Identifying Unphysical Source Reconstructions

https://arxiv.org/abs/2012.04665

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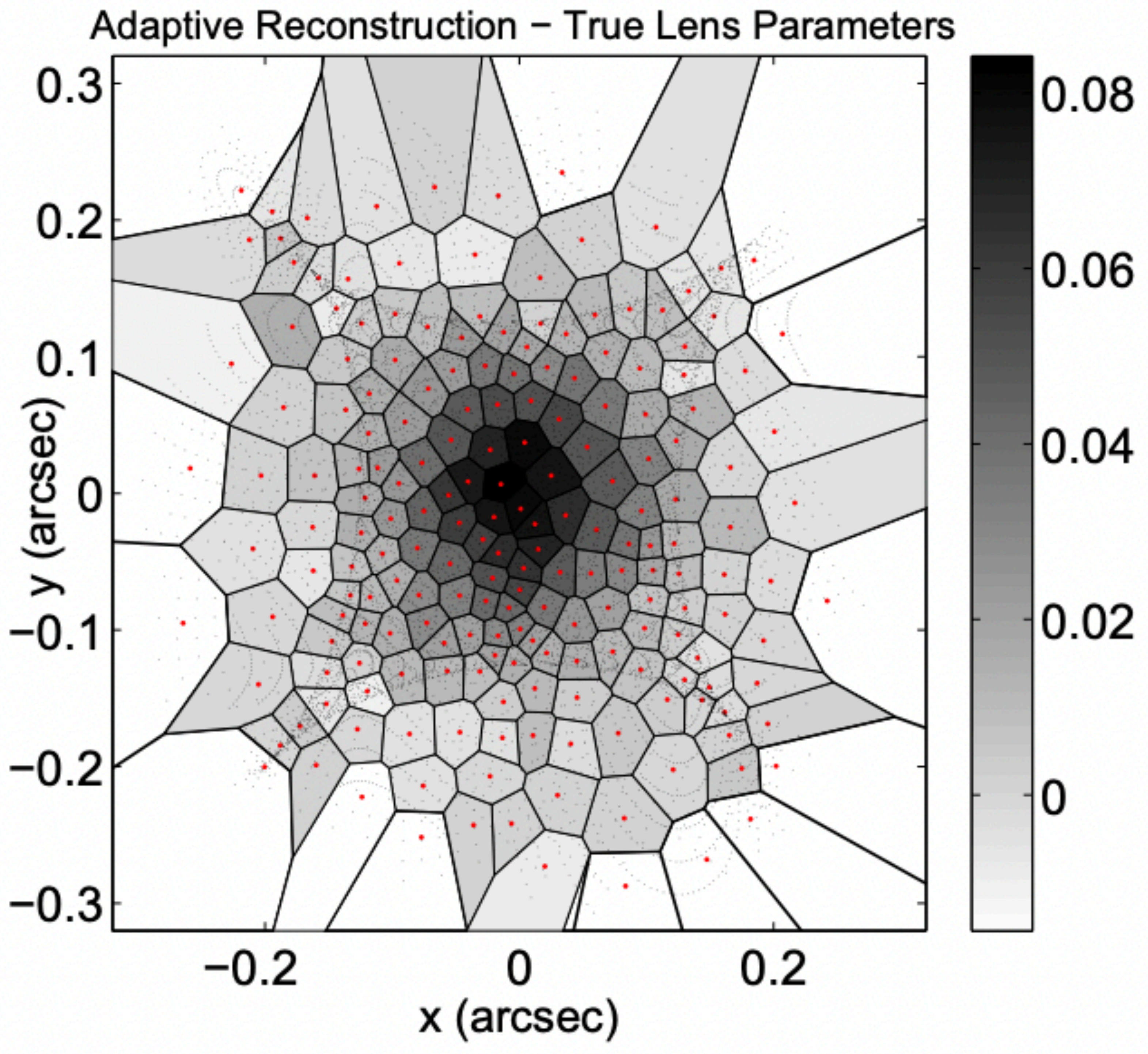
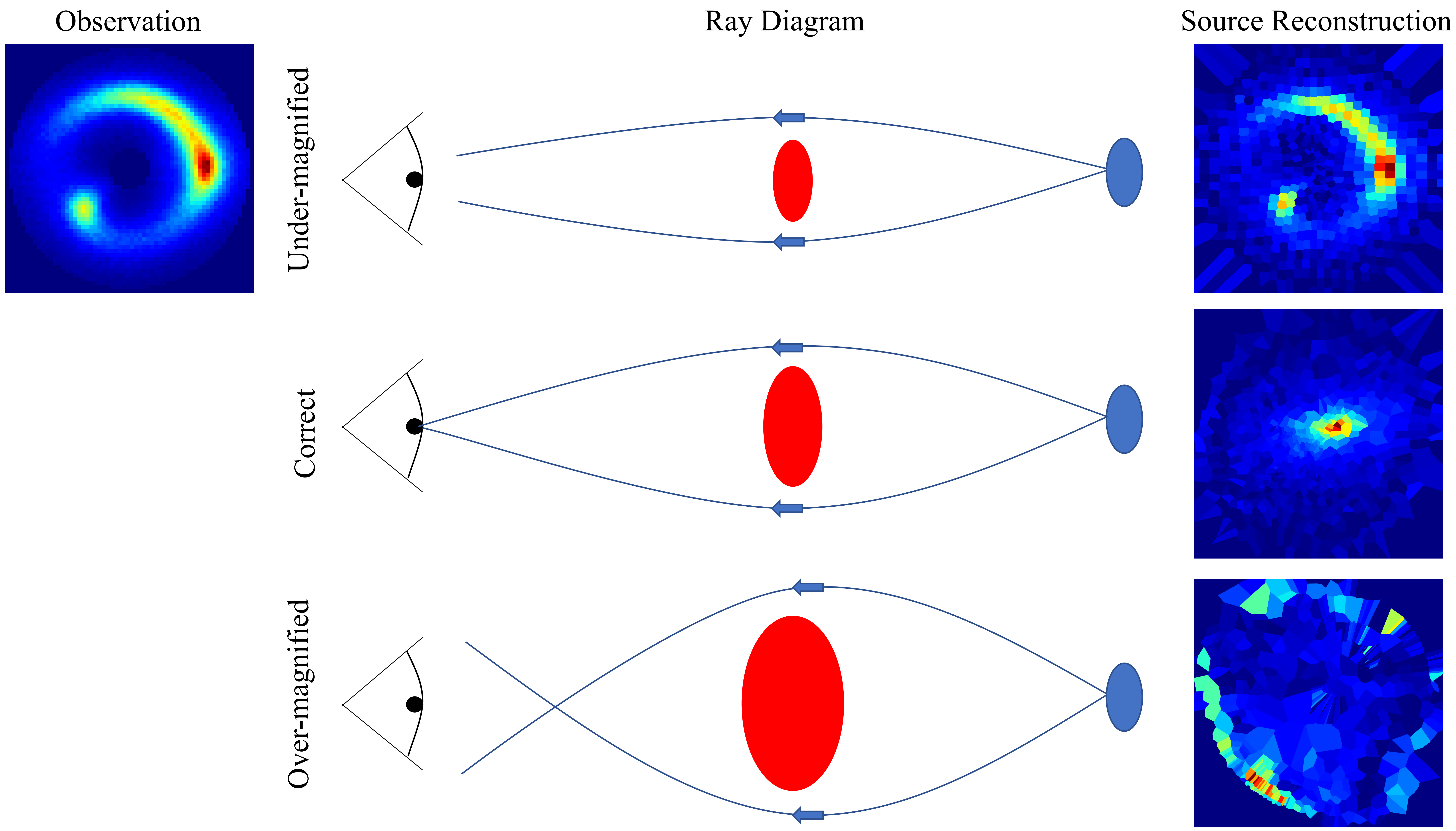
Pixelised Source Reconstructions

