

Rubin Observatory

Image Differencing in Science Pipelines

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Rubin Observatory Algorithms Workshop | Virtual | March 17-19,
2020



Many people have contributed to image differencing algorithm and pipeline development in DM.

- Yusra AlSayyad
- Andrew Becker
- Steven Bickerton
- Andrew Connolly
- Jim Bosch
- Krzysztof Findeisen
- Josh Hoblitt
- Tim Jenness
- Mario Juric
- Gabor Kovacs
- Simon Krughoff
- Lauren MacArthur
- Chris Morrison
- Fred Moolekamp
- Shu Liu
- Nate Lust
- Robert Lupton
- Russell Owen
- John Parejko
- Paul Price
- Meredith Rawls
- David Reiss
- Pim Schellart
- Jonathan Sick
- Colin Slater
- Ian Sullivan
- John Swinbank
- Michael Wood-Vasey
- *plus many more on the broader DM team*



Image Subtraction Algorithms

presentation and notation follow [this](#)
Lupton talk

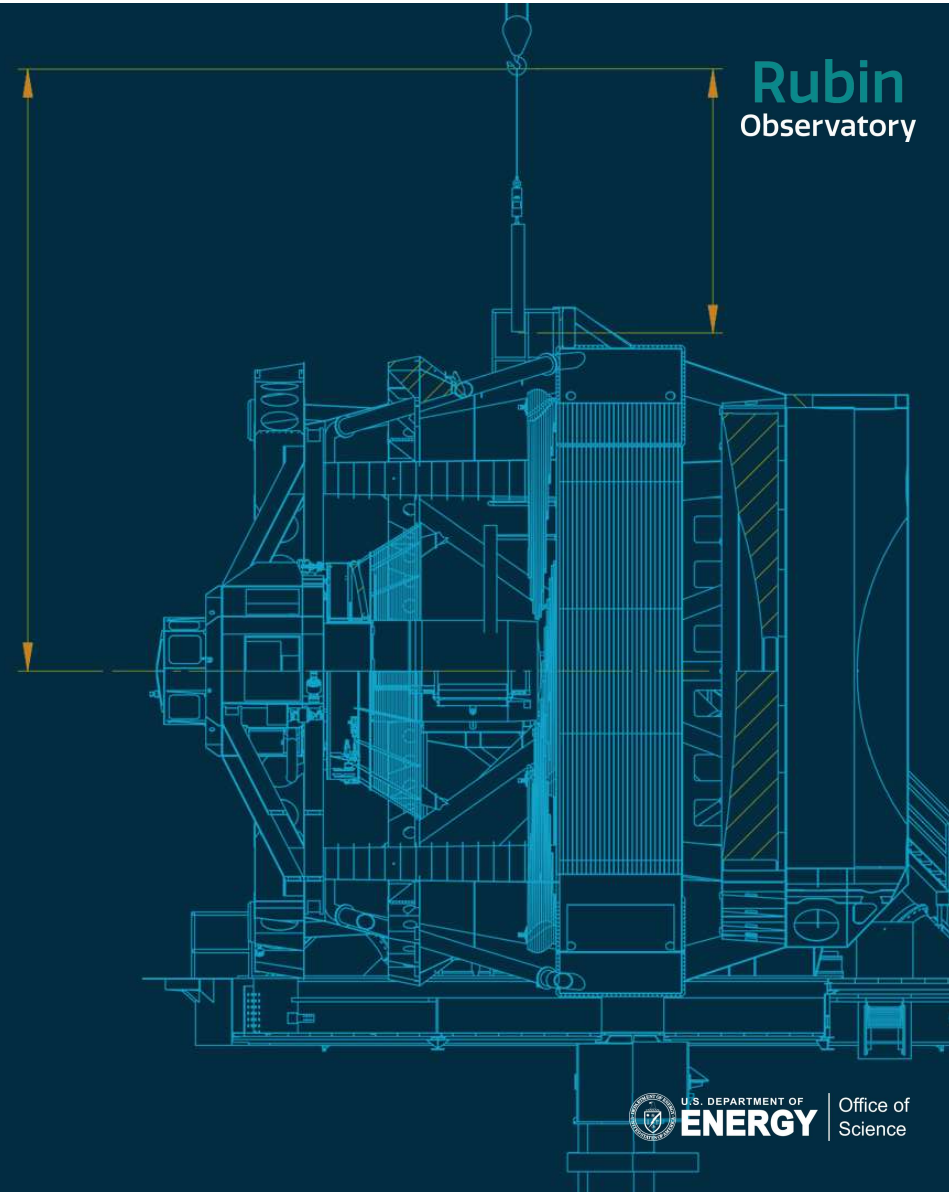
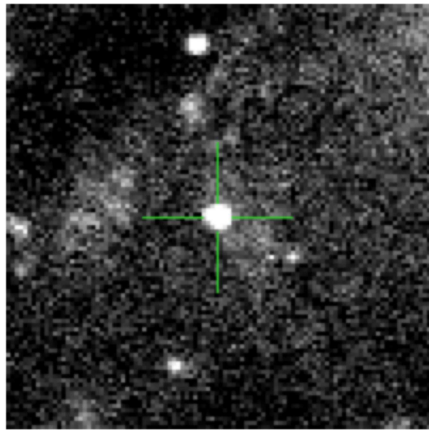
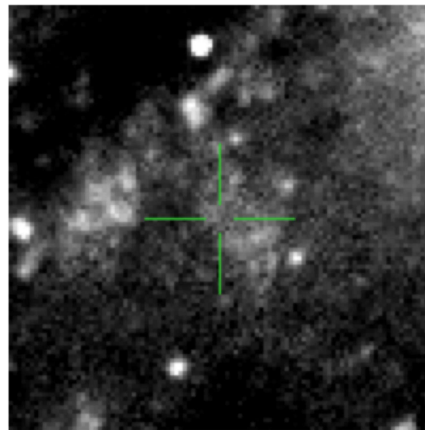


Image subtraction attempts to find sources that are changing.



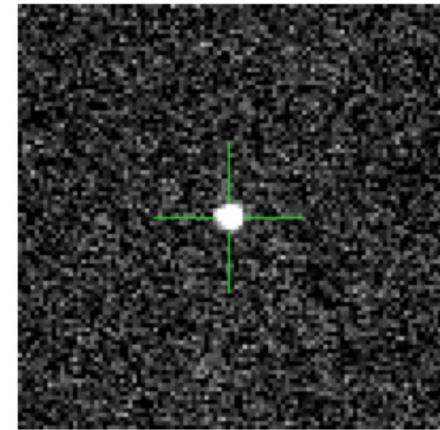
Science image

-



Template image

=



Difference image

Less sensitive to crowding, galaxy light, source association, etc. than measuring fluxes of sources on each image and comparing catalogs.
Less complex than forward modeling.

For ground-based surveys we have to account for PSFs that change from image to image.

One option is to PSF-match the images by computing an appropriate convolution kernel in Fourier space, degrading to the resolution of the worse-seeing image (e.g., Ciardullo+90, Phillips & Davis 95).

$$I'_2(k) = I_2(k) \frac{\phi_1(k)}{\phi_2(k)}$$

$$A_1 - A_2 = \frac{\sum_i (I_{1,i} - I'_{2,i}) \phi_i}{\sum_i \phi_i^2}$$

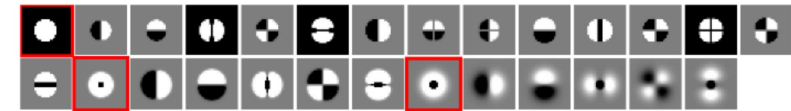
But this requires very good knowledge of the PSF, which may be difficult in crowded fields, and care to avoid numerical instability in the division.

Alard & Lupton 1998 model the convolution kernel as a series of basis functions.

Defining the convolution kernel as:

$$I'_2 = \kappa \otimes I_2 \quad \text{where} \quad \kappa = \sum_r a_r B^r$$

and B^r are a set of basis functions



in the background-dominated regime we can use least-squares fitting to determine the kernel basis function coefficients.

LDM-227

$$\left| \frac{I_1 - \sum_r a_r (B^r \otimes I_2)}{\sigma} \right|^2$$

This works nicely if the template is noise-free and the science image has better seeing than the template.

It also allows for spatial variations in the PSF as well as background matching.

Zackay, Ofek, and Gal-Yam (2016) recognized that classical A&L is not optimal if the template is noisy.

They proposed an alternative algorithm (now widely called “ZOGY”) in Fourier space:

$$\hat{D} = \frac{F_r \hat{P}_r \hat{N} - F_n \hat{P}_n \hat{R}}{\sqrt{\sigma_n^2 F_r^2 |\hat{P}_r|^2 + \sigma_r^2 F_n^2 |\hat{P}_n|^2}}$$

- fully symmetric between the science and template images
- maximizes the SNR of detected point sources when both images are noisy
- requires knowledge of the PSFs (or their ratio)

The ZOGY noise-whitening approach can also be applied within the A&L framework (Reiss & Lupton 16).

