# Gravitational Lens Finding Challenge

## HOW TO FIND A GRAVITATIONAL LENS?

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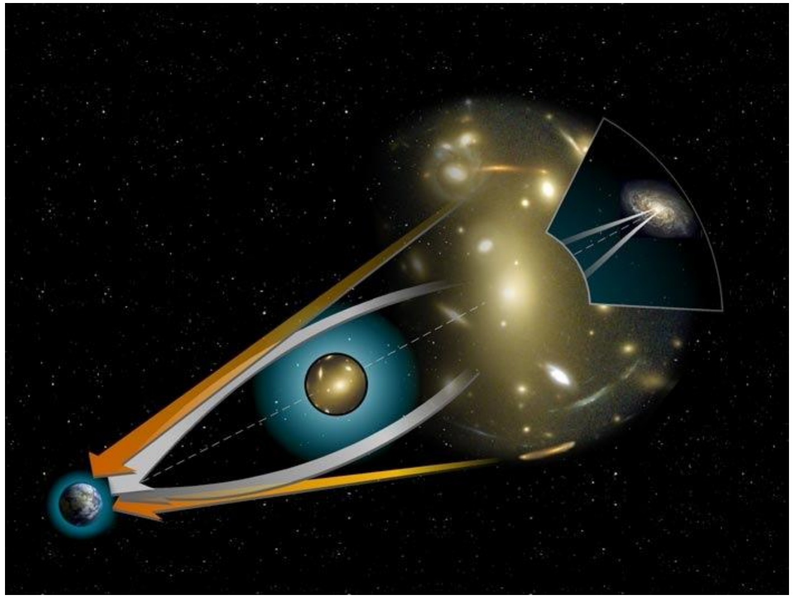
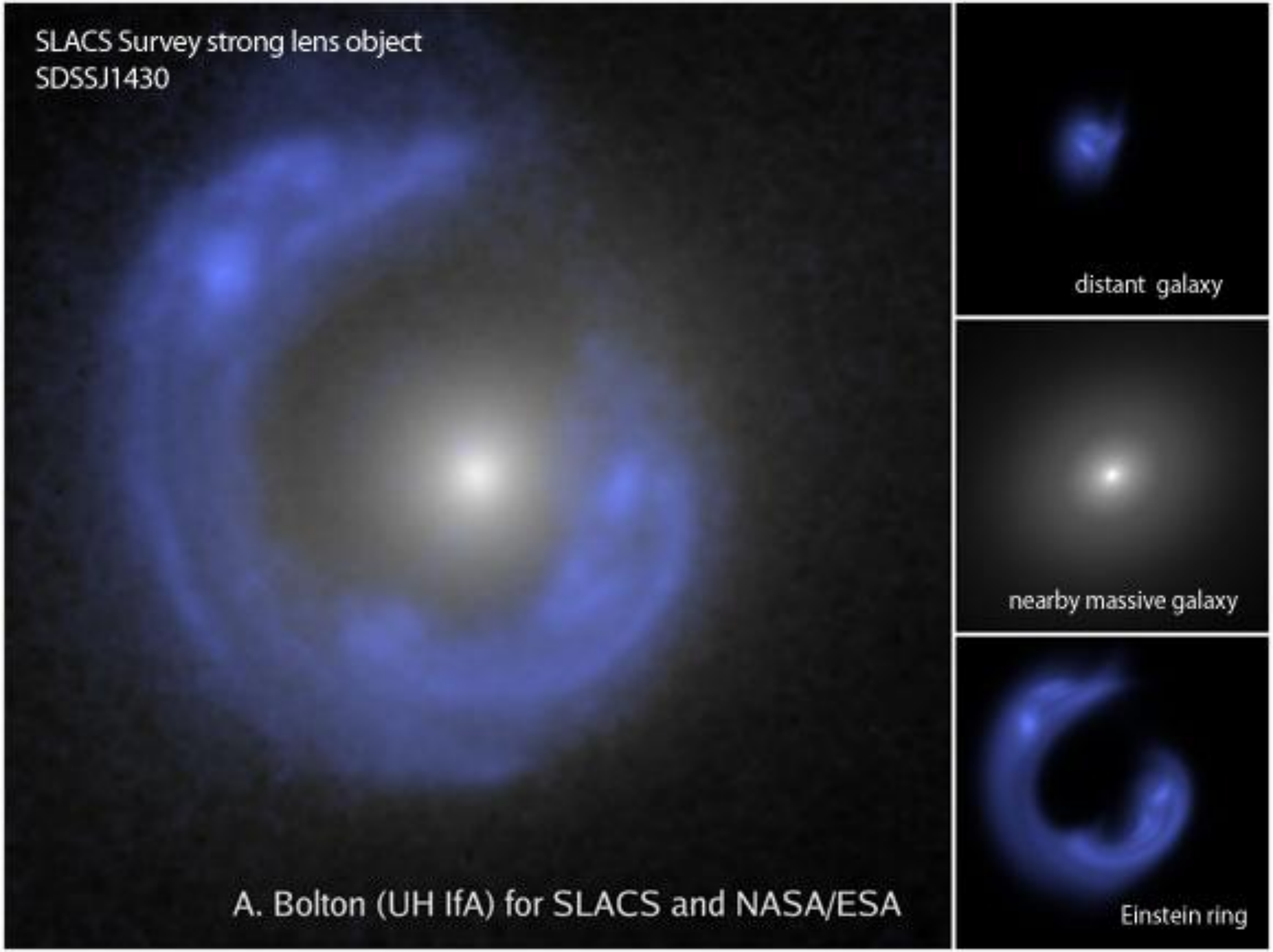
# Gravitational lens

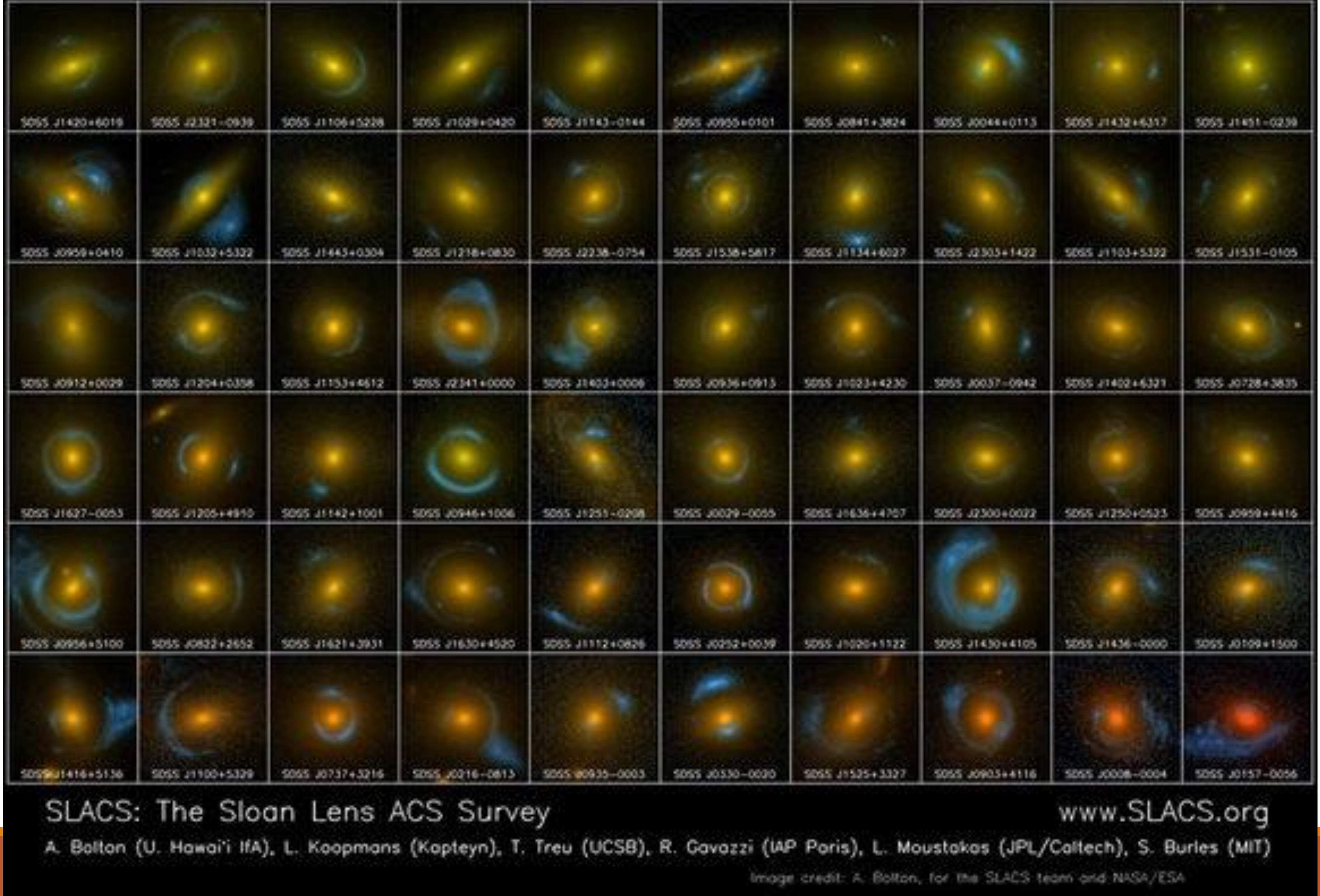
- bending of light by a dense mass distribution between a source and an observer
- Images are distorted, displaced, magnified and multiplied



