Human-Machine Collaboration: Bridging the Last Mile Between Astronomers and A.I.

Nan Li (NAOC)

In collaboration with:

Fengshan Liu, Jian Ren, Simon Dye, Xiaoji Lingchen, Haojin Yan, Mingxiang Fu, Qifan Cui, Pinsong Zhao, Zizhao He, Peng Jia, Shanshan Li, Zhen Zhang, Chenzhou Cui, etc.

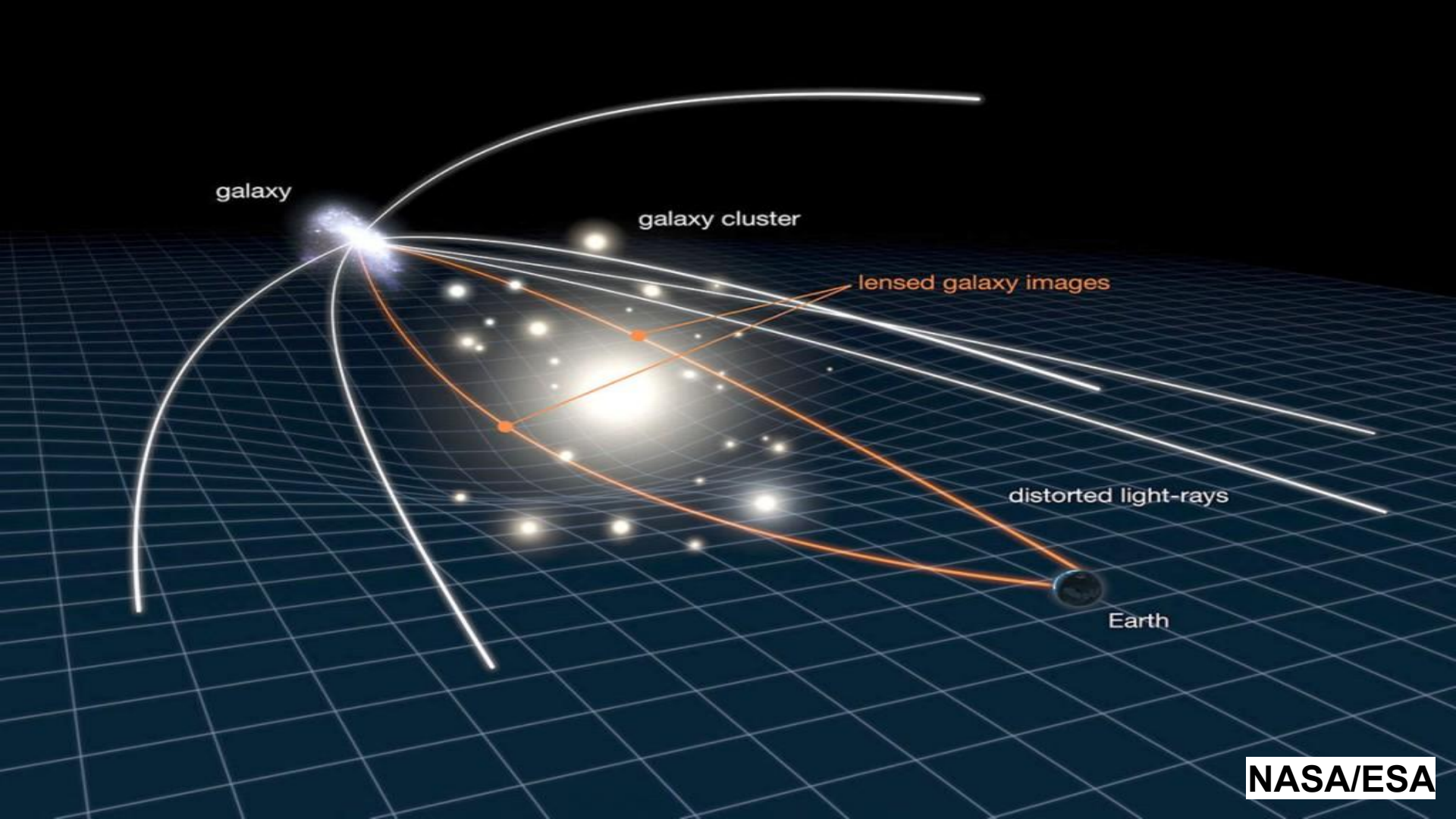
Human-Machine Collaboration: Bridging the Last Mile Between Astronomers and A.I.

Strong Lensing Analysis as an Example

Nan Li (NAOC)

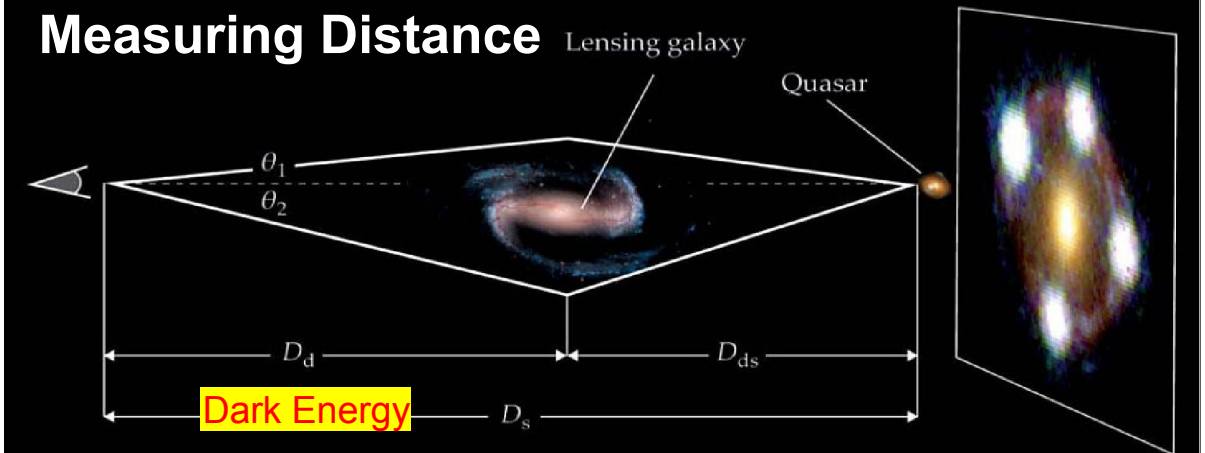
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galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth
NASA/ESA

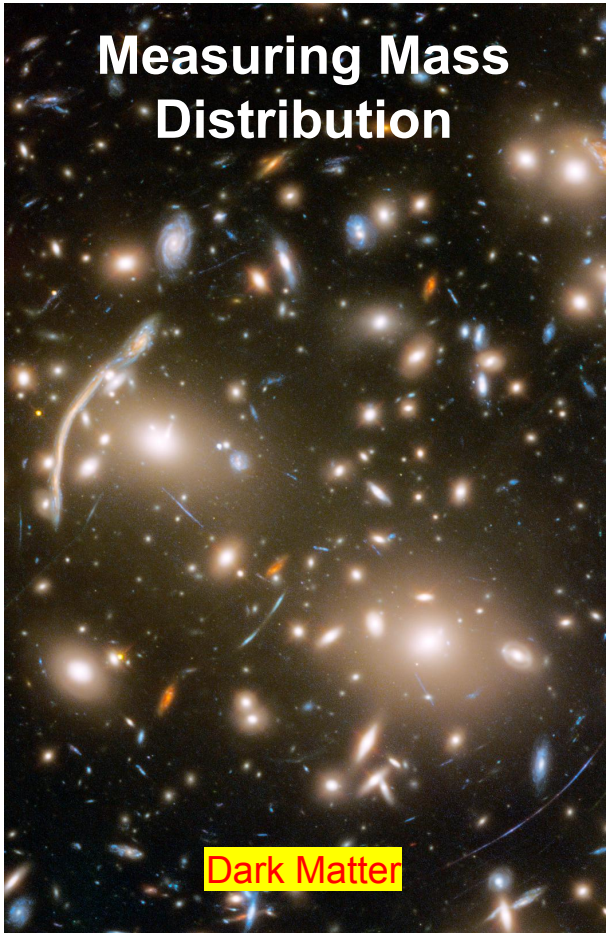
Why Strong Gravitational Lensing Matters?

