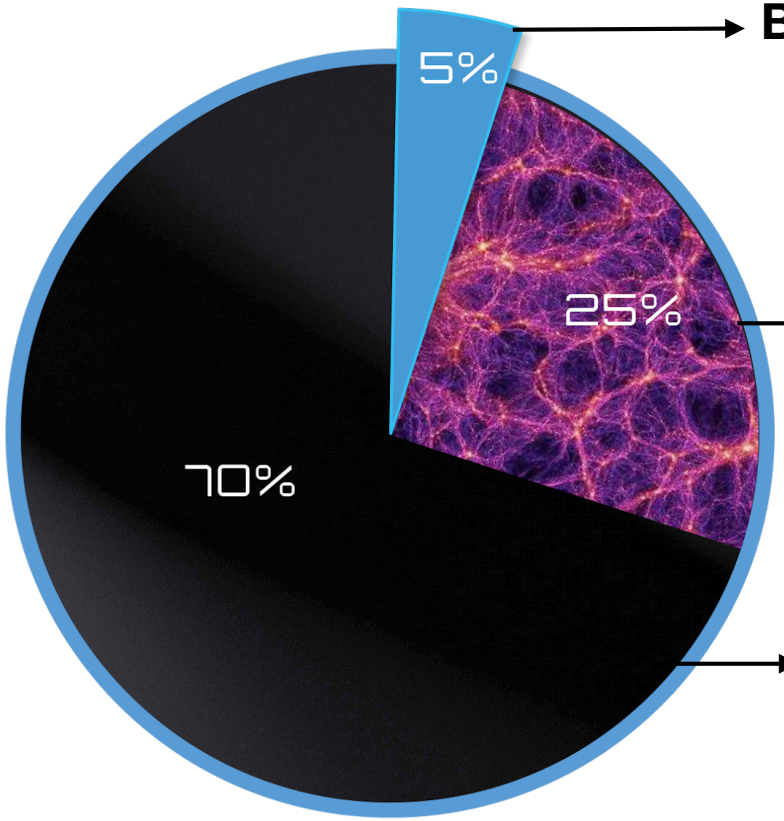
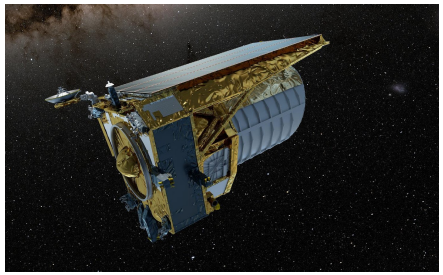
Generative modelling for shear inference

