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

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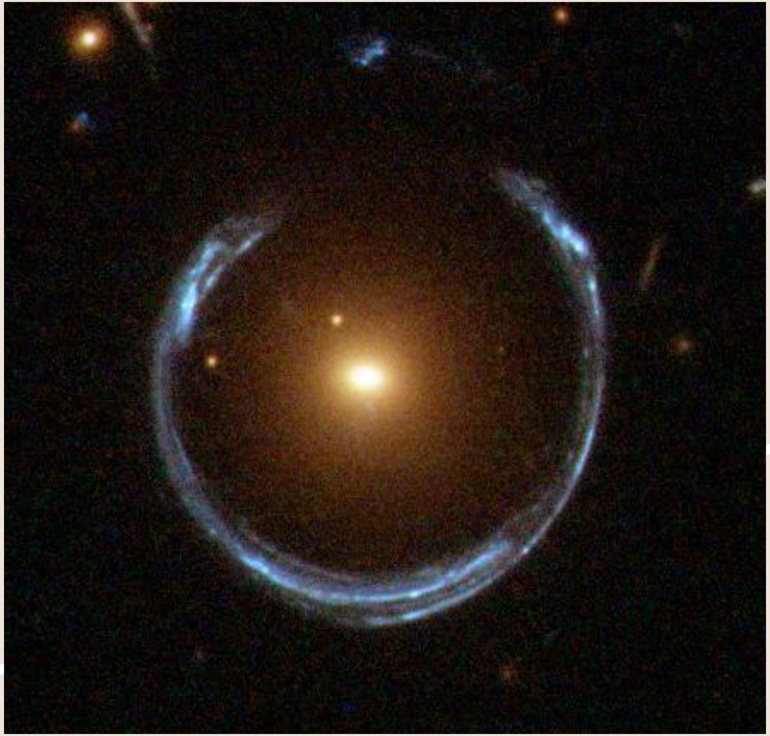
# Introduction: Strong Lensing



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

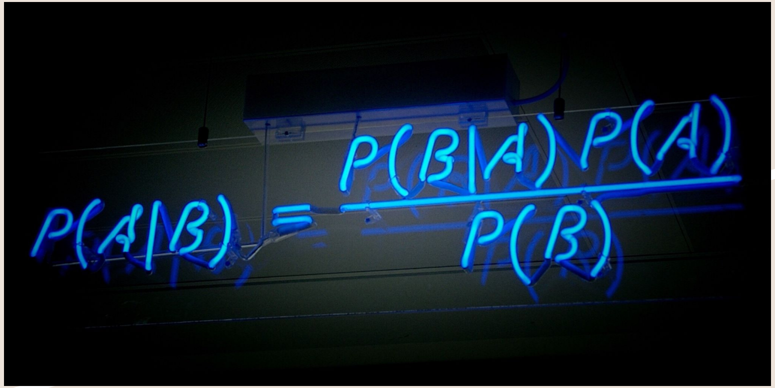
# Motivation

- 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
- Neural Posterior Estimation
  - Normalizing Flows [1]
- Trained model → Posterior reconstruction via  frequentist approach



