



Image Coaddition and Subtraction

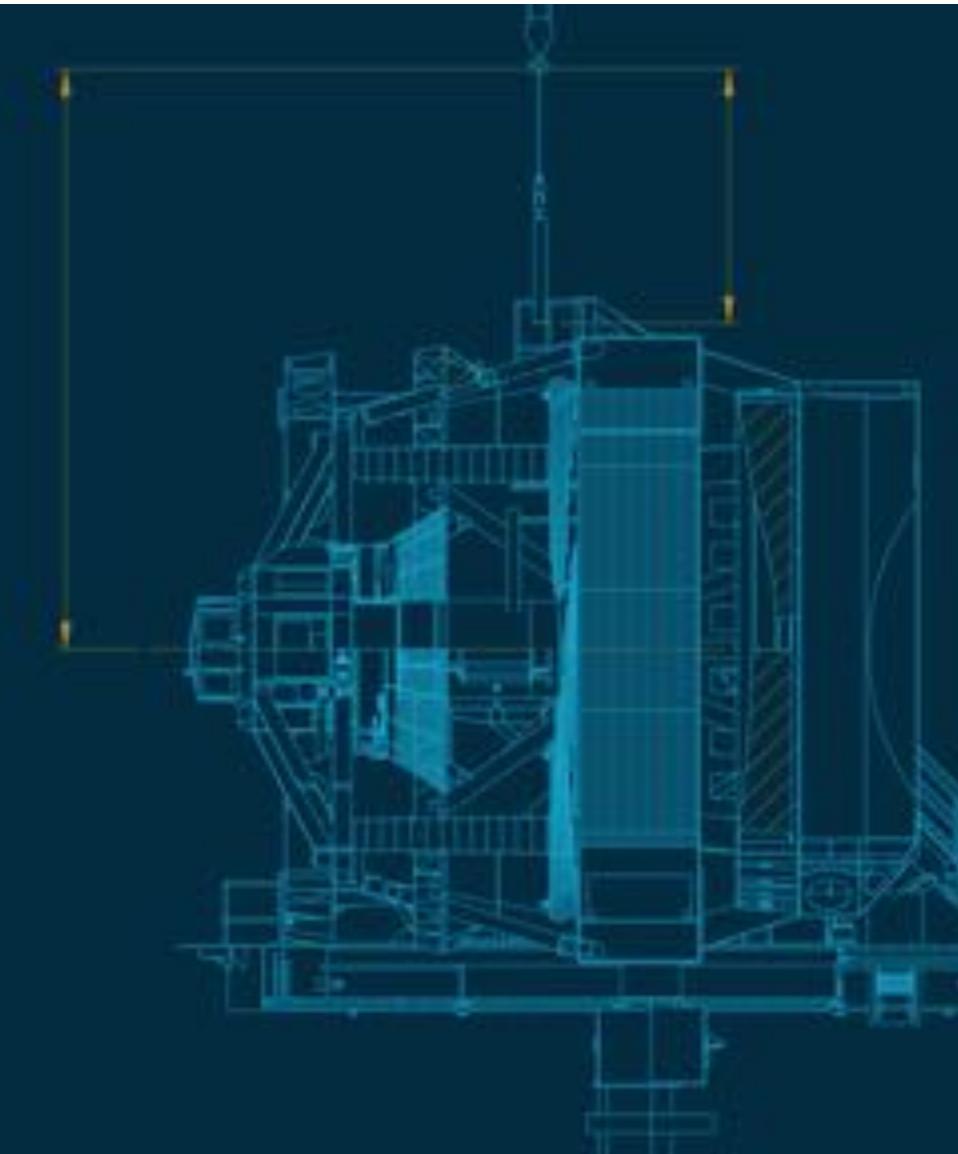
Yusra AlSayyad

LSSTC-DSFP Session 11 August 2020

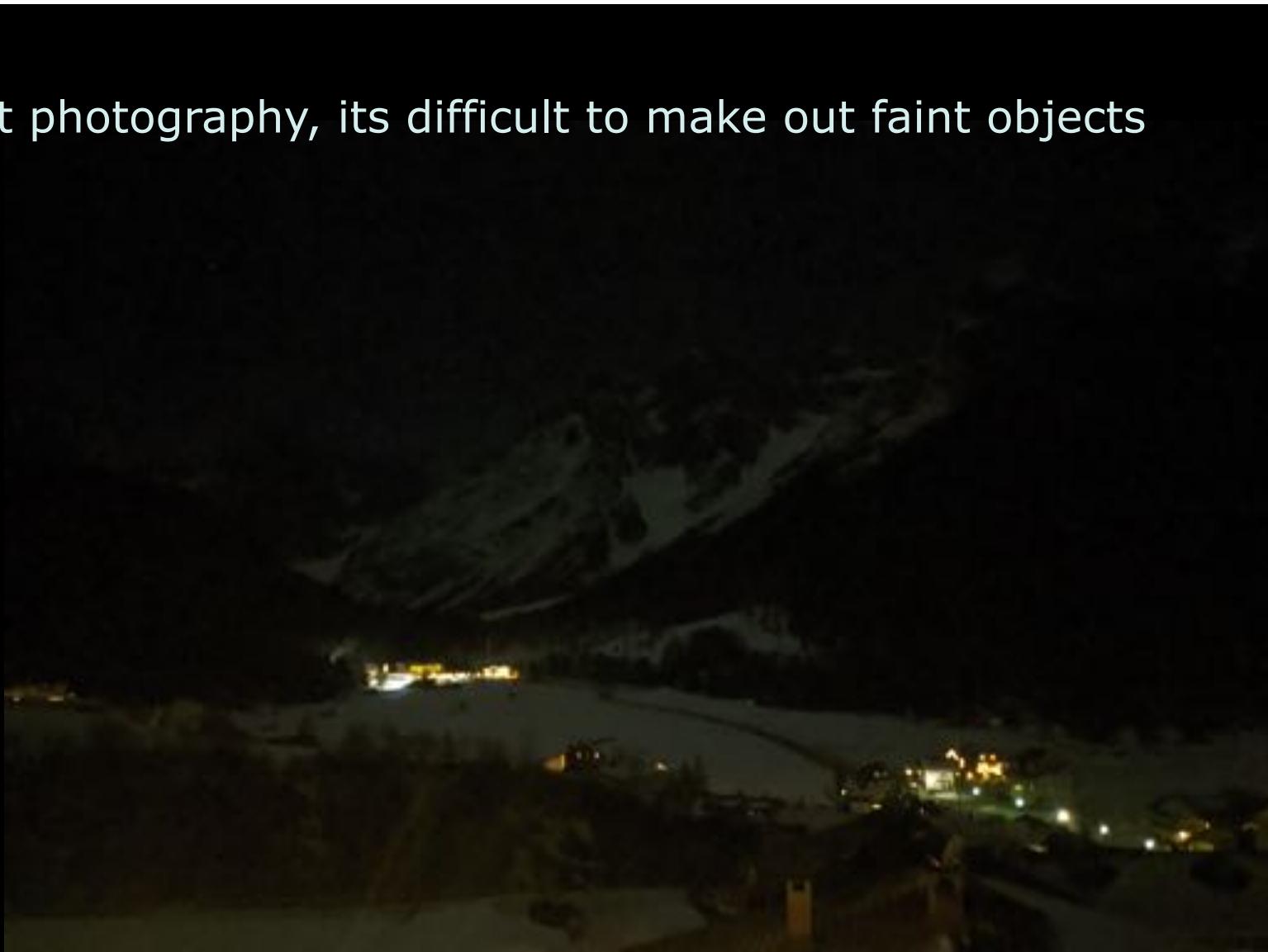
Image Credit: M. Park/Inigo Films/LSST/AURA/NSF
LSST Summit 2017

Coaddition

for deeper images



In night photography, its difficult to make out faint objects



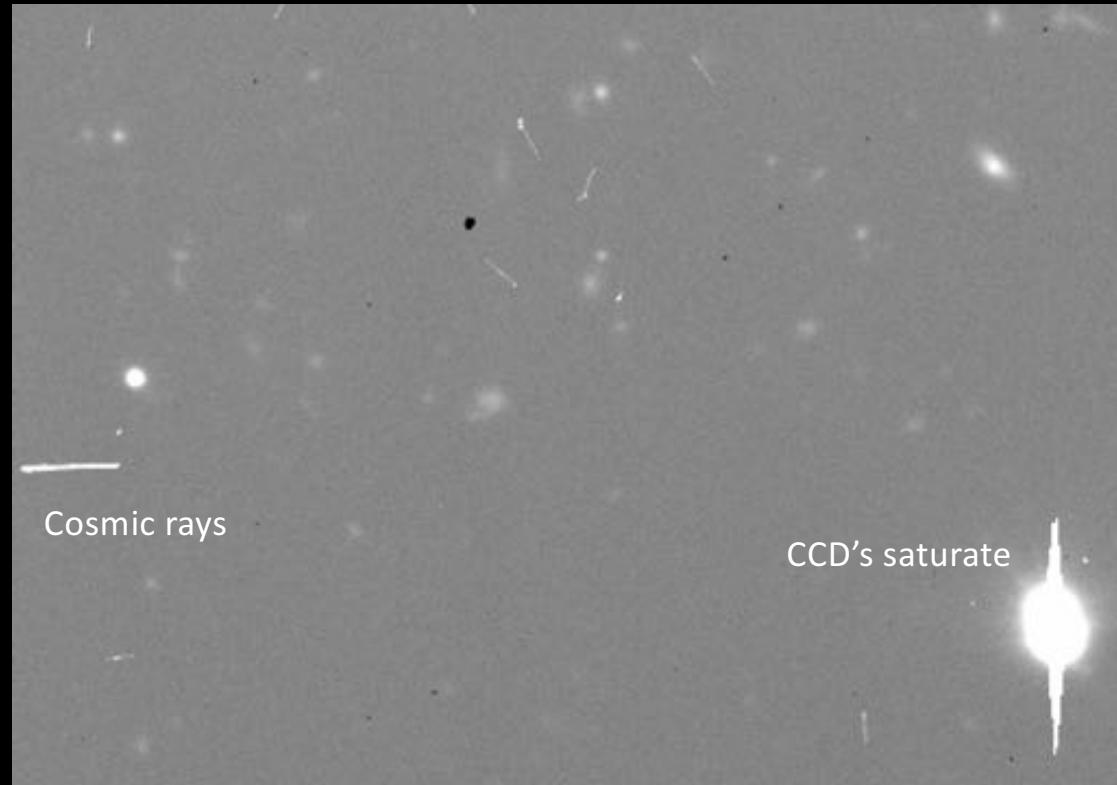
Unless you increase the exposure times



Longer exposures increase the signal-to-noise ratio (SNR)
 $\sim \text{sqrt}(\text{time})$

