Keywords: hierarchical Bayesian models, posterior inference, density estimation, uncertainty quantification, calibration
Task: supervised Bayesian image regression (image ➔ distribution over 10s of floating-point parameters)
Cosmic frontier

Large-Scale Gravitational Lens Modeling with Bayesian Neural Networks for Accurate and Precise Inference of the Hubble Constant

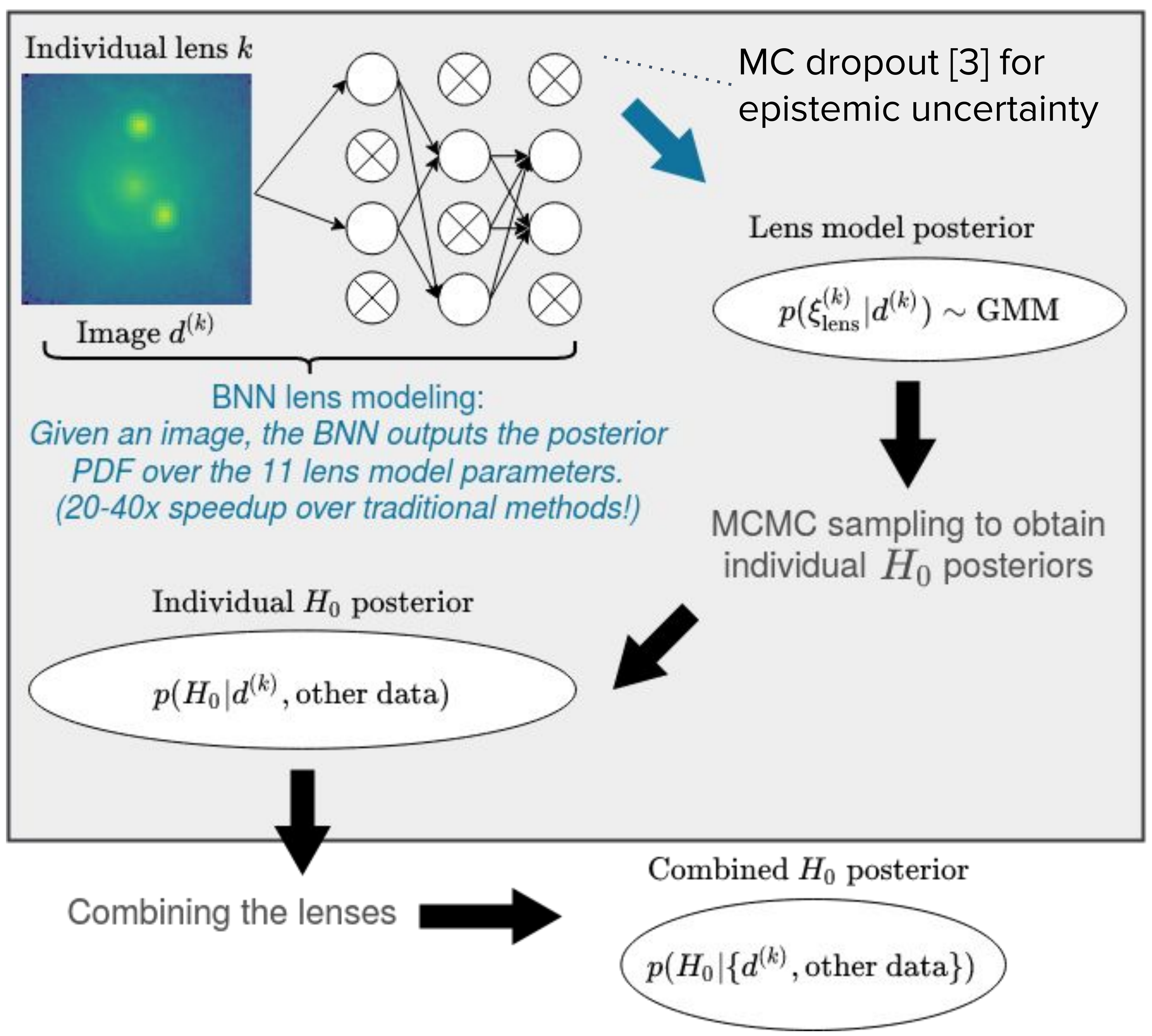
astro-ph.IM arXiv:2012.00042

Ji Won Park (jwp@stanford.edu), Sebastian Wagner-Carena, Simon Birrer, Philip J. Marshall, Joshua Yao-Yu Lin, Aaron Roodman (with LSST DESC)

