

and the hunt for Dark Matter

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But first, introducing ...

The Dark Matter Telescope

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Abstract. Weak gravitational lensing enables direct reconstruction of dark matter maps over cosmologically significant volumes. This research is currently telescope-limited. The Dark Matter Telescope (DMT) is a proposed 8.4 m telescope with a 3° field of view, with an etendue of $260 \text{ m}^2 \text{ deg}^2$, ten times greater than any other current or planned telescope. With its large etendue and dedicated observational mode, the DMT fills a nearly unexplored region of parameter space and enables projects that would take decades on current facilities. The DMT will be able to reach 10σ limiting magnitudes of 27-28 magnitude in the wavelength range $.3 - 1\mu\text{m}$ over a 7 deg^2 field in 3 nights of dark time. Here we review its unique weak lensing cosmology capabilities and the design that enables those capabilities.

Tyson, Wittman, & Angel 2000
arXiv:0005381

2000-2007 : One size fits them all!

A **wide** (large field of view), **fast** (many visit repetitions over the same fields during 10 years operation baseline), and **deep** (class-8m telescope) instrument can provide a major multi-science tool:

- Cataloging the Solar System
- Studying Milky Way Structure and Formation
- Exploring the Changing Sky
- Understanding the nature of Dark Matter and Dark Energy

Probing the Fundamental Nature of Dark Matter with the Large Synoptic Survey Telescope

arXiv:1902.01055

The following people have contributed to or endorsed the LSST dark matter science case as presented here:

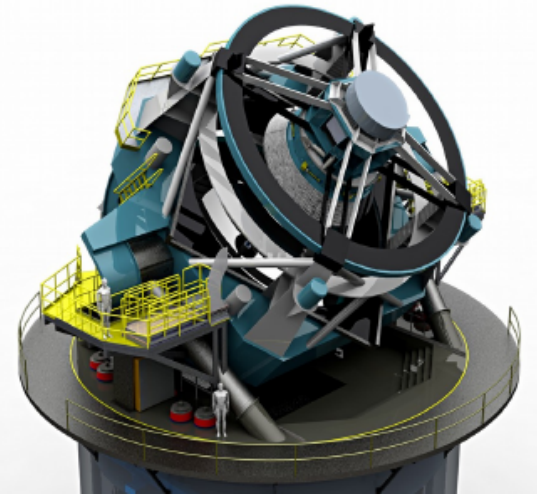
Contributors: Alex Drlica-Wagner^{1,2,3,†}, Yao-Yuan Mao^{4,*}, Susmita Adhikari⁵, Robert Armstrong⁶, Arka Banerjee^{5,7}, Nilanjan Banik^{8,9}, Keith Bechtol¹⁰, Simeon Bird¹¹, Kimberly K. Boddy¹², Ana Bonaca¹³, Jo Bovy¹⁴, Matthew R. Buckley¹⁵, Esra Bulbul¹³, Chihway Chang^{3,2}, George Chapline¹⁶, Johann Cohen-Tanugi¹⁷, Alessandro Cuoco^{18,19}, Francis-Yan Cyr-Racine^{20,21}, William A. Dawson⁶, Ana Díaz Rivero²⁰, Cora Dvorkin²⁰, Denis Erkal²², Christopher D. Fassnacht²³, Juan García-Bellido²⁴, Maurizio Giannotti²⁵, Vera Gluscevic²⁶, Nathan Golovich⁶, David Hendel¹⁴, Yashar D. Hezaveh²⁷, Shunsaku Horiuchi²⁸, M. James Jee^{23,29}, Manoj Kaplinghat³⁰, Charles R. Keeton¹⁵, Sergey E. Kopolov^{31,32}, Ting S. Li^{1,2}, Rachel Mandelbaum³², Samuel D. McDermott¹, Mitch McNanna¹⁰, Michael Medford^{33,34}, Manuel Meyer^{5,7}, Moniez Marc³⁵, Simona Murgia³⁰, Ethan O. Nadler^{5,36}, Lina Necib³⁷, Eric Nuss¹⁷, Andrew B. Pace³⁸, Annika H. G. Peter^{39,40,41}, Daniel A. Polin²³, Chanda Prescod-Weinstein⁴², Justin I. Read²², Rogerio Rosenfeld^{43,44}, Nora Shipp³, Joshua D. Simon⁴⁵, Tracy R. Slatyer⁴⁶, Oscar Straniero⁴⁷, Louis E. Strigari³⁸, Erik Tollerud⁴⁸, J. Anthony Tyson²³, Mei-Yu Wang³¹, Risa H. Wechsler^{5,36,7}, David Wittman²³, Hai-Bo Yu¹¹, Gabrijela Zaharijas⁴⁹

Endorsers: Yacine Ali-Haïmoud⁵⁰, James Annis¹, Simon Birrer⁵¹, Rahul Biswas⁵², Jonathan Blazek⁵³, Alyson M. Brooks¹⁵, Elizabeth Buckley-Geer¹, Regina Caputo⁵⁴, Eric Charles^{5,7}, Seth Digel^{5,7}, Scott Dodelson³¹, Brenna Flaugher¹, Joshua Frieman^{1,2}, Eric Gawiser¹⁵, Andrew P. Hearin⁵⁵, Renee Hložek^{14,56}, Bhuvnesh Jain⁵⁷, Tesla E. Jeltema⁵⁸, Savvas M. Koushiappas⁵⁹, Mariangela Lisanti⁶⁰, Marilena LoVerde⁶¹, Siddharth Mishra-Sharma⁵⁰, Jeffrey A. Newman⁴, Brian Nord^{1,2,3}, Erfan Nourbakhsh²³, Steven Ritz⁵⁸, Brant E. Robertson⁵⁸, Miguel A. Sánchez-Conde^{24,62}, Anže Slosar⁶³, Tim M. P. Tait³⁰, Aprajita Verma⁶⁴, Ricardo Vilalta⁶⁵, Christopher W. Walter⁶⁶, Brian Yanny¹, Andrew R. Zentner⁴



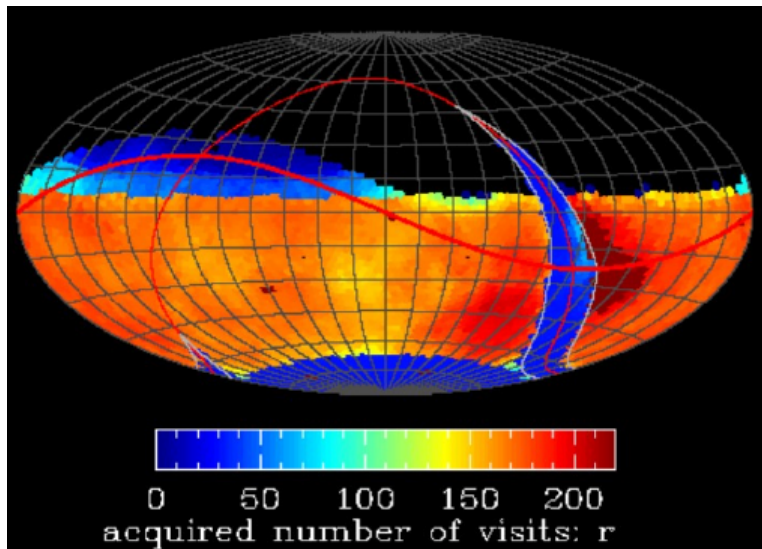
Concept

- A stage-IV survey
 - 8.4(6.7)m telescope (Cerro Pachon, Chile)
 - 3.2 Gpix camera
 - 9.6°FOV
 - 0.2" pixel/0.7" seeing
 - First Light 2020
 - Survey 2022



- A synoptic survey

- Southern sky (18000°) every 3 days
- ugrizy bands ($r \sim 24.4$ /visit)
- $\gtrsim 800$ visits everywhere (all bands)
- Dynamic time range from sub-minute (hard to use in practice) to 10 years (survey duration)

