Forward modelling UNIONS survey for Implicit Likelihood Inference (with cosmic shear)

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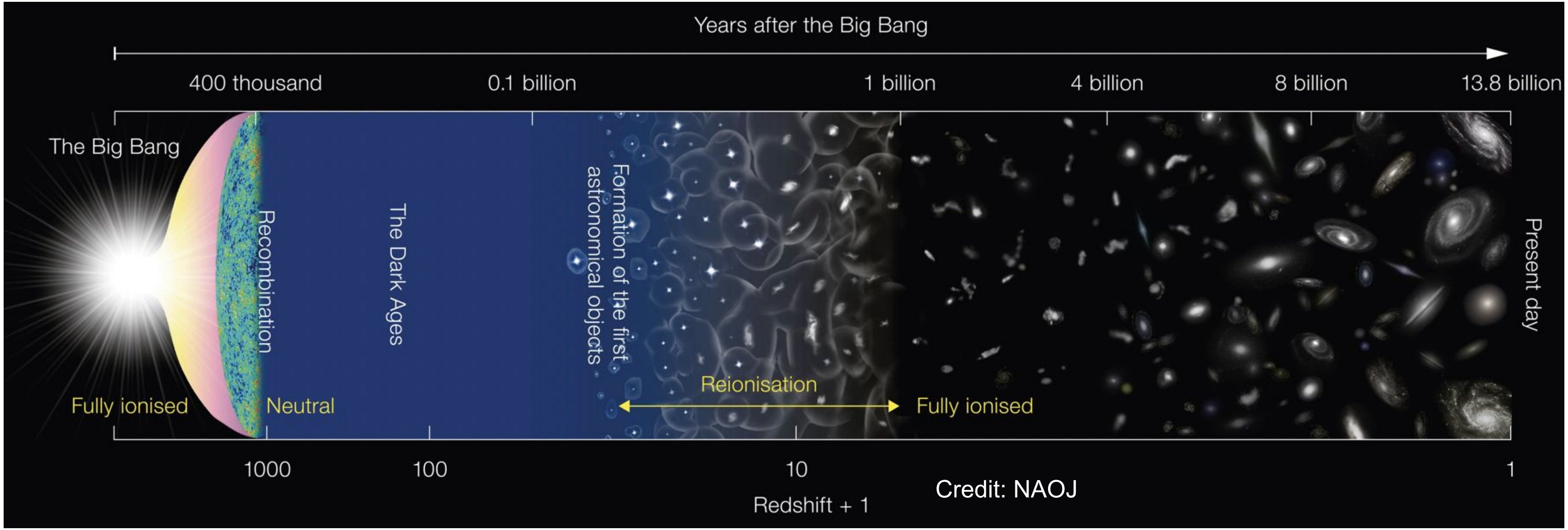
Ecole de physique des Houches - 14/07/2025

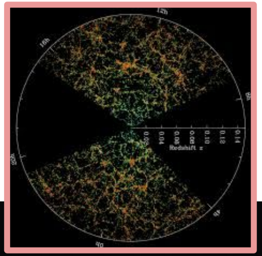
Cosmological context: ΛCDM/wCDM



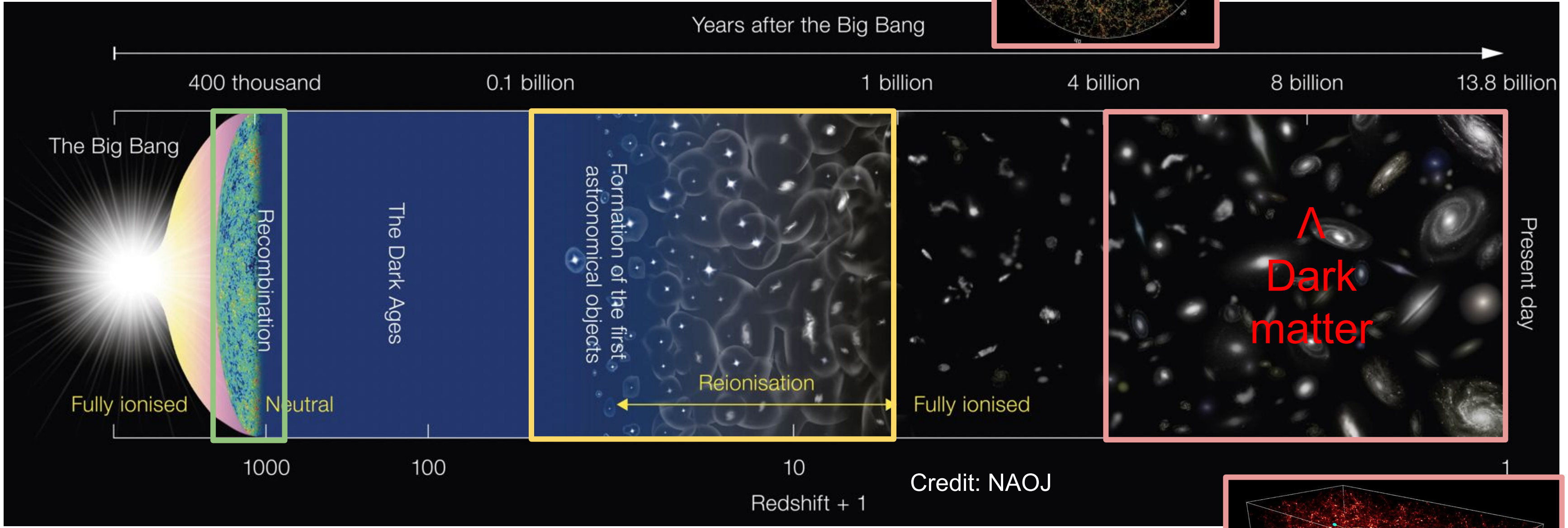
H_0: Expansion rate
Ω_m: Matter density
Ω_b: Baryon density
σ_8: Clumpiness
w: EoS of dark energy
…

Constrain using Bayesian inference

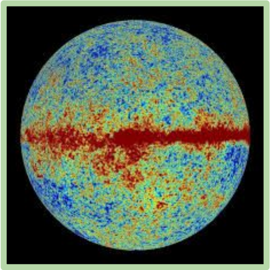
Cosmological probes and history of the Universe



