Large Synoptic Survey Telescope

Université de Paris

Paris Centre for Cosmological Physics

Deblending galaxies with variational autoencoders

Bastien Arcelin

Co-authors: Cyrille Doux, Cécile Roucelle, Eric Aubourg

IN2P3/IRFU
Machine Learning Workshop

LSST

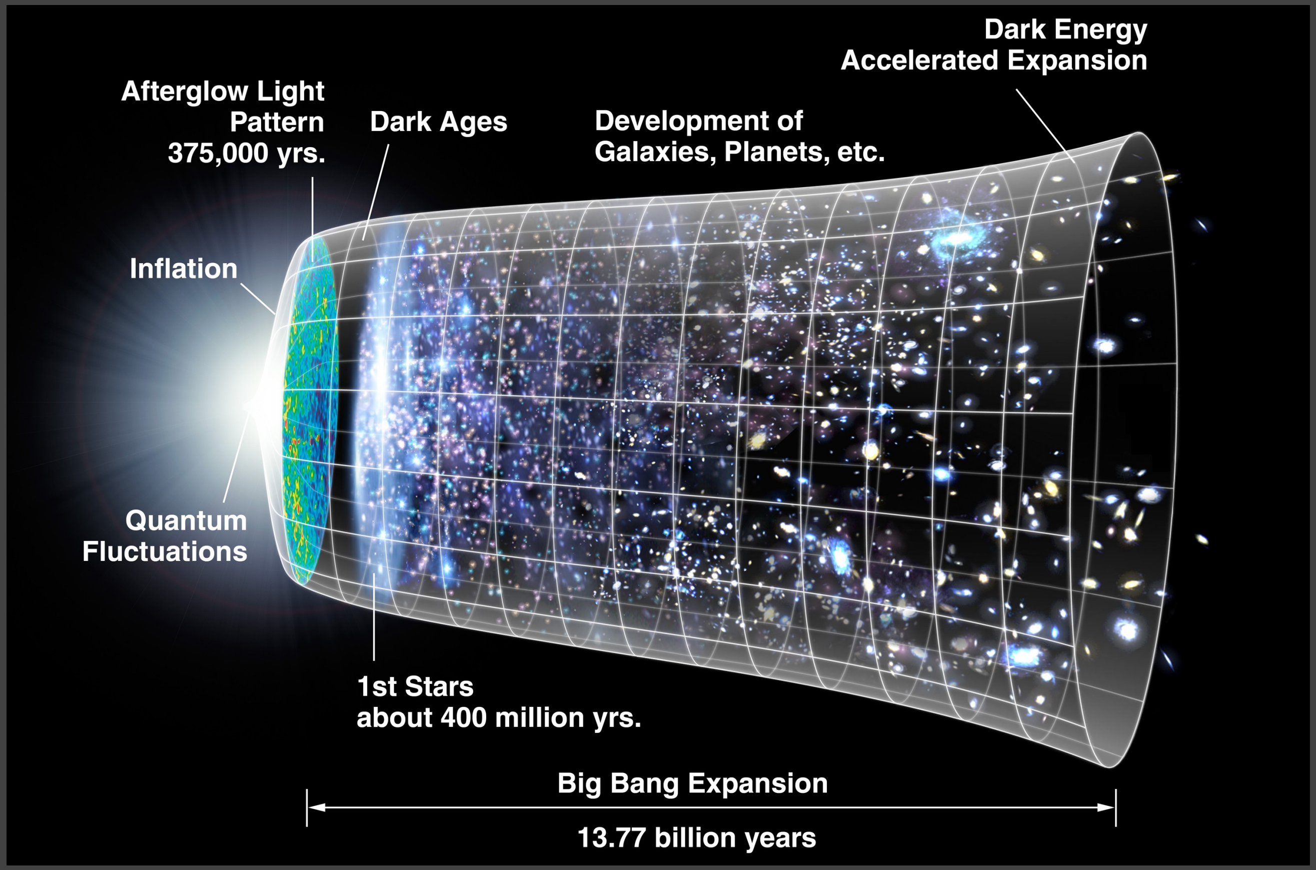
- LSST : Legacy Survey of Space and Time (Vera Rubin Observatory)
- Being built north Chile
- First light in 2021
- 10 years of operation

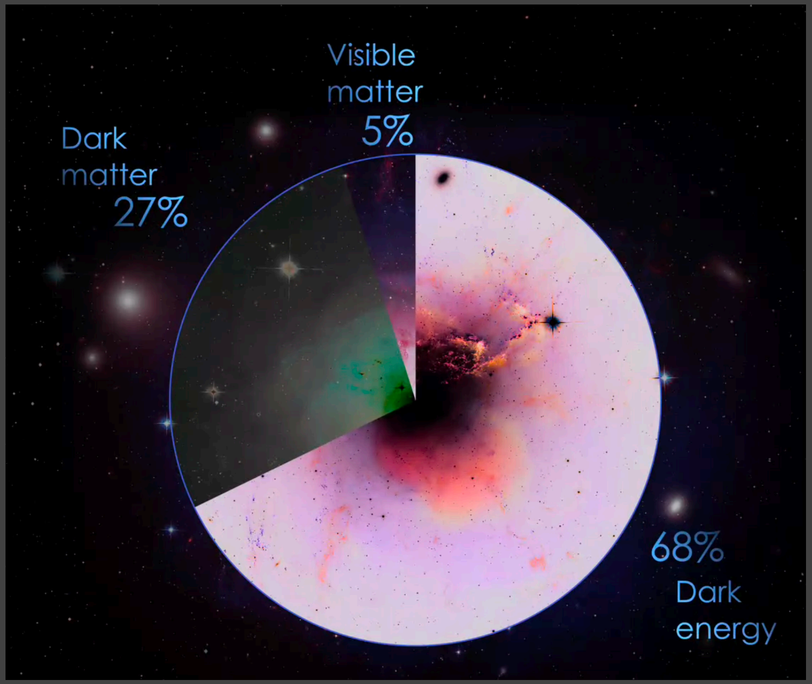
LSST

- 8,4m mirror
- 3200 megapixel camera
- **20 terabytes of data per night**
- 10 years of operation : **around 60 petabytes** of data

