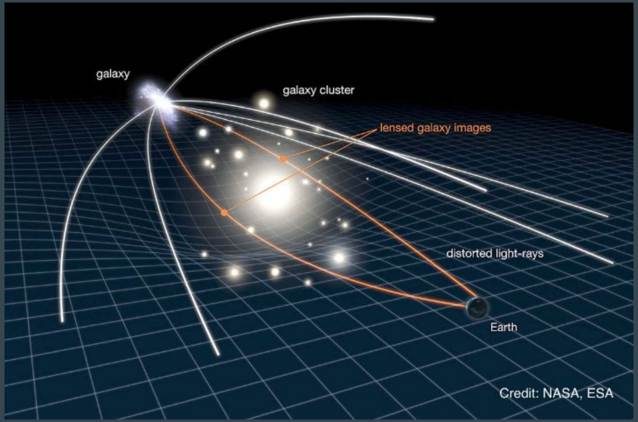
LSST Strong Lensing

Launching the statistical age of strong lensing science

…



Aprajita Verma
University of Oxford
LSST Strong Lensing Science Collaboration (co-chair)
DESC Strong Lensing Working Group (member)
Galaxies Science Collaboration SL co-ordinator
LSST:UK Strong Lensing PoC

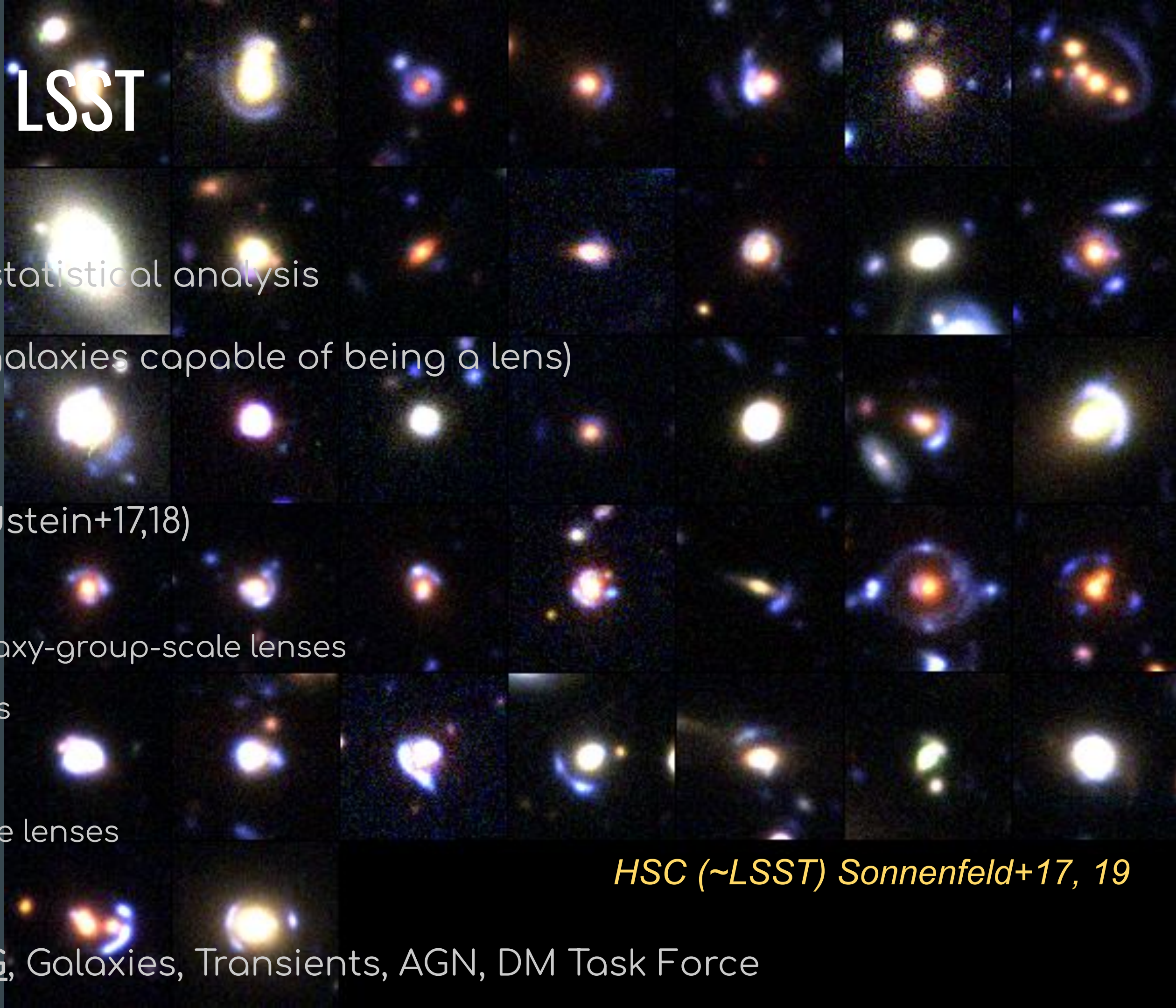
Strong Lensing with LSST

LSST+SL transformational

- Single object science → statistical analysis
- SL rare (1 in 10^4 massive galaxies capable of being a lens)
- Only ~10^3 known to date
- Expectations (OM10; Goldstein+17,18)
  - 1000s lensed AGN
  - 10^{4-5} galaxy-scale & galaxy-group-scale lenses
  - 1000s of lensing clusters
  - 100s of lensed SNe...
  - 100 double source plane lenses

Multiple Science Goals

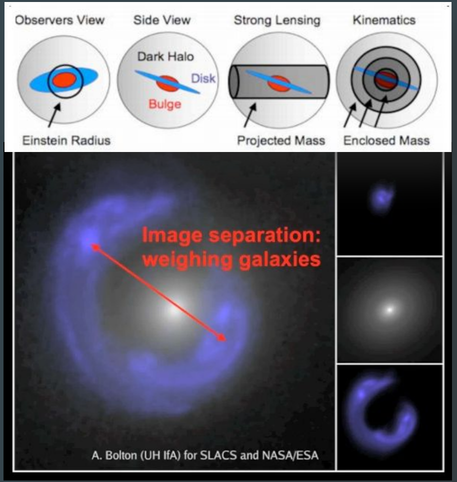
- Overlap with DESC-SLWG, Galaxies, Transients, AGN, DM Task Force



