Strong Lensing with Bayesian Neural Networks

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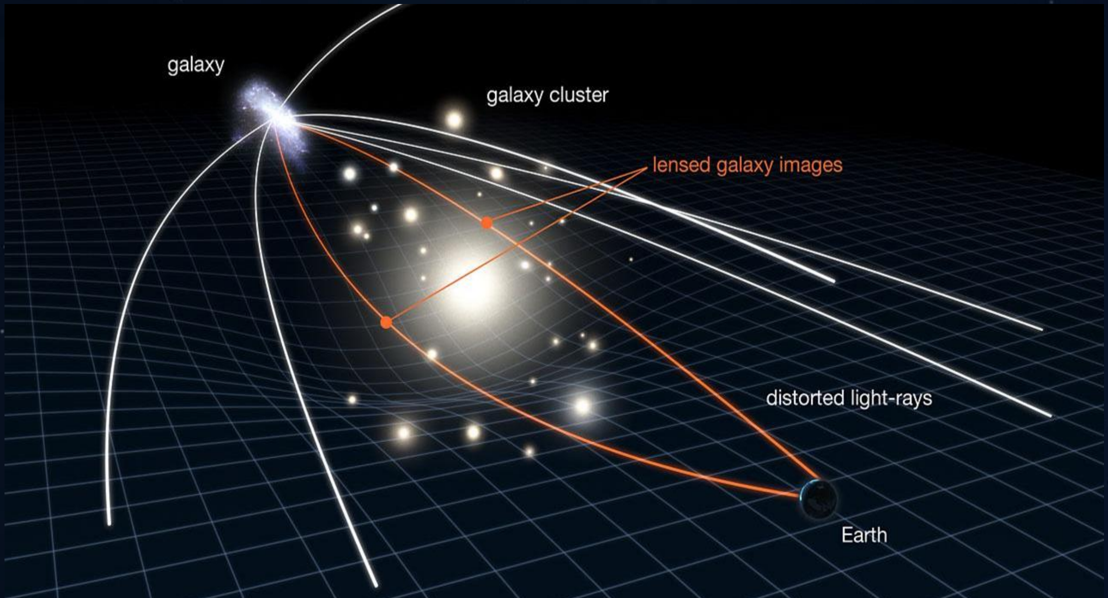
Strong Galaxy-Scale Gravitational Lensing

- This 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 galaxy (the '**lens**').
- Lensing provides a useful way of investigating the **properties of distant galaxies** and the **early Universe**, including:
    a) providing constraints on the distribution of mass (**mass profile**) and the dark matter content of the foreground lensing galaxy,
    b) combining with redshift to aid in galaxy evolution models and dark matter simulations,
    c) and providing a **magnified view of the high-redshift source galaxy**.
- But this requires **accurate modelling of the lens' mass profile**, usually through slow but accurate parametric techniques to determine parameters of the mass profile.

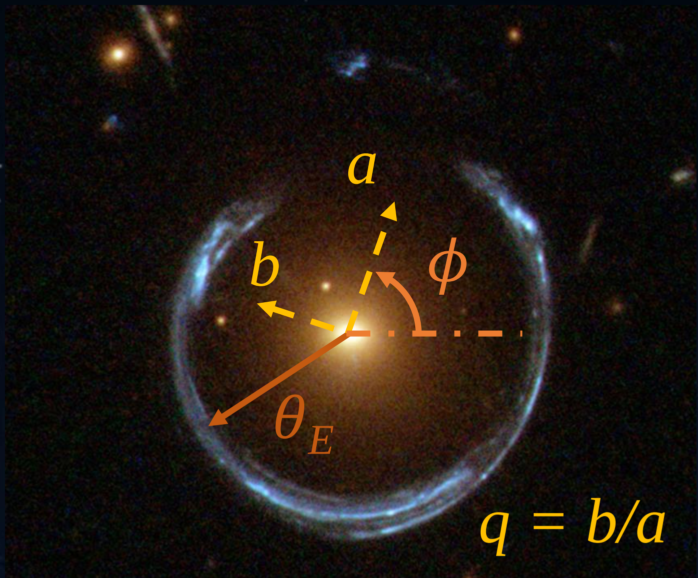
An observed gravitational lens.
[NASA, ESA, A. Bolton (Harvard-Smithsonian CfA) and the SLACS Team]



