LEMON: Lens mdeling with Bayesian neural networks

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ML4ASTRO 2024

08/07/2024

Open questions in galaxy evolution and cosmology

Open questions in galaxy evolution / cosmology

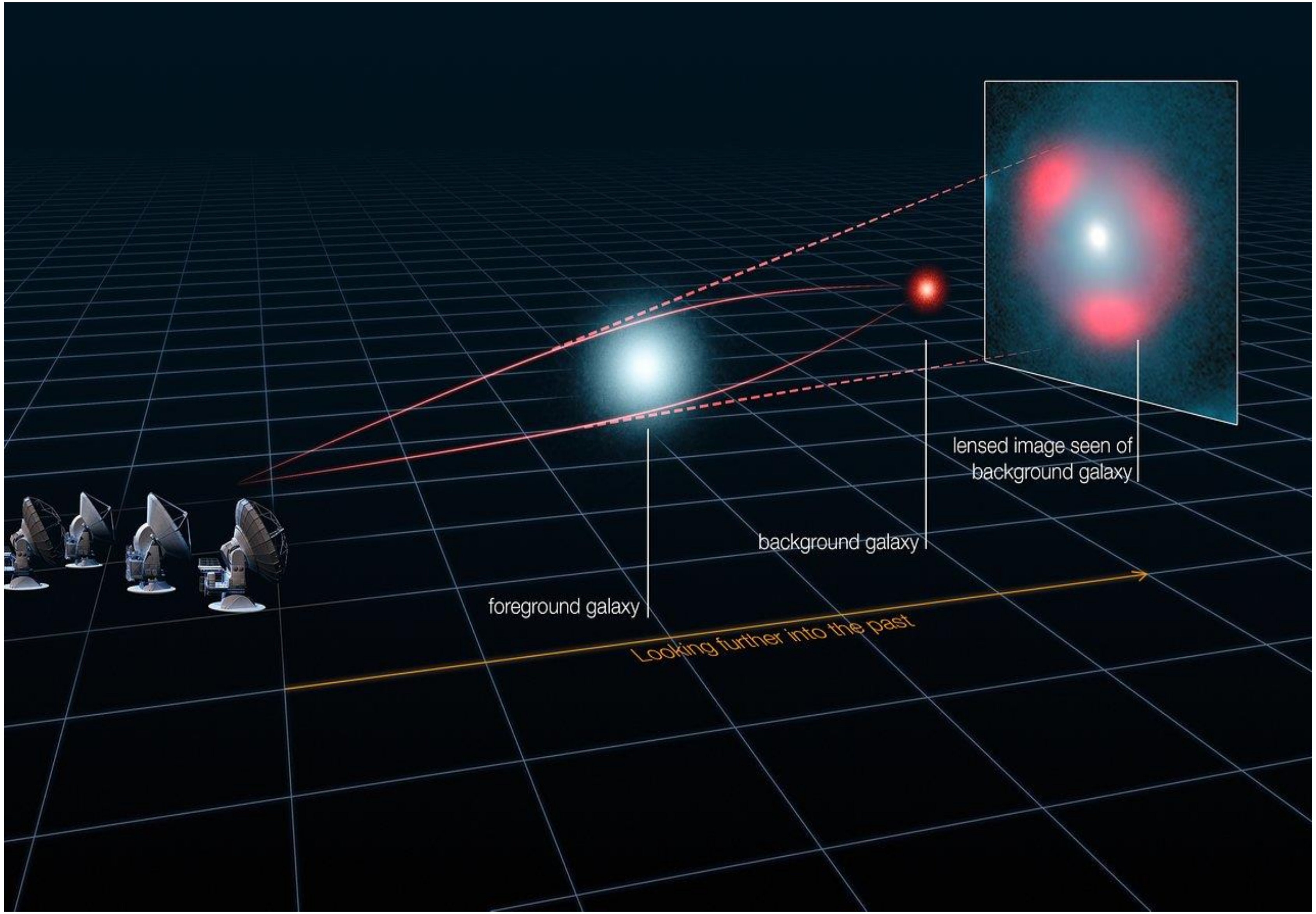
1. How do galaxies form and evolve?
2. What are the mechanisms that produce different galaxy morphologies?
3. What were the properties of the first galaxies formed in the Universe?
4. How has the star formation rate of galaxies changed over time?
5. What is the nature of dark matter? How is it distributed around galaxies?

Gravitational lensing

- **Gravitational lensing**: magnification and distortion of background objects (e.g. far galaxies) due to the presence of a strong gravitational field source (e.g. massive galaxies) in the foreground.
  Rare phenomenon, predicted by Einstein's general relativity.

- Magnification of very distant and faint sources allows for **detailed study of galaxies in the early Universe** (cosmic telescope). Time-delay allows for measurements of H_0 (cosmic clock).

- Lensing also allows to determine the mass within the Einstein radius in galaxies (cosmic scale), providing constraints on **dark matter and gravitational theories**.