See <https://dmtn-021.lsst.io/>

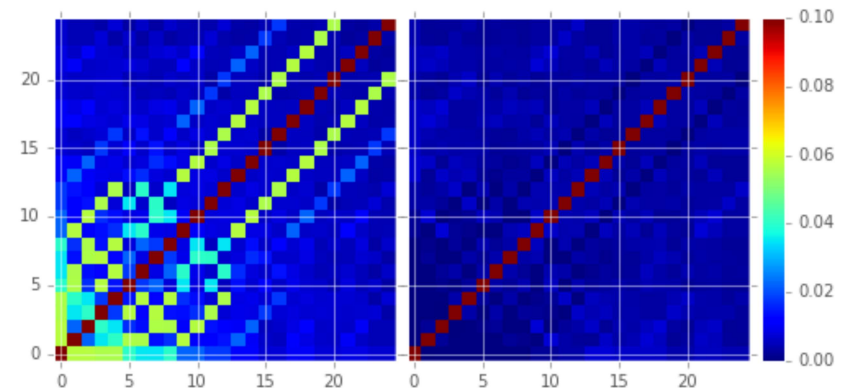
Rather than use the ratio known PSFs, retain the use of basis functions, but whiten the noise in k-space:

$$D(k) = [I_1(k) - \kappa(k)I_2(k)] \sqrt{\frac{\bar{\sigma}_1^2 + \bar{\sigma}_2^2}{\bar{\sigma}_1^2 + \kappa^2(k)\bar{\sigma}_2^2}}$$

which is identical up to normalizations to the ZOGY expression when

$$\kappa(k) = \phi_1(k)/\phi_2(k)$$

- avoids need to know the PSFs directly
- removes noise covariance as expected



All of these algorithms are implemented in the LSST Science Pipelines.

Classical Alard & Lupton

- kernels: spatially varying sum-of-Gaussians, or regularized delta-function (pixel) basis

ZOGY

- including piecewise-constant segmentation to handle spatial PSF variation

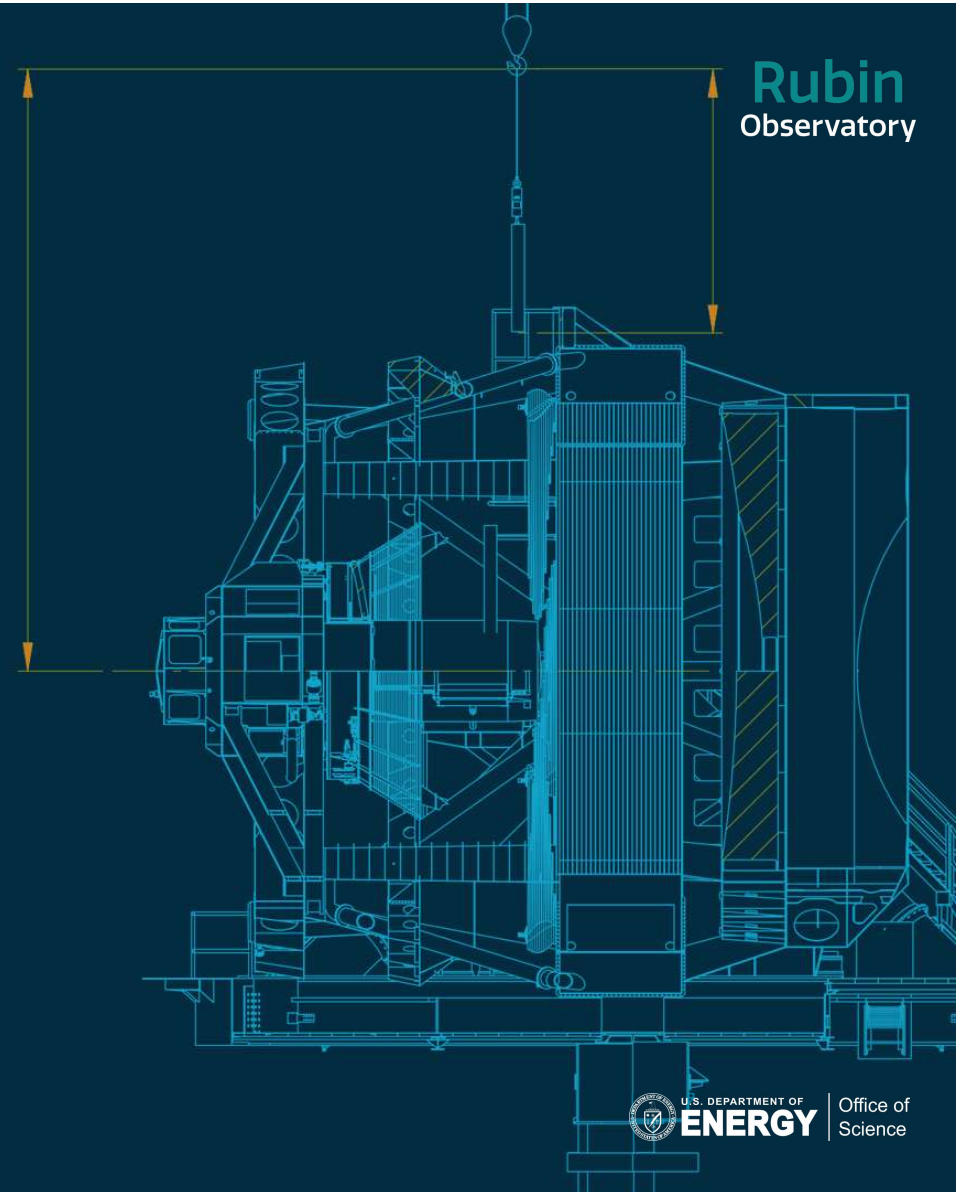
Decorrelated Alard & Lupton

Until recently implementations of both ZOGY and Decorrelated A&L had bugs in their DFT implementation—fixed in [DM-21868](#)

- Results shown today are with the corrected implementation



Other factors



Good templates are required for effective image differencing.

DM can produce a wide variety of coadds (cf. Jim Bosch's talk yesterday).

We are investigating the performance impacts of various choices.

Input image selection

- Number and seeing range (SNR & resolution; impact on artifact rejection ([DMTN-080](#)))
- Temporal range (minimizing proper motion effects vs. more inputs for DCR models)

Handling PSF discontinuities

- PSF-matching? careful bookkeeping (e.g., cell-based coadds?)

Algorithm

- direct, PSF-matched, or decorrelated



We are exploring options for template generation in the first year of LSST operations.

No all-sky DRP-produced templates are available prior to DR1.

Several options are outlined in [DMTN-107](#); these options are under review.

- likely to use templates built from any commissioning data
- incremental template generation in Year 1 is being studied

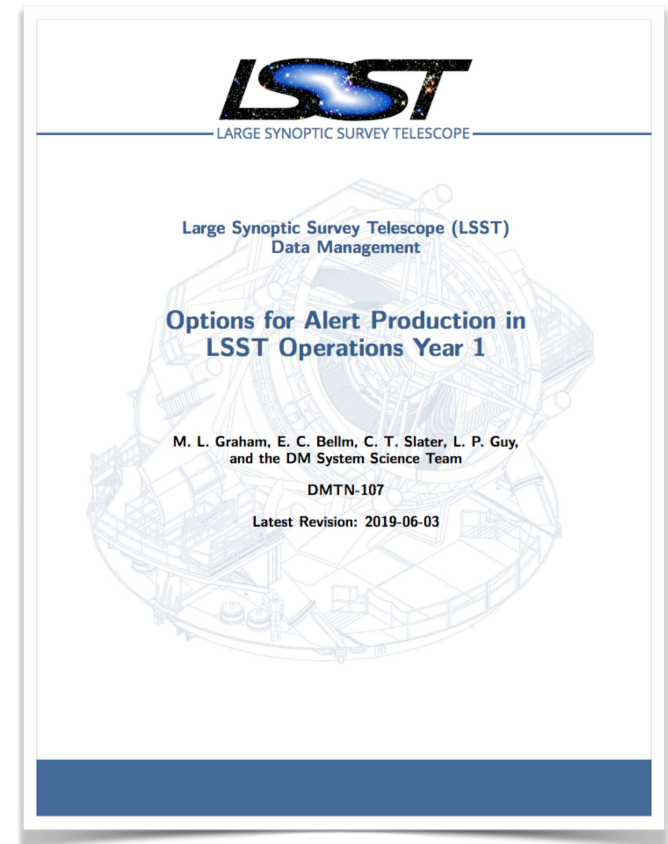
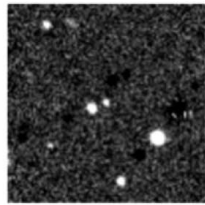
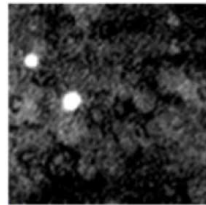


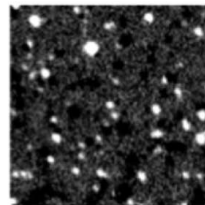
Image differencing is also sensitive to ISR, artifact rejection, and astrometric calibration.