HSC (~LSST) Sonnenfeld+17, 19

SL: Wide ranging Science Goals

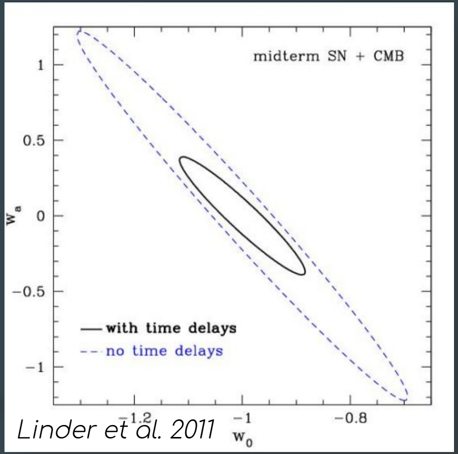
Tom Collett's talk



Galaxy Mass & structure:
Most direct measure of total (stellar & dark) mass in galaxies

Cosmography:
Constraints on the cosmic equation of state

Time delays (QSOs, SNe, Refsdal 1964) & double source plane lenses

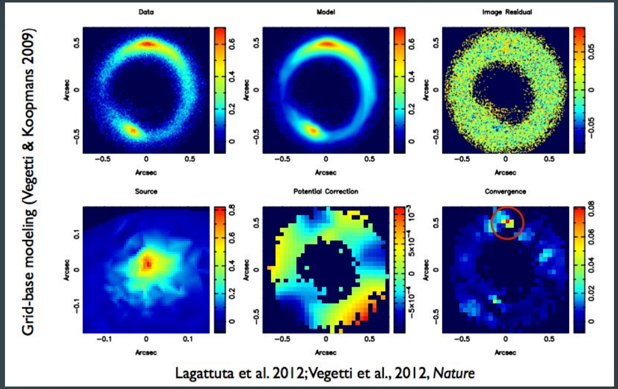



Tanaka+ 2016

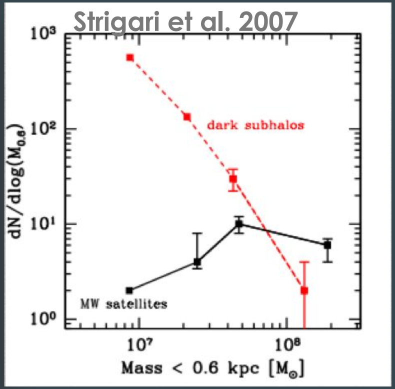
Goobar+ 2017


Kelly+ 2015,16

DM Substructure



Lagattuta et al. 2012; Vegetti et al., 2012, *Nature*



Cosmic telescopes:
structure & properties of high-z galaxies

Strong Lensing in LSST: SC Connections

DESC Strong Lensing Working Group (T. Collett, D. Goldstein)

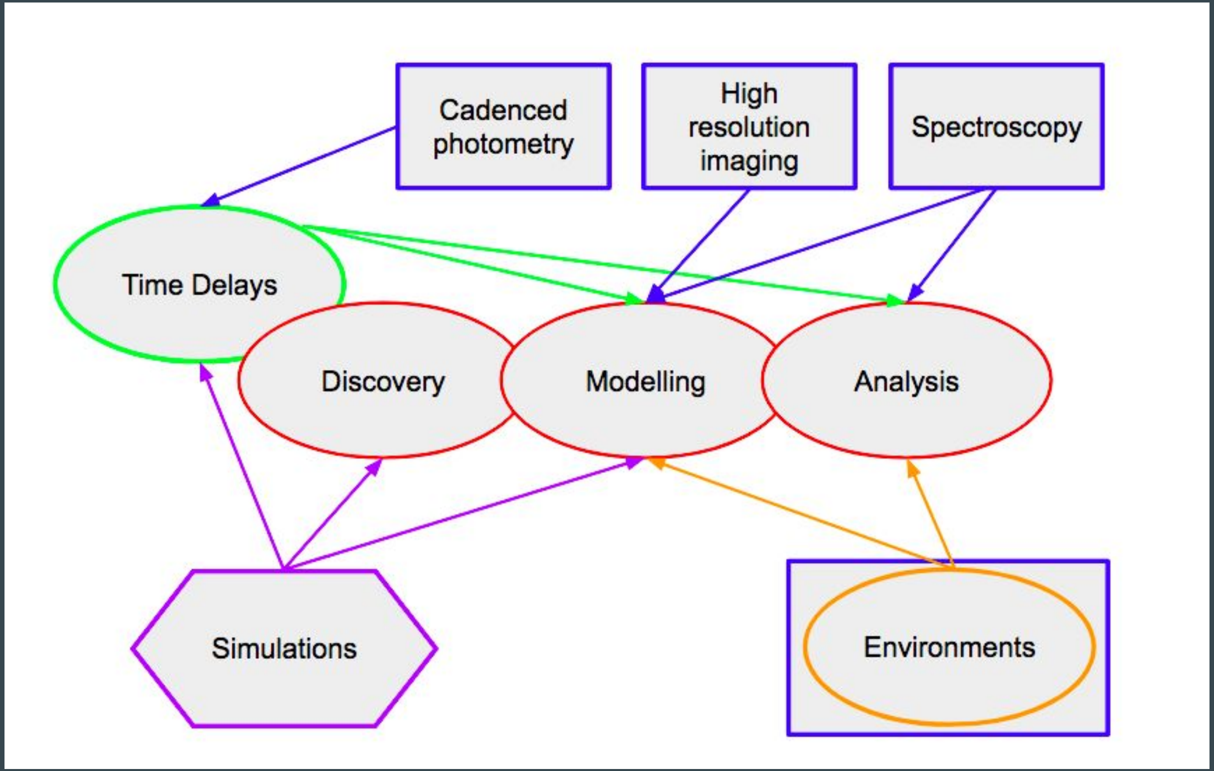
- Cosmography of ~100 qso & SNe, 100 DSPL

Strong Lensing Science Collaboration (C. Keeton, AV) e.g.

- Galaxies SC: Mass/DM structure of 10^4 lenses
- Galaxies SC: Detailed structure of high-z galaxies
- Clusters WG: SL+WL mapping DM potential ~100 clusters
- AGN SC: intrinsic variability and detailed properties of QSOs/AGN (few 10^3 microlensed AGN)
- Transients: host galaxy properties of lensed (fainter/higher z) SNe
- ...

LSST DESC
Dark Energy Science Collaboration

SLSC Roadmap Schematic



Verma, Keeton et al. in prep

DESC SL Roadmap

Tom Collett's talk

Table 2.4.1: SL key analysis steps, and their associated software tools.