- Unconstrained by analytic profiles
- Adapt to lens magnification/source brightness
- Fewer non-linear parameters



Nightingale & Dye 2015

Under/Over Magnified Solutions

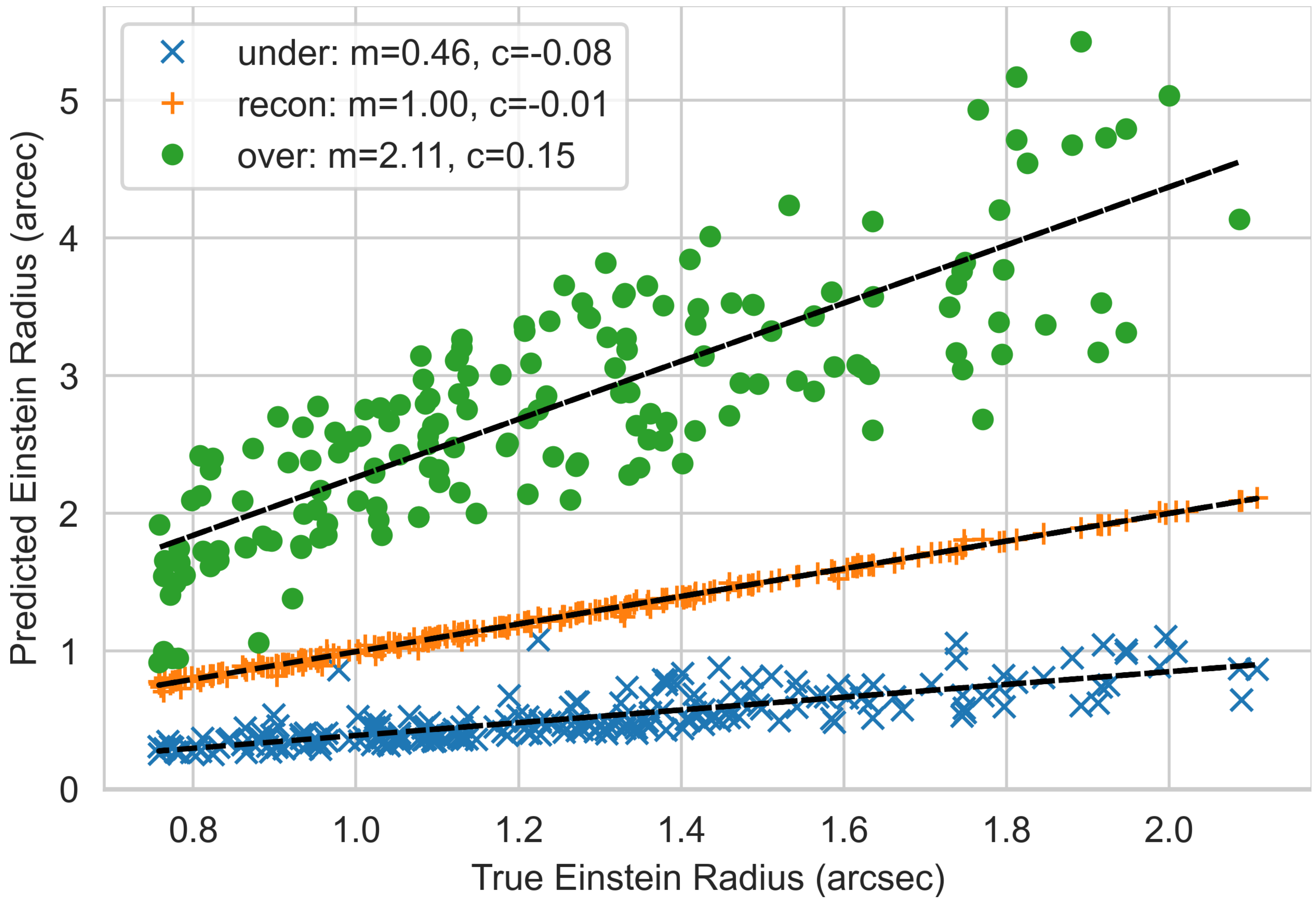


