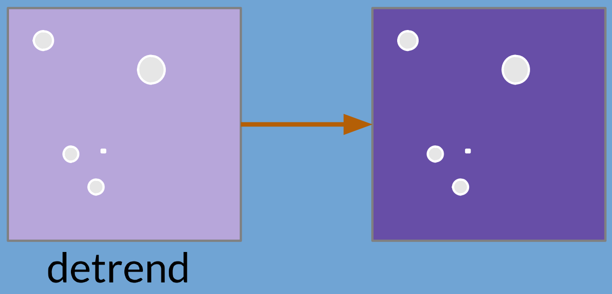
State of the Art in Difference Imaging & Lessons Learned from Pan-STARRS

Eugene Magnier
Pan-STARRS / IfA

Typical Transient / Asteroid Analysis Pipeline



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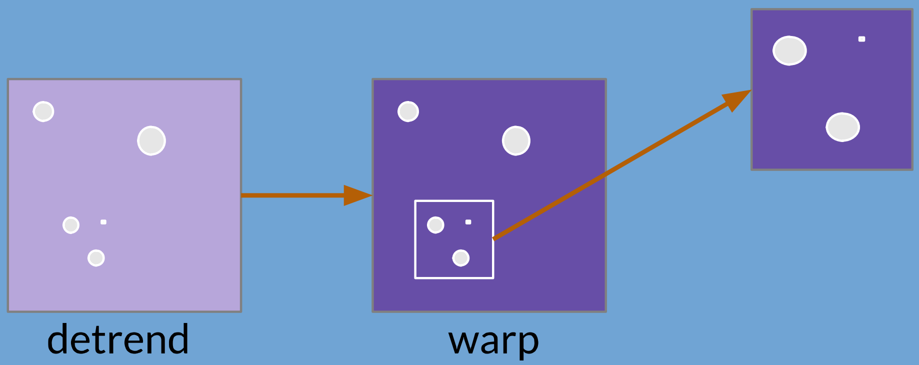

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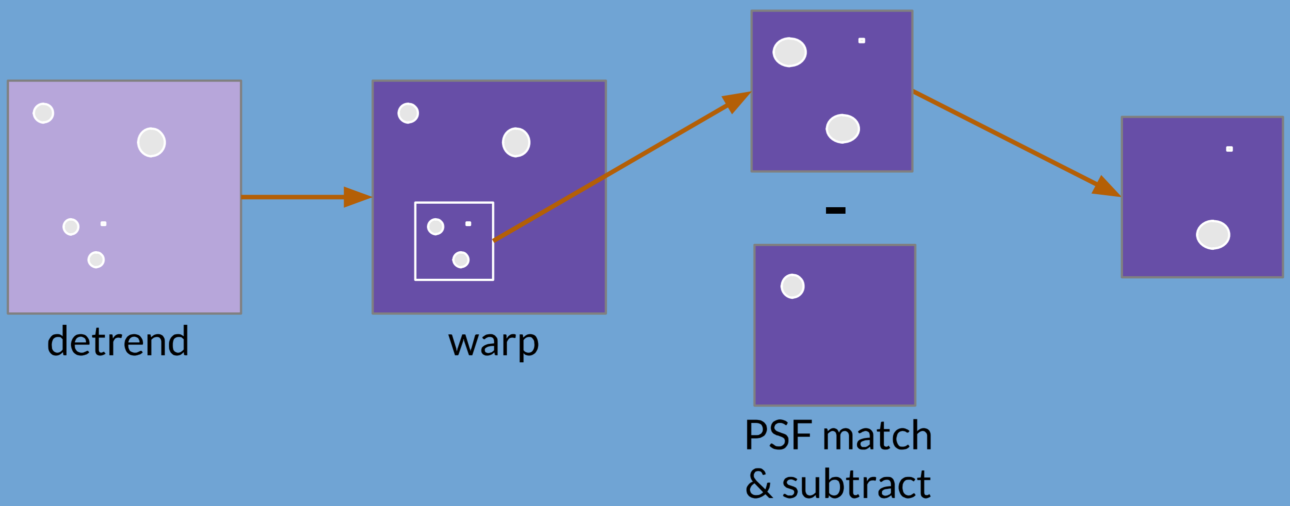