Galaxy clustering

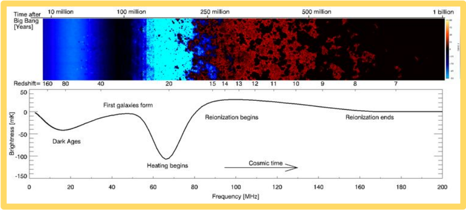


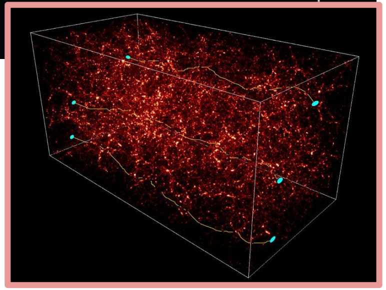
Credit: NAOJ



CMB

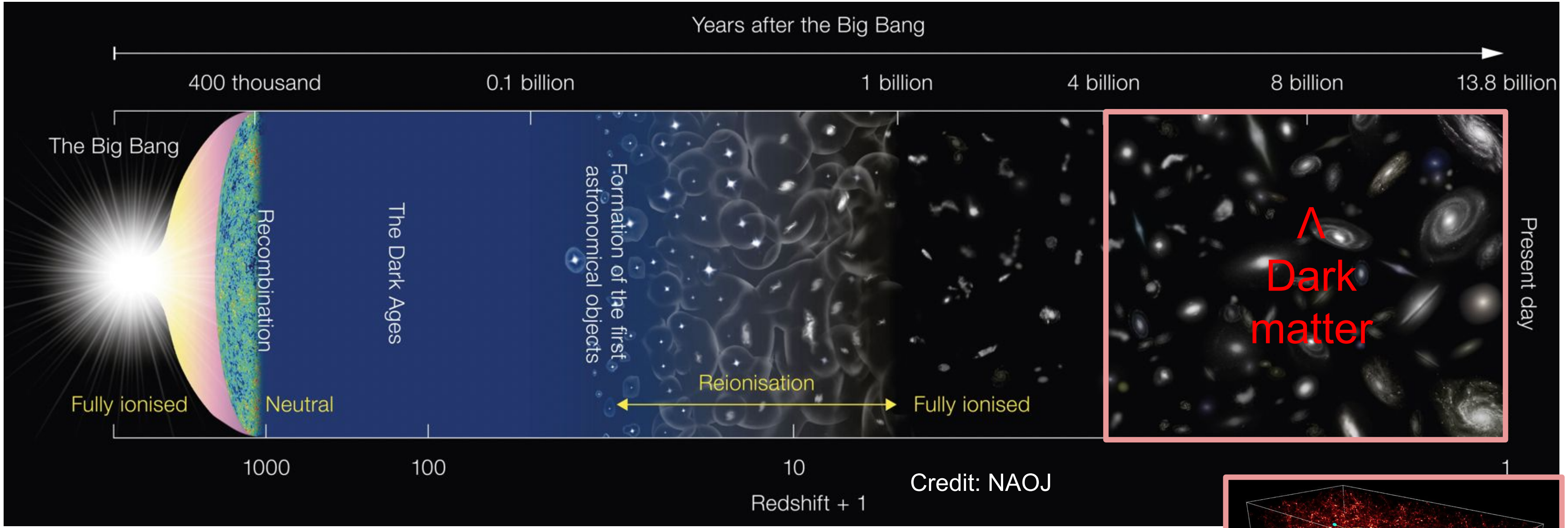
21 cm / intensity mapping

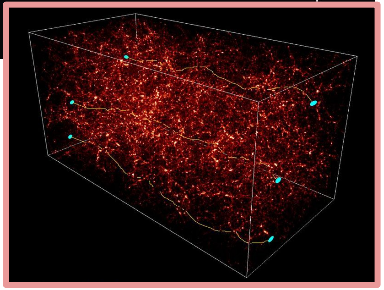




Weak lensing

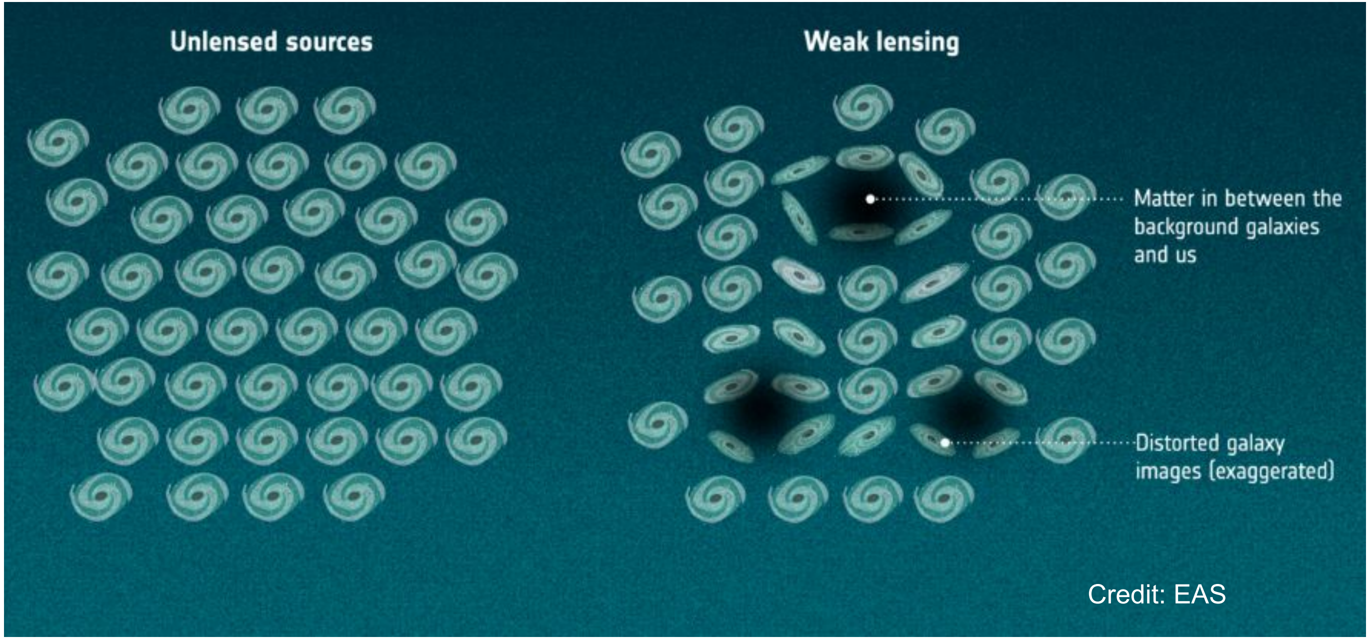
Cosmological probes and history of the Universe





Weak lensing

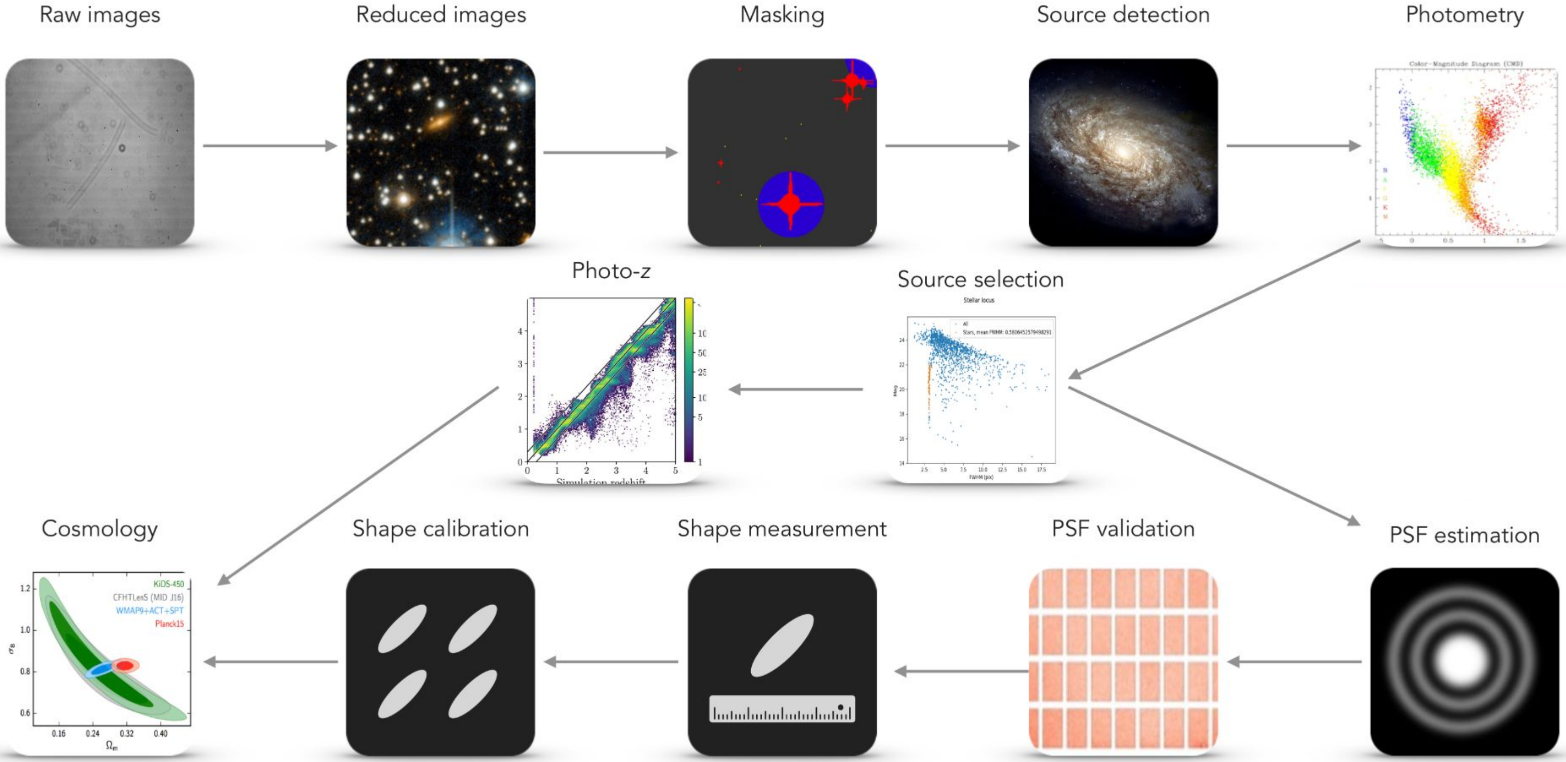
Weak gravitational lensing



- Percent-level effect.
- Polluted by shape noise.
- Requires a large number of galaxies.

