The AI Discovery Revolution in Astronomy

Cecilia Garraffo & the AstroAI team

CfA | Harvard & Smithsonian

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J. Rafael Martinez Galarza
James Steiner
Ashley Villar
Floor Broekgaarden
Joshua Wing
Carol Cuesta Lázaro
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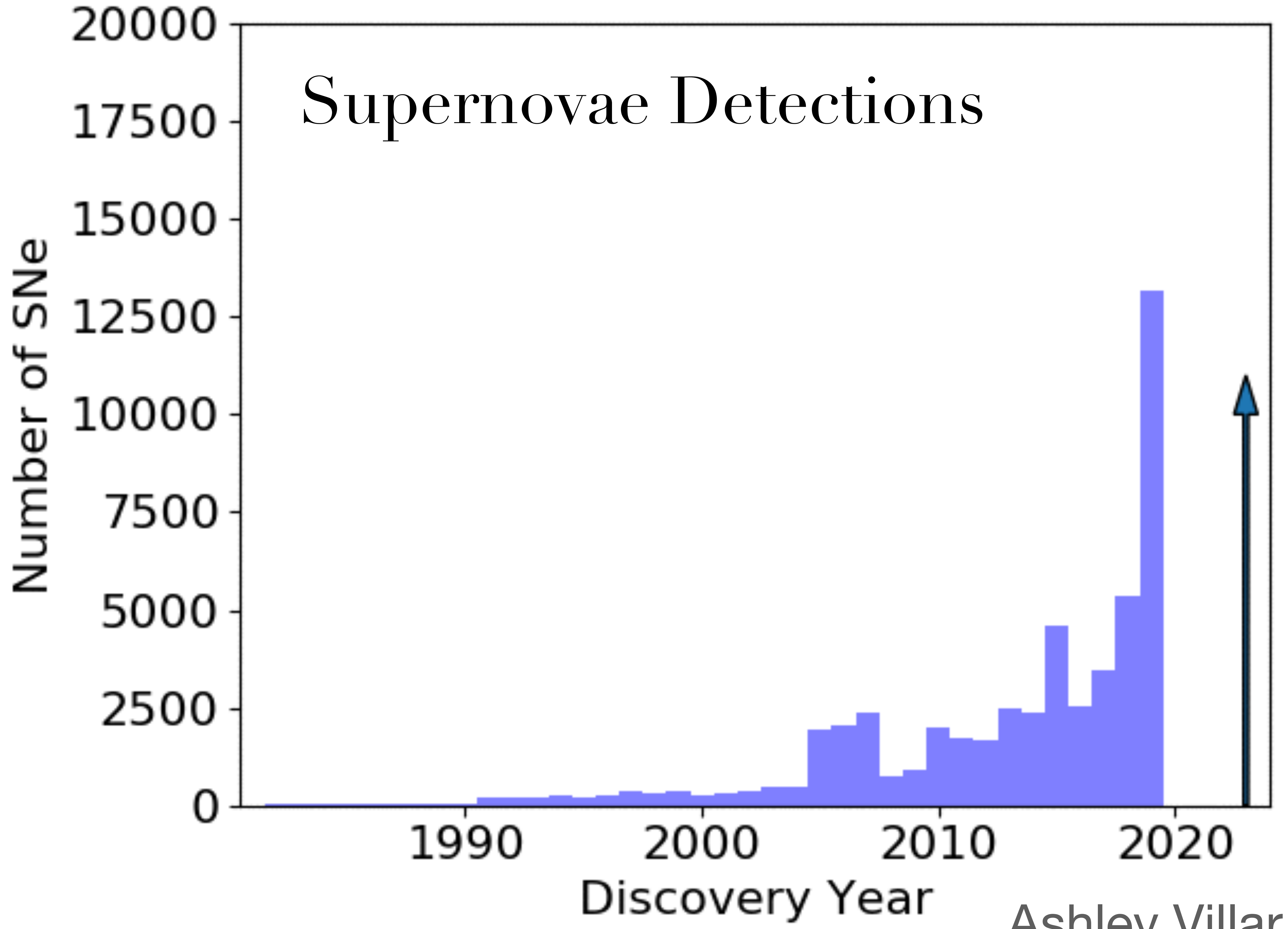
Kari Haworth
Douglas Finkbeiner
Nayantara Mudur
Core Francisco Park
Alex Gagliano
Bill Freeman
Melanie Weber
David Alvarez-Melis
Robin Walters
Katie Bouman


Fig: Ashley Villar

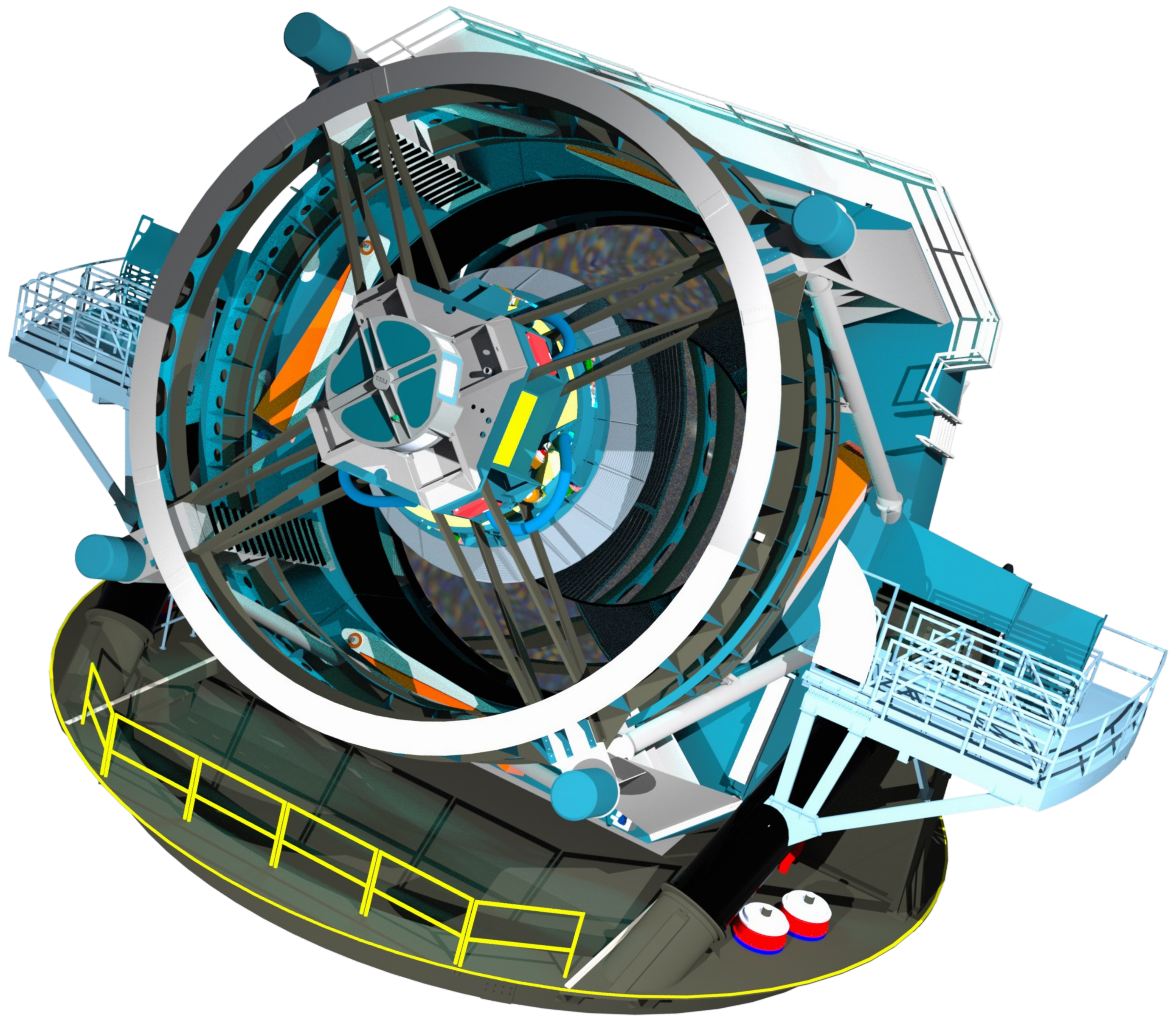

Fig: Ashley Villar
We will observe more data in one year than all our observations so far

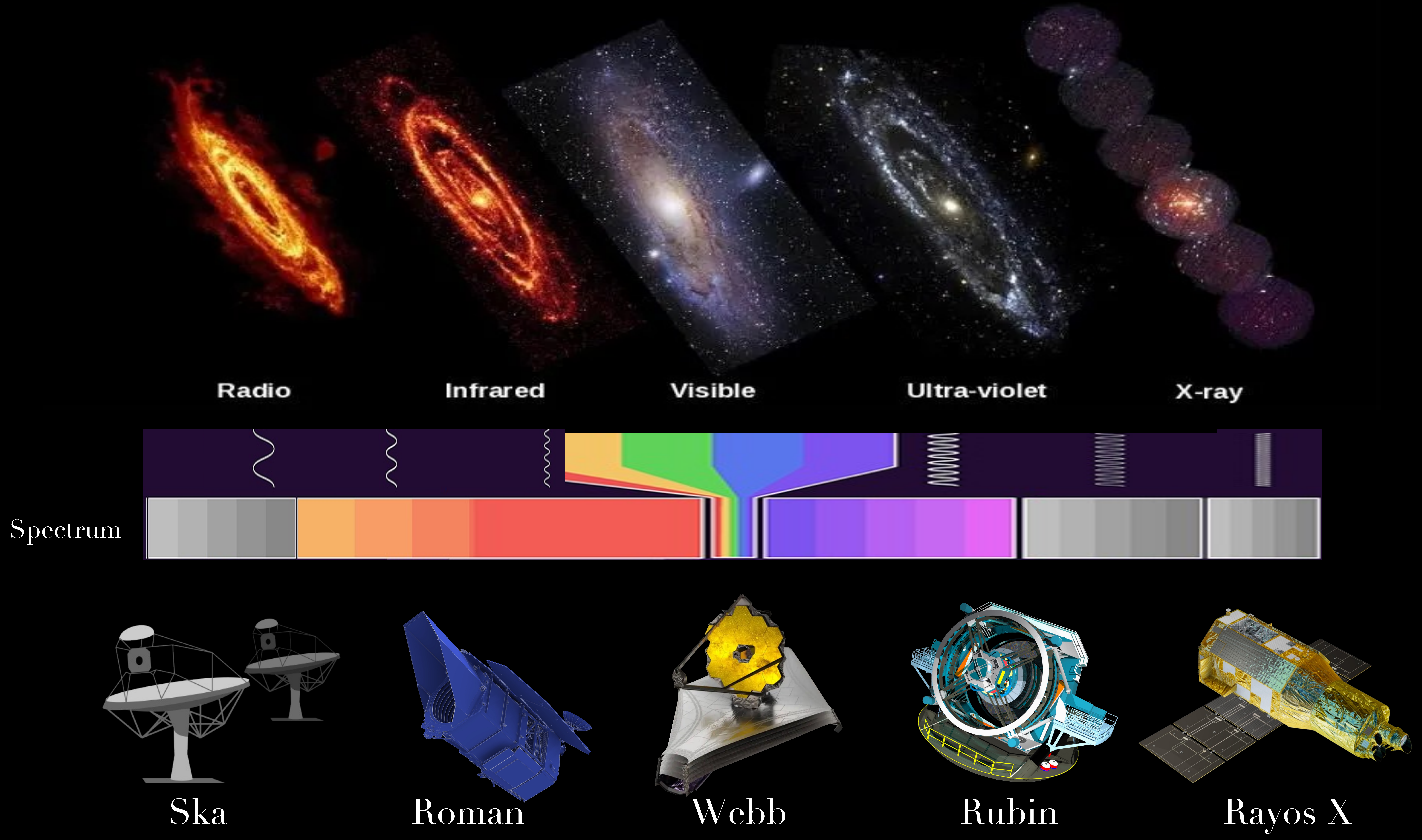

Vera Rubin Observatory
We will observe more data in one year than all our observations so far

Big Data Revolution in Astrophysics



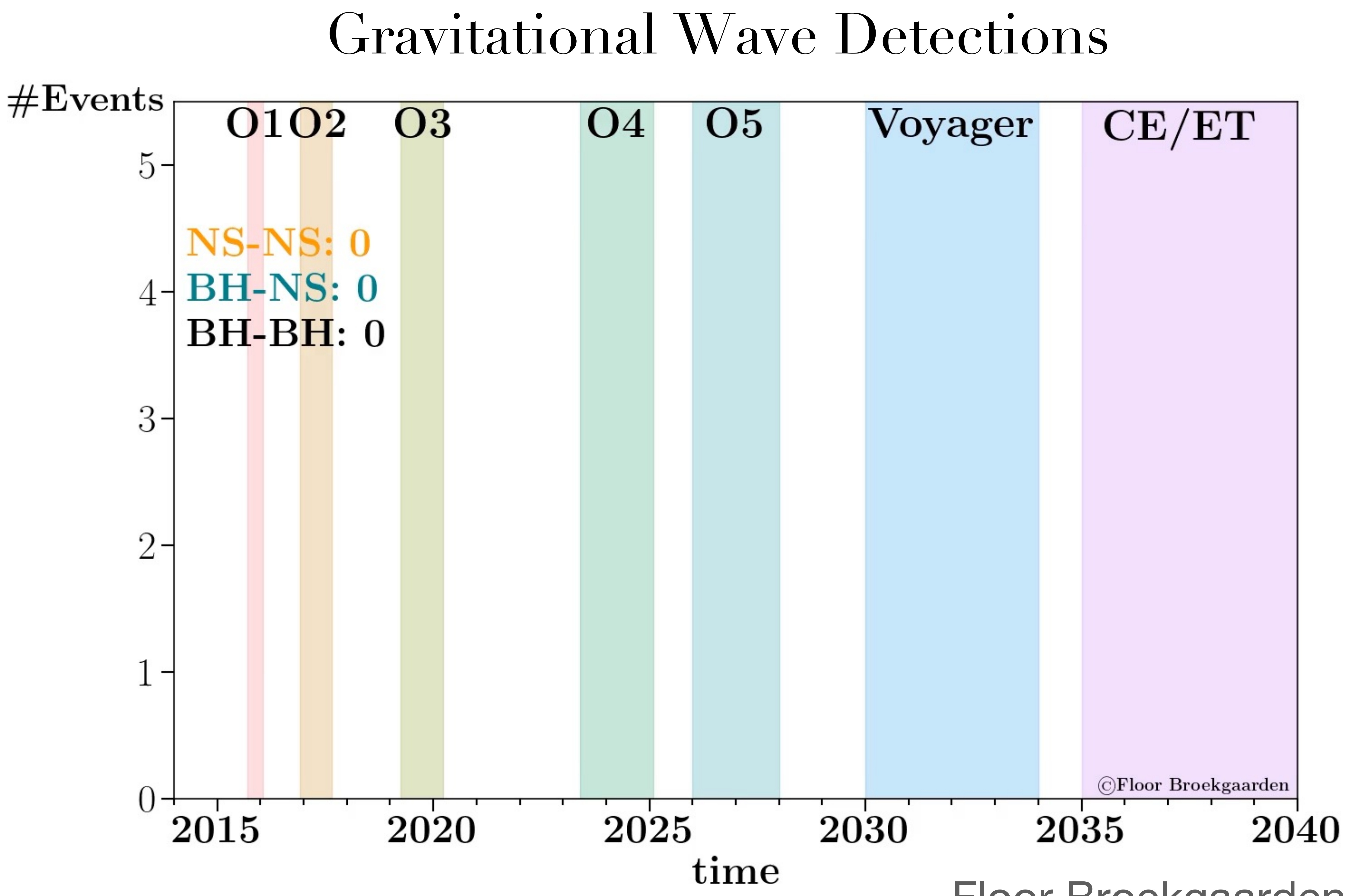
Ashley Villar




Radio
Infrared
Visible
Ultra-violet
X-ray
Spectrum
Ska
Roman
Webb
Rubin
Rayos X

New Windows into the Universe

New Windows into the Universe



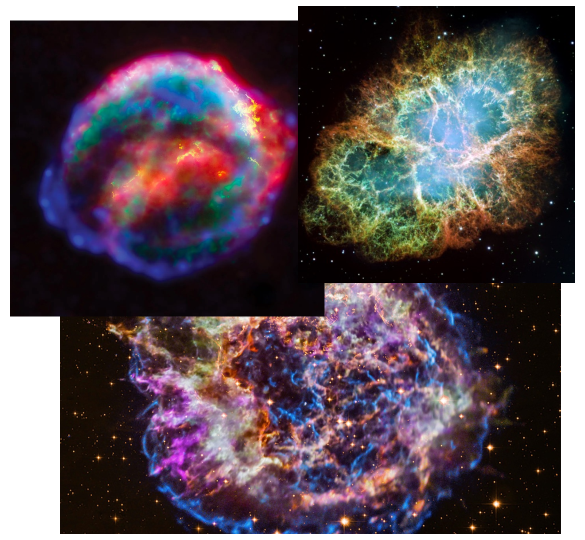
Floor Broekgaarden

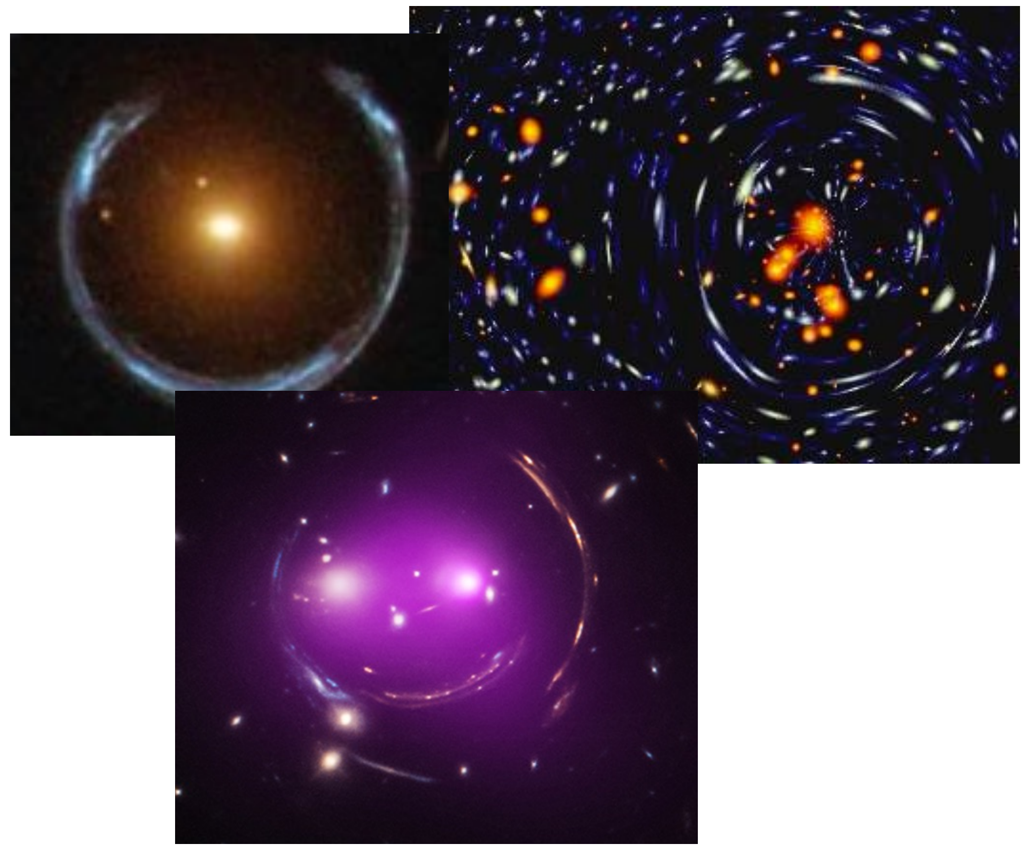

NASA, ESA, AND D. COE, J. ANDERSON, AND R. VAN DER MAREL (STSCI)

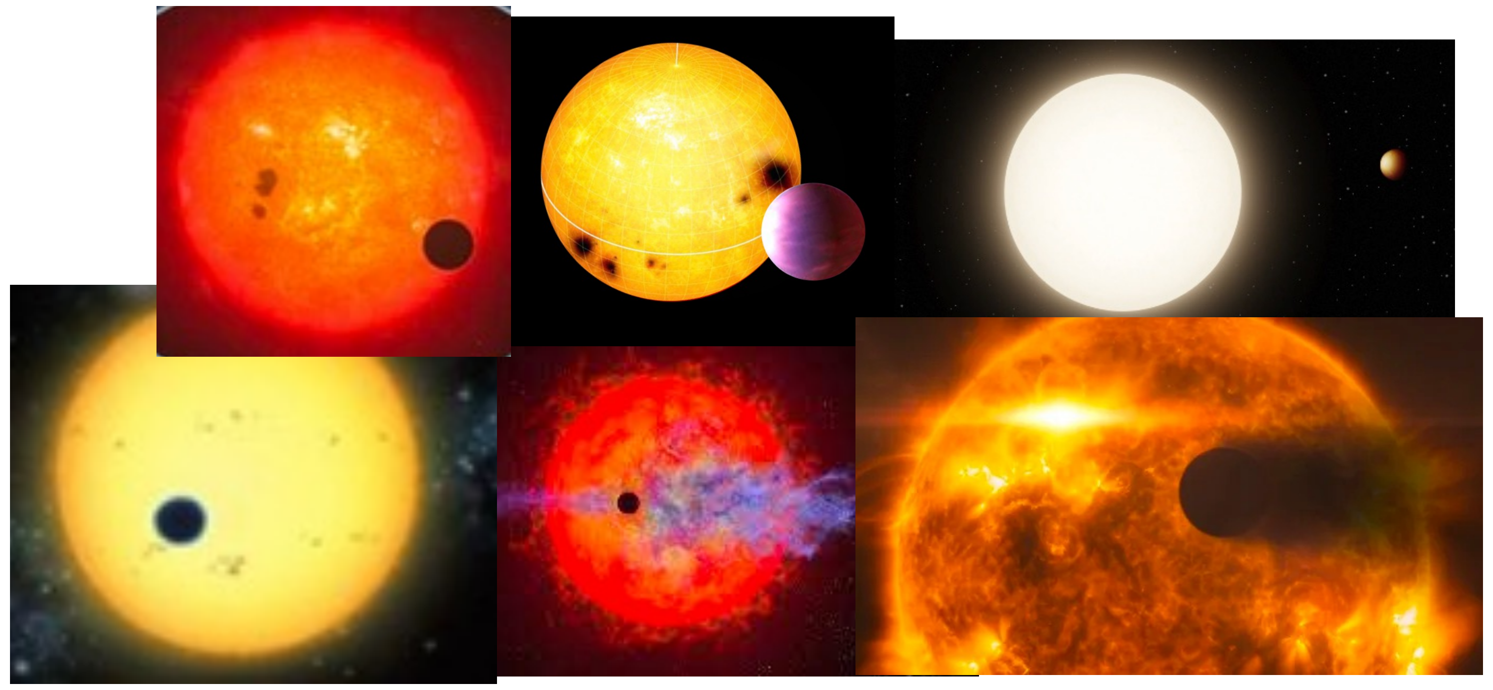
Search for the unexpected

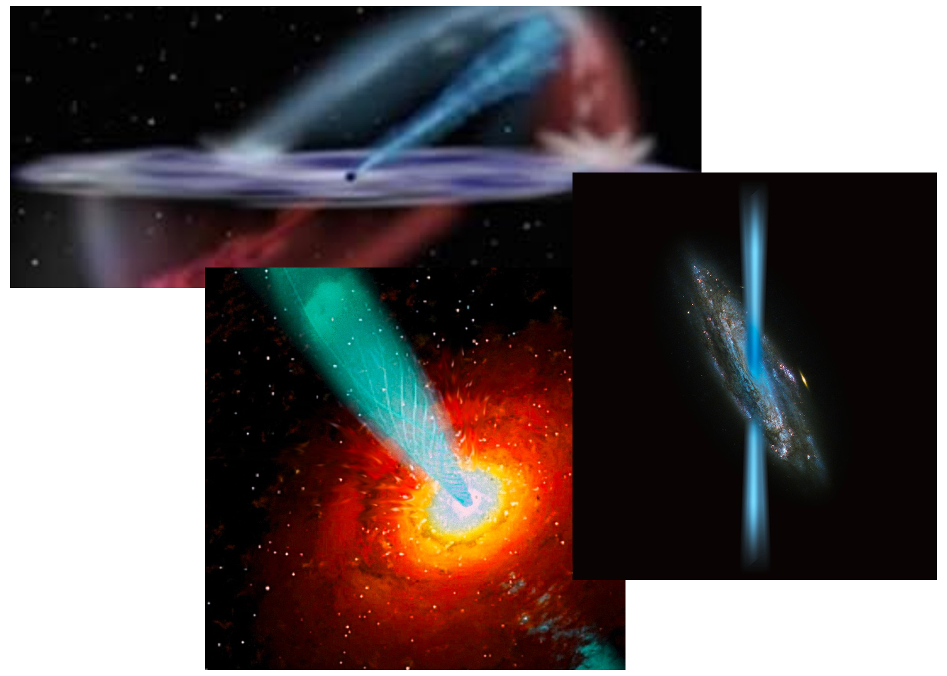
Search for the unexpected

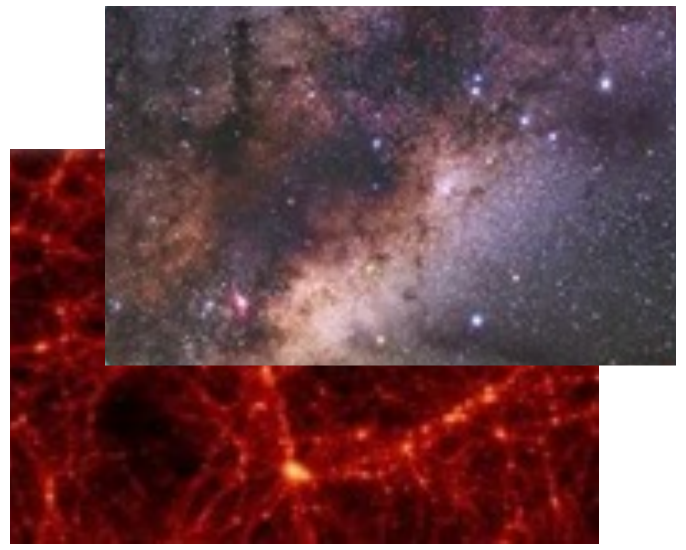
Search for the unexpected

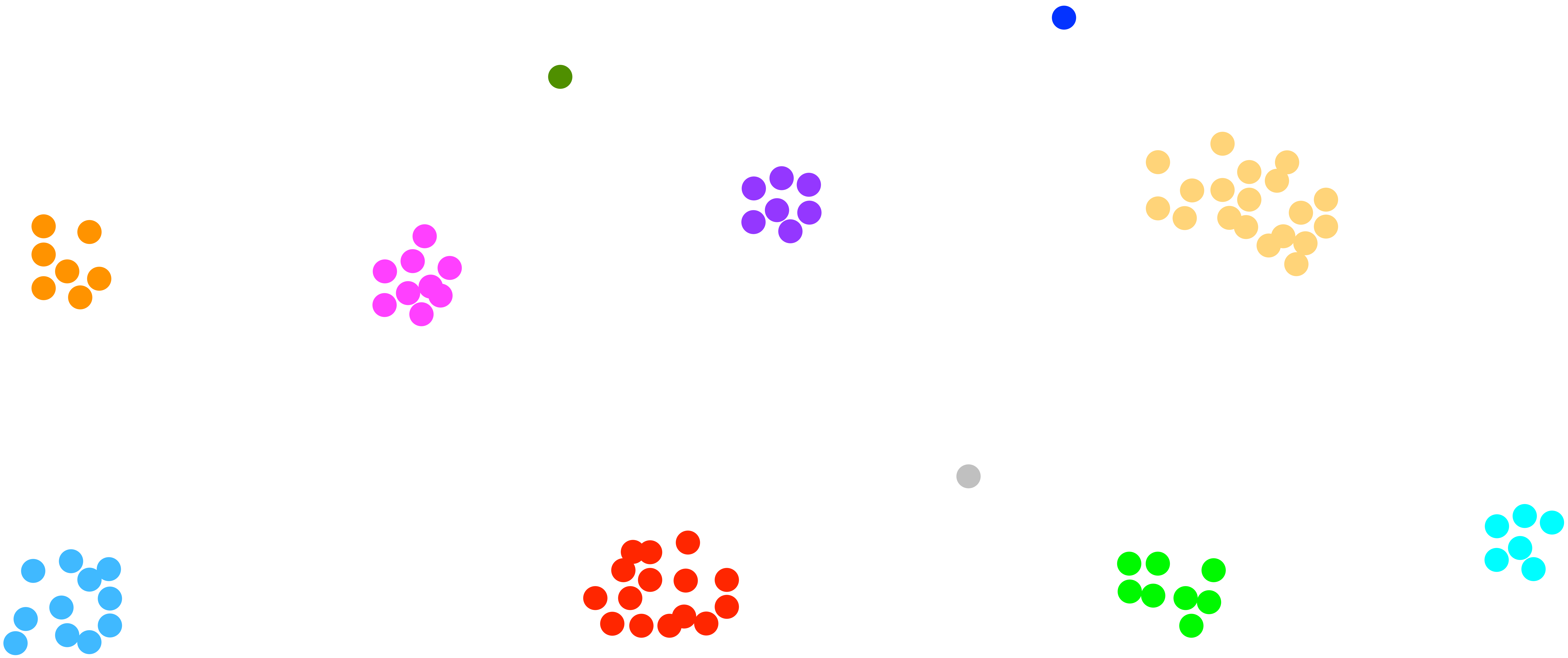


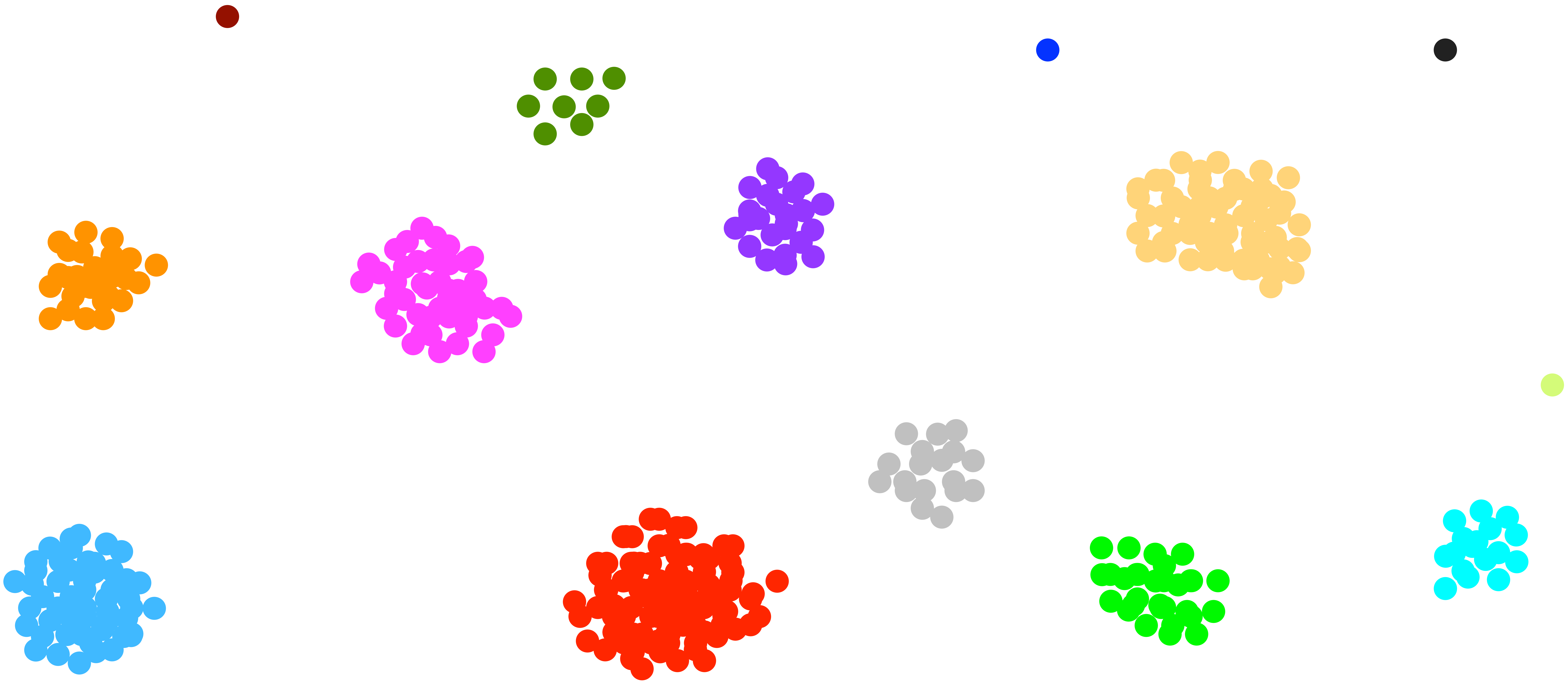






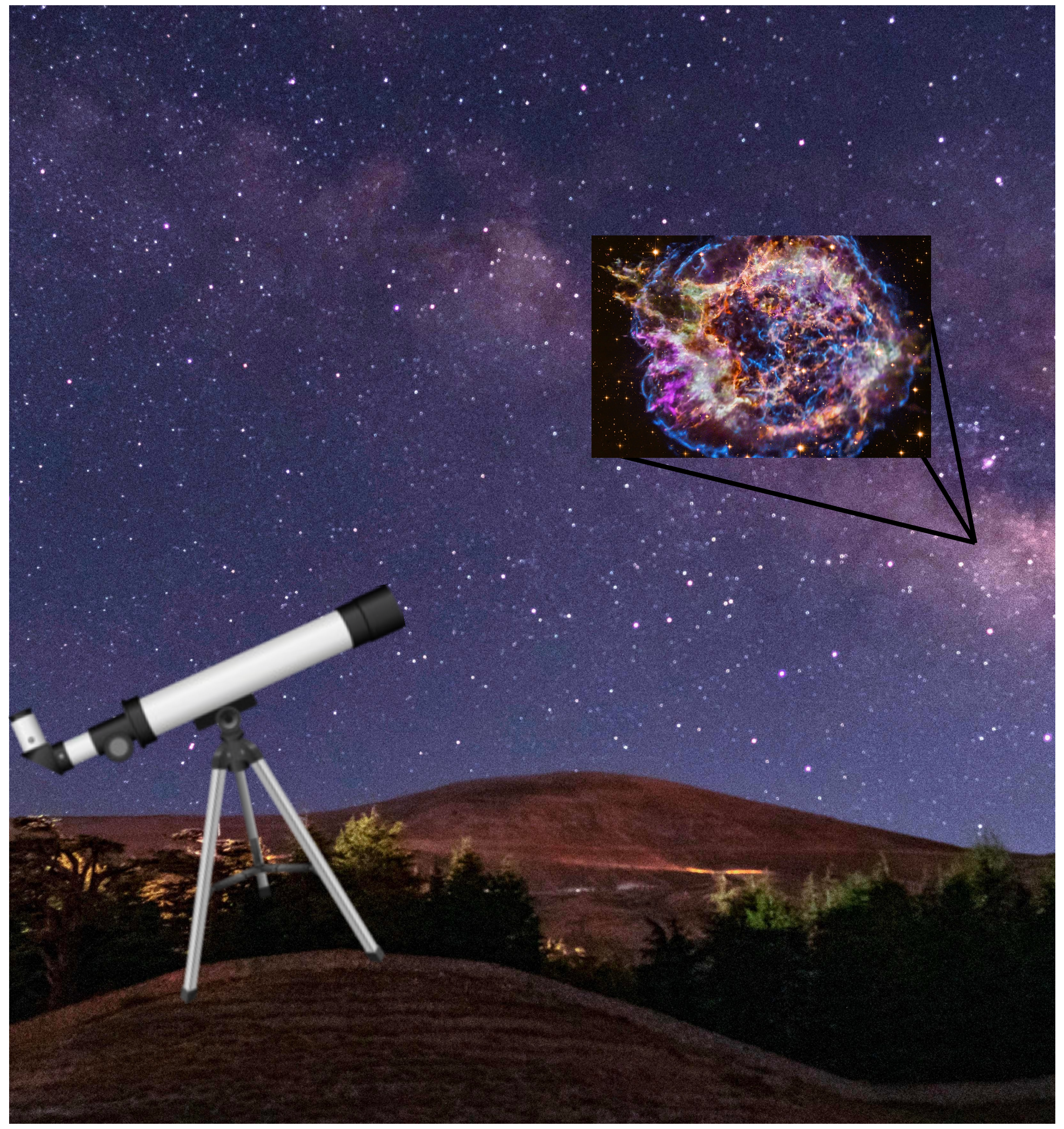




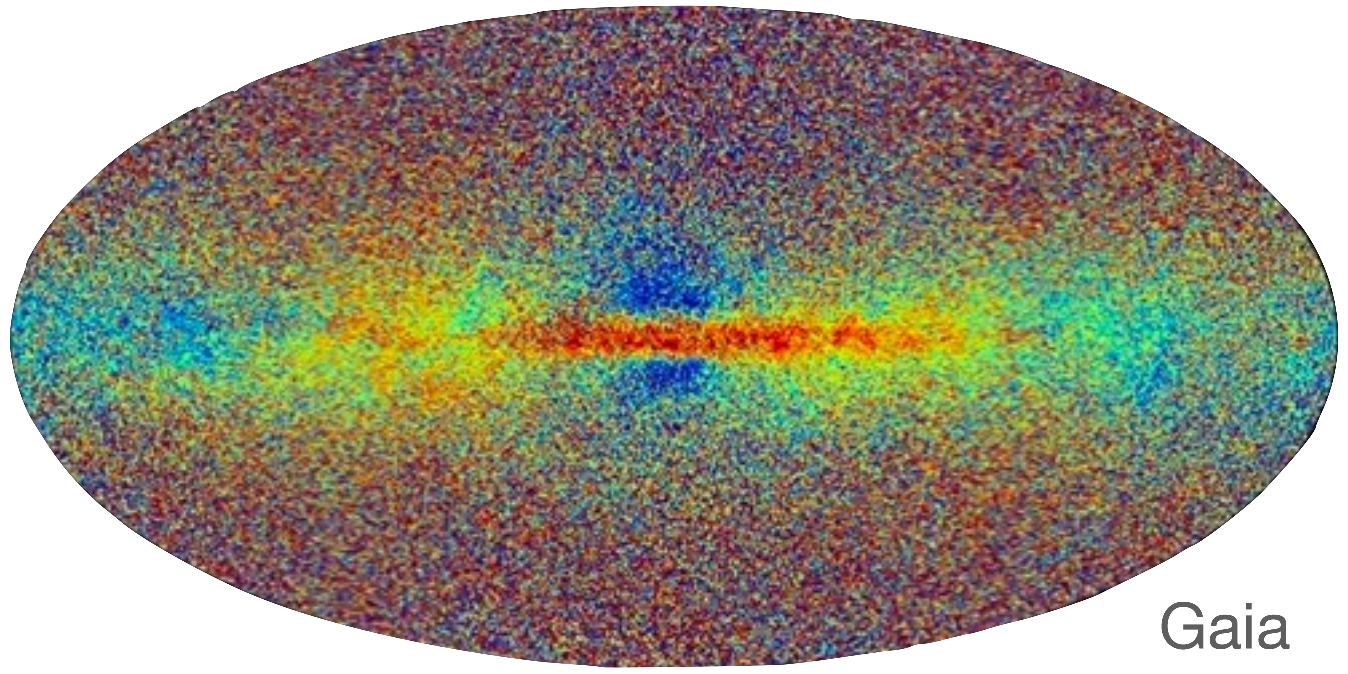


The need for new AI for Astronomy

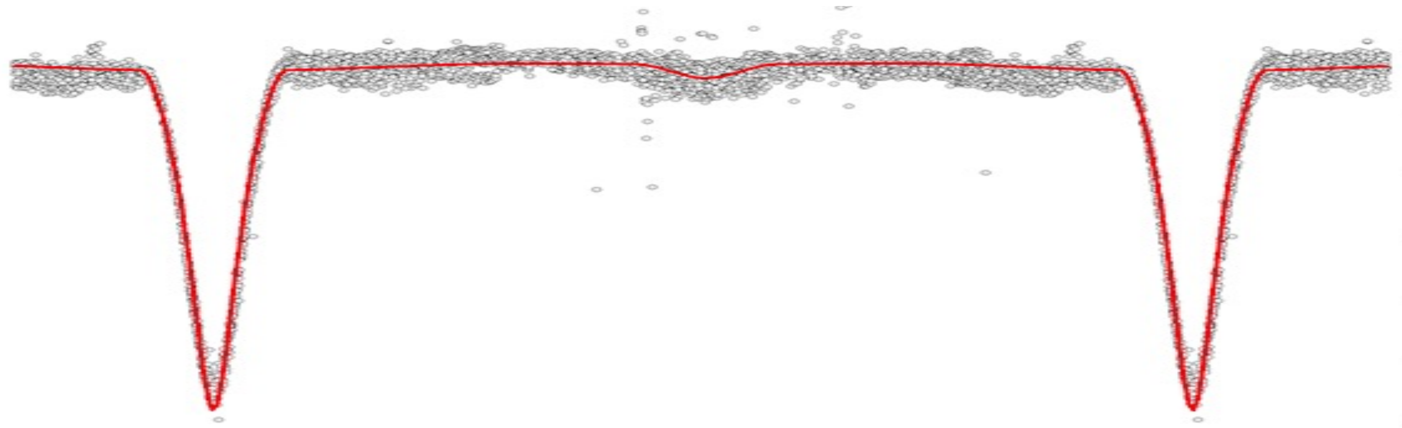
1. The Complex Nature of Astronomical Data



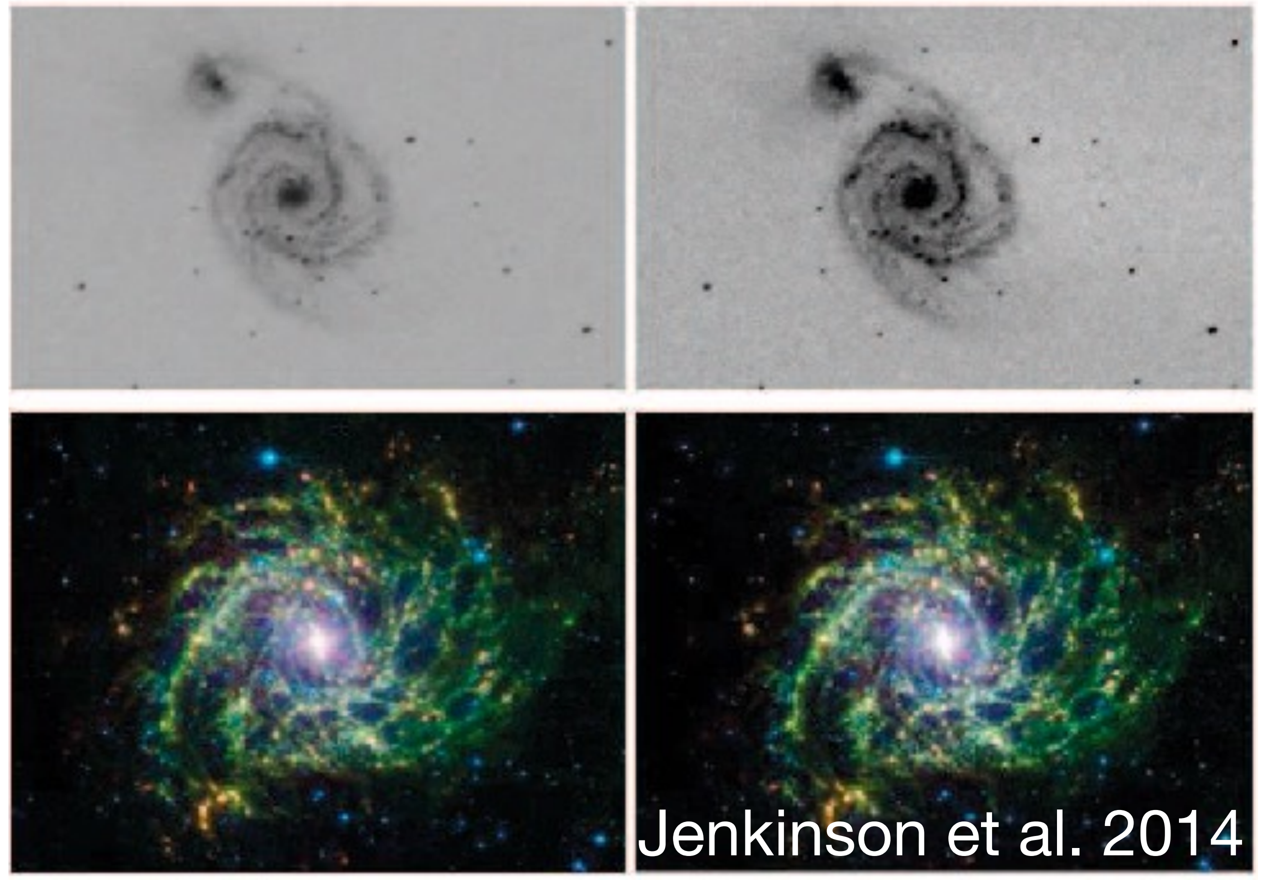
The Complex Nature of Astronomical Data



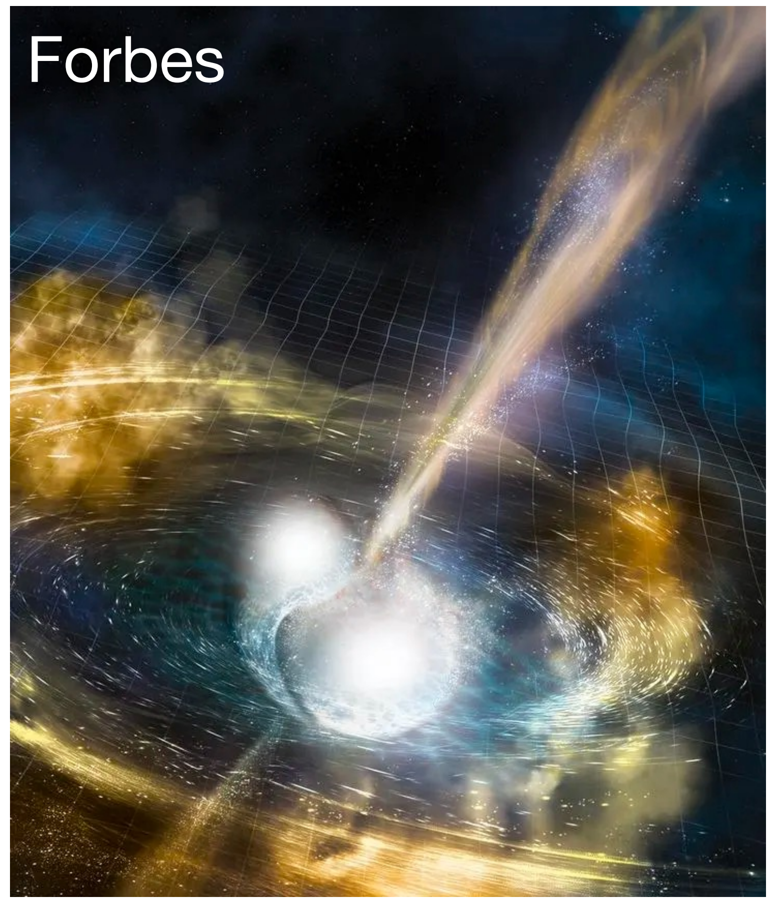
Gaia



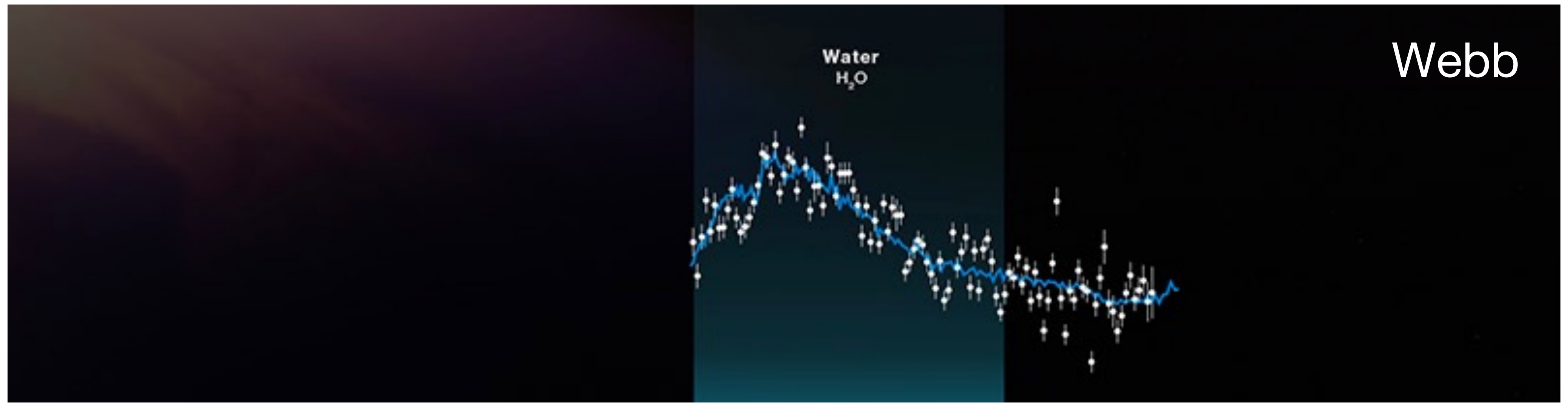
Manzoori et al. 2017



Jenkinson et al. 2014



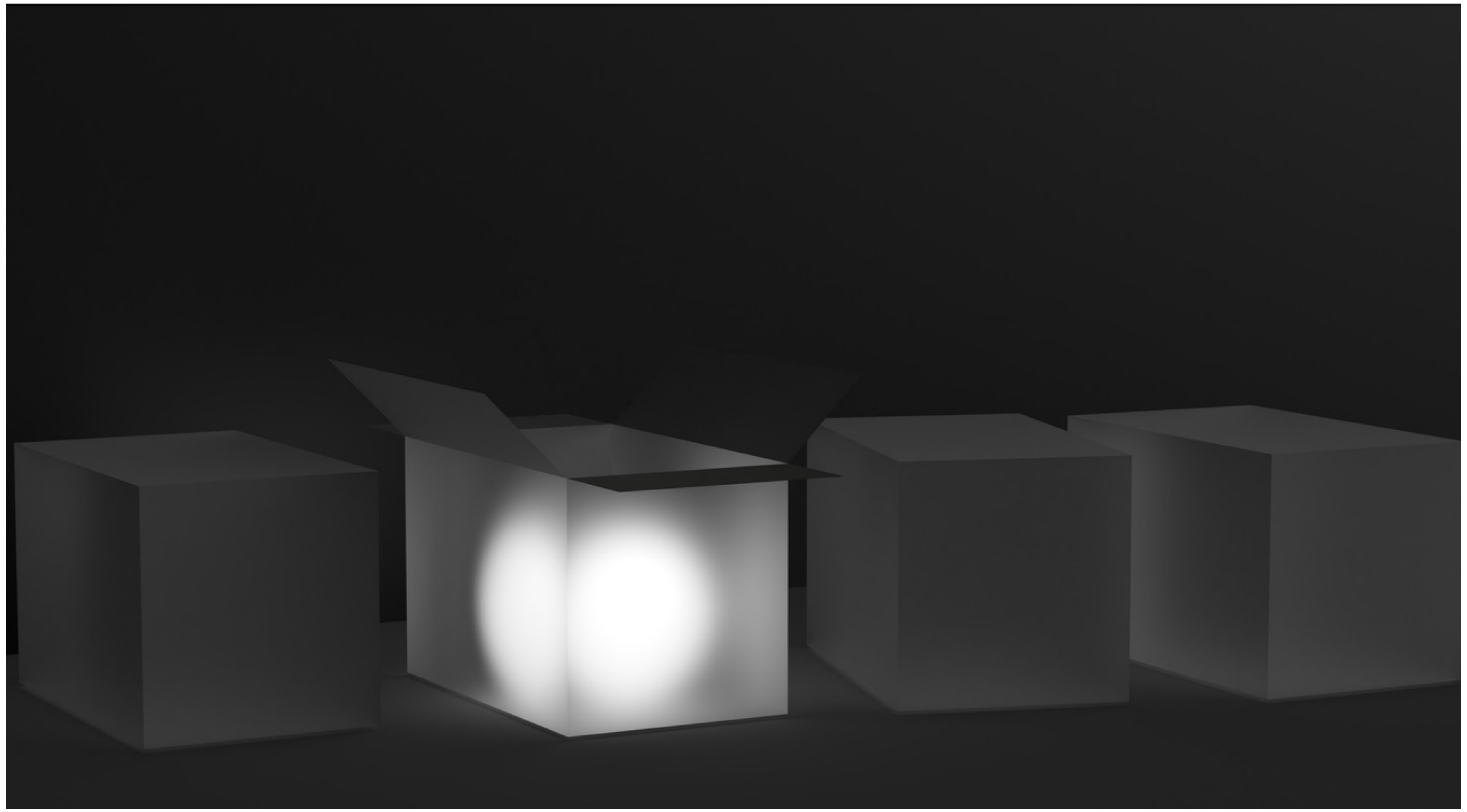
Forbes



Webb

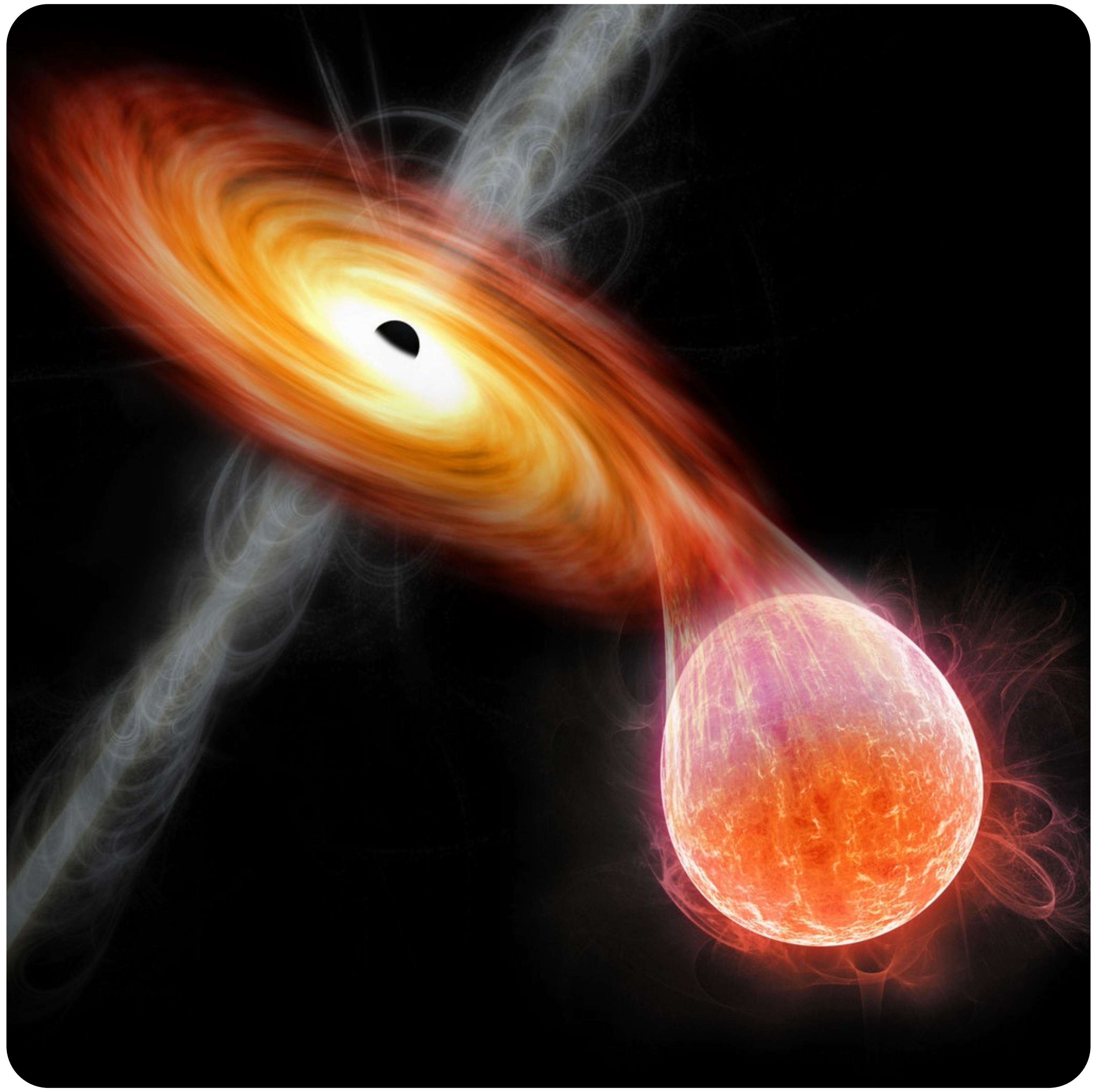
Forbes

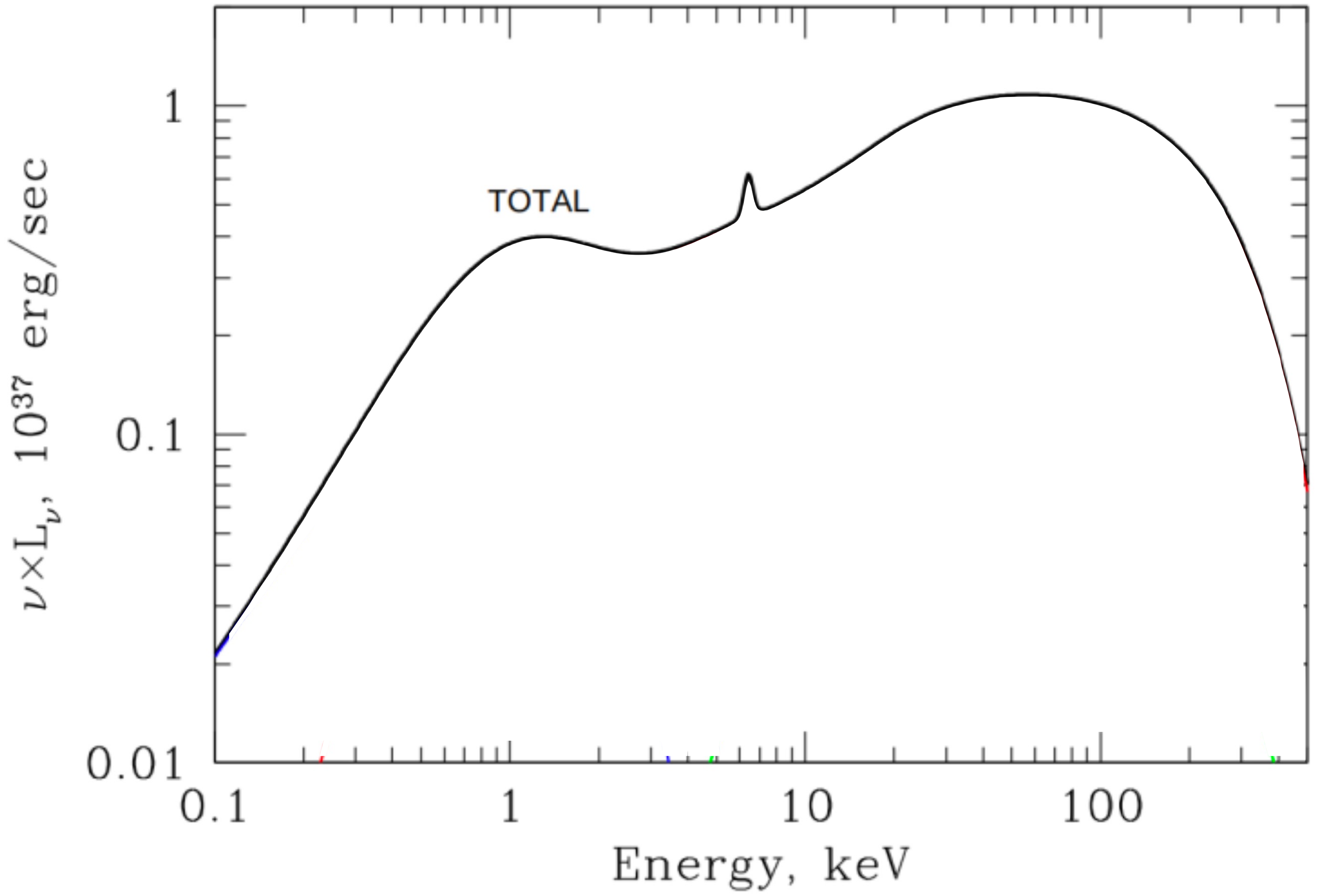
2. The Complex Nature of the Task



Physical AI Models

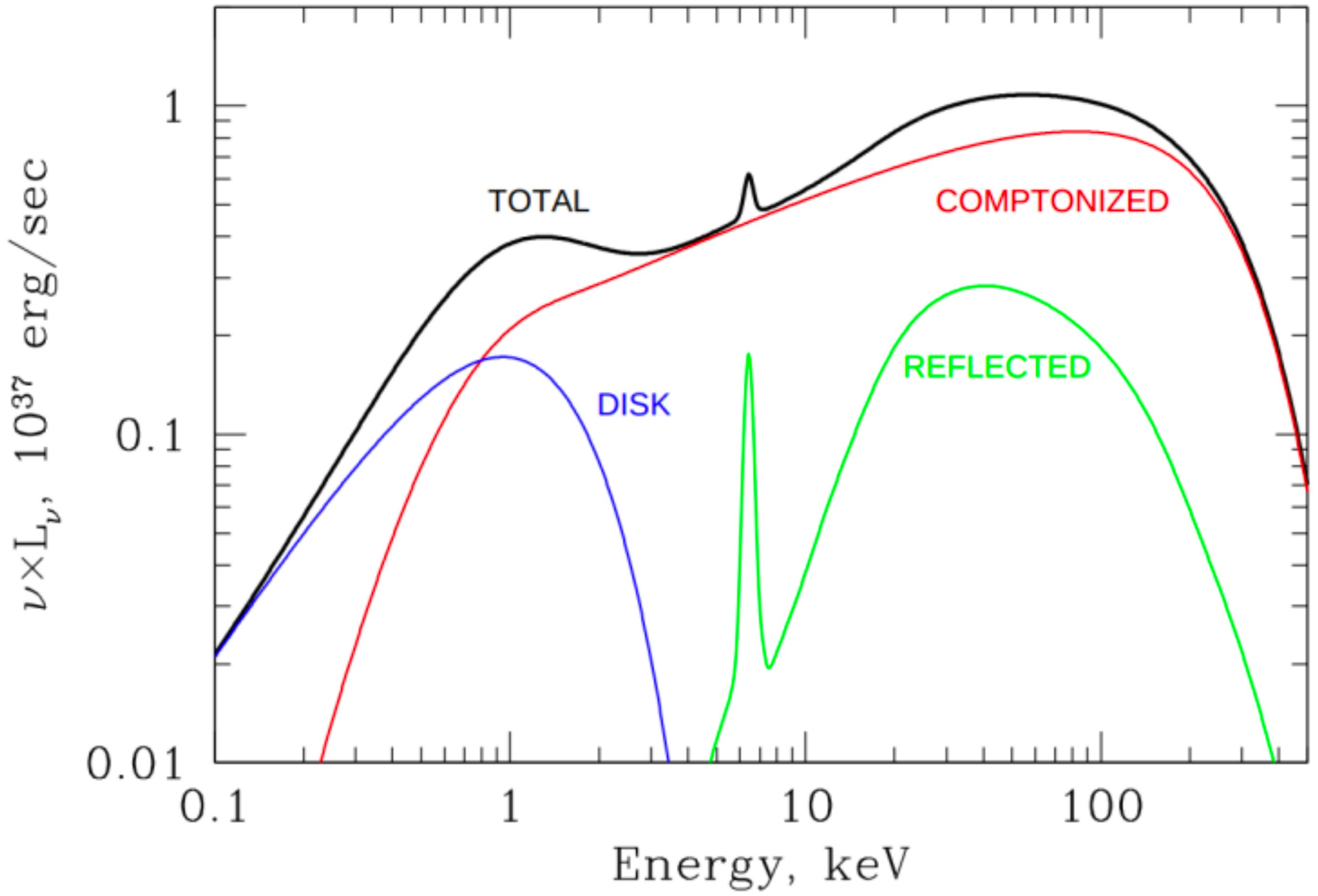
X-ray binary





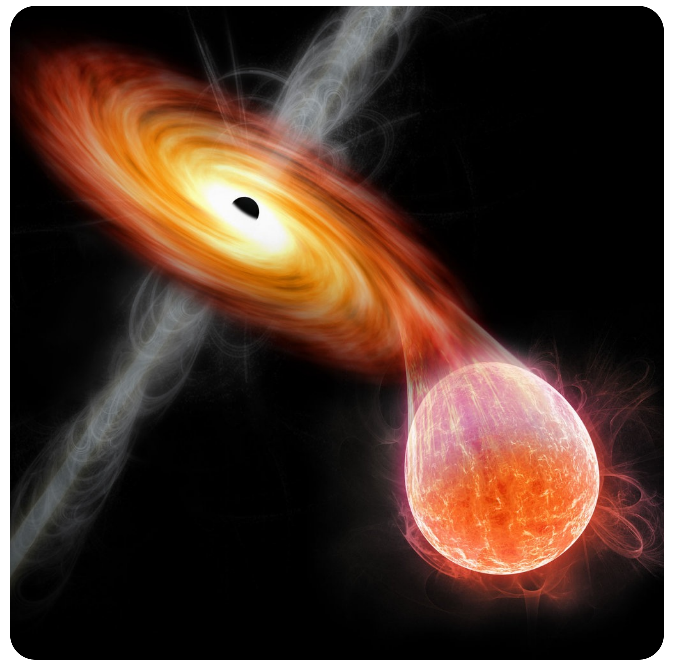
Expert

10,000 spectra
24 hours of work



Physical Parameters:
T, M, Spin

Ethan Tregigda



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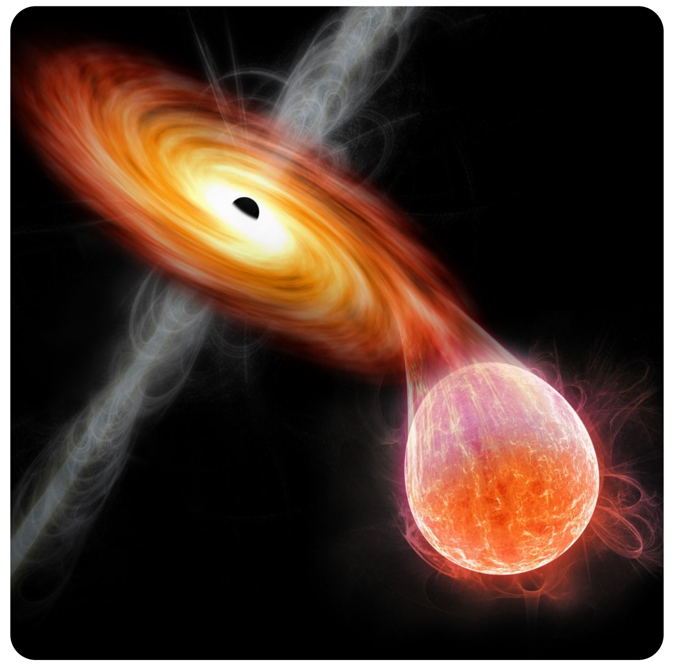
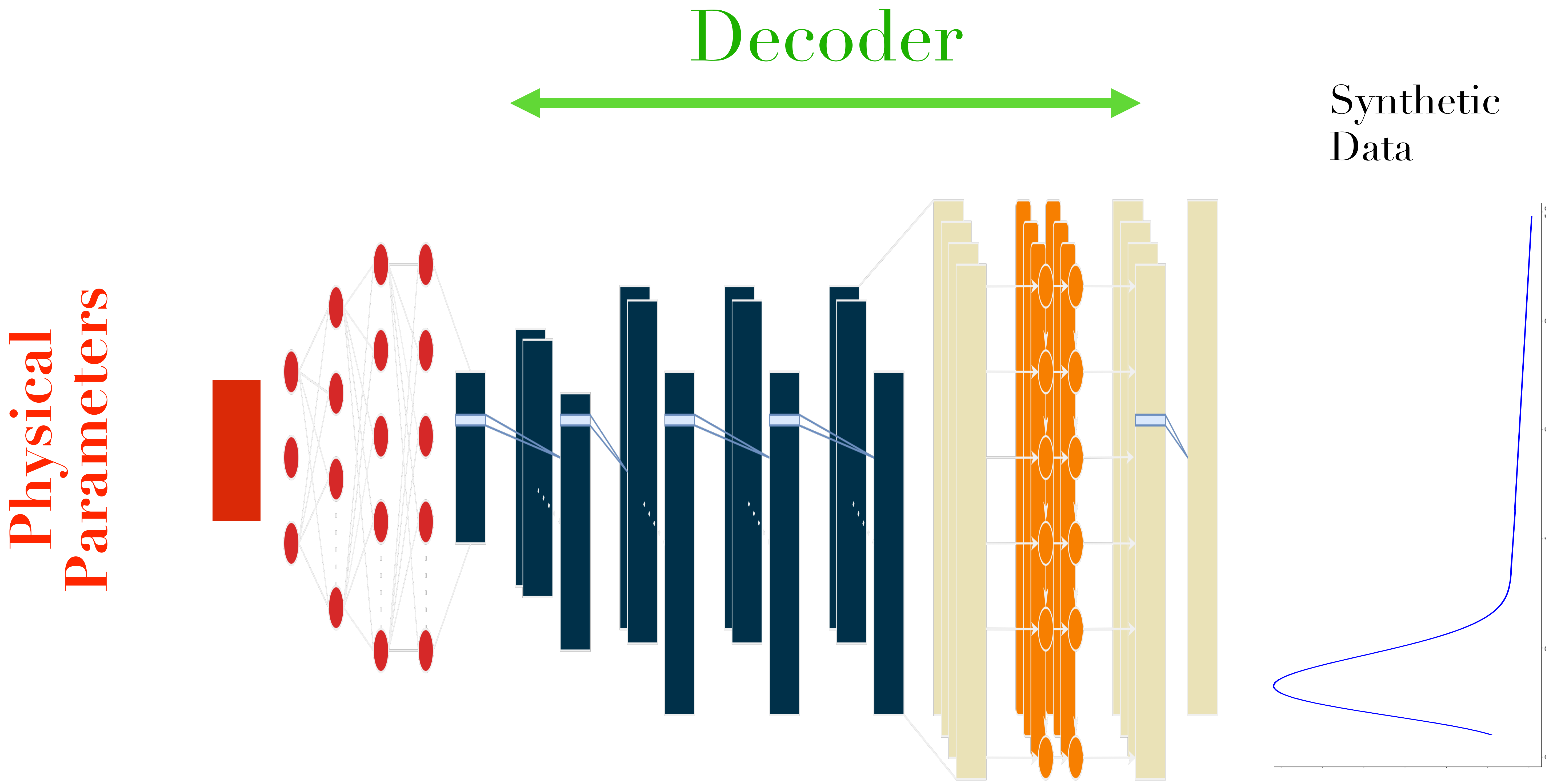
Enabling Next Generation Astrophysics

Ethan Tregigda



Physical Parameters

Tregidga et al. 2023



Tregidga et al. 2023

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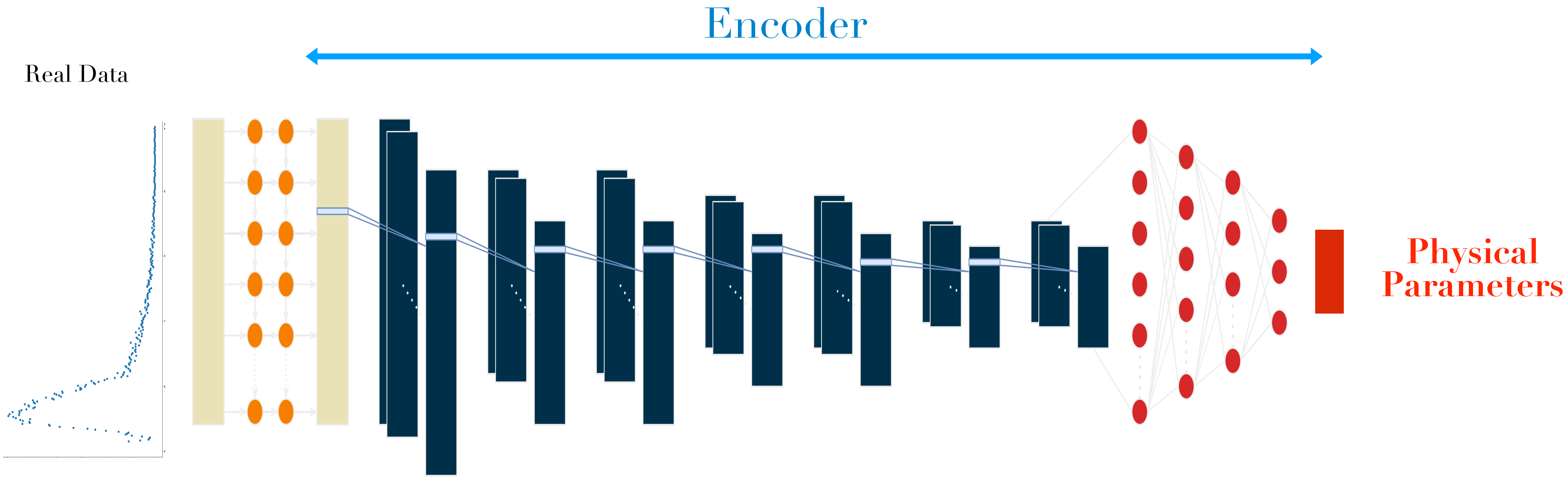
Tregidga et al. 2023



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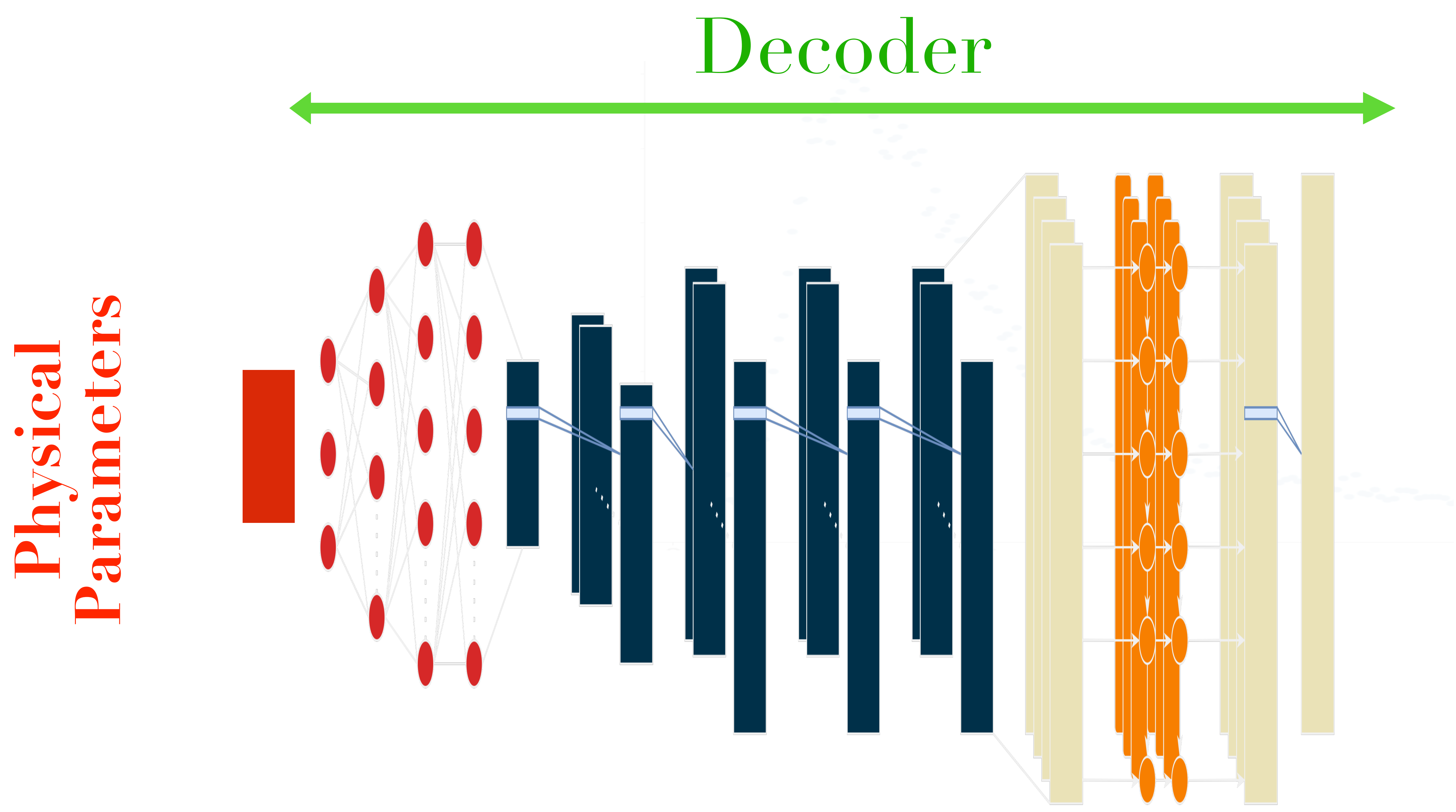
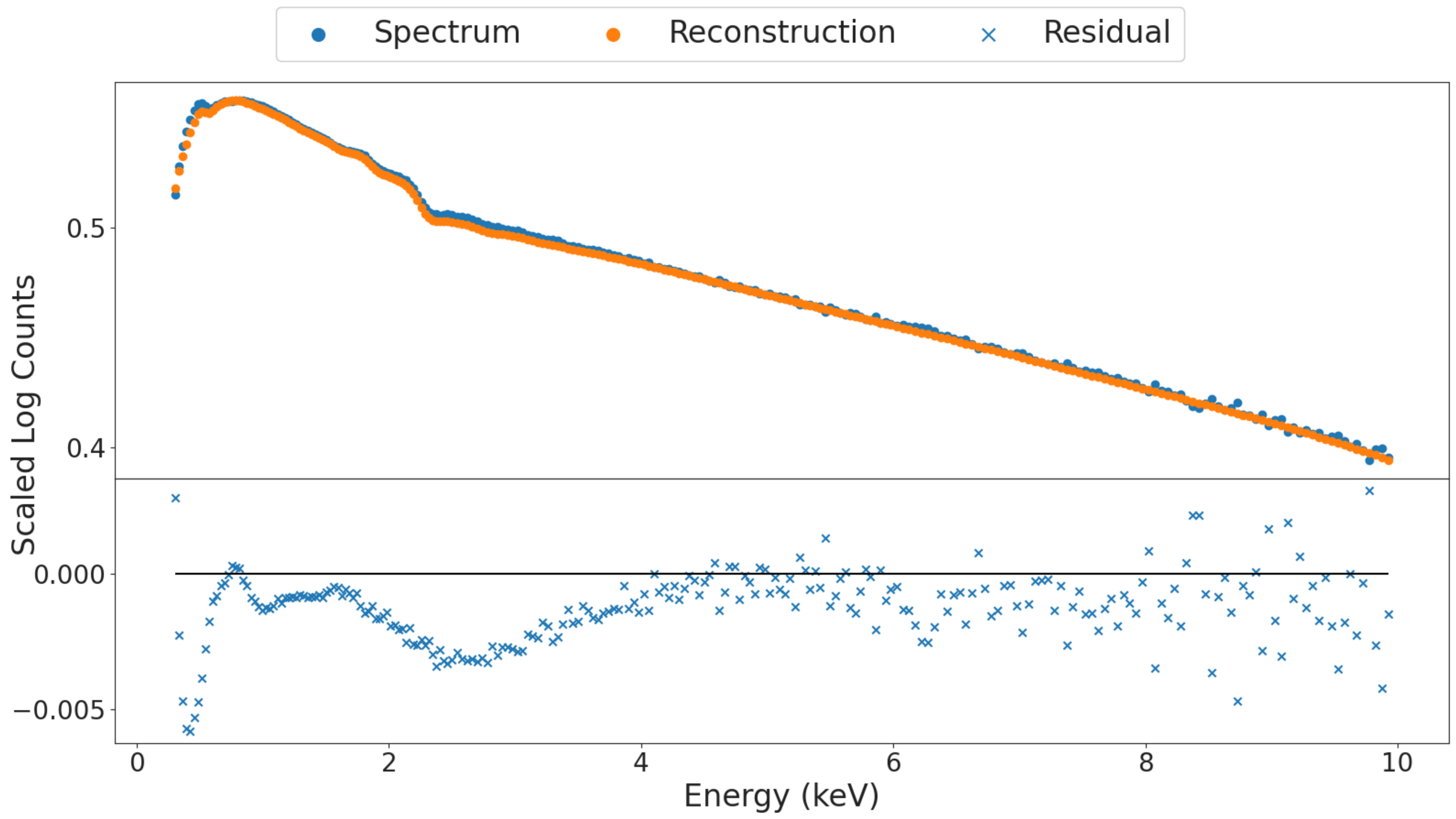
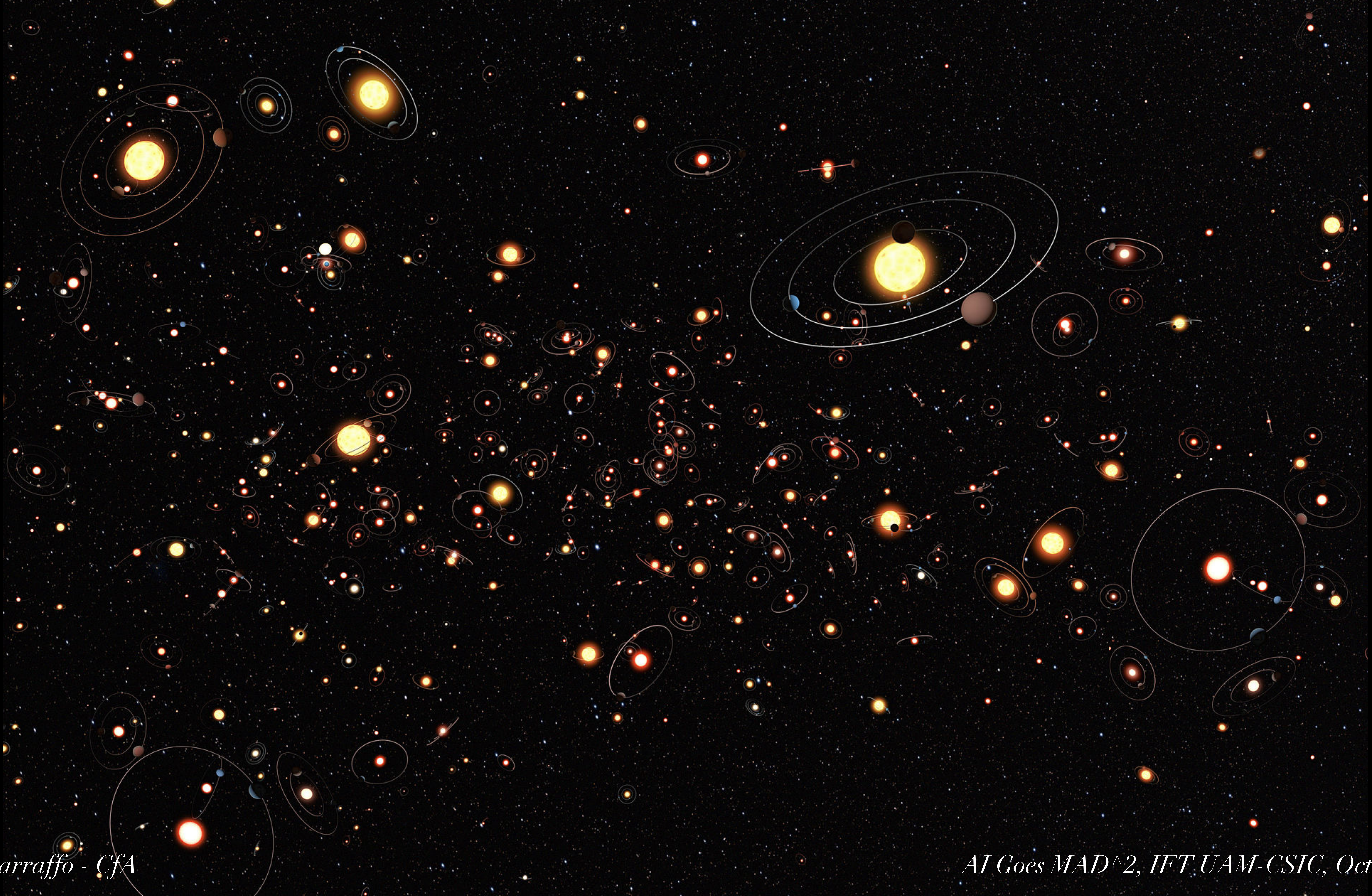


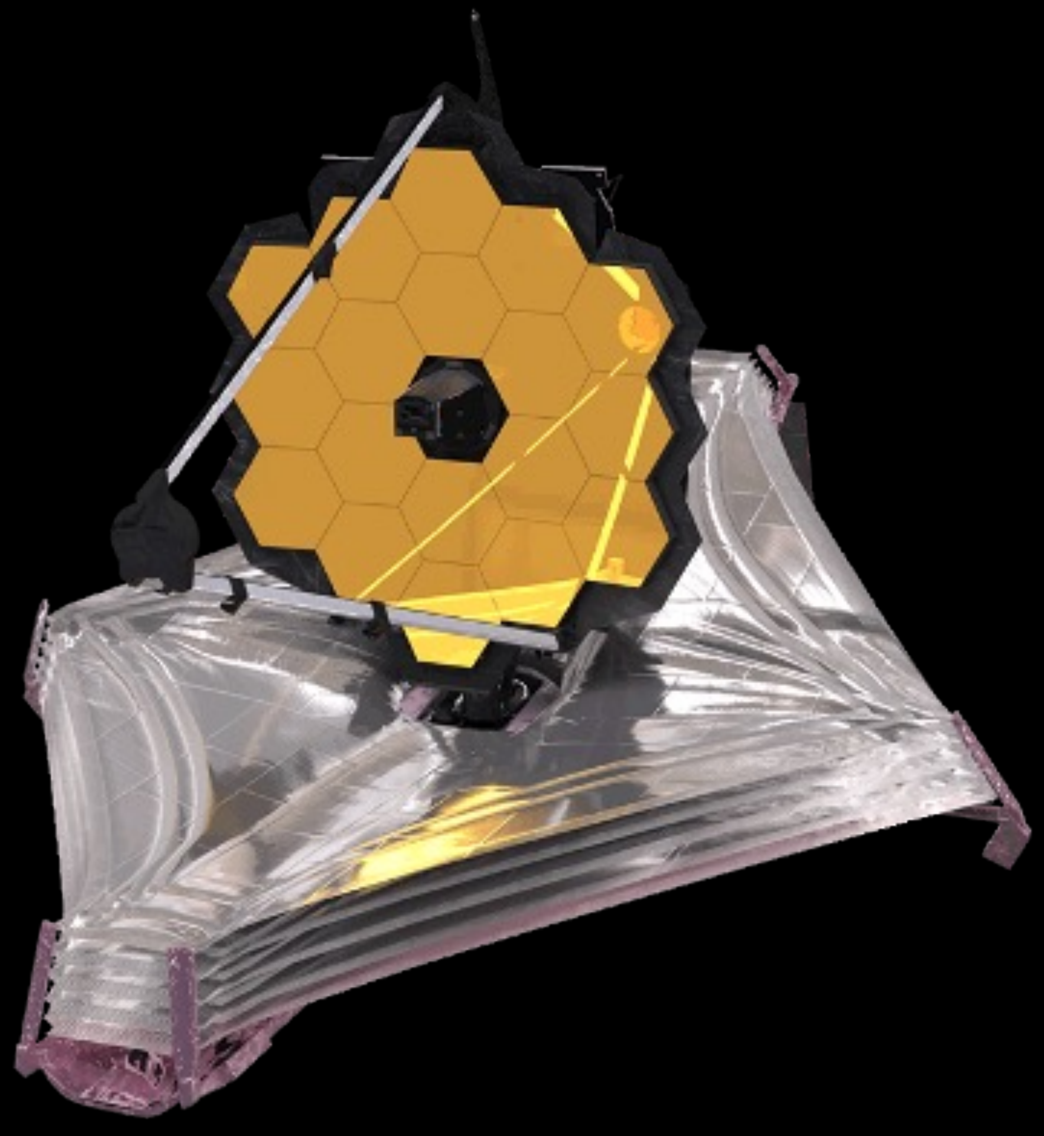


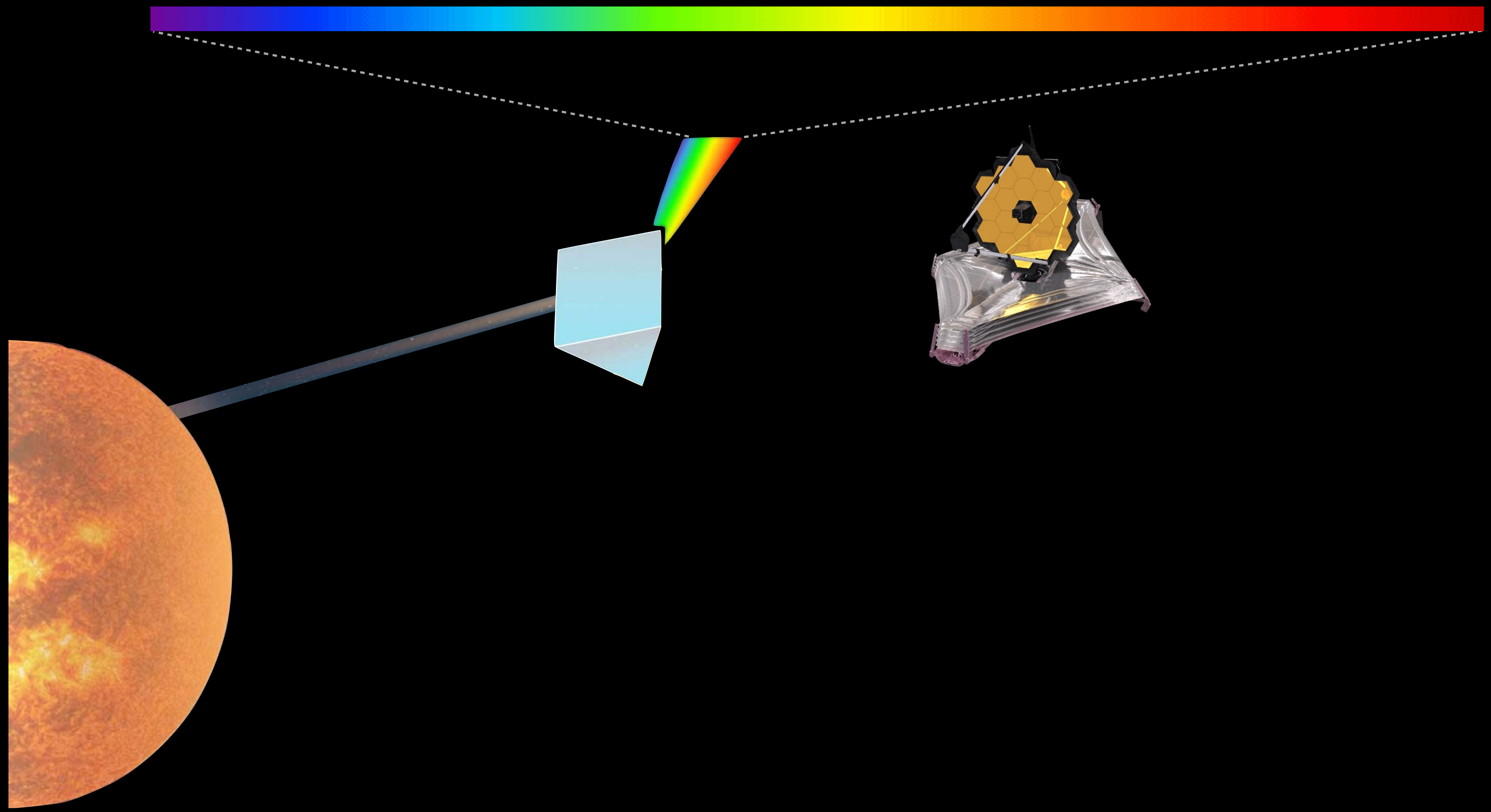
Tregidga et al. 2023

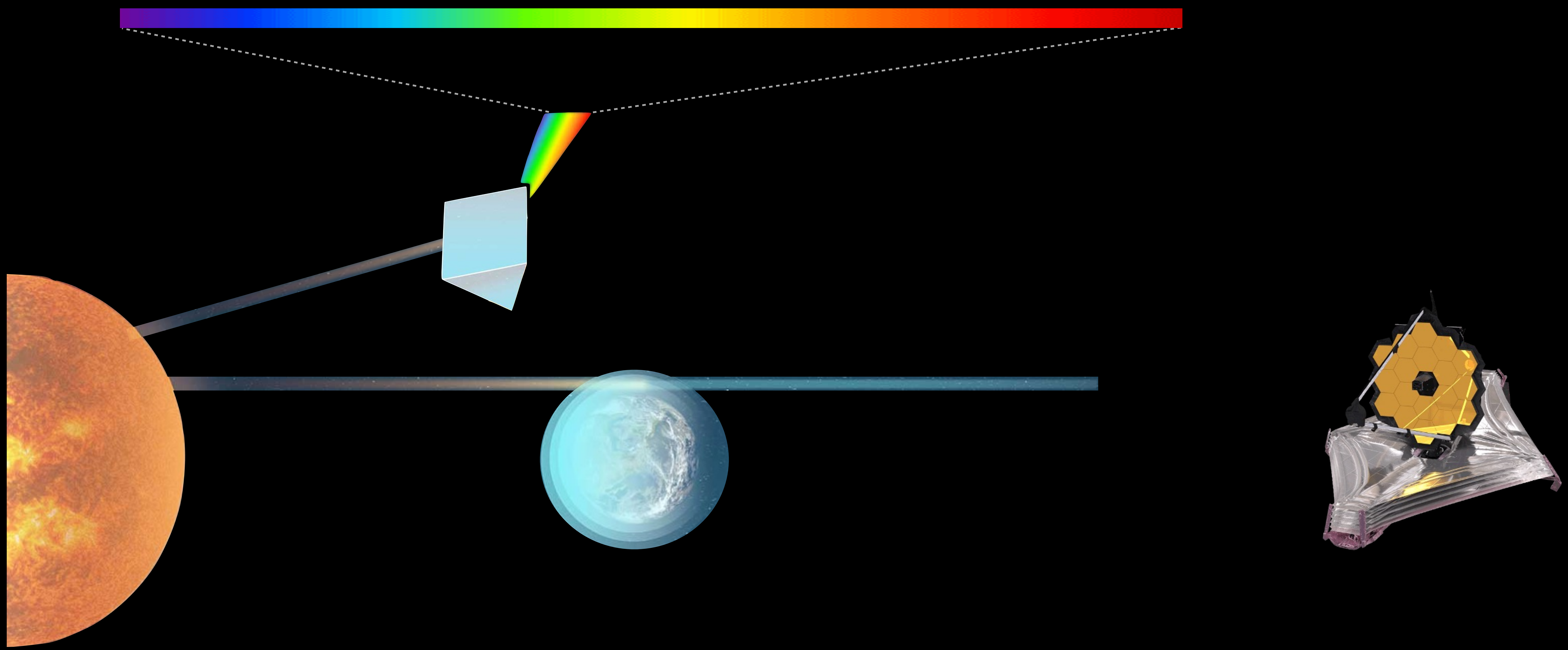


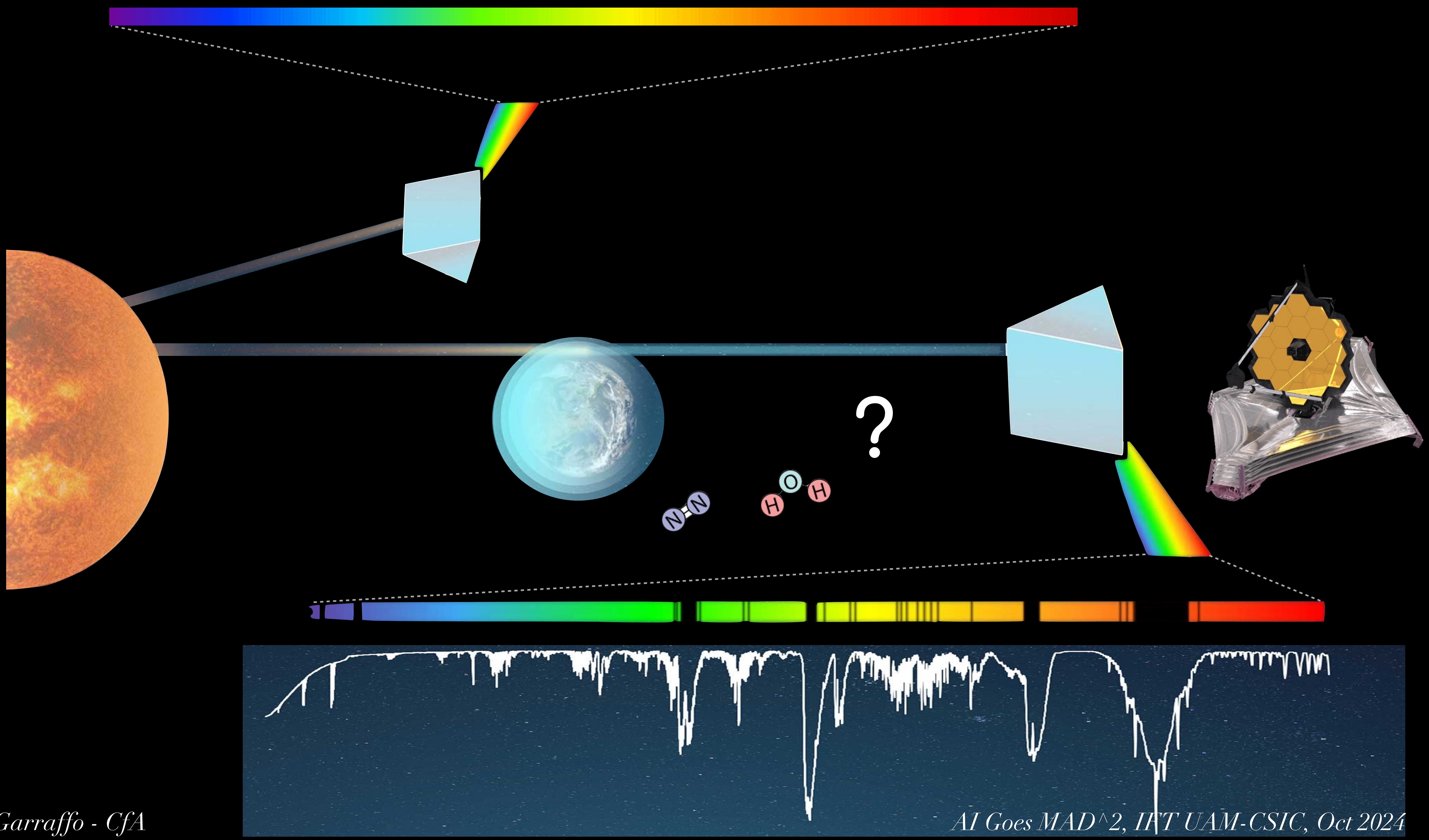
Cecilia Garraffo - CfA

James Webb Space Telescope





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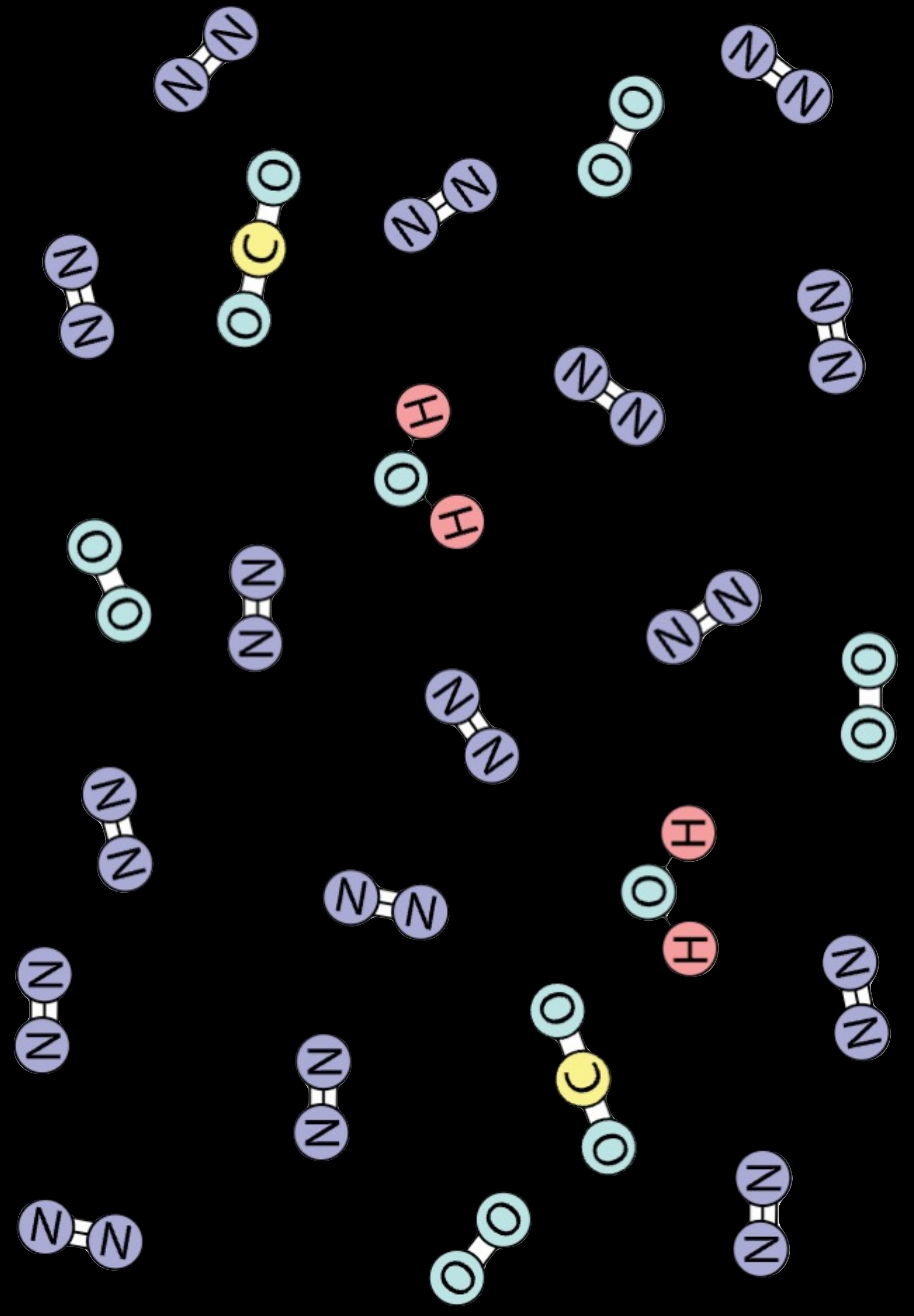
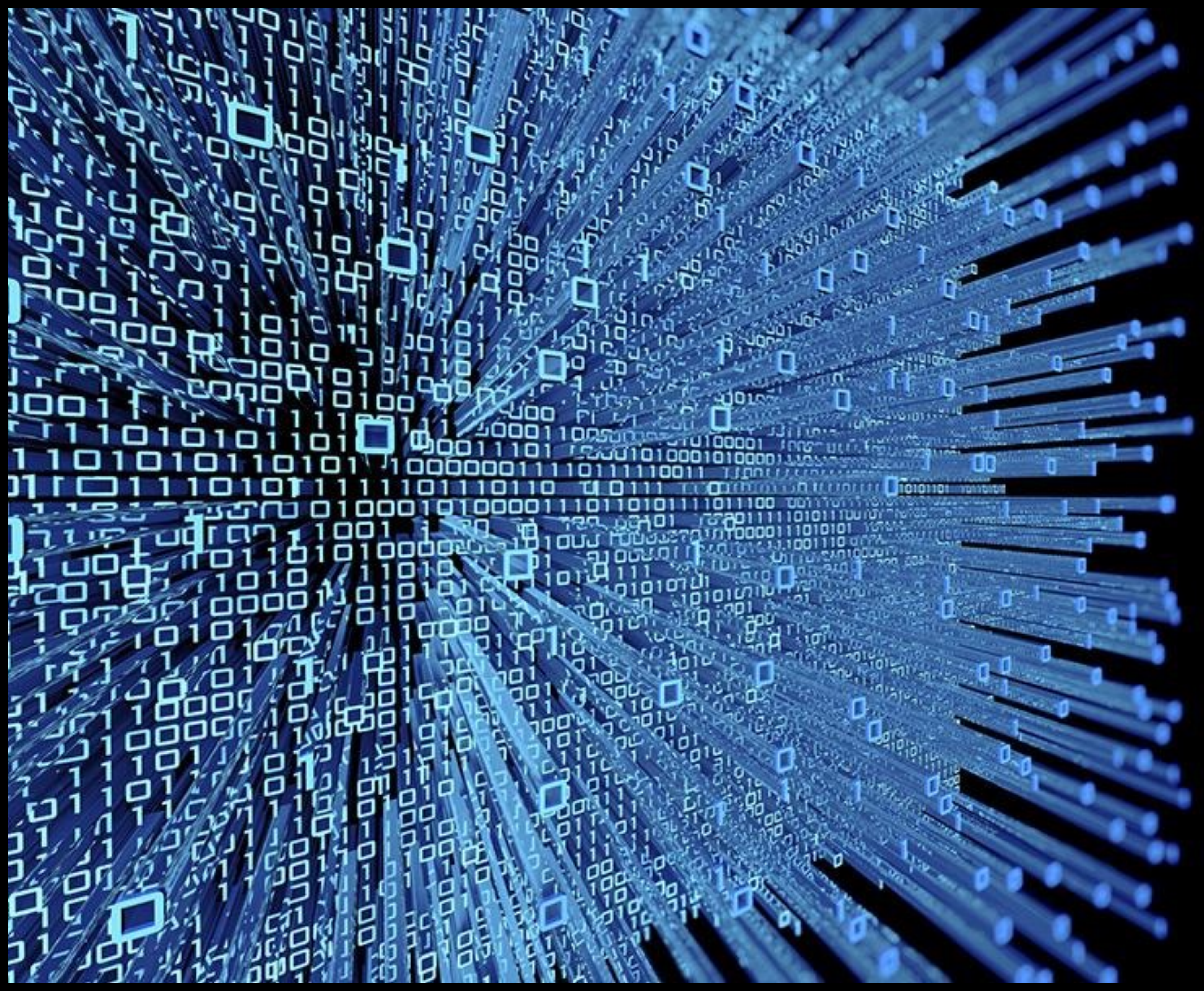
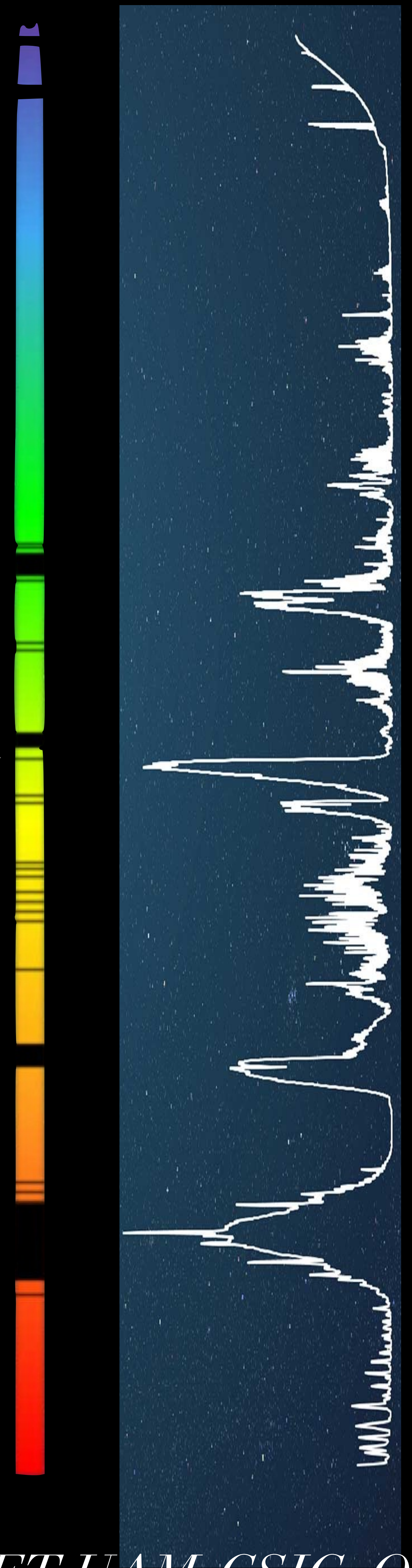
Chemical Composition



