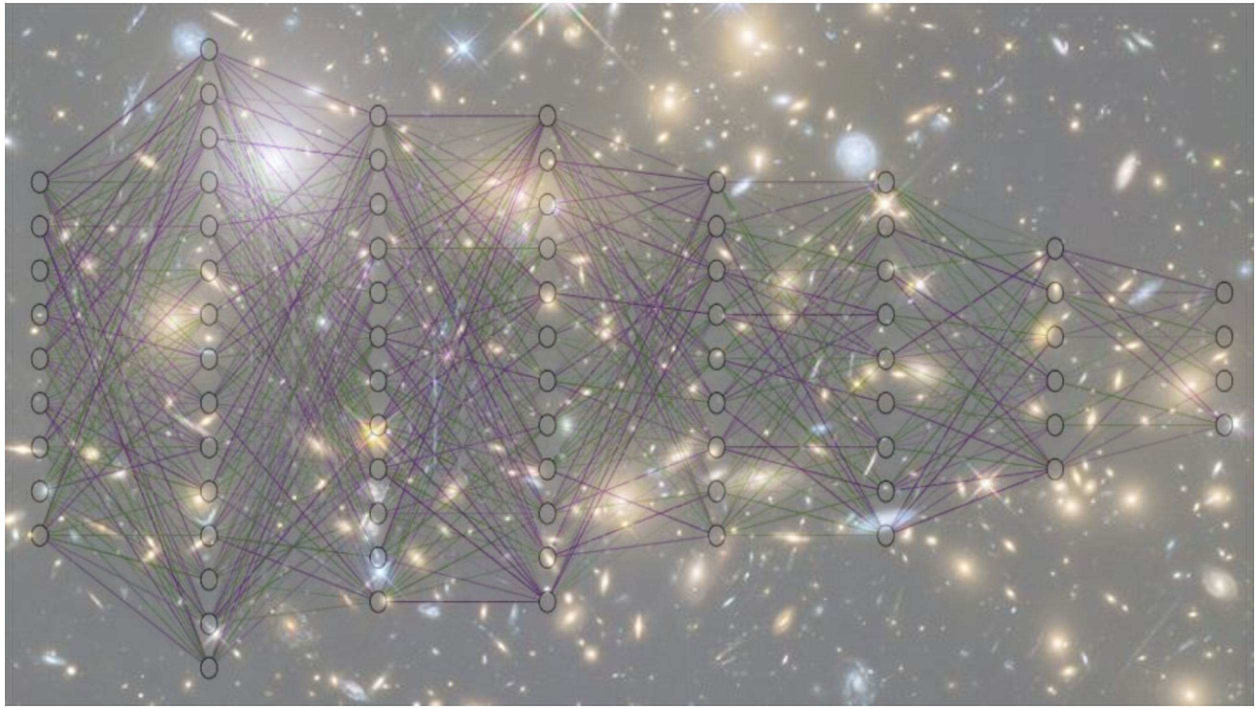
Cosmology in the Machine Learning Era

Francisco Villaescusa-Navarro

PRINCETON UNIVERSITY



Theory Seminar

University of Wisconsin-Madison

Outline

- The standard model of cosmology
- Parameter estimation
- Machine learning
- Our vision/dream

The ΛCDM model

Fritz Zwicky

The ΛCDM model

- Large mass in non-luminous matter: dark matter
  - What is the nature of dark matter?

The ΛCDM model

Edwin Hubble

$$V = H_0 D$$

The ΛCDM model

- Large mass in non-luminous matter: dark matter

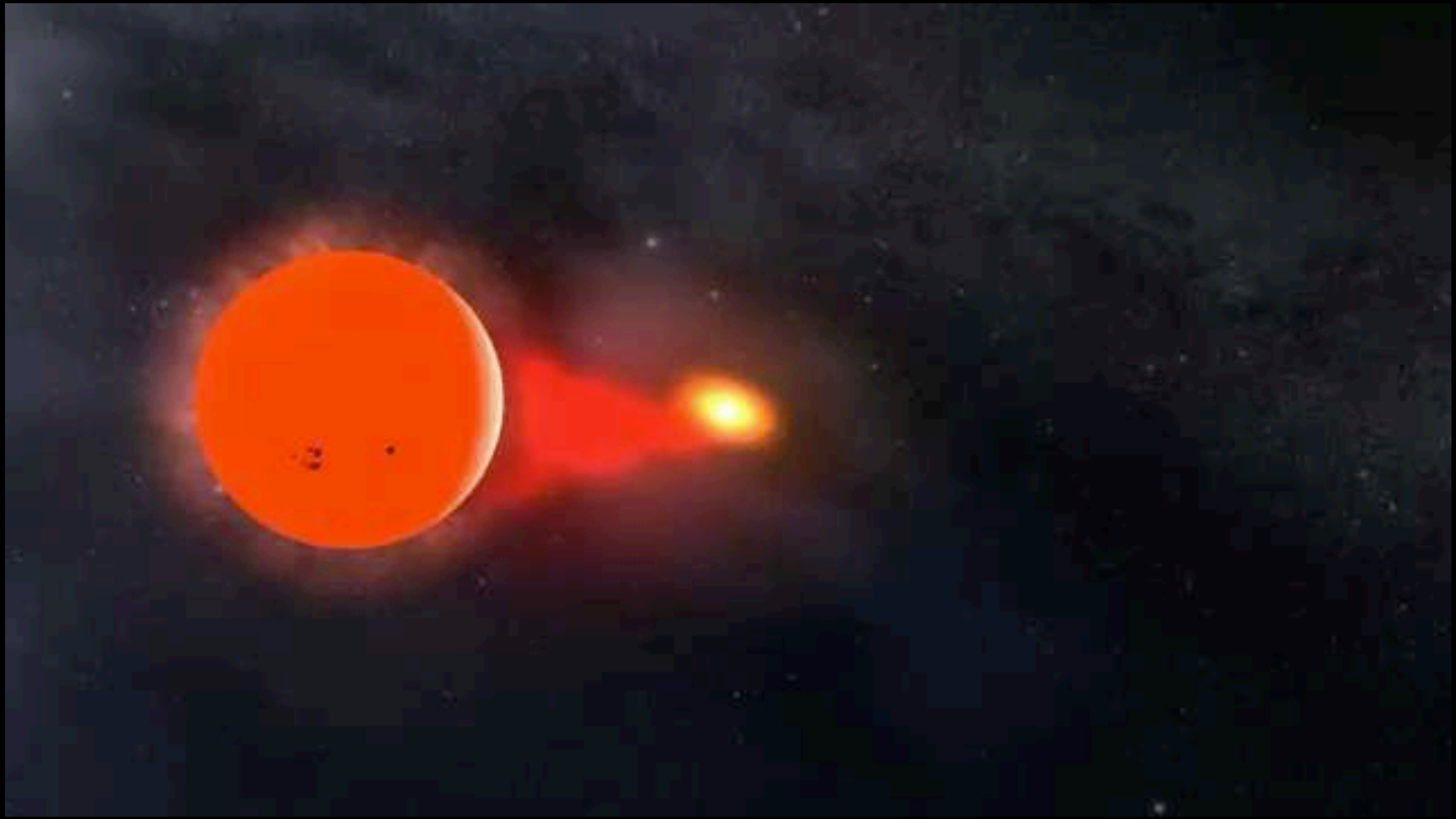
    What is the nature of dark matter?

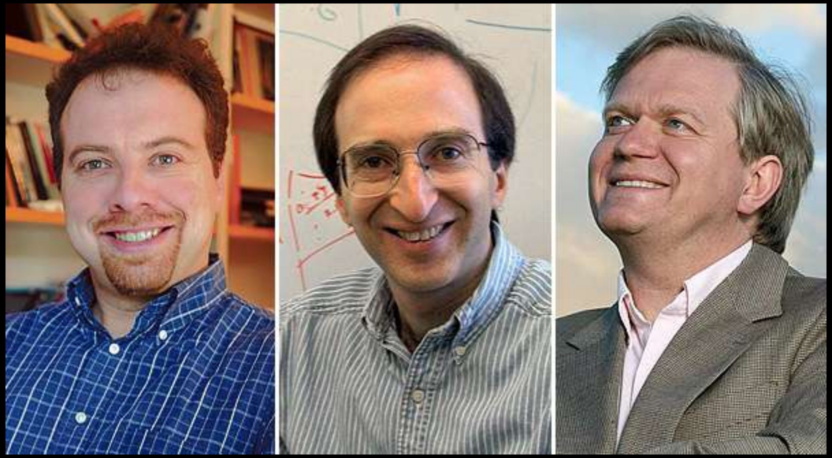
- The Universe is expanding

The ΛCDM model

Supernovae Type Ia

The Universe is accelerating its expansion!
Dark energy





Adam Riess, Saul Perlmutter & Brian Schmidt
Nobel prize 2011

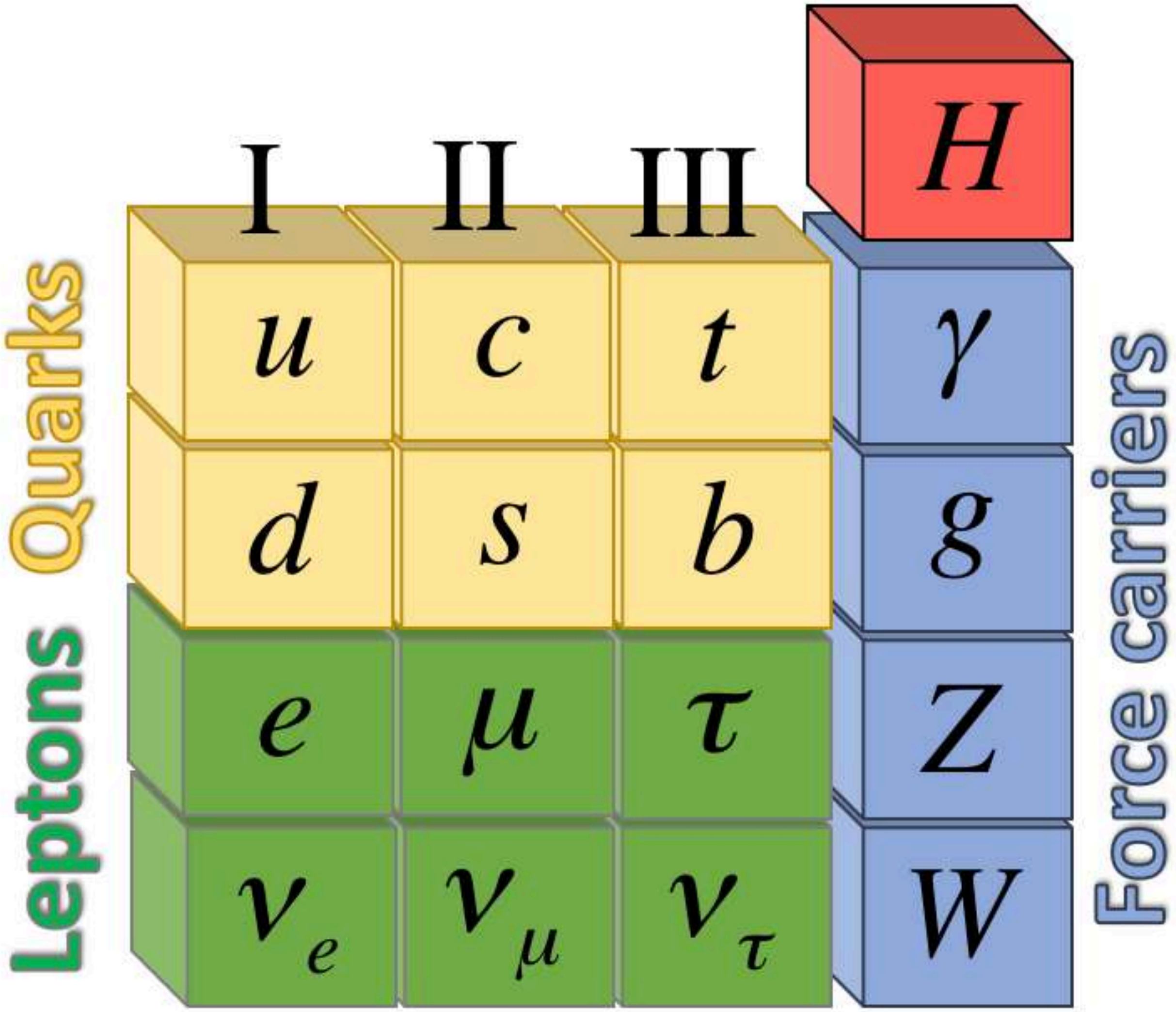
The ΛCDM model

- Large mass in non-luminous matter: dark matter
  What is the nature of dark matter?

- The Universe is expanding at an accelerated rate: dark energy
  What is the nature of dark energy?

The ΛCDM model: neutrinos

- Fundamental particles
- Very weak cross section
- <u>**Massless**</u> in the SM



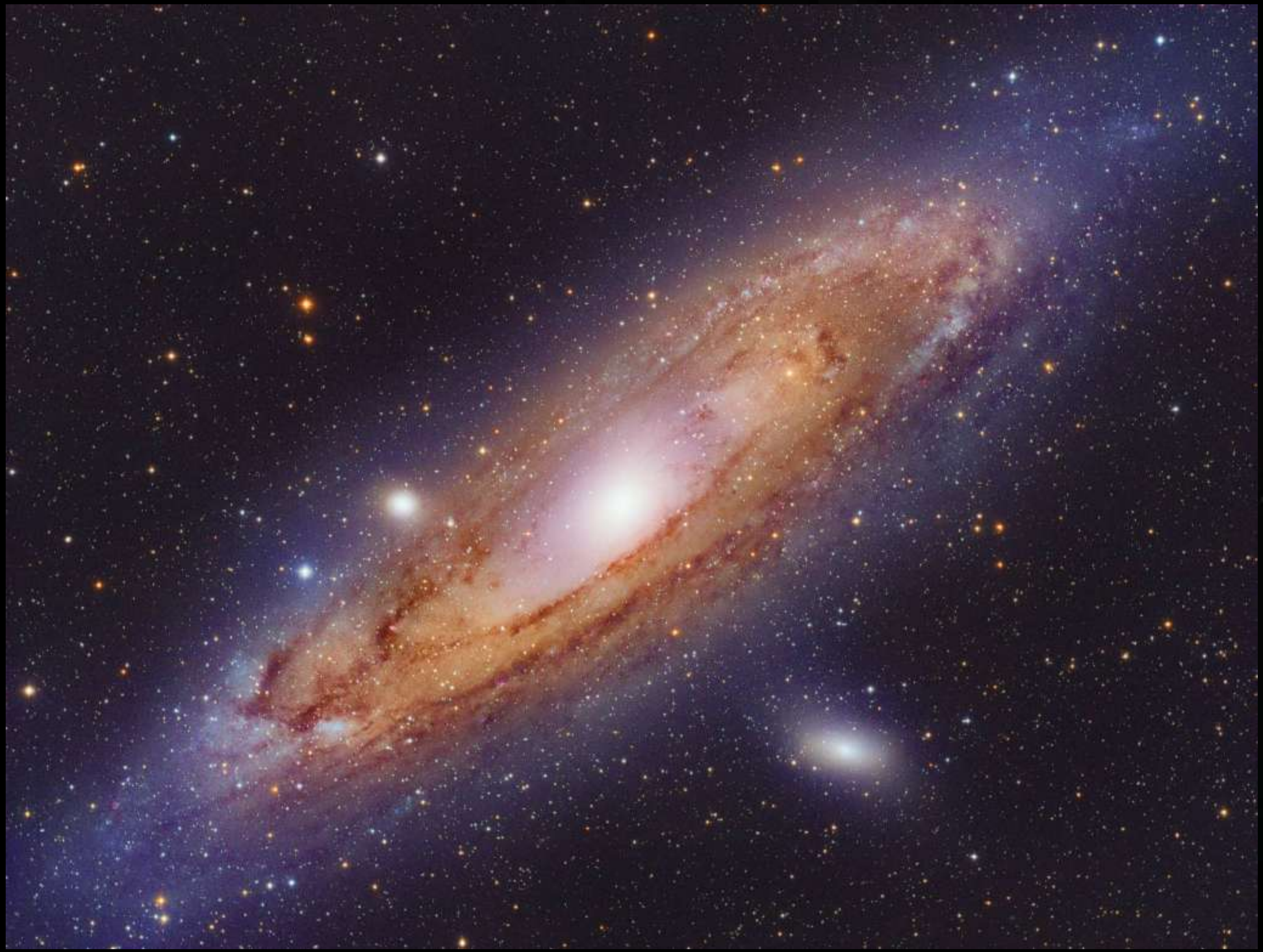
The never ending travelers

~ 1 second

~ 5 hours

~ 4 years

~ 3M years



A part of us with travel FOREVER

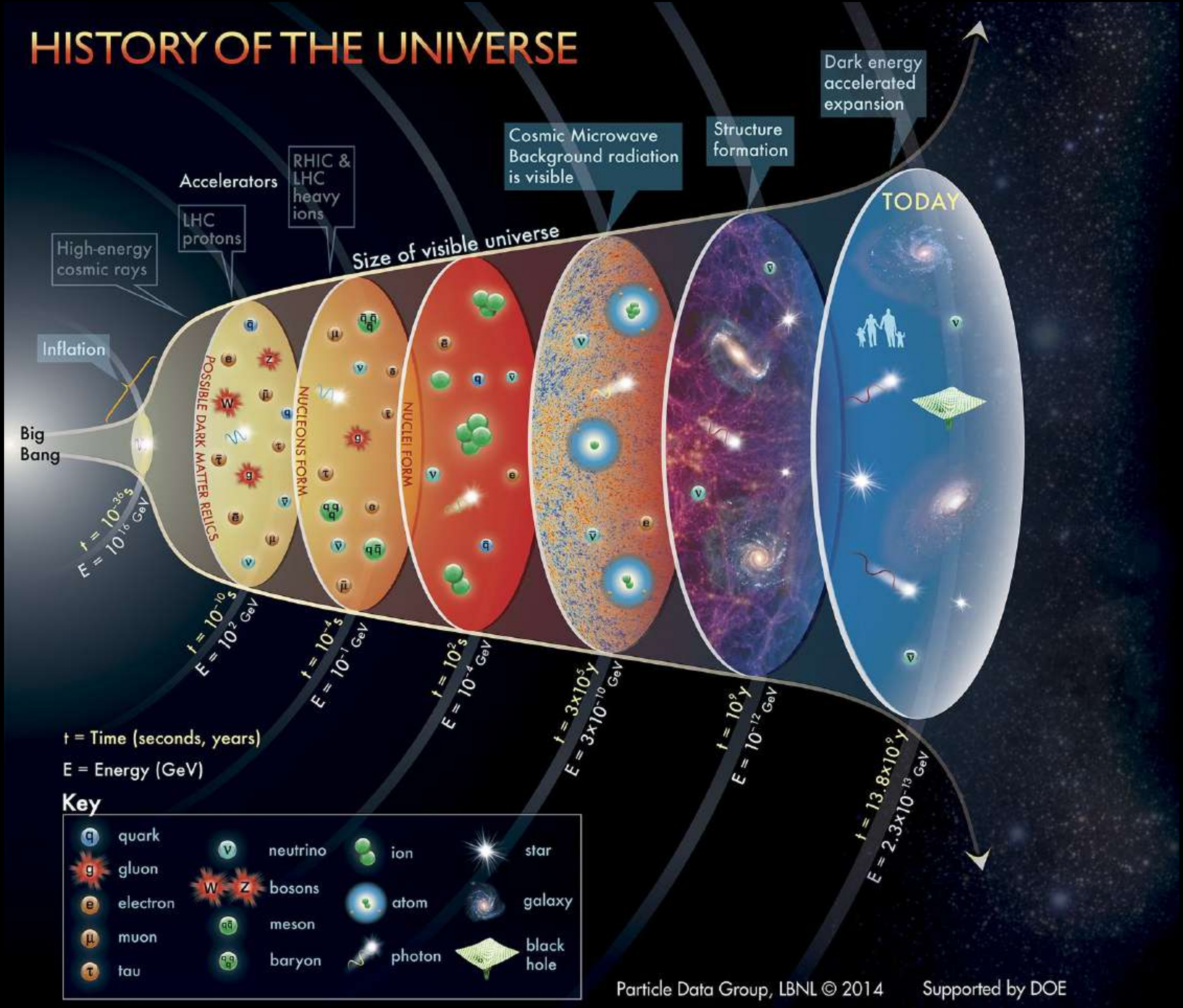
The ΛCDM model

- Large mass in non-luminous matter: dark matter
  What is the nature of dark matter?

