Strong Lensing with Neural Networks

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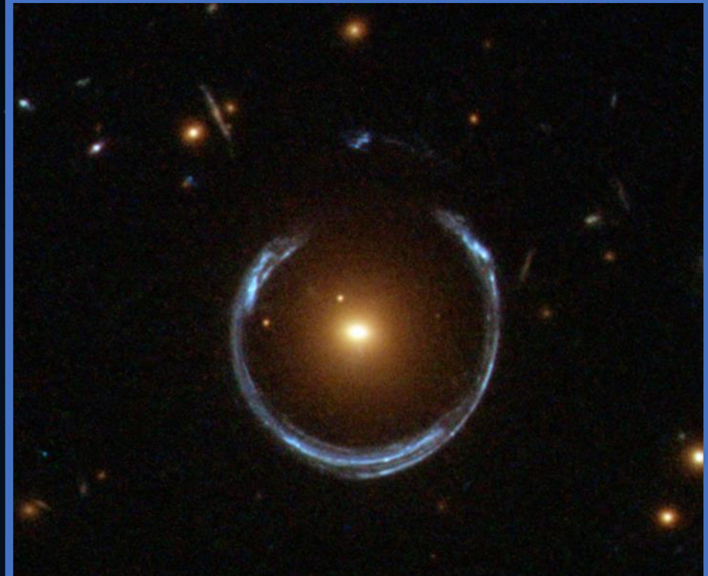
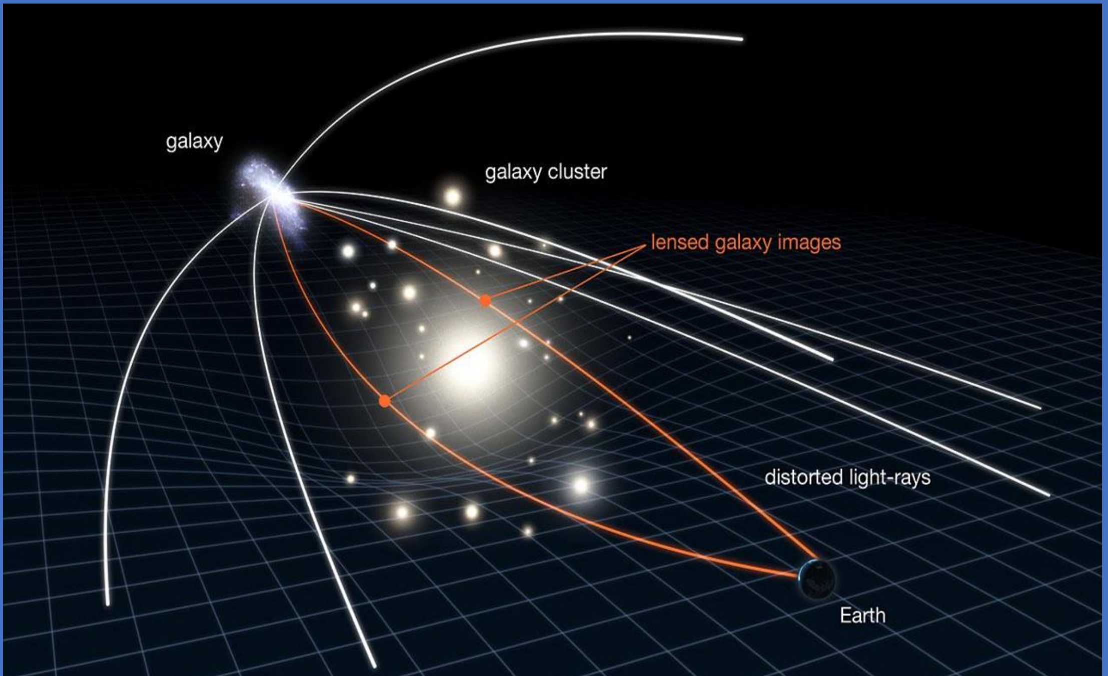


Example of an Einstein Ring. (Cosmic Horseshoe, LRG 3-757. Image Credit: ESA/Hubble & NASA)

