

PISCO : A Deep Learning Method for Shear Calibration

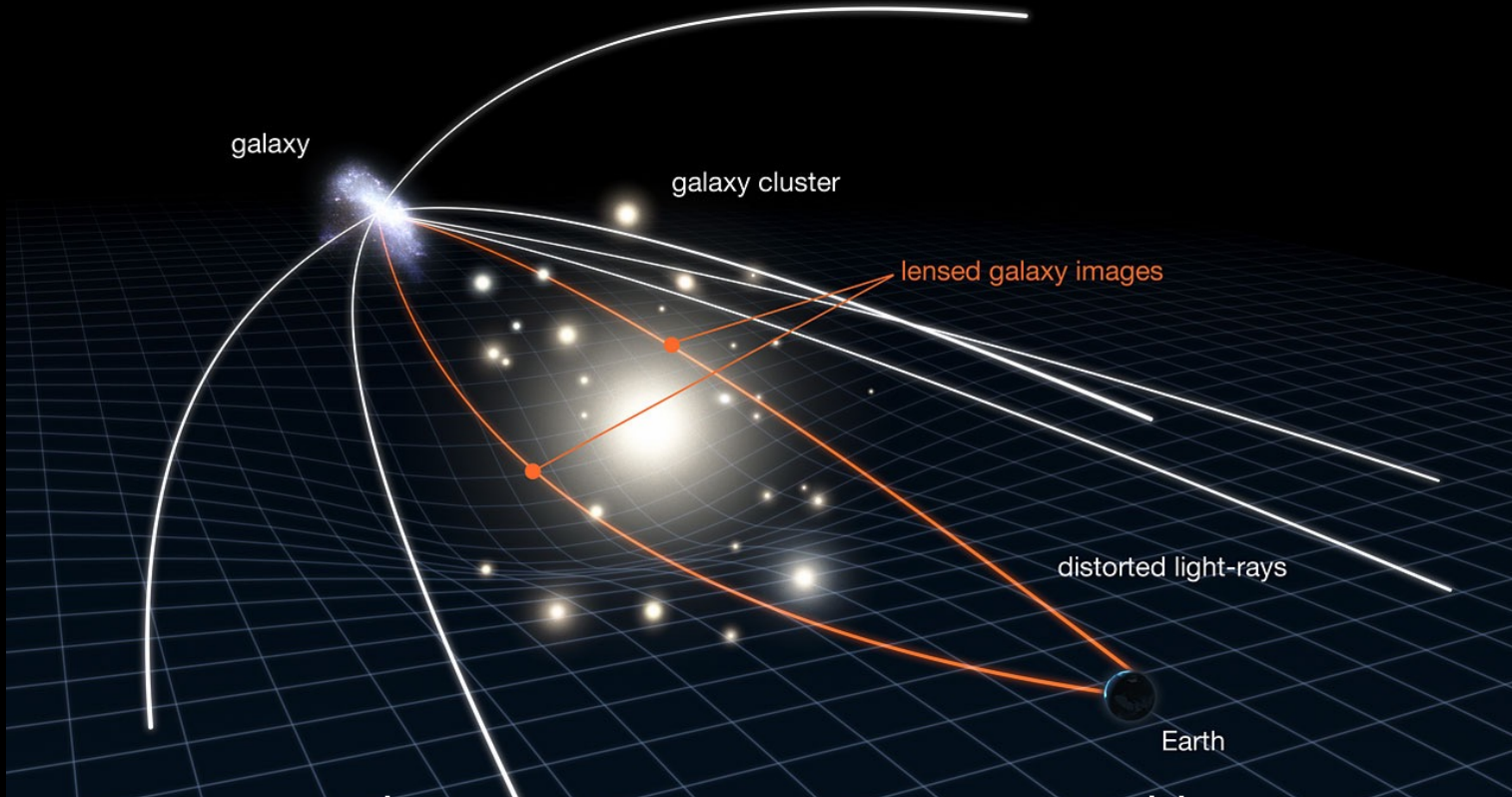
Clara Bonini – 1st year PhD student
Supervisor : **Nicolas Martinet**

LAM, CNRS, CNES, Université Aix-Marseille



SF2A 2026 – 22/06/26

GRAVITATIONAL LENSING



Strong lensing

Weak lensing

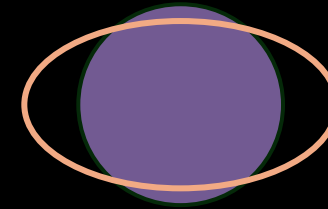
- Foreground massive object deviates the light from a background object

