

# Cosmology in the machine learning era

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SIMONS  
FOUNDATION



MODE workshop

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# Take home message

Simulations are not perfect; they may never be... Do we need perfect simulations?

*I want an beer*

*I have did the research*

*You was wrong*

*I am given a presentattion*



**To be or not to be**

# Outline

- The problem
- The potential solution
- The risks



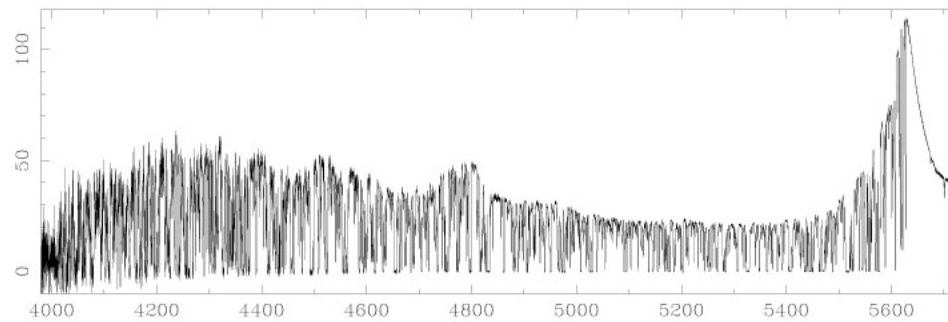
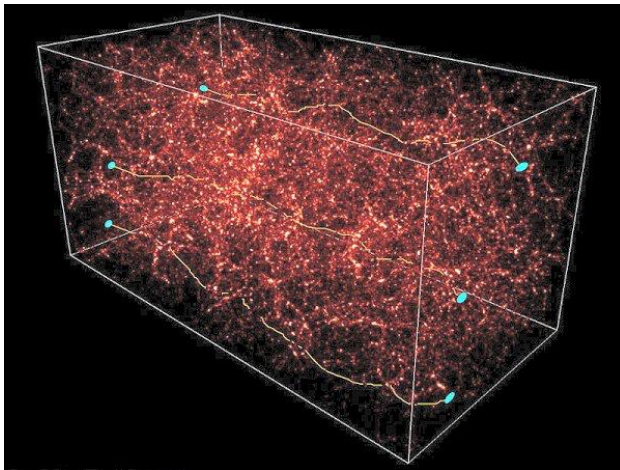
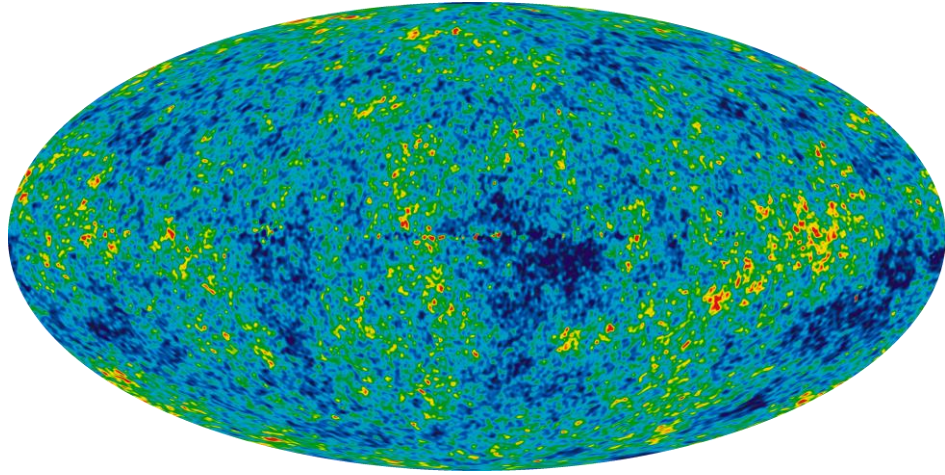
The problem







# The $\Lambda$ CDM model



$$\Omega_m \pm \delta\Omega_m$$

$$\Omega_b \pm \delta\Omega_b$$

$$h \pm \delta h$$

$$n_s \pm \delta n_s$$

$$\sigma_8 \pm \delta\sigma_8$$

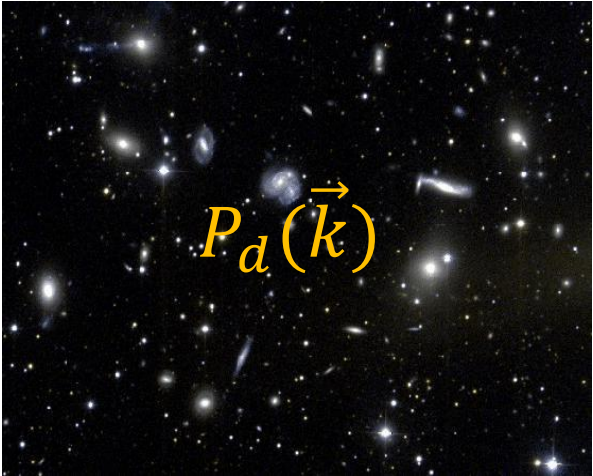
$$M_\nu \pm \delta M_\nu$$

$$w_0 \pm \delta w_0$$

$$w_a \pm \delta w_a$$

$$N_{\text{eff}} \pm \delta N_{\text{eff}}$$

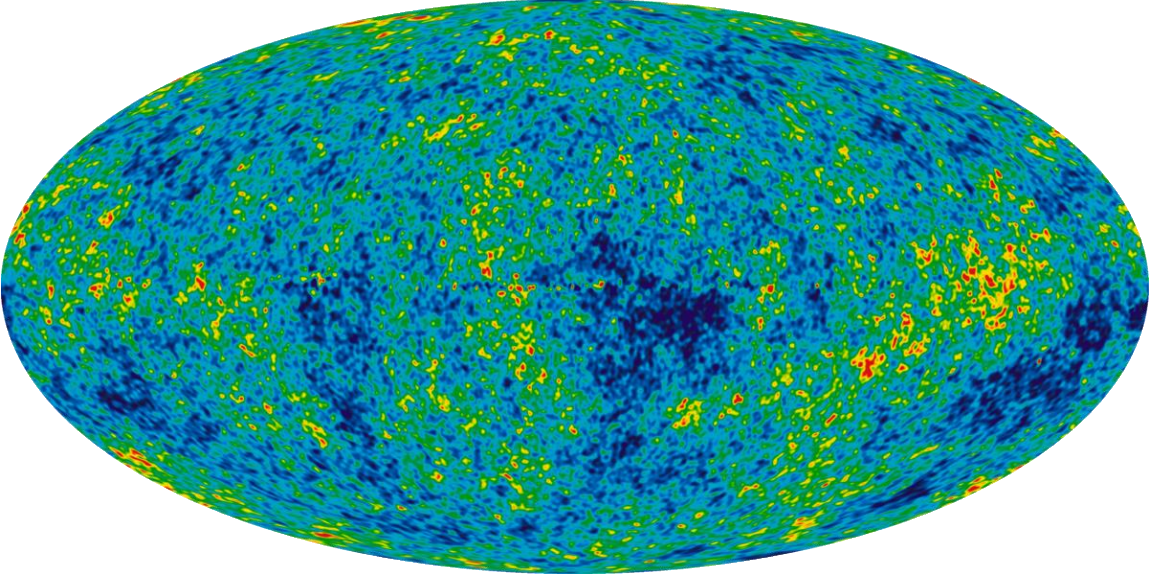
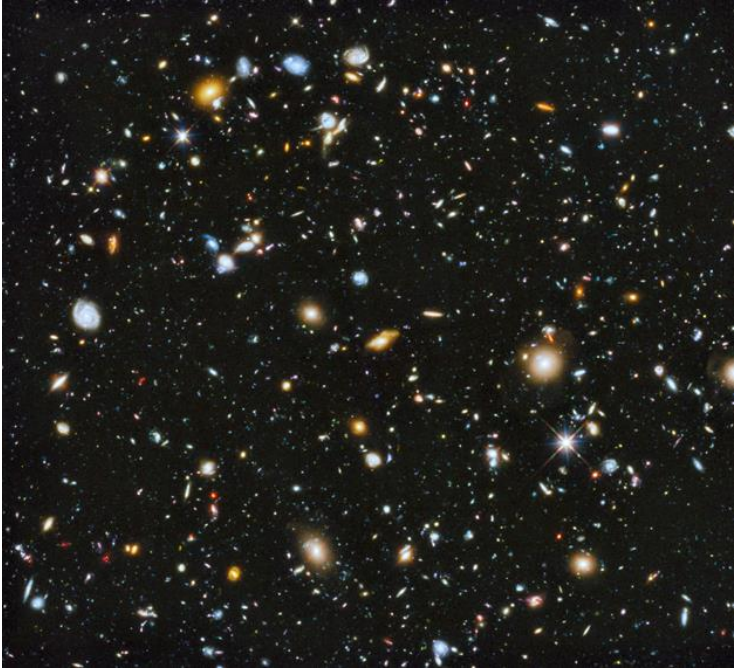
# Parameter inference

