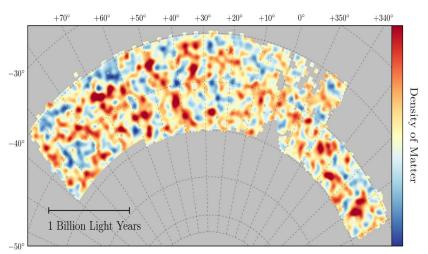
Darkness Visible: AI in Cosmological Experiments

Ofer Lahav (University College London)





DES mass map from weak lensing





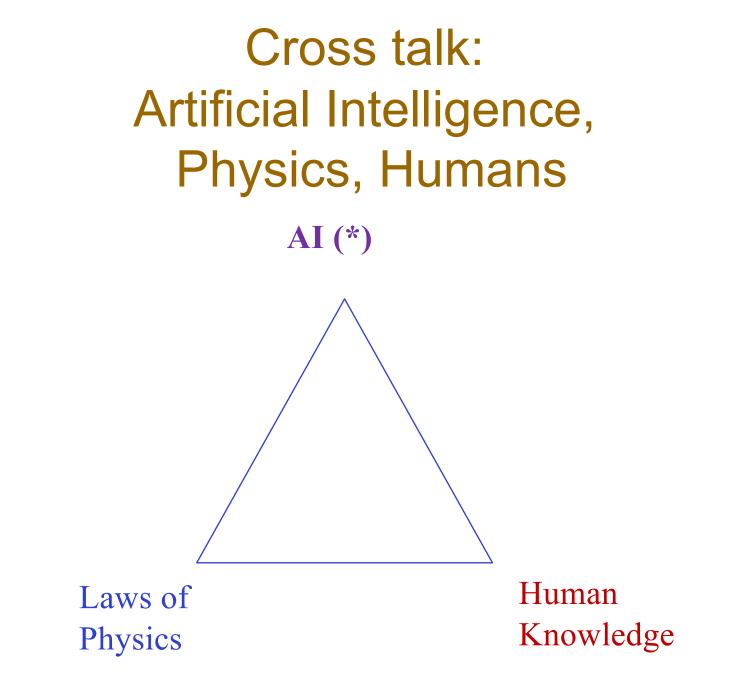




Outline

- 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)



(*) Actually better as "Augmented Intelligence"

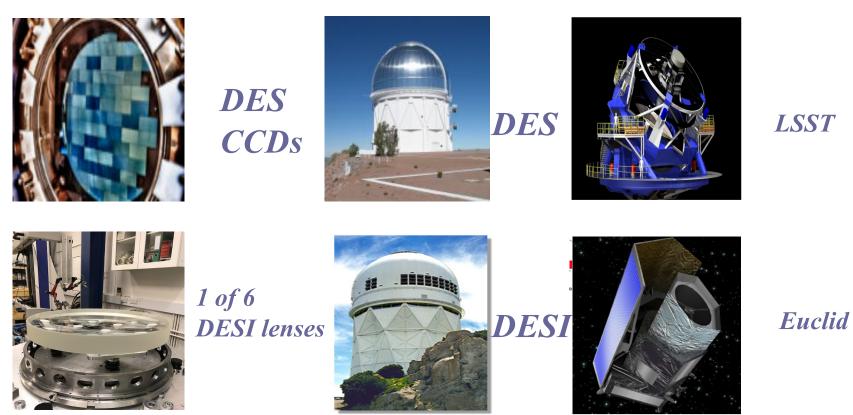


Big Data in Astronomy



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



Mayall 4-Meter Telescope



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 la
- 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

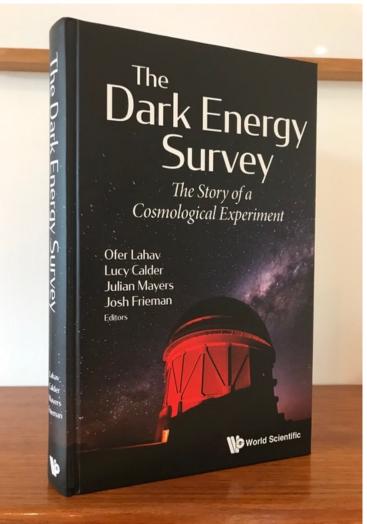


The DES book

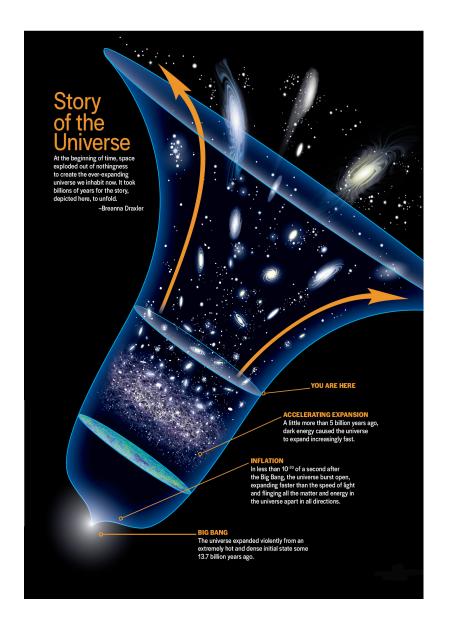


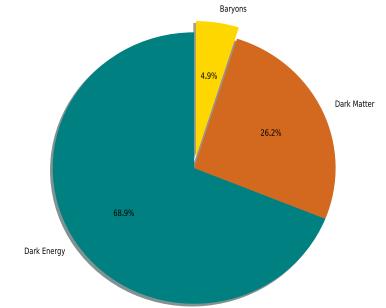
- Published by World Scientific (September 2020)
- 27 chapters in 4 sections: Building DES, DE science, non-DE, Reflections
- 88 co-authors
- Virtual book launch held on on 13 Oct 2020 (recording on YouTube)





Is Dark Energy "just" A?





