

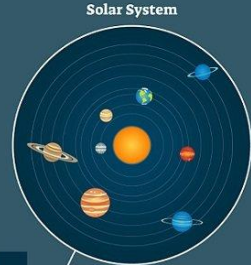
# Particle Physics and Cosmology

HCPSS  
July 2024

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 Data Science, Simulation, and Learning Division  
 aleksand@fnal.gov

# BIG BANG THEORY



**Inflation**  
Quarks Form

**First Particles**  
Neutrons,  
Protons, Dark  
Matter form

**First Nuclei**  
Helium,  
Hydrogen form

**First Light**  
First Atoms  
Form

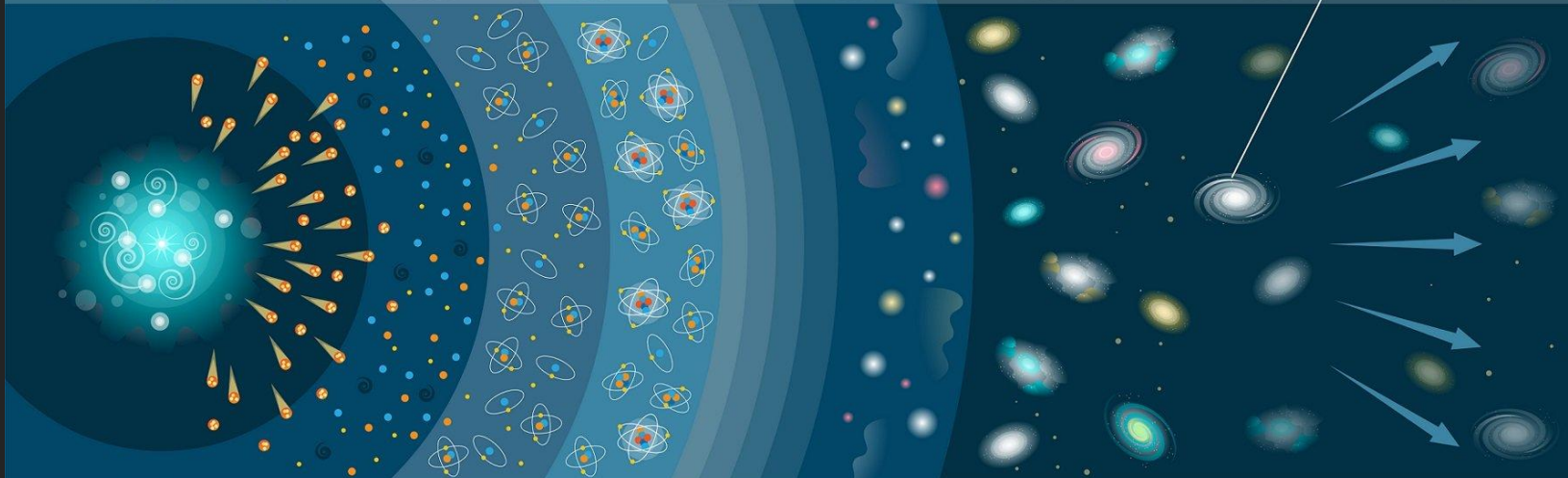
**Dark Ages**  
Clumps of  
Matter Form

**Gravity**  
Stars and  
Galaxies Form

**Antigravity**  
Universe  
Expansion  
Accelerates

**Today**  
Universe  
Continues to  
Expand

**Galaxies**  
Break Apart



milliseconds  
 $10^{-32}$

milliseconds  
0.01

seconds  
0.01 - 200

years  
380.000

years  
380.000

years  
300  
million

years  
10  
billion

years  
13.8  
billion

Present Day

**TIME**

**SIZE**



Grapefruit

0.1 - trillionth  
present size

1 - billionth  
present size

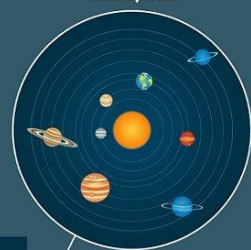
0.0009  
present size

0.9  
present size

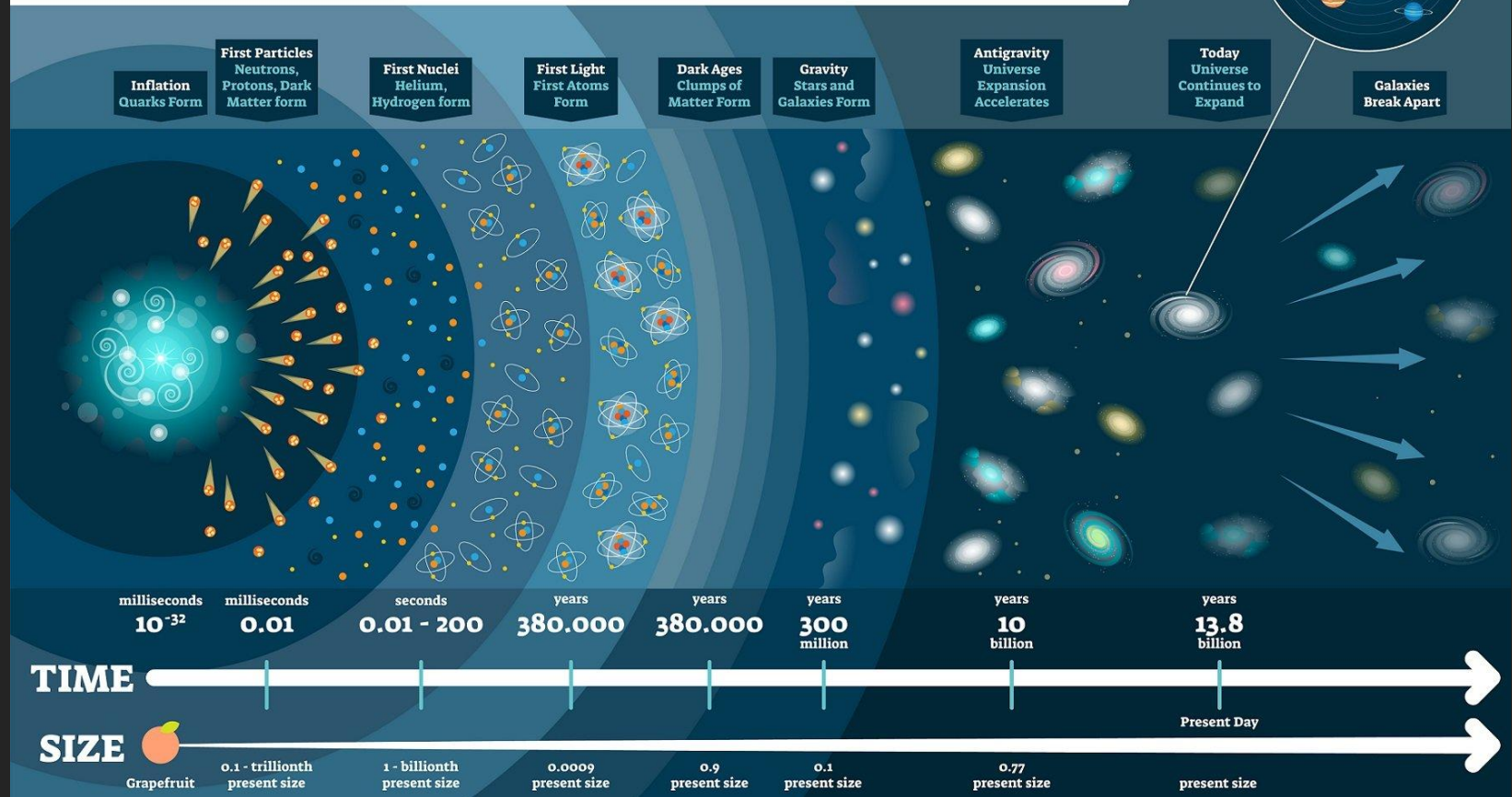
0.1  
present size

0.77  
present size

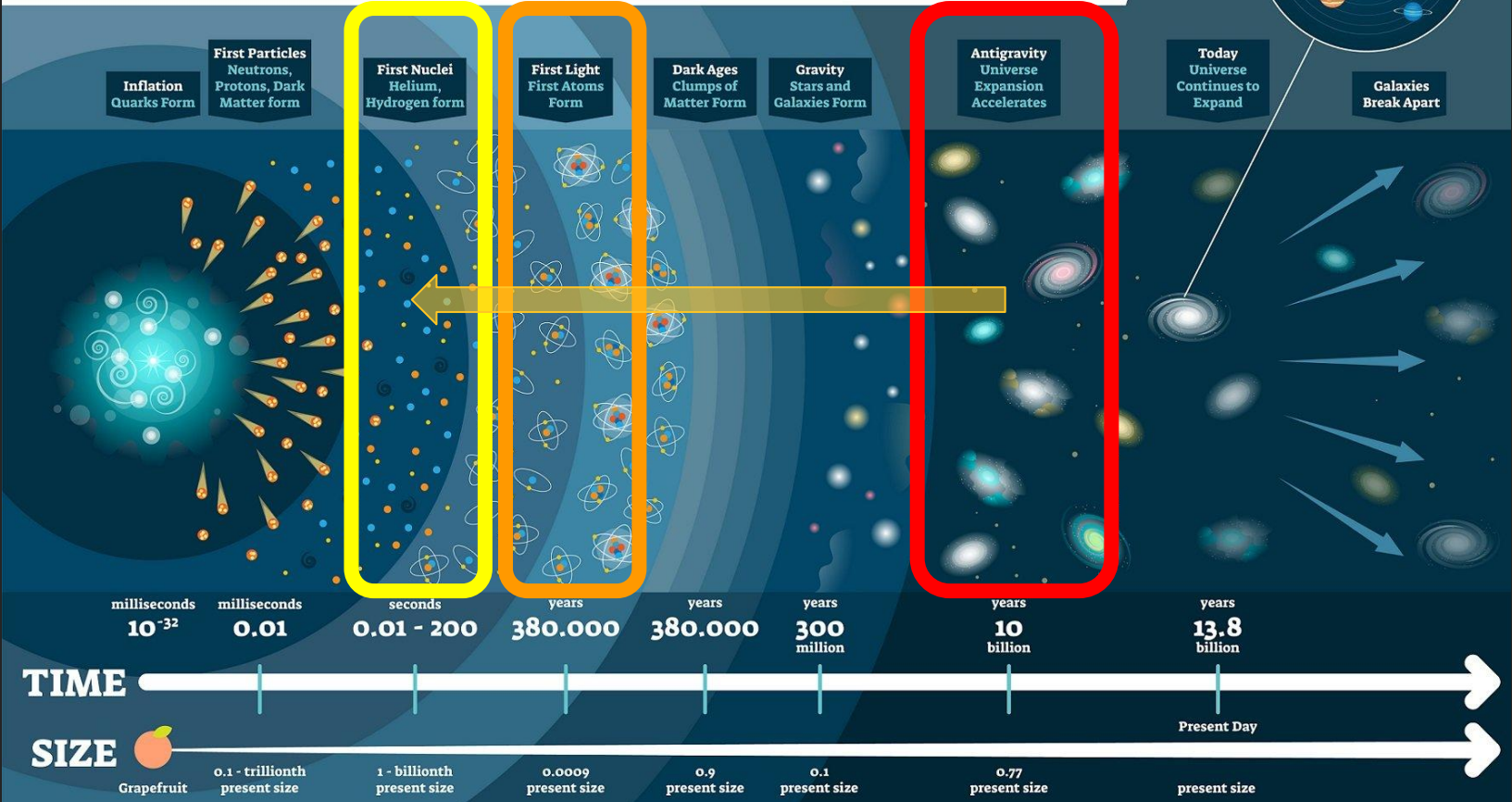
present size

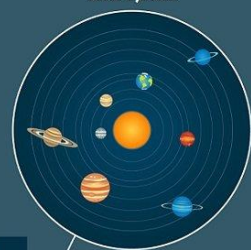


# Sounds complicated. How do we prove the theory?



# Sounds complicated. How do we prove the theory?





Galaxies Break Apart

Today Universe Continues to Expand

Antigravity Universe Expansion Accelerates

Gravity Stars and Galaxies Form

Dark Ages Clumps of Matter Form

First Light First Atoms Form

First Nuclei Helium, Hydrogen form

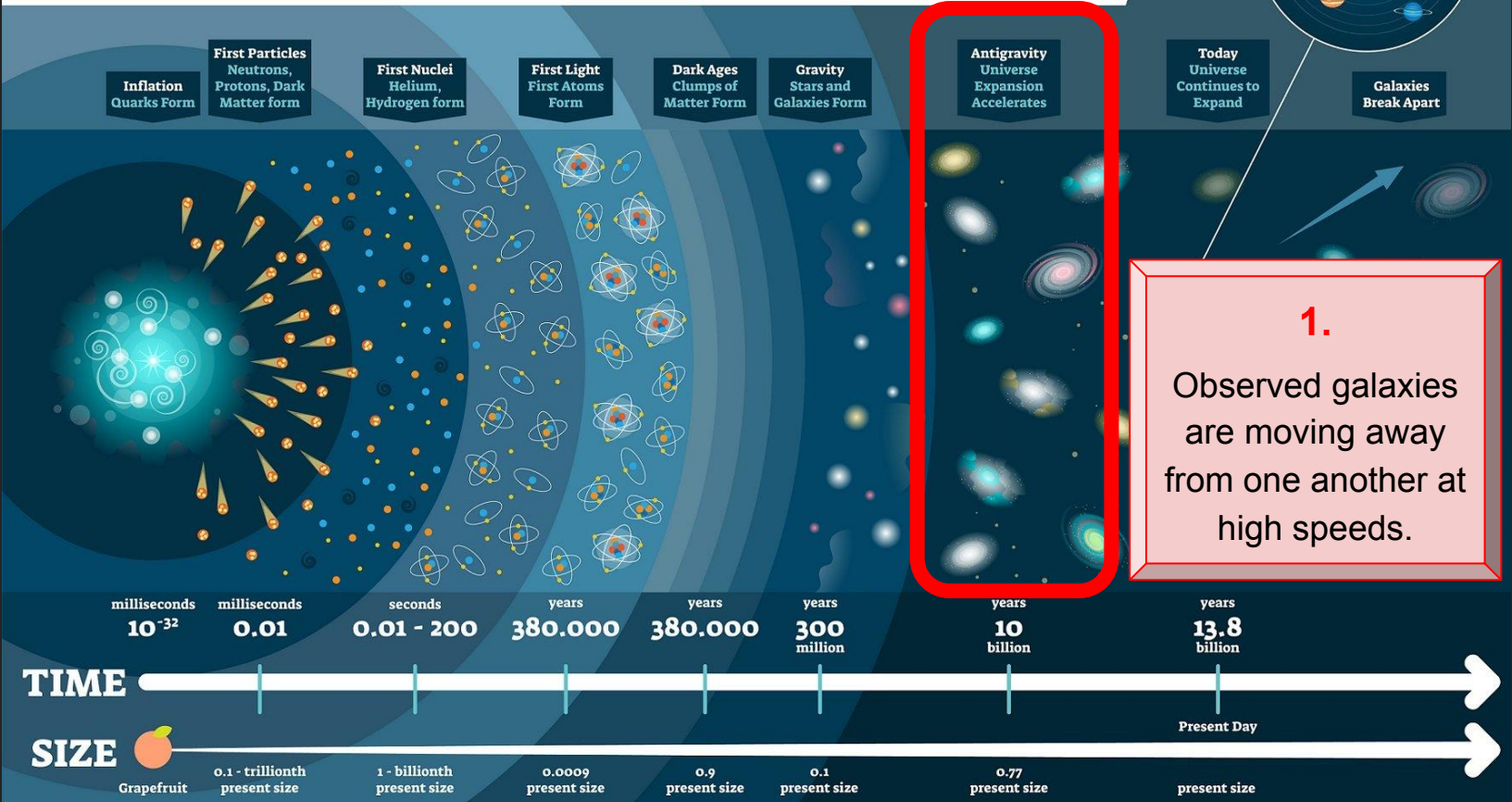
First Particles Neutrons, Protons, Dark Matter form

Inflation Quarks Form

1. Observed galaxies are moving away from one another at high speeds.



# Sounds complicated. How do we prove the theory?



## **19th century**

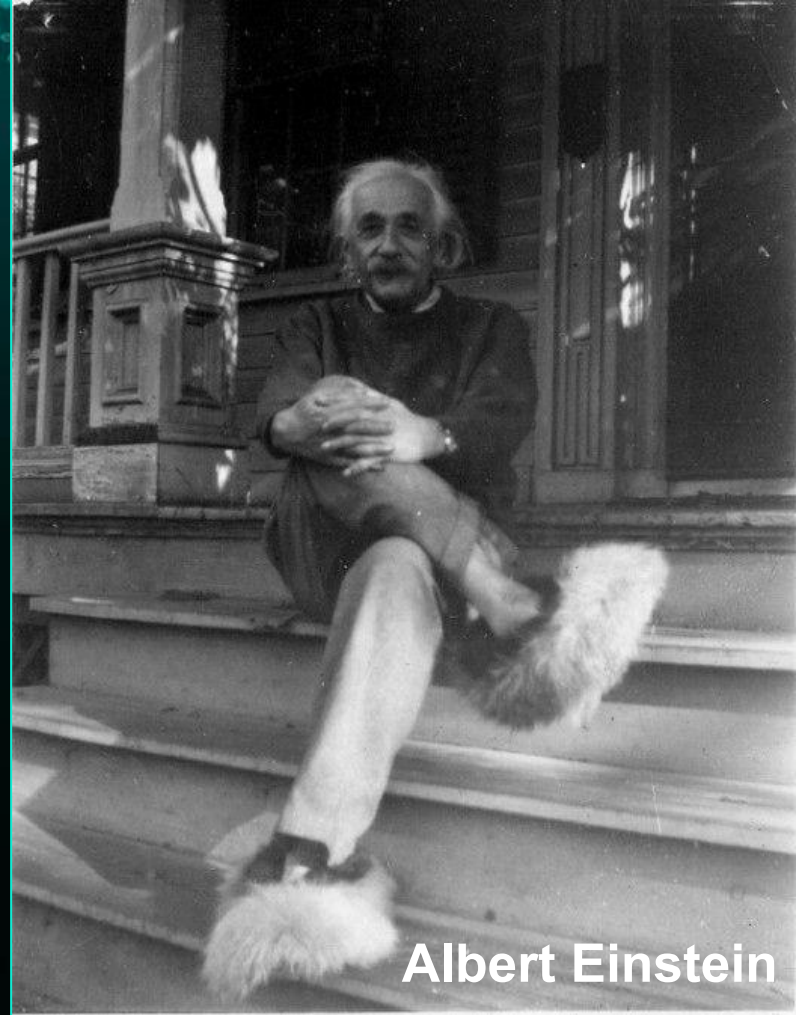
"Static cosmology" - Universe has no beginning and no end, stars move because of gravity, but structures in the universe are generally static.

## 19th century

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## 20th century

- **1905 – Special Theory of Relativity**, space and time are not separate continua.
- **1915 - General Theory of Relativity**, space can contract or expand.



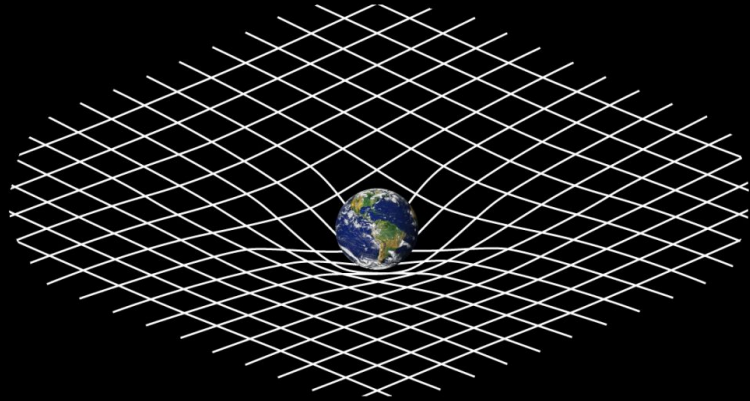
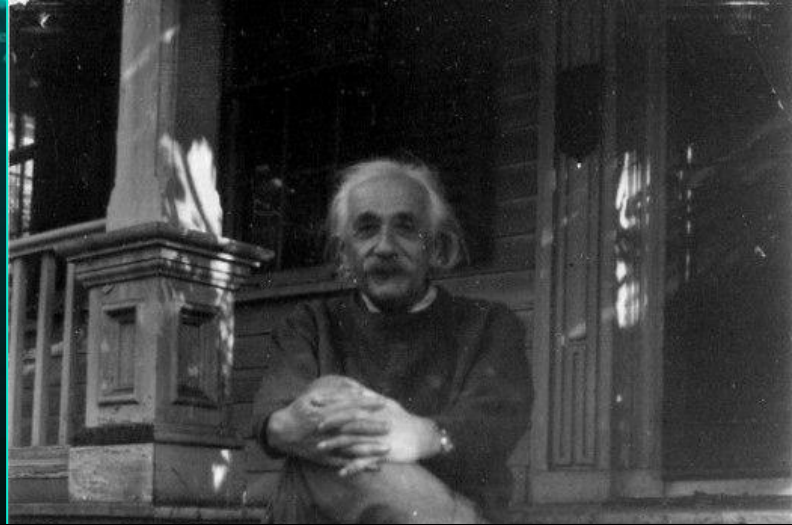
Albert Einstein

## 19th century

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$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} + \Lambda g_{\mu\nu} = \frac{8\pi G}{c^4}T_{\mu\nu}$$



## 19th century

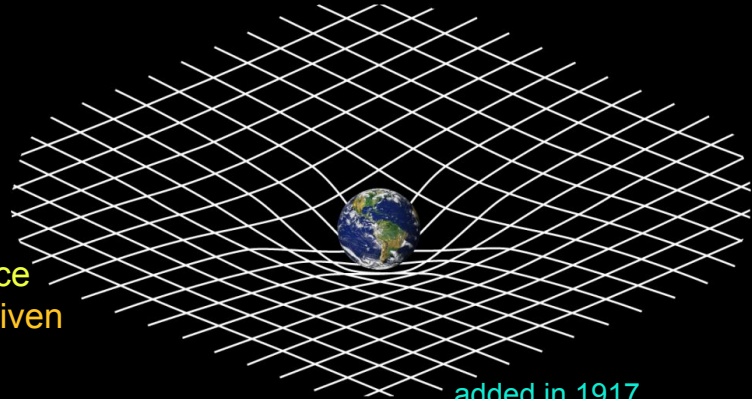
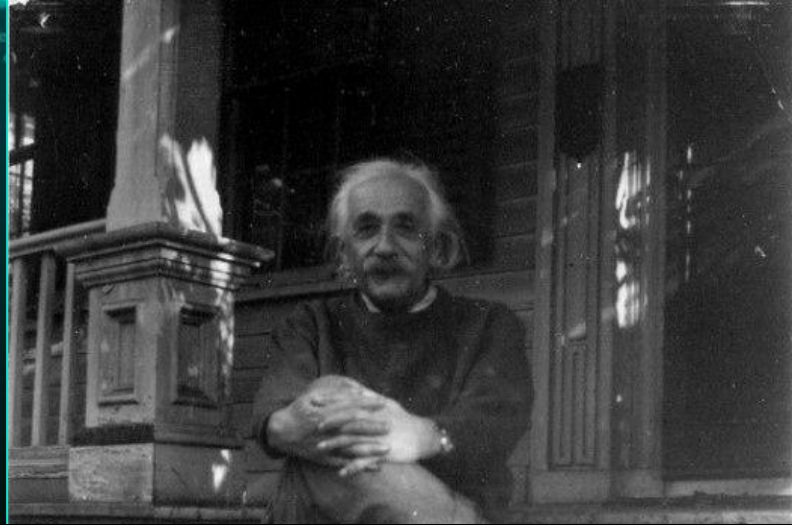
"Static cosmology" - Universe has no beginning and no end, stars move because of gravity, but structures in the universe are generally static.

## 20th century

- 1905 – **Special Theory of Relativity**, space and time are not separate continua.
- 1915 - **General Theory of Relativity**, space can contract or expand.

He accepts the idea of expanding universe in 1931.

1. Curvature change from place to place
2. How are distances calculated at a given point given the curvature
3. Mass-energy content (source of the curvature)
4. Cosmological constant opposing gravity



$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} + \Lambda g_{\mu\nu} = \frac{8\pi G}{c^4}T_{\mu\nu}$$

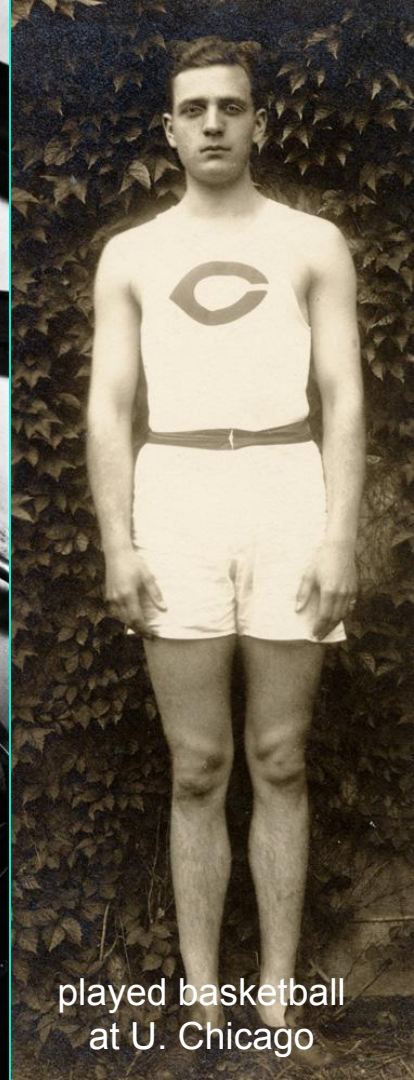
added in 1917.

# Edwin Hubble

1889 – 1953

- Born in Missouri and moved to Wheaton, IL in 1900!

100 inch telescope at Mt. Wilson (near L.A.)



played basketball  
at U. Chicago

# Edwin Hubble

1889 – 1953

- Born in Missouri and moved to Wheaton, IL in 1900!
- Discovered that nebulae we observe are in fact other Galaxies like our Milky Way!
- Measured **distances** and **velocities** to galaxies.

100 inch telescope at Mt. Wilson (near L.A.)



## FINDS SPIRAL NEBULAE ARE STELLAR SYSTEMS

*Dr. Hubbell Confirms View That  
They Are 'Island Universes'  
Similar to Our Own.*

WASHINGTON, Nov. 22.—Confirmation of the view that the spiral nebulae, which appear in the heavens as whirling clouds, are in reality distant stellar systems, or "island universes," has been obtained by Dr. Edwin Hubble of the Carnegie Institution's Mount Wilson observatory, through investigations carried out with the observatory's powerful telescopes.

The number of spiral nebulae, the observatory officials have reported to the institution, is very great, amounting to hundreds of thousands, and their apparent sizes range from small objects, almost star-like in character, to the great nebulae in Andromeda, which extends across an angle some 3 degrees in the heavens, about six times the diameter of the full moon.

"The investigations of Dr. Hubble

were made photographically with the 60-inch and 100-inch reflectors of the Mount Wilson observatory," the report said, "the extreme faintness of the stars under examination making necessary the use of these great telescopes. The revolving power of these instruments breaks up the outer portions of the nebulae into swarms of stars, which may be studied individually and compared with those in our own system.

From an investigation of the photographs thirty-six variable stars of the type referred to, known as Cepheid variables, were discovered in the two spirals, Andromeda and No. 33, of Messier's great catalogue of nebulae. The study of the periods of these stars and the application of the relationship between length of period and intrinsic brightness at once provided the means of determining the distances of these objects.

"The results are striking in their confirmation of the view that these spiral nebulae are distant stellar systems. They are about to be about ten times as far away as the small Magellanic cloud, or at a distance of the order of 1,000,000 light years. This means that light traveling at the rate of 186,000 miles a second has required a million years to reach us from these nebulae and that we are observing them by light which left them in the Pliocene age upon the earth.

"With a knowledge of the distances of these nebulae we find for their diameters 45,000 light years for the Andromeda nebulae and 15,000 light

years for Messier 33. These quantities, as well as the masses and densities of the systems, are quite comparable with the corresponding values for our local system of stars."

## FUNDS FOR SCHENCK HOUSE

*William C. Redfield Says It Was  
Built of Timbers of Old Ship.*

William C. Redfield, formerly Secretary of Commerce and now the President of the Netherland-America Foundation, 17 East Forty-second Street, was one of the many who were interested in the news printed in yesterday's TIMES that an offer had been submitted to Murray Hulbert, President of the Board of Aldermen, to sell to the city for \$10,000 the old Schenck homestead at Mill Basin, Brooklyn, which is believed to be the oldest house in New York City.

Mr. Redfield, in a letter to Mr. Hulbert yesterday, said that the Schenck house was built out of the timbers of an ancient ship. The old beams are visible and the knees of the old vessel still support the upper floors.

"I earnestly hope that funds may be made available. In order that this exceptional landmark of our city's history may be preserved," wrote Mr. Redfield. Mrs. Redfield is connected by marriage with the Schenck family.

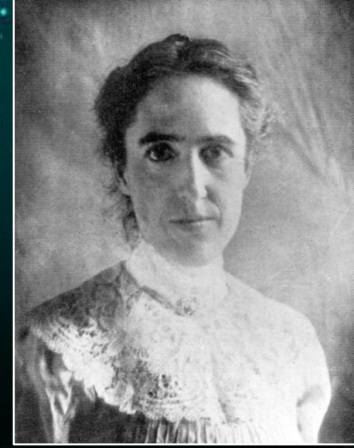
Published 1924.