Need fast analysis methods —> Machine learning

LSST to probe dark energy

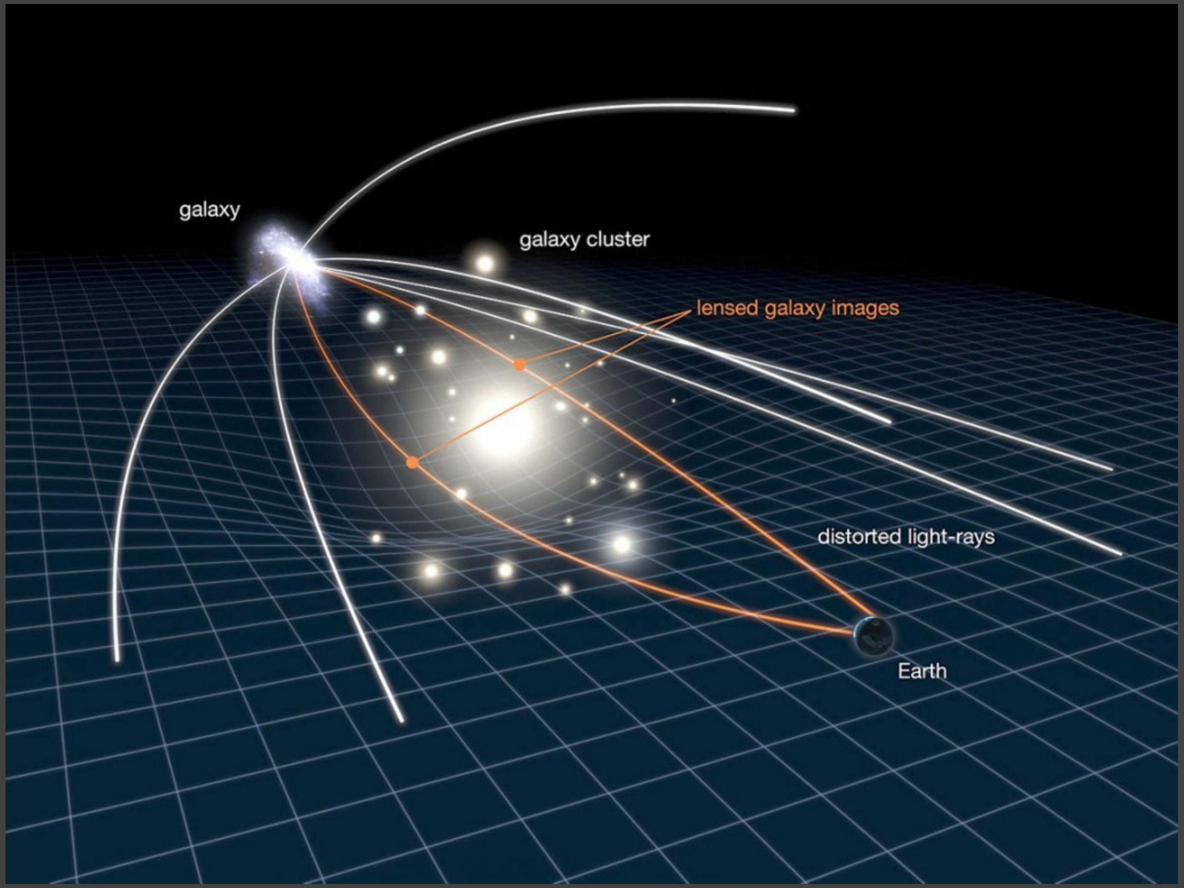


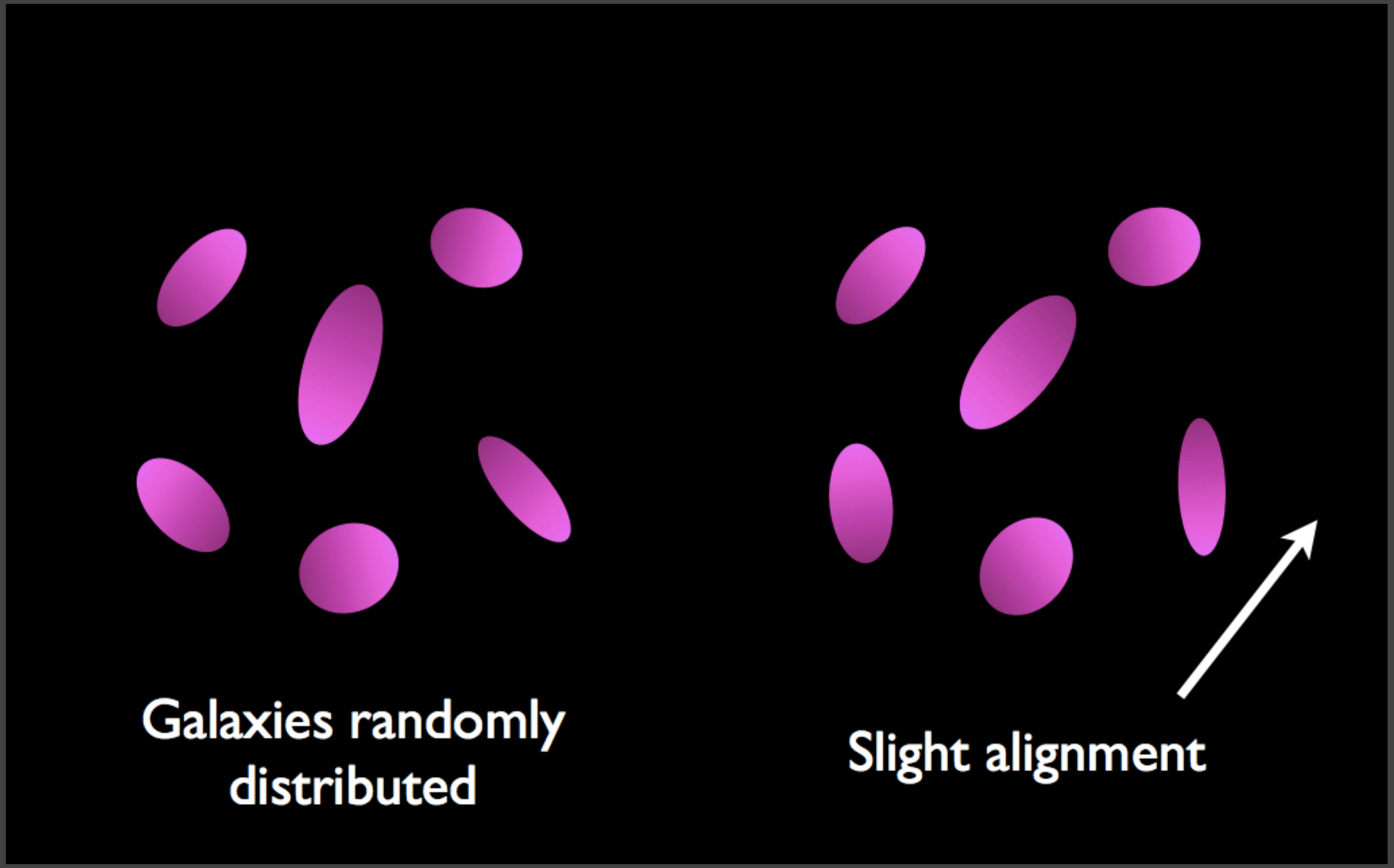


- SN Ia
- CMB
- BAO
- Clusters
- **Weak lensing**

Weak lensing

- **Lensing** due to mass: **deforms** the images of the galaxies
- Correlations between orientations and shapes of neighbour galaxies: **cosmic shear**