Introduction

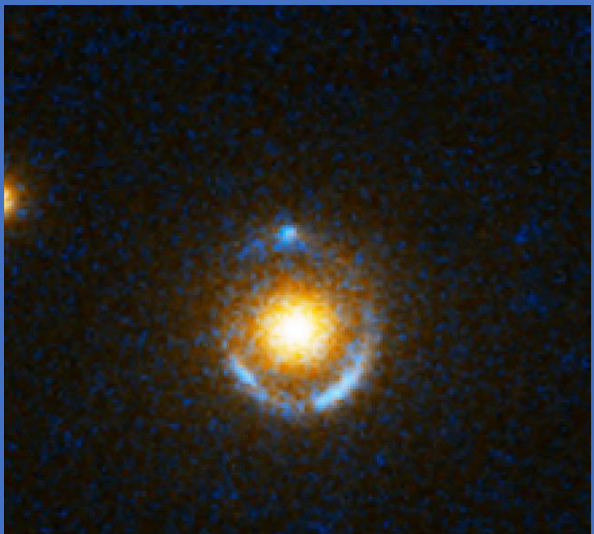
- **Strong galaxy-galaxy gravitational lensing** is the distortion of the paths of light rays from a background galaxy into arcs or rings as viewed from Earth, caused by the gravitational field of an intervening foreground lens galaxy.
- Lensing provides a useful way of **investigating the properties of distant galaxies and the early Universe**, but to do so requires **accurate modelling of the lens' mass profile**. Conventionally this is done through relatively slow parametric techniques to work out the mass profile parameters.



Gravitational Lensing. (Image Credit: NASA, ESA & L. Calçada)

Project Overview

- To date, several hundred strong lenses have been found across various surveys. However, over the next few years, surveys such as Euclid and the Legacy Survey of Space and Time (LSST) will generate billions of images containing **many tens of thousands of lensing systems**, so a **more efficient method is needed** to cope with such a large data set.
- Hence, this project aims to use machine learning to develop a **fast, automated approach to model strong gravitational lenses** straight from images, through training a **convolutional neural network (CNN).** This CNN can carry out the complex task of modelling strong lens systems with similar accuracy to parametric techniques but far more quickly.
- We aim to **investigate the effectiveness** of using CNNs to estimate lens profile parameters (Einstein radius, ellipticity and orientation) when applied to upcoming survey-style images, and **compare this to conventional parameter-fitting techniques**.



An observed gravitational lens. (Image Credit: NASA, ESA, A. Bolton (Harvard-Smithsonian CfA) and the SLACS Team)

Uses of Gravitational Lensing

When modelled correctly, lensing can:

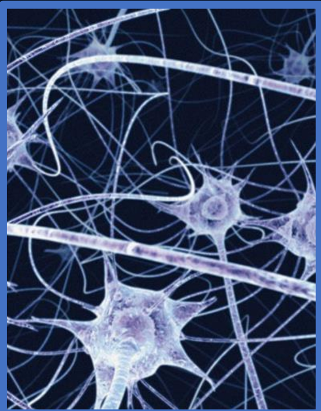
a) help us constrain the distribution of mass (**mass profile**) and the dark matter content of the foreground lensing galaxies,

b) be combined with redshift to aid in galaxy evolution models and dark matter simulations,

c) provide a distorted yet **magnified view of the source galaxy** behind the lens; techniques have been developed to reverse the lensing effect to **obtain the appearance of these high-redshift galaxies**.

What's Been Done Already?

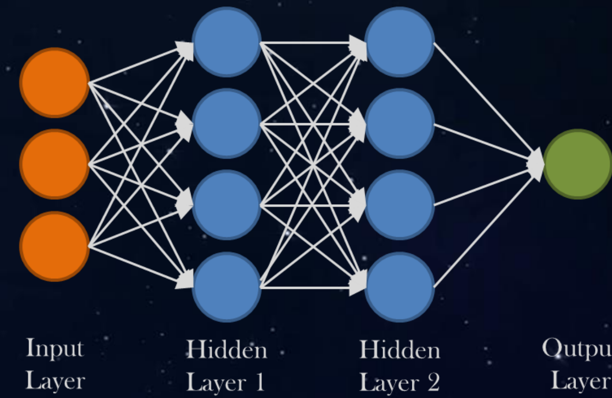
- **Conventional Lens Modelling:** This is typically done using **parametric parameter-fitting techniques** such as **PyAutoLens** (Nightingale et al. 2018), where an automated process adjusts parameters of a mass profile to best fit the observed image. However, this **requires manually-set initial ‘guess’ values (priors) and a large amount of time and computing power**.
- **CNNs:** Hezaveh et al. (2017) demonstrated the use of CNNs to model lenses much faster than previous methods. Levasseur et al. (2017) incorporated into this an approximate Bayesian framework, allowing it to predict its own errors.