Simulation



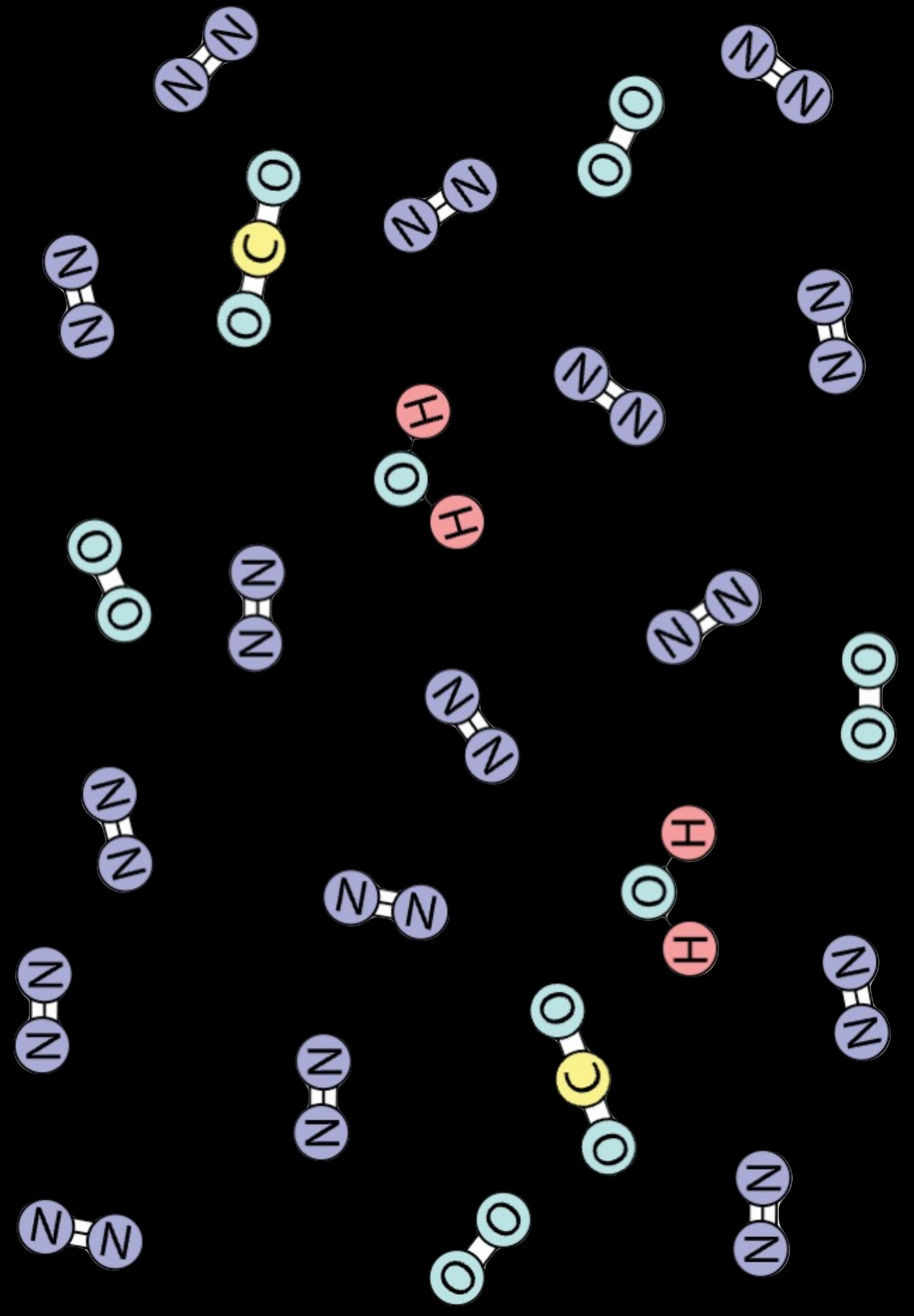
Spectrum

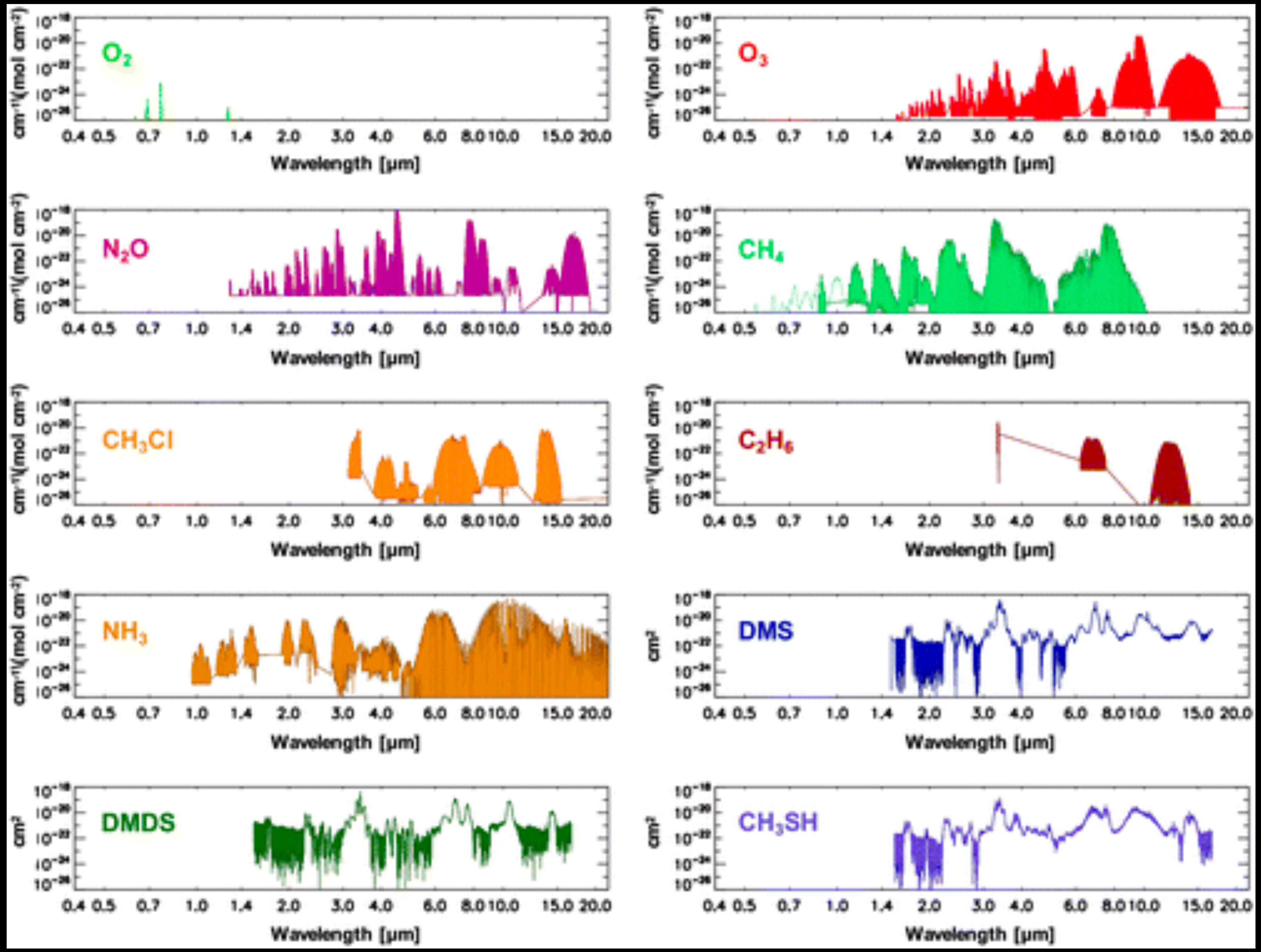


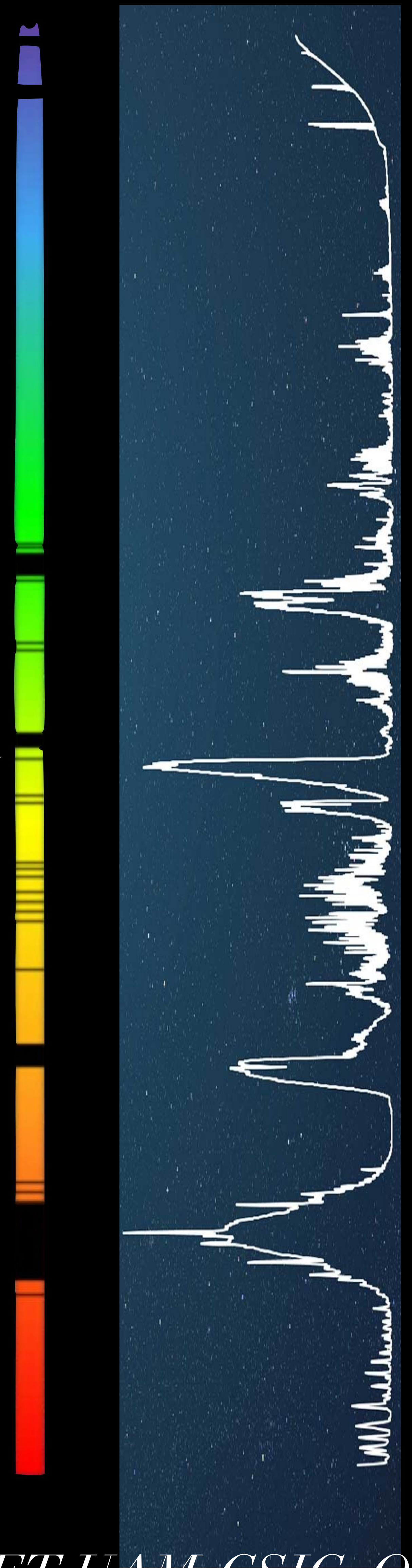
Chemical Composition

Spectrum

Simulation



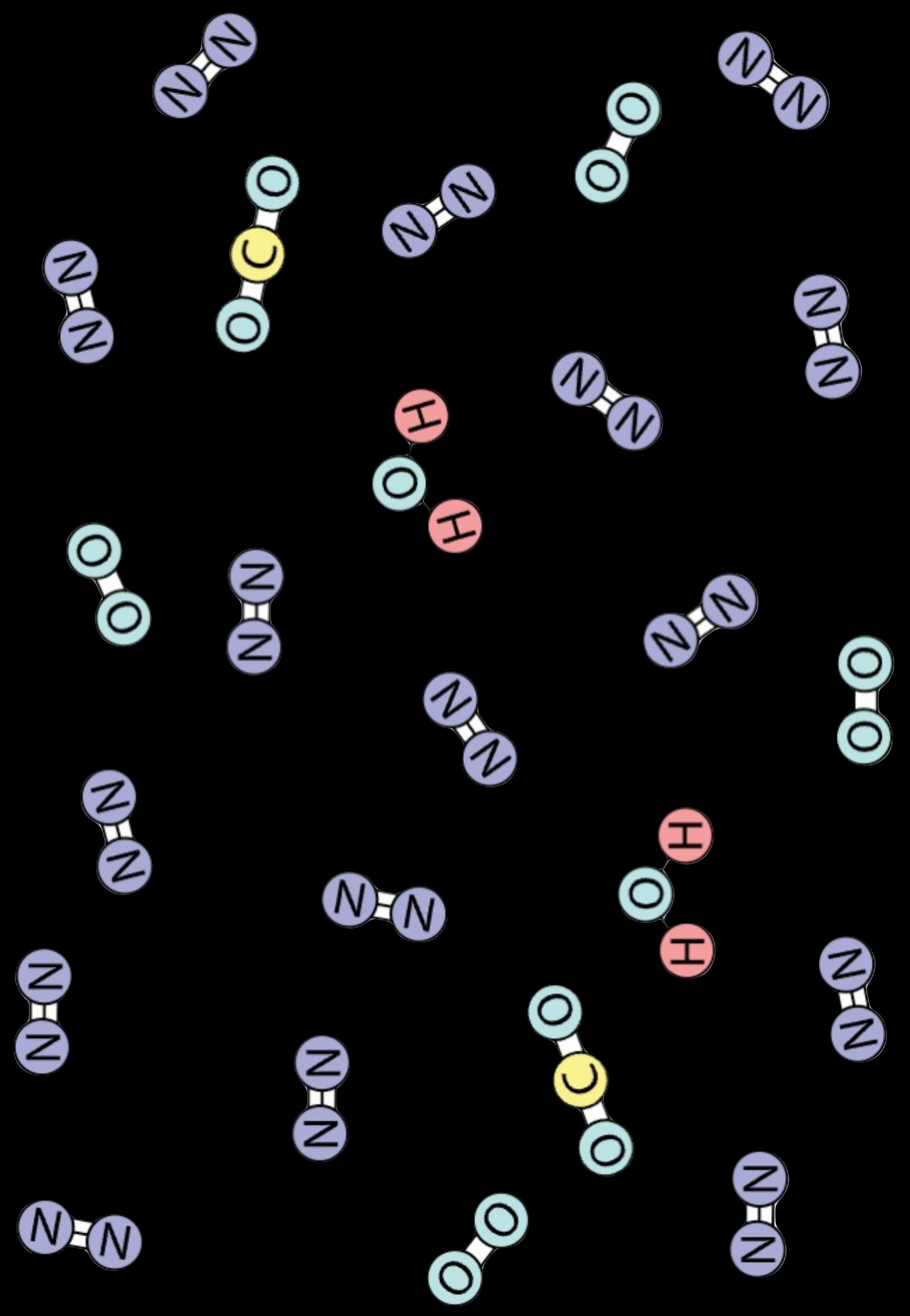


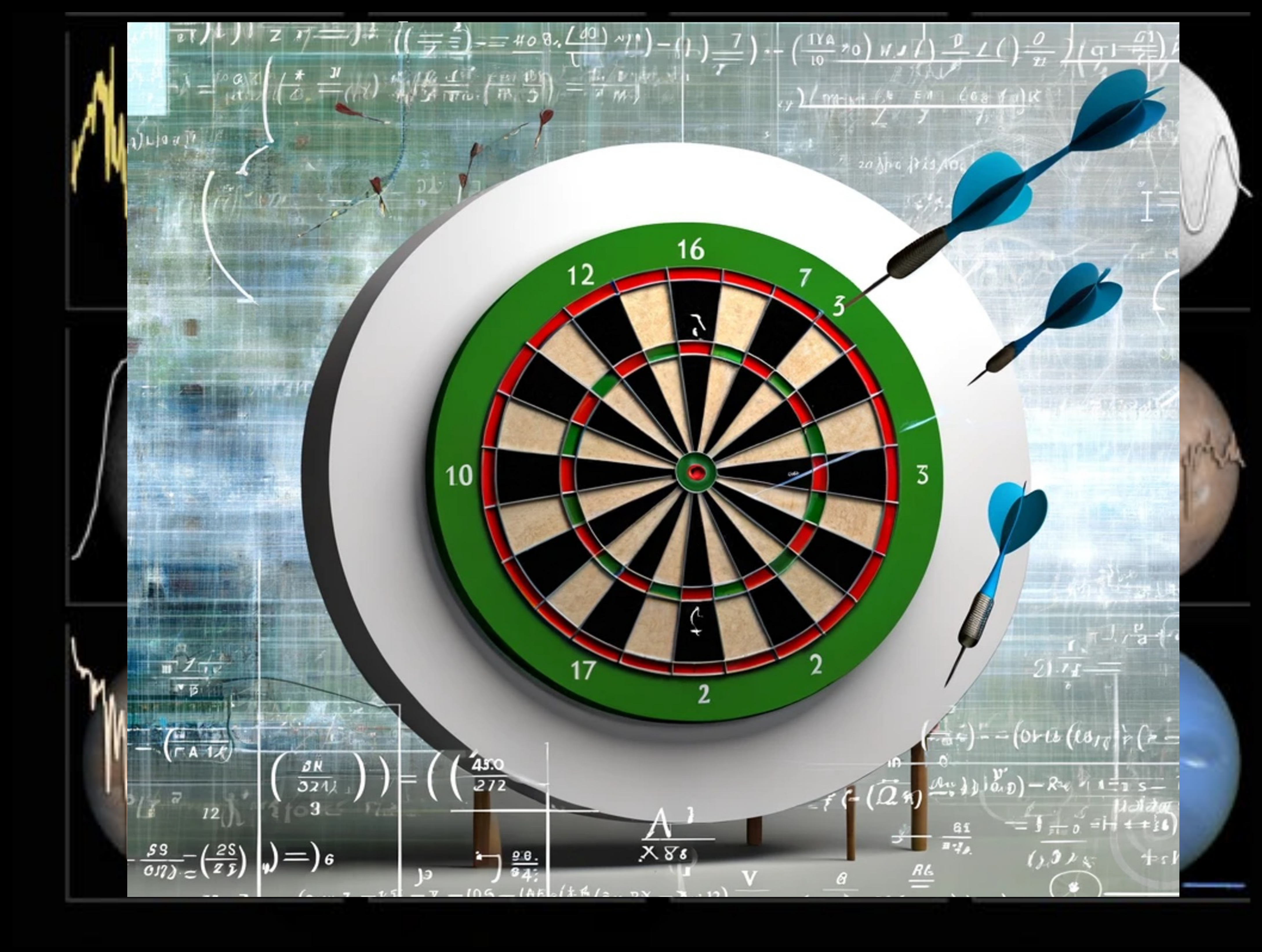


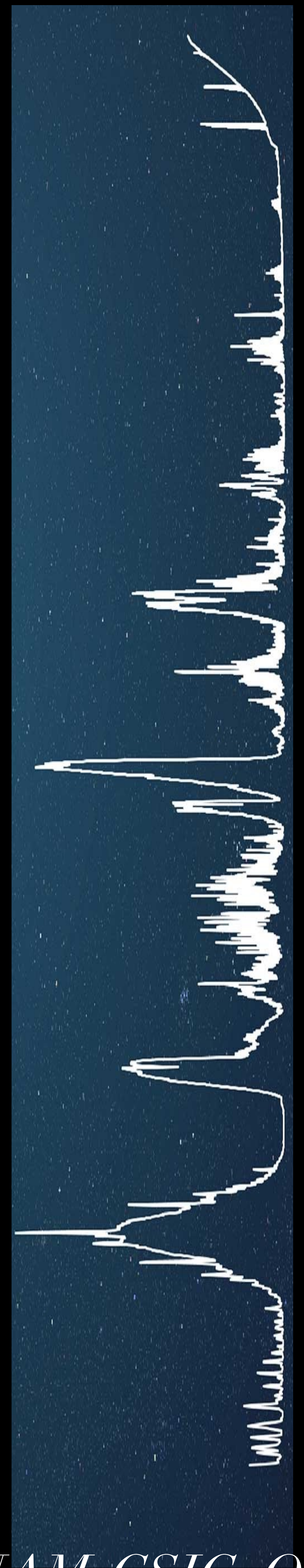
Chemical Composition

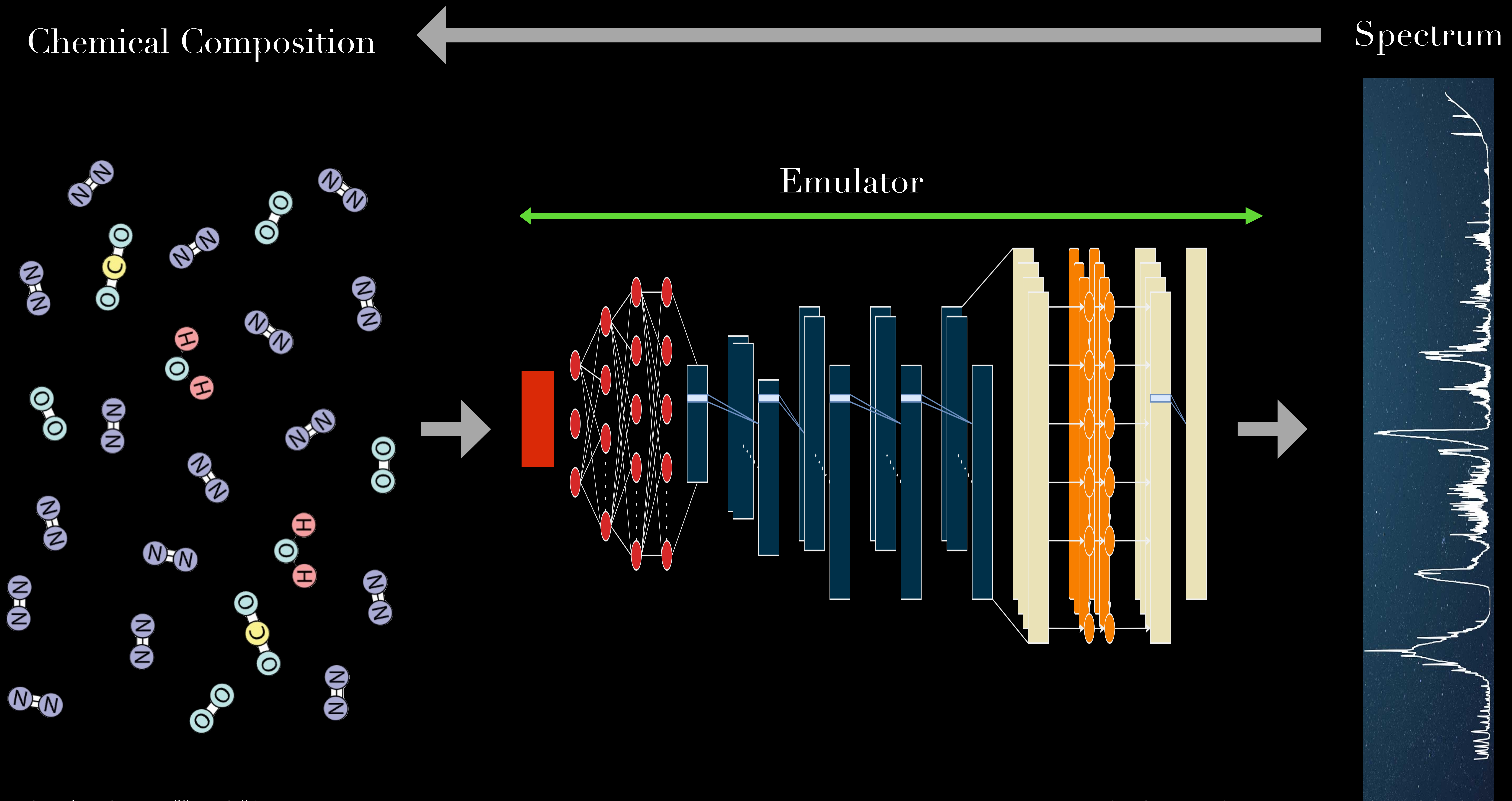
Spectrum

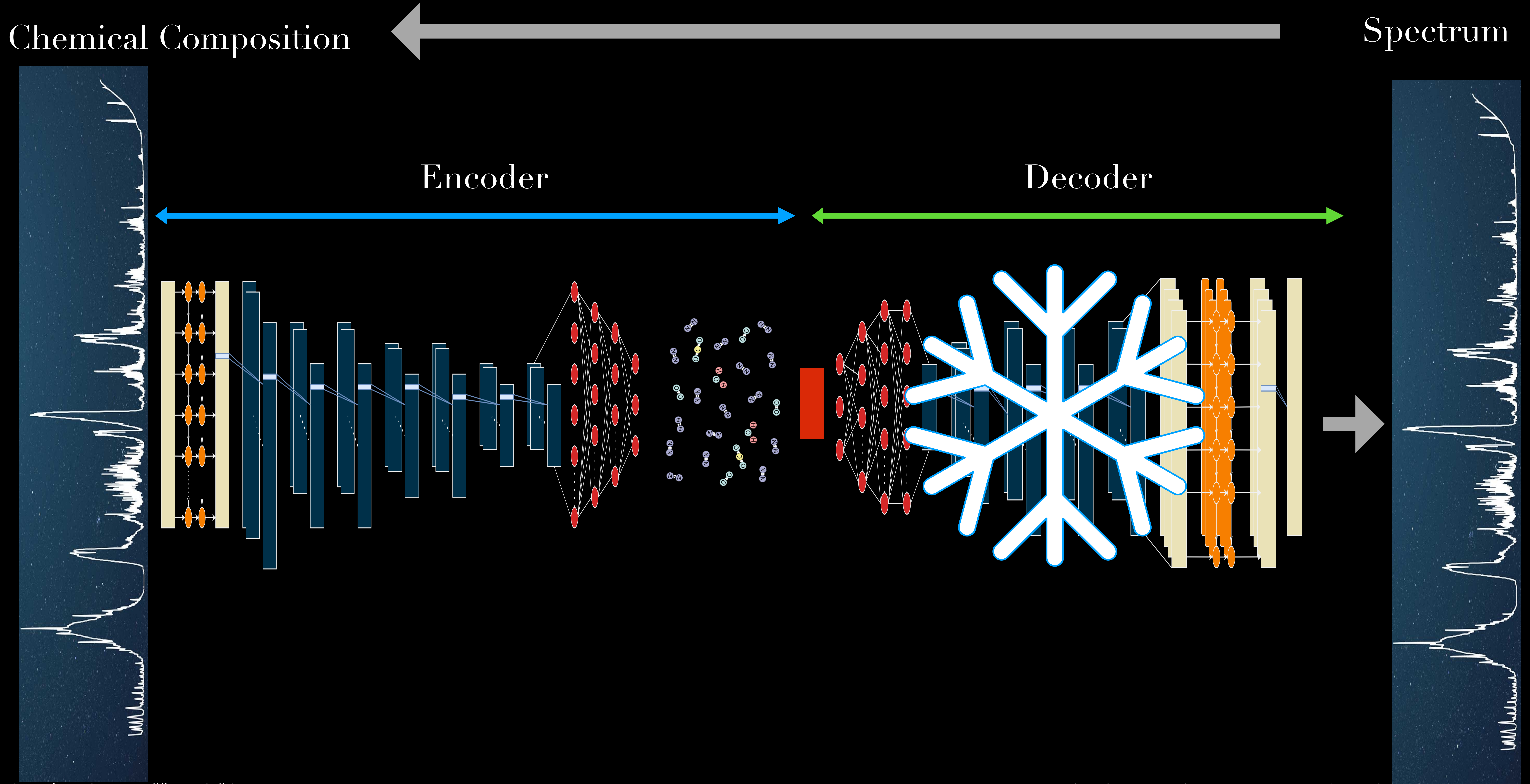
Simulation



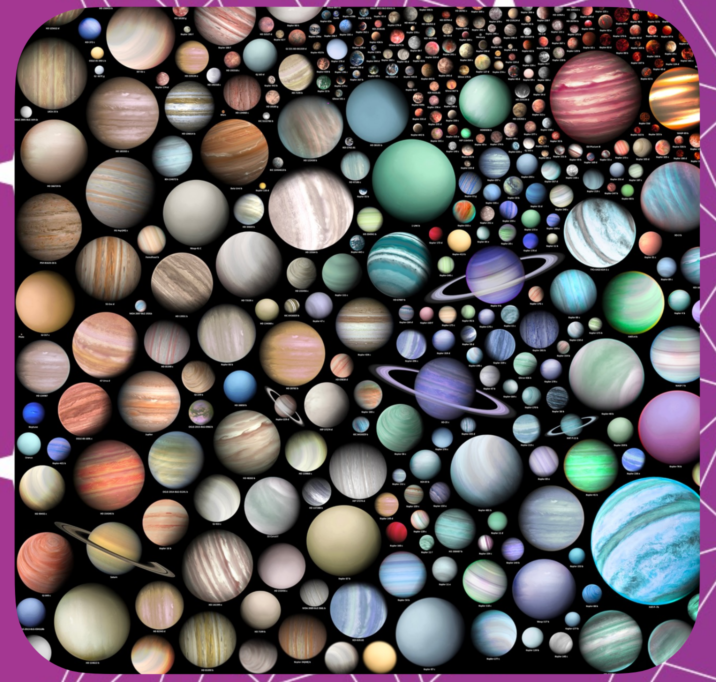





Chemical Composition
Spectrum
Emulator



Chemical Composition
Spectrum
Encoder
Decoder



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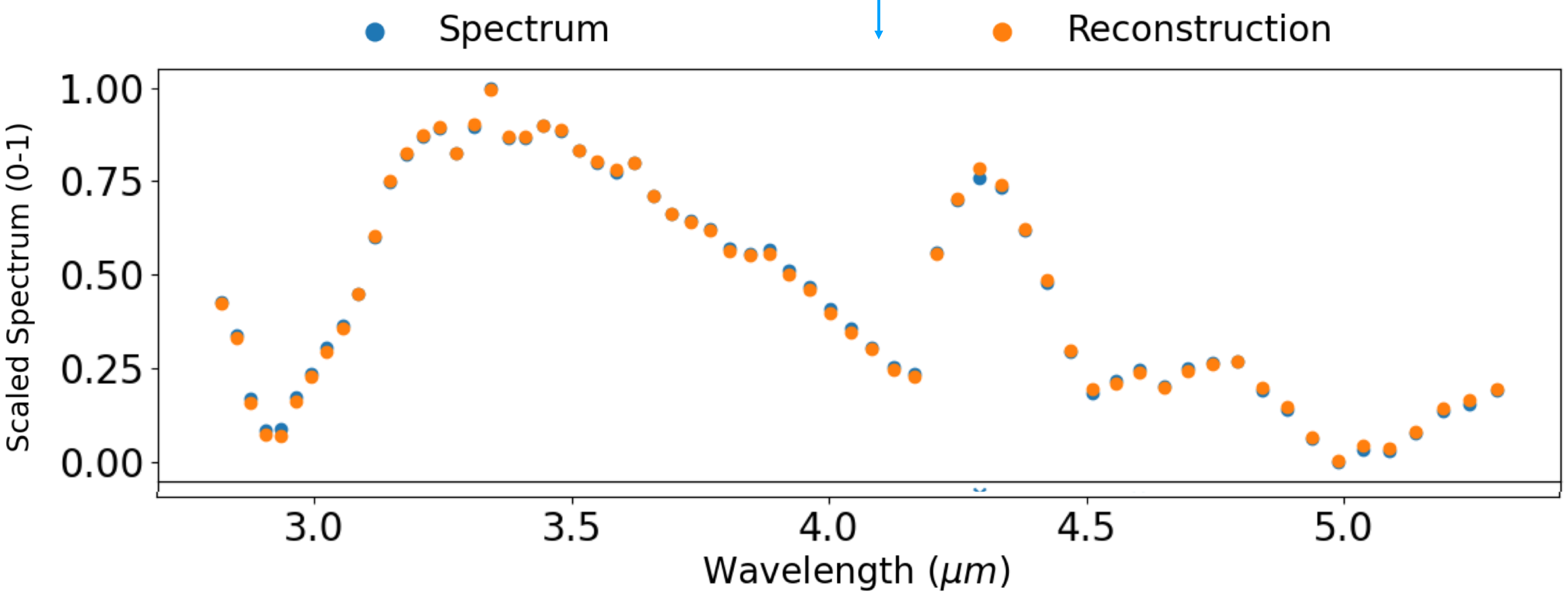
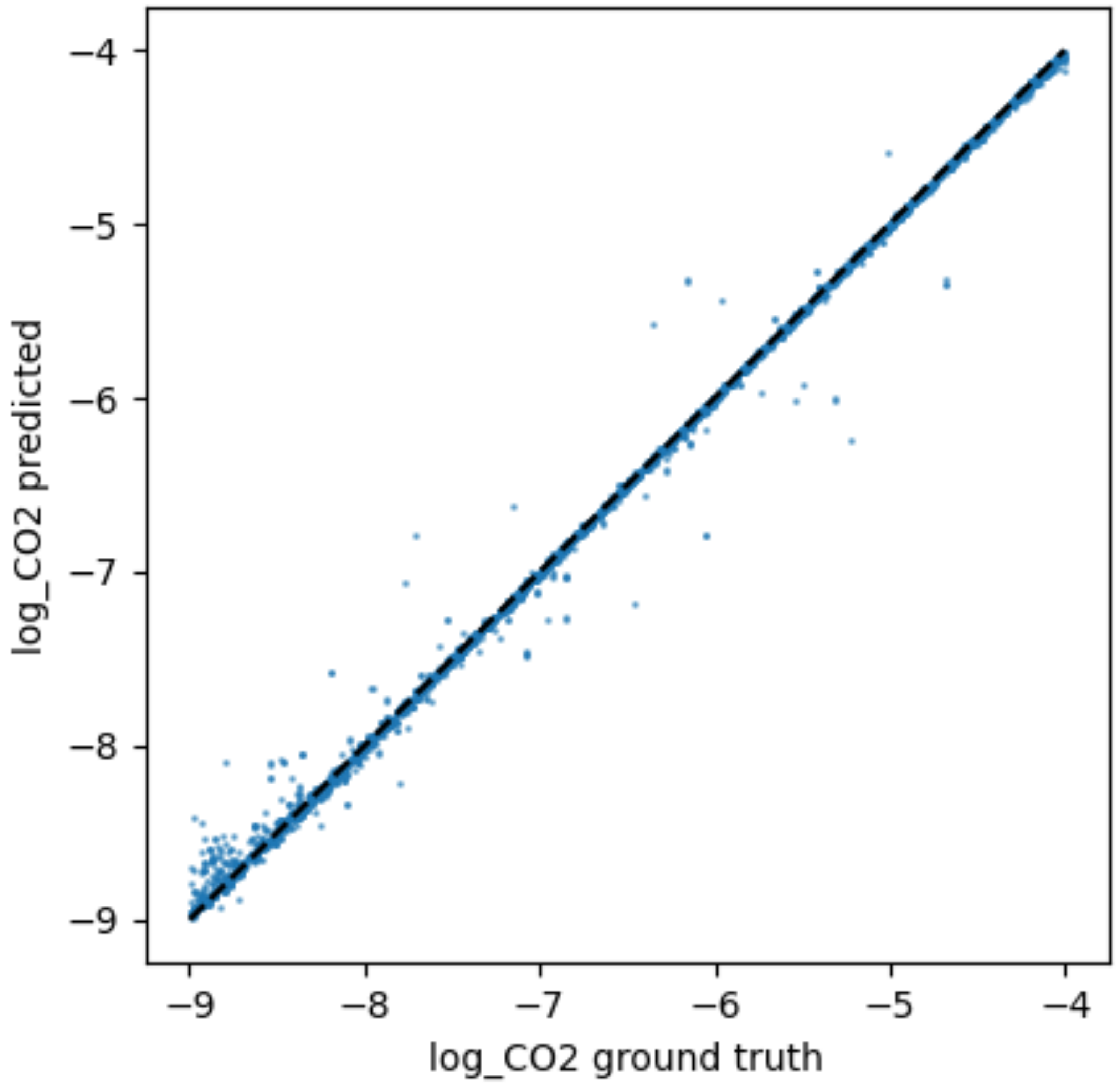
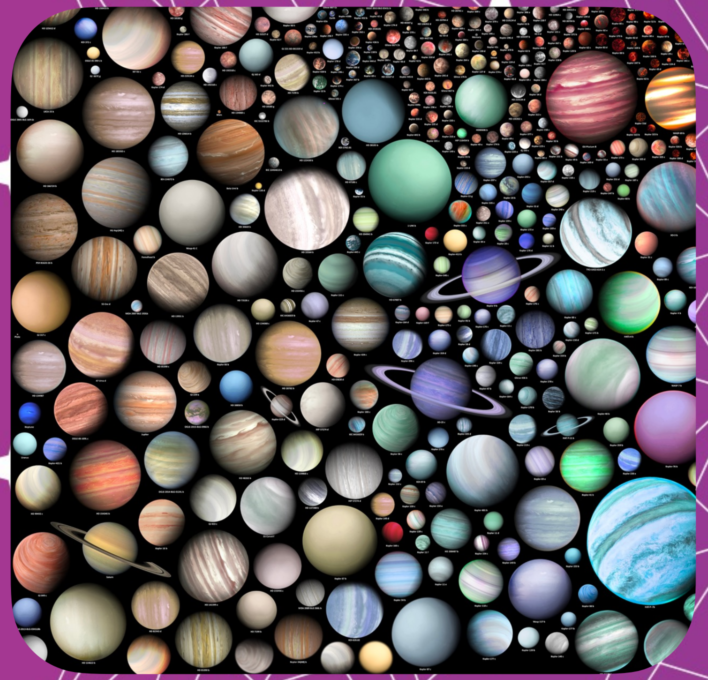


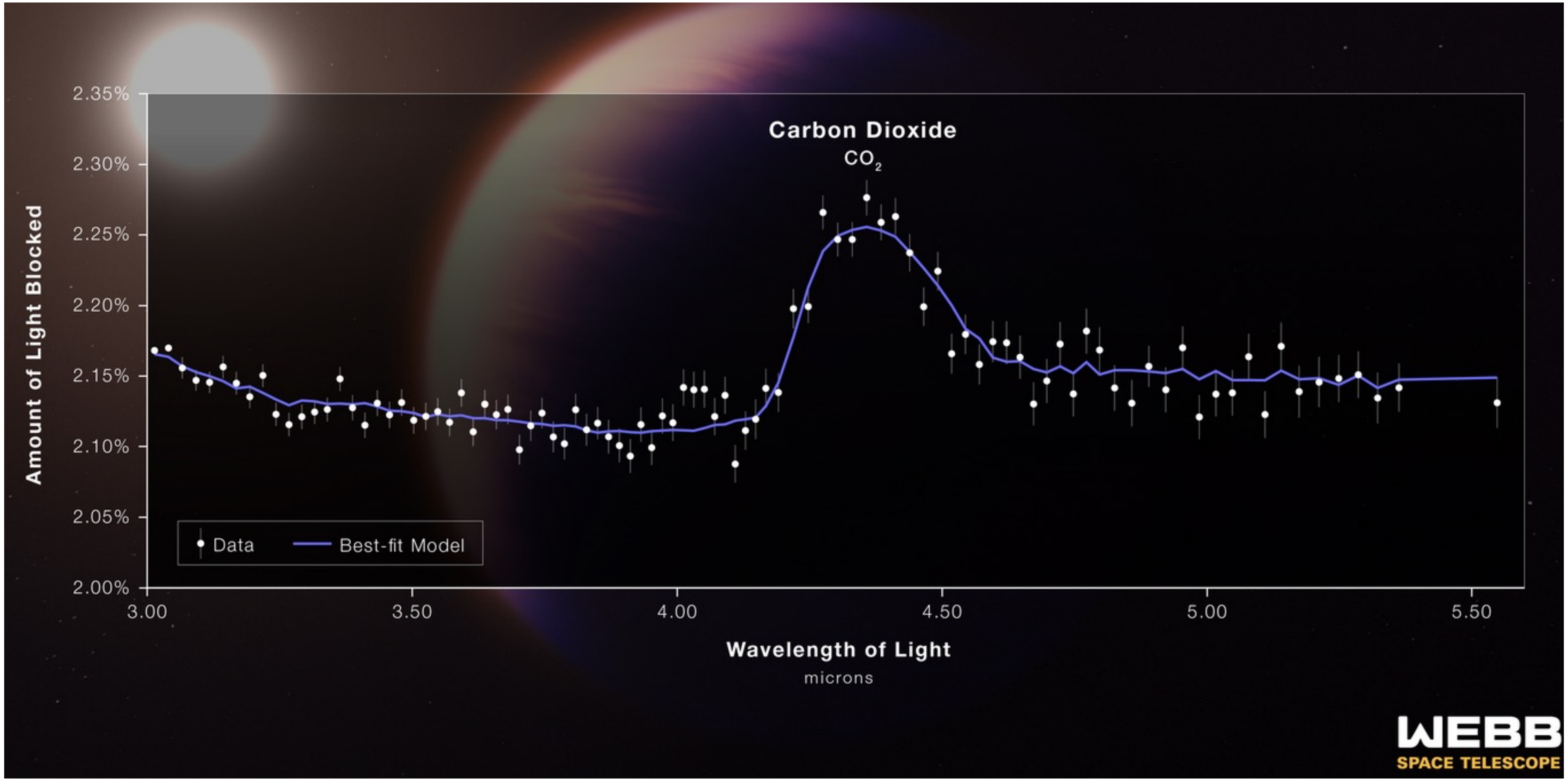
Figure 2: Reconstruction of a spectrum by the decoder

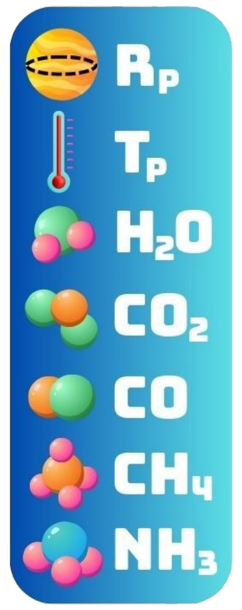
The encoder can reliably predict the target parameters



Prediction of the mass fraction of CO_2 in the atmosphere by the encoder




Carbon Dioxide
CO_2
Amount of Light Blocked
2.35%
2.30%
2.25%
2.20%
2.15%
2.10%
2.05%
2.00%
3.00
3.50
4.00
4.50
5.00
5.50
Wavelength of Light
microns
Data
Best-fit Model
WEBB
SPACE TELESCOPE



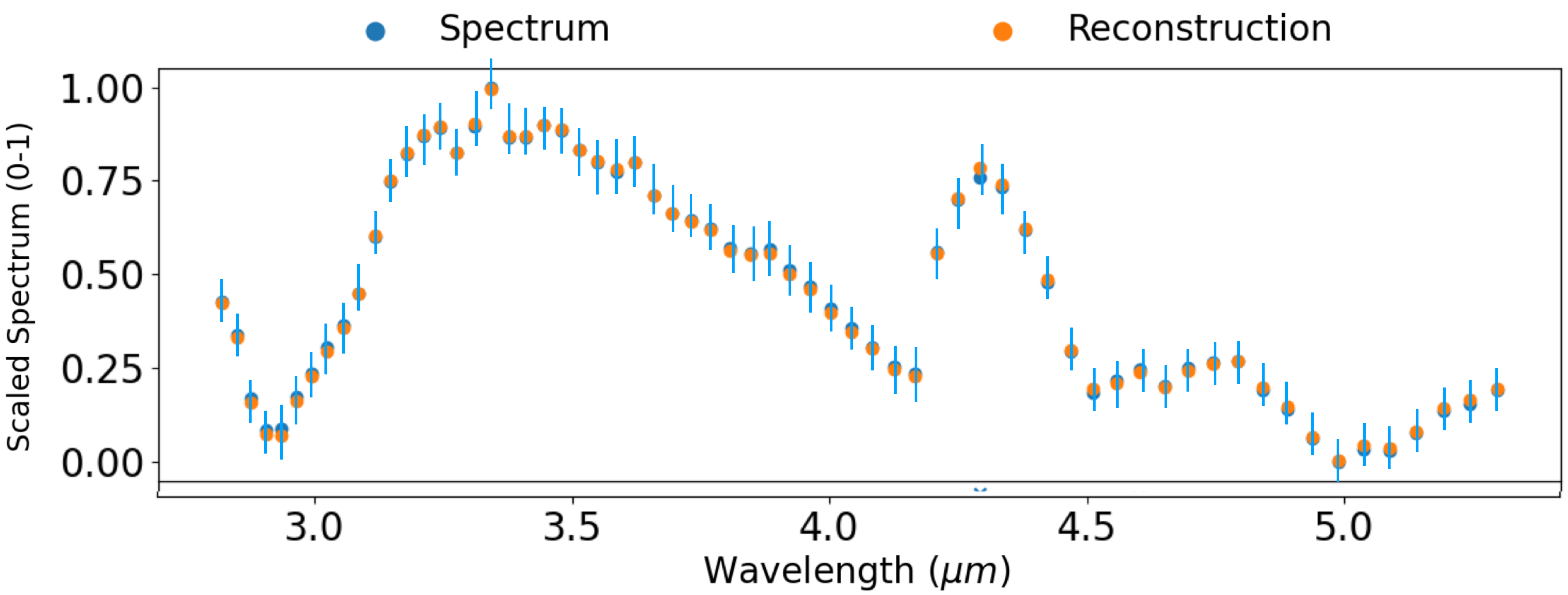
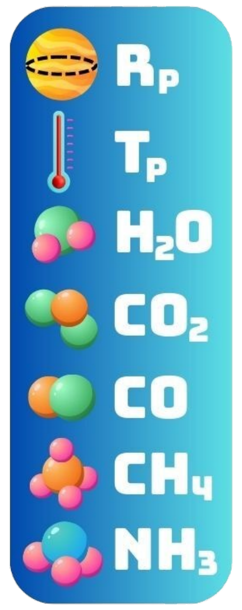


Figure 2: Reconstruction of a spectrum by the decoder



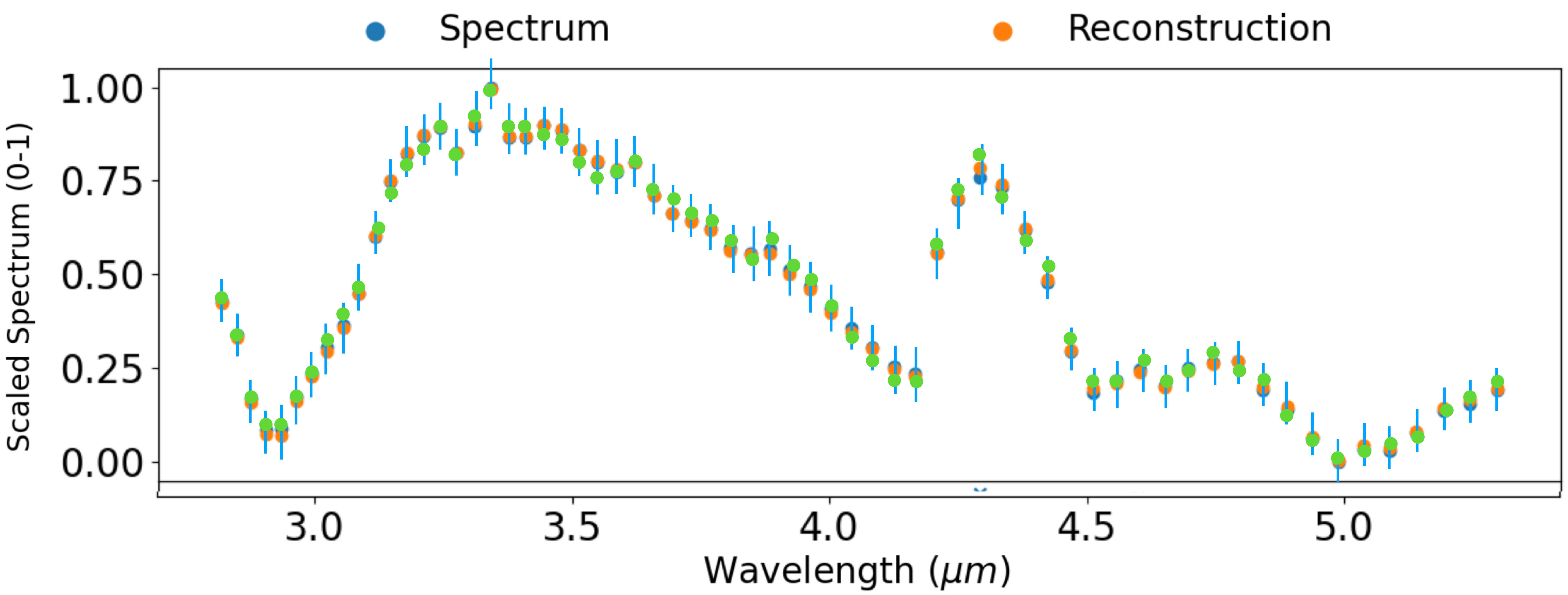
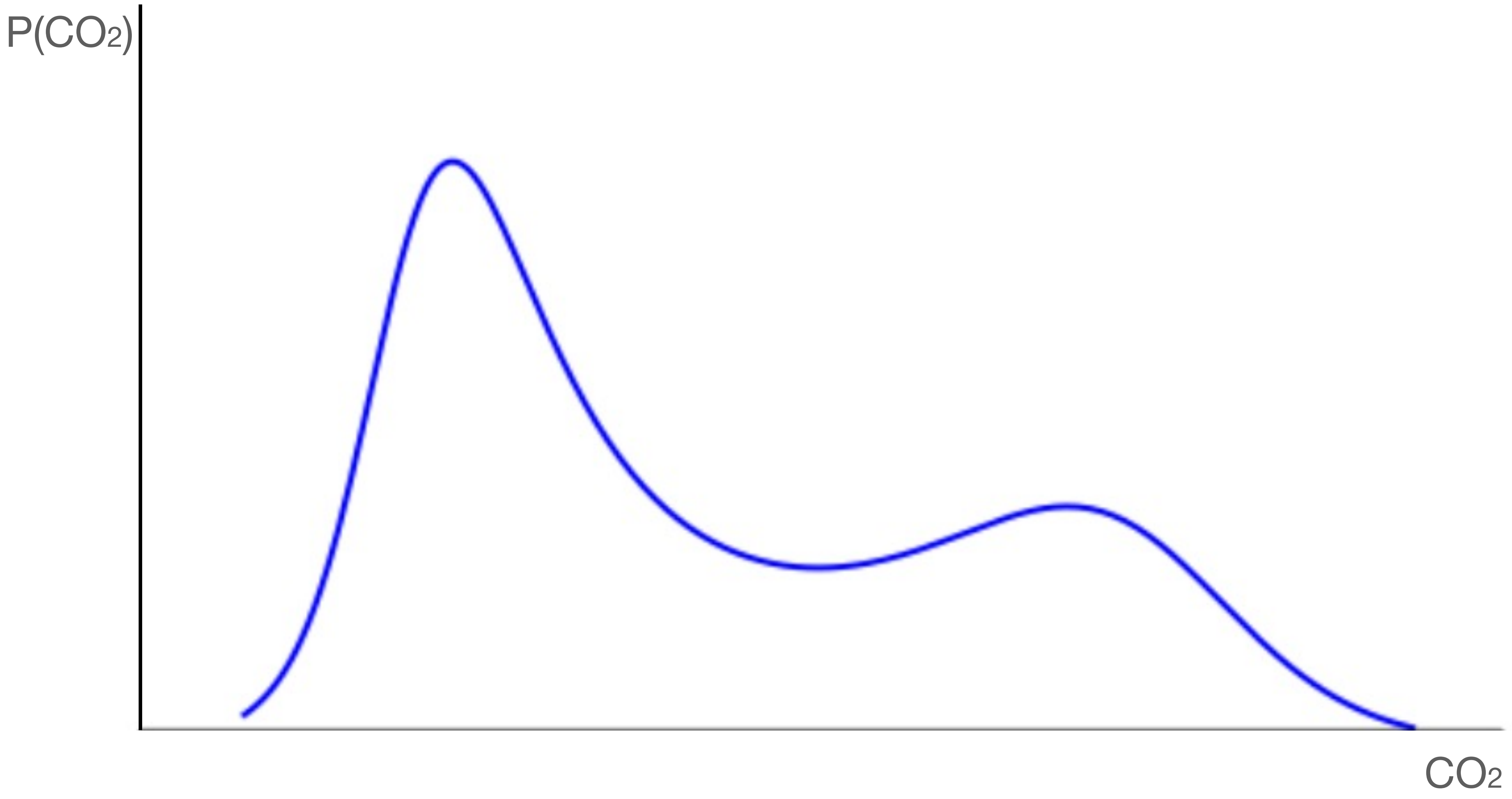
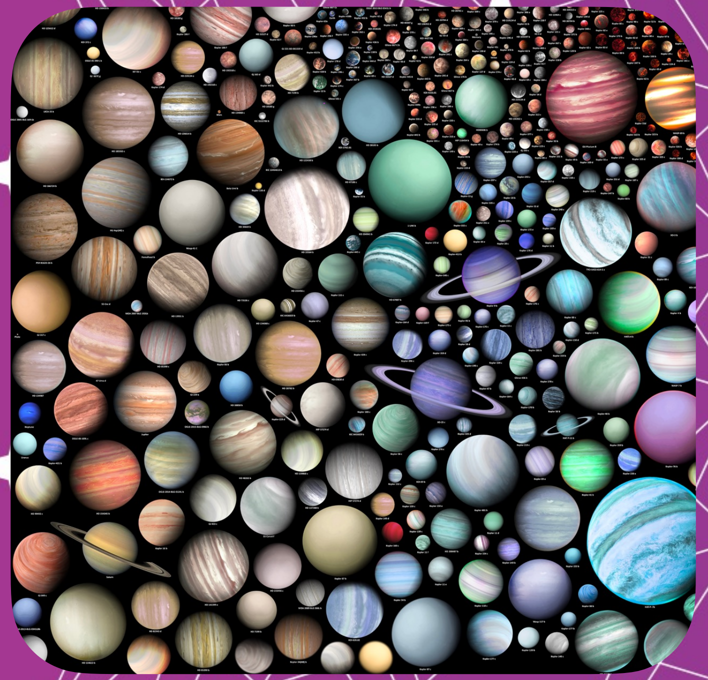


Figure 2: Reconstruction of a spectrum by the decoder


P(CO2)
CO2

Physical Probabilistic AI Models



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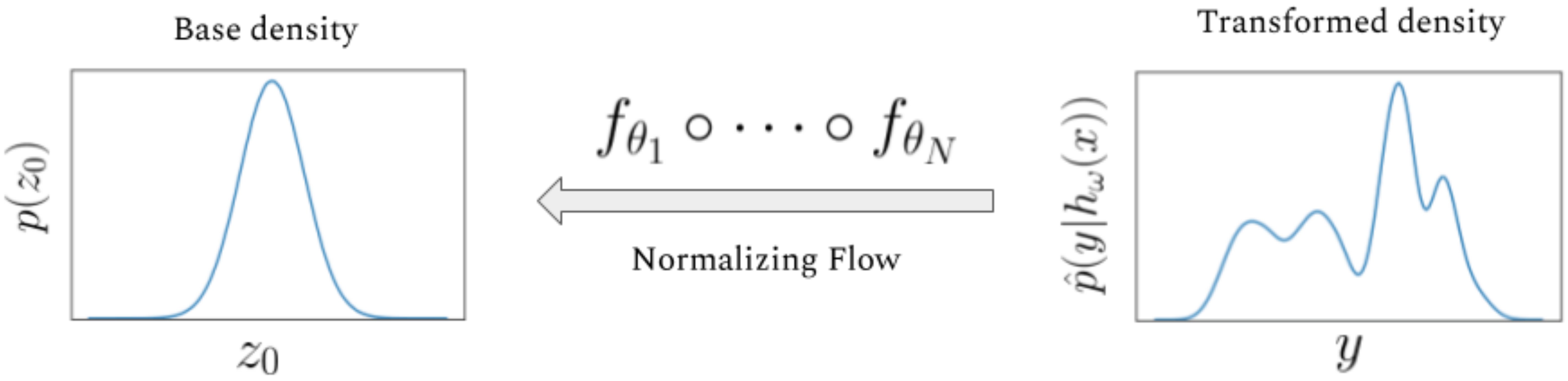
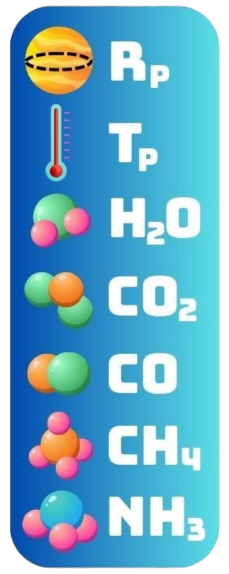
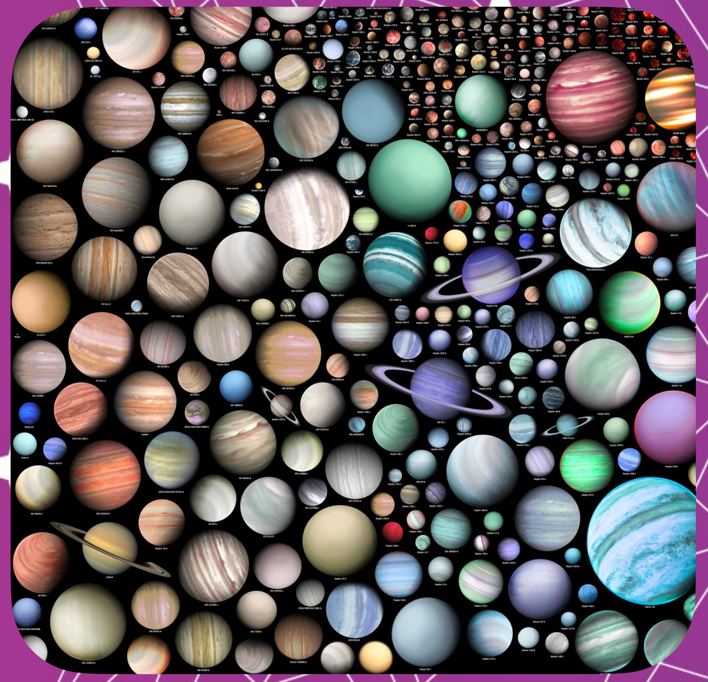
Mayeul Aubin
Carol Cuesta-Lázaro

Normalising Flows







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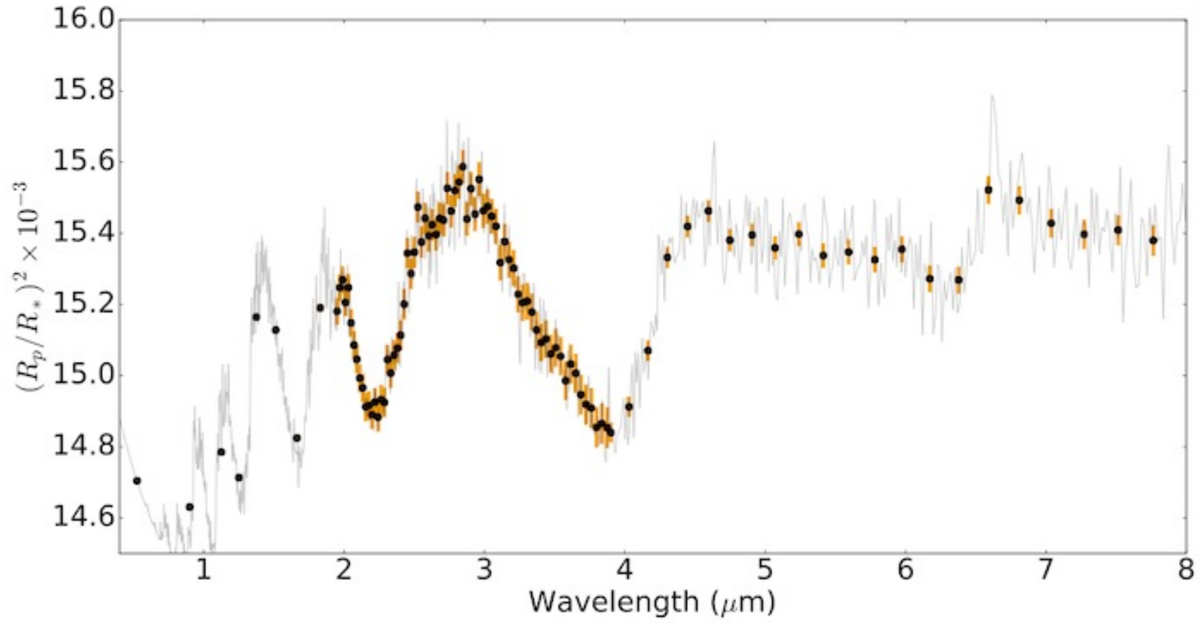
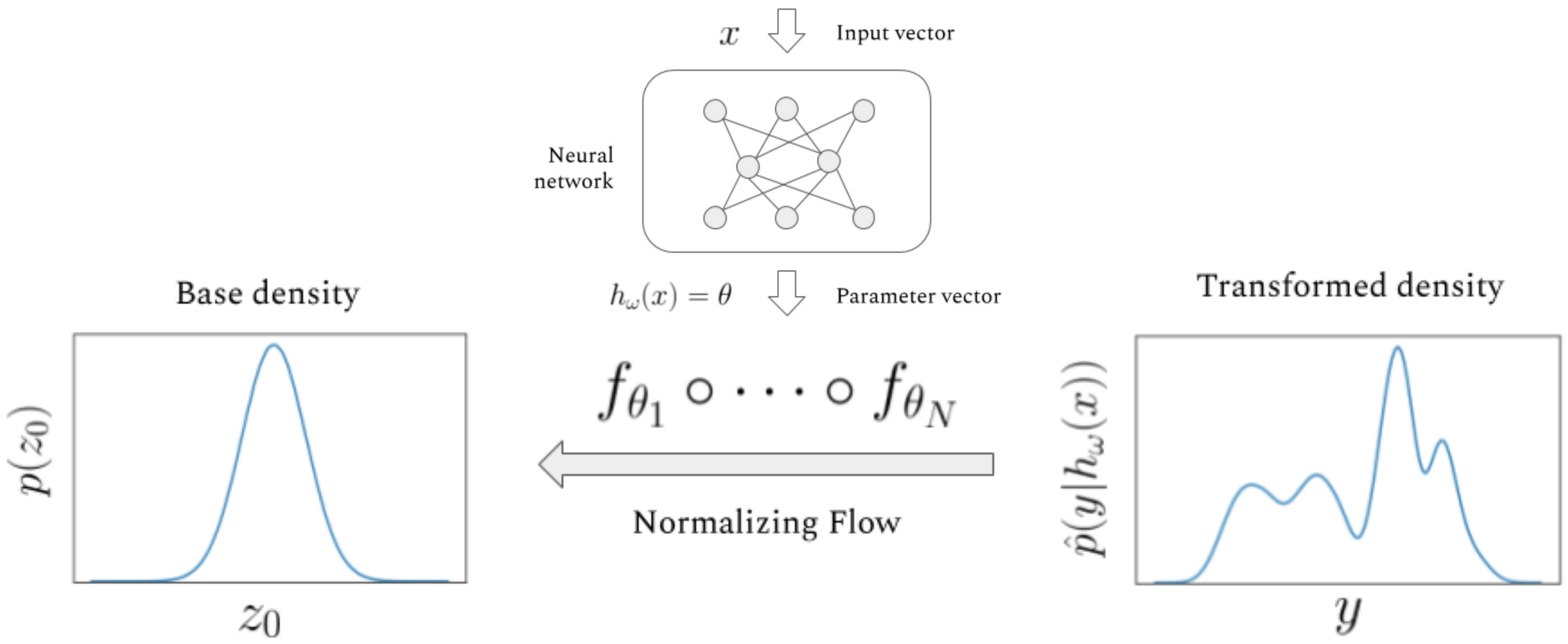
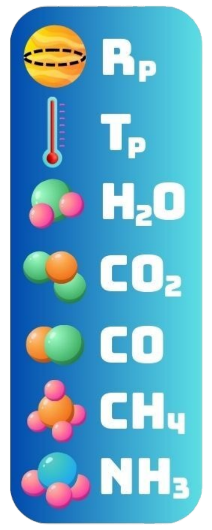
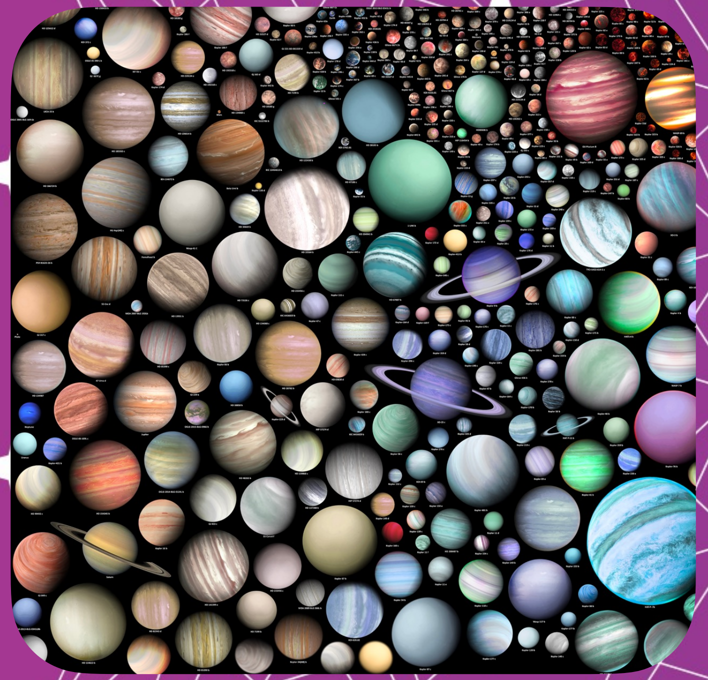
Mayeul Aubin Carol Cuesta-Lázaro

Normalising Flows









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Mayeul Aubin

The 2023 Ariel Data Challenge: Scientists invite AI experts to help study exoplanets

Ariel DATA CHALLENGE

AstroAI

1st of 293 teams!

Leader Board

Rank	Name	Score
1	Mayeul_Aubin	679
2	gators	666
3	Les3Stagios	650
4	asweet	618
5	caokyhan	615
6	hieucao	610
7	dungpt	602
8	aescalantelopez	596
9	MALTO	595
10	brian_jonestown_massacre	586
11	inosen_infinity	582

Simulation-based Inference for Exoplanet Atmospheric Retrieval: Insights from winning the Ariel Data Challenge 2023 using Normalizing Flows

Mayeul Aubin[1,2*], Carolina Cuesta-Lazaro[3,4], Ethan Tregidga[1,5], Javier Viaña[6], Cecilia Garraffo[1,7], Iouli E. Gordon[8], Mercedes López-Morales[8], Robert J. Hargreaves[8], Vladimir Yu. Makhnev[8], Jeremy J. Drake[7], Douglas P. Finkbeiner[3], and Phillip Cargile[9]

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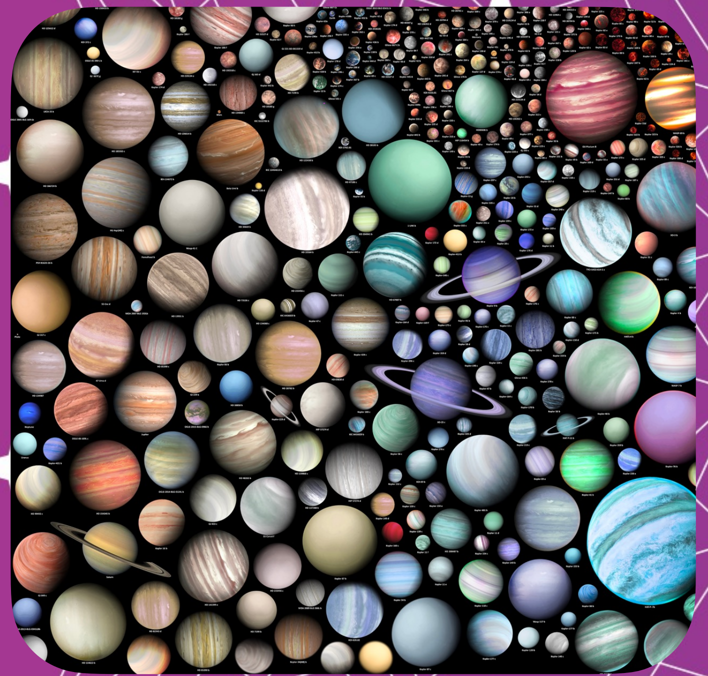
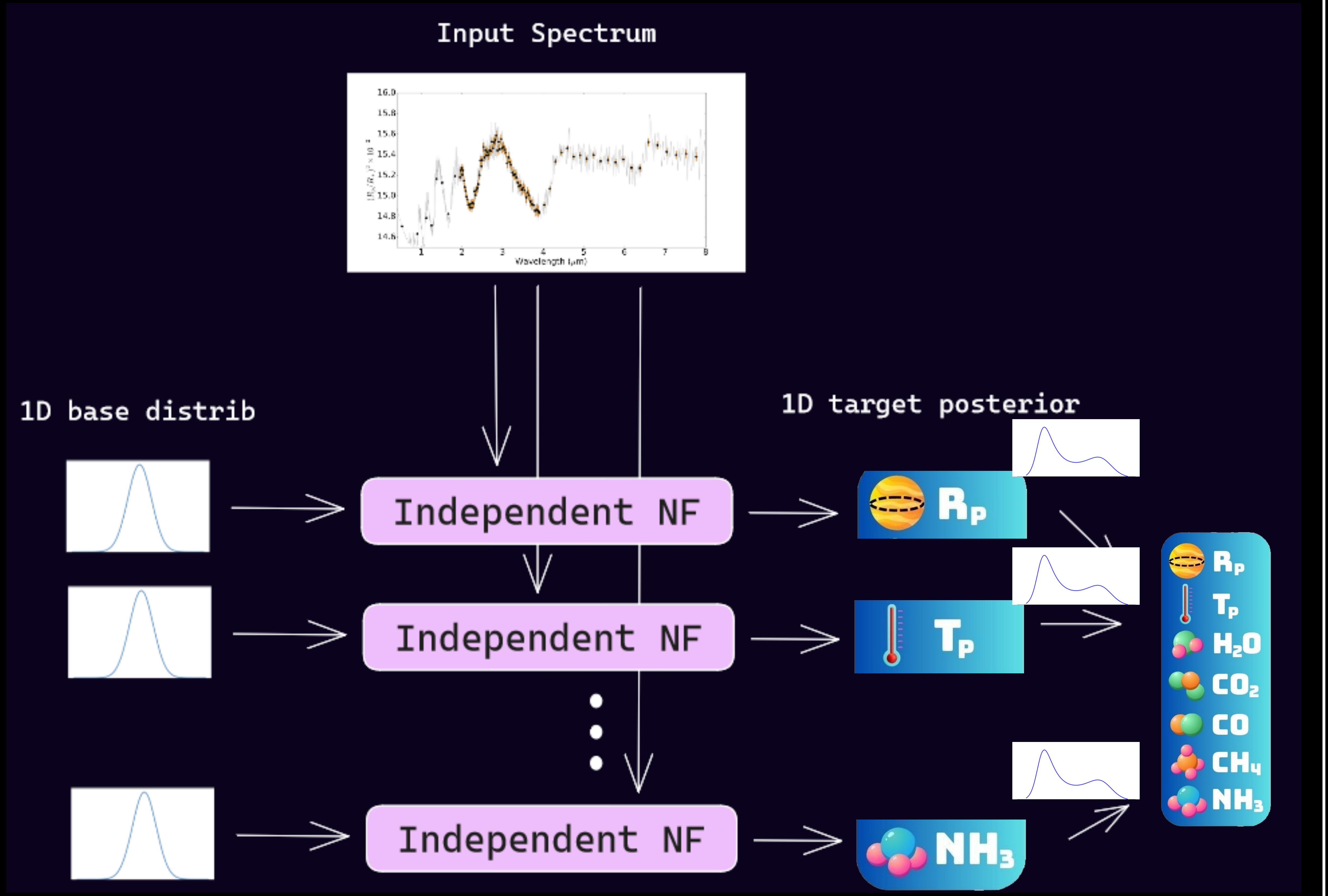
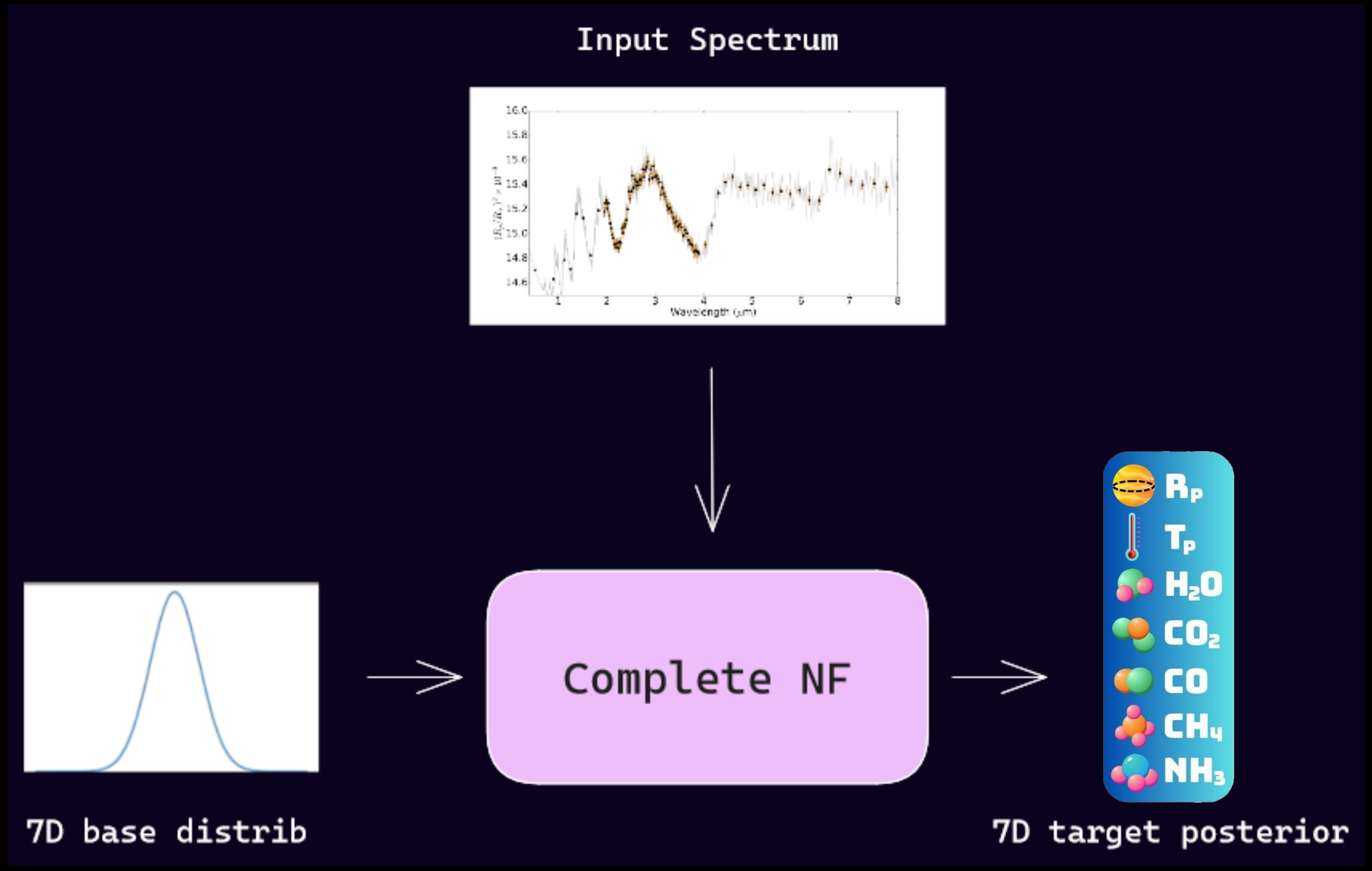


Mayeul Aubin

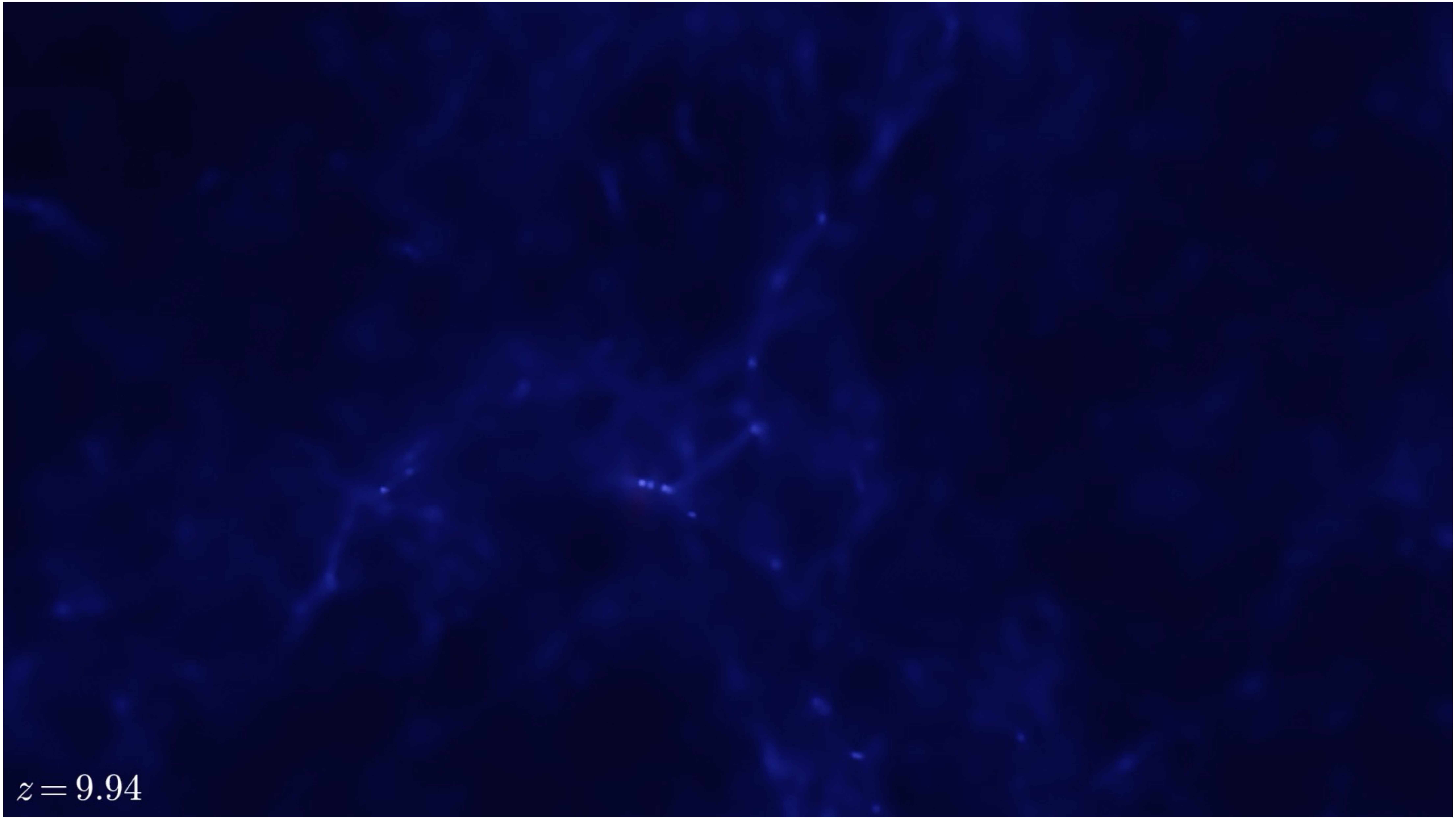


A set of independent Normalising Flows

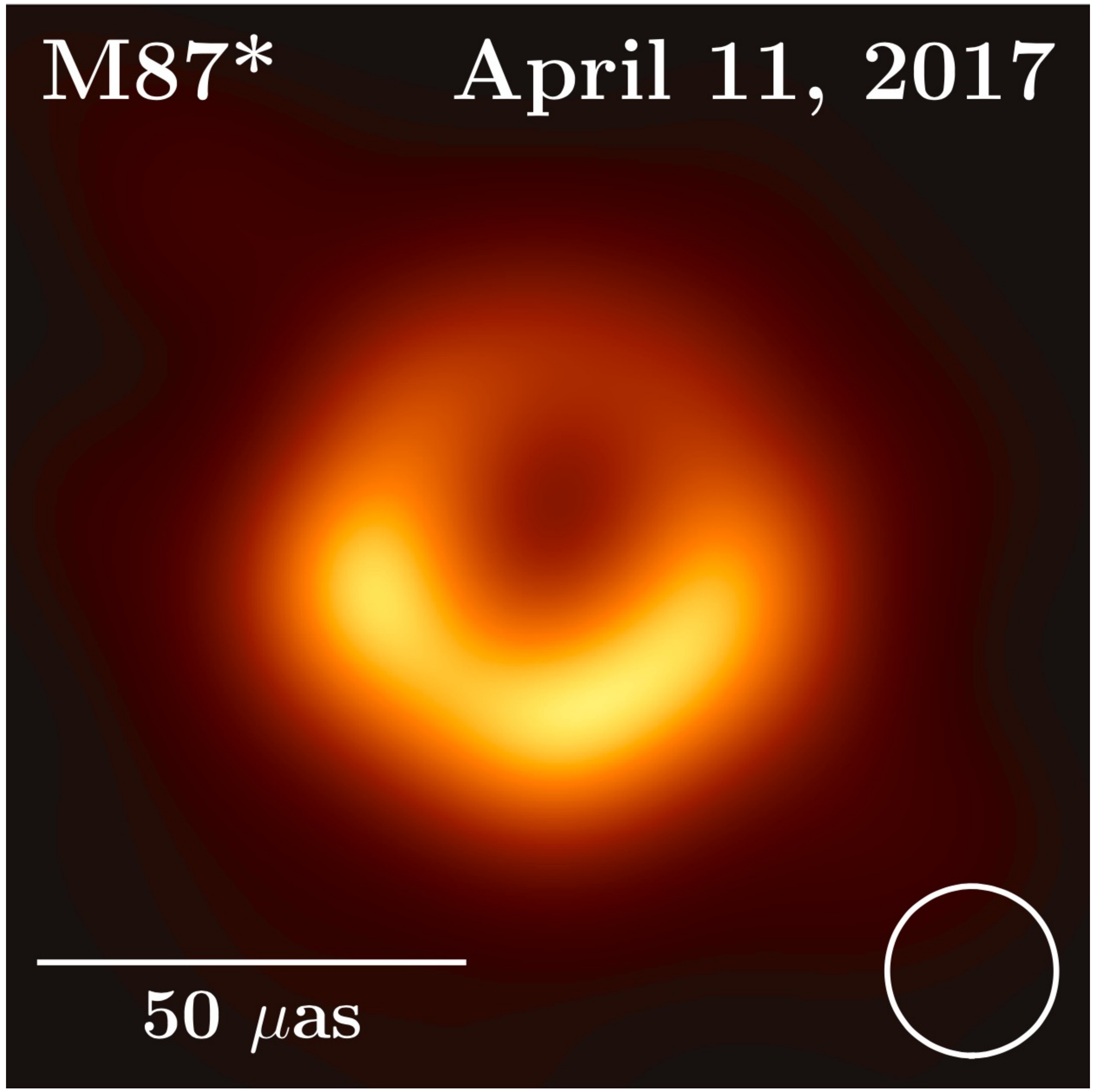


One complete Normalising Flow

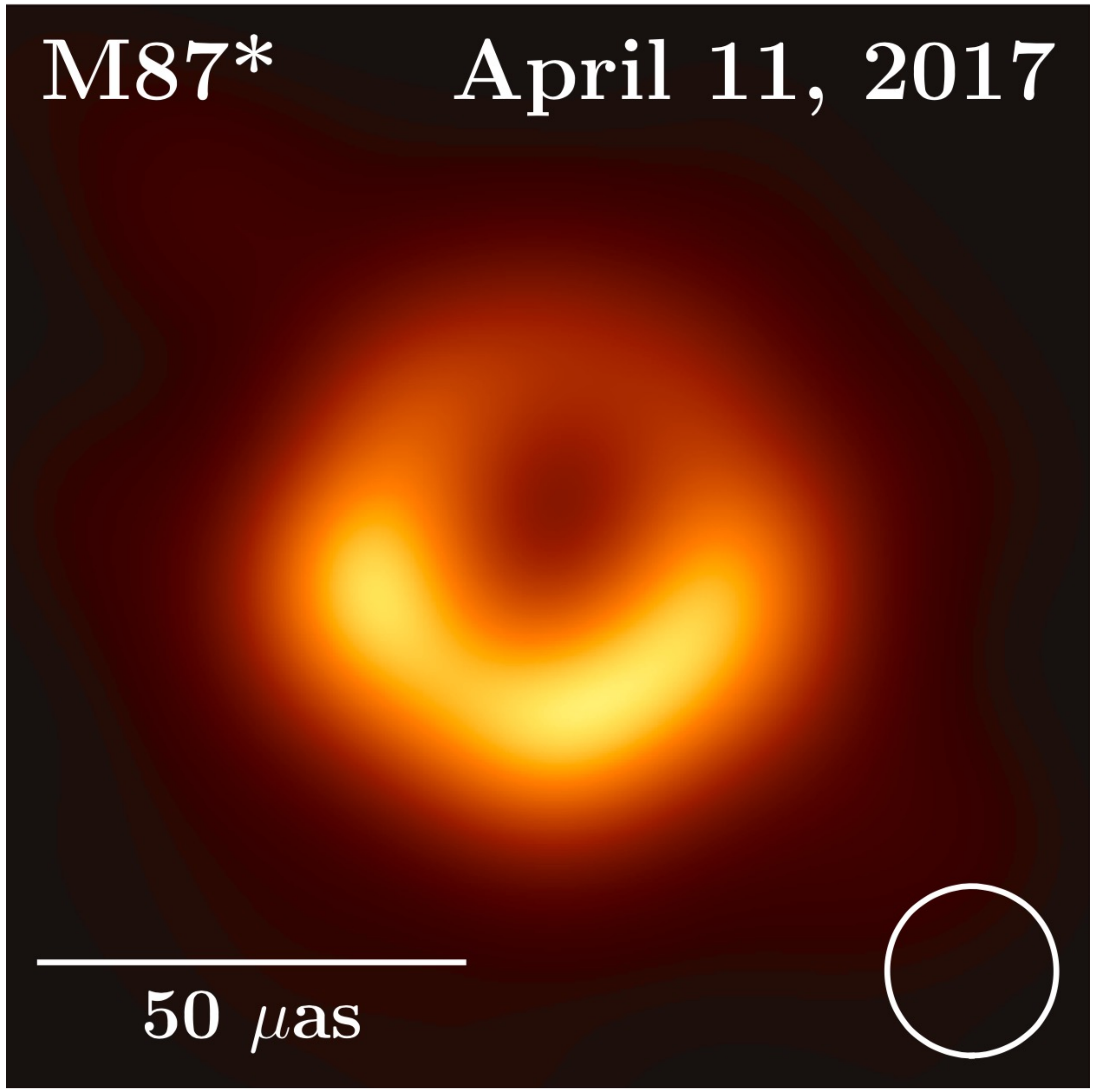
AI Simulations

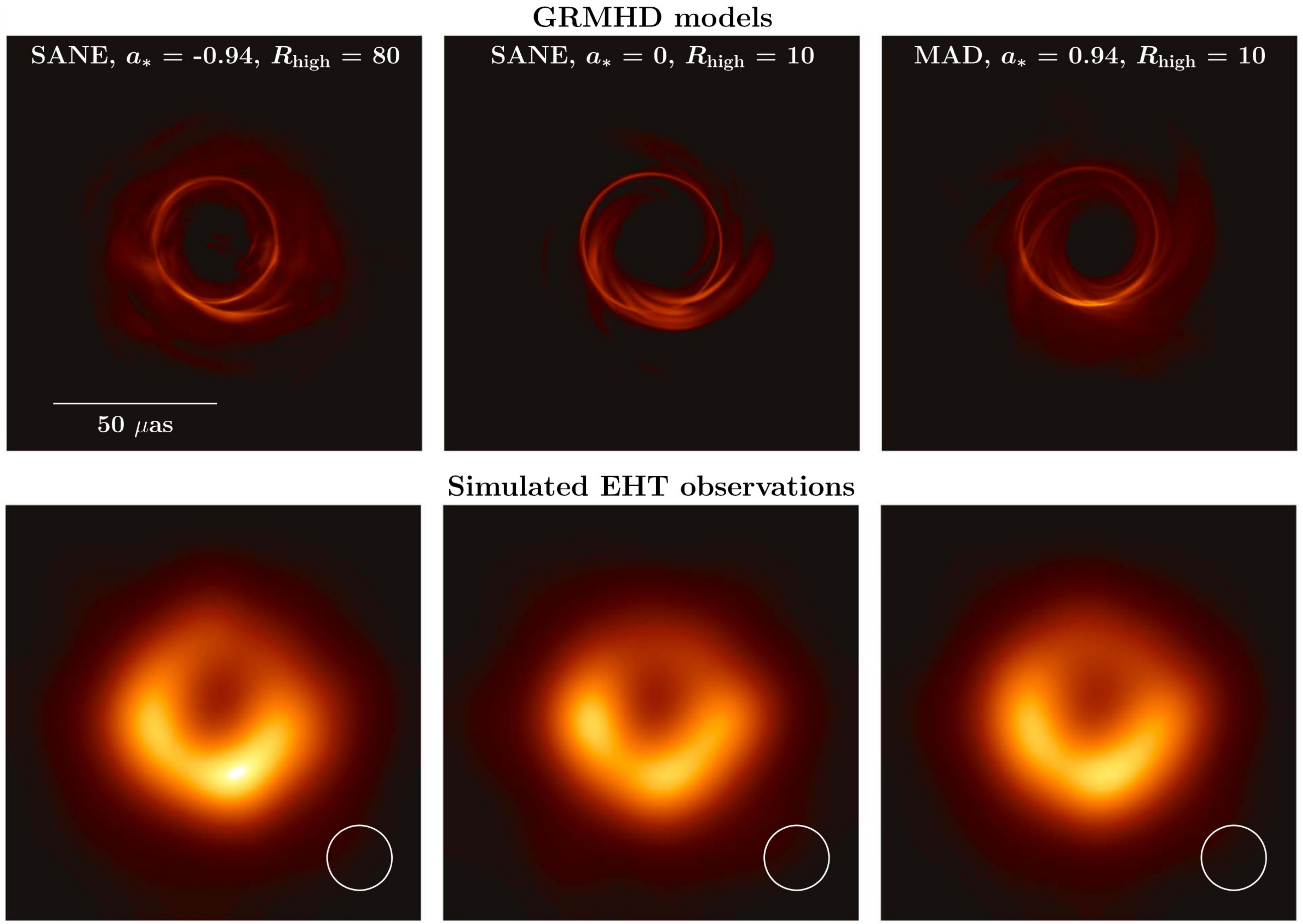


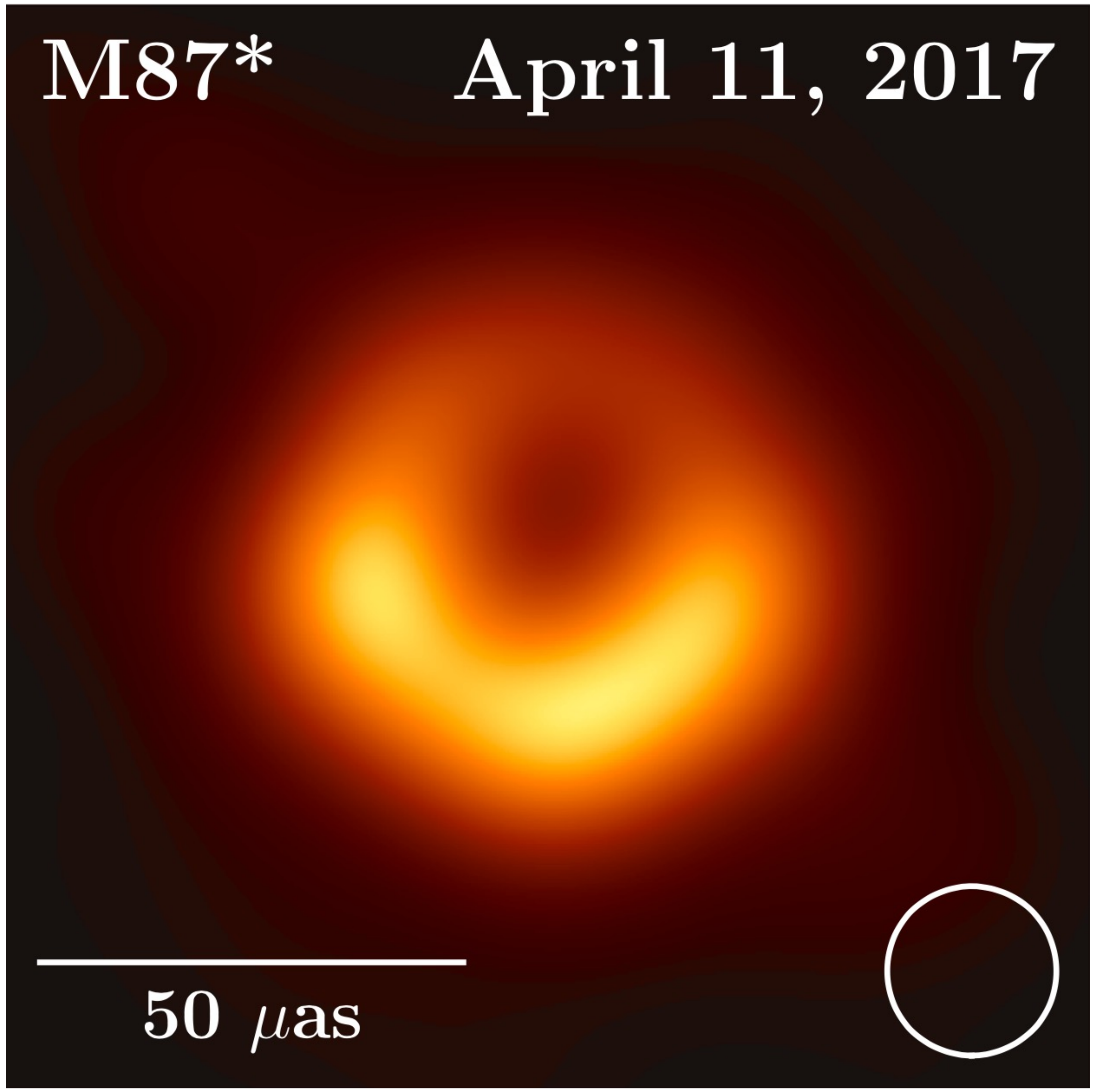
Effects of supermassive black holes feedback from a CAMELS-SIMBA cosmological simulation
Francisco Villaescusa-Navarro, CCA Flatiron Institute

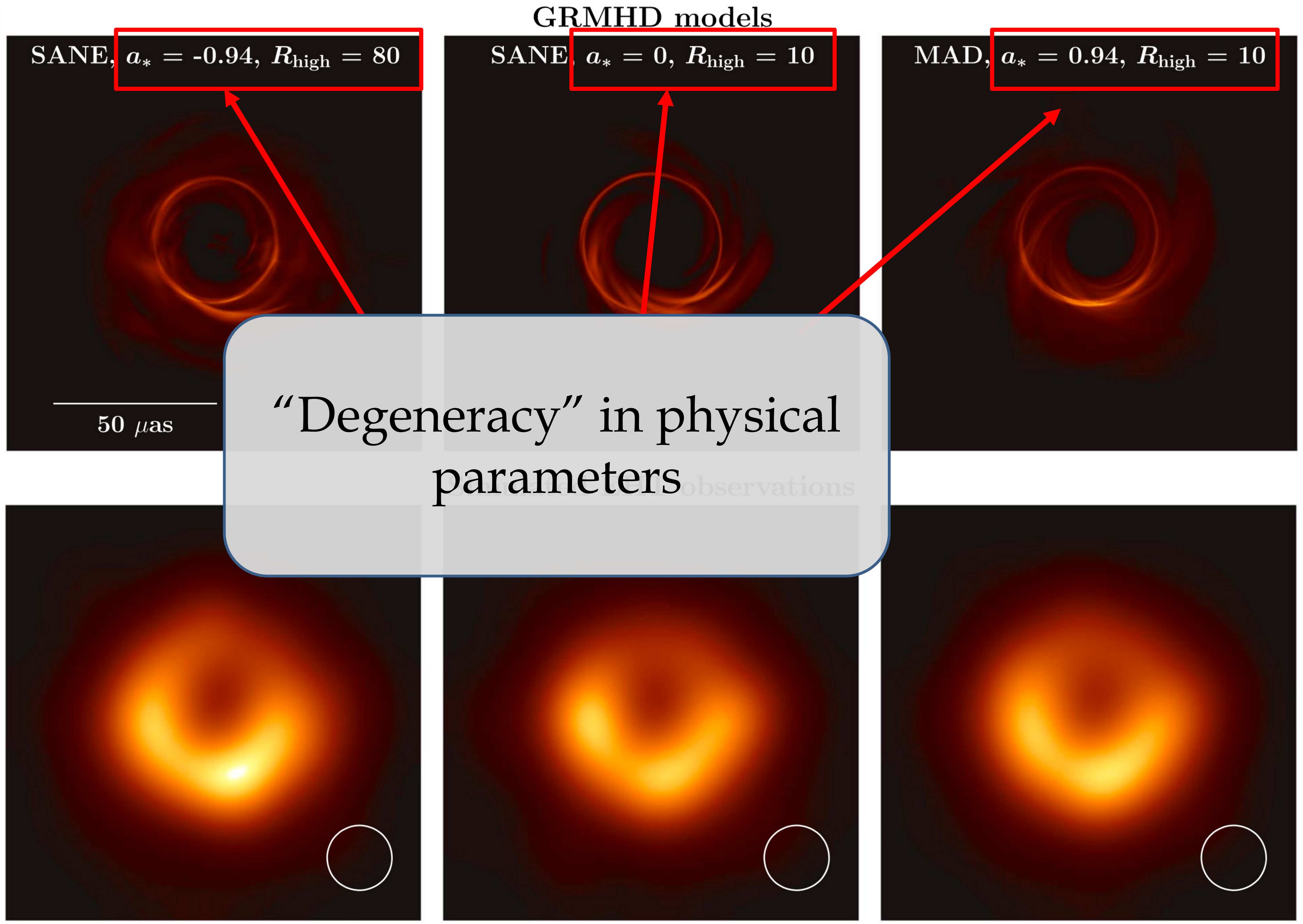


Event Horizon Telescope Collaboration 2019


M87*
April 11, 2017
50 μas


GRMHD models
SANE, $a_* = -0.94$, $R_{\mathrm{high}} = 80$
SANE, $a_* = 0$, $R_{\mathrm{high}} = 10$
MAD, $a_* = 0.94$, $R_{\mathrm{high}} = 10$
50 μas
Simulated EHT observations





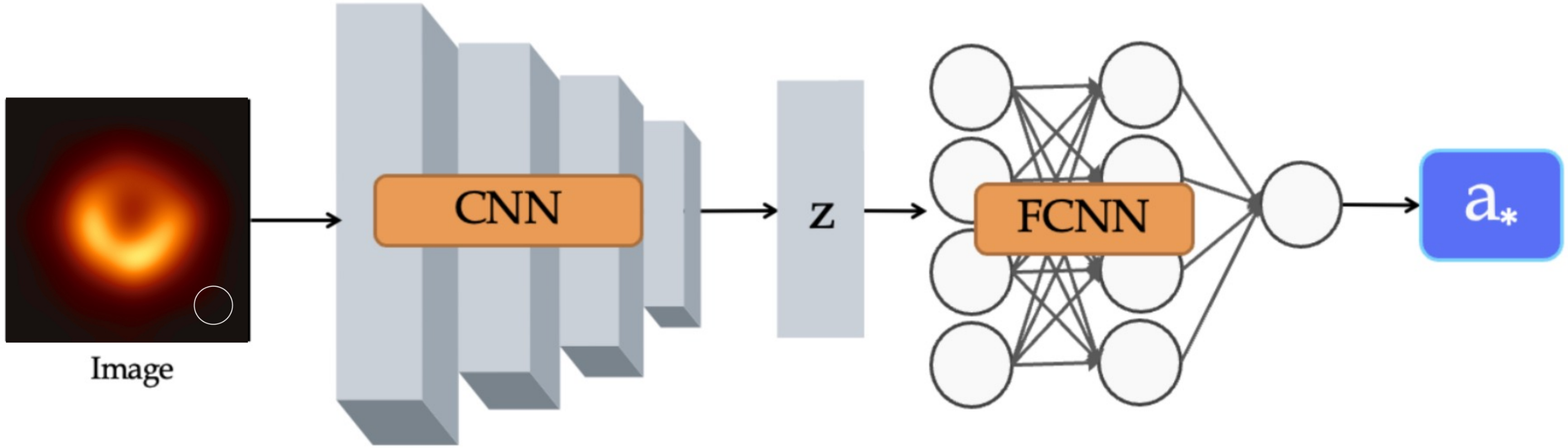
"Degeneracy" in physical parameters

AstroAI

Enabling Next Generation Astrophysics

Tao Tsui

Black Hole Characterization from EHT images



Tsui et al. in Press

AstroAI

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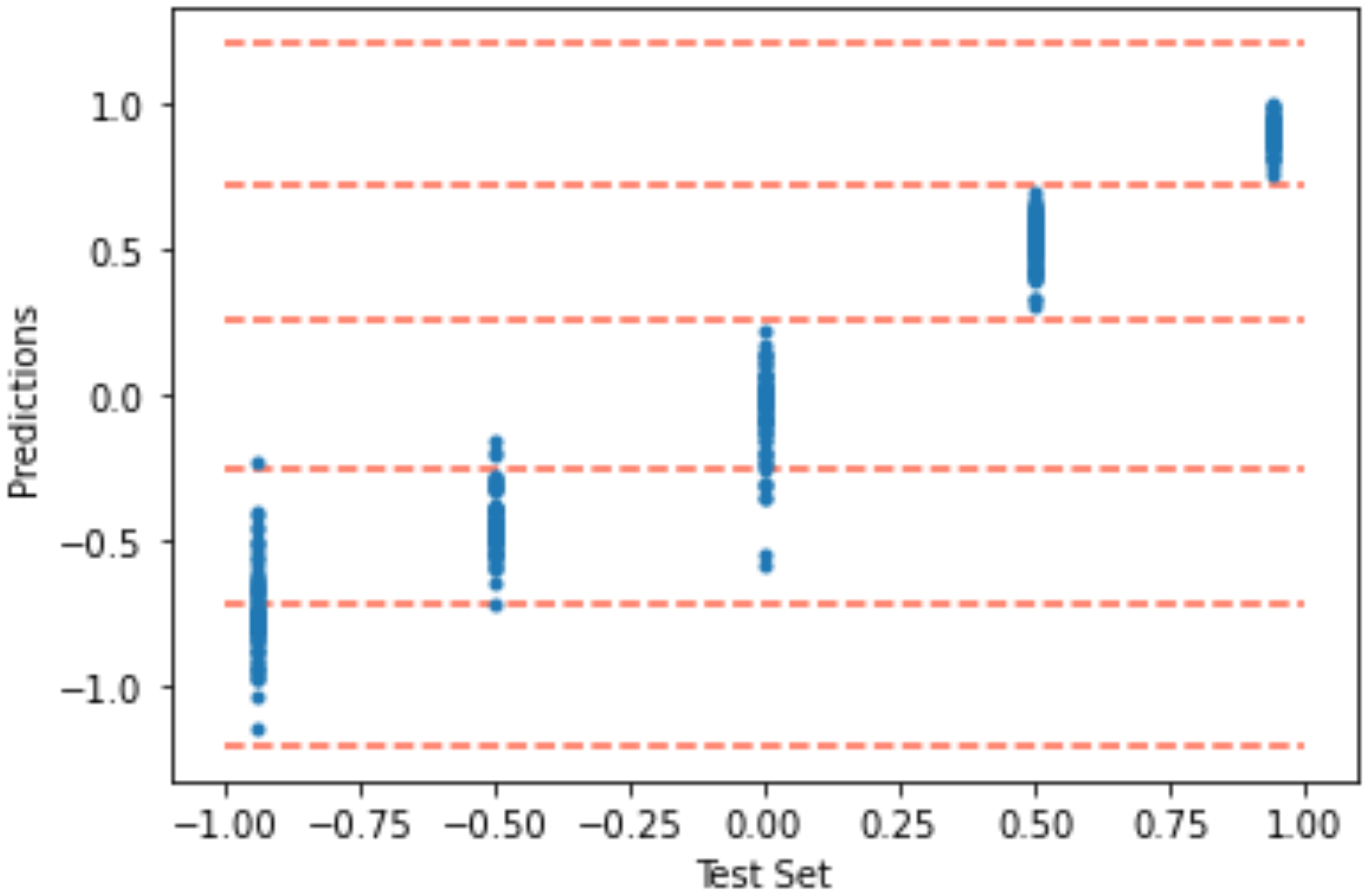
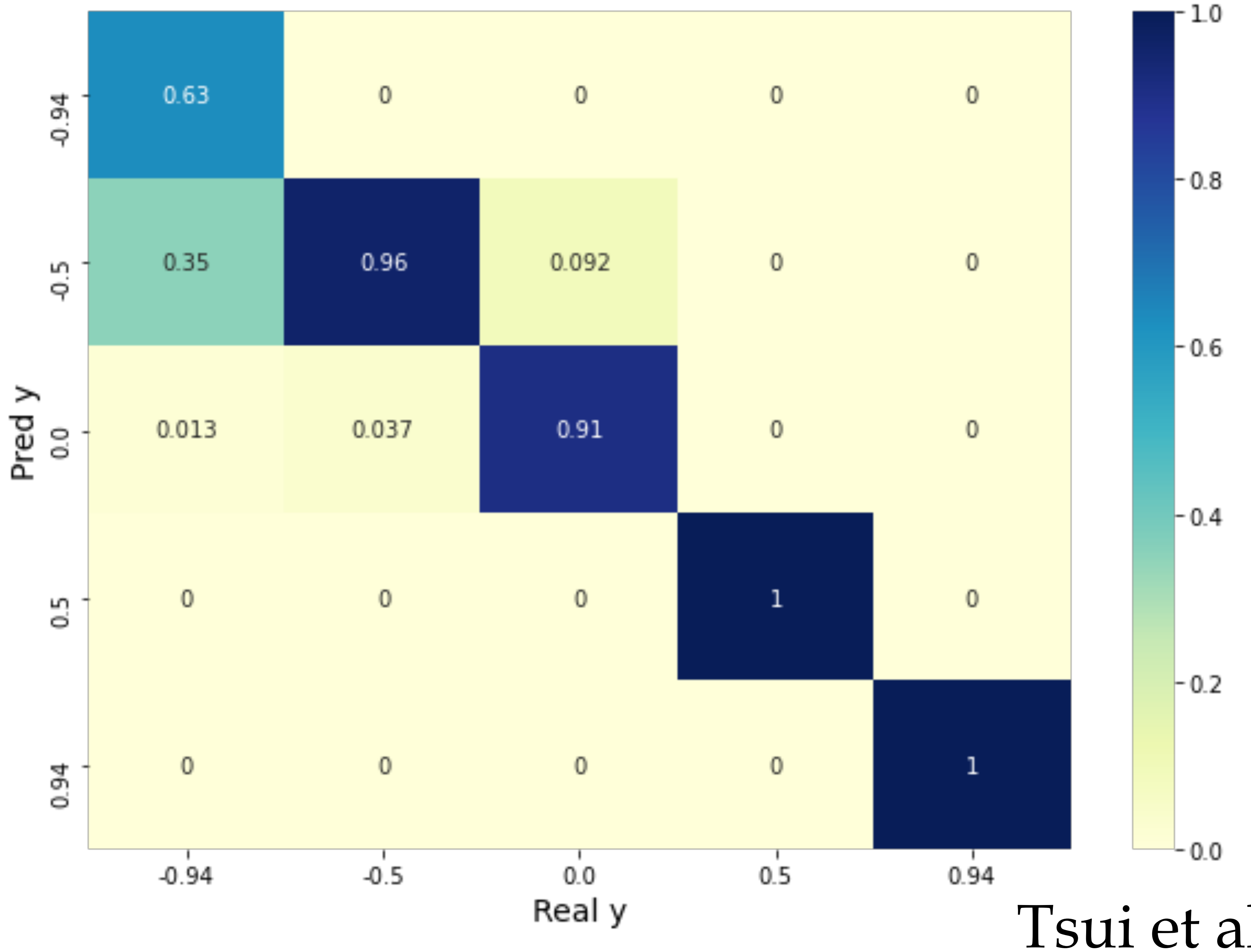
Tao Tsui

Black Hole Characterization from EHT images



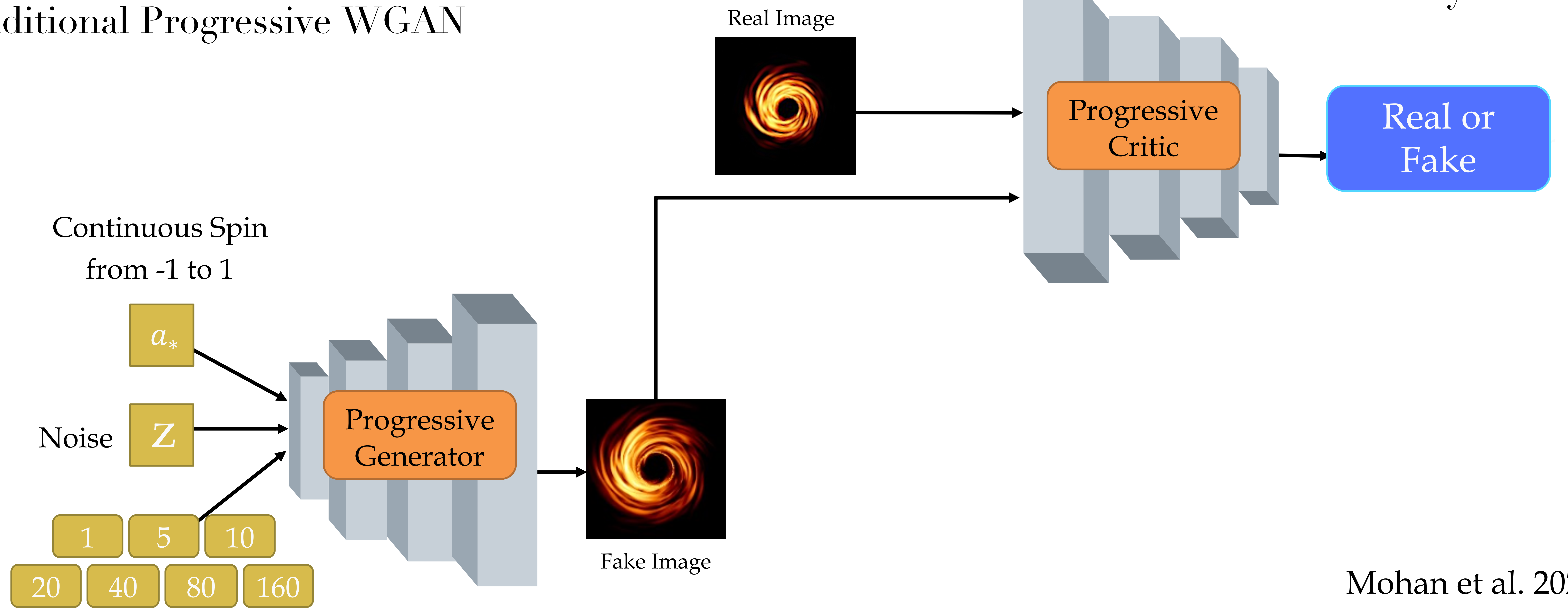


Tsui et al. in Press

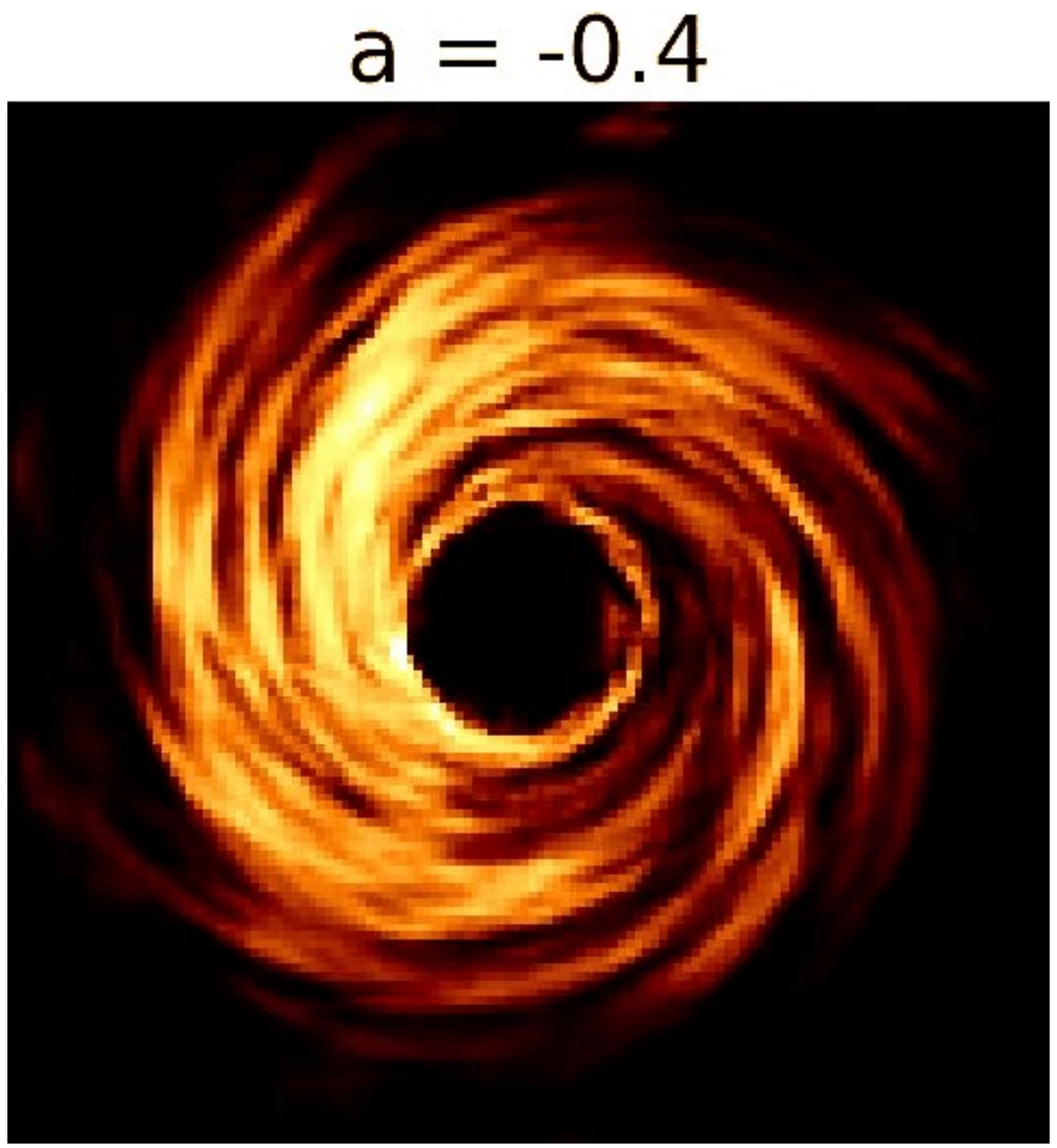
Enabling Next Generation Astrophysics

Arya Mohan

Conditional Progressive WGAN

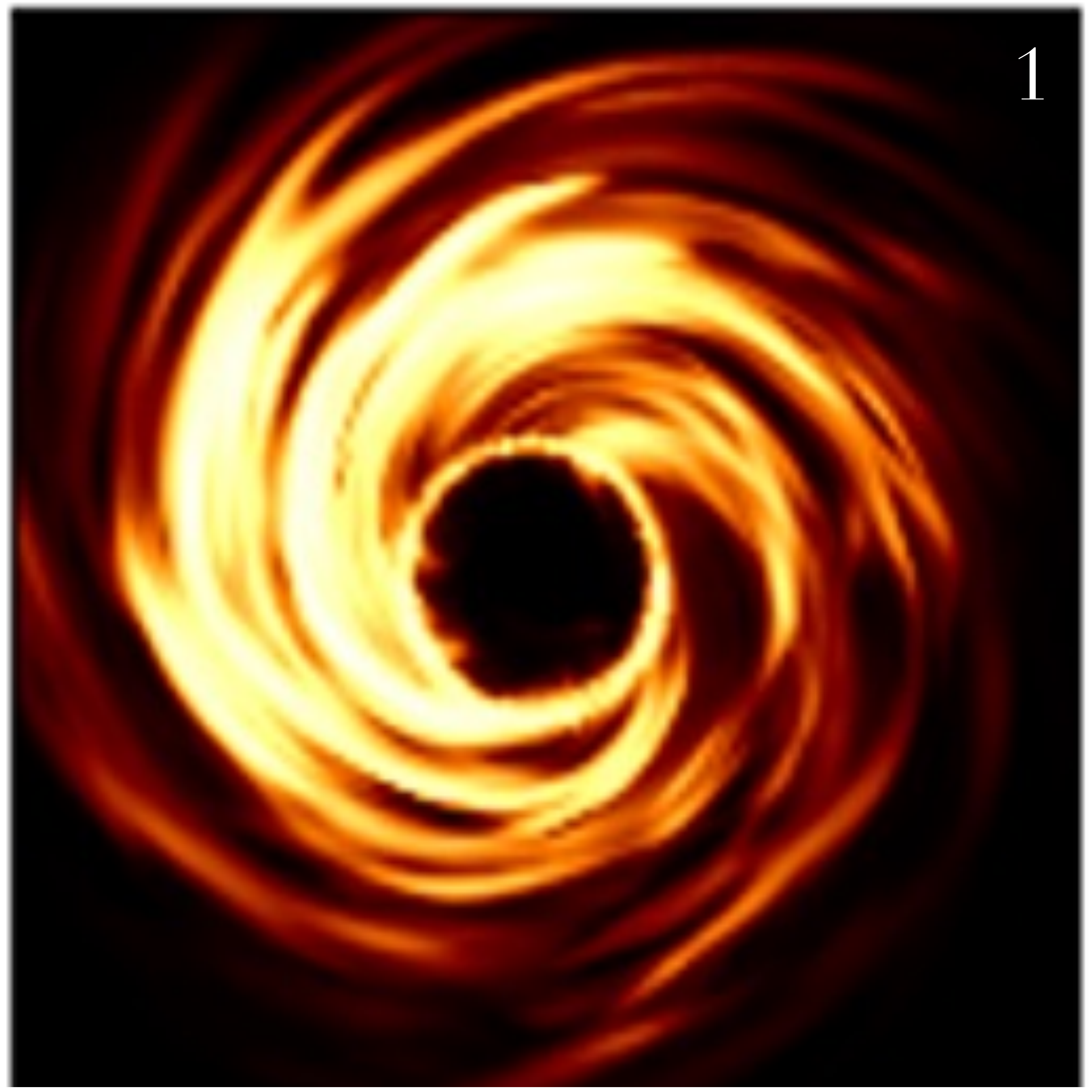


Mohan et al. 2023

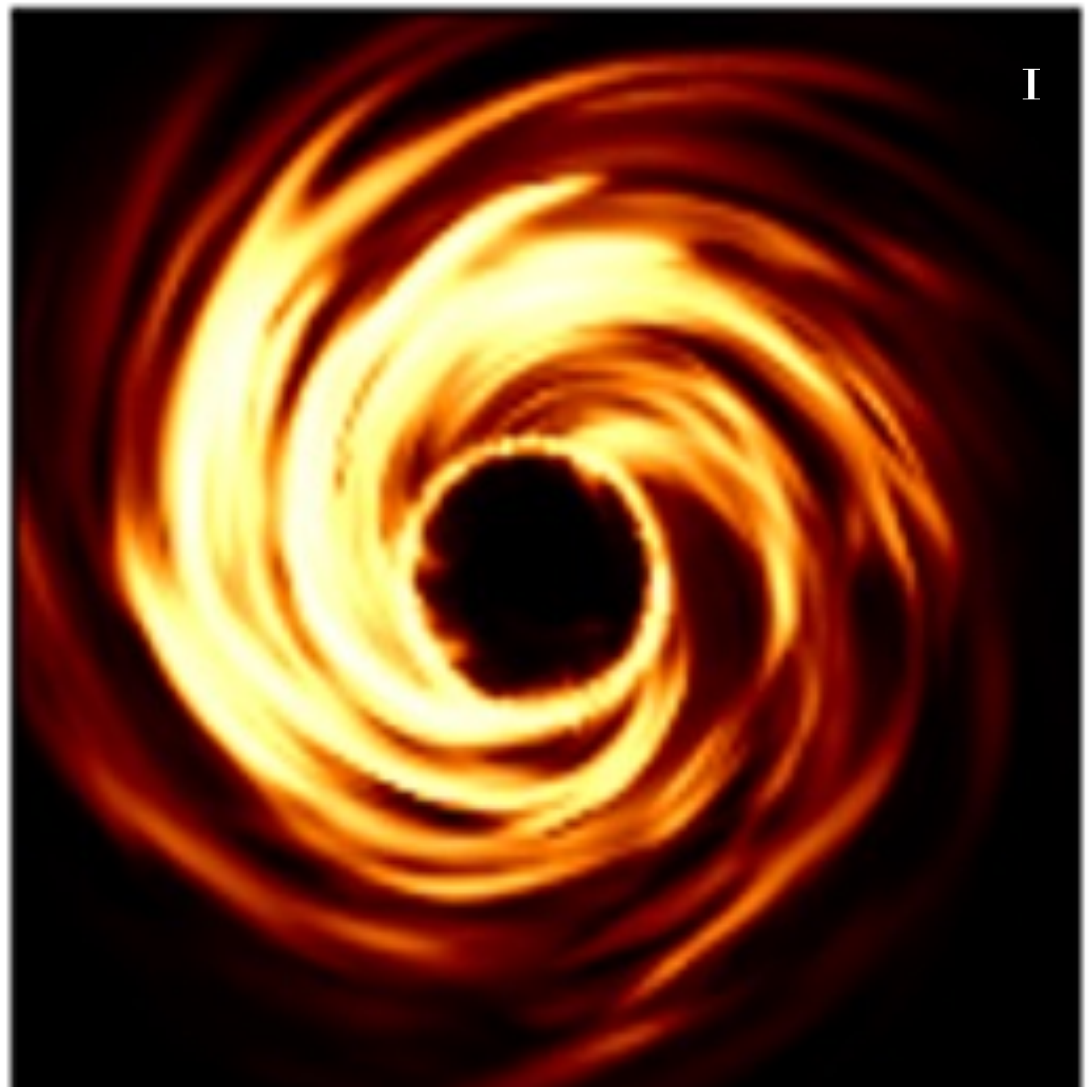


Mohan et al. 2023

Supermassive BHs



Supermassive BHs



GRMHD

GenAI

GRMHD

Generative AI for Astrophysics

Diffusion Models

DALL-E generated

Diffusion Models for Astrophysics

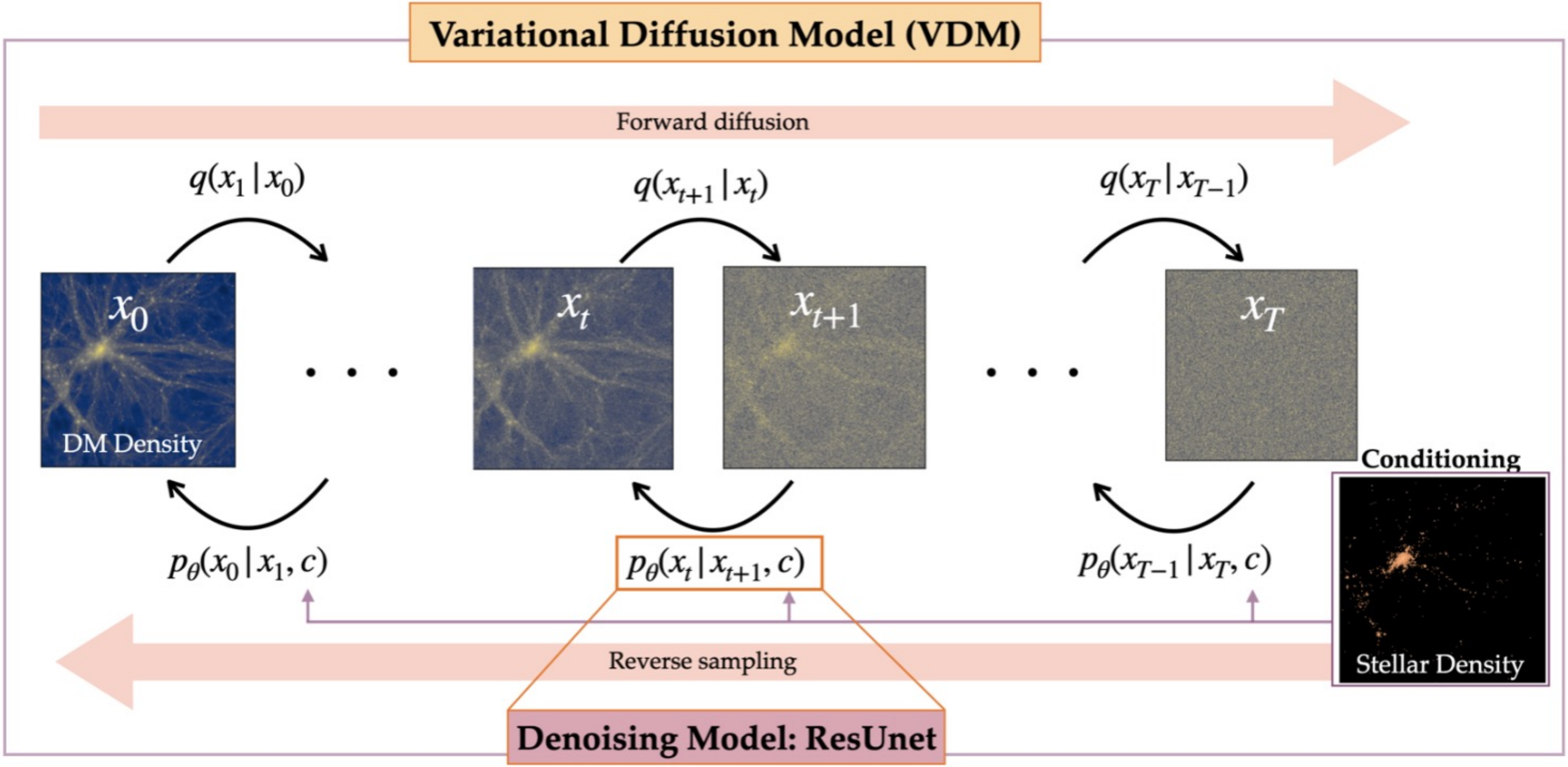
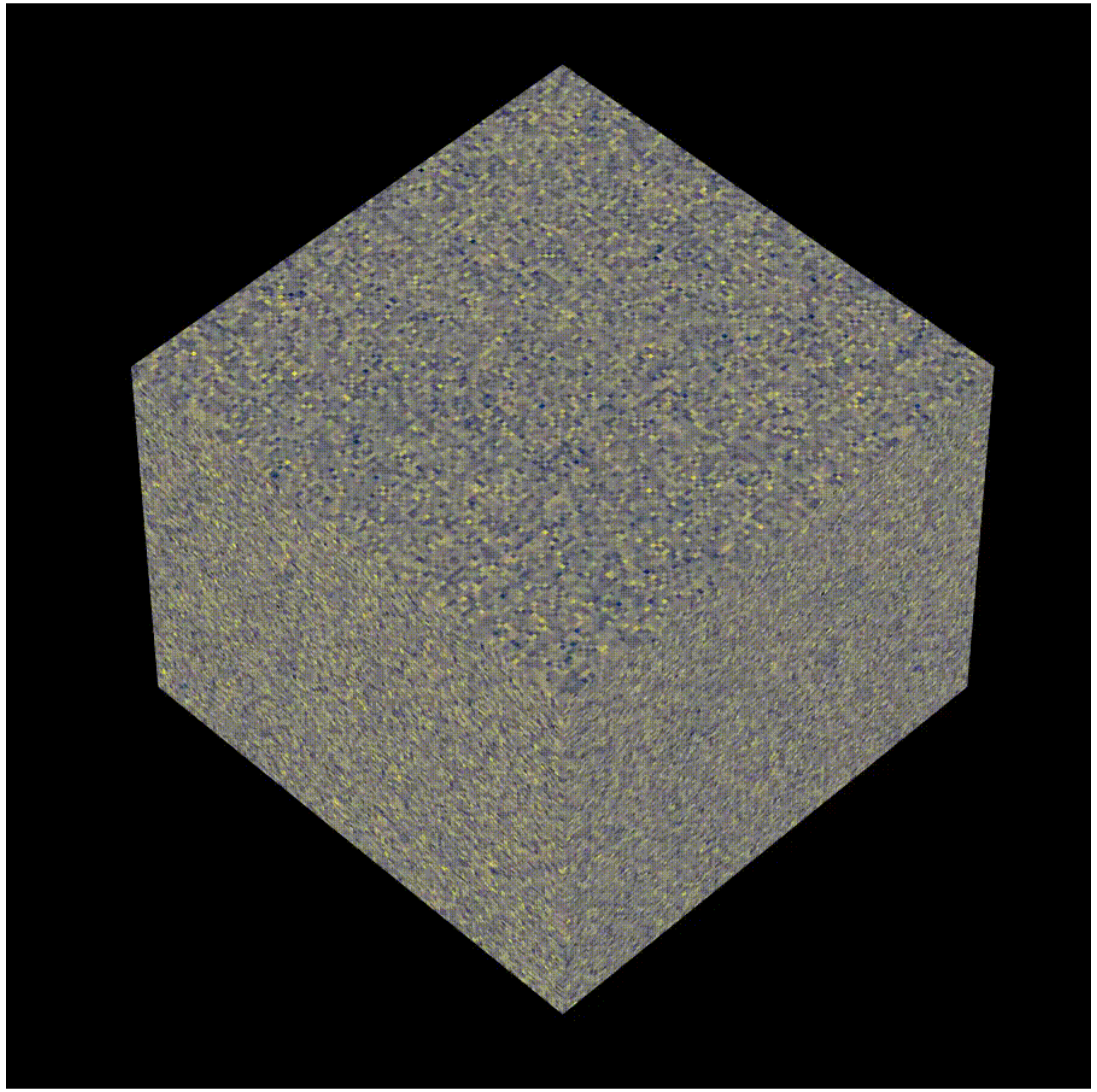
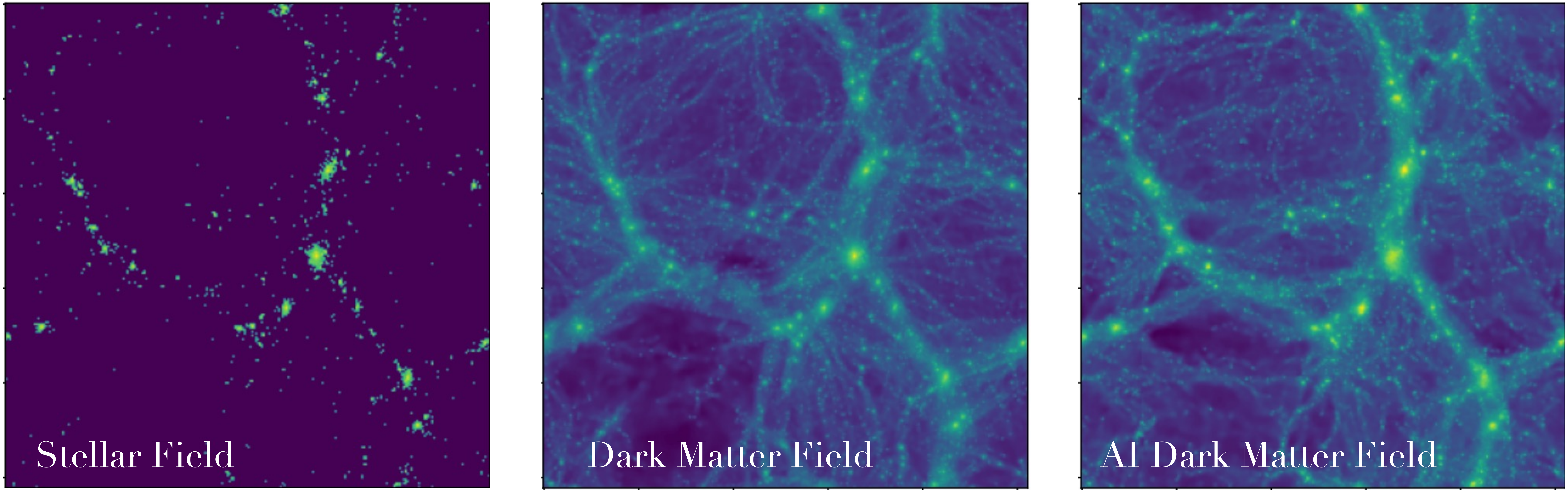