142 Sitzung der physikalisch-aathematischen Küsse vom 8. Februar 1917

Kosmologische Betrachtungen zur allgemeinen Relativitätstheorie.

Von A. Einstein.

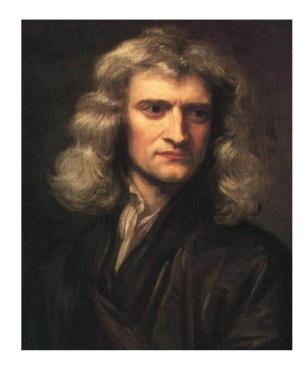
Es ist wohlbekannt, daß die Poissonsche Differentialgleichung $\Delta \phi = 4\pi K \epsilon$

(1)

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



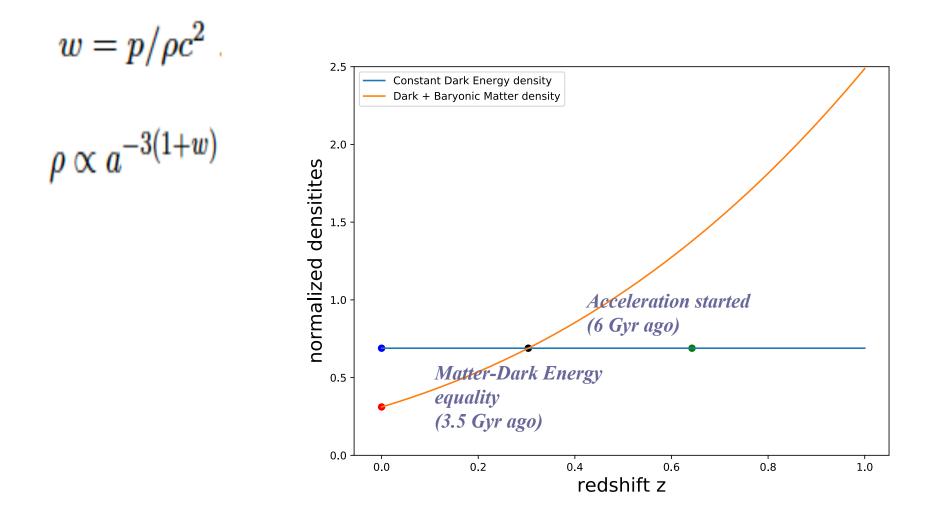
"I have now explained the TWO principle cases of attraction...which is very remarkable." Isaac Newton, Principia (1687)

"Introducing A - the blunder of my life..." Albert Einstein (1920s)

"I am a detective in search for a criminal - A." Arthur Eddington (1920s)