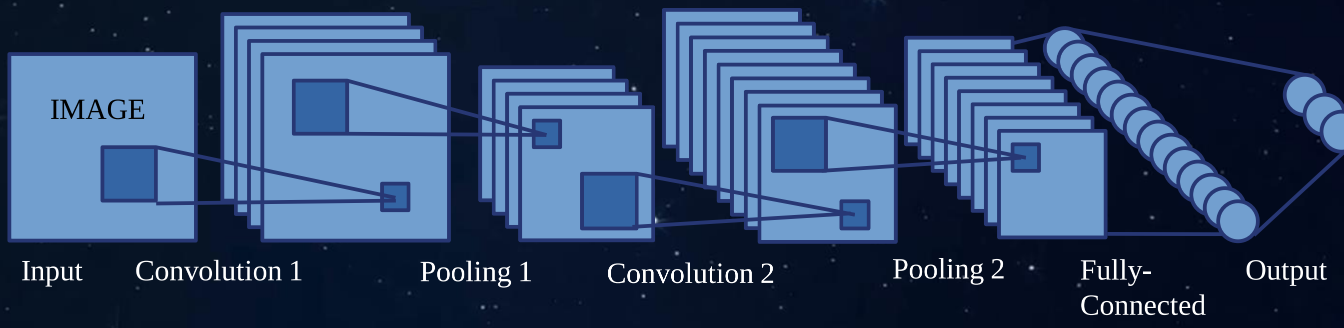


Above: Neurons in the brain. (Credit: A Moment of Science, https://indianapublicmedia.org/amomentofscience/lose-neurons/)

Convolutional Neural Networks (CNNs)

- Just as the brain is made up of interconnected neurons, a neural network consists of **layers of nodes**, with nodes connected between layers and the strengths of these connections given by a 'weight' value.
- CNNs are a subset of neural networks that have **grid-like layers** mainly for analysing images, and apply filters in order to extract information. An example CNN is shown in below.
- CNNs can be improved through training, typically requiring a minimum of tens of thousands of training images. As not enough images of real lenses exist, they must be simulated instead.



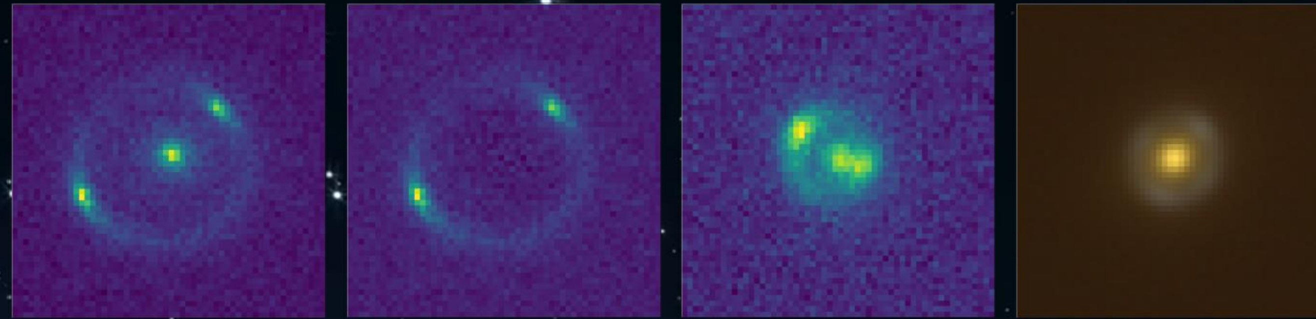


Above: Neurons in a neural network.

Left: Typical CNN structure. Pooling layers decrease image size, other layers extract features and relationships in the data.

Investigation

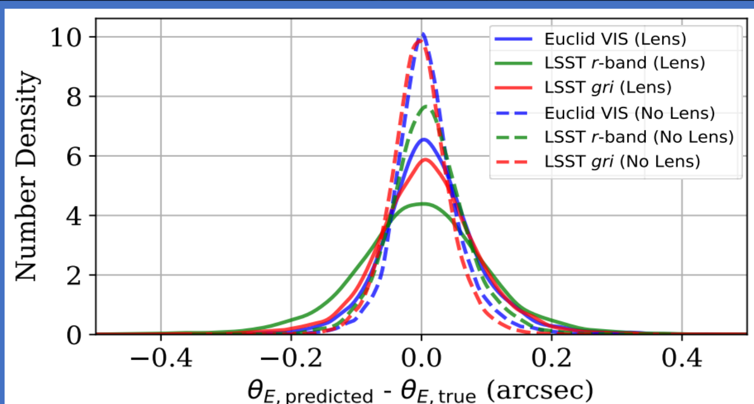
- The CNN was trained on 50,000 images generated to resemble expected observations by **Euclid (VIS band)** and **LSST (g, r, & i bands)**.
- Containing six convolutional layers, the CNN learned to predict values for the lensing galaxies' Einstein radii (size of the ring), and complex ellipticity components (which can be converted to ellipticity and orientation).
- The accuracy of the network was then obtained by testing on separate image data sets.
- Several aspects of the training were investigated, by evaluating the performance of the network:
    - for Euclid- and LSST-like data,
    - for images with and without colour,
    - for images with and without lens light,
    - and when the mass and light profiles of the lens are changed with respect to each other.