http://hubblesite.org/newscenter/archive/2000/07/image/c

http://hubblesite.org/newscenter/archive/releases/1990/20/image/a/


SLACS Survey strong lens object
SDSSJ1430
A. Bolton (UH IfA) for SLACS and NASA/ESA
distant galaxy
nearby massive galaxy
Einstein ring


SLACS: The Sloan Lens ACS Survey
www.SLACS.org
A. Bolton (U. Hawai'i IfA), L. Koopmans (Kapteyn), T. Treu (UCSB), R. Gavazzi (IAP Paris), L. Moustakas (JPL/Caltech), S. Burles (MIT)
Image credit: A. Bolton, for the SLACS team and NASA/ESA

# Astronomical Surveys: Creating catalogs of galaxies

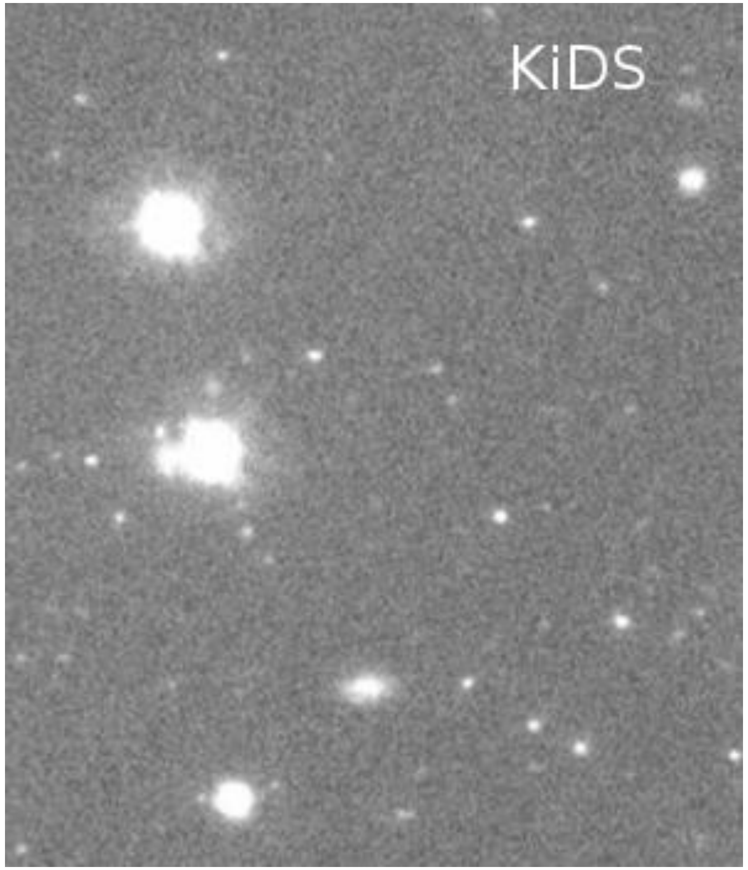
Ground Based (KiDS) or Space-based (Euclid)

Kilo-Degree Survey

- 4% area of the Sky
- 1 K estimated galaxy lenses

Euclid (ESA mission)

- 35% area of the Sky
- 5K-10K estimated cluster and group lenses
- 100 K estimated galaxy lenses




KiDs r-band image [2.]

1. https://euclidfrance.sciencesconf.org/file/21610
2. http://kids.strw.leidenuniv.nl/overview.php
3. Strong lens search in the ESO public Survey KiDS, Nicola R. Napolitano (2015)

# Survey Stamps: 101x101 pixels

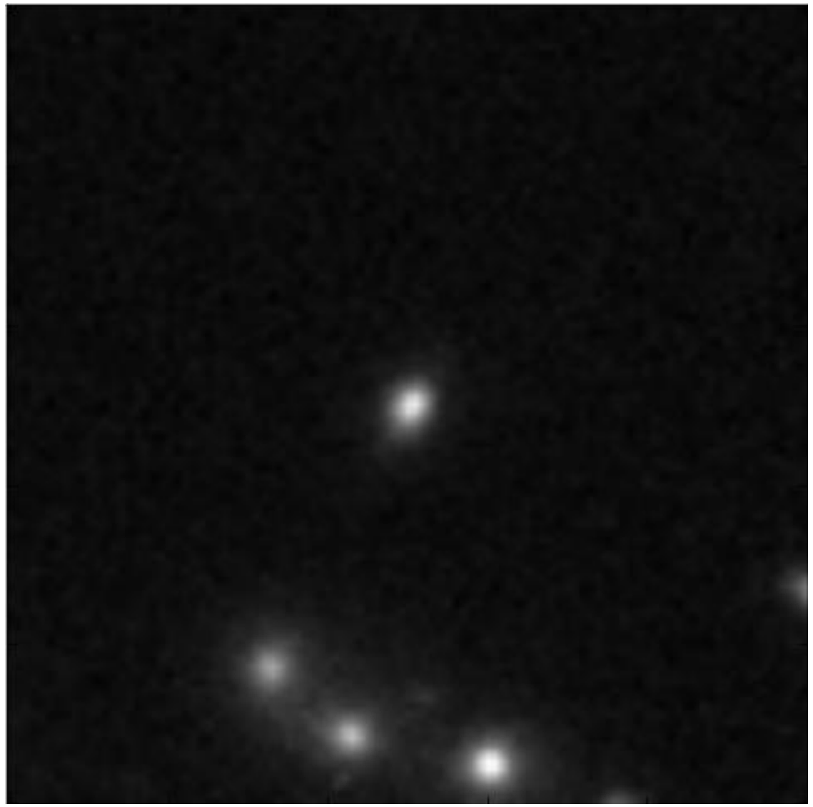
1. http://metcalf1.bo.astro.it/blf-portal/gg_challenge.html