Cosmology with cosmic shear

Credit: Samuel Farrens



Cosmology with cosmic shear

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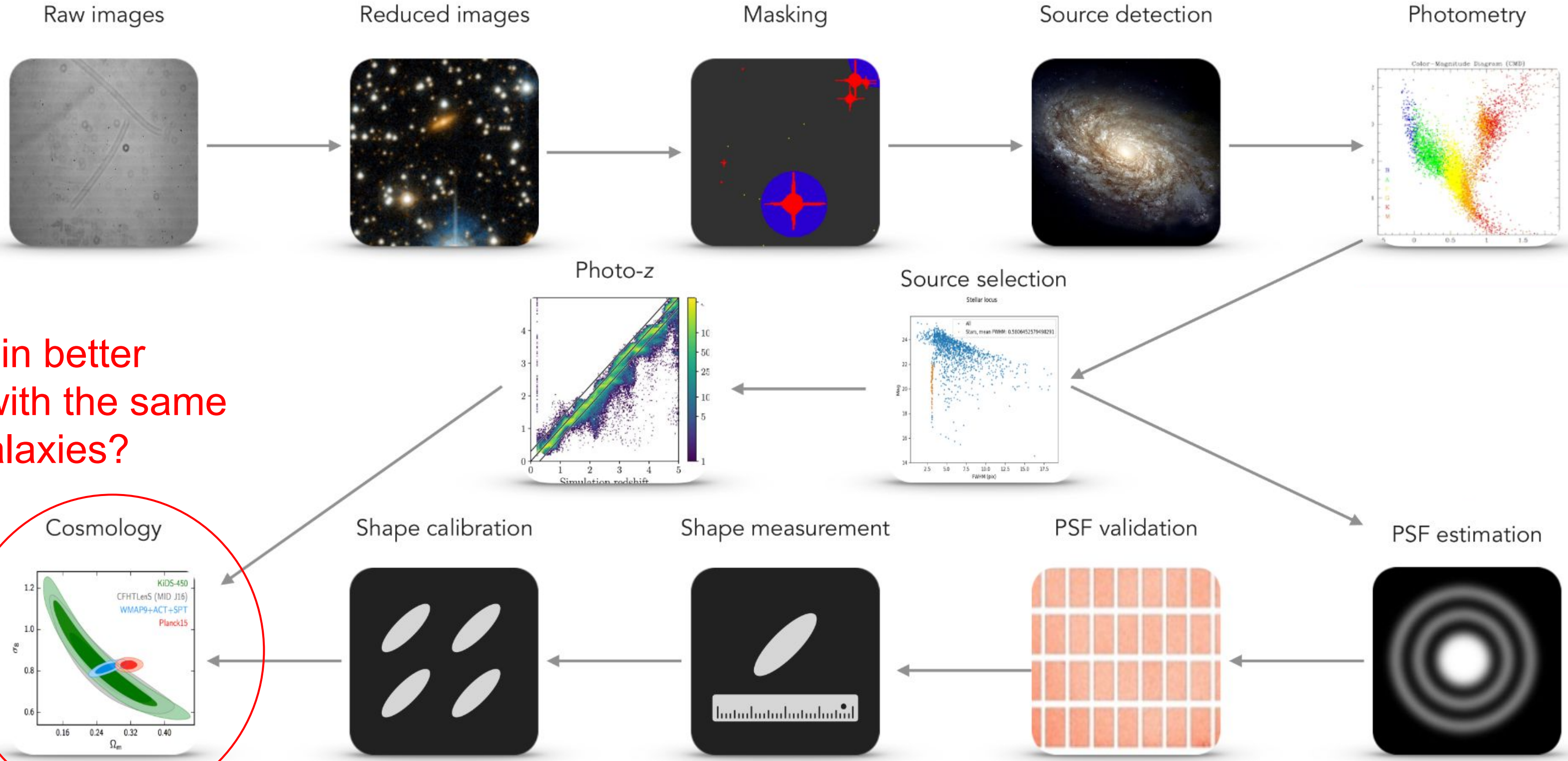
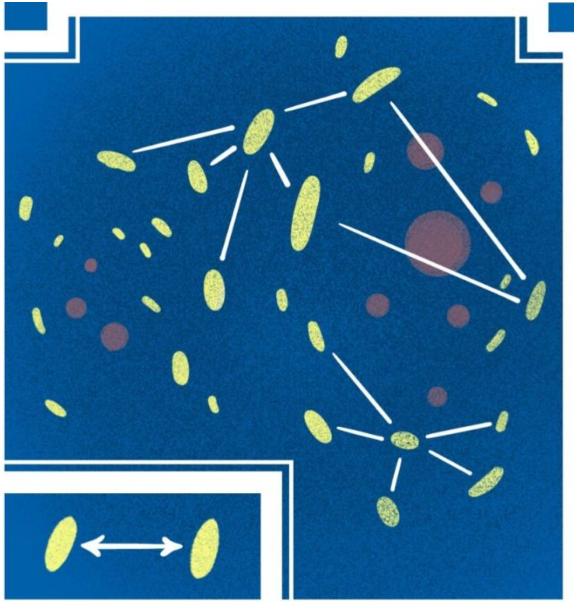
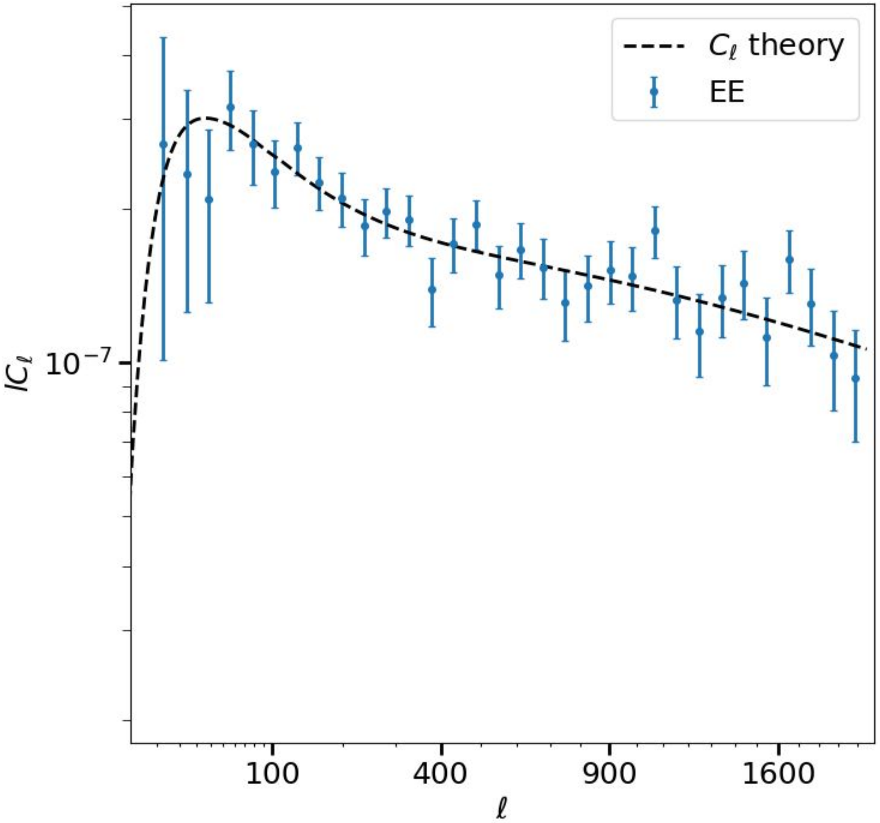


Can we obtain better constraints with the same catalog of galaxies?

Cosmic shear with 2-pt statistics

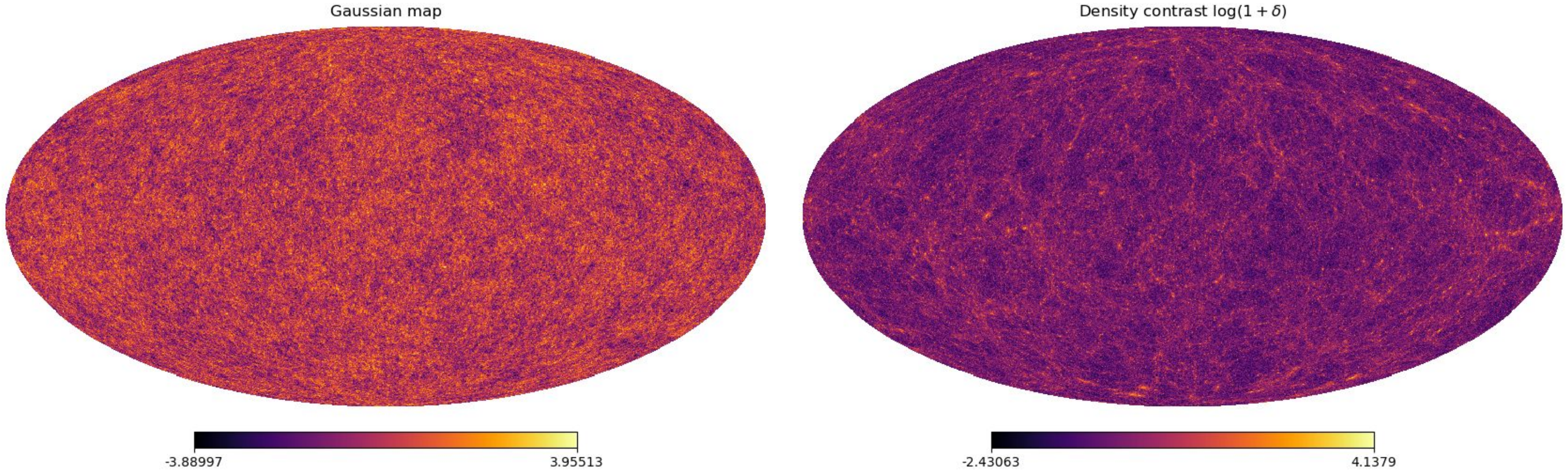


Credit: DES



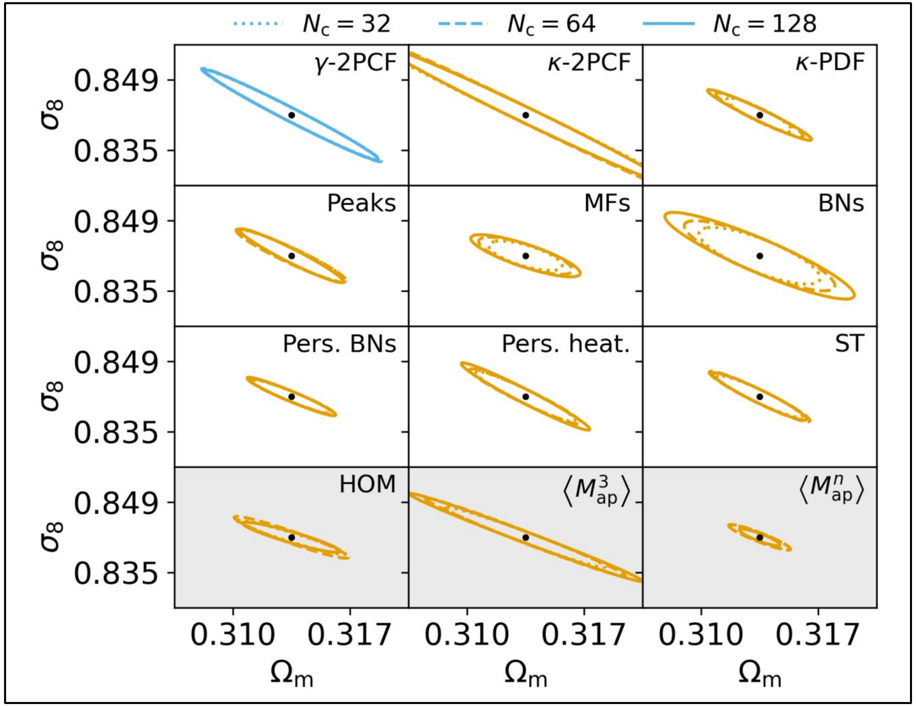
Beyond 2pt-cosmic shear

- The overdensity field is not a Gaussian field at late times.



