AI-Driven Weak Lensing Cosmology in the Era of Stage IV Surveys

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2025/10/21

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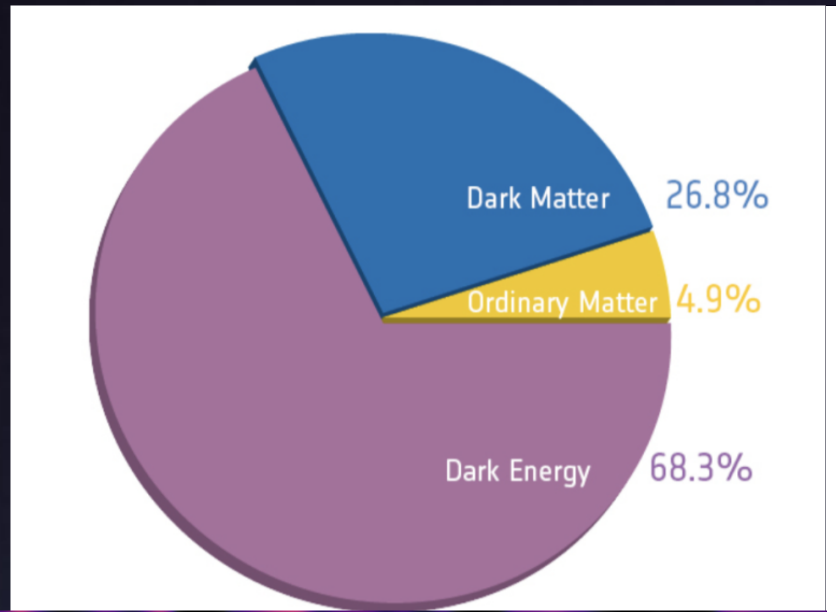
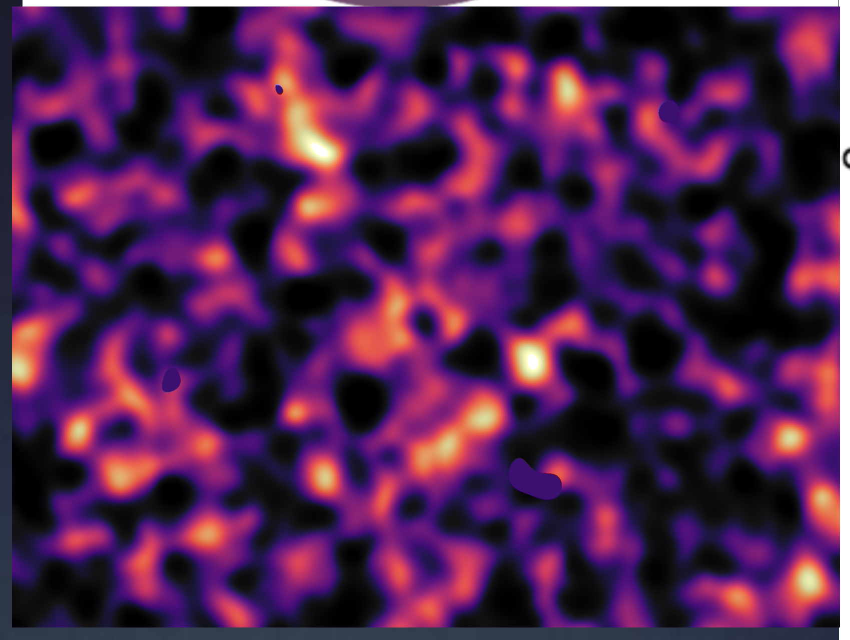
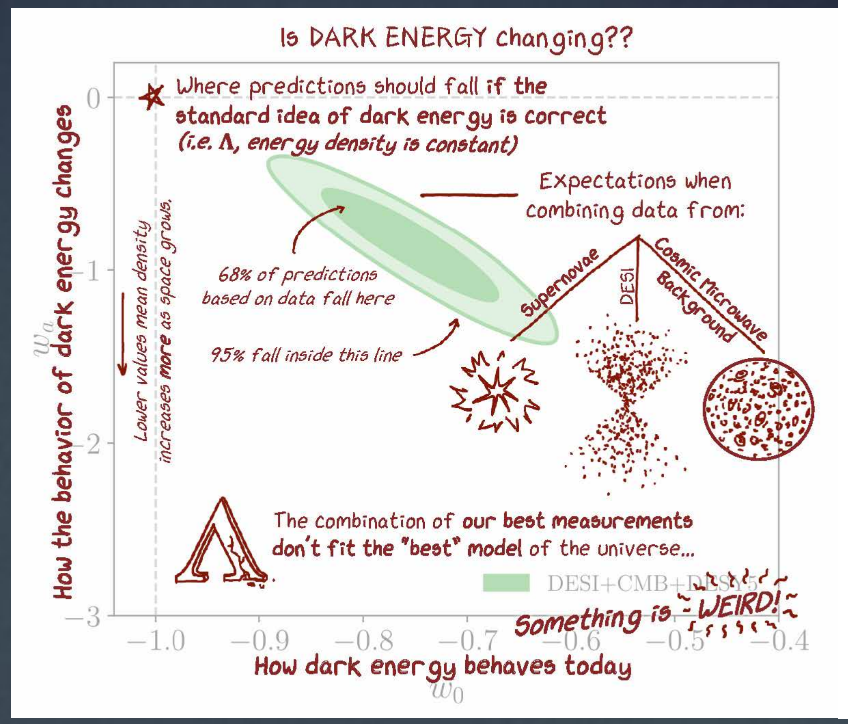
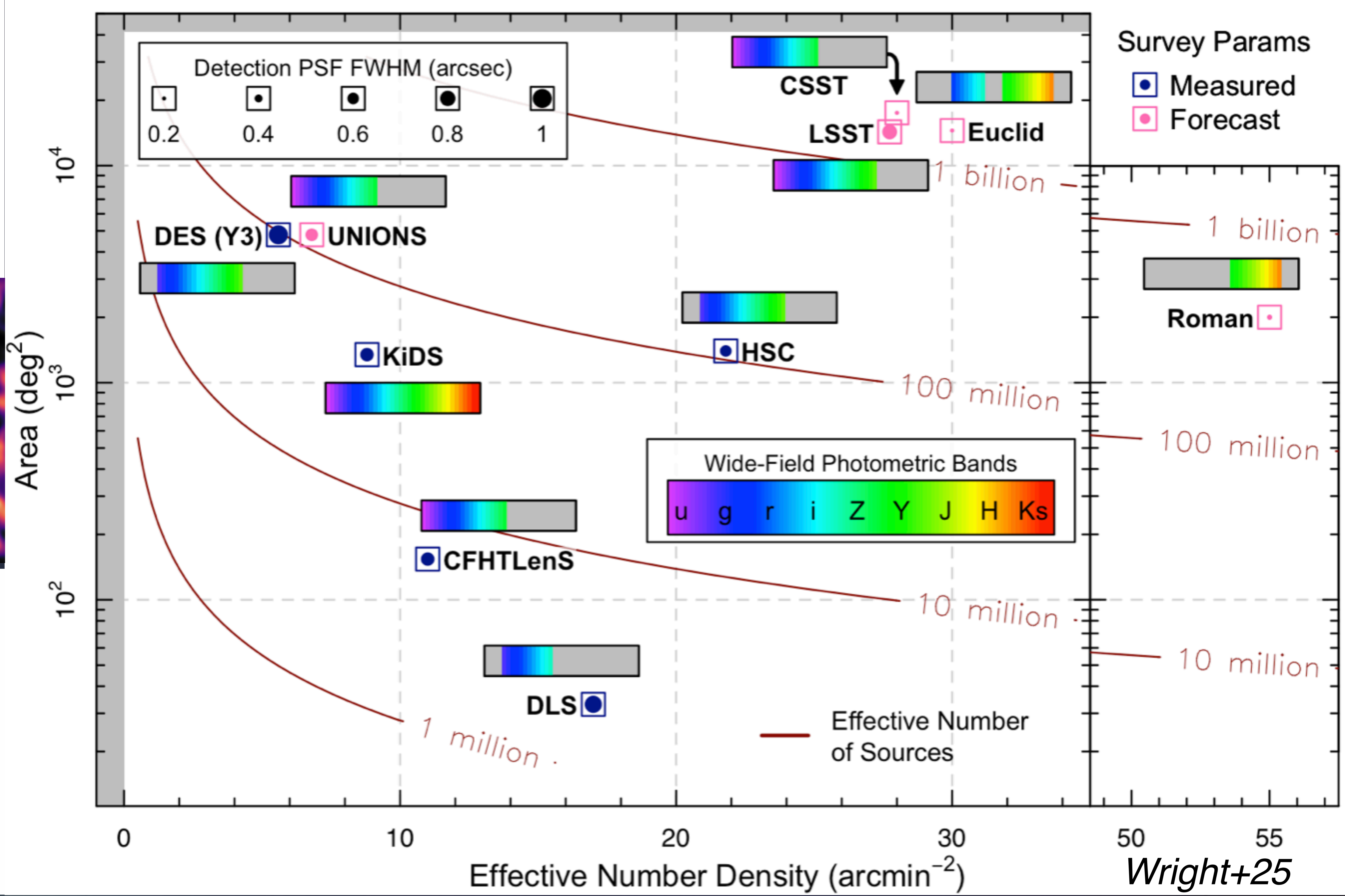
Introduction