# Finding gravitational Lenses

Einstein Ring | Arcs | Multiple Images

# Likely False Positives

Companions

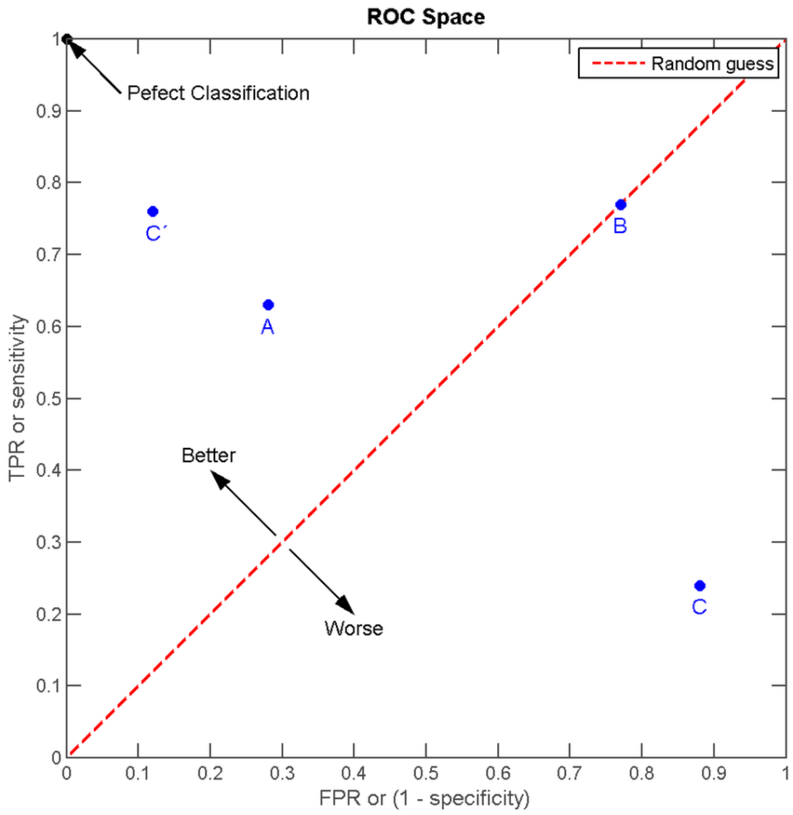


Arc-like structures

Unusual structures

# Gravitational Lens finding Challenge

- Simulated image by the Bologna Lens factory
- Ground and Space-based
- Multi-wavelength for Ground data
- Metrics based on the ROC (Receiver operating characteristic)
- Priority on reducing False Positive



# Data sets

Images

- 101x101 px

Training set

- Ground: 20k images x 4  wavelengths
- Space: 20k images

Ground Truth

- is lensed/ is not lensed

Submission

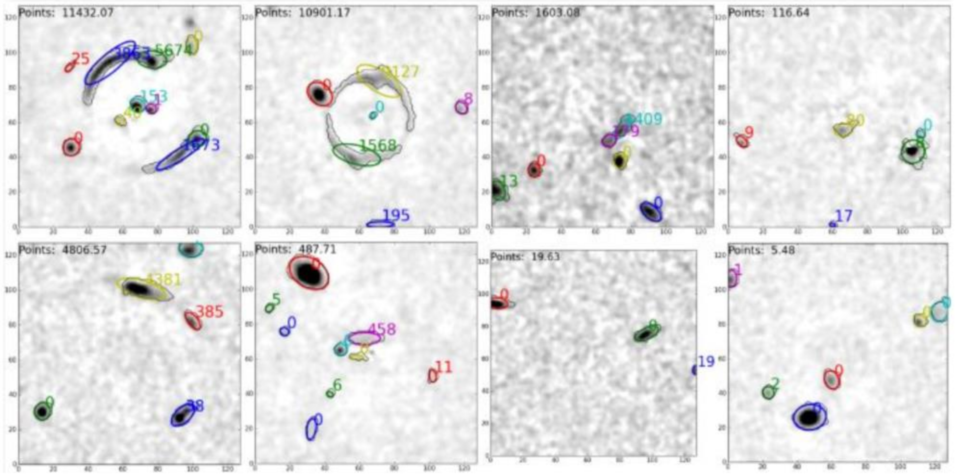
- Classification: 100k images
- Accessible only once for 48 hours

# State of the art

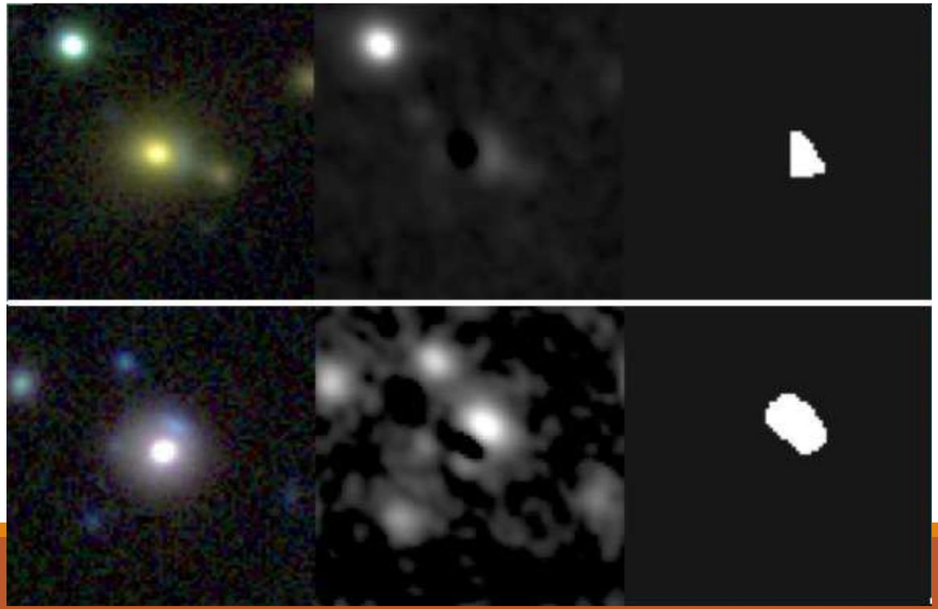
- Eye identification (https://spacewarps.org/)
- Ad hoc methods
- Making use of the physics
- First glimpse of machine learning?

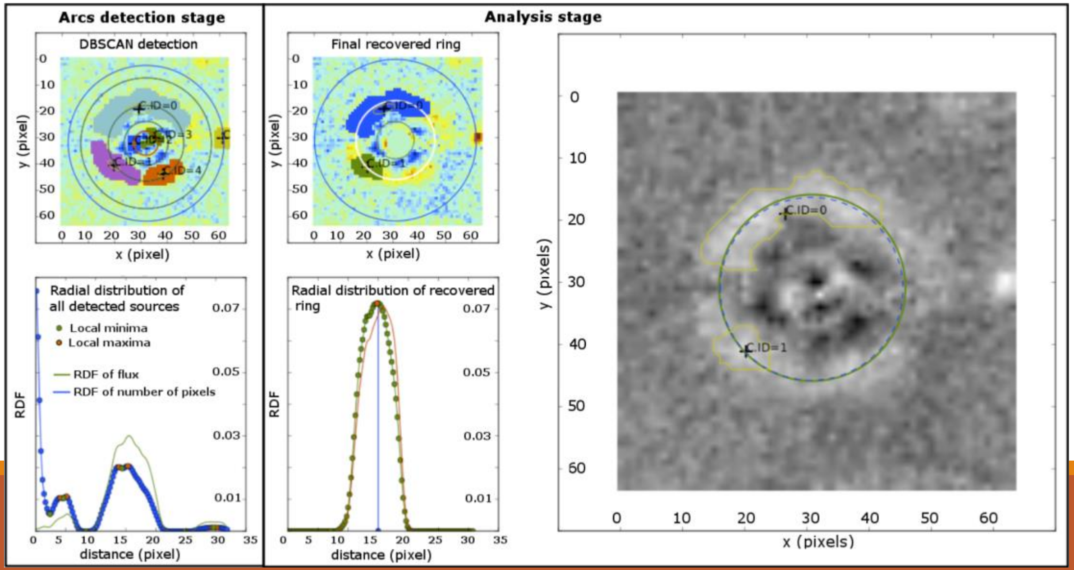
# Ad hoc methods

- Feature identification (Gavazzi et al. 2014)