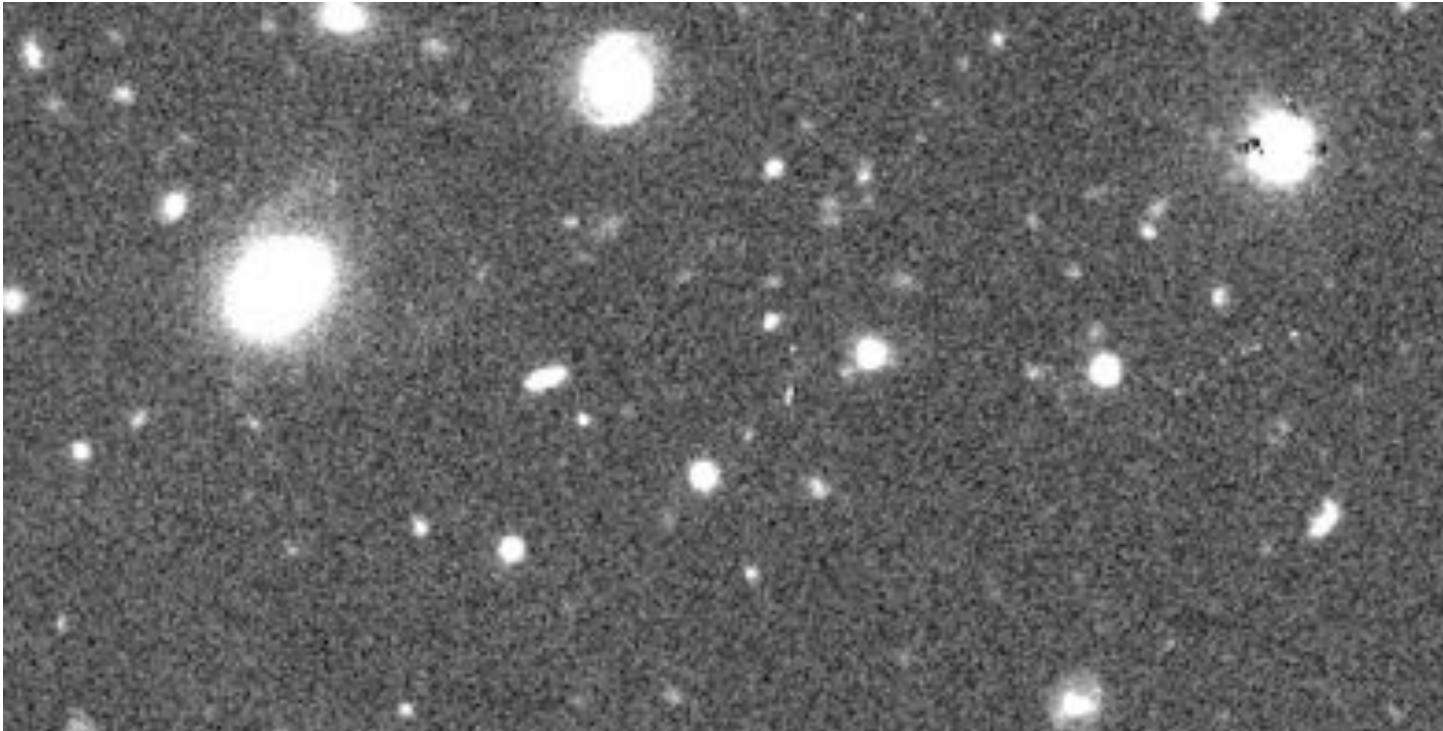


However, there is a limit to exposure times in astronomy in practice



Raw HyperSuprimeCam image
Exptime = 5 minutes

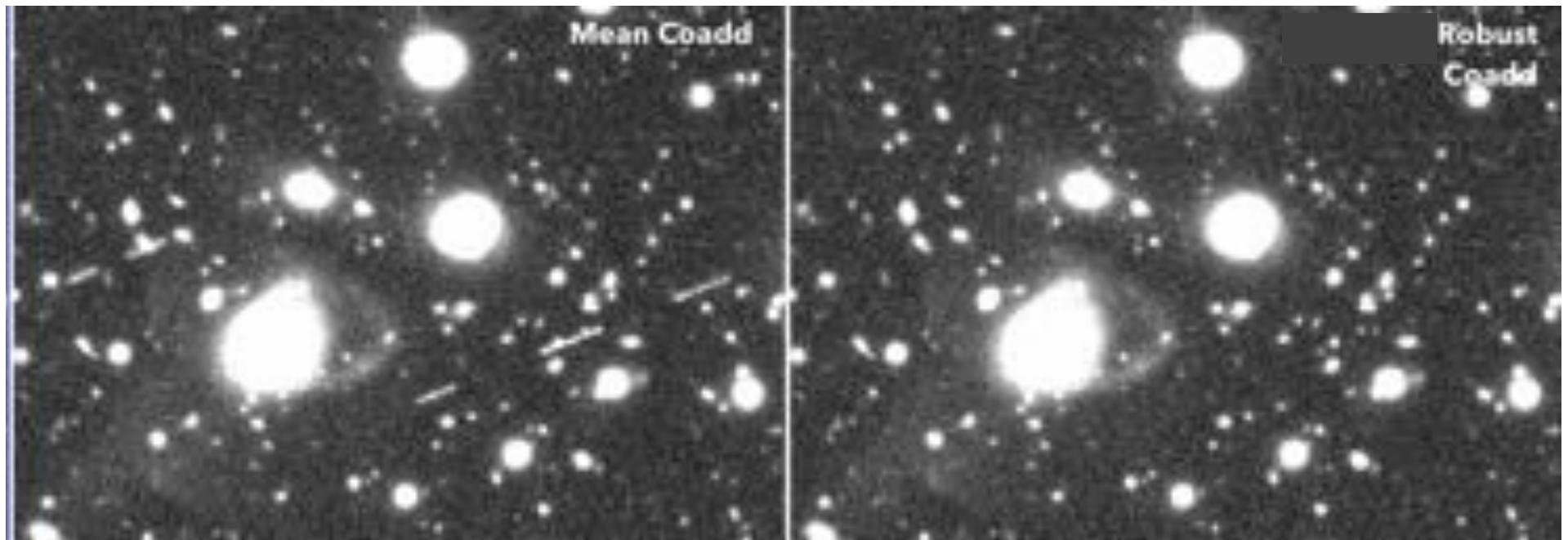
Because the sky is not static!



HSC-I COSMOS field (270s exposures)



The multiple exposures can be used to remove transients



Ask me about considerations when making coadds robust to transients and artifacts



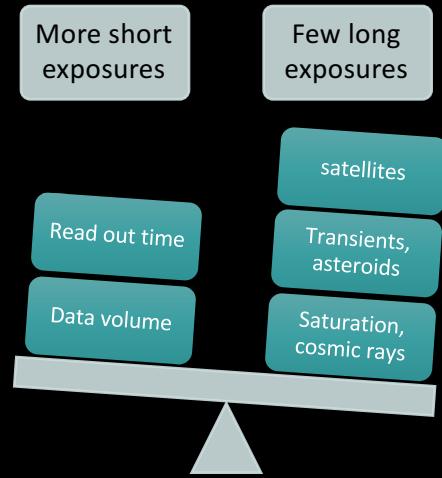
For example:

17 30s exposures of comet NEOWISE
With starlink satellites crossing

This is a **mean coadd** →
Satellites would be removed in a robust coadd.

Trade offs between many short exposures vs few long ones.

- Scales favoring shorter these days



Remember this? It's a coadd!
Many cell phone cameras have coaddition capability now



Taken with a Google
Pixel's coaddition
feature called
“NightSight”

Coadds are used for detection, measurement and templates of
the static sky for image subtraction

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How to build a coadd:

- Define the coadd projection and geometry

For each visit:

1. Resample to defined output geometry
2. Scale to coadd zeropoint
3. Match sky-levels/backgrounds

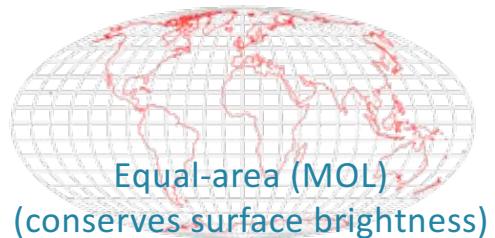
For ensemble of resampled & scaled visits:

1. Stack coadd

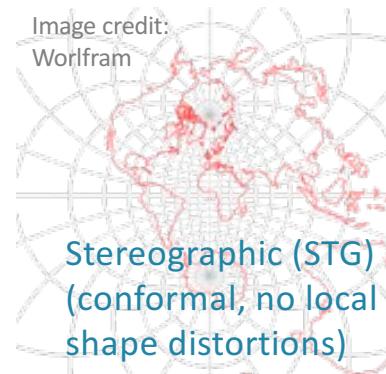


Defining the Coadd Geometry

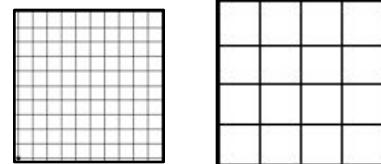
- Projection



vs.



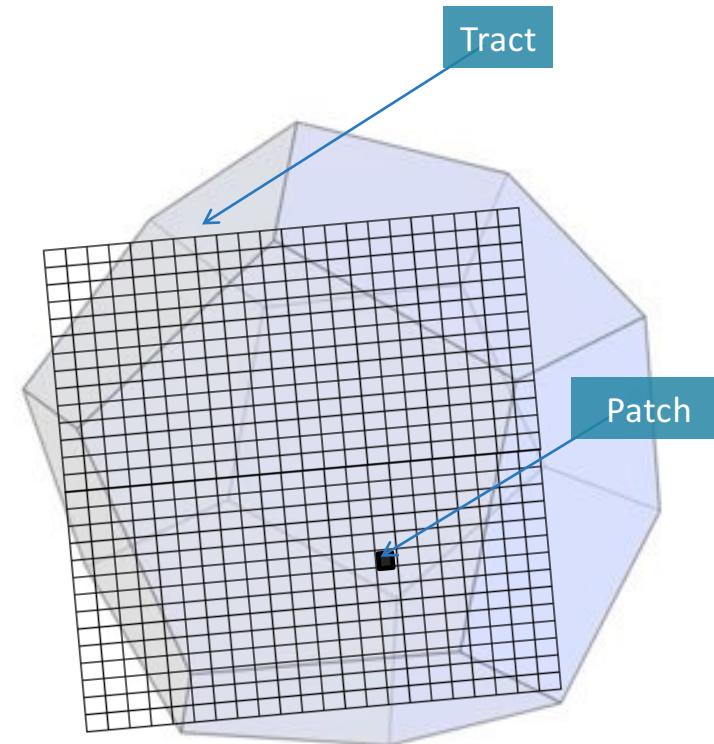
- Pixel-scale



- Image quality vs. cost
- Can optimize for depth, quality of difference imaging templates, etc
- Image geometry (tessellation of the sky)

Defining the Coadd Geometry

- For LSST, considering large coadds
 - Single projection and continuous sky-background
- Tradeoffs
 - Too big -> distortion at edges
 - Too small -> cost of overlap increases (an over



1. Resample to common WCS

- Find all images that overlap a patch
 - Coadds will be generated patch by patch
- Stitch all images per visit
- Warp/resample all visits to coadd geometry
 - Is a convolution. Most expensive step. Your laptop uses GPUs to do this.

3 visits that overlap
patch, warped to
coadd projection



Nearest Neighbor



Bilinear



Bicubic



Lanczos-3



Cubic B-Spline



Sinc



Interpolation/resampling kernels. Image credit: Getreuer+2011



2. Scale all visits to common zeropoint

- Zeropoint varies spatially over 3.5 degree field of view
- Photometric self-calibration (e.g. Burke+17)
- Use 2D model of zeropoint over the focal plane as multiplicative scale factor.