Measuring Distance

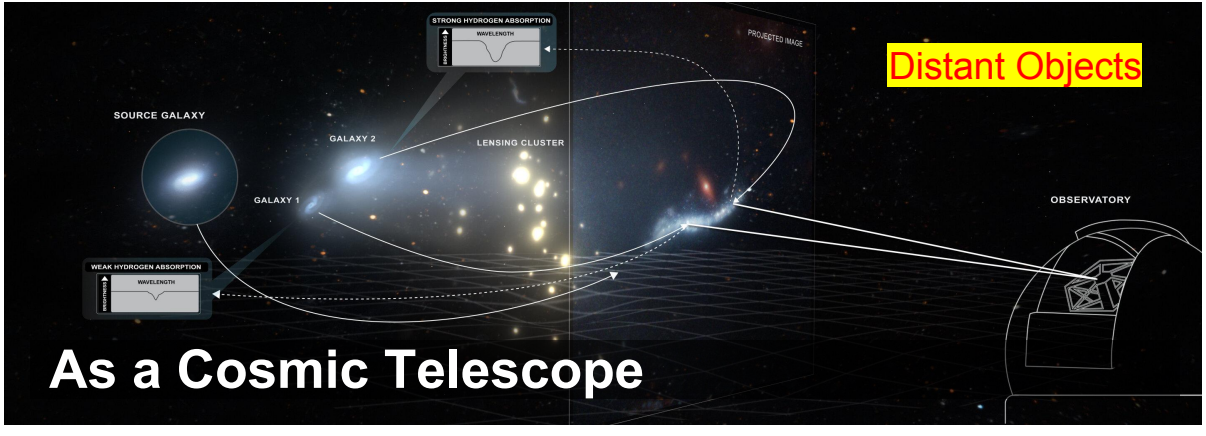


Dark Energy

Measuring Mass Distribution



Dark Matter

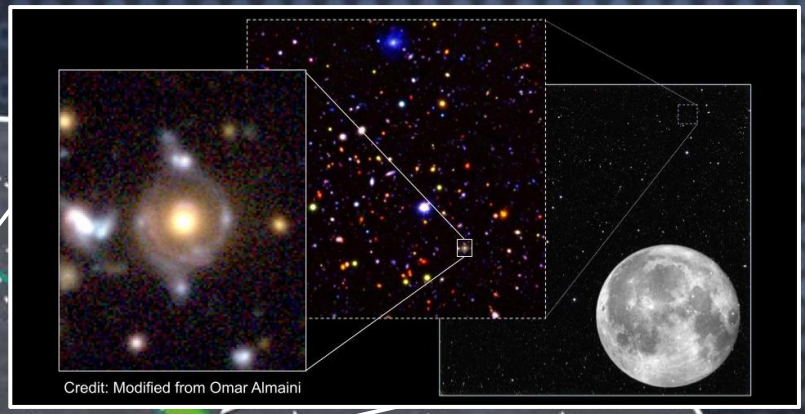


Distant Objects

As a Cosmic Telescope

Analyzing Hundreds of Strong Lenses from Millions of Objects

×10000



30°
15°
0°
-15°
-30°

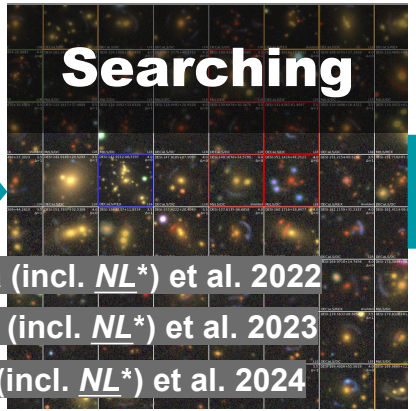
Deep Drilling Field

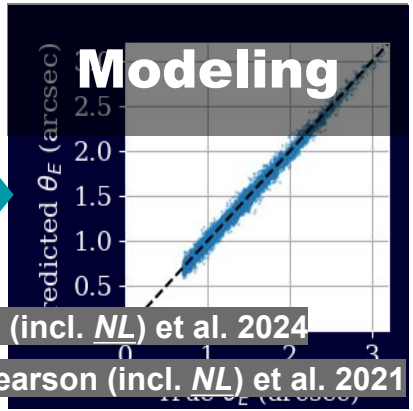
Wide-Fast-Deep Survey Region

How to identify and model tens of thousands of strong lenses from tens of billions of astronomical objects in the big data era ? ? ?

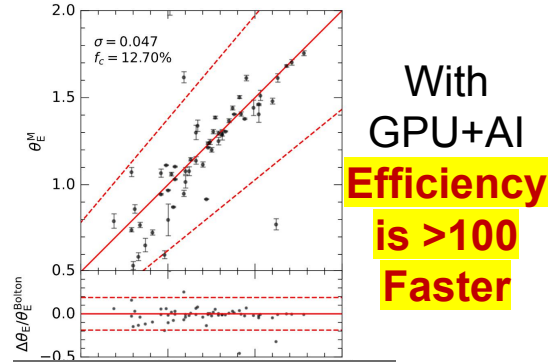
Strong Lensing Analysis with Supervised ML

