Bayesian deep learning for weak lensing analyses

Parameters estimation for blended galaxies

Bastien Arcelin (APC, Paris), Cyrille Doux, Eric Aubourg, Cécile Roucelle, Thomas Sainrat

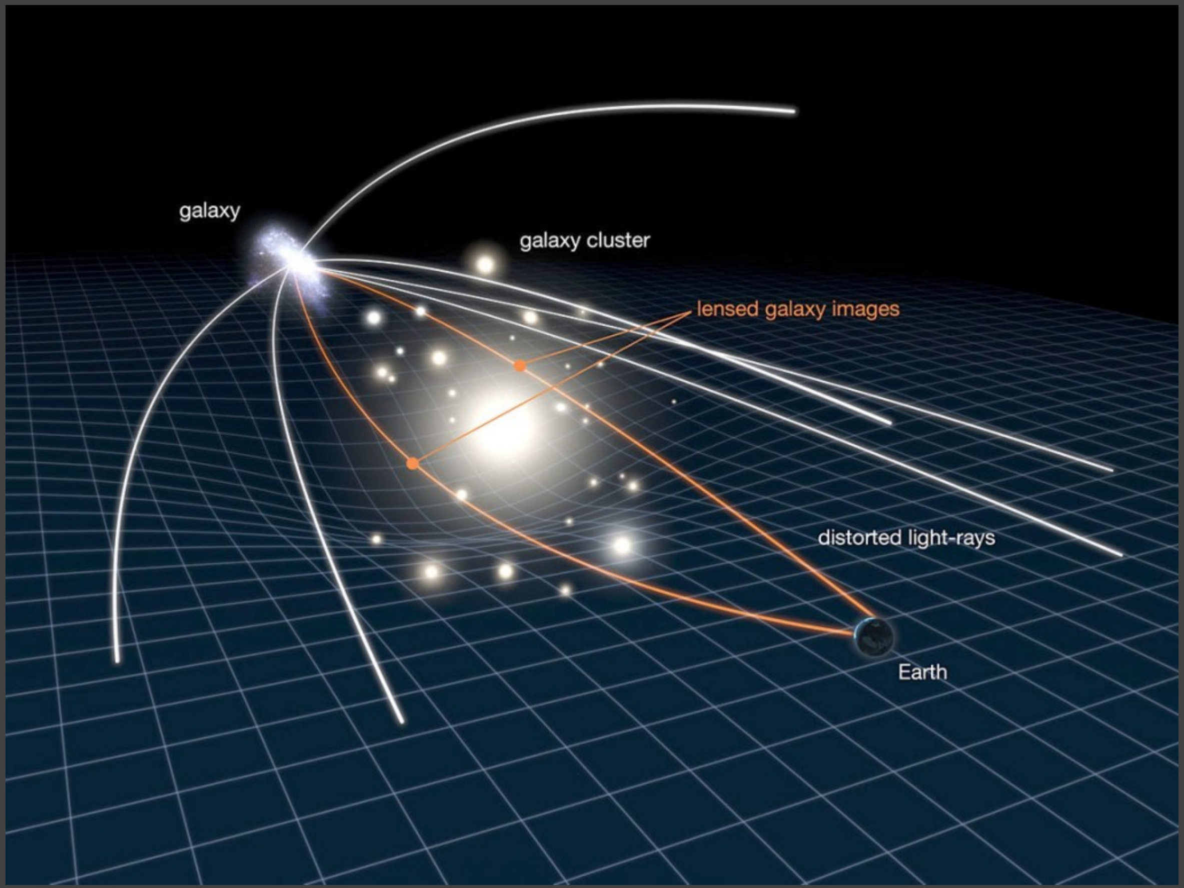
LSST France May 2021

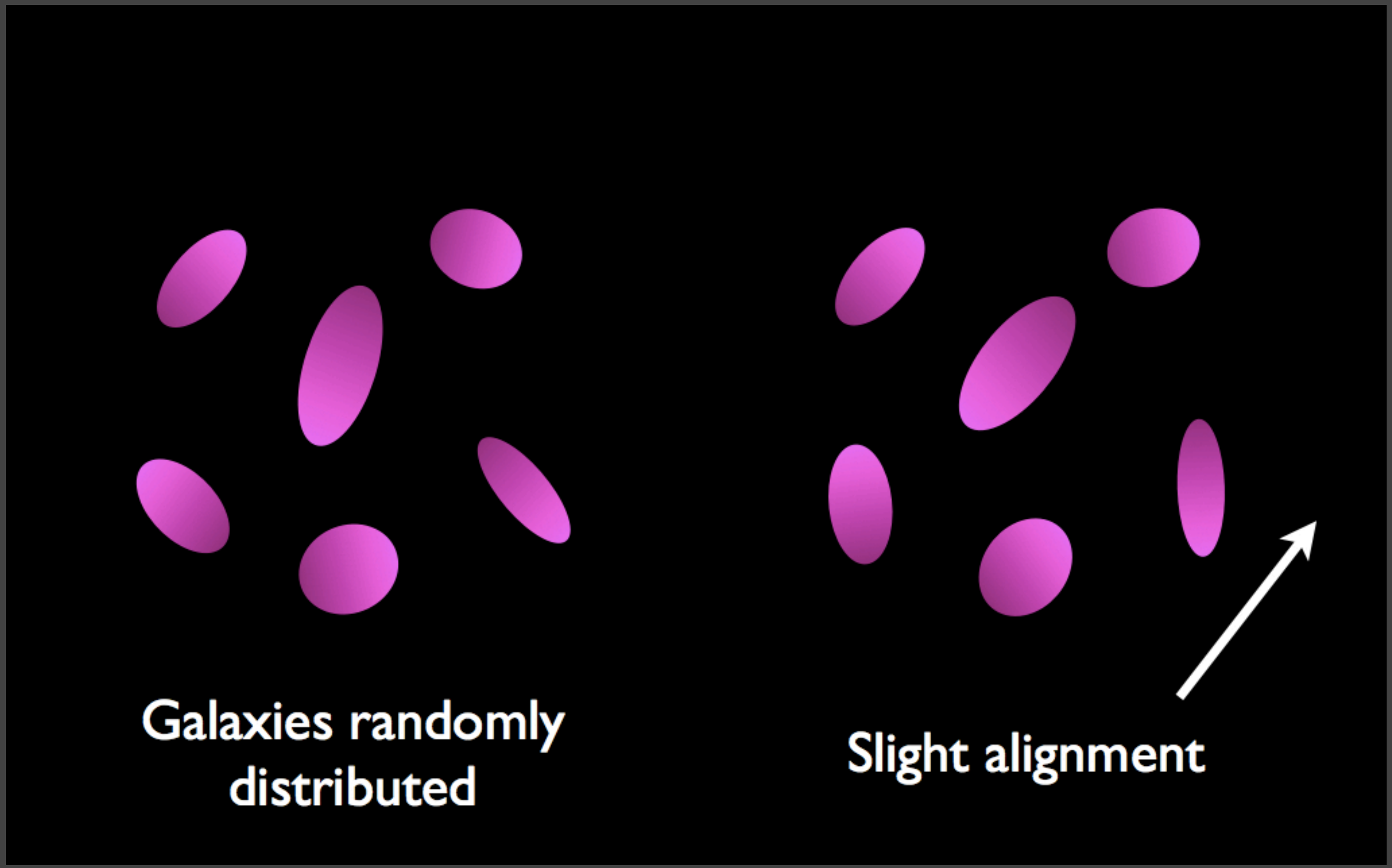
Probe dark energy

Weak gravitational lensing

- **Gravitational lensing** due to mass along the line of sight: **deforms** the images of the background galaxies

- Correlation between orientations and shapes of neighbour galaxies: **cosmic shear**





