Population-level Dark Energy Constraints from Strong Gravitational Lensing using Simulation Based Inference

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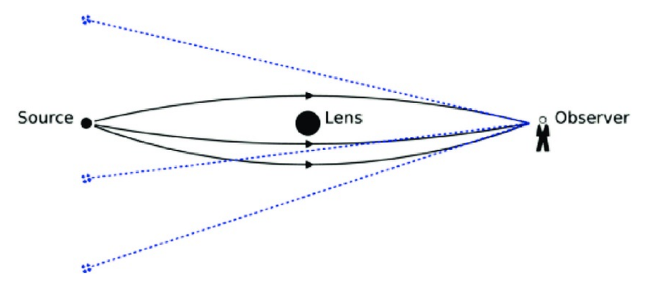
Introduction

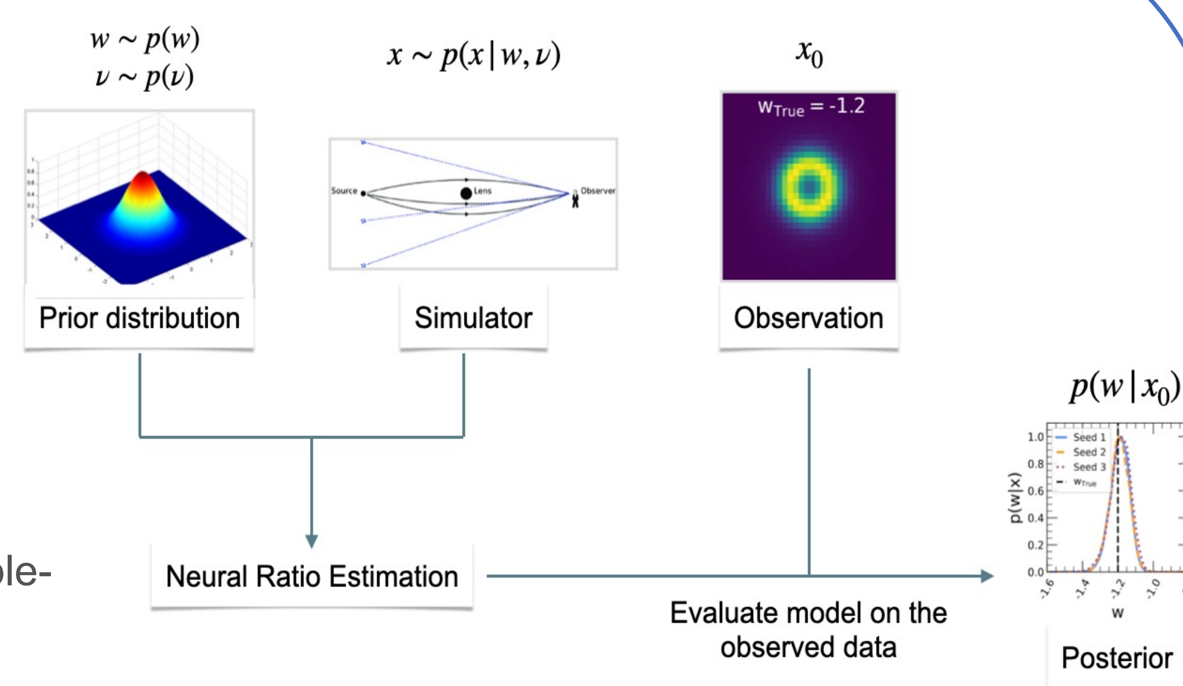
- Strong Gravitational Lensing offers crucial insights into Cosmology like Dark Energy and Dark Matter.



- Thousands of lenses are predicted to be observed from future surveys like LSST. Traditional Monte Carlo methods are computationally prohibitive for cosmological inference from this big data.
- We present a scalable approach for dark energy equation-of-state parameter (w) inference from a population of strong gravitational lens images using **Simulation Based Inference** (SBI) with **Neural Ratio Estimation** (NRE).
- We obtain better constraints on w from population-level inference compared to individual lens analysis, constraining w to within 1σ.