Parameter Space

- Under-magnified solutions exist at $\approx 0.5 \times \theta_E$

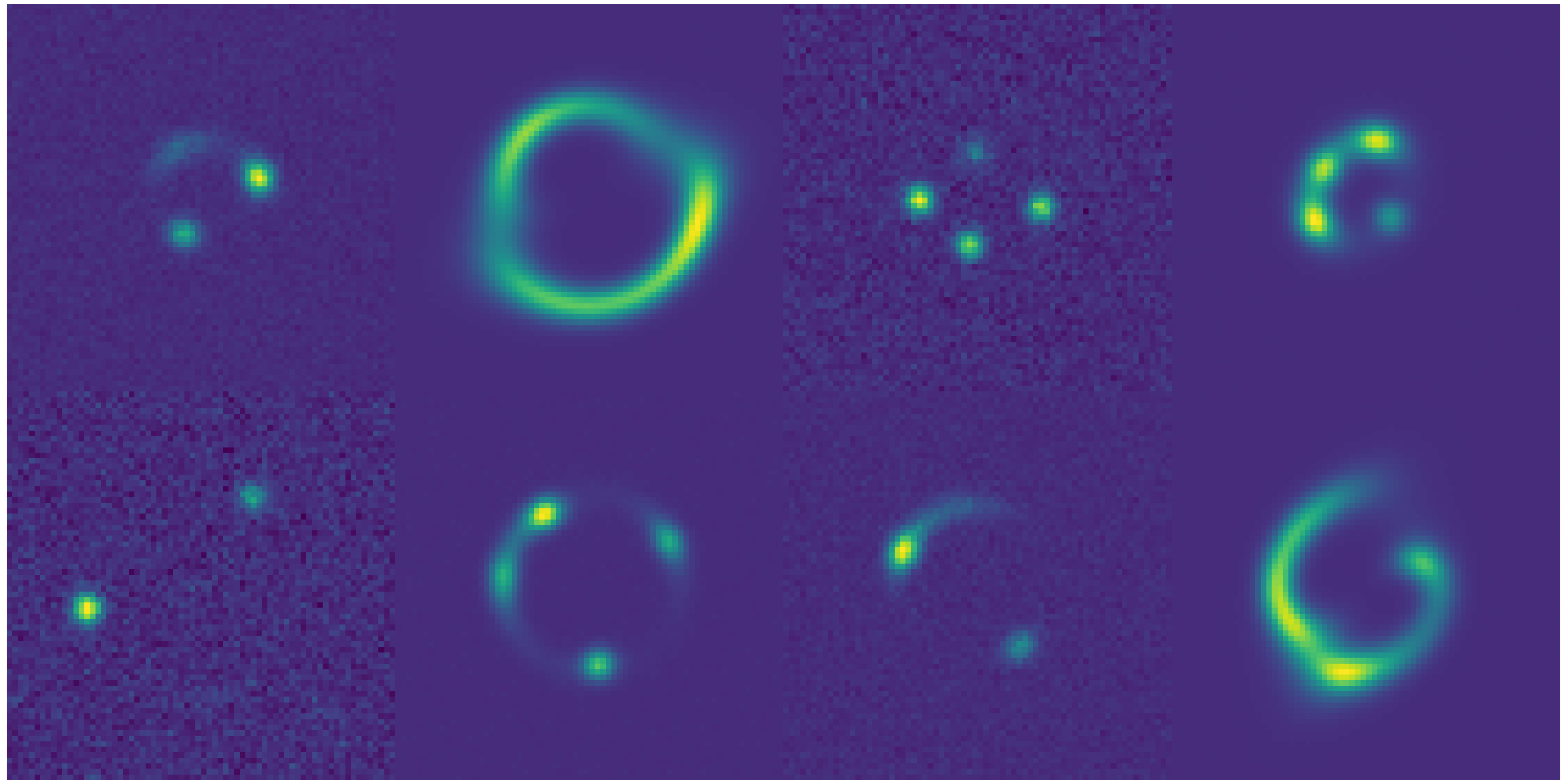
- Over-magnified solutions exist at $\approx 2 \times \theta_E$