Observable effects

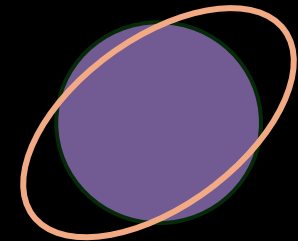
γ shear : anisotropic stretching

κ convergence : isotropic magnification

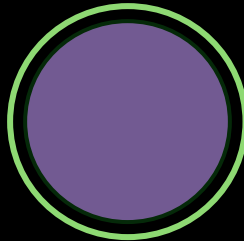
$$\gamma_1 > 0$$



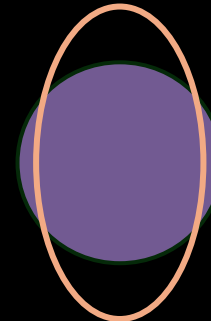
$$\gamma_2 > 0$$



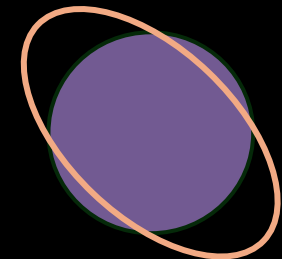
$$\kappa > 0$$



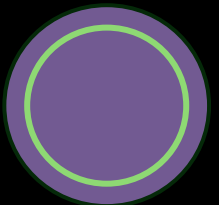
$$\gamma_1 < 0$$



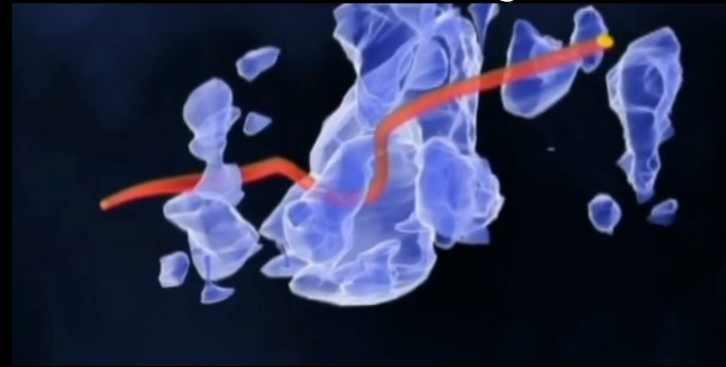
$$\gamma_2 < 0$$



$$\kappa < 0$$

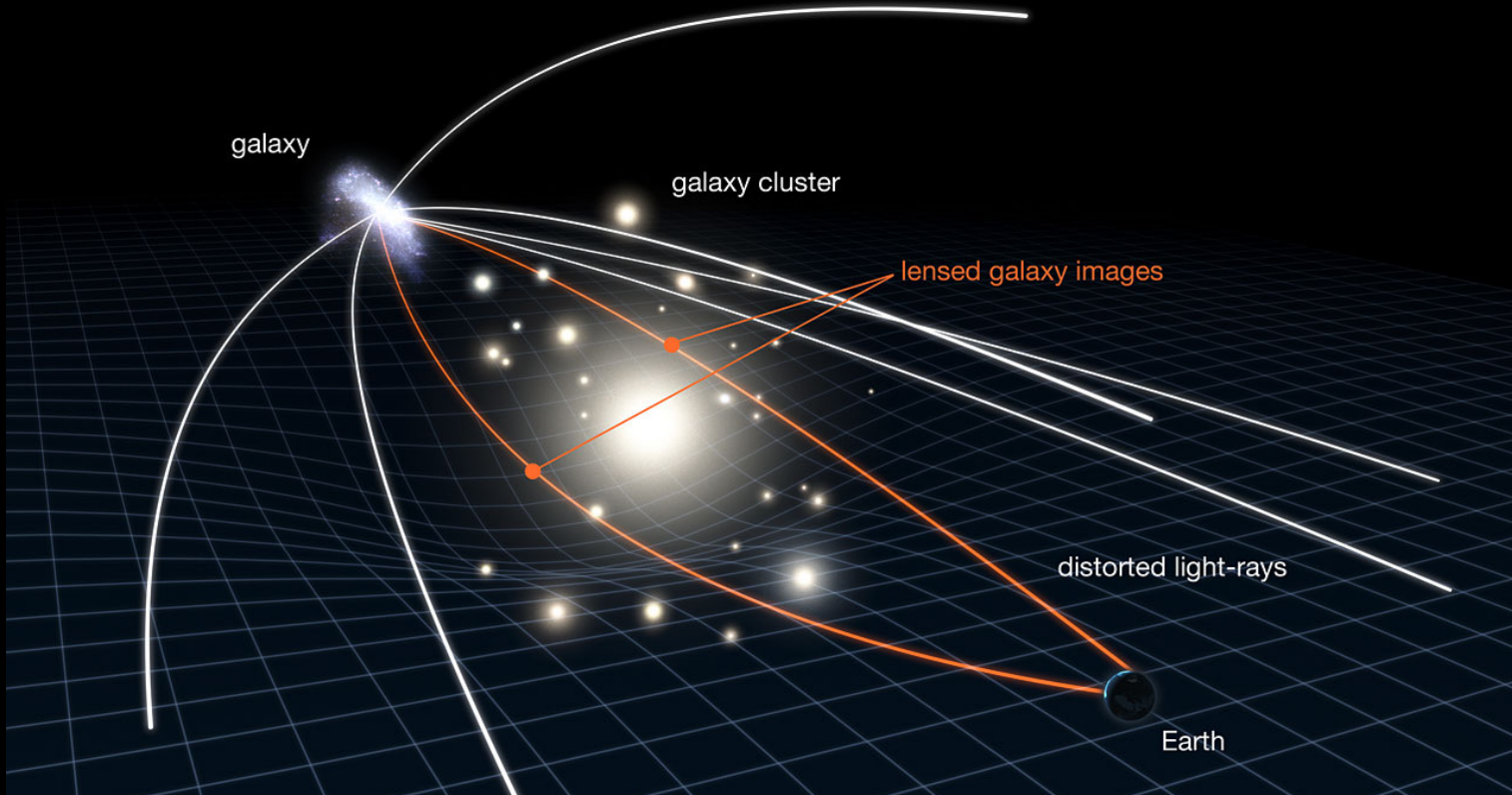


Strong effects visible by eyes



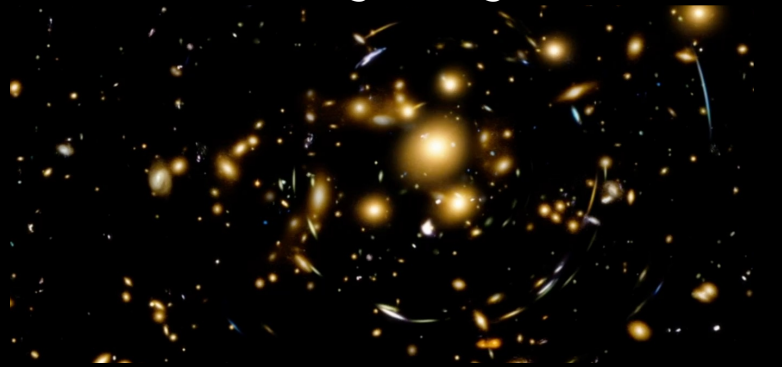
Subtle effects measured by statistics

GRAVITATIONAL LENSING

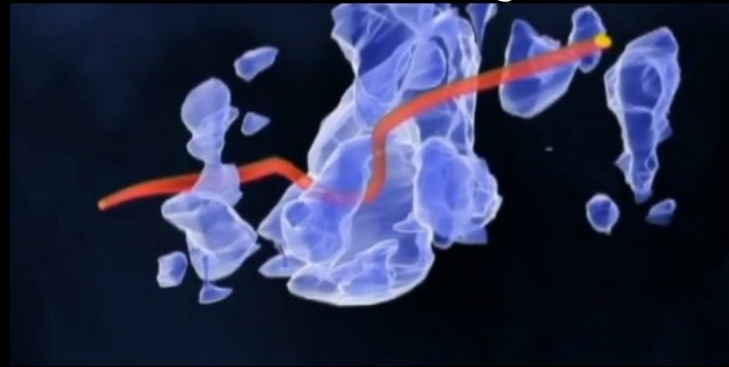


Strong lensing

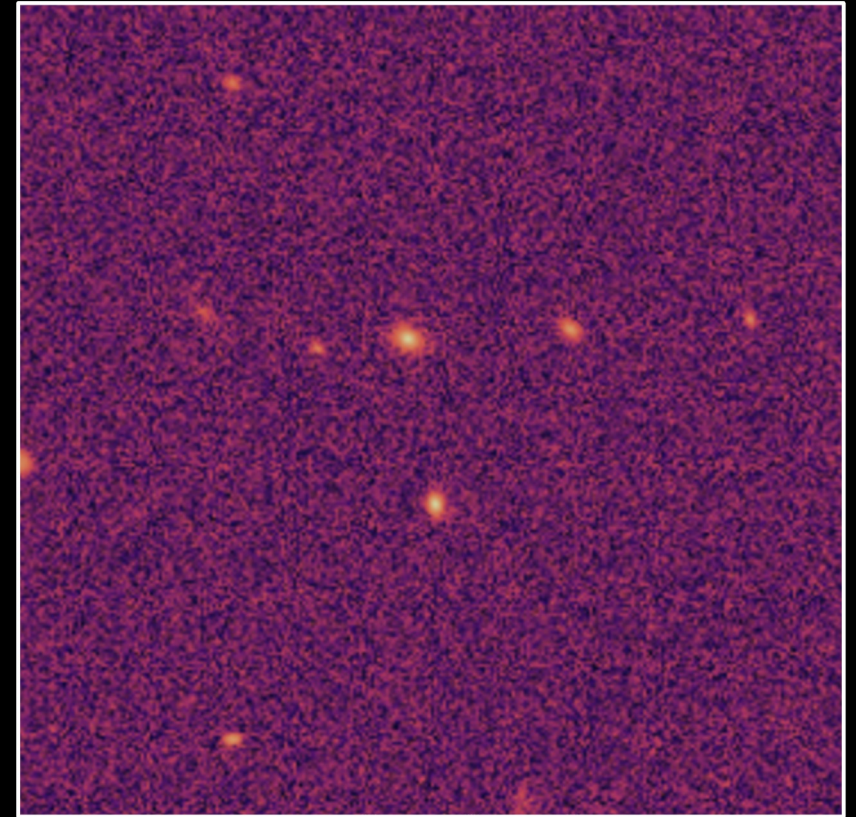
Weak lensing



Strong effects visible by eyes



Subtle effects measured by statistics



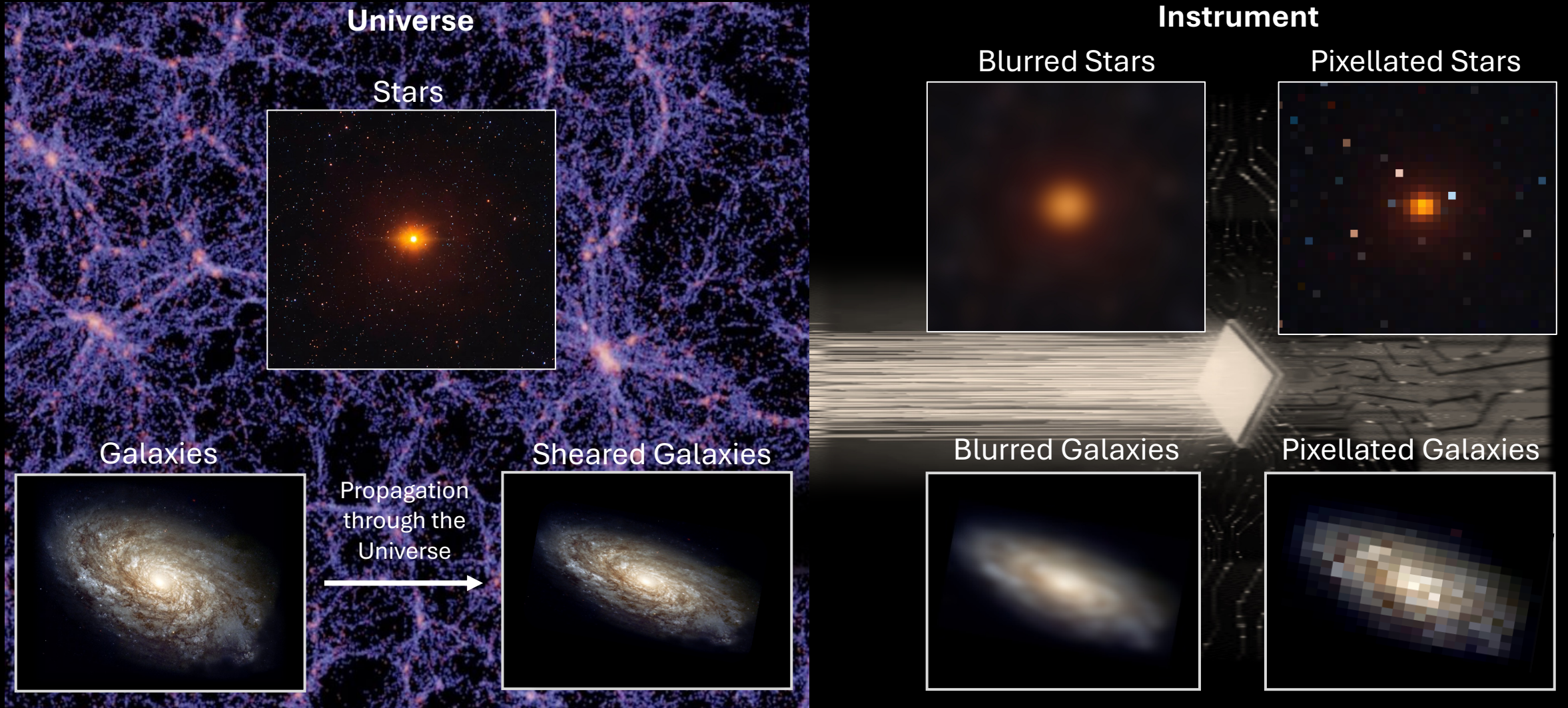
- Ellipticity measured in an image :

$$e_{\text{observed}} = e_{\text{intrinsic}} + \gamma$$

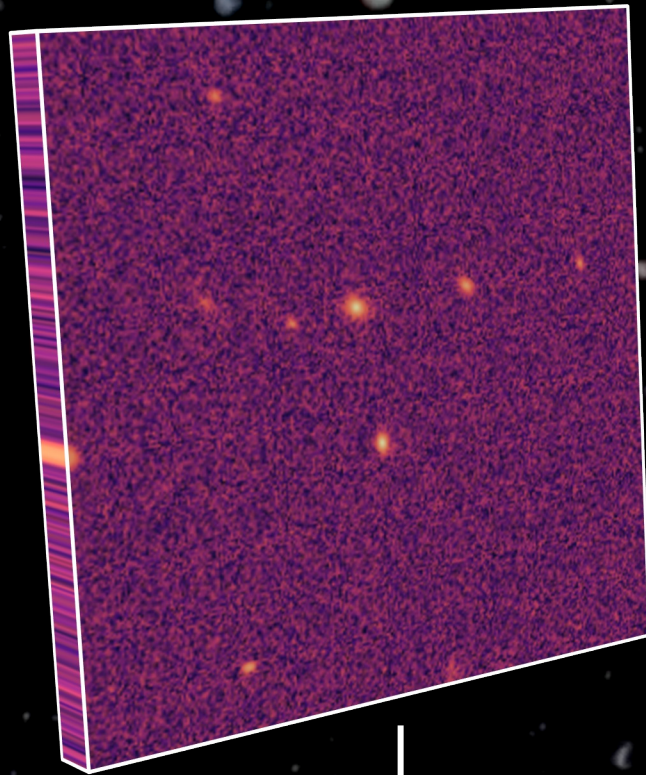
- Intrinsic ellipticity random distribution : $\langle e_{\text{intrinsic}} \rangle \sim 0$

