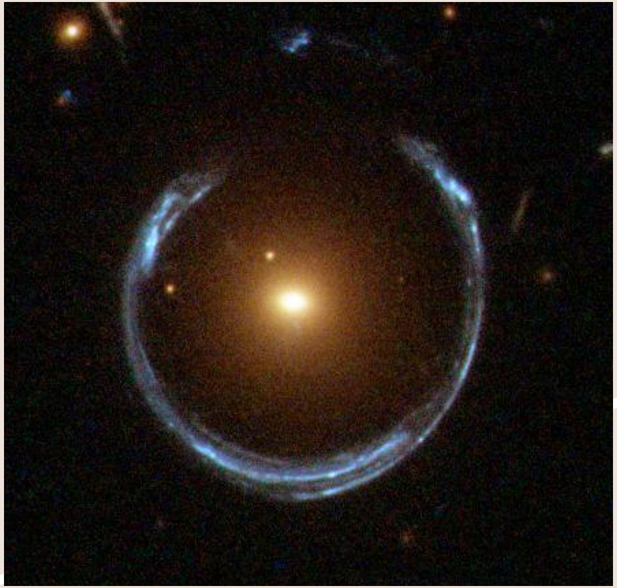
Deep Learning Simulation-Based Inference for Strong Lensing Inverse Modeling in Wide-Field Surveys

Vitor S. Ramos, Clécio R. De Bom

Contact: vsramos@cbpf.br

Sociedade Astronômica Brasileira

Introduction: Strong Lensing



- General Relativity → deformation of spacetime
- Massive objects → Source image deflected
- Deflection carries information
  - Matter distribution
  - Measurements of H_0
  - Gravitational telescopes

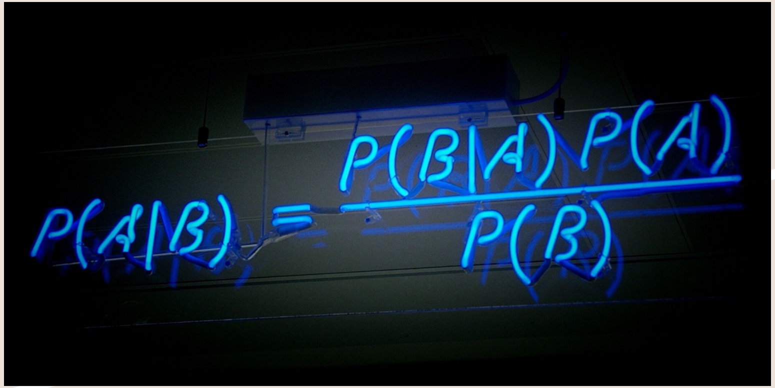
Motivation

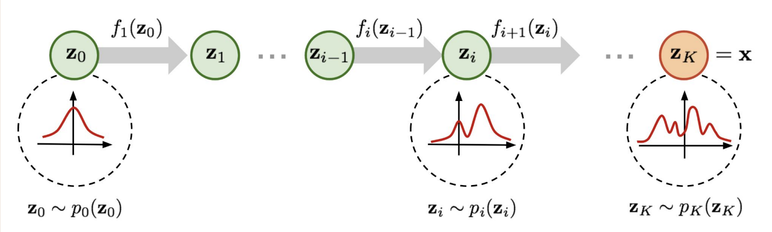
- Few currently known lenses
- Future surveys → More Lenses
- Fast and automated analysis → Neural Networks
- Uncertainty estimation → Simulation-Based Inference

Image: Rubin Observatory Gallery

Simulation-Based Inference

- Bayes' Theorem
- Intractable Likelihood → LFI
- Simulator replaces likelihood
- NN based Density Estimator
  - Normalizing Flows [1]
- Trained model → Posterior reconstruction via frequentist approach