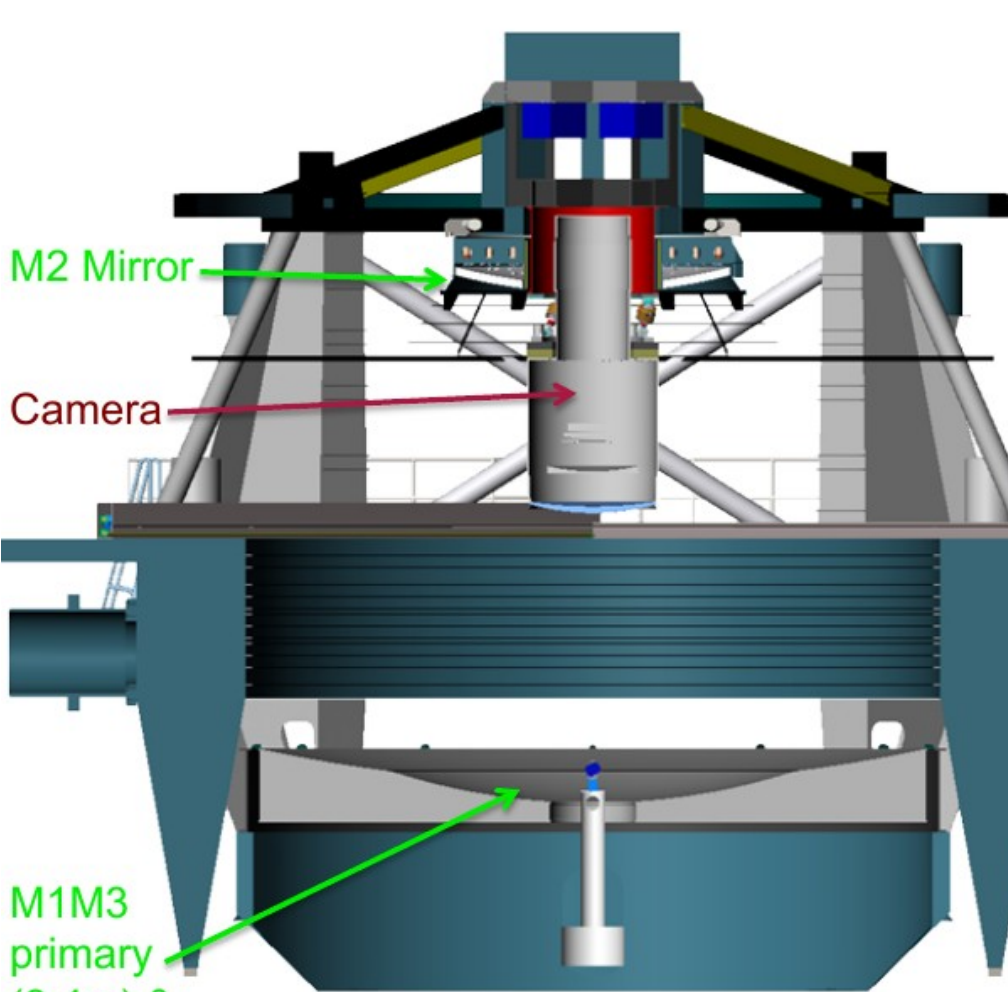




Implementation

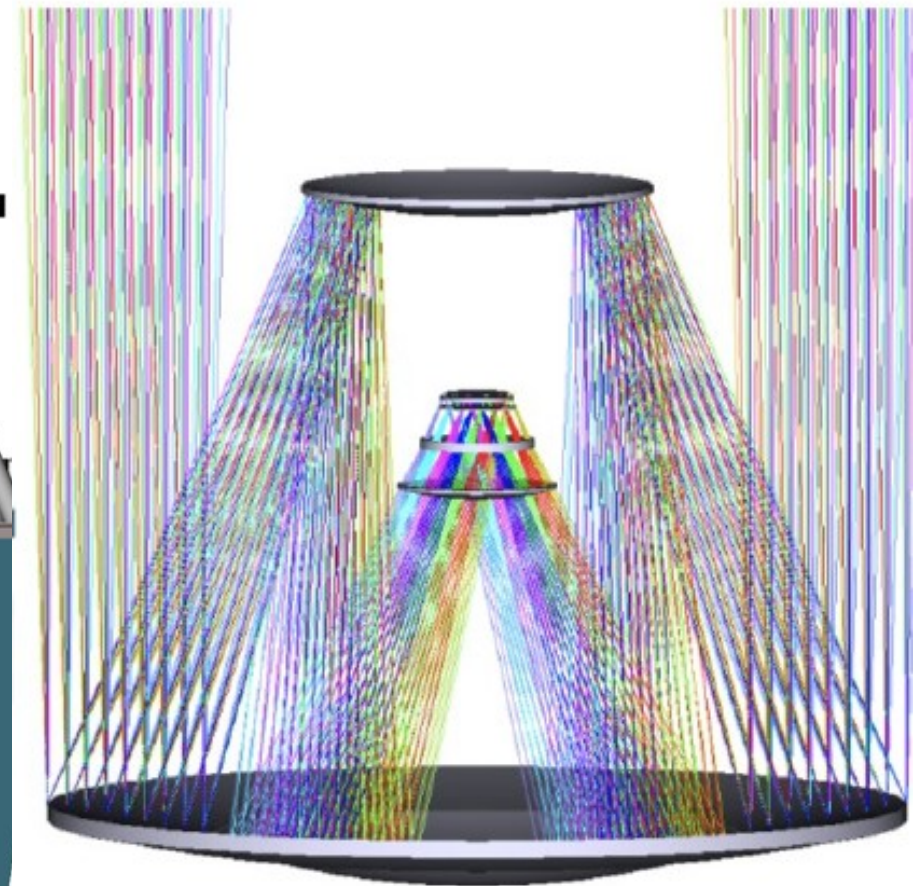
- A telescope
- A camera
- A data management system
- A survey optimized cadence

Telescope : compact Paul-Baker modified



M2 Mirror
Camera
M1M3 primary (8.4m) & Tertiary mirrors

Moving Structure 350 tons
60 tons optical systems

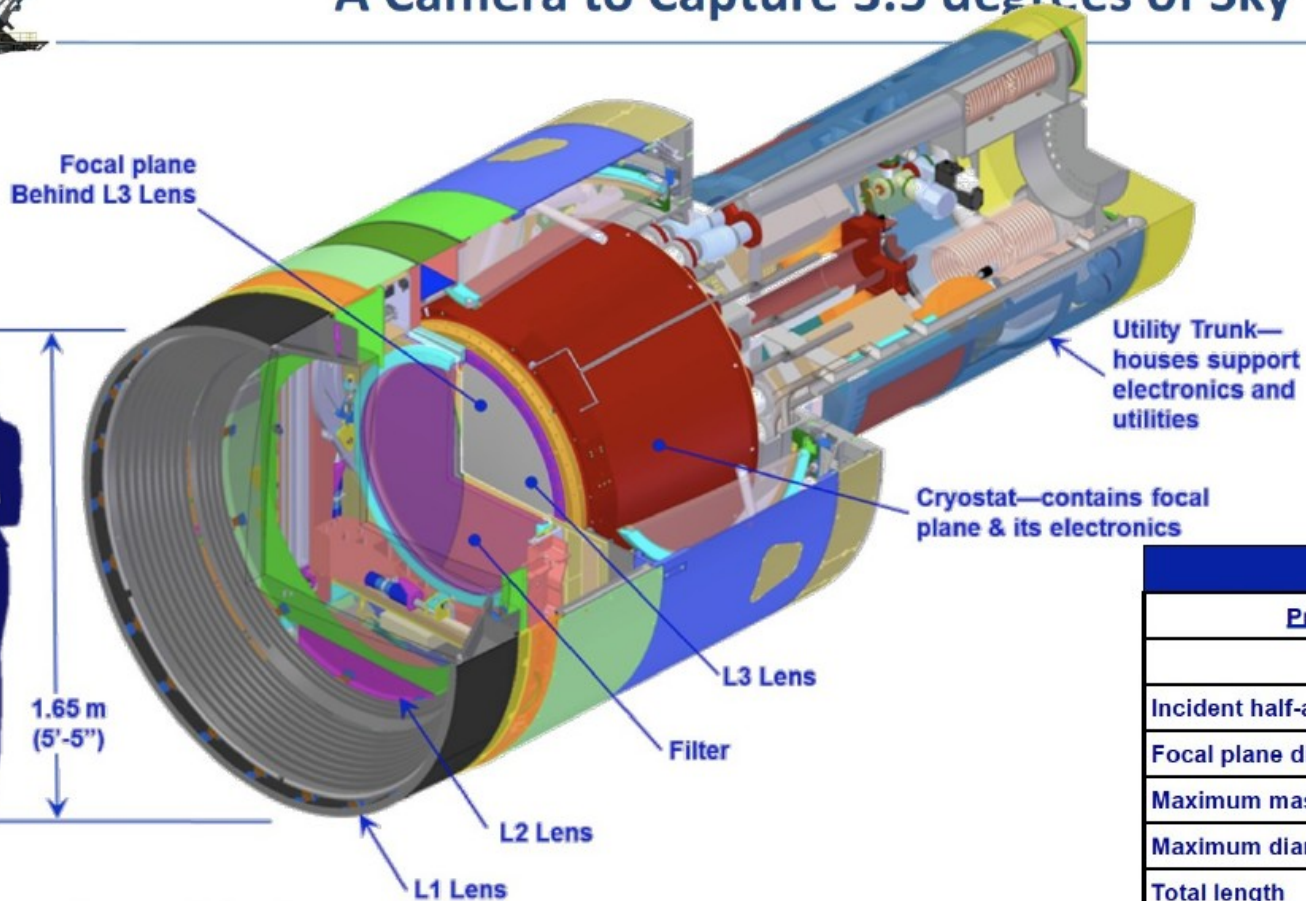


Change pointing every 40s and takes 4s to do so with an offset of 3.5°

Camera : structure

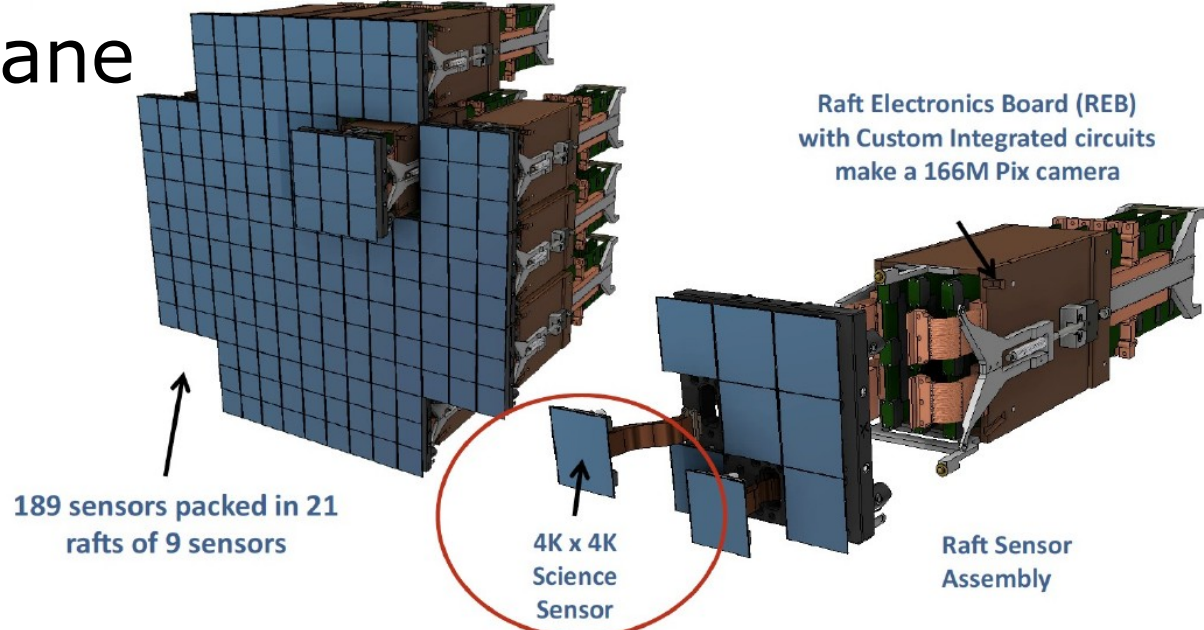


A Camera to Capture 3.5 degrees of Sky

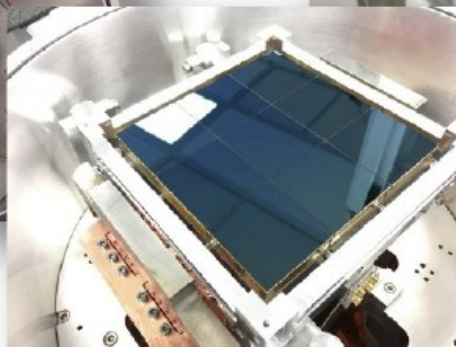
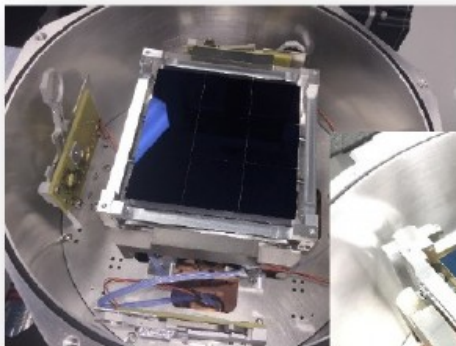