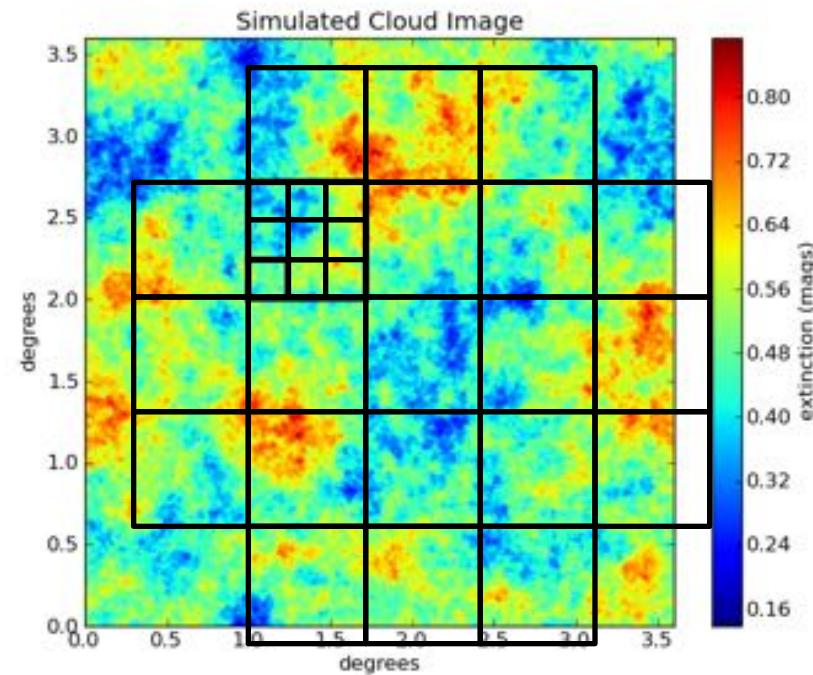


Figure: Realization of a 0.5 mag cloud based on a structure function of observed clouds and some realistic assumptions about cloud-size and velocity. (image credit: Lynne Jones)

3. Compare epochs to remove additive components artifacts and backgrounds

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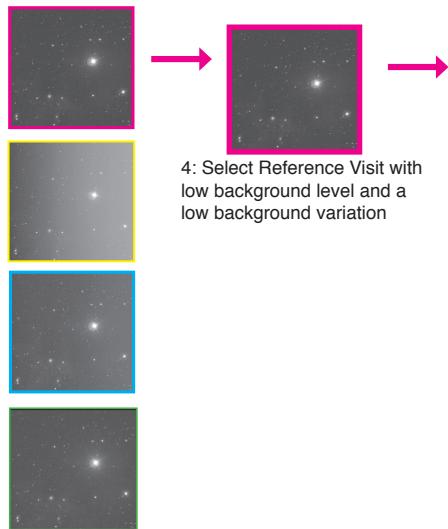
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Match backgrounds instead of pre-subtracting them

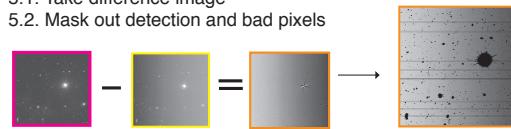
1. Resample input images to a common projection.
2. PSF-Match (optional)
3. Scale to common photometric zero-point



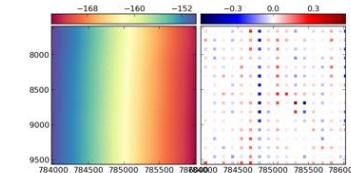
5: Match backgrounds to reference visit

For each warped input image:

- 5.1. Take difference image
- 5.2. Mask out detection and bad pixels



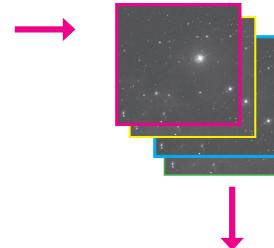
- 5.3. Fit a spatial model (e.g. 2-D Chebyshev polynomial) to the masked difference image to generate an offset image:



- 5.4. Add the offset to the input image bringing it up/down to the same level as the reference.

- 5.5. Check quality of matching. If fit is poor (such as in this example with a steep gradient), the image is held out of the coadd.

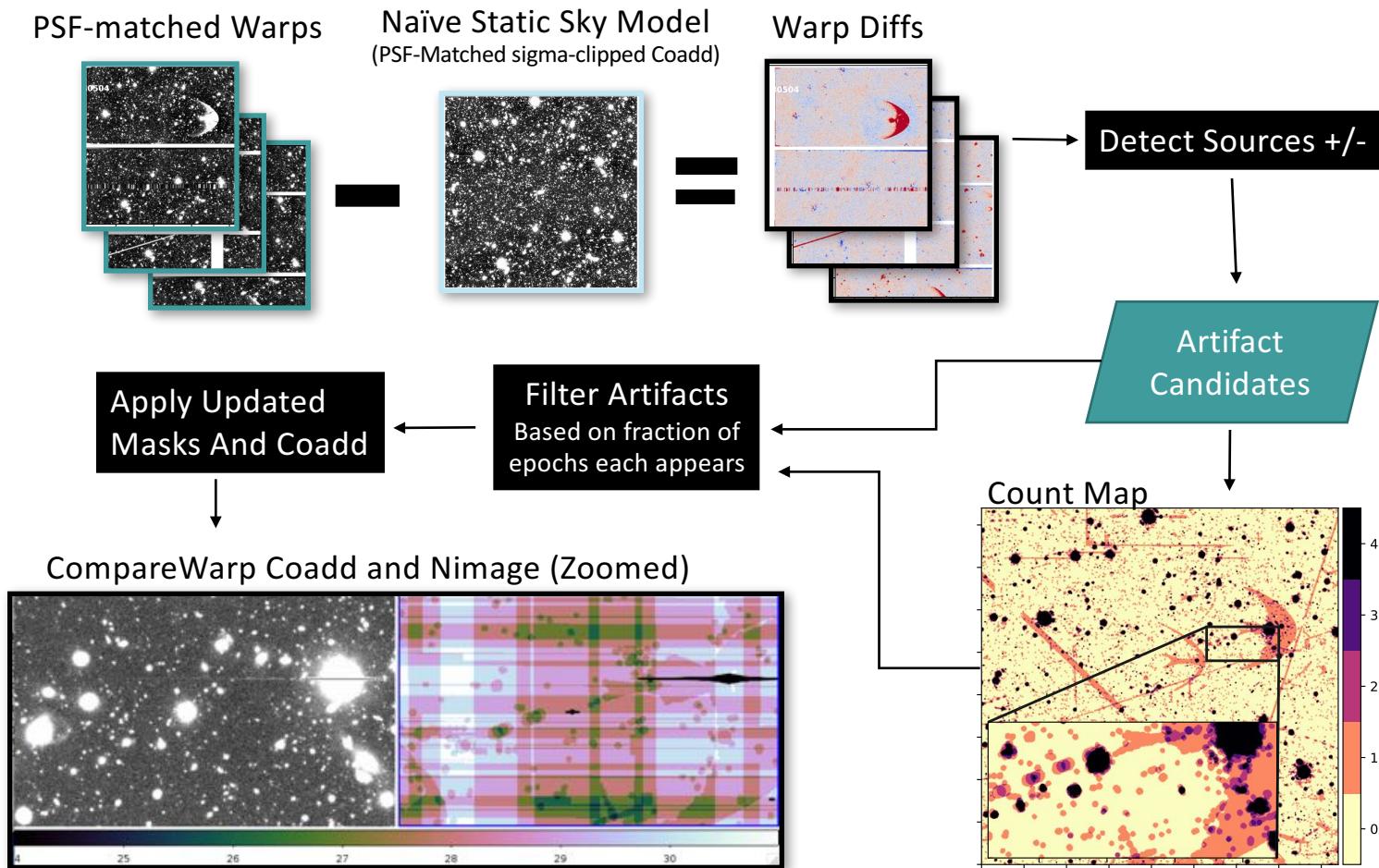
- 6: Stack matched images weighted by their inverse variance and using a sigma clipped mean to eliminate moving objects.



Result: coadd with a background of the reference image.



Use temporal differences in PSF-Matched Warps to mask temporal artifacts



4. Stack

- Use mean
 - Medians and sigma-clipped means cause problems
- Weight *whole image* by inverse variance
 - (see notebook problems for alternatives)



Final coadd with background
of reference



How do we use coadds

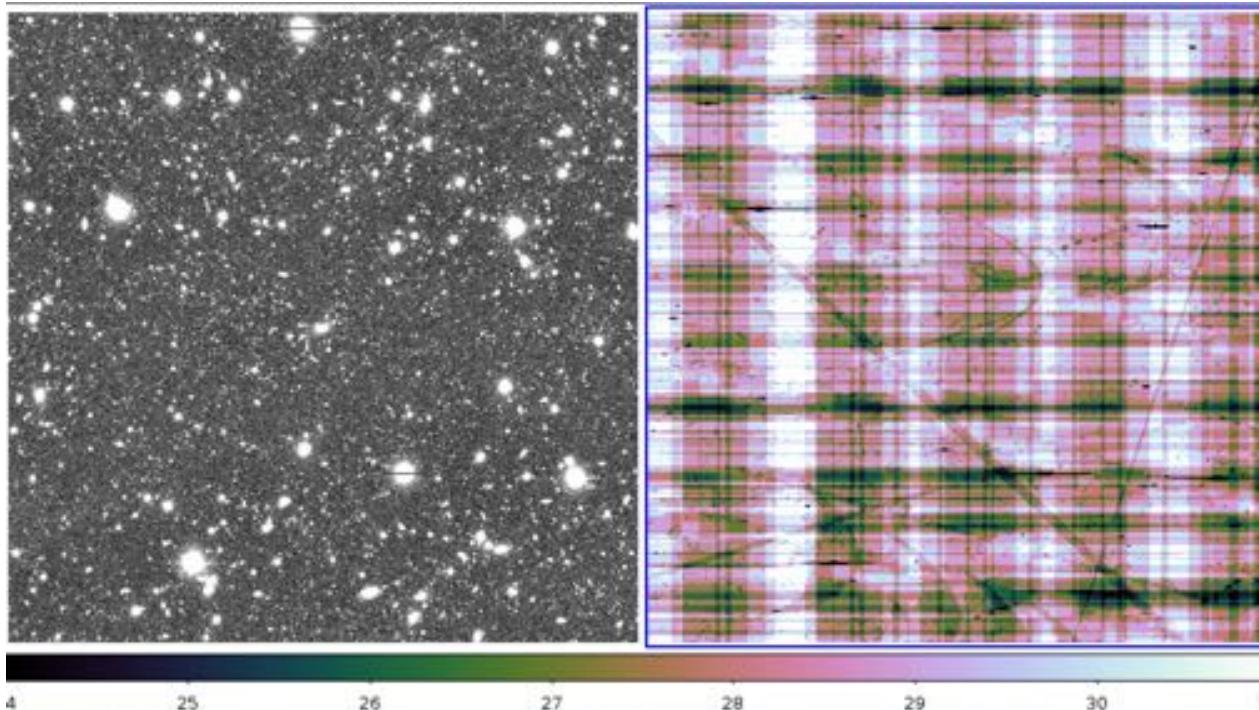
For detection, measurement and as templates for subtraction?

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- Having an accurate PSF model is very important for detection and measurement
- Solution is to coadd the PSF models with the same weighting (Jee+13)



But what about the stars that land on chip boundaries?