Code name	Purpose	DC1	DC2	DC3	ComCam
SLFINDER	Find 10^4 lensed quasars, lensed SNe and compound lenses	Develop and test prototype code on PS1, DES	**SL2 Test prototypes on Twinkles 2**	**SL5 Implement Level 3 code and apply to DC3 Mock ComCam Survey**	Find lens candidates in survey area
SLMONITOR	Extract light curves for all time-variable lens candidates	**CX2 Set up current DM Level 2 pipeline, test on Twinkles 1**	**CX10 Upgrade to Level 3 SuperFit, test on Twinkles 2**	**SL5 Apply to SLFINDER candidates in DC3 Mock ComCam Survey**	Apply to SLFINDER candidates in survey area
SLTIMER	Infer time delays from light curves	**SL1 TDC2 Good Teams develop and test prototype code**	TDC2 +DESC community code development	**SL4 Apply to TDC3 (light curves from Twinkles 2)**	Apply to lenses in survey area
SLENVCOUNTER	Predict weak lensing contamination from galaxy counts	H0LiCOW/STRIDES prototype development and testing	**SL3 Implement and test on DC2 Mock Lightcone galaxy catalogs**	**SL5 Refine and test on DC3 Mock ComCam Survey galaxy catalogs**	Apply to lenses in survey area
SLMASSMAPPER	Predict weak lensing contamination from 3D mass model	H0LiCOW/STRIDES prototype ("Pangloss") development and testing	**SL3 Implement and test on DC2 Mock Lightcone galaxy catalogs**	**SL5 Refine and test on DC3 Mock ComCam Survey galaxy catalogs**	Apply to lenses in survey area
SLMODELER	Infer distances from high resolution imaging	H0LiCOW/STRIDES prototype development and testing	STRIDES/DES development and testing	STRIDES/DES upgrade to IFU data and testing	Implementation prior to DESC follow-up observations
SLCOSMO	Infer cosmological parameters from lens ensemble	TDC1 cosmology forecast. Initial exploration of hierarchical inference using "All Ze Lenses". **Contribution CX4.3.3SL to DESC likelihood framework.**	Implement hierarchical Bayesian ensemble analysis, apply in STRIDES. **Contribute to blind analysis development (CX8.1TJP).**	**Refine/refactor for use in End-to-End test (SL5.2)**	Ongoing.

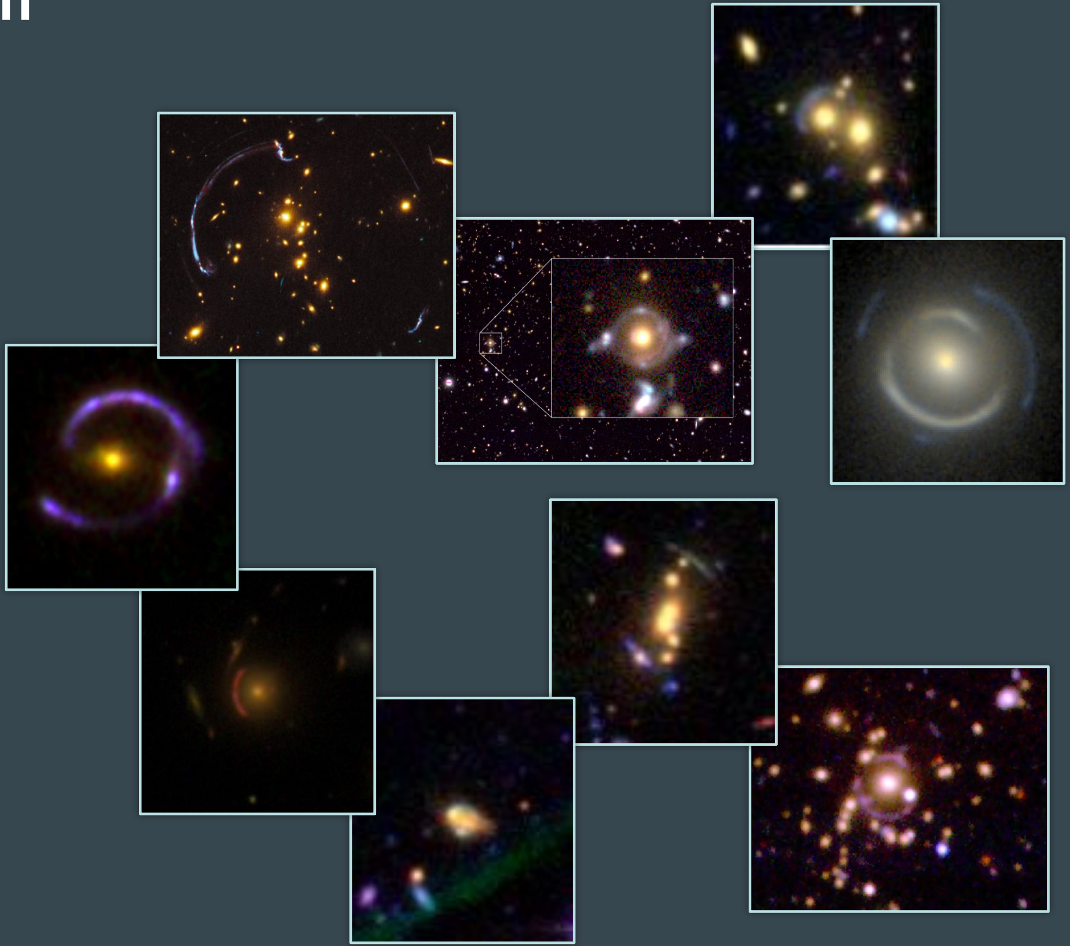
Notes: work described in gray will be done separately from the data challenges, and in some cases, by the community outside DESC. Work described in black is to be done by DESC members as part of the DC1/2/3 to LSSTComCam Roadmap. Work planned in **bold font** will be part of a DESC Data Challenge Key Project, as described in this section.

