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TOMOGRAPHY ACROSS COSMIC SCALES

RECONSTRUCTING GALAXY PROPERTIES FROM MULTI-BAND IMAGES

In collaboration with Steffen Wolf

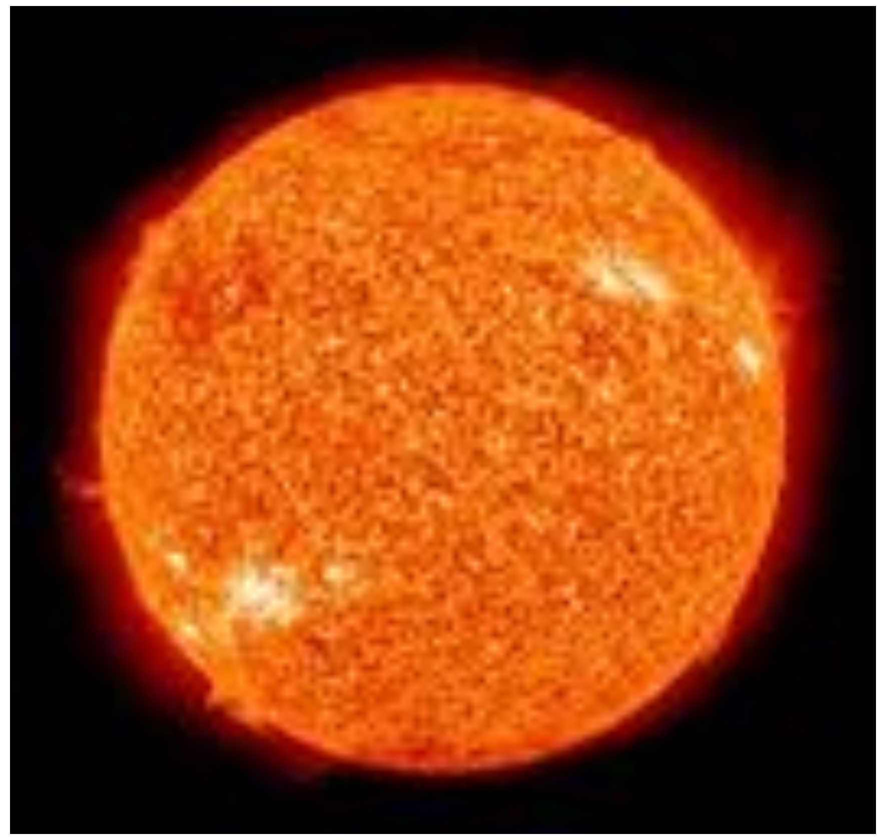
THE STRUCTURE OF THE NEXT ~40 MINUTES:

- Introduction: Reconstruction across cosmic scales
- A brief history of the Universe
- Galaxy structures in simulations and the Milky Way
- The challenge of reconstructing galaxy properties from observational images