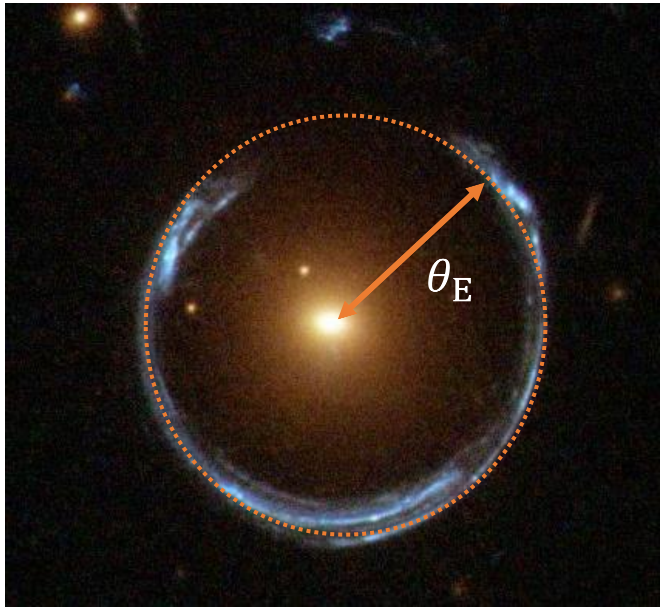
Lensing: a cosmic weighing scale

- Projected mass within Einstein radius measurement from strong lensing is **the most precise mass measurement possible**, not requiring any modeling a priori.

- Angular diameter distances for both deflector and source are required to estimate mass. Knowledge of background cosmology is also required.

$$M(\theta_{\mathrm{E}}) = \frac{c^2}{4G} \frac{D_{\mathrm{d}}(z_{\mathrm{d}}) \cdot D_{\mathrm{s}}(z_{\mathrm{s}})}{D_{\mathrm{ds}}(z_{\mathrm{d}}, z_{\mathrm{s}})} \theta_{\mathrm{E}}^2 \propto \theta_{\mathrm{E}}^2$$

- With modeling, it is possible to infer quantities related to dark matter content of galaxies and other properties (M_{DM}, f_{DM}, mass density slope, IMF, …)



Euclid: overview

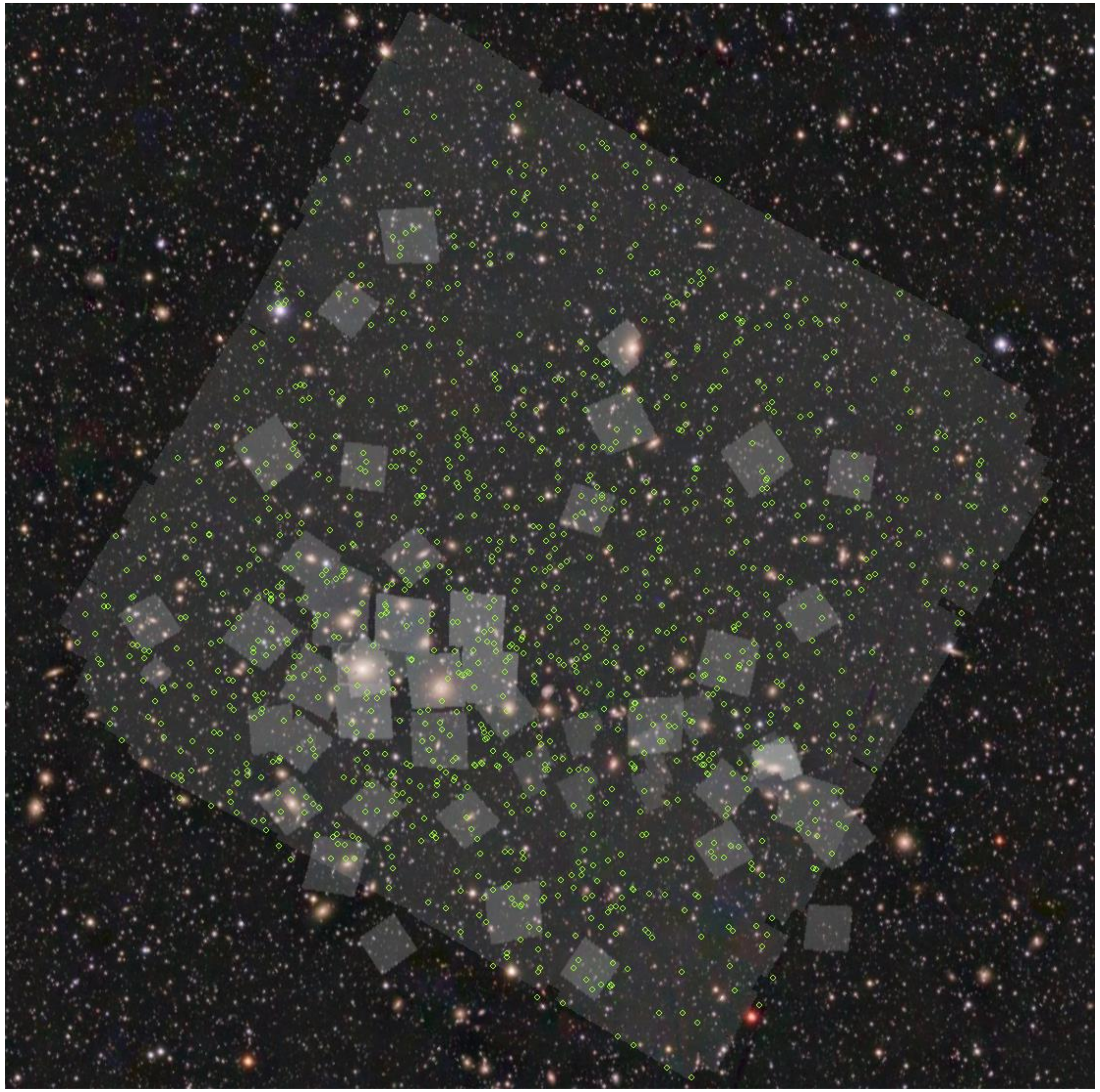
- ESA's Euclid telescope is designed to **map the geometry of the Universe**, and to understand the **nature of dark energy and dark matter**.