Observations	Theory
 <p data-bbox="708 654 901 743"><math>P_d(\vec{k})</math></p>	<p data-bbox="1600 654 1844 743"><math>P_t(\vec{k} \vec{\theta})</math></p>

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



# Parameter inference: summary statistics

Gaussian density field	Non-Gaussian density field
	
<p><u>Optimal statistic</u>: power spectrum</p>	<p><u>Optimal statistic</u>: ???</p>



# The Quijote Simulations

(<https://quijote-simulations.readthedocs.io>)

- A set of 44,100 full N-body simulations
- More than 7,000 cosmologies in  $\{\Omega_m, \Omega_b, h, n_s, \sigma_8, M_\nu, w\}$  hyperplane
- Around 10 trillion particles over a volume larger than entire observable Universe
- Catalogues with billions of halos, voids and galaxies: Molino and Gigantes datasets
- 35 Million CPU hours; 1 Petabyte of data
- Everything publicly available

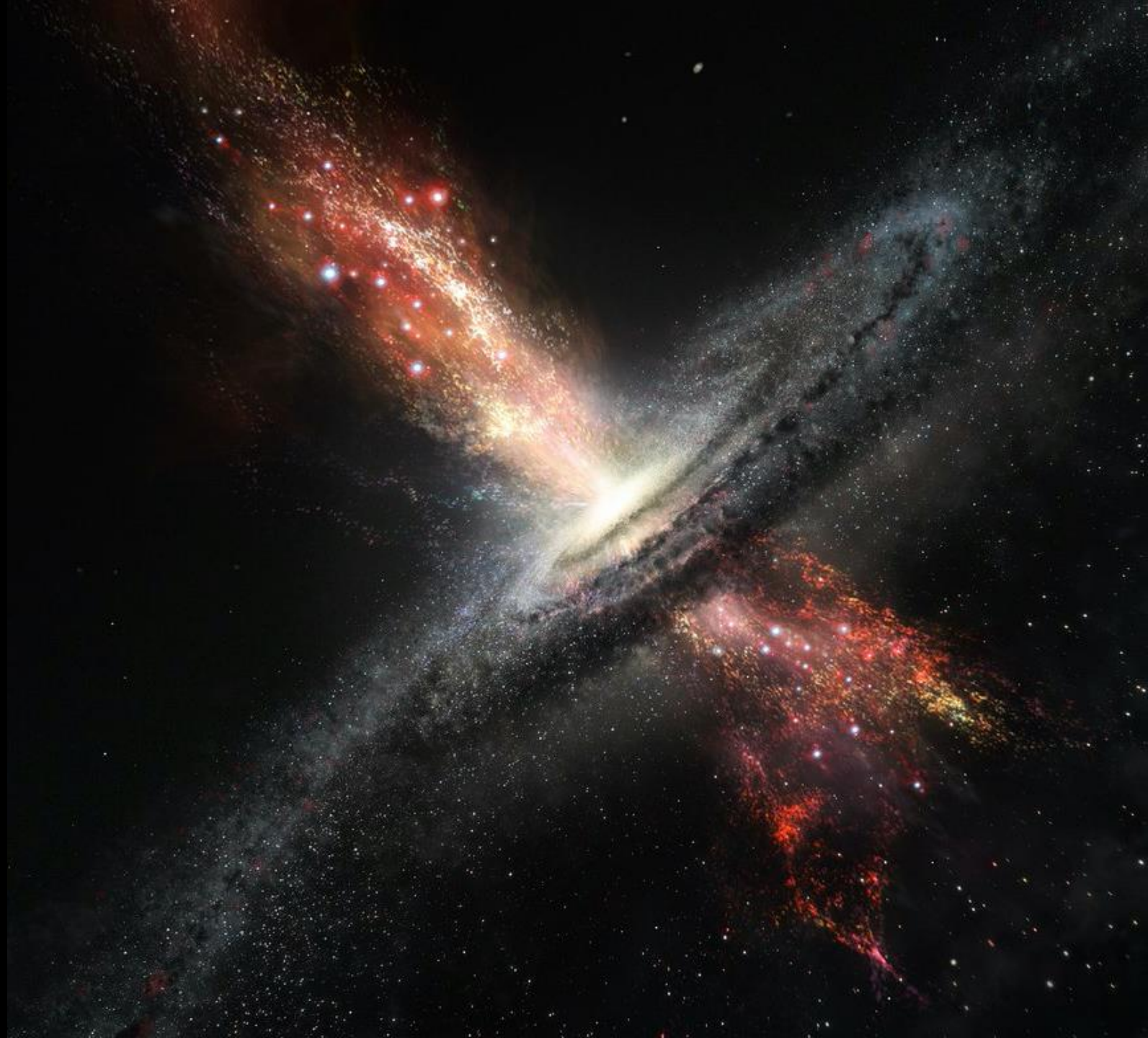




Generic conclusion:  
Lots of information on  
small scales beyond  $P(k)$

**Benefits:** Lots of information

**Problems:** Non-linearities &  
baryonic effects



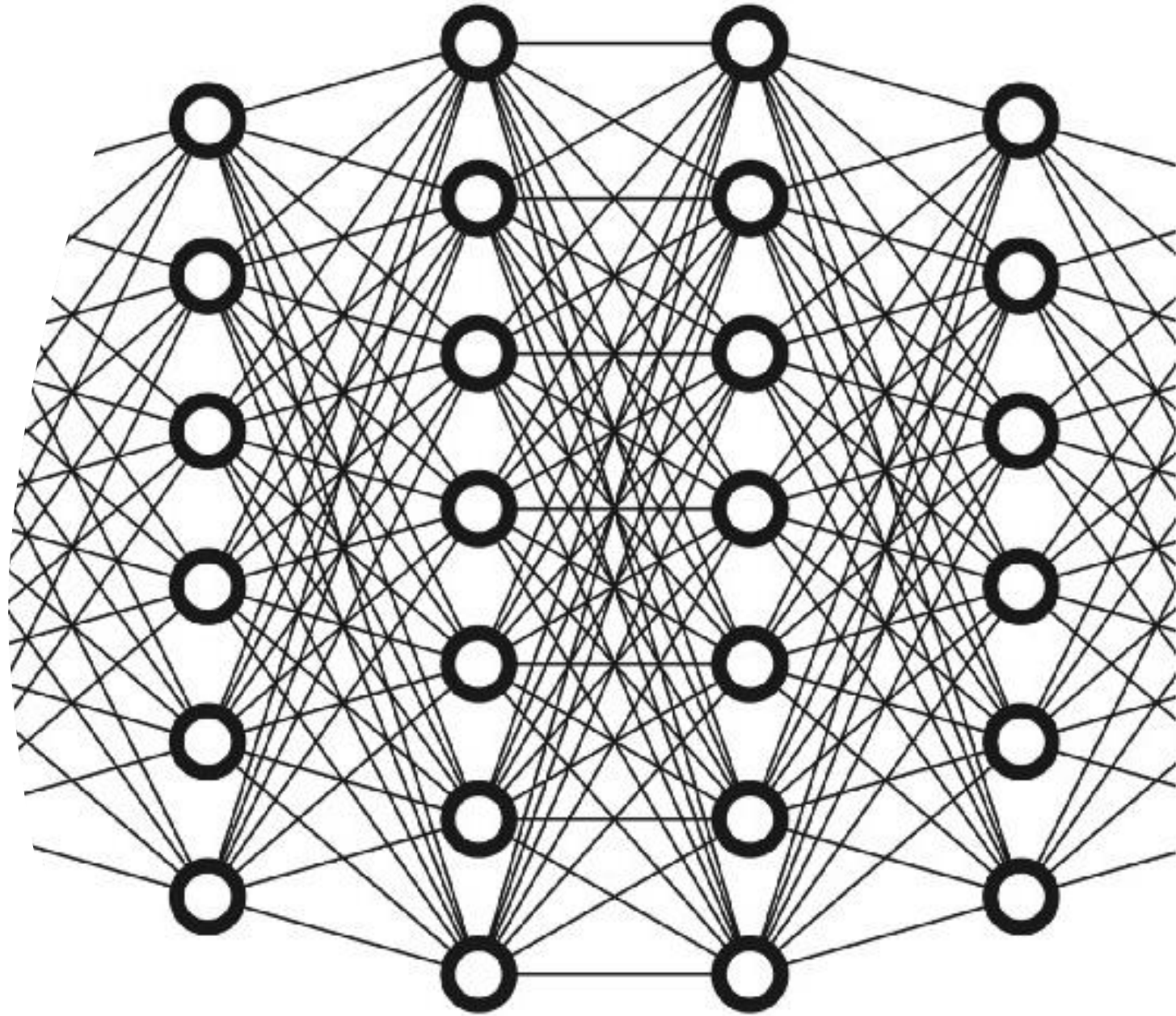


# Summary

- We don't know how to read the cosmological information written on the sky.  
We may be missing the most important part of the book
- The tools we typically use to extract information are suboptimal

The  
potential  
solution

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# A machine learning solution

