Cosmological Challenges for Artificial Intelligence

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Arnold Sommerfeld School
Physics meets Artificial Intelligence, LMU, Sep 14, 2022

To see a world in a grain of sand: Cosmological Scales

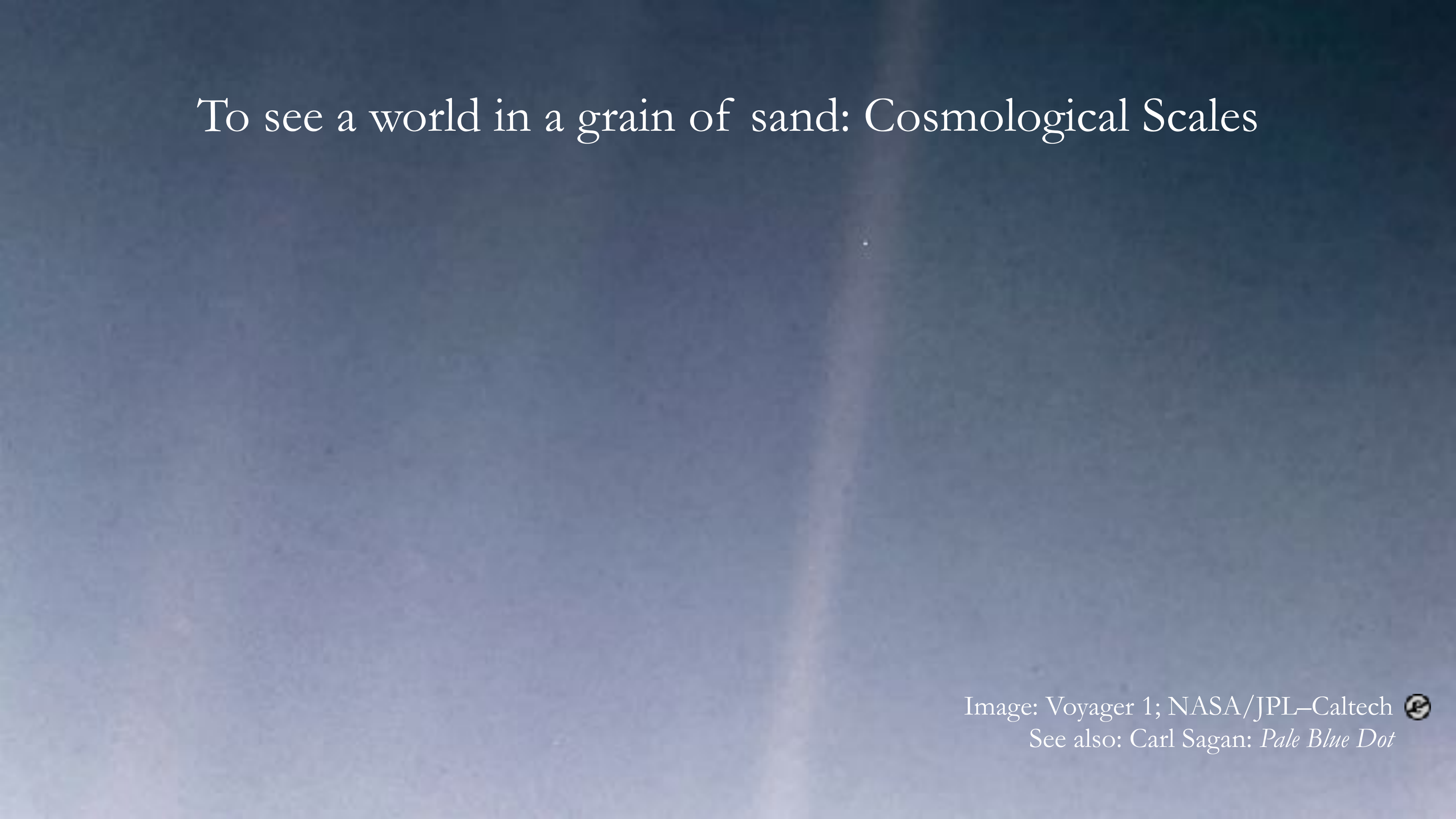


Image: Voyager 1; NASA/JPL–Caltech

See also: Carl Sagan: *Pale Blue Dot*

To see a world in a grain of sand: Cosmological Scales

Reality

10^7m

=

Model

10^{-6}m

Images: Apollo 8 / NASA; US Center for Disease Control and Prevention

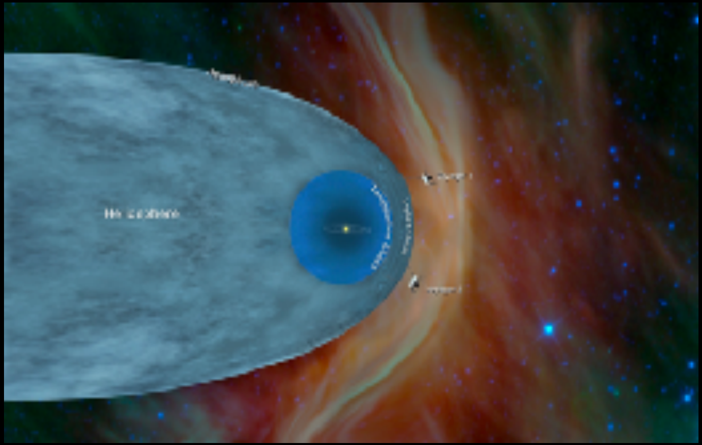
To see a world in a grain of sand: Cosmological Skales

Reality

$2x10^{13}m$

Model

$2x10^{0}m$



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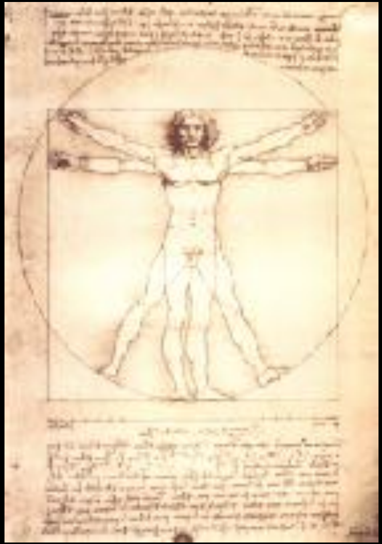


Images: Voyager 1/2 / NASA / JPL-Caltech; Leonardo da Vinci: *Der vitruvianische Mensch* (1492)

To see a world in a grain of sand: Cosmological Scales

Reality

10^{20}m

Model

10^{7}m

=

Images: Triangulum galaxy: Wendelstein Observatorium / LMU; Apollo 8 / NASA

To see a world in a grain of sand: Cosmological Scales

Reality

$5x10^{21}m$

Model

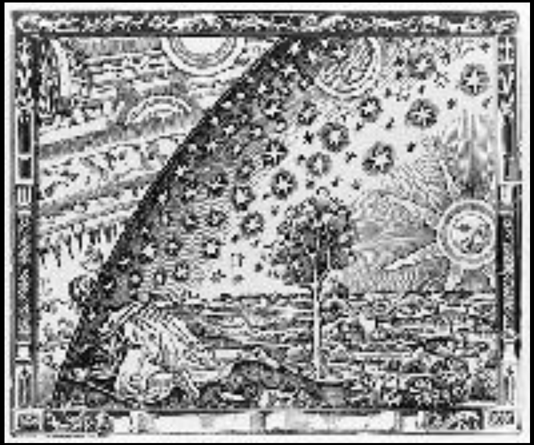
$5x10^{8}m$

=

Images: Galaxy cluster MACSJ0416: Dark Energy Survey / DG; Apollo 8 / NASA

To see a world in a grain of sand: Cosmological Scales

Reality	Model
few x 10^{26}m	$2x10^{13}$m



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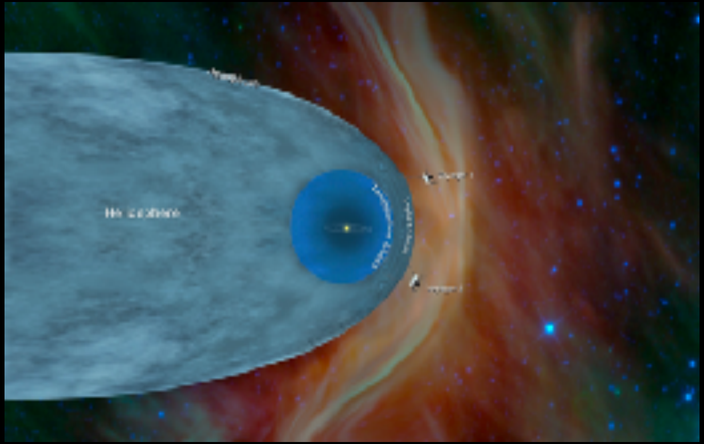
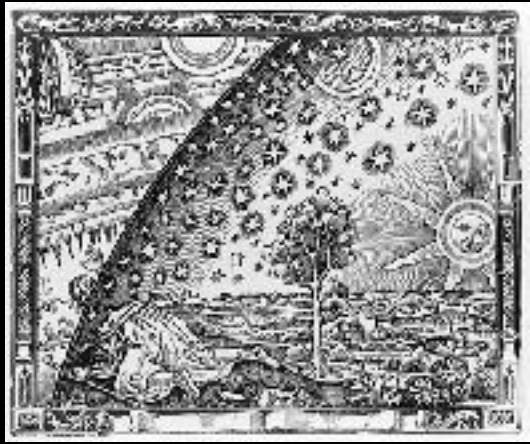


Images: Camille Flammarion: *L'Atmosphère* (Paris, 1888); Voyager 1/2 / NASA / JPL-Caltech

