GRAVITATIONAL LENSING

LECTURE 22

Docente: Massimo Meneghetti

AA 2015-2016

HOW TO FIND STRONG LENSES

- Requirements:
  - good spatial resolution (<0.2”)
  - survey area/speed/depth (many objects at once or fast one-by-one)
  - contrast between sources and lenses
  - time sampling
- Until recently, these conditions have been difficult to meet…
- Search potential lenses or potential sources, employing
  - optical/radio imaging
  - spectroscopy
  - variability
- and follow-up…

LENS SURVEYS

- CFHT-LS
- Muscles
- Haggles
- Cosmos
- **SLACS**
- **JVAS/CLASS**
- SLS-AEGIS
- OLS
- PANELS
- SOAR
- SGAS
- SDSS
- 2dF Lens Survey
- HST Snapshot Lens Survey
- FKS Lens Survey
- NOT Lens Survey
- APM Lens Survey
- MG Survey
- SARCS
- SBAS
- LoCUSS
- **CLASH**
- **Frontier Fields**

EXAMPLE 1: THE CLASS SURVEY (SOURCE ORIENTED)

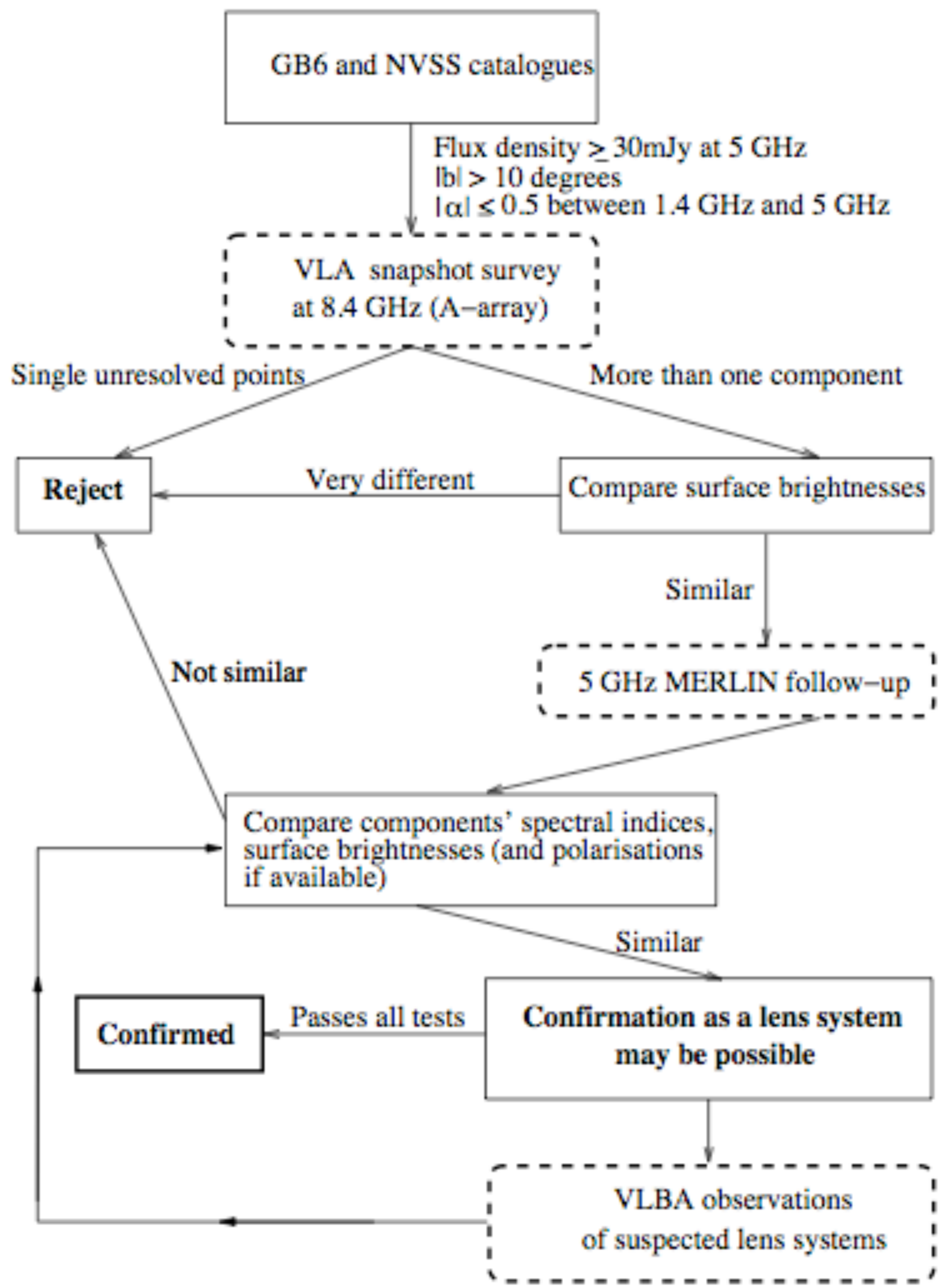
The CLASS (Cosmic Lens All-Sky Survey) was an international project (UK, USA, Netherlands) whose goal was searching for gravitational lenses in the radio domain.

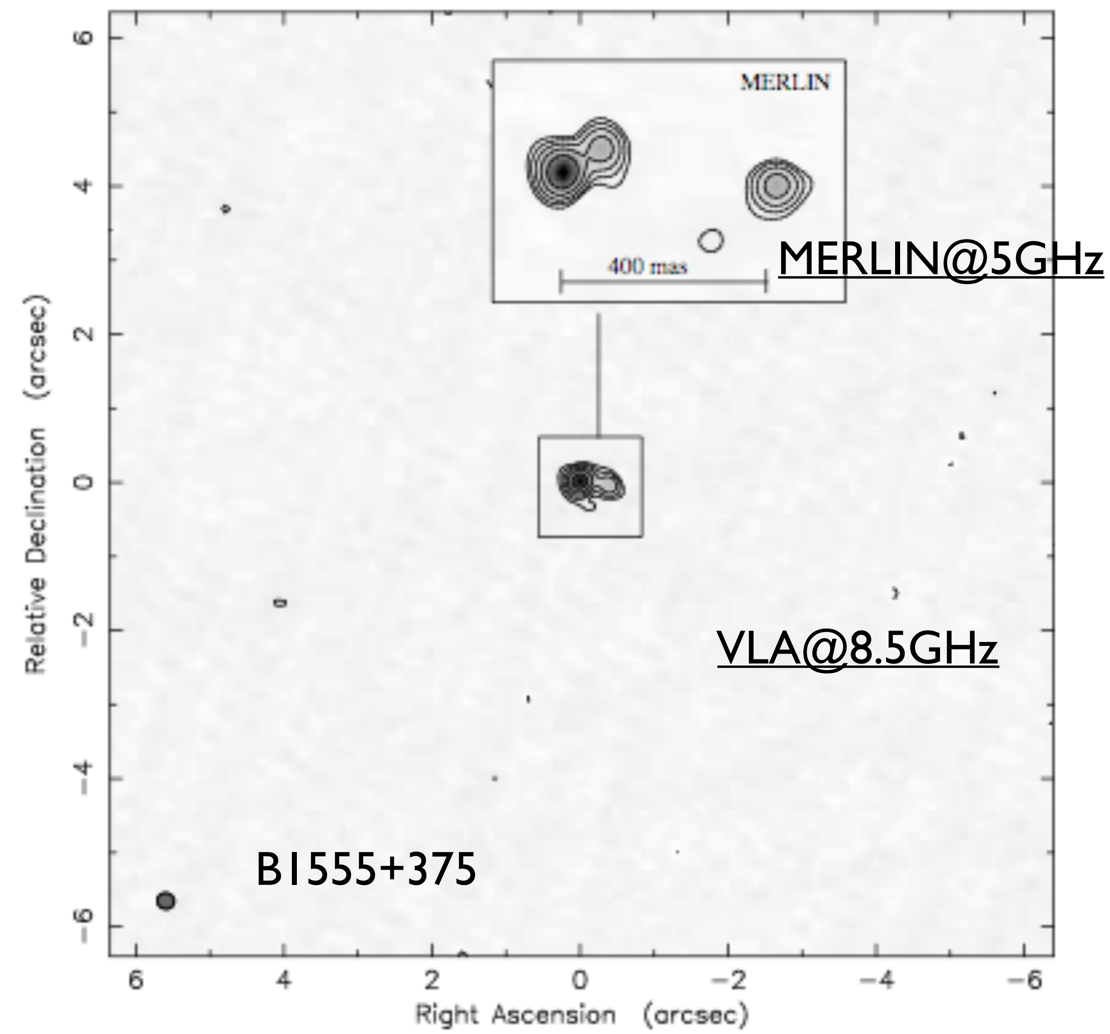
The survey was conducted between 1990 and 1999. During the survey 16503 flat-spectrum radio sources were monitored. Such objects are usually quasars and have very simple radio structures; they are typically point sources, and occasionally weak extended emission is visible. The point-like radio emission is thought to originate from the base of a relativistic radio jet in an active galaxy, which points more or less at the observer.

The simplicity of these sources is useful for gravitational lensing searches. This is because any flat-spectrum radio source which has extended structure is a possible gravitational lens, as the extended structure could represent multiple images of a point-like radio source, produced by the gravitational field of an intervening galaxy.

Instruments: VLA (radio maps at 0.2” res.) + follow-up with MERLIN (0.05” res.) and VLBA (0.003” res).