Simulation based Inference

- Simulation Based Inference (SBI) is a statistical method where simulated data is used for the inference of model parameters at the observed data.
- SBI is particularly useful for posterior inference when the likelihood is intractable and is amortized



Neural Ratio Estimation

NRE is a classifier to differentiate between sample-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

The network learns likelihood-to-evidence ratio

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

NRE facilities inference of parameters common across a population of observations $\{x\}$. The joint likelihood is written as

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

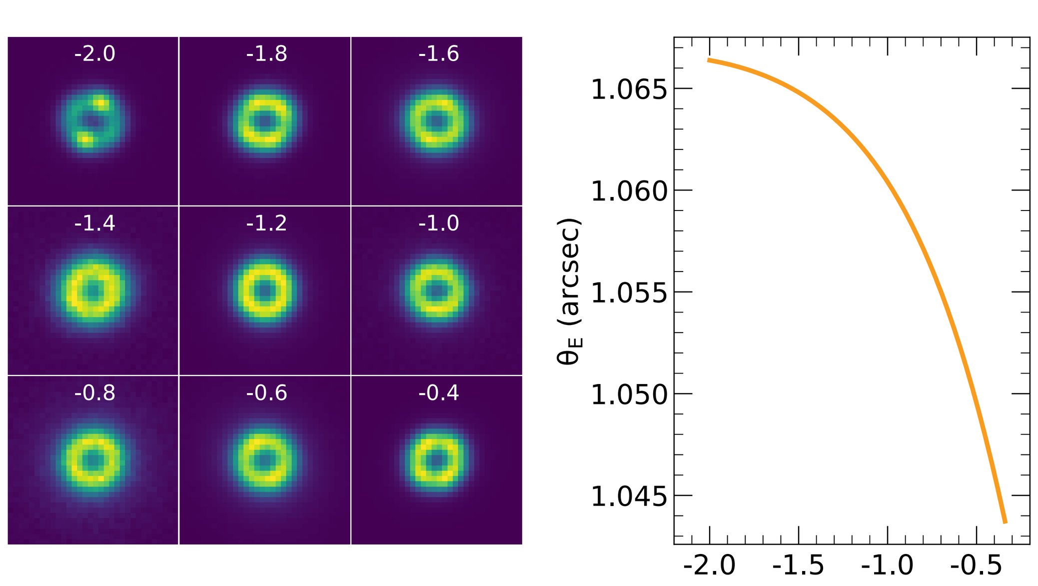
Population-level Posterior Inference

- Method 1: MCMC sampling of the joint likelihood using Metropolis-Hastings algorithm
- Method 2: Analytical calculation using the joint likelihood

$$p(w|\{x\}) = \frac{p(w)\Pi_i r(xi|w)}{\int dw' p(w')\Pi_i r(xi|w')}$$

Dataset

- We simulate galaxy-galaxy strong lenses using Deeplenstronomy [1]. The lenses are approximated by singular isothermal ellipsoid (SIE) lens profile and the source light profile by Sersic.
- Simulations are generated with Dark Energy Survey (DES) conditions using single band and image size of 32 x 32 pixels.
- Observable x : Strong lens image
  Parameter of interest w : dark energy equation-of-state parameters
  Nuisance parameters ν: lens and source ellipticity, source magnitude, effective radius, and Sersic index.



Left: A sample of simulated strong lens images for different w values.
Right: The correlation between the Einstein Radius of the lens image and w

- **Training and validation Data:**

640000 and 160000 images respectively simulated from uniform prior $w \sim U(-2.0, -0.34)$