EXAMPLES OF RECONSTRUCTION PROBLEMS IN ASTRONOMY

Stars & Planets

~10^{-8} pc



Interstellar Medium

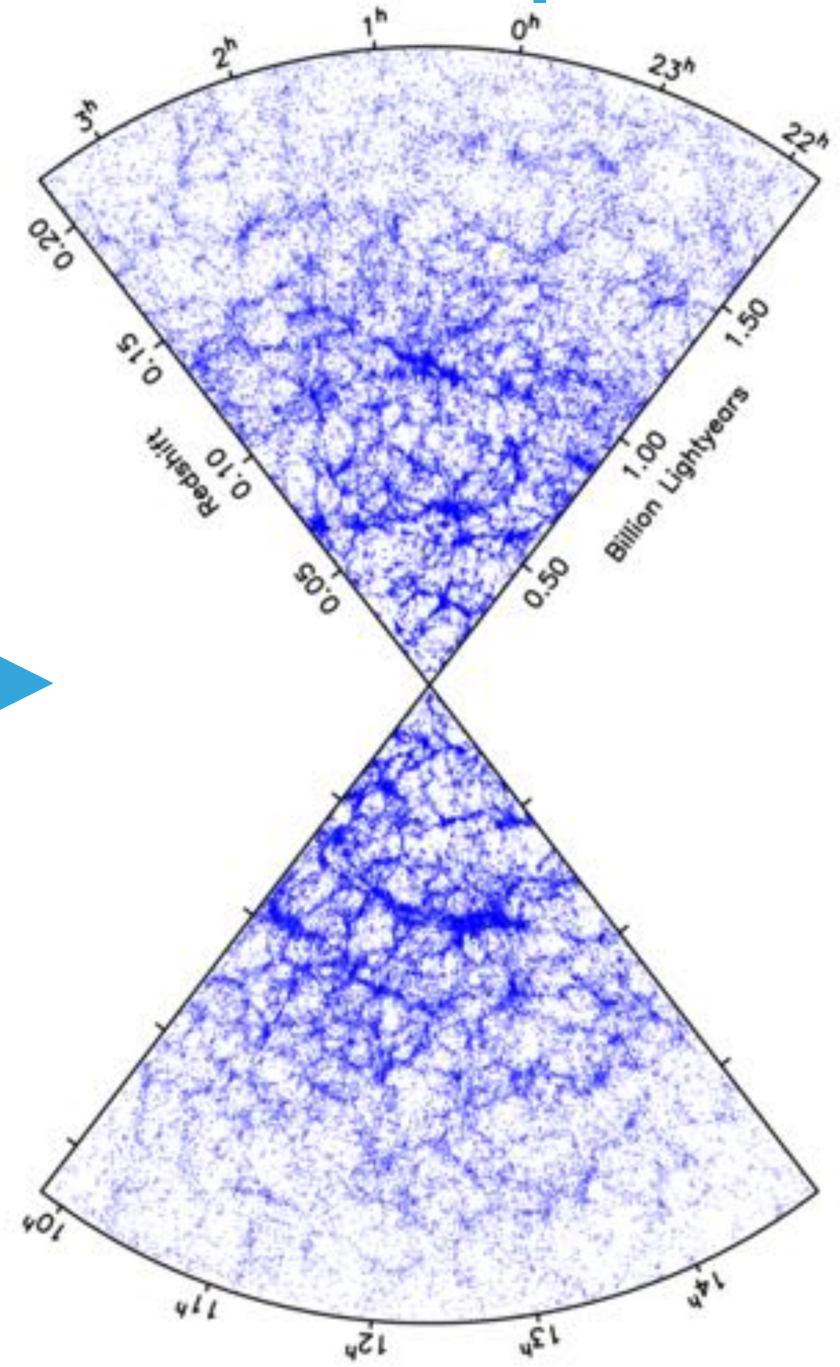
~10 pc

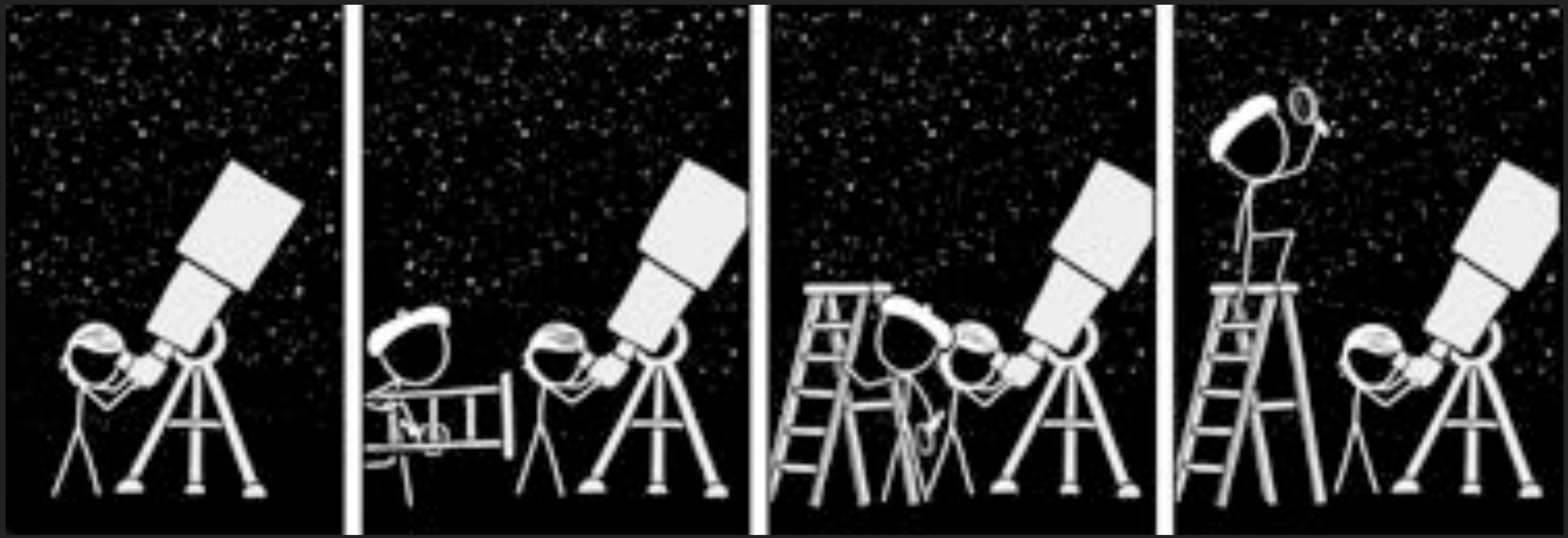
Galaxies

~10 000 pc

Universe

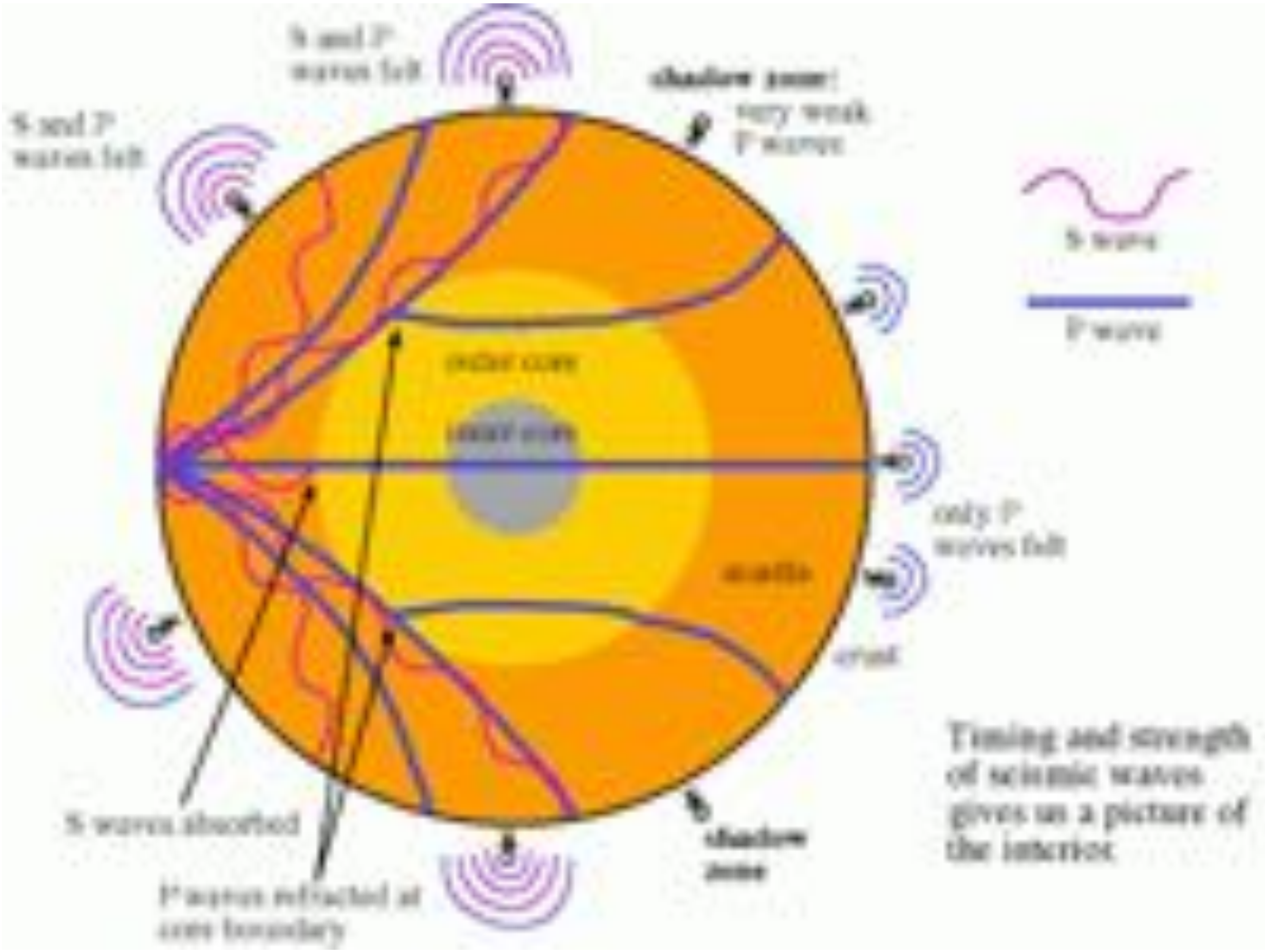
~10^{9} pc

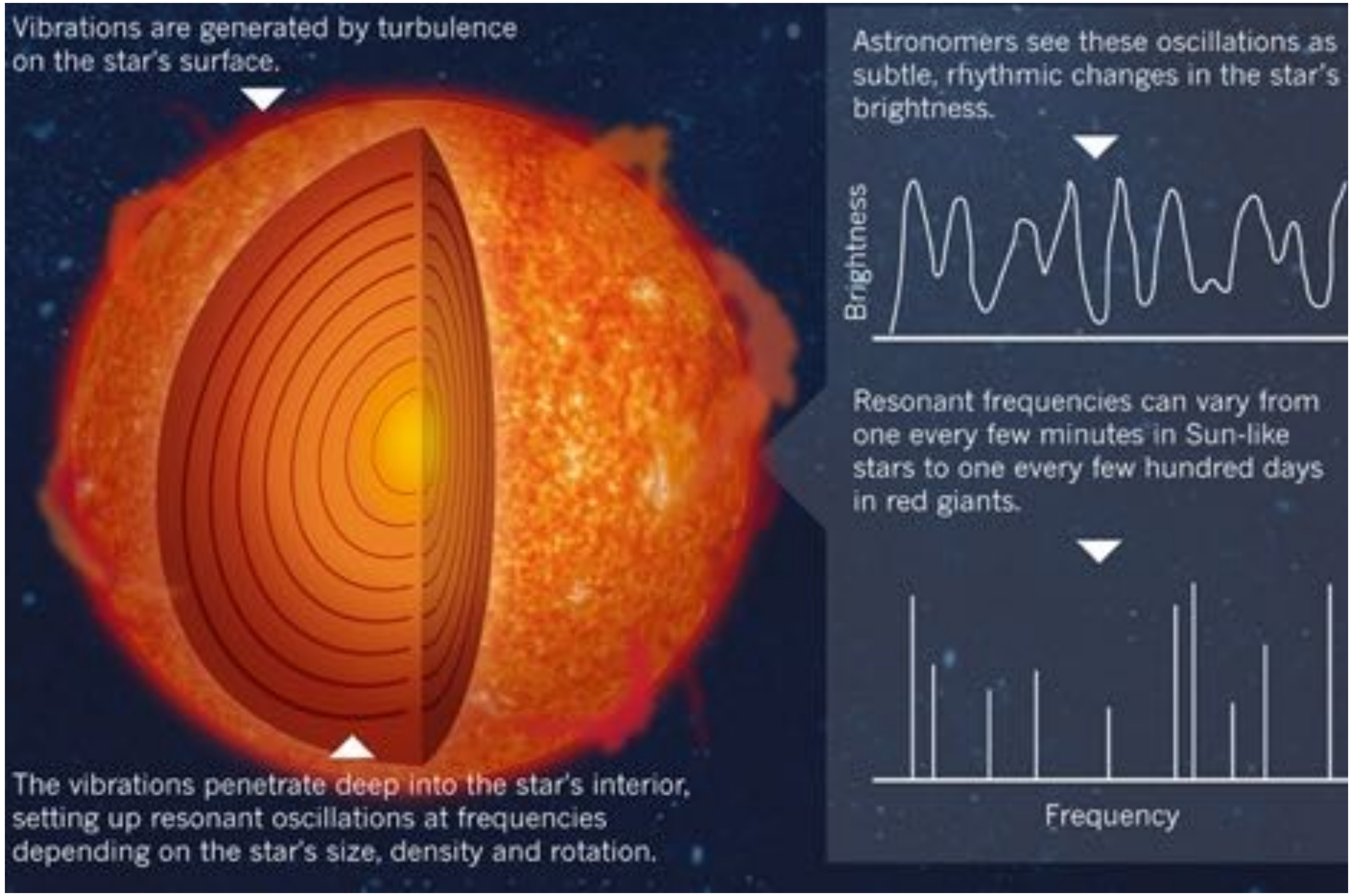




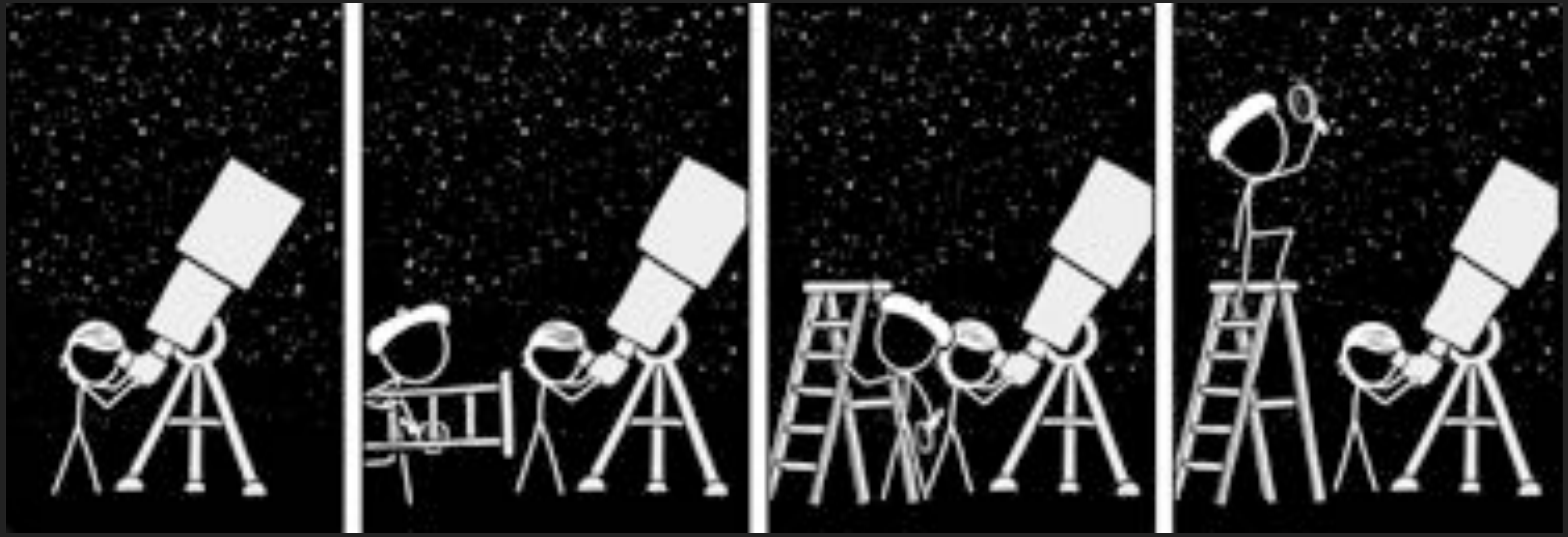
RECONSTRUCTING STELLAR INTERIORS

INSIGHTS INTO STELLAR INTERIORS VIA ASTROSEISMOLOGY





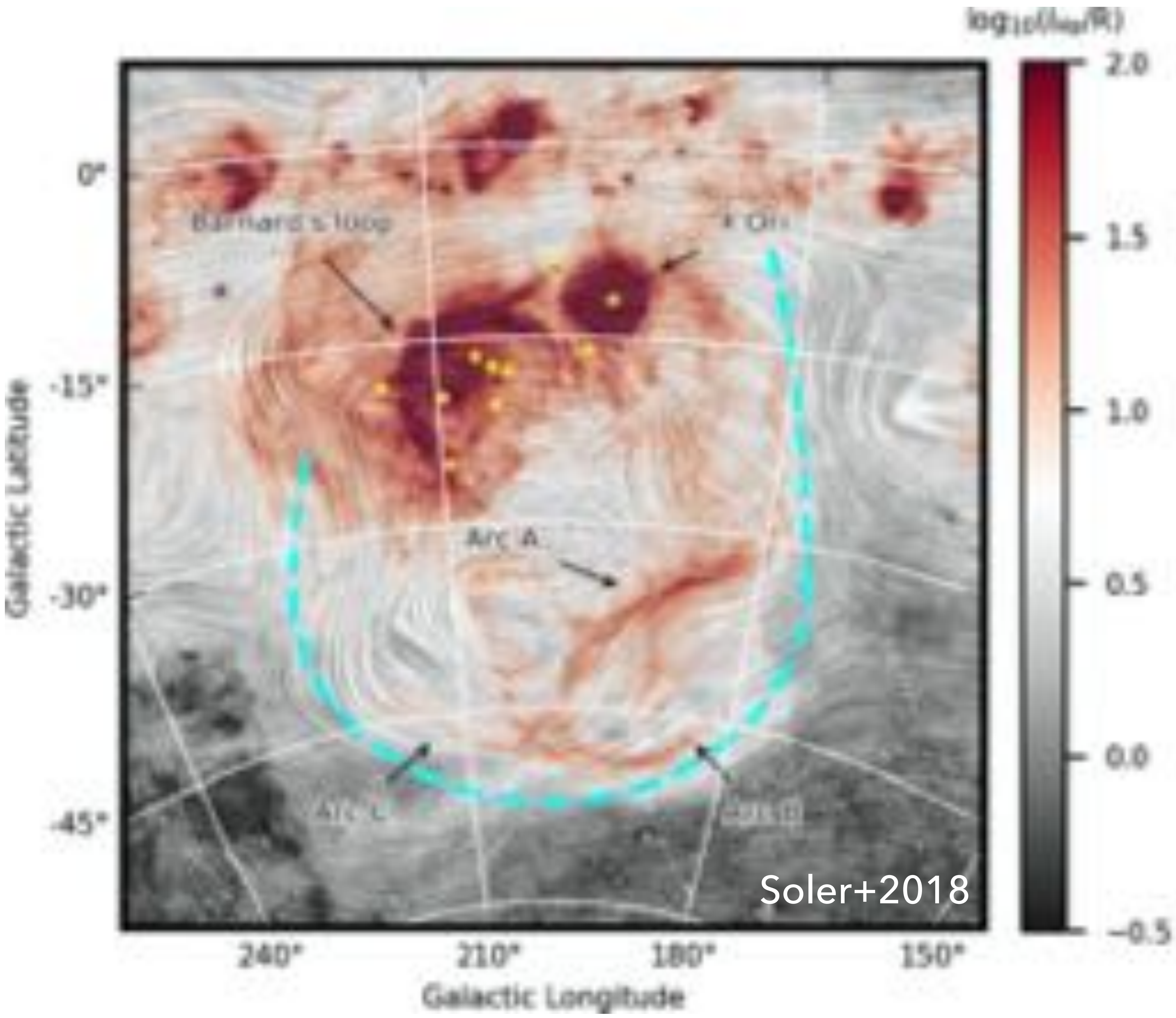
Cowen+2012

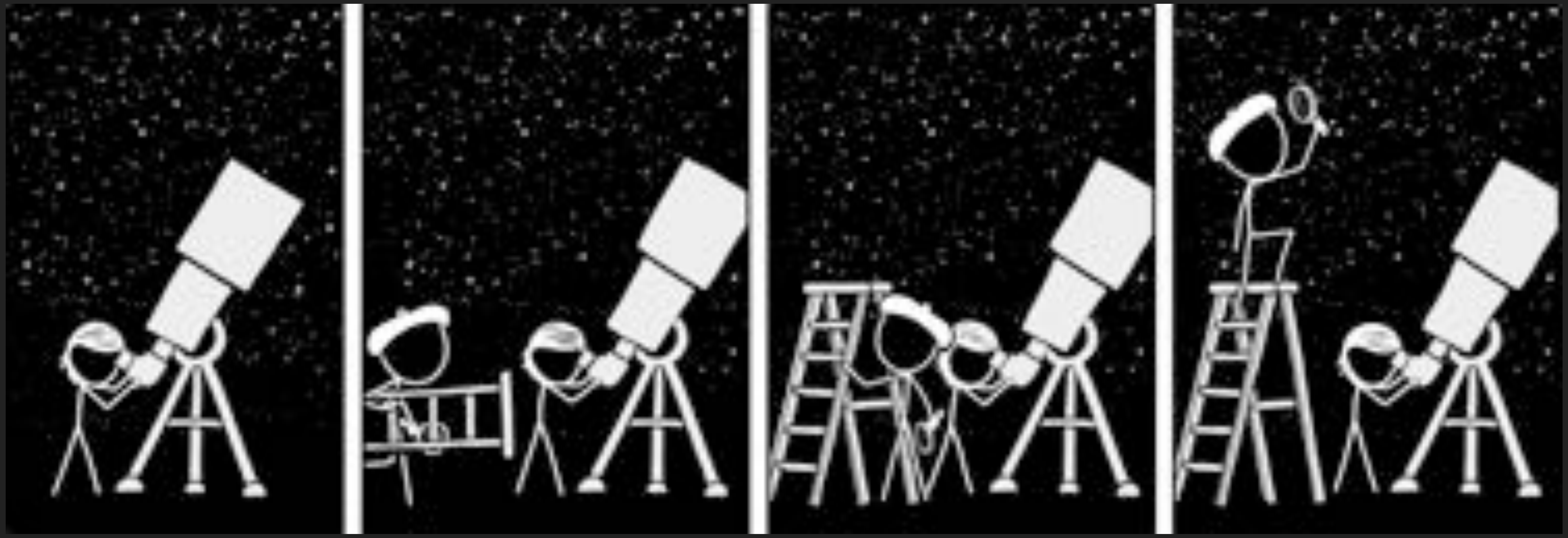


RECONSTRUCTING INTER-STELLAR GAS STRUCTURES

RECONSTRUCTING INTER-STELLAR GAS STRUCTURES

RECONSTRUCTING MAGNETIC FIELD STRUCTURES

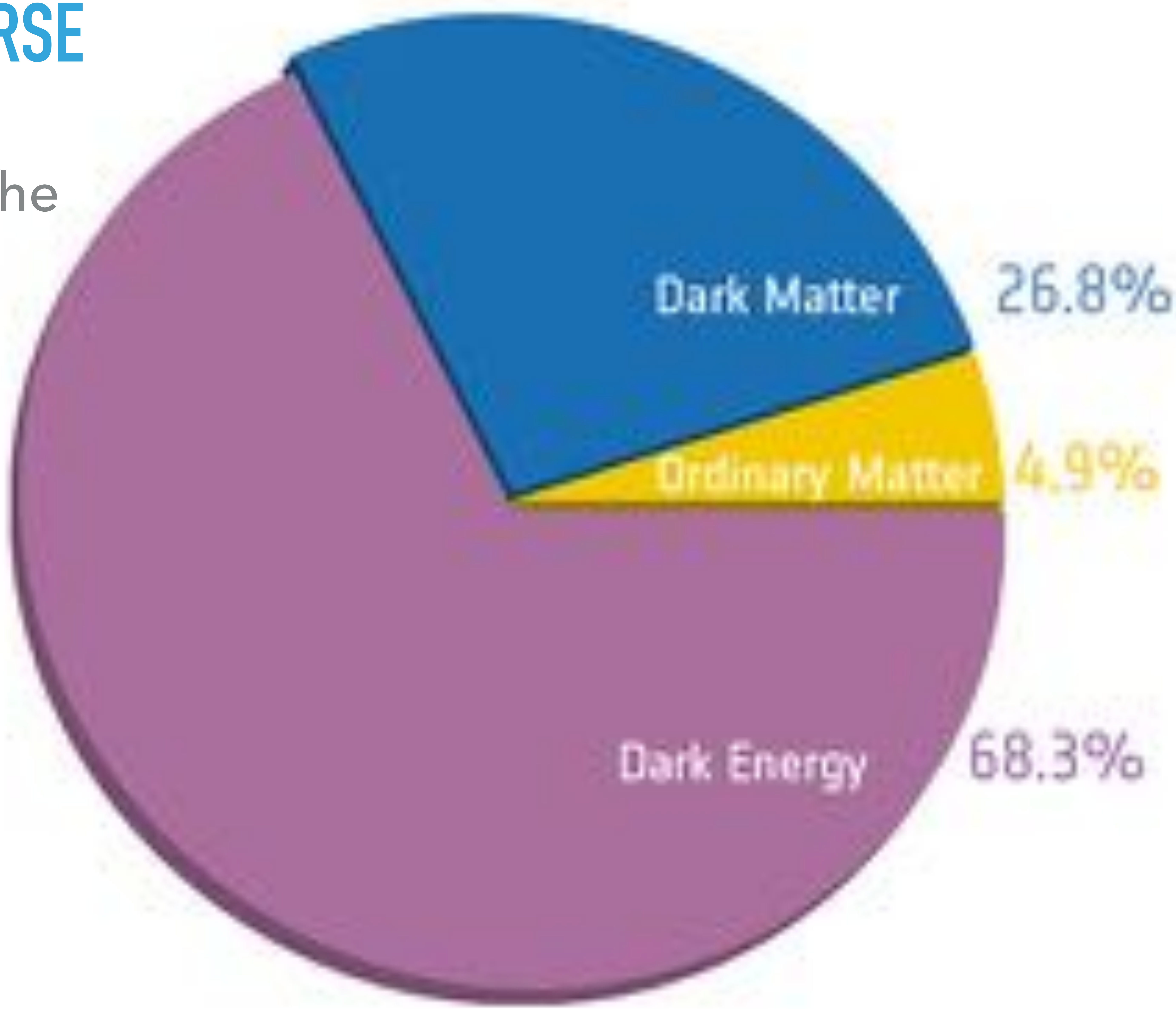




RECONSTRUCTING LARGE SCALE STRUCTURE

THE ENERGY CONTENT OF THE UNIVERSE

- Which Cosmology does describe the Universe?
- What is Dark Matter?
- What is Dark Energy?



A BRIEF HISTORY OF THE UNIVERSE

Nasa

CONSTRAINING DARK ENERGY VIA WEAK LENSING

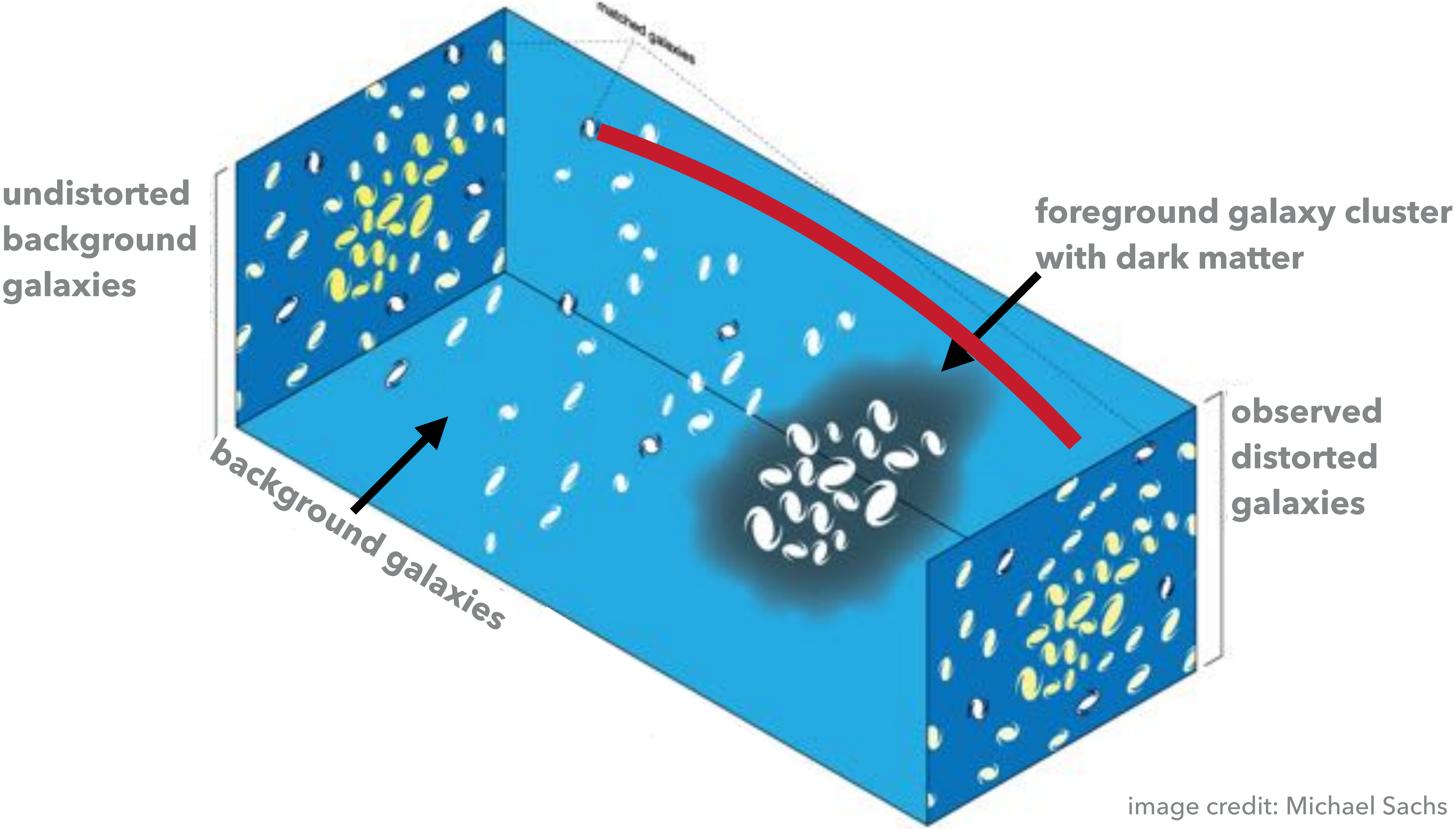
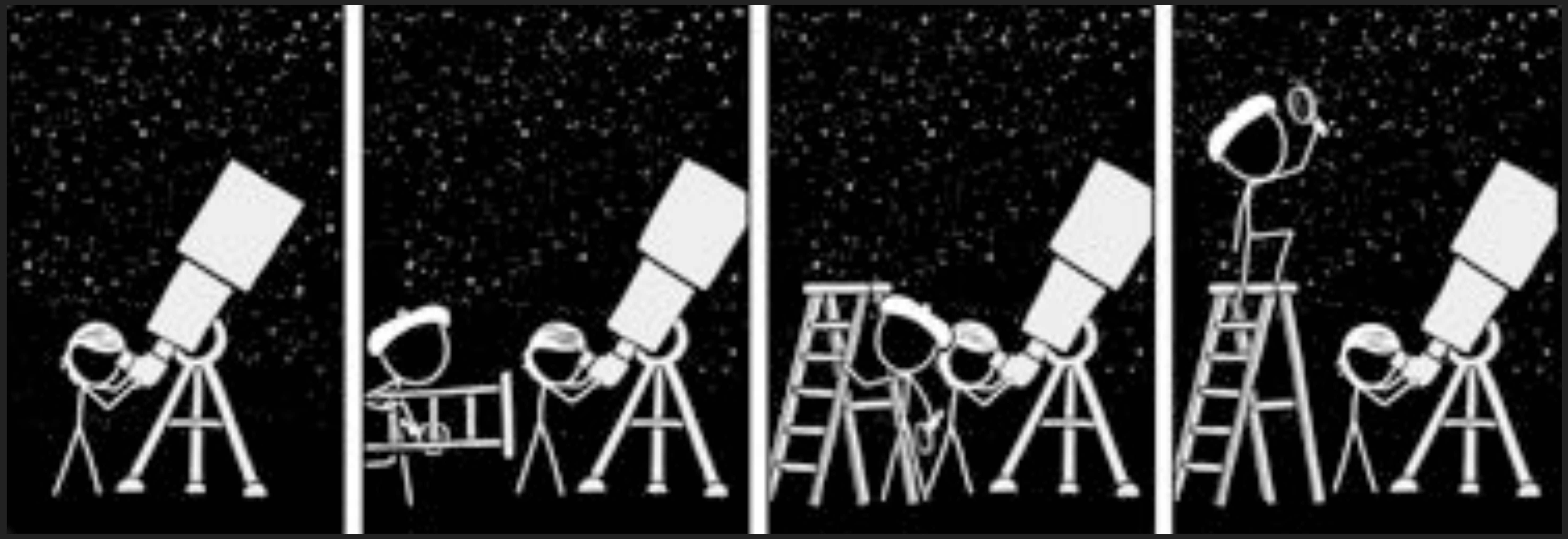