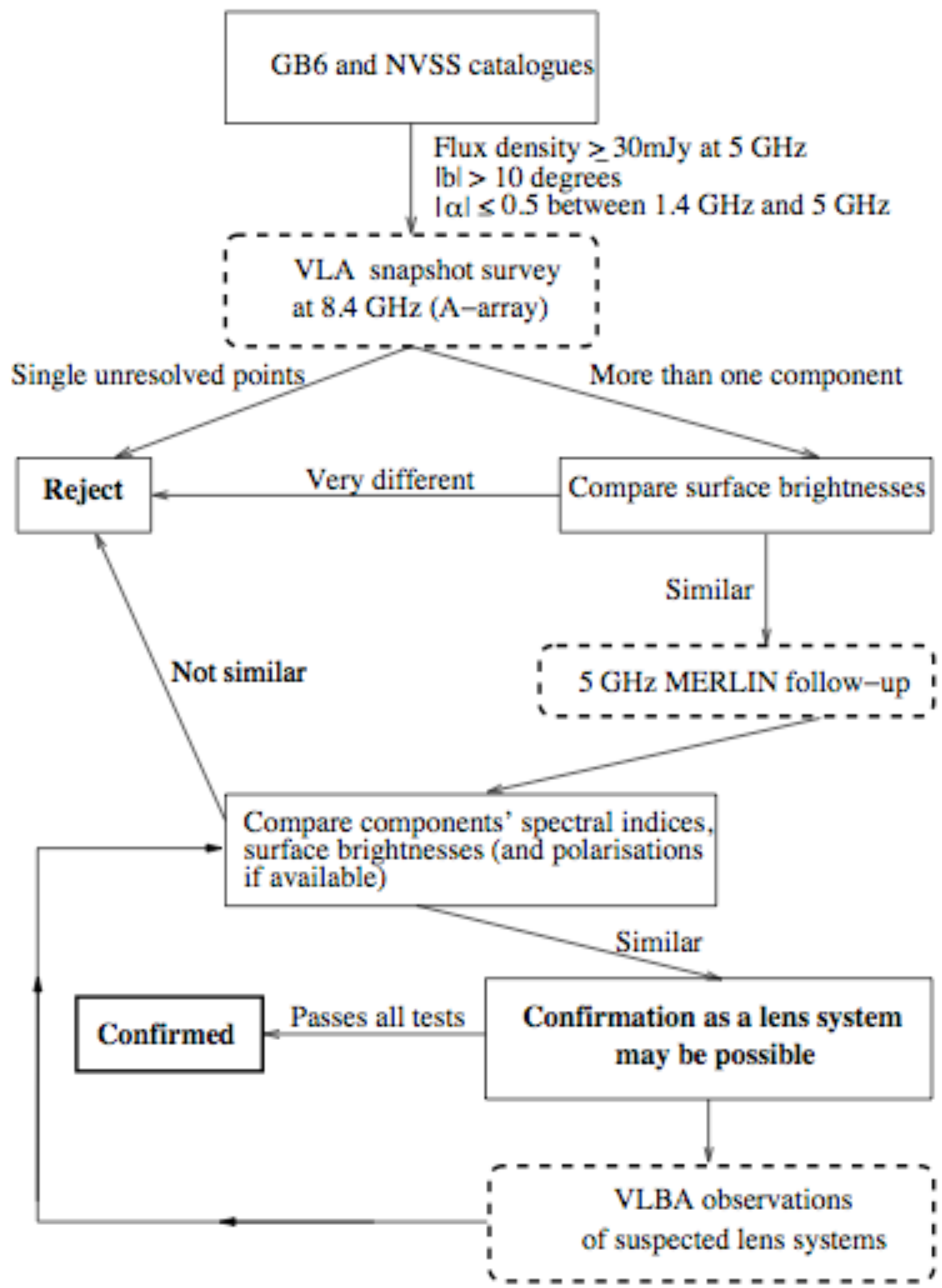
CLASS STRATEGY

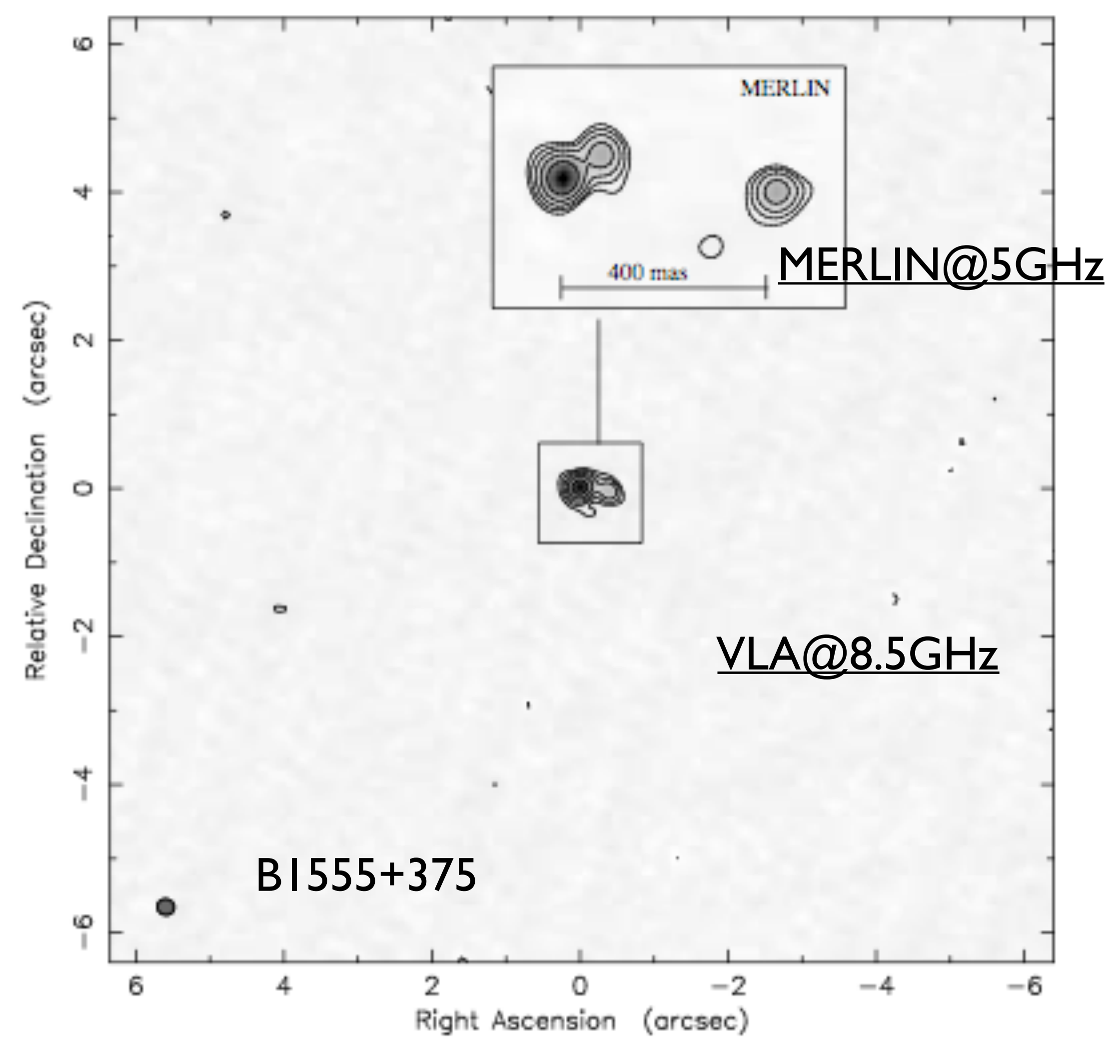




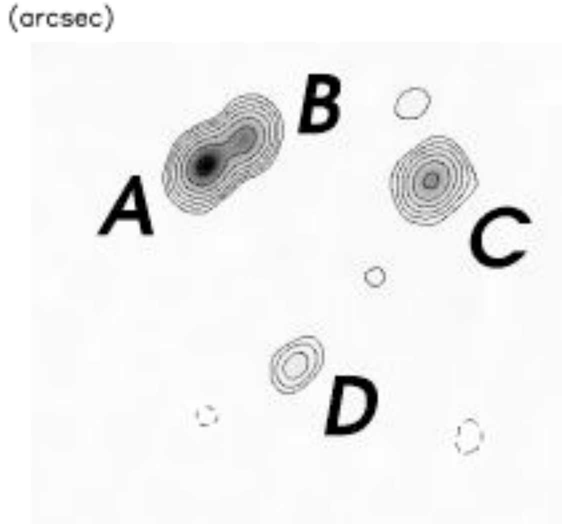
Browne et al. 2002

CLASS STRATEGY

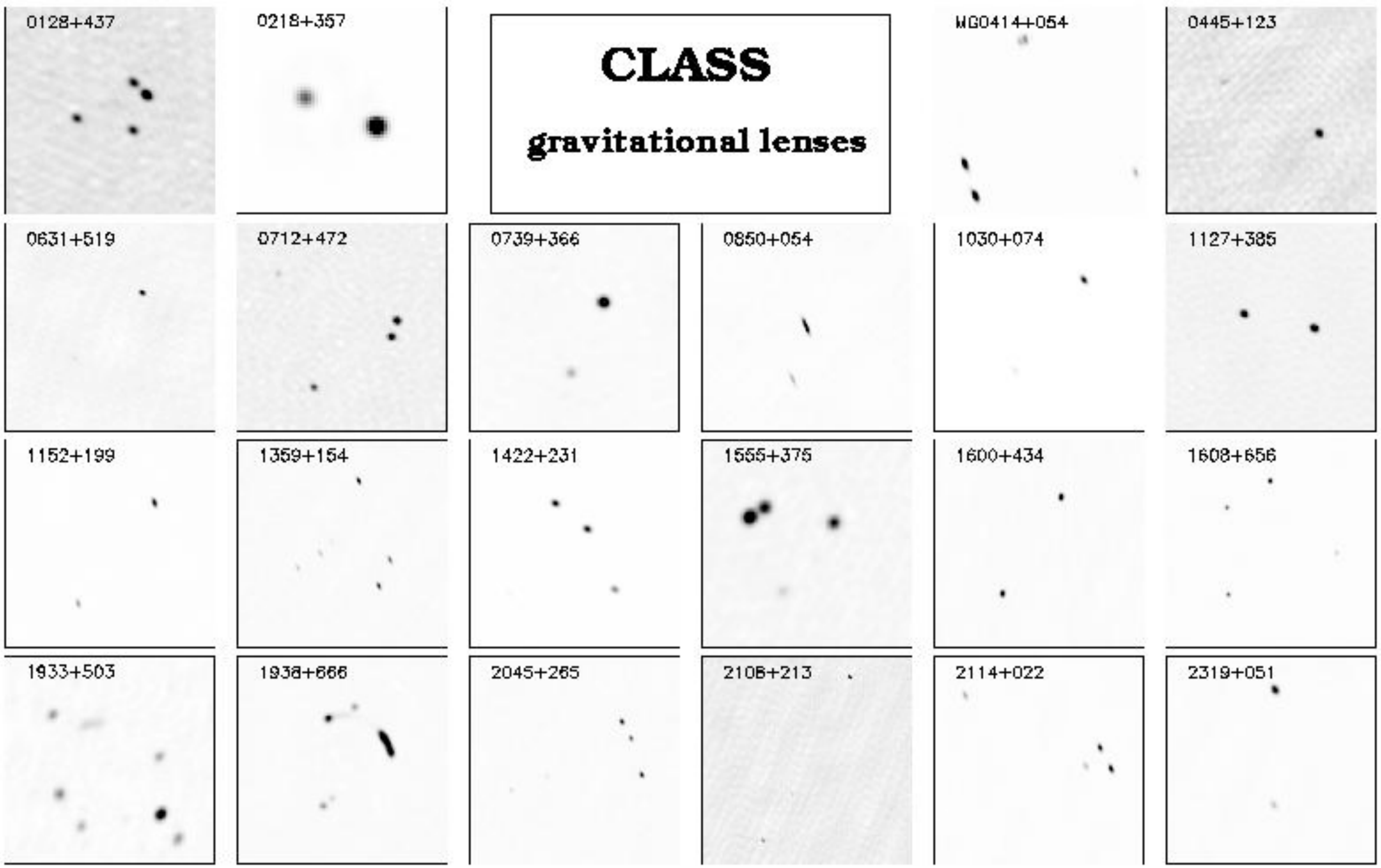




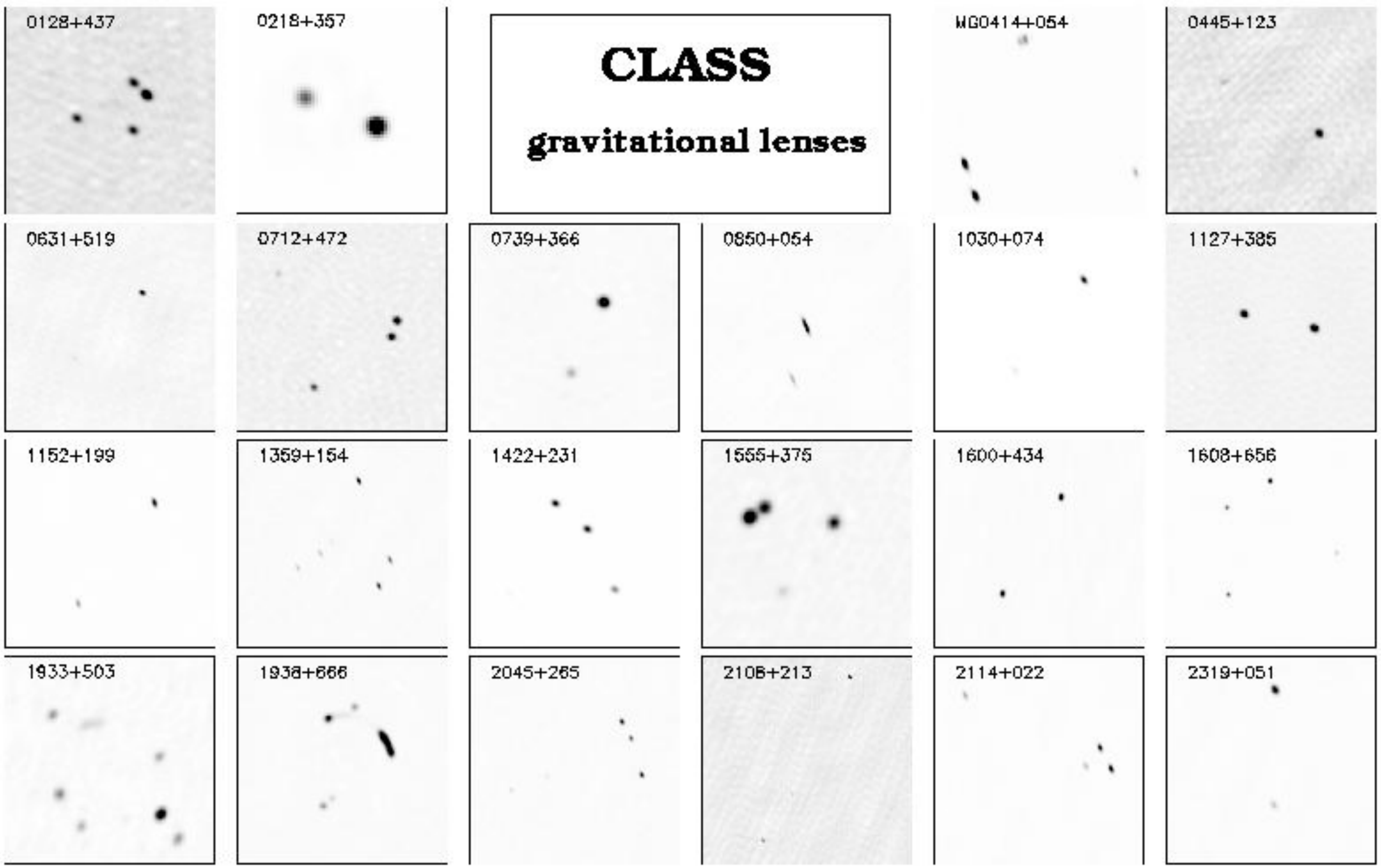
Browne et al. 2002



CLASS LENSES

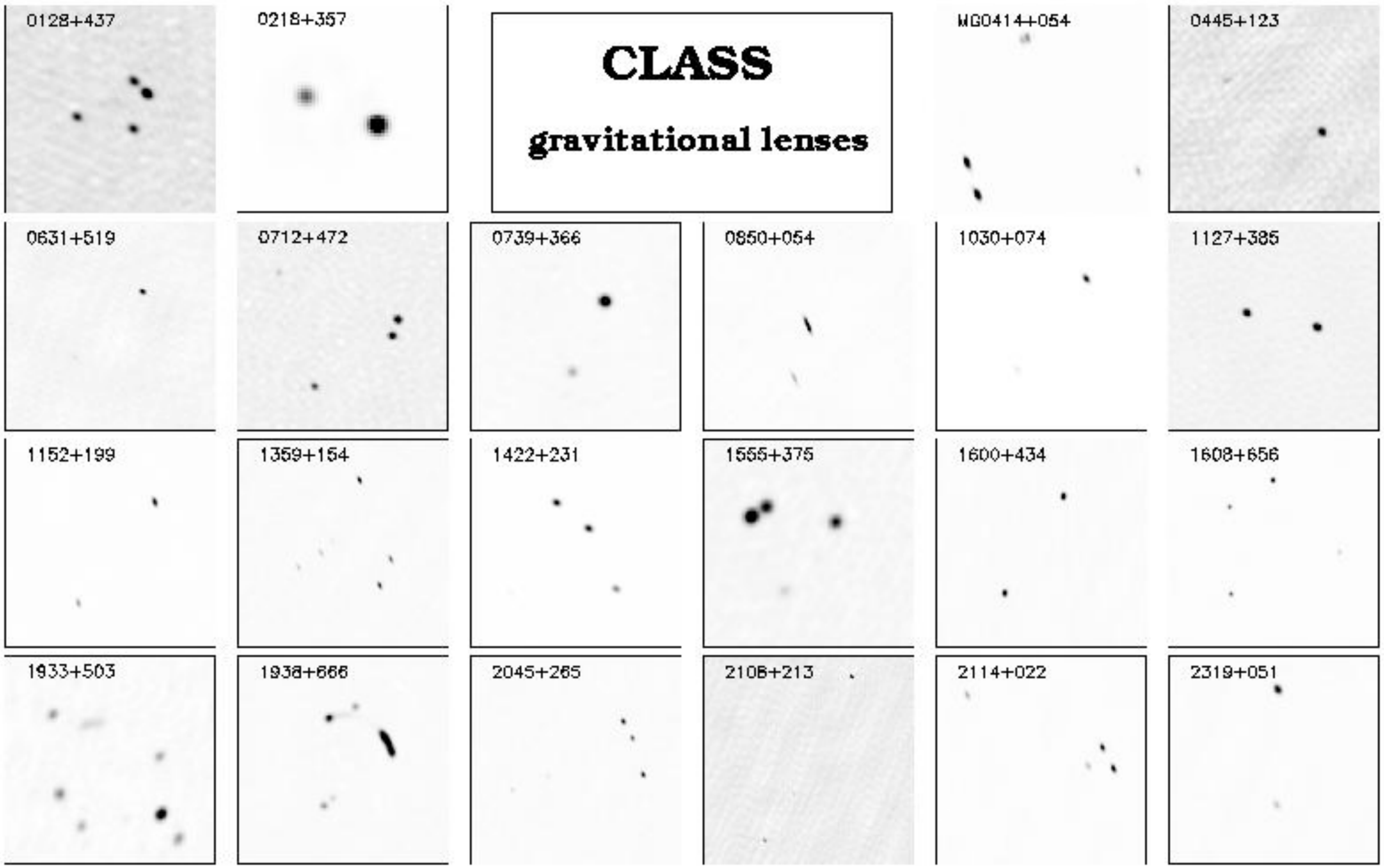


CLASS LENSES



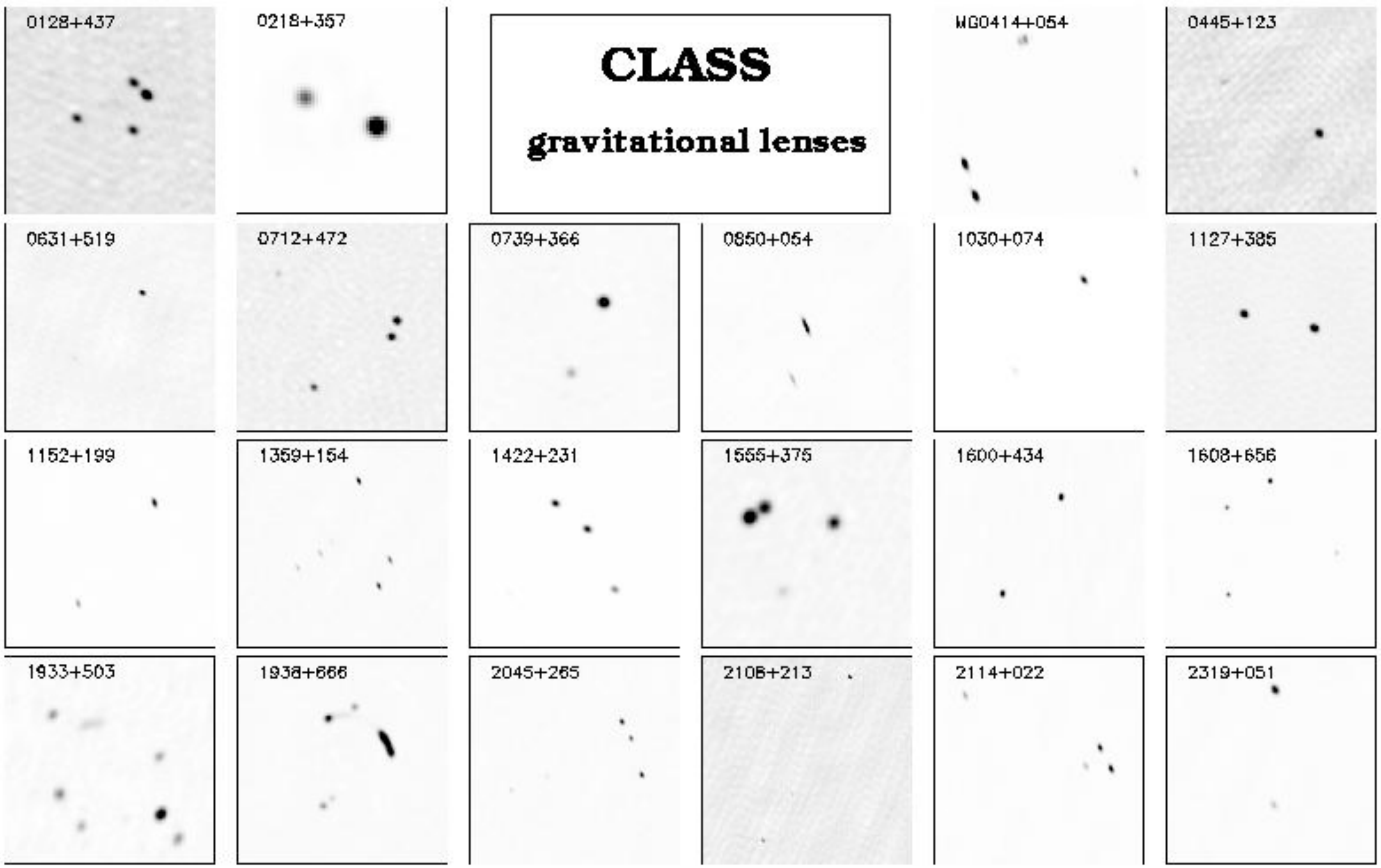
12 double

CLASS LENSES



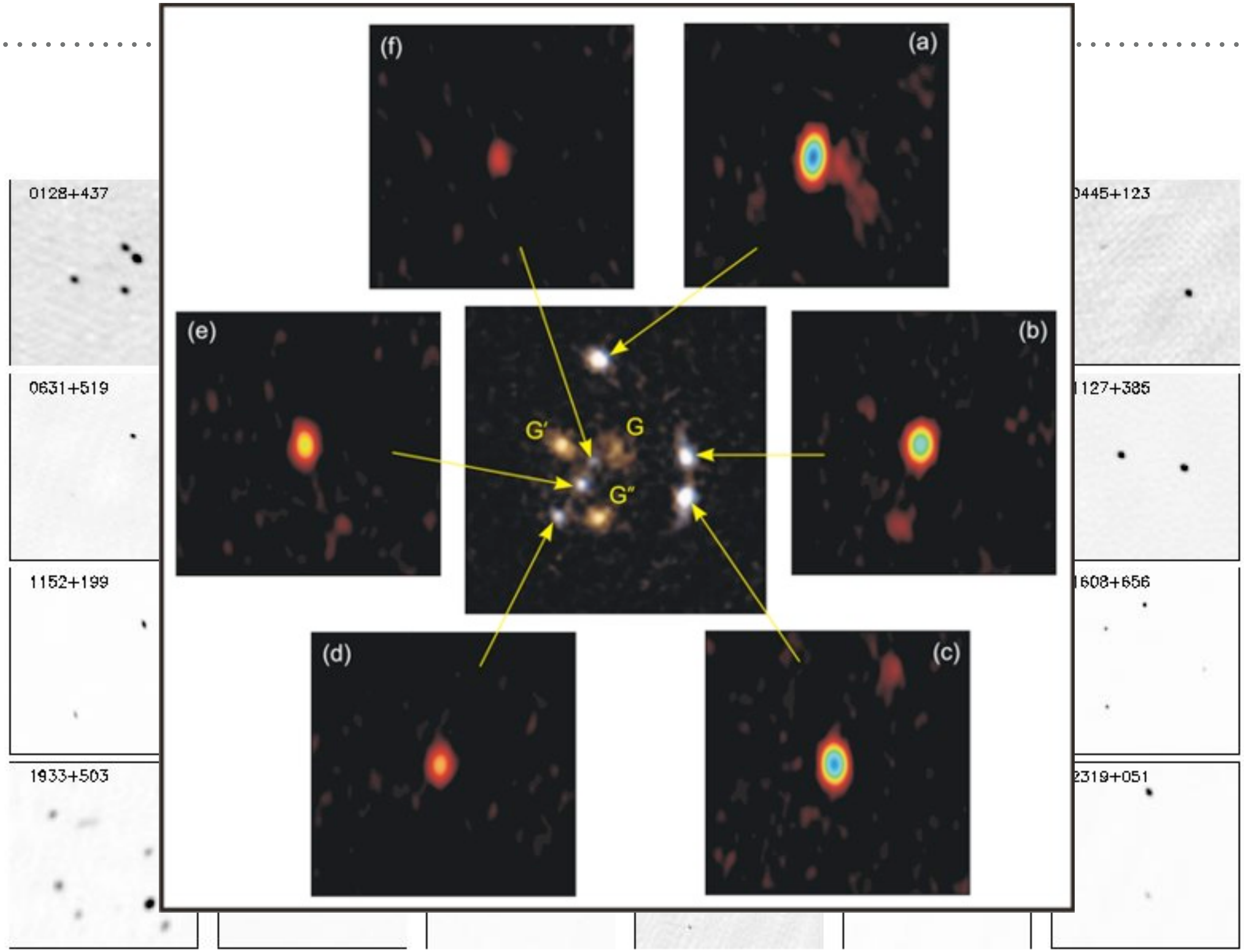
12 double 9 quadruple

CLASS LENSES



12 double 9 quadruple 1 sextuple

CLASS LENSES



12 double 9 quadruple 1 sextuple

SLACS (OPTICAL)

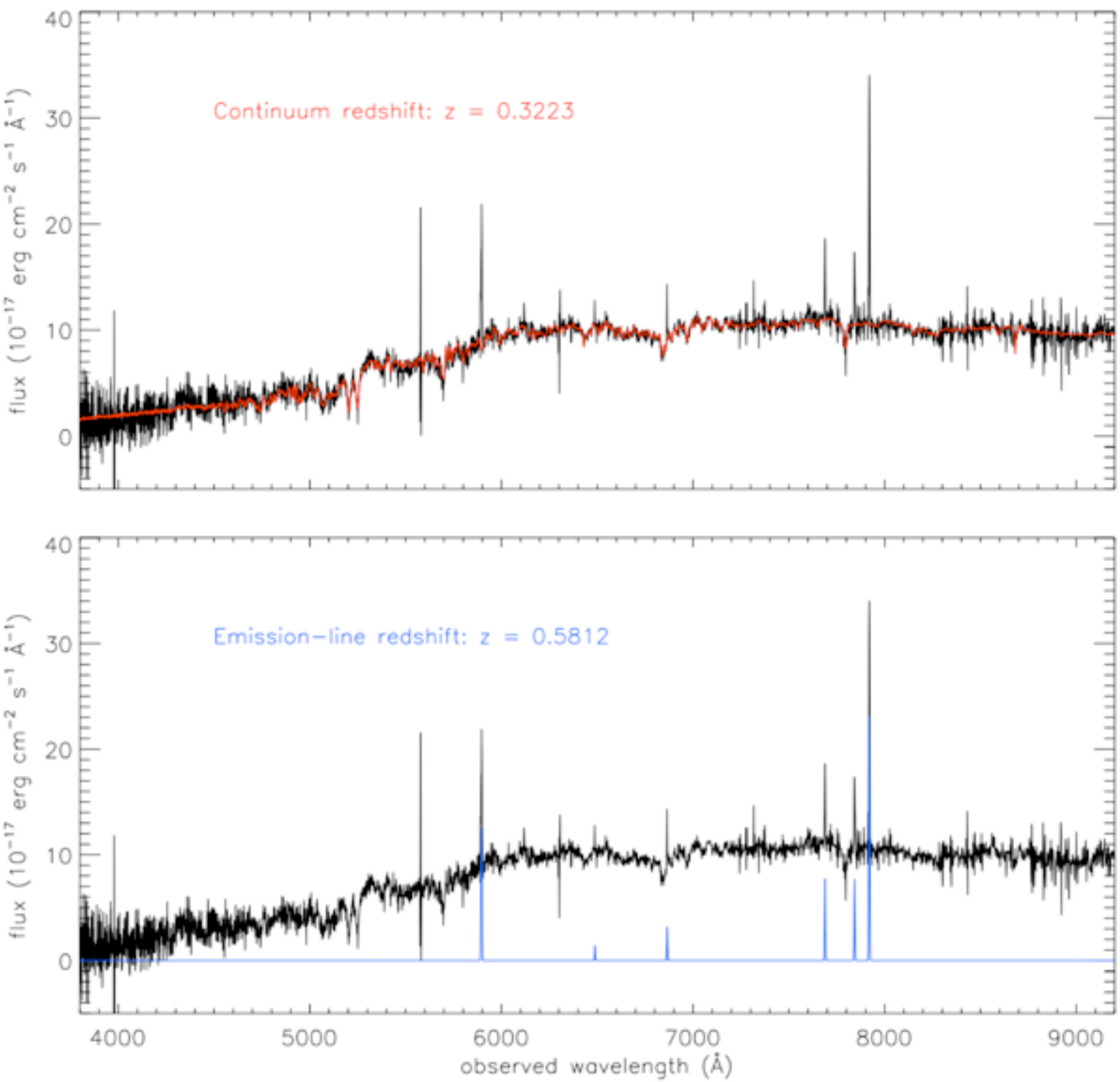
The SLACS (Sloan Lens ACS survey, Bolton et al. 2006) is a very successful project whose goal was finding strongly lensed galaxies behind SLOAN selected galaxies.