$$\langle e_{\text{observed}} \rangle \sim \langle \gamma \rangle$$

The Shear measurement challenge



PISCO (PIXELS to COsmology) project



Pixels to Shear

Shear to Cosmology

Pixels to Cosmology

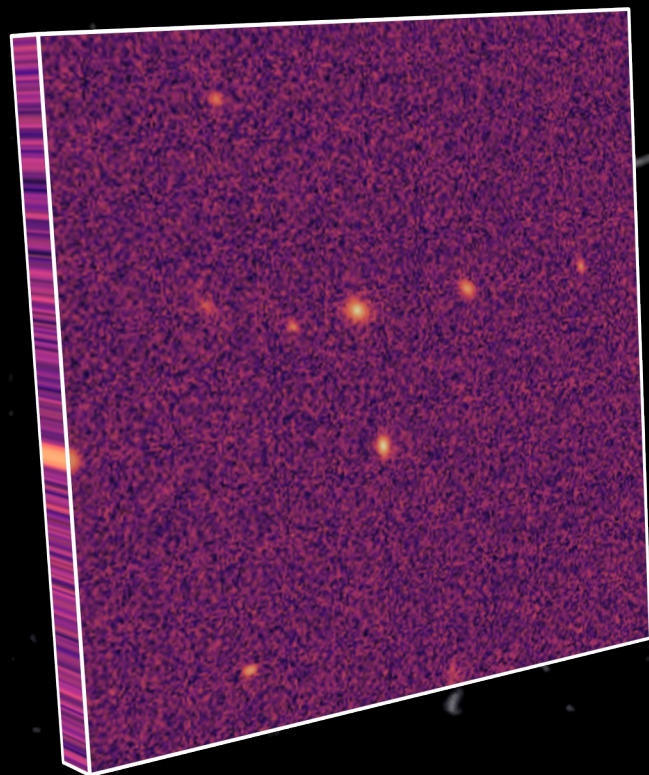
OVERVIEW OF THIS WORK

1st step of PISCO project



Input

Output



Simulated Image

Deep learning



Average ellipticity/shear
of all galaxies in an
image

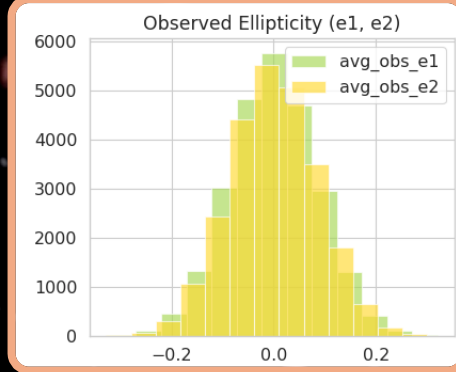
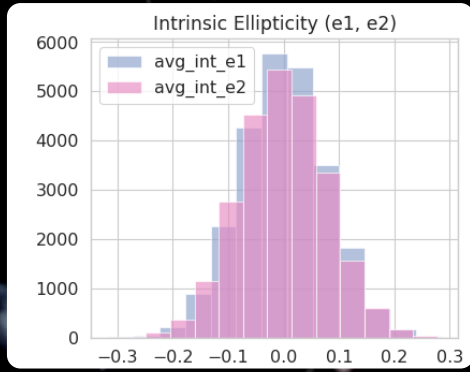
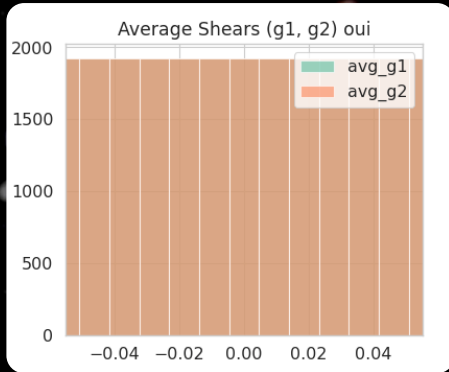
The model will predict the average ellipticity
of all galaxies in the image, and **not** the
ellipticity of individual galaxies

DATABASE

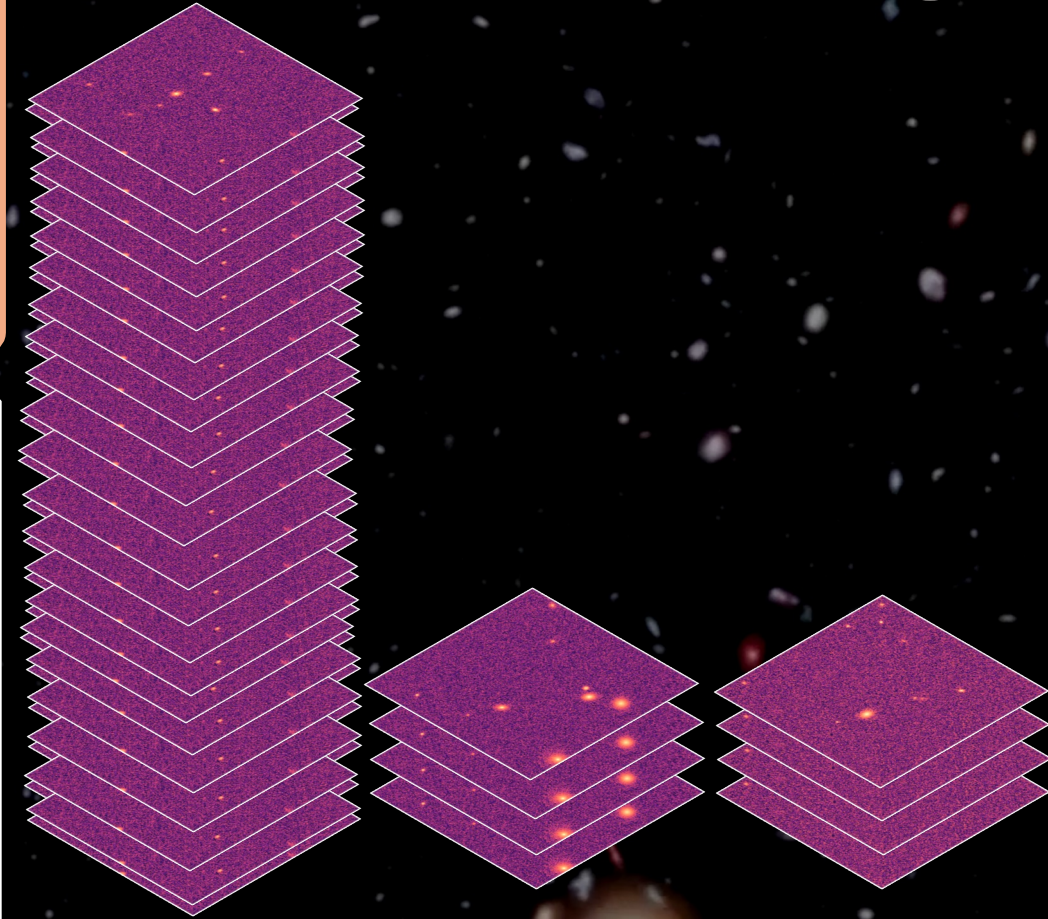
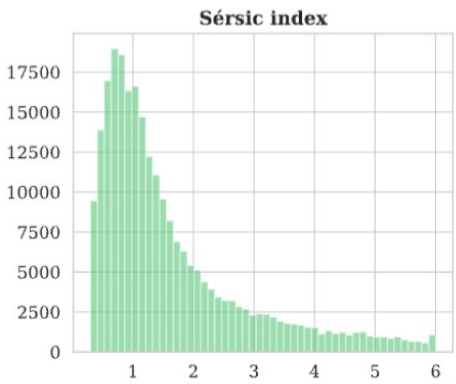
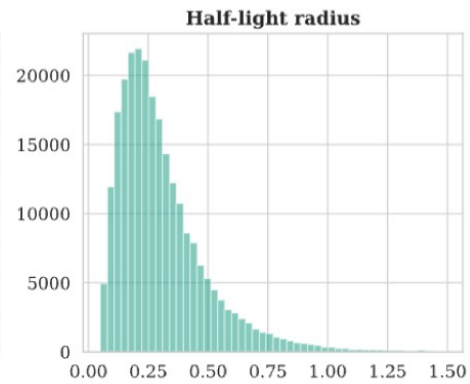
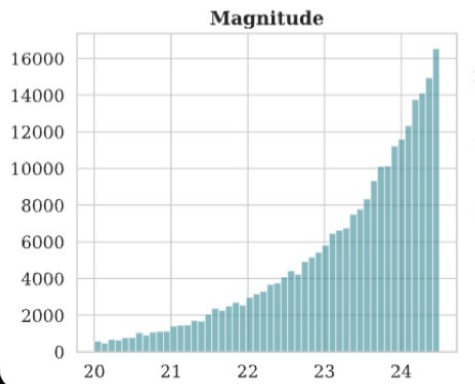
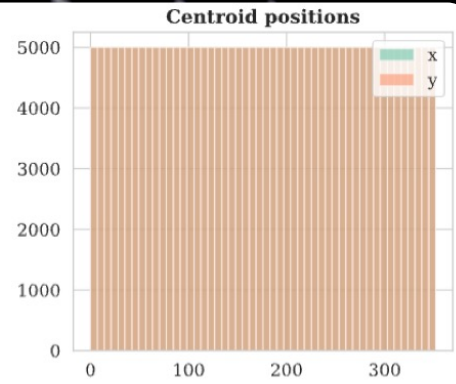
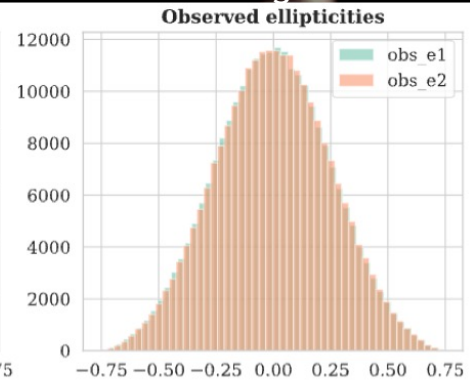
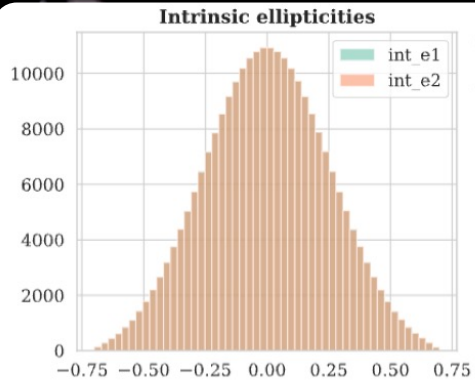
Simulations with Galsim



