Machine Learning Dynamical Models: Applications to Simulations and JAM

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Integral Field Spectroscopy

ATLAS3D

BLUE muse
multi unit spectroscopic explorer

muse

sami
galaxy survey

NIRSpec

MIRI

Key Questions

- Can Machine Learning be used to Improve Existing Methods?
- Can Machine Learning be used to Create New Methods?

Dynamical Modelling Methods

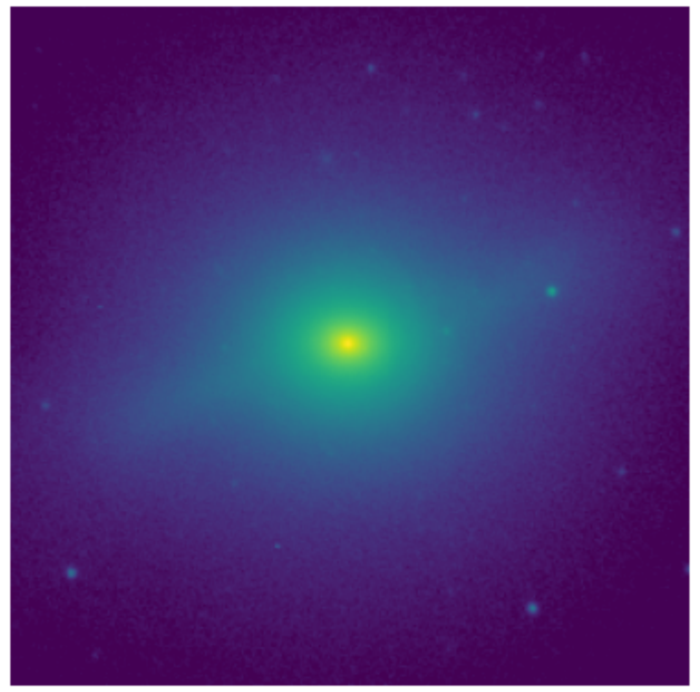
Schwarzschild Modelling

- Axisymmetric or Triaxial
- No anisotropy assumptions
- Uses full LOSVD
- Slow run time ~10 hours
- Non-smooth Chi2
- Lots of hyper-parameters

Jeans Modelling (JAM)

- Axisymmetric
- Cylindrically/spherically aligned velocity ellipsoid
- Uses 2nd moment
- Fast run time ~ 10 sec
- Smooth chi2
- Few hyper-parameters

JAM Modelling Pipeline



Photometry

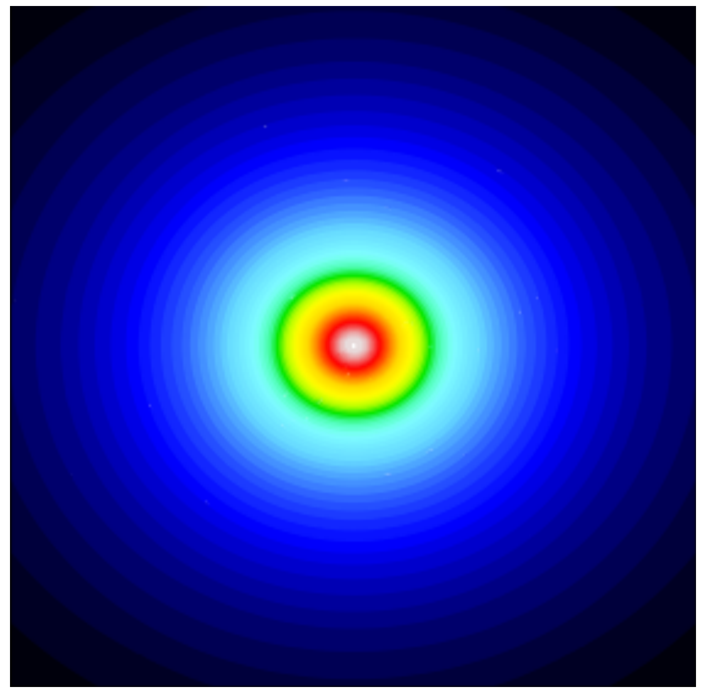
Gravitational Potential

Multi-Gaussian Expansion (MGE)

