Constraining Dark Energy with Strong Lenses and Machine Learning

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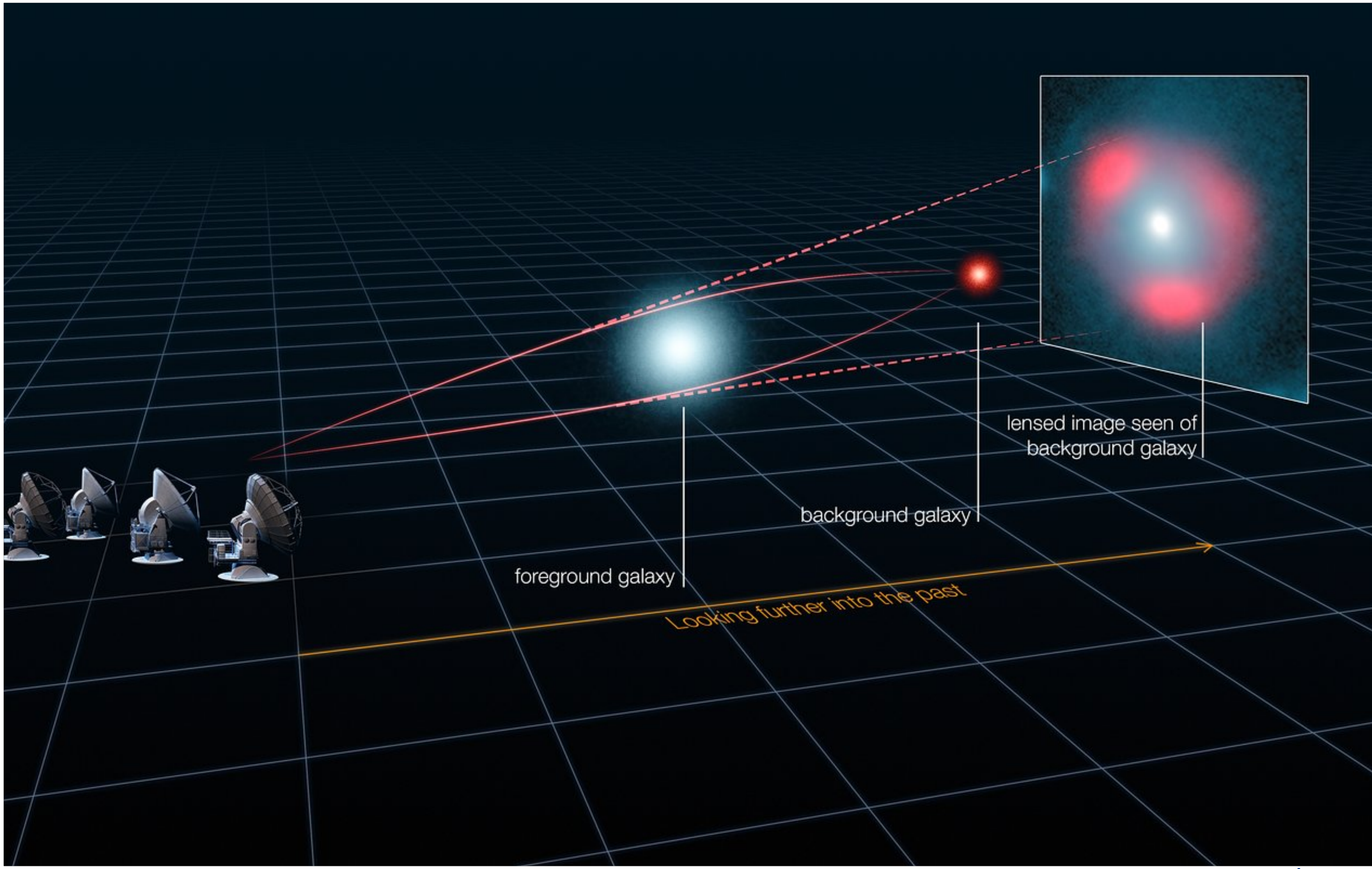
Strong Gravitational Lensing



Credit: ESA

Cosmology from Static Strong Lenses

- Combining the mass measurement within Einstein radius θ_E from lensing and stellar velocity measurements σ_v, the cosmology can be constrained through distance ratio $\frac{D_{ls}}{D_s}$

Velocity dispersion

$$\theta_E = 4\pi \left(\frac{\sigma_v}{c}\right)^2 \frac{D_{ls}}{D_s}$$

Einstein Radius

Distance Ratio

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$$D = f(z, H_0, \Omega_m, w)$$

Angular Diameter distance (D)

Redshift (z)

Hubble constant (H_0)

Dark matter density (Ω_m)

Dark energy equation of state parameter (w)

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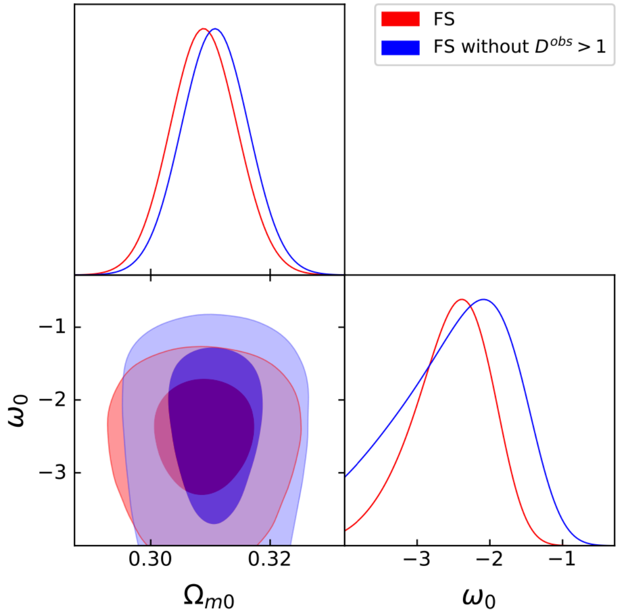
Constraints from 204 strong lens observations using MCMC



