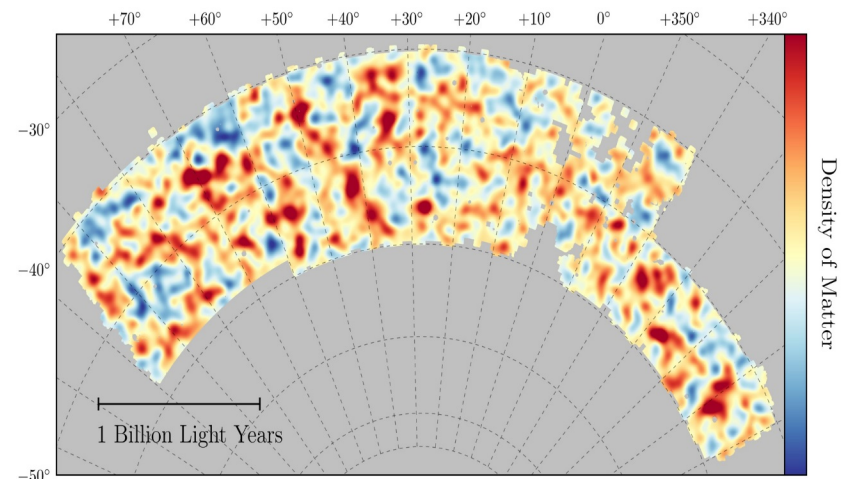
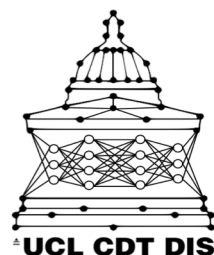


Darkness Visible: AI in Cosmological Experiments

Ofer Lahav (University College London)



DES mass map from weak lensing



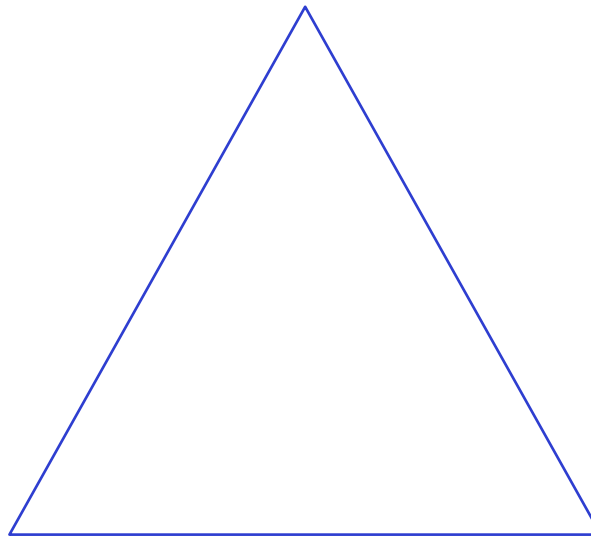
Outline

- ◆ Galaxy Surveys: present and future
- ◆ The status of Cold-Dark-Matter & Lambda model
- ◆ AI & Machine Learning in Cosmology
- ◆ Training the next generation in Data Science

A revised version of
George Darwin Lecture, Royal Astronomical Society
(9 October 2020)

Cross talk: Artificial Intelligence, Physics, Humans

AI (*)



Laws of
Physics

Human
Knowledge

(*) Actually better as “Augmented Intelligence”



Big Data in Astronomy



| Survey | Data per night/day | Galaxies | Cost | Scientists |
|-------------------|--------------------|--------------|---------|------------|
| DES | 1 TeraB | ~300 Million | ~\$40M | ~400 |
| DESI | 40 GigaB | ~35 Million | ~\$70M | ~600 |
| Rubin-LSST | 15 TeraB | ~Billions | ~\$1.0B | ~1000 |
| Euclid | 850 GigaB | ~Billions | ~\$1.5B | ~1500 |
| SKA | 1 PetaB | ~Billions | ~\$1.3B | ~1000 |

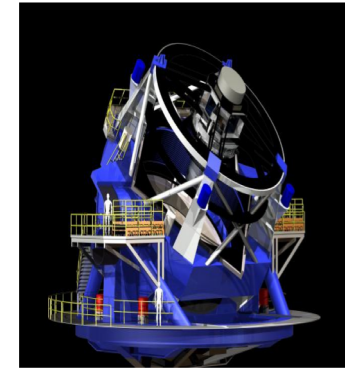
Galaxy Surveys



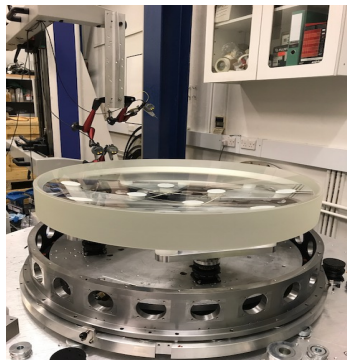
*DES
CCDs*



DES



LSST

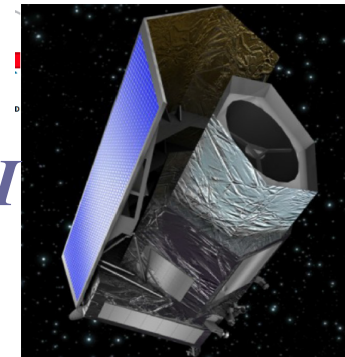


*1 of 6
DESI lenses*

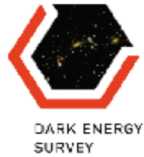


Mayall 4-Meter Telescope

DESI



Euclid



The Dark Energy Survey

Multi-probe approach

Wide field: Cluster Counts,
Weak Lensing, Large Scale Structure

Time domain: Supernovae

- ◆ **Survey strategy**
 - 300 million galaxies
 - 2500 SN Ia
- ◆ Over 400 scientists based in 7 countries
- ◆ 6 seasons of observations (2012-2019)
- ◆ Over 250 DES papers
- ◆ More to come on Y3 and Y6



<https://www.darkenergysurvey.org>

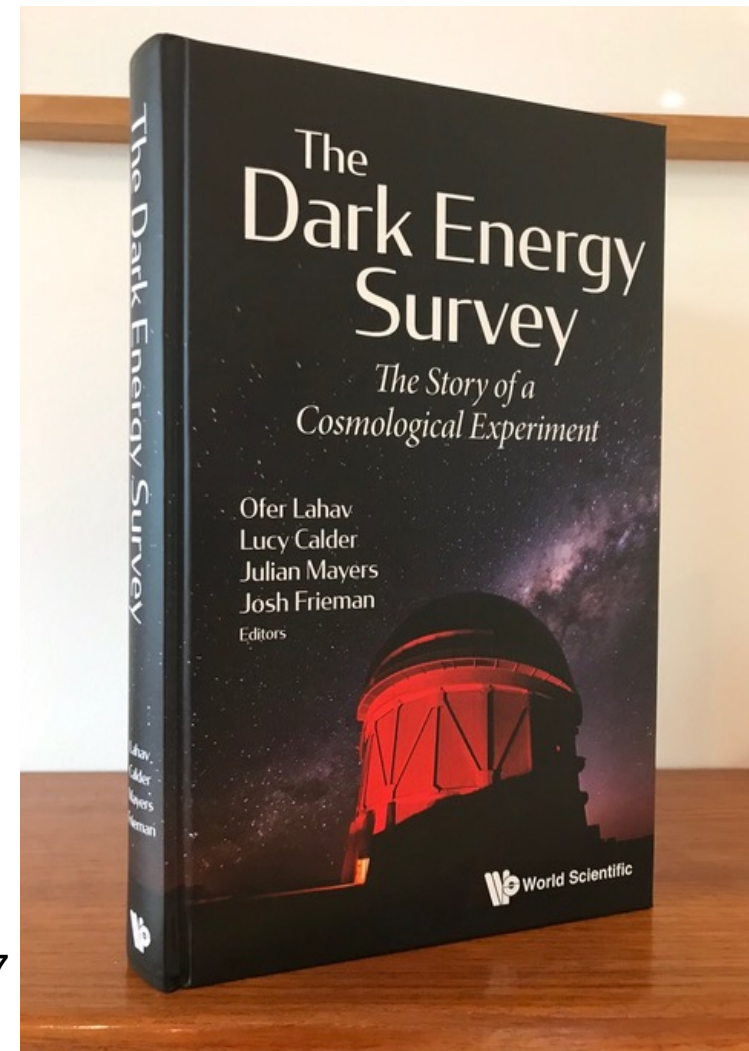


The DES book

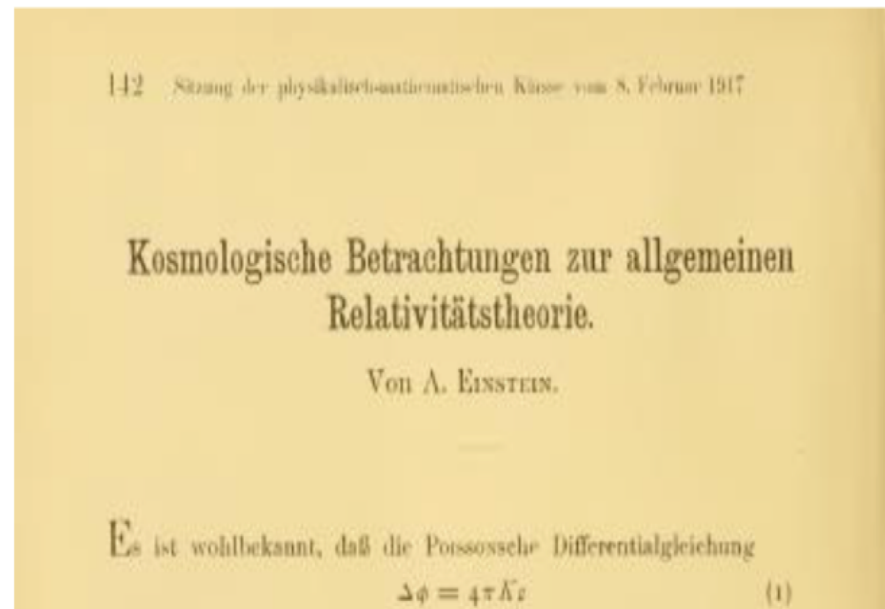
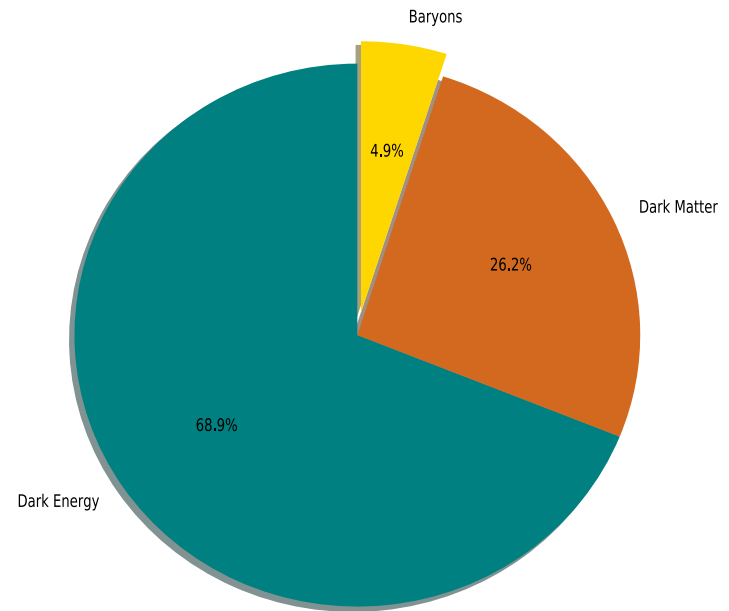


- ◆ Published by World Scientific (September 2020)
- ◆ 27 chapters in 4 sections: Building DES, DE science, non-DE, Reflections
- ◆ 88 co-authors
- ◆ Virtual book launch held on on 13 Oct 2020 (recording on YouTube)

<https://worldscientific.com/worldscibooks/10.1142/q0247>



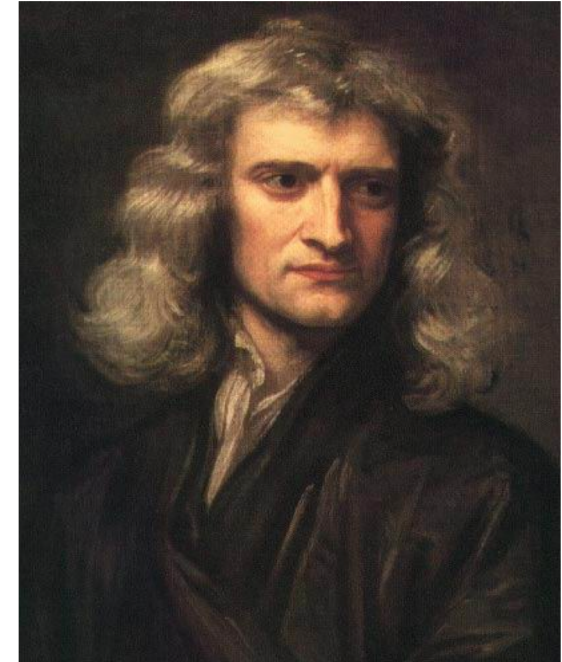
Is Dark Energy “just” Λ ?