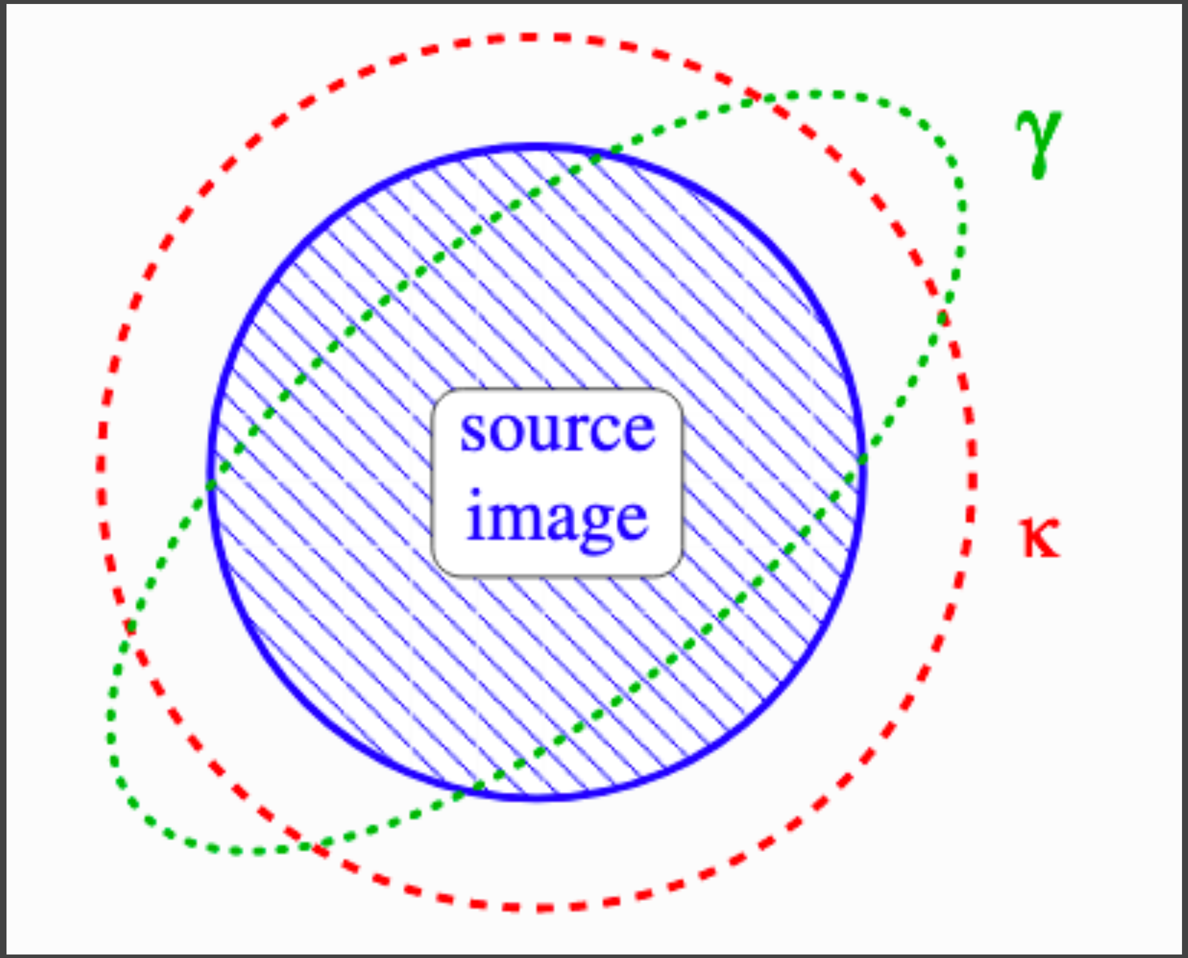


Weak lensing

Ellipticity : $\epsilon = \epsilon^s + \gamma$

$\epsilon = \epsilon_1 + i\epsilon_2$

Observed ellipticity = intrinsic ellipticity + shear

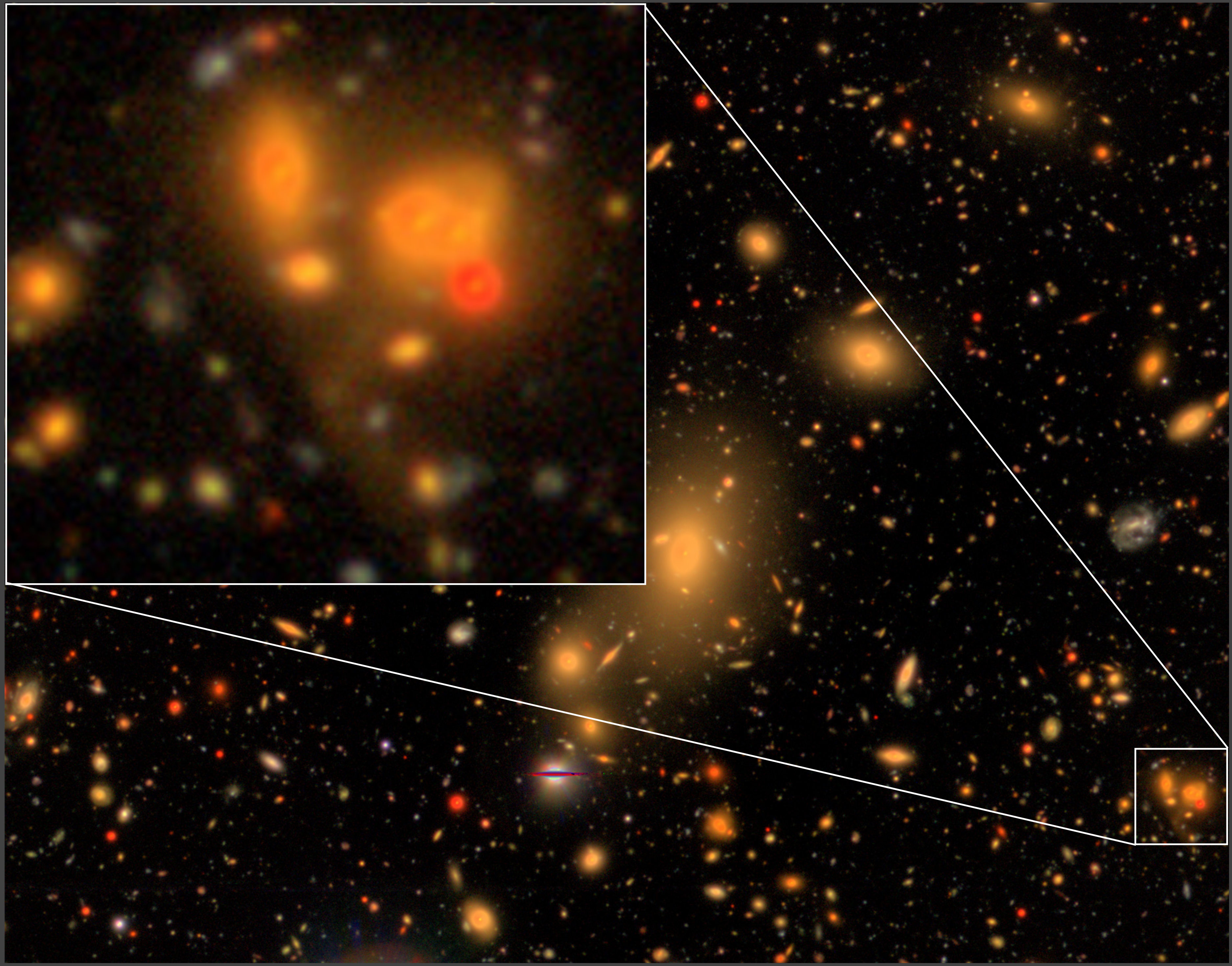


From Martin Kilbinger slides :
http://www2.iap.fr/users/kilbinge/talks/marseille08.pdf

LSST data

- Will look a lot like HSC data
- HSC: 58% of the detected objects are identified as blended*
- Systematic in shear measurement

* Bosch et al. (2017)



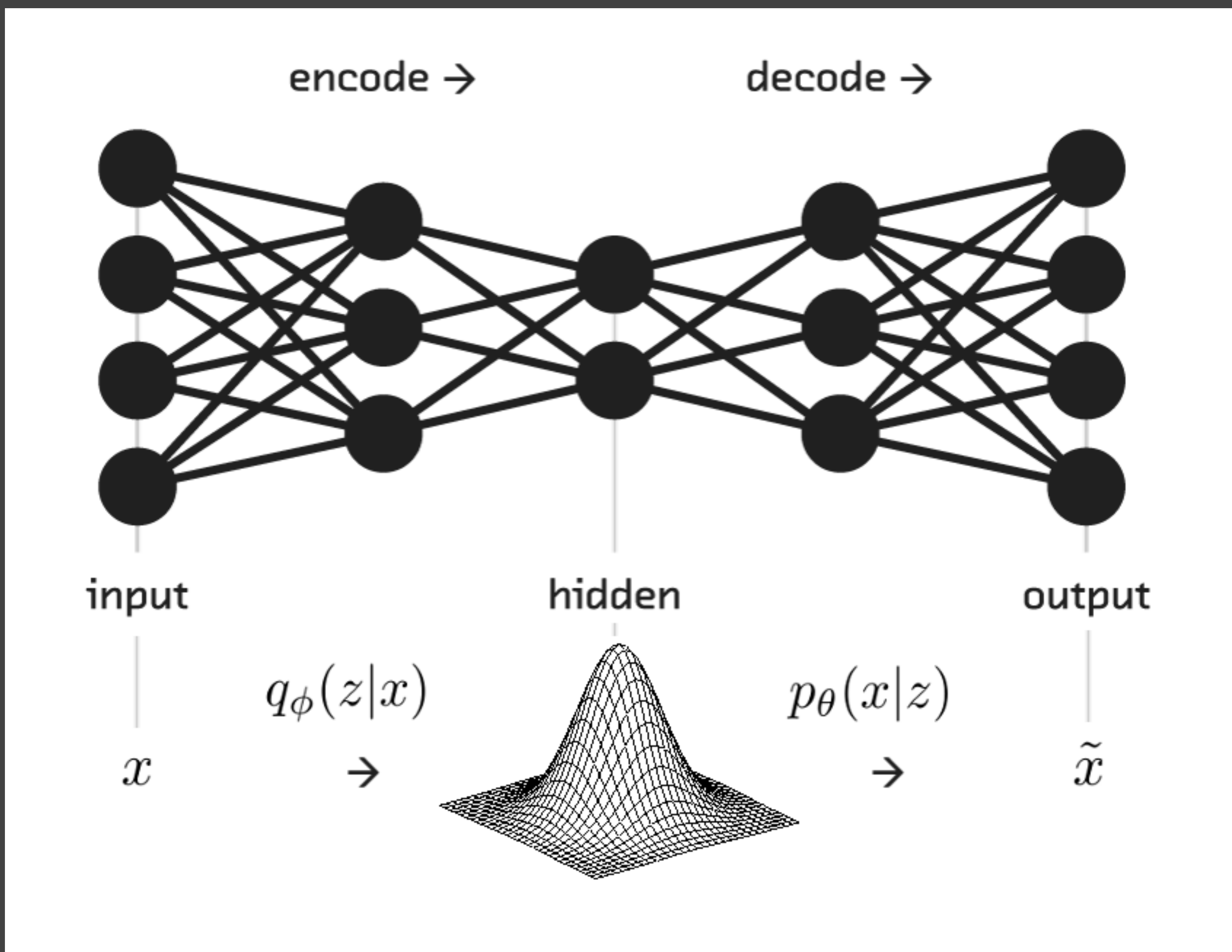
HSC image of small piece of COSMOS field (https://www.naoj.org/Topics/2017/02/27/index.html)

Goals and motivation

Which algorithm ? Which parameters ?