Amante et al. 2020

Challenges for Cosmology Inference

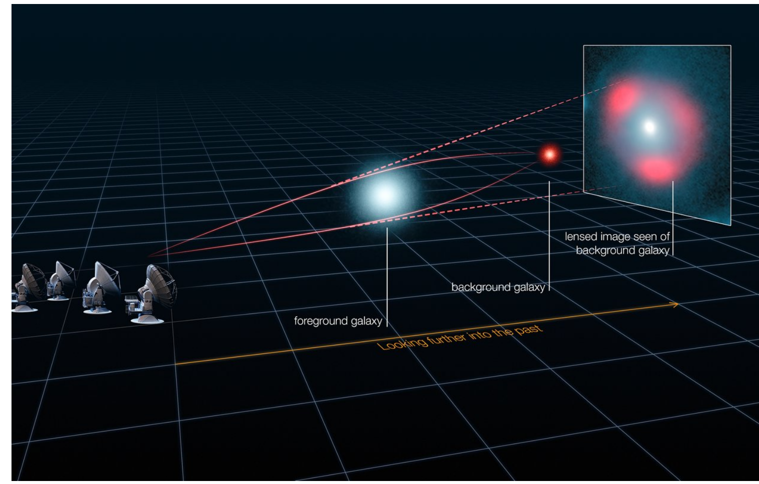
- Likelihood is intractable

Likelihood

$$p(w\,|\,x) = \frac{p(x\,|\,w)}{p(x)}\,p(w)$$

Posterior

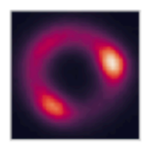
Prior



Intractable Likelihood

$$p(x\,|\,w) = \int p(x, \nu\,|\,w)\,d\nu$$

Observable x ← Detector/survey interactions ν ← Lens and source parameters ν ← Cosmology parameter w



Poisson noise, survey and detector properties

Lens and source ellipticity and positions, Sersic index, source radius, magnitude

Challenges for Cosmology Inference

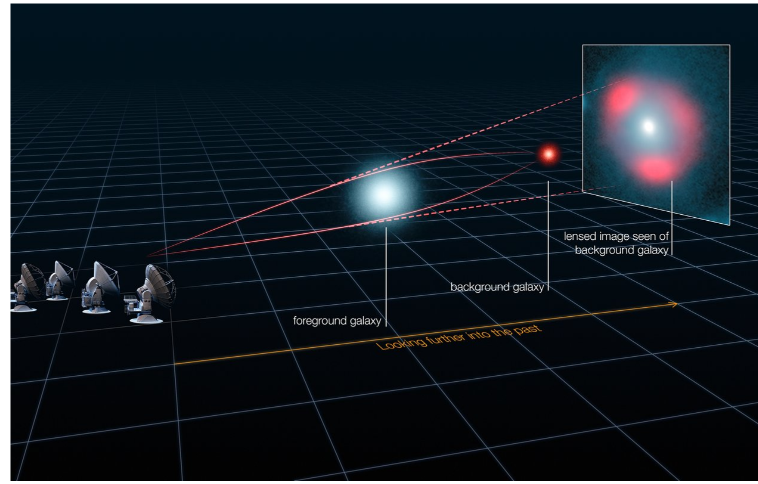
- Likelihood is intractable

$$p(w|x) = \frac{p(x|w)}{p(x)}p(w)$$

Likelihood: $p(x|w)$

Posterior: $p(w|x)$

Prior: $p(w)$



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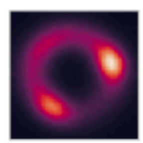

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Intractable Likelihood ⇨ Simulation Based Inference

Challenges for Cosmology Inference

- Likelihood is intractable
- $\mathcal{O}(10^5)$ strong lenses to be discovered from surveys with telescopes such as Rubin Observatory, Euclid, and Roman Space Telescope
- Traditional MCMC methods for inference are computationally prohibitive

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$\mathcal{O}(10^5)$ ⟹ Machine Learning

SBI : Neural Ratio Estimation (NRE)

- NRE is a classifier neural network to differentiate between the lens image-parameter pairs
  - $(x, w) \sim \ p(x, w)$ with class label y = 1
  - $(x, w) \sim \ p(x)p(w)$ with class label y = 0

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- The network learns the likelihood-to-evidence ratio

$$r(x \mid w) = \frac{p(x, w)}{p(x)p(w)} = \frac{p(x \mid w)}{p(x)}$$

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- The joint likelihood-to-evidence ratio from a population of strong lens observations $\{x\}$:

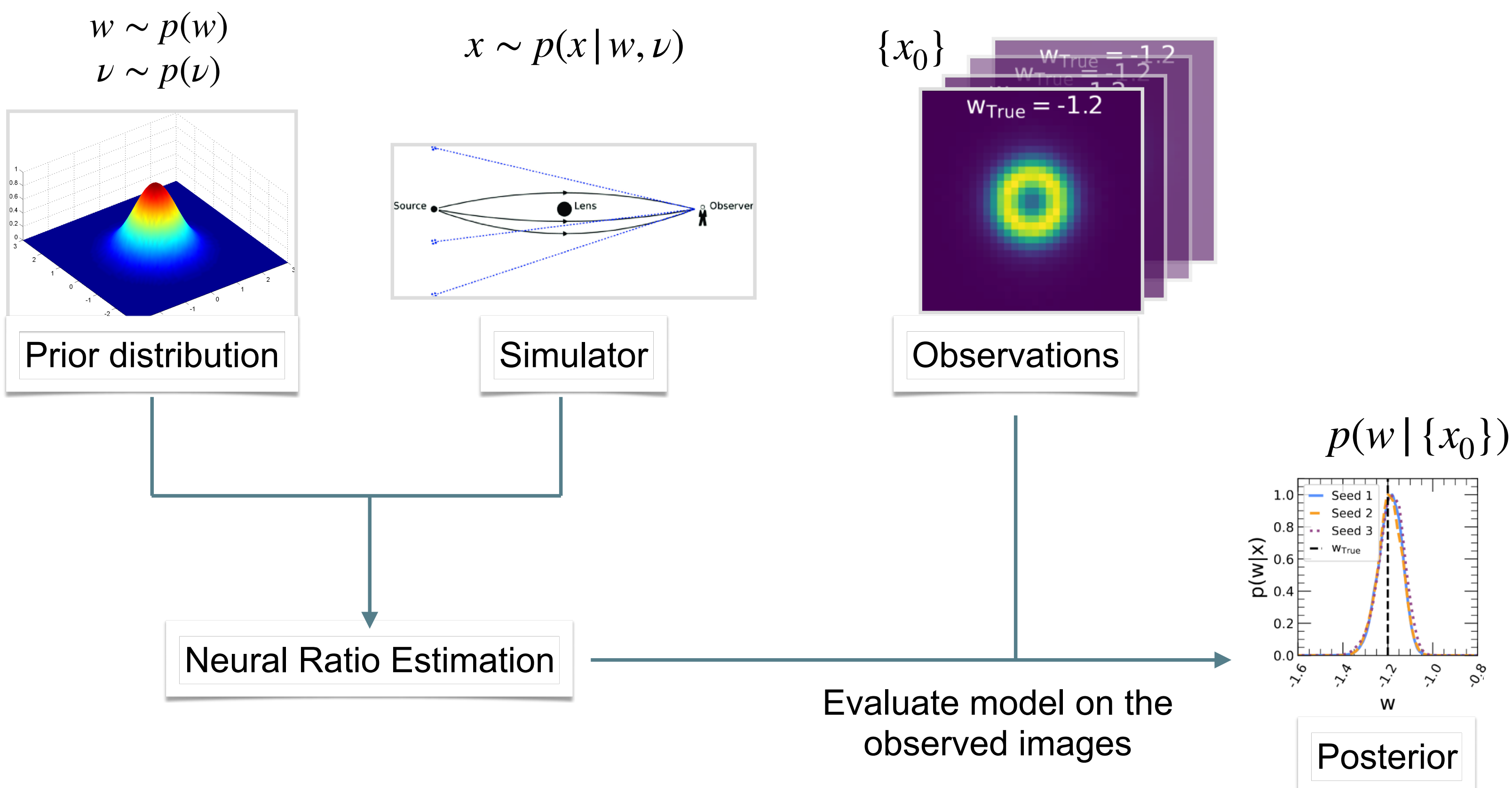
$$r(\{x\} \,|\, w) = \Pi_i \ r(x_i \,|\, w)$$

Posterior Inference of w

- Using the trained NRE model for posterior inference of w from a population of strong lens images
- Method 1 : MCMC sampling from $r(\{x\} \mid w)\, p(w)$
- Method 2 : Analytical calculation

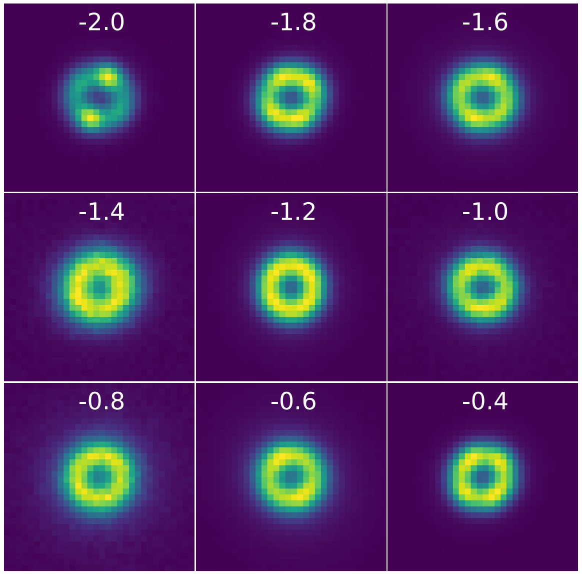
$$p(w \mid \{x\}) = \frac{p(w) \ \prod_i r(x_i \mid w)}{\int dw' \ p(w') \ \prod_i r(x_i \mid w')}$$