image credit: Michael Sachs



RECONSTRUCTING GALAXIES

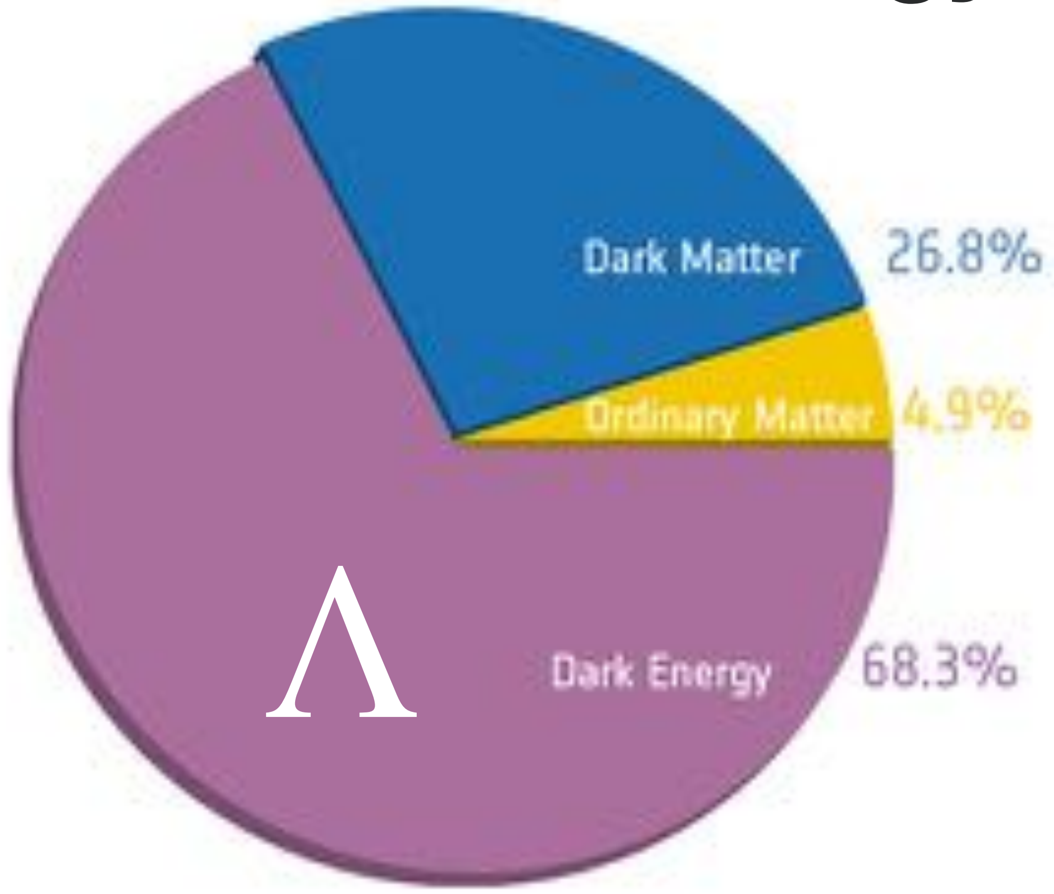
MAIN PART

NUMERICAL SIMULATIONS

A LIMITED FORWARD MODEL FOR GALAXIES

A GALAXY FORMATION MODEL IN A NUTSHELL

ΛCDM Cosmology

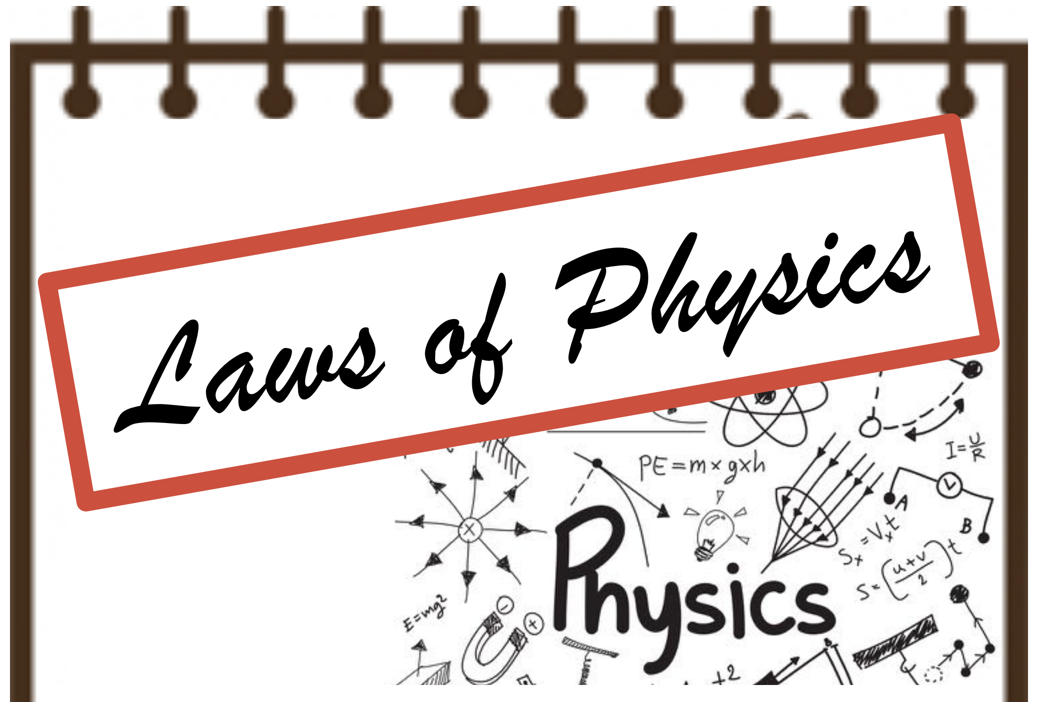


Cold dark matter = GeV mass elementary particle

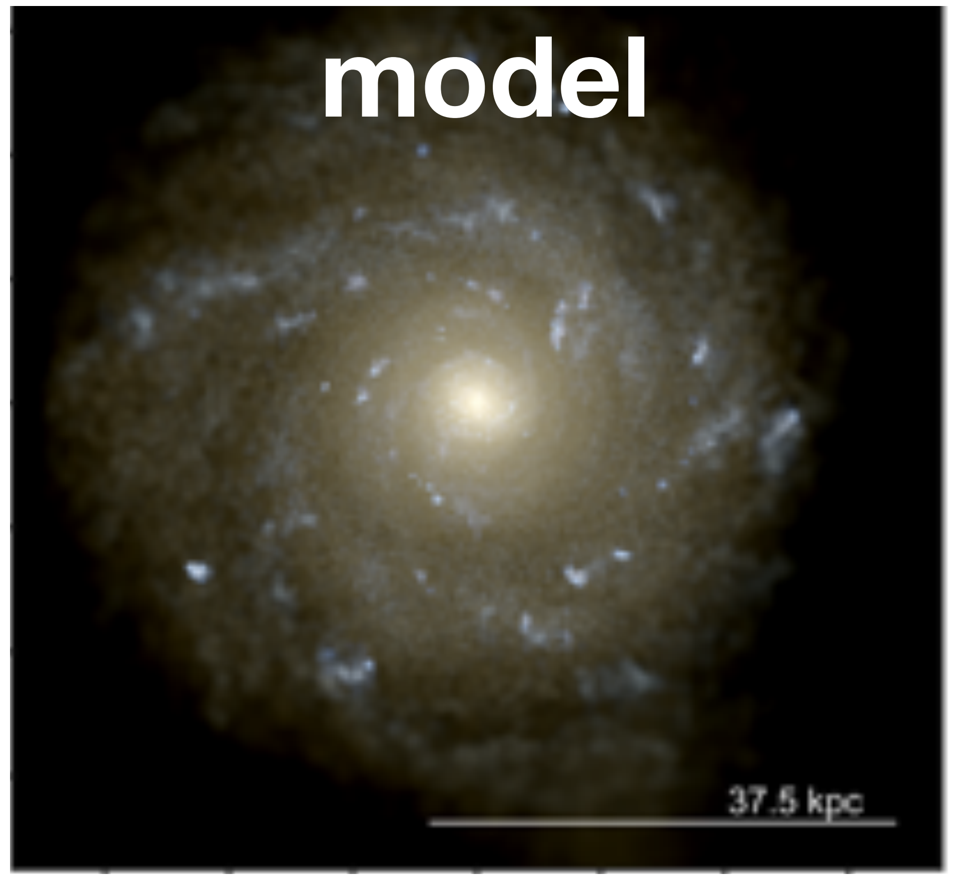
Ordinary matter = baryons

Dark energy, Λ = ???

Computer



- General Relativity
- Gas Physics
- Stellar Physics
- Radiation Physics



SIMUALTIONS: THE INPUT PHYSICS

gas cooling	inter-stellar medium	star formation	stellar feedback	super-massive black holes	active galactic nuclei	magnetic fields	radiation fields	cosmic rays
atomic/ molecular/ metals/ tabulated/ network	effective equation of state/ multi-phase	initial stellar mass function/ probabilistic sampling/ enrichment	kinetic/ thermal/ variety of sources from stars, supernovae	numerical seeding/ growth by accretion prescription/ merging	kinetic/ thermal/ radiative/ quasar mode/ radio mode	ideal MHD/ cleaning schemes/ constrained transport	ray tracing/ Monte Carlo/ moment-based	production/ heating/ anisotropic diffusion/ streaming

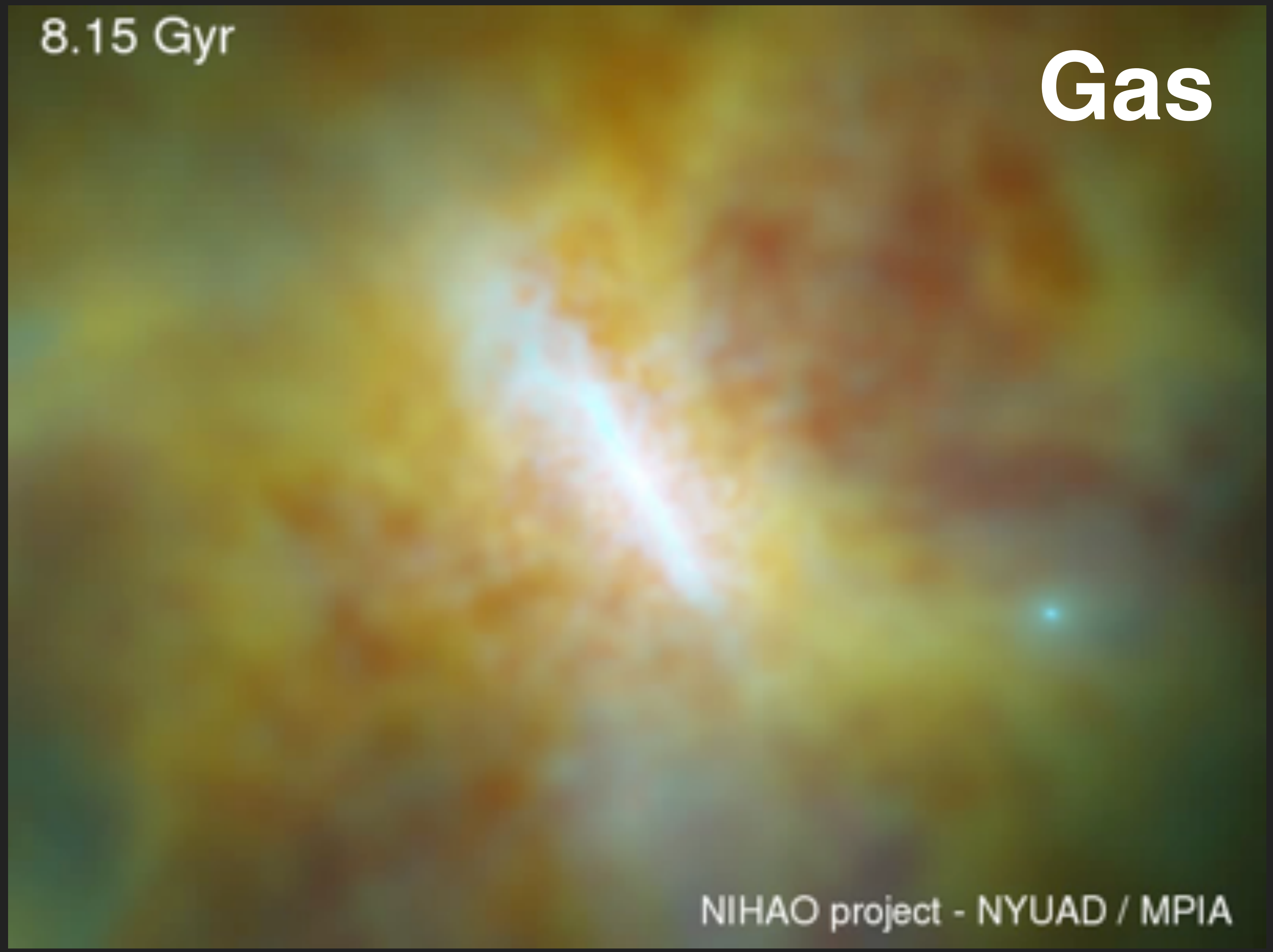
most important astrophysical processes

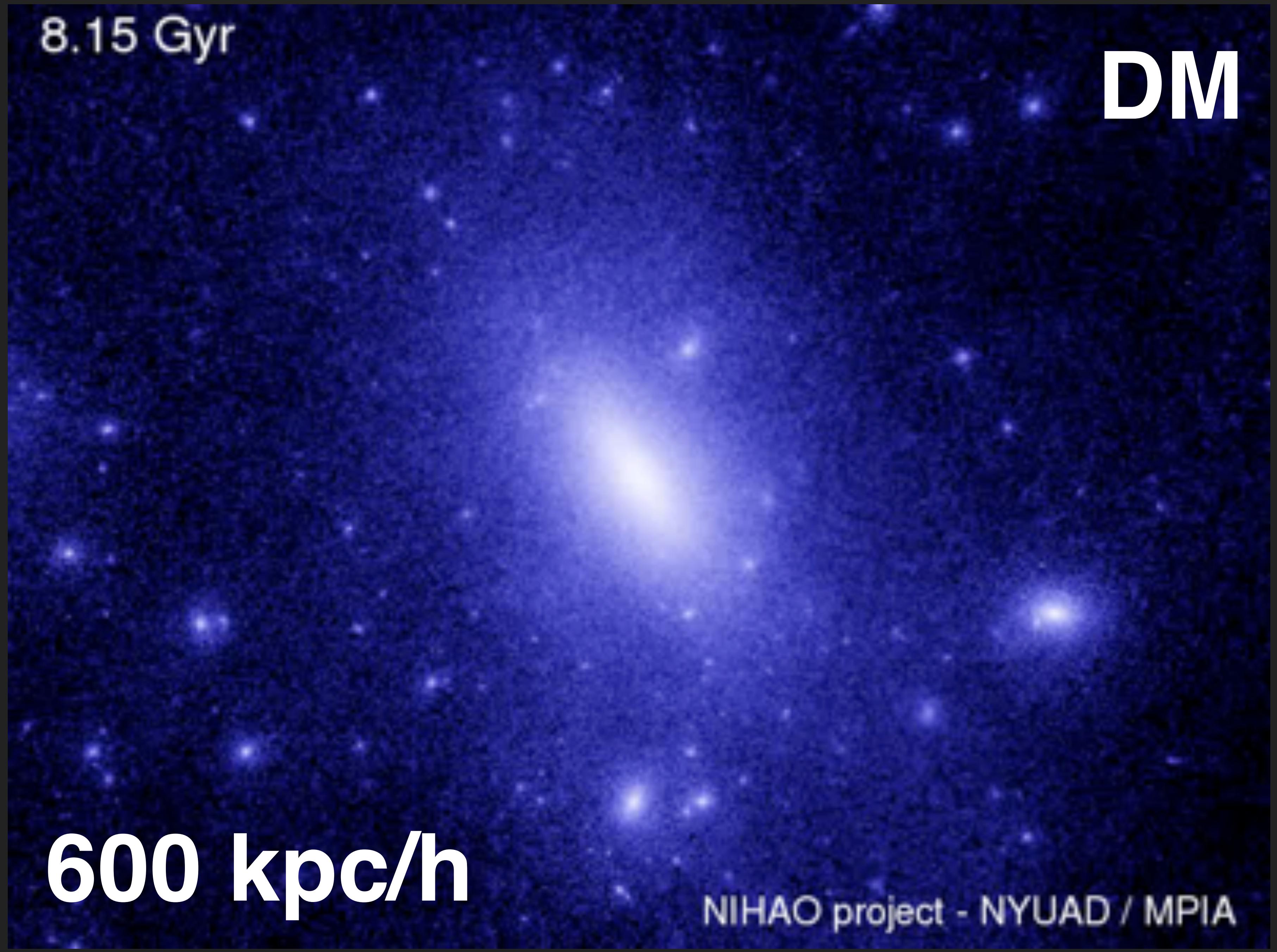
Vogelsberger+2020

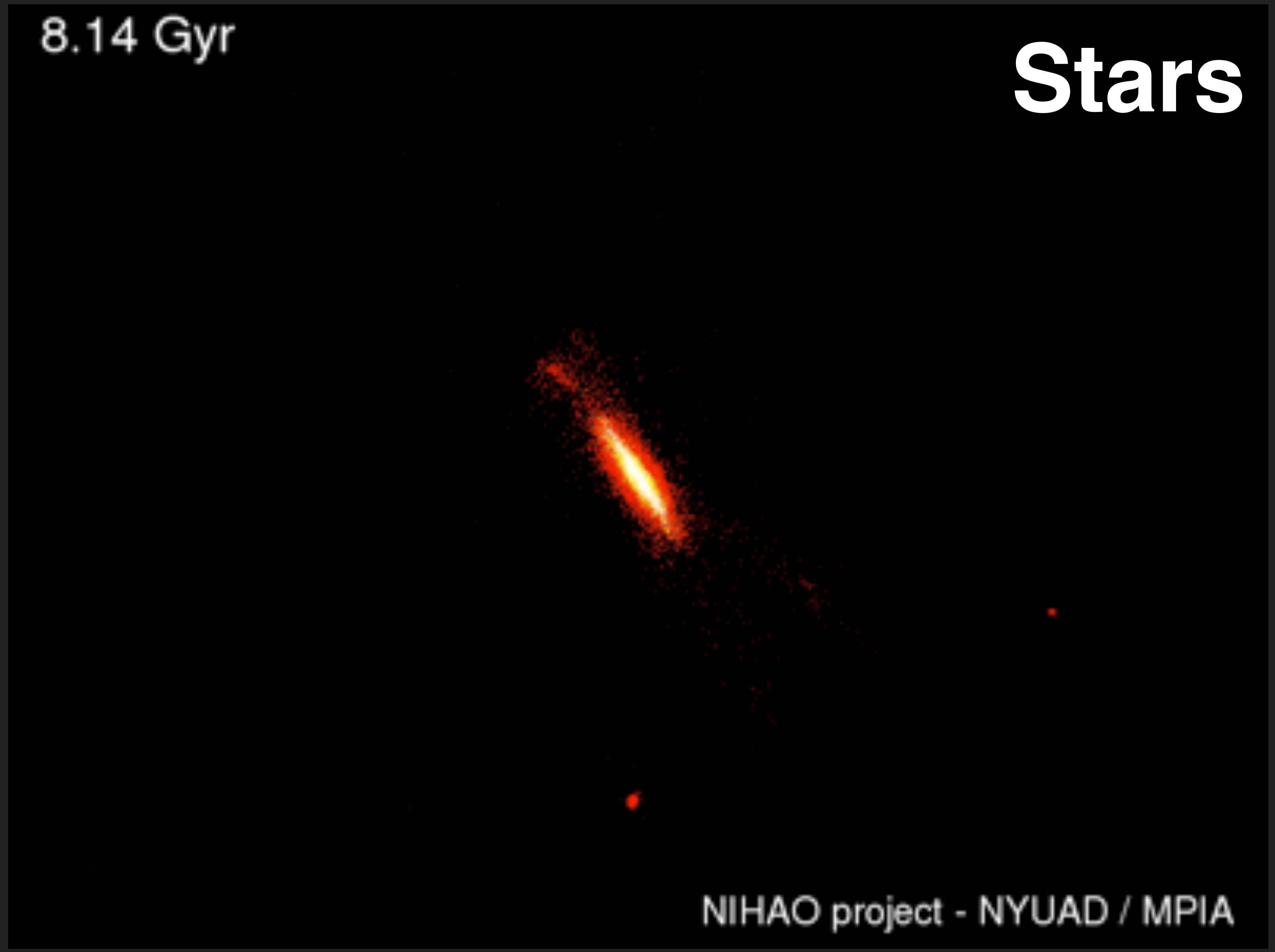
- At the same time: bridging 10^6 orders of magnitude in spatial scale from sizes of stars to entire galaxies and beyond

MOST MECHANISM PUT IN BY HAND IN A PARAMETRISED WAY.

cosmological zoom-in hydro simulations of a Milky Way analogue







SIMULATIONS ARE NUMERICAL EXPERIMENTS!