- Create a model for galaxy images from the data → Generative model
- Bayesian approach → VAE
- Accurate reproduction of relevant weak lensing parameters → Shape and flux reproduction

Variational AutoEncoder (VAE)
(Kingma +2014)



- http://blog.fastforwardlabs.com

Loss function :

$$ELBO = -D_{KL}\left(q_\phi(z|x) \parallel p(z)\right) + \mathbb{E}(\log p_\theta(x|z))$$

Encoder → Regularization term

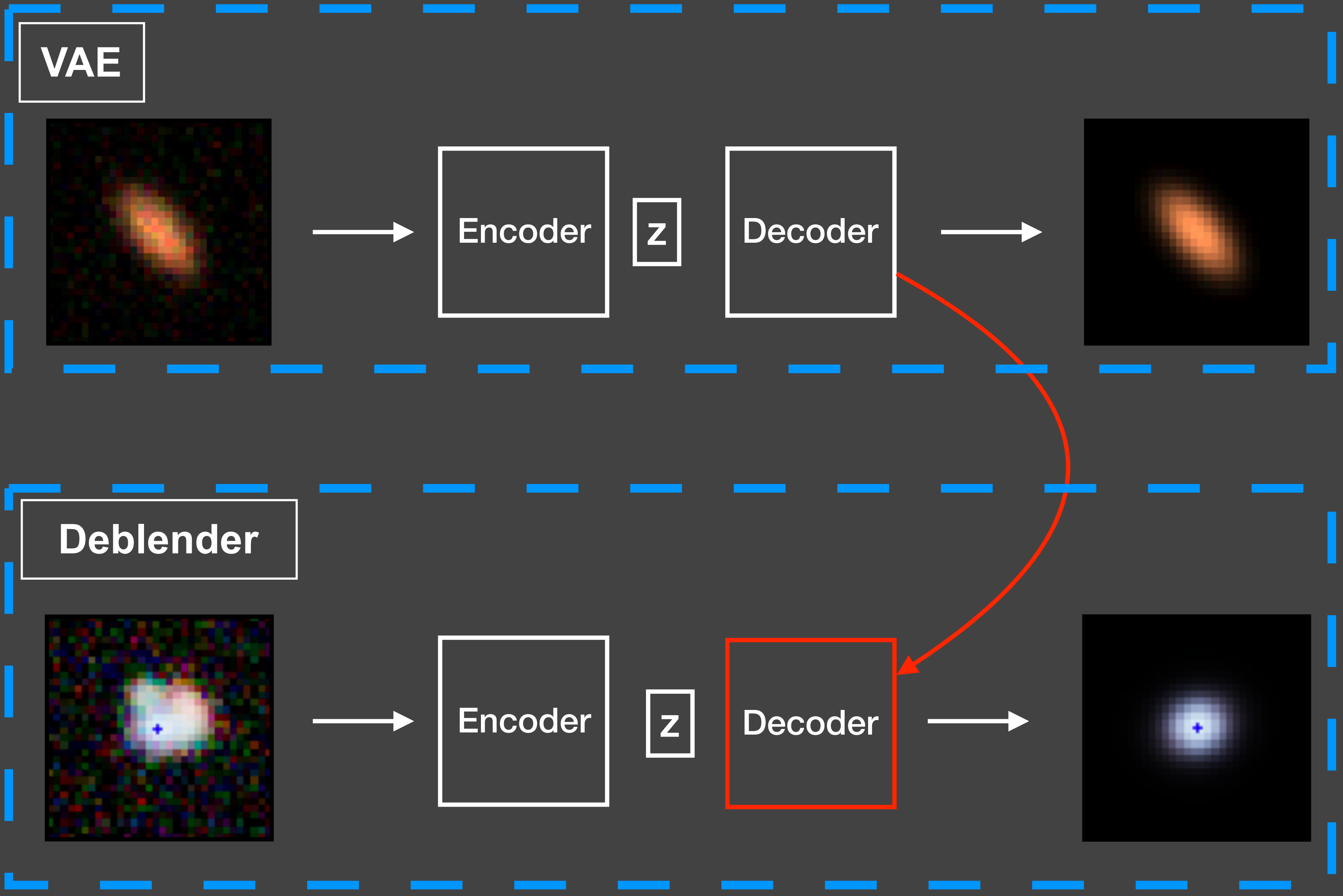
Decoder → Reconstruction term

Machine learning for deblending

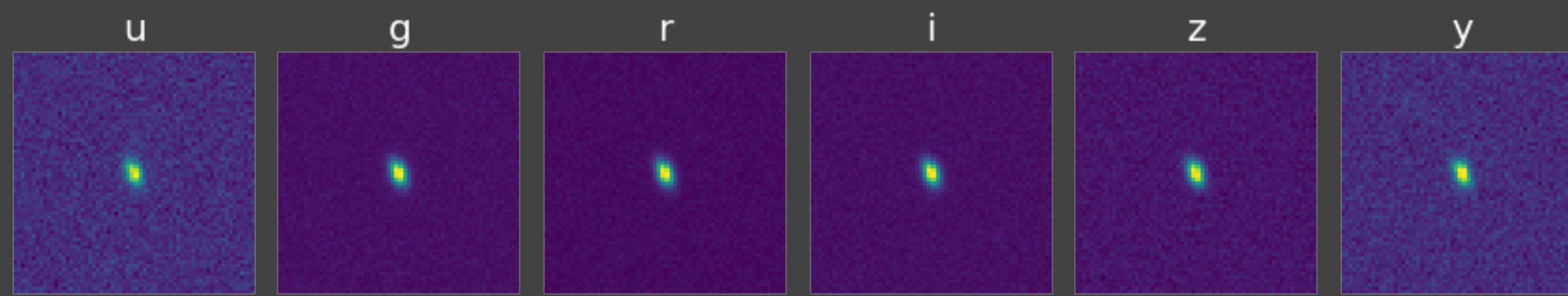
Two neural networks:

- VAE (*Kingma+2014*) :
  - Learn a latent variable (z) generative model p(X|z)
  - Approximate the posterior p(z|X) with an encoder

- Deblender:
  - Use fixed generative model from VAE
  - Train a new network that learns to approximate $p(z_{center}|X_{blended})$
  - ~ Perform deblending in latent space



Machine learning for deblending



Architecture:

- β-VAE : $\beta = 10^{-2}$
- Prior on latent space: $\mathcal{N}(0,1)$
- 8 Convolutional layers in encoder and decoder

Training sample:

- Simulated data (artificial blends) from HST COSMOS catalog (81 500 galaxies)
- Data augmentation
- Normalized in [0,1]
- Batchsize = 100
- Training sample shape (batch_size, 64,64,X)

Size of image (64x64 pixels)

X:
- 6 : if trained on images with all 6 LSST filters
- 10 : if trained on images with all LSST+Euclid filters

LSST+ Euclid data

Why using Euclid data:

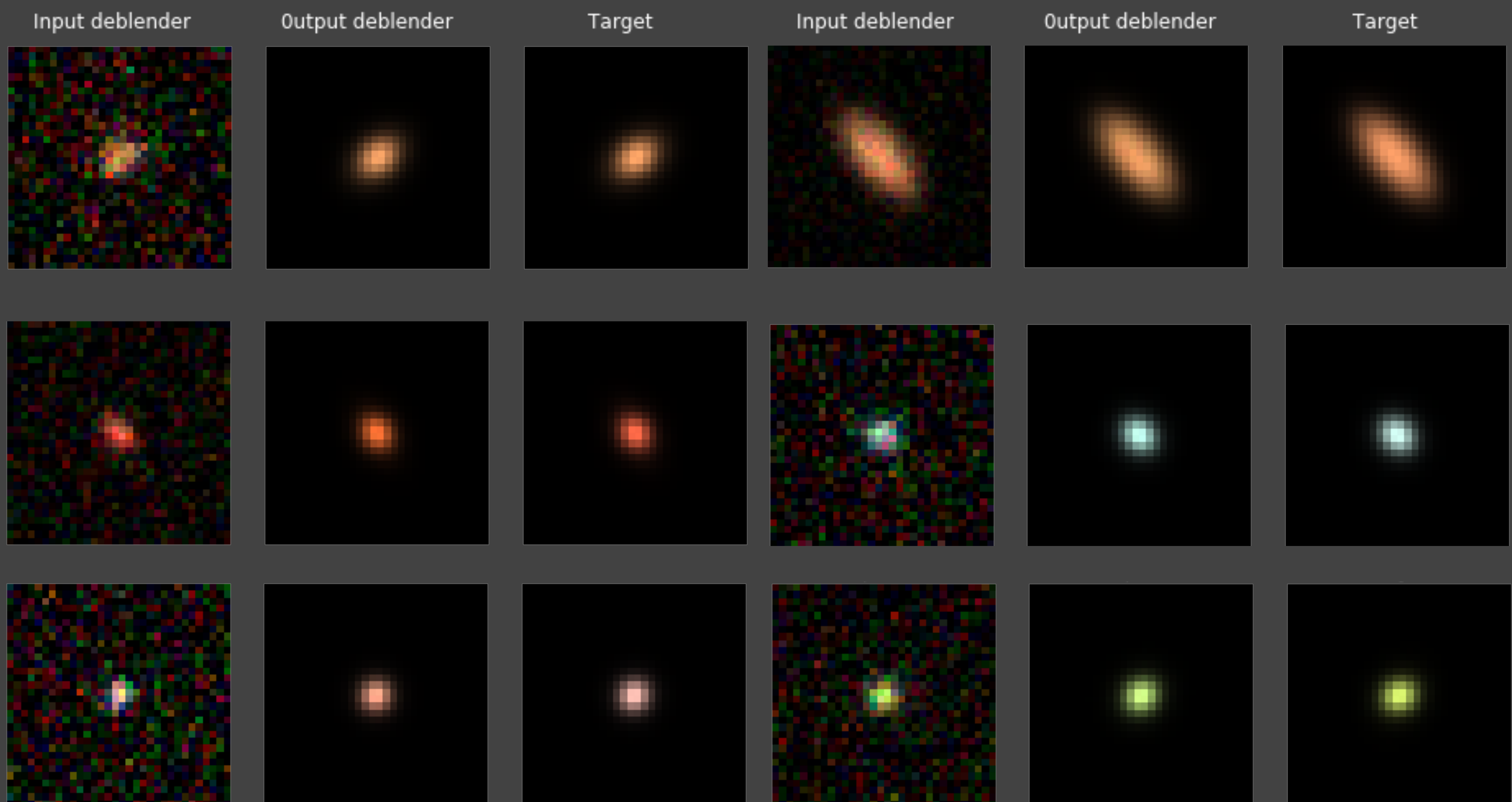
- ✓ Adding infrared bands (x3)
- ✓ Adding a wide optical band
- ✓ Better resolution (no atmospheric PSF)