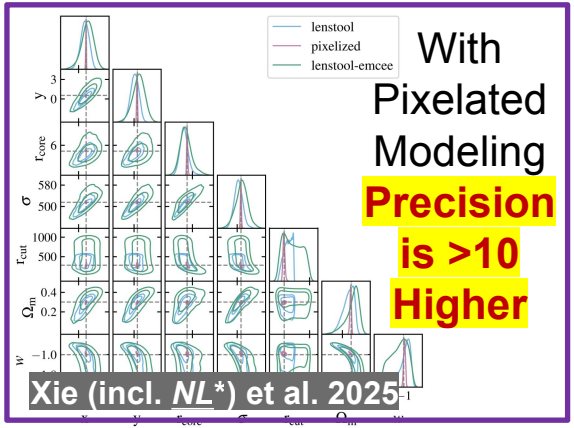


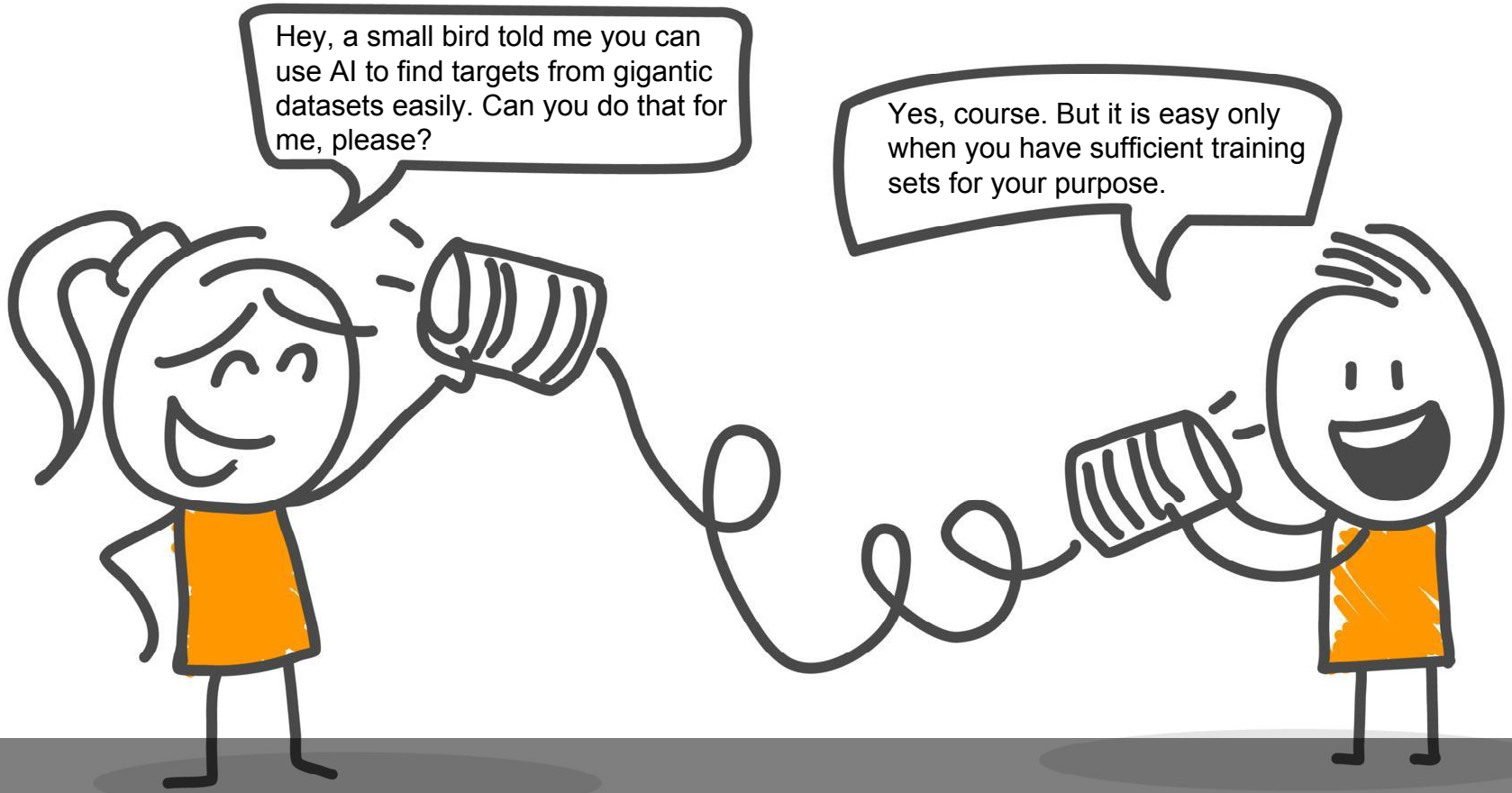




1. **A ML-empowered** Strong Lensing Analysis Pipeline for CSST
2. **1** system identification **/A100/millisecond**

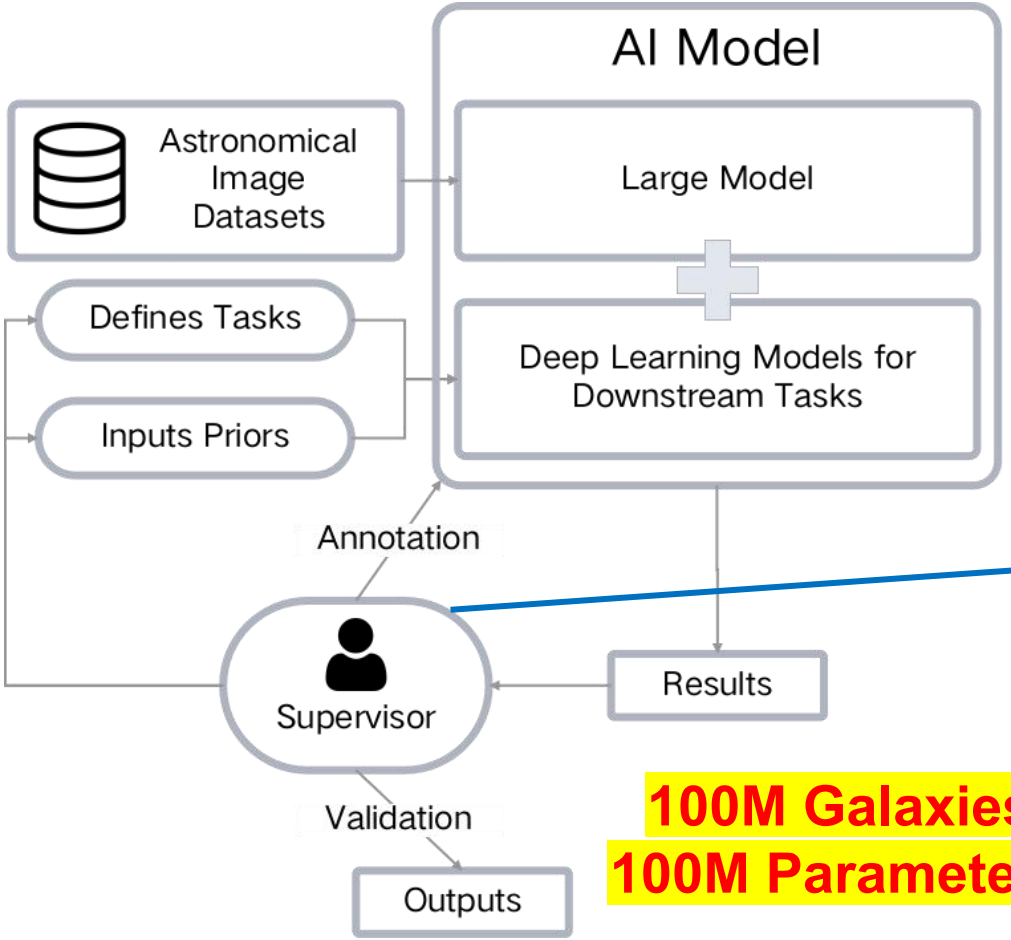






Can We Search For Specific Targets without Training Sets?