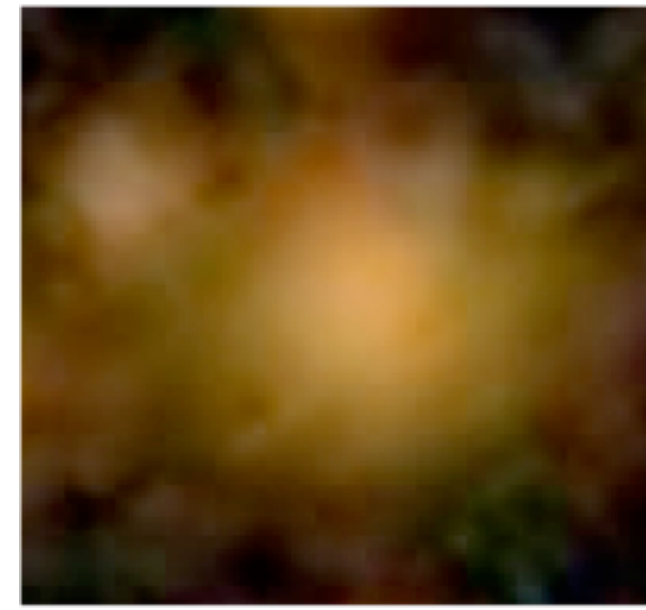
The candidate lenses are selected from the spectroscopic database of the Sloan Digital Sky Survey. This survey has produced imaging and spectra for galaxies on a huge portion of the sky (8400 sq. degree). The observations were conducted between 2000-2005 (SDSS-I) and 2005-2009 (SDSS-II) using a dedicated 2.5m-telescope at Apache Point (New Mexico).

The candidate lenses are galaxies whose spectra can hardly be fitted with a single spectrum. This is an indication of superposition of two different galaxies along the line of sight. This technique follows the discovery of a lens system by Warren et al. (1996)

The selected candidates are observed at high-resolution with the ACS onboard HST.