WP8 Building LSST’s SL Discovery System

WP8 Building LSST's SL Discovery System

LSST: Discovery problem

- ★ Rare: Only 1 in 10^4 galaxies are strong lenses (~1 deg^{-2})
- ★ Lenses are complex and varied systems
- ★ No single method is complete
- ★ High (~$10^{1\text{-}3}$:1) ML FPR requiring human visual inspection
- ★ Unsustainable in the next era of sensitive, wide area surveys
- ★ Large scale "optimal" lens finding strategies are undetermined and untested on such a large, sensitive & time resolved datasets
- ★ Current lens finding systems are untested on this scale of data



SL Discovery Ingredients

Image searches

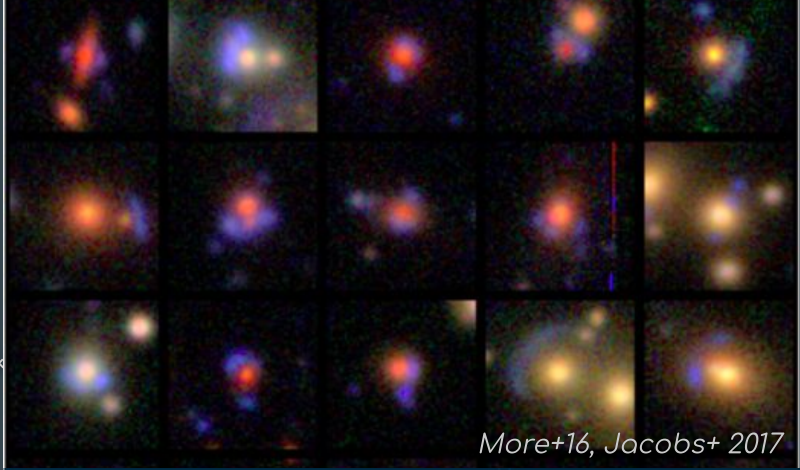
- ★ Traditional algorithms:
  - ArcFinder, RingFinder, Yattalens e.g. More+12, Gavazzi+14, Sonnenfeld+17, etc.
- ★ AI/ML:
  - CNN/DL e.g. supervised: Avestruz+17, Jacobs+17, Jackson & Hartley+17; unsupervised: Hocking+18, Lanusse, Ma, Li + 2017
- ★ Citizen Science:
  - Space Warps Marshall, More & Verma+ 16,19, in prep

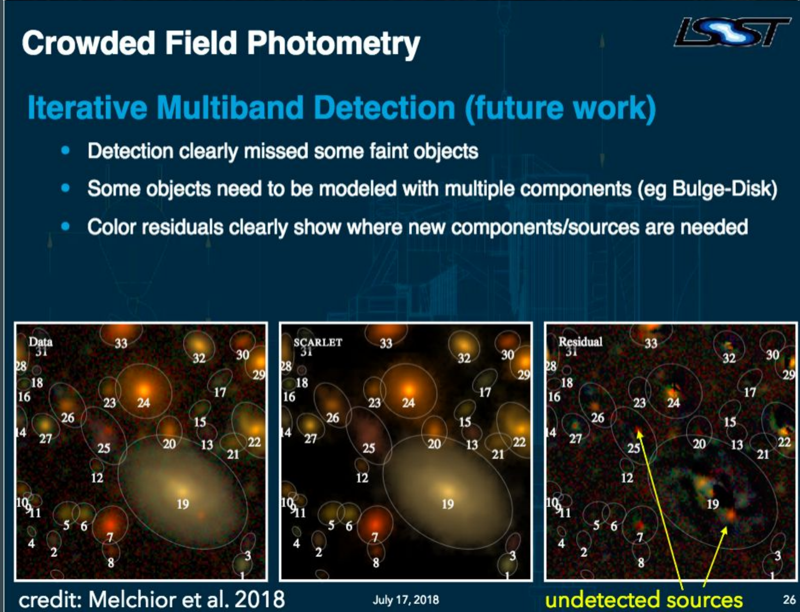
Catalogue searches

- ★ SLRealizer & Magnificat J.W.. Park, Marshall+

Require:

- ★ Sims (e.g. DESC DC2/3) & FPs (testing/training)
  - SL Li+, SNe Goldstein+, DC2 & Twinkles TF
- ★ Accurate photometry (phot-z, lens/source props):
  - Accurate lens subtraction
  - Reliable deblending (SCARLET, Melchior & Moolekamp)


More+16, Jacobs+ 2017



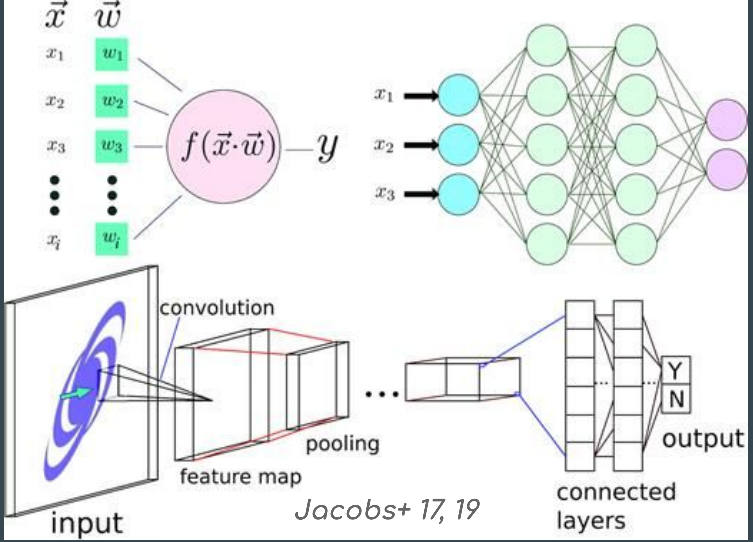
ML enabled lens discovery

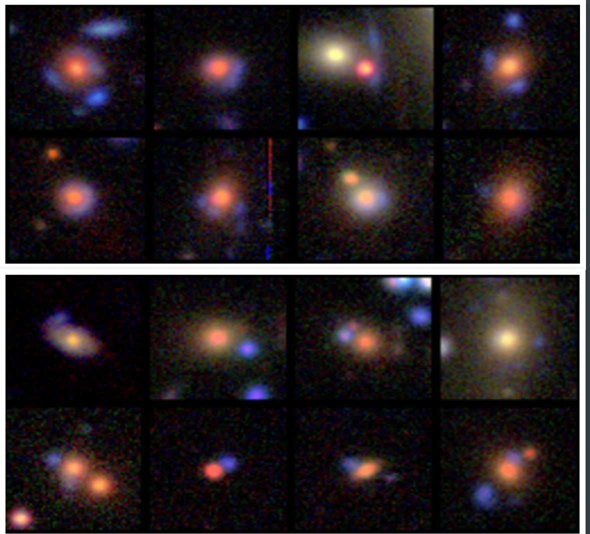
- ML discover sensitive to the input training set
- Only as good as the training sample
  - Learns imperfections
  - Full range of lens configurations needs to be included (simulations, confirmed lenses)
  - Lacking large samples of false positives (spacewarps)
  - Unsupervised training highly impure
  - More complex than other ML challenges, 1-in-10,000 candidate
  - TP:FP 1:10-100 (ypically)