CosmoStat Days

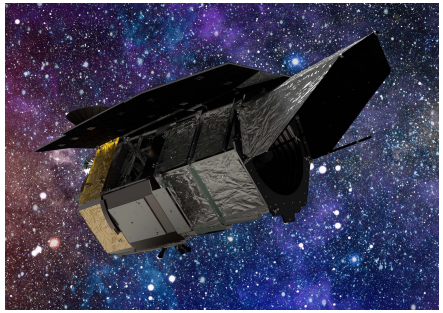
Ezequiel Centofanti

Stage IV surveys & Dark matter





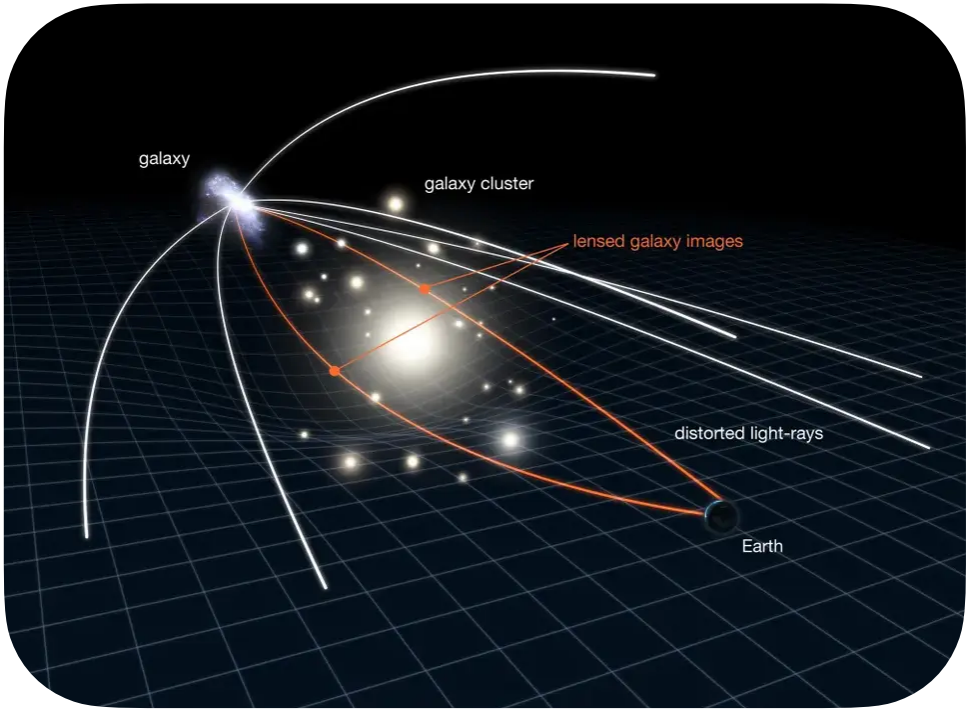
Euclid

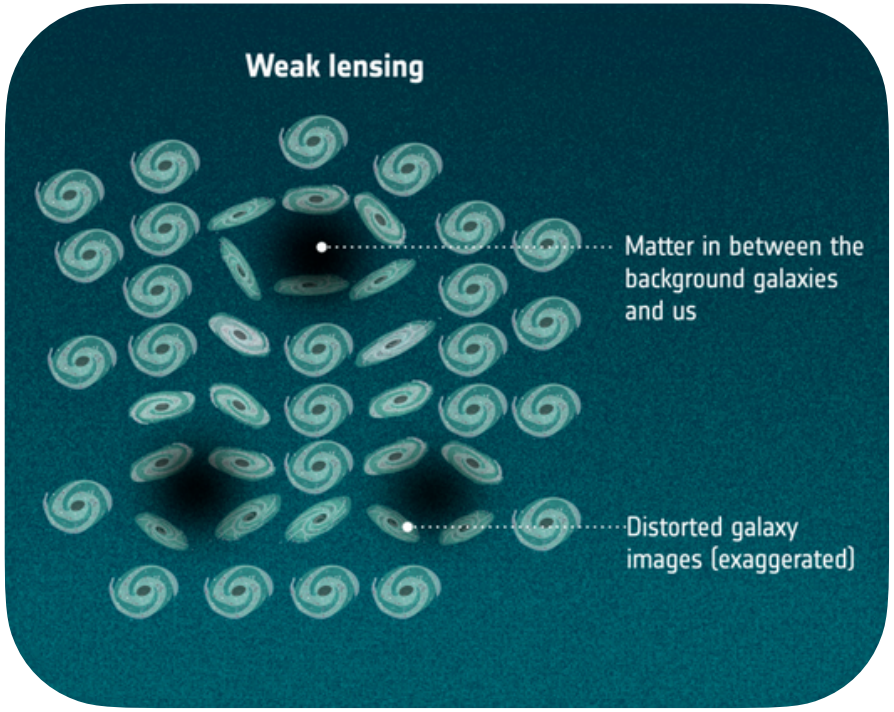


Roman

V. Rubin

Weak gravitational lensing



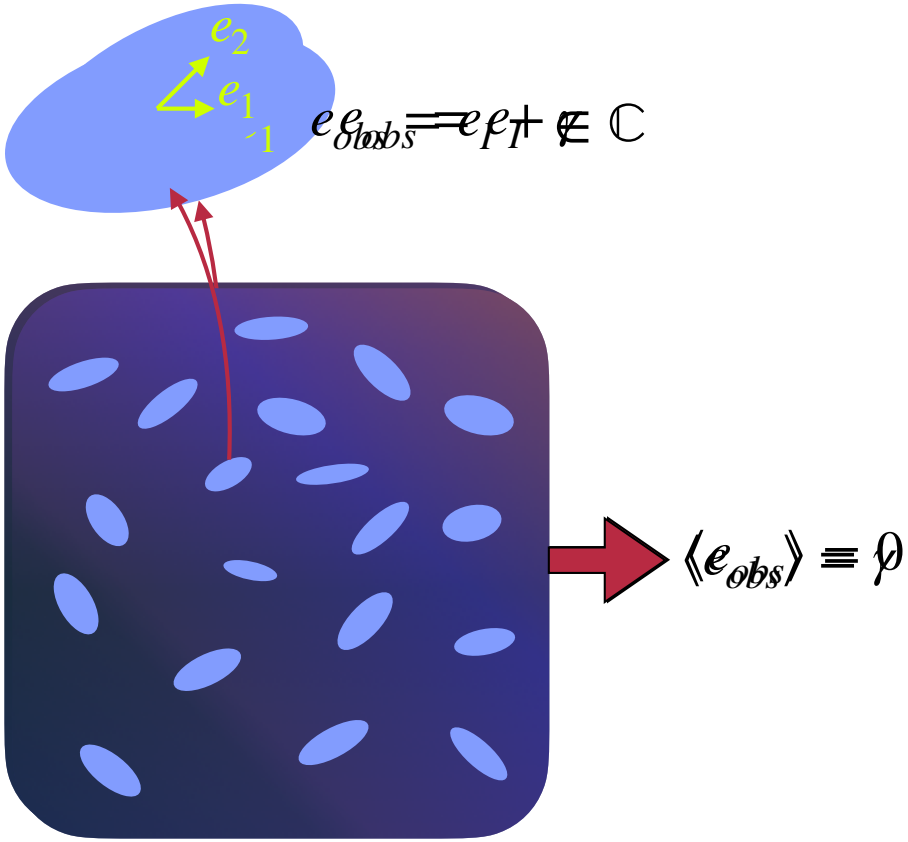


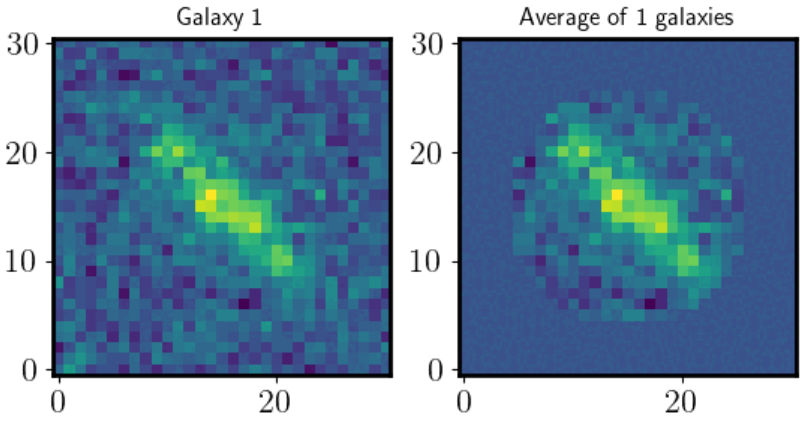
$$A = \begin{pmatrix} 1-\kappa-\gamma_1 & -\gamma_2 \\ -\gamma_2 & 1-\kappa+\gamma_1 \end{pmatrix}$$