The Dark Energy problem: 20, 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:
 $a = -GM/r^2 + \Lambda/3 r$*



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

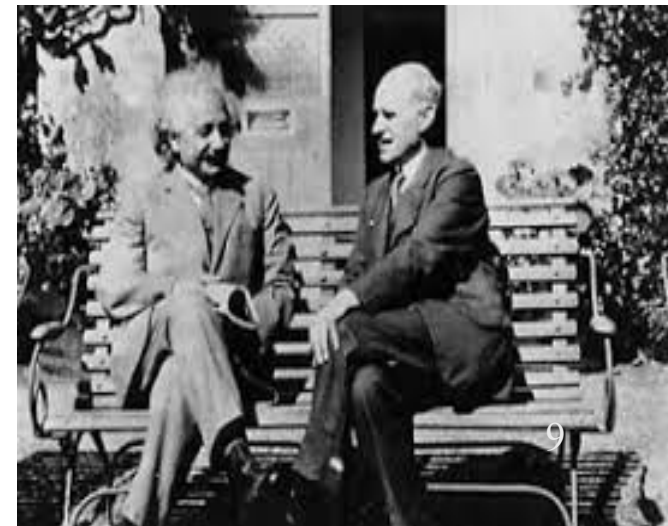
Isaac Newton, Principia (1687)

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

Albert Einstein (1920s)

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

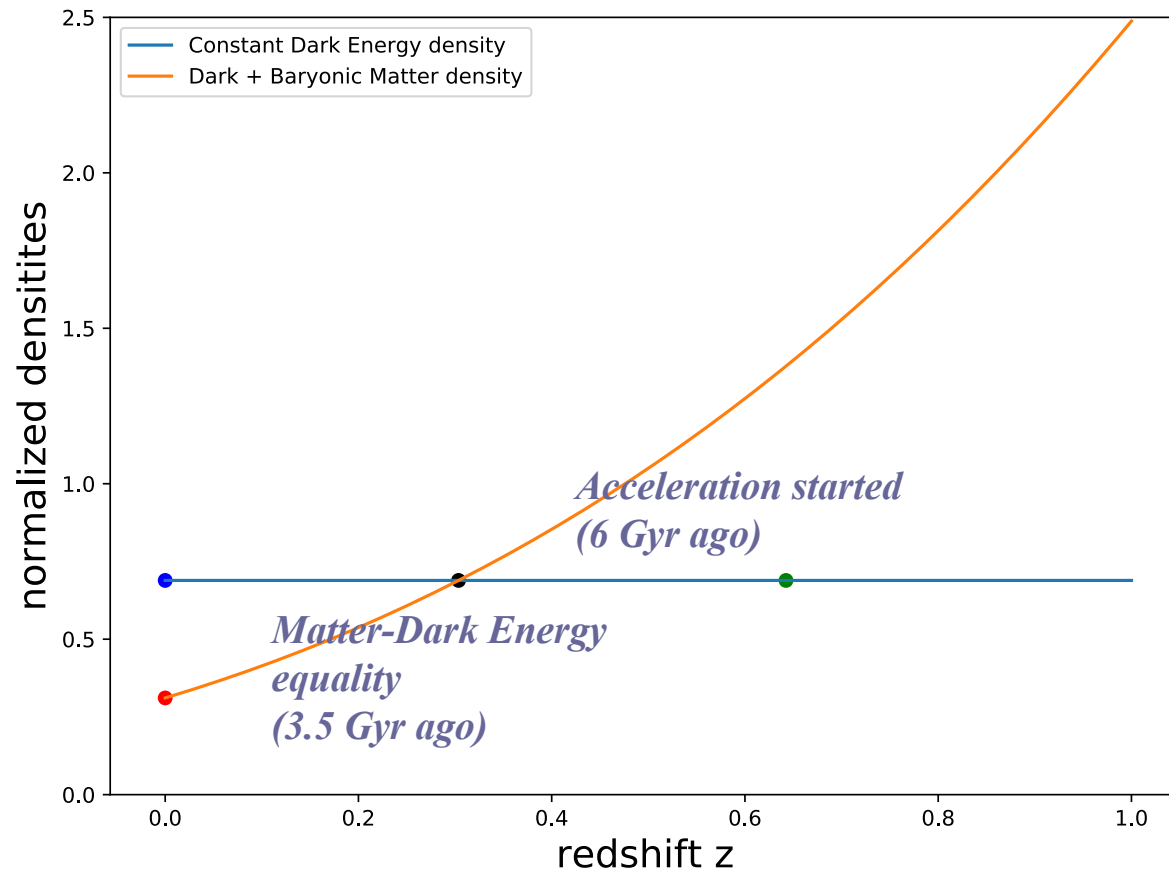
Arthur Eddington (1920s)