SLACS STRATEGY

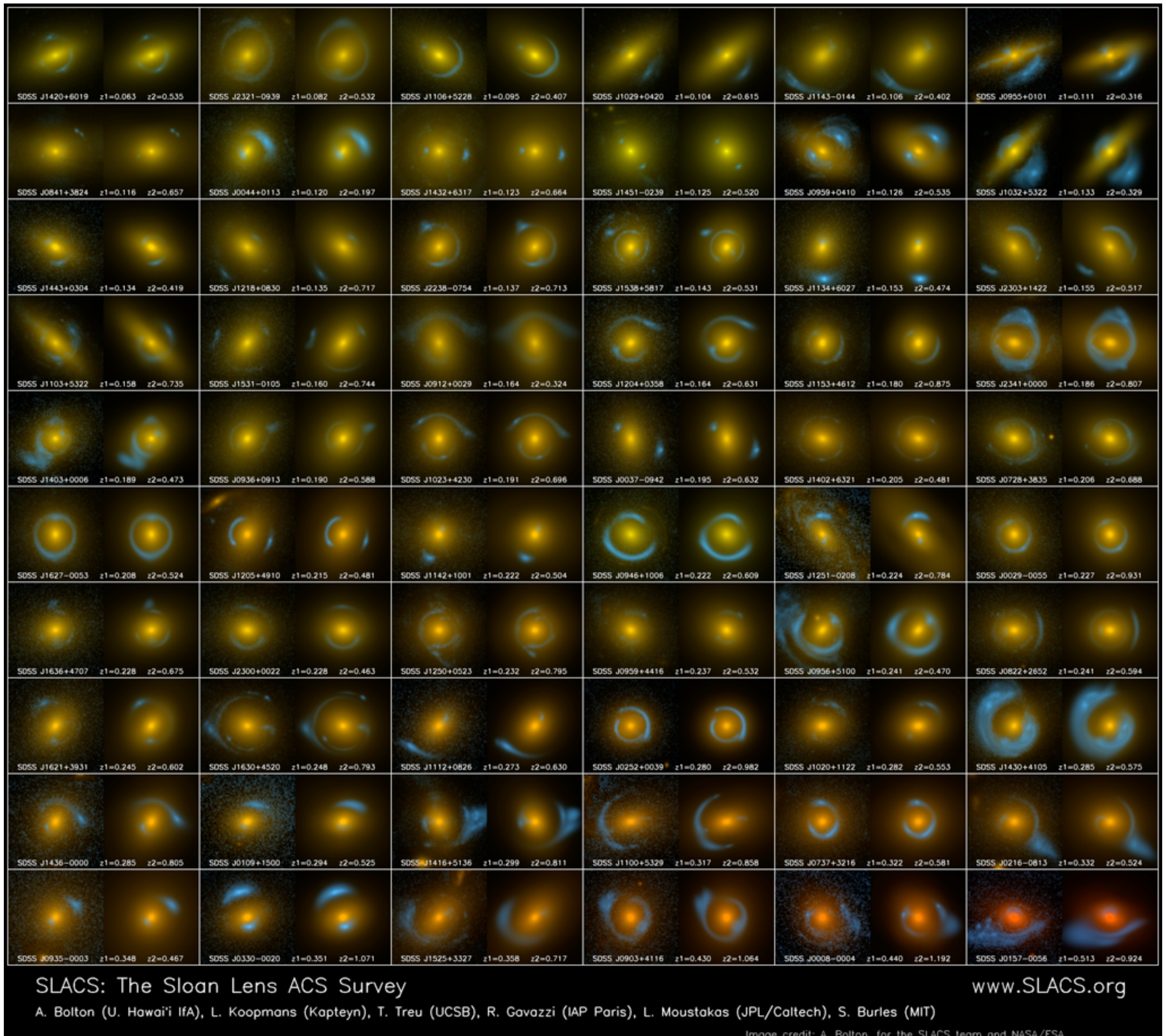




SLOAN image

HST follow-up

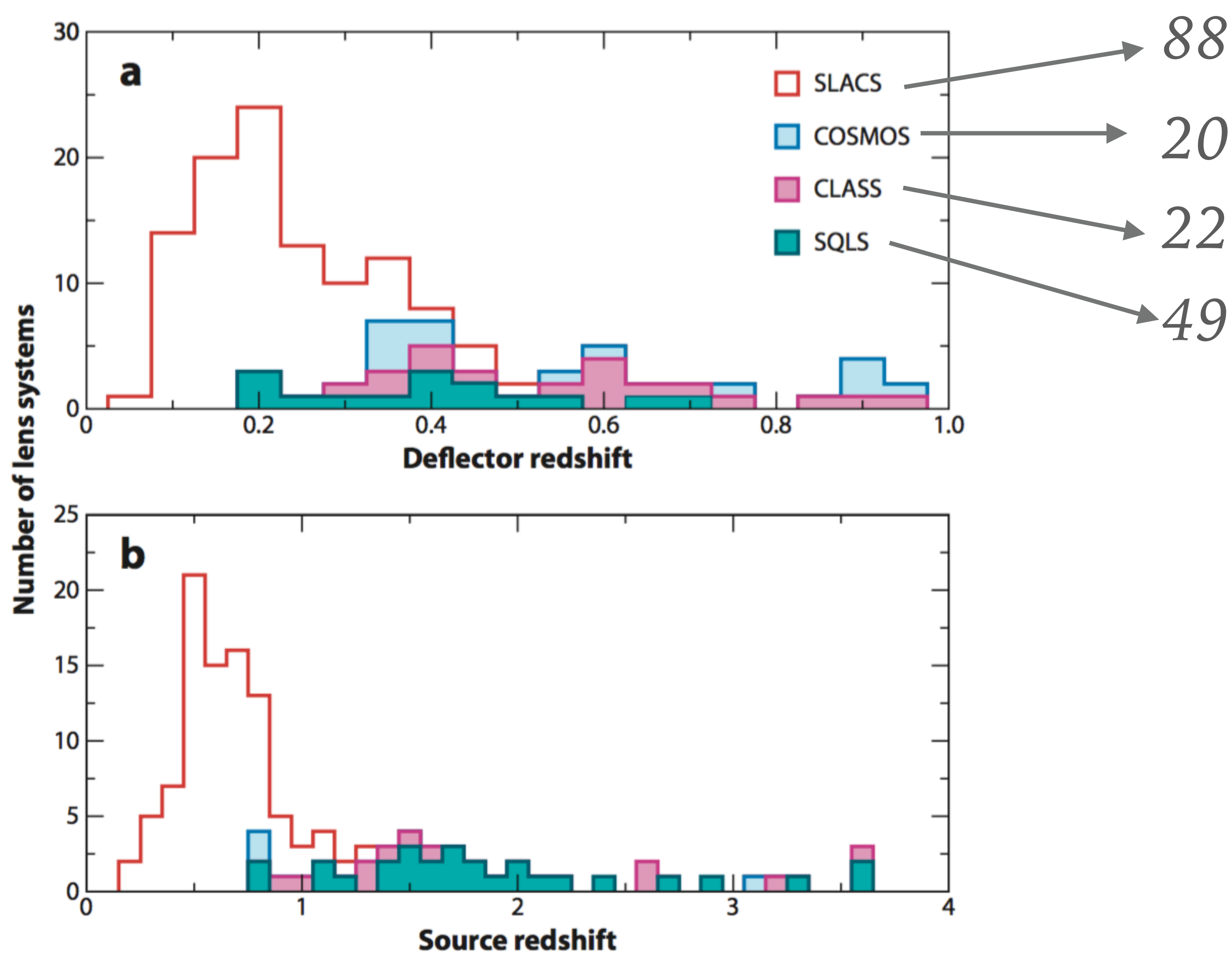
SLACS LENSES



- 85 galaxy lenses
- 13 probable lenses
- redshifts for all systems
- 80% ellipticals
- 10% lenticular
- 10% spirals (mostly bulge dominated)
- big galaxies with v. disp. ~200-300 km/s (average: 248 km/s)

CURRENT STATE OF THE ART

- ~250 galaxy strong lenses (secure; source www.masterlens.org)
- ~80 galaxy clusters (mainly found by visually inspecting ground based imaging data or HST WFC2/ACS/WFC3 images)



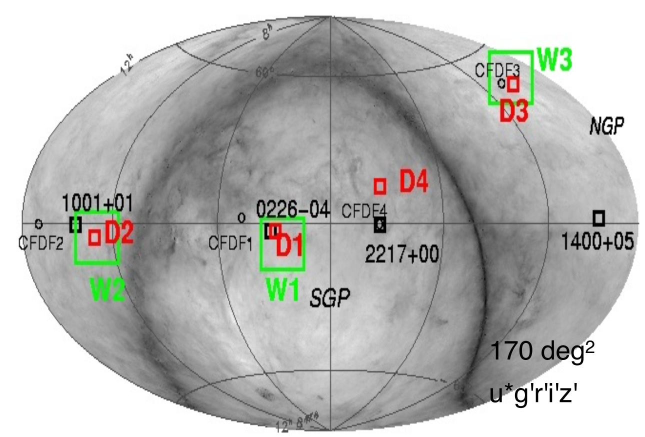
ENTERING A NEW ERA: AUTOMATED SEARCHES FOR LENSES

- Recently, some imaging surveys begun covering large areas of the sky with good depth and good spatial resolution
- These surveys were proposed manly as cosmological experiments employing weak lensing
- Despite their main goal, the data are of good quality also to exploit strong lensing
- The strategy had to be changed: large areas, big depth, large number of potential lenses, making difficult the lens identification via visual inspection.
- The idea of "automated detection" took place

AN EXAMPLE: THE SL2S SURVEY AND THE “RINGFINDER”

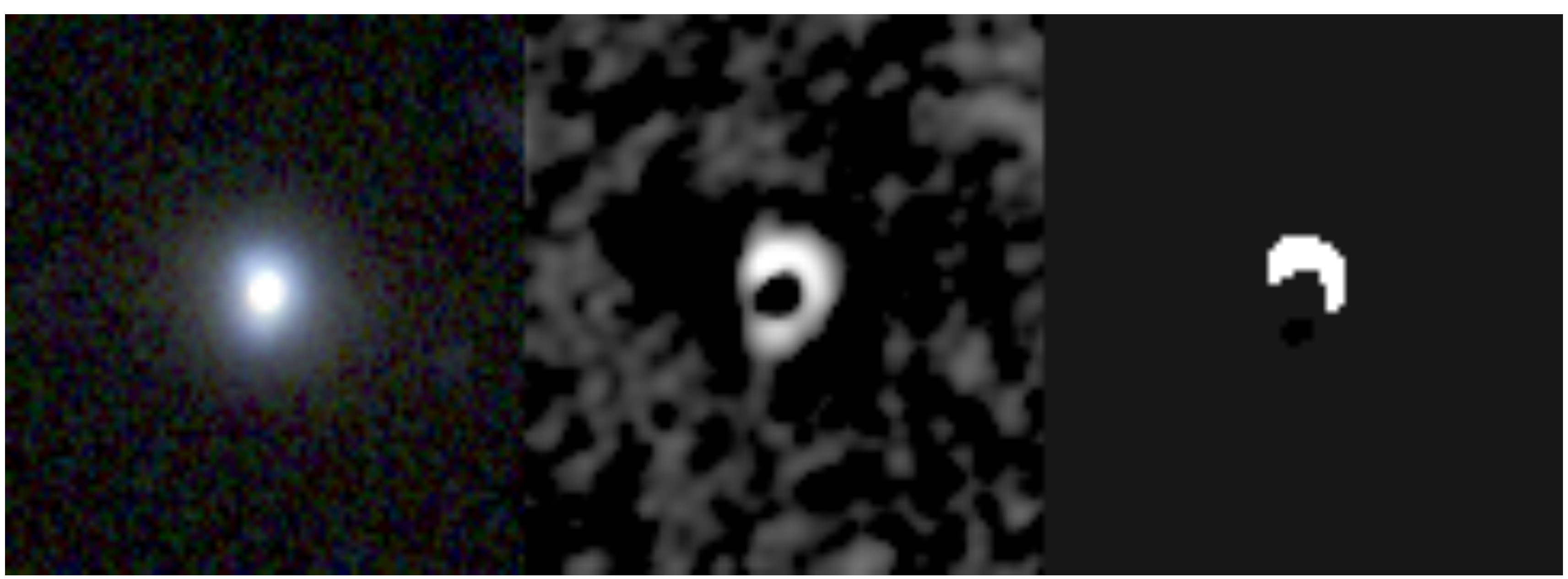
- CFHTLS: 150 sq. deg.; I<24.5; sub arcsec PSF; 640.000 potential lenses (ETGs) to be searched for SL features (Strong Lensing Legacy Survey, SL^2S)
- u,g,r,i,z

Wide Survey



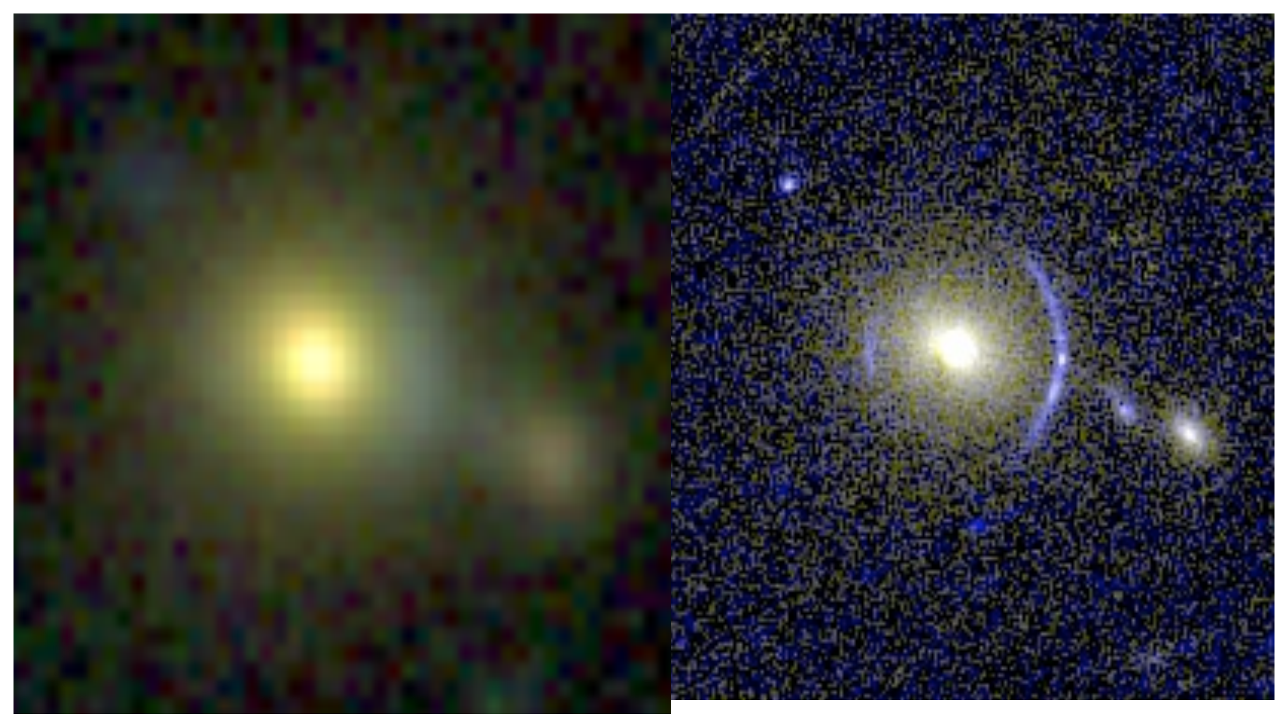
AN EXAMPLE: THE SL2S SURVEY AND THE "RINGFINDER"

- RingFinder (Gavazzi, 2012): a software to search for blue star forming faint blobs, tangentially elongated around ETGs
- Efficient lens light subtraction: g-λi, tune λ to remove the ETG
- Scan the image, looking for tangentially elongated blue residuals
- Processing time 2 CPU weeks for 150 sq. deg.



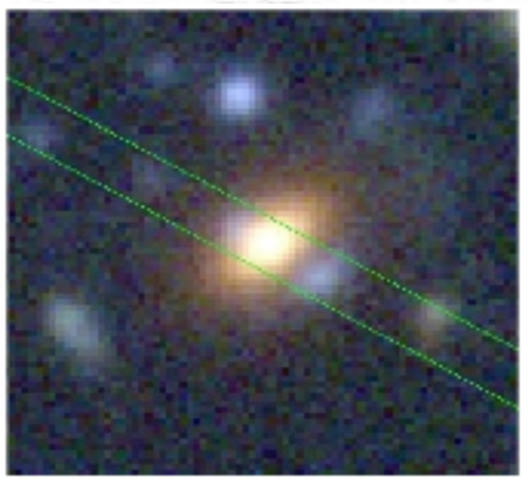
AN EXAMPLE: THE SL2S SURVEY AND THE "RINGFINDER"

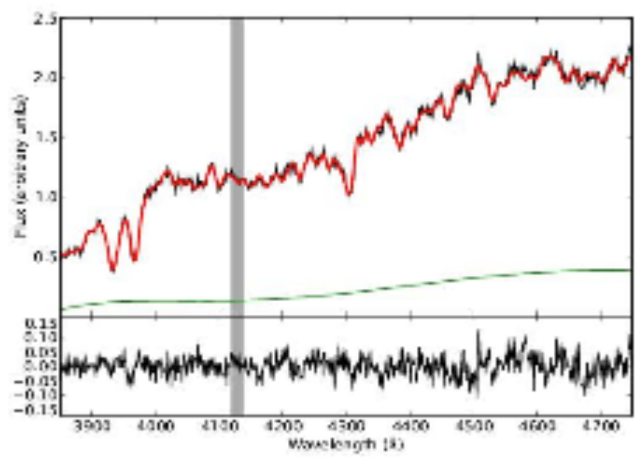
- Followed by visual inspection to remove false positives (mainly polar ring galaxies)…
- …HST follow-up…