κ Convergence → magnification

γ Shear → anisotropic stretching

Cosmic shear: γ

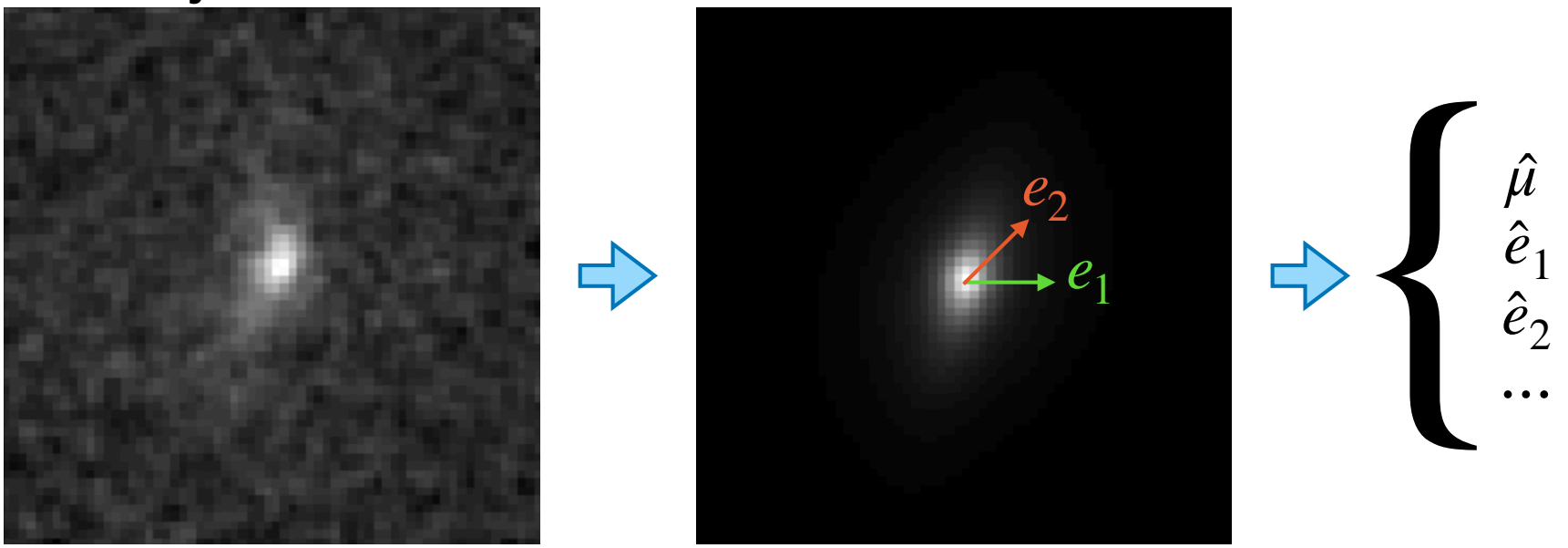




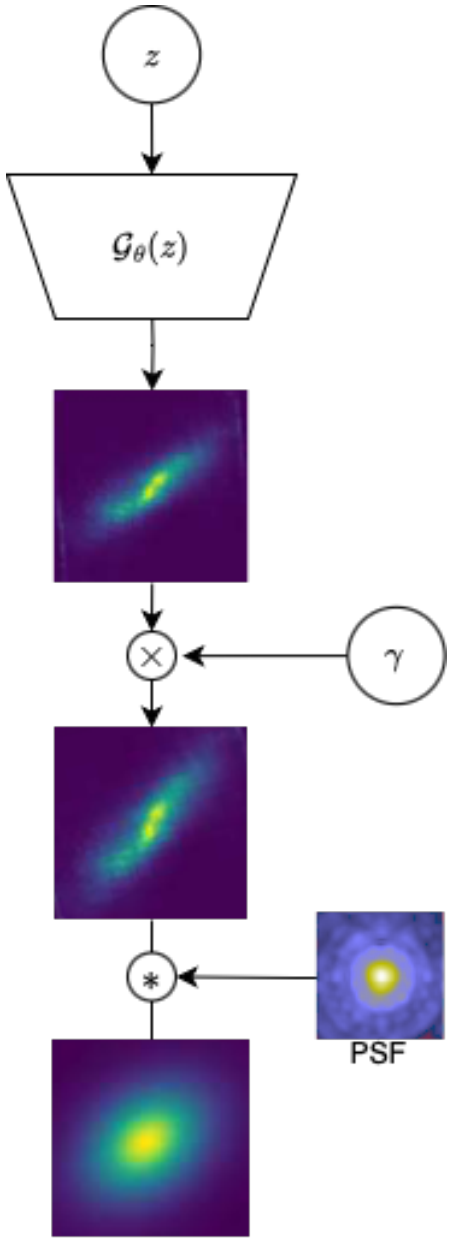
Credit: Koen Kuijken

Measuring galaxy shape

Galaxy observation | **Parametric fit** | **Moments**



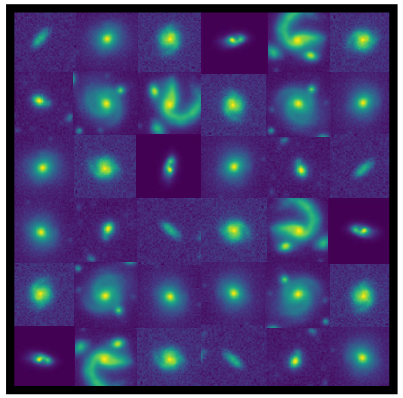
- Need to account for the PSF corrections and **calibration** of the method.
- Parametric modelling doesn't capture complex galaxy **morphologies**.
- **Ellipticity** is not a well-defined quantity for arbitrary galaxies.



B. Remy work [1]

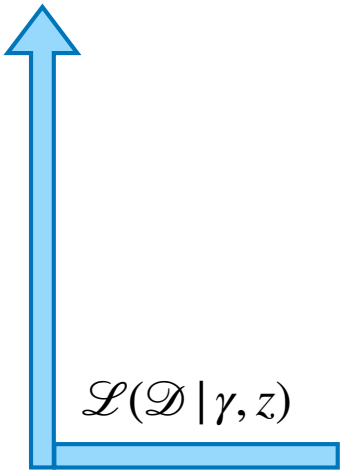
- Pixel level forward model.
- Galaxy image generative model.
- Apply shear and instrumental response.
- MCMC sampling → shear posterior.

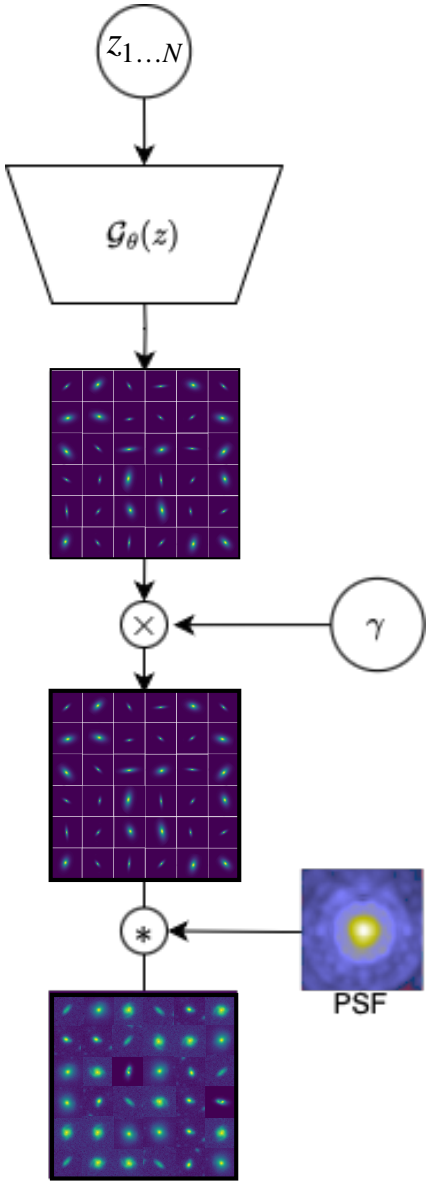
[1] Remy, B., “Generative modeling for weak lensing inverse problems.”



Observed tile

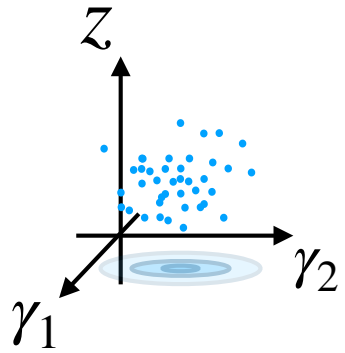
- Common γ
- Dataset: $\mathcal{D}$



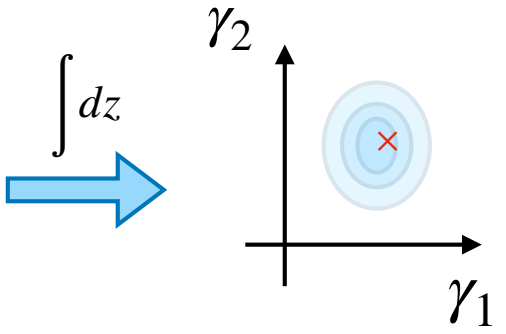


Shear inference - HMC

- Sample (z, γ)
- Generate galaxy $\mathcal{G}(z)$
- Apply shear and PSF
- Evaluate likelihood
- Accept / reject z, γ