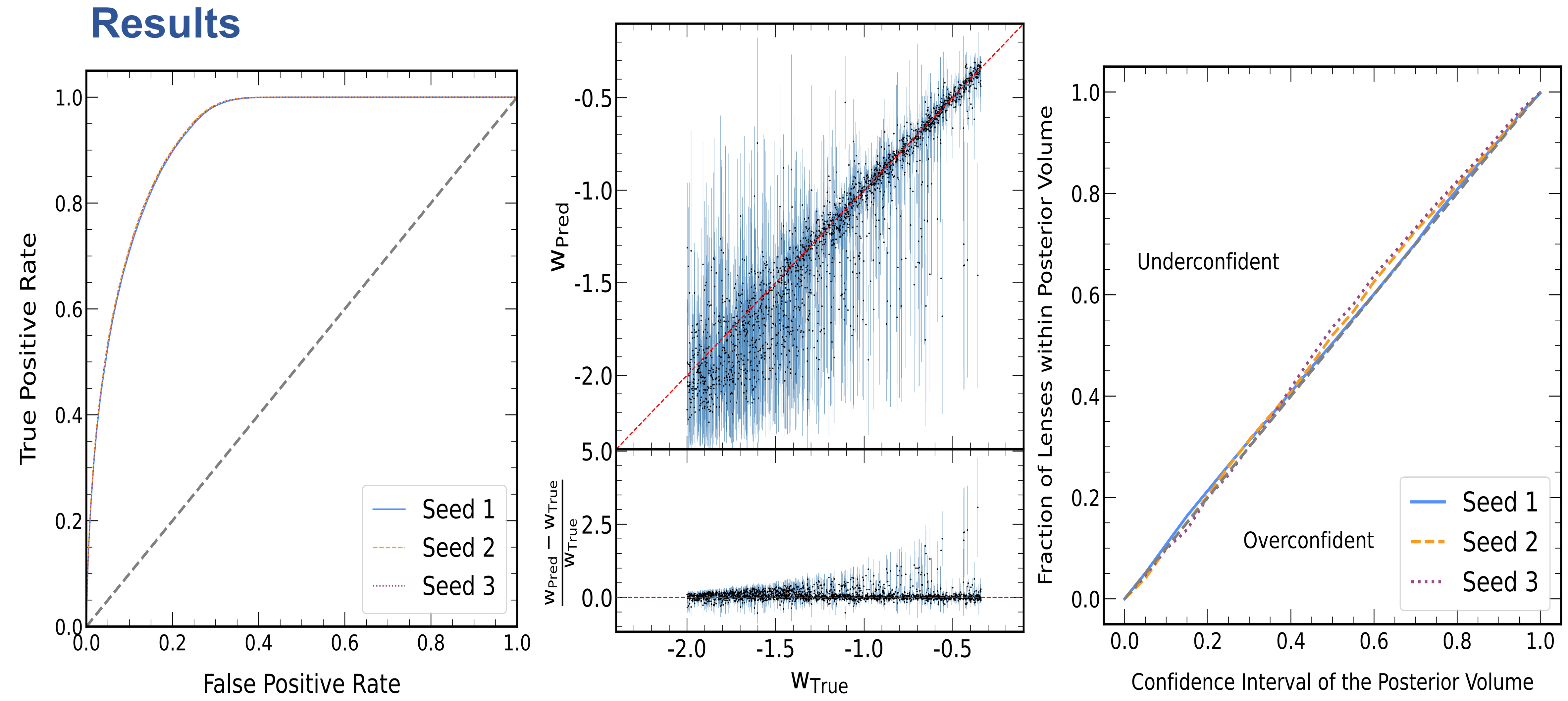
- **Test Data:**

2000 images simulated from uniform prior $w \sim U(-2.0, -0.34)$
3000 images generated with fixed w = -1.2, -1.0, -0.8 across all images respectively.

