Some have huge areas masked out (pixels set to zero) by a foreground star removal algorithm. We used a simple magnitude/redshift selection.



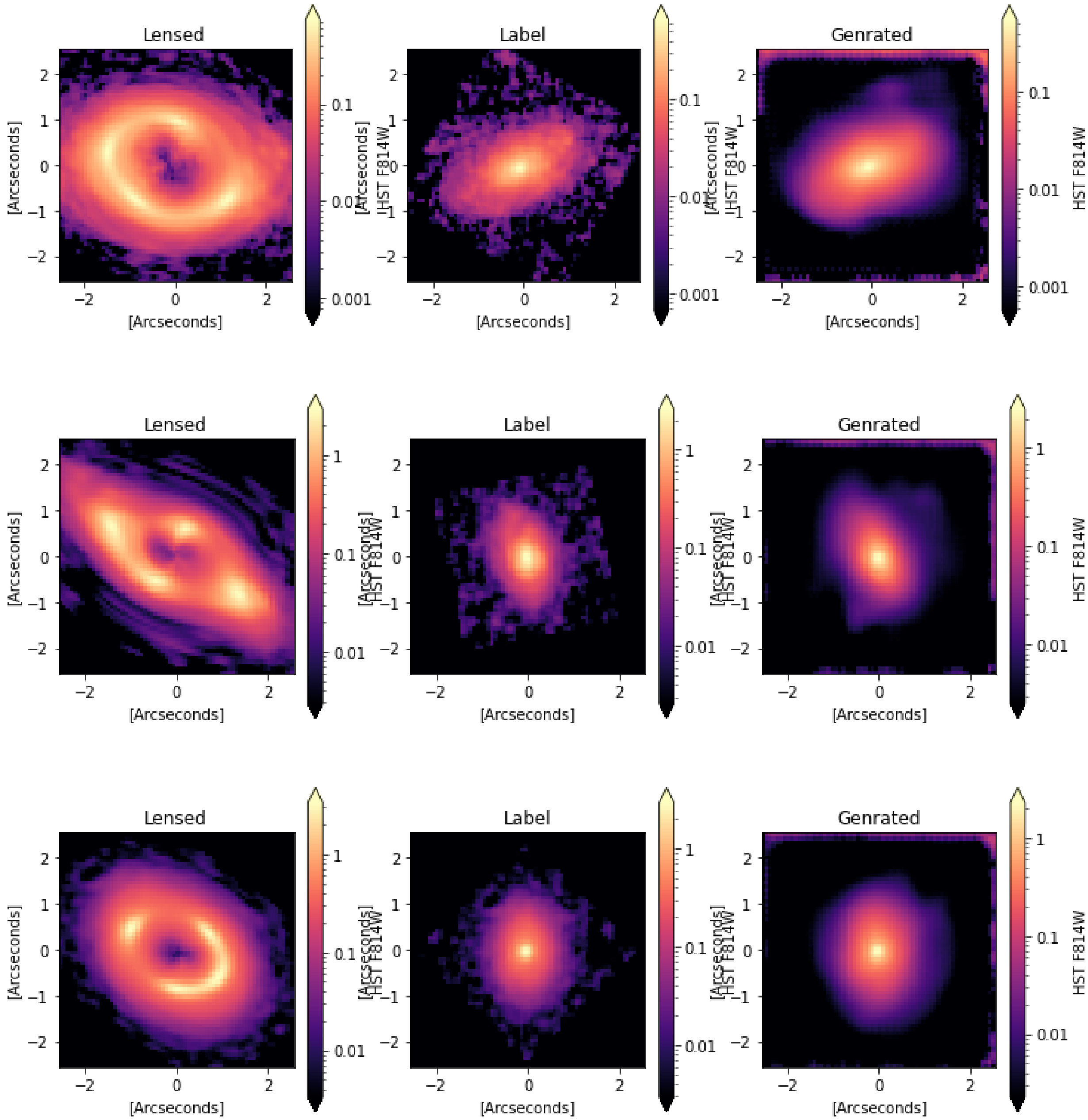
Data Augmentation

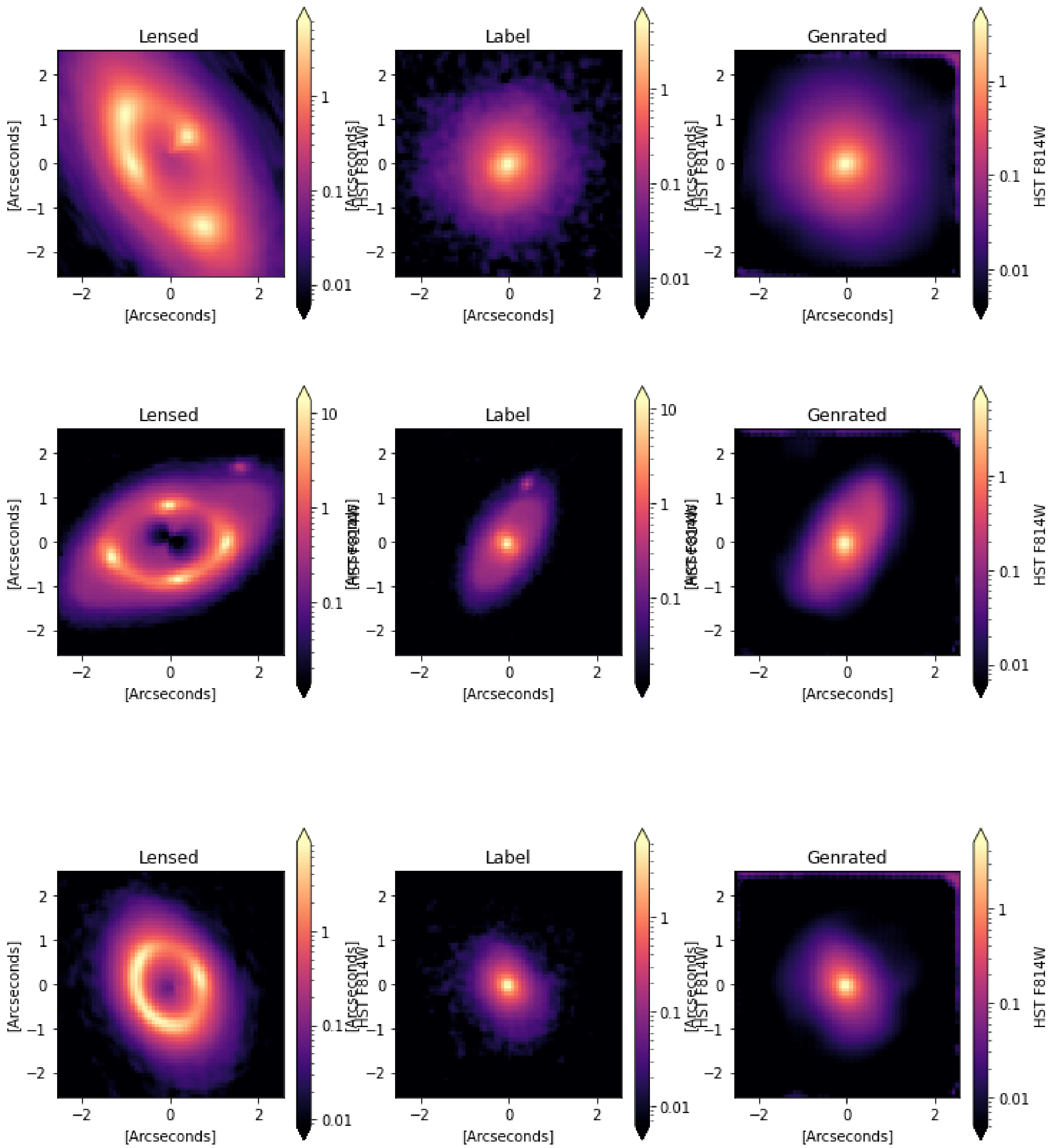
After applying a mask, the number of galaxies reduced, so we used Image Rotation/Augmentation and Lenstronomy to create simulated lensing data. These images do not have a foreground star. Now, data contains source image, its lensed image and parameters csv which is used to create simulated lensed images.



	source_index	source_rotation	theta_E	gamma	e1	e2	center_x	center_y	gamma1	gamma2	fileName
0	2720	2.974740	0.896312	2.129647	-0.007939	-0.008398	0.134042	-0.290048	0.133187	-0.036522	0