The New York Times

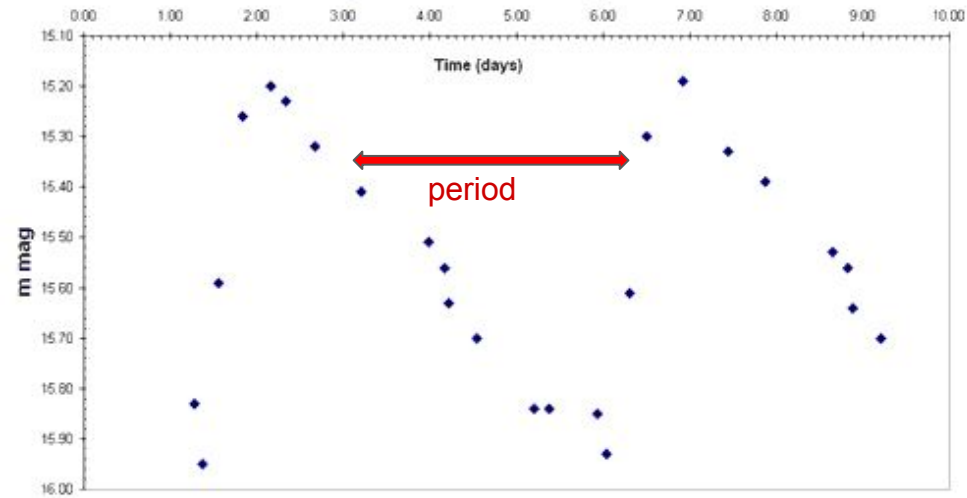
Distances are measured using **Cepheid stars**

**Henrietta Swan Leavitt**  
1868 - 1921

Harvard College Observatory  
Observing stars in Small and  
Large Magellanic Clouds

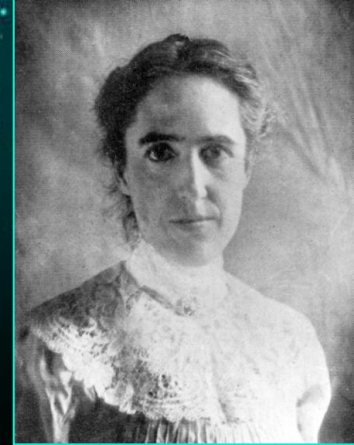


Light Curve for LMC Cepheid



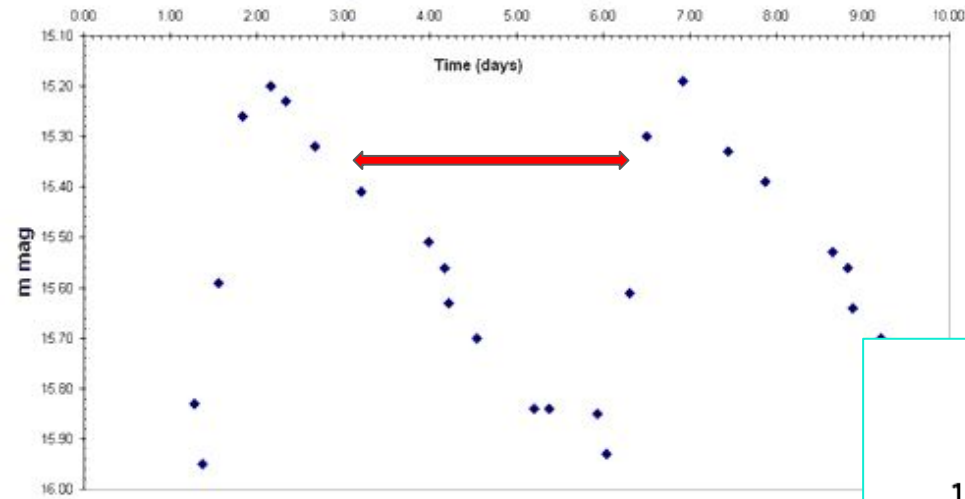
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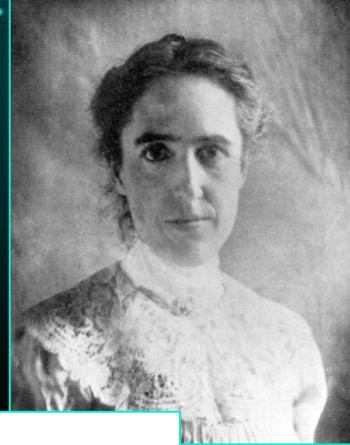
**Some stars in these two nebulae have  
variable brightnesses!**

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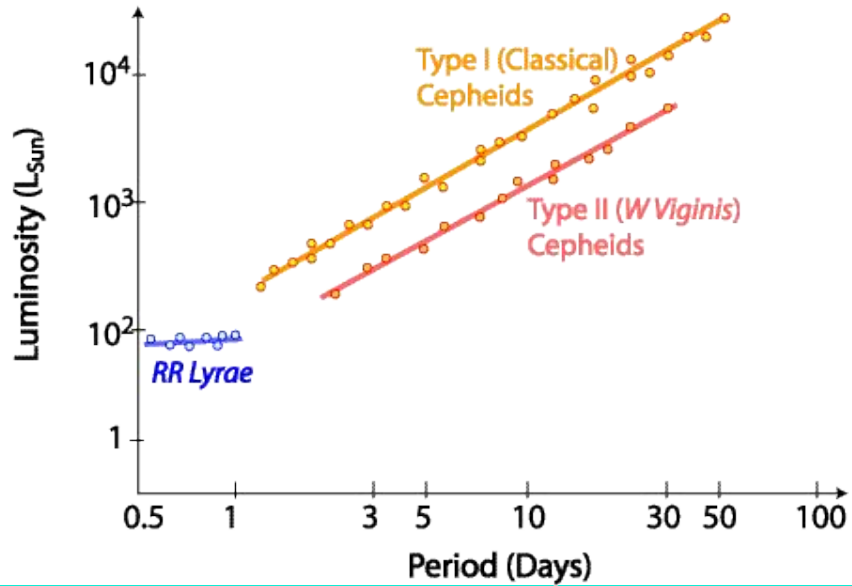
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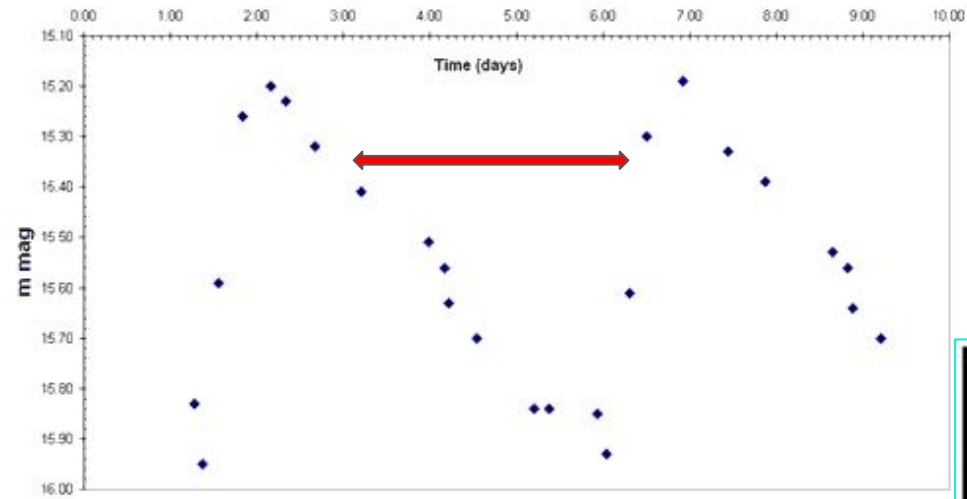
Some stars in these two nebulae have  
variable brightnesses!

Brighter stars have longer  
periods!

PERIOD - LUMINOSITY RELATIONSHIP

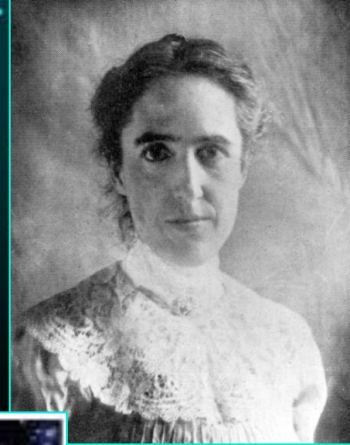


Light Curve for LMC Cepheid



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**Some stars in these two nebulae have  
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**Brighter stars have longer  
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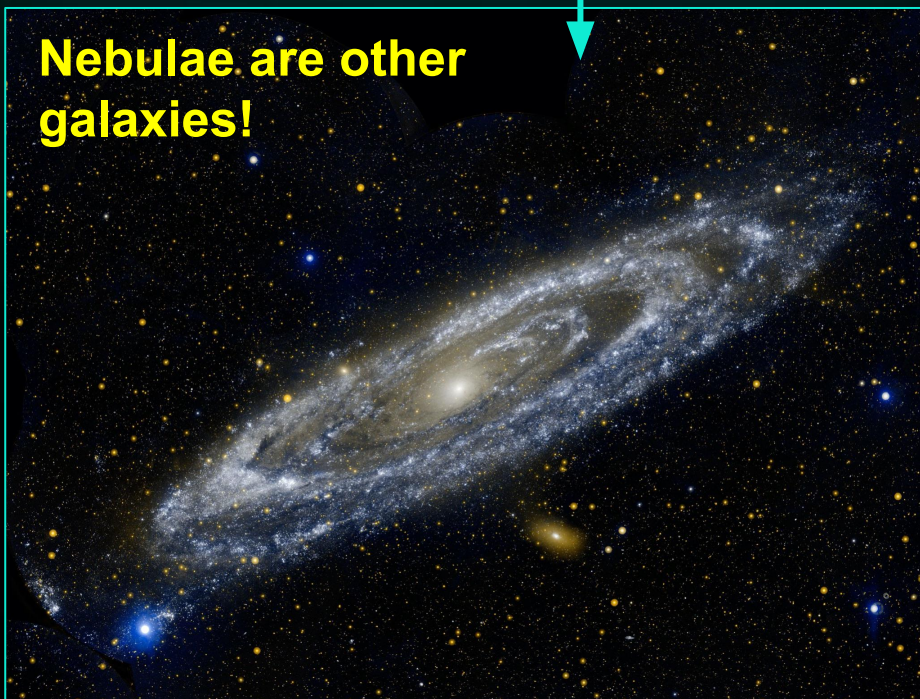


# Hubble - finds Cepheids in Andromeda and M33 (Triangulum)

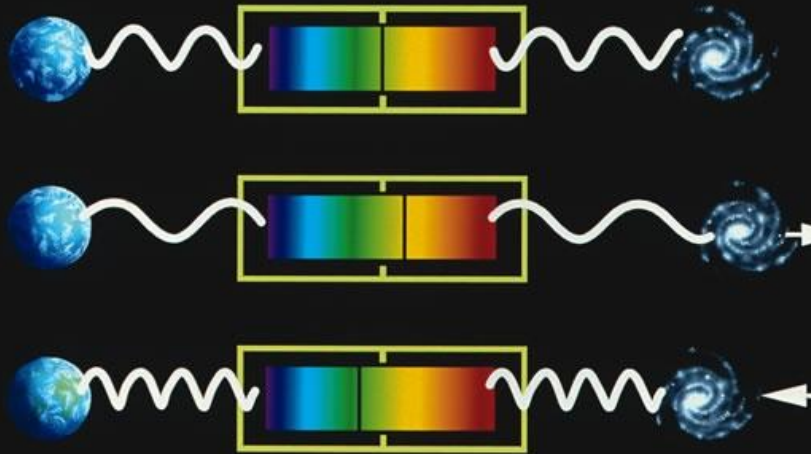
Andromeda is 930,000 light years away.

But Milky Way has a diameter of only 100,000 light years!

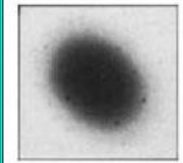
**Nebulae are other galaxies!**



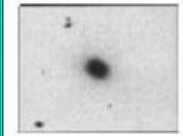




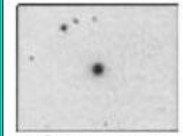
Cluster  
nebula in



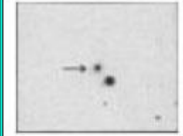
Virgo



Ursa Major



Corona  
Borealis

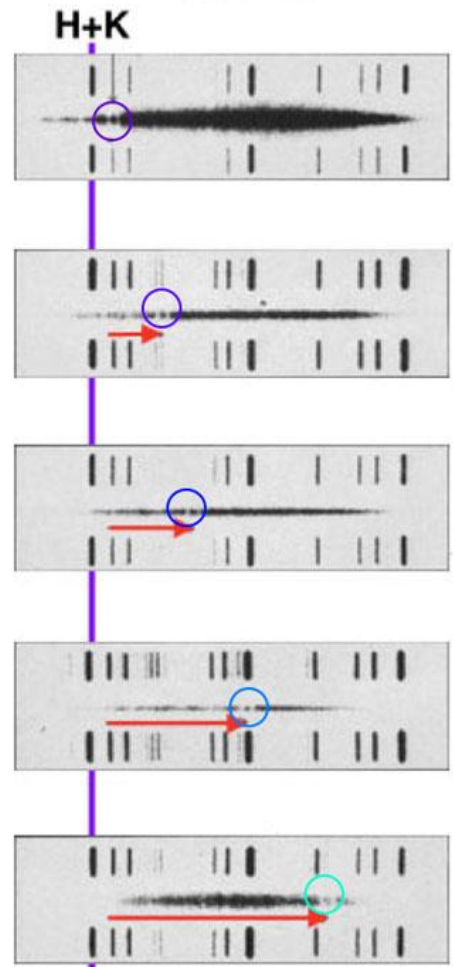


Boötes



Hydra

Redshifts



# Vesto Slipher

1875 - 1969

Lowell Observatory, Arizona

1912. - **Velocities** can be measured using the **Doppler Effect!**

Slipher was first to observe the **shift of spectral lines of galaxies**, making him the discoverer of **galactic redshifts**.

More distant galaxies seem to be moving away faster!

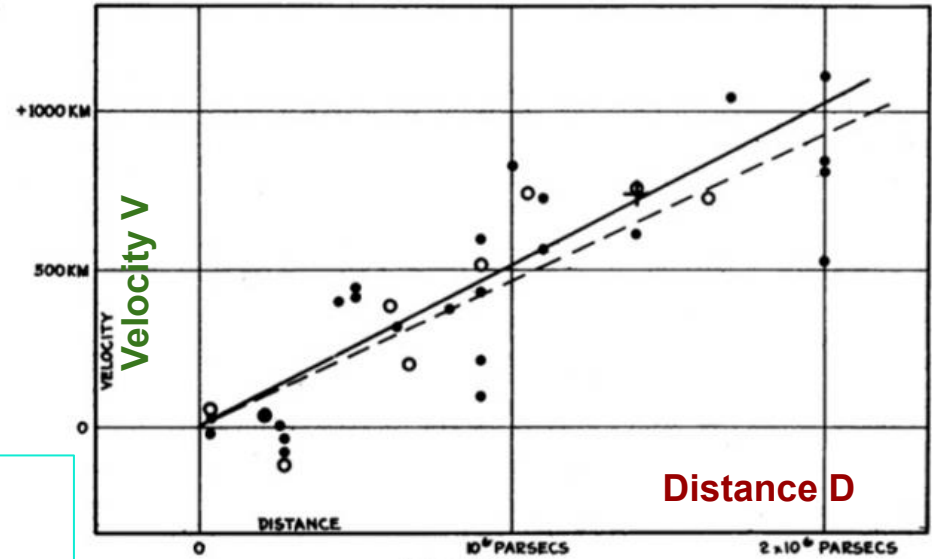
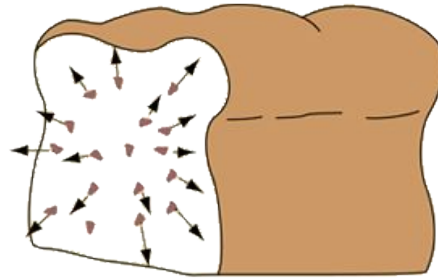
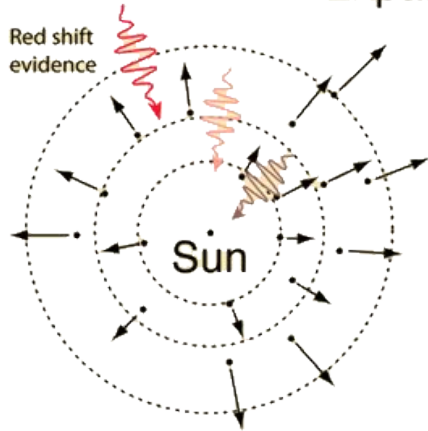


FIGURE 1

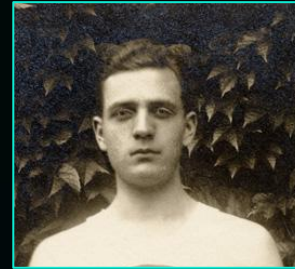
Velocity-Distance Relation among Extra-Galactic Nebulae.

### Expanding universe



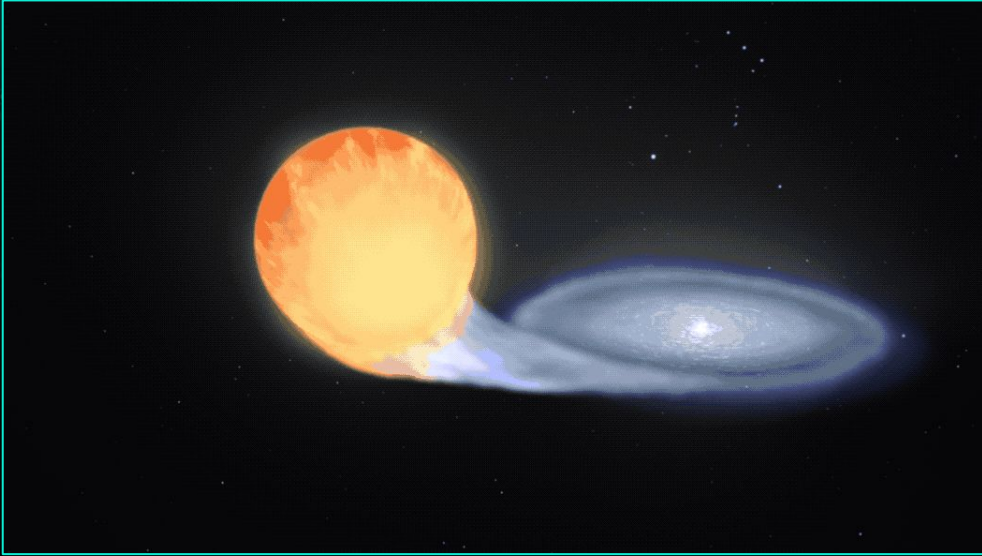
Every raisin in a rising loaf of raisin bread will see every other raisin expanding away from it.

$$V = H D$$



Back to Hubble...

# The expansion is accelerating!



S. Perlmutter



A. Riess



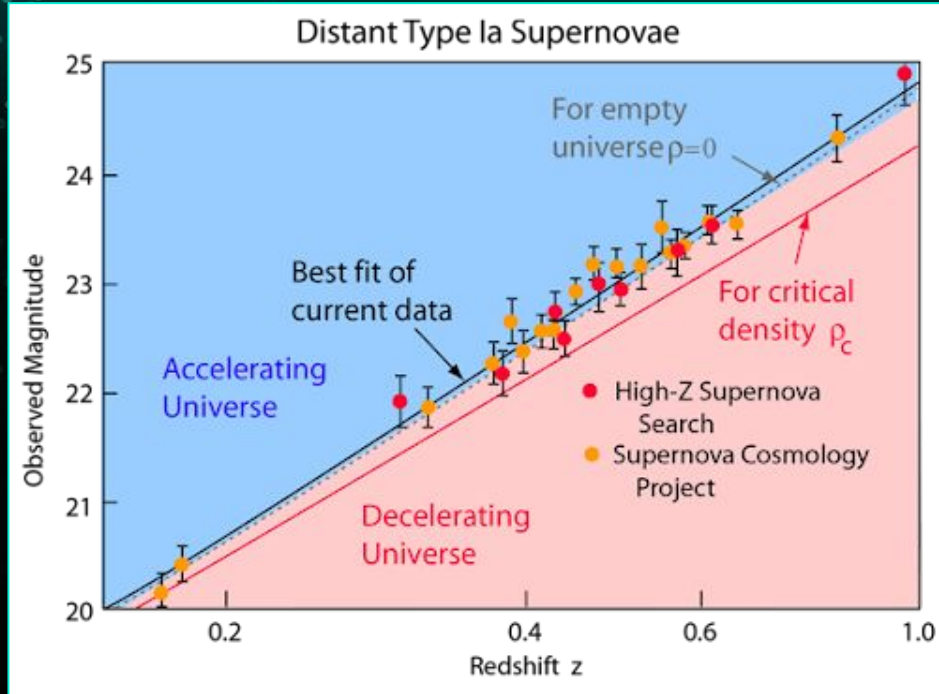
B. Schmidt

## ← Type Ia supernova

They can be used as standard candles but to much larger distances - they are super bright!

5 billion times brighter than the Sun

# The expansion is accelerating!



S. Perlmutter



A. Riess

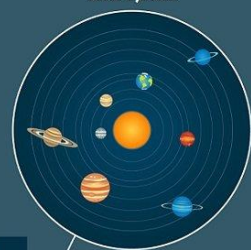


B. Schmidt

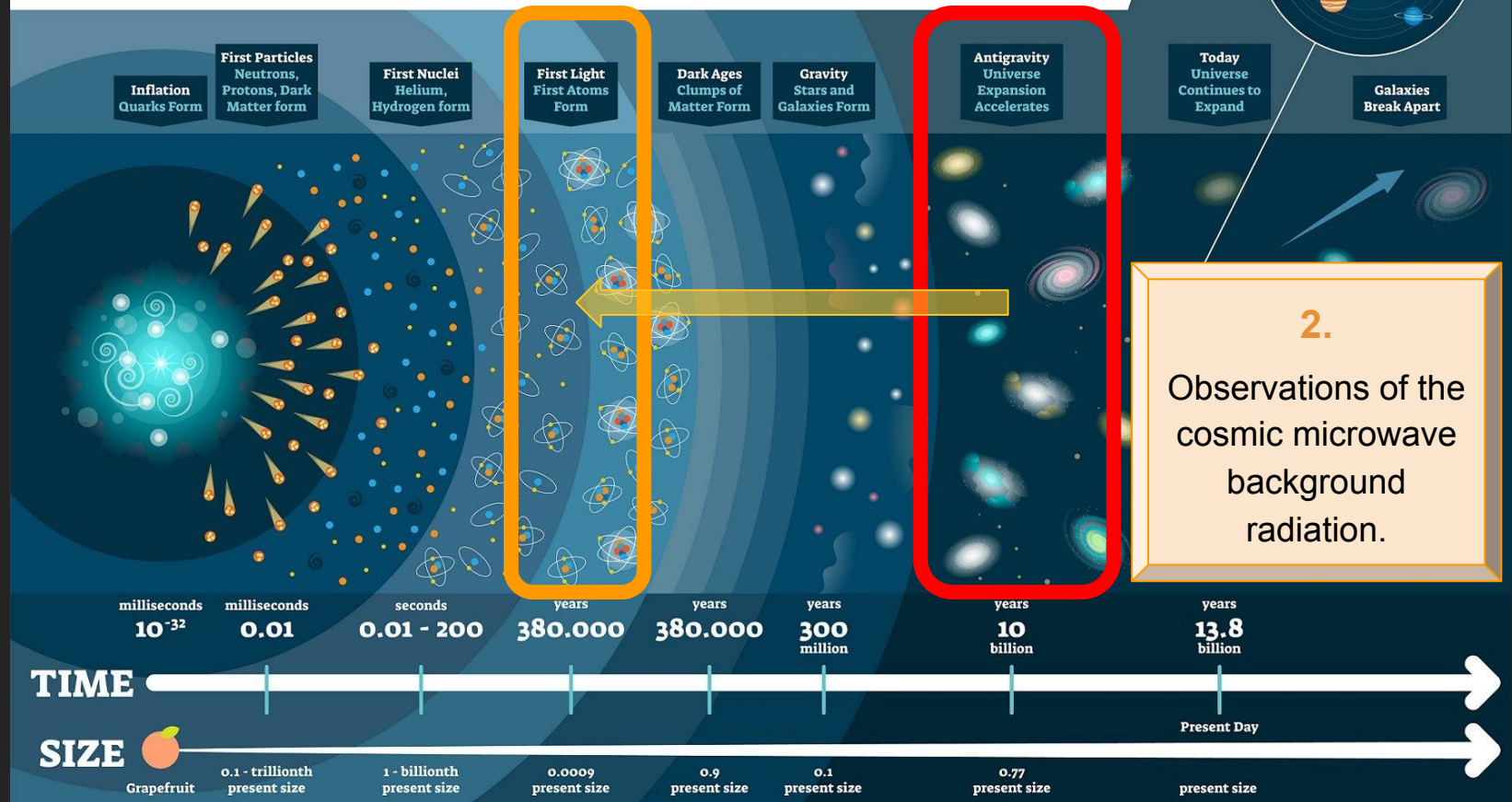
Nobel Prize 2011.



Distant supernovae show that the speed of galaxies receding in relation to the Milky Way increases over time!



# Sounds complicated. How do we prove the theory?

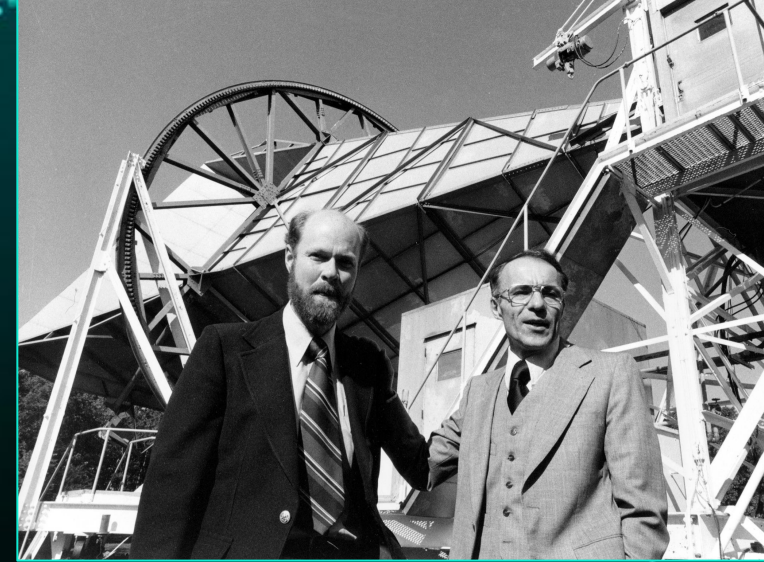
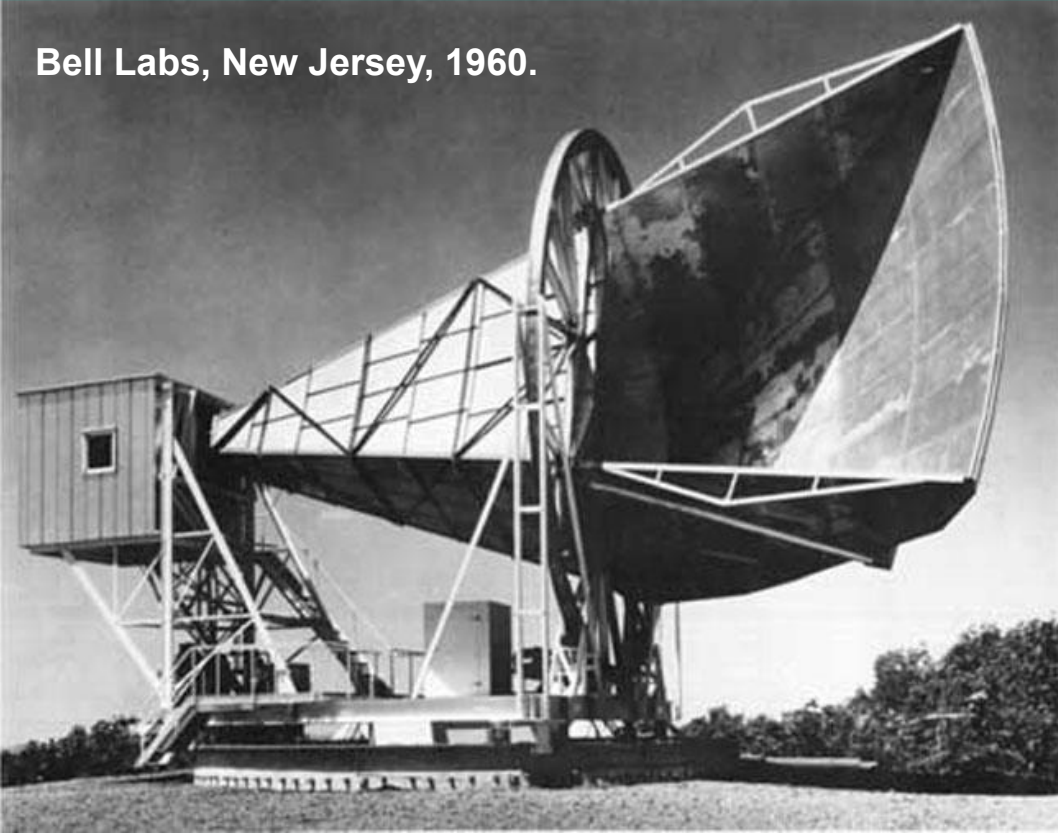


2.  
Observations of the cosmic microwave background radiation.

**We measure a 2.7 K signal.**

**380,000 yrs ago this signal was 3000K**

**Bell Labs, New Jersey, 1960.**



**Robert Wilson**

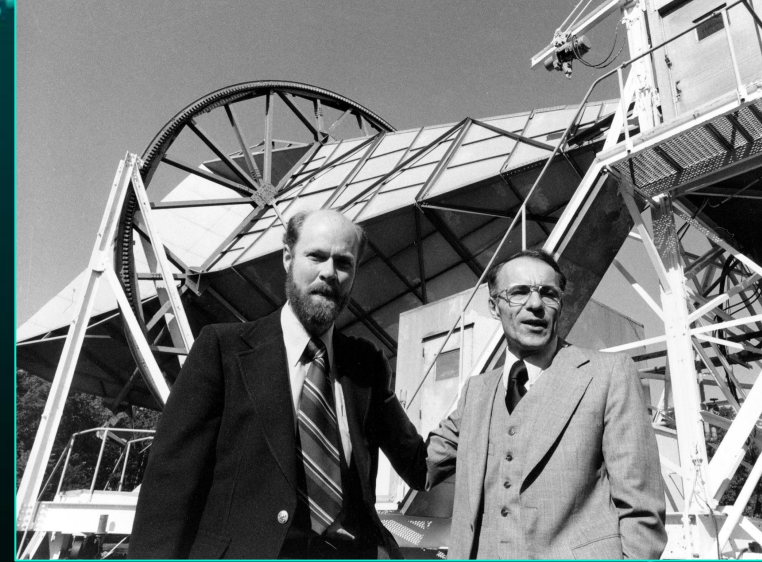
**Arno Penzias**

1965. - they publish the finding of a background "noise" coming from every direction.

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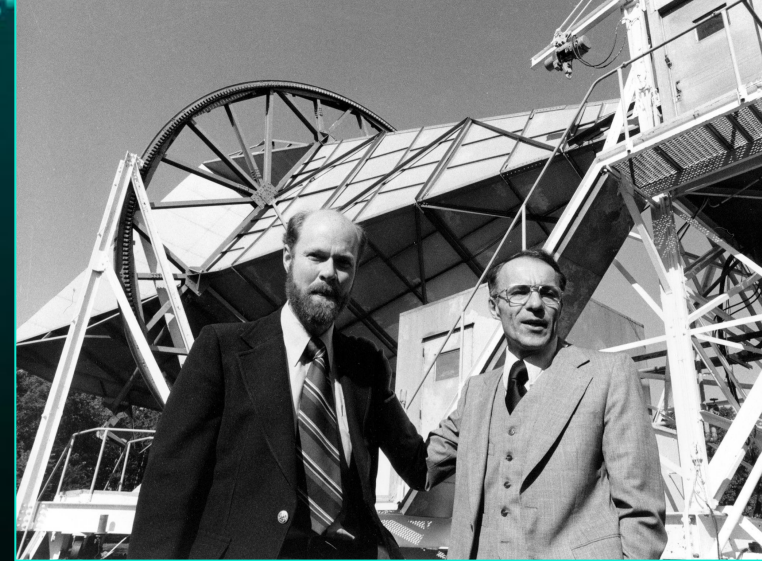
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## Robert Dicke

1916 - 1997

Princeton University



## Nobel Prize 1987.

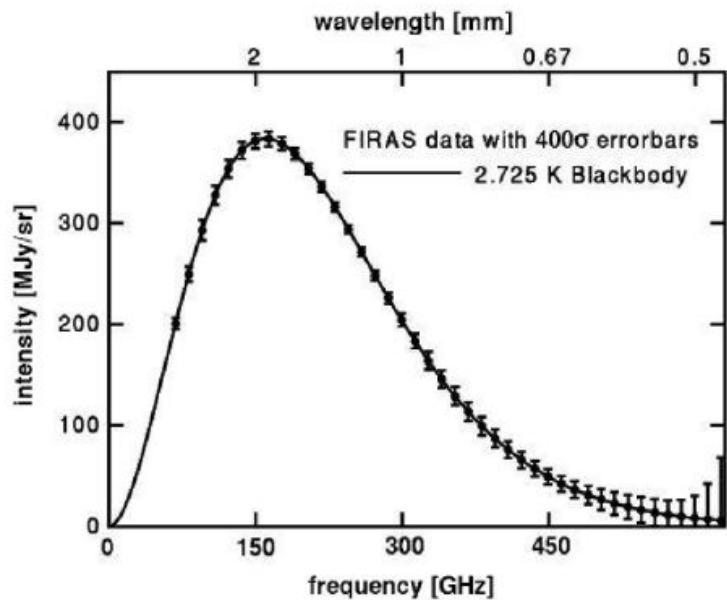
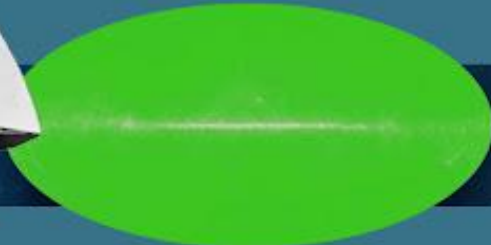
Penzias & Wilson



If there had been a big bang, the residue of the explosion should by now take the form of a low-level background radiation throughout the Universe.