To see a world in a grain of sand: Cosmological Scales

Reality | Model

=



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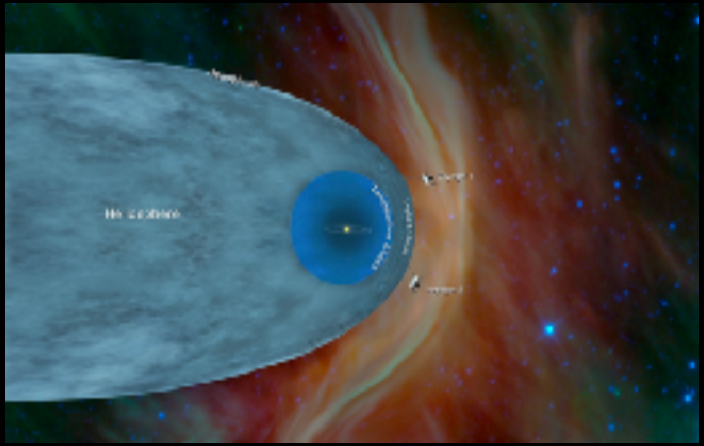
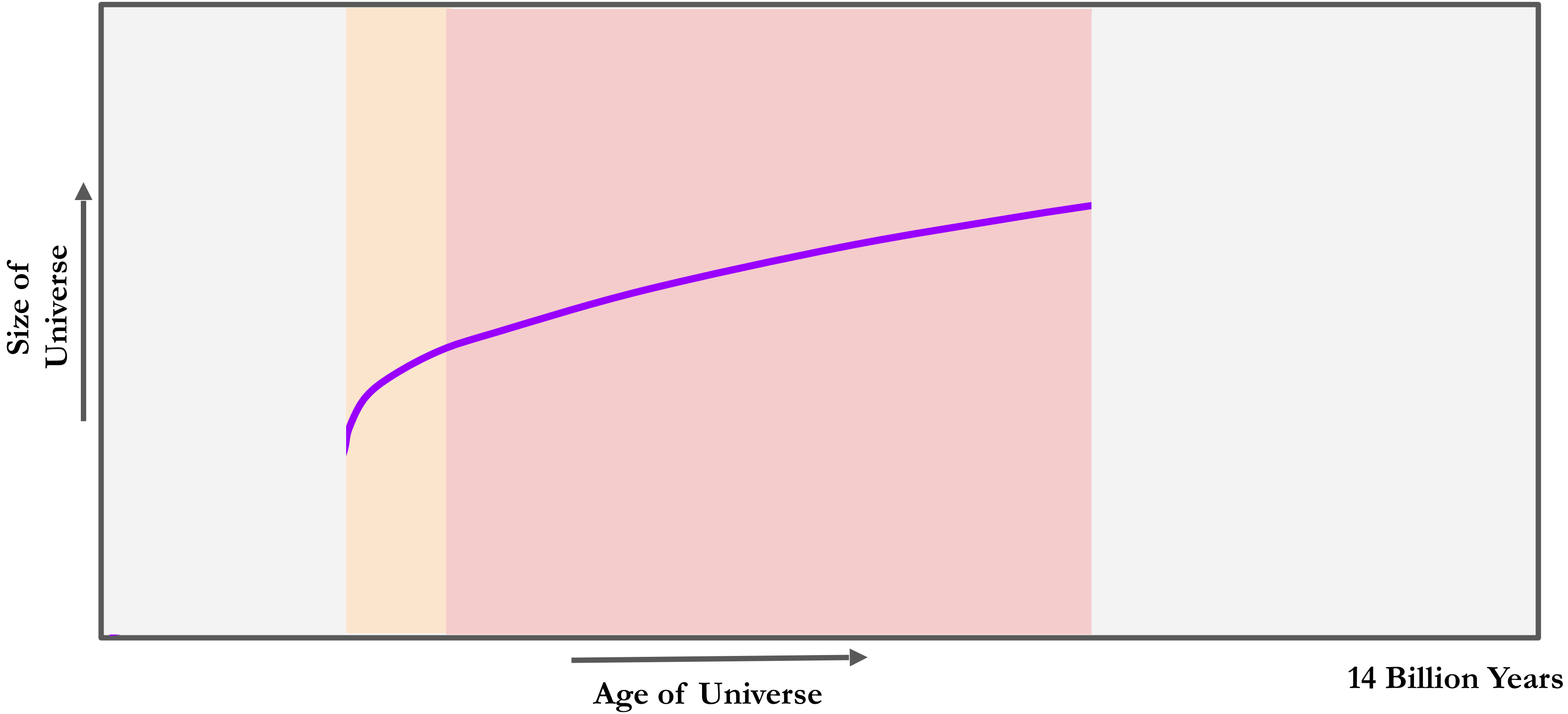
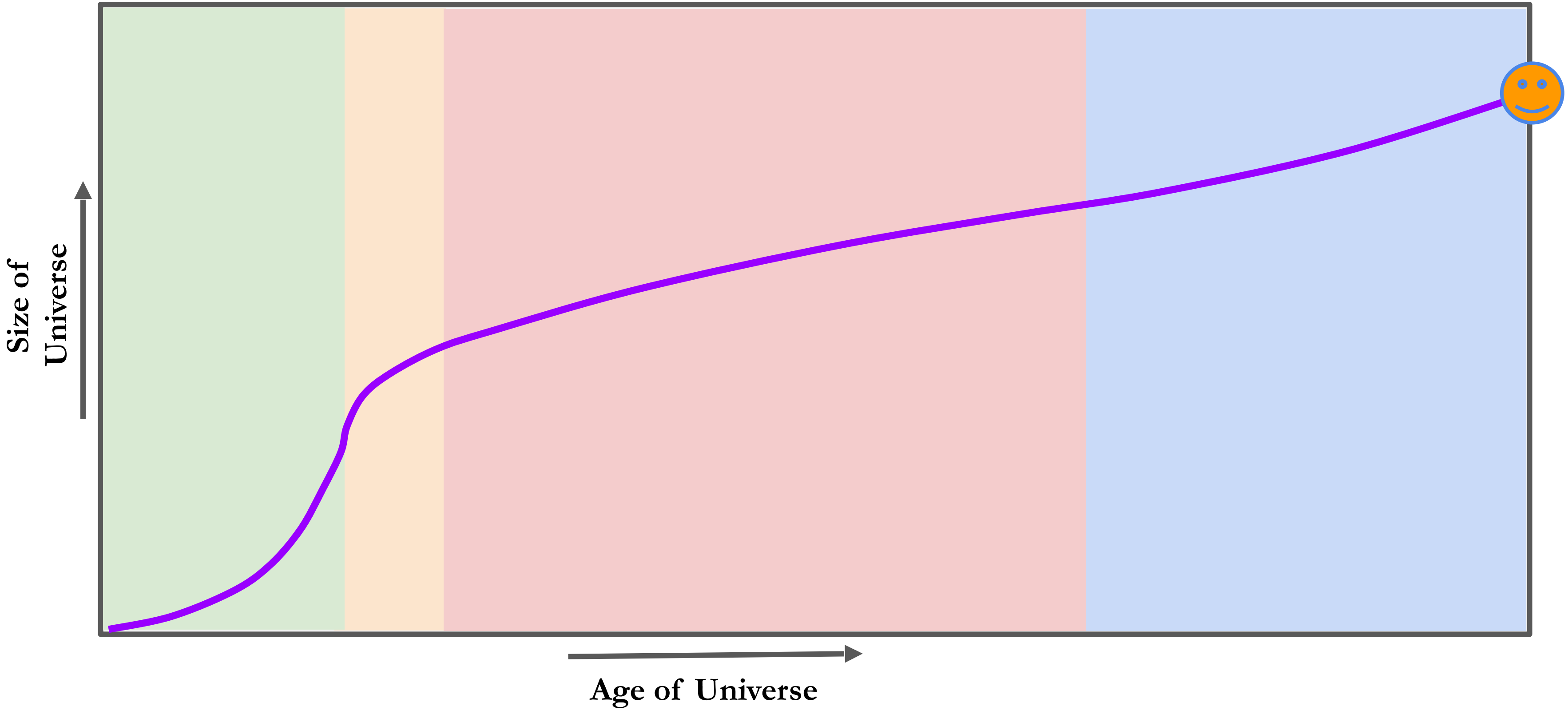


Images: Apollo 8, Voyager 1/2 / NASA / JPL-Caltech;
US Center for Disease Control and Prevention; Camille Flammarion: *L'Atmosphère* (Paris, 1888)

The story of the Universe: Playing ball



The story of the Universe as told by its expansion history



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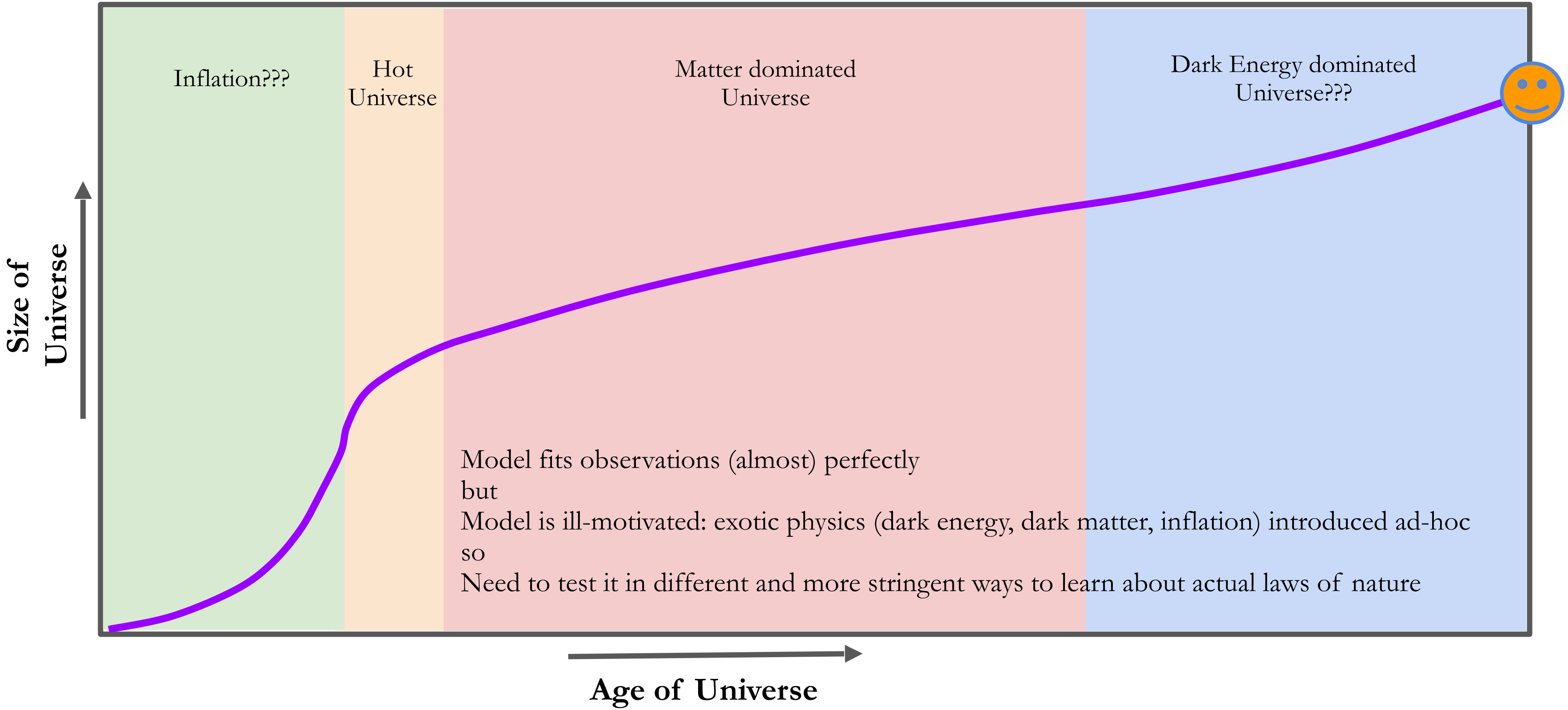
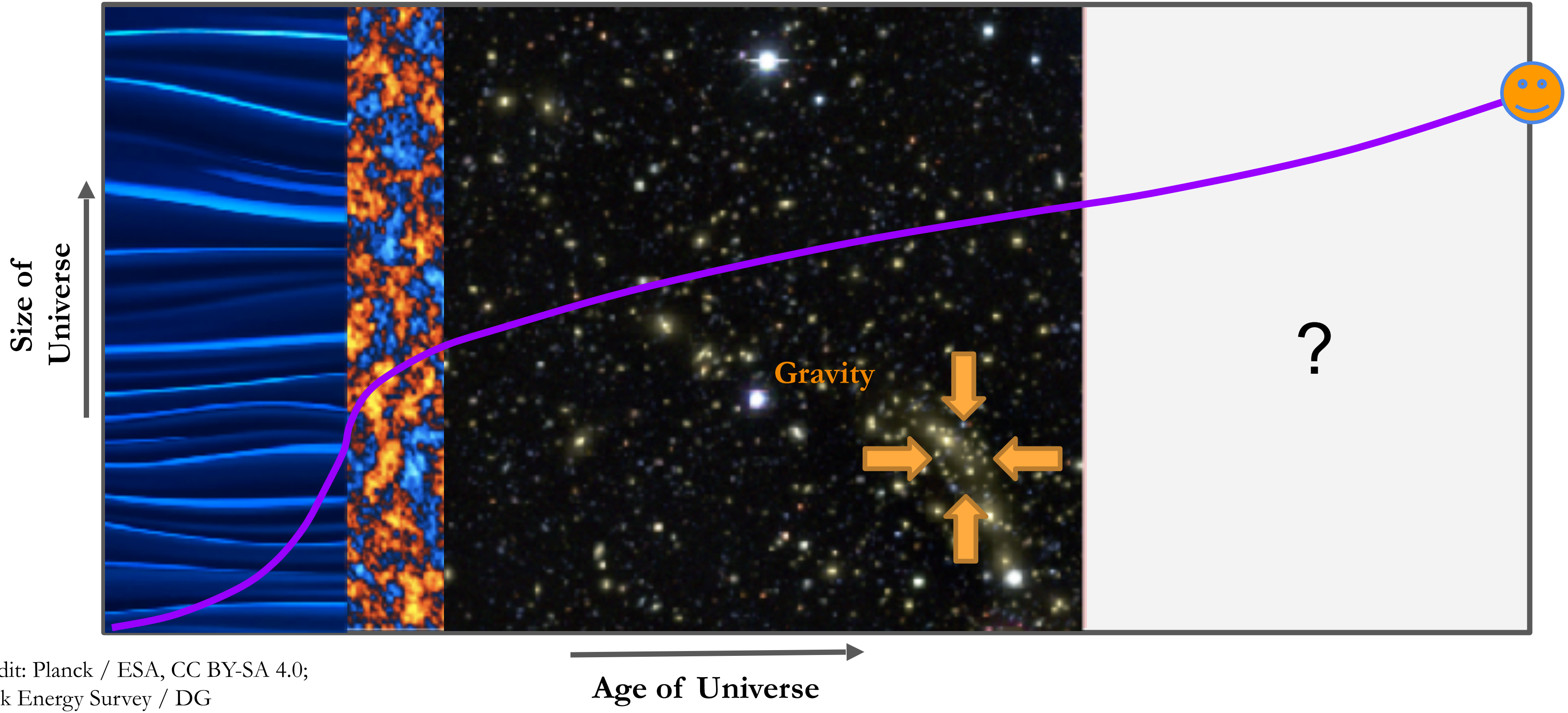