Neural Ratio Estimation workflow



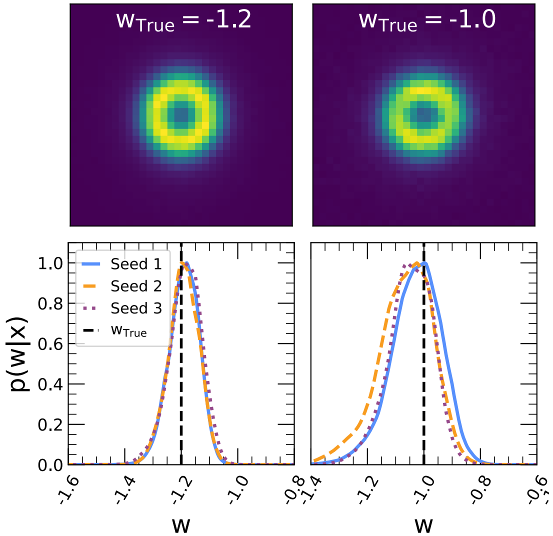
Dataset and Experimental Setup

- We simulate galaxy-galaxy strong lenses using Deeplenstronomy
- DES survey conditions with *g*-band images
- Image size : 32 x 32 pixels
- Prior: $w \sim \mathcal{U}(-2.0, -0.34)$
  - Training data: 640k images
  - Validation data: 160k images
  - Test data: 2k images
- $w = -1.2, -1.0, -0.8$
  - Test data: 3k images each



Sample set of images from training data

Fixing $z_l, z_s, \sigma_v, \Omega_m$



Posterior estimated using NRE on test data

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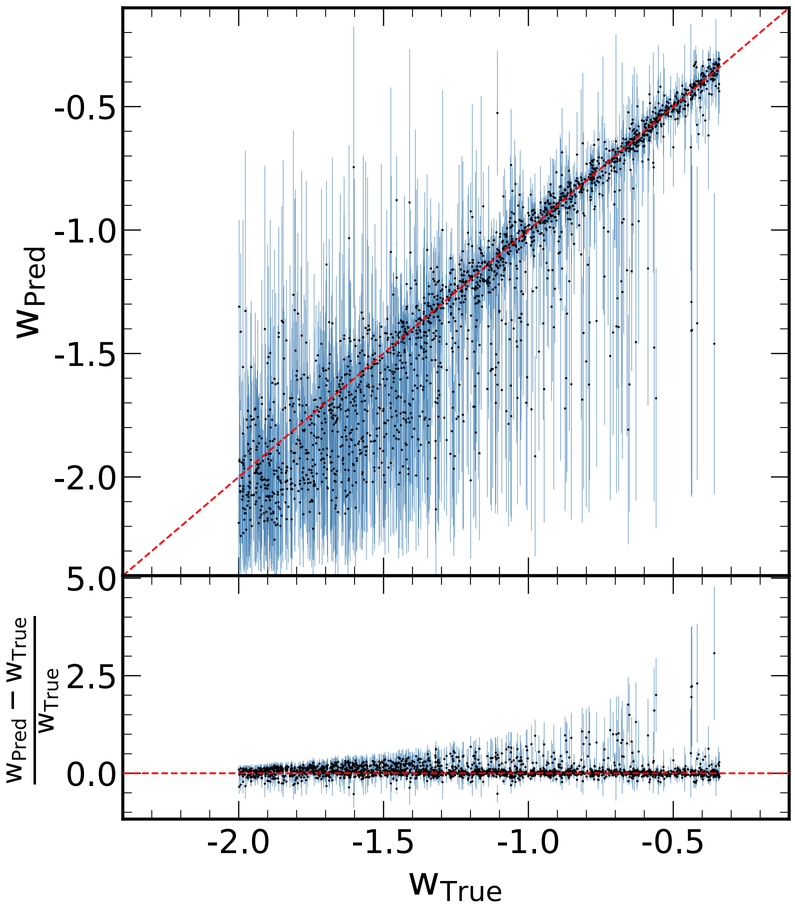
Results: Model Performance

- Robustness: Train the model with three different seed initializations
- Classifier Performance: The Area under the Receiver Operating Curve (AUC) ~ 0.92
- Model Calibration: The posterior coverage plot shows that the model is well calibrated

Results: Model Performance

The model can correctly predict w within 1σ for images which have high signal-to-noise ratio