Fig: Core Francisco Park

Diffusion Models for Astrophysics



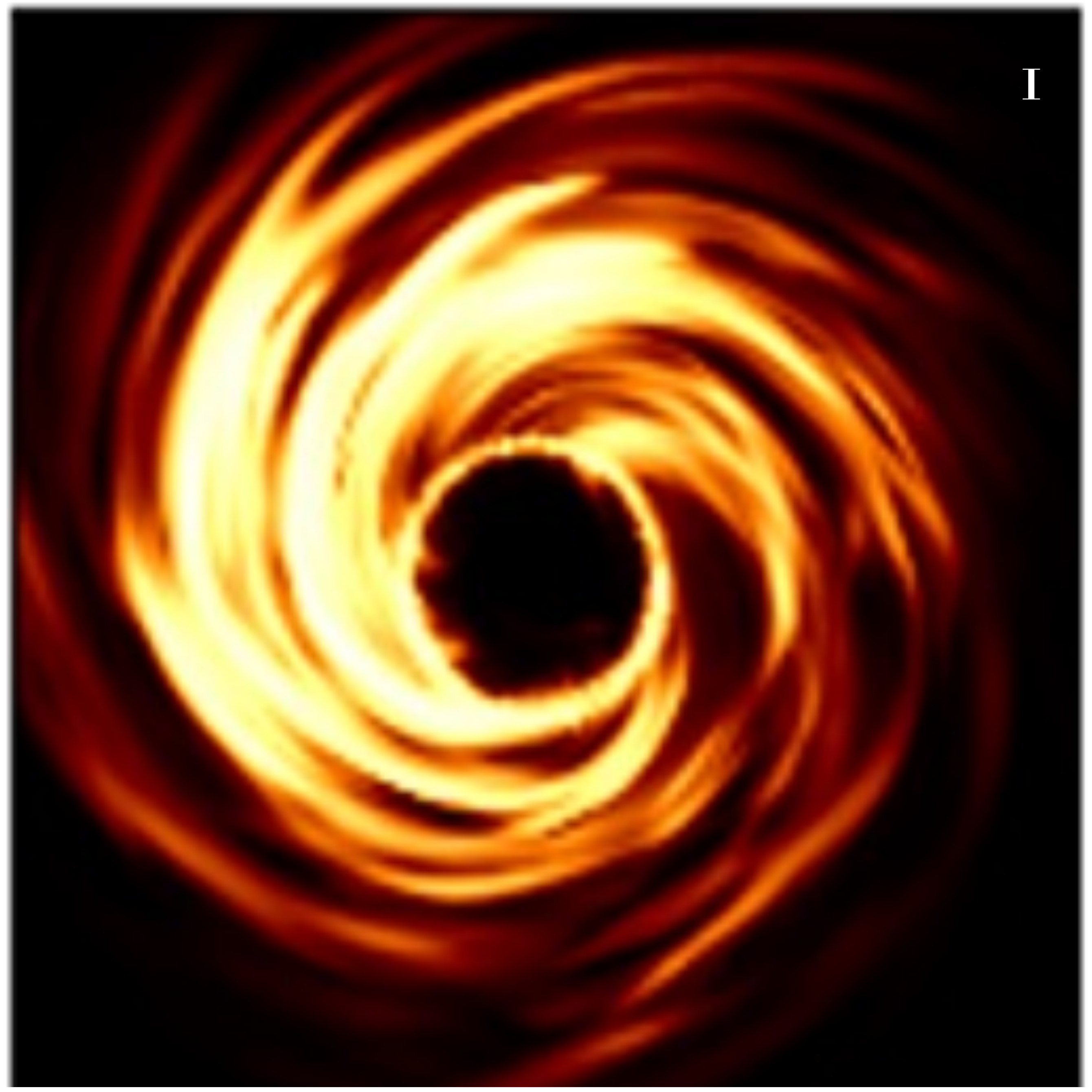
Dark Matter Field Simulations



V. Ono, C. F. Park , Y. Ni, C. Cuesta-Lázaro, F. Villaescusa-Navarro 2024

Enabling Next Generation Astrophysics

Supermassive BHs

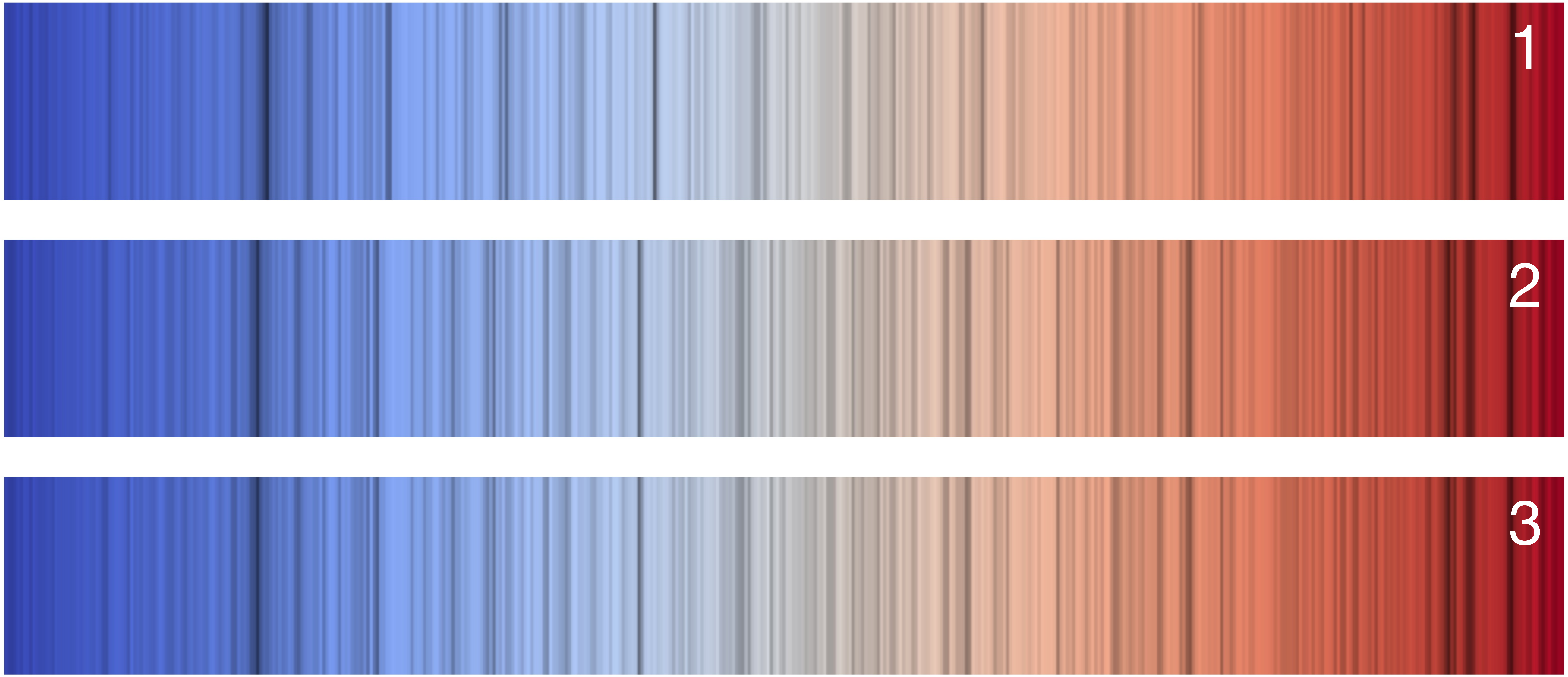


GRMHD

GenAI

GRMHD

Stellar Spectra

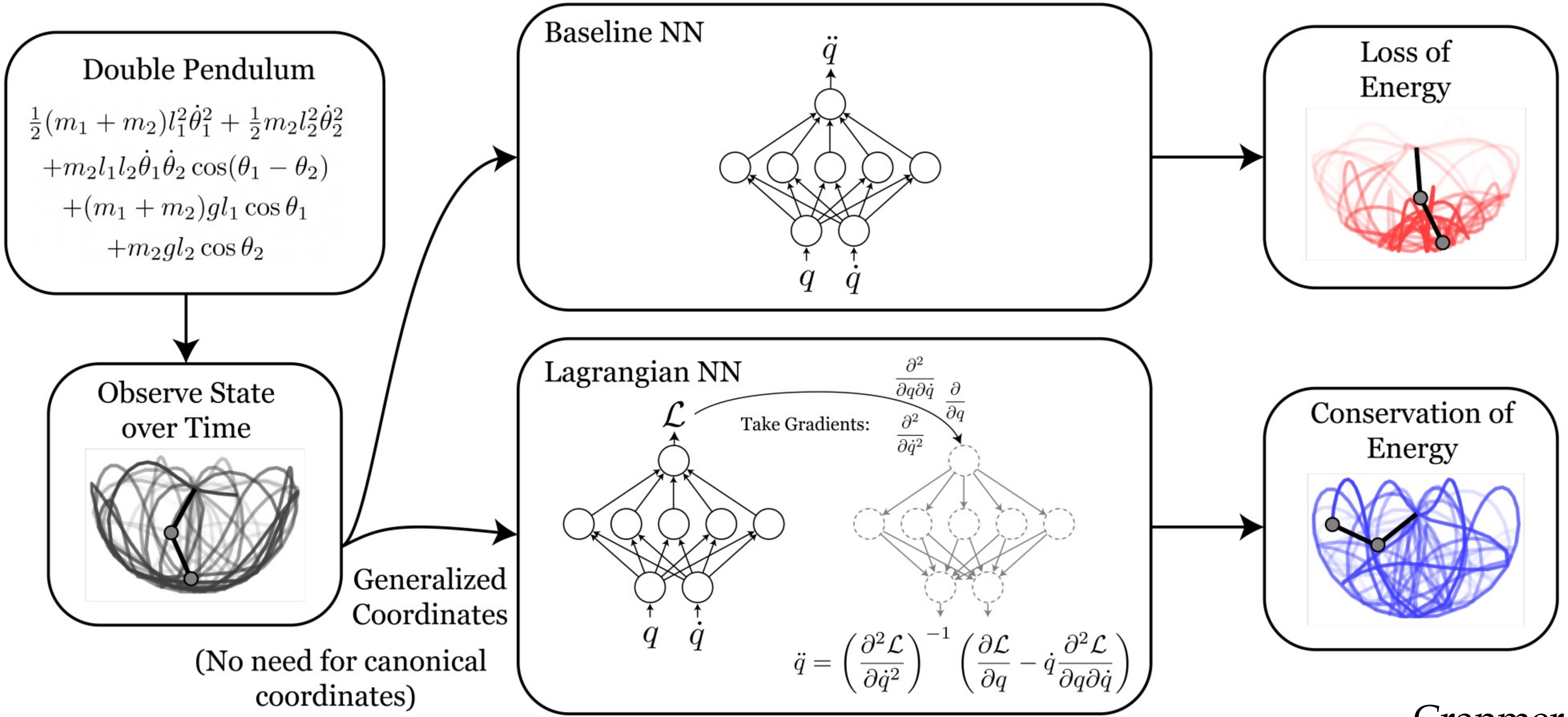


Phillip Cargile

What does realistic mean?

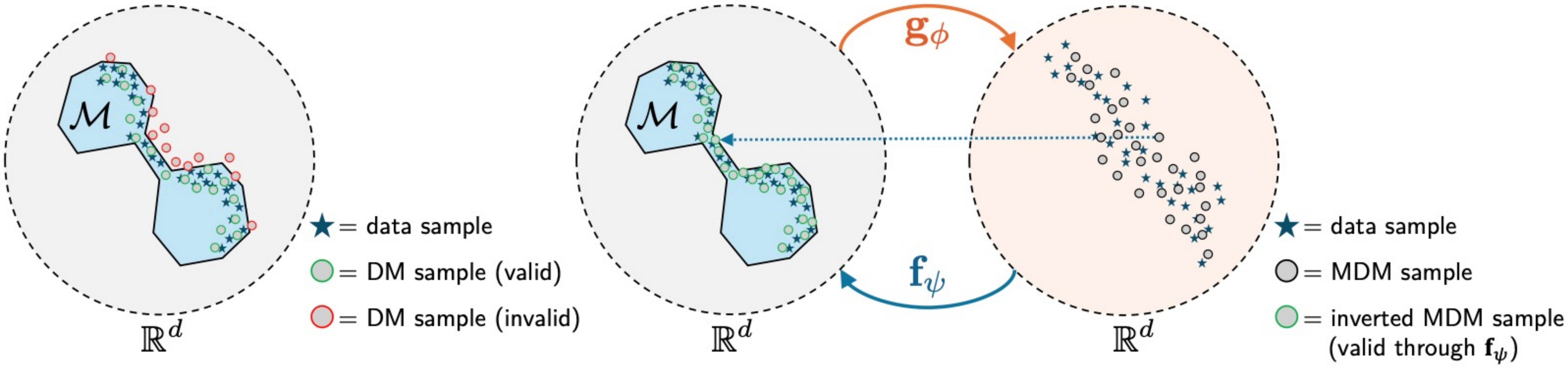
Towards Physical AI Simulations

Lagrangian Neural Networks



Cranmer et al. 2020

Constrained Diffusion Models



(a) Regular diffusion model

(b) Mirror diffusion model with NAMM

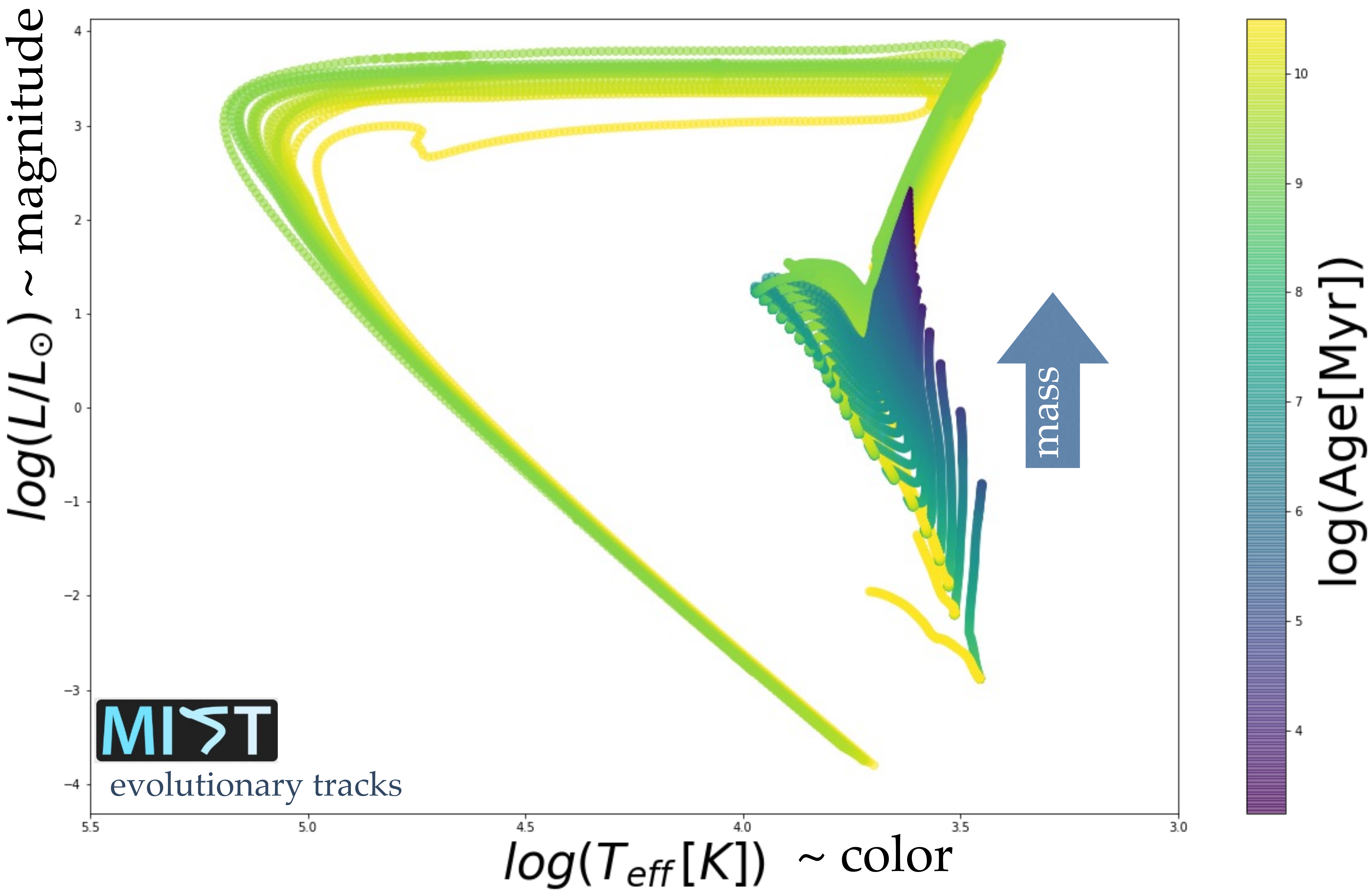
Berthy Feng, Ricardo Baptista and Katie Bouman NeurIPS 2024

Can we get the best of both worlds?

From Simulations to Observations: Transfer Learning

Automatic Stellar Characterization for Gaia

ESA



log(L/L⊙) ~ magnitude
log(T_eff[K]) ~ color
log(Age[Myr])
mass
MIST
evolutionary tracks
4
3
2
1
0
−1
−2
−3
−4
5.5
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3.0
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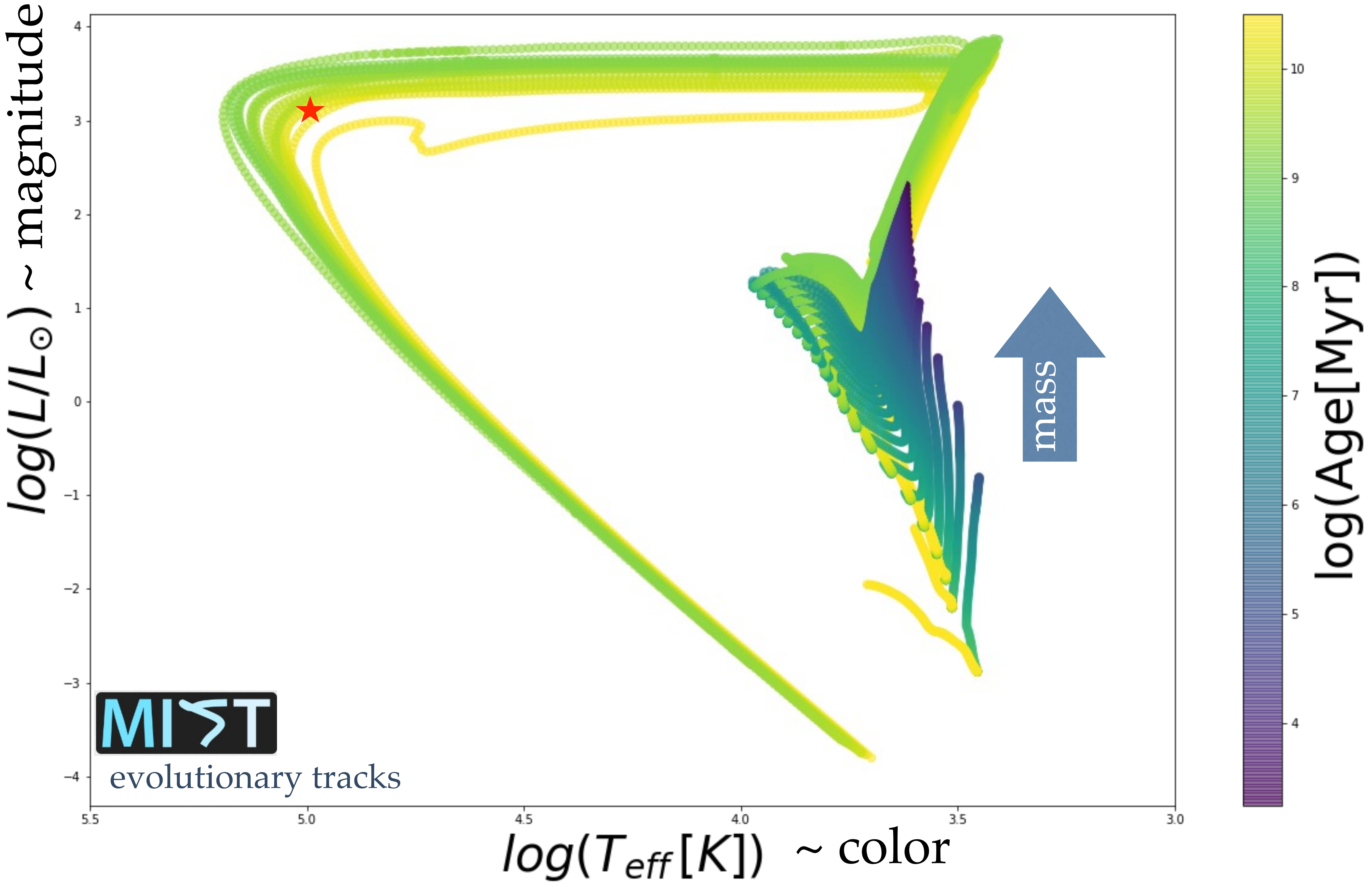
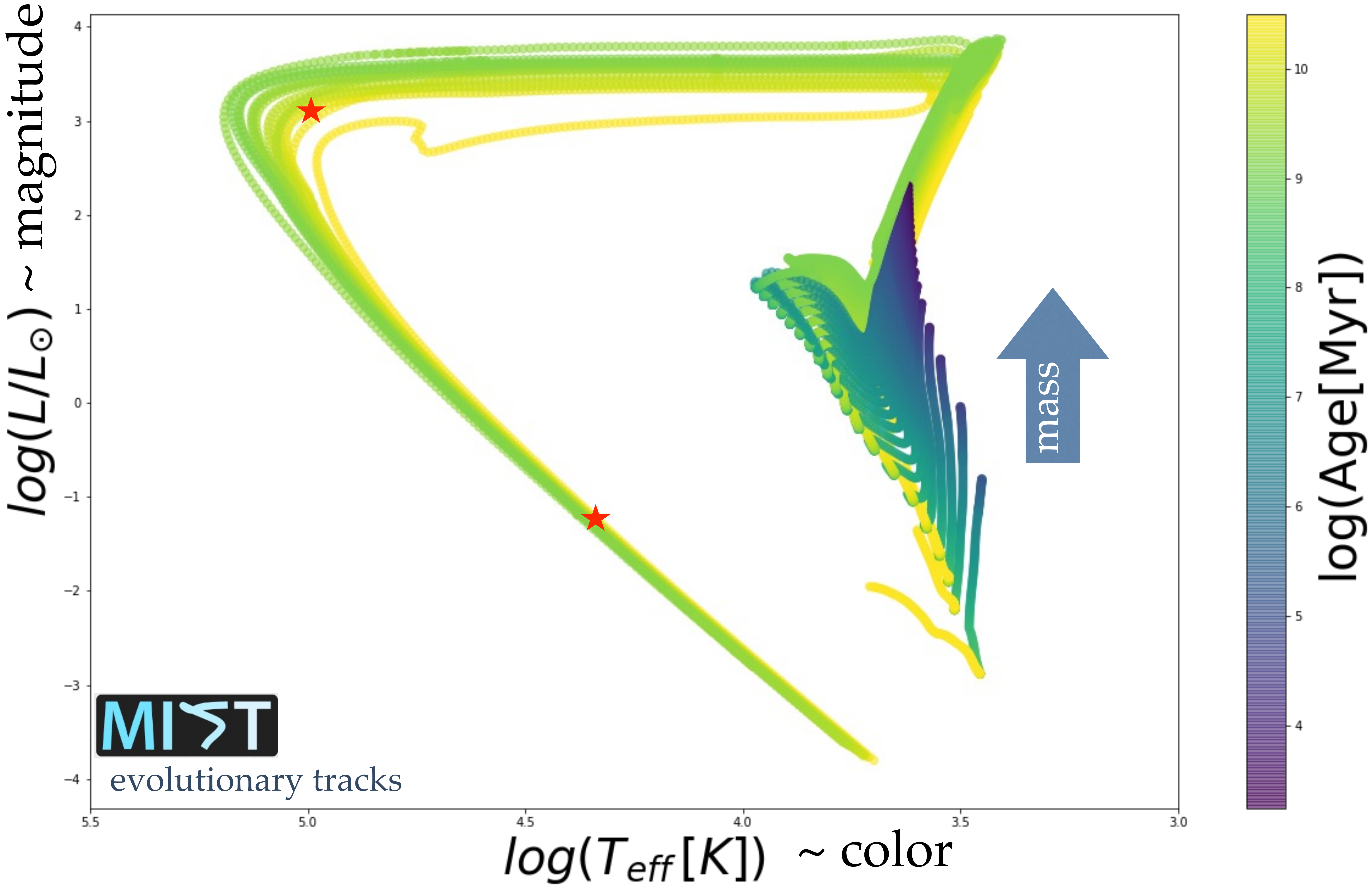
5
4

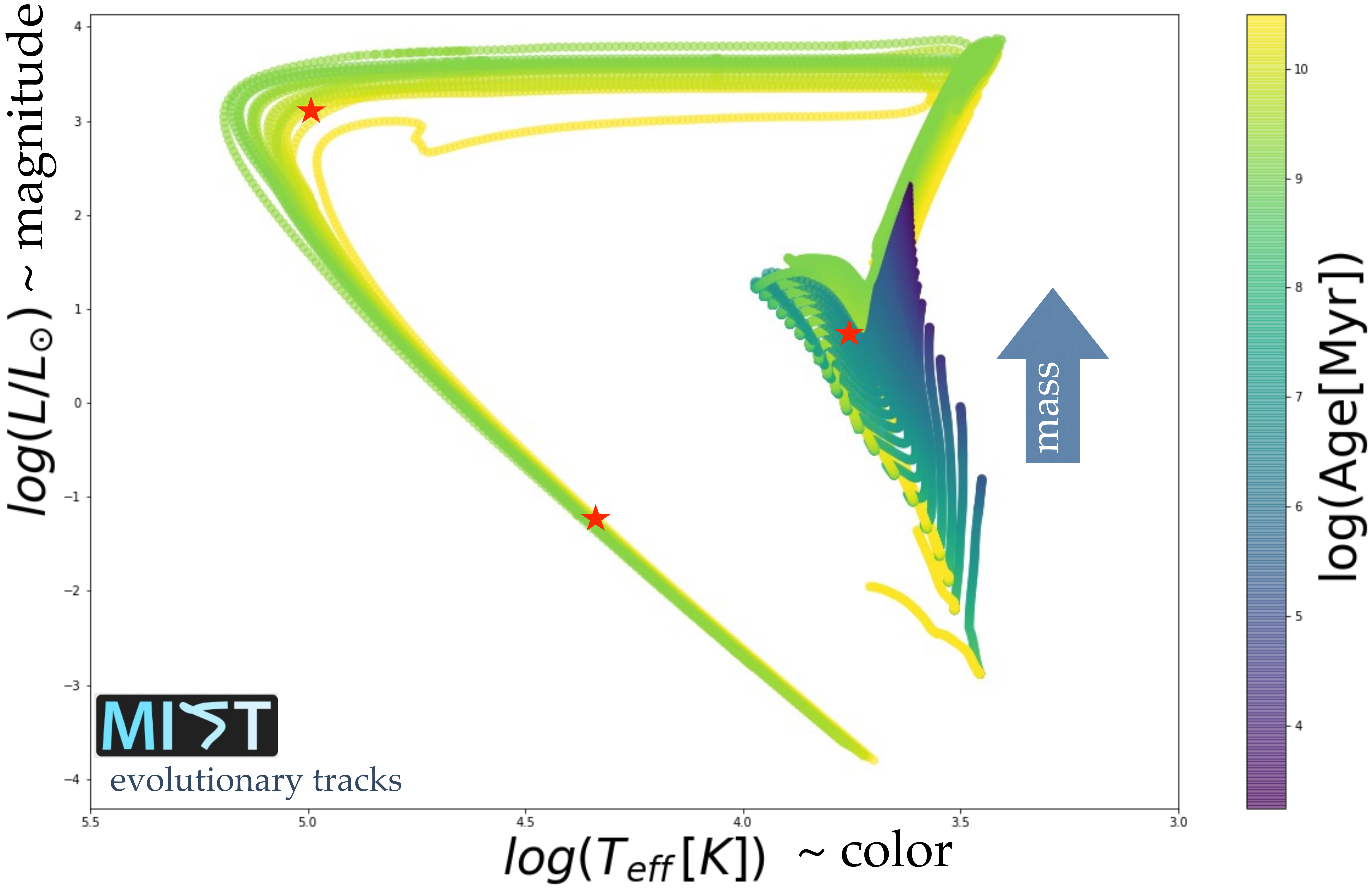
✤ Non-linearity



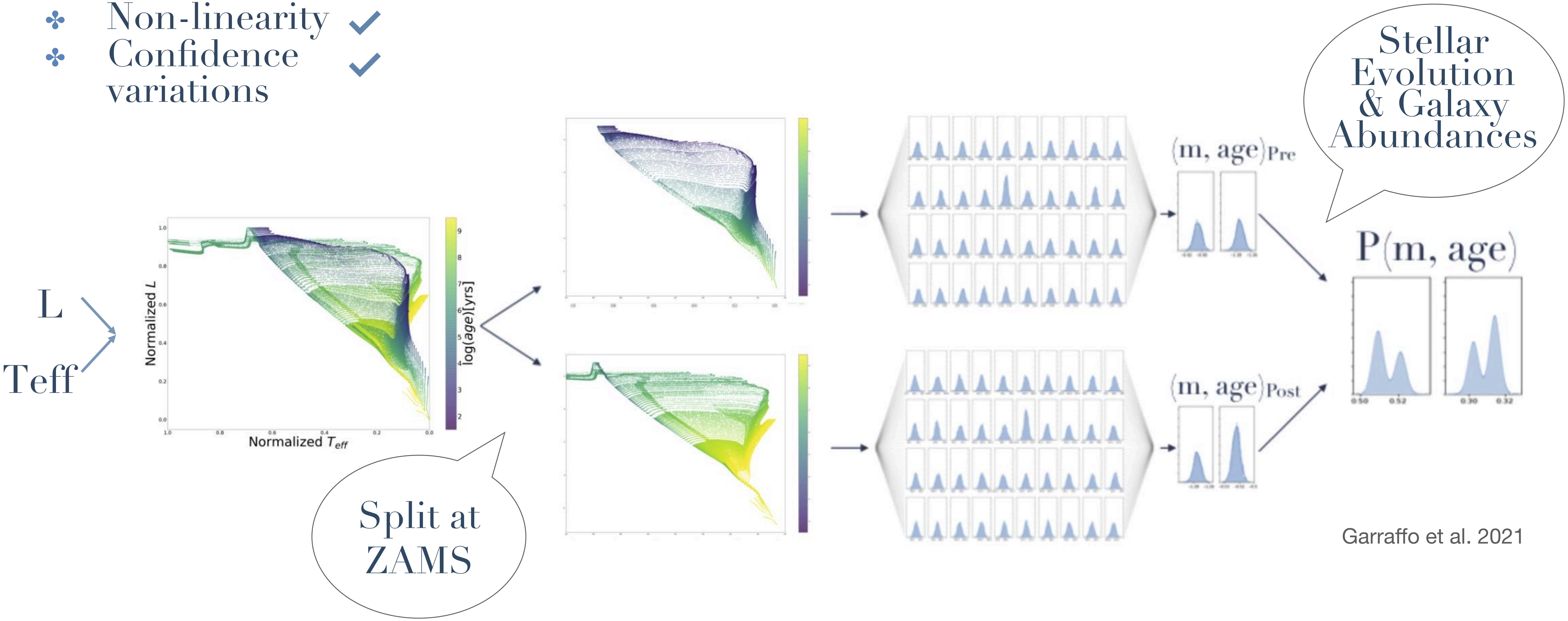
- Non-linearity
- Confidence variations



- Degeneracies
- Non-linearity
- Confidence variations



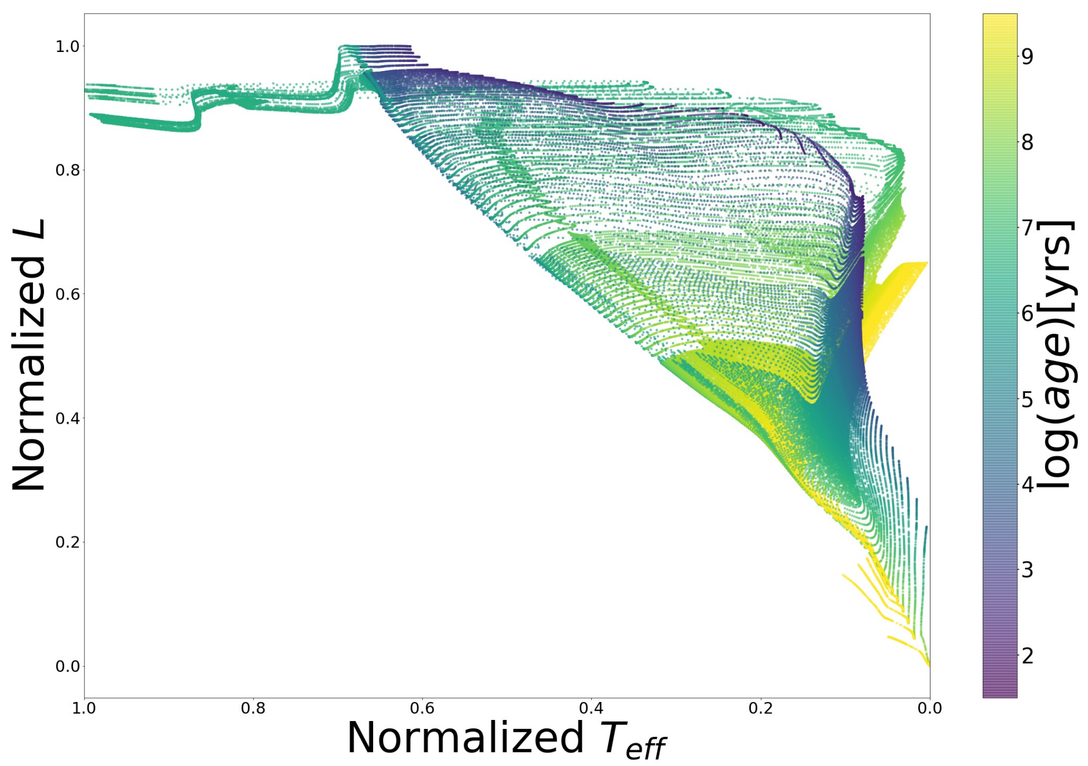
- Degeneracies ✓
- Non-linearity ✓
- Confidence variations ✓

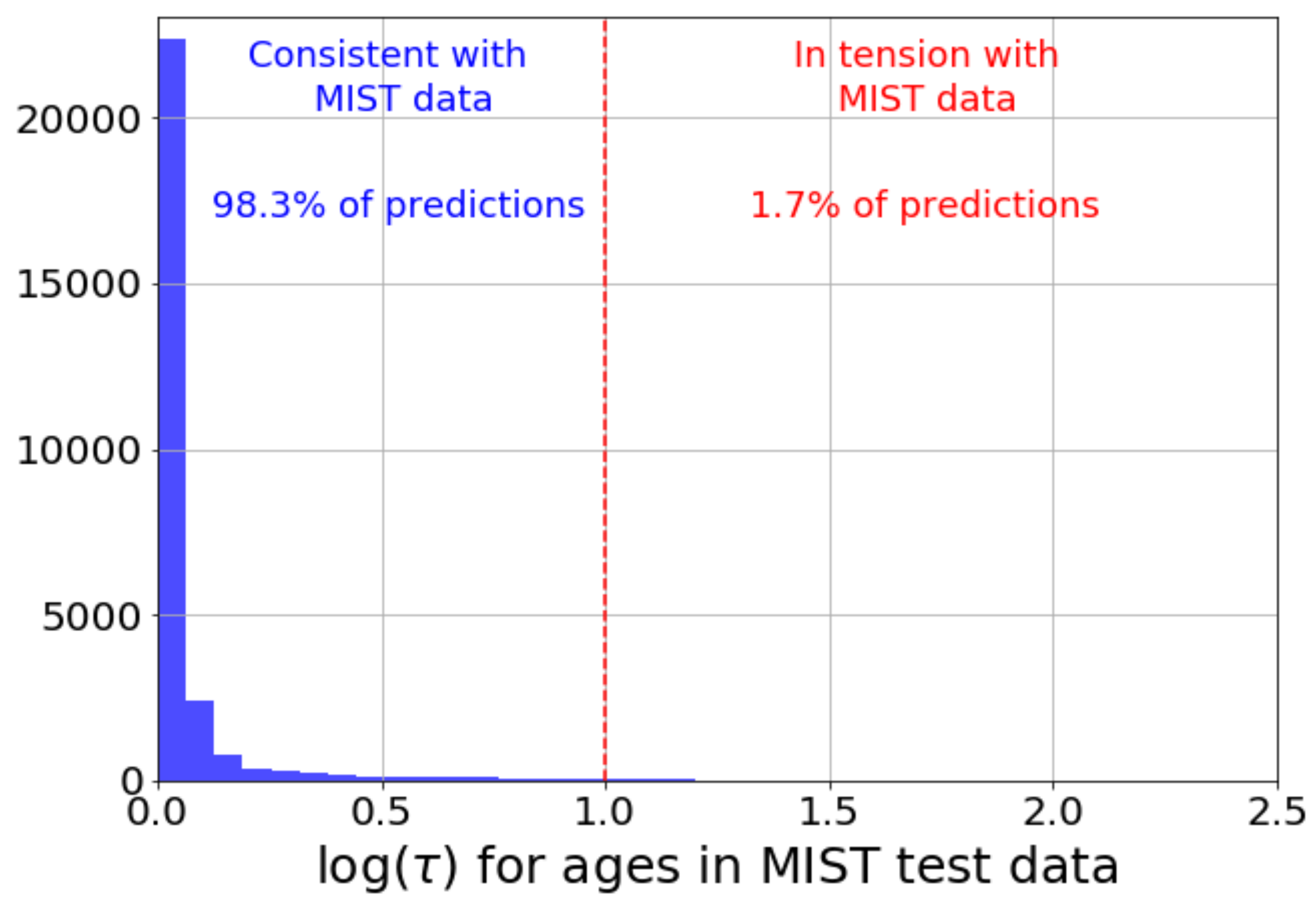


Garraffo et al. 2021

Quantifying performance on test *MIST* synthetic data and on observed data

MIST synthetic test data





Garraffo et al. 2021

Quantifying performance on test *MIST* synthetic data and on observed data

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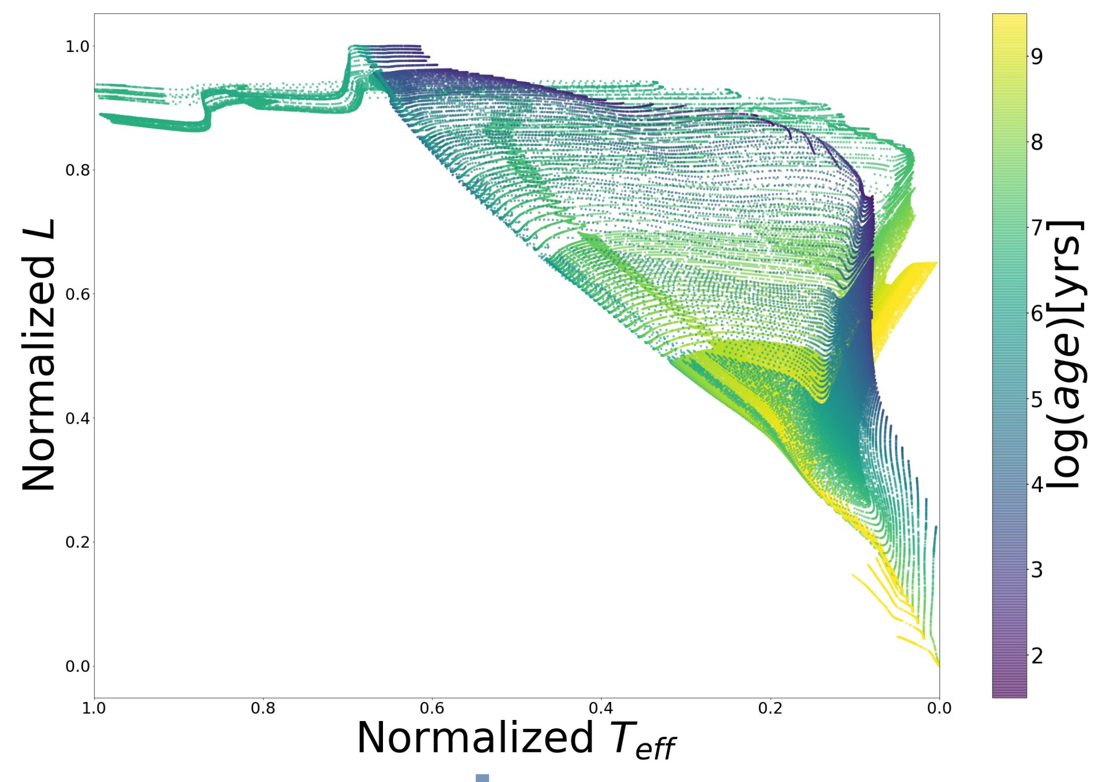
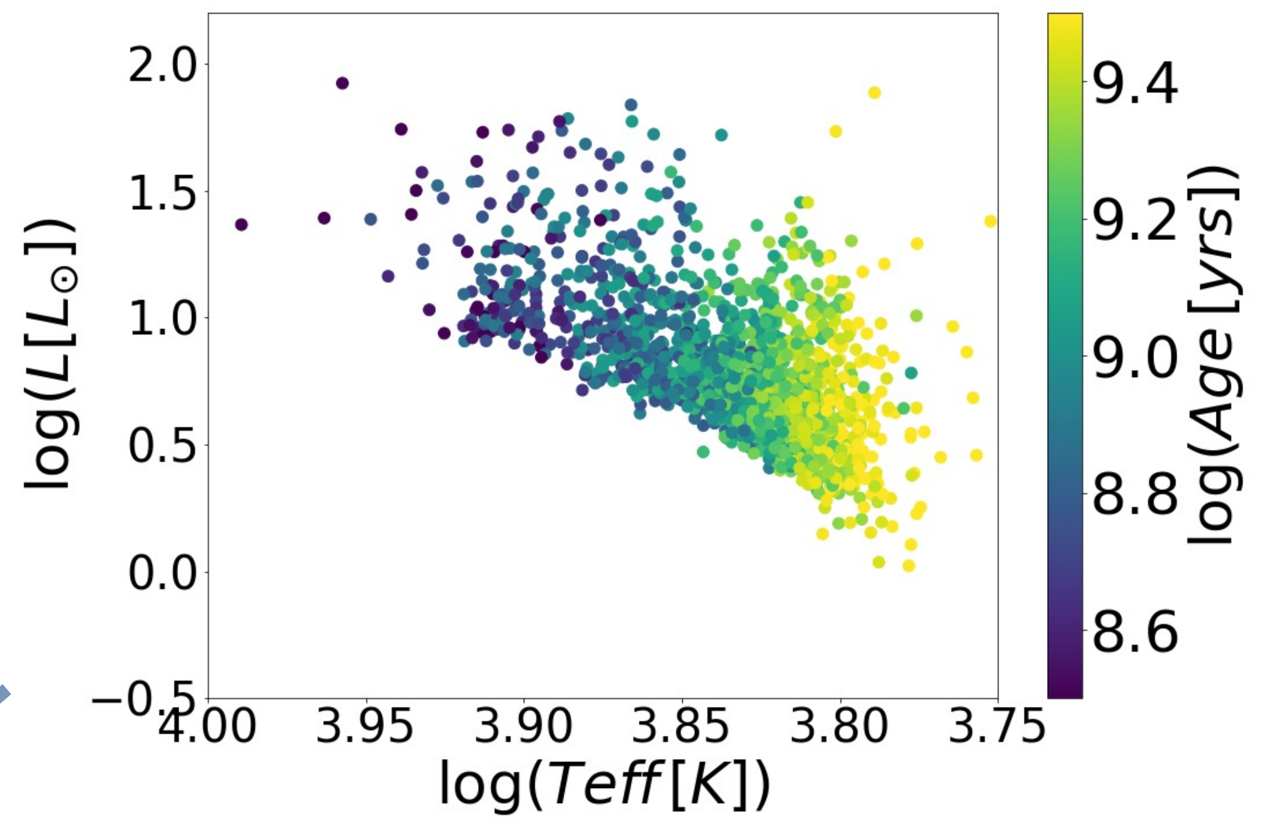
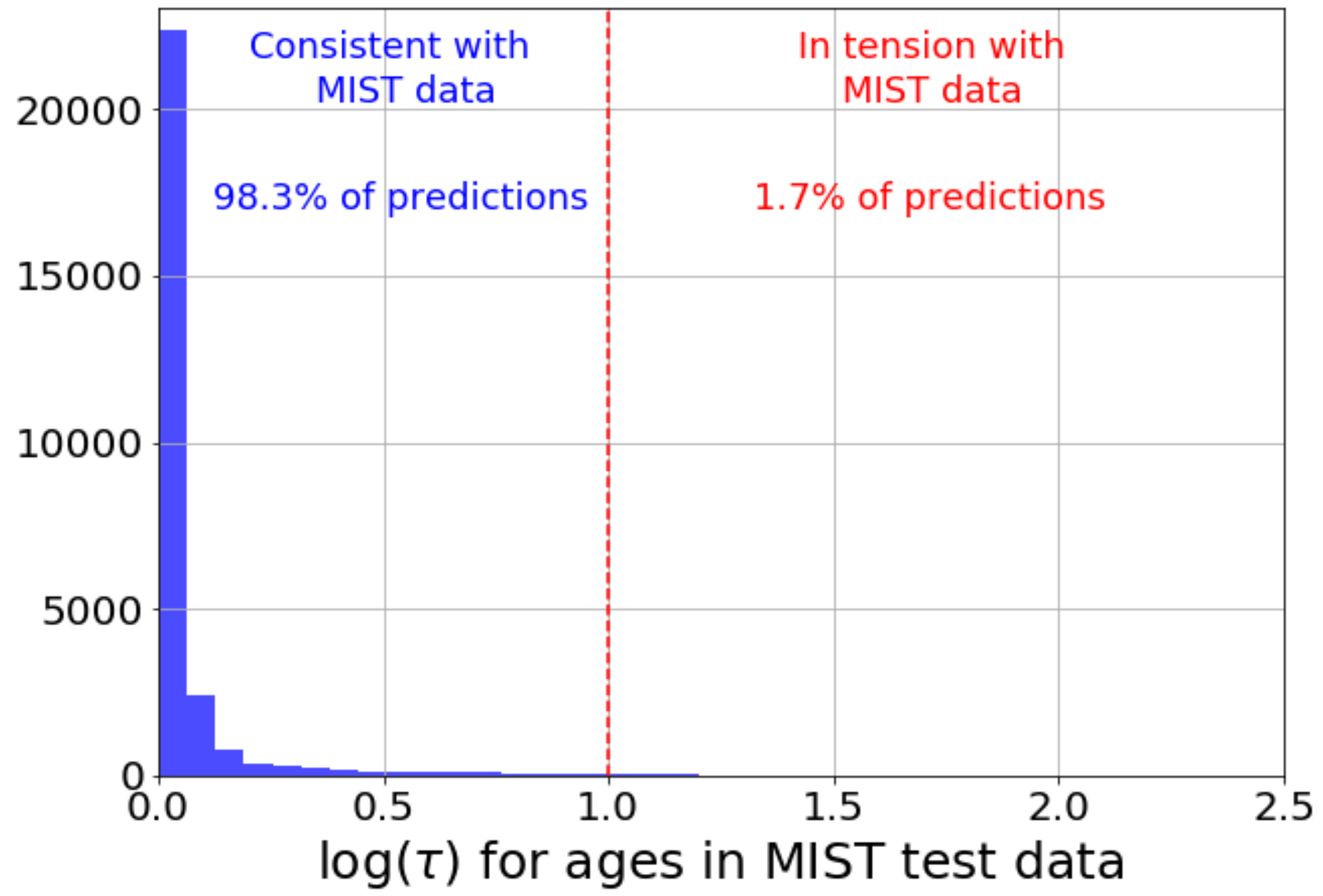
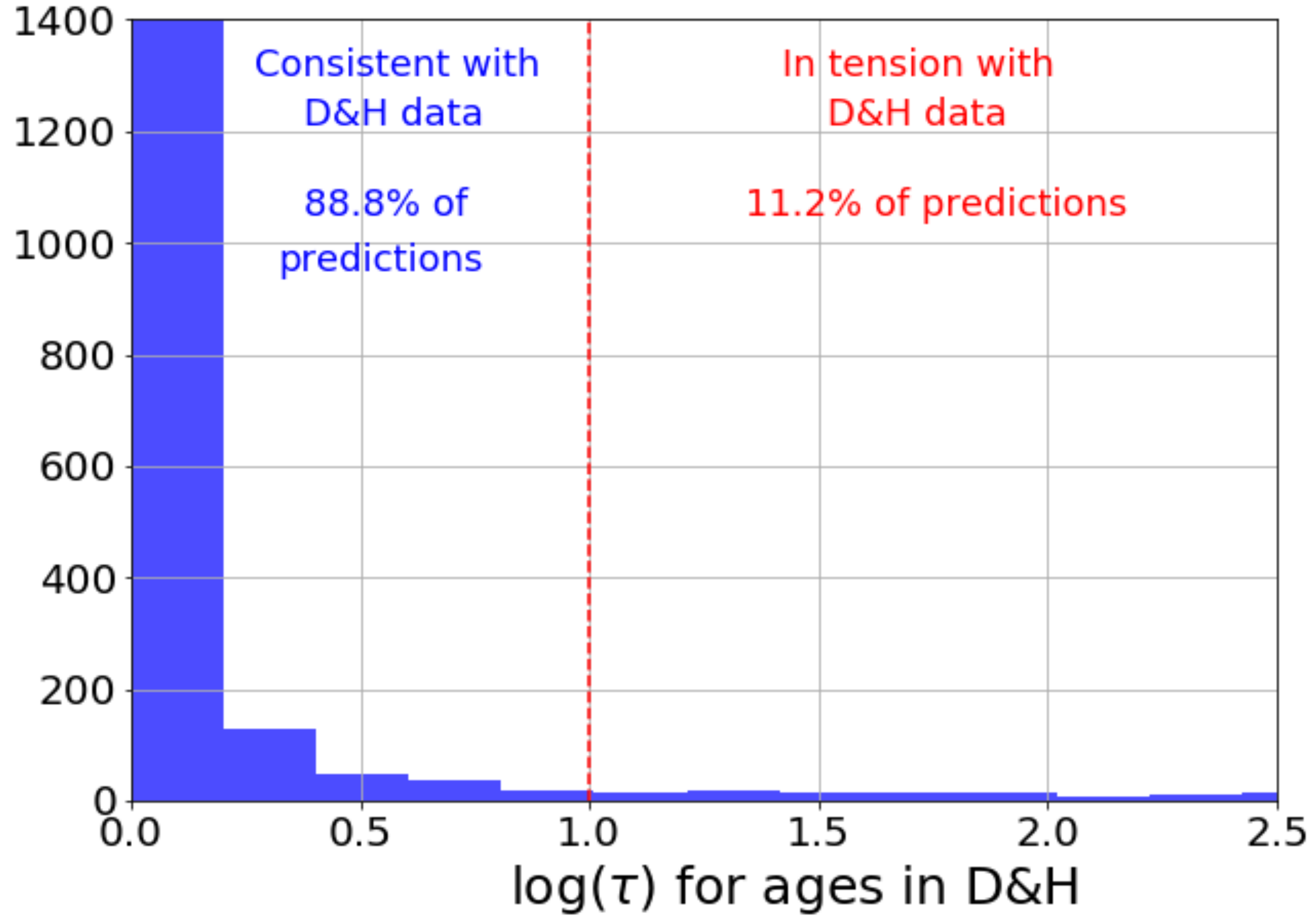


David & Hillenbrand 2015b

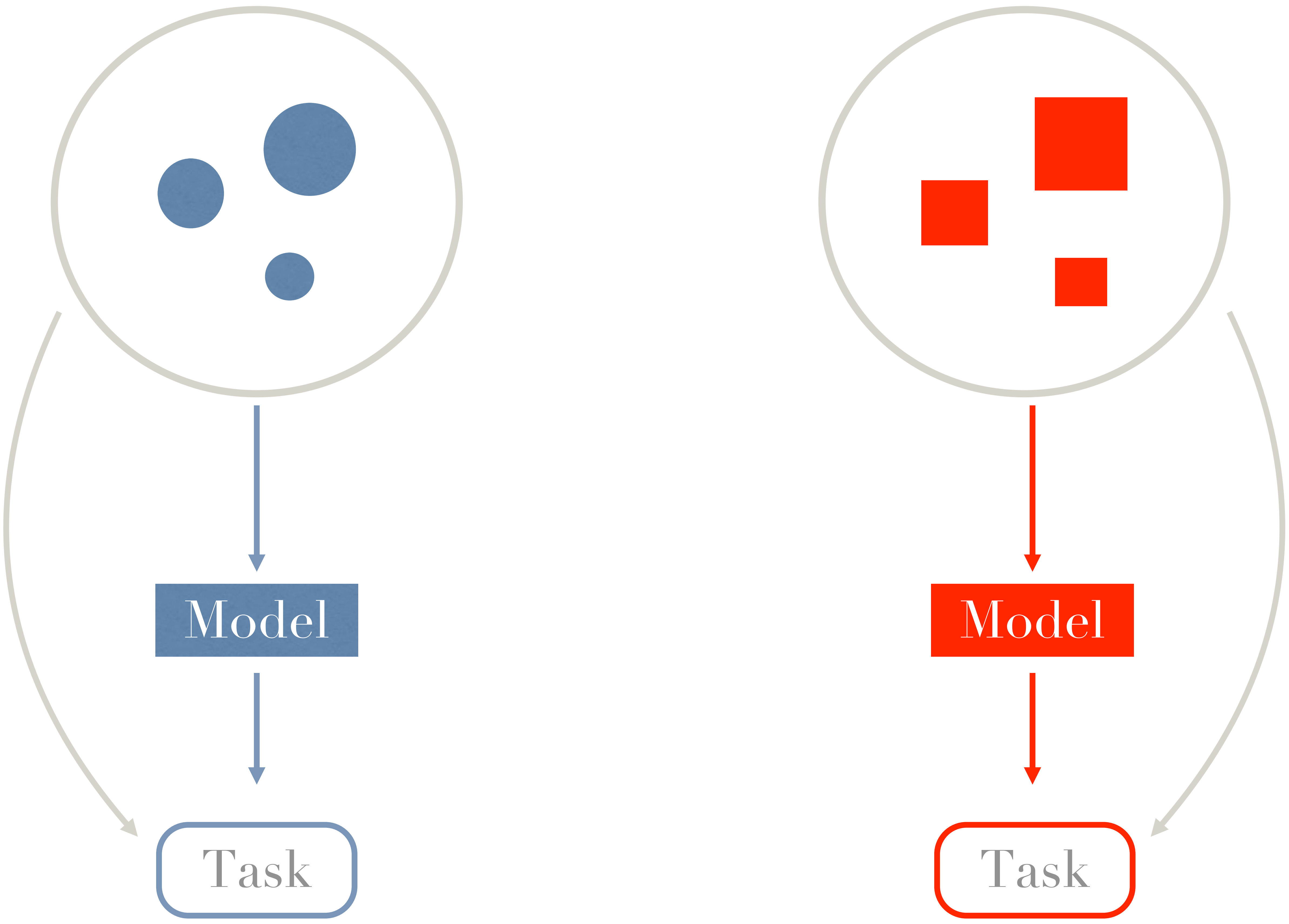




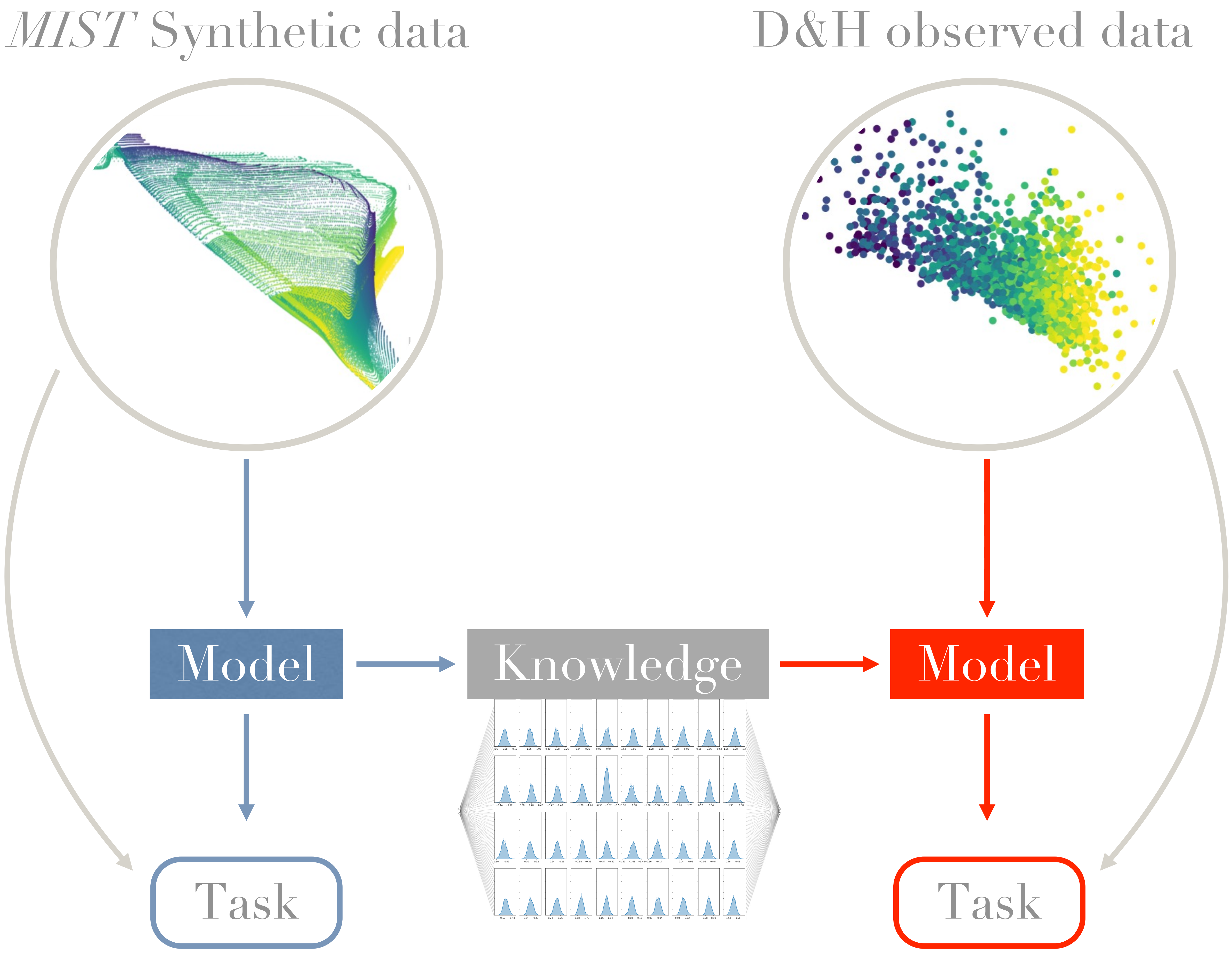


Garraffo et al. 2021

Traditional Machine Learning

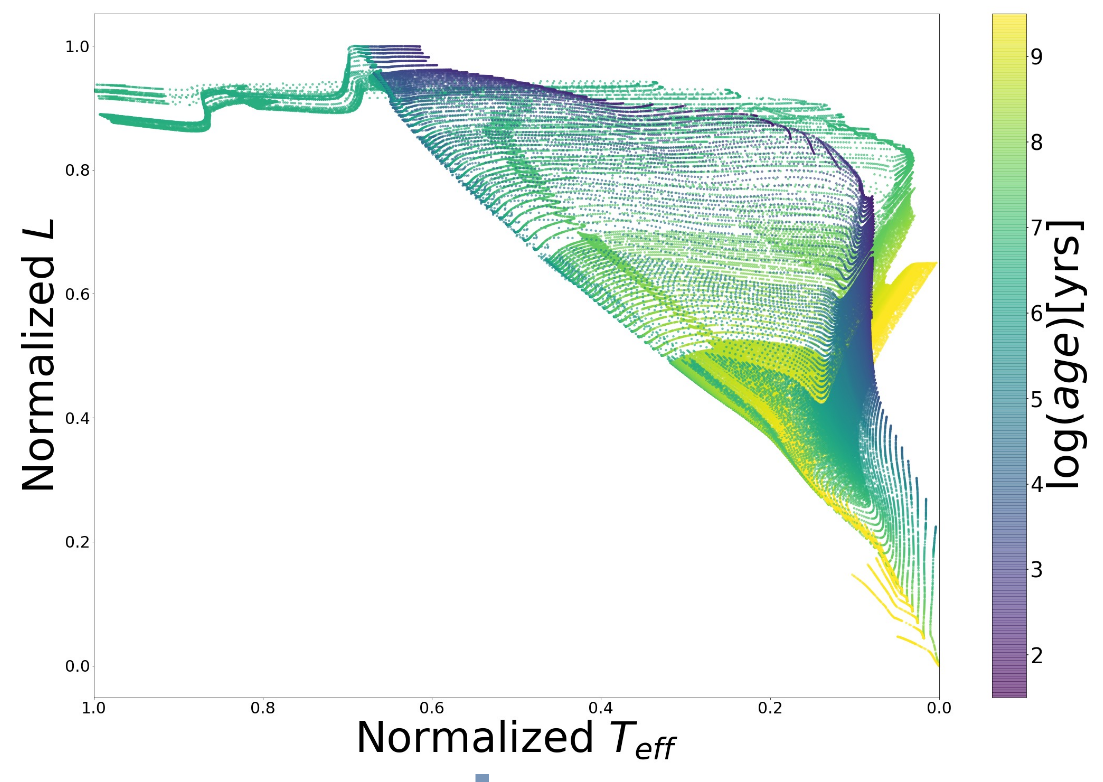


Transfer Learning

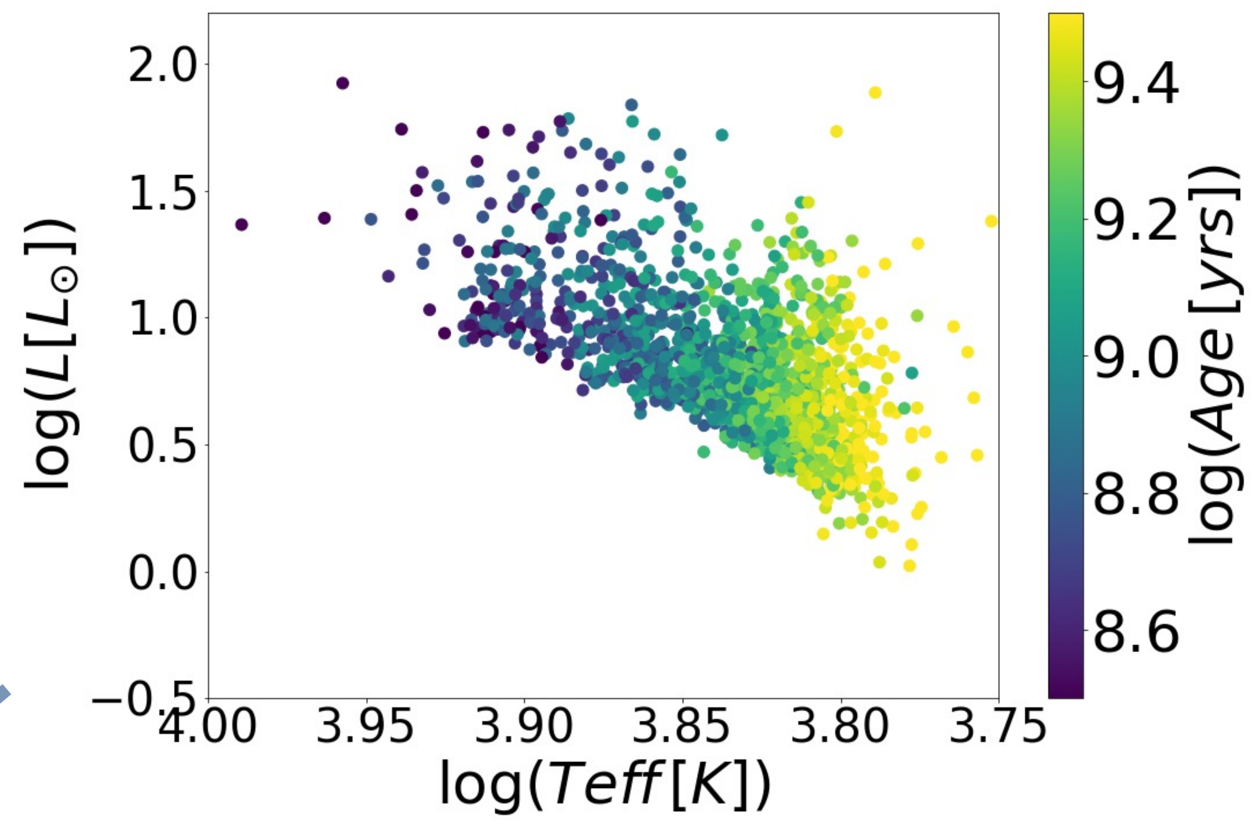


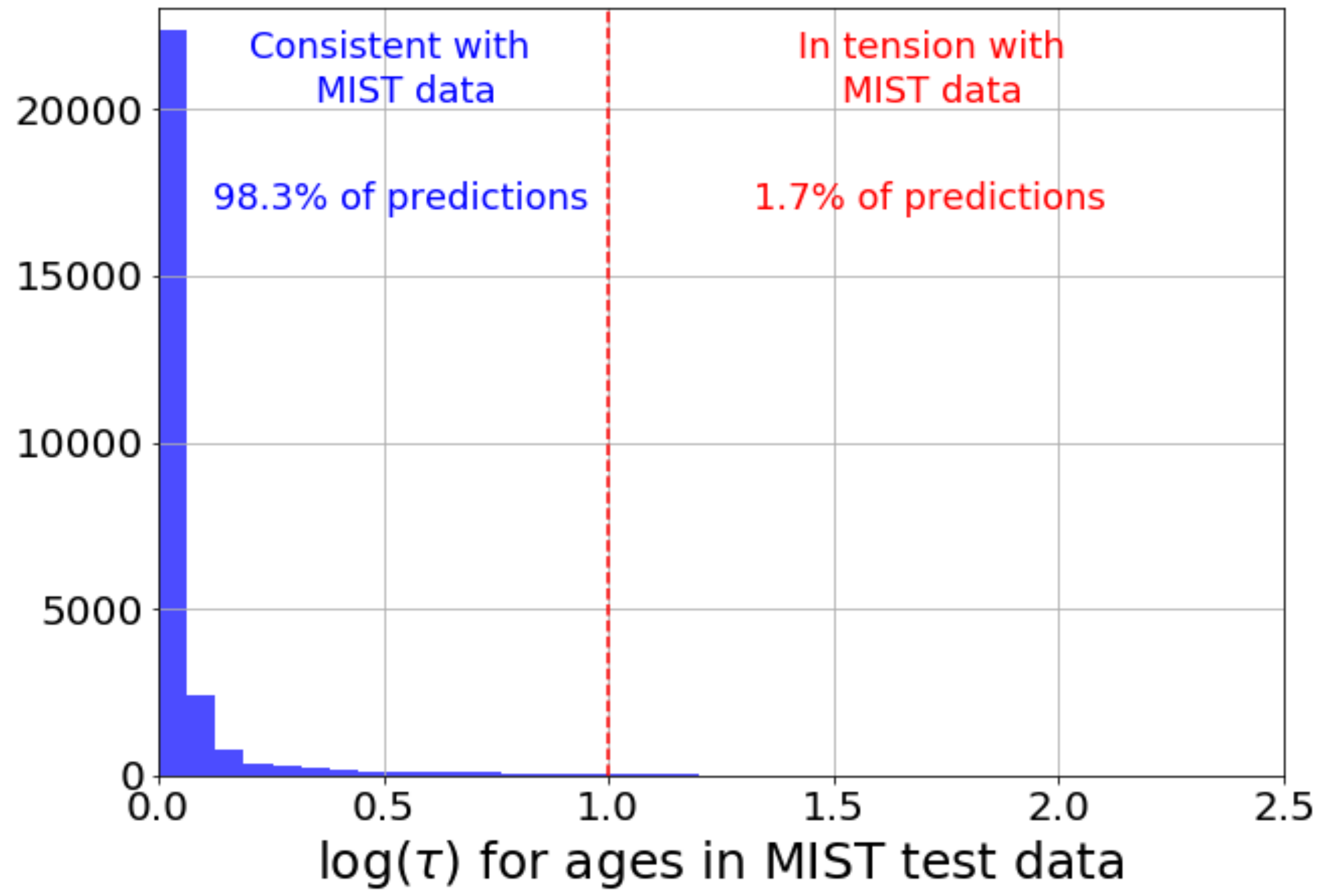
Quantifying performance on test *MIST* synthetic data and on observed data

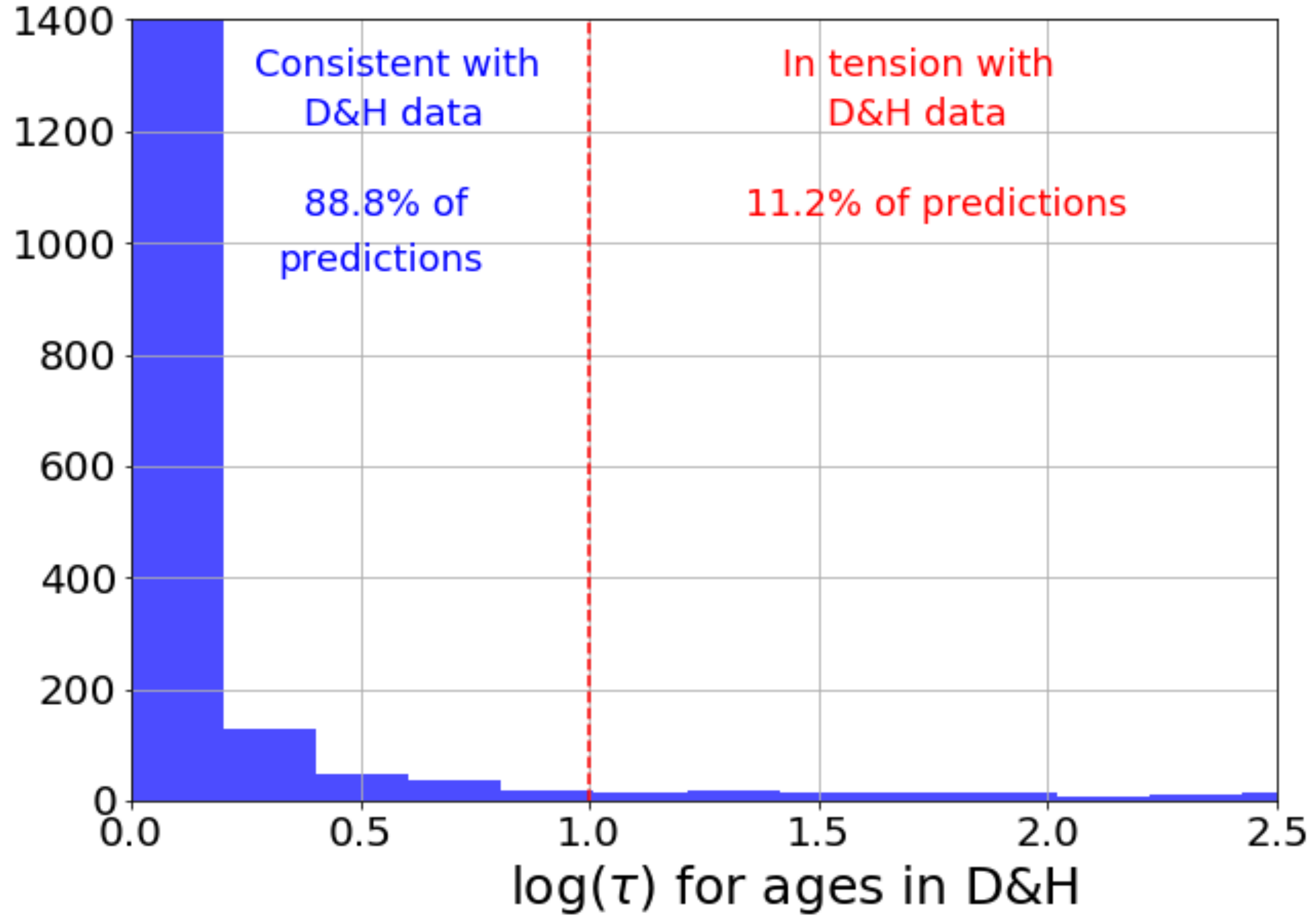
MIST synthetic test data



David & Hillenbrand 2015b



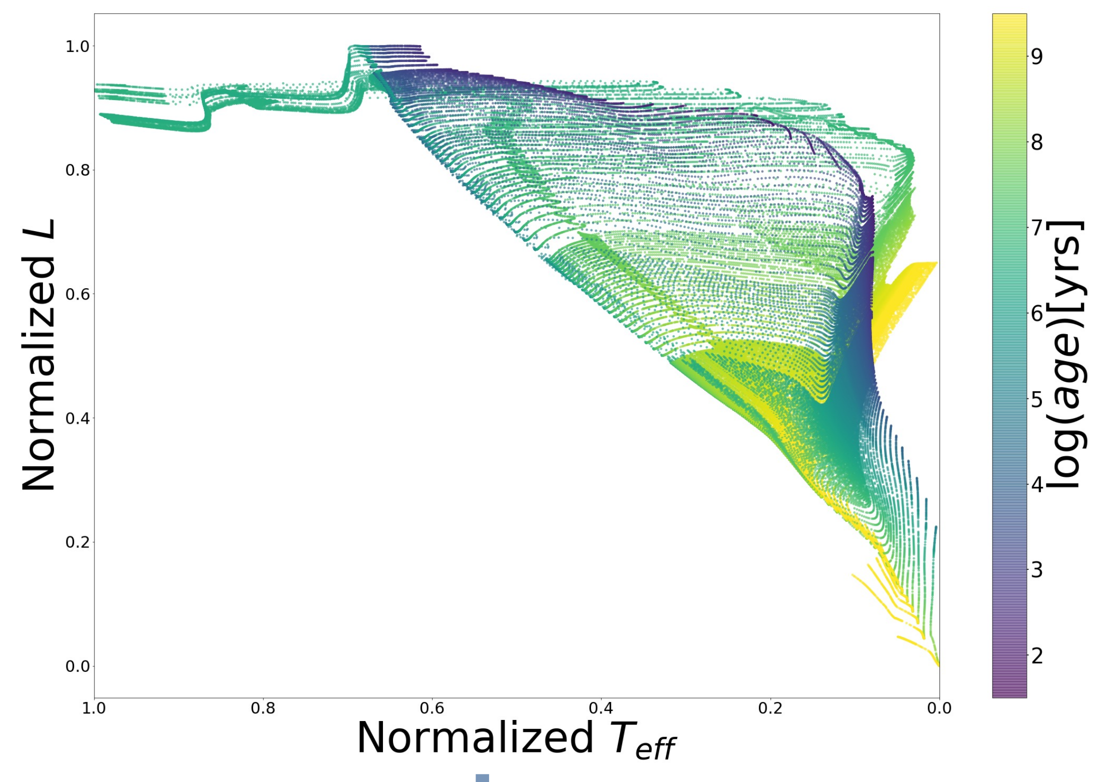




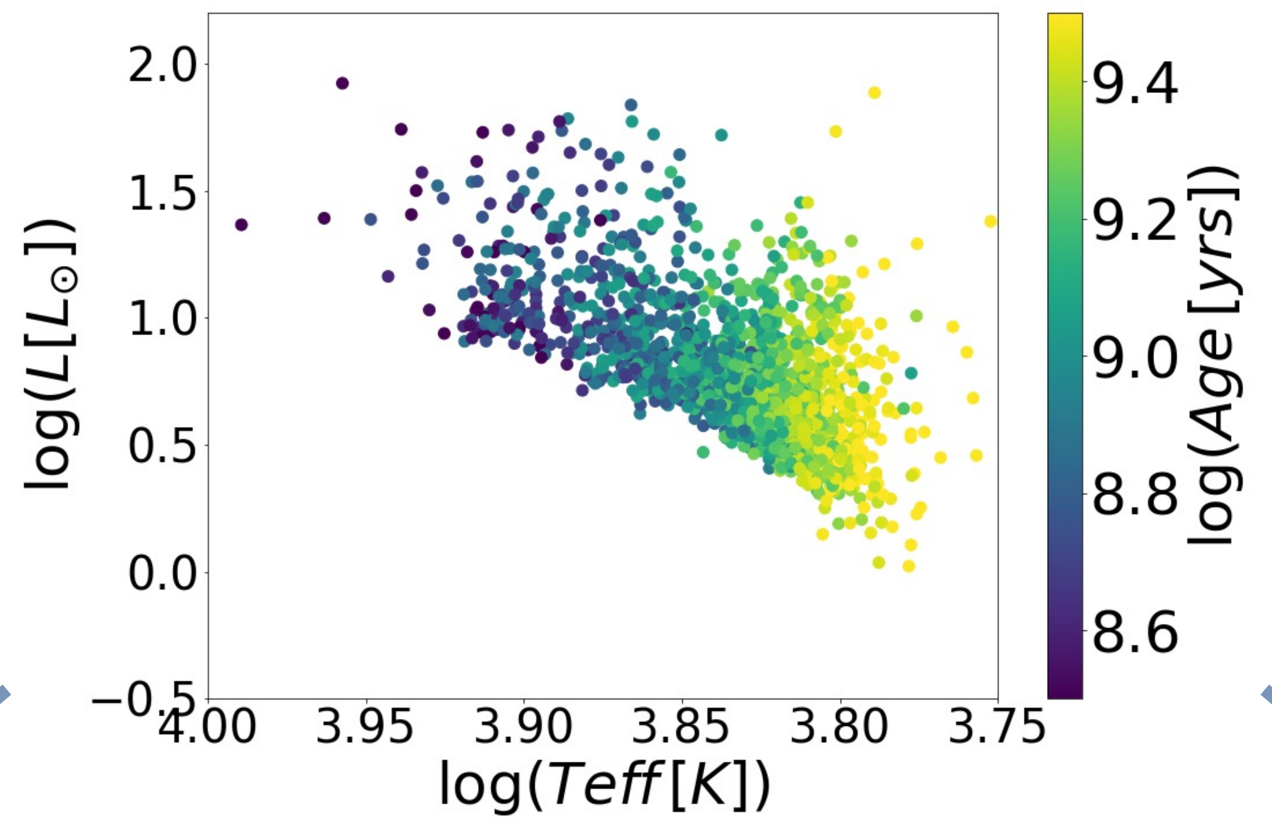
Garraffo et al. 2021

Quantifying performance on test *MIST* synthetic data and on observed data

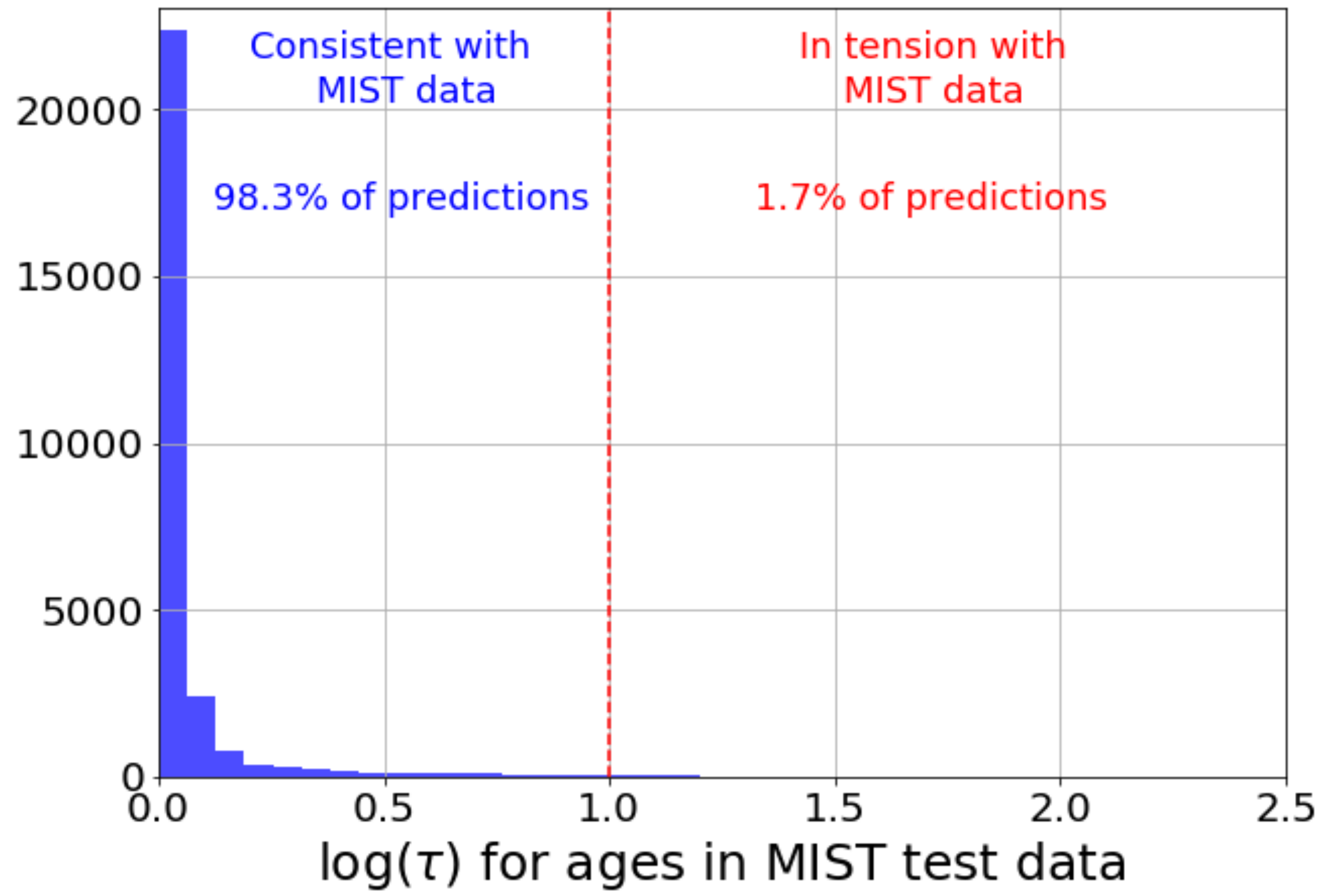
MIST synthetic test data

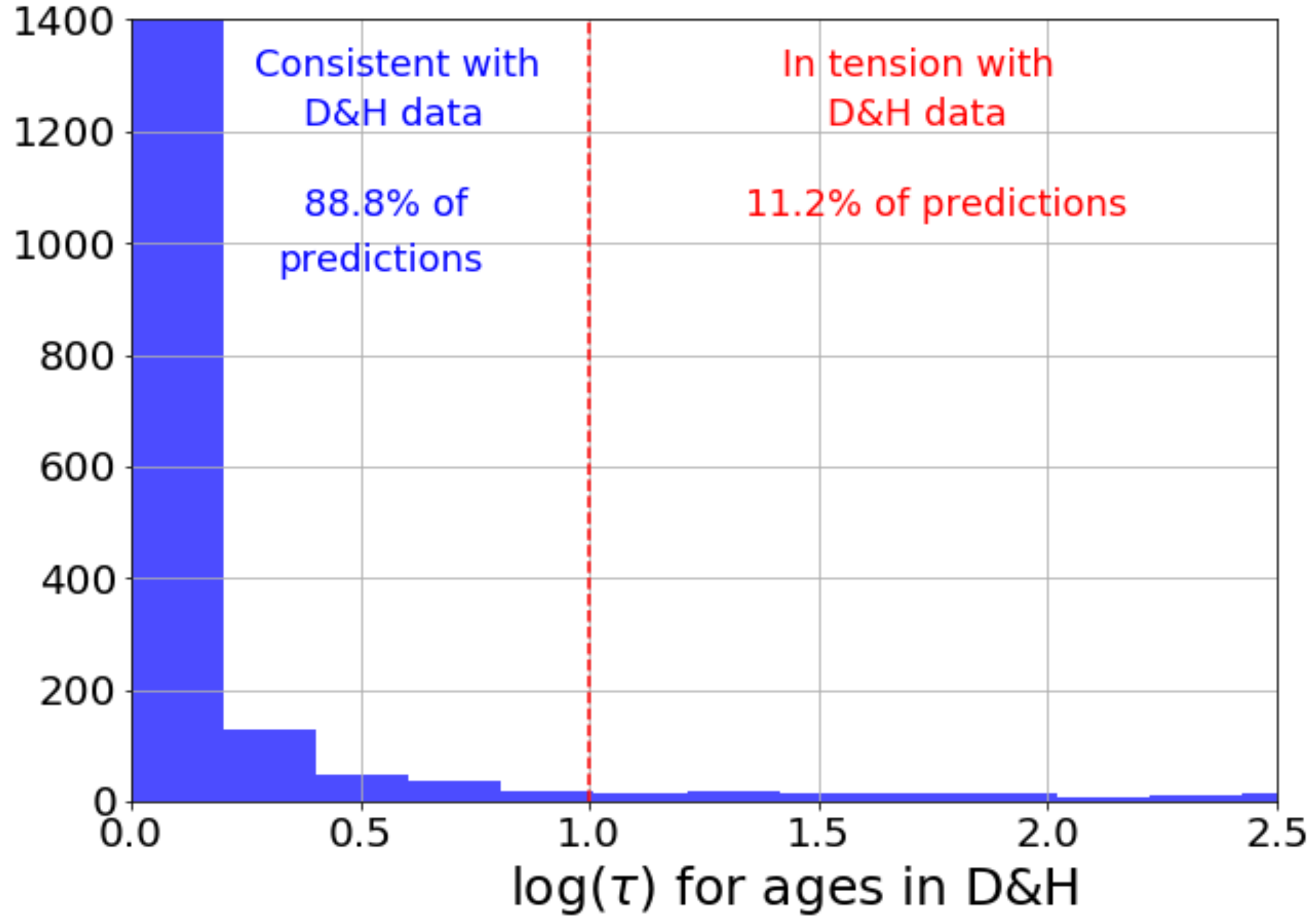


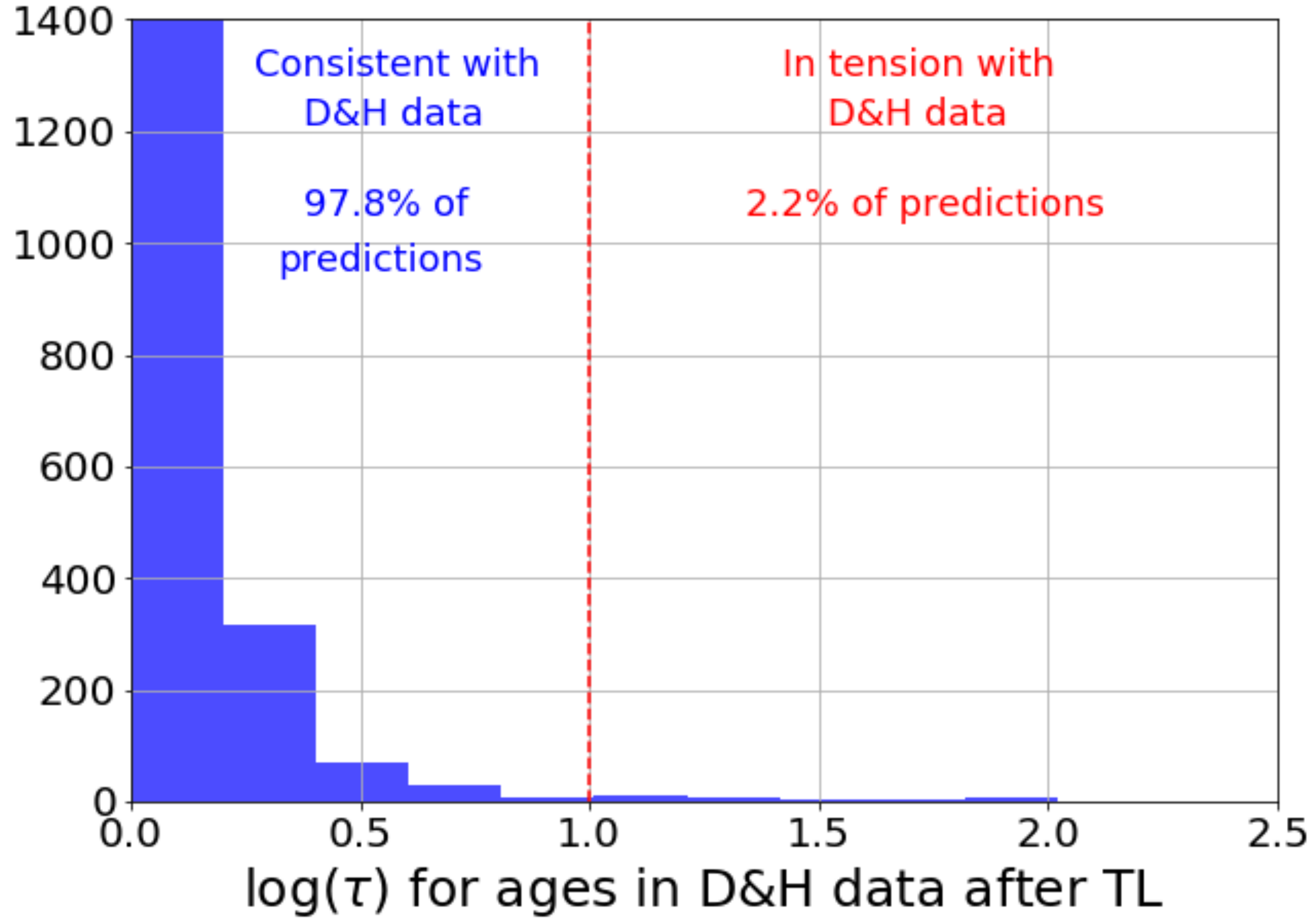
David & Hillenbrand 2015b



Using Transfer Learning







Garraffo et al. 2021

AstroAI

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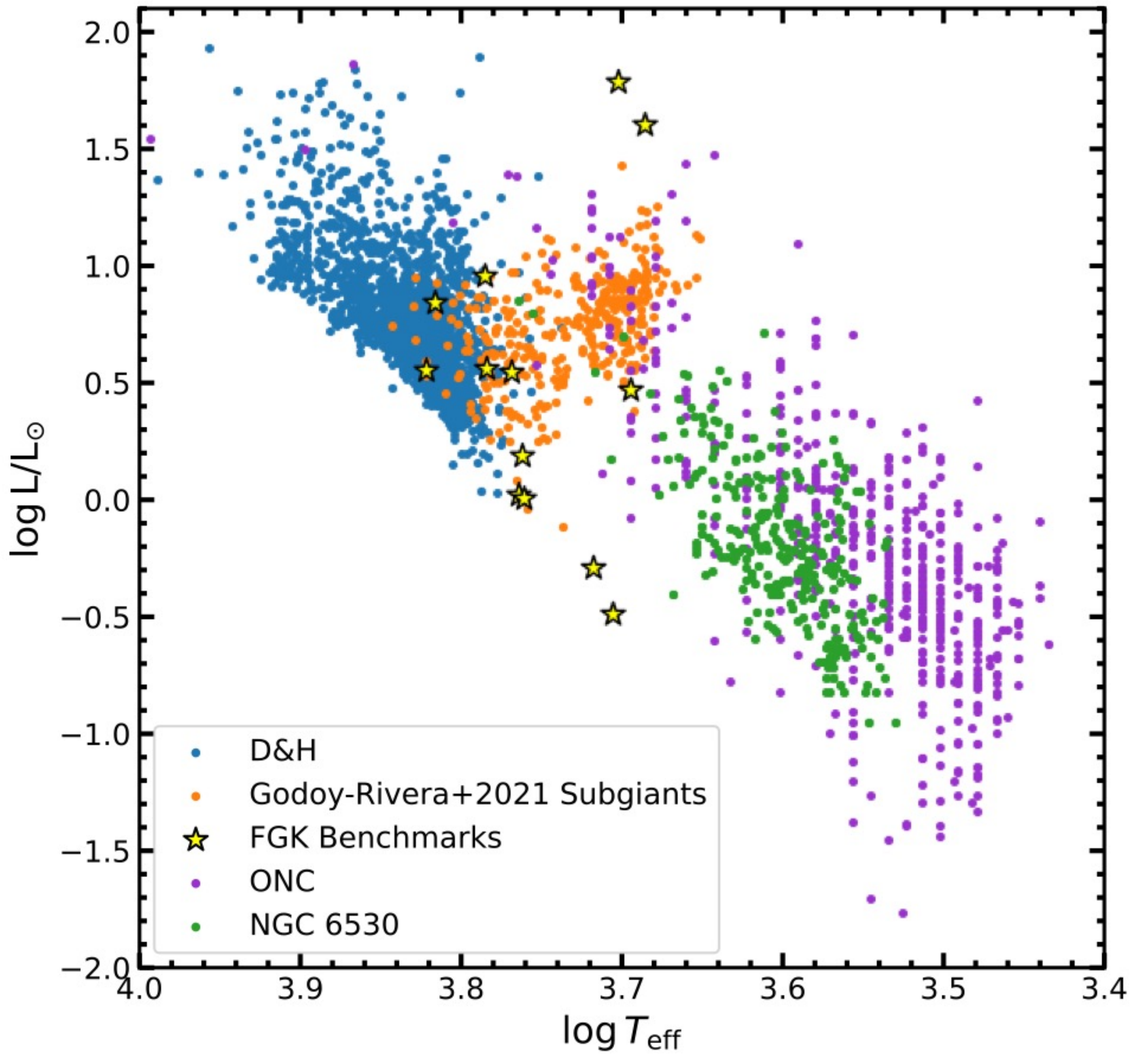
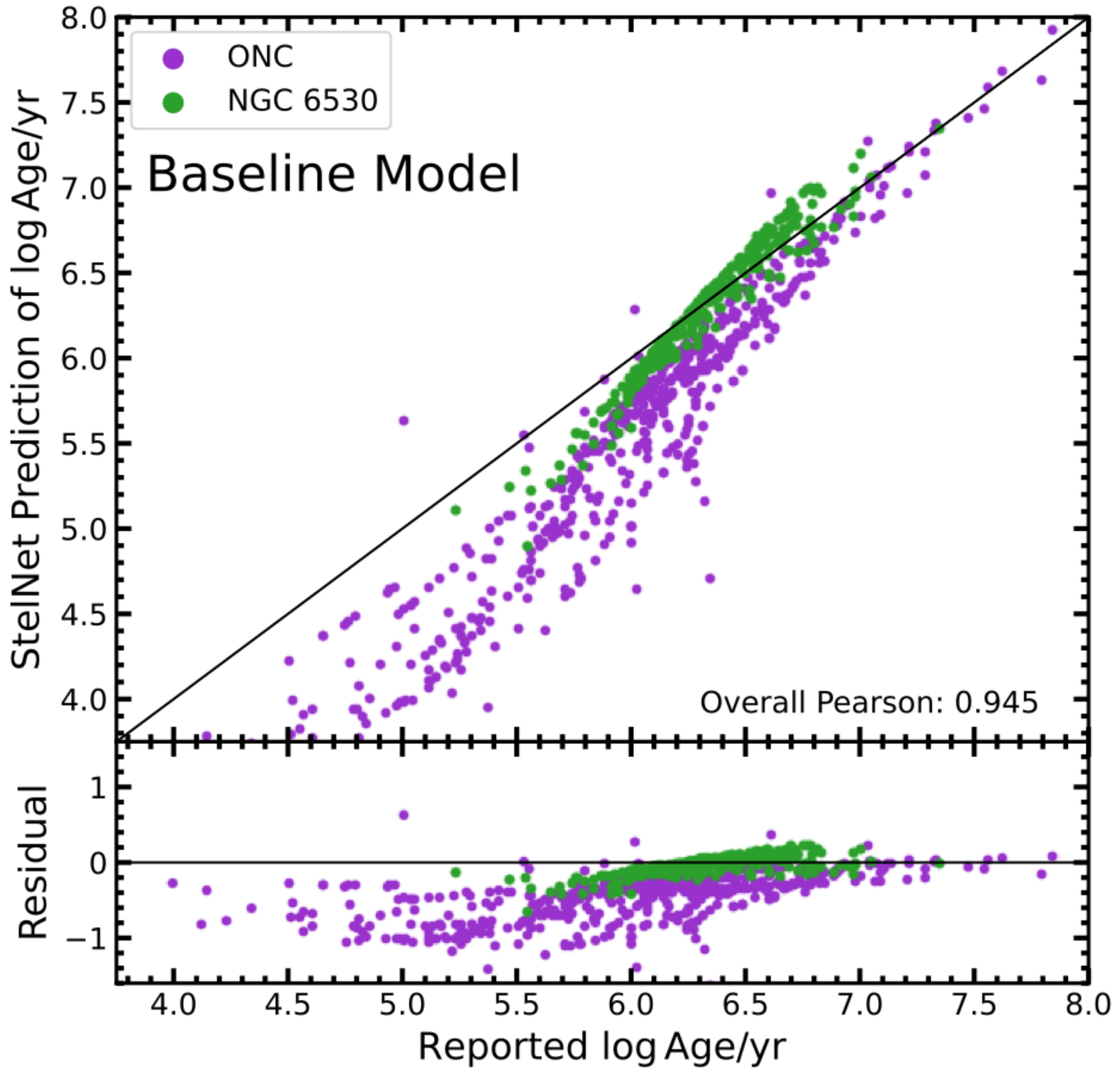
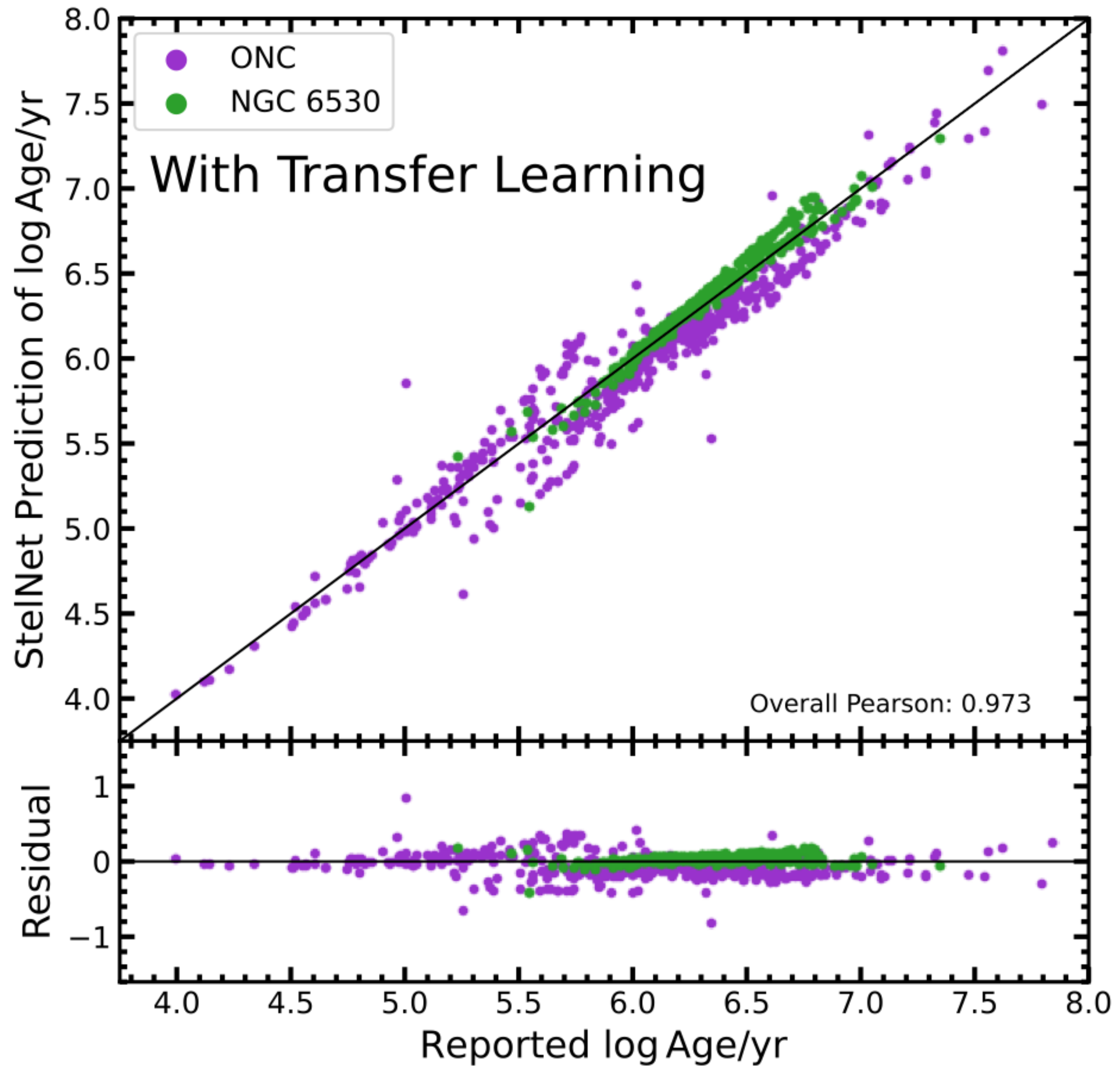
Anya Phillips

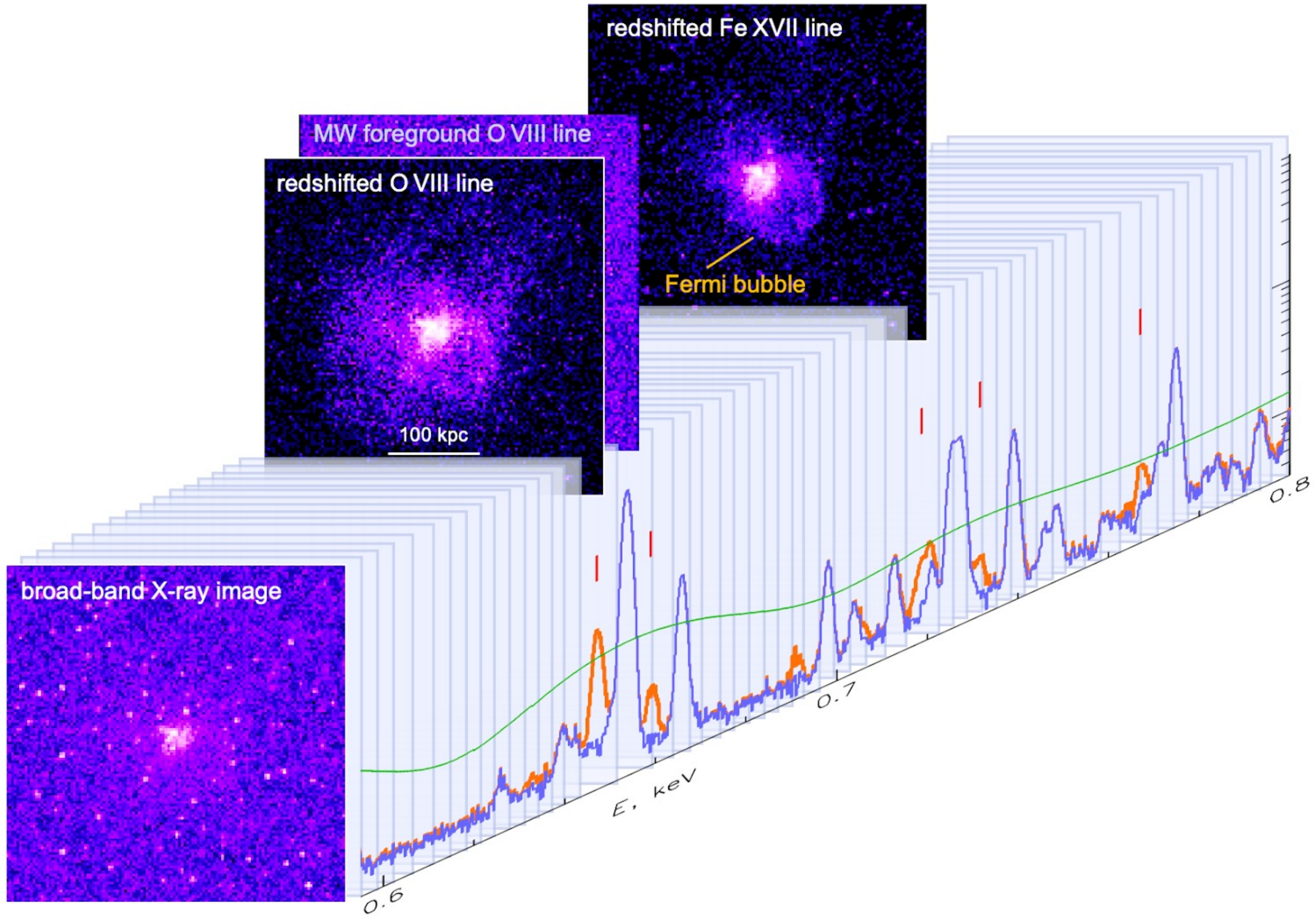






Phillips et al. in prep

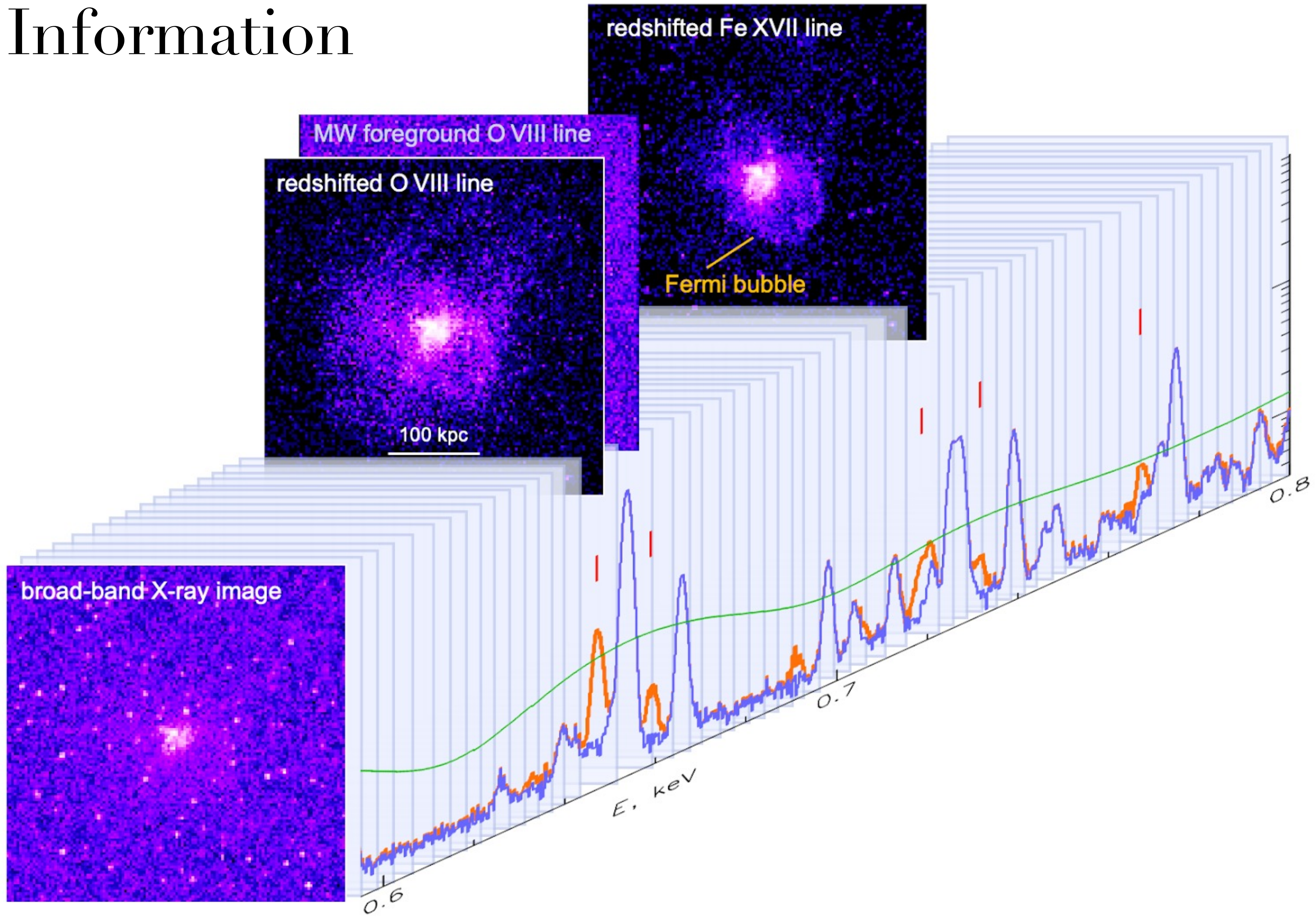
Domain Adaptation


redshifted Fe XVII line
MW foreground O VIII line
redshifted O VIII line
Fermi bubble
100 kpc
broad-band X-ray image
E, keV
0.6
0.7
0.8

Remote Sensing for Climate Science

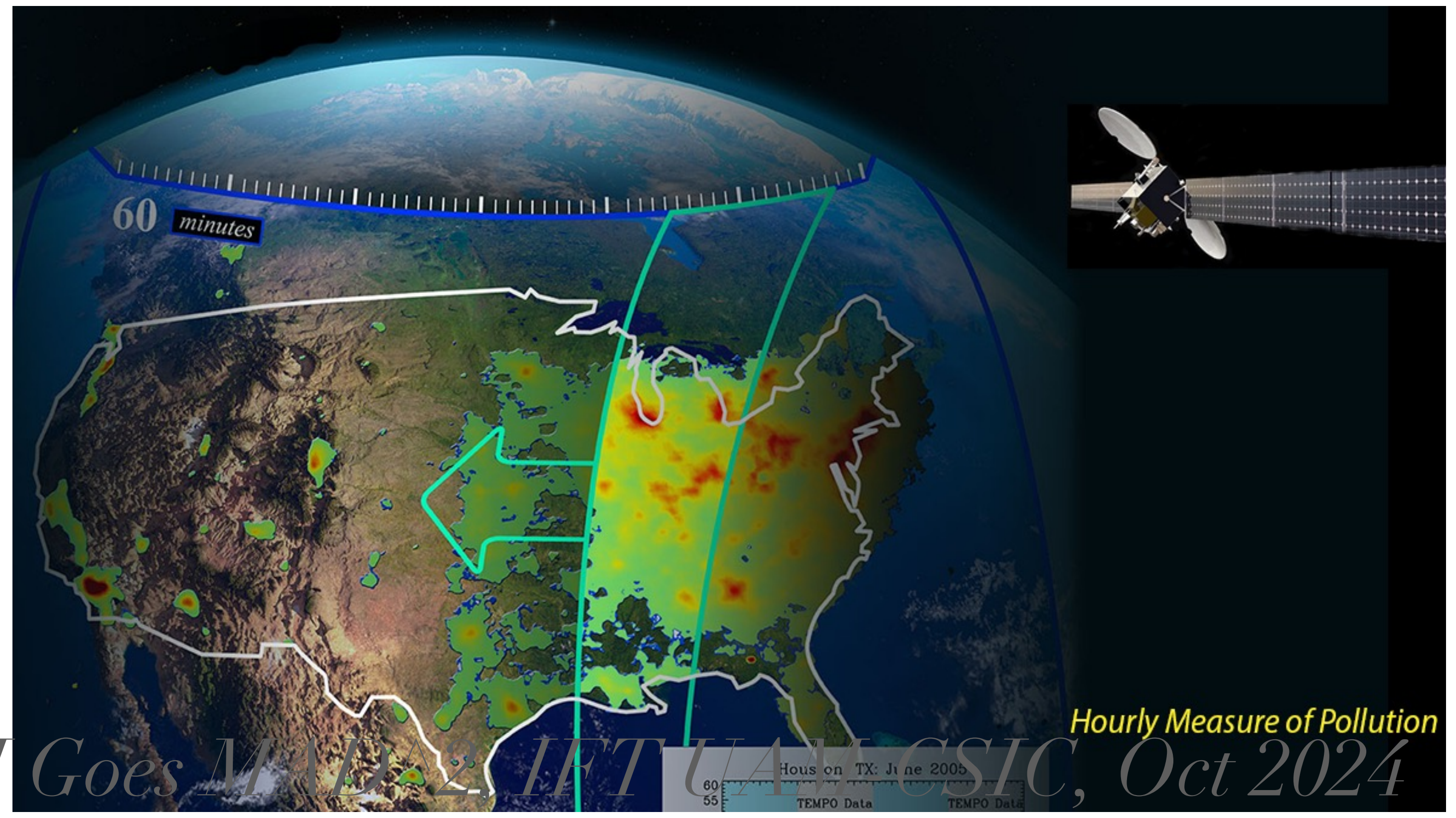
Same data and task:

- Hyperspectral Data
- Extract Physical Information



MethaneSAT

TEMPO



EarthAI
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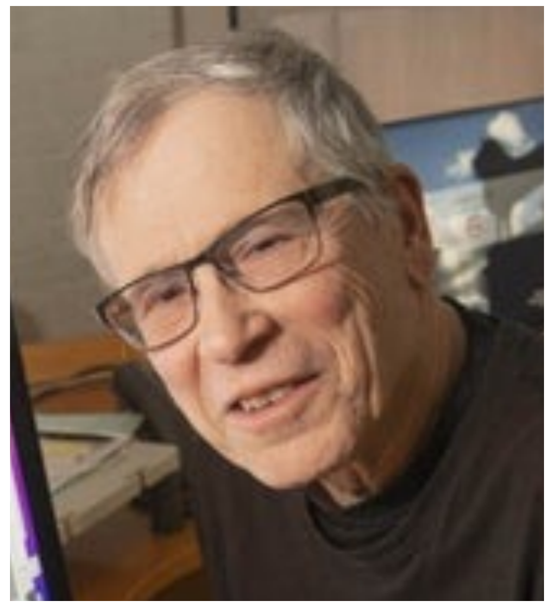
Our Partners

MethaneSAT

Maya Nasr

EAI’s MethaneSAT Lead

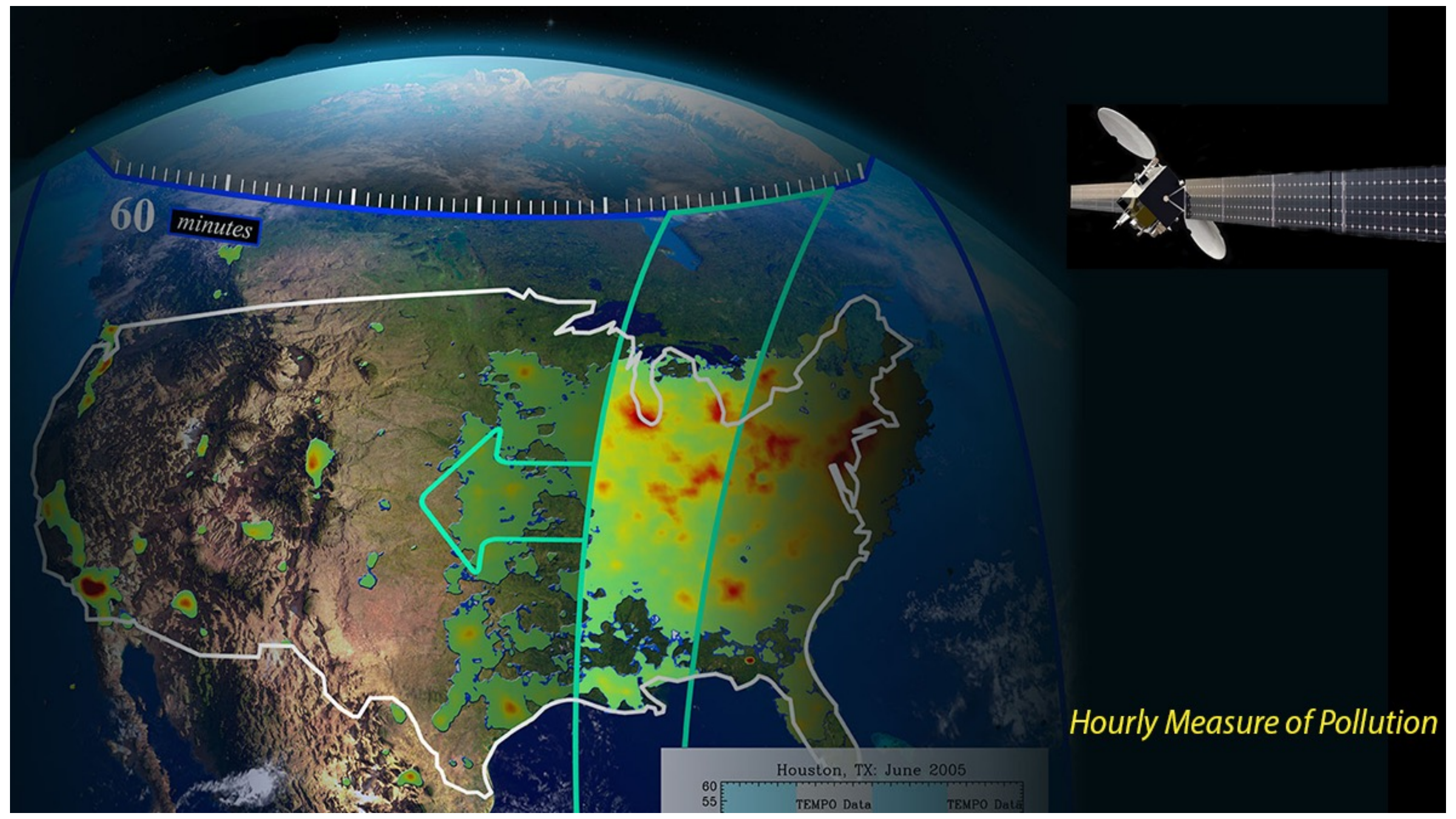


Steven Wofsy

Data Processing PI

Eleanor Walker

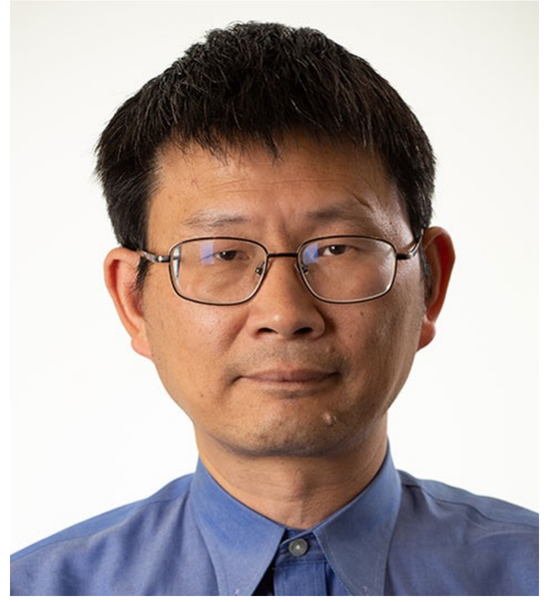
Postdoctoral Fellow



TEMPO

Caroline Nowlan

EAI’s TEMPO Lead



Xiong Liu

TEMPO’s Deputy PI

Gonzalo Gonzalez

Scientist

Thank you!

