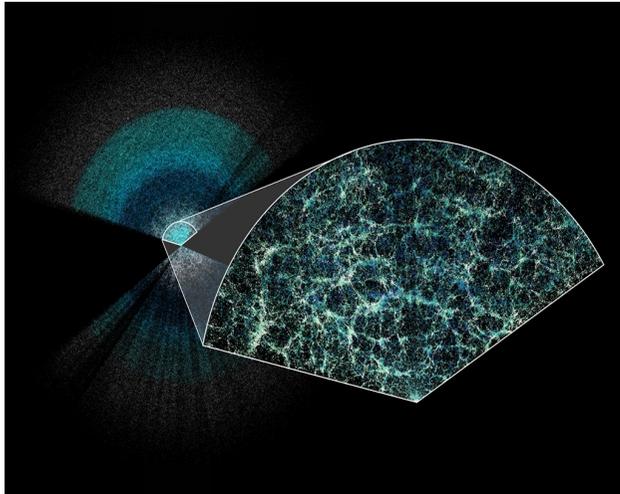
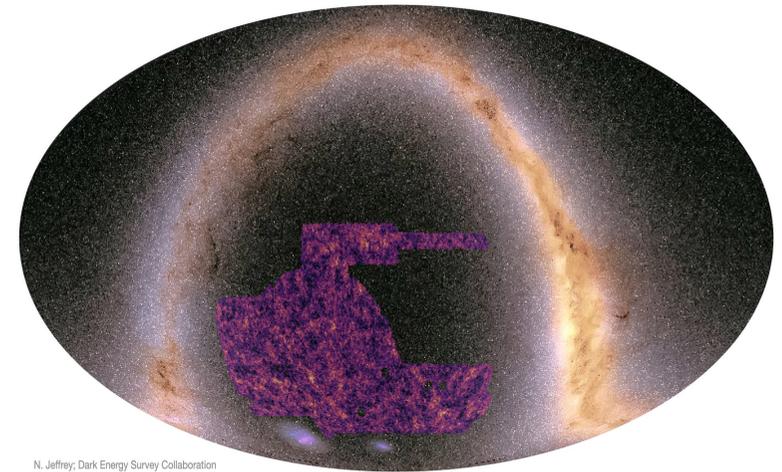


ML/AI for Cosmological Experiments

Ofer Lahav
University College London

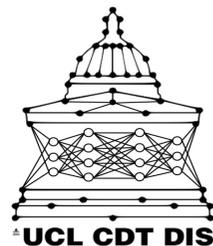


DESI galaxy map



N. Jeffrey; Dark Energy Survey Collaboration

DES dark matter map



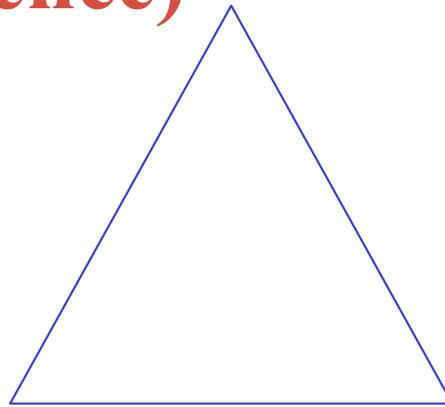
Outline

- ◆ The landscape of galaxy surveys
- ◆ The status of Cold-Dark-Matter+ Λ model:
when to stop? where to go?
- ◆ Showcases of AI for Astronomy:
 1. Image explainability
 2. Anomalies
 3. Causality
 4. Cosmic web
- ◆ Training of the next generation of
astronomers in Data Science

Cross talk: Artificial Intelligence, Physics, Humans

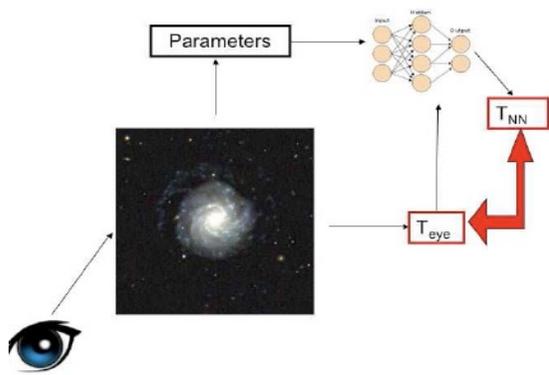
**AI (Augmented
Intelligence)**

**Laws of
Physics**



**Human
Knowledge**

[OL, arXiv:2302.04324](#) (IAU Symp 368)



Galaxy classification with ANN (early 1990's @ IoA)

Science

Current Issue

First release papers

Archive

More ▾

HOME > SCIENCE > VOL. 267, NO. 5199 > GALAXIES, HUMAN EYES, AND ARTIFICIAL NEURAL NETWORKS

REPORT



Galaxies, Human Eyes, and Artificial Neural Networks

O. LAHAV, A. NAIM, R. J. BUTA, H. G. CORWIN, G. DE VAUCOULEURS, A. DRESSLER, J. P. HUCHRA, S. VAN DEN BERGH, S. RAYCHAUDHURY, L. SODRÉ, JR.,

AND M. C. STORRIE-LOMBARDI

fewer

[Authors Info & Affiliations](#)

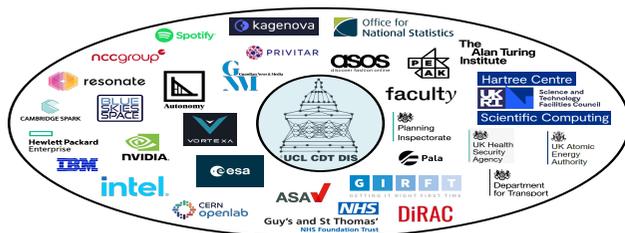
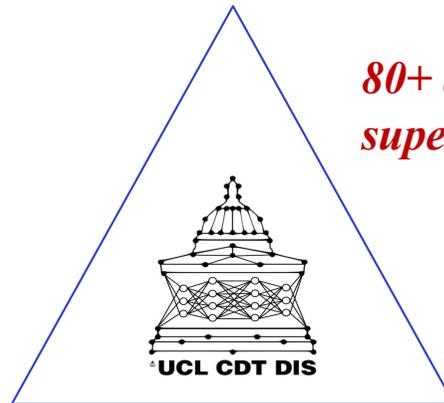
UCL Centre for Doctoral Training (CDT) in Data Intensive Science (DIS)



Running since 2017
83 CDT PhD students in 8 cohorts,
30 PhD theses submitted/defended
> 90 publications

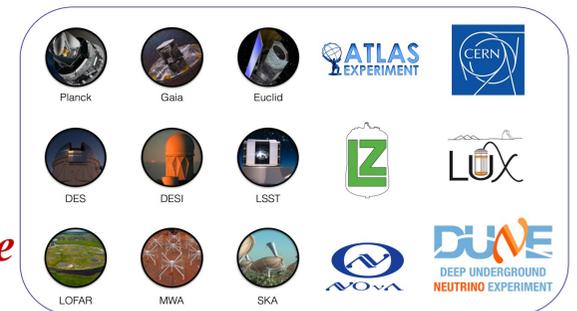


80+ academic supervisors



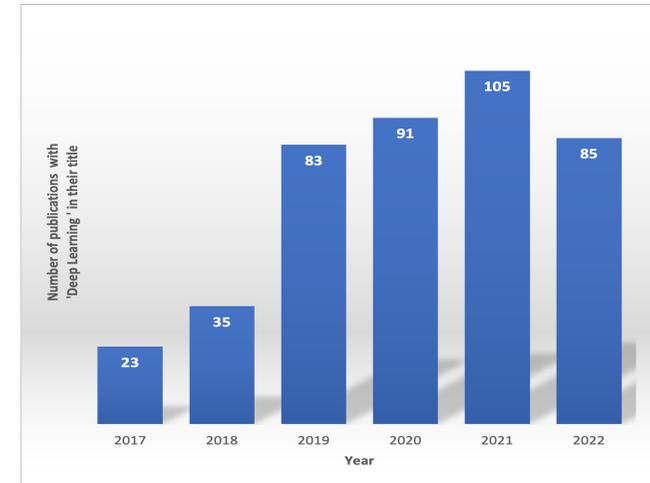
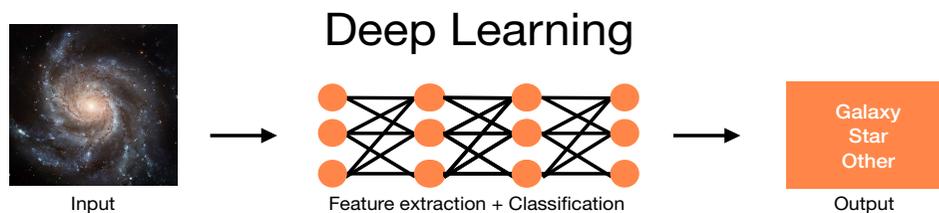
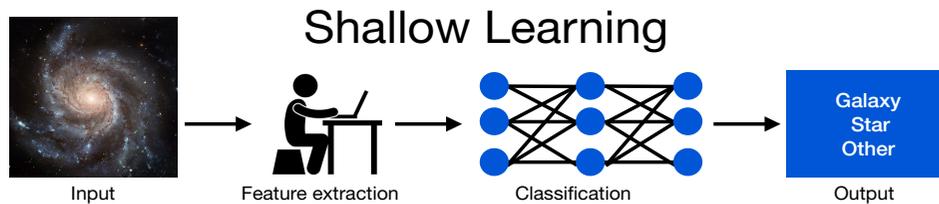
30+ industry partners

Wide coverage of STFC programme



Astro Papers on the arXiv with “Deep Learning” in the Title

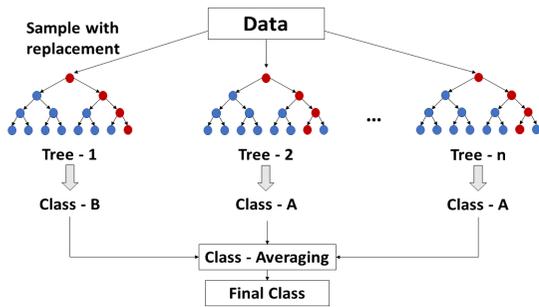
About 2 DL Astro papers per week!