The evolution of densities

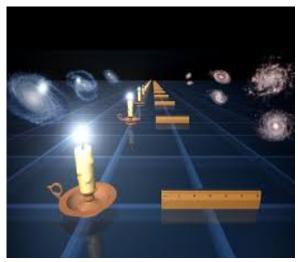


OL, Contemporary Physics, arXiv:2009.10177

Probes of Dark Energy

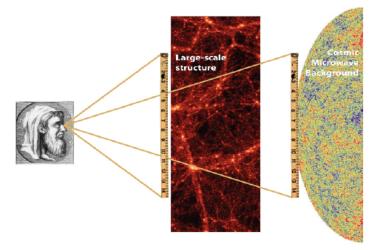
Standard candles

Standard rulers

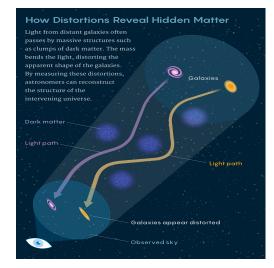


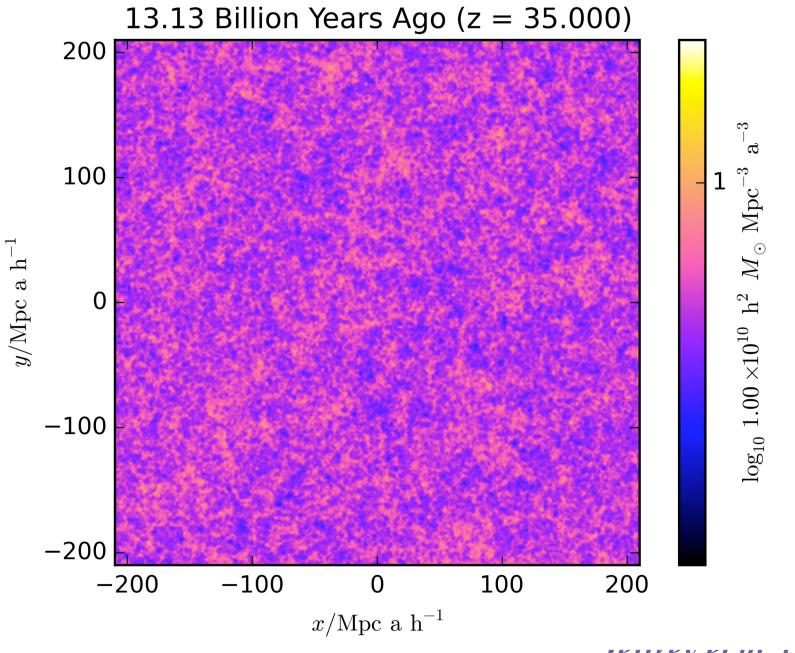
Clusters





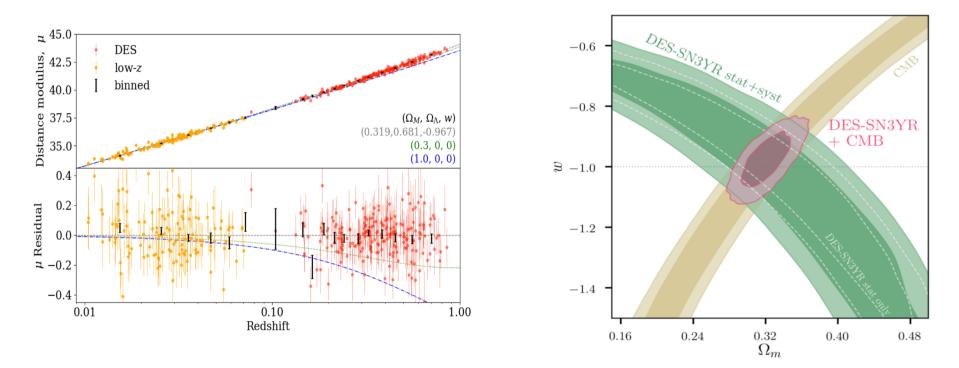
Gravitational Lensing





уејјгеу ег ш. (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)

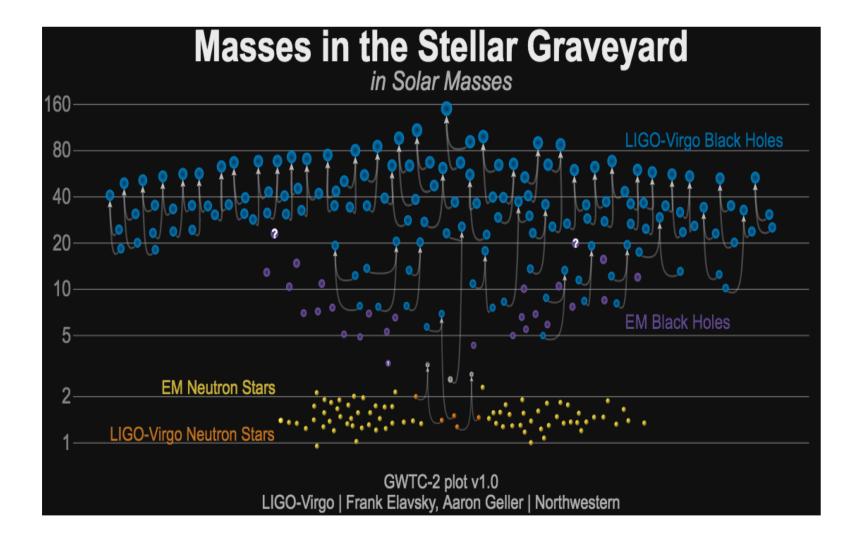
Blinding to overcome confirmation bias

Health checks of LCDM

"Tensions" –

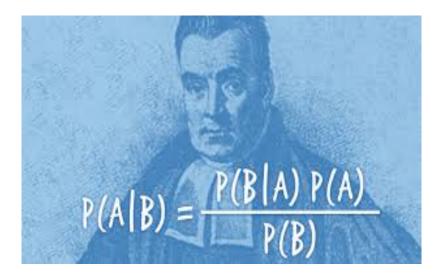
- Systematic errors in data, or new Physics?
- * Hubble Constant tension (~4 sigma)
- $H_0 = 74.0 \pm 1.4 \text{ km/sec/Mpc}$ (Riess et al. 2019)
- $H_0 = 67.4 \pm 0.5$ (Planck 2018)
- A new approach: Gravitational Wave sirens
- $H_0 = 68.6 \pm 11$ (Bright; Nicolaou et al. 2020)
- $H_0 = 72.0 \pm 10$ (Dark + Bright; Palmese et al. 2020)
- * Clumpiness σ_8 (WL vs CMB) (~2 sigma)