More Result Samples




Lensed
Label
Genrated
[Arcseconds]
HST F814W
Lensed
Label
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HST F814W
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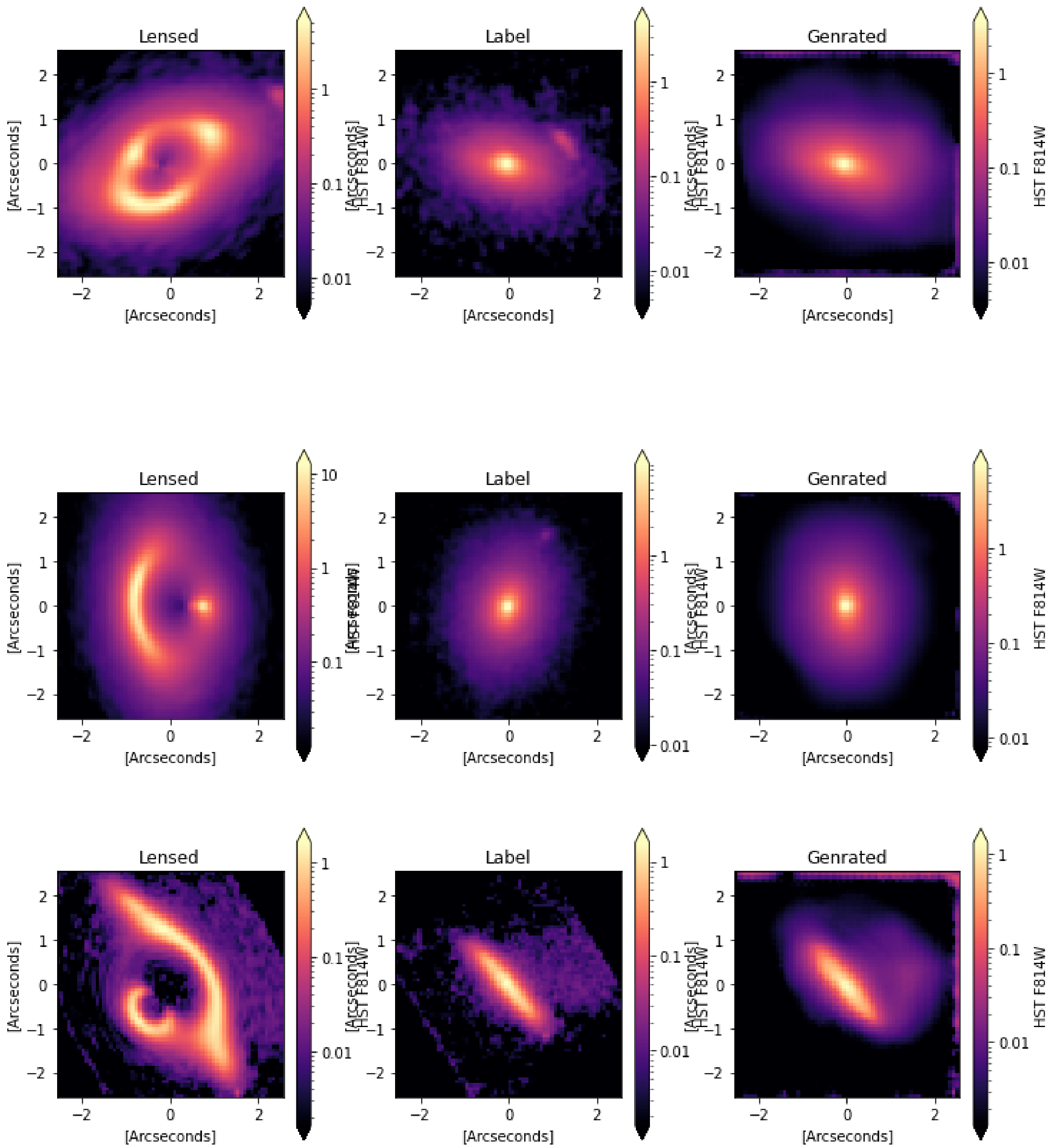
Lensed
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