DES data - Peter Melchior’s slides

CLASH WFC3/IR data - Peter Melchior’s slides

VAE results

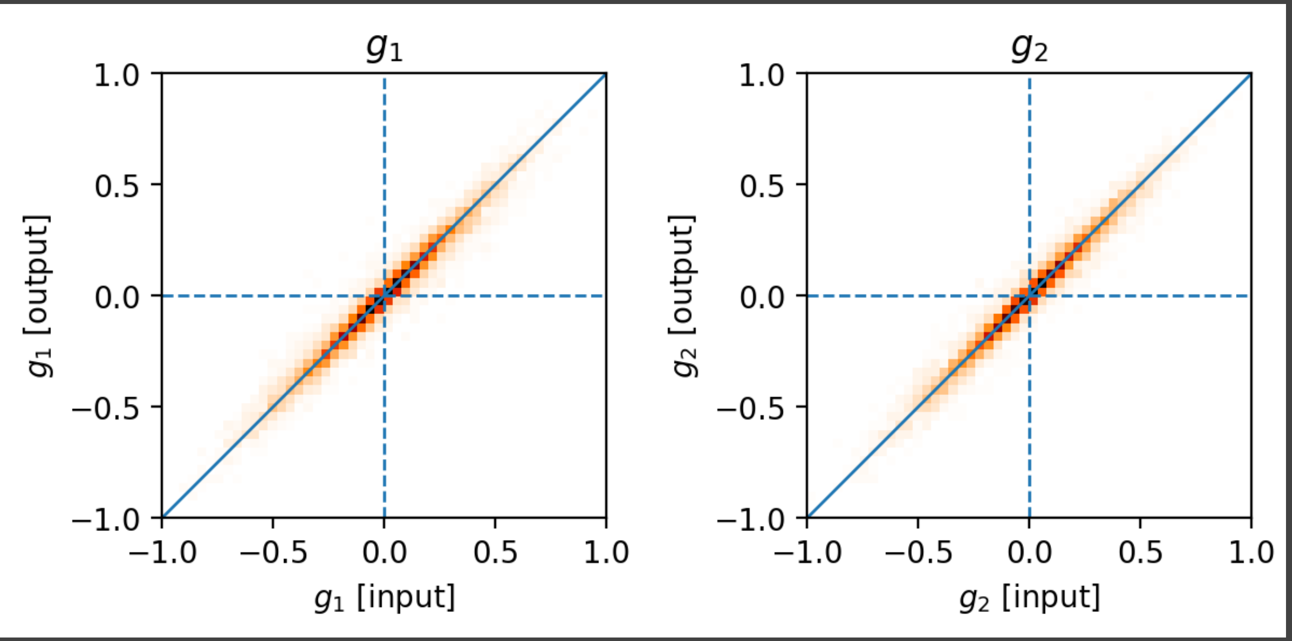
Few examples

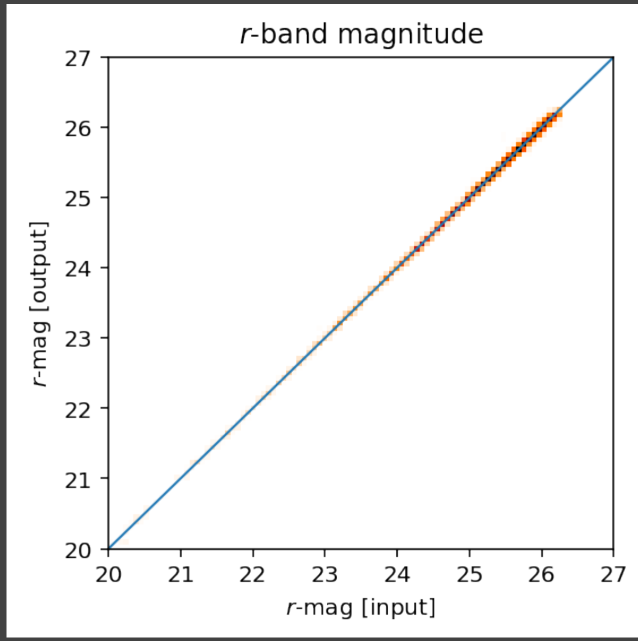


VAE results

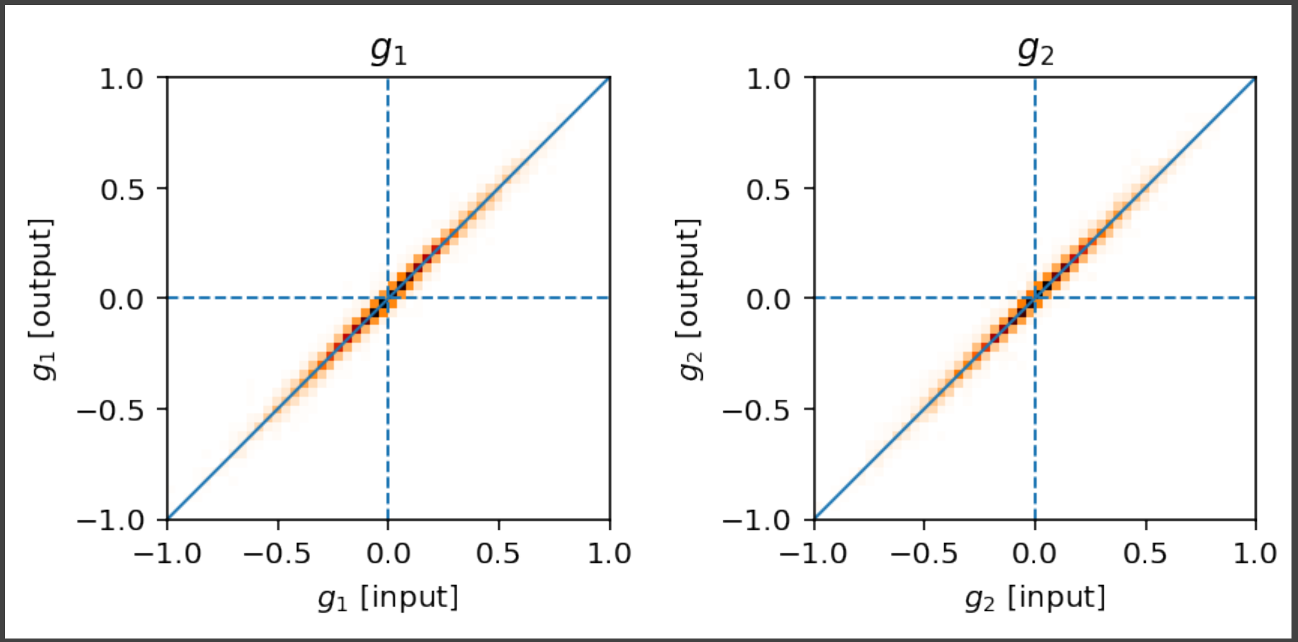
Shear and magnitude reproduction

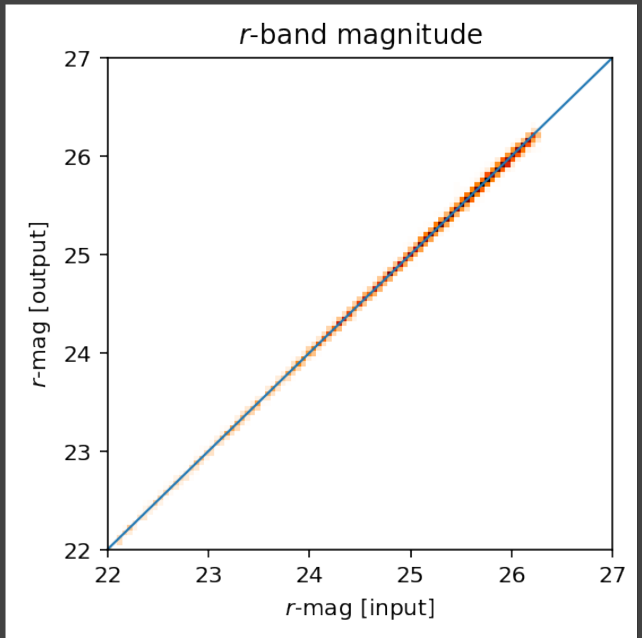
LSST





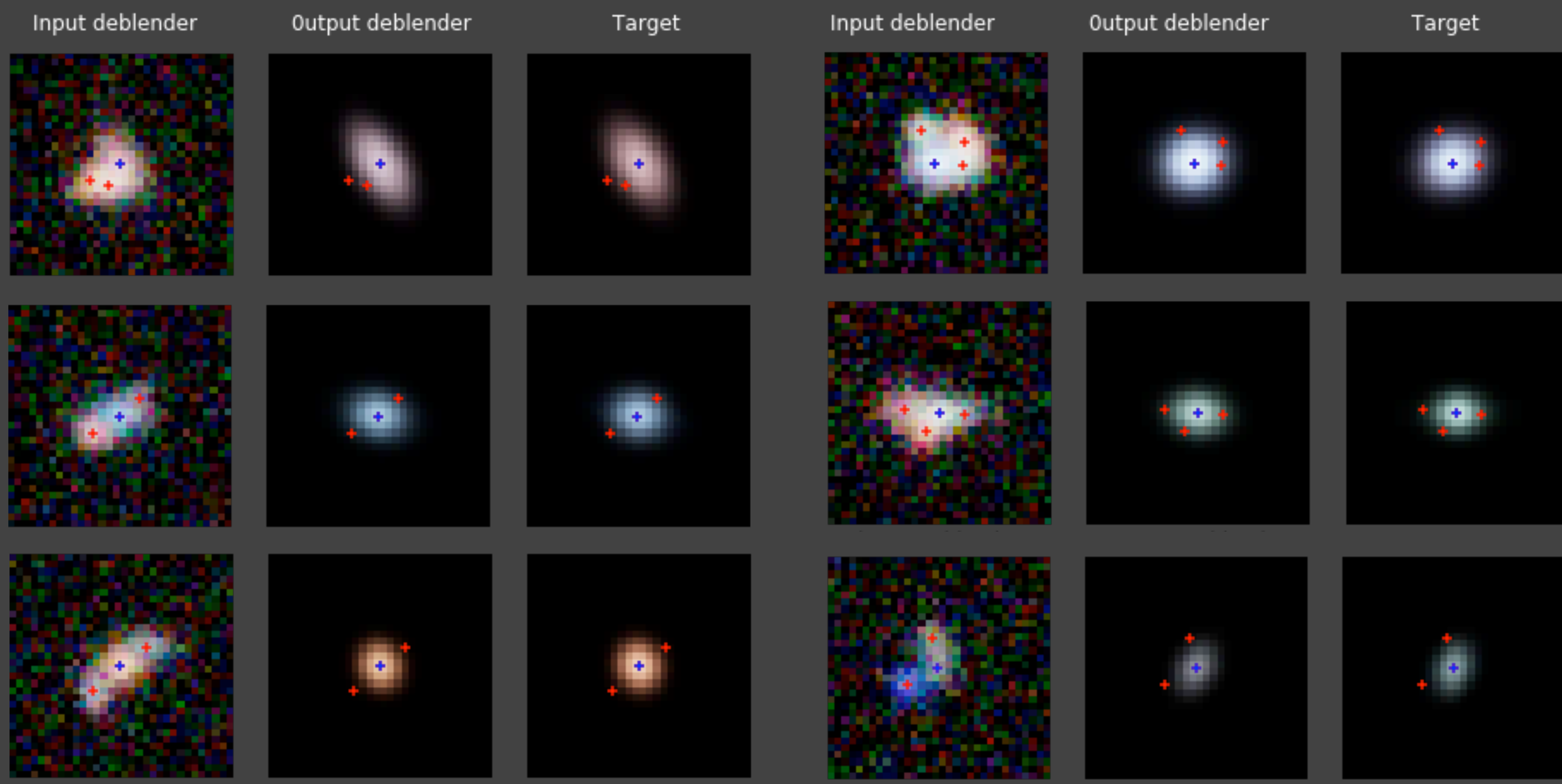
LSST + Euclid





VAE results

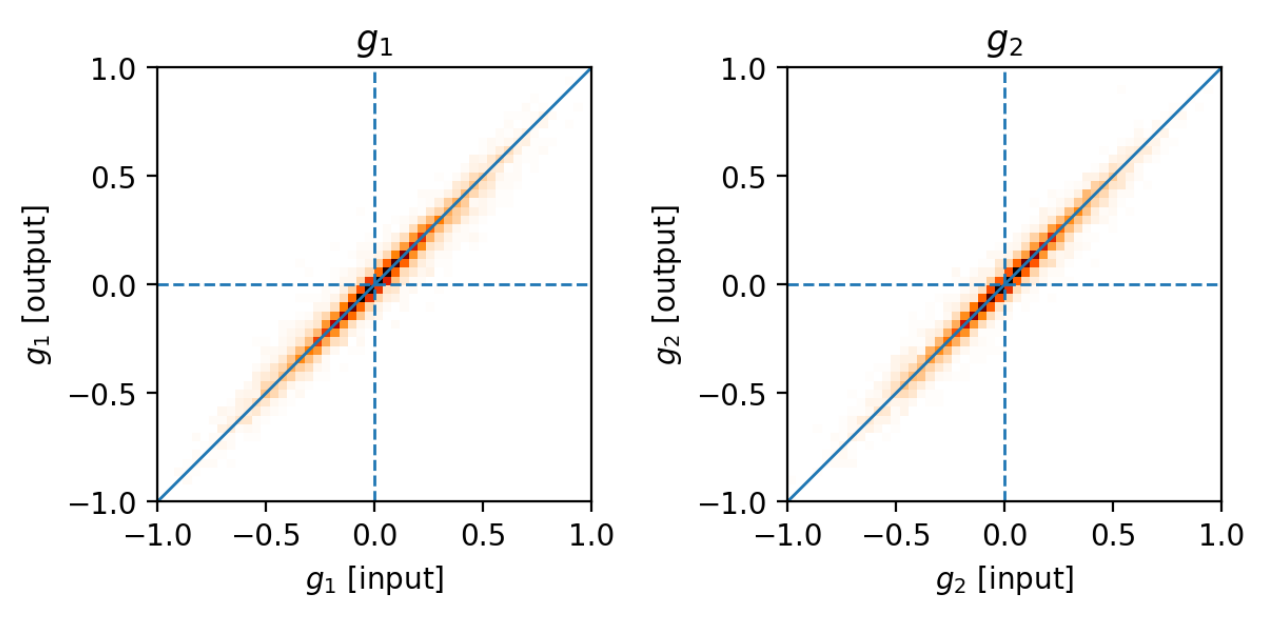