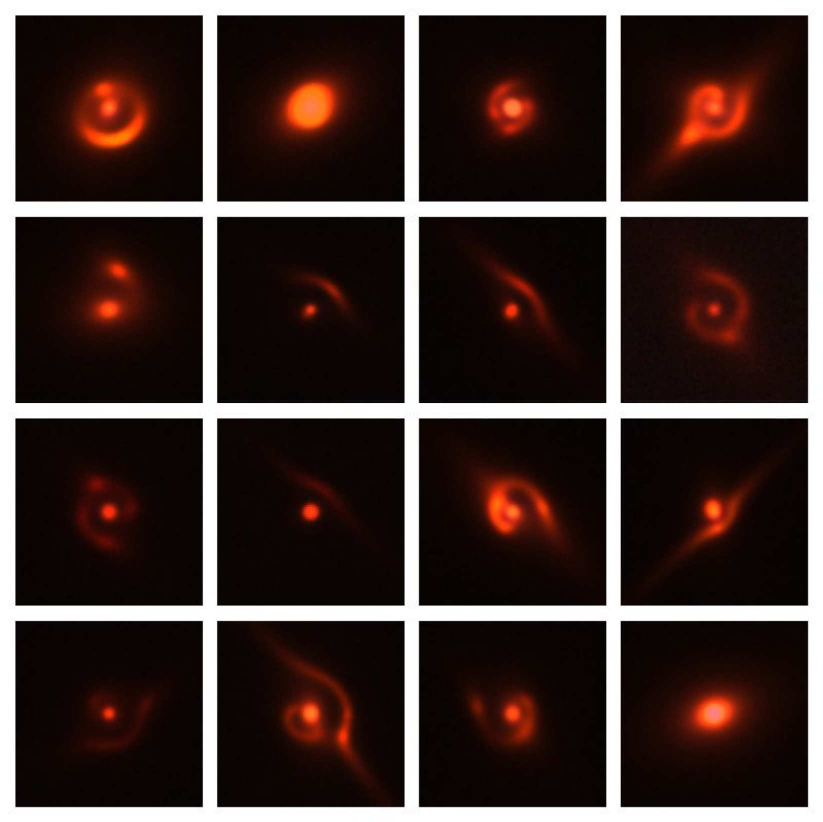


[1] arxiv:1908.09257

Image: https://lilianweng.github.io/posts/2018-10-13-flow-models/

Simulated Dataset

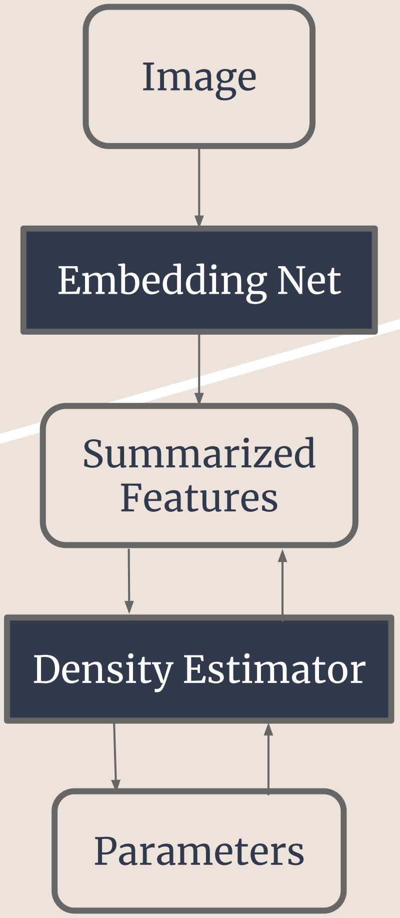
- DeepLenstronomy [2]
- DELVE preset PSF and Noise
- DECam-observable population generated by Lenspop [3]
- ~25000 GRIZ band images
- Galaxy-Galaxy