- The Universe is expanding at an accelerated rate: dark energy
  What is the nature of dark energy?

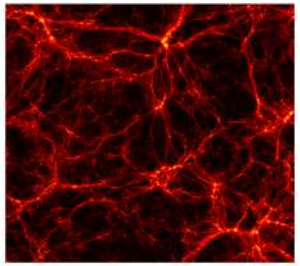
- The Universe is filled up with massive neutrinos
  What are the neutrino masses and hierarchy?

The ΛCDM model: Universe's history



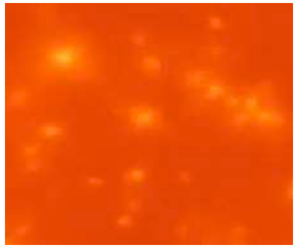
The ΛCDM model: components

Dark Energy
68%



Cold Dark Matter
27%

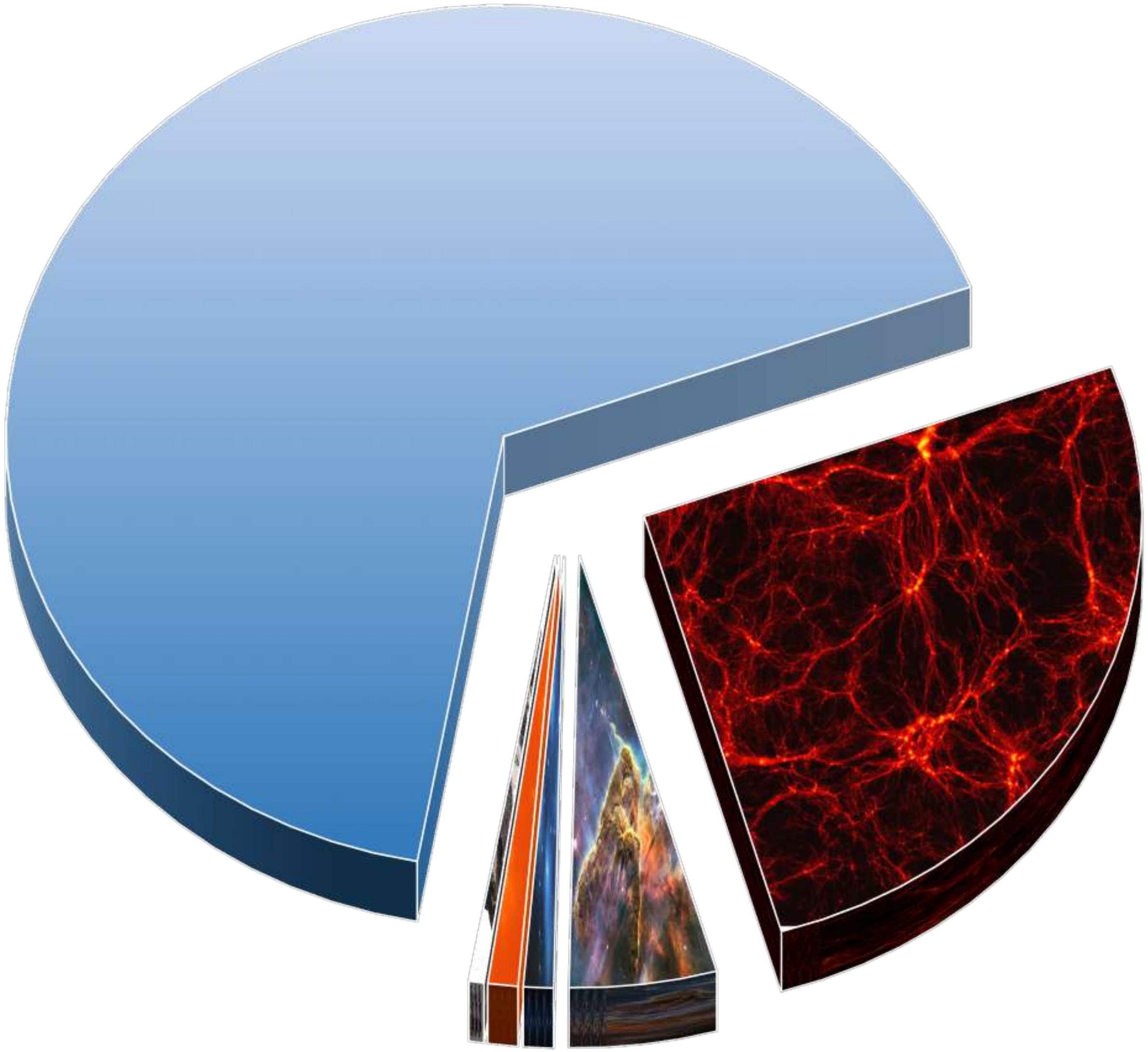
Neutrinos
0.15% - 0.3%



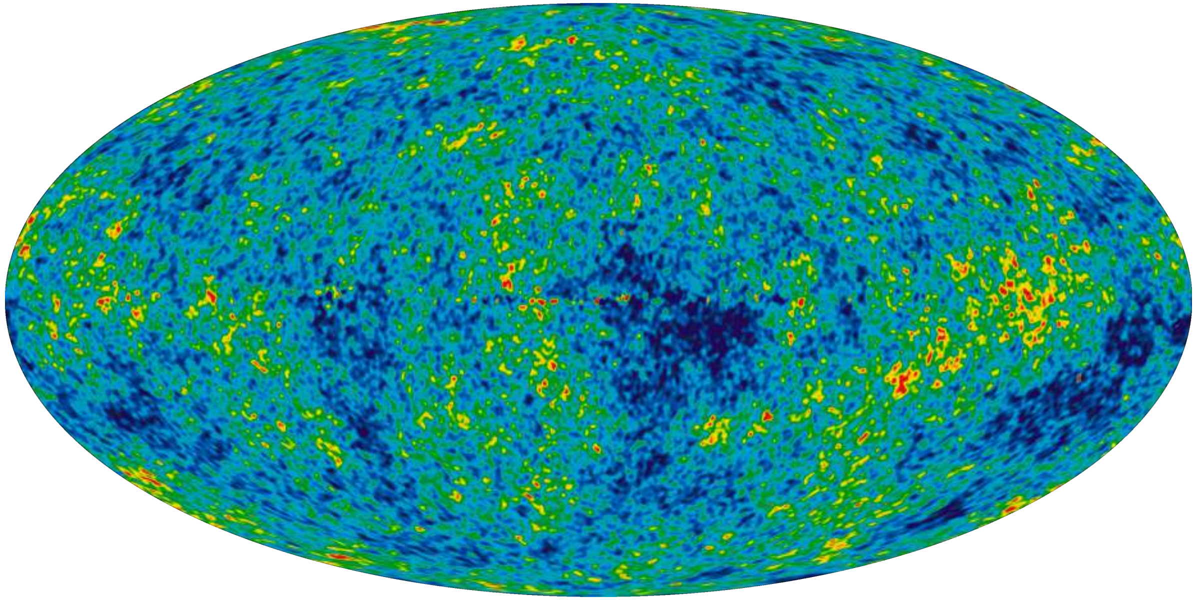
H and He
4%

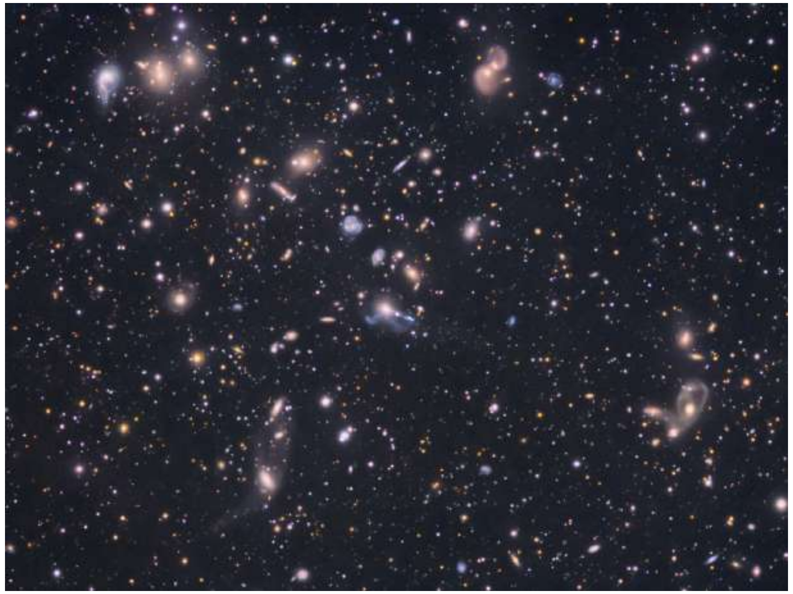
Stars
0.5%

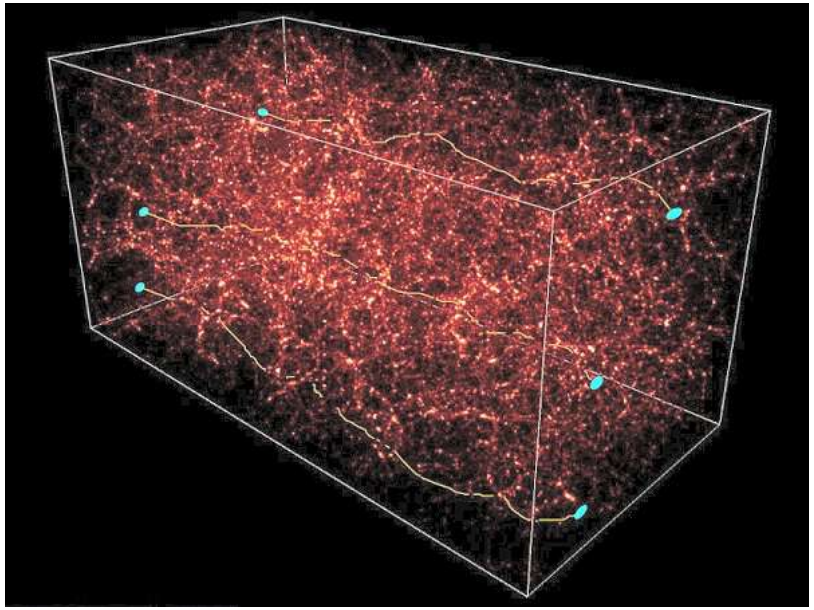
Metals
0.03%

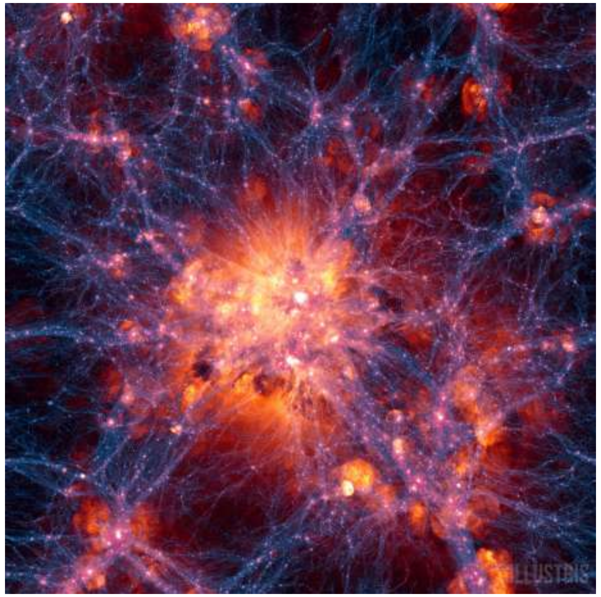


The ΛCDM model: observations









The ΛCDM model: parameters

Parameter	Description
Ω_m	Abundance of standard + dark matter
Ω_b	Abundance of standard matter
Ω_k	Geometry of the Universe
Ω_Λ	Abundance of dark energy
ω	Nature of dark energy
h	Expansion rate of the Universe
n_s	Properties of the Universe's initial conditions
σ_8	Amplitude of density perturbations
M_ν	Neutrino masses
N_{eff}	Effective number of neutrino species

Goal: Constrain these parameters with the highest accuracy

Why?: To learn about fundamental physics

- What is the nature of dark energy?
- How fast is the Universe expanding?
- What are the neutrino masses?

