IAP 2021 Conference
Debating the potential of machine learning in astronomical surveys
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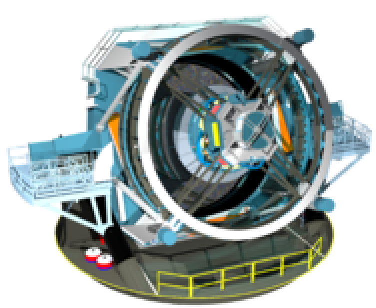
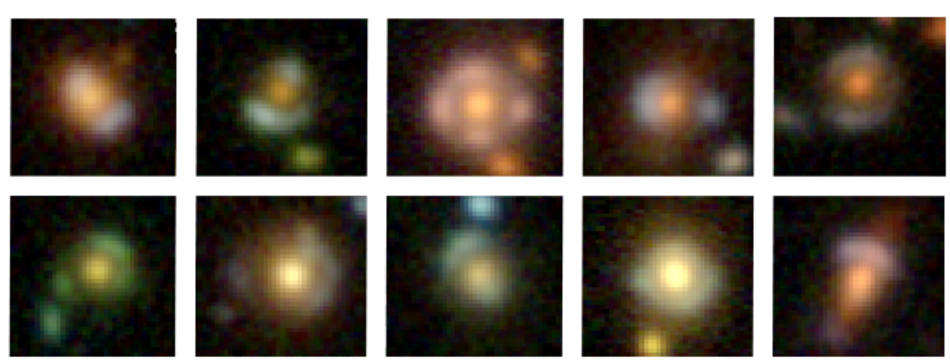
Max-Planck-Institut für Astrophysik

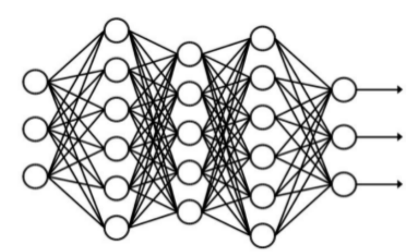
Identifying strong gravitational lenses in current and future large-scale imaging surveys

Raoul Cañameras (MPA Garching)

S. Schuldt, S. Suyu, Y. Shu, S. Taubenberger, T. Meinhardt, L. Leal-Taixé, D. Chao, B. Clément, F. Courbin, K. T. Inoue, A. T. Jaelani, C. Lemon, A. More, K. Rojas, E. Savary







Cosmology with lensing delays

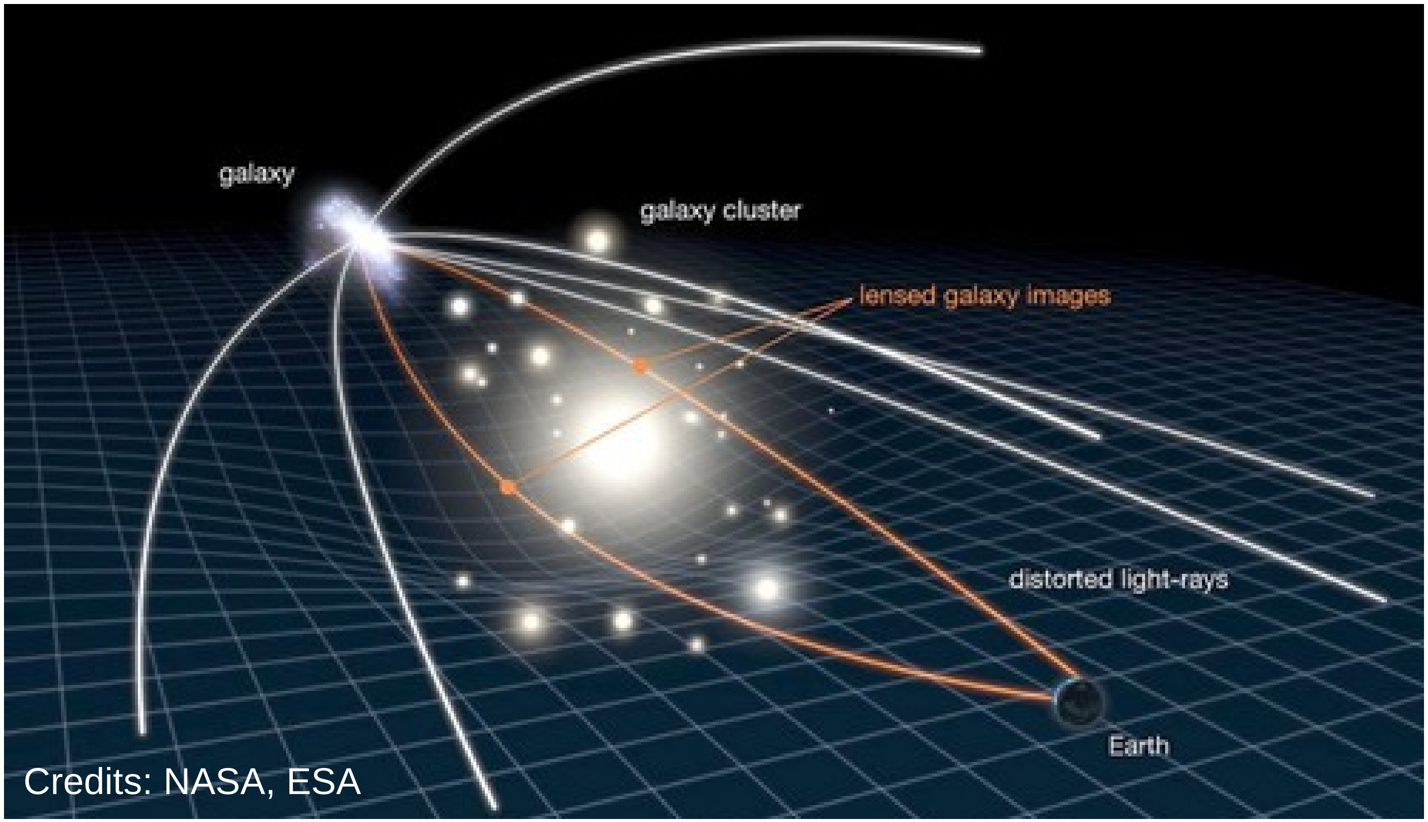


Fig. Illustration of a lensed SN event (credit S. More).