Gravitational Wave events

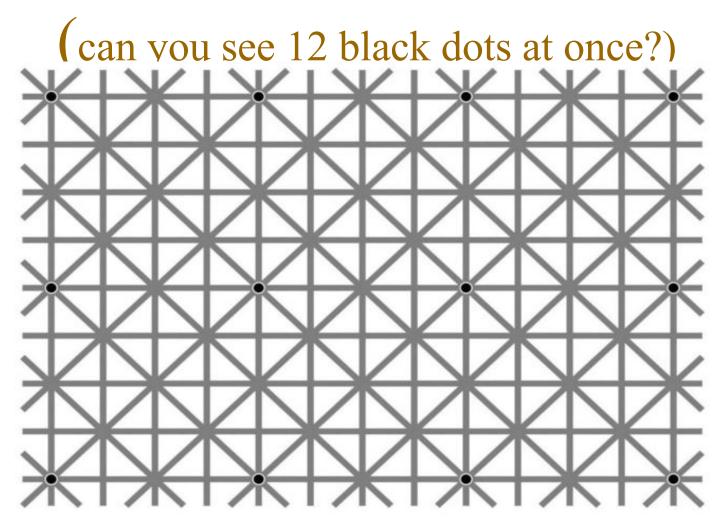


Cosmology with AI and connection to traditional statistics

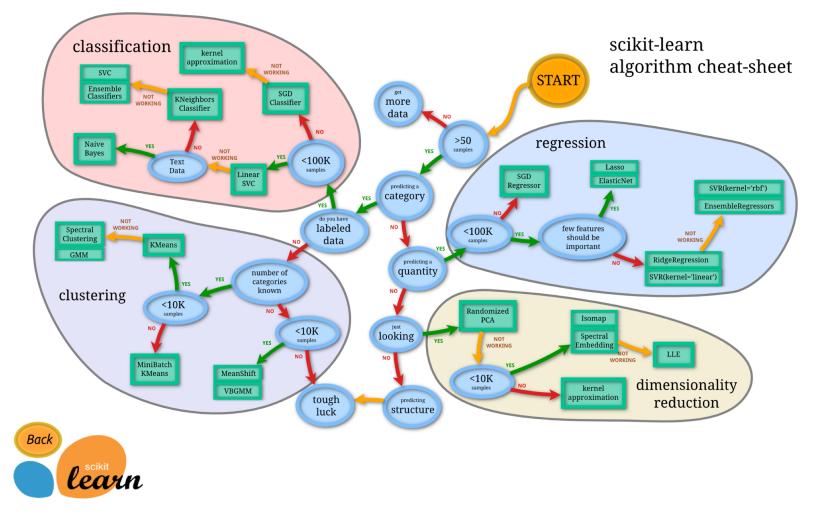
- Is AI/ML a black box?
- Can we explain/interpret it?
- How to minimise biases due to incomplete training sets?
- Can we include prior Physics?
- Can we learn new Physics?

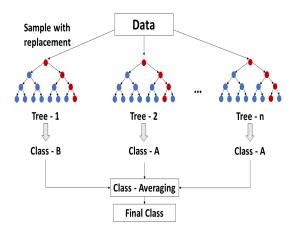


Can we trust just the human brain?

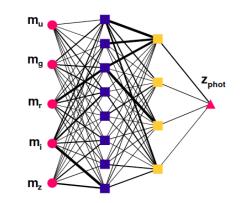


Machine Learning open sources





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)

TAGGING B'S WITH A NEURAL NETWORK

Sikos Konstantinidis*

nuary 1993

Abstract The training and performance of a feed-forward neural network for B-tagging are discussed in this report. The results are compared with the present status, and look very promising, giving an efficiency of the order of 70% with a high level of purity (well above 85%).

1 B-tagging: The present status

At present, the most popular way to obtain a clean sample of B events is to use the high-p₁ lepton tagging (fig. 1). Unfortunately, semileptonic decays make up only a small fraction of the B decays (approx. 14%) and therefore this is not a very efficient way to tag B's. Clearly, efficiency and purity are two quantities in conflict. One may be able to obtain a very clean sample of B events, but in such a case the efficiency drops significantly, and vice-verses. Thus, the optimal solution is always dependent on the particular problem one has to deal with. In general, both conventional methods [1, 2] and neural network techniques [3, 4] reach a maximum of 70% efficiency for 20% contamination.

general, both conventional methods [1, 2] and neural network techniques [3, 4] reach a maximum of 70% efficiency for 30% contamination. Before moving on, we give, for completeness, the definitions of the three quanthies which have already been mentioned above, used to describe the network's (as well as any other method's) performance:

mail N.KONSTANTINGVI PH.IC.AC.UK

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

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Galaxies, Human Eyes, and Artificial Neural Networks

Info & Metrics

O. Lahav², A. Nalm², R. J. Buta², H. G. Corwin², G. de Vaucouleurs⁴, A. Dressler⁵, J. P. Huchra⁶, S. van den Bergh⁷, S. Ra... • See all authors and affiliations

Science 10 Feb 1995: Vol. 267, Issue 5199, pp. 859-862 DOI: 10.1126/science.267.5199.859