Light MGE

Mass MGE

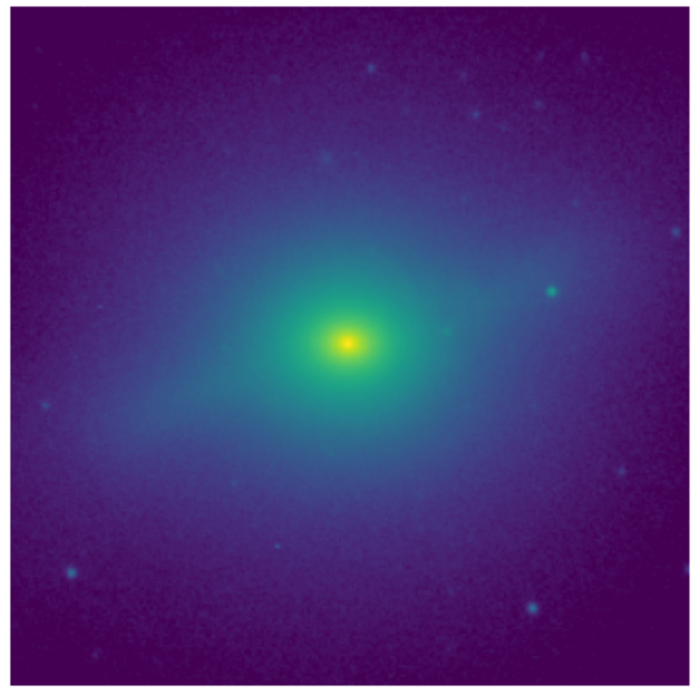
Jeans Anisotropic Modelling



Free Parameters

Inc, beta, M/L, Mbh, …

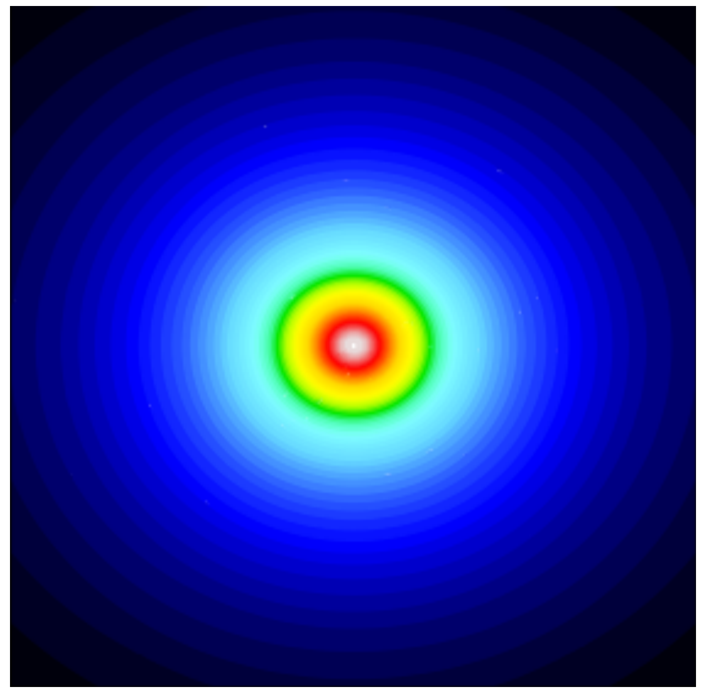
ML Modelling Pipeline



Photometry

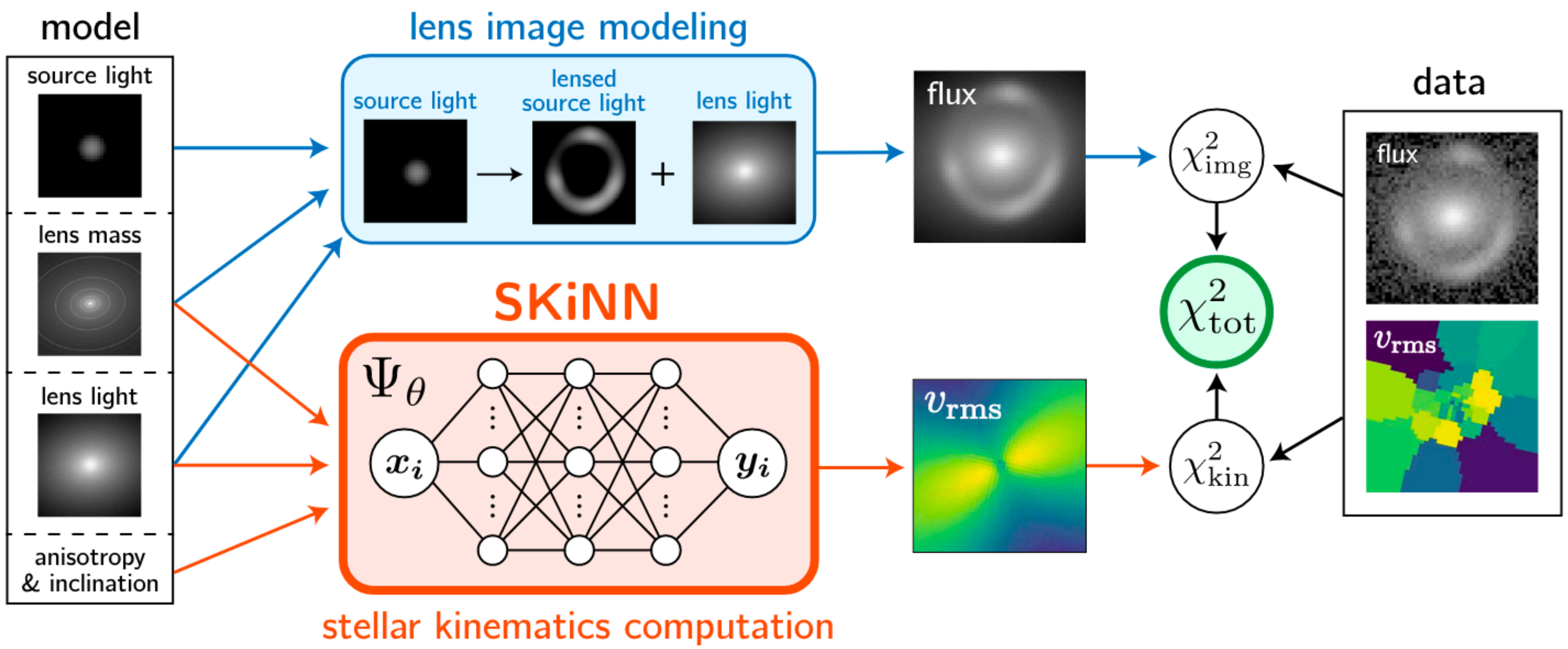
Gravitational Potential

Machine Learning Algorithm



Free Parameters

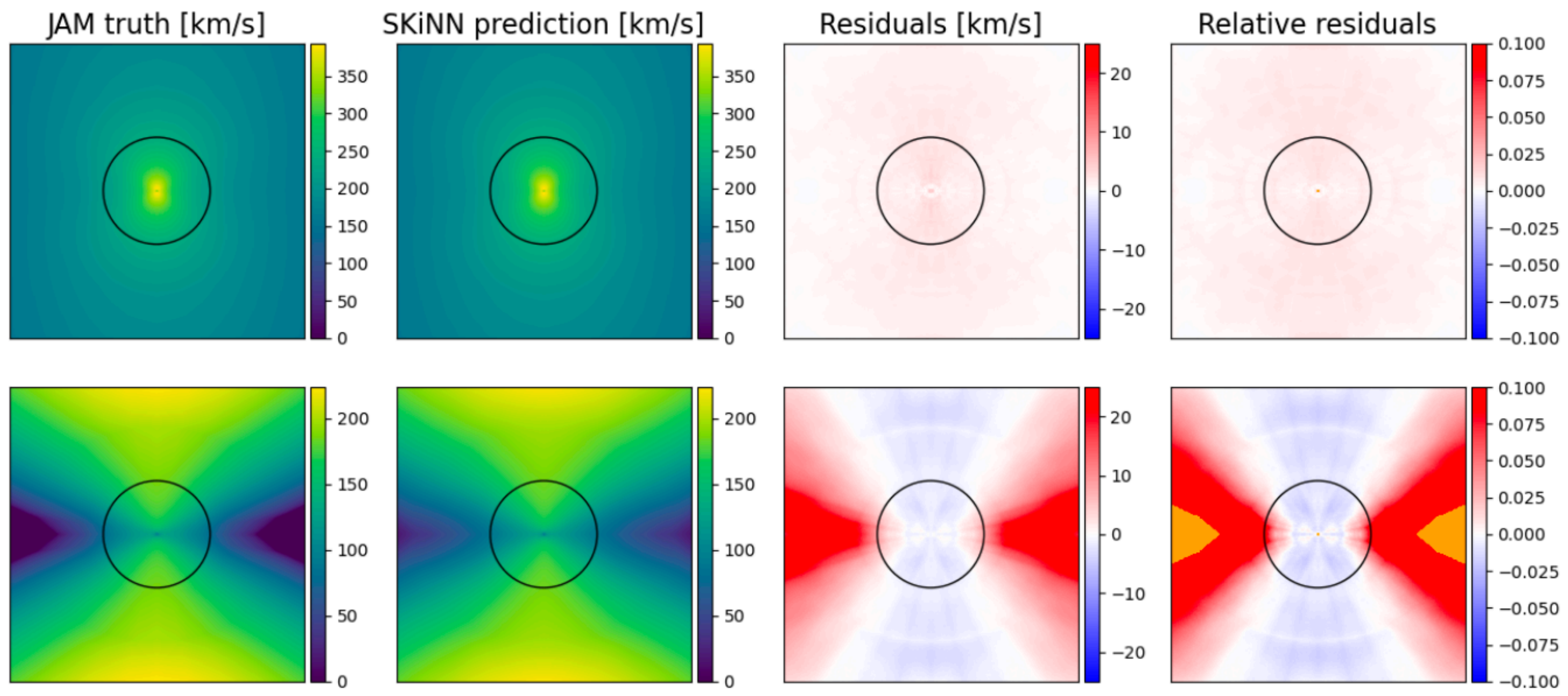
Gomer et al 2023 Architecture



- Joint lensing + kinematics inference
- Kinematics likelihood is a large bottle-neck (~500x slower than lensing likelihood)
- Conditionally Independent Pixel Synthesis (CIPS)
- Hardware requirements: GPU

(Gomer et al 2023, Fig. 1)

Gomer et al 2023 Training Set



Parameter	Description	Training set bounds
θ_E	Einstein radius	$[0.5, 2'']$
γ	2D PL slope (mass)	$[1.5, 2.5]$