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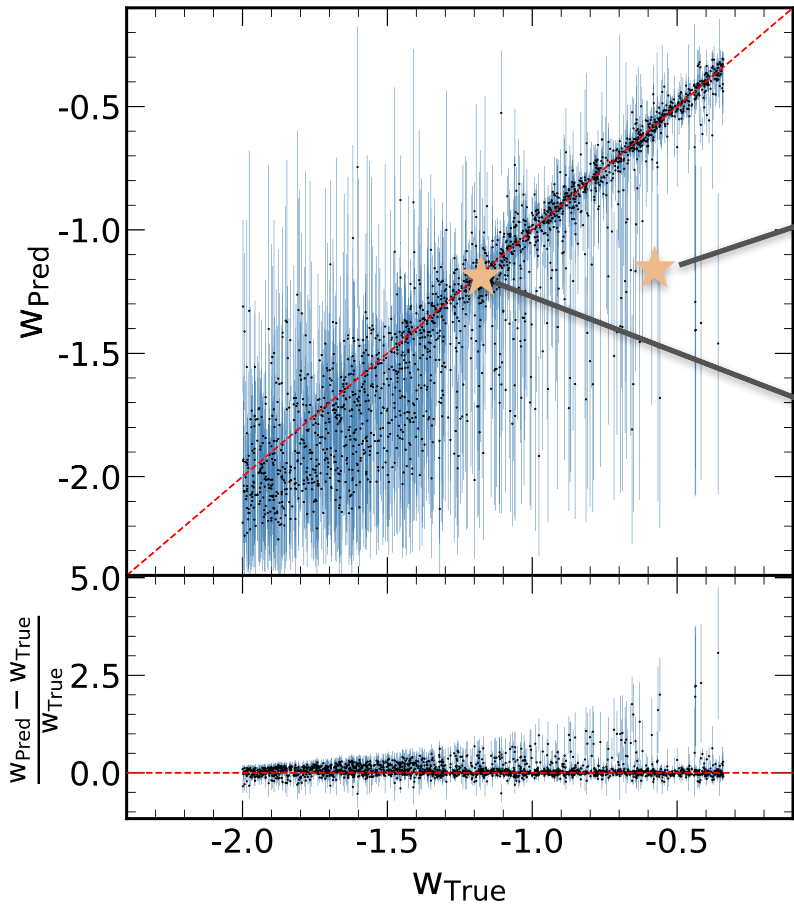
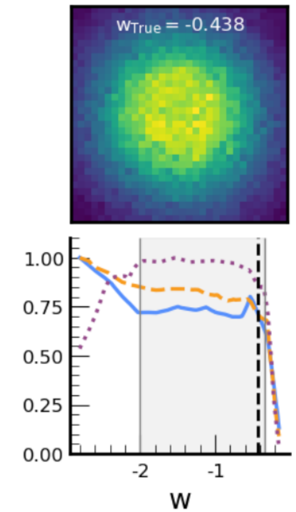
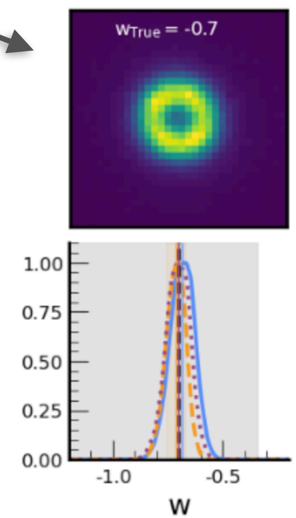
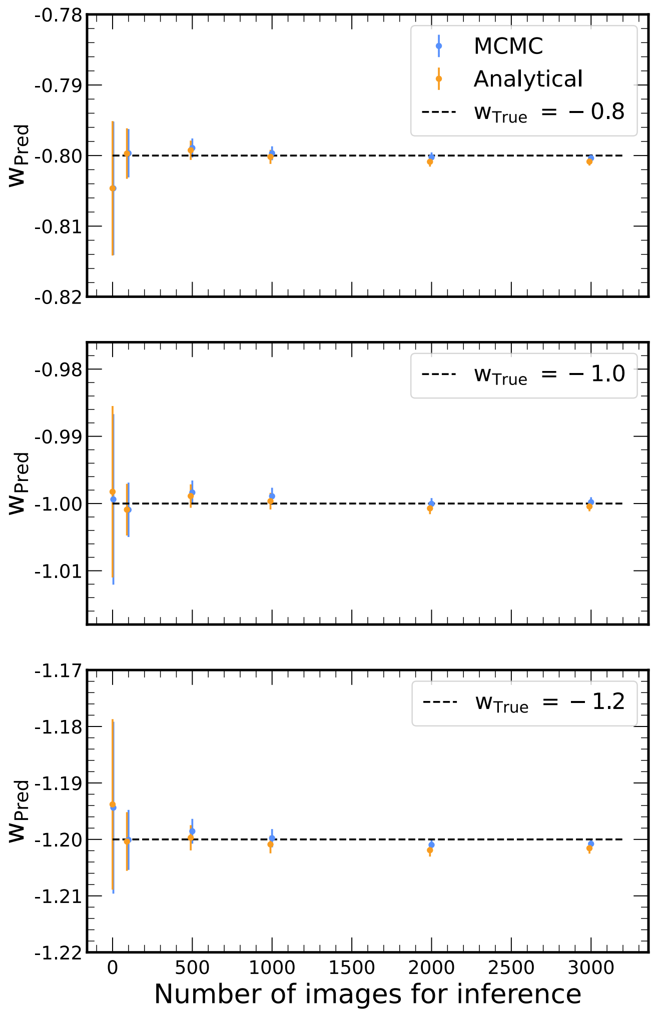






Results: Population-level w Inference

The posterior is more constrained as the number of observations in the population increase



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Summary and Conclusion

- We implemented SBI with NRE for the first time for population-level posterior inference of dark energy equation-of-state parameter from strong lens images.

- Robust and well calibrated model. Provides constraints on w within 1σ.

- The posterior is more constrained with an increasing number of observations in the inference.

- This analysis is crucial for analyzing the thousands of lenses from future surveys.