Strongly lensed time-variable sources (quasars, supernovae)

➜ Multiple images appear around the foreground lens galaxy *at different times*

Cosmology with lensing delays

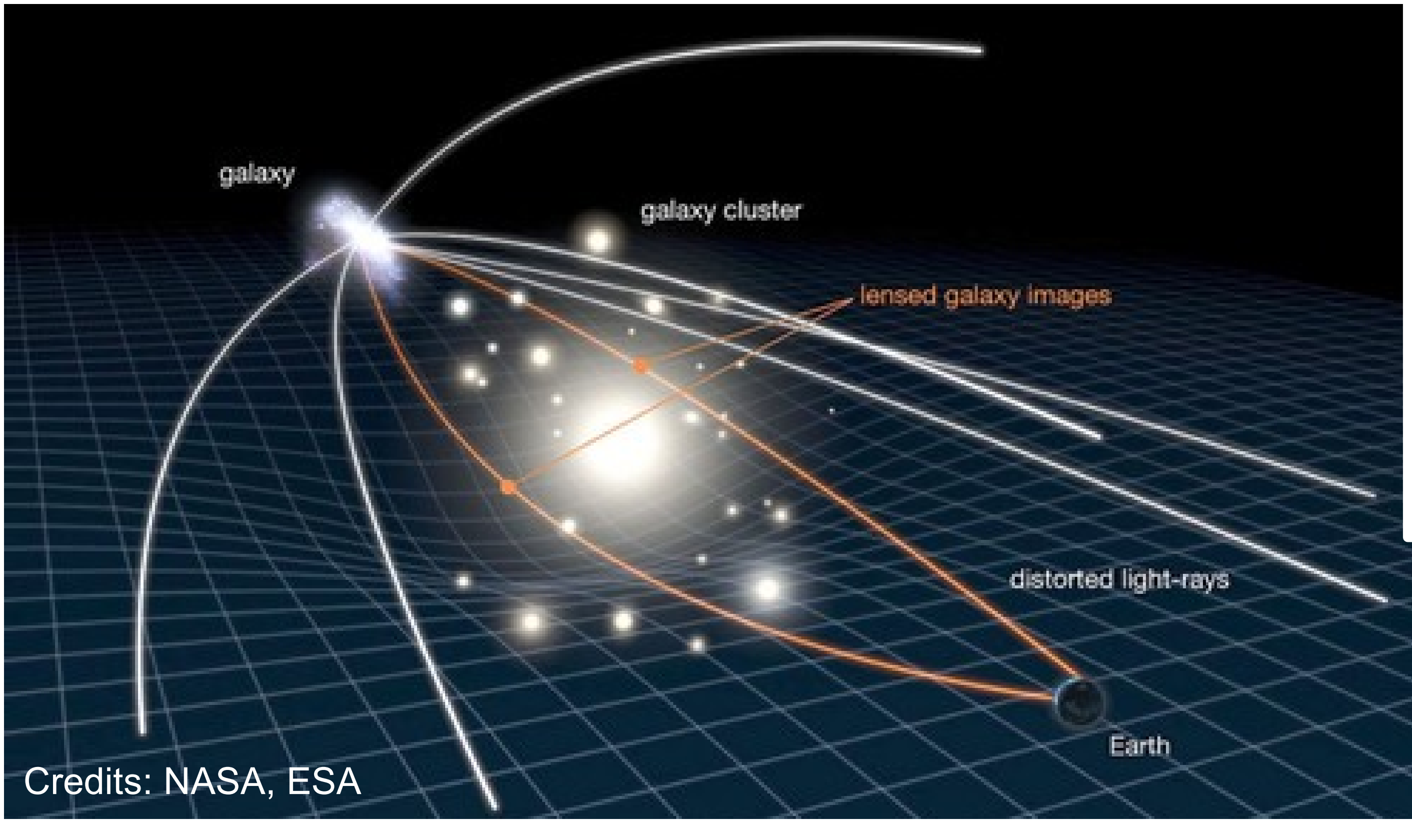


Fig. Illustration of a lensed SN event (credit S. More).

Time delay

$$t = 1/c \times D_{\Delta t} \times \Phi_{lens}$$

Time-delay distance: $\propto 1/H_0$

Strongly lensed time-variable sources

\+ Time-delays and lens modeling

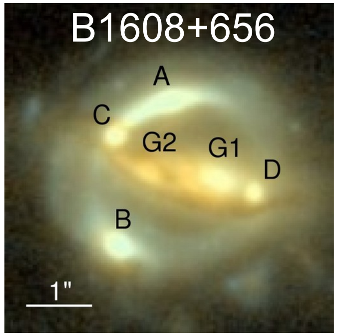
➜ One-step physical measurement of a cosmological distance

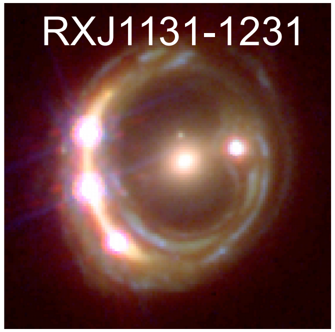
➜ **Measure of the Cosmic Expansion rate (Refsdal 1964)**

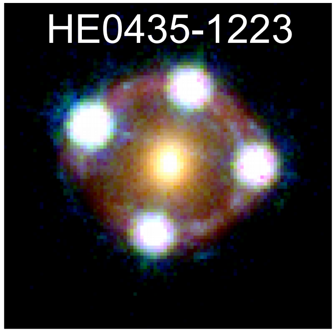
The cosmic expansion rate

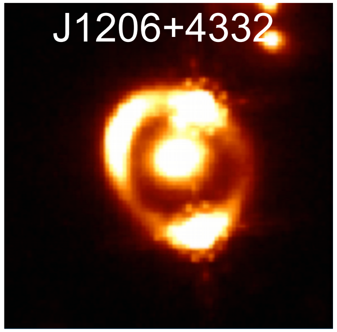
Discord between the H_0 measurements from the late-time Universe and early-time Universe → ***new physics*** beyond the current standard ΛCDM cosmological model ?

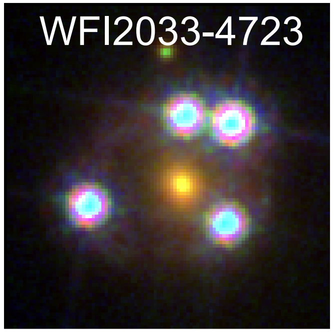
→ Independent methods necessary to assess tension

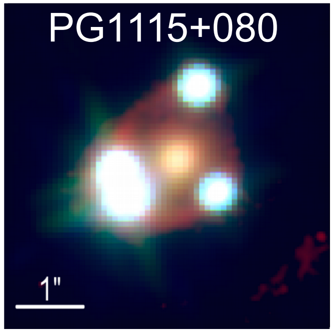








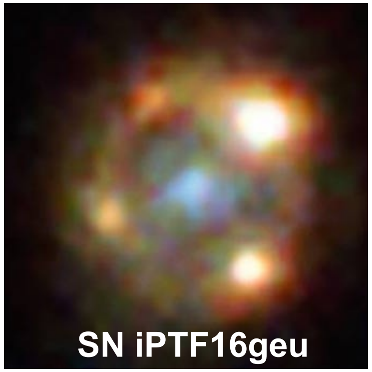




Time-delay cosmography with lensed quasars (H0LiCOW, Suyu et al. 2017)
➜ H_0 with 2.4% precision in flat ΛCDM (Wong et al. 2020, H0LiCOW XIII)

Residual systematic uncertainties ? (TDCOSMO I & IV)

➜ Use lensed supernovae to break degeneracies and improve precision on H_0 (Suyu et al. 2020)



(Goobar et al. 2017)

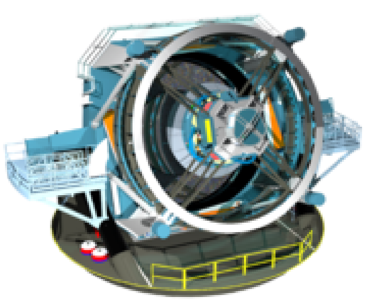
HOLISMOKES!

