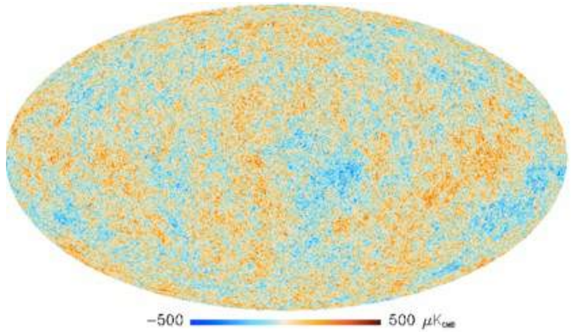
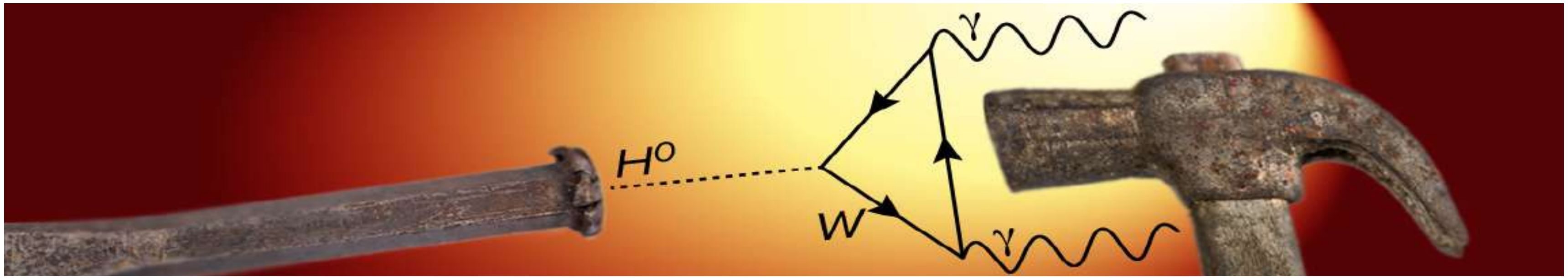
Artificial Intelligence and Machine Learning in Astronomy

Ofer Lahav (UCL)





UCL

UCL CDT DIS

Science & Technology Facilities Council

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Introduction card

Ofer Lahav

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Co-Director, Center for Doctoral Training
in Data Intensive Science
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https://www.ucl.ac.uk/astrophysics/professor-ofer-lahav

My research:

- Galaxy surveys: DES, DESI, LSST, ...
- Dark Matter, Dark Energy, Neutrino Cosmology
- Machine Learning for Astrophysics problems

My expertise is:
-Galaxy classification
-Photometric redshifts
-Galaxy and mass map reconstruction
-Parameter estimation

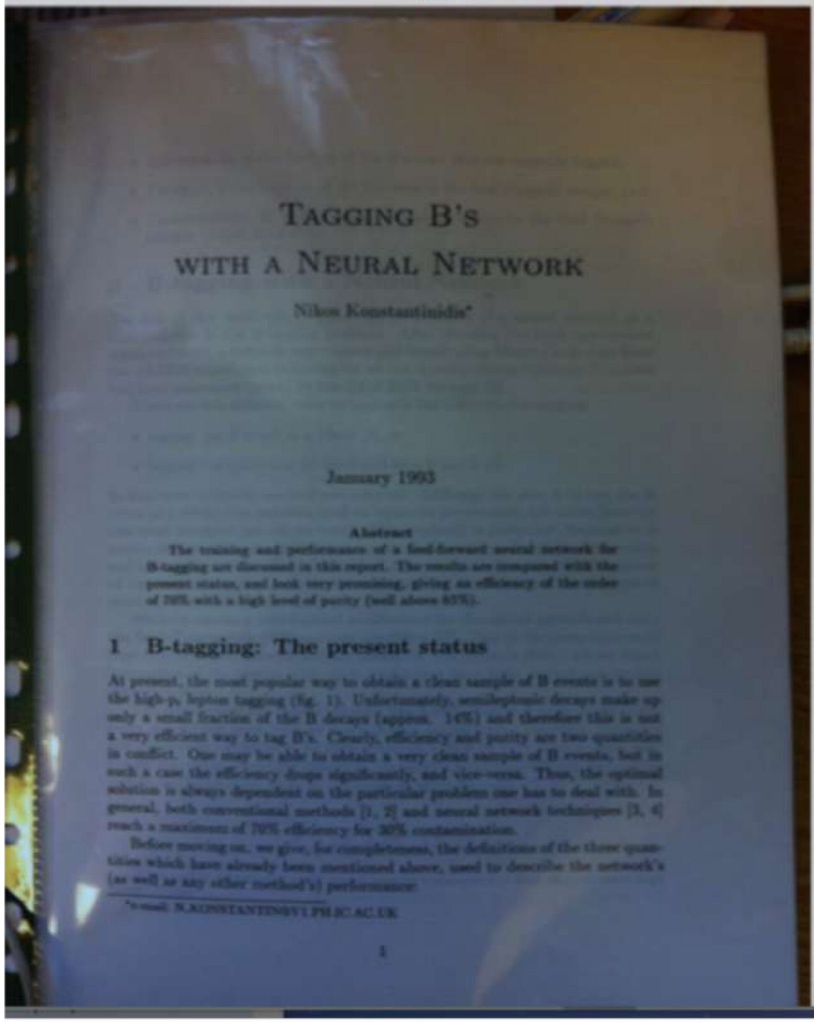
A problem I'm grappling with:
- Incorporating prior physics into algorithms

I've got my eyes on:
- Deep Learning
- Augmentation

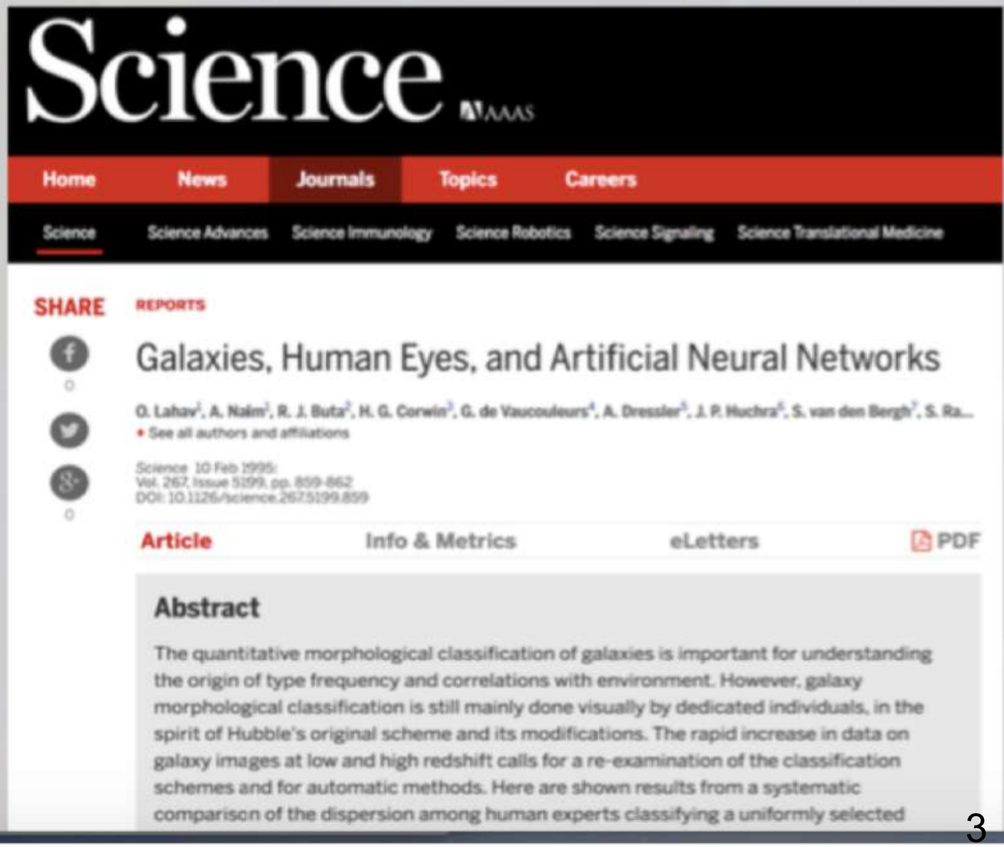
I want to know more about:
-How to interpret what Deep Learning algorithms are actually doing?

Artificial Neural Networks: early days

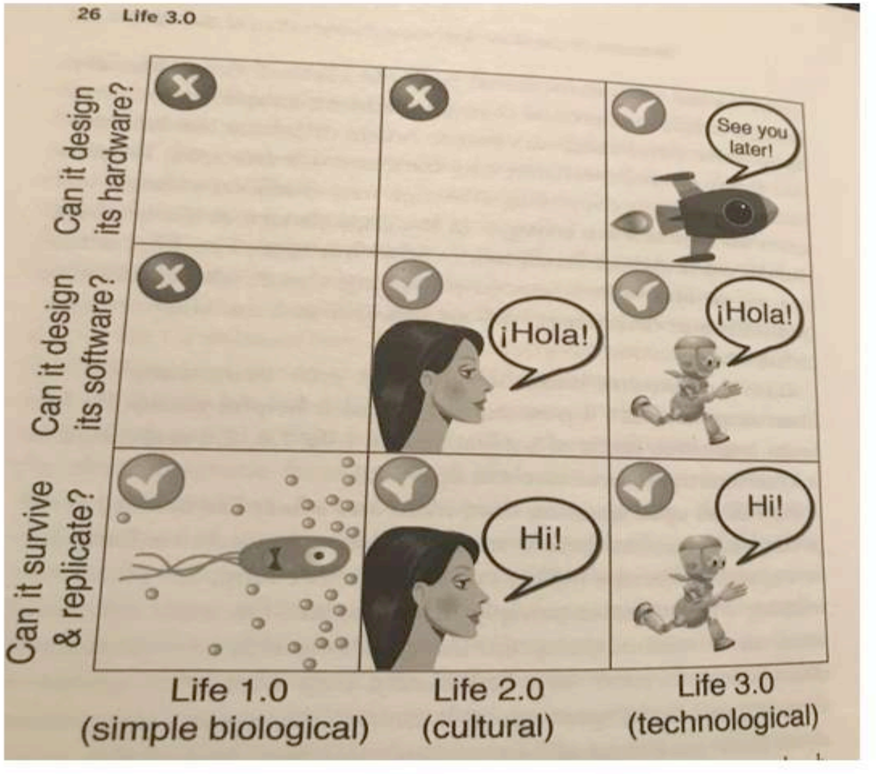
NK's 1st term PhD report (Jan 1993)



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



Life 3.0



Tegmark’s book (2018)

What is ‘Big Data’?

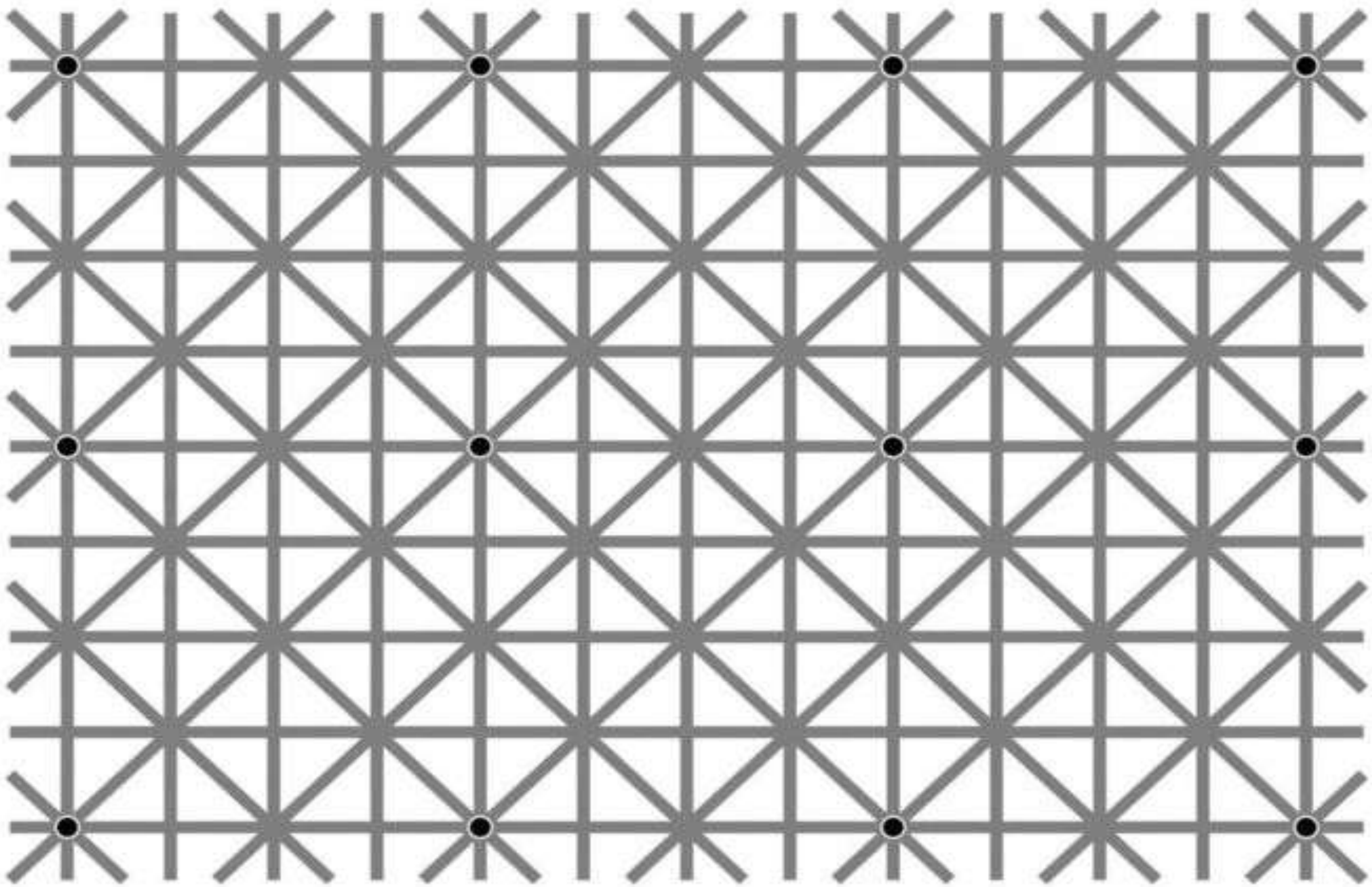
- Wikipedia’s definition: “data sets that are so large or complex that TRADITIONAL data processing applications are inadequate to deal with them”.

- Clearly, this is a ‘moving target’.

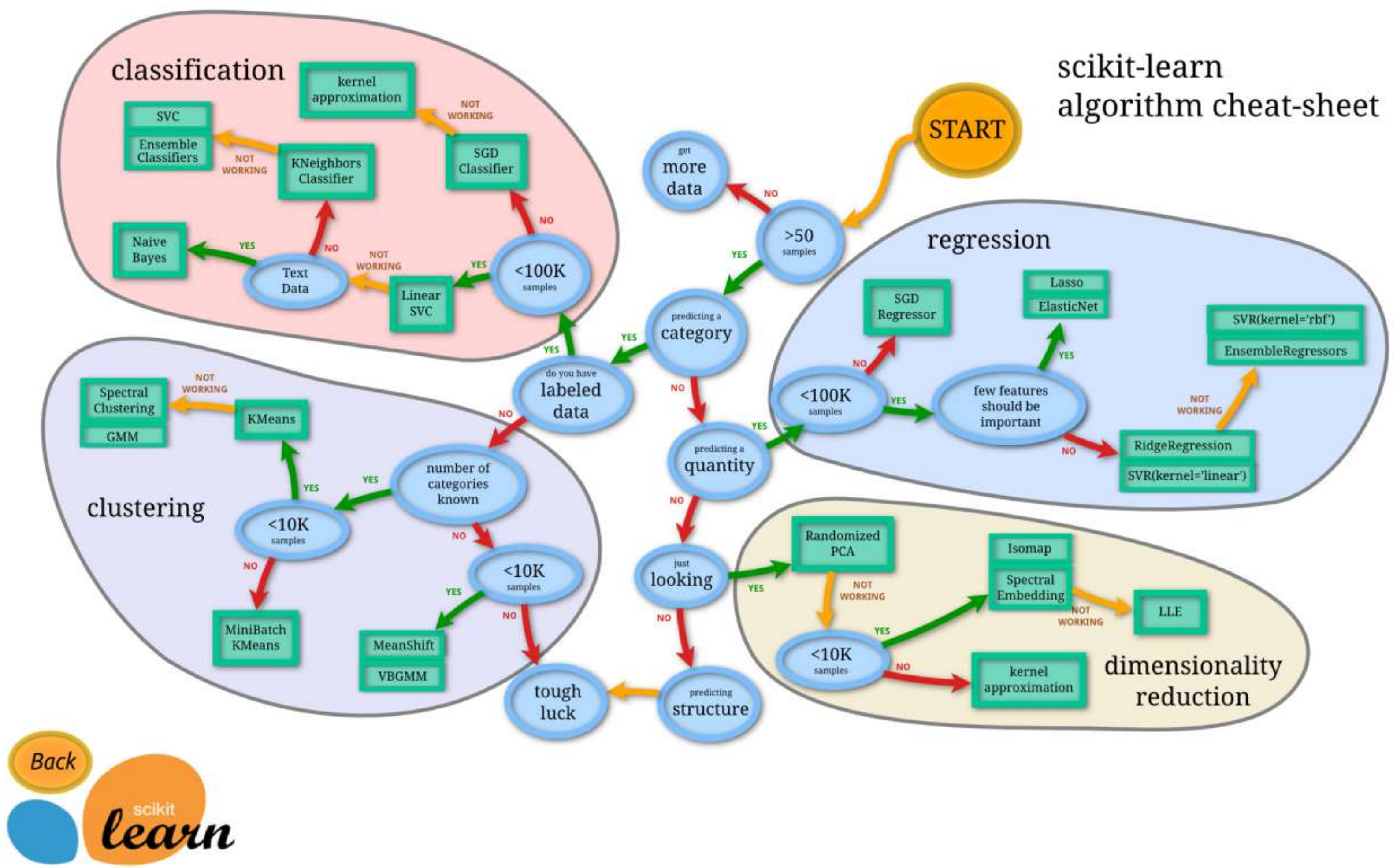
- "Big data is high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization.” (Gartner)

Can we trust just the human brain?

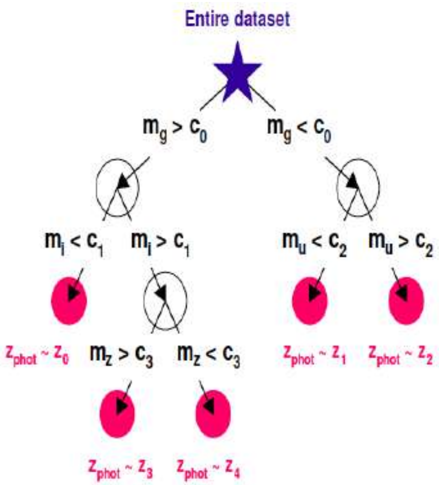
(can you see 12 black dots at once?)