Gravitational lensing of light rays on their way to the Earth. [NASA, ESA & L. Calçada]

Project Overview

- To date, only several hundred strong lenses have been found. However, upcoming surveys such as Euclid [1] and the Legacy Survey of Space and Time (LSST) [2] will generate billions of images containing **many tens of thousands of lensing systems**, so a **more efficient modelling method is needed** to cope with such a large data set.
- This project aims to use machine learning to develop a **fast, automated approach to model strong gravitational lenses** straight from images, with similar accuracy to parametric techniques.
- We train an approximate **Bayesian convolutional neural network (CNN)** to estimate lens mass profile parameters, **investigating its effectiveness** when applied to Euclid-style images and **comparing this to conventional parameter-fitting techniques**.



Mass model parameters overlaid onto an Einstein Ring. (Cosmic Horseshoe, LRG 3-757) [ESA/Hubble & NASA]

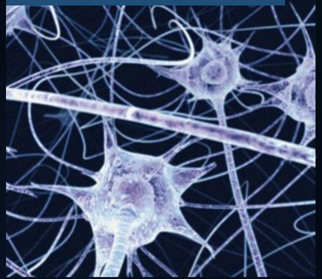
Conventional Lens Modelling – PyAutoLens

Modelling is typically done using **parametric parameter-fitting techniques** such as **PyAutoLens** [3], 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**.

Convolutional Neural Networks (CNNs)

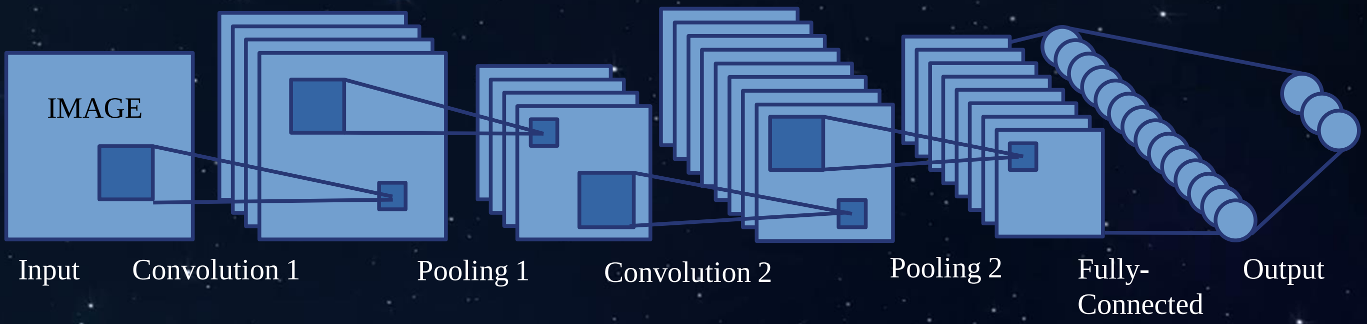
- Just as the brain is made up of interconnected neurons, a neural network consists of **layers of nodes**, with nodes connected between layers and the strengths of these connections given by 'weight' values.
- CNNs are a subset of neural networks that have **grid-like layers** mainly for analysing images, 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.

Neurons in the brain. [https://indianapublicmedia.org/amomentofscience/lose-neurons/]