Mellier+24

- **Euclid WIDE** will survey $\sim 10^9$ galaxies over a significant portion of the sky ($\sim 14{,}000\ \mathrm{deg}^2$).

- High resolution imaging + spectroscopy is ideal for detecting gravitational lenses.

Euclid: The advantage of a big FoV



- Euclid FoV: 0.57 deg^2. HST FoV (ACS): 0.003 deg^2.

Euclid has 181 times the area coverage of HST!

- The pixel scale of Euclid, however, is worse than HST:
  - ➢Euclid pixel scale: 0.1 arcsec/pixel
  - ➢HST pixel scale (ACS): $0.05 \text{ arcsec/pixel}$

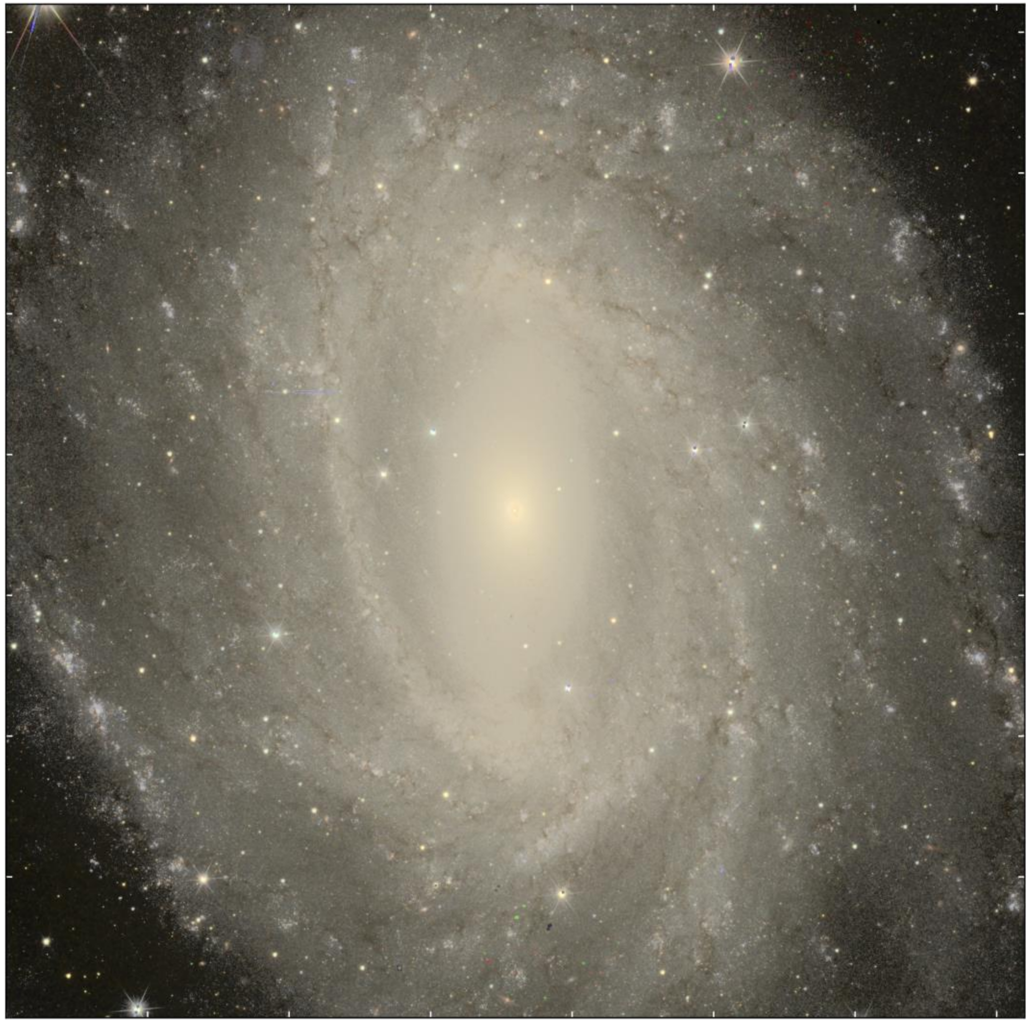
Images of gravitational lenses will be lower resolution than HST images, but we will find much more of them.