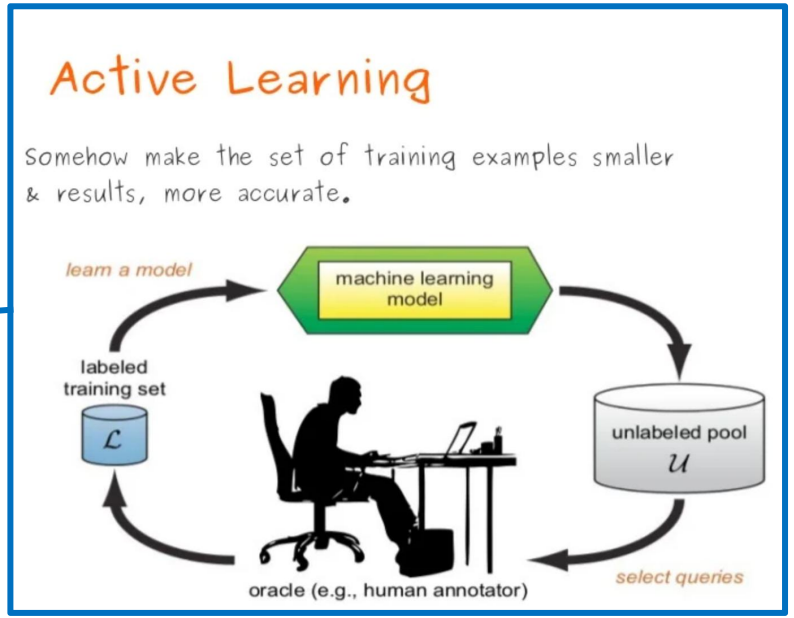
Human-machine Cooperation for Astronomy



Foundation Vision Model

+ Downstream Tasks

+ Human-in-the-loop

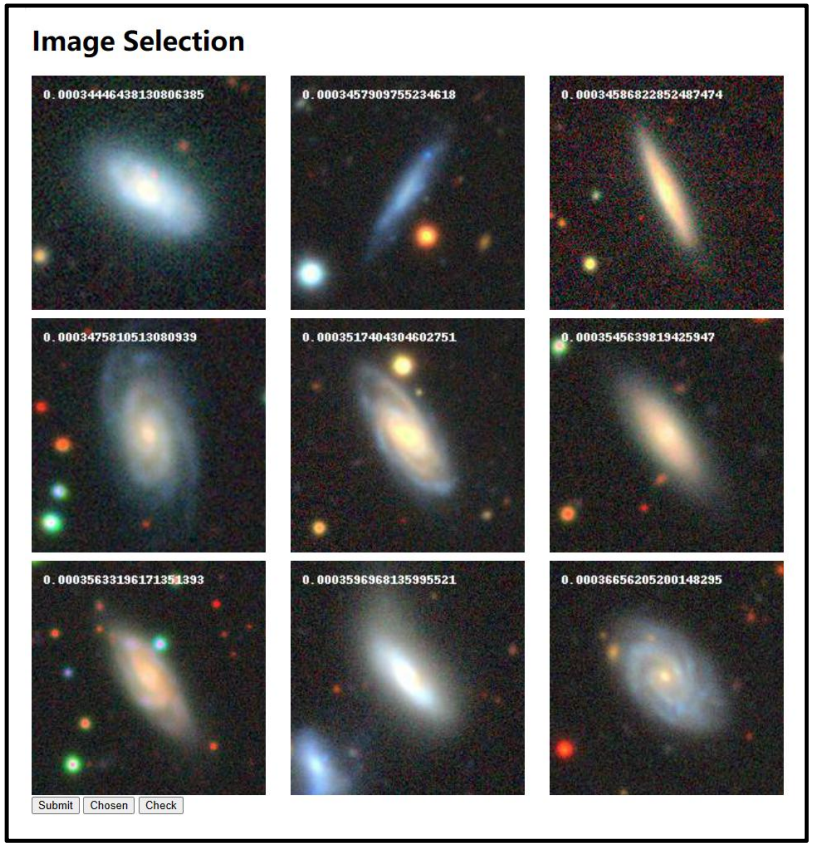


100M Galaxies

100M Parameters

Fu (incl. *NL**) et al., 2024

Classifying Galaxies with HITL: Interface





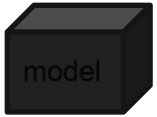
expert

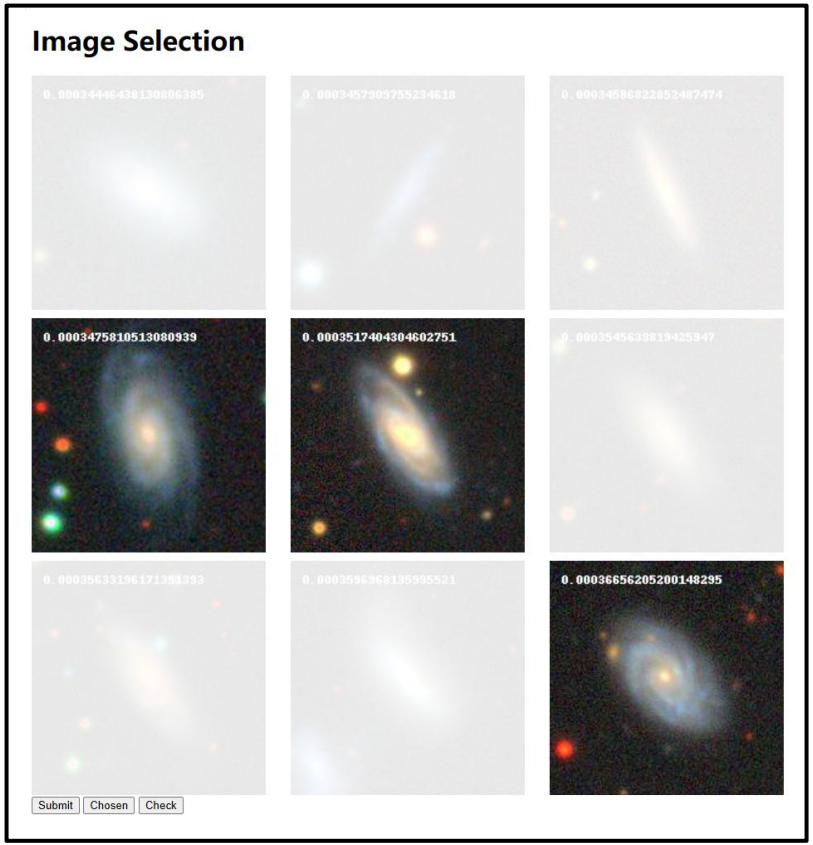
click to choose





train to recommend





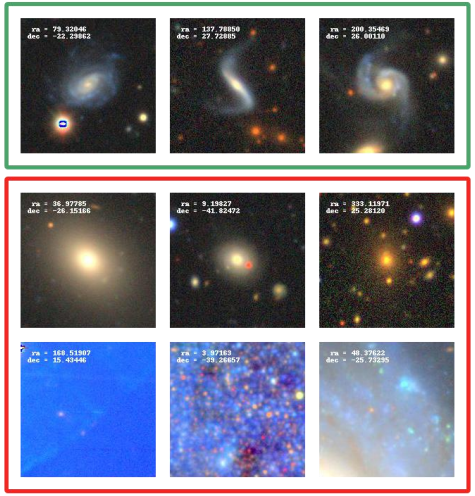
Fu, ..., *NL** et al. 2024

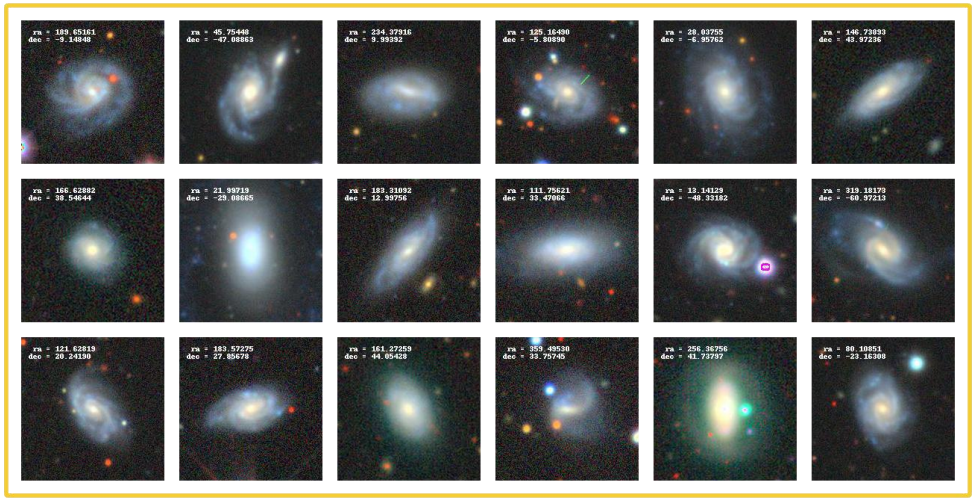
Classifying Galaxies with HITL: Examples