With better telescopes we were able to see smaller and smaller fluctuations in the **2.7K signal!**

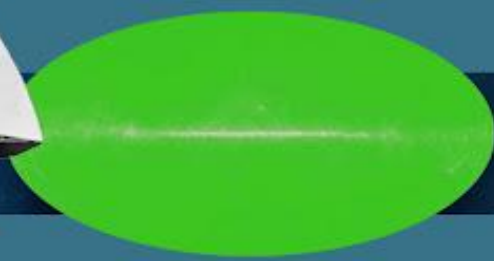
1962  
PENZIAS & WILSON



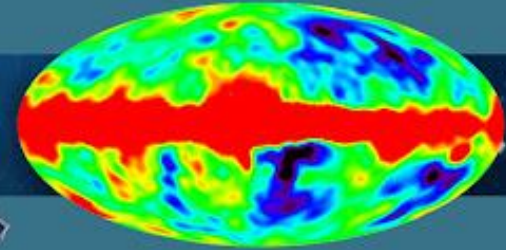
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**COBE:** Resolution  $7^\circ$   
fluctuations of 0.0002 K

1962  
PENZIAS & WILSON



1989-1993  
COBE

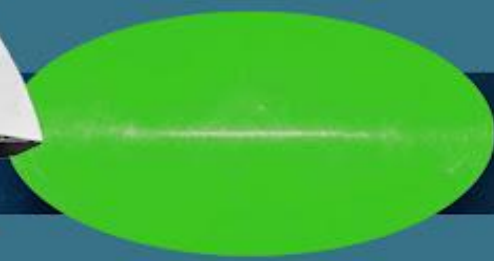


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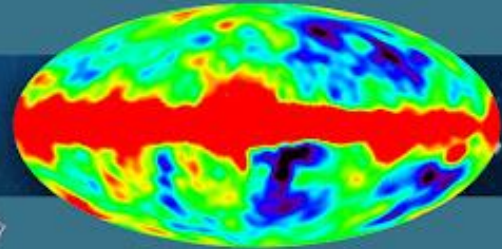
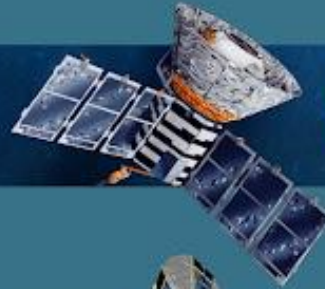
**COBE:** Resolution  $7^\circ$   
fluctuations of 0.0002 K

**WMAP:** 5 times better resolution  $0.5^\circ$   
0.00001 K

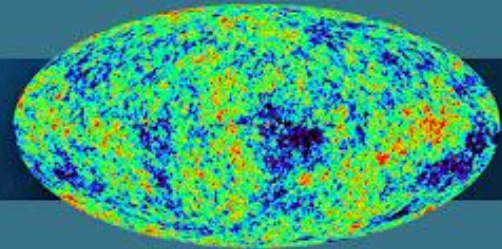
**1962**  
PENZIAS & WILSON



**1989-1993**  
COBE



**2001-2010**  
WMAP



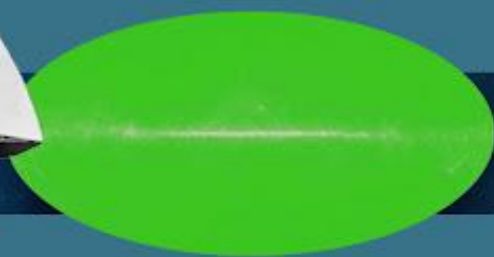
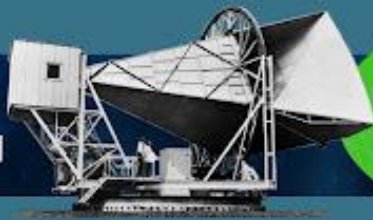
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**COBE:** Resolution  $7^\circ$   
fluctuations of 0.0002 K

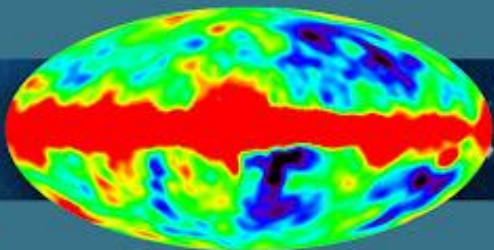
**WMAP:** 5 times better resolution  $0.5^\circ$   
0.00001 K

**PLANK:** 15 times better  $0.16^\circ$   
0.000001 K

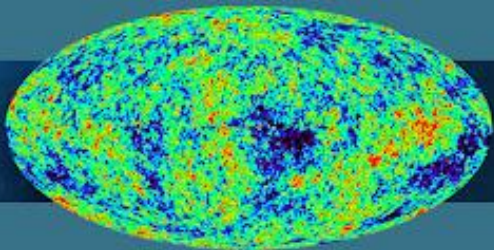
1962  
PENZIAS & WILSON



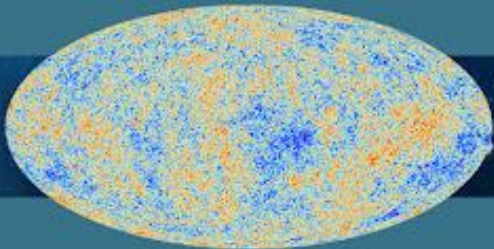
1989-1993  
COBE

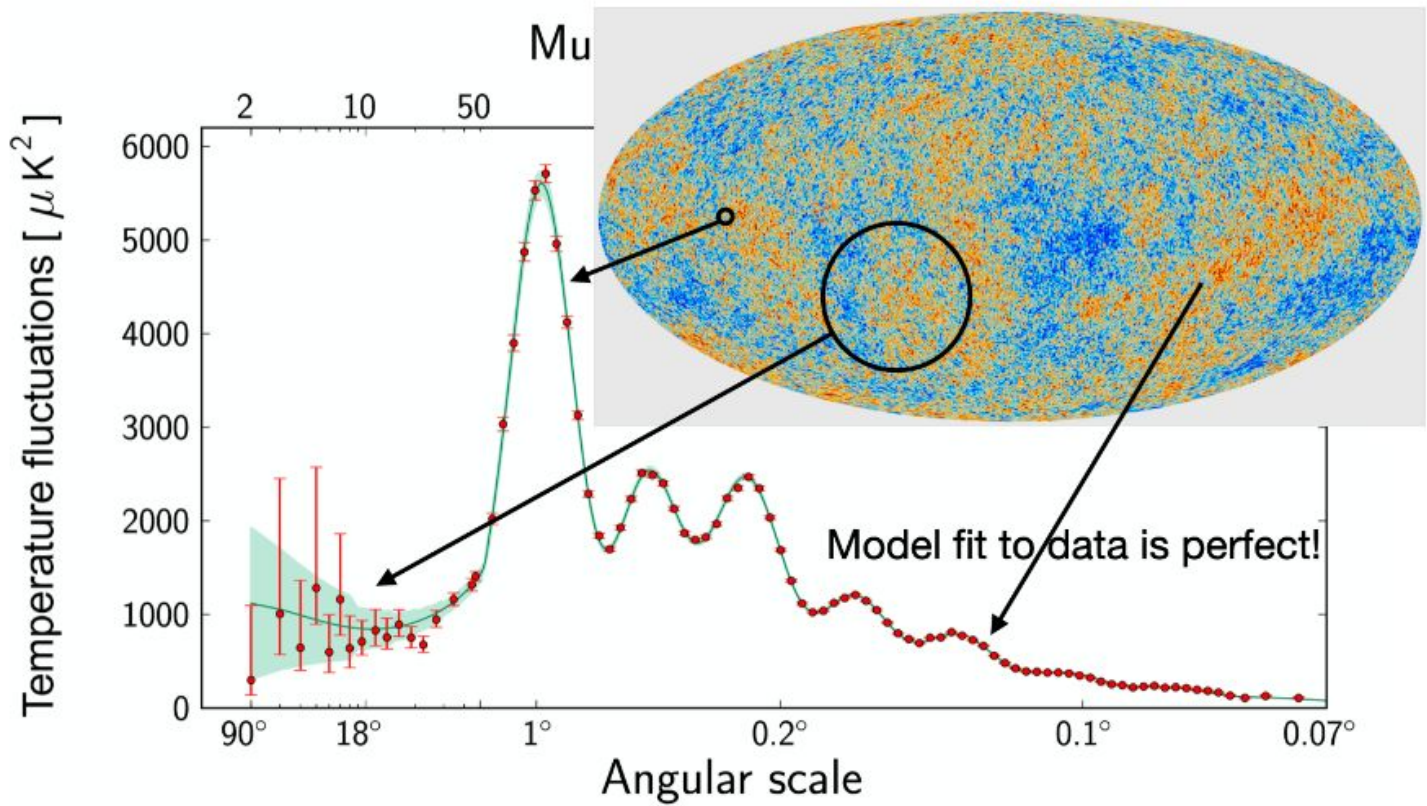


2001-2010  
WMAP



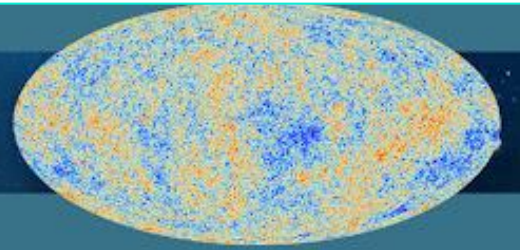
2009-2013  
PLANK

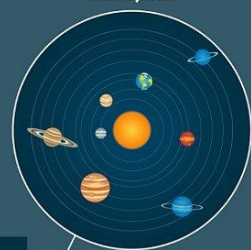




These fluctuations lead to the formation of galaxies and other structures!

2009-2013  
PLANK





Galaxies Break Apart

Today Universe Continues to Expand

Antigravity Universe Expansion Accelerates

Gravity Stars and Galaxies Form

Dark Ages Clumps of Matter Form

First Light First Atoms Form

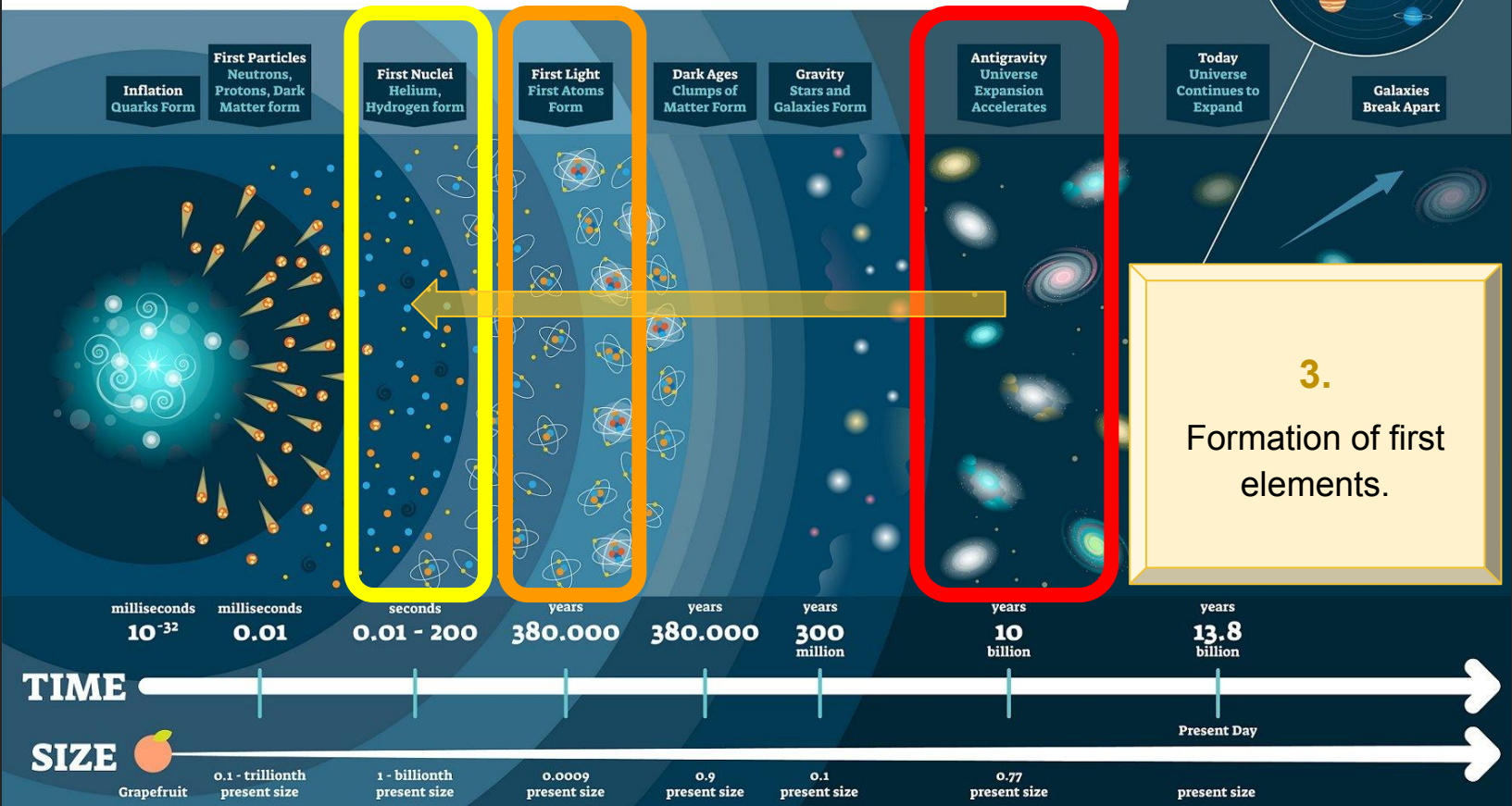
First Nuclei Helium, Hydrogen form

First Particles Neutrons, Protons, Dark Matter form

Inflation Quarks Form

3. Formation of first elements.

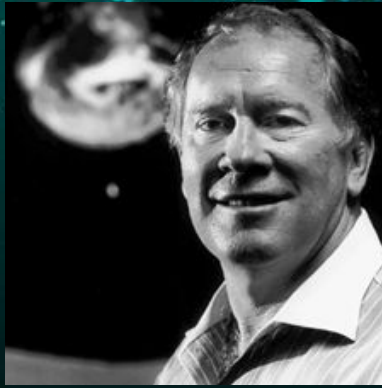
# Sounds complicated. How do we prove the theory?



# David N. Schramm

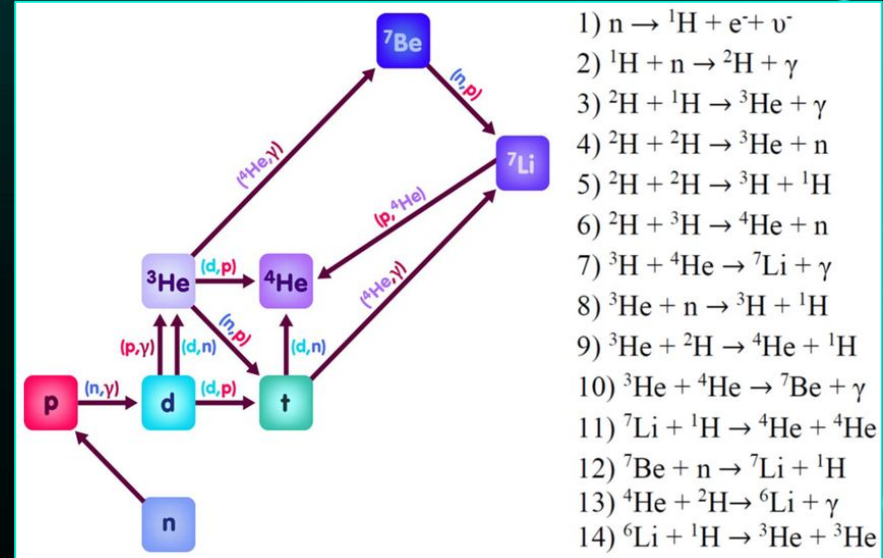
1945 - 1997

U. Chicago



10s - 20 min after the Big Bang

We know exactly the temperature (i.e. baryon-to-photon ratio) that the Universe had when it was forming first nuclei - **H**, **D**, **He**, **Li**.

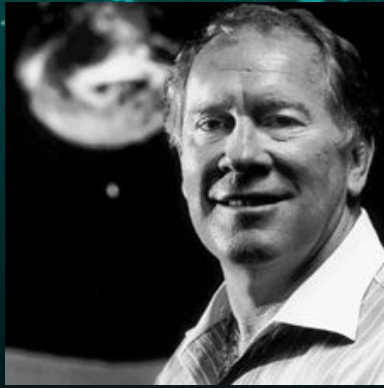




# David N. Schramm

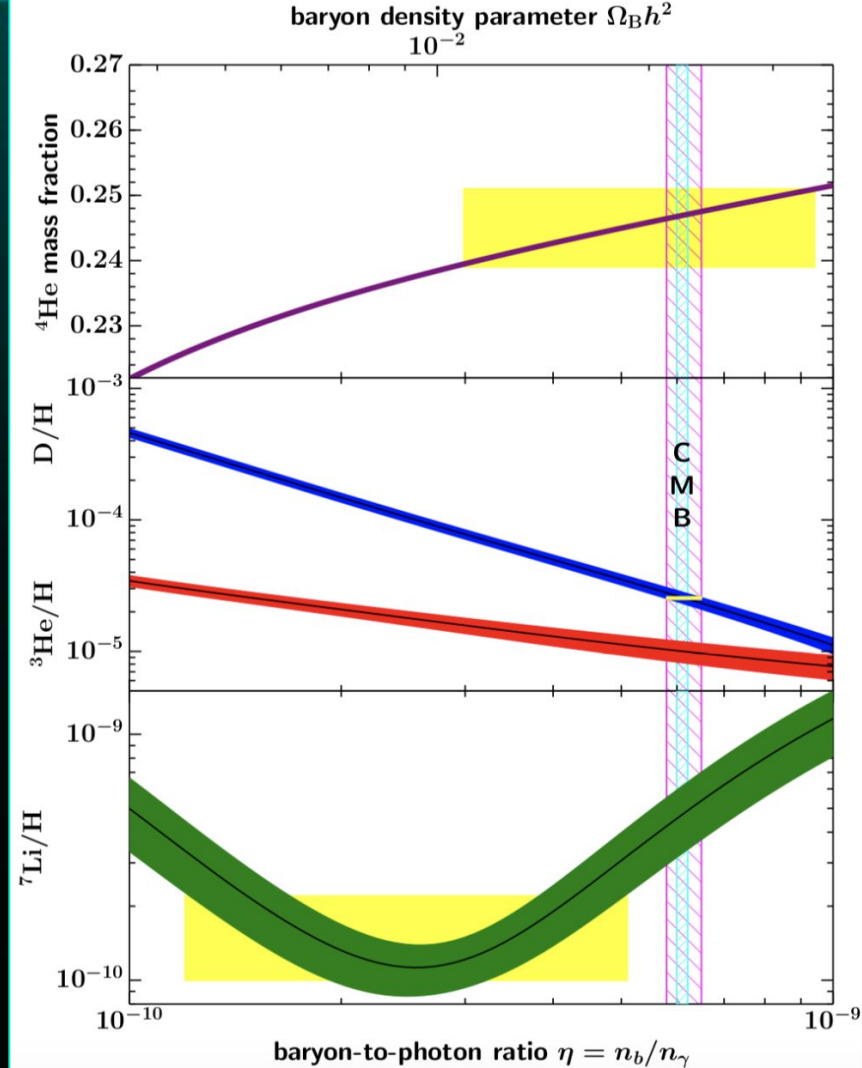
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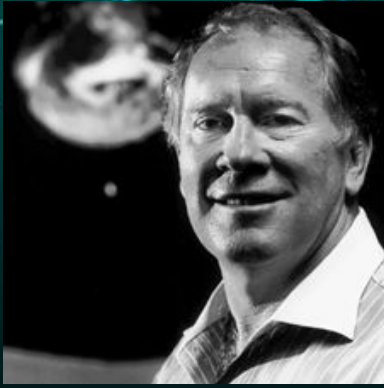
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1945 - 1997

U. Chicago



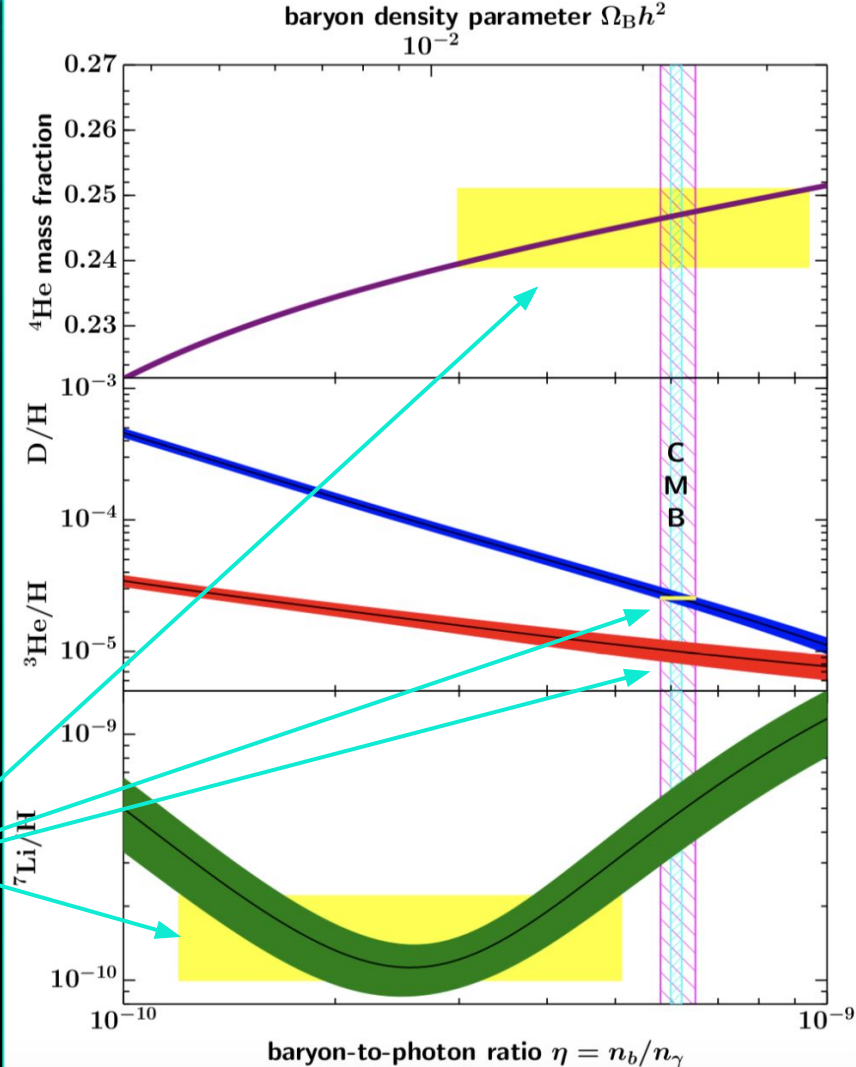
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We know exactly the temperature (i.e. baryon-to-photon ratio) that the Universe had when it was forming first nuclei - **H**, **D**, **He**, **Li**.

Let's observe some **very old stars** to see if abundances of these elements match our expectations.

**Observations and theory match very well!**

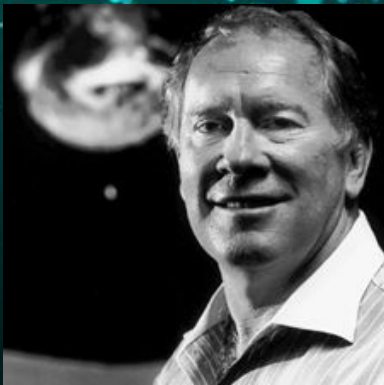
....well almost all of them (Li problem)



# David N. Schramm

1945 - 1997

U. Chicago

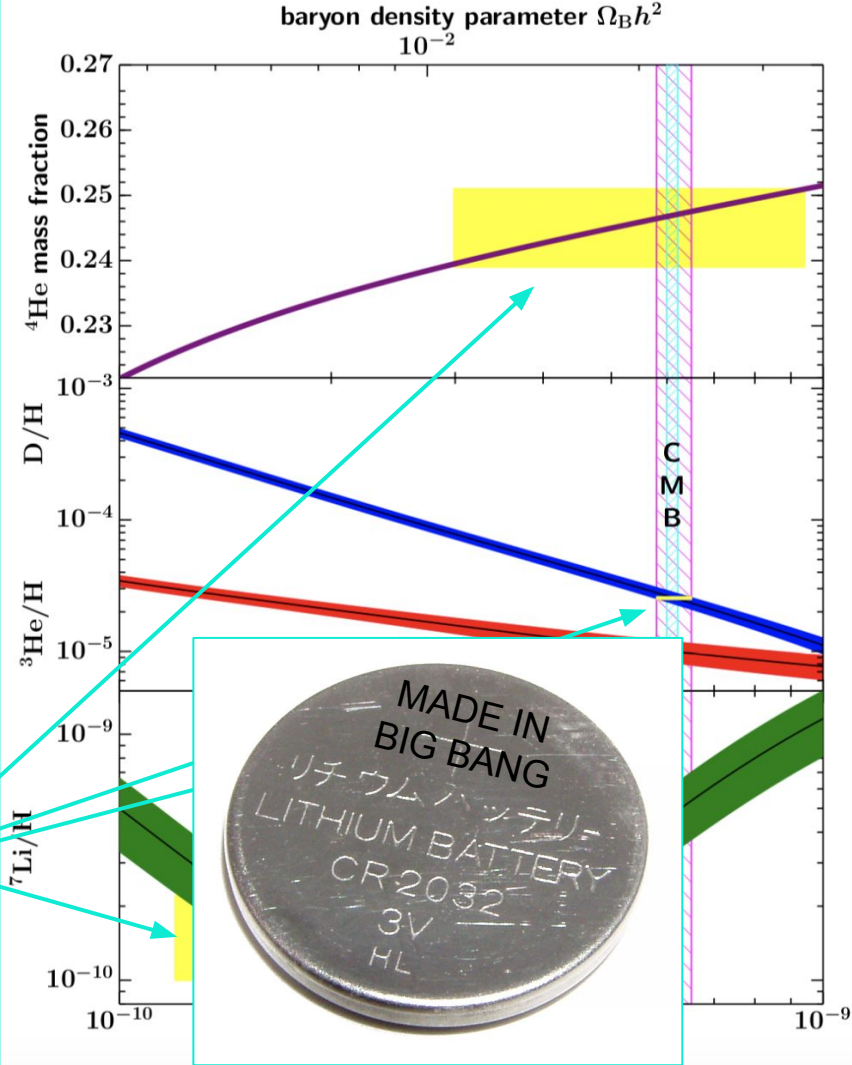


10s - 20 min after the Big Bang

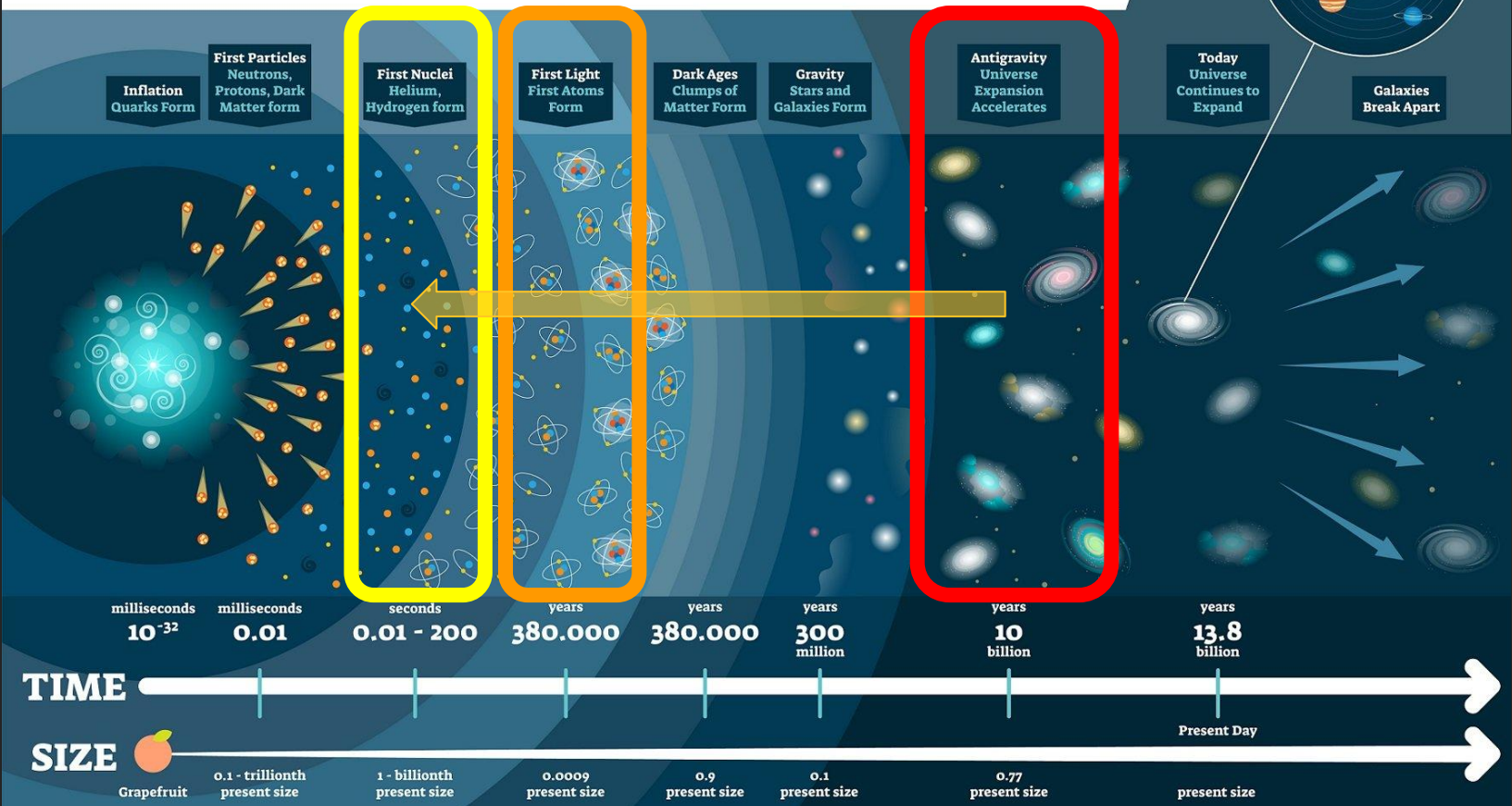
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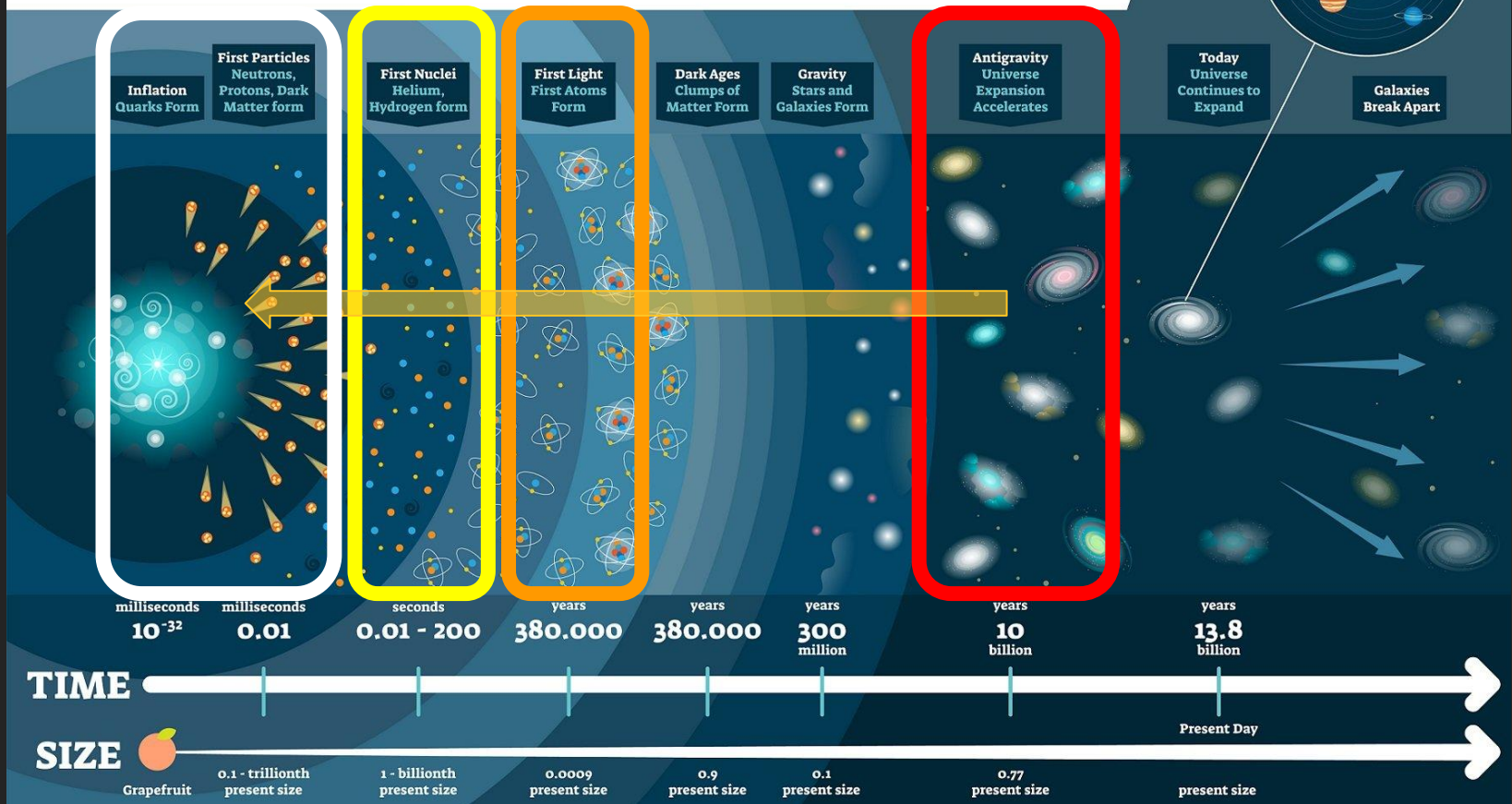
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....well almost all of them (Li problem)