The evolution of densities

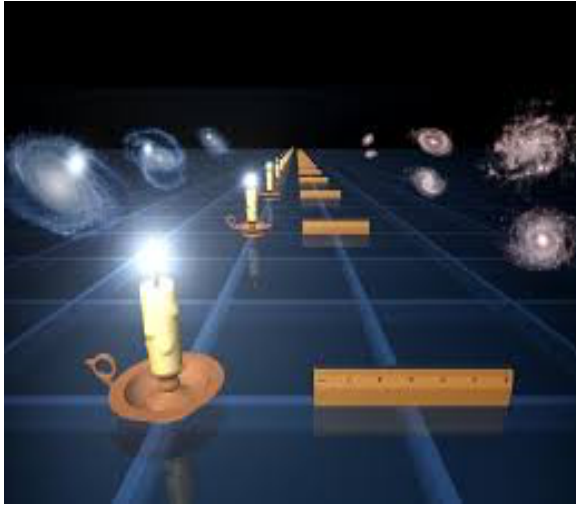
$$w = p/\rho c^2$$

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

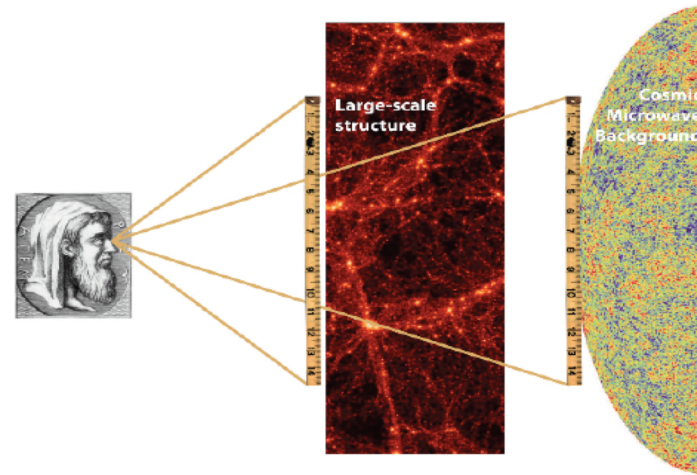


Probes of Dark Energy

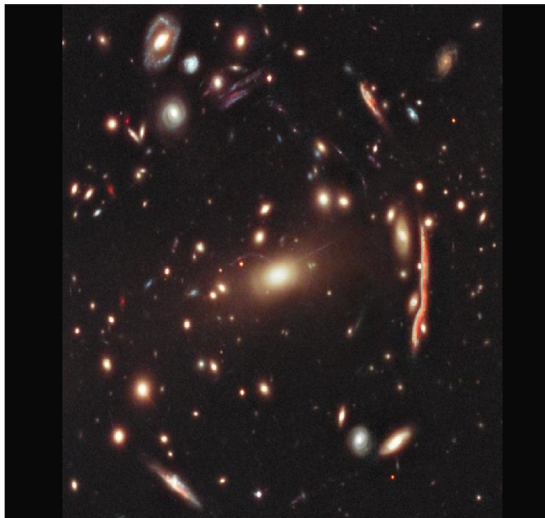
Standard candles



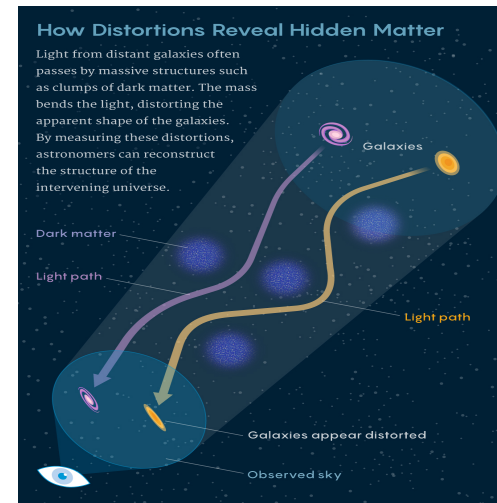
Standard rulers



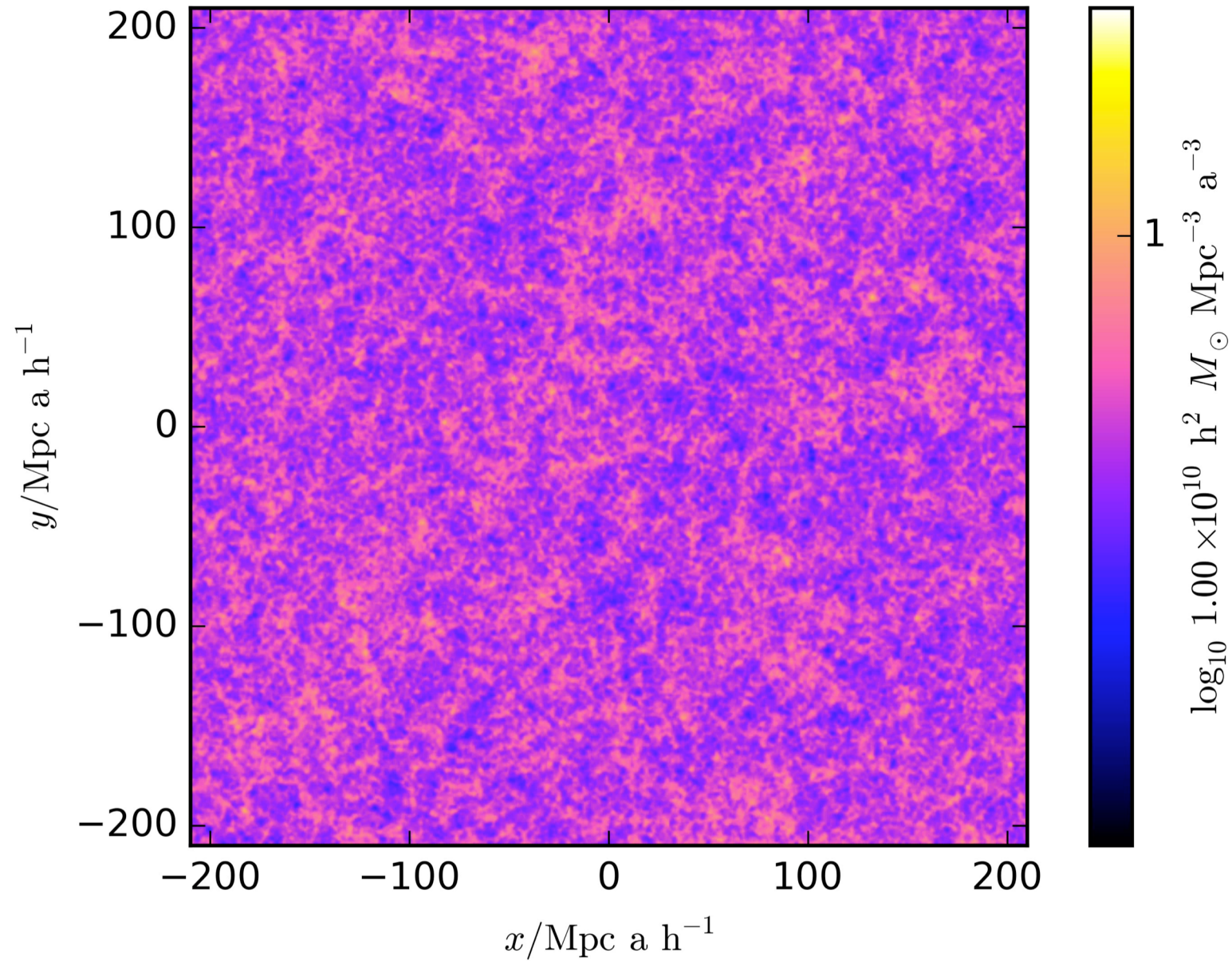
Clusters



Gravitational Lensing

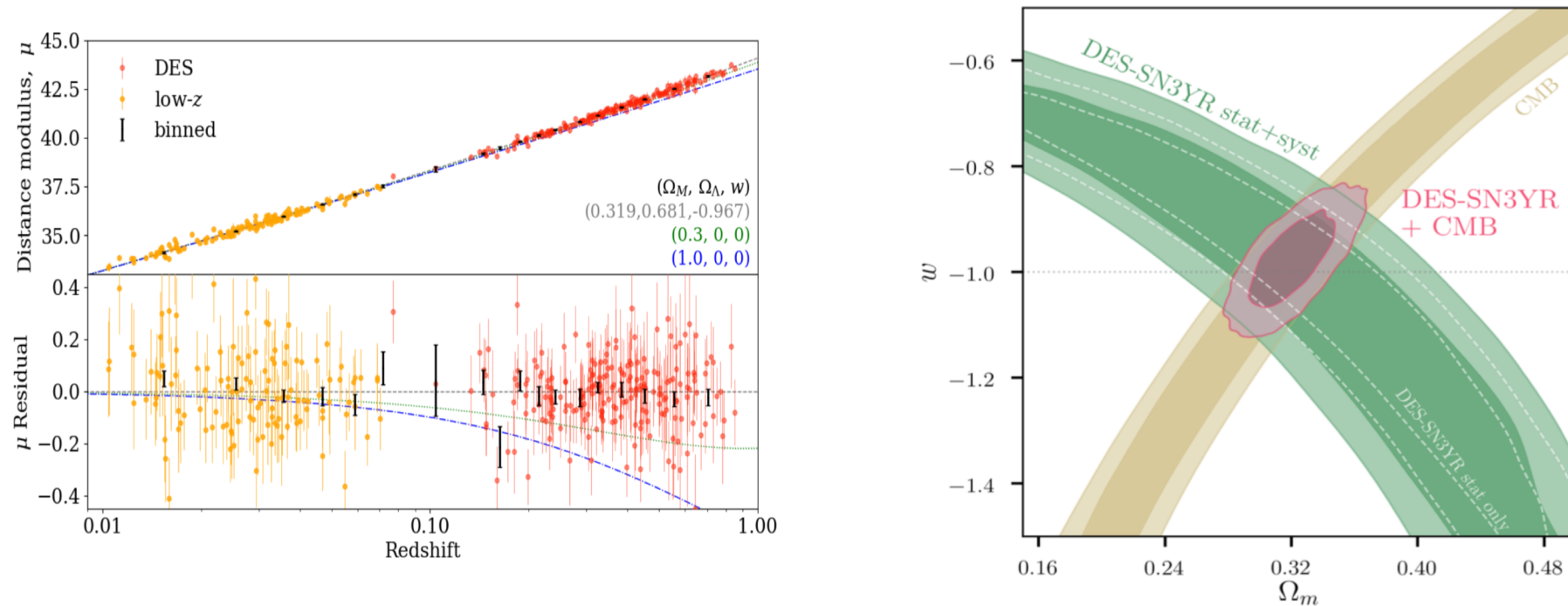


13.13 Billion Years Ago ($z = 35.000$)



Jeffrey et al. (2020)

207 DES SN Ia (+122 other SN Ia) *DES collaboration, 1811.02374*



$w = -0.978 \pm 0.059$, and $\Omega_m = 0.321 \pm 0.018$ (1-sigma)

Blinding to overcome confirmation bias

Health checks of LCDM

“Tensions” –

Systematic errors in data, or **new Physics?**

* Hubble Constant tension (~ 4 sigma)

$$H_0 = 74.0 \pm 1.4 \text{ km/sec/Mpc (Riess et al. 2019)}$$

$$H_0 = 67.4 \pm 0.5 \text{ (Planck 2018)}$$

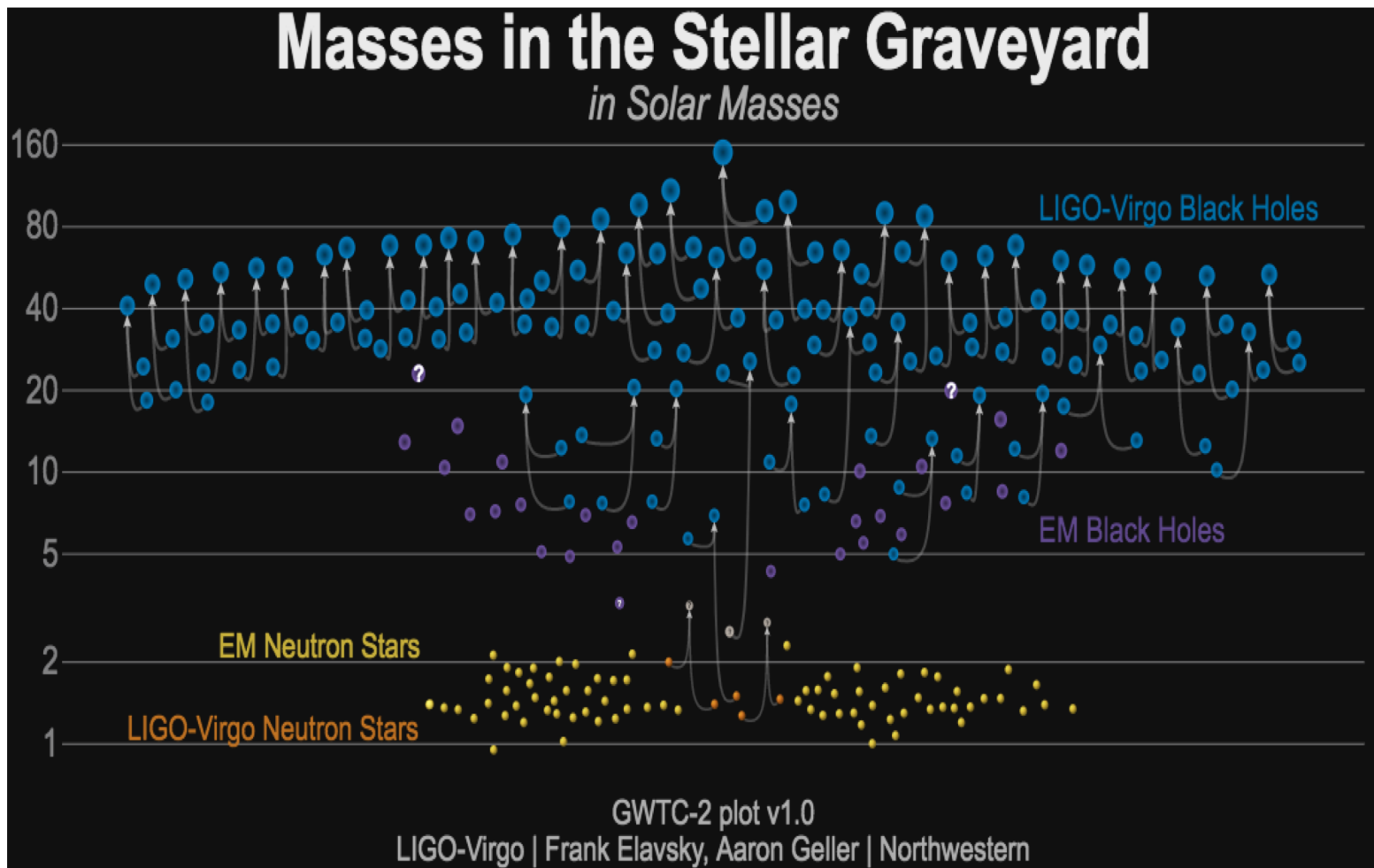
A new approach: Gravitational Wave sirens

$$H_0 = 68.6 \pm 11 \text{ (Bright; Nicolaou et al. 2020)}$$

$$H_0 = 72.0 \pm 10 \text{ (Dark + Bright; Palmese et al. 2020)}$$

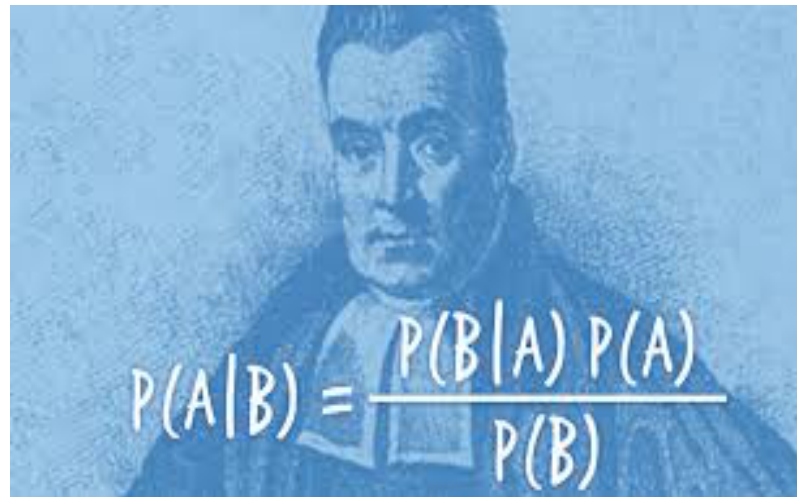
* Clumpiness σ_8 (WL vs CMB) (~ 2 sigma)

Gravitational Wave events



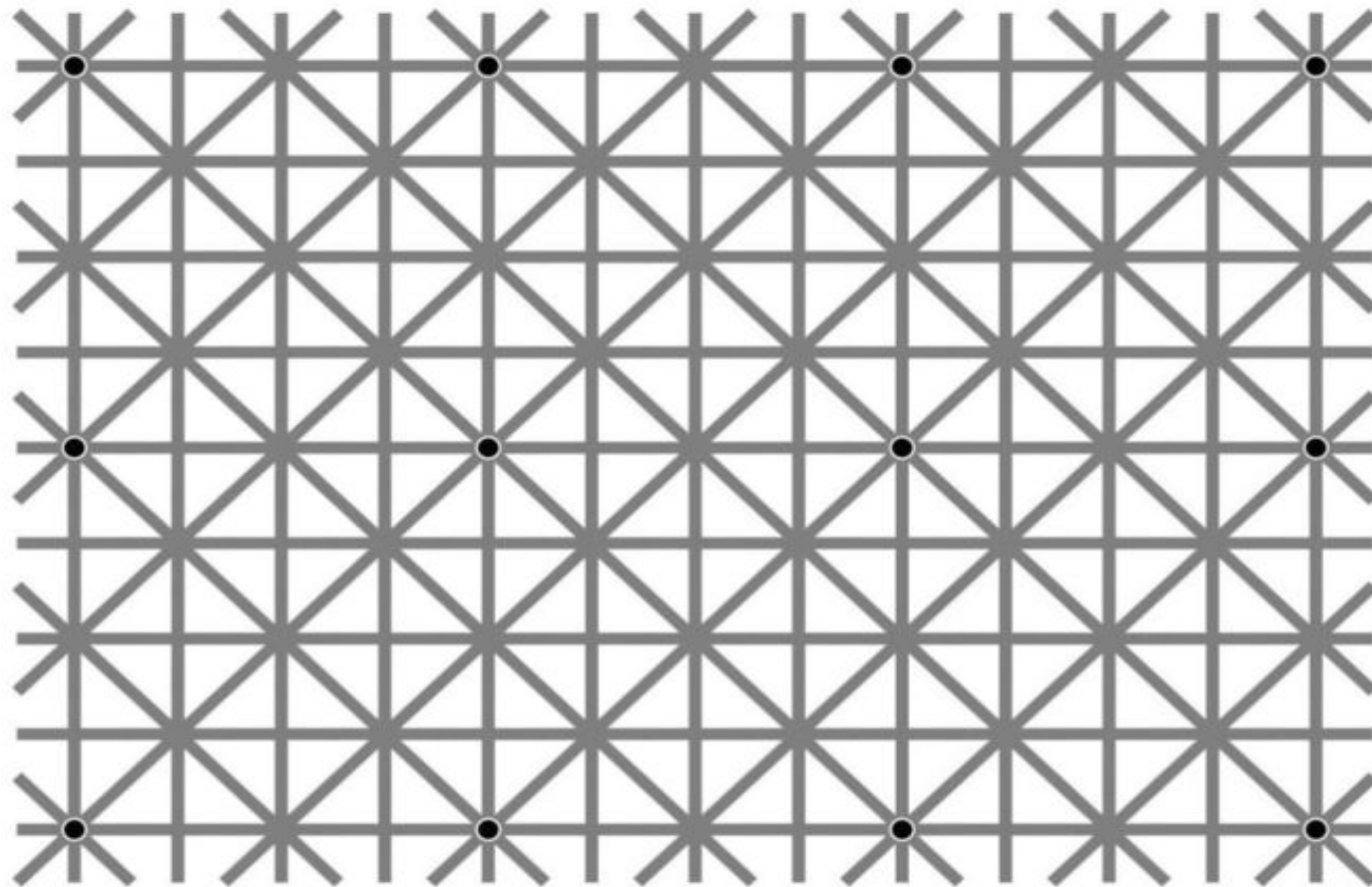
Cosmology with AI and connection to traditional statistics

- **Is AI/ML a black box?**
- **Can we explain/interpret it?**
- **How to minimise biases due to incomplete training sets?**
- **Can we include prior Physics?**
- **Can we learn new Physics?**