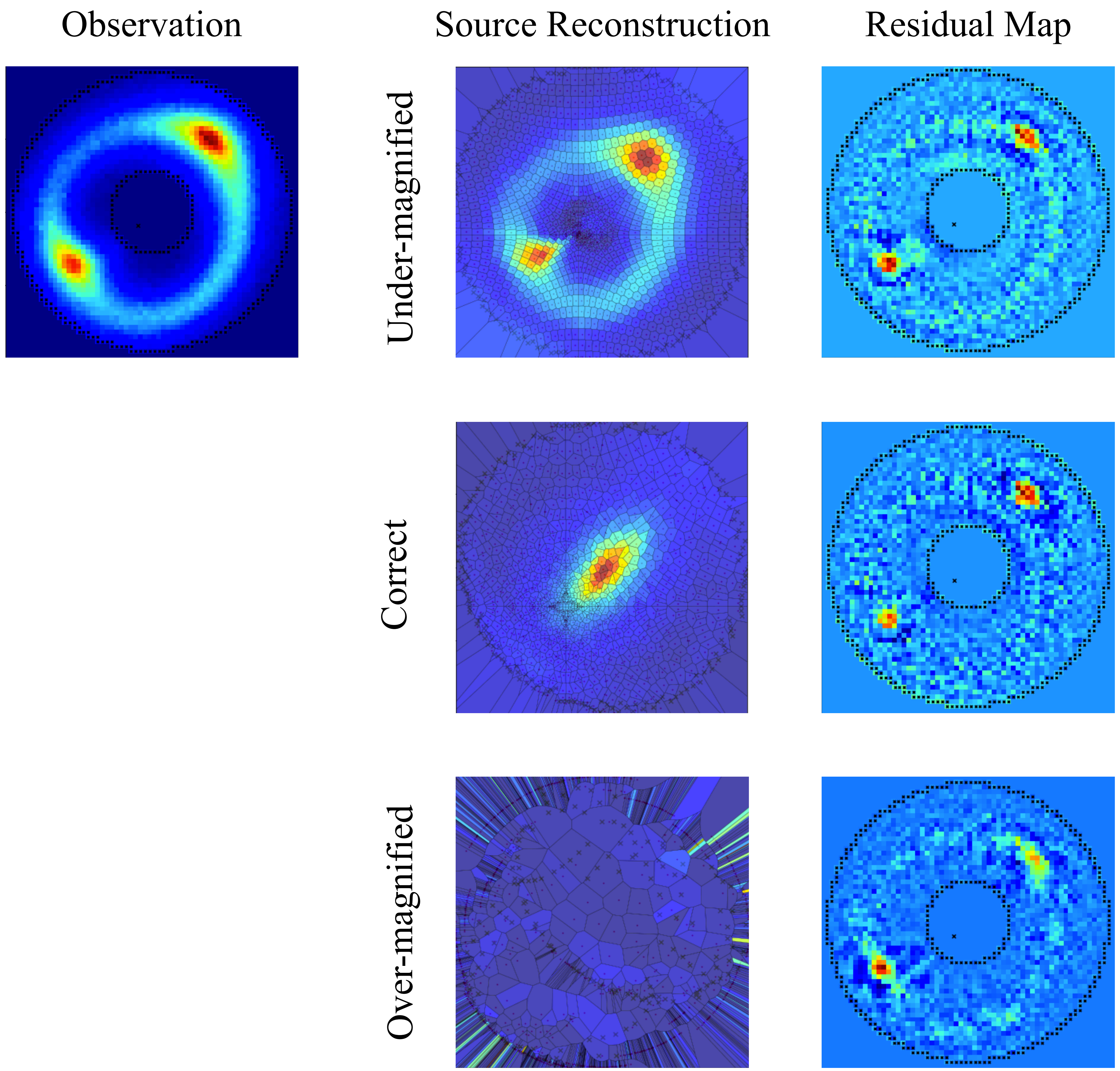
- This suggests a route back to the 'correct' solution!