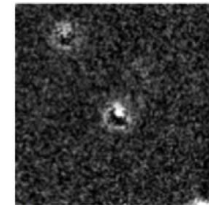
a Bad astrometry



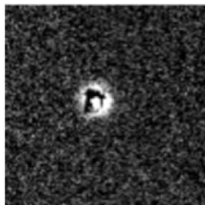
b Bad gain matching



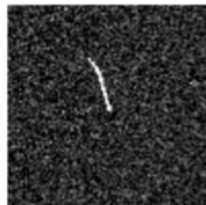
c Bad astrometry



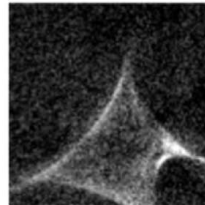
d Kernel matching failure



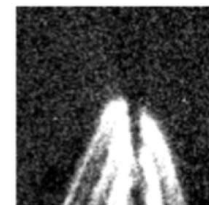
e Kernel matching failure



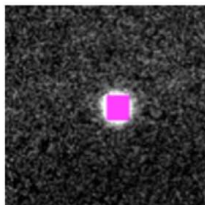
f streak



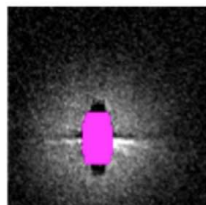
g Unmasked halo



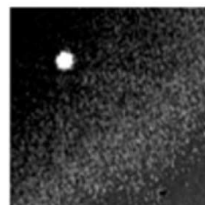
h Unmasked glint



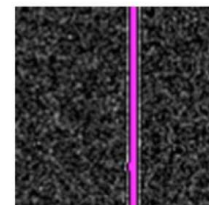
i Incomplete masking



j Incomplete masking



k Bad background matching

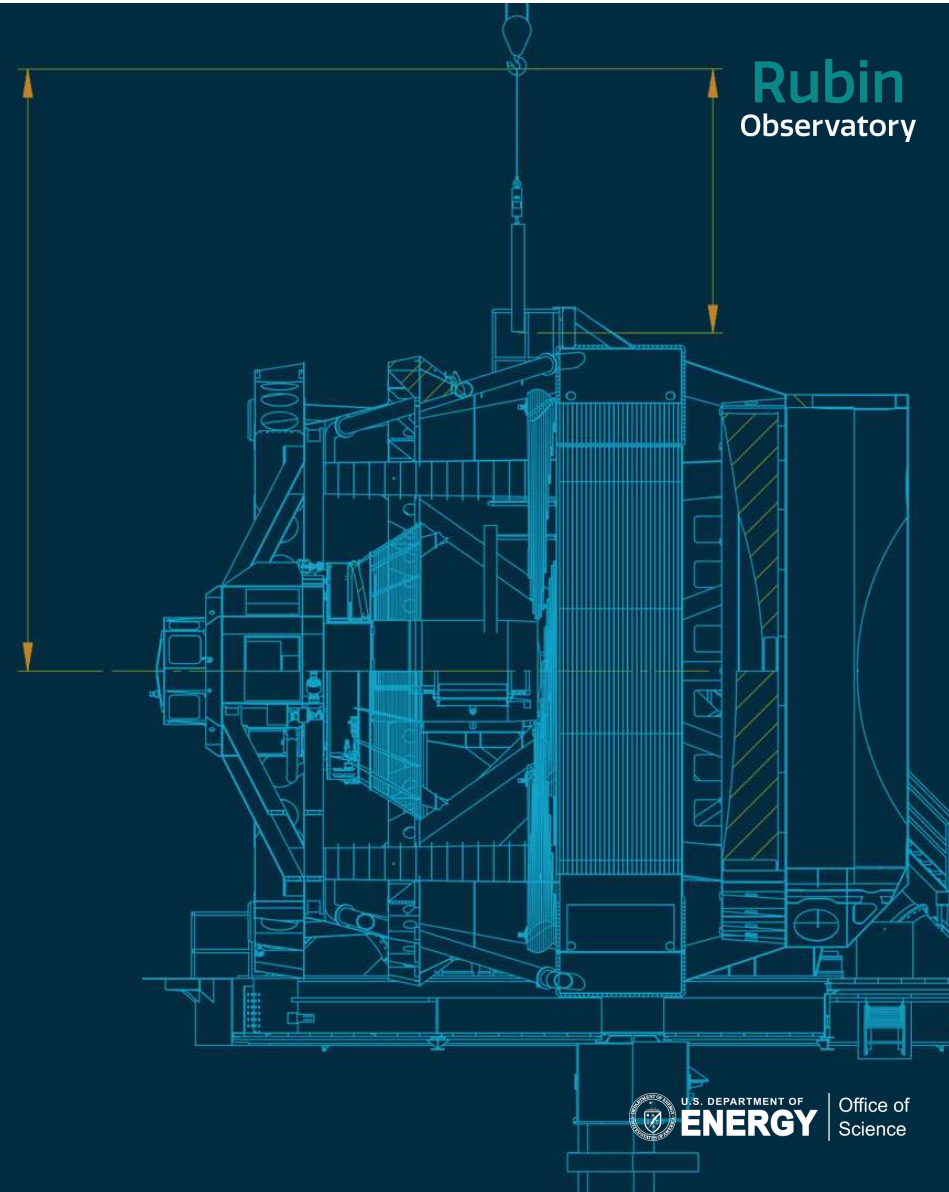


l Incomplete masking

PTFIDE
(A&L w/ pixellated basis)

Masci+17

Current Implementation and Testing



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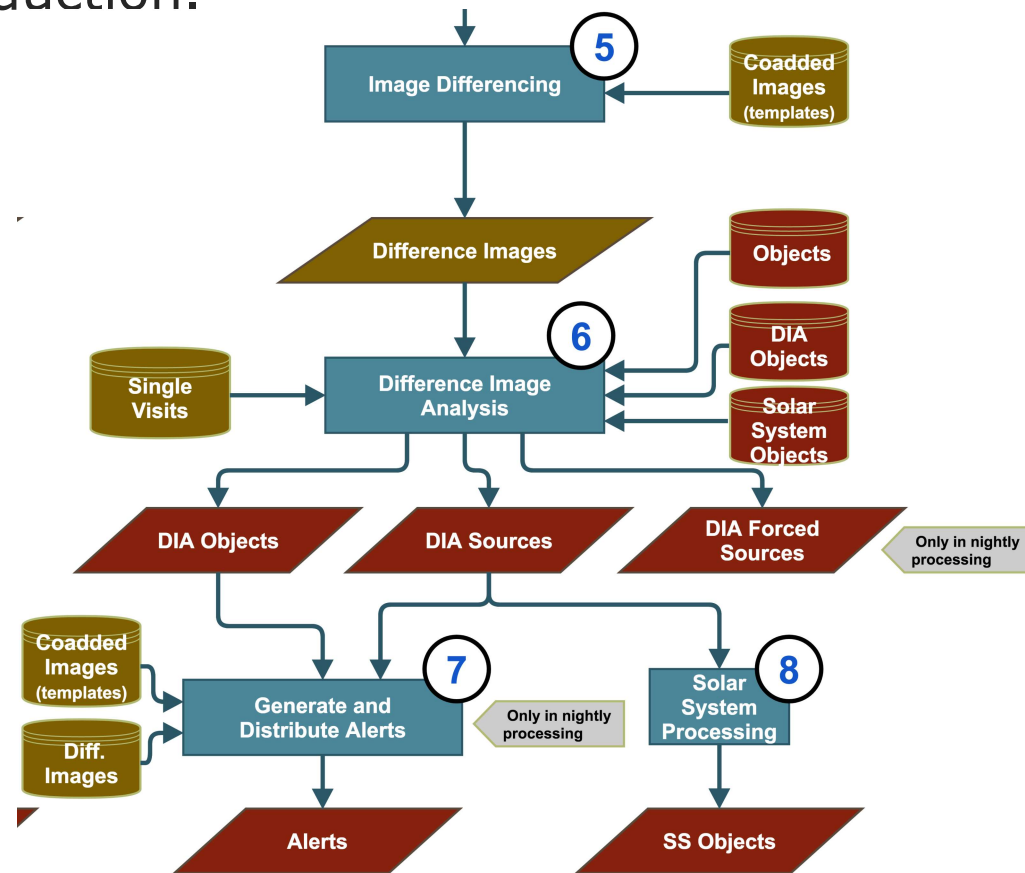


Data Management runs Image Differencing in both Alert Production and Data Release Production.

This presentation will focus mainly on implementation and testing for AP

- 60 second latency requirement between camera readout and alert transmission to brokers

DRP is expected to use the same algorithmic codebase, but integration into pipelines will differ (particularly for source association)



We are testing on a variety of precursor datasets.