Weak Lensing Surveys



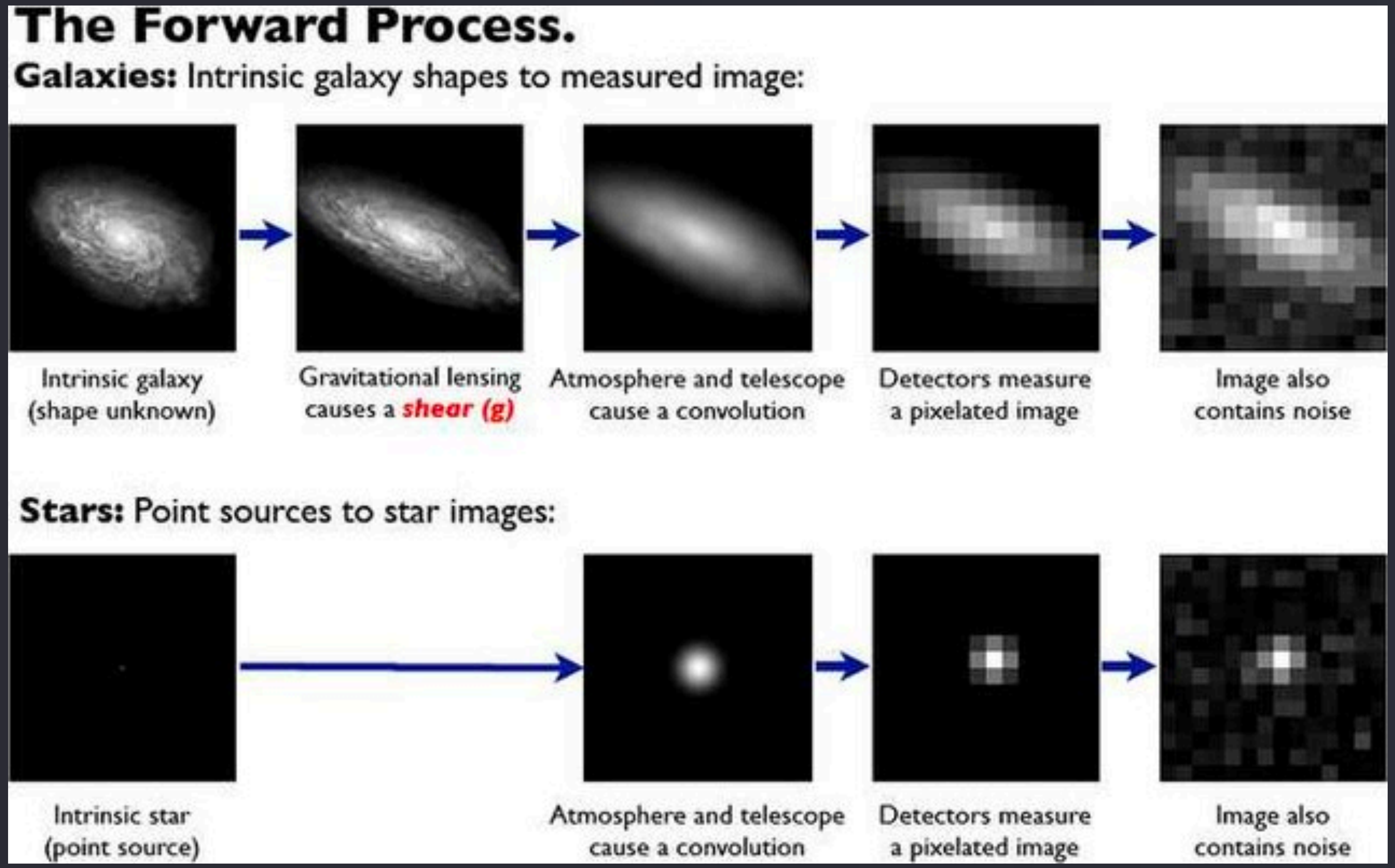






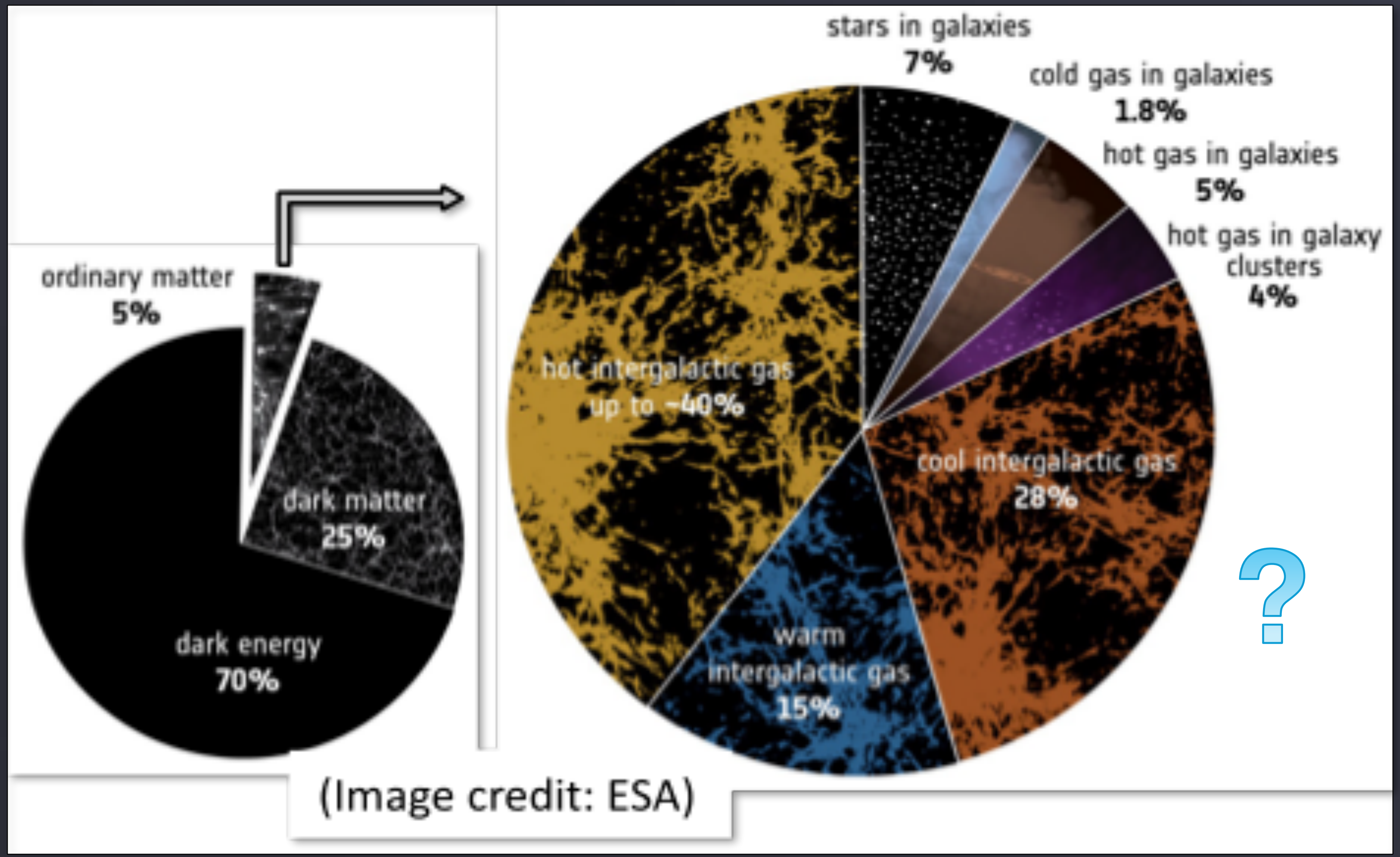
- WL maps the DM distribution in the Universe through subtle distortions in galaxy shapes. It is a key tool for studying the LSS of the Universe and the nature of DM and DE, providing direct and unbiased information about DM.
- WL Cosmology is a core scientific objective of Stage IV surveys, like CSST, Euclid, Roman and LSST.

Weak Lensing Cosmology



WL Shear Measurement

Correct for the Point Spread Function (PSF) to accurately measure pixelated galaxy shapes, **high-efficiency** and **high precision** WL shear measurement.



Cosmological Information Extraction

Use WL shear signals to constrain the properties of DM and DE, test theories of gravity, and **maximize accurate & precise** cosmological information extraction.

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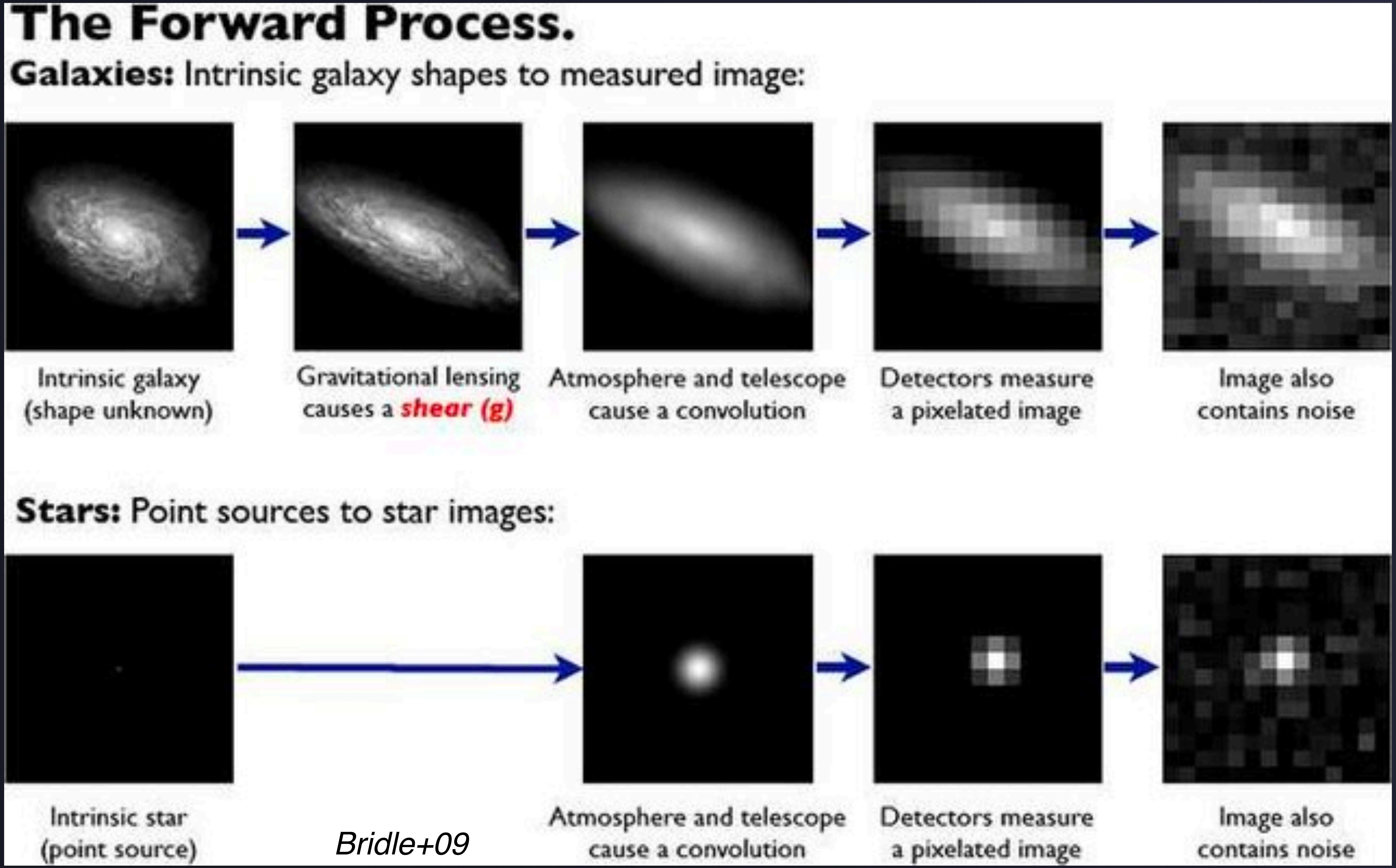
Deep-Learning Shear Measurement

One of the greatest challenges of weak lensing is shear measurement of distant galaxies.