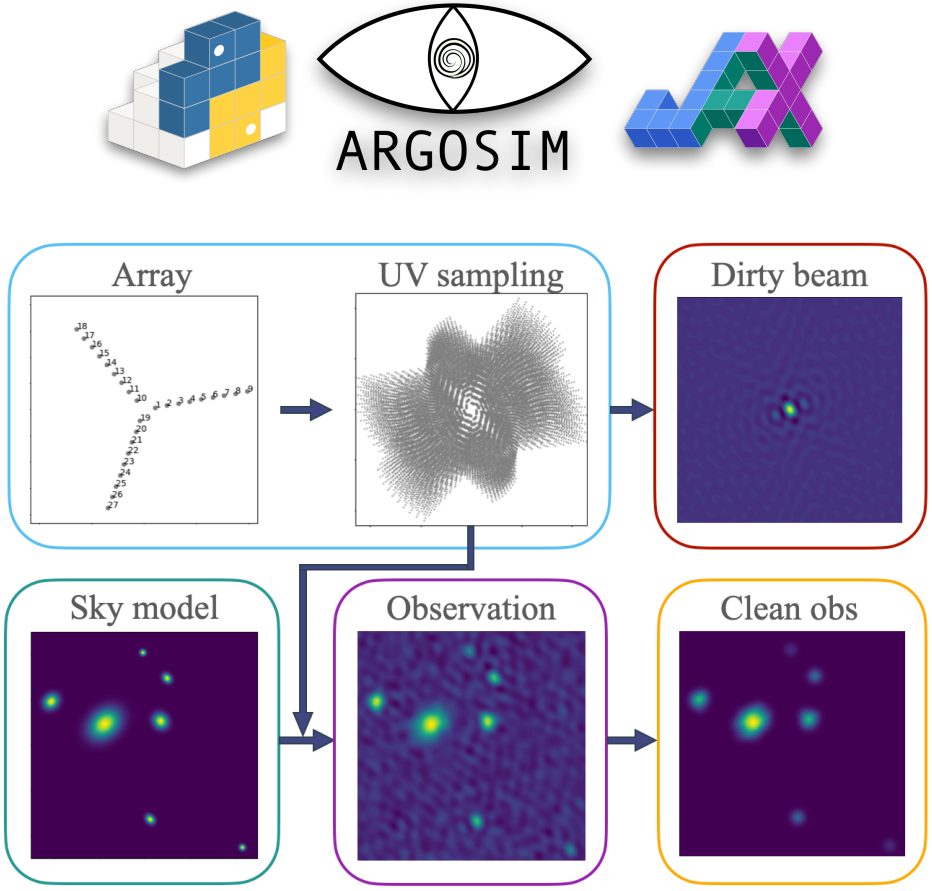


$P(\gamma, z\,|\,\mathcal{D})$



$P(\gamma\,|\,\mathcal{D})$

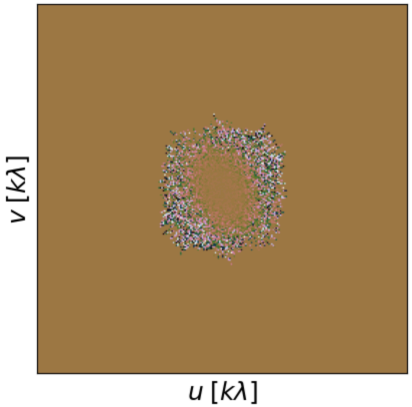
Radio Weak gravitational lensing



Centofanti et al. (submitted in 2025)

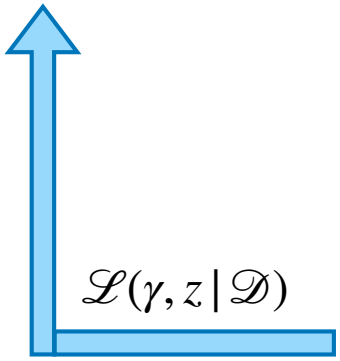
- Radio interferometric simulations.
- JAX: GPU accelerated & autodiff.
- Upcoming interferometers as SKA.
- Enables radio weak lensing!

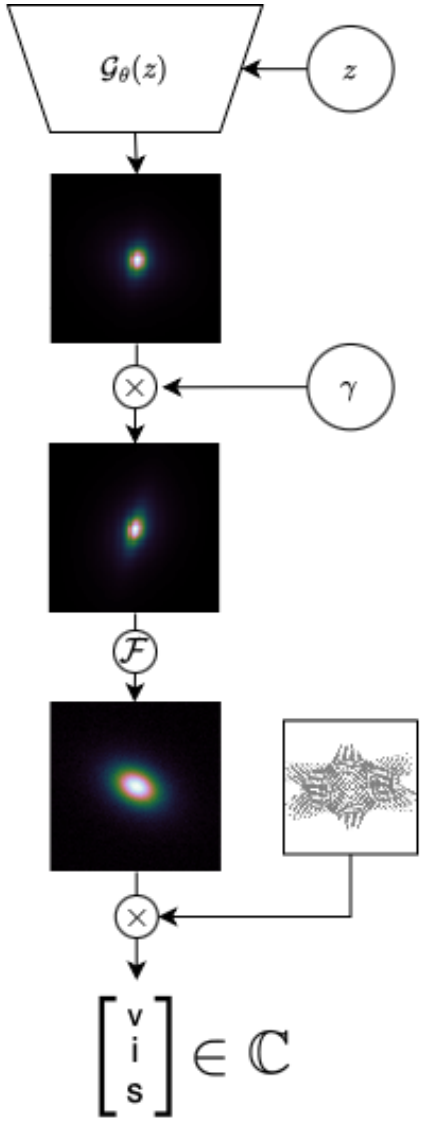
Radio analogue



Observations

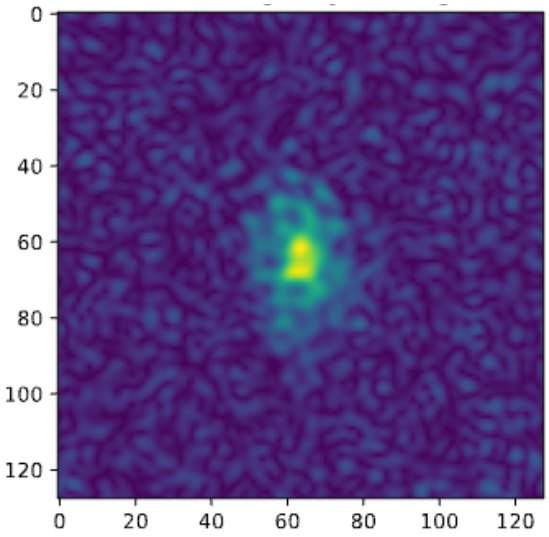
- Common γ
- Visibilities
- Dataset: $\mathcal{D}$





- Different galaxy morphology.
- Data in Fourier domain: visibilities.
- PSF → uv-sampling mask.
- PSF is more complex but known.