The ΛCDM model: builder

Jim Peebles
Nobel prize 2019

Summary

- The standard model of cosmology

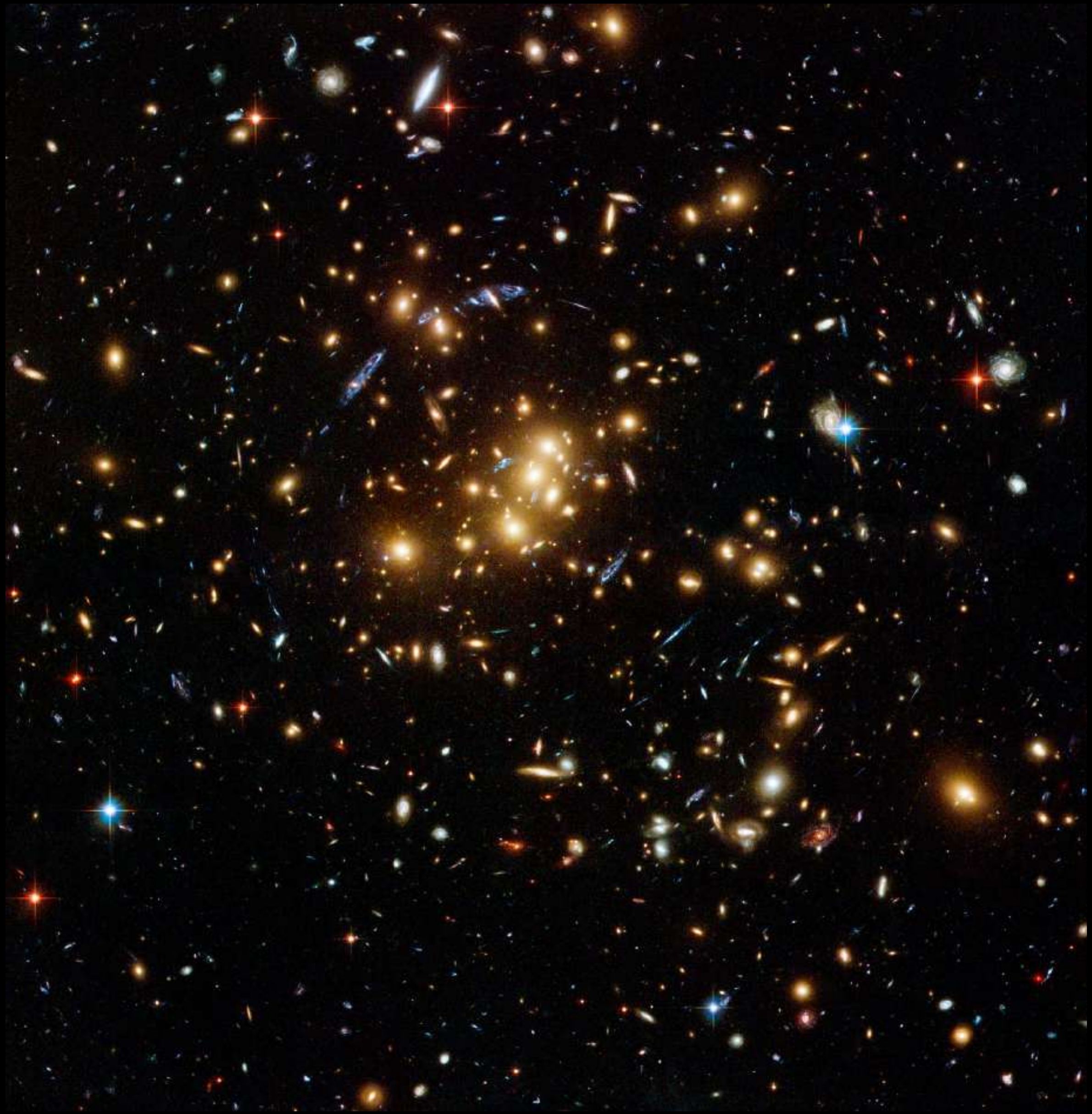
- Parameter estimation

- Machine learning

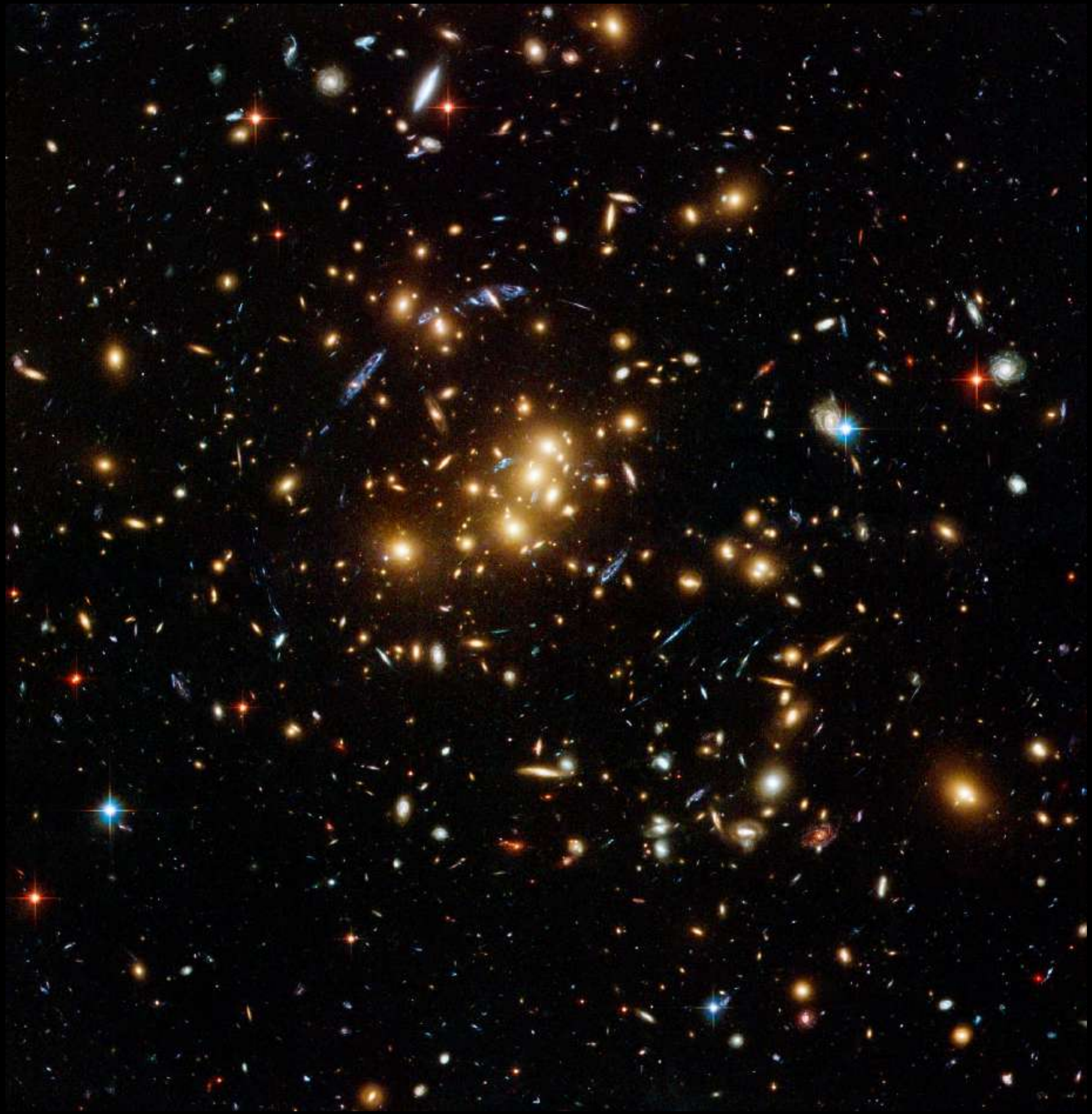
- Our vision/dream

Written in the sky

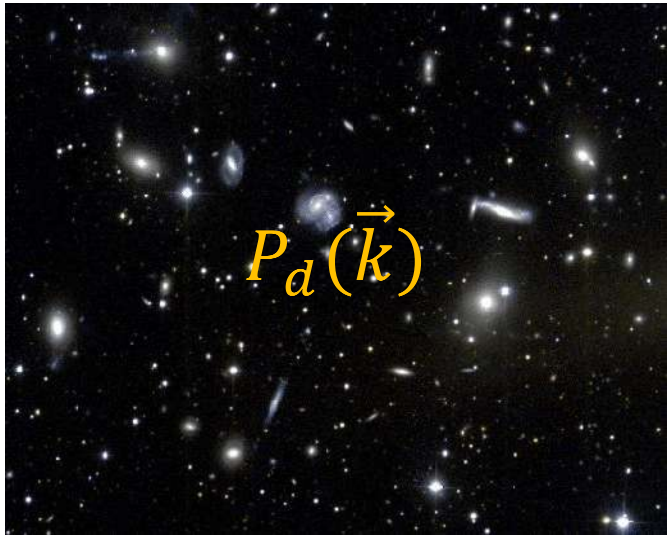
$$\vec{\theta} = \{\Omega_{\mathrm{m}}, \Omega_{\mathrm{b}}, \Omega_k, \Omega_\Lambda, w, h, n_{\mathrm{s}}, \sigma_8, M_\nu, N_{\mathrm{eff}}\}$$



Written in the sky

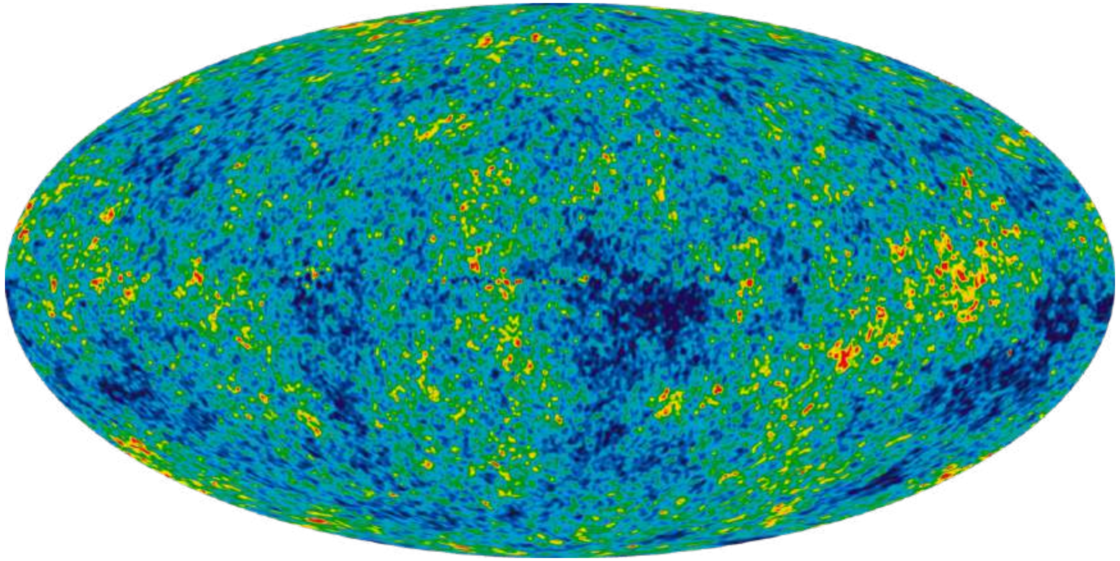


Parameter inference

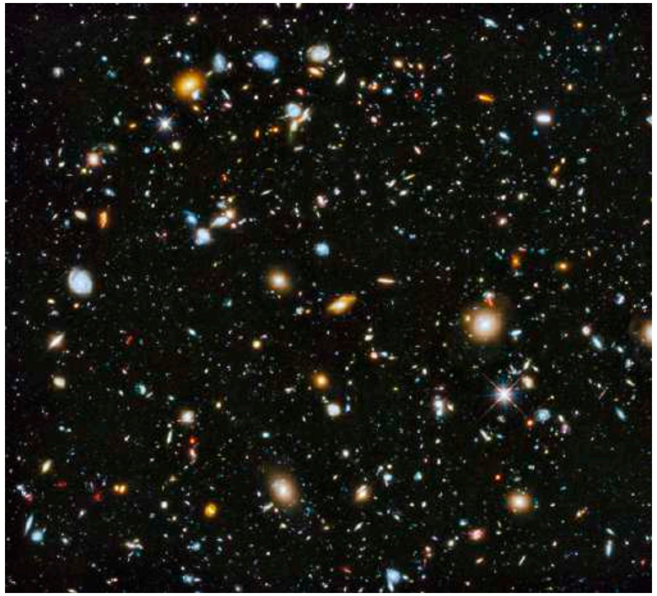
Observations	**Theory**
	$P_t(\vec{k}\|\vec{\theta})$ $\vec{\theta} = \{\Omega_{\rm m}, \Omega_{\rm b}, \Omega_{\Lambda}, w, h, n_{\rm s}, \sigma_8, M_{\nu}, N_{\rm eff}\}$

What *summary statistics* shall we use
to determine $\vec{\theta}$ with the smallest error?

Parameter inference: summary statistics



Gaussian density field
Fully described by the power spectrum



Non-Gaussian density field
Mathematically “intractable”
P(k), B(k), peaks, voids, …

Parameter inference: information content

How well can we constraint some parameters $\vec{\theta} = \{\Omega_m, \Omega_b, h, n_s, \sigma_8, M_\nu\}$ given some observables $\vec{S} = \{\mathrm{P}(\mathrm{k}_0), \mathrm{P}(\mathrm{k}_1), \mathrm{P}(\mathrm{k}_2) \ldots \mathrm{P}(\mathrm{k}_n), \ldots\}$?

$$\text{Fisher matrix} \left\{ \begin{array}{l} \mathrm{F}_{\alpha\beta} = \dfrac{\partial \vec{S}}{\partial \theta_\alpha} C^{-1} \dfrac{\partial \vec{S}}{\partial \theta_\beta} \\[2em] \delta\theta_\alpha \geq (F^{-1})_{\alpha\alpha} \end{array} \right.$$

The Quijote Simulations

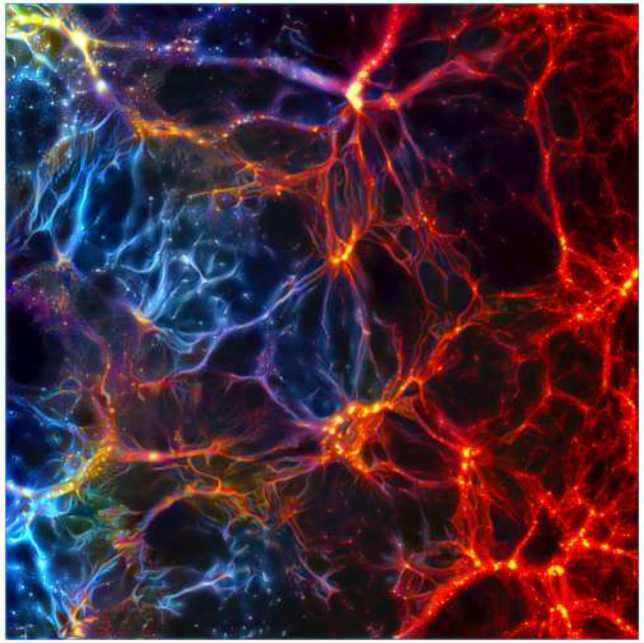
(https://github.com/franciscovillaescusa/Quijote-simulations)

Characteristics:

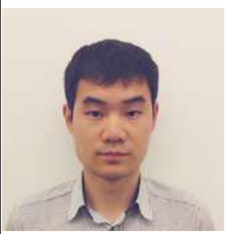
- A set of 43100 full N-body simulations; largest set to-date
- More than 7000 cosmologies in $\{\Omega_m, \Omega_b, h, n_s, \sigma_8, M_\nu, \omega\}$
- More than 50 trillion particles over a volume larger than entire observable Universe
- 35M CPU hours; 1 Petabyte of data publicly available

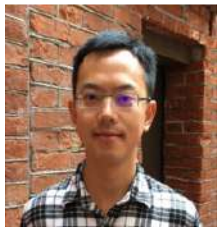
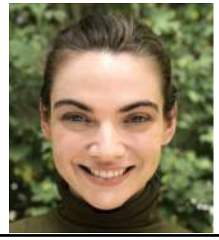
Designed to:

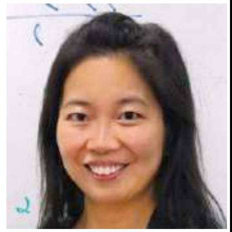
1. Quantify the information content on cosmological observables
2. Provide enough data to train machine learning algorithms



The Quijote Simulations: team

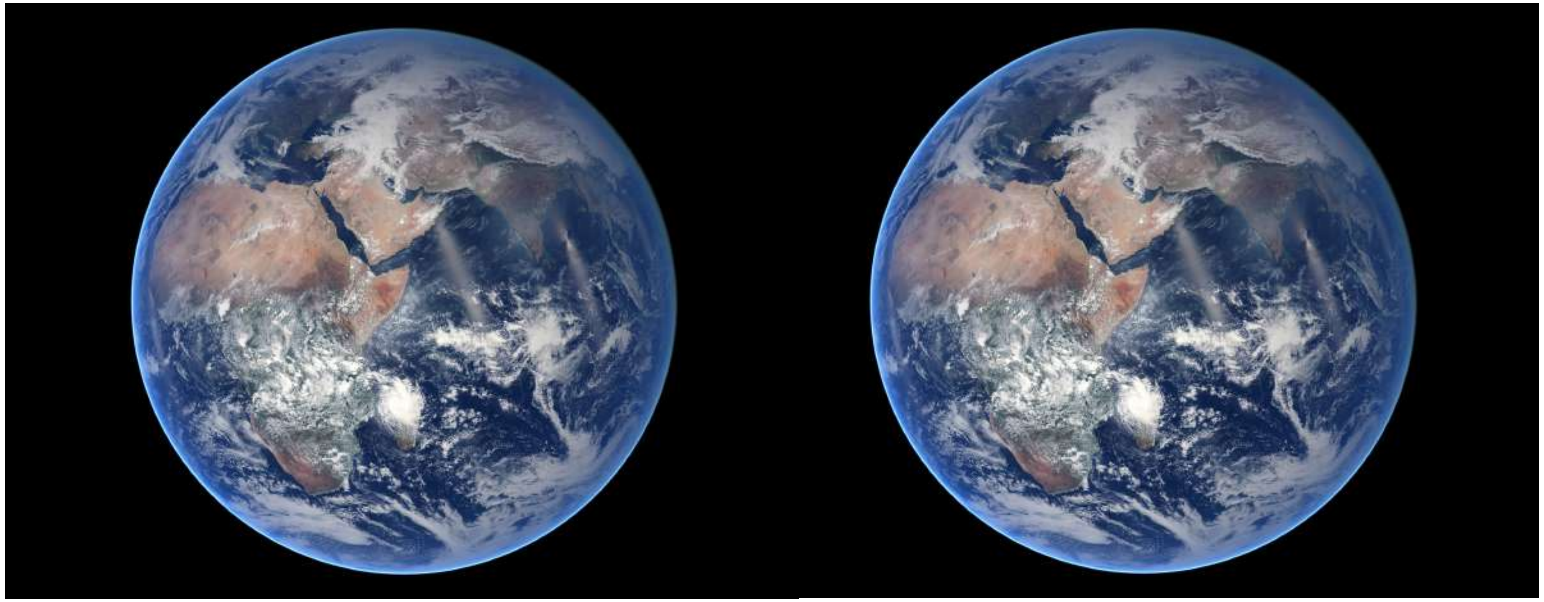
										
ChangHoon Hahn (Berkeley)	Elena Massara (Flatiron)	Arka Banerjee (Stanford)	Ana M. Delgado (Flatiron)	Doogesh Ramanah (IAP, Paris)	Tom Charnock (IAP, Paris)	Elena Giusarma (Flatiron/MTech)	Yin Li (IPMU/Berkeley)	Erwan Allys (Ecole Normale)	Antoine Brochard (Ecole Normale)	Cora Uhlemann (Cambridge)

									
Chi-Ting Chiang (BNL)	Siyu He (Flatiron)	Alice Pisani (Princeton)	Andrej Obuljen (Waterloo)	Yu Feng (Berkeley)	Emanuele Castorina (Berkeley)	Gabriella Contardo (Flatiron)	Christina Kreisch (Princeton)	Andrina Nicola (Princeton)	Justin Alsing (Oskar Klein)

						
Roman Scoccimarro (NYU)	Licia Verde (Barcelona)	Matteo Viel (SISSA)	Shirley Ho (Flatiron/Princeton)	Stephane Mallat (College de France)	Ben Wandelt (IAP, Paris)	David Spergel (Flatiron/Princeton)