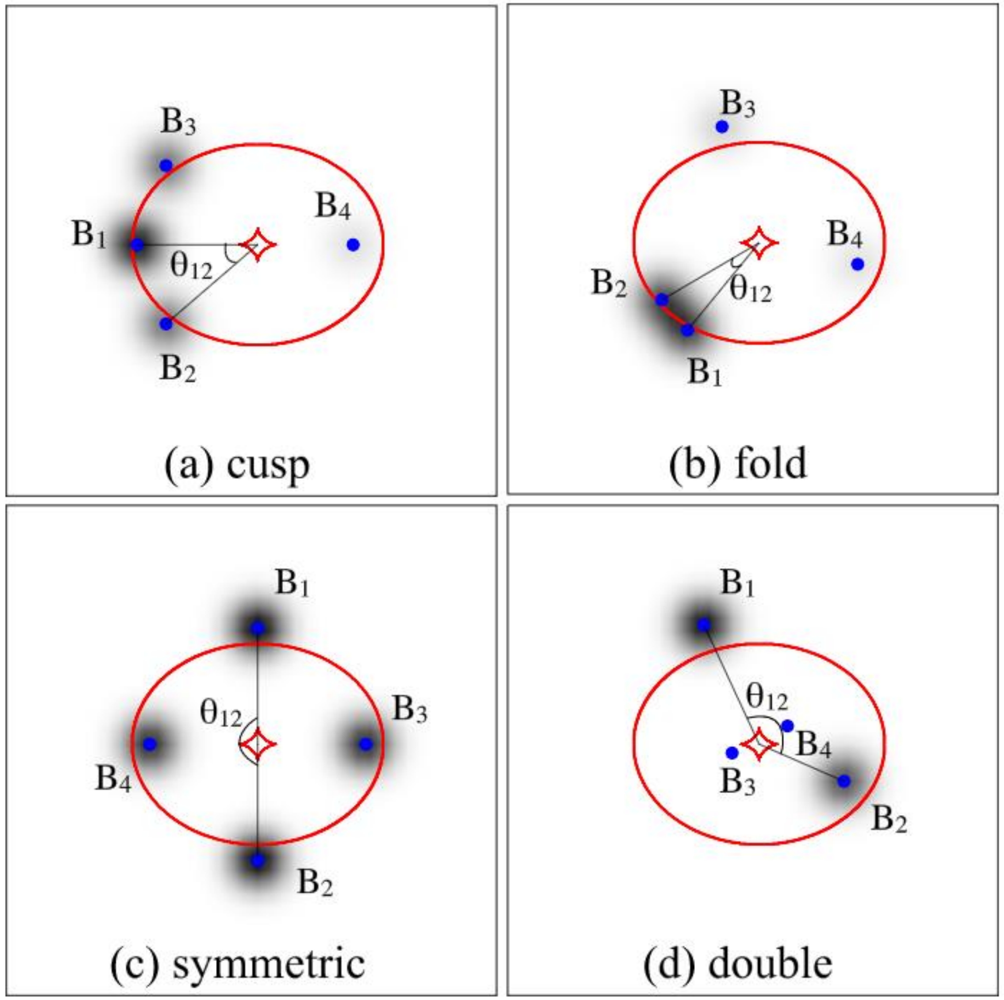
- Ring or line finding (Joseph et al. 2014, Paraficz et 2016)





# Physics-based method

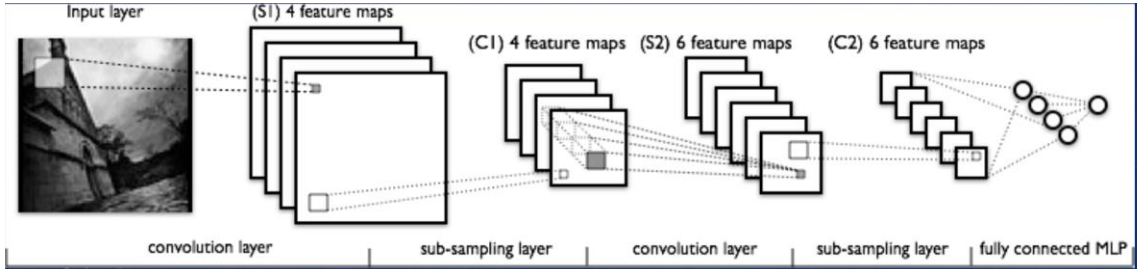
- CHITAH: Does the configuration of a potential lens system makes physical sens? (Chan et al. 2015)