# Sounds complicated. How do we prove the theory?



# How do we reach even earlier epochs?





# How do we reach even earlier epochs?

**Inflation**  
Quarks Form

**First Particles**  
Neutrons, Protons, Dark Matter form

**First Nuclei**  
Helium, Hydrogen form

**First Light**  
First Atoms Form

**Dark Ages**  
Clumps of Matter Form

**Gravity**  
Stars and Galaxies Form

**Antigravity**  
Universe Expansion Accelerates

**Today**  
Universe Continues to Expand

**Galaxies**  
Break Apart

**4.**  
Gravitational wave background!



**TIME**

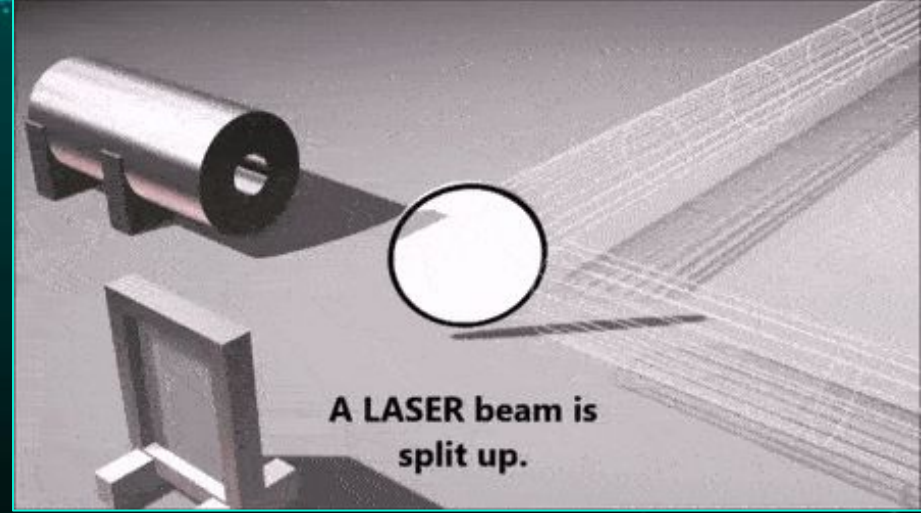
**SIZE**



Grapefruit

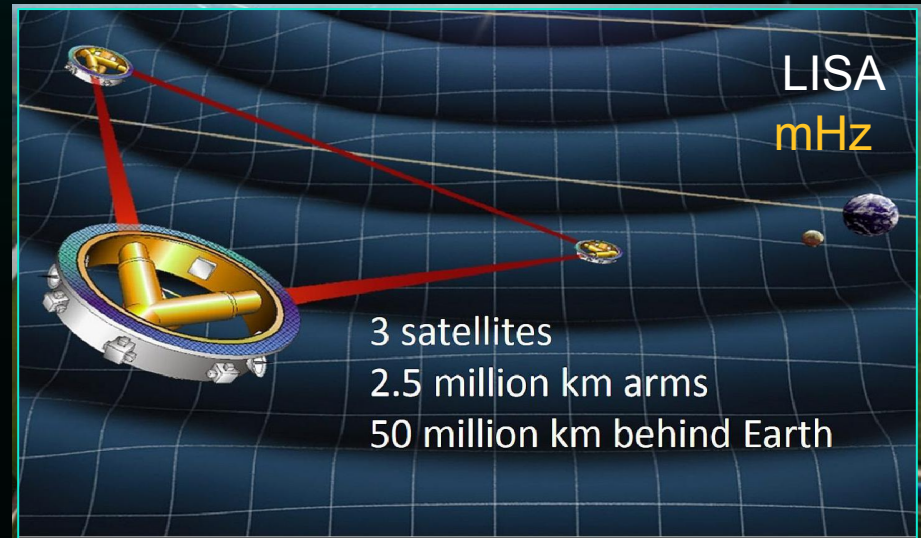
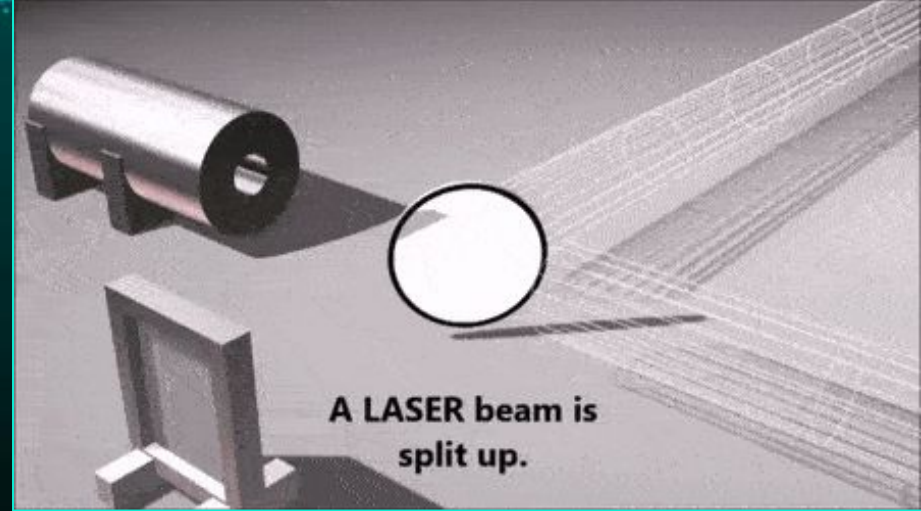
# Gravitational Waves

- **Stochastic gravitational wave backgrounds (SGWBs)** - superposition of gravitational waves with different frequencies coming from all directions.
- Evidence of the earliest moments before photons could propagate.
- Phenomena like **inflation, primordial black holes, cosmic strings, and phase transitions** as possible sources.
- In 2023 news from NANOGrav, CPTA, EPTA, and PPTA (first evidence, but still below  $5\sigma$ ).
- For higher frequencies we need longer detector arms.



# Gravitational Waves

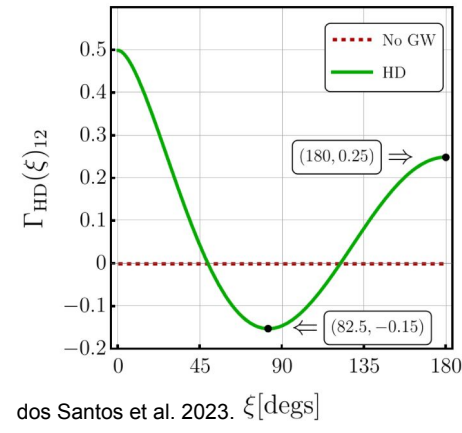
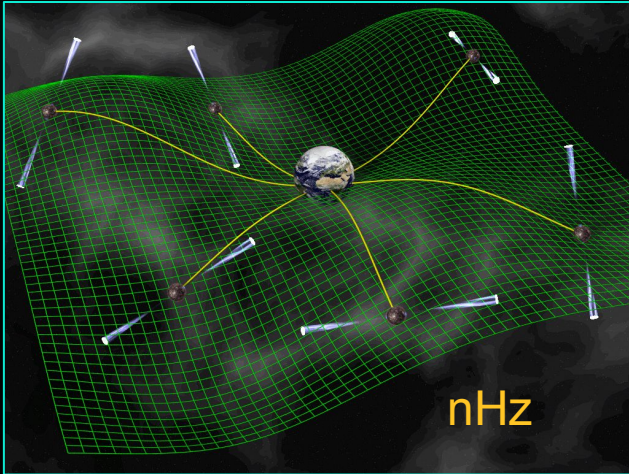
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# Gravitational Waves

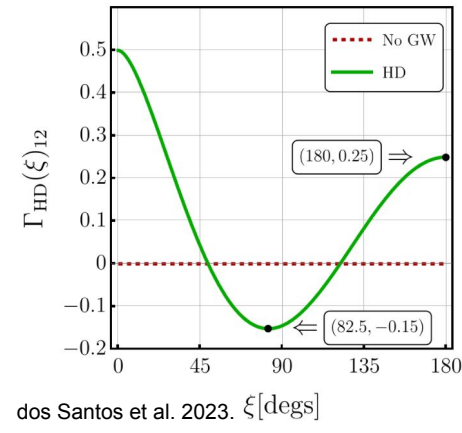
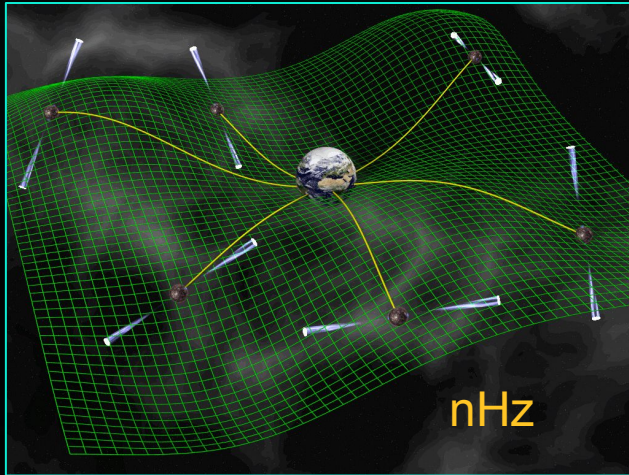
- **Pulsar Timing Arrays** - detecting gravitational waves by measuring the time of arrival of radio pulses from millisecond pulsars. Pulses are disturbed by gravitational waves between the pulsar and Earth.



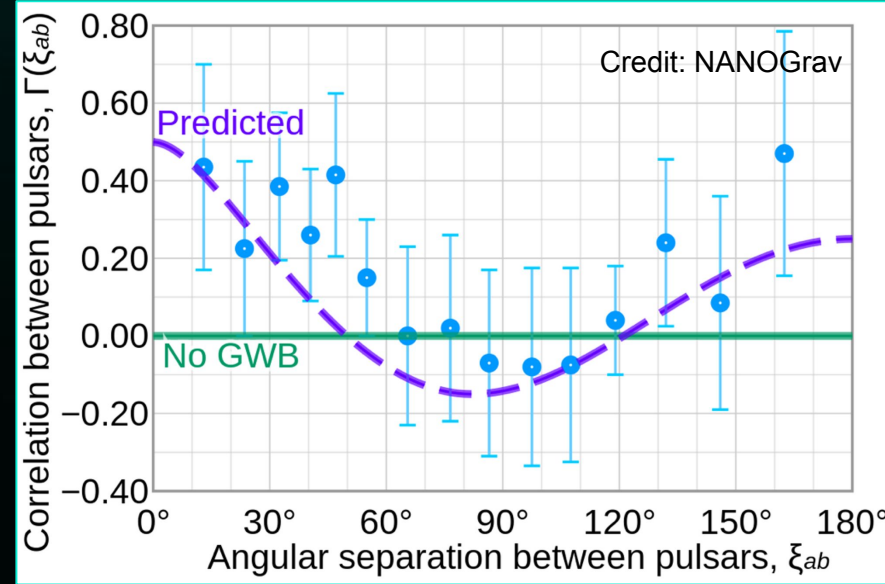
Helling-Downs Curve for 2 pulsars as a function of their separation angle.

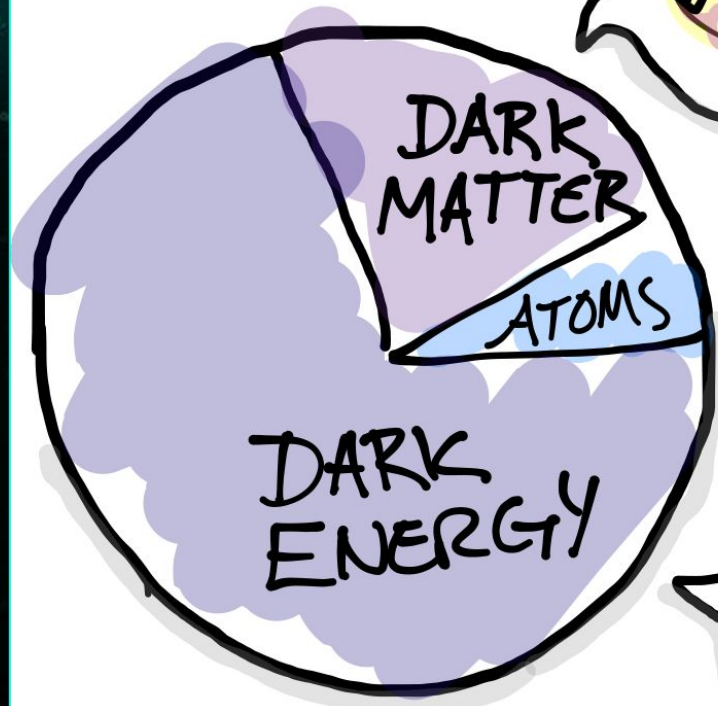
# Gravitational Waves

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Helling-Downs Curve for 2 pulsars as a function of their separation angle.





~25%, Interacts with gravity, but not light.  
Clumps into structures.

A hand-drawn diagram showing a spiral galaxy with stars and arrows indicating rotation. To its right is a cluster of several smaller galaxies, representing how dark matter clumps into structures.

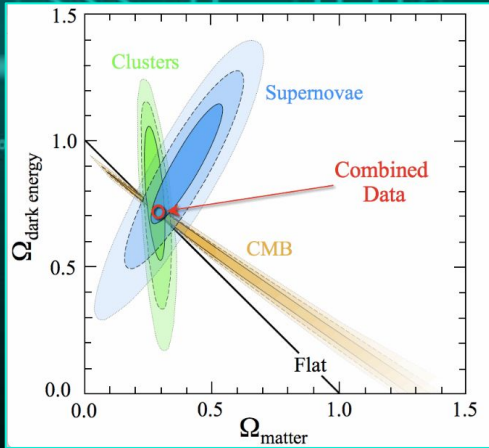
~5% Described by known physics.

A hand-drawn diagram showing four icons representing known physics: a stick figure, the Earth, the Sun, and a spiral galaxy.

~70%, "Negative pressure" associated with the vacuum.  
Drives expansion of space.

A hand-drawn diagram showing a grid of lines with arrows pointing outwards from the center, representing the expansion of space.

# Being a **cosmologist** today is all about big data



Complex Simulations

Artificial Intelligence

Experiments & Astro. Surveys

$$\Omega = \Omega_m + \Omega_{\text{rel}} + \Omega_{\Lambda}$$

Total density parameter

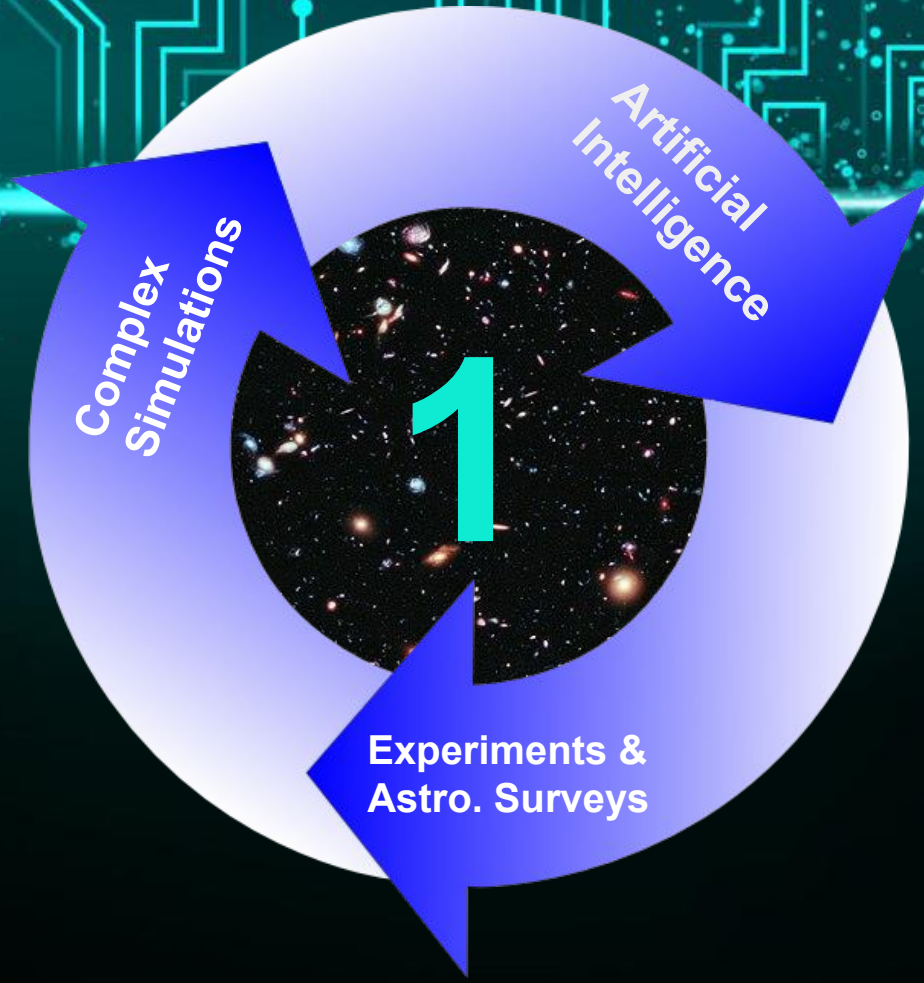
$$\Omega = \frac{\rho}{\rho_c}$$

$\Omega = 1$  for critical density universe

Mass density including ordinary mass (baryonic mass) plus dark matter.

Effective mass density of relativistic particles (light plus neutrinos).

Effective mass density of the dark energy, taking the role described as the cosmological constant.



Artificial  
Intelligence

Complex  
Simulations

Experiments &  
Astro. Surveys

1

Primordial Fluctuations

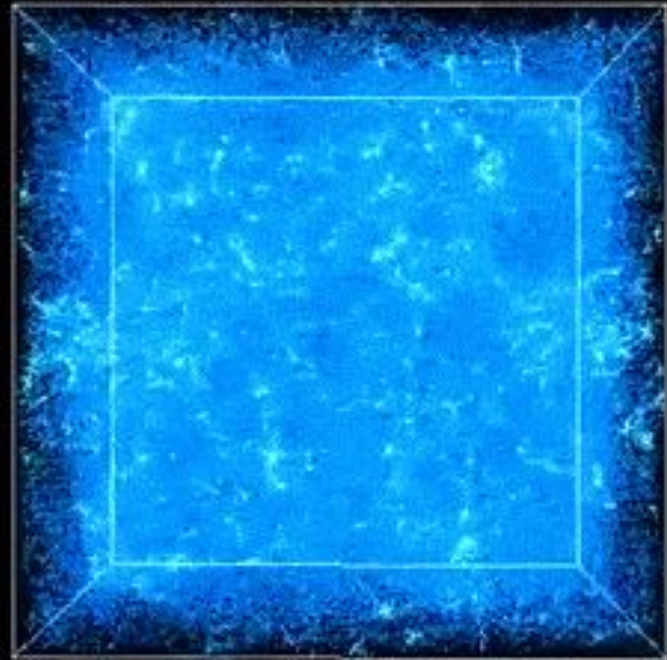
+

Gravity and Time

=

Everything We See  
Today

$Z = 7.08$



Primordial Fluctuations

+

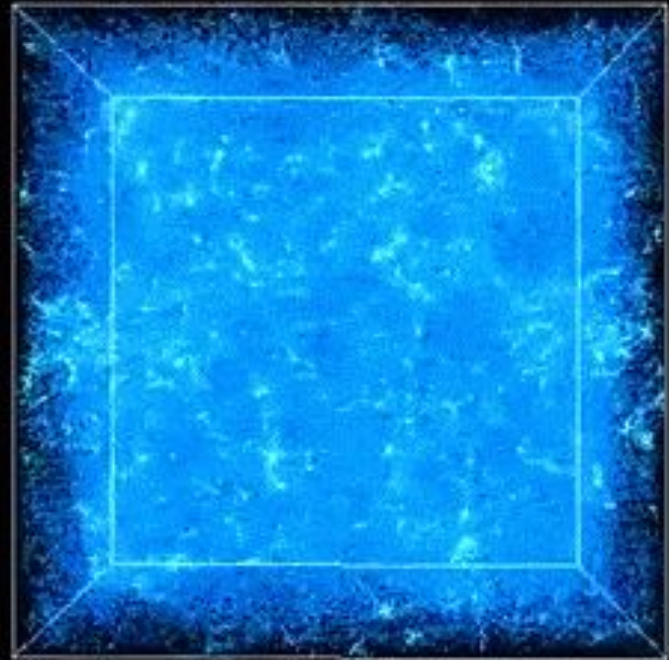
Gravity and Time

=

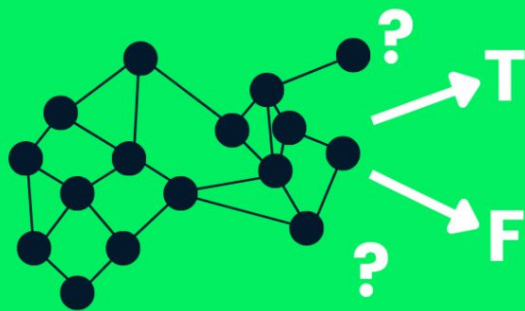
**Everything We See  
Today**

Can we encode this data into a **Graph**? Each node is a galaxy with its position and properties.

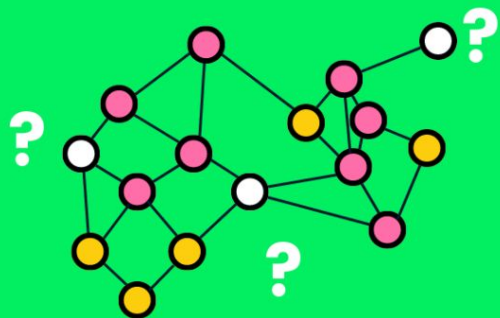
$Z = 7.08$



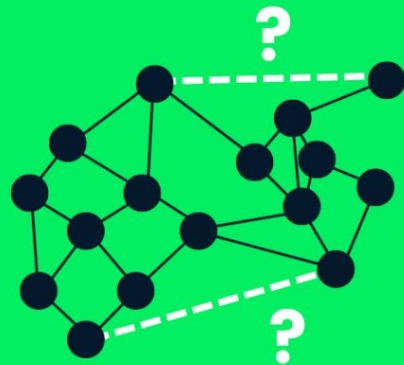
## Graph Classification



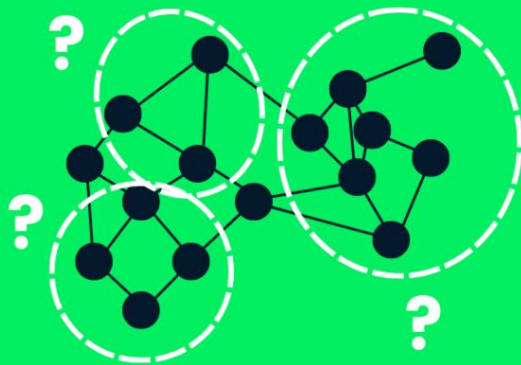
## Node Classification



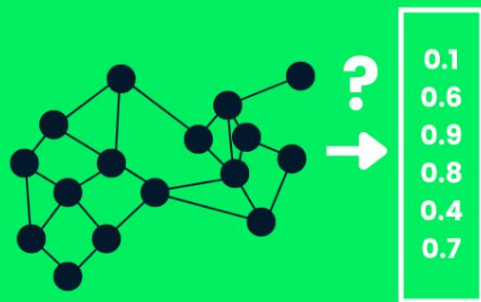
## Link Prediction



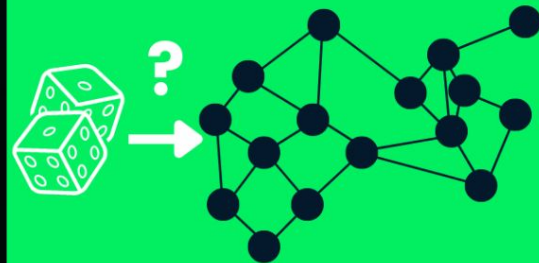
## Community Detection



## Graph Embedding

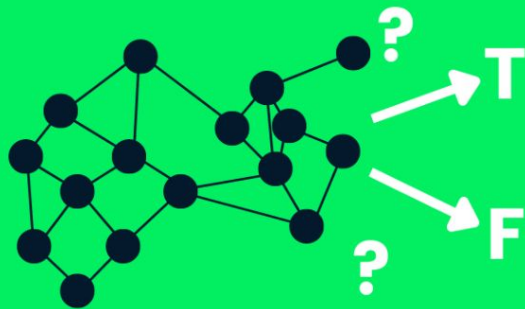


## Graph Generation

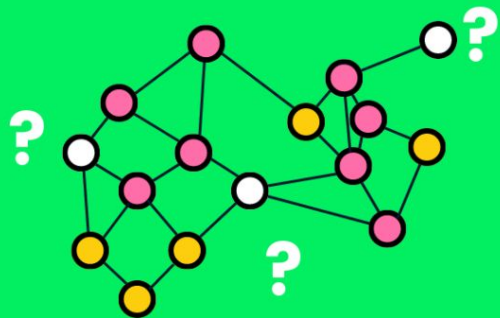




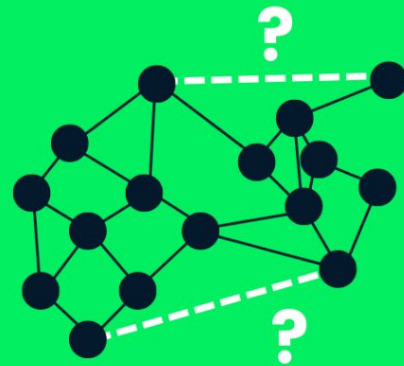
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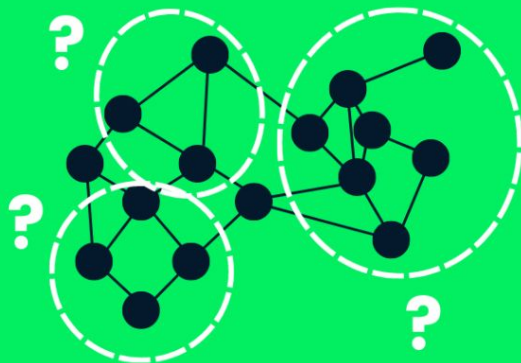
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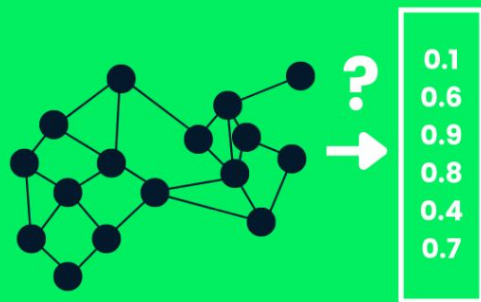
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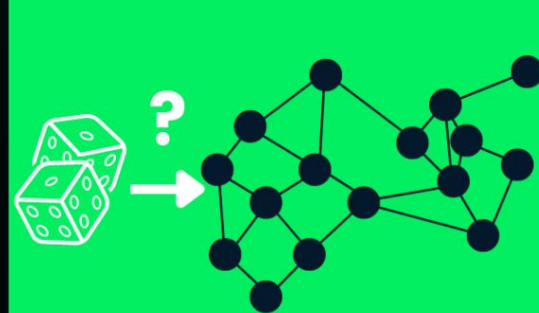
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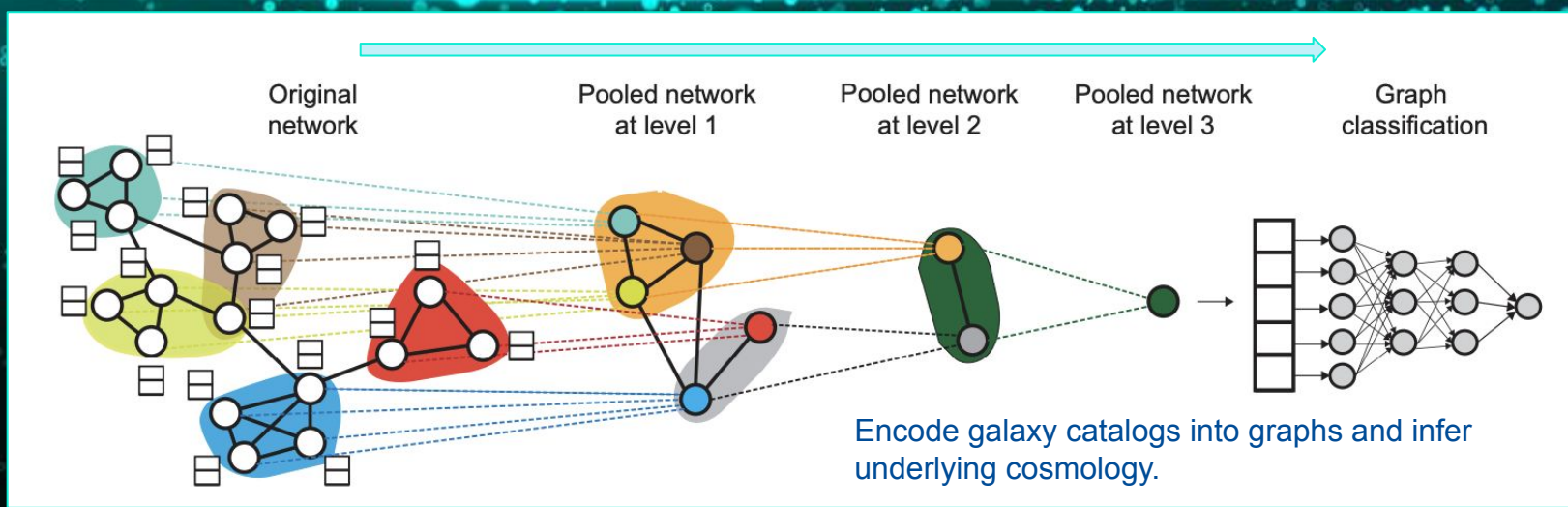