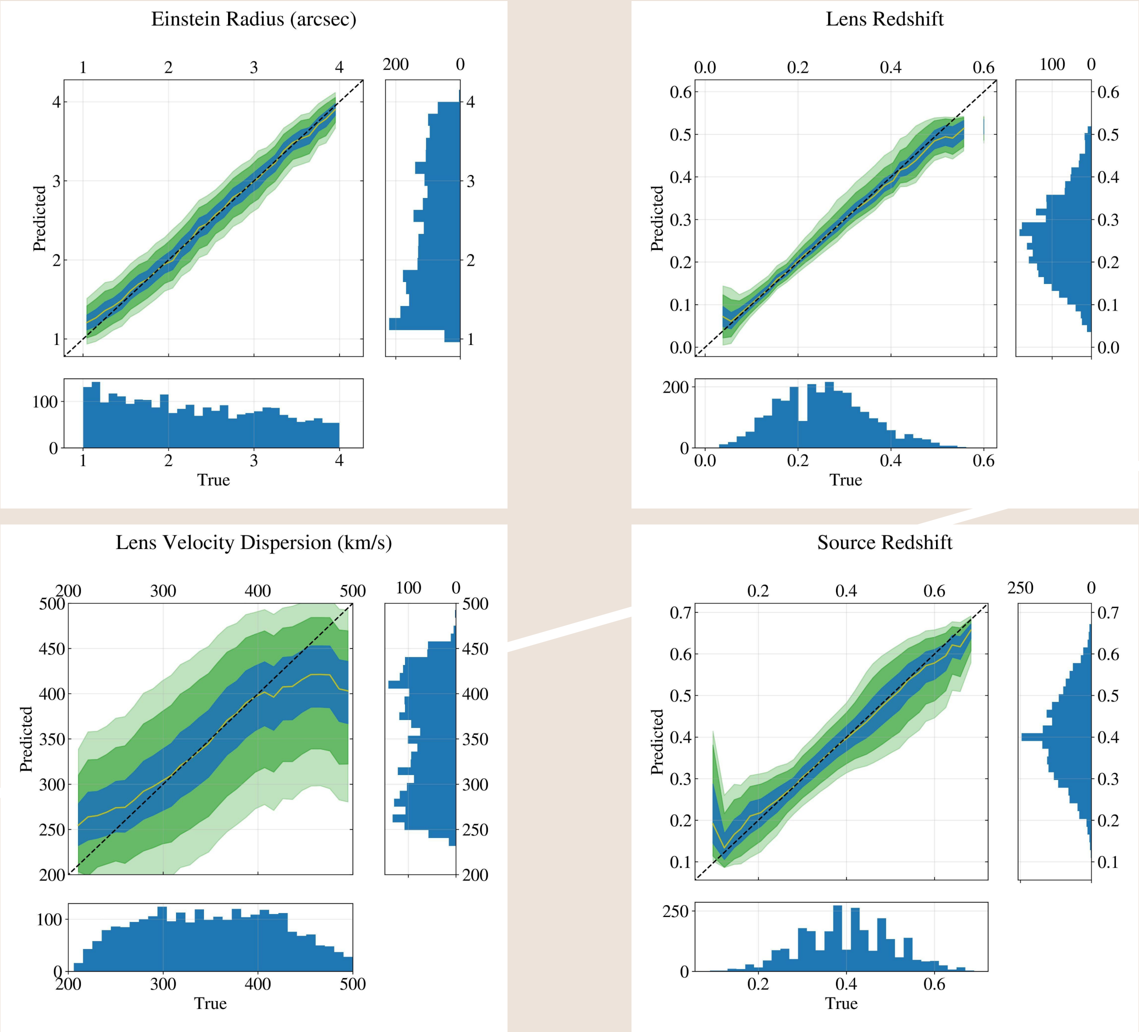


[2] arxiv:2102.02830; [3] arxiv:1507.02657

Deep Learning Architecture

- Image Preparation
  - BG removal, normalization
- Embedding Net
  - Inception
- Neural Spline Flow
- Four parameters
  - Separate network for each parameter




Einstein Radius (arcsec)
Predicted
True
Lens Redshift
Predicted
True
Lens Velocity Dispersion (km/s)
Predicted
True
Source Redshift
Predicted
True