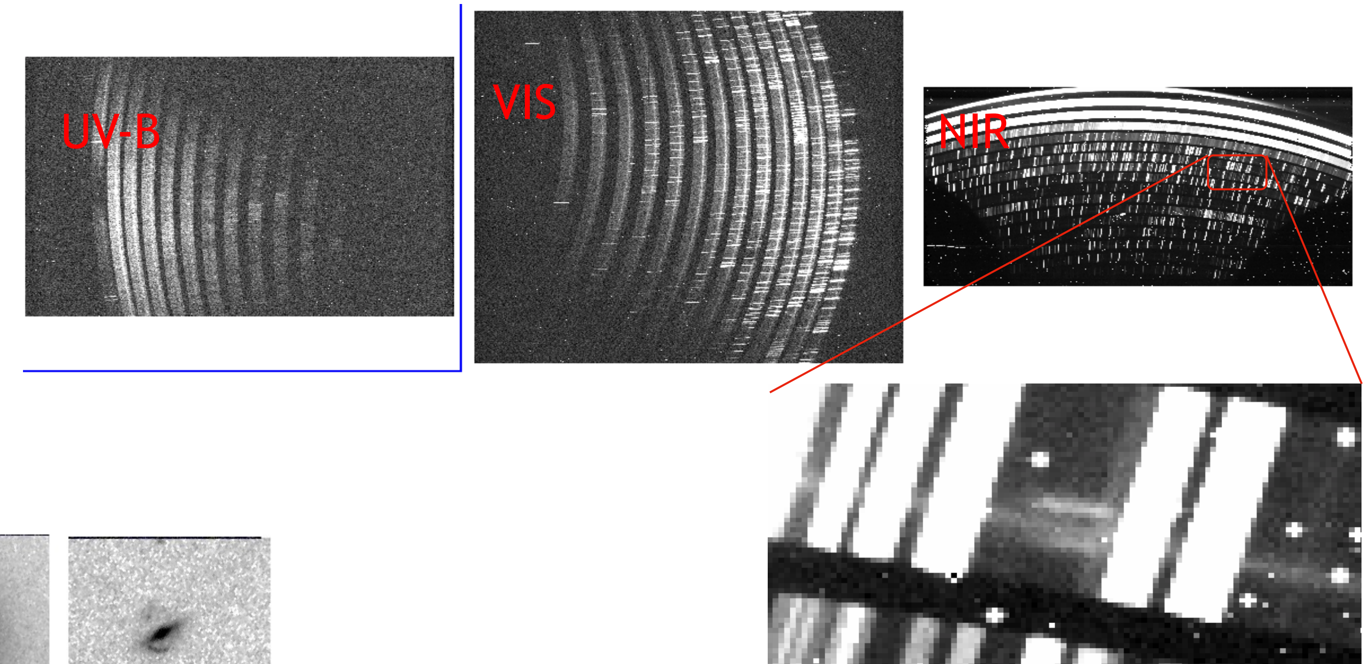


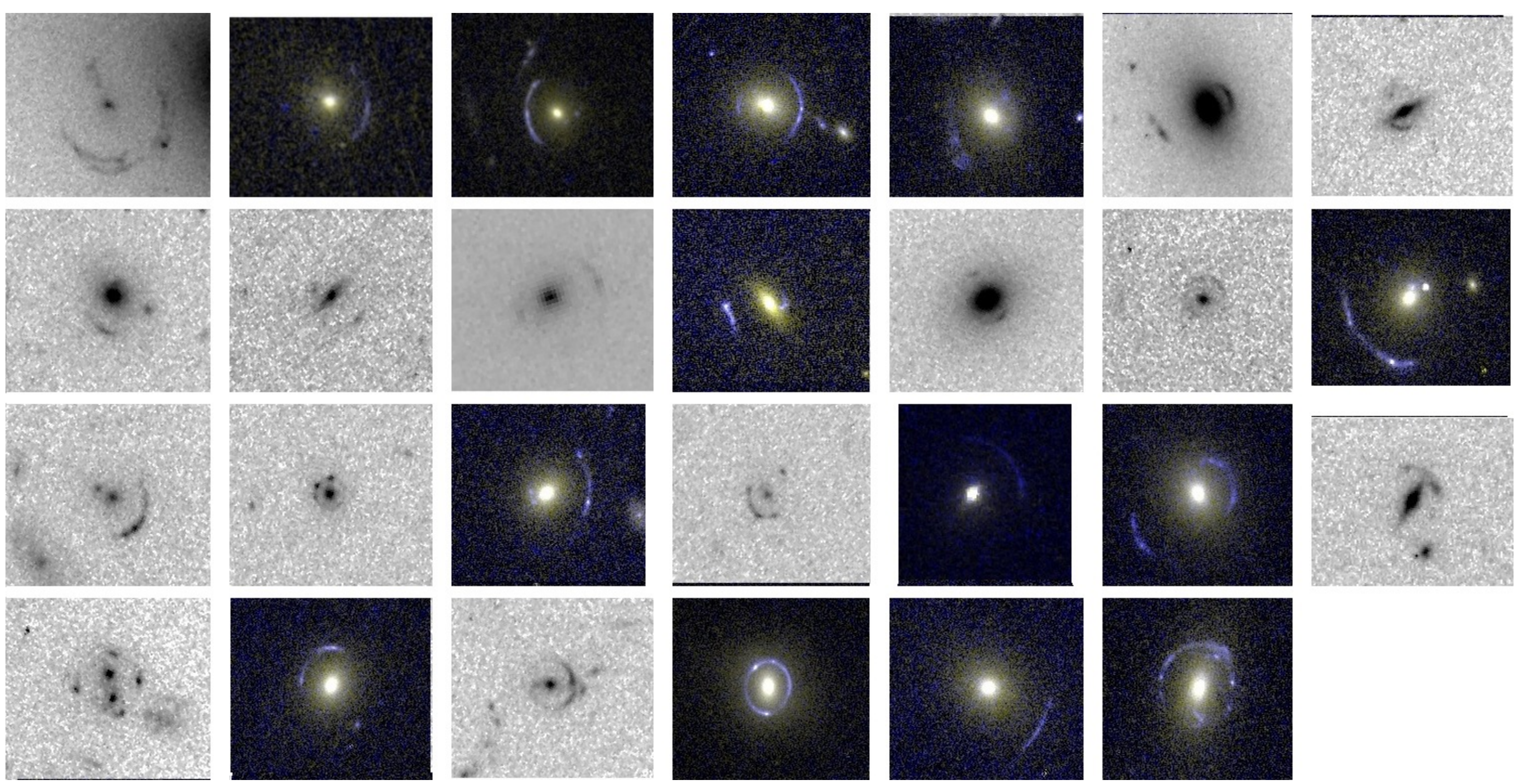
AN EXAMPLE: THE SL2S SURVEY AND THE “RINGFINDER”

➤ … and spectra (VLT-XShooter (19); Keck/LRIS (46))



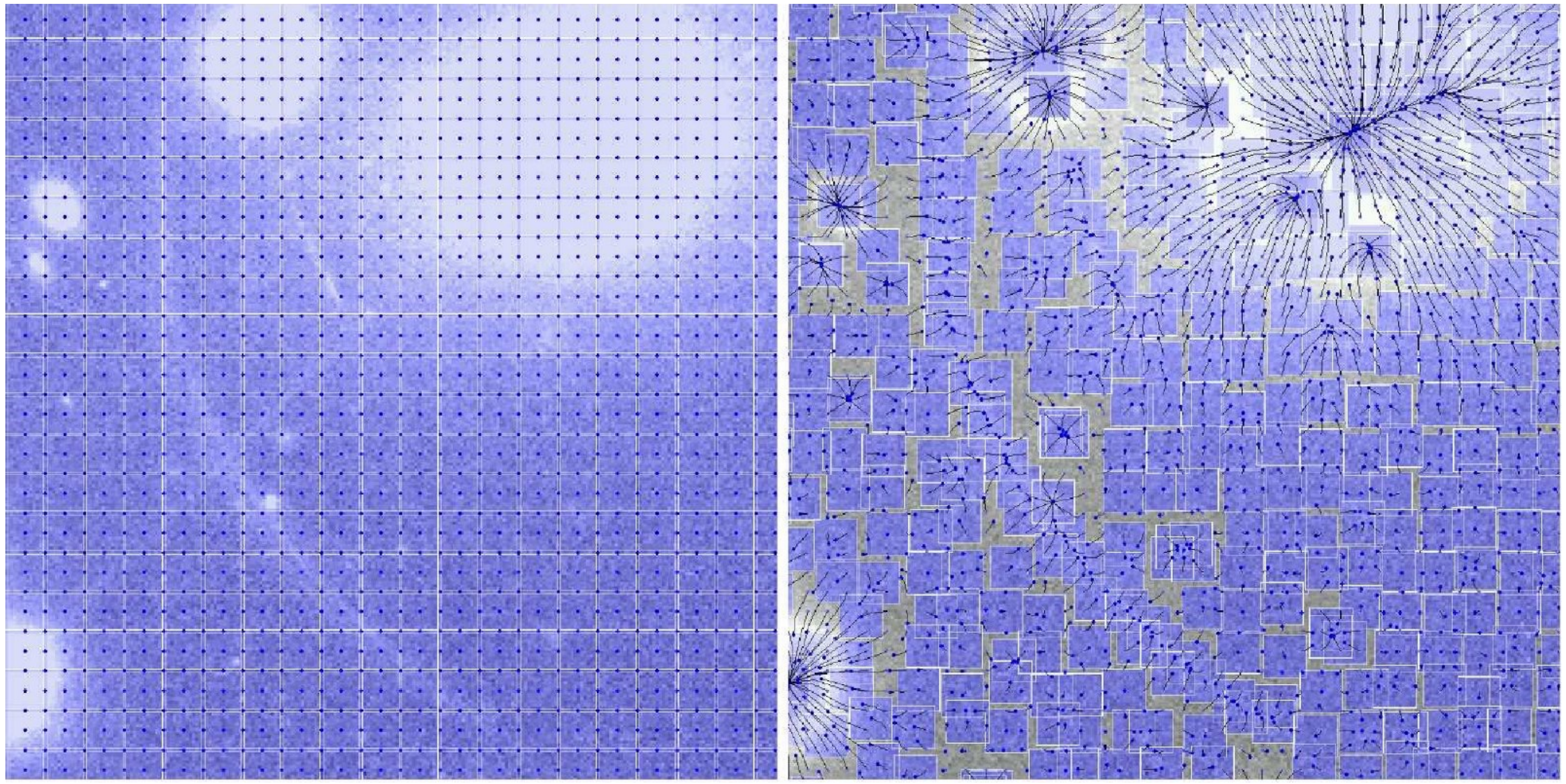




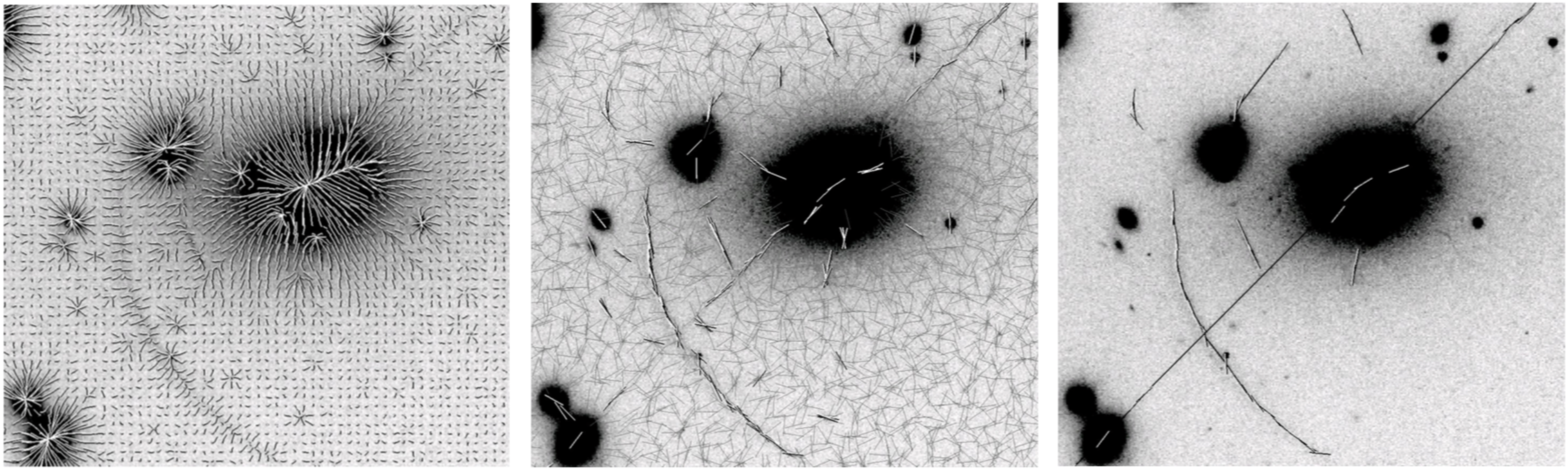


- 65 observed.
- 27 confirmed to be actual lenses from this imaging,
- success rate >= 50% and increasing with time.