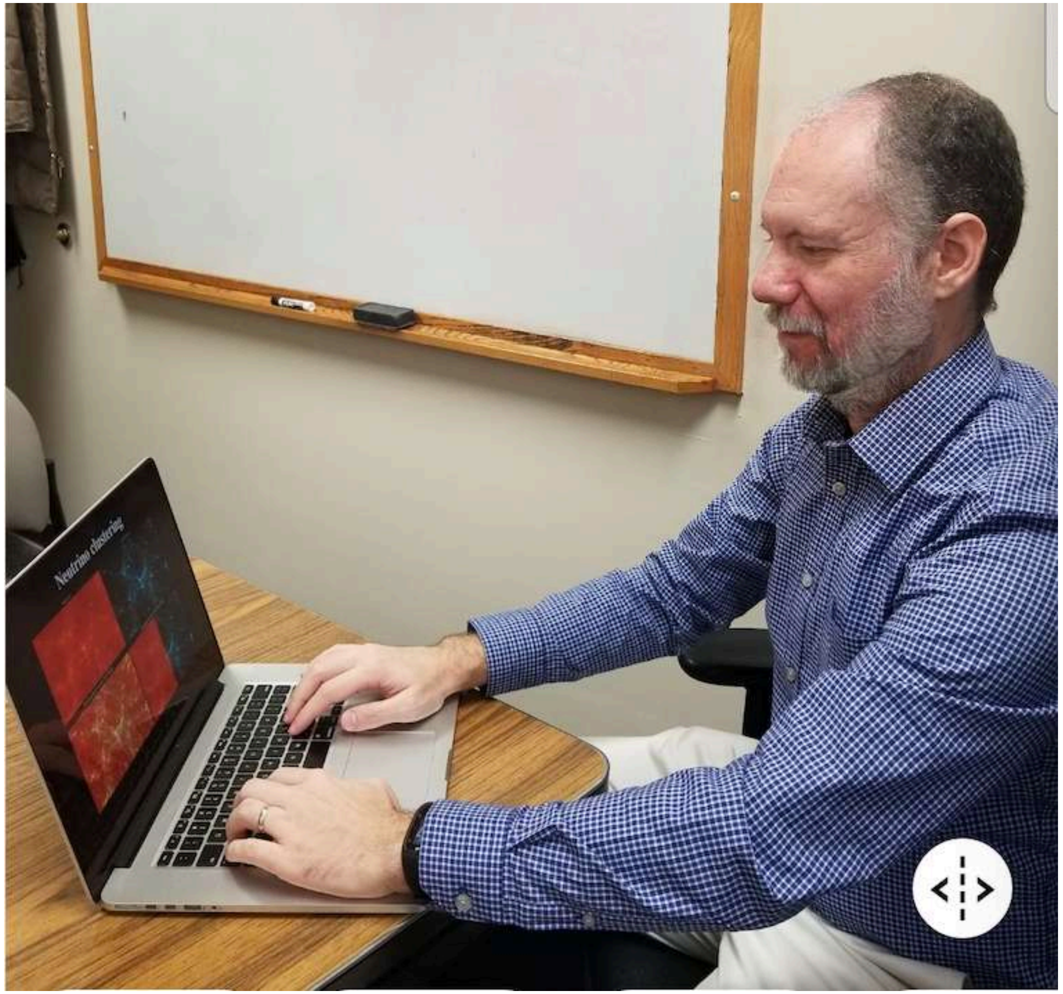
The Quijote simulations: # of particles

Manhattan	23 miles^2	1.7 Million people
USA	3 Million miles^2	100 Billion people
2 Earths	300 Million miles^2	8.5 Trillion people



The Quijote simulations: volume

The Quijote Simulations: CPU time & data

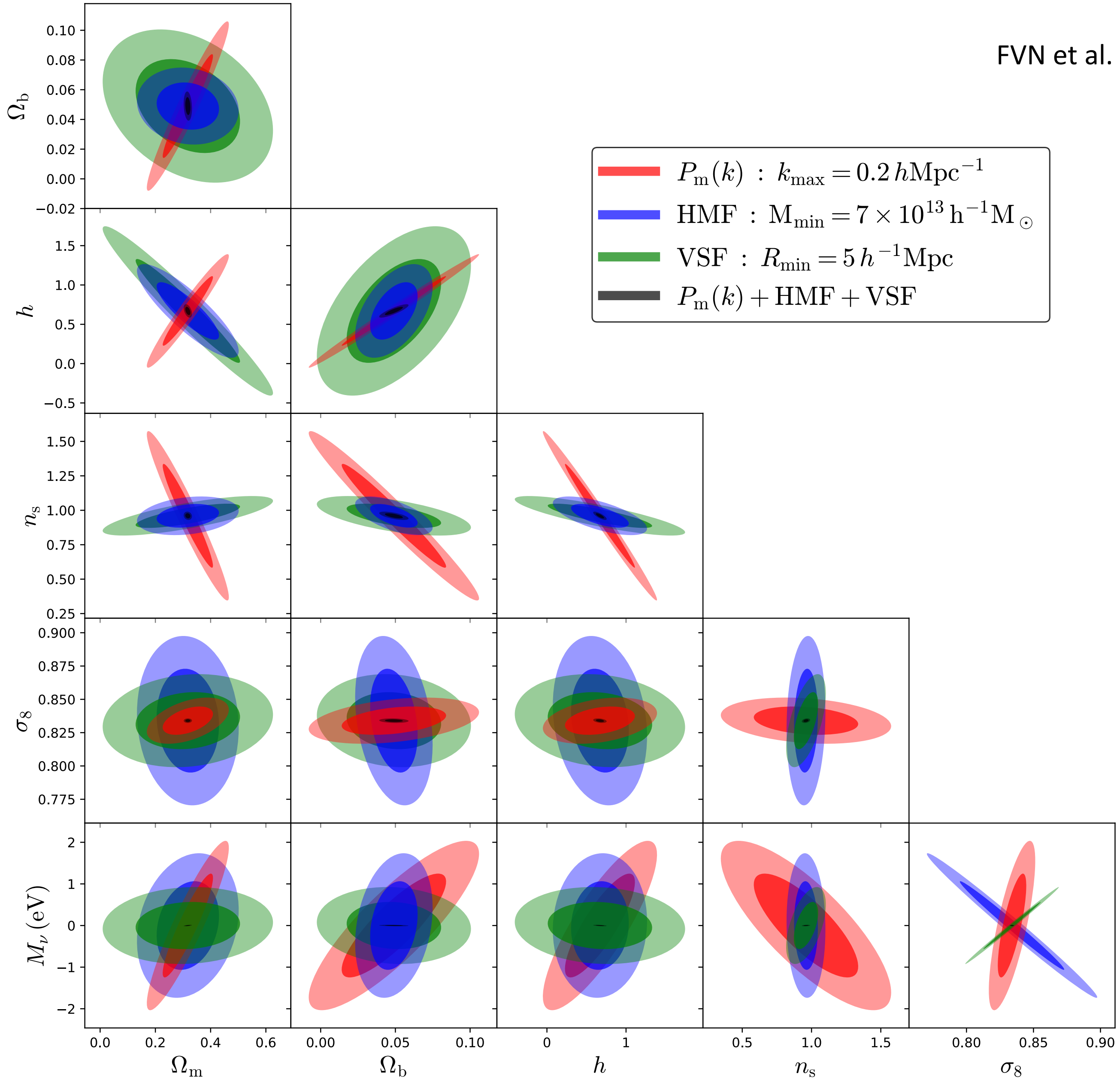


1% complete in 40 years!
(4000 years in a single computer)

- 35 Million CPU hours
- 1 Petabyte of data

Information content

FVN et al. (in prep)



Information content

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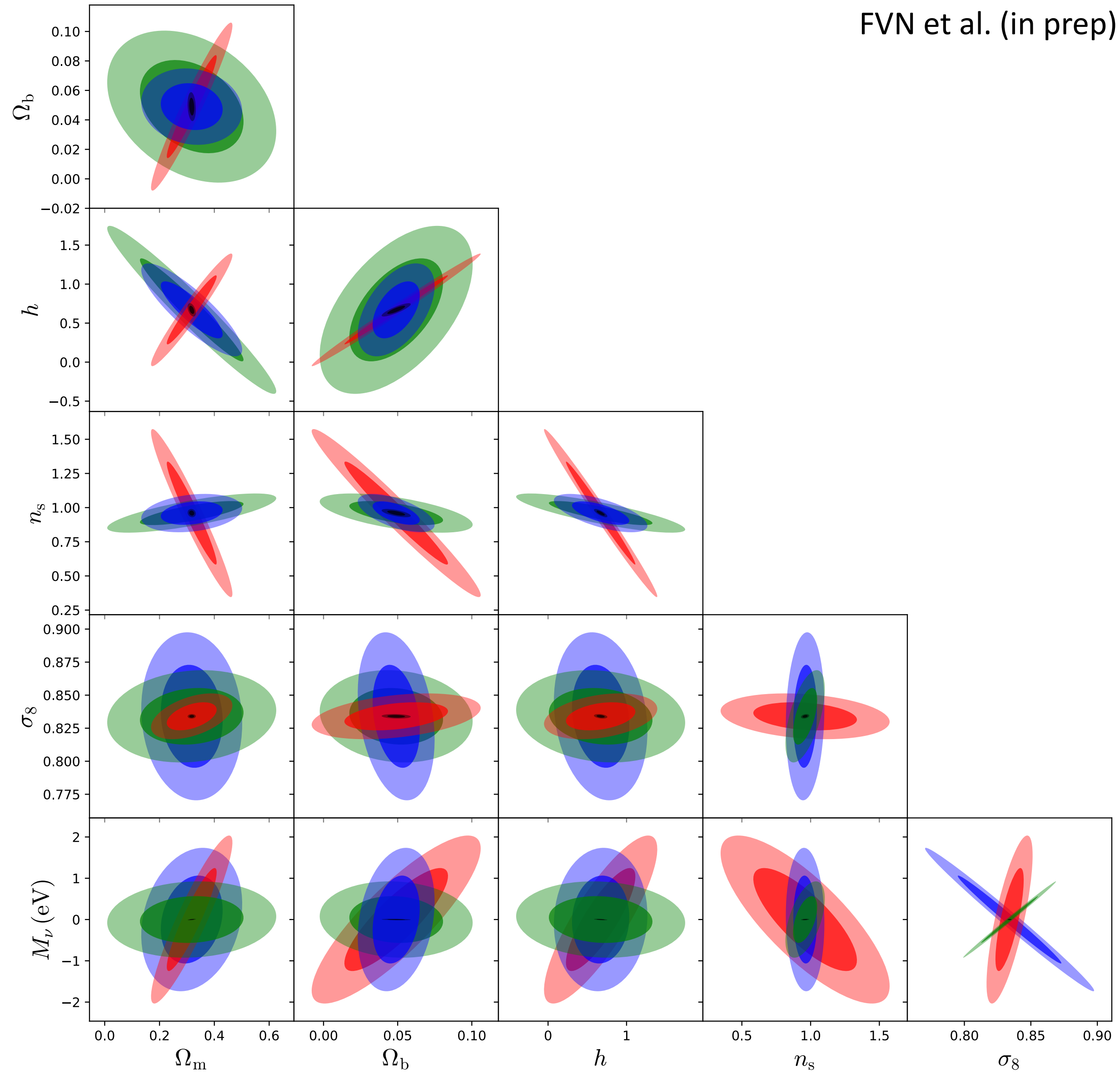
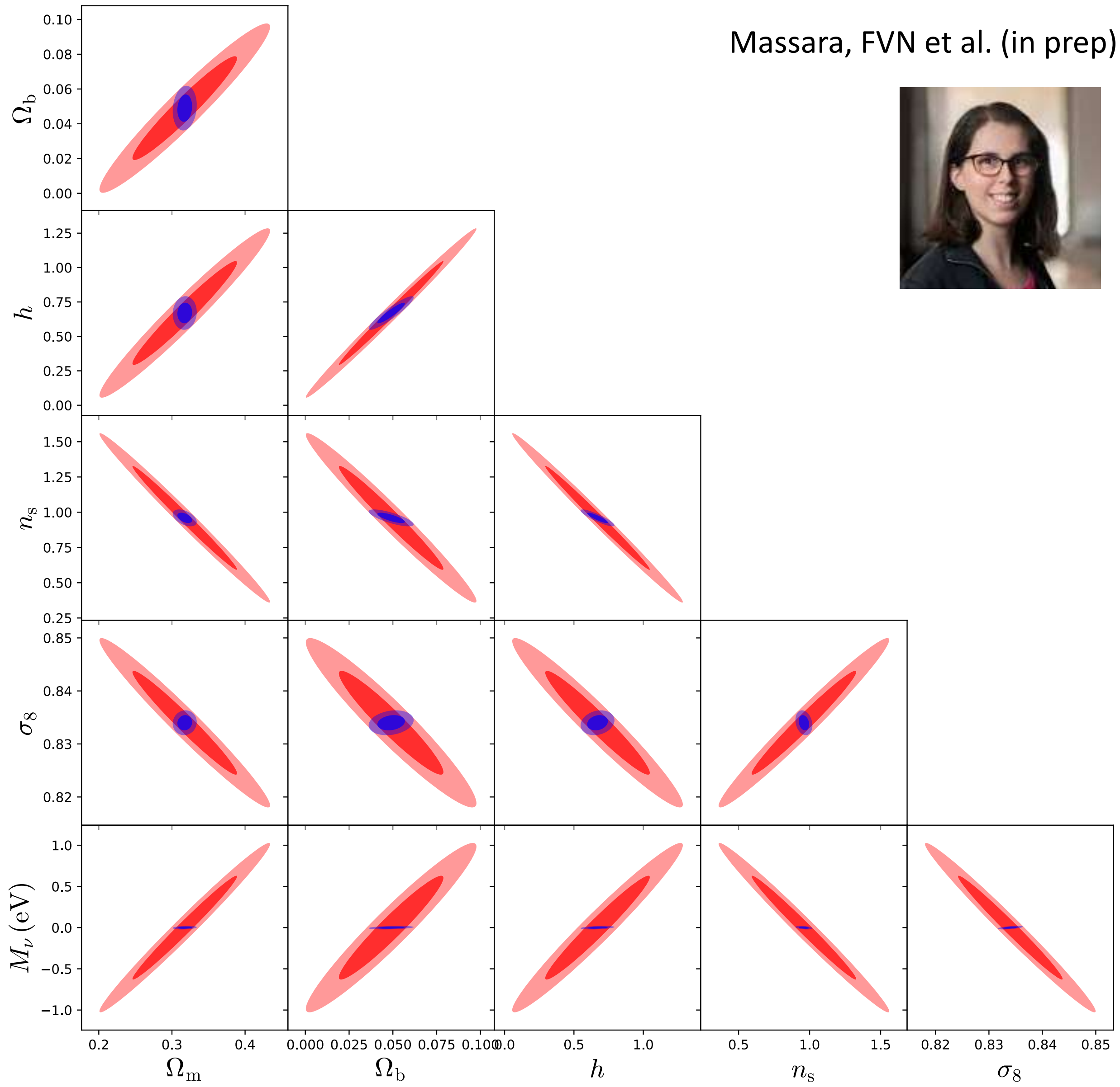
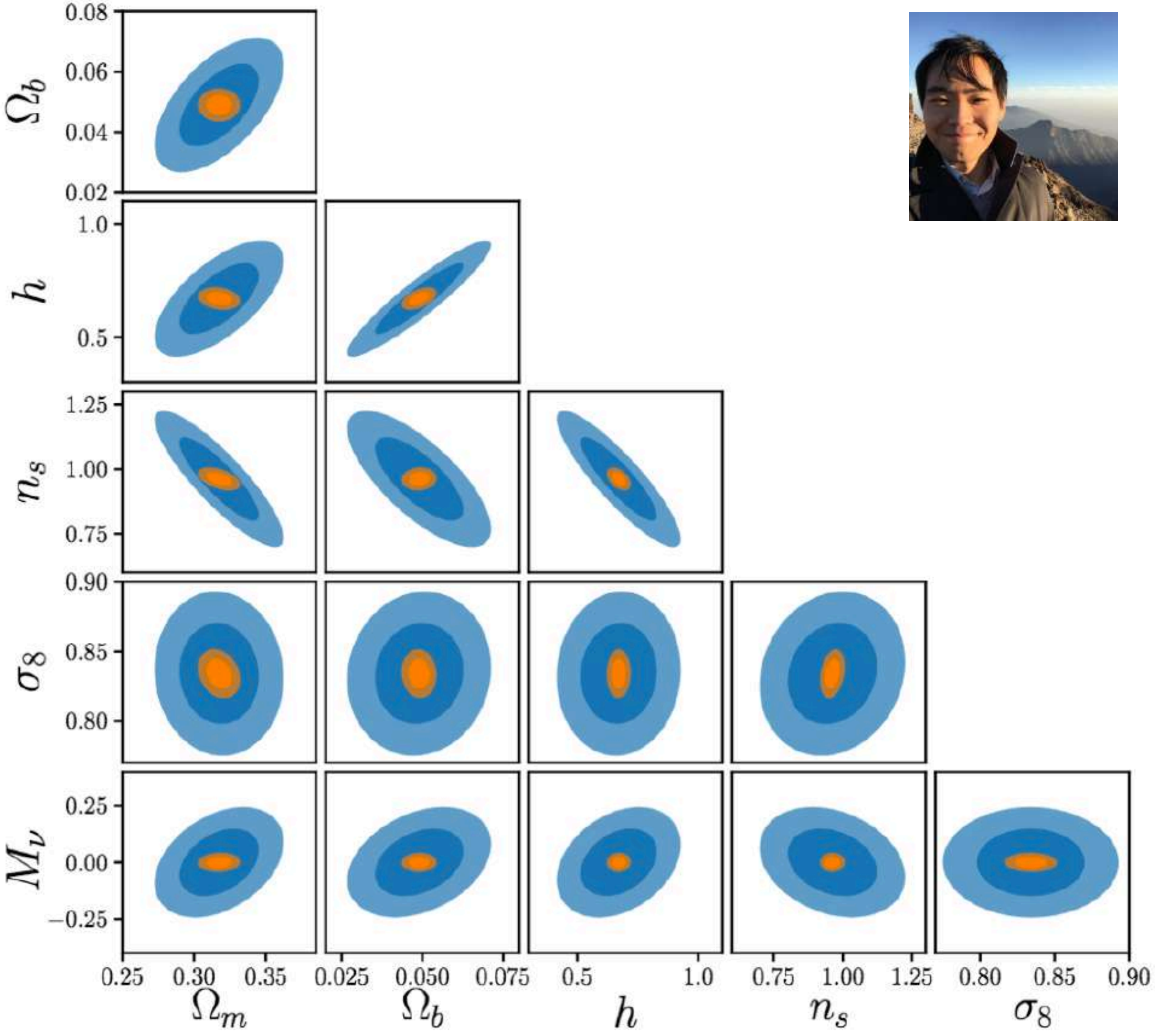