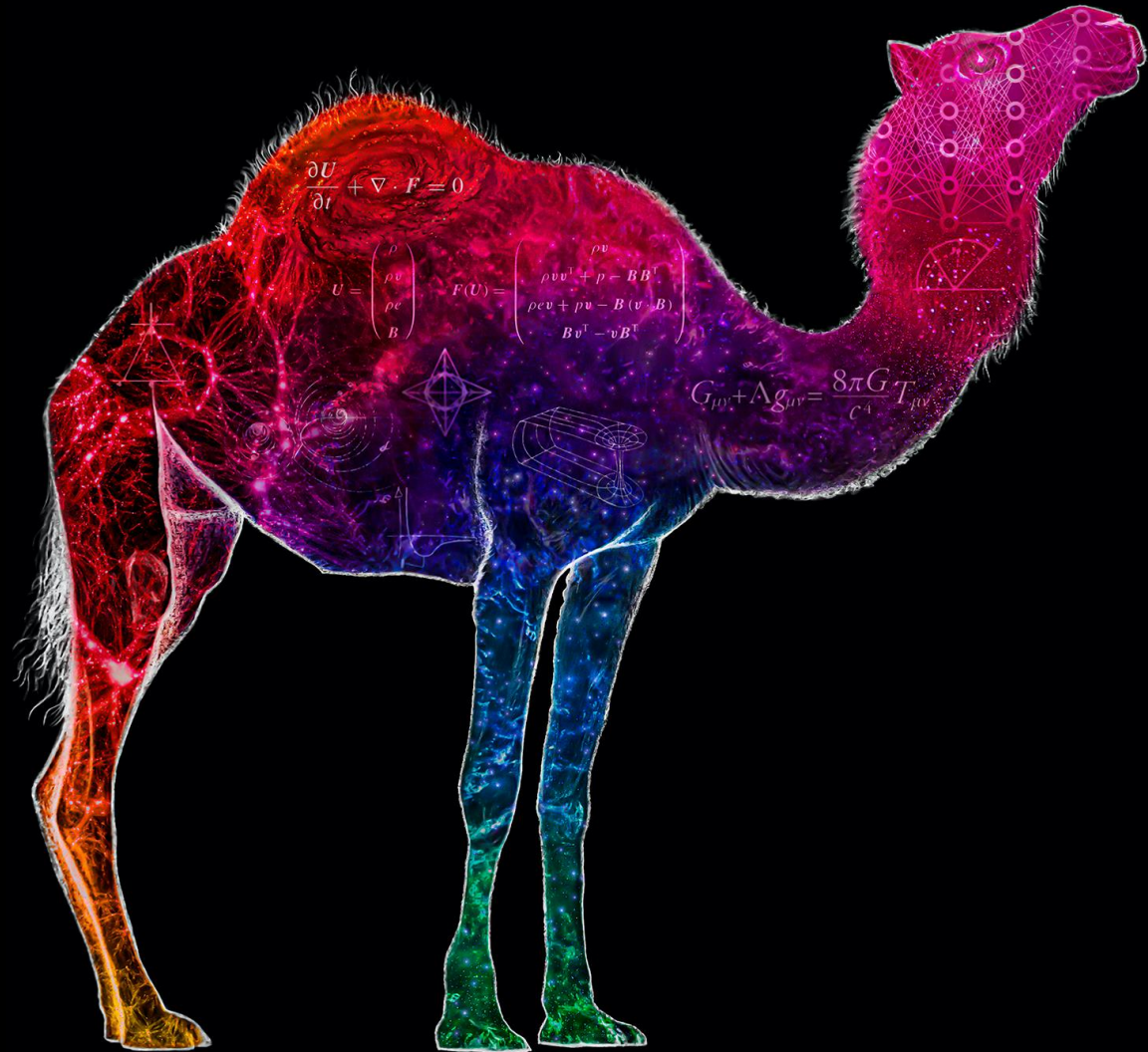
Can we extract ALL information from the field while marginalizing over uncertain baryonic effects? **YES!**

What we need?

- Many simulations with different cosmologies & astrophysics
- Train neural networks
- Check robustness of the estimators found by the networks

# CAMELS

<https://www.camel-simulations.org>



## Cosmology and Astrophysics with Machine Learning Simulations

- A suite of 4,233 simulations
- 2,049 N-body; Gadget-III
- 2,184 state-of-the-art (magneto-)hydrodynamic sims
- AREPO/IllustrisTNG + GIZMO/SIMBA
- 6 parameters:  $\{\Omega_m, \sigma_8, A_{SN1}, A_{SN2}, A_{AGN1}, A_{AGN2}\}$
- More than 100 billion resolution elements over combined volume of  $\sim(400 \text{ Mpc}/h)^3$
- More than 2,000 cosmologies & astrophysics models; more than 140,000 snapshots
- Designed for machine learning applications

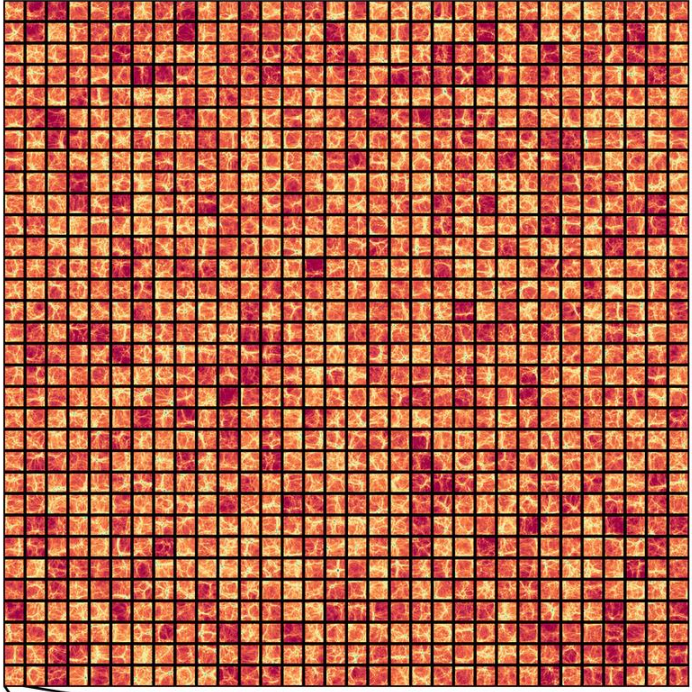
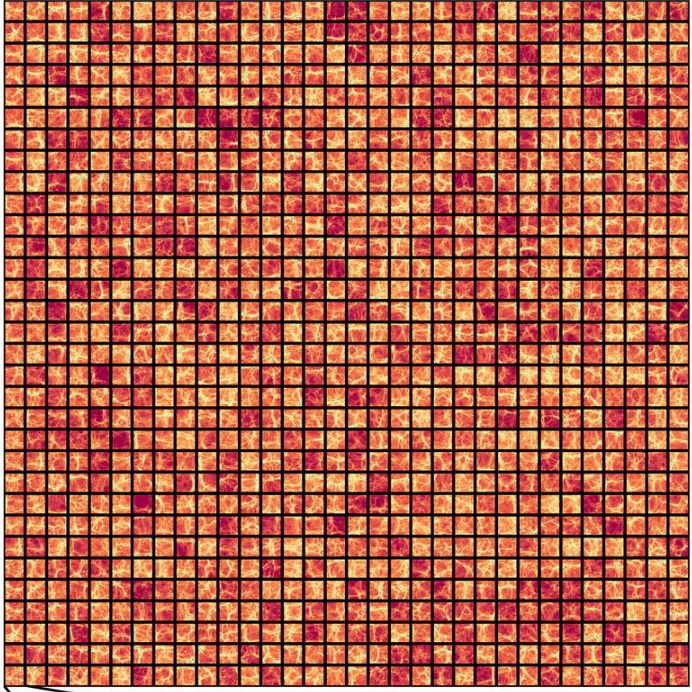