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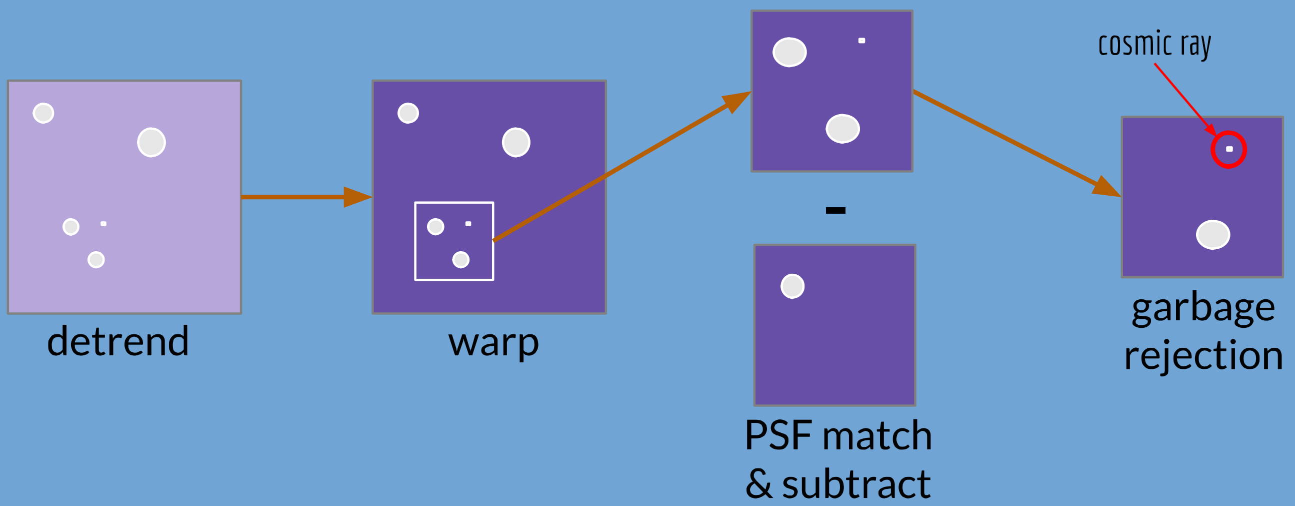

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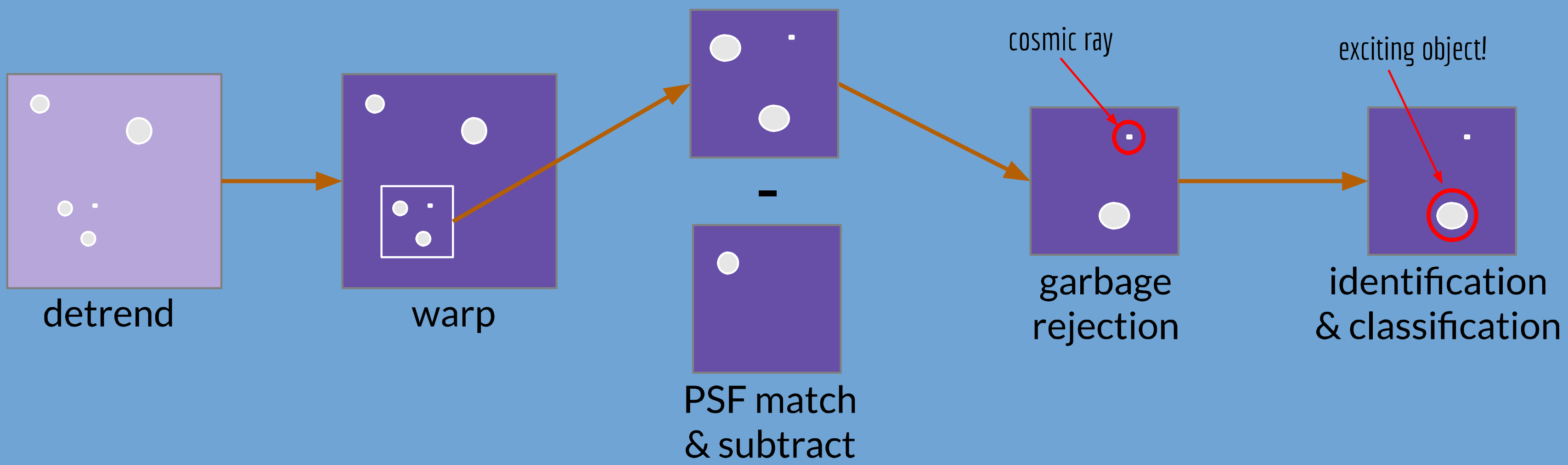