Beyond 2pt-cosmic shear

- The overdensity field is not a Gaussian field at late times.
- How can we capture the most of the information from the shear field?
  - Craft summary statistics that capture the non-Gaussian information from the field.



Euclid Collaboration+2023

Toward the same methodology than 2pt?

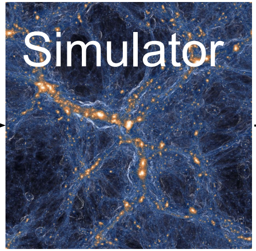
- Does the Gaussianity of the likelihood still holds?
- Do we have a theoretical model of the higher-order summary?
- Do we know how the higher-order summary respond to systematics?

$$p(\theta|x) \propto p(x|\theta)p(\theta)$$

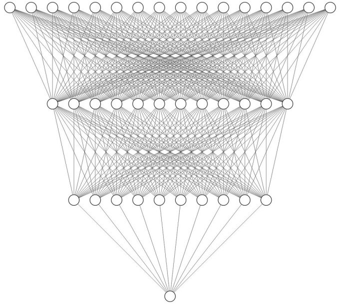
Gaussian likelihood

Implicit Likelihood Inference

Parameters
(Ω, θ)



Observation
x



Normalizing Flow
(neural net)

$q_\varphi(\Omega|x) \text{ or } q_\varphi(x|\Omega)$

Learn the posterior
or the likelihood.

Ω: cosmological parameters
θ: nuisance parameters

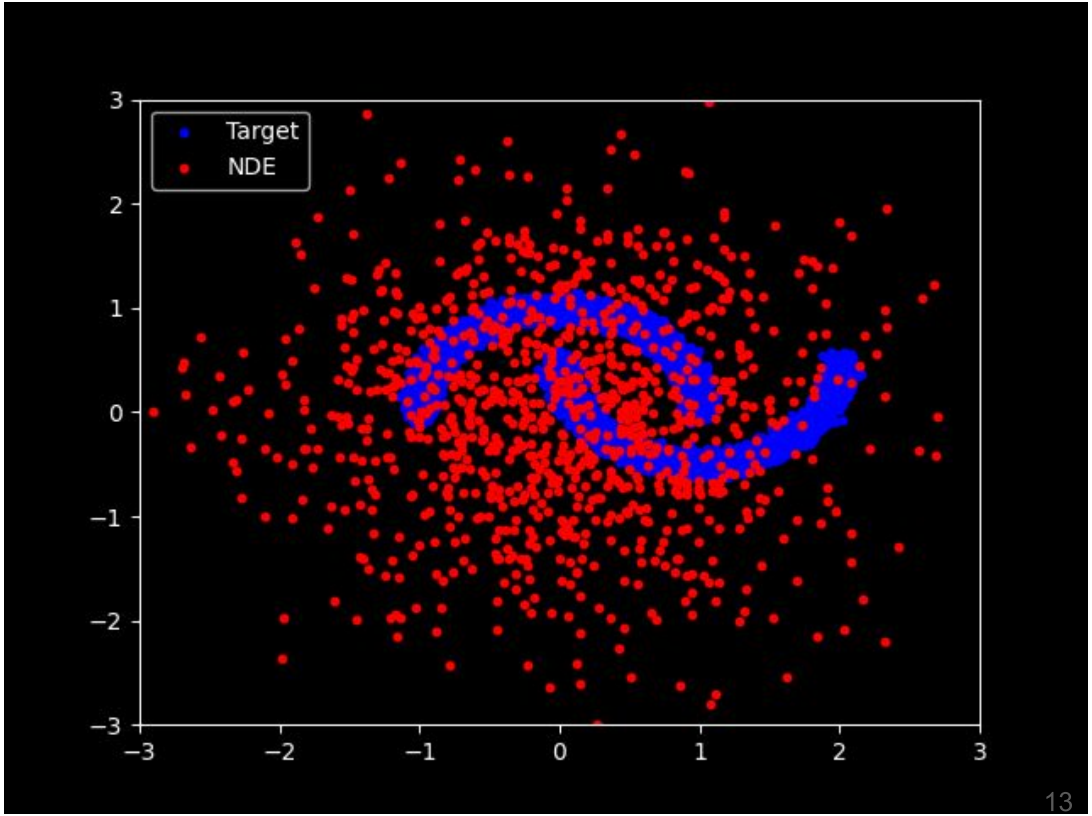
Implicit Likelihood Inference

Advantages:

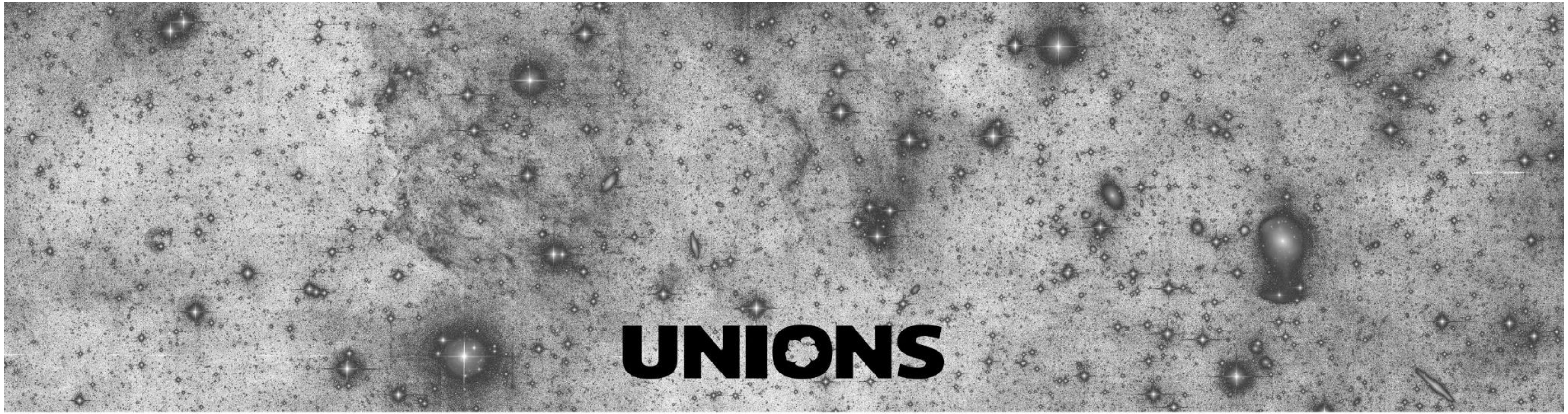
- No closed form of the likelihood.
- No theoretical model.
- Systematics can be forward modeled.

Drawback:

- One has to trust the simulations.
- The learned distribution can be overconfident/biased.



Ultraviolet Near Infrared Optical Northern Survey (UNIONS)