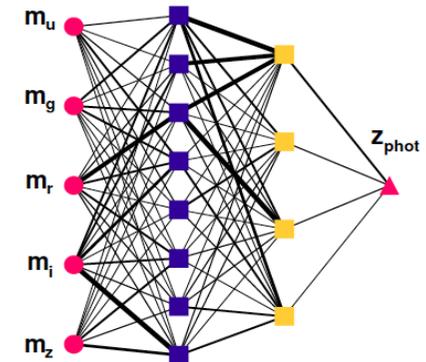
“Shallow” Learning

“Deep” Learning

Shallow learning is actually quite deep,
as based on human knowledge!



Machine Learning in Astronomy



Model			CNNs	Enc.	Gene.	BNN	RNN	Trans.	GNN
Application									
1. Computer Vision	Classification	Morphology	✓	✓					
		Strong Lenses	✓*	✓*					
		Transients					✓*)	✓*)	
	Segmentation			✓*	✓*				
2. Galaxy Properties		Photoz	✓			✓			
		Structure	✓*)						
		Stellar Populations	✓*						
		Lensing	✓*			✓*			
		Physical Processes	✓*						
		Dark Matter	✓*			✓*			✓*
3. Discovery		Visualization	✓	✓	✓				
		Outliers	✓	✓	✓		✓		
		Laws							✓*
4. Cosmology		Emulation	✓*	✓*	✓*	✓*			
		Cosmological inference	✓*		✓*	✓*			

Table 1 Overview of the different deep learning techniques used in the fields of galaxy formation and cosmology, divided by type of application (see text for details). CNNs: Standard classification and regression Convolutional Neural Networks including modern architectures such as ResNets. Enc: Encoder-Decoder networks and variants. Gene: Generative Models. BNNs: Bayesian Neural Networks; we also include Mixture Density Networks. RNNs: Recursive Neural Networks. Trans: Transformers. GNNs; Graph Neural Networks. A blue (red) background indicates supervised (unsupervised) learning. The star symbol highlights applications which require simulations to train the neural networks. The bracket after the star symbol indicates that the use of simulations is not always mandatory.

Recent reviews: Huertas-Company & Lanusse, 2210.01813

Recent ML papers

with UCL's CDT PhD students and Post-docs

- ◆ Photo-z: benchmarking, image deep learning (Henghes+ 2021a,b)
- ◆ Photo-z: stellar mass (Mucesh+ 2021)
- ◆ Explainability of galaxy morphology (Bahmbra+ 2022)
- ◆ Quantum-enhanced SVM for galaxy classification (Hassanshahi+ 2023)
- ◆ Anomalies in DESI spectra (Nicolaou, Nathan+; in prep)
- ◆ The Entropy of galaxy spectra (Ferrerias+ 2023)
- ◆ Causation in galaxy formation (Mucesh+)
- ◆ Mass maps from Weak Lensing (Jeffrey+ 2021, Williamson+, Hang+; in prep)
- ◆ Neutrino mass from Minimum Spanning Tree (Naidoo+ 2023)
- ◆ Masses of the Milky Way and Andromeda (Lemos+ 2020)
- ◆ Core-collapse supernova from Gravitational Waves (Less+ 2022)
- ◆ Trans-Neptunian objects (Henghes+ 2021)
- ◆ [Overview: OL, arXiv:2302.04324 \(IAU Symp\)](#)

The Dark Energy problem: 25, 100 or 330 years old?

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

The weak field limit of GR:

$$a = -GM/r^2 + \Lambda/3 r$$

142 Sitzung der physikalisch-mathematischen Klasse vom 8. Februar 1917

Kosmologische Betrachtungen zur allgemeinen
Relativitätstheorie.

VON A. EINSTEIN.

Es ist wohlbekannt, daß die Poisson'sche Differentialgleichung

$$\Delta\phi = 4\pi K\rho \quad (1)$$

“I have now explained the TWO principle cases of attraction...which is very remarkable.”

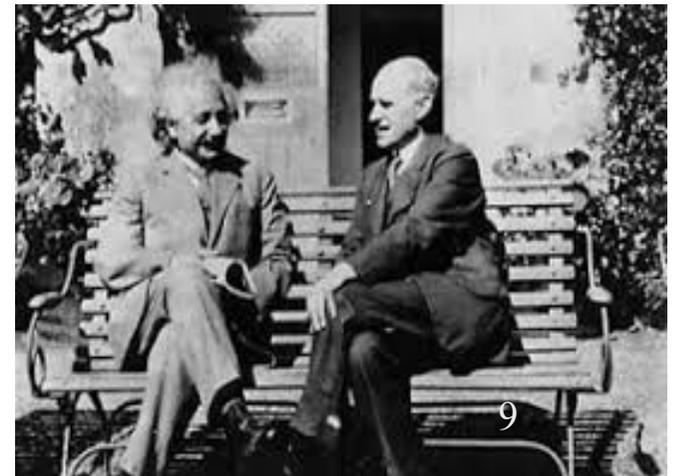
Isaac Newton, Principia (1687)

“Introducing Λ - the blunder of my life...”

Albert Einstein (1920s)

“I am a detective in search for a criminal - Λ .”

Arthur Eddington (1920s)



The Dark Energy Equation of State

$$w = p/\rho c^2$$

$$\rho \propto a^{-3(1+w)}$$

$$w = -1 \rightarrow \Lambda$$

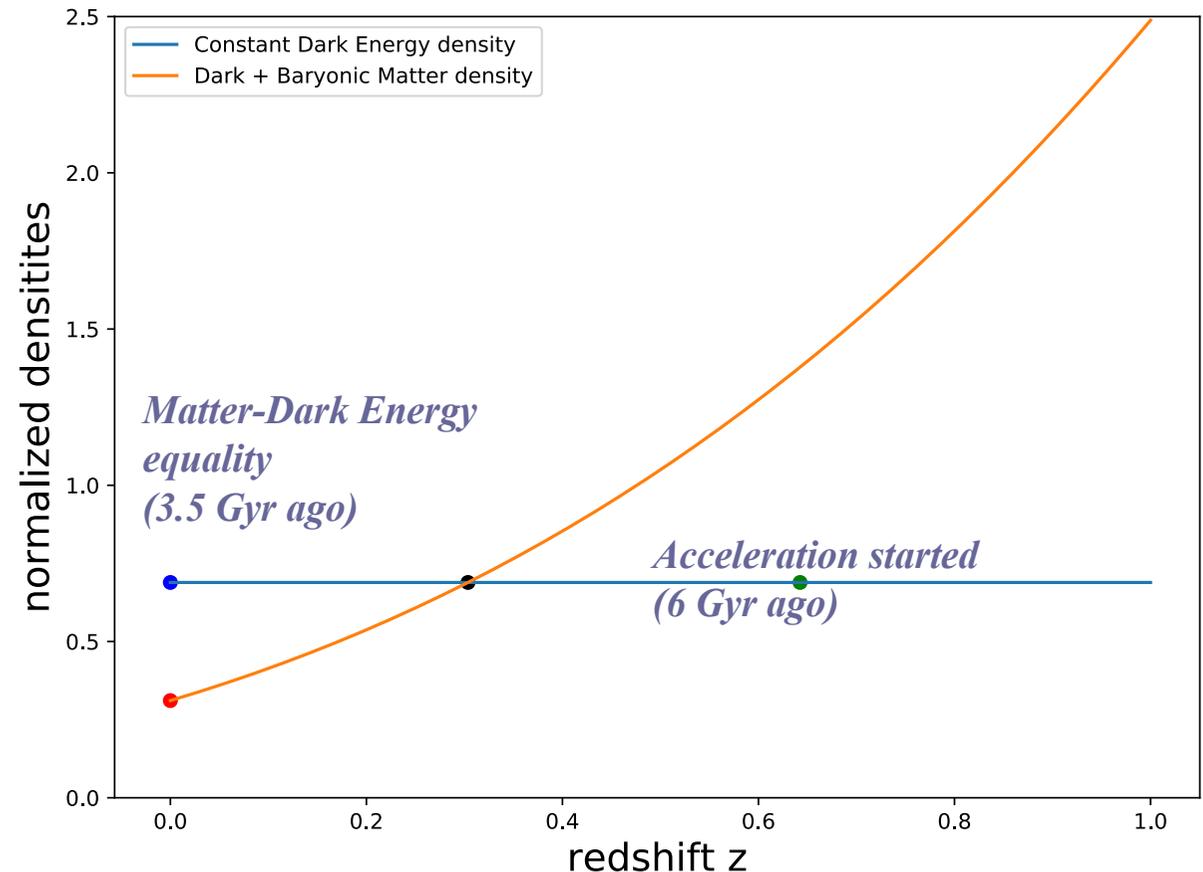
from
DES+Planck+BAO+SNIa
the equation of state

$$w = -1.031_{-0.027}^{+0.030}$$

is consistent with Λ
(*arXiv:2105.135490*)

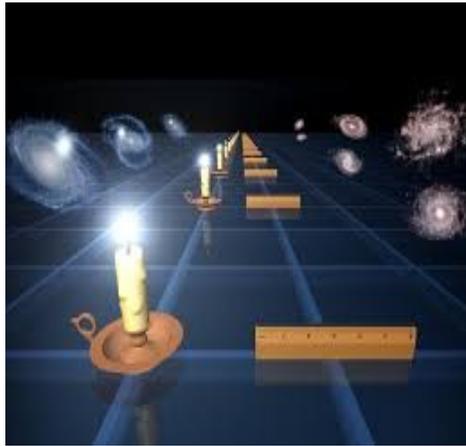
An alternative:

$$w(a) = w_0 + w_a(1 - a),$$

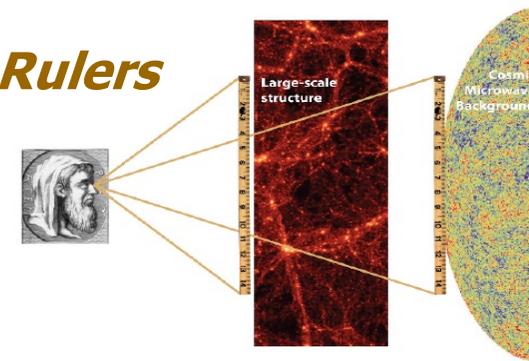


OL, arXiv:2009.10177

Key Probes of Dark Energy: expansion and growth of structure

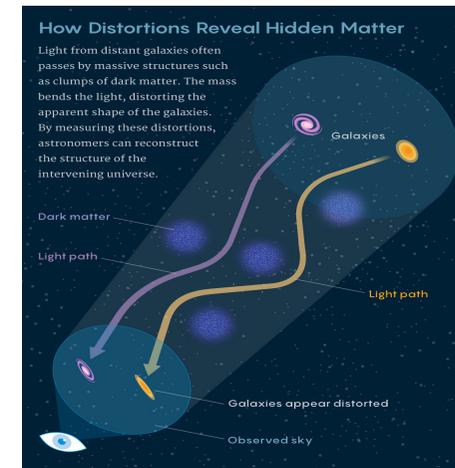


Standard Candles and Rulers



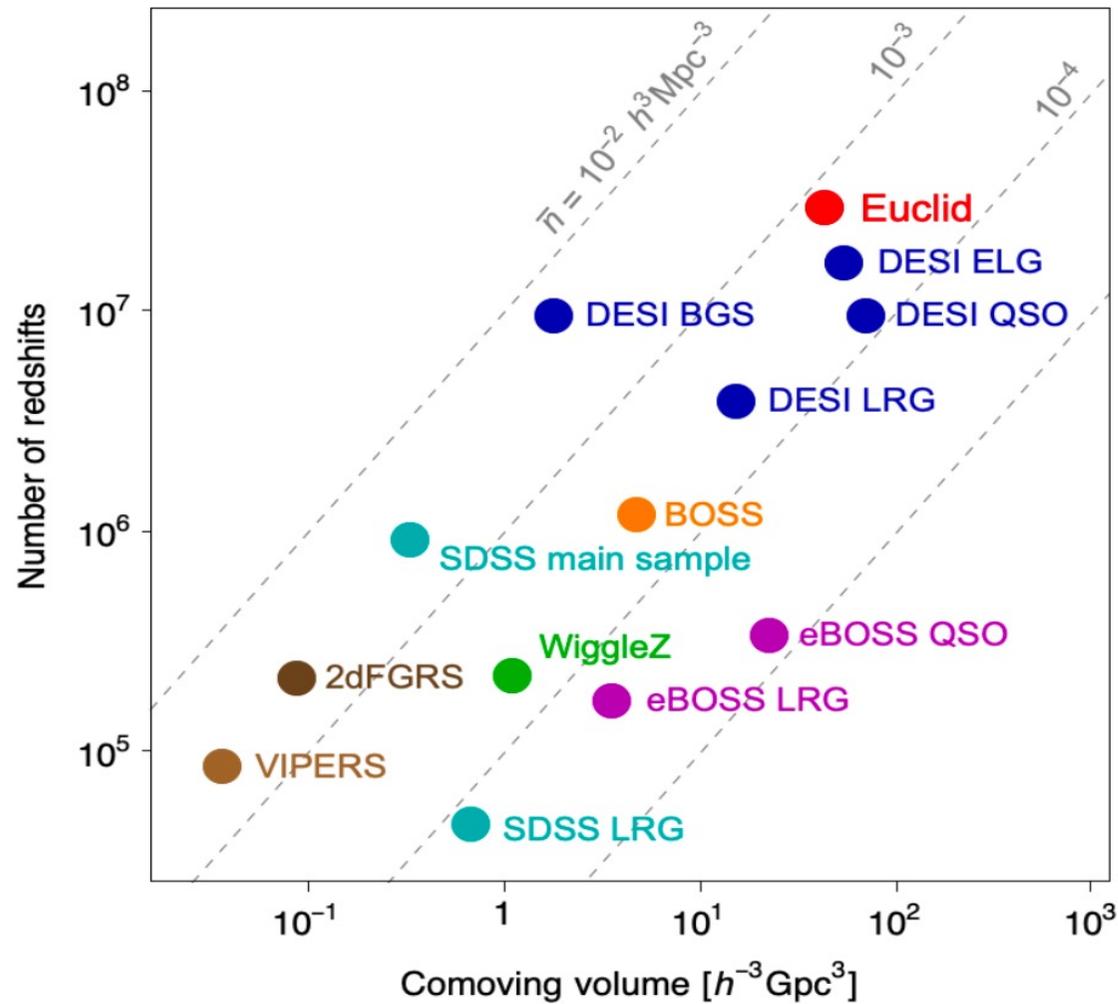
Clusters

Weak Lensing



JWST image

Spectroscopic surveys





Big Data in Astronomy



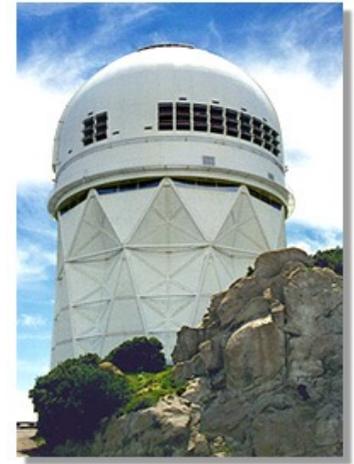
Survey	Data per night/day	Galaxies	Cost	Scientists
DES	1 TeraB	~300 Million (all observed)	~\$100M	~400
DESI	40 GigaB	~40 Million (being observed)	~\$100M	~900
Rubin-LSST	15 TeraB	~Billions	~\$1.0B	~1000
Euclid	850 GigaB	~Billions	~\$1.5B	~1500
SKA	1 PetaB	~Billions	~\$1.3B	~1000

How many surveys should one join?



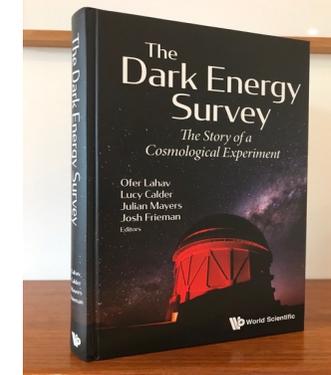
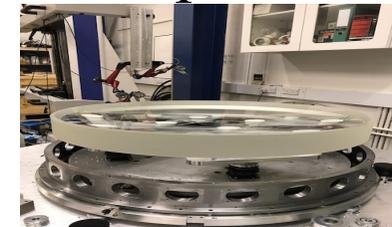
The tale of two surveys:

Dark Energy Survey (DES) &
Dark Energy Spectroscopic Instrument (DESI)