Marleau+24

Euclid: Some examples

Hunt+24

NGC6744



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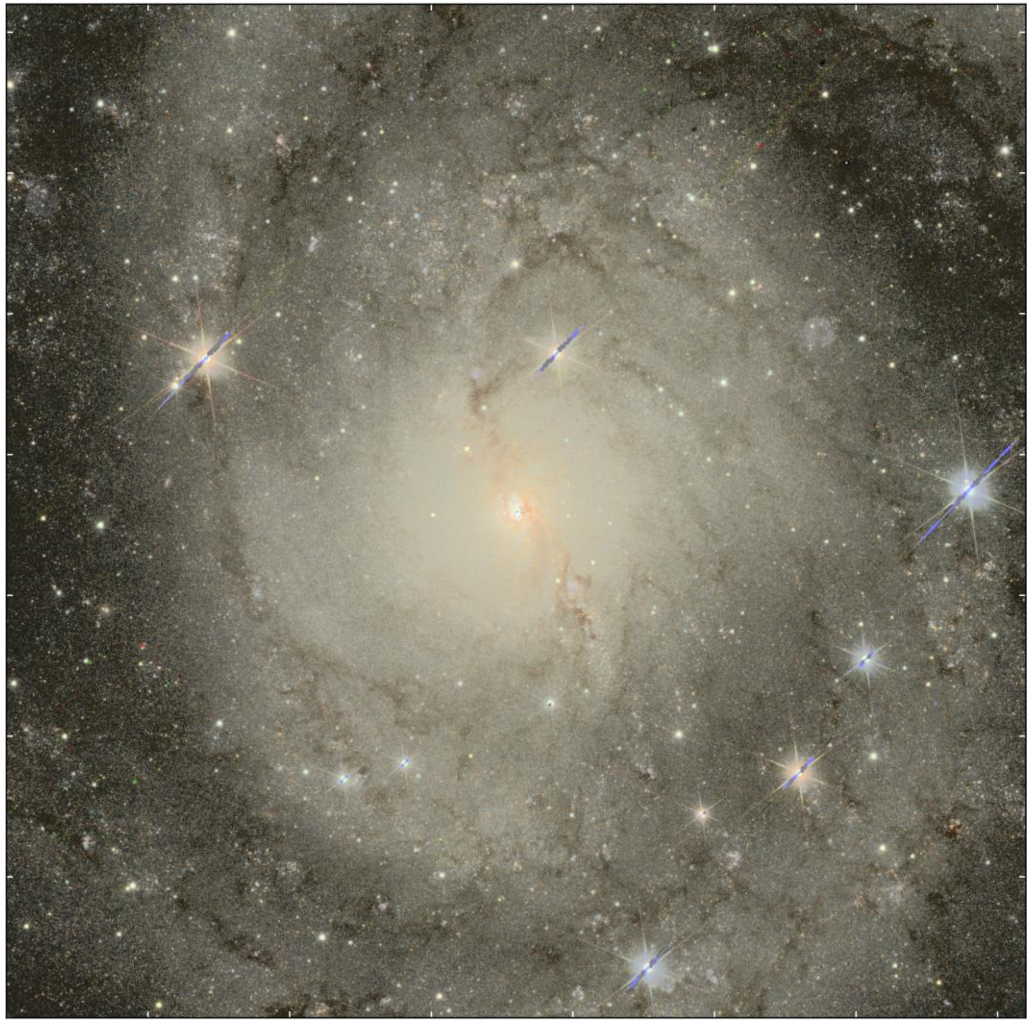


Euclid: challenges with traditional analysis

- **Issues with data volume**: Euclid WIDE will generate petabytes of data.

- Visual inspection of "interesting" galaxies (2×10^8 galaxies) in Euclid WIDE would take **30 years**, by working 24h/24, with 5 seconds per inspection.

We need automated methods for lens finding!

- Traditional modeling techniques based on maximum likelihood and MCMC techniques are **computationally expensive** (run times **between hours to months**, depending on model complexity and dataset resolution)

We need automated methods for lens modeling!

LEns MOdeling with Neural networks: LEMON

- **LEMON**[1] (LEns MOdeling with Neural networks): Bayesian Neural Network (BNN) based on a modified version of a ResNet architecture[2] (CNN for feature extraction + Bayesian fully connected layer for parameter estimation).

[1]Gentile+22
[2]He+15

- **Goal**: numerically estimate (best value + uncertainty) the lens mass (Singular Isothermal Ellipsoid) and light (Sérsic) distribution from the image of a gravitational lens.

- LEMON can estimate both *aleatoric uncertainty* (associated to **intrinsic quality of image**) and *epistemic uncertainty* (associated to the **quality of the training set**).

LEMON: general performance

- Mean LEMON training time: 85 epochs for 40,000 training lenses, $\sim 8.4 \text{ hr } (550 \text{ ms/step}^{**})$ with RTX 4080 GPU and NVMe M.2 PCIe Gen. 3 storage*.

- Training time scales with training set dimension $(830 \text{ ms/step}^{**}$ for 90,000 training lenses, same configuration).