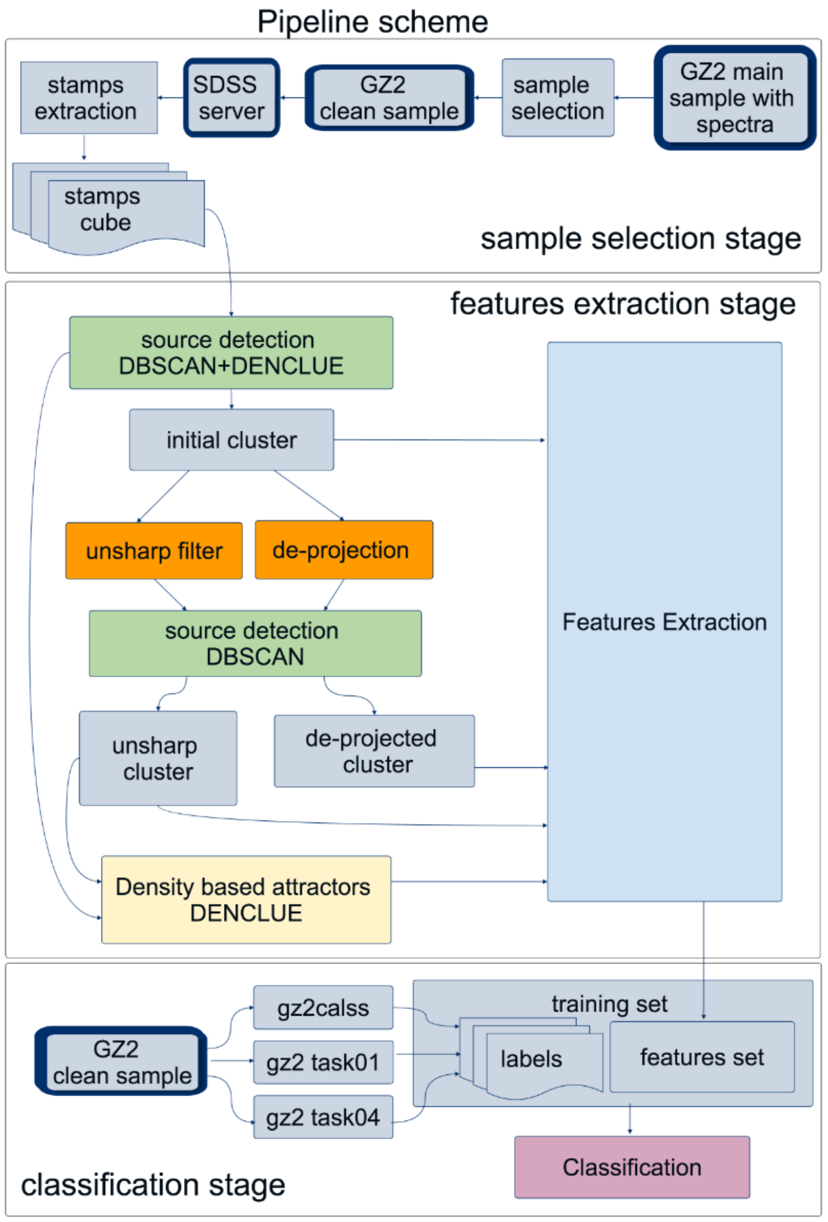


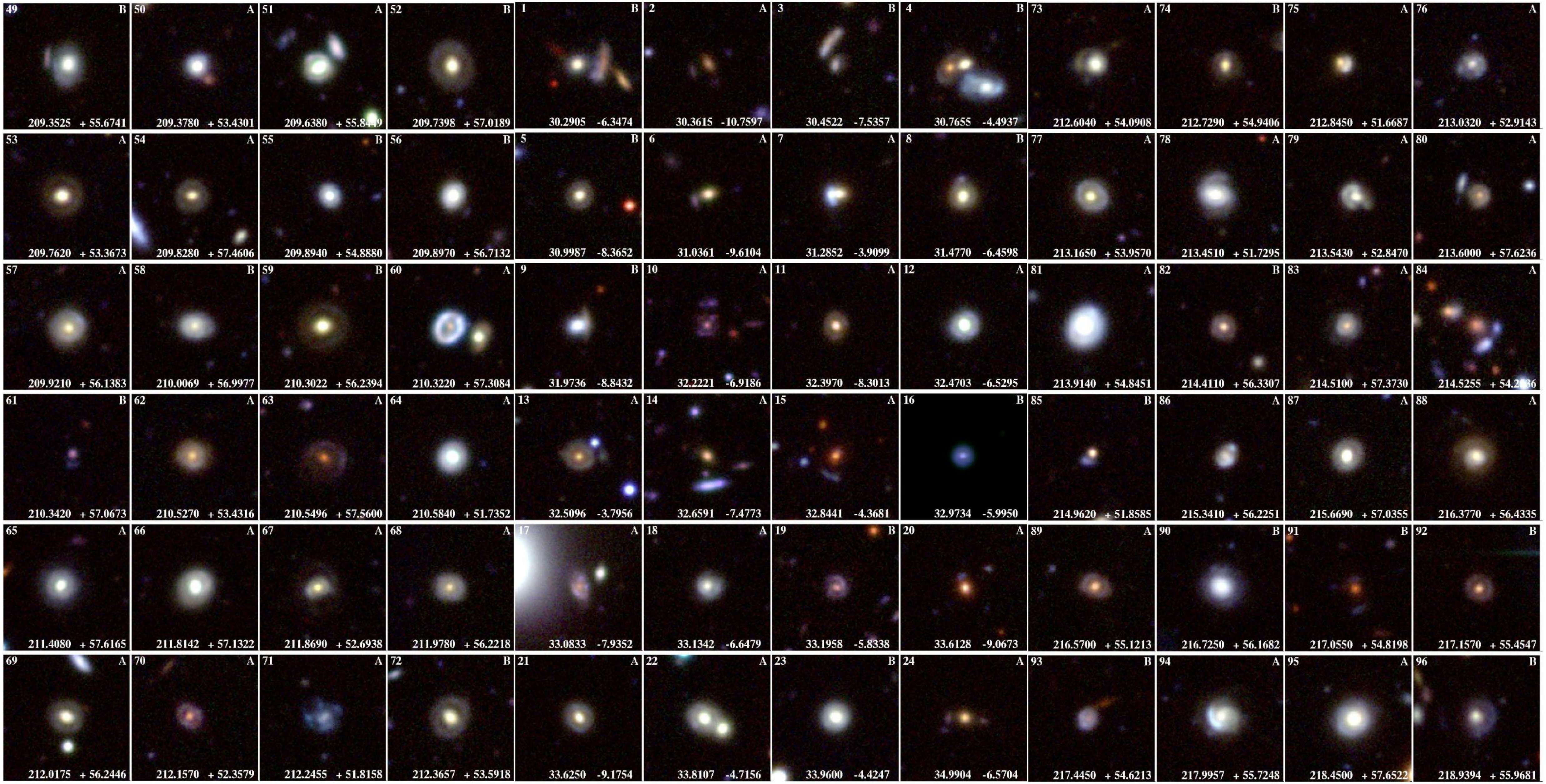
# Machine learning

- Learning of features (105 features : Tramacere et al. 2016)

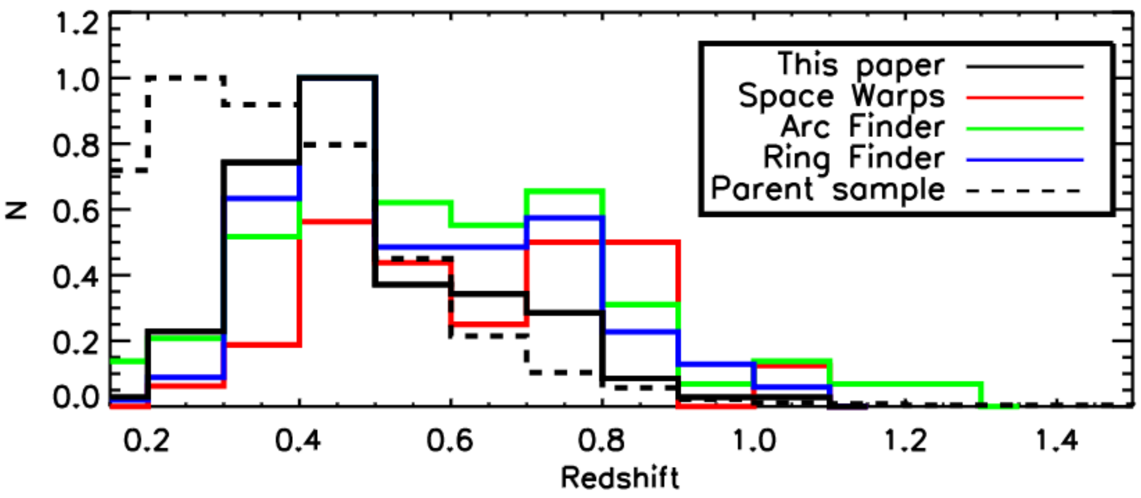
- Convolutional network for images (not published yet)

