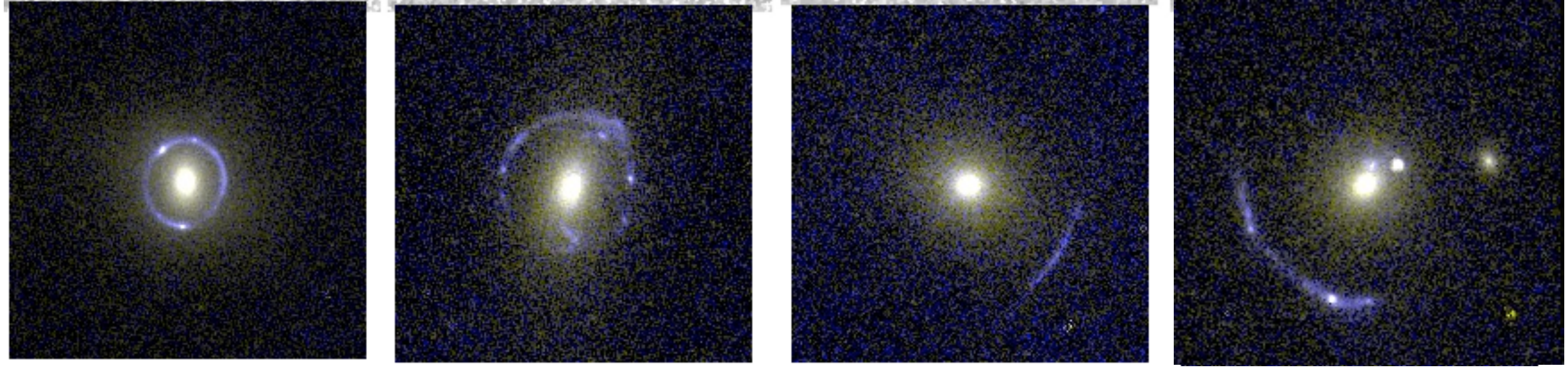
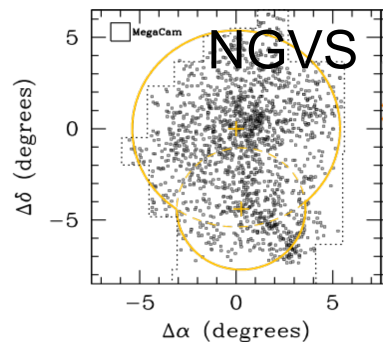


Galaxy-scale Strong lenses @CFHT

Dynamics & Strong + Weak lensing

CFHTLS



CANADA-FRANCE IMAGING SURVEY

Raphaël Gavazzi (IAP)

SF2A, *Bordeaux, July 2018*

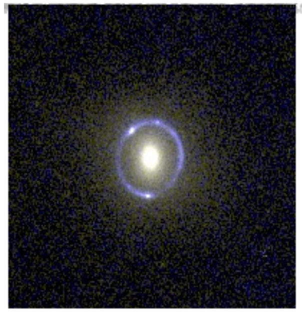
SORBONNE UNIVERSITÉ

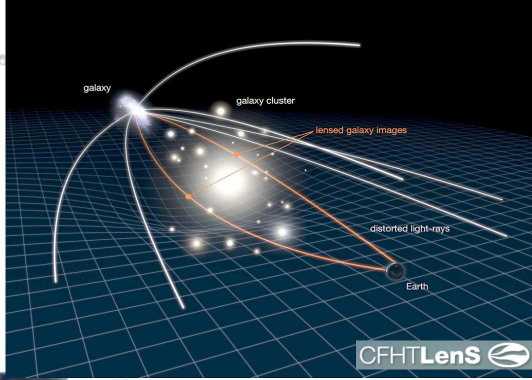
INSTITUT D'ASTROPHYSIQUE DE PARIS

Unité mixte de recherche 7095 *CNRS - Université Pierre et Marie Curie*

cnrs

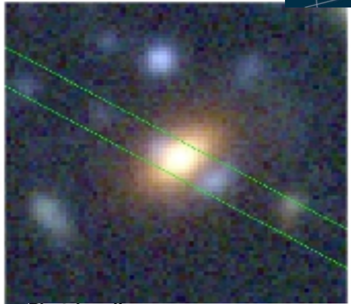
Introduction

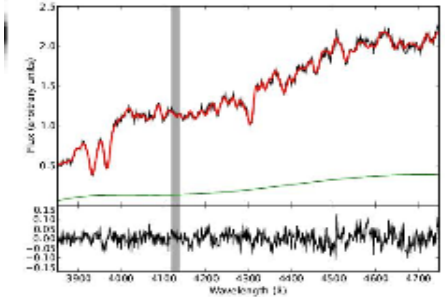


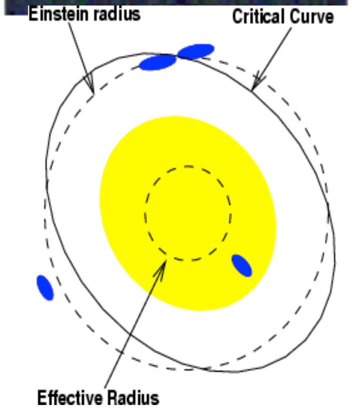


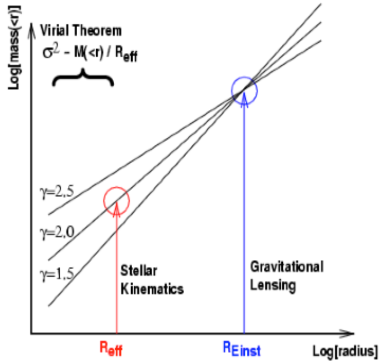
Strong lensing valuable tool to probe the inner structure of massive galaxies.

- Along with stellar kinematics and Stellar Population Synthesis tools:
  - accurate balance of dark/stellar matter
  - Inner slopes: cups/core, halo response
- Deflectors out to z~1.
- Better handle on formation scenarii (dry/wet mergers, role of minor/major mergers…)





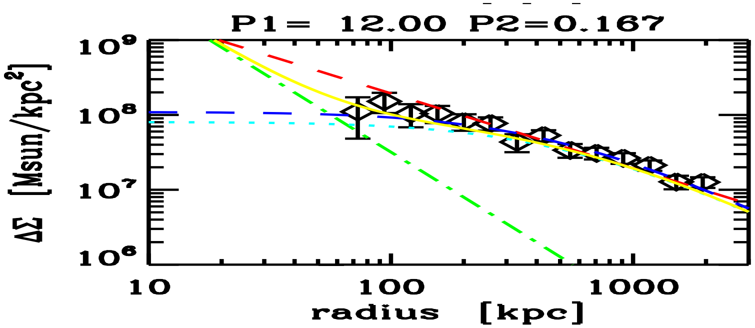


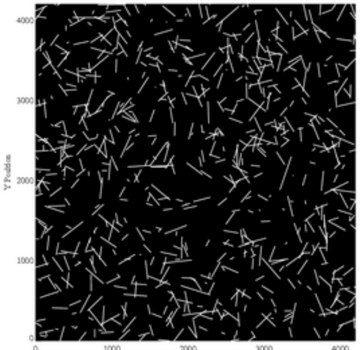


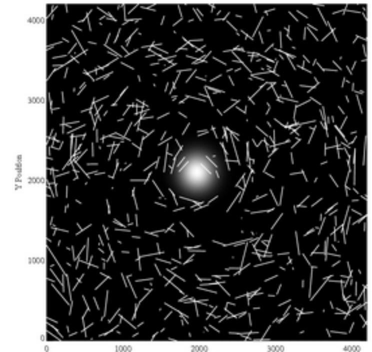
Weak lensing most suitable for the outskirts (halo)

- Probing mass out to virial radius and beyond
- EVERY galaxy is a WEAK lens!

$$\varepsilon_i = \varepsilon_s + \gamma$$
$$< \varepsilon_i > = \widehat{\gamma}$$

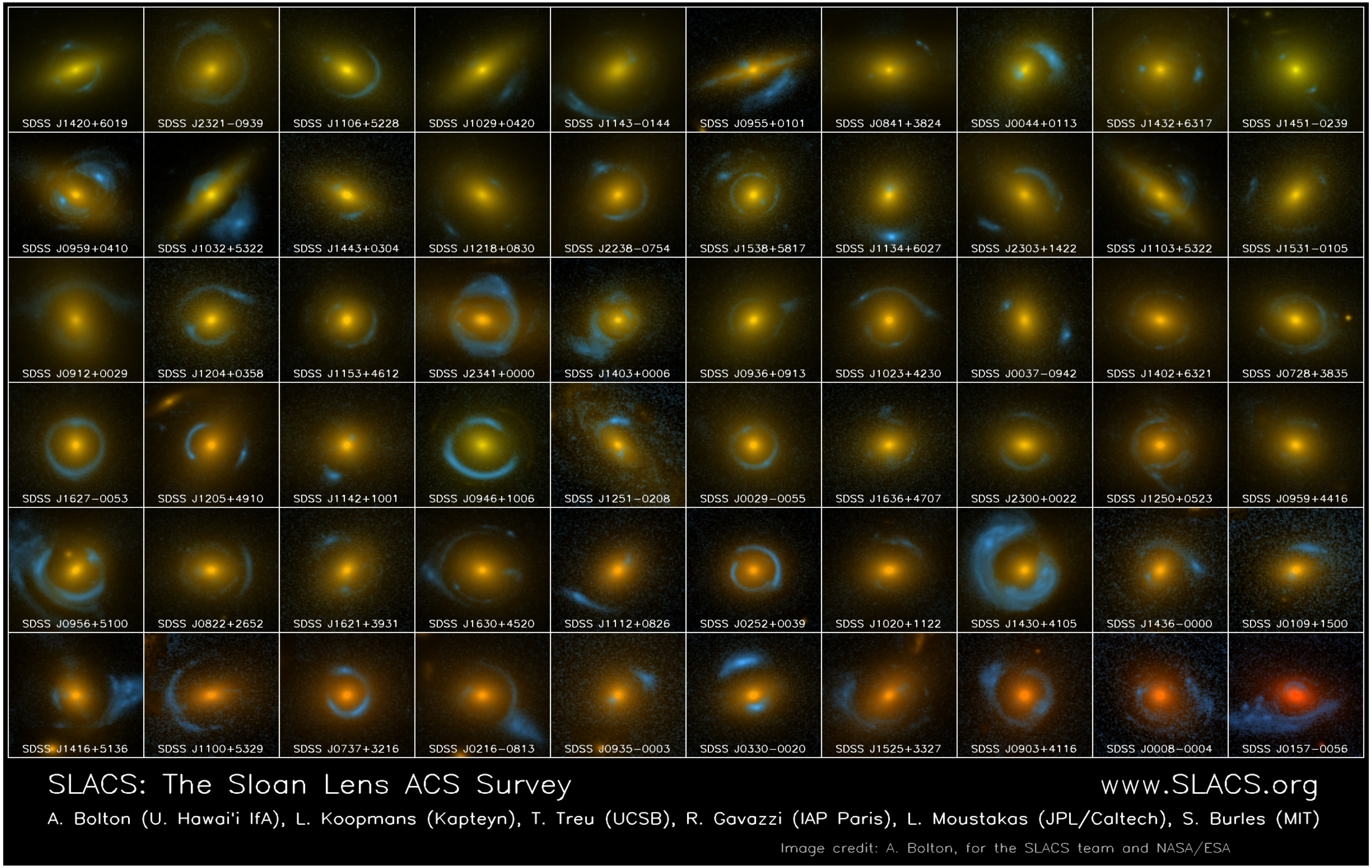






The SLACS: largest sample of low redshift lens galaxies (N~80) using:

- *SDSS spectra (yielding zl, zs, and velocity disp.)*
- *HST follow-up imaging*



Redshift evolution hardly probed because of few z>0.4 lenses.