Few examples

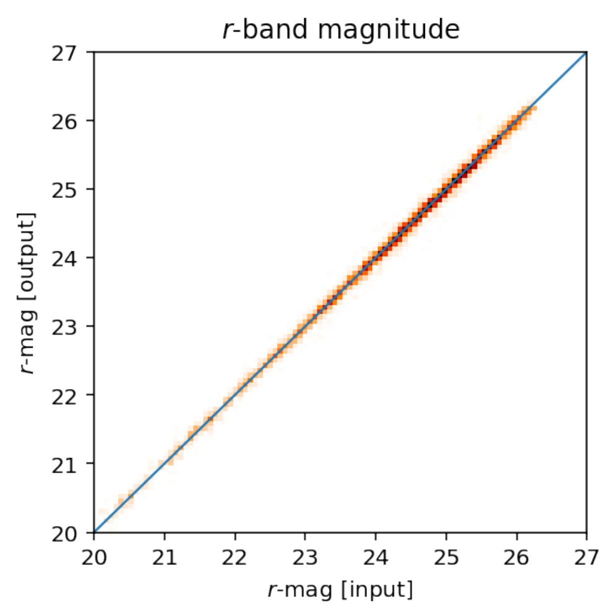


VAE results

Shear and magnitude reproduction

LSST





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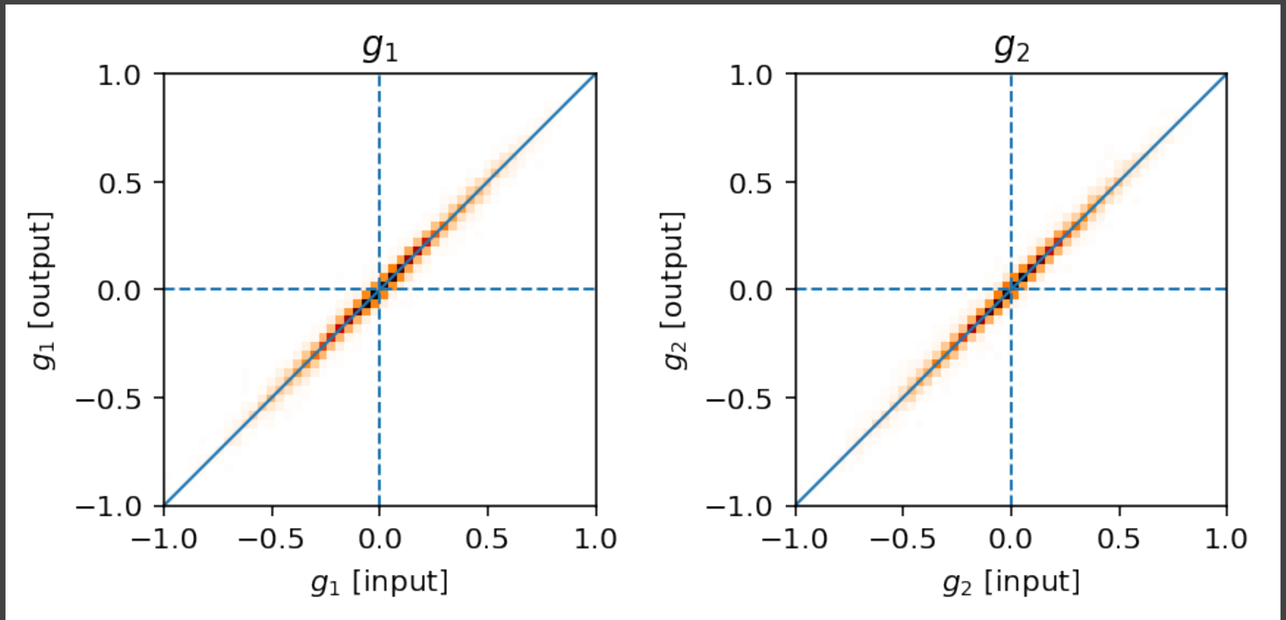
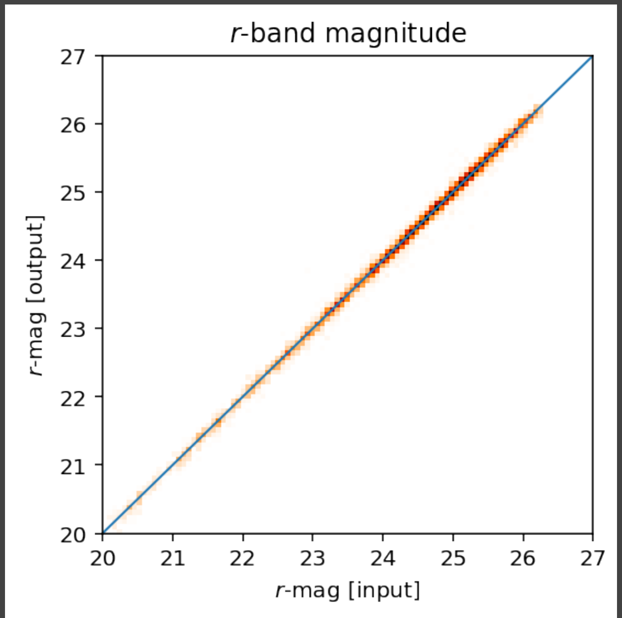




Deblend real images

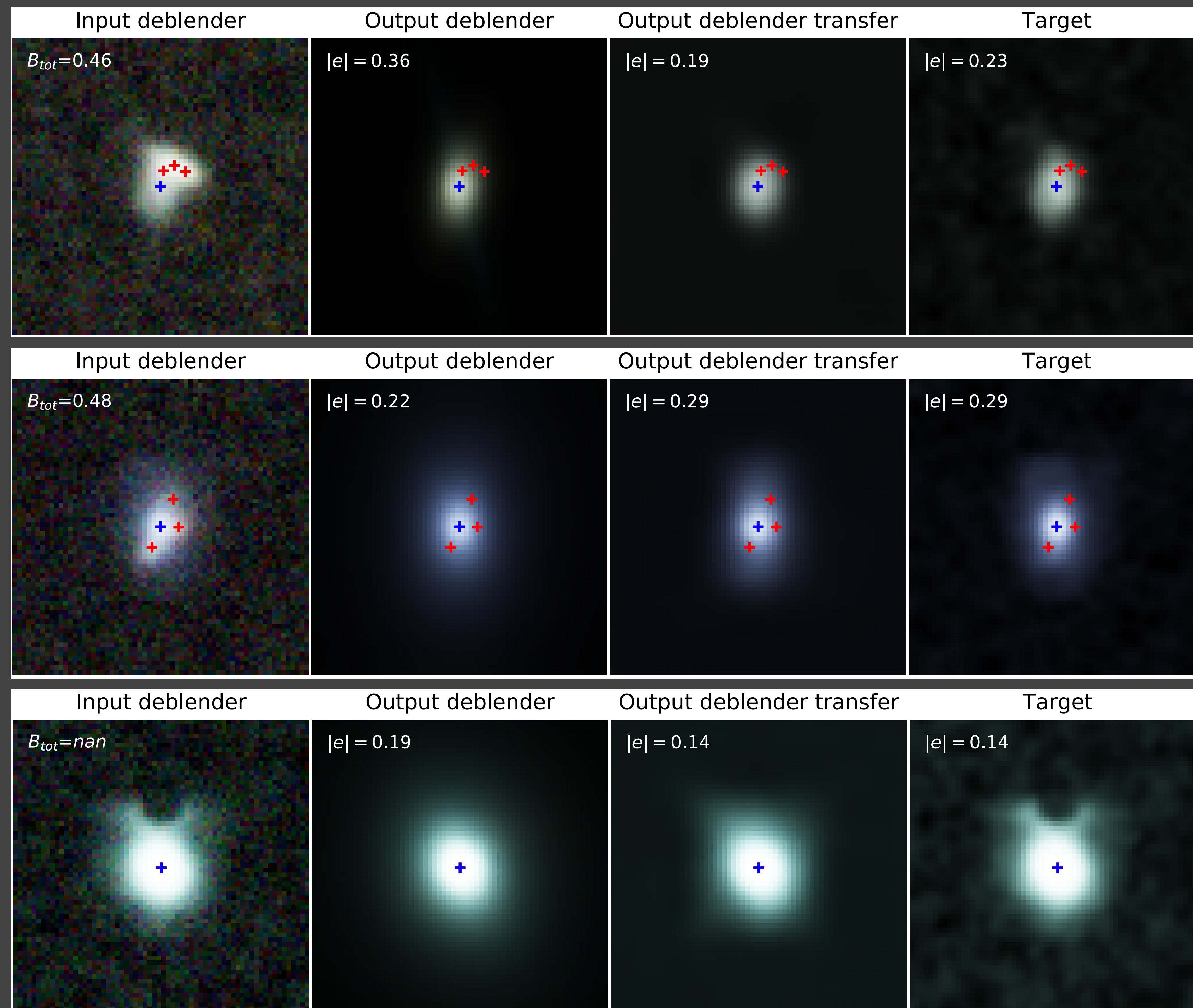
Transfer learning

Transfer learning:

- 80% of simulated data
- 20% of real data

Difficult to have a clean sample:

- Clear blends
- Residual of image processing
- Correlated noise in real images



Conclusion

- VAE:
  Learn accurately features of galaxies

- Deblender:
  Recover the distribution of latent variables encoding target galaxy

- Combining ground and space data:
  Significant improvement in shape reconstruction

- Real images:
  First test with transfer learning. Difficulty to have a clean sample of individual galaxy images.