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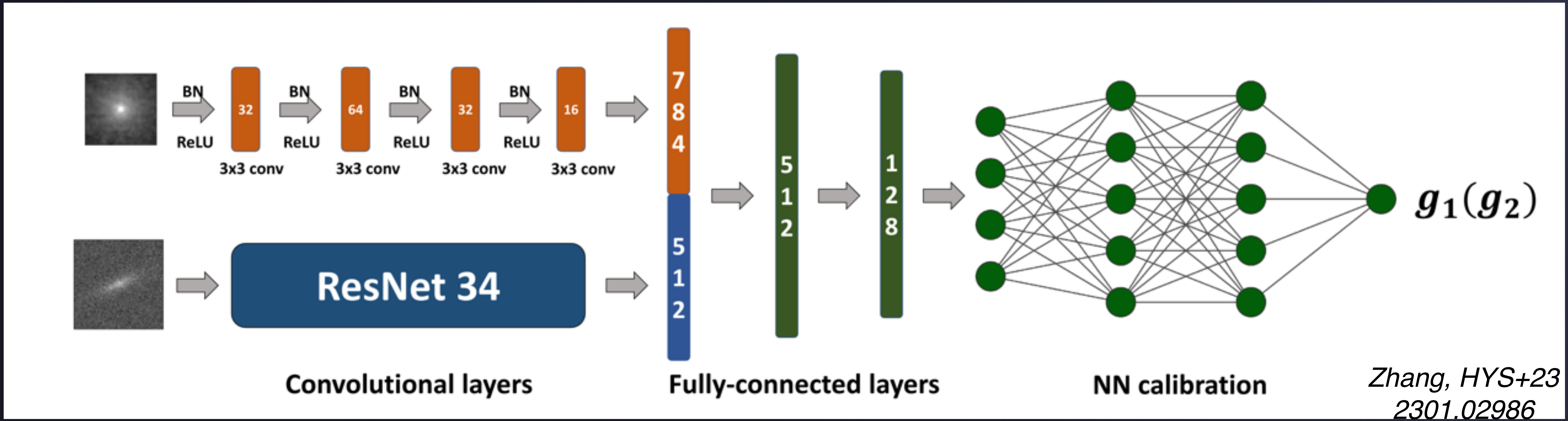
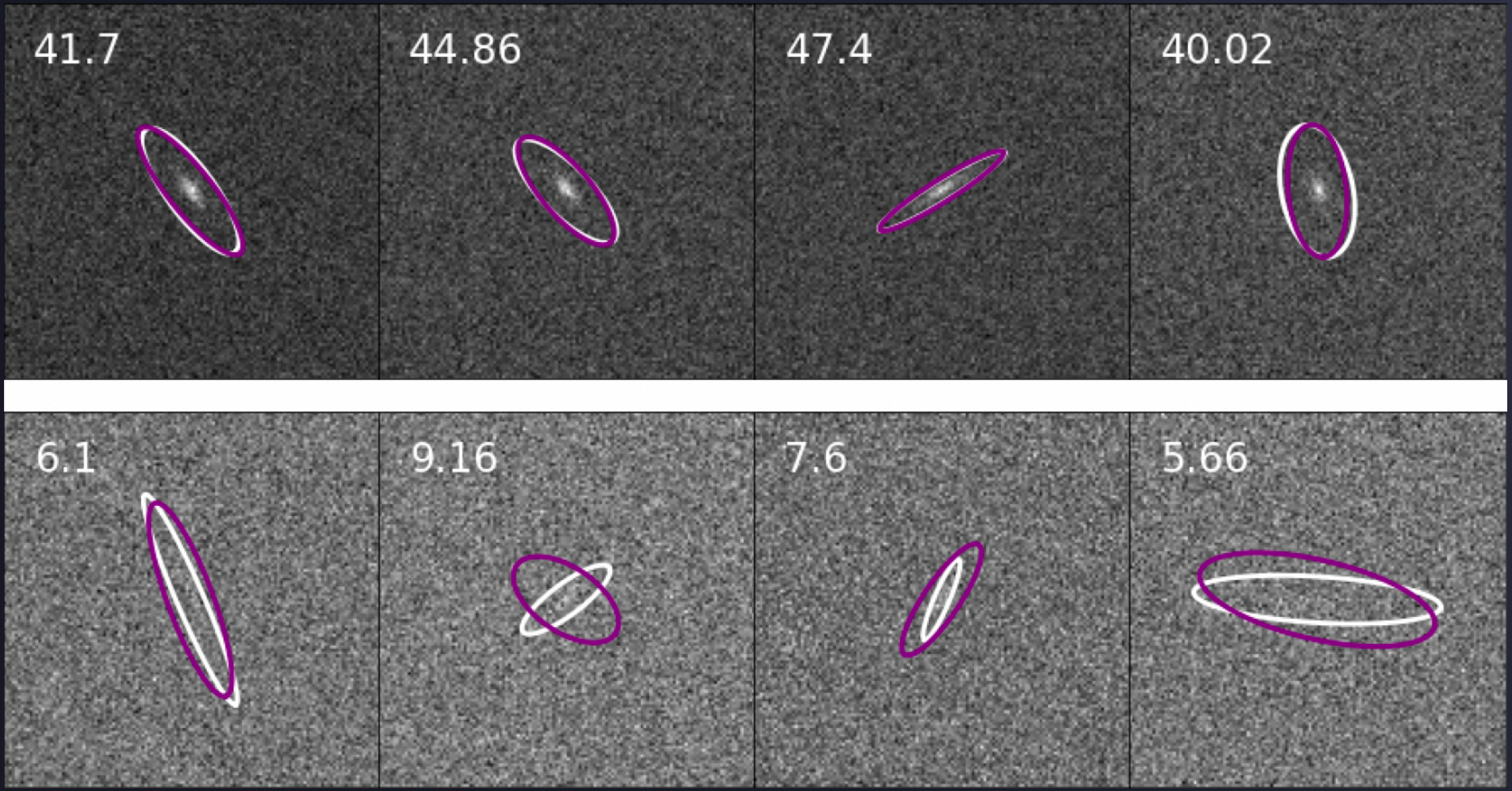
Current surveys achieve about 1% accuracy in measuring galaxy ellipticity, but the Stage IV surveys aim to improve this accuracy by an order of magnitude.

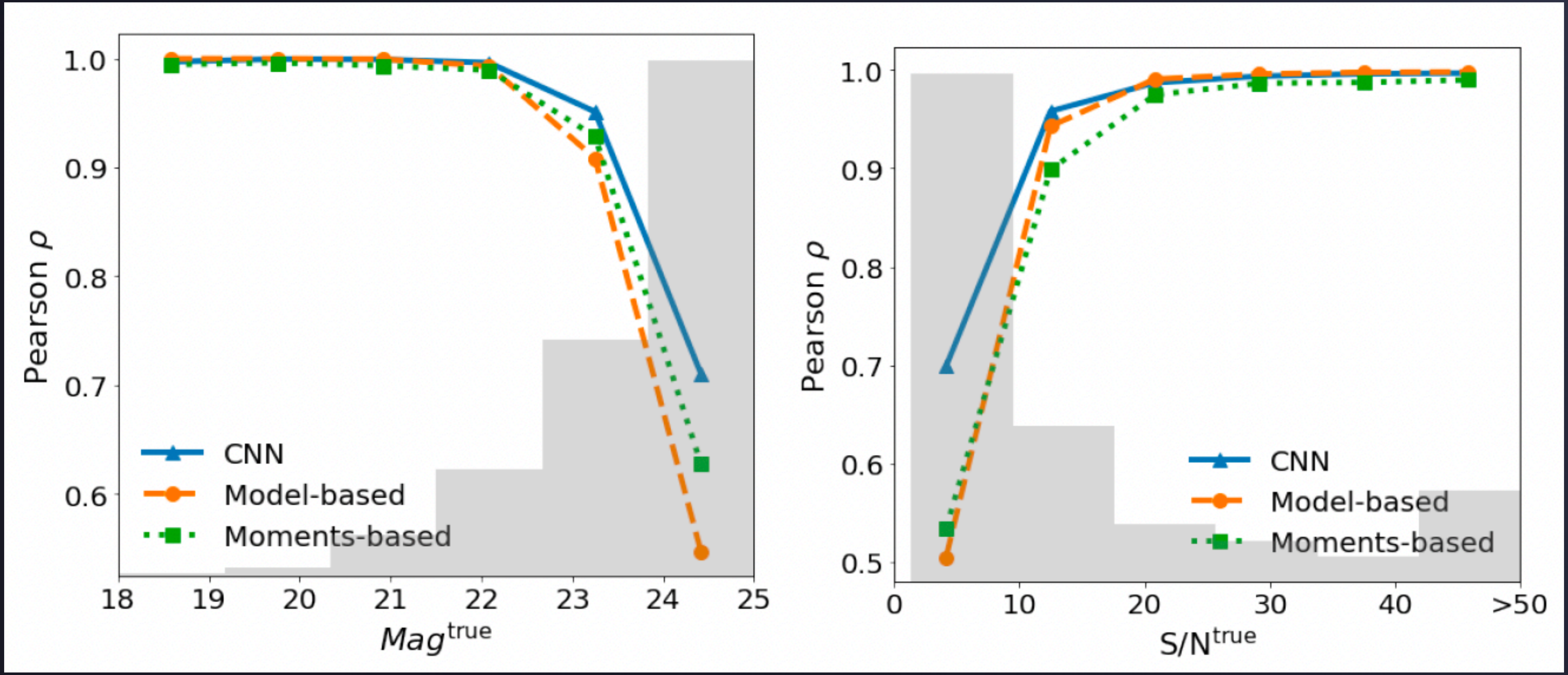
Forklens: Accurate WL Shear Measurement with Deep Learning



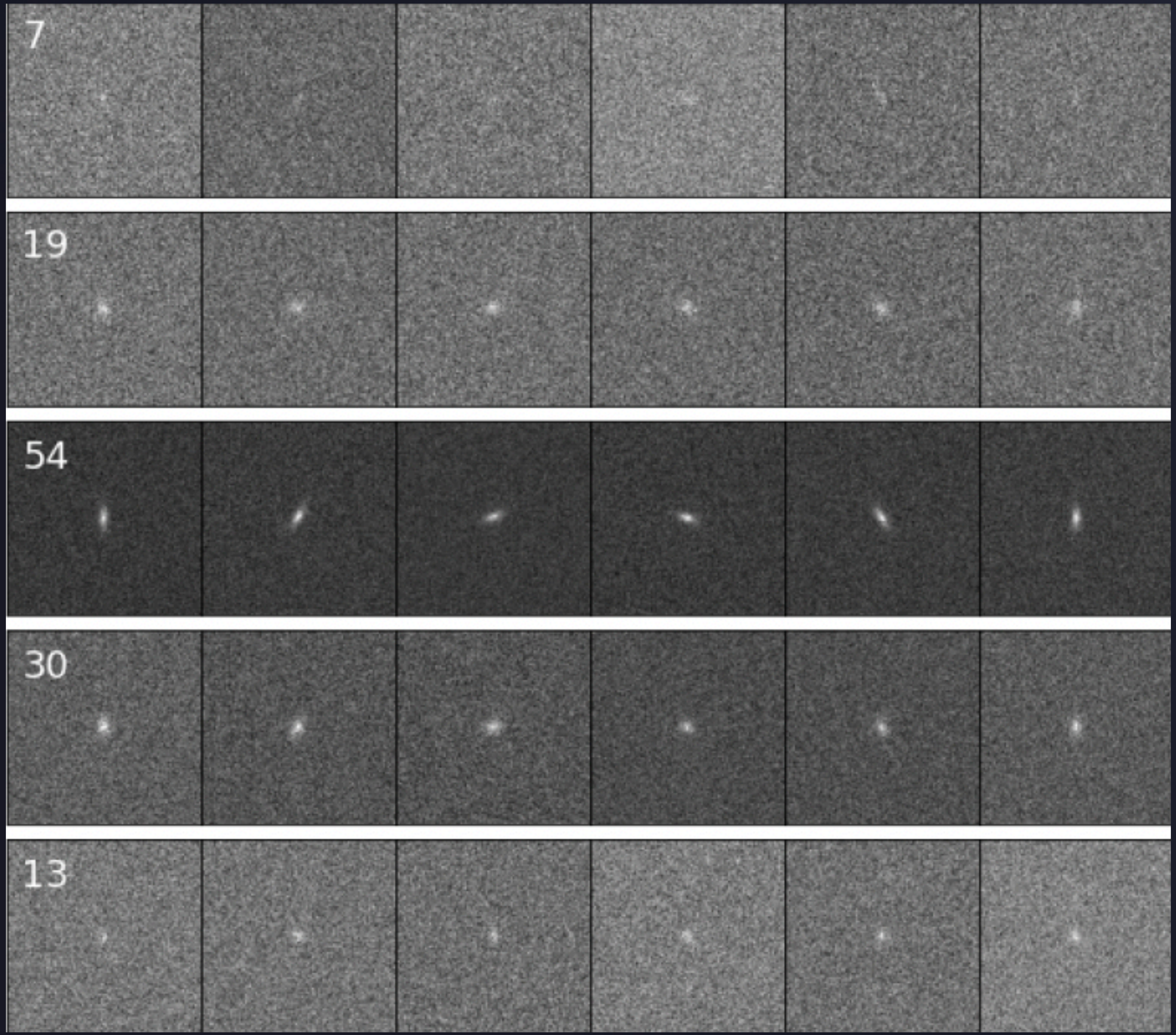
- **Module 1**: A forked CNN architecture—one branch takes galaxy images, the other takes PSF images. Features are extracted in parallel using ResNet34 and four convolutional layers, then output magnitude, half-light radius, and ellipticity, enabling simultaneous PSF deconvolution and shape measurement.
- **Module 2**: The four CNN outputs are fed into a 3-layer fully connected network trained to estimate the true shear. A separate weighting network assigns weights to galaxies to suppress low-SNR contamination, thus enabling simultaneous shear calibration and weight assignment.