One way to go further in redshift…

Strong Lensing Legacy Survey

SL^{2}S

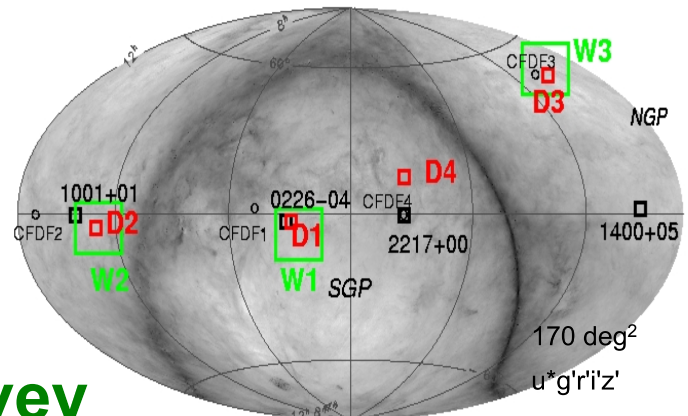
CFHTLS

MegaPrime

MegaCam

Legacy Survey

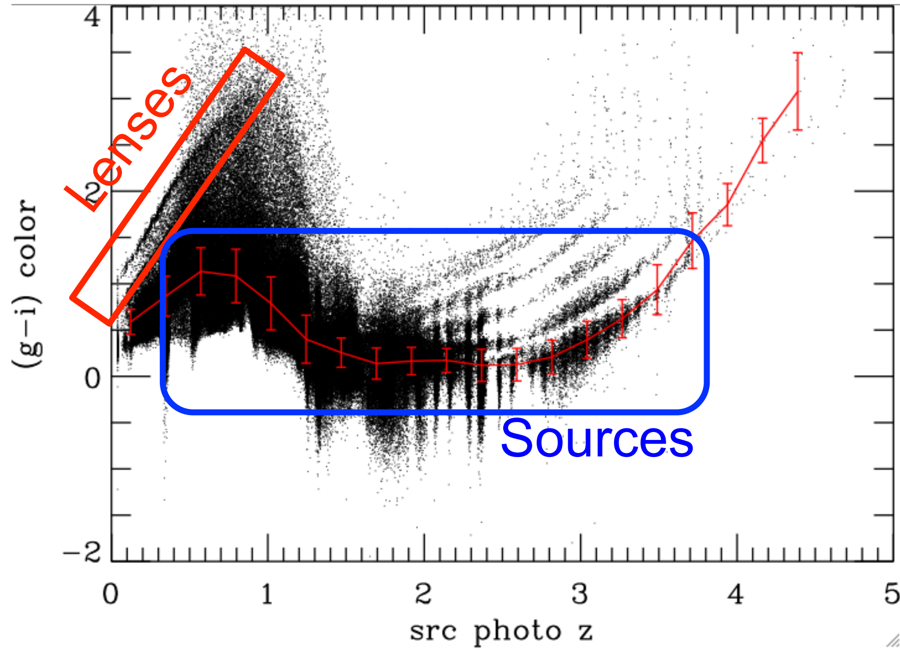
Wide Survey



4 patches: 150 deg^2 (u,g,r,i,z), I_{AB}=24.5

RingFinder

Gavazzi++14

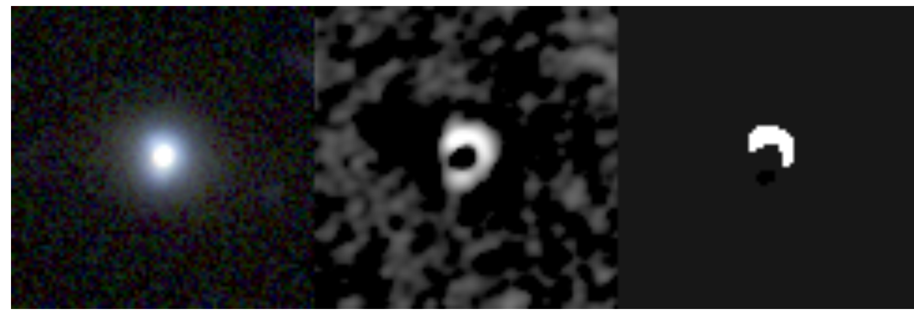


Foreground deflectors: red ETGs $N=3700\ deg^{-2}$
Background sources: blue star-forming faint blobs.

Efficient lens light subtraction technique:
g-αi difference imaging. Tune α to remove ETG (after agressive PSF matching $g*s_i - \alpha\ i*s_g$)

Processing time for the whole CFHTLS… (2 CPU.week / $150 deg^2$, ie 2 CPU. Hour/deg^2)

Visual inspection of $1.4x10^4$ candidates (1-2 days).

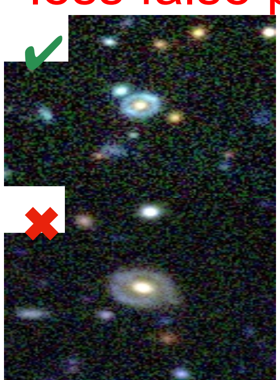


Selection of 330 good candidates in the CFHTLS

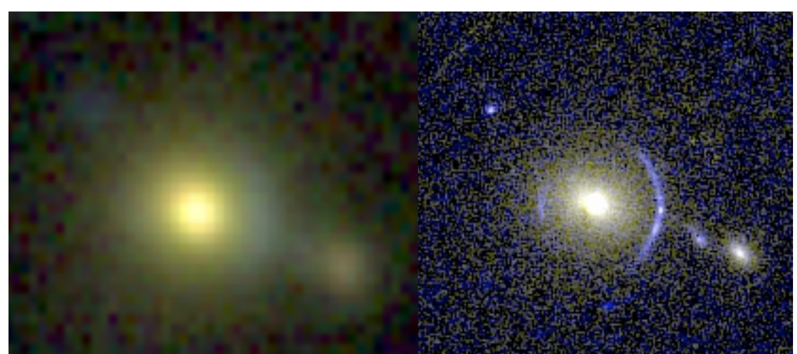
$N=2.4\ deg^{-2}$

Refinement with visual inspection
-> less false positives……….

But HST follow-up is the referee!



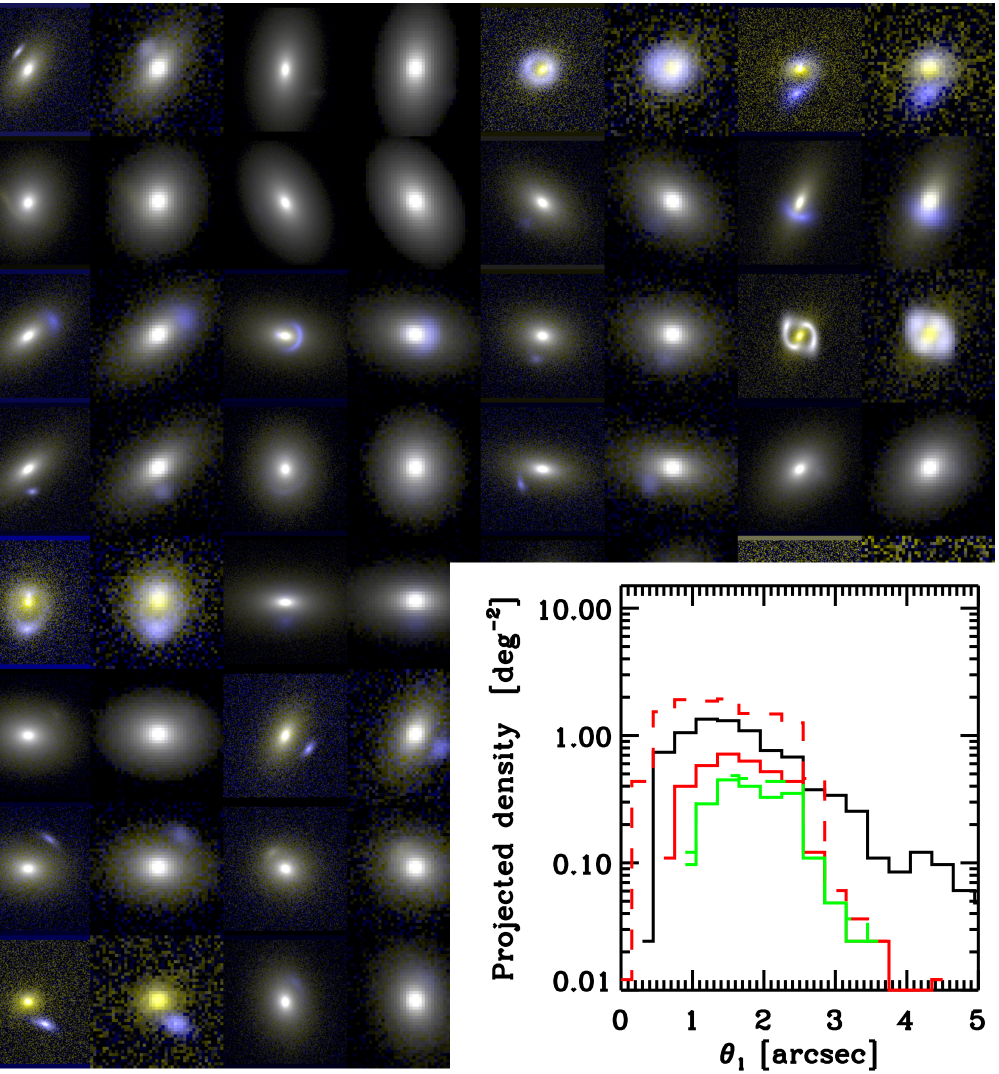
CFHTLS gri



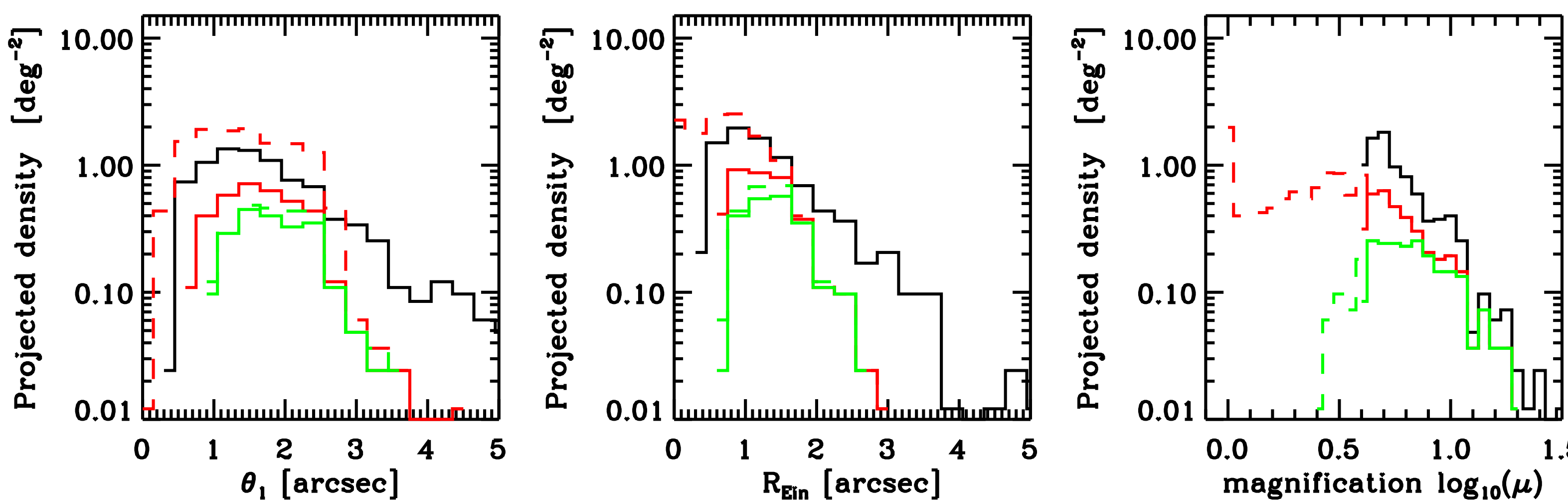
HST snapshot

Forecasting the number of lenses

For sources i<25, we simulate CFHTLS mock fg deflector + bg source



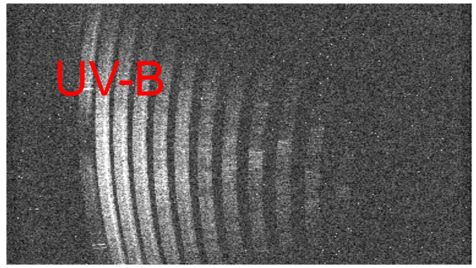
per deg^2	$\mu > 4$		
# of existing lenses		8.6	
q_flag	≥ 0	≥ 2	≥ 3
# of selected candidates	12.5	6.4	2.5
# of selected lenses	3.6	3.4	2.1
completeness (%)	42	39	25
purity (%)	29	53	84