Nan Li, Tom Collett's talks

Sugata Kaviraj's talk

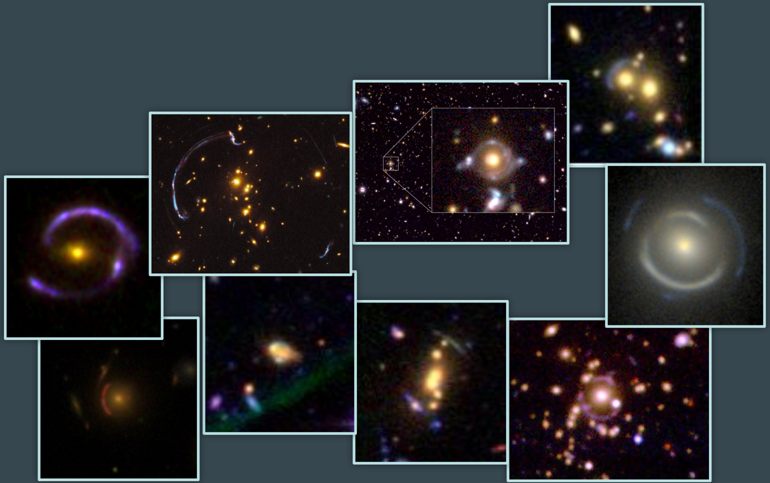
Make large samples of realistic, high-quality LSST like sims

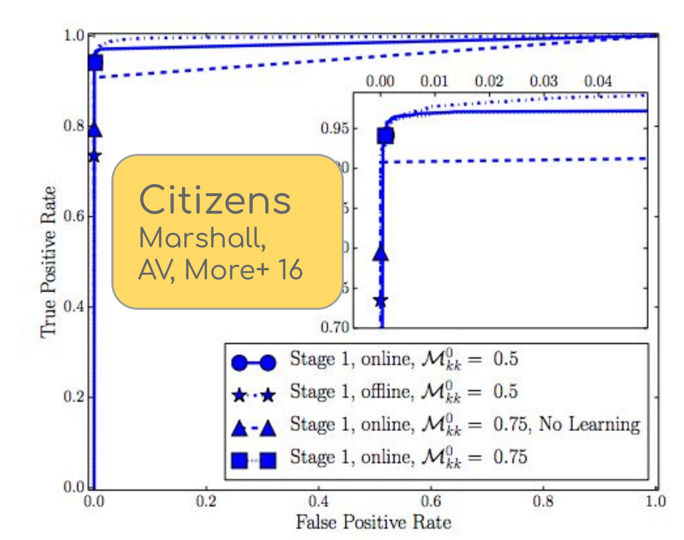


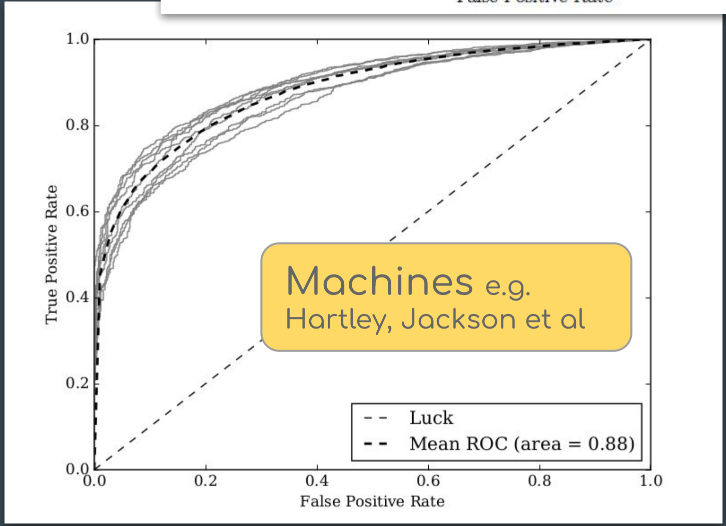


LSST: Discovery issues

- ★ Different methods sensitive to different lens types
- ★ ML (e.g. Avestruz+17, Jacobs +19) becoming increasingly successful
- ★ But human pattern recognition skills currently outperform the automated selection tools (c.f. Nan Li's talk)

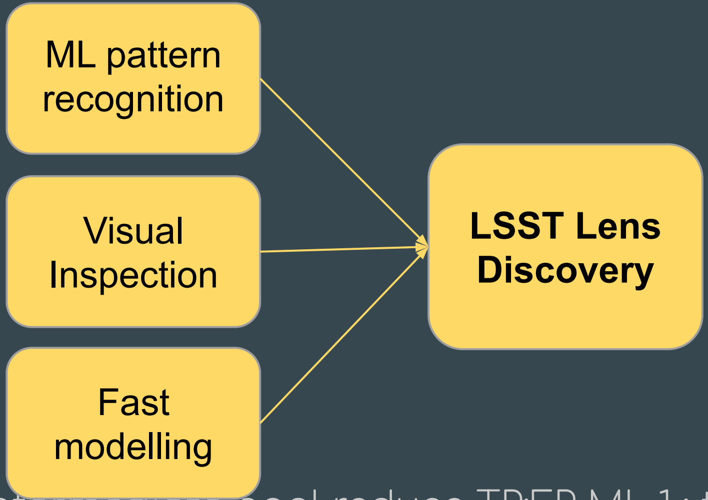




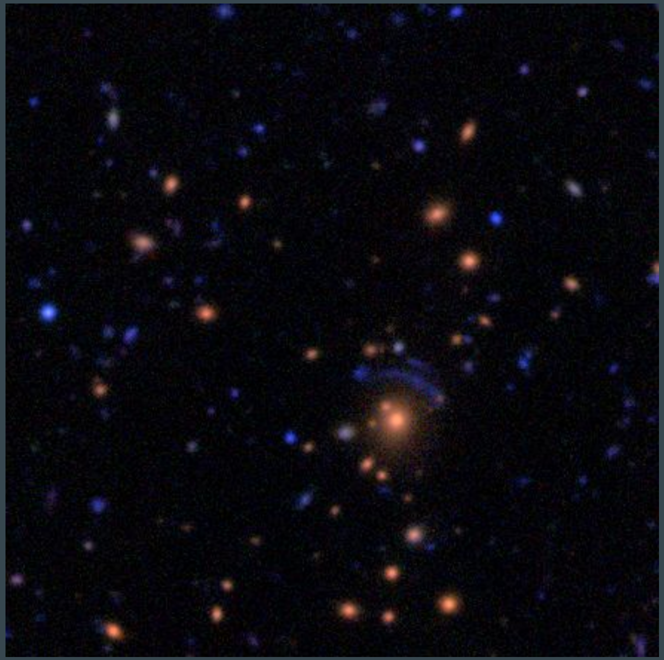


LSST SL Discovery Solution: Robots+People

- Multi-method approach



- Intermediate goal reduce TP:FP ML 1 : tens
- Longer-term goal: ML TP:FP 1 : 1-few