Massara, FVN et al. (in prep)

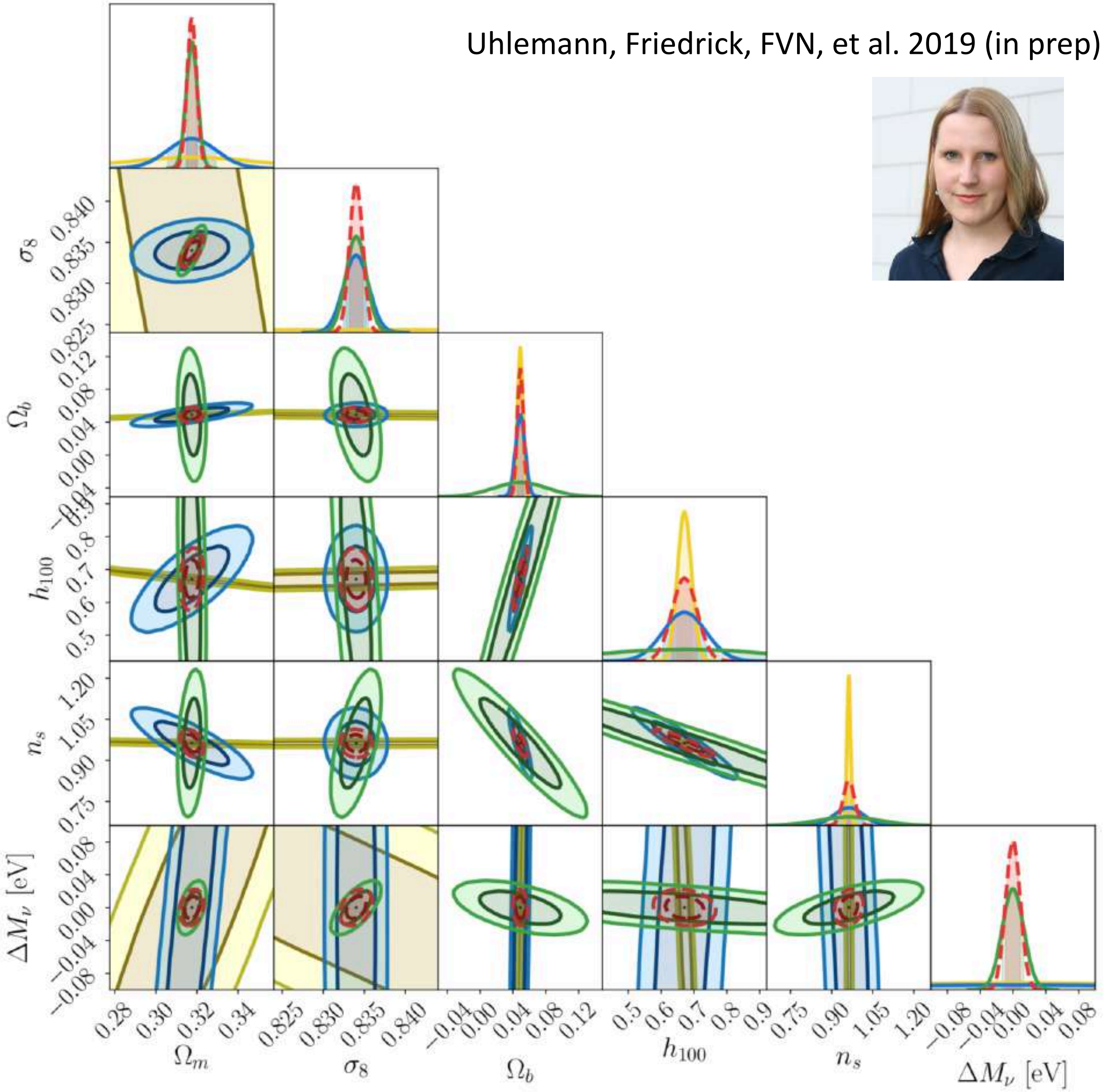


Information content

Hahn, FVN, Castorina, Scoccimarro 2019



Uhlemann, Friedrick, FVN, et al. 2019 (in prep)



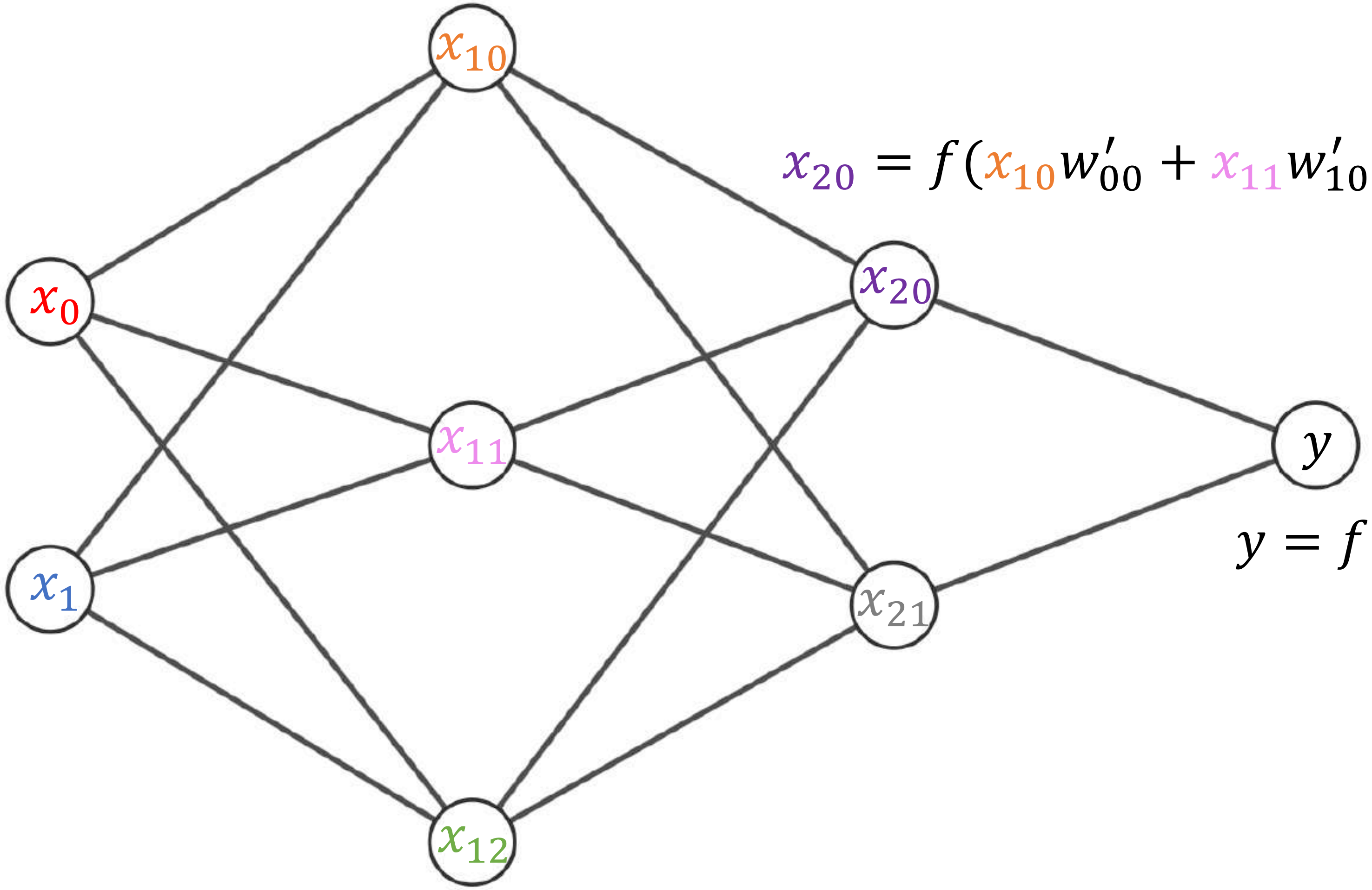
Summary

- The standard model of cosmology
- Parameter estimation
- Machine learning
- Our vision/dream

Machine Learning: neural networks

$$x_{10} = f(x_0 w_{00} + x_1 w_{10} + b_{00})$$

$$x_{20} = f(x_{10} w'_{00} + x_{11} w'_{10} + x_{12} w'_{20} + b_{10})$$

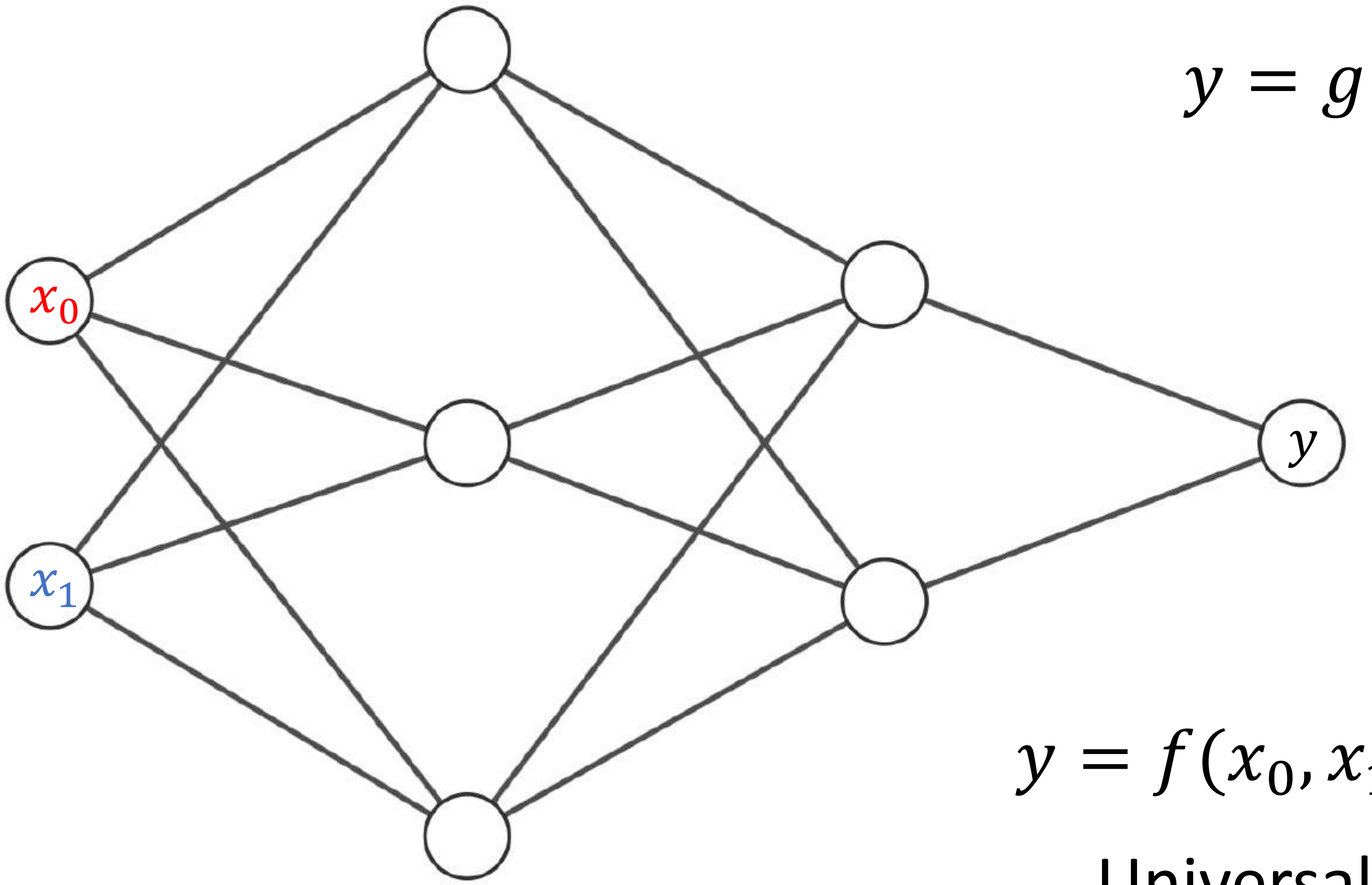


$$y = f(x_{20} w''_{00} + x_{21} w''_{10} + b_{20})$$

$$x_{12} = f(x_0 w_{02} + x_1 w_{12} + b_{02})$$

$$f(x) = \begin{cases} x & \text{if x} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Machine Learning: neural networks



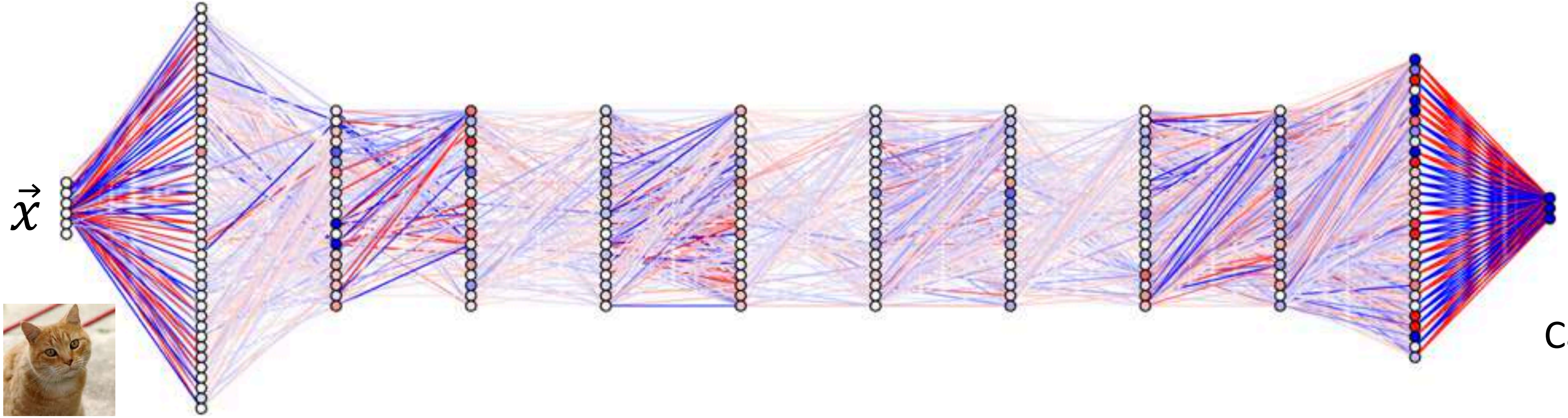
$$y = g(x_0, x_1, w_{00}, w_{10}, \dots)$$