Parametric galaxies



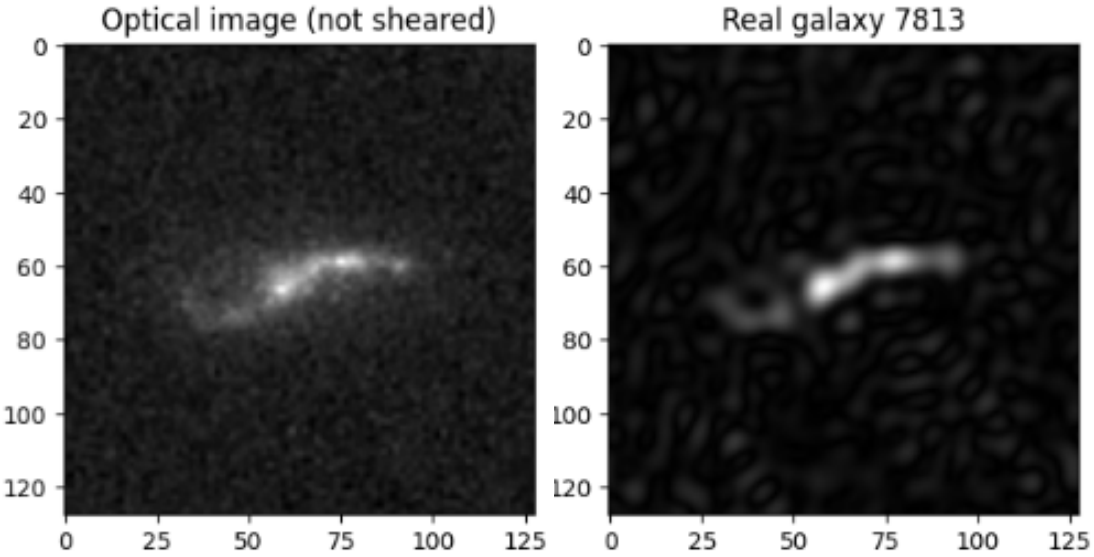
Faint star-forming radio galaxies.

- Spergel profile:
  - hlr ∈ (3 - 40) px
  - flux ∈ (50, 200) μJy
  - ν ∈ (-0.7, 1)
  - $e_{1,2}$ $\quad |e| < 1$

} T-RECS[2]

[2] Bonaldi, A., "The Tiered Radio Extragalactic Continuum Simulation (T-RECS)"

HST COSMOS

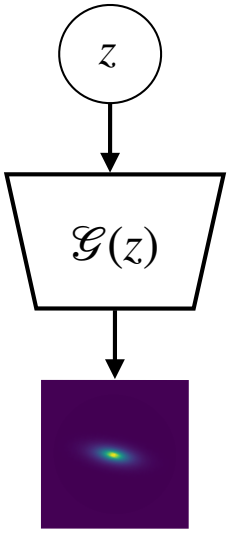


Complex galaxy morphologies:

- HST COSMOS real galaxies.
- Similar flux and size cuts.
- Apply radio PSF

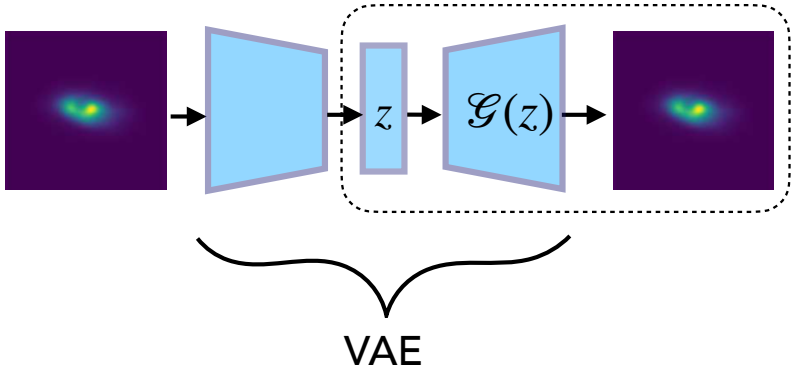
JAX GalSim

- Fast and GPU accelerated.
- Differentiable (HMC).
- Spergel profiles.
- $z \rightarrow$ flux, hlr, ν, $e_{1,2}$.

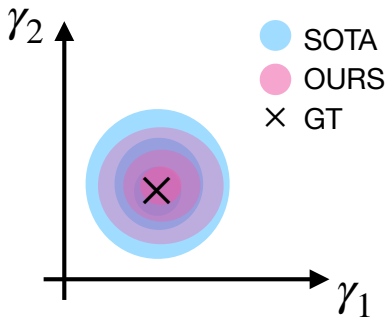


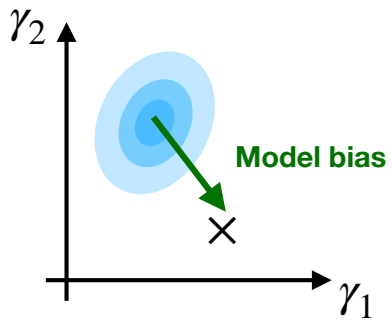
JAX VAE

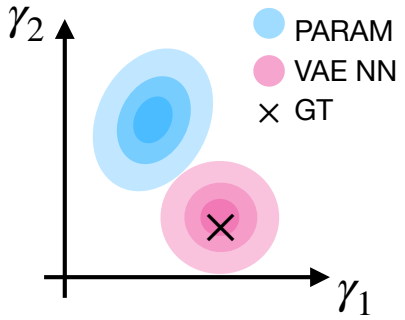
- Variational Autoencoder.
- Trained on HST images.
- $z \rightarrow$ latent representation.



- Obtain competitive (SOTA) shear constrains in simulated radio galaxies.
- Asses model bias in the case of more complex galaxy morphologies.
- Address model bias by introducing a VAE generative model trained on real galaxy images.