EARTHAI

Enabling a Sustainable Future

The Team

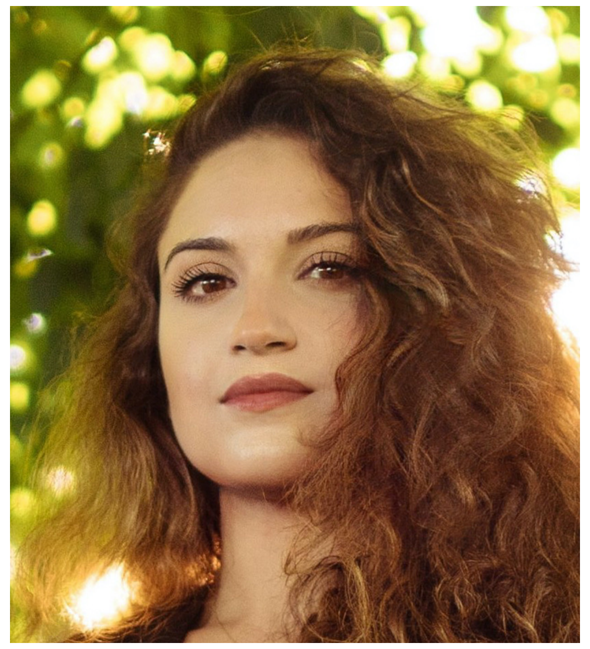
Cecilia Garraffo
Director

Douglas Finkbeiner
Project Scientist

Core Park
PhD Student

Manuel Perez Carrasco
Software Lead

Caroline Nowlan
TEMPO Lead



Maya Nasr
MethaneSAT Lead

EarthAI

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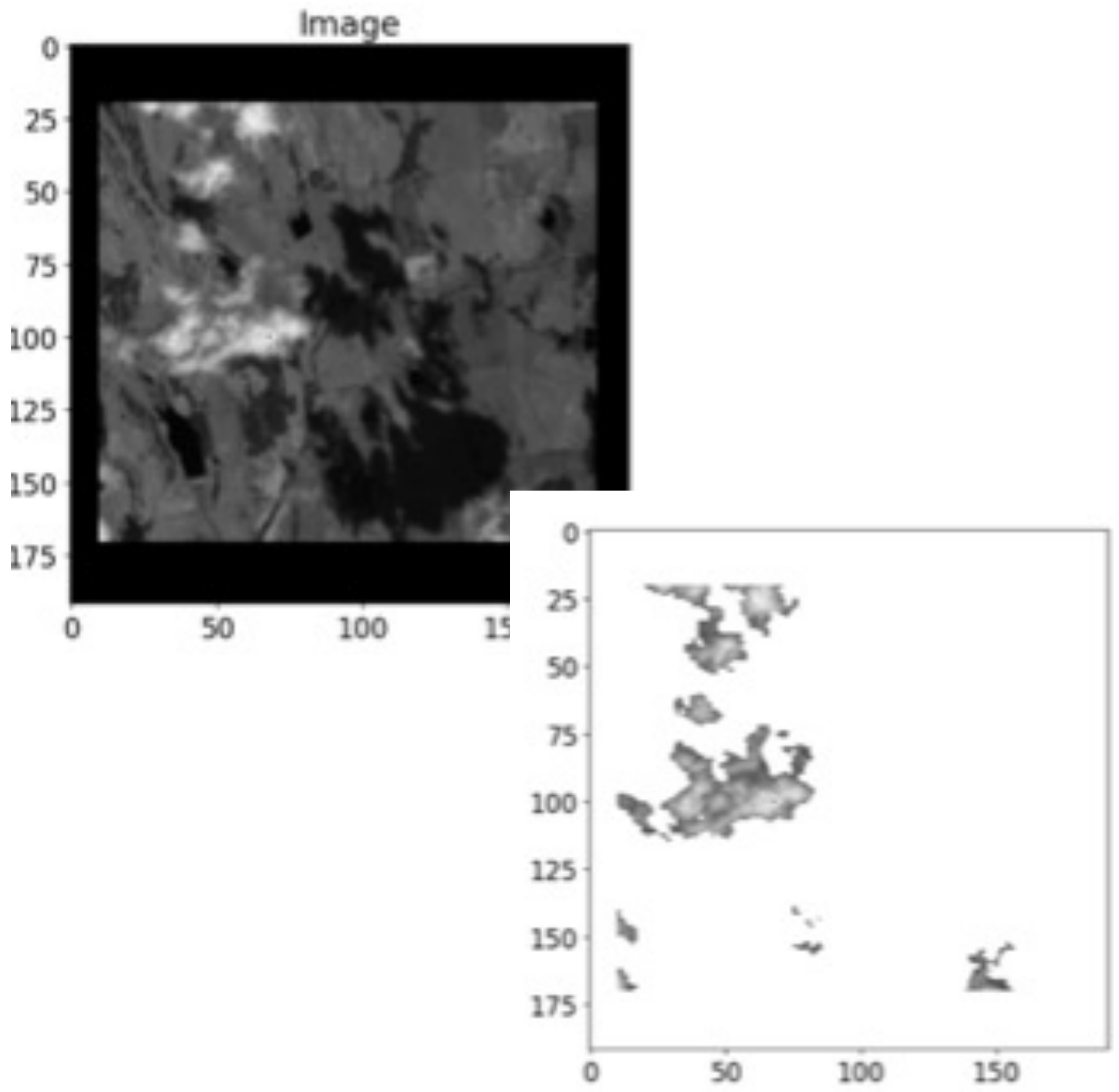
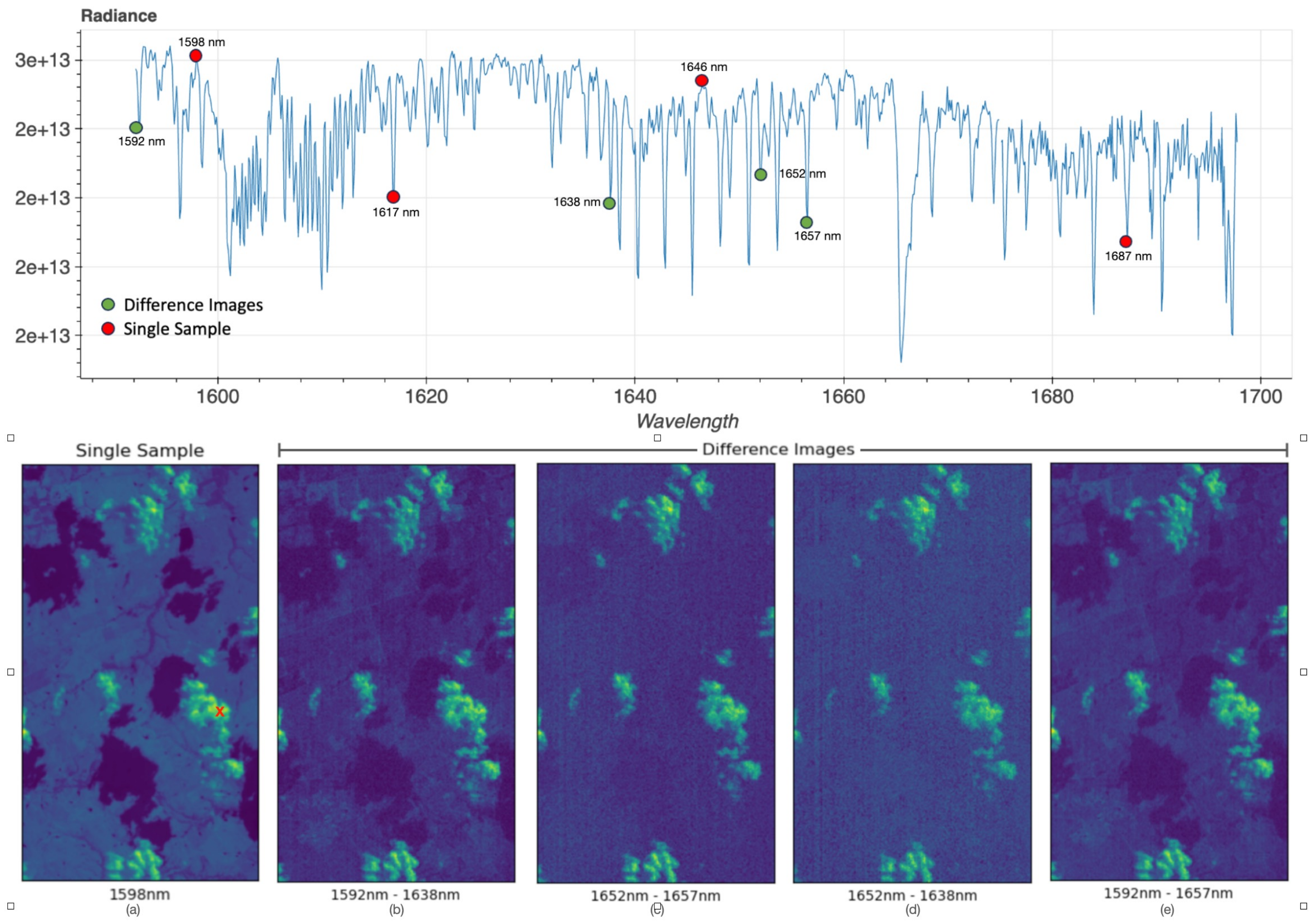
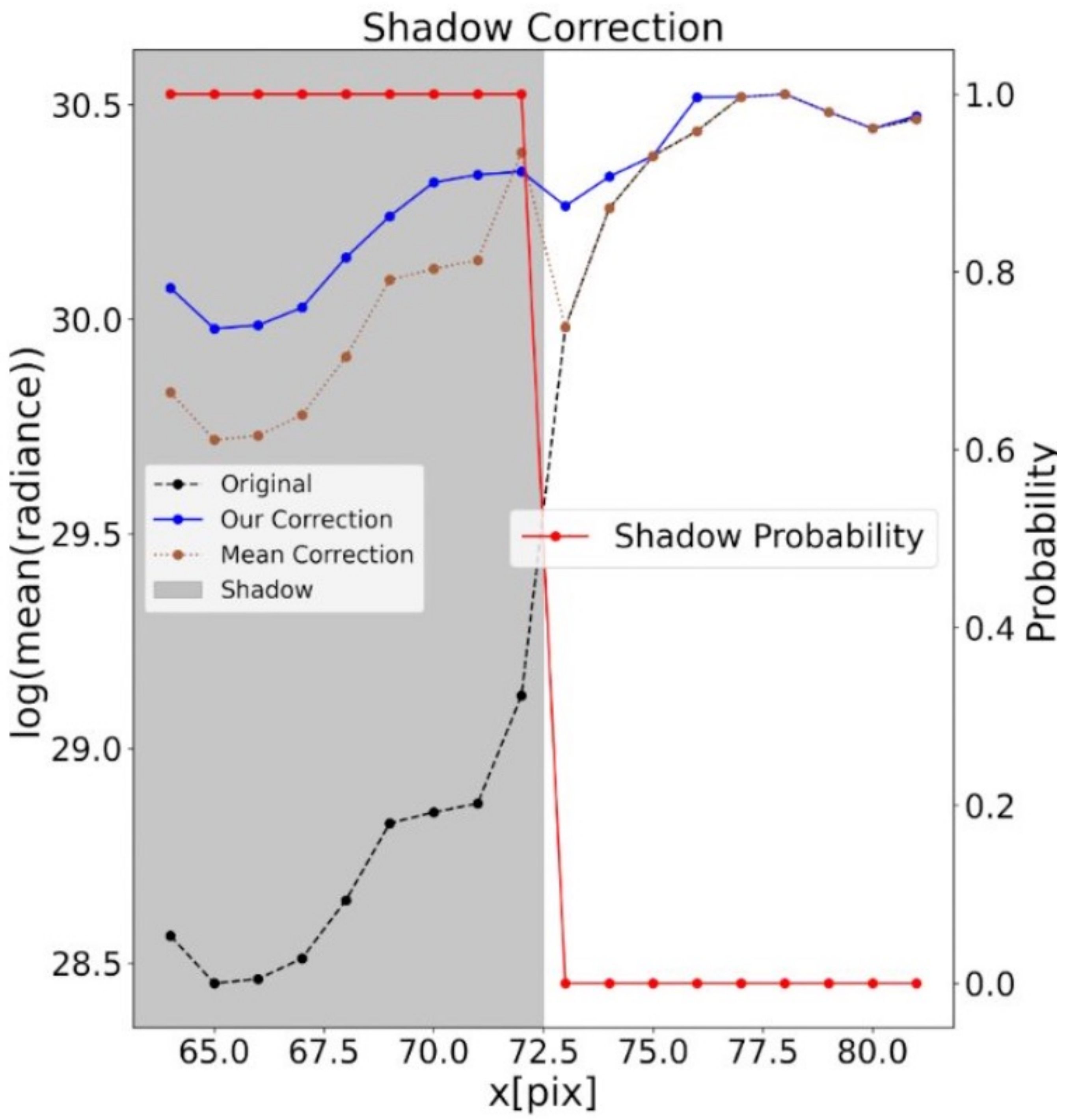
MethaneSAT: Enhanced Cloud Filtering / Correction



1. MethaneSAT Cloud Filtering Pipeline uses only the image information that let to significant data loss



2. We built an AI model that uses spectral information we enhanced the performance of cloud detection and filtering to 97%



3. We trained an AI model to remove the effect of shadows from the spectra itself, making all the data useable!

Park et al., NeurIPS 2023

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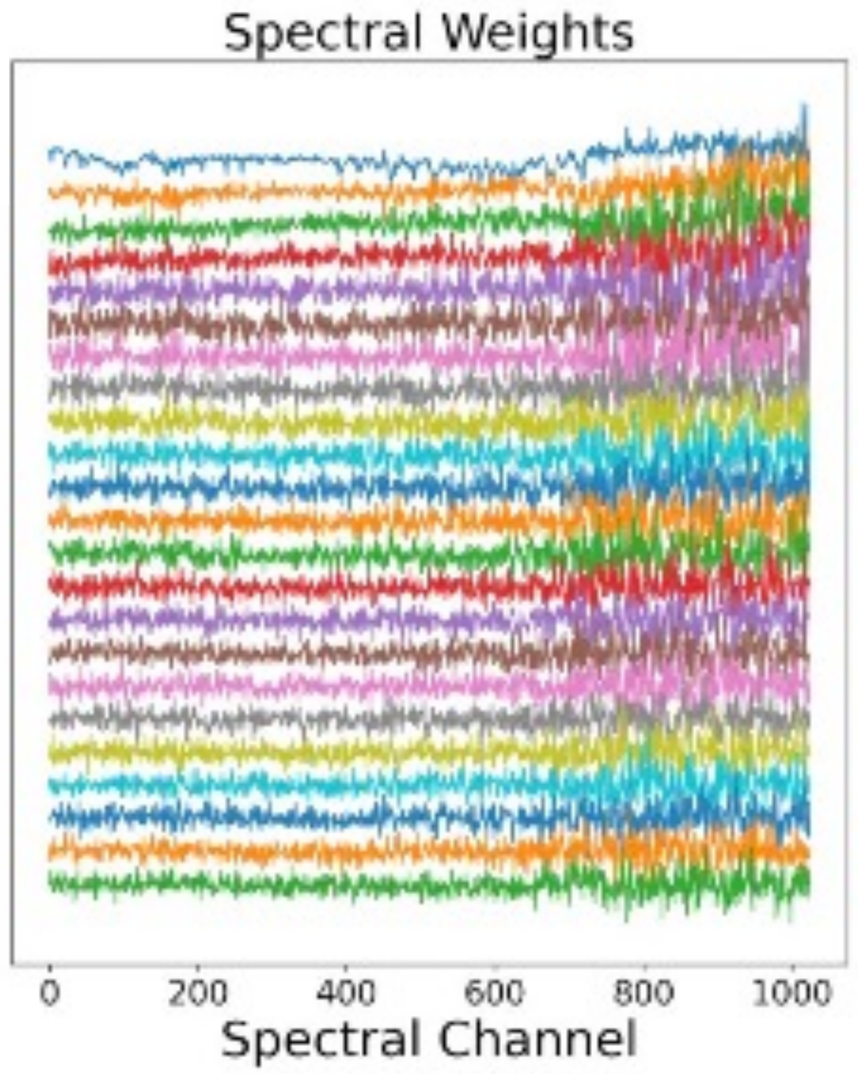
MethaneSAT: Enhanced Plume Detection

In Partnership with Google, we are building an AI model to enhance plume detection by using the full spectral information from MethaneSAT data together with Geospatial Data from Google Earth.

MethaneSAT

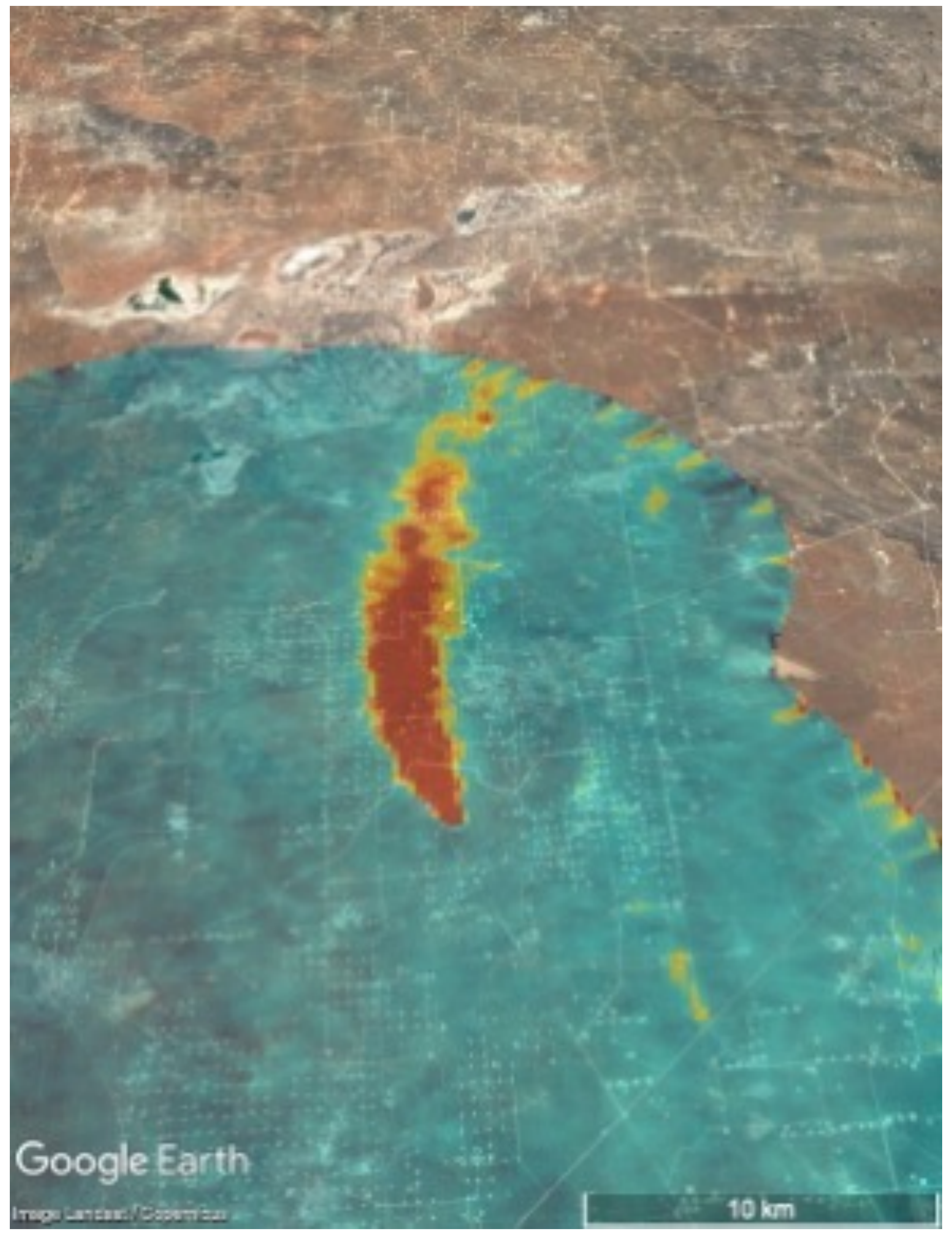


+

Google Earth

=

Reliable Plume Detection



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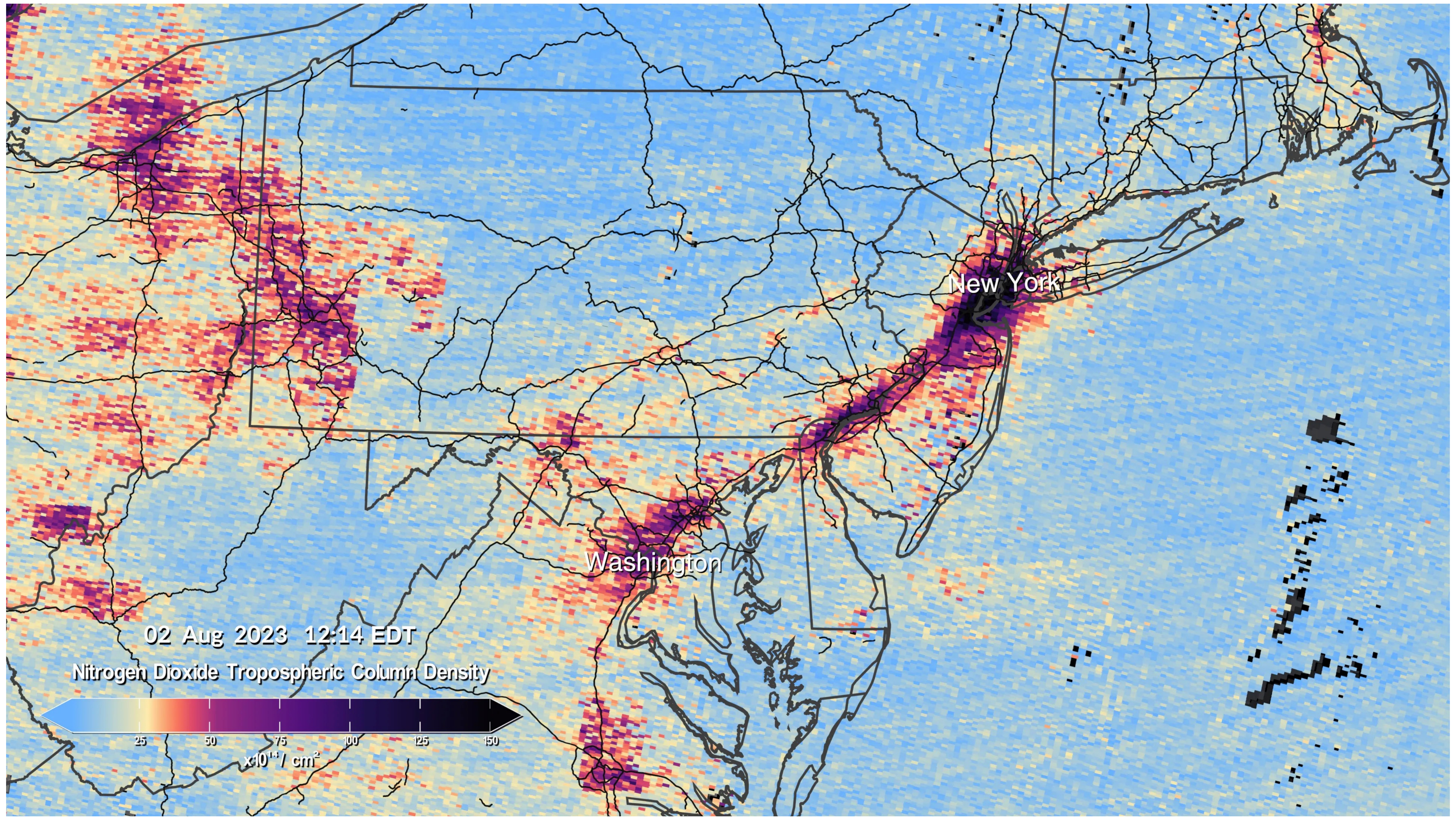
TEMPO: Resolving the Altitude of Pollutants



TEMPO nitrogen dioxide over part of the East Coast on August 2, 2023 at 12:14 EDT. High levels of NO_2 are seen over major urban regions and the I-95 corridor. High levels of NO_2 over Eastern Pennsylvania and Ohio are due to biomass burning.

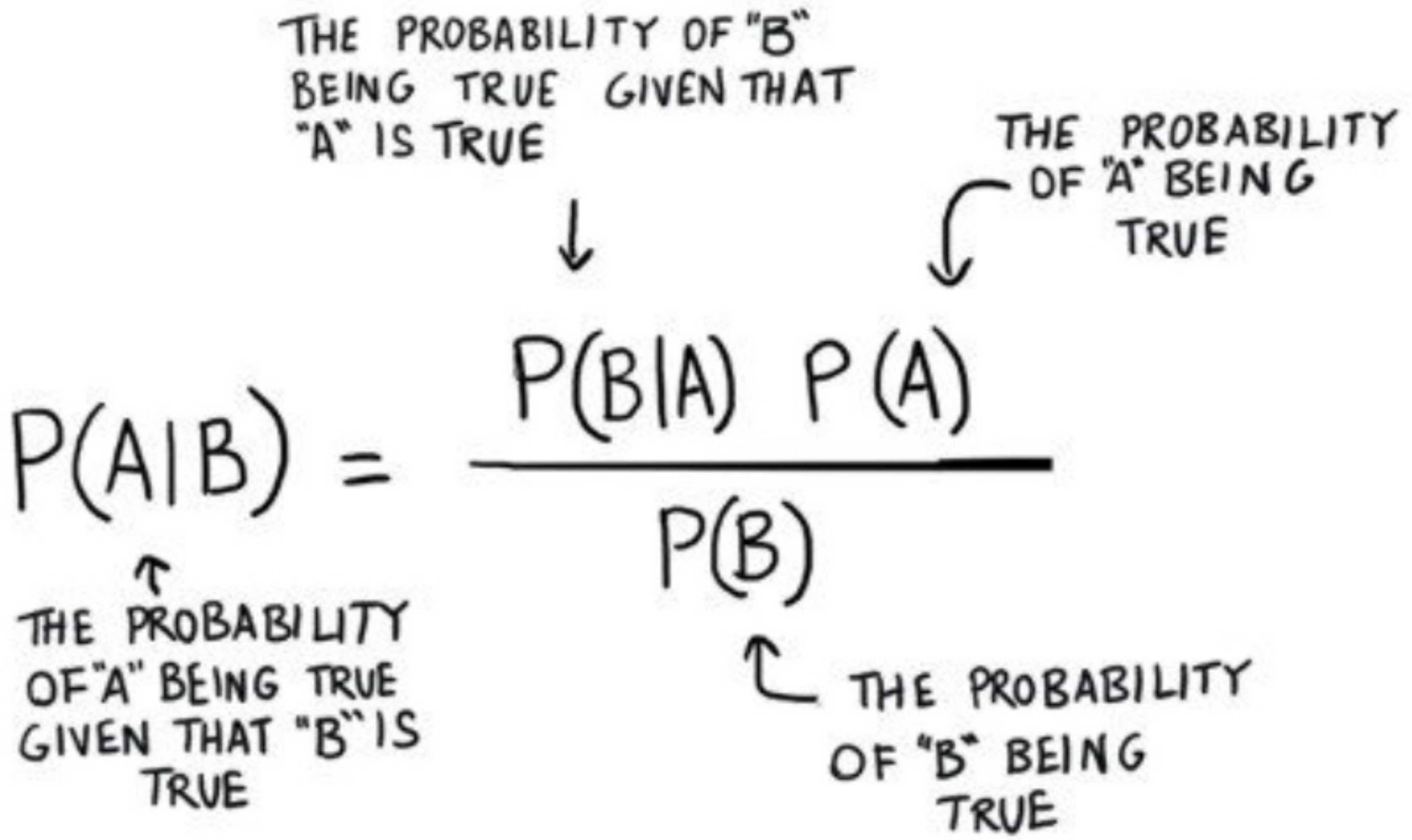
Nitrogen dioxide (NO_2) plays a central role in air quality and atmospheric chemistry, and has direct detrimental effects on human health when concentrated near the surface of Earth.

TEMPO is able to successfully retrieve the total column density of pollutants, such as nitrogen dioxide (NO_2), but not its vertical distribution.

We are building a multimodal AI model to integrate TEMPO data with other data (GEOS-CF, EPA Air Quality System, and aircraft profiles like STAQ) to resolve the vertical distribution of pollutants, like NO_2 to assess the air quality where it has human health impact

Bayesian Inference

Probability as a measure of *believability in an event*



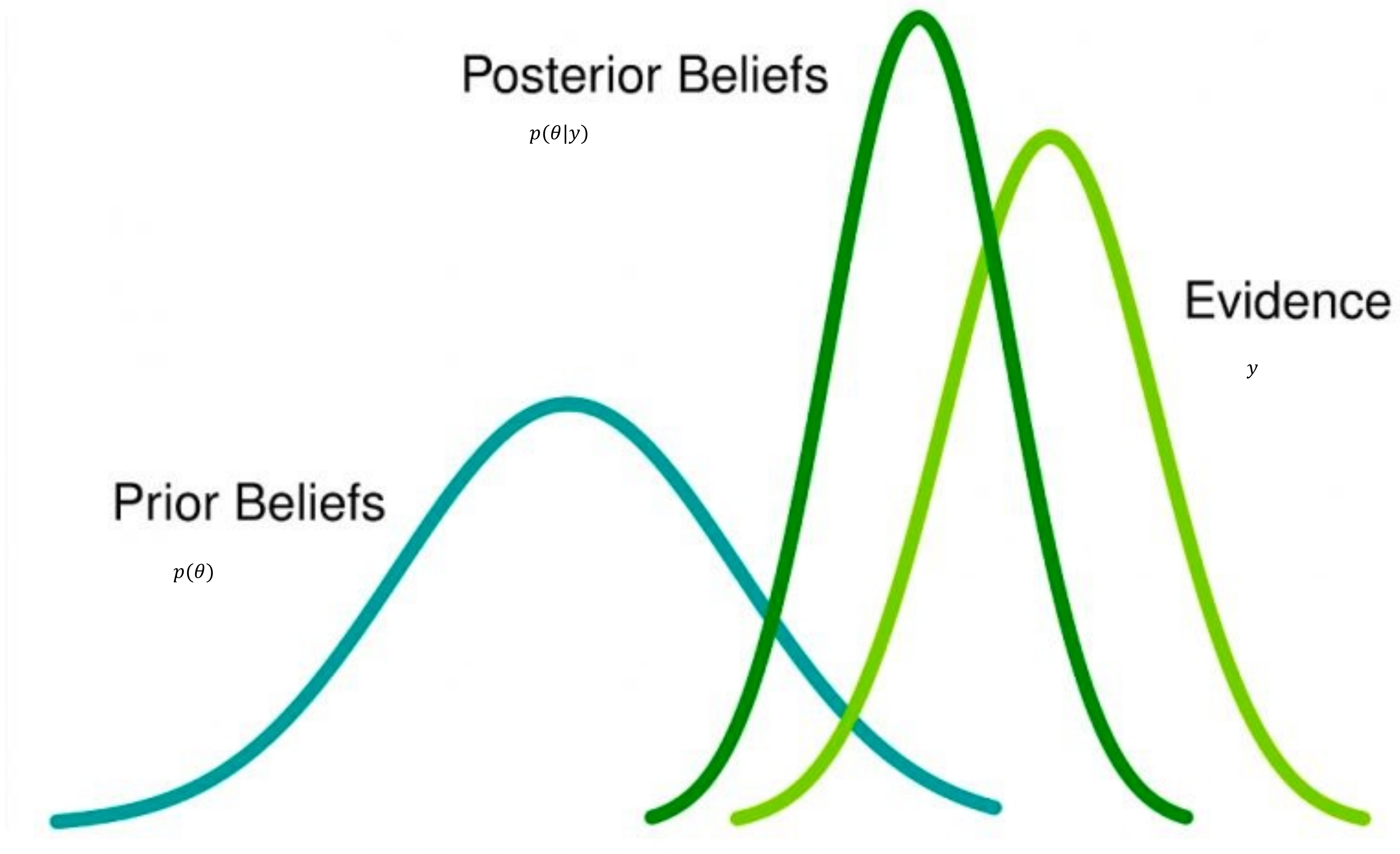
A.I. Wiki

$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

Weights & biases   Data

Bayesian Inference

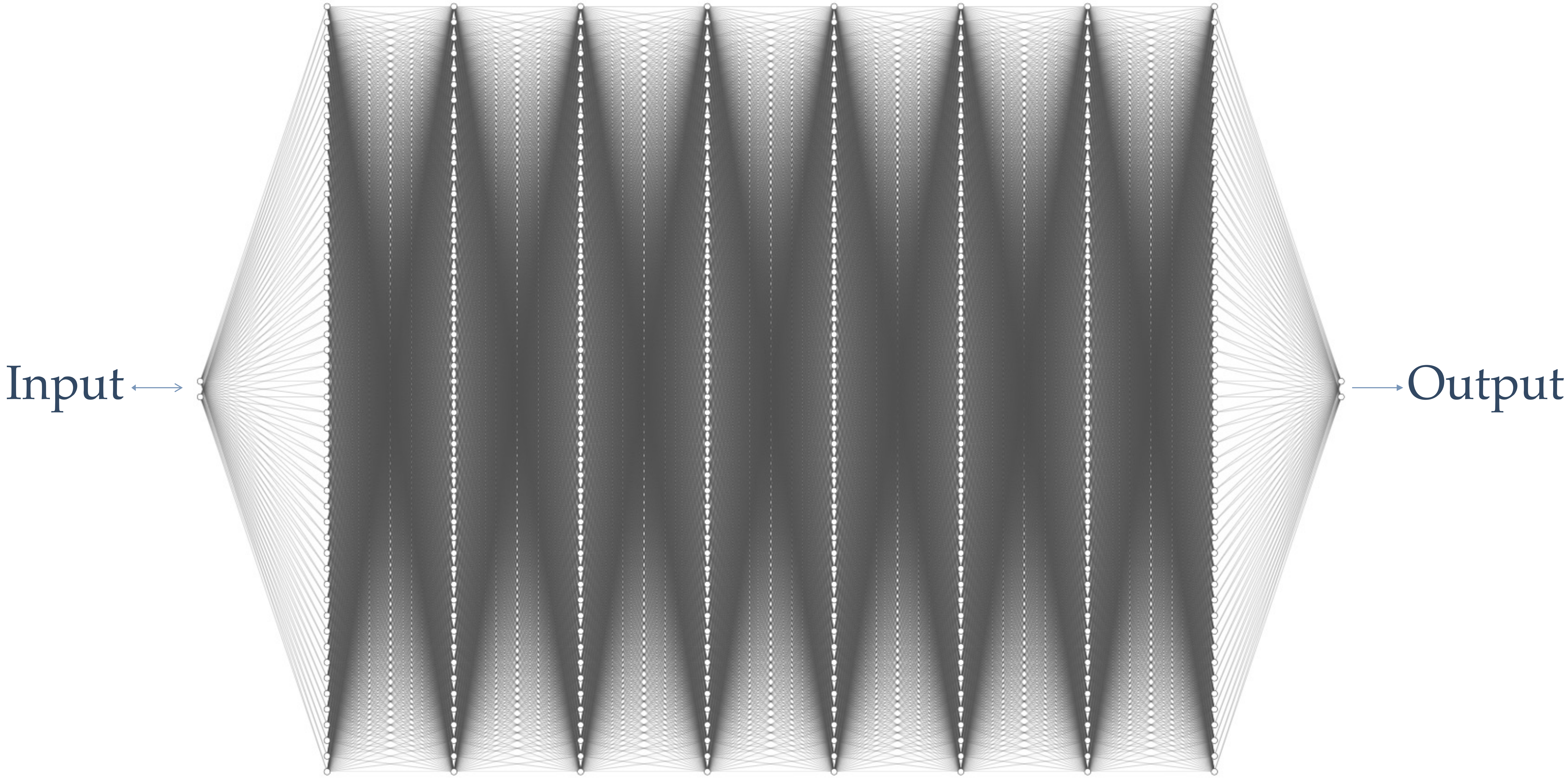
$p(\theta|y) \propto p(y|\theta)p(\theta)$



"When the facts change, I change my mind. What do you do, sir? "

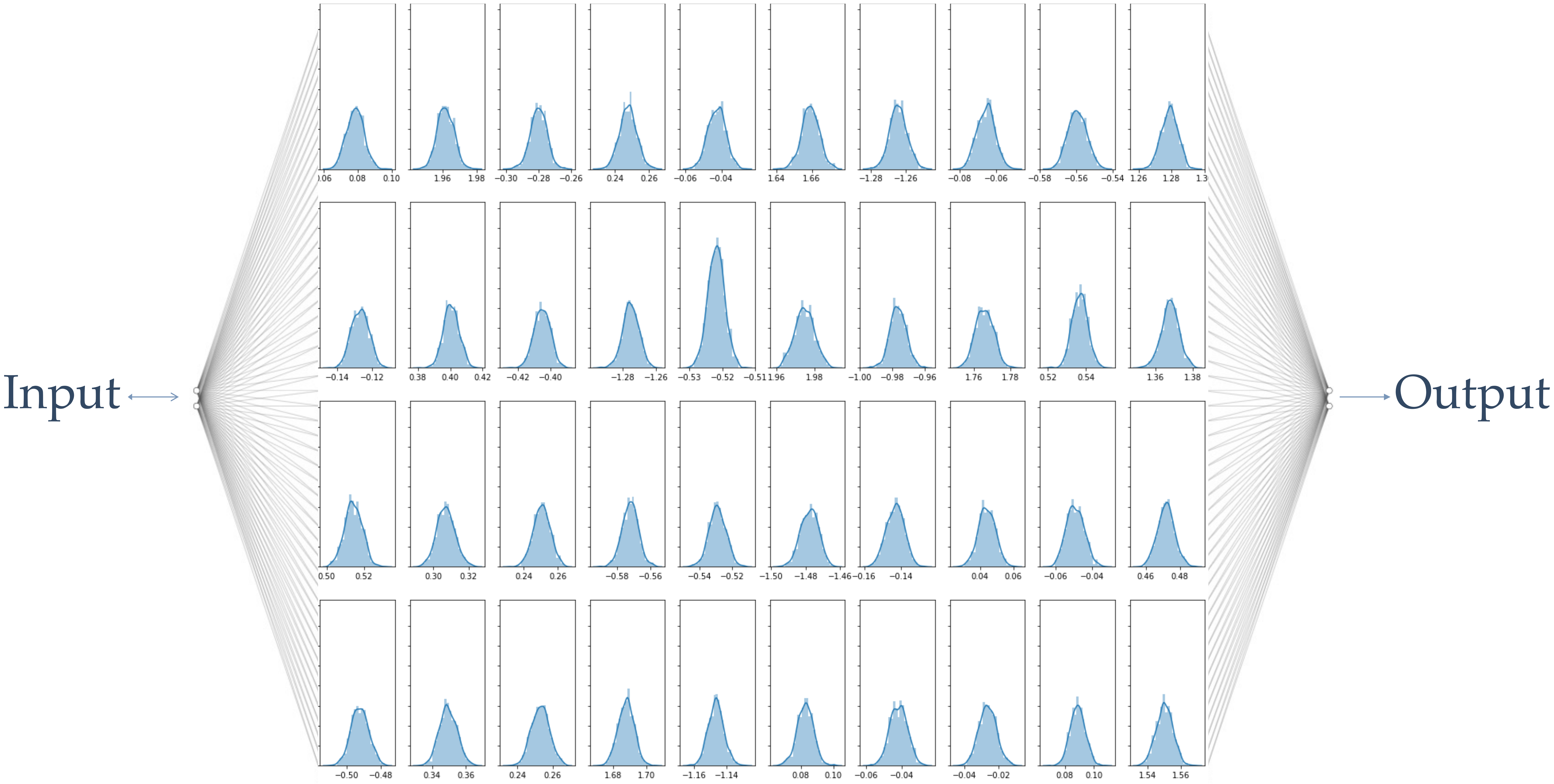
John Maynard Keynes

Bayesian Neural Networks

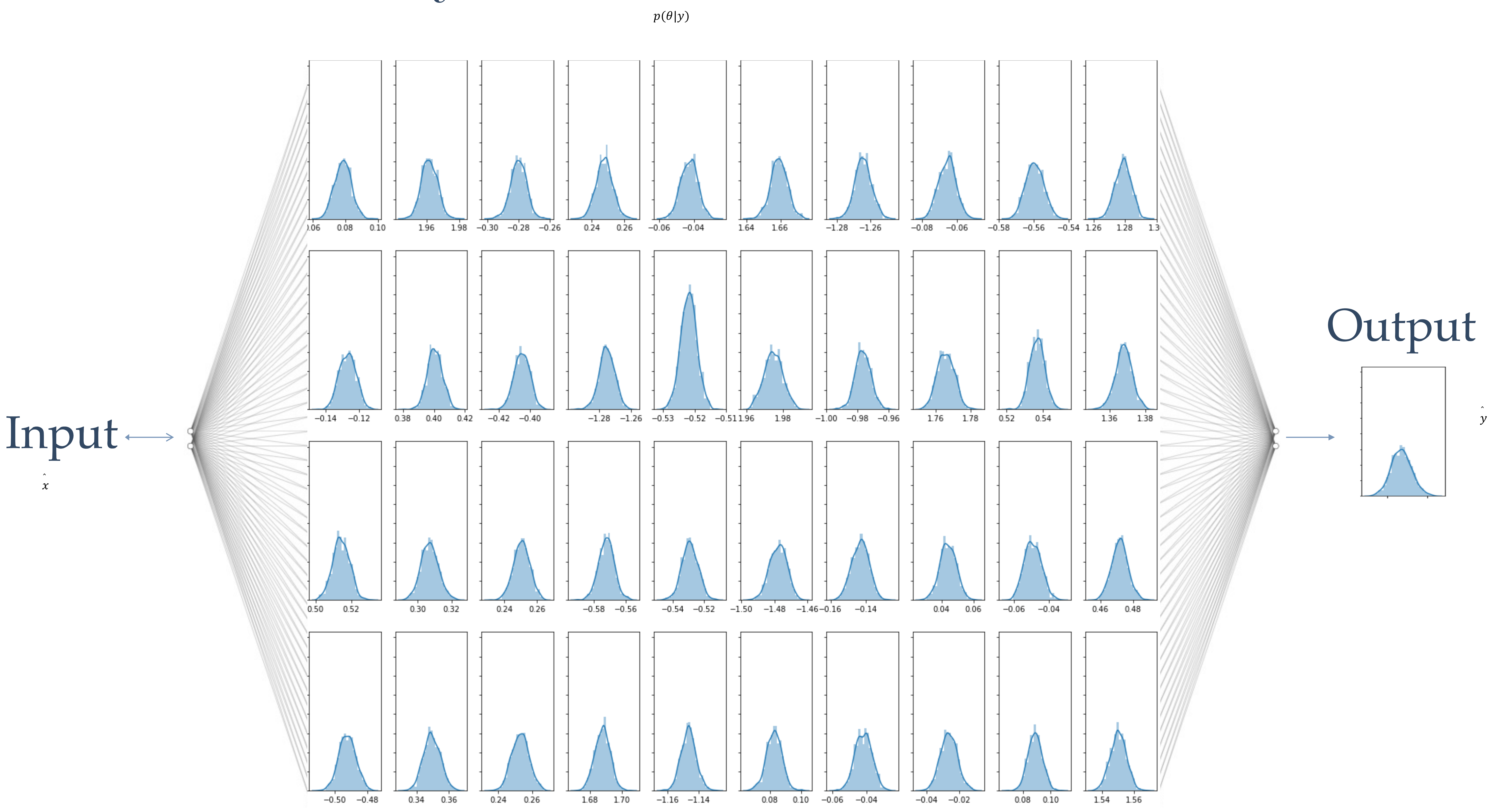


Cecilia Garraffo, Harvard-Smithsonian Center for Astrophysics

Bayesian Neural Networks



Bayesian Neural Networks



BI for NN calculates the posterior distribution of the weights given the training data

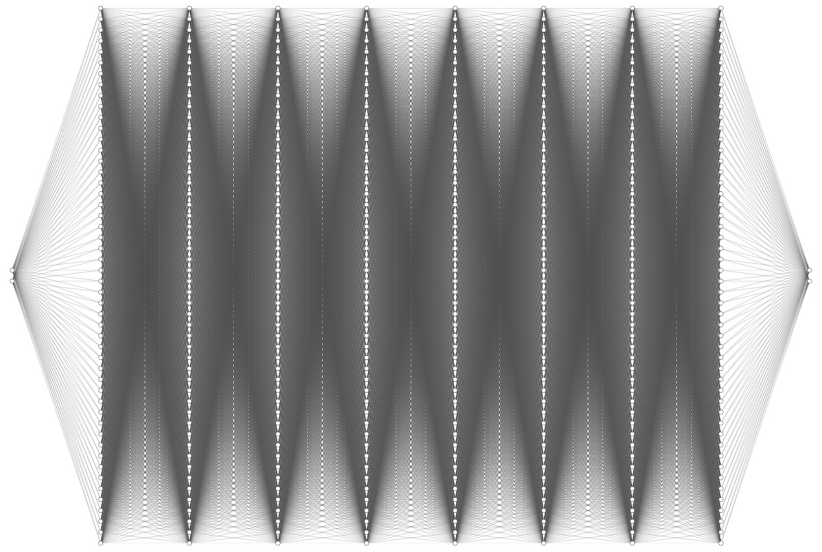
Cecilia Garraffo, Harvard-Smithsonian Center for Astrophysics

Bayesian Neural Networks

Priors $p(\theta)$ $\longleftrightarrow$ $\dfrac{p(\theta)p(y|\theta)}{\underbrace{p(y)}_{\text{intractable}}} = p(\theta|y)$

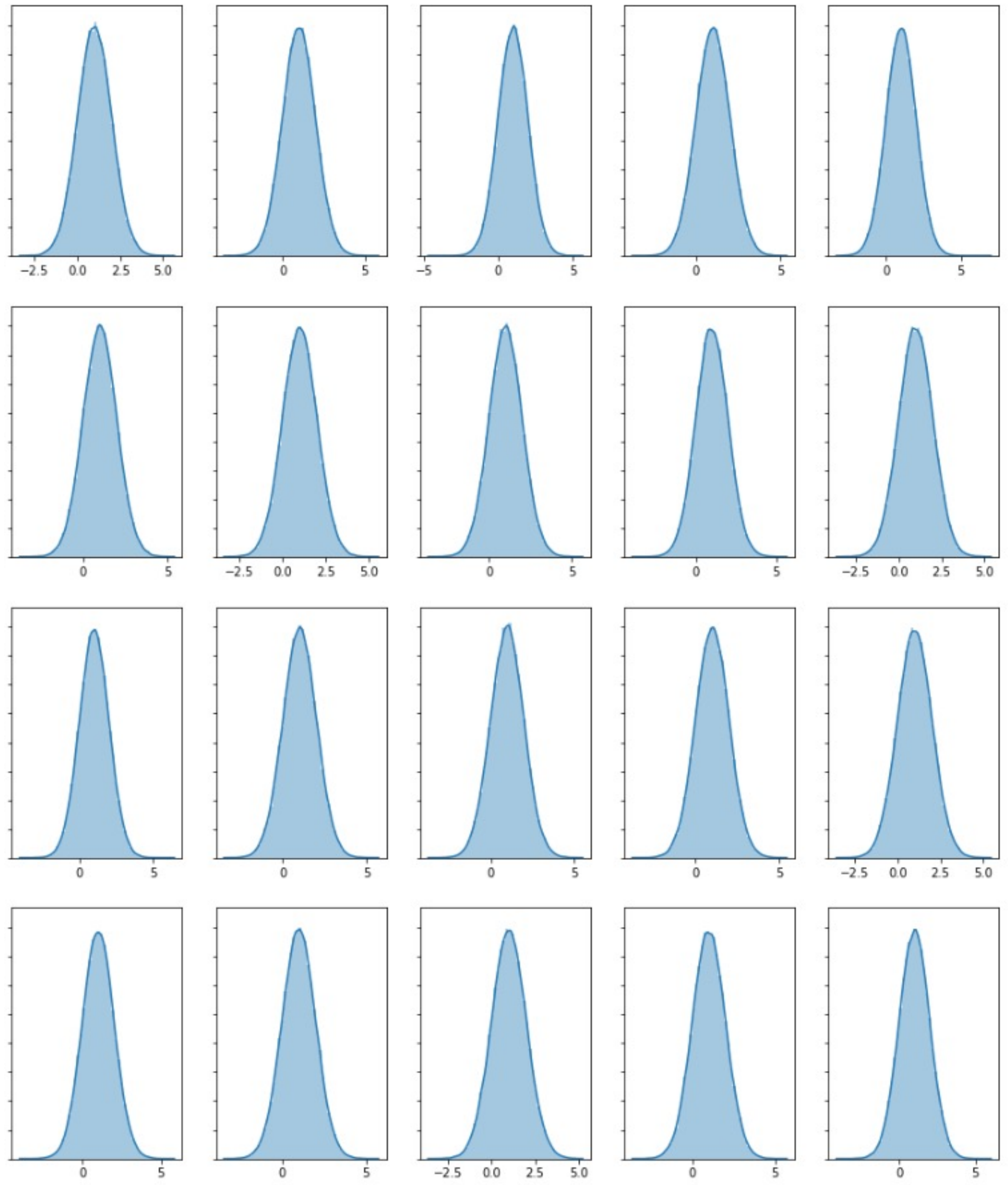
Means

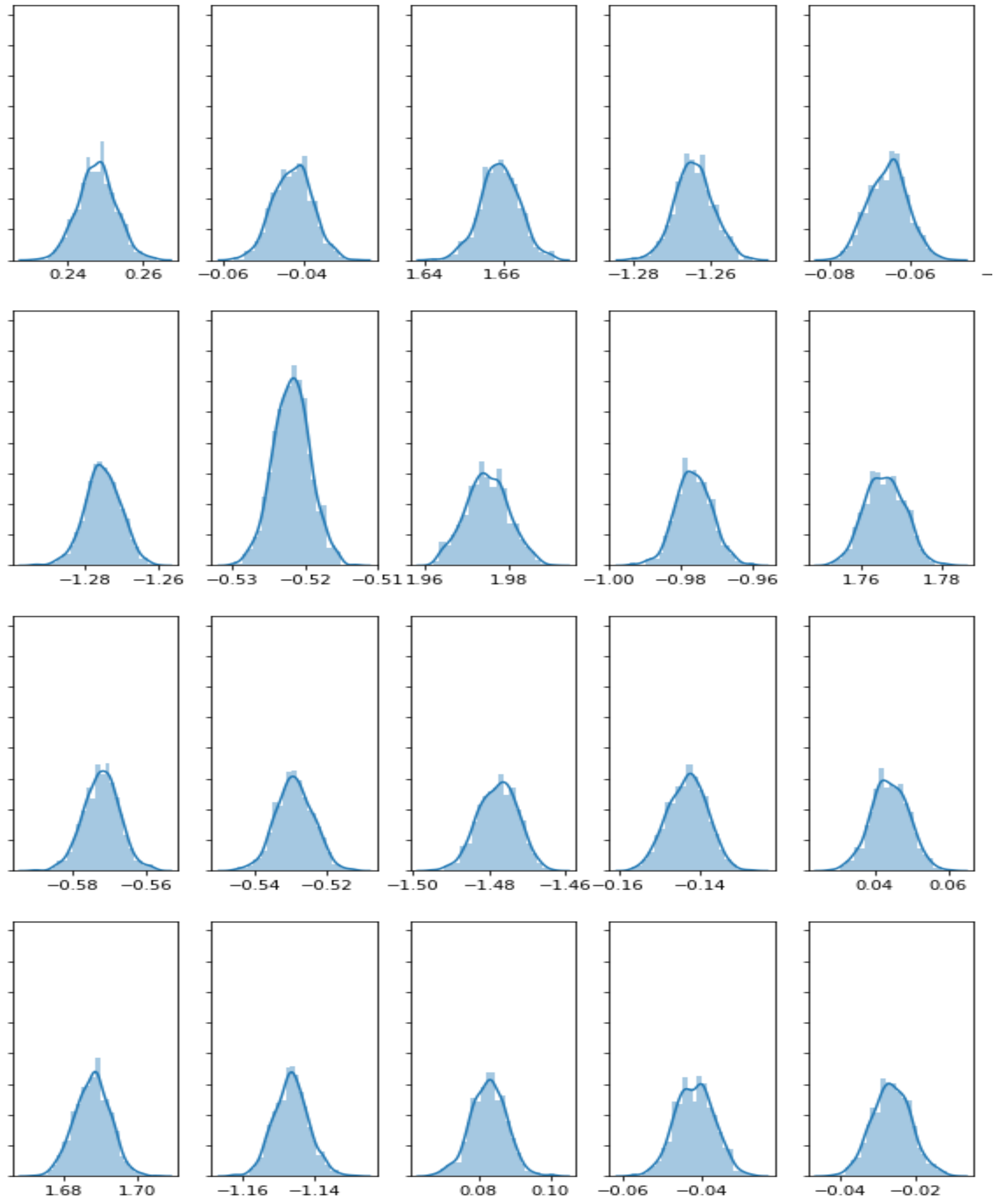
FCNN



&

Scale

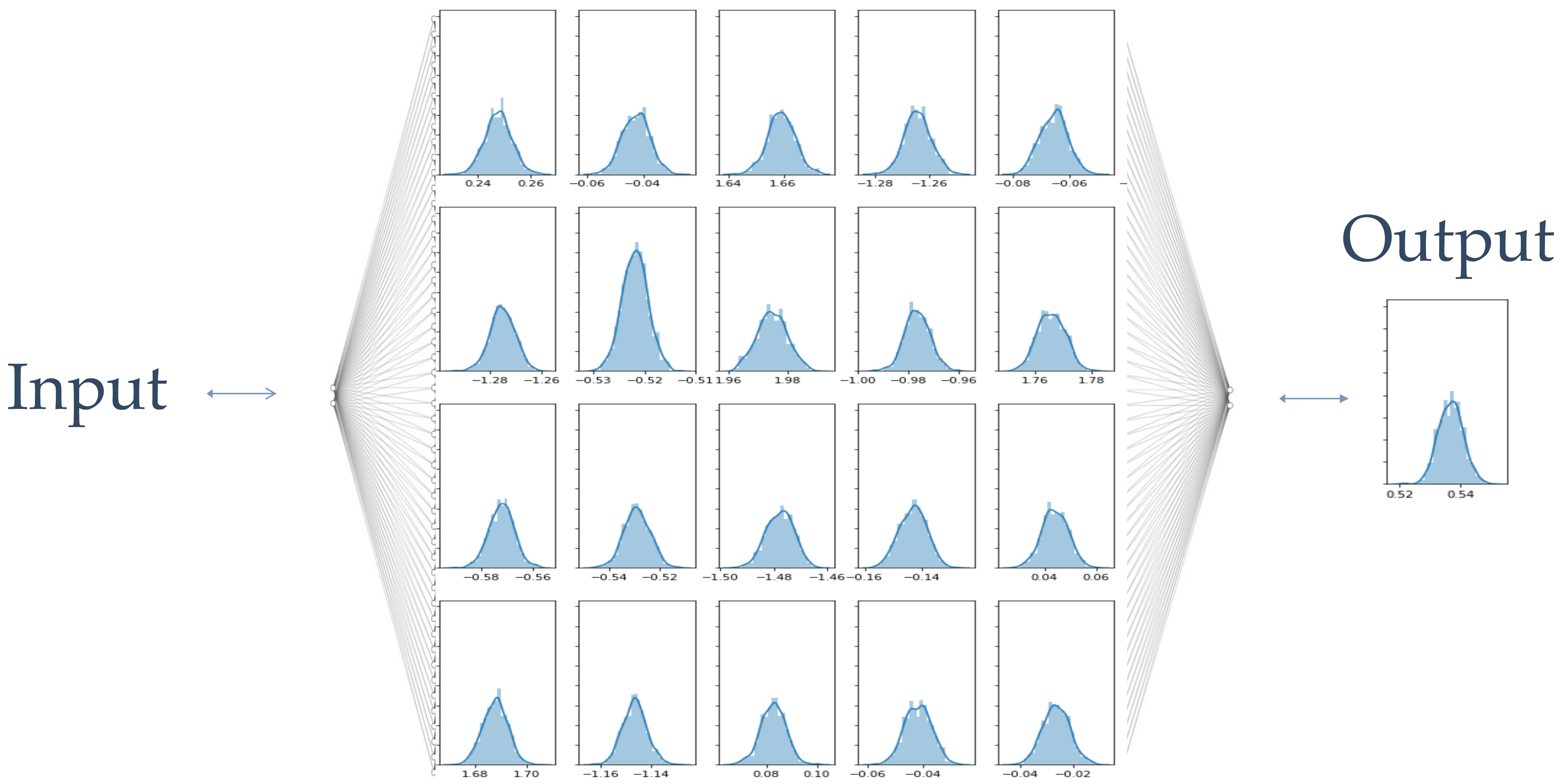




Bayesian Neural Networks

MCMC: Eventually accurate

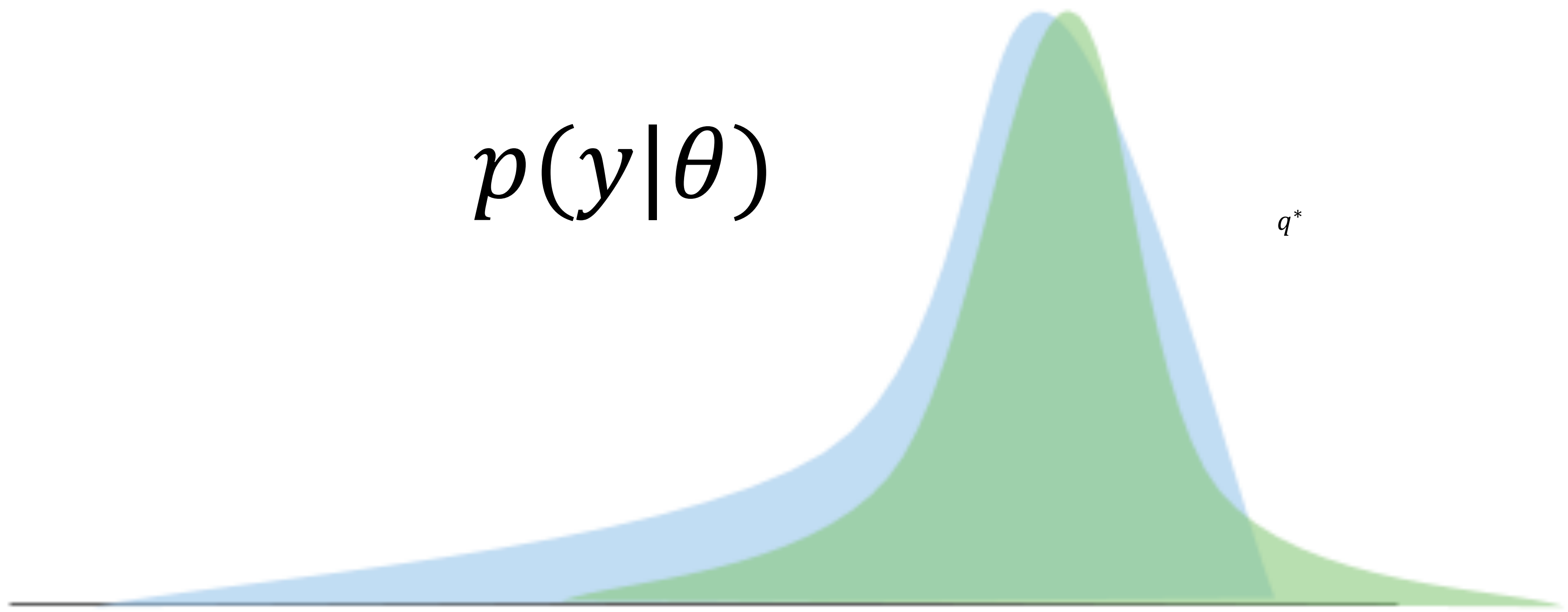
$$p(\theta) \quad \times \quad p(y|\theta) \quad \propto \quad p(\theta|y)$$

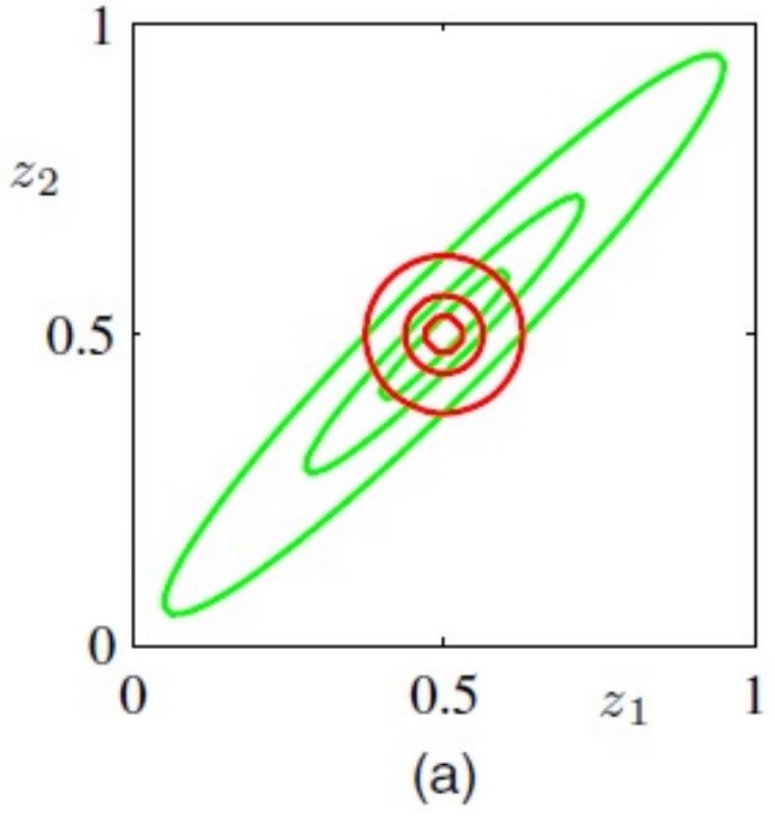


Approximate Bayesian Inference: Variational Bayes

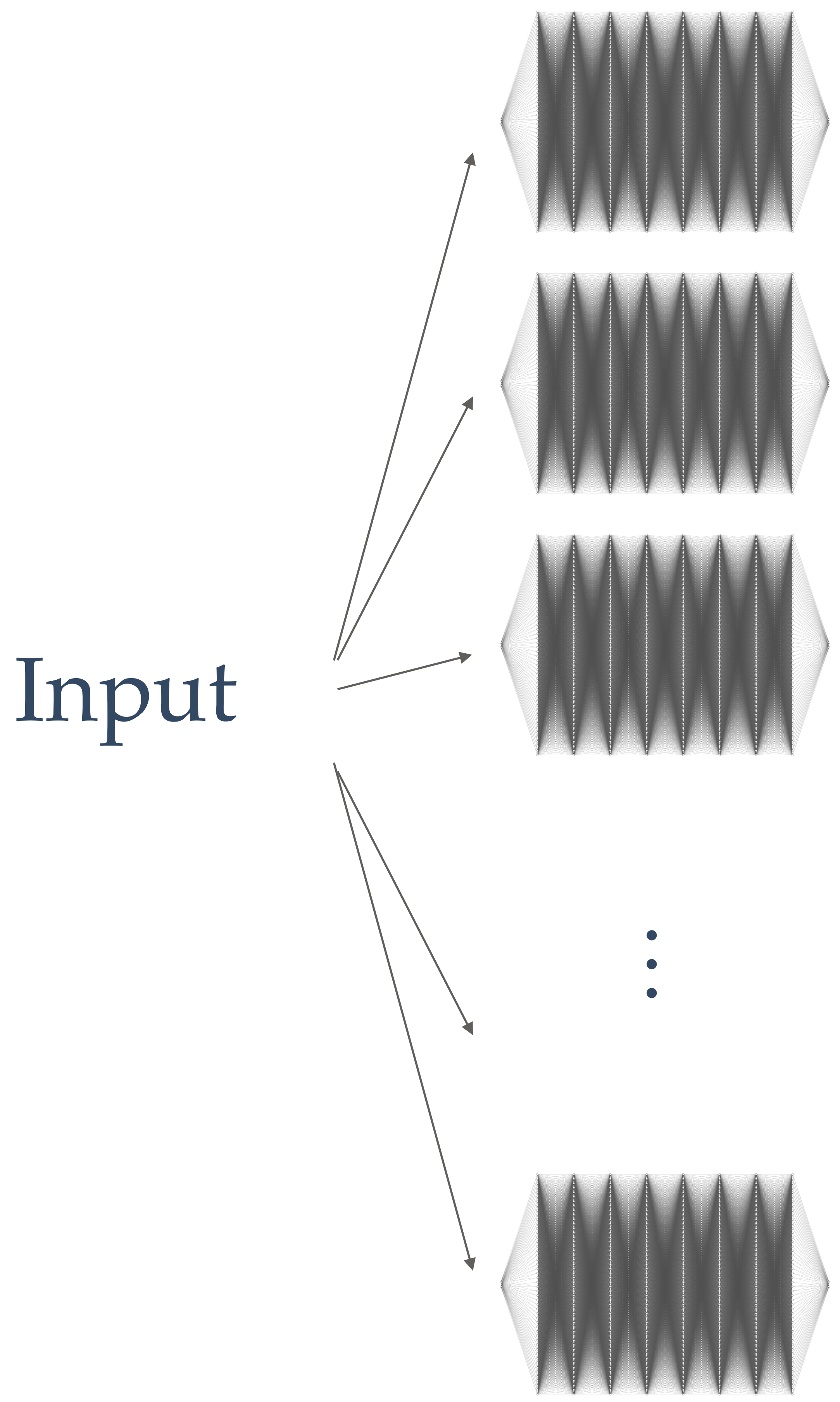
$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{\int p(y,\theta)d\theta} \approx q*$$

Optimization approach → Q a family of "nice" distributions

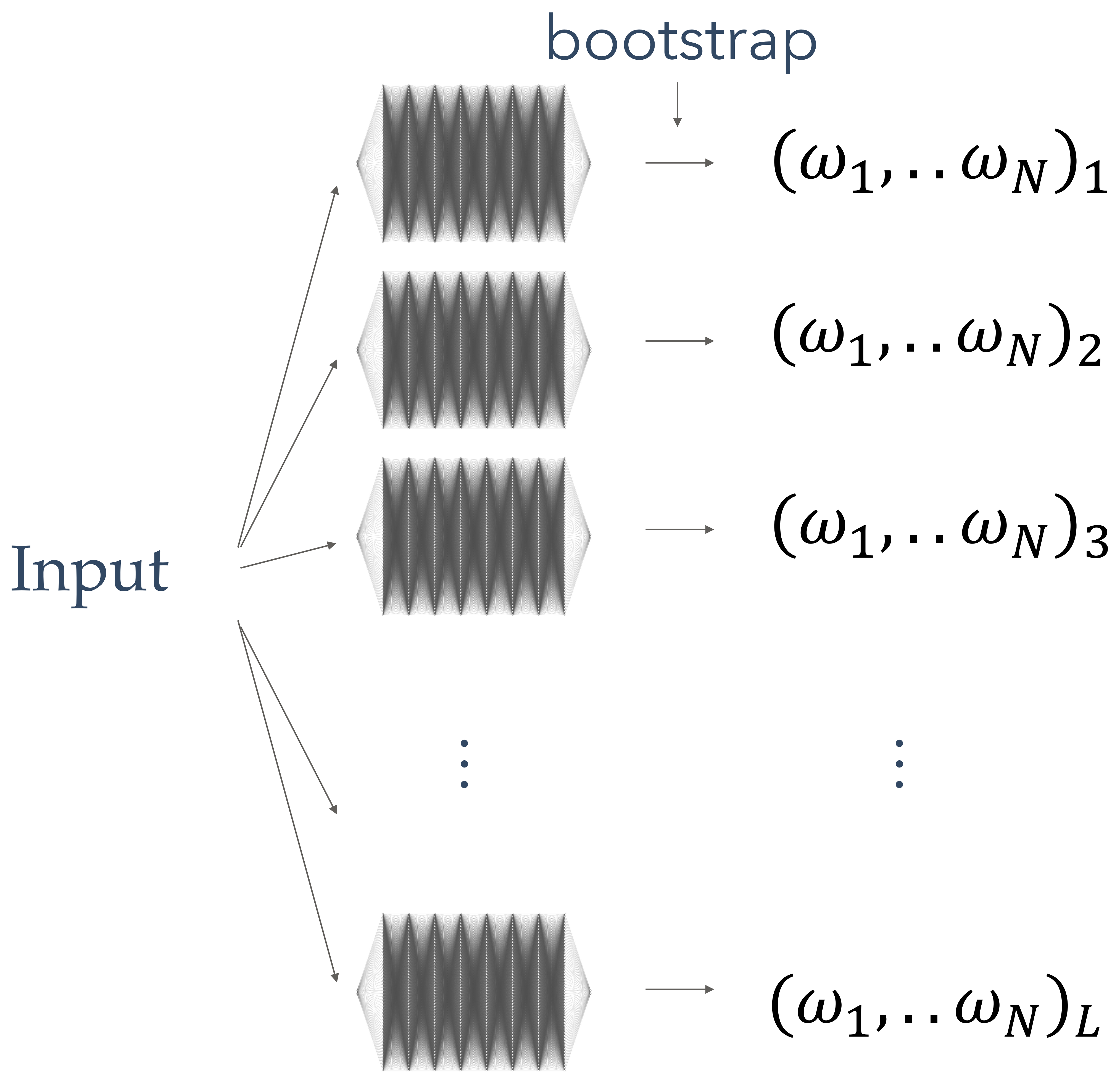




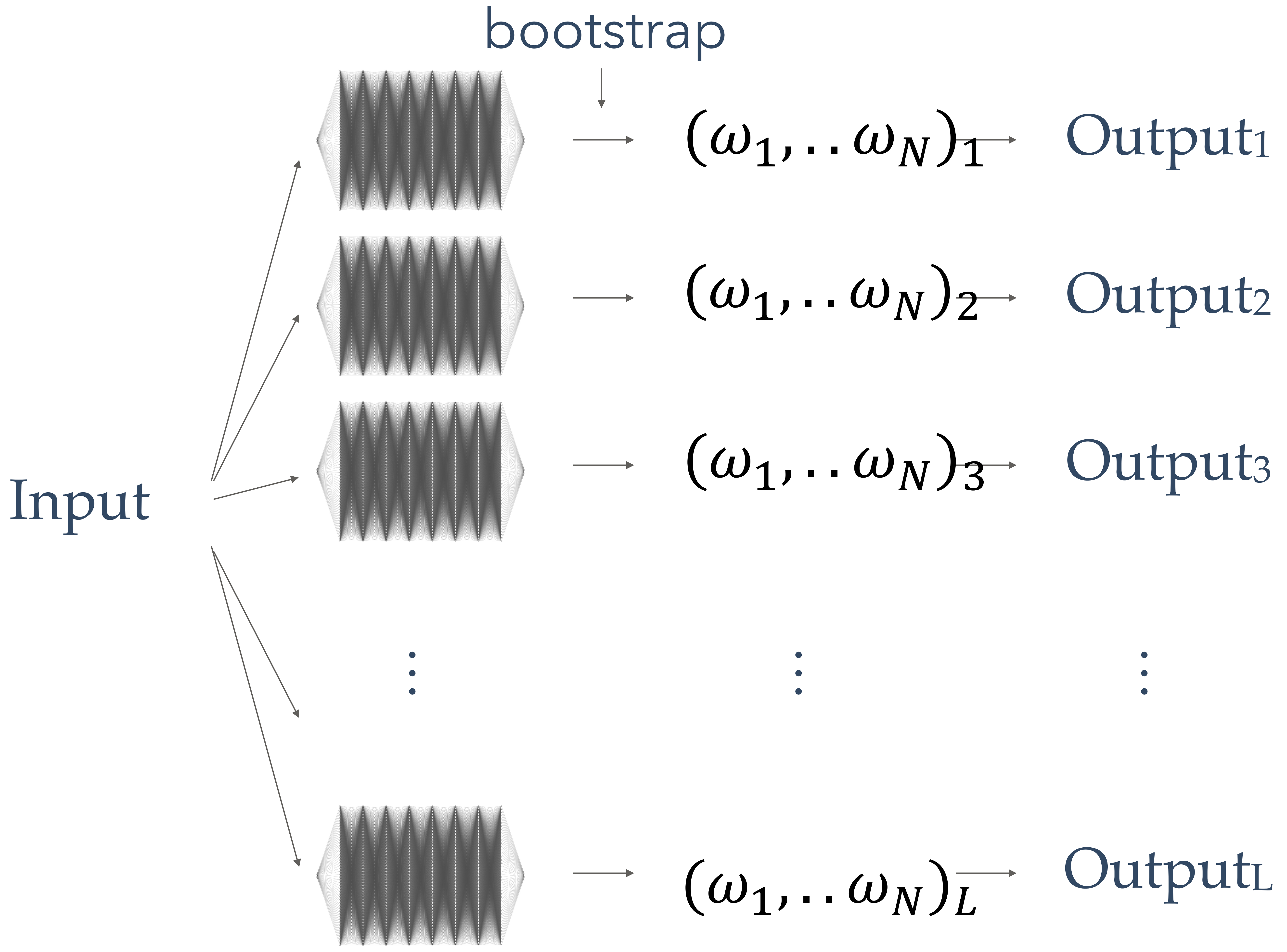
Bootstrap: L models



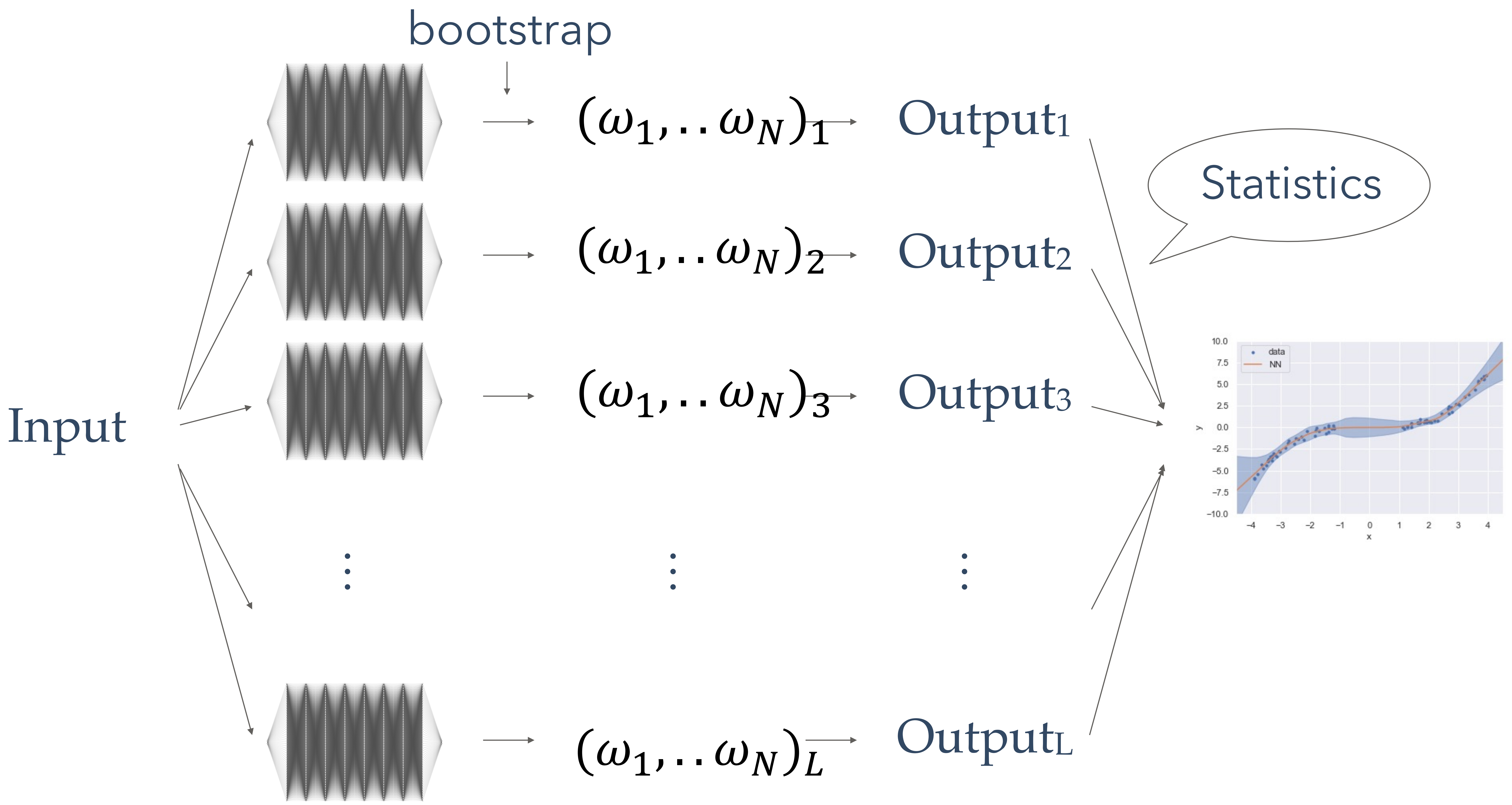
Bootstrap: L models



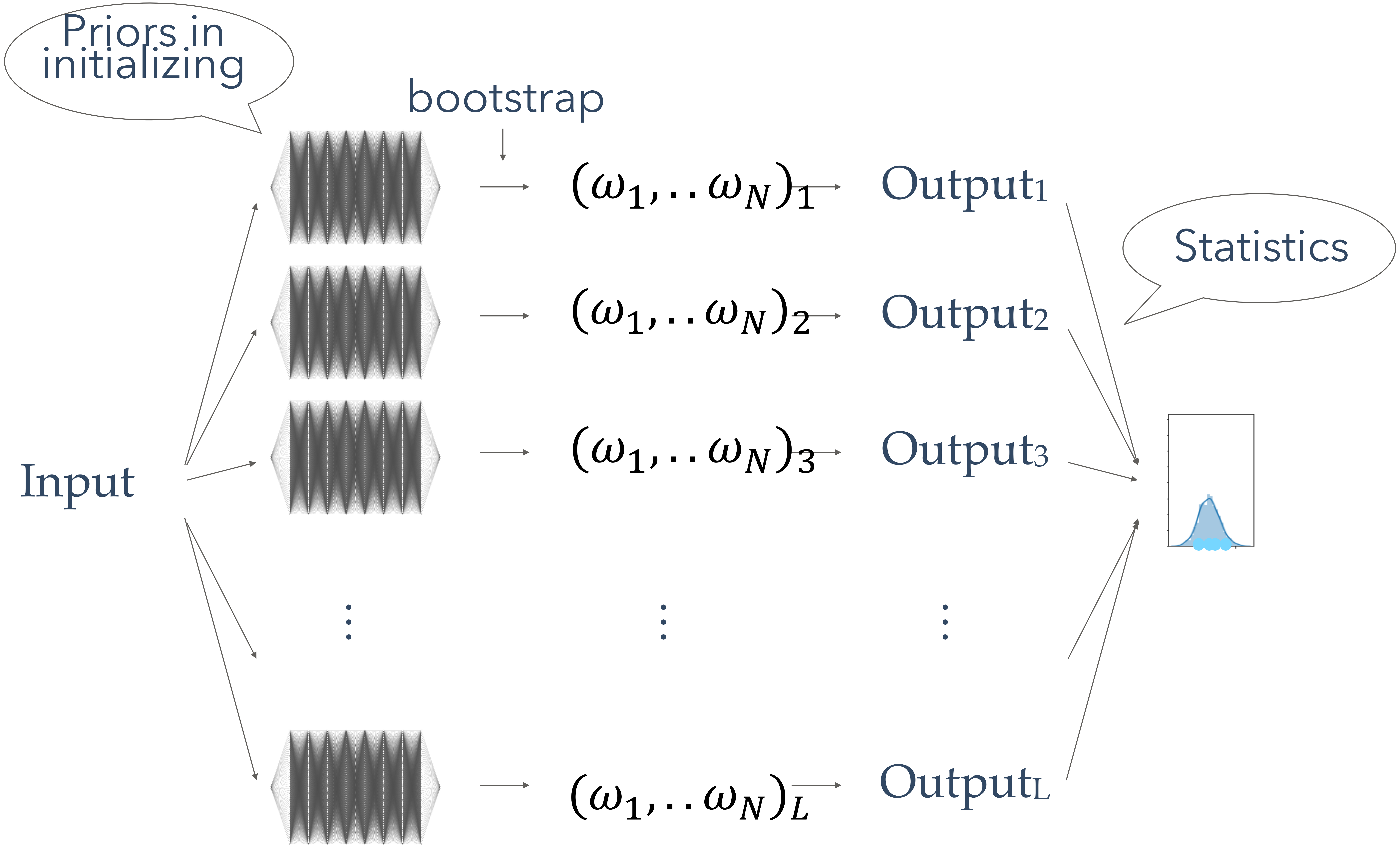
Bootstrap: L models



Bootstrap: L models

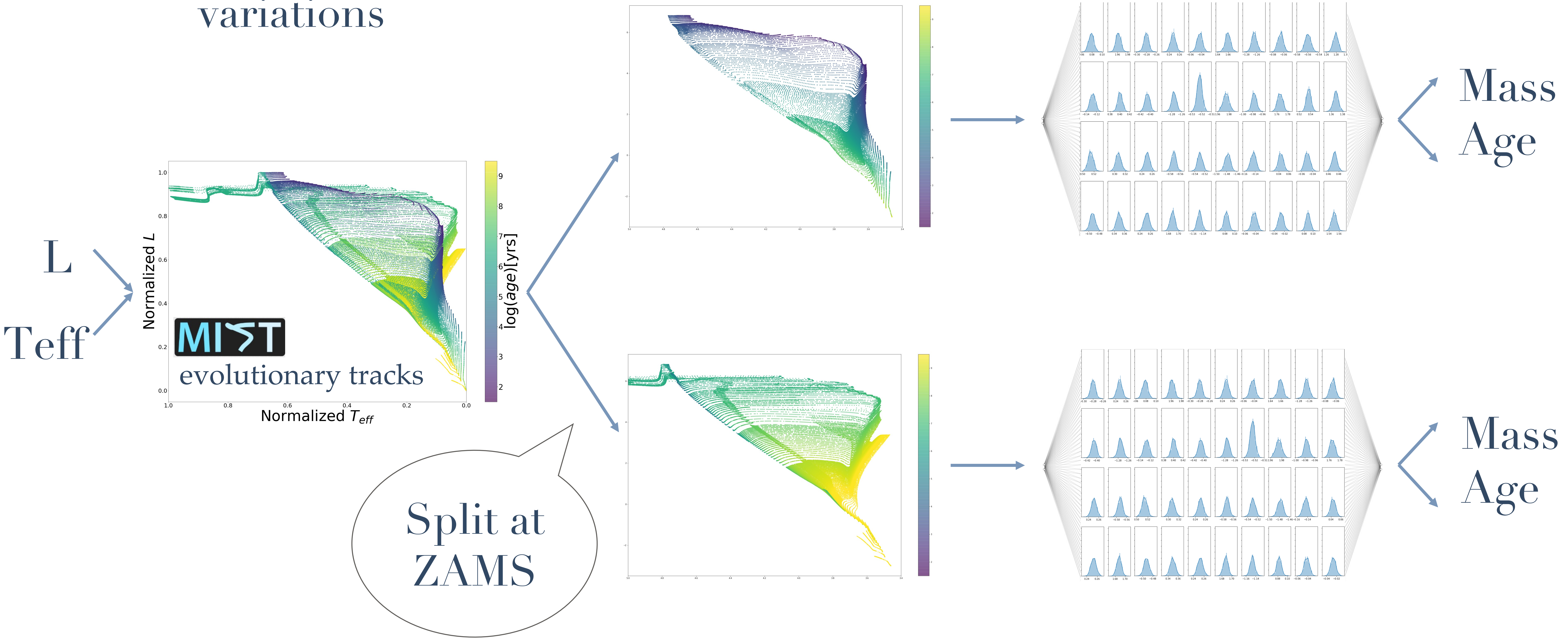


Bootstrap: L models



StelNet: A Hierarchical Neural Network for Inference in Stellar Characterization

- Degeneracies ✓
- Non-linearity ✓
- Confidence variations



StelNet: A Hierarchical Neural Network for Inference in Stellar Characterization

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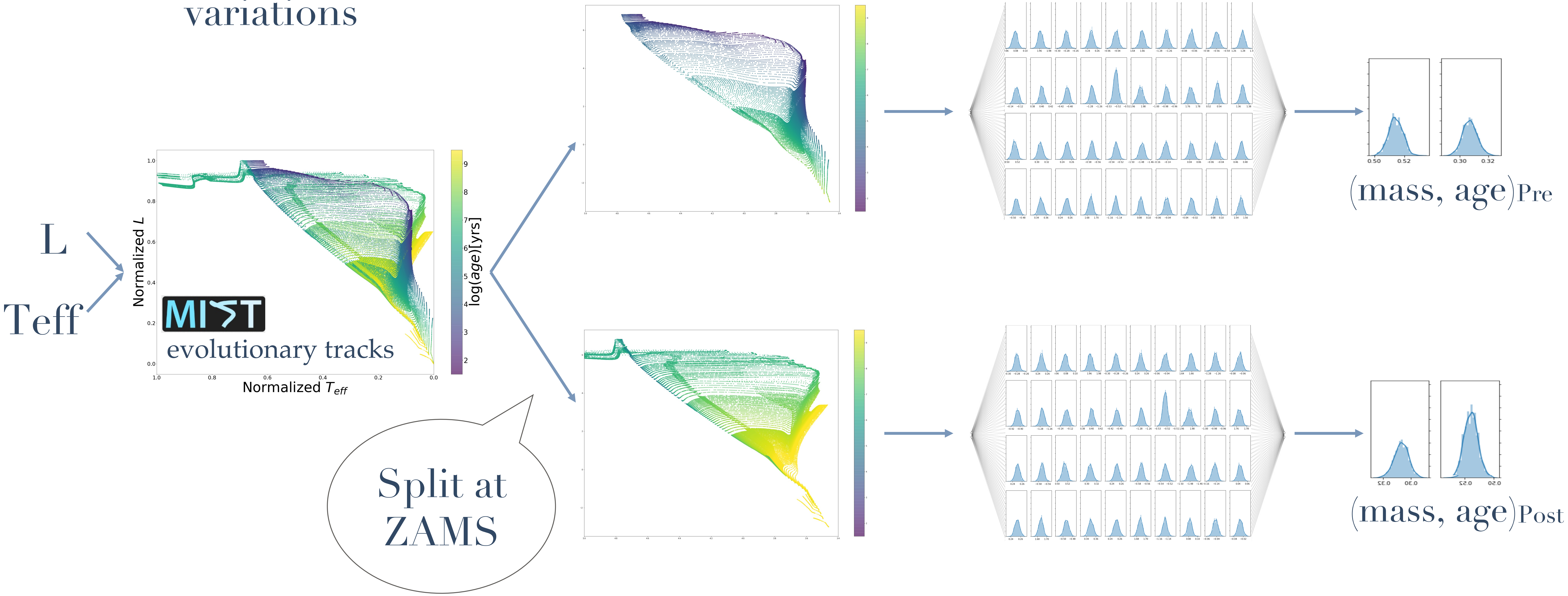

StelNet: A Hierarchical Neural Network for Inference in Stellar Characterization

- Degeneracies ✓
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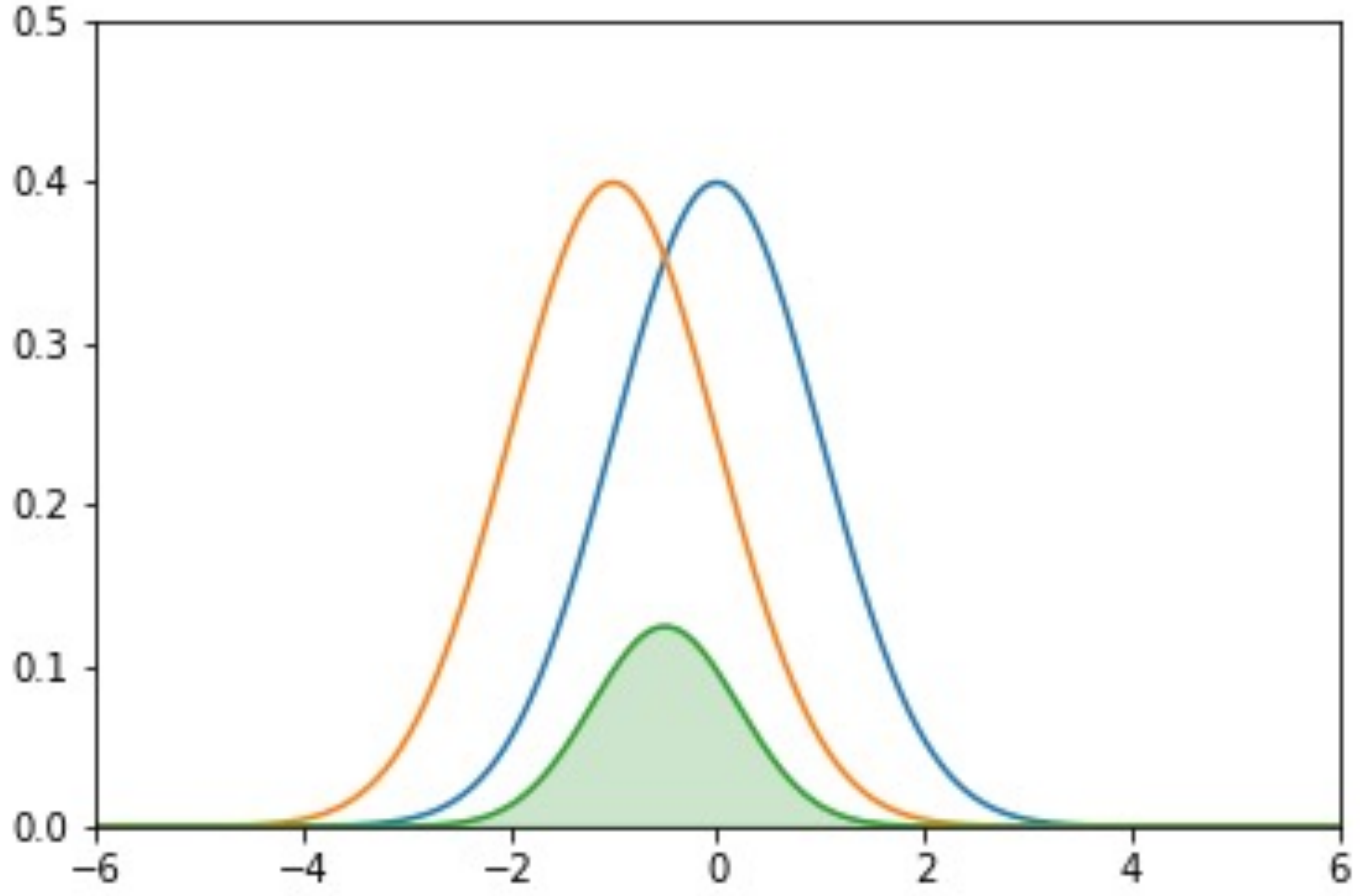
Garraffo et al. 2021

StelNet: A Hierarchical Neural Network for Inference in Stellar Characterization

Comparing distributions



$$\int \overline{P}_A \overline{P}_B dx = \overline{\varepsilon}|_{maxA=maxB}$$ Bayesian Evidence

$$\int \overline{P}_A \overline{P}_B dx = \varepsilon < \overline{\varepsilon}$$

$$\tau = \frac{\overline{\varepsilon}|_{maxA=maxB}}{\varepsilon}$$ Tension

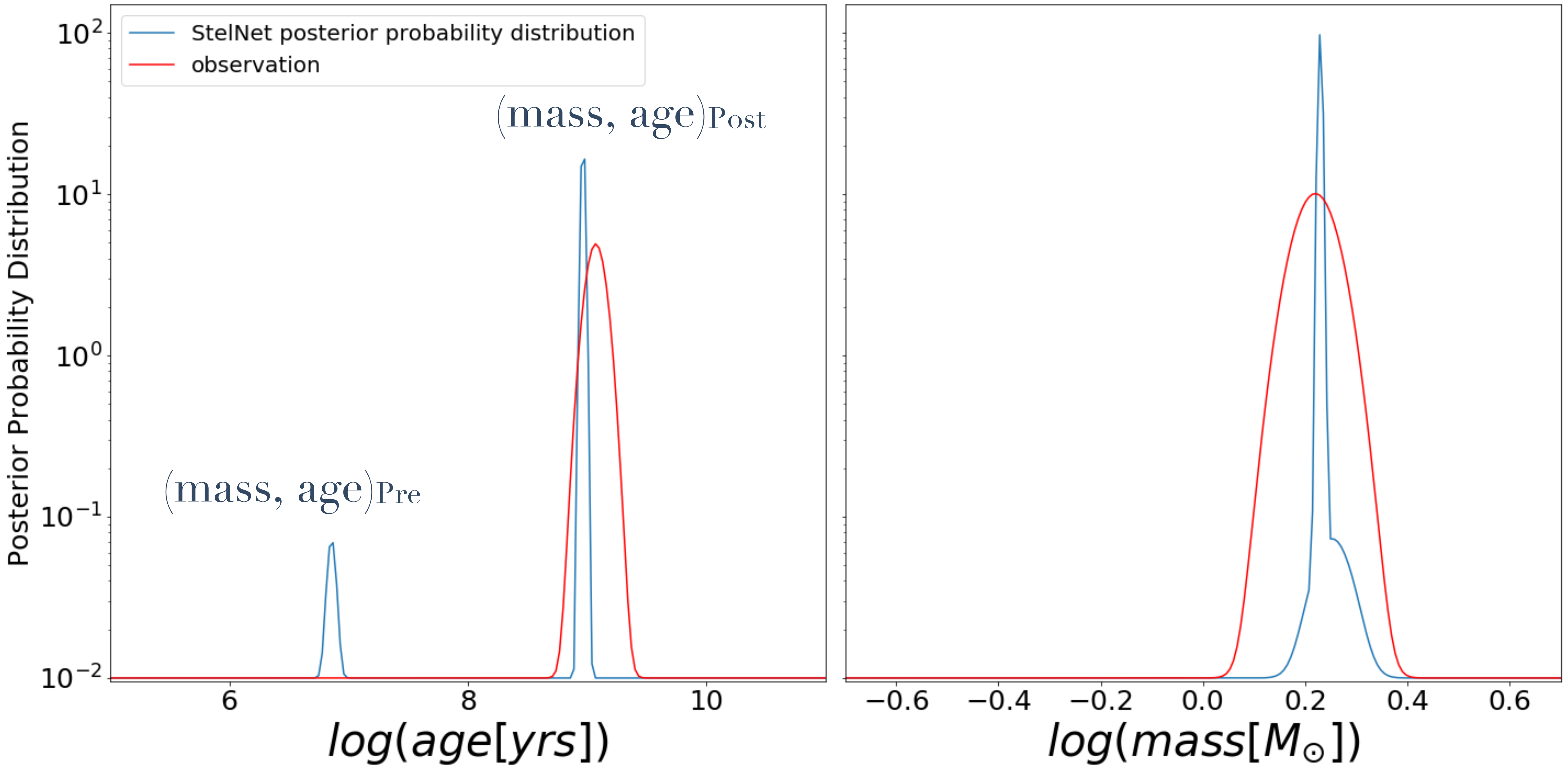
A large tension means that the null hypothesis (maxA = maxB) is unlikely

Jerffrey's scale:

$\log\tau < 1$	$1 < \log\tau < 2.5$	$\log\tau > 5$
not significant	substantial	highly significant

StelNet: A Hierarchical Neural Network for Inference in Stellar Characterization

Quantifying performance



τ : Tension

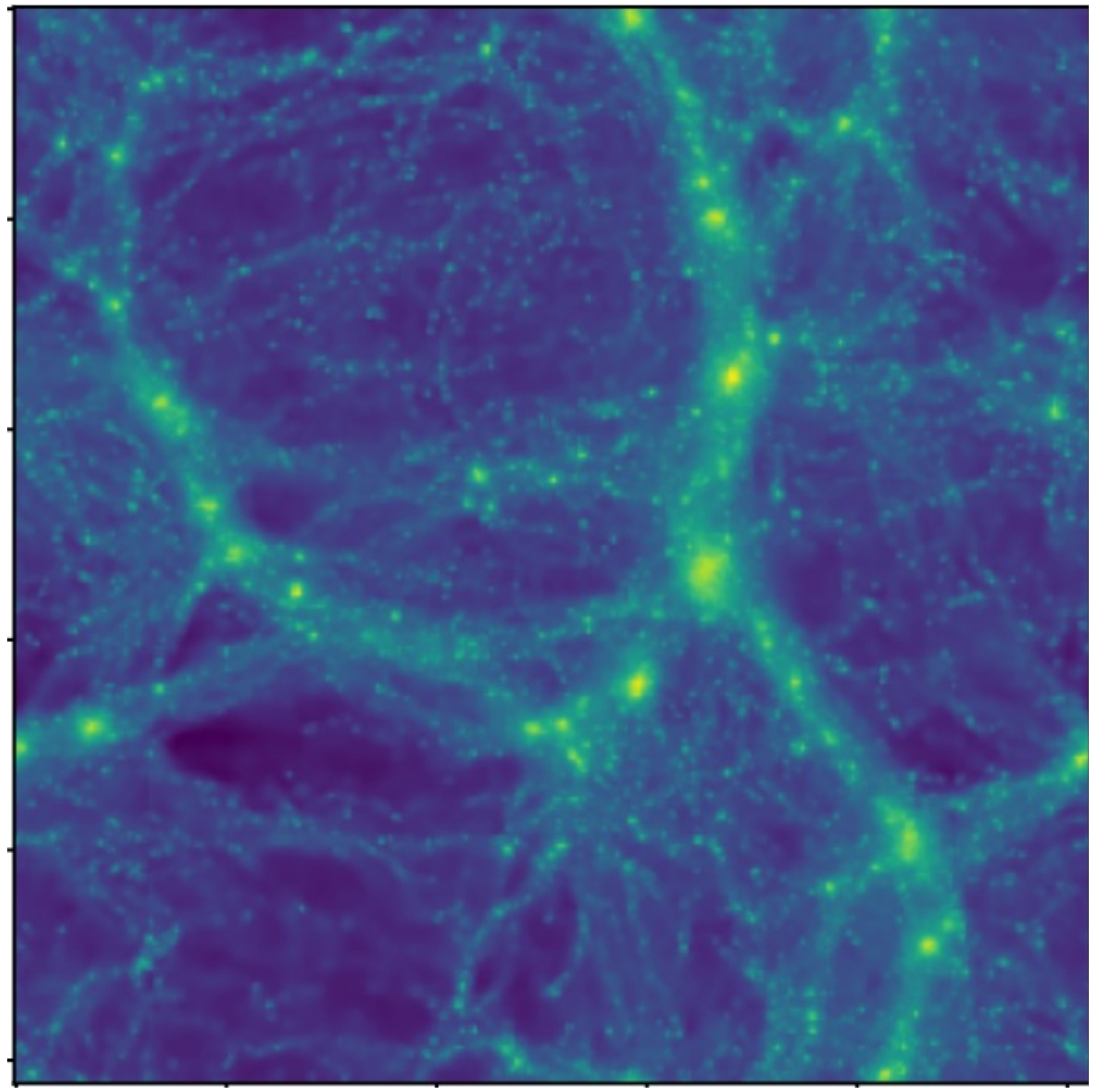
Jeffrey's scale:

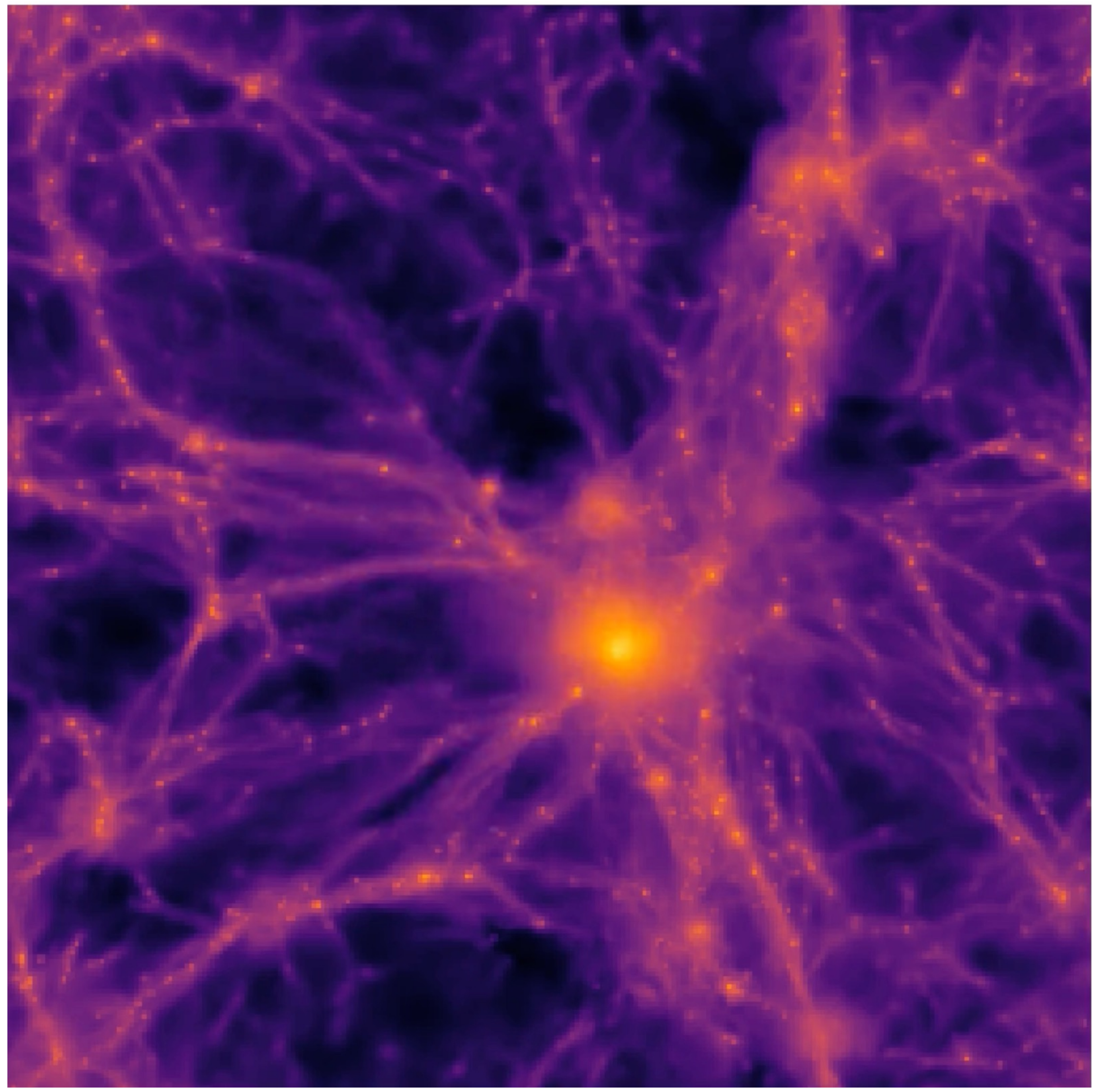
$\log\tau < 1$ not significant ✓

$1 < \log\tau < 2.5$ substantial

$\log\tau > 5$ highly significant

What does realistic mean?