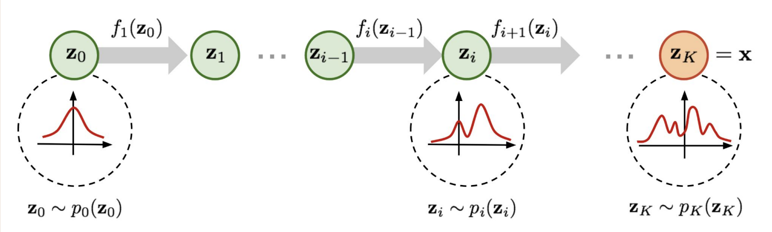



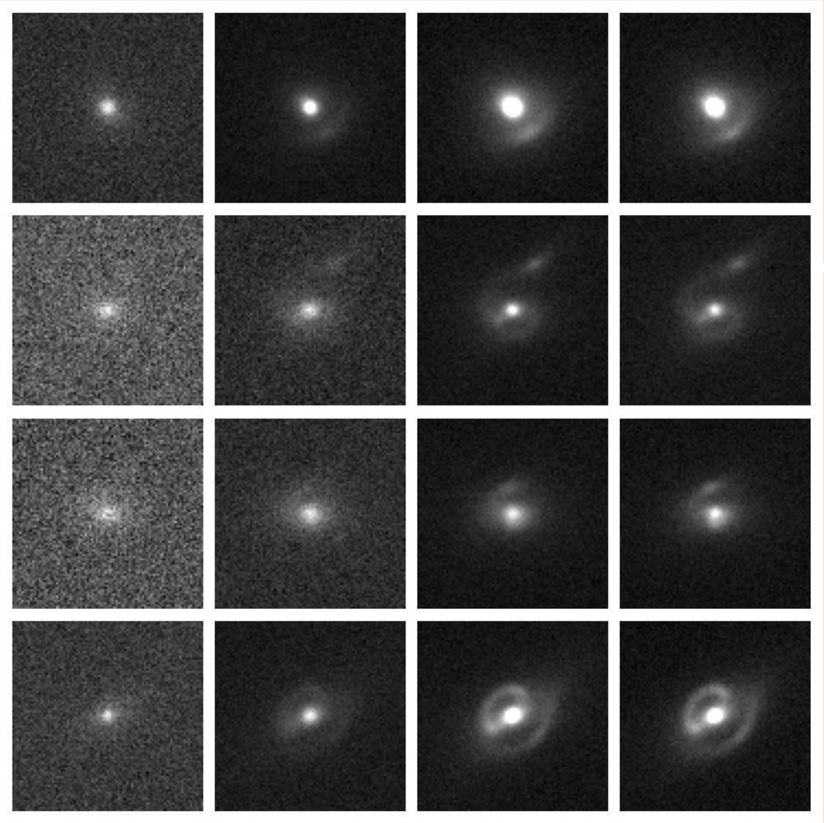

Image: Matt Buck/Flickr/CC BY-SA 2.0

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


[1] arXiv:1908.09257

# Simulated Dataset

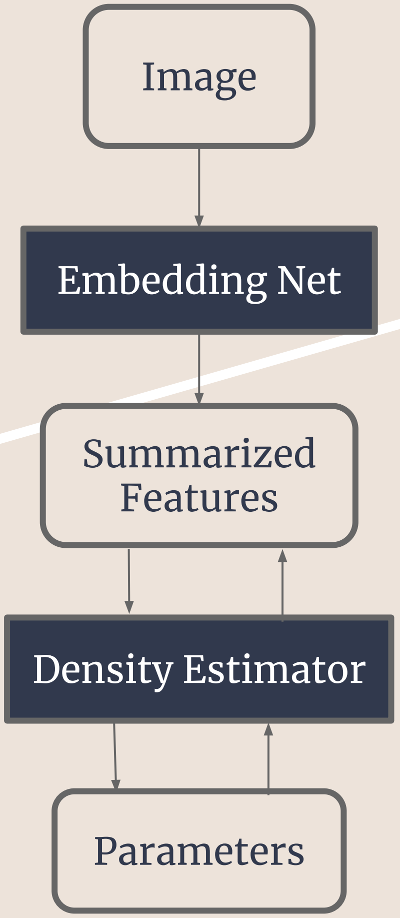
- DeepLenstronomy [2]
- DELVE preset PSF and Noise
- DECam-observable population generated by Lenspop [3]
- ~25000 GRIZ band images
- Galaxy-Galaxy