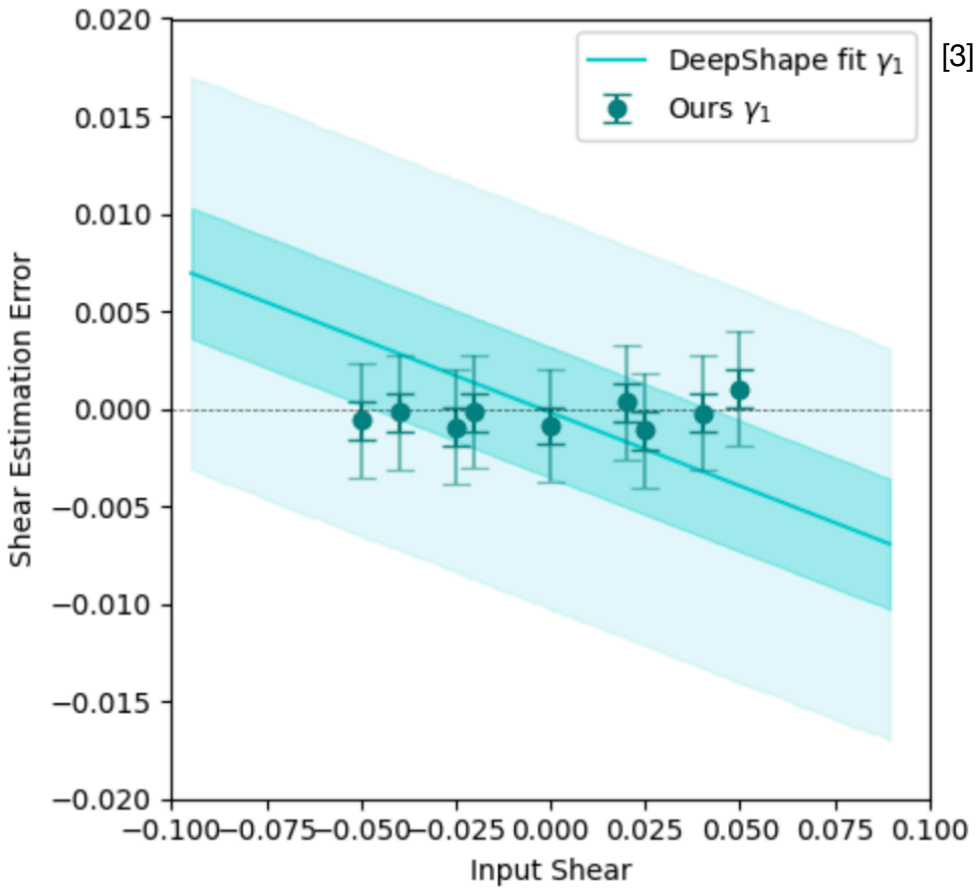






Results on T-RECS parametric galaxies sims

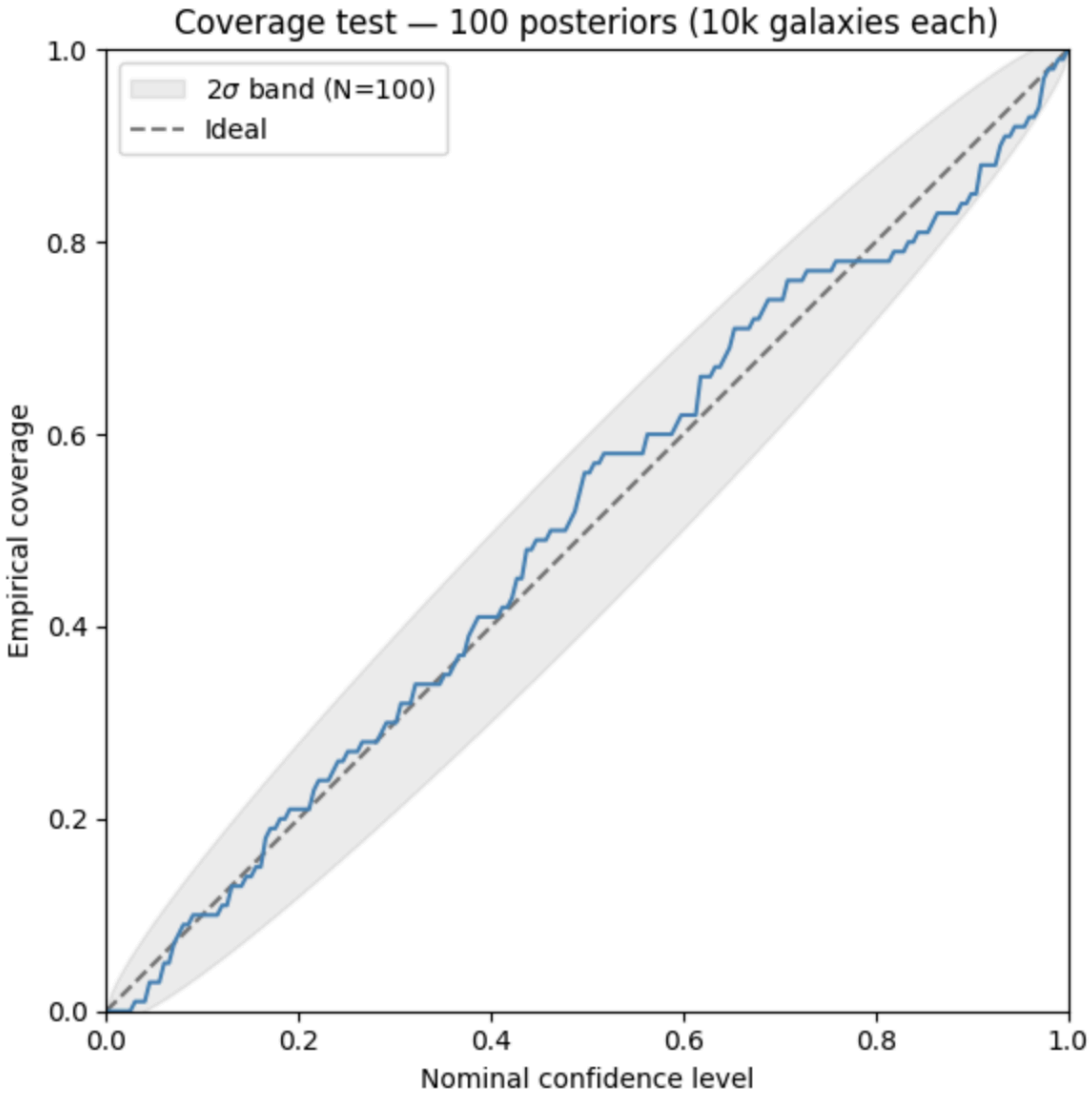
- 10.000 parametric galaxies (TRECS).
- Galsim Spergel forward model.
- Blackjax GHMC sampling.
- Better constraints tha SOTA.
- Unbiased for all tested γ.



[3]

[3] P. Tripathi, “DeepShape: Radio weak-lensing shear measurements using deep learning”