q_M	Axis ratio (mass)	$[0.6, 1.0]$
q_L	Axis ratio (light)	$[0.6, 1.0]$
R_{Sersic}	Sérsic radius (light)	$[0.5\theta_E, \theta_E]$
n_{Sersic}	Sérsic index (light)	$[2, 4]$
β_z	Anisotropy	$[-0.4, 0.4]$
i	Inclination	$[\arccos(0.6), 90°]$
Map resolution	$0.02''$	
Map size	$11''$	

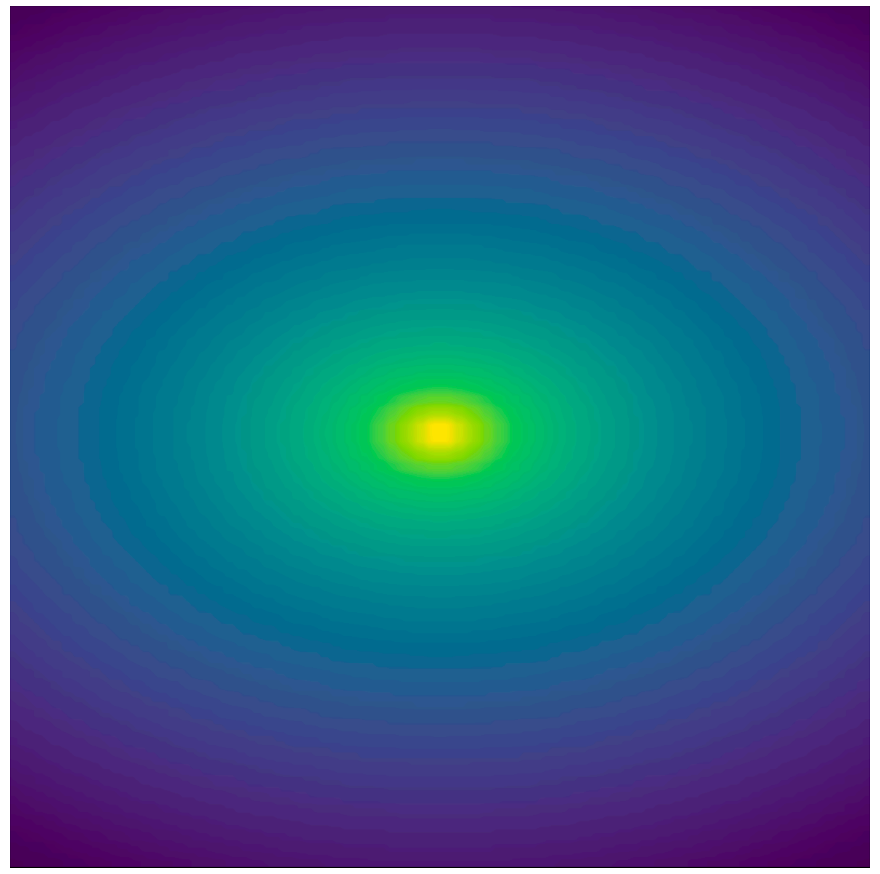
- 9000 Mock Galaxies
  - 4000 training
  - 1000 validation
  - 4000 test
- Uniformly sample Sersic galaxies
- Run time of ~100ms on GPU
- Better than 1% accuracy for most galaxies

(Gomer et al 2023, Fig.2 & Table 1)

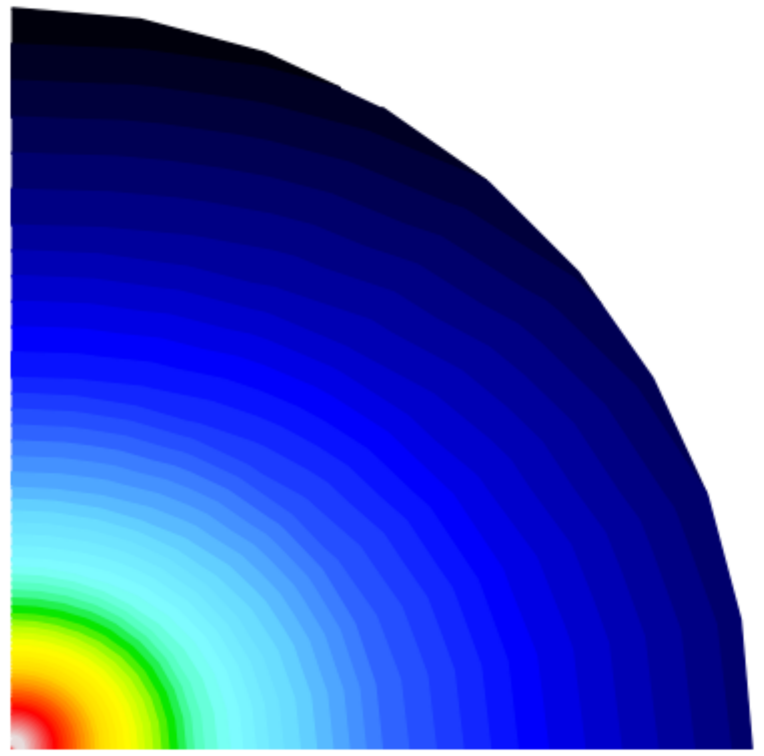
ML Architecture Requirements

- Directly use photometry
- Fast run time for MCMC
- Make use of symmetries (axisymmetry, $\overline{v_{\mathrm{los}}^2} \propto M$)
- Compatible with GPU and CPU