Average galaxies

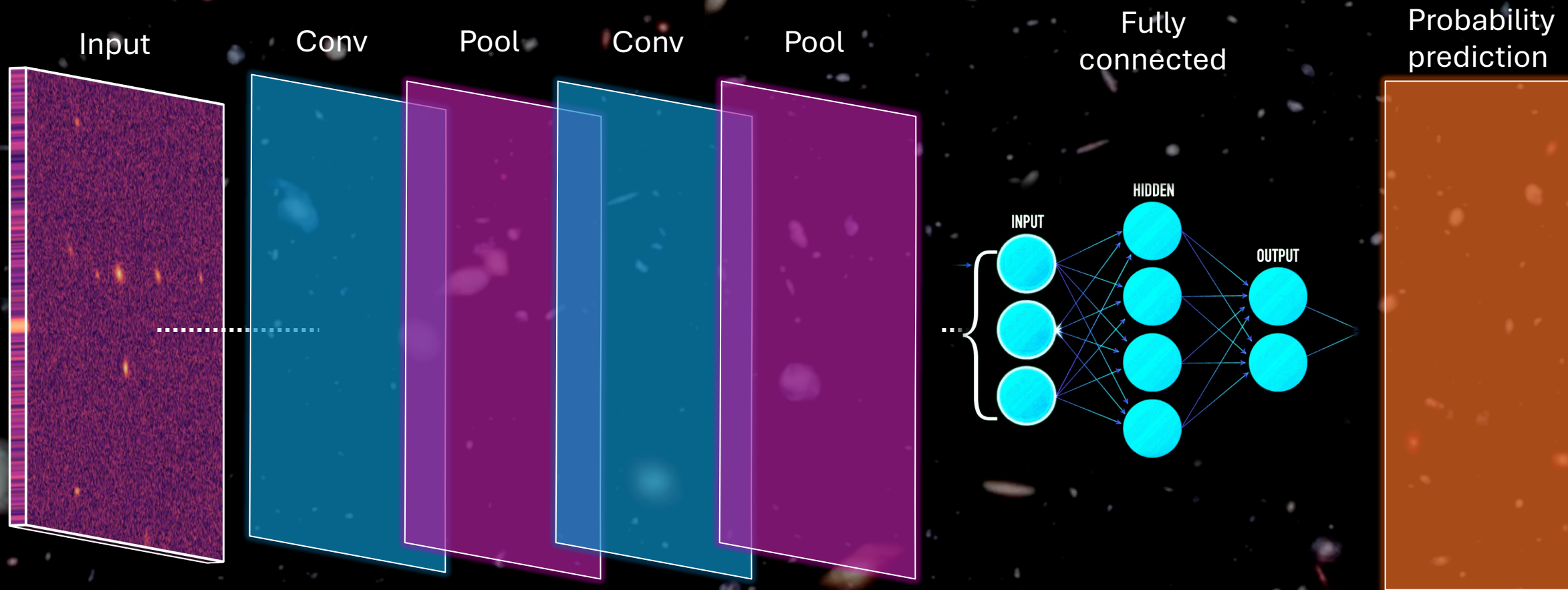


Individual galaxies

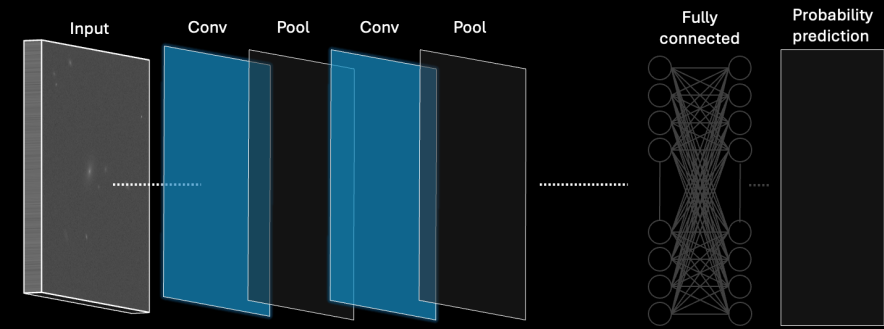
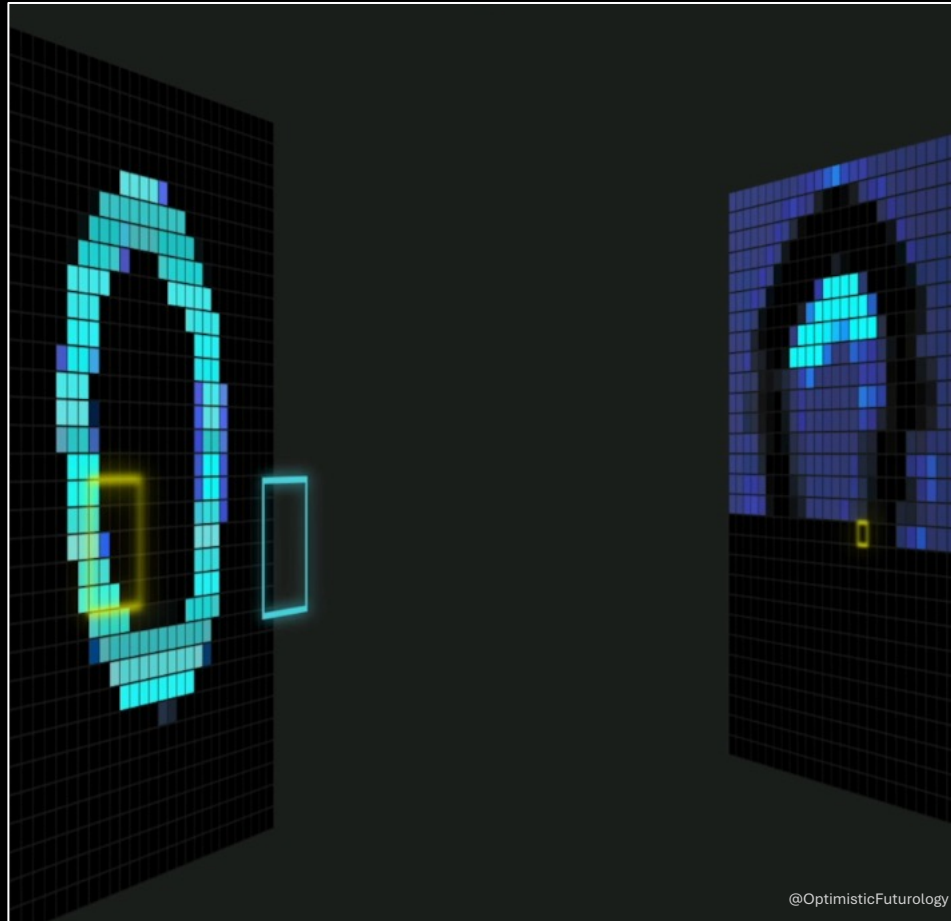


80% training + 10% validation + 10% test

CONVOLUTIONAL NEURAL NETWORK (CNN)



CONVOLUTIONAL LAYER

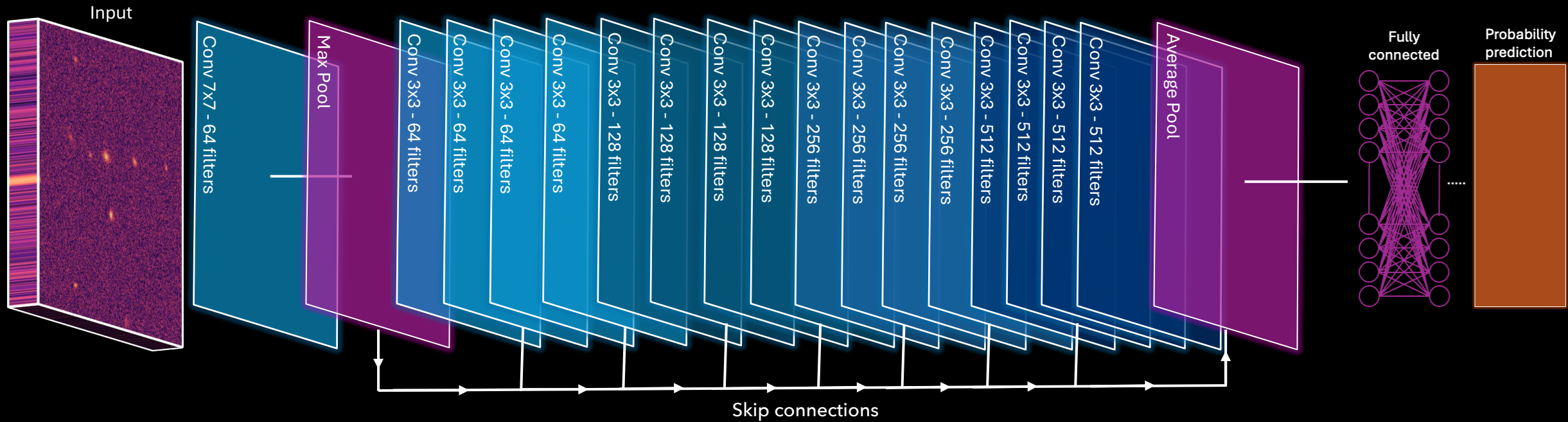


Features maps

- **Kernel/Filter** : matrix smaller than the input which slides over the input image to extract features.

RESNET

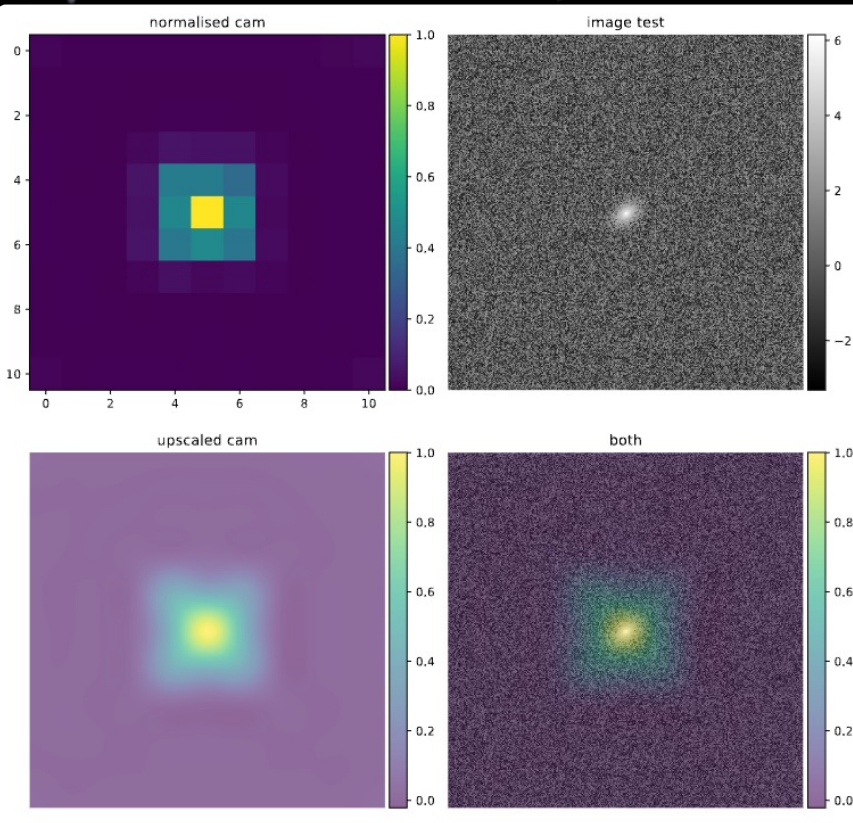
RESNET 18



- Prediction compared to the real value with the **loss function**
- Gradient of the loss is computed and backpropagate through the network
- Resnet contains **skip connection** layers which enables to train deep model with a lot of layers
→ Avoid "vanishing gradient"