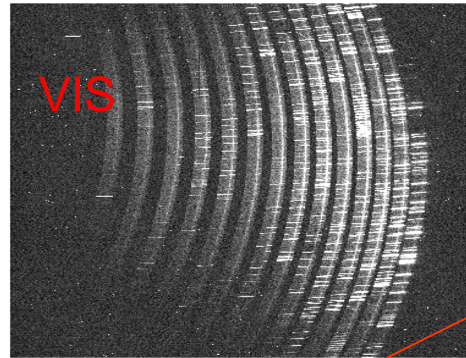


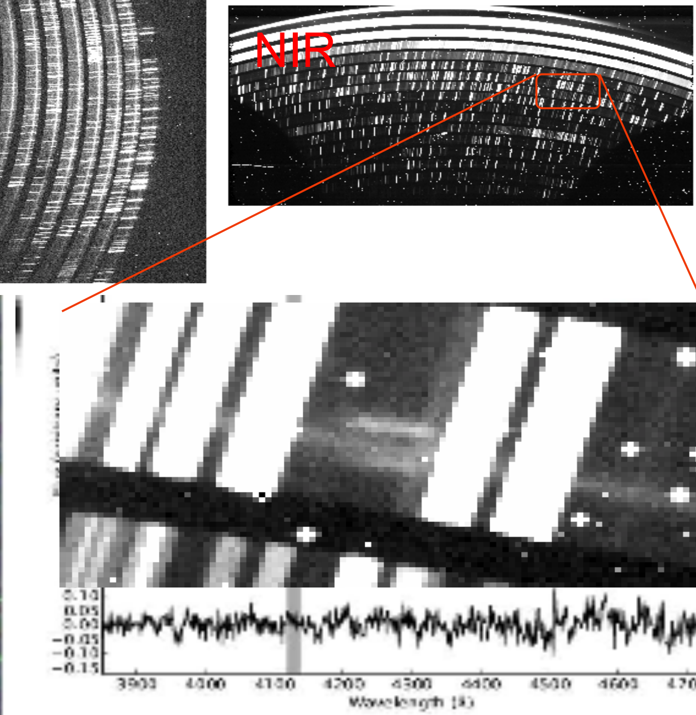
+Spectra

VLT-Xshooter
(19 systems)

Keck/LRIS
(46 systems)

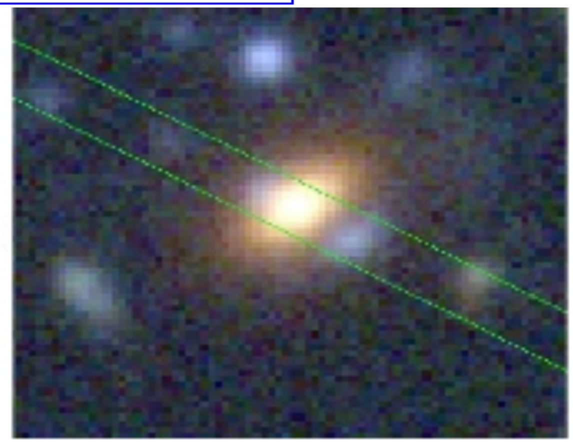


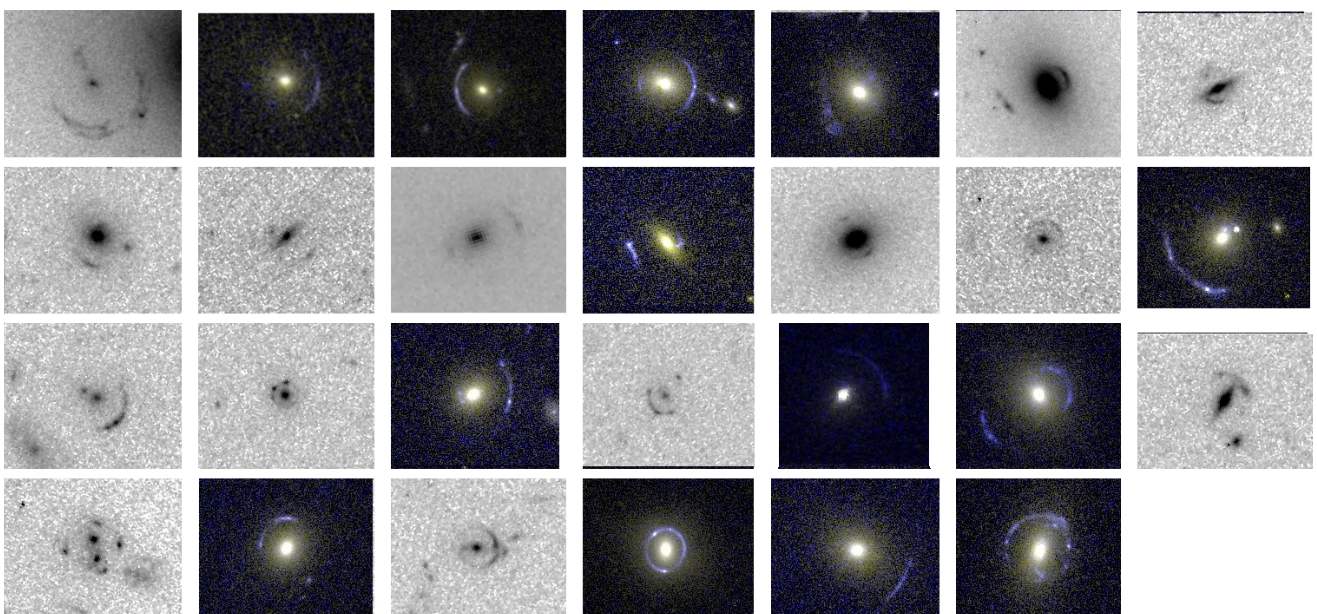




Full R~5000 coverage from 350nm to 2.2μm. Most suitable for mean source redshift ~2.1

- ⇒ ***Lens redshift (~80)***
- ⇒ ***Source redshift (~38)***
- ⇒ ***Velocity dispersion (~55).***



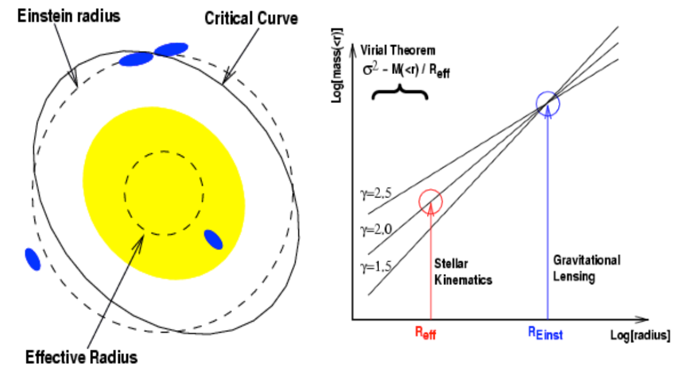


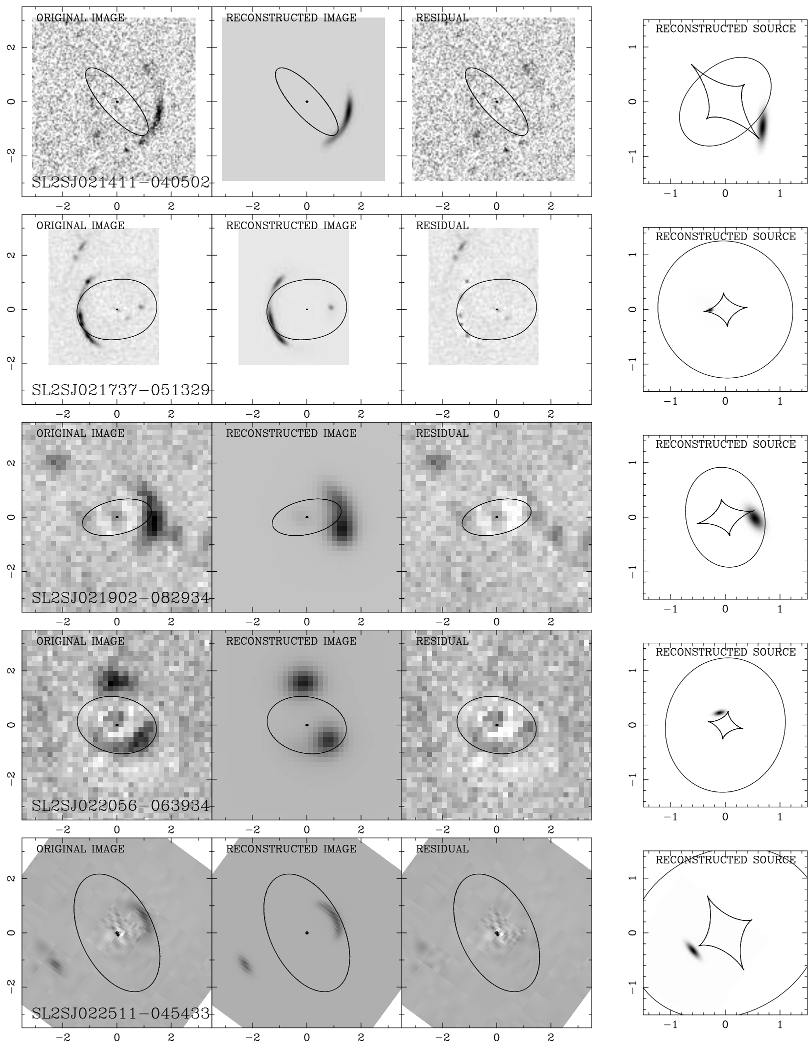
+HST imaging

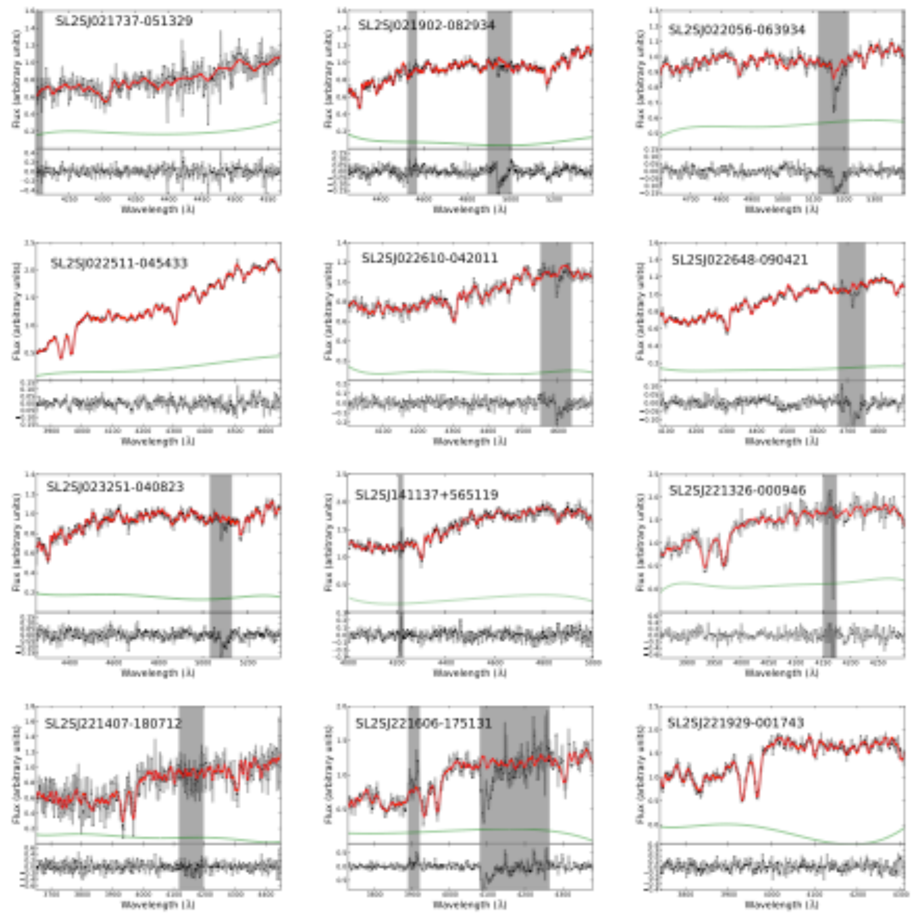
- 65 observed.
- 27 confirmed to be actual lenses from this imaging,
- success rate >= 50% and increasing with time.