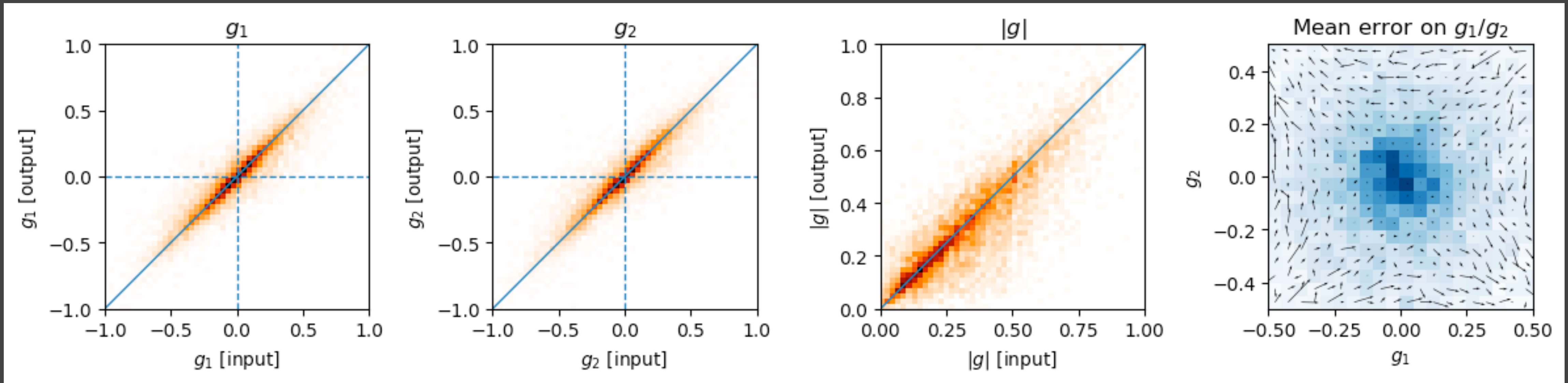
Paper under collaboration review
Arcelin et al. (2020). Deblending galaxies with variational Autoencoder: a joint multi-bands, multi-instruments Bayesian approach.

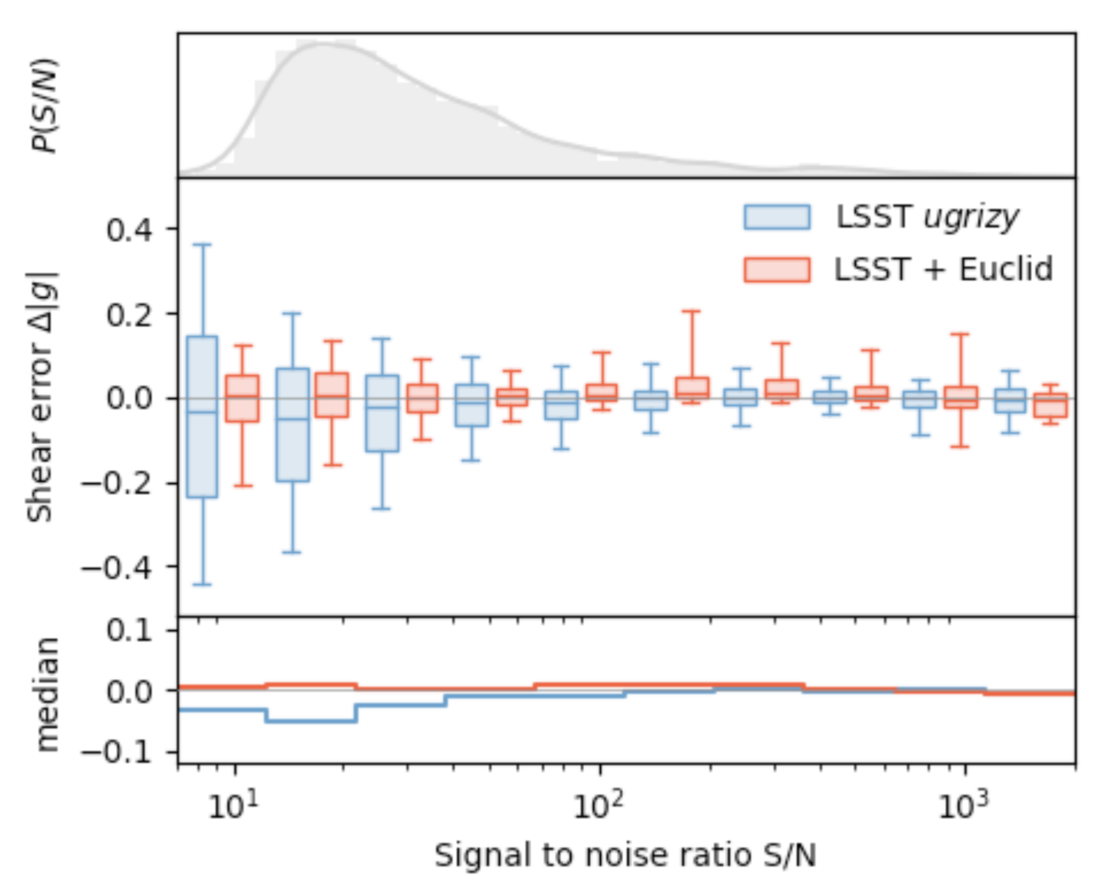
- Next step:
  Using Bayesian neural networks (TensorFlow Probability) to output ellipticities and redshift distribution from images.

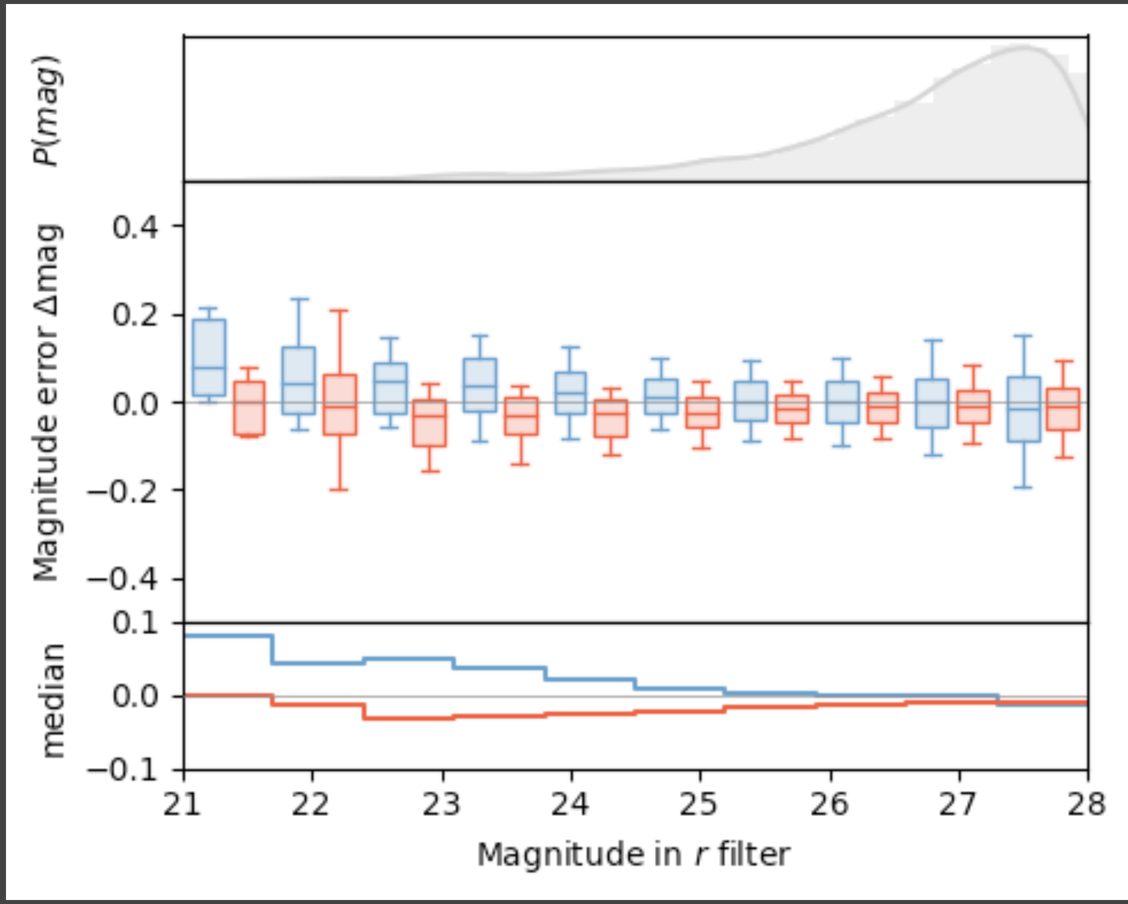
Additional slides

VAE results

Shear and magnitude reproduction







VAE results

Shear and magnitude reproduction