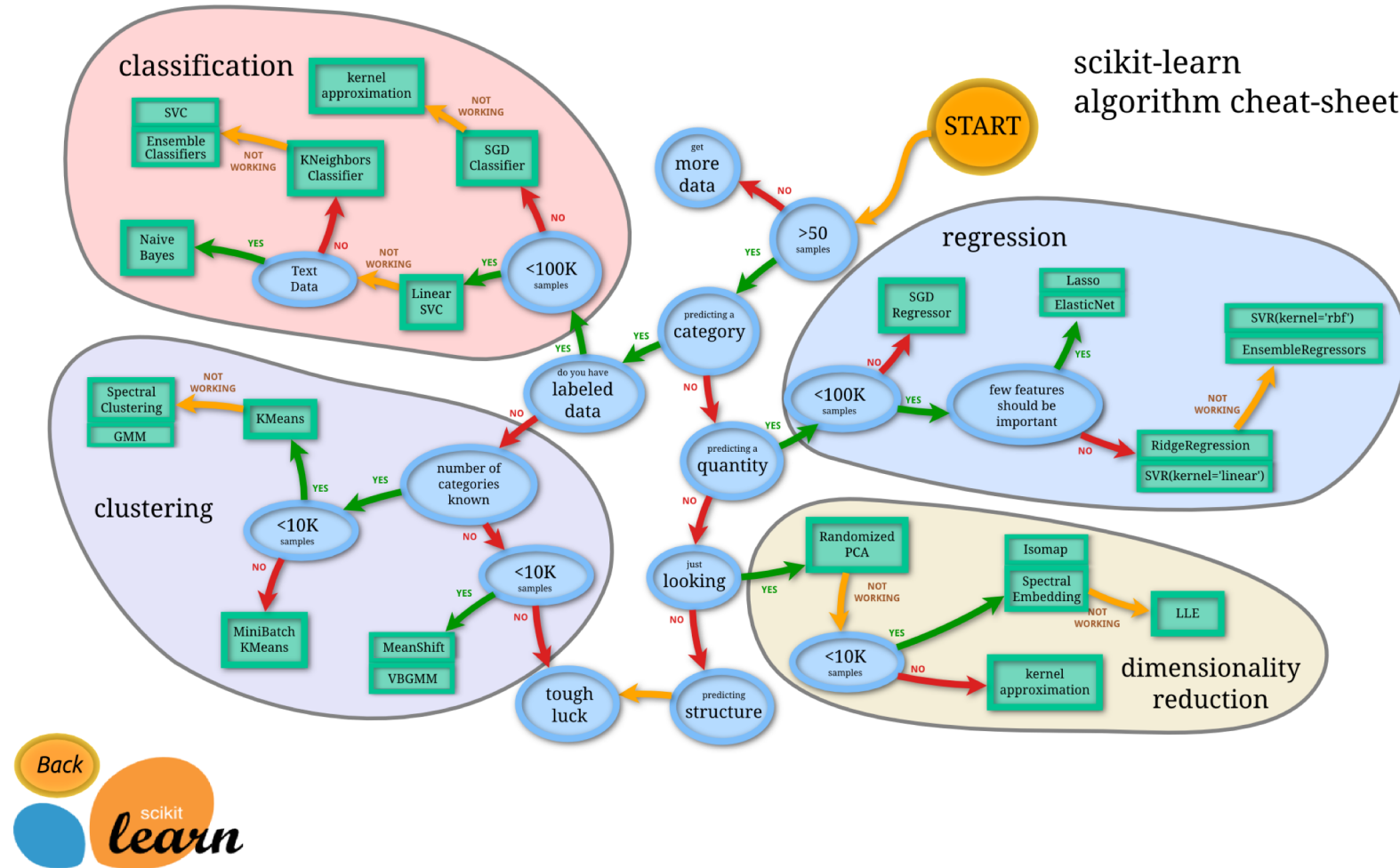


Can we trust just the human brain?

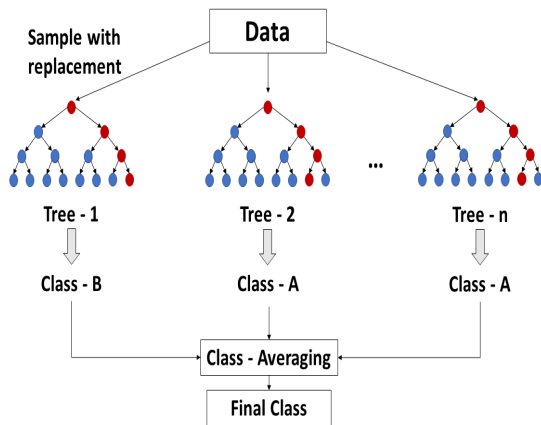
(can you see 12 black dots at once?)



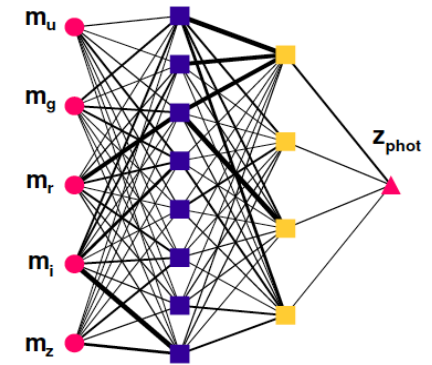
Machine Learning open sources



also Tensor Flow



Machine Learning in Astronomy: Examples



- Classification:

galaxy type, star/galaxy, Supernovae Ia,
strong gravitational lensing, de-blending

- Photometric redshifts

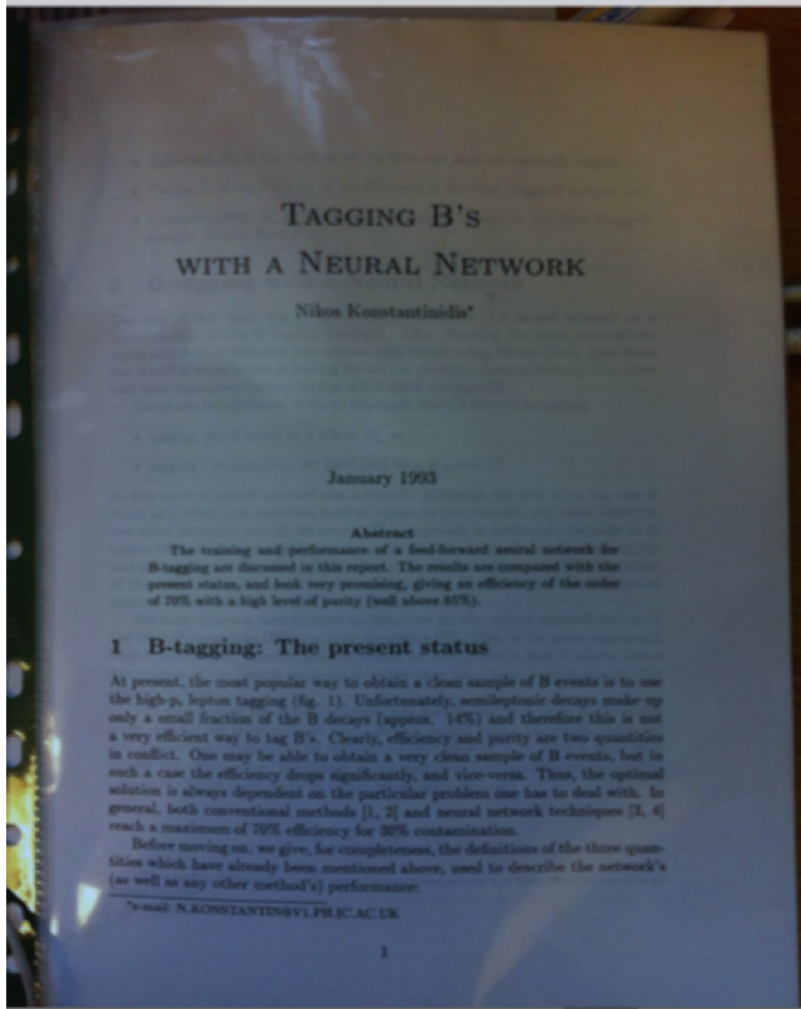
- The mass of the MW+M31

- The search for Planet 9 and exo-planets

- Gravitational Waves & follow-ups

Artificial Neural Networks: early days

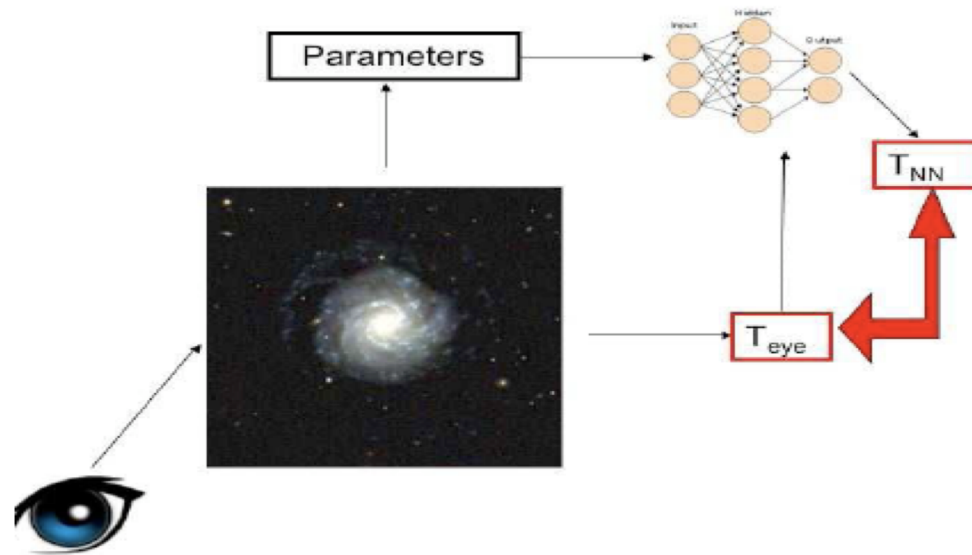
NK's 1st term PhD report (Jan 1993)



OL's early work related to ML (Feb 1995)

The image is a screenshot of the Science journal website. The top navigation bar is black with white text for "Science" and "AAAS". Below it is a red navigation bar with white text for "Home", "News", "Journals", "Topics", and "Careers". Underneath is a black navigation bar with white text for "Science", "Science Advances", "Science Immunology", "Science Robotics", "Science Signaling", and "Science Translational Medicine". The main content area is white. It features a "SHARE" section with icons for Facebook, Twitter, and a link icon. The article title is "Galaxies, Human Eyes, and Artificial Neural Networks" by O. Lahav¹, A. Naim¹, R. J. Buta², H. G. Corwin³, G. de Vaucouleurs⁴, A. Dressler⁵, J. P. Huchra⁶, S. van den Bergh⁷, S. Ra... There is a link to "See all authors and affiliations". The article is dated "Science 10 Feb 1995; Vol. 267, Issue 5199, pp. 859-862" with DOI: 10.1126/science.2675199.859. Below the article title are links for "Article", "Info & Metrics", "eLetters", and "PDF". The abstract is visible at the bottom, starting with "The quantitative morphological classification of galaxies is important for understanding the origin of type frequency and correlations with environment. However, galaxy morphological classification is still mainly done visually by dedicated individuals, in the spirit of Hubble's original scheme and its modifications. The rapid increase in data on galaxy images at low and high redshift calls for a re-examination of the classification schemes and for automatic methods. Here are shown results from a systematic comparison of the dispersion among human experts classifying a uniformly selected

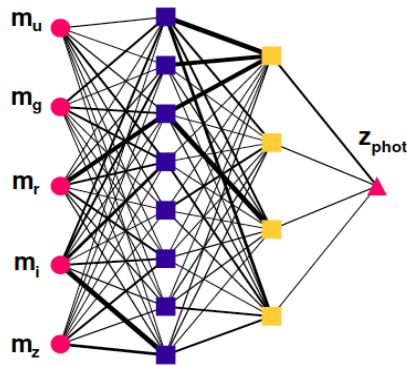
Galaxy zoo and machine learning



| | | GALAXY ZOO | | |
|---|------------|------------|--------|------------|
| | | Elliptical | Spiral | Star/Other |
| A | ELLIPTICAL | 91% | 0.08% | 0.5% |
| N | SPIRAL | 0.1% | 93% | 0.2% |
| N | STAR/OTHER | 0.3% | 0.3% | 96% |

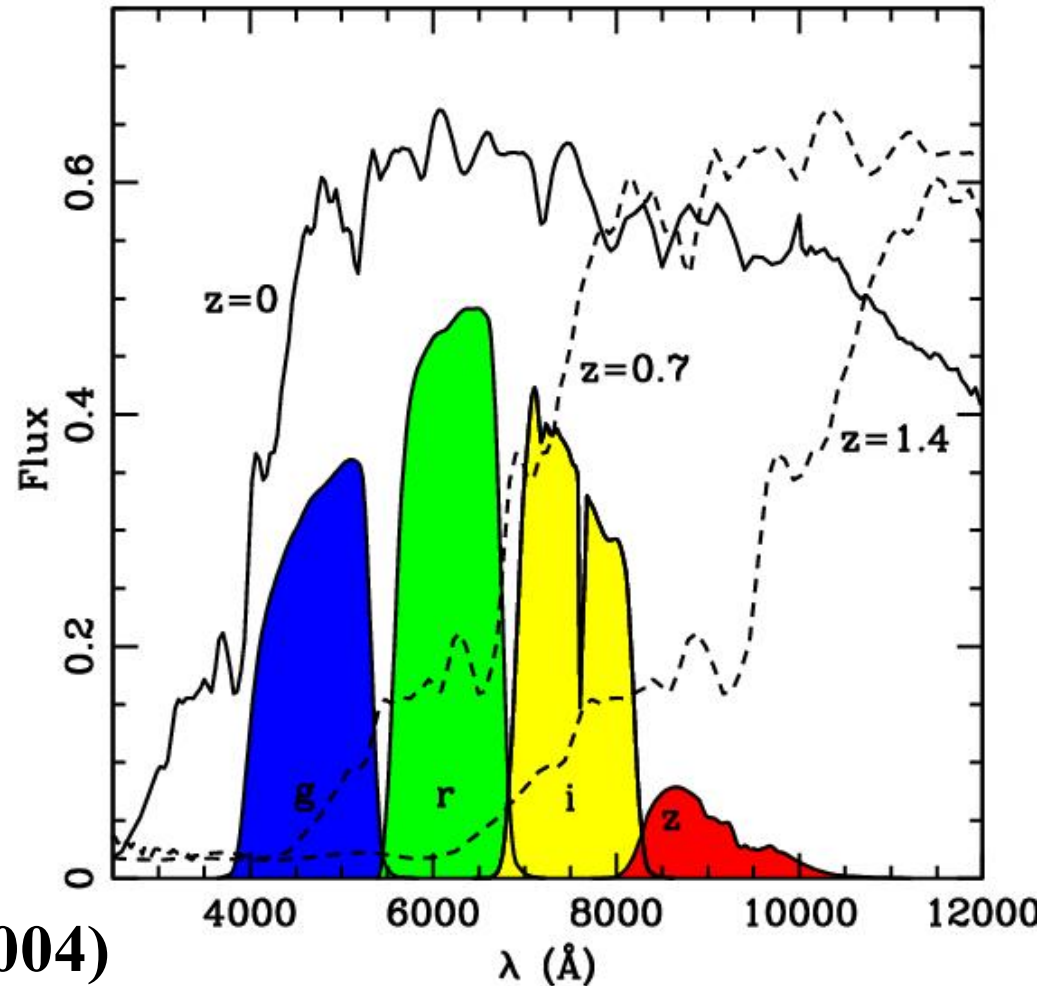
Photometric redshift

Difference in flux through filters as the galaxy is redshifted.



