

# Finding Strong Gravitational Lenses with Residual Neural Networks

### Abstract

We perform have a semi-automated search for strong gravitational lensing systems in the 14,000 deg<sup>2</sup> DESI Legacy Imaging Surveys (Dey et al.). These surveys not only cover more than a third of the sky but also achieves significant depth. This has created an environment ripe for the discovery of many things, strong gravitational lensing events among them. In order to find these systems we have developed a semi-automated process which utilizes an adopted version of Carnegie Mellon University (CMU) Deeplens (Lanusse et al.), a deep residual neural network, followed by minimal human inspection. We are the first to use a training set containing images of observed data to train a neural network for the purpose of finding strong lenses. This training set comes from the DESI Legacy Surveys and is comprised of known lensing systems, random galaxies, and potentially confusing cases for the neural network. Here we detail the process of optimization as well as the results of deployment, which has thus far yielded hundreds of new strong lensing candidates, for our version of CMU Deeplens.

### **Residual Neural Network**

Convolutional neural nets ("ConvNets") have revolutionized the image classification problem. ConvNets use stacks of convolution layers (image filters) to distill information relevant for classification. Unfortunately, there is an upper limit to the number of convolutional layers (~6 layers). A team at Microsoft Research expanded upon ConvNets by inventing Residual Neural Networks ("ResNets"). ResNets allow for significantly deeper architectures. The model below is a 46 layer ResNet. Each image to the right of the model is a visual representation of the output of each stack of layers.



"CMU DeepLens: Deep Learning For Automatic Image-based Galaxy-Galaxy Strong Lens Finding." https://arxiv.org/pdf/1703.02642.pdf

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"Hubble Finds an Einstein Ring." Edited by Karl Hille, NASA, NASA, 9 Apr. 2018, www.nasa.gov/image-feature/goddard/2018/hubble-finds-an-einstein-ring

# **Training Method**

We used Graphics Processing Units (GPUs), made available via Google's Colab, in the training process. GPUs excel at performing many simple numerical operations simultaneously, exactly what ML algorithms need to do. In order to optimize the process further, we translated the ML algorithm (previously written in Theano) to Google's Tensorflow, a ML python library which is made to run efficiently on GPUs. A full training session takes about 10 hours compared to an estimated 34 hours with distributed training on Central Processing Units (CPUs) on 3 workers.



Decay rate: 0.1

### Discoveries

We trained our most recent model using TensorFlow on Google's Colab with the full training sample (no validation set). We use the area under the receiver operating characteristic (ROC) curve, shortened as the AUC (with a perfect value being 1.0) and the purity and completeness to assess the performance of our model. We have processed approximately one third of just the elliptical galaxies in the legacy survey. After human inspection we have found over 1000 strong candidates of lensing systems. The results show that our model is amongst the most competitive machine learning techniques used to search for strong gravitational lenses.





### Hubble Space Telescope Program





We proposed to observe and confirm, on the Hubble Space Telescope (HST), 112 candidate strong gravitational lensing systems that we have discovered. Our Program has been approved (15867, Cycle 27, PI: Huang). Two systems that have recently been observed by HST from our program are shown in Fig. 9.

White arrows: lensed sources identified in both Legacy Surveys and HST images. Green arrows: lensed sources visible only in HST and not in the Legacy Surveys images.

# **Ongoing Work**

- Assemble a larger and more statistically representative training sample
- Shift ResNet training from Central Processing Units (CPUs) to Graphics Processing Units (GPUs)
- Retrain and apply our model to DR8 of the Legacy Surveys • Experiment with hyperparameter tuning and alternative architectures

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