Results

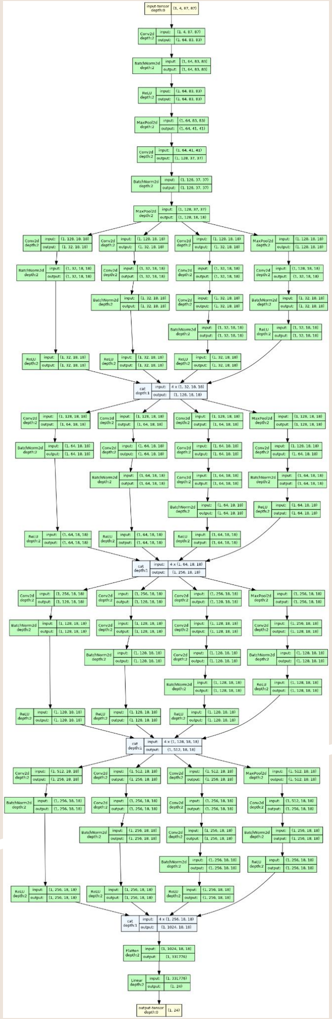
Parameter	Median Precision	Median Fractional Deviation	R^2
Einstein Radius	91.0%	3.6%	0.93
Lens Velocity Dispersion	79.6%	4.0%	0.68
Lens Redshift	91.4%	3.5%	0.97
Source Redshift	85.0%	2.4%	0.95

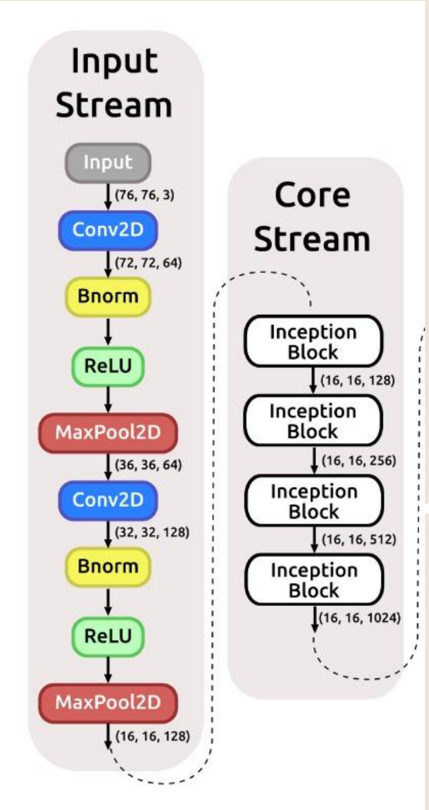
Conclusion

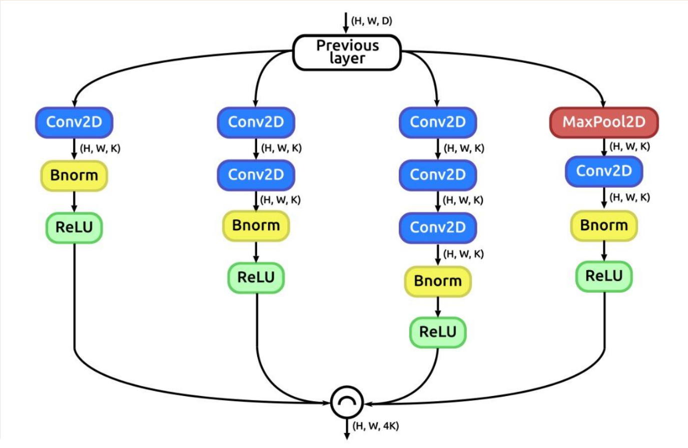
- Fast automated method for Strong Lensing parameter inference, including uncertainties
    - Less than 2 minutes for 2500 lenses
- Up to 91.4% median precision → Self-consistent
- Highest Fractional deviation: 4% → Accurate
- Results on simulated images

- Current Focus:
    - Real images → DELVE
    - Architectures, SBI methods

Thank you!







NSF: 4 transforms, 32 hidden units

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