Camera Parameters	
Property	Value
	15 years
Incident half-angle in air	14.2°-23.6°
Focal plane diameter	634 mm
Maximum mass	3060 kg
Maximum diameter	1650 mm
Total length	3732 mm

Camera : focal plane



- Need 198 for focal plane and 9 for spare raft.
- 219 Science and Science Reserve Sensors delivered -

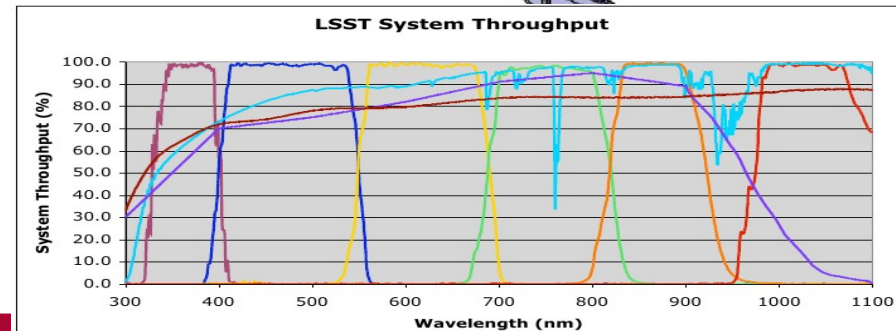
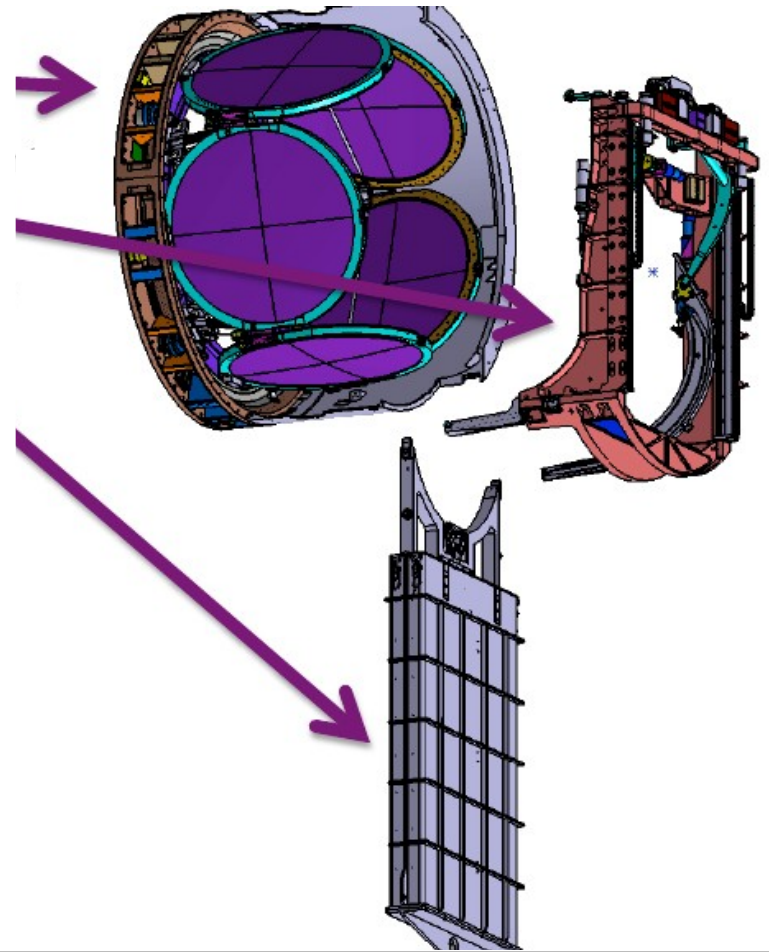
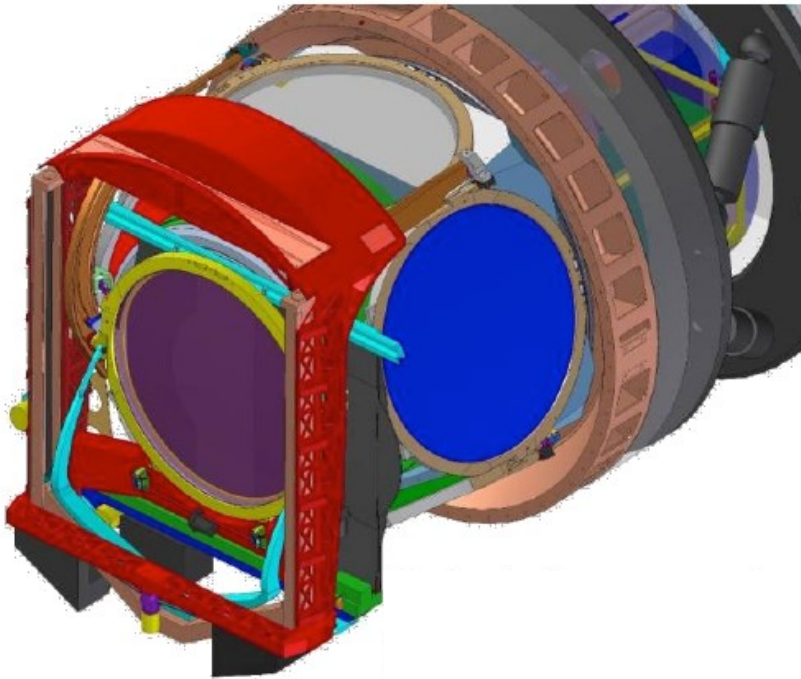


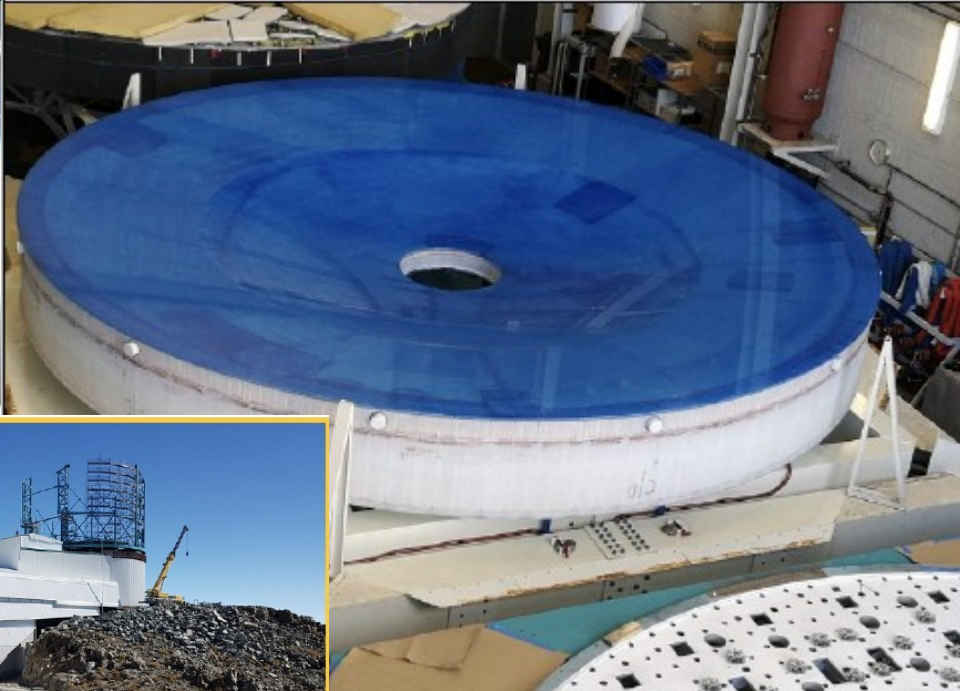
Brookhaven National Labs does Raft integration

- 8 Rafts delivered
 - 5 more completed
- Over half way!