The story of the Universe as told by the growth of structure

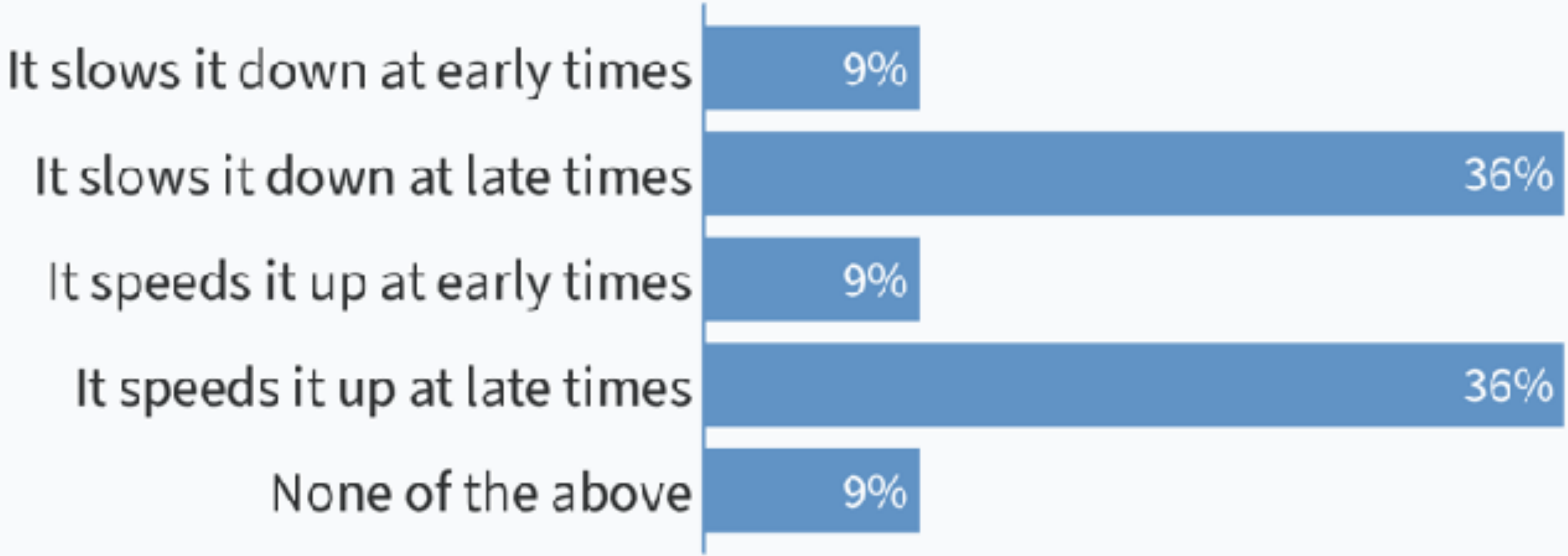


Credit: Planck / ESA, CC BY-SA 4.0;
Dark Energy Survey / DG

When poll is active, respond at **pollev.com/danielgruen878**

Text **DANIELGRUEN878** to **+49 157 3598 1046** once to join

How does Dark Energy impact the formation of structure?



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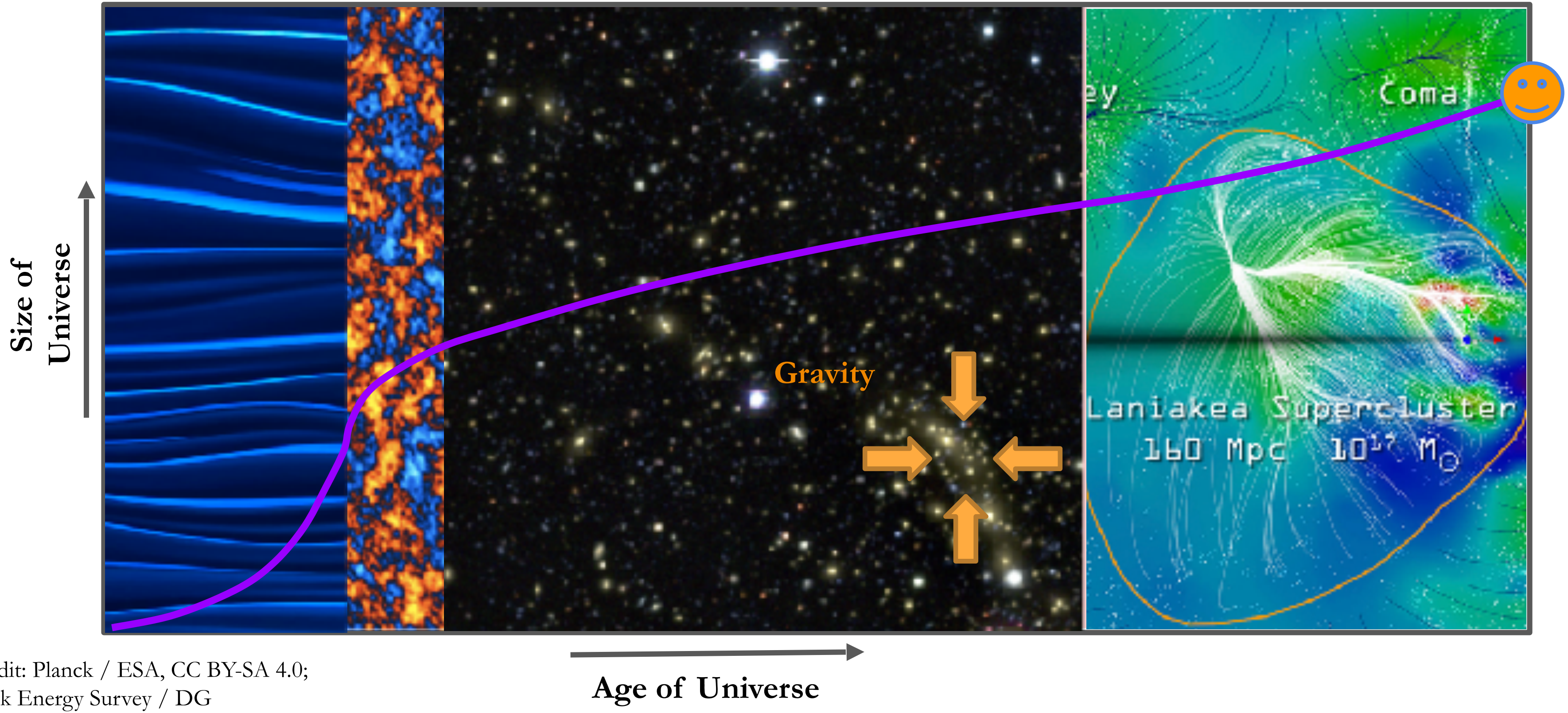

Credit: Planck / ESA, CC BY-SA 4.0;
Dark Energy Survey / DG

What we know

- What is the "Dark Matter" that enables the growth of structures by its gravitational attraction?
- What is the "Dark Energy" that accelerates the expansion of the Universe in recent times?
- What caused the exponential expansion of the Universe at its very beginning?

What we don't know

- Dark Matter makes up 80% of all matter and, as far as we can tell, only interacts via gravity, not through light or collision.
- The effect of Dark Energy is as though most energy was evenly distributed in space, with fixed density as space expands
- Only such an inflationary epoch explains some of the features of the Universe.

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- Only such an inflationary epoch explains some of the features of the Universe.

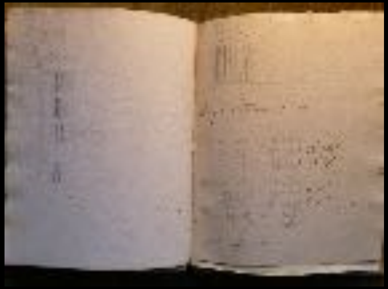
We do not know what Dark Energy, Dark Matter, and cosmic inflation "are".
Very simple, featureless equations describe all current observations well.
Clues of their true nature must lie in the detail!

The search for a small cosmological smoking gun & technological progress leads to an exponential increase in astronomical survey data taking

500 PB...

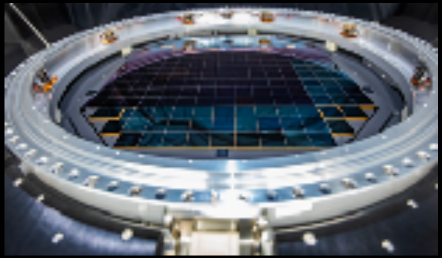
Fraunhofer Refractor,
LMU (around 1900)

Dark Energy Survey (2012-2019) and Very Rubin Observatory / LSST (2023-2033),
Cerro Tololo / Cerro Pachon, Chile



Recording stellar spectra, old school
Lamont (1836)

Development of
telescope and camera
technology



LSST: 3200 MPix camera,
40 full moons at once

DESI: 5000 robotic fibers

Credit: Jacqueline Ramseyer Orrell /
SLAC National Accelerator Laboratory; DESI Collaboration

Breakout discussion

- Form a group of 3-4 people around you.
- Briefly introduce yourselves in the group if you hadn't met before.
- In which ways are the needs of observational cosmology *similar* to other areas where the application of artificial intelligence has been successful? Find at least two and write them down!
- In which ways are the needs of observational cosmology *different* to other areas where the application of artificial intelligence has been successful? Find at least two and write them down!
- How do you think these similarities or differences manifest in the ways network architectures are chosen, and networks are trained and used in the different fields?