Extras

Cosmology from Static Strong Lenses

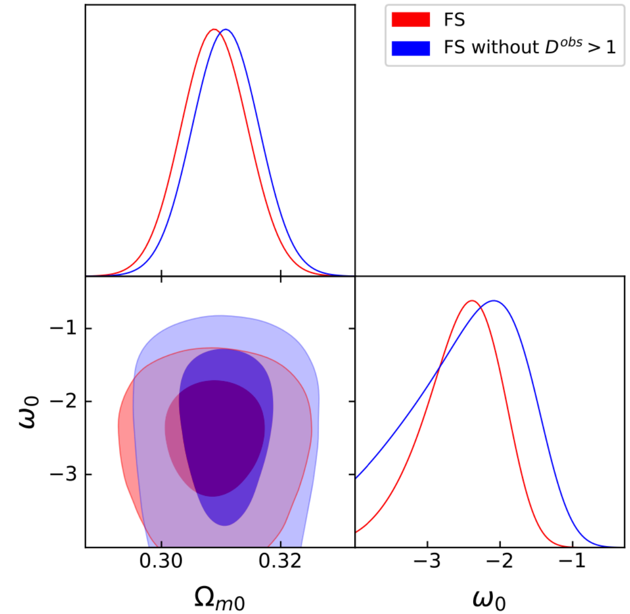
- Dark energy equation-of-state parameter w and Dark Matter density Ω_m constrain through distance ratio $\frac{D_{ls}}{D_s}$ from Einstein radius θ_E and stellar velocity dispersion σ_v

$$\theta_E = 4\pi \left(\frac{\sigma_v}{c}\right)^2 \frac{D_{ls}}{D_s}$$

$$D(z, H_0, \Omega_m, w) = \frac{1}{1+z}\frac{c}{H_0}\int_0^z \frac{dz'}{h(z', \Omega_m, w)}$$

$$h^2(z, \Omega_m, w) = \Omega_m(1+z)^3 + (1-\Omega_m)(1+z)^{3(1+w)}$$

Constraints from 204 strong lens observations using MCMC



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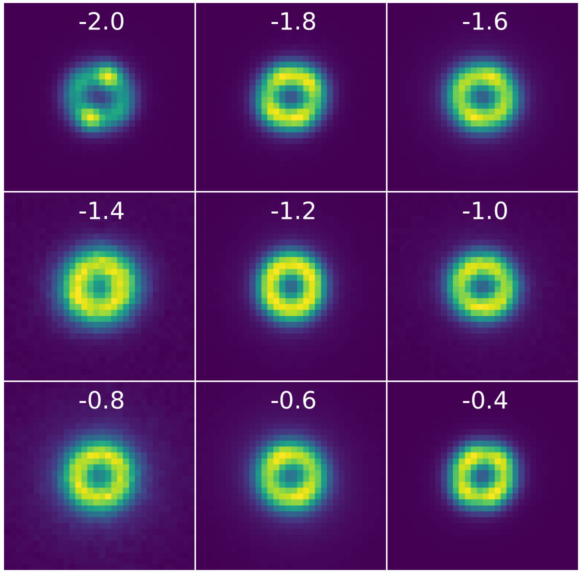
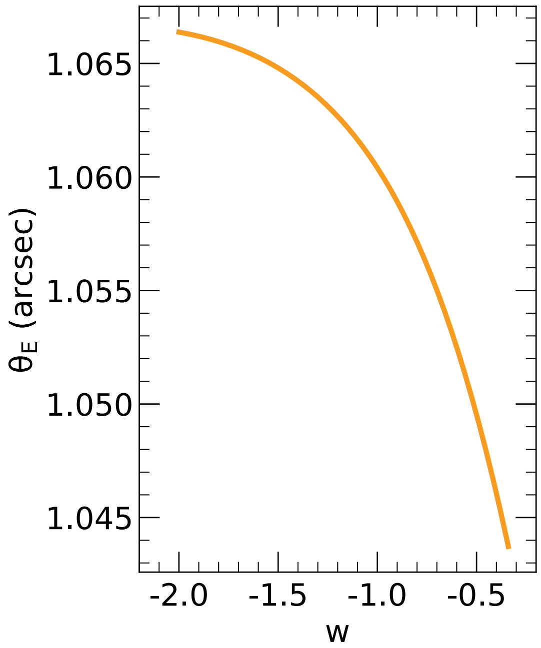


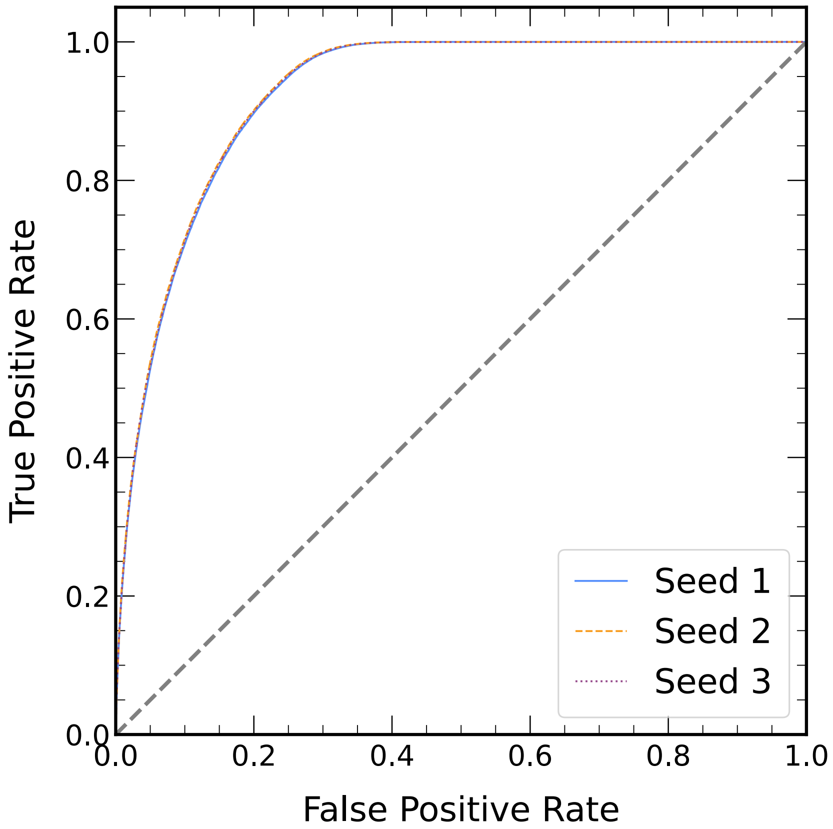
Sample set of images from training data



Correlation between Einstein Radius θ_E and w.
The variation in θ_E is larger at high-w