Training Set



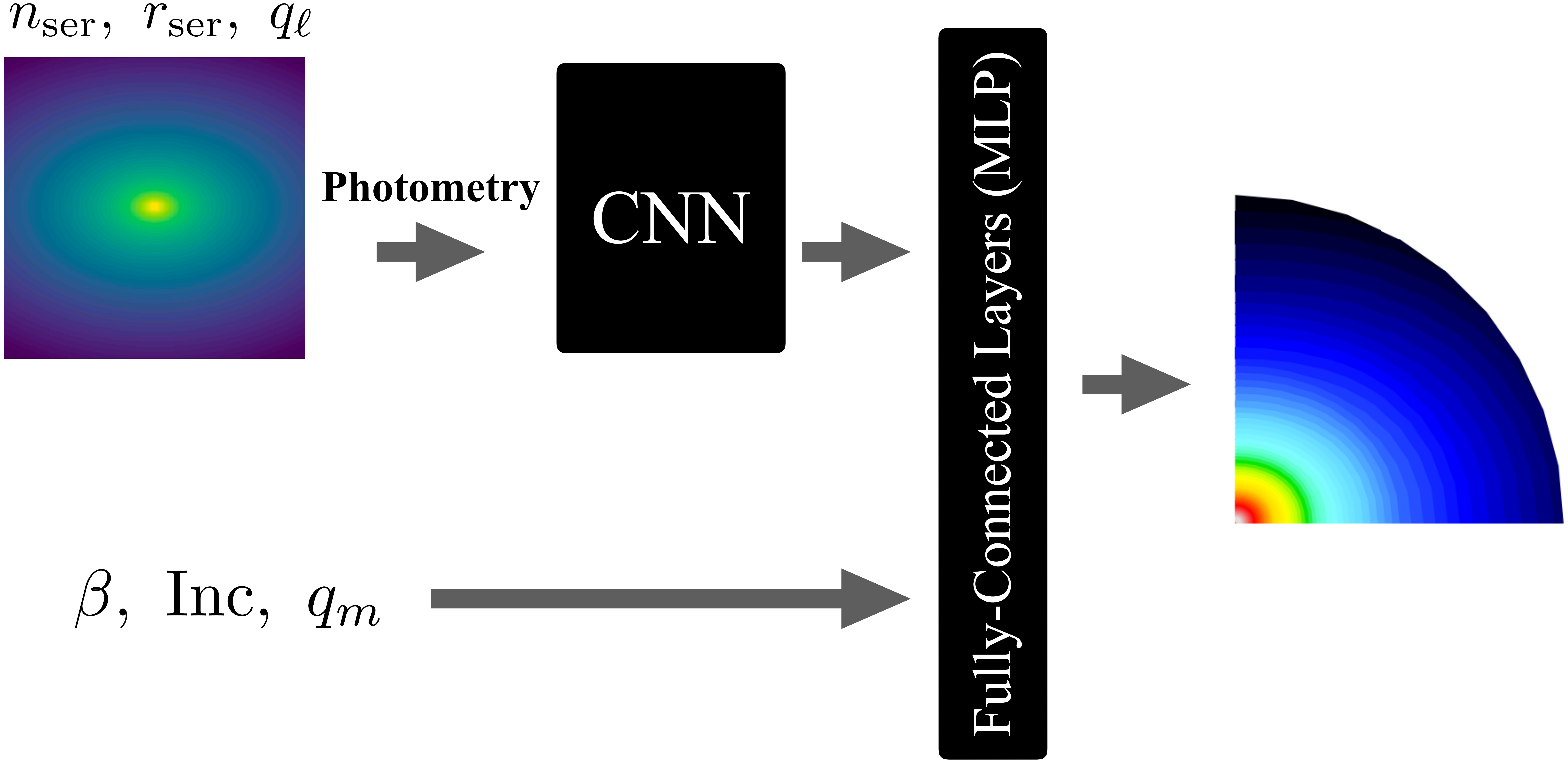
JAM Vrms



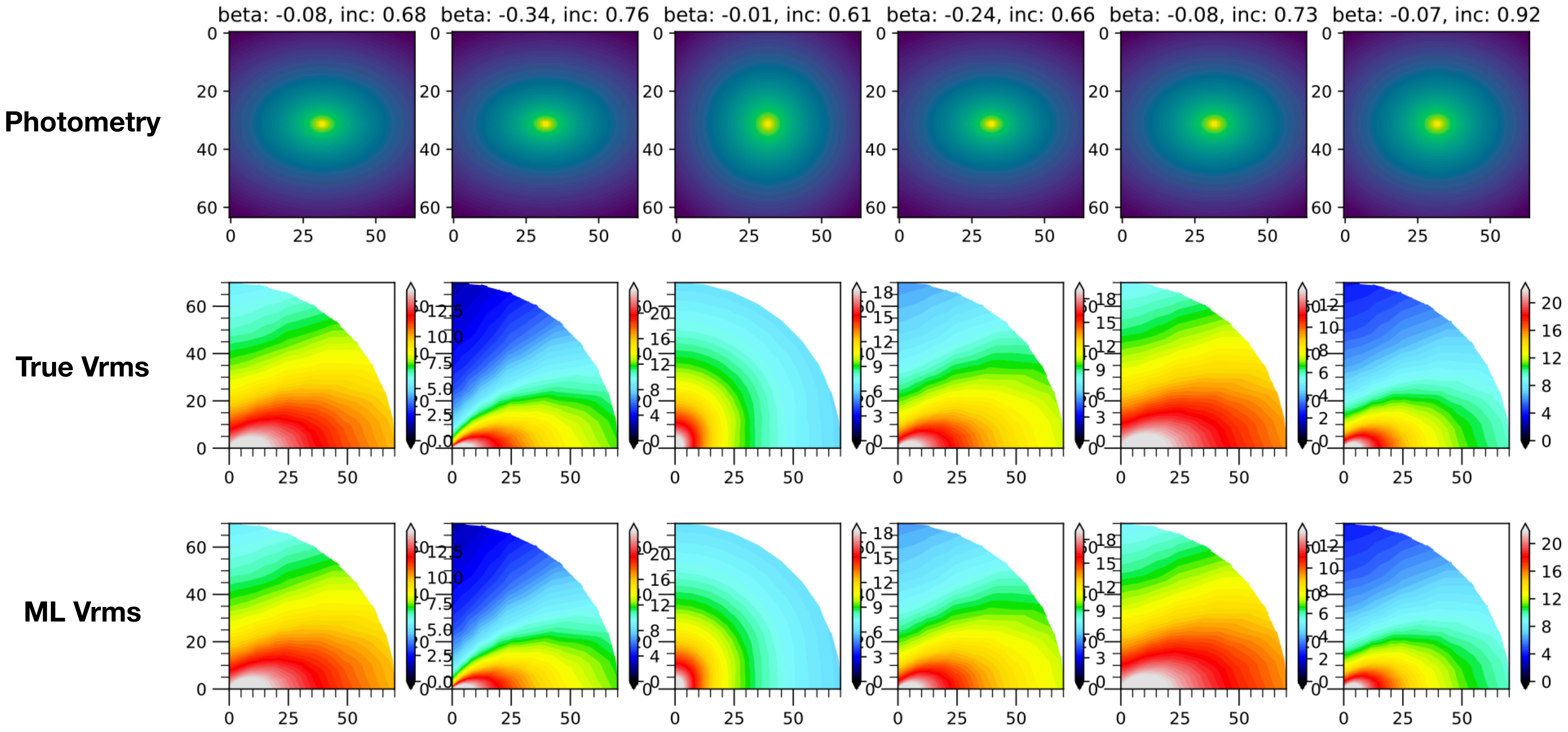
$$n_{\rm ser} \in [2, 4]$$
$$R_{\rm ser} \in [5", 20"]$$
$$q_\ell \in [0.6, 1]$$
$$\beta_{\rm z} \in [-0.4, 0.4]$$
$$q_{\rm m} \in [0.6, 1]$$
$$\mathrm{inc} \in [\arccos(0.6), 90°]$$
$$\theta \in [0°, 180°]$$

- 10,000 mock Galaxies
  - 8000 training
  - 2000 test
- Randomly sampled parameters while enforcing physical solutions
  - $\beta \leq 0.7\epsilon_{\rm intr}$ (See Wang et al 2021)