Probe dark energy

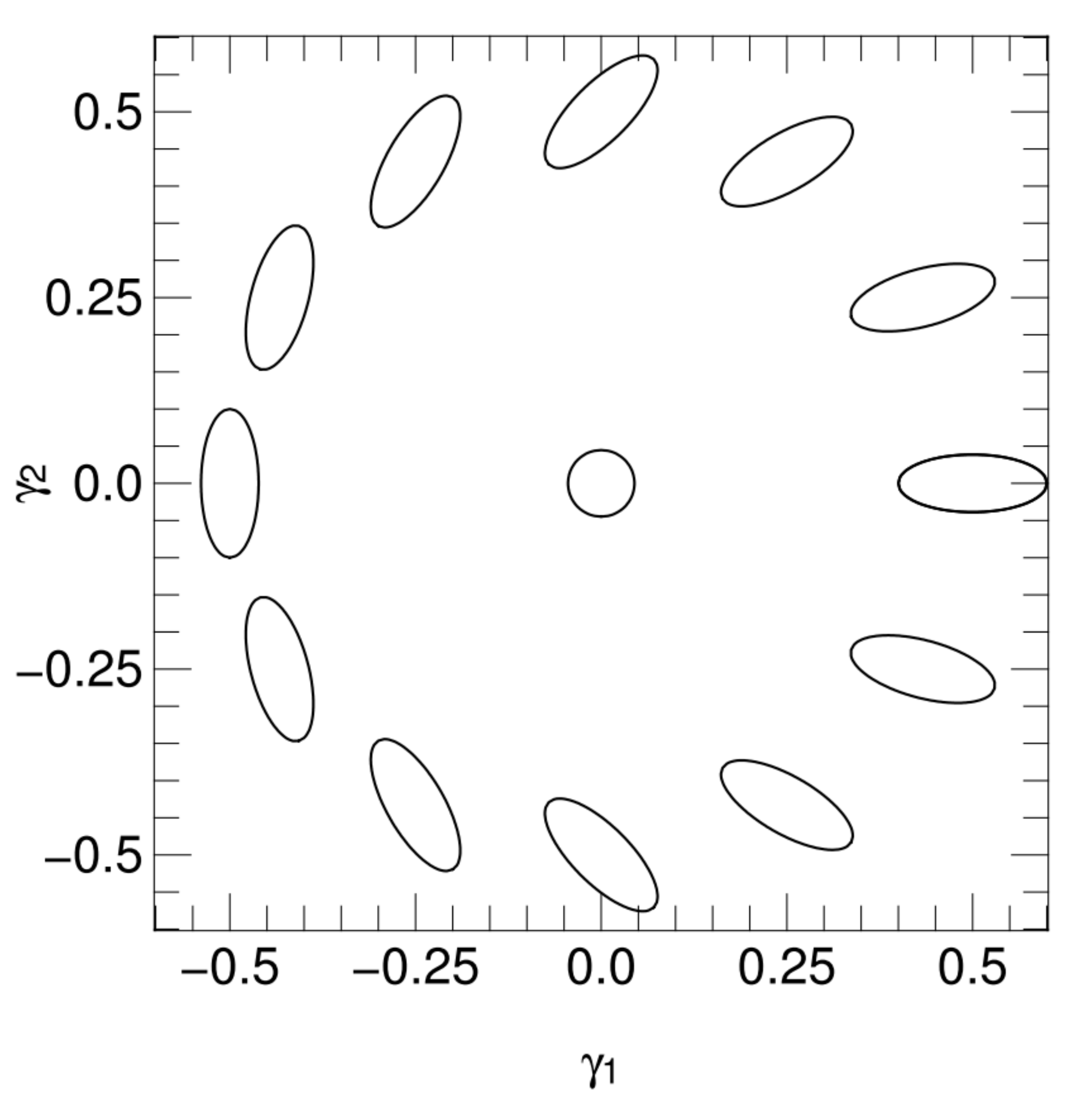
Weak gravitational lensing

Ellipticity

Observed ellipticity = intrinsic ellipticity + shear

$$\epsilon = \epsilon^s + \gamma$$
$$= (\epsilon_1^s + \gamma_1) + i(\epsilon_2^s + \gamma_2)$$
$$= \epsilon_1 + i\epsilon_2$$

$$< \epsilon > \approx \gamma$$



Credit: Kilbinger+2015

Systematic of cosmic shear

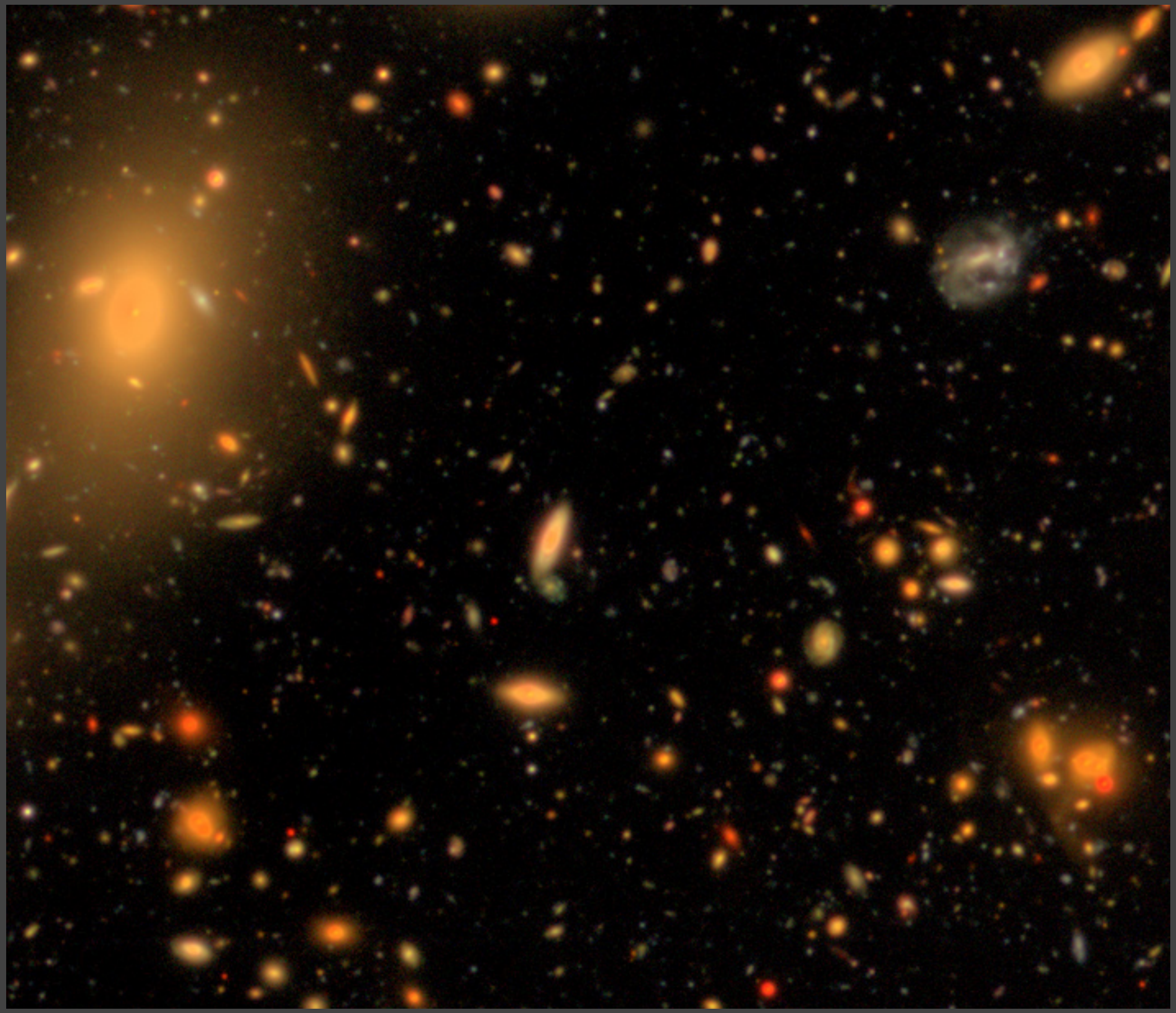
Blending

Blending

- HSC: 58% of the detected objects are identified as blended (Bosh+2017)
- LSST: at least 62% (Sanchez+2021)