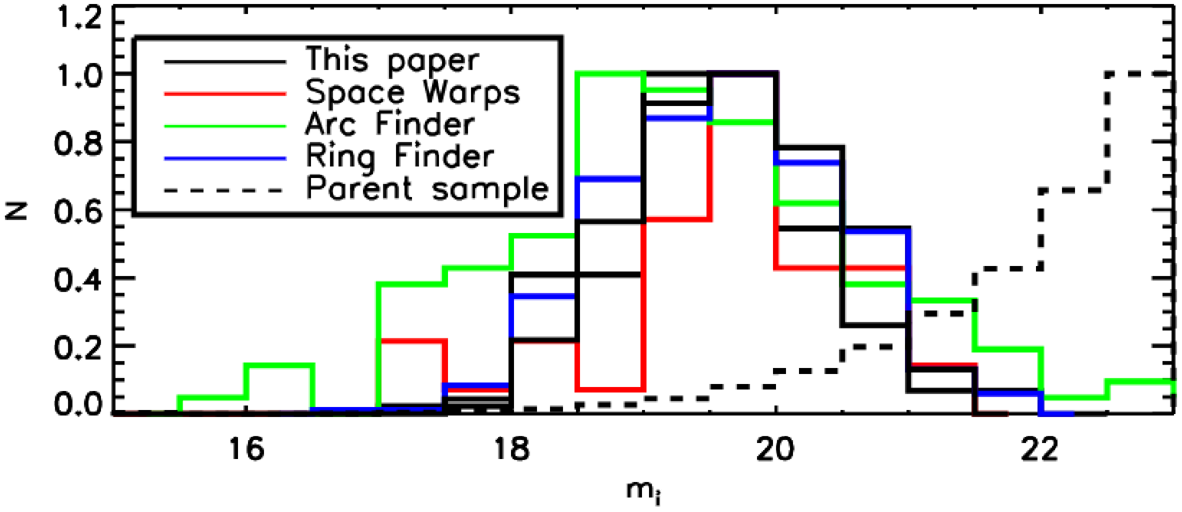


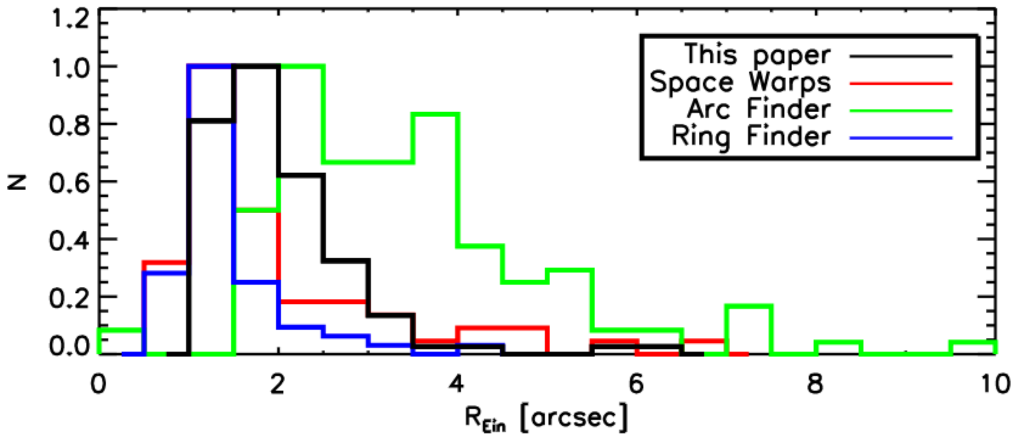




49 B 209.3525 + 55.6741
50 A 209.3780 + 53.4301
51 A 209.6380 + 55.8449
52 B 209.7398 + 57.0189
1 B 30.2905 -6.3474
2 A 30.3615 -10.7597
3 B 30.4522 -7.5357
4 B 30.7655 -4.4937
73 A 212.6040 + 54.0908
74 B 212.7290 + 54.9406
75 A 212.8450 + 51.6687
76 A 213.0320 + 52.9143
53 A 209.7620 + 53.3673
54 A 209.8280 + 57.4606
55 B 209.8940 + 54.8880
56 B 209.8970 + 56.7132
5 B 30.9987 -8.3652
6 A 31.0361 -9.6104
7 A 31.2852 -3.9099
8 B 31.4770 -6.4598
77 A 213.1650 + 53.9570
78 A 213.4510 + 51.7295
79 A 213.5430 + 52.8470
80 A 213.6000 + 57.6236
57 A 209.9210 + 56.1383
58 B 210.0069 + 56.9977
59 B 210.3022 + 56.2394
60 A 210.3220 + 57.3084
9 B 31.9736 -8.8432
10 A 32.2221 -6.9186
11 A 32.3970 -8.3013
12 A 32.4703 -6.5295
81 A 213.9140 + 54.8451
82 B 214.4110 + 56.3307
83 A 214.5100 + 57.3730
84 A 214.5255 + 54.2636
61 B 210.3420 + 57.0673
62 A 210.5270 + 53.4316
63 A 210.5496 + 57.5600
64 A 210.5840 + 51.7352
13 A 32.5096 -3.7956
14 A 32.6591 -7.4773
15 A 32.8441 -4.3681
16 B 32.9734 -5.9950
85 B 214.9620 + 51.8585
86 A 215.3410 + 56.2251
87 A 215.6690 + 57.0355
88 A 216.3770 + 56.4335
65 A 211.4080 + 57.6165
66 A 211.8142 + 57.1322
67 A 211.8690 + 52.6938
68 A 211.9780 + 56.2218
17 A 33.0833 -7.9352
18 A 33.1342 -6.6479
19 B 33.1958 -5.8338
20 A 33.6128 -9.0673
89 A 216.5700 + 55.1213
90 B 216.7250 + 56.1682
91 B 217.0550 + 54.8198
92 B 217.1570 + 55.4547
69 A 212.0175 + 56.2446
70 A 212.1570 + 52.3579
71 A 212.2455 + 51.8158
72 B 212.3657 + 53.5918
21 A 33.6250 -9.1754
22 A 33.8107 -4.7156
23 B 33.9600 -4.4247
24 A 34.9904 -6.5704
93 B 217.4450 + 54.6213
94 A 217.9957 + 55.7248
95 A 218.4500 + 57.6522
96 B 218.9394 + 55.9681

# Performance of SL classifiers



# ML in astrophysics

Classification

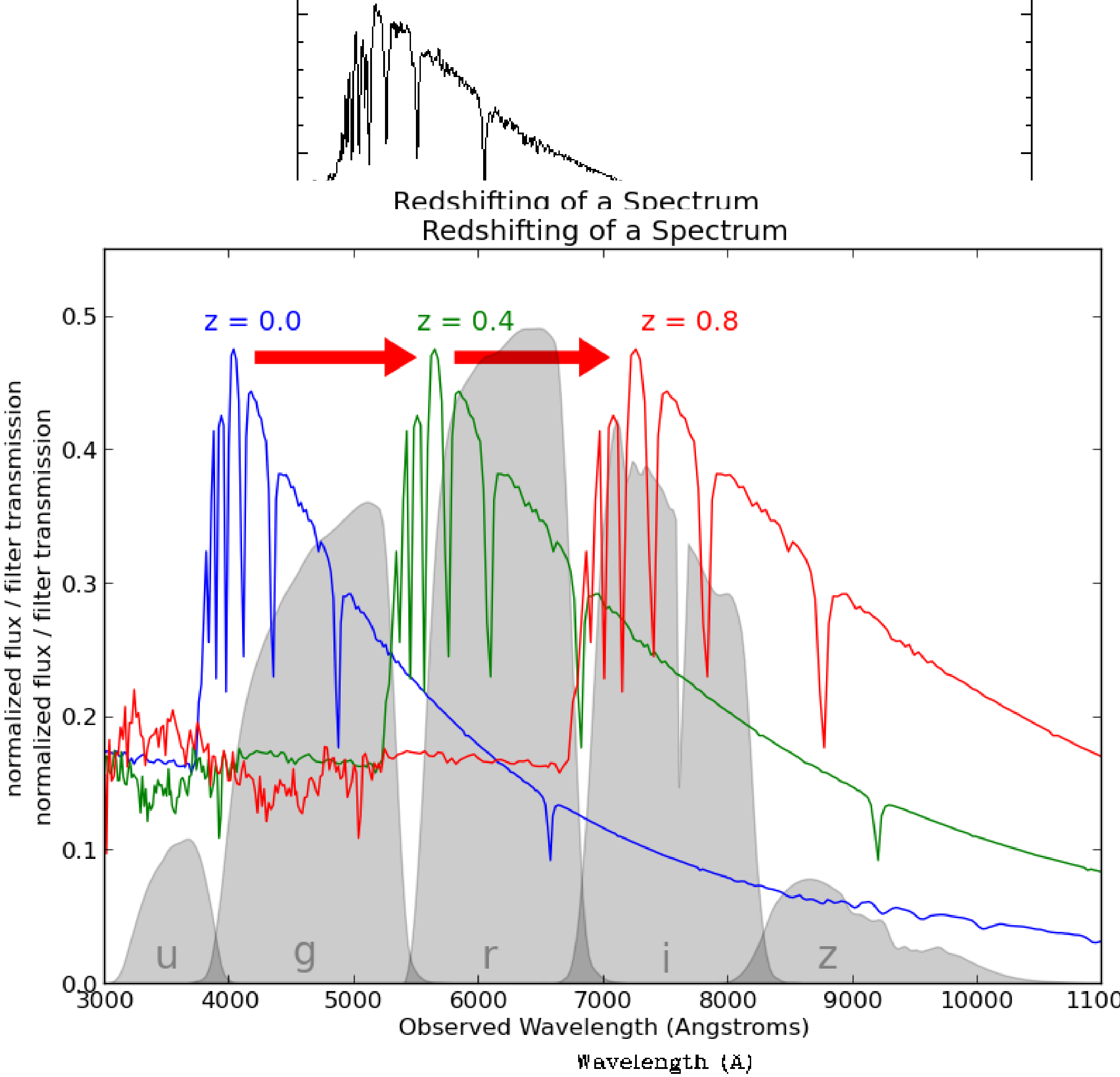
- Star/galaxy separation
- **Spectral classification**
- Galaxy morphology