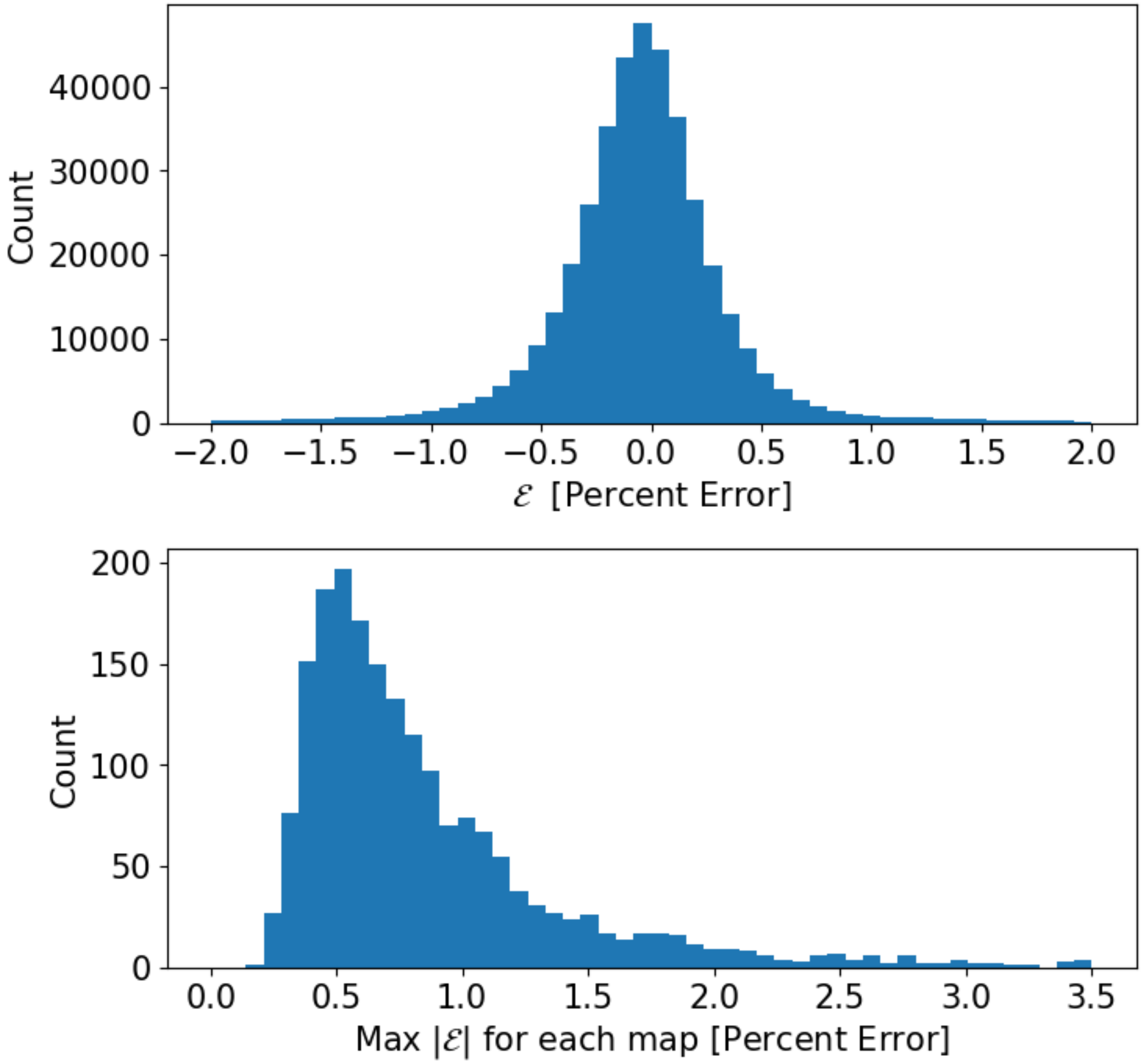
ML Modelling Pipeline



Outcomes: Maps



Outcomes: Accuracy

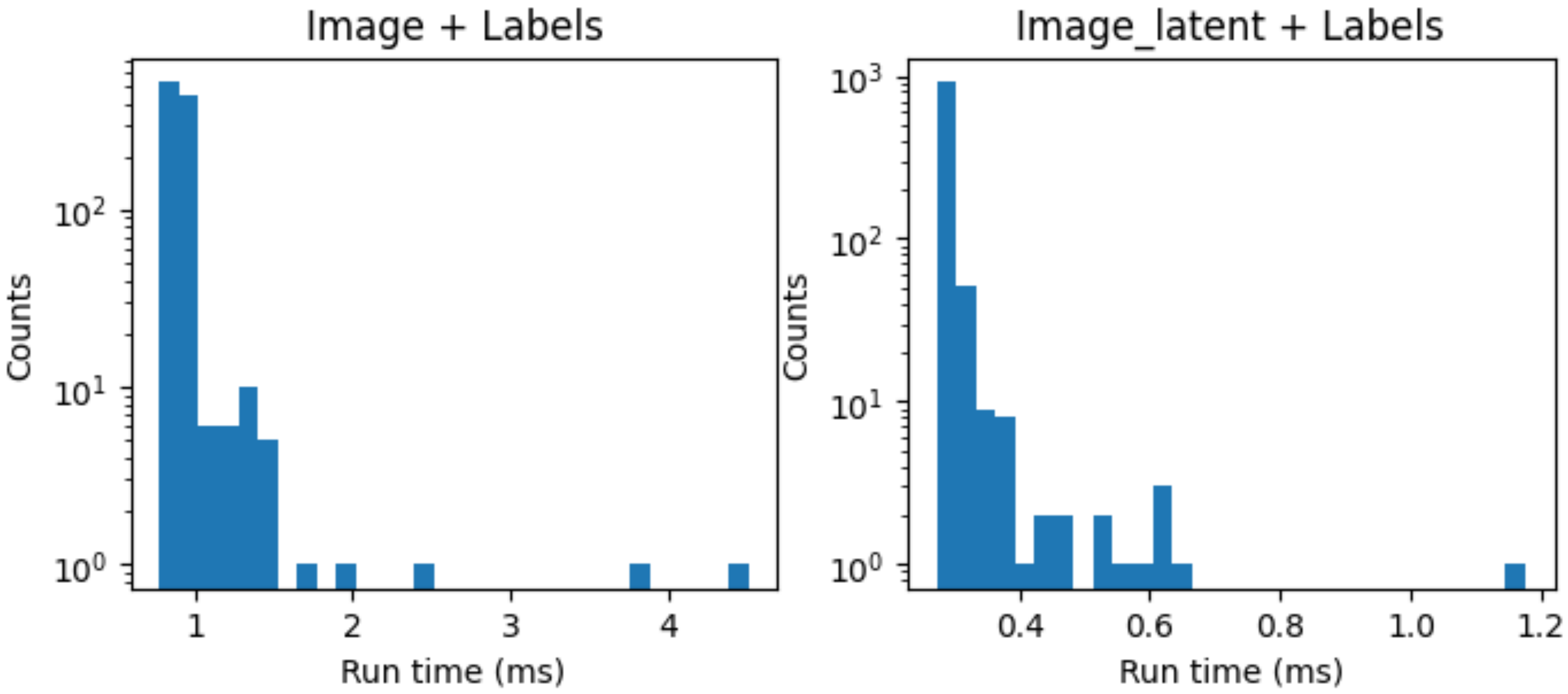


$$\mathcal{E} = \frac{\text{Model} - \text{Truth}}{\text{Truth}}$$

- The test set maps are accurate to within 1% and ninety percent of the maps have a max error less than 2%
- Real observations are accurate to within 6-7 km/s

Outcomes: Timing