# CAMELS

IllustrisTNG

SIMBA

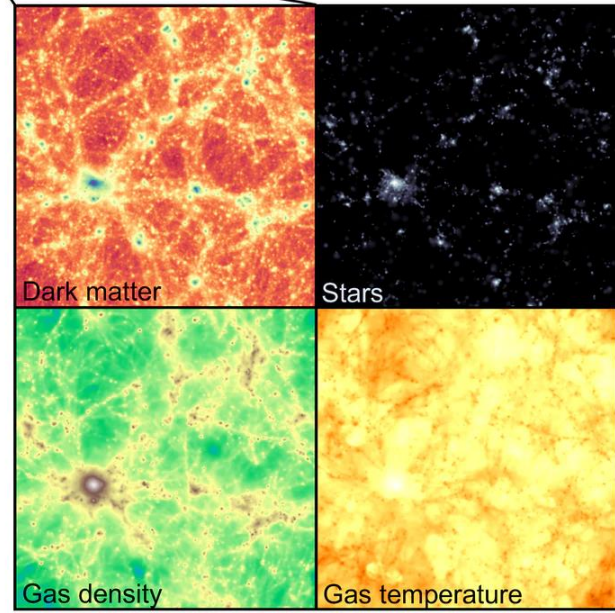
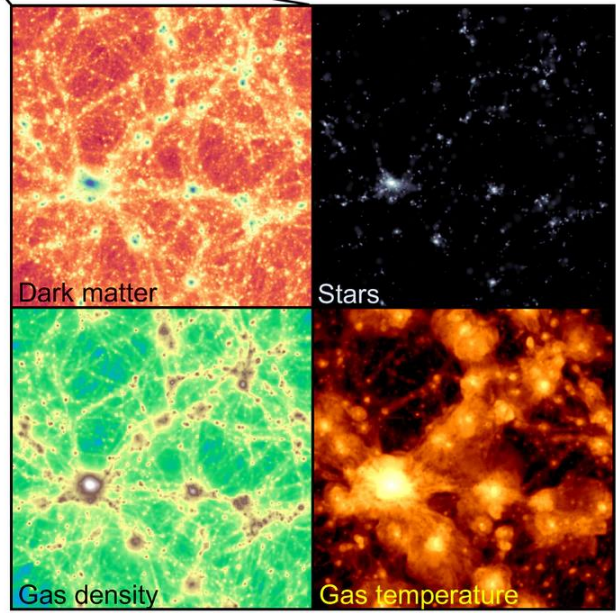


1,000 different simulations with AREPO + IllustrisTNG

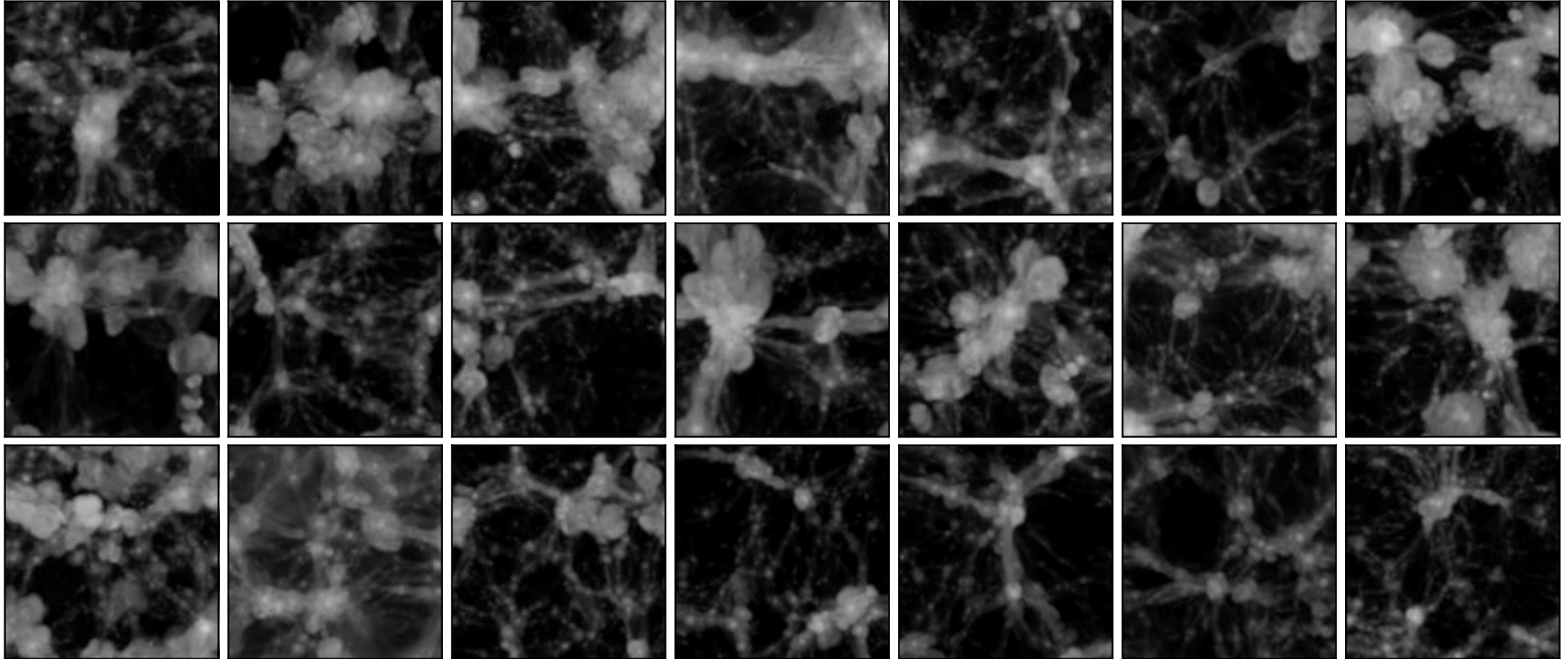
1,000 different simulations With GIZMO + SIMBA