(Highly Optimized Lensing Investigations of Supernovae, Microlensing Objects, and Kinematics of Ellipticals and Spirals; Suyu et al. 2020, A&A 644, 162)

https://shsuyu.github.io/HOLISMOKES/site/

- Lensed supernovae with wide image separations are extremely rare → need very wide-field and high-cadence imaging surveys
- Identify all static strong lenses and wait for a SN to explode in the background hosts
- Now with ZTF+PanSTARRS in the North & after 2024 with Rubin LSST in the South

→ Machine learning pipelines for systematic galaxy-scale lens searches



Sherry Suyu

Stefan Schuldt

Stefan Taubenberger

Yiping Shu

Automated pipelines for wide-field imaging surveys

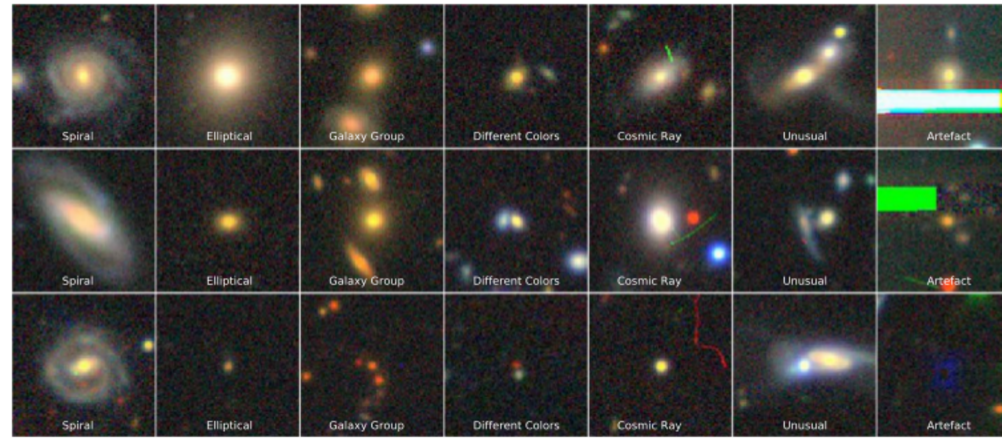
Binary classification with

- Arcfinder algos (Gavazzi+2014, Avestruz+2019)
- Principal component analysis (Joseph+2014, Paraficz+2016)
- Lens modeling and masking (Sonnenfeld+2018)
- Citizen-science projects (Marshall+2016, Sonnenfeld+2020)
- Or … **supervised deep learning**

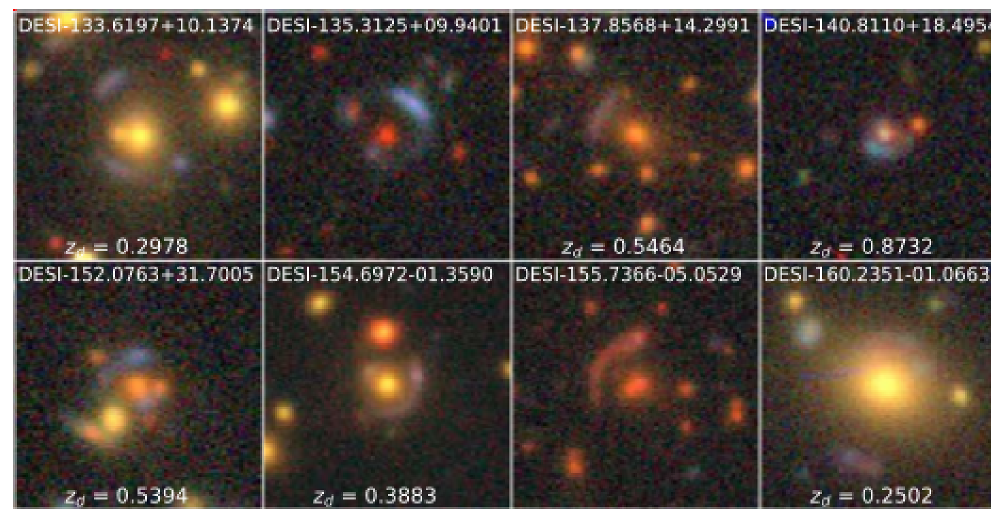
Classification with convolutional neural networks (CNNs, LeCun+1998)

in CFHTLS (Jacobs+2017), COSMOS HST (Pourrahmani+2018), KiDS (Petrillo+2017; +2019; Li+2020), DES (Jacobs+2019a,b), DECaLS (Huang+2020;+2021) …

F. Courbin’s talk yesterday → Searches in DES (Rojas+2021) and CFIS (Savary et al., in prep.)



Various types of non-lens galaxies to be excluded (Huang+2021).



CNN lens candidates in DECaLS (Huang+2021).

➜ Several 100 high-quality strong lens candidates (rely on strict catalog pre-selections)

Lens finding in Pan-STARRS

Cañameras et al. 2020, A&A 644, 163

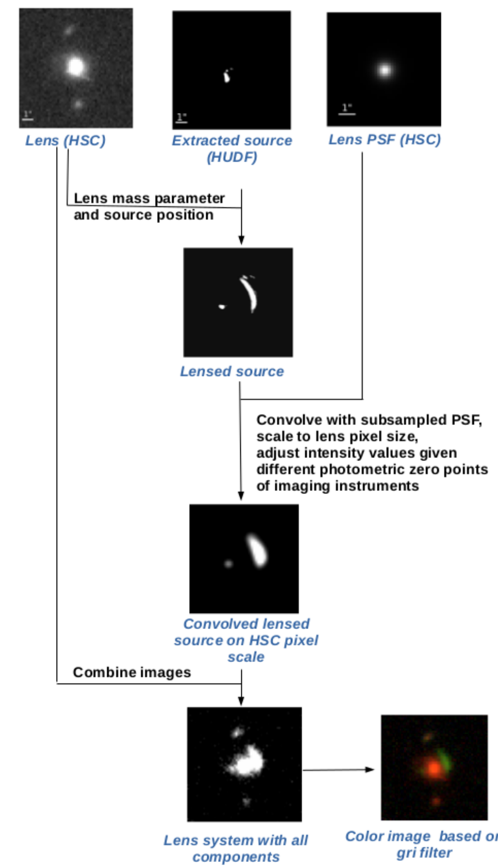
Systematic search for lensed galaxies in Pan-STARRS as potential hosts of SNe