In which ways are cosmological analyses similar to other AI applications?

Top

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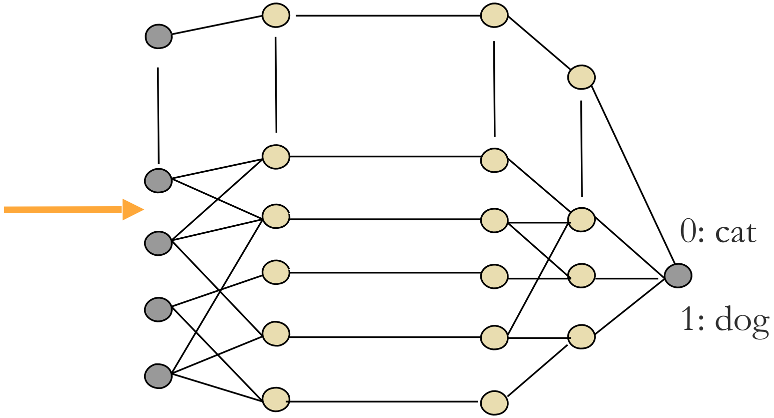
In which ways are cosmological analyses different from other AI applications?

Top

Textbook AI problem: image classification

- Problem: Which pictures show cats, which show dogs?
- Goal: High purity and completeness of selected sample
- Cost function: $(\text{estimate - truth})^2 \rightarrow \min$



Bilder: chetanimravan / kaggle

Image classification with ambiguous information

- Problem: Which pictures show cats, which show dogs?
- Goal: High purity and completeness of selected sample
- Cost function: (estimate - truth)^2 → min

Bilder: chetanimravan / kaggle

0: cat

1: dog

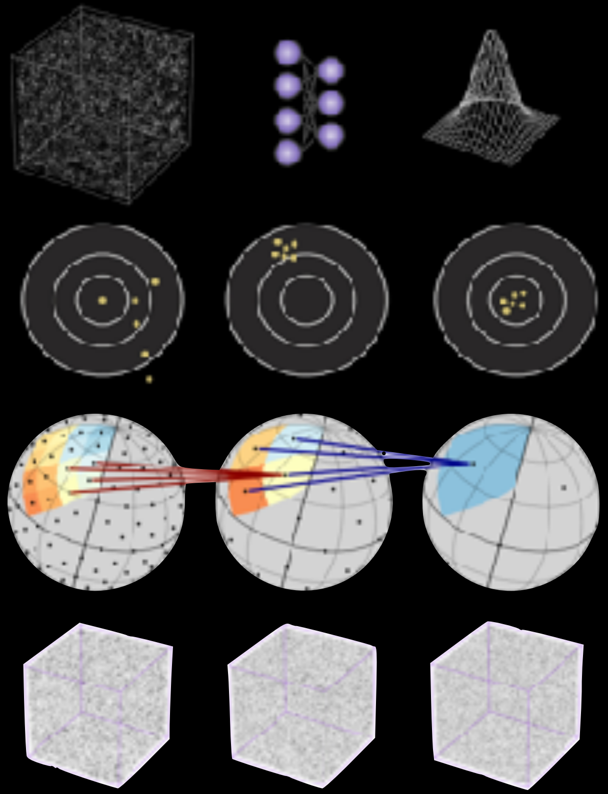
best answer might be: 0.5

Cosmological model test: Is this an equal mix of cats and dogs?

Bilder: chetanimravan / kaggle

Observational cosmology needs better algorithms

- **Data have to be processed *faster***
  - emulation of expensive algorithms with AI
- **Data have to be used for *accurate* measurements (not just *precise* measurements)**
  - specialized AI architectures to minimize / detect bias
- **Data have to be used to test cosmological models as stringently and diversely as possible**
  - deep learning to extract information from high-dimensional, correlated data
- **Complex systems have to be modeled correctly and completely**
  - generative models for astrophysical systems (galaxies, clusters, ...) & data (images, ...)



Credit: Perraudin et al. (DeepSphere); Jed Homer (LMU)

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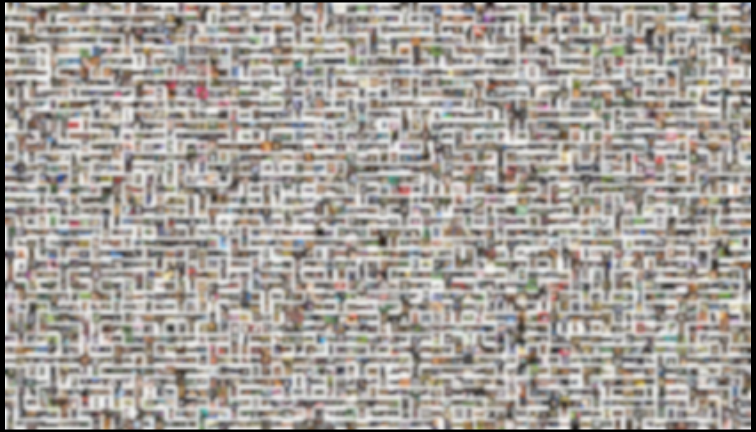


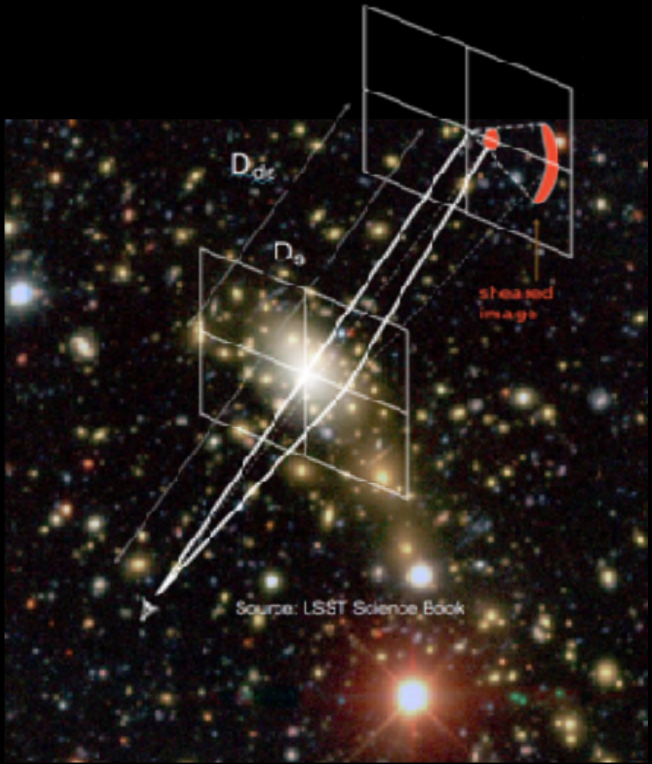


Bild: LSST Science Book / LSST Corporation;
Dark Energy Survey Deep Field MACS0416

Gravitational lensing is the direct connection from observed images to underlying (dark) matter overdensity

Tangential galaxy shapes ~ matter overdensity

$$\gamma_t(\theta) = \langle \kappa(\theta') \rangle_{\theta' < \theta} - \kappa(\theta)$$

$$\kappa = \Sigma / \left[\frac{c^2}{4\pi G} \frac{D_s}{D_d D_{ds}} \right]$$

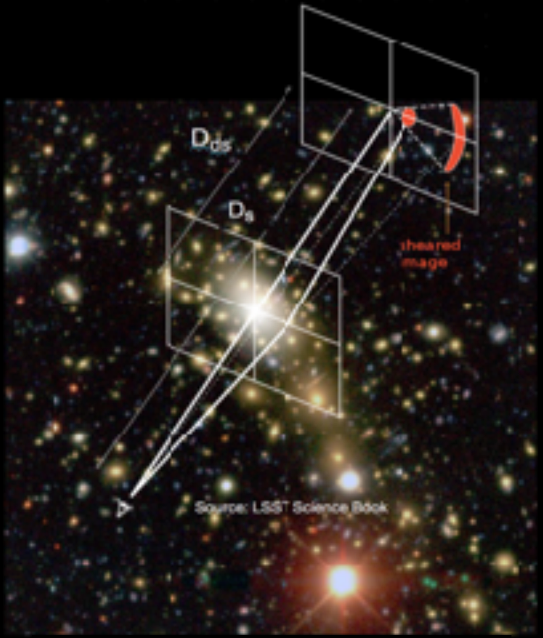
Need to measure shapes + distances of O(100 million) galaxies accurately

Accurate galaxy shape measurement for weak gravitational lensing analyses

sky images with galaxies

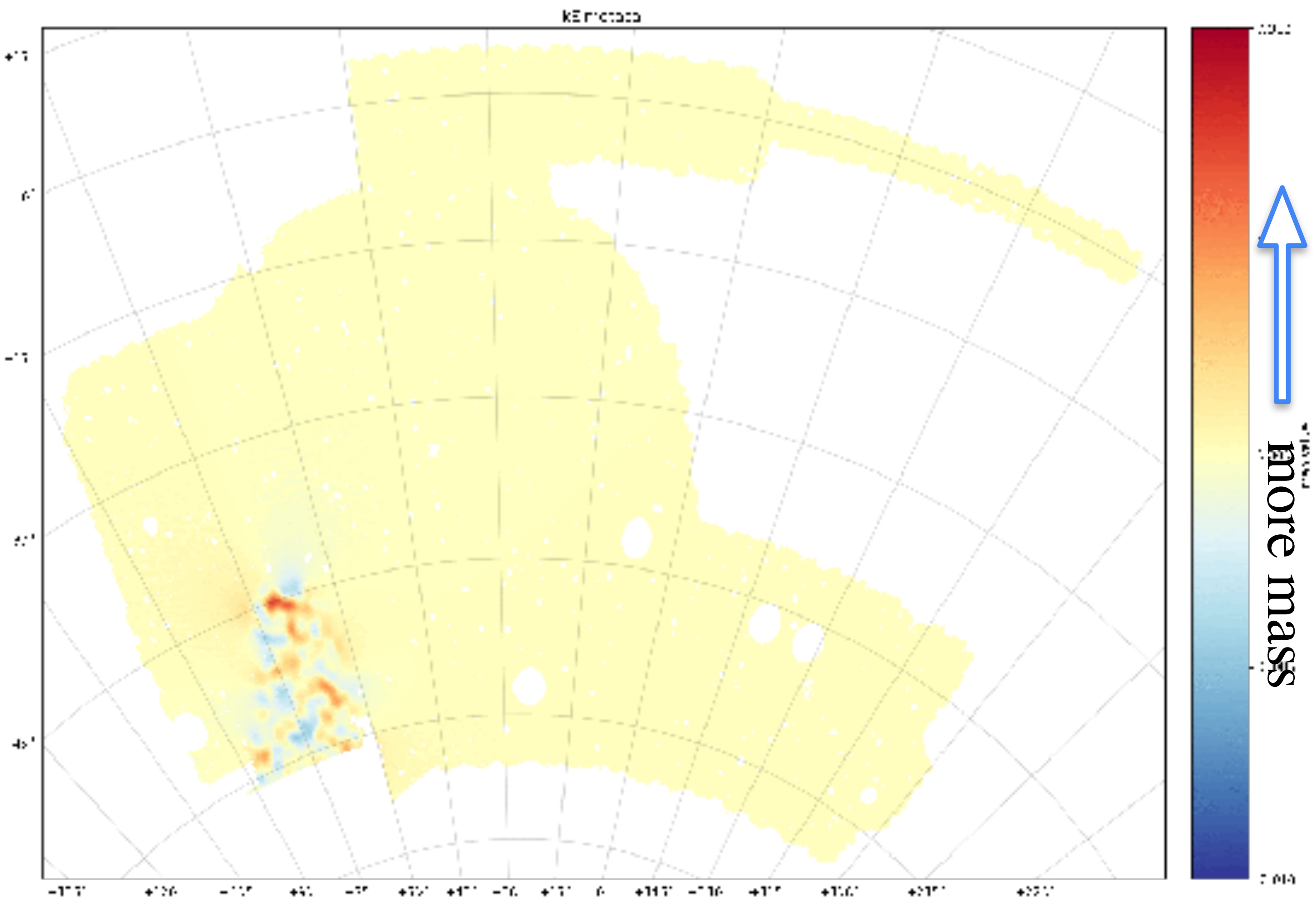
Position	Shape	Distance
…	…	…
…	…	…
…	…	…