Mass Model Parameters

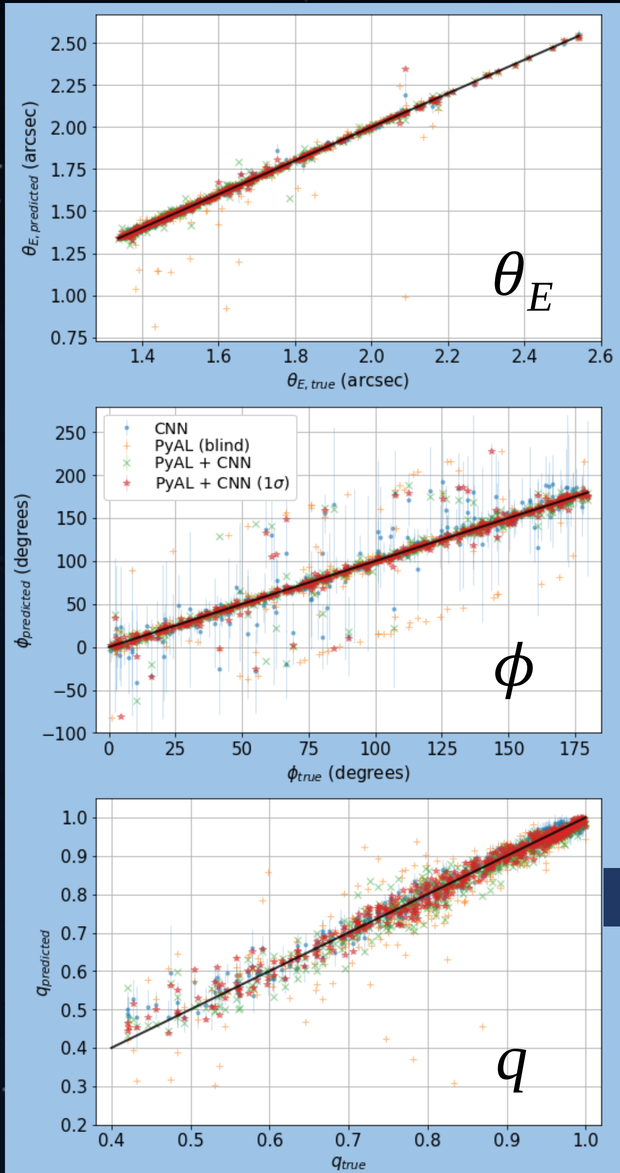
- The radius of the Einstein ring, aka the Einstein radius, θ_E
- The orientation, ϕ
- The semi-minor to semi-major axis ratio, q



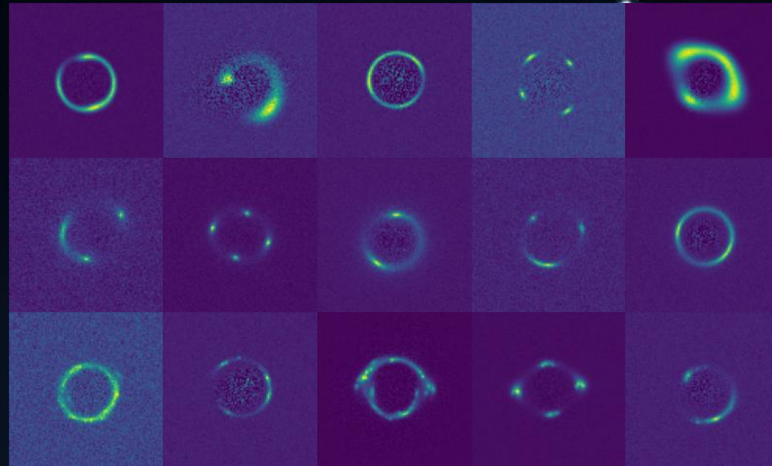
Example CNN structure. Pooling layers decrease image size, other layers extract features and relationships in the data.

Comparing & combining with conventional fitting

- The CNN was trained on **100,000 complex images** generated to resemble expected observations by **Euclid (VIS band)**.
- It's **approximate Bayesian formalism** [4] allowed the CNN to predict values for the lensing galaxies' **mass model parameters** as well as **their uncertainties, σ**.
- We compared the CNN to **PyAutoLens** for **increasingly complex test sets**, from smooth light & mass profiles to images with EAGLE simulation lenses [5,6], real HUDF sources [7] and extra line-of-sight structures (LOSS). These were generated using the Pipeline for Images of Cosmological Strong Lensing (PICS) software [8].
- We also tried **combining** the two techniques, **using CNN predictions (values & uncertainties) as priors for PyAutoLens**.