Camera filter changer

- A 3-component system
 - **Carrousel** : holds 5 filters and in charge of positioning one filter for the auto-changer
 - **Auto-Loader** : places and holds a given filter in the FOV
 - **Changer** : replaces one of the carrousel filter with a 6th one stored outside

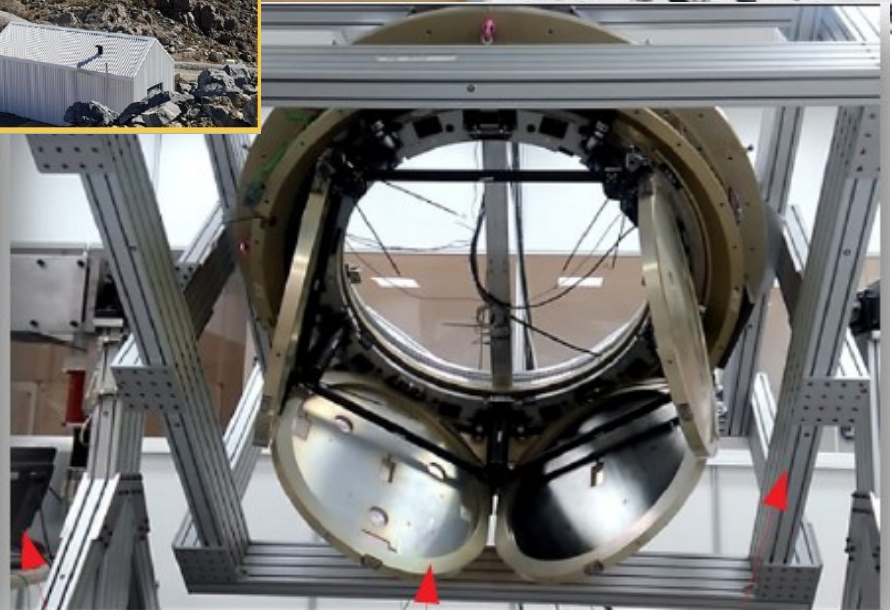




Filter Autochanger



**Filter loader on
transport cart**



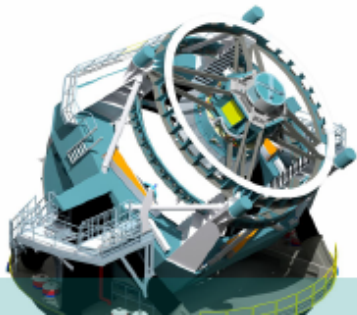
5 Filter capacity carousel

LSST Data Management System

Raw Data: 20TB/night



Sequential 30s images covering the entire visible sky every few days



Prompt Data Products

Alerts: up to 10 million per night

Raw, calibrated, and difference images and their source and object catalogs

Solar System Objects: ~ 6 million

Data Release Data Products

Final 10yr Data Release:

- Images: 5.5 million x 3.2 Gpx
- Catalog: 15PB, 37 billion objects



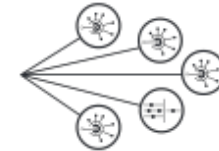
via nightly alert streams



via Prompt Products Database



via Data Releases



LSST Alert Filtering Service
Community Brokers

LSST DAC (NCSA)

Independent DACs (iDACs)

Data reduction, storage, management, and accessibility constitute a major challenge

Take away message : LSST is a telescope, a baseline cadence, and a computing framework for science!

Optimizing cadence / operation plans

The project is revisiting the observing strategy

- White papers in 2018
- Decision made in 2020

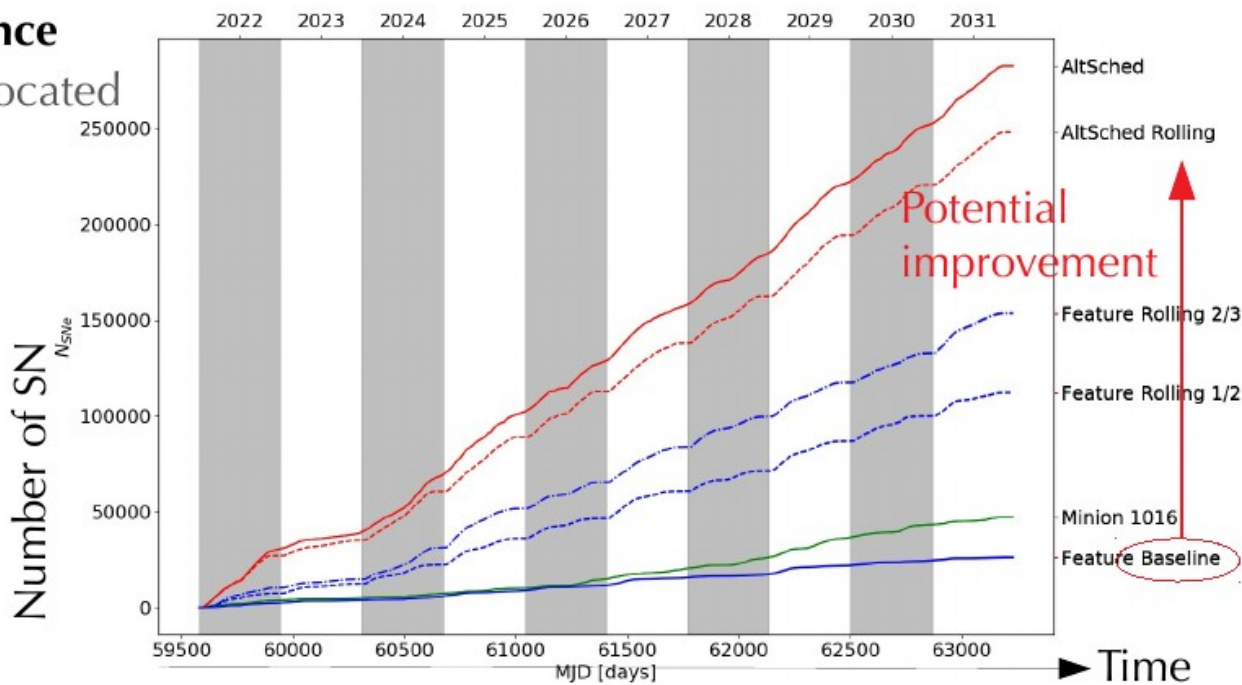
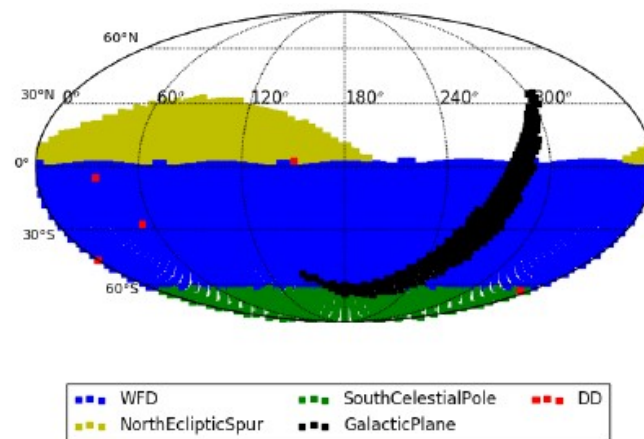
- **Wide Deep Field** : 90% of observing time

- Default cadences significantly impair the SN program
 - O(50 kSN), low z limit
- Move toward **rolling cadence**

- **Deep Drilling Fields**: 5% of allocated time

- Ongoing optimization
- From 15 to 27 kSN $z \sim 0,8$

“LSST Observing Strategy” in arxiv search engine



Science Collaborations

Note : the LSST project is **not** in charge of science

- Galaxies
- Stars, Milky Way, and Local Volume
- Solar System
- Dark Energy (DESC)
- Active Galactic Nuclei
- Transients/variable stars
- Strong Lensing

<https://www.lsstcorporation.org/science-collaborations> for further details

Dark Matter interest rose up within DESC, but clearly concerns several other collaborations (actually Dark Energy as well)

Several Dark Energy probes actually also probe Dark Matter

Probing the fundamental physics of dark matter with LSST

<https://lsstdarkmatter.github.io>

<https://lsstdarkmatter.github.io/dark-matter-graph/>

LSST Dark Matter

Probing the fundamental physics of dark matter with LSST

[Objectives](#) | [Products](#) | [Workshops](#) | [Participation](#) | [Contact](#)

[LSST Dark Matter White Paper](#)

[Astro2020 White Paper](#)

Objectives

Dark matter constitutes roughly 85% of the matter density of the Universe, and represents a critical gap in our understanding of fundamental physics. Despite these extensive experimental efforts, the only robust, positive empirical measurement of dark matter continues to come from cosmological and astrophysical observations. The [Large Synoptic Survey Telescope \(LSST\)](#) offers a unique avenue to attack the dark matter problem. Our group seeks to identify and pursue scientific avenues to utilize LSST to help us understand the fundamental physics that governs dark matter. Specifically, we hope to identify the fundamental constituents of dark matter (e.g., new fundamental particles, fields, or compact objects) and to characterize the properties of these constituents (e.g. mass, temperature, self-interaction rate).

Products

- **Dark Matter White Paper** – One of the major efforts of the LSST dark matter group has been the preparation of a white paper detailing the fundamental probes of dark matter accessible to LSST. The latest version of the white paper can be found [here](#).
- **Astro2020 White Paper** – We plan to prepare a 5-page version of the white paper for submission to Astro2020. A draft of this paper can be accessed [here](#).
- **Dark Matter Graphics** – The landscape of astrophysical probes is complex and interconnected. We have assembled [graphical representations](#) of the LSST dark matter parameter space. This graphic is intended to help conceptually organize the LSST dark matter program and to serve as a road map for future scientific investigations. We encourage the addition of new components through this [submission form](#).

Workshops

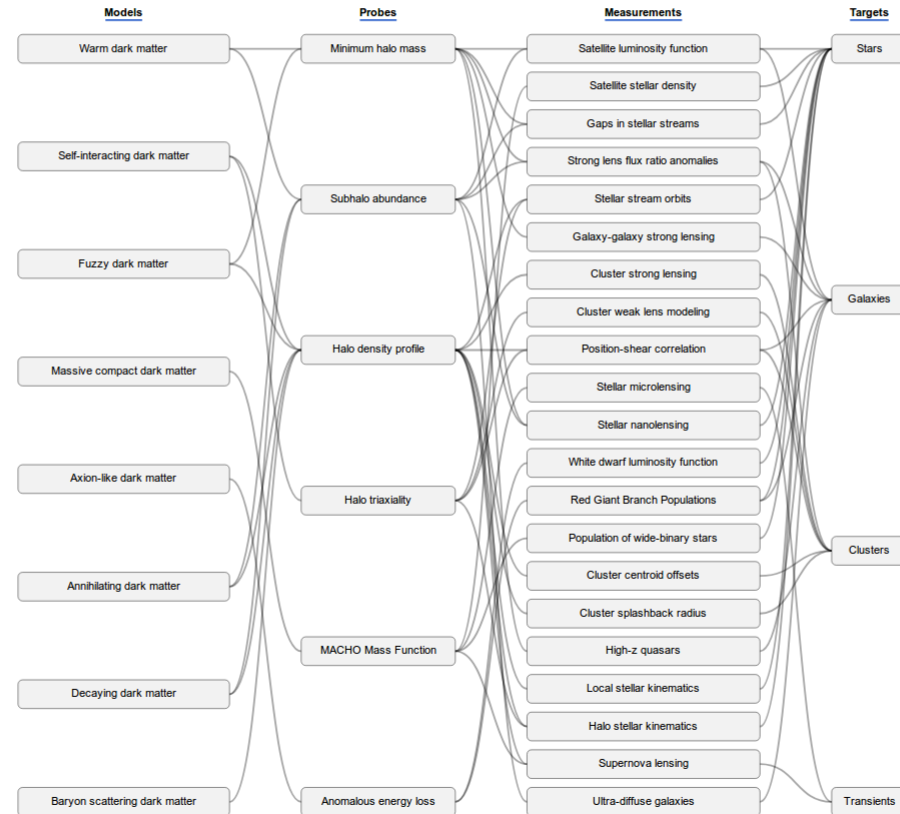
The group has organized several workshops, which have been partially funded by a grant from the LSST Corporation Enabling Science Program. These workshops seek to organize the LSST dark matter community, and to coordinate efforts on the construction of a white paper on dark matter physics with LSST. Activity from previous workshop are summarized in a series of [GitHub issues](#) and tweets to [#lsstdarkmatter](#).

