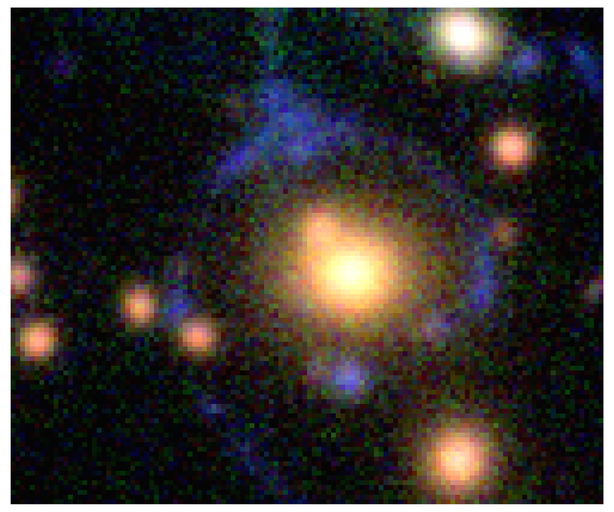
Recognizing Strong Gravitational Lenses

Chris Davis and Andrew McLeod

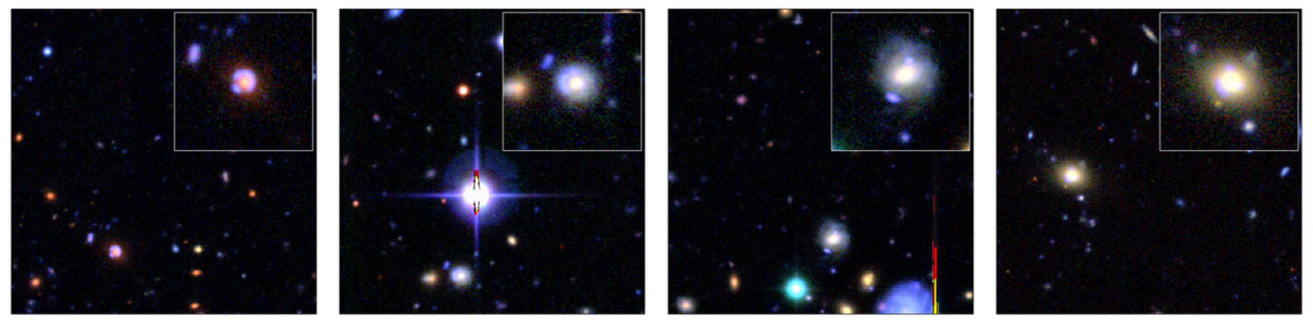
`cpd@stanford.edu ajmcleod@stanford.edu`

Strong Gravitational Lenses

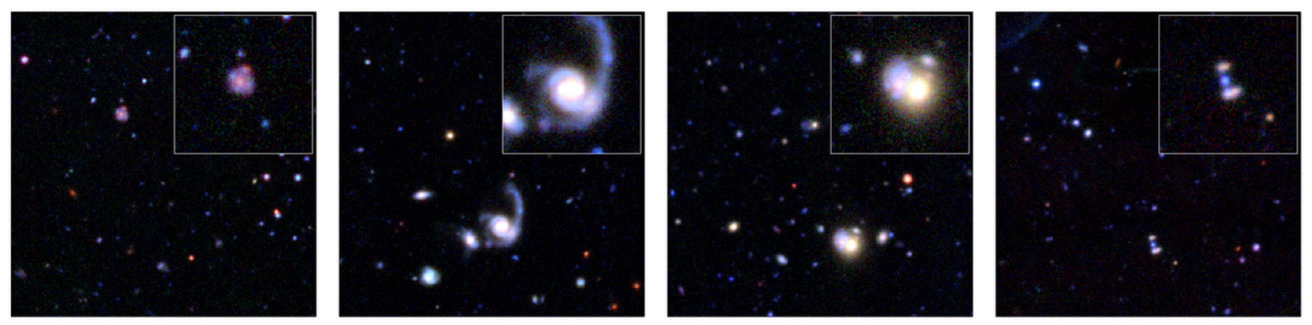


Example strong gravitational lens discovered by Space Warps.

- Strong lenses – systems with magnified and distorted images of background objects (sources) due to the deflection of light by massive foreground objects (lenses) – can be used as astrophysical tools to probe mass distributions, magnify distant objects, and measure fundamental cosmological parameters.
- The main problem with strong gravitational lenses is their rarity:
  - For modern wide-field optical surveys which observe tens of millions of galaxies over many thousand square degrees, one expects to find only several hundred such systems.
  - While strong lenses are relatively easy to spot by eye, machine learning techniques have thus far been unsuccessful in reliably identifying strong lenses and distinguishing them from image artifacts (e.g. cosmic rays) and other false positives. Maybe CNNs will help!



Example fields (with cutouts in corner) containing simulated lenses.