DECam HITS

- 3 multi-season DECam fields, g-band, 4-5 visits/night for 1 week

HSC SSP Ultra-Deep (COSMOS)

- 1 field, grizy imaging, 30-300 visits/band
- HSC has an ADC—no DCR

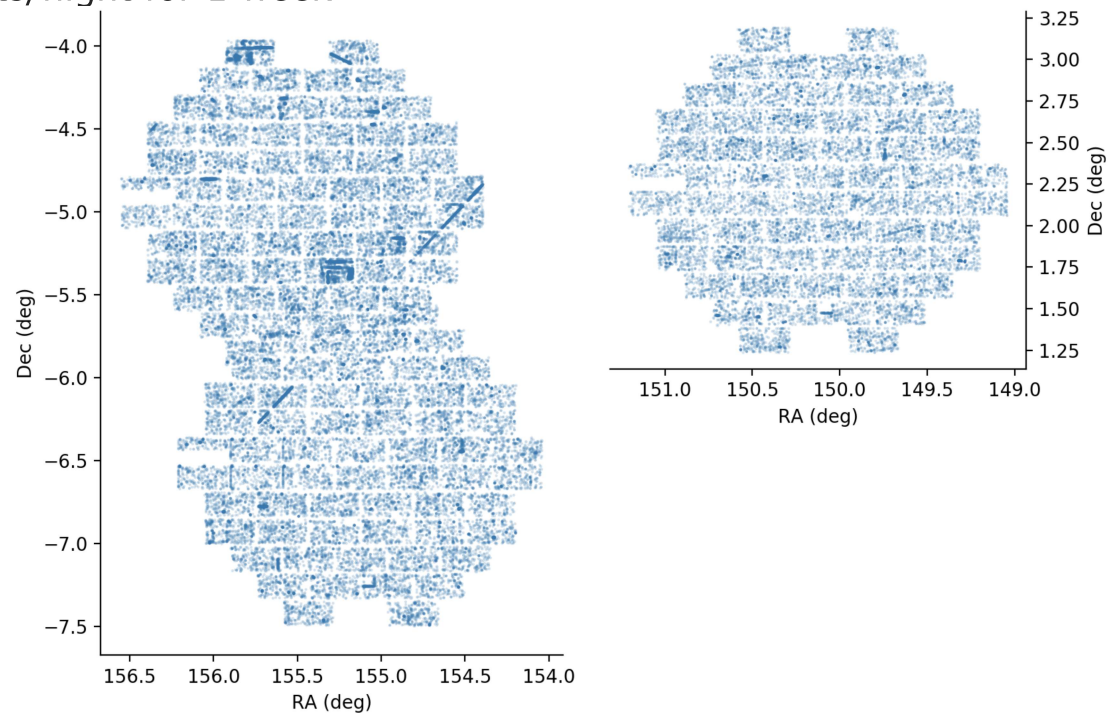
HSC, DECam Bulge data

- crowded field analysis

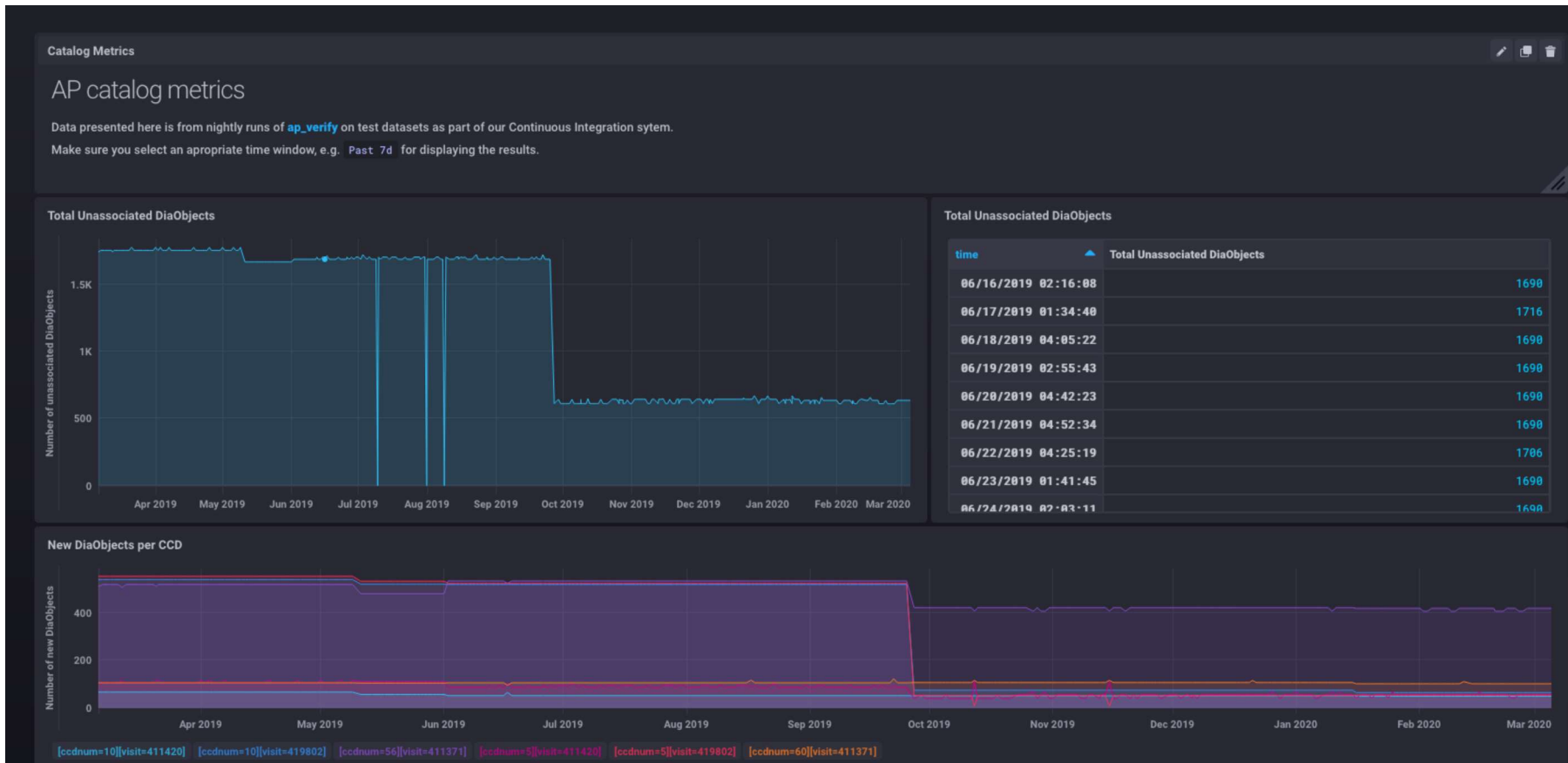
DES SN fields

- weekly griz observation sequences

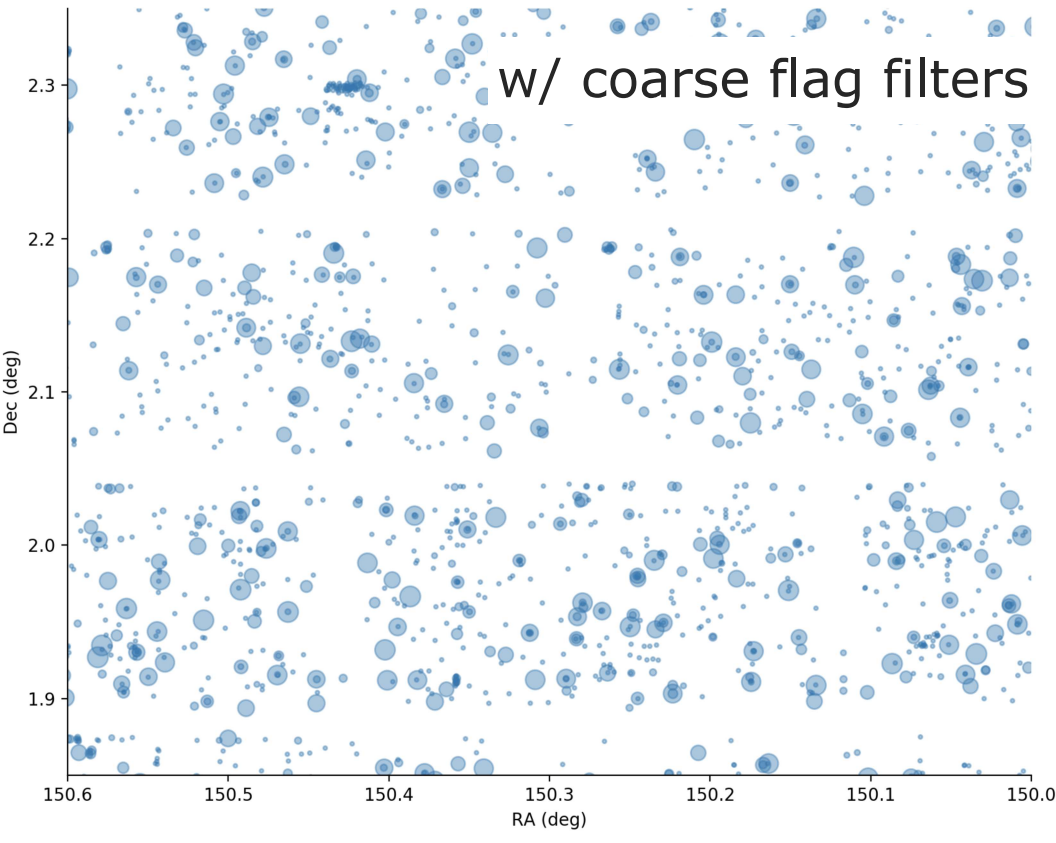
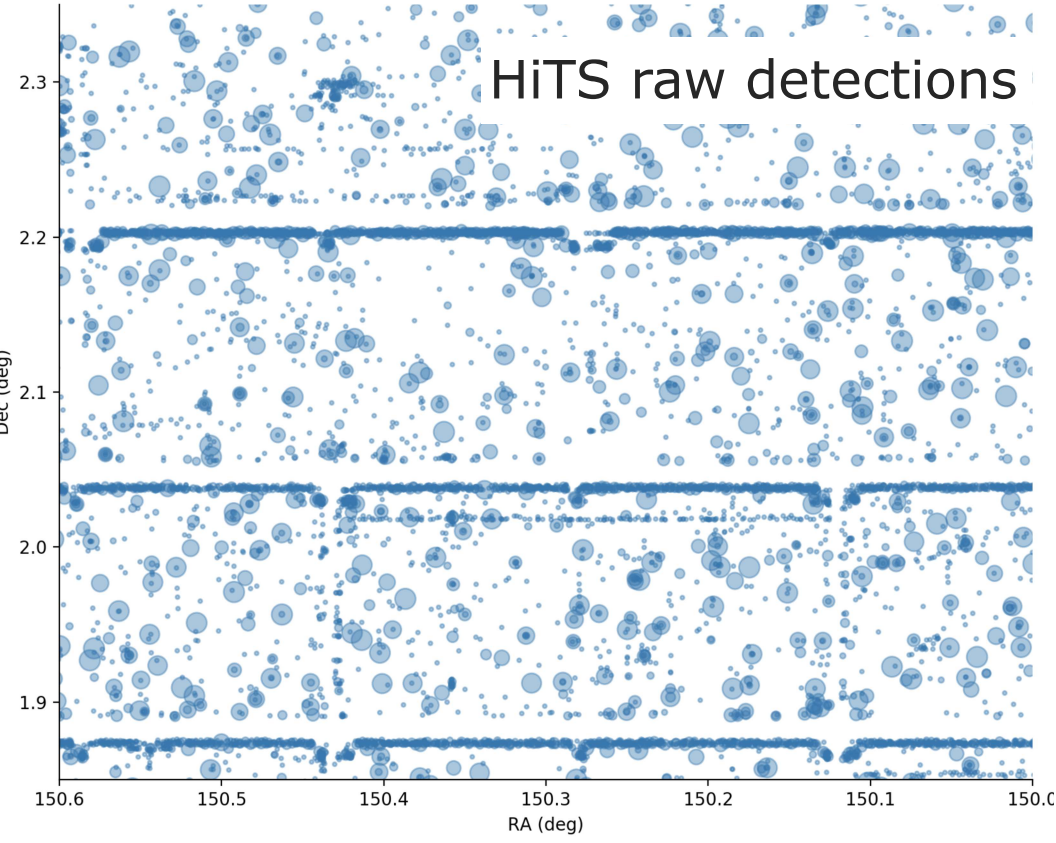
all datasets have small dithers relative to LSST