Case 1 : 1 galaxy per image

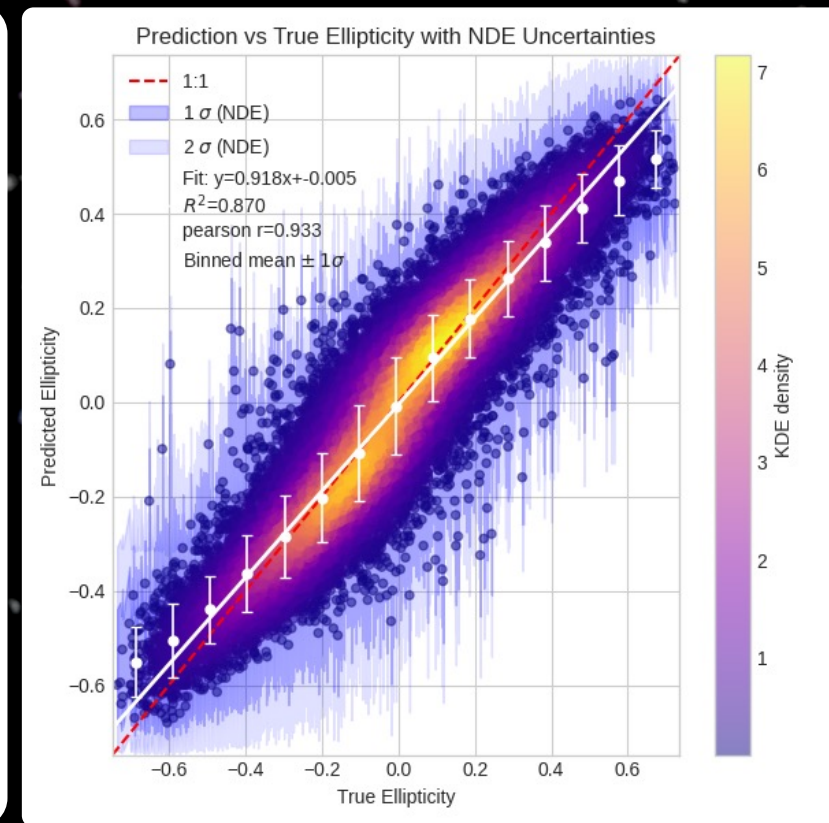
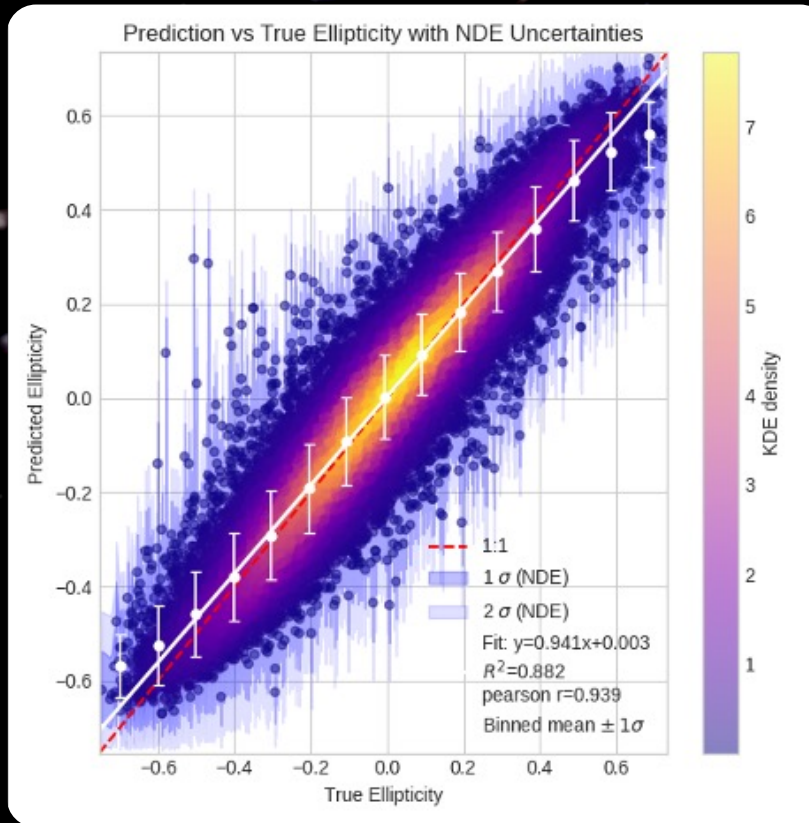
Gradcam



CNN Predicted Ellipticity vs True Ellipticity

$\langle e_1 \rangle$

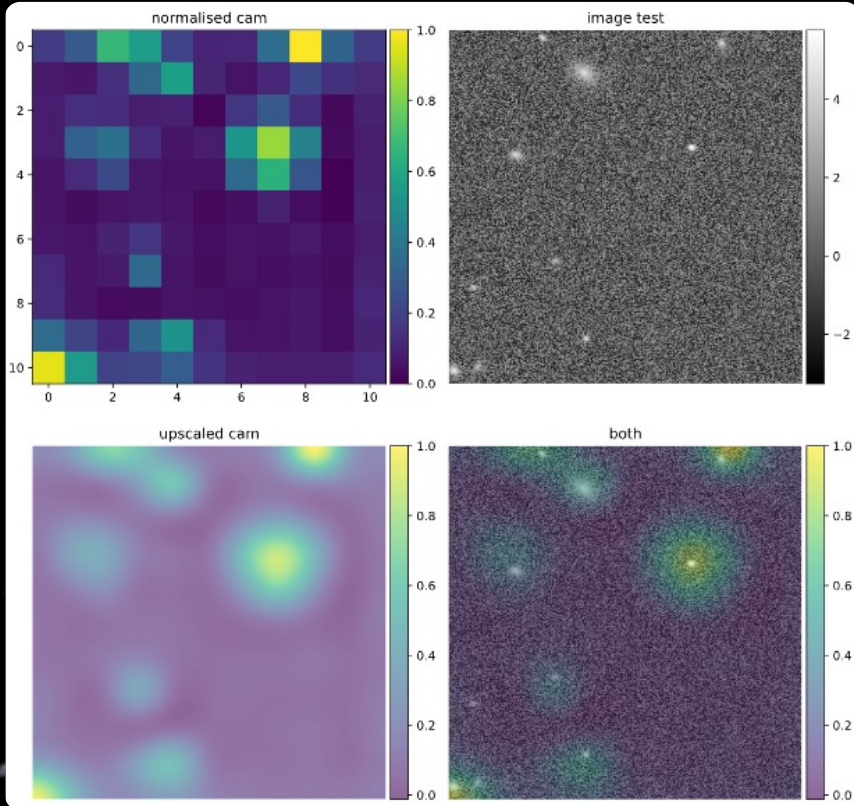
$\langle e_2 \rangle$



Accurate ellipticity prediction

Case 2 : 10 galaxies per image

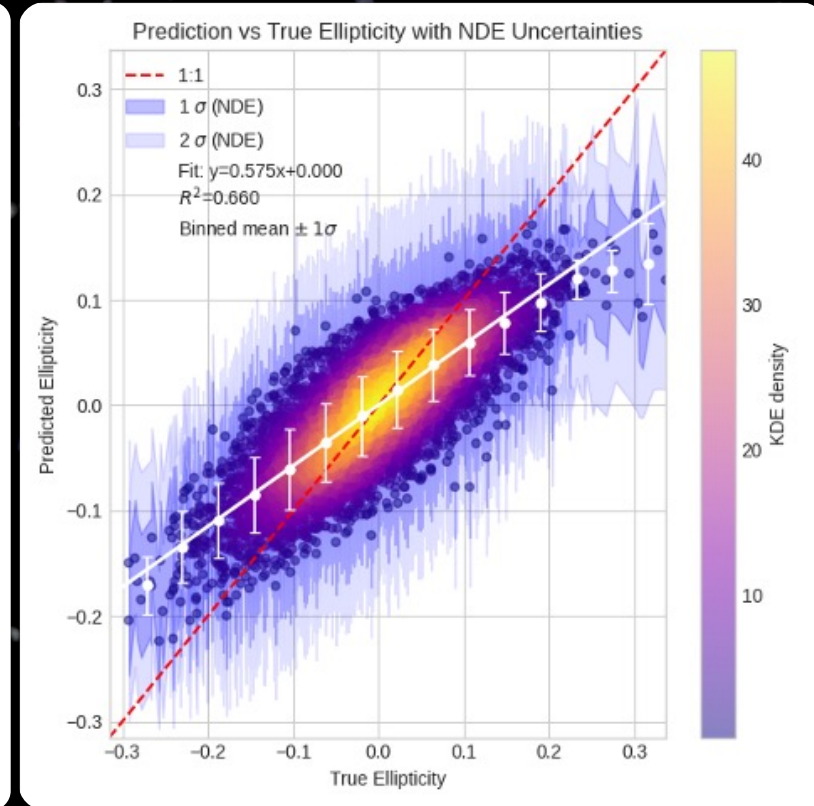
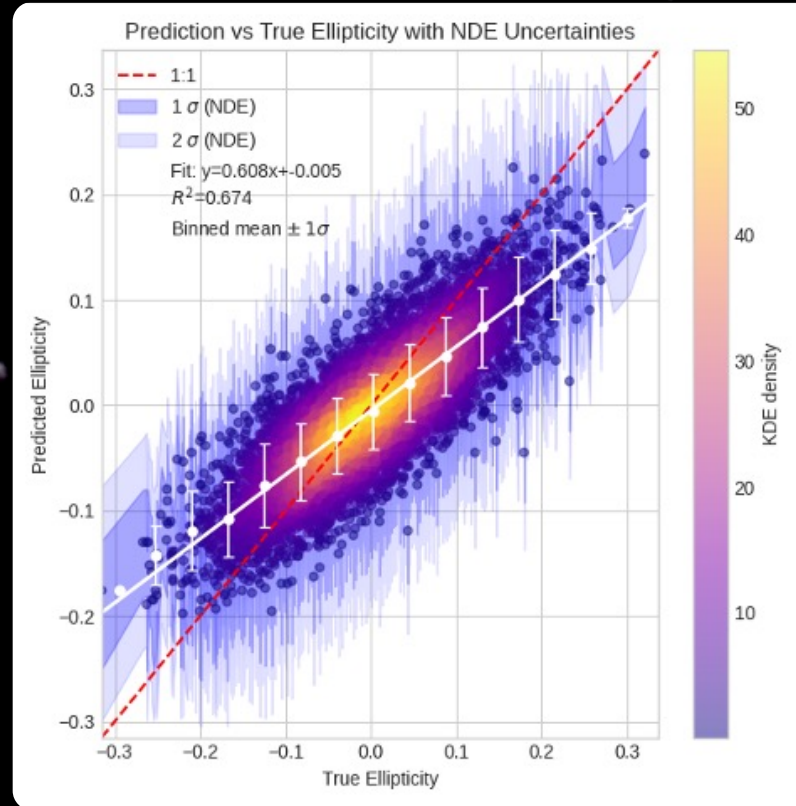
Gradcam