- Mean LEMON parameter inference time on test-set*: $\sim 8.7 \text{ ms/lens}$ (~ 279 ms/step^{**}, around 30 seconds for inference on 100,000 lenses).

*Results depend on hardware configuration and number of parameters.
**Batch sizes: 64 for training, 32 for test.

LEMON: Datasets used

Four main datasets:

1. 50,002 mock Euclid lenses "with companions" (i.e. contaminants other than main lens), produced from the Euclid Flagship simulation[1,2];

[1]Castandar+24
[2]Metcalf et al. in prep.

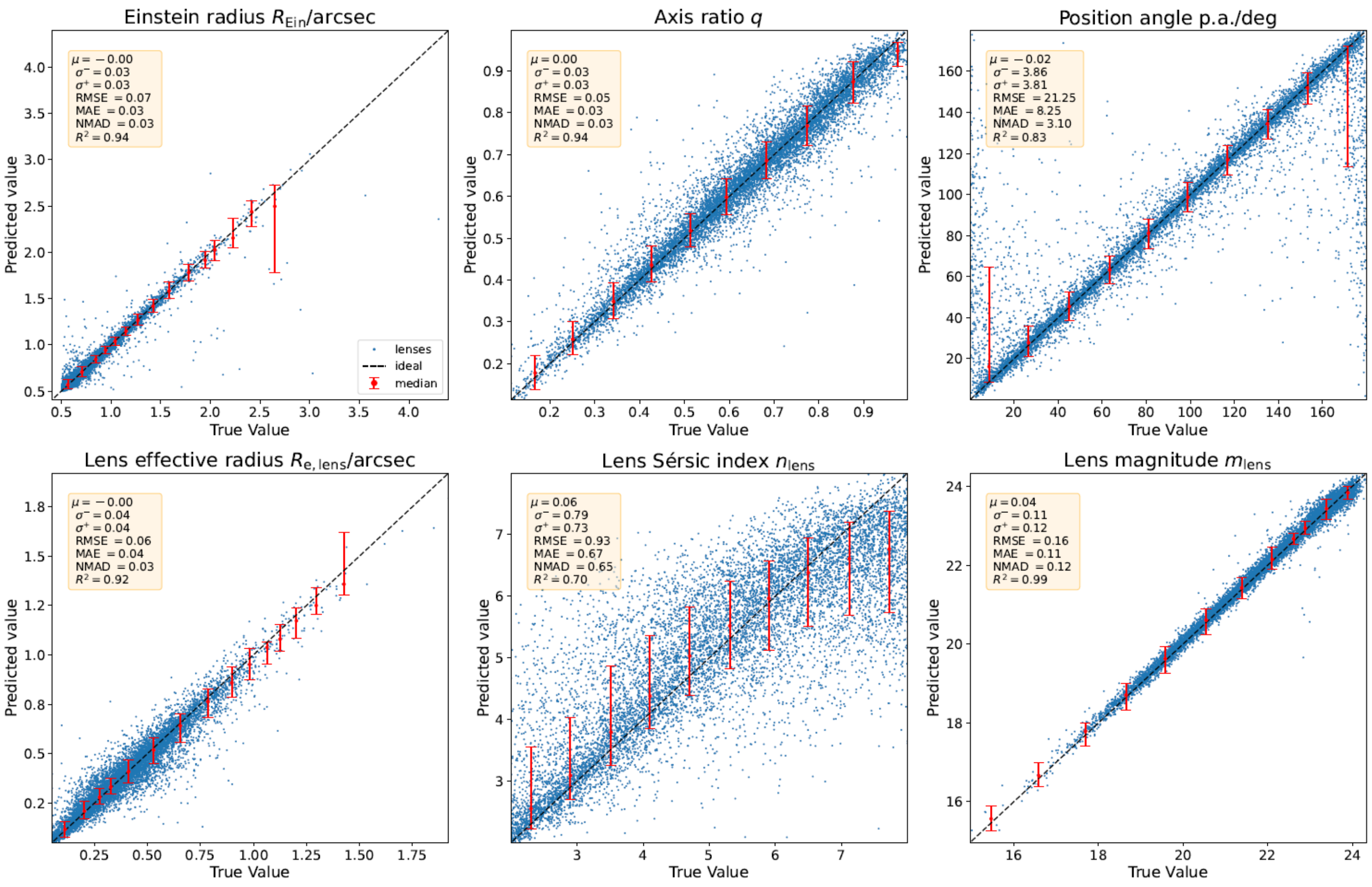
2. 50,002 mock Euclid lenses "without companions", produced as above;

3. 50,000 mock Euclid lenses produced by the lens modeling software PyAutoLens[3];

[3]Nightingale+15,18,21

4. 130 real "Euclidized" lenses.