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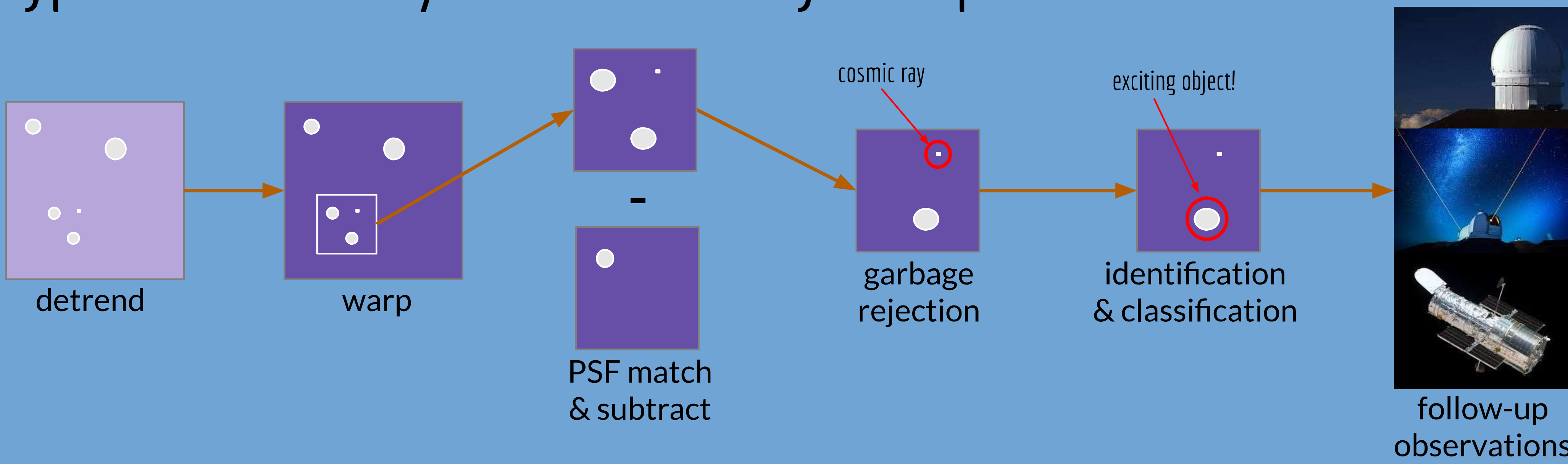