Basic Task

Spirals
VS
Ellipticals

< 10 loops

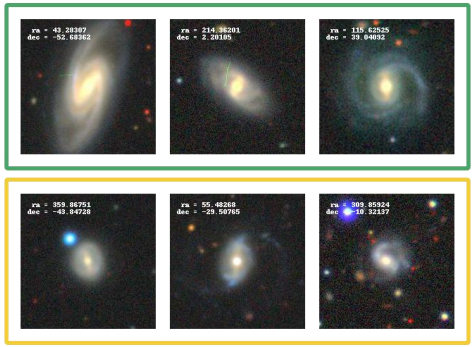




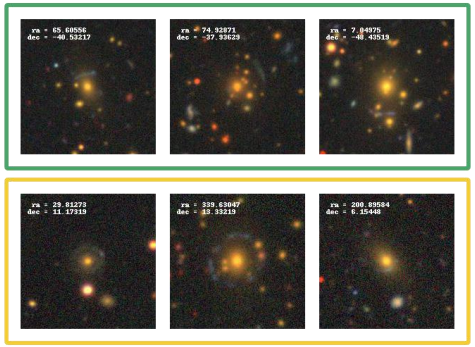
Advanced Tasks

~ 30 loops

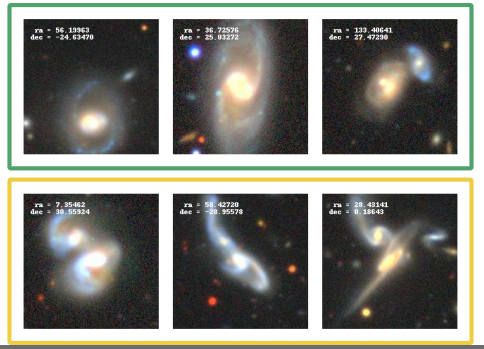
Barred Galaxies



Strong Lenses

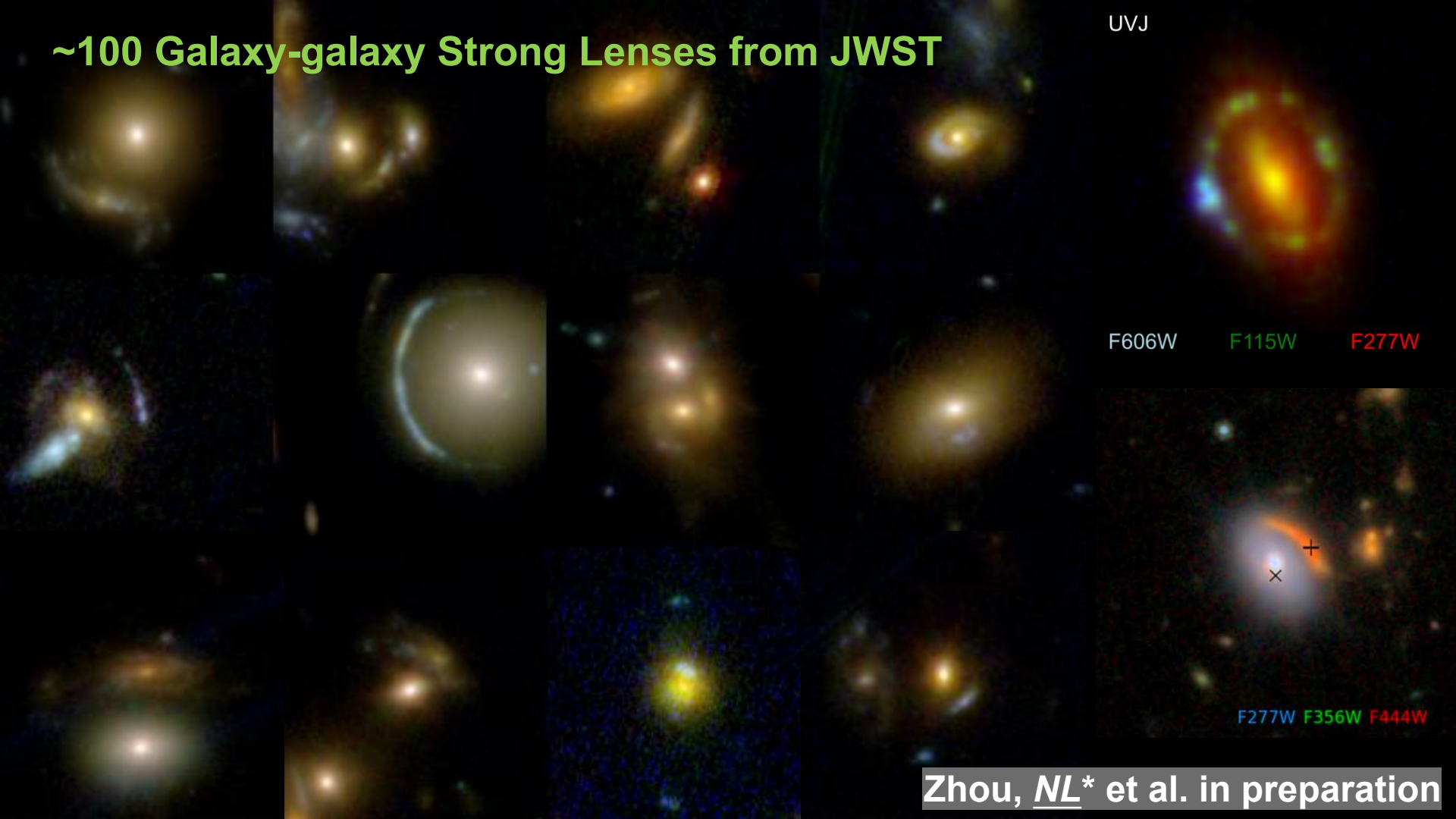


Mergers



Fu (incl. *NL**) et al. 2024

~100 Galaxy-galaxy Strong Lenses from JWST

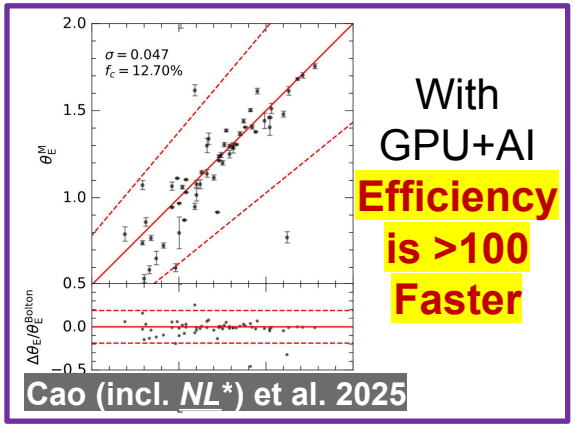


Zhou, *NL** et al. in preparation

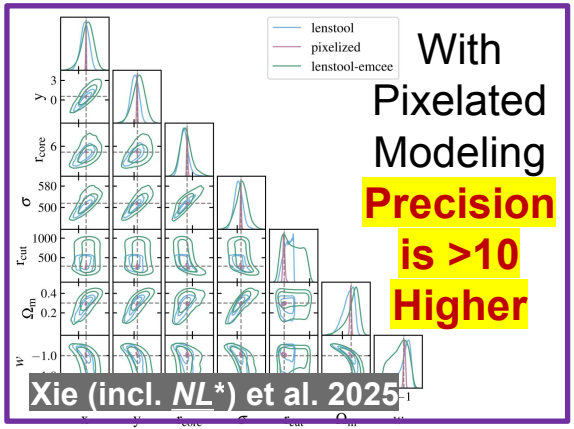
Strong Lensing Analysis with HITL



1. **A ML-empowered** Strong Lensing Analysis Pipeline for CSST