Recovery of test set lenses' parameters

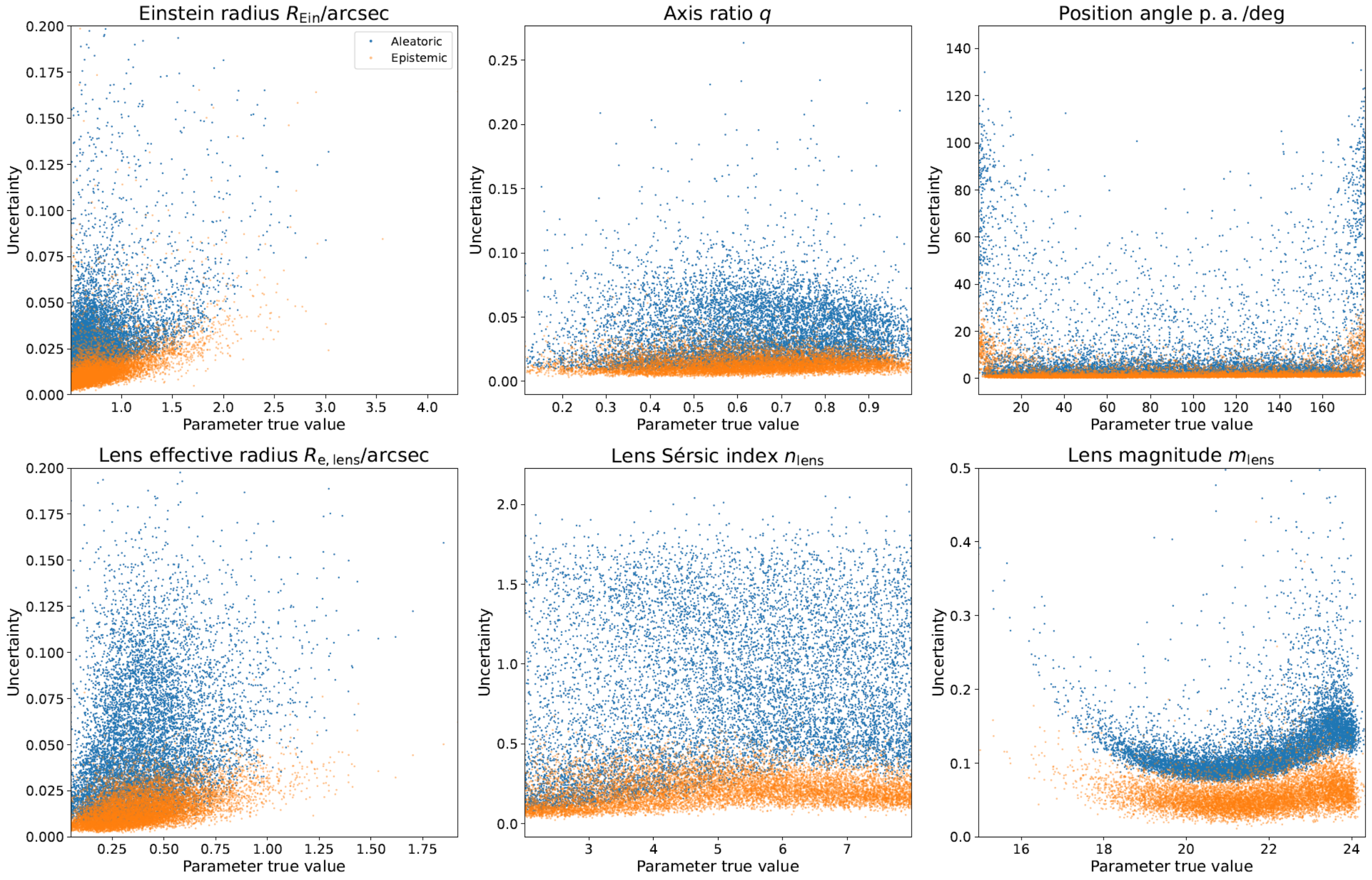


Euclid preliminary

- LEMON trained on datasets 1. + 2. (80,000 lenses of both kinds), applied on test set of 10,002 lenses of both kinds;
- All parameters are recovered by the network;
- Lens Sérsic index shows a non-linear trend with large scatter.