Article

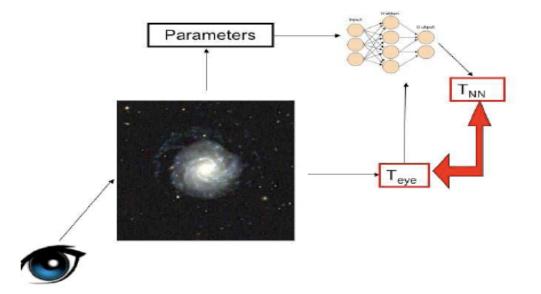
eLetters

PDF

Abstract

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

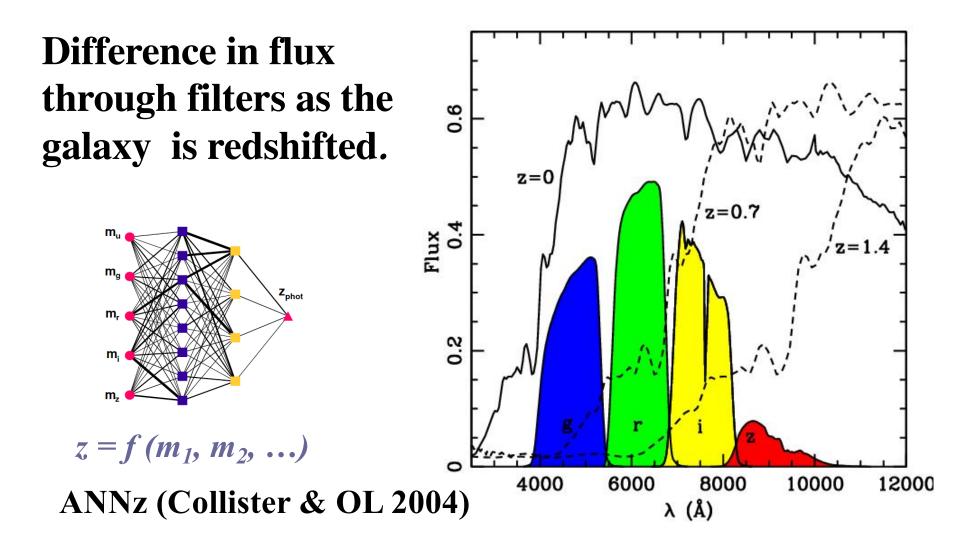
Galaxy zoo and machine learning



		GALAXY ZOO		
		Elliptical	Spiral	Star/Other
Α	ELLIPTICAL	91%	0.08%	0.5%
Ν	SPIRAL	0.1%	93%	0.2%
Ν	STAR/OTHER	0.3%	0.3%	96%

Banerji, OL et al. (0908.2033) Cf. OL. Naim et al. (1995)