$$y = f(x_0, x_1) \simeq g(x_0, x_1, w_{00}, w_{10}, \dots)$$

Universal approximation theorem

Machine Learning: neural networks

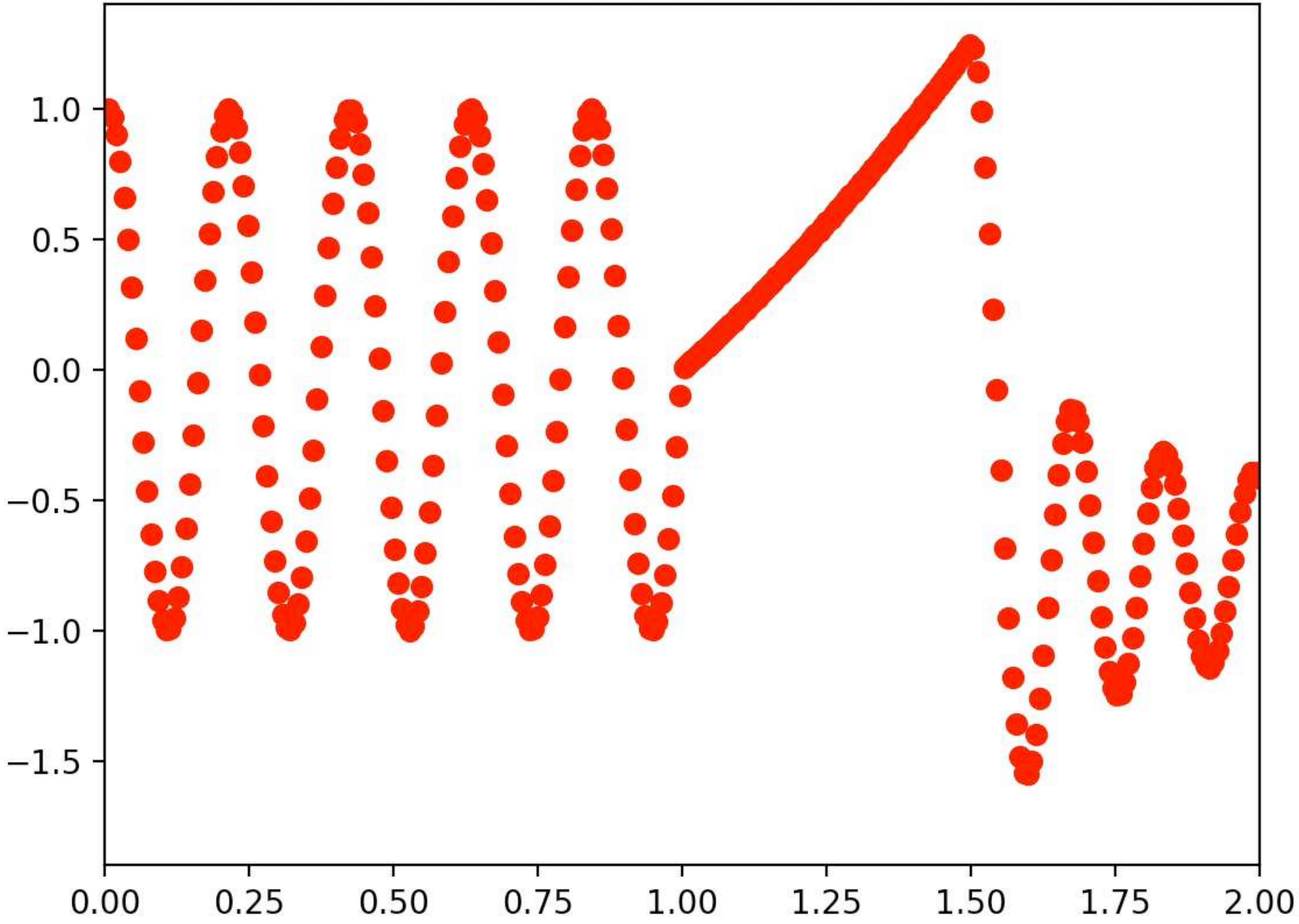
$\vec{x}$

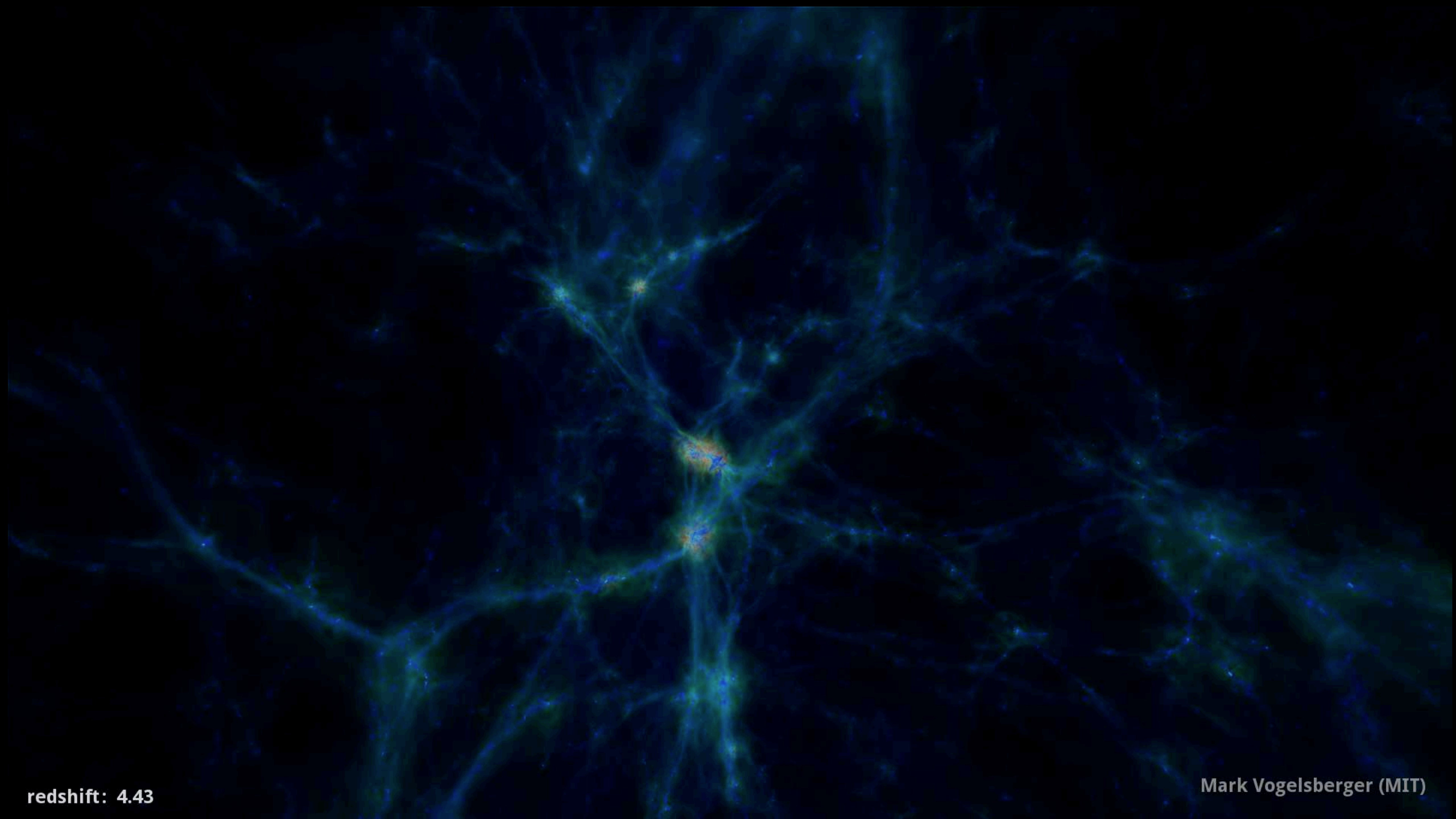


$\vec{y}$

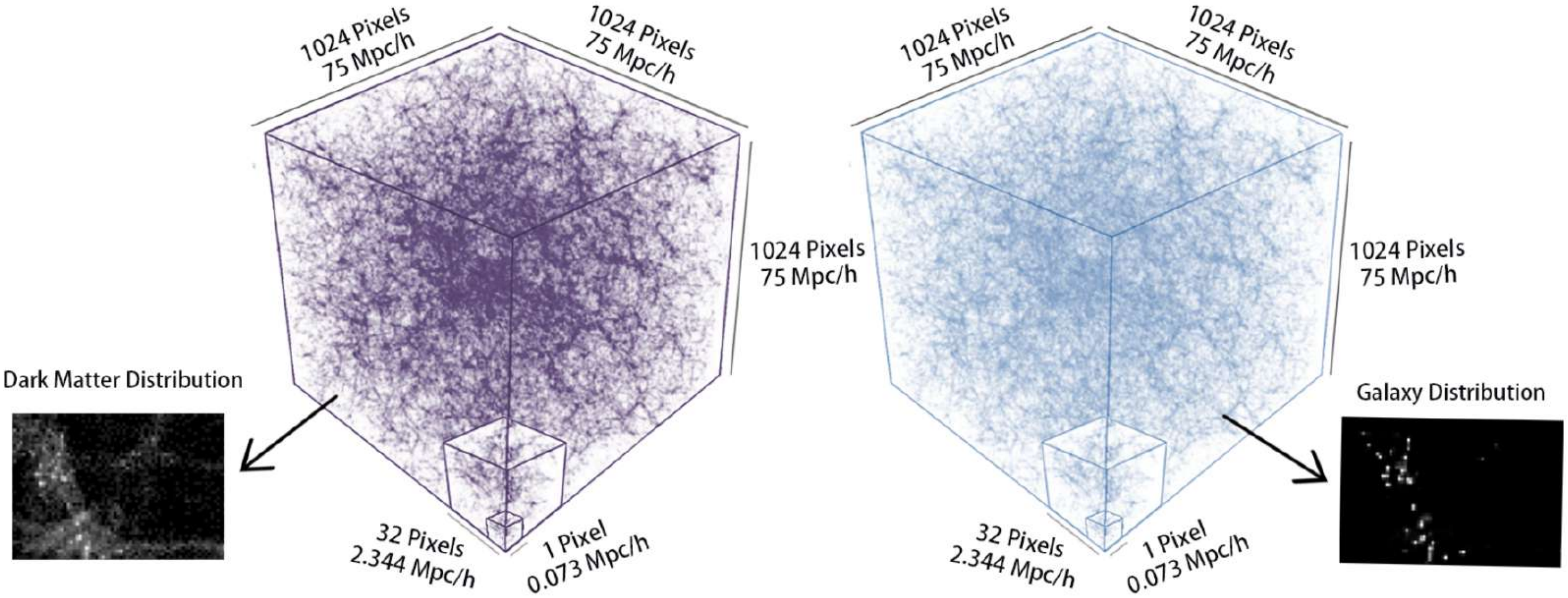
Cat

Machine Learning




redshift: 4.43
Mark Vogelsberger (MIT)

Supervised learning: dark matter to galaxies

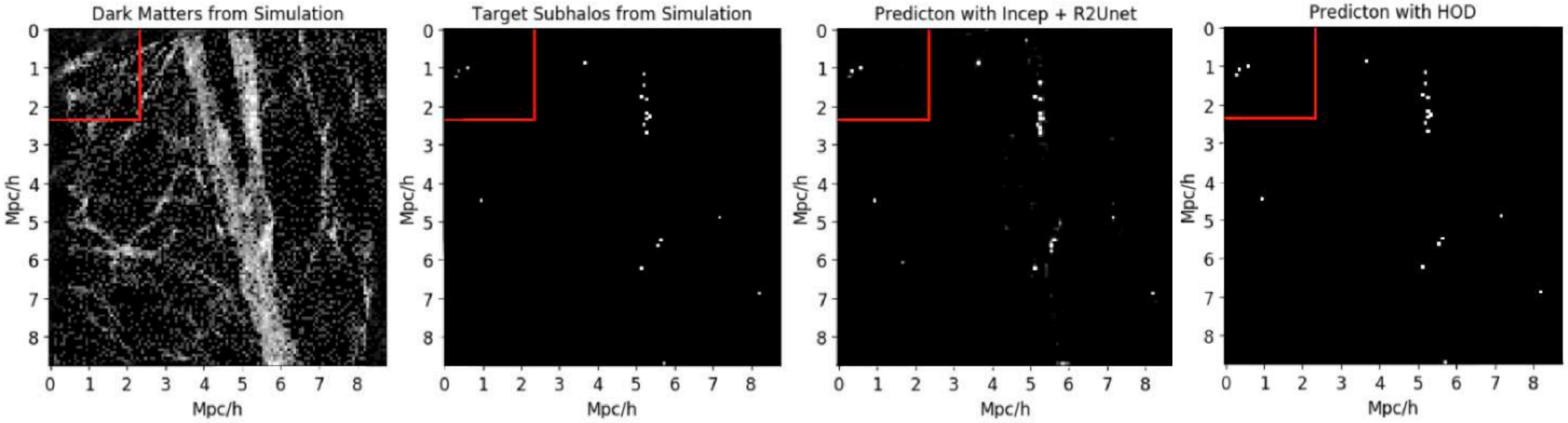


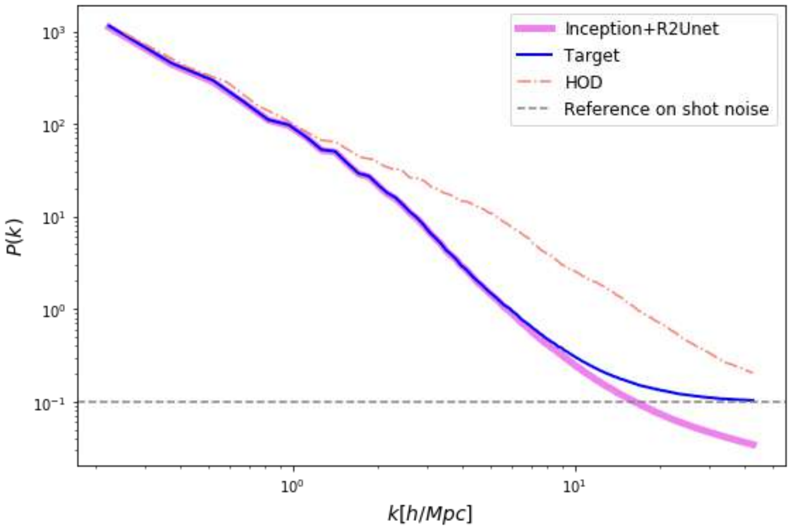
$$\delta_g(\vec{x}) = f(\delta_m(\vec{x}), \nabla_i \nabla_j \phi(\vec{x}), \ldots)$$

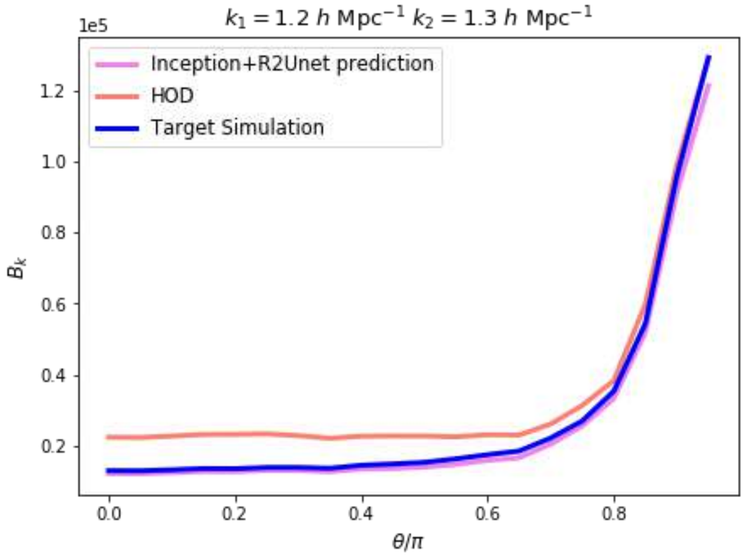
Very complicated function
Deep learning will find it

Supervised learning: dark matter to galaxies

Zhang, Wang, Zhang, Sun, He, Contardo, FVN, Ho 2019
Yip, Zhang, Wang, Zhang, Sun, Contardo, FVN, He, Genel, Ho 2019



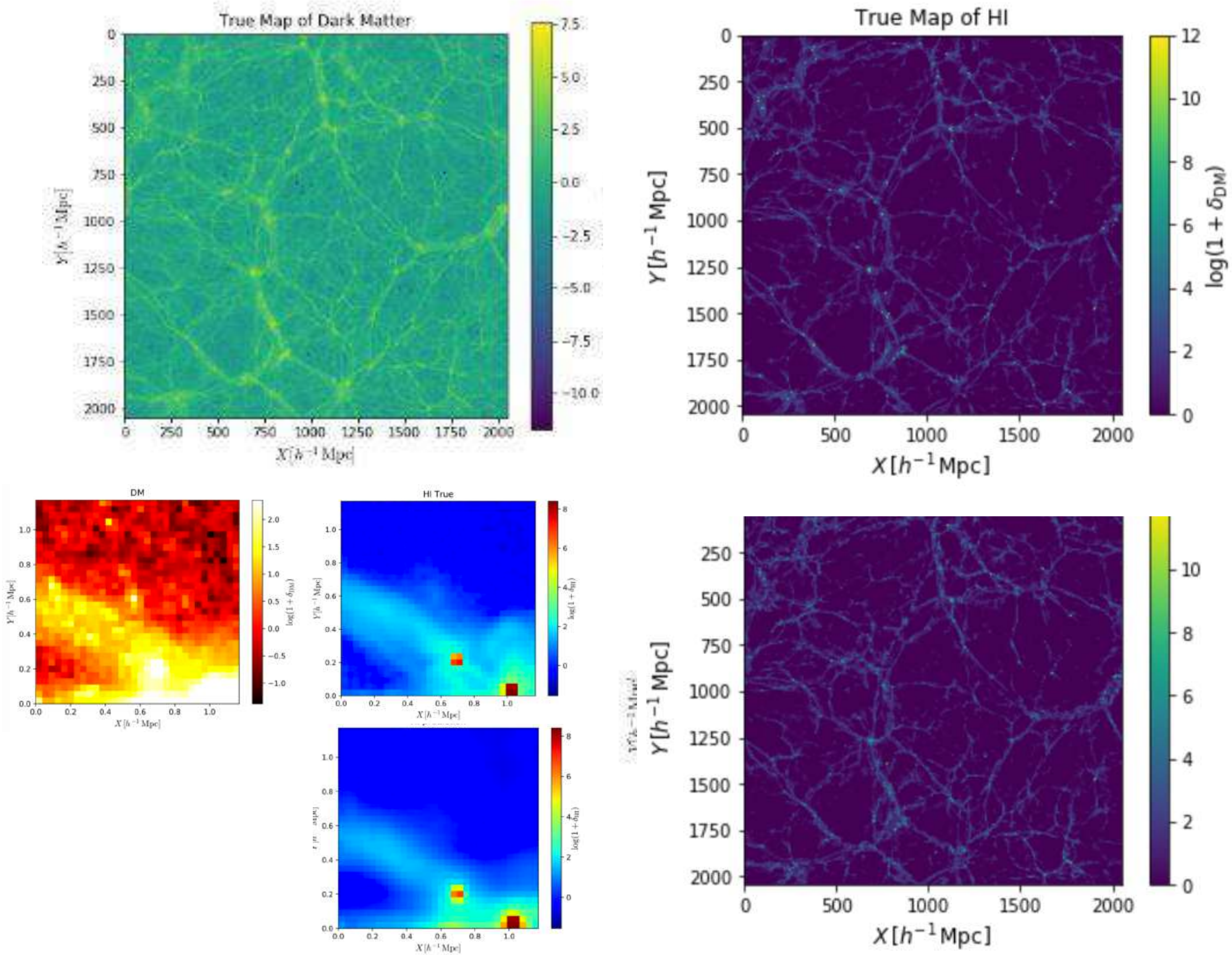




Supervised learning: dark matter to cosmic HI

Shao, FVN et al. (in prep)