Each simulation has a different cosmology and astrophysics model

Each simulation has a different cosmology and astrophysics model



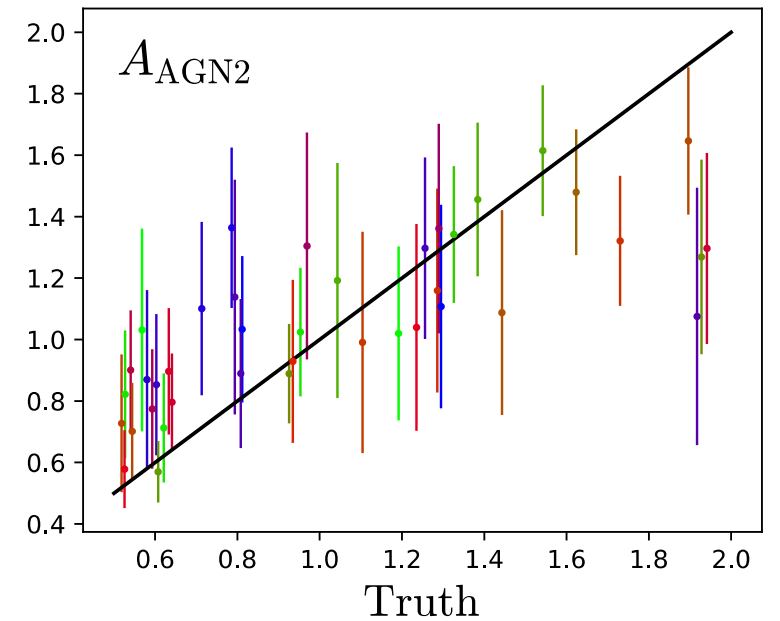
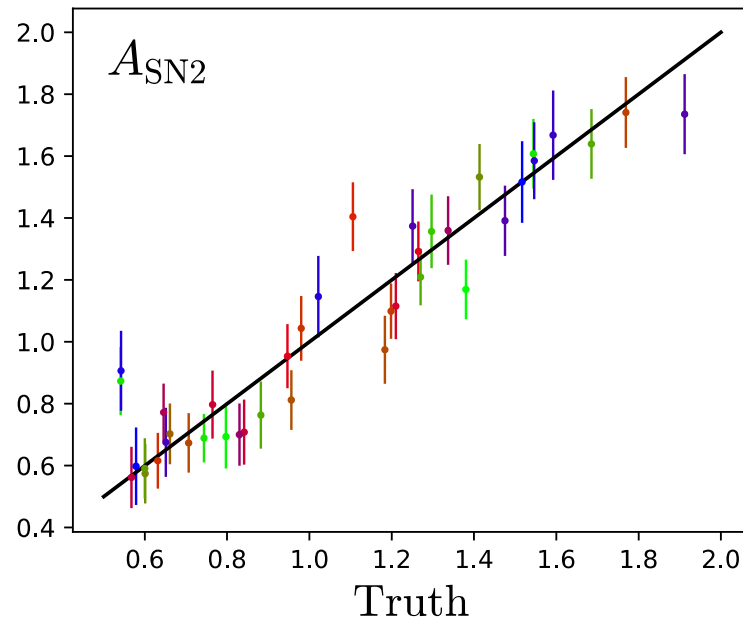
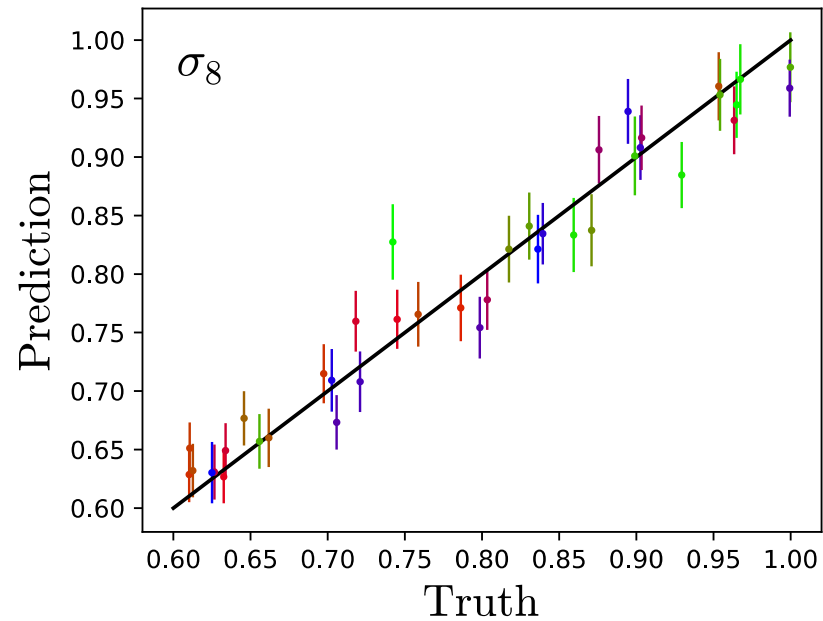
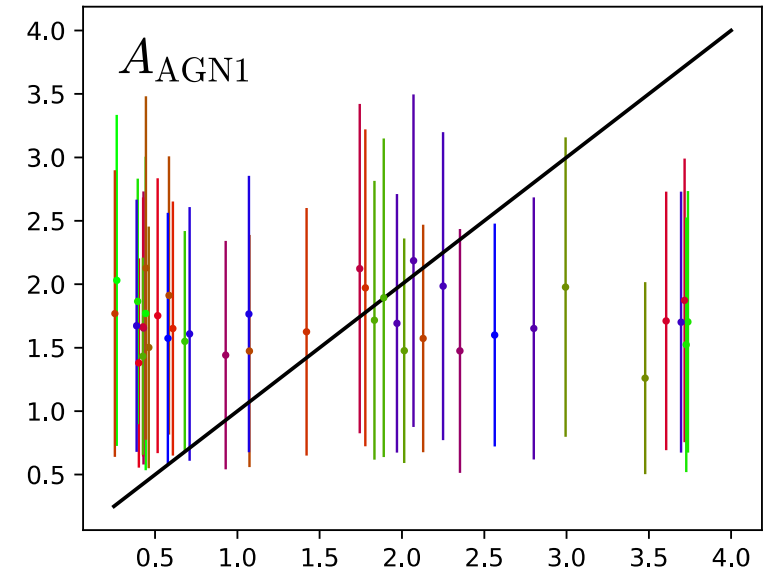
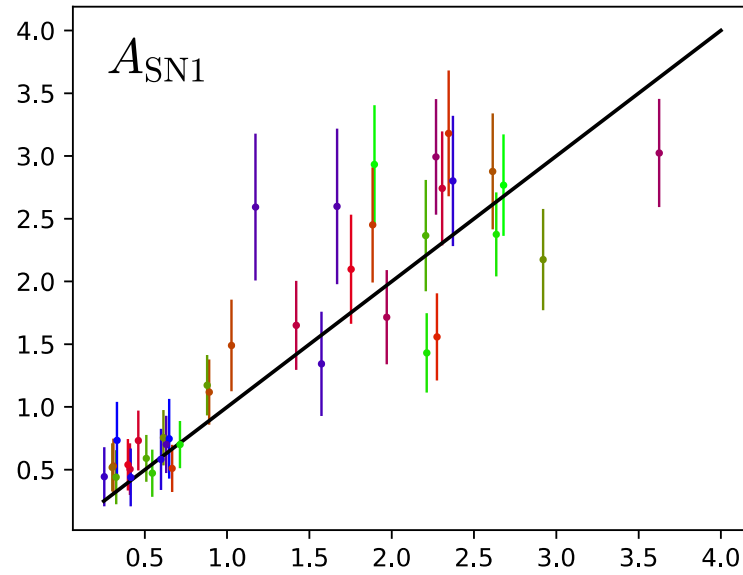
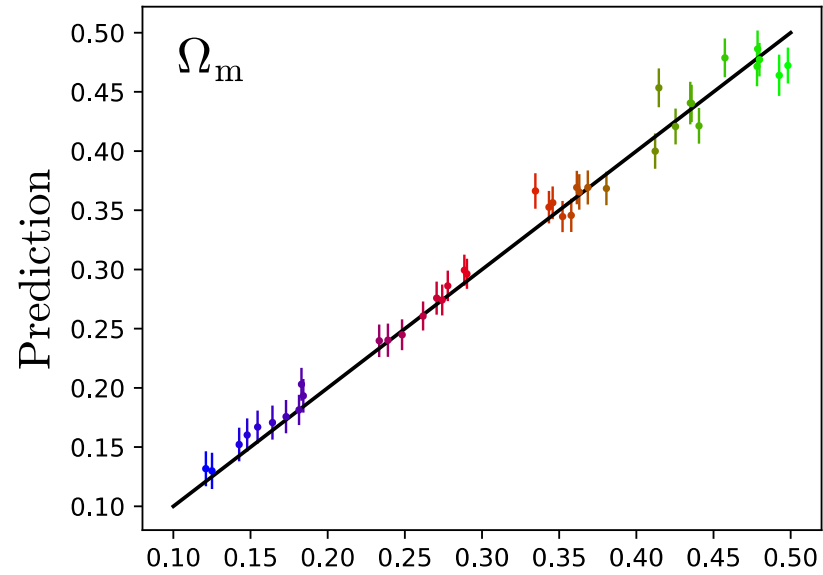
# Example I: Gas temperature



Every map has  $256 \times 256$  pixels, covers an area of  $25 \times 25 (h^{-1}\text{Mpc})^2$ , and has a different cosmology & astrophysics. 15,000 images in total.