ARC FINDERS



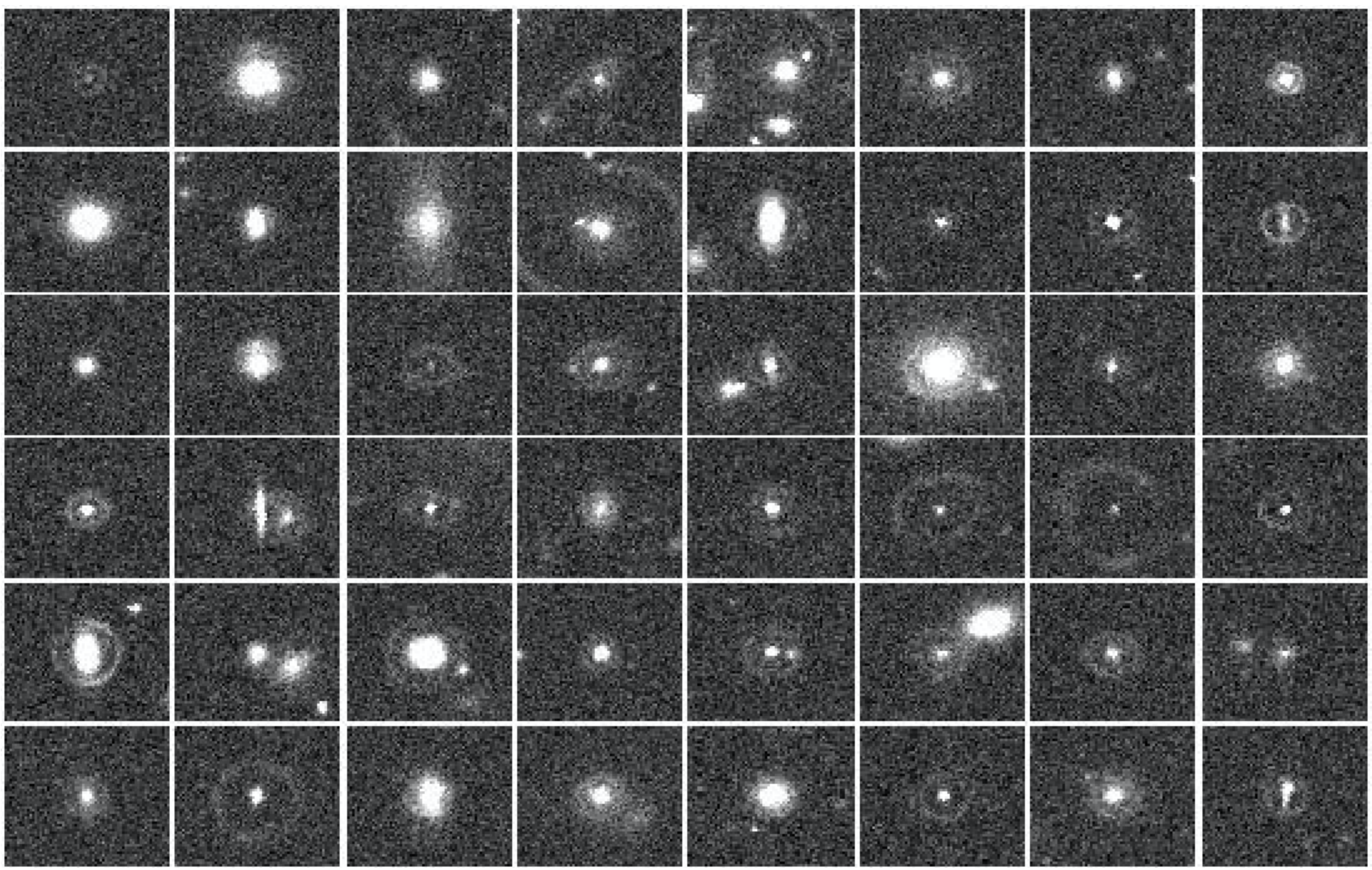
Seidel & Bartelmann 2007



OTHER TECHNIQUES BEING EMPLOYED AND DEVELOPED

- PCA for de-blending
- find lenses by fitting lens models to the data

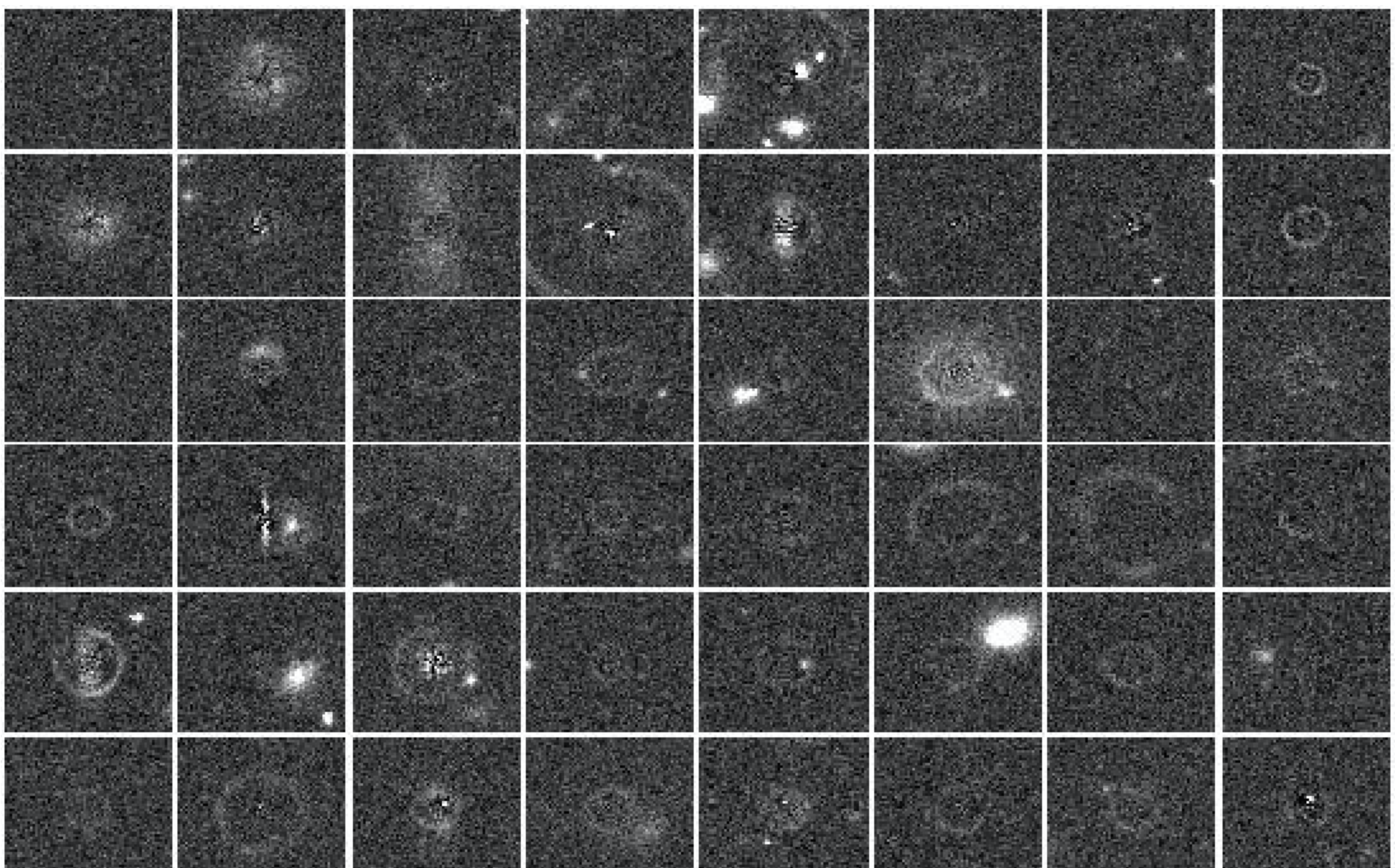
Joseph et al. 2015



OTHER TECHNIQUES BEING EMPLOYED AND DEVELOPED

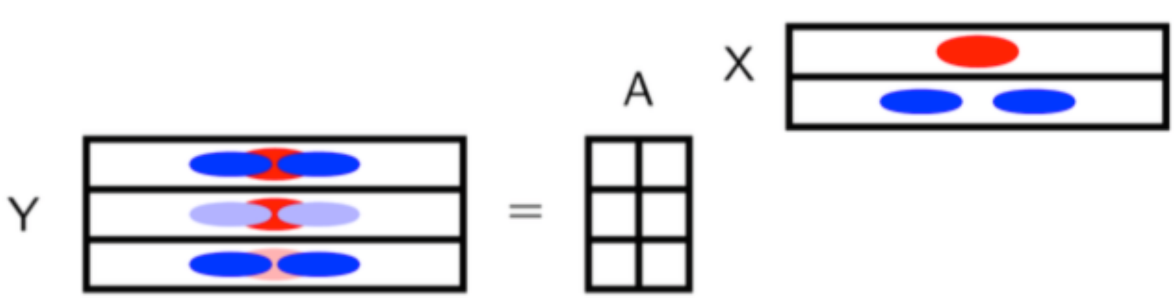
- PCA for de-blending
- find lenses by fitting lens models to the data

Joseph et al. 2015

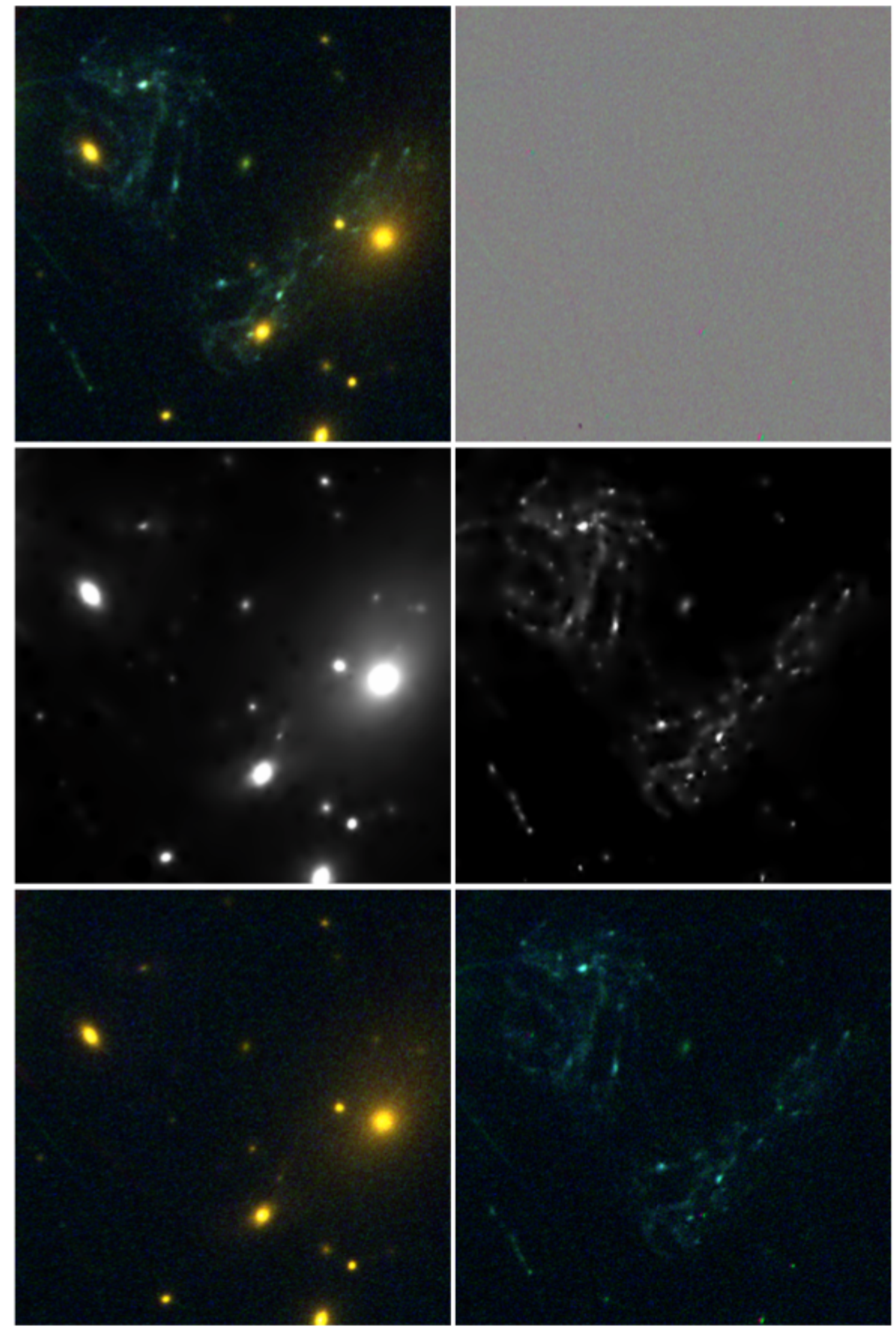


GENERALIZED MORPHOLOGICAL COMPONENT ANALYSIS

- use sparsity of astronomical images in wavelet space and in color space
- observation Y is the product of a mixing function A times the sources X



Joseph et al. 2016



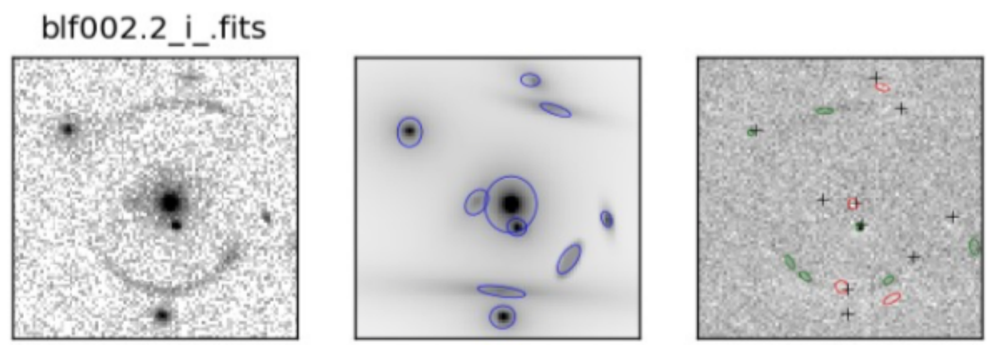
SUPPORT VECTOR MACHINES

The University of Manchester
Jodrell Bank Observatory

MANCHESTER 1824

Finding lenses with SVM

Philippa Hartley and Neal Jackson

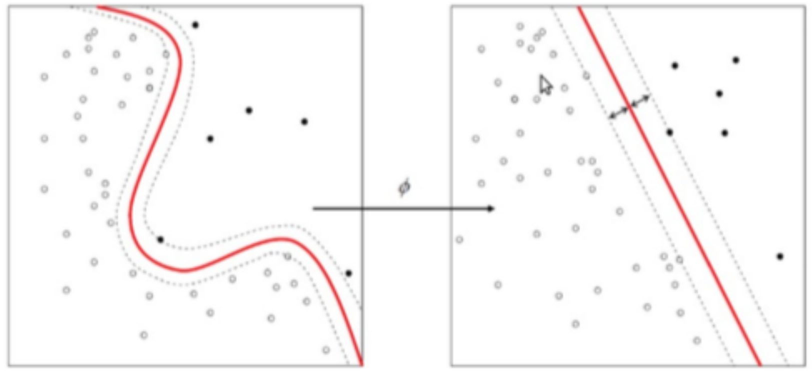


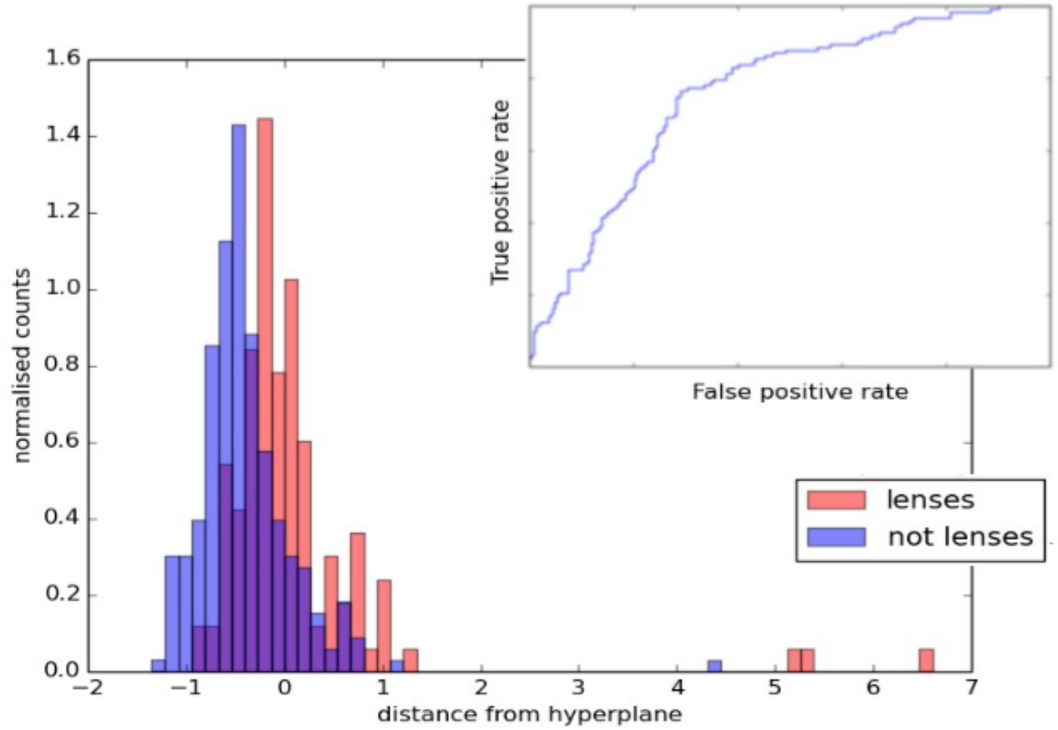
Dataset: Bologna Lens Factory 3-band simulated Euclid images

Input: 10 morphological parameters derived from image decomposition using SExtractor and Galfit