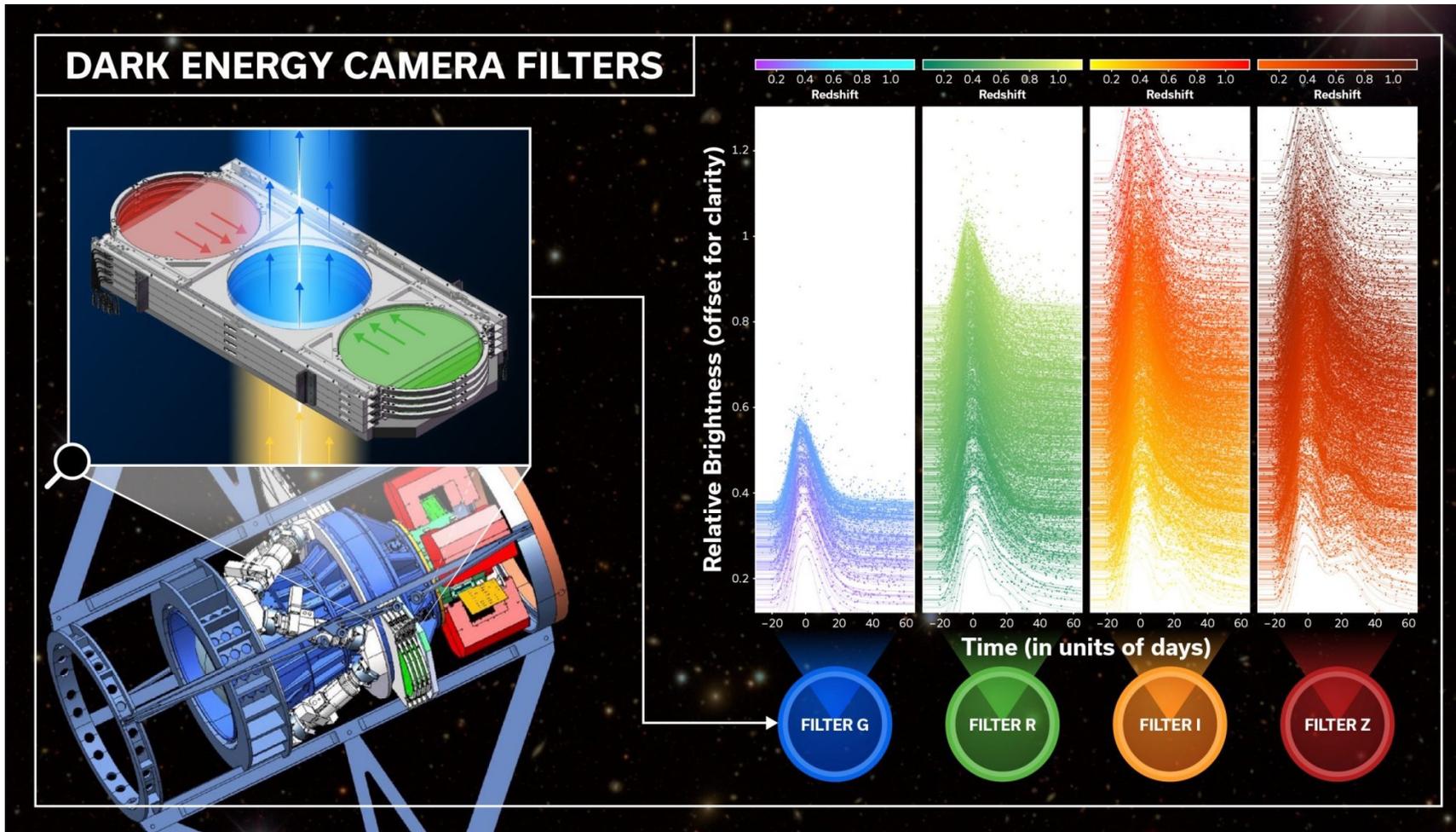


Mayall 4-Meter Telescope

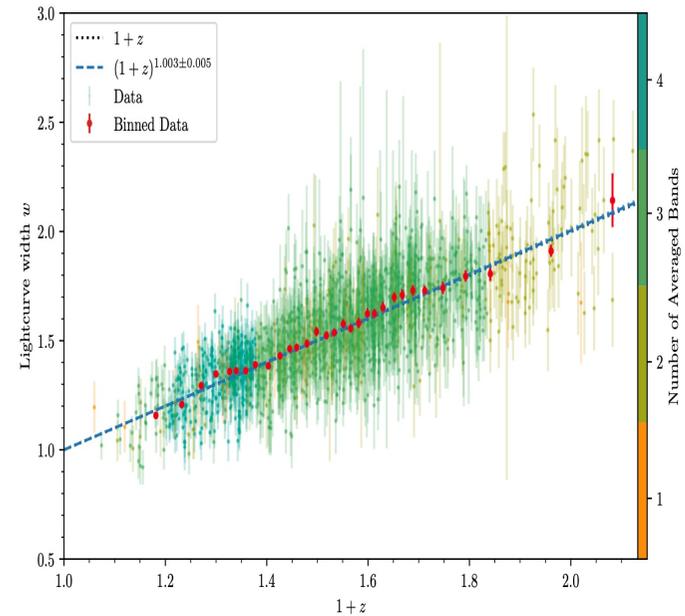
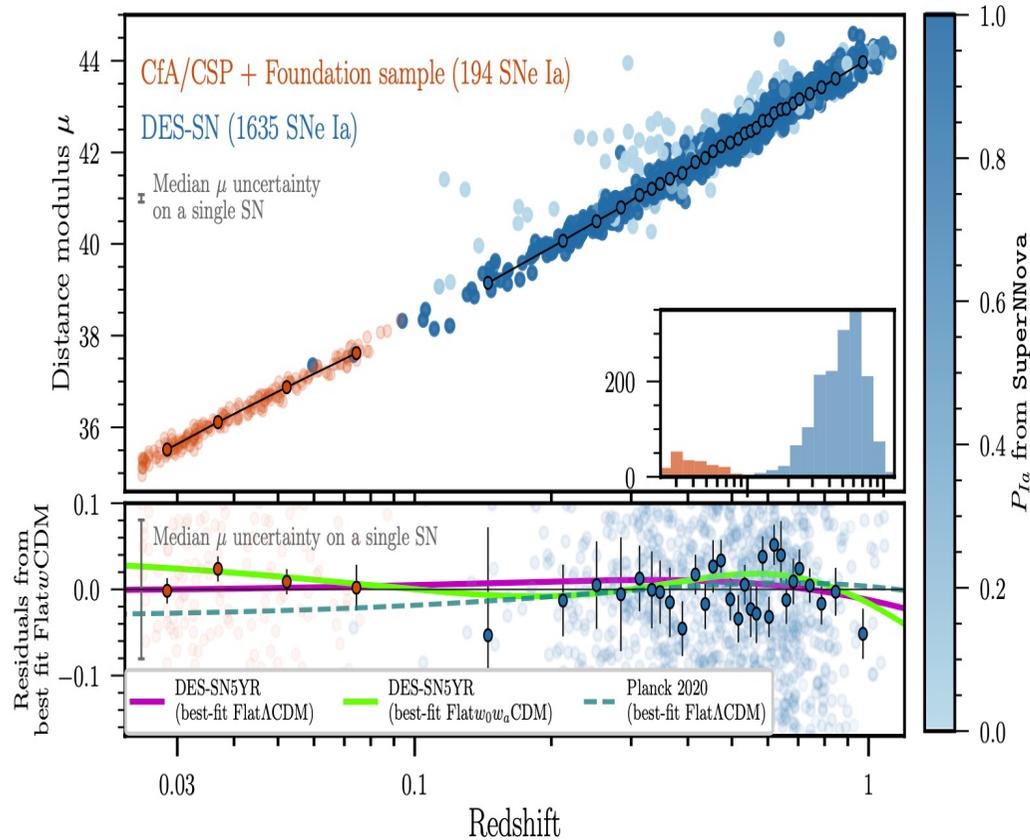
- ◆ Modern instruments on old twin 4m telescopes:
DES (imaging) on the Blanco (Chile) and DESI (spectroscopy) on the Mayall (Kitt Peak)
- ◆ DES Fermilab-led; DESI LBL-led & international partners
- ◆ UCL built both optical correctors
- ◆ DES completed 6 seasons in 2019 →
300M galaxy images and thousands of SN
- ◆ DESI started observations in 2020
40M galaxy+qso spectra.



1500 DES Yr5, Supernovae Ia



Results from 1500 DES Supernovae Ia (Yr5, Jan 2024)



(1+z) time dilation in SN Ia light curve width
White & DES, arXiv:2406.05050

WL magnification
Shah & DES, arXiv:2406.05047

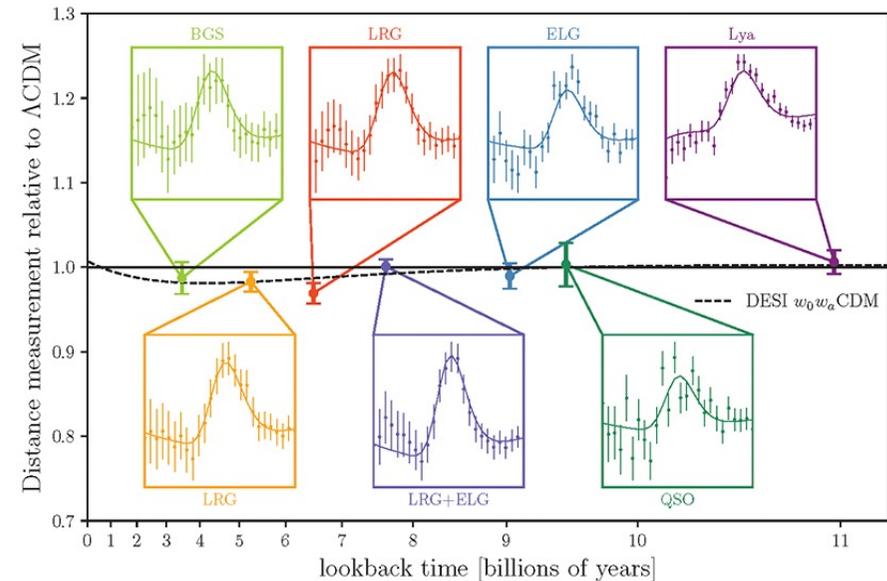
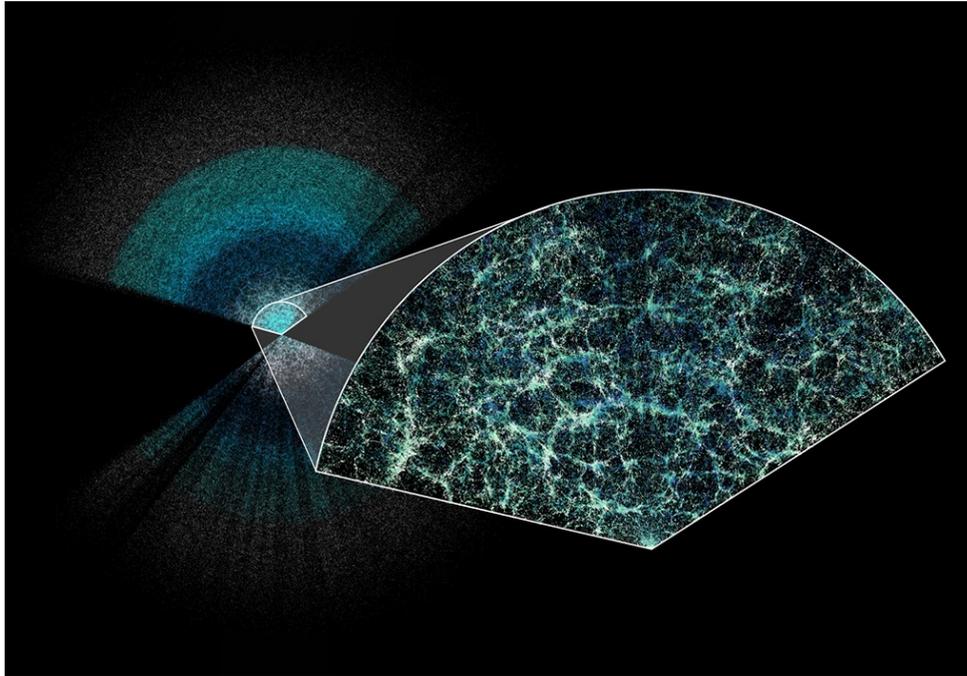
arXiv:2401.02929

From DES SN+ 3x2pt + SDSS BAO + Planck

$(\Omega_M, w) = (0.321 \pm 0.007, -0.941 \pm 0.026)$.

DESI Y1 BAO results (April 2024)

arXiv:2404.03002



The measurement of the dark energy equation of state w is a key science goal of DESI. Assuming the w CDM model where the equation-of-state parameter is constant in time, we find $w = -0.99^{+0.15}_{-0.13}$ from DESI alone, and $w = -0.997 \pm 0.025$ from the combination of DESI BAO, CMB, and SN Ia results from the Pantheon+ compilation, in good consistency with Λ CDM. This result does not appreciably change when the Pantheon+ data are replaced

**Consistent with Λ CDM, but time variation of w is still possible.
Einstein was right that Lambda exists, but at a different value!
(an accelerated rather than a static universe)**