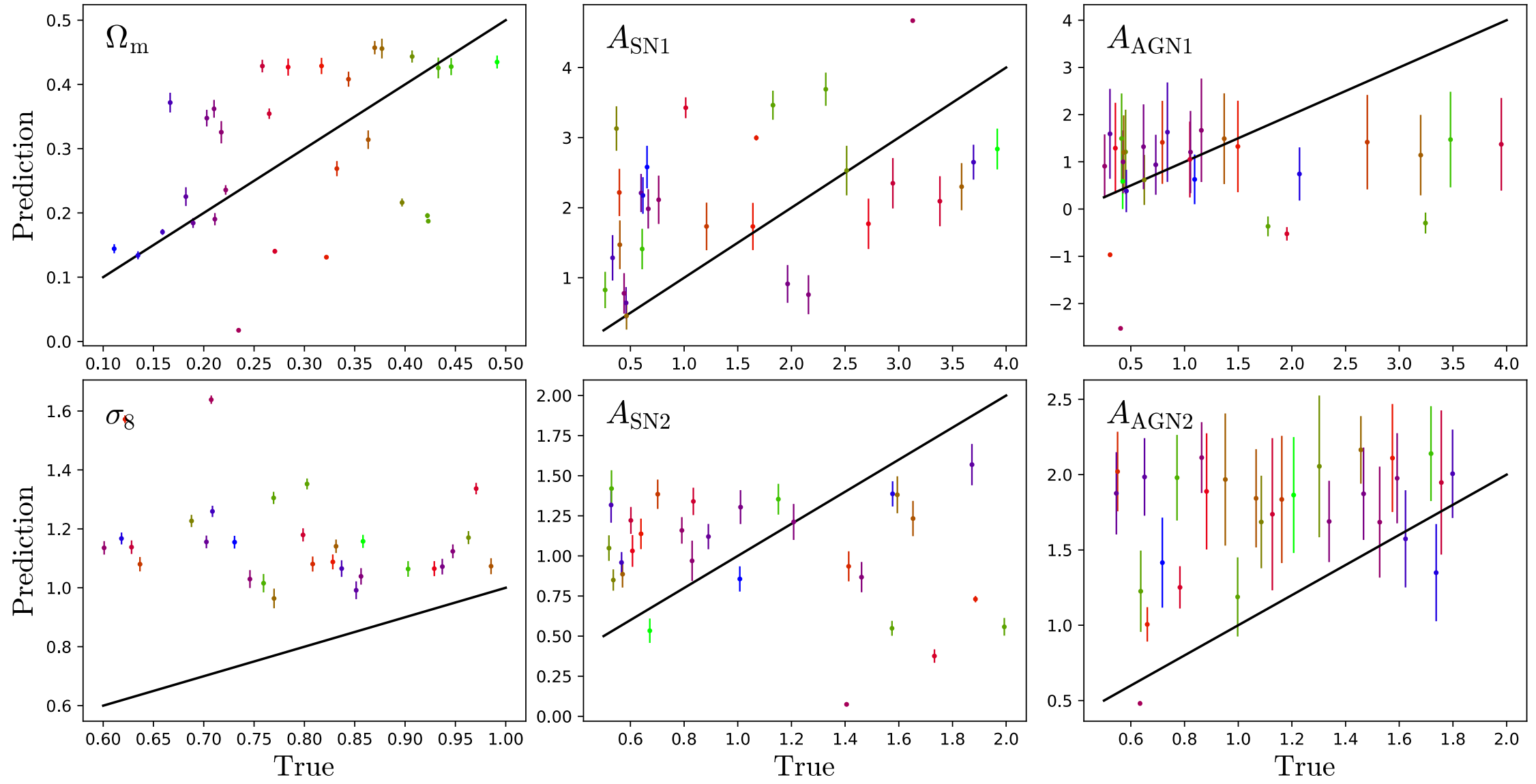


# Likelihood-free inference: gas temperature



# Robustness: gas temperature

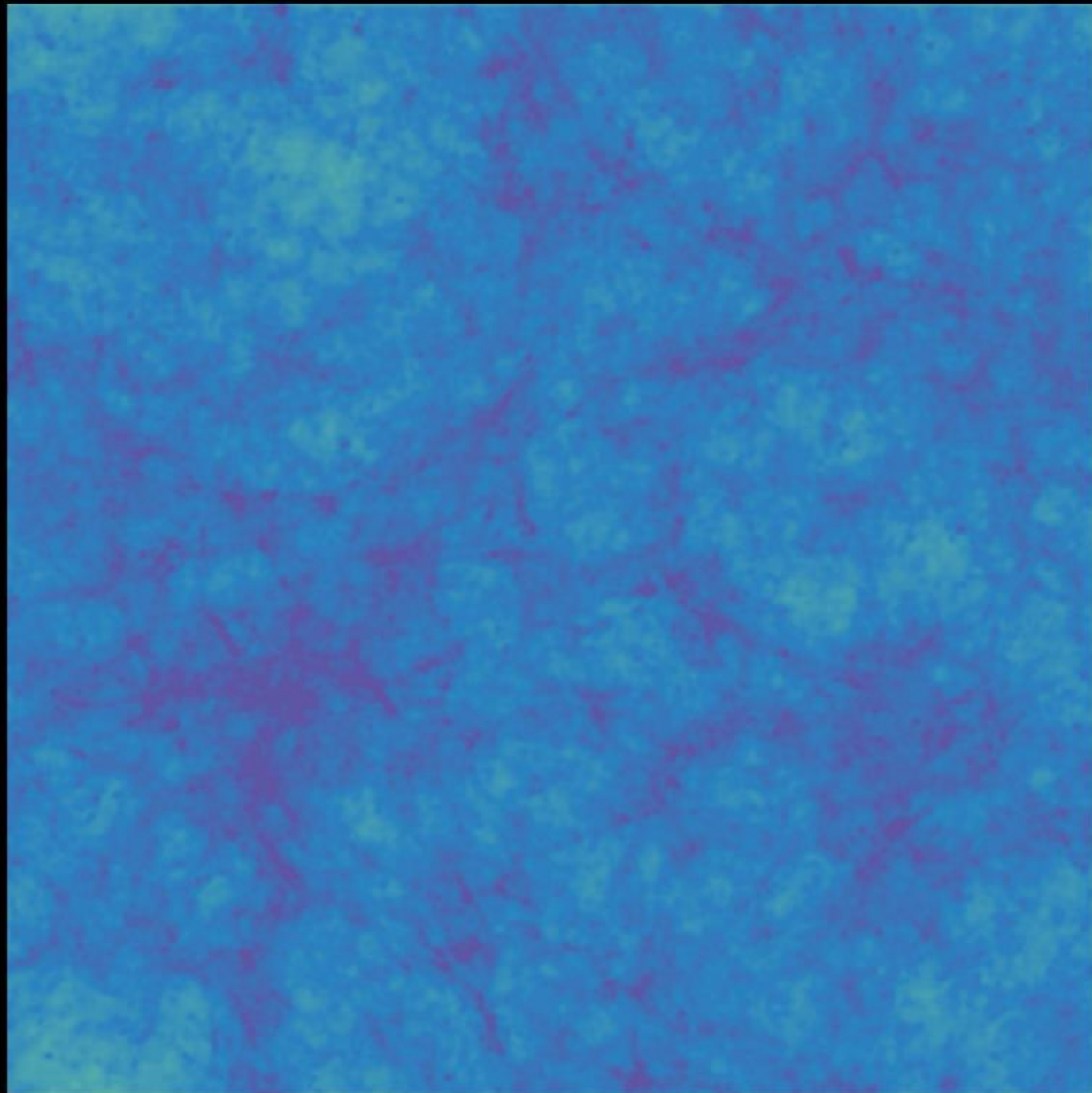
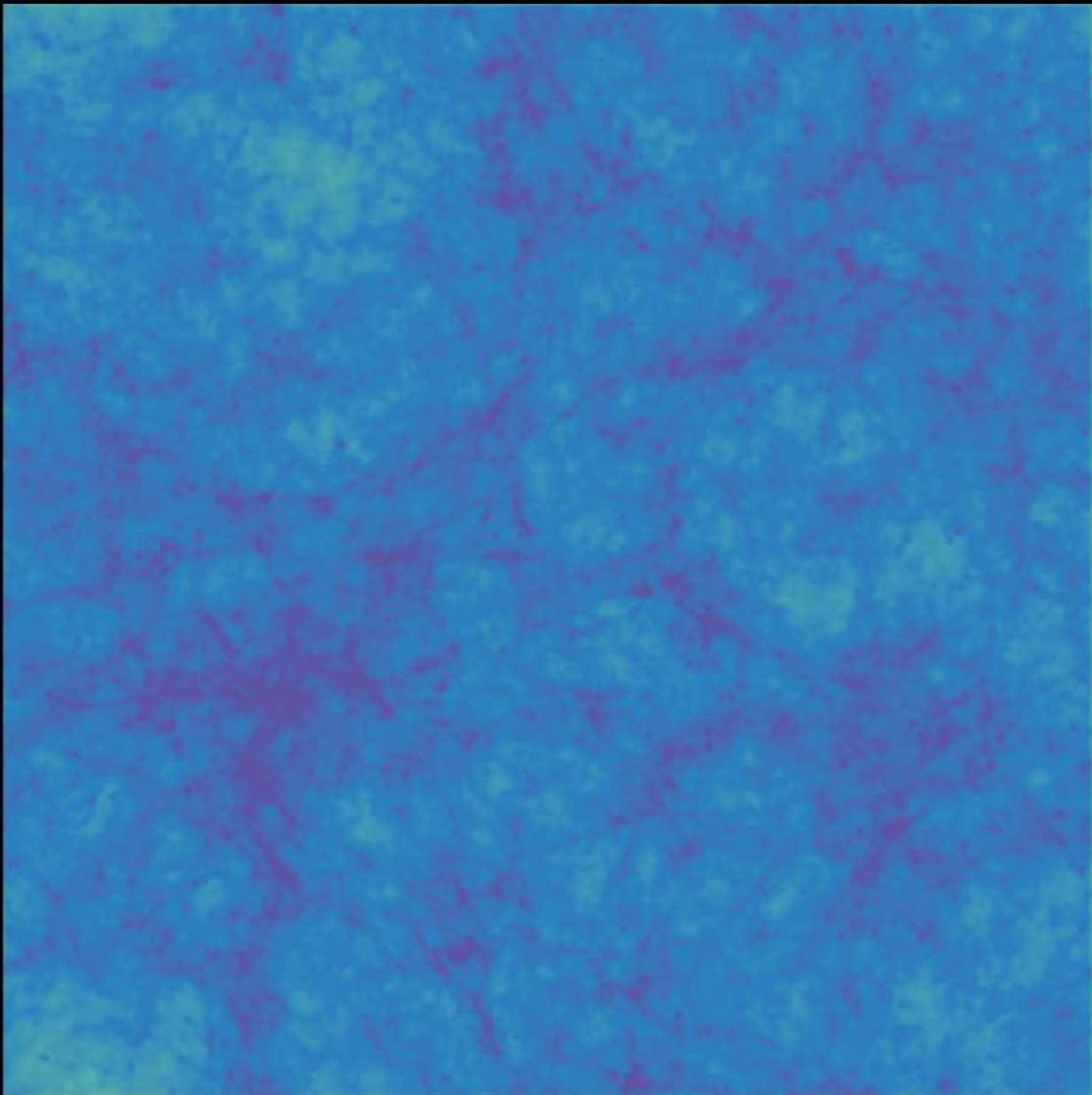
Network trained on IllustrisTNG and tested on SIMBA