LEFT: Coadd Artifacts removed

RIGHT: Color corresponds to number of images that contributed
HSC-I tract 9813 patch=6,4



So far, we've discussed "direct coadds" There are other flavors too

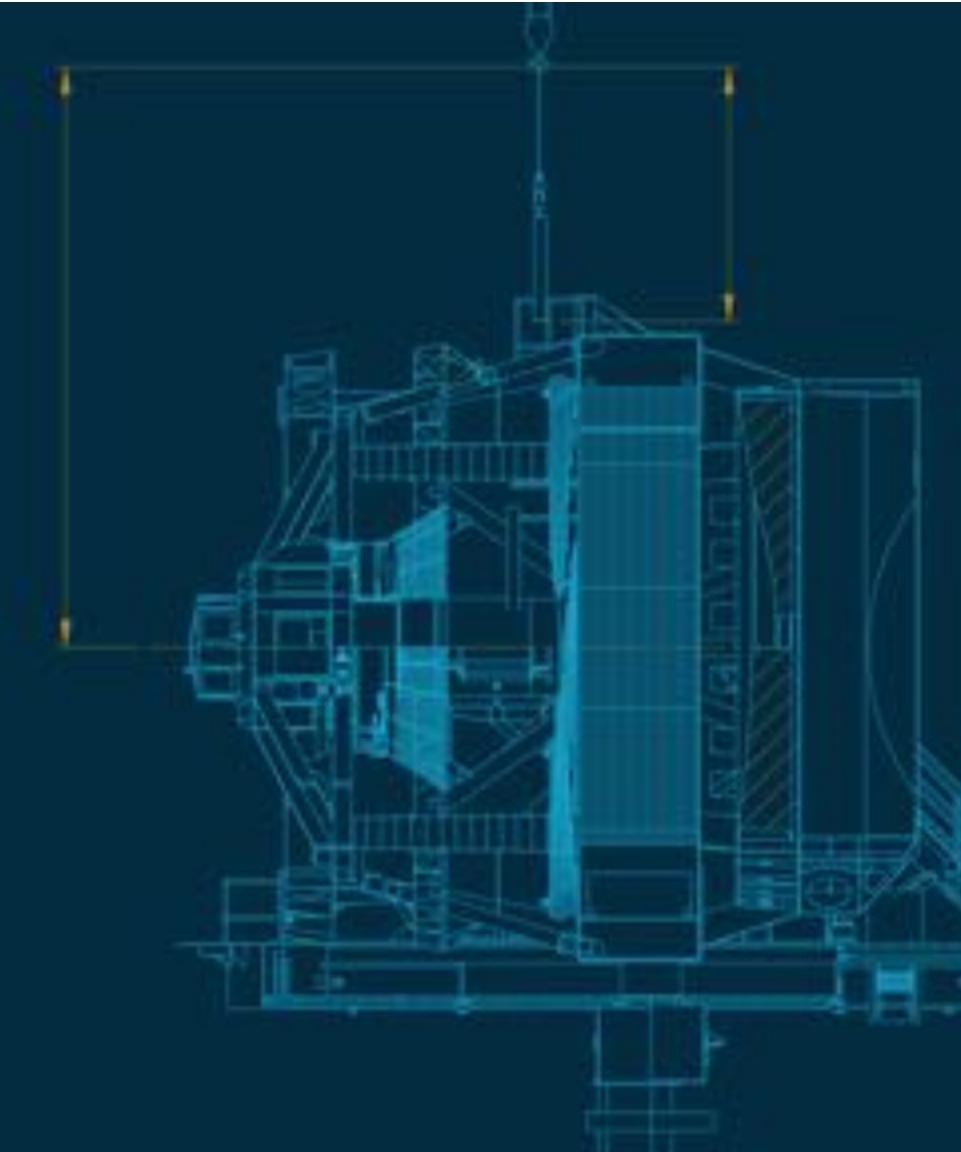
- Direct coaddition with PSF propagation (what we just covered)
- More convolutions:
 - PSF-matched coaddition (will cover more in image subtraction next)
 - After warping, match all input images to a model target PSF.
 - Detection-map/likelihood-image coaddition
 - An optimal coadd detection map can be built by summing single-visit detection maps (adding log likelihoods = multiplying likelihoods)
 - Kaiser/decorrelated coaddition (Kaiser04, Zackay+15)
 - Detection maps are an *inconvenient* sufficient statistic - they have such highly correlated noise that we can't really treat them as a regular image.
 - We can decorrelate after coaddition. If the input noise and PSFs are spatially constant, and there is no missing data or edges, this is actually very straightforward - in Fourier space.
- Multi-band and χ^2 coaddition (Szalay+99)
 - The optimal multi-band detection map is a weighted sum of per-band detection maps, where the weights depend on the SED of the object you want to detect.
 - A χ^2 coadd is a particular weighted sum that's optimal for SED of the sky (because it frames detection as rejecting a null hypothesis that a pixel is sky).

For more info on flavors of coadds in the eyes of Rubin ~March 2020 see [Jim Bosch's talk on coadd flavors](#) and [slides](#)

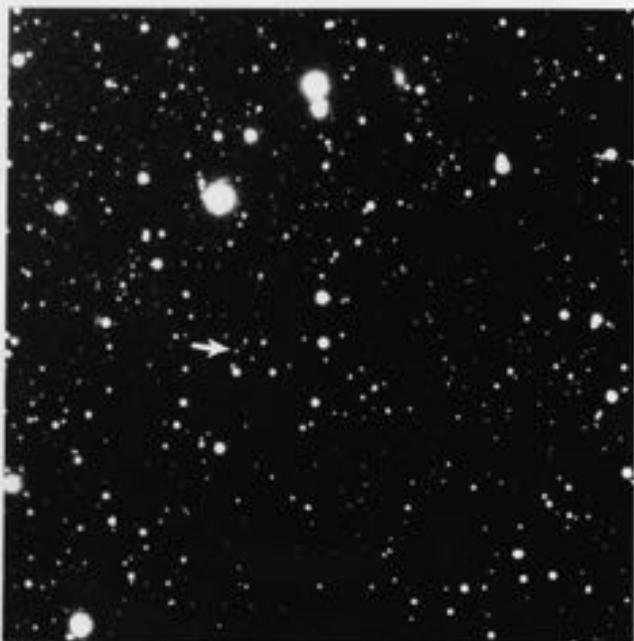


Image Subtraction

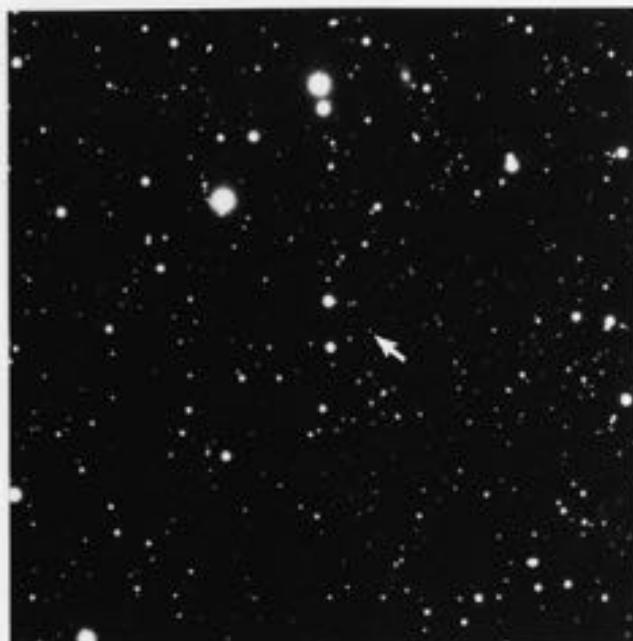
To find what's changed



DISCOVERY OF THE PLANET PLUTO



January 23, 1930



January 29, 1930

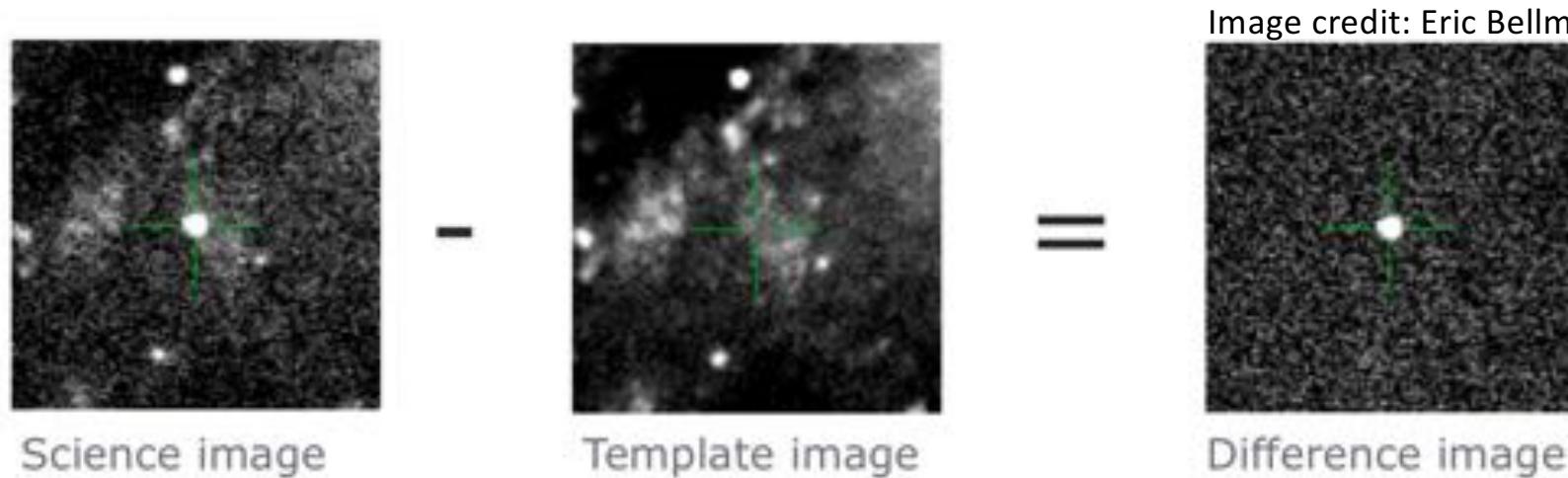
These are copies of small sections of the discovery plates showing images (those marked) of Lowell's mathematically predicted trans-Neptunian planet afterward named PLUTO. It was found by Mr. C. W. Tombaugh on February 18, 1930, while engaged in the search program and upon examination of these plates.

Lowell Observatory Photograph



We subtract a template from a science image to detect what has changed

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Now we need to match the PSFs which change from observation to observation

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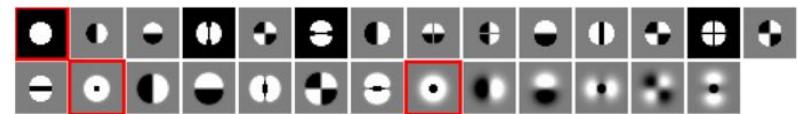
- Want to solve for the kernel k , that when convolved with the template image T reproduces the PSF of the science image I . $T \otimes k = I$
- Approaches in image processing literature assume you know the PSF precisely and is subject to numerical instabilities.
 - One option is to PSF-match the images 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).