Calibrated posteriors: coverage testing



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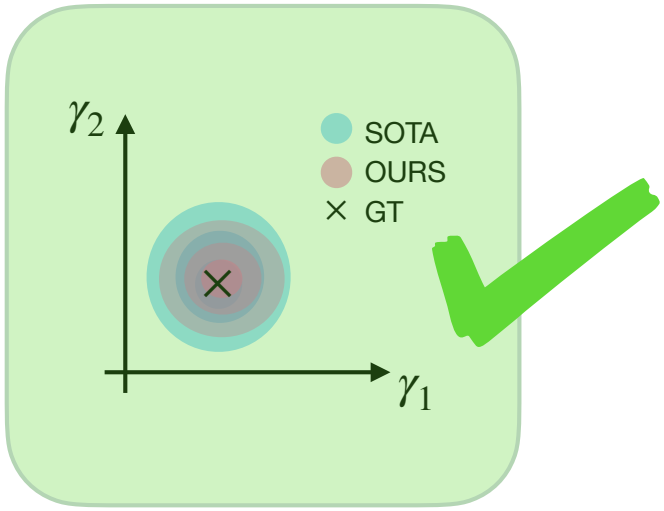
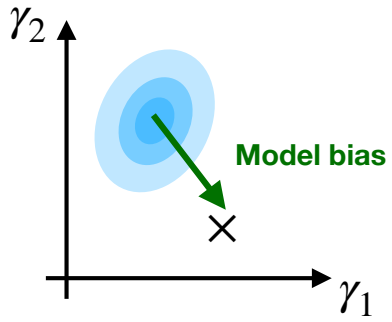
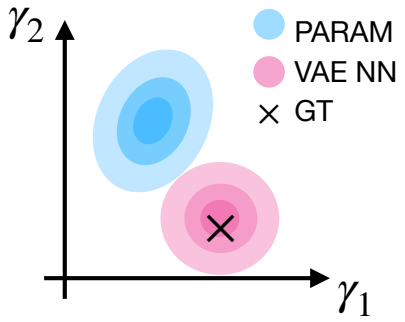
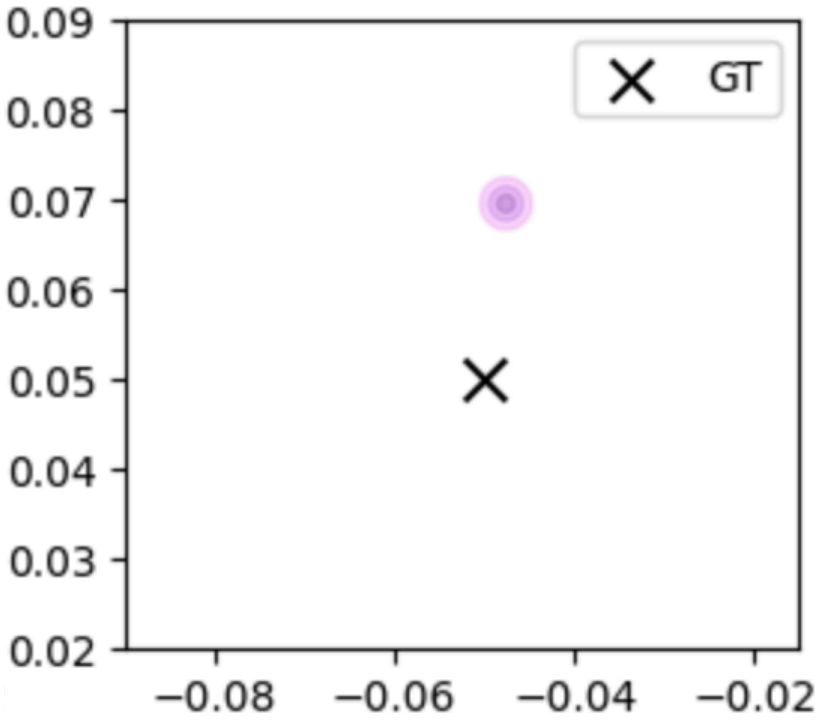




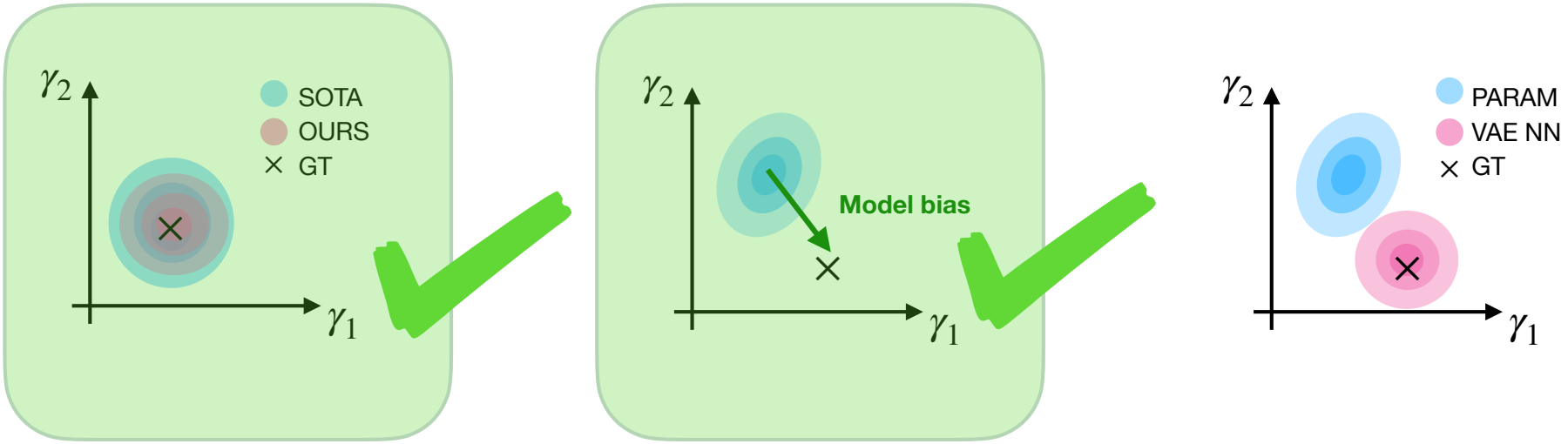


Results on COSMOS real galaxies

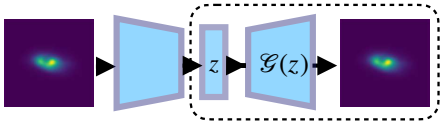


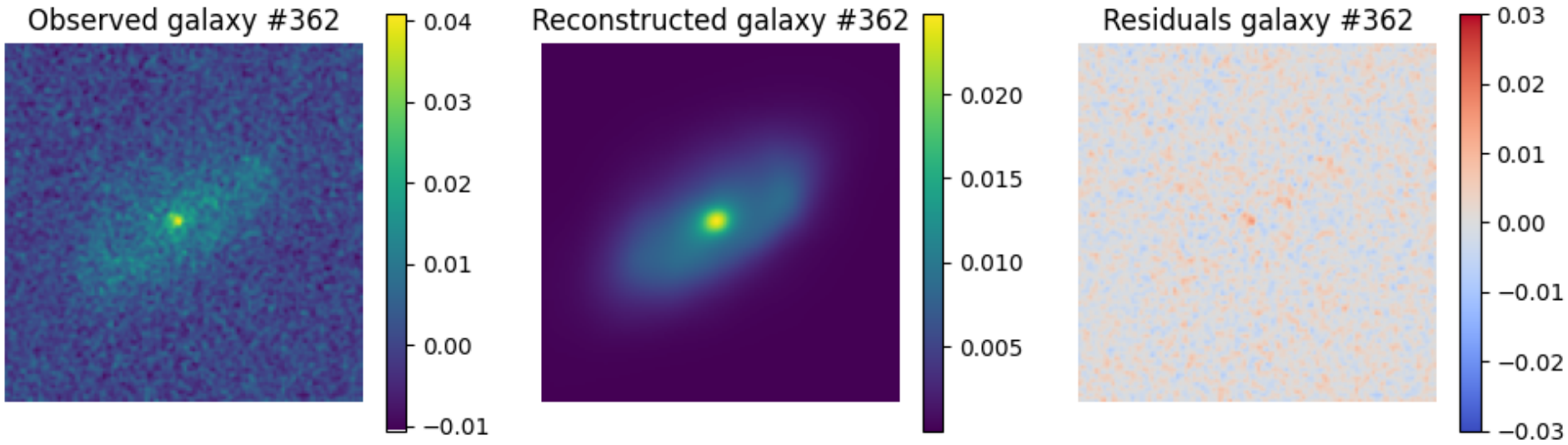
- 10.000 real galaxies (COSMOS).
- Galsim Spergel forward model.
- Blackjax GHMC sampling.
- The γ estimation is clearly biased.

- Obtain competitive (SOTA) shear constrains in simulated radio galaxies.
- Asses model bias in the case of more complex galaxy morphologies.
- Address model bias by introducing a VAE generative model trained on real galaxy images.