SL2S observational results

Ruff++11, Gavazzi++12, Sonnenfeld++13ab

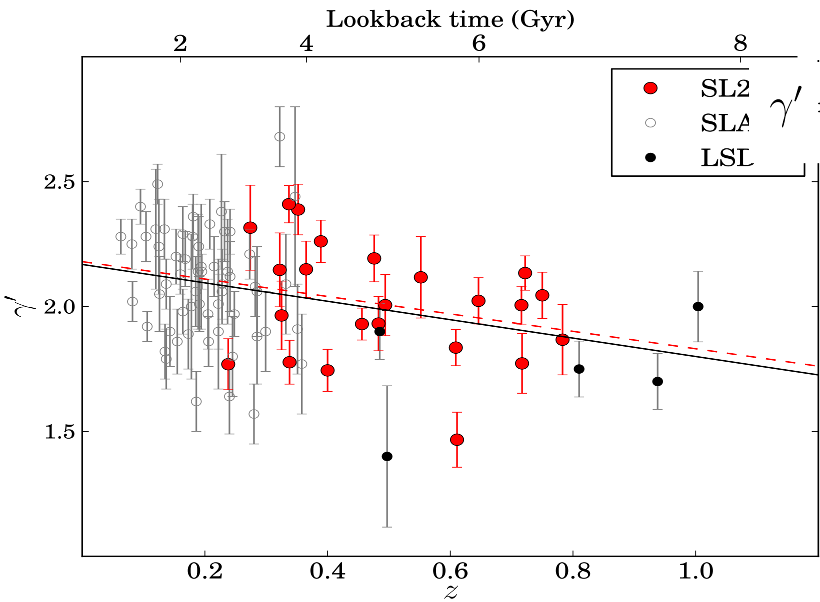






(No)-Evidence for steepening with time

Sonnenfeld++14



$$\rho(r) \propto r^{-\gamma'}$$

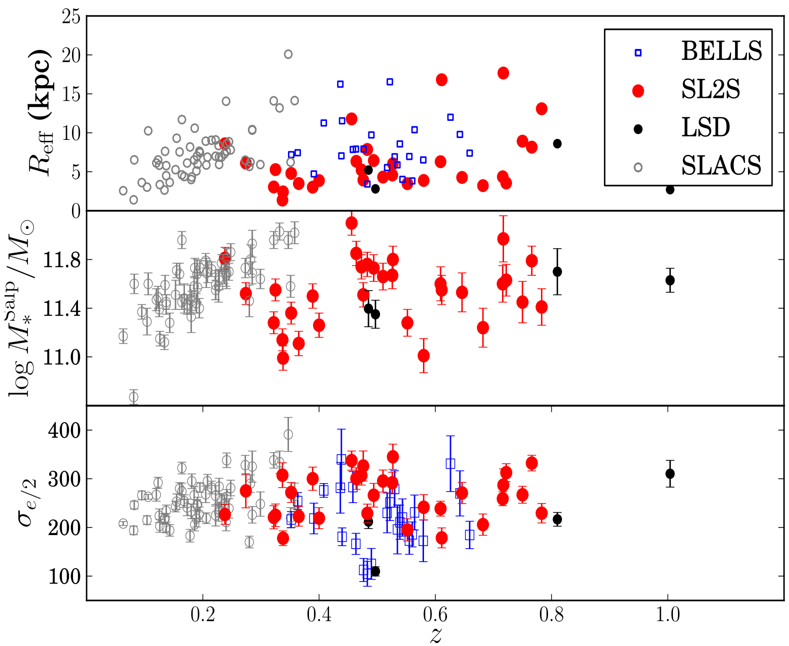
$$\gamma' = \gamma_0 + \alpha(z - 0.3) + \beta(\log M_* - 11.5) + \xi(\log \Sigma_* - 9.0) + N(0, \sigma_{\gamma'})$$

$$\frac{\partial \gamma'}{\partial z} = \alpha = -0.31 \pm 0.10,$$

$$\frac{\partial \gamma'}{\partial \log M_*} = \beta = 0.40 \pm 0.16,$$

$$\frac{\partial \gamma'}{\partial \log R_{\rm eff}} = \xi = -0.76 \pm 0.15.$$

γ_0	$2.08^{+0.02}_{-0.02}$
$\sigma_{\gamma'}$	$0.12^{+0.02}_{-0.02}$



High-z sample is not the progenitor of low-z one!

$$\frac{{\rm d}\gamma'(z, \log M_*, \log R_{\rm eff})}{{\rm d}z} =$$

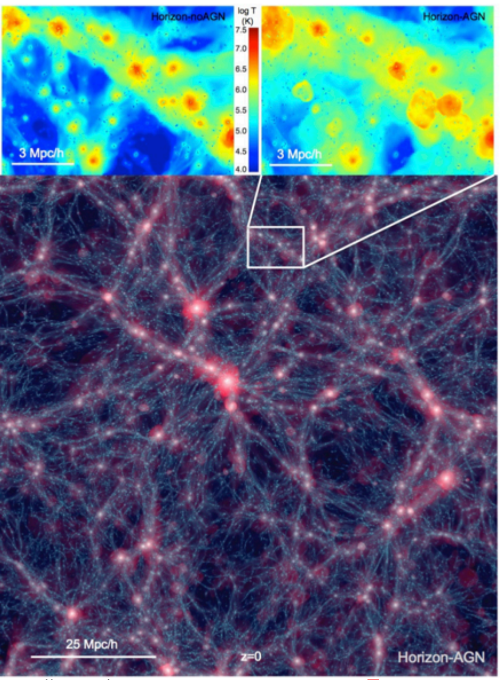
$$= \frac{\partial \gamma'}{\partial z} + \frac{\partial \gamma'}{\partial \log M_*}\frac{{\rm d}\log M_*}{{\rm d}z} + \frac{\partial \gamma'}{\partial \log R_{\rm eff}}\frac{{\rm d}\log R_{\rm eff}}{{\rm d}z}.$$

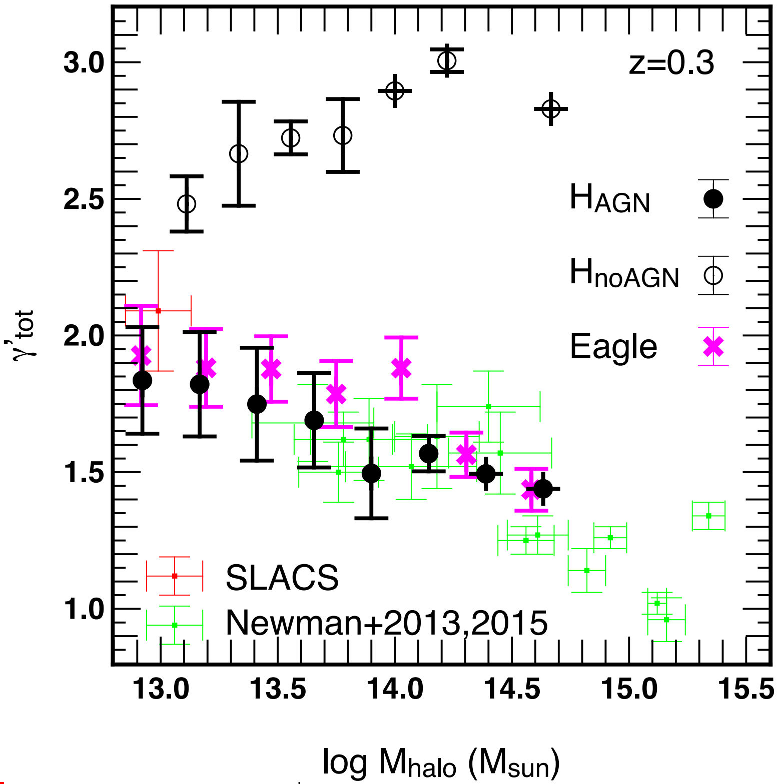
$$\frac{{\rm d}\gamma'}{{\rm d}z} = -0.10 \pm 0.12$$

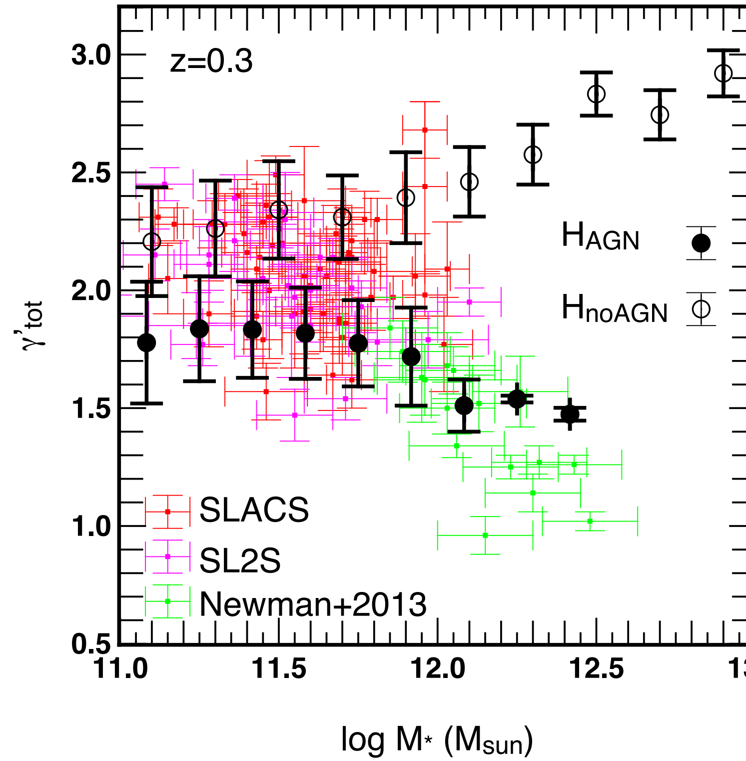
→ Mild steepening with time if anything!

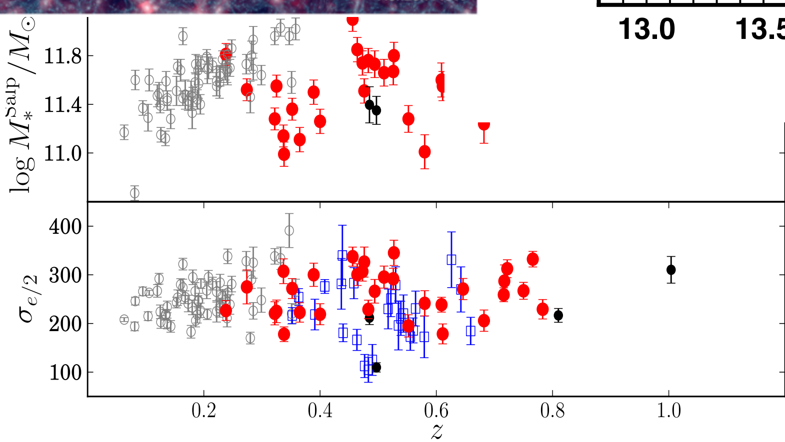
(No)-Evidence for steepening with time

Excellent agreement with cosmological Hydro simulations
(eg. Horizon-AGN, Peirani, Dubois++18)









$$\frac{d\gamma'}{dz} = -0.10 \pm 0.12$$

→ Mild steepening with time if anything!