➜ $3\text{x}10^9$ sources in Pan-STARRS 3π survey (30 000 deg^2)

➜ $2.3\text{x}10^7$ after simple photometric cuts, star removal

➜ $1.0\text{x}10^6$ after apply neural network on photometry

➜ $1.2\text{x}10^4$ after apply convolutional neural network on g, r, i-band image cutouts



Realistic lens simulations for higher classification accuracies

– realistic lens galaxies, good proxies of lens mass
– Einstein radius distributions, number of multiple images
– source colors and morphologies, inclusion of neighbours
– background sky properties and artefacts, local PSF models

➜ **Paint lensed arcs on survey stacks**

See poster by S. Schuldt!

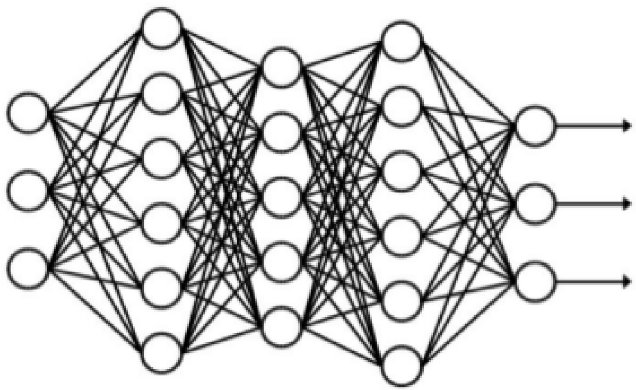
Step 1- Catalog-level neural network

Cañameras et al. 2020, A&A 644, 163

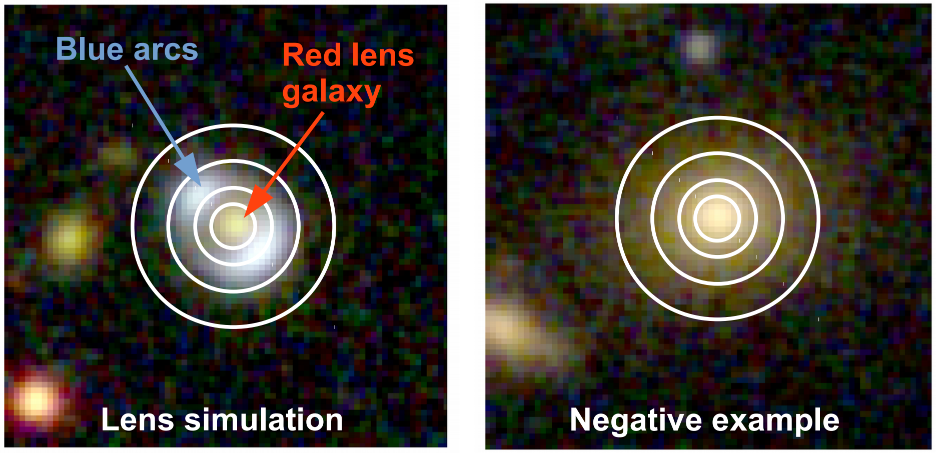
1) Aperture photometry of mocks in *gri* bands
→ 1.04”, 1.76”, 3.00”, and 4.64” radii

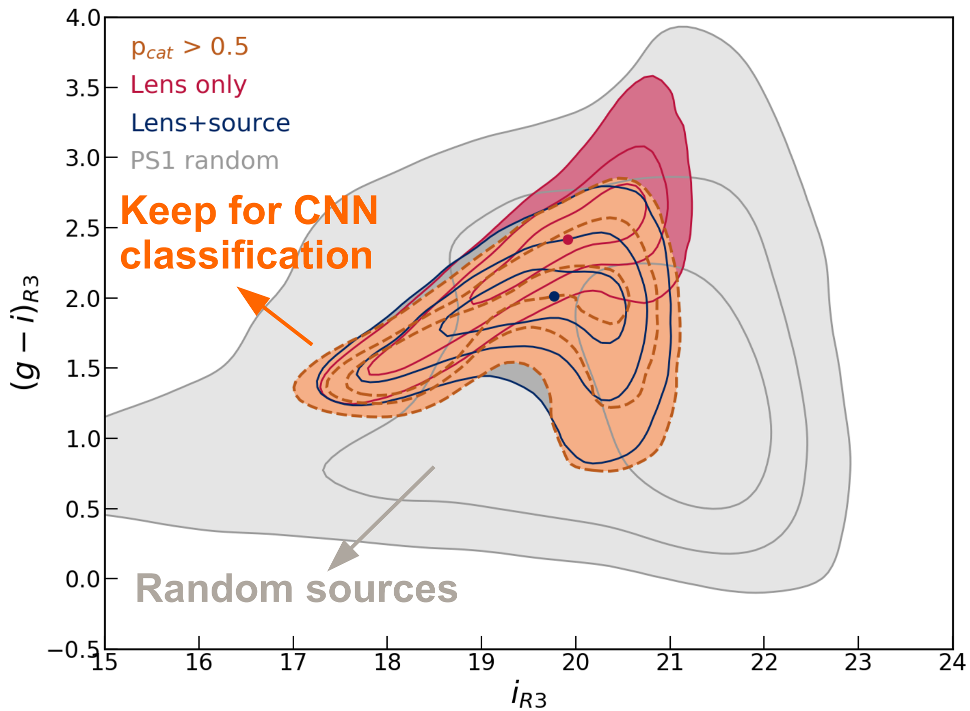
2) Aperture photometry of negative examples