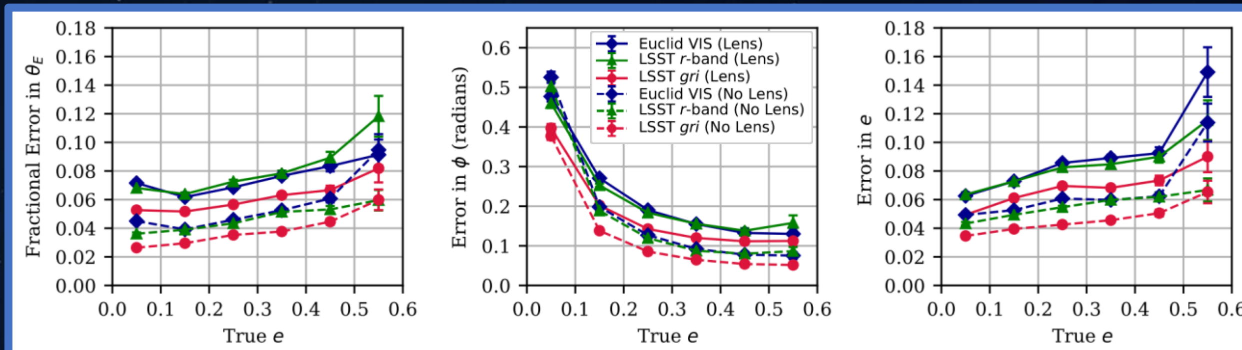
Left to right: Simulated Euclid, Euclid with lens light removed, LSST r-band, and LSST g,r,i-band images.

Results

- The CNN is now at a stage where it can accurately measure mass profile parameters for image catalogues simulated **in the style of expected LSST and Euclid observations**, for example those seen above.
- While network performance improved for Euclid images over single-band LSST images, it did equally well or better than Euclid when given multi-band LSST g,r,i images, which allow it to more easily distinguish between the lens and source (for example, see bottom left).
- The investigation provided other insights as well that can inform future training. For example, CNN errors are shown below when test images are binned by ellipticity. We see that while more elliptical lenses make it easier to obtain orientation (as expected), the other parameters become increasingly harder to predict.



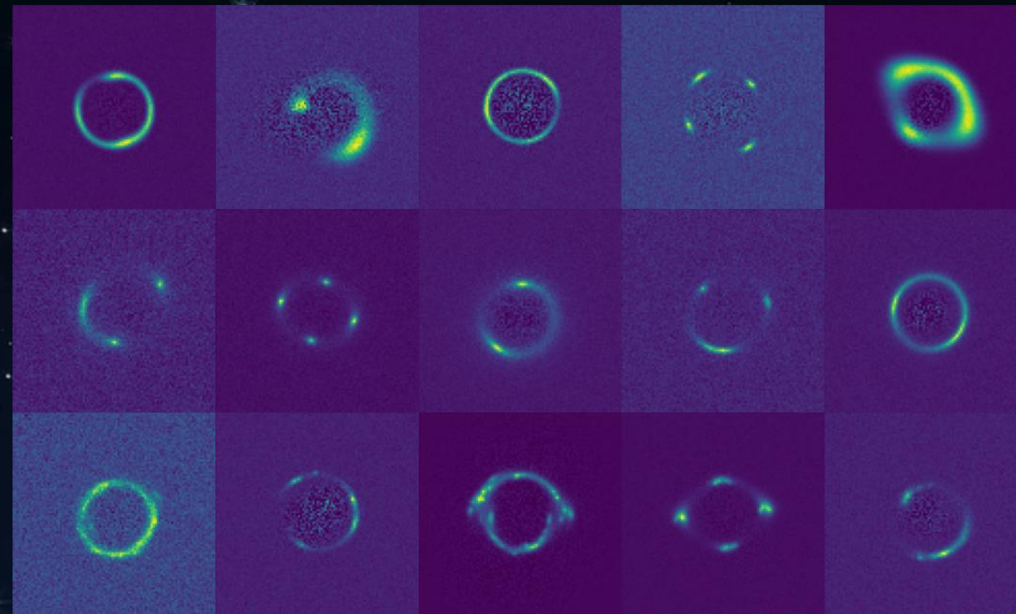
Differences between Einstein radii predicted by the CNN and their true values for Euclid VIS, LSST r-band and LSST g,r,i-bands, both with and without their lens light.