Evidence for non-universal IMF

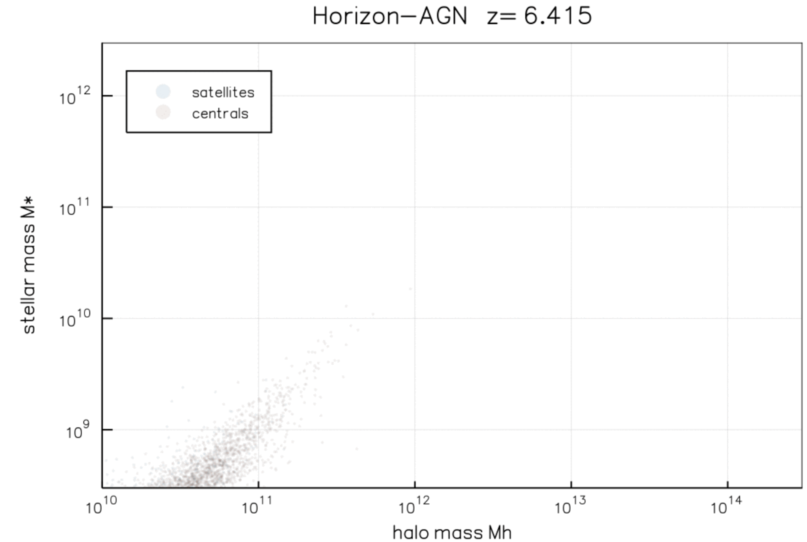
Treu++10,
Auger++10,
Sonnenfeld++15

$$\log \frac{M_*^{SPS}}{M_*} = -\eta \log \frac{M_*}{10^{11} M_\odot} - \log \alpha,$$

- α~1 : In ETGs, IMF is more Salpeter-like
- η~0.4 : More massive galaxies are more massive!
- Local dynamical studies (eg SAURON/ATLAS-3D) in agreement (Cappellari++)
- One cannot have both universal IMF and universal NFW DM profile
- Degeneracy with DM response to baryons cooling…
- But faint spectral lines (Na, TiO, CaI) support the result (Spinielli++, Conroy++)
- Moreover: Evidences for radial gradients of M_*/L (and hence IMF normalisation: Martin-Navarro, La Barbera++, van Dokkum++, Sarzi++)

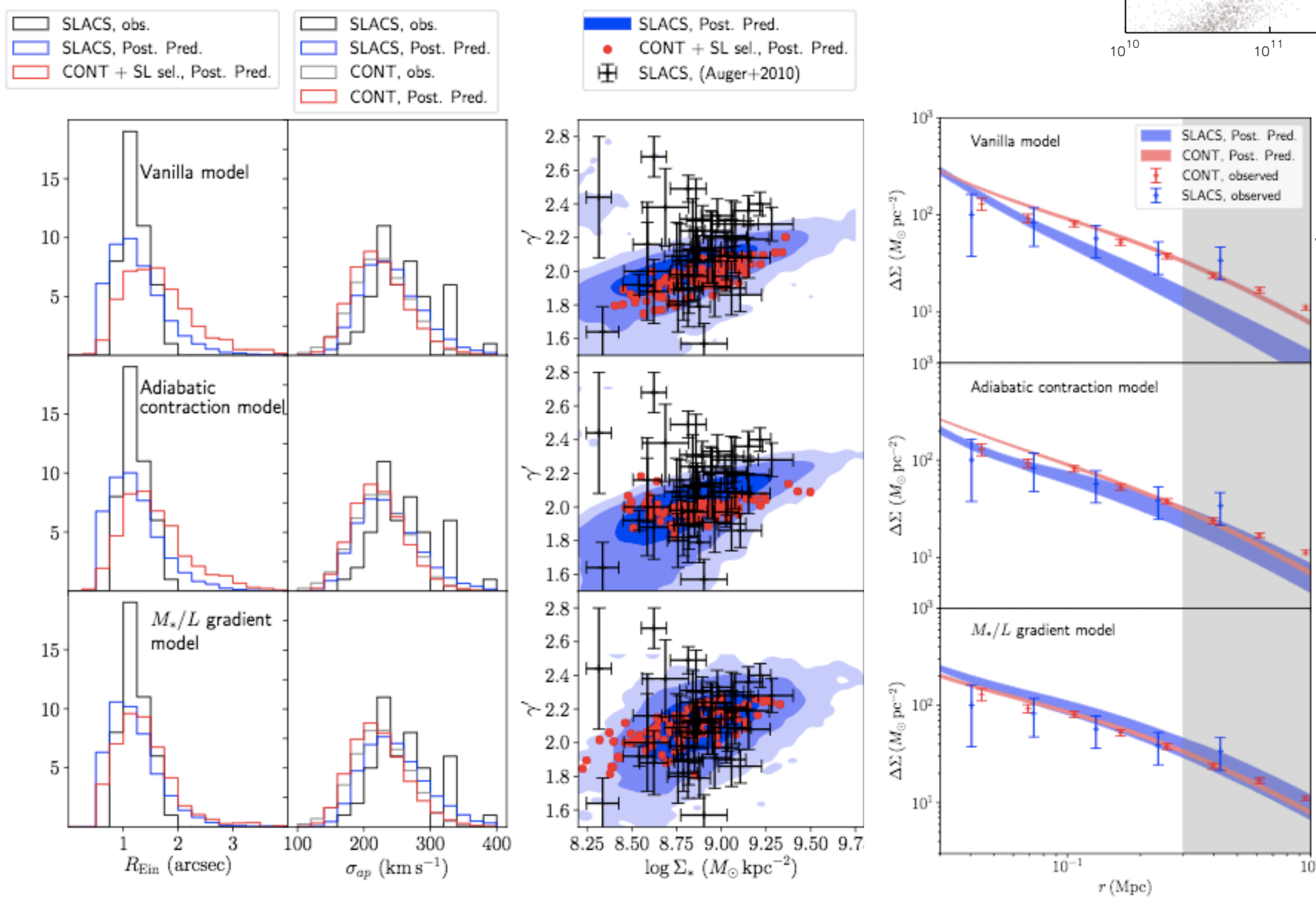
Addition of weak GG-lensing

Complex relation between halo and stellar masses



Fitting SL, dynamics and WL:
45 SLACS SLs, 1400 HSC LRGs for WL)

Sonnenfeld++18

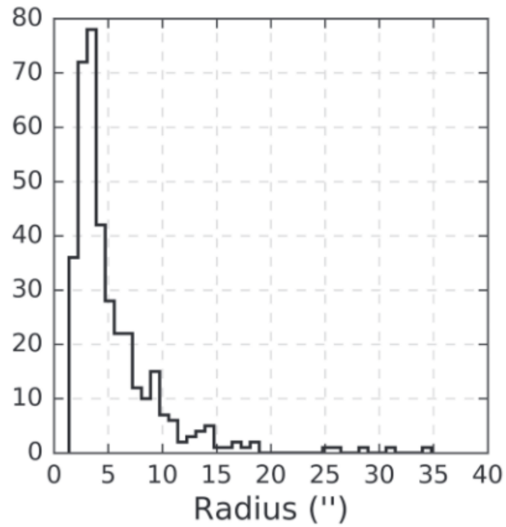


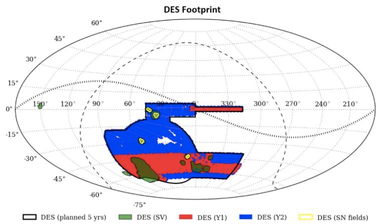
Vanilla: constant IMF
+NFW halo

+ Dark Matter
contraction/expansion

+IMF gradients!

Current efforts

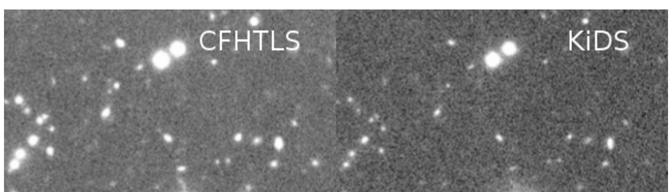




DES, year1 , Diehl++17:

370 lenses over 2000 deg^2 (0.18 deg^{-2})

Sonnenfeld++17: 330 lenses over 442 deg^2 (0.75 deg^{-2})



Petrillo++18: 56 solid lenses over 225 deg^2 (0.25 deg^{-2})

(when completed + CNNs pushed··· 2400/1000=2.4 deg^{-2})

Methodological improvements

Parametric bayesian forward modeling

Machine learning (CNNs...)

Forward modelling of all massive ETGs

Simultaneous fit in all u g (r) i z bands of a (red) deflector and a (blue) ring.

Optimization over a many-parameter space (with strong priors on color of fg/bg).

R_{ein}, q, PA,

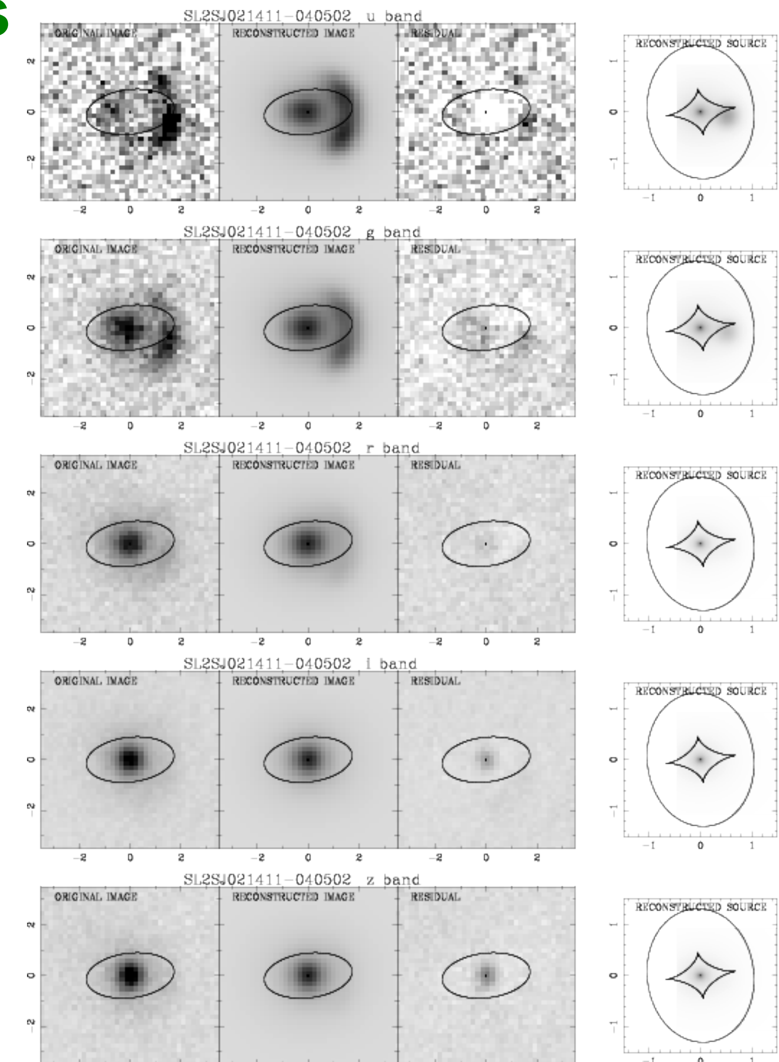
q_d, PA_d, size, $Flux_{d1}$, $Flux_{d2}$…

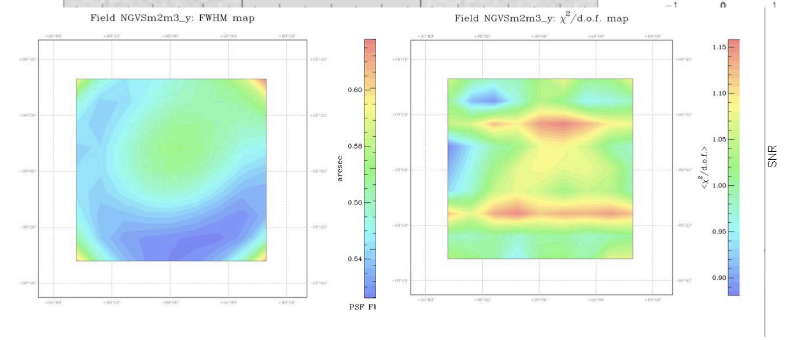
x_s, y_s, q_s, PA_s, size, $Flux_{s1}$, $Flux_{s2}$…