MODEL PARAMETERS FIXED BY HAND

THEY ARE ONLY A LIMITED FORWARD MODEL FOR OBSERVED GALAXIES…

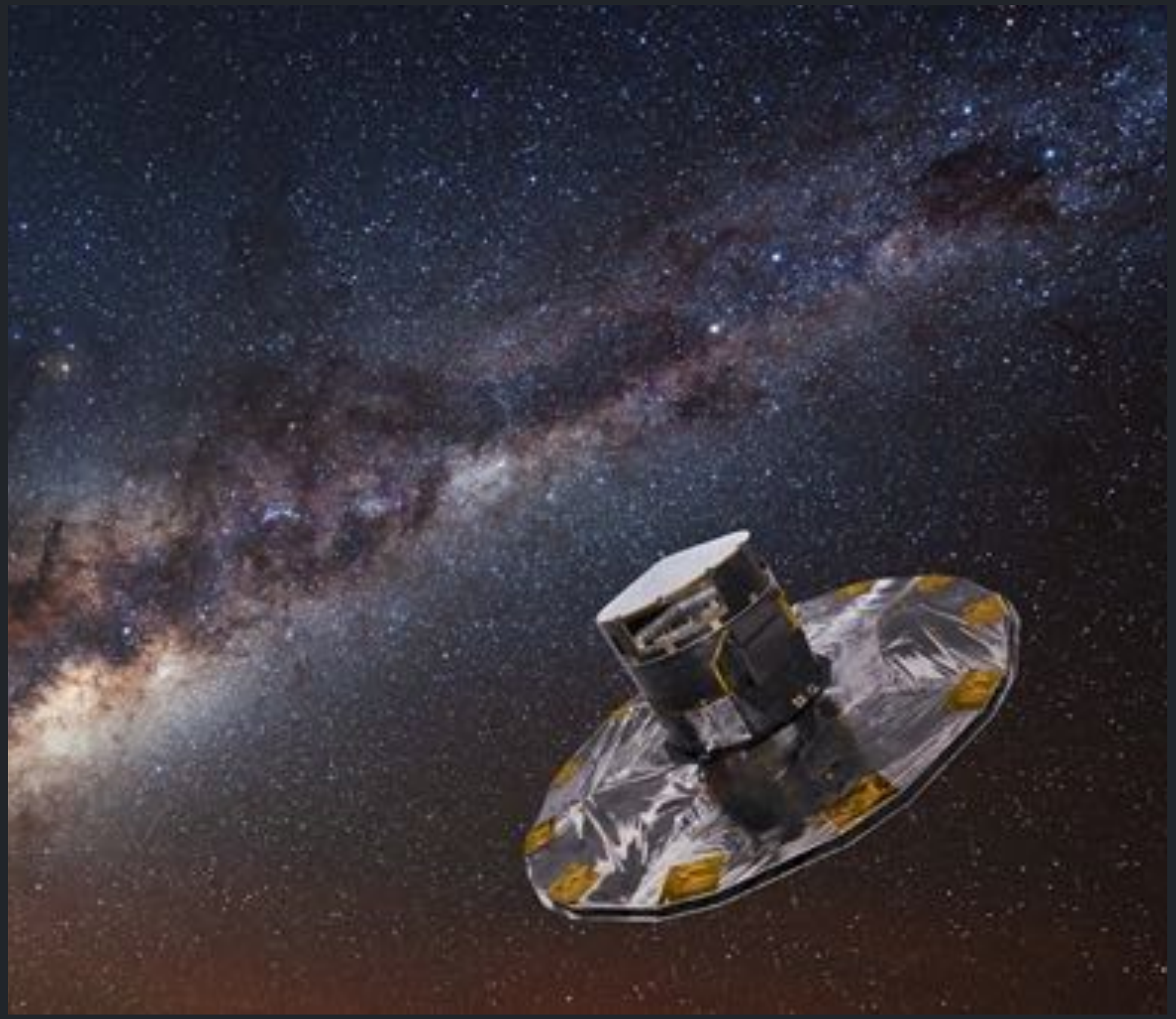
WE WILL NEVER MODEL A CLOSE ANALOGUE TO AN OBSERVED GALAXY.

Buck+2020

OBSERVATIONS

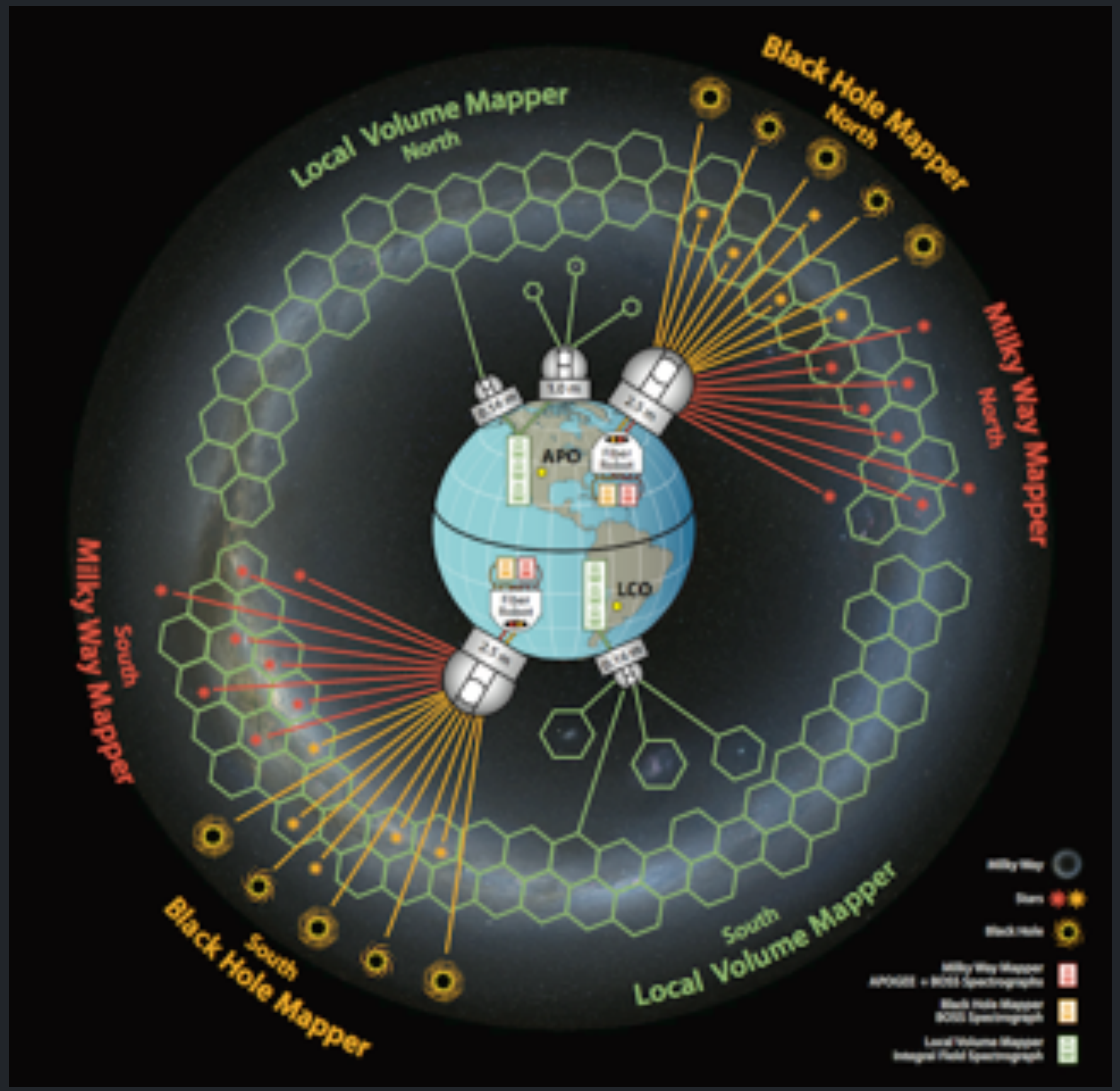
THE ERA OF LARGE GALAXY SURVEYS

MILKY WAY SURVEYS



Gaia

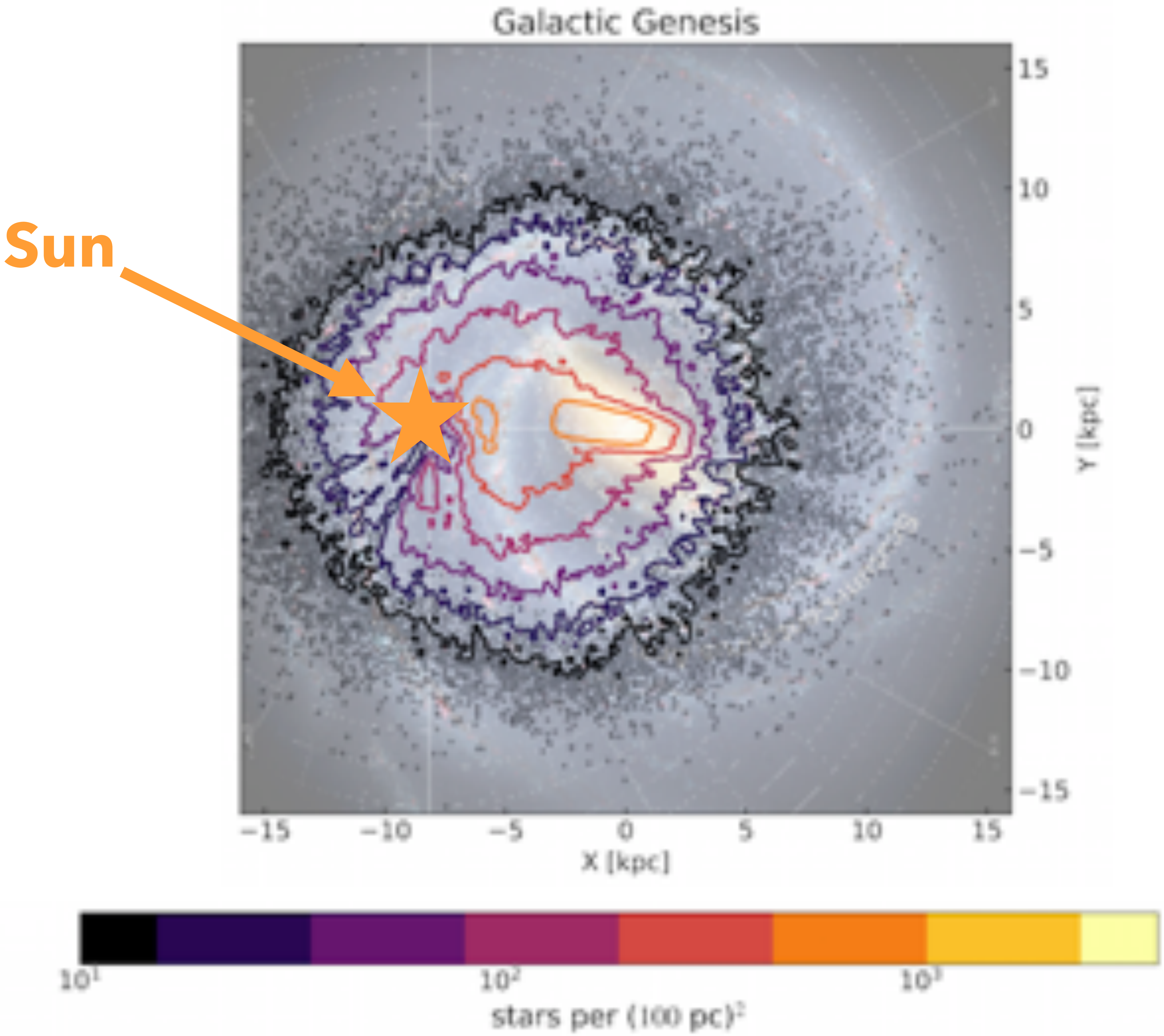
4MOST



SDSS-V

MAIN DATA PRODUCT: ~10^7 STELLAR SPECTRA

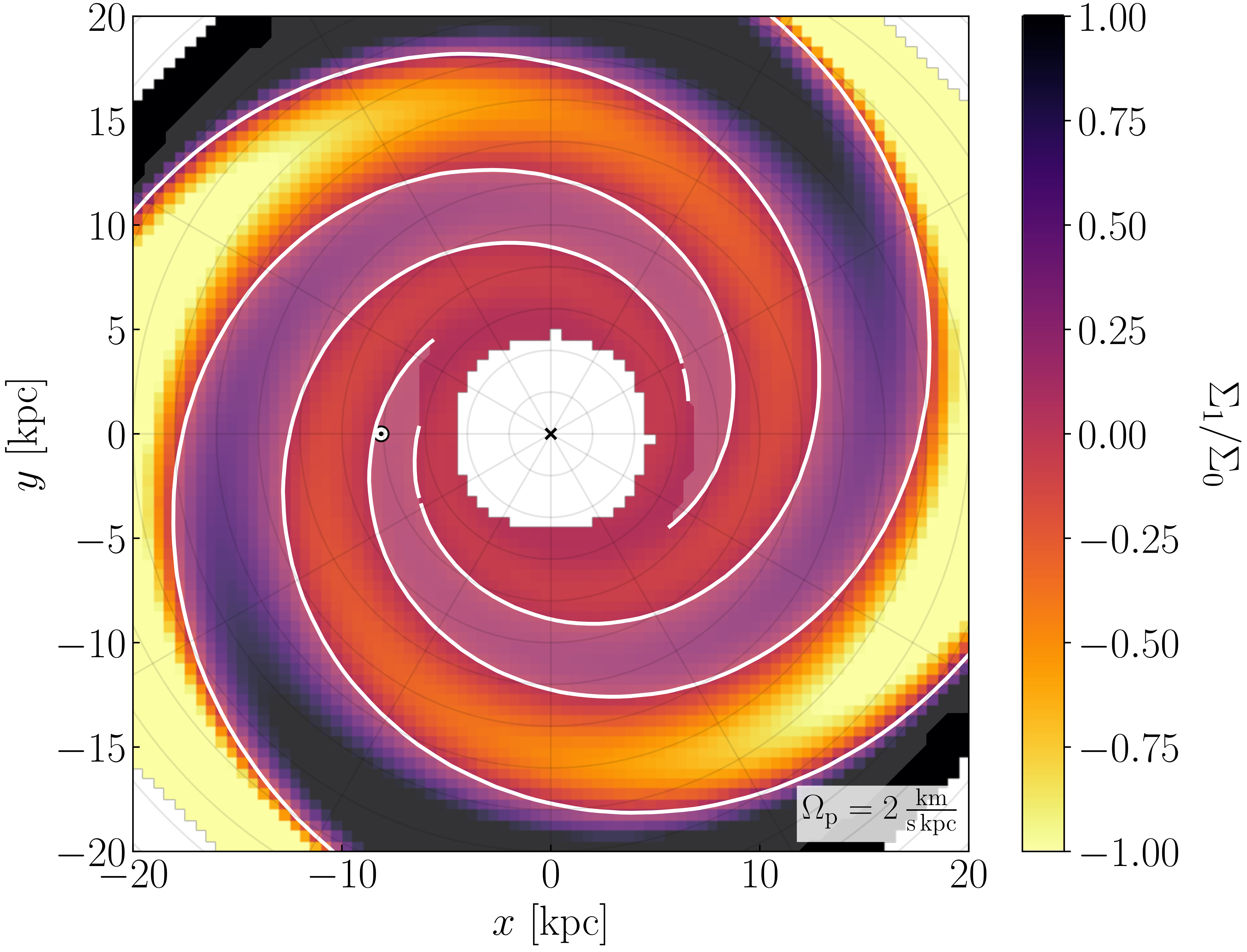
MILKY WAY AS A RESOLVED MODEL GALAXY:



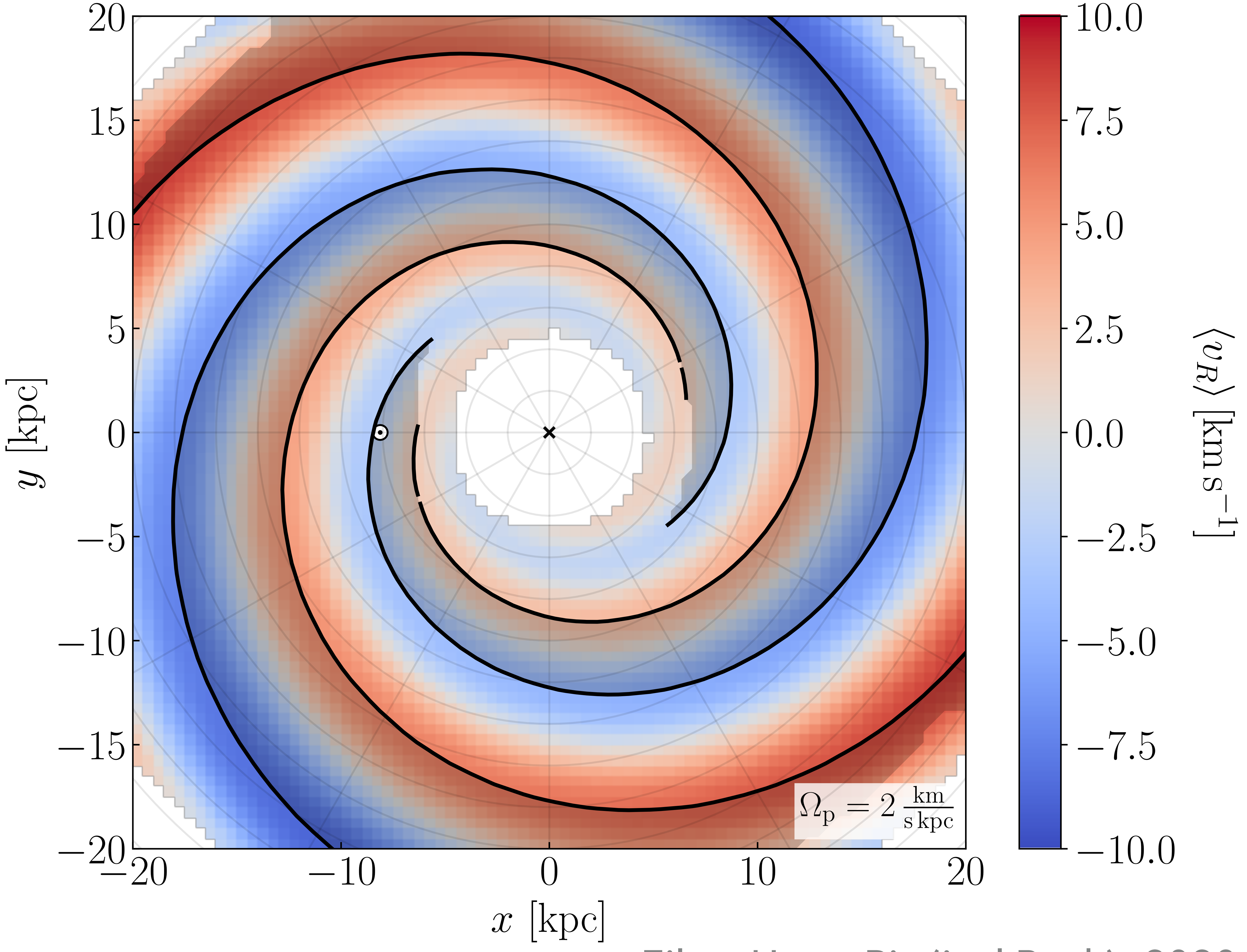
- Milky Way's formation history is encoded in its structure
- Stellar properties like age and chemical composition correlate with stellar orbits
- Stellar orbits in turn are set by global properties like gravitational potential (dark matter, gas and stars), size and shape
- –> Need to understand Milky Way in context