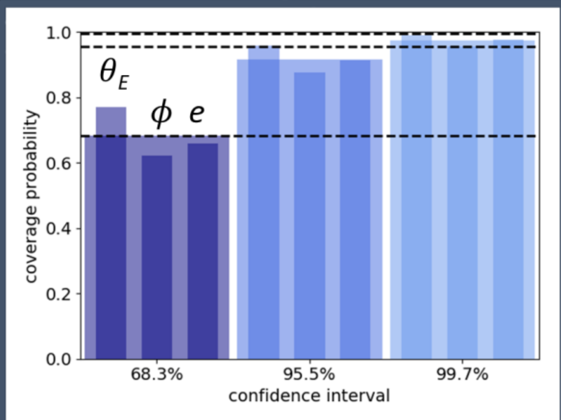


Magnitudes of differences between CNN-predicted parameters and true values as functions of ellipticity. From left to right: Einstein radius, orientation and ellipticity. Results include Euclid VIS, LSST r-band and LSST g,r,i-band images. Solid and dashed lines correspond to images with lens light included and removed, respectively.

Comparing to conventional fitting

- Shifting focus to Euclid-style images, the CNN was retrained on a larger set of more **complex images** (figure on the right).
- Additionally, changes were made to the CNN to allow it to **predict its own uncertainties**.
- We compared the CNN to a conventional parameter-fitting technique, **PyAutoLens**, for different test sets, such as images with real HUDF sources, with & without line-of-sight structure (LOSS).
- We also tried a **combination of the two techniques**, using CNN predictions as priors for PyAutoLens.





0.997
0.955
0.683

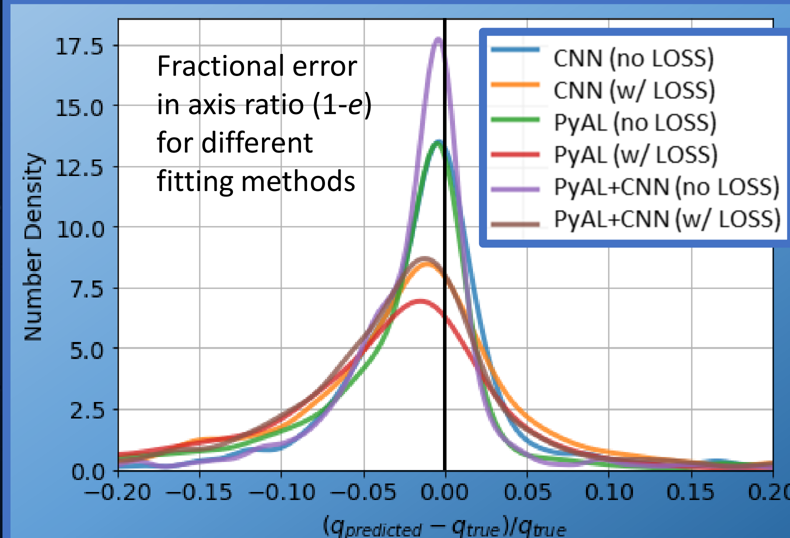
Ideally, coverage probabilities should match confidence intervals

Results

- First, the CNN was fine-tuned so that the uncertainties it predicted were suitable, i.e. that its 1-sigma uncertainty predictions actually covered ~68% of the results (figure on the left).
- Current work suggests that while CNN accuracy appears to be equal to or slightly worse than PyAutoLens, the combination of the two is significantly better than either one separately (see below).

Summary

- This project has so far achieved high accuracies for parameter estimation, on par with conventional fitting techniques, and with future training could even outperform such techniques.
- Regardless, the **combination of CNNs with conventional parameter-fitting approaches** is a promising new method that can achieve even better results.
- More work is needed on testing the CNN and this combination method, testing on highly realistic images containing EAGLE hydrodynamically-simulated lenses, with potential LOS structure.
- Additionally, work will be done training and testing on power law profiles, the more general form of the currently investigated singular-isothermal ellipsoid (SIE) lens models.



References

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