- [Probing the Nature of Dark Matter with LSST](#) – Kavli Institute of Cosmological Physics, Summer 2019
- [Probing the Nature of Dark Matter with LSST](#) – Lawrence Livermore National Laboratory, October 29-31, 2018
- [Astrophysical Probes of Dark Matter with LSST](#) – LSST Project and Community Workshop, Tucson, AZ August 16, 2018
- [Probing the Nature of Dark Matter with LSST](#) – University of Pittsburgh, March 5-7, 2018
- [Dark Matter Science with LSST](#) – LSST Project and Community Workshop, Tucson, AZ August 16, 2017

Participation

The LSST dark matter group encourages broad participation from the dark matter community, including cosmologists, astrophysicists, and particle physicists. Experimentalists, observers, and theorists are all welcome. We encourage the participation from early career scientists and scientists with diverse backgrounds.

If you are interested in joining the LSST Dark Matter effort, please [fill out this form](#) to join our mailing list. If you are already a member of the LSST Project or Science Collaborations, you can join our effort on the LSSTC Slack at [#desc-dark-matter](#).

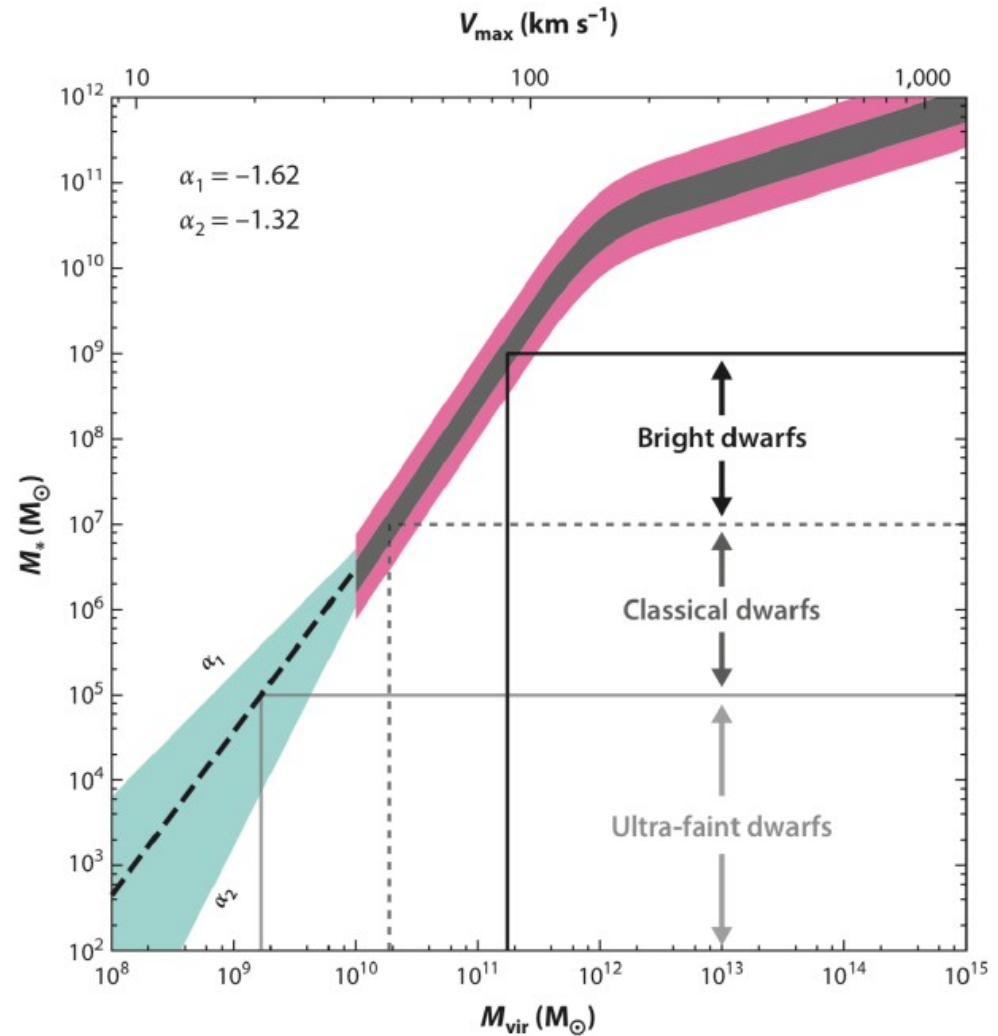
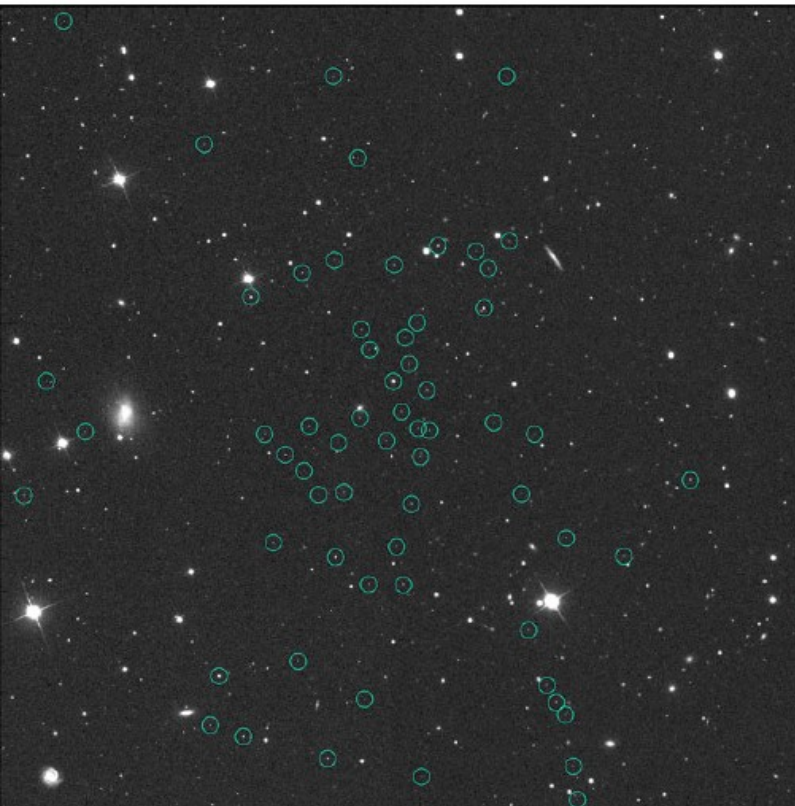


Dark Matter probes in the LSST sky

- Minimum halo mass
 - Satellite galaxies
 - Stream gaps
 - strong lensing
- Halo profiles
 - Lensed dwarf galaxies
 - Galaxy clusters
- Compact object abundance
- Anomalous energy loss
- Large scale structure