- CNN Measurement Results: Shape measurements after PSF correction for galaxies at different SNR. The white ellipses represent the true values, while the purple ellipses denote the predicted values.
- Forked-CNN Advantages: simultaneous PSF deconvolution and shape measurement; features extraction from pixelated image, allowing for more accurate modeling of complex galaxy morphologies. The network also exhibits strong robustness to noise, delivering reliable shape measurements even in noisy conditions.

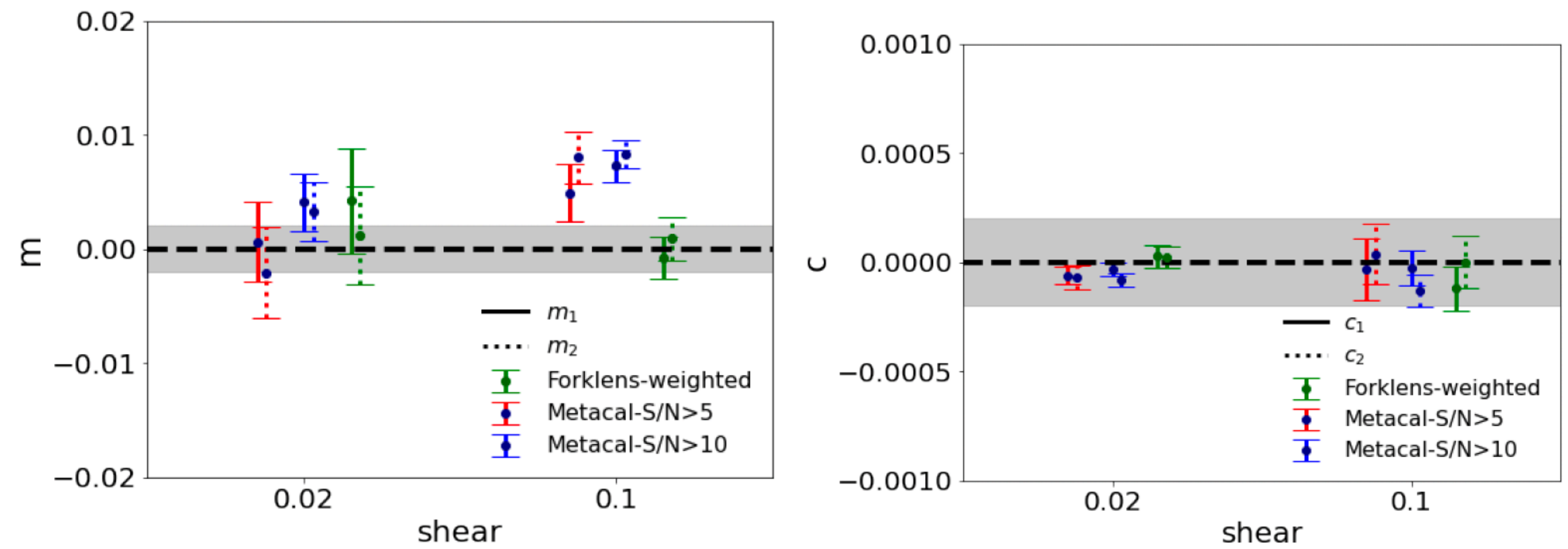


- Forklens performs comparably to moment-based and model-fitting methods at high SNR in 20 million CSST simulations.
- At SNR<10, Pearson correlation improves by **~36%**.



- Structured data set to train the calibration NN. Each row corresponds to one case containing 2000 galaxies, which differ only in the orientations sharing the same shear and PSF. 5000 cases (i.e., 5000 rows) in total are used to train the NN.

- NN network: learns the mapping between the CNN shape parameters and true shear; assigns weights by SNR, suppressing the impact of noisy galaxies on the shear; adapts to diverse data through training, delivering reliable shear estimates across all observing conditions.



- Forklens can achieve **~2×10^{-3}** accuracy across different shear values, meeting the requirements of Stage IV surveys.
- Each galaxy takes **~0.7 ms** to process, making it highly scalable.
- The measurements of Forklens do not require a strict SNR cut, demonstrating the stronger robustness of the Forklens pipeline against noise.

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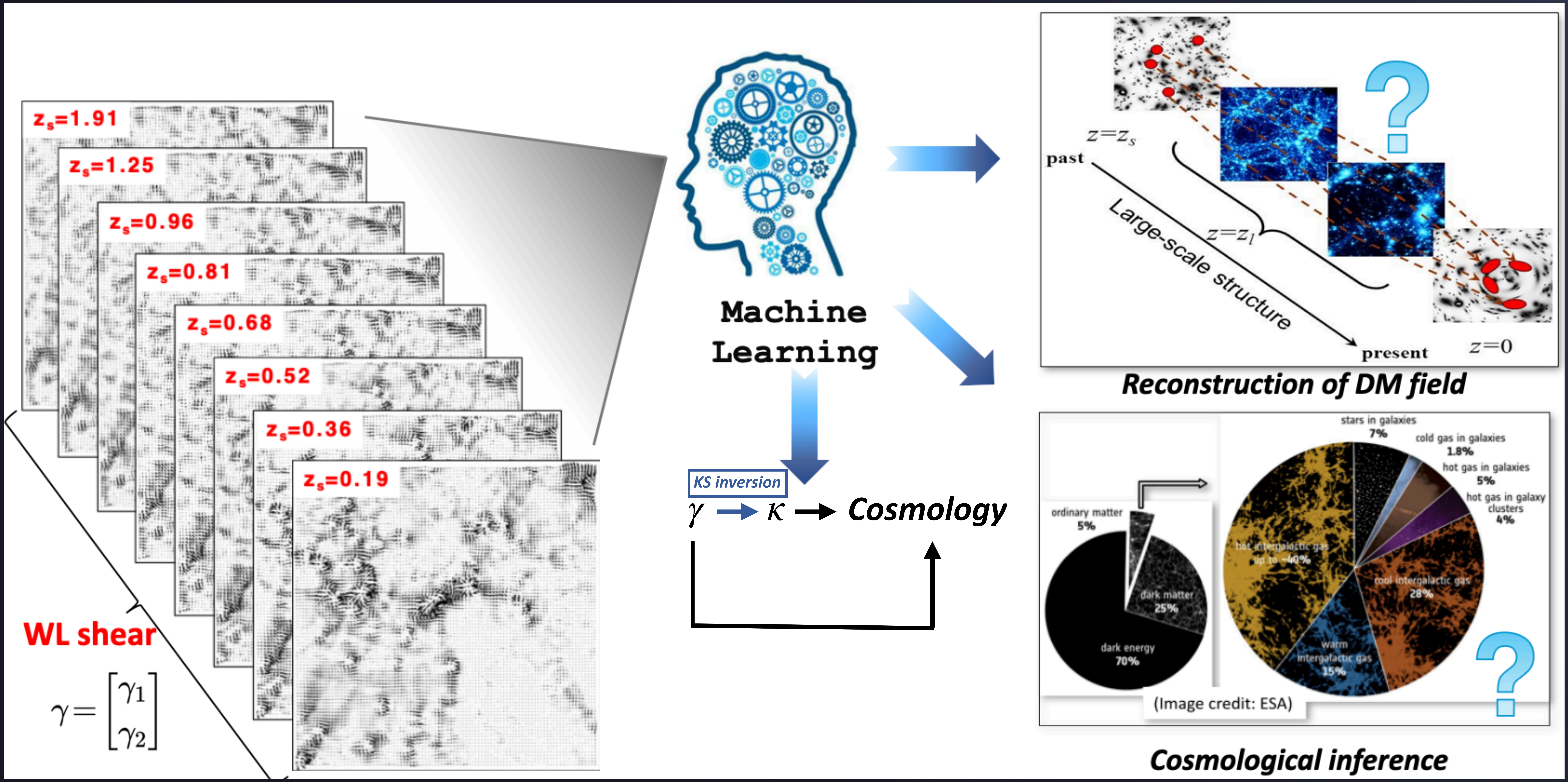
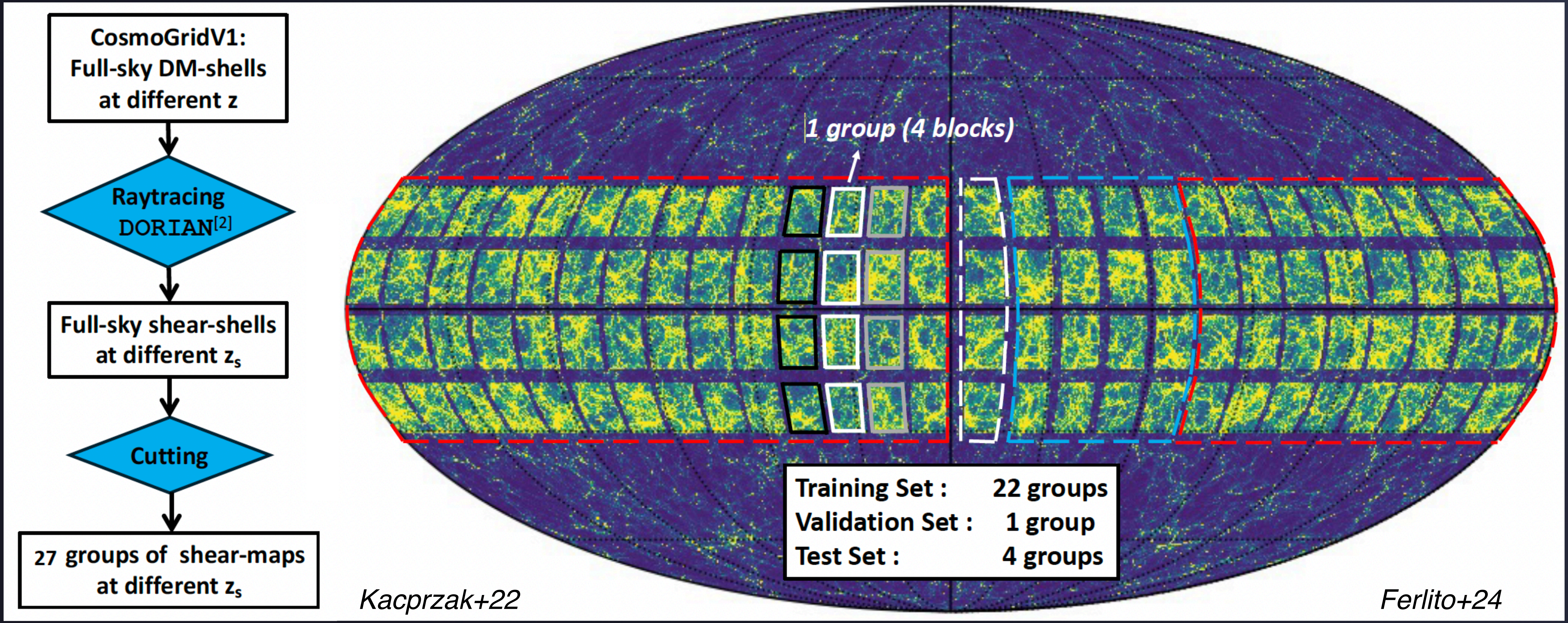
Field-Level Inference Weak Lensing Cosmology