catalog of galaxy shapes

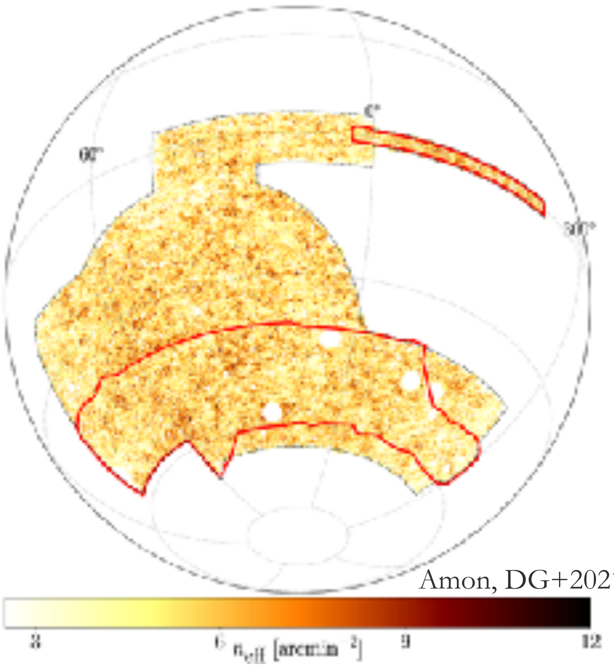


map of matter density

Dark Energy Survey Year 1-3 lensing-based mass map

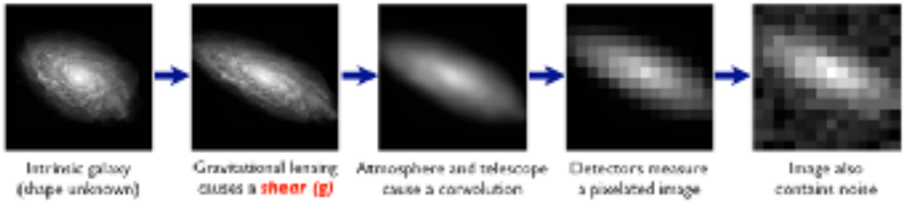


Accurate galaxy shape measurement for weak gravitational lensing analyses



Amon, DG+2021

100 million galaxies, soon billions

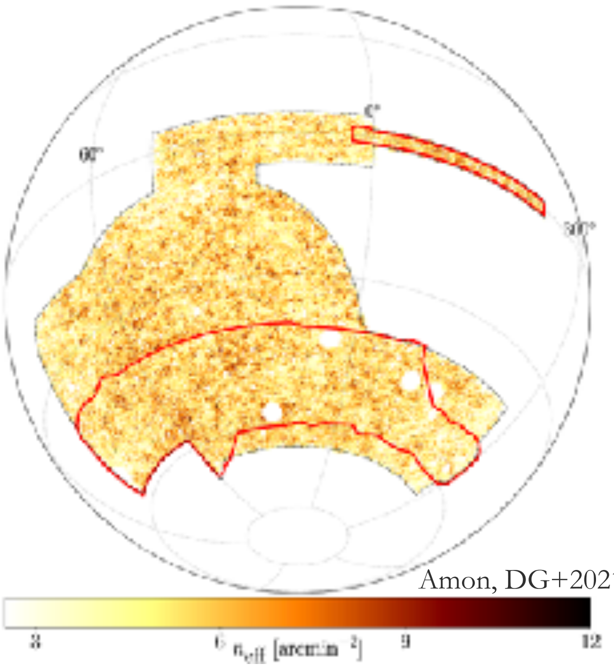


Bridle+2009

[measured signal] = (1 + m)[true signal]

need $|m| < 0.01$, soon < 0.002

Accurate galaxy shape measurement for weak gravitational lensing analyses



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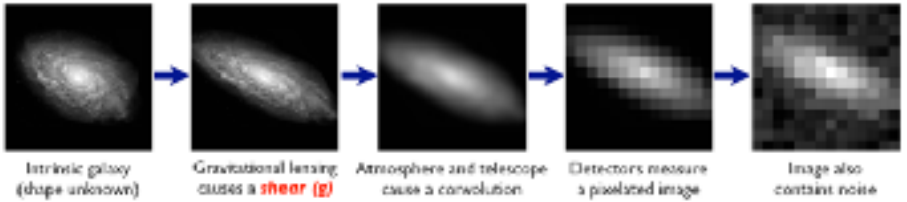


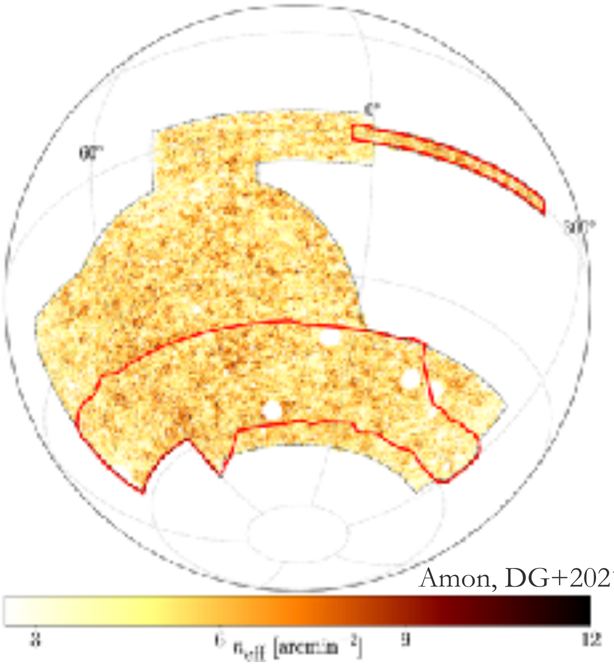
Bridle+2009

[measured signal] = (1 + m)[true signal]

need |m|<0.01, soon <0.002

Domain-specific AI approach: put m in the cost function
(DG+2010; Tewes+2012; Pujol+2020)

Accurate galaxy shape measurement for weak gravitational lensing analyses



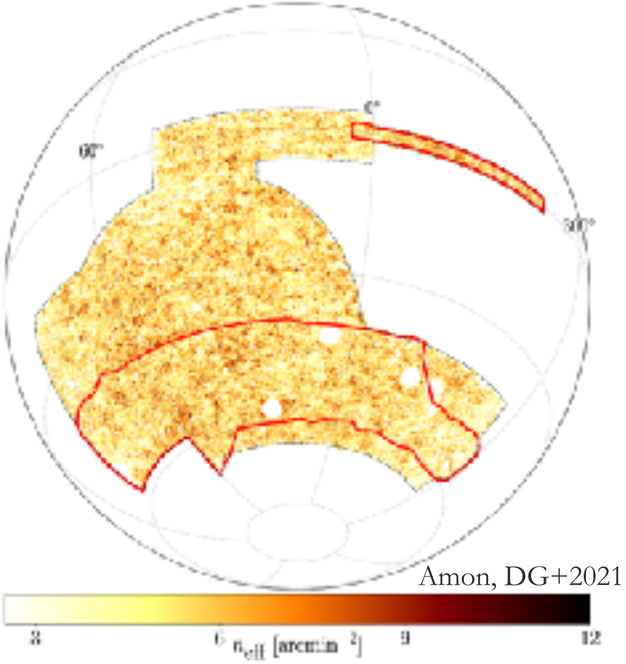
Amon, DG+2021

100 million galaxies, soon billions

Good news!

We have found an algorithm for self-calibrating shape measurement of isolated galaxies to $|m|<0.001$ in 2017!
(Huff & Mandelbaum, Sheldon & Huff 2017: metacalibration)

Accurate galaxy shape measurement for weak gravitational lensing analyses



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(Huff & Mandelbaum, Sheldon & Huff 2017: metacalibration)

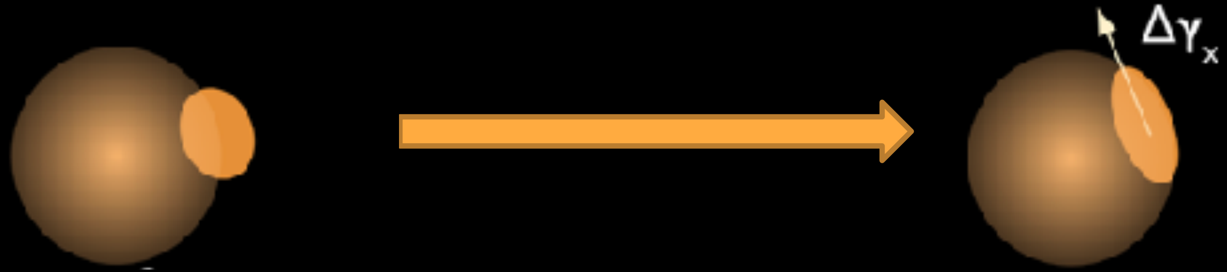
Bad news!

There is no isolated galaxy in the sky.

Shear calibration is really a calibration of the effective distance distribution of selected sources of light.

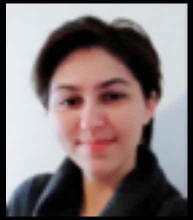
Instead of a 0-dimensional problem,

we have an infinite-dimensional problem.

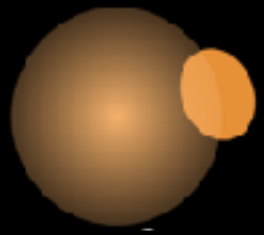


Problem:

Galaxies overlap in the sky, causing systematic error in shape measurement



Jamie McCullough,
PhD student (Stanford/LMU)

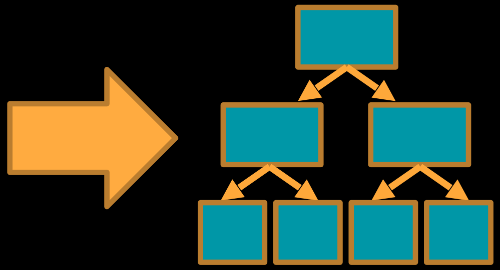


Systematic error in shape measurement depends on configuration of galaxies:

Positions, shapes, colors, sizes, light profile of a galaxy and all its neighbors in the sky; noise and resolution of observational data, ...