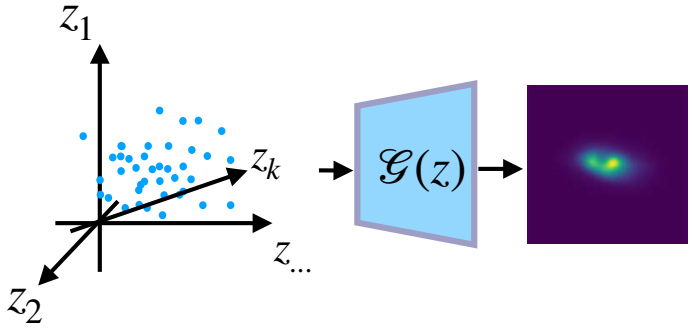
Variational autoencoder



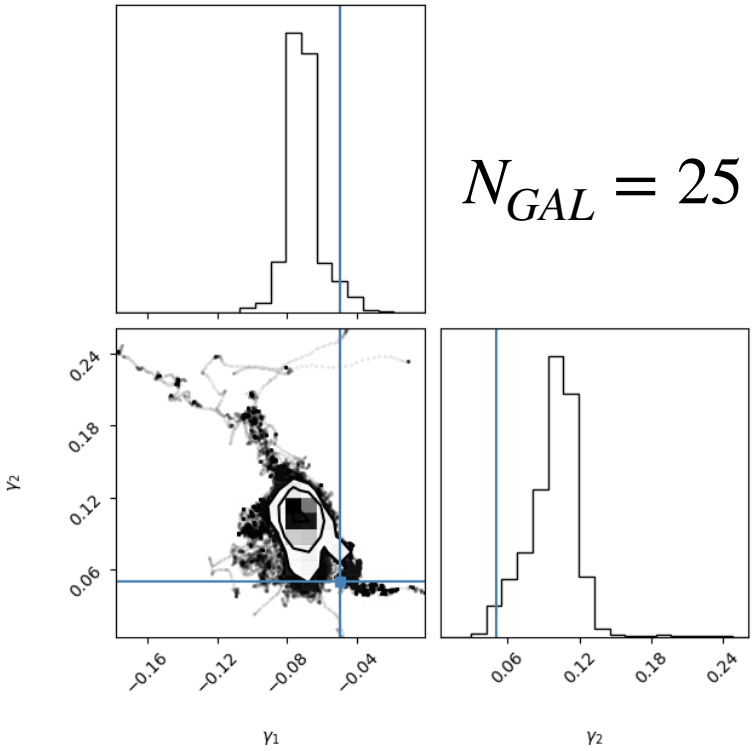


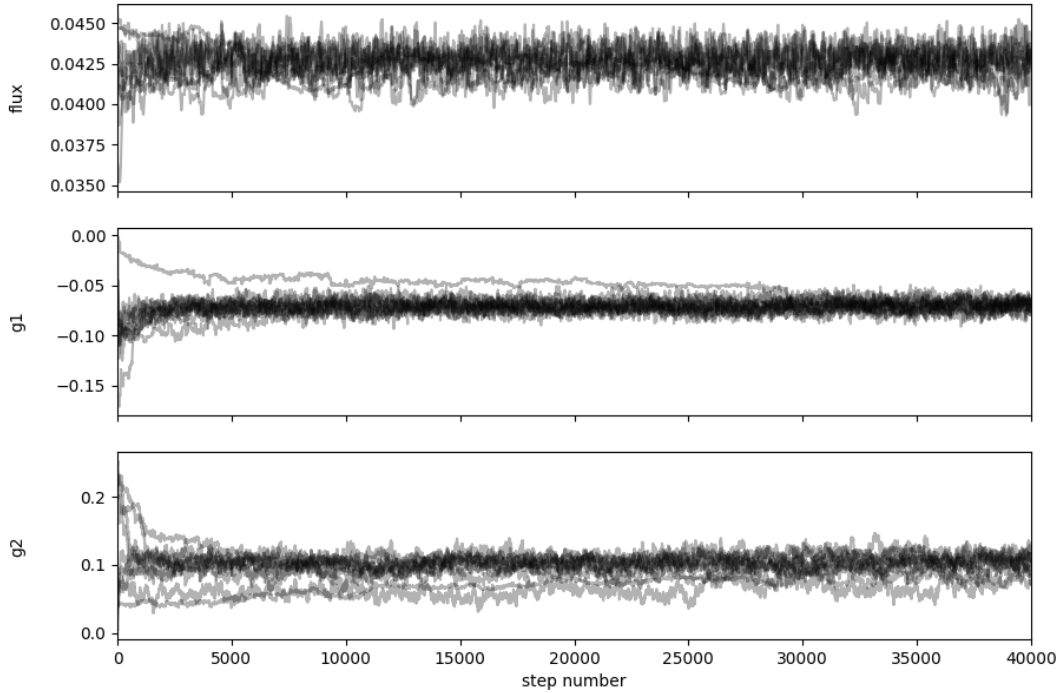
Challenges

- Non-gaussian latent space
- HMC: VAE gradients ~ Gb
- Even slower than Galsim



VAE results

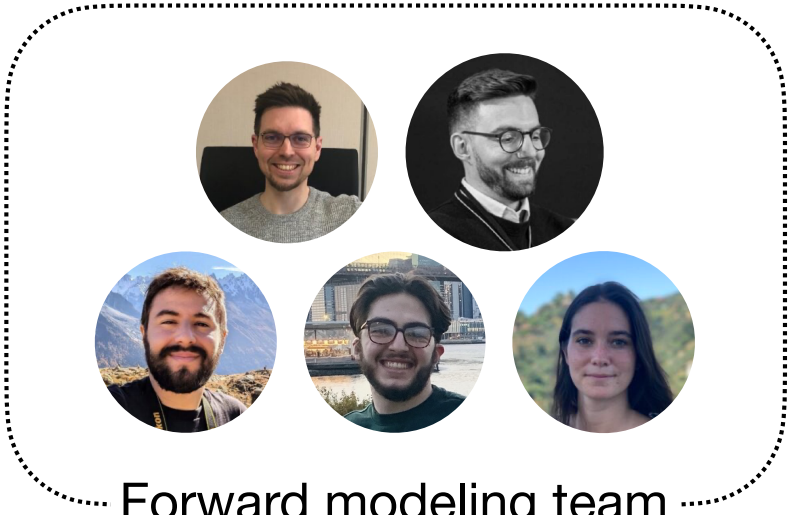




- Latent space complex geometry → Normalising Flow
- More efficient sampling algorithms → MCLMC (Langevin)

Perspectives and future work

- Competitive shear estimates for simulated parametric galaxies ✅
- Show model bias arising from galaxy morphology mismatch ✅
- Address model bias by upgrading generative model to a VAE ⏳


Forward modeling team

🚀 High performance framework for probabilistic shear estimation in WL.

JAX-powered: automatic differentation, JIT compilation, GPU acceleration.

🧩 Modular Design: flexible architecture for easy extension and customization.

🔧 Versatile: able to handle both optical and radio weak lensing data.

Thank you for your attention!

Questions?