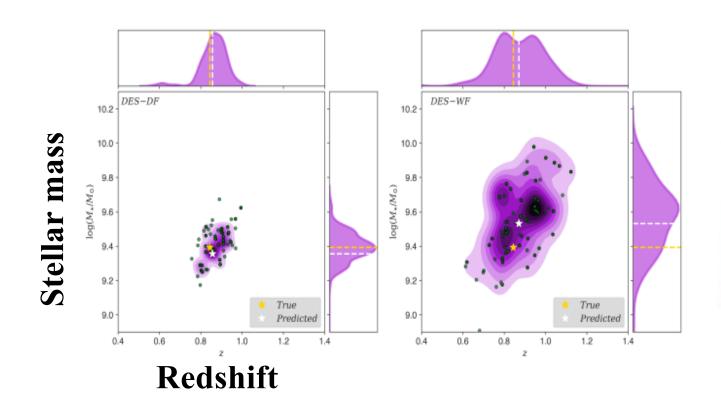
Photometric redshift



A dozen or so templae and ML methods are now available

22

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

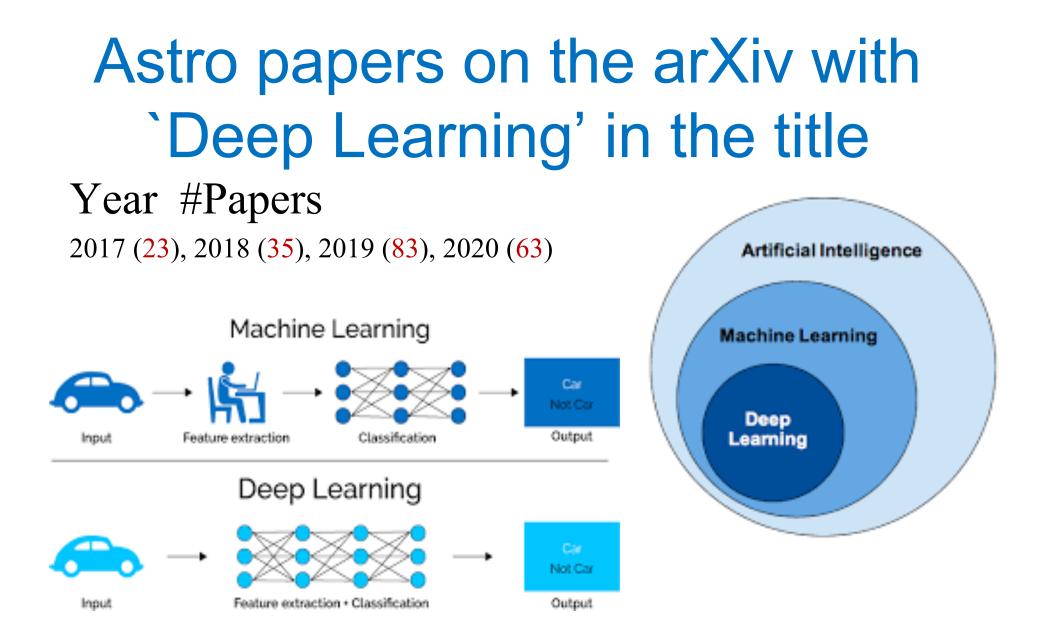




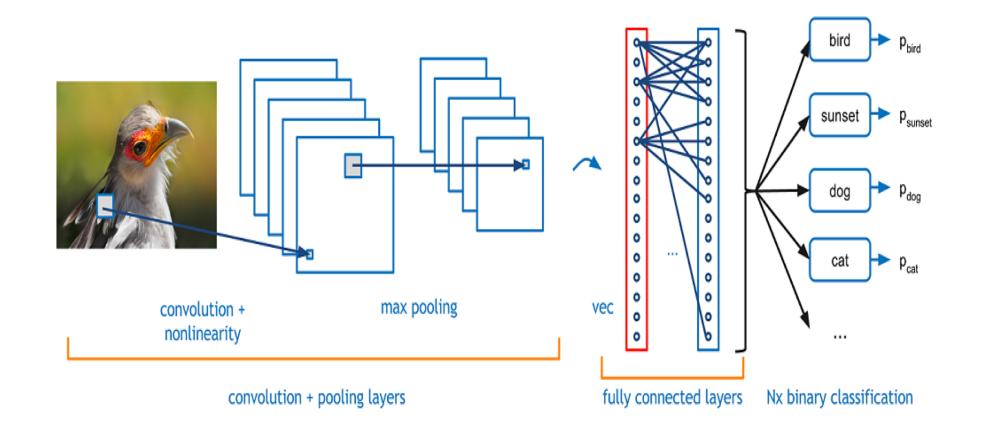


Mucesh, Hartley,OL, Palmese et al.(in prep)23

Gold-true; White-predicted



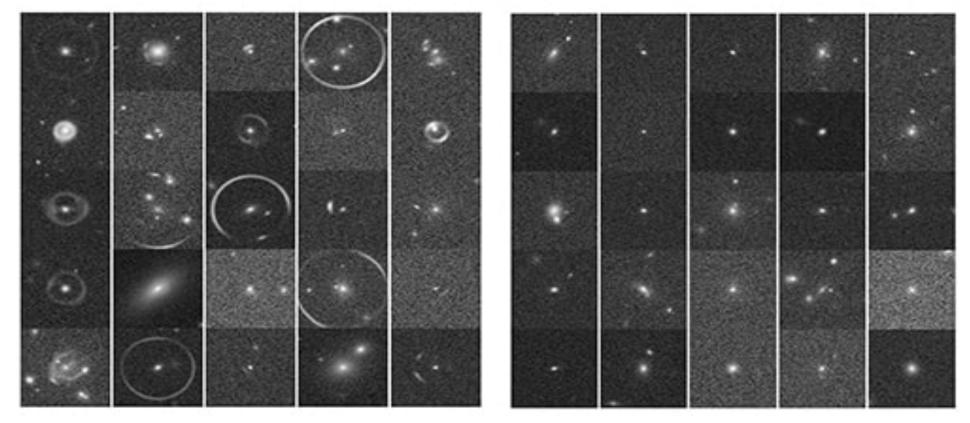
Deep Learning: Do we understand it?



CMUDeepLens (Lanusse et al. 1703.02642)

Mocks with arcs

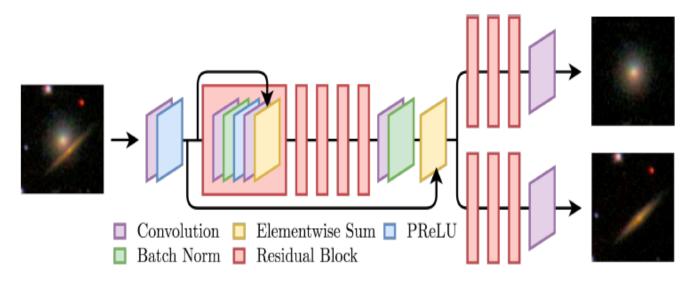
Mocks without arcs



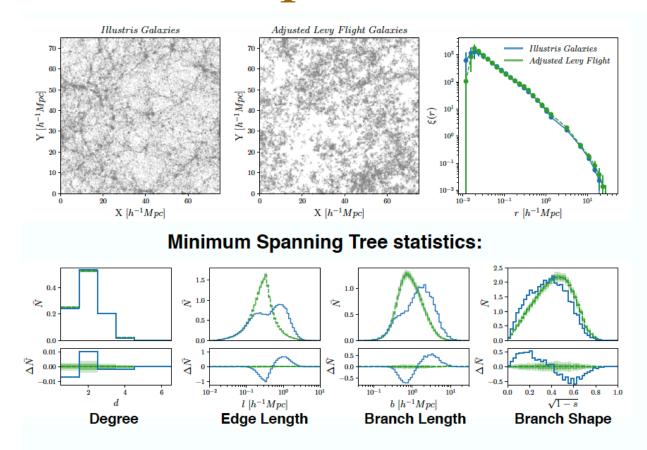
Expected in LSST: about one million strongly lensed galaxies out of an estimated 20 billion galaxies. The approach: supervised Convolutional Neural Networks. Completeness of 90% can be achieved.