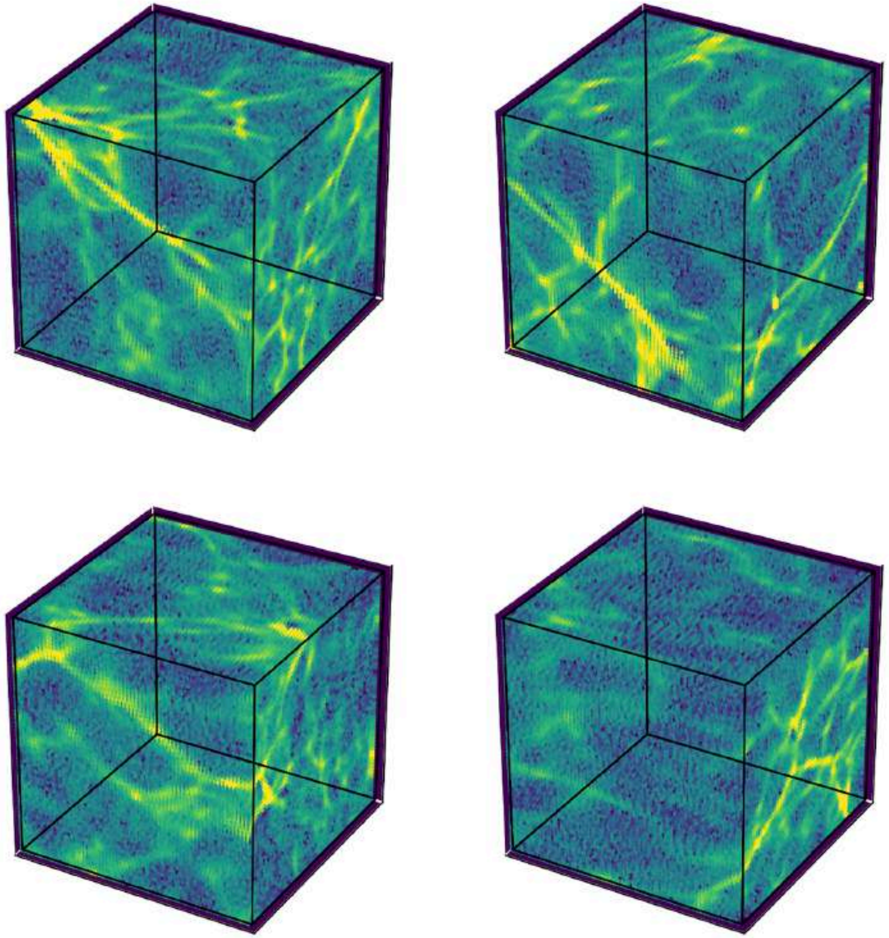
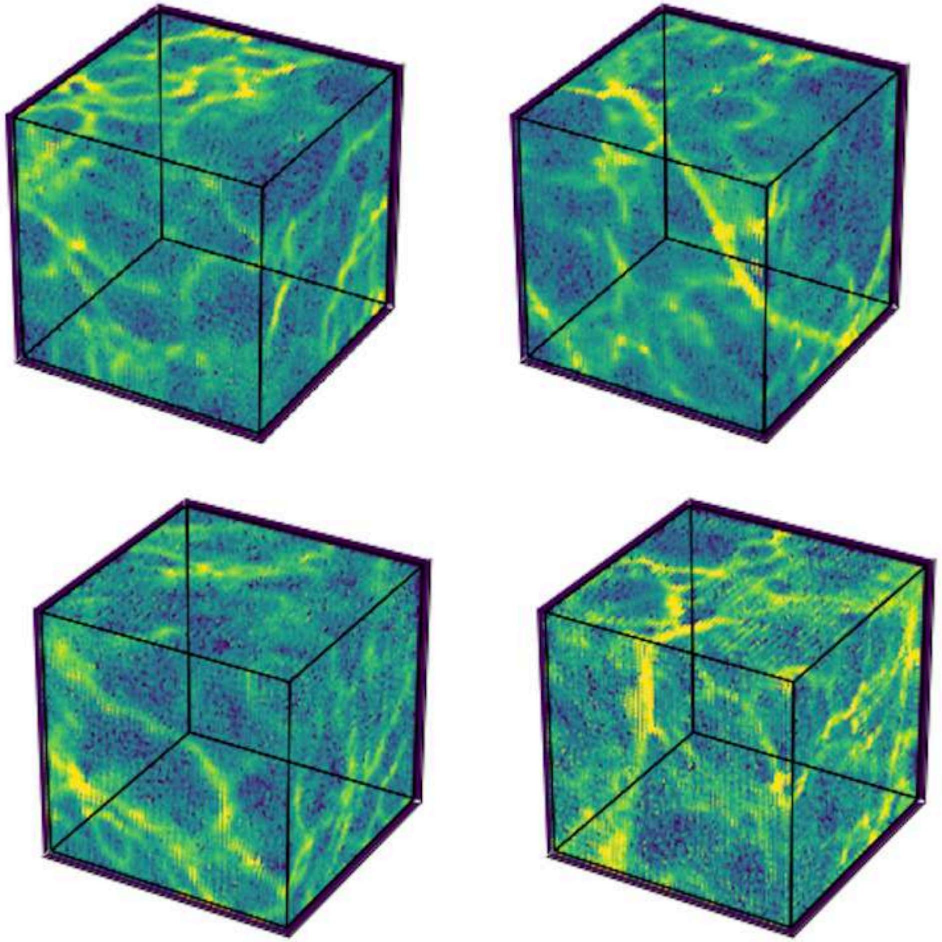
Helen Shao
Bronx high-school Science



Unsupervised learning: cosmic HI

Zamudio, Okan, FVN, Cengiz, Bilaloglu, He, Ho 2019



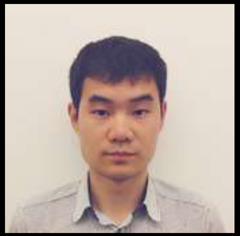




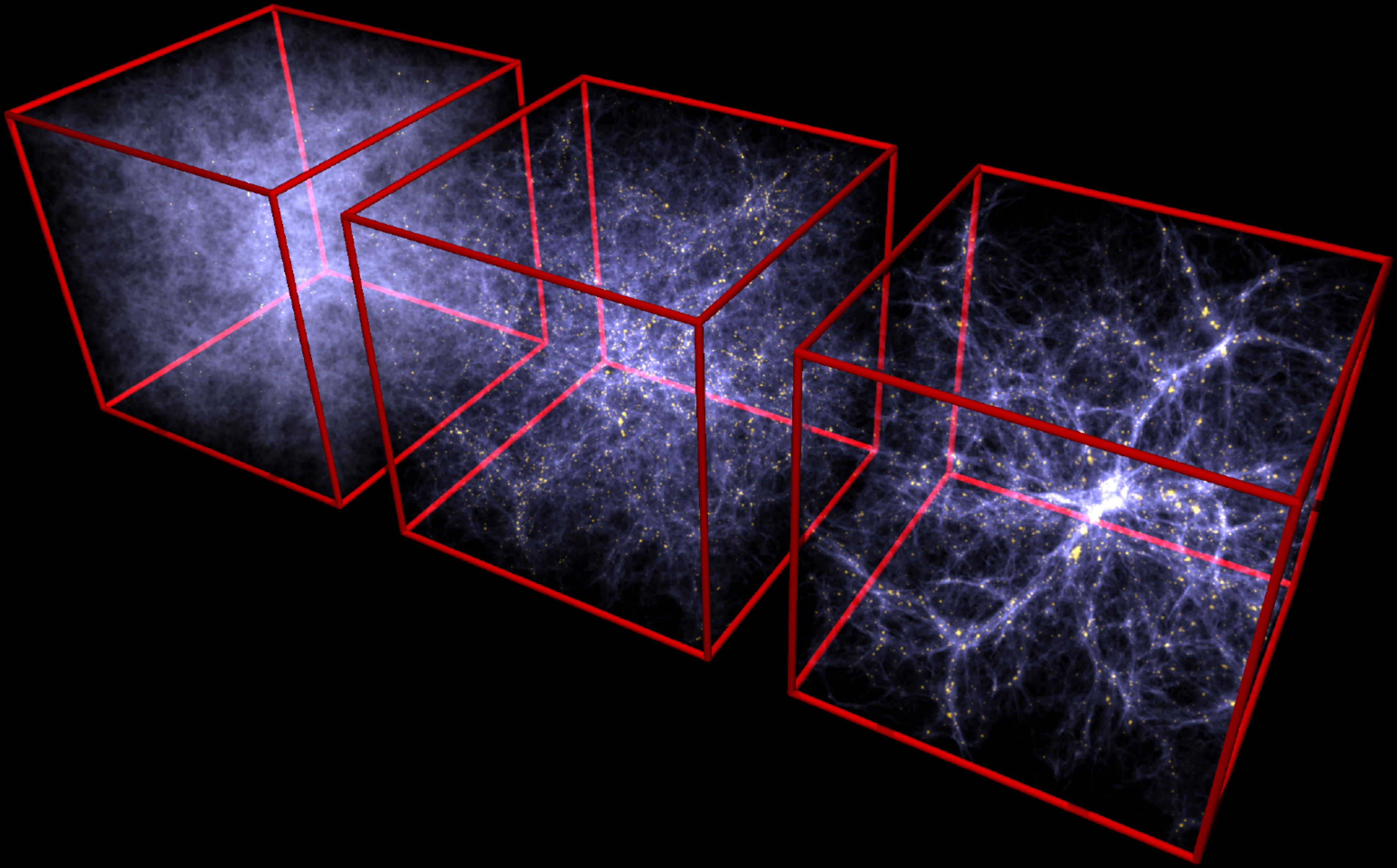
Unsupervised learning: human faces

https://www.thispersondoesnotexist.com/

Supervised learning: N-body simulations

He, Li, Feng et al. 2018
Li et al. 2019 (in prep)





Summary

- The standard model of cosmology
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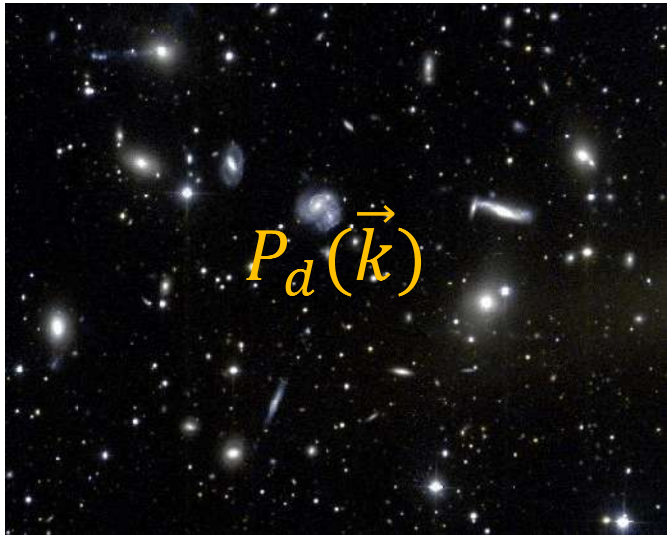
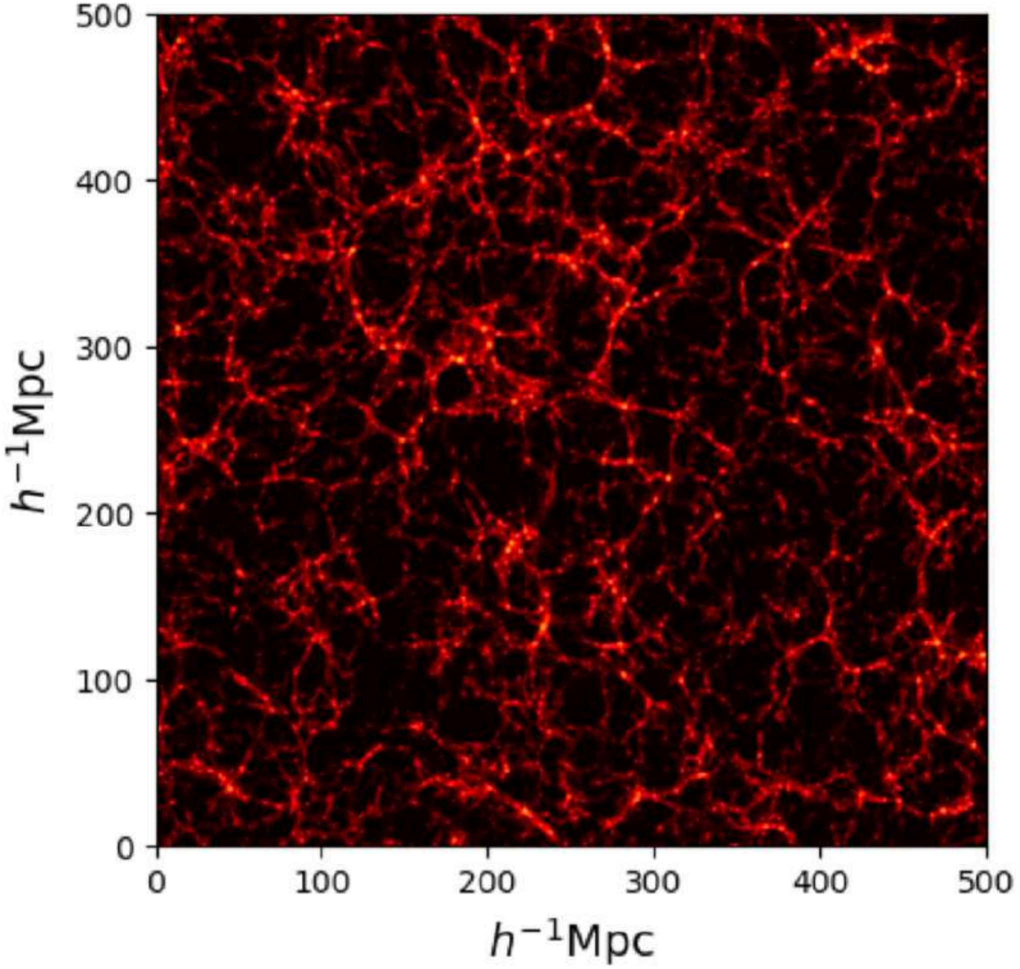
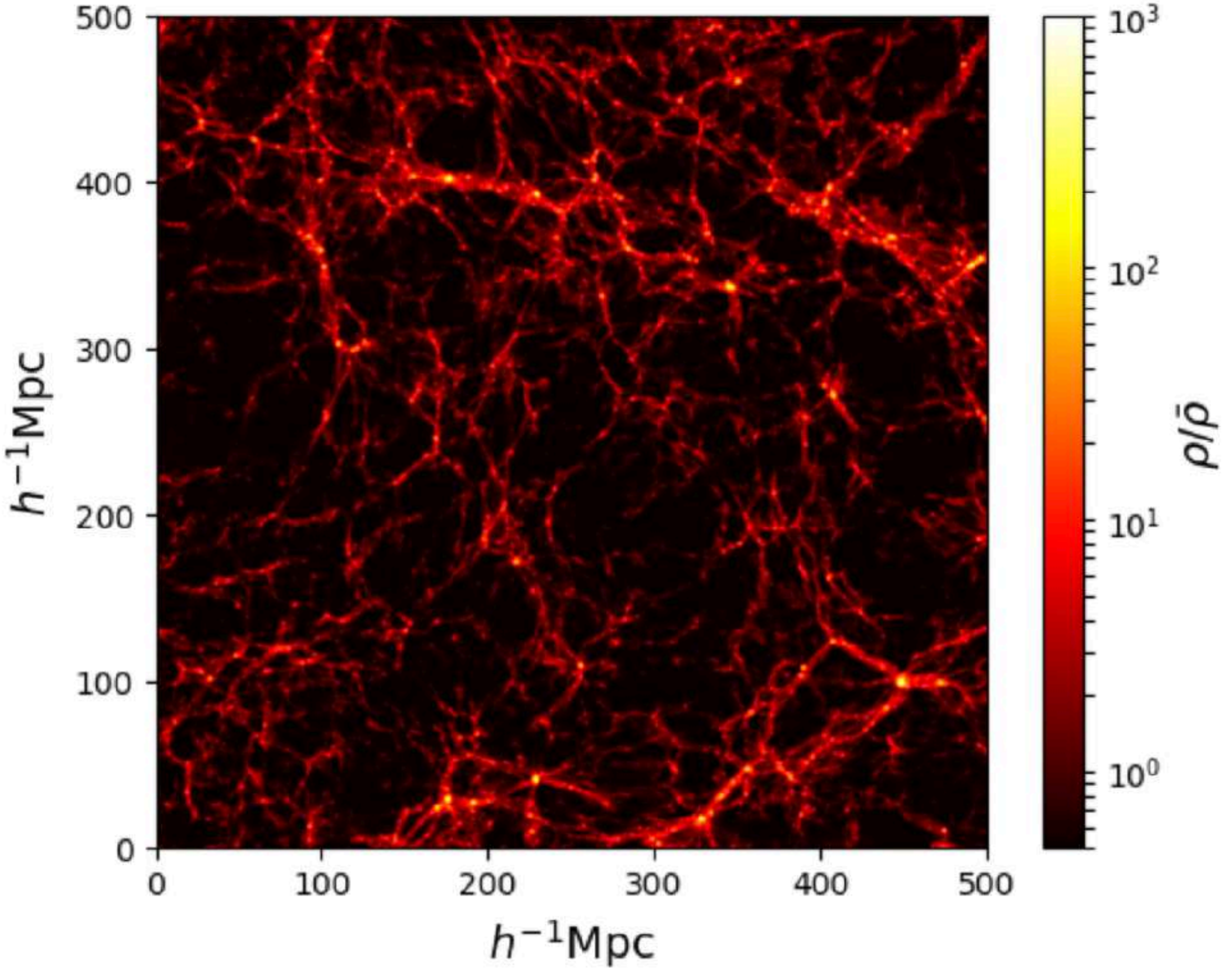
Parameter inference

Observations	**Theory**
	$P_t(\vec{k}\vert\vec{\theta})$ $\vec{\theta} = \{\Omega_{\mathrm{m}}, \Omega_{\mathrm{b}}, \Omega_{\Lambda}, w, h, n_{\mathrm{s}}, \sigma_8, M_\nu, N_{\mathrm{eff}}\}$

What *summary statistics* shall we use
to determine $\vec{\theta}$ with the smallest error?

Parameter inference: neural networks





$\overrightarrow{\theta_1} = \{\Omega_\mathrm{m}, \Omega_\mathrm{b}, \Omega_\Lambda, w, h, n_\mathrm{s}, \sigma_8, M_\nu, N_\mathrm{eff}\}$

$\overrightarrow{\theta_2} = \{\Omega_\mathrm{m}, \Omega_\mathrm{b}, \Omega_\Lambda, w, h, n_\mathrm{s}, \sigma_8, M_\nu, N_\mathrm{eff}\}$

Parameter inference: neural networks

What do we need?