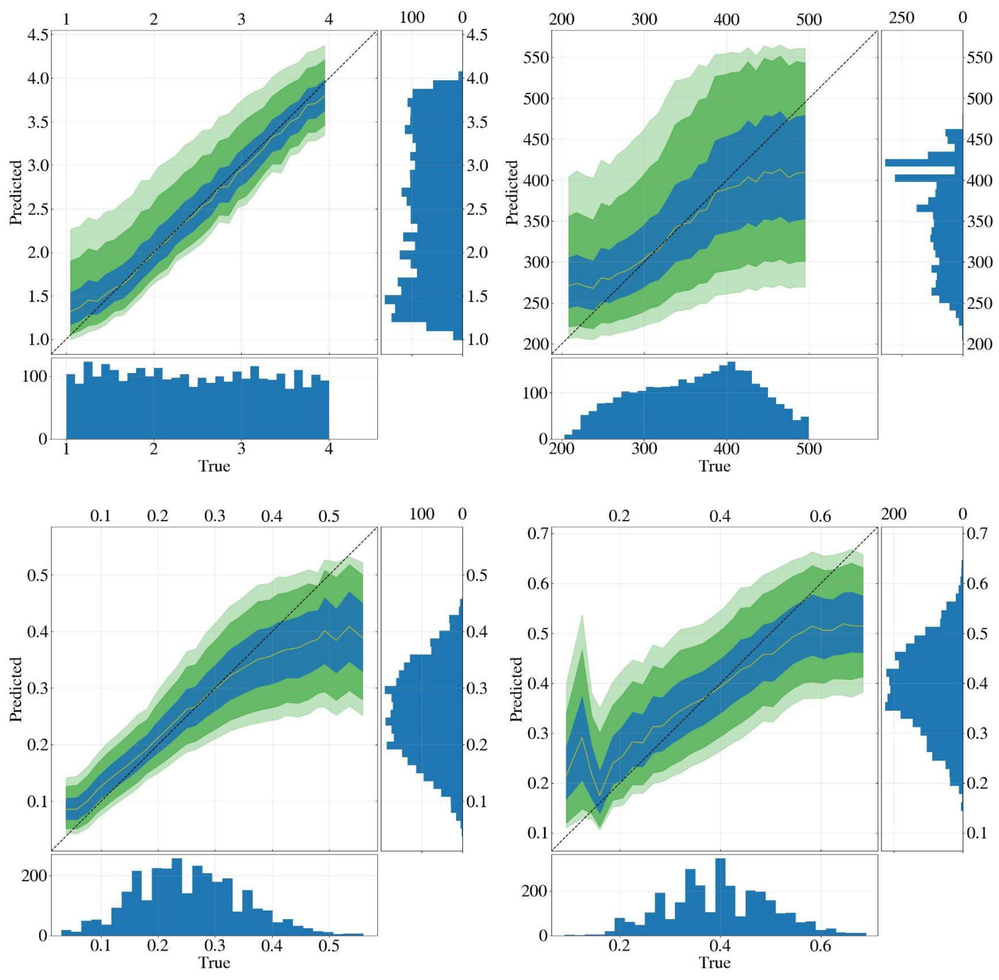
[2] arXiv:2102.02830; [3] arXiv:1507.02657

# Deep Learning Architecture

- Image Preparation
  - Flux conversion, BG removal, normalization
- Embedding Net
  - Inception
- Neural Spline Flow [4]
- Four parameters
  - Separate network for each parameter




[4] arXiv:1906.04032



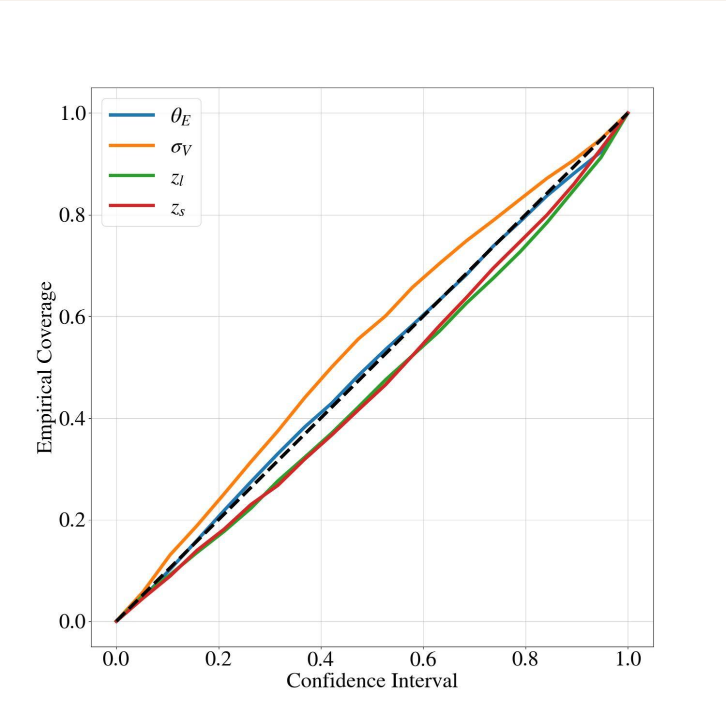
Predicted
True
Predicted
True
Predicted
True
Predicted
True

# Results

| Parameter | Median Precision | Median Fractional Deviation | Pearson |
|---|---|---|---|
| Einstein Radius | 84.4% | 4.5% | 0.94 |
| Lens Velocity Dispersion | 71.6% | 7.5% | 0.76 |
| Lens Redshift | 73.0% | 10.3% | 0.90 |
| Source Redshift | 72.6% | 10.1% | 0.77 |