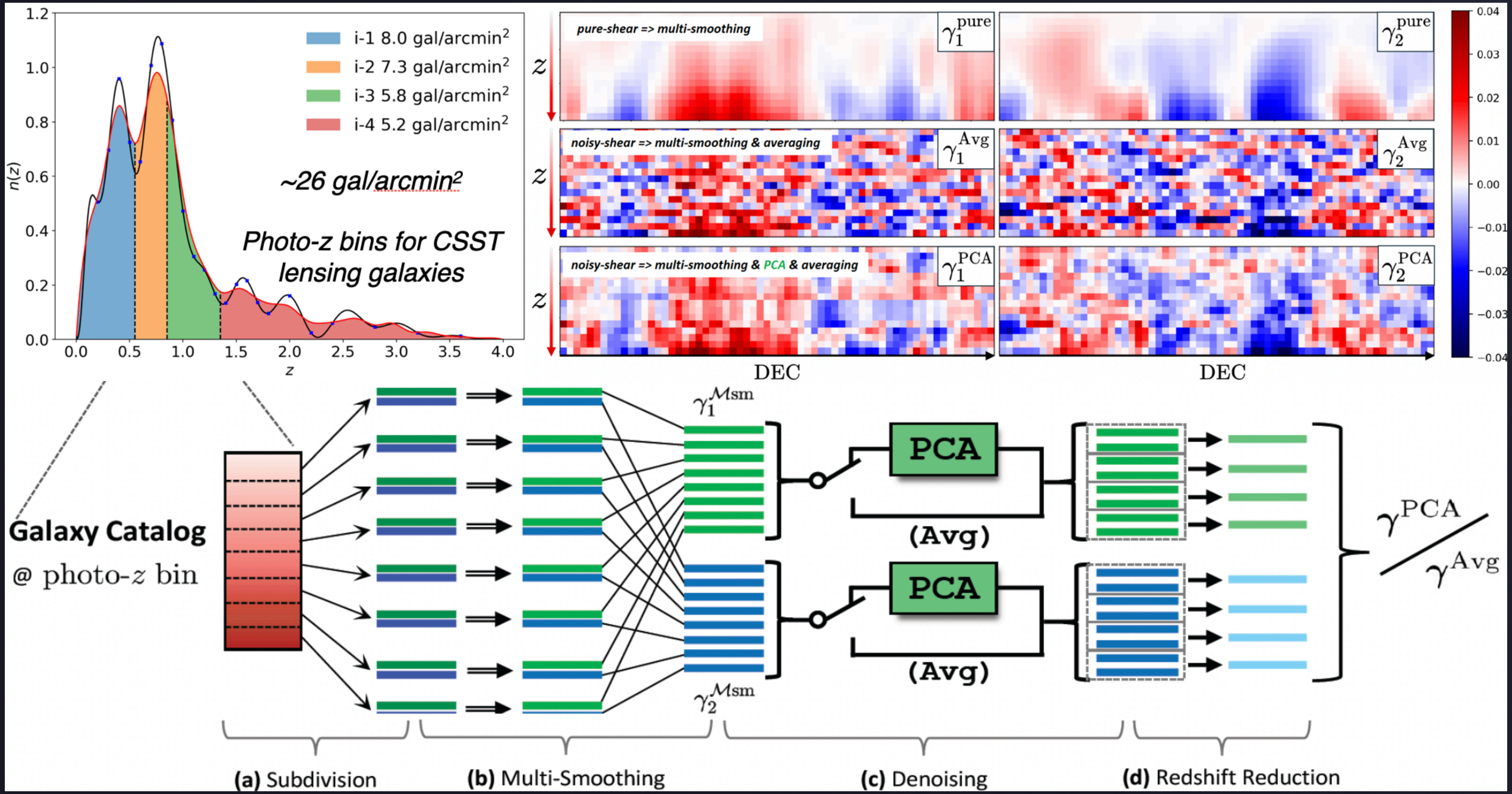
Field-Level Inference Weak Lensing Cosmology





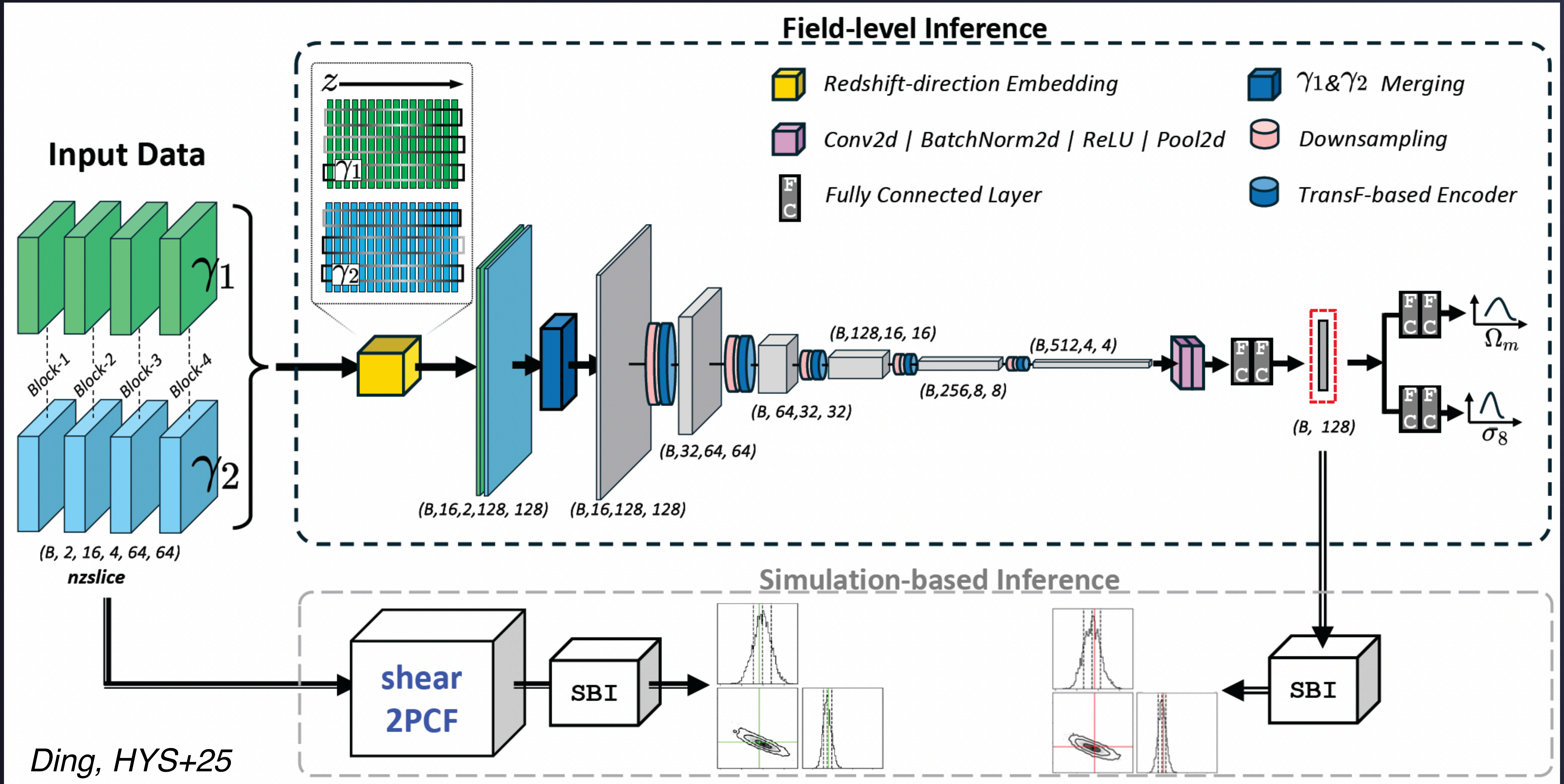
- Simulation: Full-sky shear maps are generated from CosmoGrid N-body simulations via the DORIAN ray-tracing algorithm.
- Illustration of the sky-region partitioning: 108 blocks of 12.8°×12.8° are divided into non-overlapping training/validation/test sets to ensure the robustness of the machine-learning results.