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Now we need to match the PSFs which change from observation to observation

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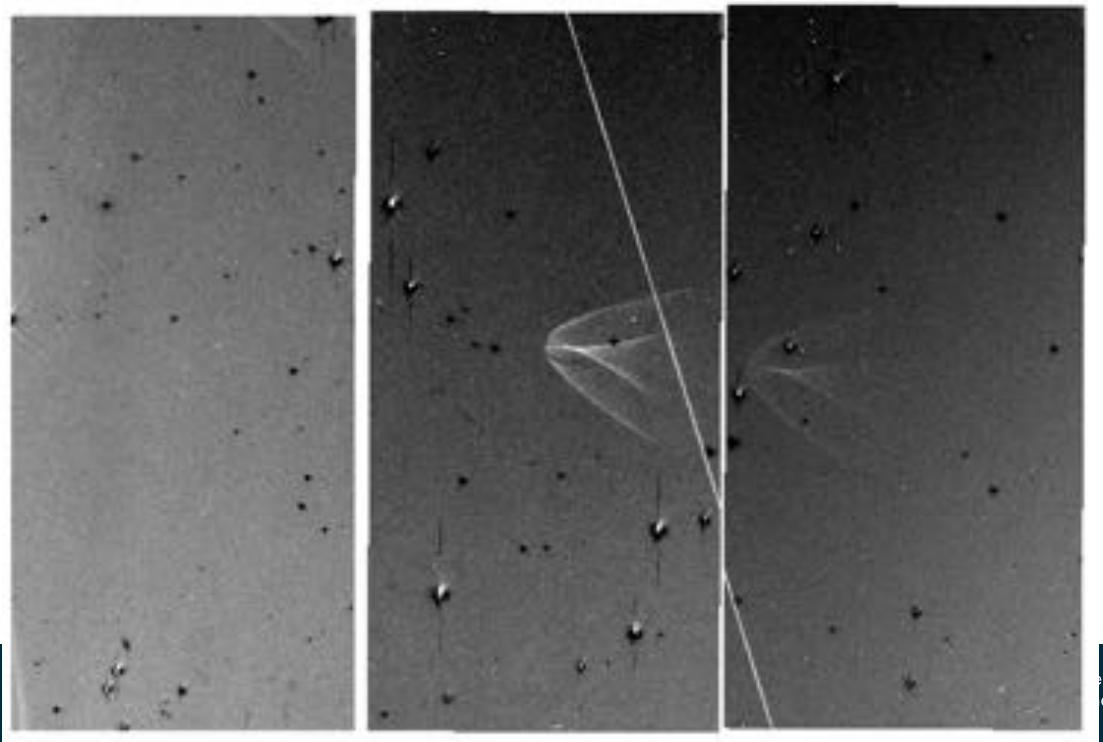
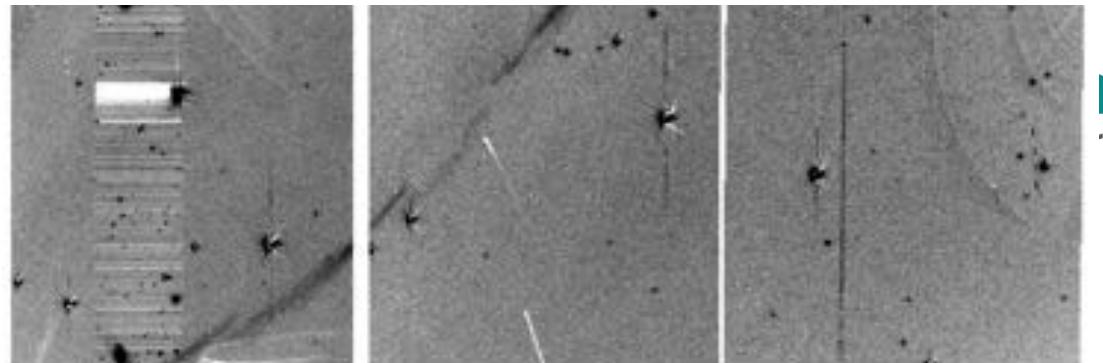


- Alard&Lupton98 model the convolution kernel as a series of basis functions.
 - Assumes Template noise << Image noise (holds for coadd template)
 - Robust and allows for spatial variations in the PSF as well as background matching
 - Implemented by Becker 2012: *High Order Transform of Psf ANd Template Subtraction code ([hotpants](#))* and the [LSST Science Pipelines](#)
- Zackay+16 recognized that classical A&L is not optimal if the template is noisy.
 - Proposed an alternative algorithm (“ZOGY” after author initials) in Fourier space
 - Symmetric between the science and template images
 - Maximizes the SNR of detected point sources when both images are noisy
 - But requires knowledge of the PSFs again ☹



- For more info on PSF-matching:
 - [Watch Gene Magnier's talk](#)
 - See [Robert Lupton's talk at LSST2019](#)
 - Status of difference imaging on Rubin's Science pipelines. ([Eric Bellm's Talk](#))



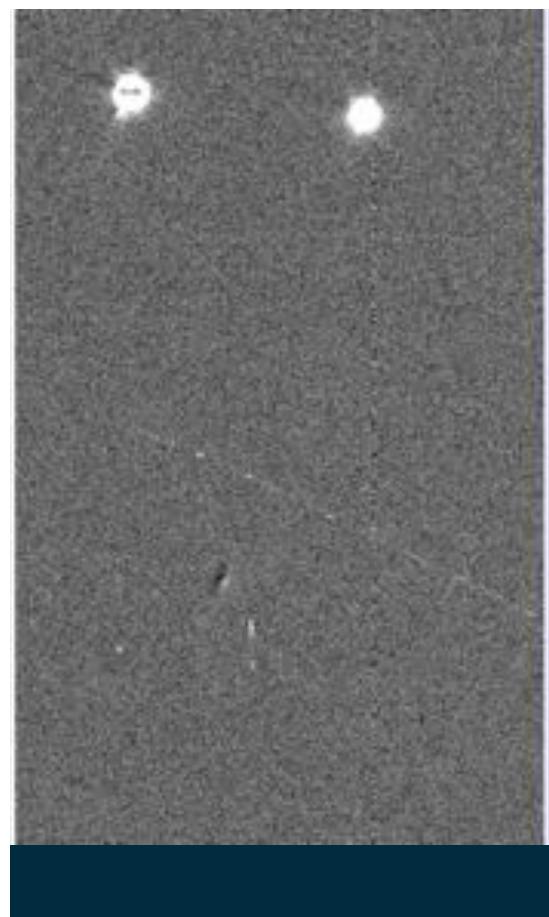


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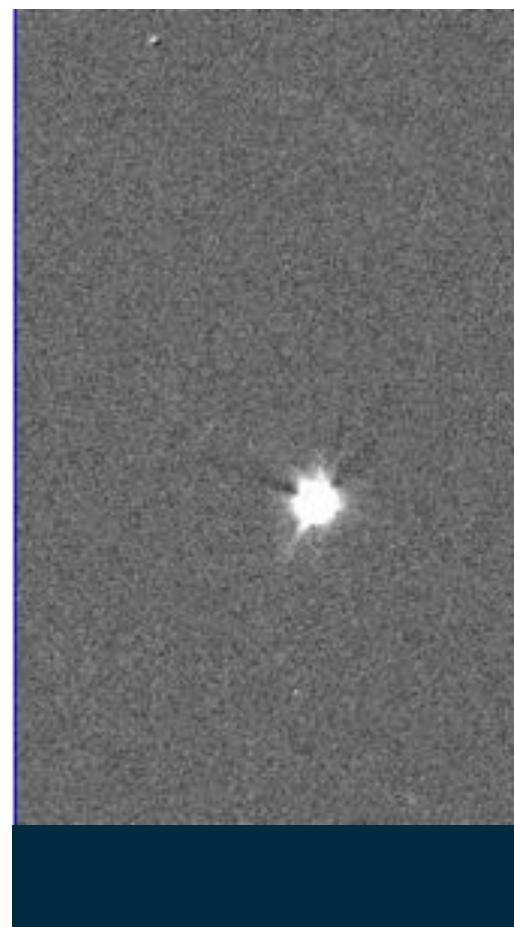
Difference



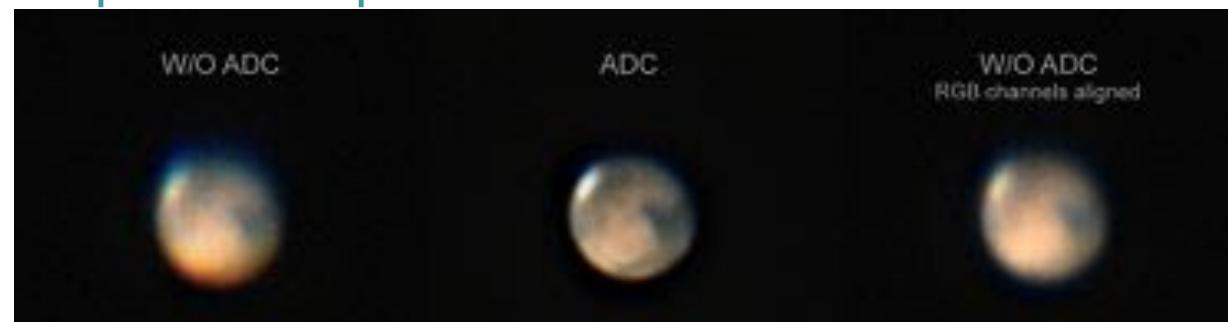
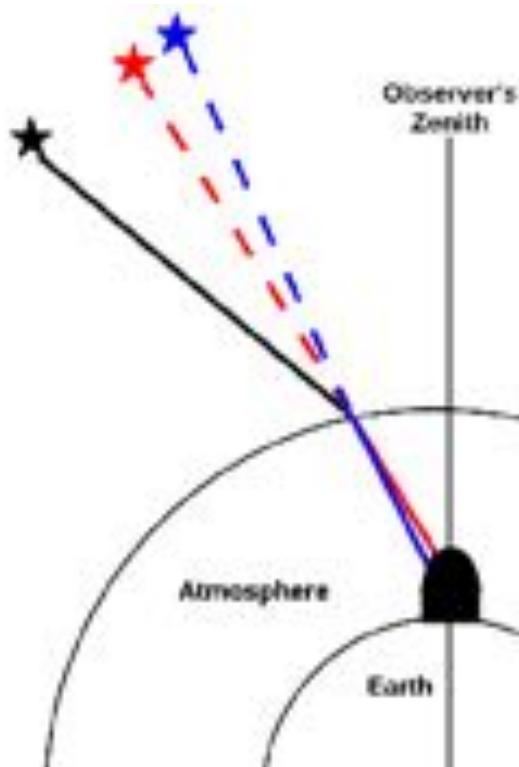
Difference



Difference



Rubin does not have an atmospheric dispersion corrector

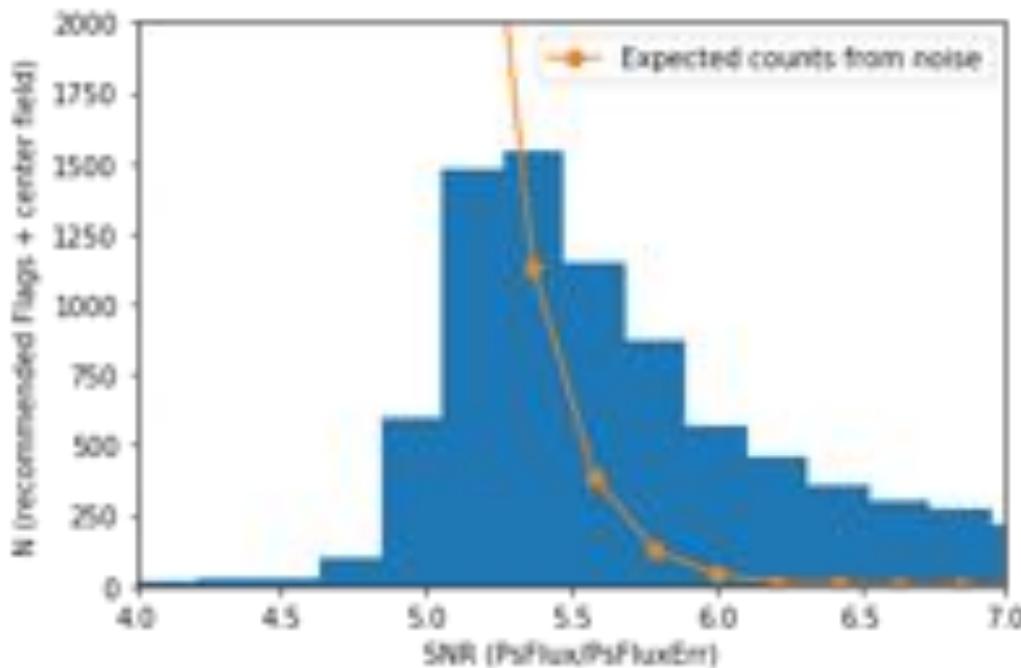


Mars at 44deg altitude
Image Credit: John Boudreau



[For more info about how to correct for DCR see Ian Sullivan's Talk](#)

Detection on difference images



Example experiment running detection on a diffim.
OK but Room for improvement

From ls.st/lsm227

Run detection on one Gaussian random field matched and subtracted from another yields detections that are statistical fluctuations.

