Recognizing Strong Gravitational Lenses

Chris Davis
cpd@stanford.edu

Andrew McLeod
ajmcleod@stanford.edu

1. Introduction

A consequence of Einstein's Theory of General Relativity is that mass bends the path of light. Most of the time the deflections are very small; the original 'gravitational lens' that tested the veracity of Einstein's theory in the years after the first world war was the sun, which deflected light from stars behind it only a few seconds of arc. However, when light passes through a particularly deep gravitational potential (say, near the center of the dark matter halo of a galaxy cluster), the deflections can be particularly large, resulting in brilliant arcs and multiple images. These strong deflections due to light passing through a deep gravitational potential are termed strong gravitational lenses.

The very existence of these potentials acts as a verification of the Theory of General Relativity, but they can also be used for much more. Strong gravitational lenses are one of the few ways to directly probe the distribution of dark matter, a particle (or possibly family of particles) that does not emit electromagnetic radiation but does have mass and hence interacts gravitationally with normal baryonic matter. This allows us to tally the mass of the largest gravitationally-bound structures in the universe, galaxy clusters, which can give us insight into the formation history of these massive objects. In this way, strong gravitational lenses can then tell us something about the expansion history of the universe, by setting limits on how massive the most massive objects in the universe can be. The properties of the bent light itself can also say much about that expansion history. When an object is strongly-lensed into multiple images, each image travels a different span of space and time. When an object does not vary much with time, these different path lengths have no practical import. However, if the object varies appreciably quickly (say it is a distant supermassive black hole at the center of a galaxy whose accretion disk emits high-energy radiation at varying rates) then these different path lengths can be used to pin down the rate of expansion of the universe.

Unfortunately, for how useful strong gravitational lenses are, they are also extremely rare. A next generation optical survey like the Large Synoptic Survey Telescope can expect to find only ten thousand lenses in the whole sky, while it will find ten billion galaxies. Currently in astronomy there are only order hundreds of strong gravitational lenses known, mostly discovered by 'eyeball squads' of graduate students. The small number means that target criteria must be somewhat broad in order to maintain a relatively high completeness. Using reasonable target criteria to find strong lenses such as looking only at massive galaxies still means that nearly ten million objects will need to be inspected in the next generation in order to find those ten thousand lenses. A team of ten graduate students could expect to spend about 14 years looking at these objects. Computer algorithms are not much better: most current machine learning algorithms are woefully-underpowered for this task, and generally have poor completeness or poor purity – and often poor both. Additionally, some algorithms are better at finding some types of lenses than others; some perform well on the brilliant arcs, but poorly on the multiply-imaged objects, or vice versa. New algorithms need to be developed to find more strong gravitational lenses, and more strong lenses need to be found to power these algorithms.

SPACE WARPS (Marshall et. al, in prep.) is a citizen-science initiative designed to overcome these two problems. The program has users examine images from the Canada-France-Hawaii Telescope Legacy Survey (CFHTLS) and vote on where they see lenses. Users are also assessed and trained with simulated lenses and known empty fields. By having thousands of users analyze a survey for short amounts of time each, it is hoped that a more complete sample of lenses can be discovered, which can then be fed into lens-finding algorithms to further improve their performance.

2. Problem Statement

In this project we will use images collected by the Canada-France-Hawaii Telescope Legacy Survey to analyze how Convolution Neural Networks can improve automated detection of strong lens systems. We will also assess the performance of citizen scientists by comparing our results to them. From other graduate work (but not coursework), we have the locations and categories of around one hundred and twenty known strong lenses, three thousand large fields verified to contain no strong lenses, six thousand simulated strong lenses, and several thousand classi-

Figure 1. Typical Space Warps duds. Insets indicate regions where volunteers typically clicked.