2. **1** system per A100 GPU **per millisecond**



With GPU+AI **Efficiency is >100 Faster**



With Pixelated Modeling **Precision is >10 Higher**

Hoopla

Lens Modeling in Javascript with Elliptical Lenses and Sources

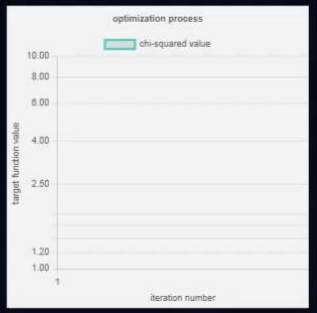
Mass Model



Source Model



Chi-Square Curve



Source Plane



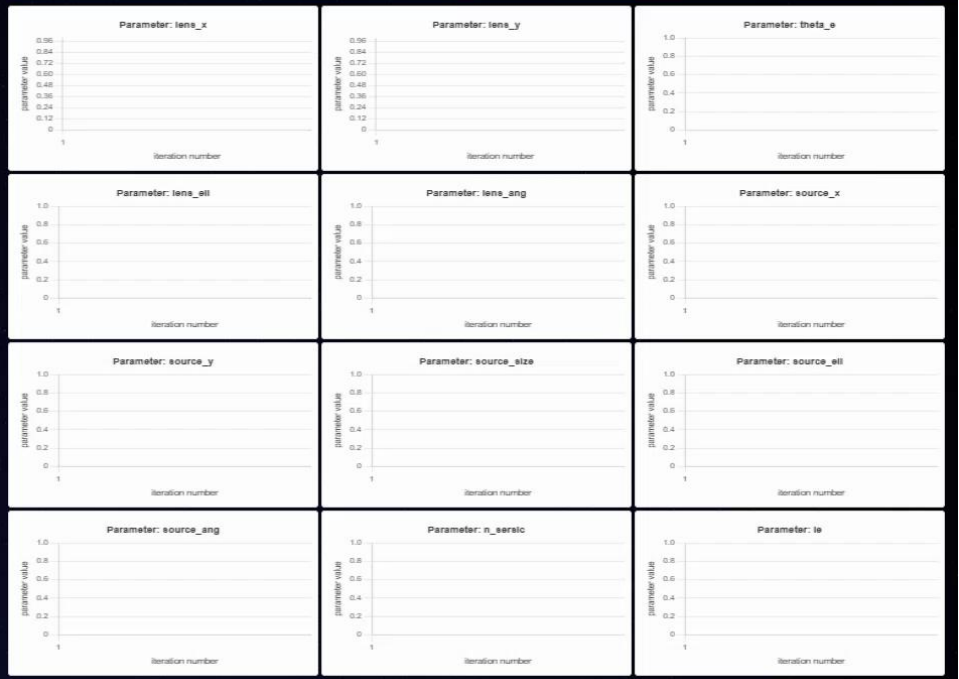
Image Plane



Residual Map



Parameter Trending Charts

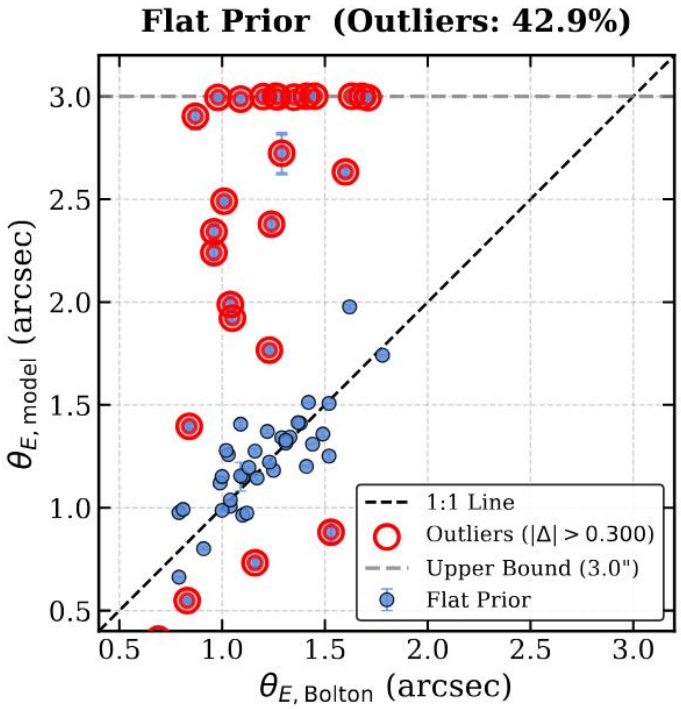


Save Models | Load Models | Upload Images | Upload PSF | Extract Lens Arc | Optimization | MCMC