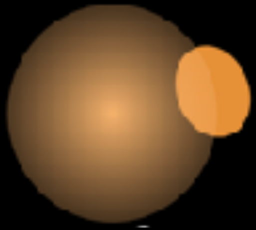
The result of the systematic error for weak lensing is that the "distance" of a detected object is really a distribution of distances of all the contributing sources of light.

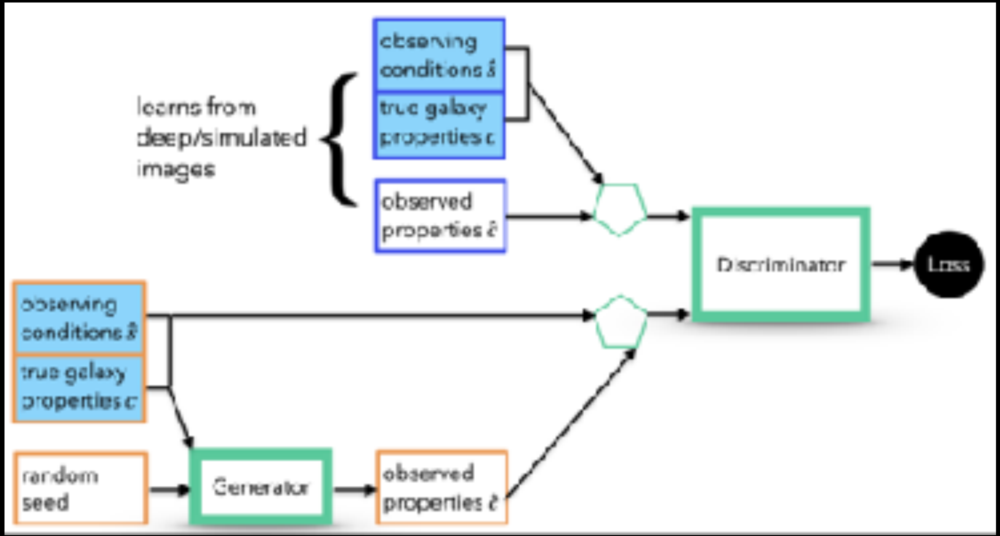
Brute-force approach would require simulation of millions of images for each configuration



Reduction of distinguishable configurations with modified decision tree that utilizes linearity

Patrick Gebhardt,
PhD student (LMU / GRS)

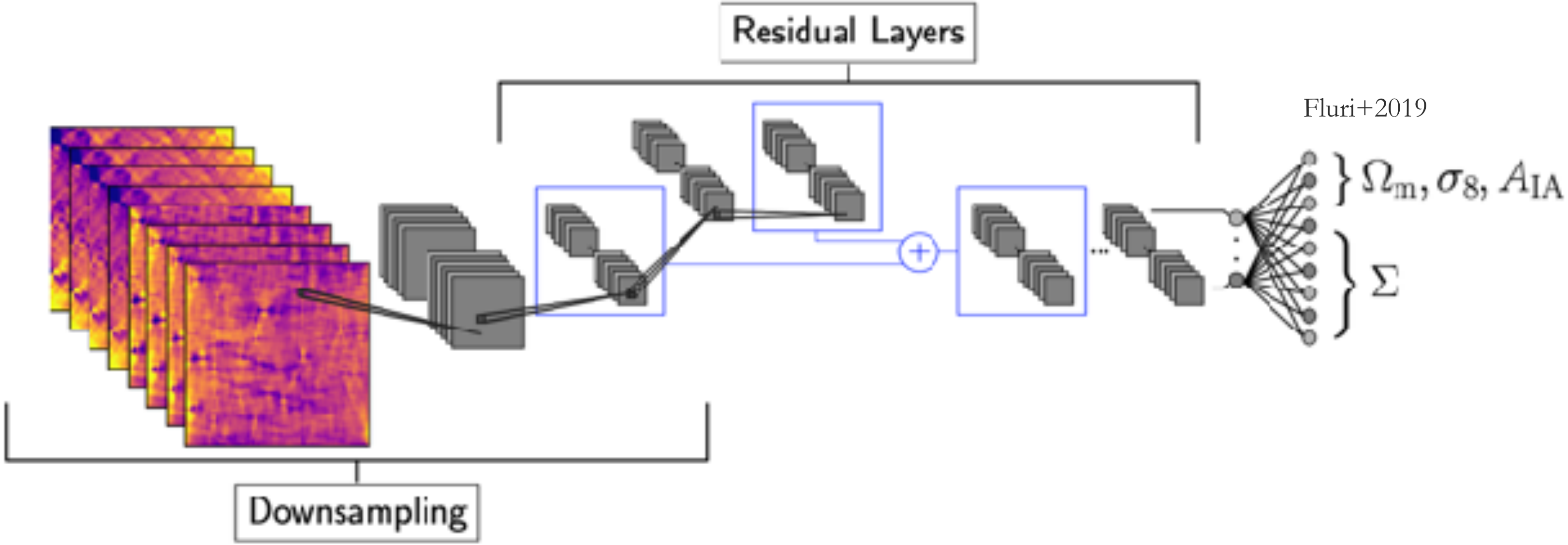




Emulating image simulations

Deep learning insights from cosmic structure

Fluri+2019

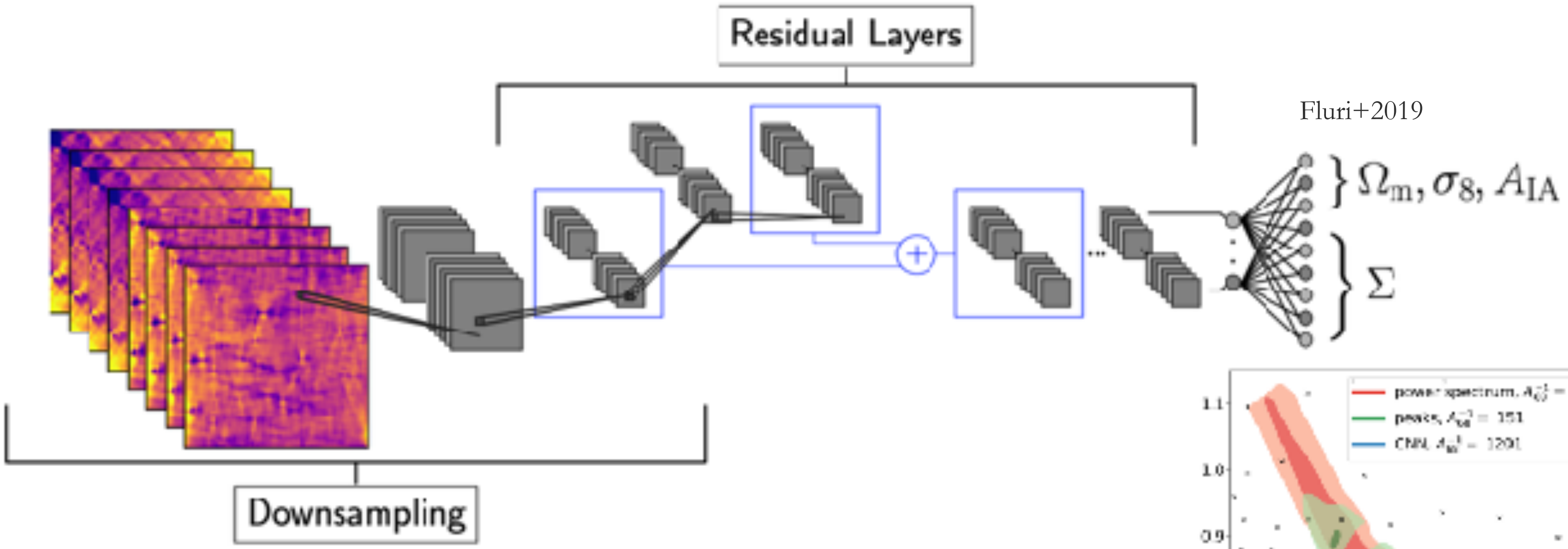


High dimensional data (e.g. map of gravitational lensing signal)

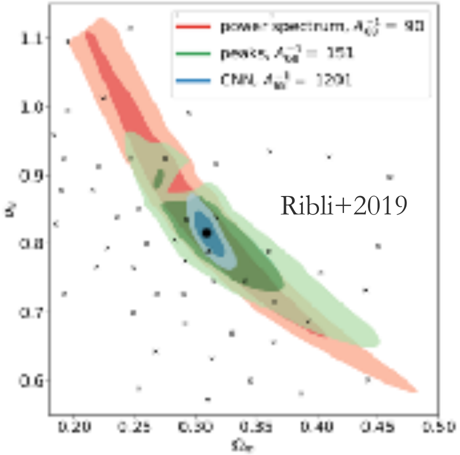
Compressed versions of data that mostly preserve cosmological information

Cosmological parameter and covariance matrix estimates

Deep learning insights from cosmic structure



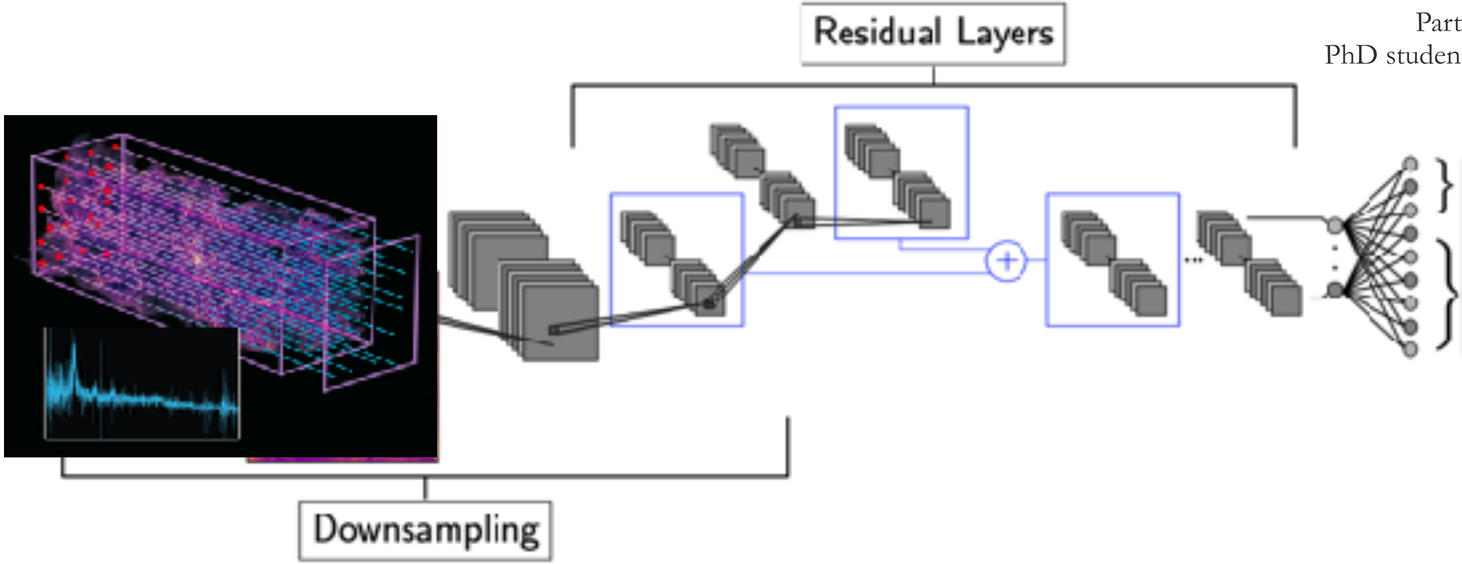
Fluri+2019



Ribli+2019

Deep learning insights from cosmic structure

Parth Nayak
PhD student (LMU)



Cosmological and astrophysical parameters and their covariance

Questions?