IllustrisTNG

Dark matter density

SIMBA

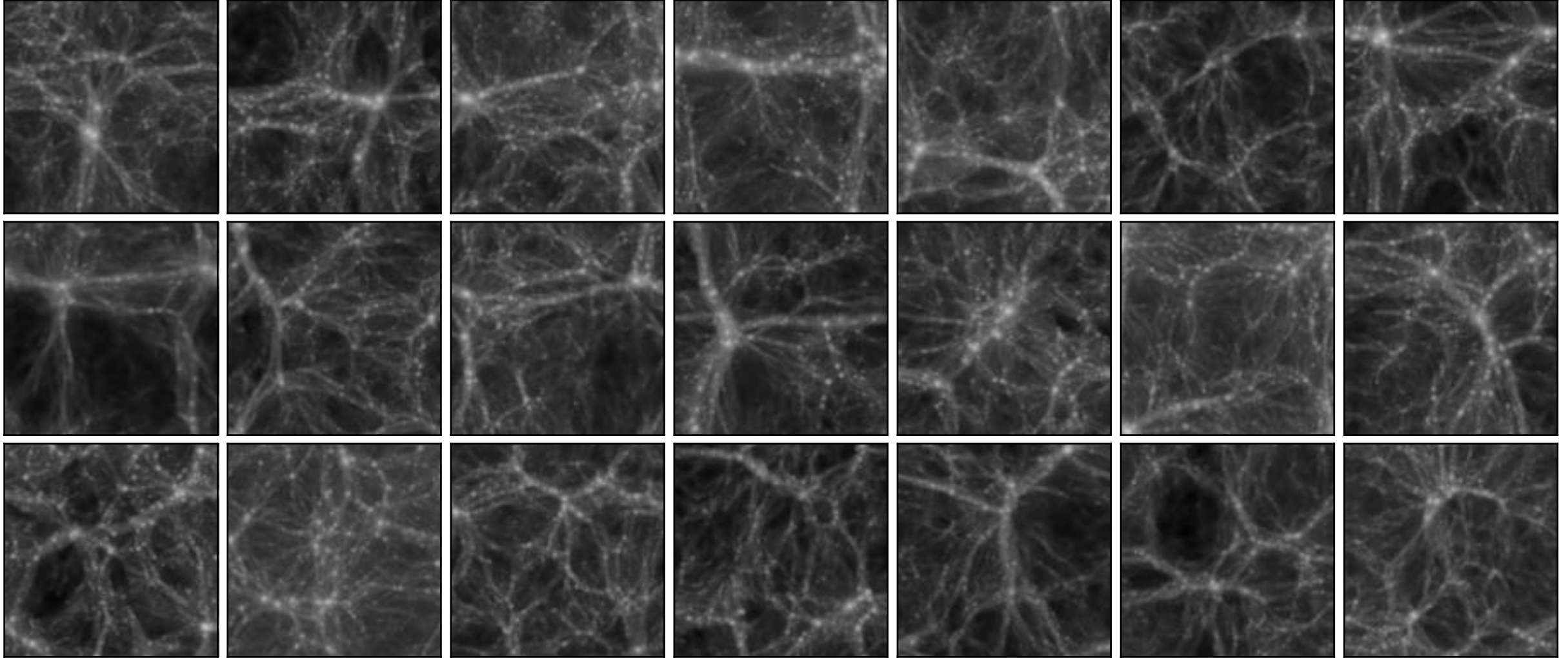




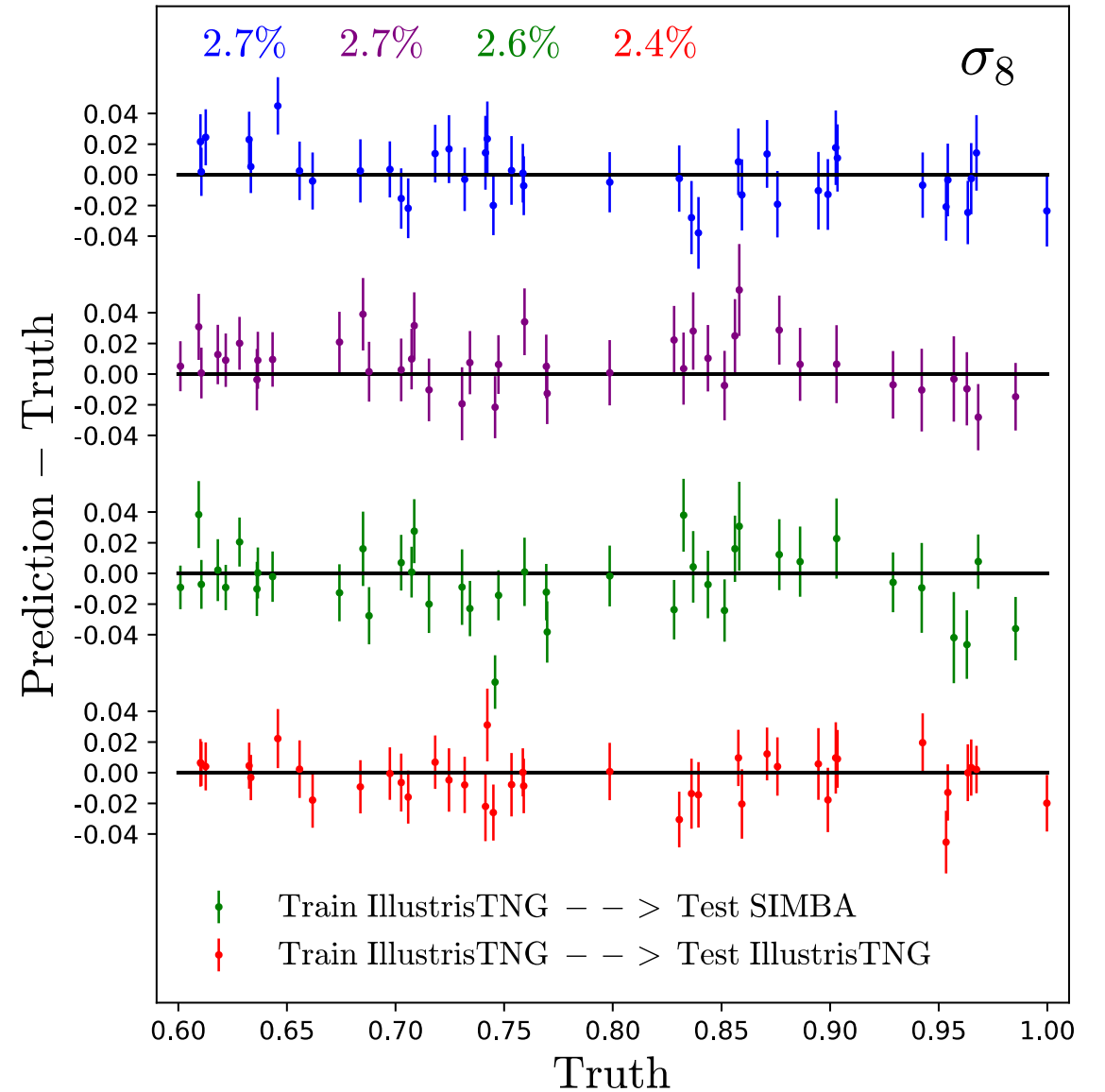
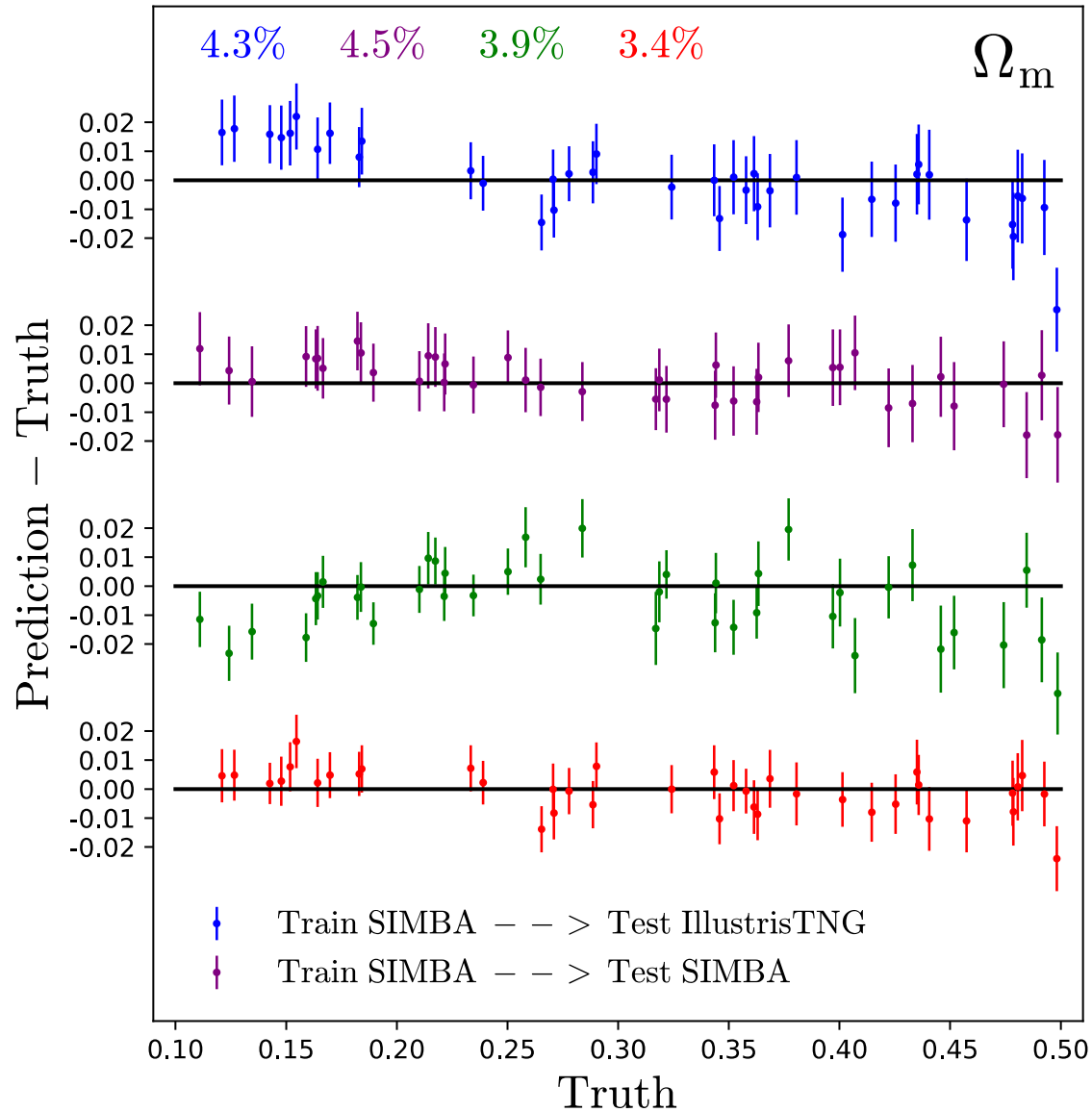
# Summary