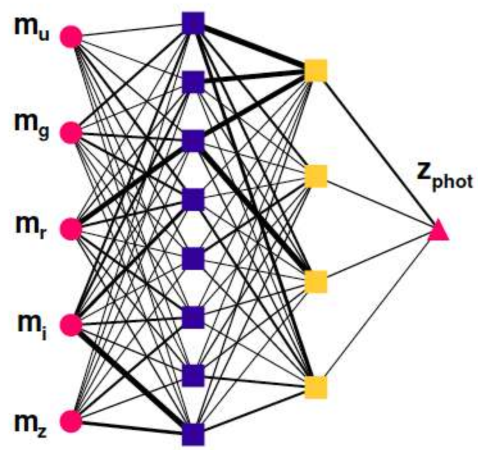


Machine Learning



Machine Learning Methods

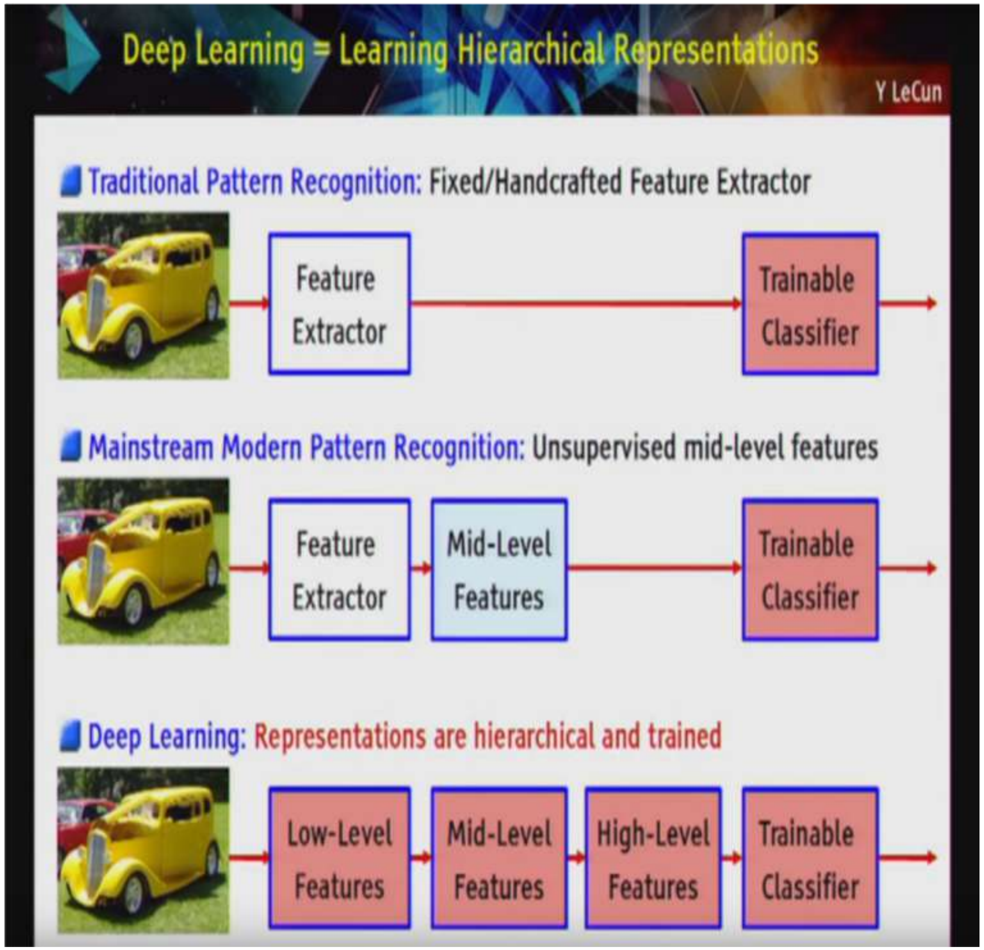


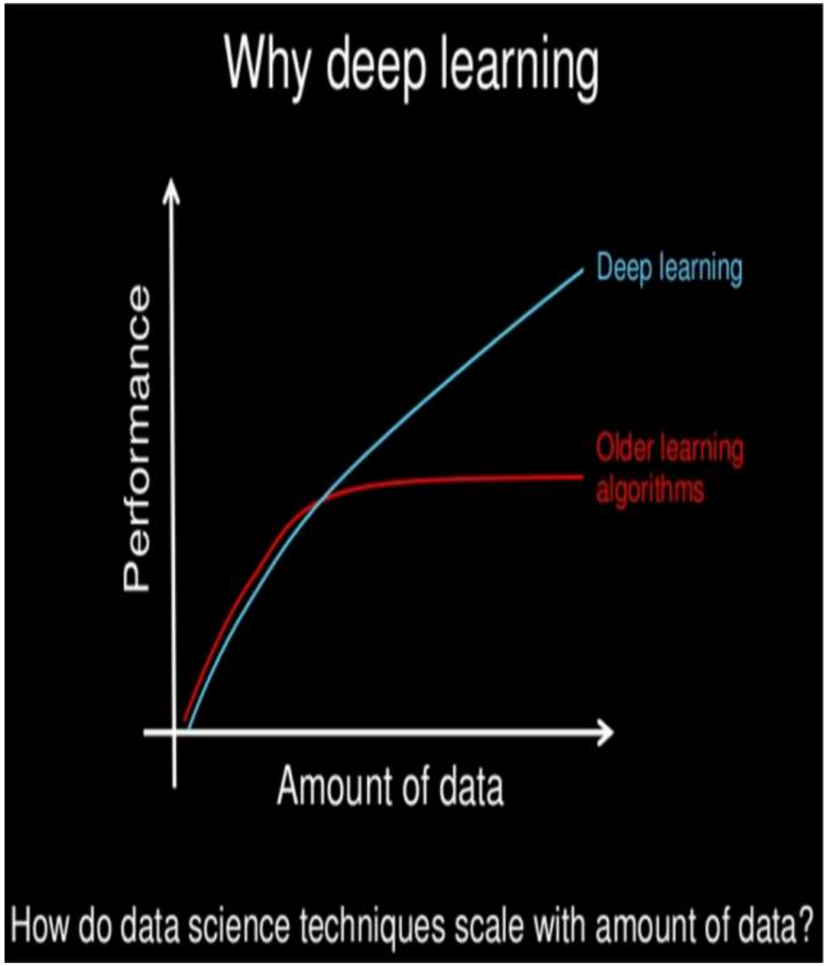


Decision Trees

Artificial Neural Networks

On a Deep Learning Curve…

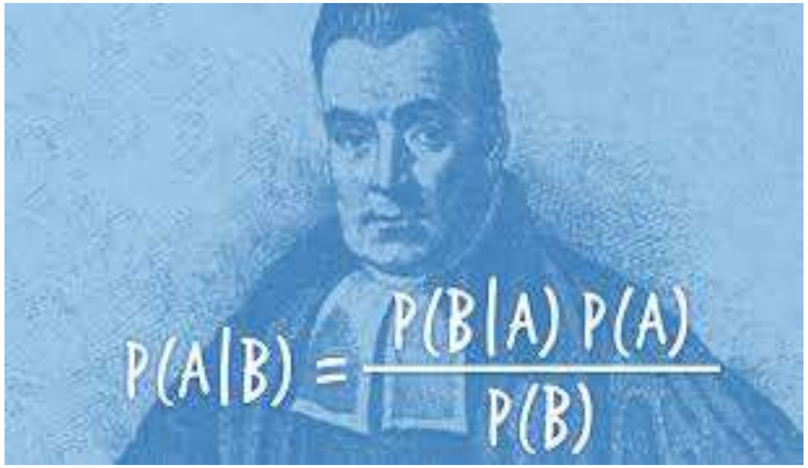


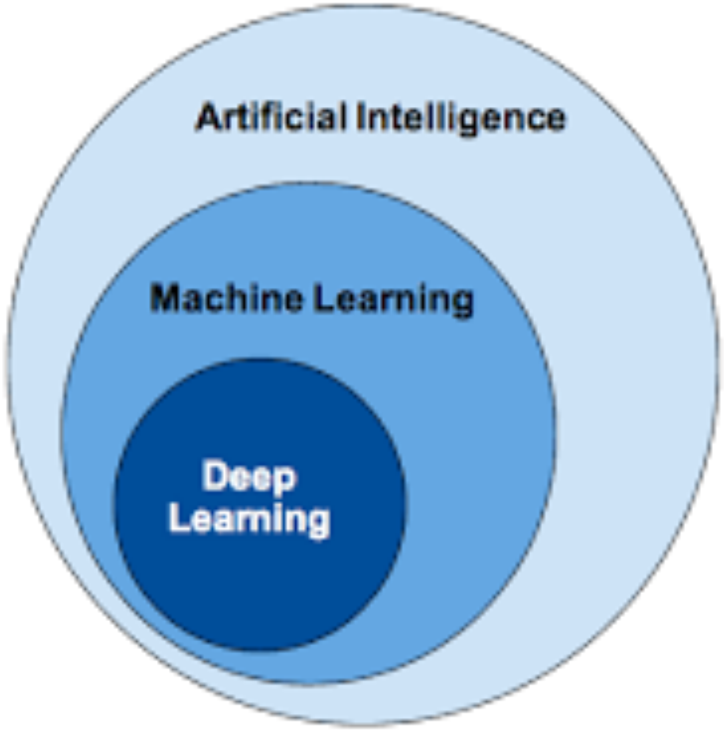


credit:Y. LeCun

credit: A. Ng

Artificial Intelligence, Machine Learning, Deep Learning: are they ‘explainable’ ?

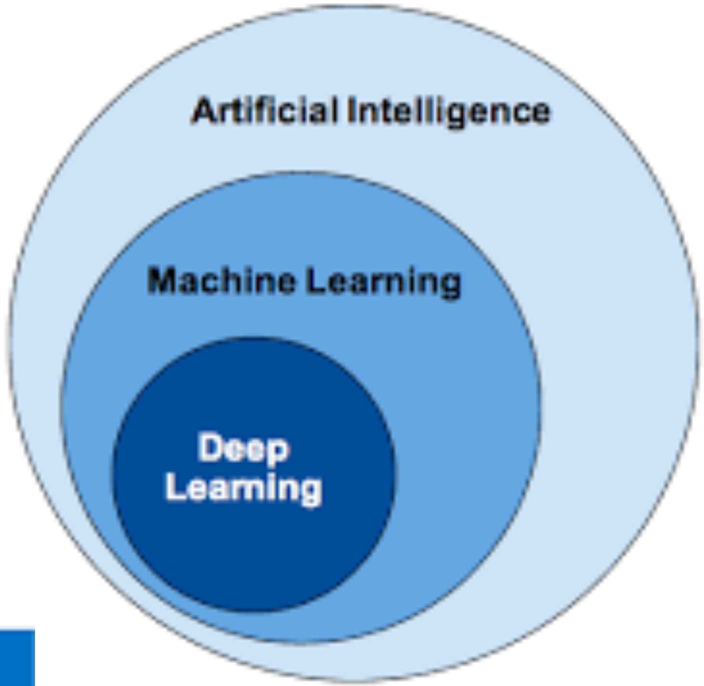


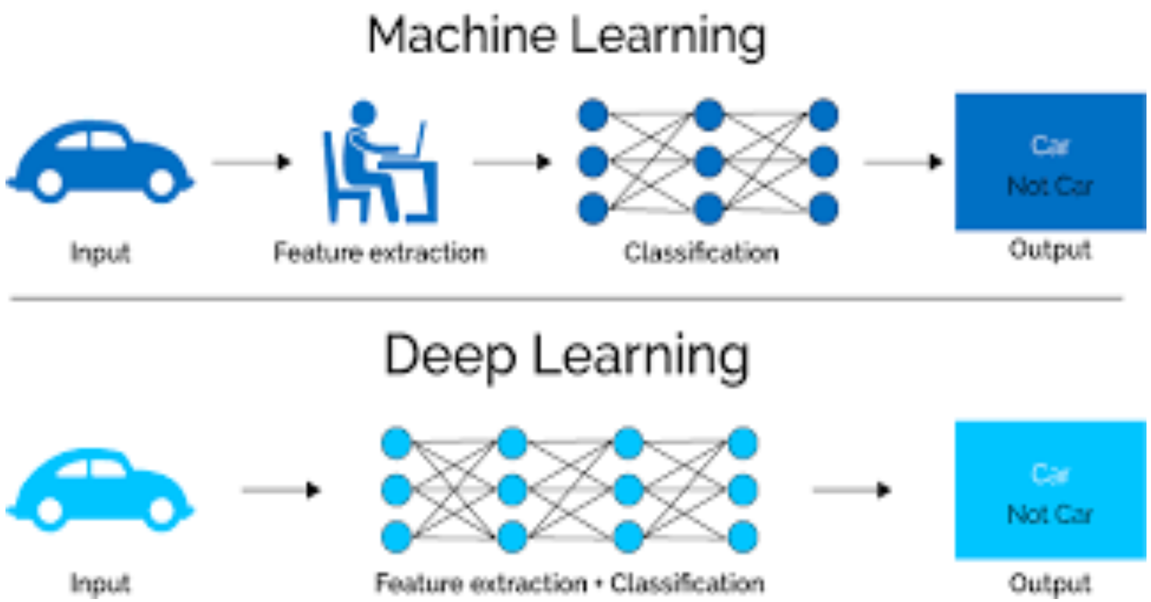


Astro papers on the arXiv with `Deep Learning' in title

Year #Papers

- 2019: 83
- 2018: 35
- 2017: 23

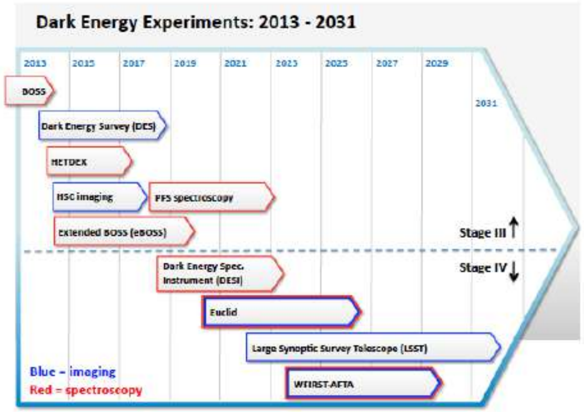


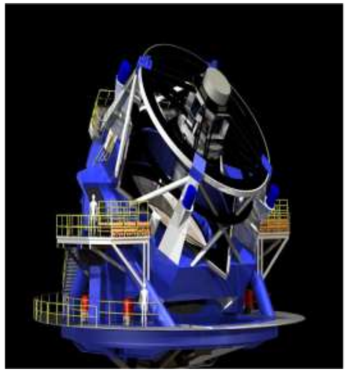


Big Data in Astronomy

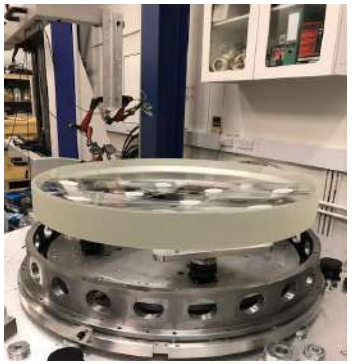
Survey	Data volume per night/day	Galaxies	Cost	Scientists
DES (2012-)	1 TeraB	~300 Million	~$40M	~400
DESI (2019-)	40 GigaB	~35 Million	~$70M	~600
LSST (2021-)	15 TeraB	~1 Billion	~$1.0B	~1000
Euclid (2021-)	850 GigaB	~1 Billion	~$1.5B	~1500
SKA (2020-)	1 PetaB	~1 Billion	~$1.3B	~1000

Galaxy surveys timeline

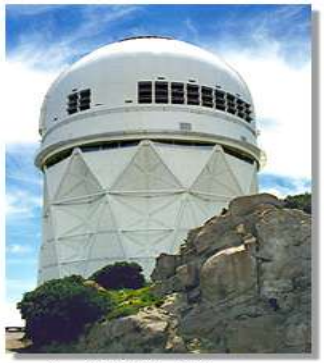




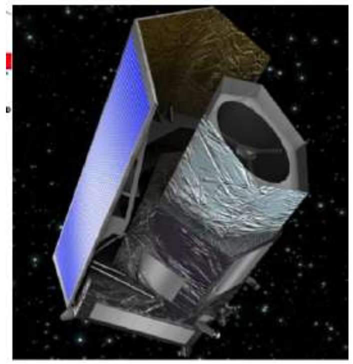
LSST



DESI
1 of 6
lenses
@ UCL



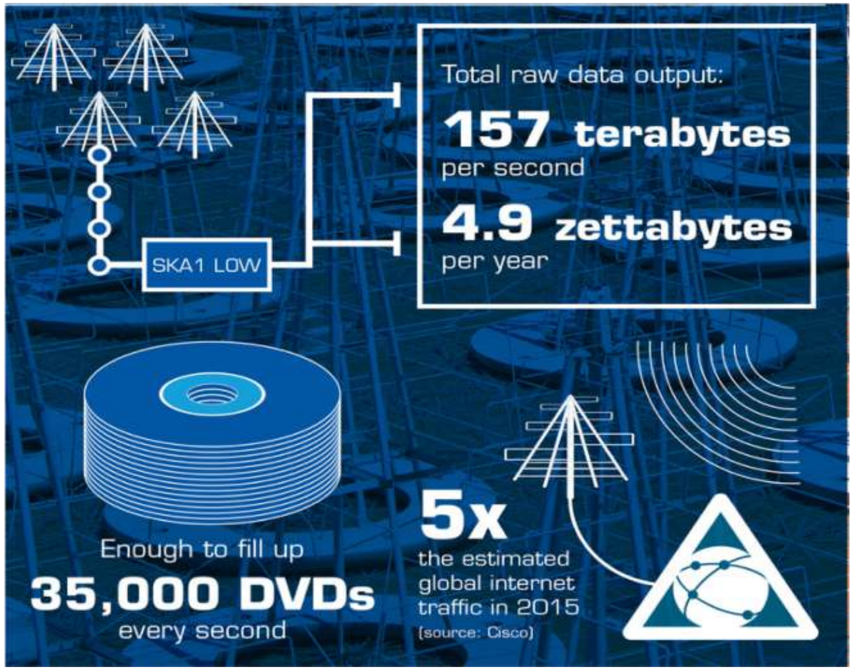
Mayall 4-Meter Telescope



Euclid

DESI had its first light in October 2019

SKA Big Data Challenge



www.skatelescope.org

Machine Learning in Astronomy

- Machine learning examples from Astronomy:

  - **Classification:**

  galaxy type, star/galaxy, Supernovae Ia, strong gravitational lensing

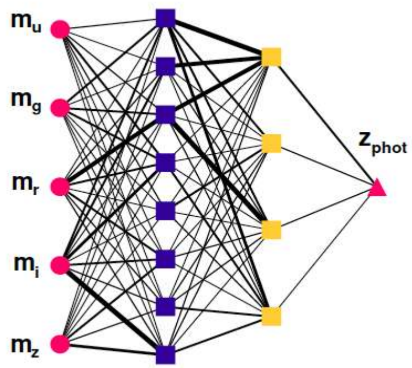
  - Photo-z

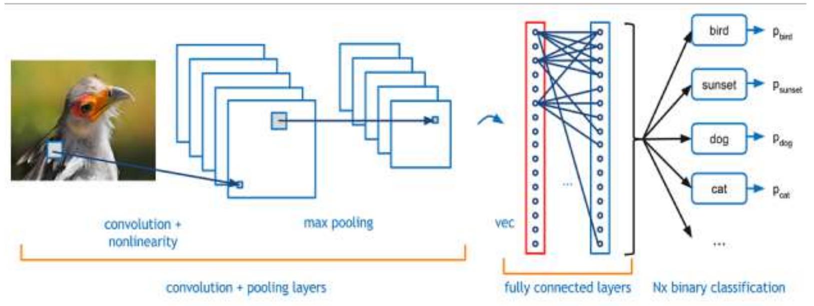
  - Mass of the Local Group

  - The search for Planet 9 and exo-planets

  - Gravitational Waves & follow-ups

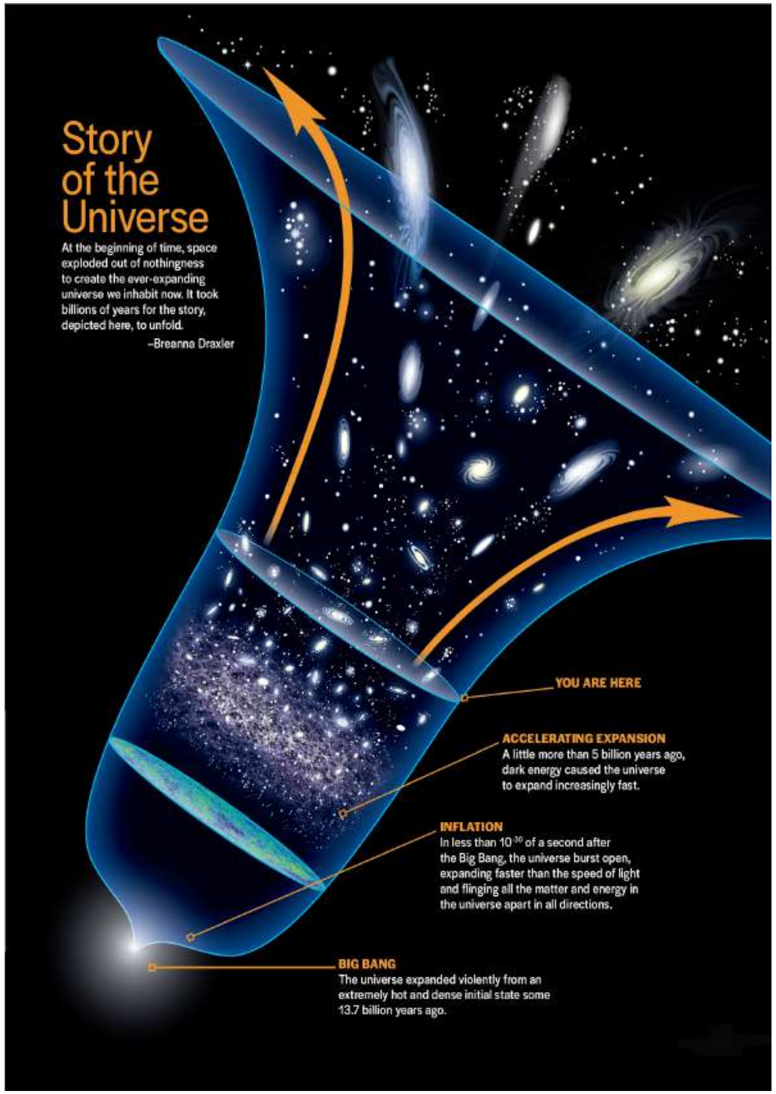
  - Likelihood-free parameter estimation

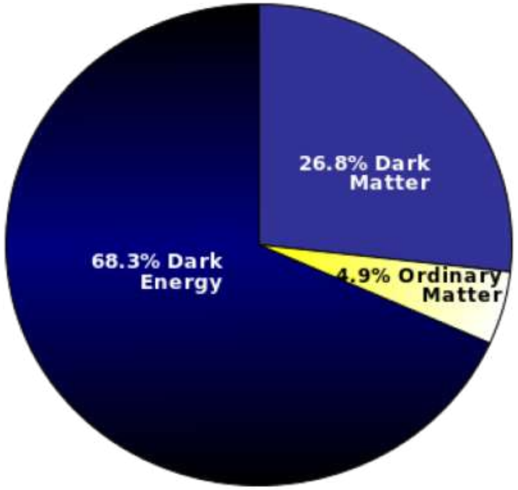


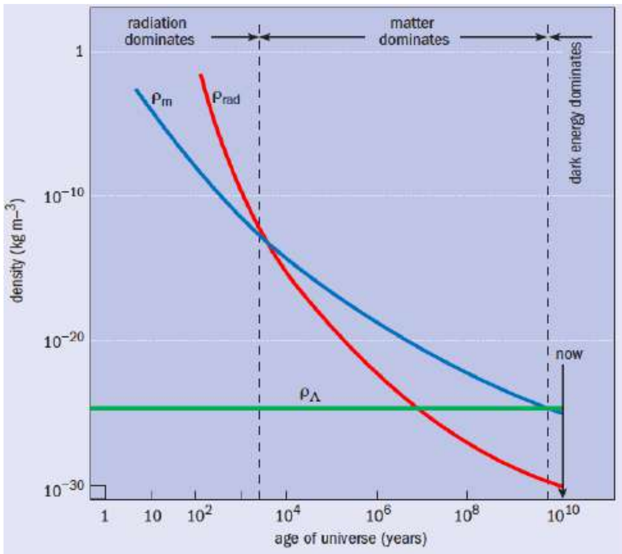


Deep Learning

What accelerates the Universe?