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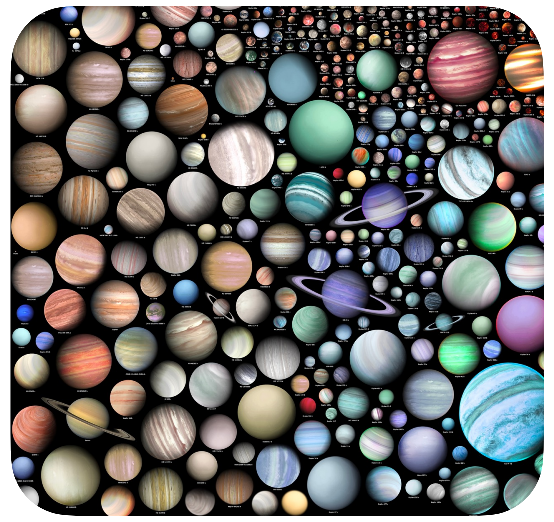
Enabling Next Generation Astrophysics

AI for Astronomy

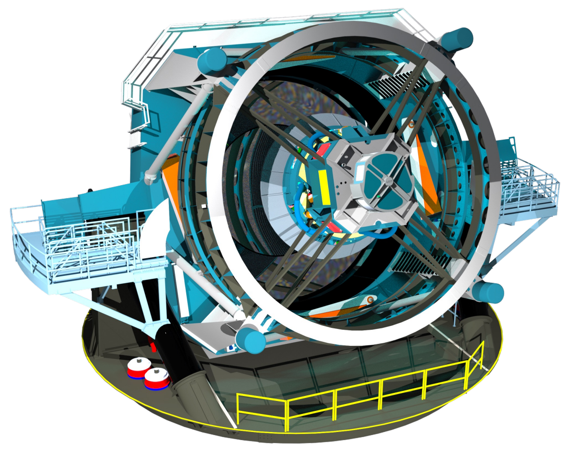
Probabilistic | Physical | Interpretable | Robust

Multimodal | Multi-Scale | Generative | Open Source

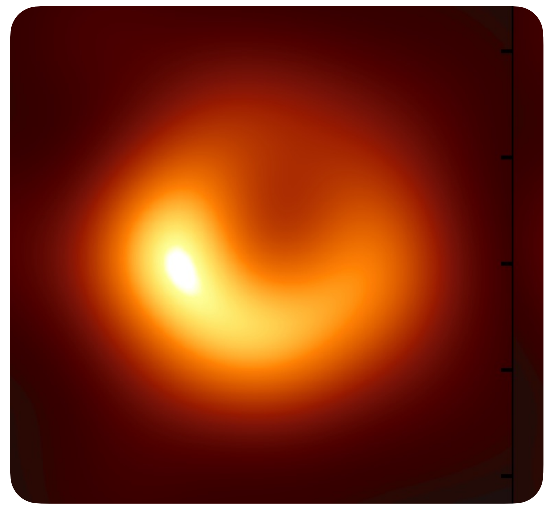


Biomarkers

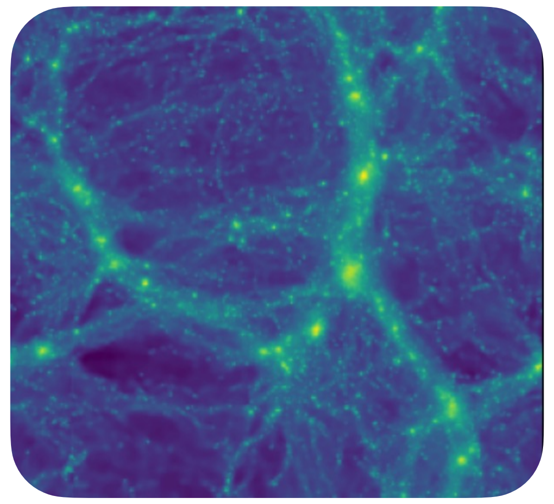
Stars



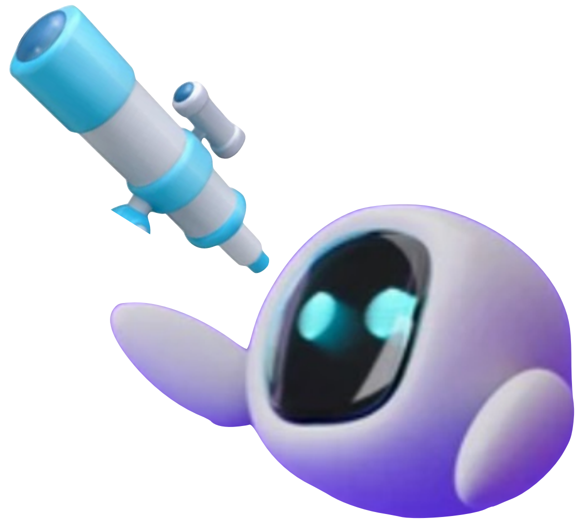
Dynamic Sky



Black Holes



Cosmology



LLMs for Astronomy

GravAI

AstroAI

Enabling Next Generation Astrophysics

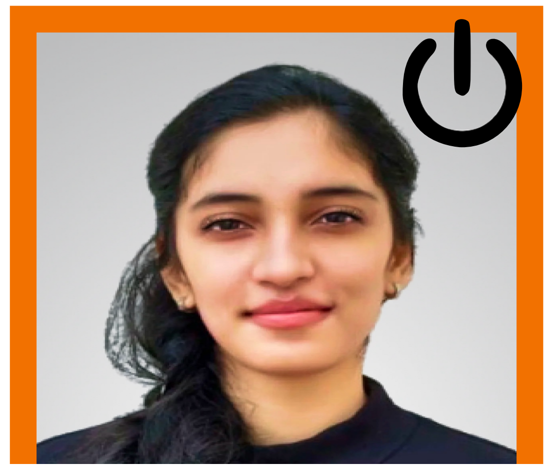
A bit of (modern!) History

November 2022

13 Members

Cecilia Garraffo

Rafael Martinez



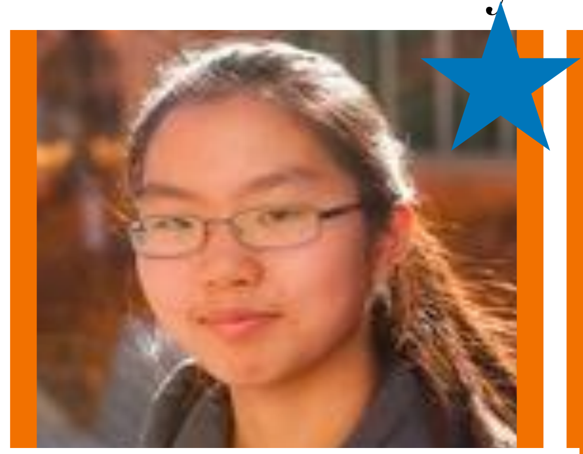
Varshini Reddy

Thaddaeus Kiker

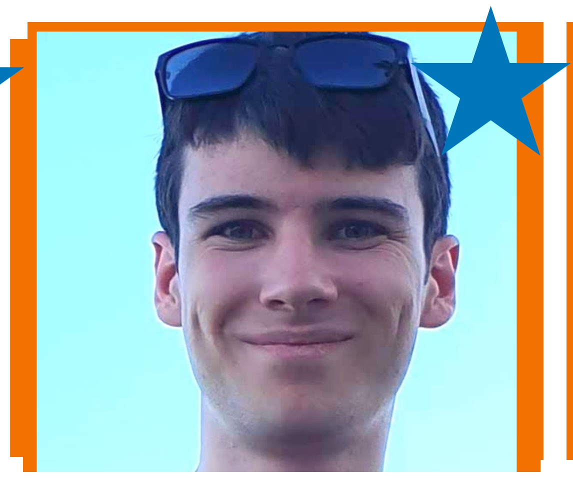
Farah Fauth

James Steiner

Floor Broekgaarden



JustinaYang



Ethan Tregigda

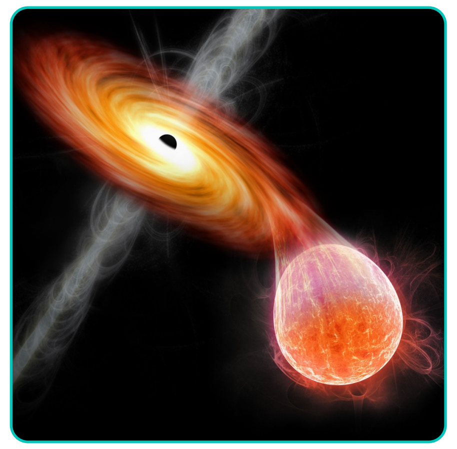
Leticia Schettino

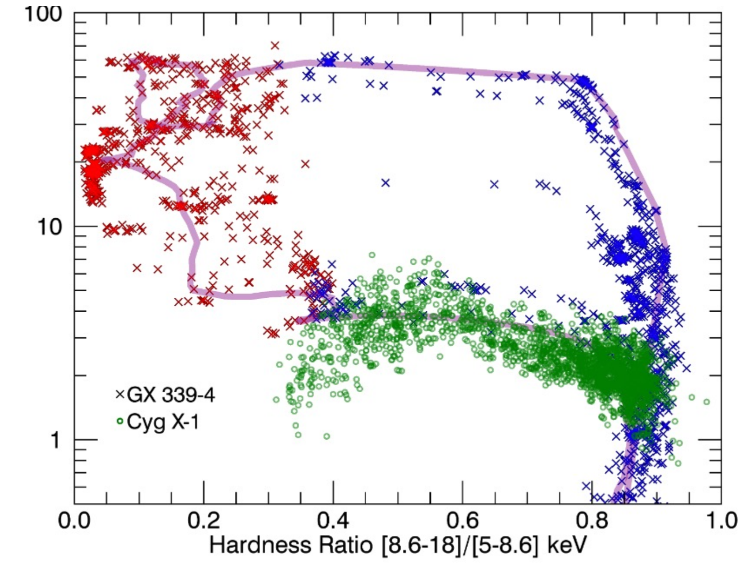
Augusto Chantad

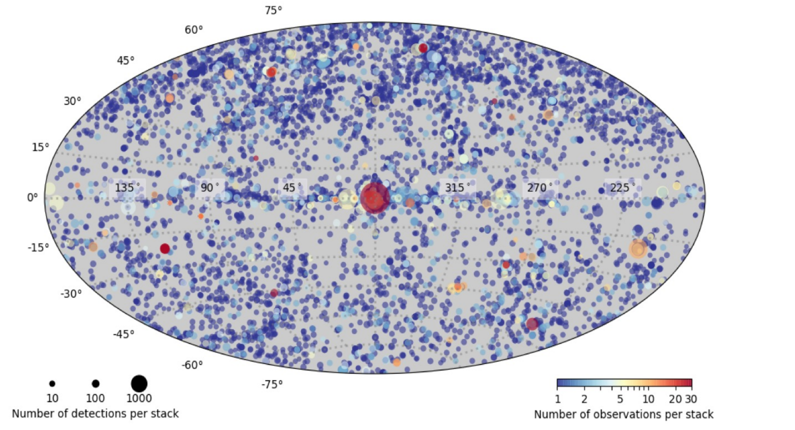
Arya Mohan

Ben Ricketts

4 Projects







Source: CSC Website

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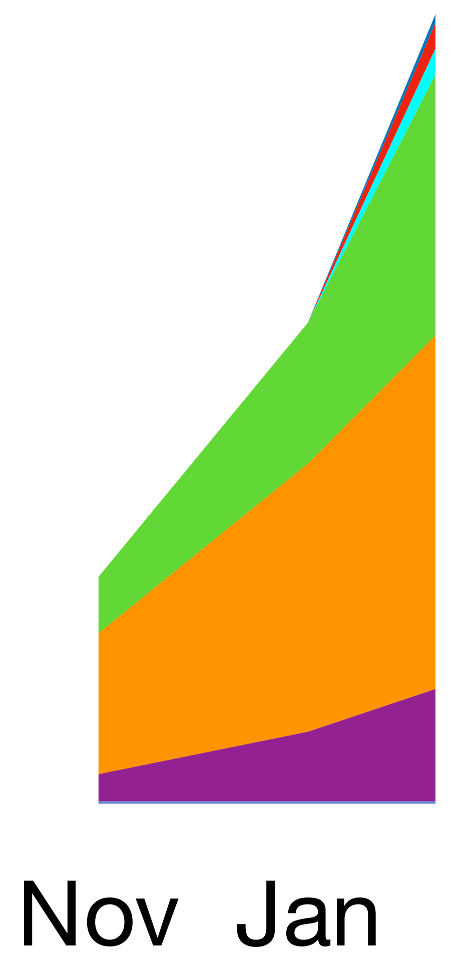
January

5 Partners

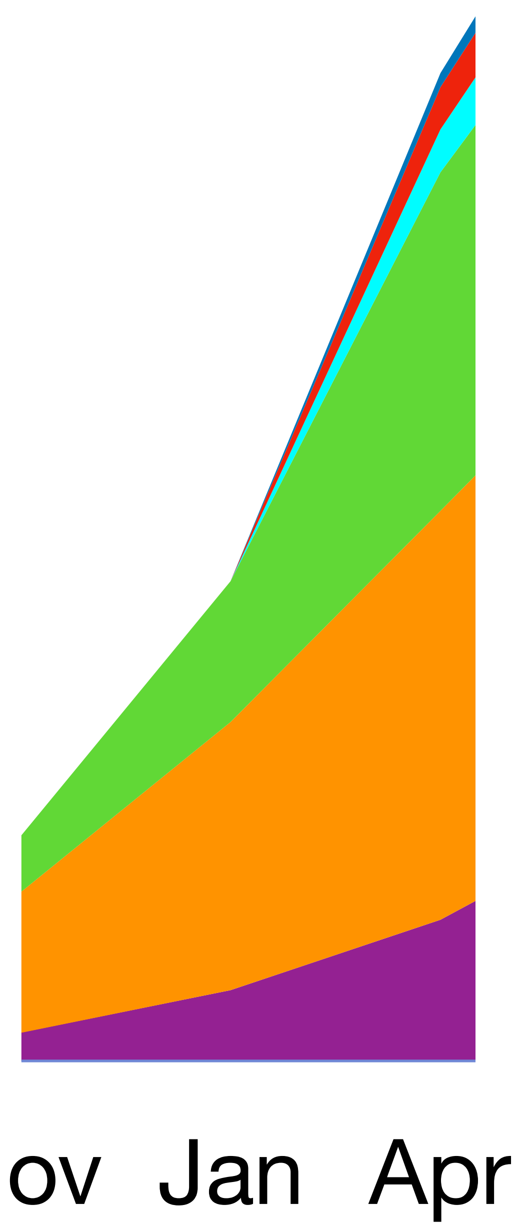
19 Members

10 Projects



Enabling Next Generation Astrophysics

January	April
5 Partners	18 Partners
19 Members	36 Members
10 Projects	29 Projects
	5 Invited talks
	3 Papers
	1 Internship Program



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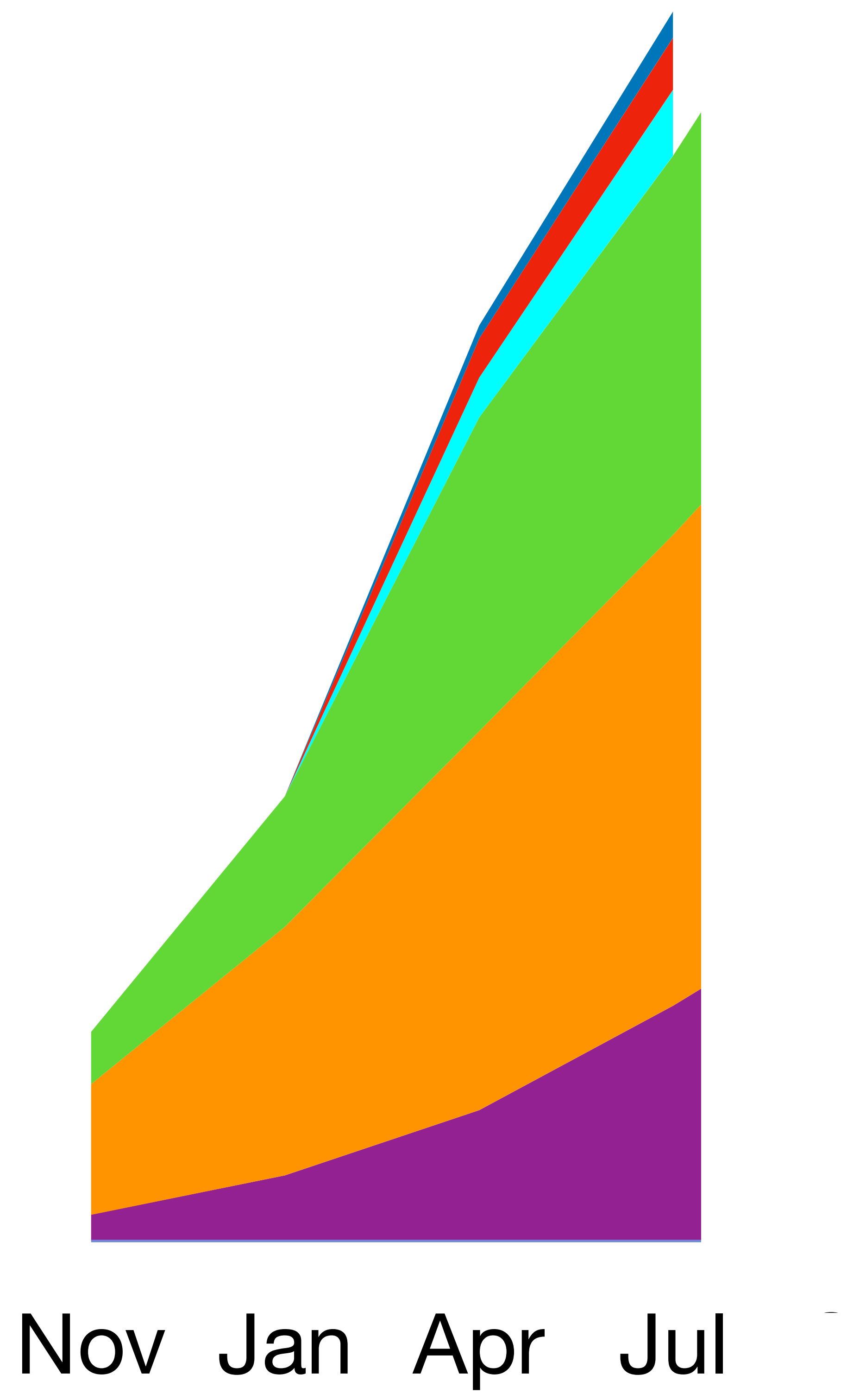
Enabling Next Generation Astrophysics

January	April	July
5 Partners	18 Partners	27 Partners
19 Members	36 Members	43 Members
10 Projects	29 Projects	31 Projects
	5 Invited talks	7 Invited talks
	3 Papers	6 Papers
	1 Internship Program	1 Internship Programs
		2 Small funds
		1 Position



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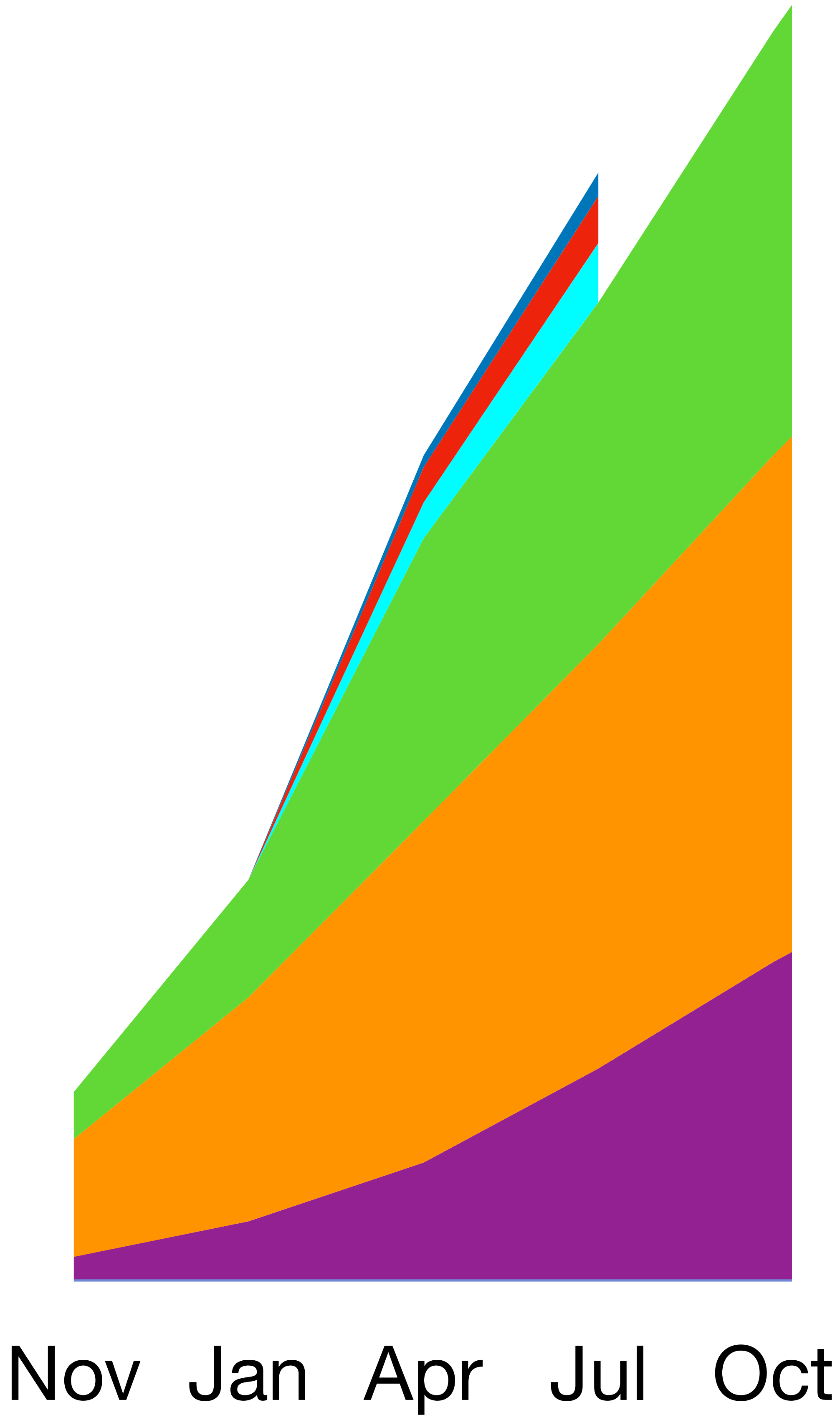
Enabling Next Generation Astrophysics

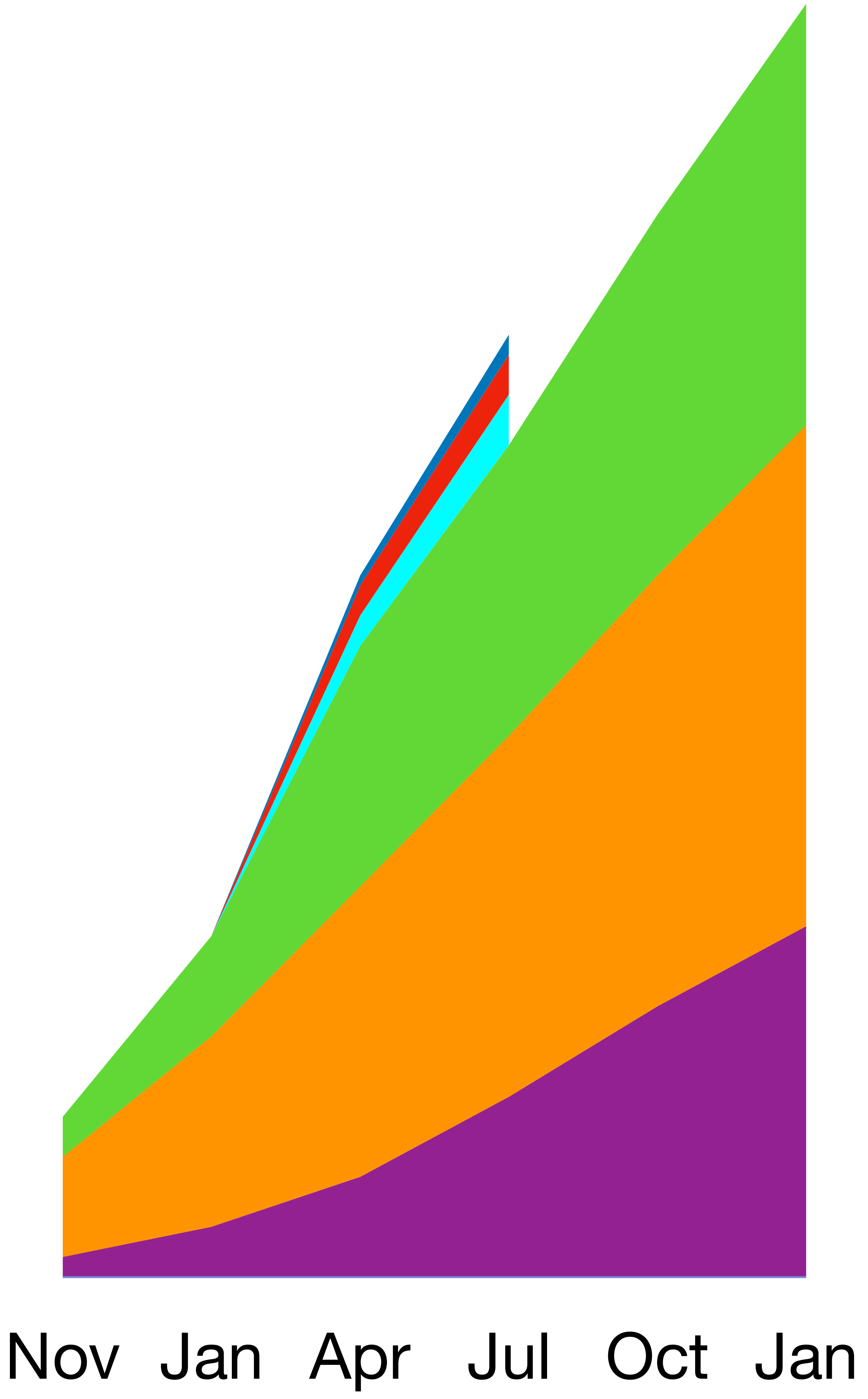
January	April	July	October
5 Partners	18 Partners	27 Partners	32 Partners
19 Members	36 Members	43 Members	45 Members
10 Projects	29 Projects	31 Projects	37 Projects
	5 Invited talks	7 Invited talks	18 Invited talks
	3 Papers	6 Papers	10 Papers
	1 Internship Program	1 Internship Programs	2 Internship Programs
		2 Small funds	5 Small funds and B&P fund
		1 Position	1 Position



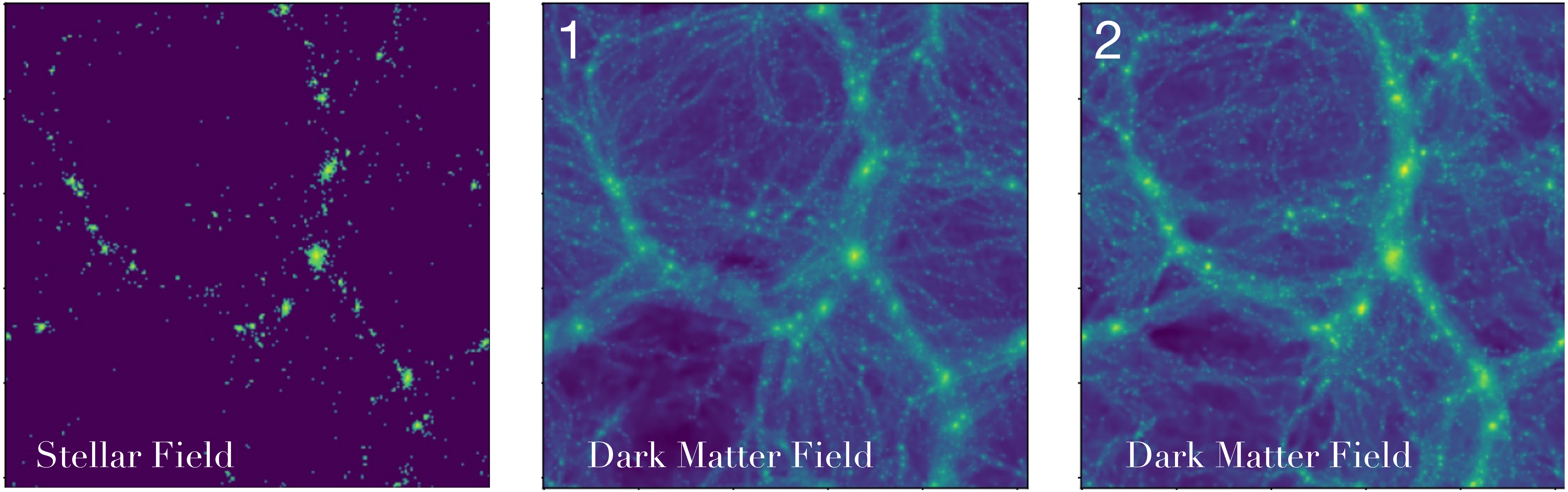
AstroAI

Enabling Next Generation Astrophysics

January	April	July	October	January
5 Partners	18 Partners	27 Partners	32 Partners	>35 Partners
19 Members	36 Members	43 Members	45 Members	>50 Members
10 Projects	29 Projects	31 Projects	37 Projects	37 Projects
	5 Invited talks	7 Invited talks	18 Invited talks	>20 Invited talks
	3 Papers	6 Papers	10 Papers	14 Paper
	1 Internship Program	1 Internship Programs	2 Internship Programs	2 Internship program
		2 Small funds	5 Small funds and B&P fund	5 Small funds and B&P fund
		1 Position	1 Position	1 Position

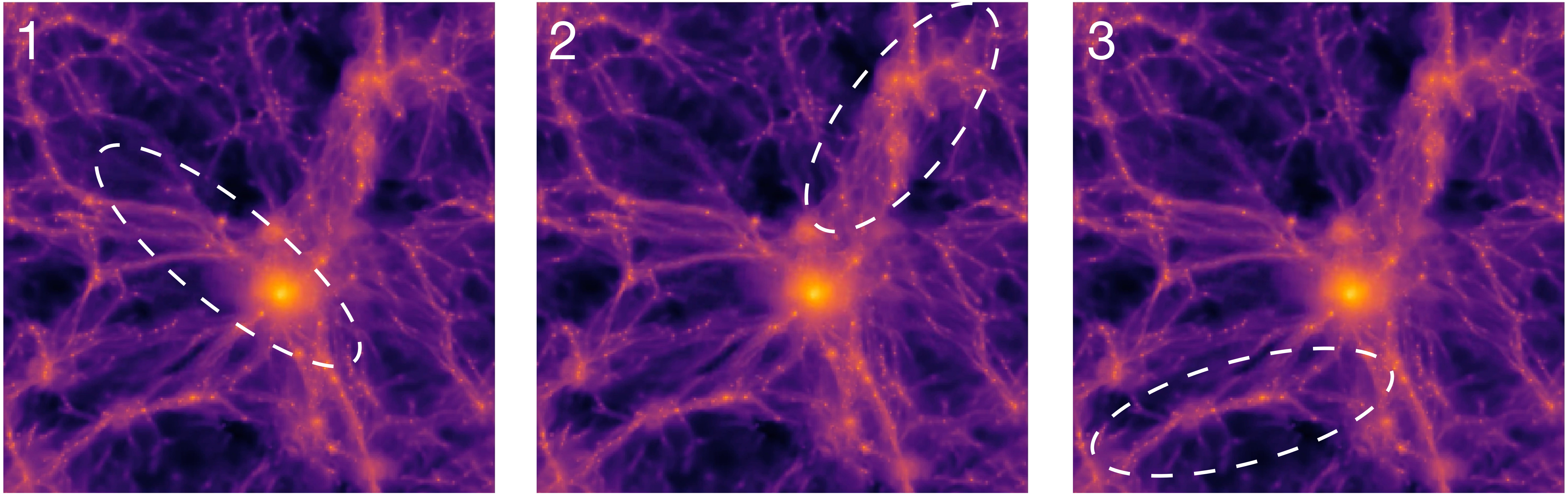


Dark Matter Field Simulations



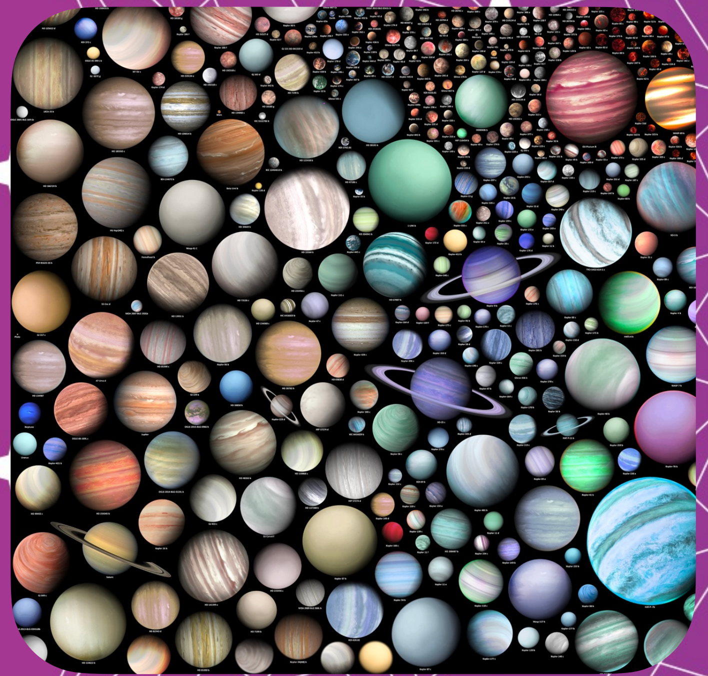
Carolina Cuesta-Lázaro & Core Park

Galaxy Filament AI-Infill



Core Parke

2. AI for Instrument Design



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Cecilia Garraffo
Director of AstroAI

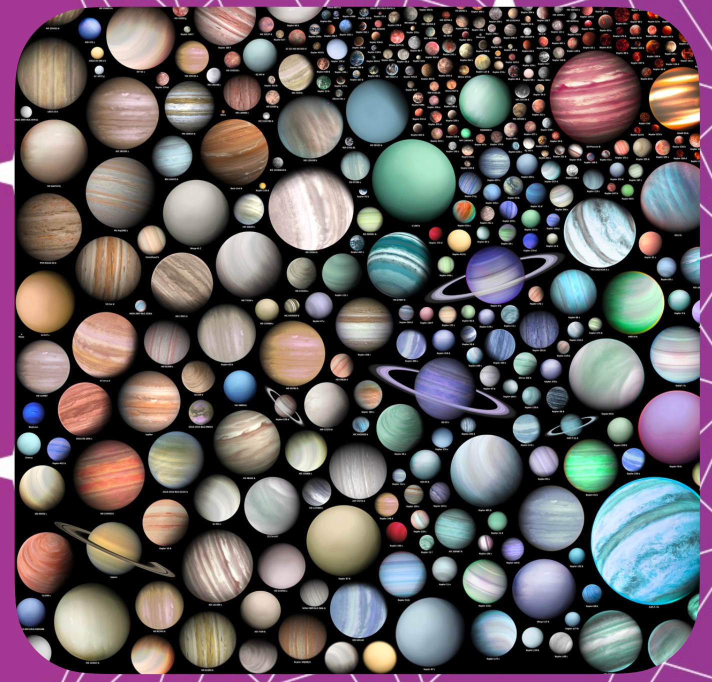
Mercedes Lopez-Morales
Exoplanet Atmospheres
World Expert

Bill Freeman, CS
Head of Computer
Vision Institute
MIT
Microsoft

Robin Walters,
Applied Math
Expert on
Equivariant Neural
Networks

Iouli Gordon
Physicist /
Spectroscopist
HEAD of HITRAN

Extend the search with Computer Vision!



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Physicist /
Spectroscopist
HEAD of HITRAN

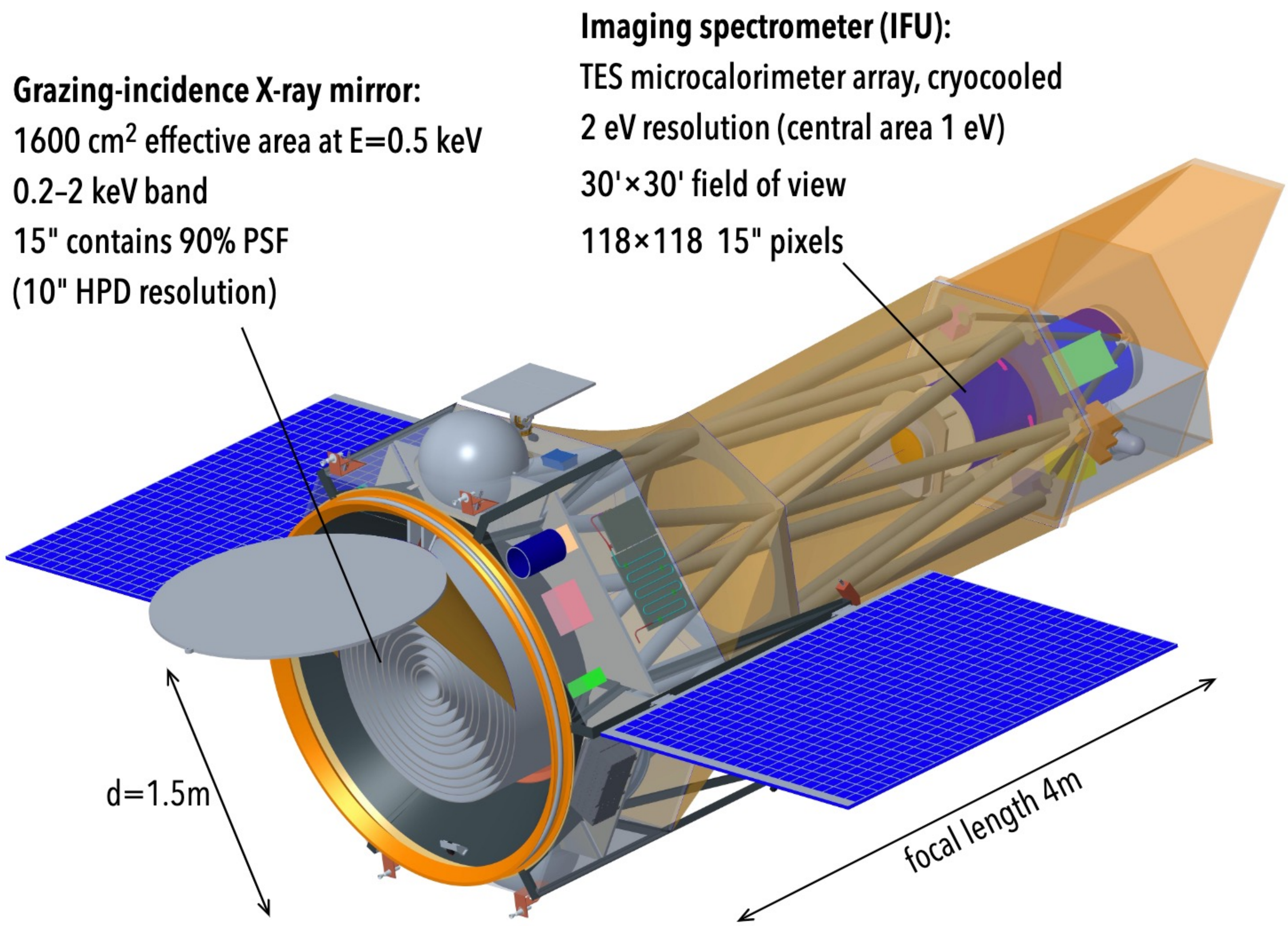
Computer Vision to inform HWO's instrument design

AstroAI

Enabling Next Generation Astrophysics

LEM

LINE EMISSION MAPPER



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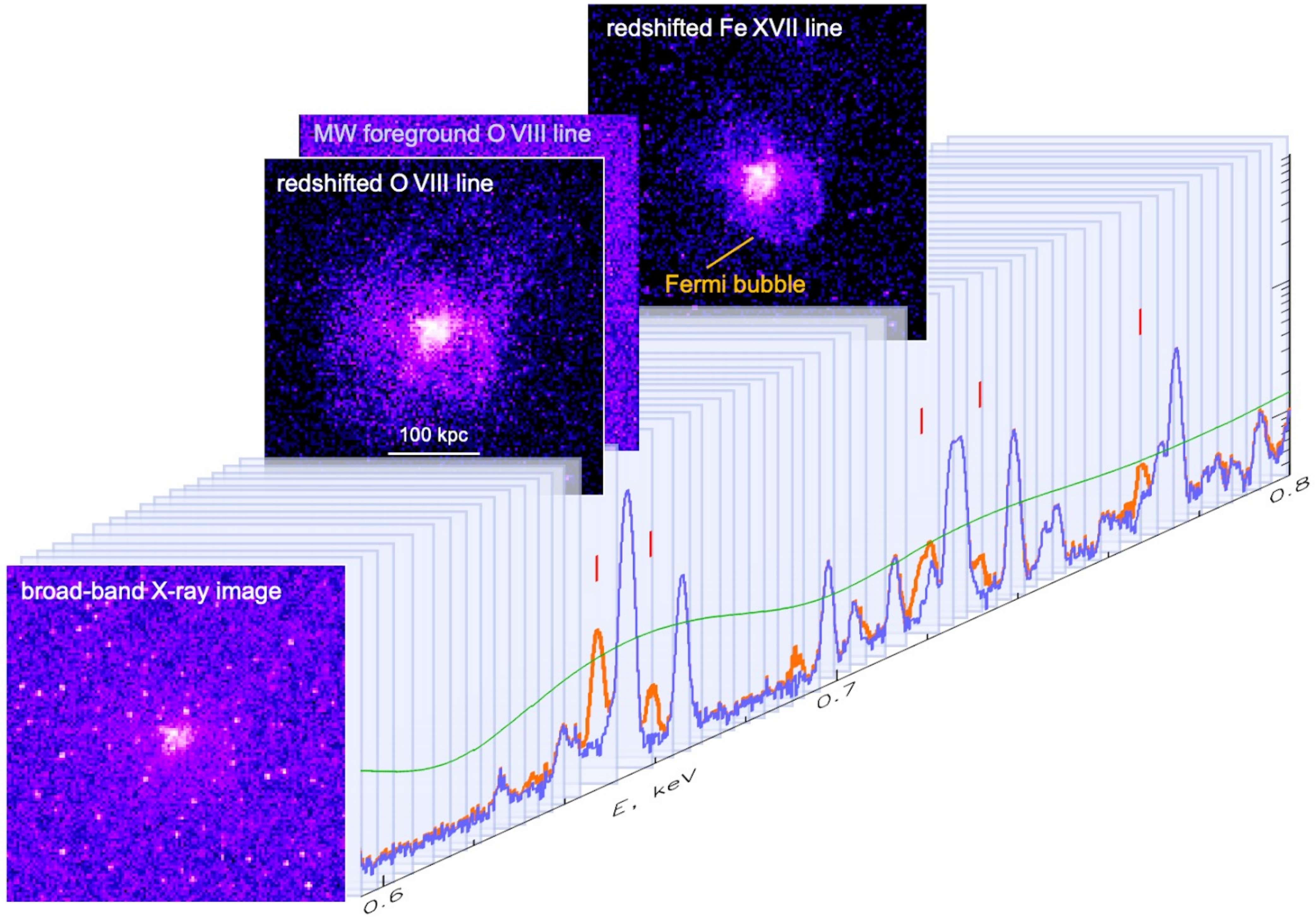
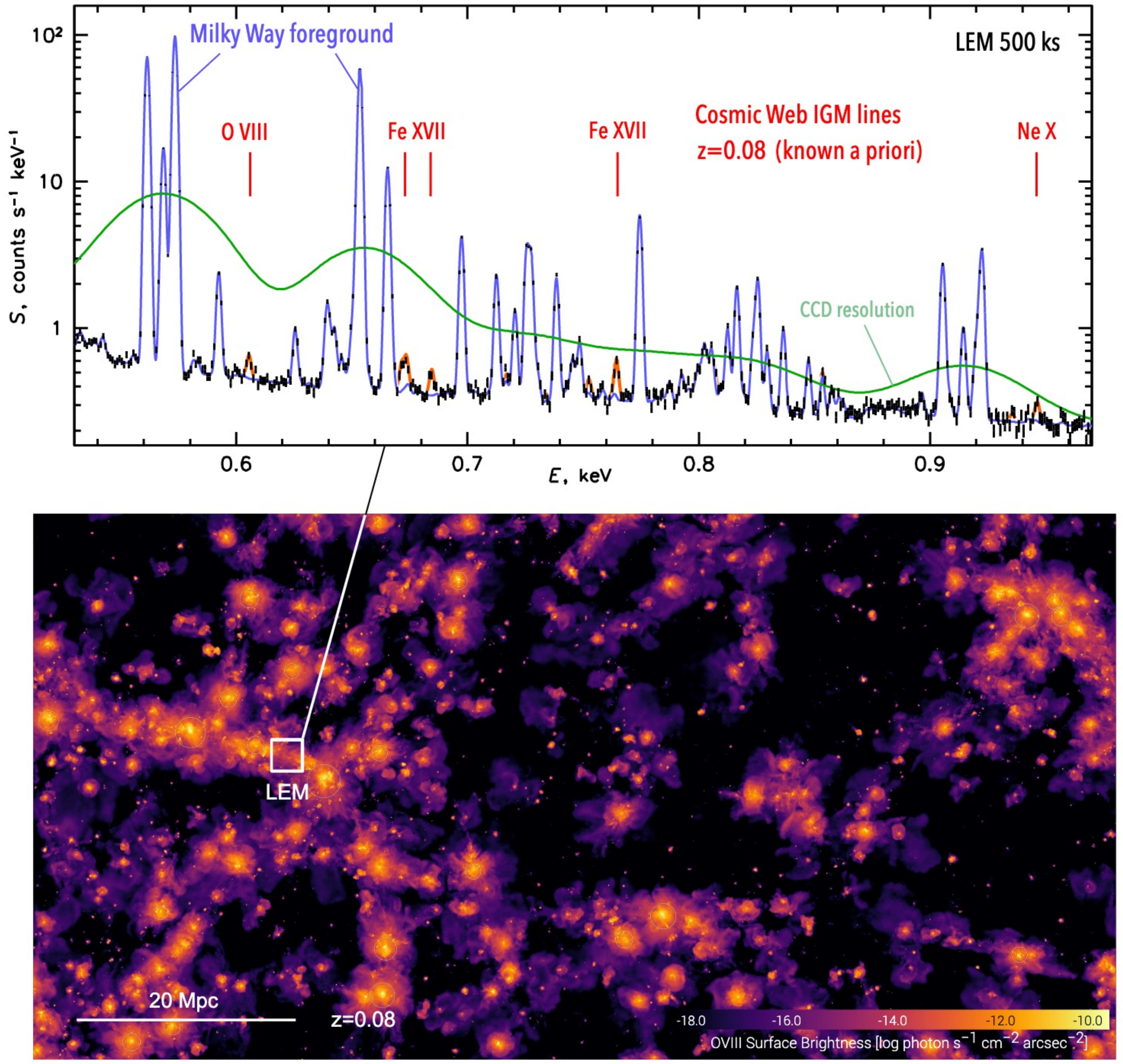
Enabling Next Generation Astrophysics

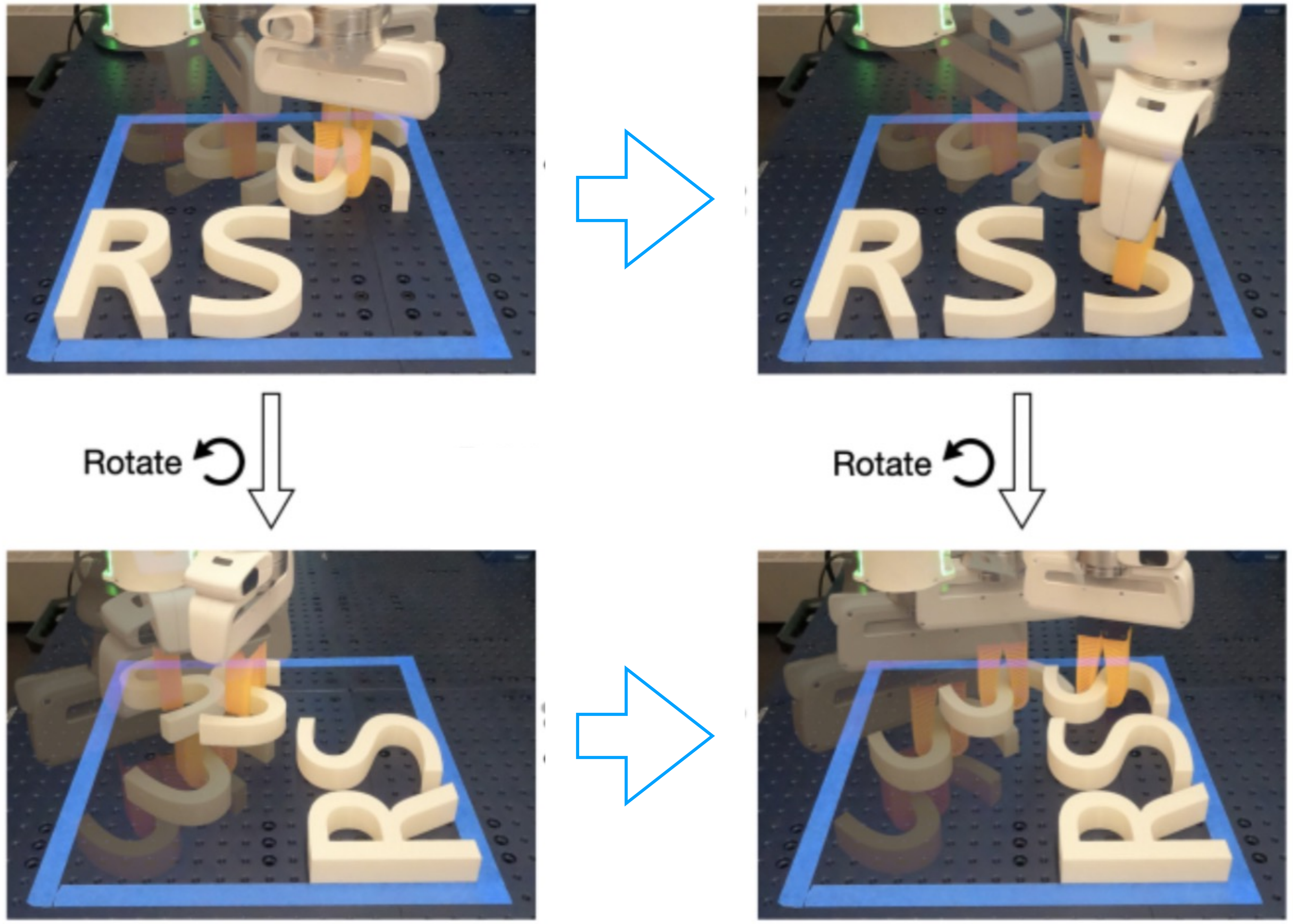
Josh Wing

Automatic Detection of Sources from LEM

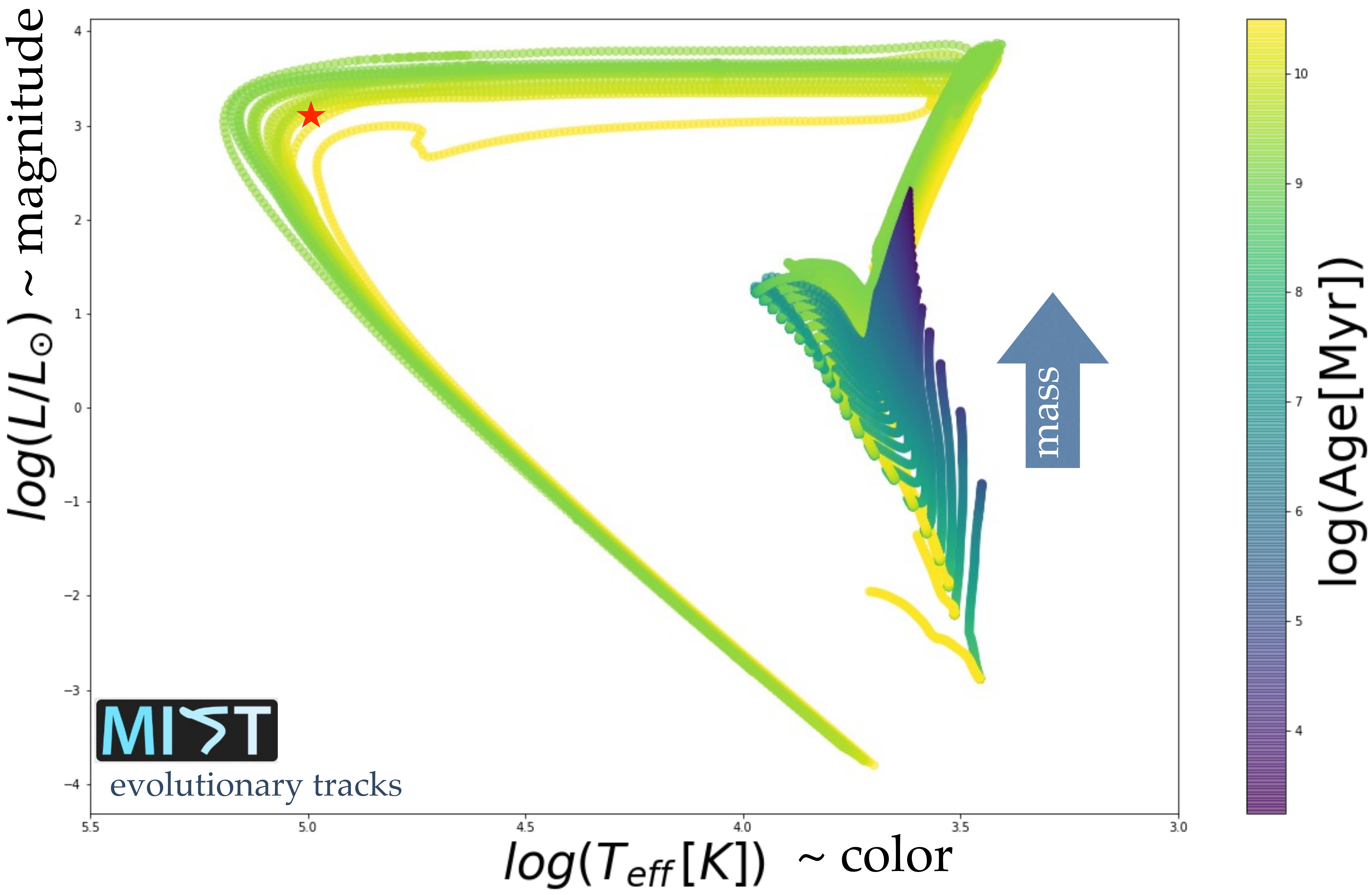




Equivariant Neural Networks

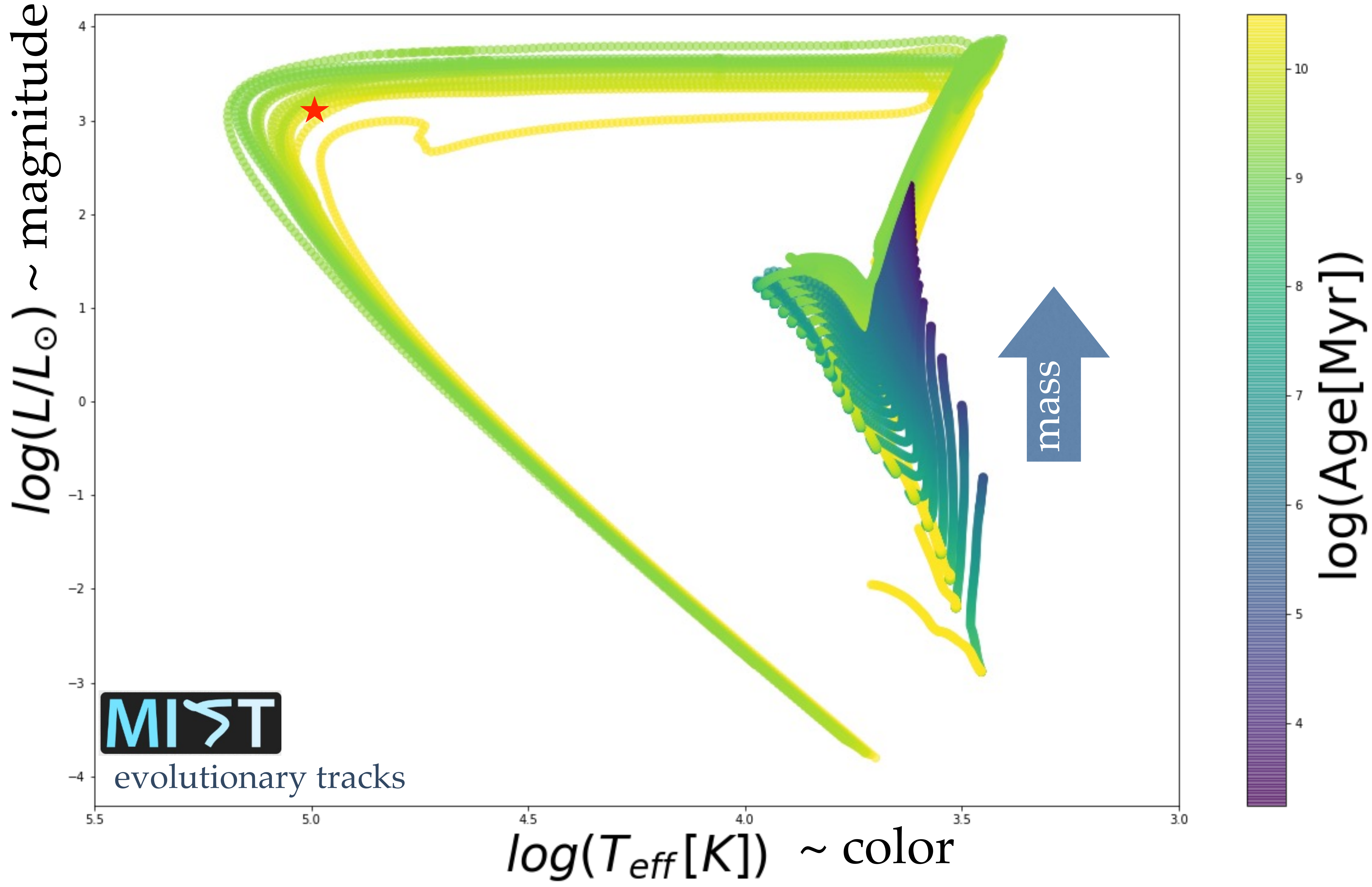


D. Wang, S. Hart, D. Surovik, T. Kelestemur, H. Wang, H. Zhao, J. Wang, R. Walters, R Platt submitted to NeurIPS

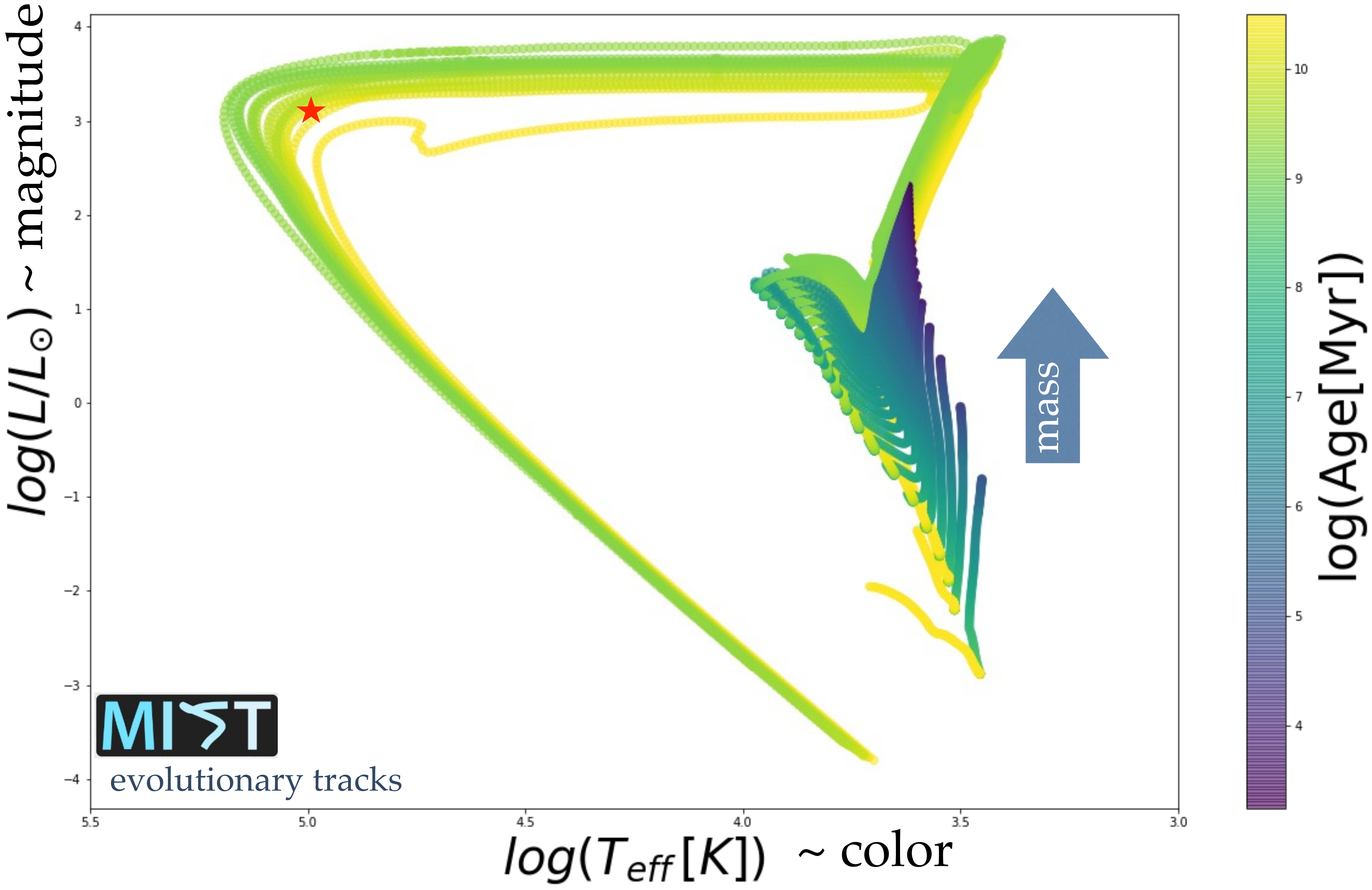


log(L/L⊙) ~ magnitude
4
3
2
1
0
−1
−2
−3
−4
5.5
5.0
4.5
4.0
3.5
3.0
log(T_eff[K]) ~ color
MIST
evolutionary tracks
mass
log(Age[Myr])
10
9
8
7
6
5
4

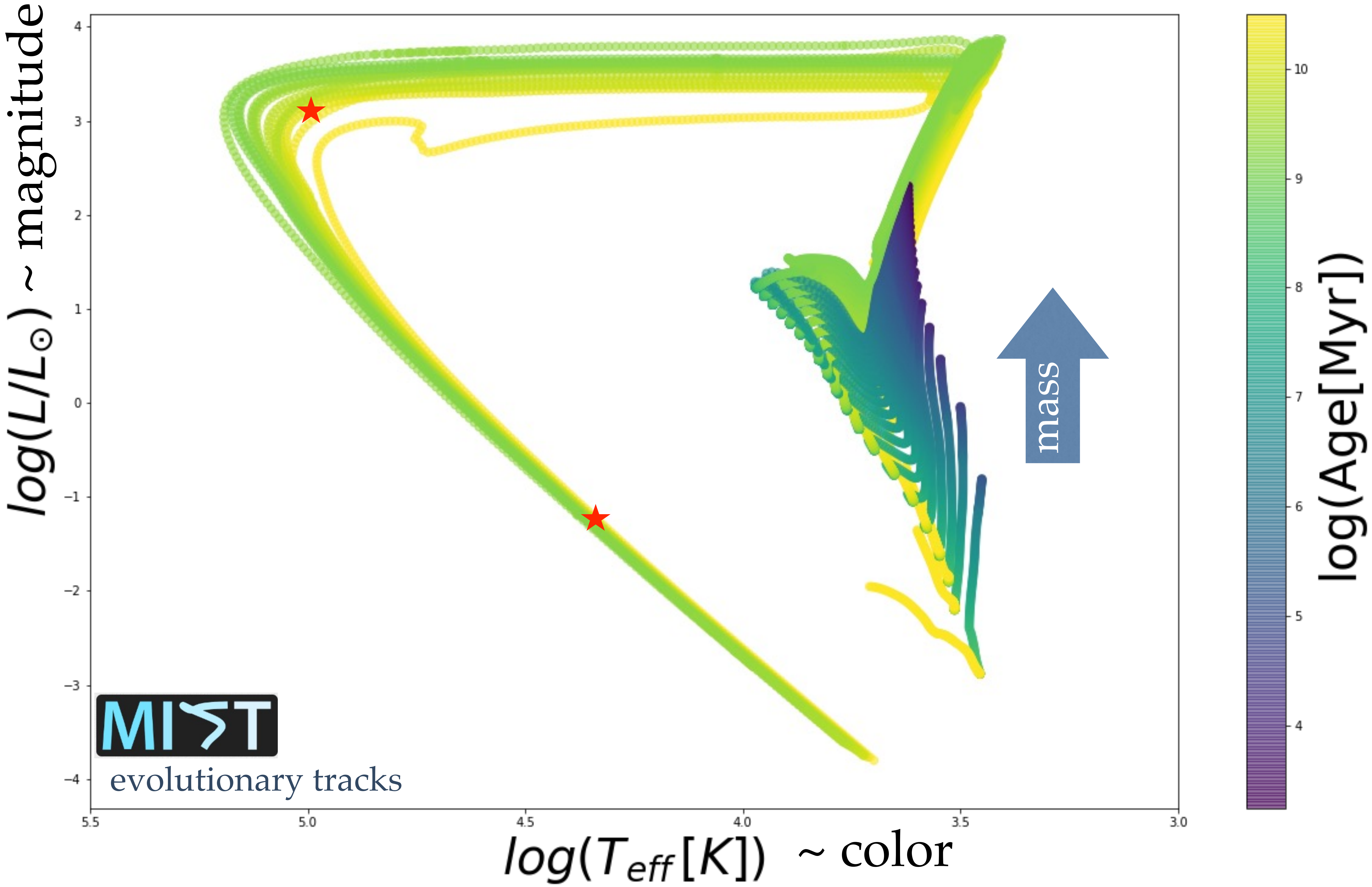
- Non-linearity



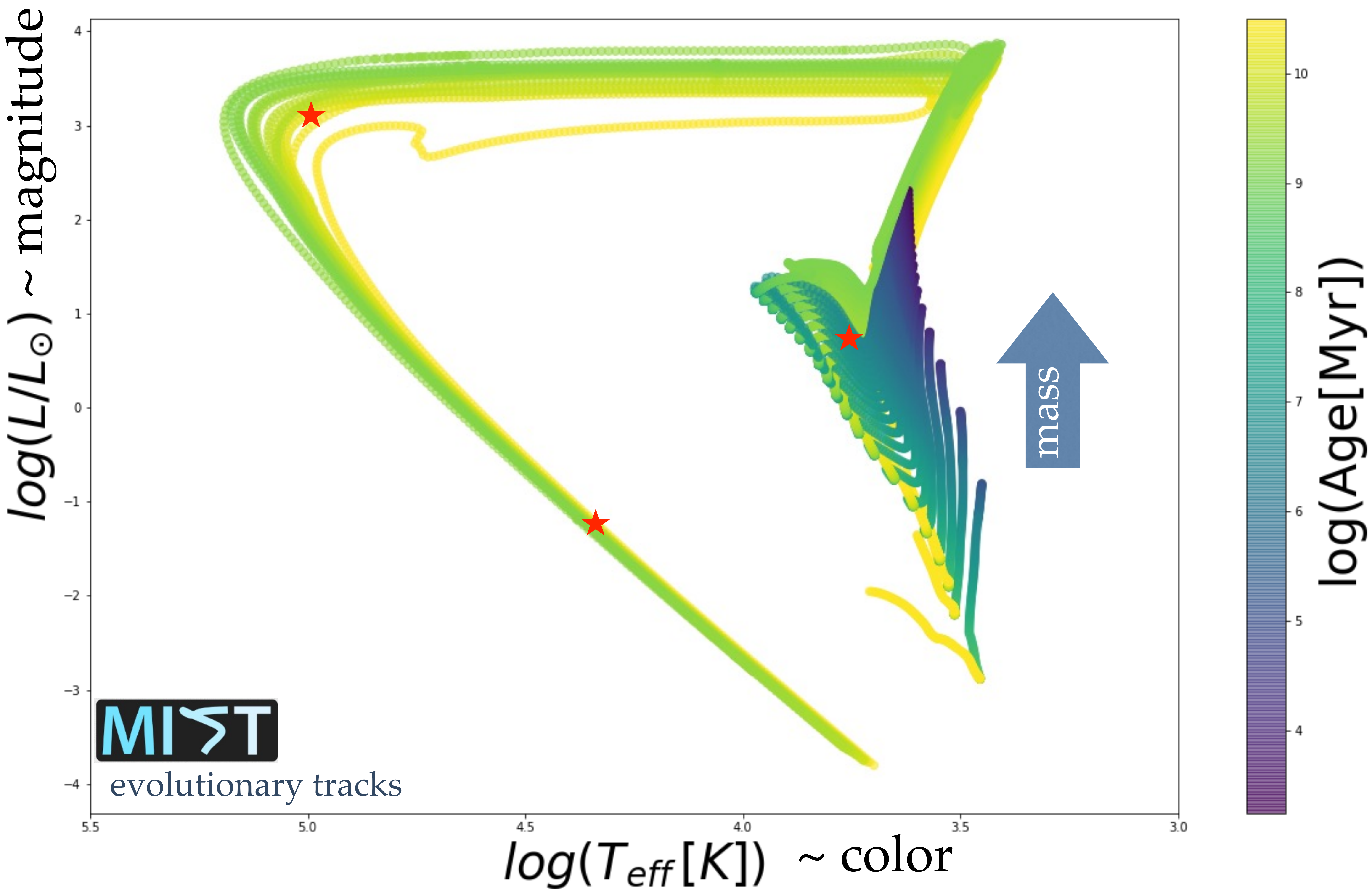
- Non-linearity
- Confidence variations



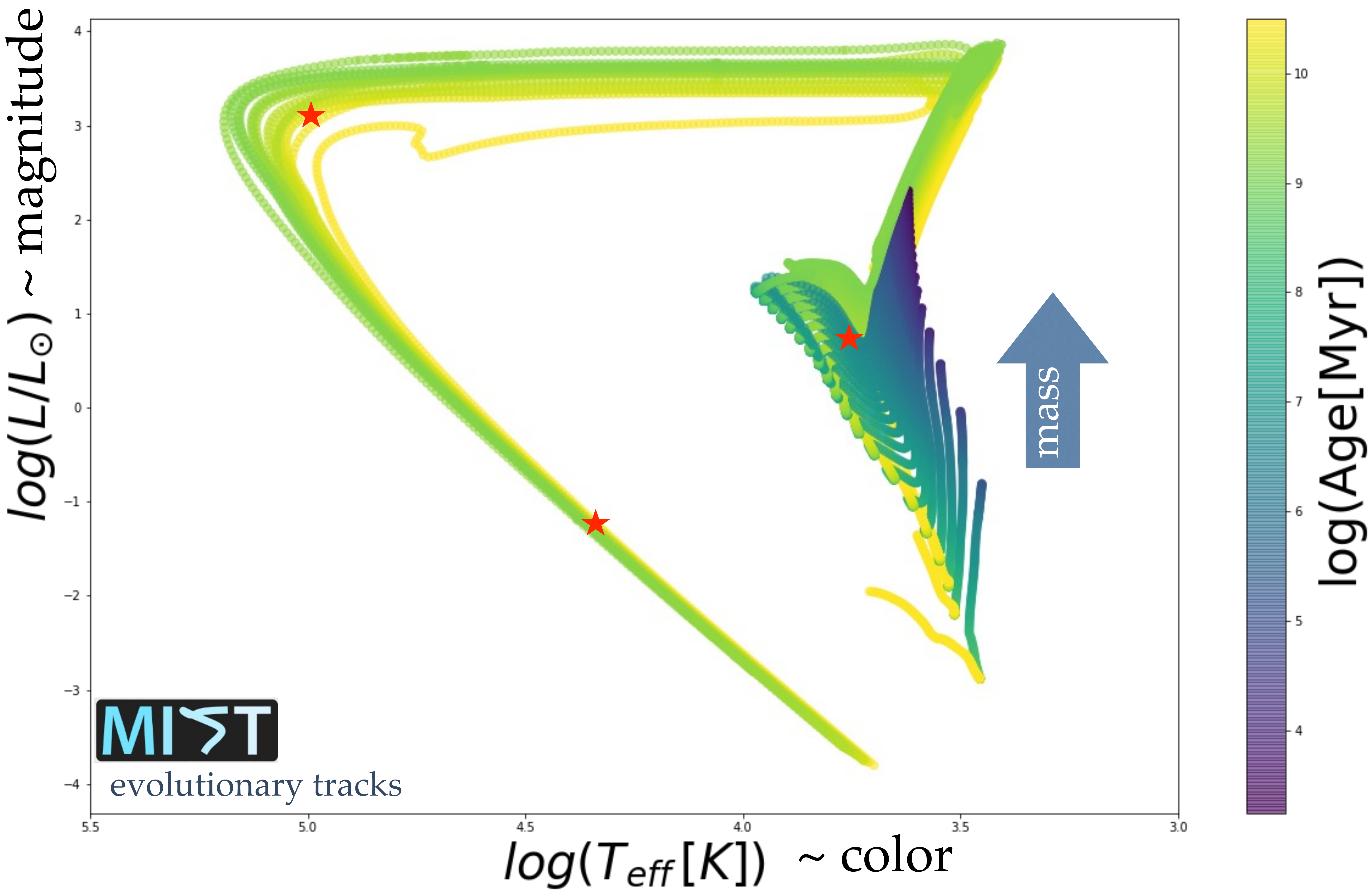
- Non-linearity
- Confidence variations



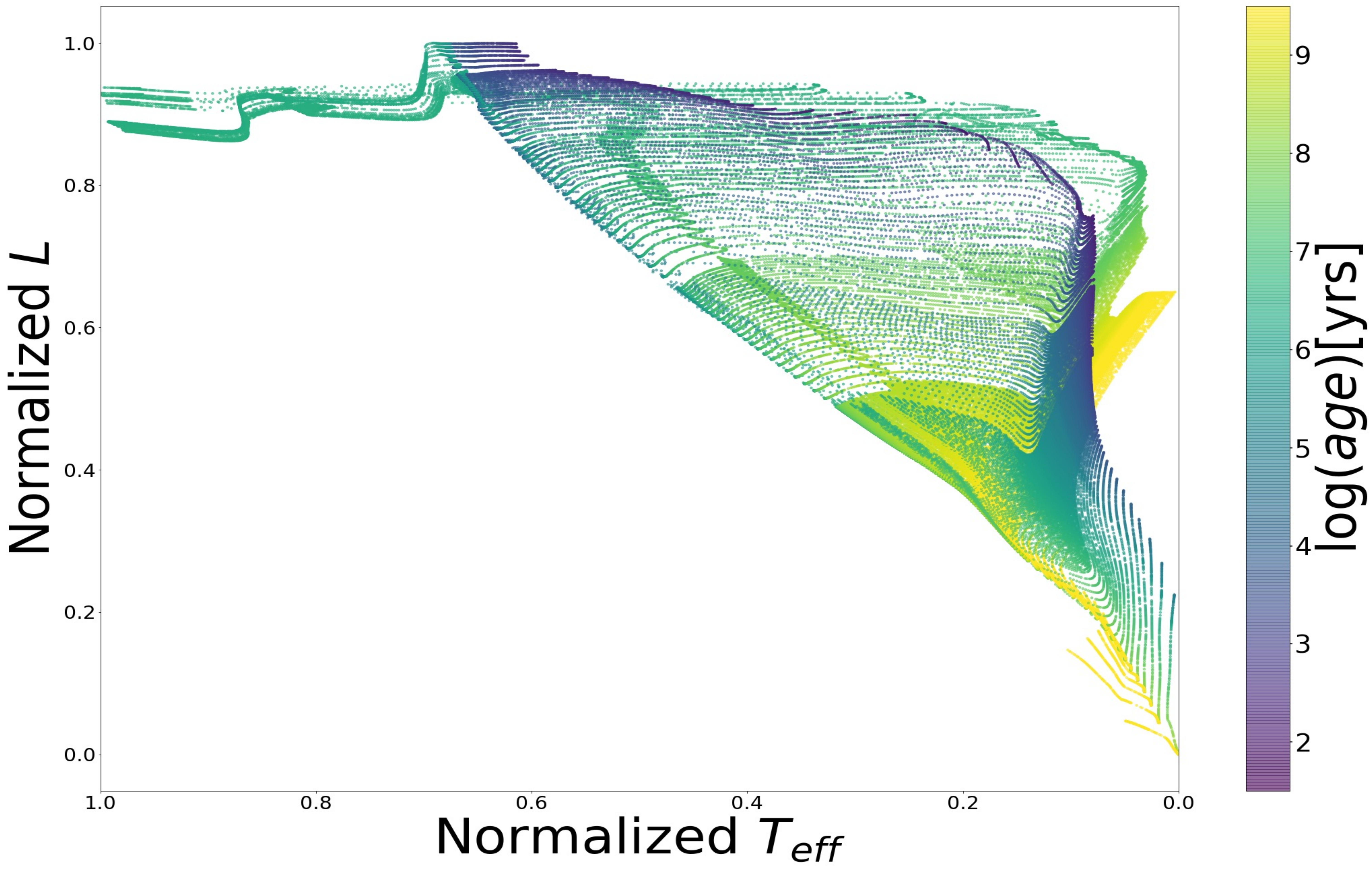
- Non-linearity
- Confidence variations



- Degeneracies
- Non-linearity
- Confidence variations



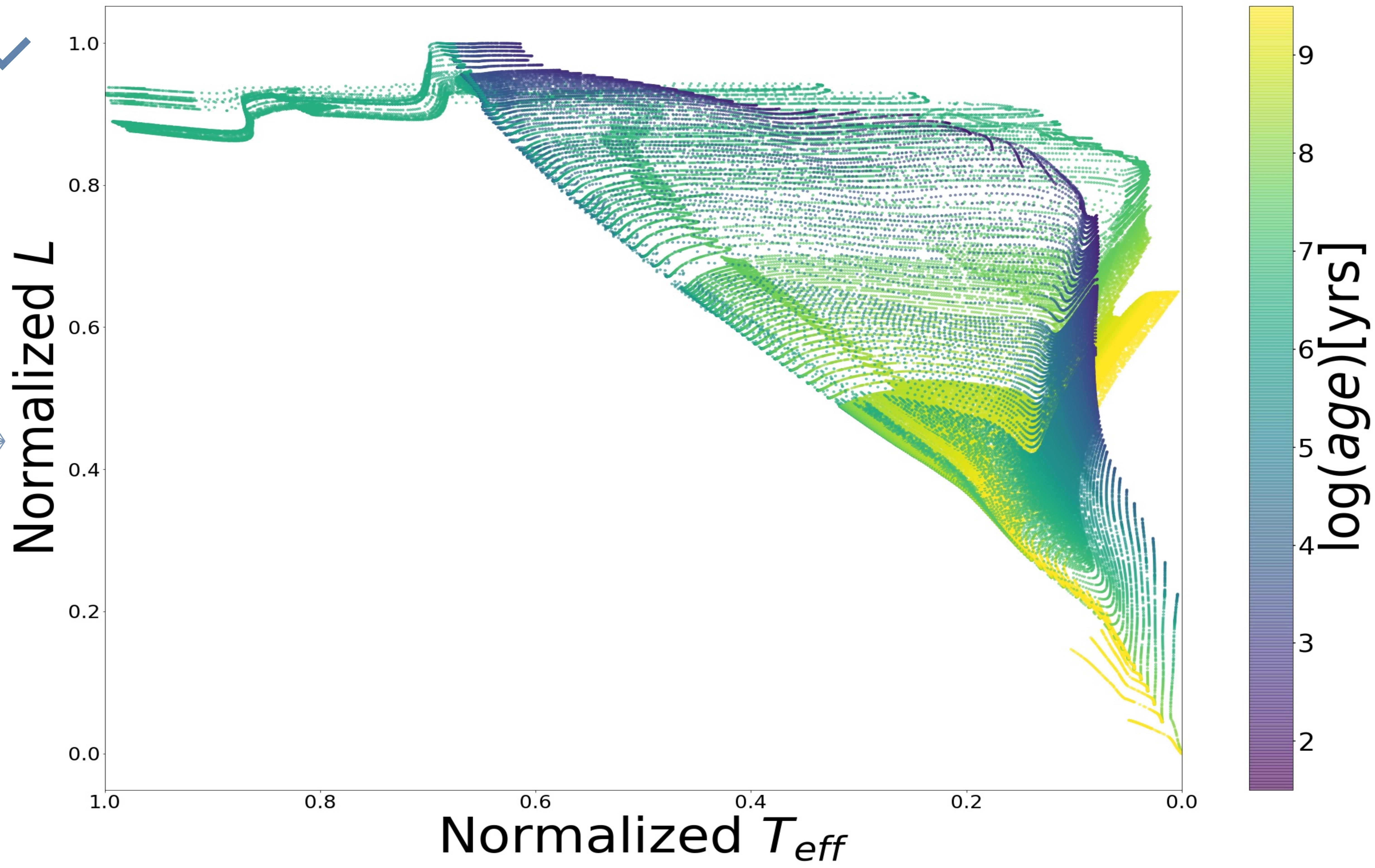
- Degeneracies
- Non-linearity
- Confidence variations



- Degeneracies
- Non-linearity ✓
- Confidence variations

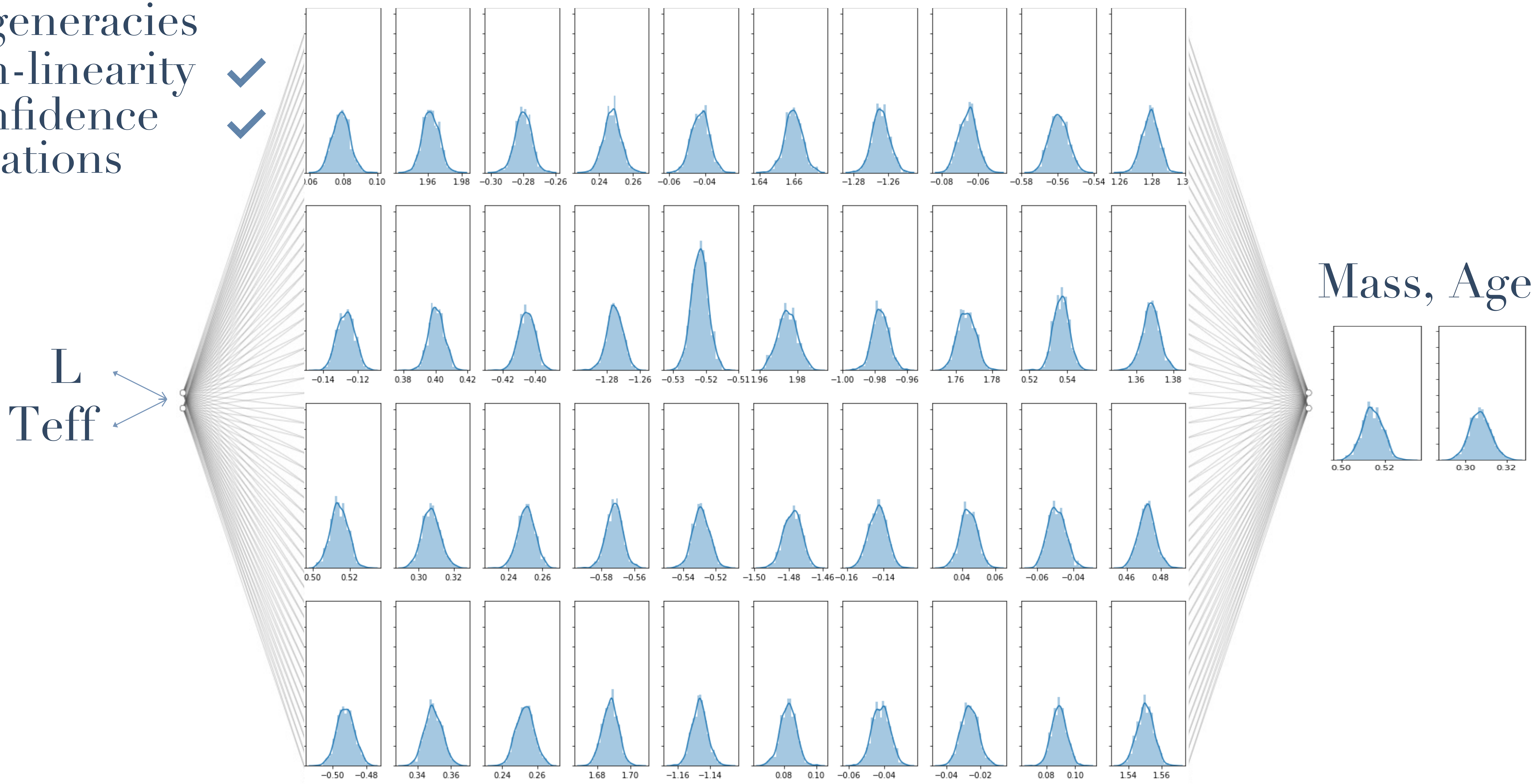
L
Teff

inputs



Mass
Age
outputs

- Degeneracies
- Non-linearity ✓
- Confidence variations ✓



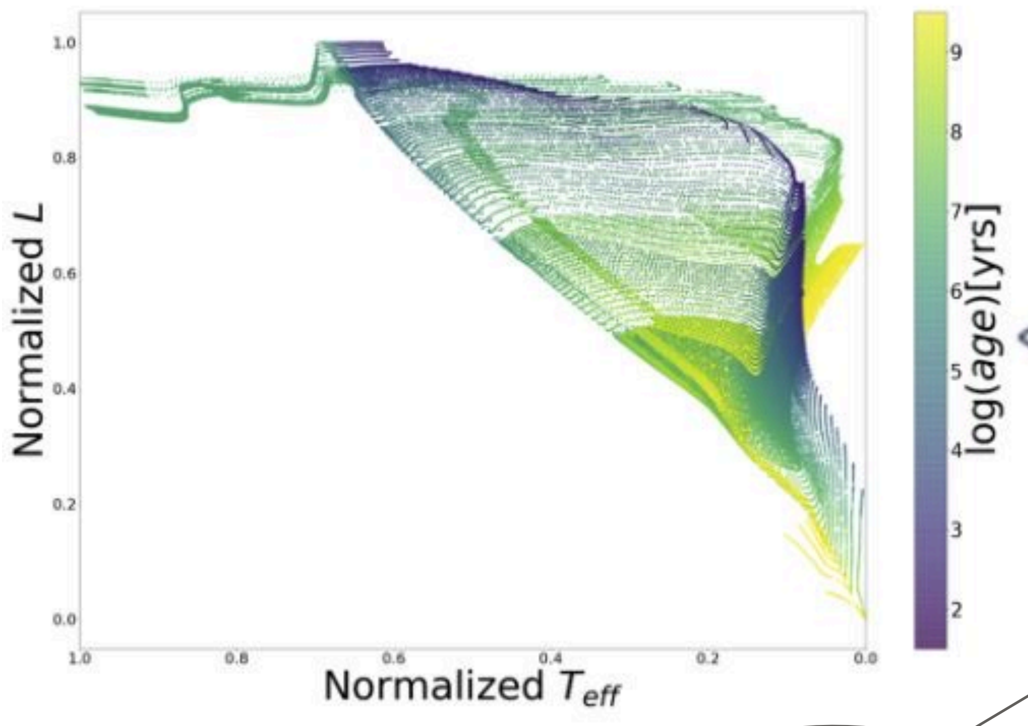
Automatic Stellar Characterization

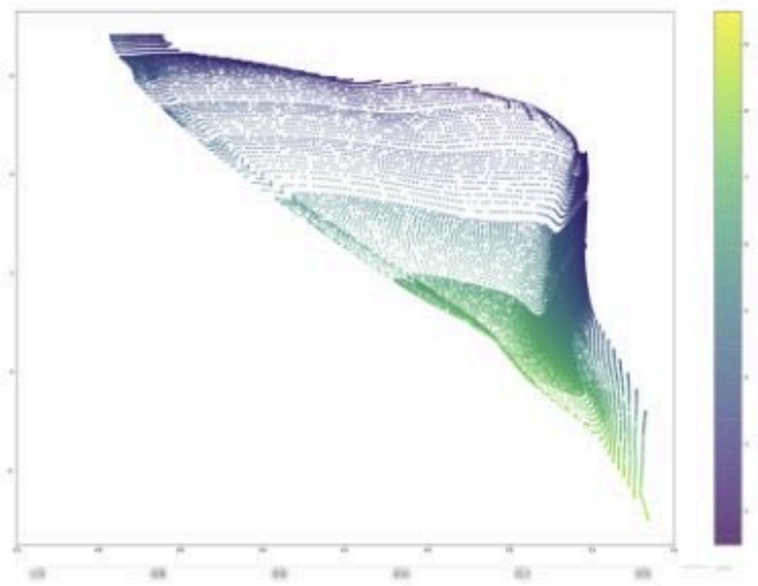
- Degeneracies ✓
- Non-linearity ✓
- Confidence variations ✓

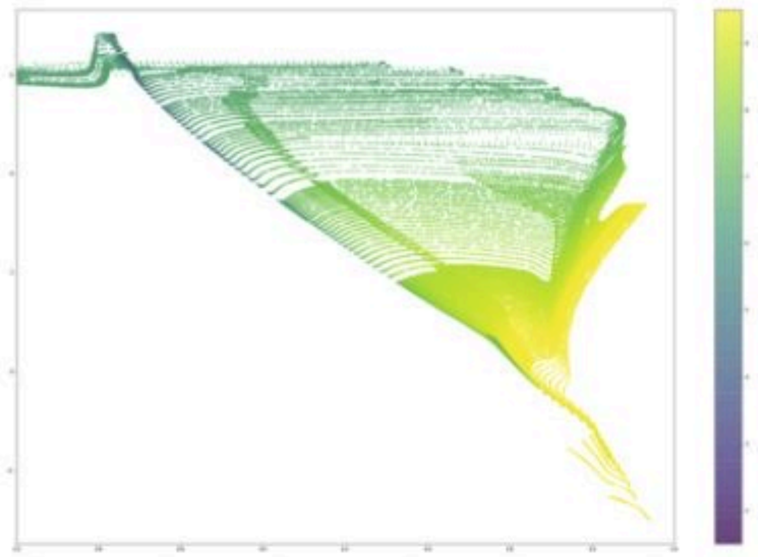
StelNet: Hierarchical, Bayesian, Efficient

L

Teff





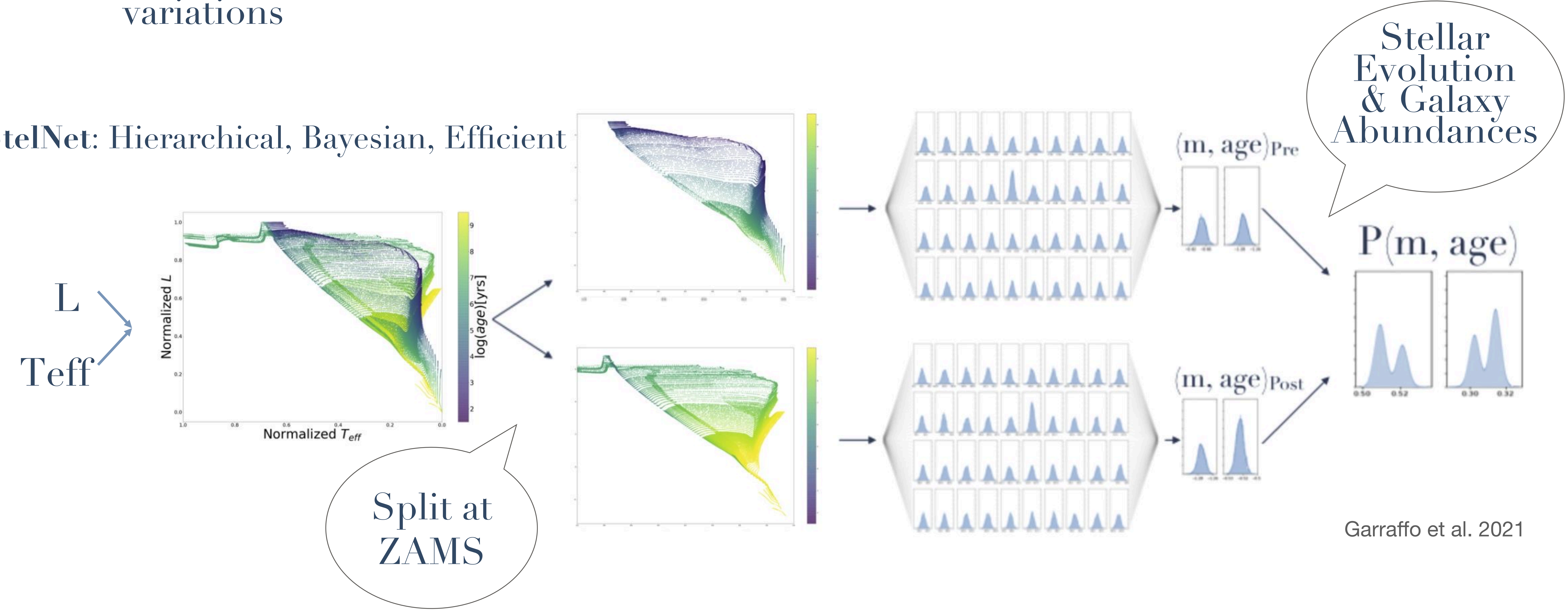


Split at ZAMS

Automatic Stellar Characterization

- Degeneracies ✓
- Non-linearity ✓
- Confidence variations ✓

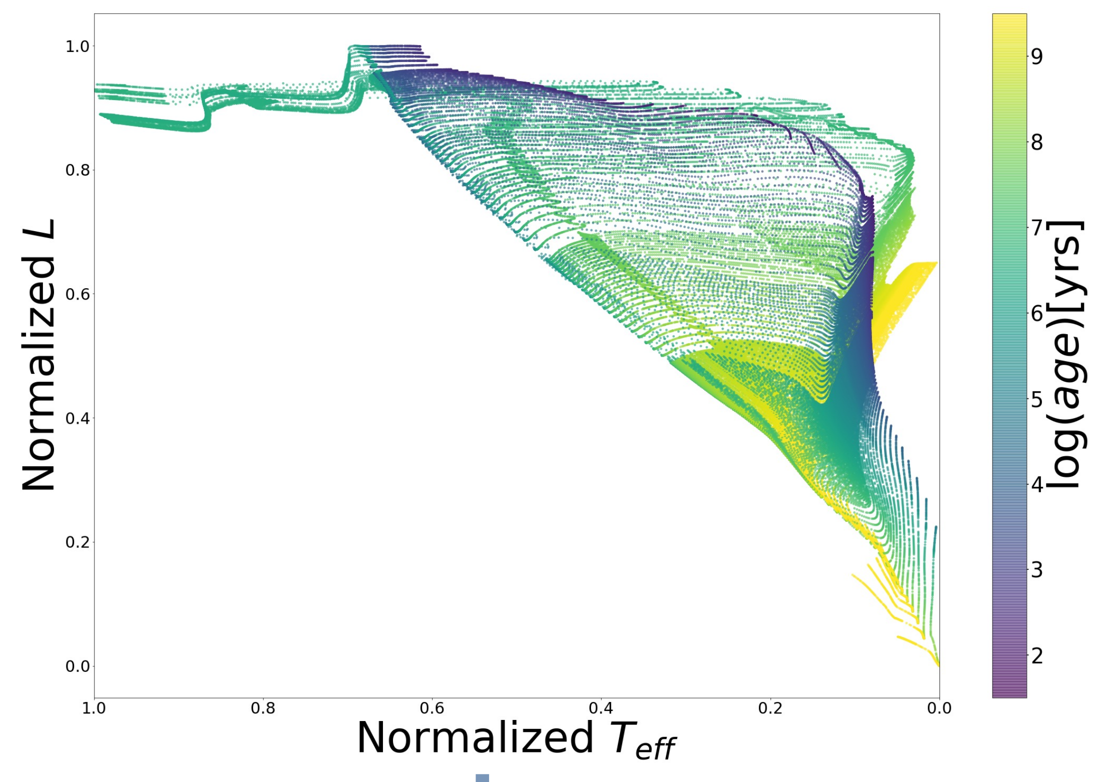
StelNet: Hierarchical, Bayesian, Efficient



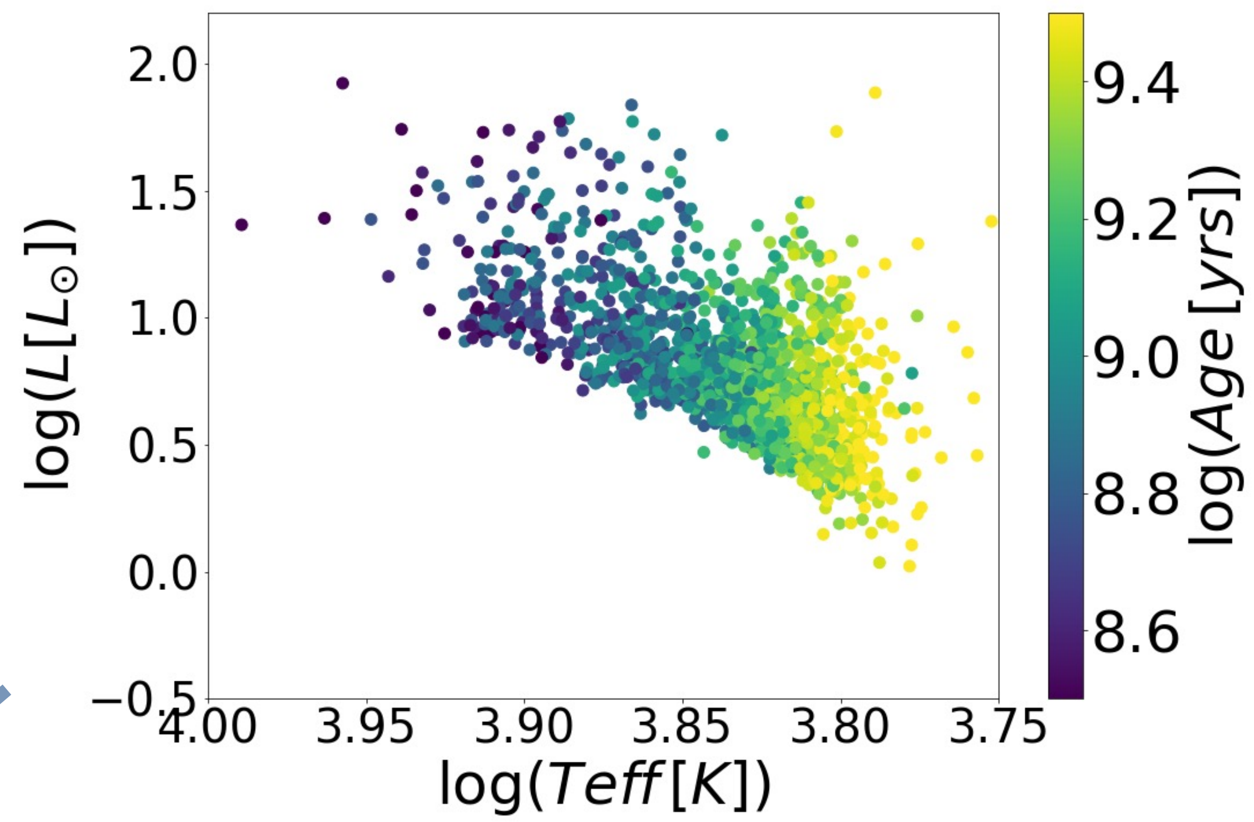
Garraffo et al. 2021

Quantifying performance on test *MIST* synthetic data and on observed data

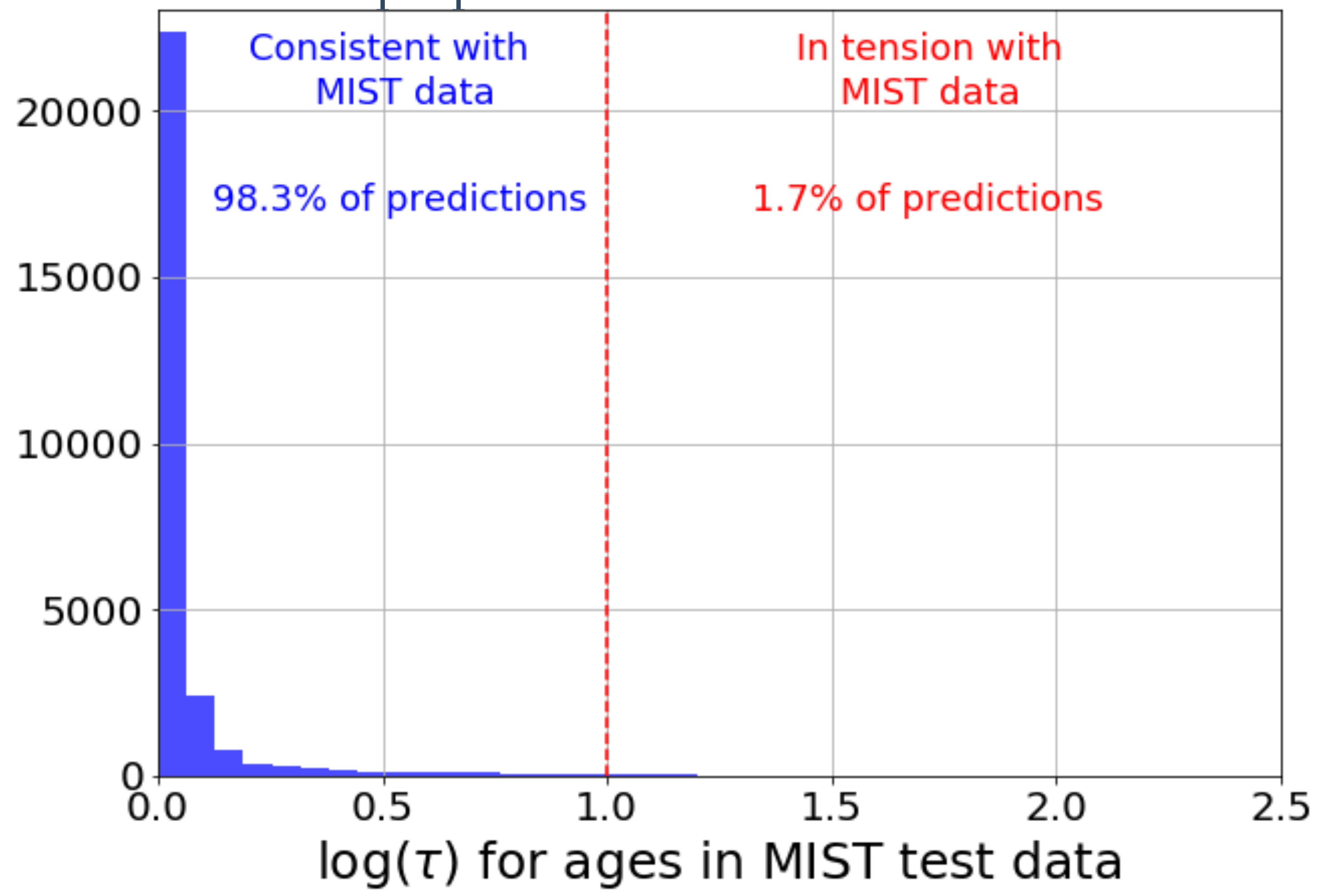
MIST synthetic test data

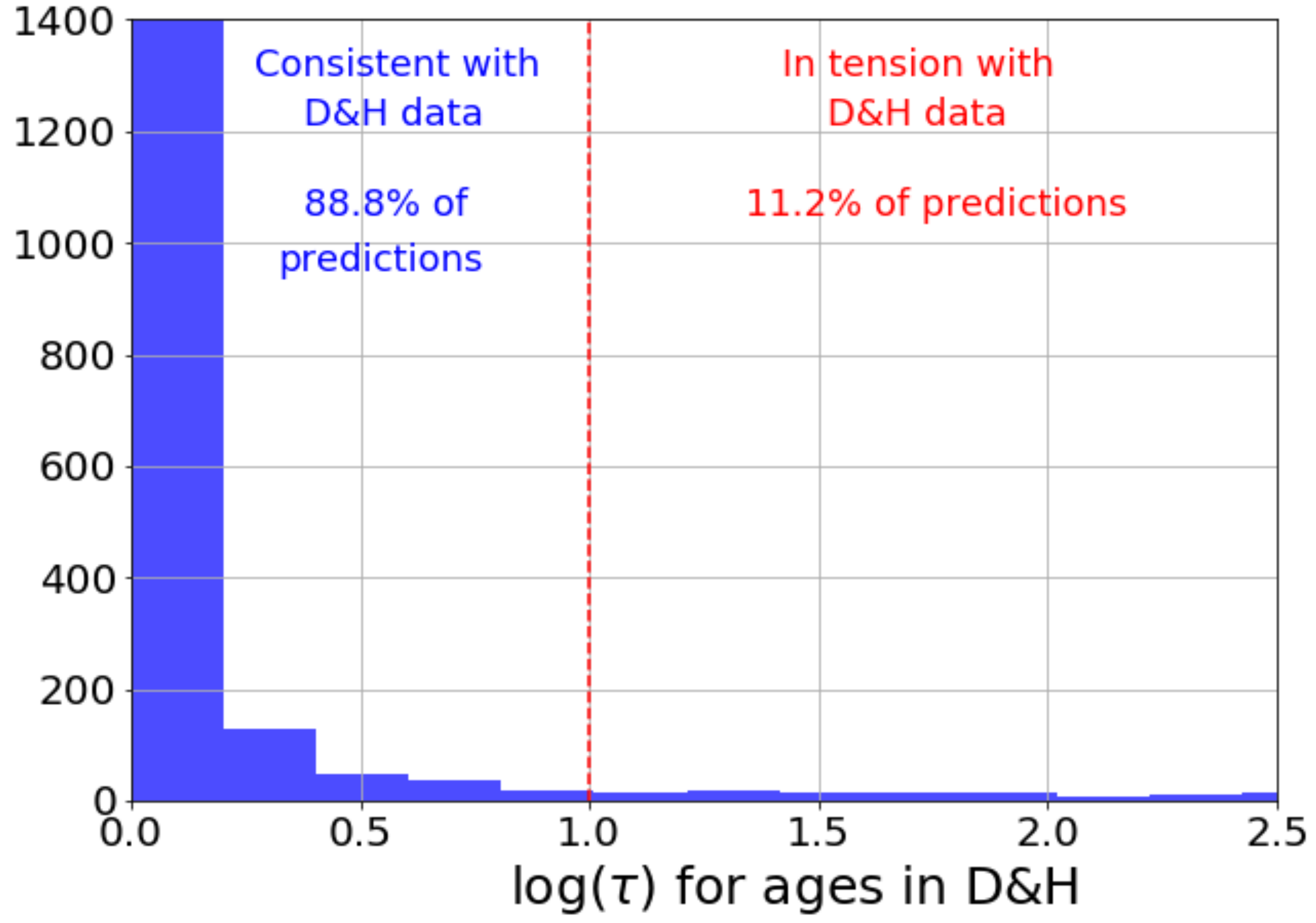


David & Hillenbrand 2015b



Garraffo et al. in prep.