r, *u* bands

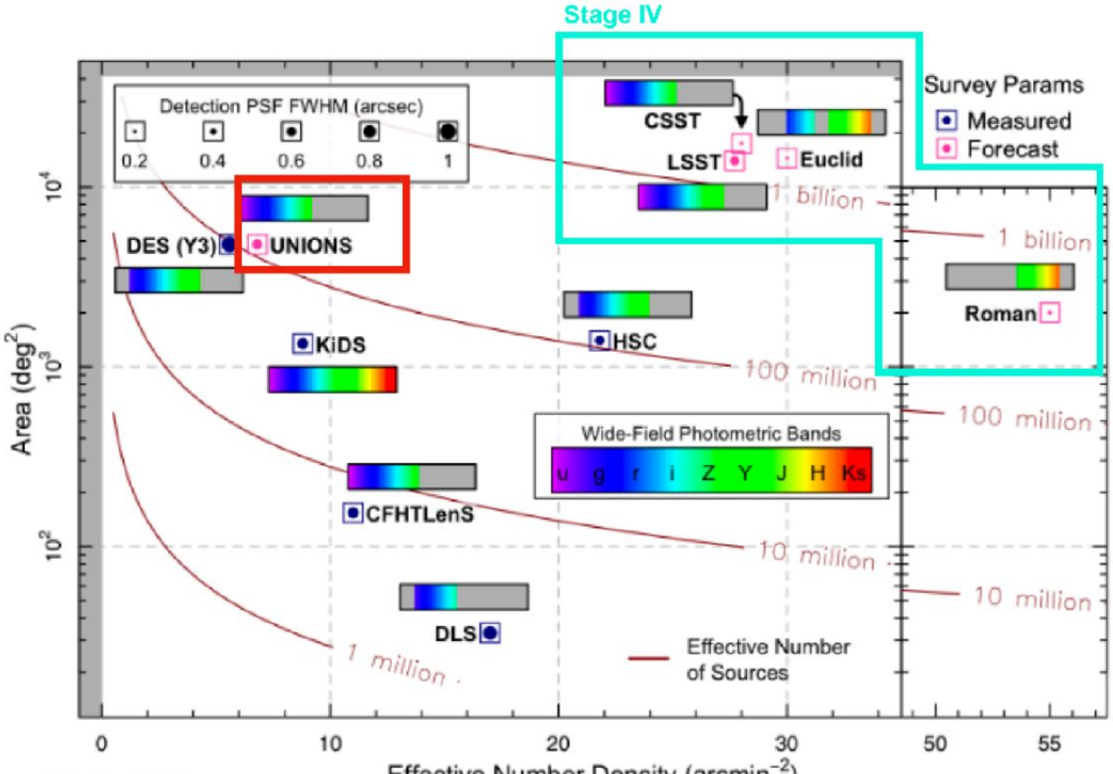
g, *z* bands

i band

UNIONS - the last Stage-III survey

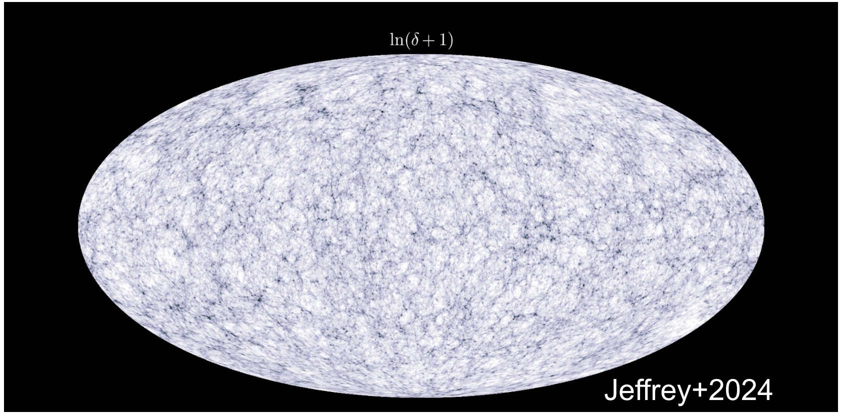
Technical specifications of UNIONS:

- Target area ~5000 deg^2
- Depth of 24.5 (r-band)
- Seeing ~ 0.69” (r-band)
- Processing done with ShapePipe (Farrens+2022)
- ~100 million galaxies



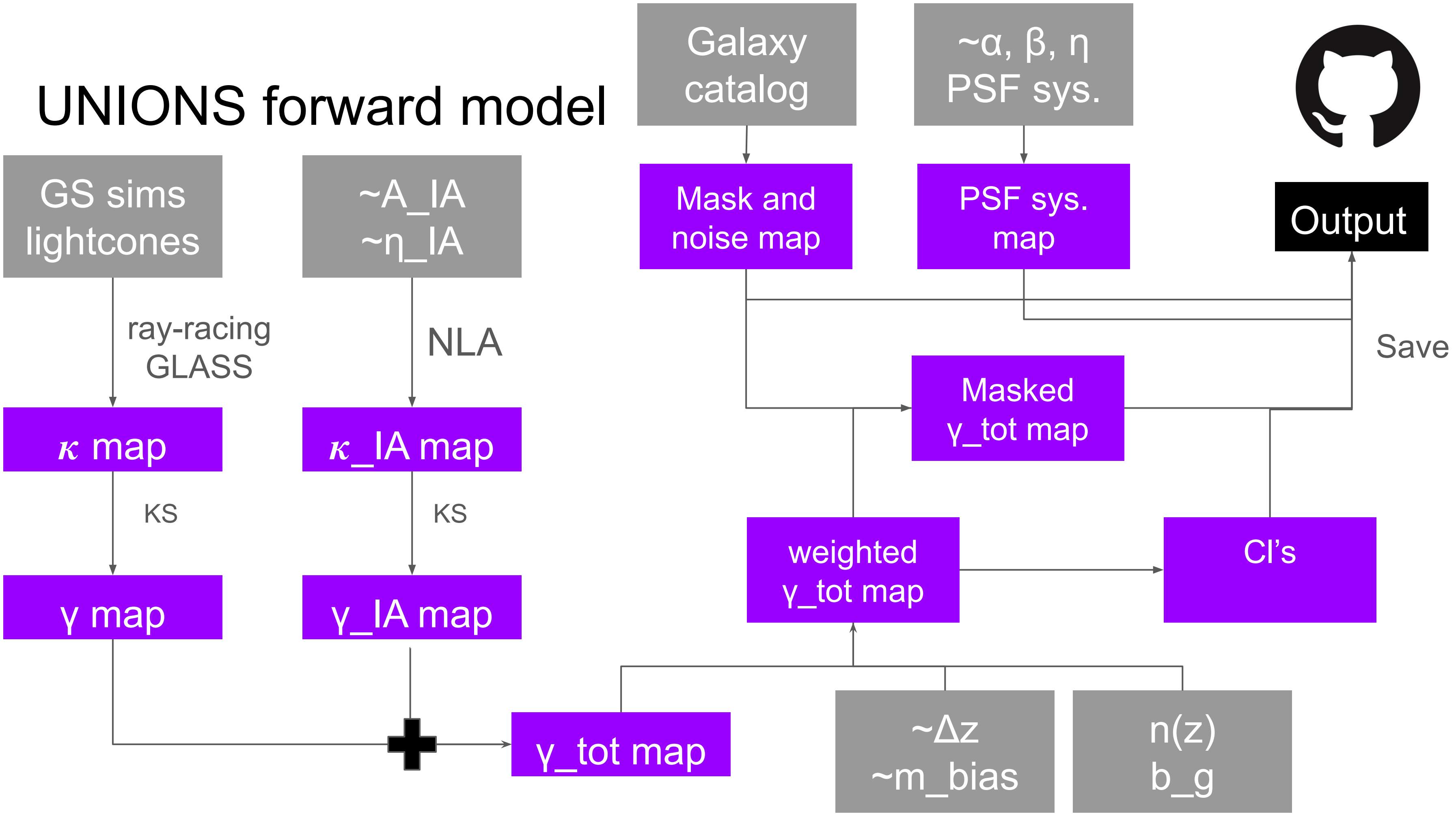
Credit: Angus Wright

UNIONS forward model



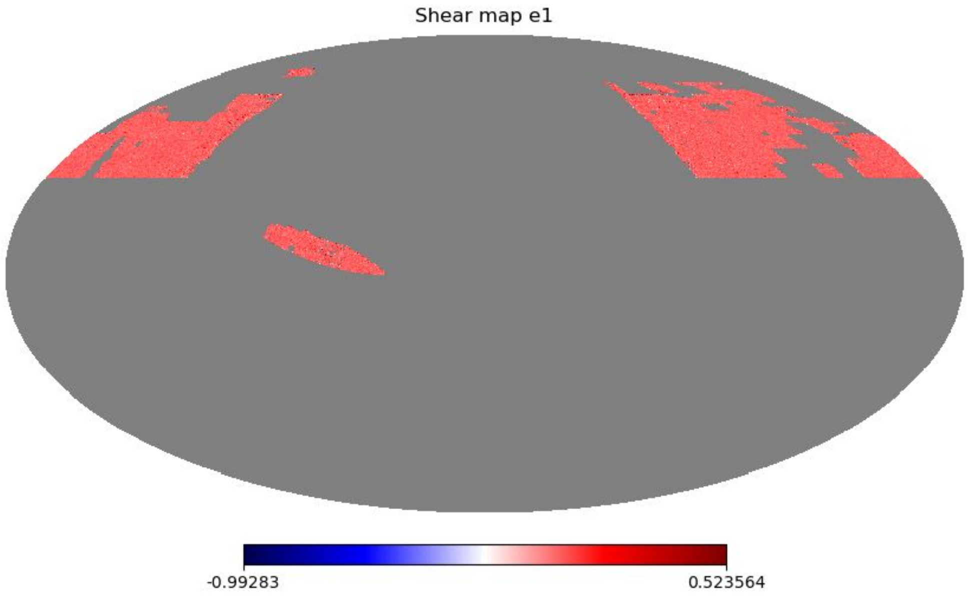
- Gower Street simulations
  - wCDM with massive neutrinos
  - 791 N-body simulations
  - L=1250 h^{-1} Mpc, N=1080
  - HEALPix pixelization: nside=2048
  - Prior on the cosmological parameters informed by Planck and SH0ES.
  - “Active learning” in Ω_m - σ_8 plane
- Goal: “UNIONS-ize” the lightcones to account for (survey specific) systematics
  - Intrinsic Alignment
  - PSF systematics
  - Mask and shape noise
  - Source clustering