Current pixel-scale: | Reset Pixel-Scale | Mask Radius: | Apply Mask

☑ Draw Model Comparison Line ✕ PSF Not Uploaded

Long, *NL** et al. in preparation



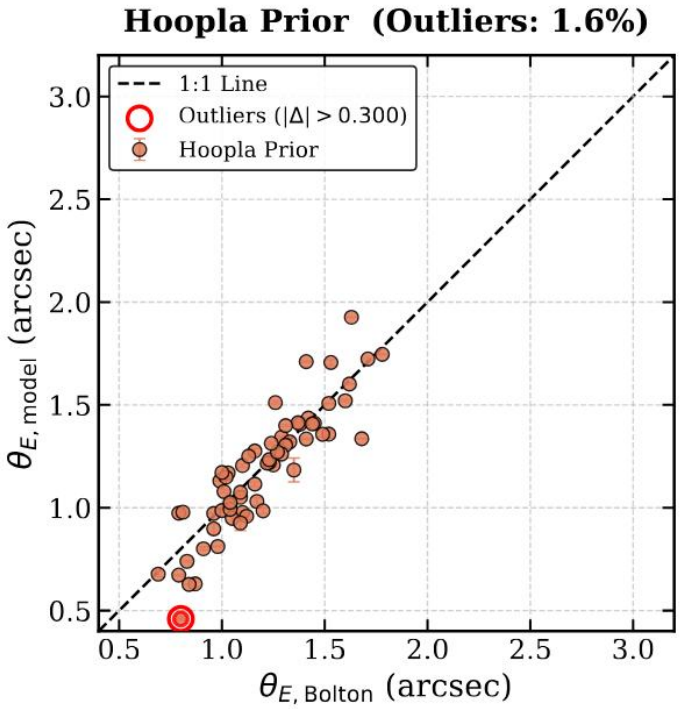


Figure 5: Recovered Einstein radii with posterior uncertainties against the Bolton reference values for 63 SLACS systems under Group A configurations. Left: Flat Prior mode. Right: Hoopla Prior mode. The black dashed line indicates the 1:1 identity relation. Points enclosed by red circles denote physically discrepant systems ($|\Delta_{\theta_E}| > 0.3$), comprising 42.9% and 1.6% of the sample under Flat and Hoopla priors, respectively. The gray dashed horizontal line in the left panel marks the upper boundary of the default TinyLensGPU prior range for θ_E (3.0″); systems clustered at this boundary indicate prior truncation rather than convergence to a physical solution.

Long, *NL** et al. in preparation

Agentic Strong Lens Modeling: Workflow

Images & Spectra

Datasets

Automated modeling

Inspect & configure
Mask contaminants
Einstein-radius prior
Priors

Physical modeling
Mass SIE / EPL + shear
Lens light MGE
Source light MGE / pixelized

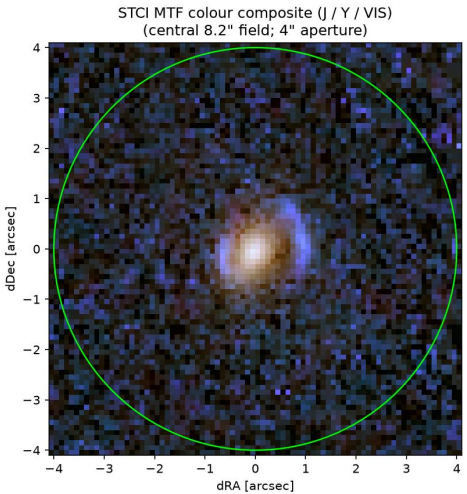
Diagnose
Images · residuals
Source · posteriors
Evaluation

Adjust & retry
Permitted settings

Accept / advance

Stop & refer

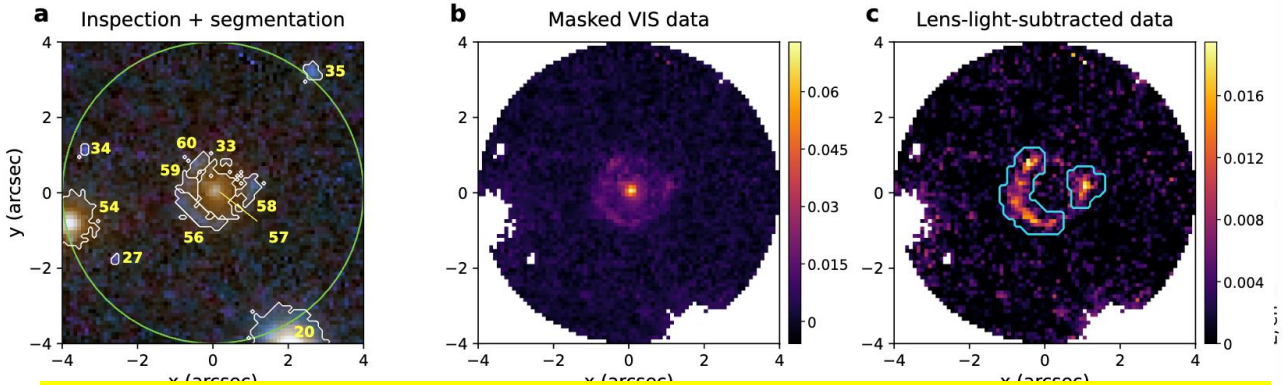
Human-in-the-loop



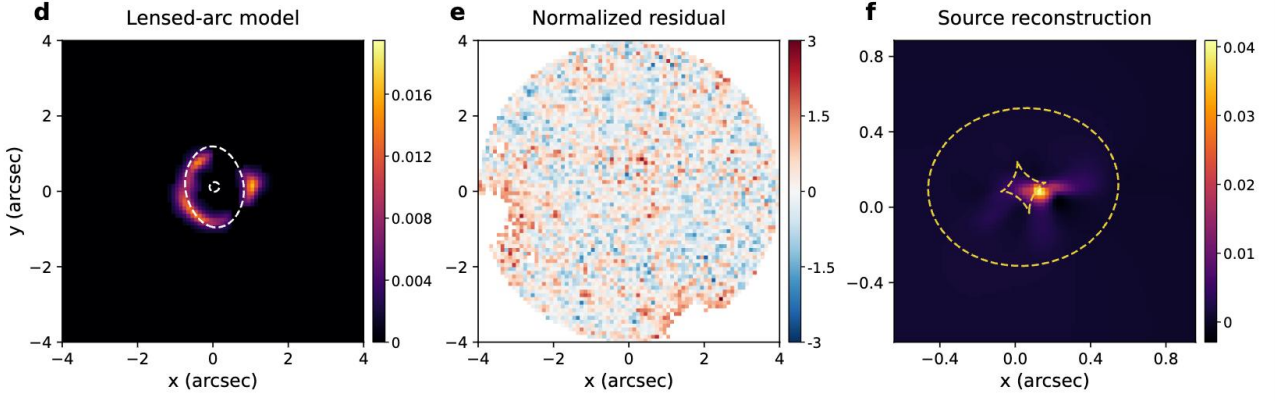
Post-run human assessment

Cao (incl. *NL*) et al. in preparation

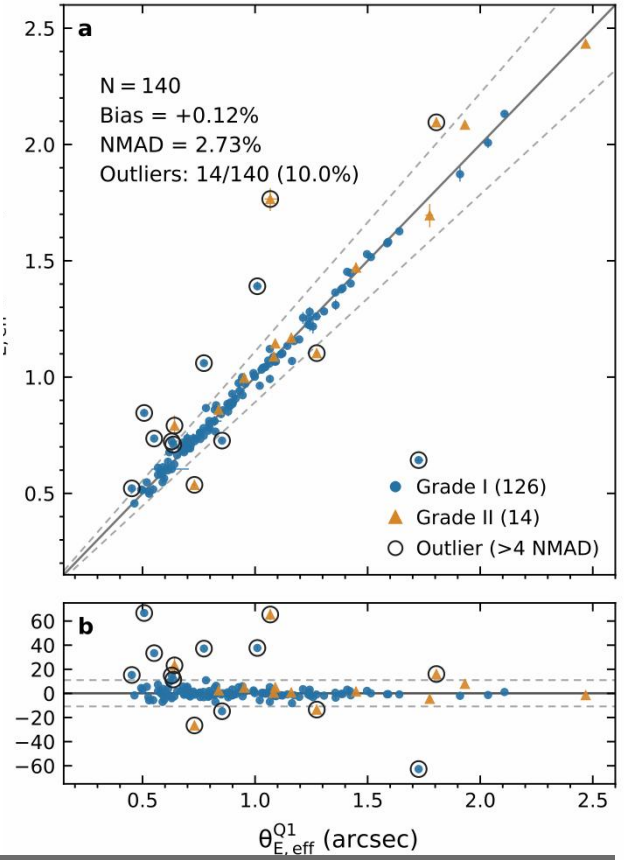
Agentic Strong Lens Modeling: Outcomes



Modeling 140 Euclid Q1 Strong Lenses by just chatting with your computer !