Denoising for Galaxy Shape Noise

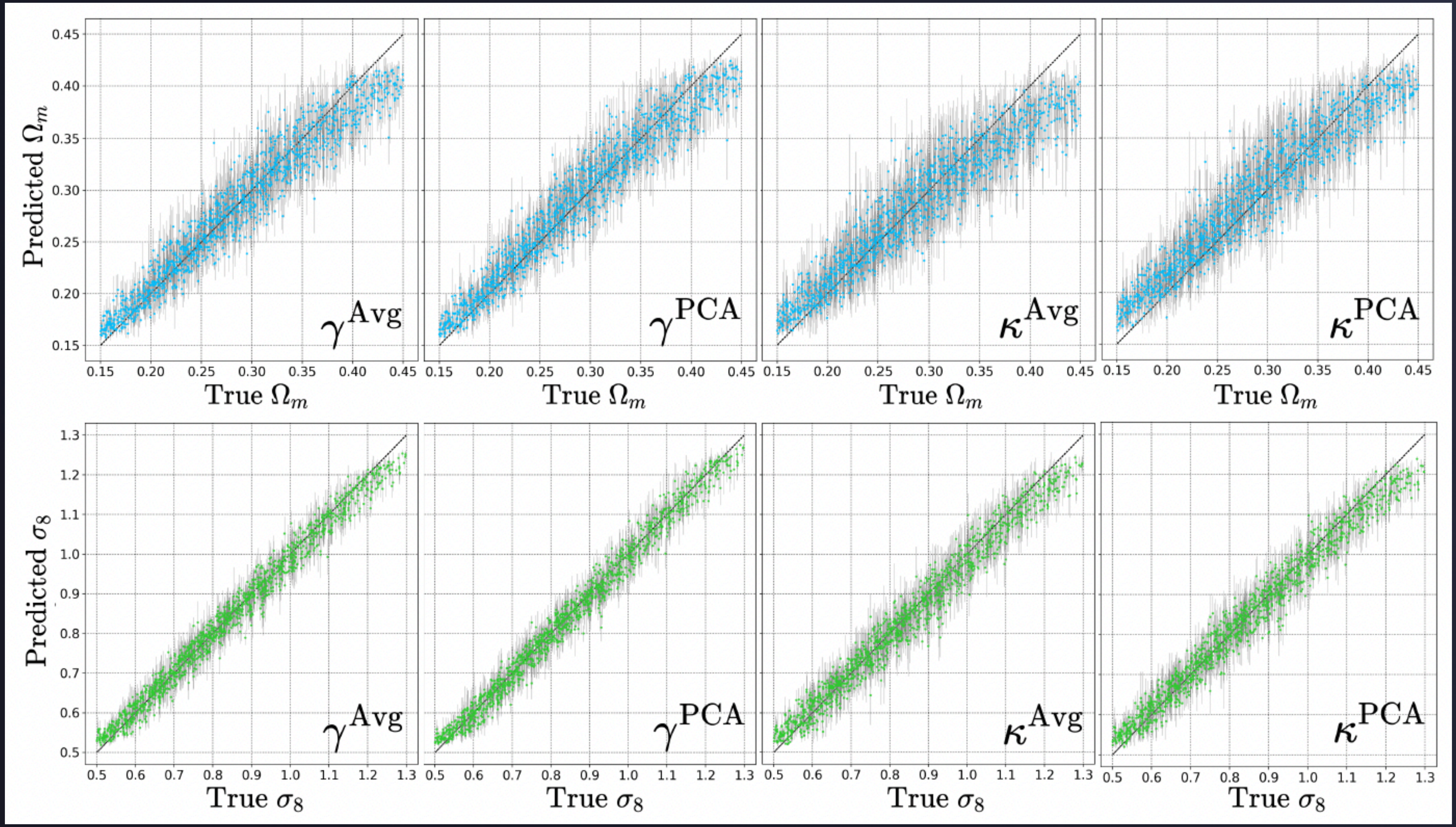


- The high-z regions of γ^{Avg} are dominated by shape noise, showing random speckles that do not match the large-scale coherent patterns of γ^{pure}.
- These speckles disappear in γ^{PCA}; the redshift direction becomes smooth and closely follows the structures in γ^{pure}, demonstrating that PCA successfully removes random fluctuations while preserving the cosmological signal.
- The PCA denoising boosts the SNR by roughly a factor of 2 and reduces the subsequent network training loss by about 15%.

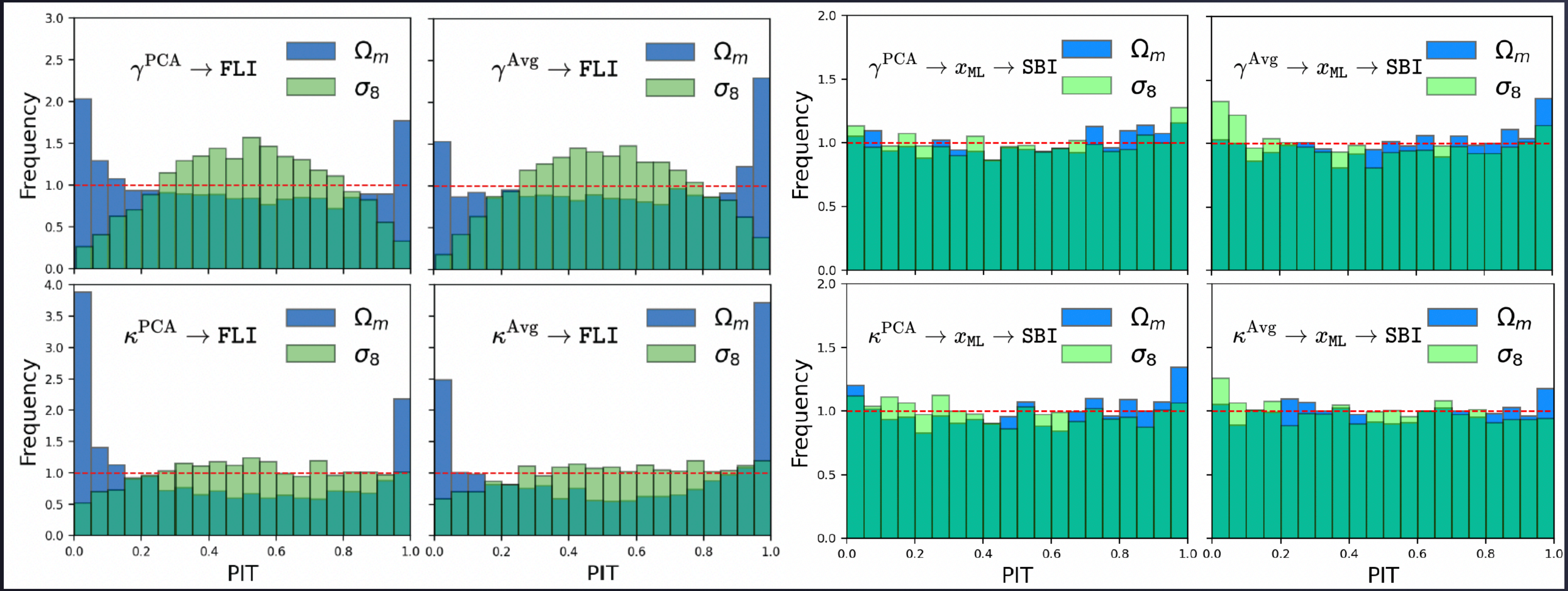
- Subdivision: Divide each photo-z slice into 8 sub-slices and compute the mean ellipticity to obtain noisy shear maps γ^{n_s}.
- Multi-smoothing: Convolve each map with three Gaussian kernels, average the three smoothed versions to get $\gamma^{M_{sm}}$.
- PCA denoising: Stack the 8 $\gamma^{M_{sm}}$ maps into an 8D vector, perform PCA, retain the two smoothest principal components, and reconstruct the cleaned shear γ^{PCA}.
- Redshift Reduction: Merge the 4 photo-z bins and average every two adjacent redshift layers, yielding 16 final layers with boosted SNR.



- Framework: Includes a field-level inference (FLI for feature extraction) and simulation-based inference (SBI for posterior distribution).
- Input Data: A 6D tensor including batch size, shear components, photo-z slices, sky patch count, and spatial dimensions.
- Parameter Inference: The network predicts (Ω_m, S_8) using redshift embedding, shear merging, Transformer encoder, and fully connected layers.

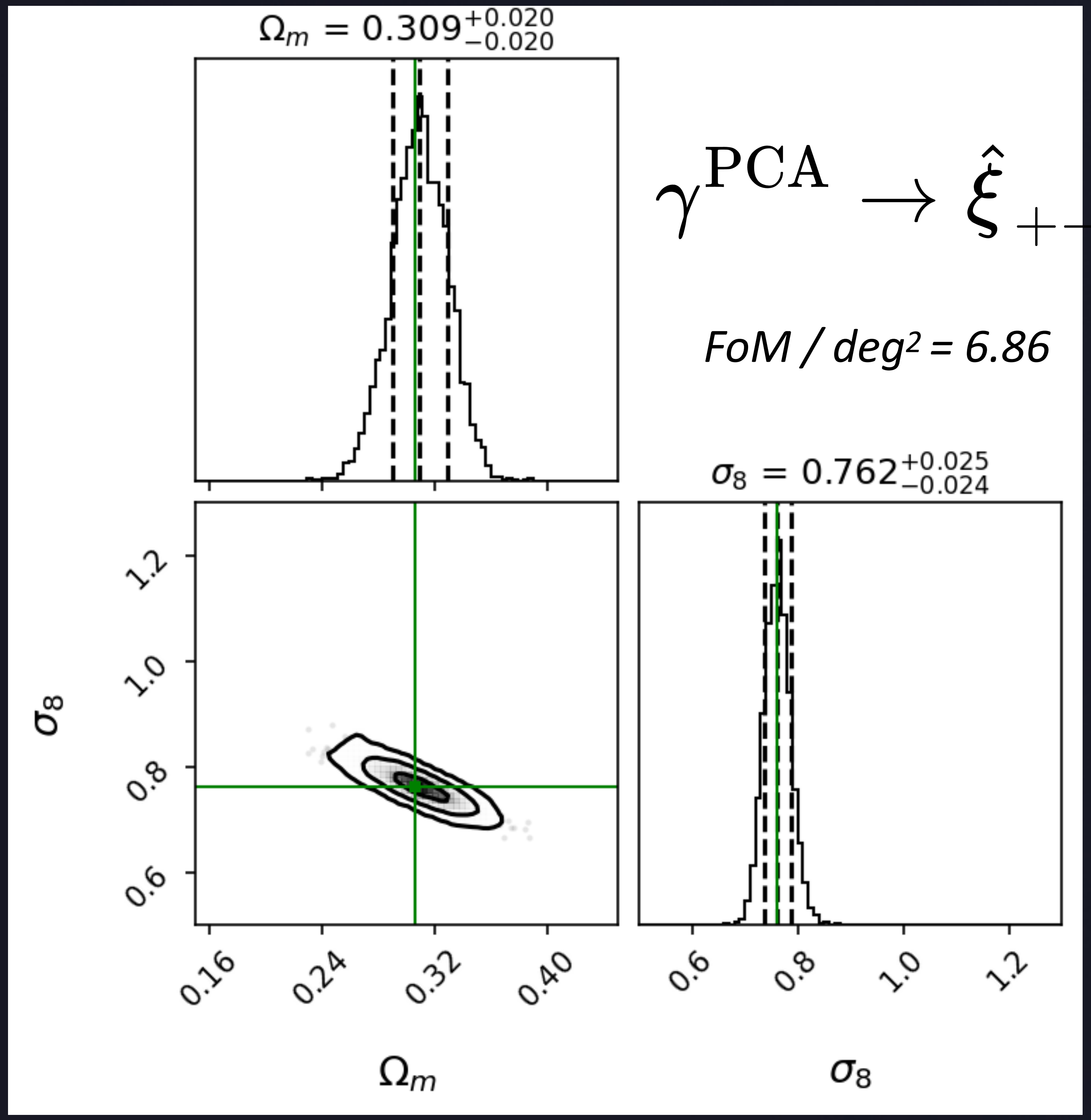


- The network is trained and tested directly on input data (γ^{Avg}, γ^{PCA}, κ^{Avg}, κ^{PCA}) to predict (Ω_m,S_8) with the same architecture, but training is performed independently for each.
- Shear outperforms convergence: γ^{PCA} lie almost on the y=x line with systematic bias < 0.01, whereas κ^{PCA} are systematically offset, underestimating Ω_m by ≈0.02 and overestimating S_8 by ≈0.015.
- PCA denoising reduces errors: PCA versions show 20-30% smaller error bars than Avg versions, demonstrating that shape noise is effectively suppressed.