CNN Training

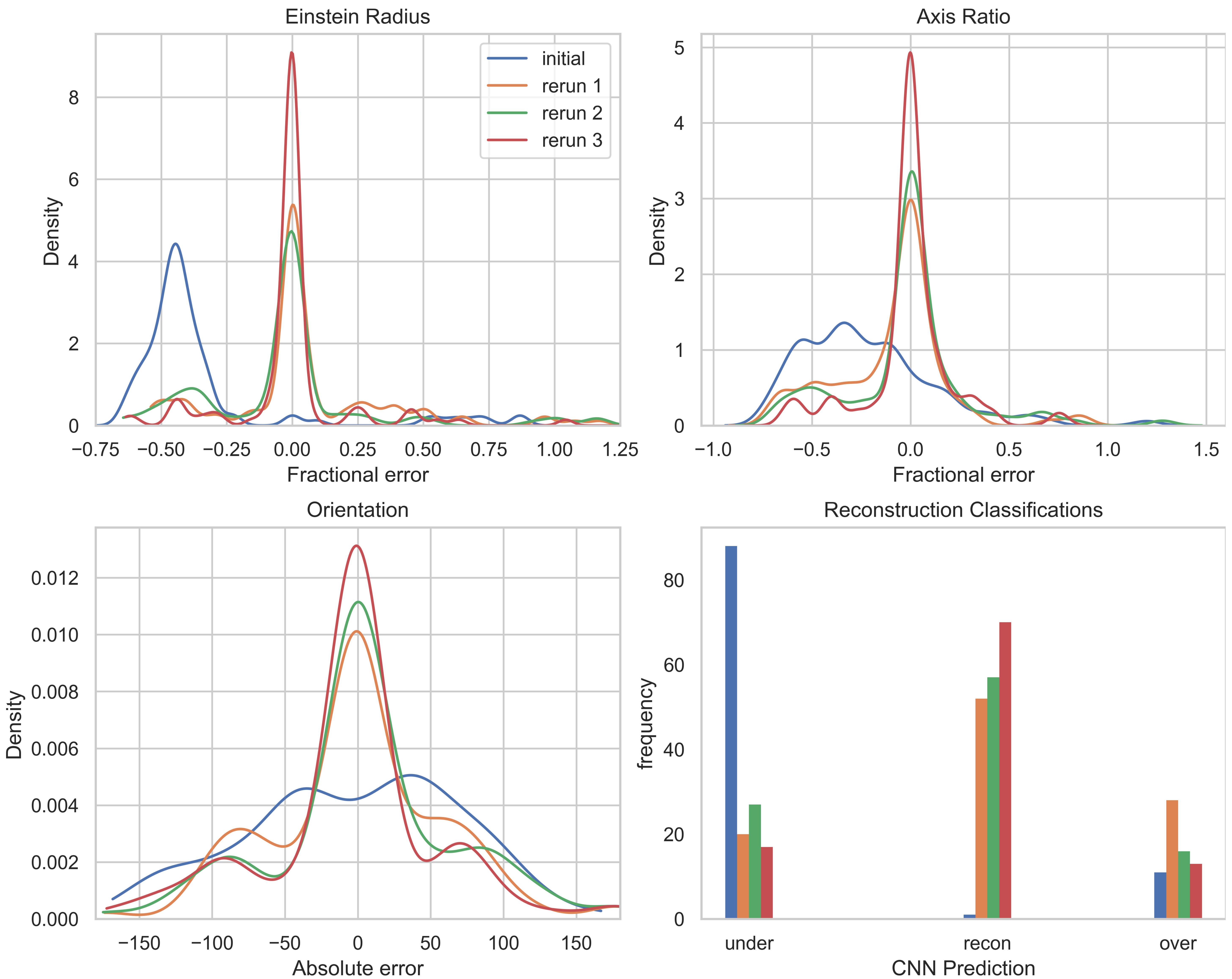
- Generate simulated lensed images (simple Sérsic sources)
- Produce pixelised source reconstructions for each class of solution