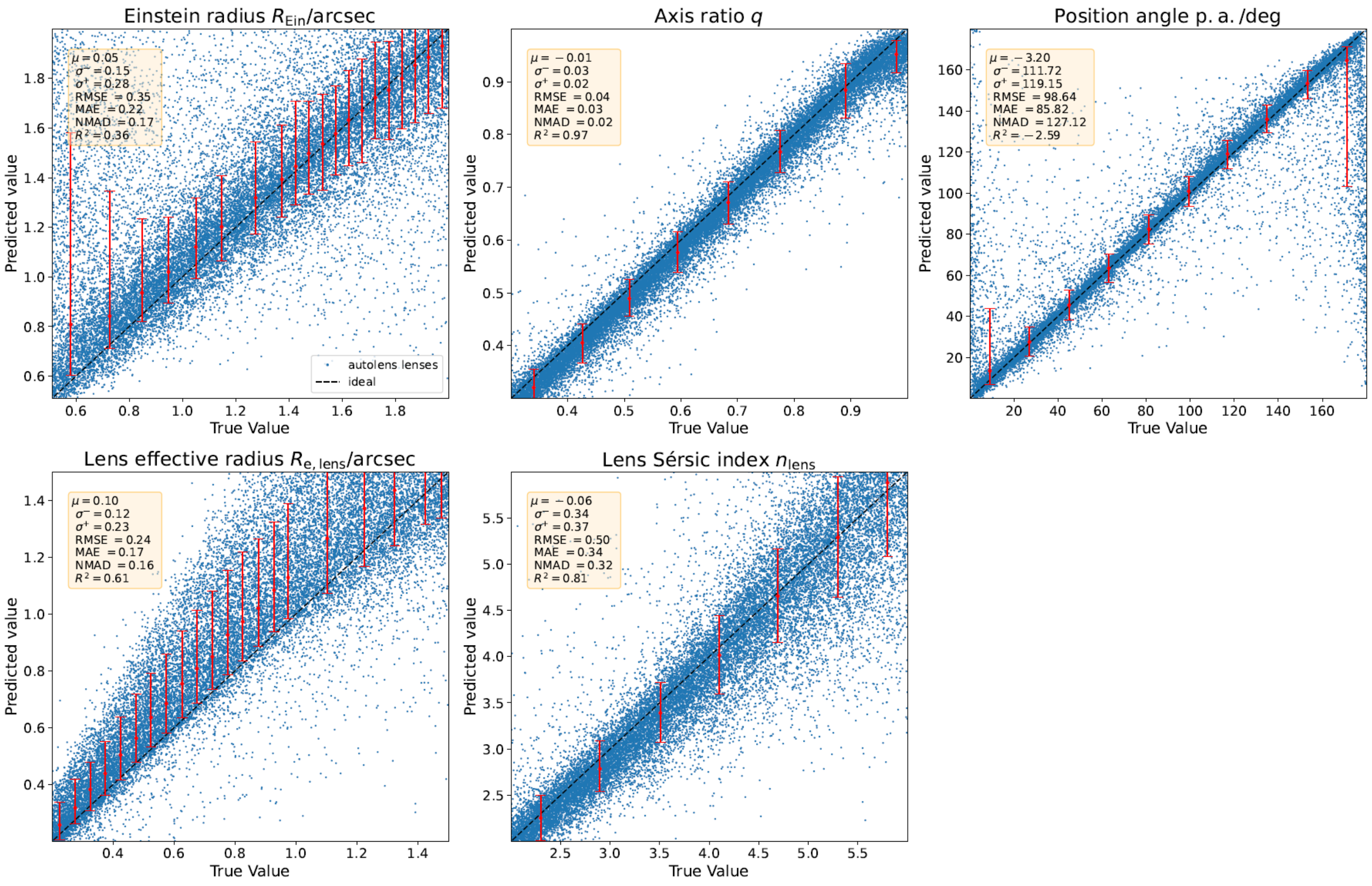
Aleatoric and epistemic uncertainties' trends

Epistemic uncertainty as a function of the mass and light parameters shows systematically lower values with respect to the aleatoric uncertainty.



Euclid preliminary

Recovery of AutoLens lenses' parameters



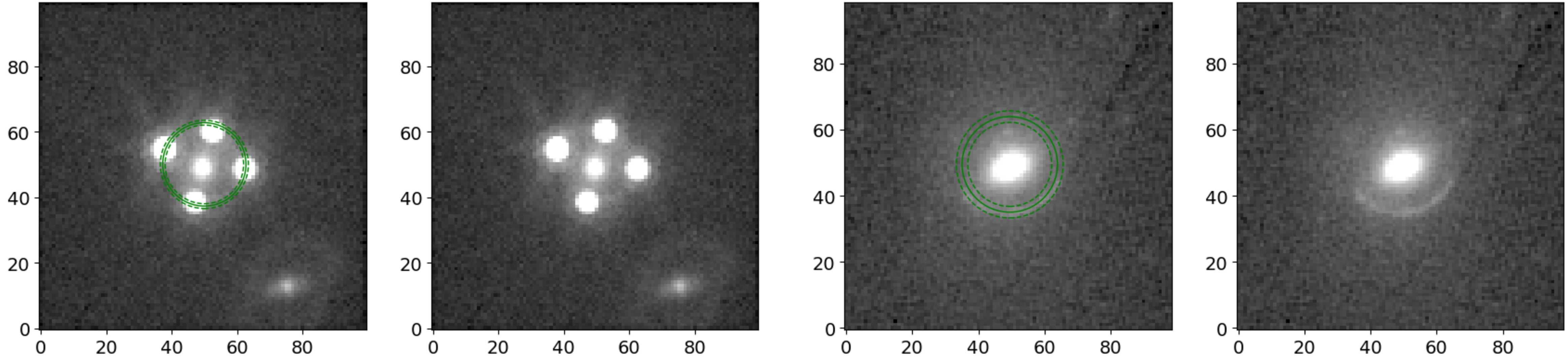
Euclid preliminary

- LEMON trained on datasets 1. + 2. again, applied on AutoLens lenses such that $R_{\mathrm{Ein}} \in [0.5, 2.0]$ (23,256 lenses);
- All parameters are recovered by the network;
- Einstein radius for $R_{\mathrm{Ein}} \lesssim 1$ arcsec and lens effective radius are systematically overestimated.