## Graph Embedding




## Graph Generation





# CAMELS

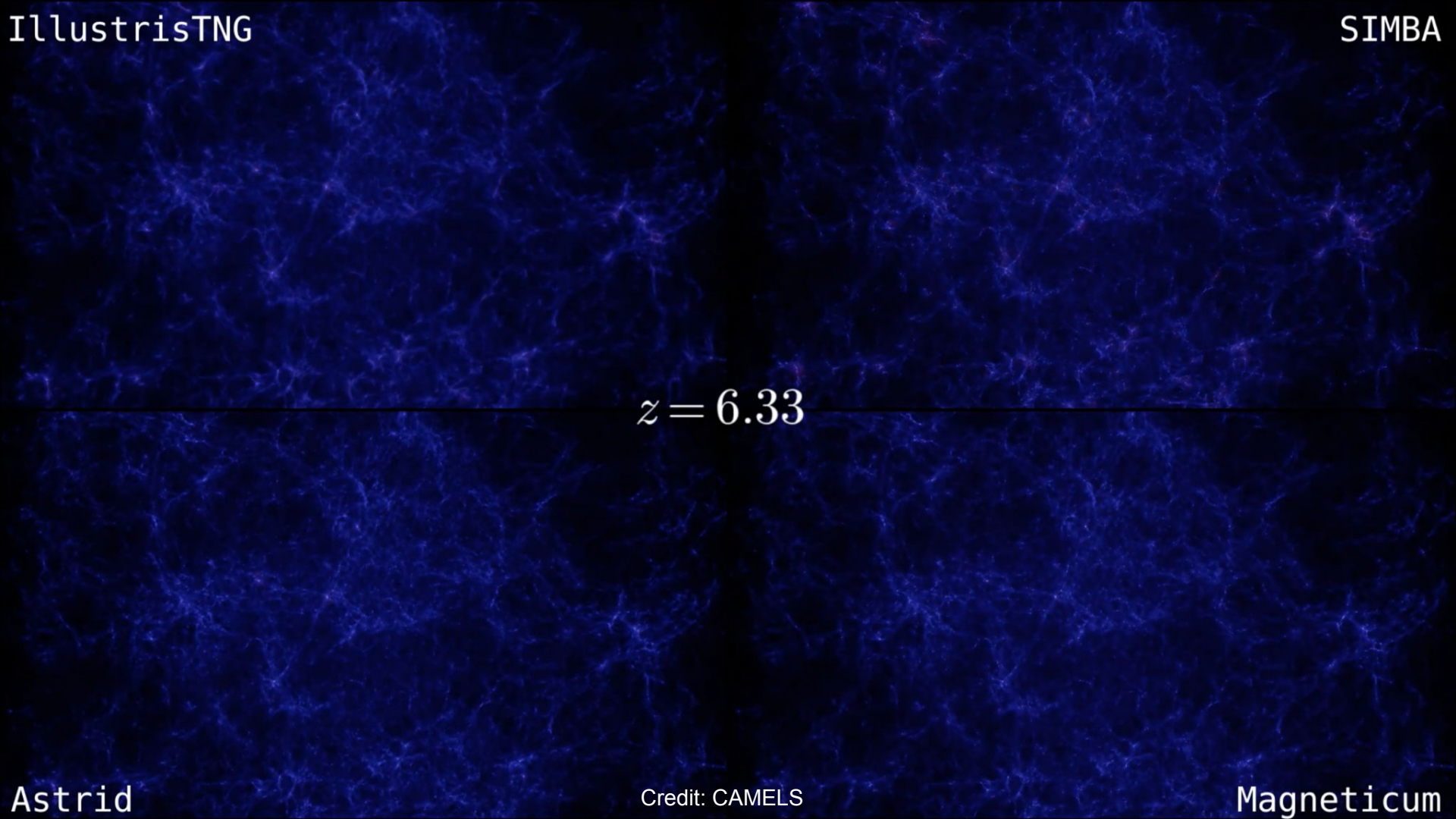


Cosmology and  
Astrophysics  
with **Machine Learning Simulations**

✉ 🐙 🐦

Several great simulations are available.  
Which one do we choose?

$z = 6.33$

A visualization of the cosmic web at redshift  $z = 6.33$ . The image shows a complex network of blue filaments and nodes against a black background, representing the distribution of matter in the universe at this early stage. A horizontal black line is drawn across the center of the image, passing through the text  $z = 6.33$ .

IllustrisTNG

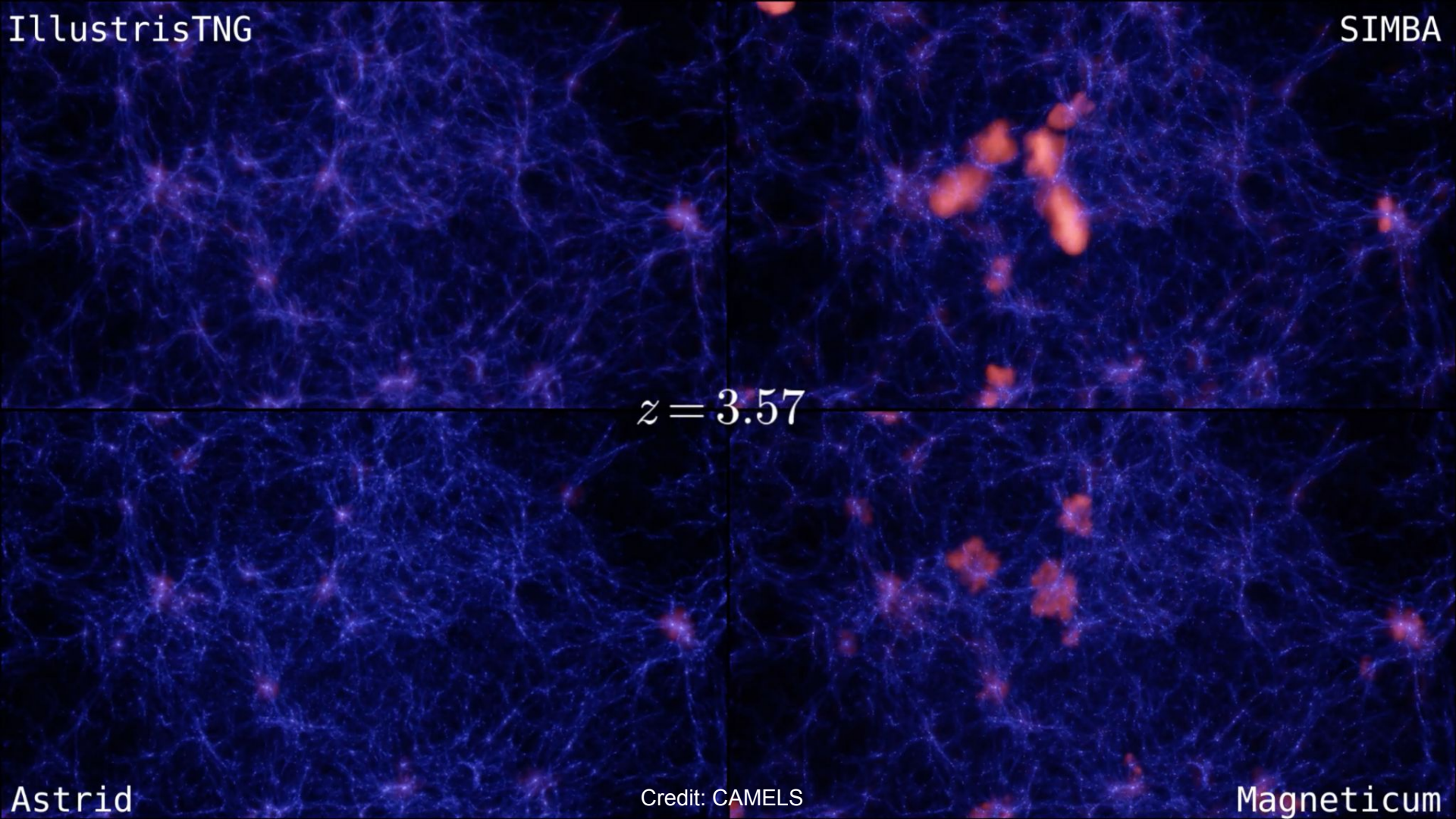
SIMBA

$z = 3.57$

Astrid

Credit: CAMELS

Magneticum



IllustrisTNG

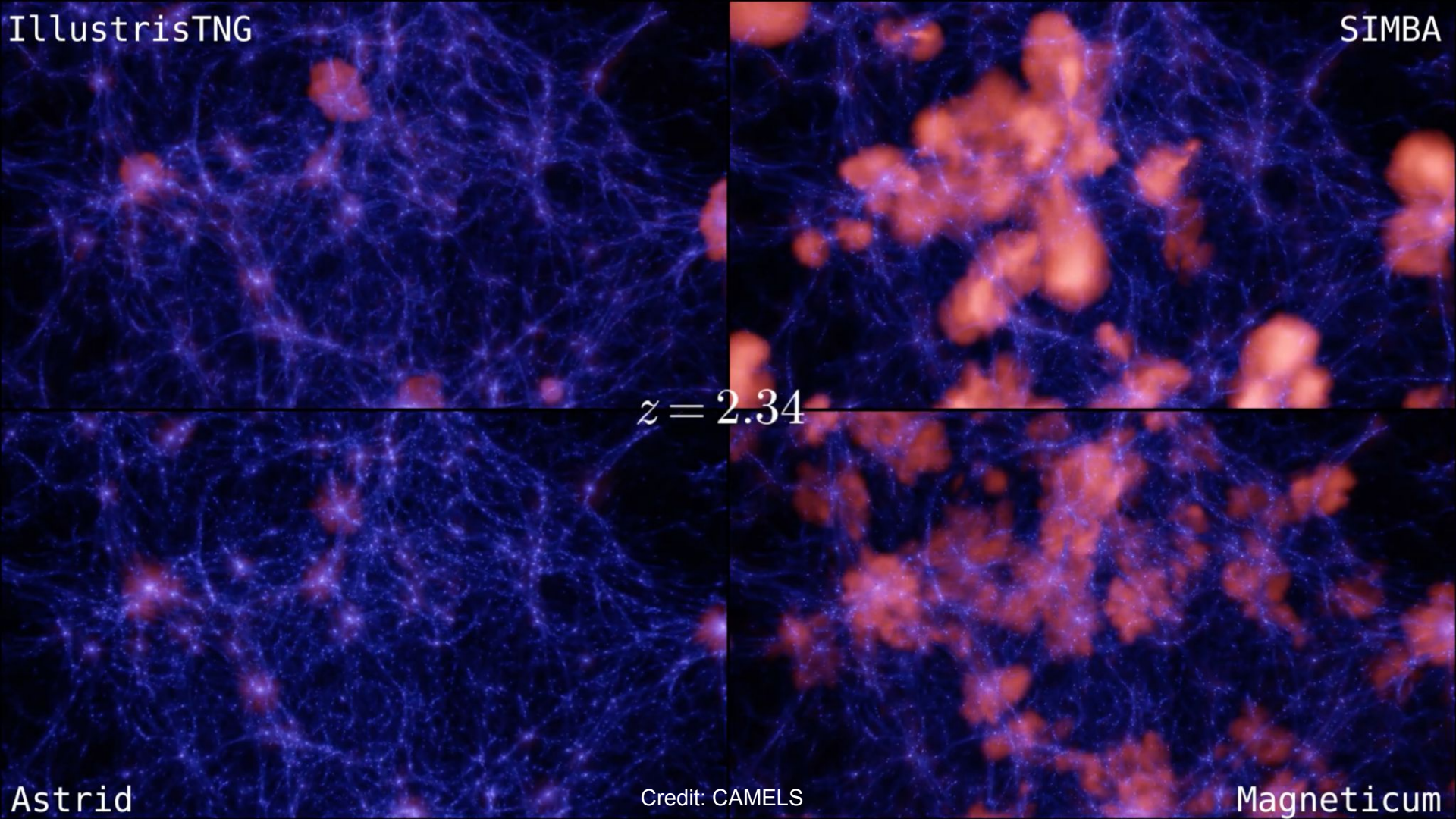
SIMBA

$z = 2.34$

Astrid

Credit: CAMELS

Magneticum



IllustrisTNG

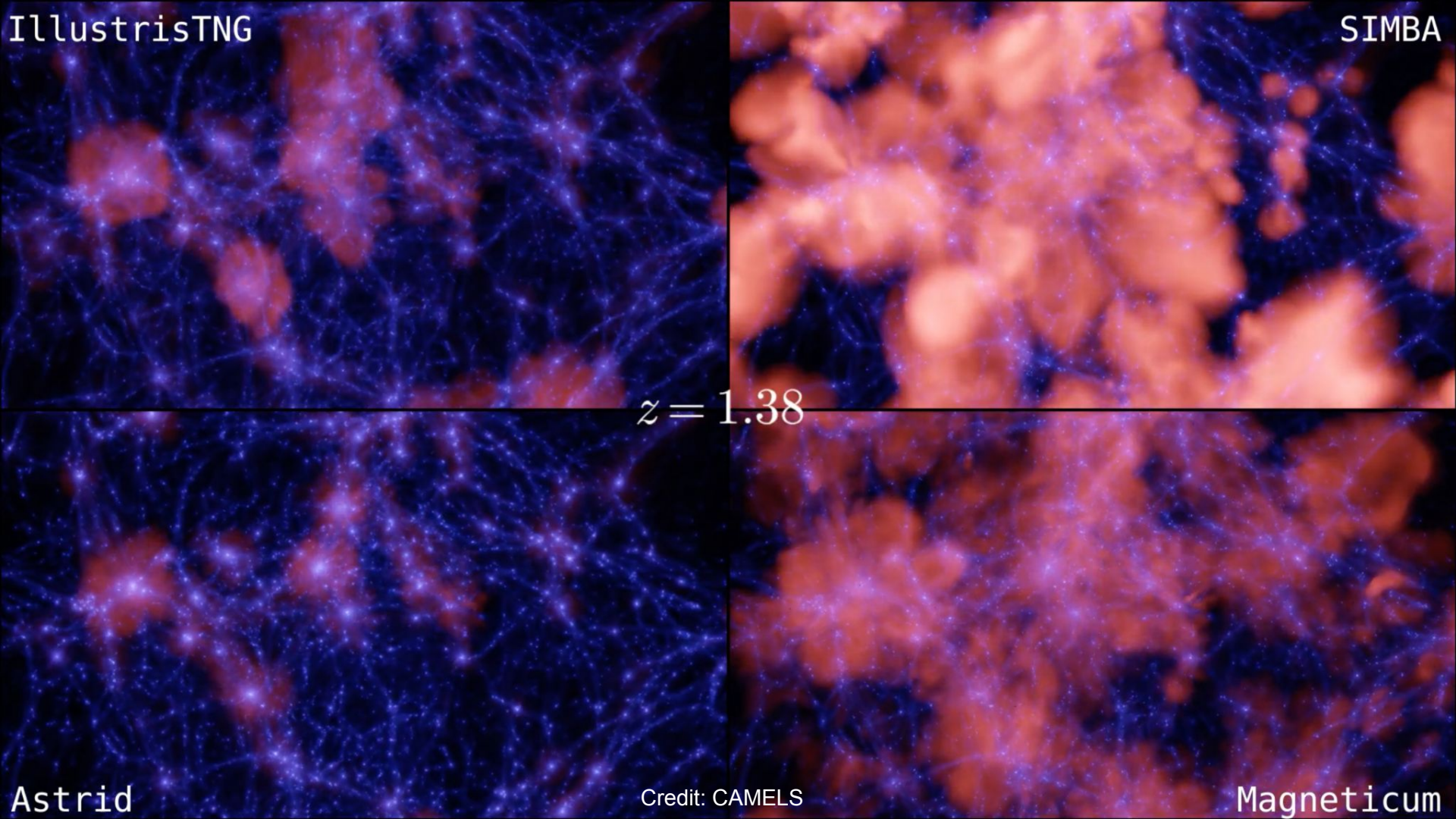
SIMBA

$z = 1.38$

Astrid

Credit: CAMELS

Magneticum



IllustrisTNG

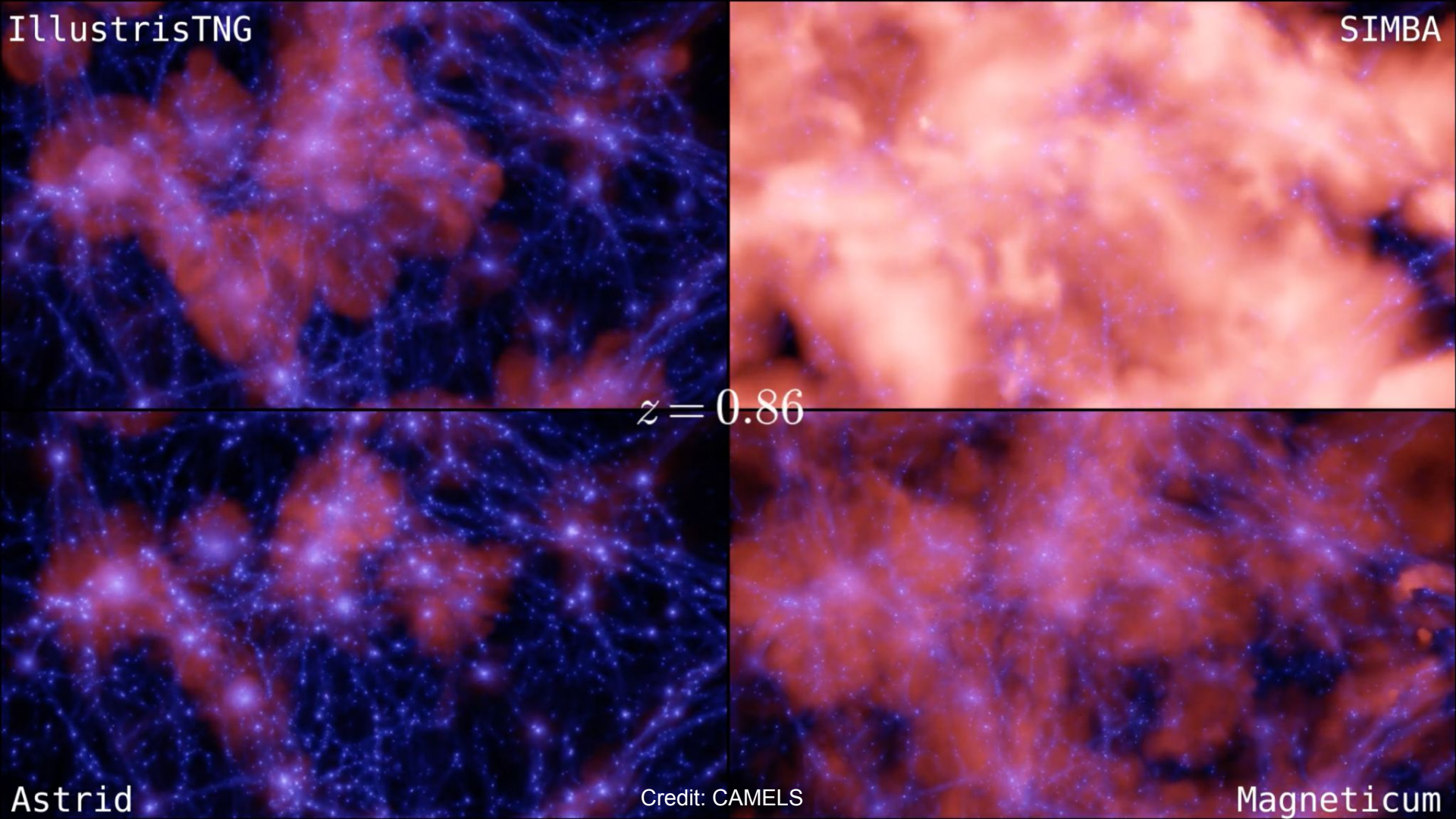
SIMBA

$z = 0.86$

Astrid

Credit: CAMELS

Magneticum



IllustrisTNG

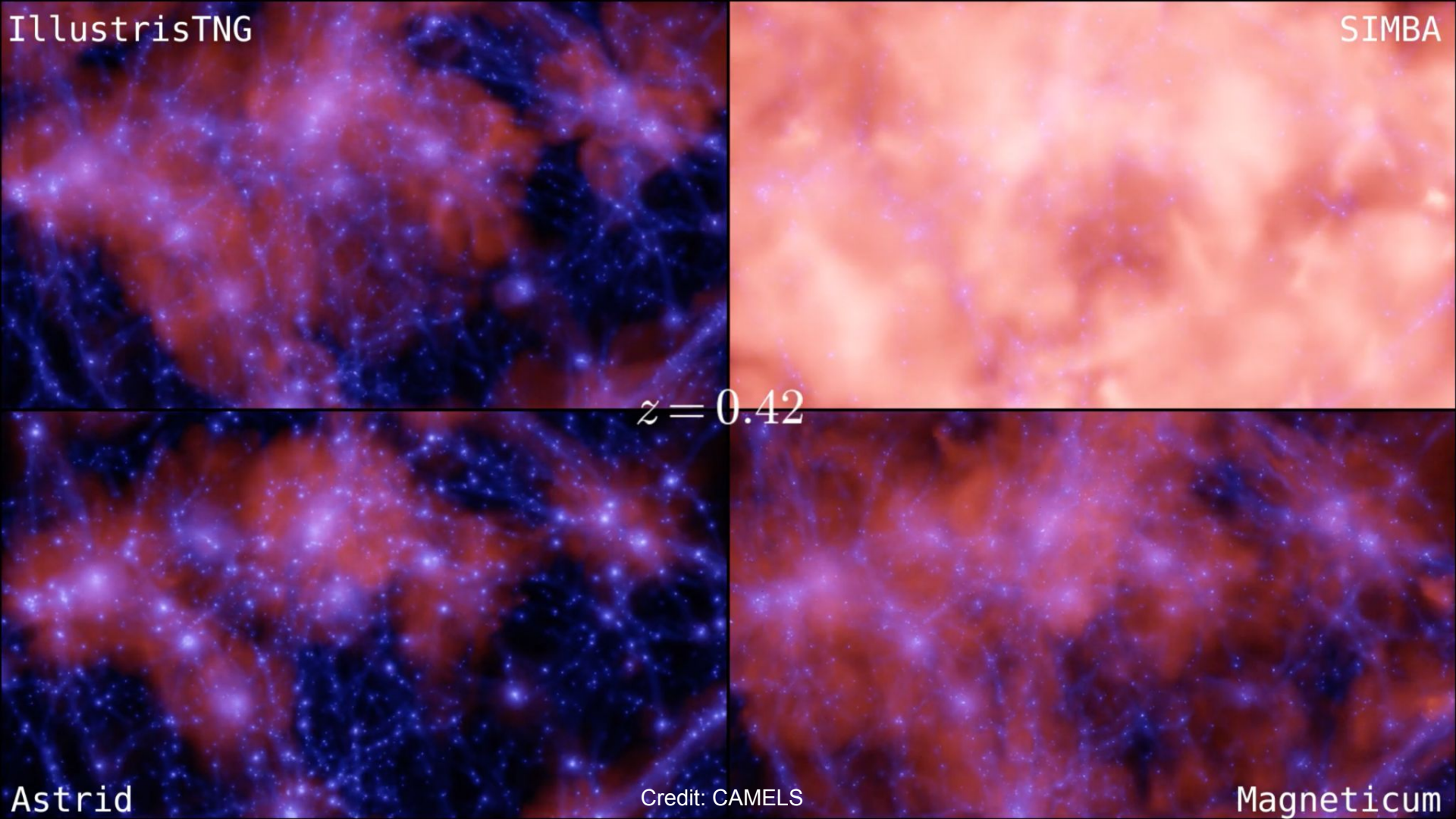
SIMBA

$z = 0.42$

Astrid

Credit: CAMELS

Magneticum





IllustrisTNG

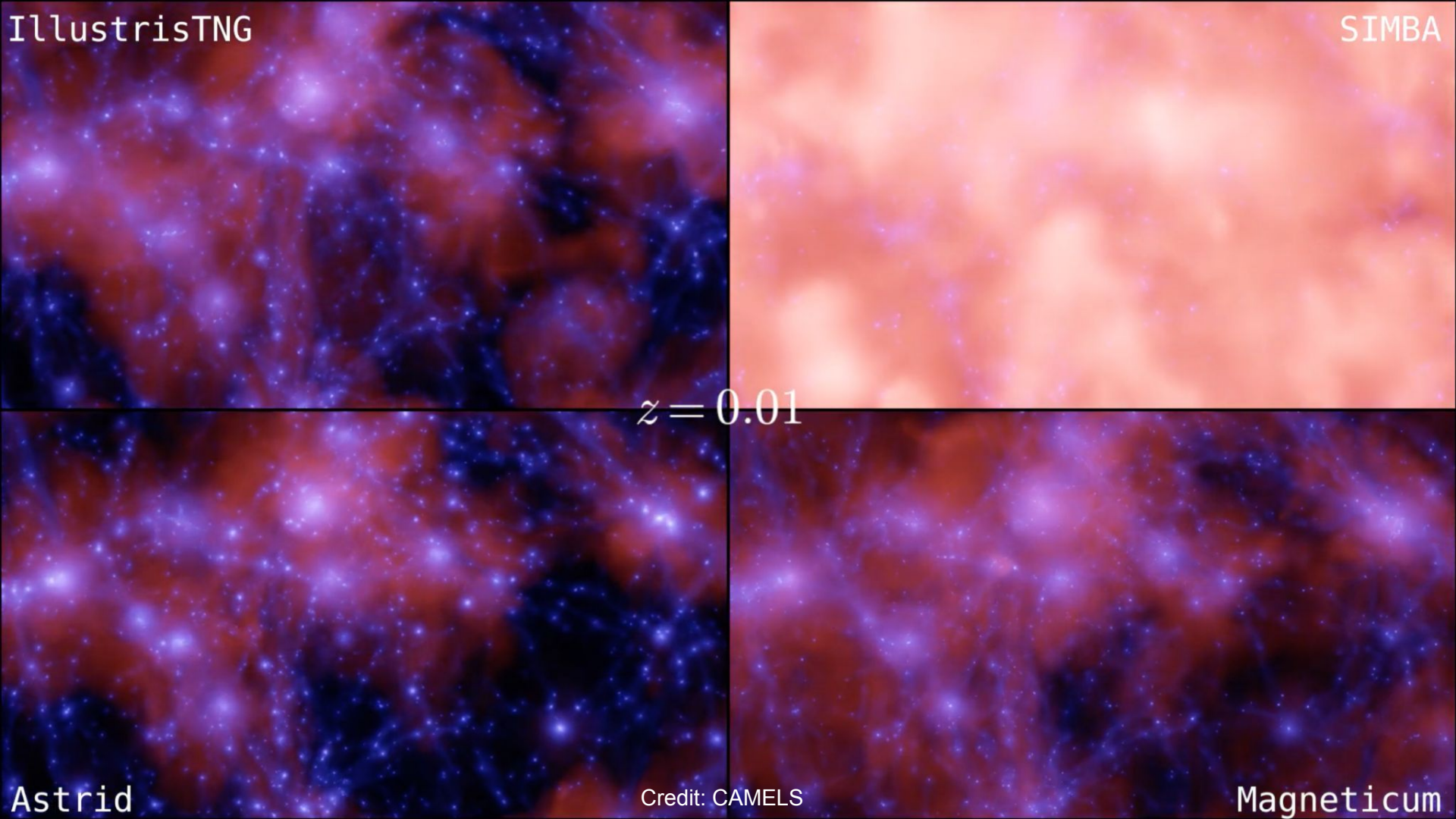
SIMBA

$z = 0.01$

Astrid

Credit: CAMELS

Magneticum



IllustrisTNG

SIMBA



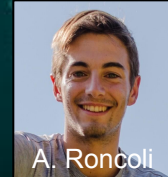
Astrid

Credit: CAMELS

Magneticum

# Regression - Cosmology With Graphs

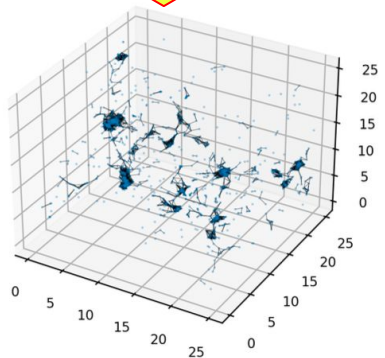
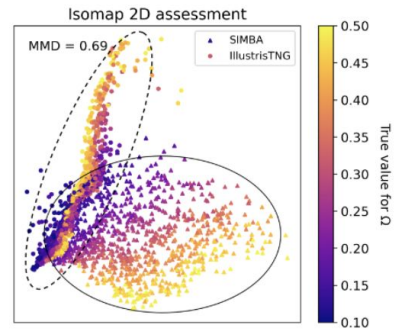
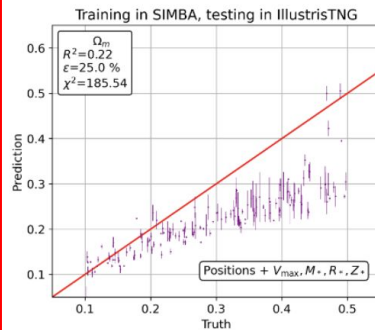
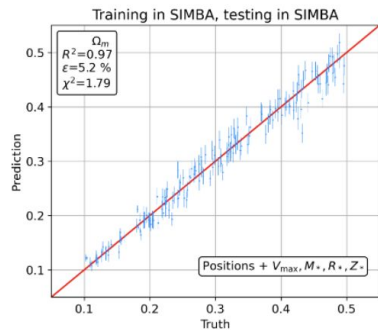
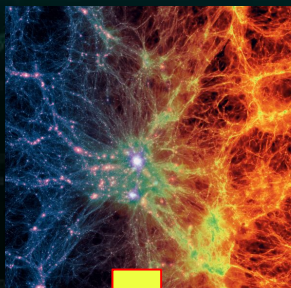
NeurIPS 2023.  
Roncoli et al. 2023.