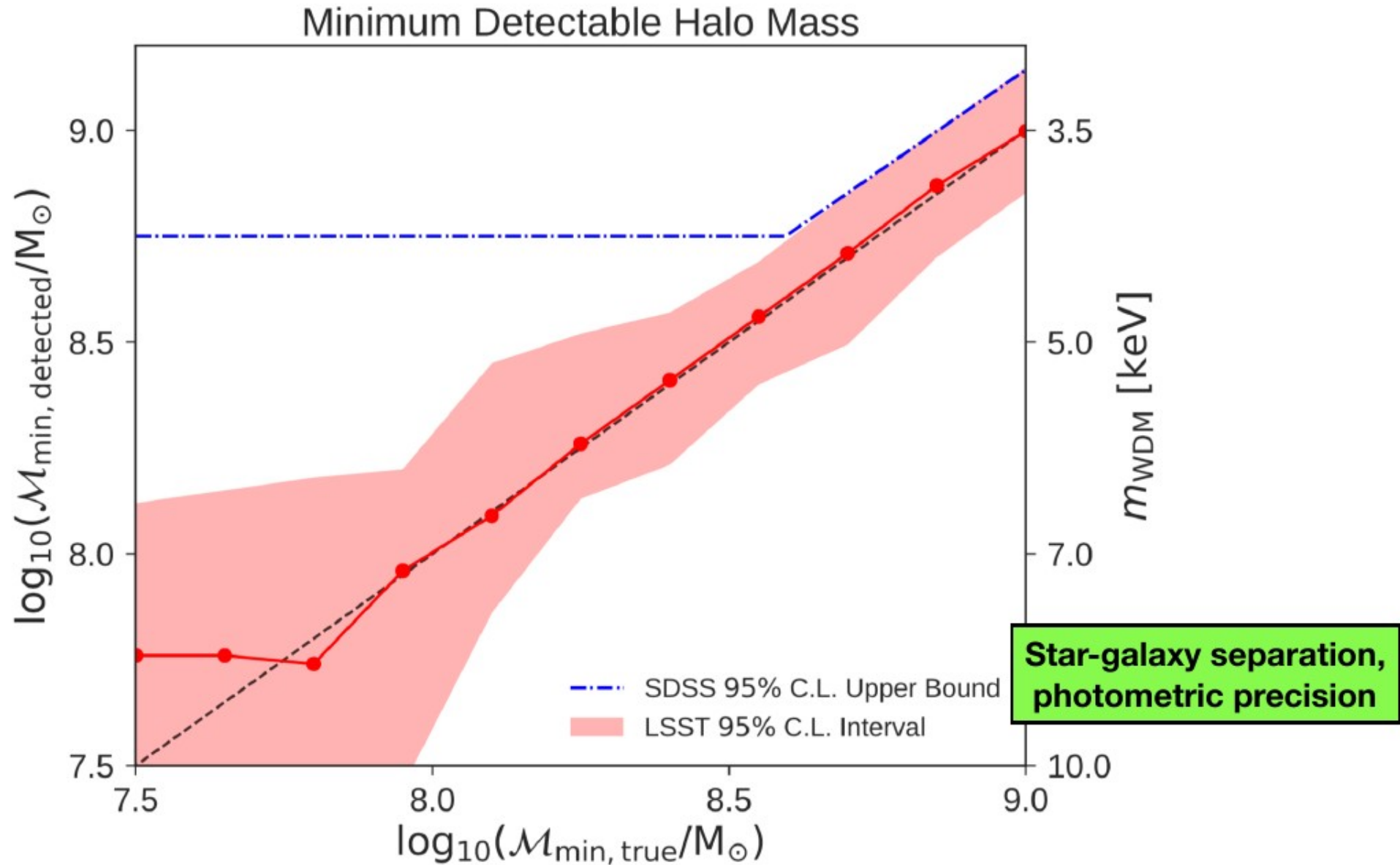
Threshold for Galaxy formation

Ultra-faint dwarf galaxies are the most numerous, oldest, most chemically pristine, and most dark-matter-dominated galaxies known

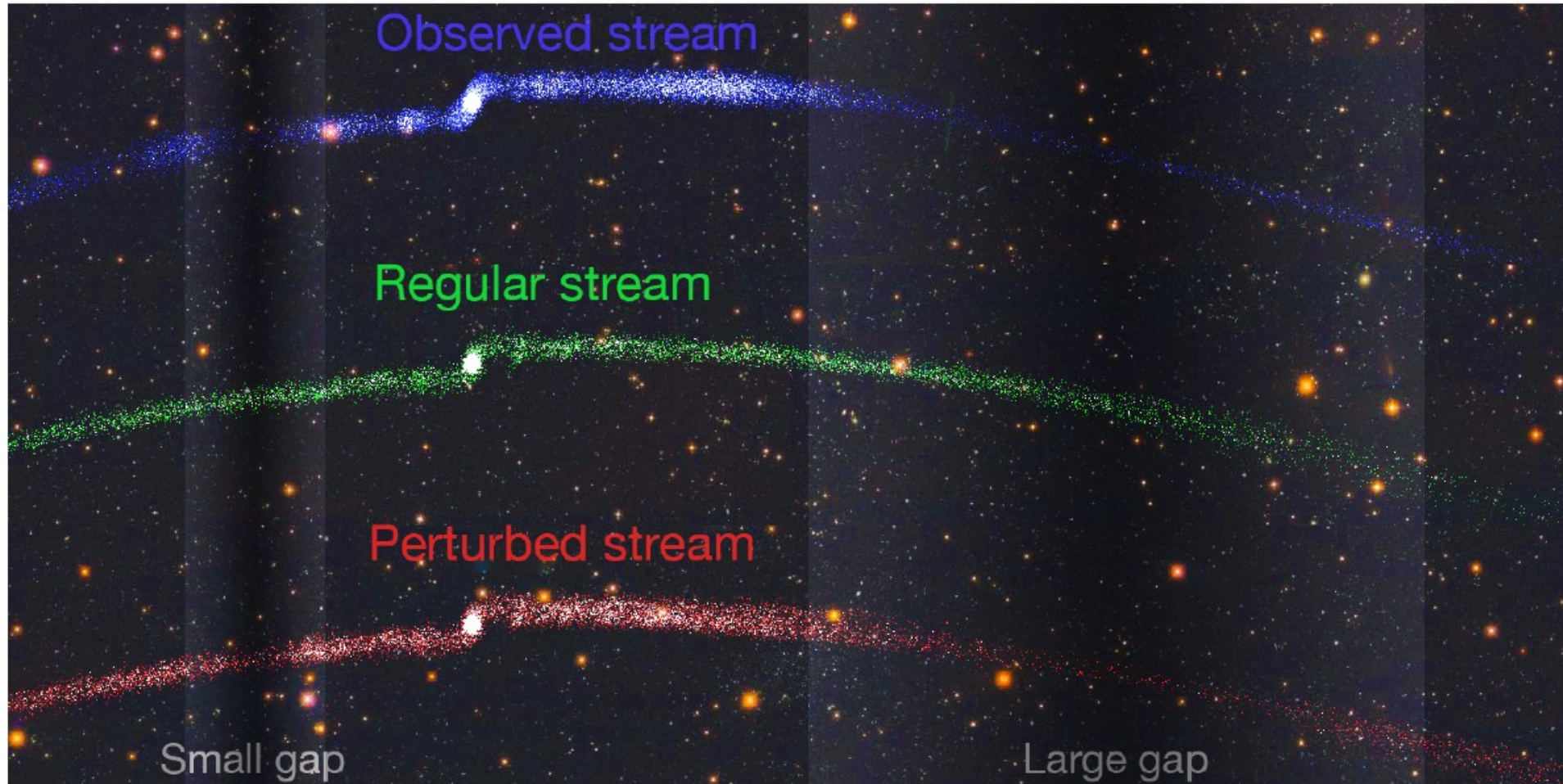


Identified as arcminute-scale over-densities of individually resolved stars (~tens of stars)