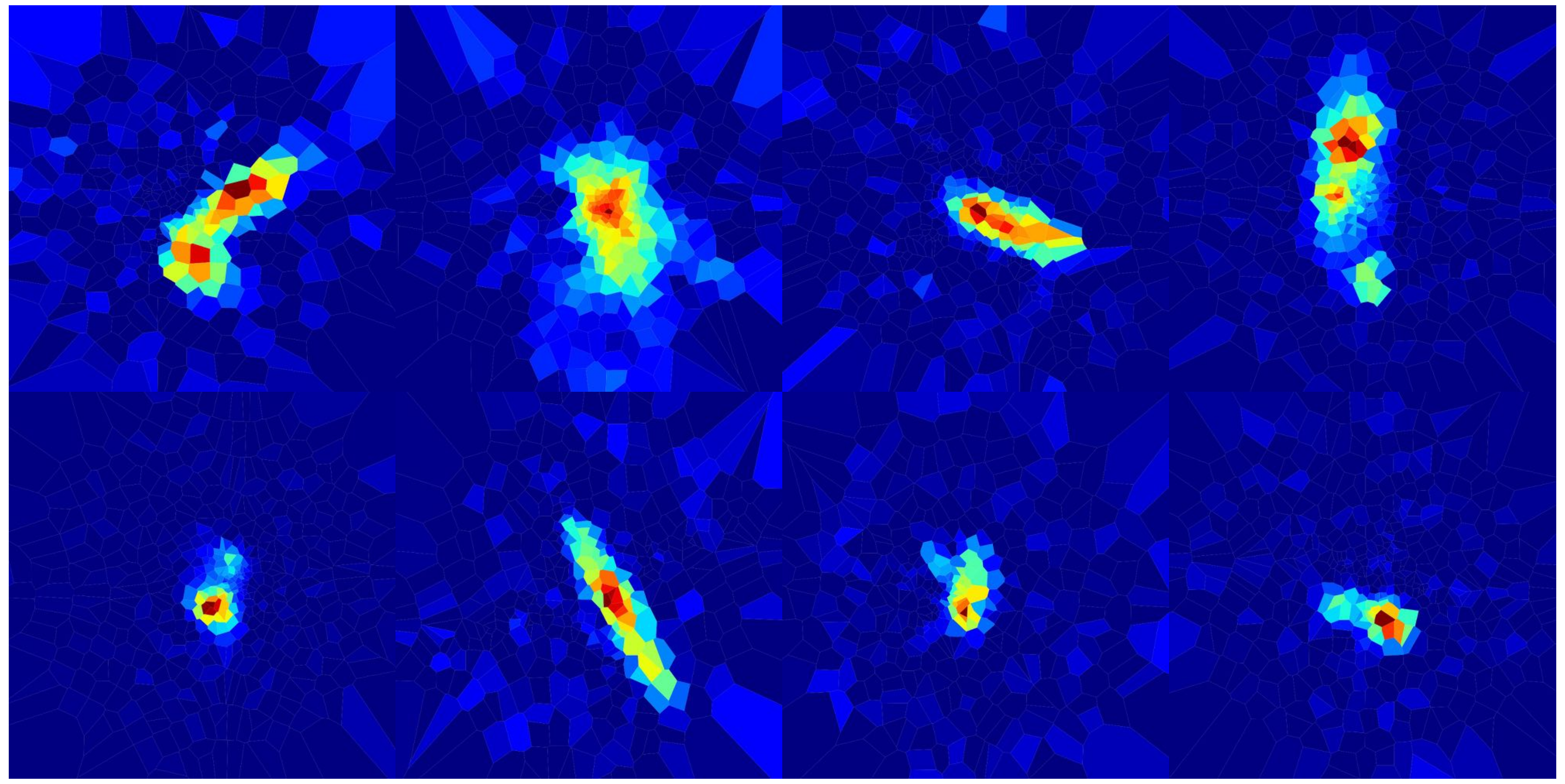


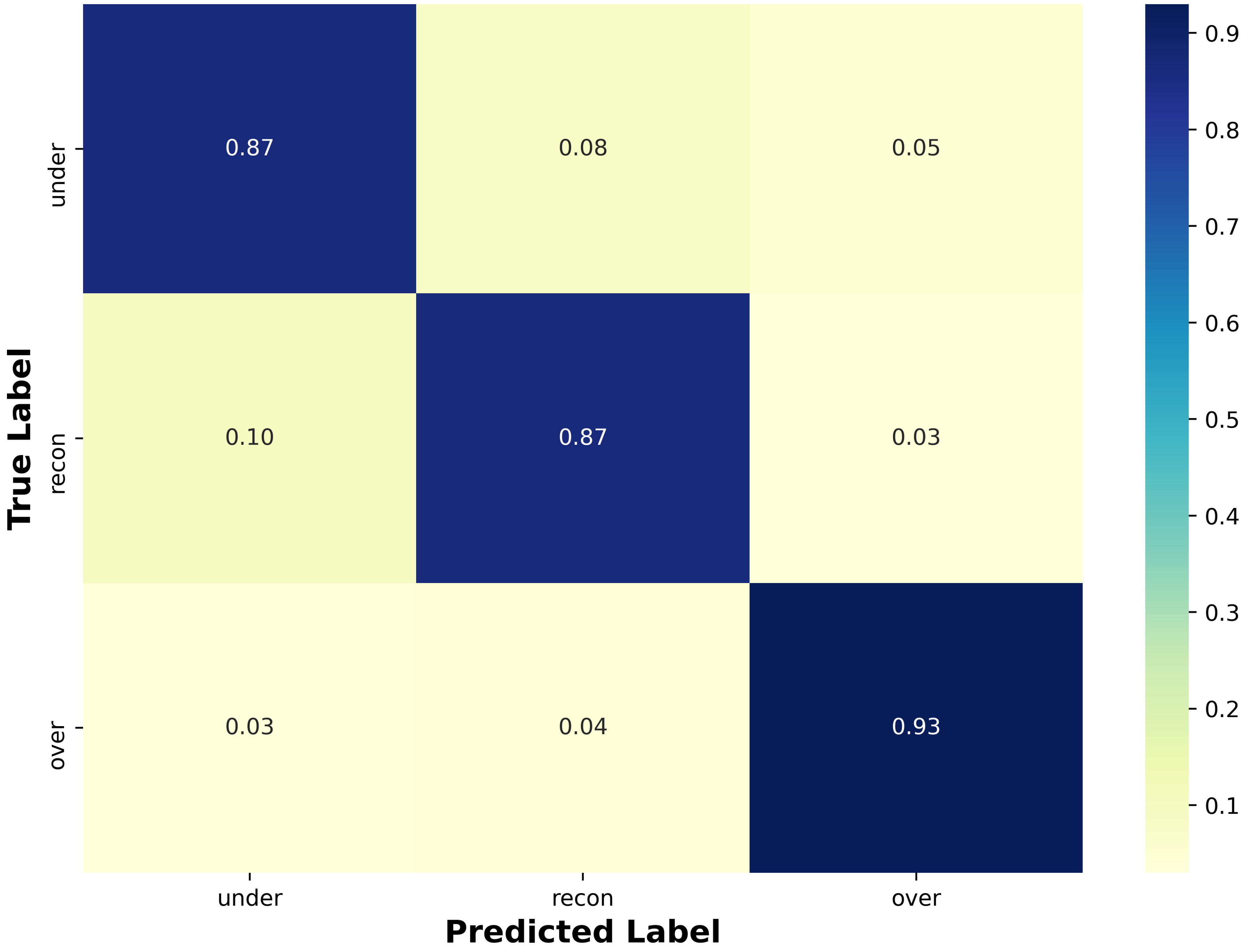
Combining CNN with PyAutoLens