CNN Predicted Ellipticity vs True Ellipticity

$\langle e_1 \rangle$

$\langle e_2 \rangle$



Increased bias in ellipticity prediction

Residuals plots

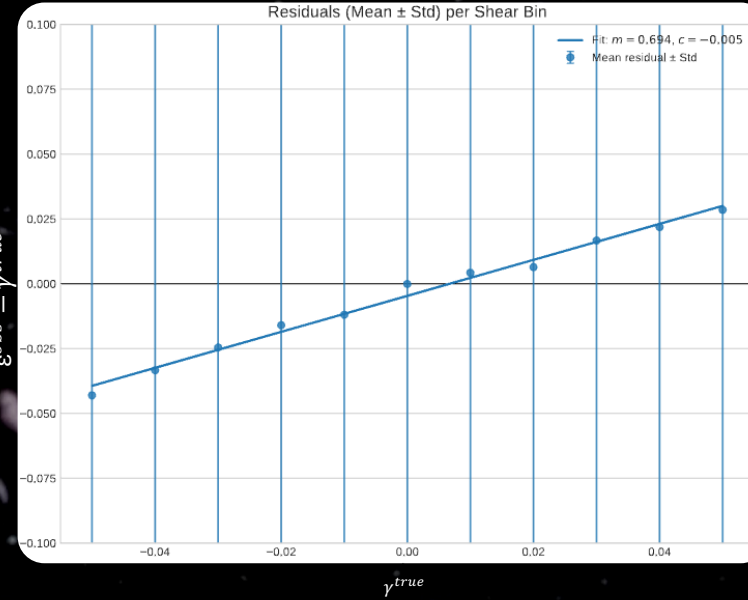
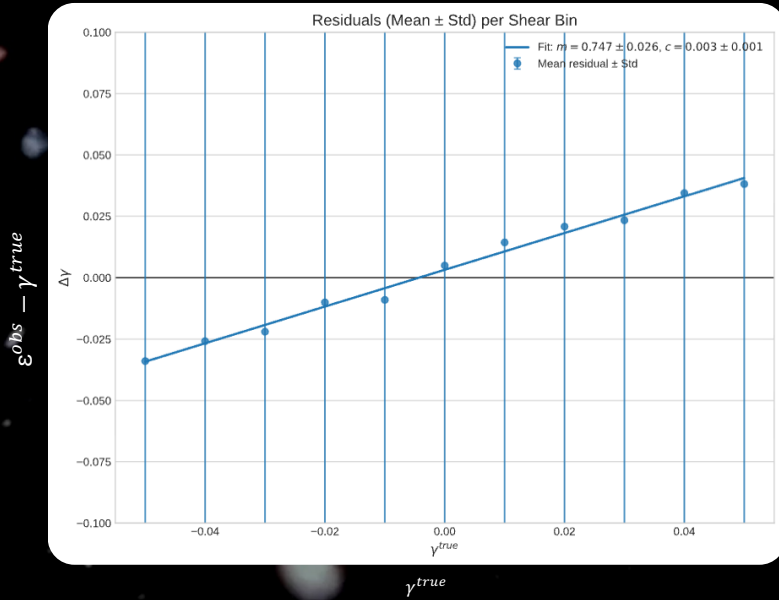
Multiplicative and additive bias

$$\gamma_{1,2}^{obs} - \gamma_{1,2}^{true} = m\gamma_{1,2}^{true} + c$$

$\langle e_1 \rangle$

$\langle e_2 \rangle$

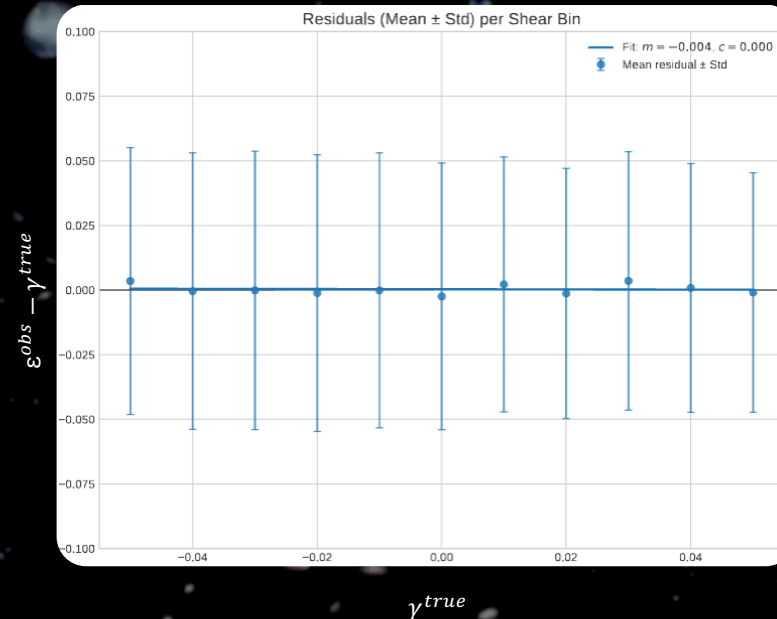
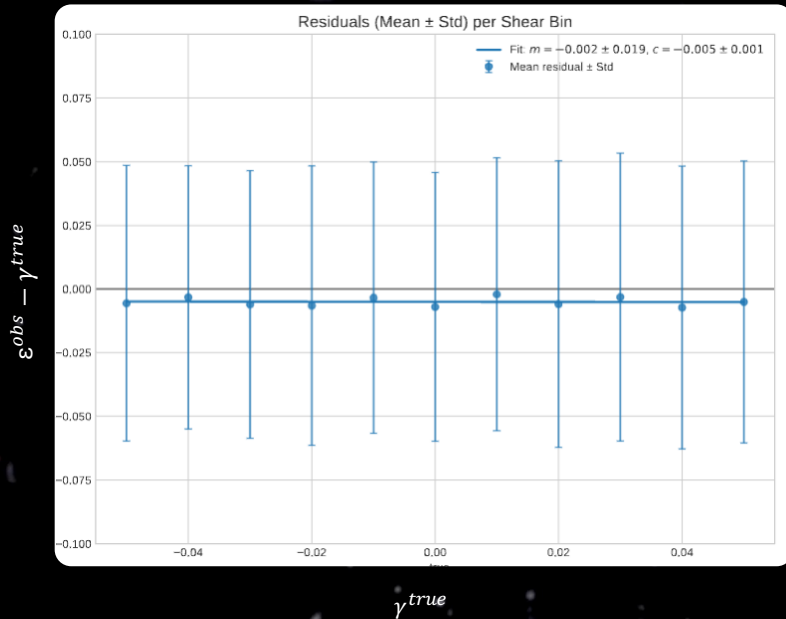
1 galaxy
per image



Very bad
multiplicative bias :(

Euclid requirements :
 $m < 10^{-3}$ et $c < 10^{-4}$

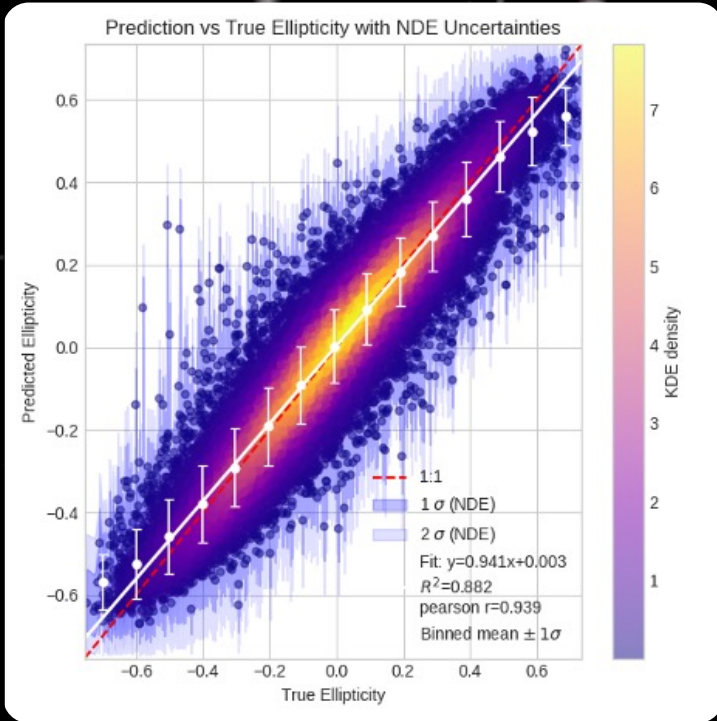
10 galaxies
per image



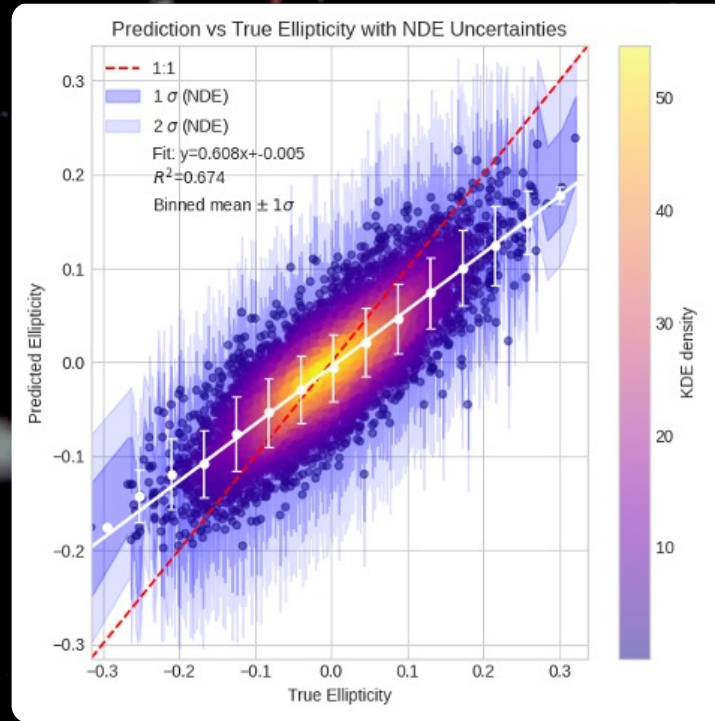
Multiplicative bias m
 $\sim 10^{-3}$ for the two
components

Impact of Shape Noise

$\langle e_1 \rangle$

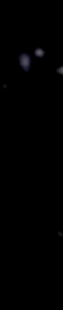


1 galaxy per image

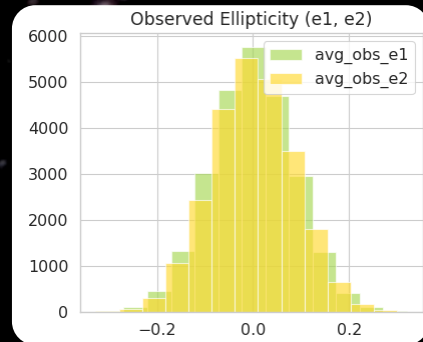
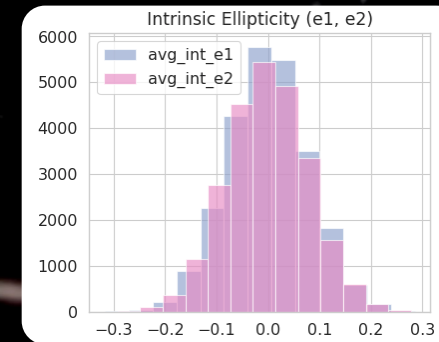
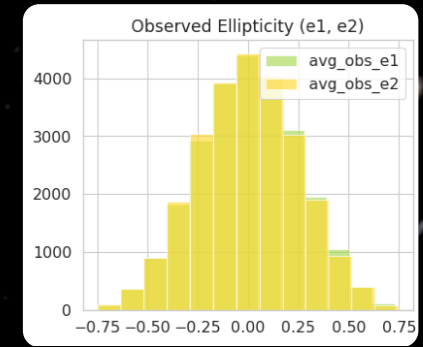
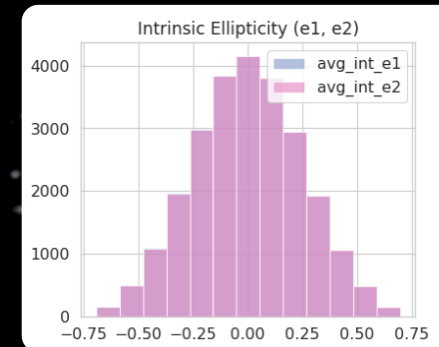