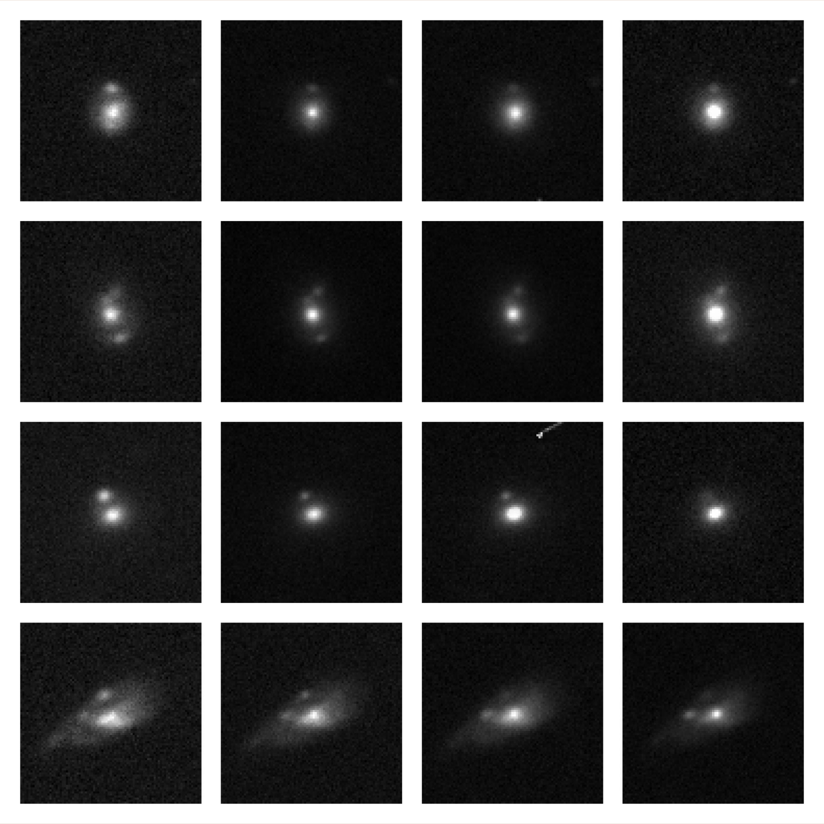
# Simulation-Based Calibration

| Parameter | KS p-vals | C2ST |
|---|---|---|
| Einstein Radius | 0.052 | 0.53 |
| Lens Velocity Dispersion | 0.063 | 0.54 |
| Lens Redshift | 0.058 | 0.53 |
| Source Redshift | 0.048 | 0.52 |