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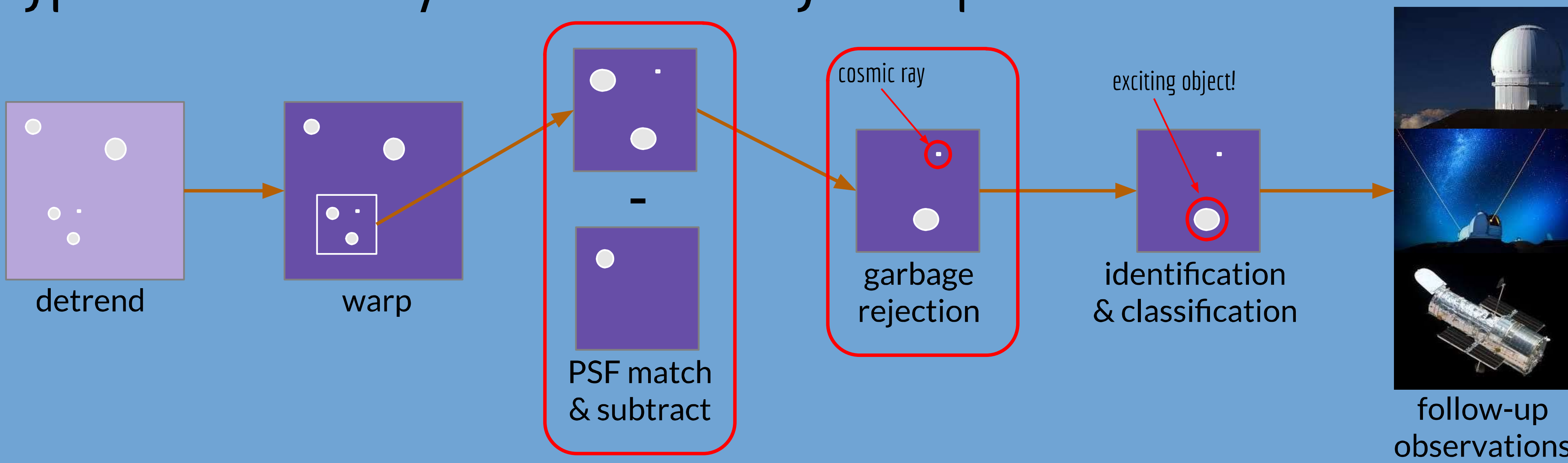

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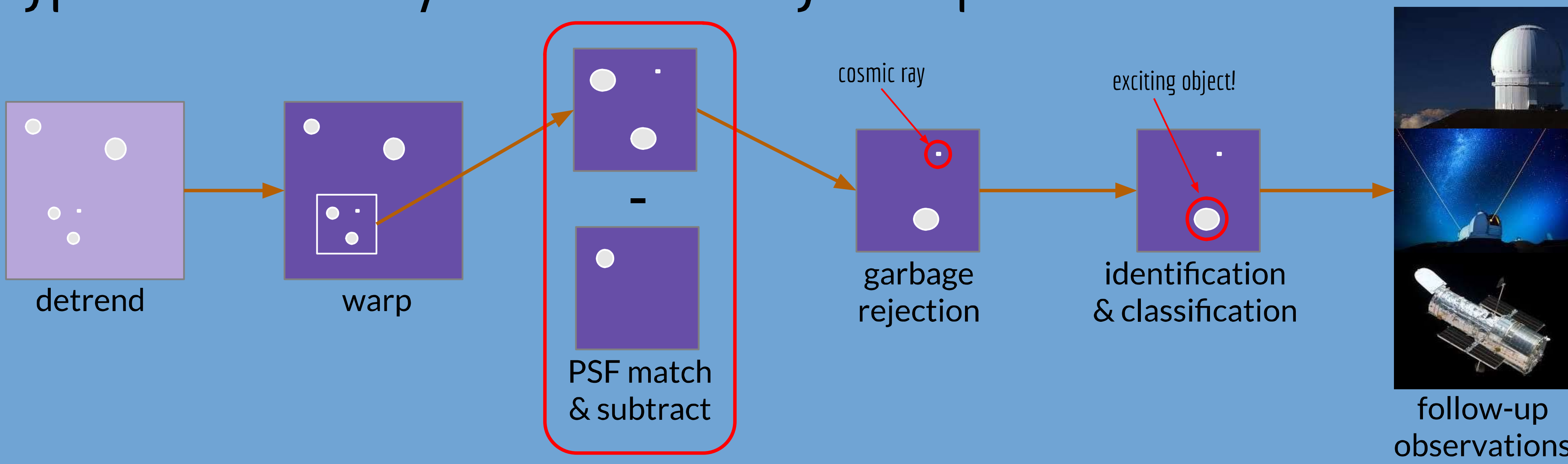
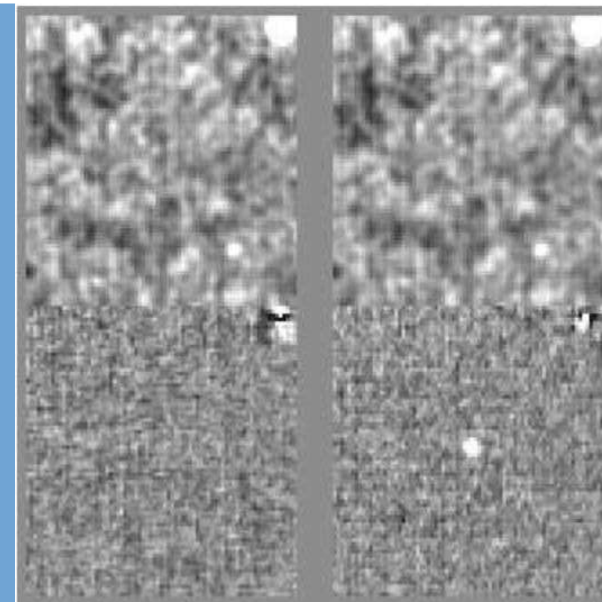