"a simple but strange universe"

Einstein 1917 Lambda

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

Kosmologische Betrachtungen zur allgemeinen Relativitätstheorie.

Von A. Einstein.

Es ist wohlbekannt, daß die Poissonsche Differentialgleichung

(1)

Modified Newtonian

$$\nabla^2\phi - \lambda\phi = 4\pi\kappa\rho$$

Modified GR

$$G_{\mu\nu} - \lambda g_{\mu\nu} = -\kappa\left(T_{\mu\nu} - \frac{1}{2}g_{\mu\nu}T\right)$$

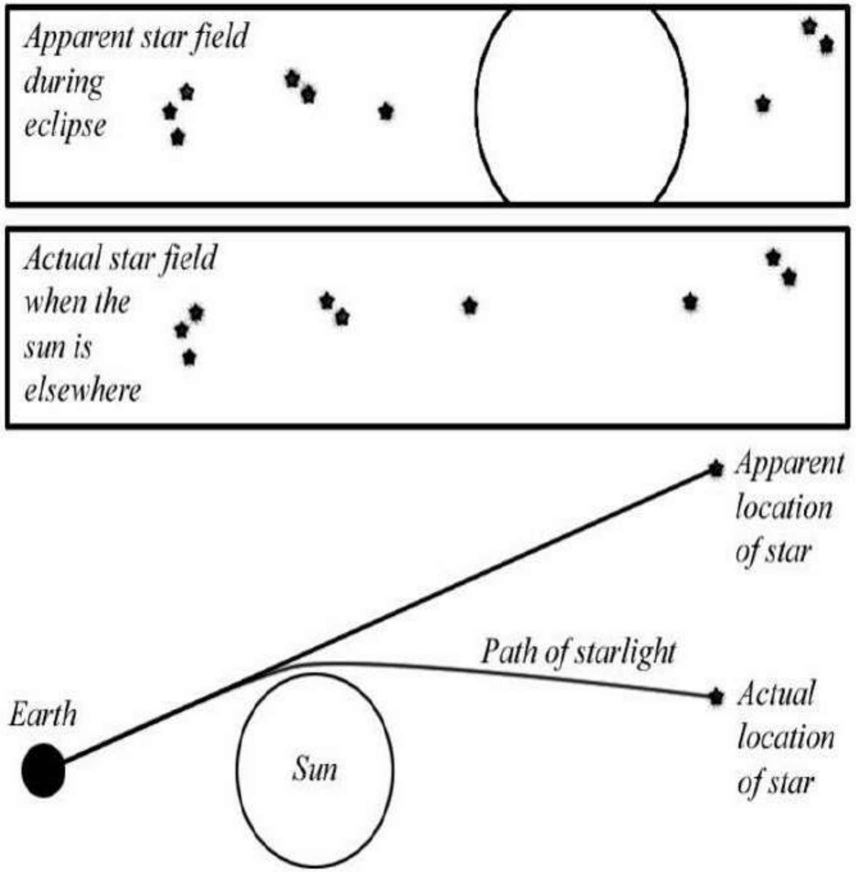
In a static universe:

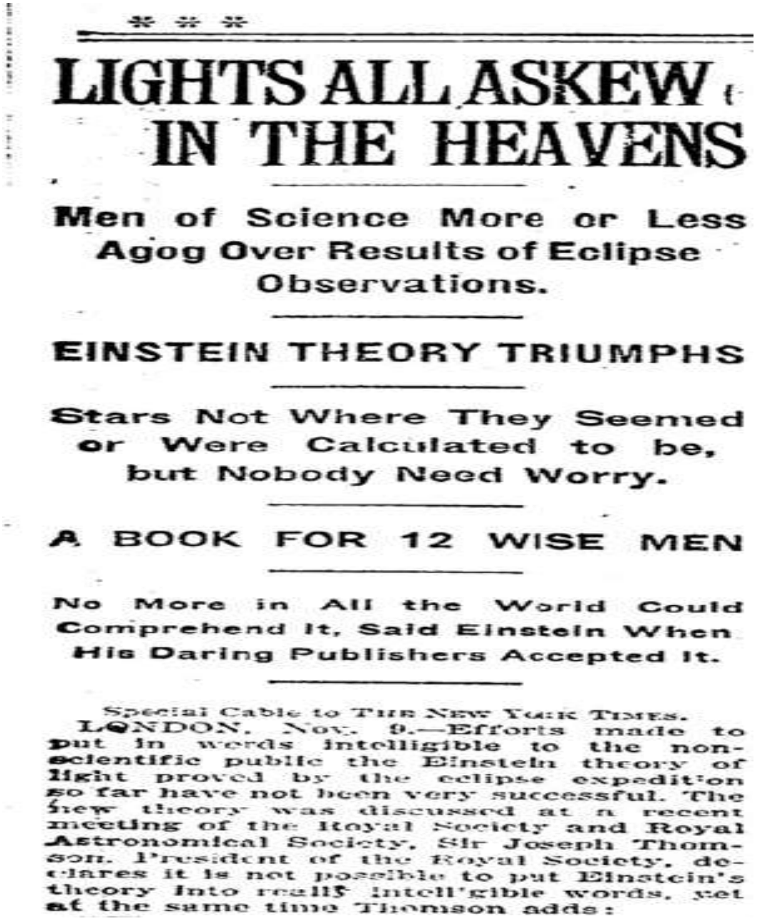
$$\lambda = \frac{\kappa\rho}{2} = \frac{1}{R^2}\,.$$

Einstein (February 1917)

English translation: http://einsteinpapers.press.princeton.edu/vol6-trans/433?ajax

The 1919 Eclipse Eddington's experiment





LIGHTS ALL ASKEW IN THE HEAVENS

Men of Science More or Less Agog Over Results of Eclipse Observations.

EINSTEIN THEORY TRIUMPHS

Stars Not Where They Seemed or Were Calculated to be, but Nobody Need Worry.

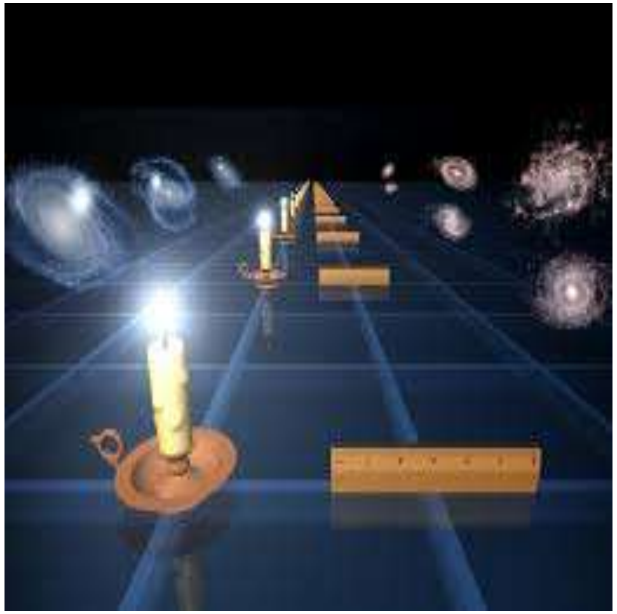
A BOOK FOR 12 WISE MEN

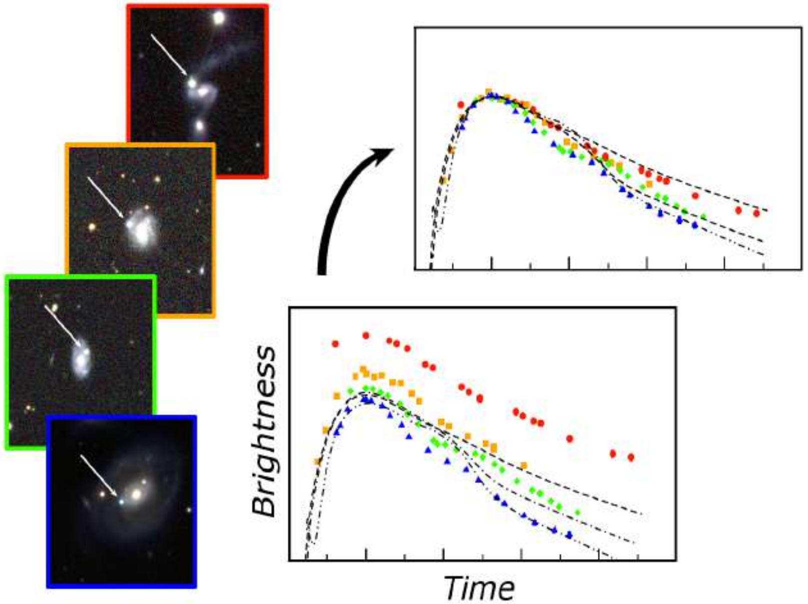
No More in All the World Could Comprehend It, Said Einstein When His Daring Publishers Accepted It.

Special Cable to THE NEW YORK TIMES.

LONDON, Nov. 9.—Efforts made to put in words intelligible to the non-scientific public the Einstein theory of light proved by the eclipse expedition so far have not been very successful. The new theory was discussed at a recent meeting of the Royal Society and Royal Astronomical Society. Sir Joseph Thomson, President of the Royal Society, declares it is not possible to put Einstein's theory into really intelligible words, yet at the same time Thomson adds:

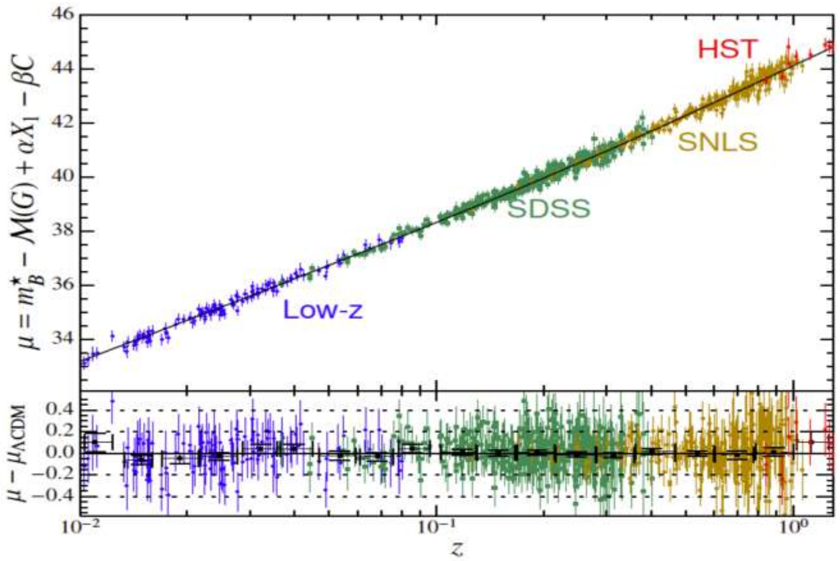
Standard candles: Supernovae Ia



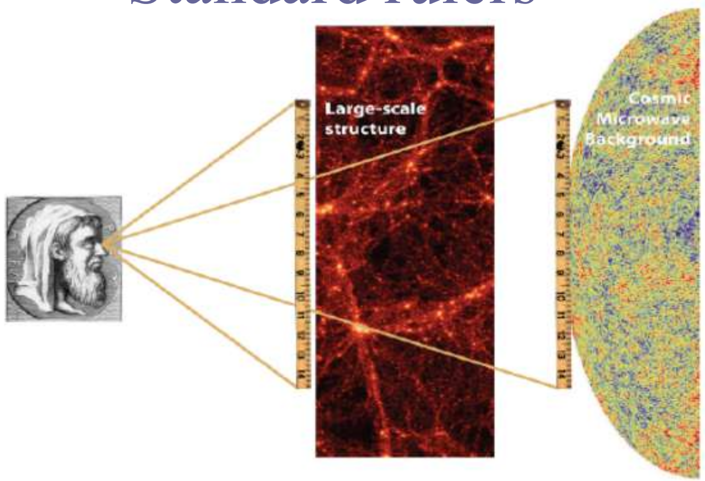


Probes of Dark Energy

Standard candles

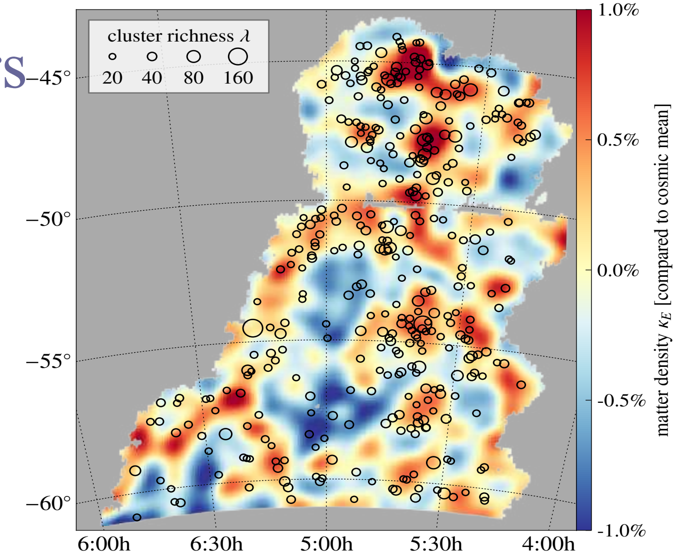


Standard rulers

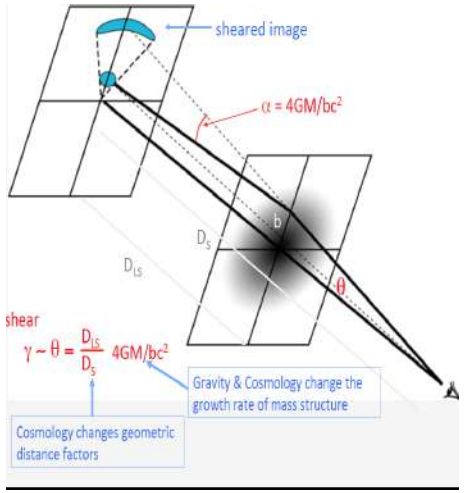


Clusters

DES SV mass map
(Chang et al. 2016)



Gravitational Lensing



The Bayesian approach

Bayesian inference for parameter estimation
Case study: CMB

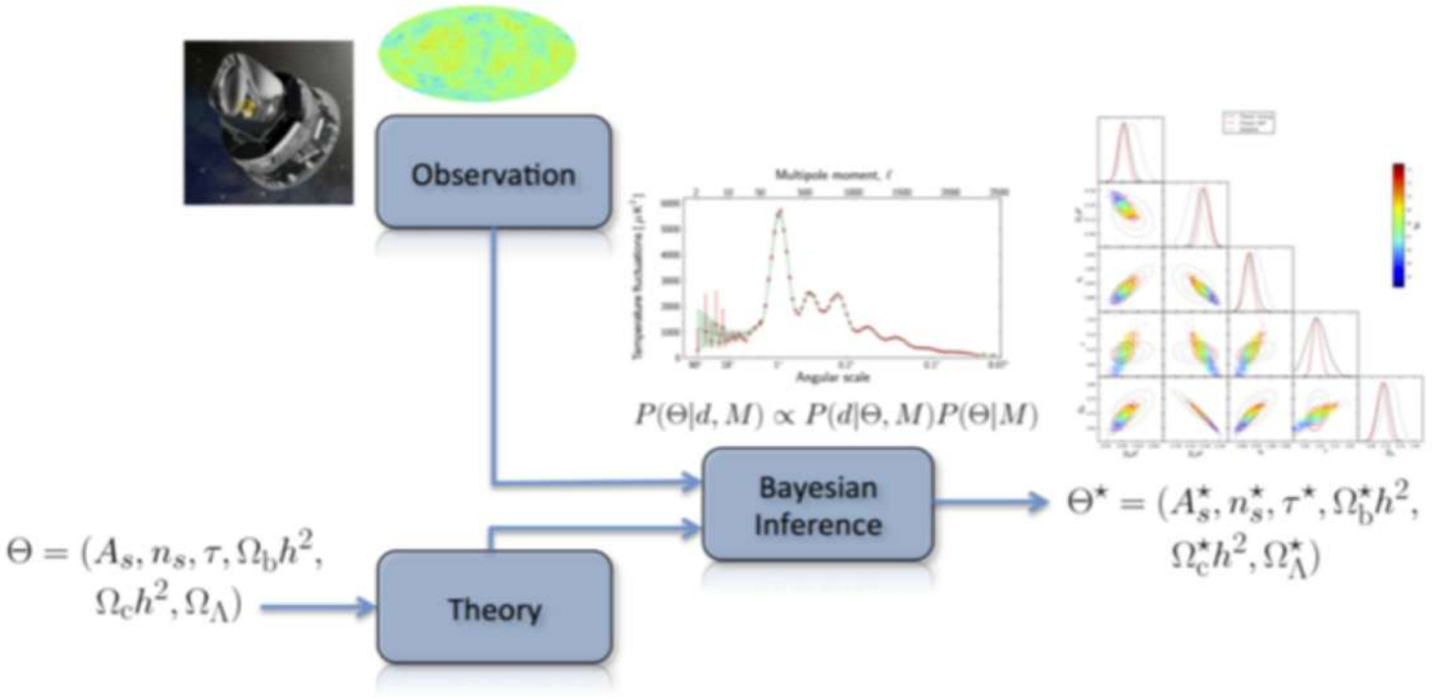


Figure: CMB Bayesian inference pipeline.

Cf. Planck results 2018

Credit: Jason McEwen

Open Questions on Dark Energy

DE equation of state:

Pressure/density = $w(a) = w_0 + w_a (1-a)$

- Is there a fundamental reason for **w=-1** (Lambda)?
- Is it on the **LHS or RHS** of Einstein's equation?
- Is there a physical case for **w<-1**?
- What is the case for a time-dependent **w(z)** ?
- When should we **stop** with w?

  (note **'precision' vs 'accuracy'**, cf. curvature)
- Does **Anthropic reasoning** make sense?
- Is a **higher level theory** to be discovered, connecting GR to Quantum Mechanics and Thermodynamics? Will it take **another 100 years** ?

The Dark Energy Survey

* Multi-probe approach
  Wide field: Cluster Counts,
  Weak Lensing, Large Scale Structure
  Time domain: Supernovae

* Survey strategy
  - 300 million galaxies with photometric redshifts
  - 2500 SN Ia

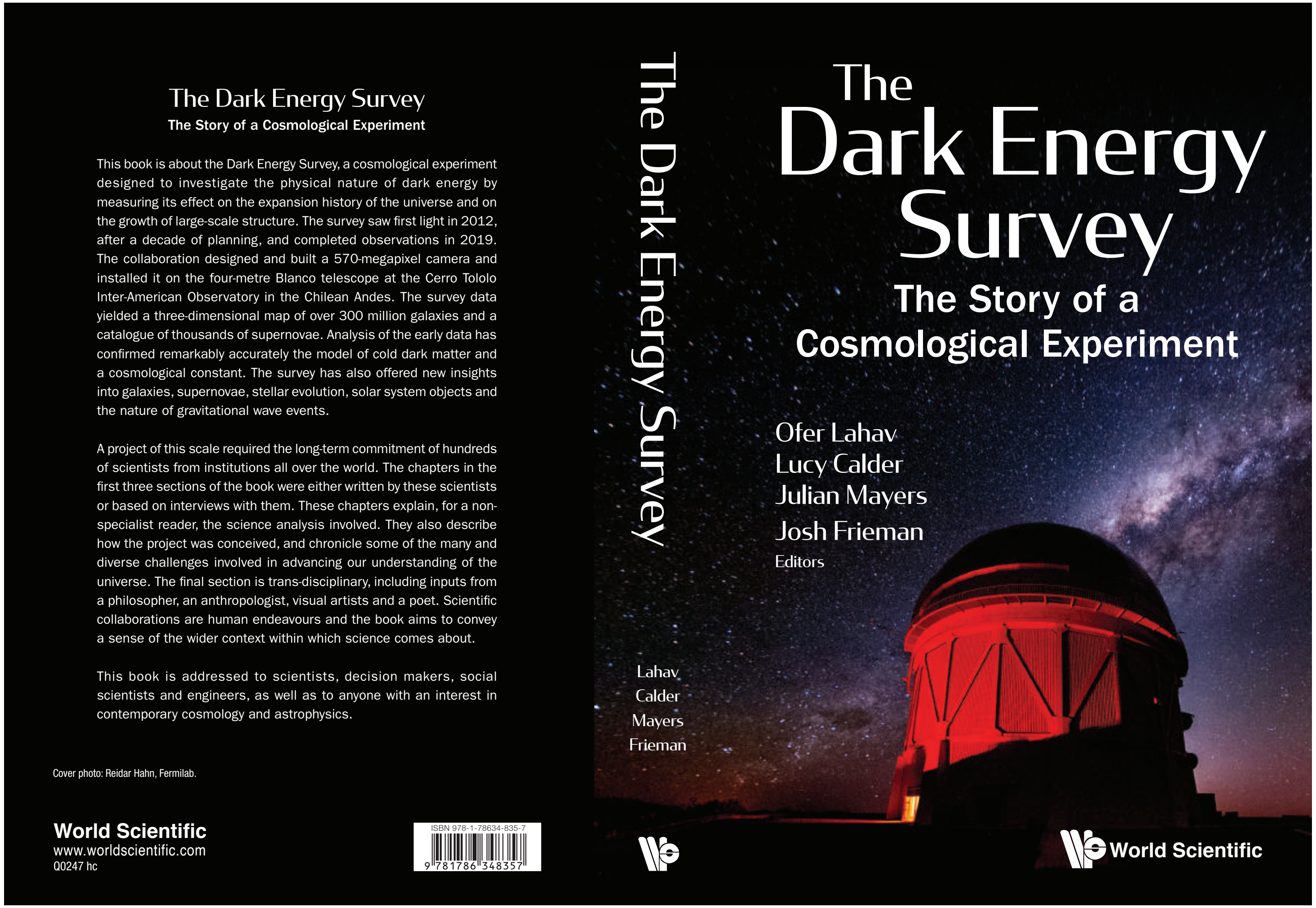
* Over 400 scientists based in 7 countries