→ color variations and radial gradients



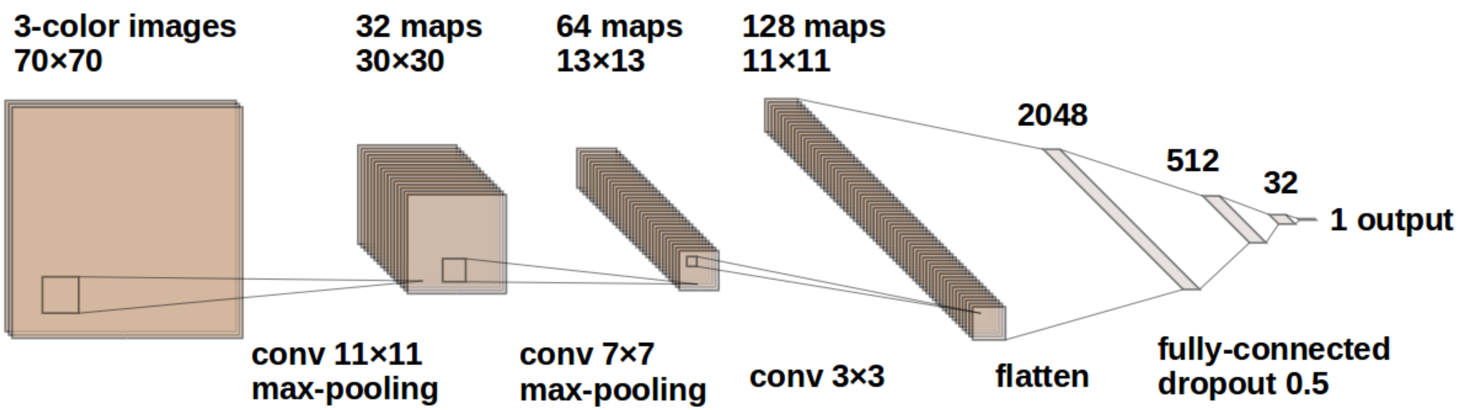
- Total of $10^5 + 10^5$ labelled examples
- Classify with a fully-connected network
- Safe → Zero known lenses excluded

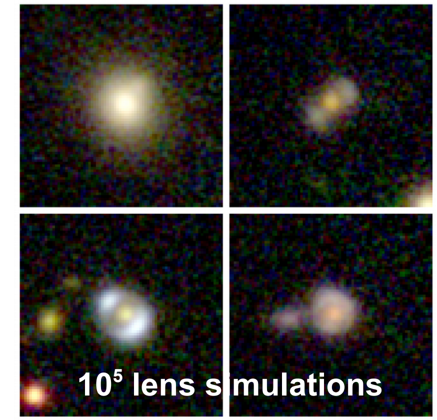


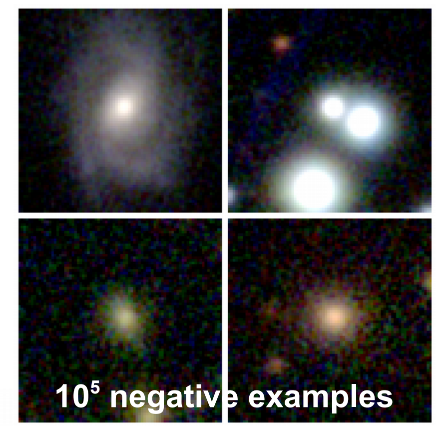


Step 2- Convolutional neural network

Cañameras et al. 2020, A&A 644, 163



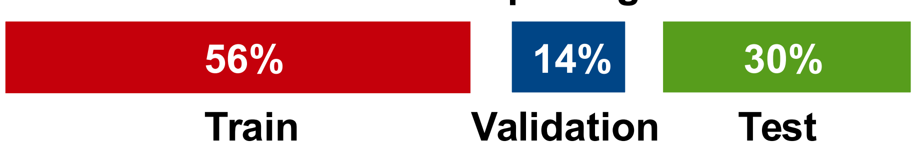


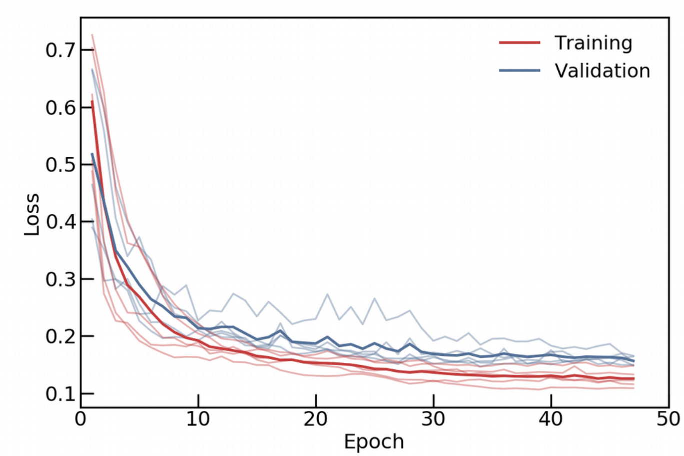


- Negative examples: LRGs, face-on spirals, rings, groups from GalaxyZoo + different fractions
- Extensive tests on the CNN architecture
- Hyperparameter optimization
- Cross-validation and best epoch