Regression

- **Measurement of shape of galaxies**
- Distance of far-away objects (redshifts)

**Dimensionality reduction**

…

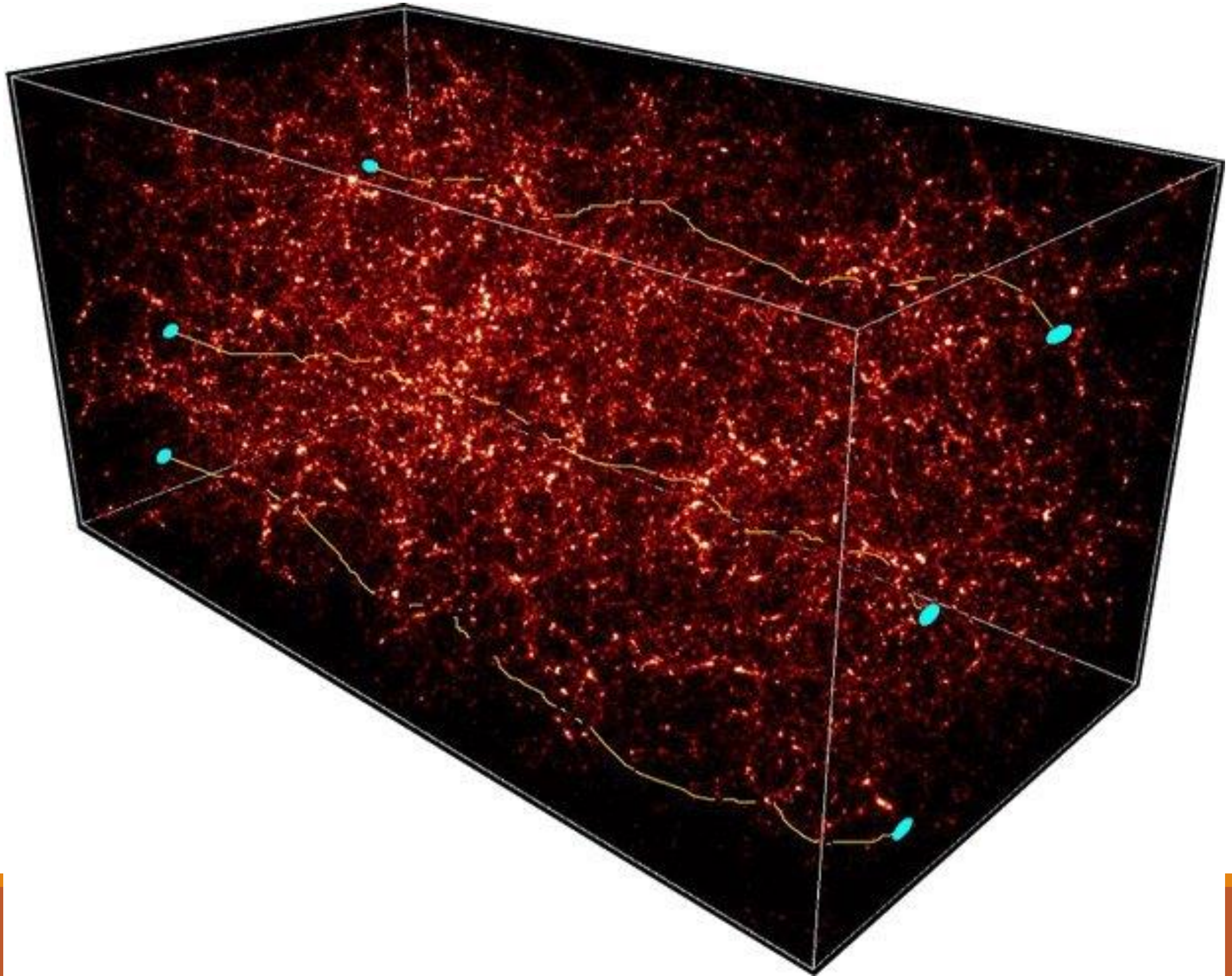


# Measuring the shape of galaxies

- Same as Strong Lensing
- Much smaller effect
- Probe of Dark Matter

- WEAK GRAV. LENSING:
  - 1 image
  - shape is modified
  - Effect O(1%)
  - slightly magnified

- Statistical approach



Intrinsic Galaxy (shape unknown)

Gravitational Lensing causes a shear

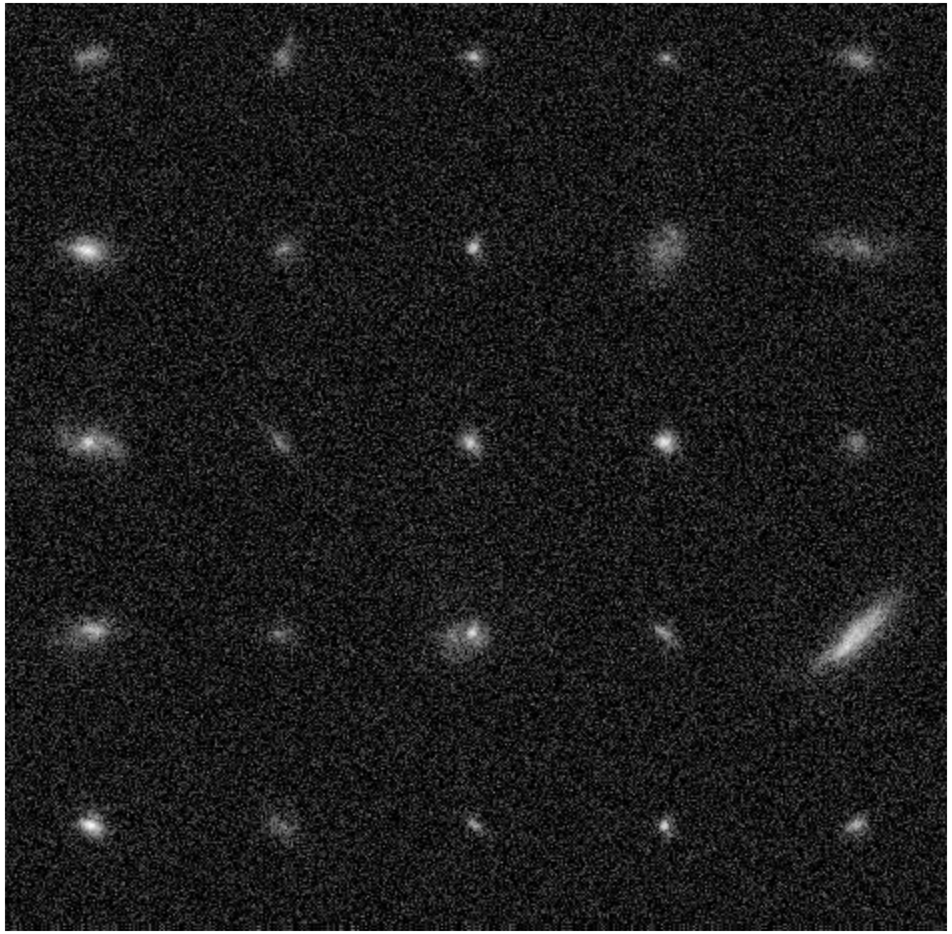
Image is convolved with the PSF

Image produced by detector is pixelated

Various sources of noise degrade the image

# A wealth of data to measure and do it well

- Now: O($10^{6-7}$) galaxies
- Euclid: O($10^{9}$) (!) galaxies
- A few pixels across
- Signal-to-noise ~2-30 (quite noisy!)
- Error on the shape ~1% per galaxy



# MegaLUT: a ML shape estimator

- Artificial Neural Networks

  5 inputs: (physical quantities: shape & intensity)

  2 outputs: “shear” (effect of WL)

- Few features, no need for large capacity

- How to deal with noise?