Results: Model Performance

- We run the model training with three different seed initializations to check robustness
- The Area under the Receiver Operating Curve (AUC) ~ 0.92
- Model can differentiate between the two classes $p(x, w)$ and $p(x)p(w)$



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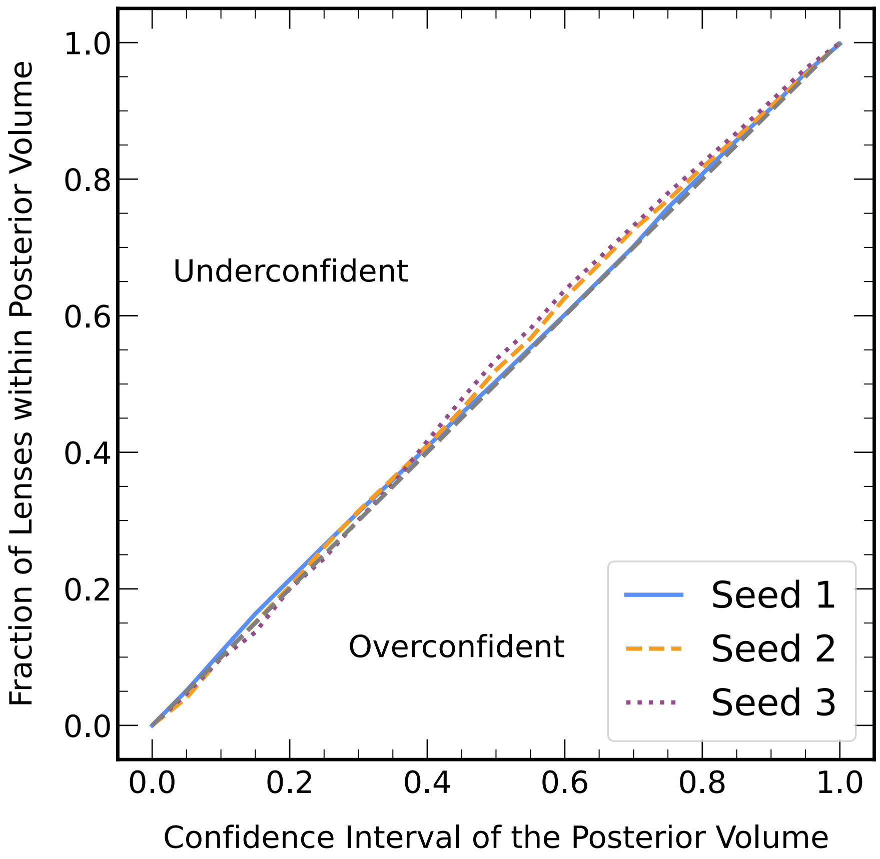
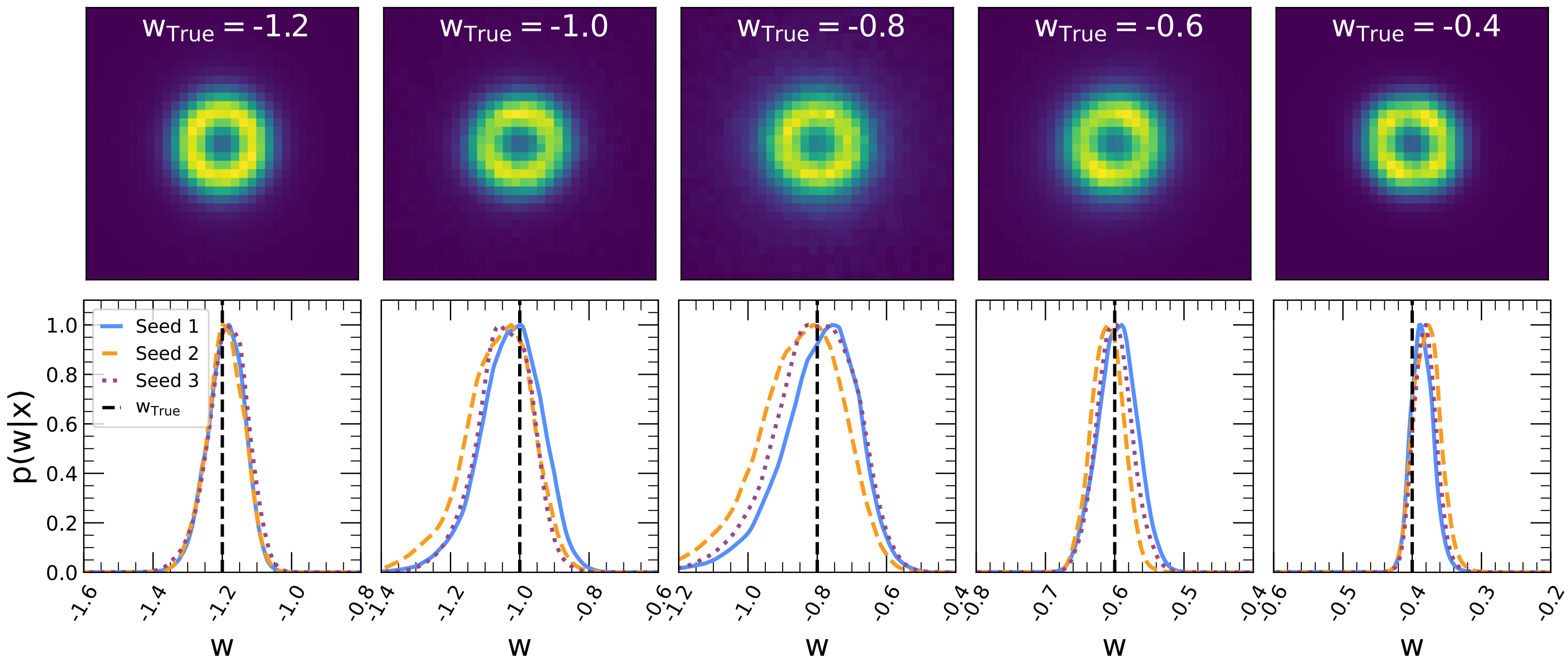
Results: Model Performance