* 6 seasons of observations completed - 758 nights in total

* Over 250 DES papers on the arXiv

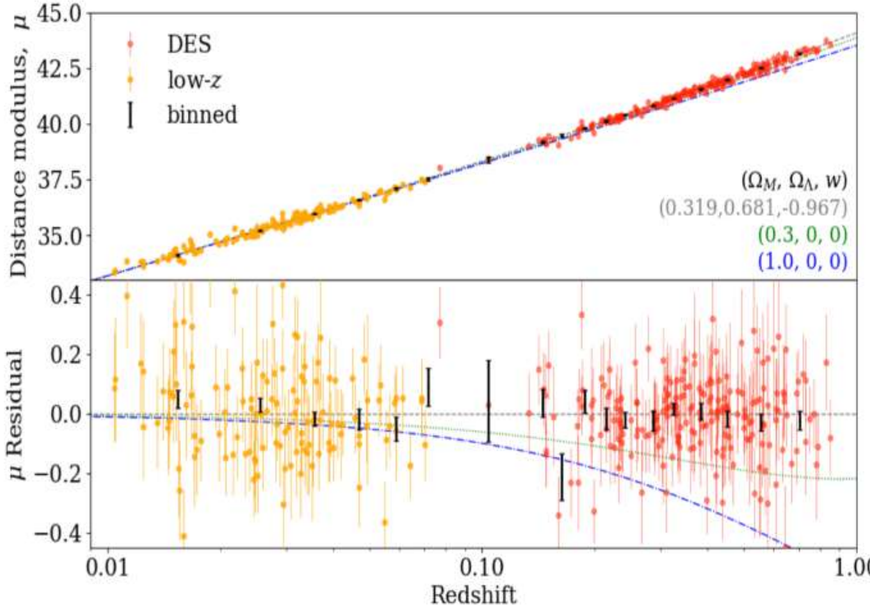
* DES book

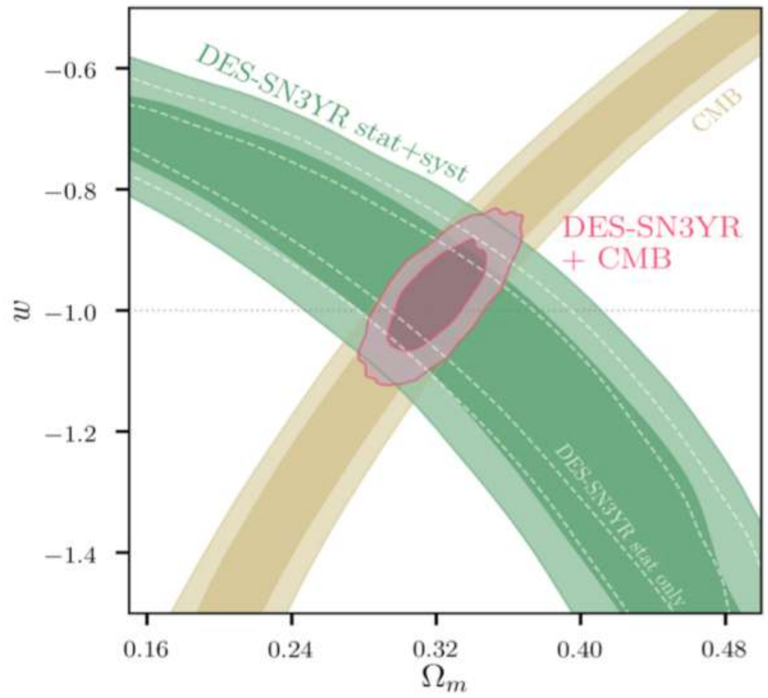
The DES book


The Dark Energy Survey
The Story of a Cosmological Experiment
This book is about the Dark Energy Survey, a cosmological experiment designed to investigate the physical nature of dark energy by measuring its effect on the expansion history of the universe and on the growth of large-scale structure. The survey saw first light in 2012, after a decade of planning, and completed observations in 2019. The collaboration designed and built a 570-megapixel camera and installed it on the four-metre Blanco telescope at the Cerro Tololo Inter-American Observatory in the Chilean Andes. The survey data yielded a three-dimensional map of over 300 million galaxies and a catalogue of thousands of supernovae. Analysis of the early data has confirmed remarkably accurately the model of cold dark matter and a cosmological constant. The survey has also offered new insights into galaxies, supernovae, stellar evolution, solar system objects and the nature of gravitational wave events.
A project of this scale required the long-term commitment of hundreds of scientists from institutions all over the world. The chapters in the first three sections of the book were either written by these scientists or based on interviews with them. These chapters explain, for a non-specialist reader, the science analysis involved. They also describe how the project was conceived, and chronicle some of the many and diverse challenges involved in advancing our understanding of the universe. The final section is trans-disciplinary, including inputs from a philosopher, an anthropologist, visual artists and a poet. Scientific collaborations are human endeavours and the book aims to convey a sense of the wider context within which science comes about.
This book is addressed to scientists, decision makers, social scientists and engineers, as well as to anyone with an interest in contemporary cosmology and astrophysics.
Cover photo: Reidar Hahn, Fermilab.
World Scientific
www.worldscientific.com
Q0247 hc
ISBN 978-1-78634-835-7
The Dark Energy Survey
Lahav
Calder
Mayers
Frieman
The Dark Energy Survey
The Story of a Cosmological Experiment
Ofer Lahav
Lucy Calder
Julian Mayers
Josh Frieman
Editors
World Scientific

207 DES SN Ia
(+122 other SN Ia)

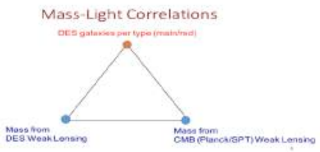
DES collaboration, 1811.02374





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

Blinding to overcome confirmation bias



3x2pt statistic: DES Year 1 (1300 sq deg) results from galaxy clustering (650K LRGs) and weak lensing (26M source galaxies)

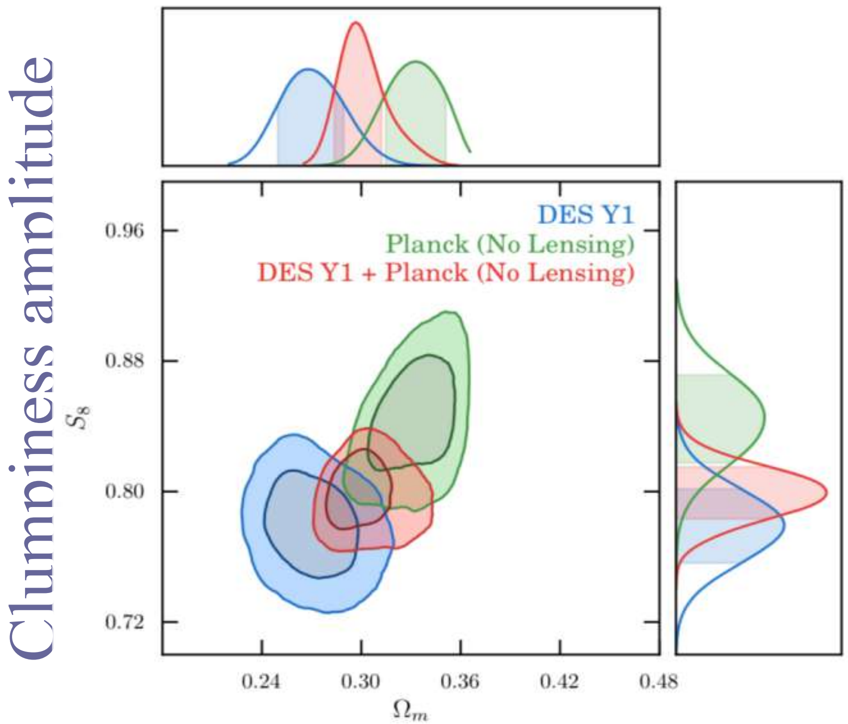
from DES+Planck+BAO+SNIa

$w = -1.00_{-0.05}^{+0.04}$

Neutrino mass < 0.29 eV

note ~ 20 nuisance parameters:

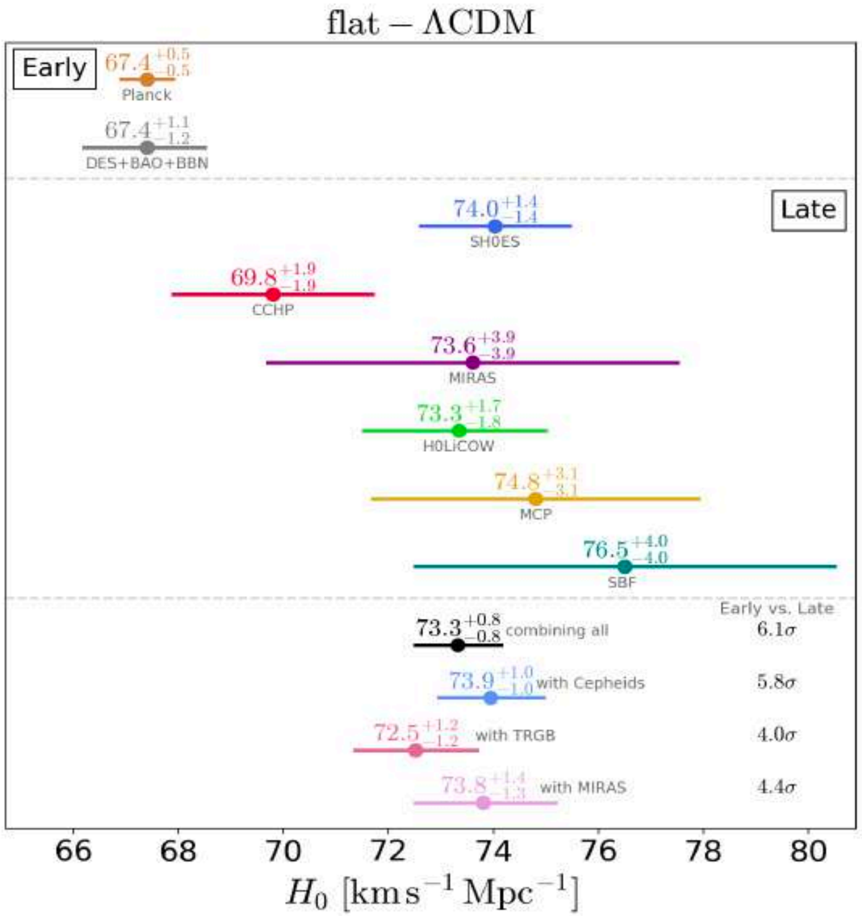
Parameter	Prior
Cosmology	
Ω_m	flat (0.1, 0.9)
A_s	flat $(5\times10^{-10}, 5\times10^{-9})$
n_s	flat (0.87, 1.07)
Ω_b	flat (0.03, 0.07)
h	flat (0.55, 0.91)
$\Omega_\nu h^2$	flat$(5\times10^{-4}, 10^{-2})$
w	flat $(-2, -0.33)$
Lens Galaxy Bias	
$b_i (i = 1, 5)$	flat (0.8, 3.0)
Intrinsic Alignment	
$A_{\rm IA}(z) = A_{\rm IA}[(1+z)/1.62]^{\eta_{\rm IA}}$	
$A_{\rm IA}$	flat $(-5, 5)$
$\eta_{\rm IA}$	flat $(-5, 5)$
Lens photo-z shift (red sequence)	
Δz_l^1	Gauss (0.001, 0.008)
Δz_l^2	Gauss (0.002, 0.007)
Δz_l^3	Gauss (0.001, 0.007)
Δz_l^4	Gauss (0.003, 0.01)
Δz_l^5	Gauss (0.0, 0.01)
Source photo-z shift	
Δz_s^1	Gauss $(-0.001, 0.016)$
Δz_s^2	Gauss $(-0.019, 0.013)$
Δz_s^3	Gauss $(+0.009, 0.011)$
Δz_s^4	Gauss $(-0.018, 0.022)$
Shear calibration	
$m^i_{\rm METACALIBRATION}(i = 1, 4)$	Gauss (0.012, 0.023)
$m^i_{\rm IM3SHAPE}(i = 1, 4)$	Gauss (0.0, 0.035)



matter density

arXiv:1708.01530 (and follow up multi-probe; extensions)

H_0 Tension



arXiv:1907.10625

Will LCDM survive?

(I) Will the tension in

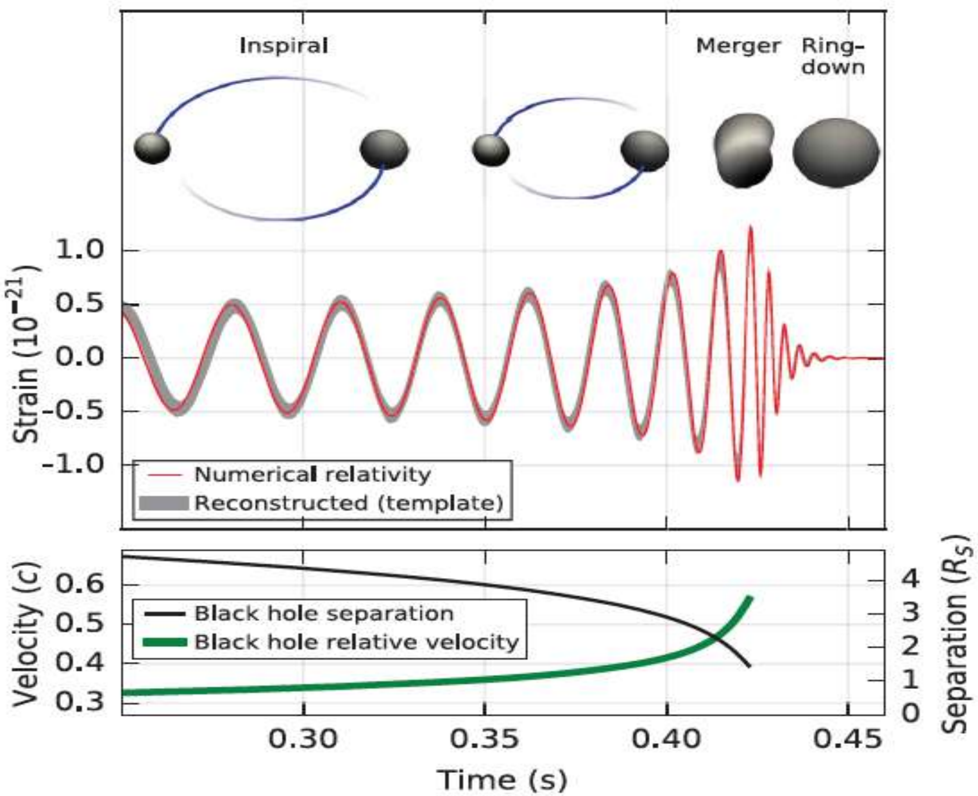
(a) H_0 (ladder vs CMB) ~4 sigma

(b) S_8-$Omega_m$ (WL vs CMB) ~2 sigma

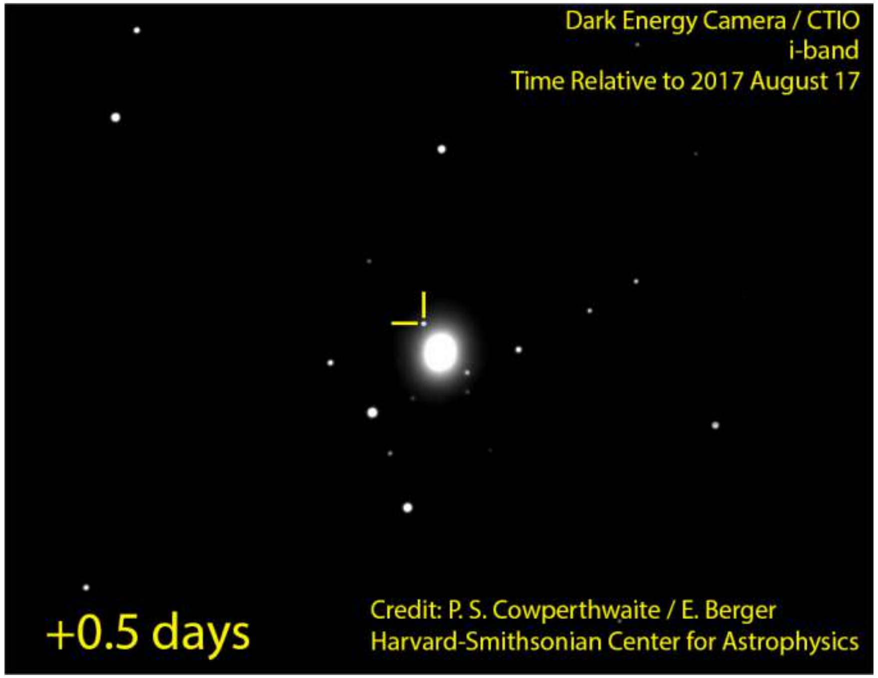
go away after more ‘bread and butter’ work?

(II) If the tension remains/grows, would it lead to new Physics or a departure from LCDM?

The first Black Hole Binary detected by LIGO GW150914



Gravitational Waves:
The visible light from the Kilonova fading away



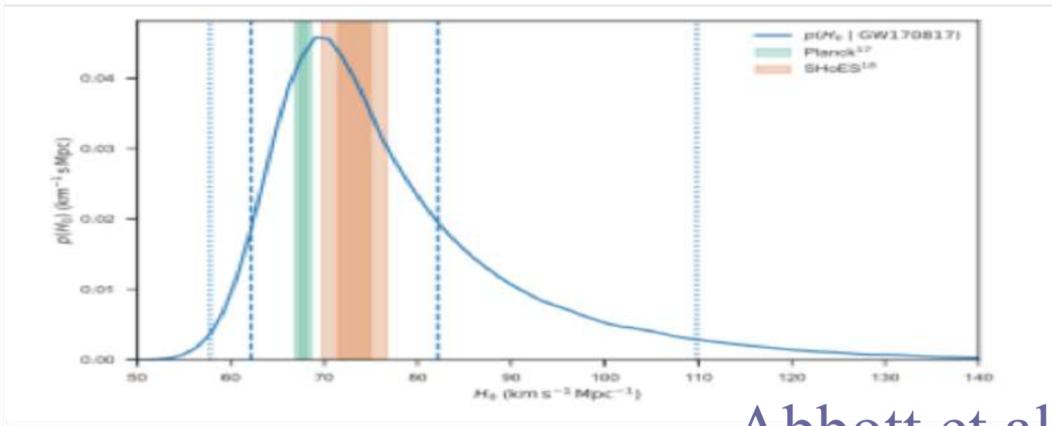
Galaxy NGC 4993,
~40Mpc away

The Hubble constant H_0 from GW170817

- Hubble Constant from GW standard siren:

$H_0 = v_H/d = 70\ (^{+12}_{-8})$ km/sec/Mpc

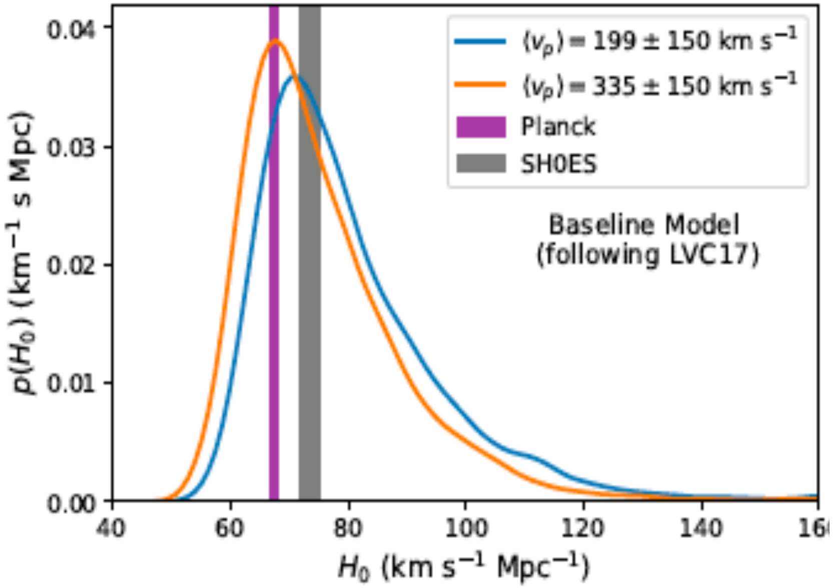
With these 68% CL, consistent with both Planck and SNIa, which are in tension with each other.