Abstract

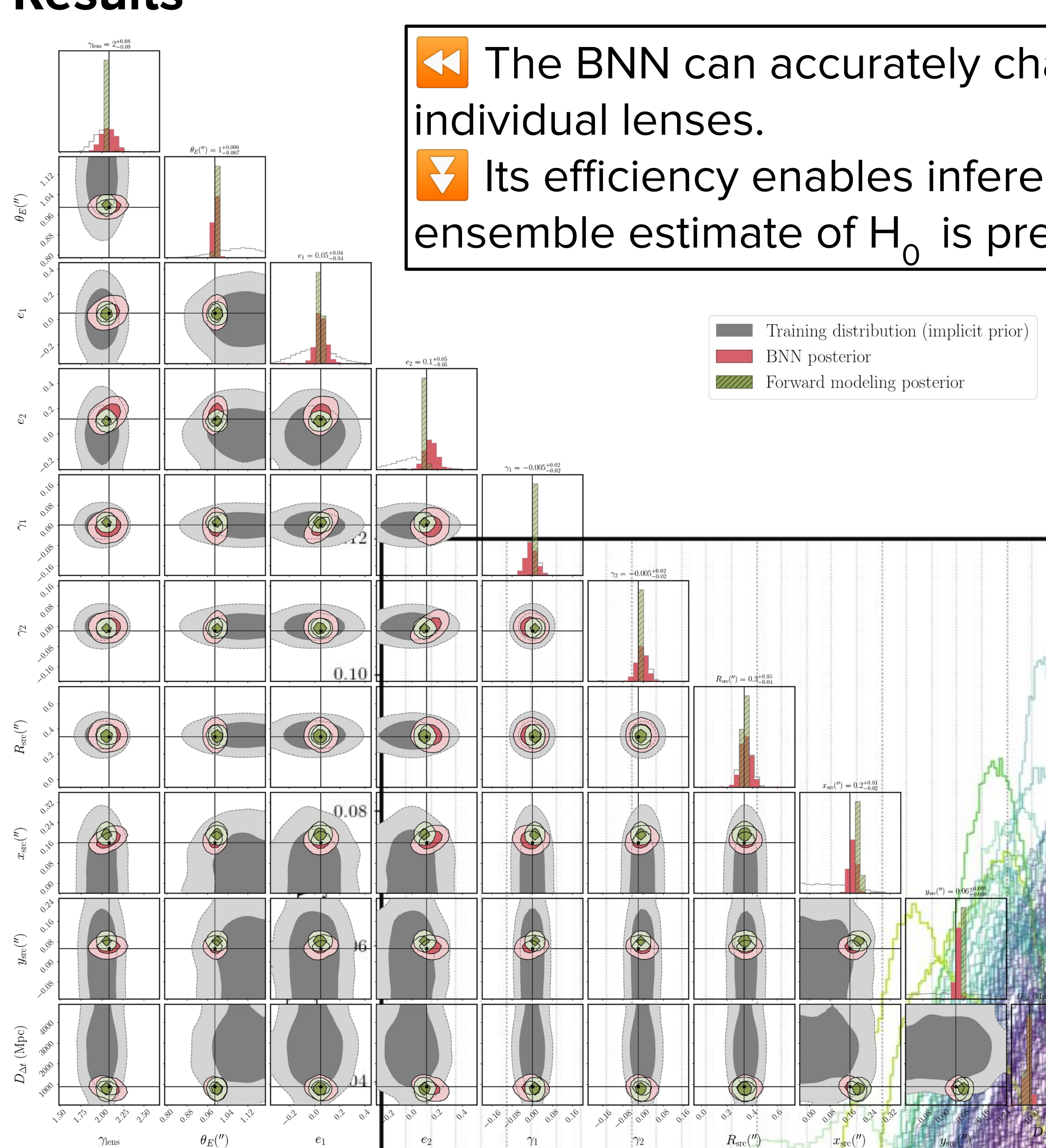
Strong gravitational lensing is a valuable probe of the Hubble Constant (H_0), fully independent of other probes. Seven lenses have been "hand-analyzed" over a 10-year program [1] but the Rubin Observatory Legacy Survey of Space and Time (LSST) will discover thousands more [2]. We use Bayesian neural networks (BNN) to rapidly model a simulated set of 200 lenses and propagate the resulting posterior PDFs toward H_0 inference. A simple combination of the lenses results in a precise (0.7%) recovery of the input truth H_0, with no evidence of bias. Being accurate and efficient, the BNN pipeline is a promising tool for including *all the lenses* in large-scale hierarchical inference.