QUANTIFYING MILKY WAY'S SPIRAL STRUCTURE FROM STELLAR SPECTRA

Mass perturbation

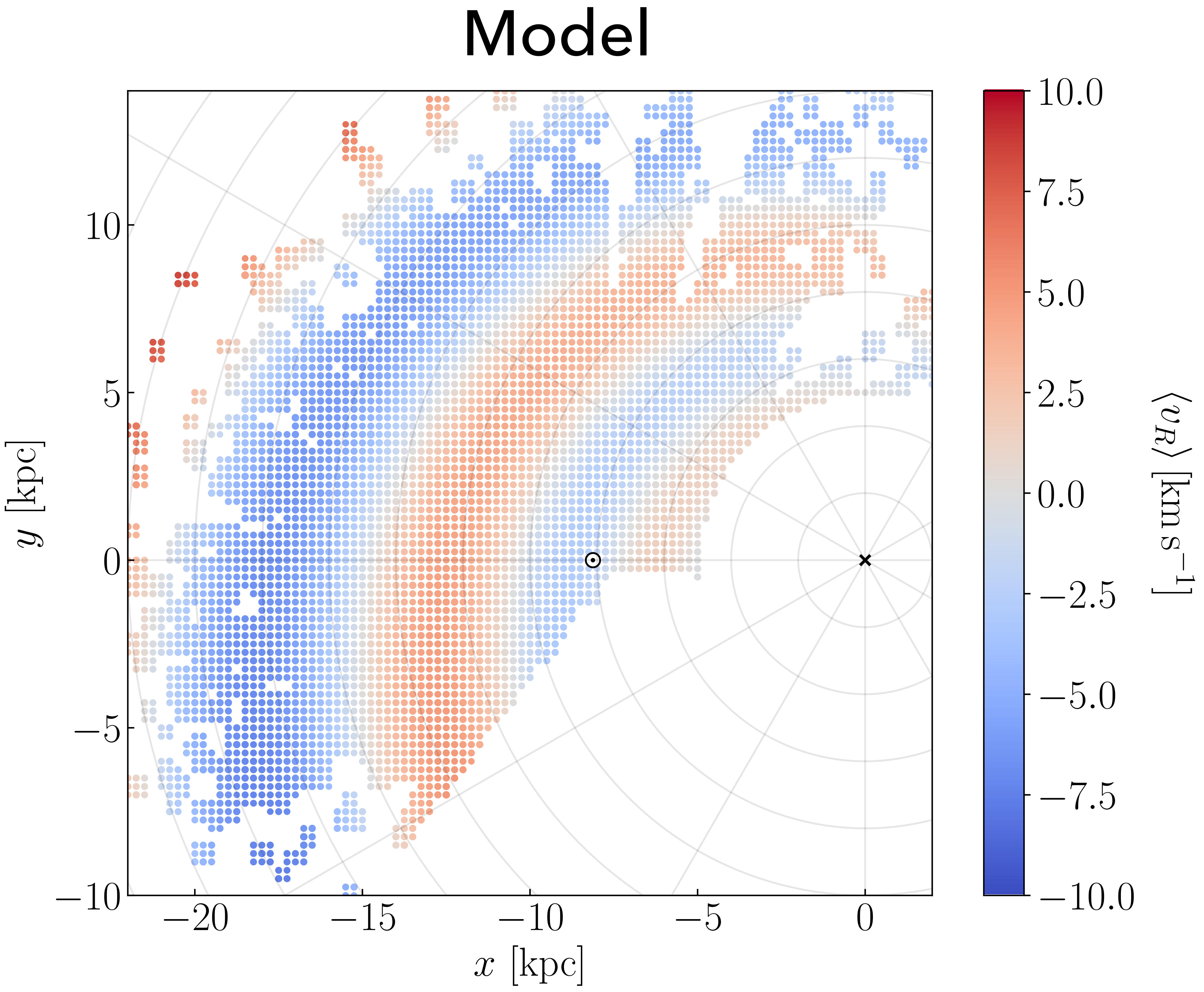


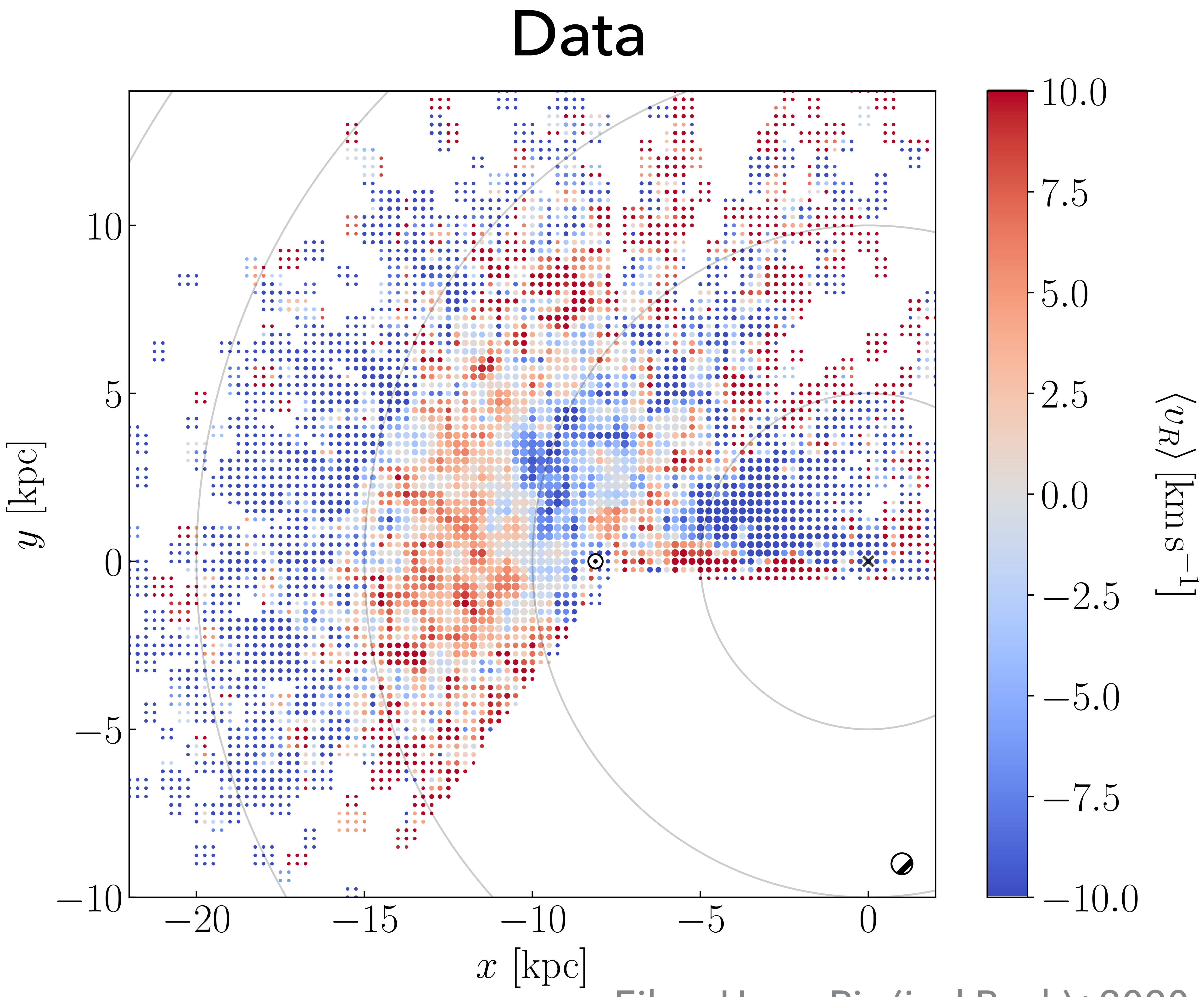
Velocity perturbation



Eilers,Hogg,Rix,(incl.Buck)+2020

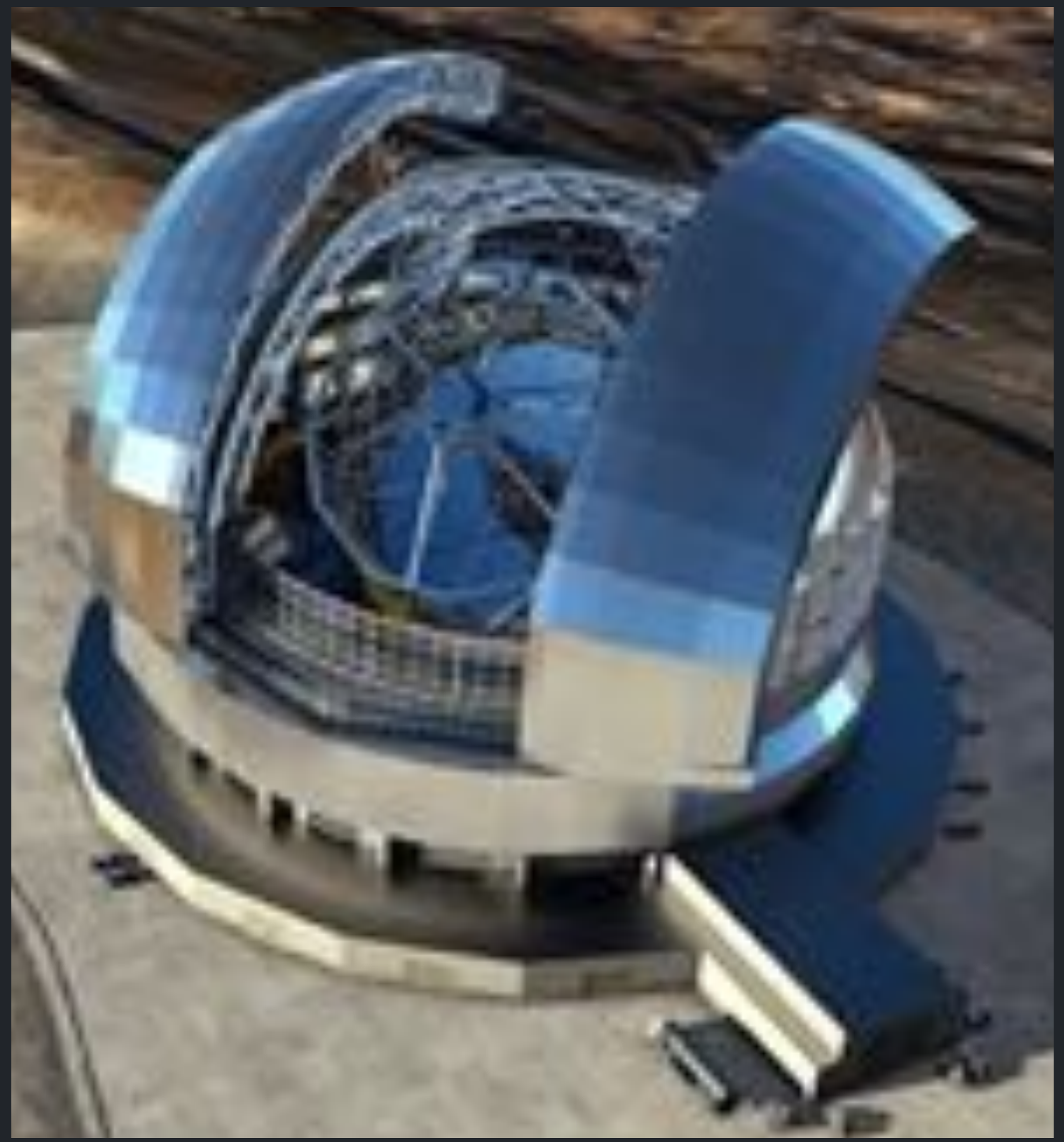
QUANTIFYING MILKY WAY'S SPIRAL STRUCTURE FROM STELLAR SPECTRA





Eilers,Hogg,Rix,(incl.Buck)+2020

EXTRAGALACTIC SURVEYS



European Extremely Large Telescope

Nancy Roman Space Telescope

Vera Rubin Observatory

DESI

Euclid

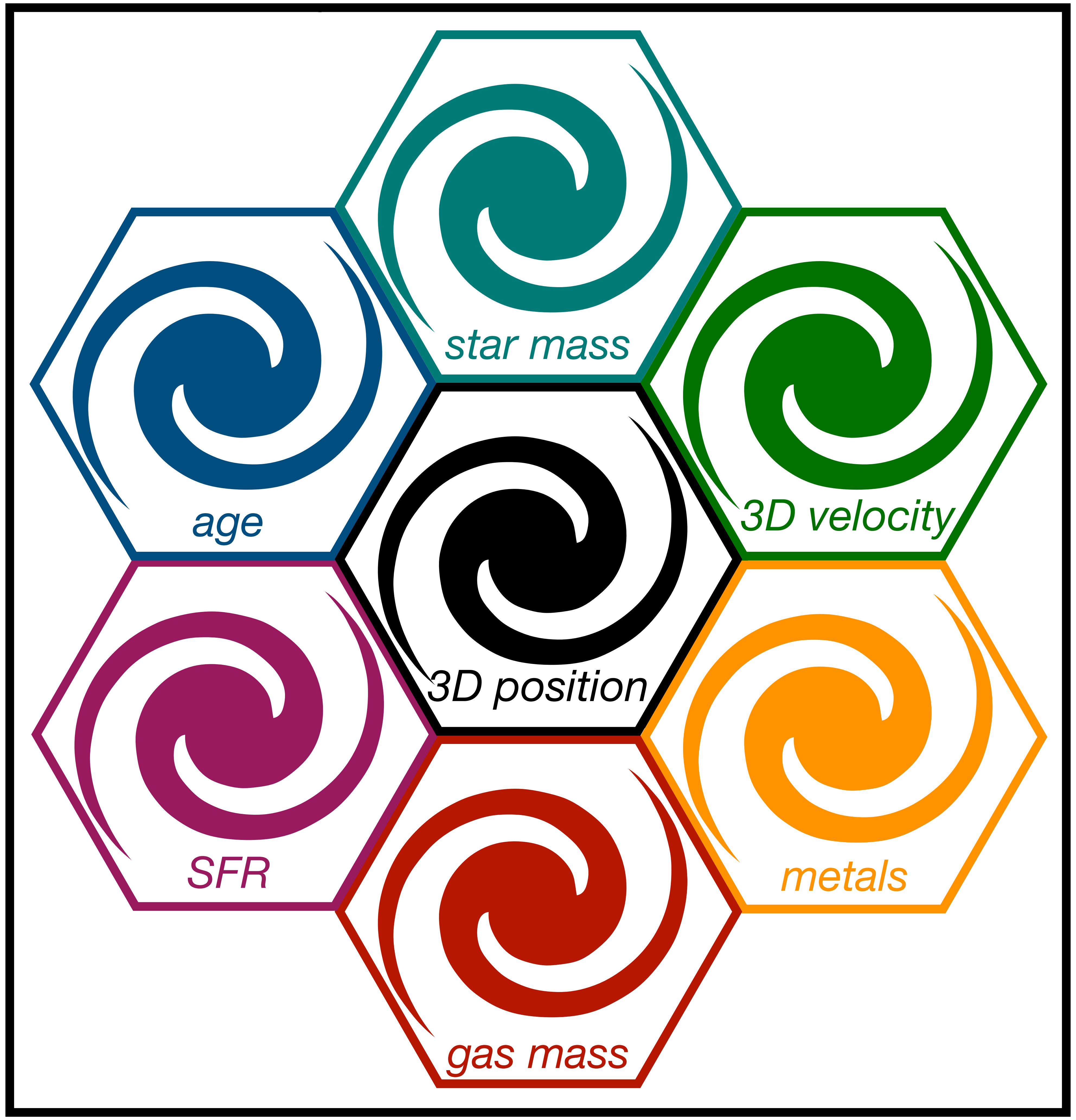
MAIN DATA PRODUCT: $\sim 10^6$ GALAXY IMAGES

~30 TERABYTES PER NIGHT

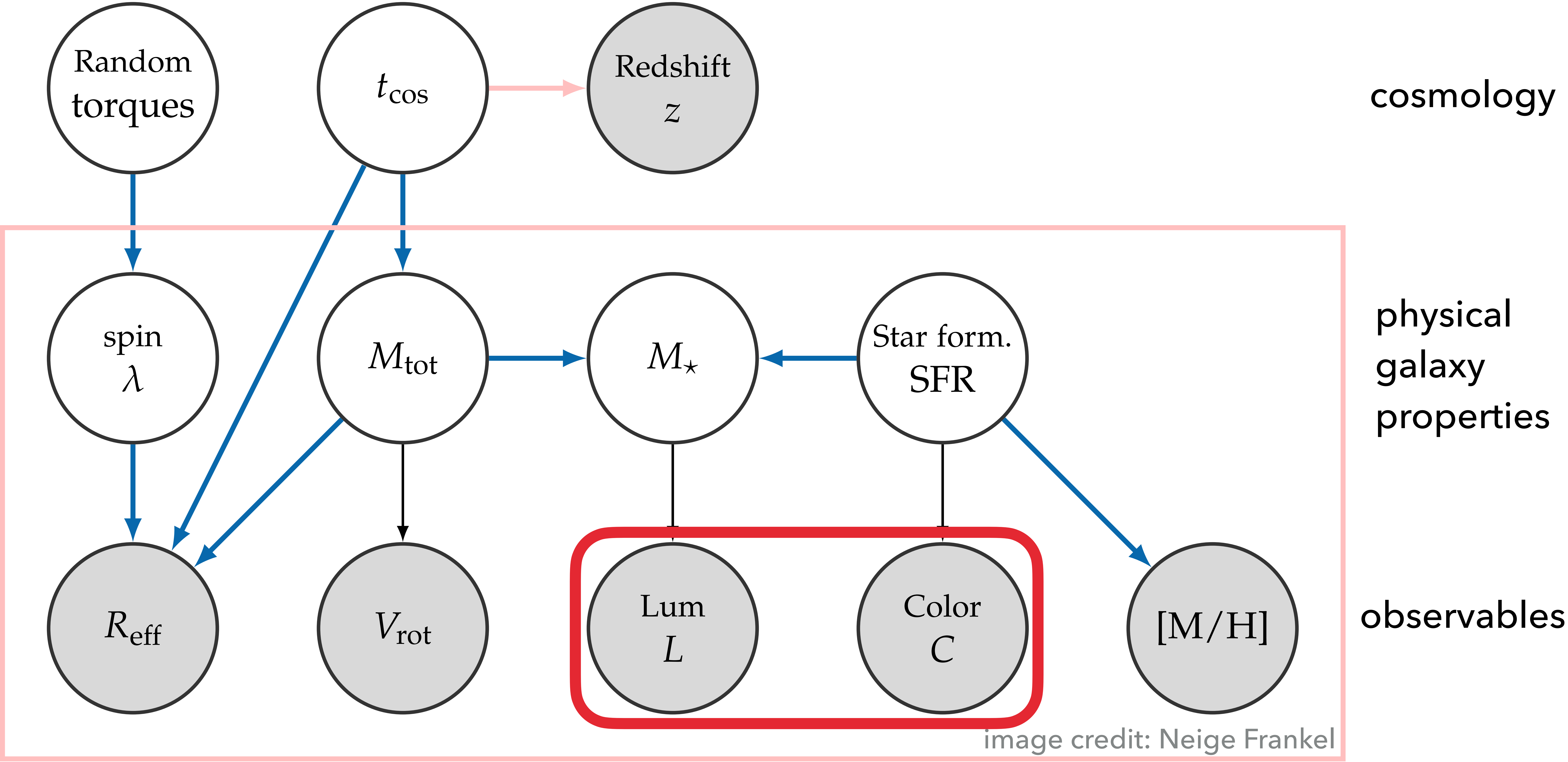
EXTRACTING GALAXY PROPERTIES FROM THOSE IMAGES?