Animations: Yuan-Sen Ting (Australian National University), Jakub Misiek, Fabio Albertelli

Generative approach

Discriminator

Generator

Animations: Yuan-Sen Ting (Australian National University), Jakub Misiek, Fabio Albertelli

Generative approach

Discriminator

Generator

Generative approach

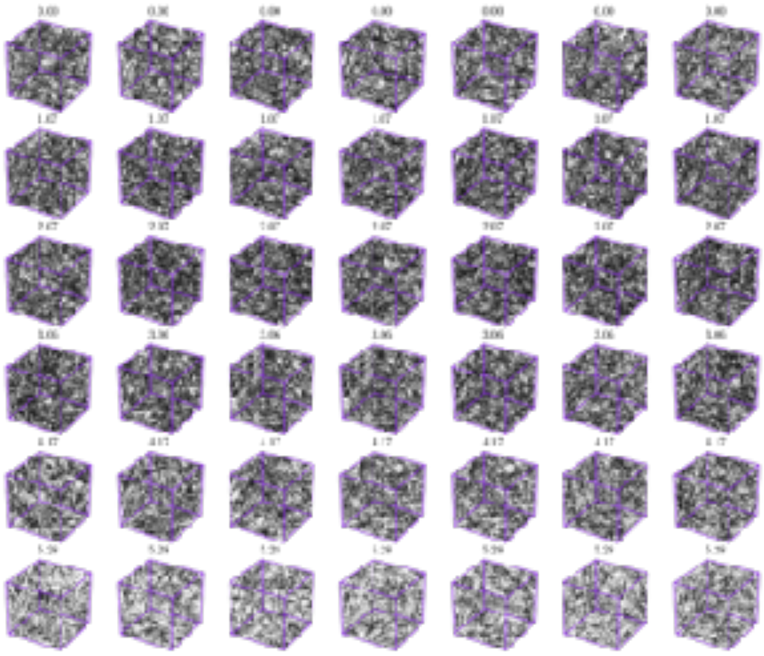
cosmological simulations, symmetries of systems, description of measurement process, understanding of relevant properties

generative AI

fast synthetic complex data that represents samples of astrophysical systems with known underlying "true" properties

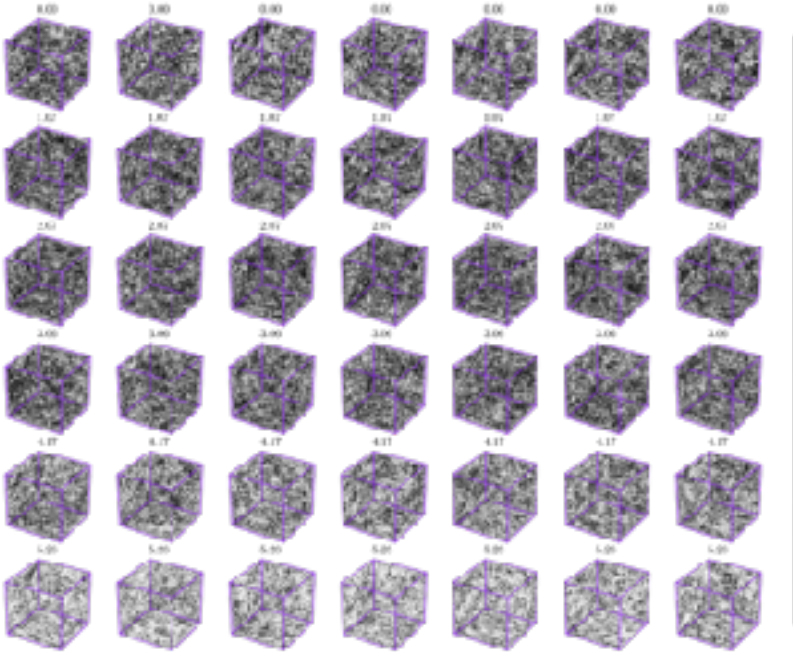
Generative approach for cosmic density fields

Jed Homer,
PhD student (LMU)



A

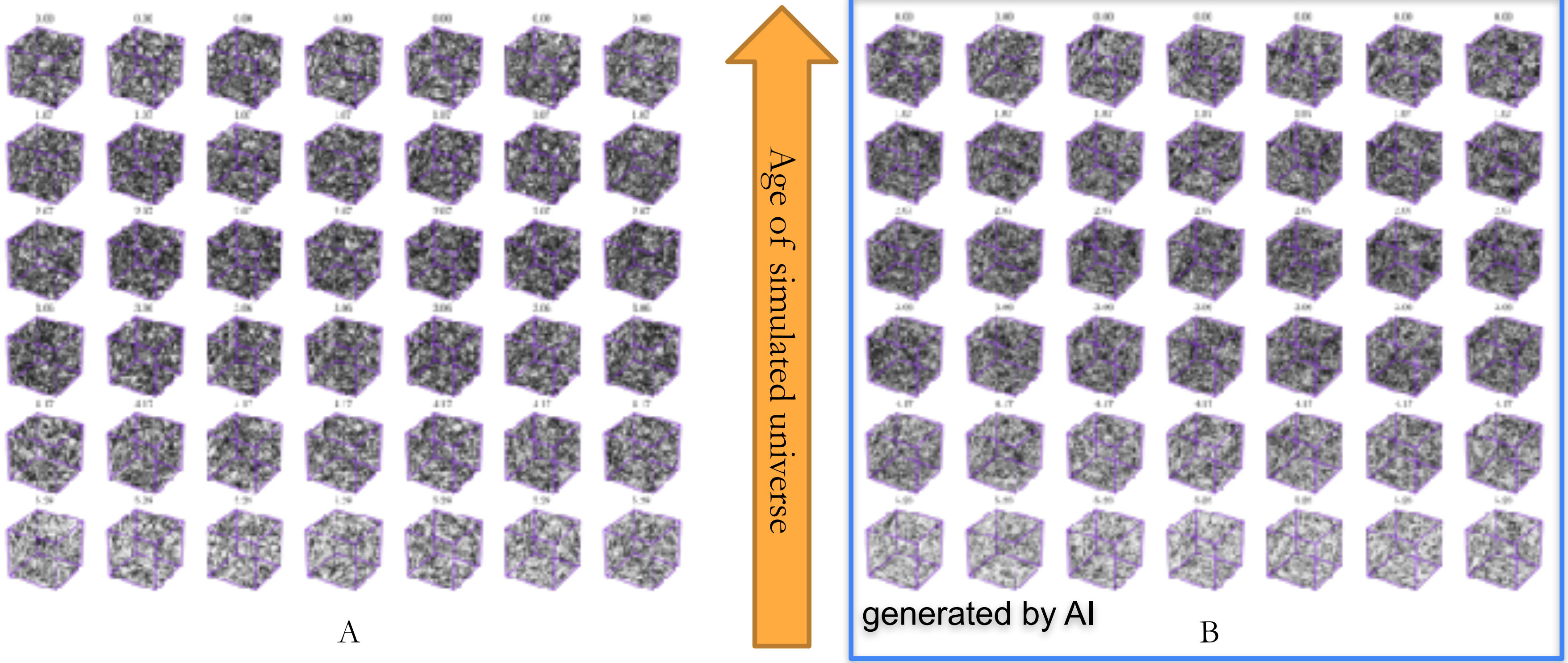
Age of simulated universe



B

Generative approach for cosmic density fields

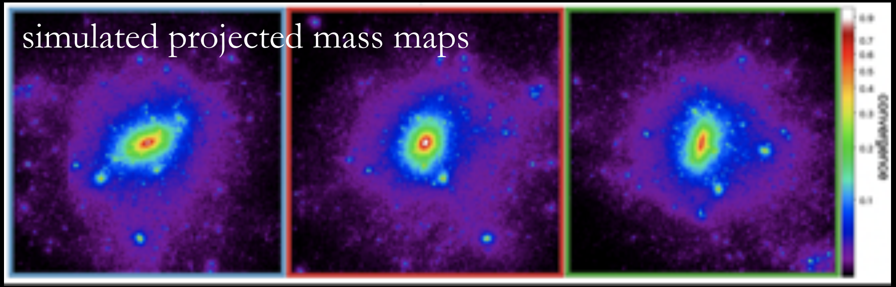
Jed Homer,
PhD student (LMU)

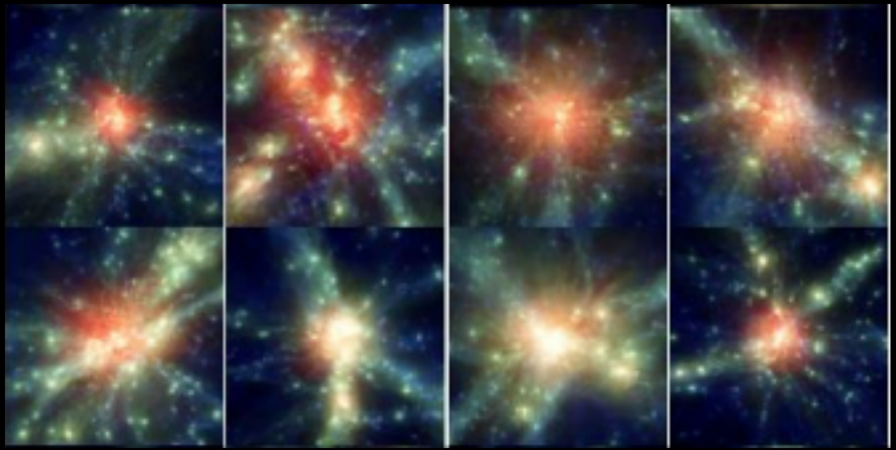


Galaxy clusters are very complex objects

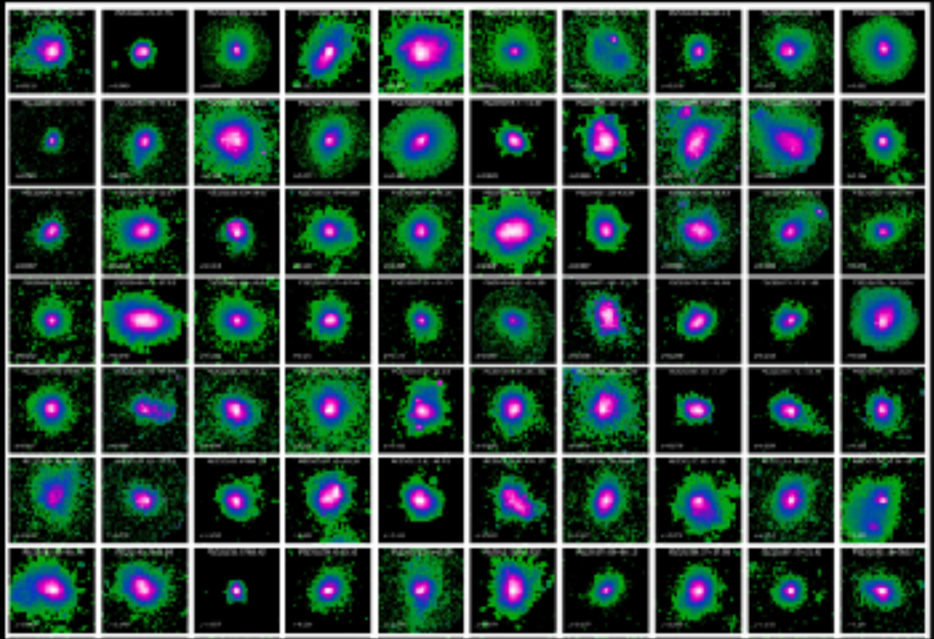
observed X-ray emission
from hot cluster gas