DESI Y1 BAO+Full Shape

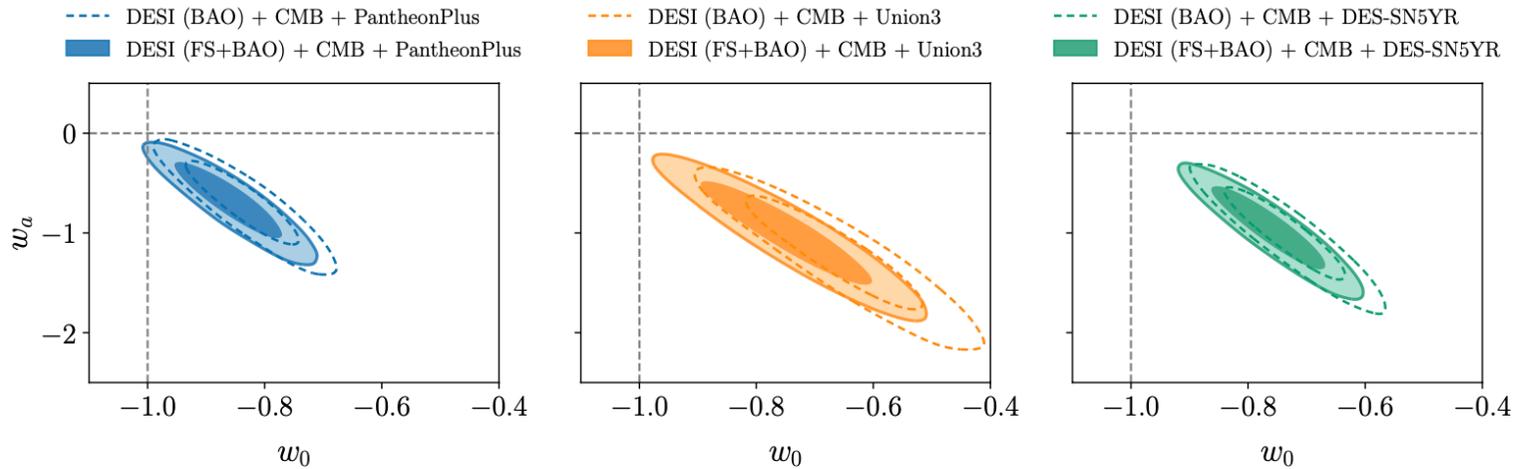
arXiv:2411.12022

scalar spectral index, determines matter density to $\Omega_m = 0.2962 \pm 0.0095$, and the amplitude of mass fluctuations to $\sigma_8 = 0.842 \pm 0.034$. The addition of the cosmic microwave background (CMB) data tightens these constraints to $\Omega_m = 0.3056 \pm 0.0049$ and $\sigma_8 = 0.8121 \pm 0.0053$, while further addition of the the joint clustering and lensing analysis from the Dark Energy Survey Year-3 (DESY3) data further improves these measurements, and leads to a 0.4% determination of the Hubble constant, $H_0 = (68.40 \pm 0.27) \text{ km s}^{-1} \text{ Mpc}^{-1}$. In models with a time-varying dark energy equation of state parametrised by w_0 and w_a , combinations of DESI (FS+BAO) with CMB and type Ia supernovae continue to show the preference, previously found in the DESI DR1 BAO analysis, for $w_0 > -1$ and $w_a < 0$ with similar levels of significance. DESI data, in combination with the CMB, improve the upper limits on the sum of the neutrino masses relative to the case when only the DR1 BAO was available, giving $\sum m_\nu < 0.071 \text{ eV}$ at 95% confidence. We finally constrain deviations from general relativity represented by two modified gravity parameters. DESI (FS+BAO) data alone measure the parameter that controls the clustering of massive particles, $\mu_0 = 0.11^{+0.45}_{-0.54}$, in agreement with the zero value predicted by general relativity. The combination of DESI with the CMB and the clustering and lensing analysis from DESY3 constrains both modified-gravity parameters, giving $\mu_0 = 0.04 \pm 0.22$ and $\Sigma_0 = 0.044 \pm 0.047$, again in agreement with general relativity.

Next: DESI Y3 results, in March

BAO + Full Shape

$$w(a) = w_0 + w_a(1 - a), \quad w_0 = -0.761 \pm 0.065,$$
$$w_a = -0.96^{+0.30}_{-0.26},$$



2.5 sigma

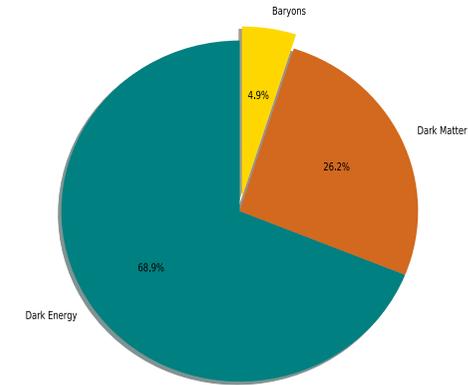
3.4 sigma

3.8 sigma

Preference for $w_0 w_a$ over LCDM



When to Stop?



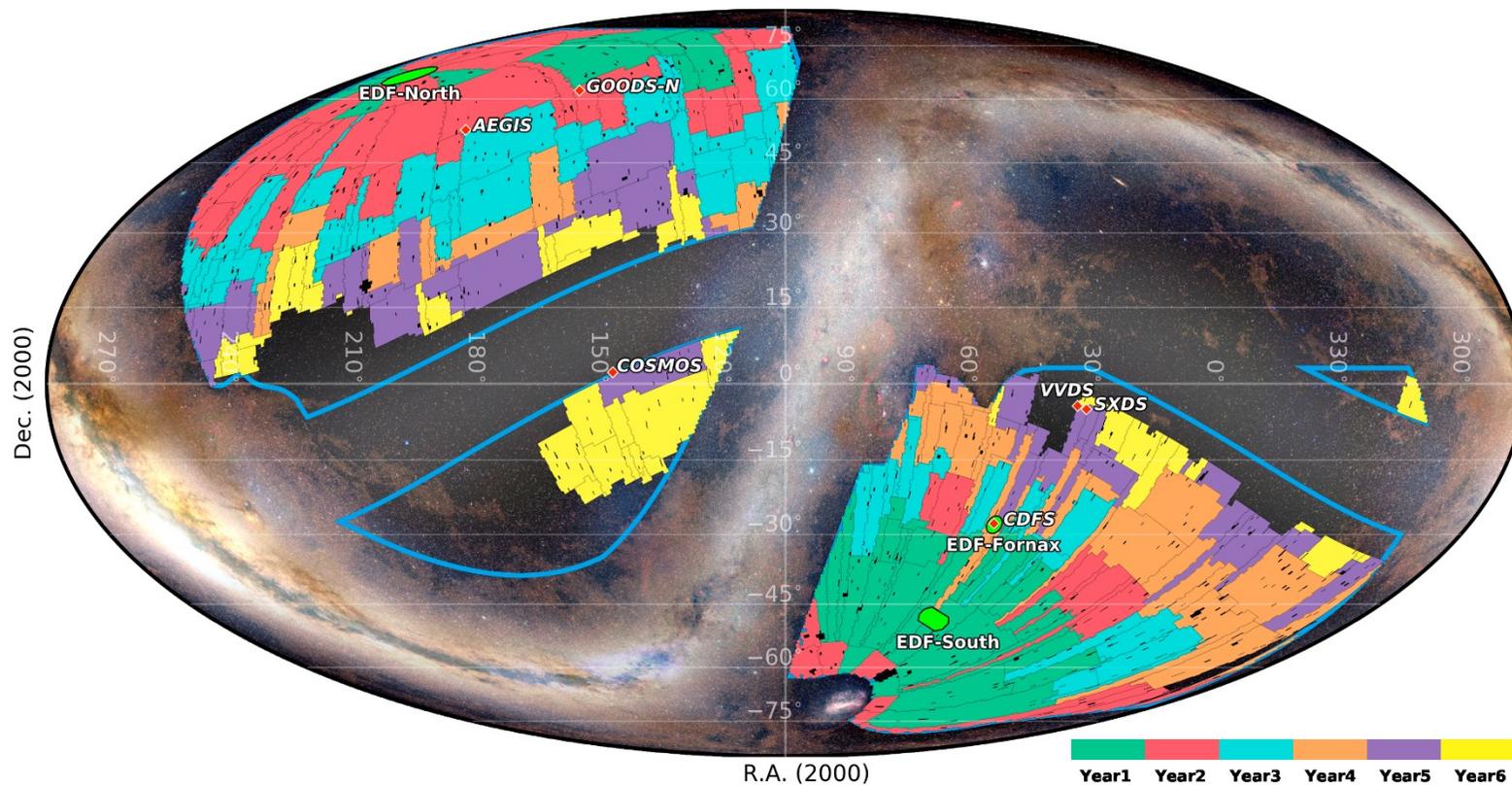
- ◆ Current observations from e.g. DES/KidS/DESI/Planck... approximately $w = -1.00 \pm 0.03$
Should we still measure it more precisely?
- ◆ It depends if there is an alternative viable theory and/or patience for something to emerge at the sub-percent level.

OL & Silk (Nature Astronomy, arXiv:2109.08190)

Offer & OL (arXiv:2305.17982)

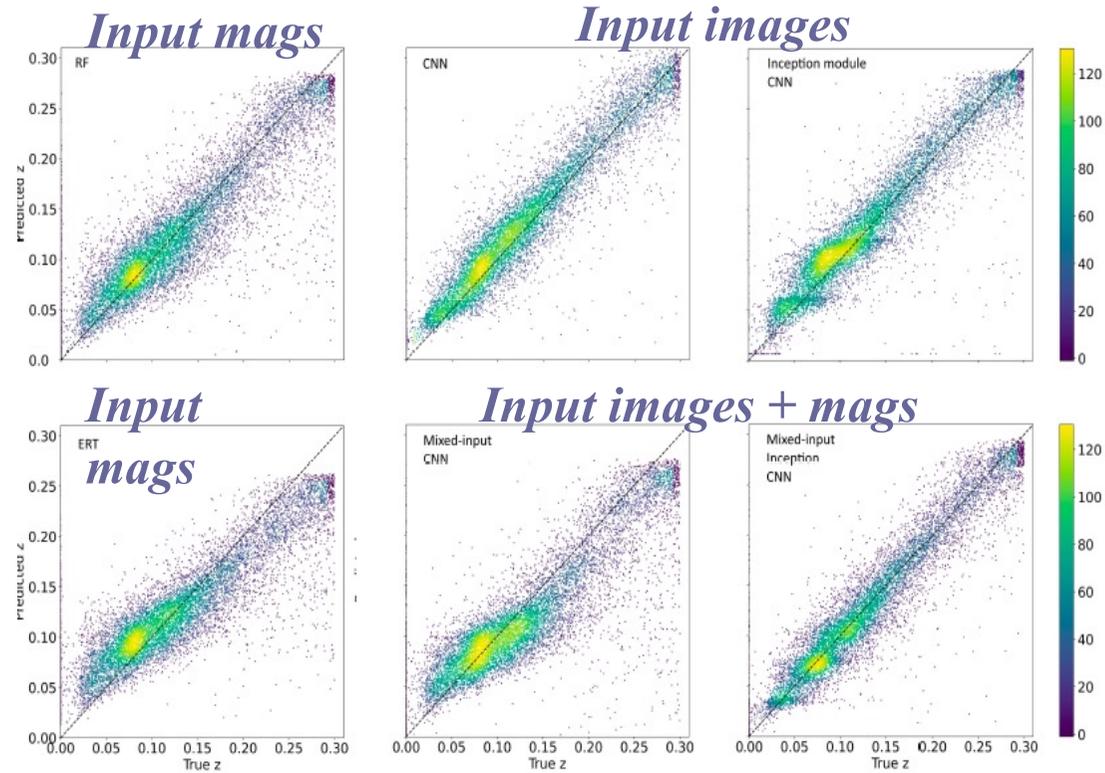
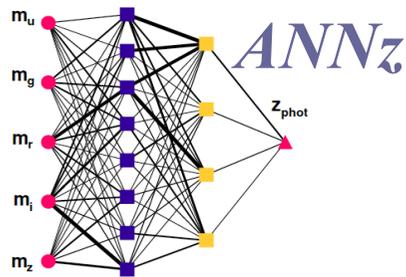
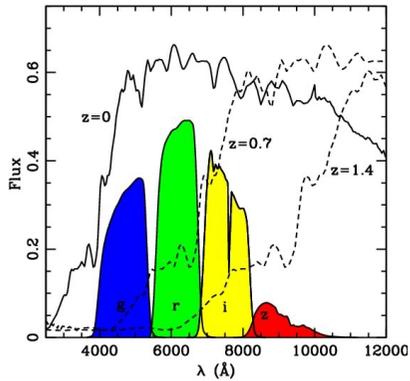
Euclid sky coverage