Systematic

- Unrecognised blends: several objects detected as one object
- Recognised blends



Credit: HSC

Systematic of cosmic shear

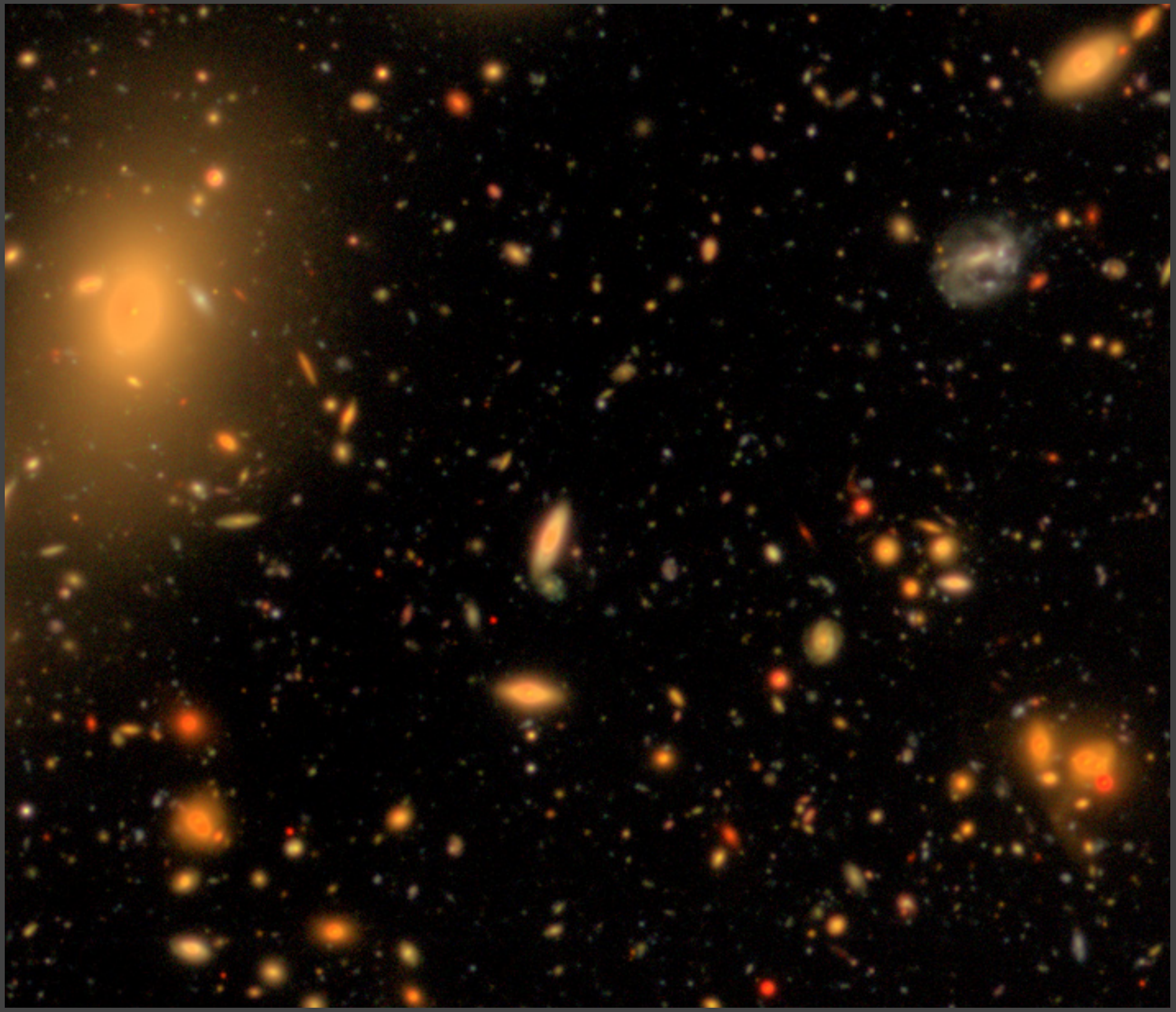
Blending

Blending

- HSC: 58% of the detected objects are identified as blended (Bosh+2017)
- LSST: at least 62% (Sanchez+2021)

Systematic

- Unrecognised blends: several objects detected as one object
- Recognised blends



Credit: HSC

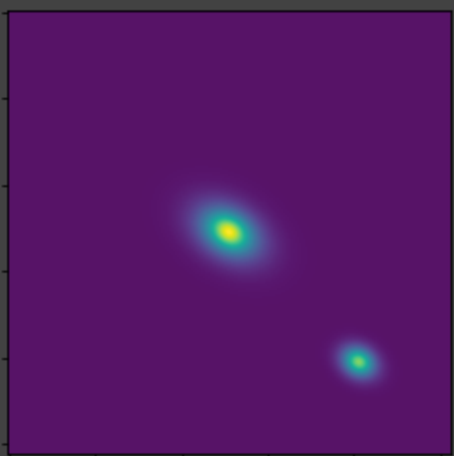
→ **Shear bias**

Systematic of cosmic shear

Blending

Measurements with KSB (Kaiser+1995)