de-blending of galaxy images

4 D. M. Reiman and B. E. Göhre



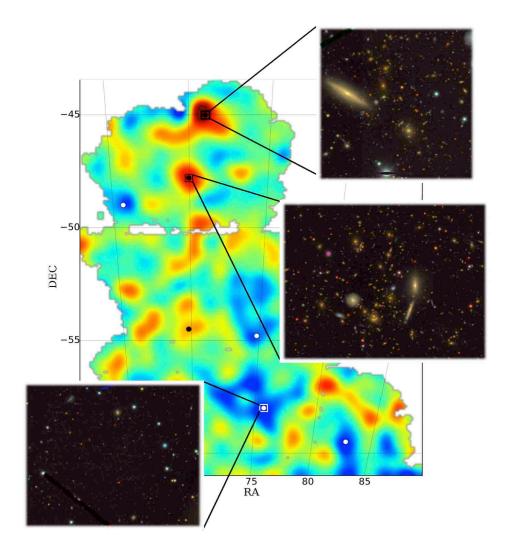
Minimum Spanning Tree vs. 2pt statistic





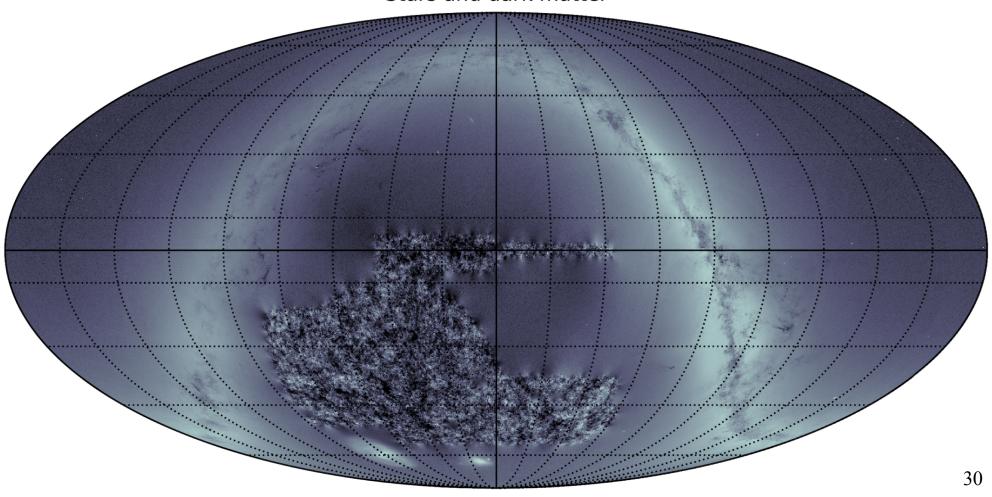
Naidoo, Whiteway, ...OL et al. (1907.00989)

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 $\gamma = A\kappa + n$ Deep Learning mass reconstruction ('DeepMass')

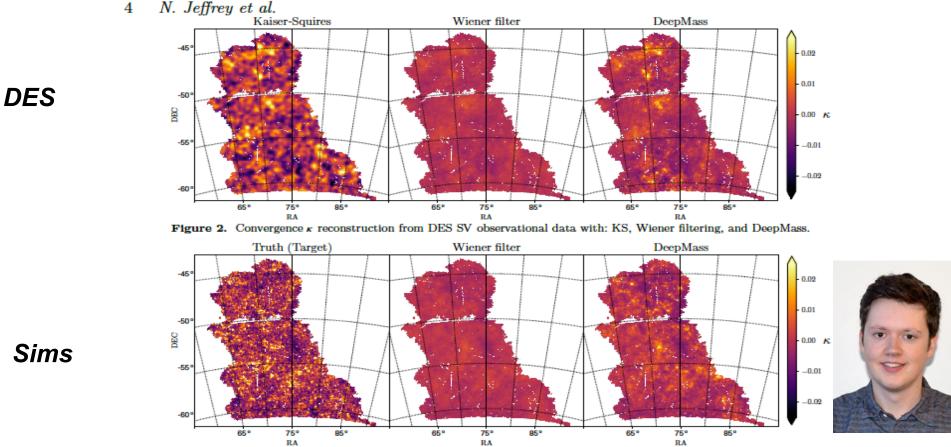
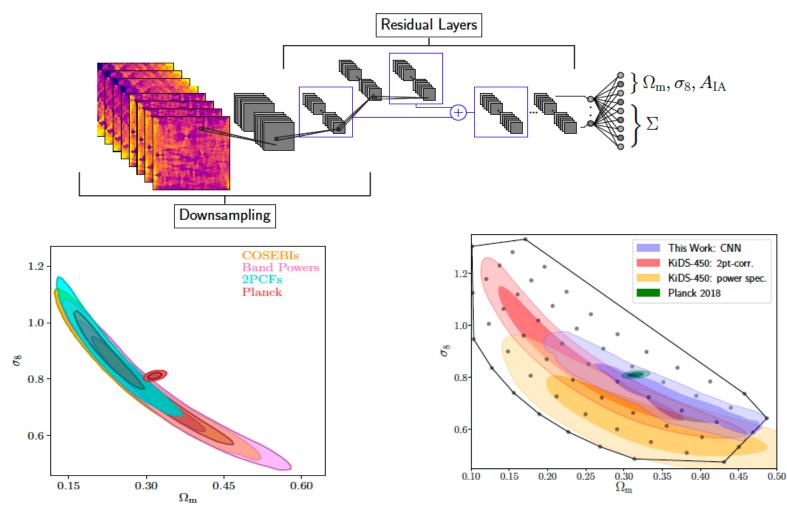