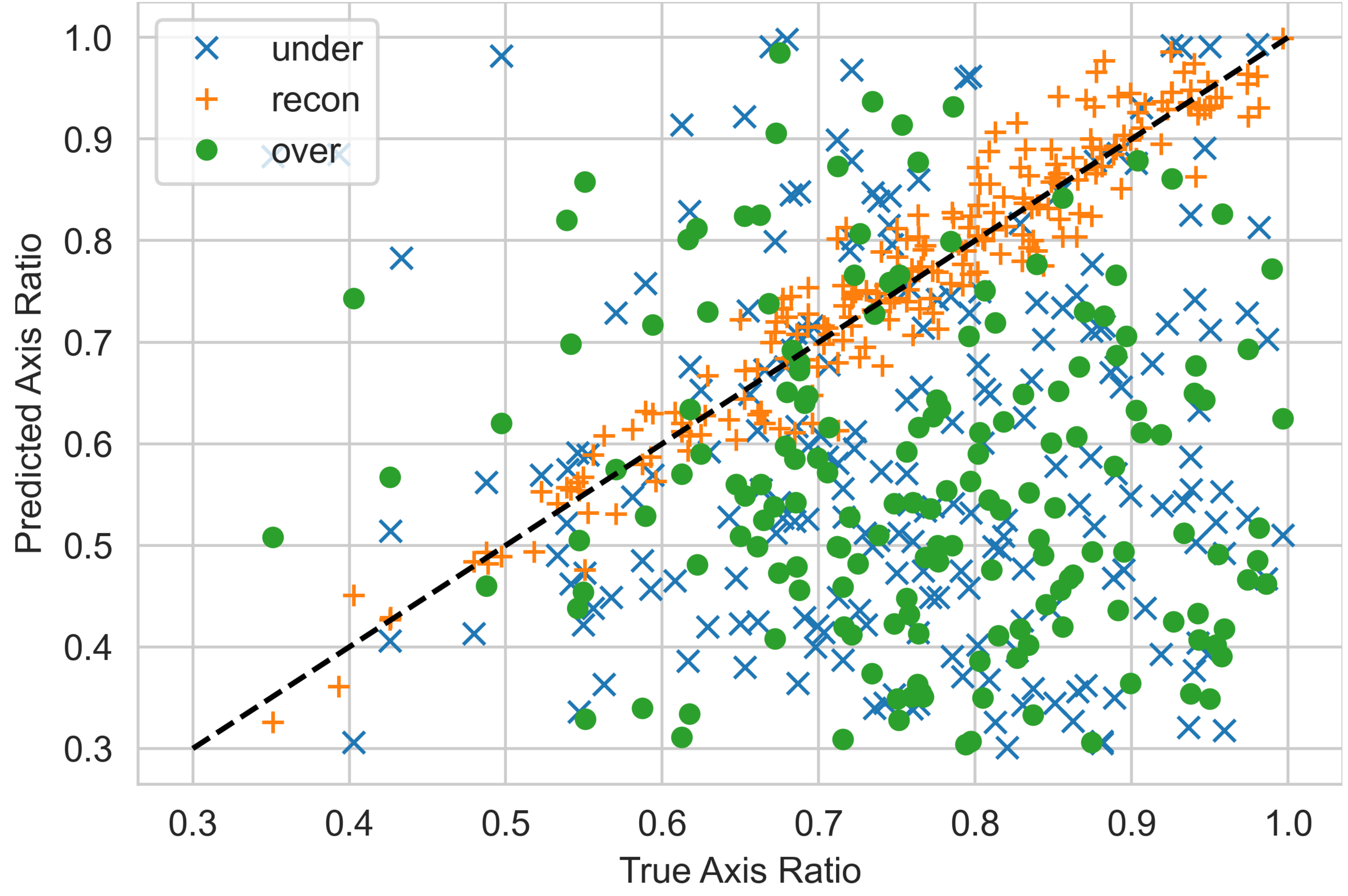
- Blindly model 100 strong lenses
- Ask the CNN for predictions
- Remodel with updated priors on θ_E
- Repeat