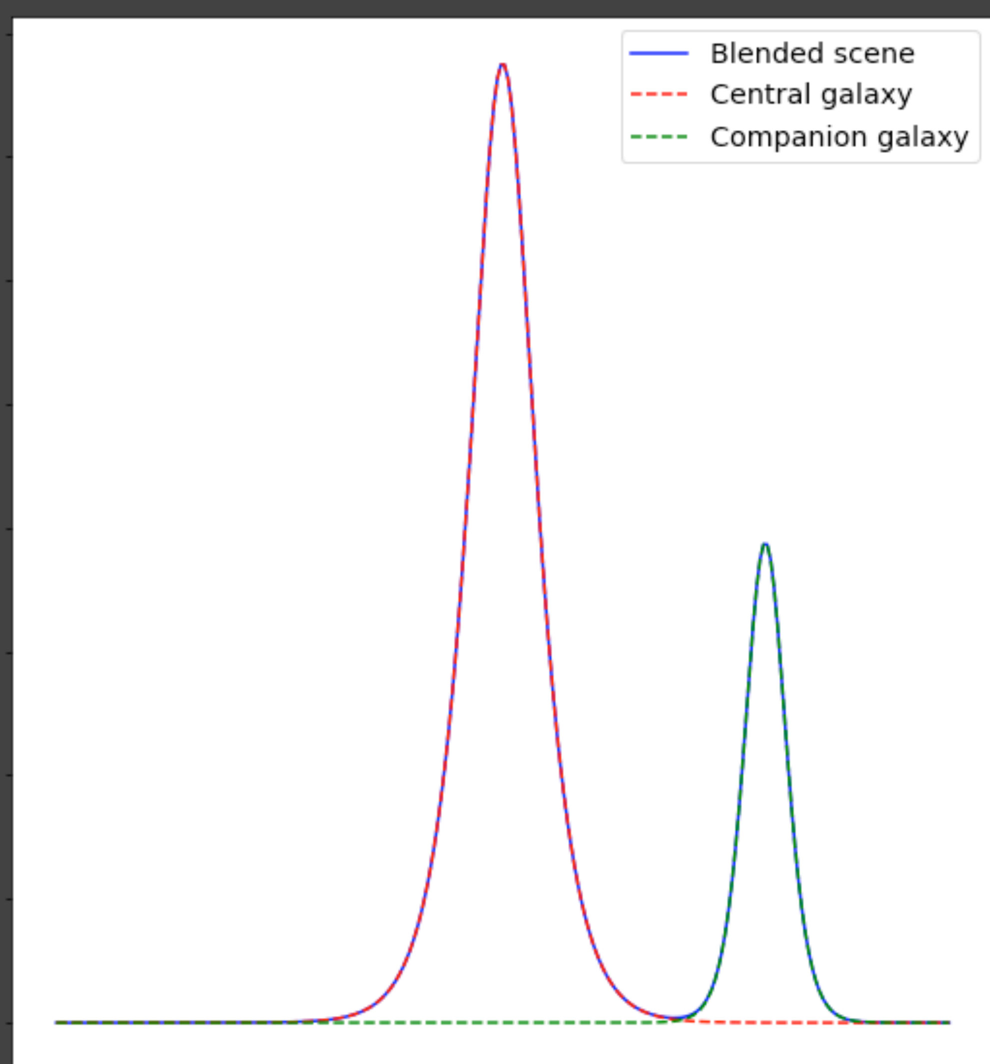
Credit: Thomas Sainrat

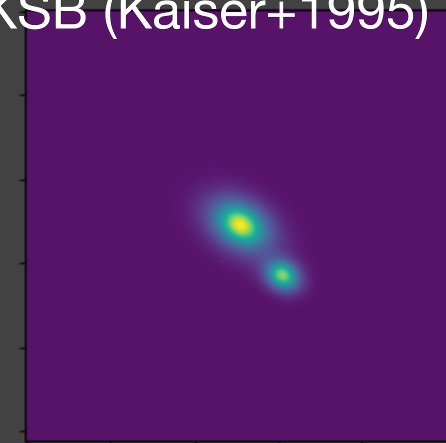


$\epsilon_1^{true} = 0.1 \quad \epsilon_2^{true} = 0.2$

$\epsilon_1^{meas} = 0.103 \quad \epsilon_2^{meas} = 0.206$

$\delta\epsilon_1 = 2.8\ \% \quad \delta\epsilon_2 = 2.8\ \%$

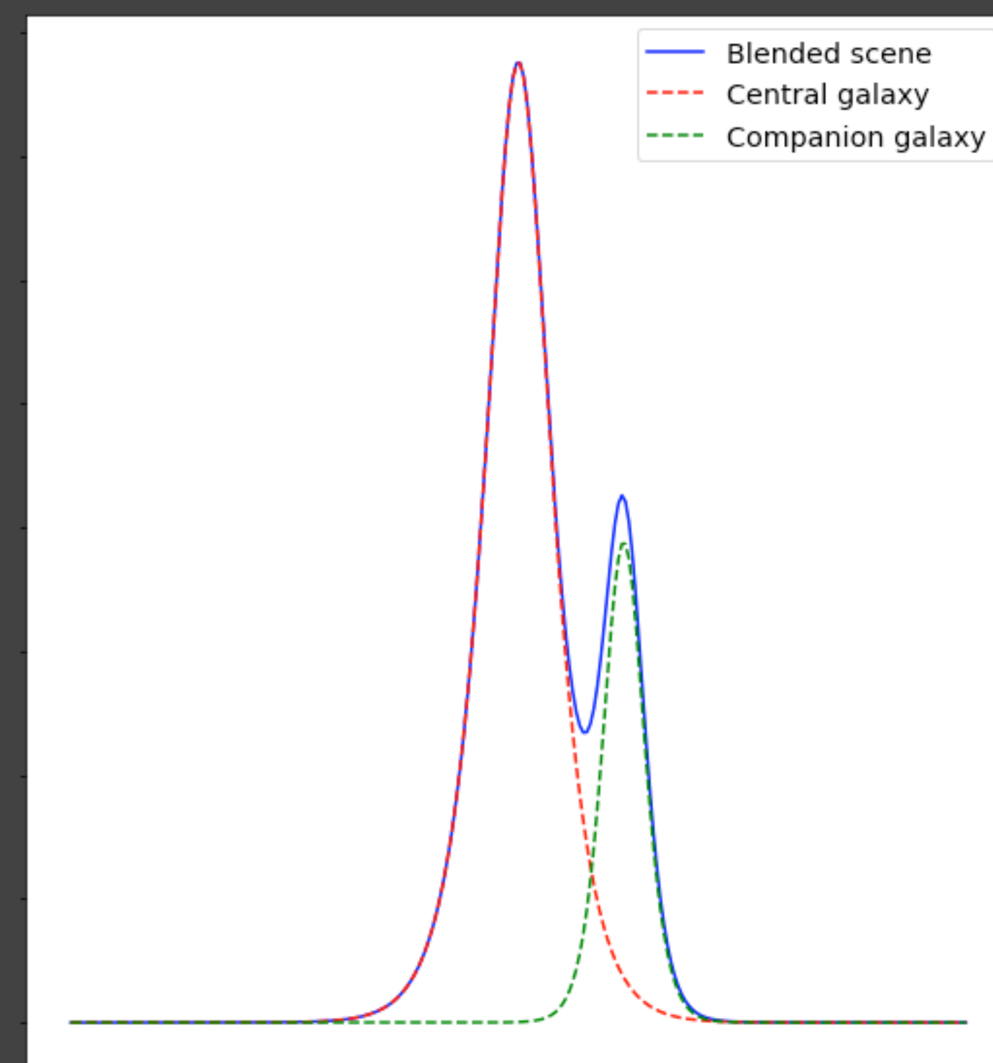




$\epsilon_1^{true} = 0.1 \quad \epsilon_2^{true} = 0.2$

$\epsilon_1^{meas} = 0.07 \quad \epsilon_2^{meas} = 0.296$

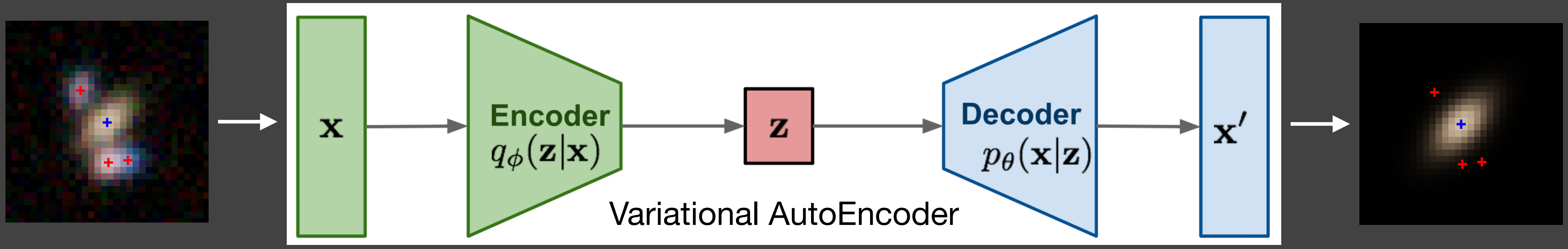
$\delta\epsilon_1 = -30.5\ \% \quad \delta\epsilon_2 = 47.8\ \%$



Address blending with Deep learning

Deblending galaxies

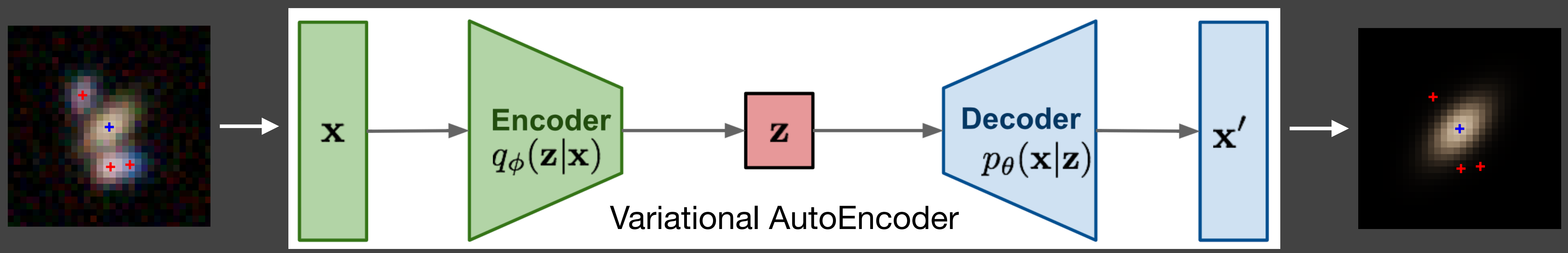
- Deblending galaxies with Variational AutoEncoders combining space and ground data (Arcelin+2021)