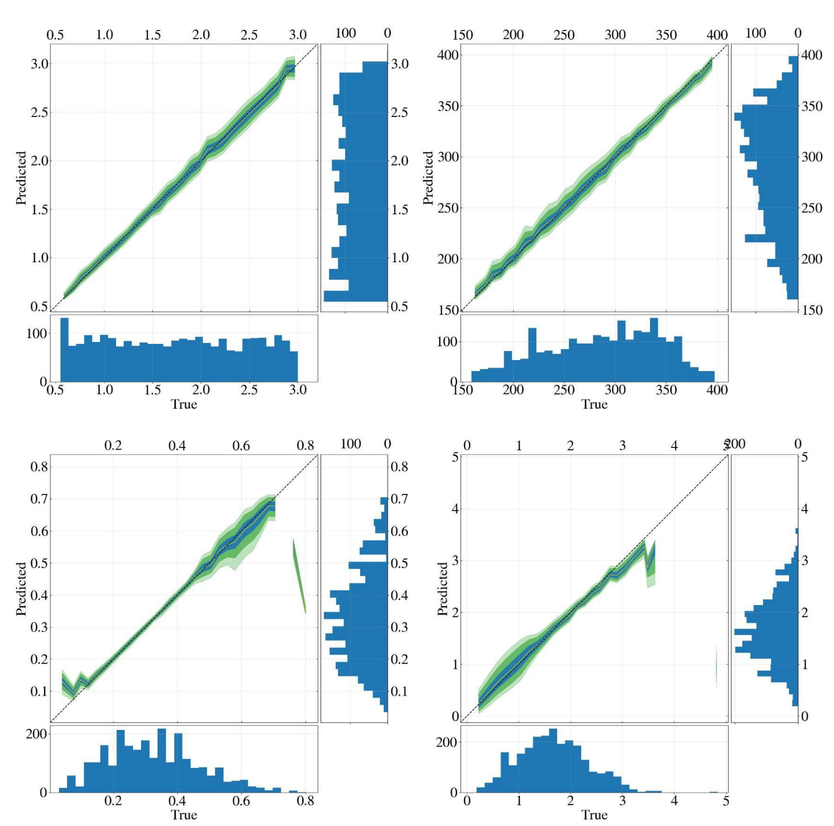
# Arc simulation

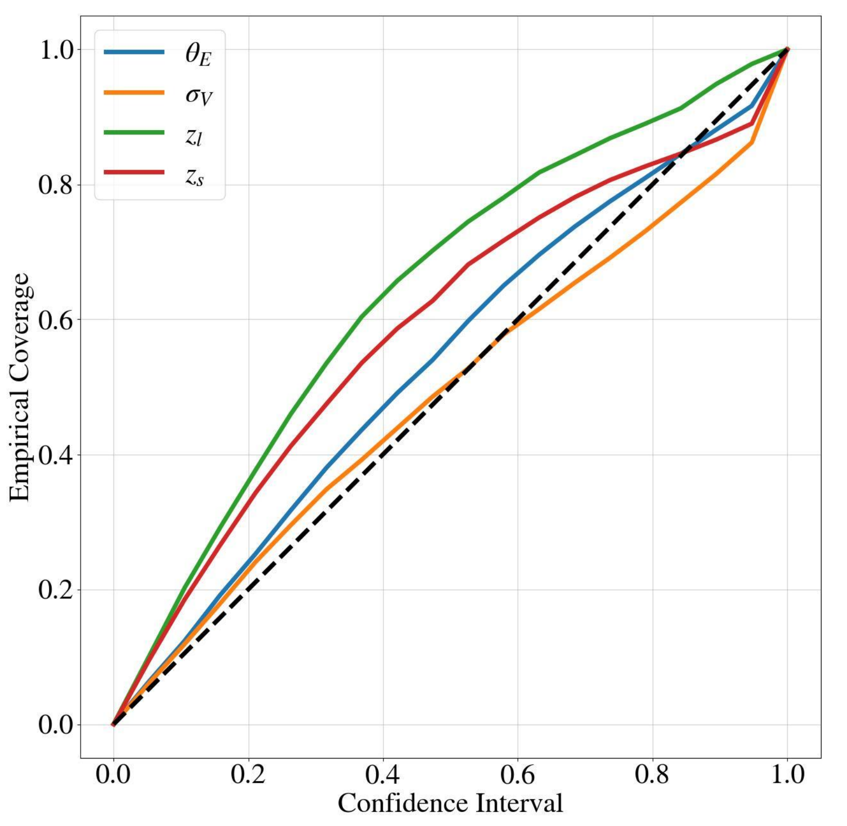
- Lenstronomy [5]
- Images of galaxies from DELVE survey
- Parameters of LensPop population to simulate arc
- Preparation: Flux conversion, Normalization (no sigma clipping)