→ Classify image cutouts in *gri* bands

Data set splitting



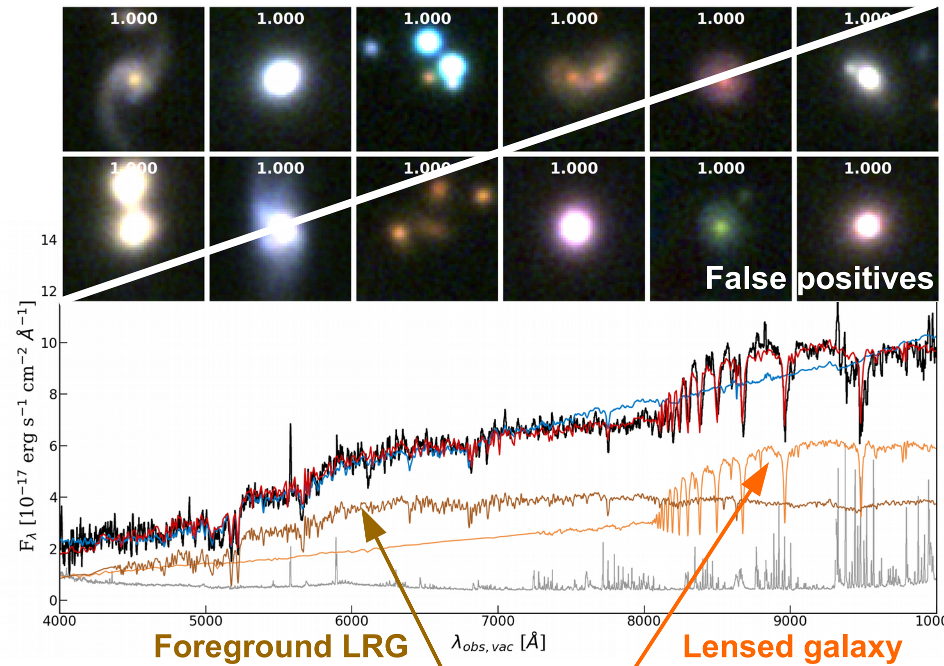


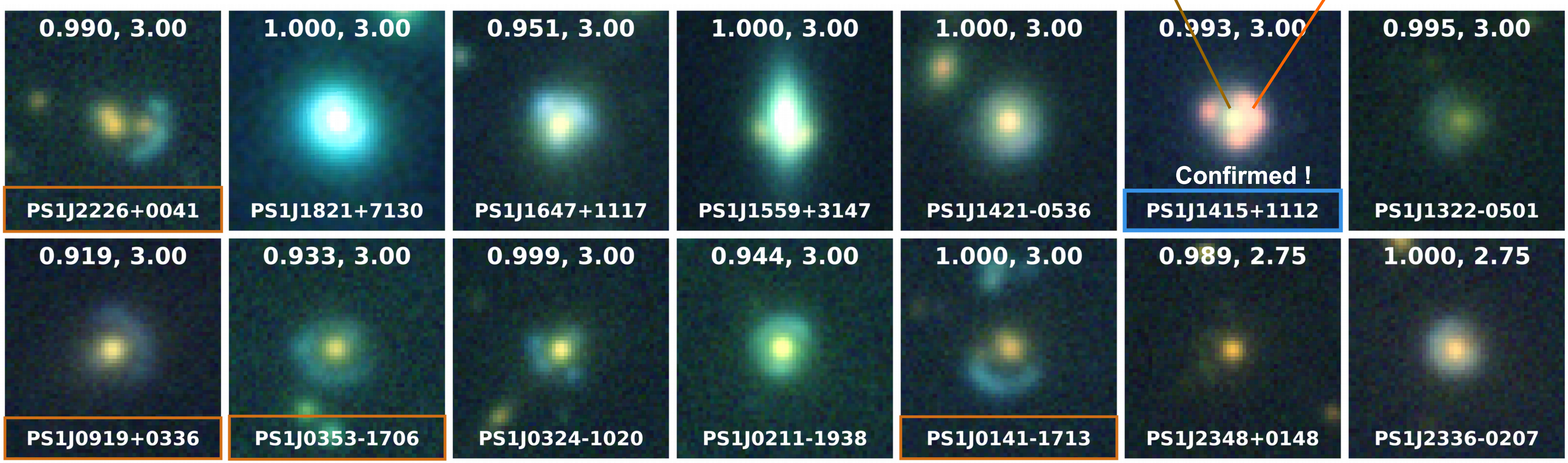
New lenses in Pan-STARRS

Cañameras et al. 2020, A&A 644, 163

→ 330 new high-quality lens candidates after visual inspection

- Recover known lenses
- One system spectroscopically-confirmed
- Spectroscopic follow-up and lens modeling on-going (Taubenberger et al., in prep.)
- Many false positives from CNN (inspection time would be x 50 for Rubin LSST)





Improving lens finding pipelines for Rubin LSST

Cañameras et al. 2021, A&A 653, L6

Method very sensitive to the design of training data sets → Quantifying recall and completeness need representative test sets (with all contaminants, artefacts...)

Test on high-quality multiband imaging from Subaru Hyper Suprime-Cam

220 lenses from previous non-ML searches in HSC + 50,000 non-lenses in COSMOS + 1000 ambiguous cases from SpaceWarps (Sonnenfeld+2020)

1) Construction of the ground truth data set: design of lens simulations and choice of negative examples

2) Influence of neural network architectures, number of bands, data augmentation, ...

False-positive rate can be reduced from 1% to ~0.01%!

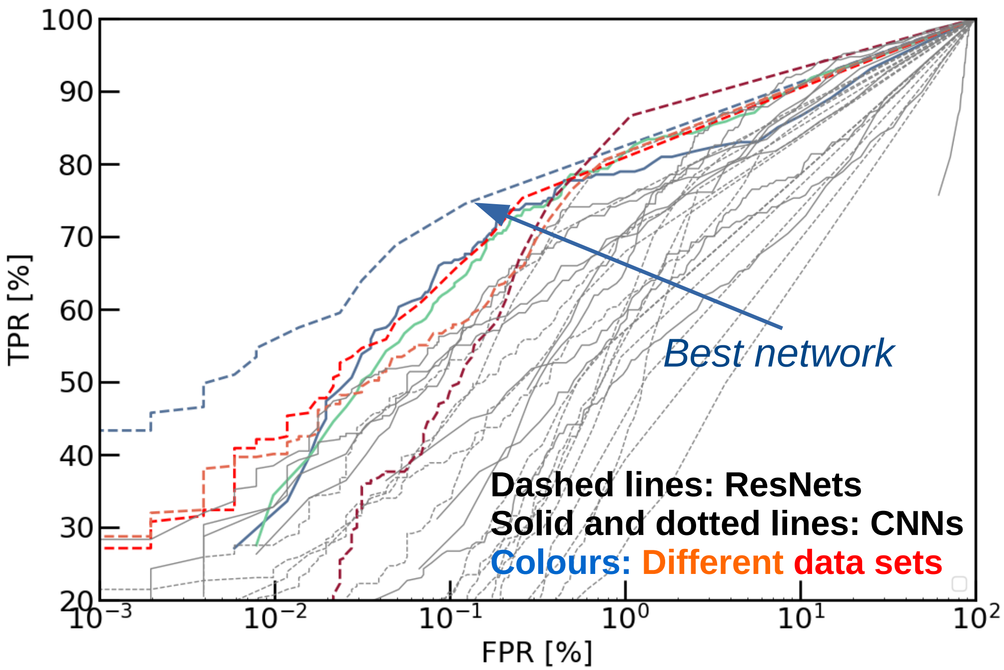


Fig. Receiver Operating Characteristic (ROC) curves using observed HSC lenses and non-lenses.