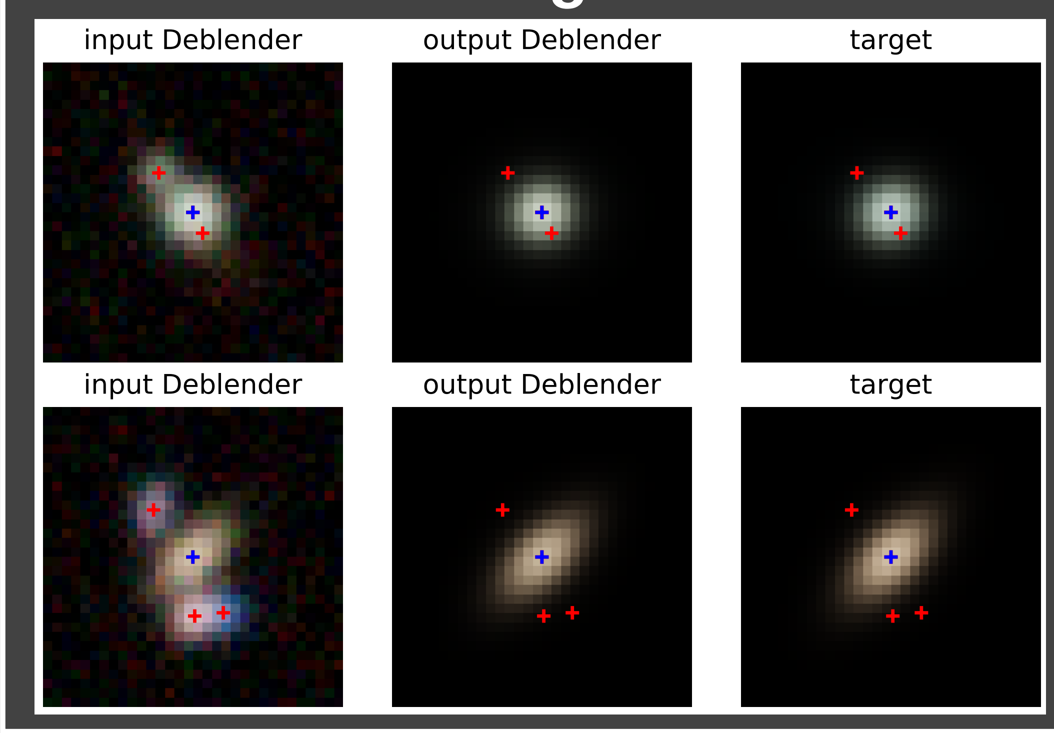
Address blending with Deep learning

Deblending galaxies

- Deblending galaxies with Variational AutoEncoders combining space and ground data (Arcelin+2021)



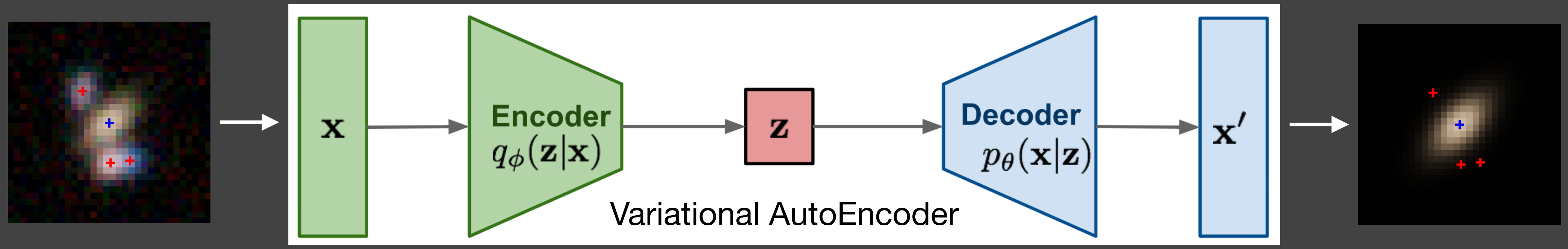
Simulated galaxies



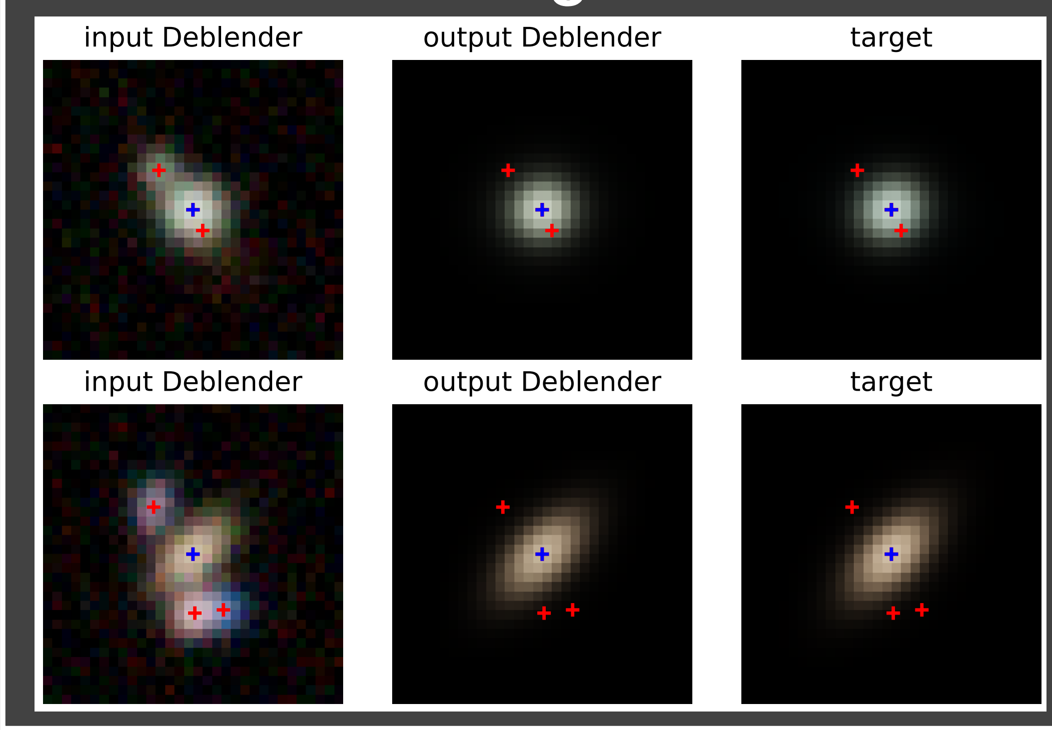
Address blending with Deep learning

Deblending galaxies

- Deblending galaxies with Variational AutoEncoders combining space and ground data (Arcelin+2021)