Image Difference Algorithm History

- 1990 : Ciardullo et al 1990 discussed early implementation
- 1995 : Phillips & Davis : fourier-space calculation of kernel
- 1996 : Tomaney & Crotts : fourier-space kernel
- 1998 : Alard & Lupton : real-space kernels (Gaussians * polynomials)
- 2008 : Bramich : pixel kernel basis function
- 2008 : Miller et al : pixel kernel basis function
- 2008 : Yuan & Akerlof : A/L-style cross-convolution
- 2016 : Zackay et al : fourier-space cross-convolution & noise whitening
- 2017 : Reiss & Lupton : real-space A/L with ZOGY-style whitening
- 2017 : Sedaghat & Mahabal : CNN implementation

Pre-History



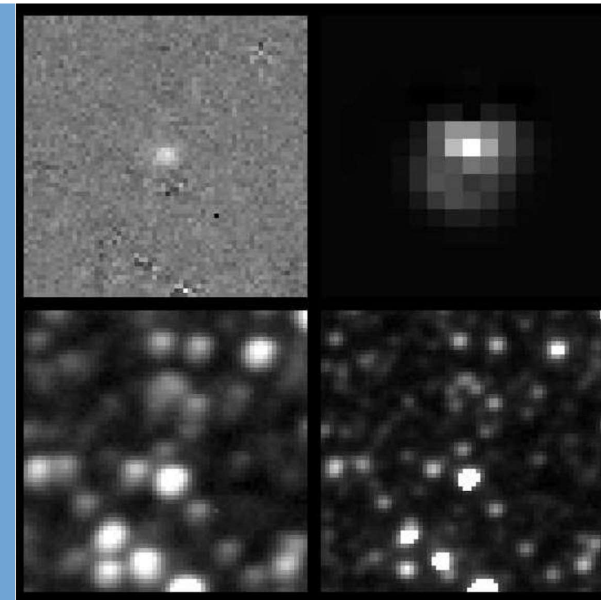
- 1990 - Ciardullo et al : mentioned early implementation
- 1995 - Phillips & Davis : describe fourier-space calculation of kernel
- 1996 - Tomaney & Crotts : use fourier-space kernel for microlensing

$$I = R \otimes k \xrightarrow{\text{Fourier Space}} \tilde{I} = \tilde{R} \times \tilde{k}$$

$$\tilde{k} = \frac{\tilde{I}}{\tilde{R}}$$

- measure *k* on bright, isolated star(s)
- apply to reference image
- suppress noisy high-frequency modes with Gaussian fit

Optimal Image Subtraction



- 1998 : Alard & Lupton : kernel built from Gaussians

$$I = R \otimes k$$

Fit for kernel in real space

$$k = \sum_{n,i,j} a_n u^i v^j e^{-(u^2+v^2)/2\sigma_n^2}$$

- measure *k* on all / many star(s)
- apply to reference image
- coefficients can vary in 2D to follow PSF variations
- HOTPANTS (Becker 2015) perhaps most popular