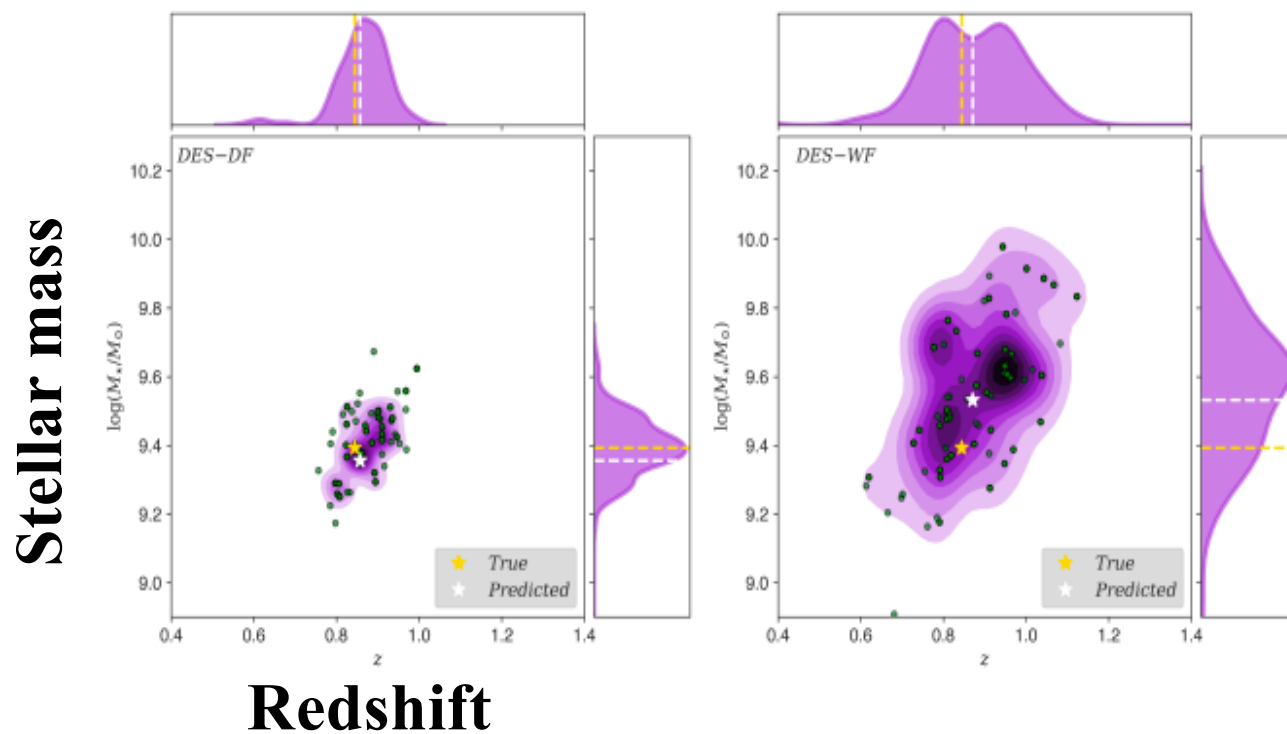
$$z = f(m_1, m_2, \dots)$$

ANNz (Collister & OL 2004)



A dozen or so templates and ML methods are now available

Joint pdf (photo-z, stellar mass) with Machine Learning (Random Forest) using DES (Cosmos Deep Field) and Wide Field



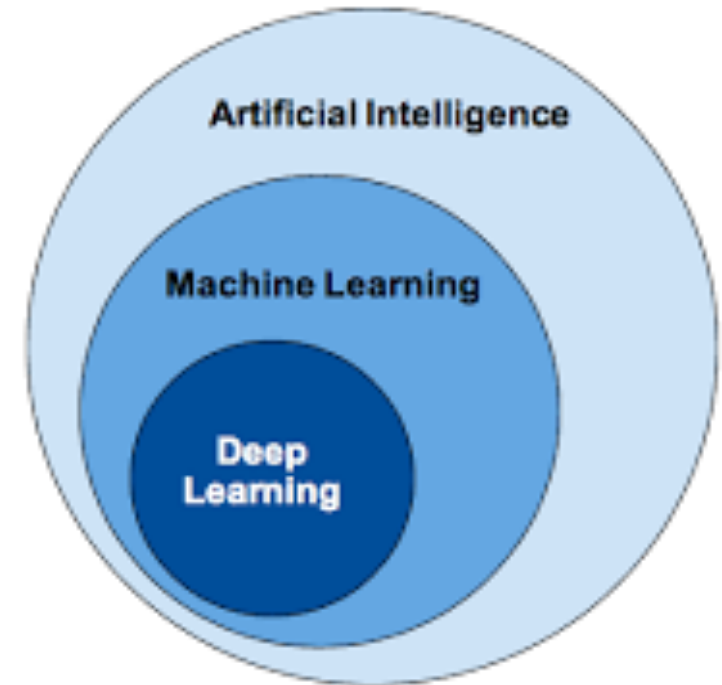
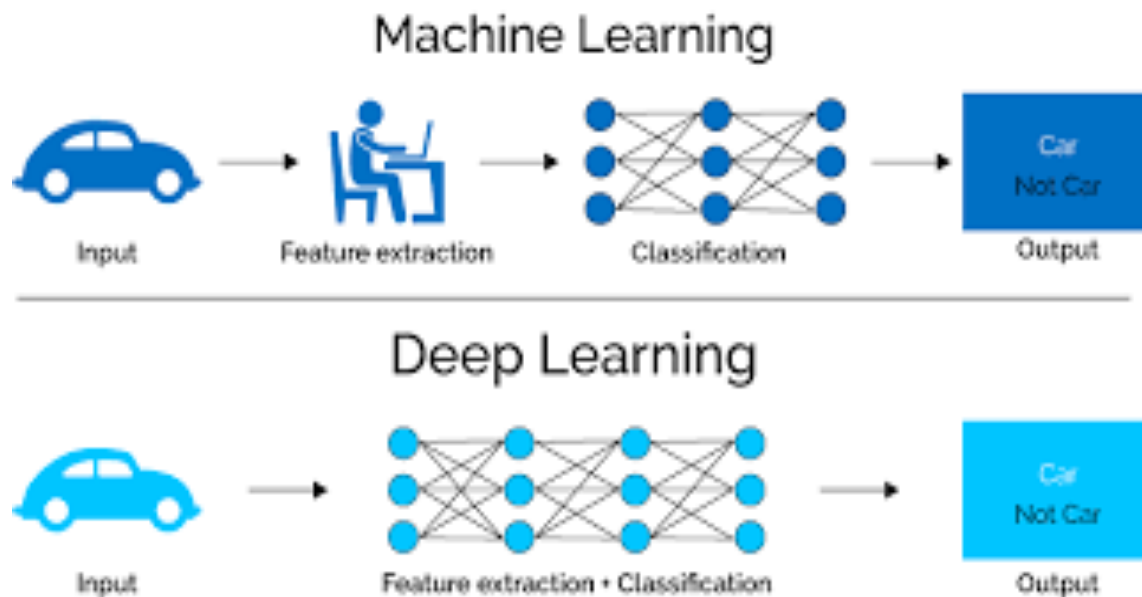
*Mucesh, Hartley,
OL, Palmese et al.
(in prep)*

Gold-true; White-predicted

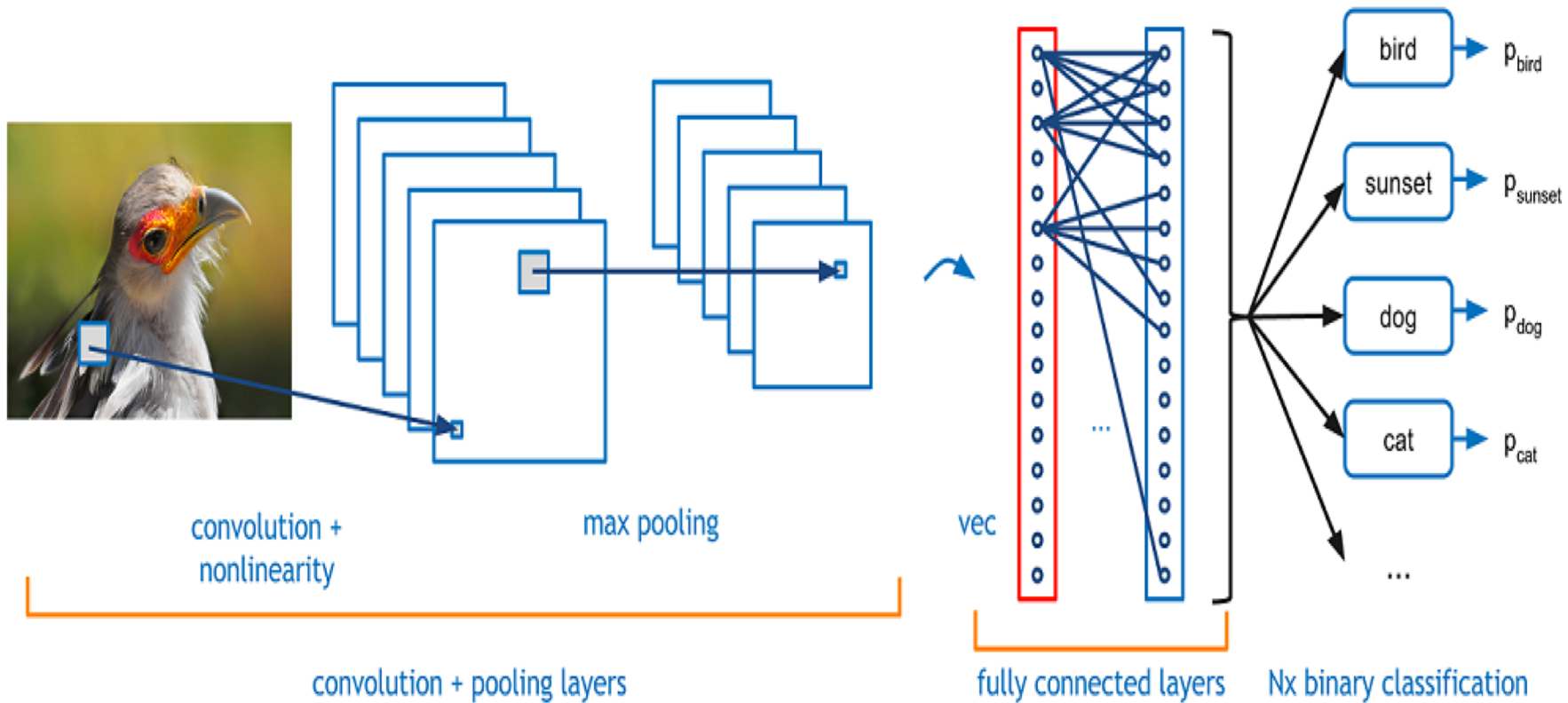
Astro papers on the arXiv with 'Deep Learning' in the title

Year #Papers

2017 (23), 2018 (35), 2019 (83), 2020 (63)

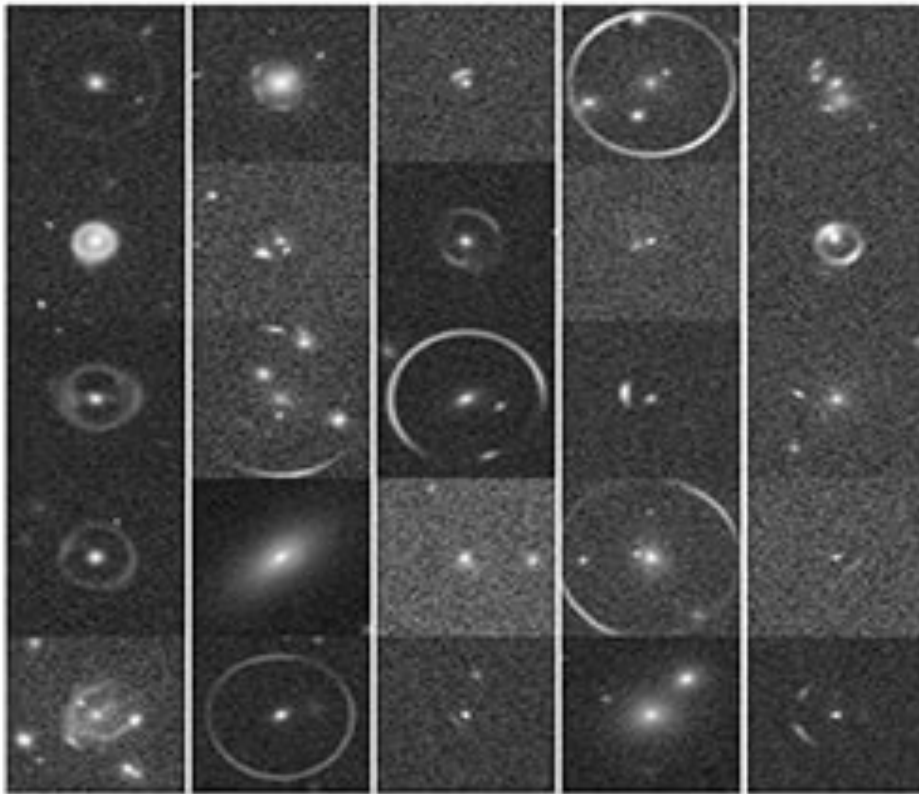


Deep Learning: Do we understand it?