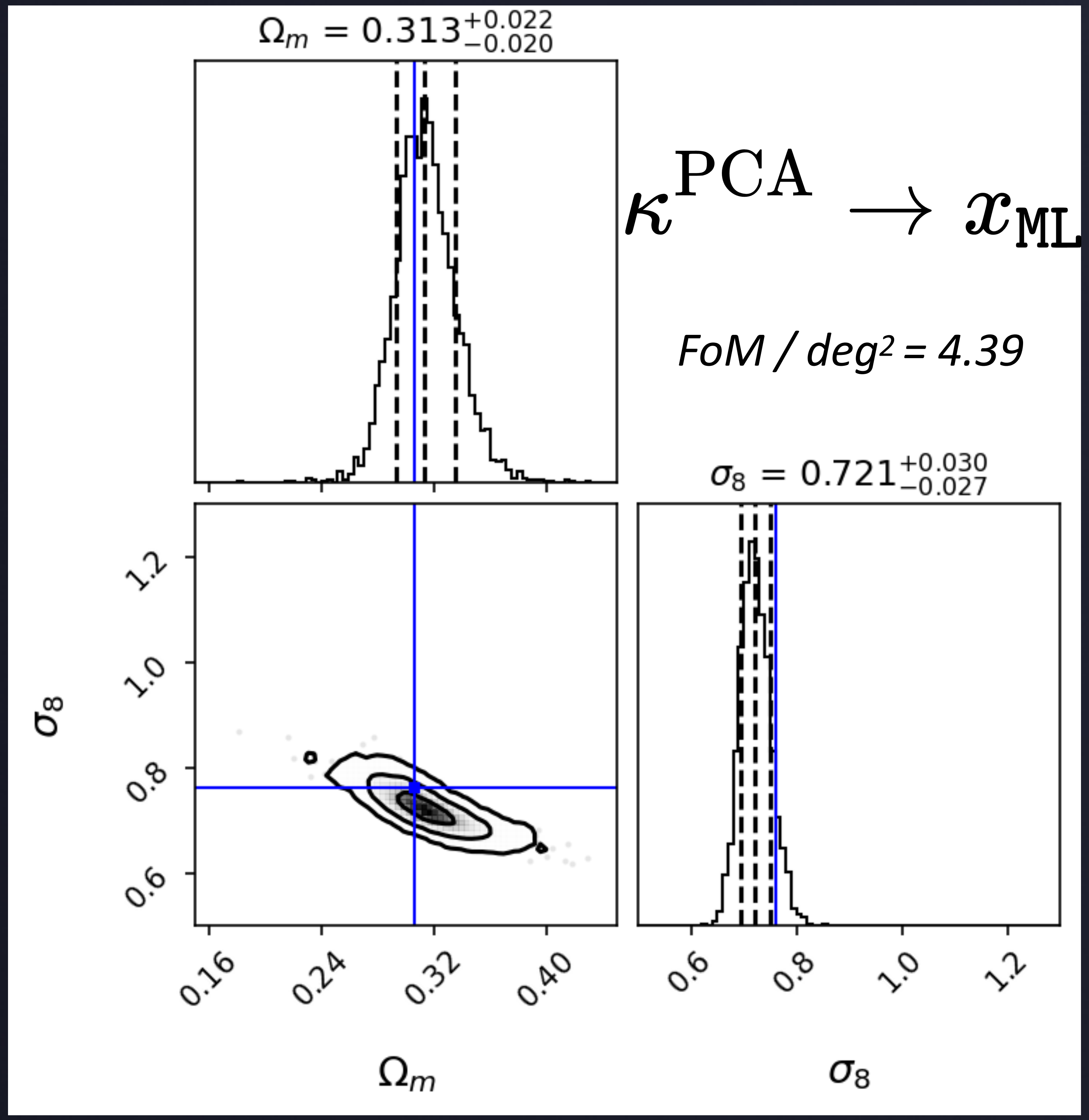


- PIT validation: transforms the model-predicted full posterior into Uniform samples.
- FLI results: direct-network PIT histogram is ∩-shaped, showing a narrow posterior and ~15-20% underestimated errors; PCA denoising drops the peak slightly, leaving substantial deviation from Uniform and still no reliable error.
- SBI results: Transformer+SNPE+Normalizing Flow yields flat PIT, demonstrating that SBI converts the non-Gaussianity, masking and noise in the simulations into a statistically rigorous posterior for CSST cosmological inference.

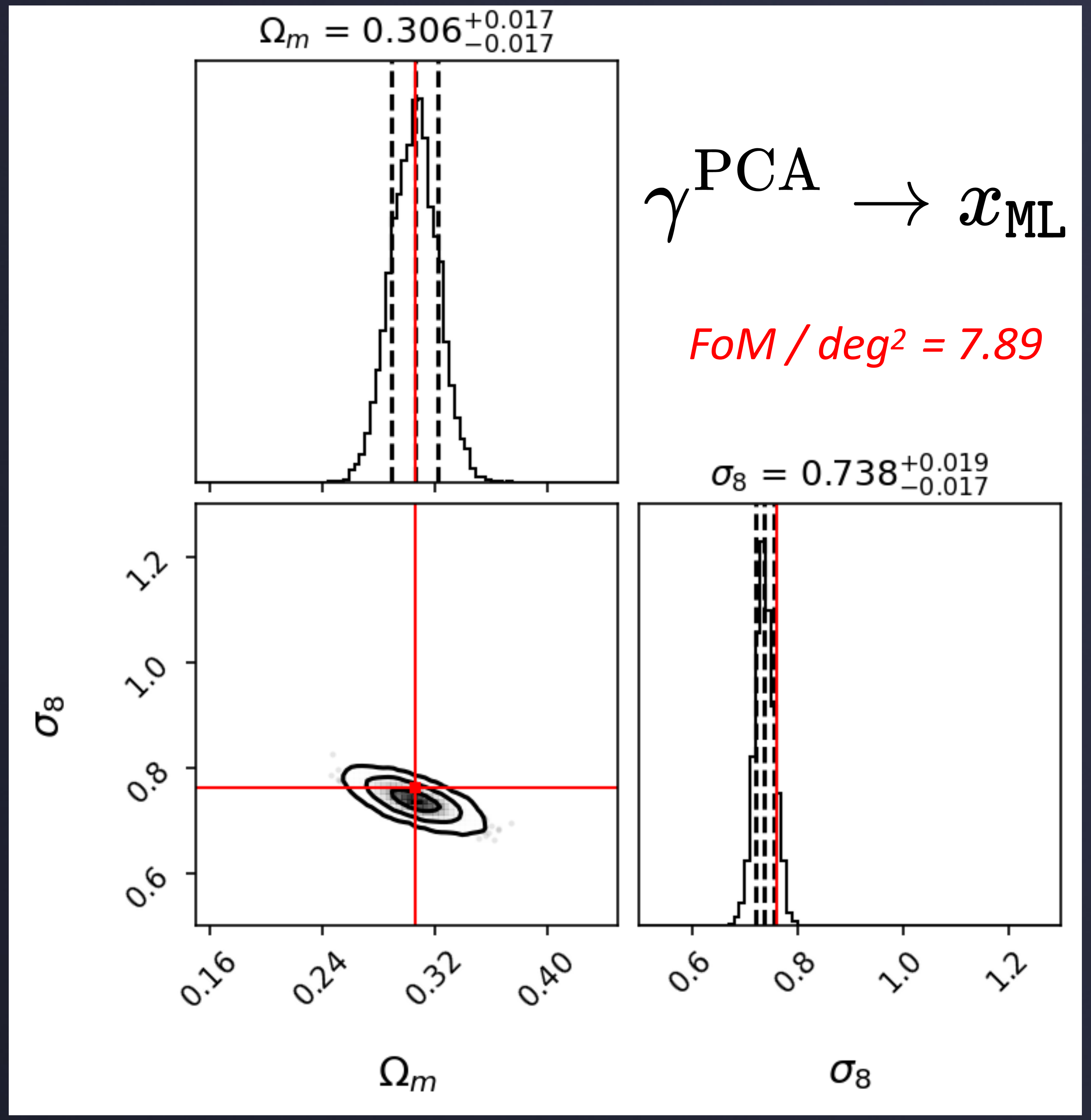
Transformer-extracted features + SBI neural posterior deliver the correct posterior



Shear-2PCF



Convergence-ML-Features



Shear-ML-Features

- FLI on the shear map boosts the cosmological information by **~15%** over with the 2-point correlation function and by **~80%** over FLI on the convergence map reconstructed with KS inversion.
- Mass reconstruction amplifies noise and mixes E/B-modes at mask edges, shifting the inferred parameters; FLI on the shear map bypasses this reconstruction step and avoids the information loss.

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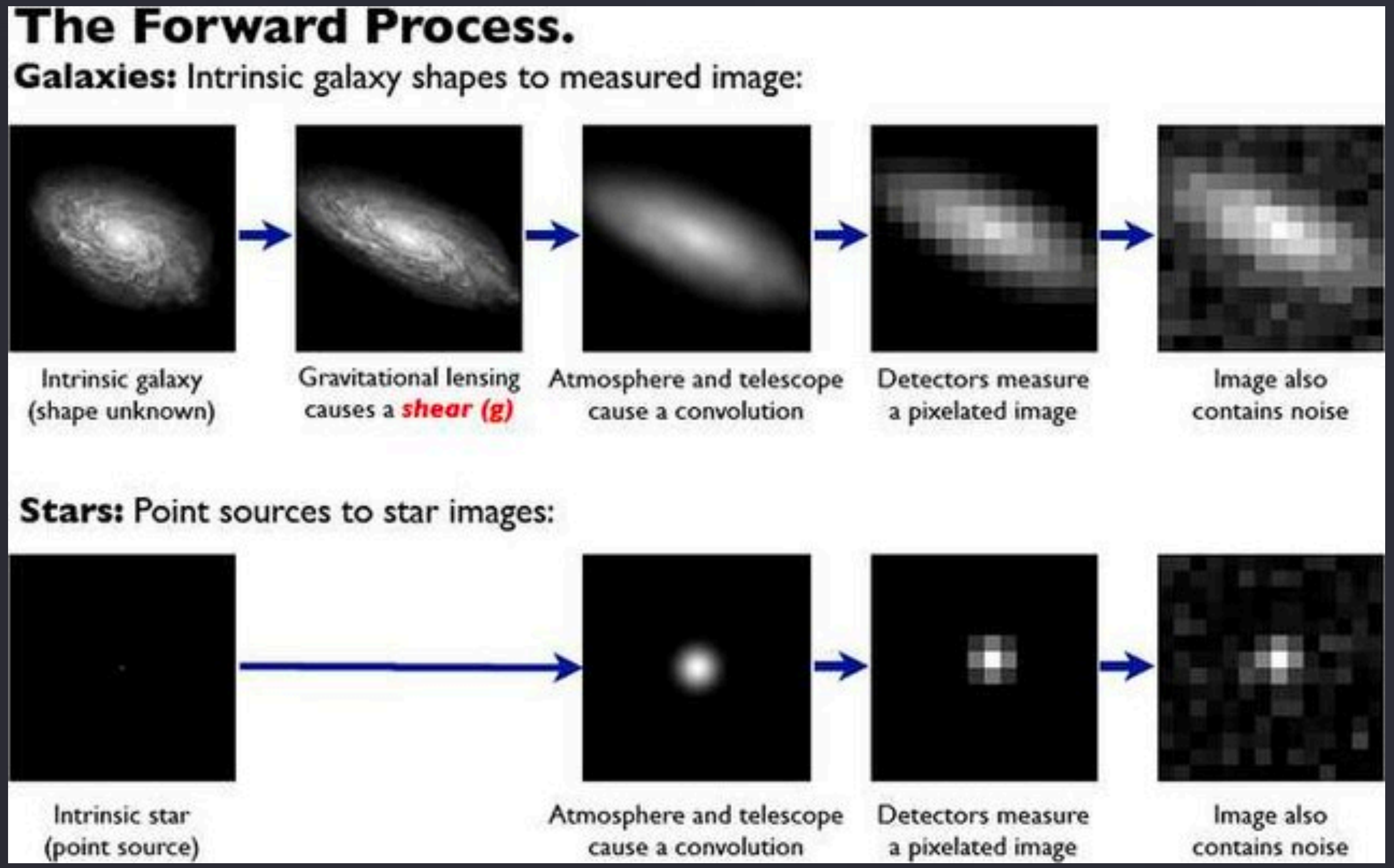
SECTIONS