- Can we reconstruct intrinsic galaxy properties from their images?
- Can we build a galaxy model from multi-band images?

derive maps of physical parameters

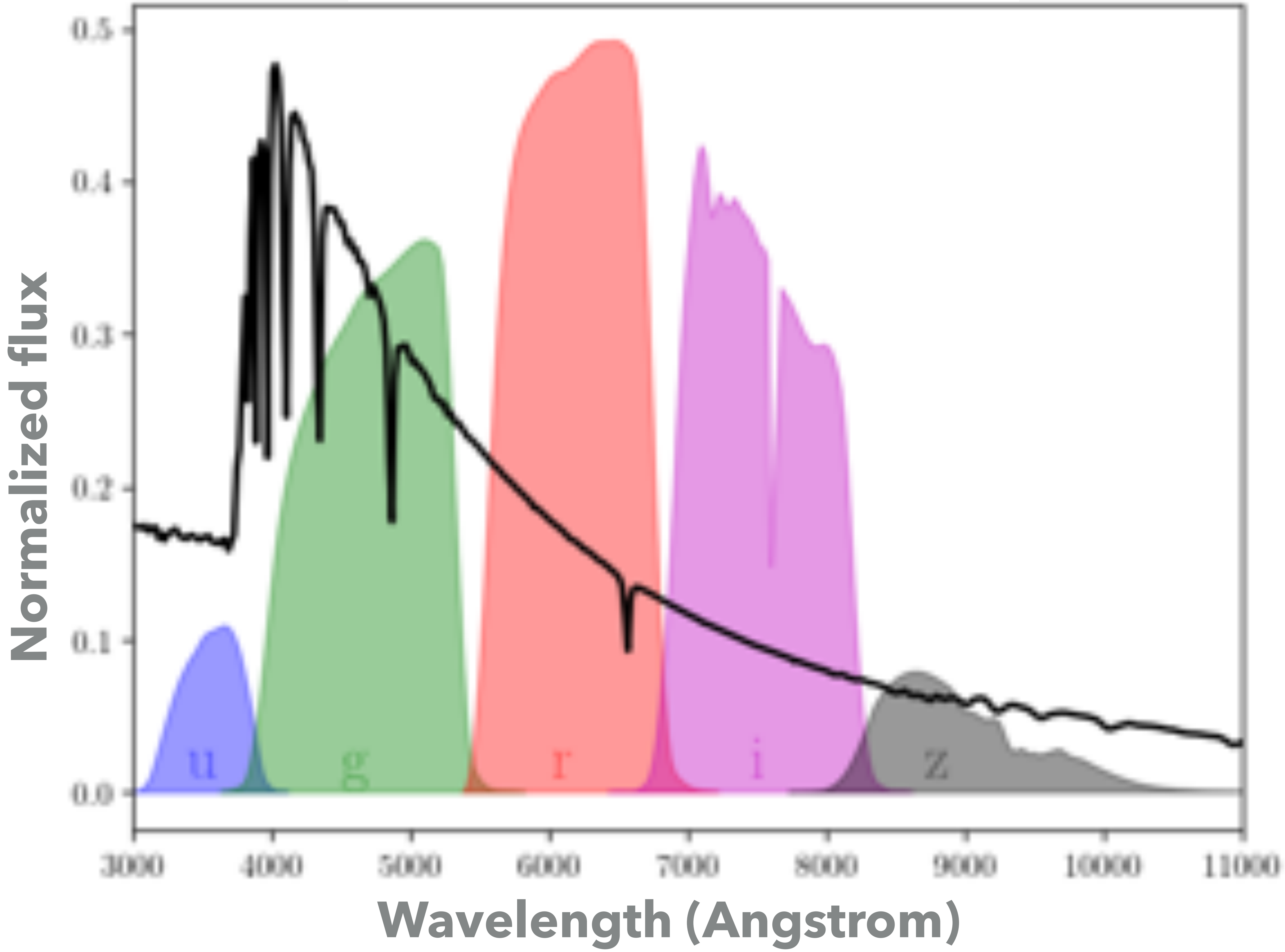


ESTABLISHED CORRELATIONS BETWEEN OBSERVABLES AND PHYSICAL PROPERTIES

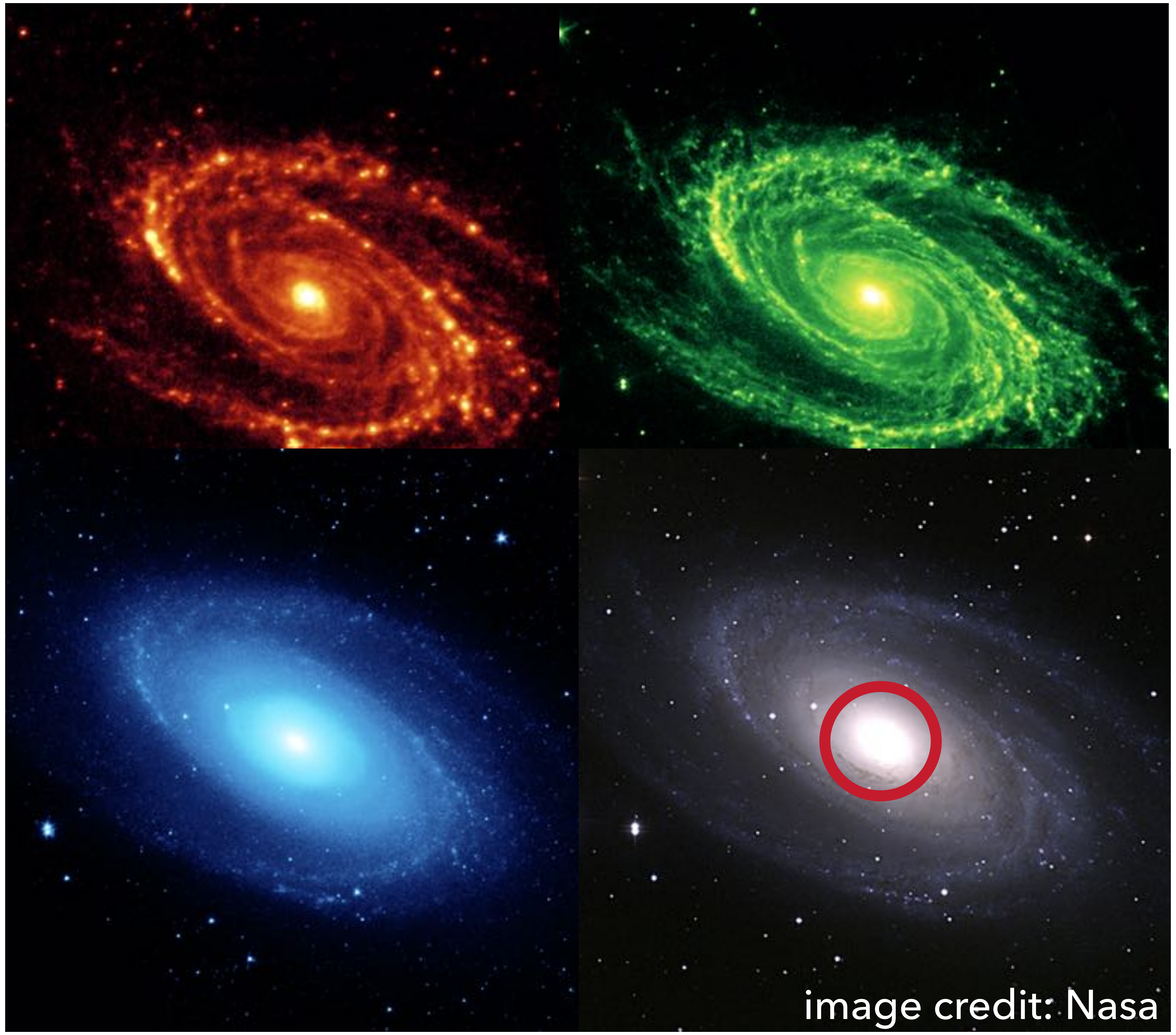


OBSERVATIONS: SPECTROSCOPY VS. PHOTOMETRY

Spectroscopy



Photometry



THE HYBRID APPROACH: INTEGRAL FIELD SPECTROSCOPY

THE HYBRID APPROACH: INTEGRAL FIELD SPECTROSCOPY

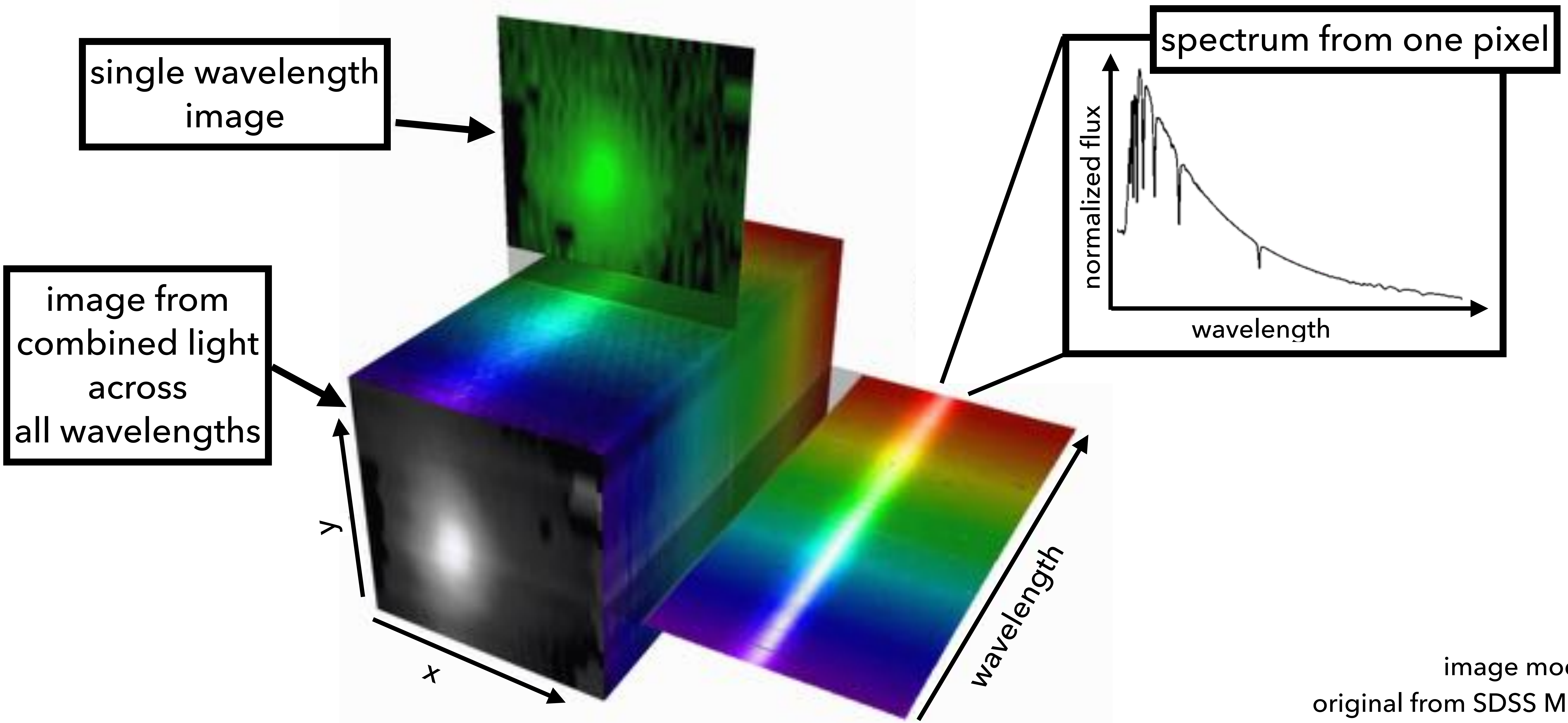


image modified,
original from SDSS MaNGA

THE TECHNICAL LIMITATIONS…

- IFU observations expensive!
  - low spatial resolution
  - Relative small sample size: CALIFA: ~300, SAMI: ~1.500, MaNGA: ~10.000 compared to ~10^6 images

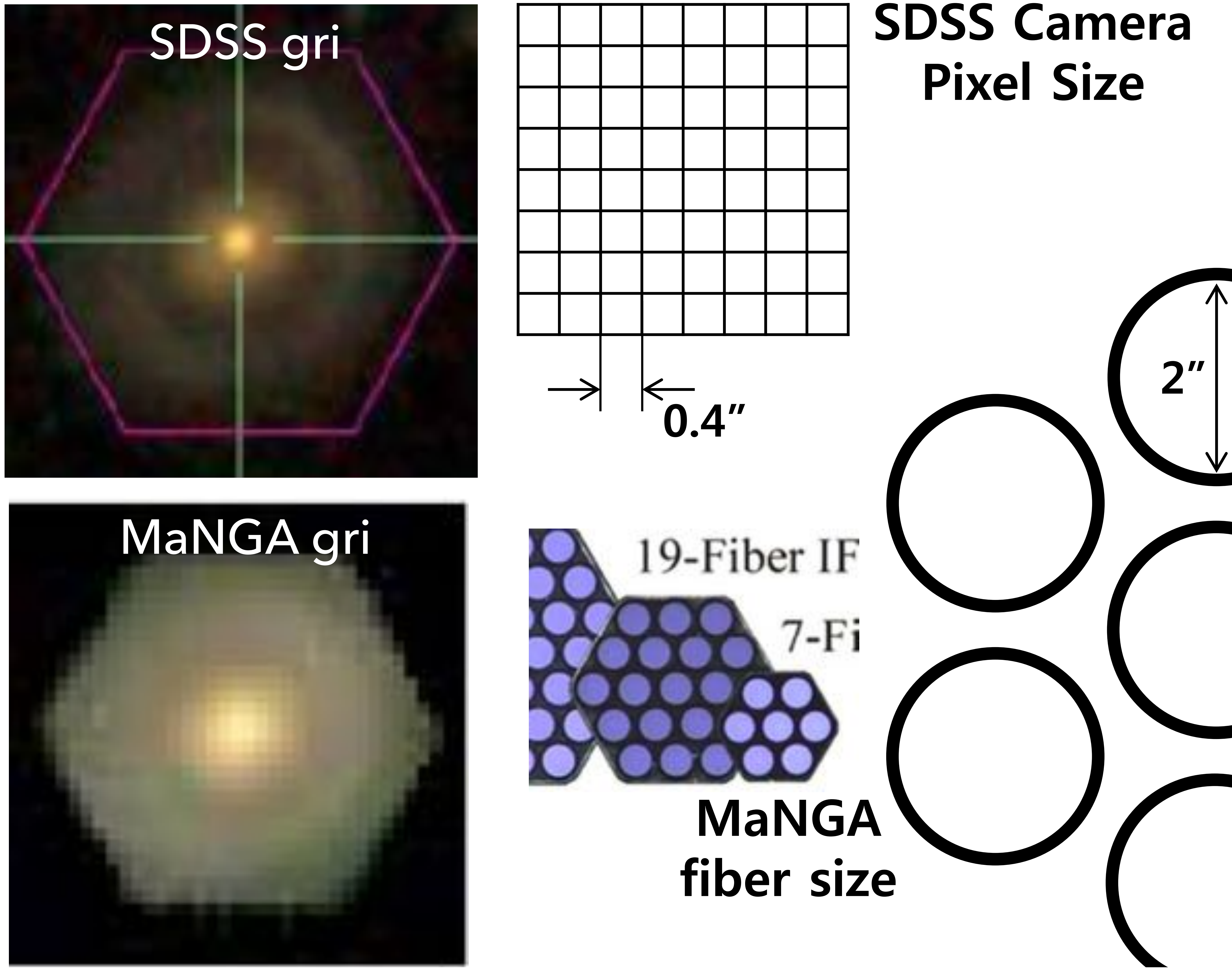


image credit: Chung+2017

HOW MUCH INFORMATION

CAN WE BUILD AN ANALYSIS TOOL WHICH:

- WORKS ON LARGE DATA SETS, LARGE NUMBER OF GALAXIES
  - A. FAST
- IS EASY TO HANDLE
  - C. AUTOMATION
  - D. GENERALIZATION

➡ MACHINE LEARNING

PROOF OF CONCEPT

- Does multi-band photometry contain enough information to recover resolved maps of intrinsic properties –> knowledge transfer from IFU surveys
- Which properties can we recover?

- What do we learn about galaxies? –> How does the machine reconstructs galaxies?
- Can we make the model physically interpretable?
- How can we incorporate such models in future pipelines?
  –> Sampling from latent space to create close analogues to observed galaxies

MULTI-BAND PHOTOMETRY TO PHYSICAL PROPERTIES

SIMILAR APPLICATIONS

Share a common Architecture:

UNet (Ronneberger+2015)

U-NET ARCHITECTURE: PIX2PIX (CONDITIONAL GAN)

Isola+ CVPR 2017

WHAT IS DIFFERENT WHEN PREDICTING PHYSICAL PROPERTIES?