Threshold for Galaxy formation

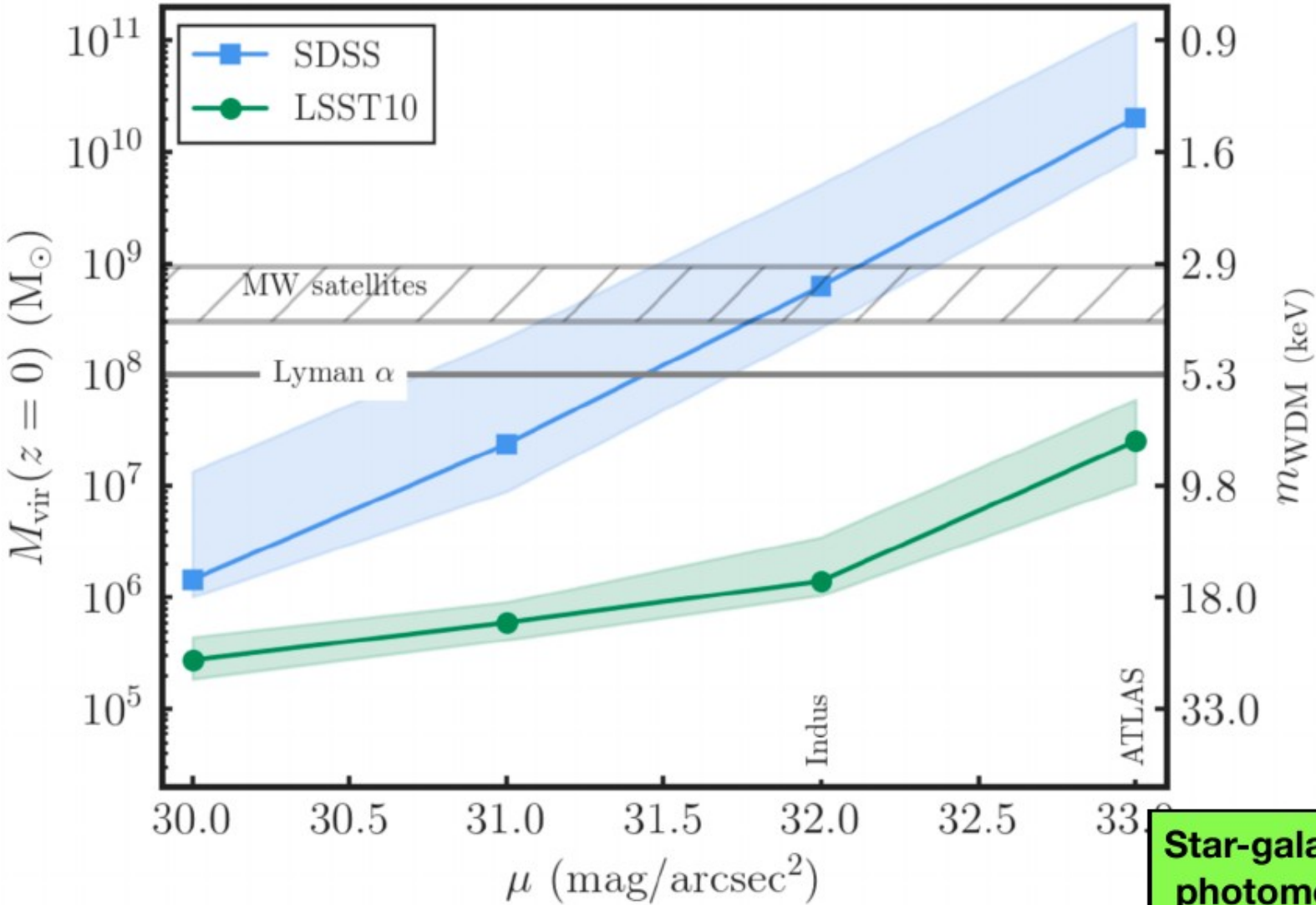


MW Stellar Stream perturbation



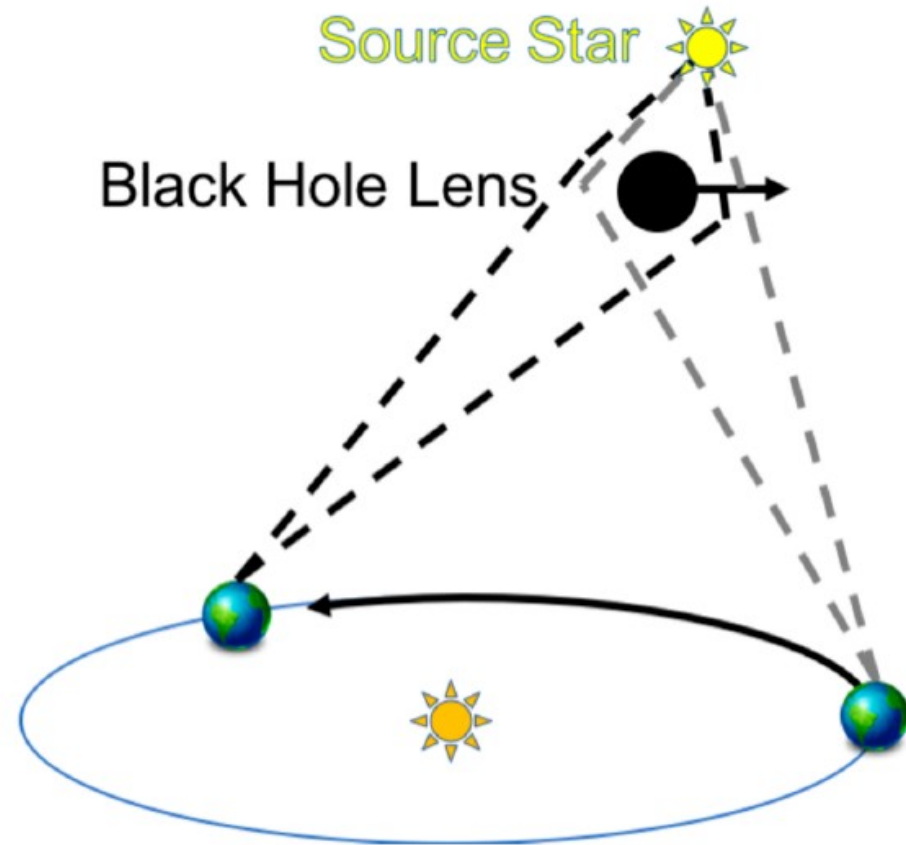
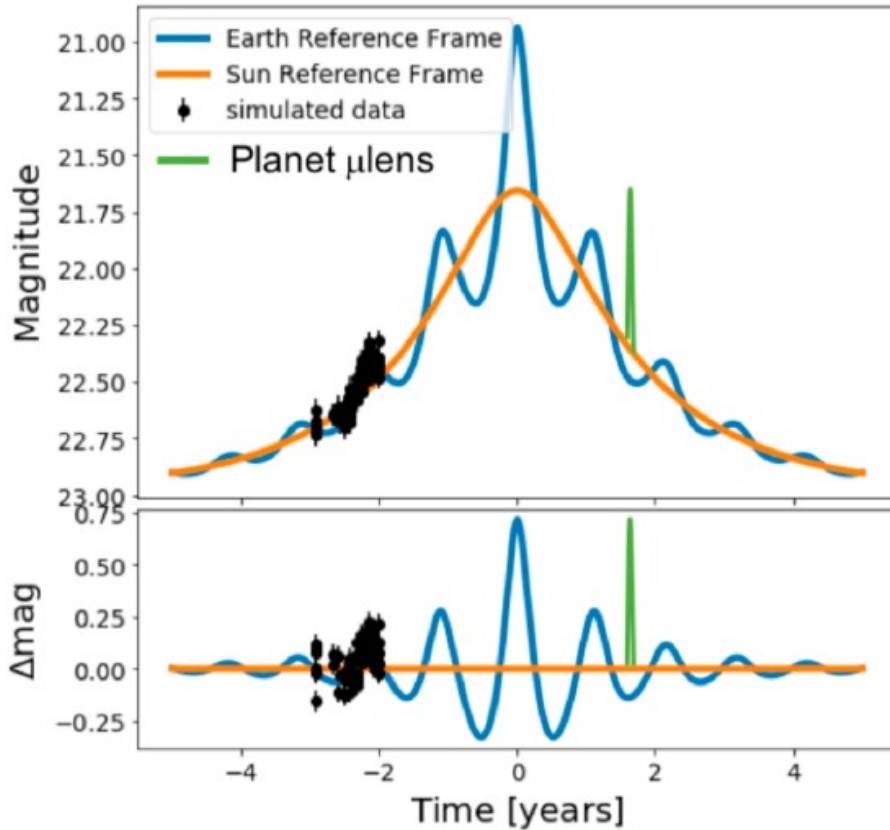
Threshold for Galaxy formation

Minimum Detectable Halo Mass

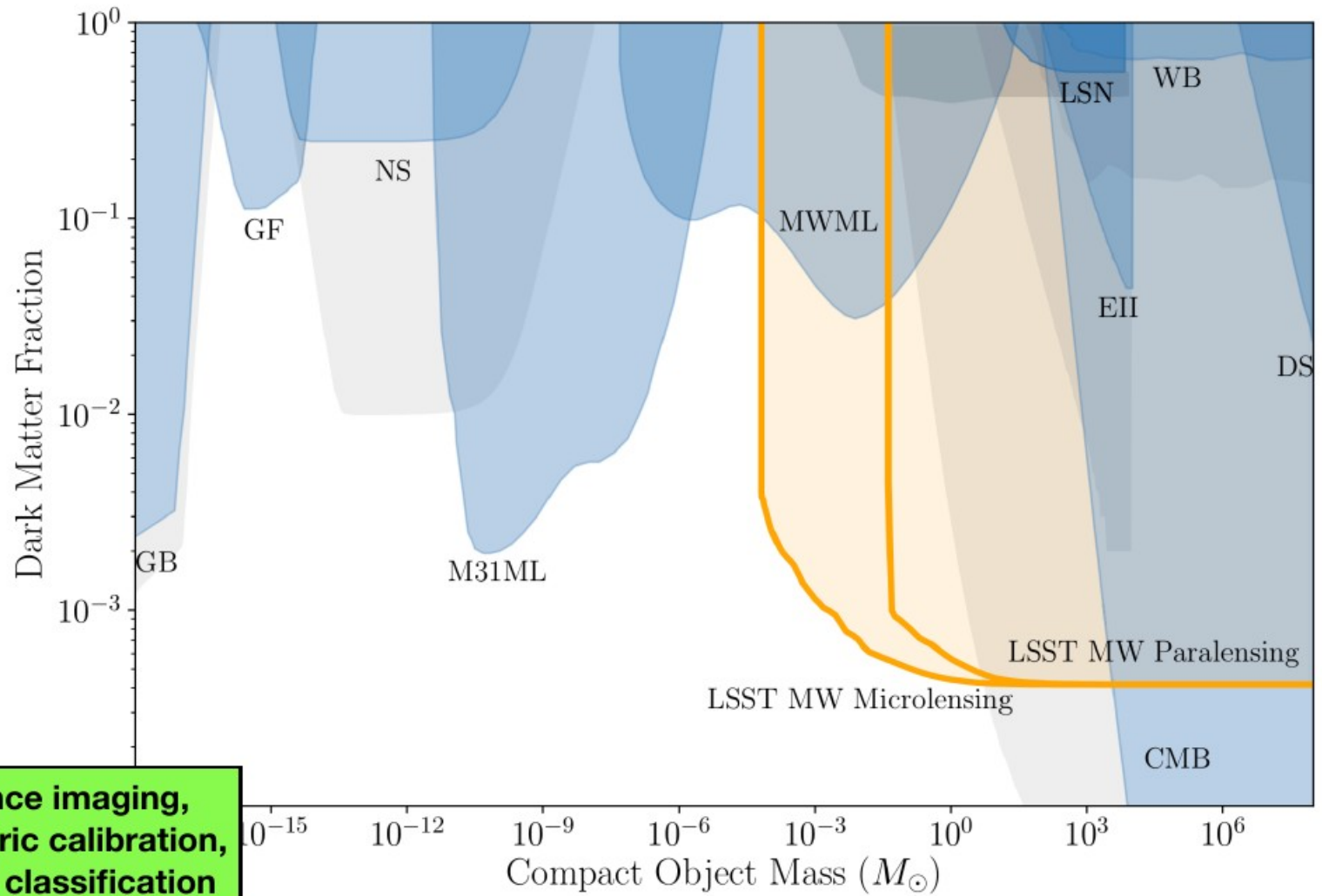


**Star-galaxy separation,
photometric precision**

Micro-lensing : in time and mag space



Lensing geometry changes over 6 months, allowing measurements of individual black hole masses. Goal is to measure mass spectrum of stellar-mass black holes in the Milky Way



Reach could be further extended with fast observing cadences in dense stellar fields

Micro-lensing (from E. Fedorova last workshop)

class	Lensing objects	Observational appearances
Macrolensing	Galaxies, $> 10^9 M_{\text{Sun}}$	Astrometric (static multiple images) Photometric (time delays between images)
Mesolensing	Globular clusters, DM substructure $10^4 - 10^8 M_{\text{Sun}}$	Photometric (slow changes, <u>> monthly-yearly timescales</u> , anomalous <u>flux ratios</u>) Astrometric (\sim milliarcsec image splitting)
Micro-lensing	Stellar-mass objects, $10^{-1} - 10^3 M_{\text{Sun}}$	Photometric (caustic crossing high amplification events, <u>daily-weekly timescales</u>) Spectral (emission lines profiles distortions)
Nanolensing	Planetary mass objects, $< 10^{-2} M_{\oplus}$	Photometric, complementary to microlensing

- The LSST dynamic range goes from sub-hour to several years
- But a lot depends on the observation scheduling and mini-surveys...

Machine Learning in all that?