- We don't know how to read the cosmological information written on the sky. We may be missing the most important part of the book
- The tools we typically use to extract information are suboptimal
- Neural networks can find the optimal estimator to extract every single bit of cosmological information while marginalizing over uncertain astrophysical processes

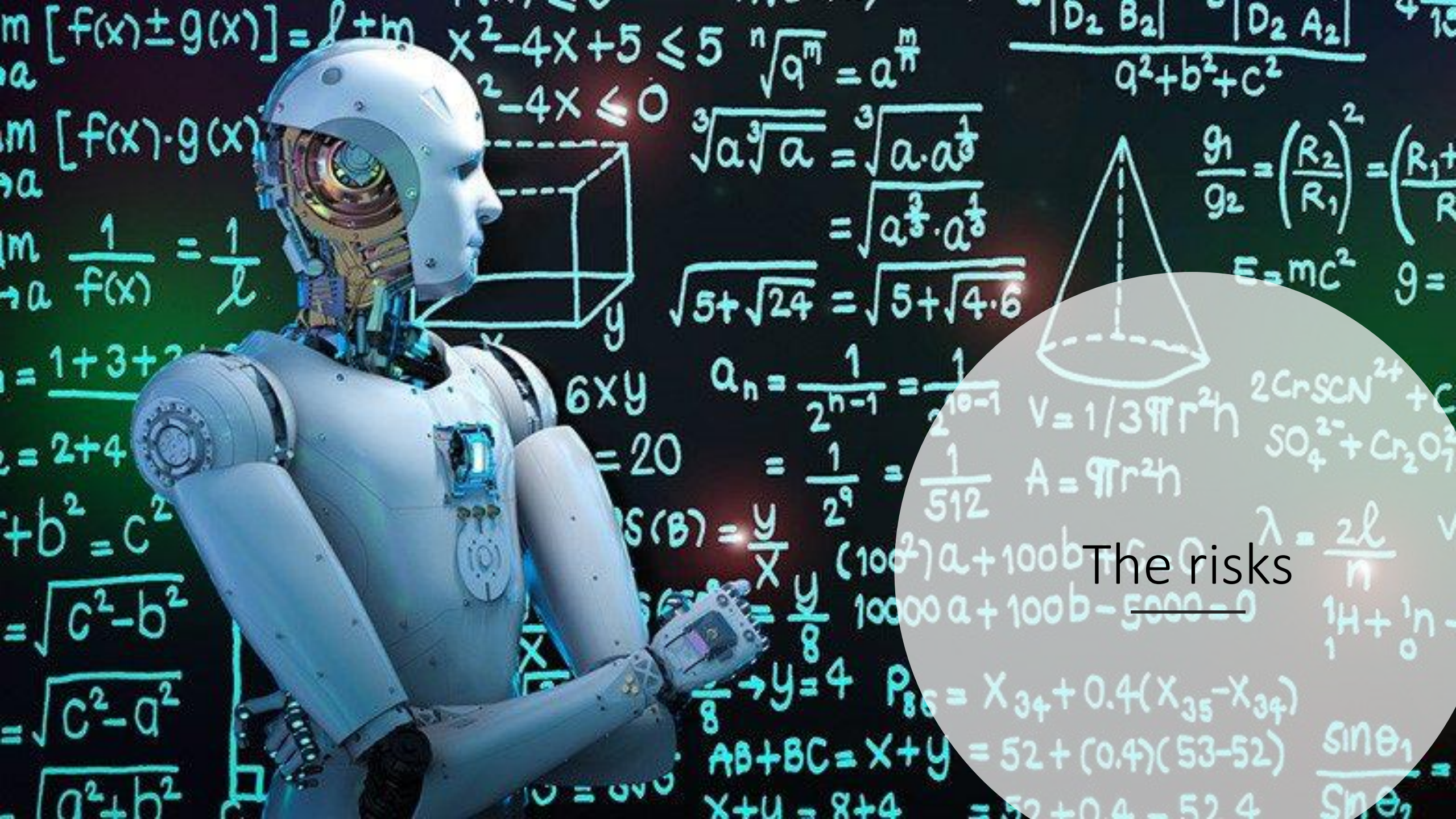
# Example II: Total matter



# Robustness: total matter







The risks

# The risks

Our simulations may never be perfect...

Can we train a perfect translator with imperfect sentences?

Do we need our simulations to overlap with reality?

How can we be sure it is not learning some artifacts/biased introduced by us?

How can we identify new physics in this formalism?



# Conclusions

If we could simulate the Universe we could potentially learn everything about it.

How good should our simulations be to do this?

How many different kinds of simulations do we need to find a robust estimator that marginalize over subgrid physics, numerical effects, bugs...etc?

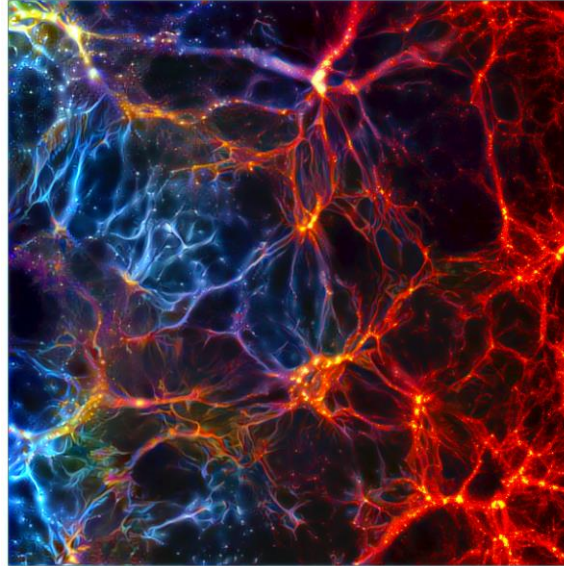




# Vision/Dream

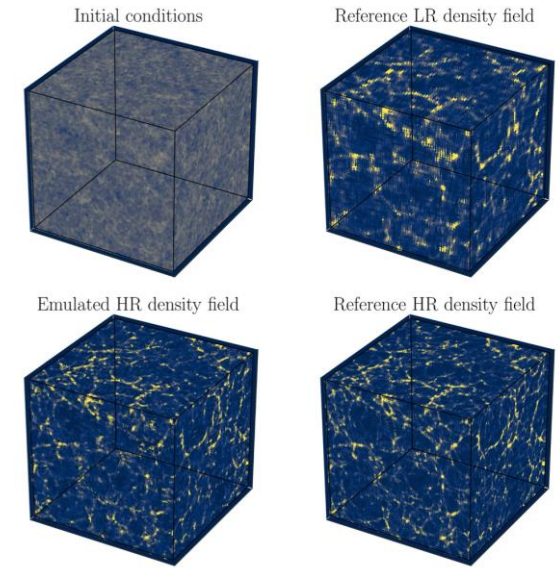
## Quijote

Thousands of cosmologies



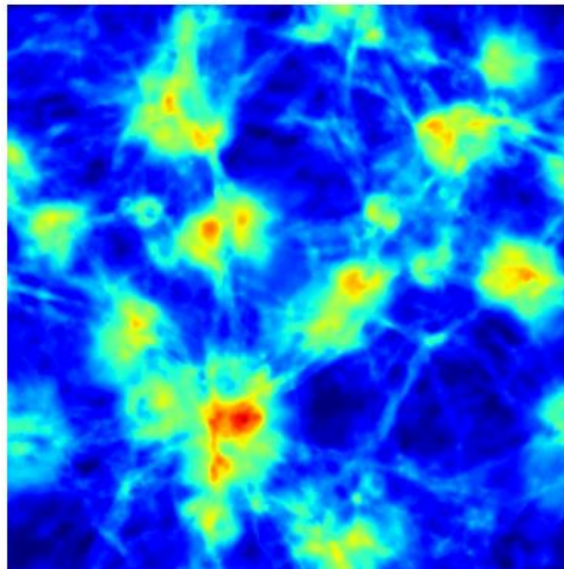
## Super Resolution

$10^9 h^{-1} M_{\odot}$



## CAMELS

Thousands of astrophysics models



## Likelihood-free inference

Extract all information. Marginalize over baryonic effects