[5] ArXiv:1803.09746

# Preliminary Results



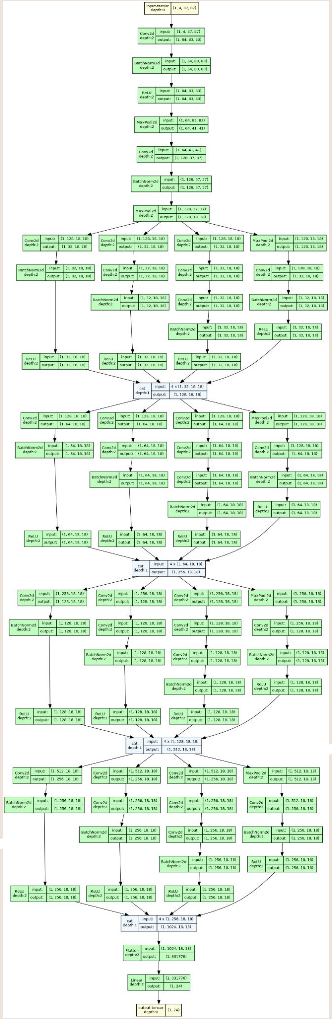
# Preliminary Results

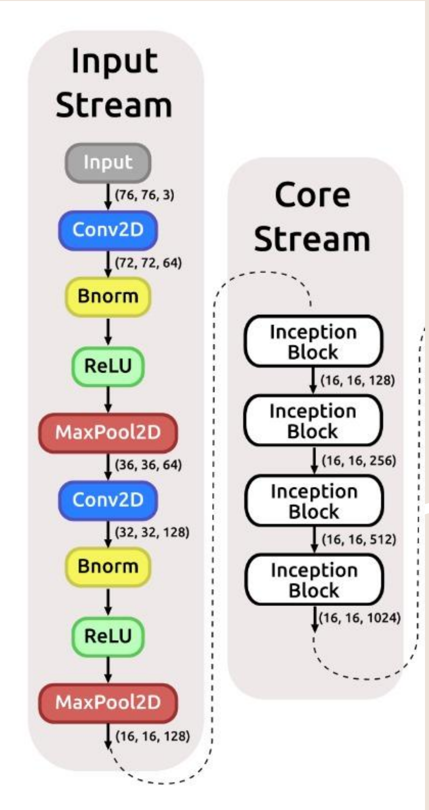
| Parameter | Median Precision | Median Fractional Deviation | Pearson |
|---|---|---|---|
| Einstein Radius | 96.2% | 1.0% | 0.99 |
| Lens Velocity Dispersion | 98.2% | 0.6% | 0.99 |
| Lens Redshift | 97.4% | 0.4% | 0.98 |
| Source Redshift | 93.6% | 1.6% | 0.94 |

# Final Remarks

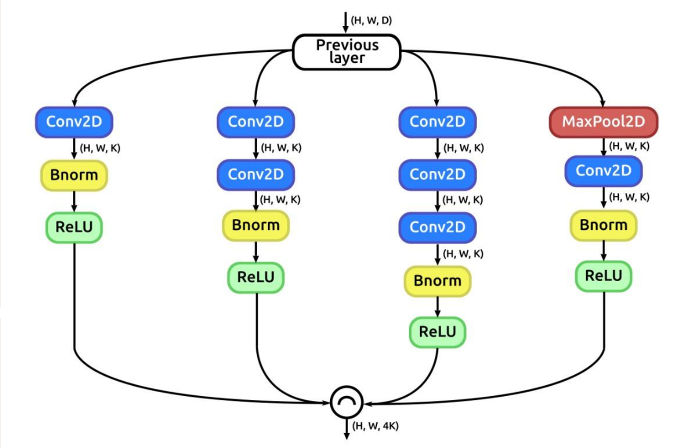
- Fast automated method for Strong Lensing parameter inference, including uncertainties
  - Less than 2 minutes for 2500 lenses
- Up to 84.4% (98.2%) median precision → Self-consistent
- Highest Fractional deviation: 10% (1.6%) → Accurate
- SBC ensures uncertainties are well-calibrated or underconfident
- Current Focus:
  - Are arc sim results reliable?
  - Simulation Realism
  - Architectures, Hyperparameters
  - Results on real images → DELVE, LaStBeRu compilation

Thank you!





Input Stream
Input
(76, 76, 3)
Conv2D
(72, 72, 64)
Bnorm
ReLU
MaxPool2D
(36, 36, 64)
Conv2D
(32, 32, 128)
Bnorm
ReLU
MaxPool2D
(16, 16, 128)
Core Stream
Inception Block
(16, 16, 128)
Inception Block
(16, 16, 256)
Inception Block
(16, 16, 512)
Inception Block
(16, 16, 1024)

(H, W, D)
Previous layer
Conv2D
(H, W, K)
Bnorm
ReLU
Conv2D
(H, W, K)
Conv2D
(H, W, K)
Bnorm
ReLU
Conv2D
(H, W, K)
Conv2D
(H, W, K)
Conv2D
(H, W, K)
Bnorm
ReLU
MaxPool2D
(H, W, K)
Conv2D
(H, W, K)
Bnorm
ReLU
(H, W, 4K)

# Architectures - DeepLenstronomy

| Parameter | CNN outs | Transforms | Hidden Units |
|---|---|---|---|
| Einstein Radius | 16 | 6 | 32 |
| Lens Velocity Dispersion | 16 | 4 | 48 |
| Lens Redshift | 16 | 6 | 24 |
| Source Redshift | 16 | 6 | 24 |

# Architectures – Arc simulation

| Parameter | CNN outs | Transforms | Hidden Units |
|---|---|---|---|
| Einstein Radius | 8 | 6 | 24 |
| Lens Velocity Dispersion | 8 | 6 | 32 |
| Lens Redshift | 16 | 4 | 48 |
| Source Redshift | 16 | 4 | 32 |

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