Abbott et al, Nature 2017

The Impact of Peculiar Velocities on H_0 from Gravitational Wave Bright Sirens

Constantina Nicolaou, OL, et al. 1909.09609

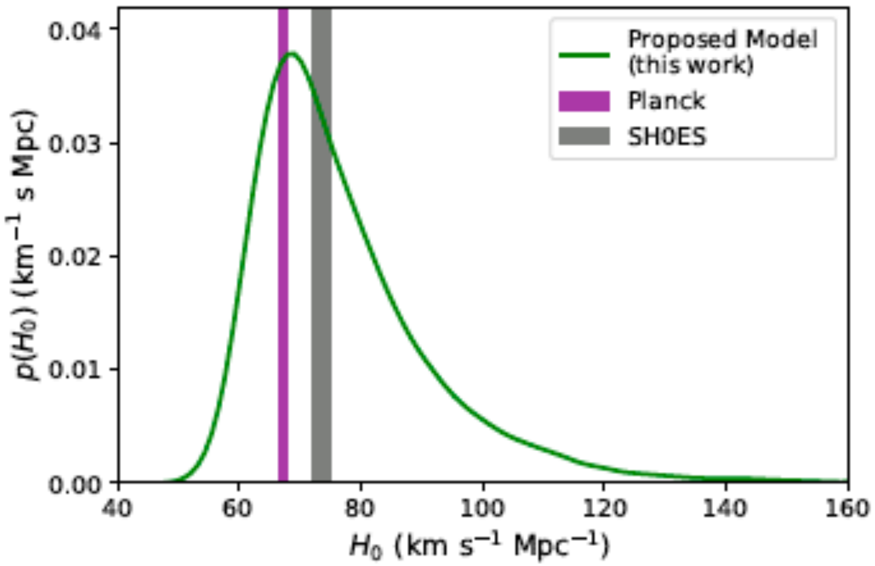


GW 170817 in NGC4993

At distance of 40 Mpc,
Uncertainty of 200 km/sec
corresponds to 4km/sec/Mpc

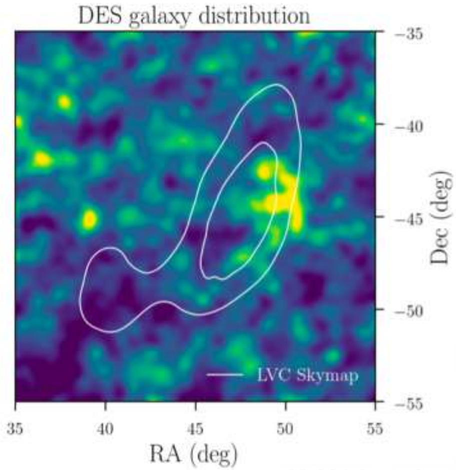
$H_0 = 68.6^{+14.0}_{-8.5}$ km/sec/Mpc

Bayesian Marginalization
over smoothing scales =>

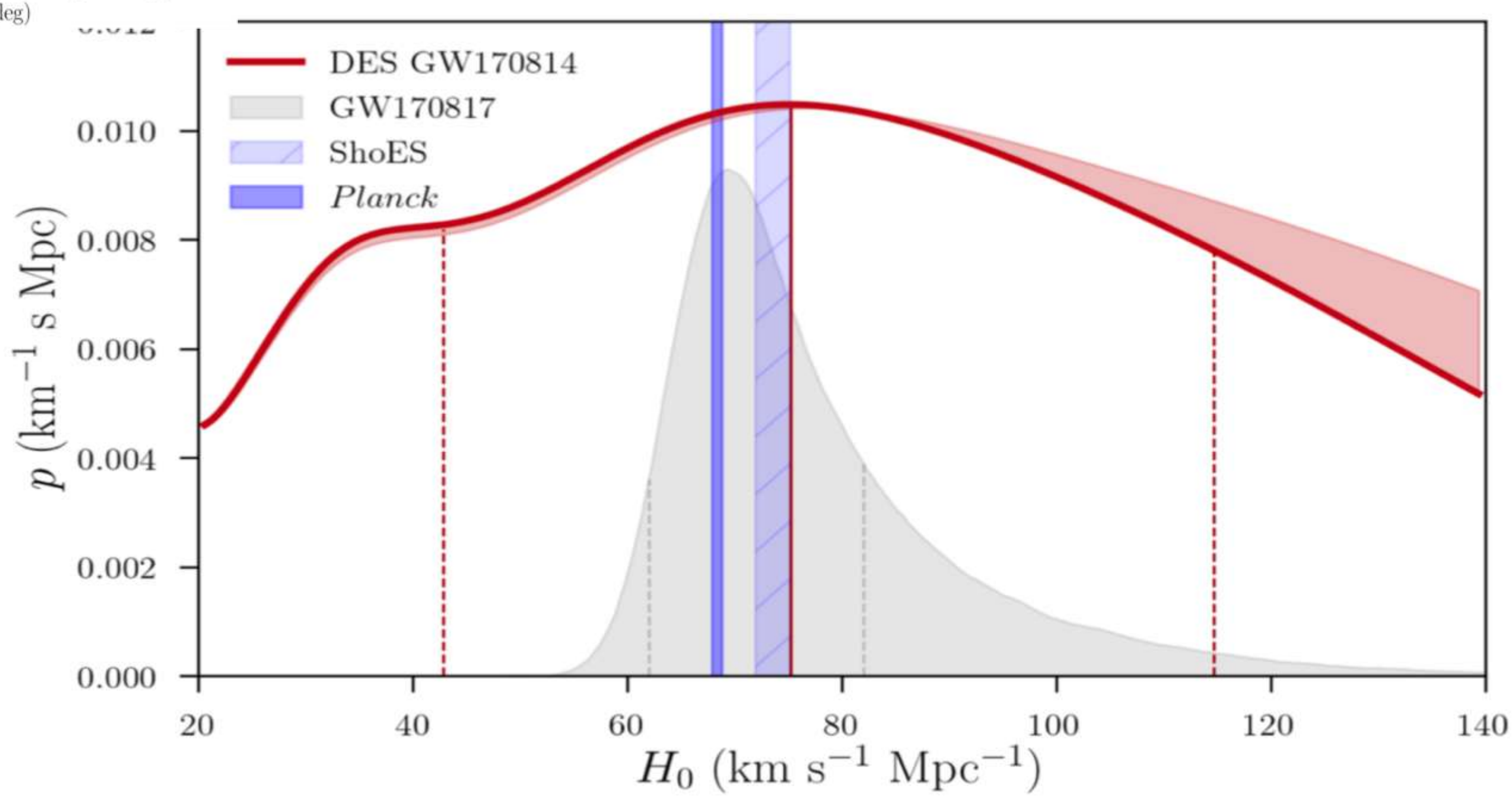


Cf. Abbott et al (2019)
Howlett & Davis (2019),
Mukherjee et al. (2019), …

H_0 from one Dark Siren + 77k DES galaxies



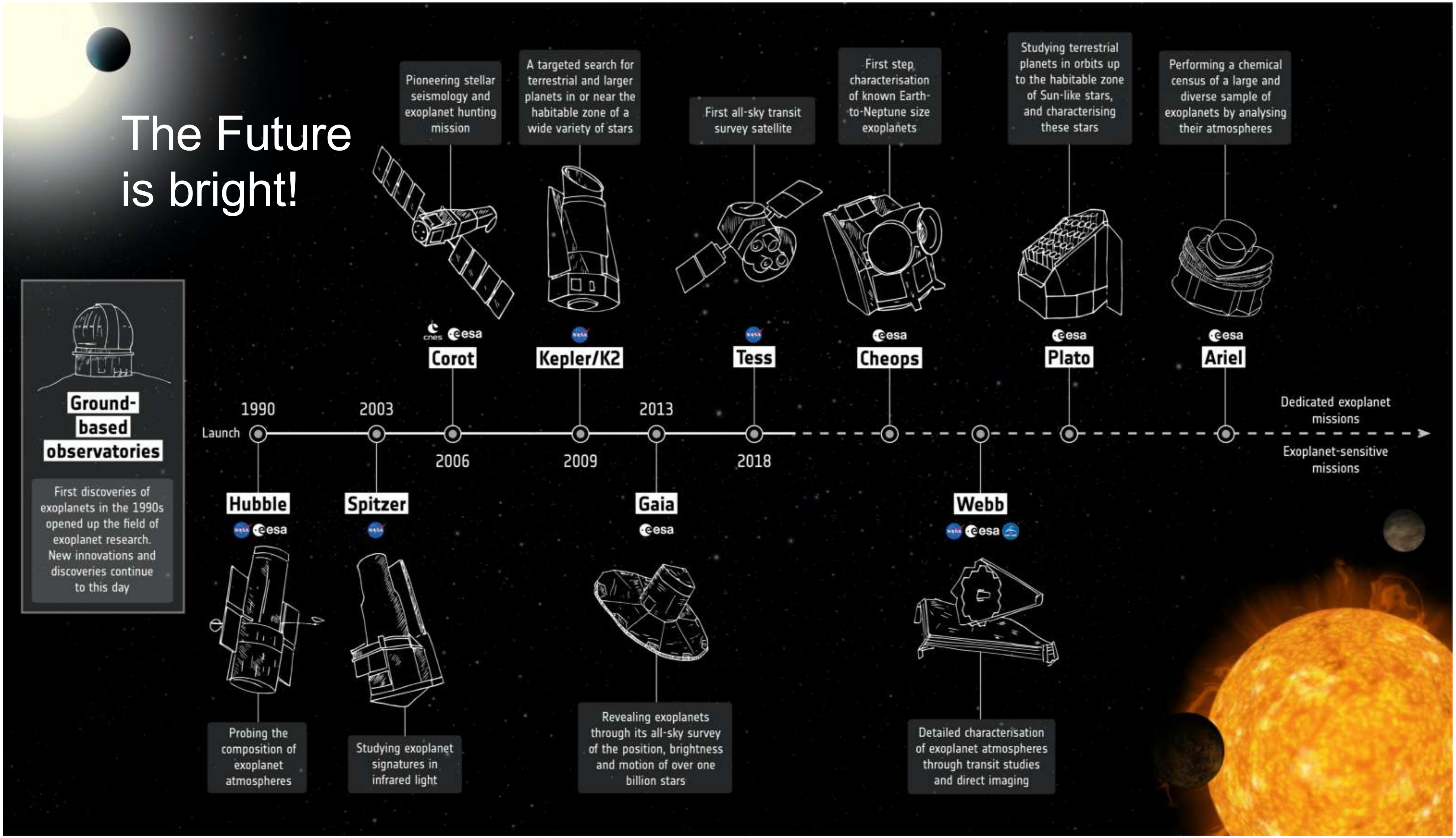
MEASUREMENT OF THE HUBBLE CONSTANT FROM GW170814



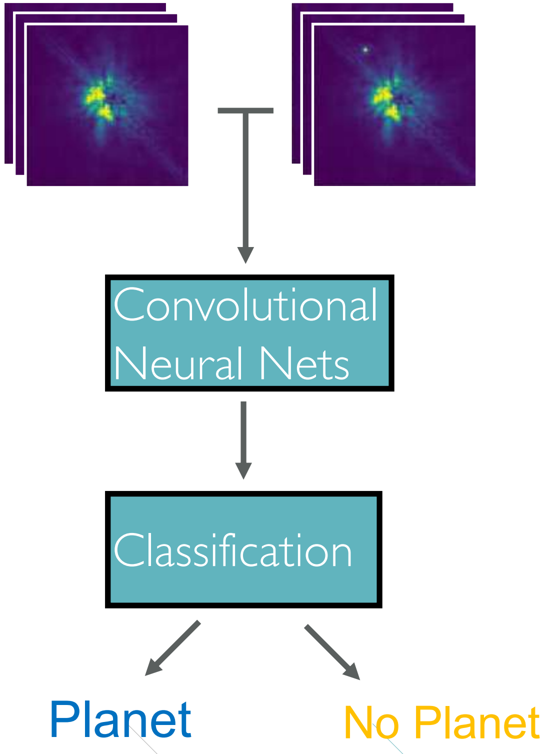
Soaers-Santos, Palmese, Hartley...OL & DES, LVC; 1901.01540

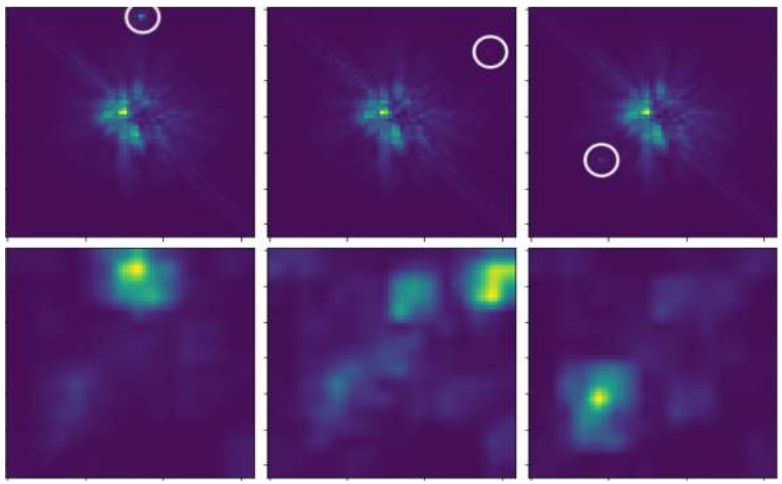
(i) Object Classification with ML

Exo-planet space missions



Machine Learning for detecting Exo-planets

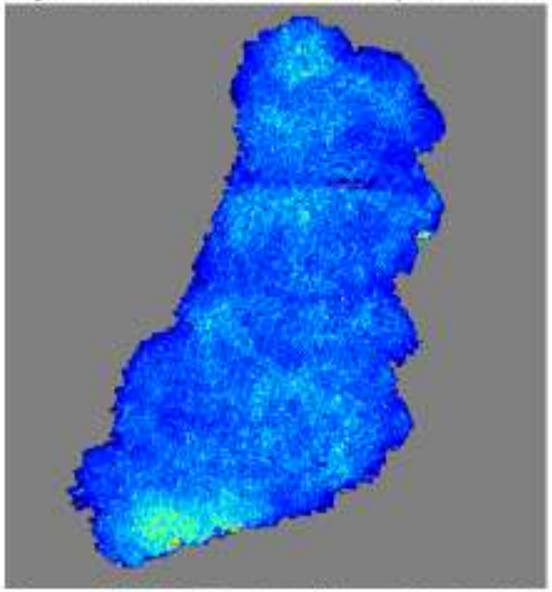




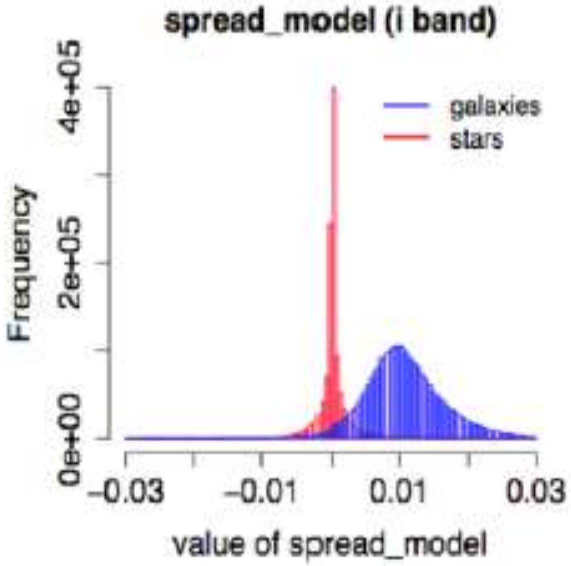
Yip, Waldmann et al. (2019)

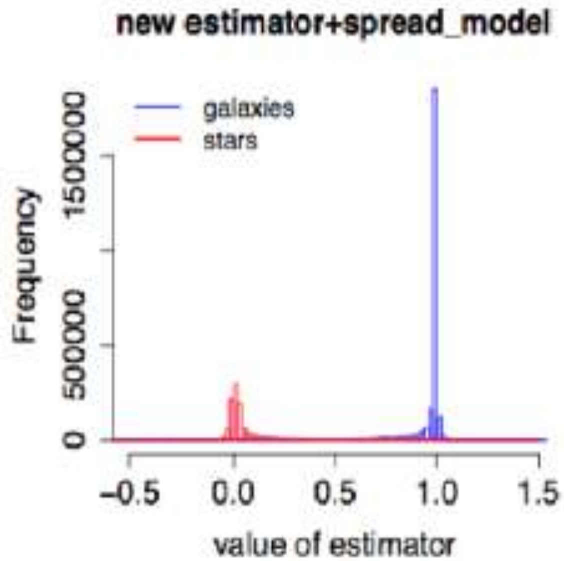
Star/galaxy separation in DES

Galaxy nb counts for SVA1-SPTE with spread model cut



Square of 200 deg² centered at ra=74, dec=-55





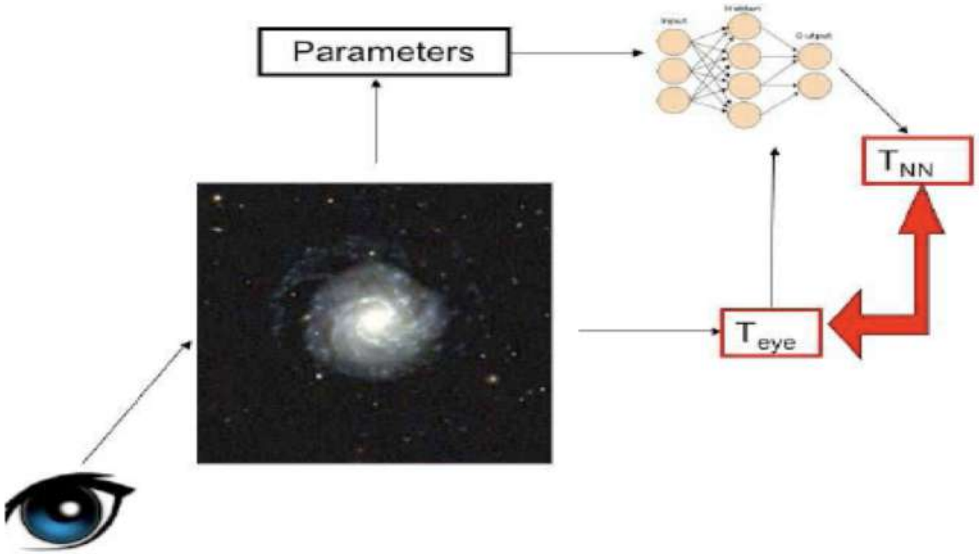
Soumagnac et al (1306.5236)

GALAXY ZOO 2

- One Million galaxies classified by 100,000 people!

Lintott et al.

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%

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

Photometric redshift

- Probe strong spectral features (4000 break)
- Difference in flux through filters as the galaxy is redshifted.

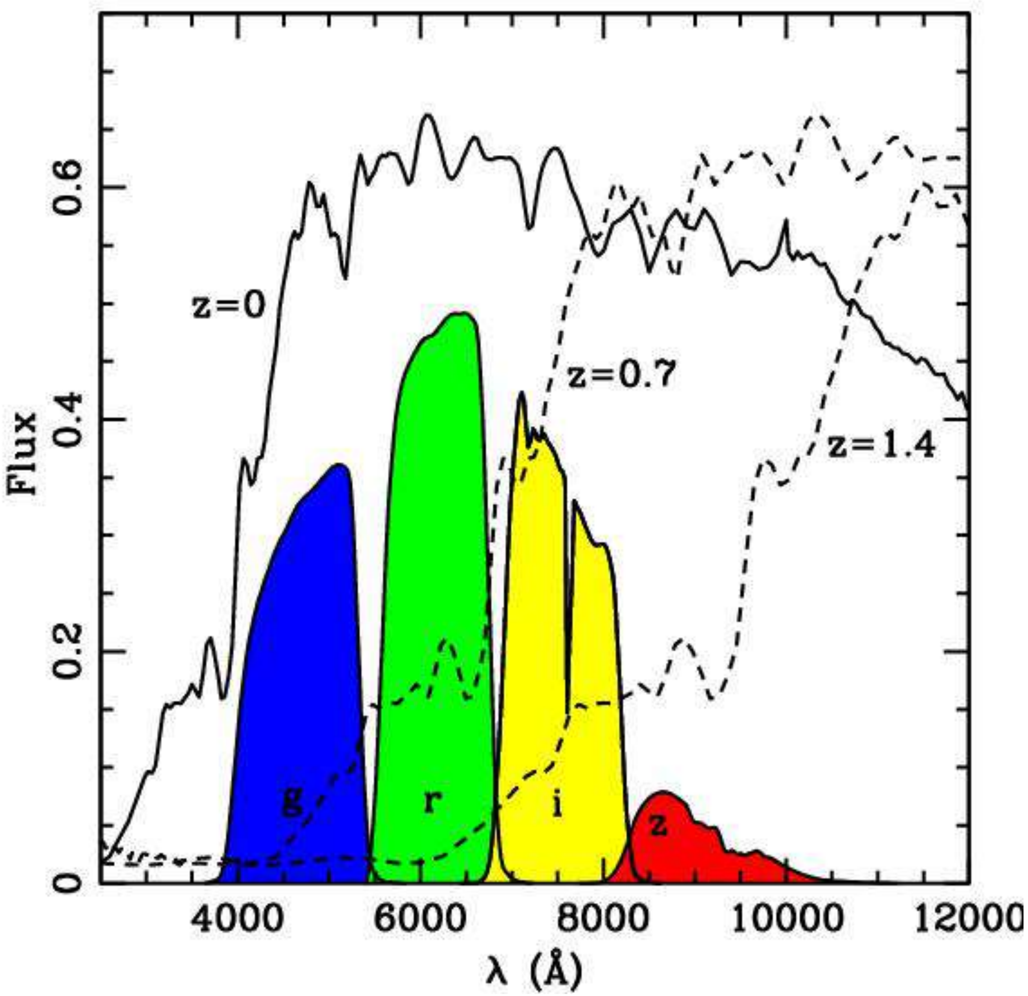
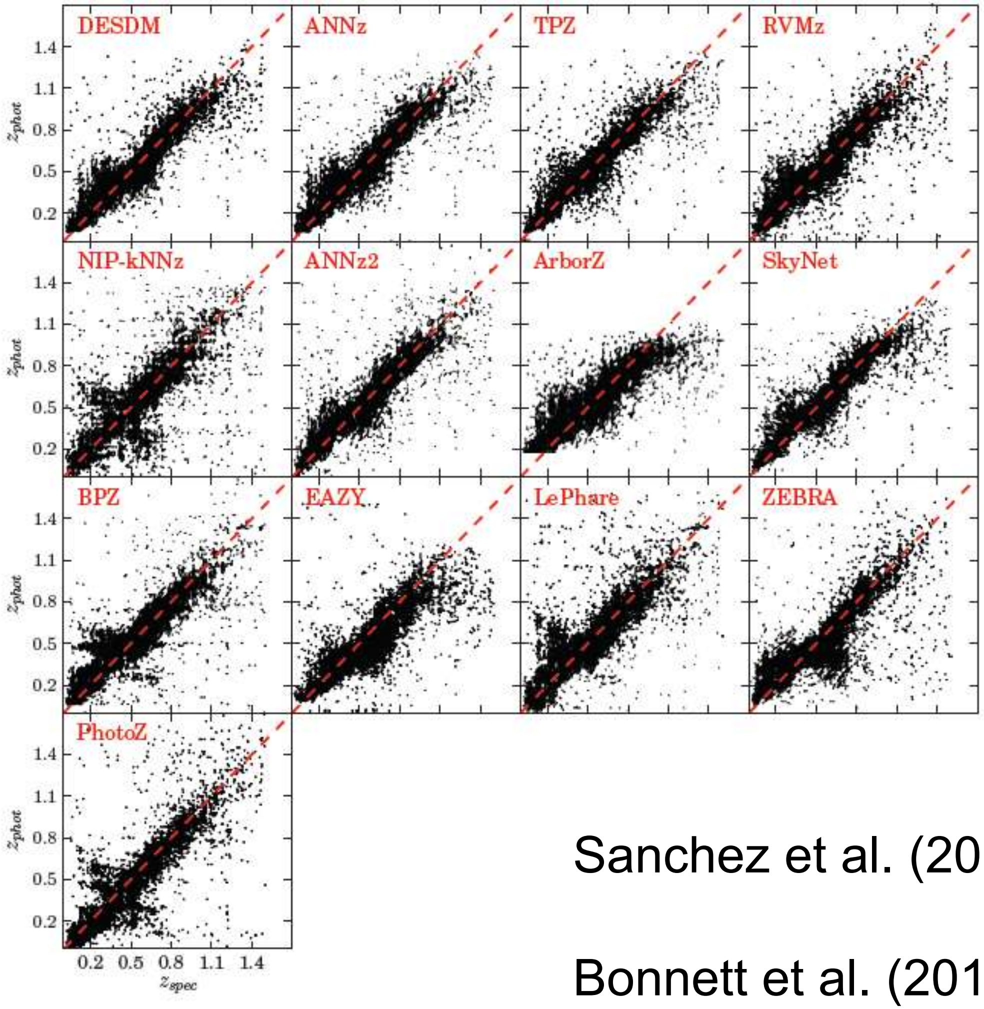