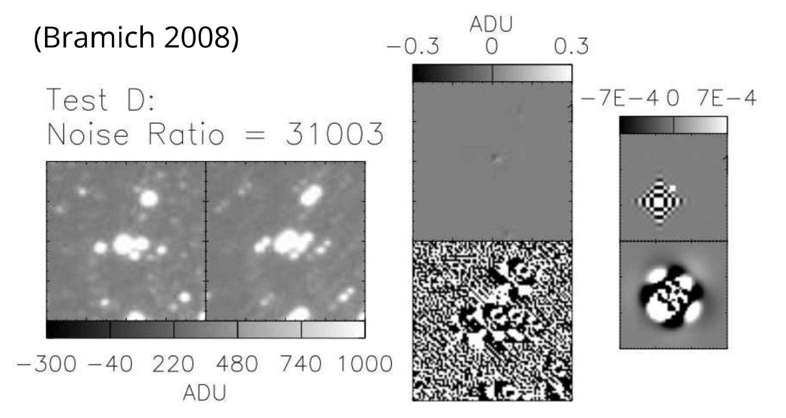
Many papers on the implementation details:

- Israel et al 2006
- Becker et al 2012
- etc..

Pixel Basis Function

- 2008 : Bramich
- 2008 : Miller et al

$$I = R \otimes k$$



Fit for kernel in real space

$$k = \sum_n a_n \delta_n(u, v)$$

- measure *k* on bright star(s)
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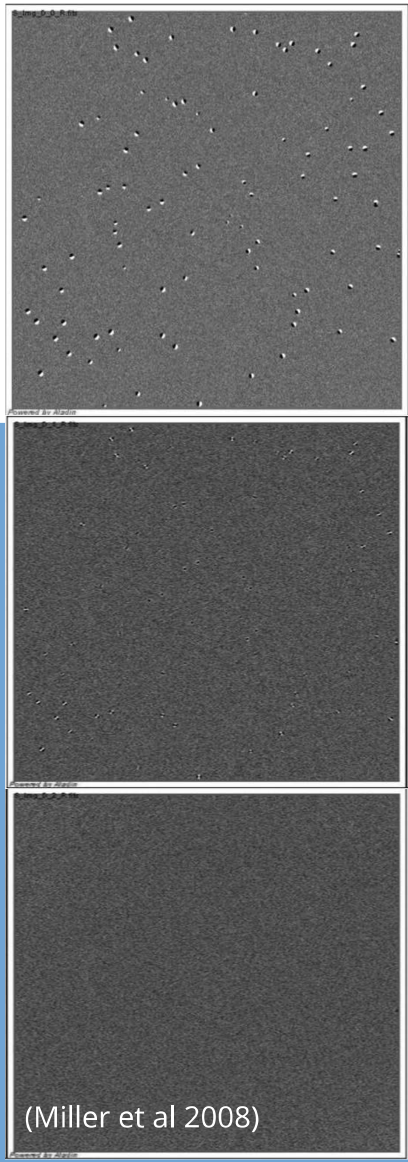
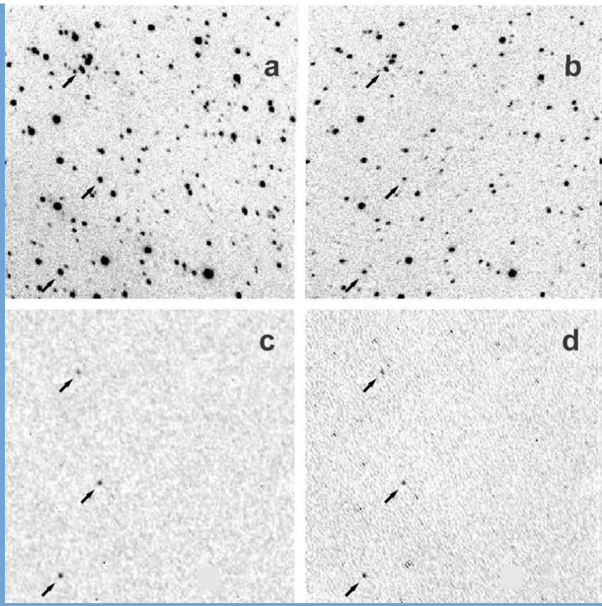
- coefficients can vary in 2D to follow PSF variations