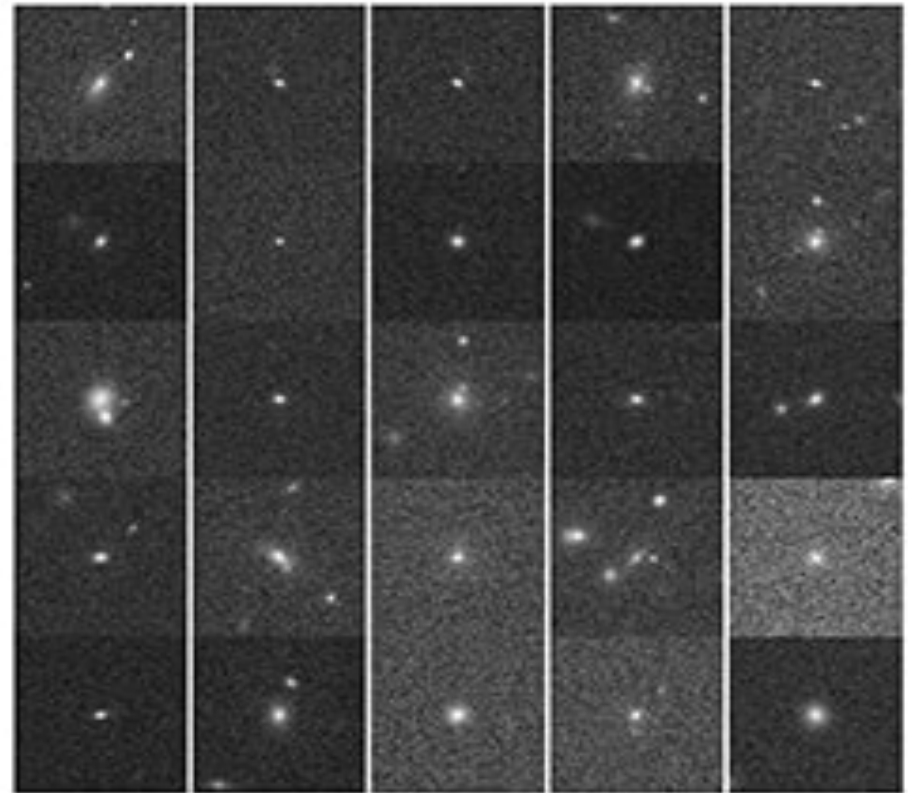


CMUDeepLens (Lanusse et al. 1703.02642)

◆ Mocks with arcs



◆ Mocks without arcs



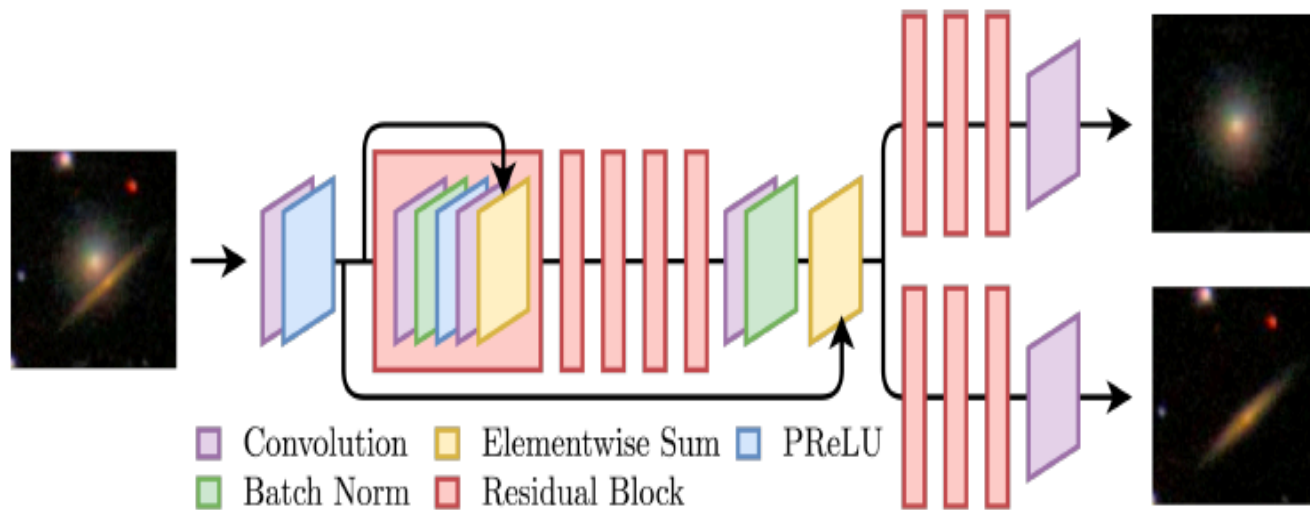
Expected in LSST: about one million strongly lensed galaxies out of an estimated 20 billion galaxies.

The approach: supervised Convolutional Neural Networks.

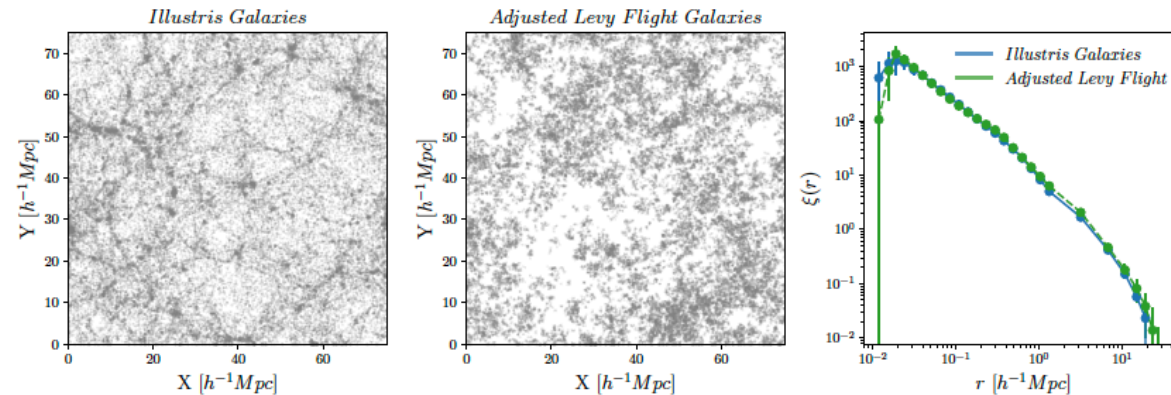
Completeness of 90% can be achieved.

de-blending of galaxy images

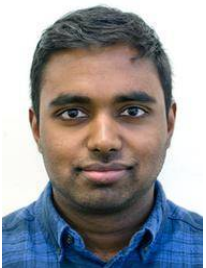
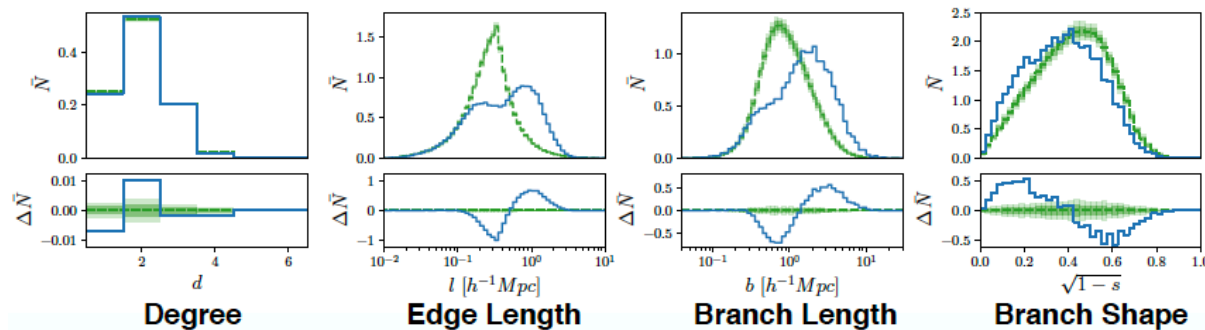
4 *D. M. Reiman and B. E. Göhre*



Minimum Spanning Tree vs. 2pt statistic

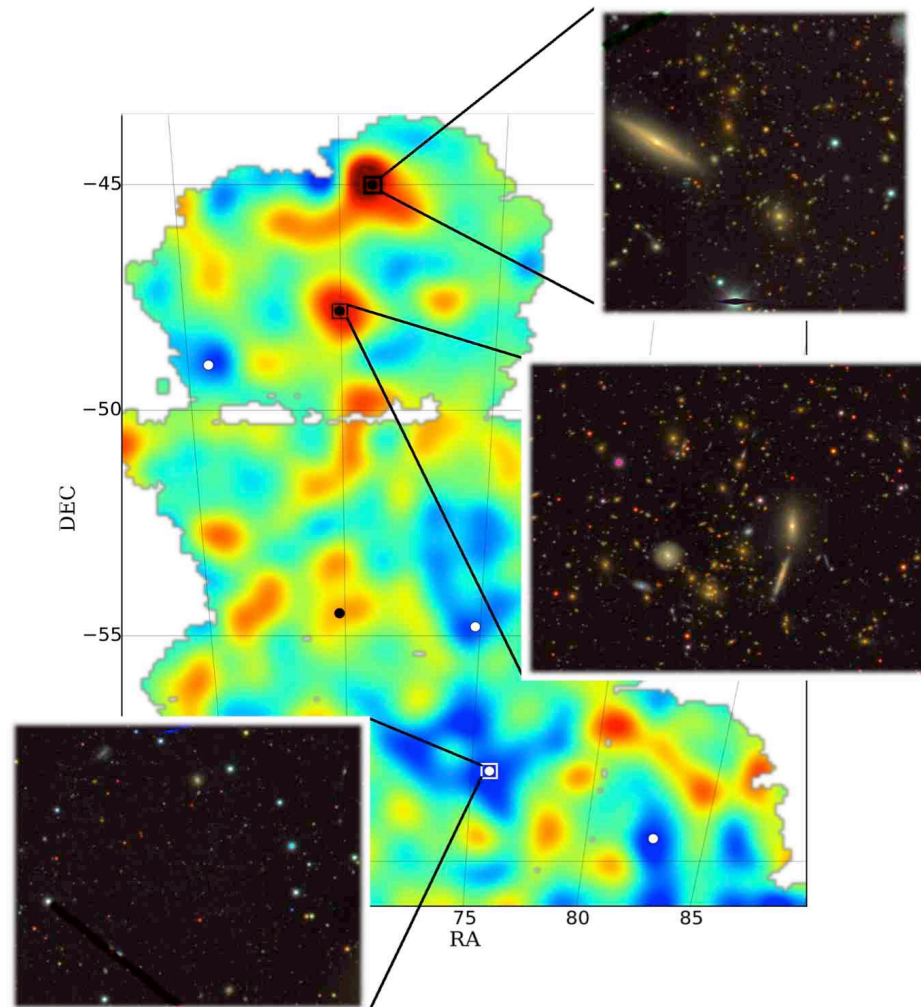


Minimum Spanning Tree statistics:



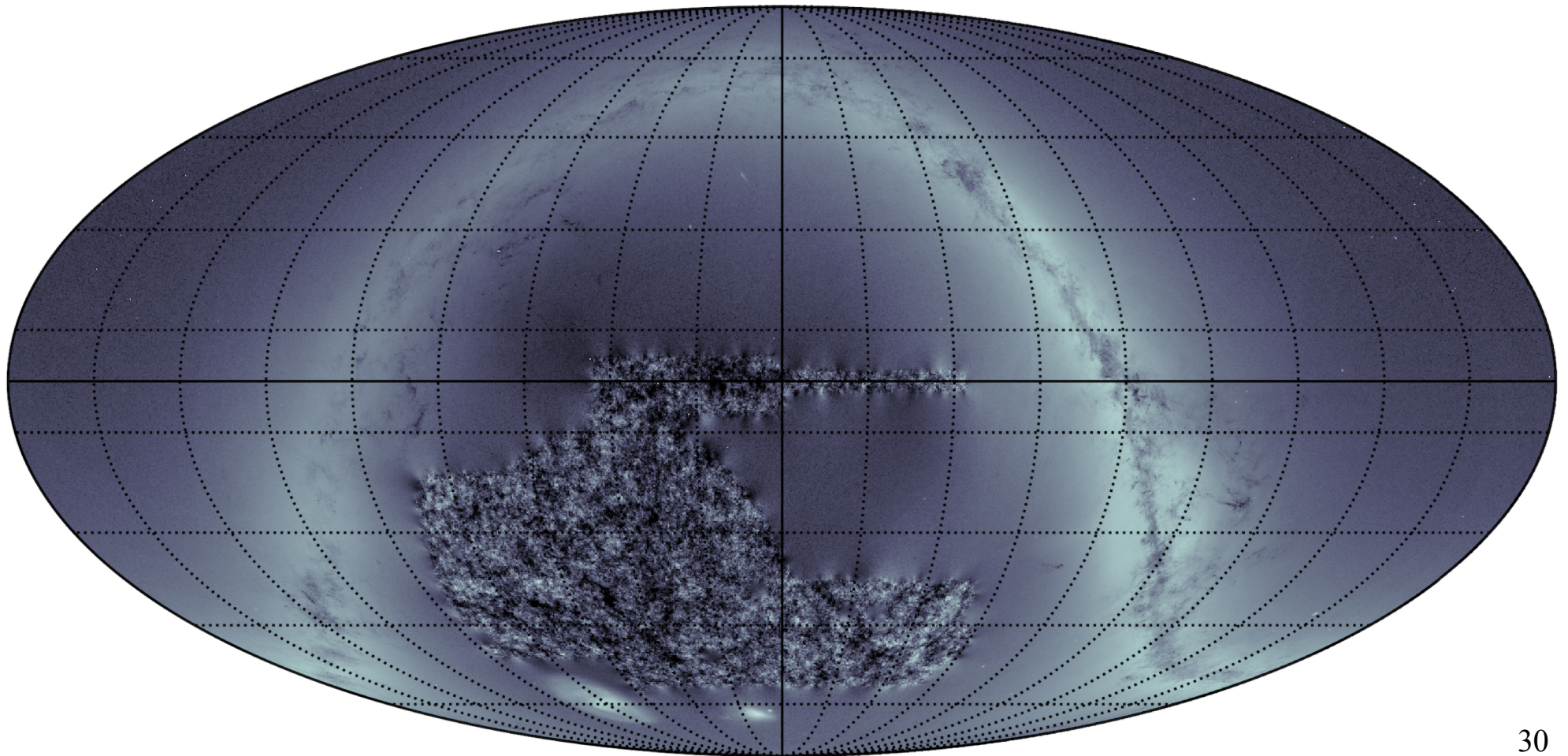
Naidoo, Whiteway, ...OL et al.
(1907.00989)

Darkness Visible: Dark Matter map from DES Weak Lensing



DES Y3 mass map (background- Gaia map)

Stars and dark matter



Jeffrey et al. (in prep – preliminary and blinded)

Shear-Convergence inverse problem

$$\gamma = \mathbf{A}\kappa + \mathbf{n}$$

Deep Learning mass reconstruction ('DeepMass')

4 N. Jeffrey et al.

DES

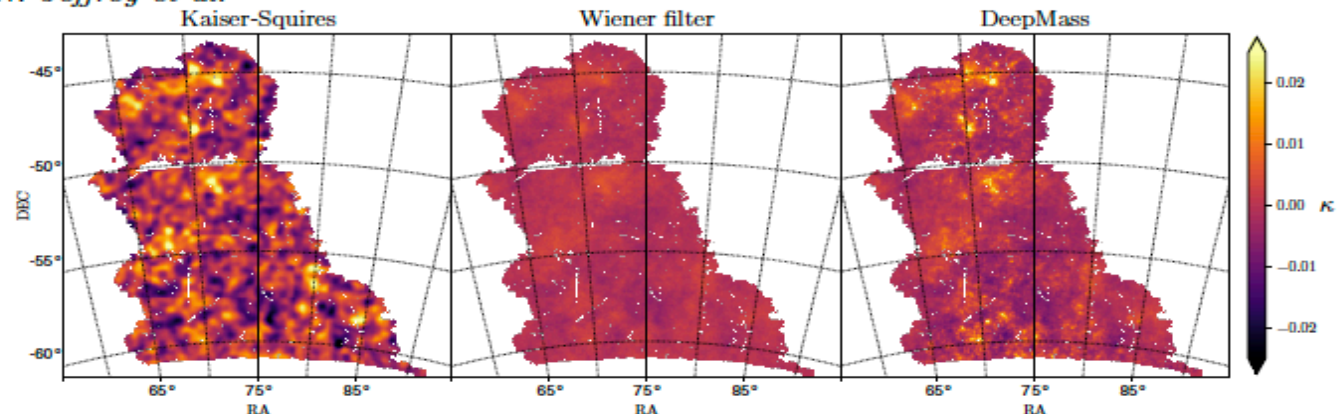


Figure 2. Convergence κ reconstruction from DES SV observational data with: KS, Wiener filtering, and DeepMass.

Sims

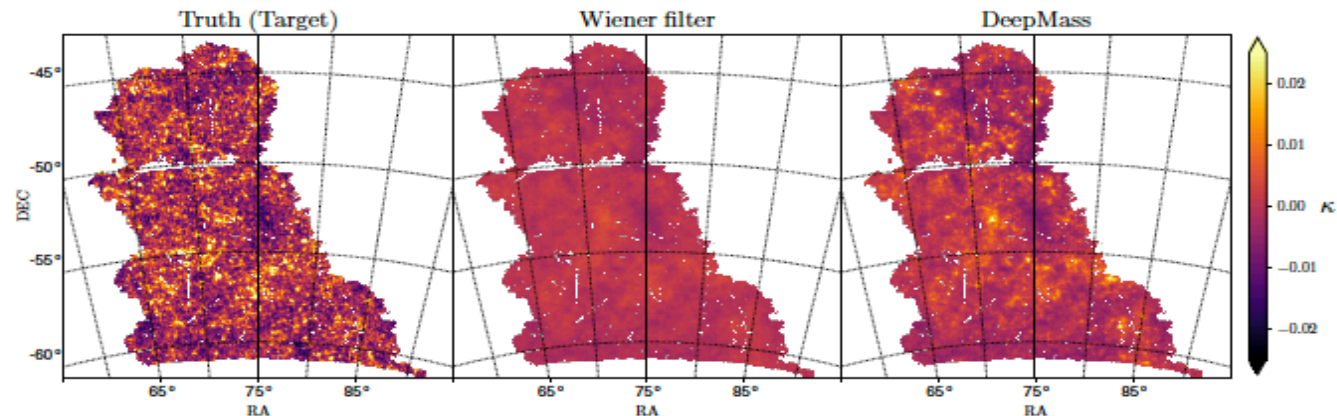
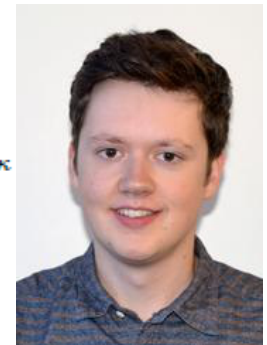


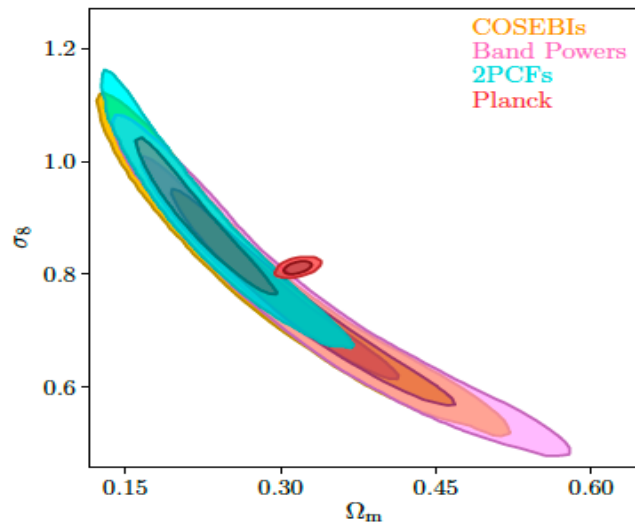
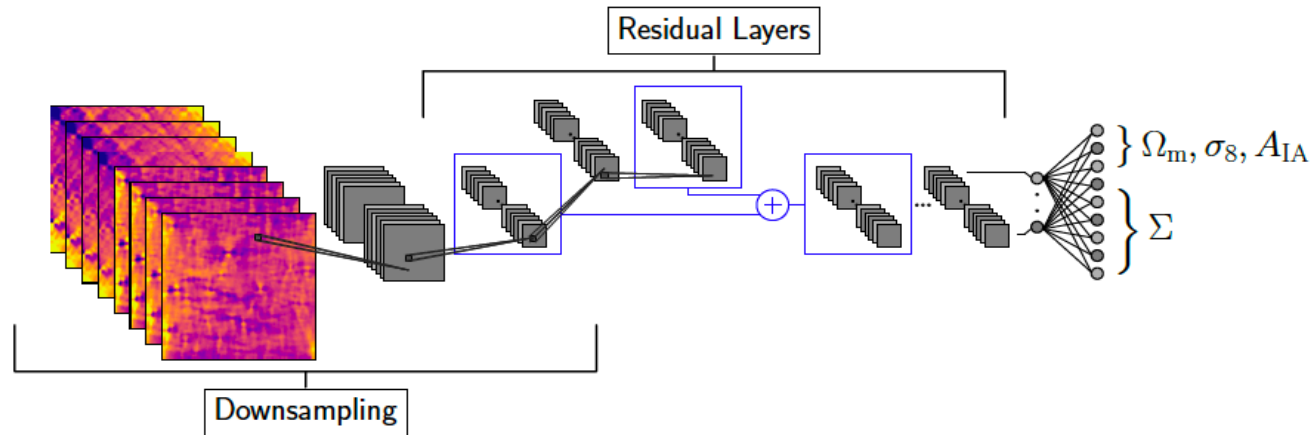
Figure 3. Example L-PICOLA validation simulation (left) and the corresponding Wiener (centre) and DeepMass (right) reconstructions.



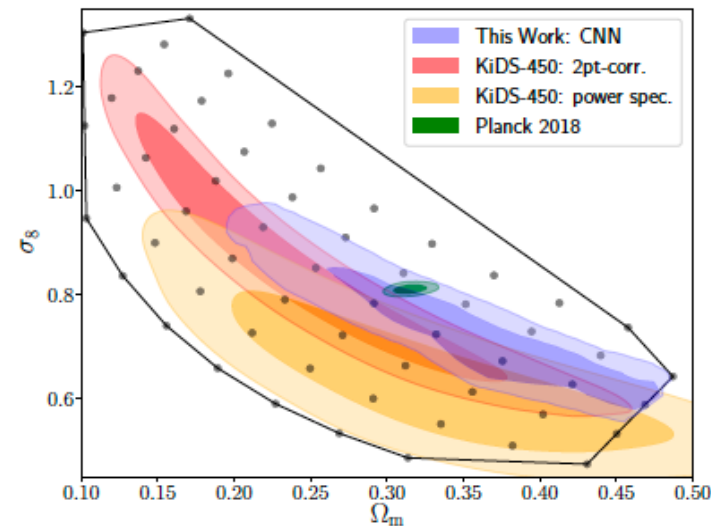
CNN (U-net) trained on 3.6×10^5 simulations
11% improvement in MSE wrt Wiener

Jeffrey, Lanusse, OL, Starck
arXiv:1908.005543

Cosmology from Weak Lensing maps with Deep Learning



Cf. KiDS WL (2007.15633)