Photo-Z codes

CODE	METHOD	REFERENCE
HyperZ	Template	Bolzonella et al. (2000)
BPZ	Bayesian	Benitez (2000)
TPZ	Trees	Carraso Kind & Brunner (2013)
ANNz1	Training	Collister & Lahav (2004)
ANNz2		Sadeh, Abdalla & Lahav (2016)
ZEBRA	Hybrid, Bayesian	Feldmann et al. (2006)
LePhare	Template	Ilbert et al. (2006)

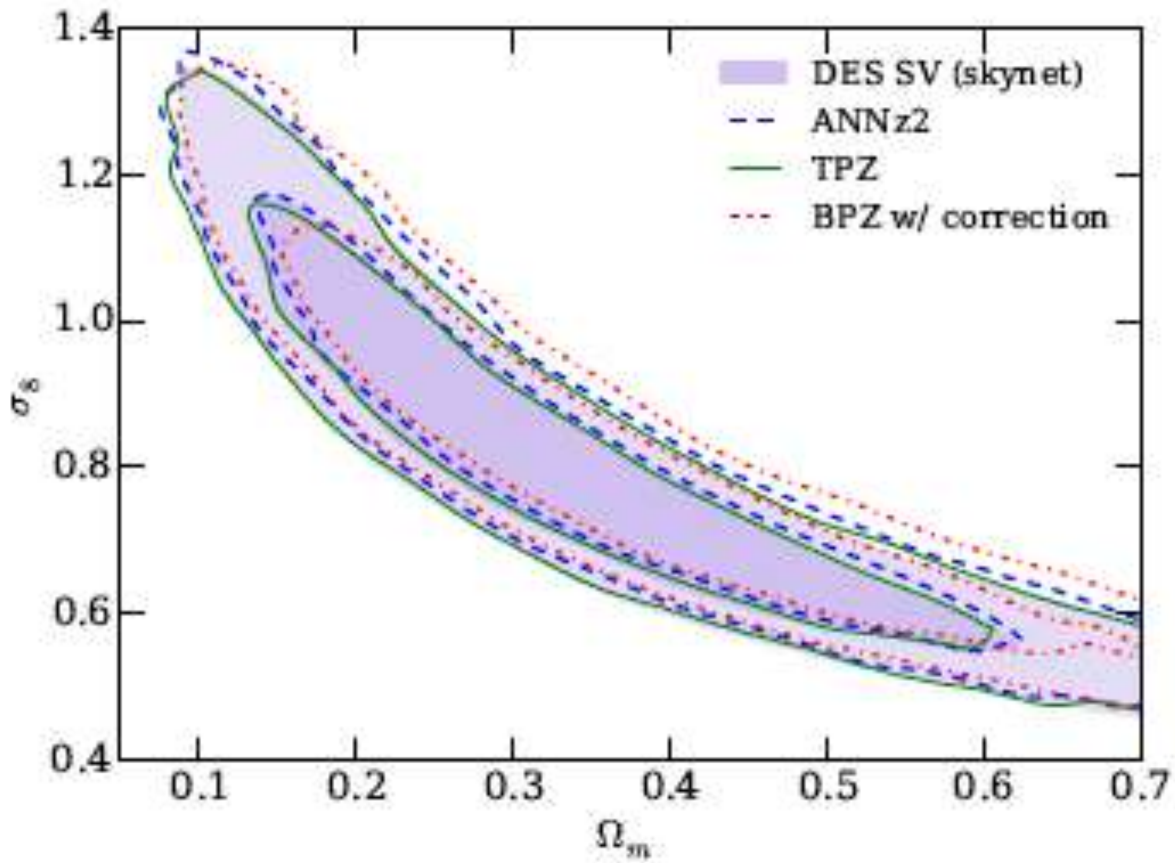
Photo-z: DES SV data



Sanchez et al. (2015)

Bonnett et al. (2015)
incl. new ANNz2,
Sadeh, Abdalla & OL (2016)

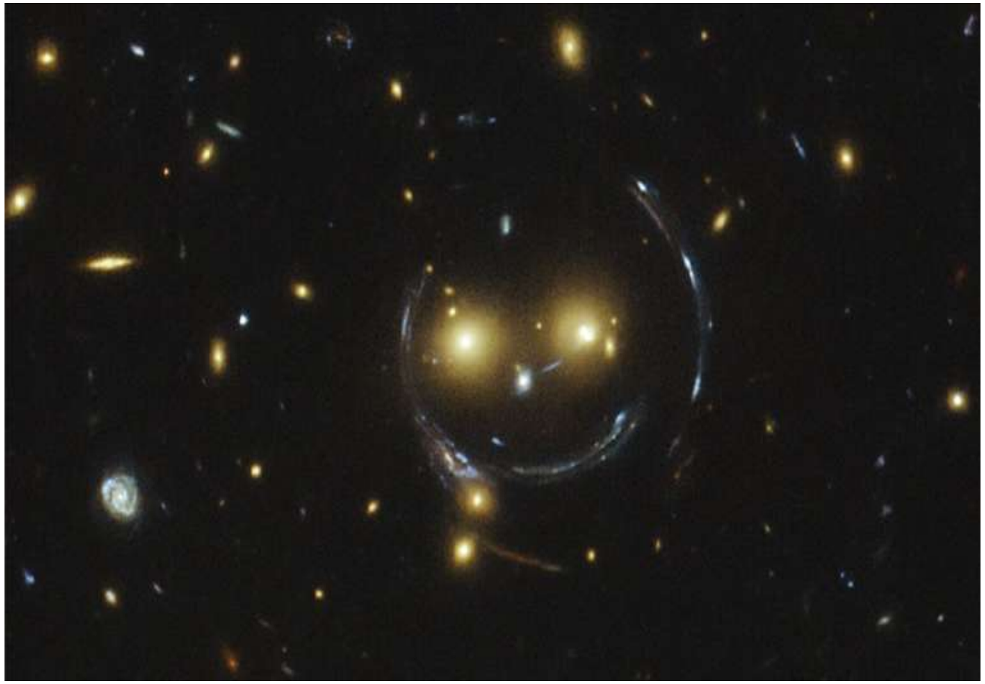
End-to-end: the impact of different PhZ codes on DES-SV WL



DES collaboration 2015

Finding Strong Lensing Arcs with Machine Learning

- HST image *of cluster SDSS J1038+4849*



- Data Challenge

Metcalf et al.

Astronomy & Astrophysics manuscript no. paper
February 20, 2018

The Strong Gravitational Lens Finding Challenge

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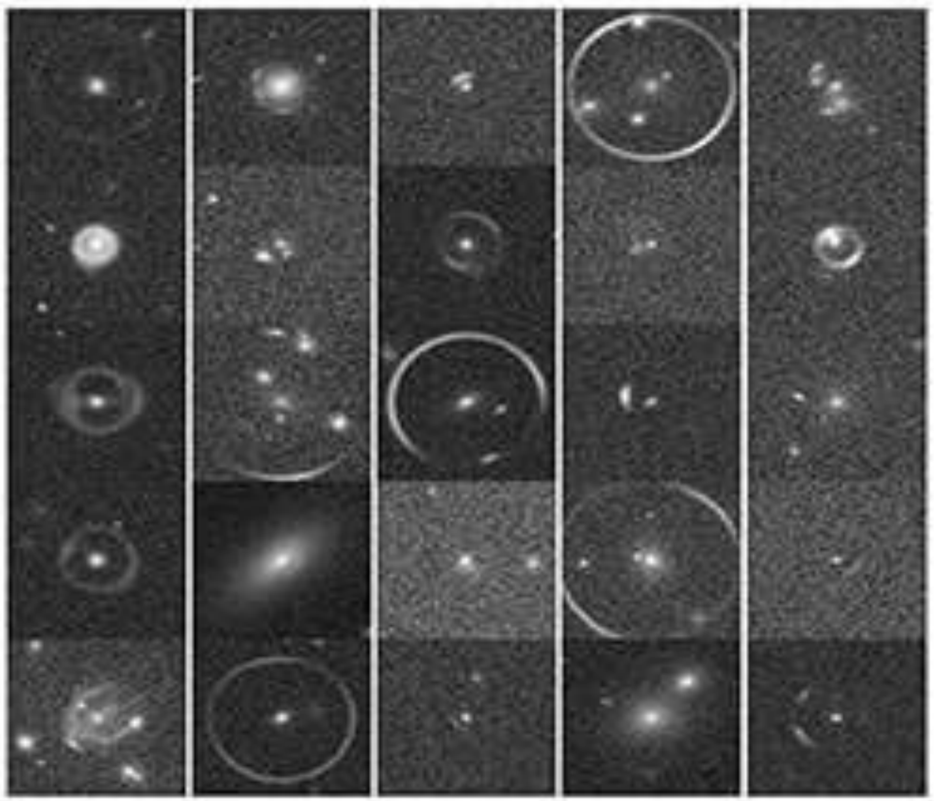
February 20, 2018

ABSTRACT

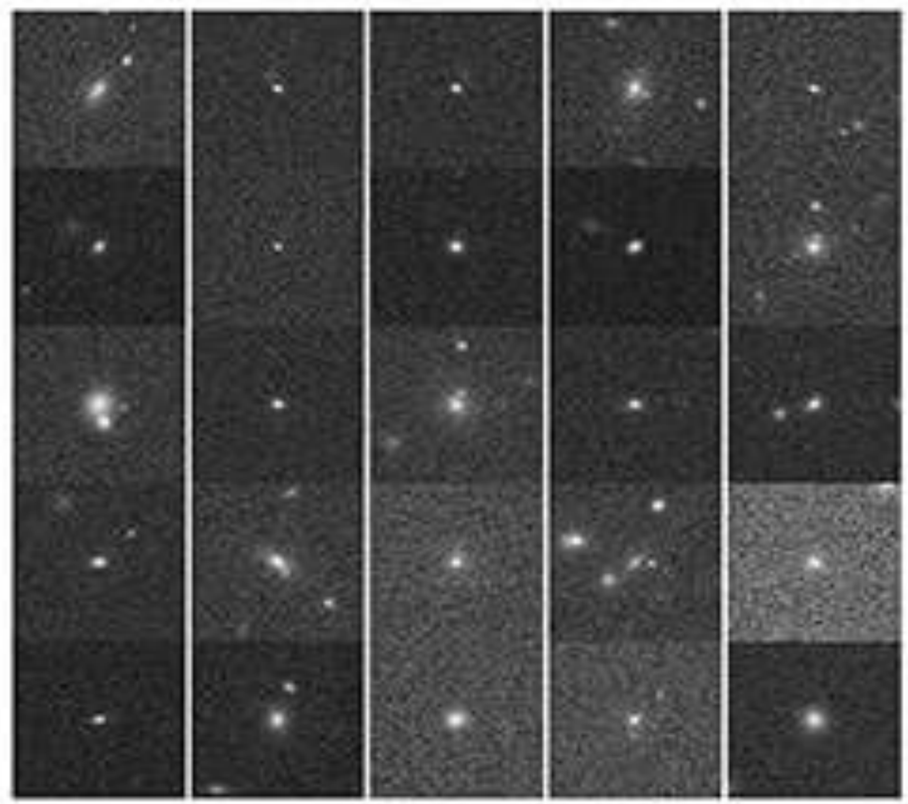
Large scale imaging surveys will increase the number of galaxy-scale strong lensing candidates by maybe three orders of magnitudes beyond the number known today. Finding these rare objects will require picking them out of at least tens of millions of images and deriving scientific results from them will require quantifying the efficiency and bias of any search method. To achieve these objectives automated methods must be developed. Because gravitational lenses are rare objects reducing false positives will be particularly important. We present a description and results of an open gravitational lens finding challenge. Participants were asked to classify 100,000 candidate objects as to whether they were gravitational lenses or not with the goal of developing better automated methods for finding lenses in large data sets. A variety of methods were used including visual inspection, arc and ring finders, support vector machines (SVM) and convolutional neural networks (CNN). We find that many of the methods will be easily fast enough to analyse the anticipated data flow. In test data, several methods are able to identify upwards of half the lenses after applying some thresholds on the lens characteristics such as lensed image brightness, size or contrast with the lens galaxy without making a single false-positive identification. This is significantly better than direct inspection by humans was able to do. Having multi-band, ground based data is found to be better for this purpose than single-band space based data with lower noise and higher resolution, suggesting that colours bring a crucial additional information. The most difficult challenge for a lens finder is differentiating between rare irregular and ring-like face-on galaxies and true gravitational lenses. The degree to which the efficiency and biases of lens finders can be quantified largely depends on the realism of the simulated data on which the finders are trained.

CMUDeepLens (Lanusse et al. 1703.02642)

- Mocks with arcs



- Mocks without arcs

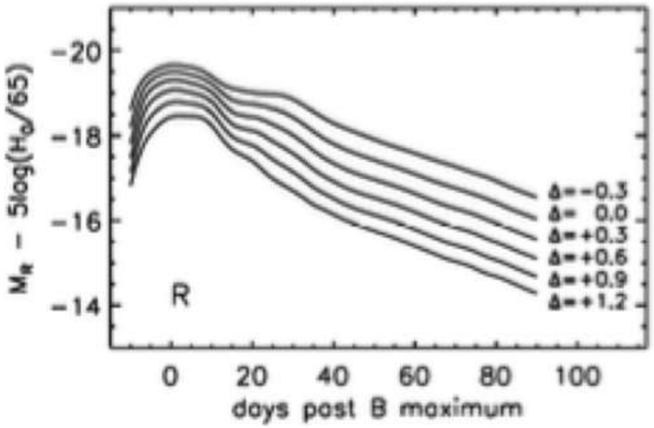


Expected in LSST: about one million strongly lensed galaxies out of an estimated 20 billion galaxies.

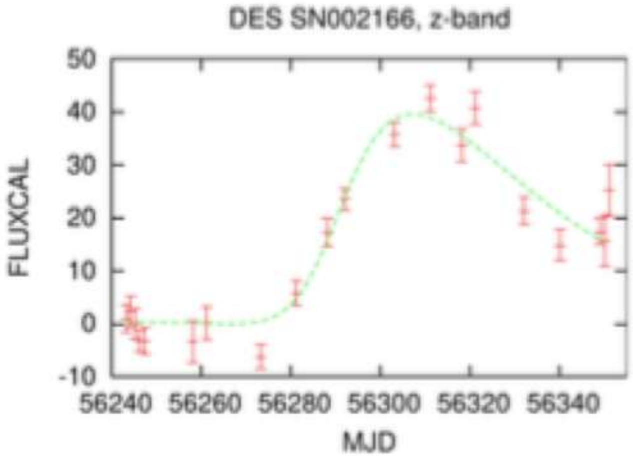
The approach: supervised CNN. Completeness of 90% can be achieved

(ii) Time Domain with ML

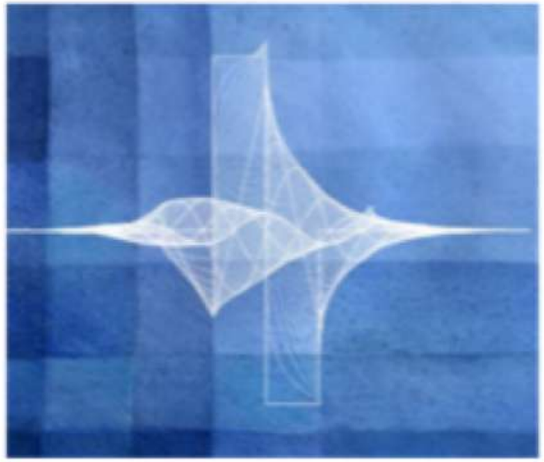
Light-curve feature selection



1) Template fitting

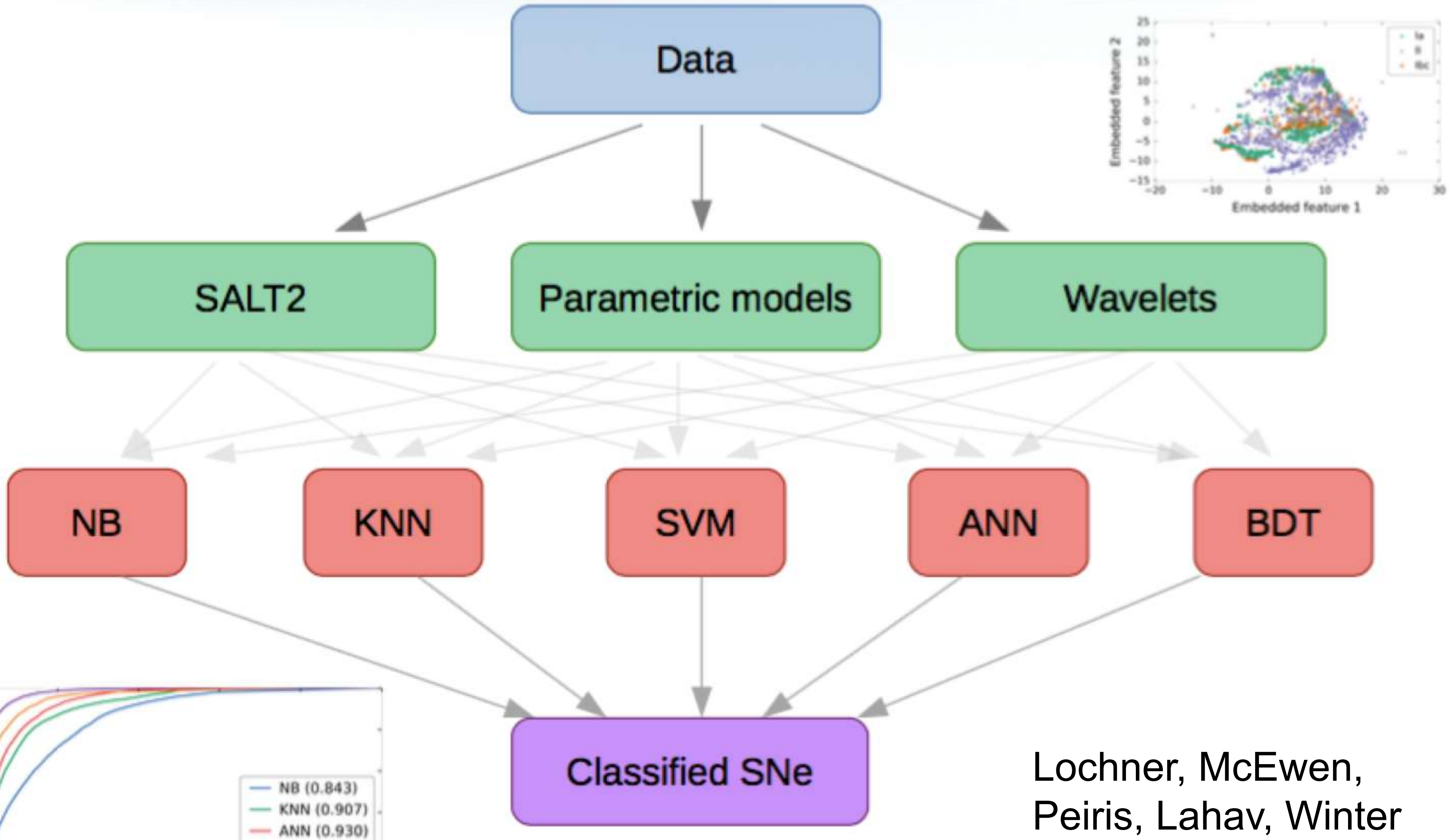


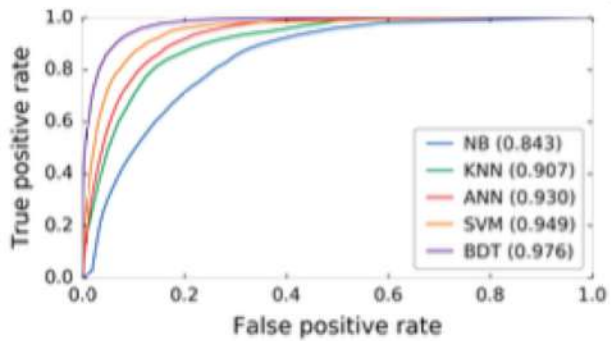
2) General light curve parameterisations