Simple smooth lens and source profiles



Above: Example simulated training images

← Predicted vs. True Parameters →

Blue = CNN

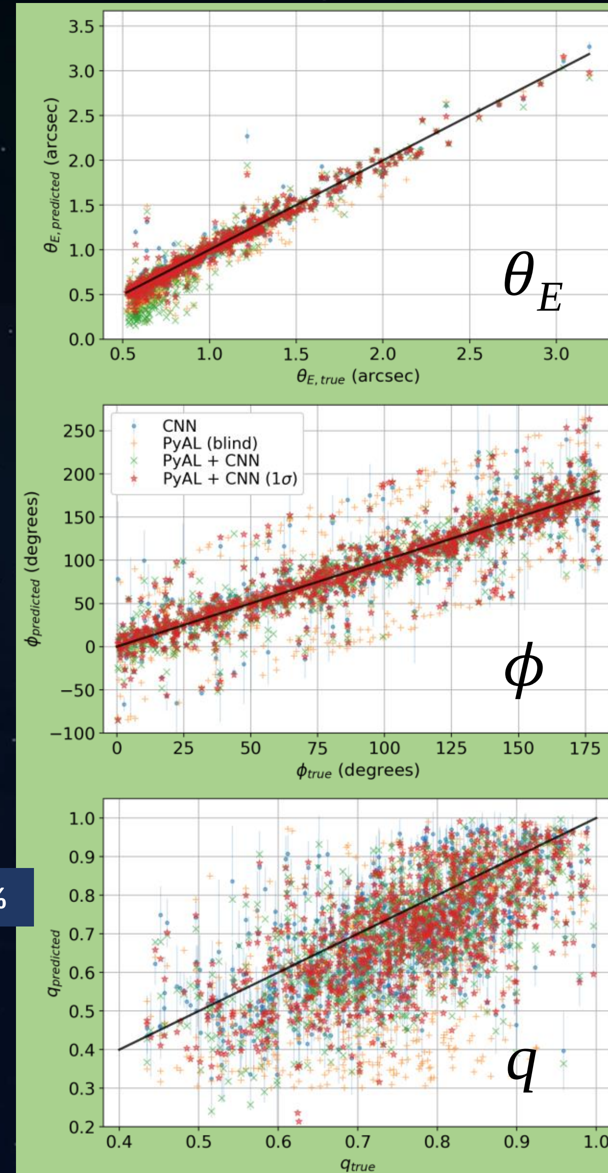
Orange = PyAutoLens (PyAL)

Green = PyAL + CNN values as priors

Red = PyAL + CNN values & (1σ) uncertainties as priors

Incorporating CNN predictions and uncertainties reduces PyAutoLens errors by:

37-44% **15-34%**



EAGLE lenses + HUDF sources + LOSS

Accuracy

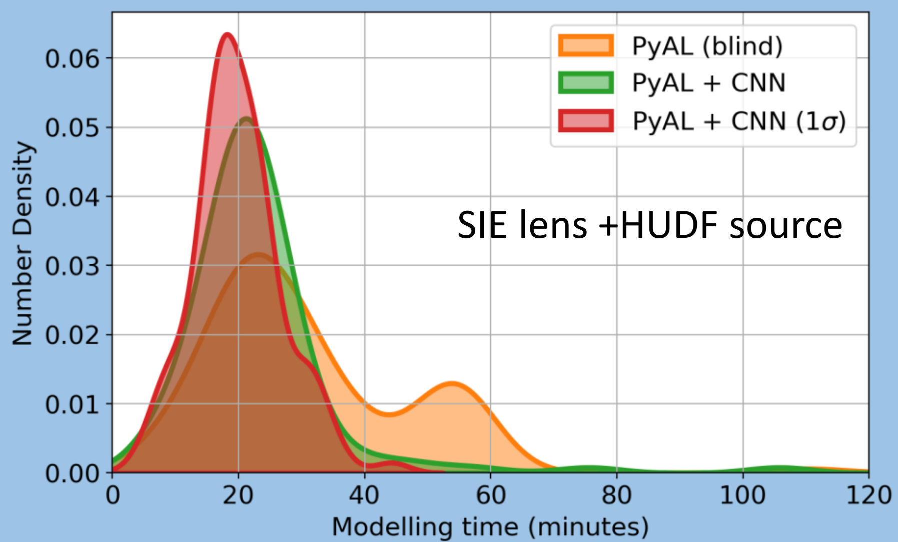
- Overall, CNN errors were **19 ± 22%** lower than PyAutoLens' blind modelling.
- The combination method instead achieved **27 ± 11%** lower errors, reduced further to **37 ± 11%** when incorporating **CNN-predicted uncertainties** into the priors.
- These modelled mass profiles were singular isothermal ellipsoids. While not included here, similar results were obtained for the more general and difficult-to-model power law mass profile.