10 galaxies per image

$\sigma = 0.26$



$\sigma = 0.08$



10 galaxies per image

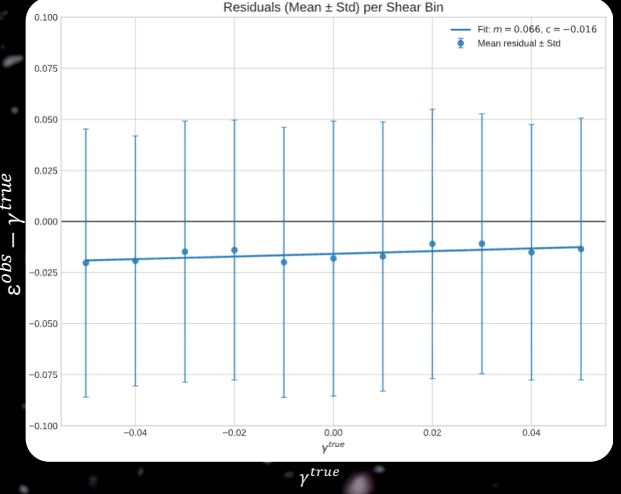
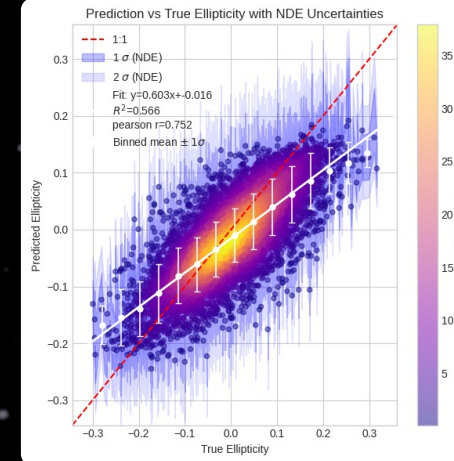
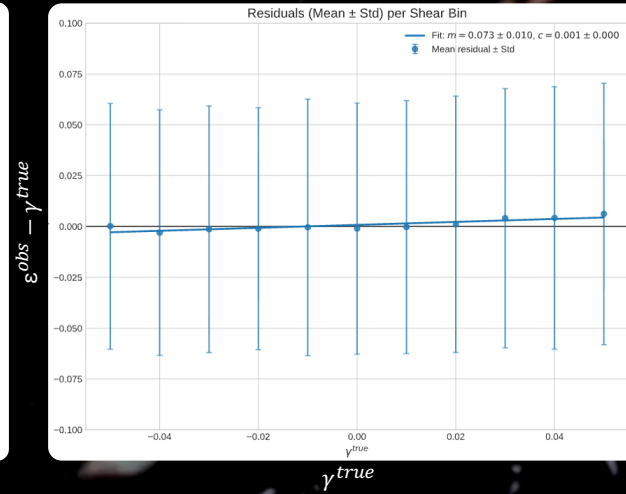
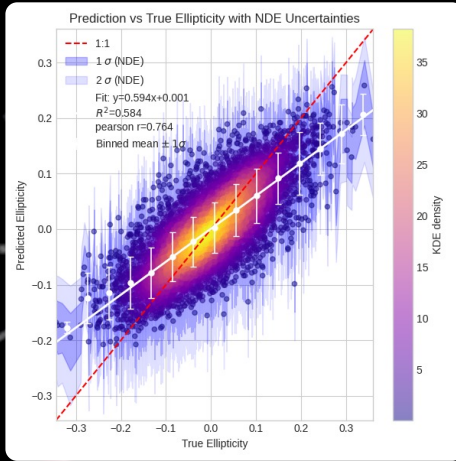
Averaging 10 galaxies = reducing shape noise

Impact of Shape Noise

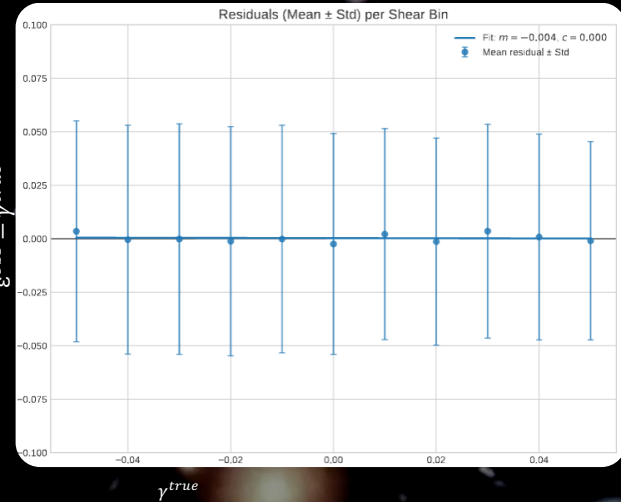
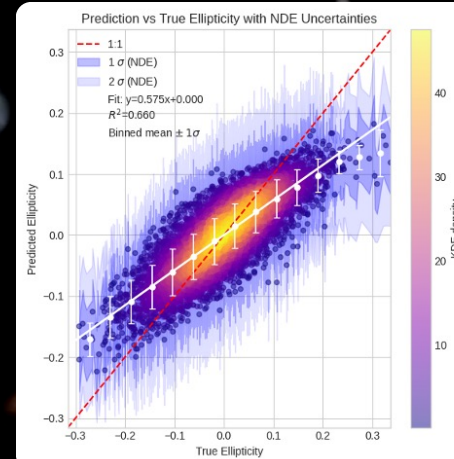
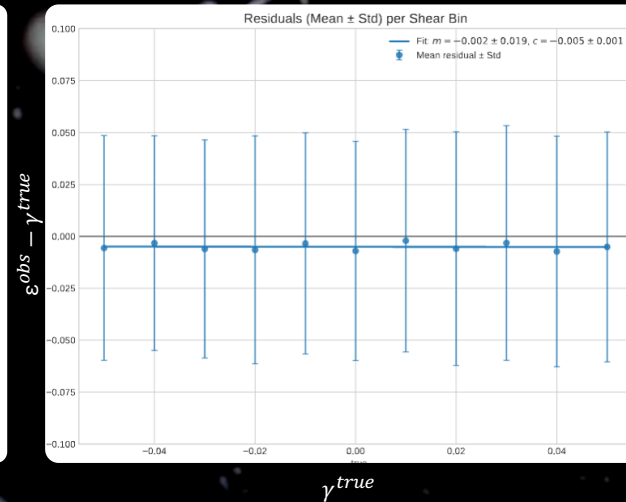
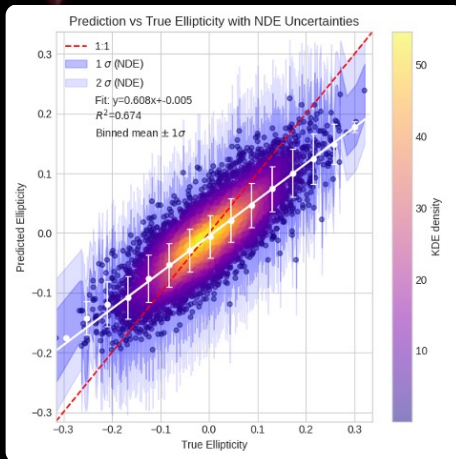
$\langle e_1 \rangle$

$\langle e_2 \rangle$

1 galaxy
per image
 $\sigma = 0.08$



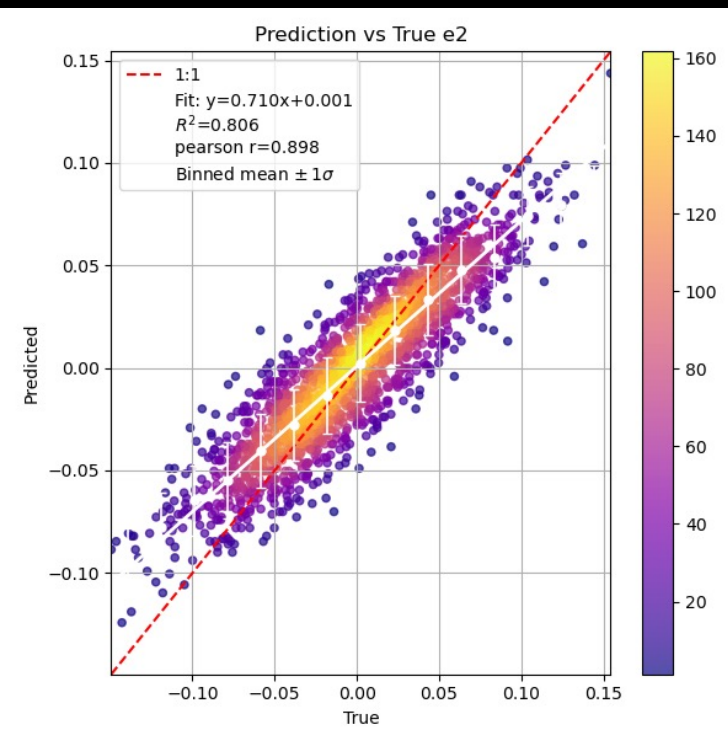
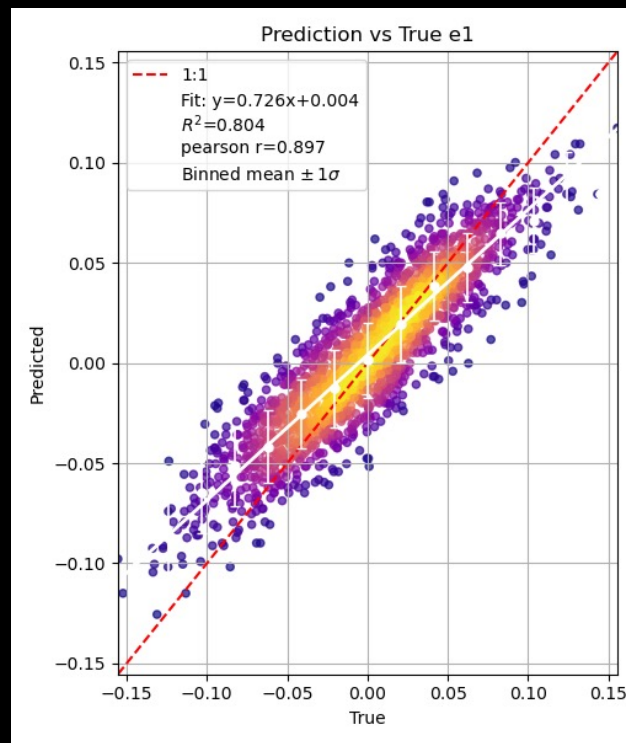
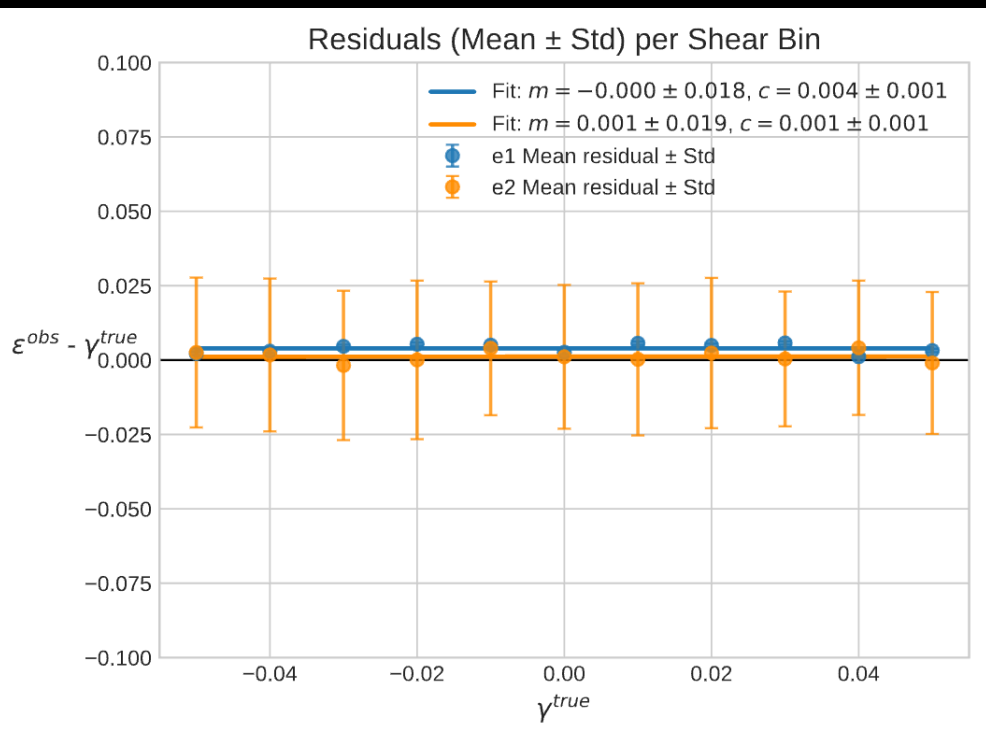
10 galaxies
per image