Garraffo et al. 2021

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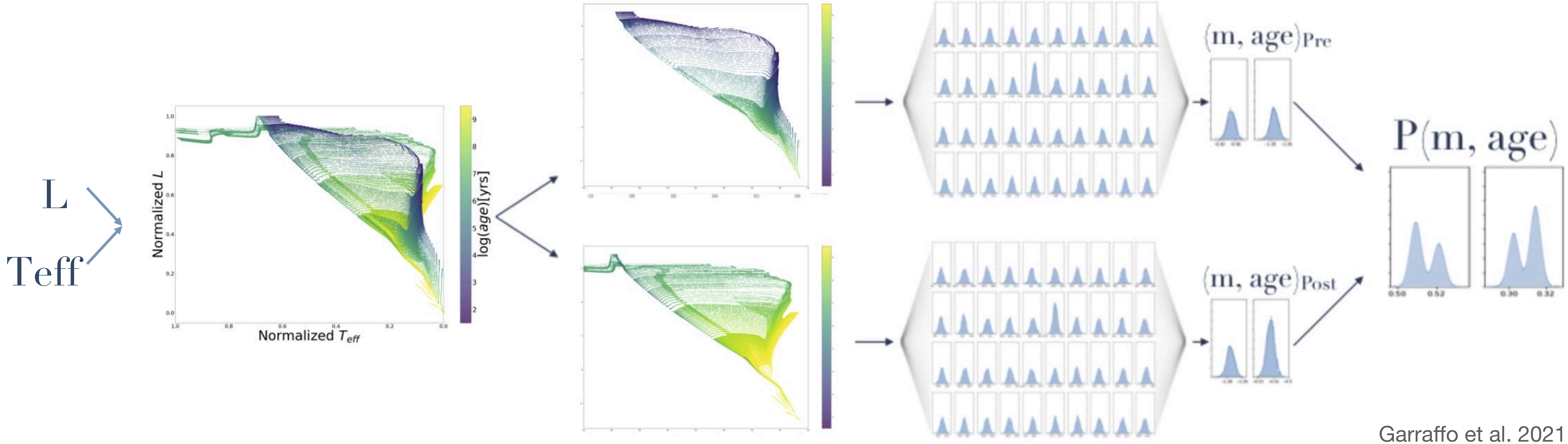
Anya Phillips

Automatic Stellar Characterization for Gaia



Garraffo et al. 2021

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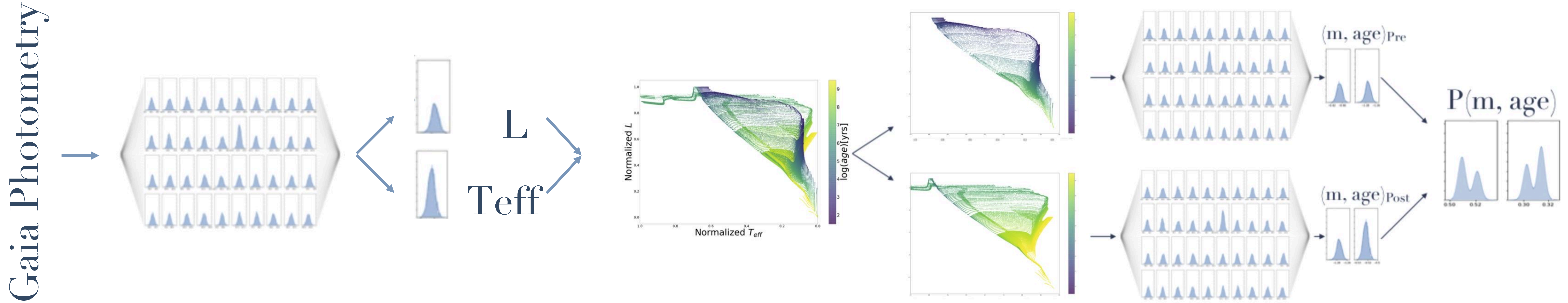
One Step Approach: directly from photometry

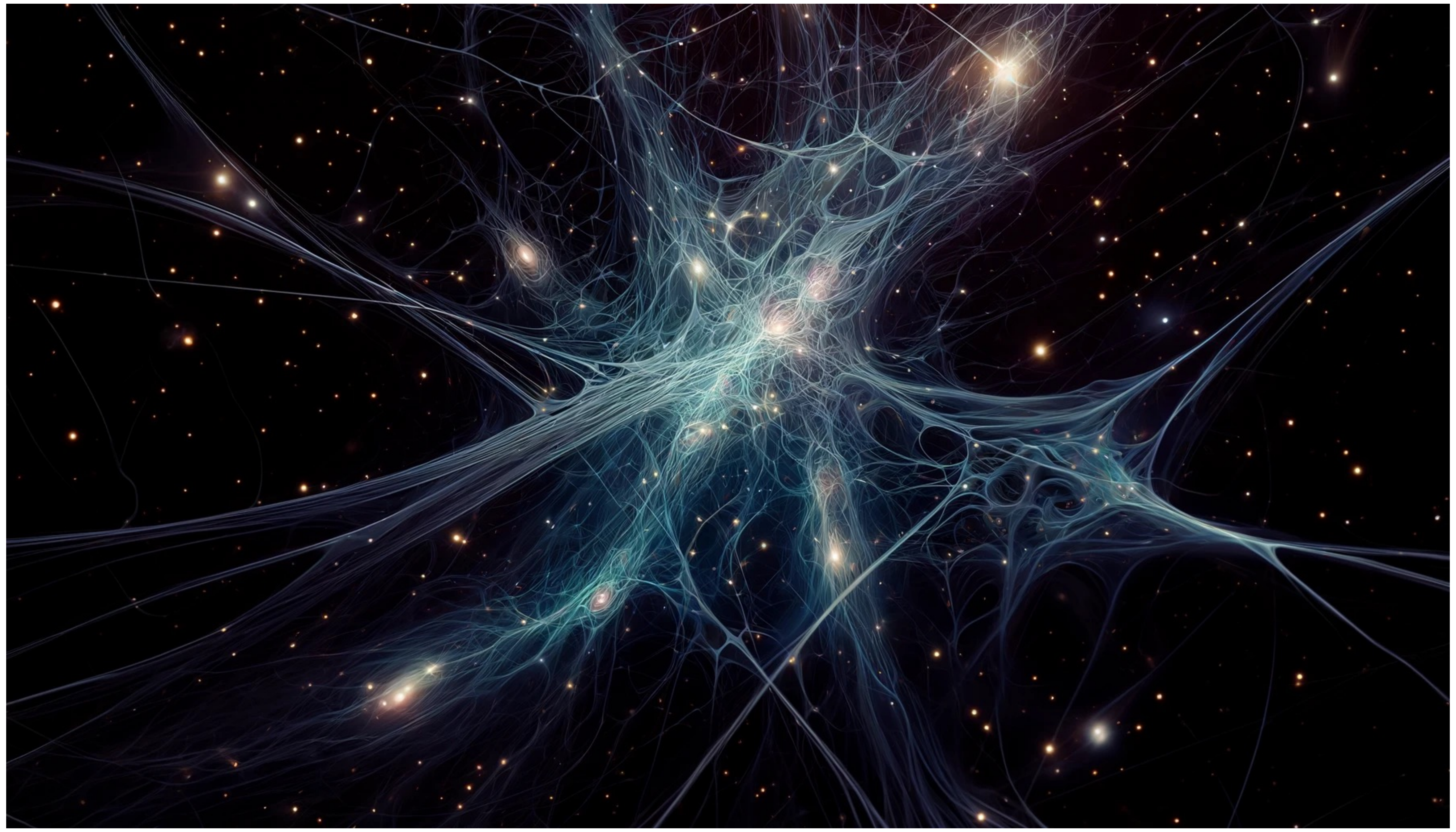


Phillips et al. in prep

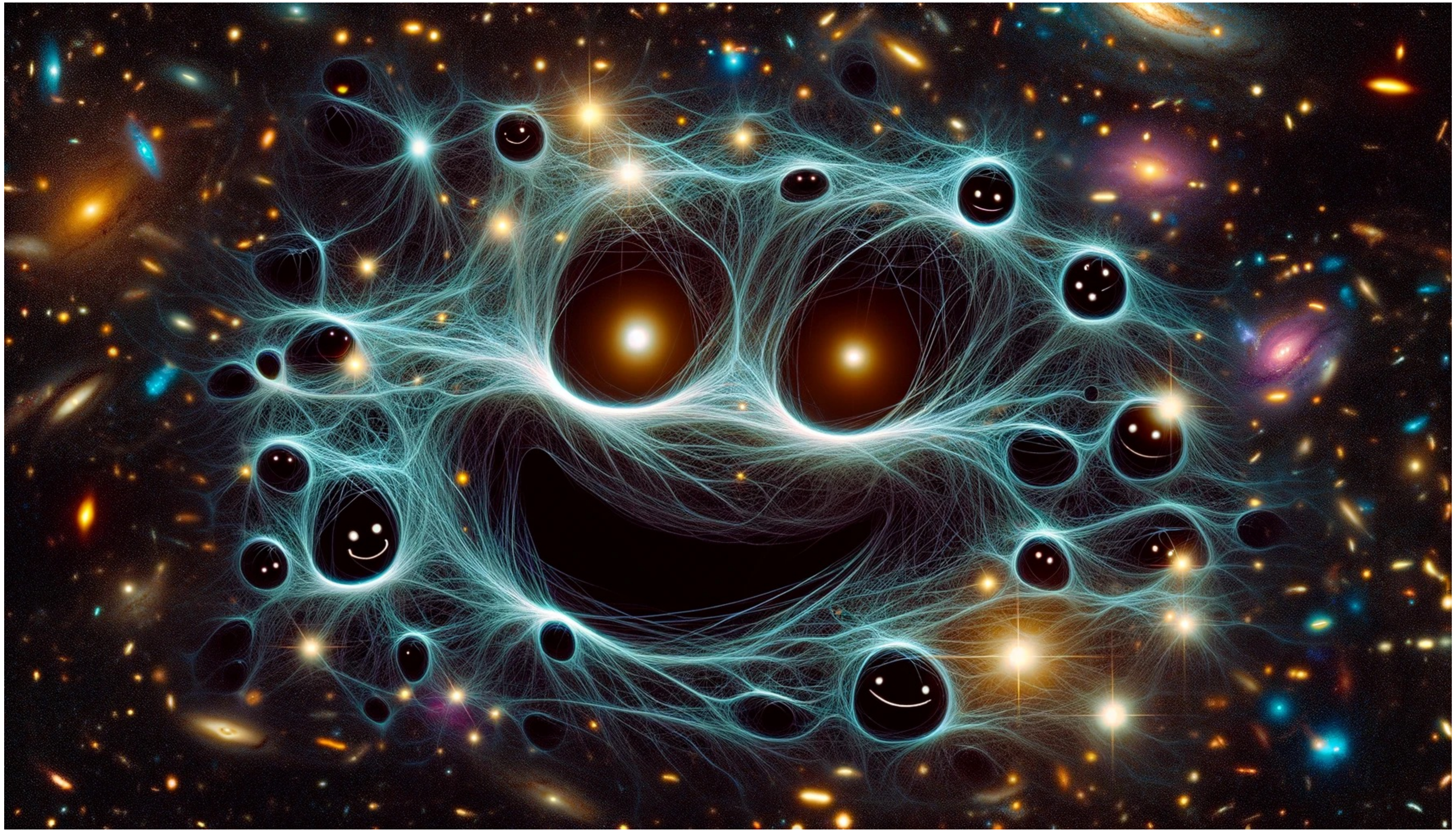
Diffusion Models for Astrophysics

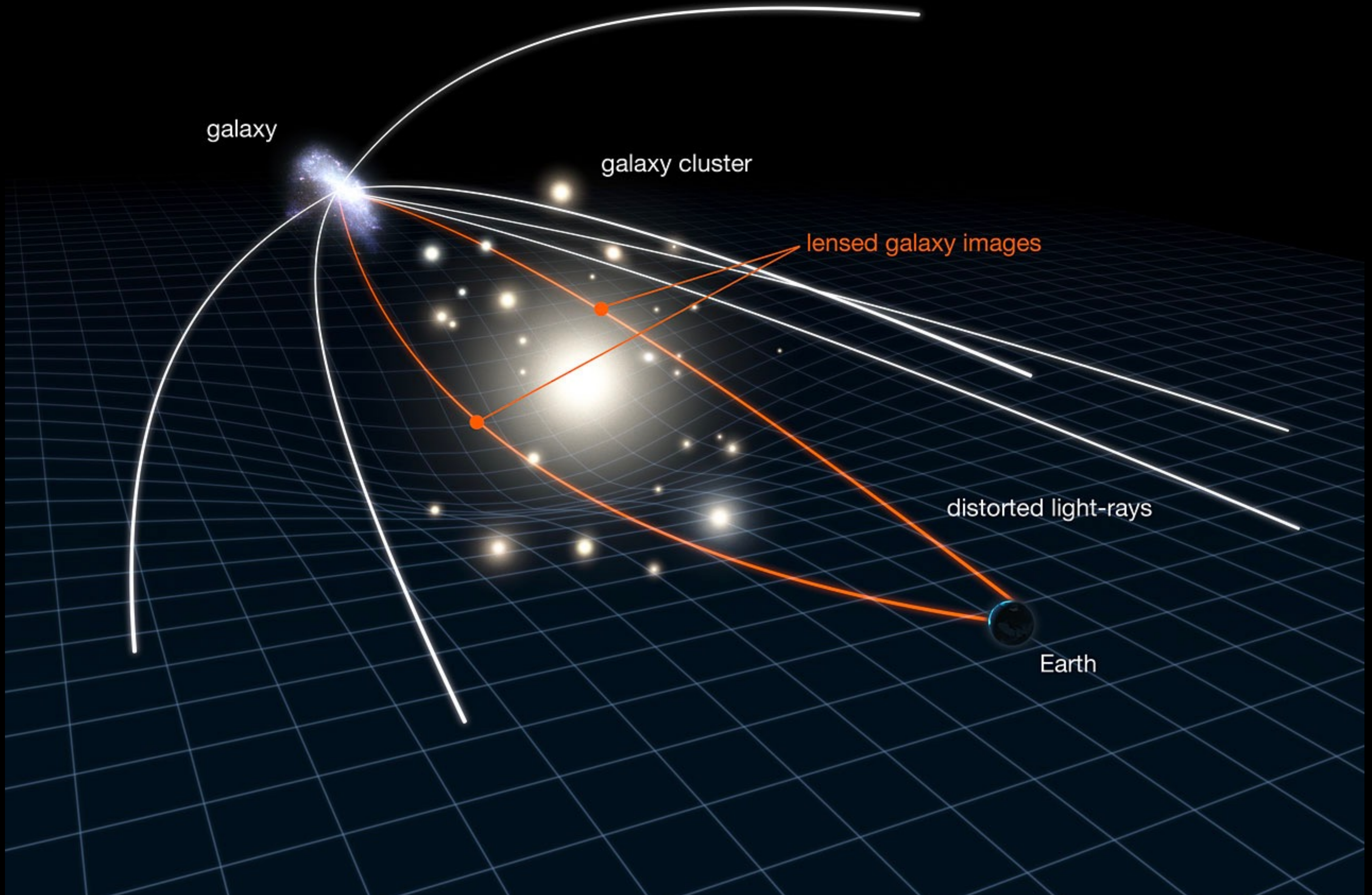
DALL-E prompt:
A dark matter field

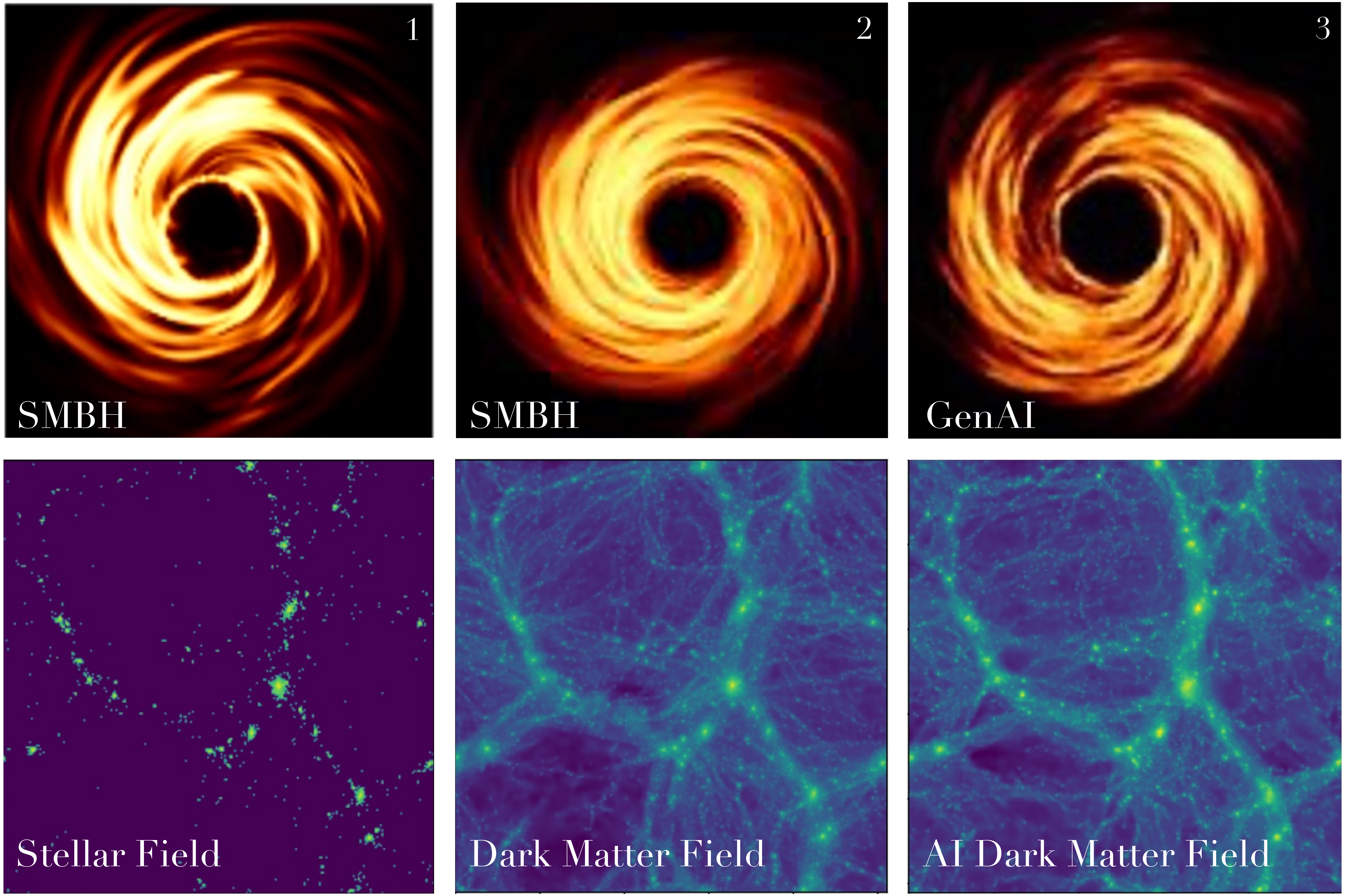
DALL-E prompt:
Dark matter field from a cosmological simulation,
showing filaments of dark matter in intergalactic medium



Diffusion Models for Astrophysics




galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth


1
SMBH
2
SMBH
3
GenAI
Stellar Field
Dark Matter Field
AI Dark Matter Field

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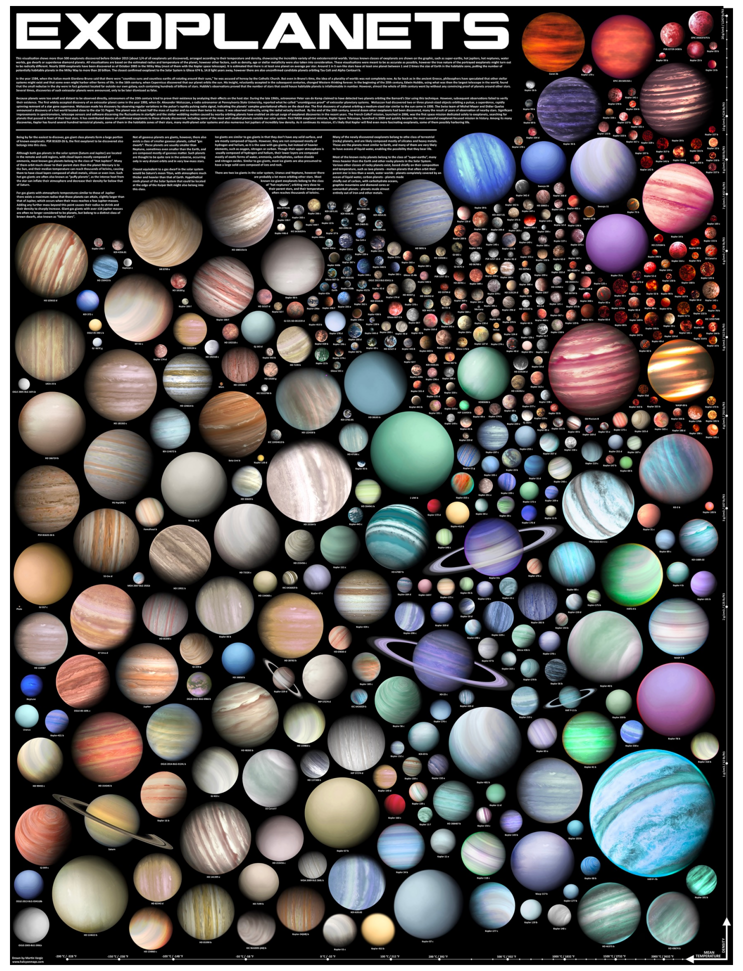
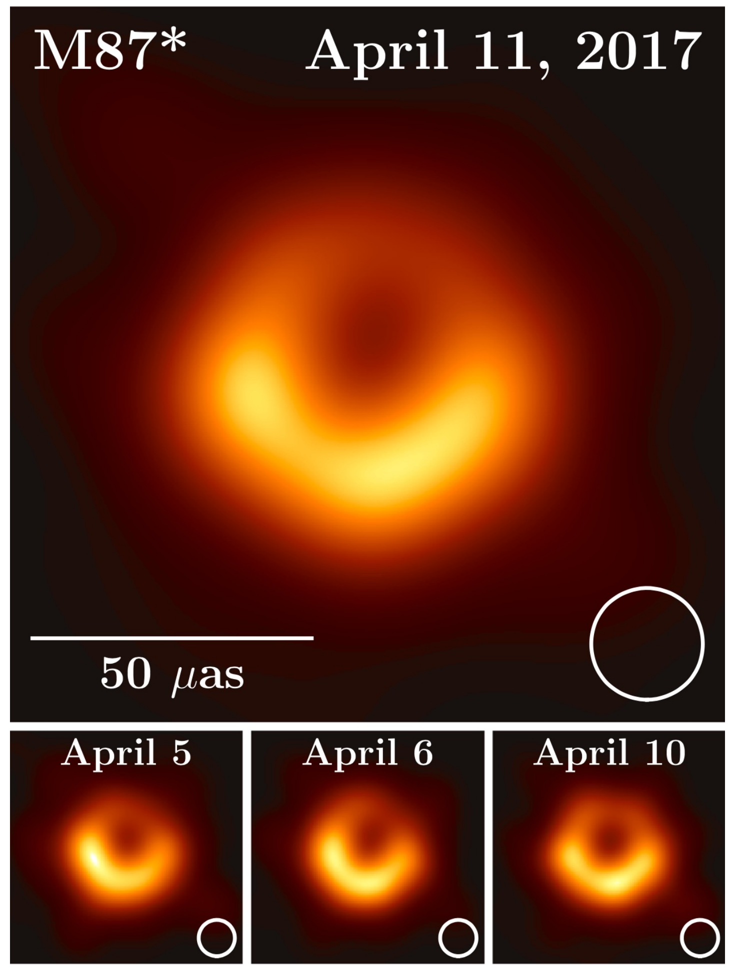
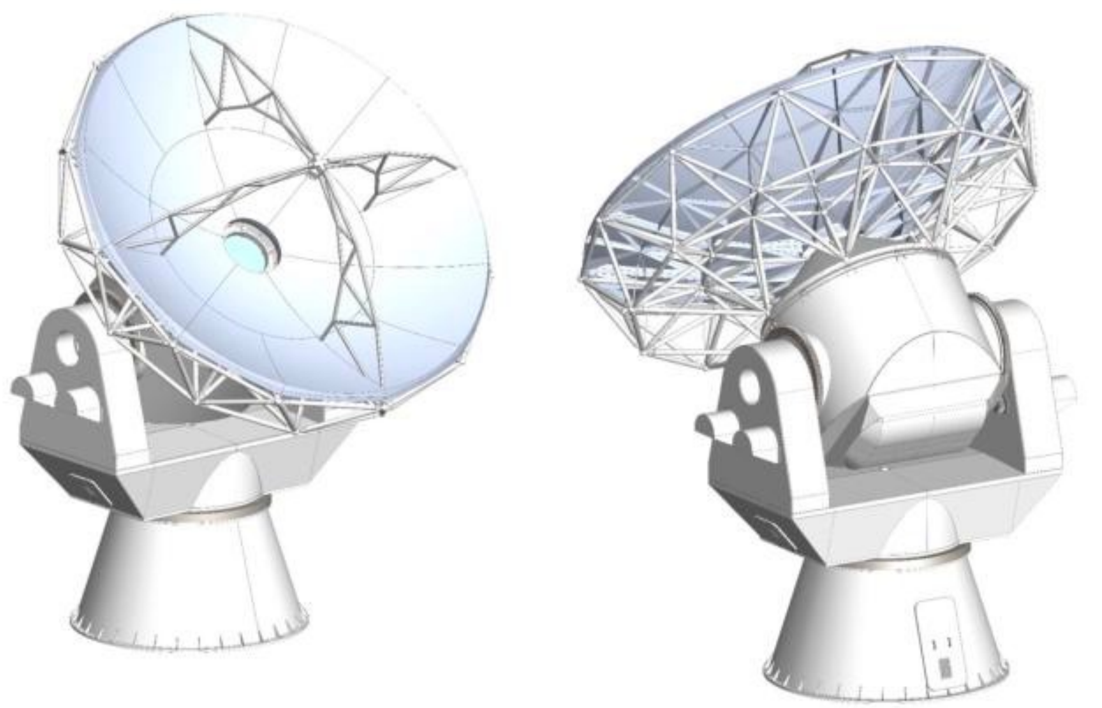
The CfA

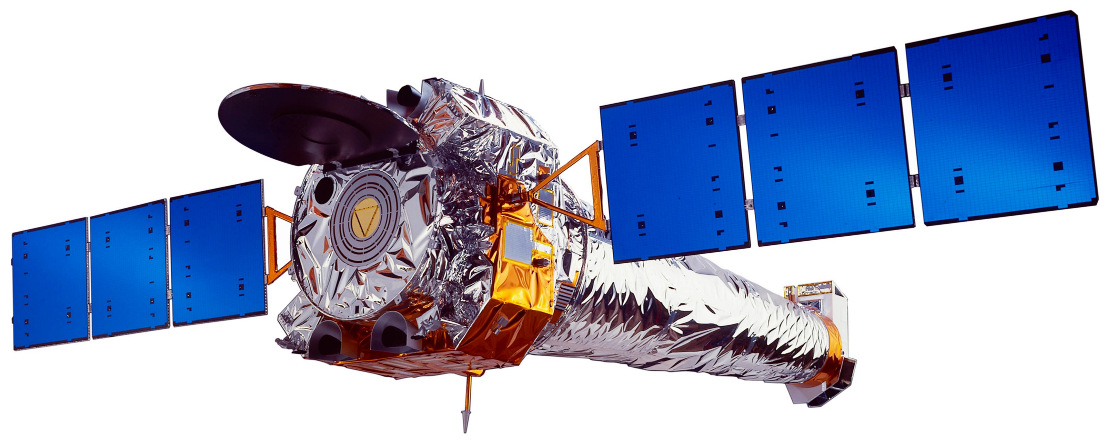
CENTER FOR ASTROPHYSICS
HARVARD & SMITHSONIAN





A lot of Astronomy





Data from Ground-based Space & Telescopes

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IACS Institute for Applied Computational Science

HDSI | Harvard Data Science Initiative

ads NASA

FAS RC FAS Research Computing Harvard University Faculty of Arts & Sciences

AI+Physics @MIT

A home for the intersection of artificial intelligence and physics at MIT

MIT EECS

Electrical Engineering | Computer Science | Artificial Intelligence + Decision-making

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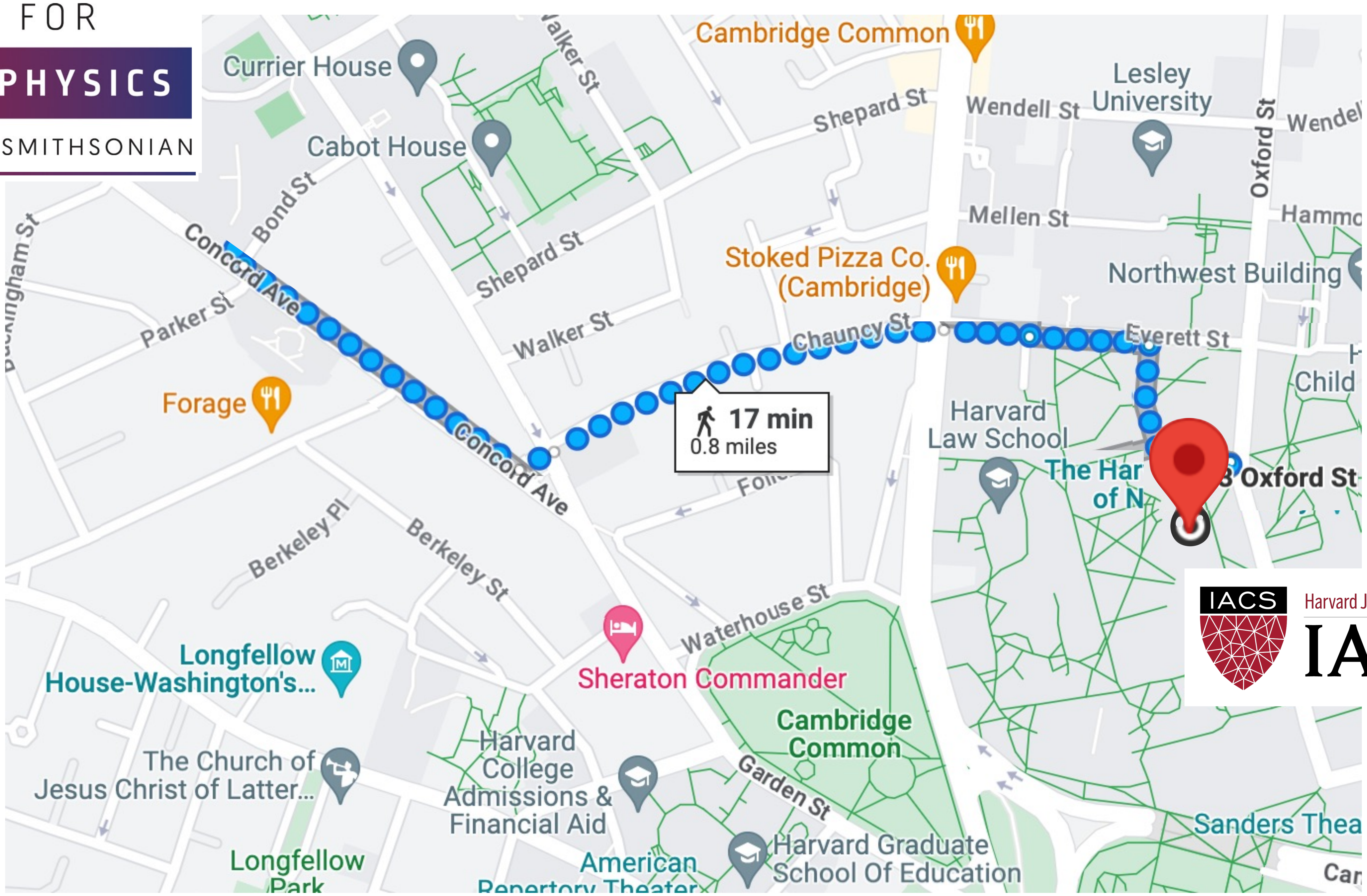

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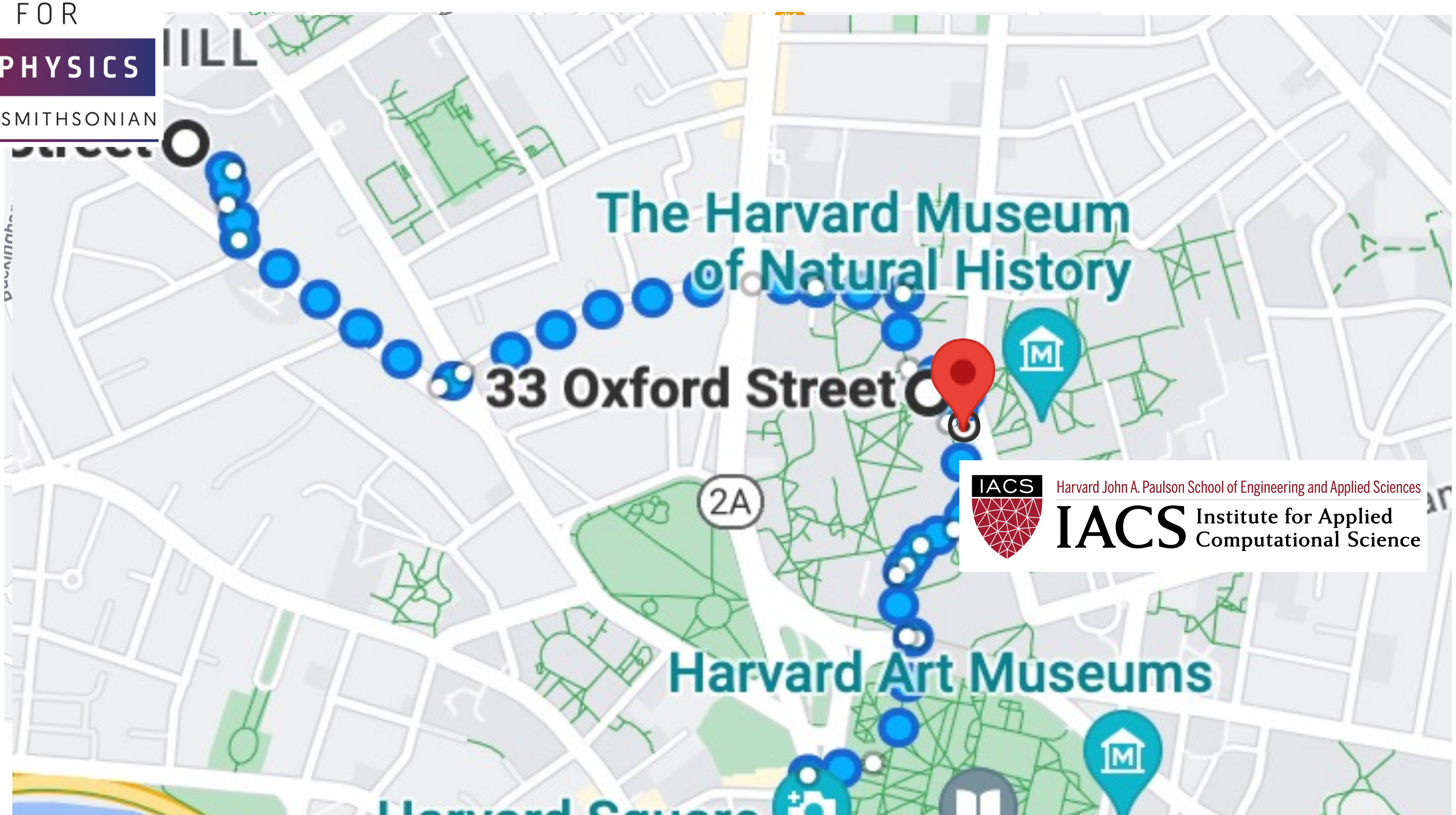

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Why AstroAI?

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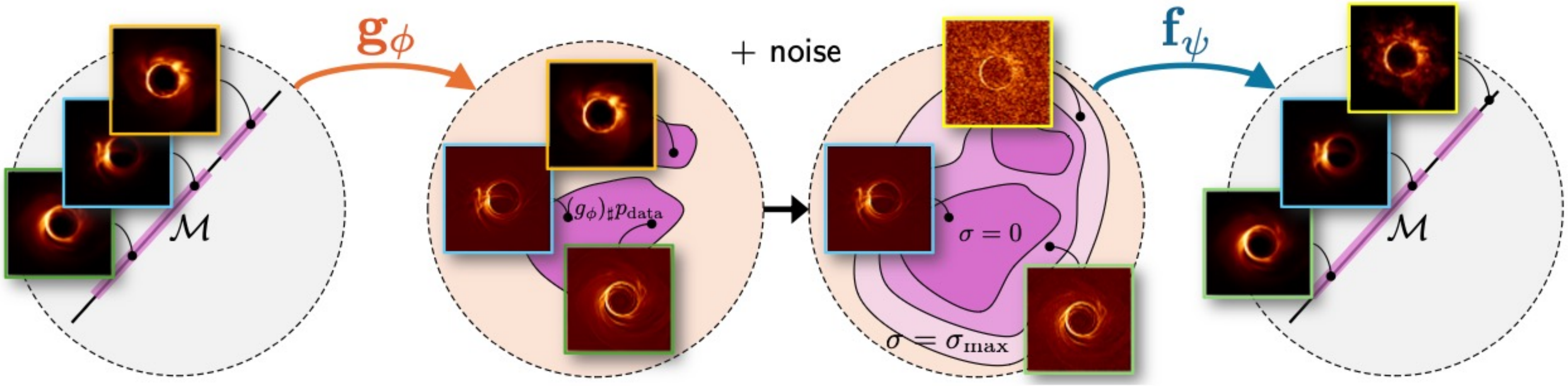
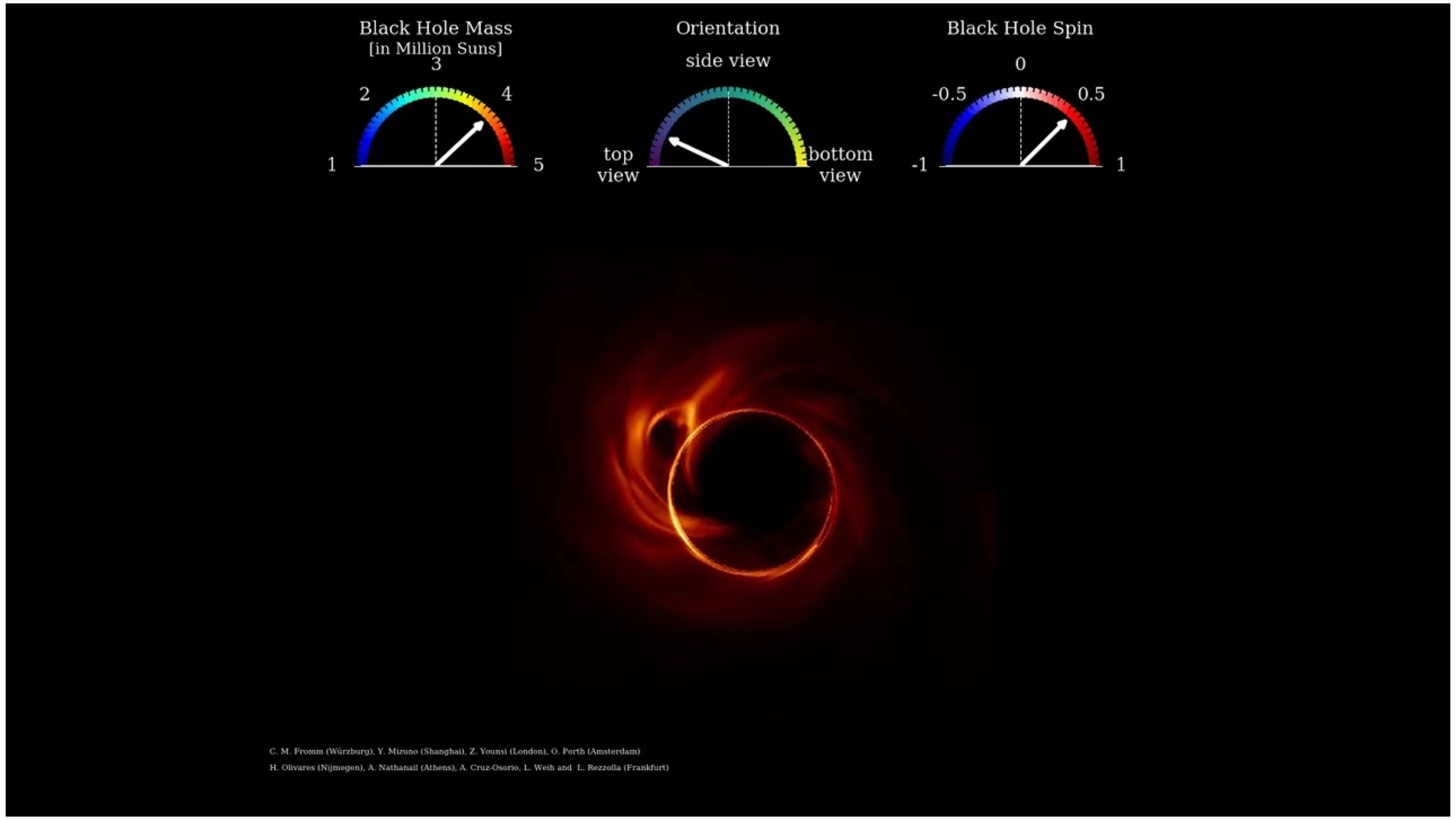
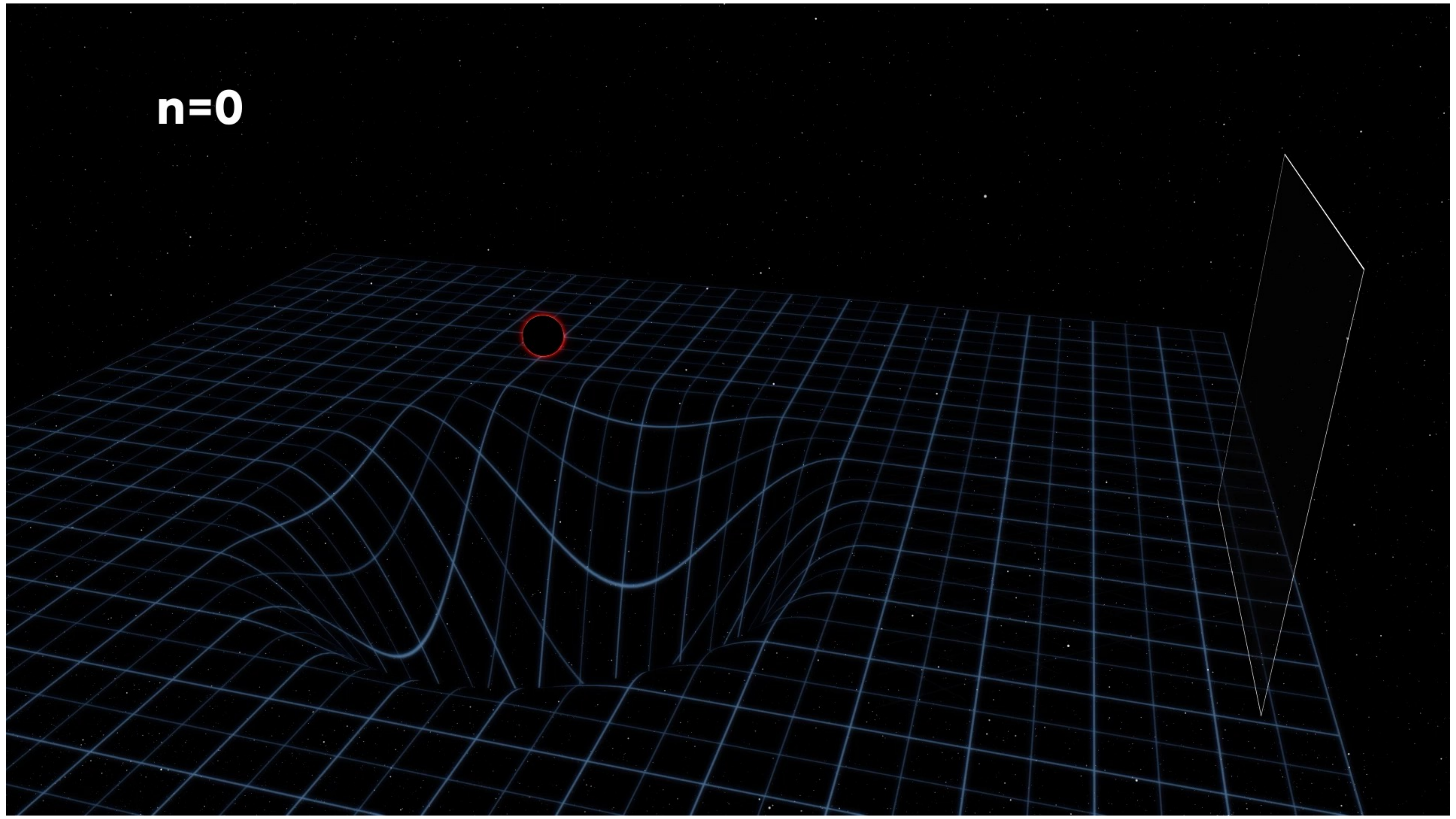
Constrained Diffusion Models

Mirror Diffusion Models for Constrained Generation





GRMHD Simulations and Best-bet Model for Sagittarius A*
ITP Goethe University, Frankfurt



Imaging a BH - Charles Gammie's group

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The Team

AI Experts

Bill Freeman, CS

Melanie Weber, A. Math

Robin Walters, CS

David Alvarez-Melis, CS

AstroAI Leadership

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Rafael Martinez

Ashley Villar

Doug Finkbeiner

Carol Cuesta-Lazaro

Alex Gagliano

Jack Steiner

Kari Haworth

Phill Cargile

Floor Broekgaarden

Josh Wing

Nayantara Mudur

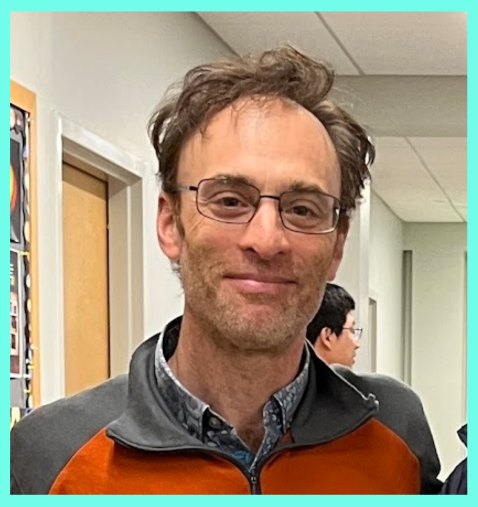
Physicists

Adam Foster
AtomDB

Iouli Gordon
HITRAN

Astronomers

Mercedes Lopez-Morales



Shep Doeleman, EHT

Alberto Acomazzi
NASA / ADS

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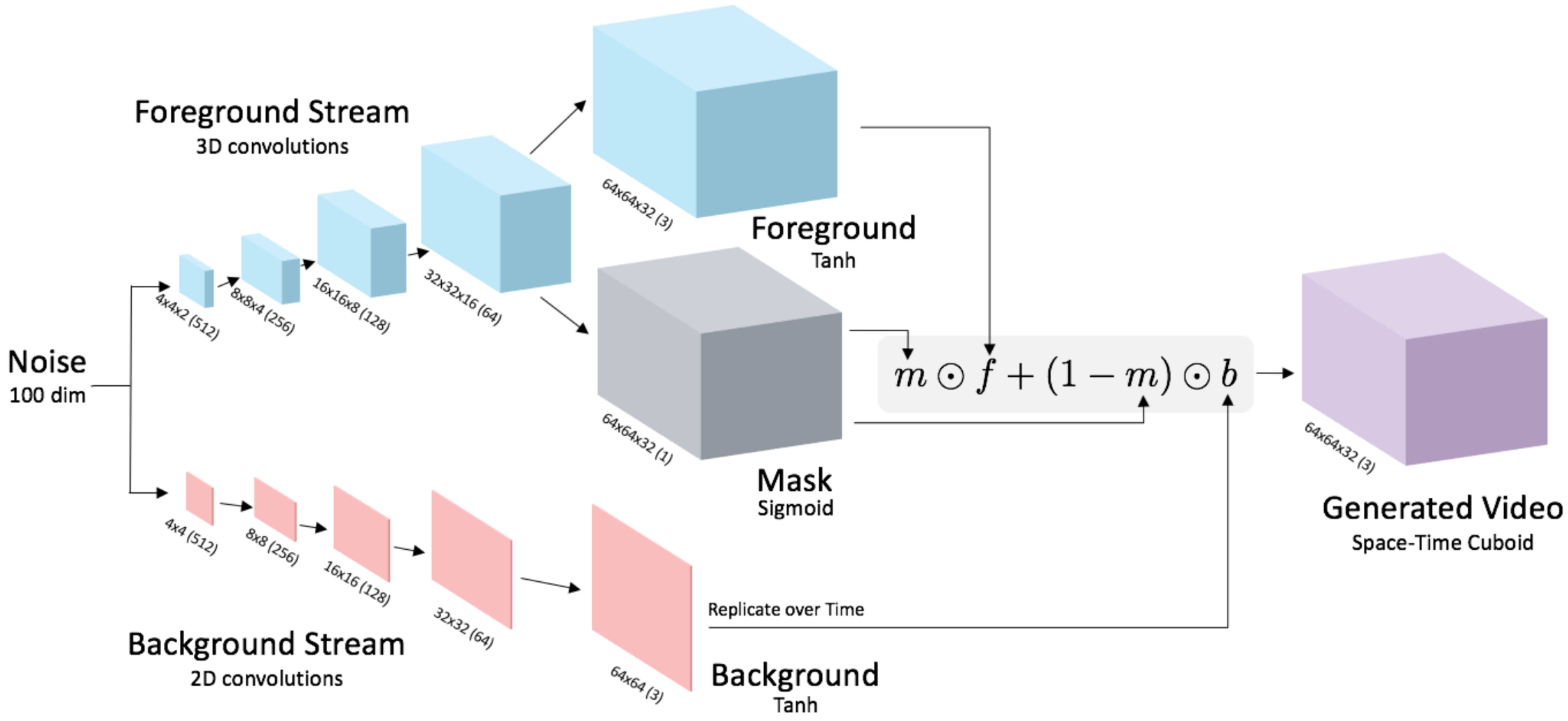
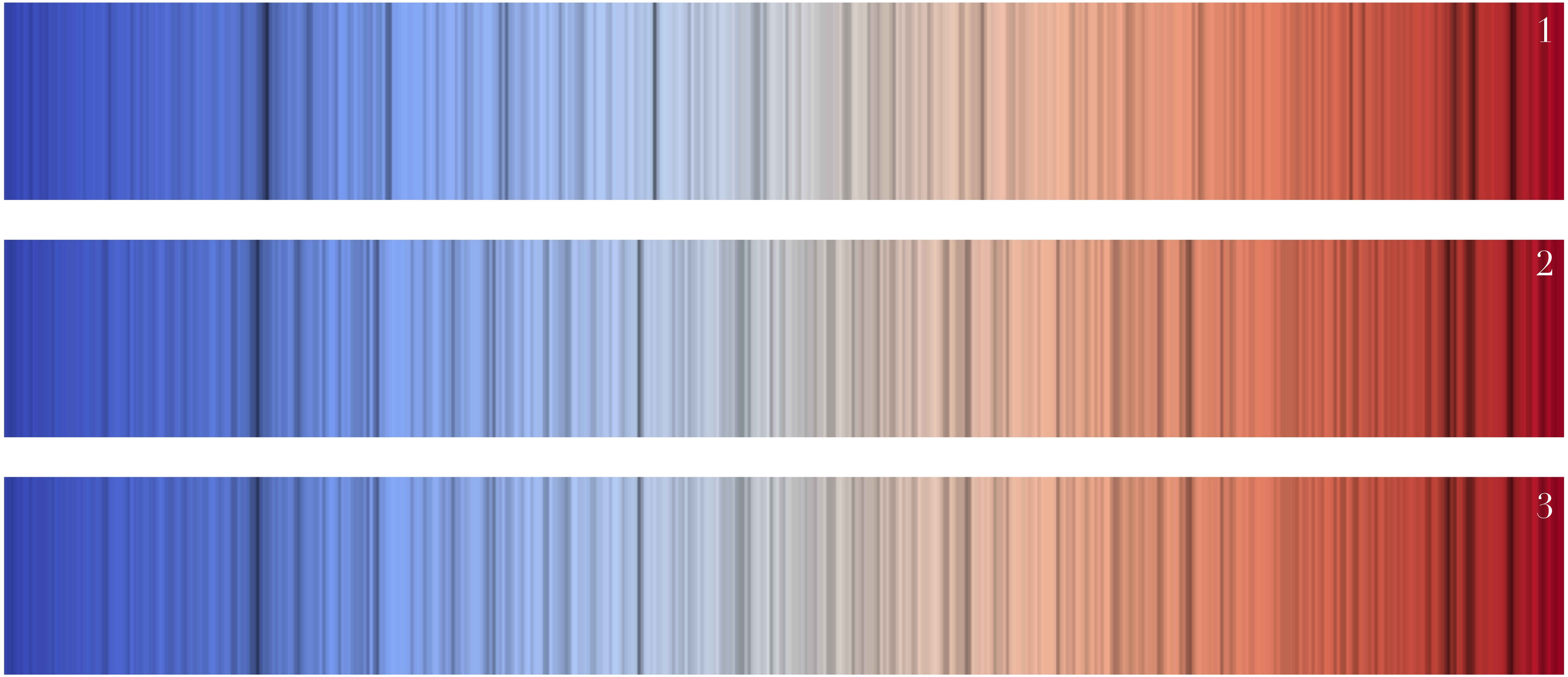
David Loving

Generative Model for Black Holes' Dynamics



Stellar Spectra



Phill Cargile

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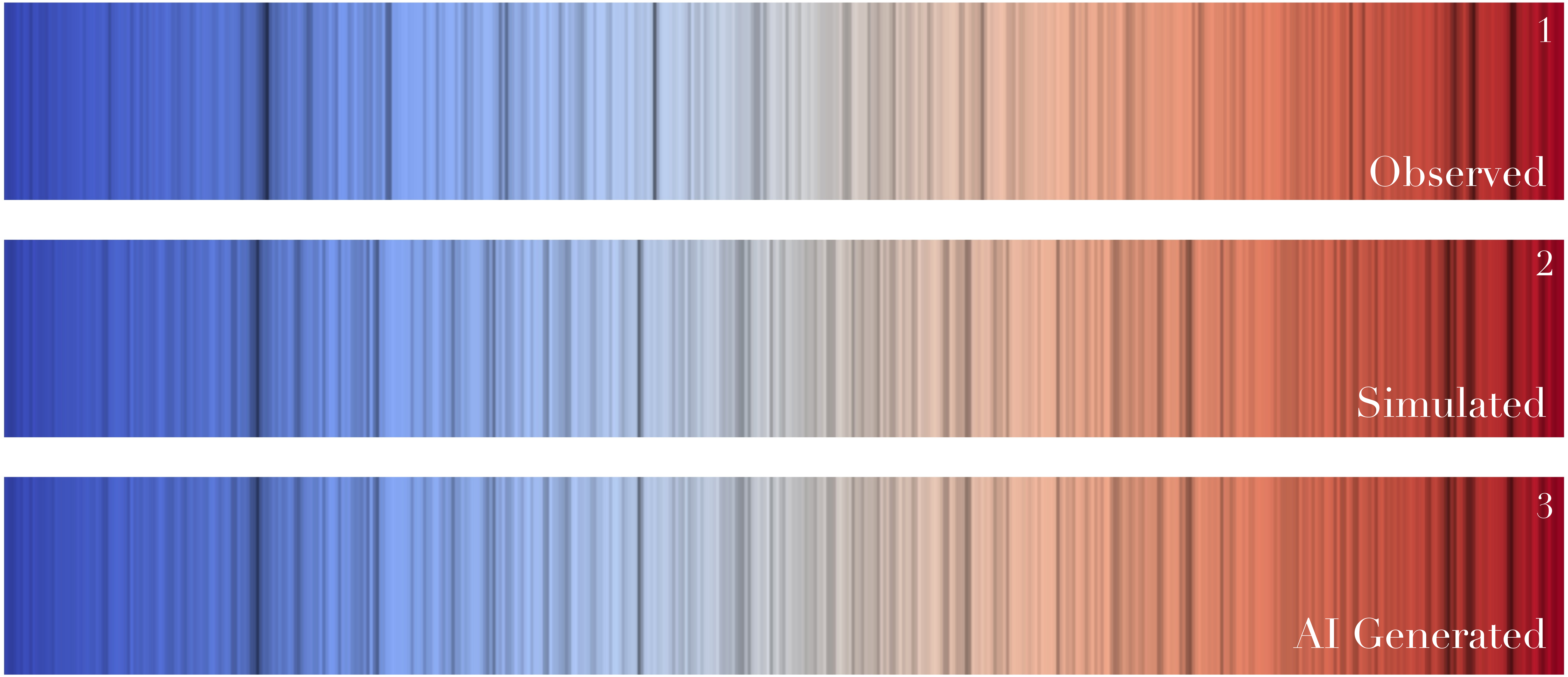
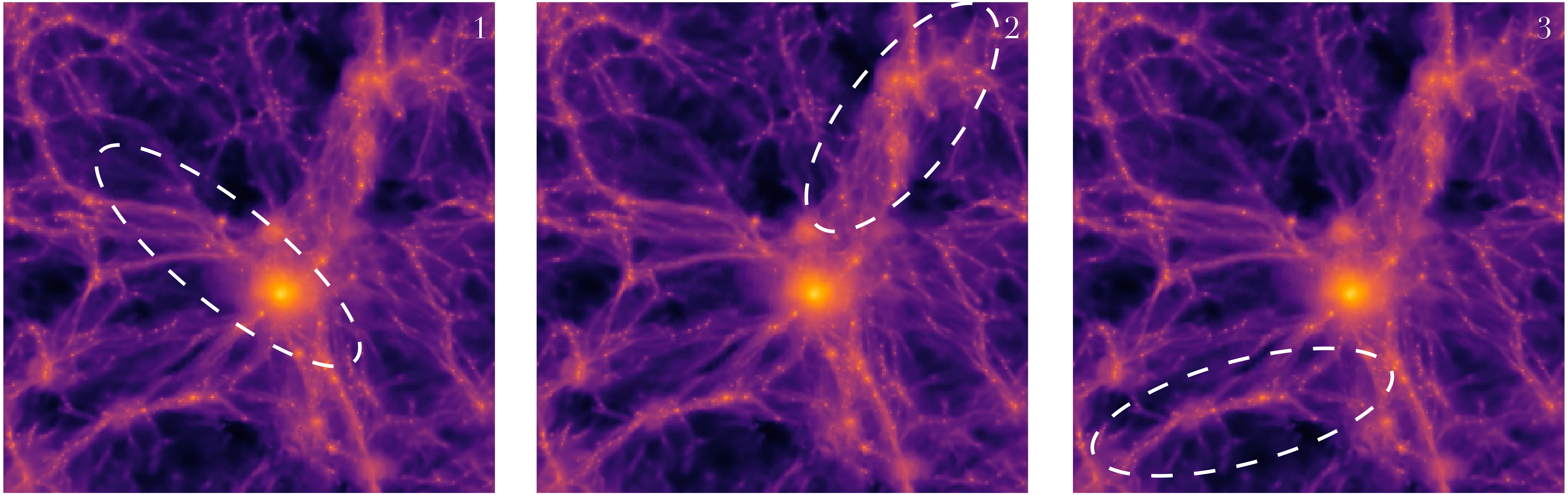
Stellar Spectra



Phill Cargile

Galaxy Filament AI-Infill



Carolina Cuesta-Lázaro & Core Francisco Park

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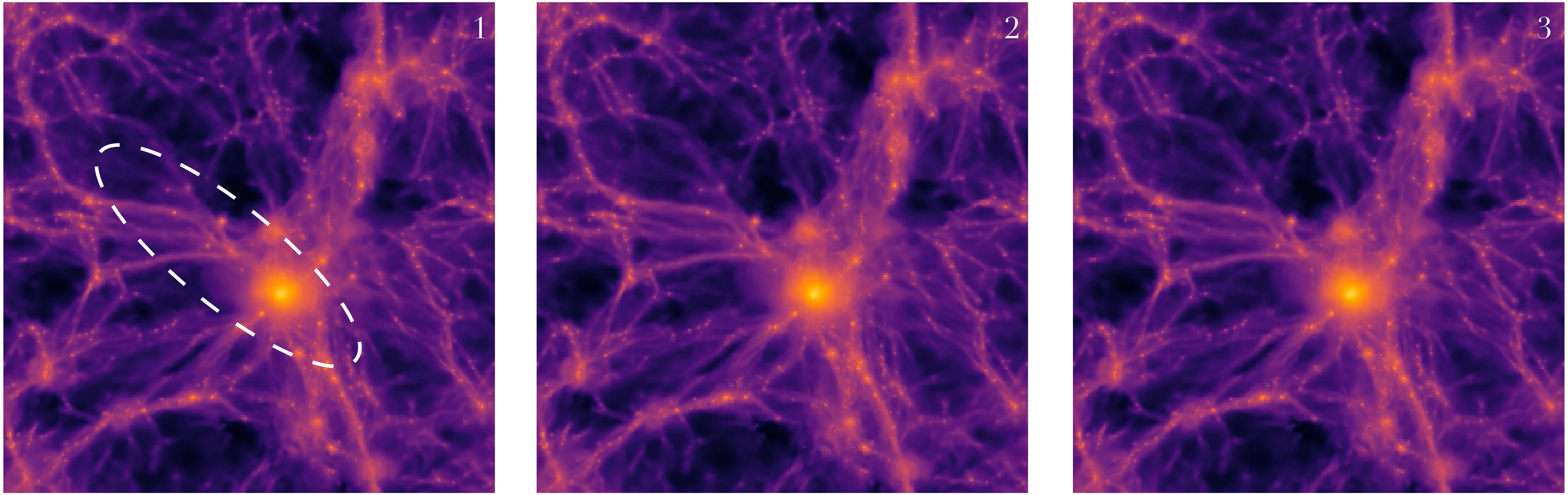
Galaxy Filament AI-Infill



Carolina Cuesta-Lázaro & Core Francisco Park

The Scientific Questions

- Are we alone in the Universe?
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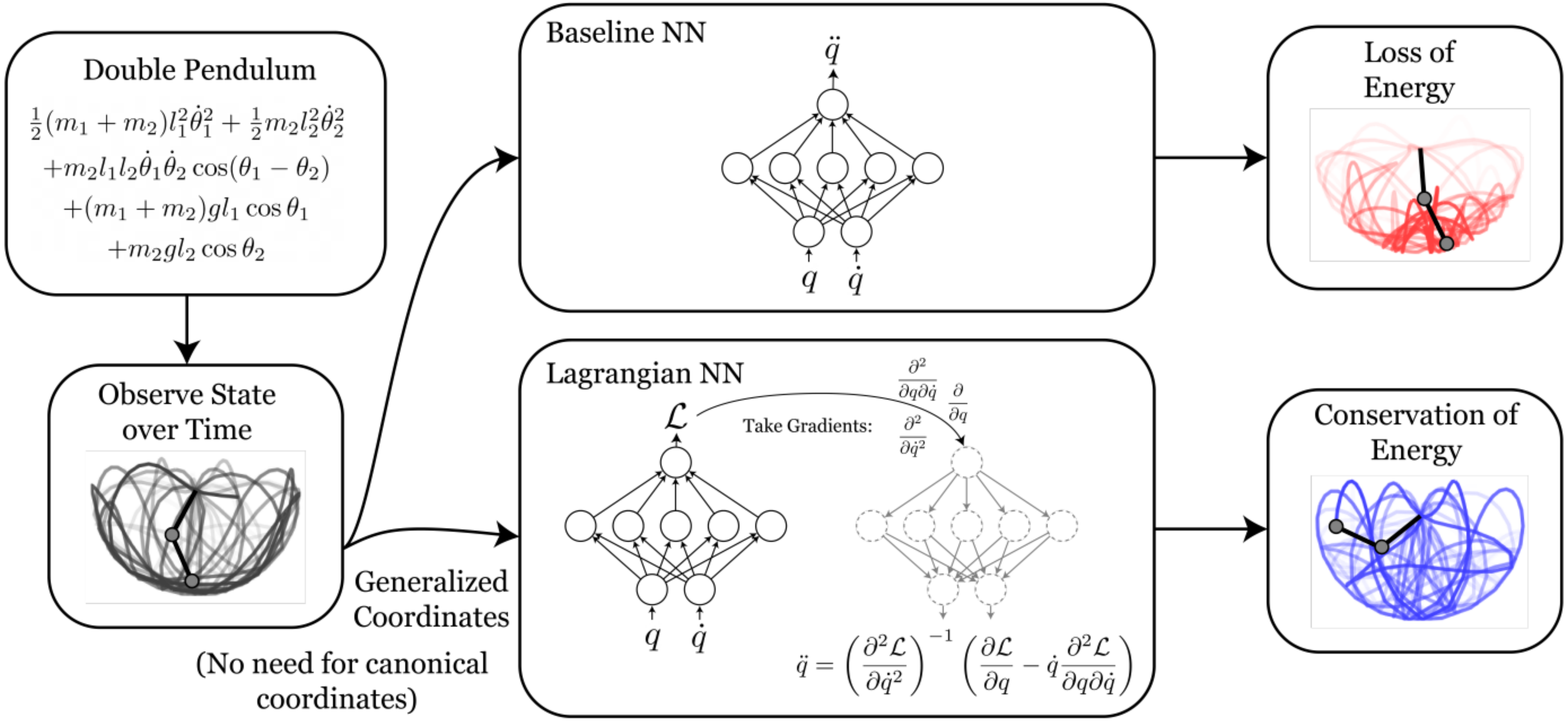
- What are the fundamental laws of physics?

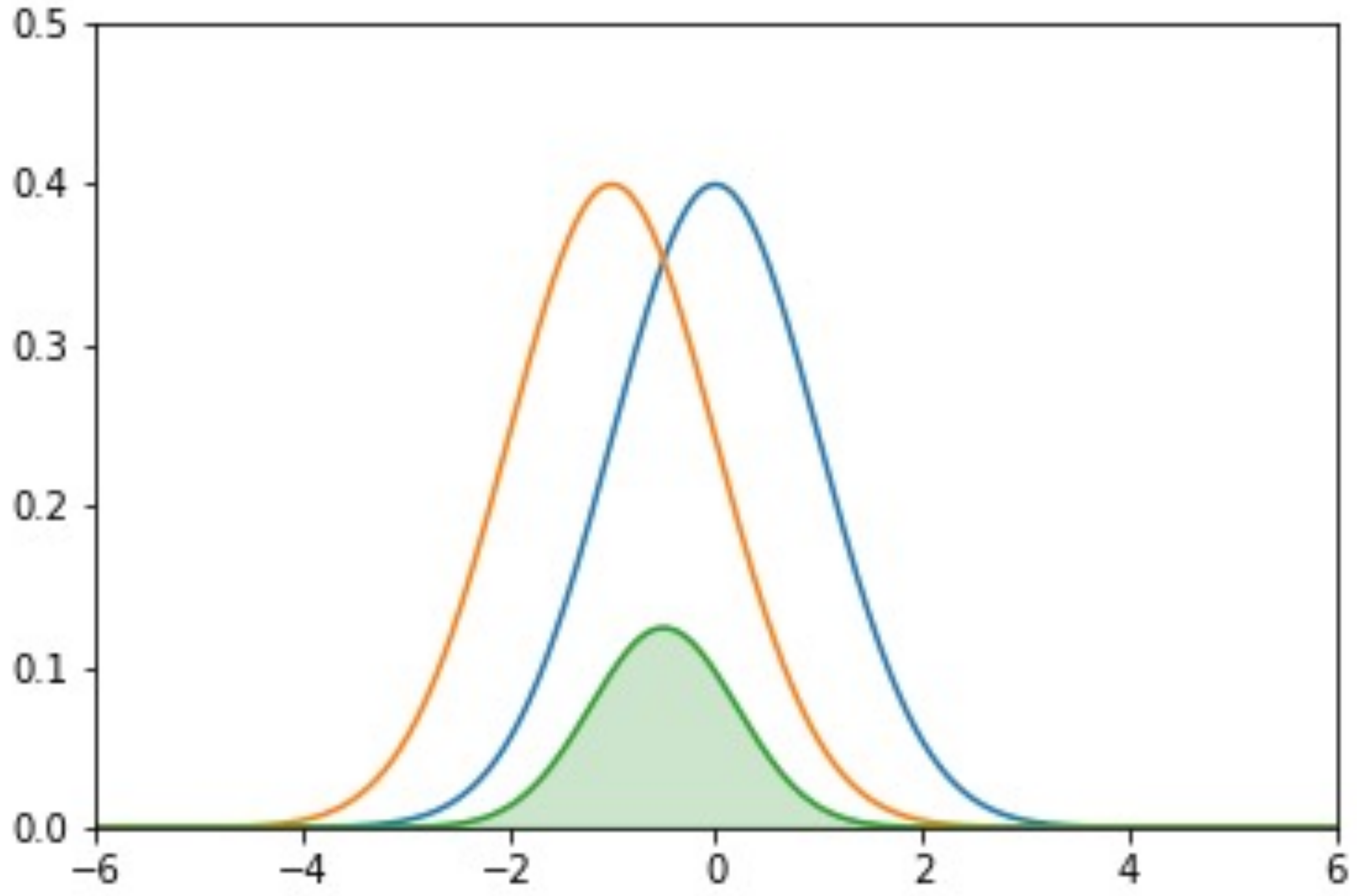
Lagrangian Neural Networks



Cranmer et al . 2020

StelNet: A Hierarchical Bayesian Neural Network

Comparing distributions



$$\int \overline{P}_A \overline{P}_B dx = \overline{\varepsilon}|_{maxA=maxB}$$

$$\int \overline{P}_A \overline{P}_B dx = \varepsilon < \overline{\varepsilon}$$

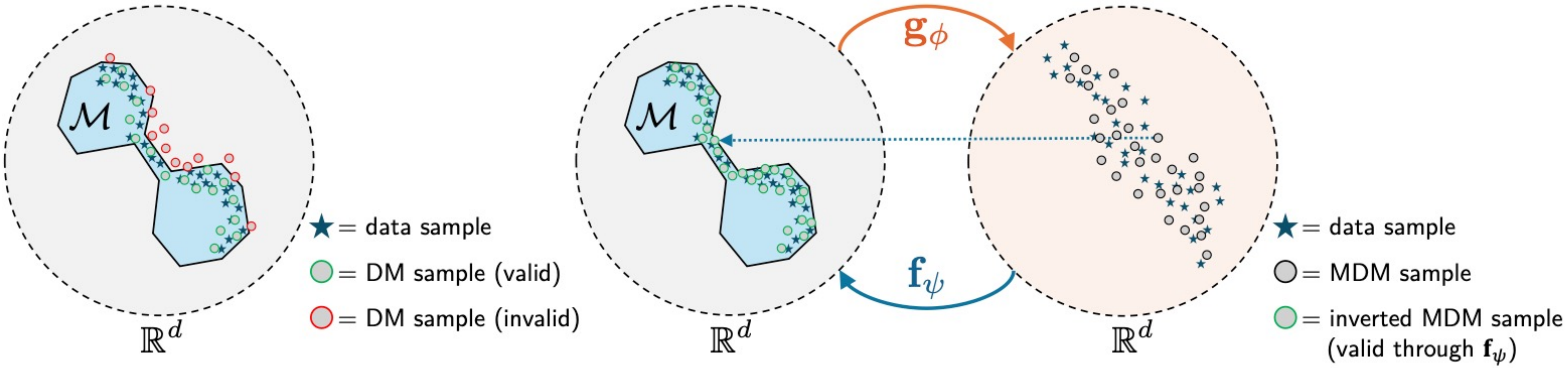
$$\tau = \frac{\overline{\varepsilon}|_{maxA=maxB}}{\varepsilon}$$ Tension

A large tension means that the null hypothesis (maxA = maxB) is unlikely

Jerffrey's scale:

$\log\tau < 1$	$1 < \log\tau < 2.5$	$\log\tau > 5$
not significant	substantial	highly significant

Soft Constraints



(a) Regular diffusion model

(b) Mirror diffusion model with NAMM

K. Bouman

Physical GenAI

Symmetric Diffusion for Models with Conservation Laws

$$T : \phi \longmapsto \phi + \Delta\phi$$

$$\& \qquad \mathcal{L} \xmapsto{T} \mathcal{L}$$

$$\Longrightarrow \quad \boxed{\partial_\mu j^\mu = 0 \quad , \quad j^\mu = \frac{\partial \mathcal{L}}{\partial(\partial_\mu \phi)} \Delta\phi}$$

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Towards a Quantum Theory of Gravity

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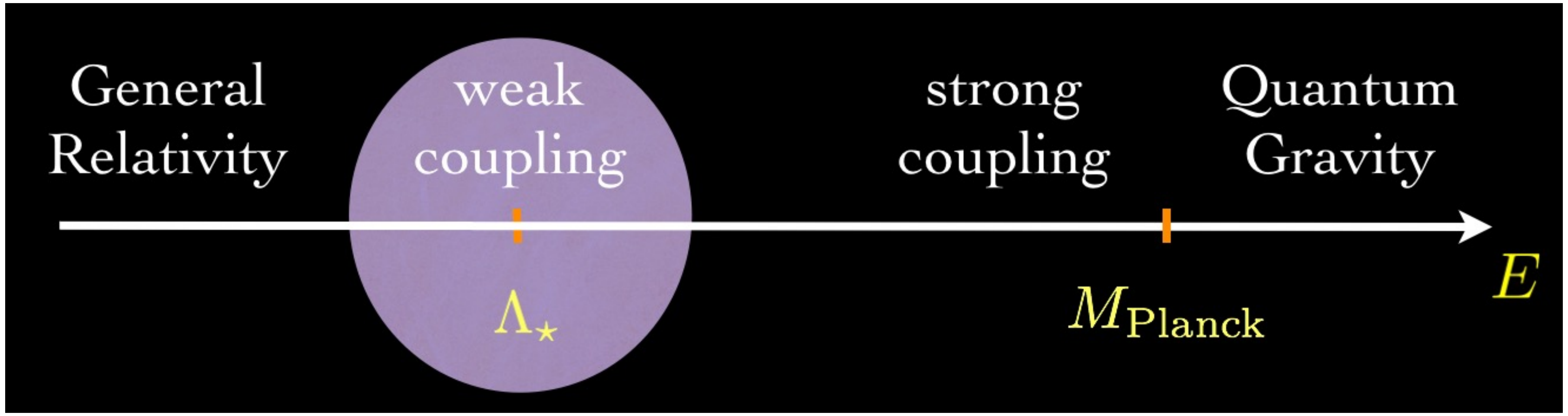
Classical vs Quantum Gravity



It is generally understood that GR is a low energy effective theory of a more general theory of Gravity. Low energy means low space-time curvature (large distance): there must be a scale at which higher-derivative terms arise

Higher Order Gravity

Einstein-Hilbert Action
General Relativity

$$\mathcal{L} = \int d^4x\sqrt{-g}(R - 2\Lambda)$$

Einstein Gauss Bonnet
Lovelock Gravity

$$\mathcal{L} = \int d^4x\sqrt{-g}(R - 2\Lambda + \alpha(\frac{1}{3}R^2 - 2R_{\alpha\beta}R^{\alpha\beta} + R_{\alpha\beta\mu\nu}R^{\alpha\beta$$

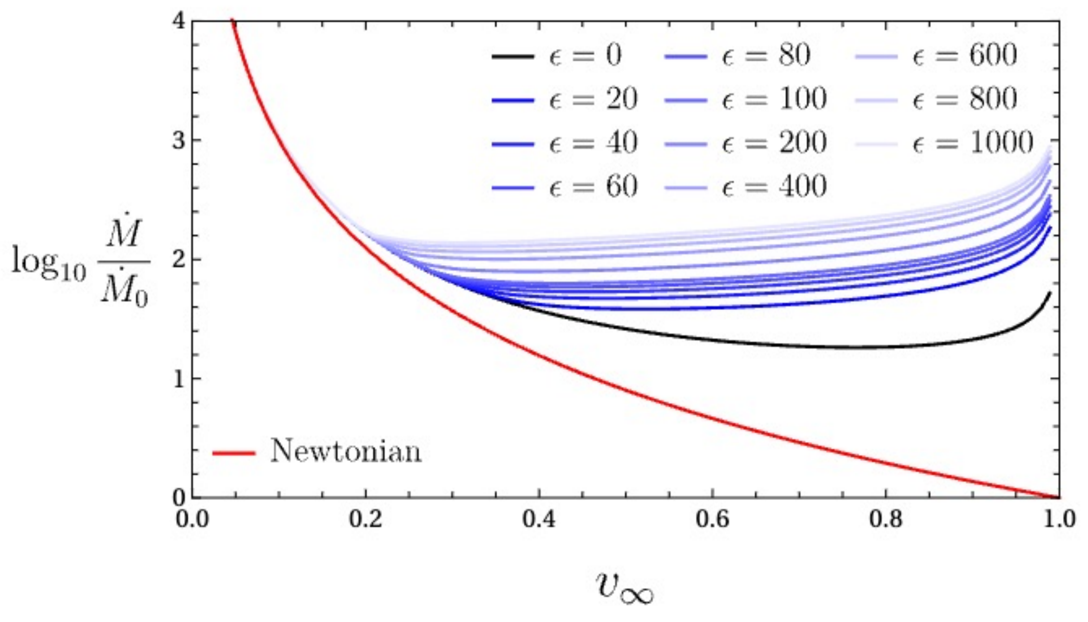
A single combination at every order leads to second order Euler-Lagrange equations [Lovelock, 1971].
It is non-trivial iff $D \geq 2k + 1$ (for a k-th order term in the Riemann curvature).

Natural Extensions of GR

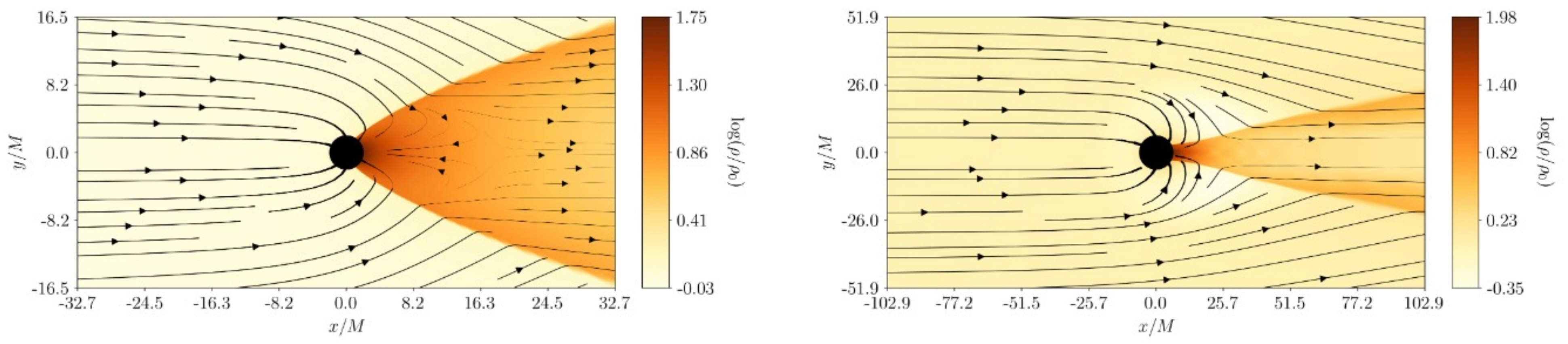
Cubic Gravity

$$\mathcal{L} = \int d^4x\sqrt{-g}\left(R - 2\Lambda + \sum_{n=2} \lambda_n \ell_\star^{2n-2}\mathcal{R}_{(n)}\right)$$

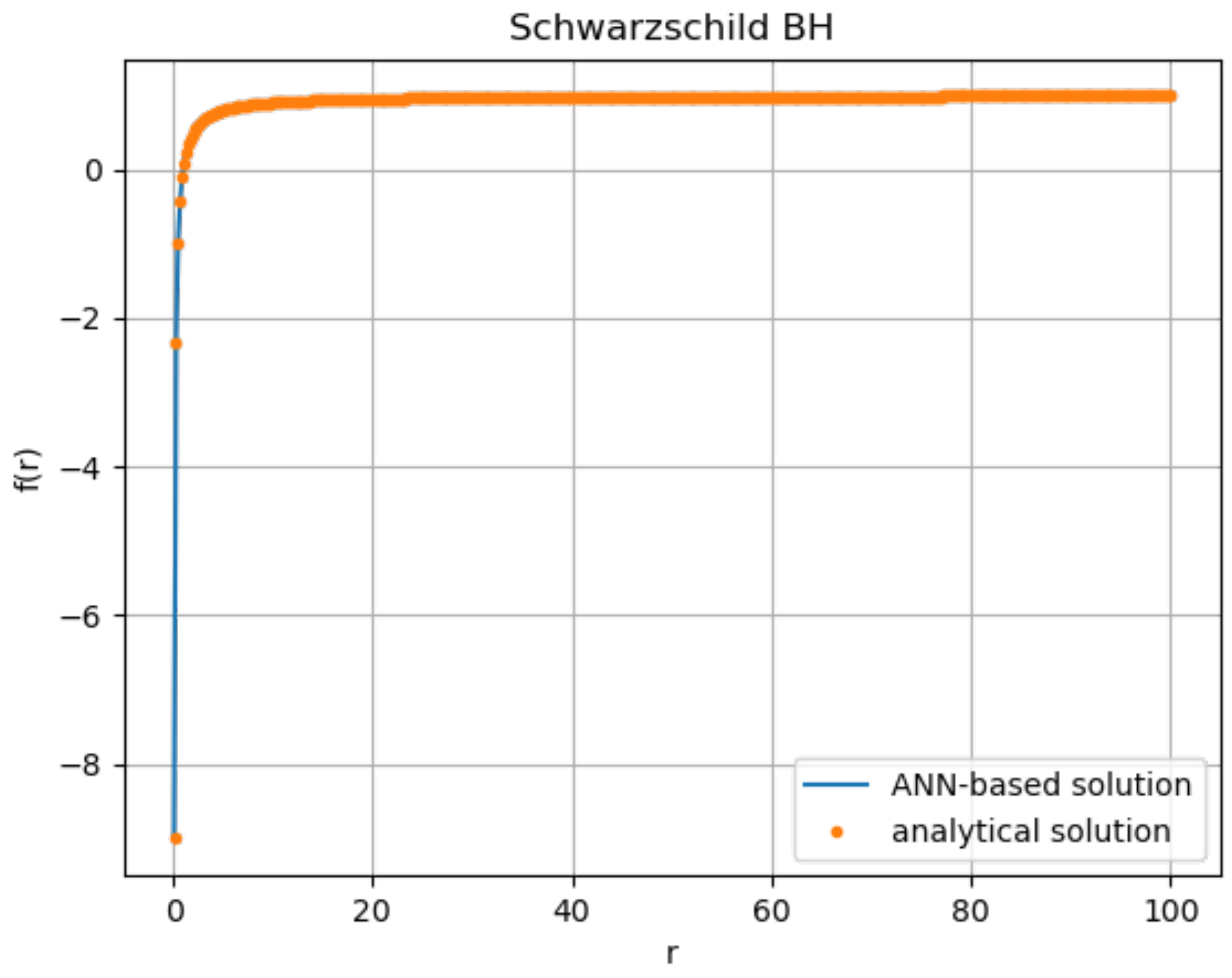
Interestingly enough, higher curvature terms magnify the black holes accretion rate [Edelstein, Rivadulla Sánchez, Rodríguez Moris, Tejeda, 2024])

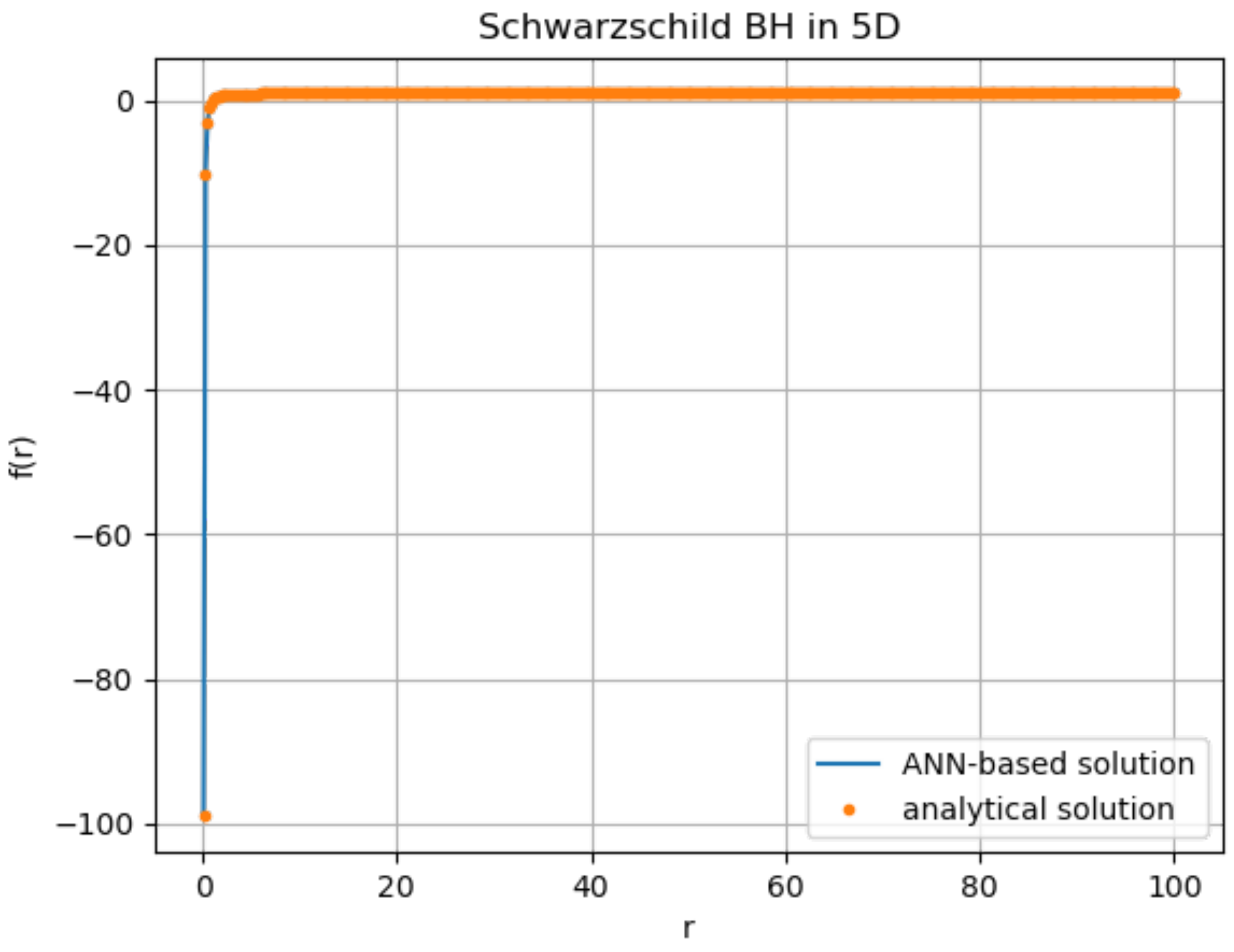


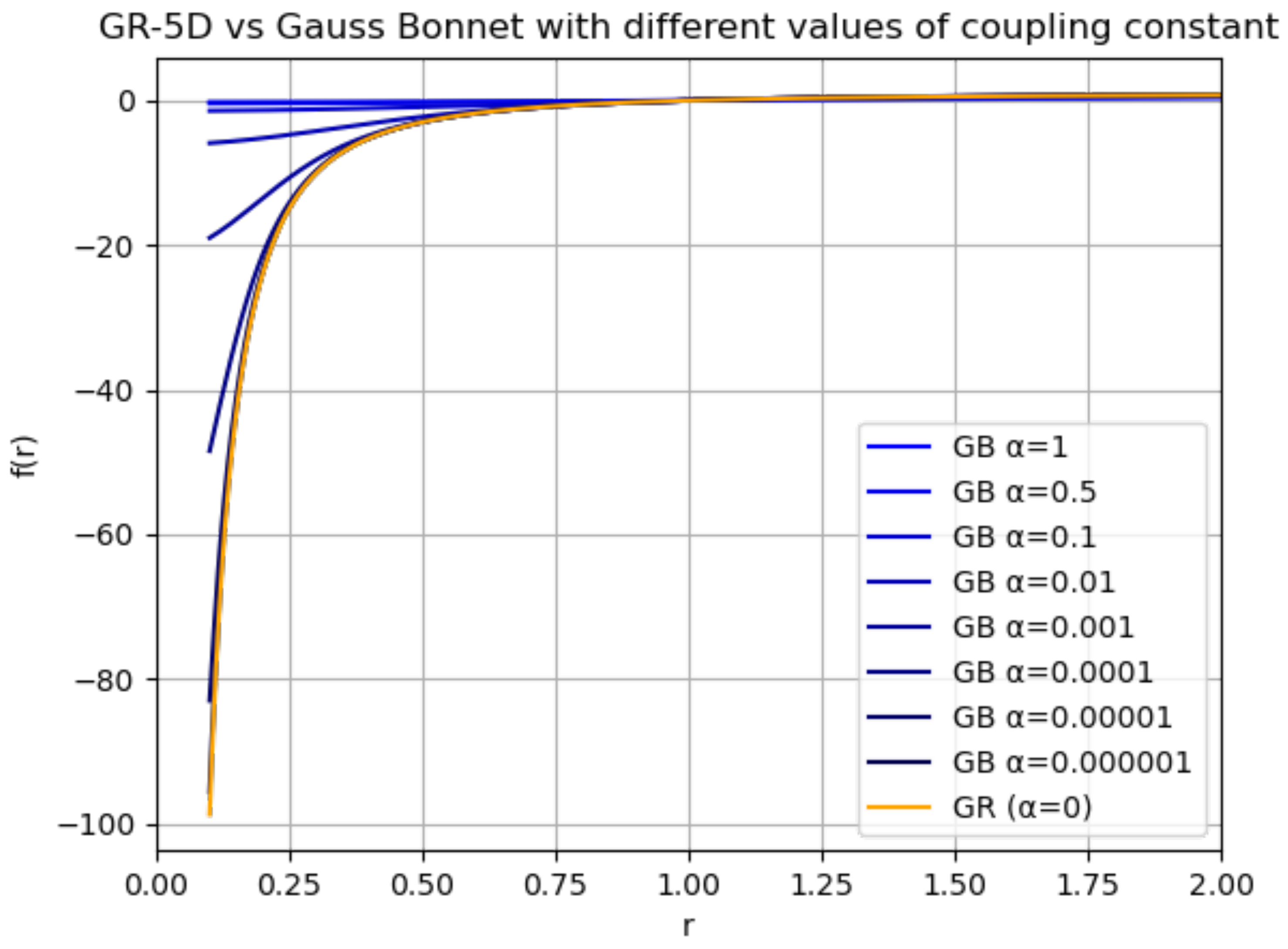
where $\epsilon = \lambda_3 L_\star^4/M^4$, both for wind and spherical accretion. They also tend to increase the contrast in density and decrease the aperture angle of the shock cone



Finding Solutions in Seconds







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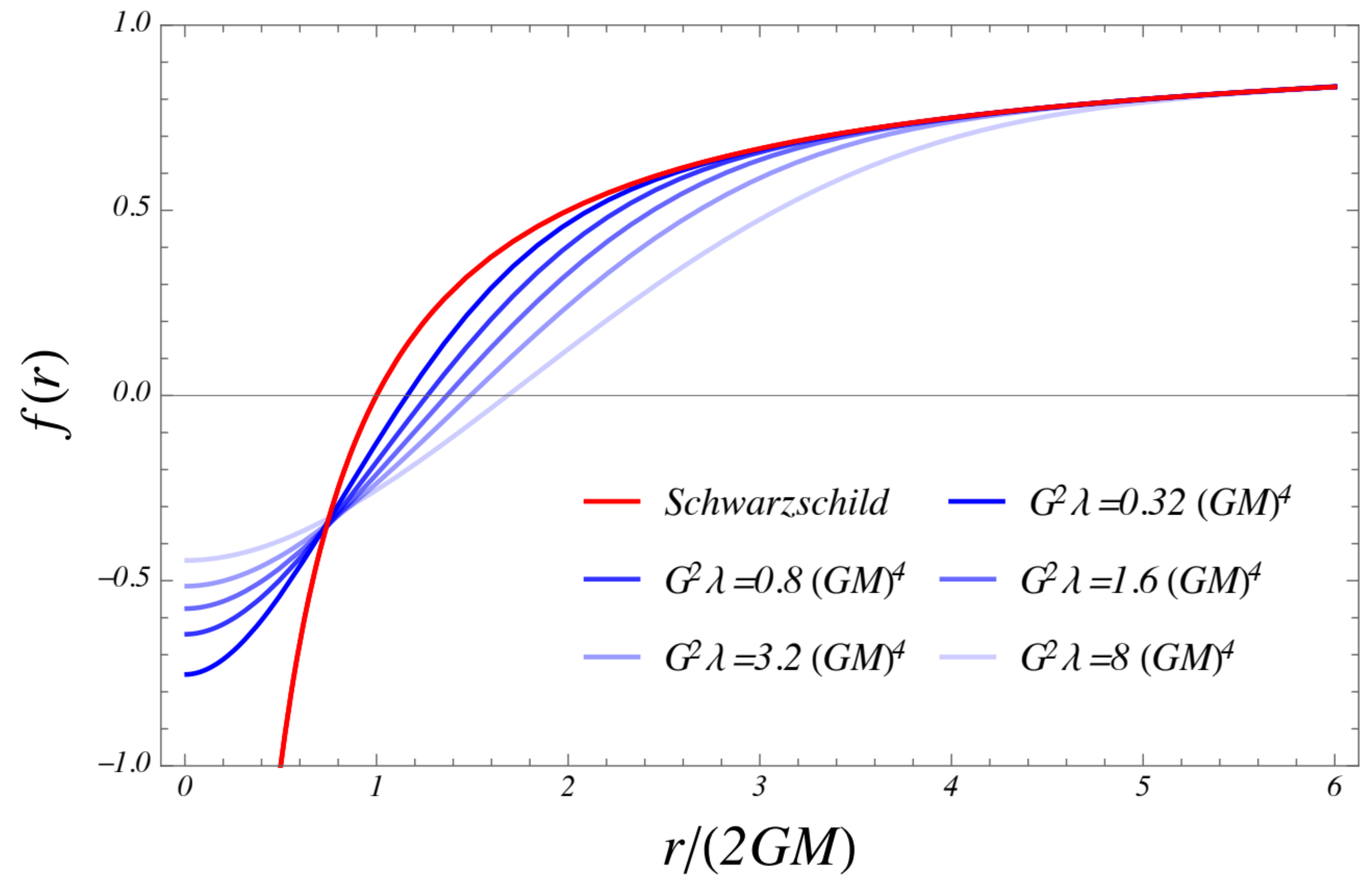
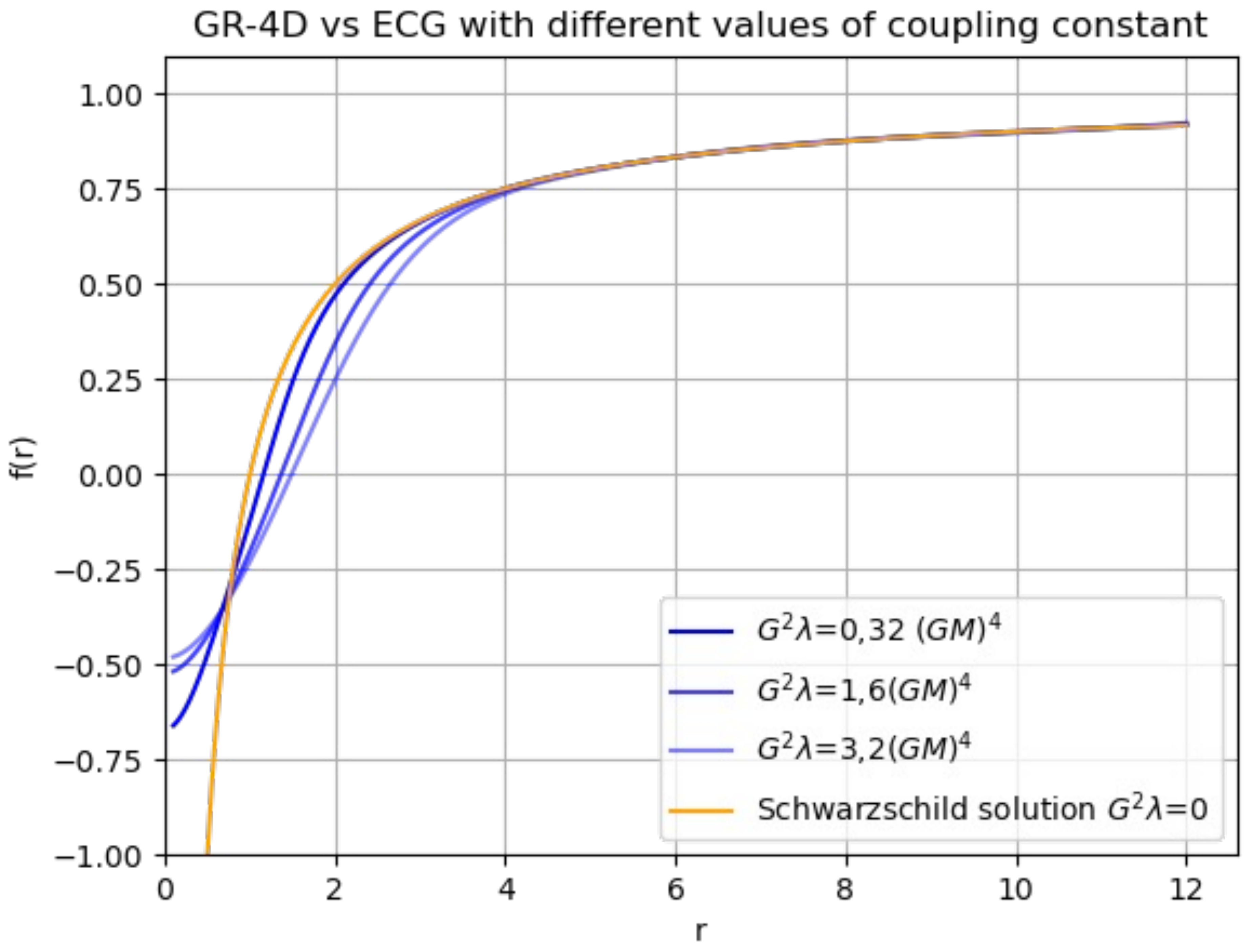
Finding Solutions in Seconds





Breaking the Multiscale Barrier

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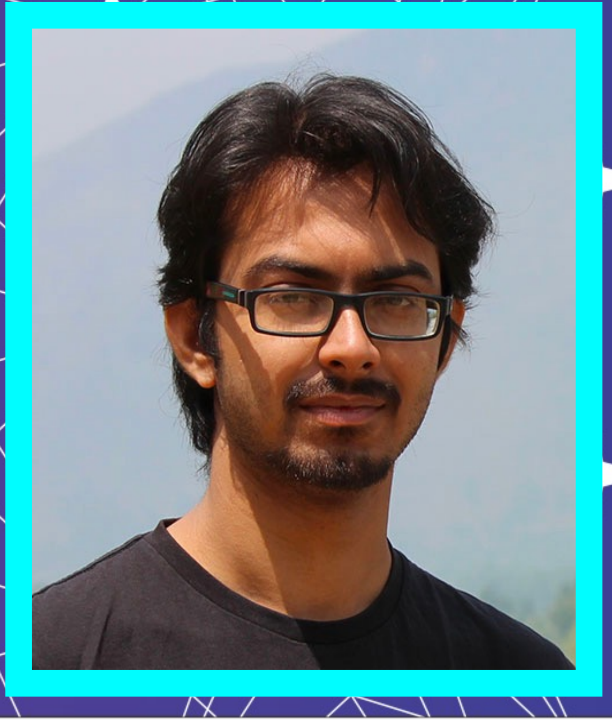
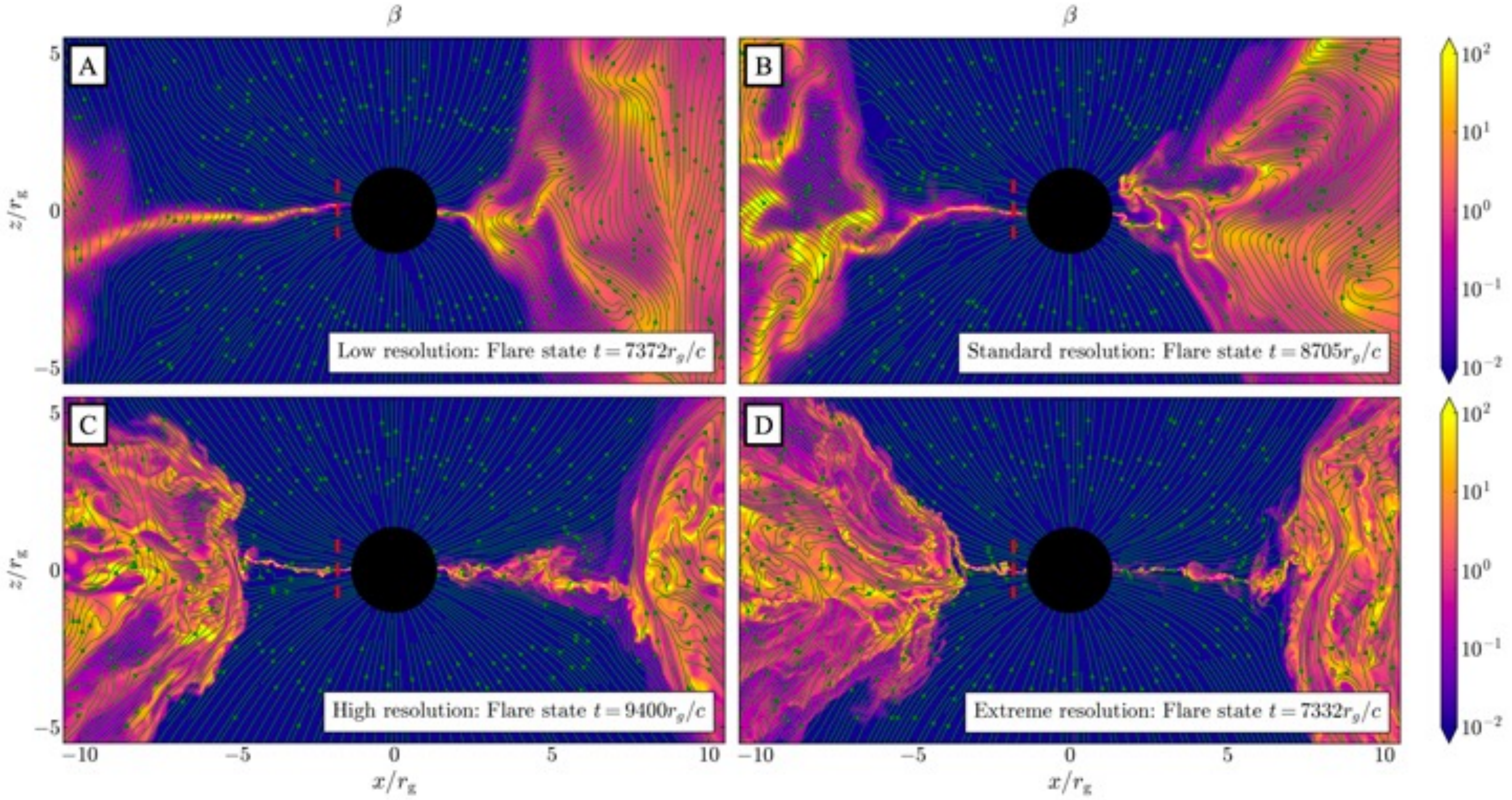


Koushik Chatterjee

Super resolution Model for GRMHD simulations for EHT



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AI for Astronomy

Probabilistic

Multimodal

Physical

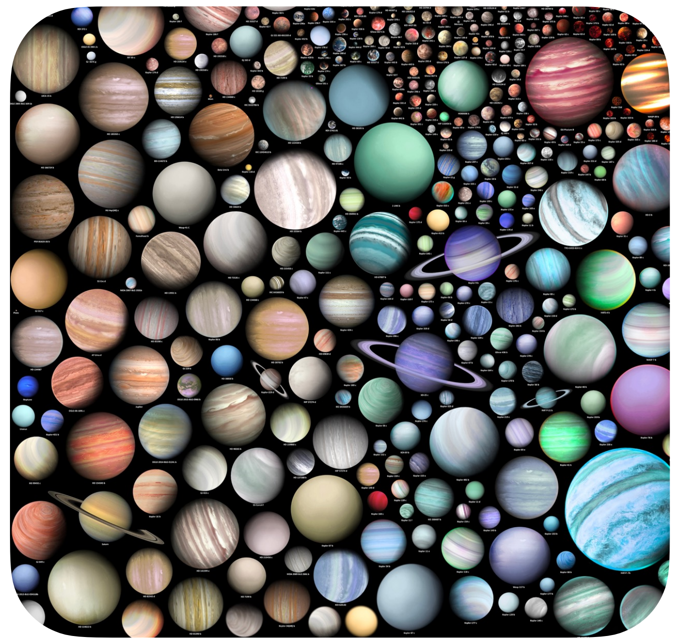
Multi-Scale

Interpretable

Generative

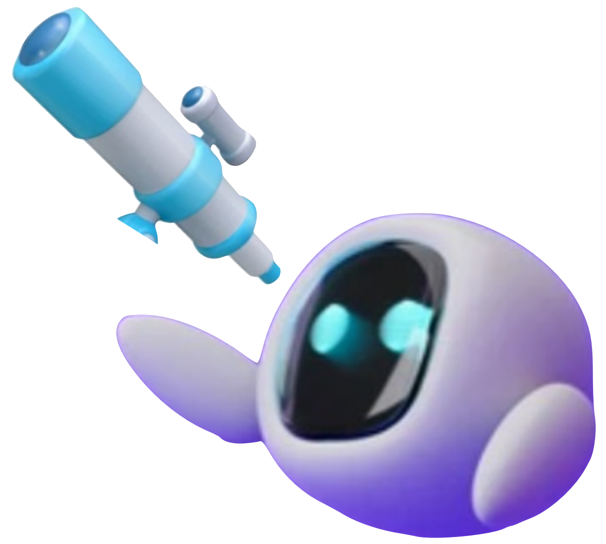
Robust

Open Source

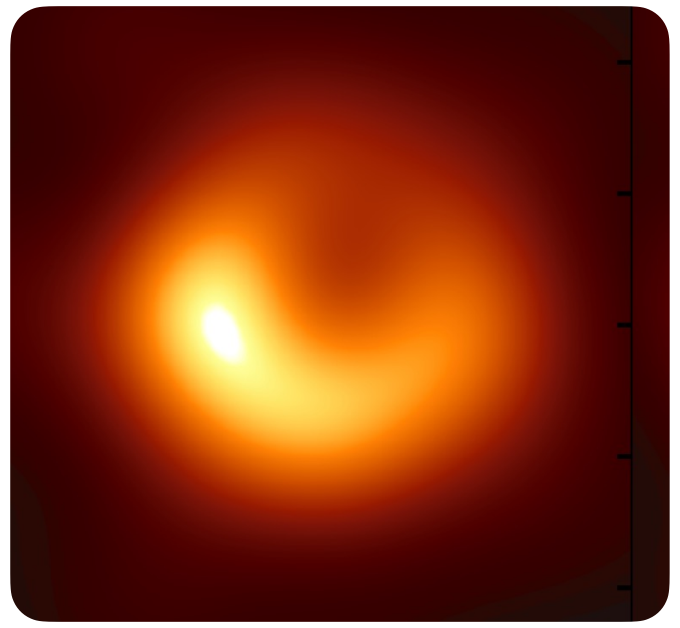


Biomarkers

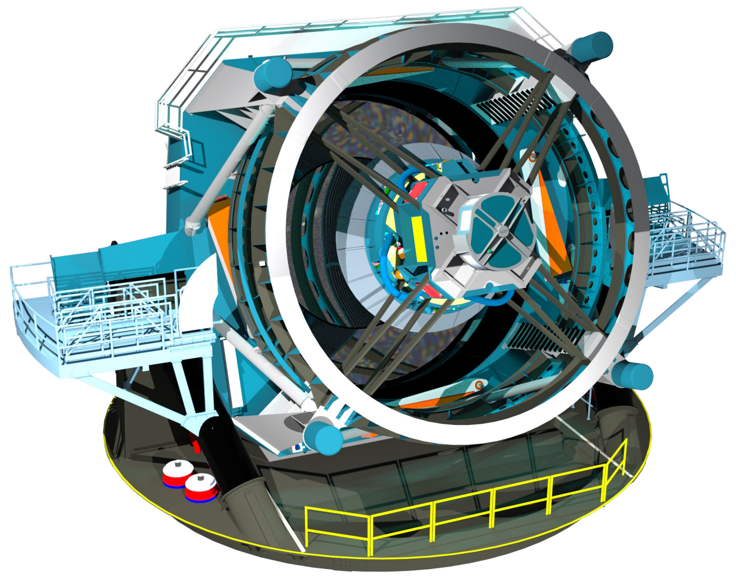
Stars



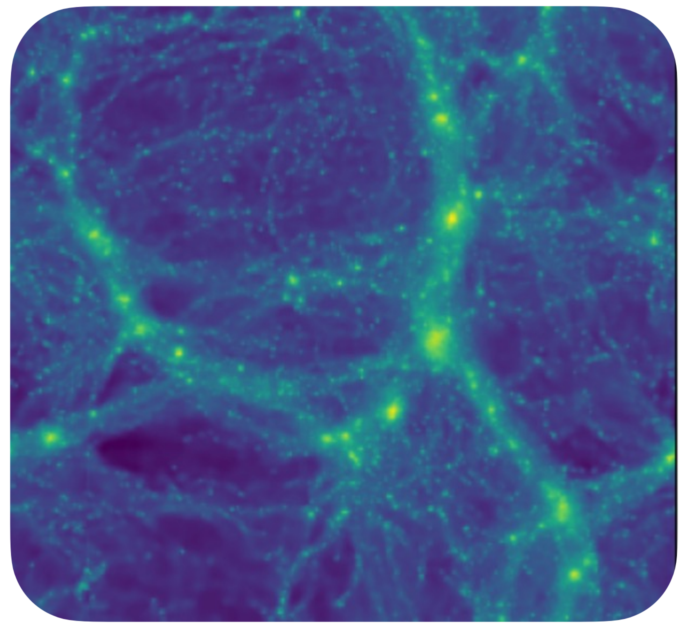
LLMs for Astronomy



Black Holes



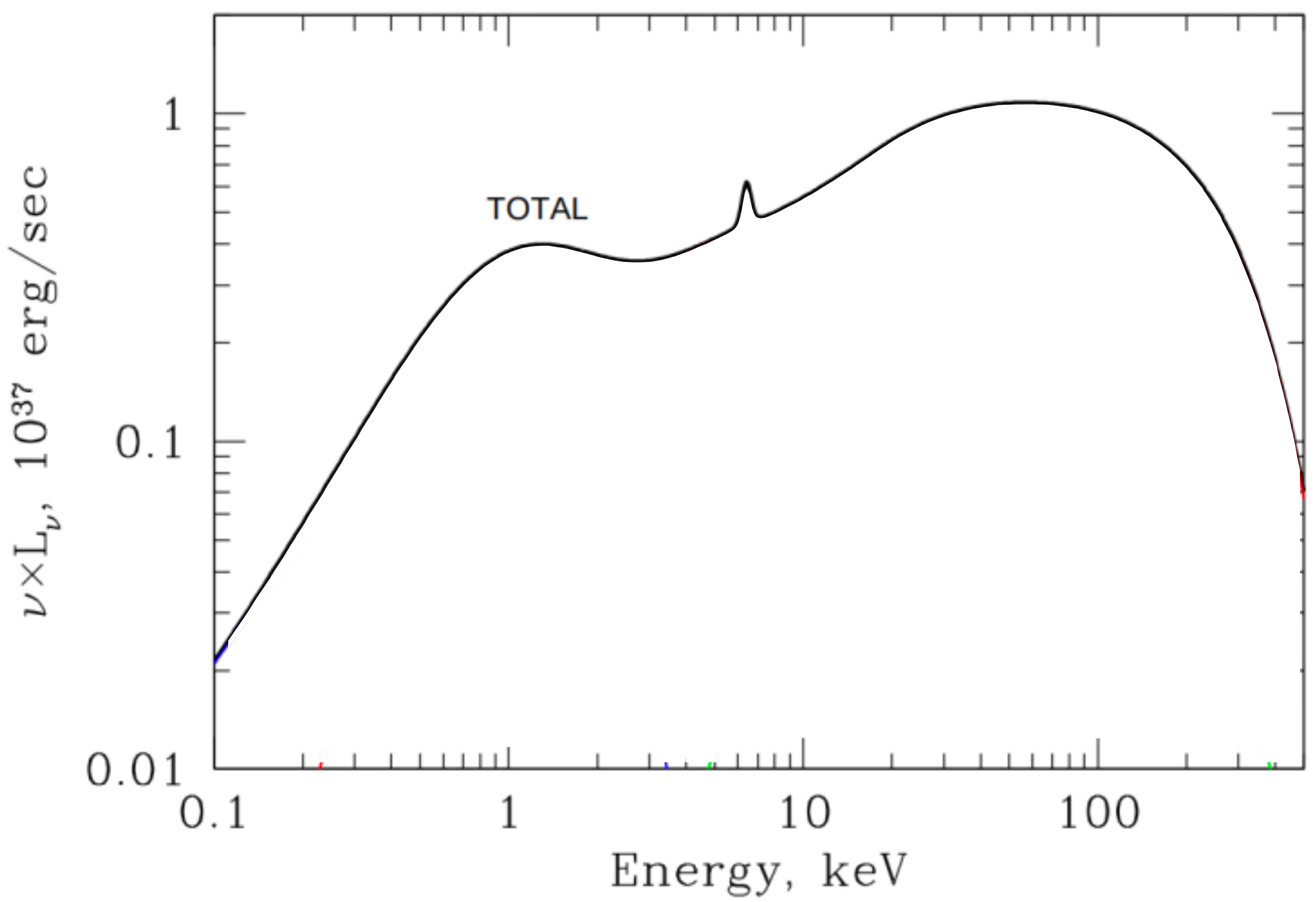
Dynamic Sky

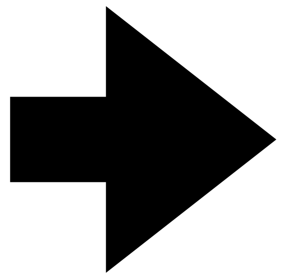


Cosmology

The Projects

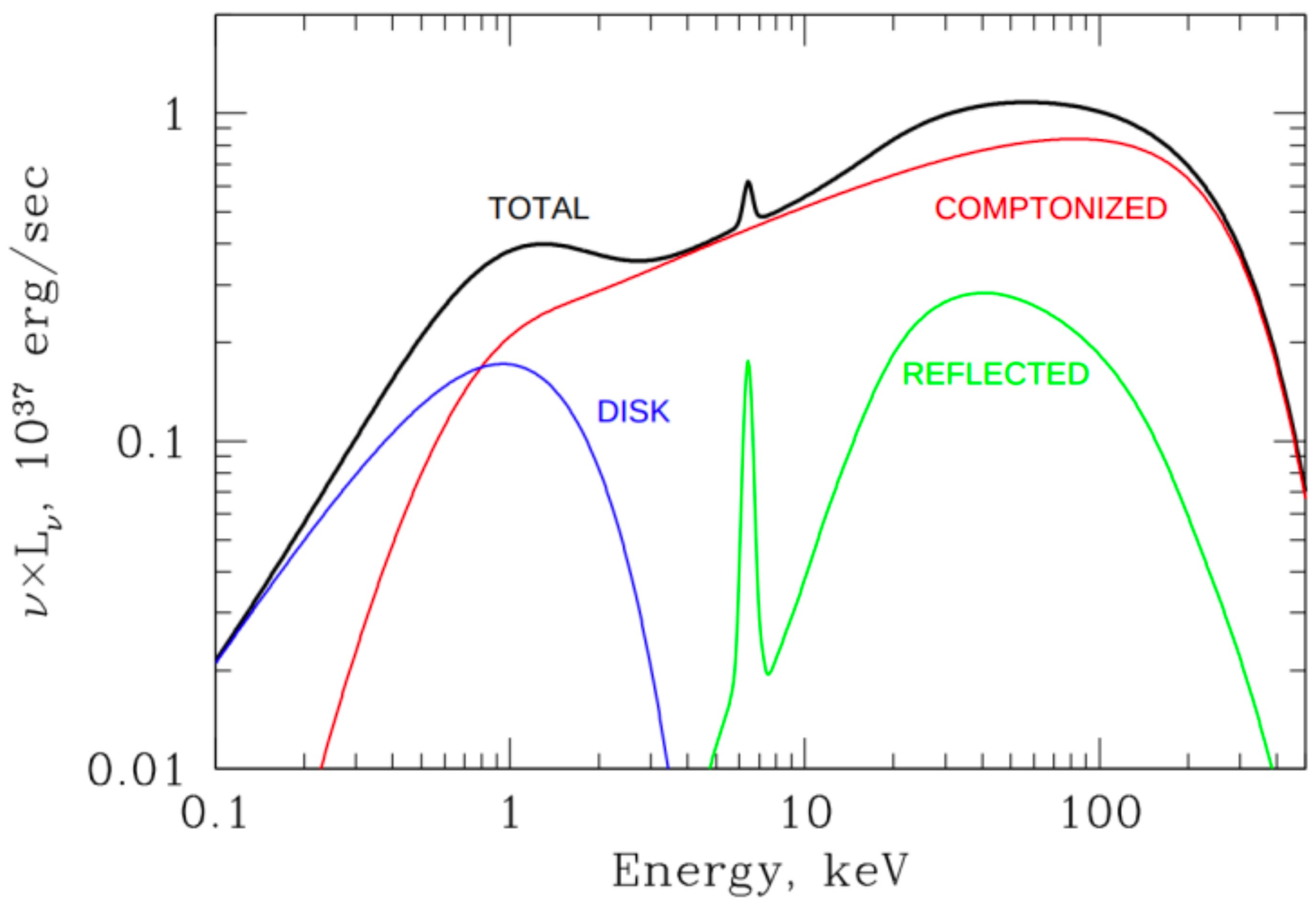
Jack Steiner





Expert

10,000 times!