Cross-convolution

- 2008 : Yuan & Akerlof : A/L-style cross-convolution



$$R \otimes k_R = I \otimes k_I$$

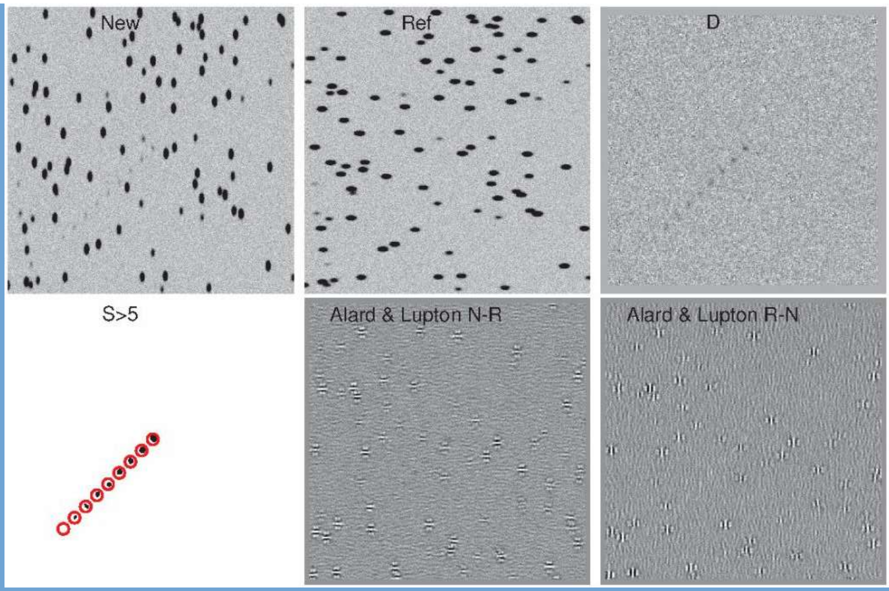
$$D = R \otimes k_R - I \otimes k_I$$

$$Q = \sum D^2 + \lambda \sum (u^2 + v^2)^2 \left[k_R^2 + k_I^2\right]$$

- measure *k* on all / many star(s)
- apply to reference image
- coefficients can vary in 2D to follow PSF variations
- target & reference can both be 'larger'

Back to the Fourier?