- The posterior coverage plot shows that the model is well calibrated



Results



Posterior obtained from single observation using NRE

Results: Population-level w Inference

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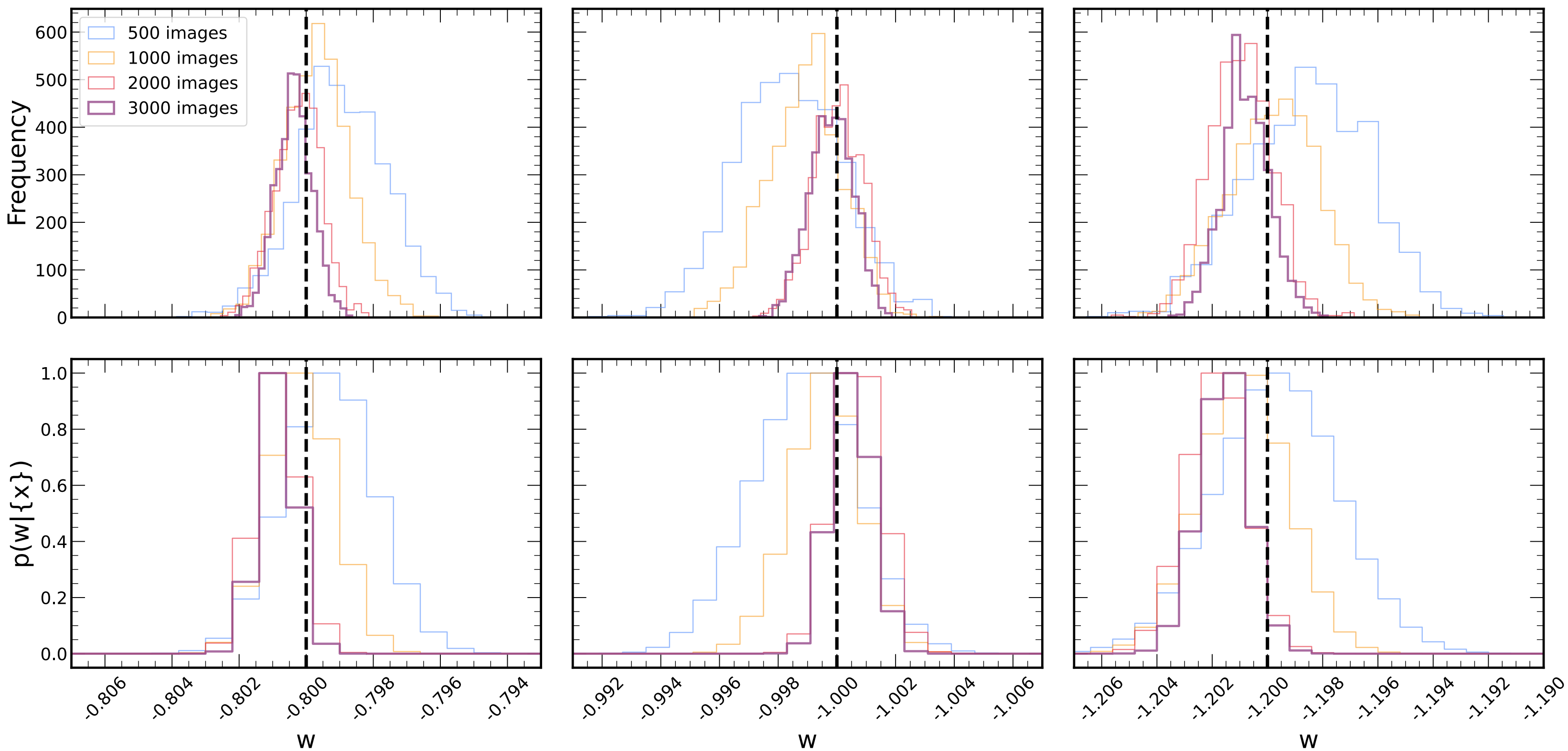

The posterior inference $p(w \mid \{x\})$ from the joint population analysis of 500, 1000, 2000, and 3000 strong lens images using MCMC (Top) and Analytical method (Bottom)