New lenses in HSC PDR2

Cañameras et al. 2021, A&A 653, L6

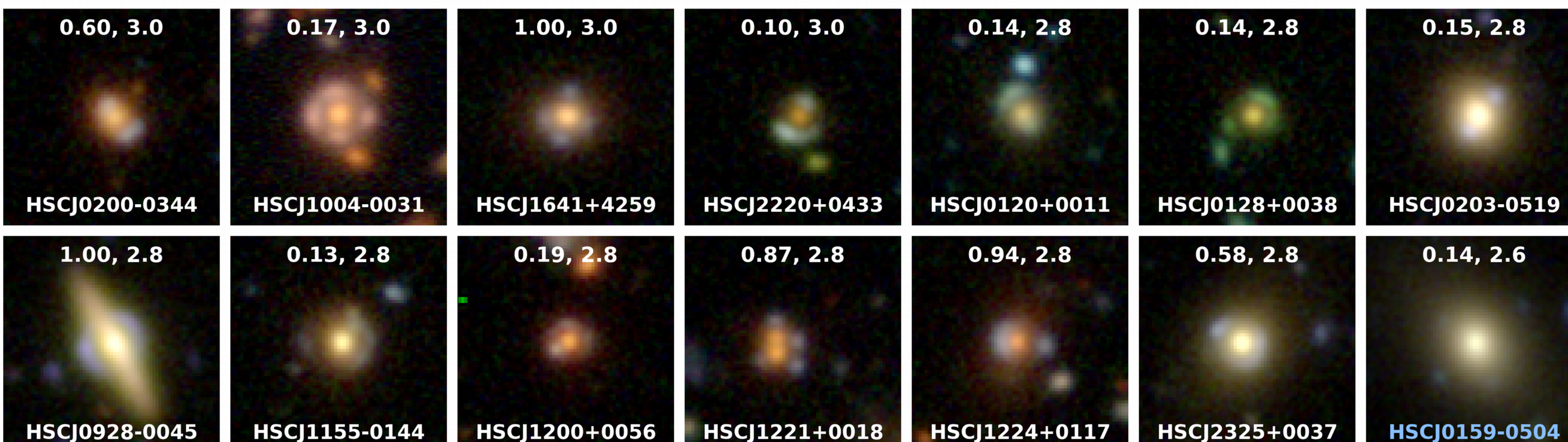
Validation and application to 6.3×10^7 galaxies with Kron radius ≥0.8” from Hyper Suprime Cam (HSC) Public Data Release 2 + dedicated search for high-z lenses (Shu et al., in prep.)

→ Can minimize dependence on rotation and on local seeing variations between bands

→ 470 lens candidates (>40% are newly discovered)

Current best networks would select ~250,000 candidates in LSST footprint (for ~40,000 detectable galaxy-galaxy lenses, Collett+2015) → OK for crowdsourced classification

Or try combine unsupervised and supervised ML techniques to bypass visual inspection?



Examples of new ResNet high-quality lens candidates from HSC DR2.

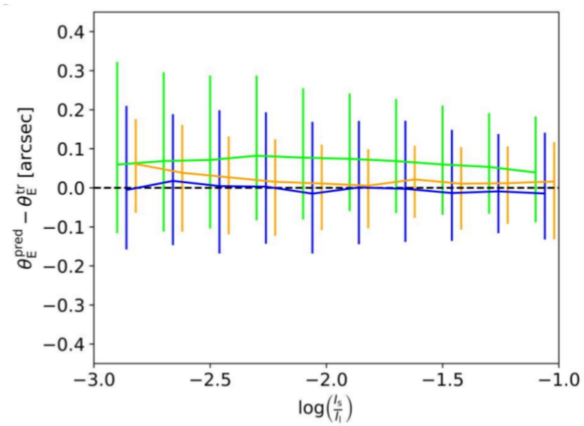
Lens modeling with machine learning

Stefan Schuldt

Schuldt et al. 2021, A&A 646, 126

Regression convolutional neural network

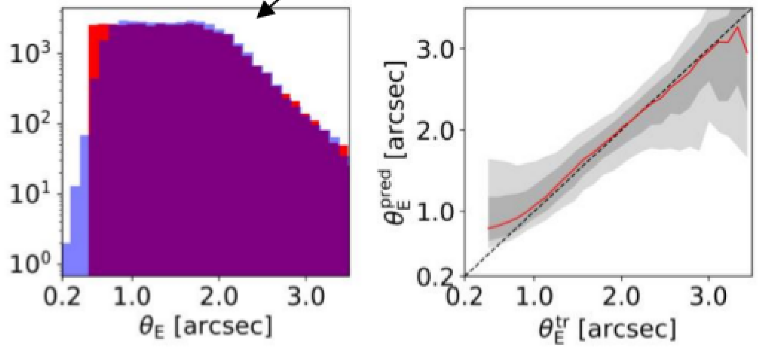
- Train and test on HSC Wide *griz* to prepare for LSST
- **Lens mass profile parameters are recovered**
- Results are stable, e.g. for fainter lensed sources
- Translates into accurate predictions of image positions and time delays



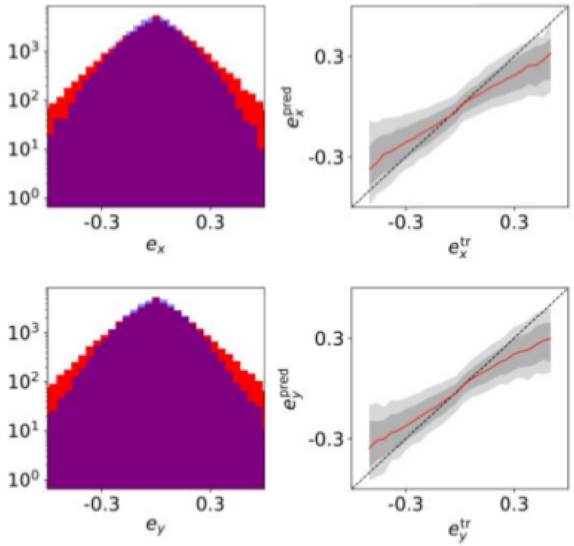
See poster by S. Schuldt!

Einstein radius

Flat up to ~2"



Complex ellipticity



Summary

- Lensed SNe provide excellent opportunities to constrain cosmology and stellar physics
- Current and future surveys will have hundreds of new lensed supernovae

  ➜ Need a rapid identification of static galaxy-galaxy strong lenses as potential SN hosts

- Combining highly-realistic simulations and supervised machine learning pipelines speeds up lens searches in large-scale imaging surveys

  ➜ about 500 new high-quality candidates in Pan-STARRS1 and HSC Wide PDR2 + on-going spectroscopic confirmation

- Visual inspection to exclude contaminants → Can be minimised for Rubin LSST
- Testing performance requires representative sets from real observed images
- Lens modeling with machine learning yields huge gain in speed (Schuldt+2020; see also Hezaveh+2017, Perreault-Levasseur+2017, Park+2020, Pearson+2019,+2021, ...)