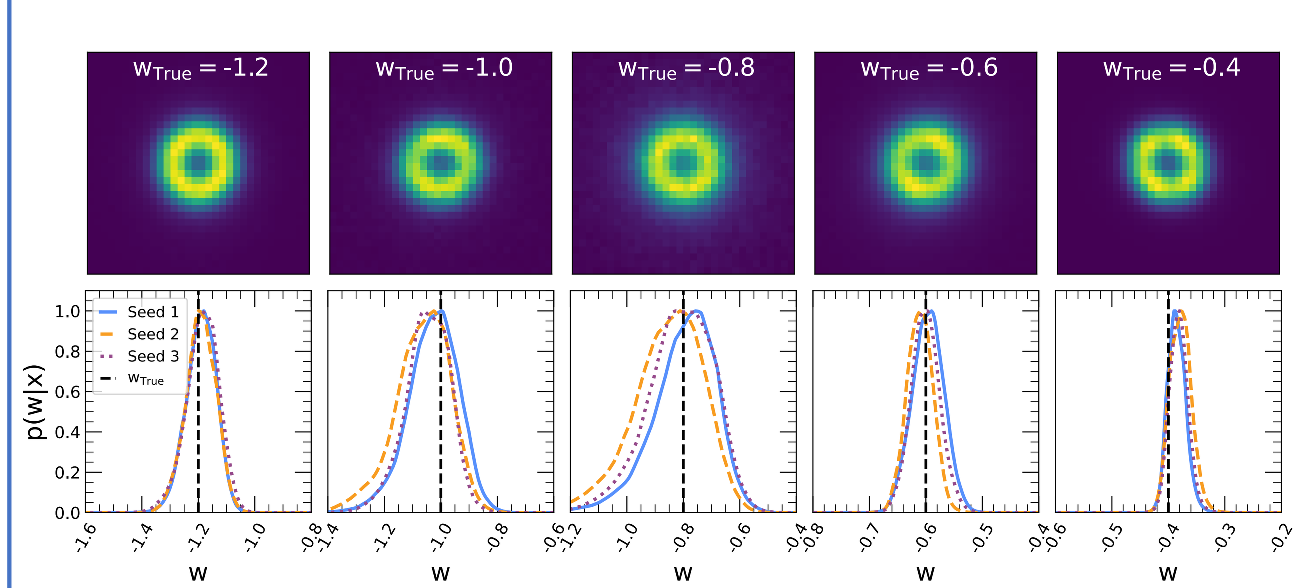
Experimental Details

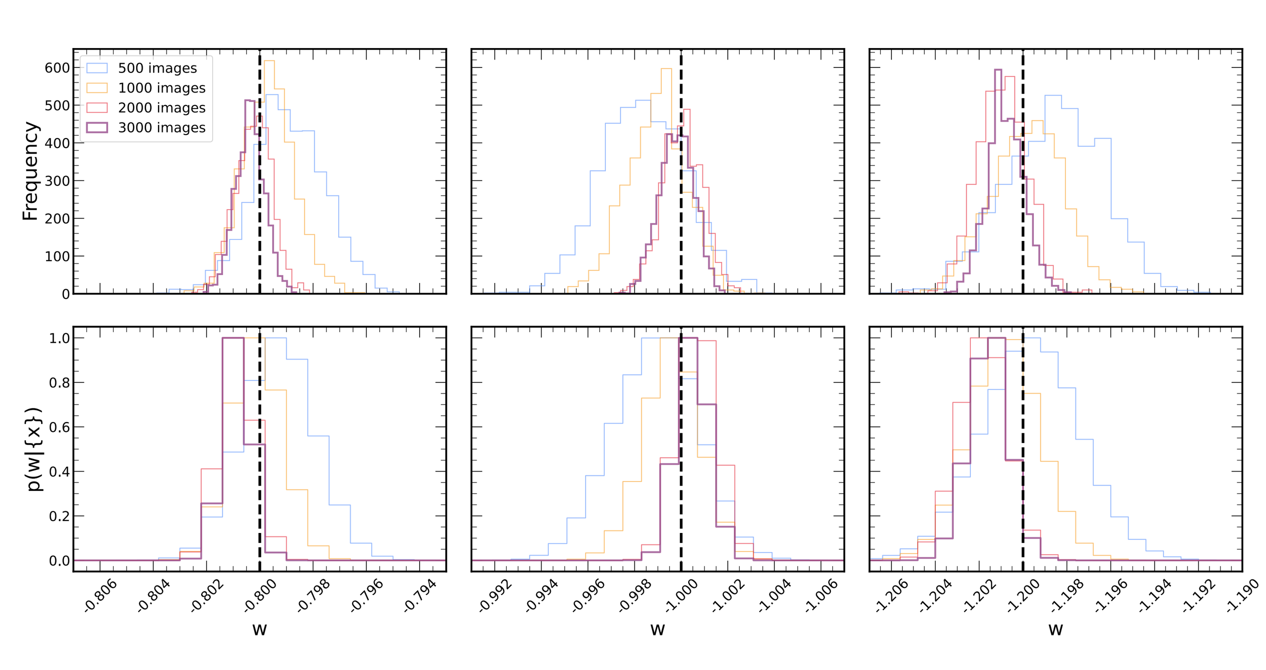
NRE is a classifier network with ResNet Architecture. The model is trained using Binary Cross Entropy Loss Function with Adam optimizer