Figure 3. Example L-PICOLA validation simulation (left) and the corresponding Wiener (centre) and DeepMass (right) reconstructions.

CNN (U-net) trained on 3.6x10⁵ simulations 11% improvement in MSE wrt Wiener

Jeffrey, Lanusse, OL, Starck ³¹ 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.

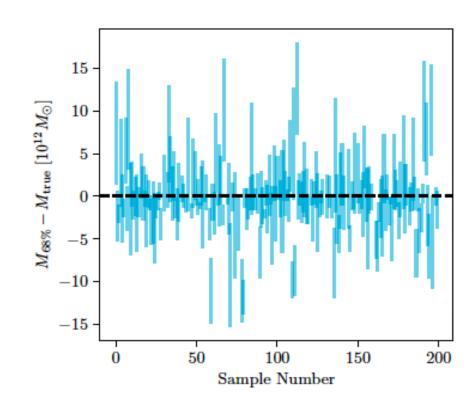
Without Λ: Kahn & Waltjer (1959), Lynden-Bell (1981), ...
With Λ: Binney & Tremaine (2008), Partridge, OL & Hoffman (2012), McLeod et al. (2017), McLeod & OL (2020), Benisty et al. (2019)

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

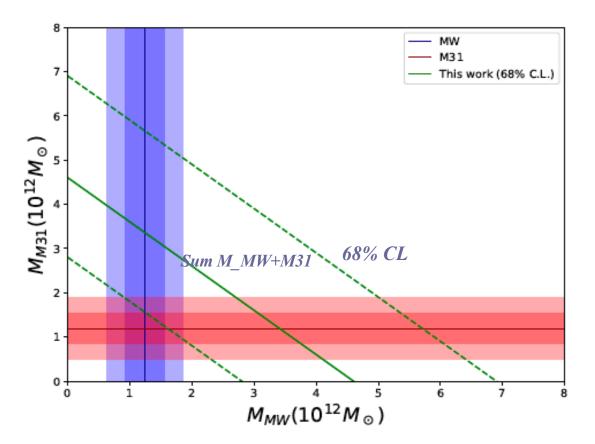
- Checking sensitivity to H₀ etc via analytic model





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

Masses of MW, M31 and their sum (from LFI): $M = 4.6^{+2.3}_{-1.8} \ 10^{12} M_{\odot}$

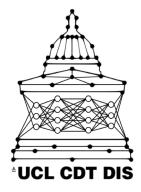


Lemos et al. (in prep)

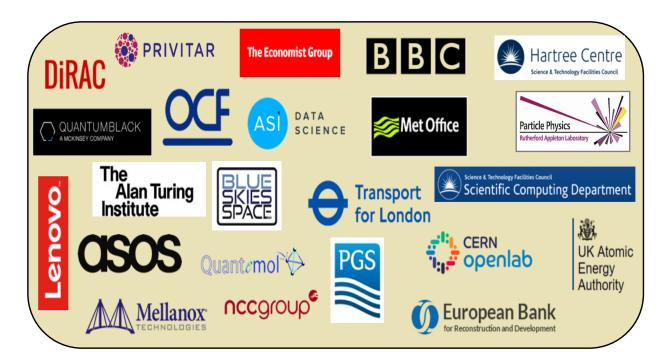
*Cf. ML approach (McLeod et al. 2017)*³⁶

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 <u>machine learning</u> and <u>deep</u> <u>learning</u> algorithms to discover relationships and solve problems.



UCL CDT in Data Intensive Science http://www.hep.ucl.ac.uk/cdt-dis/





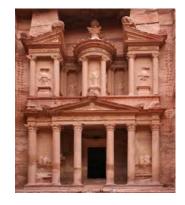
AUC



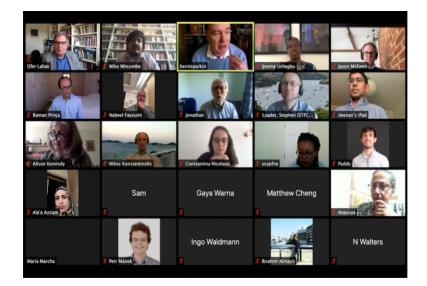
2017, 2018, 2019 & 2020 cohorts: 45 CDT PhD students at UCL

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)