simulated projected mass maps



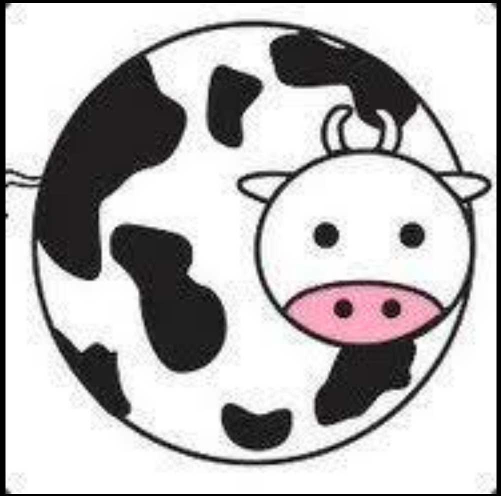


Clusters in simulations of matter, gas and stars



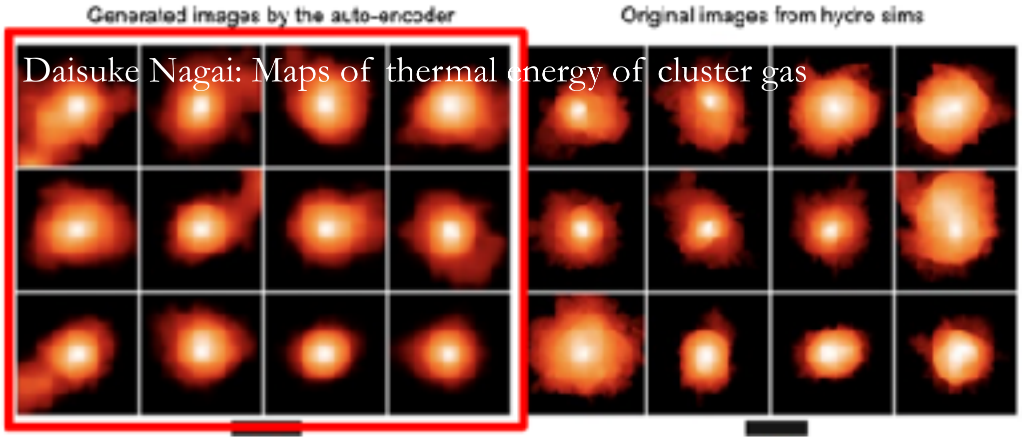
We usually describe galaxy clusters by very few features

Total mass
Distance
Total mass of gas
...



Why? It is not possible to "write down" a model for these that is complete.

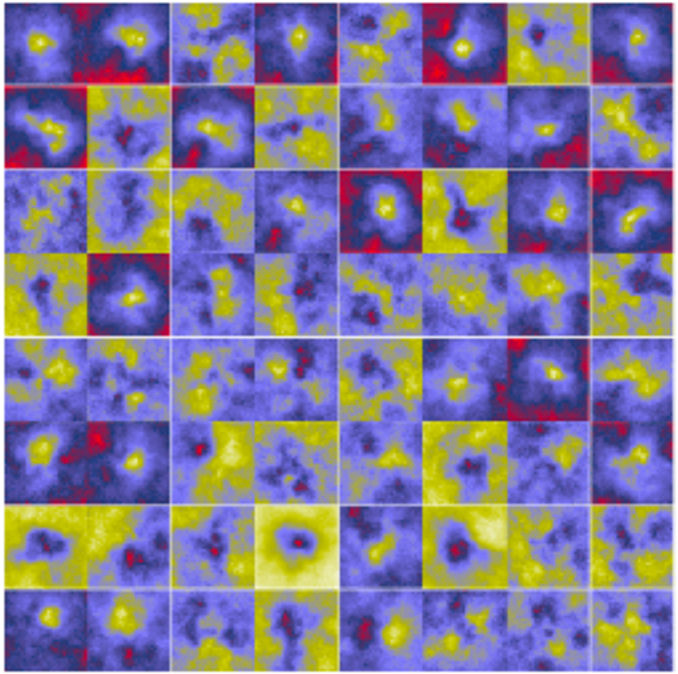
Generative approach for galaxy clusters



Daisuke Nagai: Maps of thermal energy of cluster gas

Jed Homer Yun-Hsin Hsu Phd students, LMU

+Sven Krippendorf (LMU),
+Jakob Knollmueller (ORIGINS)



Jed Homer:
Maps of motions of cluster gas
(kinetic SZ effect)

Suspension of disbelief

For a minute, imagine:

- A generative model has been trained to actually produce samples of cosmological objects that are exactly like a full hydrodynamical N-body simulation, conditioned on whatever you like

- We're able to mock-observe and select them like in reality

- The full hydrodynamical N-body simulation is exactly like The Real Universe aside from the values of Puzzling Physics Parameters we do not know but can condition on and are trying to find

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- We're able to mock-observe and select them like in reality

- The full hydrodynamical N-body simulation is exactly like The Real Universe aside from the values of Puzzling Physics Parameters we do not know but can condition on and are trying to find

Stable Diffusion (LMU Machine Vision & Learning Group) conditioned on 'dragonfruit hedgehogs'

Bayesianism and Generative Models

Jakob Knollmueller
ORIGINS Data Science Lab
arXiv:2001.11031

$$\mathcal{P}(\theta \,|\, d) = \frac{\mathcal{P}(d \,|\, \theta)\mathcal{P}(\theta)}{\mathcal{P}(d)}$$

- d: data at hand
- θ: model, parameters
- P(d|θ): probability for a measurement to produce d if model/parameters are θ
- P(θ): prior knowledge of model / parameters

Bayesianism and Galaxy Clusters: the old way

$$\mathcal{P}(\theta \mid d) = \frac{\mathcal{P}(d \mid \theta)\mathcal{P}(\theta)}{\mathcal{P}(d)}$$

- d: richness, velocity dispersion, X-ray flux, Compton y [lossy compression]
- θ: cluster mass and z [definitely incomplete, not even sure where to continue]
- P(d|θ): scaling relations with scatter / bias and measurement error [few-D]
- P(θ): prior of cluster mass from cosmology / mass function emulator

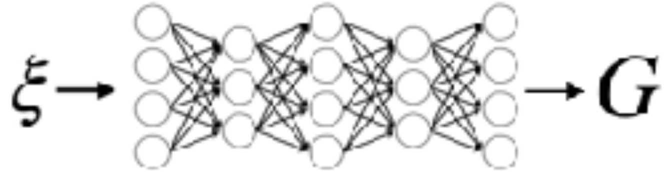
Breakout exercise: Generative models in Bayesian Inference

- Form a group of 3-4 people around you.
- Briefly introduce yourselves in the group if you hadn't met before.
- Recall the expression for a Bayesian posterior

$$\mathscr{P}(\theta \,|\, d) = \frac{\mathscr{P}(d \,|\, \theta)\mathscr{P}(\theta)}{\mathscr{P}(d)}$$

- How would you write / evaluate the posterior if you had some map-like data d and a generative model $G(\xi = [\theta, \phi])$ that is conditioned on physical parameters θ and random (noise) inputs ϕ?

Bayesianism and Generative Models



$$\mathscr{P}(\xi \mid d) = \frac{\mathscr{P}(d \mid G(\xi))\mathscr{P}(\xi)}{\mathscr{P}(d)}$$

- d: positions, redshifts, shapes of galaxies, maps of X-ray photons, CMB, radio...
- ξ: any cluster parameters whose PDF you can predict, and random numbers
- P(d|G): probability for the measurement to produce d if cluster is G
- P(ξ): prior of cluster parameters and random numbers
- G: generated cluster including all you need to evaluate the likelihood of d

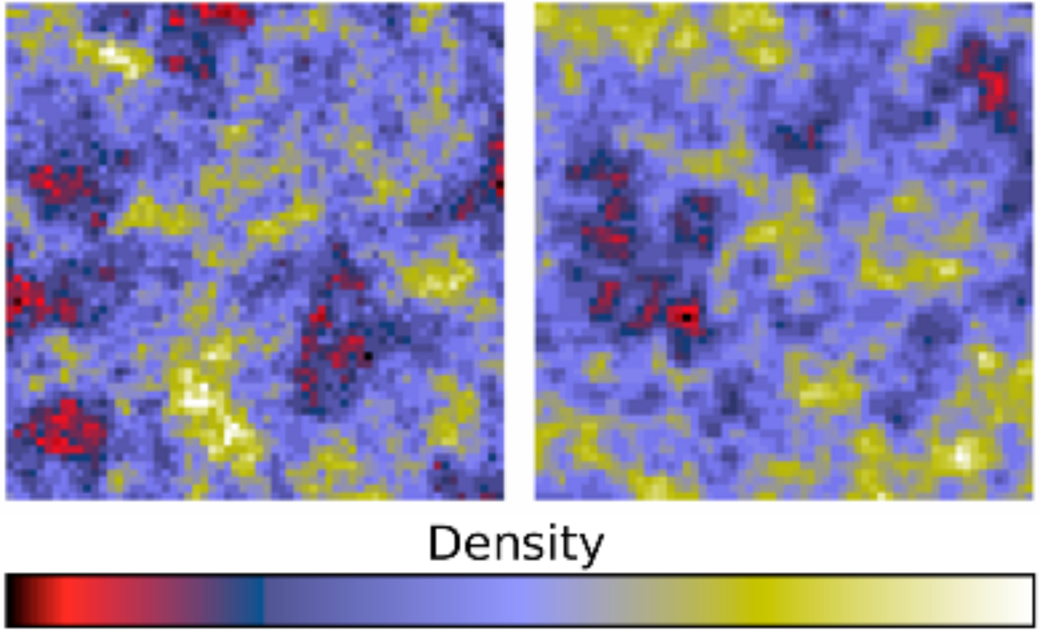
Bayesianism and Generative Models

Oliver Friedrich,
Fraunhofer-Schwarzschild
Fellow (LMU)

Jed Homer,
PhD student (LMU)

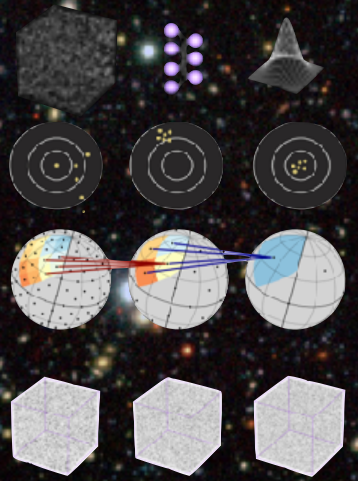
observed projected
density field

generative model
evaluated along a
trajectory in latent space



Cosmology with AI support

- Challenge: measuring small, unexpected signals in big data
- Artificial intelligence can:
  - Enable otherwise infeasibly slow analyses
  - Match statistics of the problem
  - Learn which features of data are informative
  - Build models for complex families of objects that couldn't be characterized sufficiently well by a human
- We are on the verge of cosmological analyses being impossible without the use of such AI!



Questions?