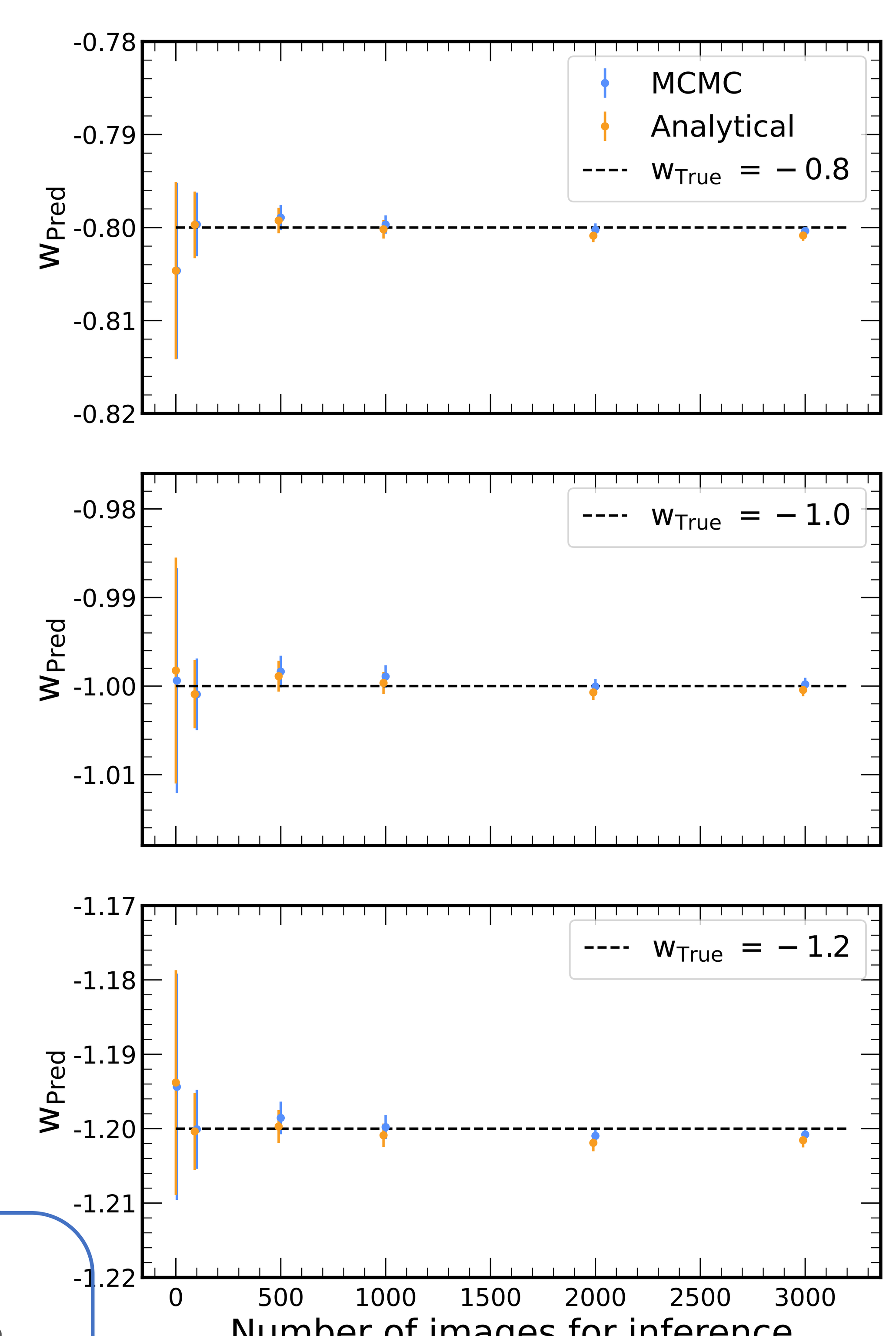
Results



Left: The ROC curve for three models with different weight initializations. The AUC ~ 0.92 **Middle Top:** The parity plot showing true Vs predicted w with 1σ error. **Middle Bottom:** The bias plot with scaled error. Red line shows expected value. Right: The posterior coverage plot for three models showing that the model is well-calibrated.







Conclusions

- The model is well calibrated irrespective of the weights initialization
- We perform population-level analysis by estimating the posterior using the joint likelihood-to-evidence ratio. We observe that the posterior width decreases with an increasing number of observations in the inference population.

References: [1] Morgan, R., et al. deeplenstronomy: A dataset simulation package for strong gravitational lensing The Journal of Open Source Software, 6(58):2854, February 2021. doi: 10.21105/joss.02854. [2] Hermans, J., Begy, V., and Louppe, G. Likelihood-free mcmc with amortized approximate ratio estimators, 2020. [3] Zhang, G., et. al. Inferring subhalo effective density slopes from strong lensing observations with neural likelihood-ratio estimation. MNRAS, 517(3):4317–4326, December 2022. doi:10.1093/mnras/stac3014

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