Past lensed supernova discoveries

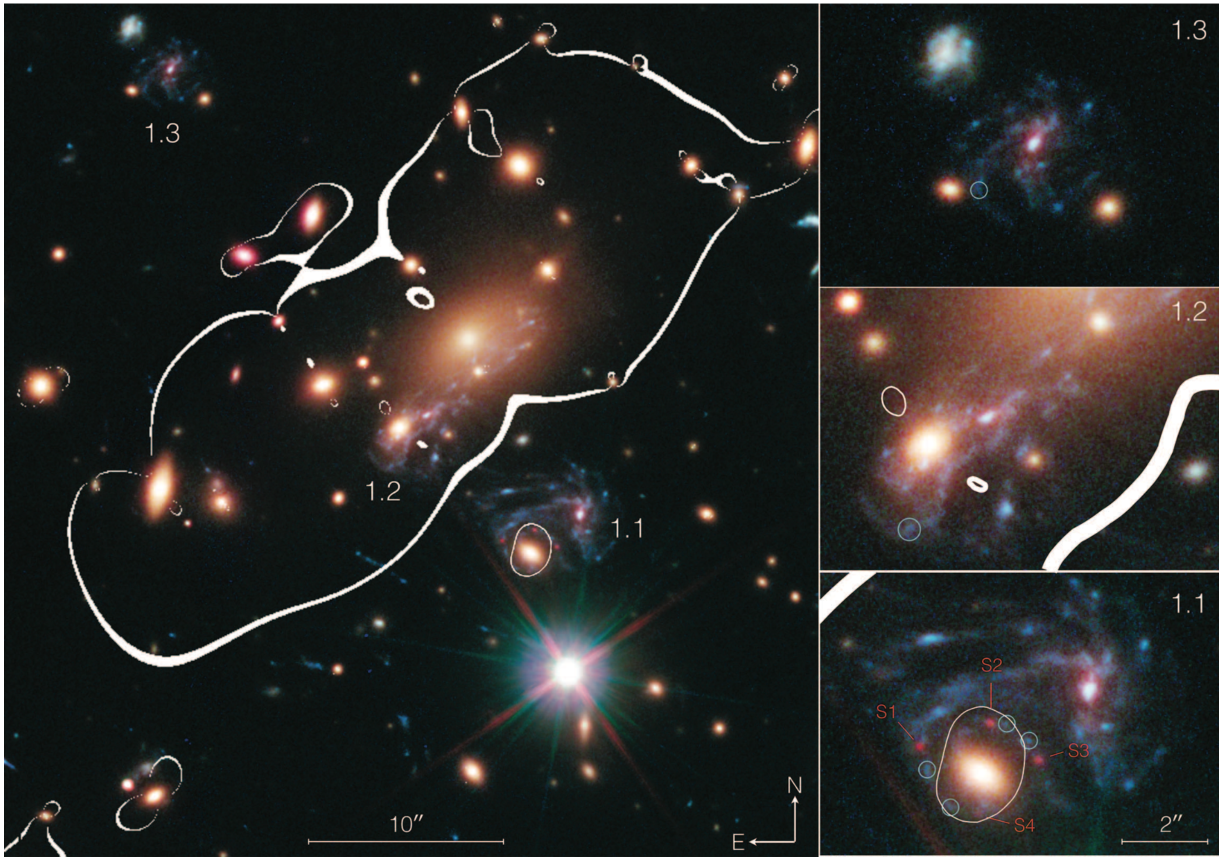


Fig. SN Refsdal behind MACS J1149.6+2223 (Kelly et al. 2015).

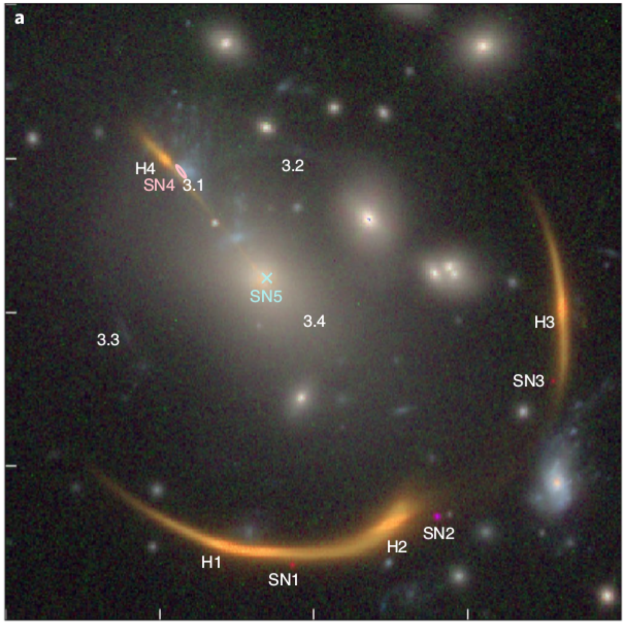


Fig. SN Requiem behind MACS J0138.0-2155 (Rodney et al. 2021).

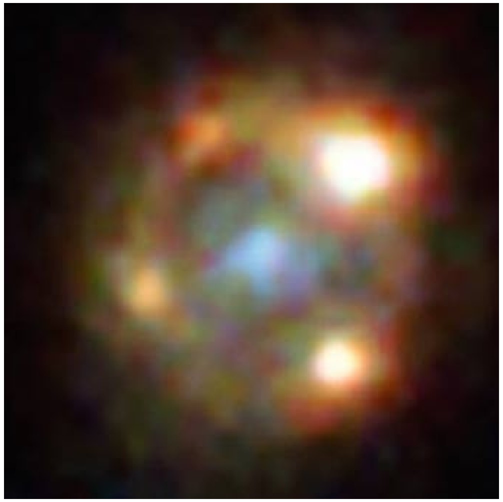


Fig. SN iPTF16geu (Goobar et al. 2017), Credit NASA/ESA.

Cosmology with lensed supernovae

Advantages:

SNe have characteristic light curves, enabling time-delay measurements.

Lens mass modeling is more straightforward, after SNe fade (quasars outshine other components).

SNe are standard candles.

Challenges:

Microlensing of SN by stars in the foreground lens.

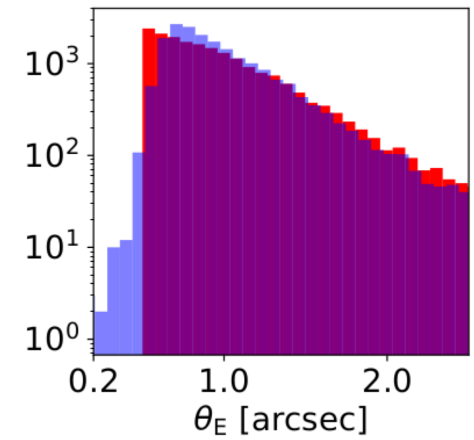
Lensed SNe are very rare.

→ Better precision on H_0 than lensed quasars (Suyu et al. 2020)

Fig. Illustration of a lensed SN event (credit S. More).

slide material from Sherry Suyu

Influence of lens simulations



We have tested multiple combinations of positive/negative examples

- Highly-realistic lens simulation with
  - Various distributions on physical parameters (e.g. natural/flat distributions in Einstein radius?)
  - Various selections of lens and source galaxies (colors, redshifts, ...)
  - Various configurations (ratio of doubles/quads), min S/N, min μ

→ Parameter distributions play a major role (do not need to follow nature)

- Negative examples including
  - Random non-lens galaxies, or boosted fractions of usual interlopers (spirals, rings, isolated LRGs, groups, etc…)
  - Draw interlopers from GalaxyZoo + *Unsupervised classifications*

→ Need to include sufficient examples in each class for training