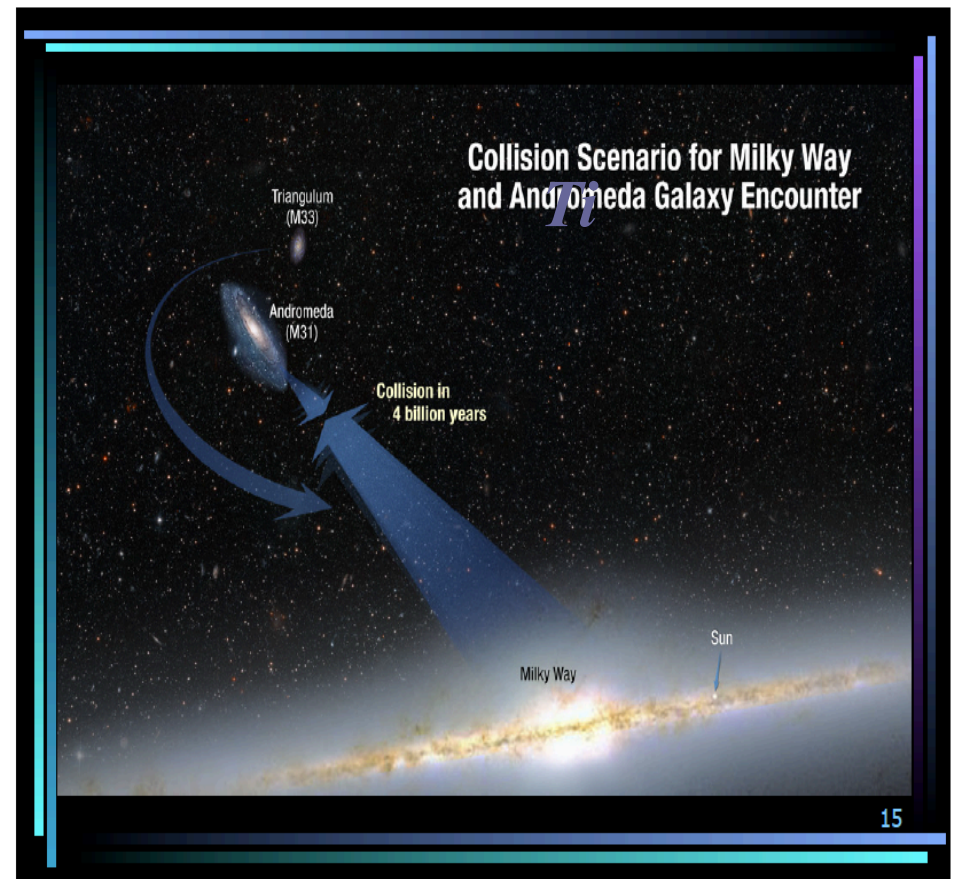


Fluri et al. 1906.03156

AI and Dynamics: The mass of the MW+M31

Approaches for estimating the mass:

- **Timing Argument (2 bodies)**
- **Least Action (all LG galaxies)**
- **Machine Learning +simulations**
- **Likelihood Free Inference (LFI)**
+ **simulations; using DELFI for
density estimation**





Cosmology with 2 galaxies: Weighing the MW+M31 in the presence of Dark Energy

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

- ◆ At present the Milky Way and Andromeda galaxies are separated by $r=770$ kpc and are “falling” towards each other at $v=109$ km/sec.
- ◆ We find from the Timing Argument that the estimated mass is **13%** larger than in the absence of Dark Energy.

Without Λ : Kahn & Waltjer (1959), Lynden-Bell (1981), ...

With Λ : Binney & Tremaine (2008), Partridge, OL & Hoffman (2012), McLeod et al. (2017), McLeod & OL (2020), Benisty et al. (2019)

AI approach

Density Estimation Likelihood Free Inference:

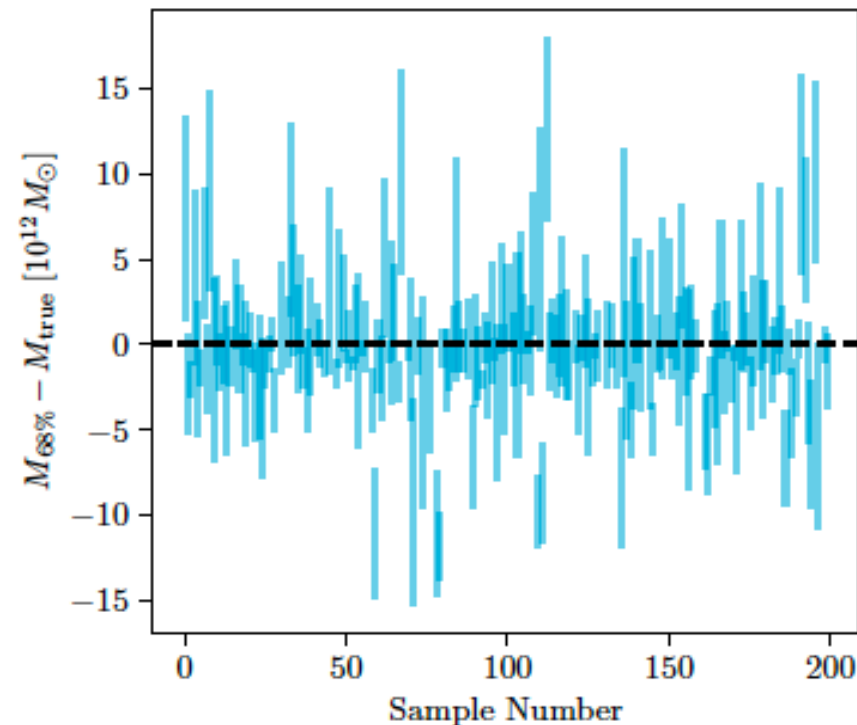
Training on 2M mock pairs; Testing on 10k ‘galaxy’ pairs

$$p(\theta|D_{\text{obs}}, I) = \frac{p(D_{\text{obs}}|\theta, I)p(\theta|I)}{p(D_{\text{obs}}|I)}$$

- **New tangential velocity from Gaia+HST**
- **Checking sensitivity to H_0 etc via analytic model**

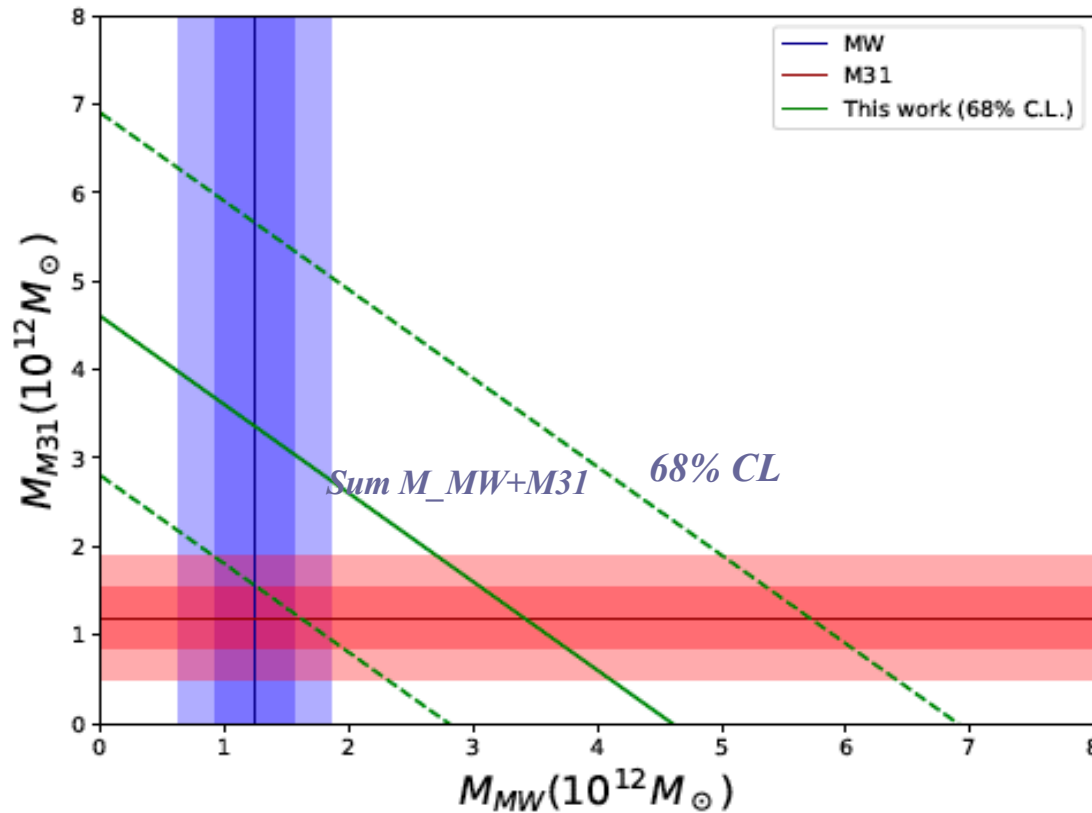


Lemos, Jeffrey, Whiteway, OL, Libeskind, Hoffman
(*arXiv:2010.08537*)



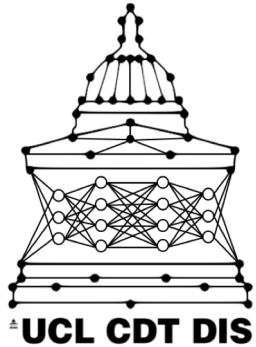
Masses of MW, M31
and their sum (from LFI):

$$M = 4.6^{+2.3}_{-1.8} 10^{12} M_{\odot}$$



The other AI: Augmented Intelligence

- ◆ Cognitive technology is designed to enhance human intelligence rather than replacing it.
- ◆ It reinforces the role human intelligence plays when using machine learning and deep learning algorithms to discover relationships and solve problems.



UCL CDT in Data Intensive Science

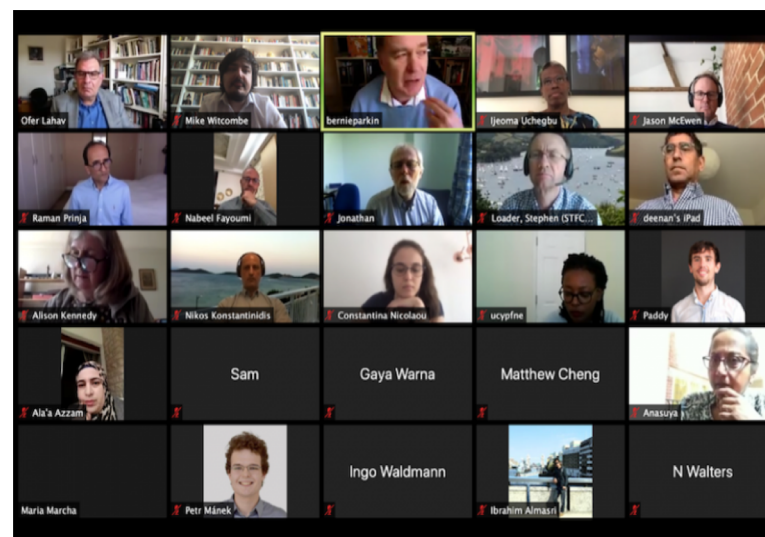
<http://www.hep.ucl.ac.uk/cdt-dis/>



*2017, 2018, 2019 & 2020 cohorts:
45 CDT PhD students at UCL*

Newton Fund UCL-Jordan

- ◆ The programme supports building Jordanian capacity in data science.
- ◆ Remote Machine Learning course (by Jason McEwen) for 46 students (62% female)



Launch event on
24 April 2020

Cosmology with AI/ML

- ◆ Cosmology is undergoing 'industrial revolution'
- ◆ In both spatial and time domains

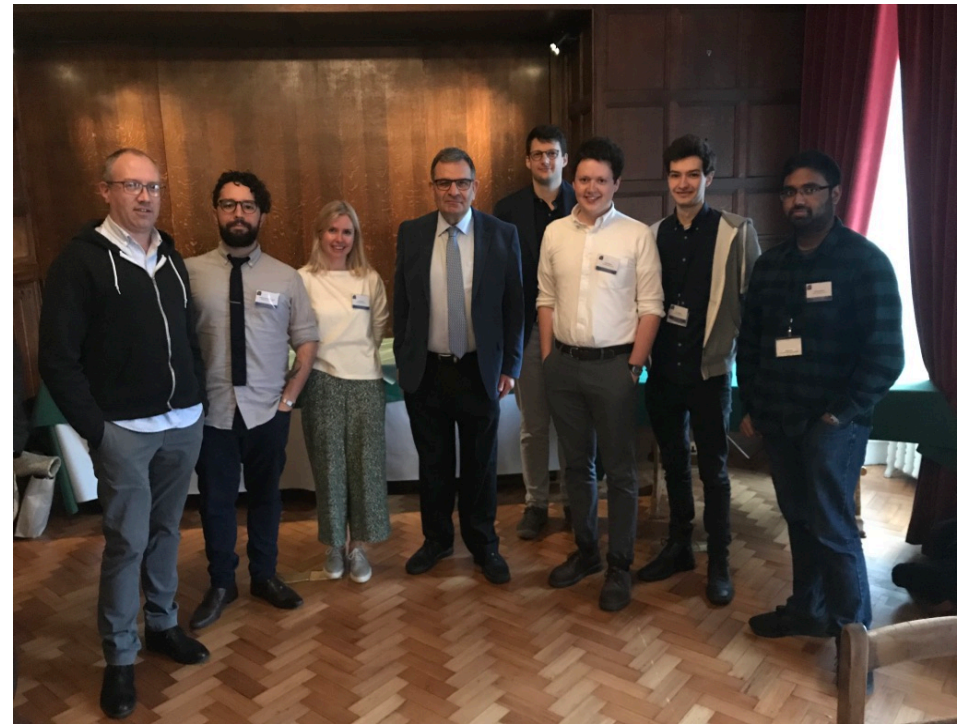
Challenges:

- ◆ Incomplete training sets and augmentation
- ◆ Incorporating physics
- ◆ Understanding/explaining/interpreting algorithms (esp Deep Learning)
- ◆ Benchmarking and up-scaling of algorithms to exa-scale (e.g. BASE)

- ◆ Great training of PhDs and Post-docs, beyond academia

- ◆ Will AI produce better knowledge?
(well, it depends in part on Nature...)

Credits and many thanks
to my mentors, collaborators,
Post-docs and
PhD students



Cumberland Lodge, Windsor (April 2019)