We monitor high-level performance metrics through daily continuous integration.



Monthly reprocessing enables us to identify larger-scale effects.



Alert Production has high-level requirements on our knowledge of completeness and purity.

OSS-REQ-0353:

Description	Value	Unit	Name
SNR threshold at which the above are evaluated	6	unitless	transSampleSNR
Minimum average purity for transient science	95	percent	transPurityMin
Minimum average completeness for transient science	90	percent	transCompletenessMin

OSS-REQ-0354:

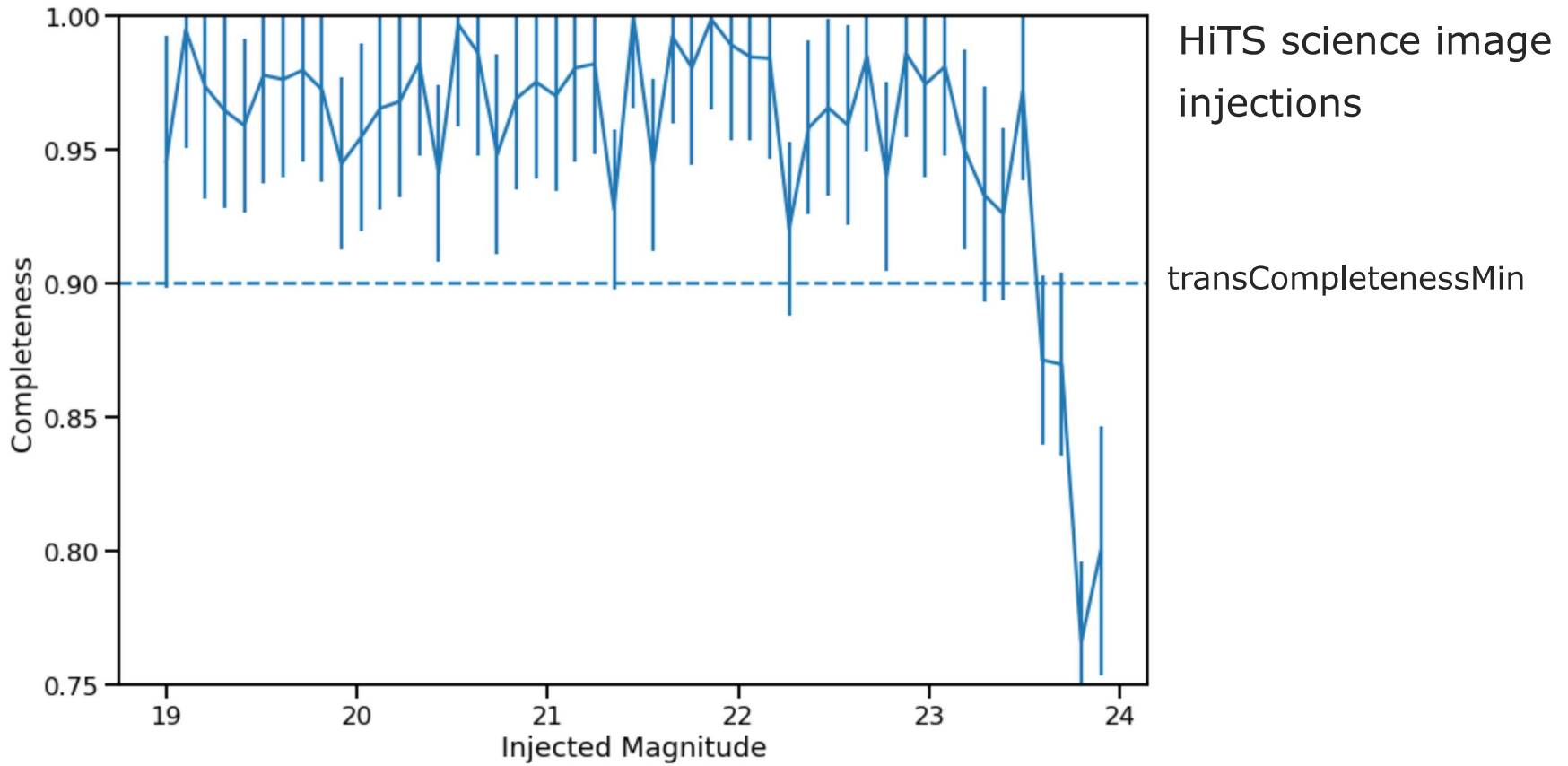
Description	Value	Unit	Name
Minimum average completeness for Solar System object discovery	99	percent	mopsCompletenessMin
Minimum average purity for Solar System object discovery	50	percent	mopsPurityMin

Verifying these will benefit from an ML algorithm, which can also help us improve the pipeline.