Graph Neural Networks:  
ideal for sparse  
galaxy catalogs!

SIMBA -> SIMBA

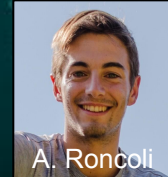
SIMBA->IllustrisTNG



z=0 1000 simulations each

# Regression - Cosmology With Graphs

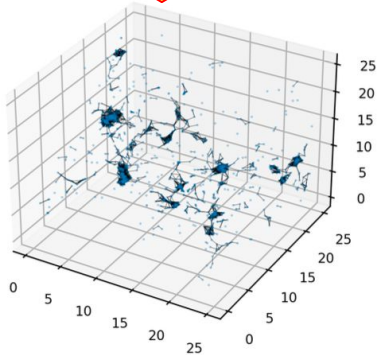
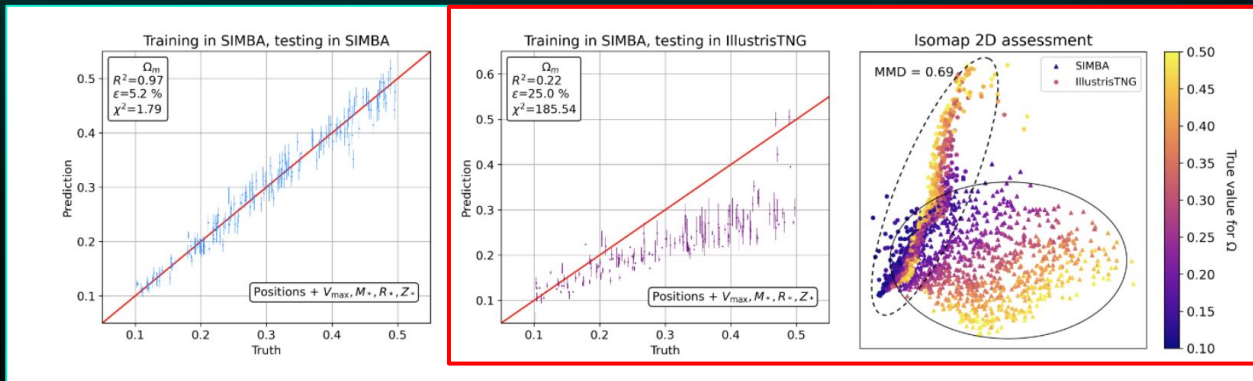
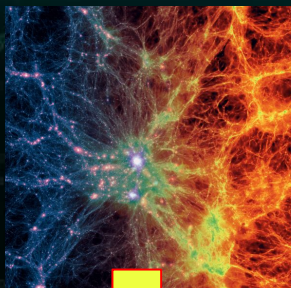
NeurIPS 2023.  
Roncoli et al. 2023.



Graph Neural Networks:  
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SIMBA -> SIMBA

SIMBA->IllustrisTNG



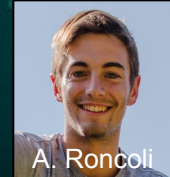
$z=0$  1000 simulations each

## DOMAIN ADAPTATION

Align data distributions in the latent space of the network by forcing the network to **find more robust domain-invariant features**.

# Regression - Cosmology With Graphs

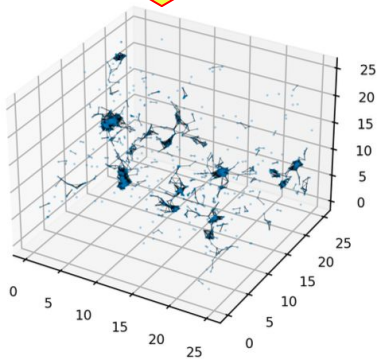
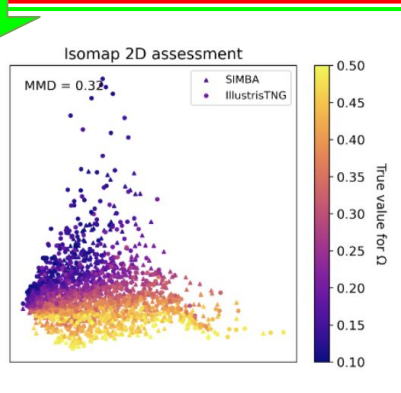
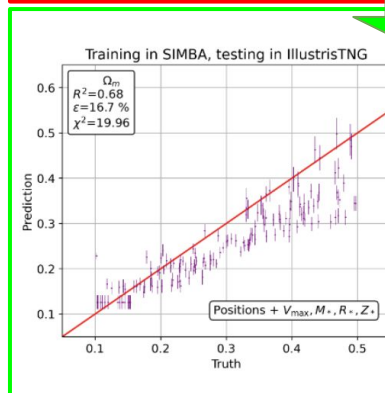
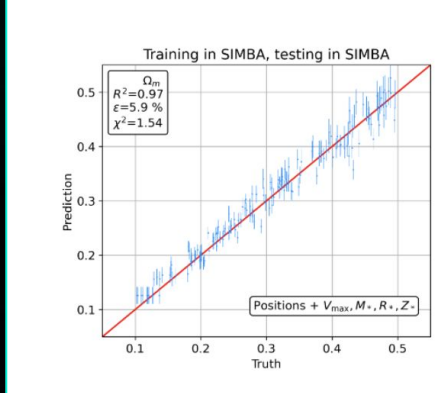
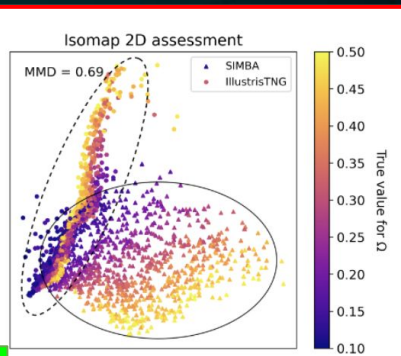
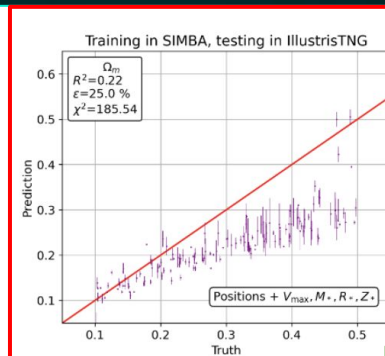
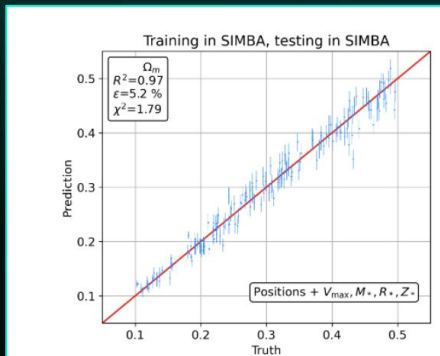
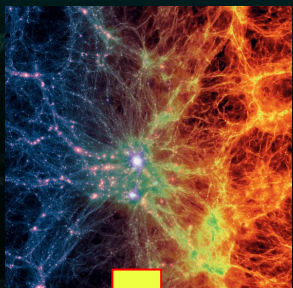
NeurIPS 2023.  
Roncoli et al. 2023.



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ideal for sparse  
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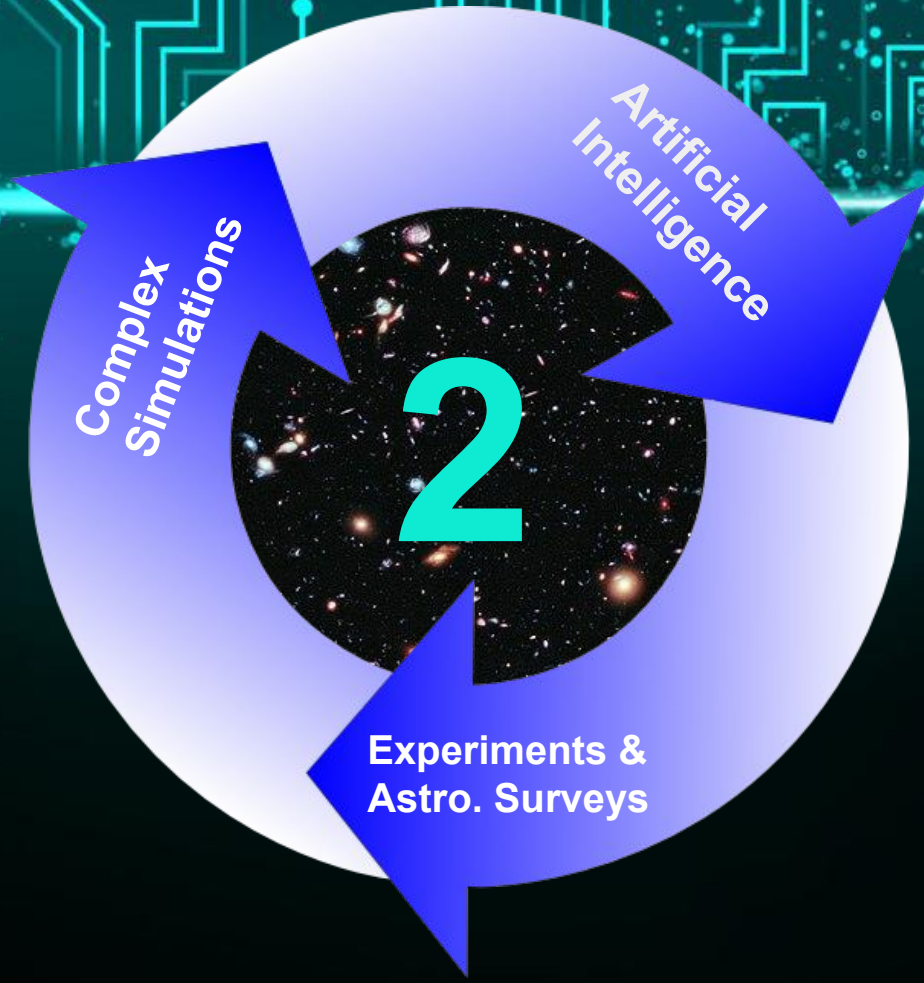
SIMBA -> SIMBA

SIMBA->IllustrisTNG



z=0 1000 simulations each

28%  
better  
relative  
error  
  
order of  
mag.  
better  $\chi^2$



**Complex  
Simulations**

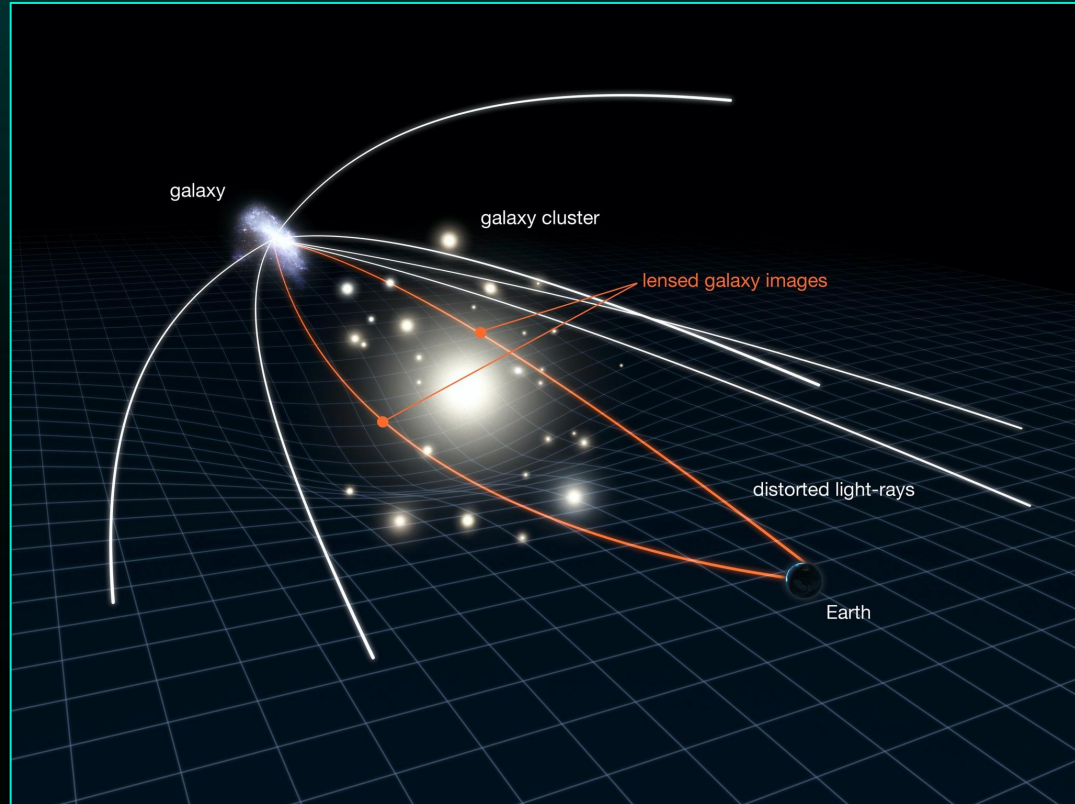
**Artificial  
Intelligence**

**Experiments &  
Astro. Surveys**

**2**

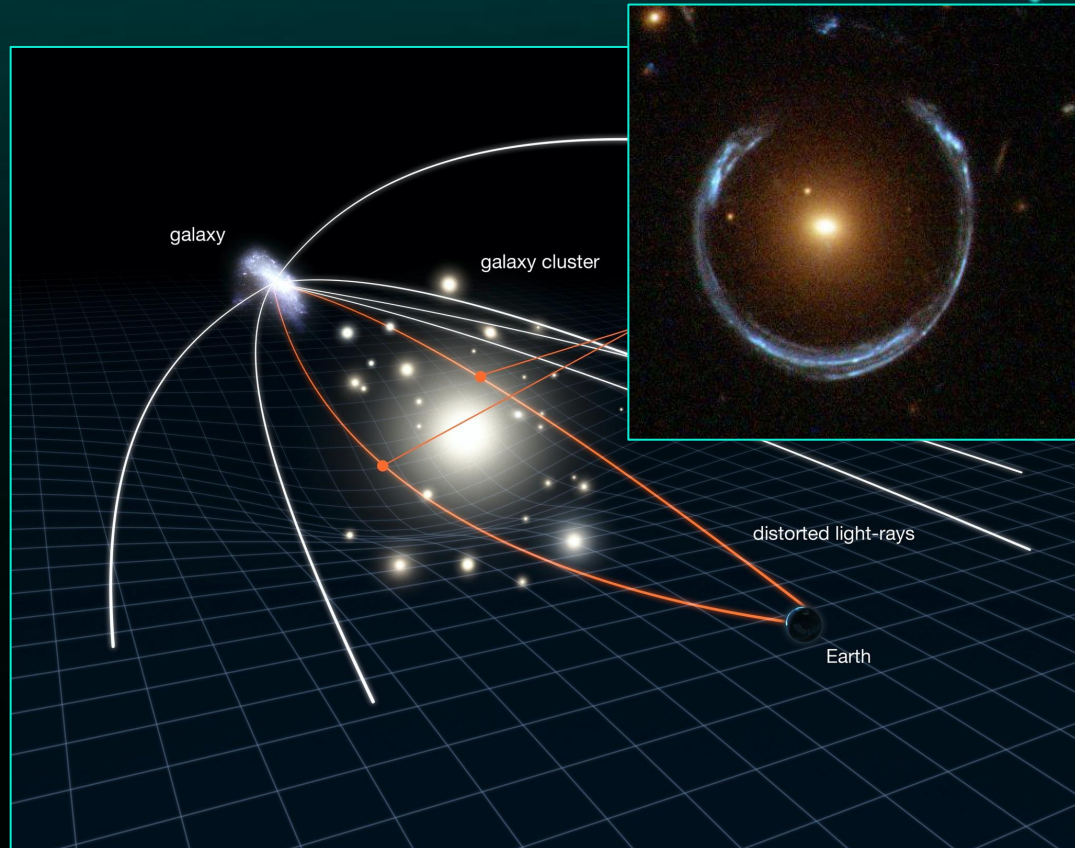
# Strong gravitational lensing

- When light from a distant galaxy passes near a massive galaxy cluster the **light bends** because the space-time has strong curvature near massive objects.
- We **can now see light from a galaxy that would otherwise be obscured** and too distant.
- And use it to infer cosmological parameters (and learn about dark matter)!



# Strong gravitational lensing

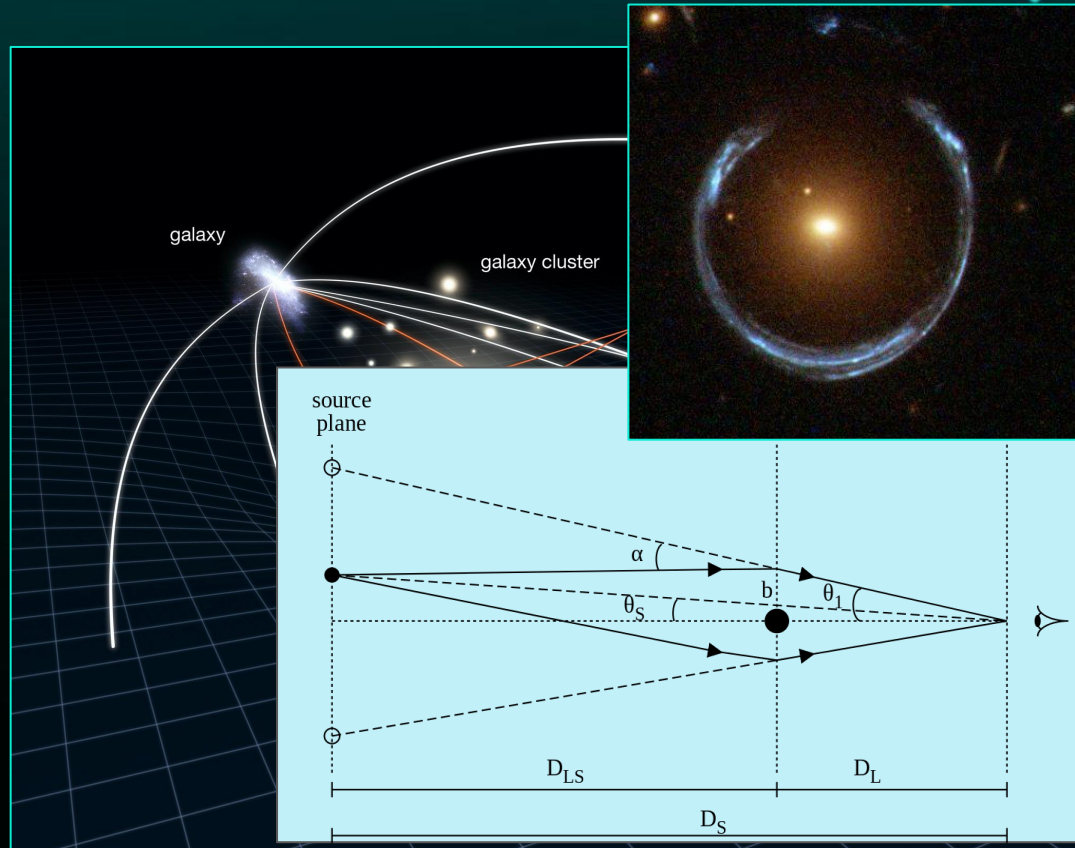
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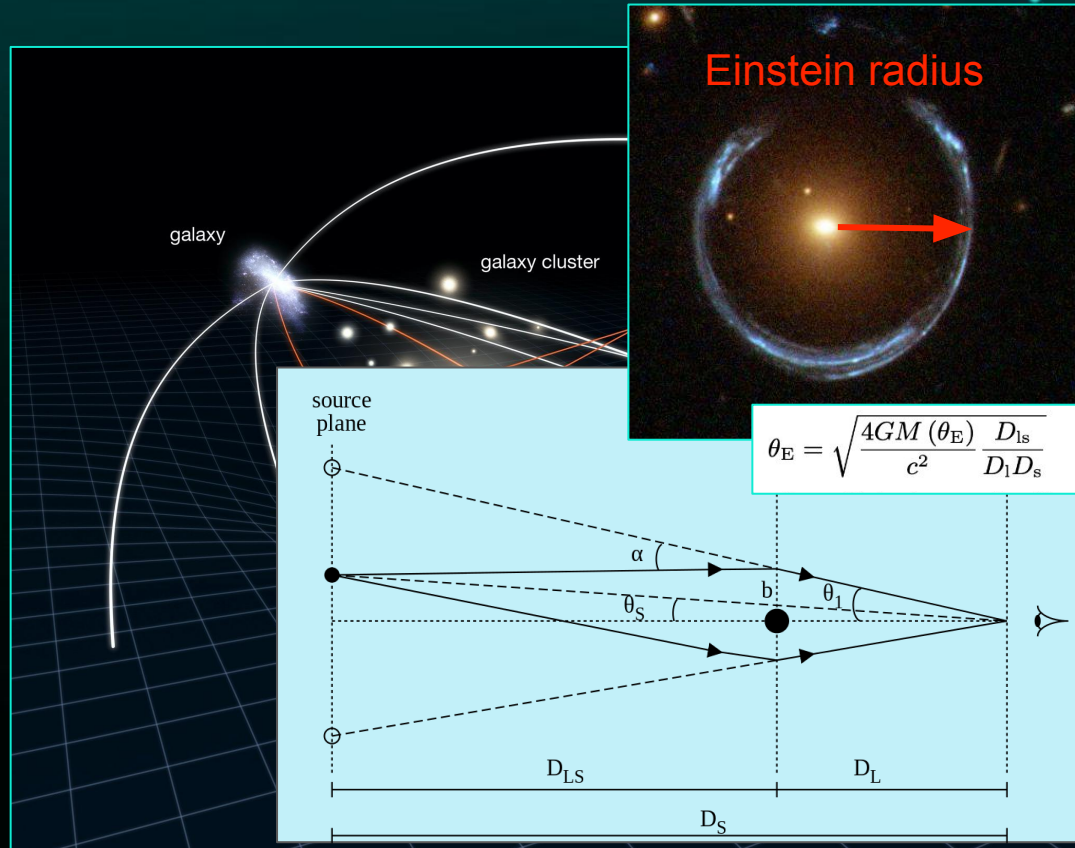
# Strong gravitational lensing

- When light from a distant galaxy passes near a massive galaxy cluster the **light bends** because the space-time has strong curvature near massive objects.
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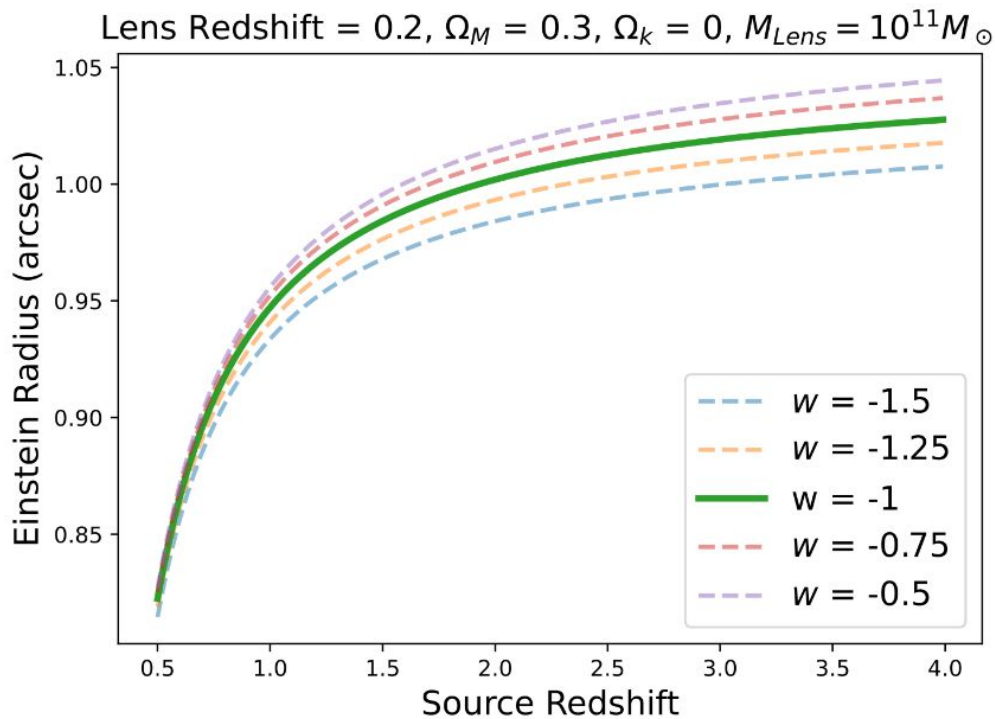


# Strong gravitational lensing

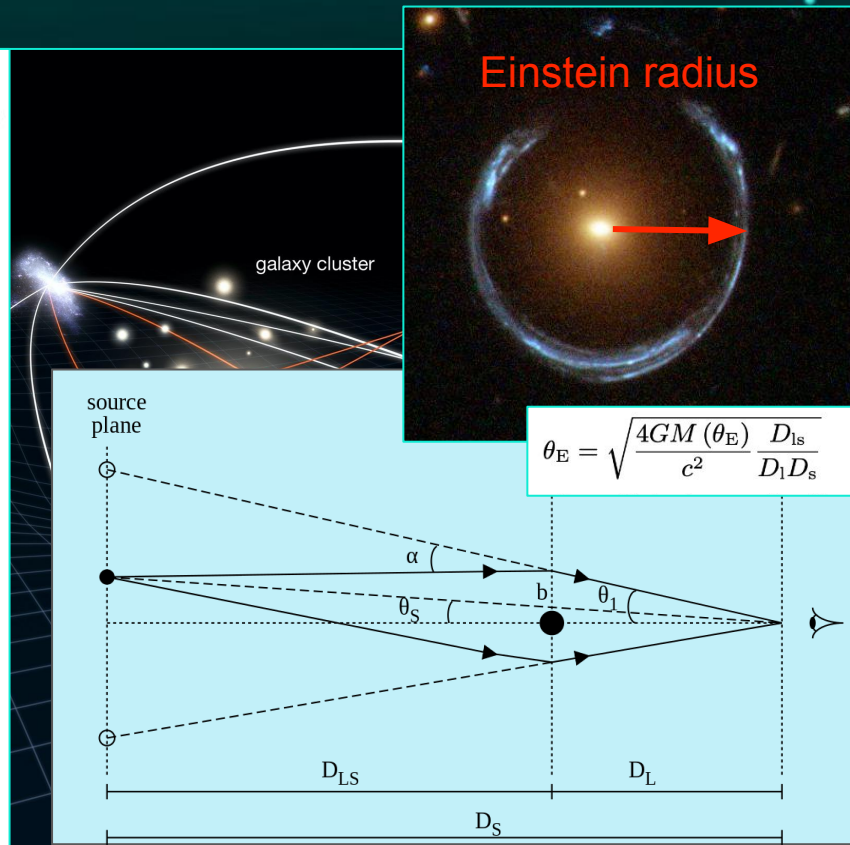
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# Strong gravitational lensing

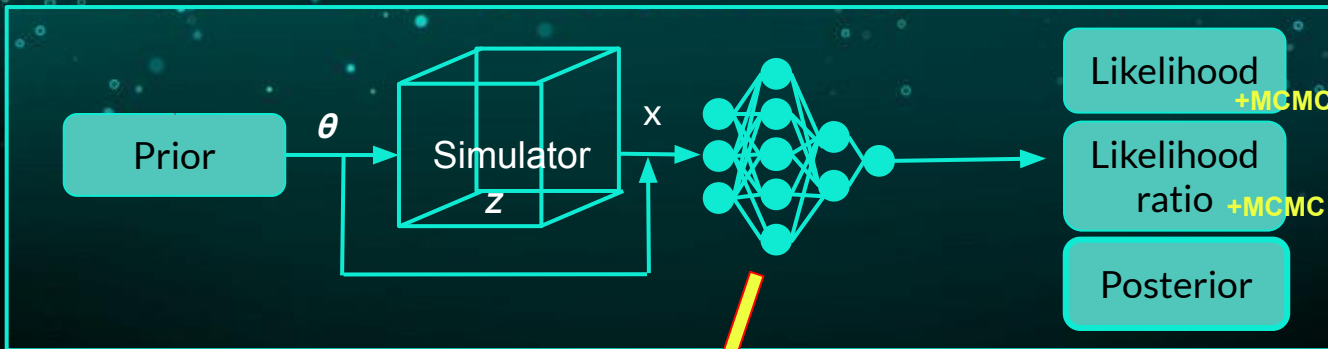


Tian et al. 2023.



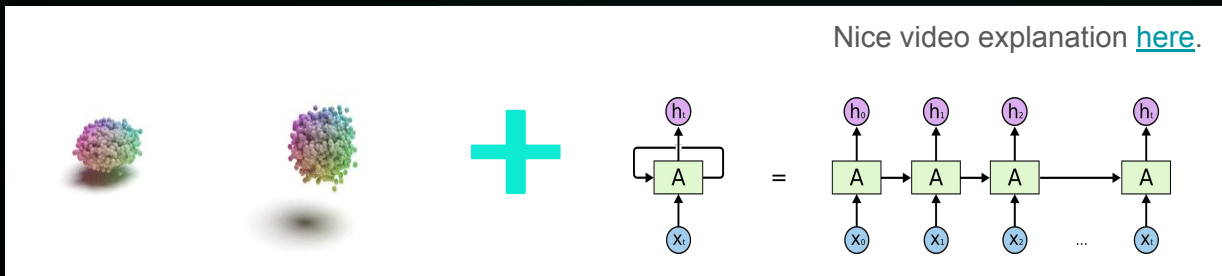
# Being Bayesian with AI

## Simulation-Based Inference (SBI)



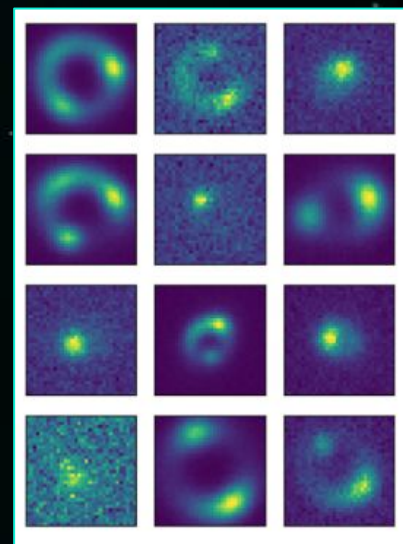
Poh et al. 2022; 2024. in prep  
Swierc et al. 2023.  
Jarugula et al. 2024.