Euclid Collaboration: Y. Mellier et al.: Overview of the *Euclid* mission



Showcase 1a: Photo-z from 1M SDSS Deep Learning from full images:

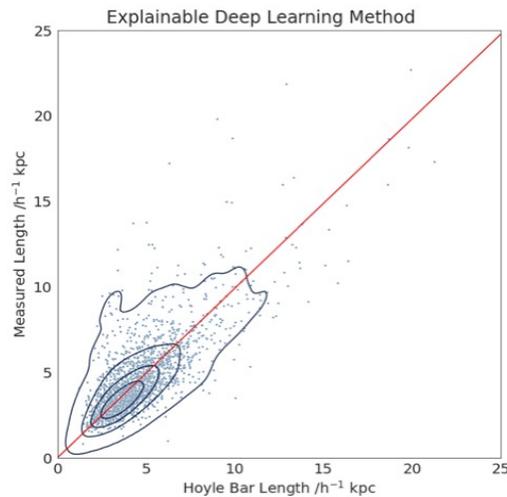
factor 2 improvement in MSE



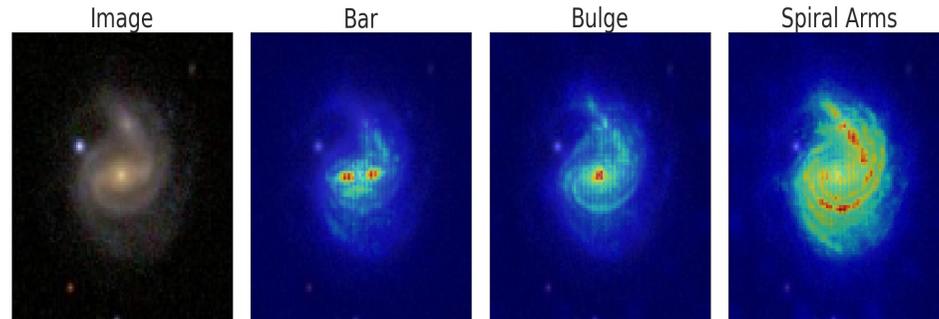
Henghes, Pettitt, Thiyagalingam, Hey, OL (2109.02503)

Showcase 1 b: Explaining Galaxy Morphology with Saliency Mapping

XAI vs. Galaxy Zoo cataloged bar length



Bhambra, Joachimi, OL
arXiv:2110.08288



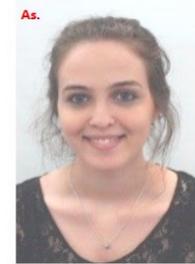
SmoothGrad: Calculate in each pixel the (smoothed) gradient of the score per class y^c wrt the pixel intensity x . (note the internal architecture is bypassed.)

$$L^c(x) = \frac{\partial y^c}{\partial x}$$

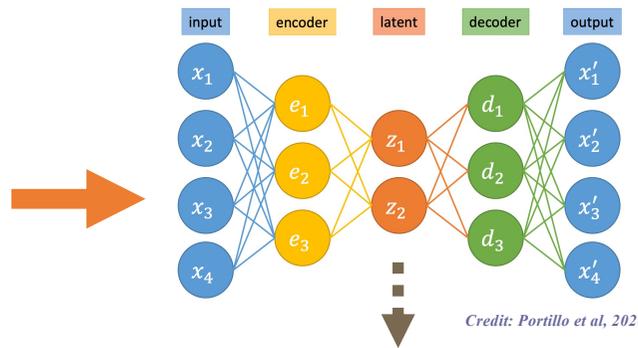
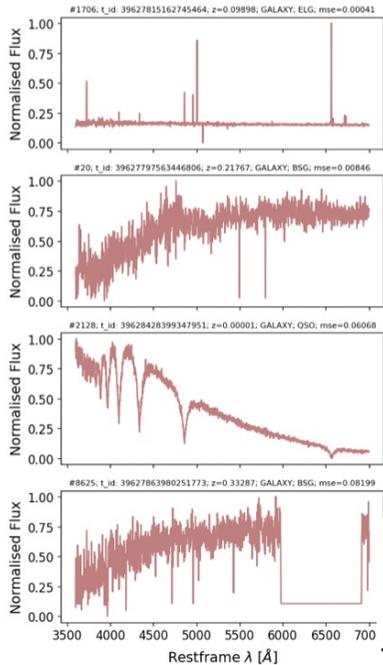


Showcase 2: Anomaly Detection in DESI Spectra

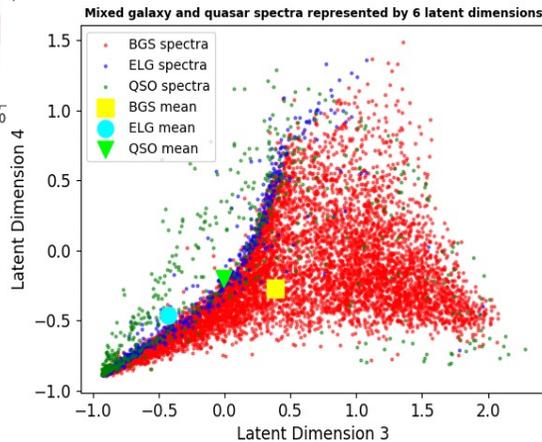
Using Autoencoders and other ML techniques
Constantina Nicolaou, Paul Nathan, OL & DESI (in prep)



DESI Spectra (de-redshifted)

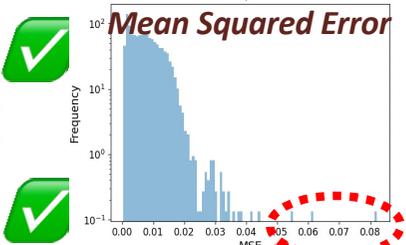
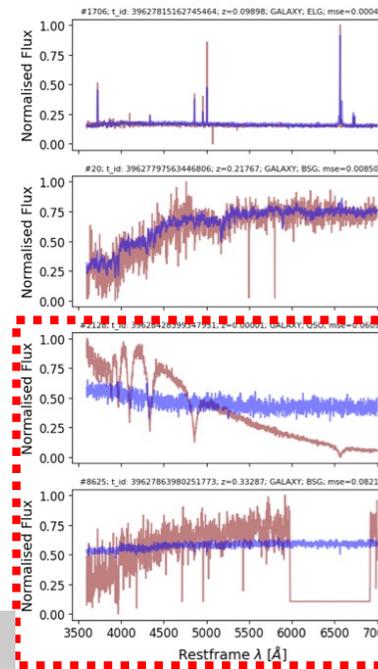


Credit: Portillo et al, 2020



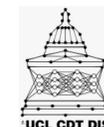
Some separation seen between DESI target types in latent space