Summary

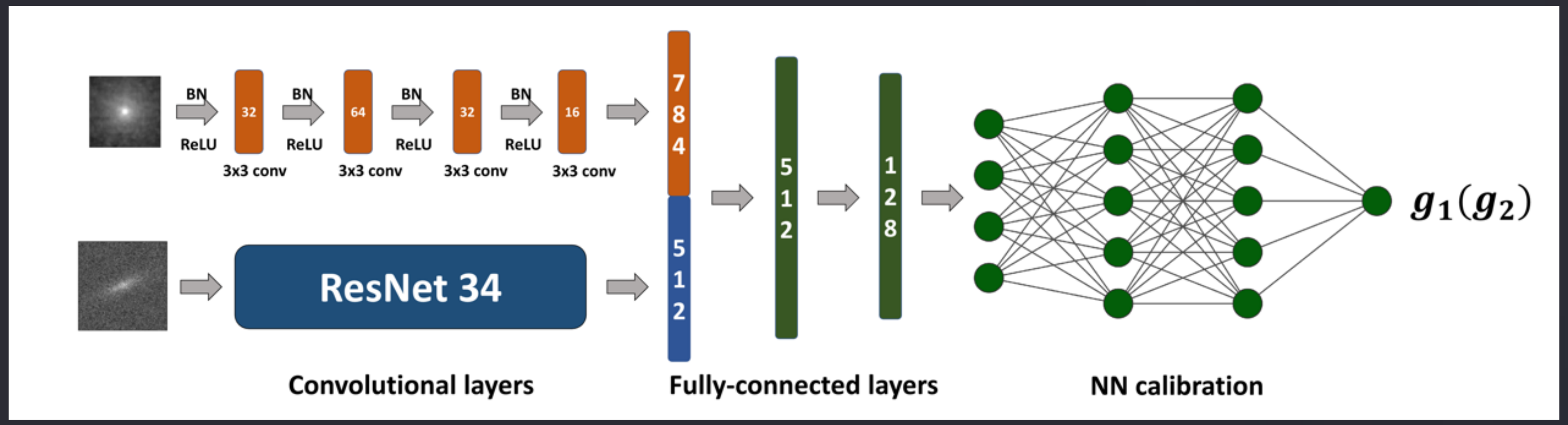
AI-Driven Weak Lensing Cosmology

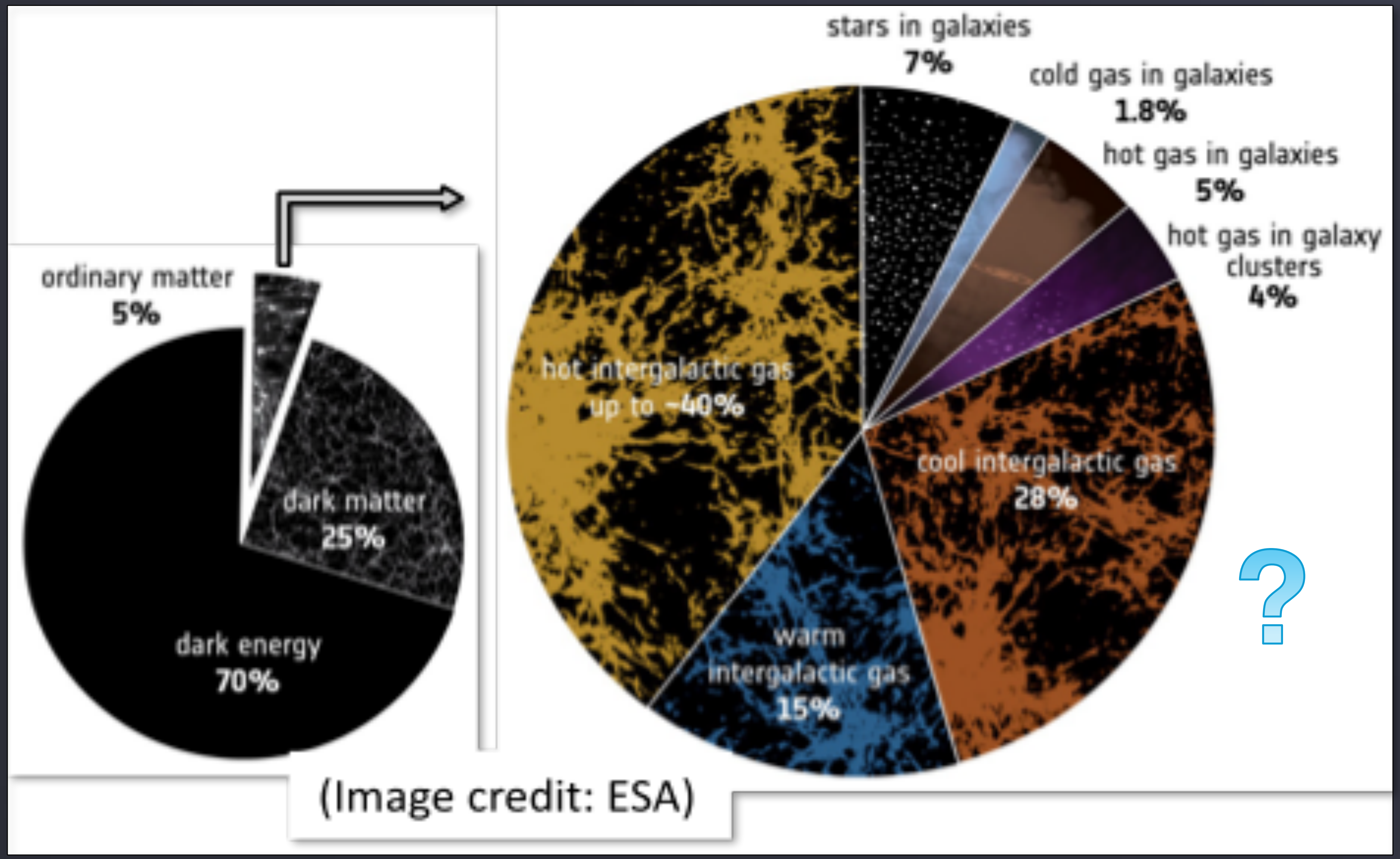


High-efficiency & **High-precision**

Shear Measurement:

Deep Learning Pipeline **Forklens**

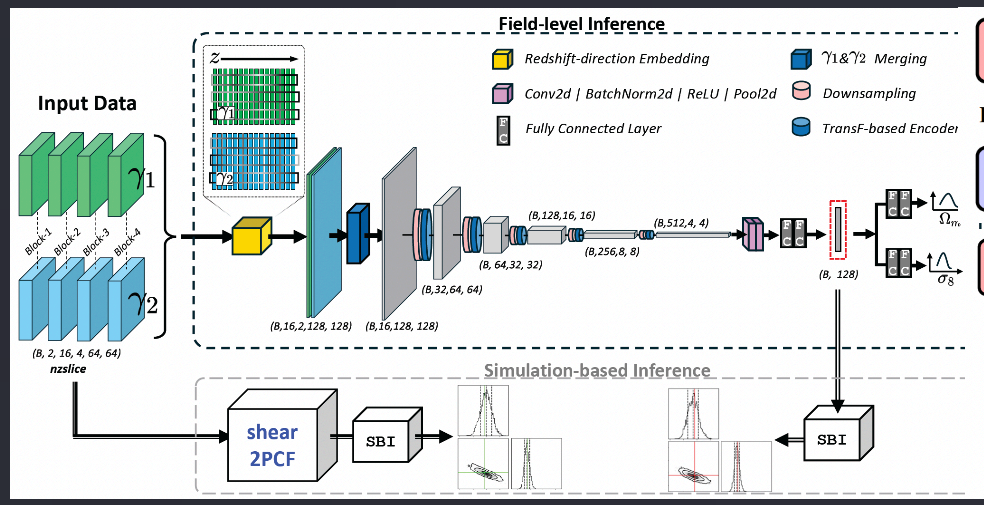


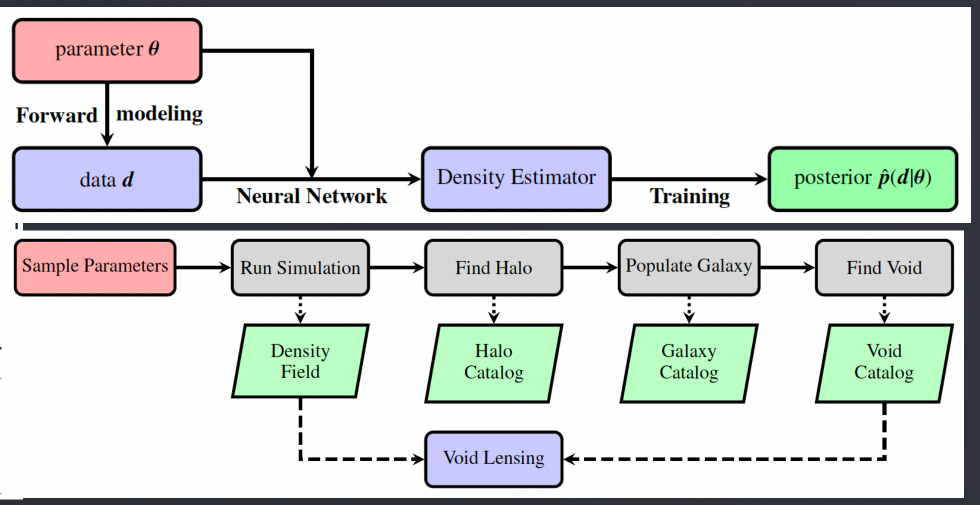


Maximizing Accurate & Precise

Cosmological Information Extraction:

Field-Level and Simulation-Based Inference





THANKS