Support Vector Machine: Each sample is plotted as a point in space. SVM finds optimal hyperplane to linearly separate patterns

Output: Score of distance from hyperplane





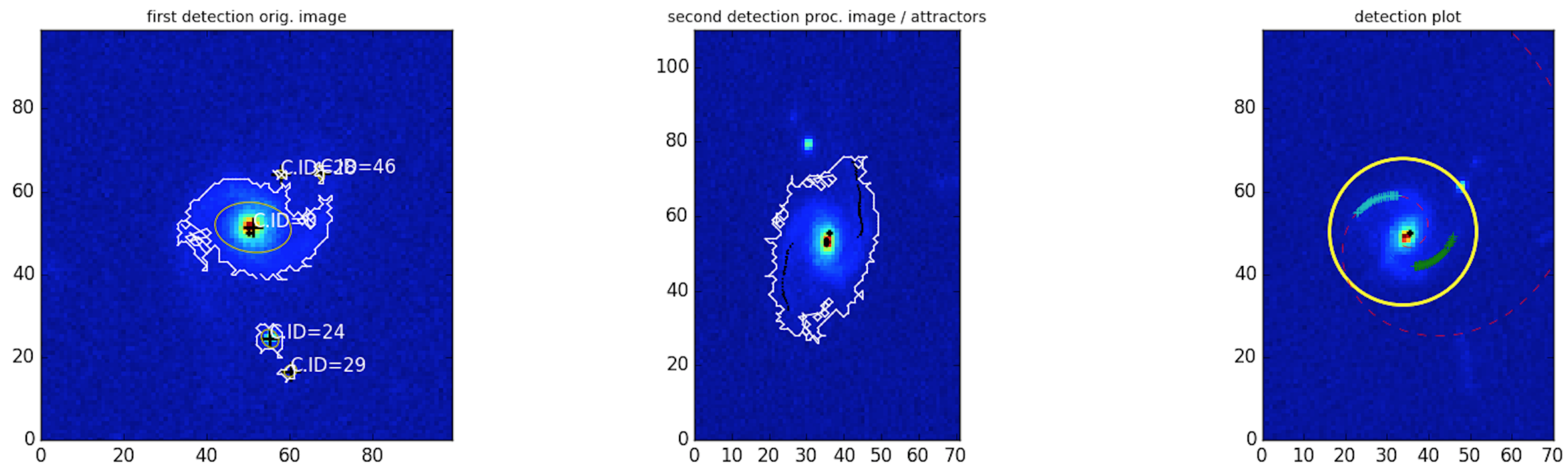
Results so far for SNR > 10:

- Area under ROC curve 0.76
- False positive rate of 37% for a completeness (true positive rate) of 80%

investigation to be continued...

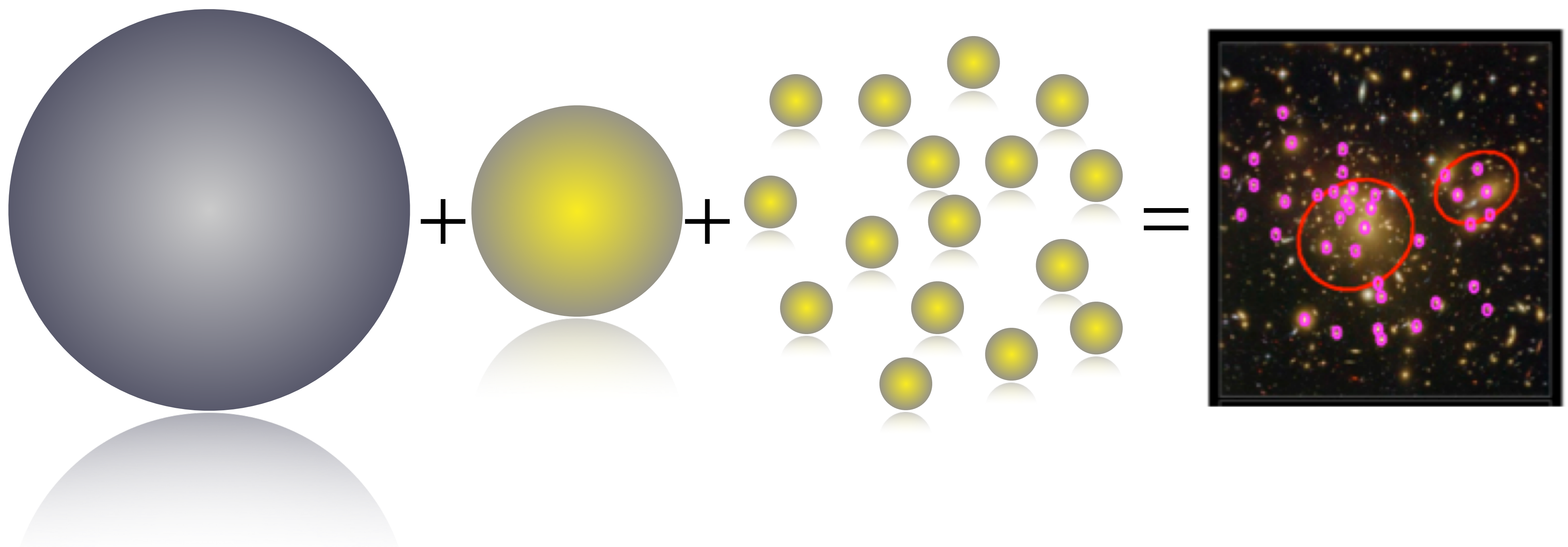
NEURAL NETWORKS

Analysing the shape of curved structures and classifying them with machine learning



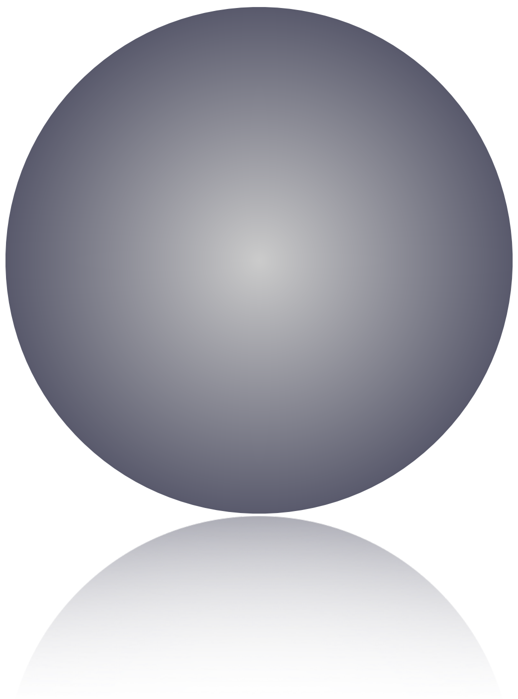
(Tramacere et al. 2015)

LENS MODELING: THE PARAMETRIC APPROACH



- lenses as complex mass distributions (DM+baryons)
- use stars to trace mass $[\mathbf{x_c}]$
- smooth halo + clumpy structure

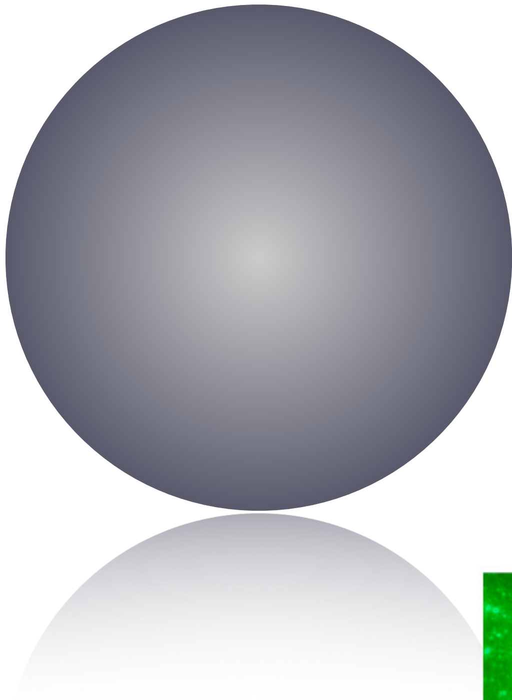
SMOOTH COMPONENT (AND MOST IMPORTANT SUBSTRUCTURES)

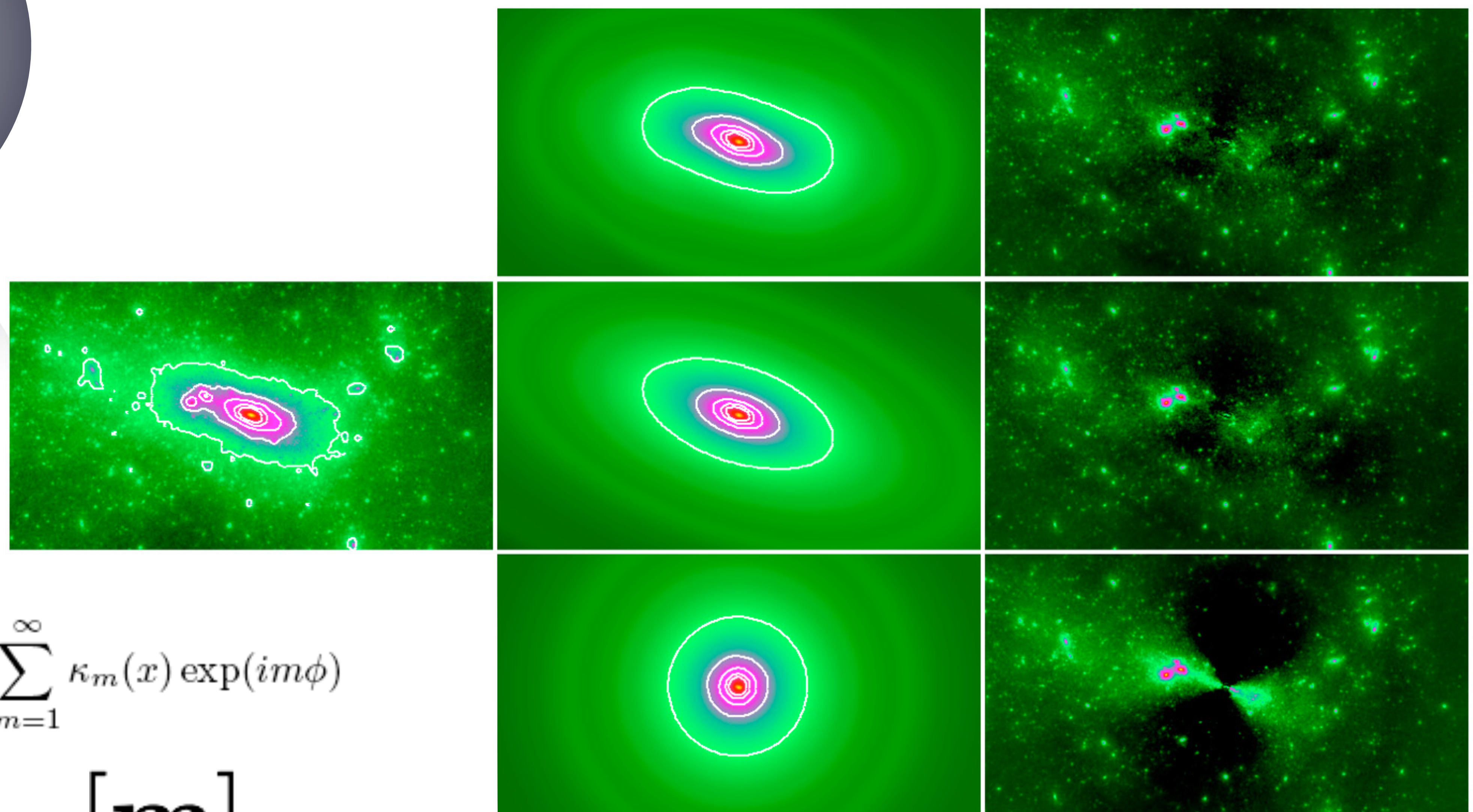


$[\mathbf{q}]$ *density prof.*

$[\mathbf{m}]$ *shape*

SMOOTH COMPONENT (AND MOST IMPORTANT SUBSTRUCTURES)



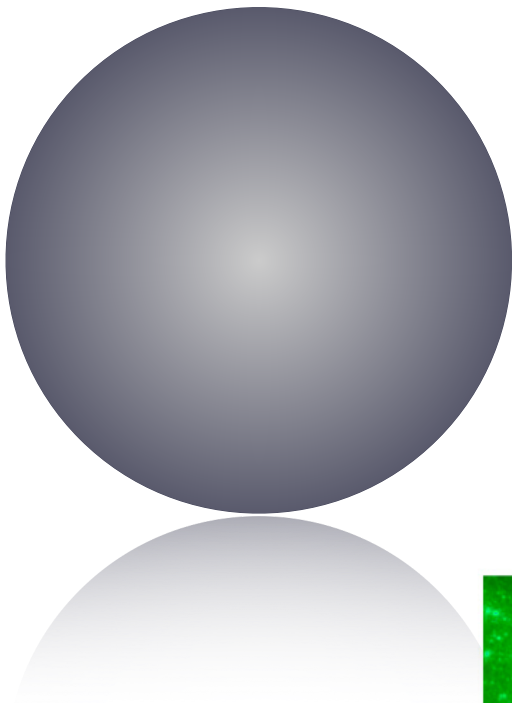


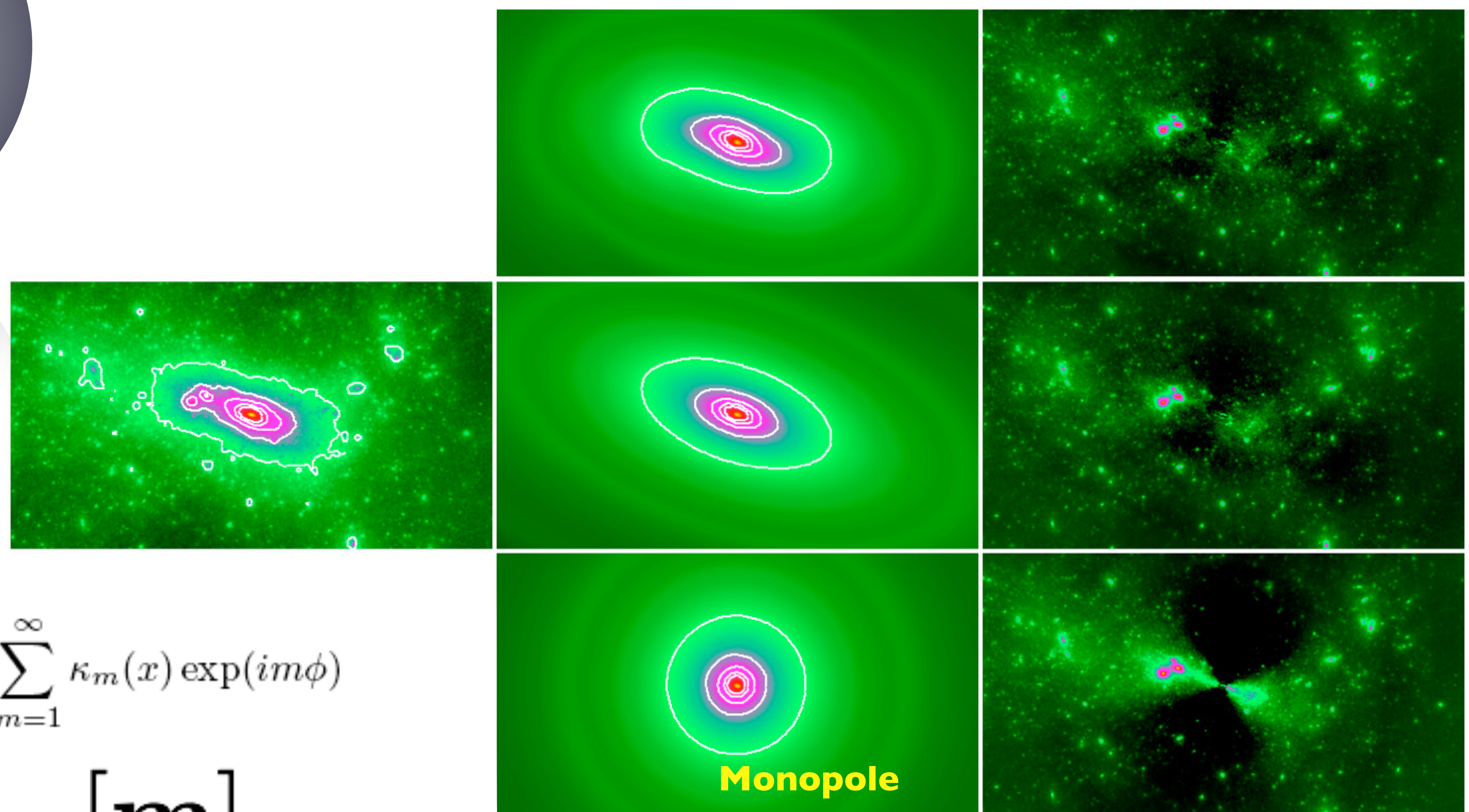
$$\kappa(\vec{x}) = \kappa_0(x) + \sum_{m=1}^{\infty} \kappa_m(x) \exp(im\phi)$$