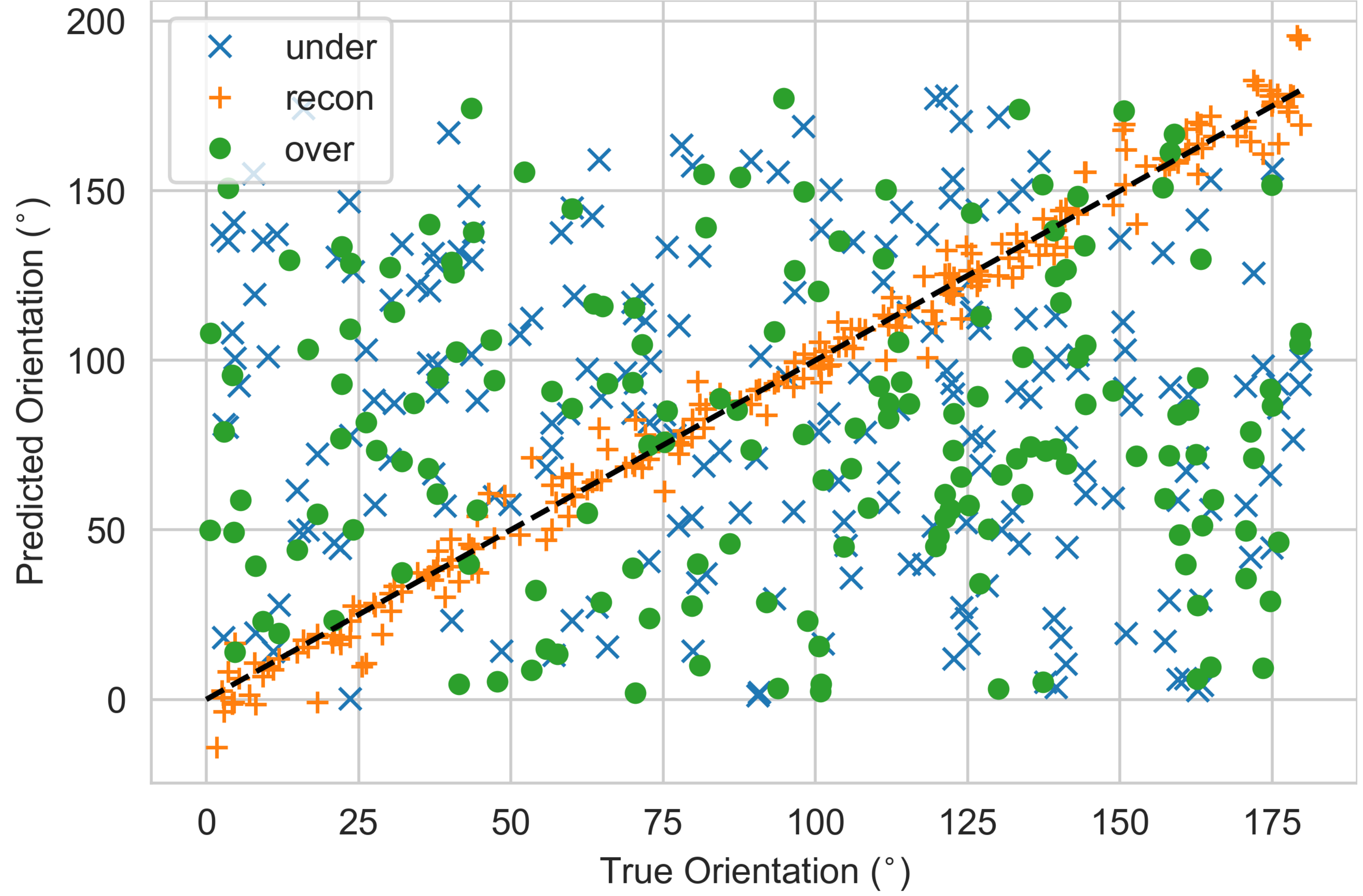


Additional Plots



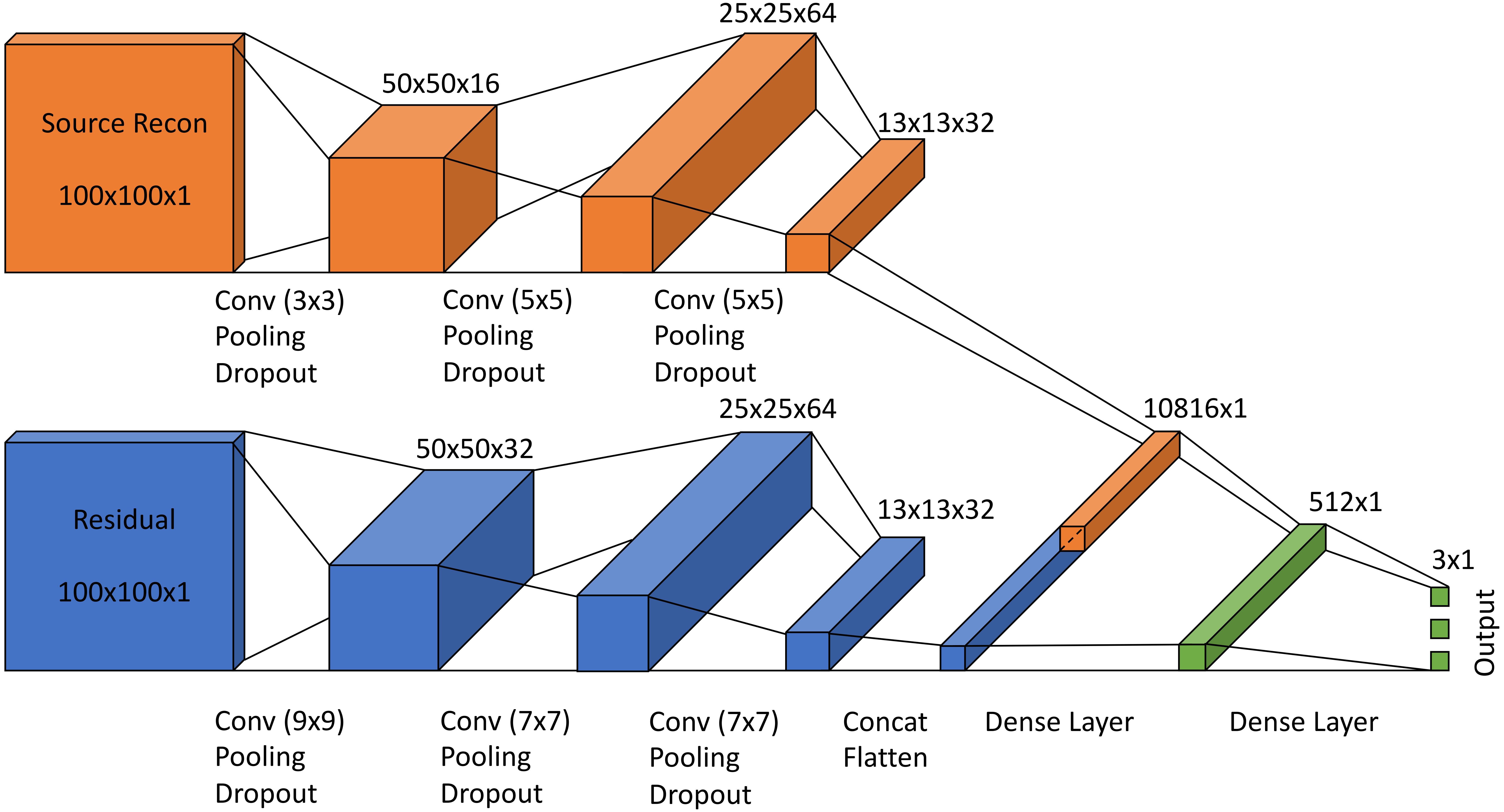






CNN

- Dual inputs
- 3 convolutional layers
- Predicts UM, C, OM



CNN Testing

- Tested on simple sources

- Precision > 0.99
  Recall > 0.99

- Tested on HUDF sources

- Precision ~ 0.89
  Recall ~ 0.89