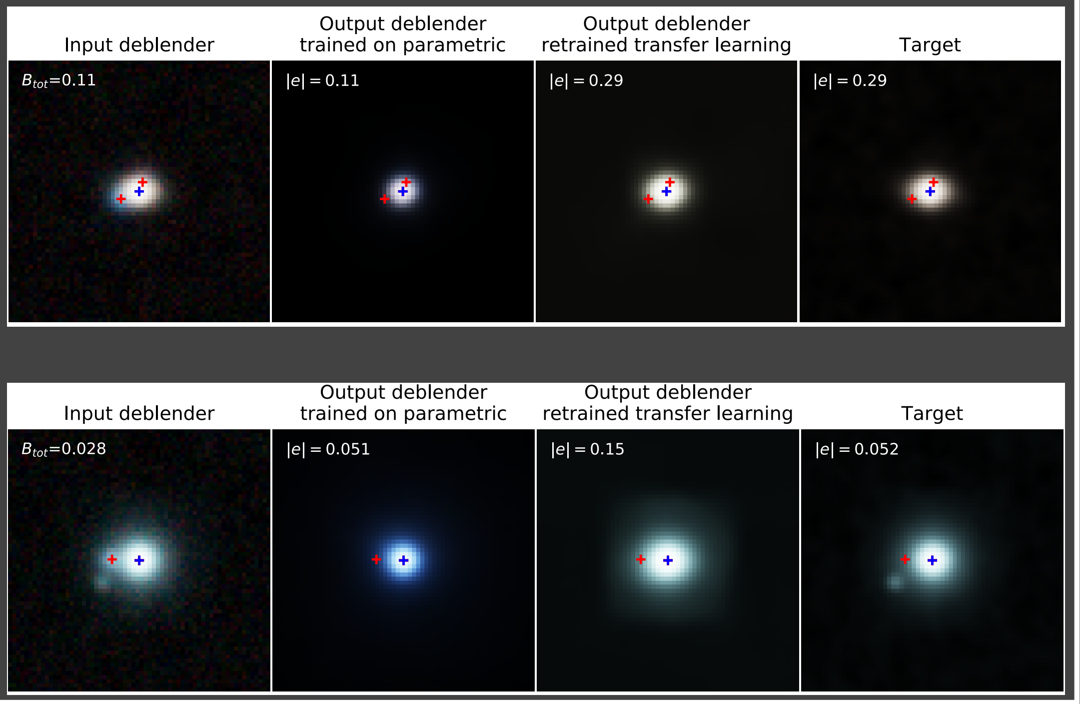


Simulated galaxies



Transfert Learning

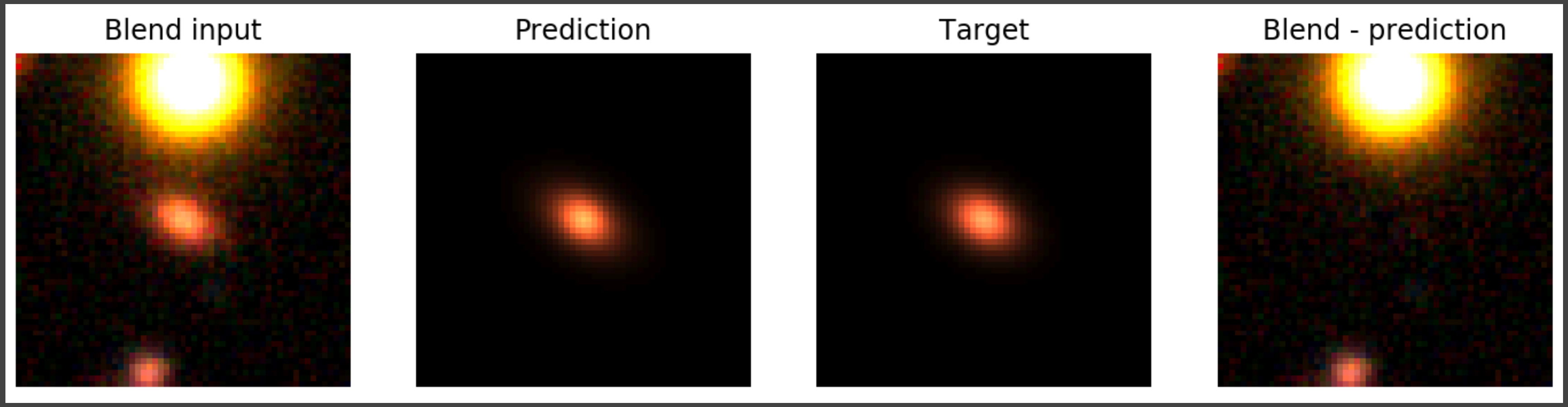
Real galaxy images



Address blending with Deep learning
Deblending galaxies

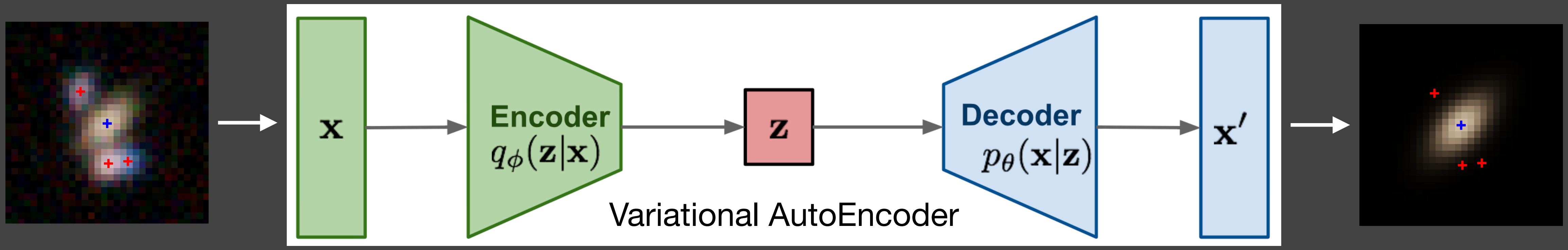
- Deblending galaxies with Variational AutoEncoders combining space and ground data (Arcelin+2021):

➡ Going to DC2 images (more realistic images: PSF, defaults of CCDs…)

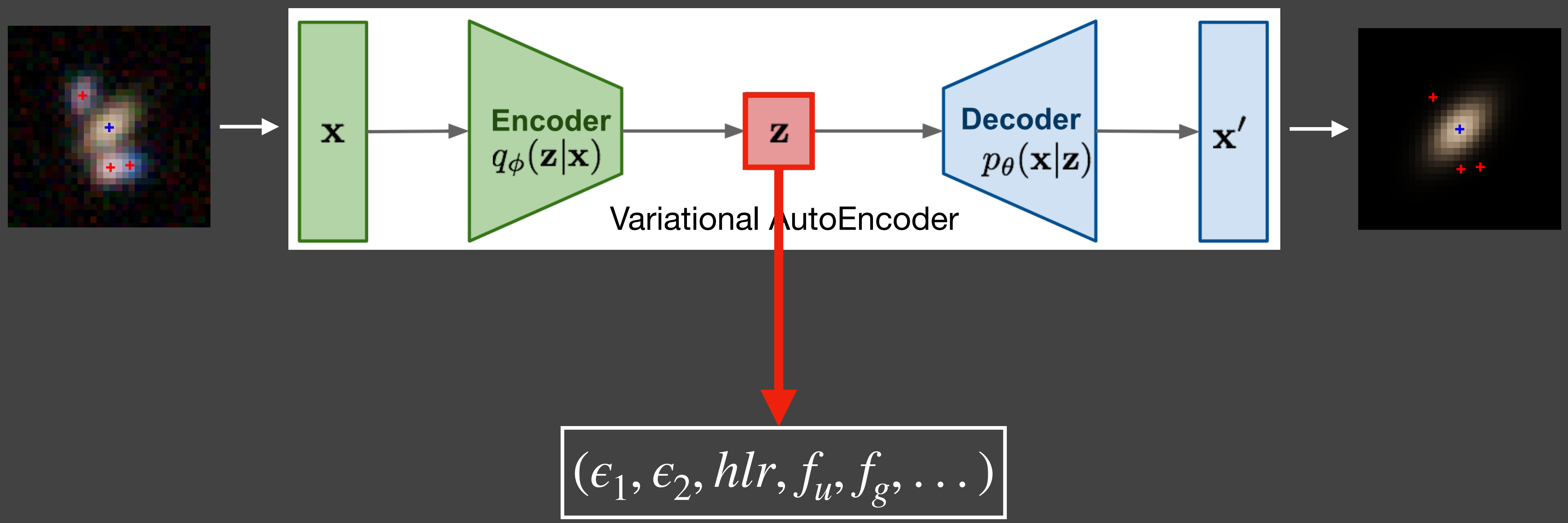


➡ Designing deblending procedure (iterative process: detection, classification, deblending): Thomas Sainrat, Biswajit Biswas