- Thousands of high-resolution simulations with different cosmologies and different astrophysics
- Deep neural network to go map 3D galaxy fields to the parameters

Parameter inference: neural networks

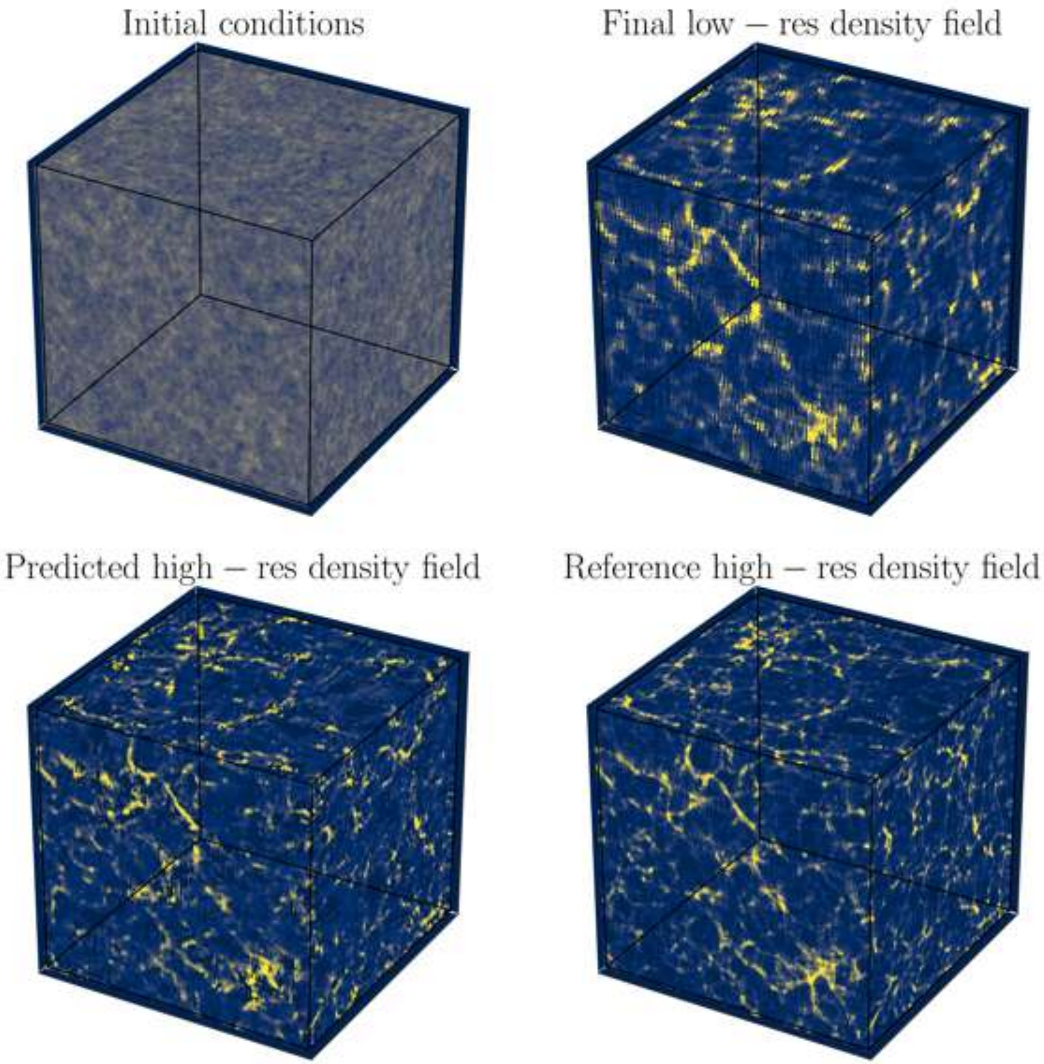
- **Thousands** of high-resolution simulations with different **cosmologies** and different astrophysics

- A set of 43100 full N-body simulations
- $\{\Omega_m, \Omega_b, h, n_s, \sigma_8, M_\nu, \omega\}$. More than 7000 cosmologies
- More than 8.5 trillion particles at a single redshift
- 35M CPU hours; 1 Pb of data publicly available

Parameter inference: neural networks

- Thousands of **high-resolution** simulations with different cosmologies and different astrophysics

Ramanah, Charnock, FVN, Wandelt (in prep)



Parameter inference: neural networks

- Thousands of high-resolution simulations with different cosmologies and different **astrophysics**

FVN et al. (in prep)

CAMEL simulations

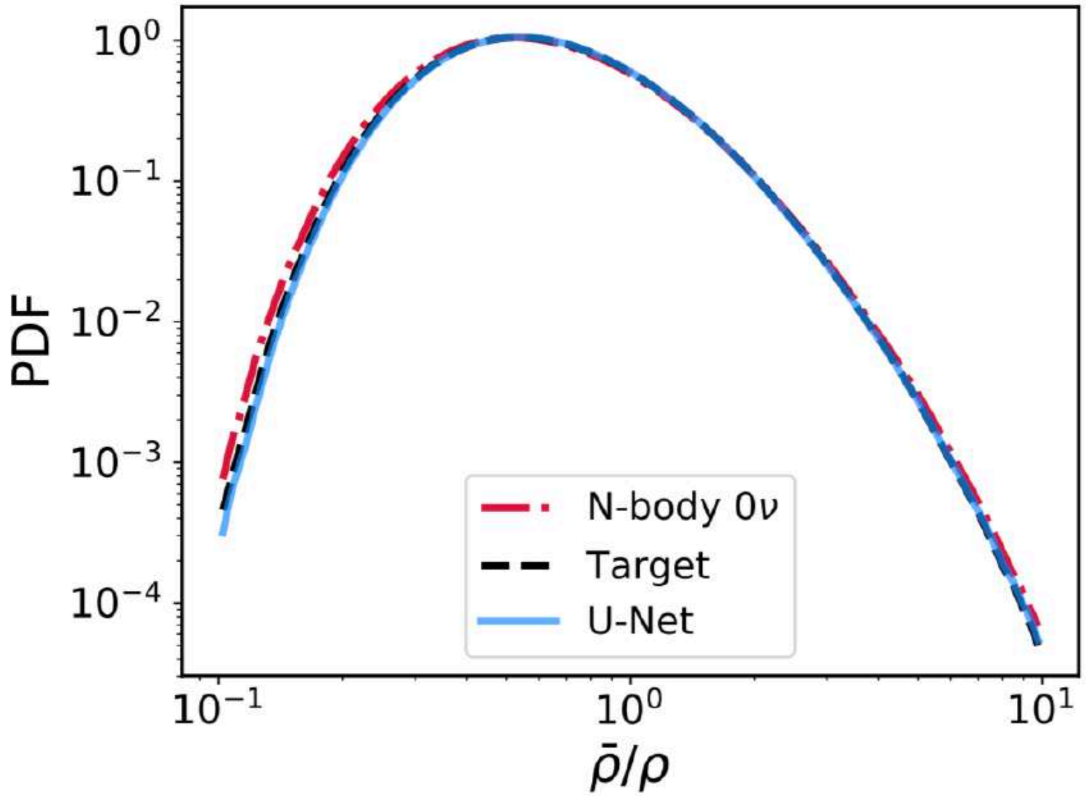
(Cosmology and Astrophysics with MachinE Learning)

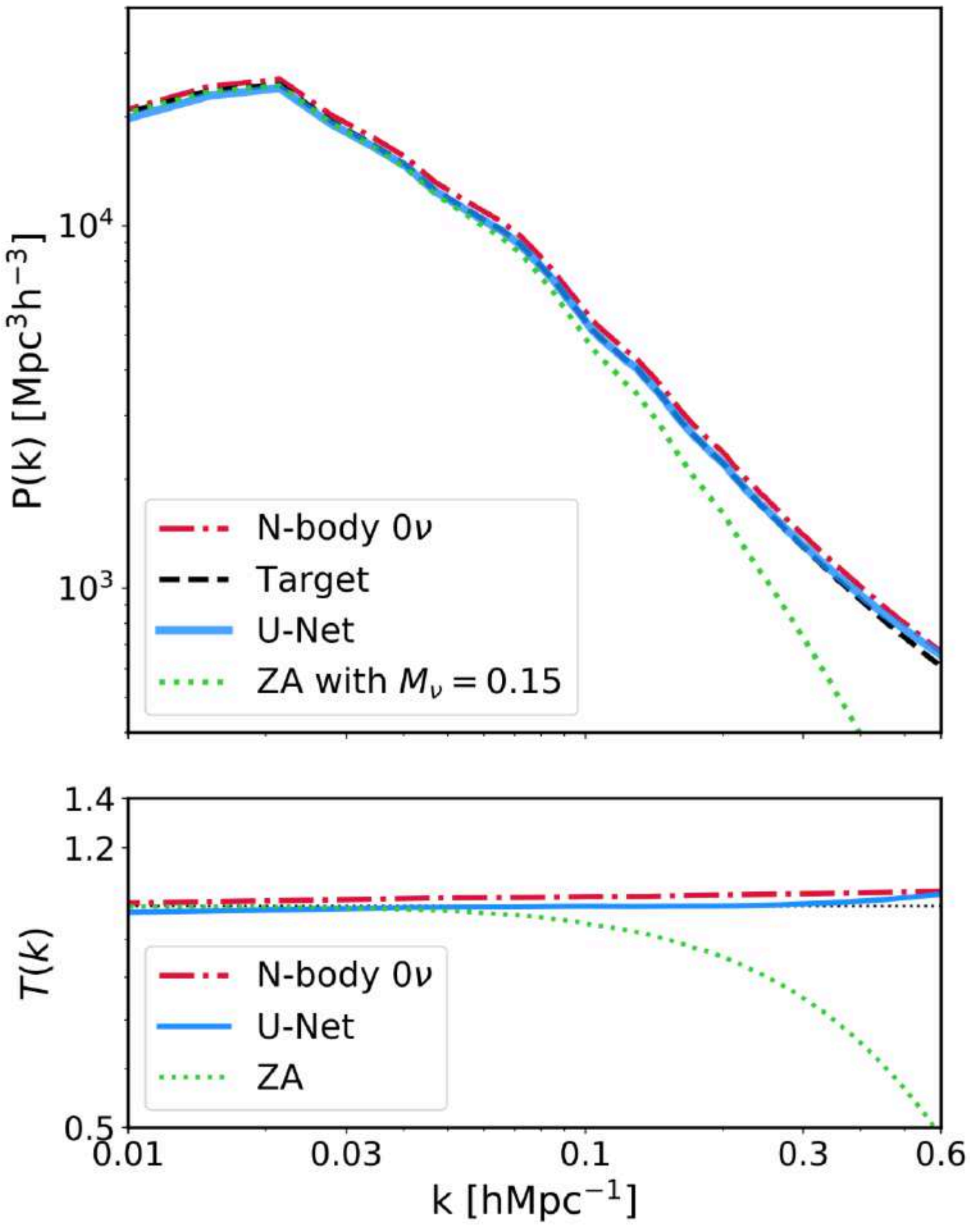
- A set of 4000 simulations: 2000 hydrodynamic + 2000 N-body
- Different cosmologies and astrophysics
- Two different codes/subgrid physics: AREPO/IllustrisTNG & GIZMO/SIMBA
- 8 Million CPU hours; 200 Terabytes

Parameter inference: neural networks

Giusarma, Reyes, FVN, He, Ho, Hahn, 2019

Map points in parameter space
with neural networks

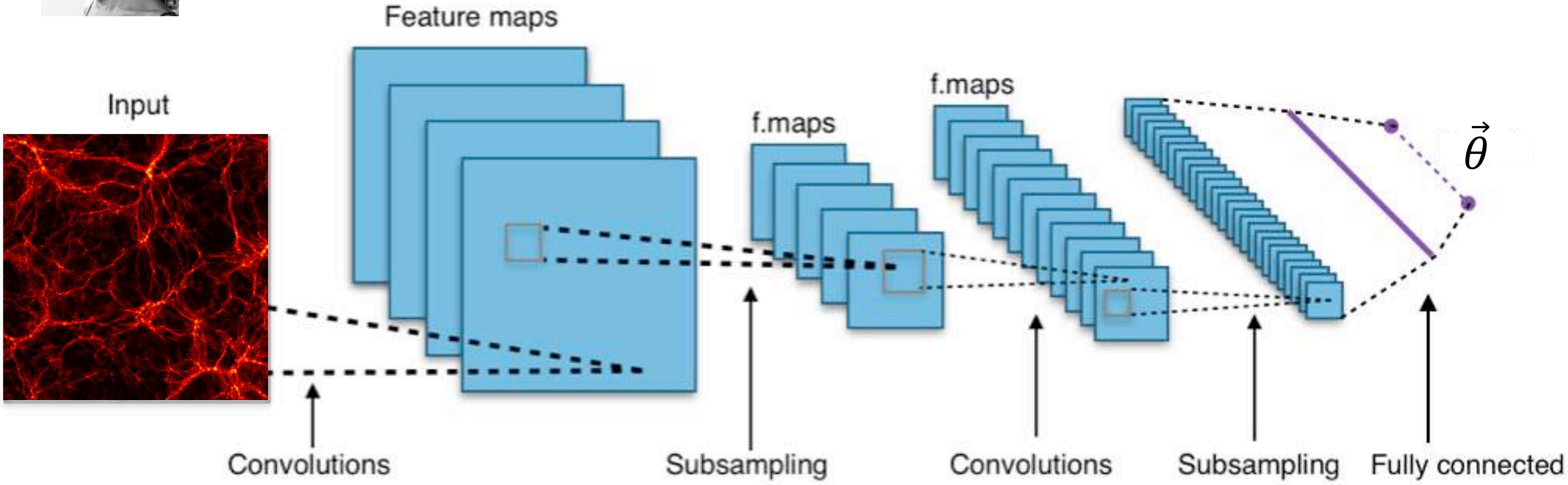




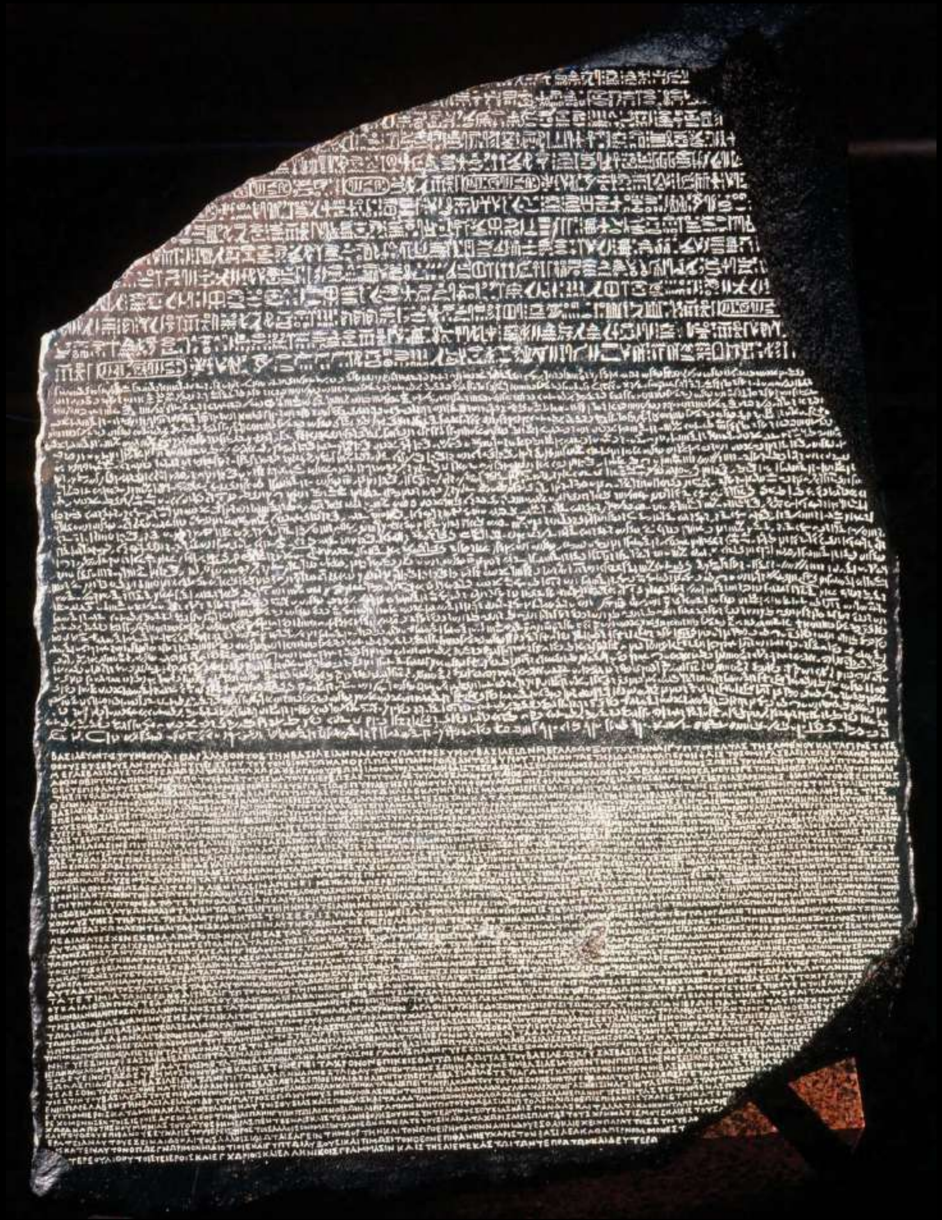
Parameter inference: neural networks

- Deep neural network to go map 3D galaxy fields to the parameters

Delgado, FVN et al. (in prep)



Parameter inference: neural networks



Conclusions

- We want to improve our understanding of the fundamental constituents and laws governing our mysterious Universe
- The answers are written in the sky
- We do not know how to read it
- Machine learning can be our *Rosetta Stone*