Sampling time a few min.CPU, still being improved

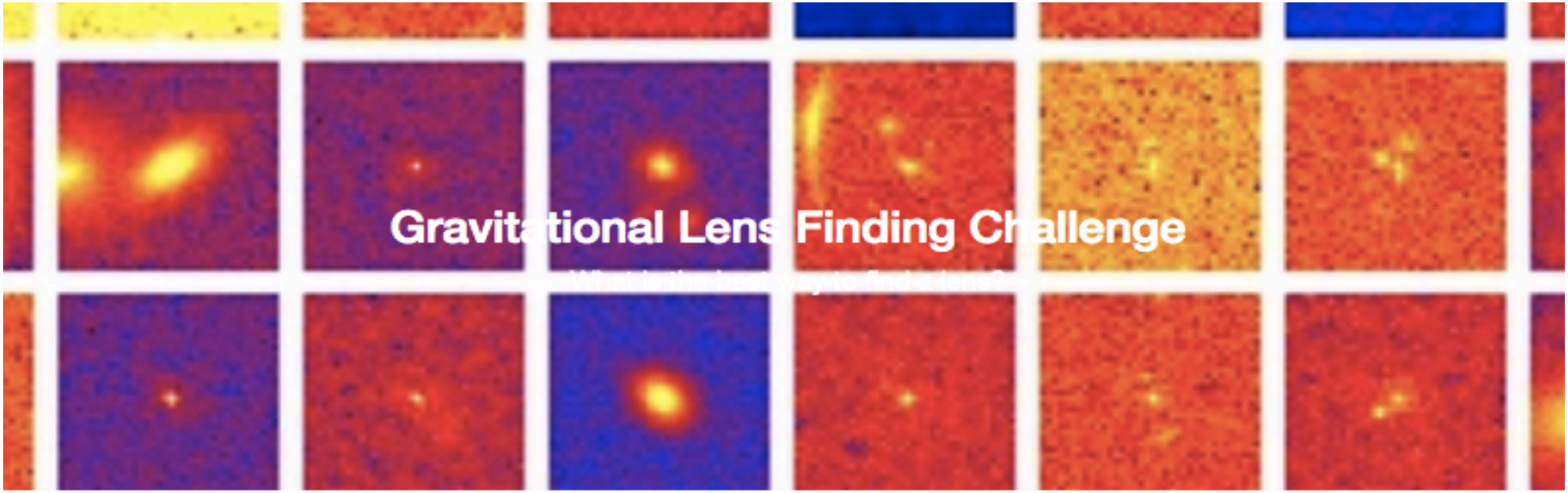
PSFEx: multiband PSF model over a given FOV

Sextractor run (in model-fitting mode!) used to start the lens modeling and isolate nearby objects.





Machine learning techniques



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

Introduction

Finding strong gravitational lenses in the current imaging surveys is difficult. Future surveys will have orders of magnitude more data and more lenses to find. It will become impossible for a single human being to find them by inspection. In addition, to properly interpret the science coming out of strong lens samples it is necessary to accurately quantify the detection efficiency and bias of automated lens detectors. These open challenges are designed as a friendly way of stimulating activity and helping to quantify results in this regard.

Challenges

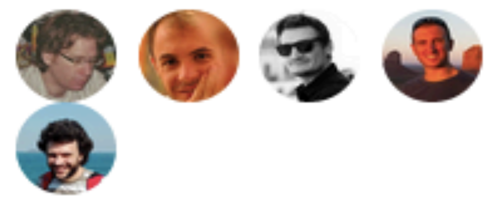
First Generation

This is the first of what we expect to be at least two generations of challenges, each becoming harder and more realistic. This challenge will concentrate on galaxies that are lensed by galaxies (i.e. no clusters and no quasars).

There are two parts to the challenge, C.1 and C.2, designed to mock different types of data sets. They require separate entries. You can entering both or either one.

Training sets of 20,000, 101px x 101px images are provided for both challenges. For each image in the training sets a classification as a lens or not lens is provided in a ASCII log file. Additional information about each lensed image is also provided such as the brightness of the lensed images. The training sets also contain images of the lens galaxy by itself and the lensed image by itself.

People



Funding

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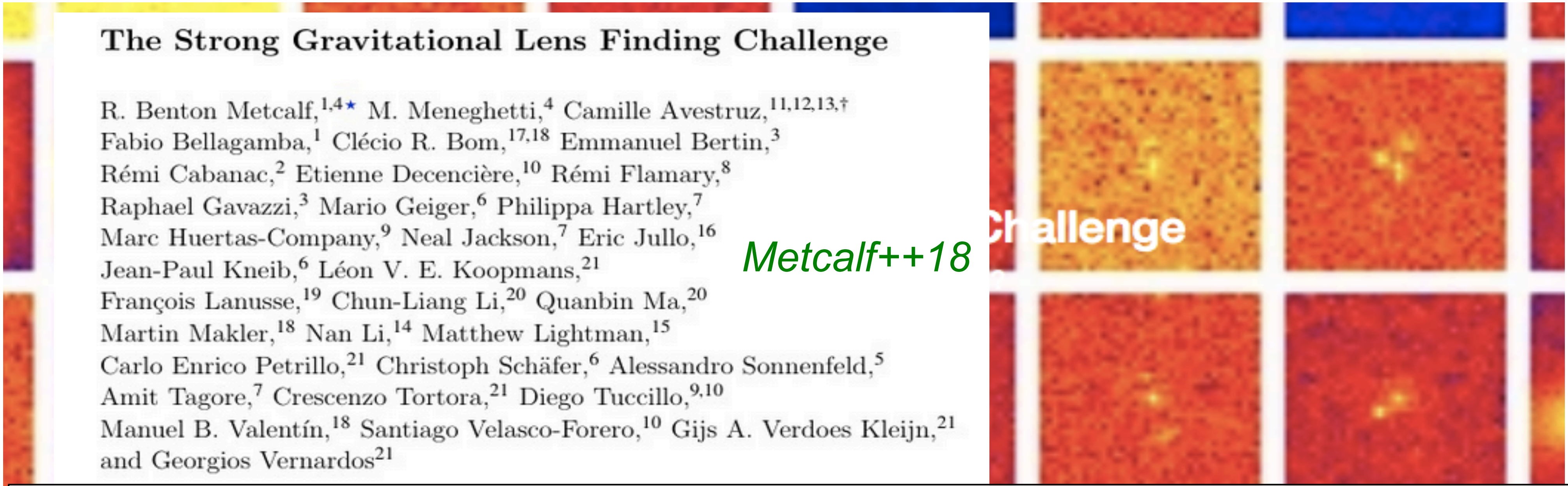
Machine learning techniques


The Strong Gravitational Lens Finding Challenge

R. Benton Metcalf,[1,4★] M. Meneghetti,[4] Camille Avestruz,[11,12,13,†] Fabio Bellagamba,[1] Clécio R. Bom,[17,18] Emmanuel Bertin,[3] Rémi Cabanac,[2] Etienne Decencière,[10] Rémi Flamary,[8] Raphael Gavazzi,[3] Mario Geiger,[6] Philippa Hartley,[7] Marc Huertas-Company,[9] Neal Jackson,[7] Eric Jullo,[16] Jean-Paul Kneib,[6] Léon V. E. Koopmans,[21] François Lanusse,[19] Chun-Liang Li,[20] Quanbin Ma,[20] Martin Makler,[18] Nan Li,[14] Matthew Lightman,[15] Carlo Enrico Petrillo,[21] Christoph Schäfer,[6] Alessandro Sonnenfeld,[5] Amit Tagore,[7] Crescenzo Tortora,[21] Diego Tuccillo,[9,10] Manuel B. Valentín,[18] Santiago Velasco-Forero,[10] Gijs A. Verdoes Kleijn,[21] and Georgios Vernardos[21]

Metcalf++18

Simulation of Euclid-VIS and ground-based KiDS-like strong lenses

Training: get 10^4 cutout images with known truth (lens / not lens)

Testing: classify 10^5 cutout images within 48 hours (avoid visual classif)

Closed February 5th 2017!

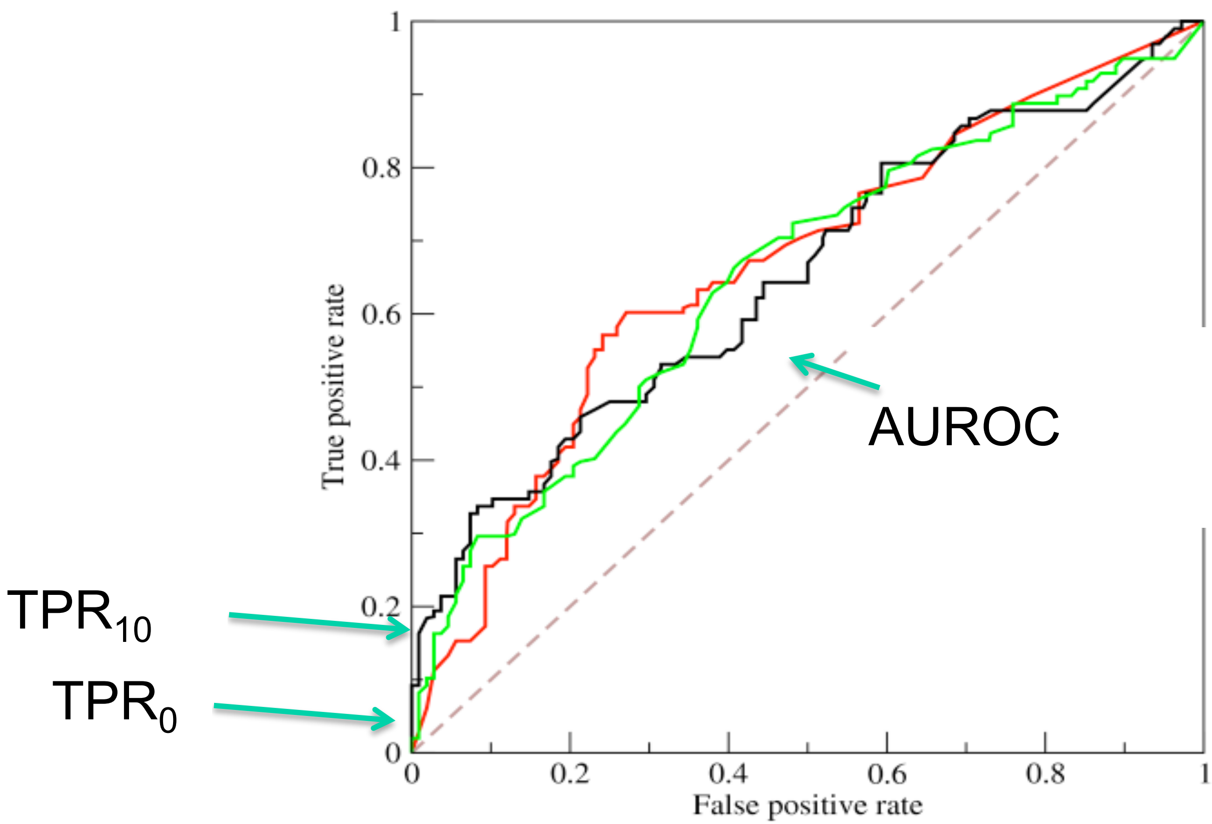
Future steps for SL Challenge:

New issue to be completed by Fall 2018 with VIS + 3-band NIR channels (color!!)