## Masked Autoregressive Flows (MAF)



Normalizing flows

Autoregressive models



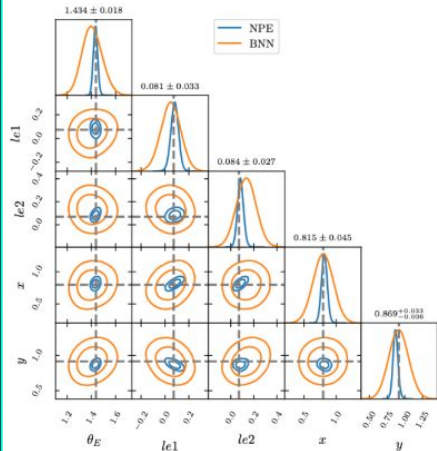
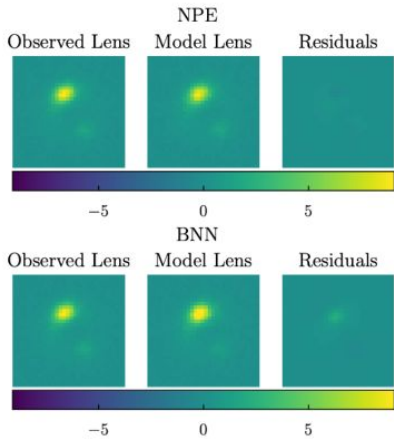
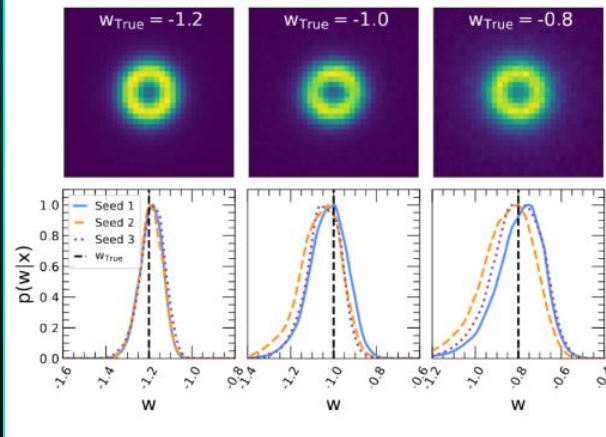
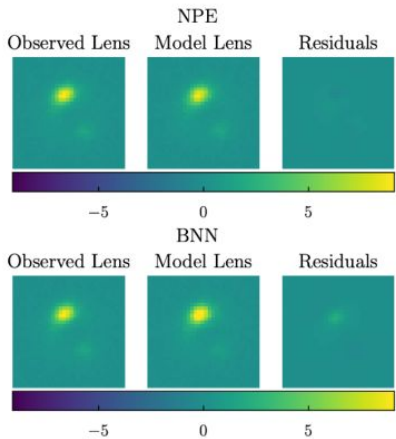


Figure 6. Single Image Inference Example for 5 parameter model.

- Estimate **posteriors of lens parameters** (up to 12) without the need for slow MCMC and manual modeling.
- NPE is **mode flexible and accurate** than Bayesian NN which have a Gaussian constraint.



- Use a **regular CNN to estimate likelihood ratio** and then the posterior of  $w$ .

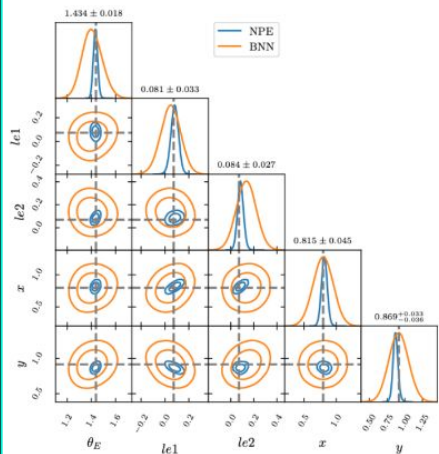


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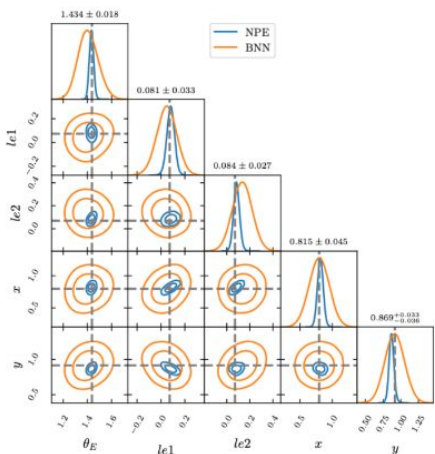
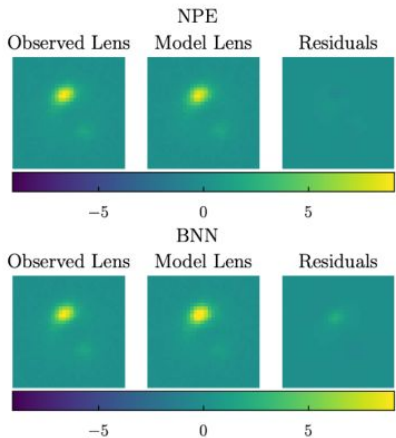
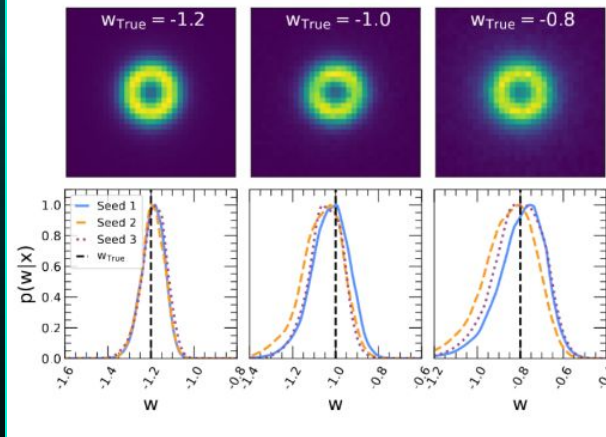
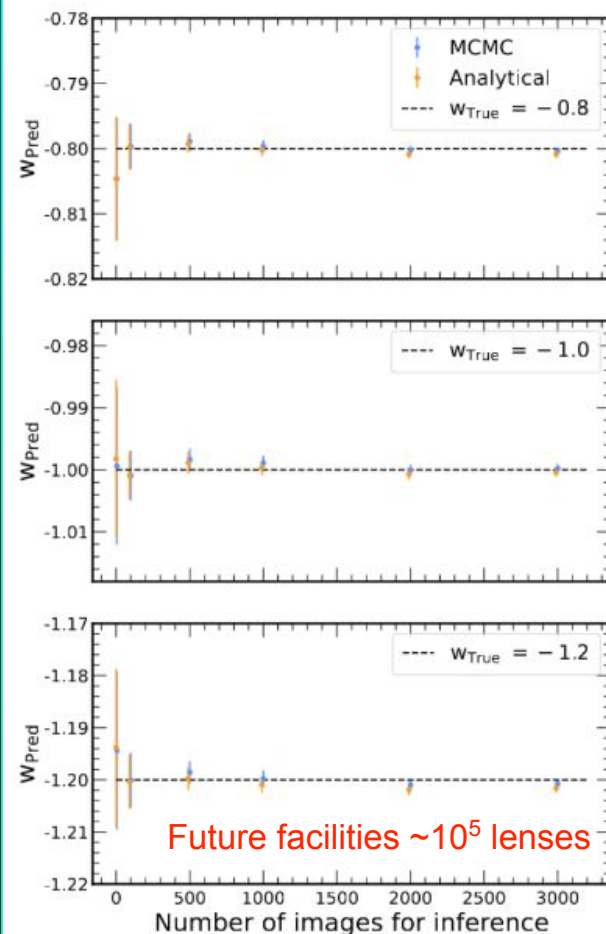
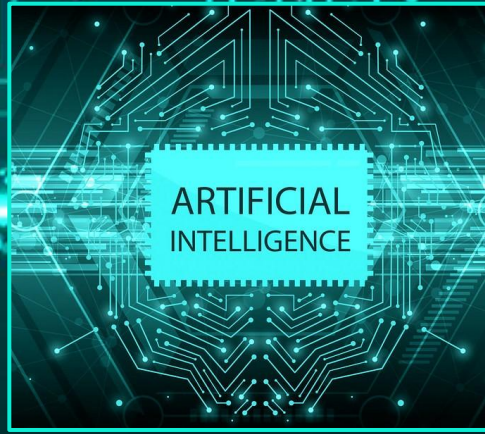


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- Use a **regular CNN** to estimate likelihood ratio and then the posterior of  $w$ .
- By combining likelihoods from multiple lenses we get **tighter constraints** on the cosmology.





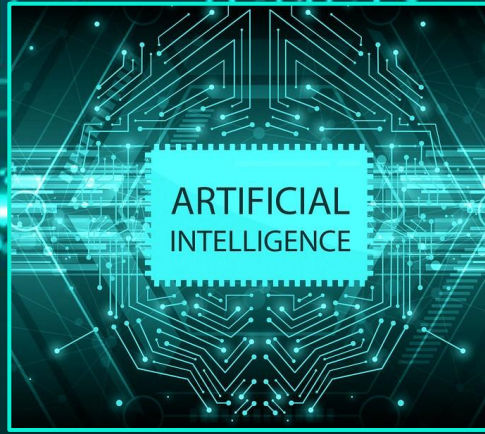
**Complex models  
based on data.**

**Help constrain  
cosmology.**

### PROS

- Enabling work with huge datasets.
- Speed of analysis.
- Avoid compound biases in analysis.
- Help us understand and work with multi-dimensional data.
- Models include details, no need for approximations.





**Complex models  
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**Help constrain  
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### PROS

- Enabling work with huge datasets.
- Speed of analysis.
- Avoid compound biases in analysis.
- Help us understand and work with multi-dimensional data.
- Models include details, no need for approximations.

### CONS

- Model is as good as the data.
- Watch out for biased data!
- Often do not work for out-of-distribution data.
- We have to carefully think about the data and how to apply AI methods.
- It will learn even the biases we are not aware of.

- There is no cosmology without particle physics.

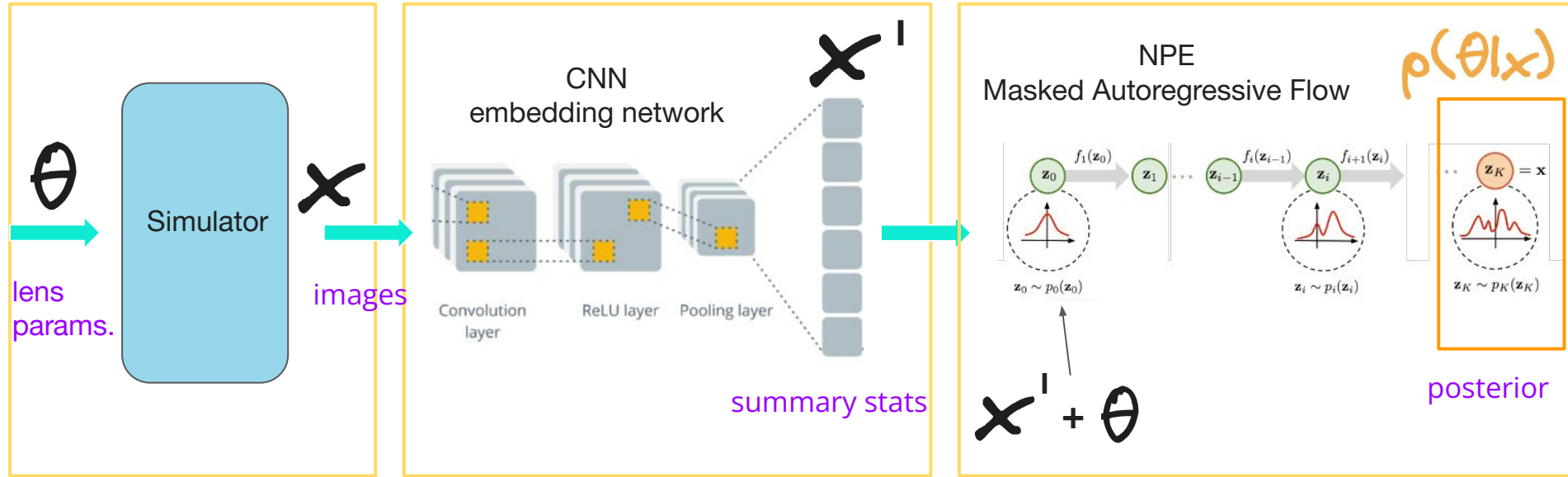
- There is no cosmology without particle physics.
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  - Origin of the matter-antimatter asymmetry
  - Dark energy

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**THANK YOU!**

# SBI setup



Poh et al. 2022 (NeurIPS 2022) [arXiv:2211.05836](https://arxiv.org/abs/2211.05836)  
Poh et al. 2024 - coming very soon!

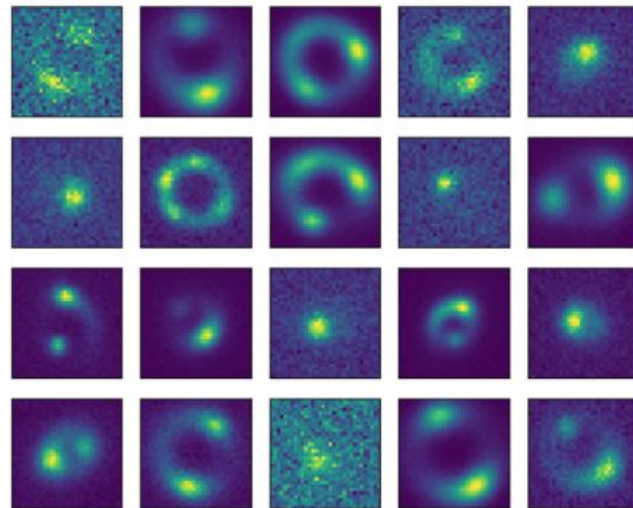
# Data - DES mocks (ground-based observations)



PRELIMINARY

	Parameter	Applicable Models	Training Set Priors
Einstein radius	$\theta_E$ (")	1,5,12	$\mathcal{U}(0.3, 4.0)$
Ellipticity components	$le_2$	5,12	$\mathcal{U}(-0.8, 0.8)$
	$le_2$	5,12	$\mathcal{U}(-0.8, 0.8)$
lens-source offset	$x_c$ (")	5,12	$\mathcal{U}(-2, 2)$
	$y_c$ (")	5,12	$\mathcal{U}(-2, 2)$
external shear	$\gamma_1$	12	$\mathcal{U}(-0.8, 0.8)$
	$\gamma_2$	12	$\mathcal{U}(-0.8, 0.8)$
Sersic profile with:			
apparent magnitude	$m_s$	12	$\mathcal{U}(18, 25)$
half-light radius	$R$ (")	12	$\mathcal{U}(0.1, 3.0)$
Sersic index	$n$	12	$\mathcal{U}(0.5, 8.0)$
ellipticity components	$se_1$	12	$\mathcal{U}(-0.8, 0.8)$
	$se_2$	12	$\mathcal{U}(-0.8, 0.8)$

1, 5, 12 parameter models



Model	Training	Test
1-parameter	200, 000	1000
5-parameter	400, 000	1000
12-parameter	800, 000	1000

Test Set Priors	OOD Priors Test Set 1	OOD Priors Test Set 2	OOD Priors Test Set 3
<b>Lens Mass Parameters</b>			
$\mathcal{U}(0.5, 3.0)$	$\mathcal{N}(2.0, 0.2)$	$\mathcal{N}(1.0, 0.2)$	$\mathcal{N}(1.0, 0.2)$
$\mathcal{U}(-0.2, 0.2)$	$\mathcal{N}(-0.2, 0.2)$	$\mathcal{N}(-0.1, 0.2)$	$\mathcal{N}(-0.2, 0.2)$
$\mathcal{U}[-0.2, 0.2]$	$\mathcal{N}(-0.2, 0.2)$	$\mathcal{N}(-0.1, 0.2)$	$\mathcal{N}(0.2, 0.2)$
$\mathcal{U}(-1, 1)$	$\mathcal{N}(0.2, 0.2)$	$\mathcal{N}(-0.1, 0.2)$	$\mathcal{N}(-0.2, 0.2)$
$\mathcal{U}(-1, 1)$	$\mathcal{N}(-0.2, 0.2)$	$\mathcal{N}(-0.1, 0.2)$	$\mathcal{N}(0.2, 0.2)$
<b>Lens Environment Parameters</b>			
$\mathcal{U}(-0.05, 0.05)$	$\mathcal{N}_{\log}(-3, 1)$	$\mathcal{N}(0.00, 0.05)$	$\mathcal{N}(0.00, 0.01)$
$\mathcal{U}(-0.05, 0.05)$	$\mathcal{N}_{\log}(-3, 1)$	$\mathcal{N}(0.00, 0.05)$	$\mathcal{N}(0.00, 0.01)$
<b>Source Light Parameters</b>			
$\mathcal{U}(19, 24)$	$\mathcal{N}(22, 1)$	$\mathcal{N}(21, 1)$	$\mathcal{N}(21.0, 0.5)$
$\mathcal{U}(0.5, 1.0)$	$\mathcal{N}(0.7, 0.1)$	$\mathcal{N}(1.0, 0.2)$	$\mathcal{N}(0.8, 0.1)$
$\mathcal{U}(2, 4)$	$\mathcal{N}(4, 1)$	$\mathcal{N}(3.0, 0.5)$	$\mathcal{N}(5.0, 0.1)$
$\mathcal{U}(-0.2, 0.2)$	$\mathcal{N}(-0.2, 0.2)$	$\mathcal{N}(-0.1, 0.2)$	$\mathcal{N}(0.1, 0.1)$
$\mathcal{U}(-0.2, 0.2)$	$\mathcal{N}(-0.2, 0.2)$	$\mathcal{N}(0.1, 0.2)$	$\mathcal{N}(-0.1, 0.1)$

- We also run tests for:
  - 3 OOD tests sets
  - 3 initial random seeds



# 5-parameter results

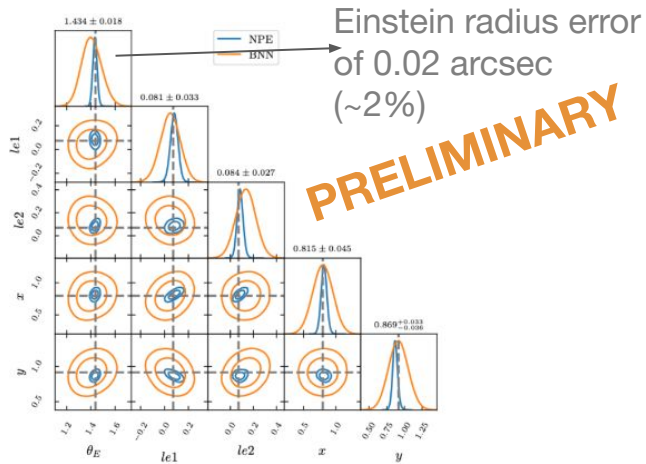
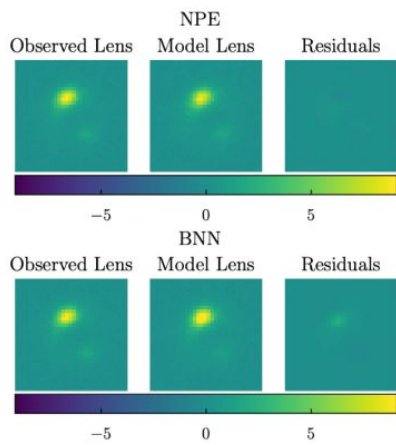


Figure 6. Single Image Inference Example for 5 parameter model.

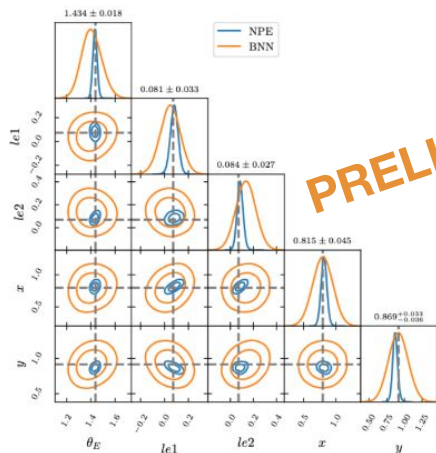
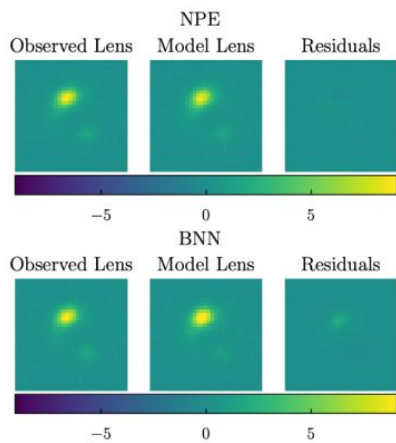


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## 5-parameter results

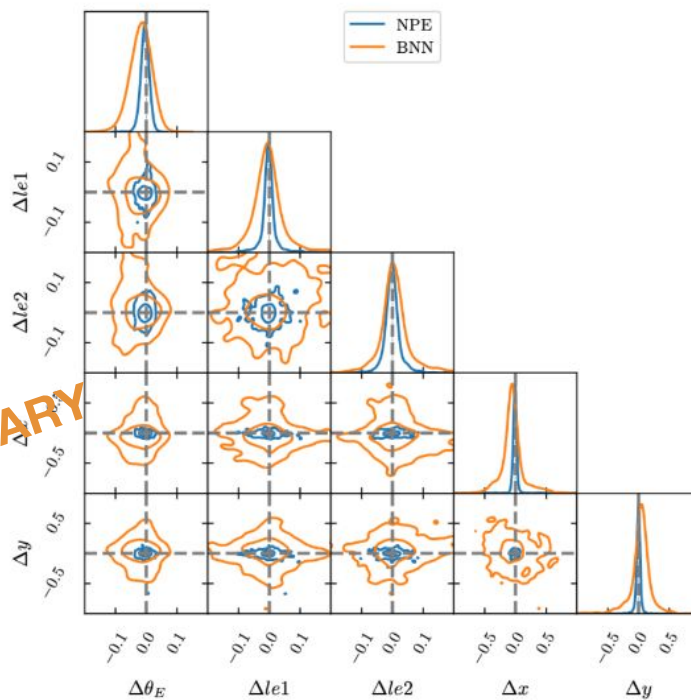


Figure 8. 5 parameter error corner plot.

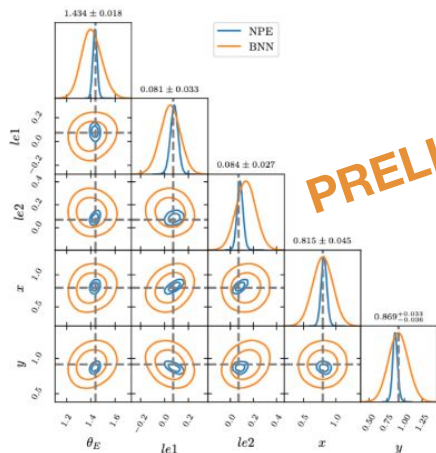
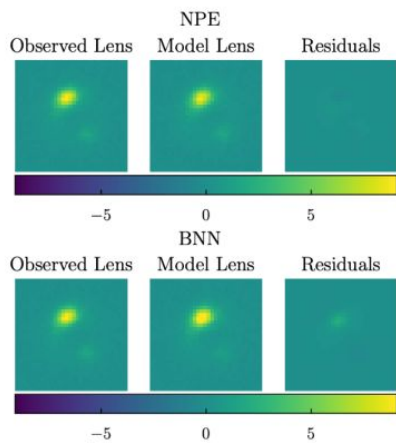


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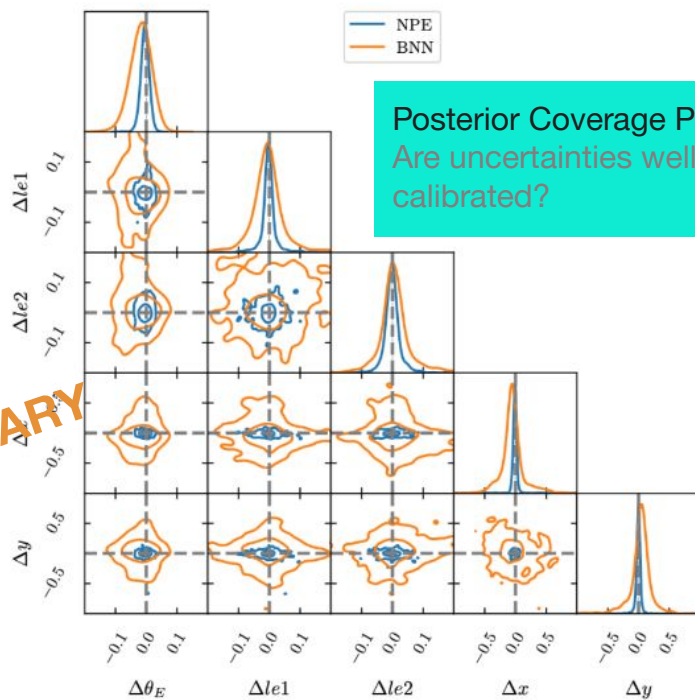
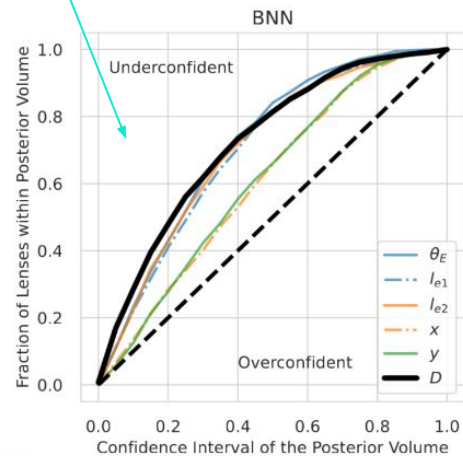
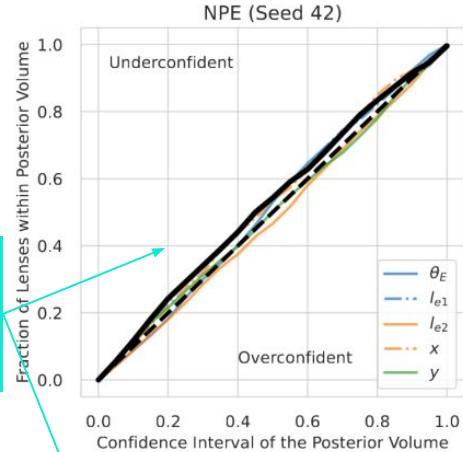


Figure 8. 5 parameter error corner plot.

Posterior Coverage Plot  
Are uncertainties well calibrated?



# Solving the Friedmann Equation

Expansion rate  $\left(\frac{\dot{a}}{a}\right)^2 = \frac{8\pi G}{3}\rho - \frac{Kc^2}{a^2} + \frac{\Lambda}{3}$  Density measures

In order to solve it, we also need to define the behavior of the mass/energy density  $\rho(a)$  of any given mass/energy component. Recall the basic GR paradigm:



Each component will lead to a different evolution in redshift

We already saw that:

$$\rho_m(t) = \rho_{m,0} a^{-3}(t)$$
$$\rho_r(t) = \rho_{r,0} a^{-4}(t)$$
$$\rho_v(t) = \rho_v = \text{const.}$$

# The Equation of State

- Defines the dependence of the density vs. volume for a given matter/energy component, to enter in the Friedman eq.
- Usually written as  $p = w \rho$
- This is not necessarily the best way to describe the matter / energy density; it implies a fluid of some kind... This may be OK for the matter and radiation we know, but maybe it is not an optimal description for the dark energy
- Special values:
  - $w = 0$  means  $p = 0$ , e.g., non-relativistic matter
  - $w = 1/3$  is radiation or relativistic matter
  - $w = -1$  looks just like a cosmological constant
  - ... but it can have in principle any value, and it can be changing in redshift

Matter dominated ( $w = 0$ ):  $\rho \sim a^{-3}$

Radiation dominated ( $w = 1/3$ ):  $\rho \sim a^{-4}$

Dark energy ( $w \sim -1$ ):  $\rho \sim \text{constant}$

- Radiation density decreases the fastest with time
  - Must increase fastest on going back in time
  - Radiation must dominate early in the Universe
- Dark energy with  $w \sim -1$  dominates last; it is the dominant component now, and in the (infinite?) future

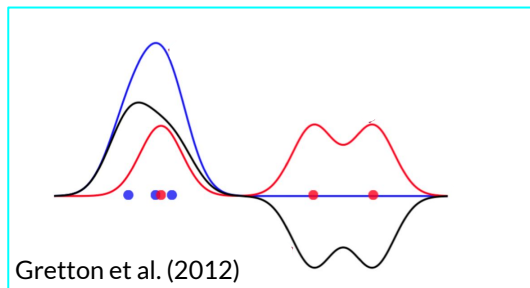


# Combining Datasets

## DOMAIN ADAPTATION

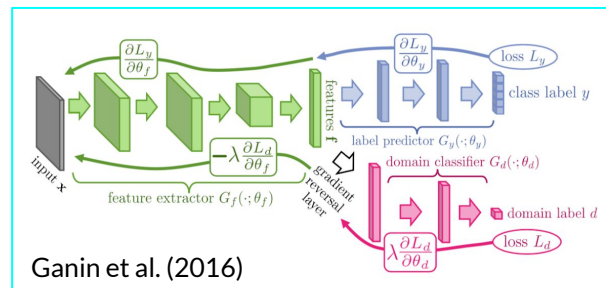
Align data distributions in the latent space of the network by forcing the network to **find more robust domain-invariant features**.

Distance-based methods



Training  
=  
Task Loss  
+  
DA Loss

Adversarial methods



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Distance-based methods

Adversarial methods

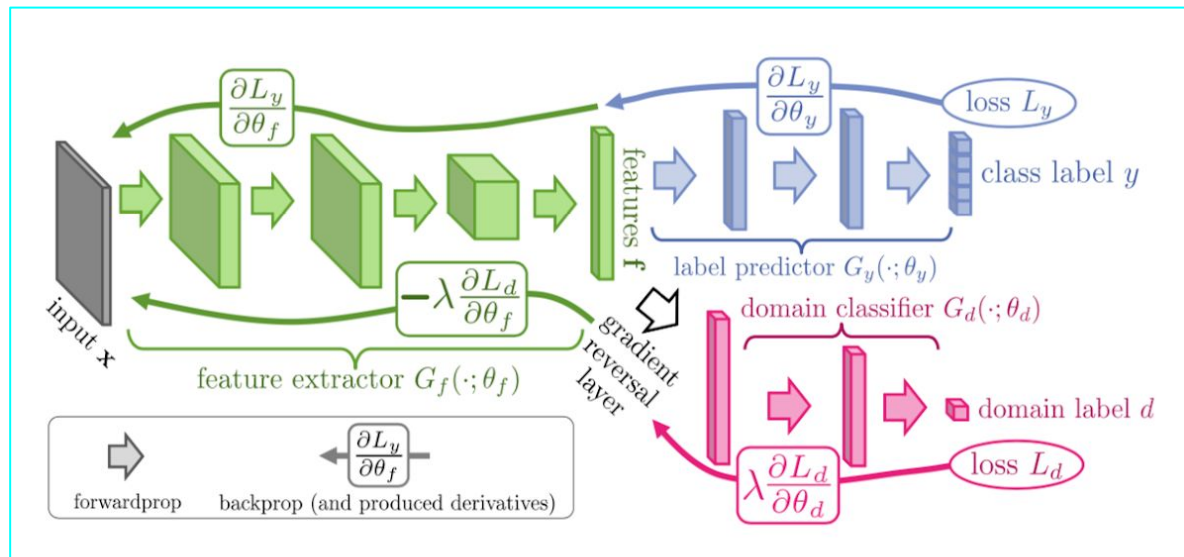
Works on **unlabeled target domain!**  
Can be applied to **new data**, no need for  
scientists to label anything.