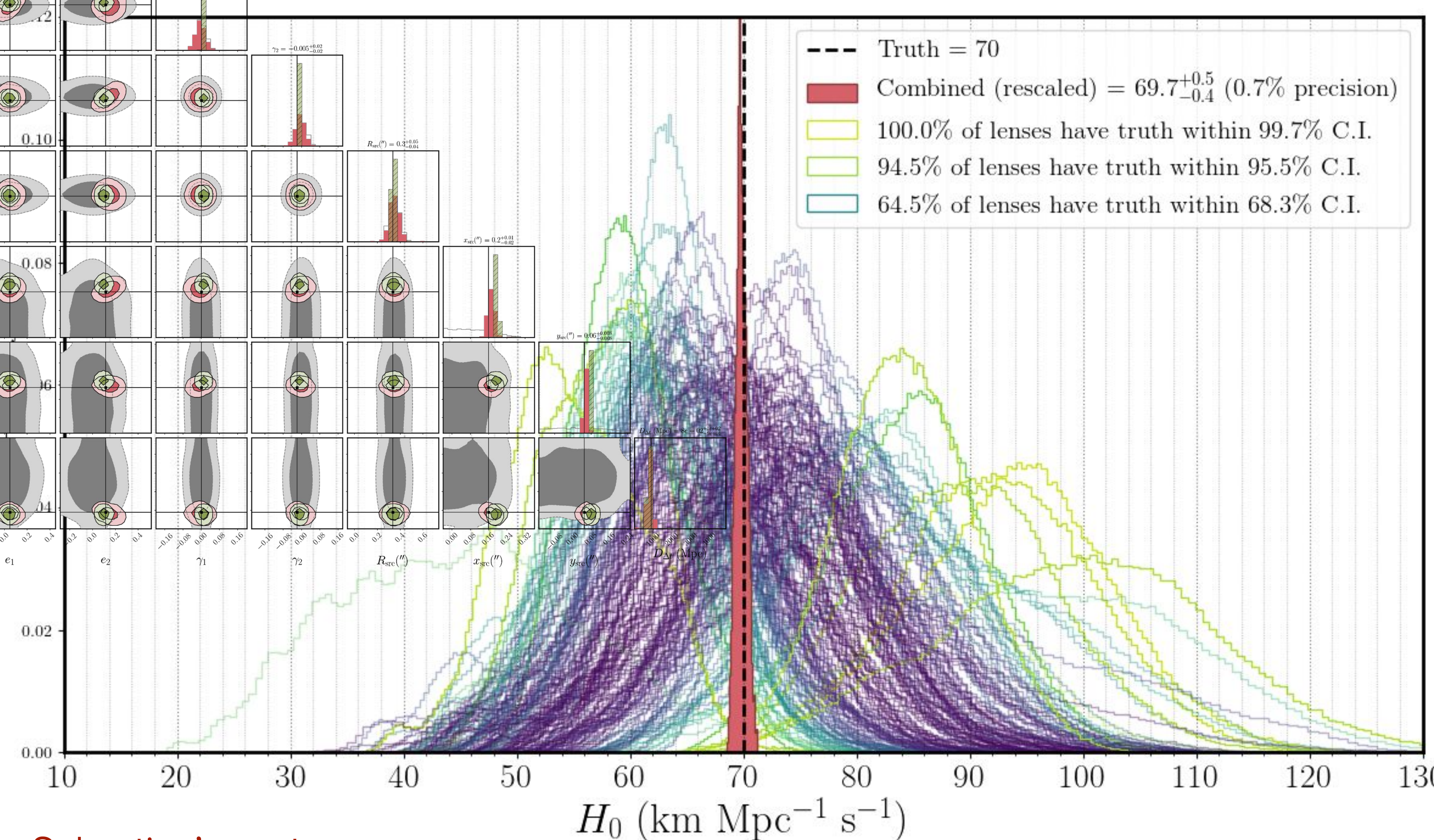
Method



Results

⏪ The BNN can accurately characterize the posterior PDFs of individual lenses.
⏬ Its efficiency enables inference over a large sample size. The ensemble estimate of H_0 is precise and unbiased.





Next steps (collaborators welcome!)

- Hierarchical inference of population hyperparameters (not just H_0)
- More flexible density estimators (e.g. flow-based models)
- Alternative estimators of the epistemic uncertainty (e.g. ensembles)
- More complex lens models (bigger target space)

See Sebastian's poster on hierarchical inference with BNNs!

Interested in our code and data?

- Our pipeline is implemented using H0rton, a public Python package (https://github.com/jiwoncpark/h0rton).
- Datasets, model weights, and inference results are on Zenodo: DOI 10.5281/zenodo.4300382

References

[1] Birrer, S., et al. *A&A* (2020).
[2] Oguri and Marshall. *MNRAS* (2010).
[3] Gal and Ghahramani. *PMLR* (2016).