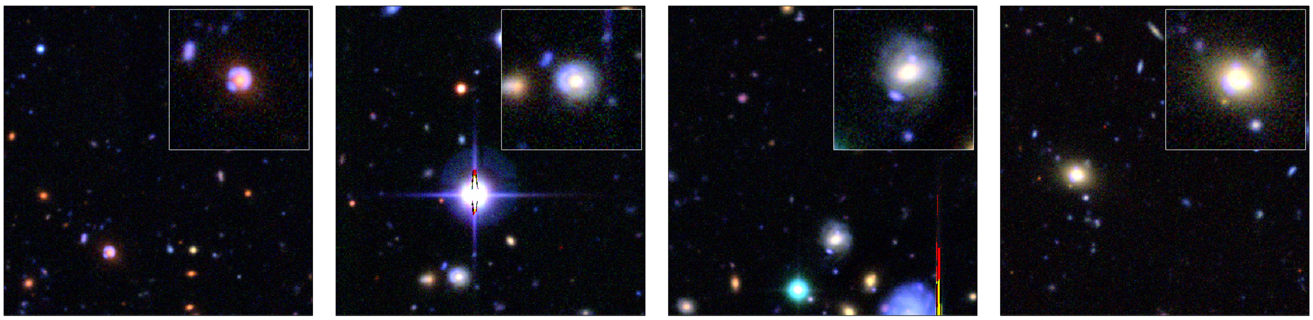

Figure 2. Typical sims. Insets indicate the location of the lens in the image.

fications by citizen-scientists of other potential strong lens systems. These will form the core of our training and testing datasets; our metric will be how well a CNN correctly identifies known and simulated lenses and non-lens systems.

We would like to examine the following questions:

- Do we have enough data to reasonably train and test a CNN? Can we get around this by artificially inflating the data, e.g. by adding rotated images?
- What processing needs to be done on the data? What kind of scaling of pixel data is appropriate for automated detection? Should we compress the five different 'colors' to a smaller number of dimensions?
- How do citizen-scientists do compared with this automated system?
- Can we use the results of citizen-scientists to train the CNN?
- What sets of classifications are needed? Are we better served sticking to 'lens' and 'not lens', or should we use several classification categories ('lensed arcs', 'lensed multiple images', 'non-lens pixel noise')?

3. Technical Approach

From approximately 12000 fields of $440 \times 440 \times 3$ fields, we have constructed approximately 30000 cutouts sized $96 \times 96 \times 3$. These cutouts are selected based on where citizen scientists clicked, on the theory that both 'correct' and 'incorrect' selections provide useful information about the characteristics of gravitational lenses. In general, we have access to two broad classes of images: 'training' and 'test' images. The 'training' images include fields that were verified in advance to not contain any lenses as well as simulated lensed galaxies, quasars, and clusters. Many of the simulated objects are over-exaggerated and extremely obvious, but we also have access to a second 'refinement stage' of the project, where much harder simulations were given to users. The 'test' images are the fields that citizen scientists viewed, assessing whether a lens was in the field or not. In these 'test' images are 120 known strong gravitational lens systems, which are also included in this set. (The project confirms roughly half of these known lenses for reasonable definitions of completeness and purity.) For all the images we also have an associated probability that the project would evaluate that system as containing a lens.

It is clear that we do not have enough data. Luckily, we also know that our lens objects must obey certain symmetry properties, so it is quite easy to augment our data. For example, we know that strong lens systems should be independent of rotations as well as small amounts of stretching and translation, so our data can be augmented by applying those transformations to our images.

We plan to train a classifier on this data using two different methods. First, we will code our own convolutional net in python using theano. Second, we will apply transfer learning techniques to train on a convolutional net galaxy morphology classifier, which has graciously been made available to us by Ryan Keisler and which achieved 7th place in the 2014 Galaxy Zoo Kaggle competition. This classifier runs 96×96 images through 3 convolutional layers and 2 fully-connected layers and predicts a galaxy to have one of 37 enumerated morphologies. We plan to train our classifier on top of the first fully-connected layer, which has 500 neurons.

4. Intermediate/Preliminary Results

We have created the cutouts of our images from the catalogs. We have begun constructing our own convolutional network with two convolutional/max-pool layers and two fully-connected layers. Although we have not yet trained on our images, we can load these images and run them through our initialized classifier. Figures 1 and 2 show example fields with cutouts inlaid.