# Domain Adversarial Neural Networks - DANNs

DANN - feature extractor + label predictor + domain classifier

- **Gradient reversal layer** - multiplies the gradient by a negative constant during the backpropagation.
- Results in the extraction of **domain-invariant features**.
- Only source domain images are labeled during training.

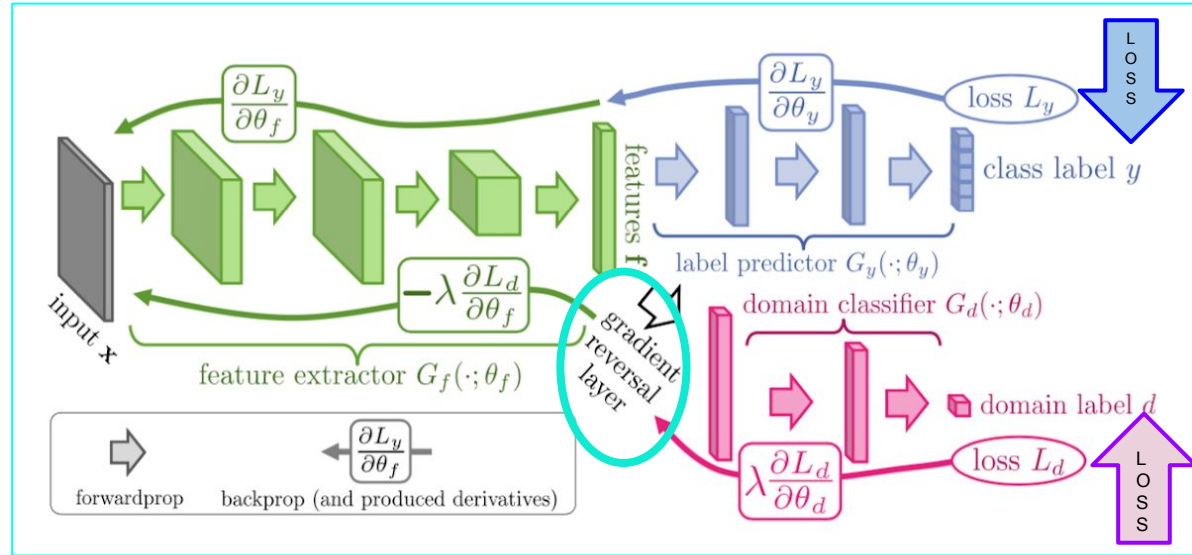


Ganin et al. (2016)

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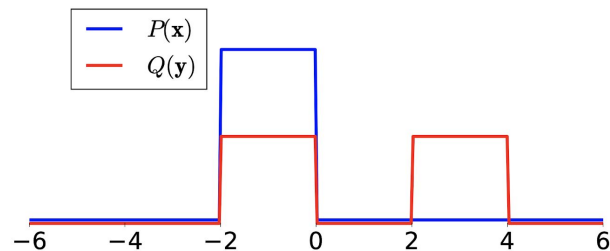


Ganin et al. (2016)

# Maximum Mean Discrepancy - MMD

Smola et al. (2007)  
Gretton et al. (2012)

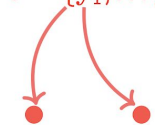
Are  $P$  and  $Q$  different?



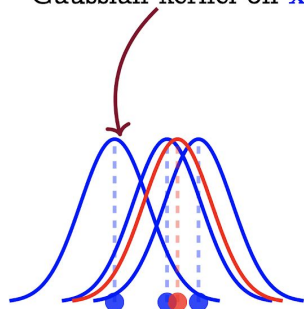
Observe  $X = \{\mathbf{x}_1, \dots, \mathbf{x}_n\} \sim P$



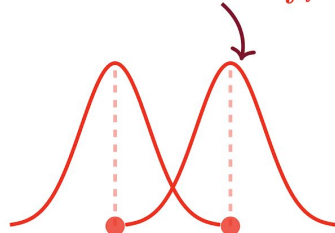
Observe  $Y = \{\mathbf{y}_1, \dots, \mathbf{y}_n\} \sim Q$



Gaussian kernel on  $\mathbf{x}_i$

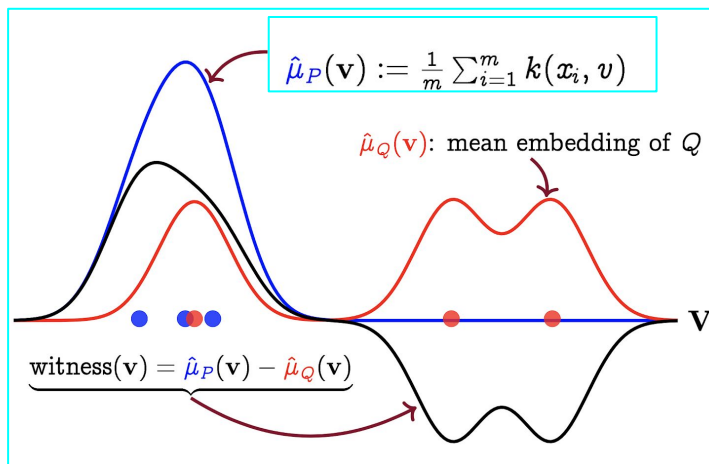


Gaussian kernel on  $\mathbf{y}_i$



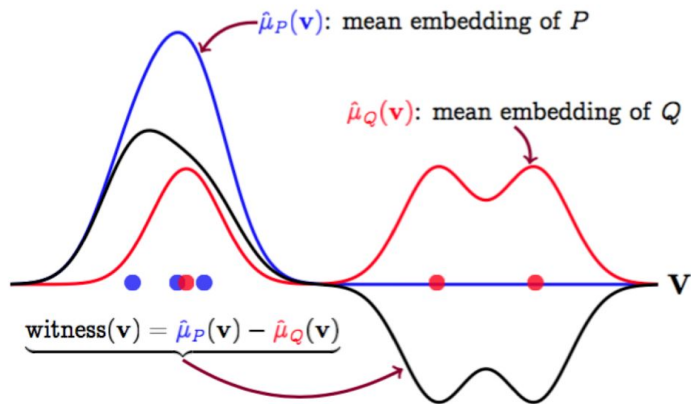
$$\hat{\mu}_P(\mathbf{v}) := \frac{1}{m} \sum_{i=1}^m k(\mathbf{x}_i, \mathbf{v})$$

$\hat{\mu}_Q(\mathbf{v})$ : mean embedding of  $Q$



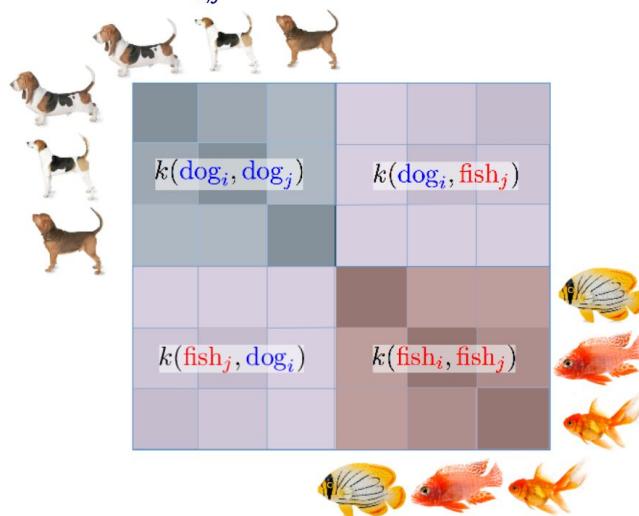
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Smola et al. (2007)  
Gretton et al. (2012)



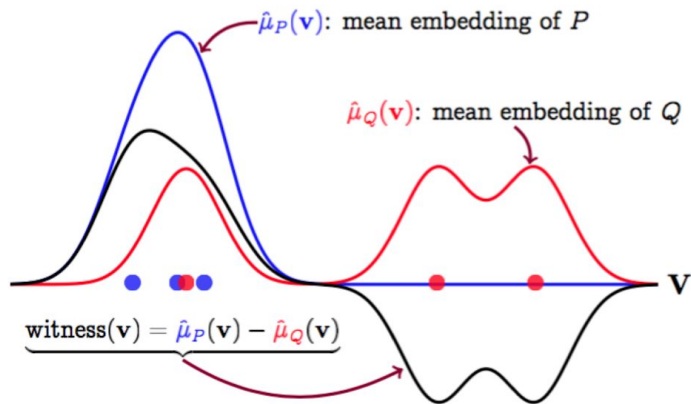
$$\begin{aligned} \widehat{MMD}^2 &= \|\text{witness}(\mathbf{v})\|_{\mathcal{F}}^2 \\ &= \frac{1}{n(n-1)} \sum_{i \neq j} k(\mathbf{x}_i, \mathbf{x}_j) + \frac{1}{n(n-1)} \sum_{i \neq j} k(\mathbf{y}_i, \mathbf{y}_j) \\ &\quad - \frac{2}{n^2} \sum_{i, j} k(\mathbf{x}_i, \mathbf{y}_j) \end{aligned}$$

$$\begin{aligned} \widehat{MMD}^2 &= \frac{1}{n(n-1)} \sum_{i \neq j} k(\text{dog}_i, \text{dog}_j) + \frac{1}{n(n-1)} \sum_{i \neq j} k(\text{fish}_i, \text{fish}_j) \\ &\quad - \frac{2}{n^2} \sum_{i, j} k(\text{dog}_i, \text{fish}_j) \end{aligned}$$



# Maximum Mean Discrepancy - MMD

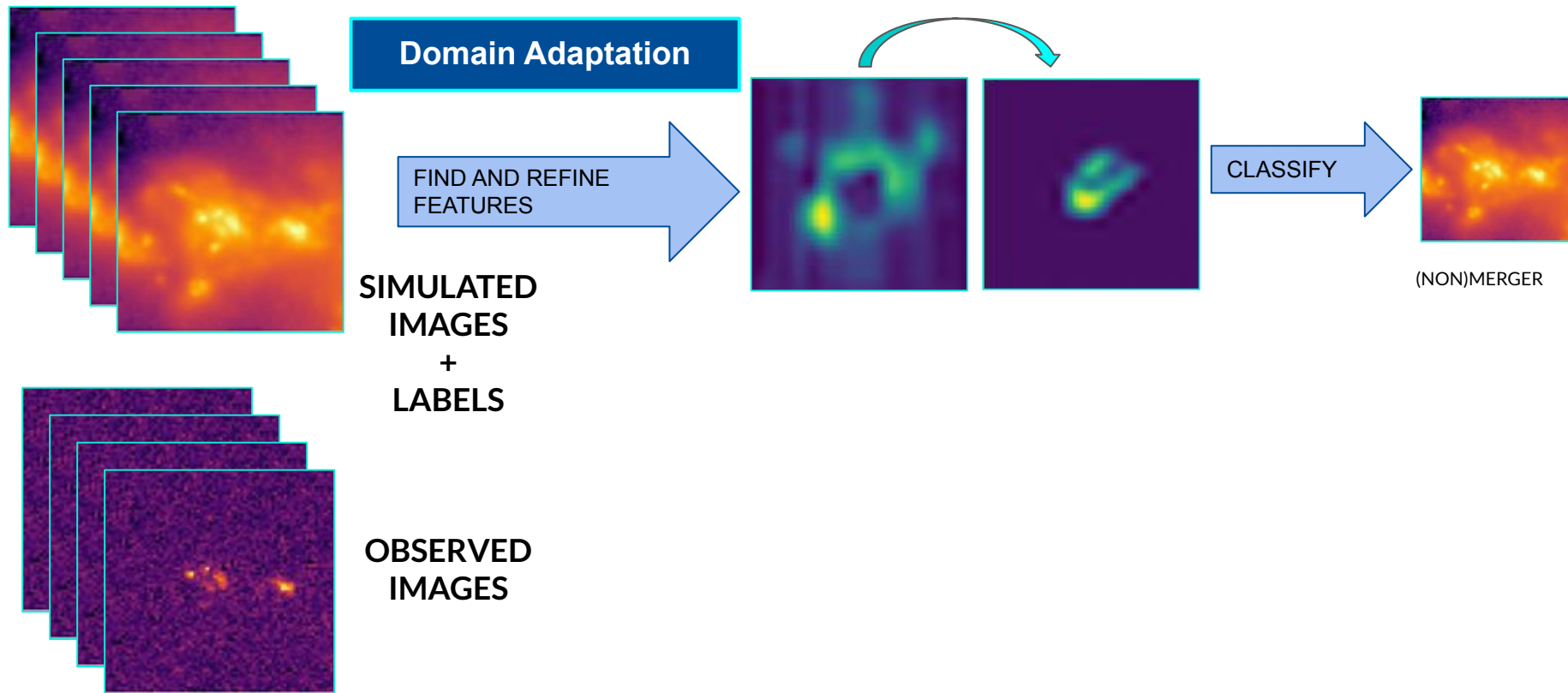
Smola et al. (2007)  
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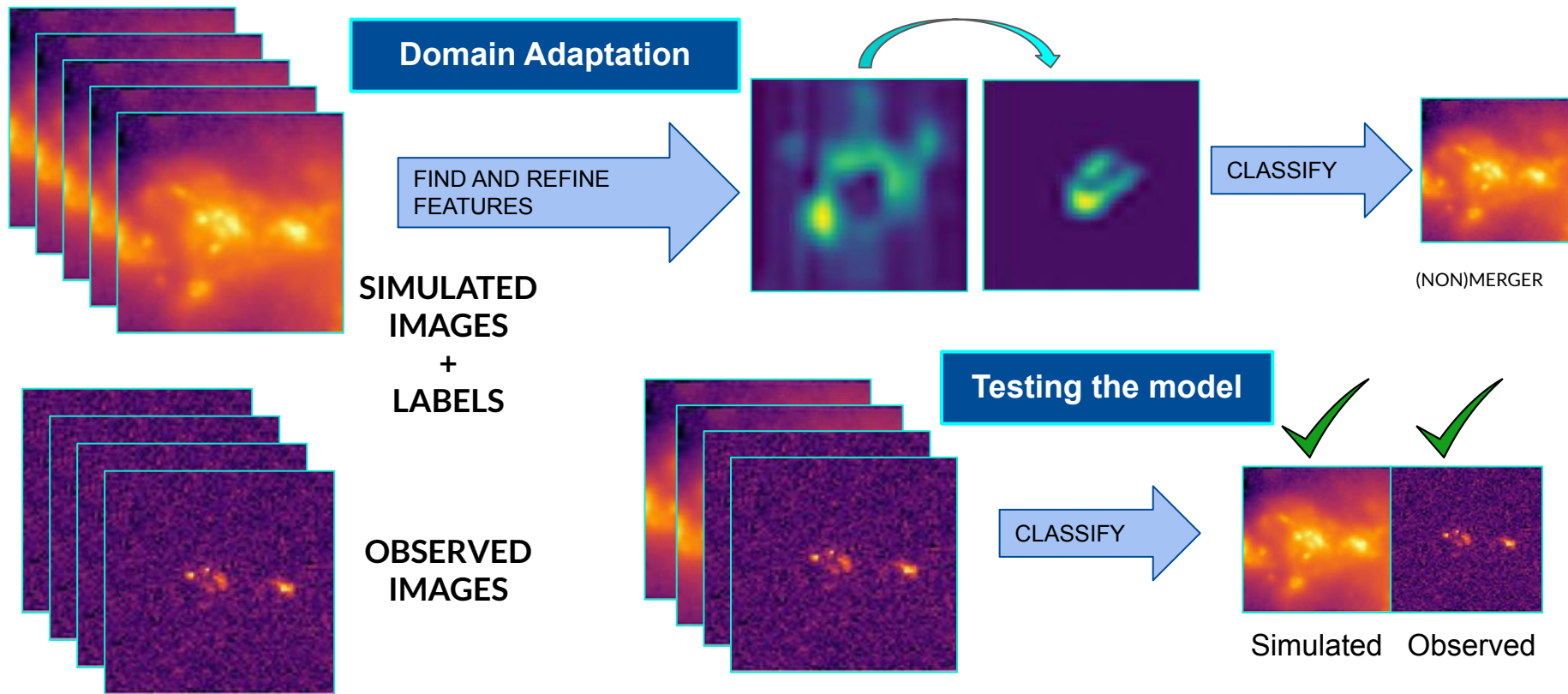
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# Combining Datasets

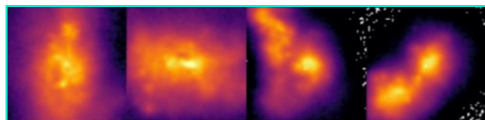


# Combining Datasets

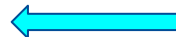
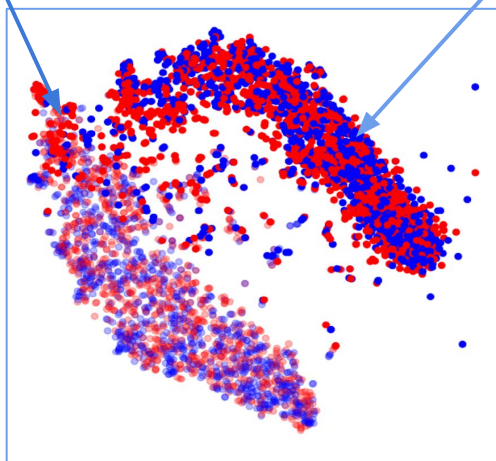
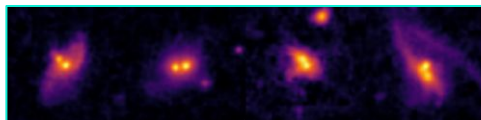


# Combining Datasets

Source - Illustris



Target - SDSS observations



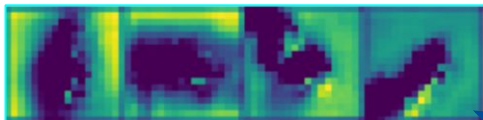
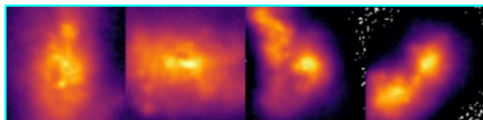
This is how the network sees the data.  
2D representation of network's latent space.

Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

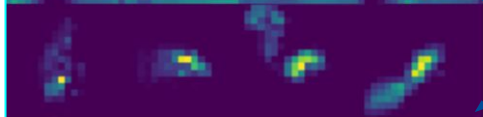


# Combining Datasets

Source - Illustris



NM



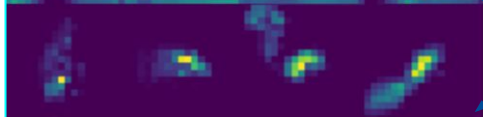
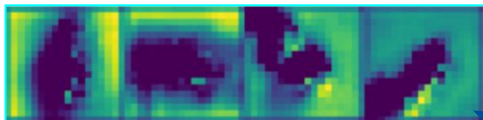
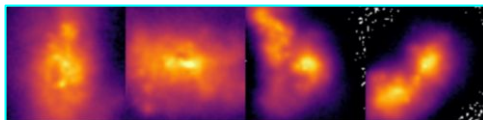
Important regions are highlighted!

Regular Training

Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

# Combining Datasets

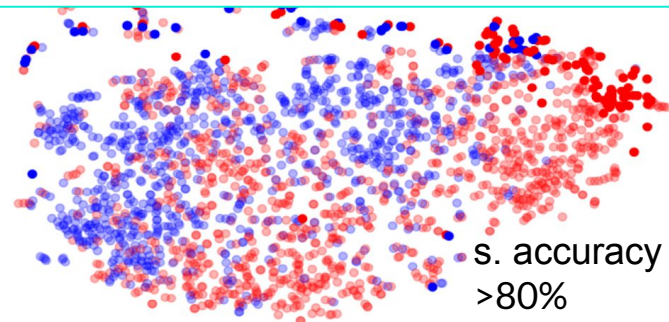
Source - Illustris



Important regions are highlighted!

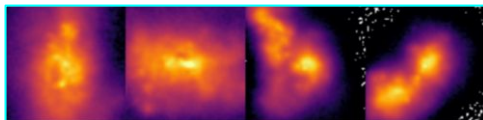
Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

Regular Training

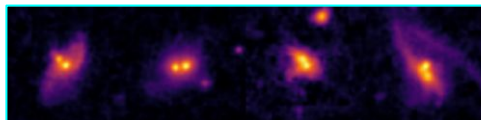


# Combining Datasets

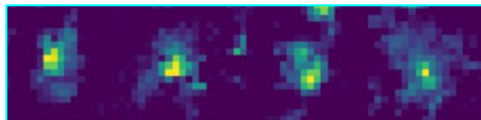
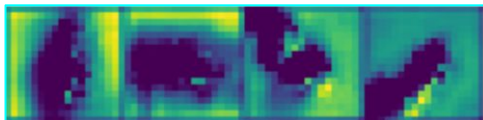
Source - Illustris



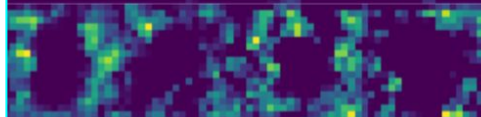
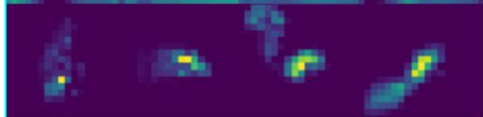
Target - SDSS observations



M

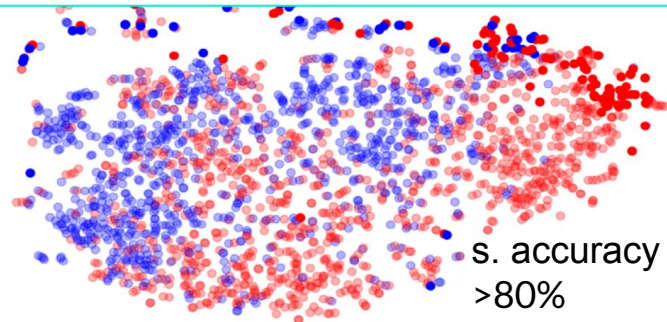


NM



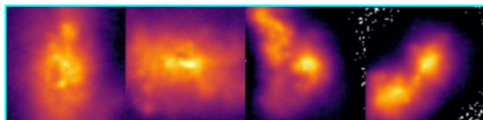
Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

Regular Training

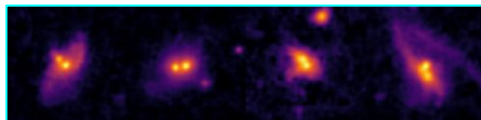


# Combining Datasets

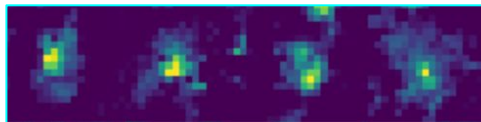
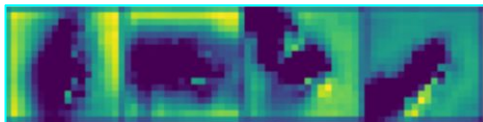
Source - Illustris



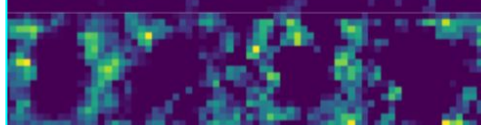
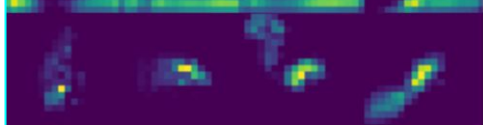
Target - SDSS observations



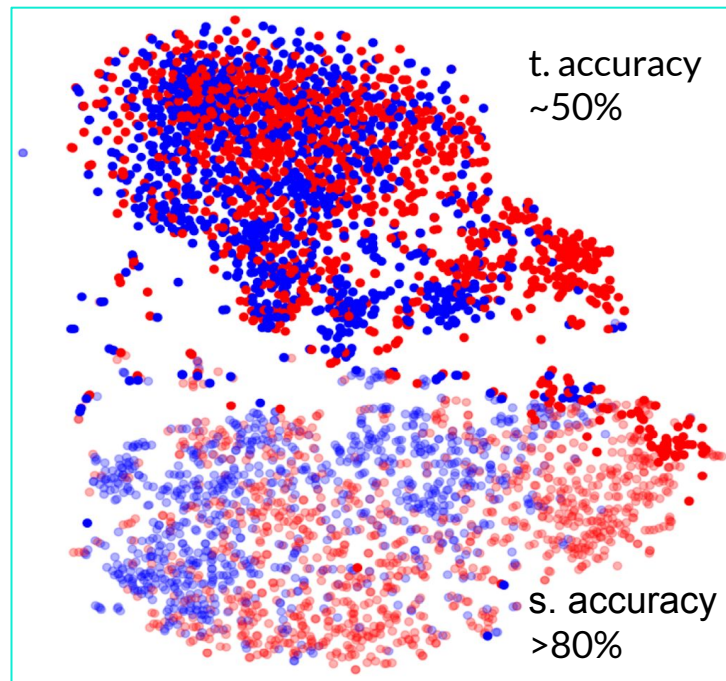
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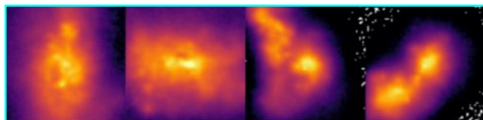


Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

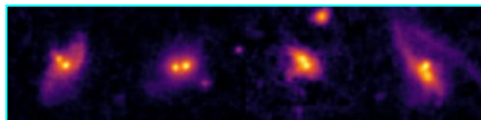


# Combining Datasets

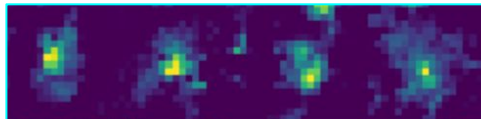
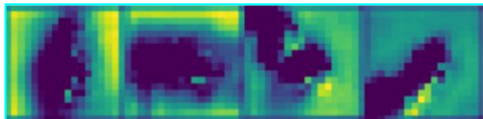
Source - Illustris



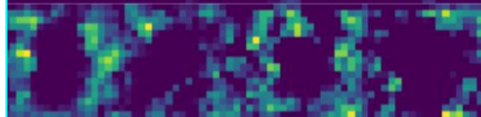
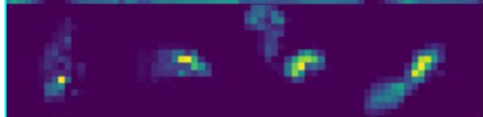
Target - SDSS observations



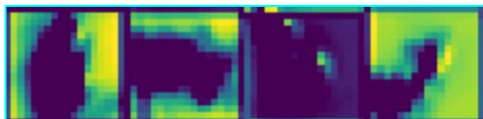
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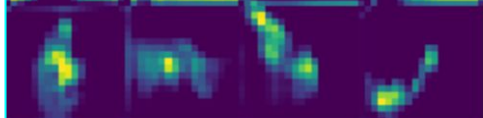
NM



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NM

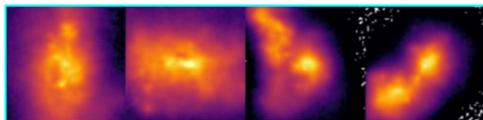


Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

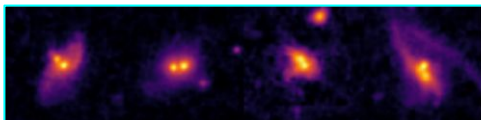
Domain Adaptation

# Combining Datasets

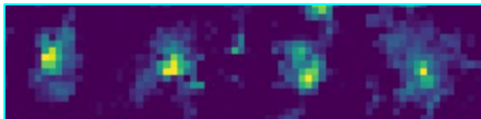
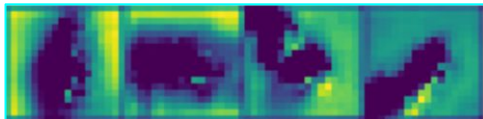
Source - Illustris



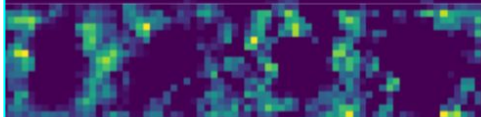
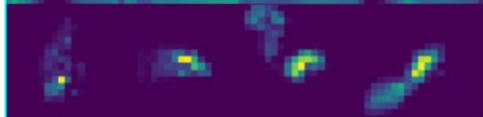
Target - SDSS observations



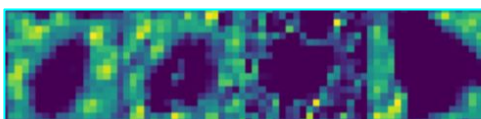
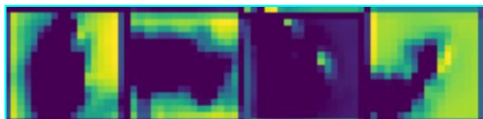
M



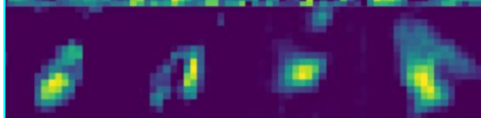
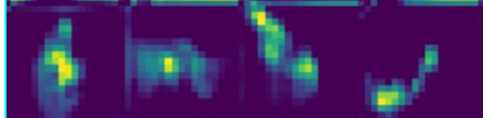
NM



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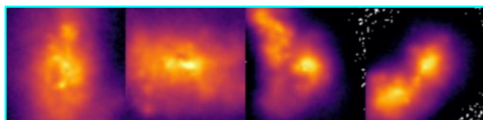


Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

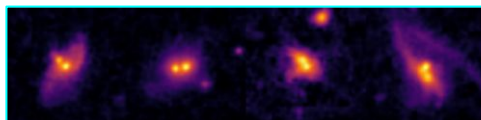
Domain Adaptation

# Combining Datasets

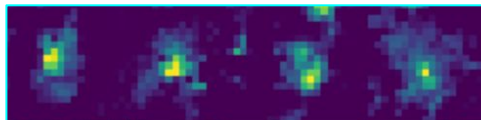
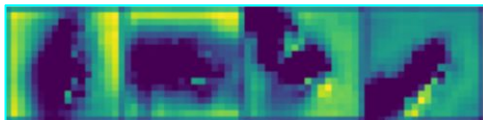
Source - Illustris



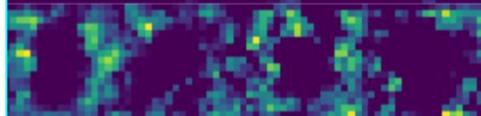
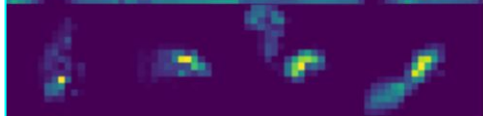
Target - SDSS observations



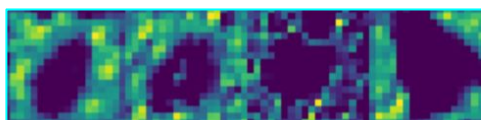
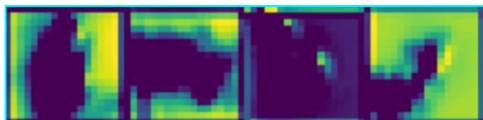
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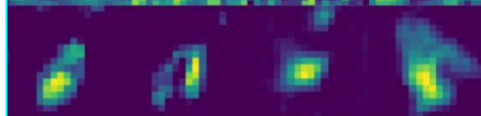
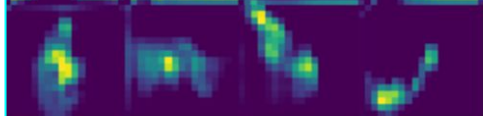
NM



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Ćiprijanović et al. 2020.  
Ćiprijanović et al. 2021.

Up to 30% increase!