Reconstructed Spectra

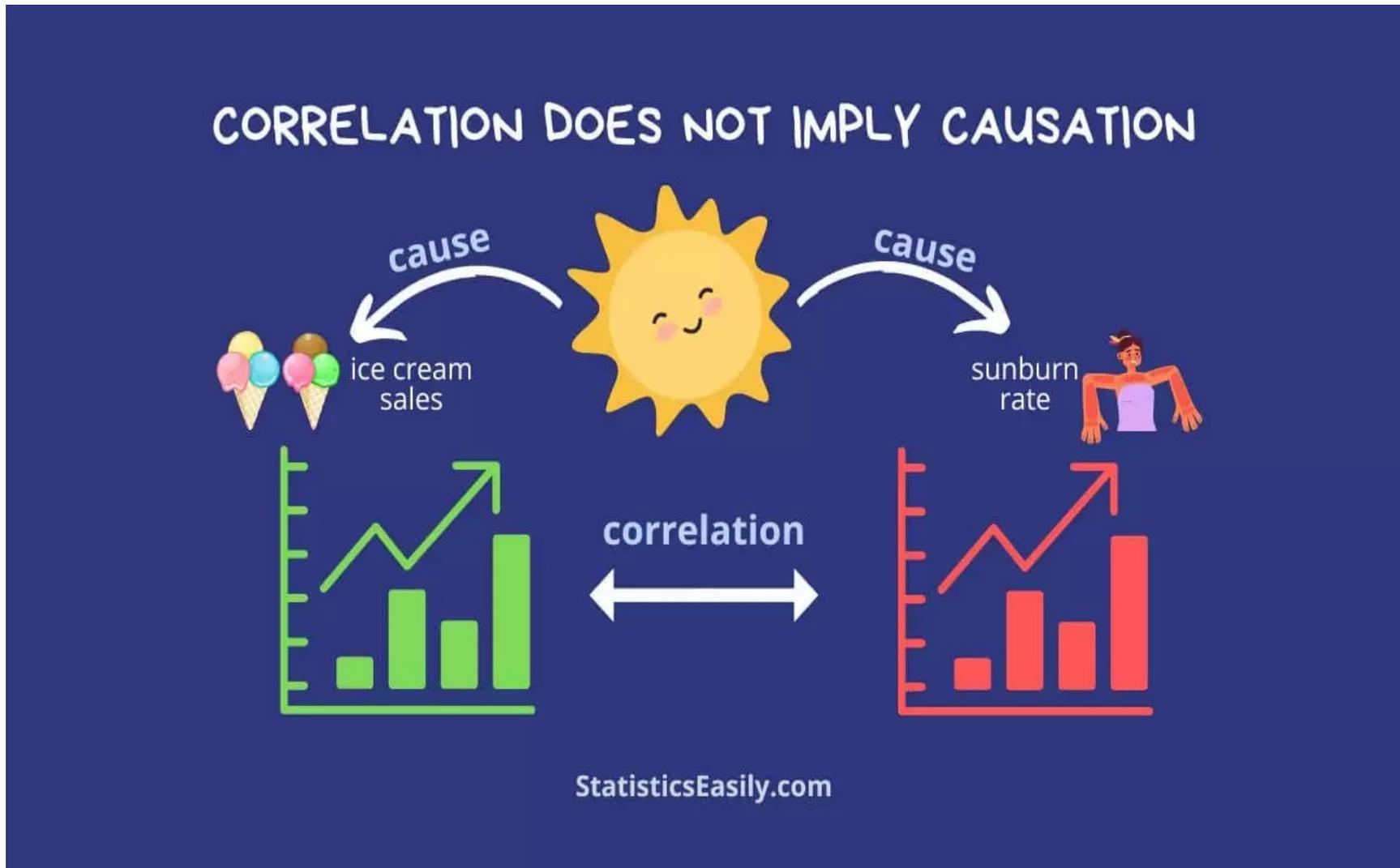


DARK ENERGY SPECTROSCOPIC INSTRUMENT

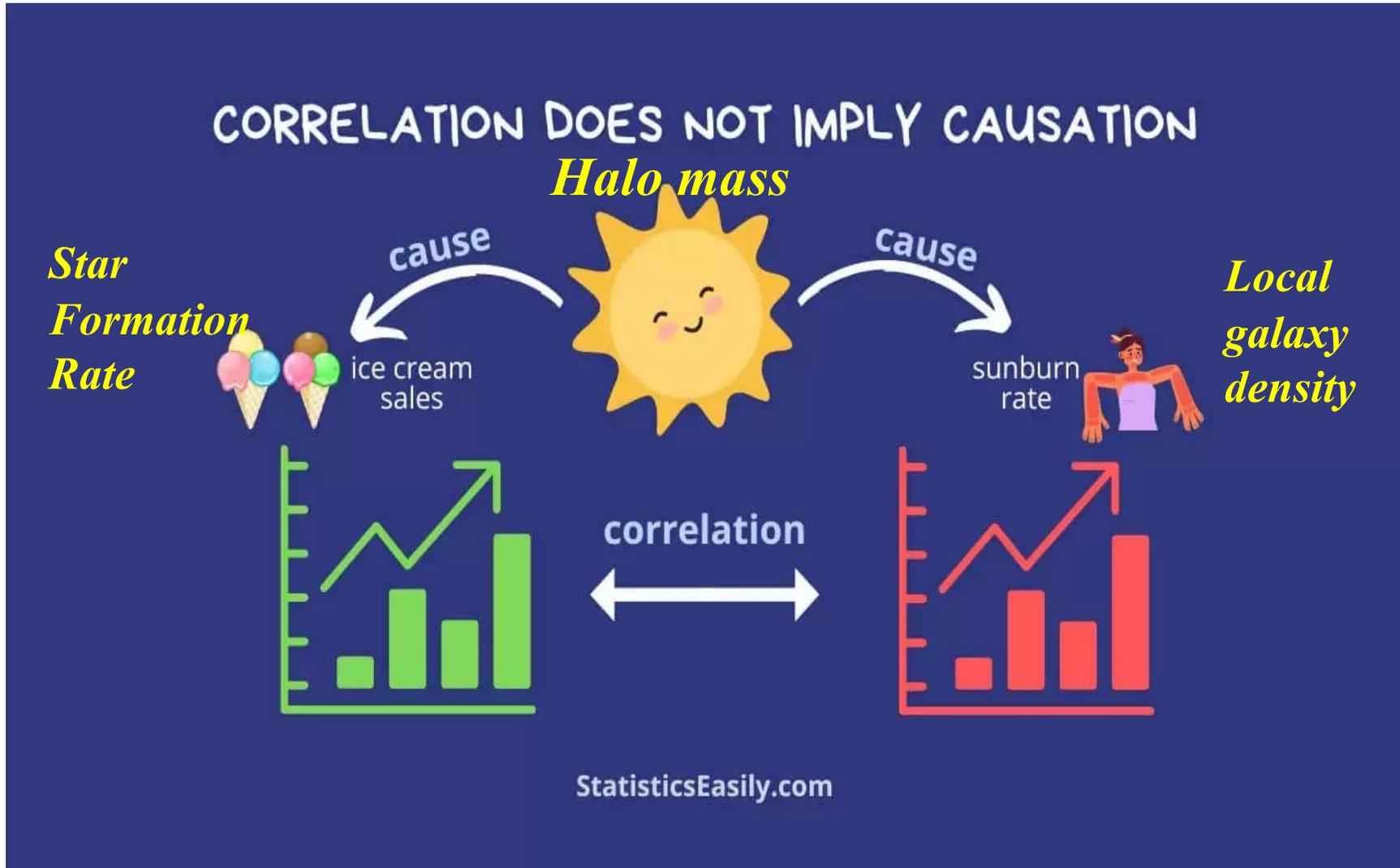
U.S. Department of Energy Office of Science



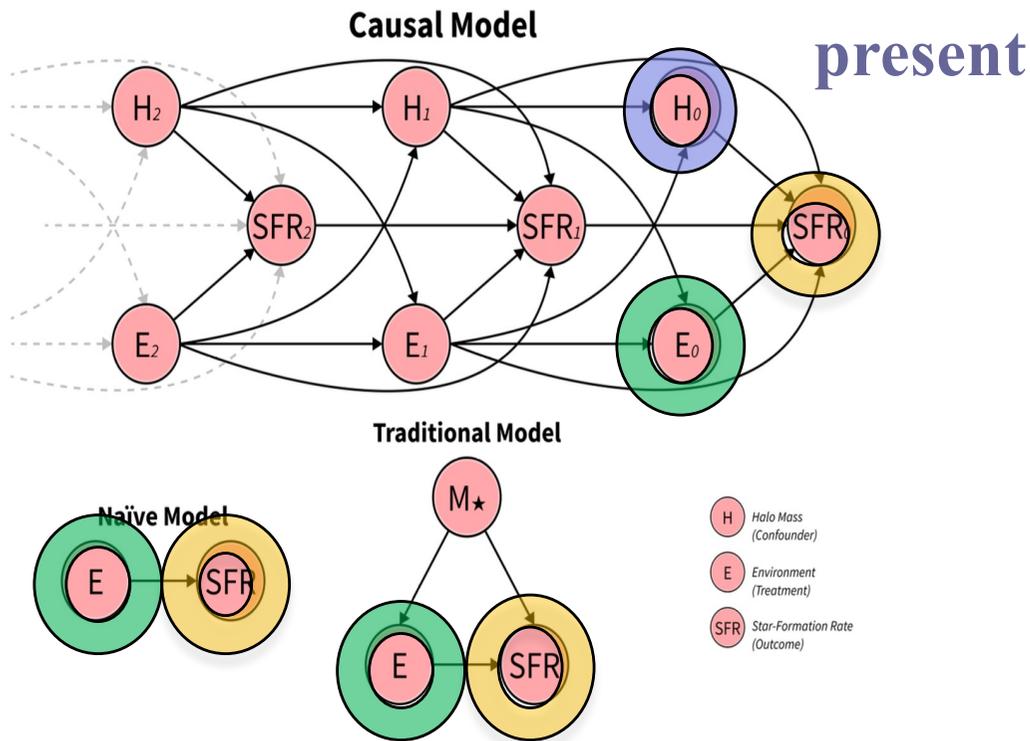
Causation: what is the confounder?



Causation: what is the confounder?

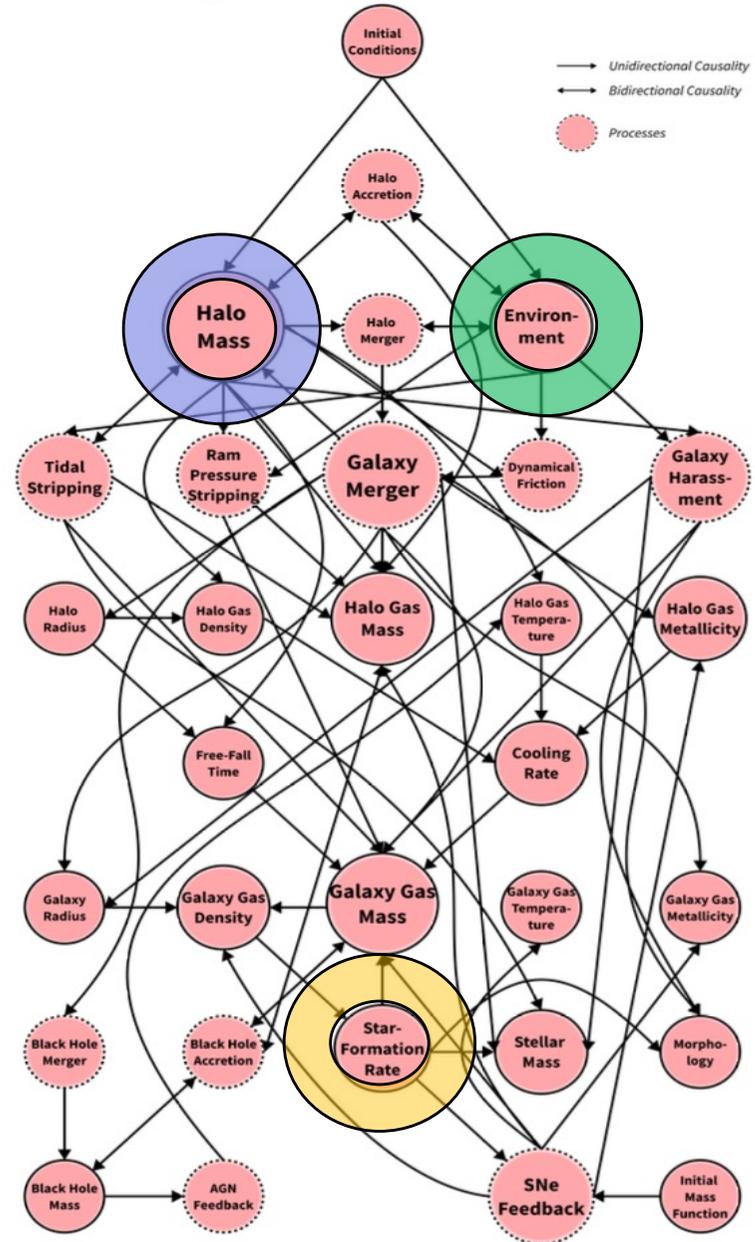


Showcase 3: Physics-inspired Machine Learning



Mucesh, Hartley,
Gilligan-Lee, OL (in prep)