- Training set can be generated in ~3 hours on a single CPU core
  - 2.5 days for Gomer et al 2023
- Model can be trained on a single NVIDIA V100 GPU in ~30 minutes
  - 3 days for Gomer et al 2023



Almost 100x faster than (Gomer et al 2023) and on CPU

Key Questions

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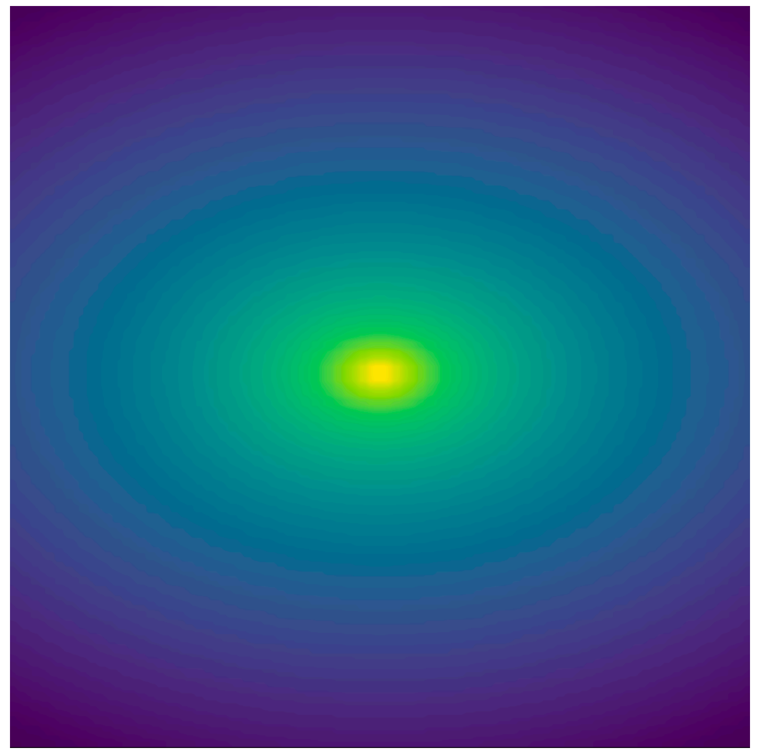
- Can Machine Learning be used to Create New Methods?

(Preliminary results!)