3) Wavelets

Photometric Classification of Supernovae

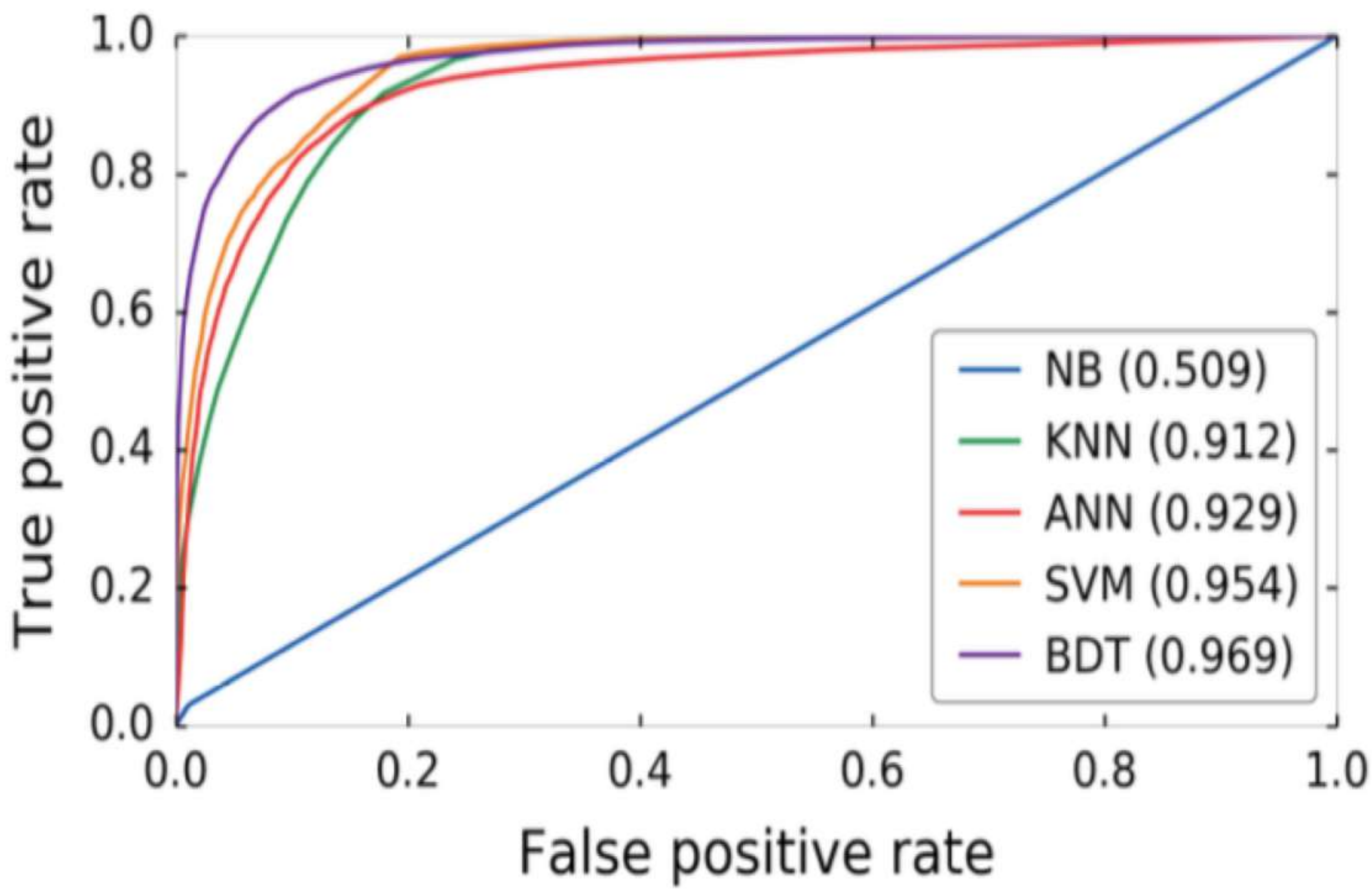




Lochner, McEwen, Peiris, Lahav, Winter

arXiv: 1603.00882

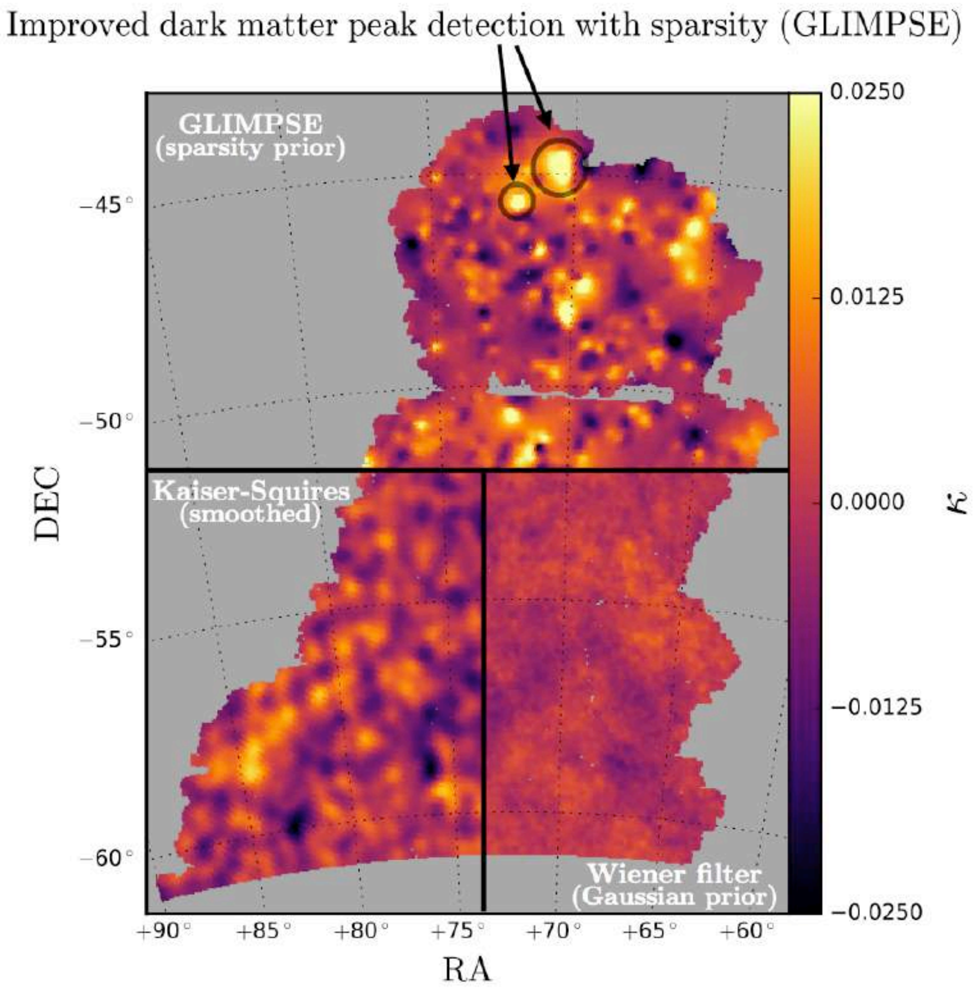
Feature extraction with Wavelet + 6 classifiers



Lochner et al. (2016)

(iii) Map reconstruction

Mass mapping from DES WL



Dark Matter Map with 3 Methods

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

$$\underset{\alpha}{\arg\min} \quad ||\mathbf{y} - \mathbf{A}\mathbf{\Phi}\alpha||_2^2 + \lambda||\alpha||_1 \ ,$$

Sparsity prior (Starck et al. 2015)

N. Jeffery et al.
arXiv:1801.08945

DeepMass

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

- We seek to approximate the mean posteriors:

$$\hat{\kappa} = \mathcal{F}_\Theta(\gamma) = \int \kappa \, P(\kappa|\gamma) \, \mathrm{d}\kappa$$

- Minimize:

$$J(\Theta) = ||\mathcal{F}_\Theta(\gamma) - \kappa_{\mathrm{true}}||_2^2$$

- Approximate function as a Convolutional Neural Network (CNN)
- The unknown parameters are mainly convolution filters
- Minimize J using 360k simulations (noisy gamma, clean kappa)

Deep Learning mass reconstruction ('DeepMass')

DES

Sims

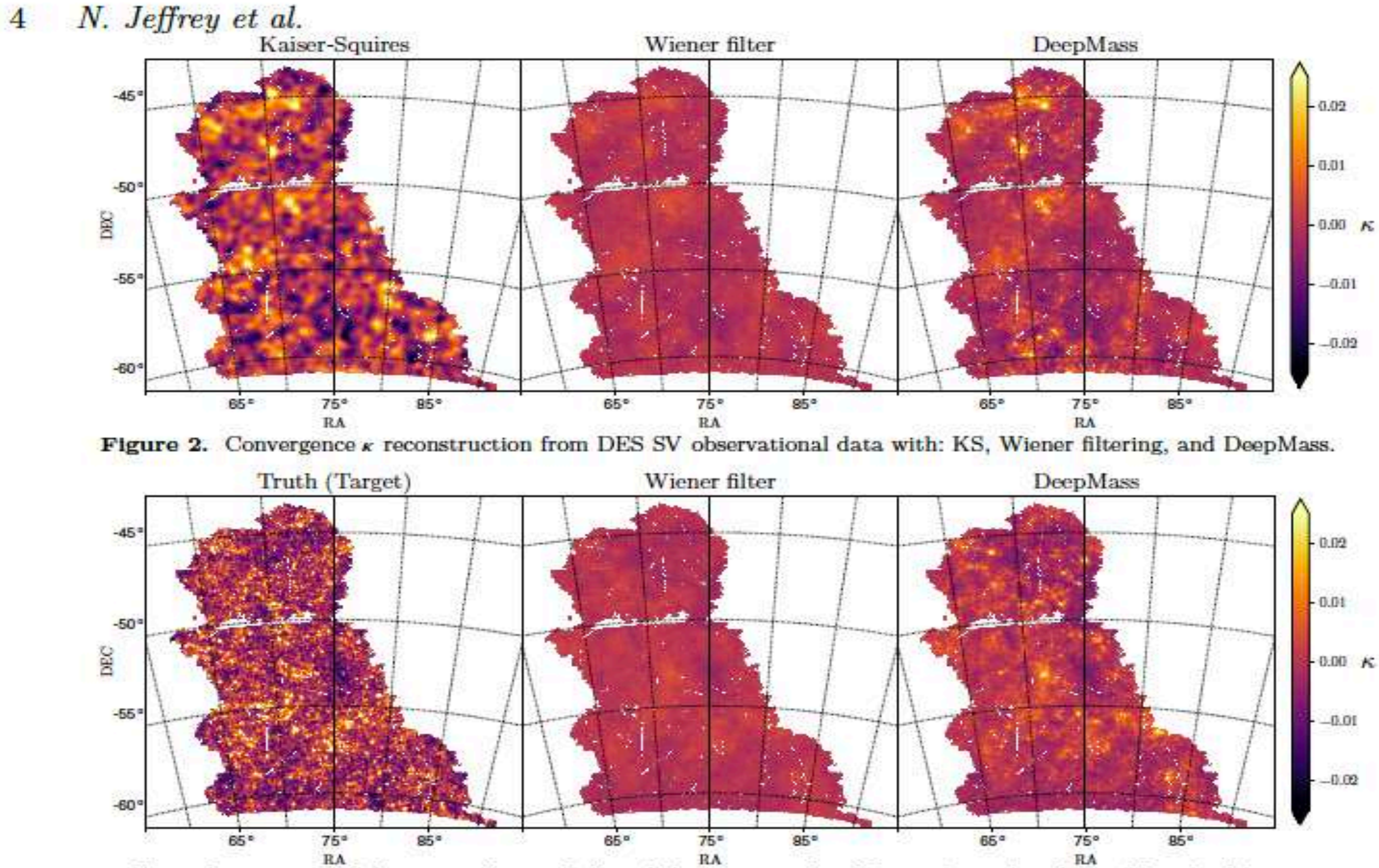


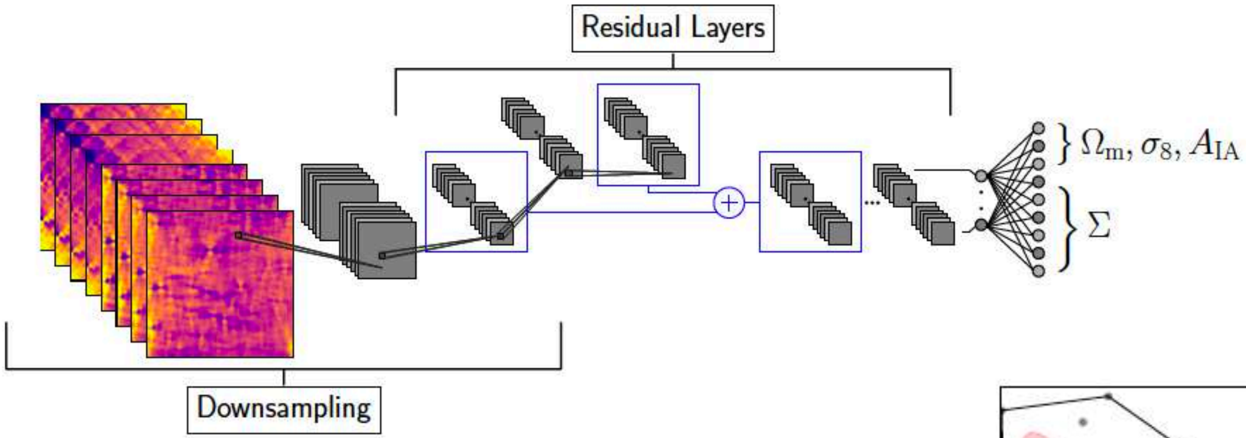
Figure 2. Convergence κ reconstruction from DES SV observational data with: KS, Wiener filtering, and DeepMass.

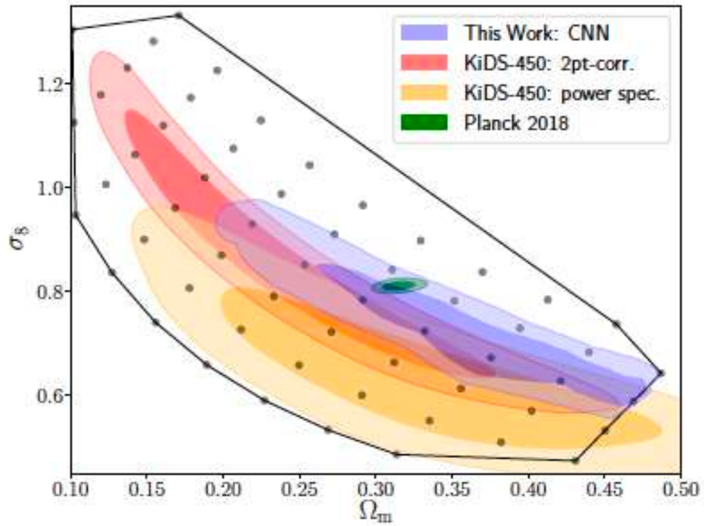
Figure 3. Example L-PICOLA validation simulation (*left*) and the corresponding Wiener (*centre*) and DeepMass (*right*) reconstructions.

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





Fluri et al. 1906.03156

Cosmology with AI/ML

- Cosmology is going ‘industrial revolution’
- In both spatial and time domains

Challenges:

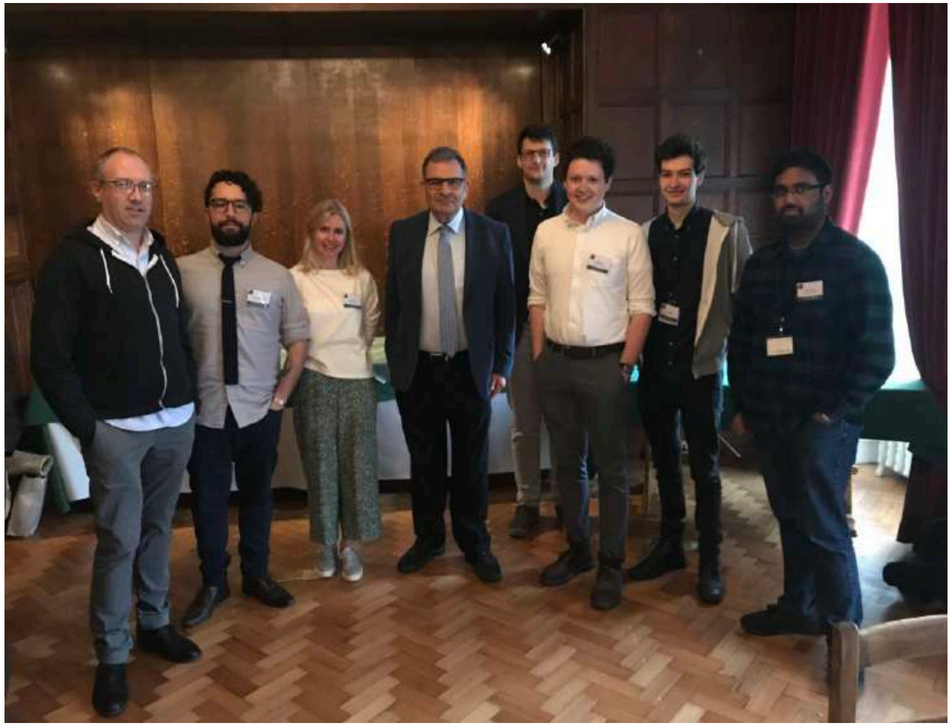
- Incomplete training sets and augmentation
- Incorporating physics
- Understanding Deep Learning
- Benchmarking and up-scaling of algorithms

- Great training of PhDs, beyond academia

- Will DIS produce better knowledge?

(well, it depends in part on Nature…)

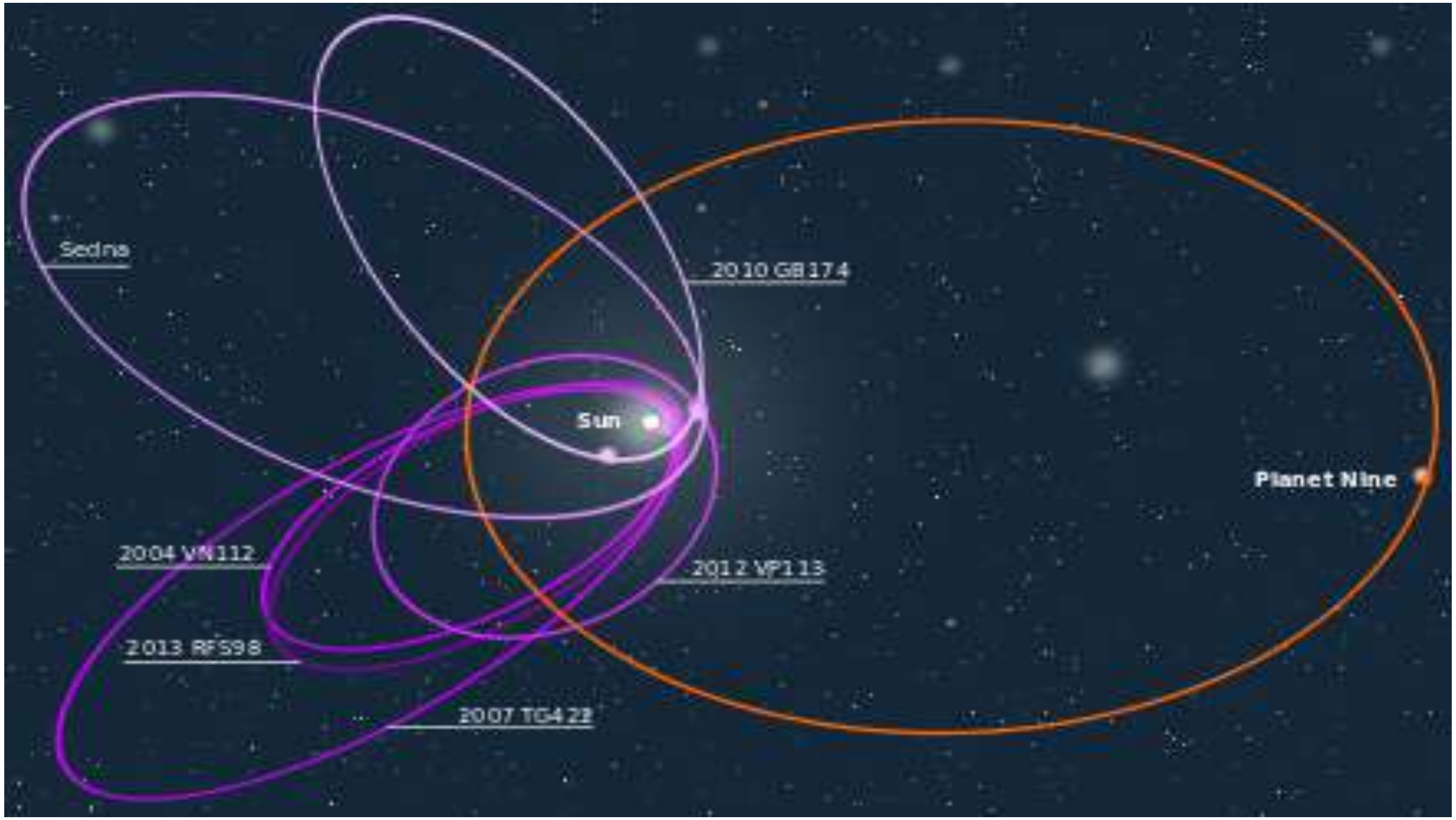
Credits and Thanks to collaborators and PhD students



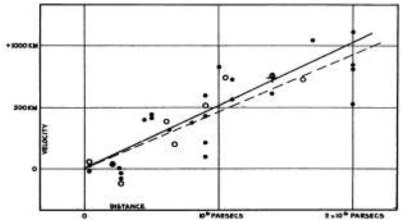
Ofer@60, Windsor, 8-10 April 2019
"From Deep Learning to the Dark Universe"

Extra slides

The search for Planet 9
(one of the 6 minor planets discovered by DES)



David Gerdes et al, DES TMO WG



H_0 from Cosmic Ladder vs. CMB

- Ladder: empirical, H_0 is a direct parameter, local universe, photometry (crowding)
- CMB: Physics-based (Boltzmann eq), but H_0 is one of N parameters, early universe