- There is a very basic level where ML is used in the context of LSST
 - Star/galaxy separation
 - Photometric classification
 - Photometric distance (photo-z) estimation
 - Deblending

Star/Galaxy separation

- At the bright end, this is easy : Gaia!
 - And we need it anyway for astrometric and photometric calibration
 - This allows for PSF modeling actually
- At the faint end, this is hard (small galaxy vs point-like source?)
 - Usually use the COSMOS field and/or SDSS spectro dataset
 - NN and random forests stand out in a catalog-based comparison:
<https://ieeexplore.ieee.org/document/7727189>
 - ConvNet on images : <https://arxiv.org/abs/1608.04369> and
<http://proceedings.mlr.press/v80/kennamer18a/kennamer18a.pdf>
- But beware of blending (close stars mis-identification)
- And convnets typically use cutouts
- Is it possible to do global star/galaxy separation at the same as you do PSF modeling on full images

Transient photometric classification

PELICAN: deeP architecture for the Light Curve ANalysis

Johanna Pasquet¹, Jérôme Pasquet², Marc Chaumont³ and Dominique Fouchez¹

- 1901.01298 : 04/01/19
- CNN with light-curve as image (band x time) + a VAE as feature extractor
- Needs full curves

SuperNNova: an open-source framework for Bayesian, Neural Network based supernova classification

A. Möller,^{1,2*} T. de Boissière³ †

- 1901.06384 : 18/01/19
- standard RNN
- Early and improving classification
- SN-oriented

RAPID: Early Classification of Explosive Transients using Deep Learning

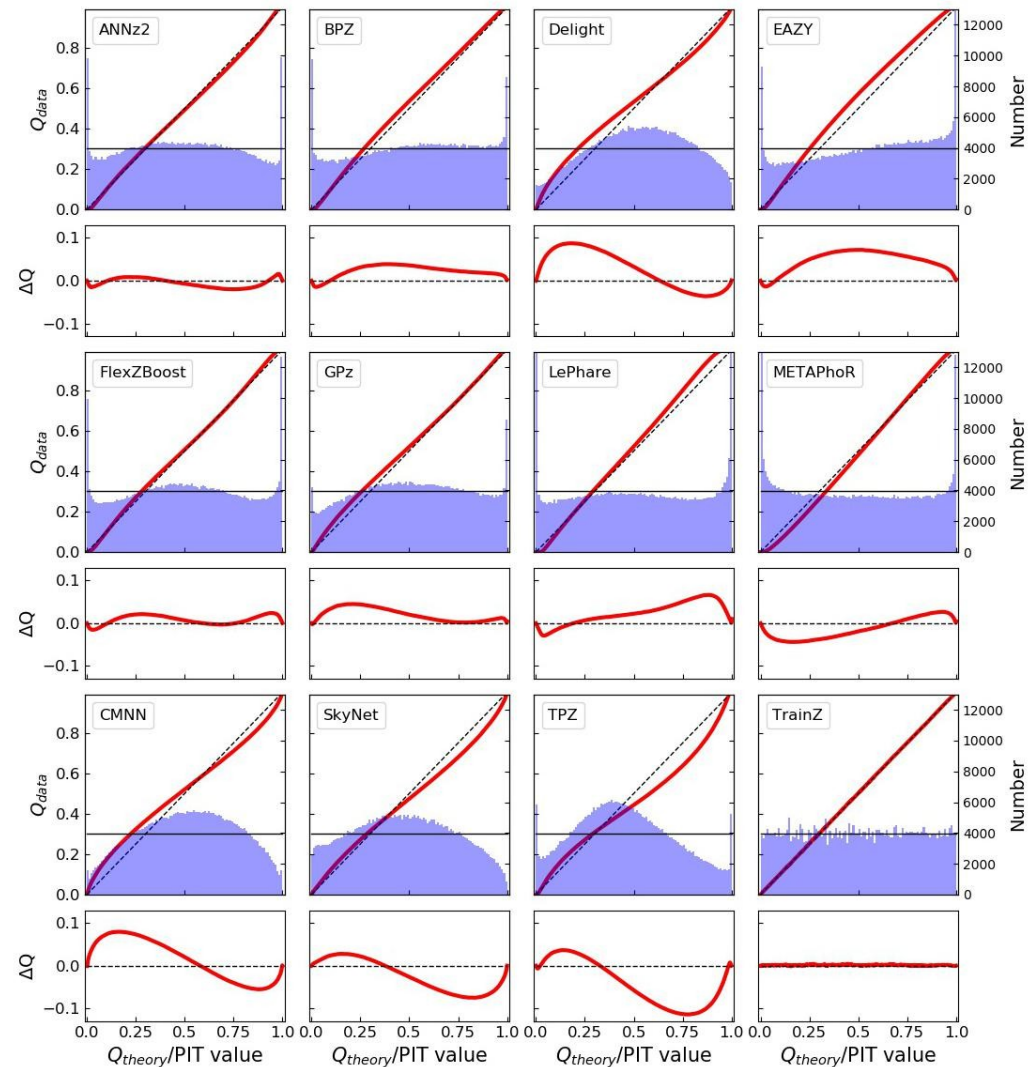
DANIEL MUTHUKRISHNA,¹ GAUTHAM NARAYAN,^{2,*} KAISEY S. MANDEL,^{1,3,4} RAHUL BISWAS,⁵ AND RENÉE HLOŽEK⁶

- 1904.00014 : 29/03/19
- GRU-type RNN
- Early and improving classification with time
- Transient-agnostic

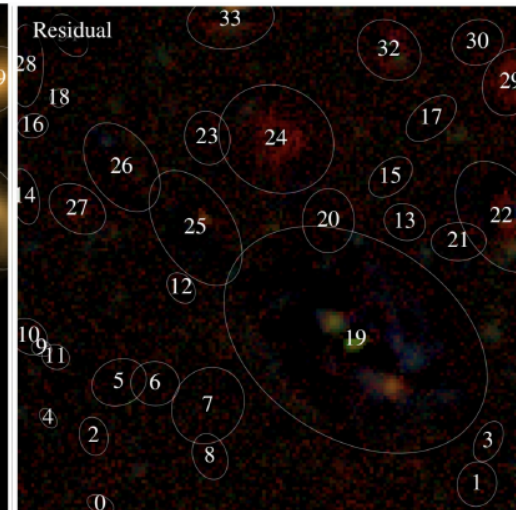
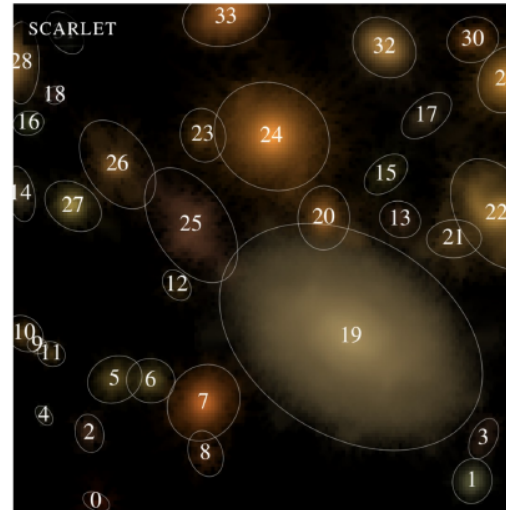
All trying to provide a response to LSST future wealth of alerts

Photometric redshift estimators

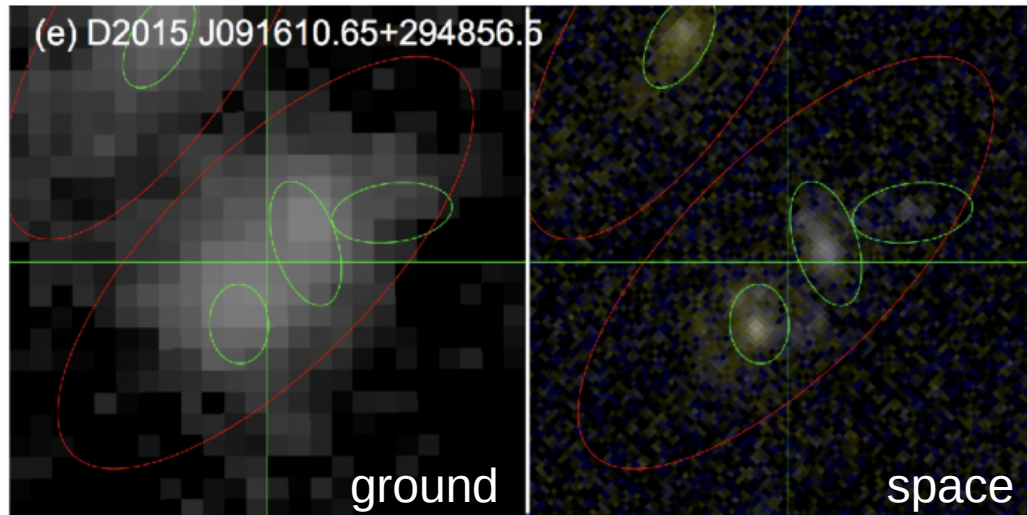
- Technical paper from DESC about behavior of several estimators with a \sim LSST-like simulated catalogue
- Both template-based and learning-based codes evaluated
- In all cases the real issue will be to deal with incompleteness in training or template libraries, erroneous labeling, etc...



Deblending a crowded sky



- SCARLET <https://github.com/fred3m/scarlet> is state-of-the-art non-ML alg around
- Neural Nets are closing in
- How to efficiently incorporate external observations when LSST dataset is already so large?



Machine Learning in all that?

- There is a very basic level where ML is used in the context of LSST
 - Star/galaxy separation
 - Photometric classification
 - Photometric distance (photo-z) estimation
 - Deblending
- But there is a lot also beyond these “standard” applications
 - Transfer Learning and Domain adaptation?
 - Continuous Training?
 - Active Learning?
 - Adversarial training?
 - Reinforcement Learning?

The real ML issues with LSST

- Completeness
 - My training set is from the same distribution than my test set, but truncated, and the censoring may not be trivial
- Representativeness
 - My test set is not sampled from the same distribution as my training set....
- Treason
 - Mislabeling or error in the training set; can I be robust, detect, and or recover?
- Committee/hybrid voting
 - I have several ML tools that do equally well on my training, but yield different results on my test set
- Anomaly detection / continuous learning
 - Ooops I *did not expect* that kind of weird transient.....
- Experimental design / active learning
 - I need to tell a spectro to look at *that* specific transient

Conclusion

- **LSST** has a very rich potential for **Dark Matter** search
 - From stars to large scale structure
 - and from static to multi-timescale transient sky
- **Dark Matter** search needs **Machine Learning** to deal with larger and more complex/heterogeneous data
 - and clearly the low hanging fruit season is over....
- **LSST** image reduction is still rule-based, but science is already largely enabled by **Machine Learning** techniques
 - Many areas are still ML-R&D !

Thus there is every reason to believe that LSST will open new avenues in utilizing Machine Learning techniques for constraining Dark Matter nature
But this has not (yet?) been concretely investigated
So let's get started!