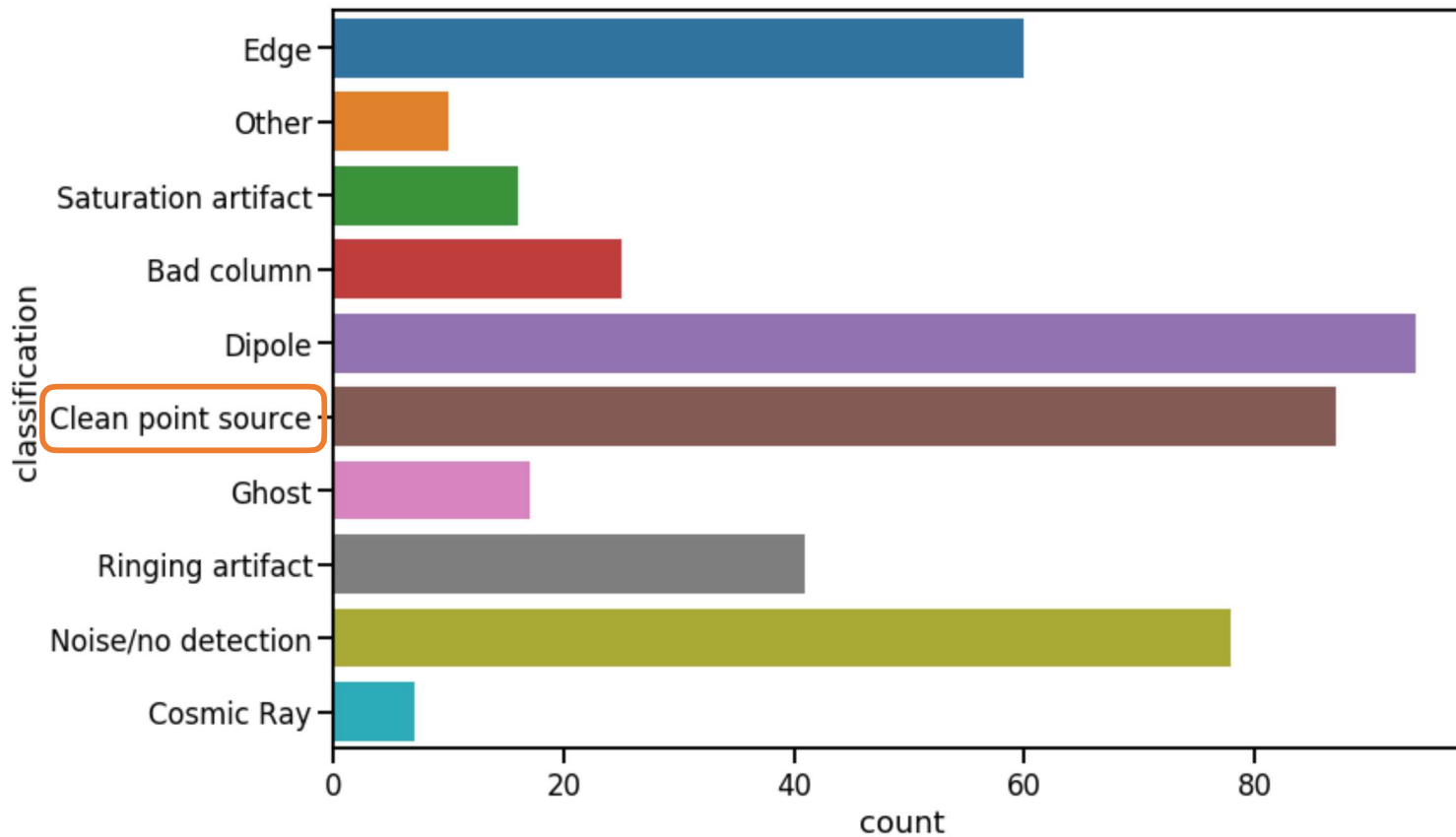


<http://ls.st/LSE-030>

We measure completeness by injecting fake point sources.

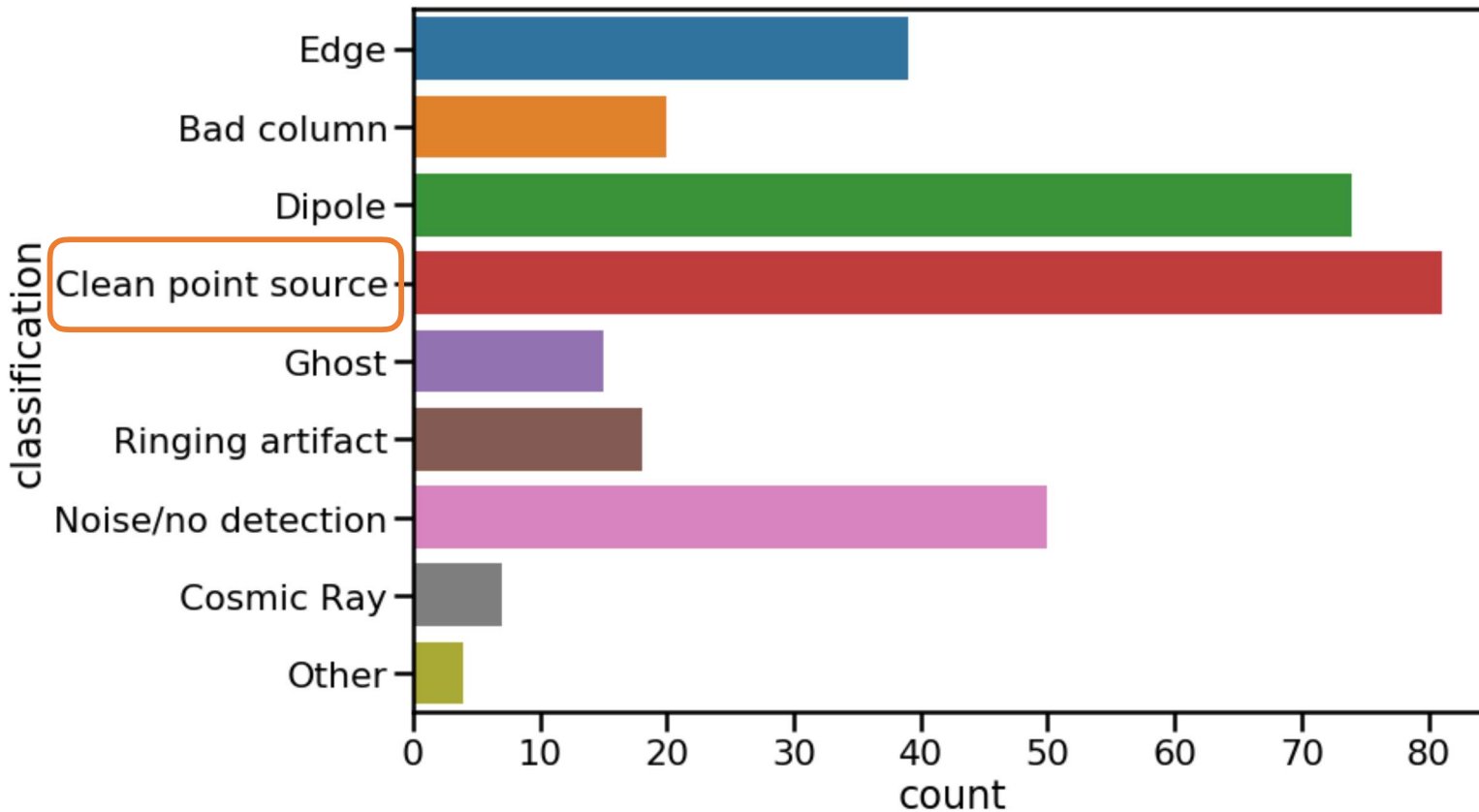


We measured purity by manually classifying several hundred random diaSources from the most recent HiTS processing run.



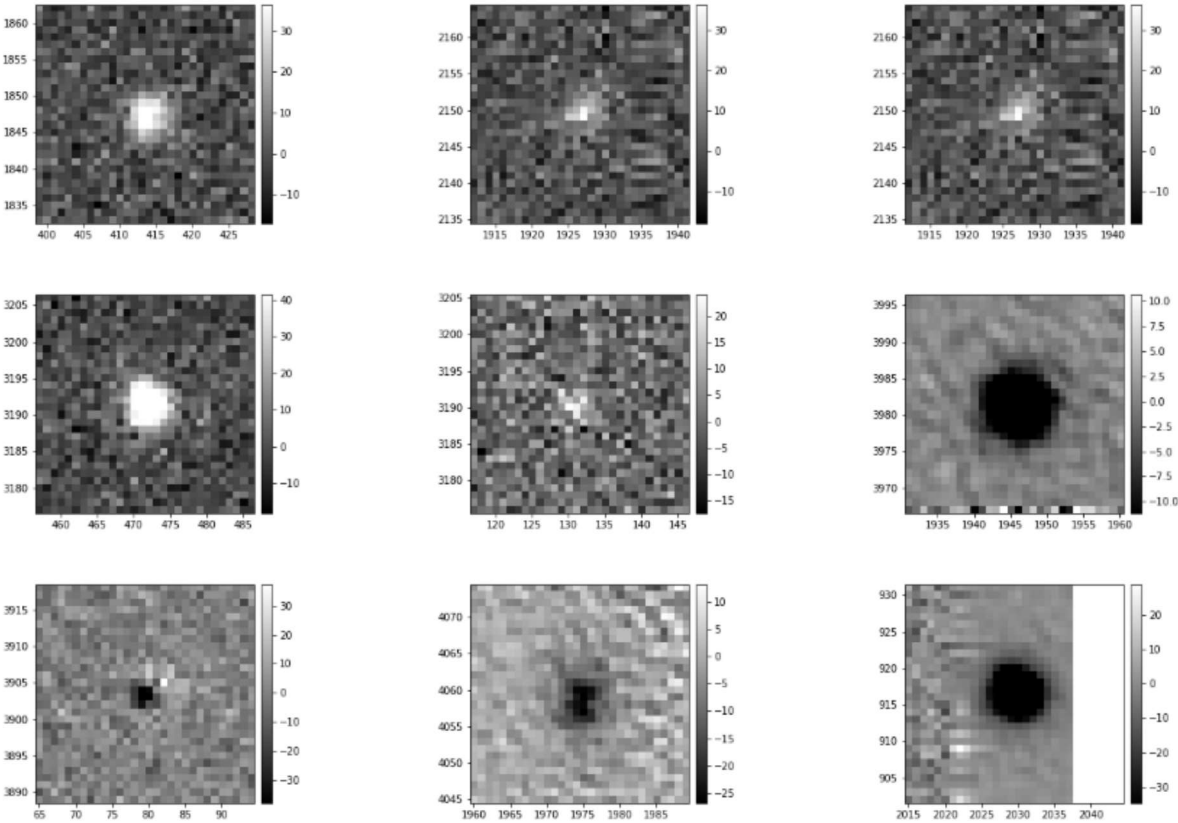
raw detections

We measured purity by manually classifying several hundred random diaSources from the most recent HiTS processing run.