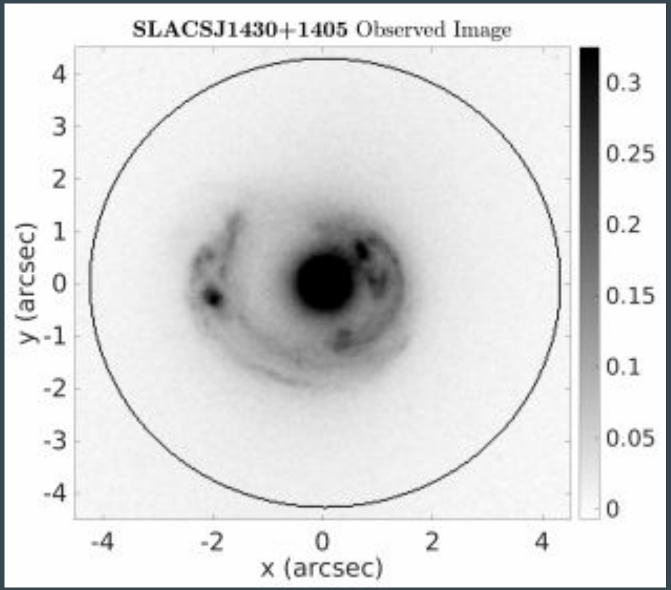
UK has expertise in **all of these** fields, synergy with EUCLID strong lensing efforts & leadership

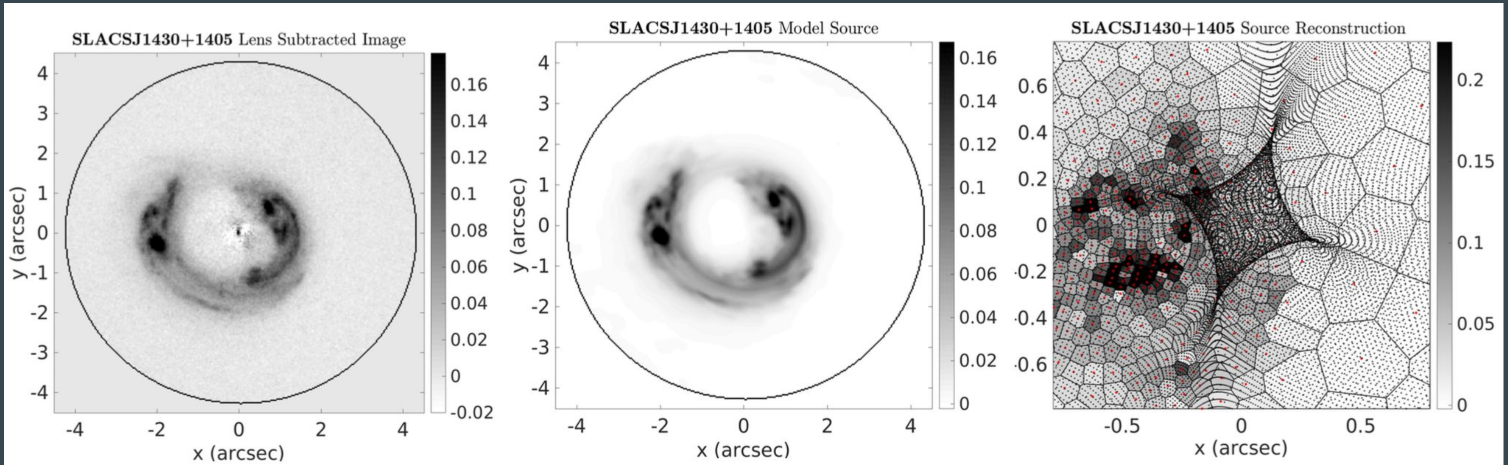
SL Modelling

Fast automated modelling - AutoLens J. Nightingale+ 15,18

Free-form Voronoi grid

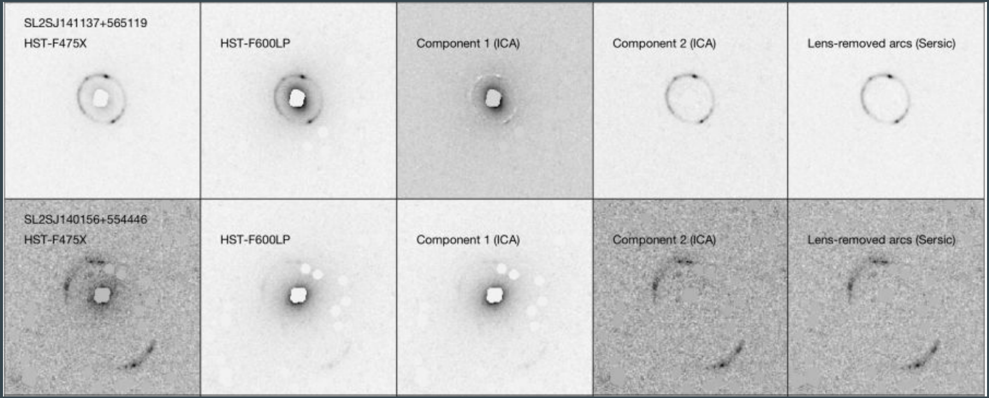
Fast iterative modelling pipeline



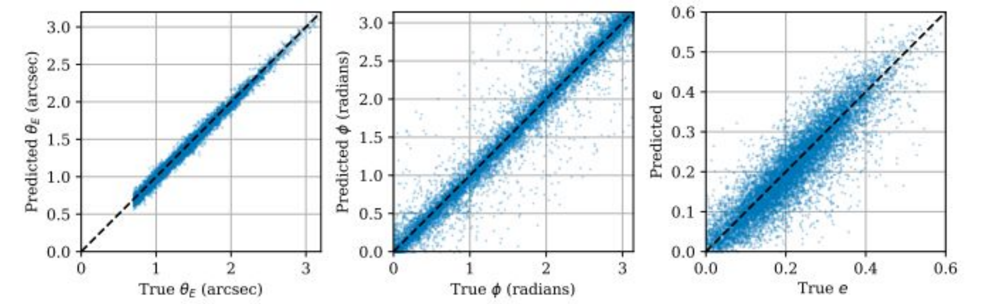


CNN assisted fast Lens Modelling

Artificial Intelligence Analyzes Gravitational Lenses 10 Million Times Faster *Symmetry, SLAC News*