$[\mathbf{q}]$ $[\mathbf{m}]$

density prof. *shape*

SMOOTH COMPONENT (AND MOST IMPORTANT SUBSTRUCTURES)



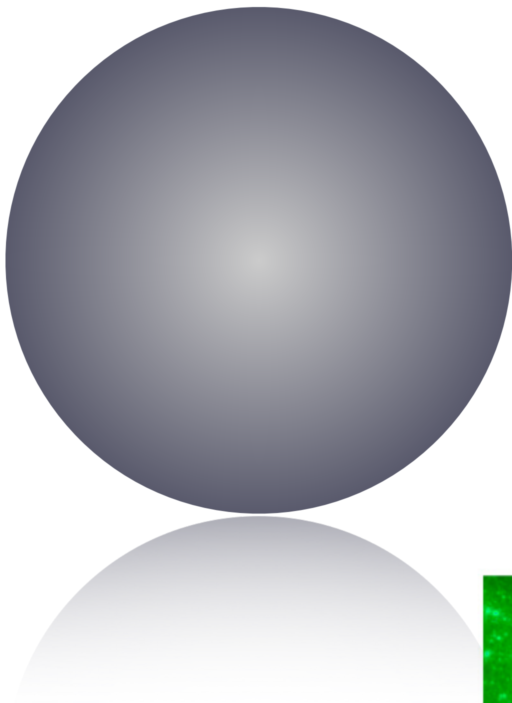


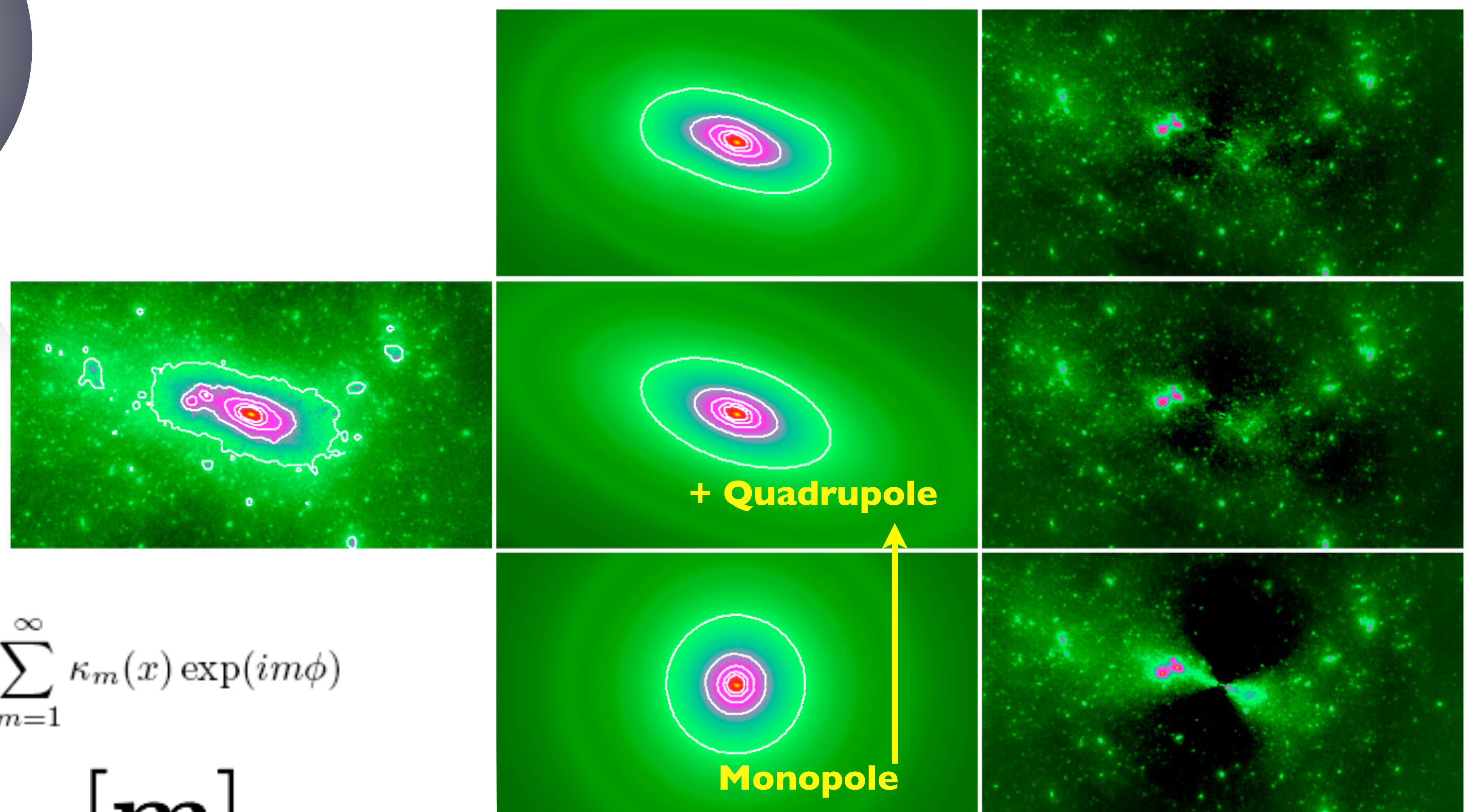
$$\kappa(\vec{x}) = \kappa_0(x) + \sum_{m=1}^{\infty} \kappa_m(x)\exp(im\phi)$$

[q] **[m]**

density prof. *shape*

SMOOTH COMPONENT (AND MOST IMPORTANT SUBSTRUCTURES)



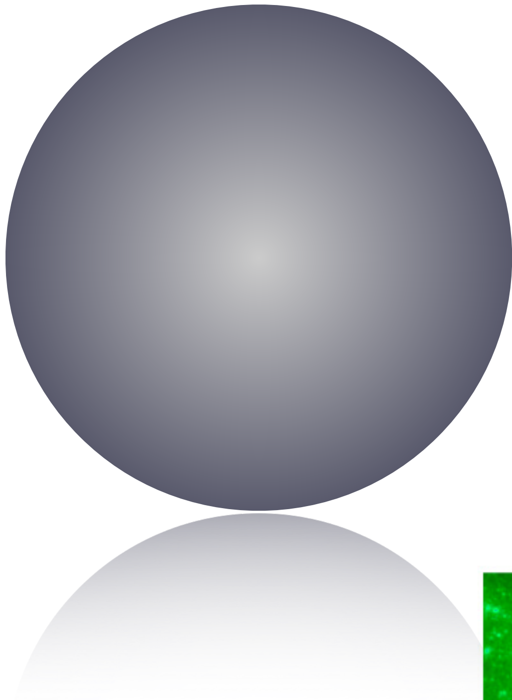


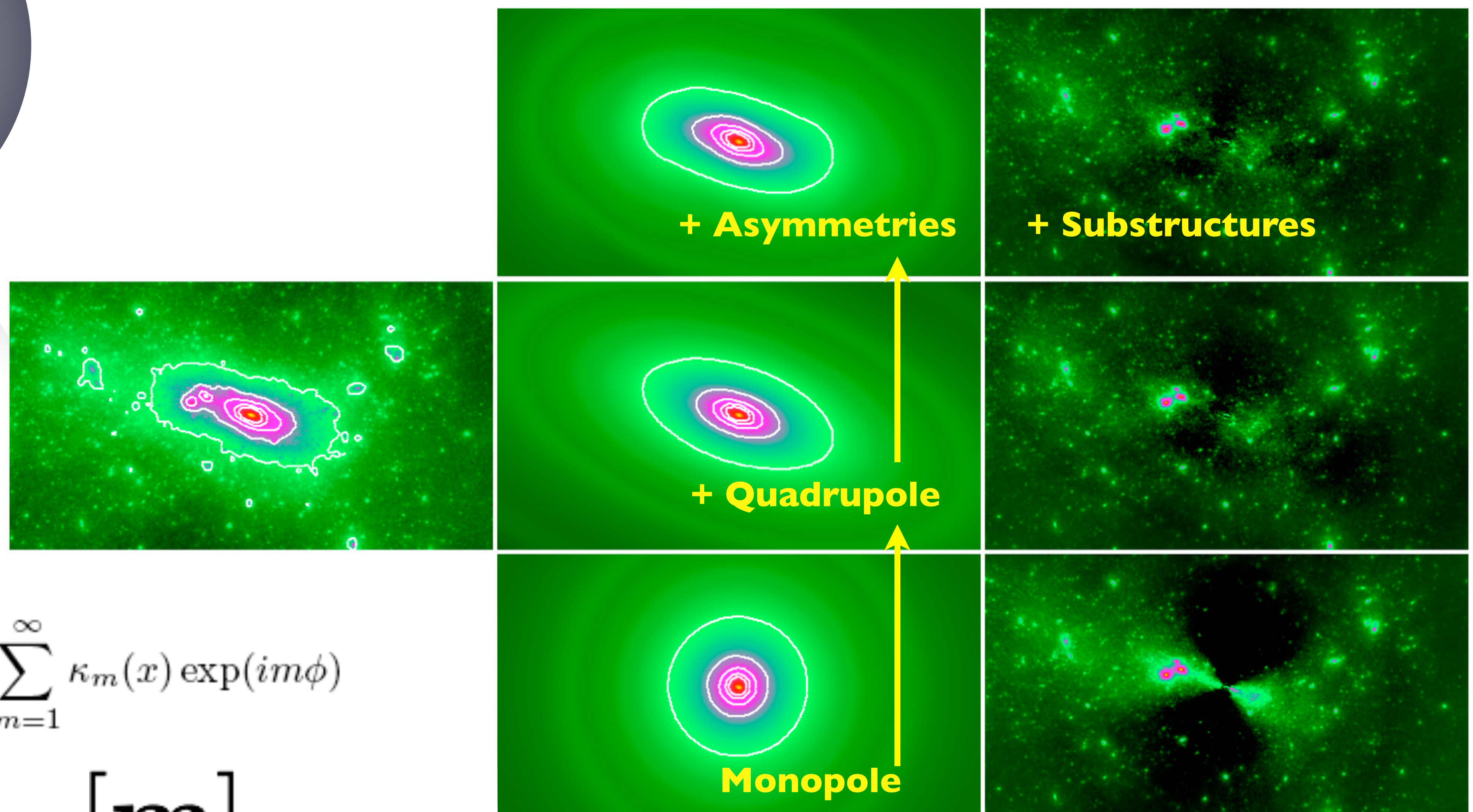
$$\kappa(\vec{x}) = \kappa_0(x) + \sum_{m=1}^{\infty} \kappa_m(x) \exp(im\phi)$$

$[\mathbf{q}]$ $[\mathbf{m}]$

density prof. *shape*

SMOOTH COMPONENT (AND MOST IMPORTANT SUBSTRUCTURES)



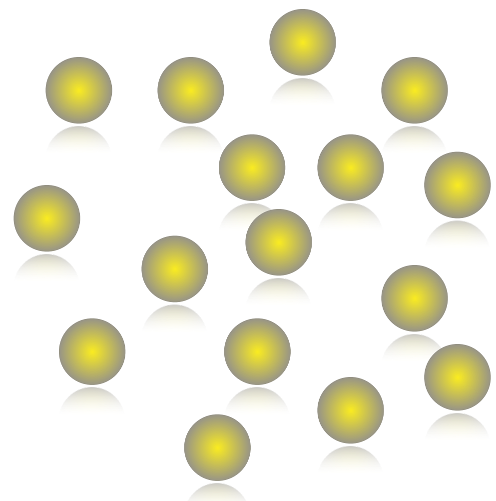


$$\kappa(\vec{x}) = \kappa_0(x) + \sum_{m=1}^{\infty} \kappa_m(x)\exp(im\phi)$$

$$[\mathbf{q}] \qquad [\mathbf{m}]$$

density prof. *shape*

SUBSTRUCTURES



Impossible to optimize each substructure individually… (too many parameters)

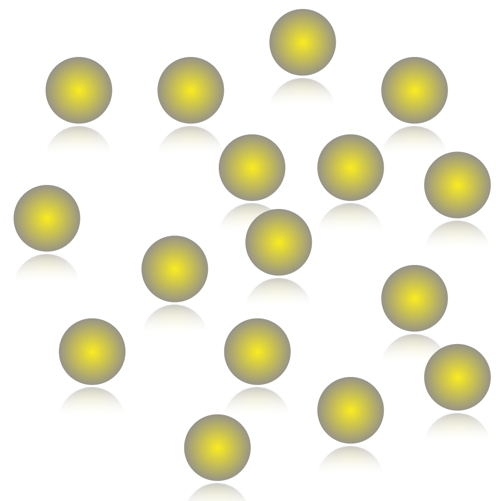
Alternative:

1) *adopt a density profile*
2) *fix the shape, orientation, position*
3) *scale the mass using scaling relations!*

$$\sigma = \sigma_\star \left(\frac{L}{L_\star} \right)^{1/4}$$

$$r_t = r_{t,\star} \left(\frac{L}{L_\star} \right)^{\eta}$$

SUBSTRUCTURES



Impossible to optimize each substructure individually… (too many parameters)

Alternative:

1) *adopt a density profile*
2) *fix the shape, orientation, position*
3) *scale the mass using scaling relations!*

$$\sigma = \sigma_\star \left(\frac{L}{L_\star}\right)^{1/4}$$

$$r_t = r_{t,\star} \left(\frac{L}{L_\star}\right)^{\eta}$$

$$[\mathbf{S}]$$

THE MODEL

$$\mathbf{p} = [\mathbf{q}, \mathbf{m}, \mathbf{s}, \mathbf{x_c}]$$