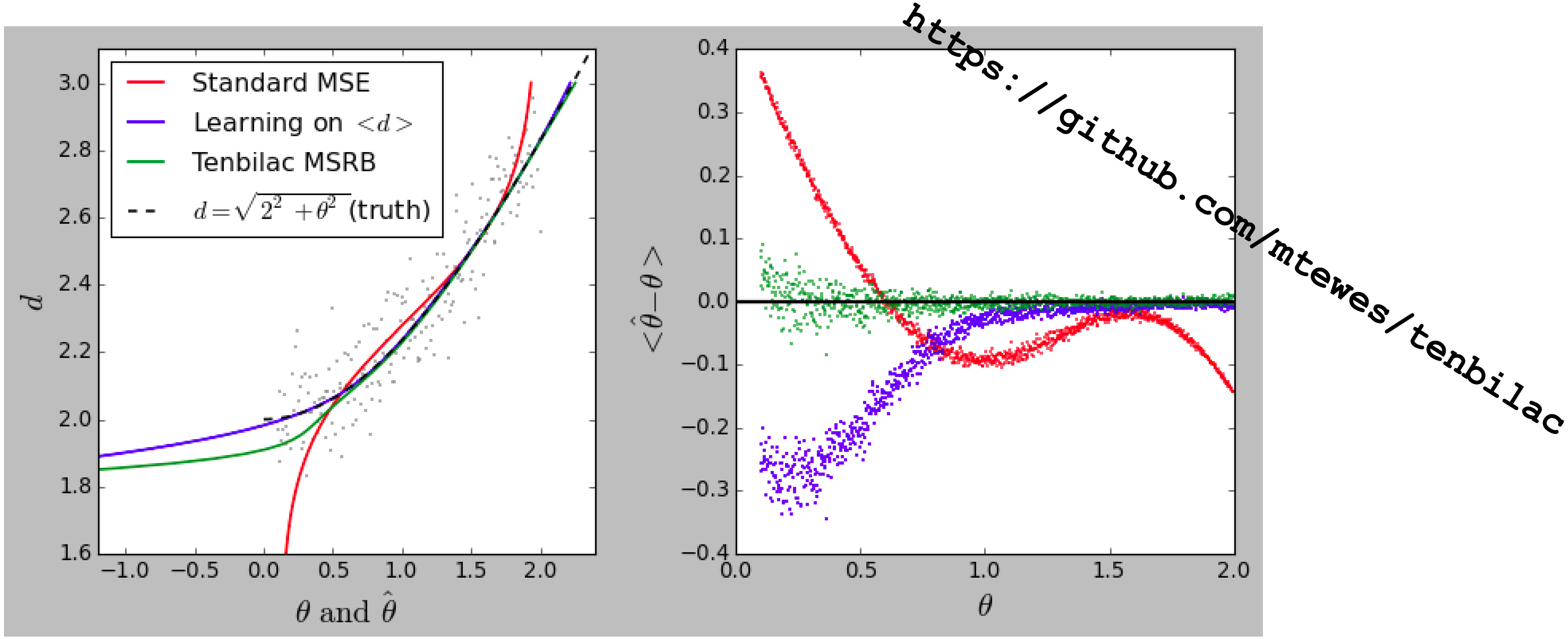
# Regression of noisy data points

Goal: accurate regression ⇒ **minimise bias**

- The network is shown several realisations of the same object
  "case": same shear, different galaxies
  "rea" same shear & galaxy, different noise
- Cost function is no longer Mean Square Error, but MS Bias

$$\mathrm{MSB}(\boldsymbol{p}) \doteq \frac{1}{n_{\mathrm{case}}} \sum_{k=1}^{n_{\mathrm{case}}} \left( \frac{1}{n_{\mathrm{rea}}} \sum_{i=1}^{n_{\mathrm{rea}}} o_{i,j,k}(\boldsymbol{p}) - t_{j,k} \right)^2$$

# Regression of noisy data points



# ML in astrophysics

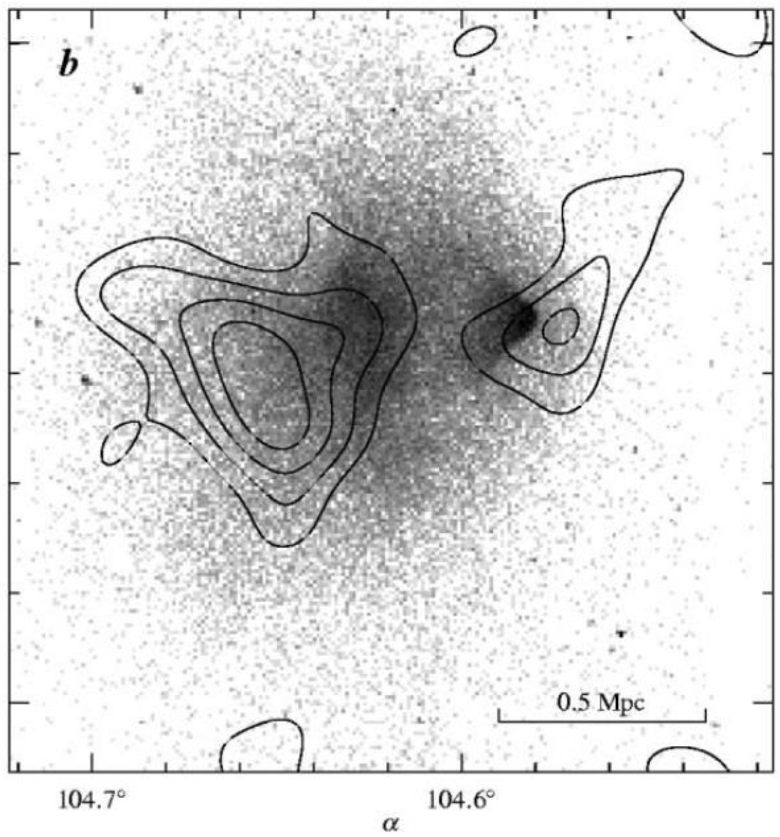
- ML is just kicking in strong gravitational lensing
- Feel free to try yourselves at the challenge: http://metcalf1.bo.astro.it/blf-portal/gg_challenge.html

- ML for accurate predictions of shape
- Dealing with noisy inputs

- Applications of ML very diverse
- Tailored approaches are necessary (e.g. changing the usual cost function)

# Applications for gravitational lenses

- Perfect for the study of Dark Matter
  - Dark-matter cross-section in colliding clusters (Markevitch et al. (2004))
- Act as natural cosmic telescopes
  - Magnification of distant sources (Kneib & Natarajan (2011))
  - Factor 4 to 12 (Richard et al. (2011)).




Source (Markevitch et al. (2004))

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Dimensionality reduction
- **Information compression for interpolation**