Hezaveh, Perreault-Levasseur, Marshall Nature 2017

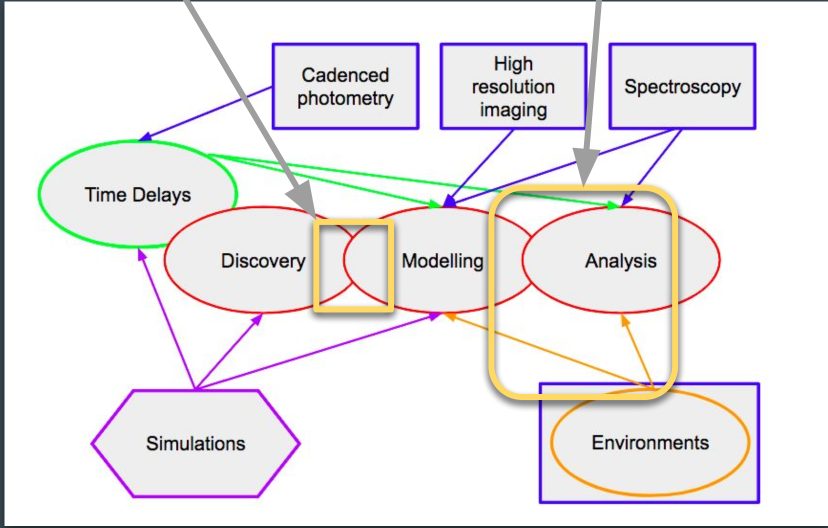


Pearson, Li, Dye 2019

Nan Li's talk

Reduce FPR by folding fast modelling into lens discovery

Detailed modelling still required (outliers and improved analysis)



R8 : Requirements for Image recognition and machine learning: building LSST's strong lens discovery system

LSST will be the first wide field survey of sufficient depth to discover $>10^5$ strongly lensed (SL) systems beginning a new era of statistical analysis. The rarity, varied morphologies and high rates of false positives in automated selection, makes SL discovery from the billion galaxies in the LSST surveys non-trivial and requires development of sophisticated discovery algorithms and methods, infrastructure, as well interfaces to the LSST data archive (both data release and prompt products) and delivery of user generated products. Our challenge is to find 1 SL in 10^6 galaxies, harder than typical machine learning problems; the neural net must be highly trained and work almost perfectly to produce samples of manageable purity. For this reliable, large and realistic training sets are required.

The main science requirements pertain to the annual Data Release Products from which we will create user generated products for strong lensing discovery and science. However, timely identification (for follow-up and analysis) of strongly-lensed variable sources will be enhanced by knowing where LSST's strong lenses are in advance. By cross-matching our increasing catalogue of LSST strong lens candidates (with value added information such as modelling, photometry and photo-z) with the 10^7 alerts per night brokered by LASAIR (R1.04), or other LSST transient broker outputs, will allow rapid identification of the even rarer strongly lensed transients.

Over the 10 year full depth we anticipate strong lensing samples of several 10^5 reliable lensed galaxies, however this implies image generation and inspection, by citizens or with machine learning, of $>10^{8\text{-to-}9}$ sources with multi-band imaging. Furthermore, strong lens detection, particularly for the more numerous systems with low Einstein radii, is improved when using 'best seeing' and/or lens-subtracted images. These require processing beyond the data release products.

WP 3.8 is focussed on development of software, infrastructure and user-generated products in preparation for operations at the end of phase B and beyond.

Funding is not currently secured for this WP. If funding is secured, then **WP8 should provide**:

Inputs

- **R8.01** large sets of high quality, realistic simulations of strong lenses within the LSST data framework
- **R8.02** DAC compatible software/Jupyter notebooks to query data release catalogue based lens candidate identification
- **R8.03** DAC compatible scripts to extract multi-colour imaging data (fits files) for strong lens candidates
- **R8.04** *user generated* 'best seeing' multi-filter image stacks
- **R8.05** *user generated* 'lens subtracted' multi-filter images
- **R8.06** *user generated* lens candidate colour composites

Discovery tools and infrastructure

- **R8.07** at least one deep learning neural network (NN) for lens discovery optimized for LSST data
- **R8.08** development of the interface and analysis software for the LSST Citizen Science platform
- **R8.09** infrastructure to deliver the user generated products to the LSST Citizen Science platform and machine learning codes

Data and modelling challenges

- **R8.10** run lens discovery challenge (platform, test data and ability to report results) for machine learning and inspection methods

LSST:UK SRM v2.1

Unfunded but lots of requirements :-)

Donations welcome

Examples Other areas of UK SL LSST interest (incomplete)

Realistic sims for training, testing and determination of follow-up strategy for source/lens and time-domain sources (Verma, Collett, Dye ...)

Multi-wavelength selection (Serjeant, Davies, Jackson, Hartley...)

Further development of fast modelling software (Li, Pearson, Dye, Nightingale, Massey...)

Implementation of a detailed mass modeller for complex/challenging lenses (Dye, Li, Nightingale, Massey....)

Deblending strategies for lenses (Serjeant, Davies, Verma, ...)

Statisical properties of galaxy ensemble (Jackson, Hartley, ...)

Tides follow-up of SL (Collett, Nichol, + TiDES team)

Observing Strategy Input

SL Observing Strategy Input

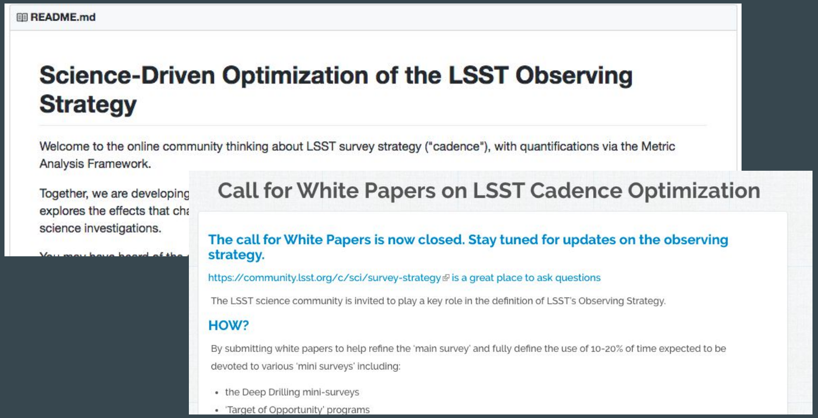
★ Requirements for general strong lens discovery *Verma, Collett+ arXiv:1902.05141*