Recovery of Einstein radius for Euclidized/real Euclid lenses

Euclid preliminary

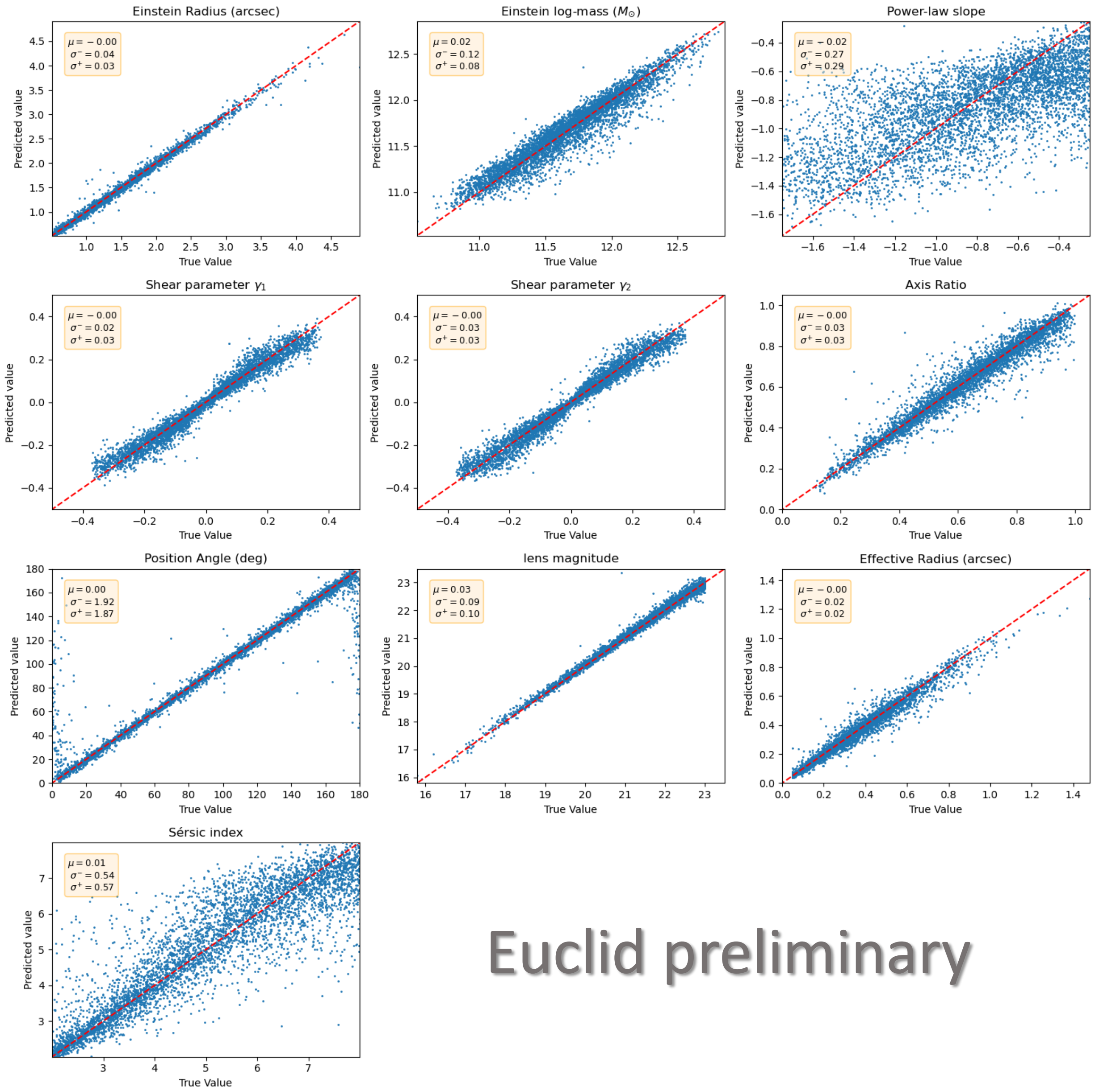
Euclidized lens | Euclid lens (Perseus)



Acevedo Barroso et al. in prep.

Einstein radii are recovered with great accuracy for both Euclidized and Euclid real lenses.

Future prospects: power-law+shear mass profile results



Euclid preliminary

- Training set size: 40,000 Euclid-like power-law lenses without companions. Validation and test set sizes: 5,001 lenses.
- All mass and light profile parameters are recovered; large scatter for power-law slope and Sérsic index.
- Training and testing only on the lens light does not improve the recovery of the light profile parameters.

Recovery of power-law slope improves substantially by removing the light of the lens.

Can be obtained by subtracting the lens' light from the images and training LEMON on images without the lens light.

Conclusions

- LEMON trained on mock Euclid-like Singular Isothermal Ellipsoid lenses recovers correctly all the parameters of the test set. Sérsic index is recovered less precisely.
- LEMON can generalize its parameter inference capabilities on different mock Euclid-like samples, such as those produced by PyAutoLens.
- LEMON manages to recover the Einstein radius for both Euclidized lenses and real Euclid lenses from the Perseus ERO field.