Physical Parameters:
T, M, Spin

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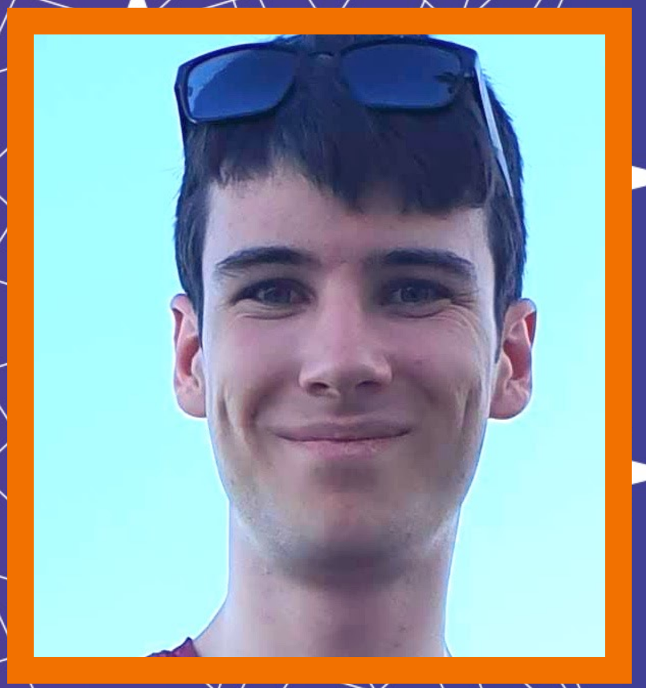
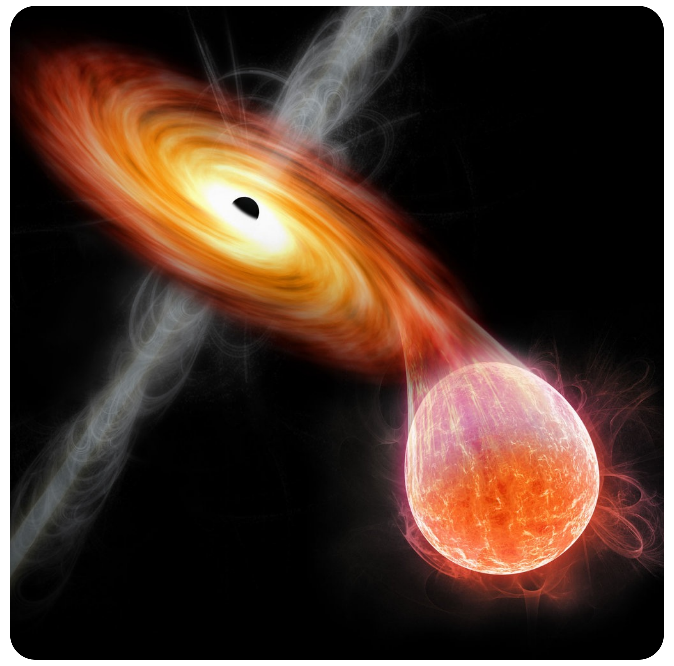
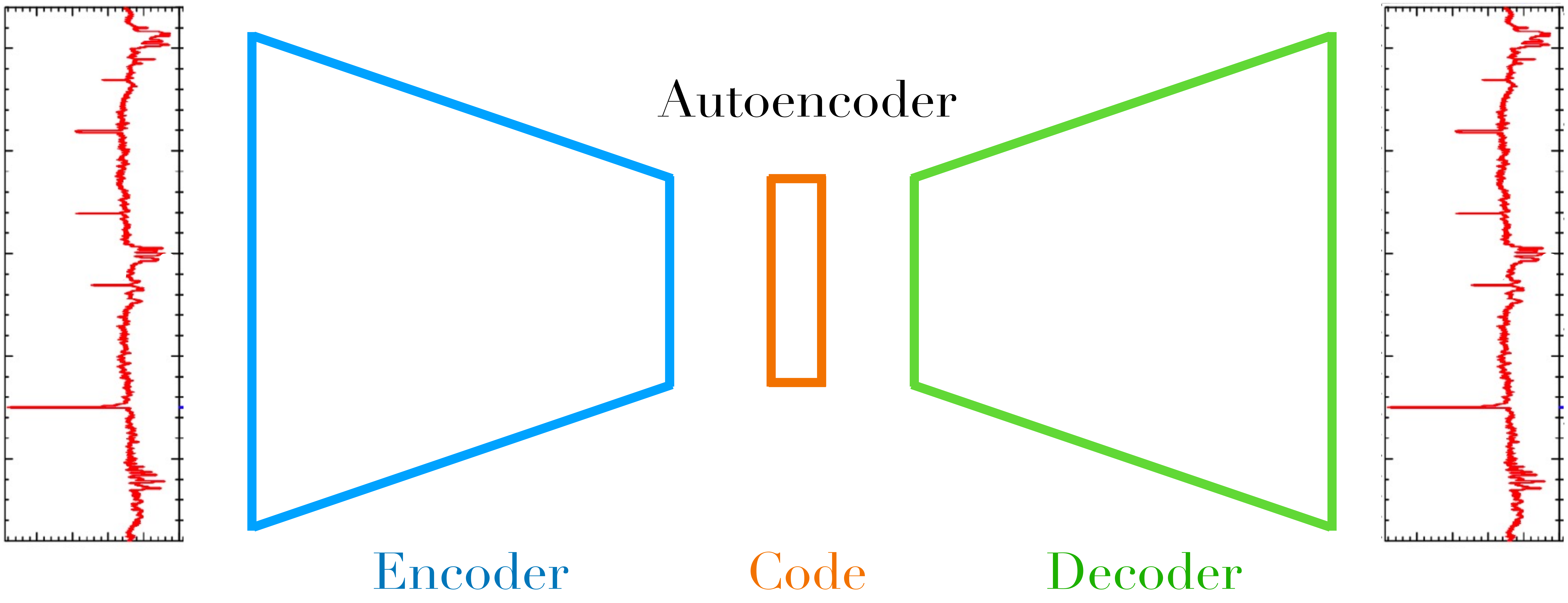
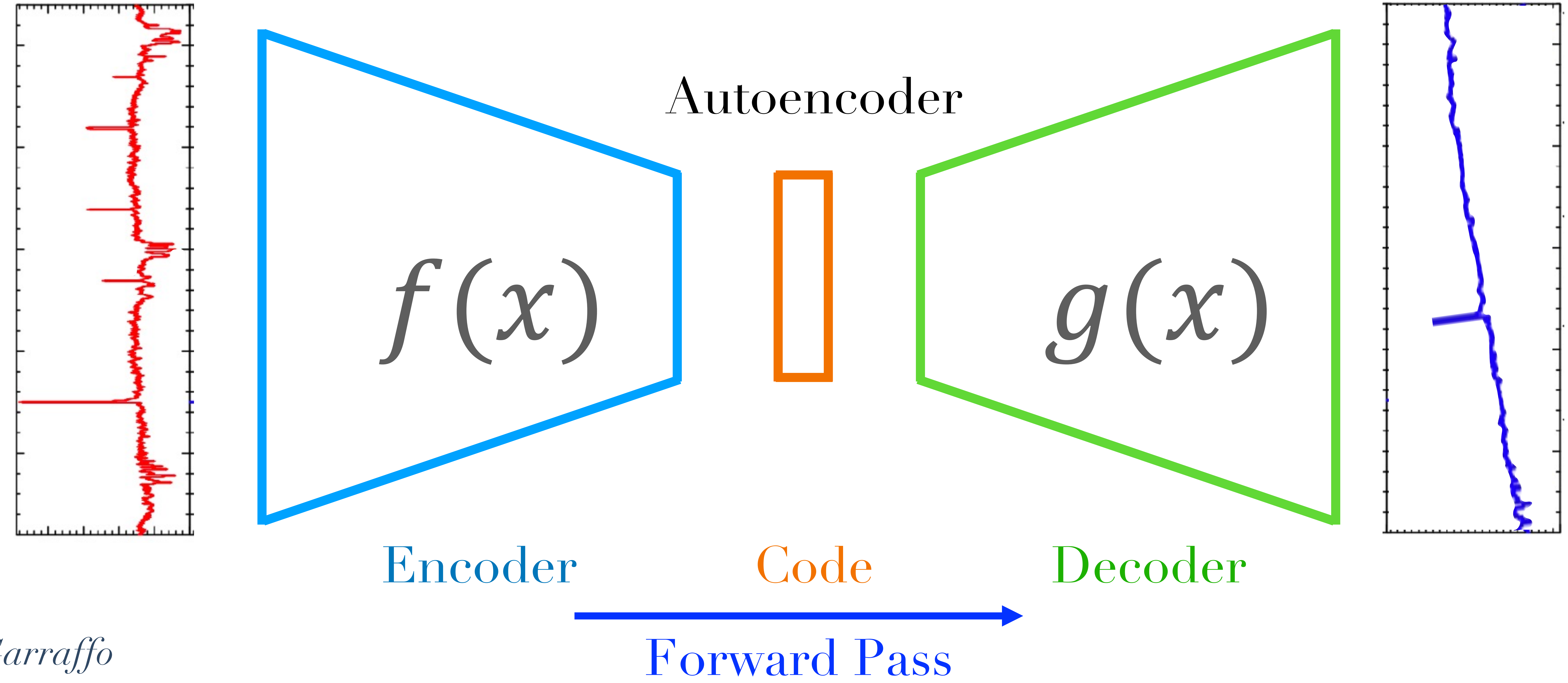
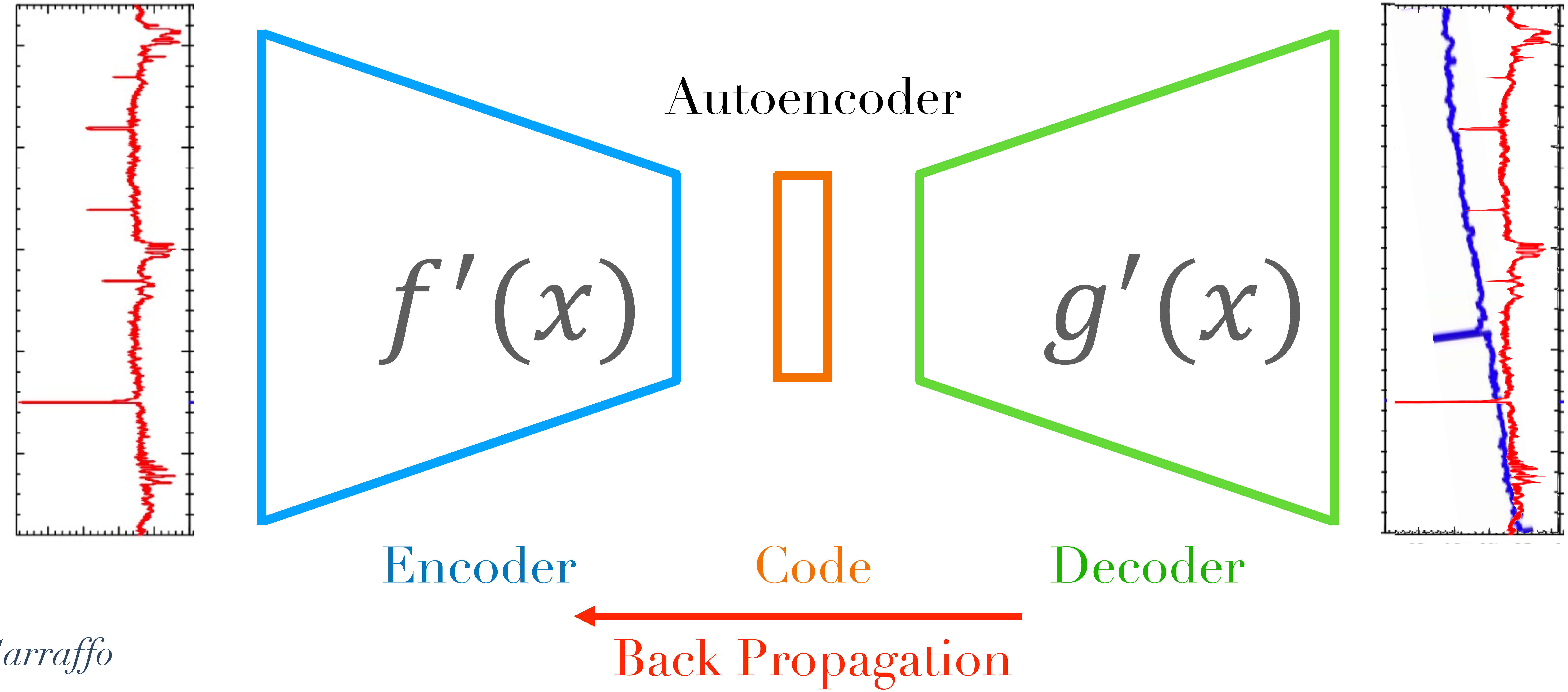


Ethan Tregidga

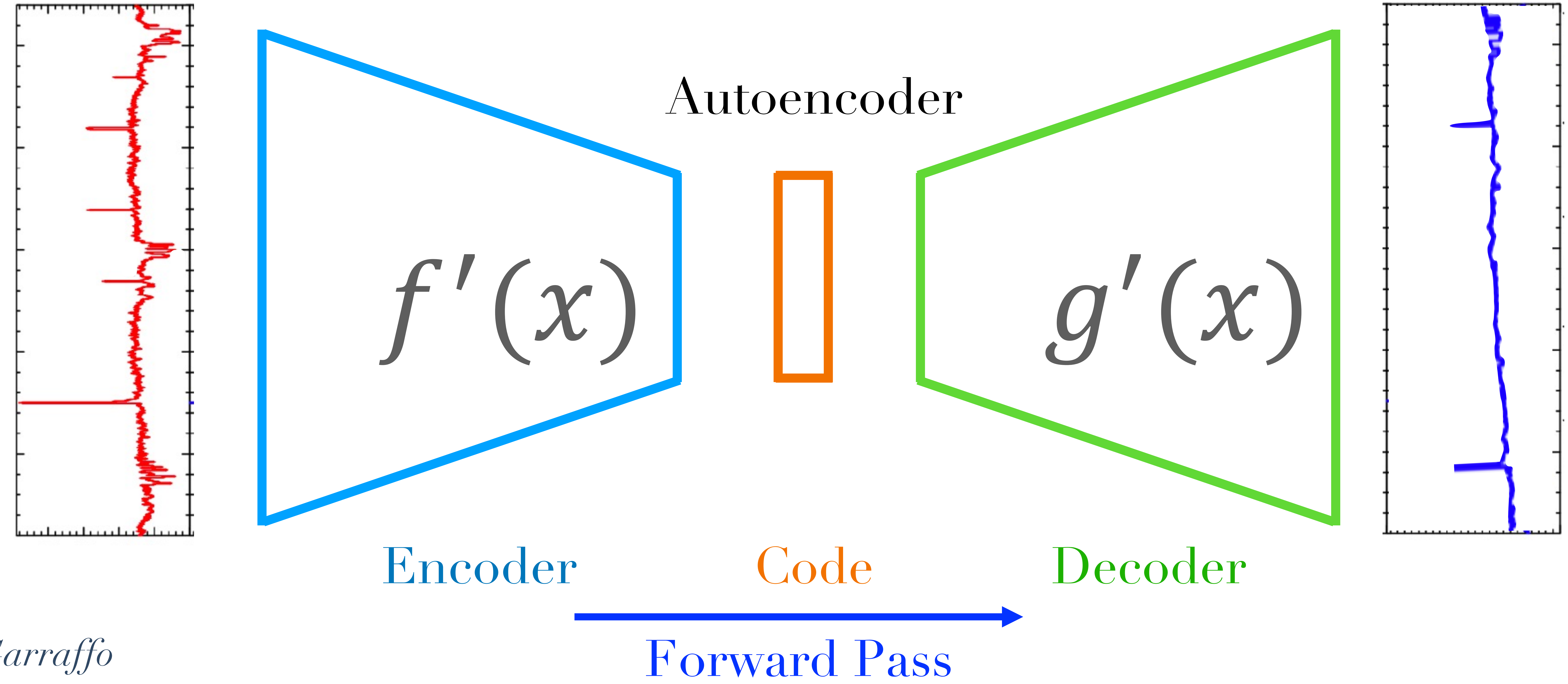



Autoencoder
Encoder
Code
Decoder

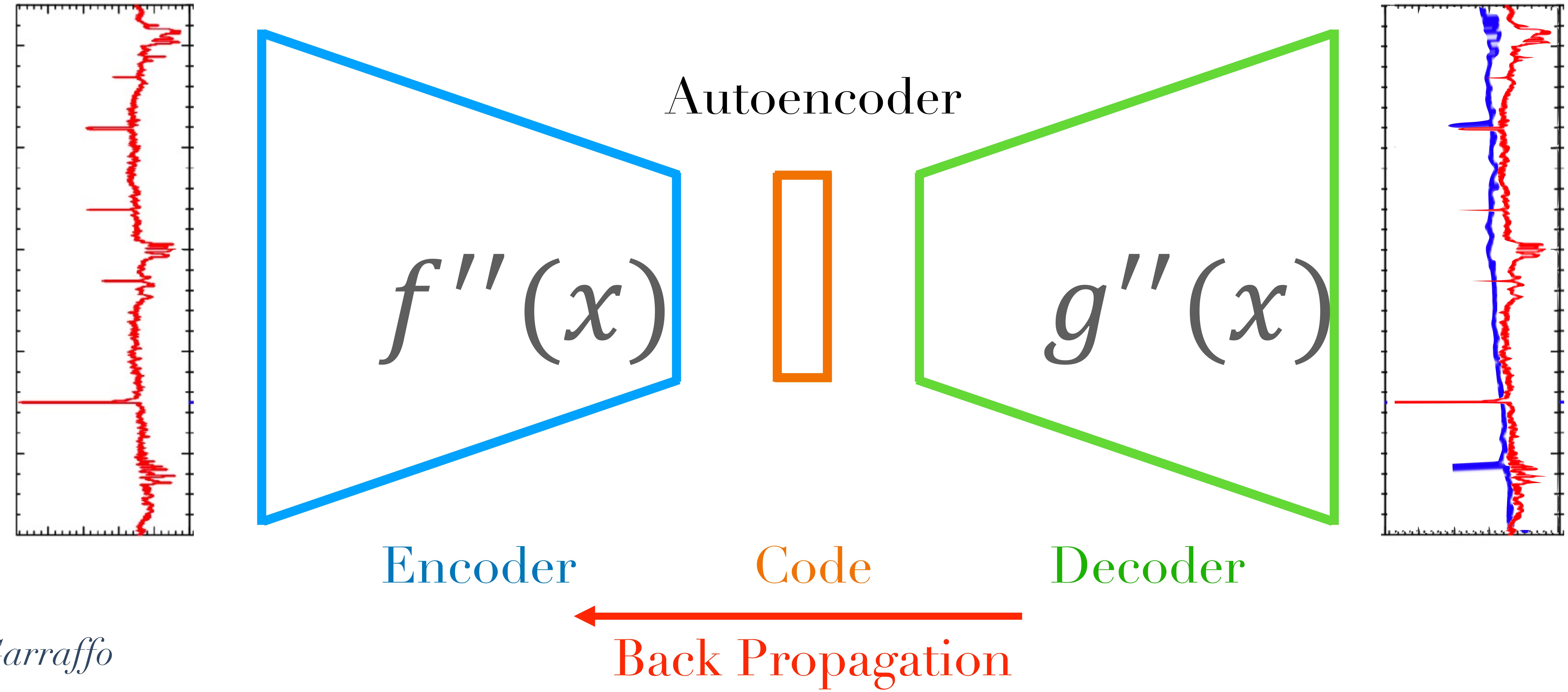

Autoencoder
$f(x)$
$g(x)$
Encoder
Code
Decoder
Forward Pass



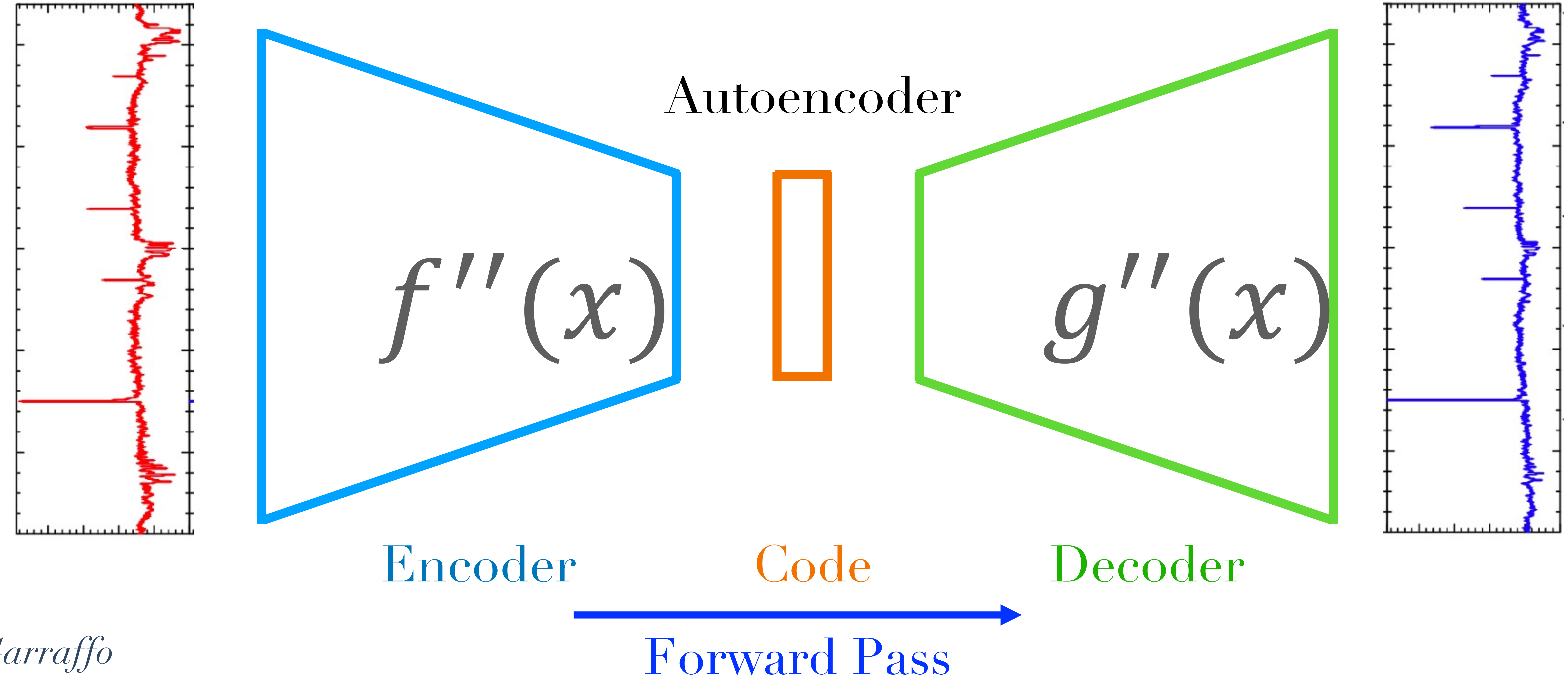
Cecilia Garraffo

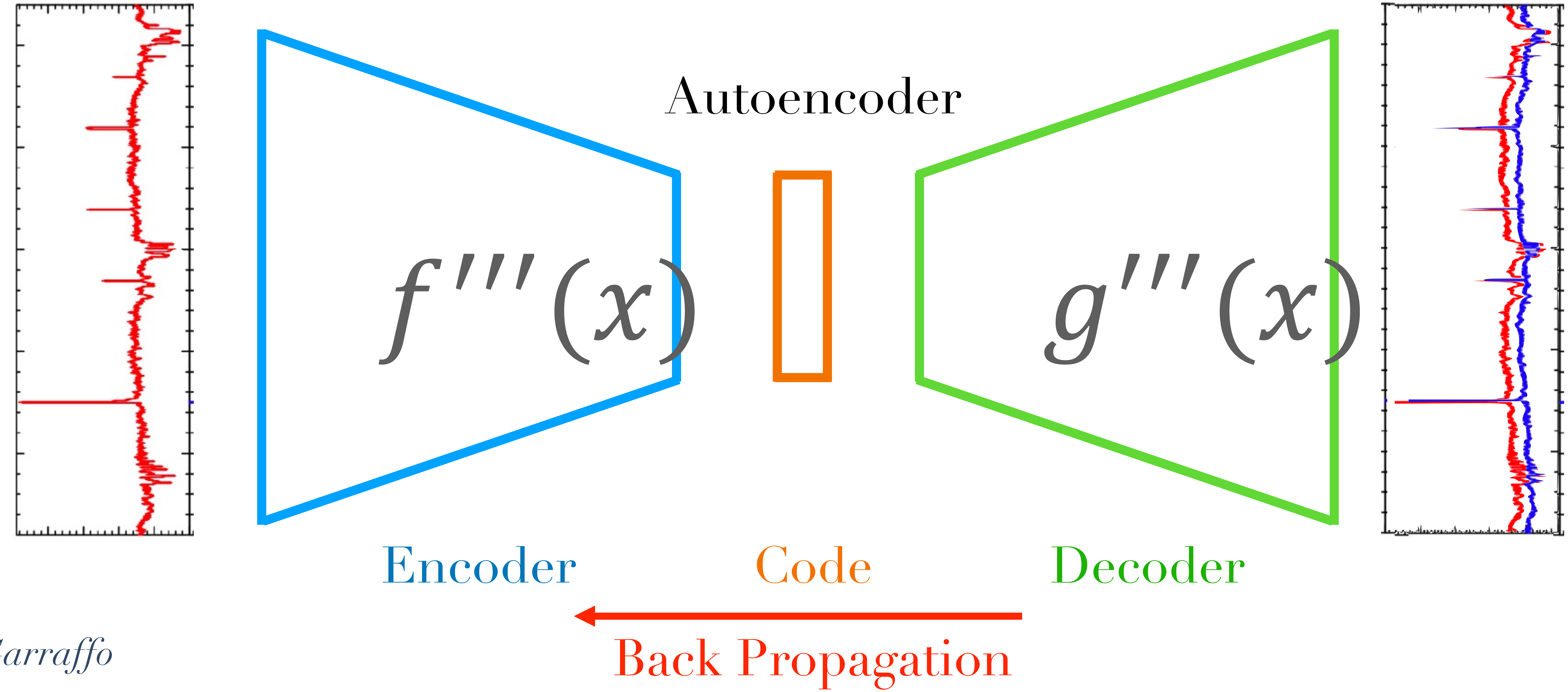


Cecilia Garraffo

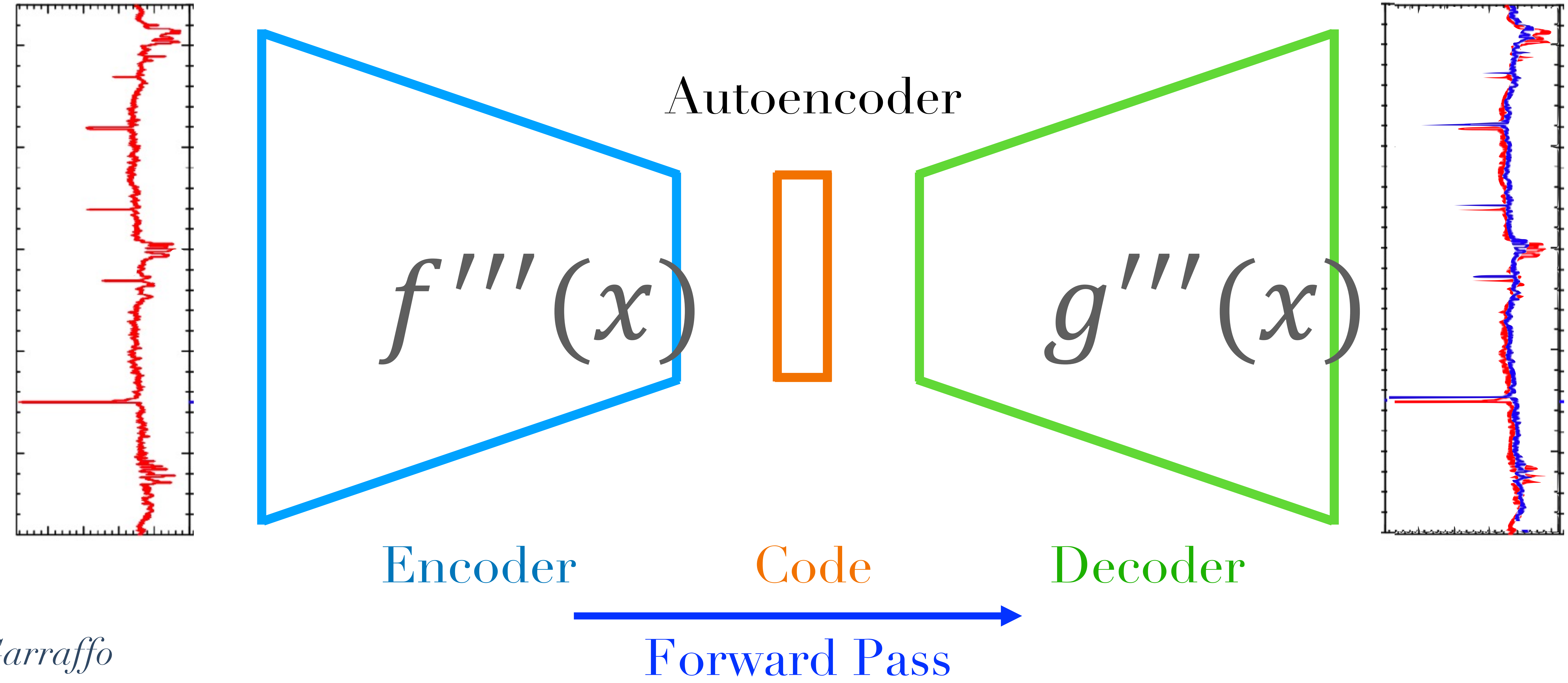


Cecilia Garraffo


Autoencoder
$f''(x)$
$g''(x)$
Encoder
Code
Decoder
Forward Pass



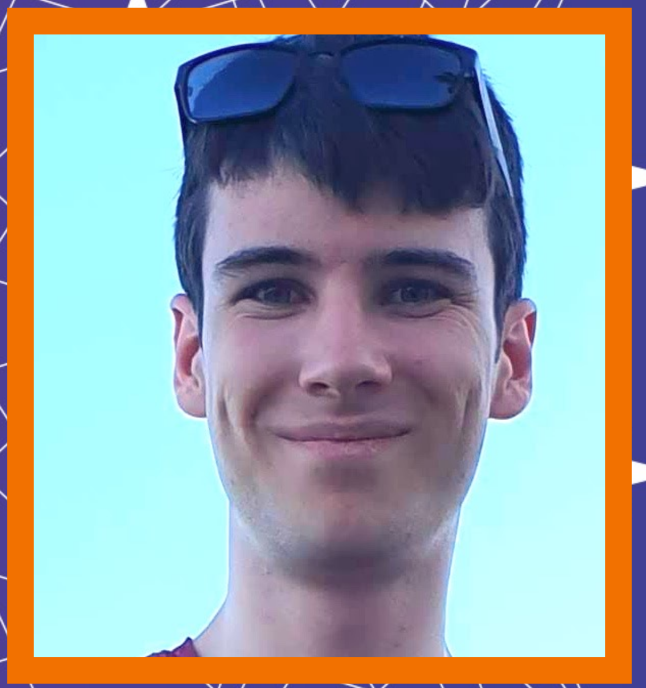
Cecilia Garraffo



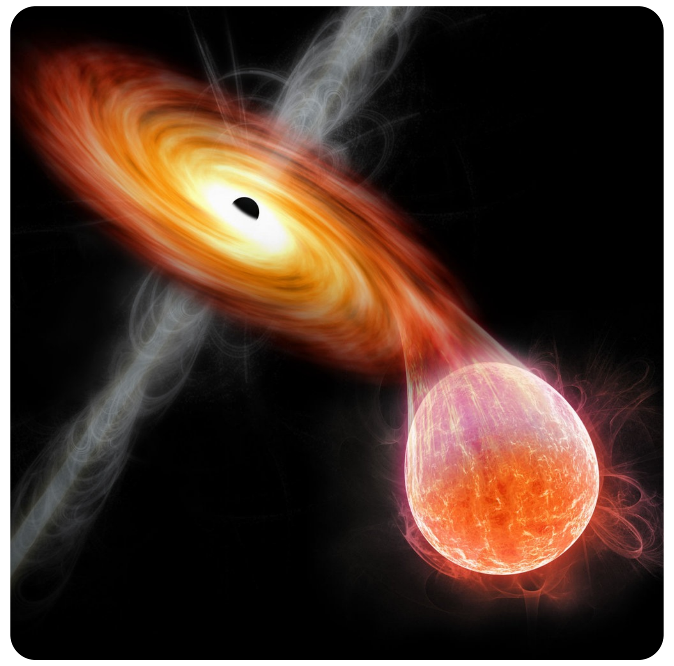
Cecilia Garraffo

AstroAI

Enabling Next Generation Astrophysics



Ethan Tregidga



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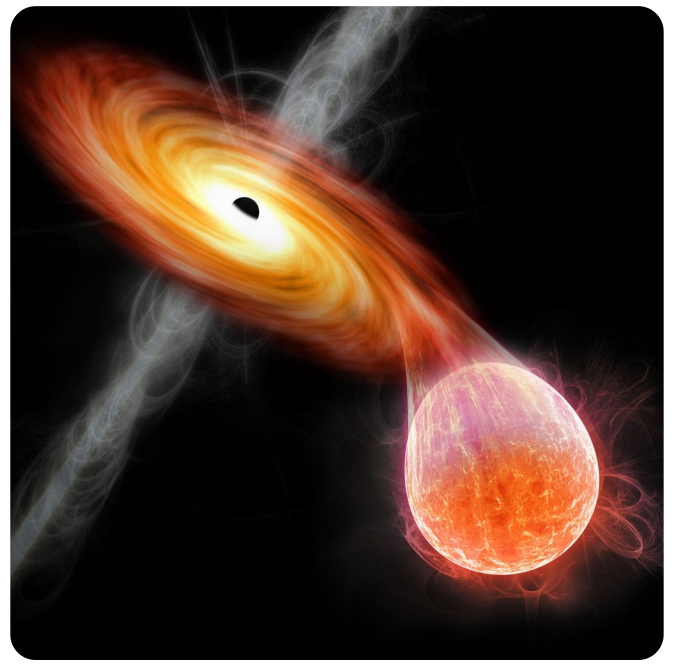
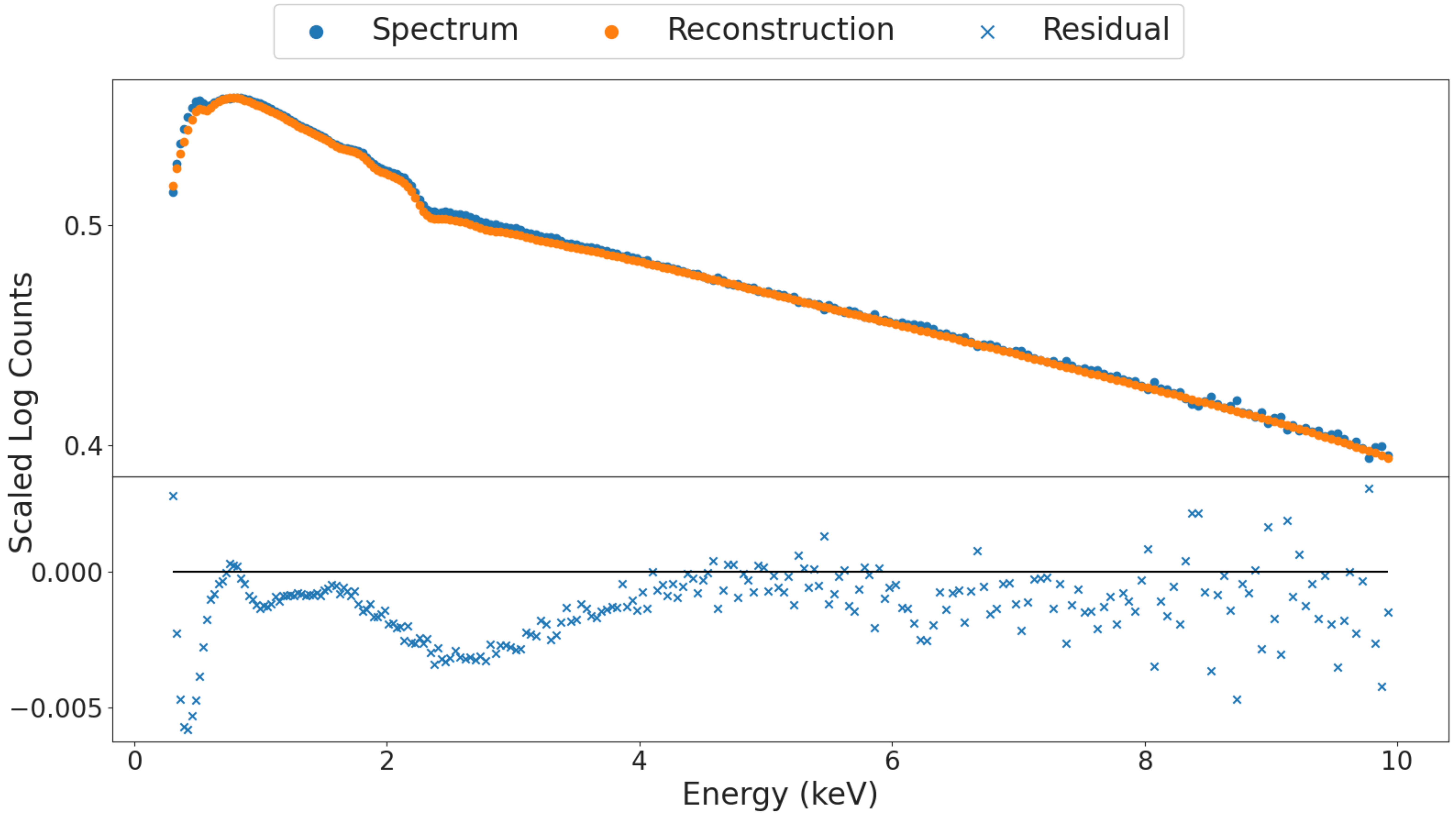
Ethan Tregidga

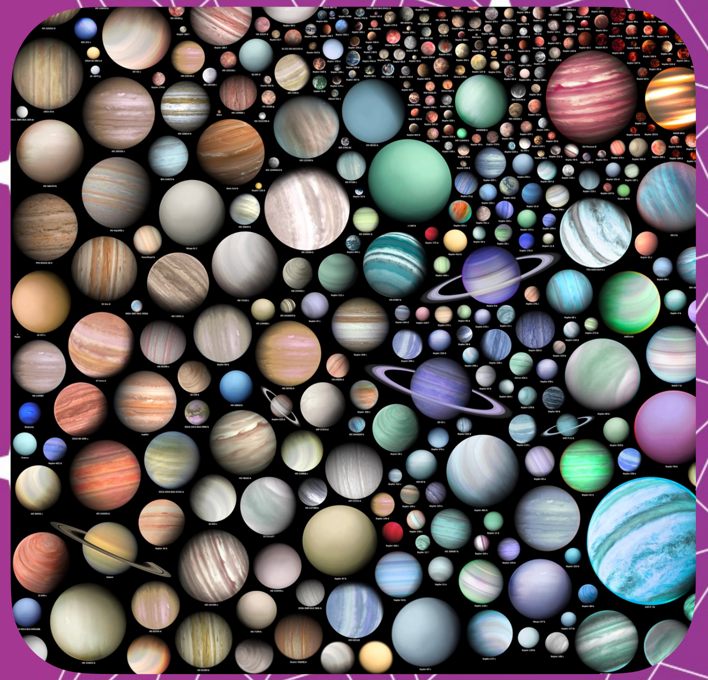


Physical Parameters

Ethan Tregidga



Tregidga et al. 2023



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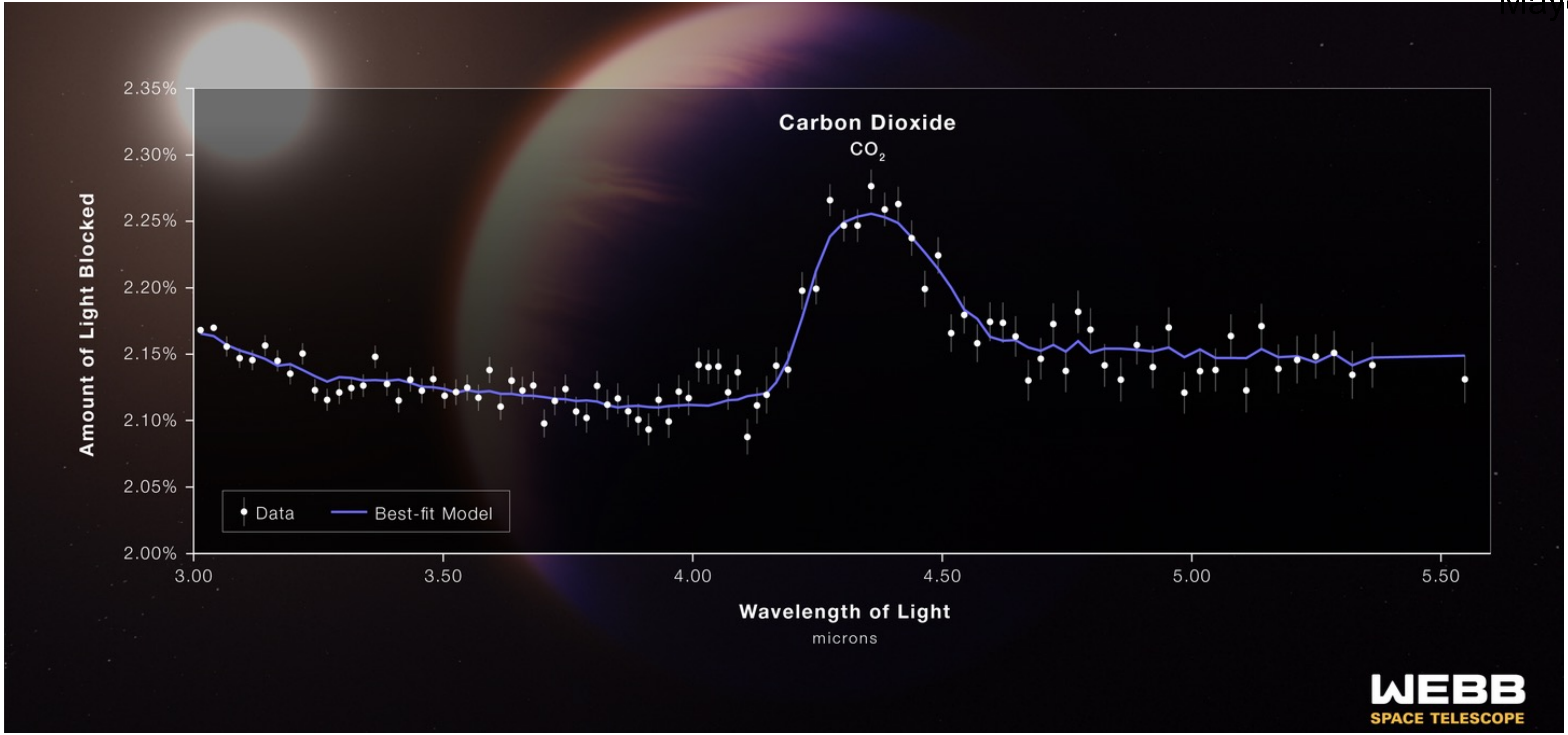
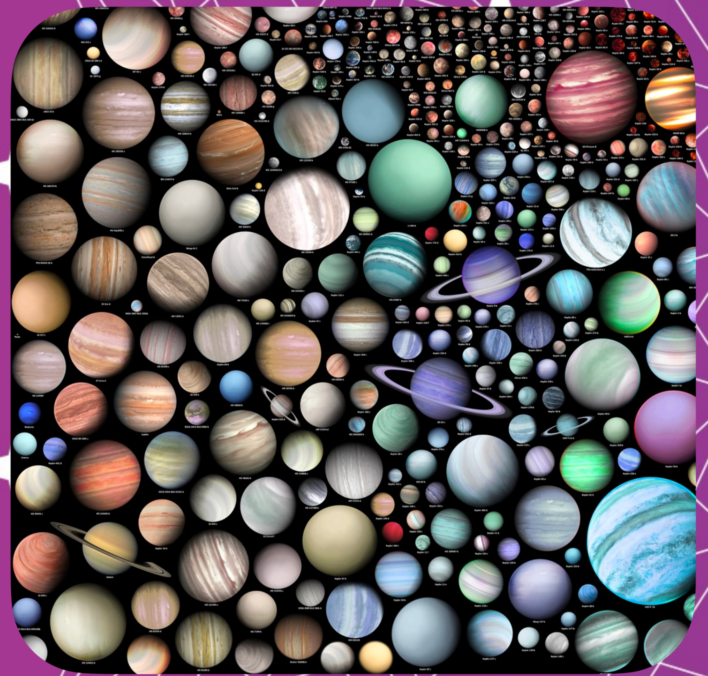
Mayeul Aubin





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Ethan Tregigda

Carol Cuesta-Lazaro

Iouli Gordon

Mercedes López-Morales

Javier Viana

Robert Hargreaves

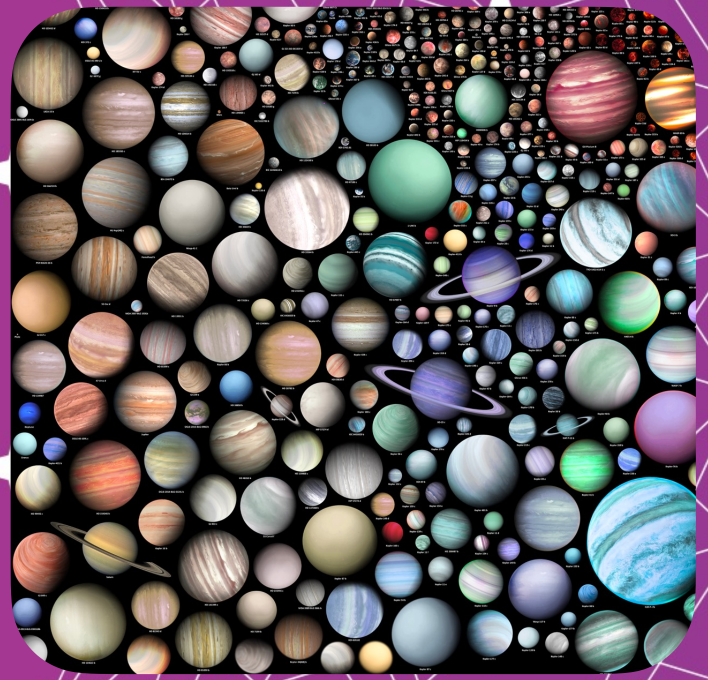
Cecilia Garraffo

Vladimir Makhnev

Jeremy Drake

Phillip Cargile

- Students
- Astronomers
- AI Experts
- Spectroscopists
- AstroAI



AstroAI

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Cecilia Garraffo

Vladimir Makhnev

Jeremy Drake

Phillip Cargile

Students

Astronomers

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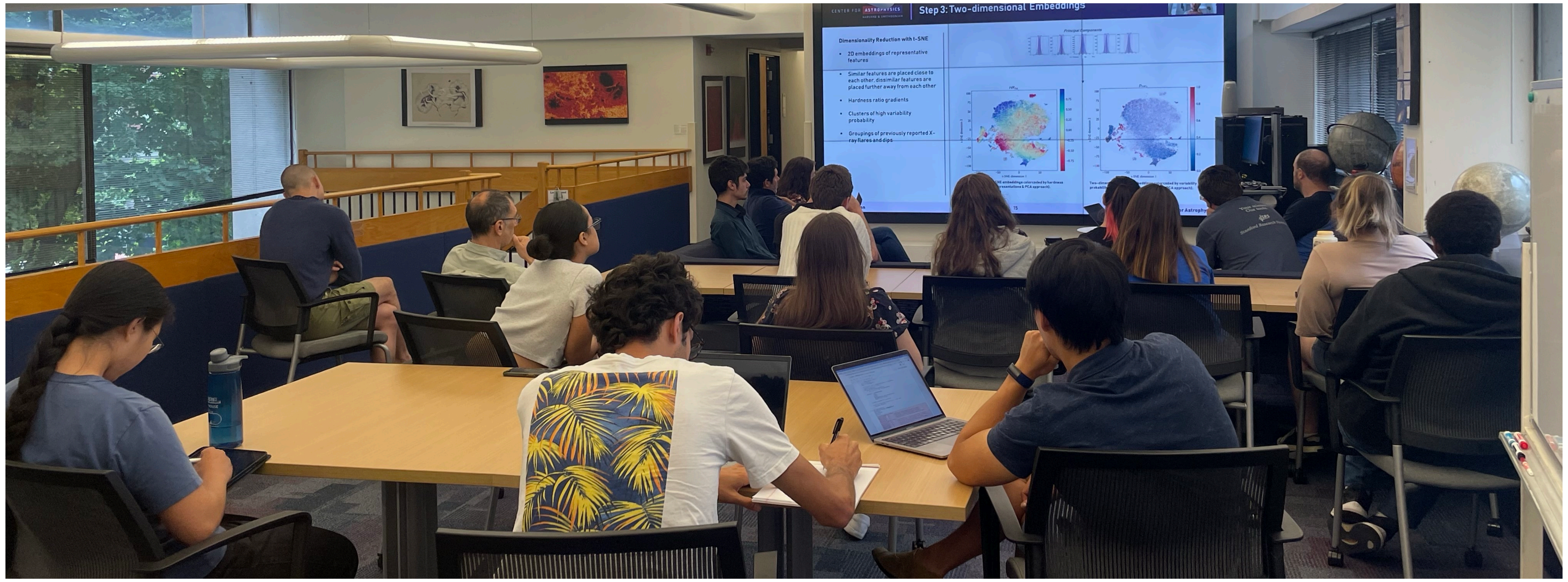
Spectroscopists

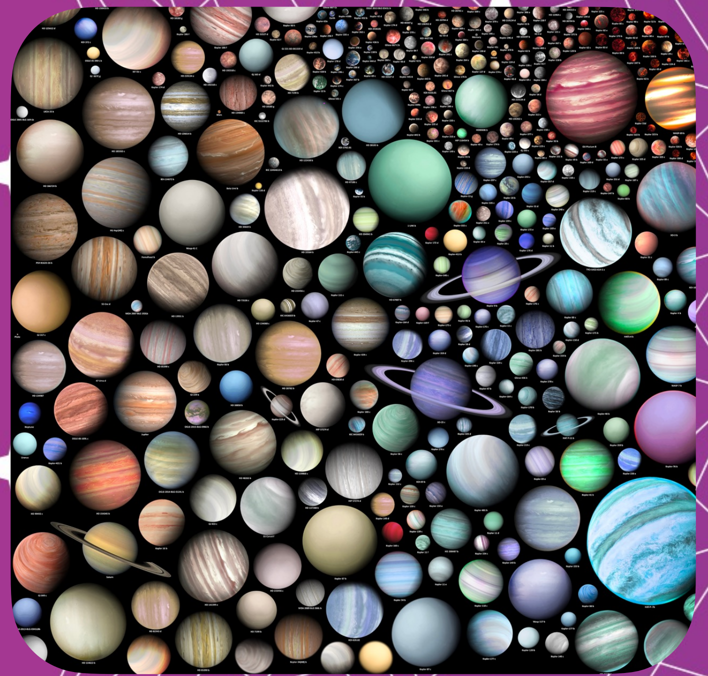
AstroAI

Building Community:



Hybrid AstroAI meetings every Monday. Join us!

www.astroai.cfa.harvard.edu



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Bill Freeman, CS

Robin Walters, CS

Brandon Feng, CS

David, CS

Yuanyuan , CS

Sara Seager

Cecilia Garraffo

Iouli Gordon

Eddie , CS

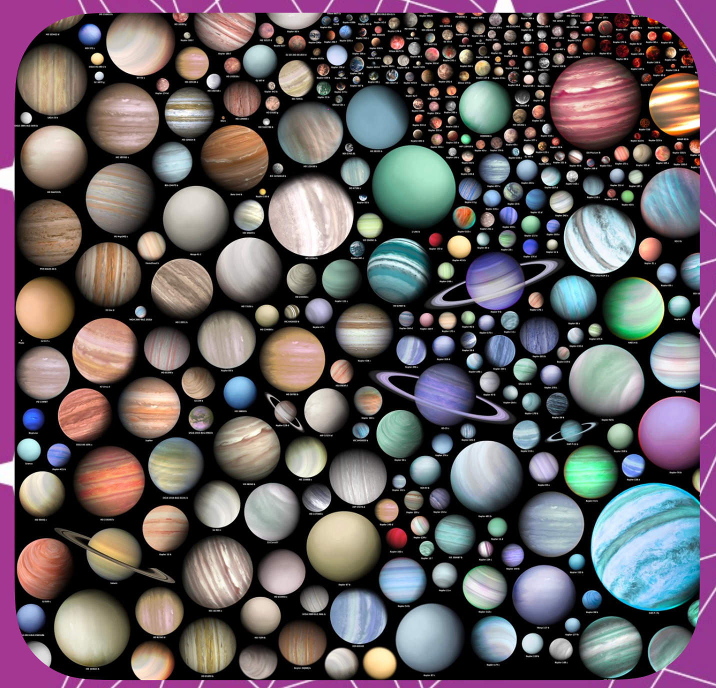
Students

Astronomers

AI Experts

Spectroscopists

AstroAI



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Mayeul Aubin

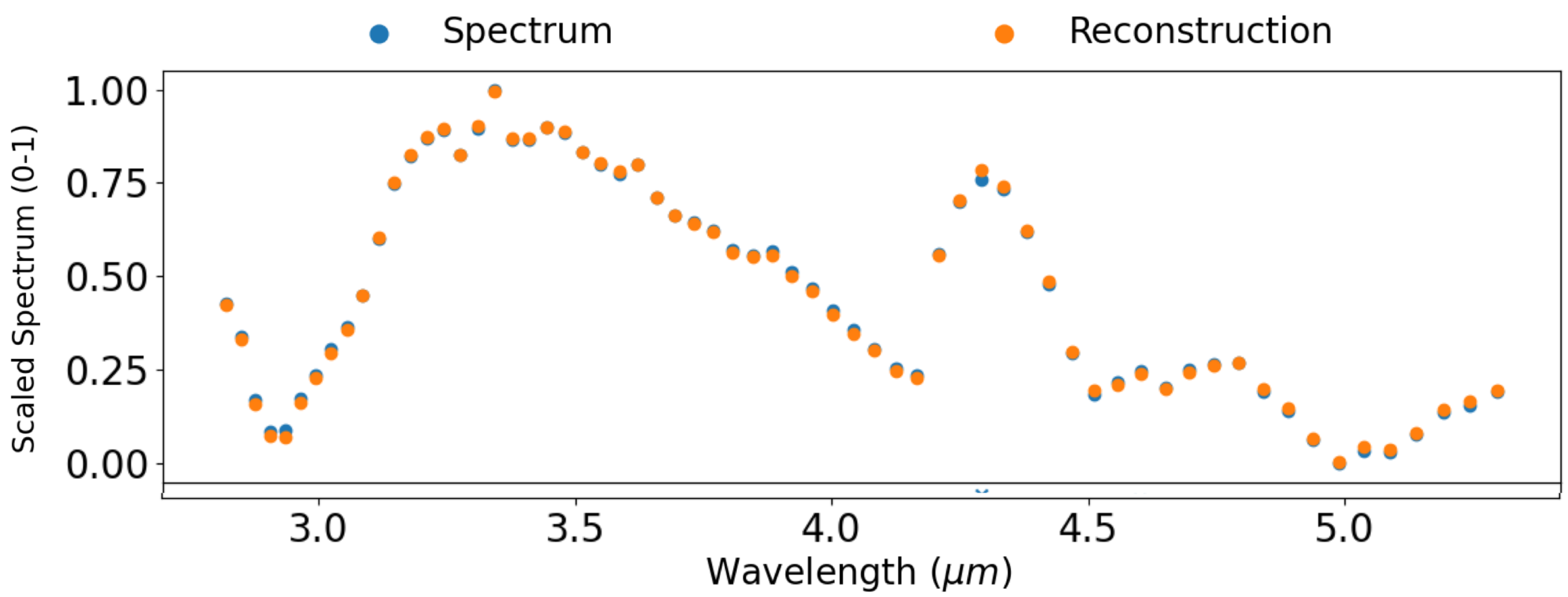
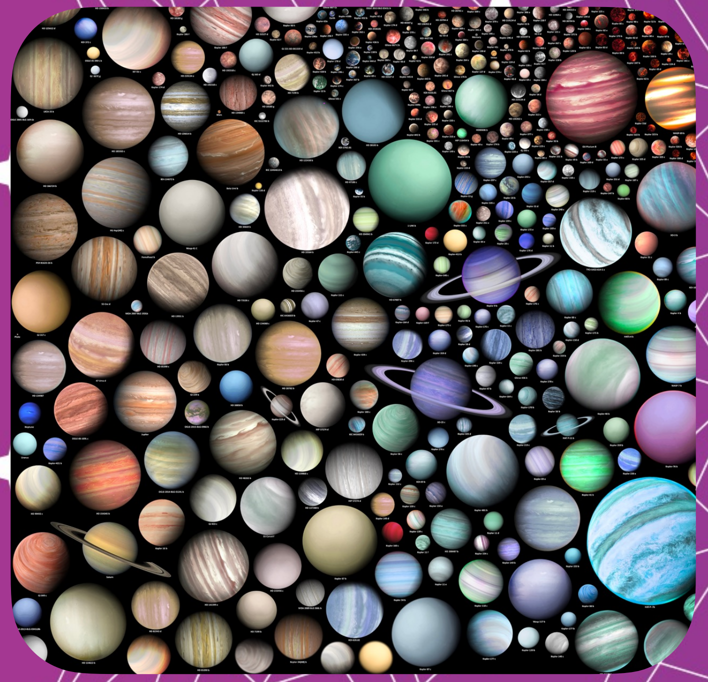
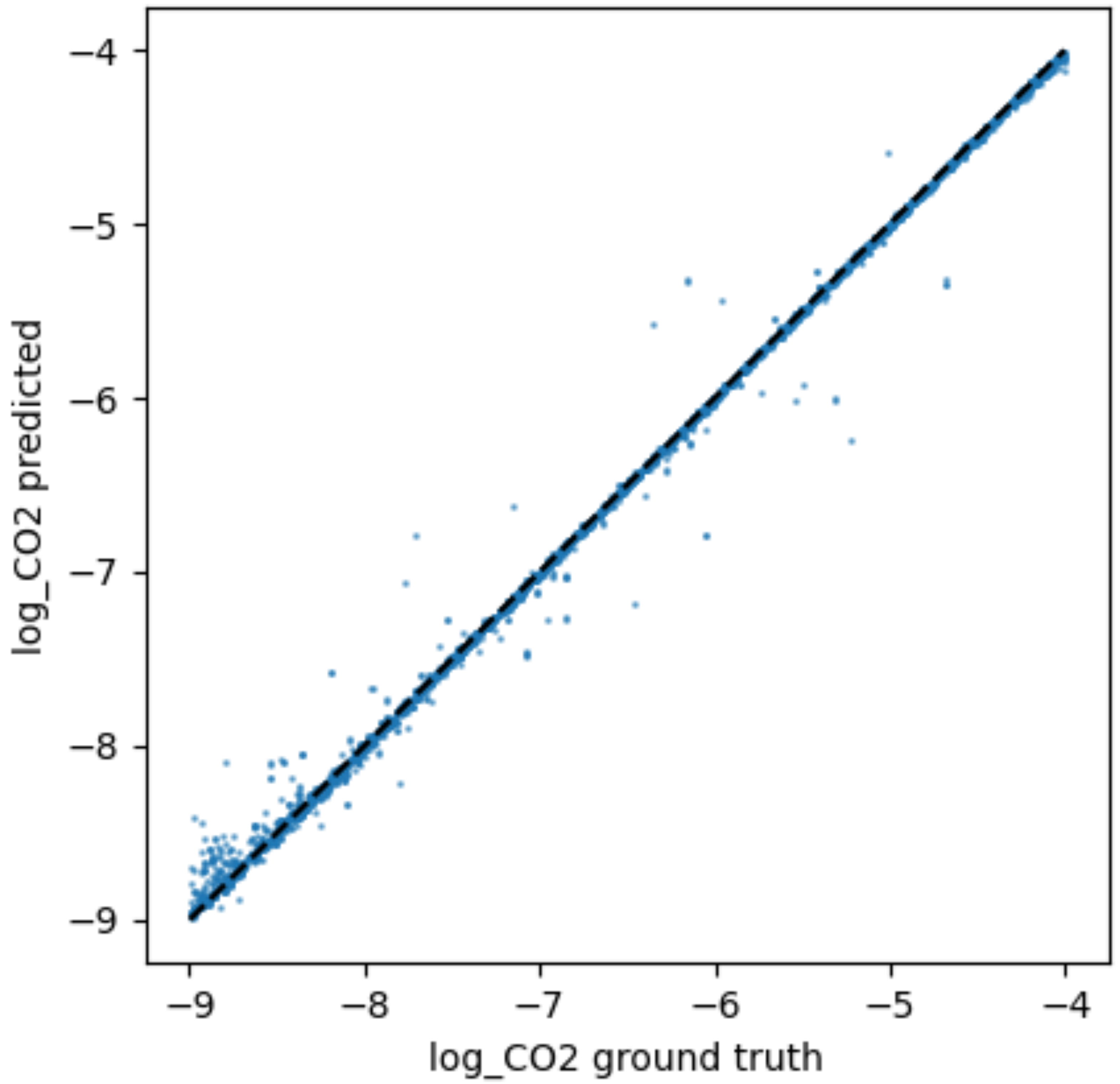


Figure 2: Reconstruction of a spectrum by the decoder

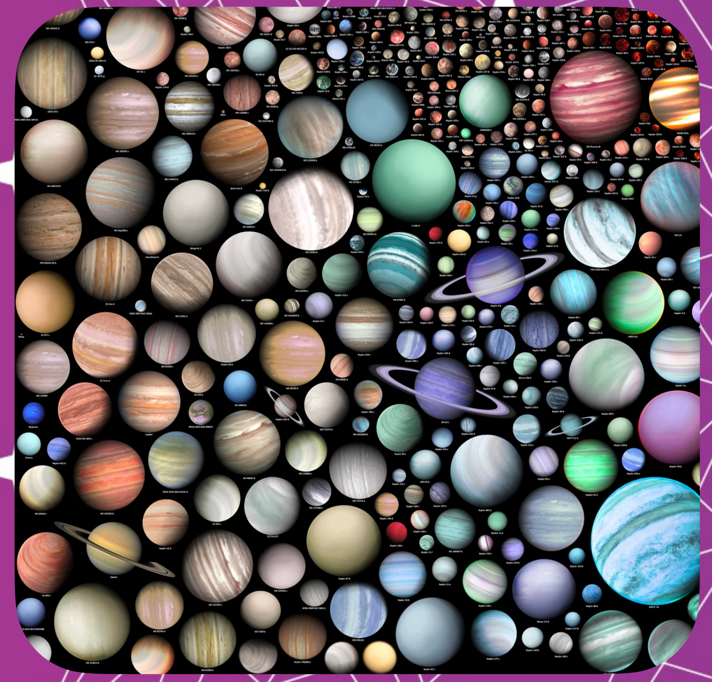


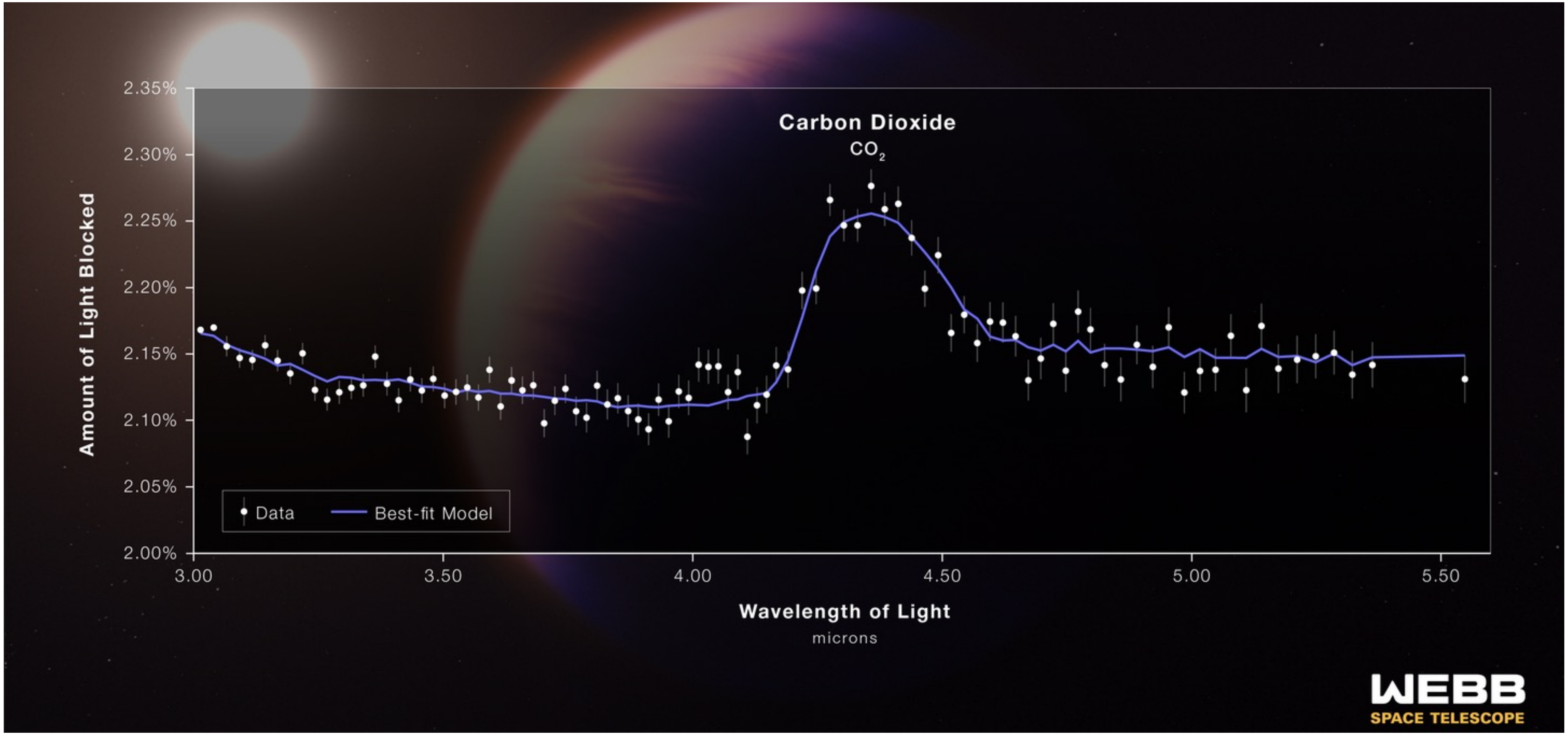
Mayeul Aubin

The encoder can reliably predict the target parameters



Prediction of the mass fraction of CO2 in the atmosphere by the encoder




Carbon Dioxide
CO_2
Amount of Light Blocked
2.35%
2.30%
2.25%
2.20%
2.15%
2.10%
2.05%
2.00%
Data
Best-fit Model
3.00
3.50
4.00
4.50
5.00
5.50
Wavelength of Light
microns
WEBB
SPACE TELESCOPE

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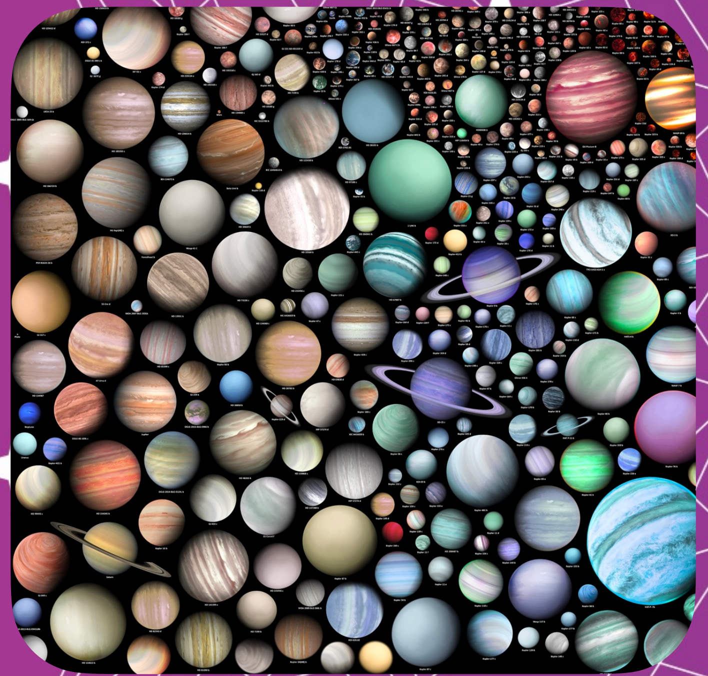


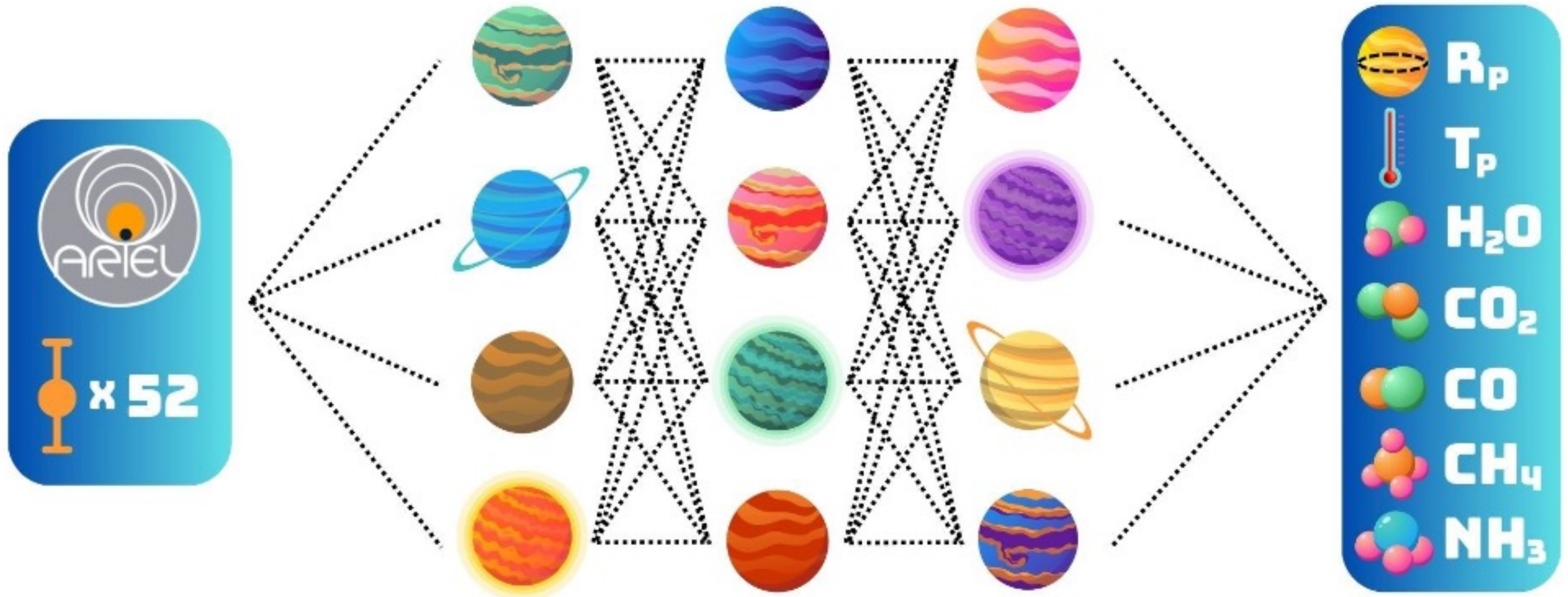
Mayeul Aubin

The 2023 Ariel Data Challenge: Scientists invite AI experts to help study exoplanets

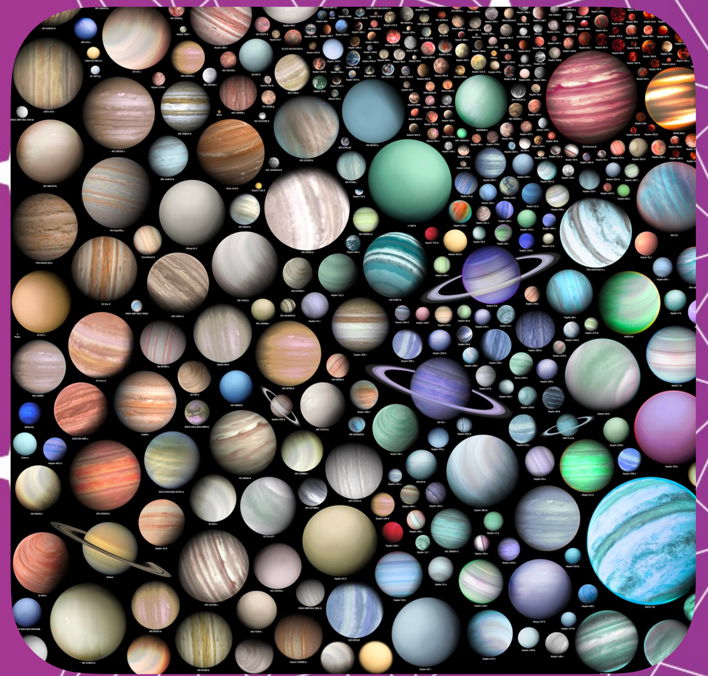
"Astronomers are struggling to keep up with the complexity and volume of incoming exoplanetary data.
The challenge is an excellent platform to facilitate cross-disciplinary solutions with AI experts."

Ariel DATA CHALLENGE

Quite a lot harder than last year



UK SPACE AGENCY · esa · UKRI Science and Technology Facilities Council · RAL Space · DiRAC High Performance Computing Facility · SPACEFLUX · europlanet society · UCL Centre for Space Exoplanet Data · ML Analytics · The Alan Turing Institute · cnes · NAOJ National Astronomical Observatory of Japan · Sapienza · Università degli Studi di Padova · universität wien



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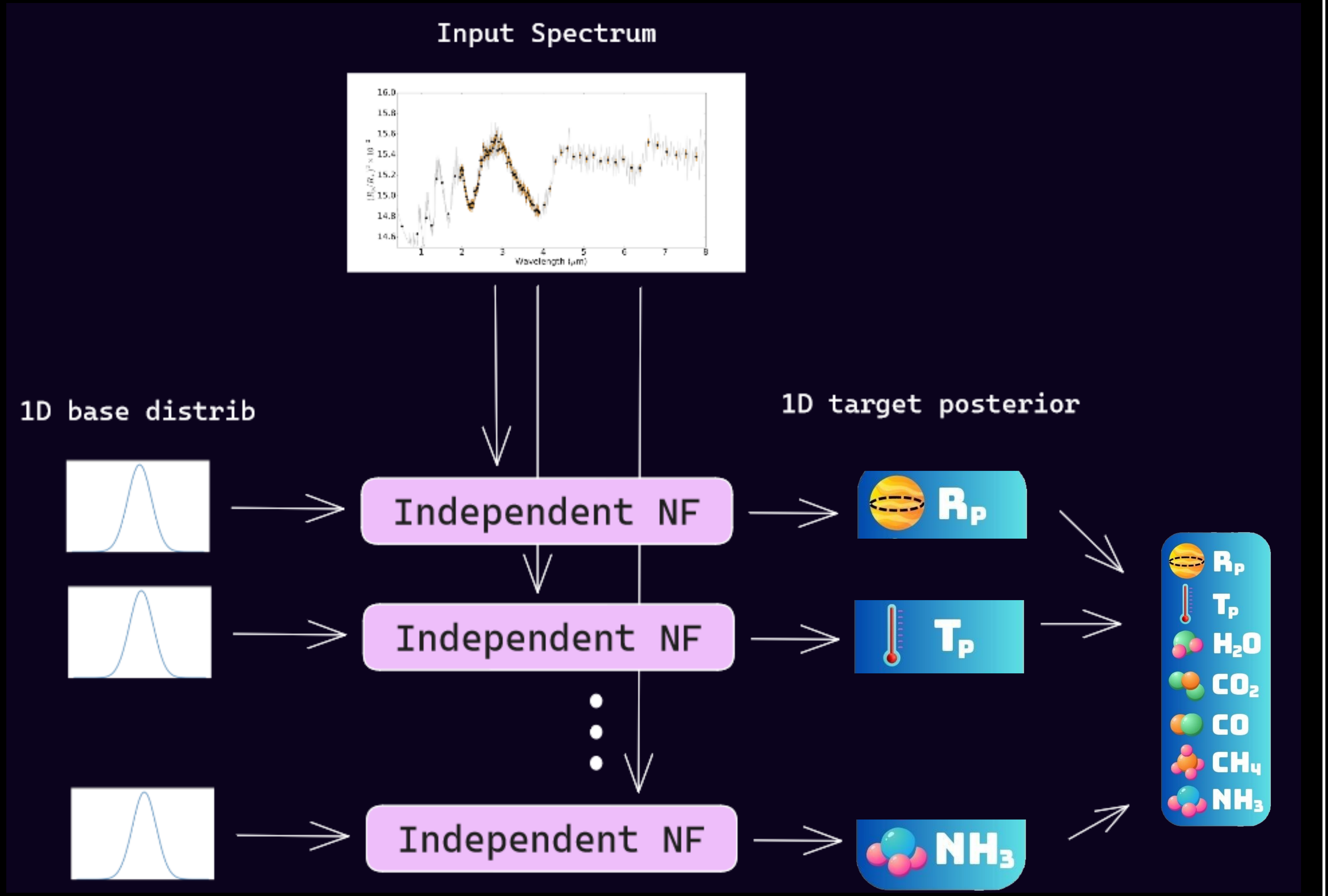
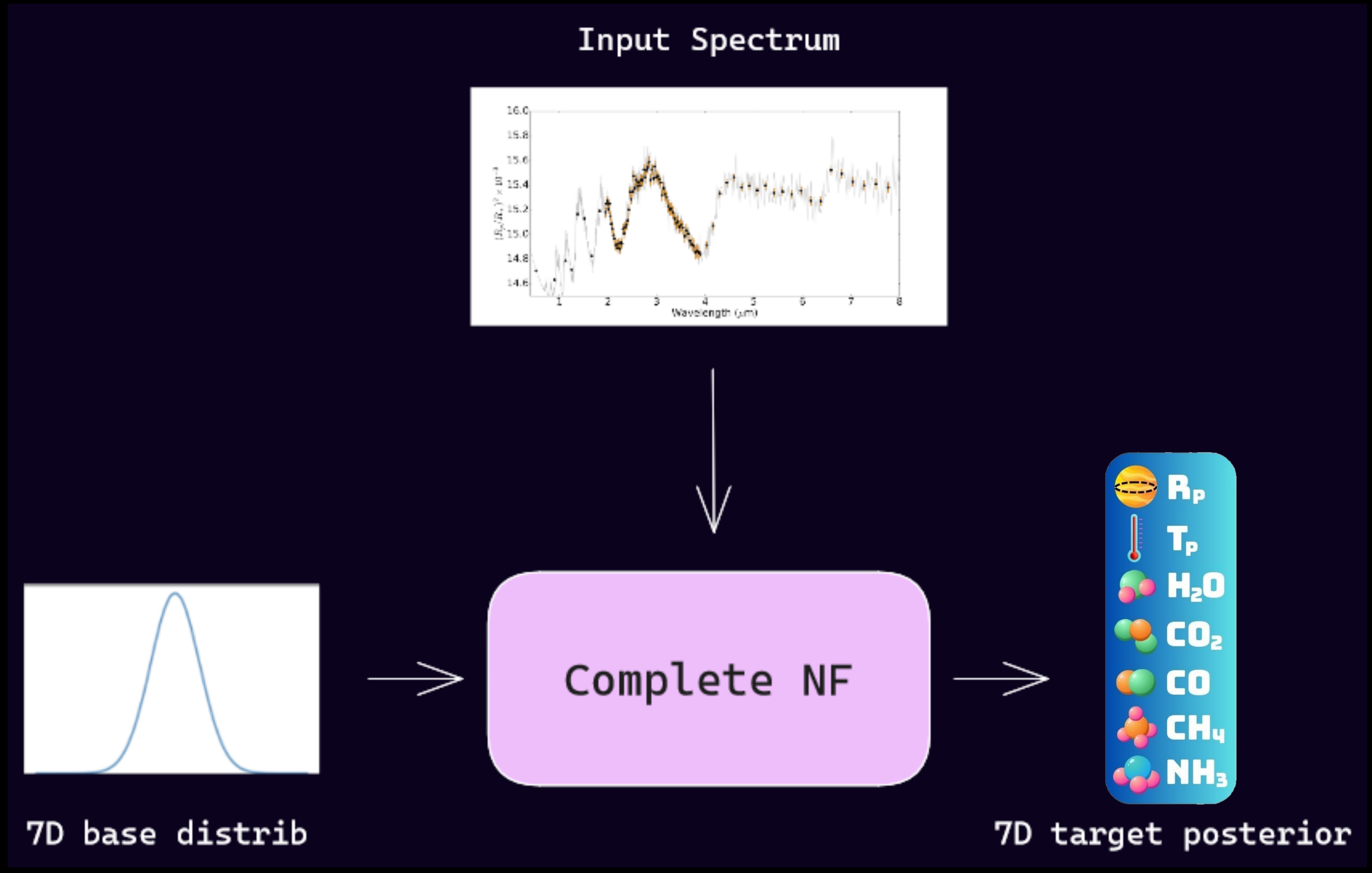
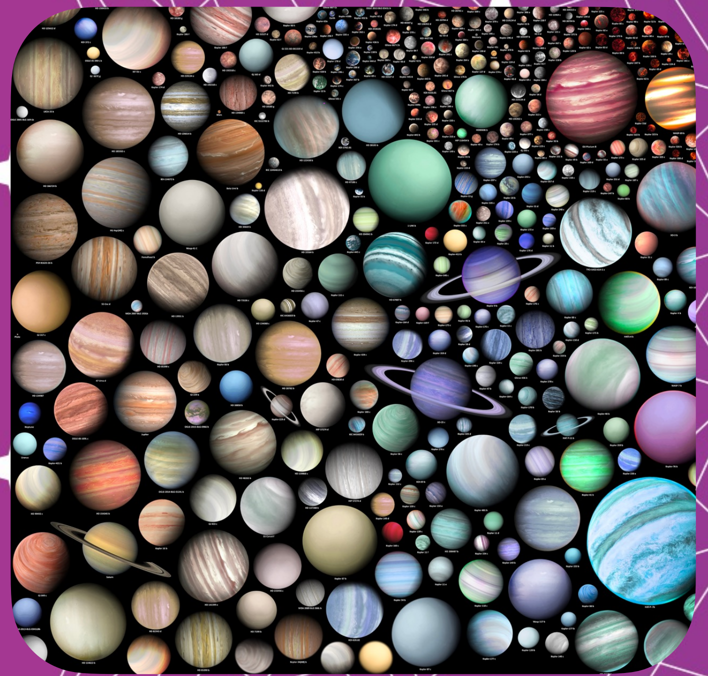
We used 7 independent normalising flows



A set of independent Normalising Flows



One complete Normalising Flow



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Mayeul Aubin

AstroAI

1st of 293 teams!

Leader Board

In-competition

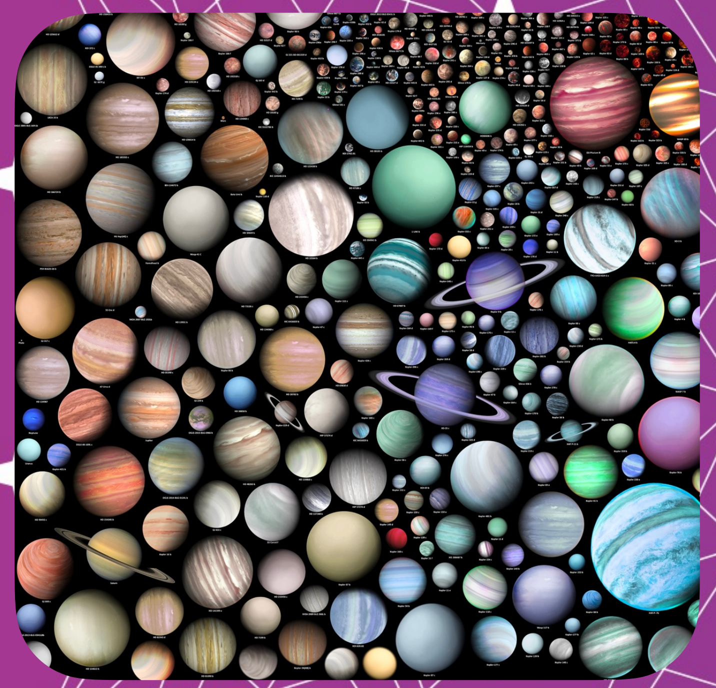
Rank	Name	Score
1	Mayeul_Aubin	679
2	gators	666
3	Les3Stagios	650
4	asweet	618
5	caokyhan	615
6	hieucao	610
7	dungpt	602
8	aescalantelopez	596
9	MALTO	595
10	brian_jonestown_massacre	586
11	inosen_infinity	582
12	diogo4u	560

Simulation-based Inference for Exoplanet Atmospheric Retrieval: Insights from winning the Ariel Data Challenge 2023 using Normalizing Flows

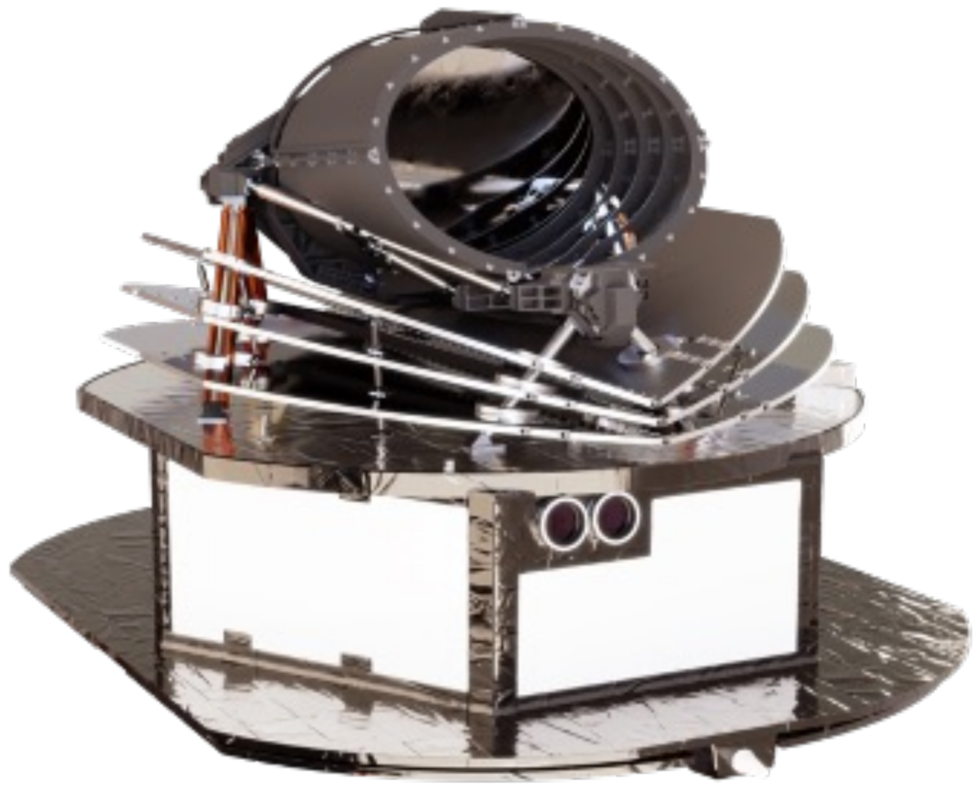
Mayeul Aubin[1,2*], Carolina Cuesta-Lazaro[3,4], Ethan Tregidga[1,5], Javier Viaña[6], Cecilia Garraffo[1,7], Iouli E. Gordon[8], Mercedes López-Morales[8], Robert J. Hargreaves[8], Vladimir Yu. Makhnev[8], Jeremy J. Drake[7], Douglas P. Finkbeiner[3], and Phillip Cargile[9]

Exoplanet Atmospheric Parameter Retrieval: The AstroAI winning model for the 2023 Ariel Data Challenge using Normalizing Flows

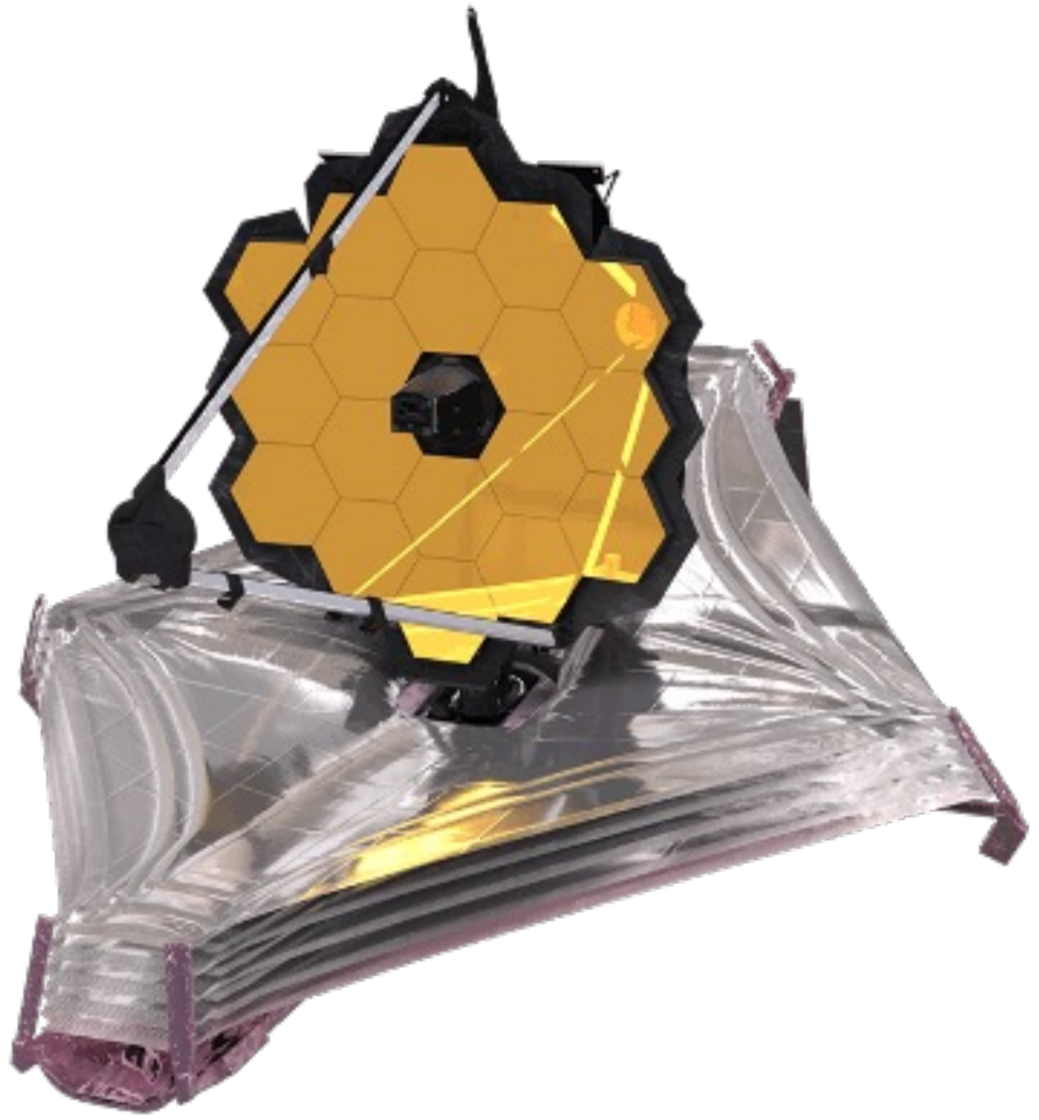
Mayeul Aubin,[1,2] Carolina Cuesta-Lazaro,[3,4] Ethan Tregidga,[1,5] Javier Viaña,[6] Cecilia Garraffo,[1,7] Iouli E. Gordon,[8] Mercedes López-Morales,[8] Robert J. Hargreaves,[8] Vladimir Yu. Makhnev,[8] Jeremy Drake,[7] Douglas P. Finkbeiner,[9] and Phillip Cargile[3]



Next Small Steps: Generalize for other missions.



Ariel Space Mission



JWST

Nancy Grace Roman Space Telecope

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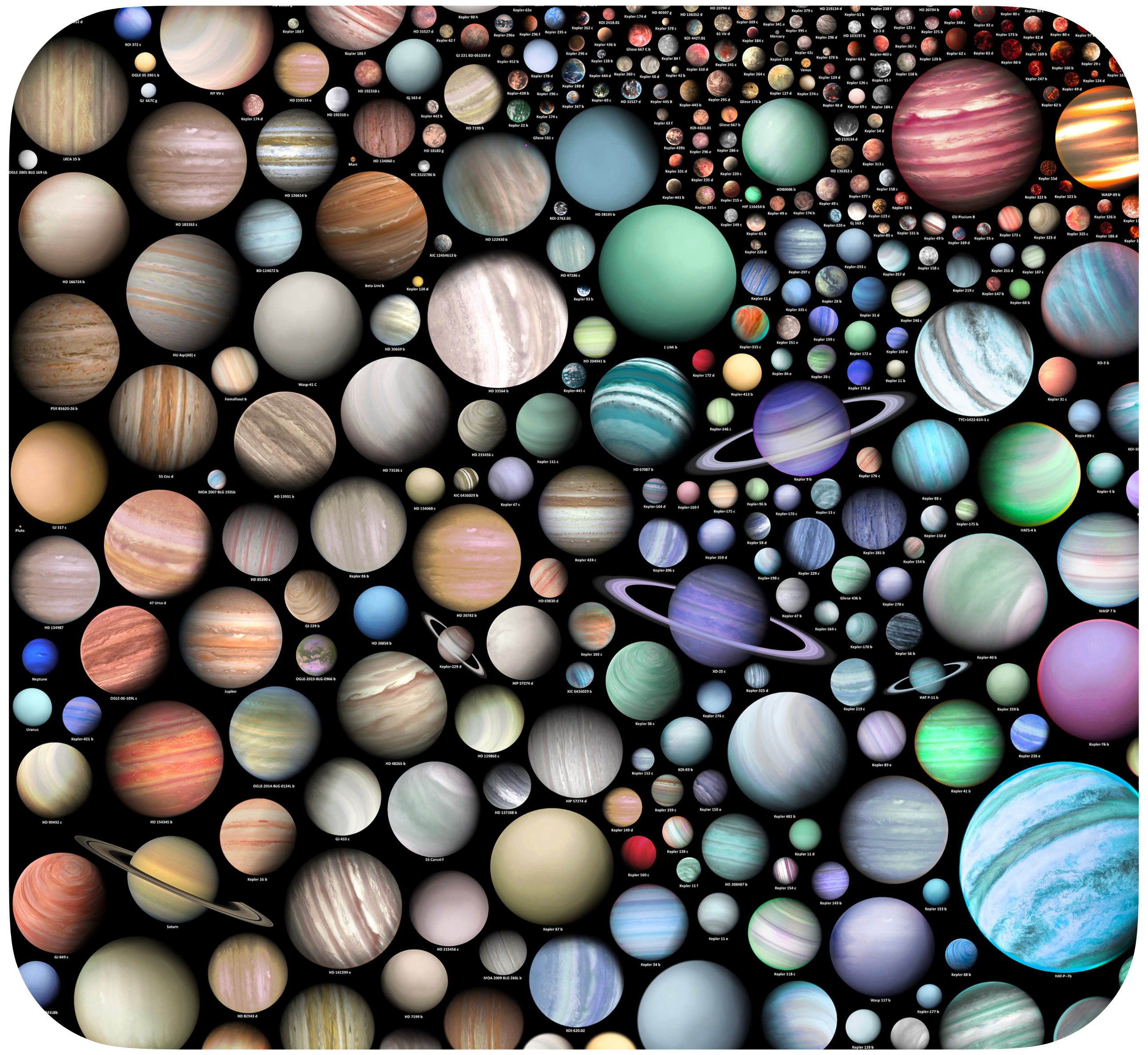
Exoplanet Atmospheres & Biosignatures Team



Mercedes López-Morales

Bill Freeman

Robin Walters

Breakthrough: Find Life Elsewhere in the Universe!

ASTROAI

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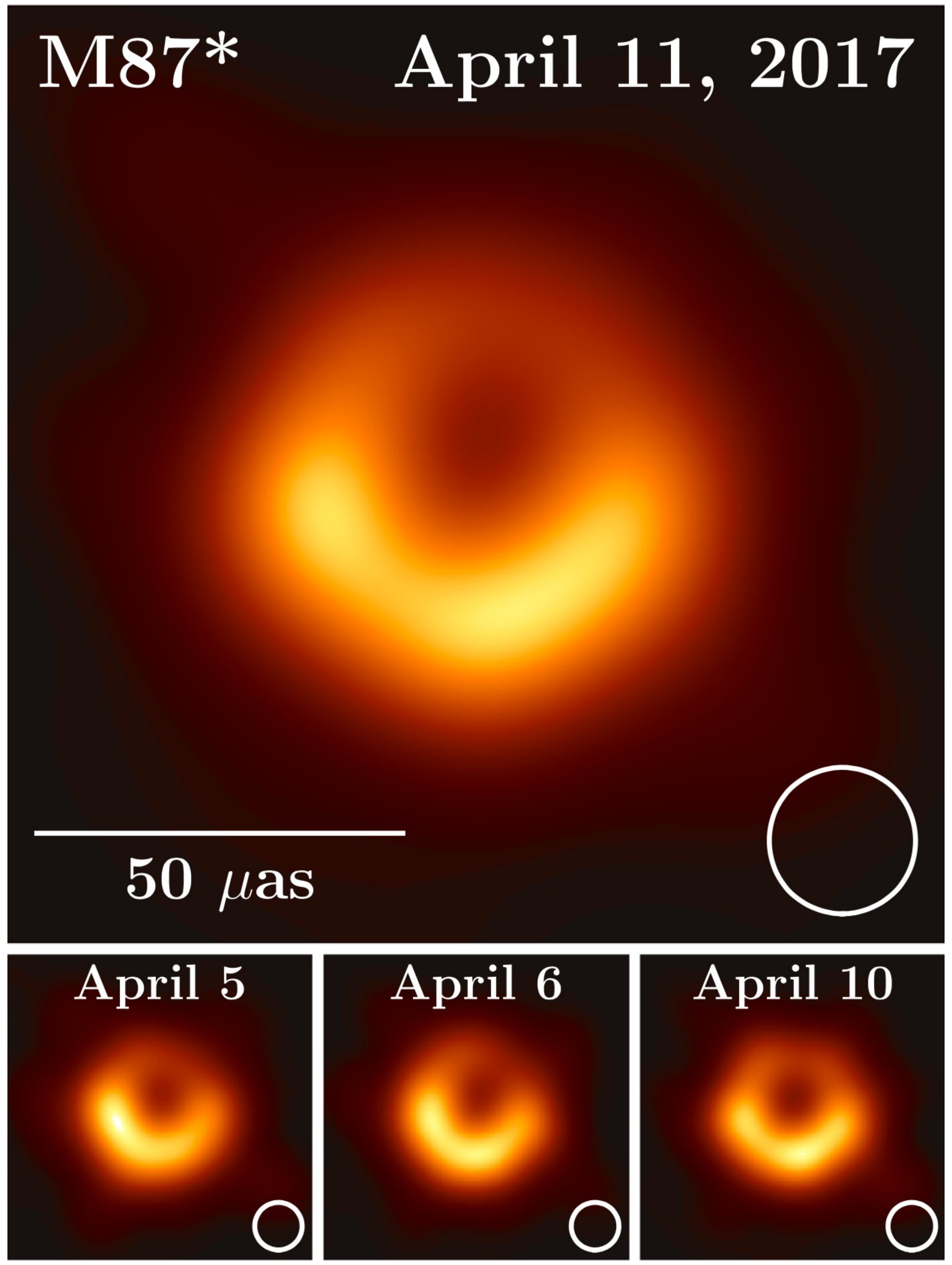
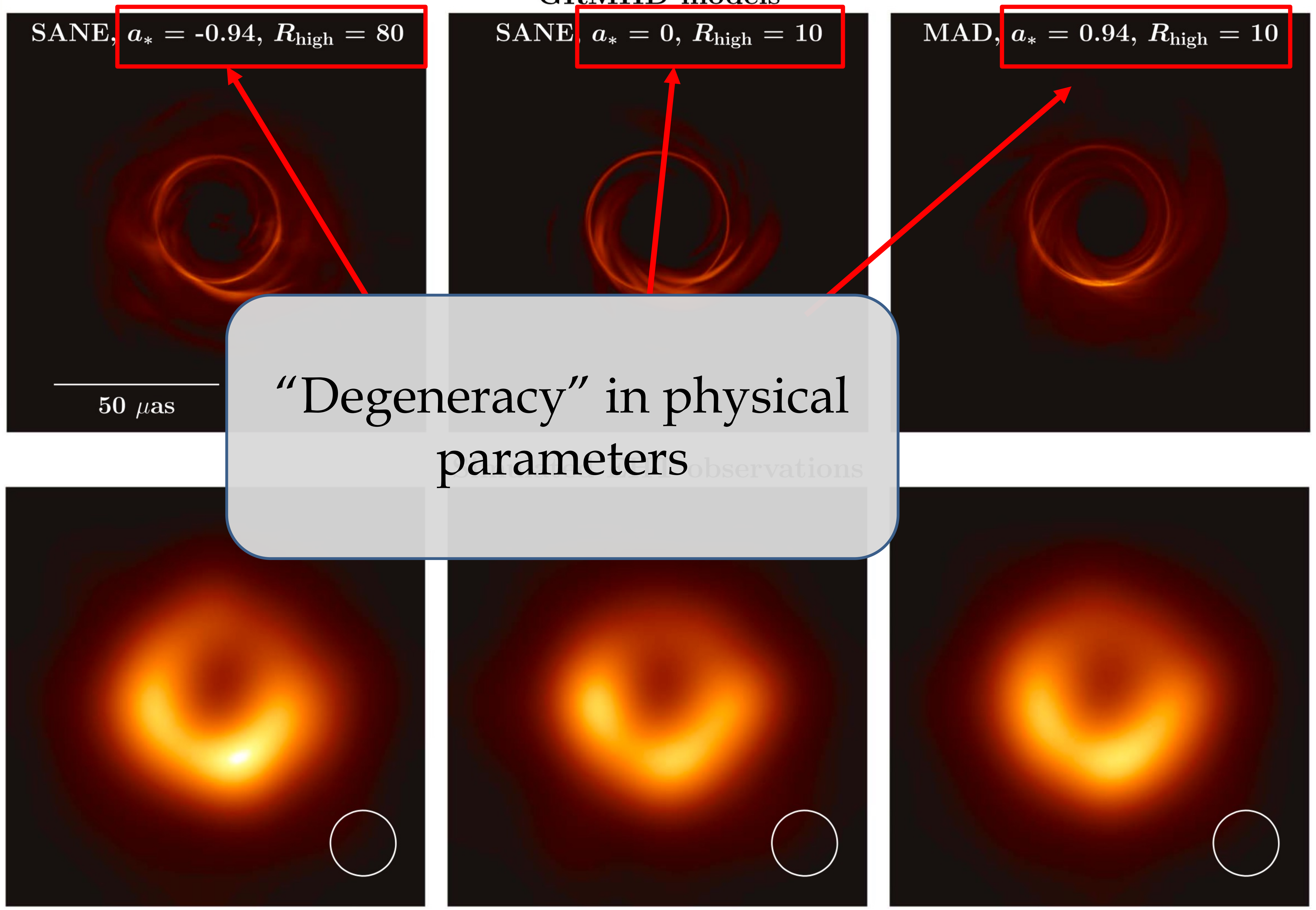
Shep Doeleman

Supermassive BHs: EHT

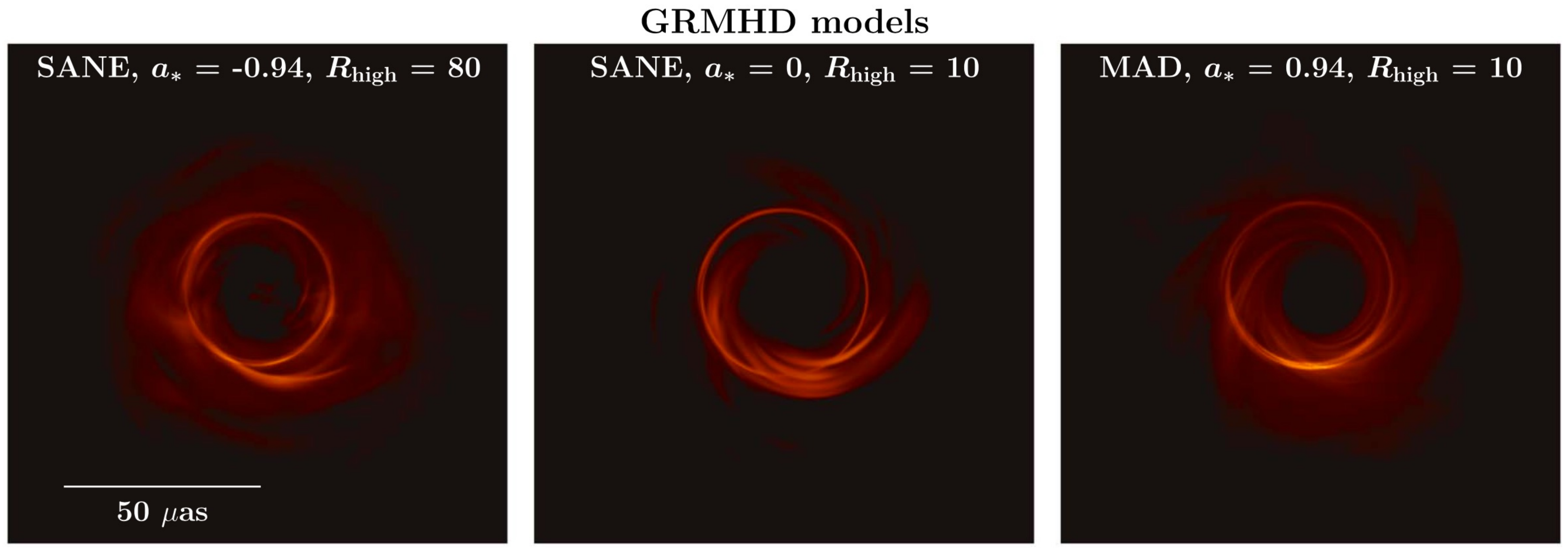




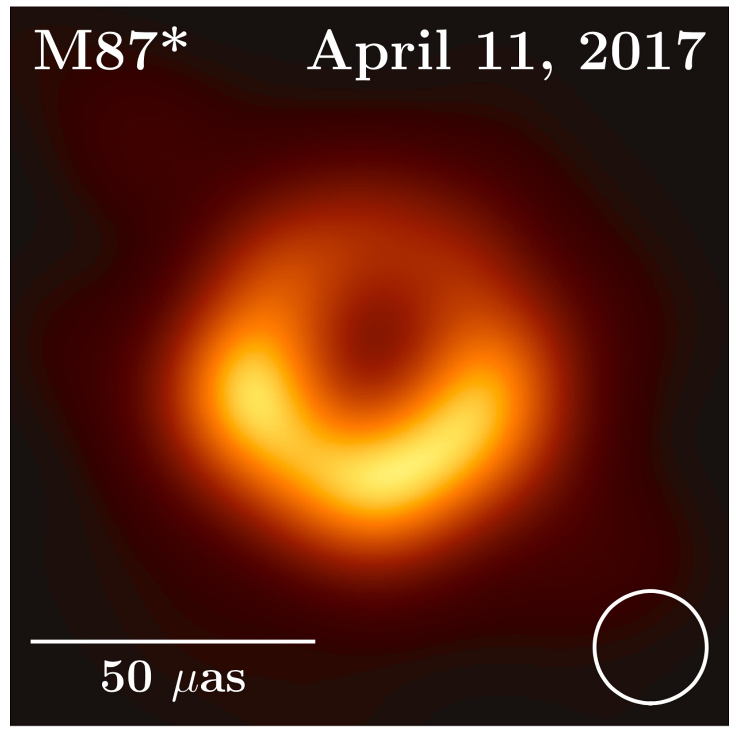
“Degeneracy” in physical parameters

We have data from two sources:

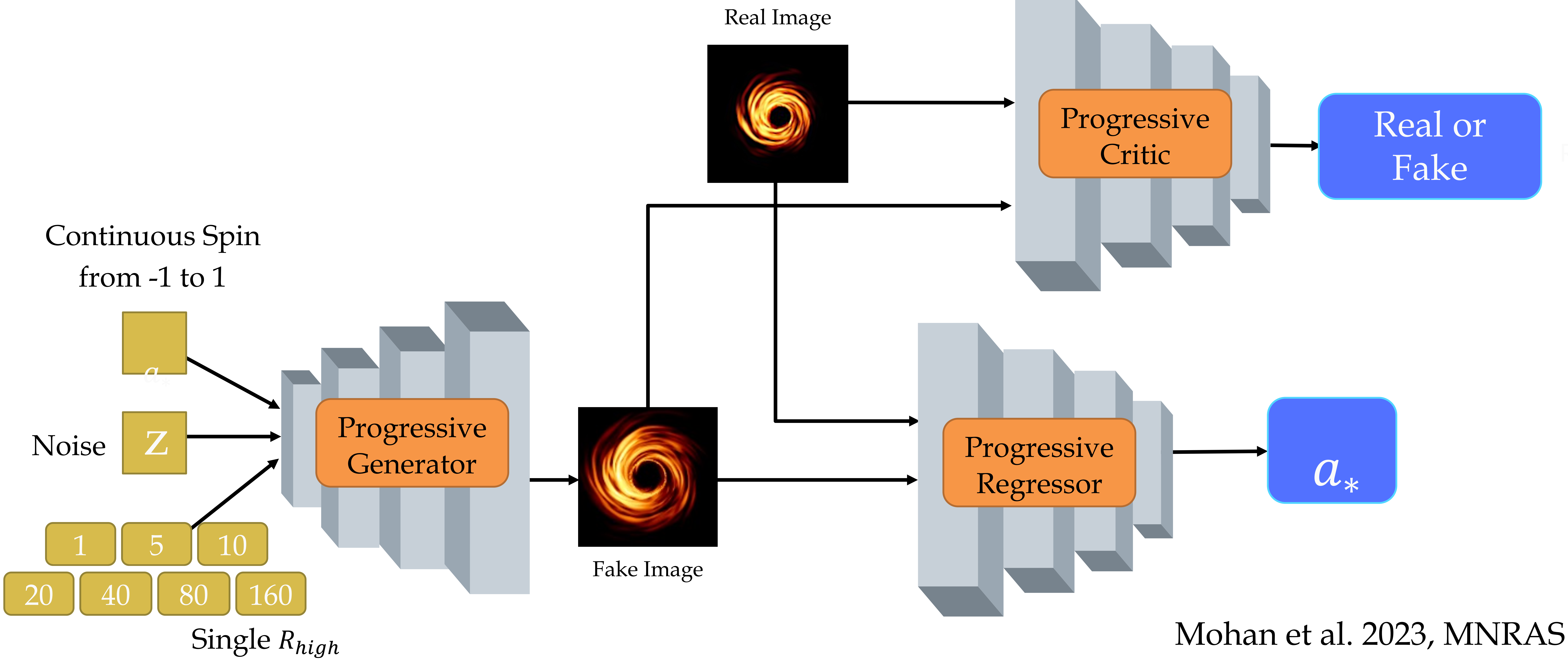
- GRMHD simulated images



- Real EHT observations

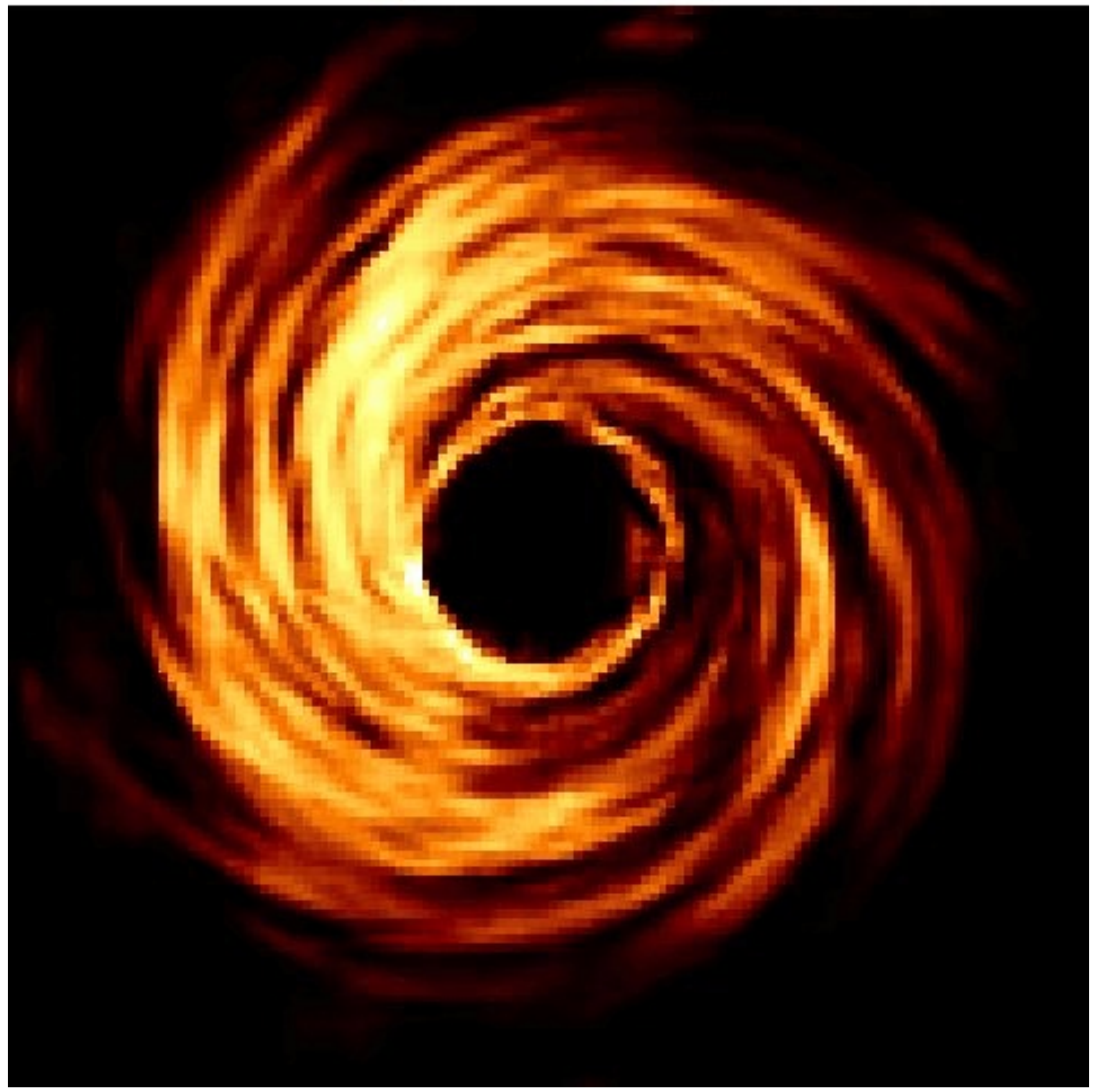


Arya Mohan



Mohan et al. 2023, MNRAS in Press

a = -0.4



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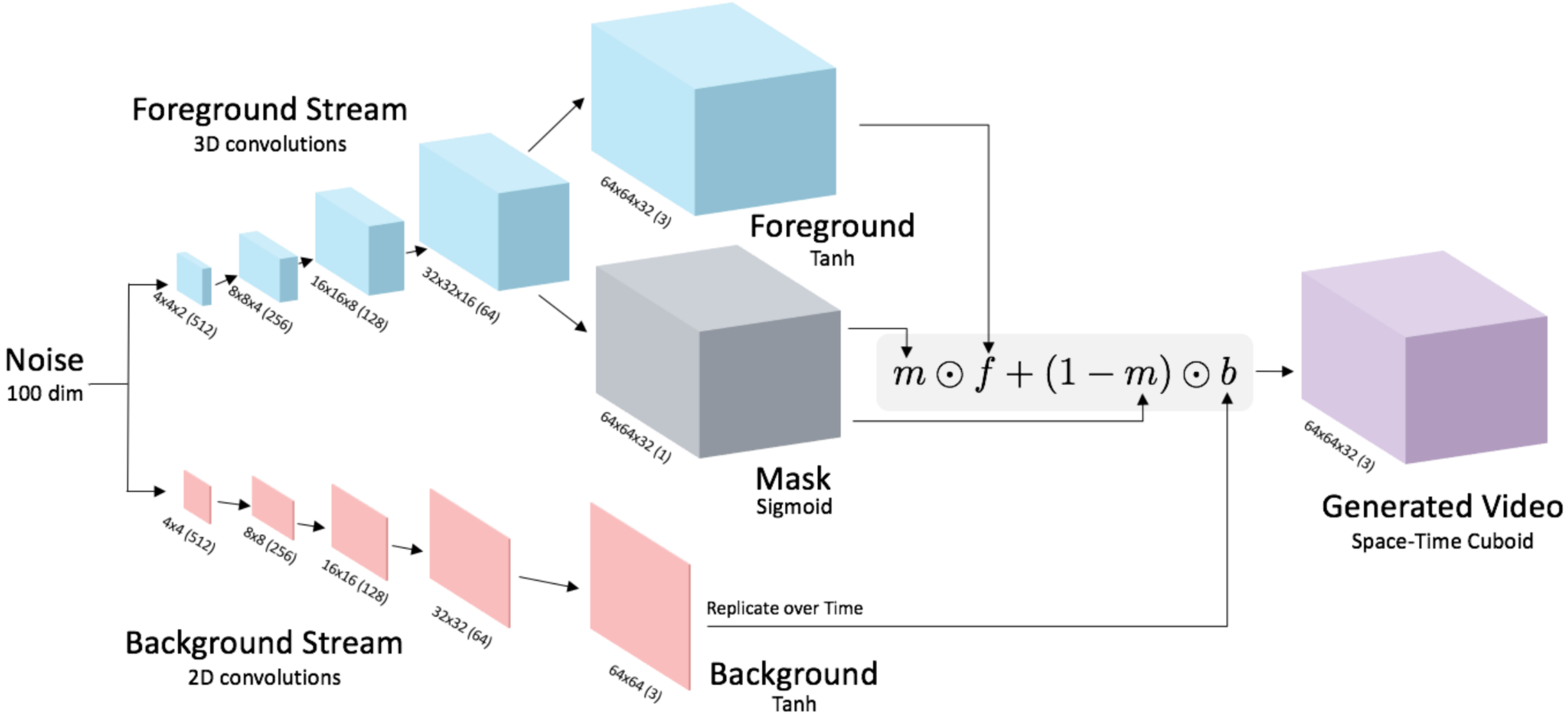
David Loving

Generative Model for Black Holes' Dynamics



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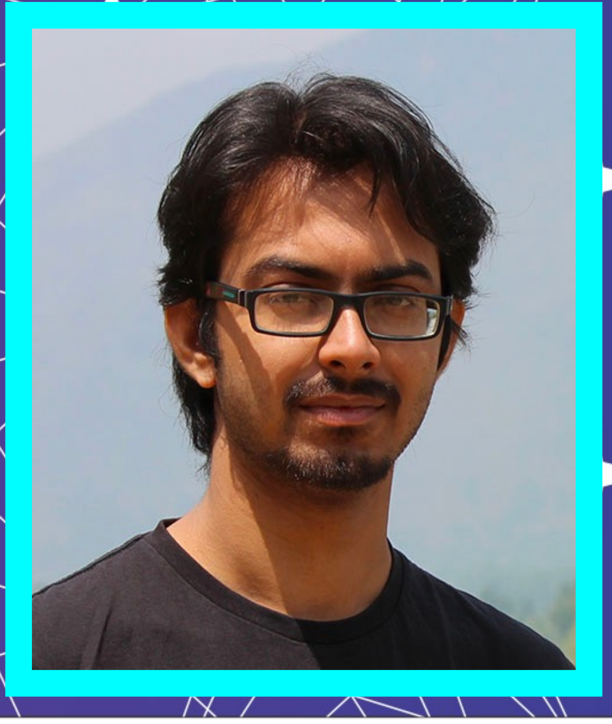
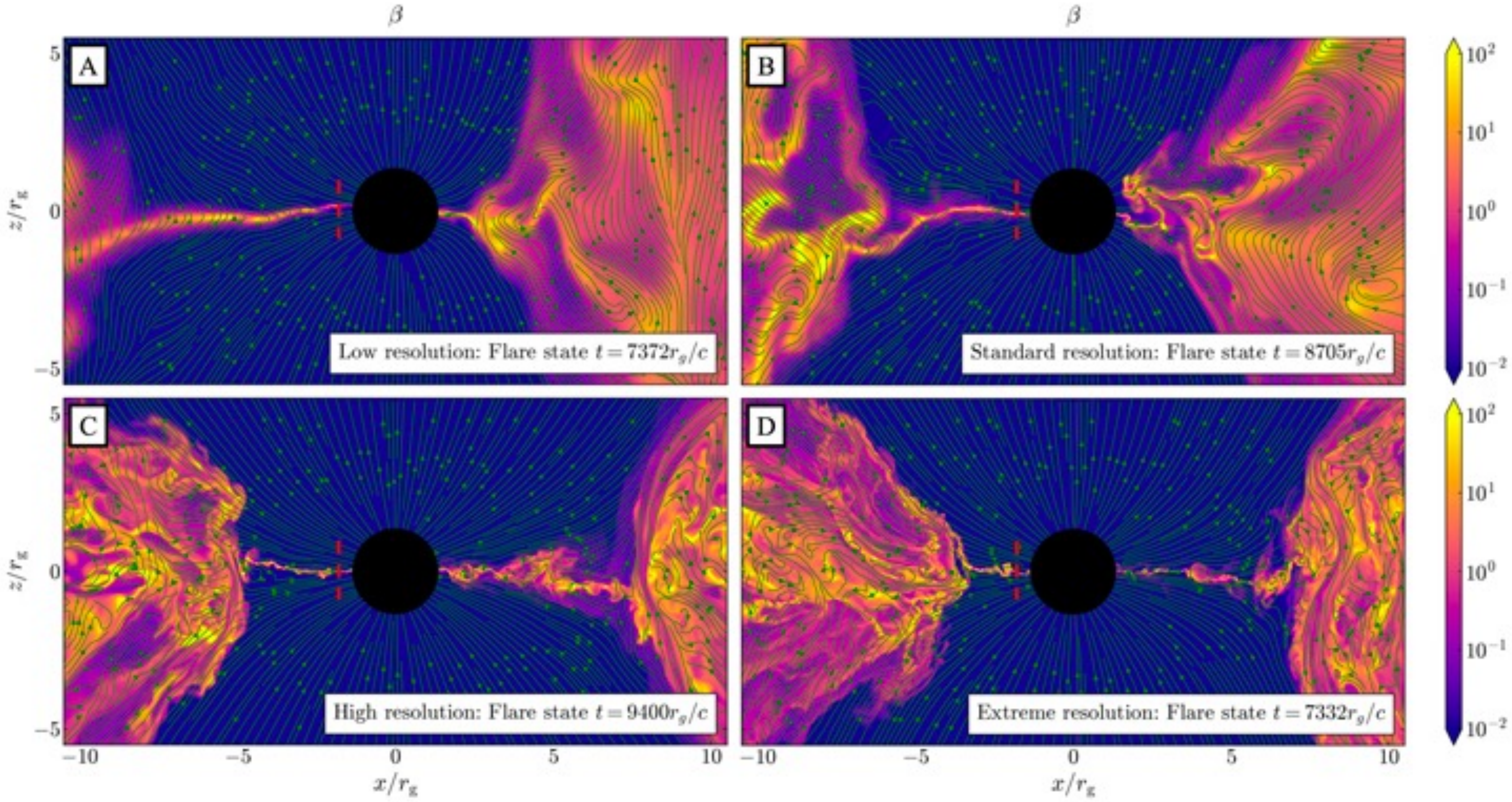


Koushik Chatterjee

Super resolution Model for GRMHD simulations for EHT

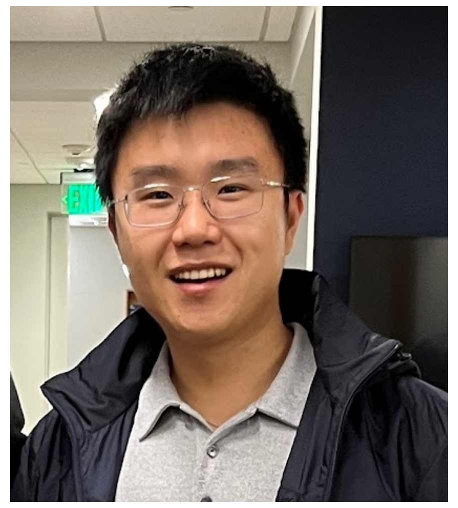


The Impact

The Students

Thaddaeus Kiker

Aryan Mohan



Tao Tsui

Leticia Schettino

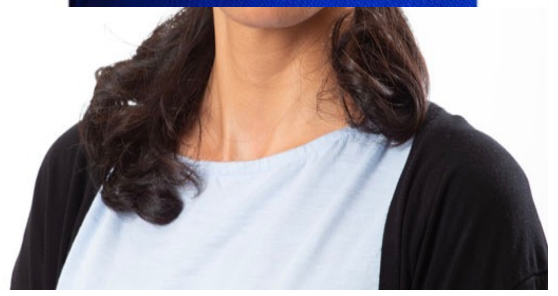
Farah Fauth

Ethan Tregigda

Varshini Reddy

Benjamin Ricketts

David Loving



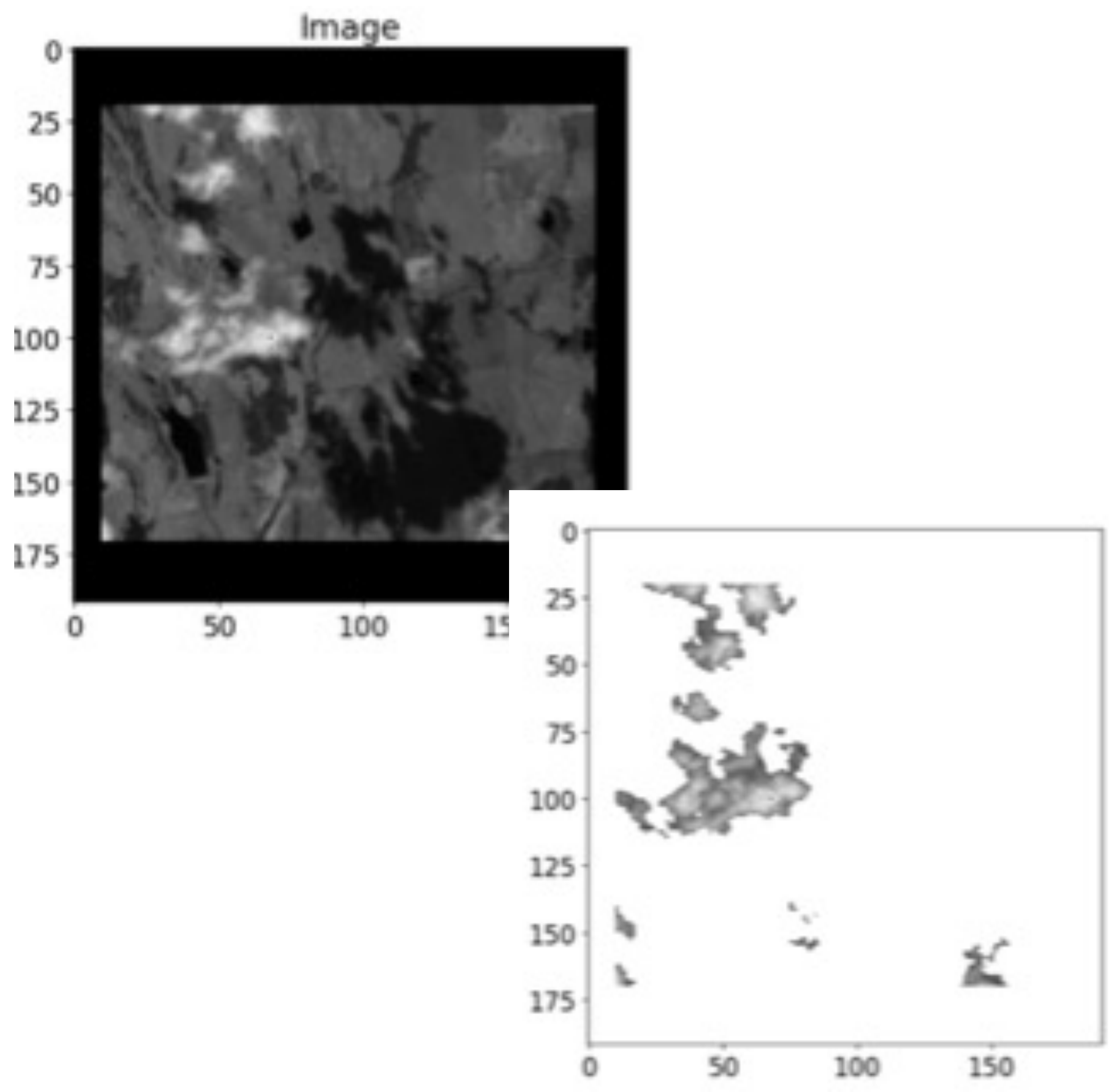
Mayantara Mudur

Lily Pan

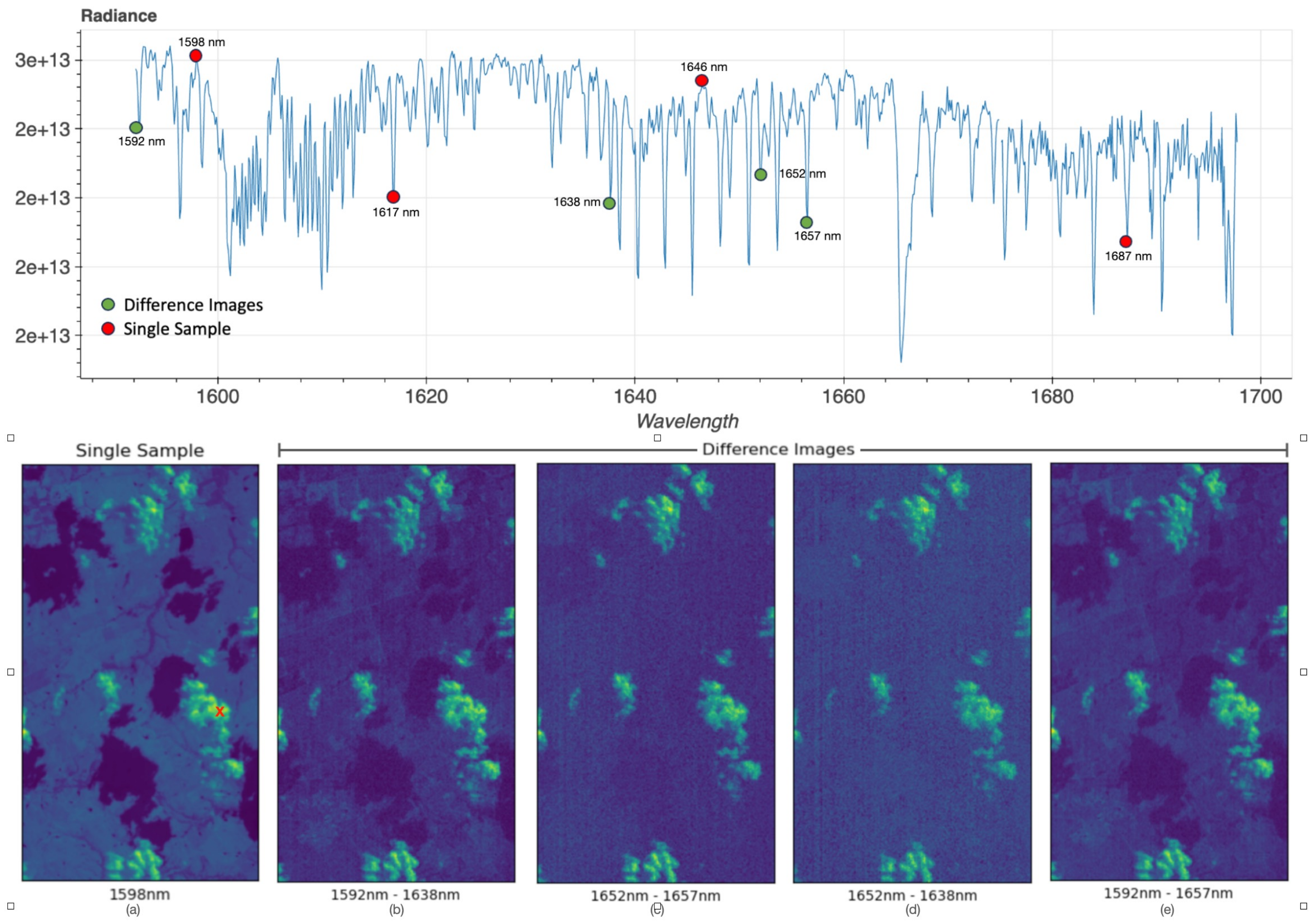
EARTHAI

Enabling a Sustainable Future

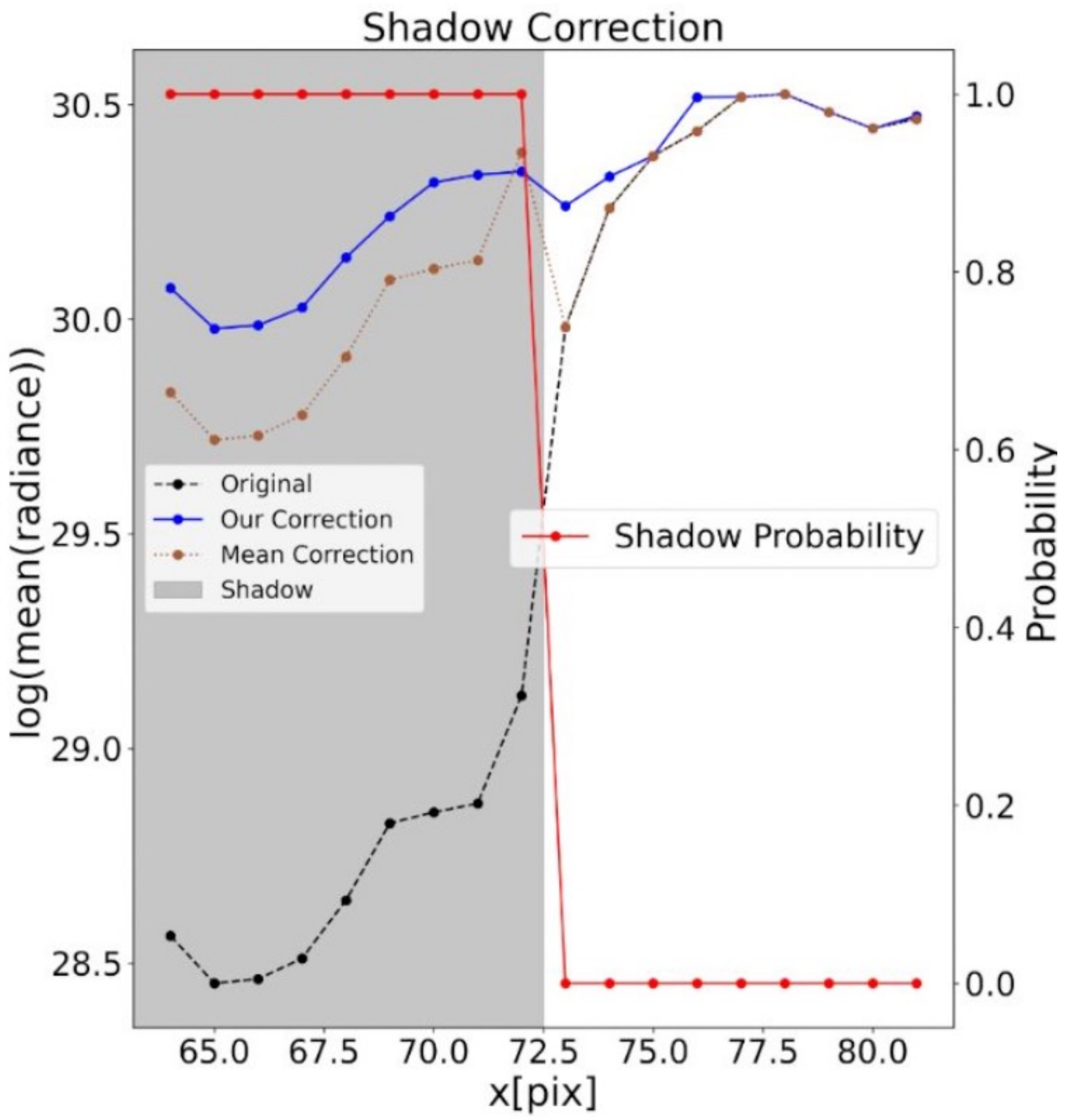
MethaneSAT: Enhanced Cloud Filtering / Correction



1. MethaneSAT Cloud Filtering Pipeline uses only the image information that let to significant data loss



2. We built an AI model that uses spectral information we enhanced the performance of cloud detection and filtering to 97%



3. We trained an AI model to remove the effect of shadows from the spectra itself, making all the data useable!

Park et al., NeurIPS 2023

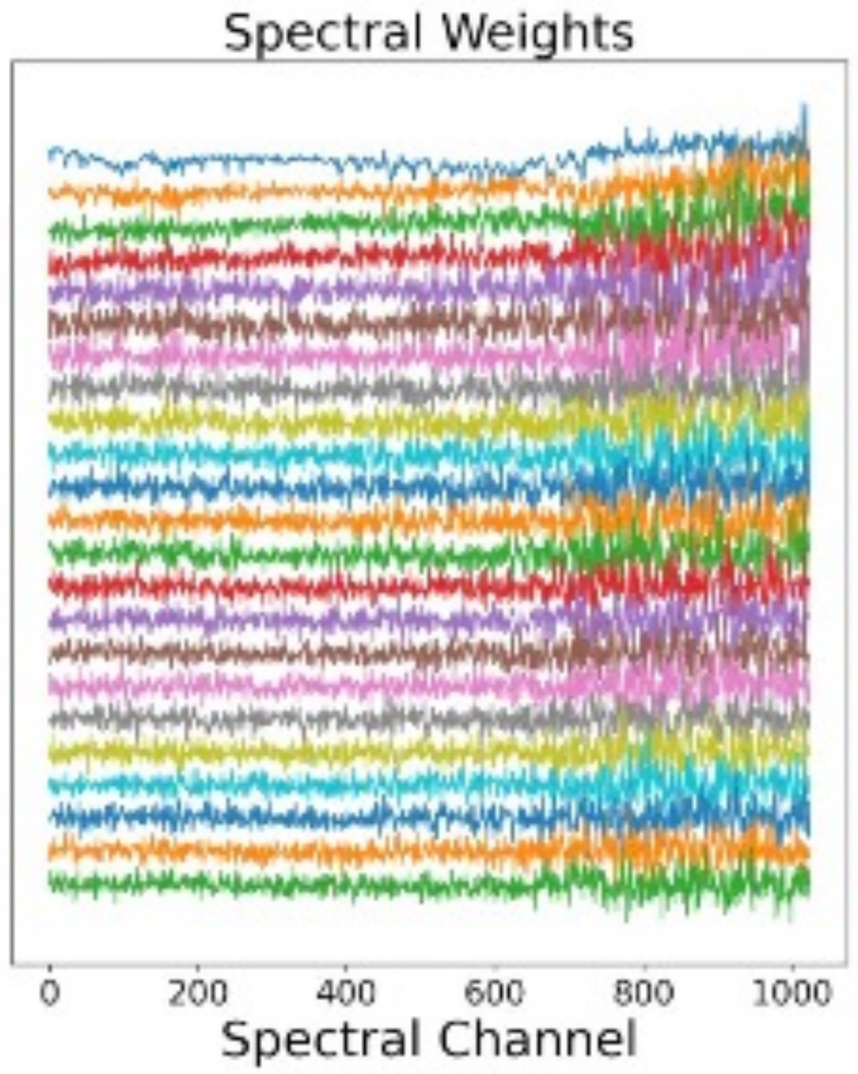
EARTHAI

Enabling a Sustainable Future

MethaneSAT: Enhanced Plume Detection

In Partnership with Google, we are building an AI model to enhance plume detection by using the full spectral information from MethaneSAT data together with Geospatial Data from Google Earth.