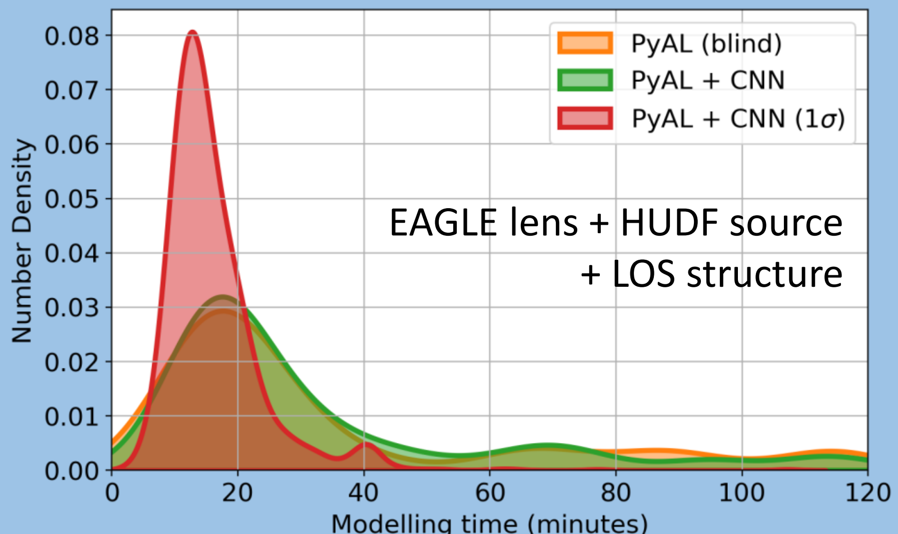
Modelling Times

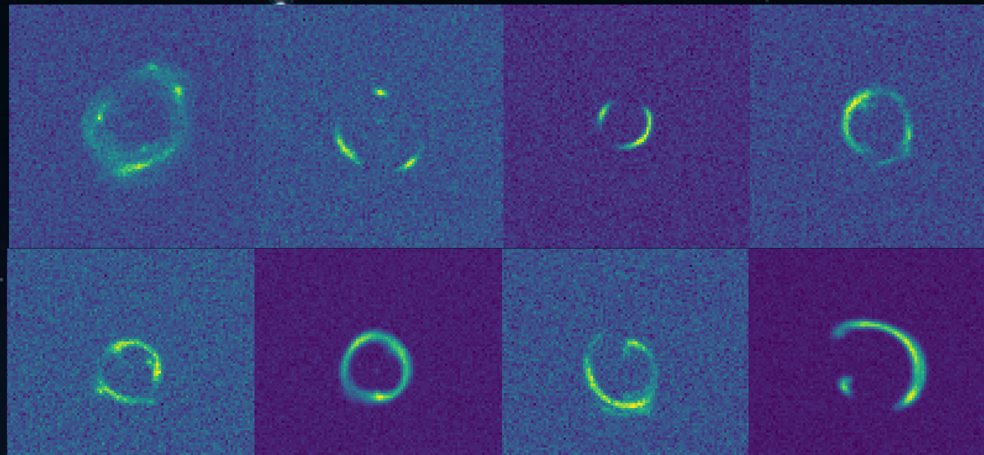
(CNN times not included as they are less than a second!)

Incorporating CNN predictions makes PyAutoLens more consistent, and compared to PyAL (blind) modelling speed is increased by a mean factor of:

1.19x for PyAL + CNN, **1.73x for PyAL + CNN (1σ)**







Example simulated test images containing EAGLE galaxy lenses

Summary

- The CNN can accurately measure mass profile parameters for Euclid-style images, much more rapidly than conventional modelling.
- CNN accuracy is equals or exceeds an automated PyAutoLens, while the **combination of the two significantly improves upon both**, especially when including CNN-predicted uncertainties.
- Using CNN predictions as priors additionally **increases the modelling speed** of PyAutoLens.
- Hence, the **combination of CNNs with conventional parameter-fitting approaches** is a promising new method that for automated lens modelling can potentially outperform either separately.
- Additionally, training on larger, more complex data sets could improve performance even further!

This Research

Pearson, et al. (2021), *Strong lens modelling: comparing and combining Bayesian neural networks and parametric profile fitting.* MNRAS, 505(3), pp.4362-4382, doi:10.1093/mnras/stab1547

References

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[8] Li et al., 2016. ApJ, 828(1), p.54

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