- GW Standard Sirens: Physics Based (GW) H_0 is direct, local universe

(iv) Gravitational Dynamics with ML

Weighing the Local Group in the presence of Dark Energy

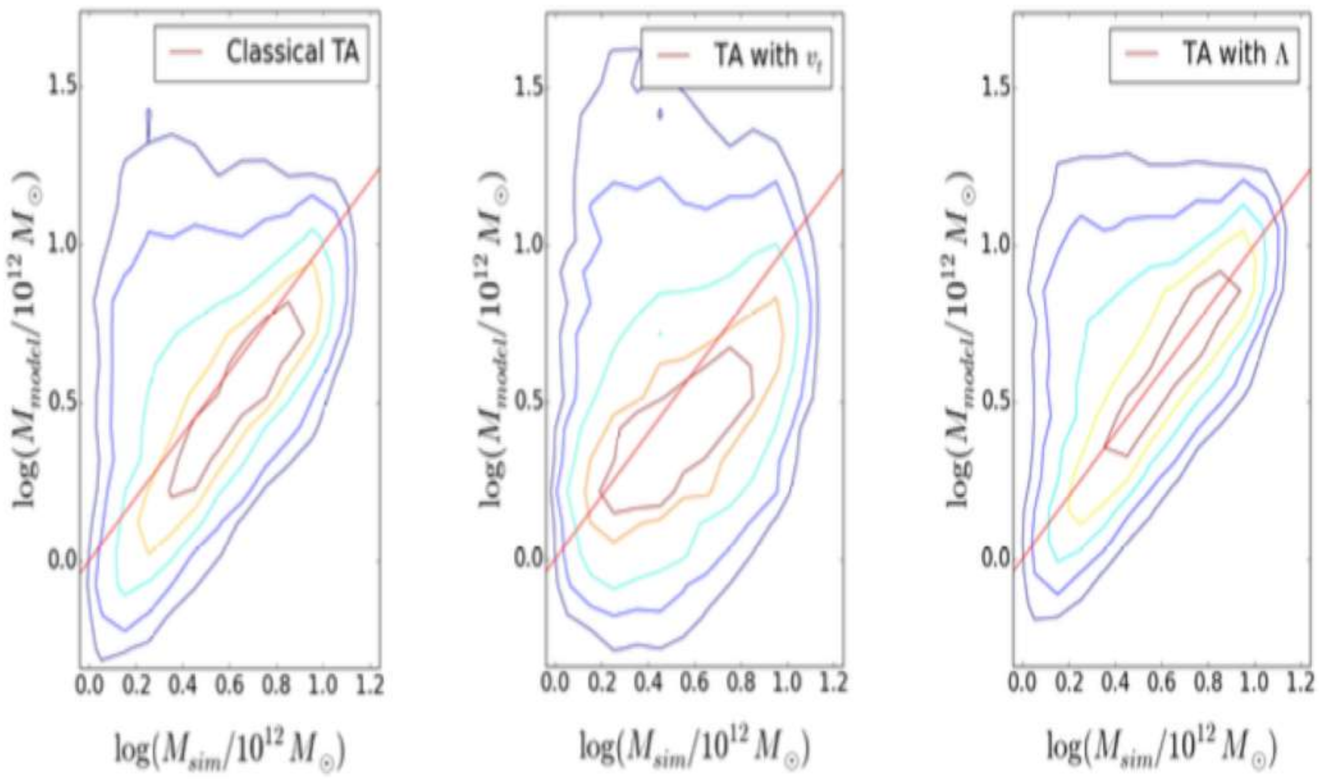
$$a = -GM/r^2 + \Lambda/3 \; r$$

- At present the Milky Way and Andromeda galaxies are separated by r=784 kpc and are "falling" towards each other at v=130 km/sec.
- Given the age of the universe t=13.8 Gyr and Dark Energy fraction of 70% we find that the mass is $(4.73 \pm 1.03) \times 10^{12}\, M_{sun}$
- 13% more than in the absence of Dark Energy

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

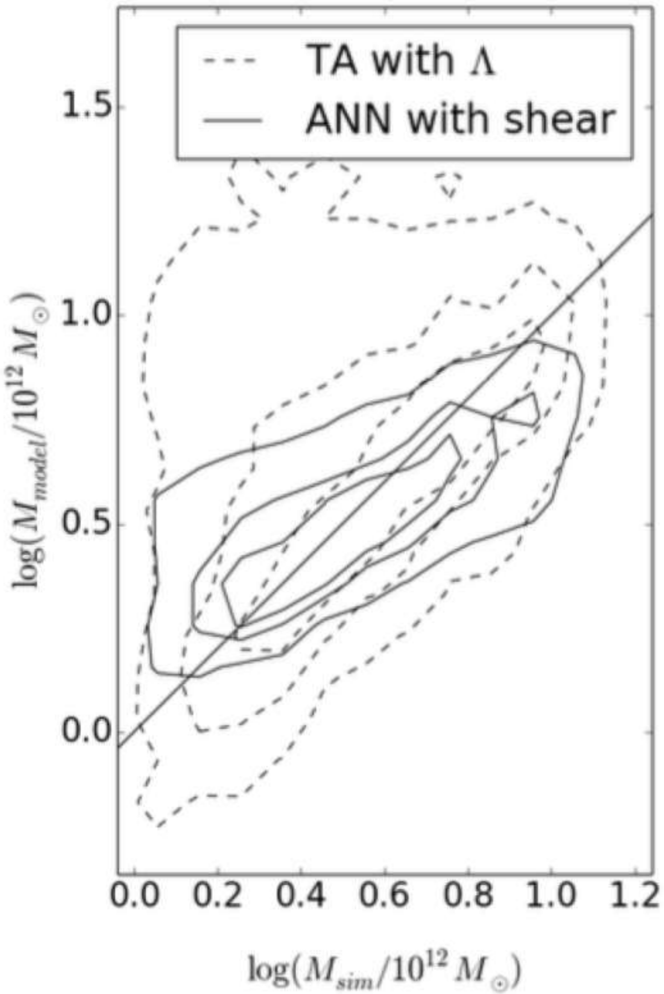
With Lambda: Binney & Tremaine (2008), Partridge, OL & Hoffman (2012)

30k LG-like pairs in MultiDark simulations



McLeod, Libeskind, Hoffman & OL (arXiv:1606.02694)

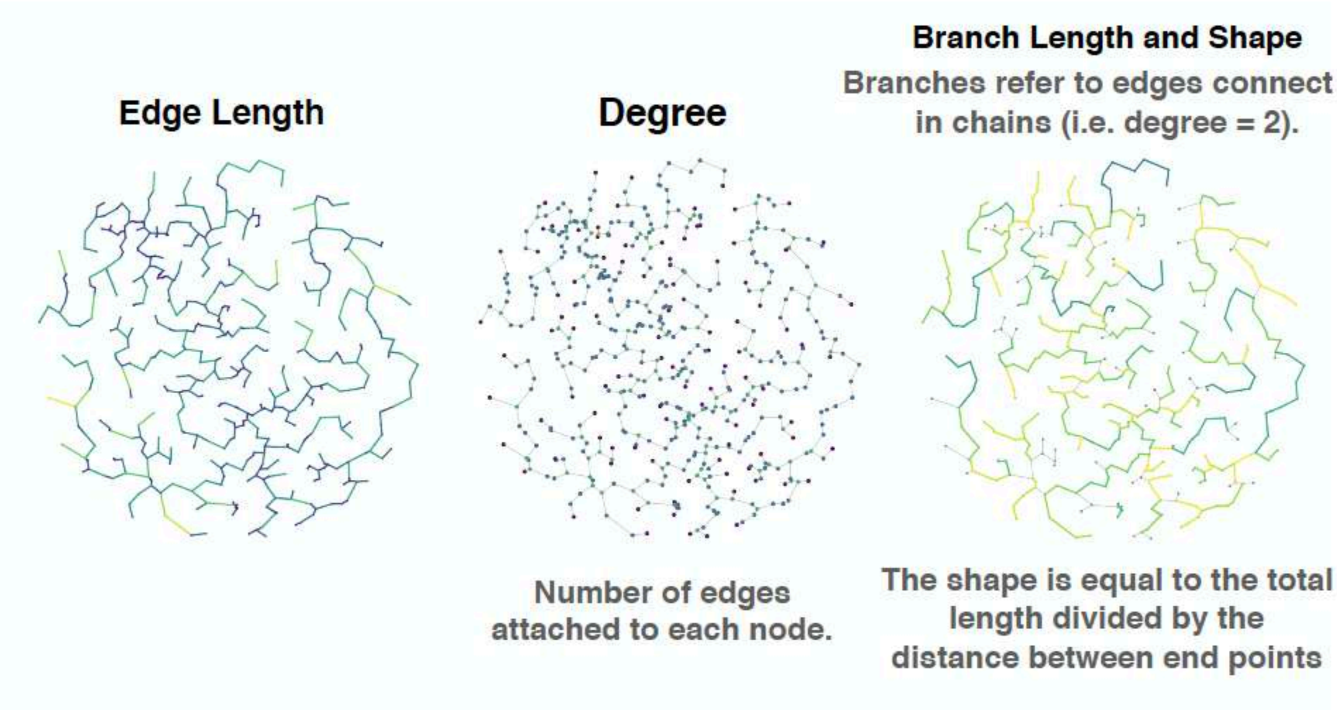
LG mass with Machine Learning: known 2-body gravity + unknown dynamics



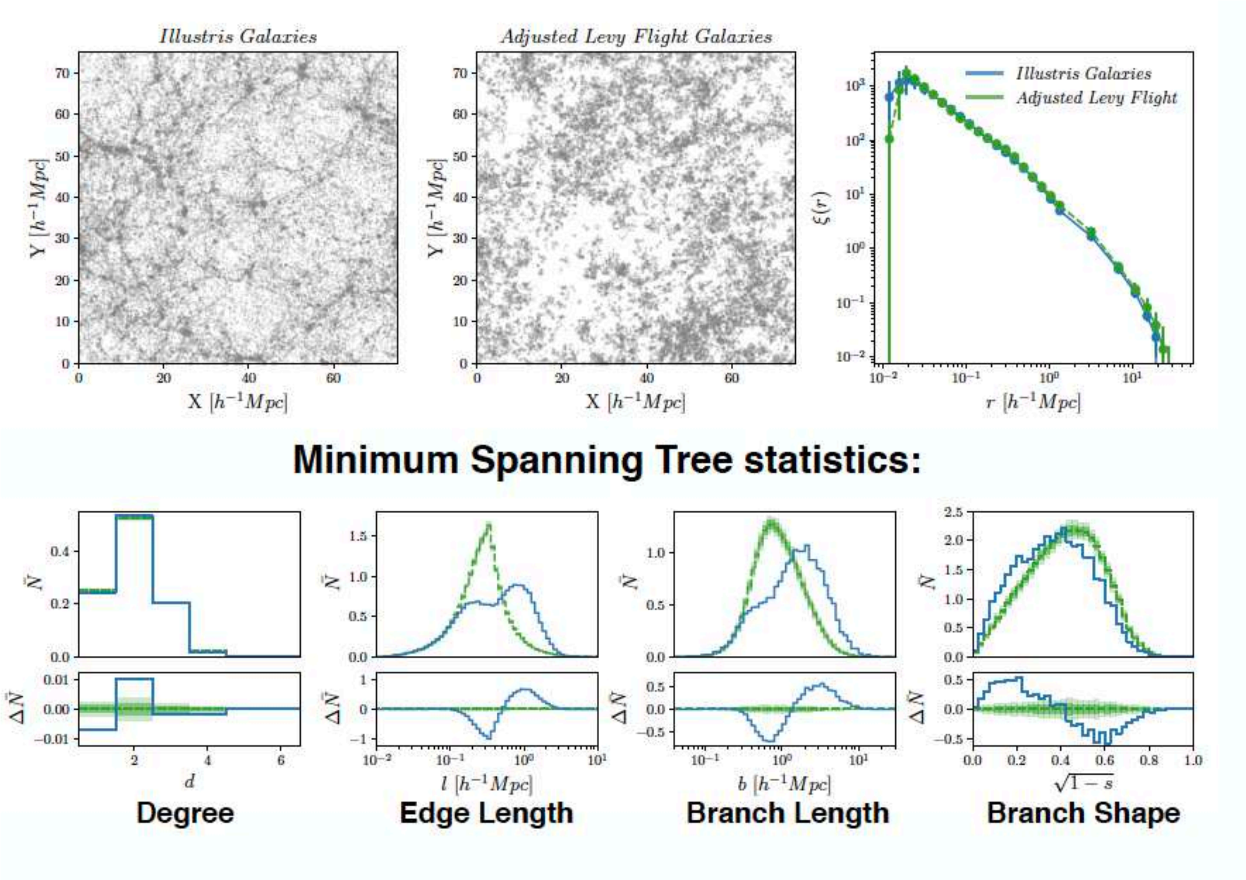
$$\Sigma_{ij} = -\frac{1}{2H_0}\left(\frac{\partial v_i}{\partial r_j} + \frac{\partial v_j}{\partial r_i}\right)$$

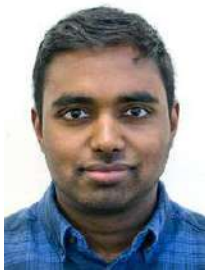
	M_{LG} / $10^{12} M_\odot$		
Model	(vdM. 2008)	(vdM. 2012)	(Sal. 2015)
TA_Λ	$5.8^{+1.0+4.7}_{-0.9-3.0}$	$4.7^{+0.7+3.9}_{-0.6-2.4}$	$3.8^{+1.1+3.1}_{-0.9-2.0}$
ANN	$3.7^{+0.3+1.5}_{-0.3-1.5}$	$3.6^{+0.3+1.4}_{-0.3-1.4}$	$3.3^{+0.6+2.0}_{-0.5-1.5}$
ANN + Shear	$6.1^{+1.1+1.6}_{-1.1-1.8}$	$\mathbf{4.9^{+0.8+1.3}_{-0.8-1.4}}$	$3.6^{+1.3+1.7}_{-1.1-1.5}$
Bayesian	$3.4^{+1.9}_{-1.2}$	$3.1^{+1.3}_{-1.0}$	$3.4^{+2.3}_{-1.3}$

Minimum Spanning Tree



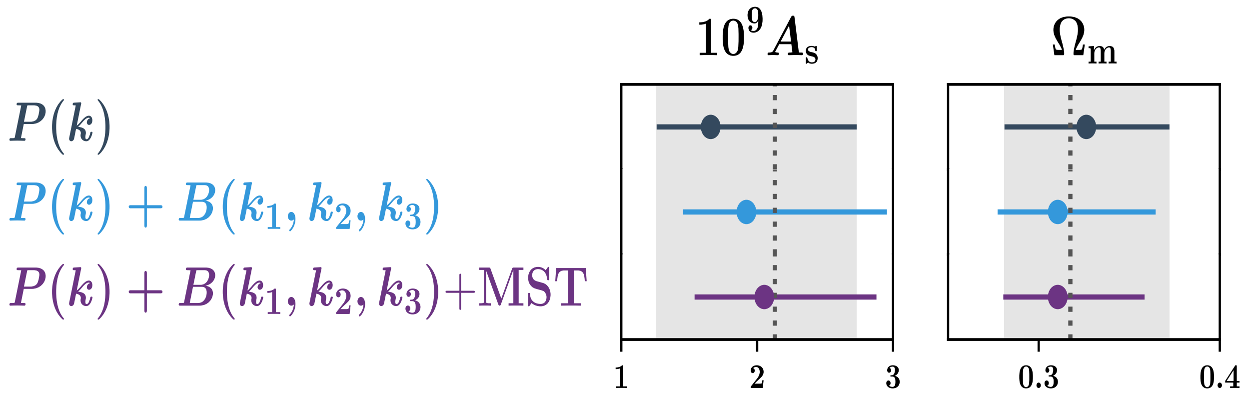
MST vs. 2pt statistic





Krishana Naidoo, Whiteway, …OL et al.
arXiv:1907.00989

MST: better accuracy and precision



DeepMass

We take a standard deep learning approach. We seek an approximation $\mathcal{F}_\Theta$ to the function that maps the pixelised shear to the convergence map

$$\hat{\kappa} = \mathcal{F}_\Theta(\gamma) \ , \tag{5}$$

where the parameters of the function Θ are to be learned (Goodfellow et al. 2016). We learn these parameters by minimising a mean-square-error (MSE) cost function

$$J(\Theta) = ||\mathcal{F}_\Theta(\gamma) - \kappa_{\mathrm{true}}||_2^2 \ , \tag{6}$$

evaluated on a set of training data which consists of pairs of realistic shear and "truth" (noise-free) convergence maps. If the training data "truth" maps are drawn from a prior distribution $P(\kappa)$, and the corresponding noisy shear map is drawn from the likelihood $P(\gamma|\kappa)$, this MSE cost function corresponds to $\mathcal{F}_\Theta(\gamma)$ being a mean[1] posterior estimate (Jaynes 2003), such that $\hat{\kappa}$ is approximating:

$$\hat{\kappa} = \mathcal{F}_\Theta(\gamma) = \int \kappa \ P(\kappa|\gamma) \ \mathrm{d}\kappa \ . \tag{7}$$

We use a deep convolution neural network (CNN) to approximate the function $\mathcal{F}_\Theta$, where the parameters Θ are primarily elements of learned filters in convolutional layers. CNNs are particularly suited for two-dimensional image or one-dimensional time series data with translation invariant features in the underlying signal.

Jeffrey et al. (2019)

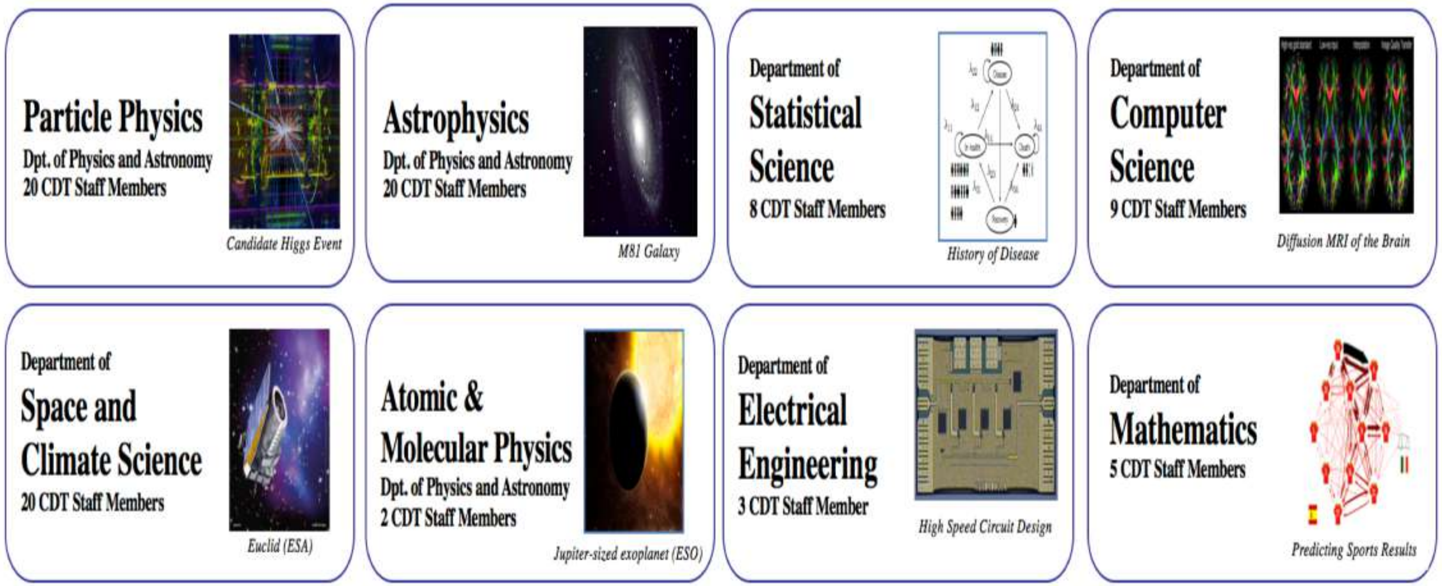
UCL CDT
in Data Intensive Science

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

2017, 2018 & 2019 cohorts:
33 CDT PhD students at UCL
(> 200 students nation-wide in 8 CDTs)

PhD work related to International projects

PhD supervisors from 6 UCL Departments



CDT-DIS 4yr Programme

	Activities
Year 1	• Taught courses • Group project • Exams • PhD project assignment • Software (SW) Carpentry • CDT Summer School **Transferable Skills** *Communication skills,* *Scientific writing, Media training*
Year 2	• **MPhil to PhD transfer** • Placement assignment • SW Carpentry (tutor) **Transferable Skills** *Entrepreneurship,* *Intellectual property,* *Science in the economy*
Year 3	• Placement • International training school • CDT Summer School (tutor) **Transferable Skills** *Research planning, Proposal writing*
Year 4	• International conference • **PhD Award** **Transferable Skills** *Interview skills, Careers workshop*

Industry Partners

Partner Organisation	Sector Activity
ASI	Consultancy in Data Science
ASOS	Retail Fashion
ATI	National institute for data science and artificial intelligence
BBC	News and Media
Blue Skies Space Ltd	Enable cost-effective, quickly-delivered scientific instruments for users
CERN openlab	Innovation in advanced detectors and advanced computing
DiRAC HPC Facility	Innovation in advanced computing
European Bank for Reconstruction	Finance and Banking
Hartree Centre	Supporting Industry through Data Science
Lenovo	IT Technology
Mellanox	IT Technology
NCC Group	Cyber Security and Mitigation
OCF	IT technology
Petroleum Geo-Services	Data and Modelling Services for Oil and Gas Industry
Privitar	Analysis of Sensitive Data
Quantemol Ltd	Scientific Data for Industry
Quantum Black	Consultancy in Data Science
RAL Particle Physics Division	Innovation in advanced detectors
RAL Scientific Computing Division	Innovation in advanced computing
The Economist Group	News and Media
The Met Office	Weather Modelling and Prediction Services
Transport for London (TfL)	Mass transportation
UKAEA	Advanced Engineering Systems for Nuclear Fusion

+ Newton Fund for DIS with Jordan