UNIONS forward model

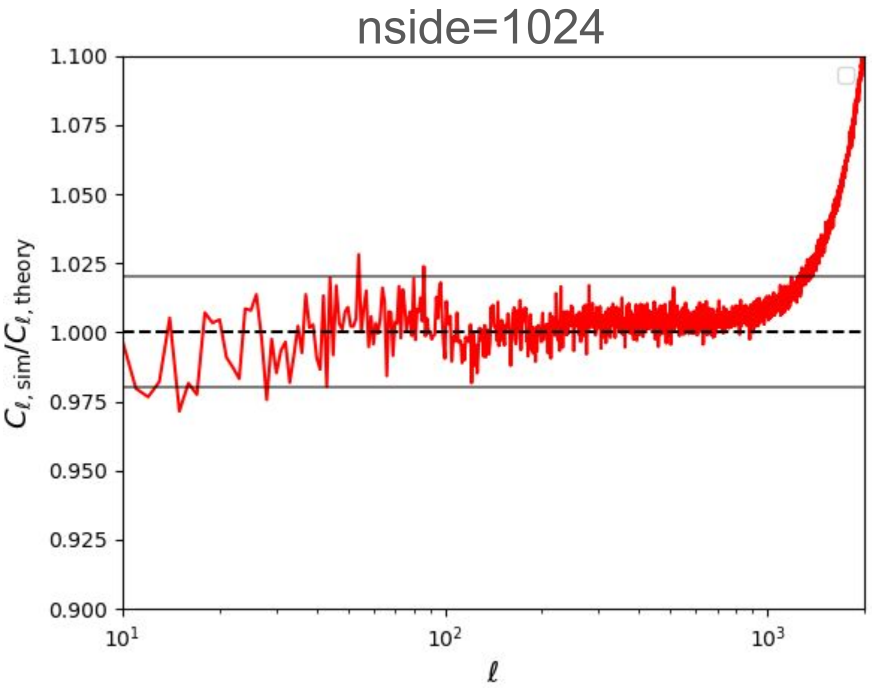


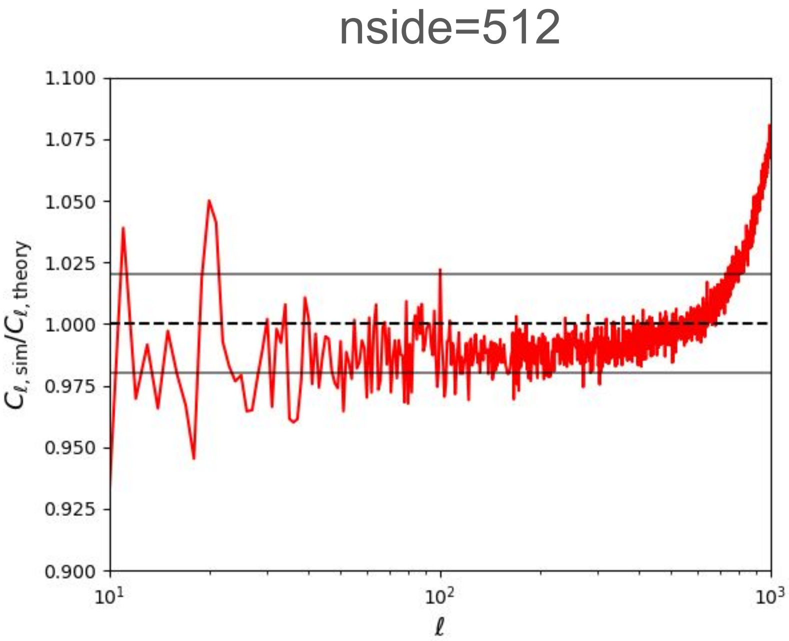
UNIONS forward model - shear map

- Rotated the footprint to fit many simulations in a full-sky map
- ~39k pseudo-independent simulations are produced.
- Pixel resolution: 7’ (nside=512)



UNIONS forward model - Full-sky power spectrum

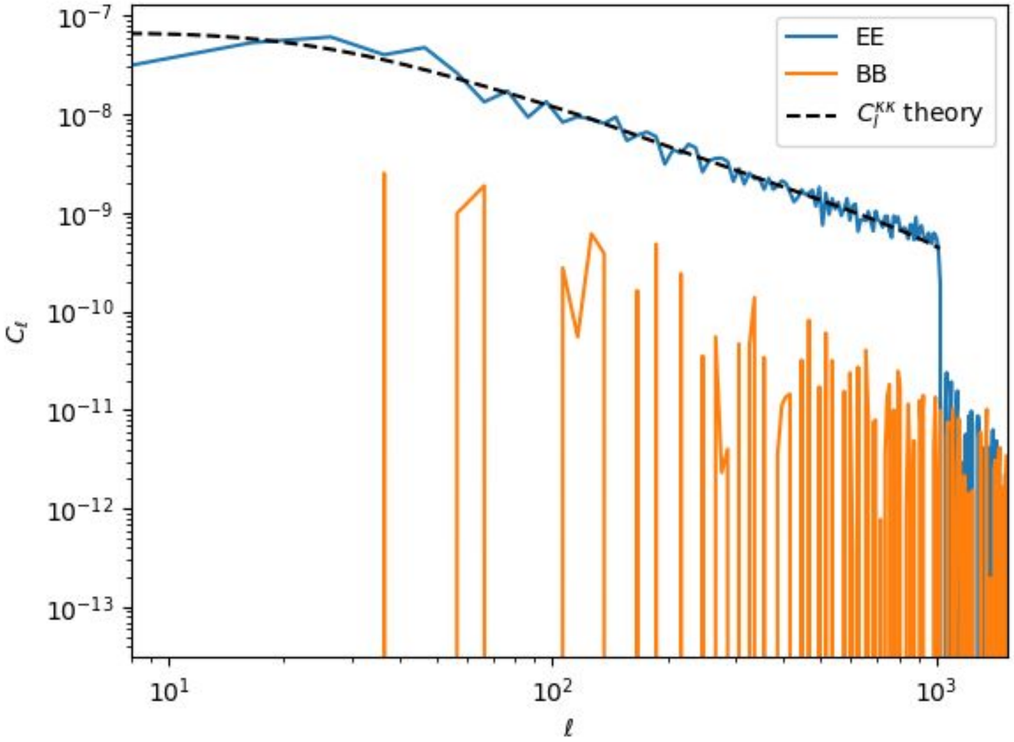




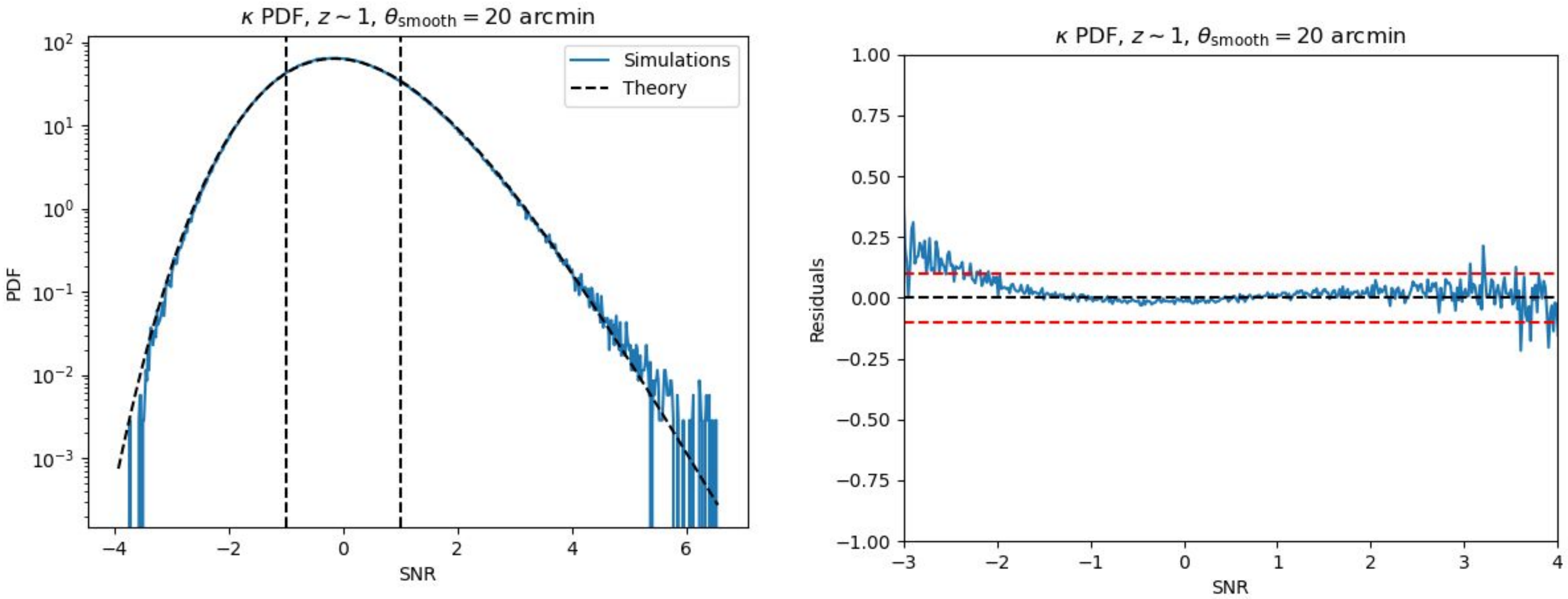
Shot noise dominates on small scales.

UNIONS forward model - Pseudo-Cl's

- Good agreement with the theory.