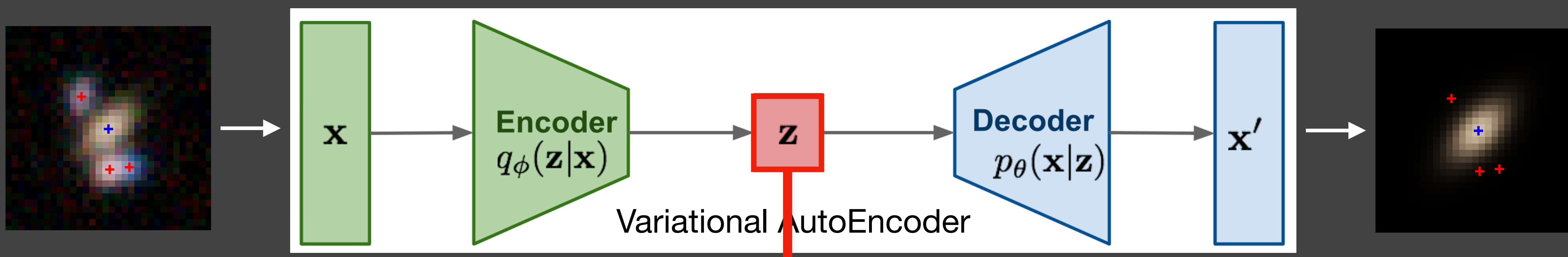
Address blending with Deep learning



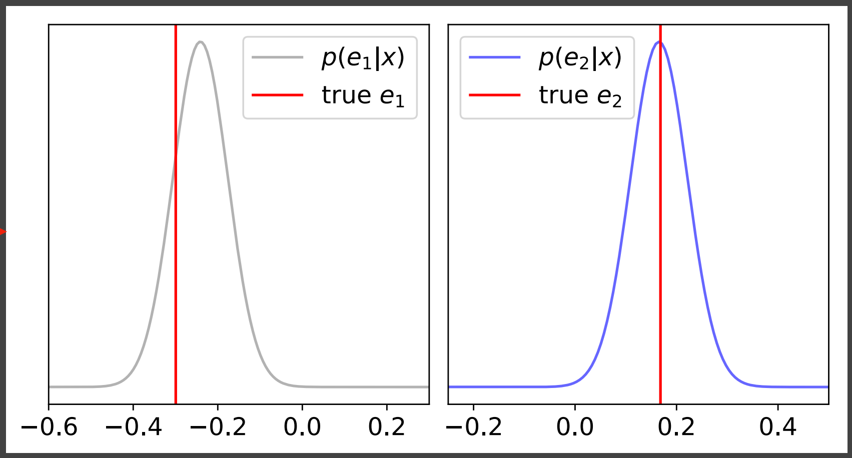
Address blending with Deep learning



Address blending with Deep learning



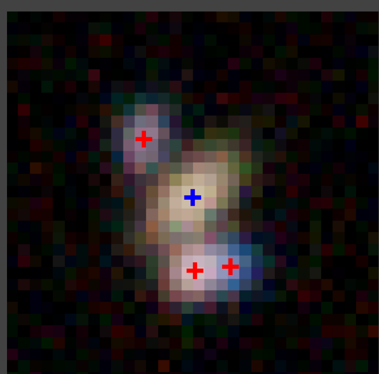
$$(e_1, e_2, hlr, f_u, f_g, \ldots)$$



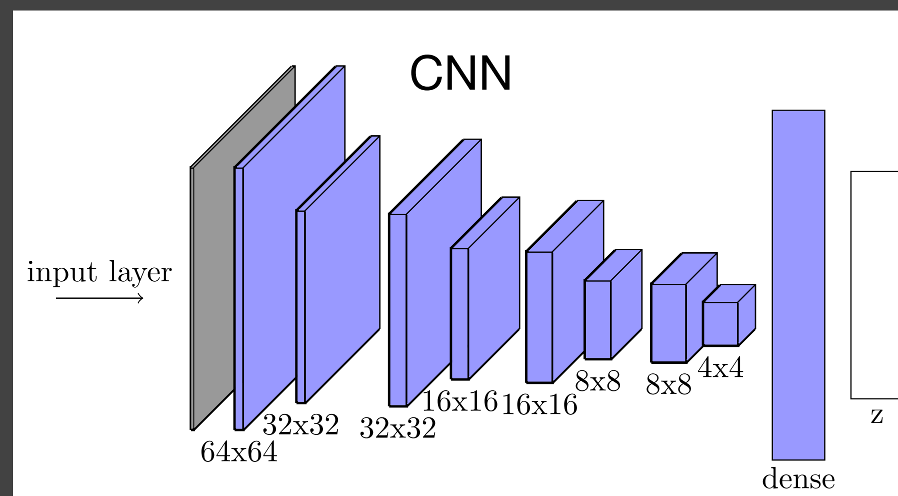
Address blending with Deep learning

Galaxy parameters estimation

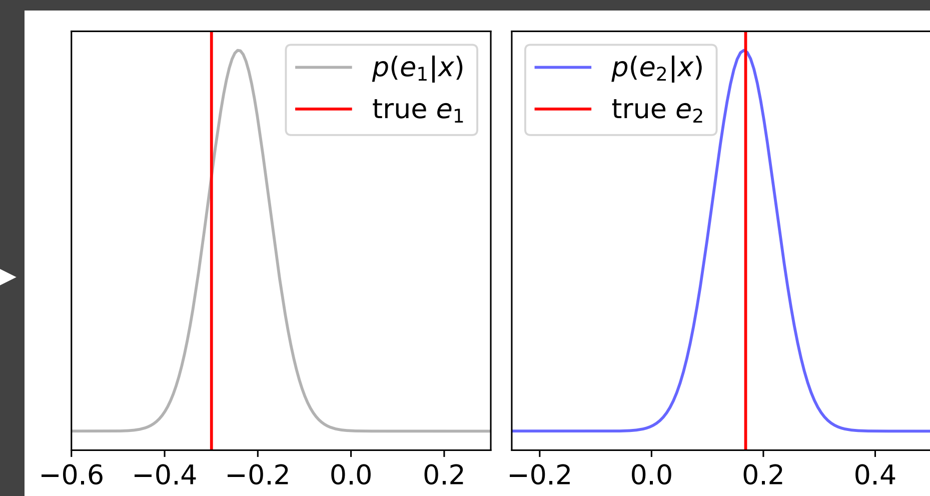
- Galaxy parameters (ellipticity, redshift) estimator



→



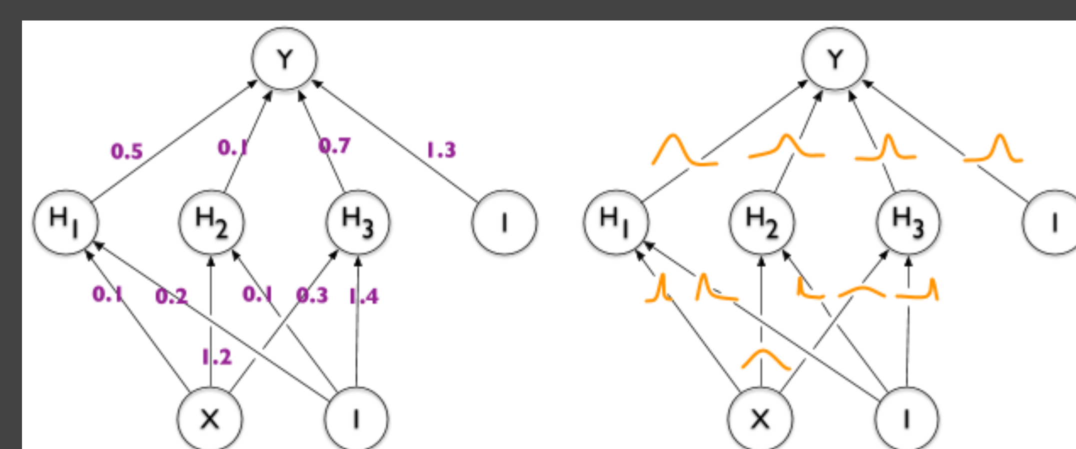
→



➡ not biased by blending (for recognized blends)