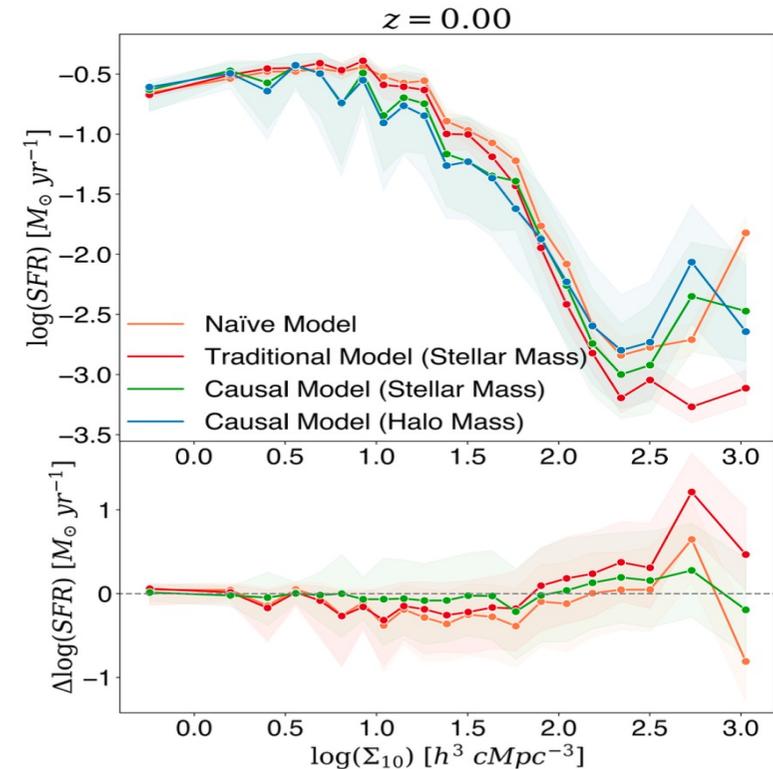
Causal Model of Galaxy Formation and Evolution



50 years of literature

Causation in galaxy formation: Nature vs. Nurture

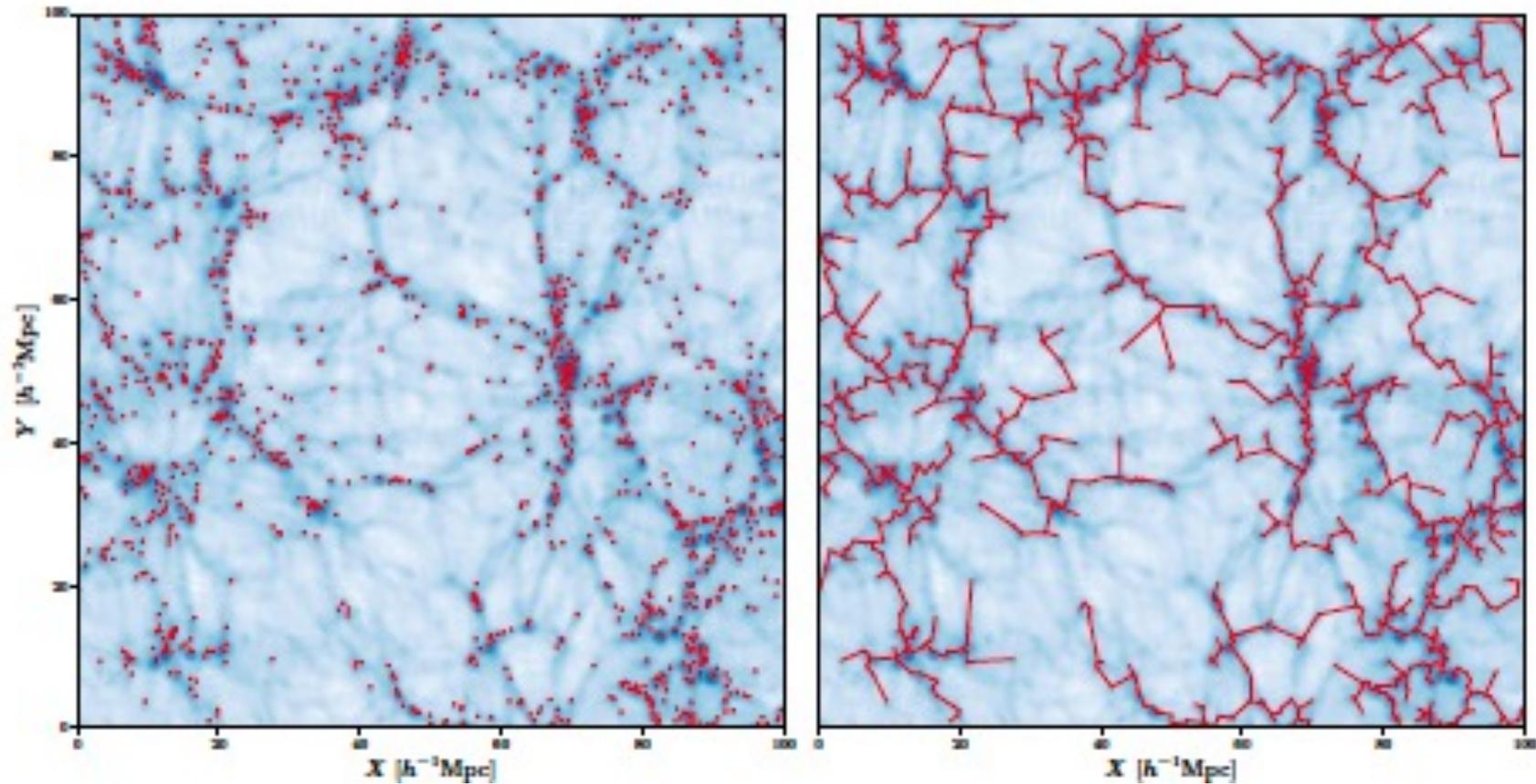
- ◆ Star Formation Rate vs. local density
(10 neighbours in 3D)
- ◆ IllustrisTNG-100 simulations
- ◆ At $z=0$ the environment suppresses SFR by a factor of 100 at $\log(\text{density}) < 2.5$, but enhances it at a denser environment.



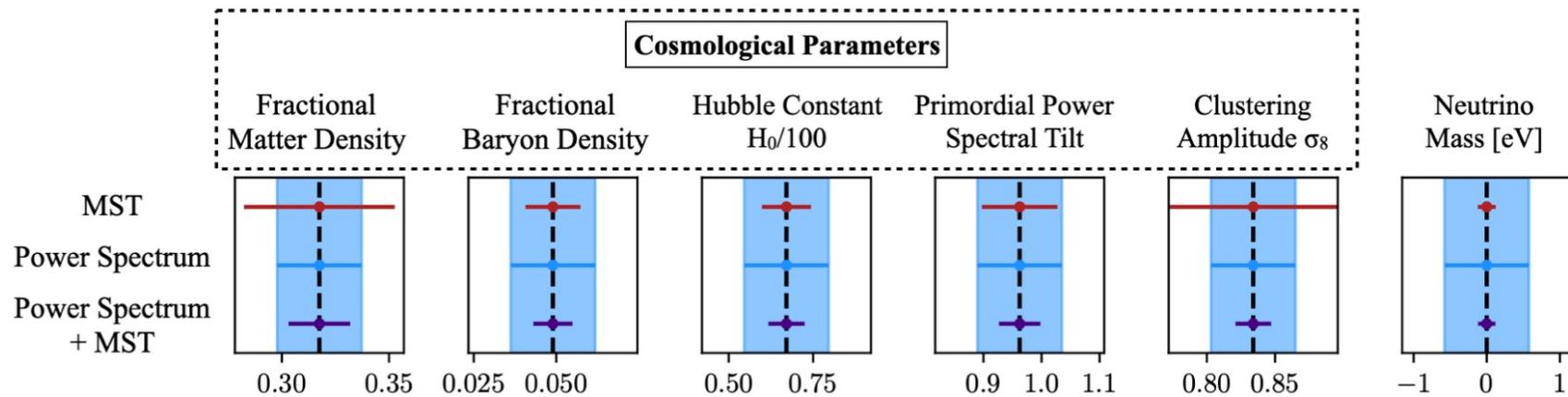
Mucesh, Hartley, Gilligan-Lee, OL
(arXiv:2412.02439)

$$w_j = \prod_{k=0}^j \frac{f(E_k | \bar{E}_{k-1})}{f(E_k | \bar{E}_{k-1}, \bar{H}_{k-1})}$$

Shawcase 4 : Field-level Cosmic Web Statistic: Minimum Spanning Tree



MST improvement wrt to P(k)



**Error bars on neutrino mass
are 4 times tighter with
MST wrt to P(k)**



*Naidoo, Massara & OL,
2111.12088*

Open issues in Cosmology with AI/ML

- ◆ Huge data sets in both spatial and time domains
- ◆ Cosmology can no longer be done without ML
- ◆ Evolution or Revolution?
- ◆ The best is still to come, with ‘killer ML applications’

Challenges:

- ◆ How to enhance ‘deep’ vs. ‘shallow’ performance?
- ◆ How to understand/explain/interpret Deep Learning?
- ◆ How to incorporate known Physics in the input and getting out new Physics
- ◆ How to up-scale ML algorithms to exa-scale
- ◆ Ethics and sustainability
- ◆ Great training of PhDs and Post-docs,
beyond academia

The future of AI for cosmology

- ◆ Discovery of new phenomena in huge data sets
- ◆ Automated processing from the telescope to science results
- ◆ Complex simulations and emulators
- ◆ Discovery of new theories
- ◆ Literature search, paper writing and refereeing
- ◆ AI augmentation of the brain to help it to figure out the universe!