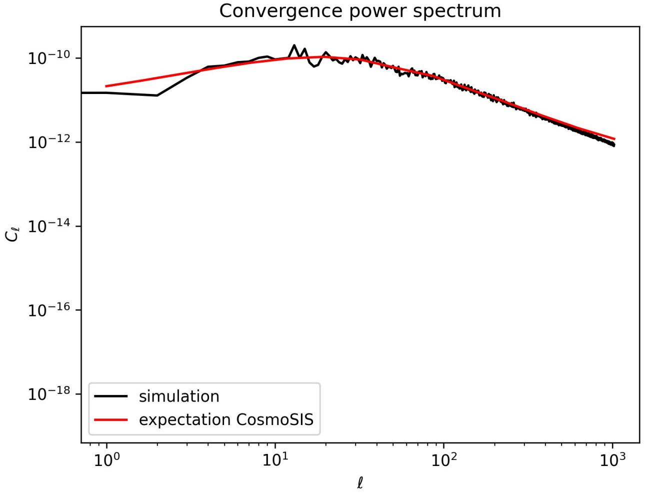
UNIONS forward model - Convergence PDF at z ~ 1

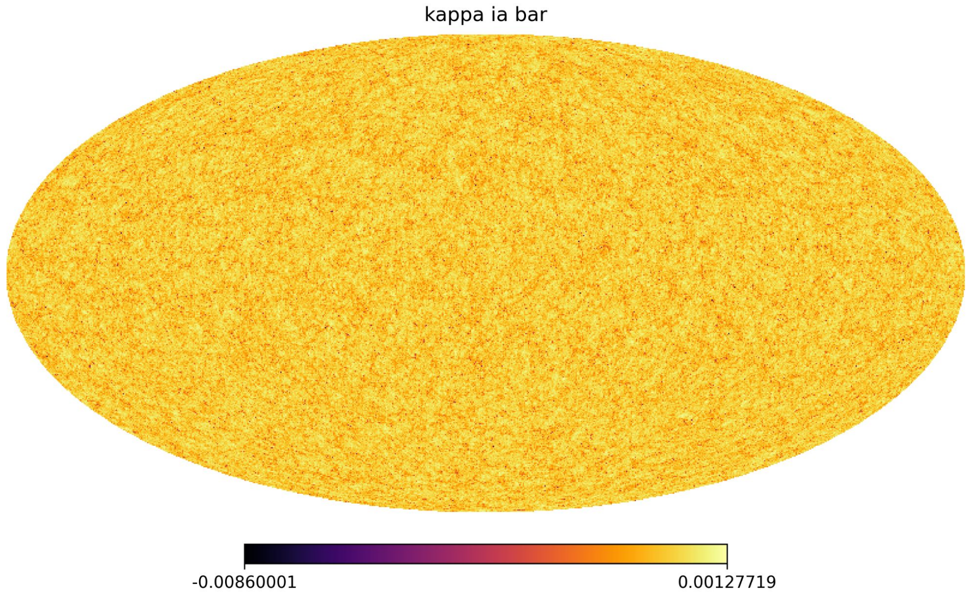


Intrinsic alignment

- NLA model:

$$\kappa_{\rm IA}(\phi, z) = -A_{\rm IA} C_1 \rho_{\rm crit} \frac{\Omega_M}{D(z)} \left(\frac{1+z}{1+z_0}\right)^{\eta_{\rm IA}} \delta(\phi, z)$$

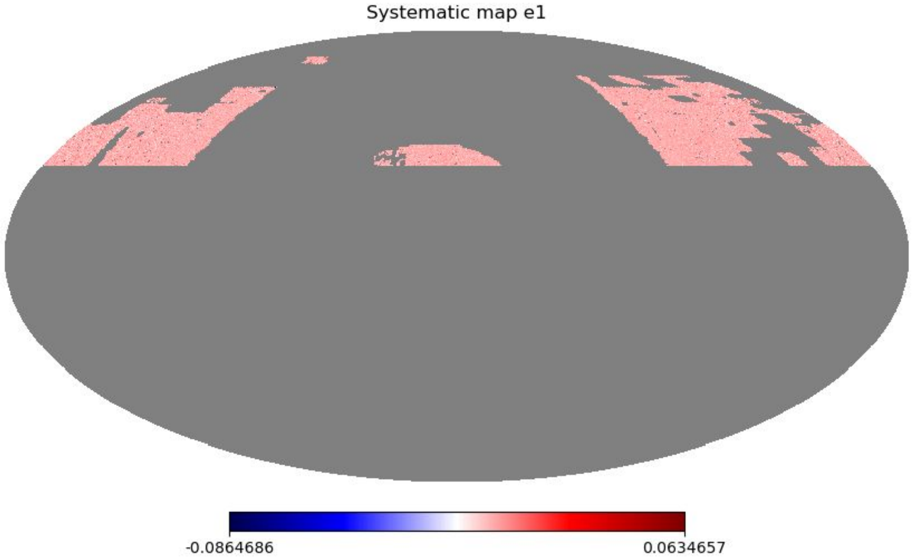




UNIONS forward model - PSF systematic map

$$\delta \mathbf{e}^{\mathrm{sys}}_{\mathrm{model}} = \alpha \underbrace{\mathbf{e}_{\mathrm{model}}}_{\text{Leakage}} + \beta \underbrace{(\mathbf{e}_{*} - \mathbf{e}_{\mathrm{model}})}_{\text{Ellipticity error}} + \eta \underbrace{\left(\mathbf{e}_{*} \frac{T_{*} - T_{\mathrm{model}}}{T_{*}} \right)}_{\text{Size error}}$$

- PSF systematic maps sampled using Rho-/Tau-statistics analysis.
- Sampled at star positions.



Plan for UNIONS

Perform an analysis of:

- Pseudo-Cl's   2-pt statistic
- Peak counts
- Wavelet l1-norm

Higher-order statistics

- CNN optimal compression (Intern: Matthis Maupas)   "Field-level" inference

Implicit Likelihood Inference pipeline - JaxILI

- Train your normalizing flows in a few lines of code.
- Implement different neural compression methods.
- Validated against existing code.
- Get in touch if interested!

```
inference = NPE()
inference = inference.append_simulations(theta, x)

learning_rate = ... #Choose your learning rate
num_epochs = ... #Choose the number of epochs
batch_size = ... #Choose the batch size
checkpoint_path = ... #Choose the checkpoint path
checkpoint_path = os.path.abspath(checkpoint_path) #Beware, this should be an absolute path.

metrics, density_estimator = inference.train(
    training_batch_size=batch_size,
    learning_rate=learning_rate,
    checkpoint_path=checkpoint_path,
    num_epochs=num_epochs
)
```

You can then fetch the posterior to sample from it.

```
posterior = inference.build_posterior()

observation = ... #The observation should have the shape [1, data vector size].
samples = posterior.sample(x=observation, num_samples=..., key=...) #You have to give a PRNGKey
```

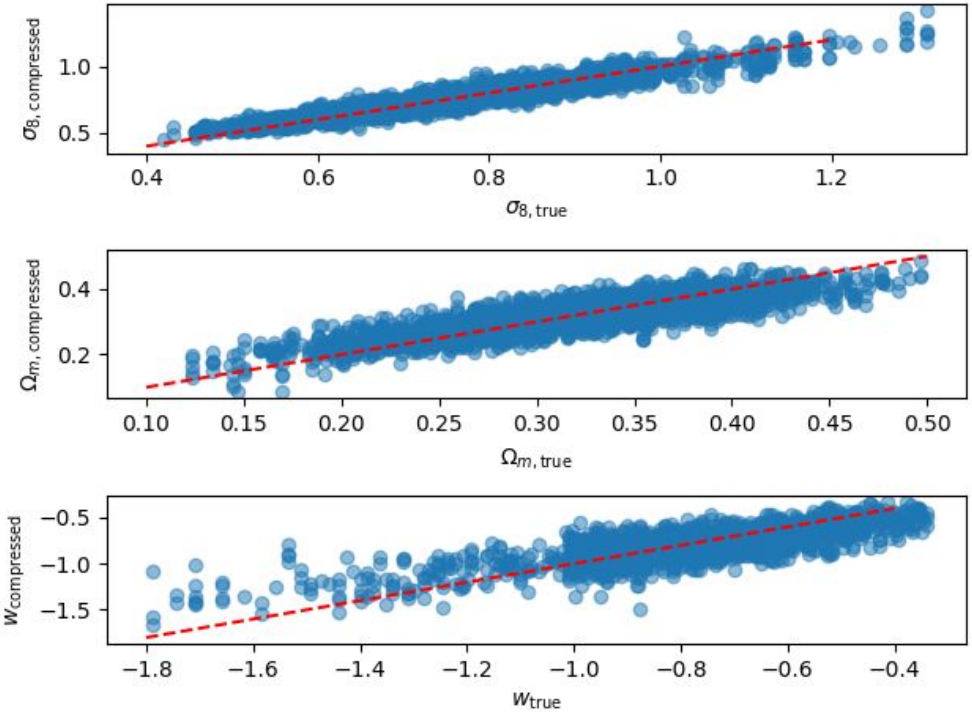
Neural compression - Mean Squared Error

$$\mathcal{F}_\varphi : \mathbb{R}^d \to \mathbb{R}^n$$
$$x \longmapsto t$$

minimizing

$$\mathrm{MSE}(\mathcal{F}_\varphi(x), \theta) = ||\mathcal{F}_\varphi(x) - \theta||^2$$

θ : cosmological parameters $(\mathrm{dim} = n)$
x : observation $(\mathrm{dim} = d)$