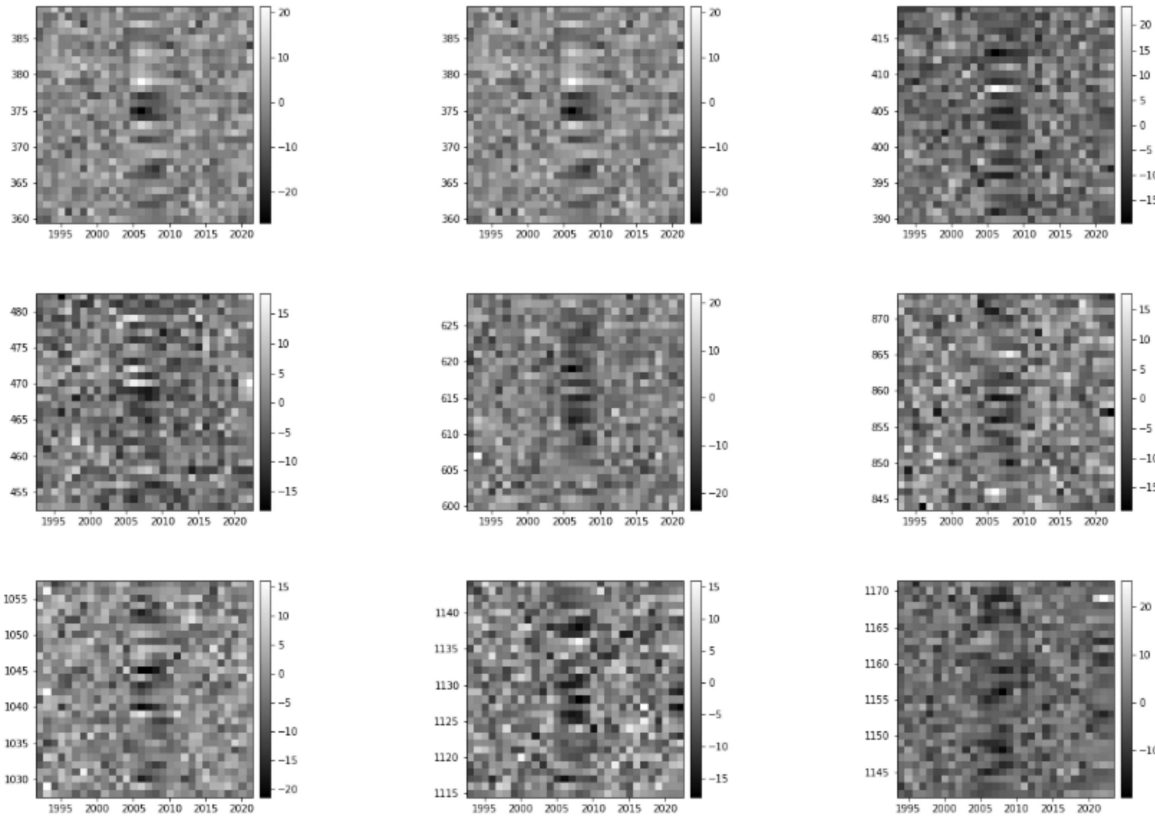


filtered for edge
and saturation
flags

There are lots of solid detections...

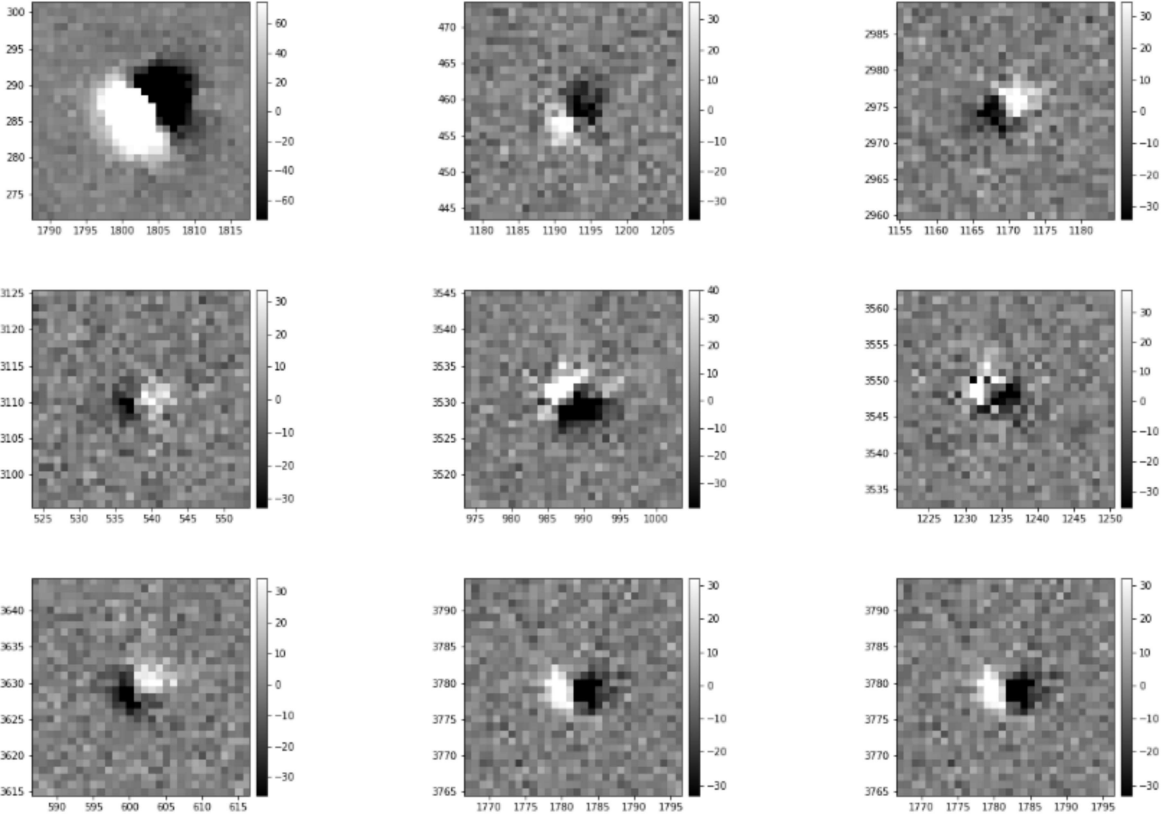


Detections on interpolated bleed columns...



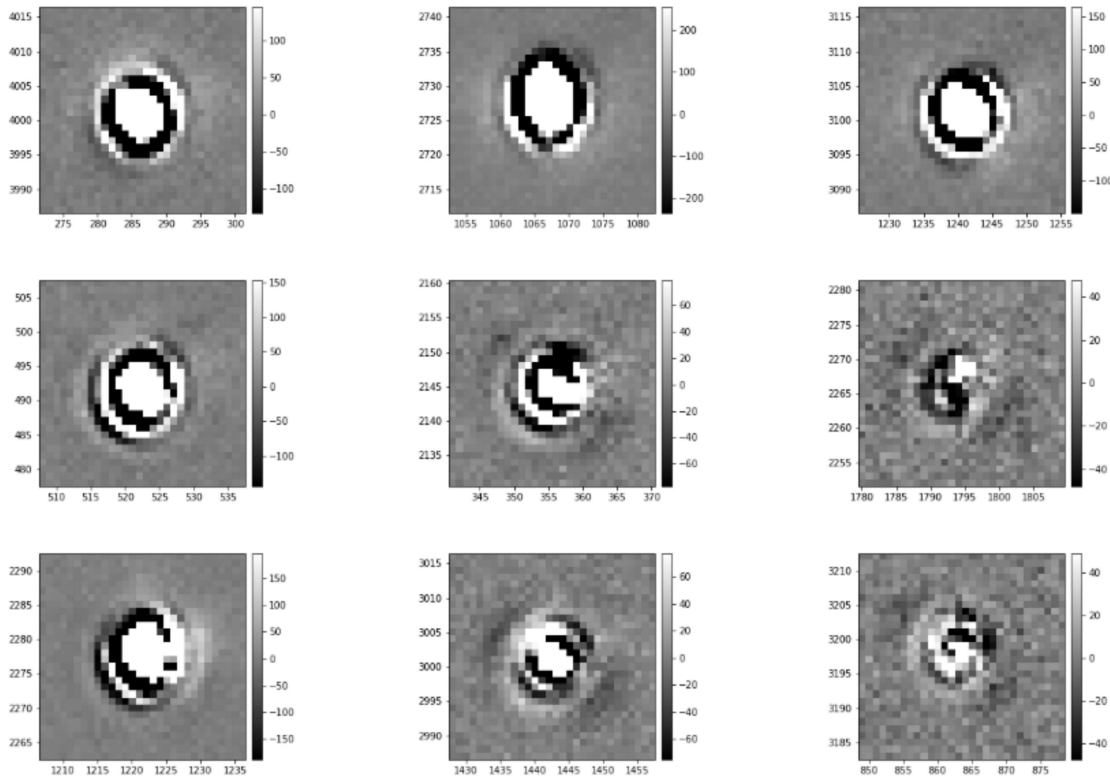
*address by masking
appropriate flags*

Dipoles...