Same behavior between the two for the same label distribution
→ Good shear prediction but biased ellipticity prediction

Impact of Shape Noise

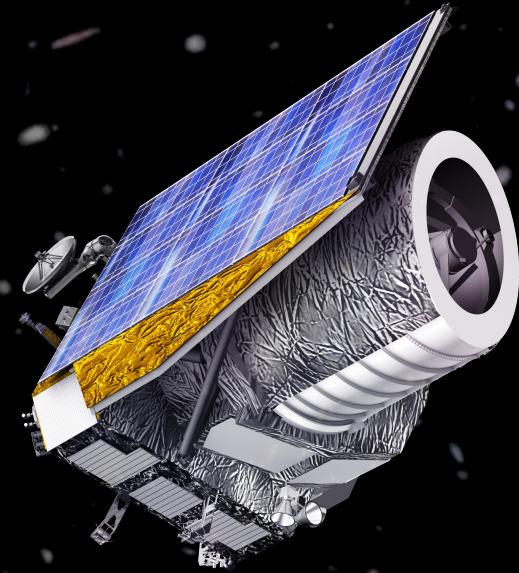
Test on 40 galaxies per images



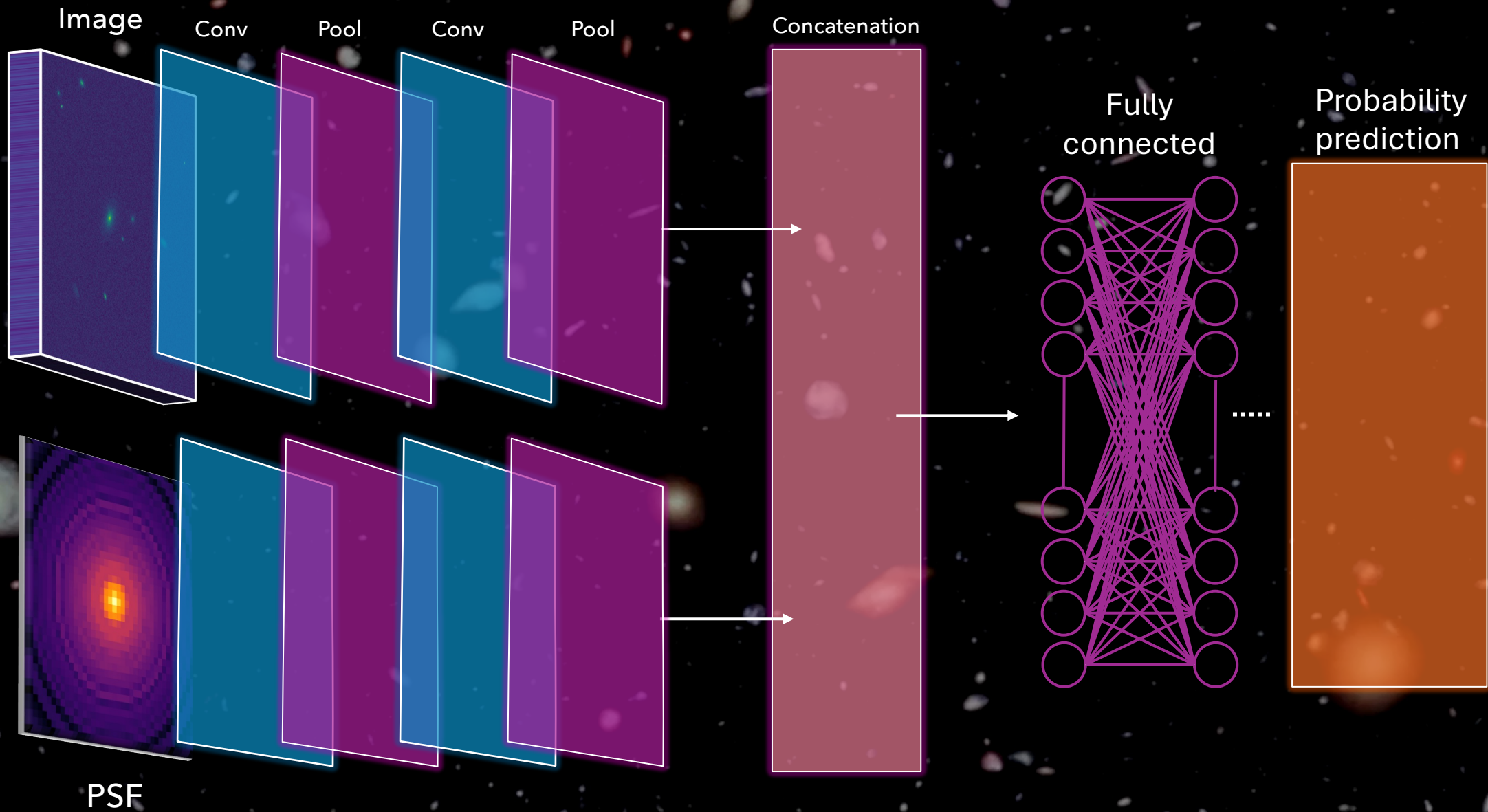
Multiplicative bias $m \sim 10^{-3}$ for the two components even one at $m \sim 10^{-4}$!

Perspectives and evolution

- Finishing the test of the shape noise impact
- Comparison with SExtractor
- Detection bias test with SNR variation
- Blending test
- Realistic galaxies implementation with COSMOS catalog
- Using Euclid data to test the model



PSF features

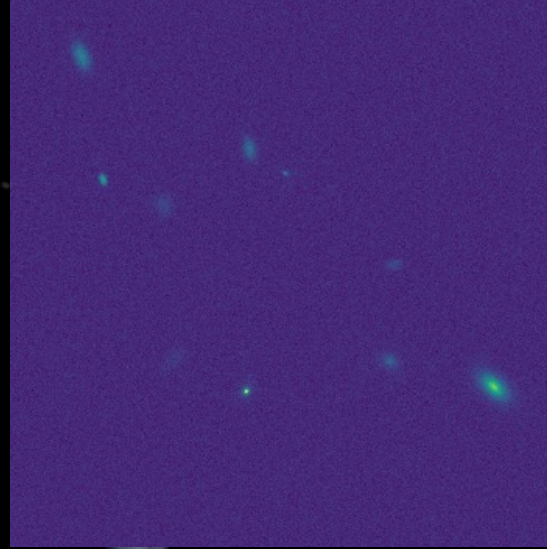
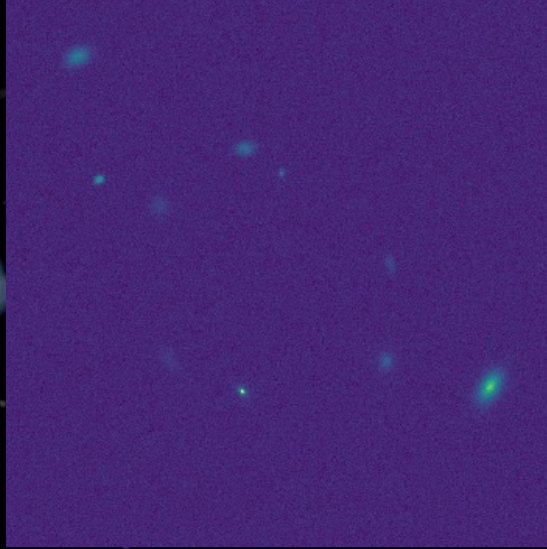


Shape and Pixel Noise Cancellation Database

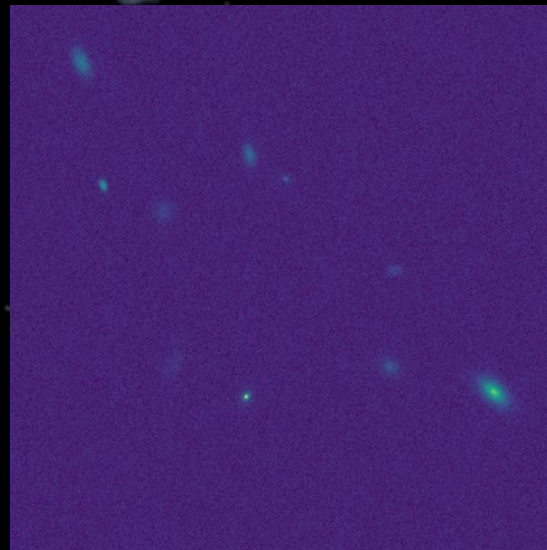
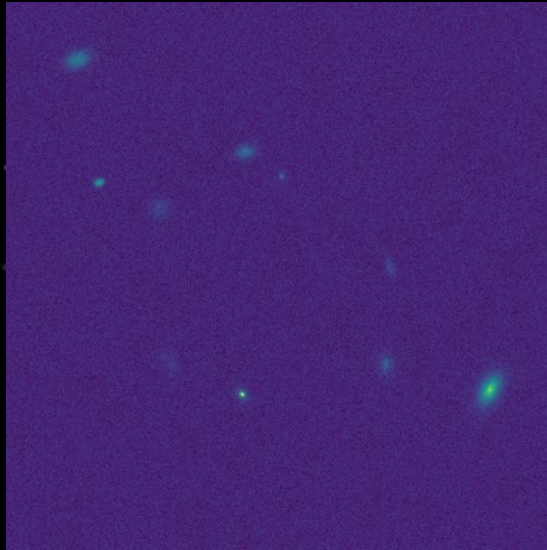
No Rotation

Rotation 90°

Add Noise



Subtract Noise



- Intrinsic shapes of galaxies orthogonal but same shear
→ during training helps to isolate the true lensing signal

- help reduce the number of samples needed to achieve a given statistical precision