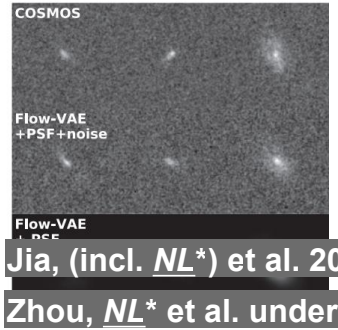
Cyan: arc-fit boundary White dashed: critical curve Yellow dashed: caustics



Cao (incl. *NL*) et al. in preparation

An E2E Agentic Pipeline for Galaxy Analysis

1. Simulation



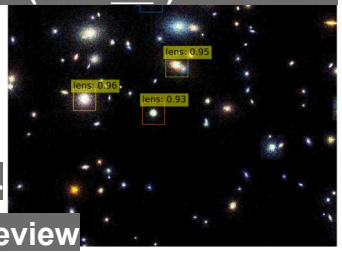
Jia, (incl. *NL**) et al. 2024

Zhou, *NL** et al. under Review

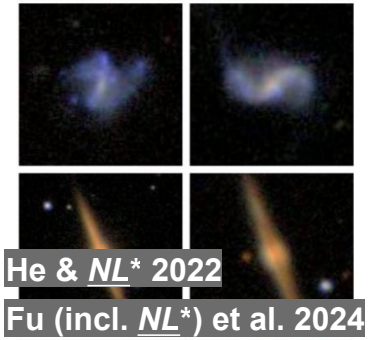
2. Detection

Jia (incl. *NL**) et al. 2022

Li (incl. *NL**) et al. 2024



3. Classification



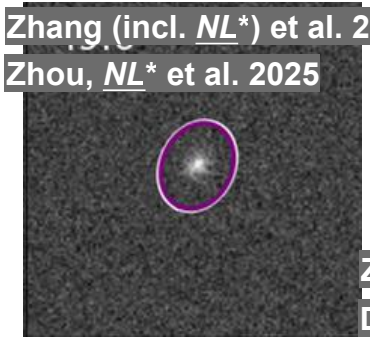
He & *NL** 2022

Fu (incl. *NL**) et al. 2024

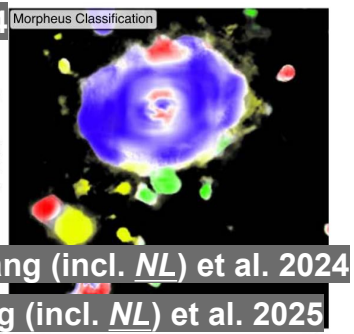
4. Modeling

Zhang (incl. *NL**) et al. 2024

Zhou, *NL** et al. 2025

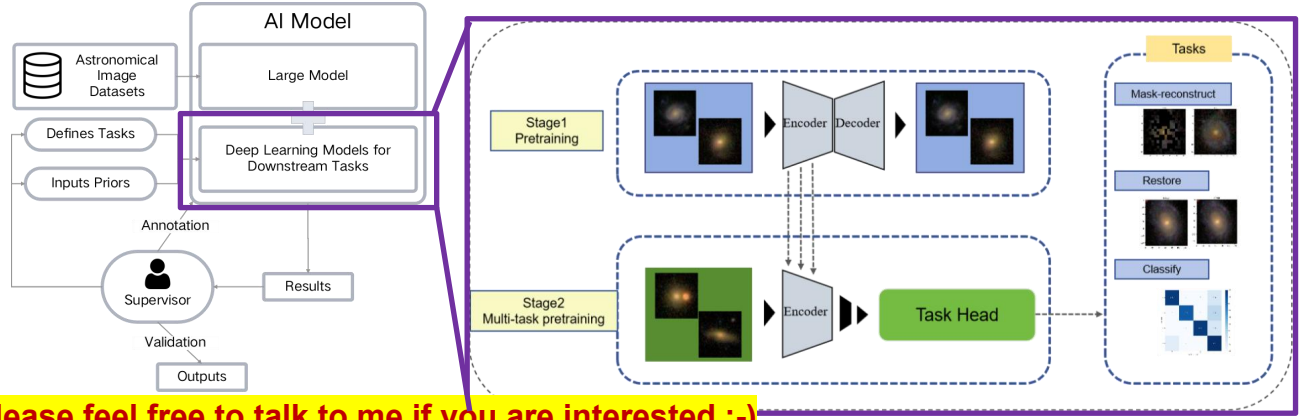


5. Decomposition



Zhang (incl. *NL*) et al. 2024

Ding (incl. *NL*) et al. 2025



Please feel free to talk to me if you are interested ;-)

Beyond Strong Lenses Towards All Galaxies

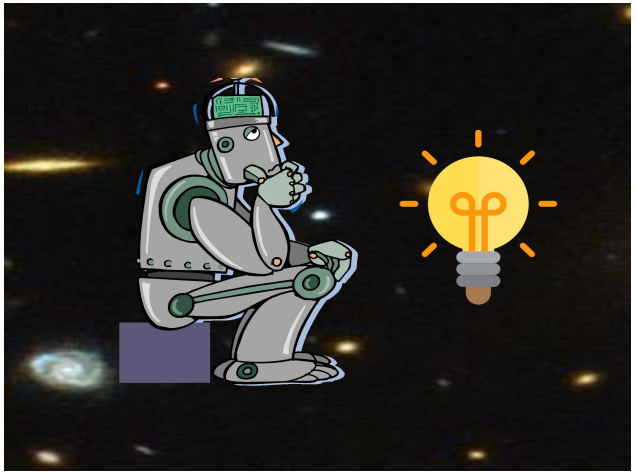
Optimizing priors and evaluation in the analysis galaxy structures with **Human-In-The-Loop**

Take Home Points

Bridging the Last Mile Between Astronomers and A.I.:
Strong Lensing in the Era of Big Data

- **Supervised Learning Works Well for SL**
- **A ML Empowered SL Pipeline for CSST**
- **Hard to Transfer for Different Experiments**
- **HITL Improves the Fexibility & Universality**
- **Agents Make Strong Lensers' Lives Easier**

An E2E Agentic Pipeline for Galaxy Analysis





Invitation to attend the Peony conference



Conference Website (under construction): **https://conf.koushare.com/conf/TDUEABD/**