ML Modelling Pipeline

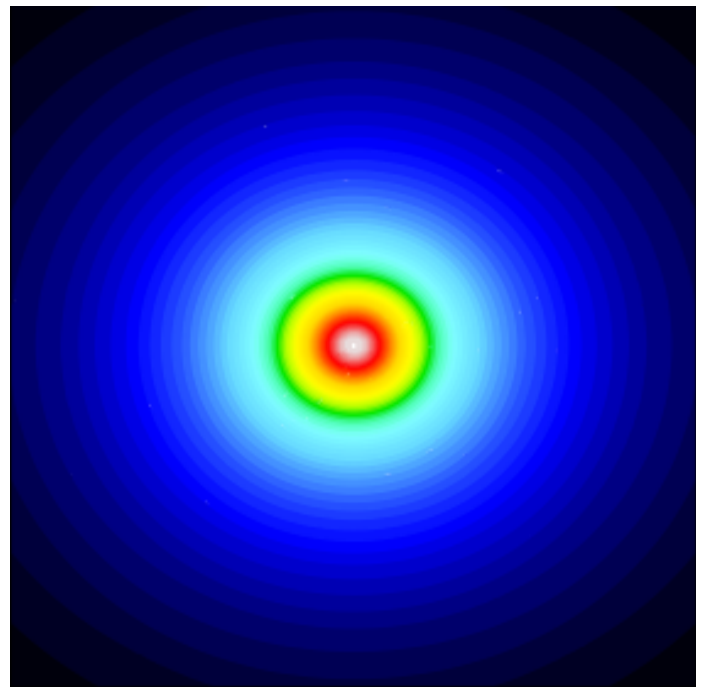


Photometry

Gravitational Potential

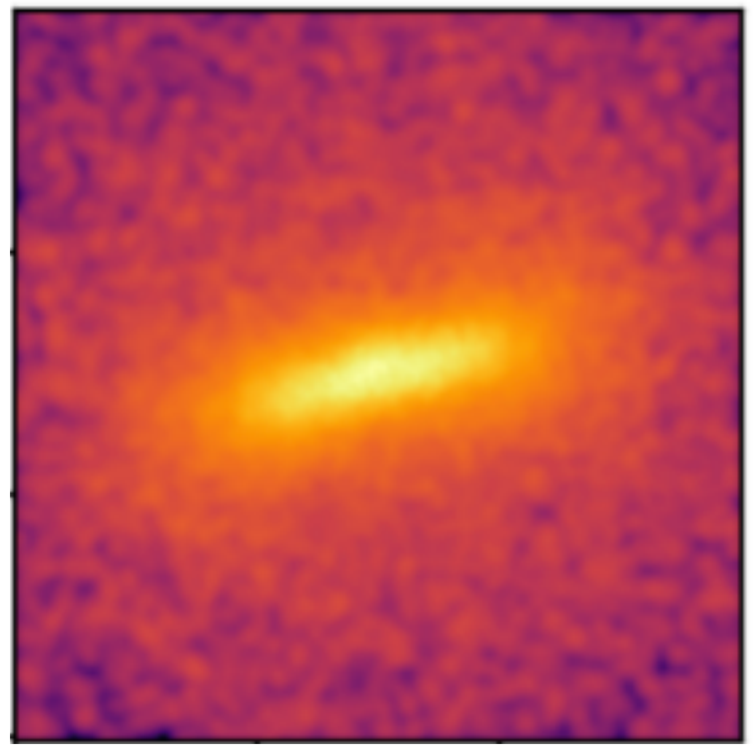
Free Parameters

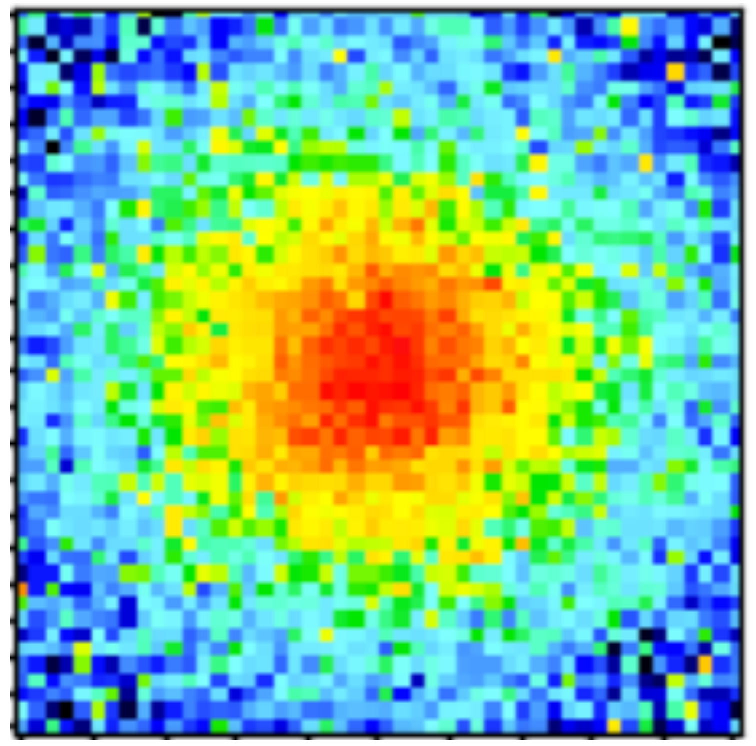
Machine Learning Algorithm



TNG100 Mock Observations

Training Set





Inc

$\beta(r < R_e)$

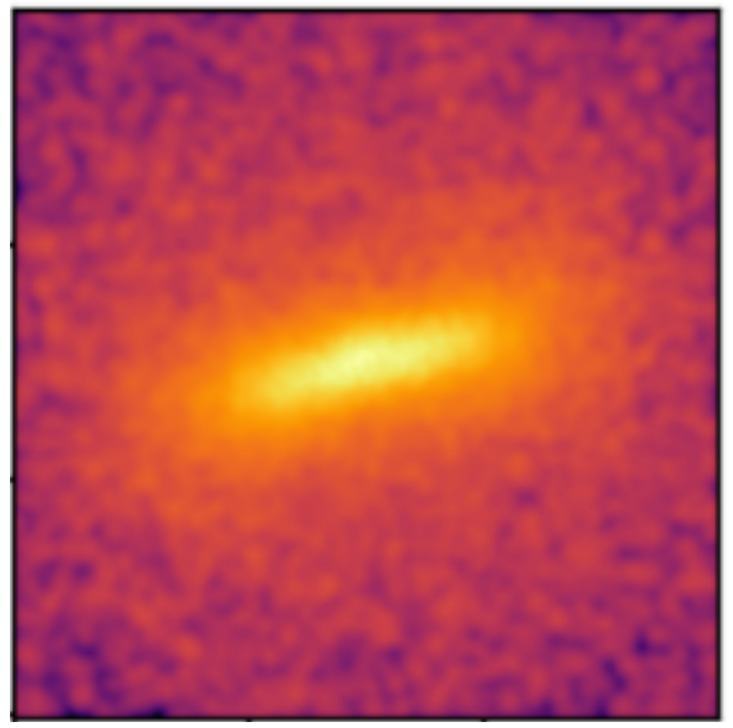
$M/L(r < R_e)$

$f_{\rm dm}(r < R_e),\ \gamma,\ r_s$

$\theta \in [0^\circ, 180^\circ]$

- TNG100 Mock Observations
  - 1.4e6 solar mass resolution for stars
  - Stellar mass within 30 kpc > 5e9 solar mass
  - Total mass < 1e14 solar mass
- ~5000 galaxies
- Mock observations along x,y, and z axis
- Field of view out to 3 Re