Aiming at more complexity in the deflectors geometry…

$$\text{TPR} = \text{true positive rate} = \frac{\#\ \text{true lenses classified as lenses}}{\#\ \text{true lenses}}$$

$$\text{FPR} = \text{false positive rate} = \frac{\#\ \text{nonlenses classified as lenses}}{\#\ \text{nonlenses}}$$



Completeness

Name	type	AUROC	TPR_0	TPR_{10}	short description
CMU-DeepLens-ResNet-ground3	Ground-Based	0.98	0.09	0.45	CNN
CMU-DeepLens-Resnet-Voting	Ground-Based	0.98	0.02	0.10	CNN
LASTRO EPFL	Ground-Based	0.97	0.07	0.11	CNN
CAS Swinburne Melb	Ground-Based	0.96	0.02	0.08	CNN
AstrOmatic	Ground-Based	0.96	0.00	0.01	CNN
Manchester SVM	Ground-Based	0.93	0.22	0.35	SVM / Gabor
Manchester-NA2	Ground-Based	0.89	0.00	0.01	Human Inspection
ALL-star	Ground-Based	0.84	0.01	0.02	edges/gradiants and Logistic Reg.
CAST	Ground-Based	0.83	0.00	0.00	CNN / SVM
YattaLensLite	Ground-Based	0.82	0.00	0.00	SExtractor
LASTRO EPFL	Space-Based	0.93	0.00	0.08	CNN
CMU-DeepLens-ResNet	Space-Based	0.92	0.22	0.29	CNN
GAMOCLASS	Space-Based	0.92	0.07	0.36	CNN
CMU-DeepLens-Resnet-Voting	Space-Based	0.91	0.00	0.01	CNN
AstrOmatic	Space-Based	0.91	0.00	0.01	CNN
CMU-DeepLens-ResNet-aug	Space-Based	0.91	0.00	0.00	CNN
Kapteyn Resnet	Space-Based	0.82	0.00	0.00	CNN
CAST	Space-Based	0.81	0.07	0.12	CNN
Manchester1	Space-Based	0.81	0.01	0.17	Human Inspection
Manchester SVM	Space-Based	0.81	0.03	0.08	SVM / Gabor
NeuralNet2	Space-Based	0.76	0.00	0.00	CNN / wavelets
YattaLensLite	Space-Based	0.76	0.00	0.00	Arcs / SExtractor
All-now	Space-Based	0.73	0.05	0.07	edges/gradiants and Logistic Reg.
GAHEC IRAP	Space-Based	0.66	0.00	0.01	arc finder

Table 3. The AUROC, TPR_0 and TPR_{10} for the entries in order of AUROC.

Ground-based yields higher completeness due to color information

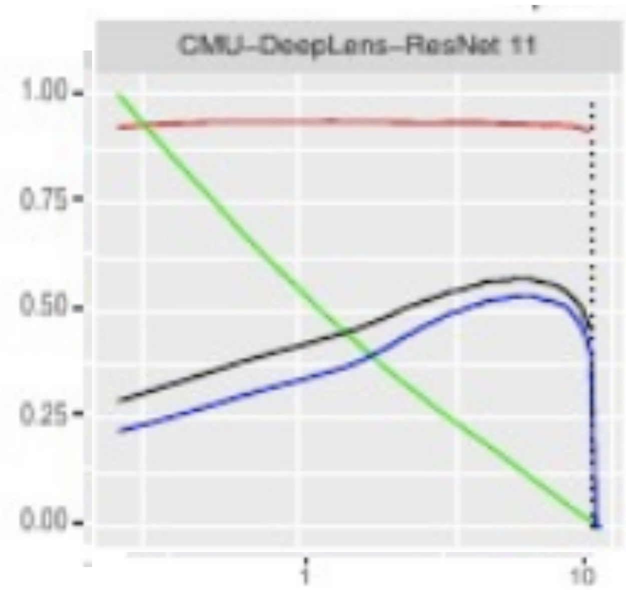
Completeness | high purity

Name	type	AUROC	TPR_0	TPR_{10}	short description
Manchester SVM	Ground-Based	0.93	0.22	0.35	SVM / Gabor
CMU-DeepLens-ResNet-ground3	Ground-Based	0.98	0.09	0.45	CNN
LASTRO EPFL	Ground-Based	0.97	0.07	0.11	CNN
CMU-DeepLens-Resnet-Voting	Ground-Based	0.98	0.02	0.10	CNN
CAS Swinburne Melb	Ground-Based	0.96	0.02	0.08	CNN
ALL-star	Ground-Based	0.84	0.01	0.02	edges/gradiants and Logistic Reg.
Manchester-NA2	Ground-Based	0.89	0.00	0.01	Human Inspection
YattaLensLite	Ground-Based	0.82	0.00	0.00	SExtractor
CAST	Ground-Based	0.83	0.00	0.00	CNN / SVM
AstrOmatic	Ground-Based	0.96	0.00	0.01	CNN
CMU-DeepLens-ResNet	Space-Based	0.92	0.22	0.29	CNN
GAMOCLASS	Space-Based	0.92	0.07	0.36	CNN
CAST	Space-Based	0.81	0.07	0.12	CNN
All-now	Space-Based	0.73	0.05	0.07	edges/gradiants and Logistic Reg.
Manchester SVM	Space-Based	0.80	0.03	0.07	SVM / Gabor
Manchester1	Space-Based	0.81	0.01	0.17	Human Inspection
LASTRO EPFL	Space-Based	0.93	0.00	0.08	CNN
GAHEC IRAP	Space-Based	0.66	0.00	0.01	arc finder
AstrOmatic	Space-Based	0.91	0.00	0.01	CNN
Kapteyn Resnet	Space-Based	0.82	0.00	0.00	CNN
CMU-DeepLens-ResNet-aug	Space-Based	0.91	0.00	0.00	CNN
CMU-DeepLens-Resnet-Voting	Space-Based	0.91	0.00	0.01	CNN
NeuralNet2	Space-Based	0.76	0.00	0.00	CNN / wavelets
YattaLensLite	Space-Based	0.76	0.00	0.00	Arcs / SExtractor

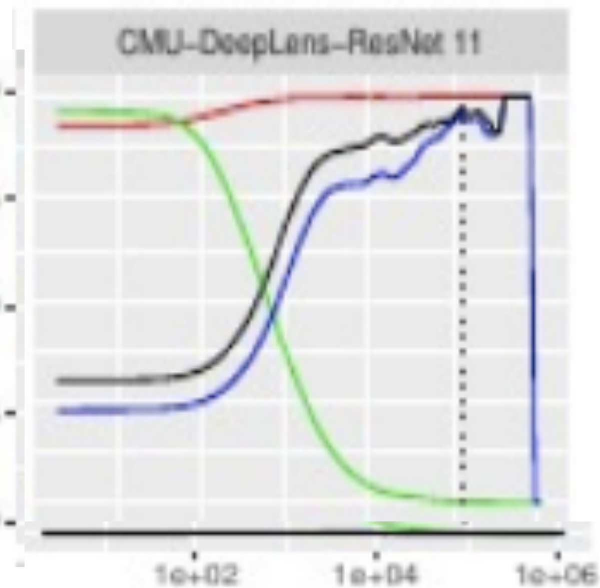
Table 4. The AUROC, TPR_0 and TPR_{10} for the entries in order of TPR_0.

Small chances requiring high purity…. Crucial for rare events ($\tau \sim 10^{-3}$)

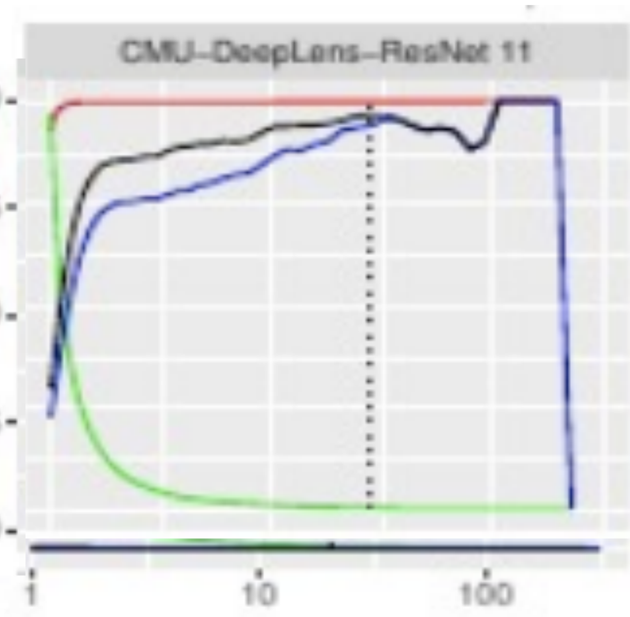
Results depend on



Einstein radius (arcsec)



Lensed Flux (AU)



Magnification

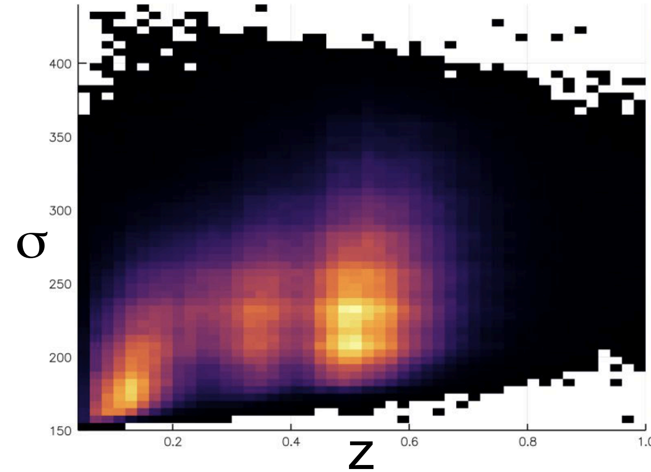
Several recent papers: (Bom++16, Avestruz++17, Jacobs++17, Petrillo++17, Schaefer++18, Lanusse++18, Hartley++17 SVM)
→ Heavy training effort. So far, only applied

Ongoing work for CFIS

As of July 2018:

CFIS tiles with both u and r : 750 deg^2
(1800 deg^2 some/full r)

Work currently using candide cluster as part of CALET initiative at IAP.



Track 1: Spectro SDSS (0.05<z<1, σ>150km/s) → 130 deg^{-2} : expect ~700 SL

Forward modeling : ~3000 CPU.hours / filter . Ongoing!!!!

- Scaled to full CFIS 4500 deg^2 →17,000 CPU.hours. Tractable (~4000 SL)
- Scaled to 2000 photometric ETGs/deg^2 → 300,000 CPU.hours

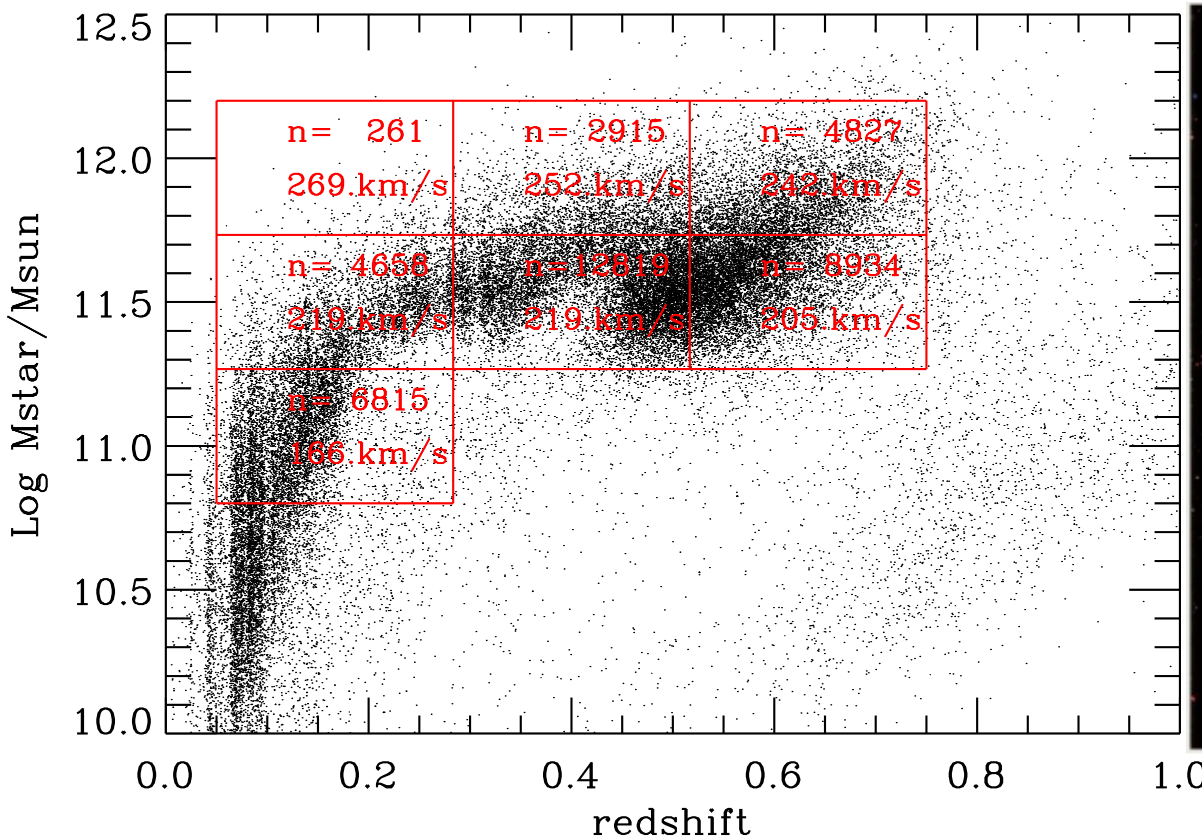
Track 2: Train CNNs on dedicated image simulations… Build on effort for Euclid