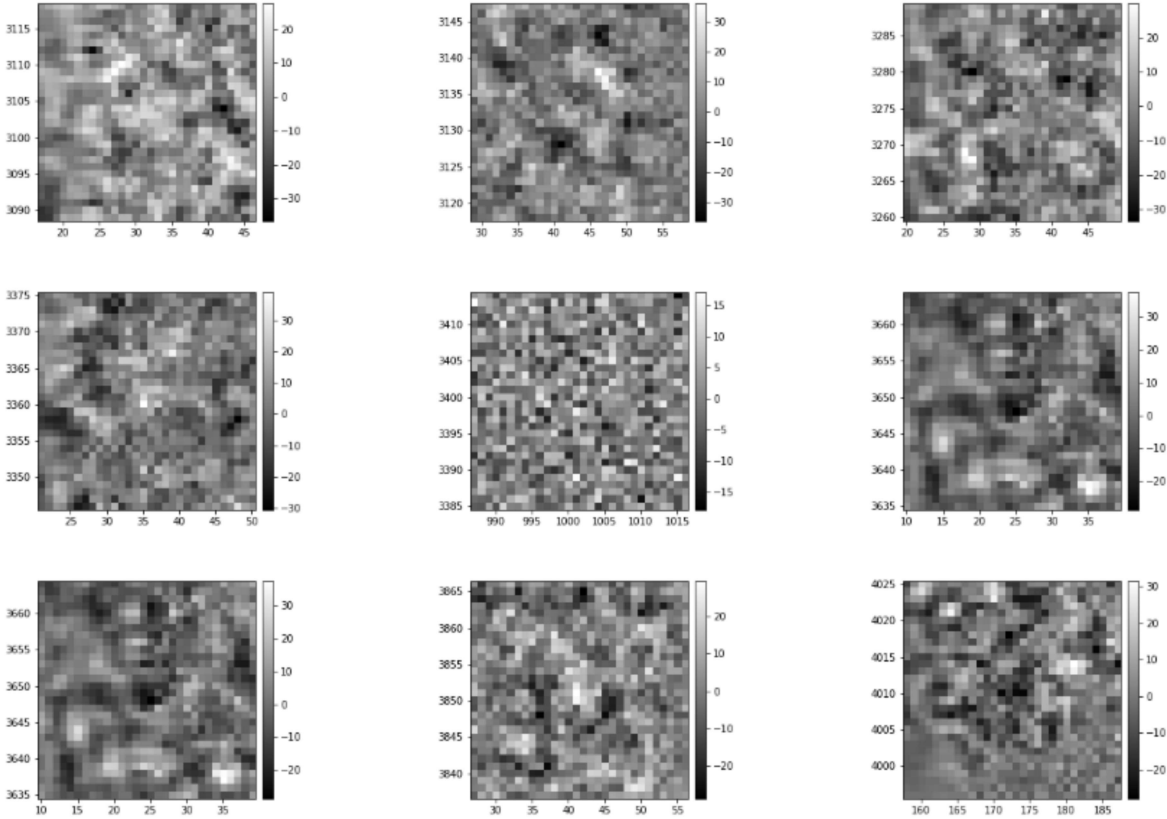
*address by improving
astrometric calibration*

Kernel deconvolution artifacts...



*address with
algorithmic
improvements to
differencing*

...and noise detections.



*debug potential
problems with variance
planes*

How do the raw detection rates compare to other surveys?

PS1 (A&L):

- raw artifact/non-artifact ratio of 10:1-50+:1 (Denneau+13)

DES Y1 (A&L; HOTPANTS):

- raw artifact/non-artifact ratio of 13:1 before ML (Goldstein+15)

ZTF (ZOGY):

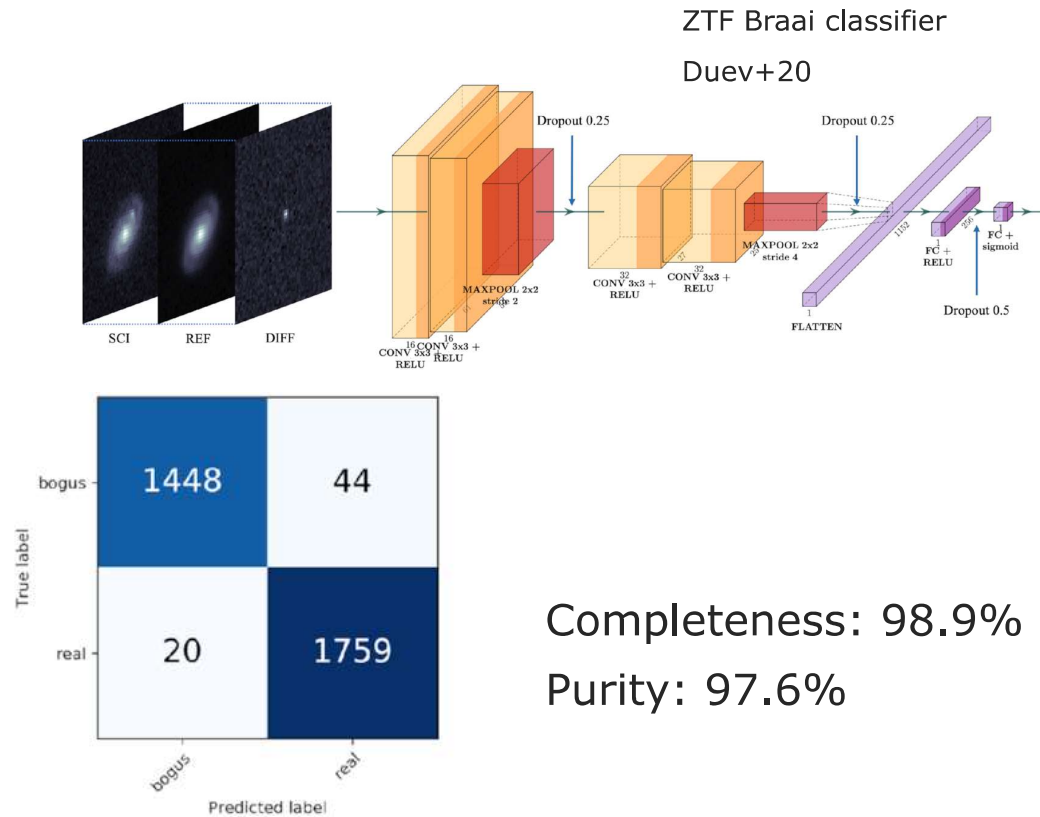
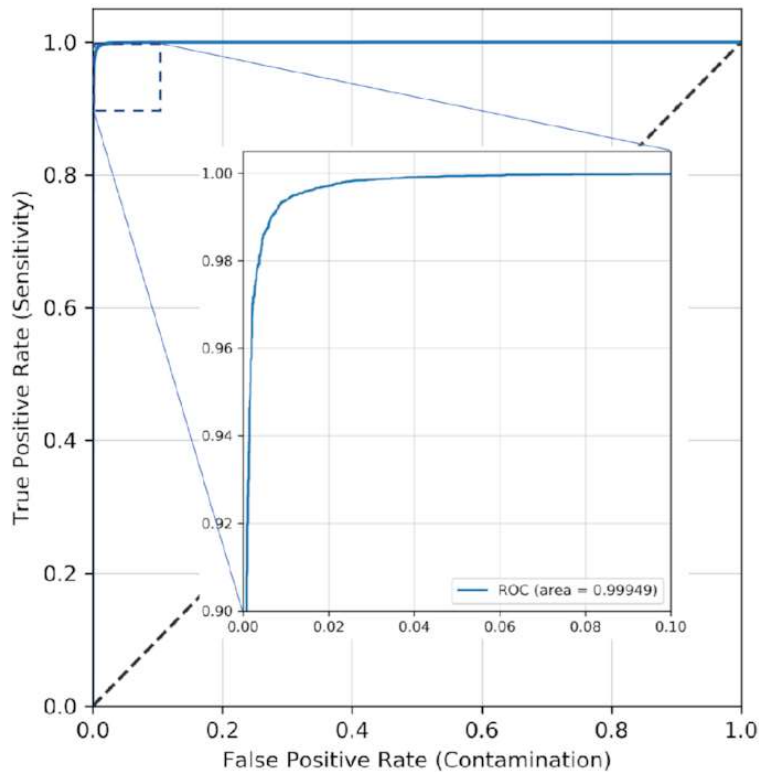
- raw artifact/non-artifact rate between 2.5:1 and 25:1

Current Science Pipelines (decorrelated A&L):

- HiTS: raw artifact/non-artifact rate $\sim 4:1$ (no filtering), $\sim 3:1$ (coarse flag filtering, minor loss of completeness)



Machine Learning algorithms run on precursor surveys have demonstrated the required performance.



Completeness: 98.9%
Purity: 97.6%

We will continue to refine the pipelines on precursor data as we approach commissioning.

Ongoing QA and performance tuning efforts

Process new precursor datasets

- Crowded fields
- larger scale runs
- DESC DC2 simulations

Push on the state of the art for difference image kernels

Production-scale fake insertion

Trailed source fitting & known SSObject attribution

Begin developing Real/Bogus infrastructure



Image Differencing is a key component of our pipelines; algorithmic development and evaluation are ongoing.

- Results are sensitive to effects at all stages of data reduction
- We have flexible pipelines with implementations of the major algorithms.
- We are performing studies with data with precursor survey and commissioning data to choose algorithms and tune parameters for best performance.
- Initial completeness and purity results are promising, although testing on data representative of the full LSST survey is needed.