ML Modelling Pipeline



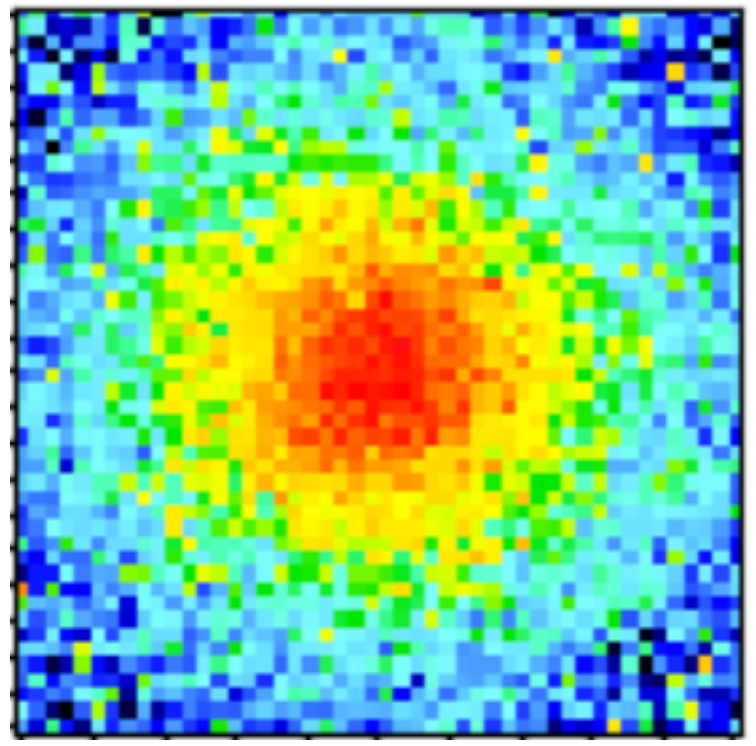
Photometry

CNN

Fully-Connected Layers

β, Inc, M/L,

$f_{\rm dm}$, γ, r_s, θ



Use non-standard loss to mask empty pixels

TNG100 Results

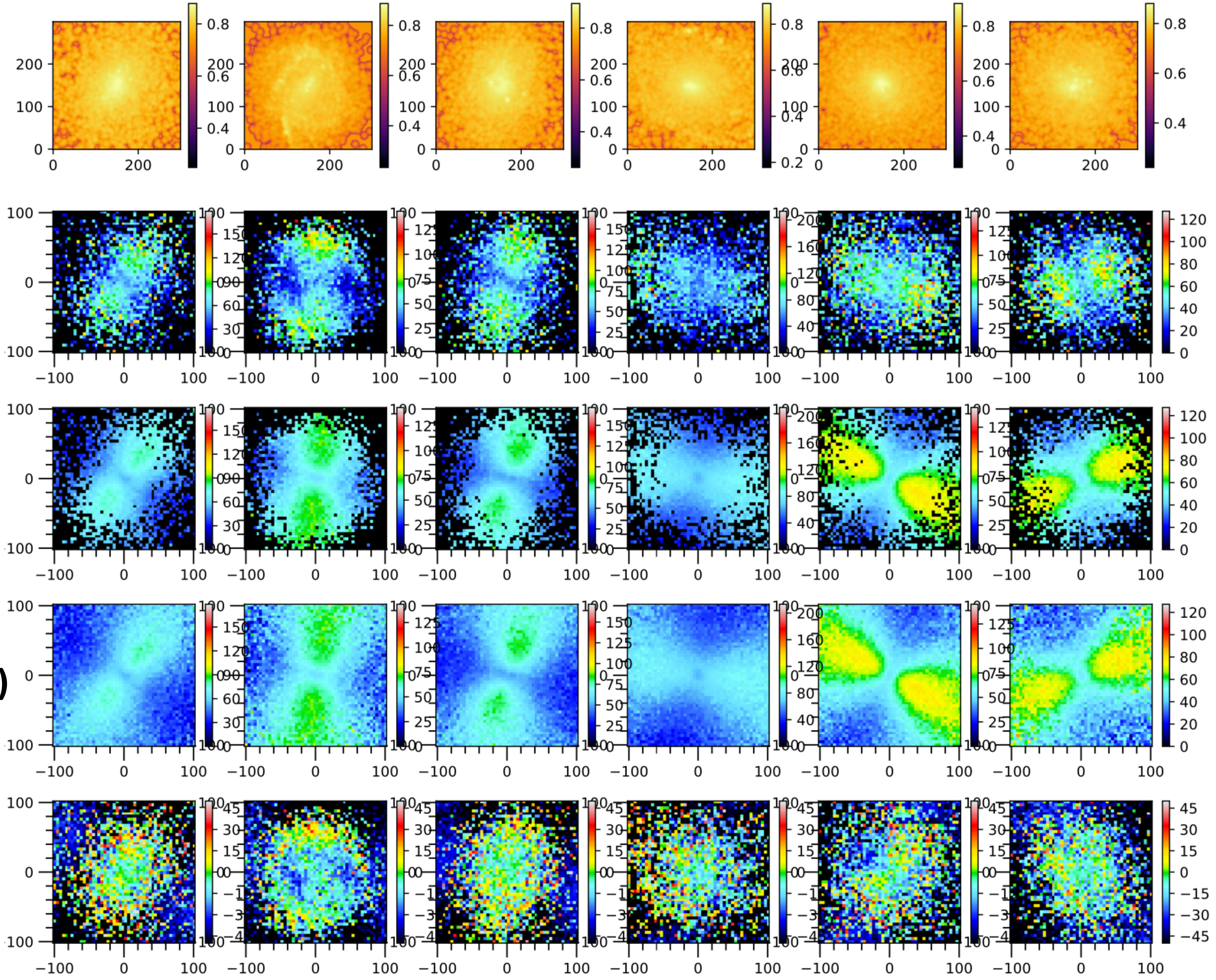
TNG100 Photometry

TNG100 Vrms

ML Vrms (with mask)

ML Vrms (without mask)

Residuals



Conclusions

- Simple machine learning algorithms can sometimes outperform complicated ones
- Close to 10,000 data points are required in order to machine learn dynamical models (less with more complicated models)
- Machine Learned dynamical models have the potential to outperform existing methods