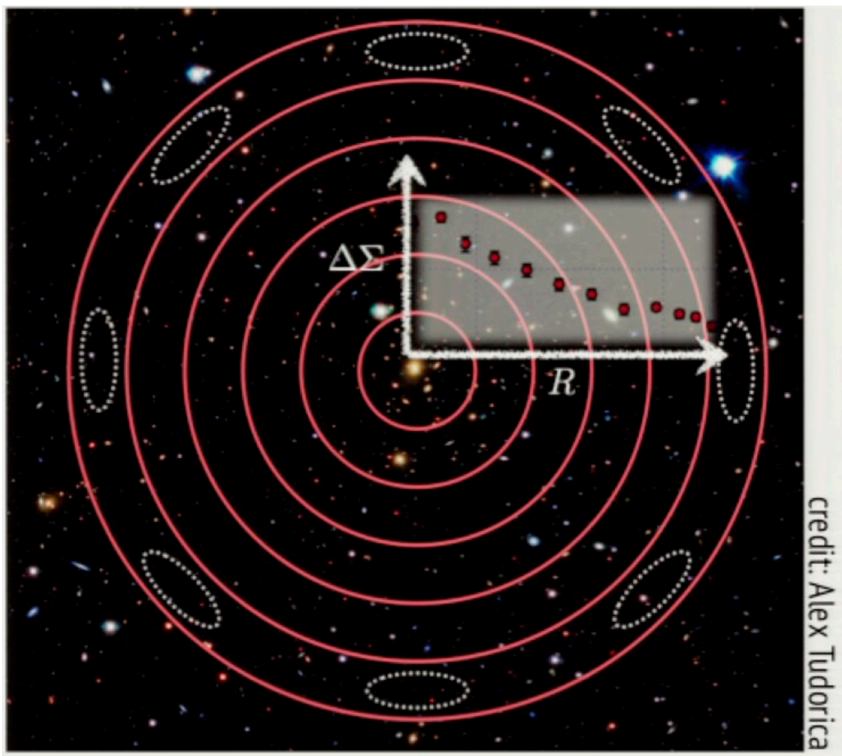
→ Organize spectroscopic follow-up of lensed arcs/rings (cherrypick high-z, high-snr)
→ Combine strong & weak GG lensing!!

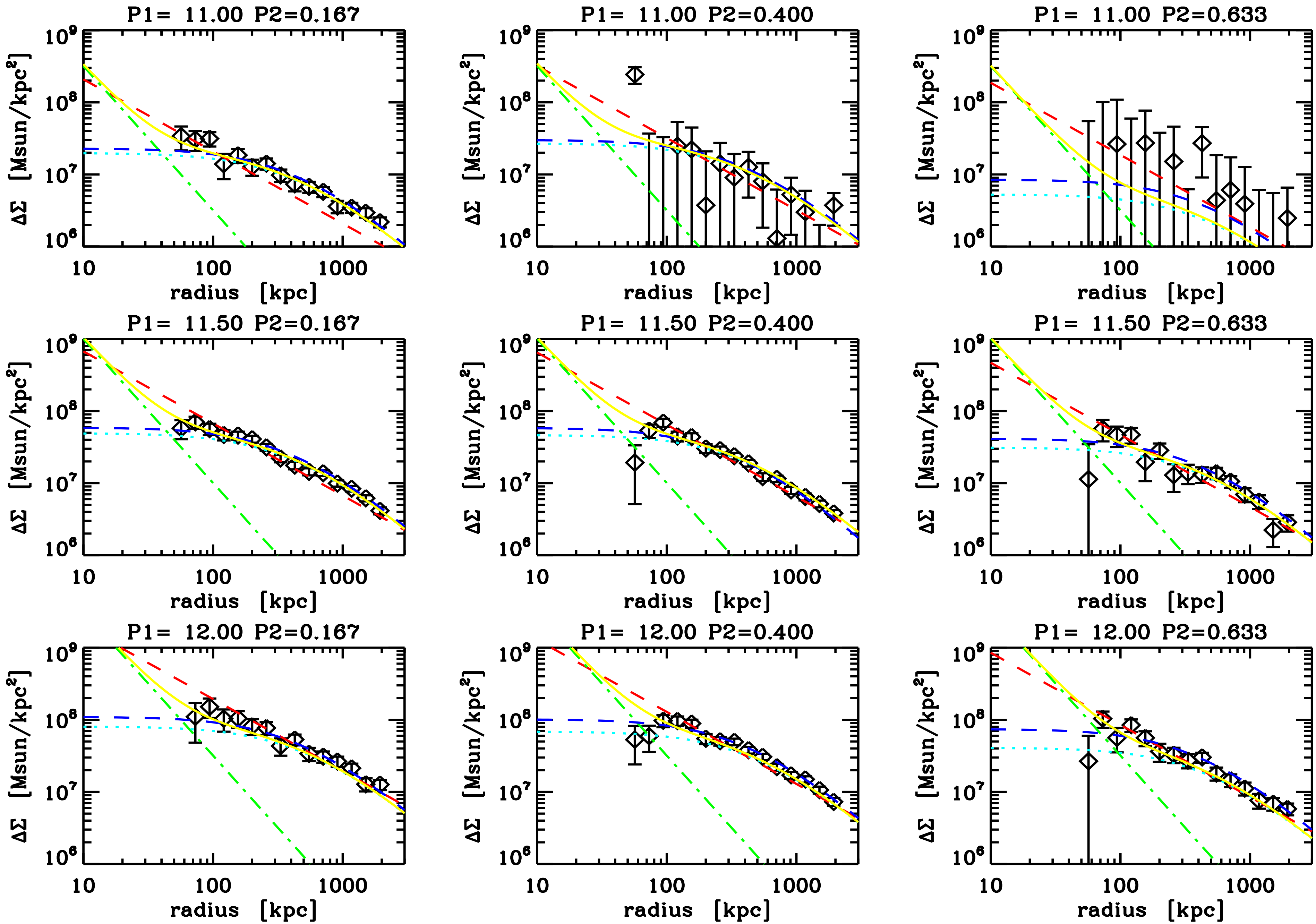
Bonus Tracks

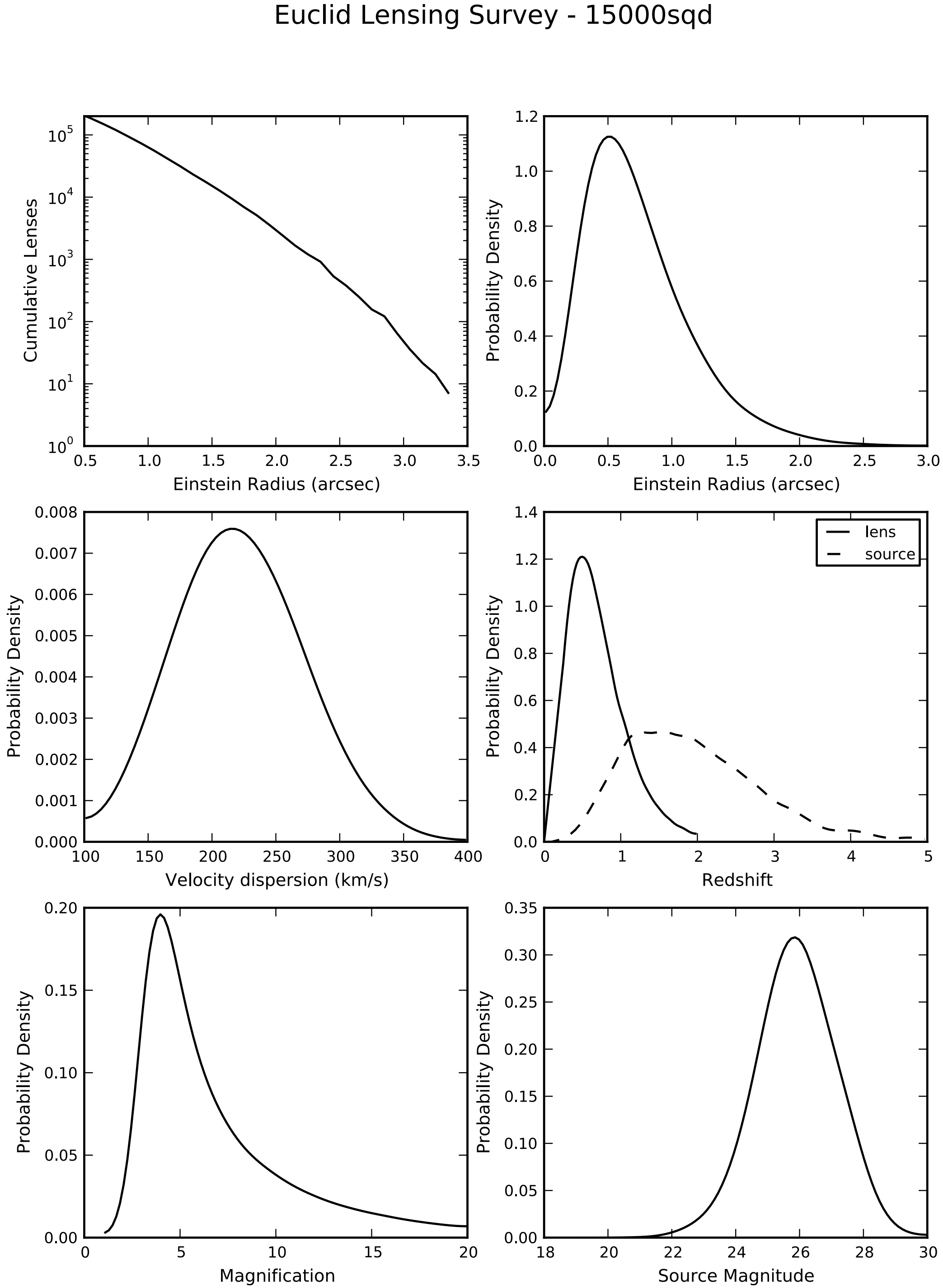
Adding Weak lensing constraints

- 41000 foreground SDSS (spectroscopic redshift & velocity dispersion)
- Background sources: CFHTLenS (150deg^2), NGVS (100deg^2), down to i~24.5, in ug(r)iz bands, with 0.65-0.75'' seeing in lensing band and <1'' in other bands.






P1= 11.00 P2=0.167
P1= 11.00 P2=0.400
P1= 11.00 P2=0.633
P1= 11.50 P2=0.167
P1= 11.50 P2=0.400
P1= 11.50 P2=0.633
P1= 12.00 P2=0.167
P1= 12.00 P2=0.400
P1= 12.00 P2=0.633
ΔΣ [Msun/kpc²]
radius [kpc]


Euclid Lensing Survey - 15000sqd
Cumulative Lenses
Einstein Radius (arcsec)
Probability Density
Einstein Radius (arcsec)
Probability Density
Velocity dispersion (km/s)
Probability Density
Redshift
lens
source
Probability Density
Magnification
Probability Density
Source Magnitude