➡ can be calibrated by the Metacalibration algorithm (Huff+2017)

➡ Bayesian neural networks



Credit: Sanjay Thakur

Address blending with Deep learning

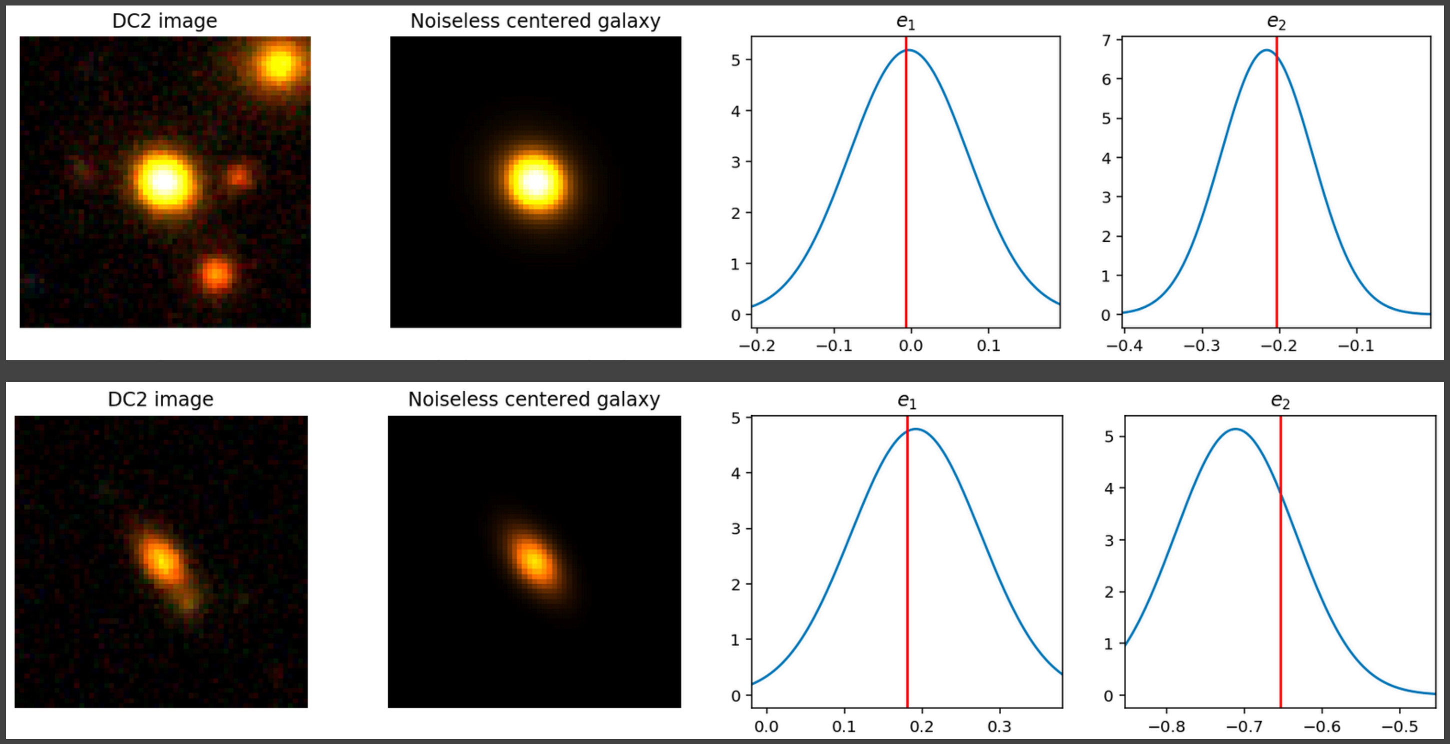
Galaxy parameters estimation

- Galaxy parameters (ellipticity, redshift) estimator

  ➡ Ongoing work on DC2 images:

  - Test of architectures
  - Noiseless images then DC2 images
  - Different inputs: image+PSF or PSF-deconvolved image

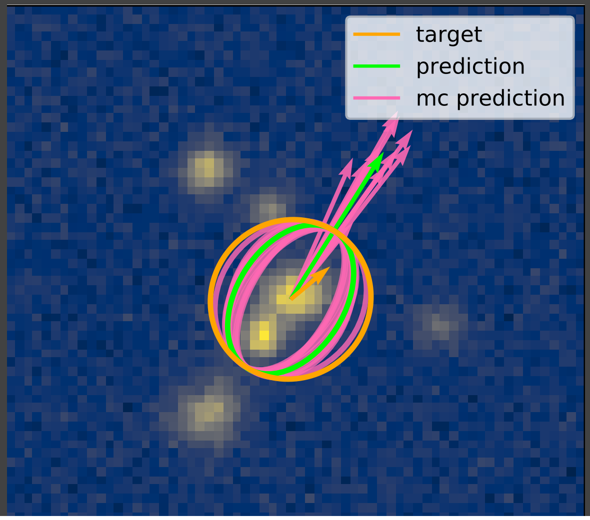
Preliminary results

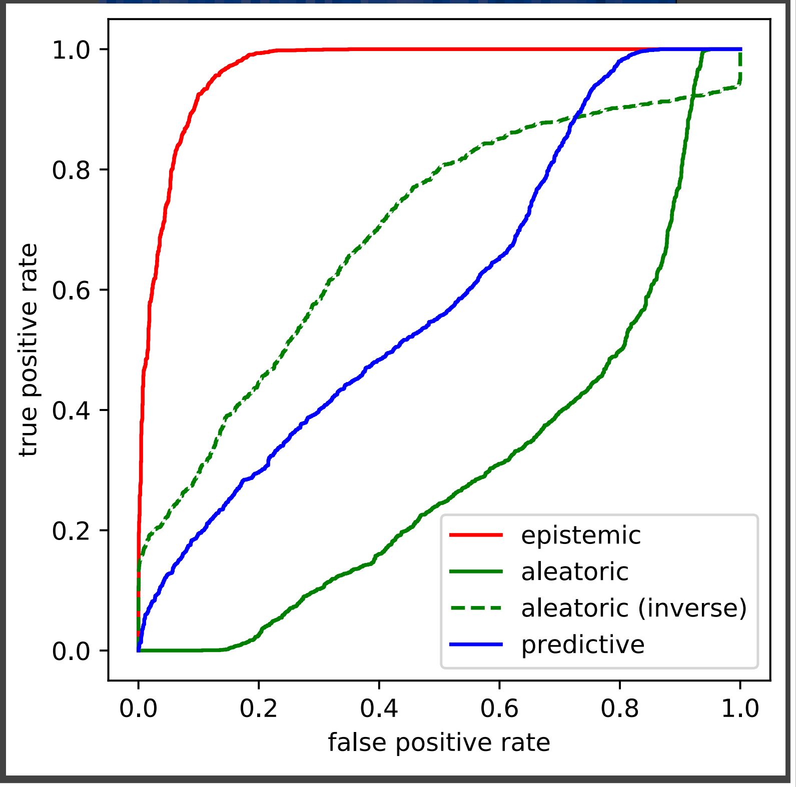


Address blending with Deep learning

Galaxy parameters estimation

- Galaxy parameters (ellipticity, redshift) estimation with Bayesian neural networks (Theobald, Arcelin+2021)
  - ➡ MC Dropout (Gal+2016)
  - ➡ Set training procedure
  - ➡ Calibrated estimation of aleatoric uncertainty (from the data)
  - ➡ Epistemic uncertainty (from the training set) estimation
    - Well suited to identify outliers (here blends)
    - Anticipate high predictive ellipticity error





Address blending with Deep learning

Deblending and Galaxy parameters estimation

- Conclusion:

  ➡ Deblending with VAE

  - Can be applied on simulated images, robust to decentring, transfer learning for real galaxy images (Arcelin+2021)
  - DC2 images
  - Deblending procedure

  ➡ Galaxy parameters (ellipticity, redshift) estimator for blended galaxies

  - DC2 images
  - Bayesian neural network (Theobald, Arcelin+2021)