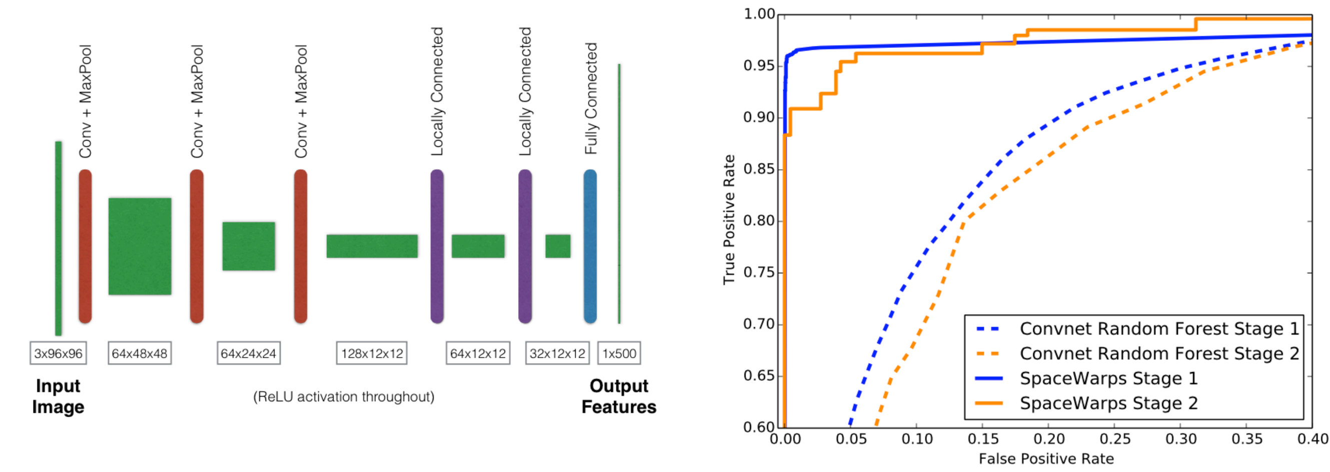
Example fields (with cutouts in corner) containing no lenses.
Cutouts indicate regions used as inputs for 'duds'.

Space Warps Dataset

- Space Warps (`www.spacewarps.com`) is an online crowd-sourced gravitational lens detection system that invites citizen scientists to interpret real data from the Canada-France-Hawaii Telescope Legacy Survey.
- Volunteers also analyze artificial "training" images of simulated lenses as well as images confirmed to have no strong gravitational lenses. Simulated lenses are further demarcated by lens type (lensed quasar, lensing galaxy, lensing cluster), each of which has different potential cosmological applications.
- Space Warps is divided into two stages, where the second stage refines the results of the first by using considerably more difficult training images. There are 24177 training images in Stage 1 and 1876 in Stage 2. We also have 9030 "test" images (cutouts whose status is not known but for which we are interested in making reasonable guesses).
- Space Warps will provide a curated dataset of gravitational lenses and lens look-alikes to facilitate the training of future automated detection algorithms.
- We train our networks on the "training" images only, of which there are 20743 "duds" and 5310 "sims". From fields of 440 x 440 x 3, we cut out 96 x 96 x 3 stamps based on Space Warps inputs.

Transfer Learning with Galaxy Zoo

- Kaggle held a competition to classify galaxy morphology using galaxies from the Sloan Digital Sky Survey, a comparable (but older) survey to the Canada-France-Hawaii-Telescope.
- We examined how well we could transfer the learning of morphology to identifying strong gravitational lenses by taking a convolution neural network trained on the Kaggle Galaxy Zoo data by Ryan Keisler and running our cutouts through to obtain a length 500 feature vector.
- We then trained these feature vectors on a random forest, which is an ensemble of decision trees wherein the order and feature vectors used in a given tree is random.
- For comparison, we plot the results from citizen scientists on these two stages as well. While we do worse overall, our results were extremely quick to compute, while the Space Warps project involved the efforts of tens of thousands over several months.



Architecture of the convolution neural network trained on the galaxy zoo morphologies and Receiver Operating Curves for the Random Forest Transfer Learning and the Space Warps systems.

Convolution Neural Network

- Using theano, we have built a 5-layer CNN which we are training from scratch on the Space Warps Dataset.
- Our algorithm uses RMSprop and dropout at each layer, and has an architecture of:
  - Convolution Layer of stride 4 and depth 10
  - Max Pool Layer of stride 2
  - Convolution Layer of stride 4 and depth 10
  - Max Pool Layer of stride 2
  - Fully Connected Layer with 50 neurons
- Our classifier has been tested and works, but more training epochs are needed before it will be competitive with our transfer learning results.

Future

- Explore deeper transfer learning (e.g. retraining parts of the network).
- Continue training our own CNN on the Space Warps Dataset directly.

Acknowledgements

We received access to the dataset through Phil Marshall (`pjm@slac.stanford.edu`), who also graciously explained to us how Space Warps currently works. The convolutional neural network upon which the transfer learning is based was kindly provided to us by Ryan Keisler (`rkeisler@stanford.edu`). All errors in interpretation or otherwise are entirely our own.