- Almost all CNNs are classifiers: $Y \in \{0, 1\}^N$
- Here $Y \in \mathbb{R}^N$ with multiple orders of magnitude

1. Predict log(Y)
2. Quantized Regression [Güler et al. *CVPR* 2017]

Bins $B = \{-14, -12, \ldots, 0, 2\}$

quantiles $q \in [0,1]^{|B|-1}$

residuals $r \in [0,1]^{|B|-1}$

$$f_\theta(x) = \sum_{i=0}^{|B|-2} q_i \left(B_i + r_i \left(B_{i+1} - B_i \right) \right)$$

PROOF OF CONCEPT: SIMULATED GALAXY IMAGES

- SDSS MOCK IMAGES 256X256 PIXELS TORREY+2014, SNYDER+2015
- RADIATIVE TRANSFER, BACKGROUND STARS, PSF, NOISE, SURFACE BRIGHTNESS CUT
- PHYSICAL PROPERTIES ON SAME SCALE

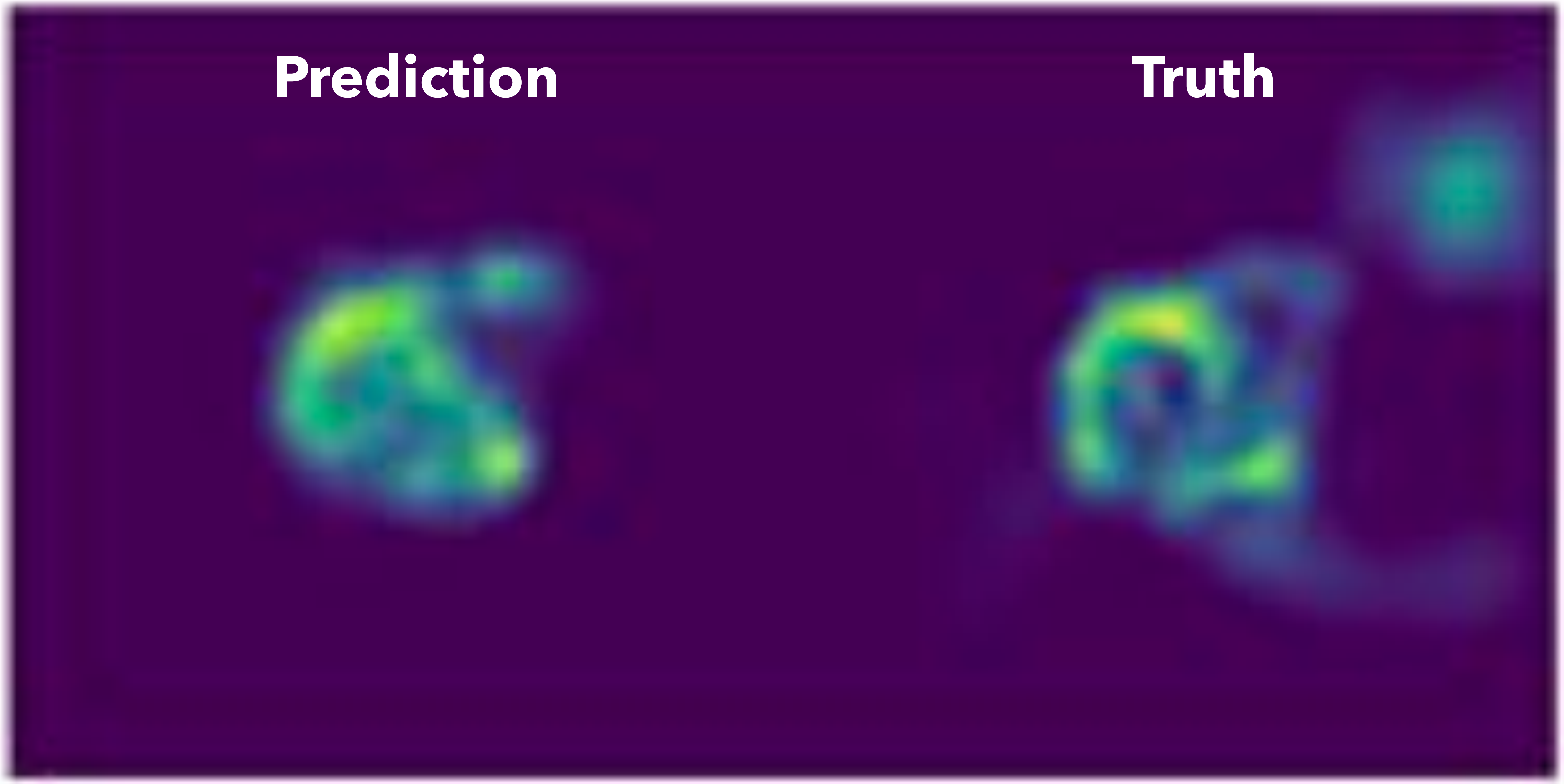
RESULTS


THE DATA CLEARLY PROVES THAT—
ARE YOU INDIANA JONES?
BECAUSE YOU'VE GOT A LOT OF ARTIFACTS THERE, AND I'M PRETTY SURE YOU DIDN'T HANDLE THEM RIGHT.

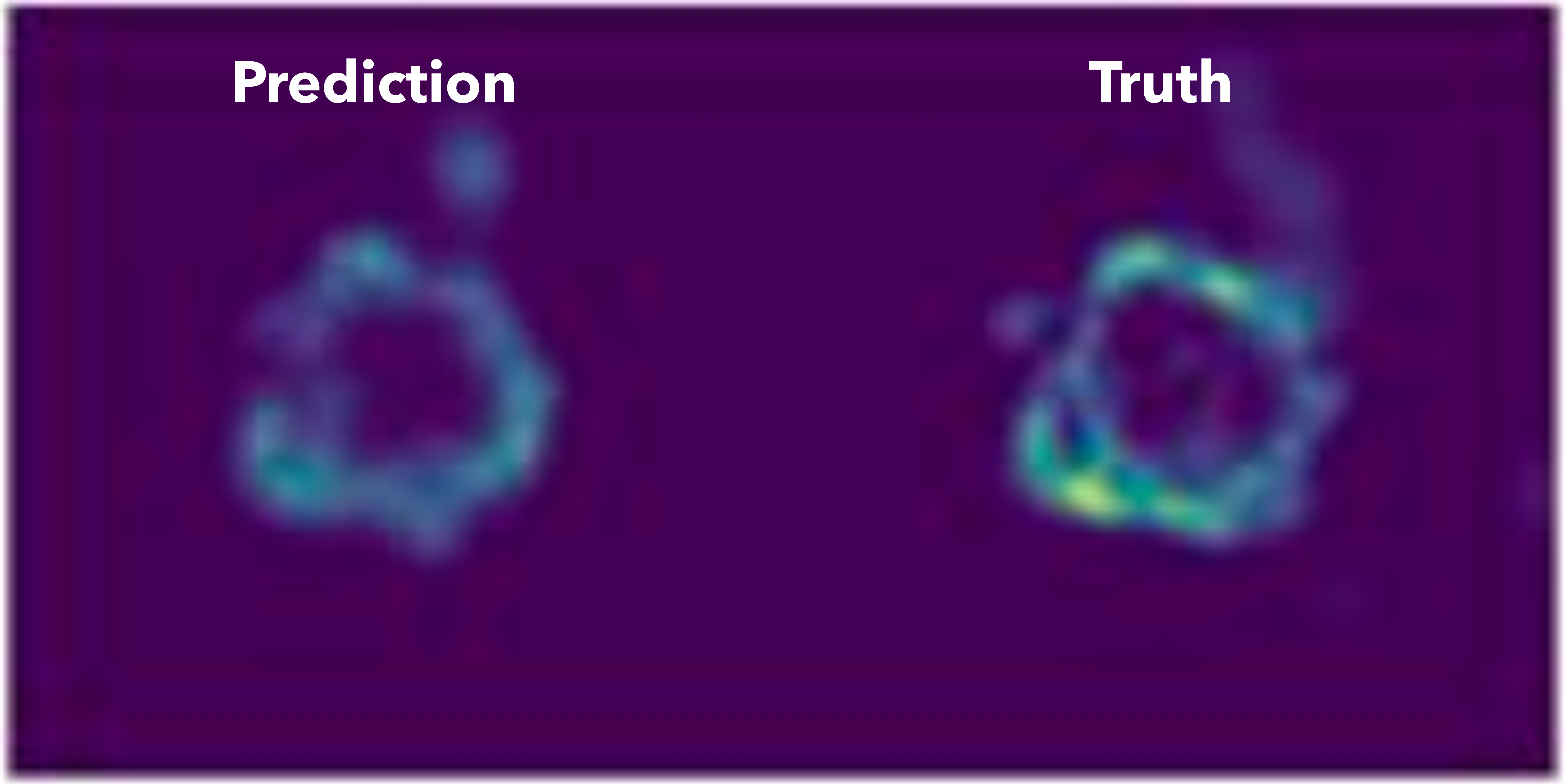
Input
RGB
u
g
r
i
z
197 kpc
Truth
$M_{\rm star}^{\rm true}$
$Z_{\rm star}^{\rm true}$
$\tau_{\rm star}^{\rm true}$
$\log(M_{\rm star}/M_\odot)$
7 8 9
$\log(M_Z^{\rm star}/M_\odot)$
6 8
$\tau_{\rm star}$ [Gyr]
0 10
Prediction
$M_{\rm star}^{\rm pred}$
$Z_{\rm star}^{\rm pred}$
$\tau_{\rm star}^{\rm pred}$
Difference
$\Delta M_{\rm star}$
$\Delta Z_{\rm star}$
$\Delta \tau_{\rm star}$
$\log(M_{\rm star}^{\rm true}/M_{\rm star}^{\rm pred})$
−1 0 1
$\log(Z_{\rm star}^{\rm true}/Z_{\rm star}^{\rm pred})$
−1 0 1
$\log(\tau_{\rm star}^{\rm true}/\tau_{\rm star}^{\rm pred})$
−1 0 1

Input
RGB
u
g
r
i
z
223 kpc
Truth
Prediction
Difference
$M_{\rm star}^{\rm true}$
$Z_{\rm star}^{\rm true}$
$\tau_{\rm star}^{\rm true}$
$\log(M_{\rm star}/M_\odot)$
7 8 9
$\log(M_Z^{\rm star}/M_\odot)$
6 8
$\tau_{\rm star}$ [Gyr]
0 10
$M_{\rm star}^{\rm pred}$
$Z_{\rm star}^{\rm pred}$
$\tau_{\rm star}^{\rm pred}$
$\Delta M_{\rm star}$
$\Delta Z_{\rm star}$
$\Delta \tau_{\rm star}$
$\log(M_{\rm star}^{\rm true}/M_{\rm star}^{\rm pred})$
−1 0 1
$\log(Z_{\rm star}^{\rm true}/Z_{\rm star}^{\rm pred})$
−1 0 1
$\log(\tau_{\rm star}^{\rm true}/\tau_{\rm star}^{\rm pred})$
−1 0 1