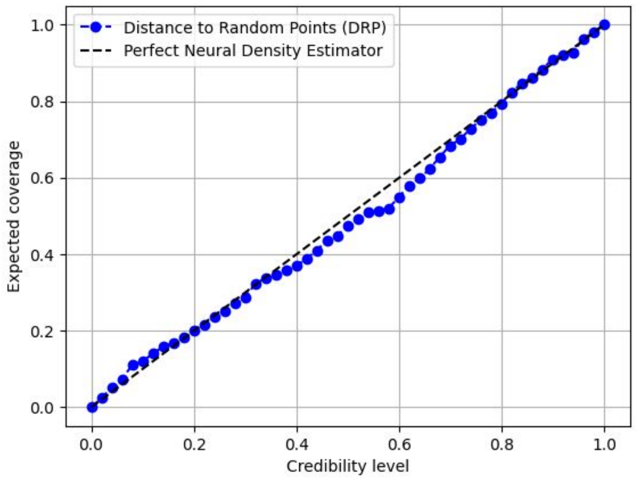


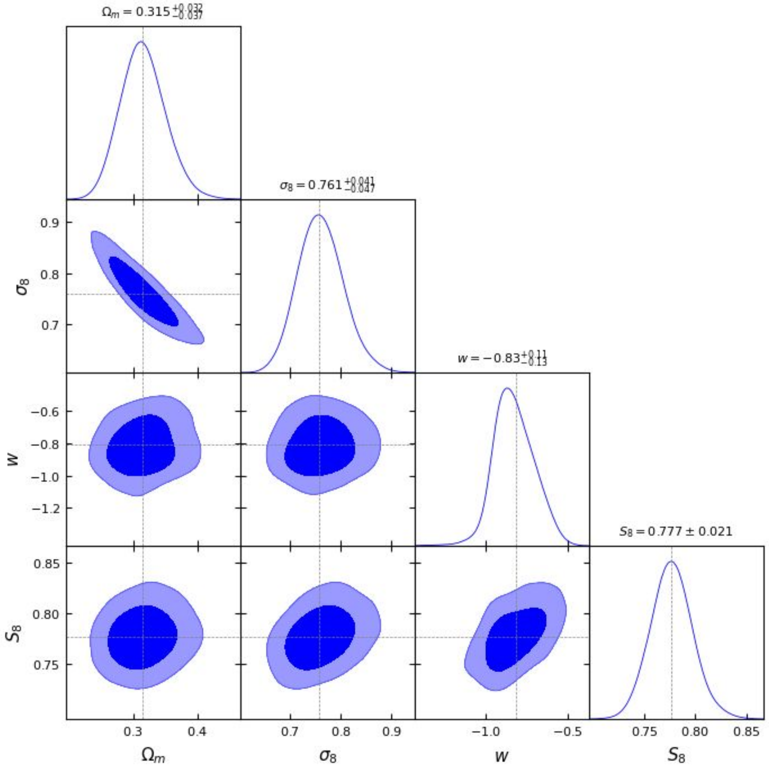
Applied on simulations with cosmology + Gaussian noise

Neural Density Estimation

With the power spectrum.

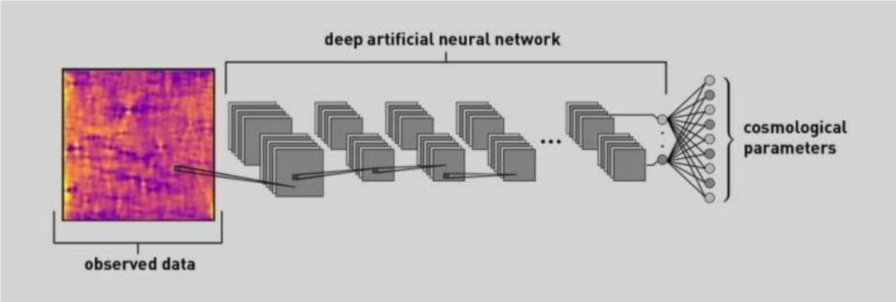
- Optimistic setup ran on convergence with gaussian noise (no systematics).

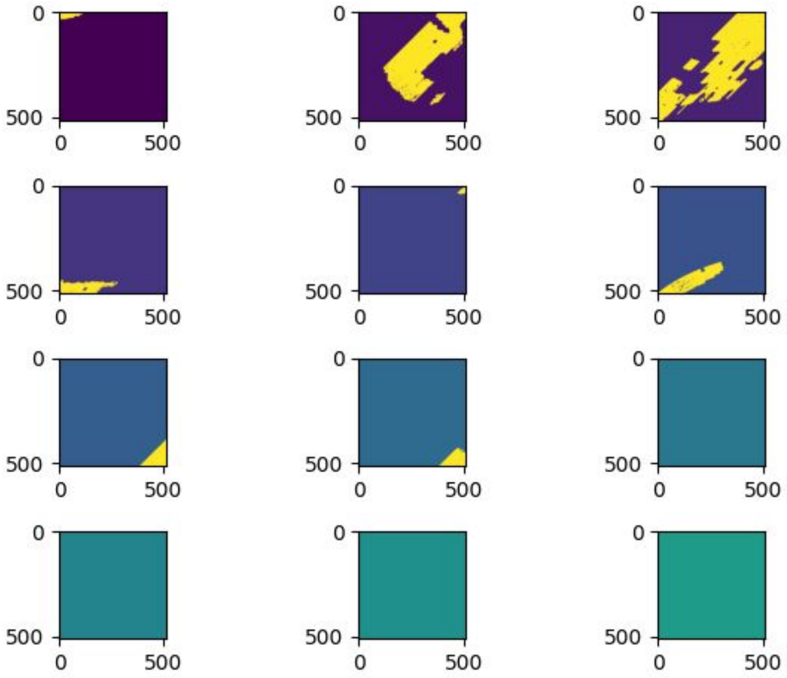




CNN neural compression (Credit: Matthis Maupas)

- Cut the footprint in patches.
- Select the ones with most information.
- Compress the pixel information to a lower-dimensional data vector.





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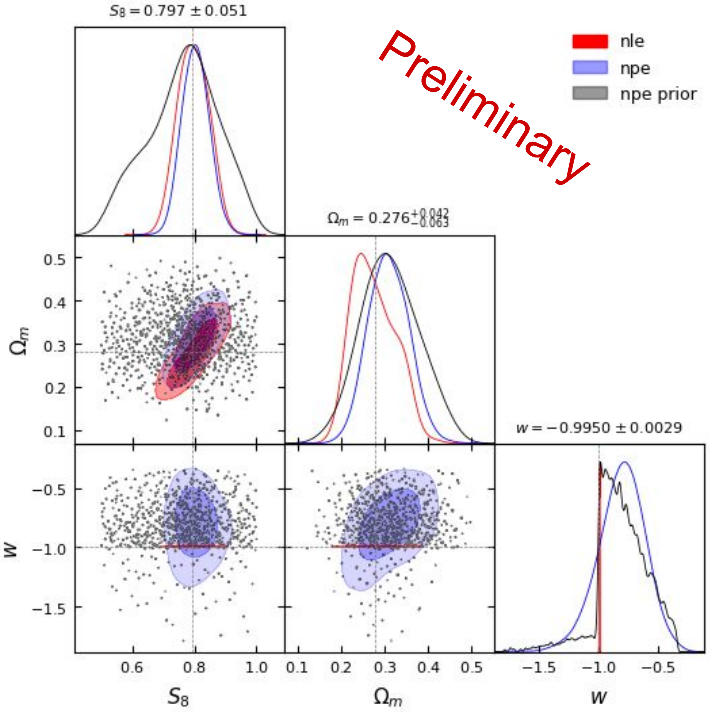

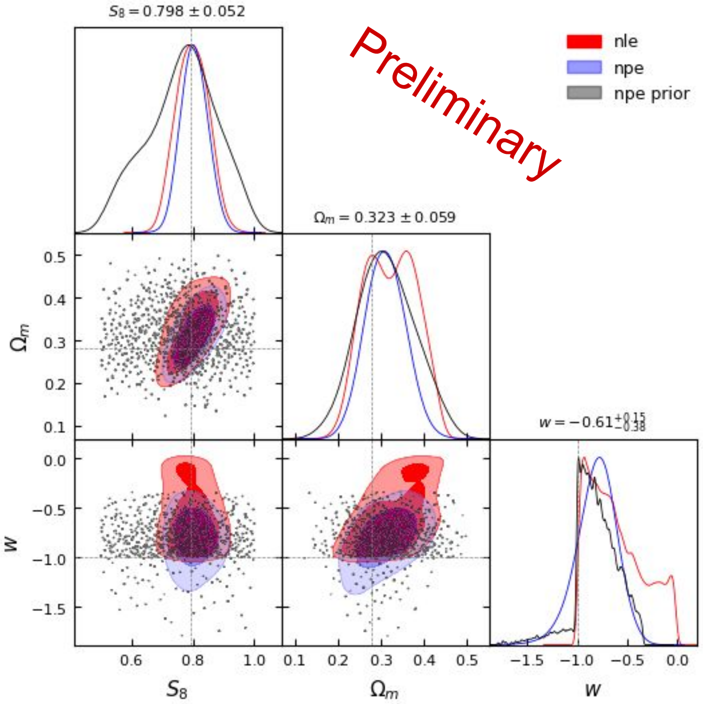

Conclusion and next steps

- Cosmic shear probes the projected matter density.
- Many systematics can pollute the cosmic shear signal.
- Forward-modelling allows accounting for the systematics.
- Implicit Likelihood Inference is a useful tool for cosmological analysis with higher-order statistics that requires accurate forward modelling of the observations.