The expected false positive rate is:

$$N_{total}(> \nu) = n(> \nu) * nrow * ncol / \sigma_g^2$$

$$n(> \nu) = \frac{1}{2^{5/2}\pi^{3/2}} \nu e^{-\nu^2/2}$$

You can't do better than this.

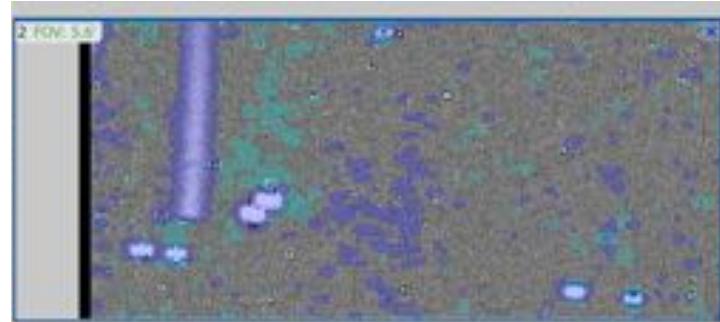


Detection on difference images: noise estimates critical!

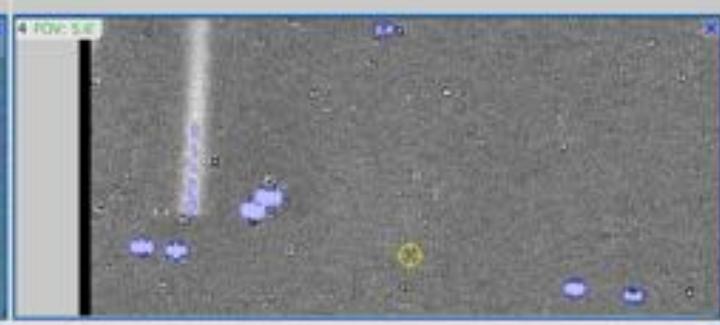
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<input checked="" type="checkbox"/> DETECTED - bit 5	<input type="button" value="Color"/>	<input type="button" value="Delete"/>
<input checked="" type="checkbox"/> DETECTED_NEGATIVE - bit 6	<input type="button" value="Color"/>	<input type="button" value="Delete"/>

Just an example of how bad it can be



doDecorrelation=False

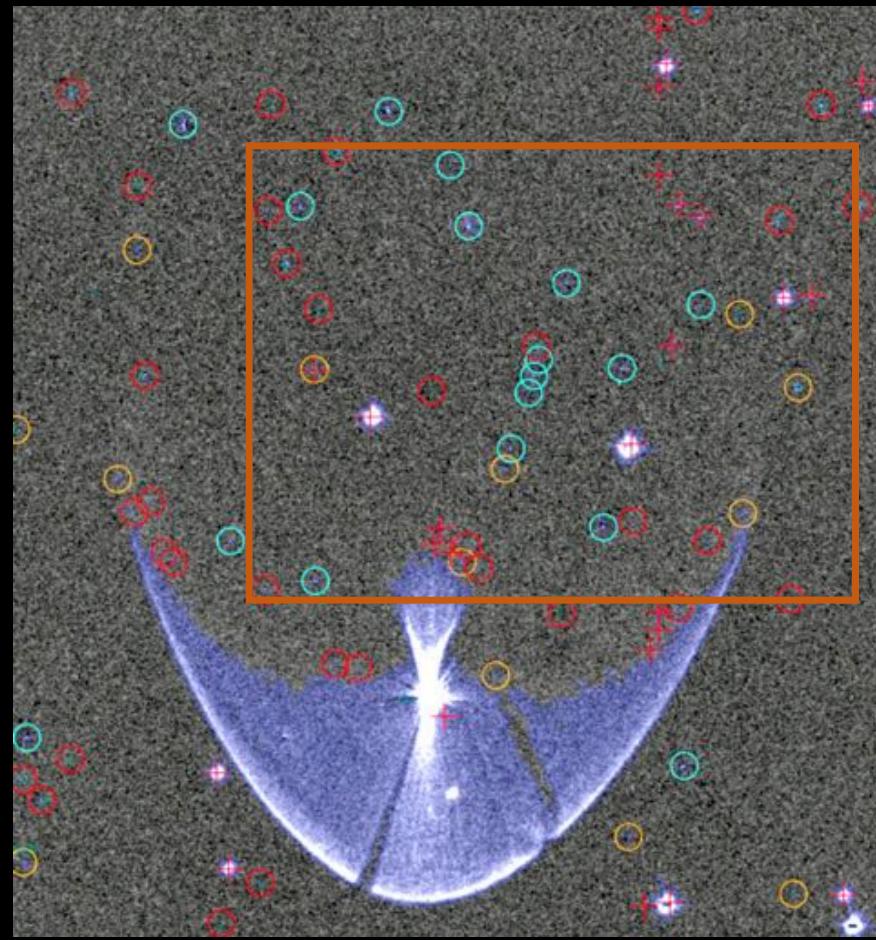


doDecorrelation=True

Variance Plane noise est empirical noise est



Real PDR1 HSC-I DiffIm (COSMOS, template=11 visits)



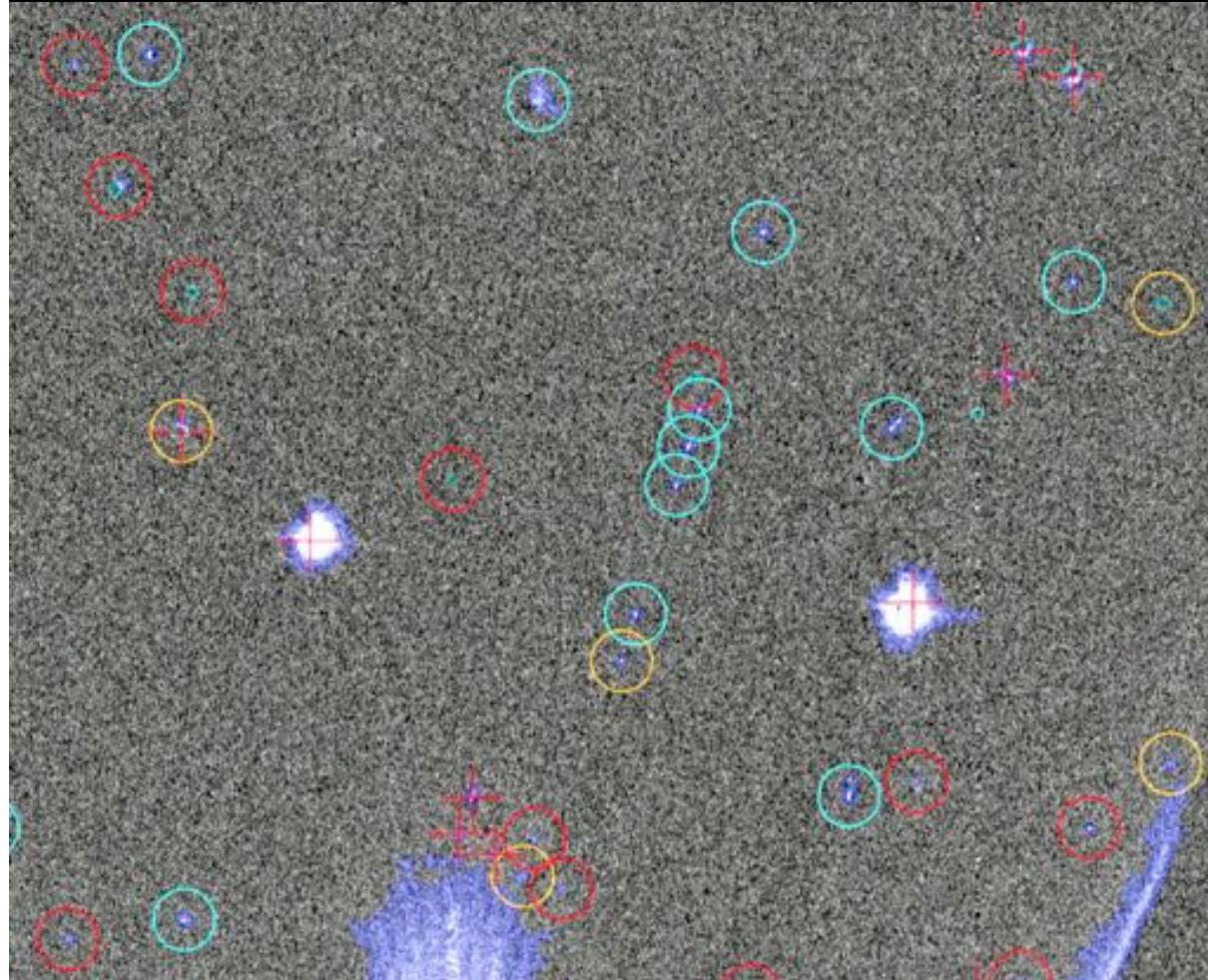
+ Flagged
BAD, SAT, SUSPECT

O $|\text{SNR}| < 5\sigma$

O Flagged
Shape Measurement Failure

O Remaining “Good” DiaSources

Real PDR1 HSC-I DiffIm (COSMOS, template=11 visits)



+ Flagged
BAD, SAT, SUSPECT

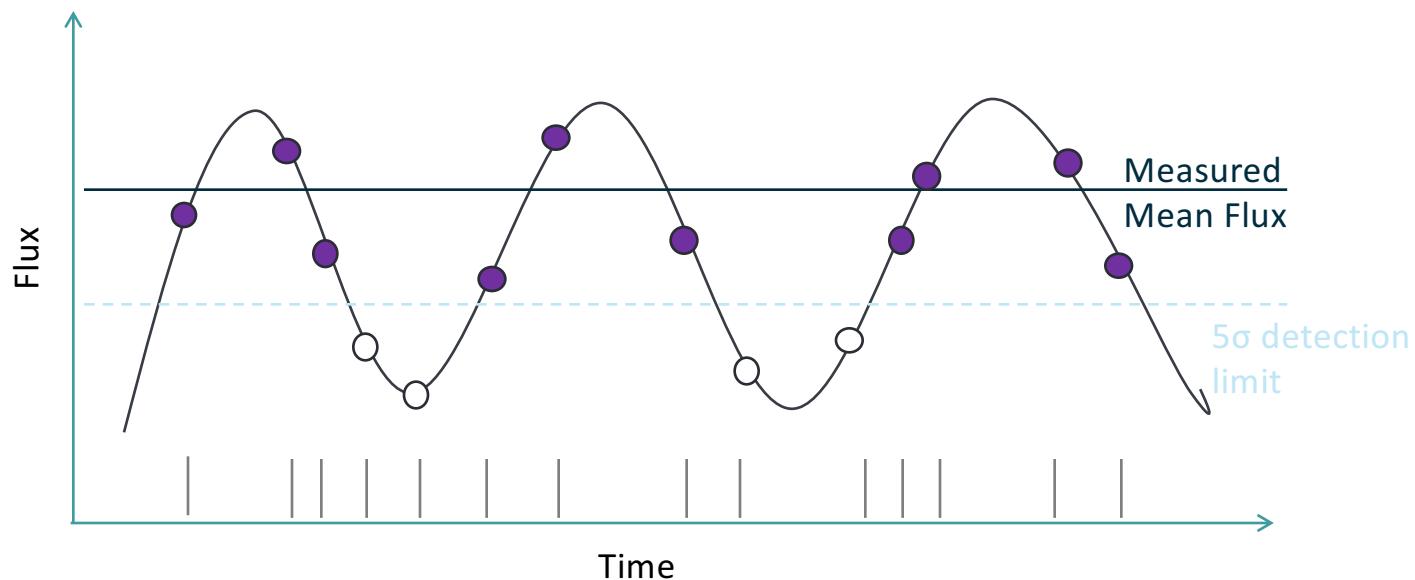
O $|\text{SNR}| < 5\sigma$

O Flagged
Shape Measurement
Failure

O Remaining "Good"
DiaSources

Light-curves derived from detecting on single-epoch images misses information

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Force PSF photometry at centroids detected and measured on a **Rubin**
co-add:



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Force PSF photometry on either a single epoch image or a difference image:

- Single-epoch: lower variance
- Difference image: lower bias

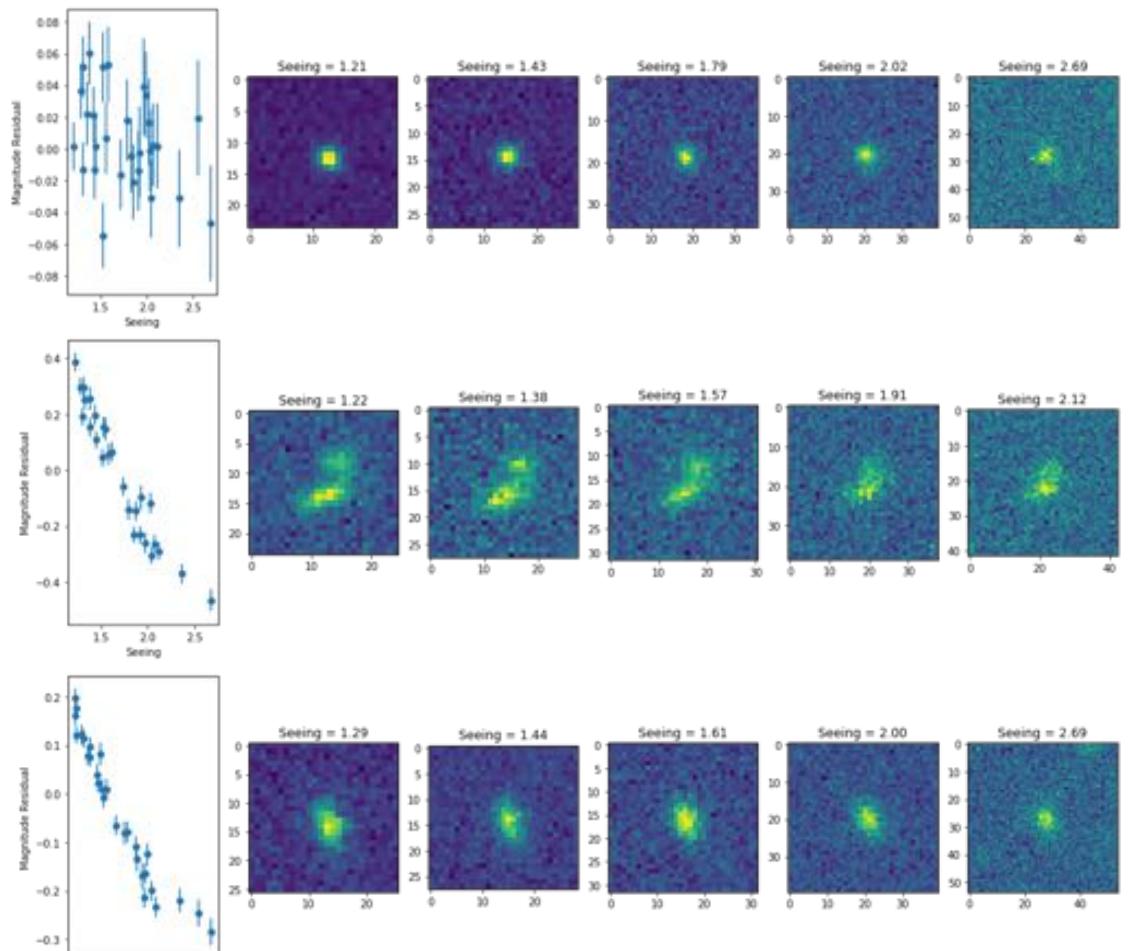
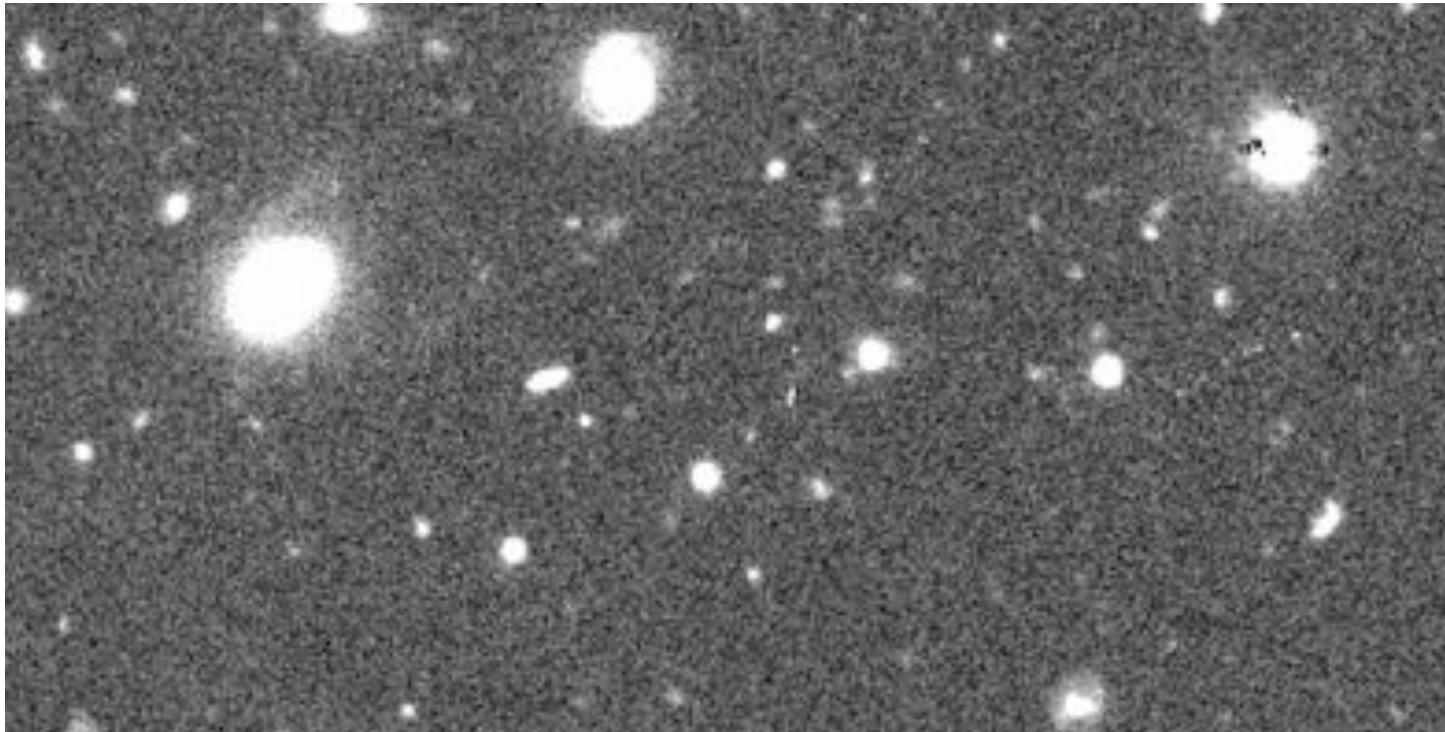


Image Credit: Clare Saunders
Multiple observations vs seeing
On single epoch images

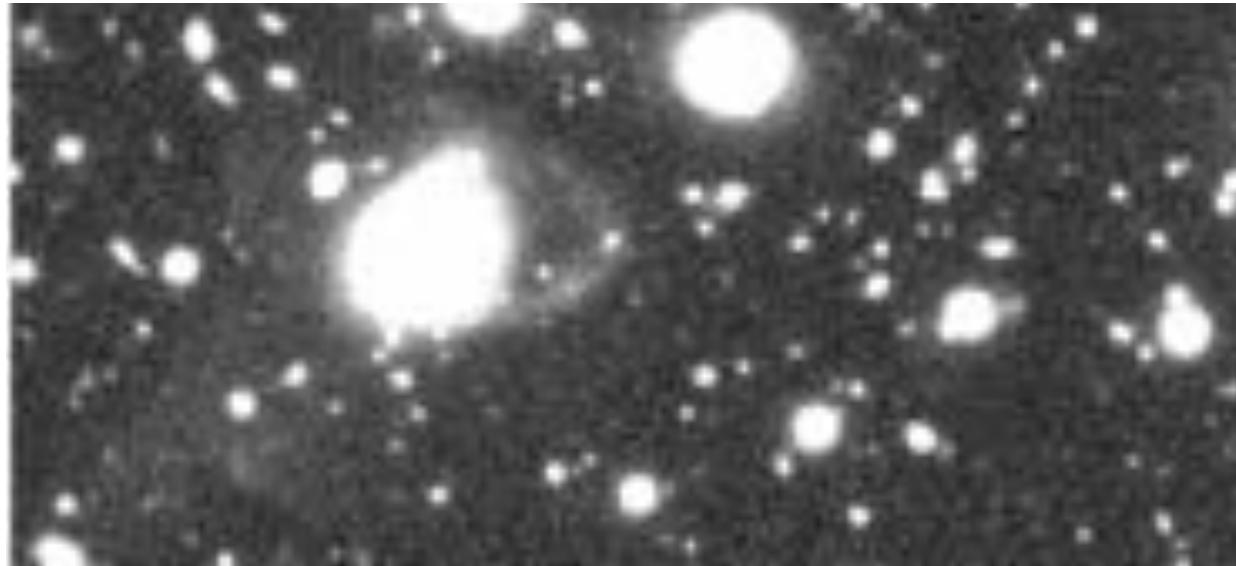
We've taken the multi-epoch images



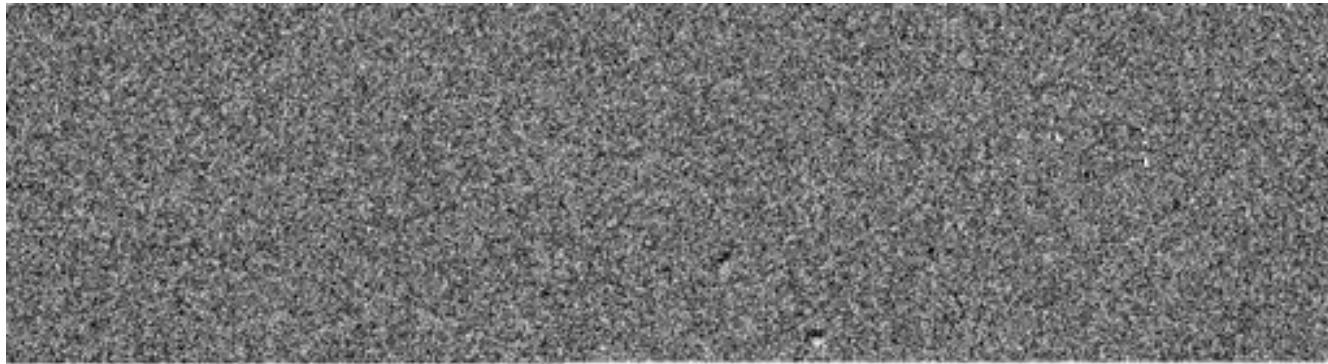
HSC-I COSMOS field (270s exposures)