- Wide area with reasonable sensitivity in all bands (increases sample size) - *early reference survey*
- Good image quality (to discern lensed images from lenses, better R_{ein} sampling, accurate image positions, majority have low R_{ein})
- Blue sensitivity (detect typically blue SFGs)
    - Good "blue"/g-band seeing

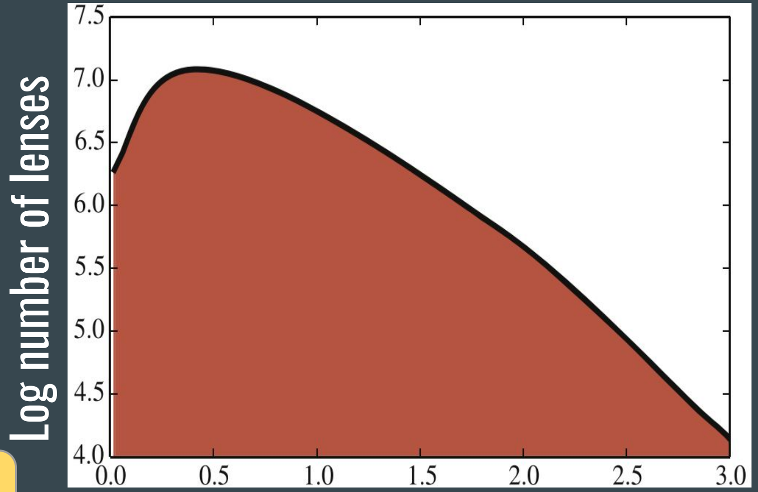
★ Strongly Lensed Gravitational Wave events *Smith+ arXiv:1902.05140*

- ToO & early reference survey

Matteo Bianconi

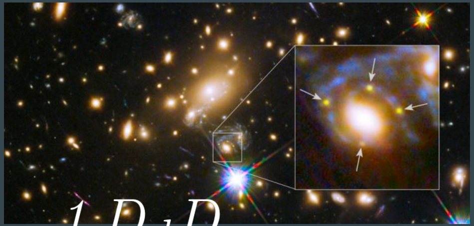


Theoretical Einstein Radius distribution



Einstein Radius (") *Collett 2015*

SL Observing Strategy Input



Kelly et al. 2015, 2016

- **Strong gravitational lens time delays** (lensed QSOs & SNe)
  - Strongest observing constraints:
  - Early WFD - know where SL candidates are, nightly alert stream
  - DESC Obs Strat WFD WP arXiv:1812.00515

Lens model
Predict the delays

$$t = \frac{1}{c}\frac{D_d D_s}{D_{ds}}(1+z_d)\left[\frac{1}{2}(\Theta-\beta)^2-\psi(\Theta)\right]$$

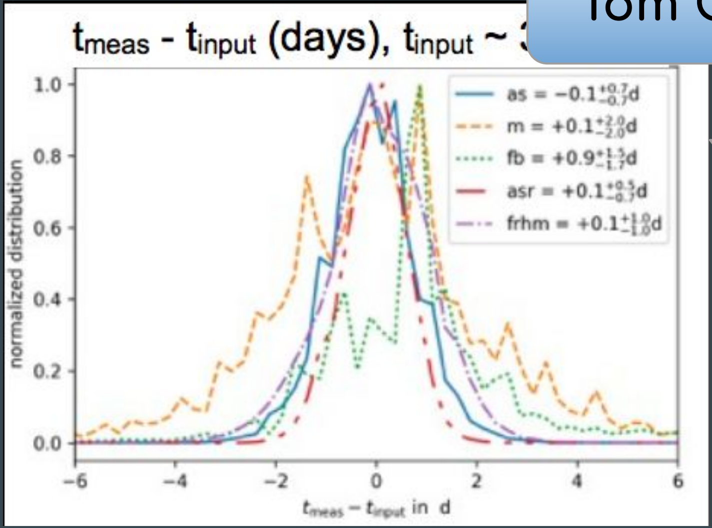
$1/H_0$

Image position
Astrometry

Source position

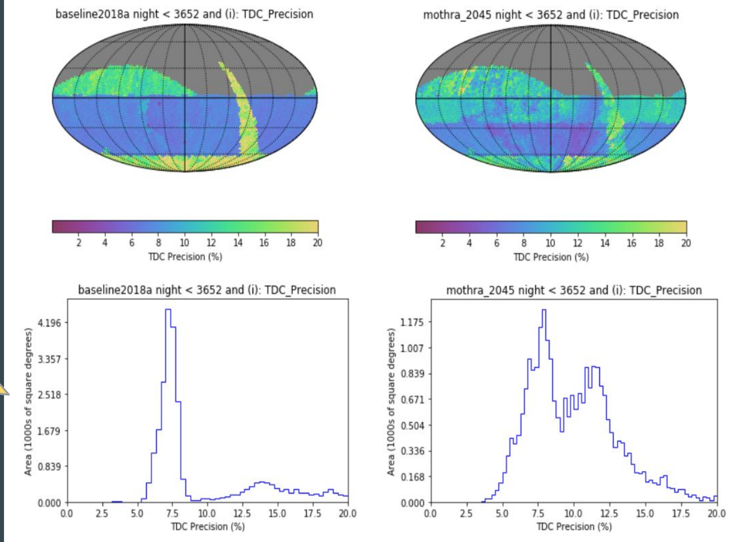
Lens potential

Tom Collett's talk



alt_sched_rolling performs best: recover dt_{input} within ~4%
S. Huber & S. Suyu
arXiv:1903.00510

SL QSOs
Precision is comparable between rolling cadence and baseline
T. Anguita & P. Marshall



SLSC priority tasks

Roadmap - middle of year

LSST SL simulations DC3

Preparations for commissioning & early ops

SL discovery & modelling challenges

SL discovery and server system

SLSC/DESC-SLWG face-to-face

LSST Strong Lensing Science Collaboration Roadmap (in development)

Prepared by Aprajita Verma & Chuck Keeton

Contents

SUMMARY

- Strong lensing activities address a wide variety of science cases from in line with science interests in the UK
- Potential lead contributions complementing the international effort in lens finding, lens modelling, SNe/DSPL cosmography, detailed simulations, galaxy evolution…
- Further development of software, simulations and analysis tools needed through now to be ready to exploit ComCam & early operations data
- Computational resources required are moderate, large-scale fast lens modelling will require parallel architecture
- Potentially run LSST"s SL server through the UK DAC