MethaneSAT

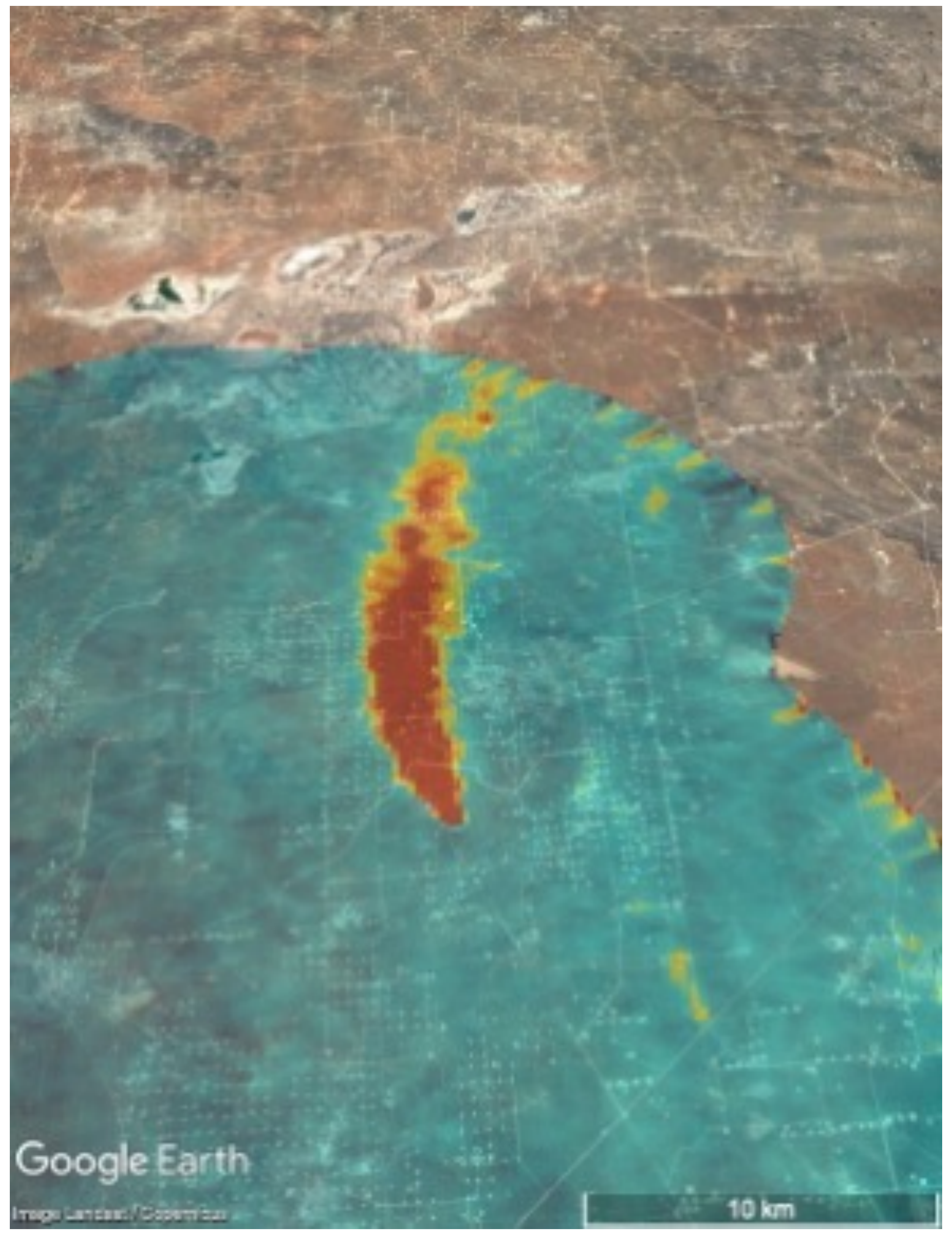


+

Google Earth

=

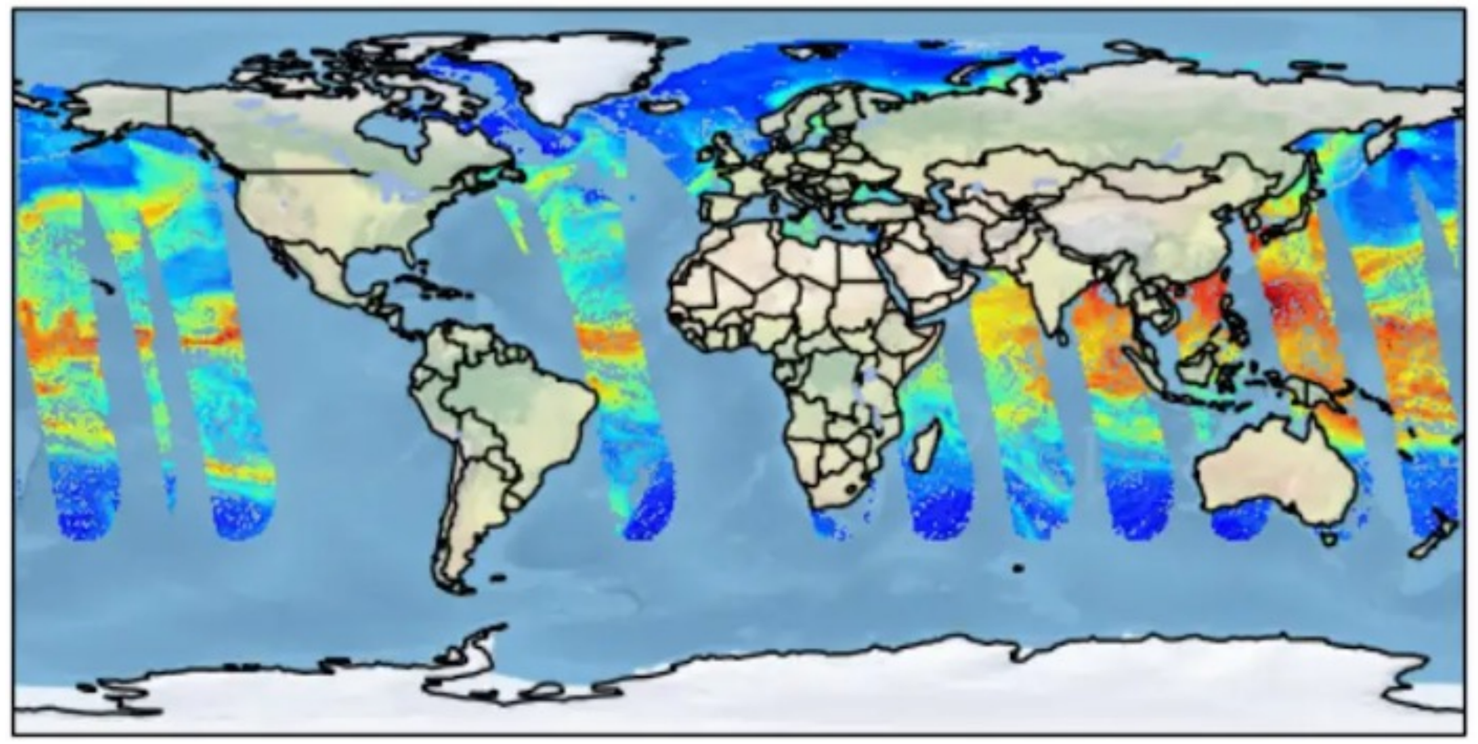
Reliable Plume Detection



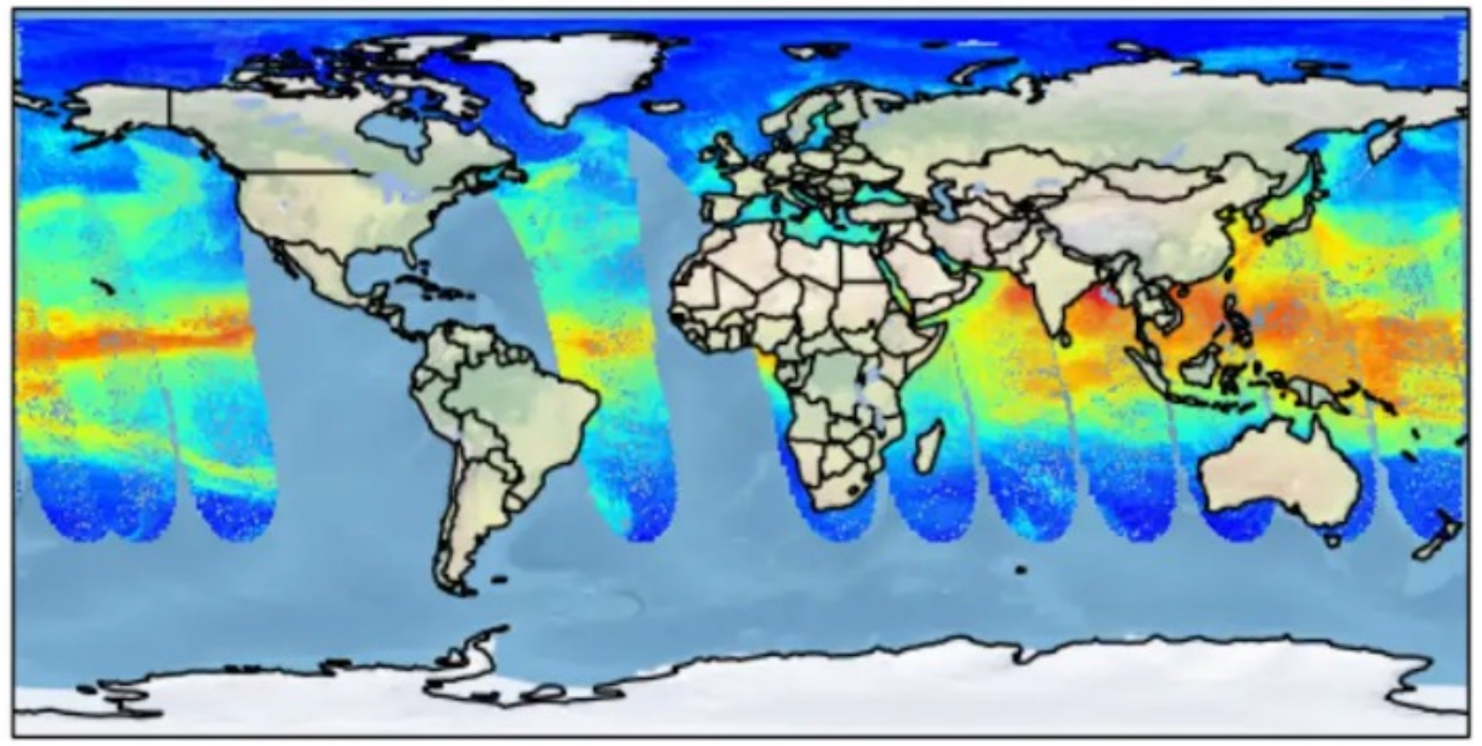
EarthAI

Enabling a Sustainable Future

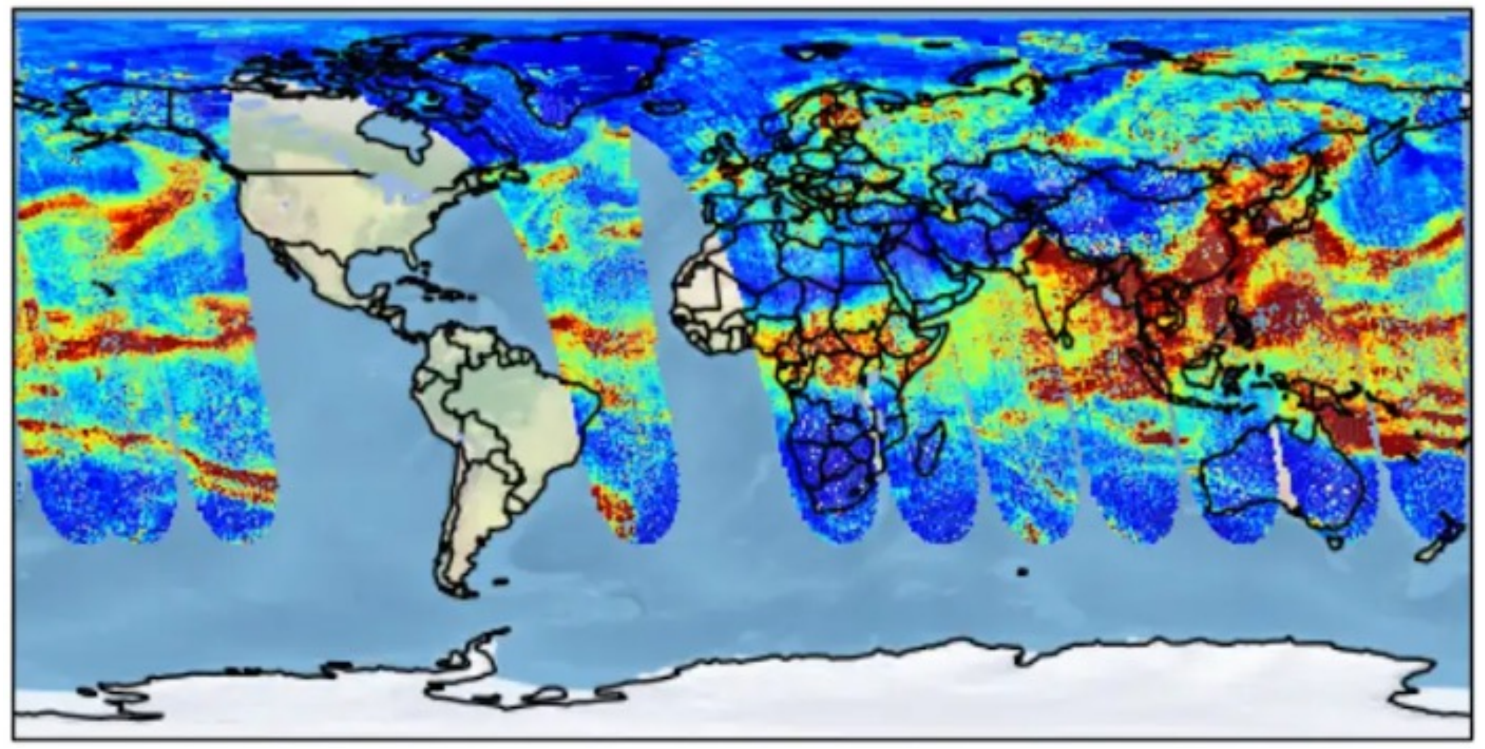
TEMPO: Computer Vision for Water Vapor Imaging



Classic Model strongly dependent on prior assumptions



Light Gradient Boosting (LGB) , prior independent and improved image coverage and quality

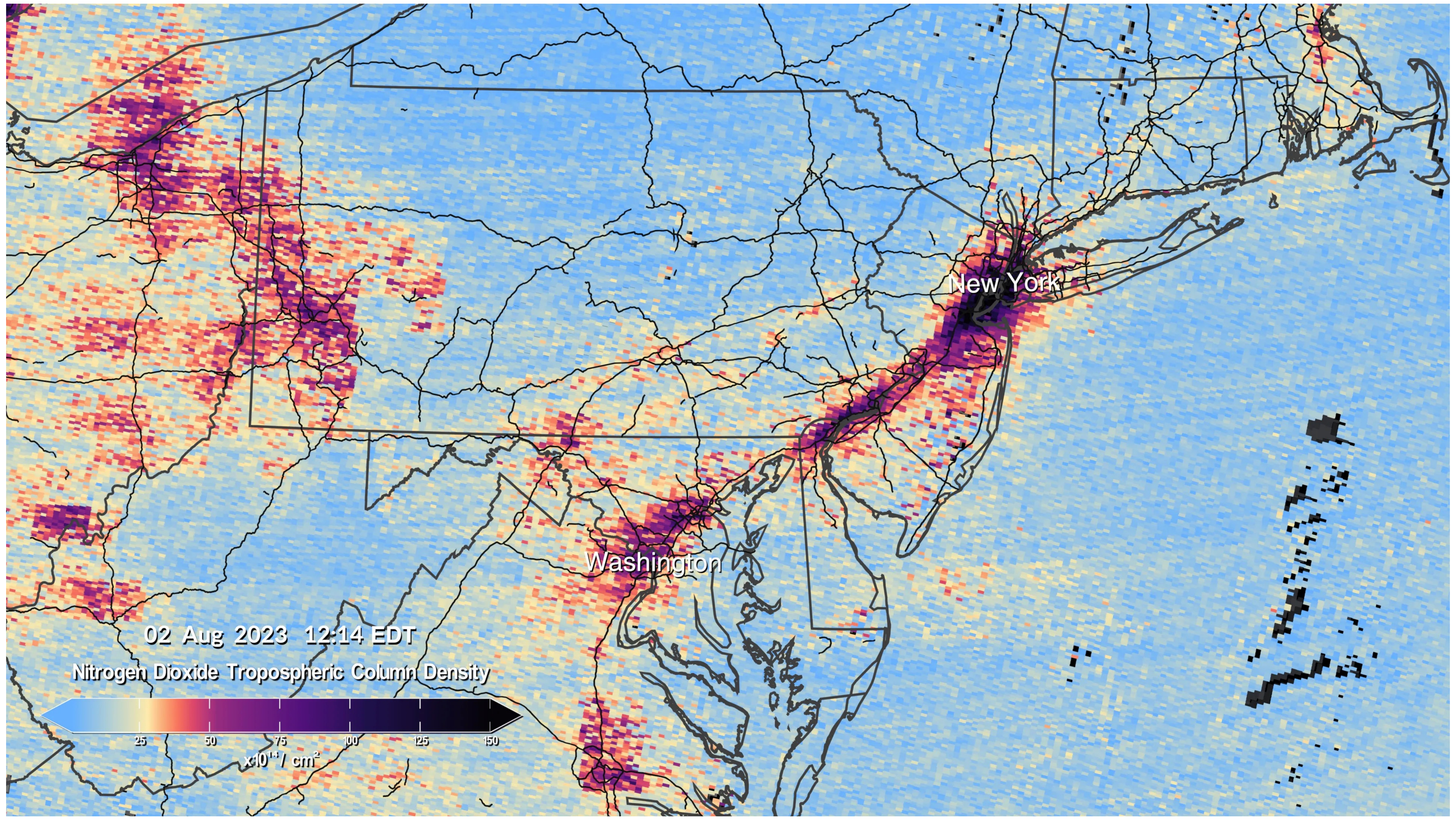


MEaSuRES overestimates in cloudy skies regime and underestimates in clear sky regime.

Goal: Build a well calibrated model to predict pollutants robustly across weather conditions

Enabling a Sustainable Future

TEMPO: Resolving the Altitude of Pollutants



TEMPO nitrogen dioxide over part of the East Coast on August 2, 2023 at 12:14 EDT. High levels of NO_2 are seen over major urban regions and the I-95 corridor. High levels of NO_2 over Eastern Pennsylvania and Ohio are due to biomass burning.

Nitrogen dioxide (NO_2) plays a central role in air quality and atmospheric chemistry, and has direct detrimental effects on human health when concentrated near the surface of Earth.

TEMPO is able to successfully retrieve the total column density of pollutants, such as nitrogen dioxide (NO_2), but not its vertical distribution.

We are building a multimodal AI model to integrate TEMPO data with other data (GEOS-CF, EPA Air Quality System, and aircraft profiles like STAQ) to resolve the vertical distribution of pollutants, like NO_2 to assess the air quality where it has human health impact

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The future of Astronomy is AI driven.
We need to be ready.

Thank you!

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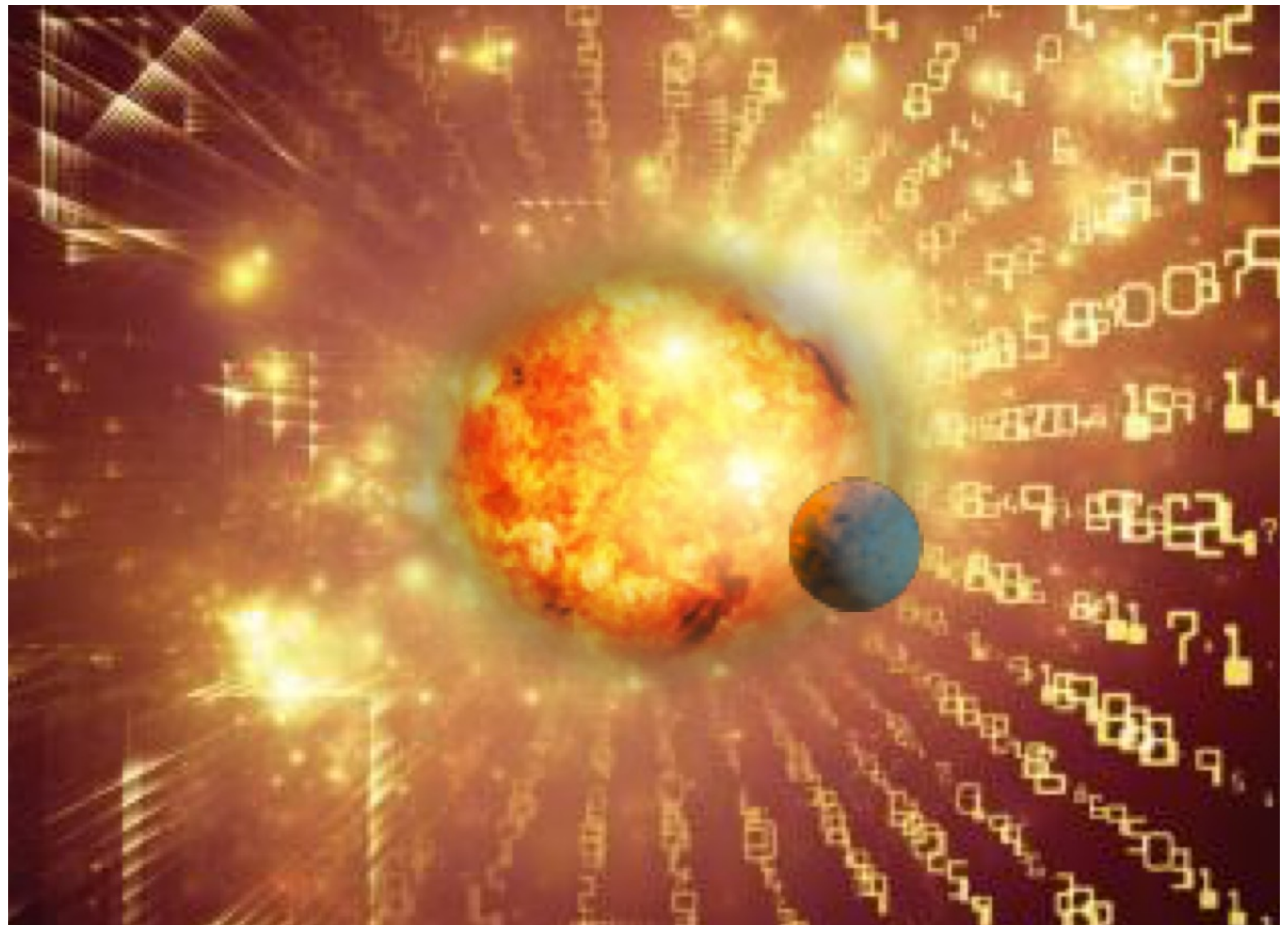
The Lives of Stars Team



Cecilia Garraffo

Phill Cargile

Josh Speagle

AstroAI

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Garraffo et al. 2021

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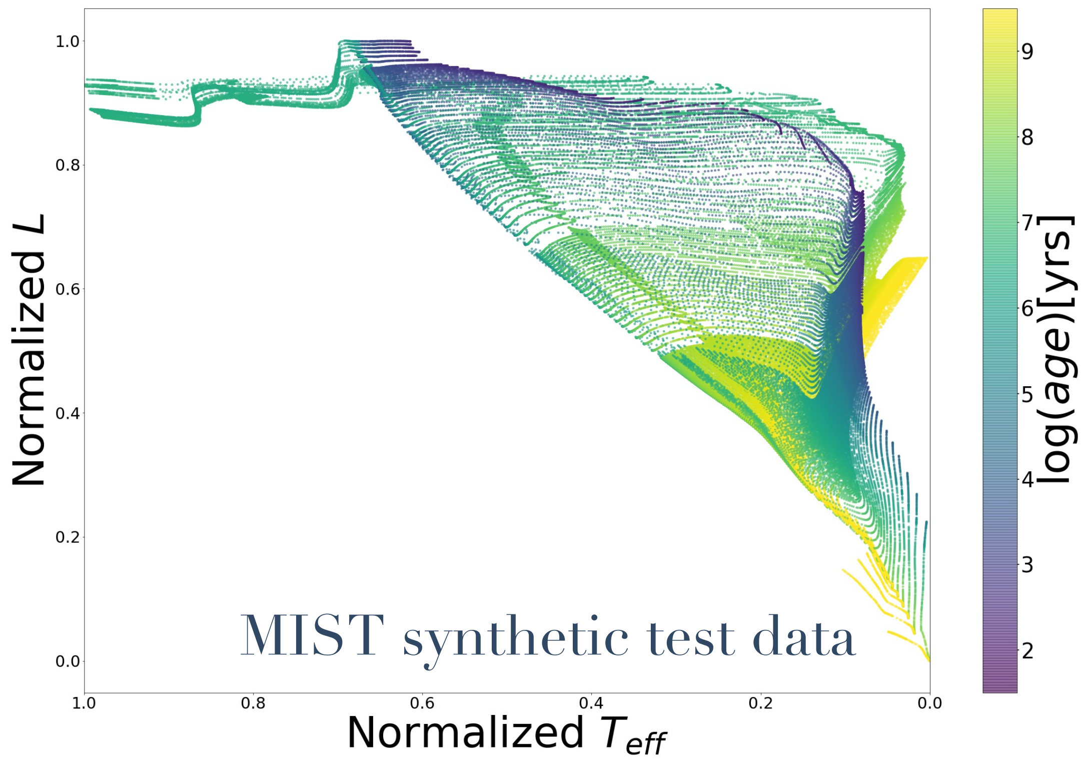
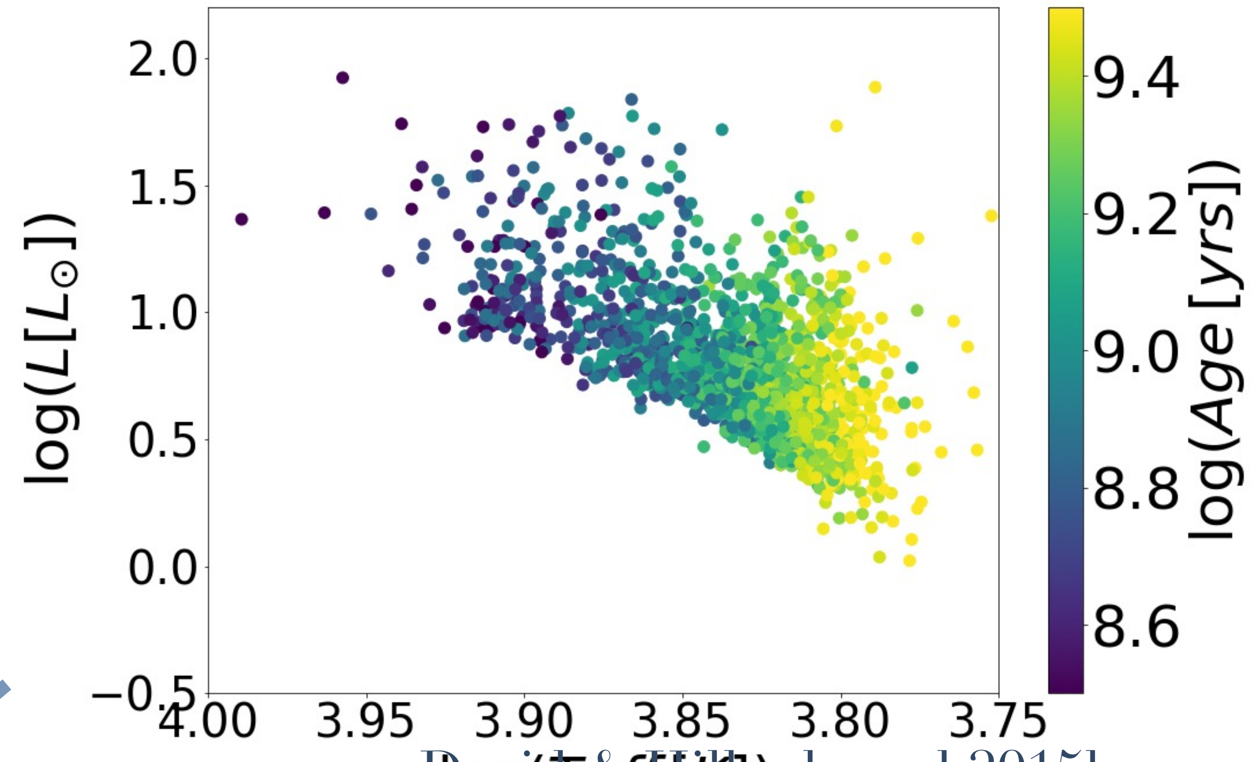
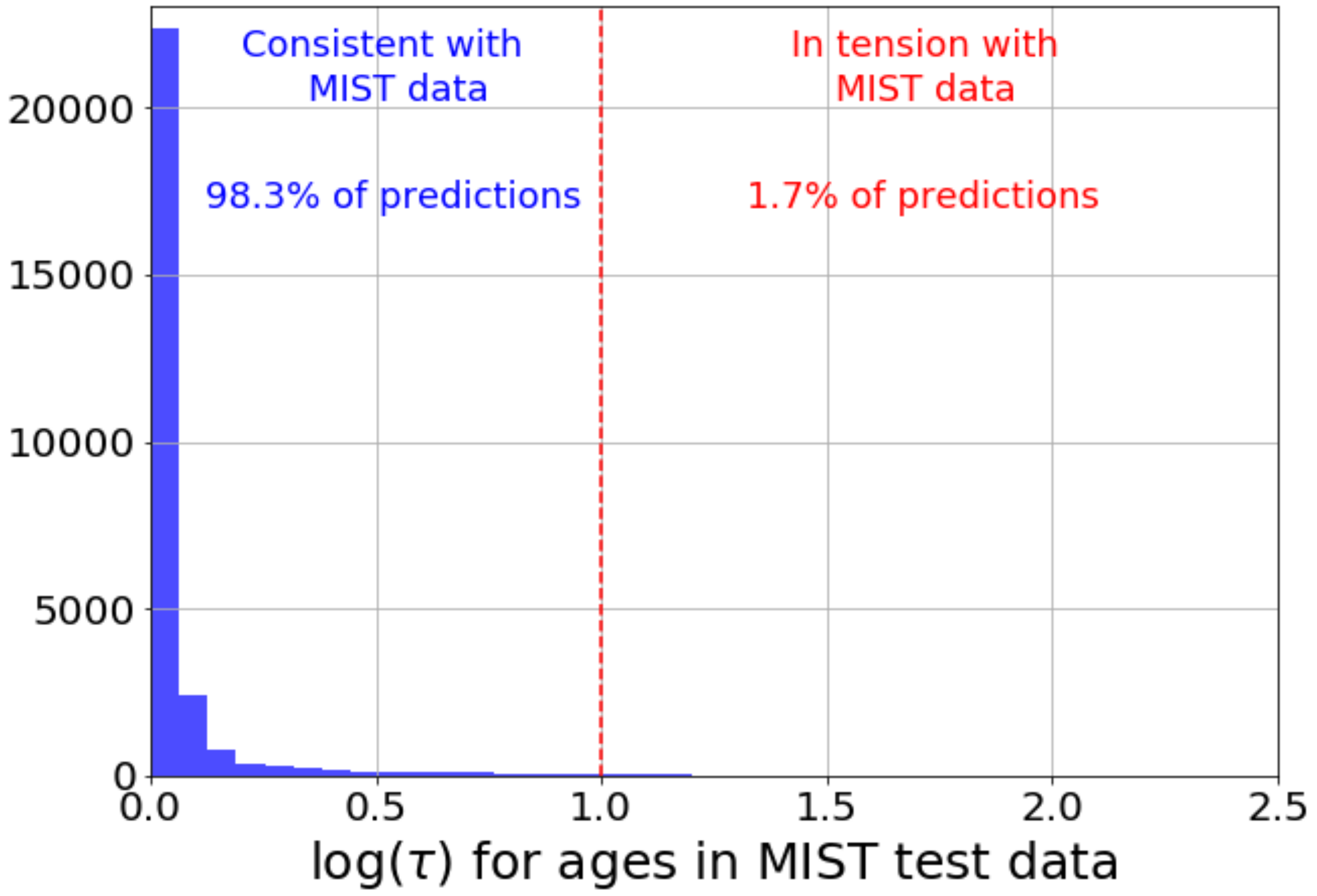


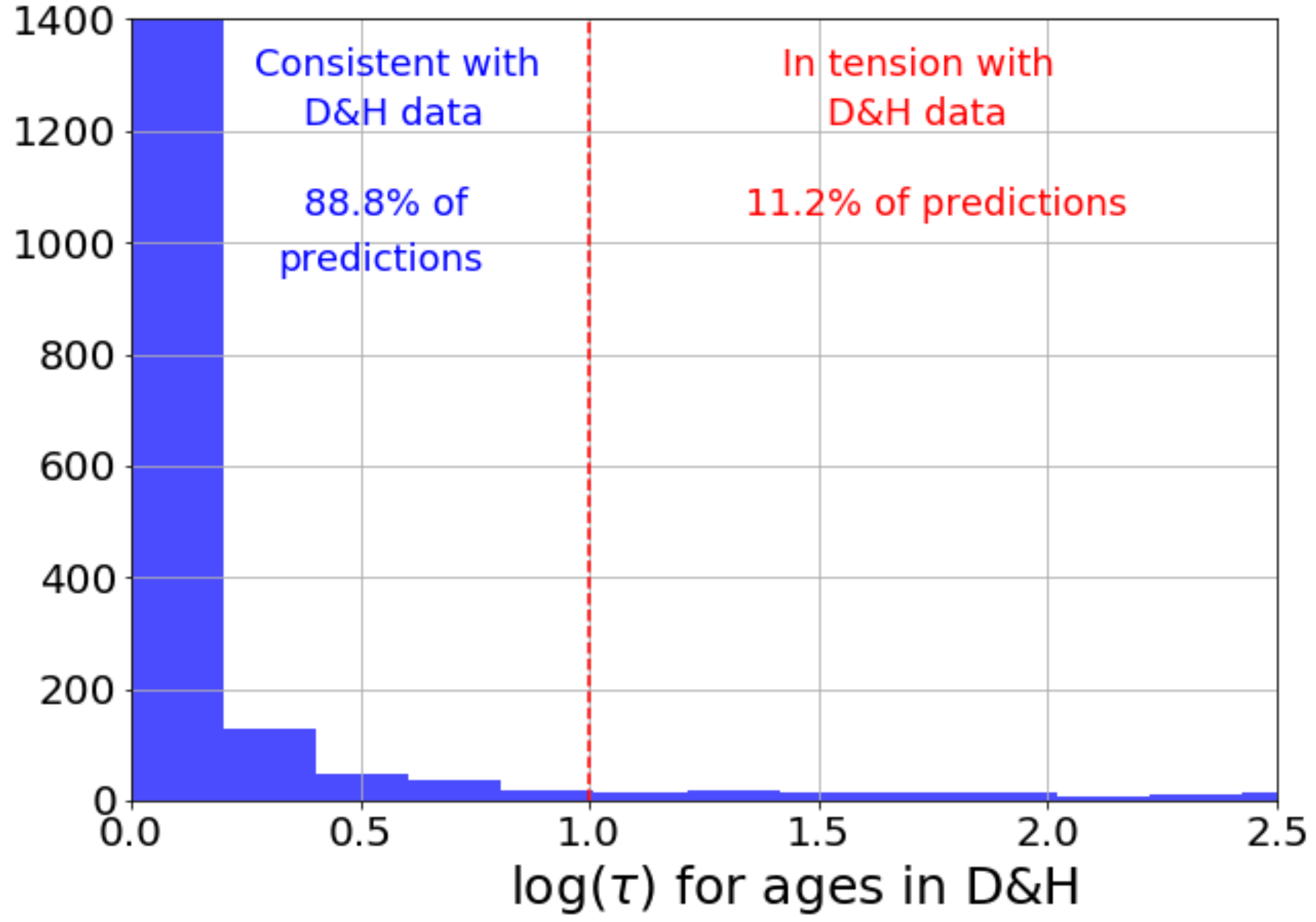


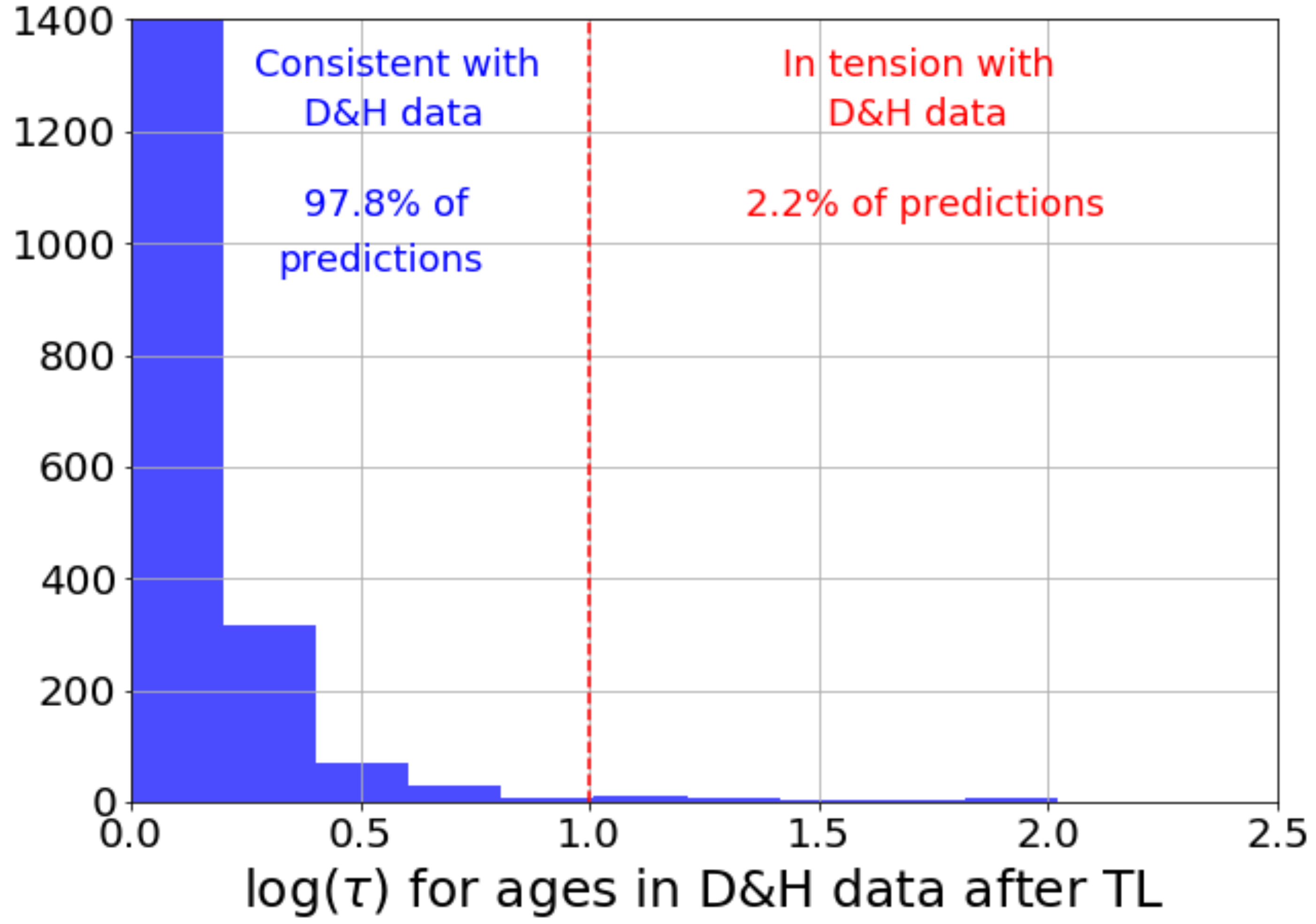
Davis & Hillenbrand 2015b

Using Transfer Learning

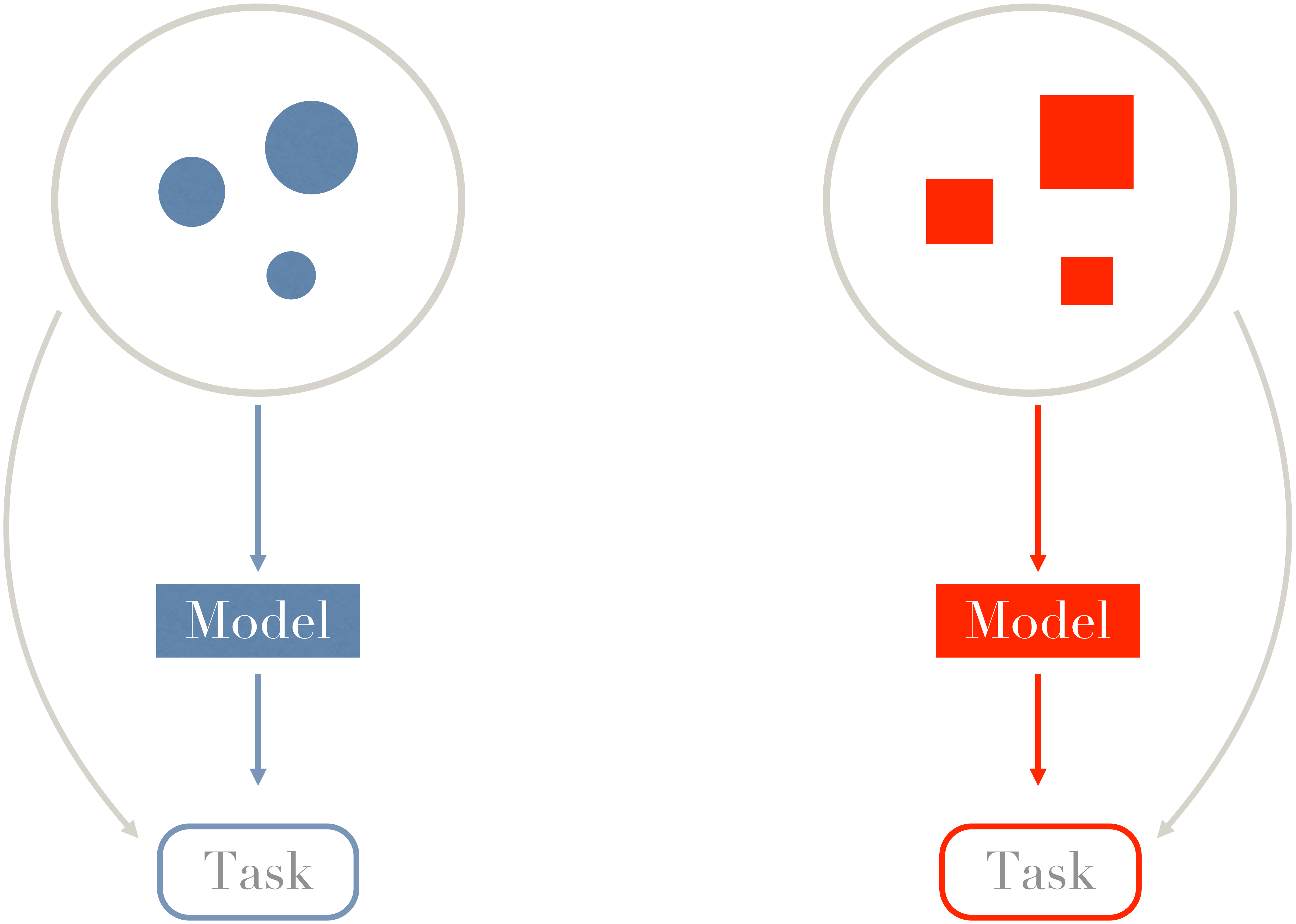
Garraffo et al. 2021



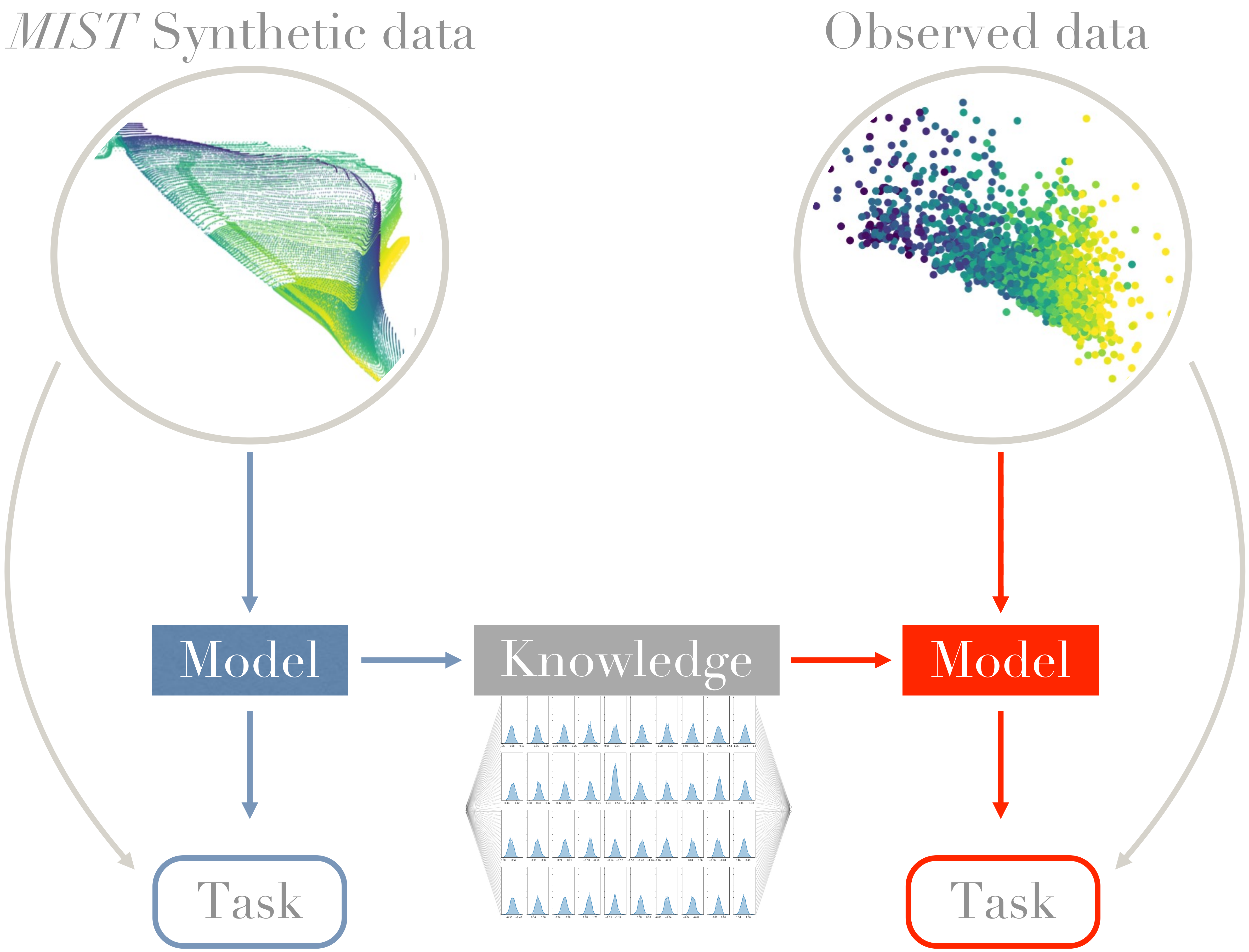




Traditional Machine Learning



Transfer Learning



AstroAI

Enabling Next Generation Astrophysics

Pre-ZAMS mass estimation

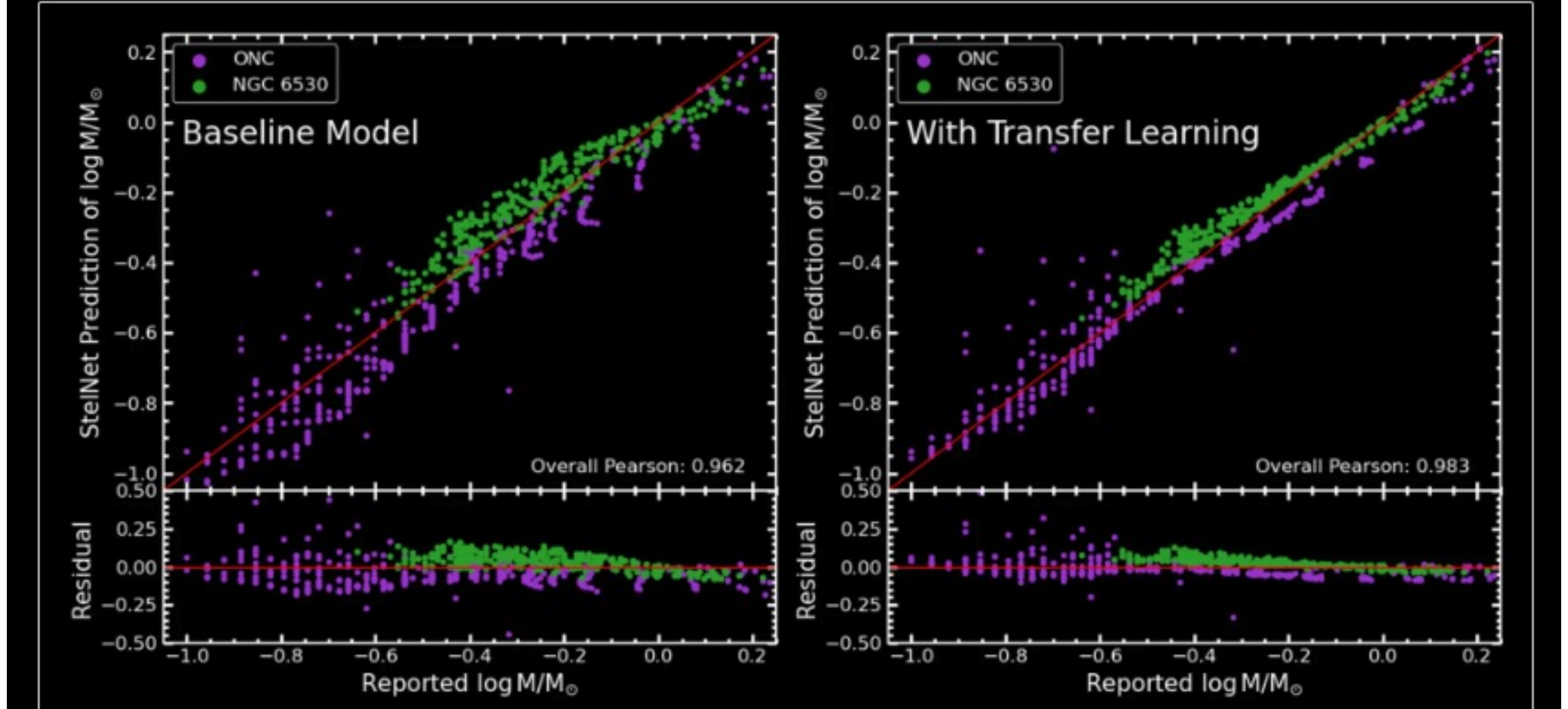
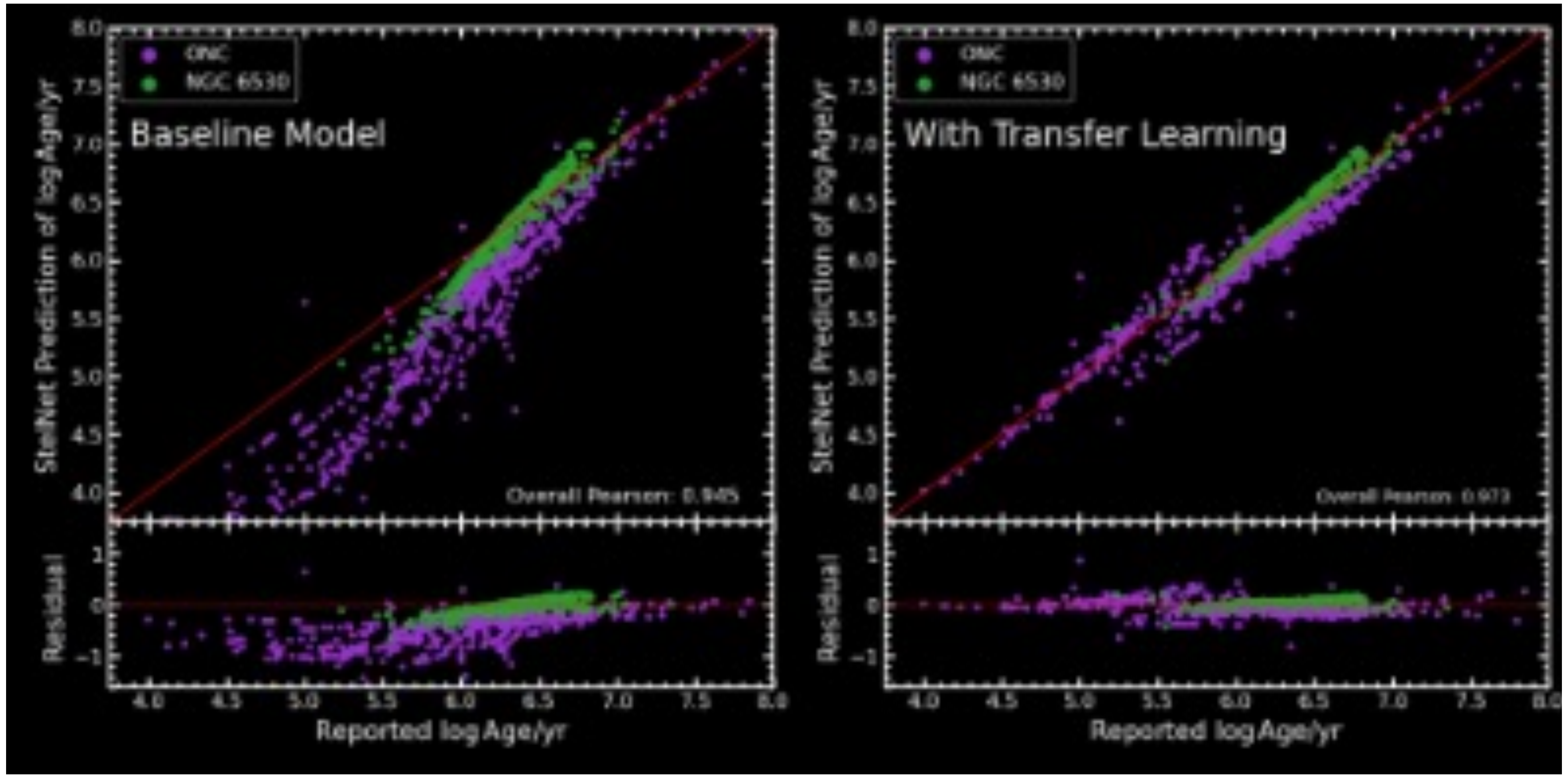


Figure 6. StelNet mass predictions versus reported values for each test catalog of pre-ZAMS stars for the baseline model (left) and the model after transfer learning.



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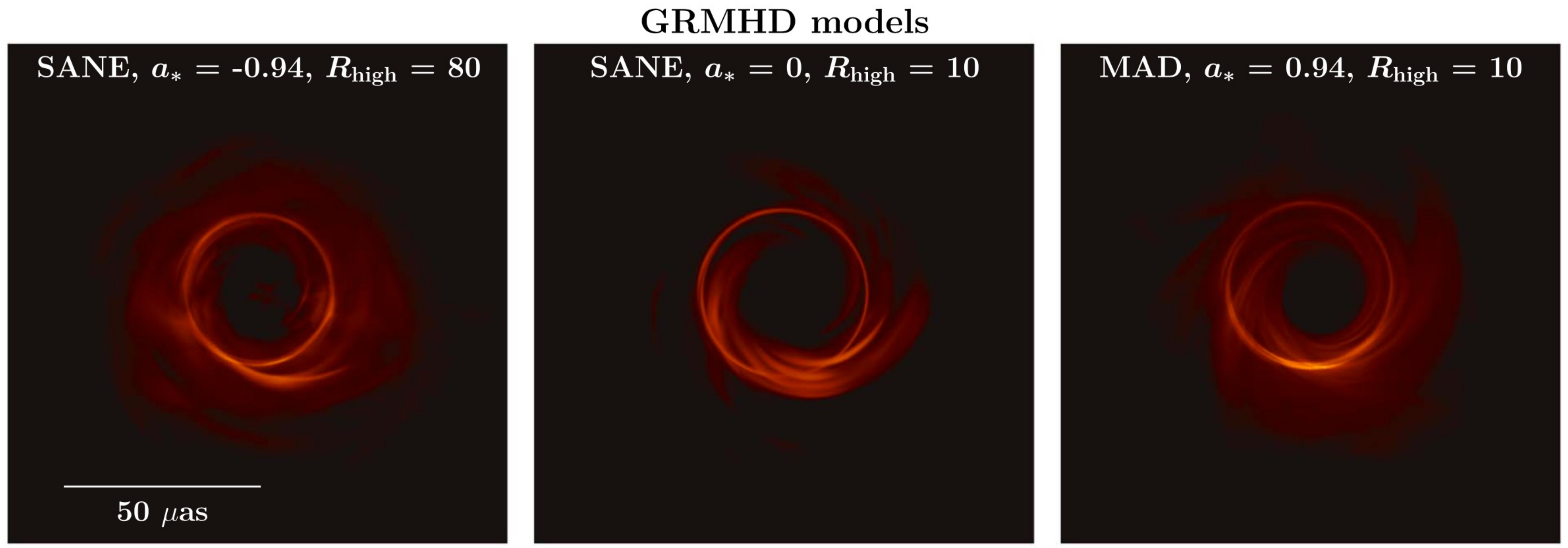
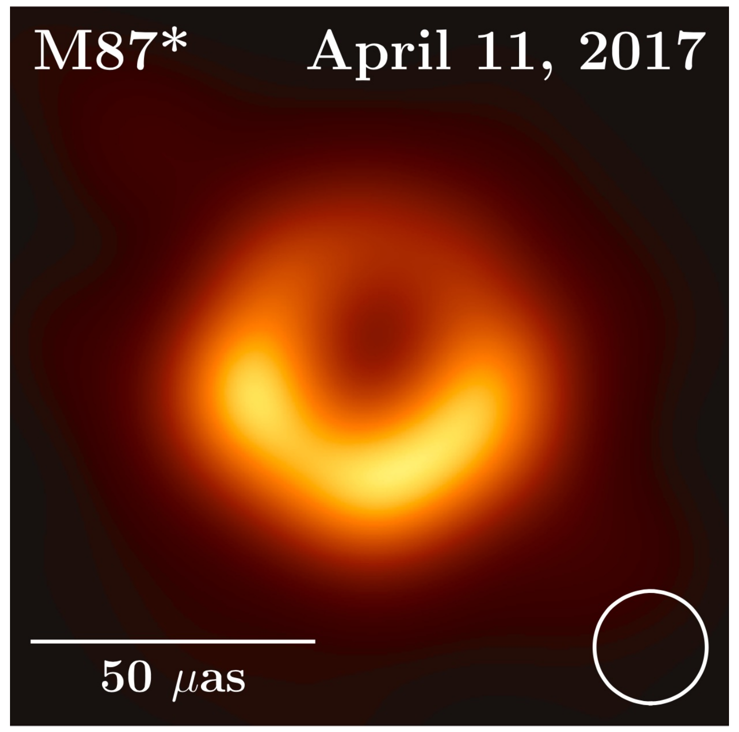
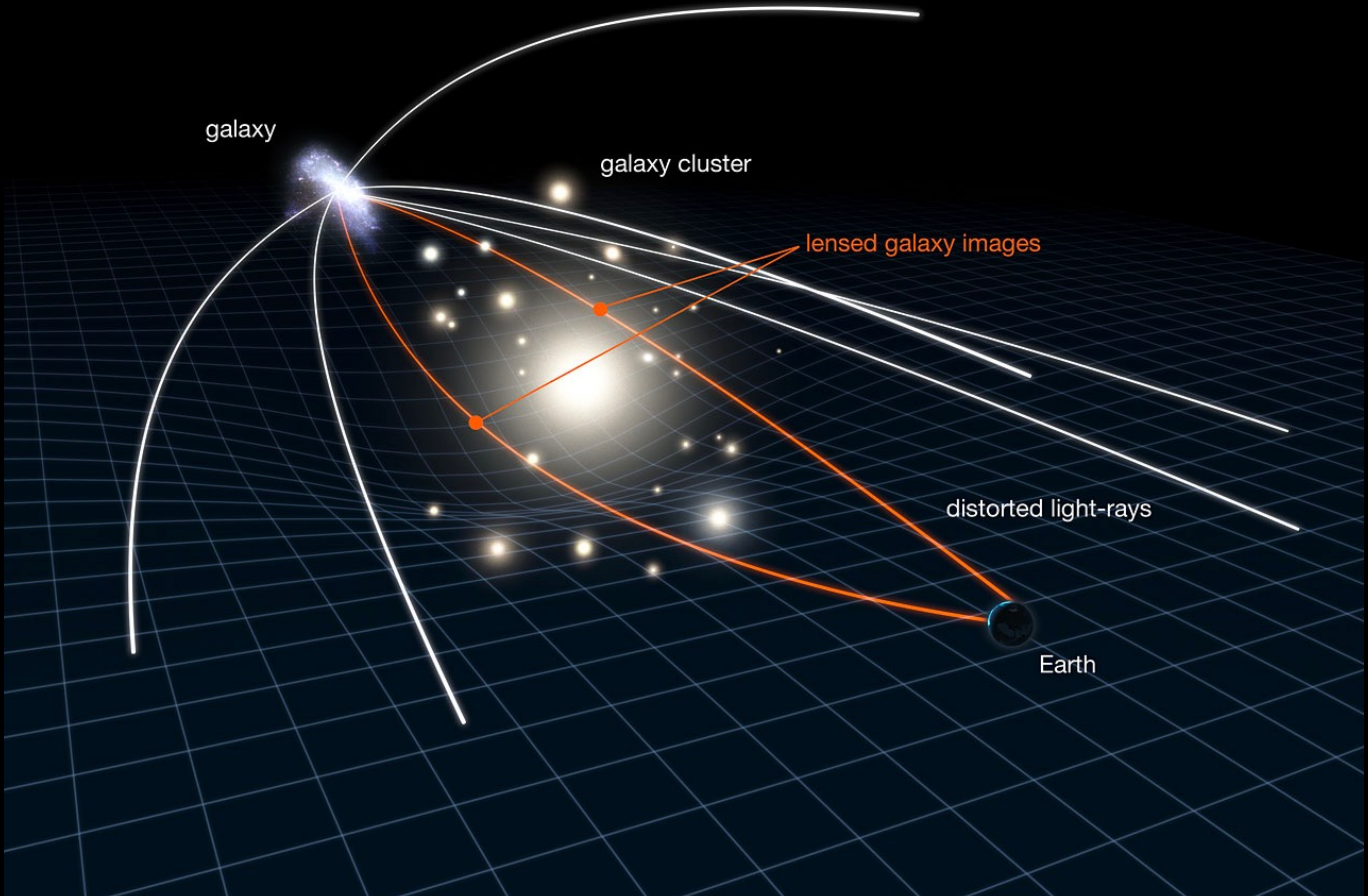
We have data from two sources:

- GRMHD simulated images



- Real EHT observations




galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth

The way we do Astronomy is rapidly changing

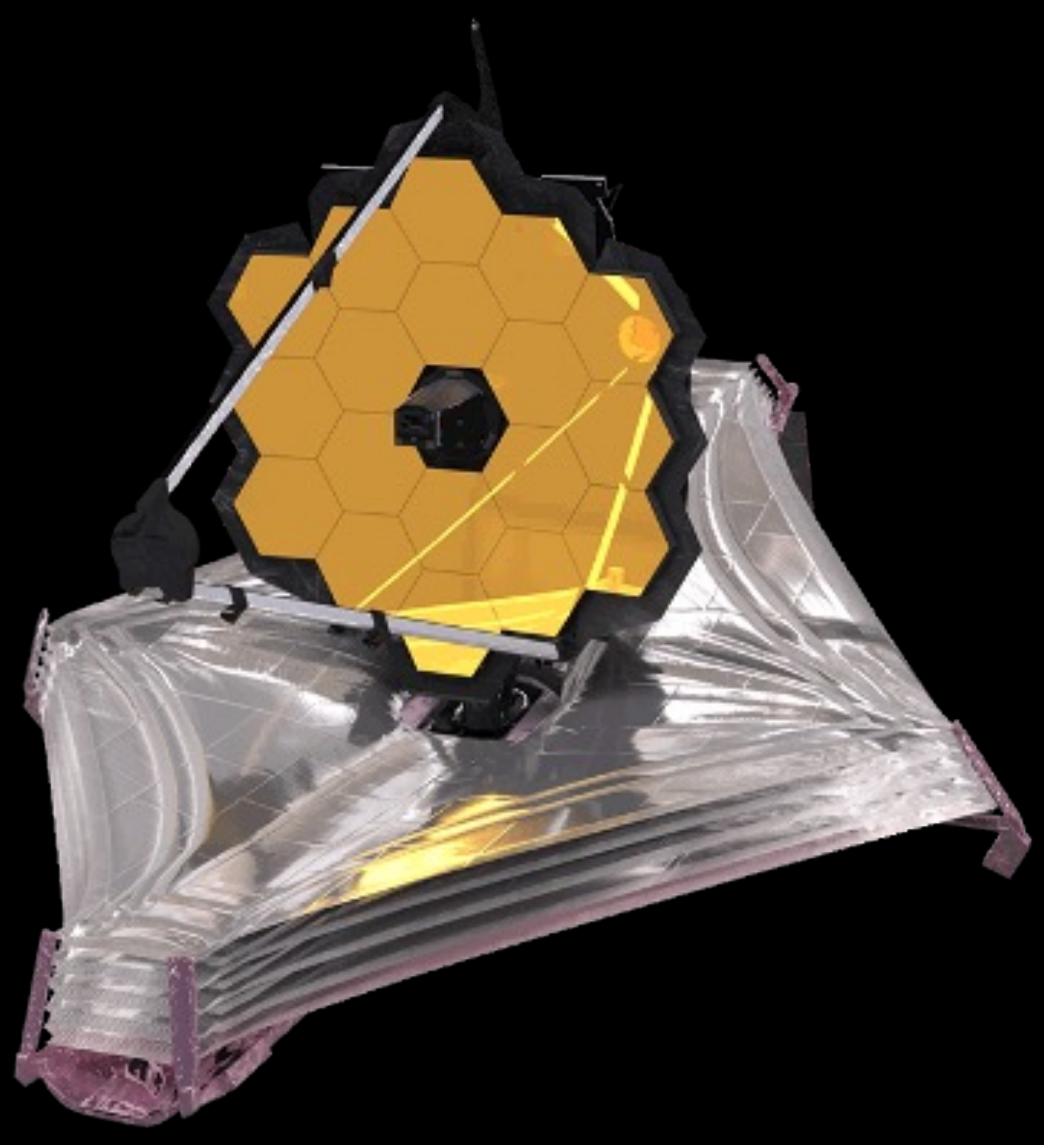
Credit: LSST

New windows into the Universe:

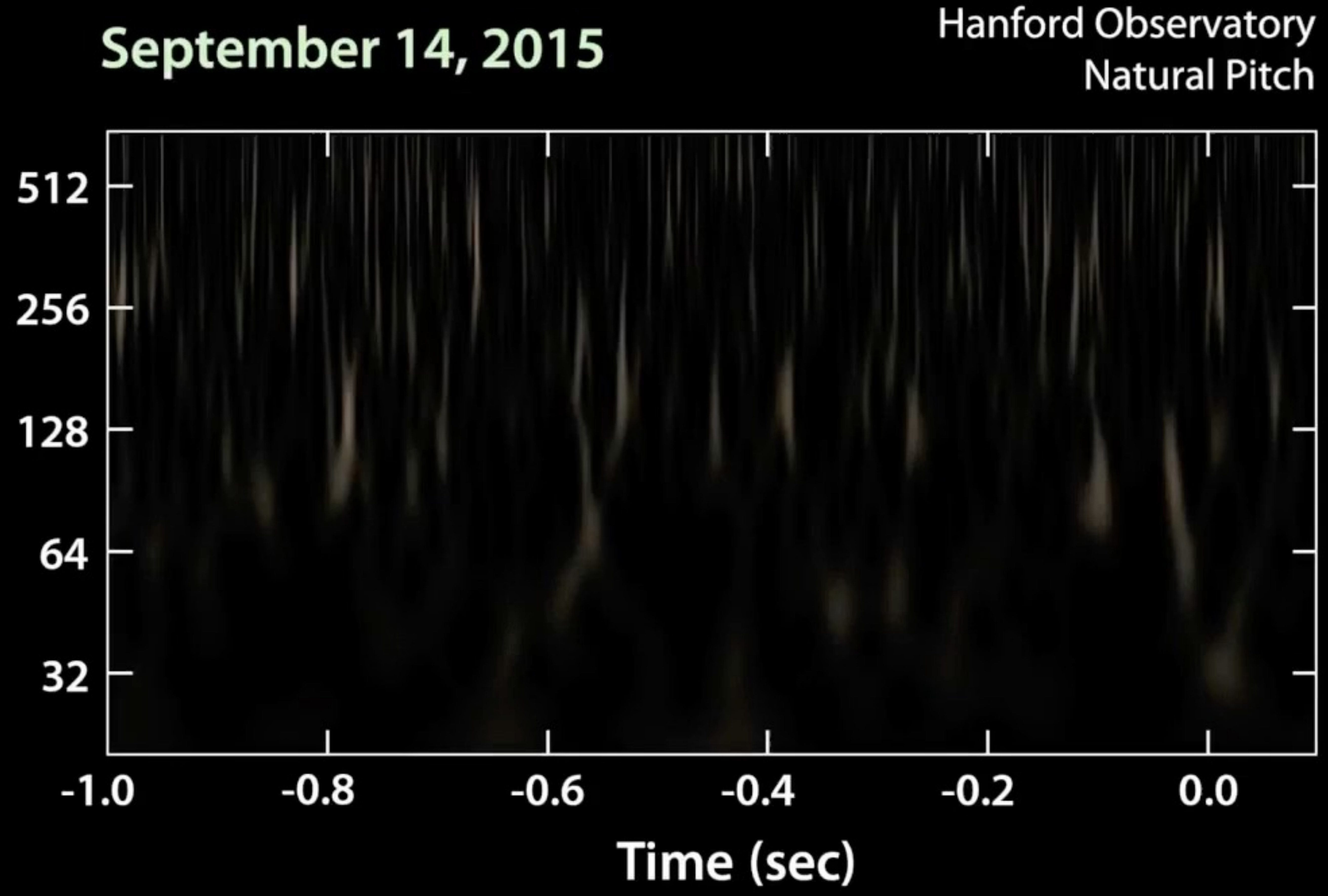

n=0

New windows into the Universe:

James Webb Space Telescope



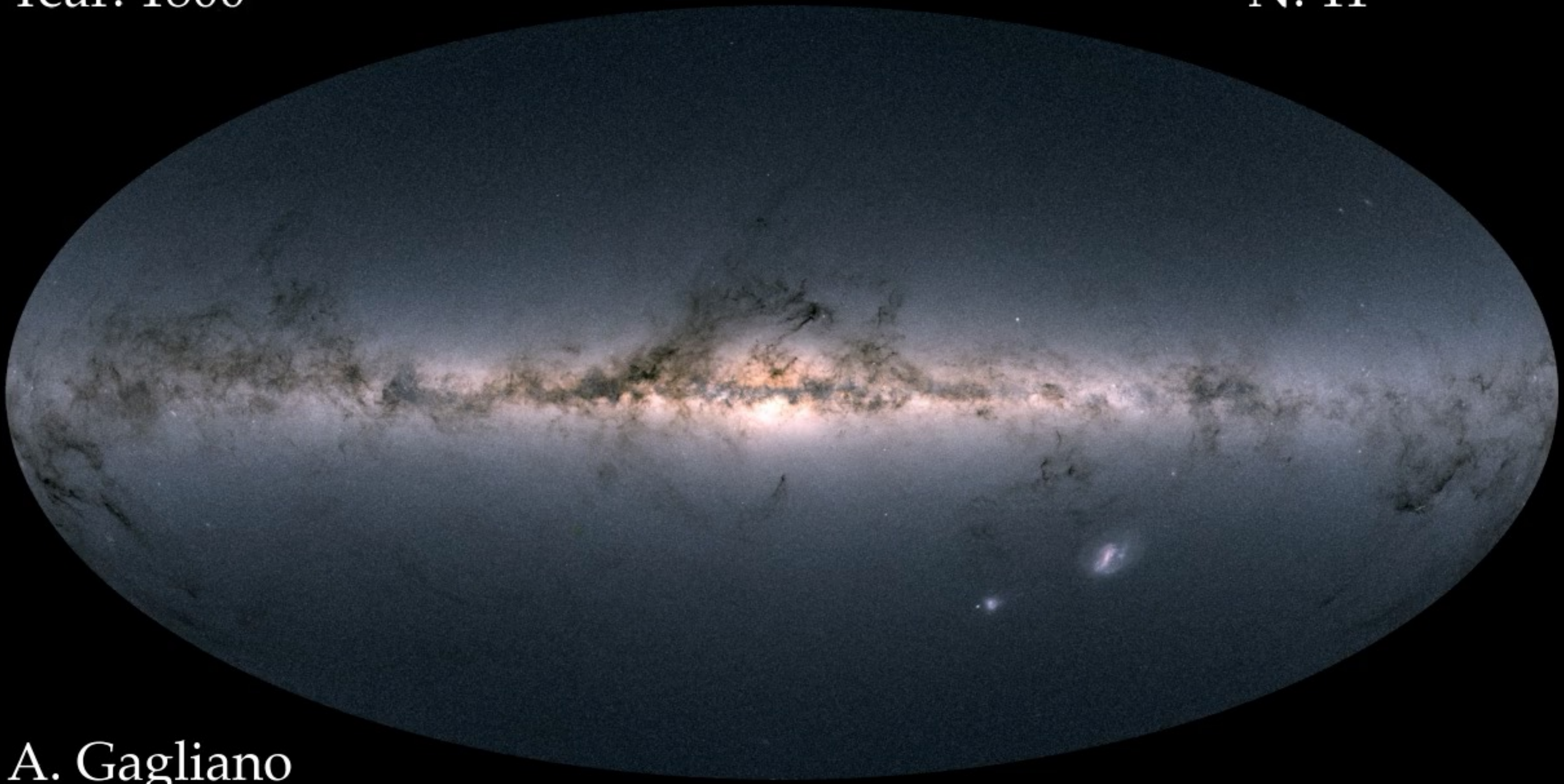
New windows into the Universe:



Radio/Gravitational Waves

Year: 1800

N: 11



A. Gagliano

Observing more data in 1 year, than all observations so far

New eyes

Big Data

How do we make discoveries in this new era?

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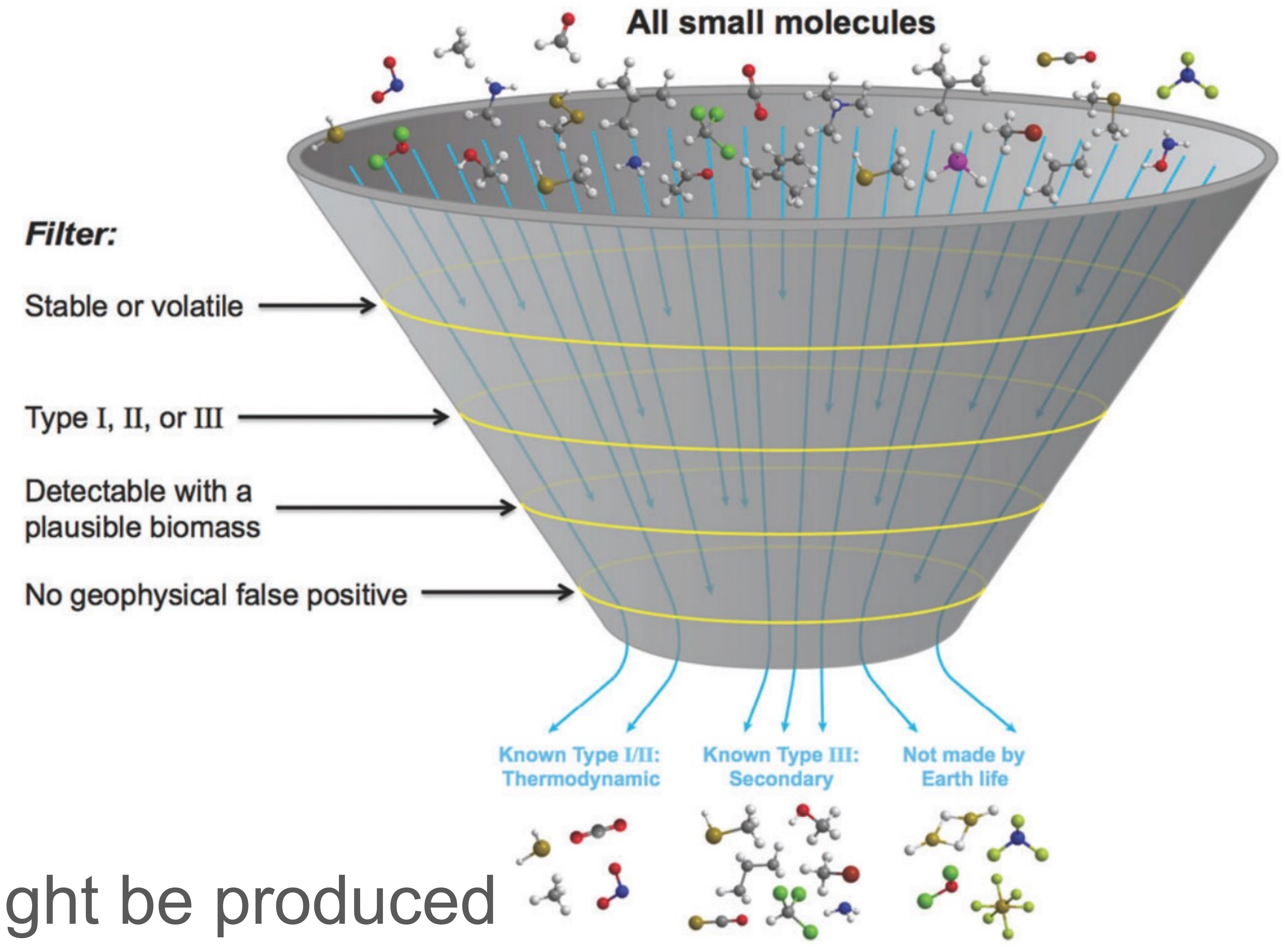
Exoplanet Atmospheres and Biosignatures

<u>What is the big Science Question?</u>

- Is there life elsewhere in the universe?

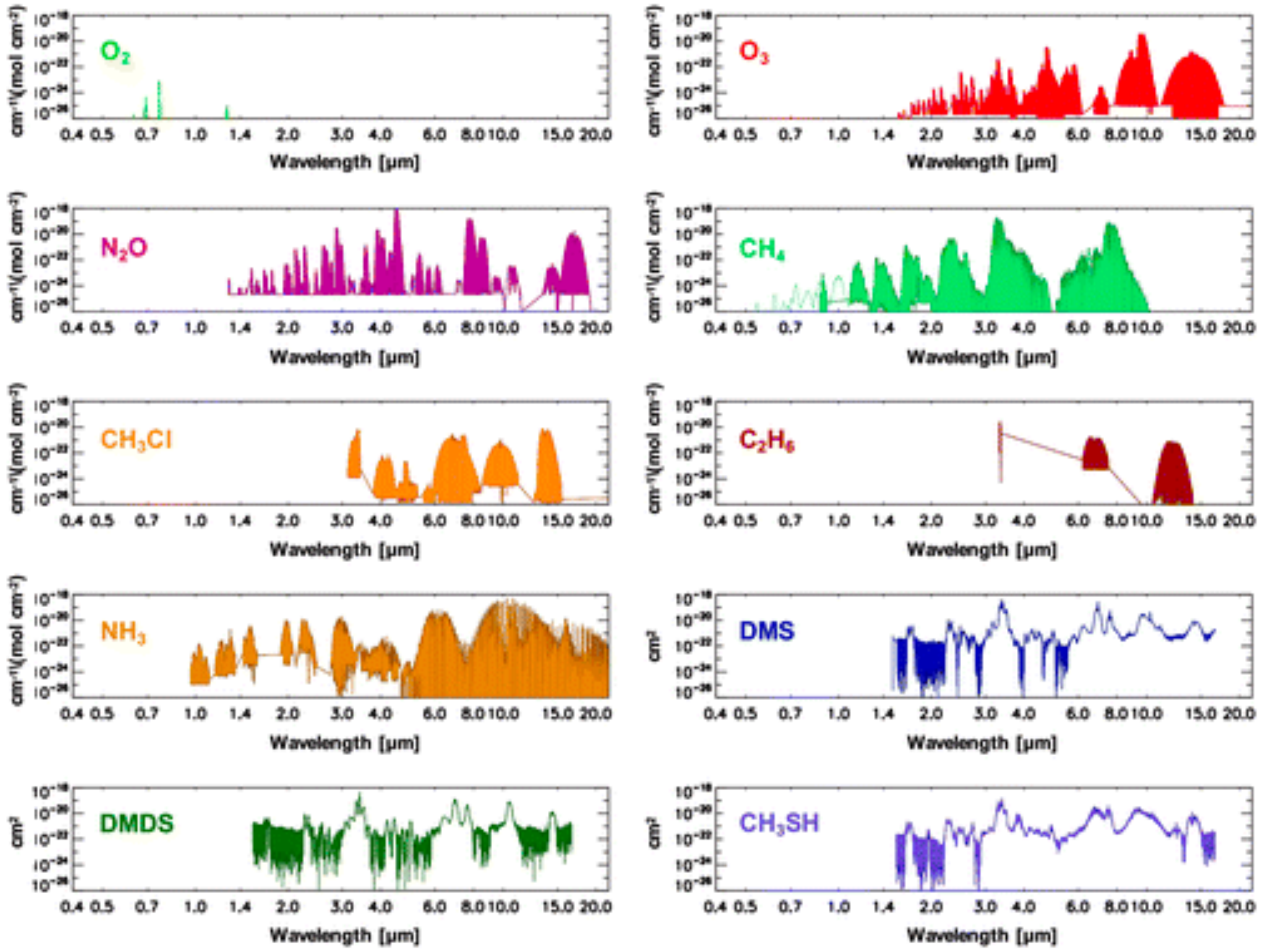
<u>How will our work answer it?</u>

- Classic Molecules: H_2O, CH_4, NH_3, O_2, CO_2, CO
- Seager+2016 proposed a list of 14,000 molecules that might be produced by life

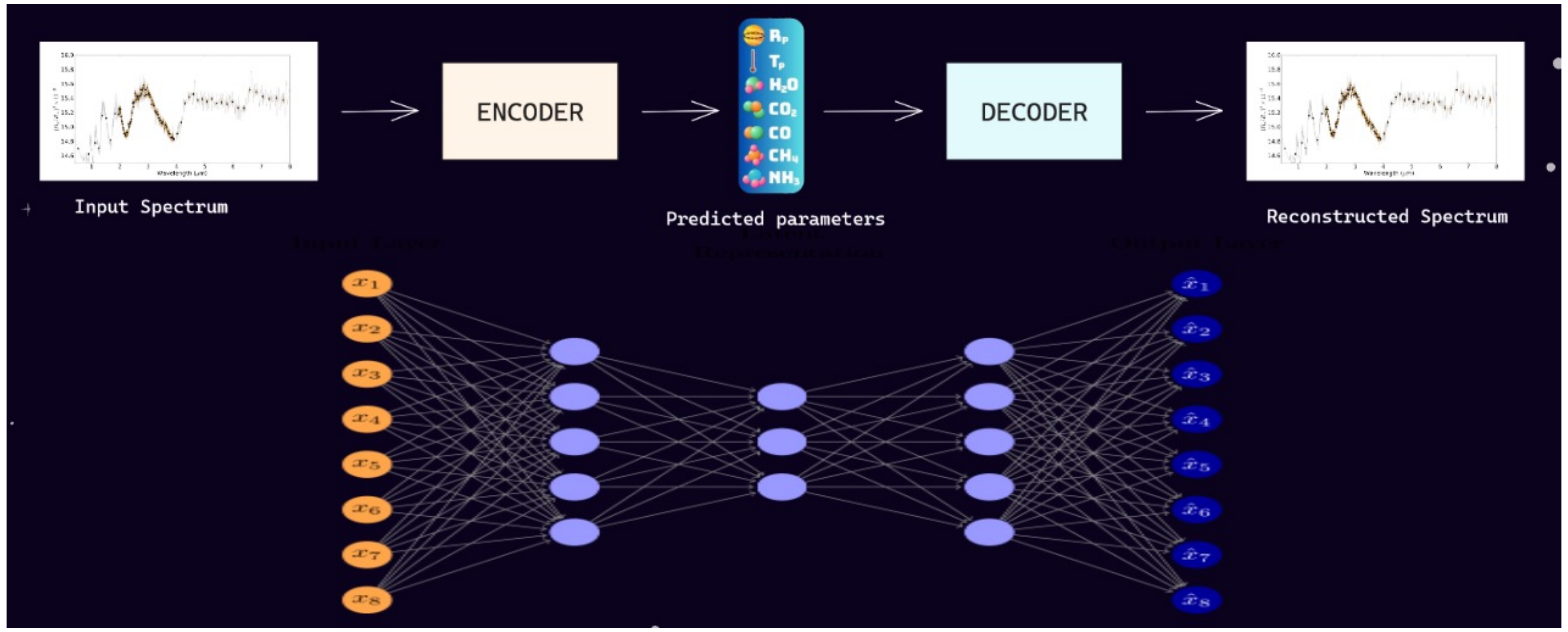


Next Big Steps: Do this for 14K molecules

1- Detection of Biosignature Gases



2- Exoplanet Atmospheric Retrievals with AI



Breakthrough: Find Life Elsewhere in the Universe!

First dedicated center for Astrophysical AI

AstroAI

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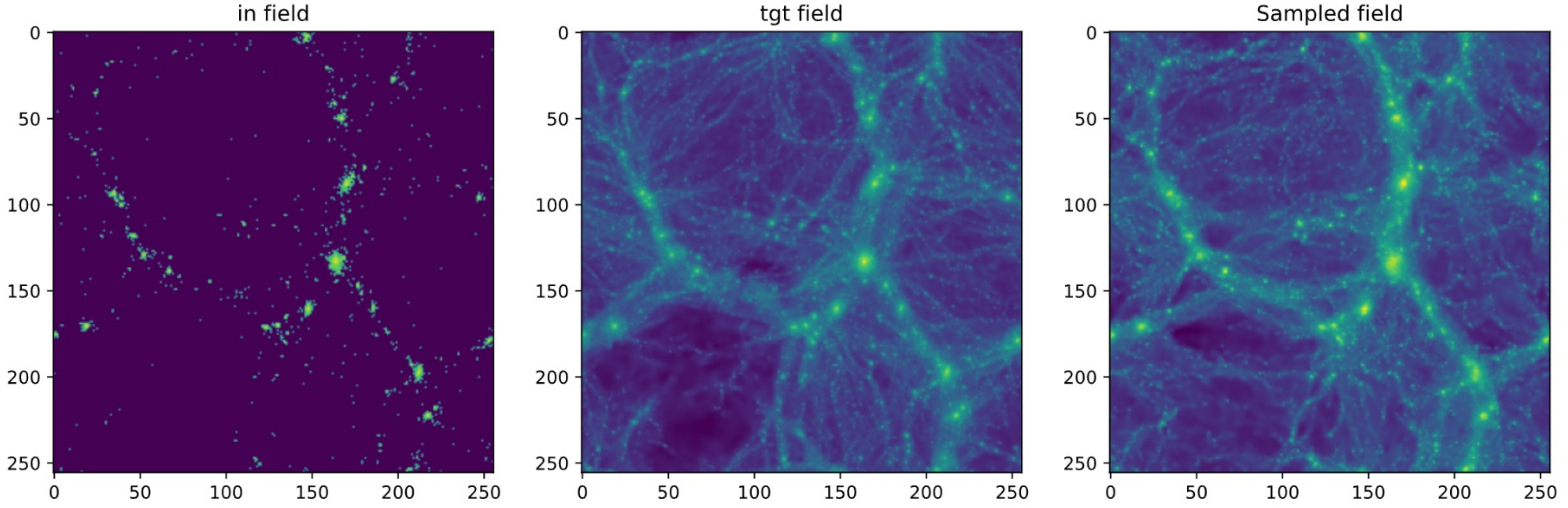
Carolina Cuesta-Lázaro

Modeling the Universe

Inferring Dark Matter



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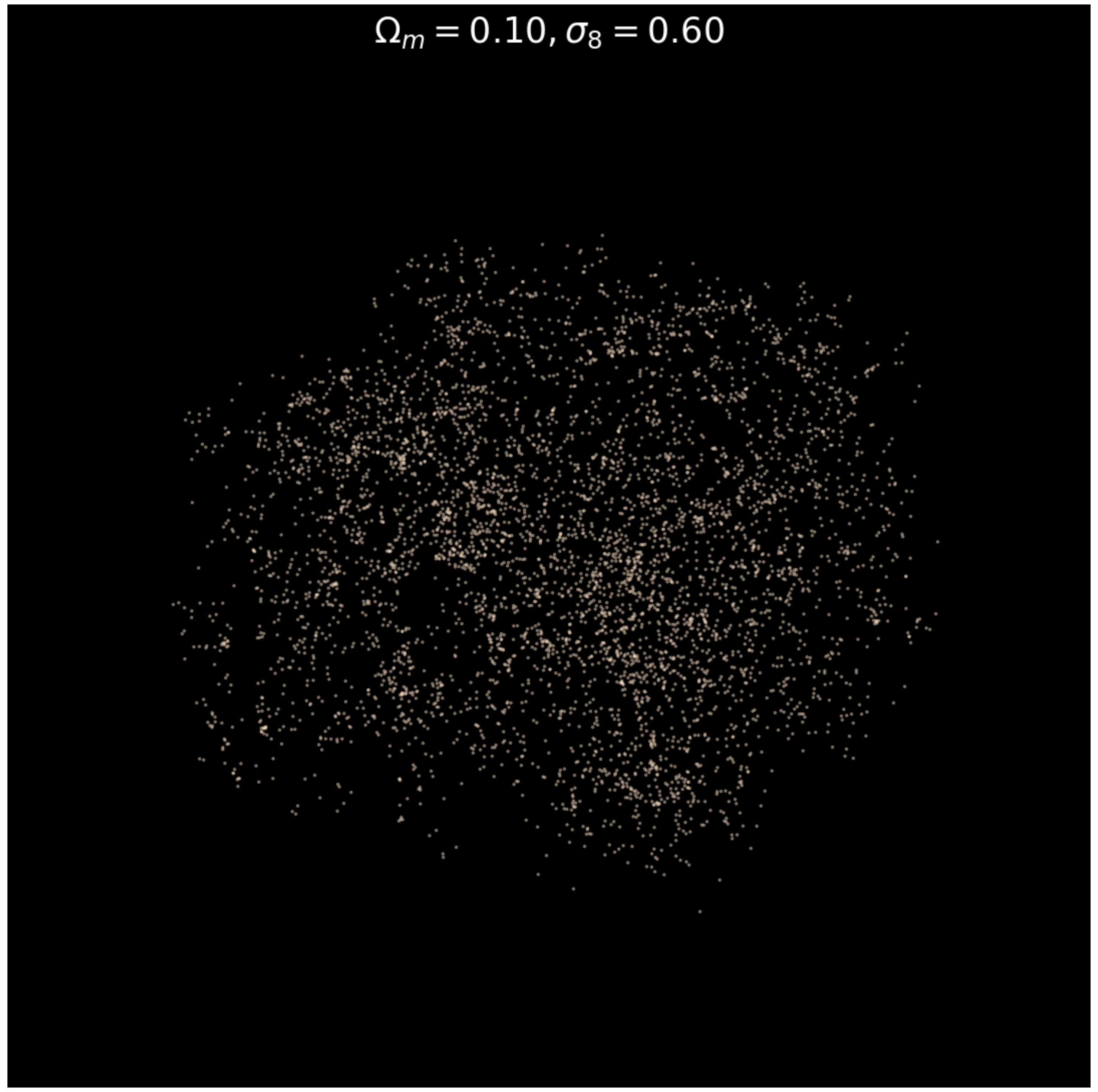
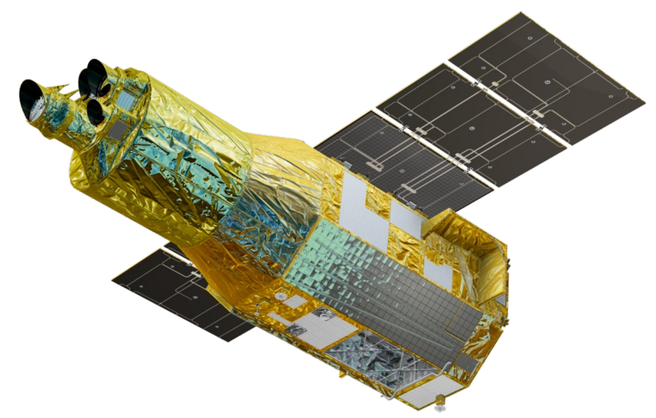
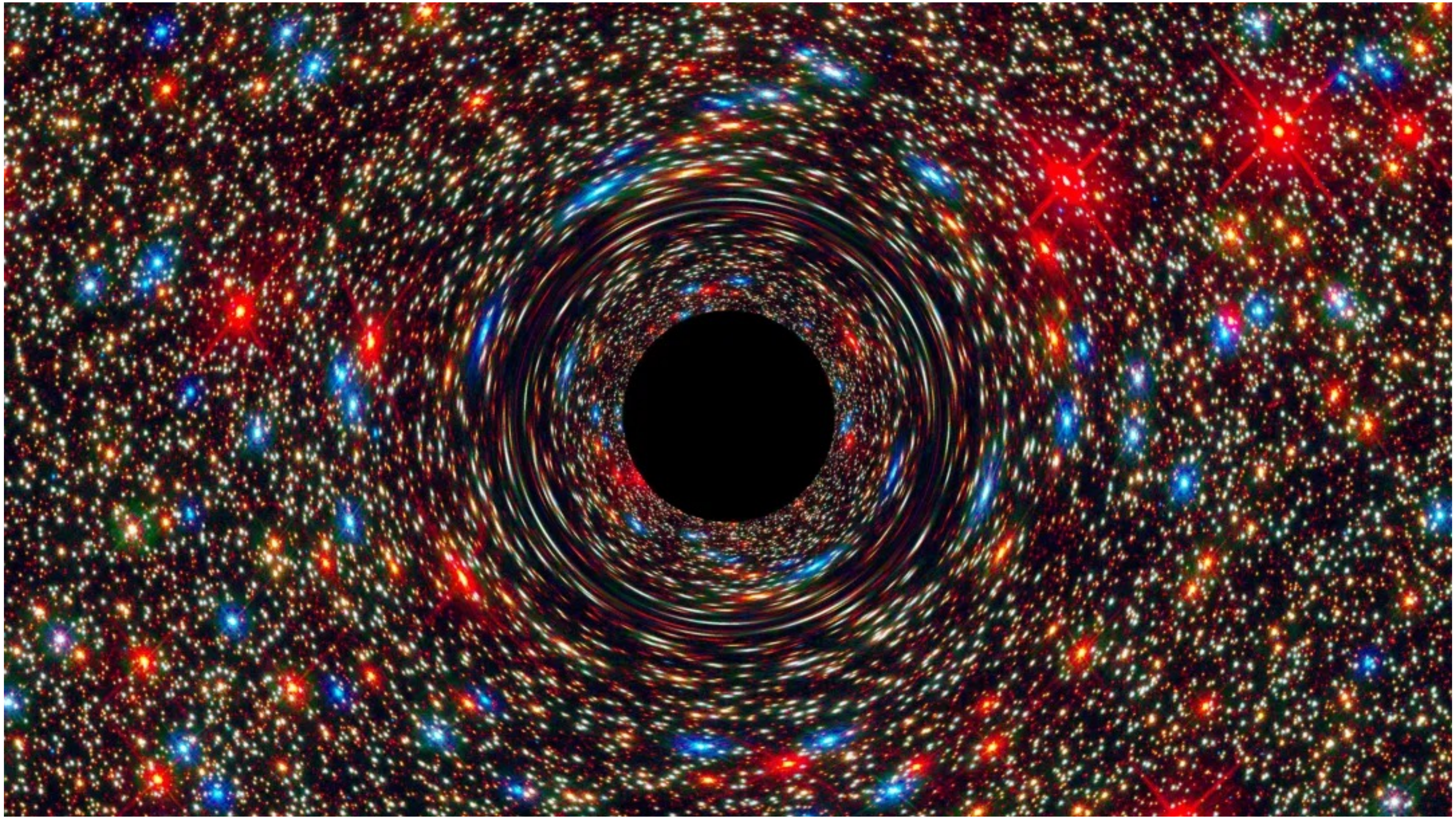


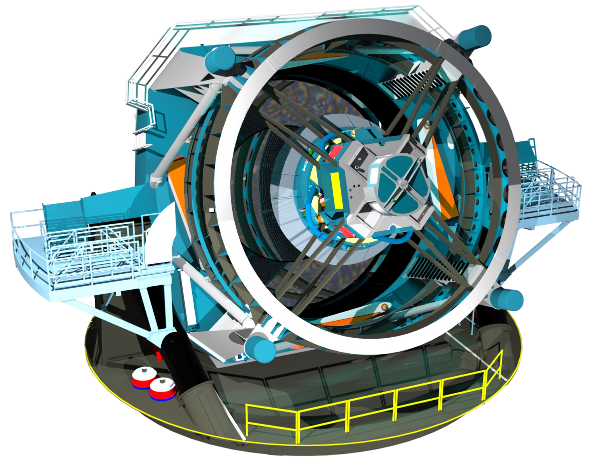
Big Data Revolution in Astrophysics



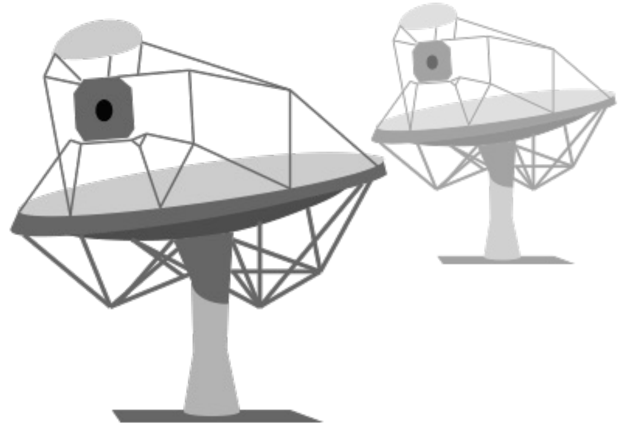
Next Gen X-ray
Observatories



NASA Roman
Space
Telescope



Vera Rubin
Observatory



Square Kilometer
Array (SKA)

Chandra X-ray Observatory