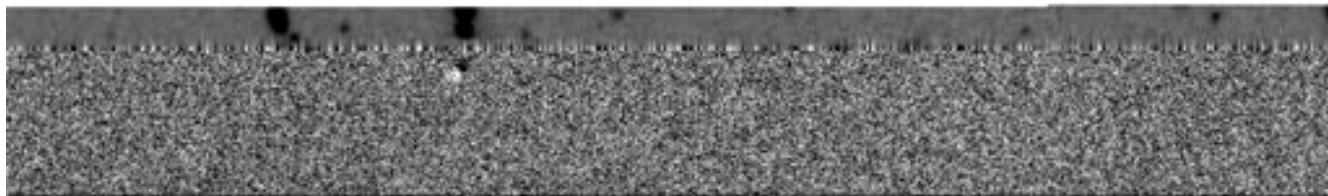
Gone deeper, by adding them



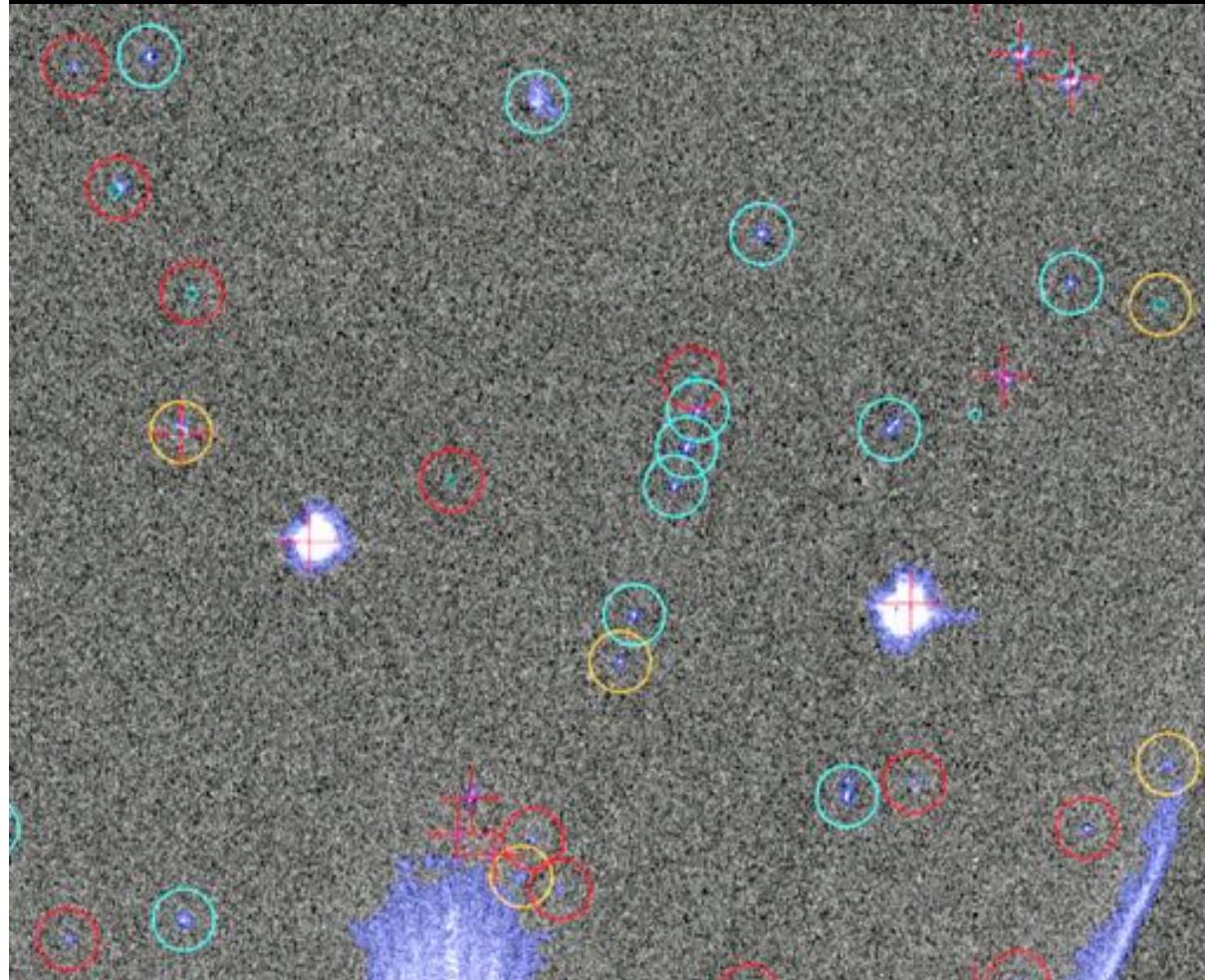
And detected what's changed, by subtracting them



HSC-I COSMOS field (difference images)



Real PDR1 HSC-I DiffIm (COSMOS, template=11 visits)



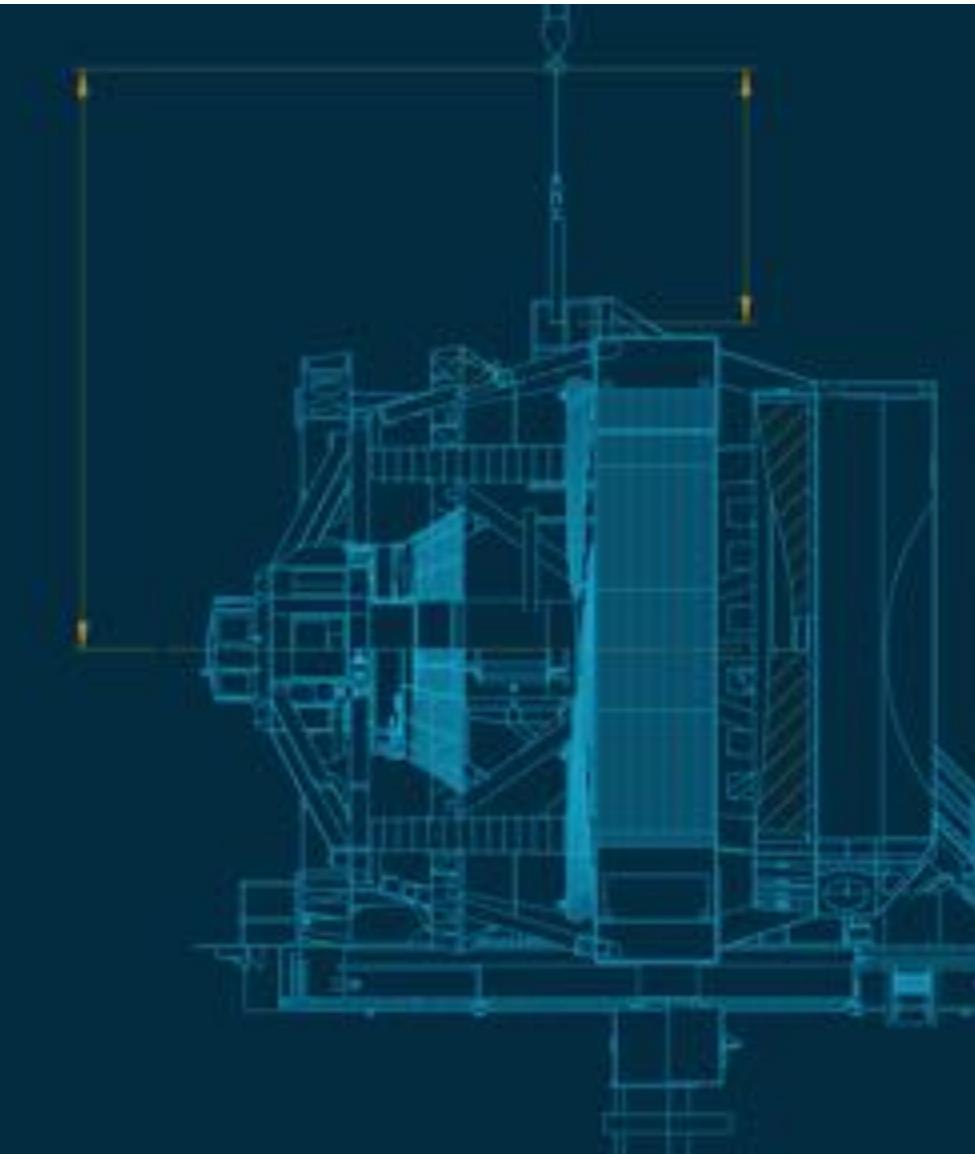
+ Flagged
BAD, SAT, SUSPECT

O $|\text{SNR}| < 5\sigma$

O Flagged
Shape Measurement
Failure

O Remaining "Good"
DiaSources

Appendix



Signal to noise ratio

- $\frac{S}{N} = \frac{\text{Counts}_*}{\sqrt{\sigma_*^2 + \sigma_{sky}^2 + \sigma_{read}^2 + \sigma_{dark}^2}}$

$$S/N = \frac{R_* \times t}{[(R_* \times t) + (R_{sky} \times t \times n_{pix}) + (RN^2 + (\frac{G}{2})^2 \times n_{pix}) + (D \times n_{pix} \times t)]^{1/2}}$$

R_*	count rate from star	e^-/second
R_{sky}	count rate from background	$e^-/\text{second/pixel}$
t	exposure time	seconds
r	radius of aperture	pixels
n_{pix}	number of pixels in aperture	$\pi \times r^2$
G	inverse-gain	e^-/DN
D	dark current	$e^-/\text{pixel/sec}$

http://www.ucolick.org/~bolte/AY257/s_n.pdf

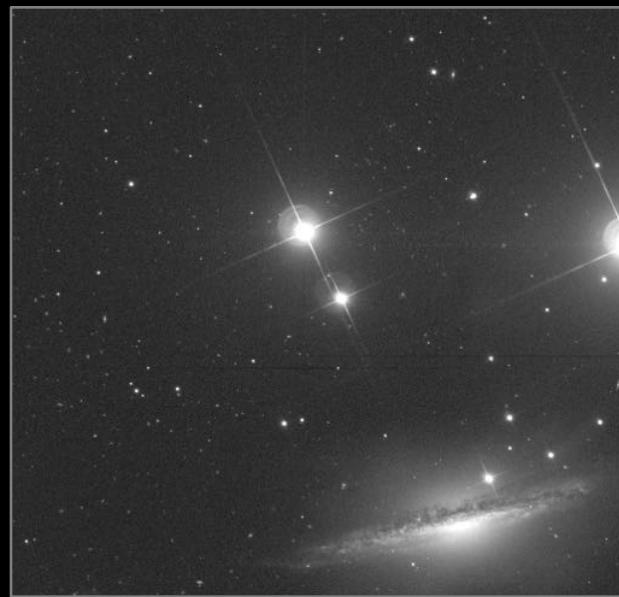


Background-subtracted coadd



5 arcmin

Single-epoch visit



Background-subtracted coadd



Background-matched coadd



5 arcmin