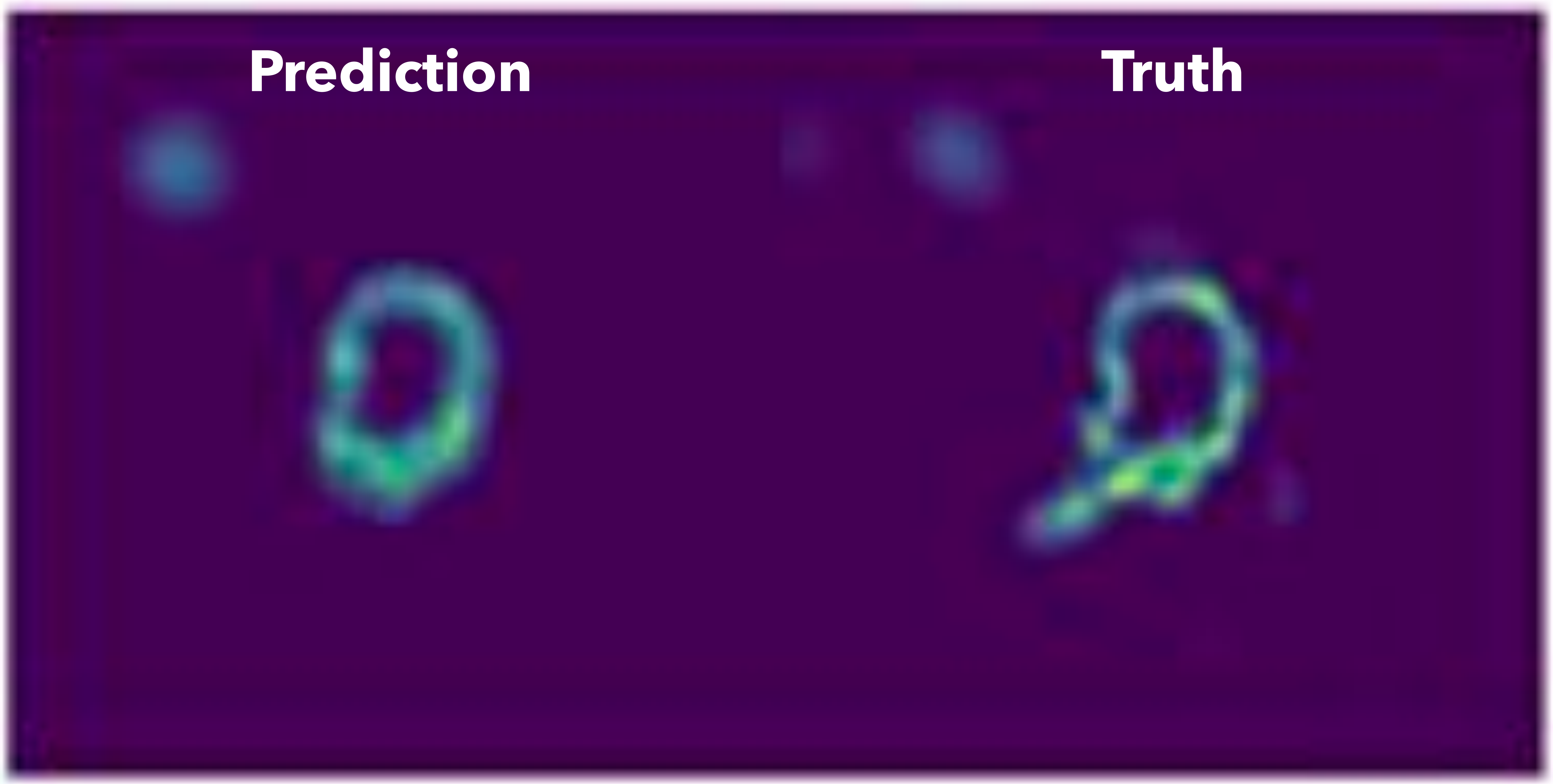
STAR FORMATION RATE MAPS: EXAMPLE FROM 100TH PERCENTILE BEST FIT



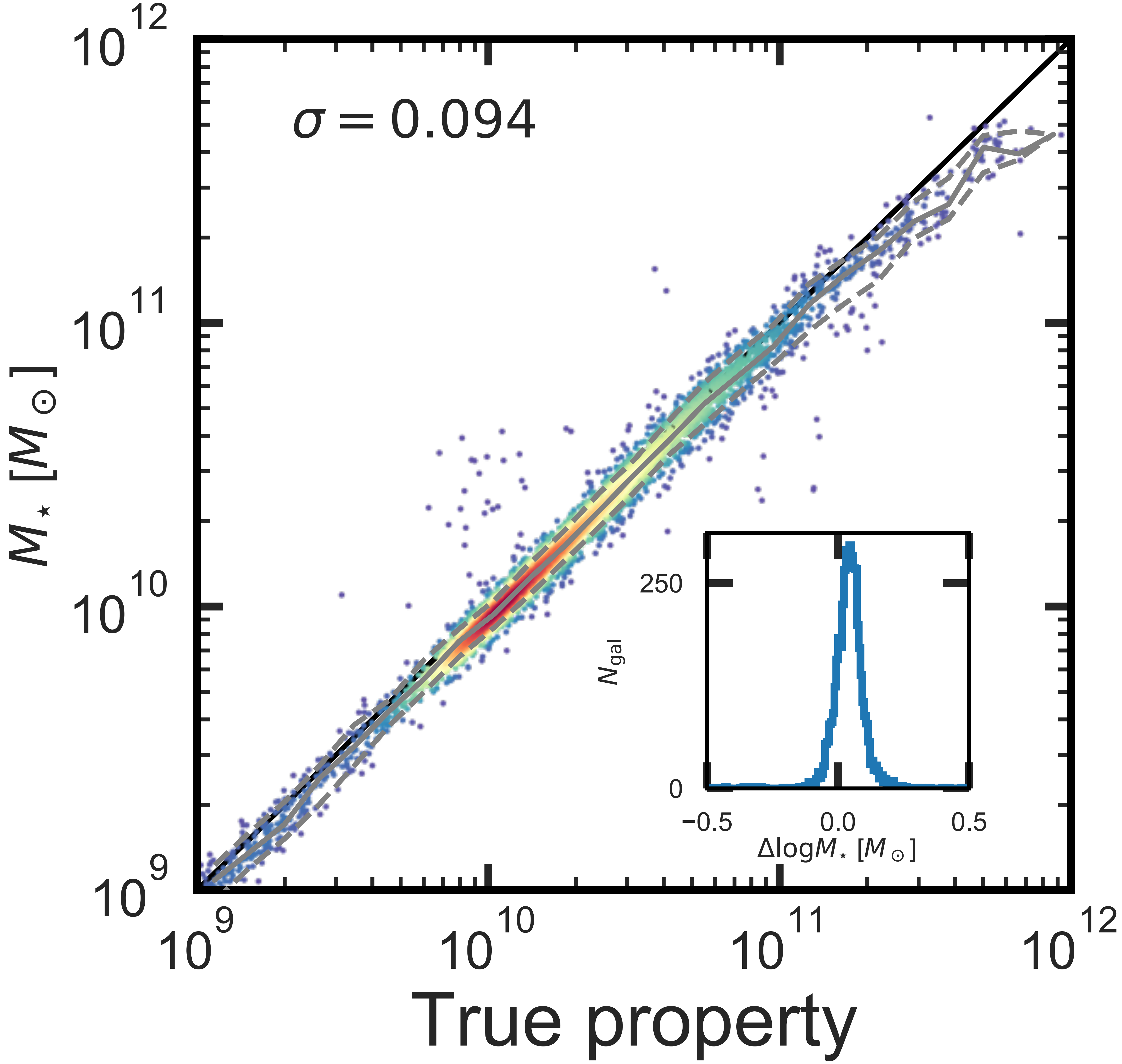
STAR FORMATION RATE MAPS: EXAMPLE FROM 70TH PERCENTILE BEST FIT

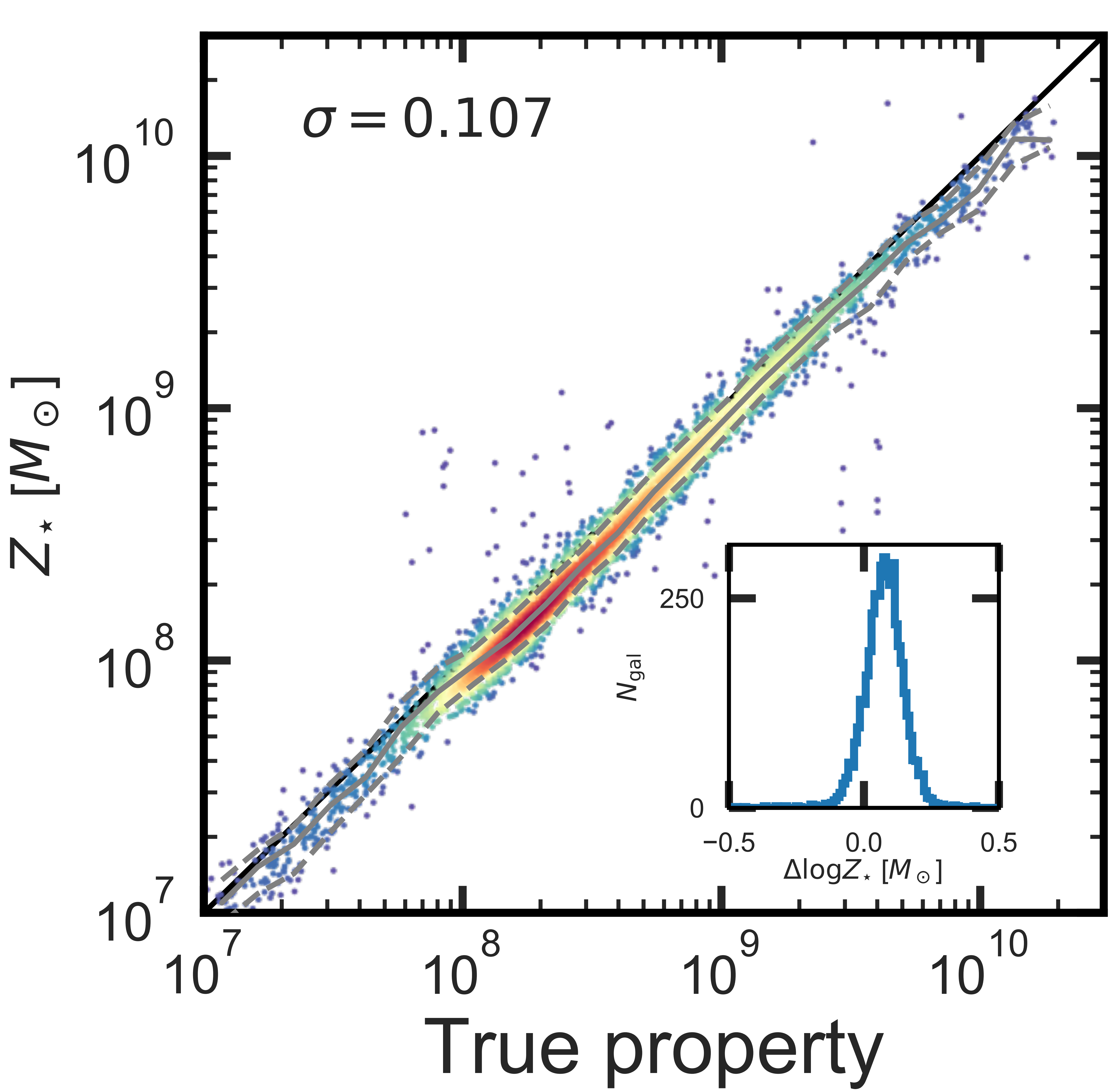


STAR FORMATION RATE MAPS: EXAMPLE FROM 40TH PERCENTILE BEST FIT

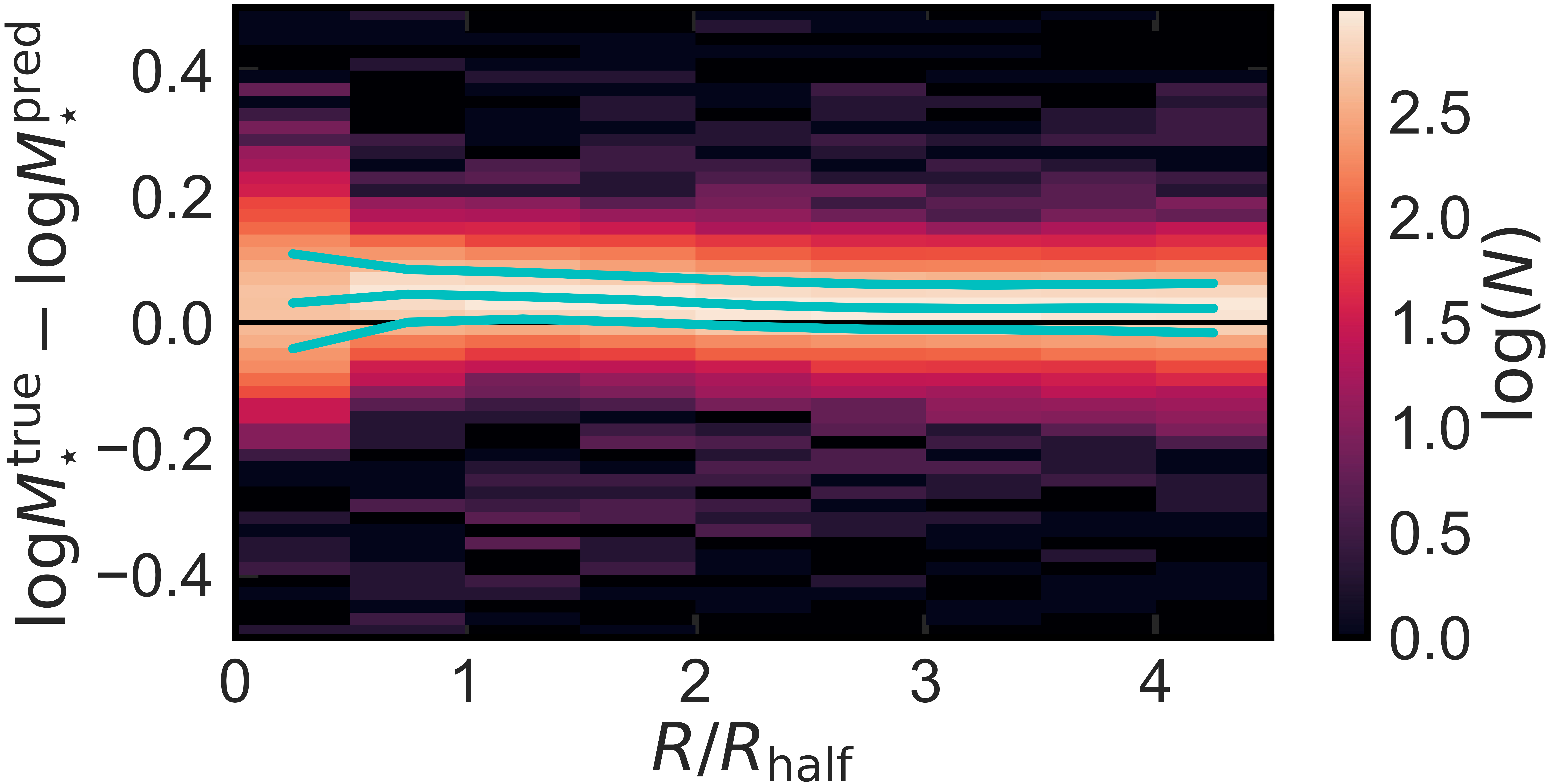


MORE QUANTITATIVE: GLOBAL STELLAR PROPERTIES

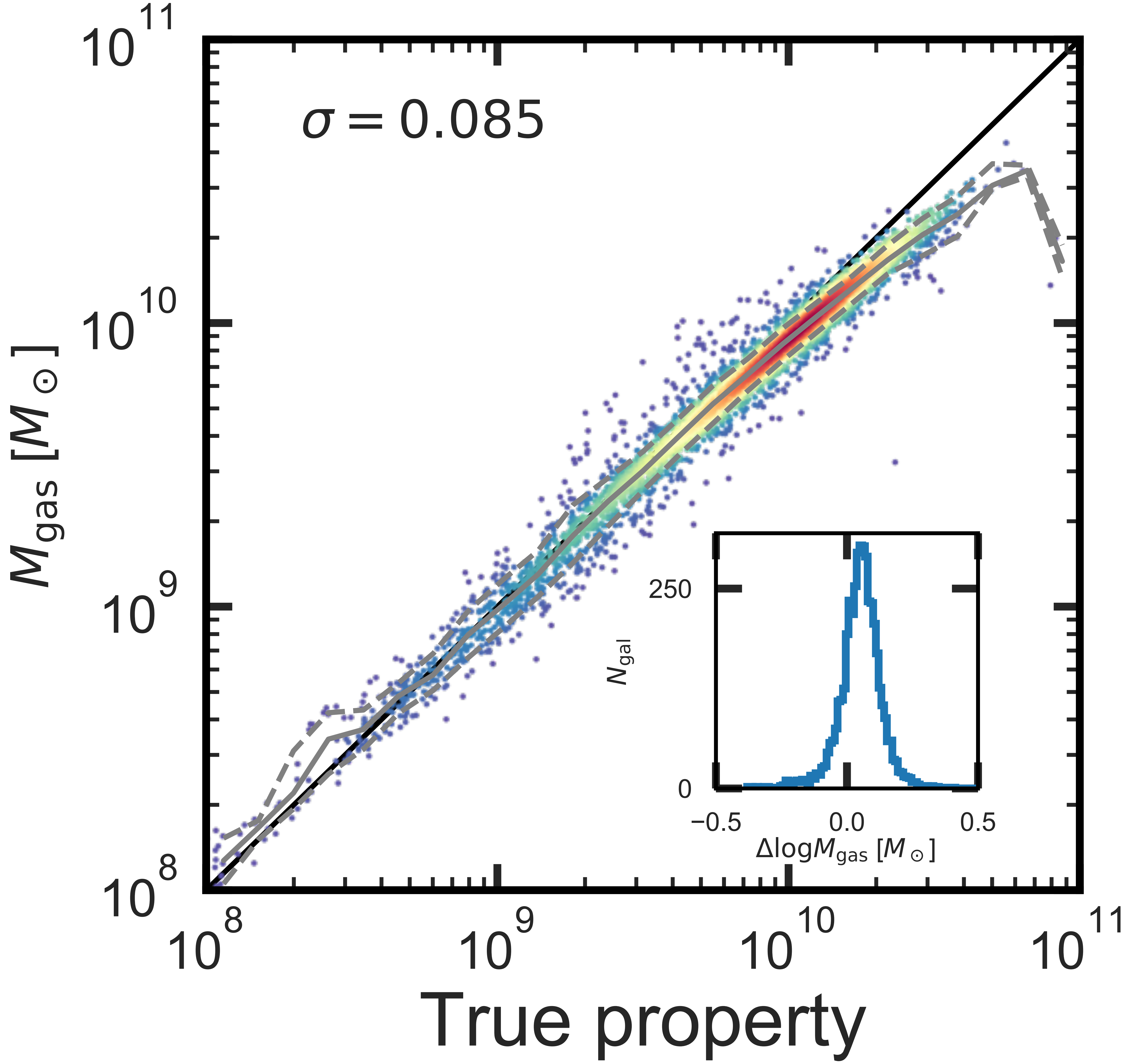


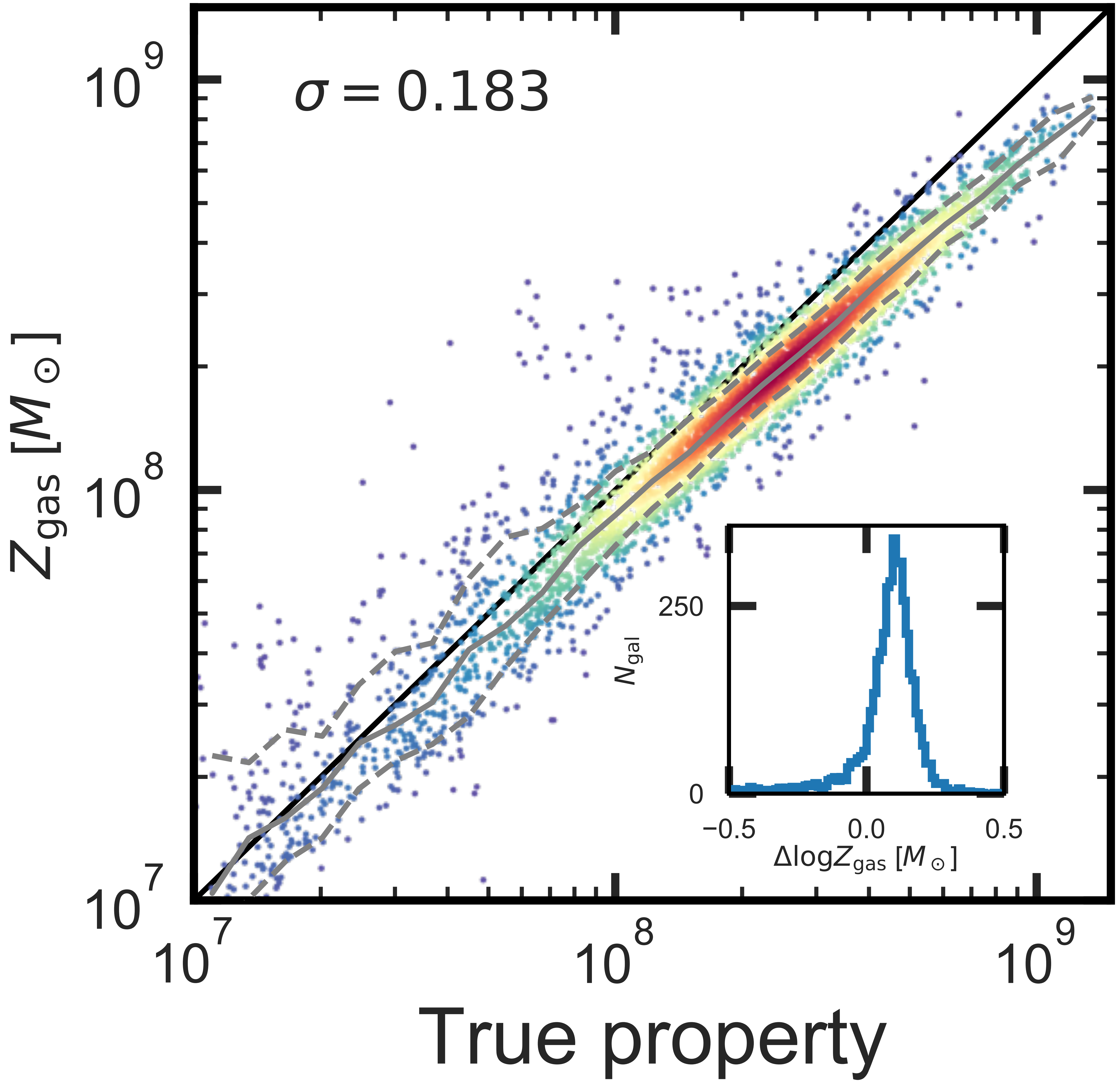


MORE QUANTITATIVE: RADIAL STELLAR PROPERTIES

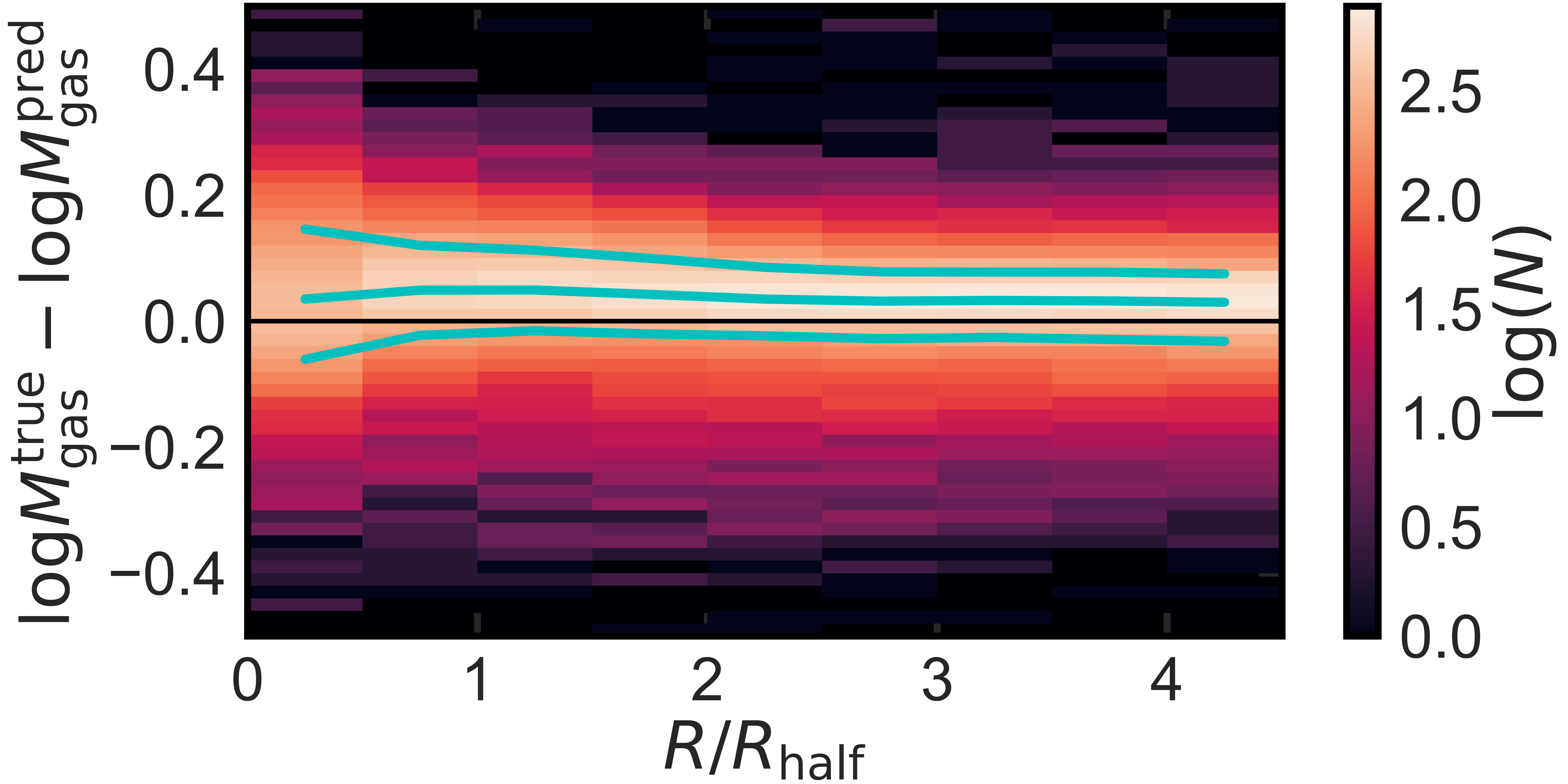


MORE QUANTITATIVE: GLOBAL GASEOUS PROPERTIES





MORE QUANTITATIVE: RADIAL GASEOUS PROPERTIES



SUMMARY: WHAT DO WE LEARN FROM THIS EXERCISE?

- Multi-band Photometry contains enough information to predict galaxy properties on a pixel-by-pixel basis
  - How much information is added by the morphology vs color of the galaxy?
  - Real life application: train on real galaxy images
  - What happens in the limit of large numbers of bands –> IFU data cubes
  - Can we go 3D?

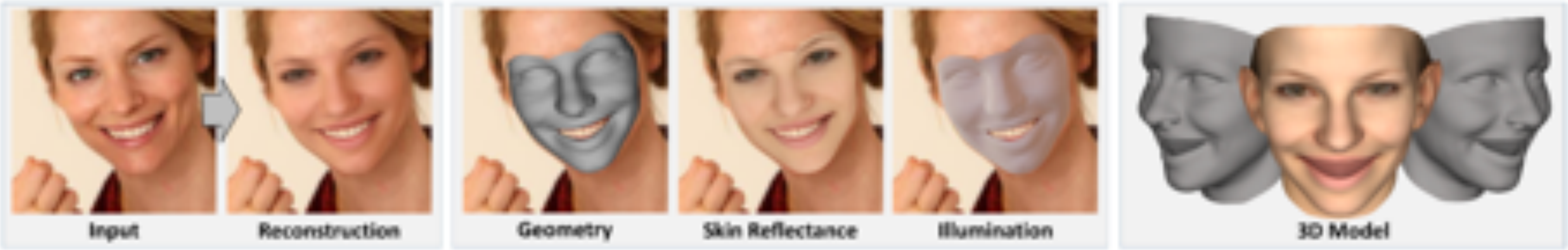
THANKS FOR YOUR ATTENTION

SUMMARY AND CONCLUSION

- simulations: great success in modelling the formation of galaxies
  - can describe statistical properties of galaxies well
  - but limited in describing individual objects
- observations: exquisite data for Milky Way and external galaxies
  - big data challenge in astronomy
  - Need to think about smart methods to process the data

MoFA: Model-based Deep Convolutional Face Autoencoder for Unsupervised Monocular Reconstruction

Ayush Tewari[1] Michael Zollhöfer[1] Hyeongwoo Kim[1] Pablo Garrido[1]
Florian Bernard[1,2] Patrick Pérez[3] Christian Theobalt[1]
[1]Max-Planck-Institute for Informatics [2] LCSB, University of Luxembourg [3]Technicolor



Our model-based deep convolutional face autoencoder enables unsupervised learning of semantic pose, shape, expression, reflectance and lighting parameters. The trained encoder predicts these parameters from a single monocular image, all at once.

Abstract

In this work we propose a novel model-based deep convo-

tailed three-dimensional face reconstruction from a single arbitrary in-the-wild image, e.g., downloaded from the Internet, is still an open research problem due to the high degree

THE IDEA: RECONSTRUCTING GALAXY MODELS FROM IMAGES

idea credit: Bernhard Schölkopf based on face reconstruction by Tewari+2017