- 2016 : Zackay et al (ZOGY) : Fourier-space cross-convolution & noise whitening



$$R \otimes k_R = I \otimes k_I$$

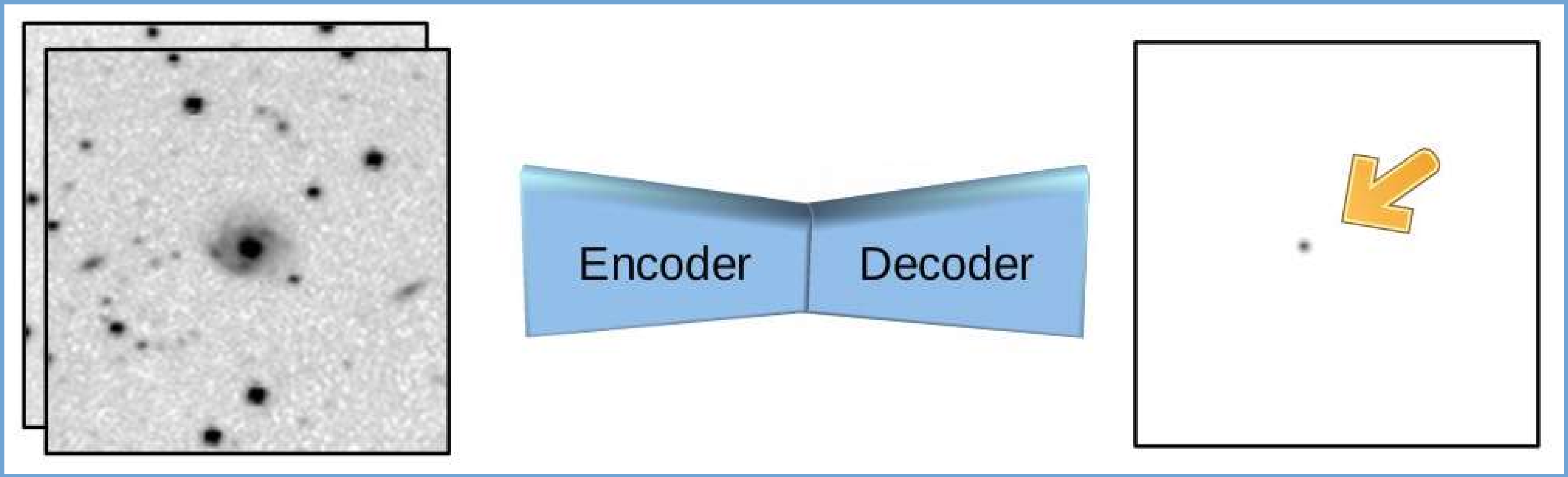
$$\xrightarrow{\text{Fourier Space}}$$

$$\tilde{D} = \frac{\tilde{P}_I \tilde{R} - \tilde{P}_R \tilde{I}}{\sqrt{\sigma_R^2 |\tilde{P}_I|^2 + \sigma_I^2 |\tilde{P}_R|^2}}$$

- $D \otimes P_D$ is defined as optimal matched filter
- noise whitening removes pixel correlations
- Reiss & Lupton 2017 describe real-space version

Machine Learning to the Rescue

- 2017 : Sedaghat & Mahabal : Convolutional NN implementation



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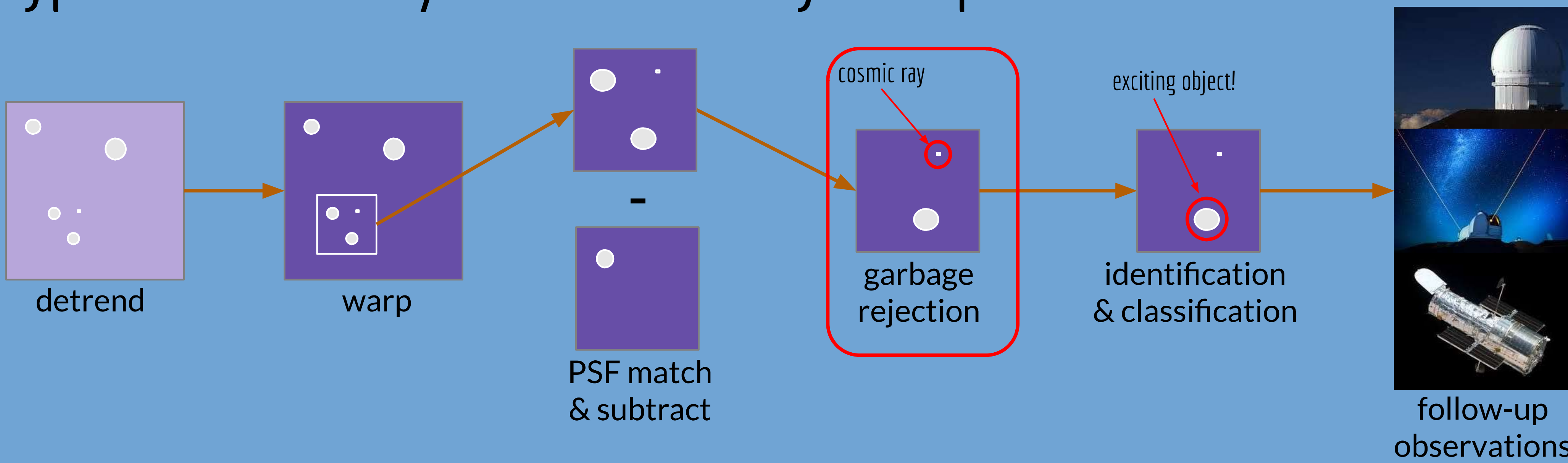

Garbage Rejection : Typical Sources

- cross-talk
- glows
- persistence
- non-linearity
- ghosts
- glints
- diffraction spikes
- vignetting changes
- cosmic rays
- dipoles
- variance mis-estimation

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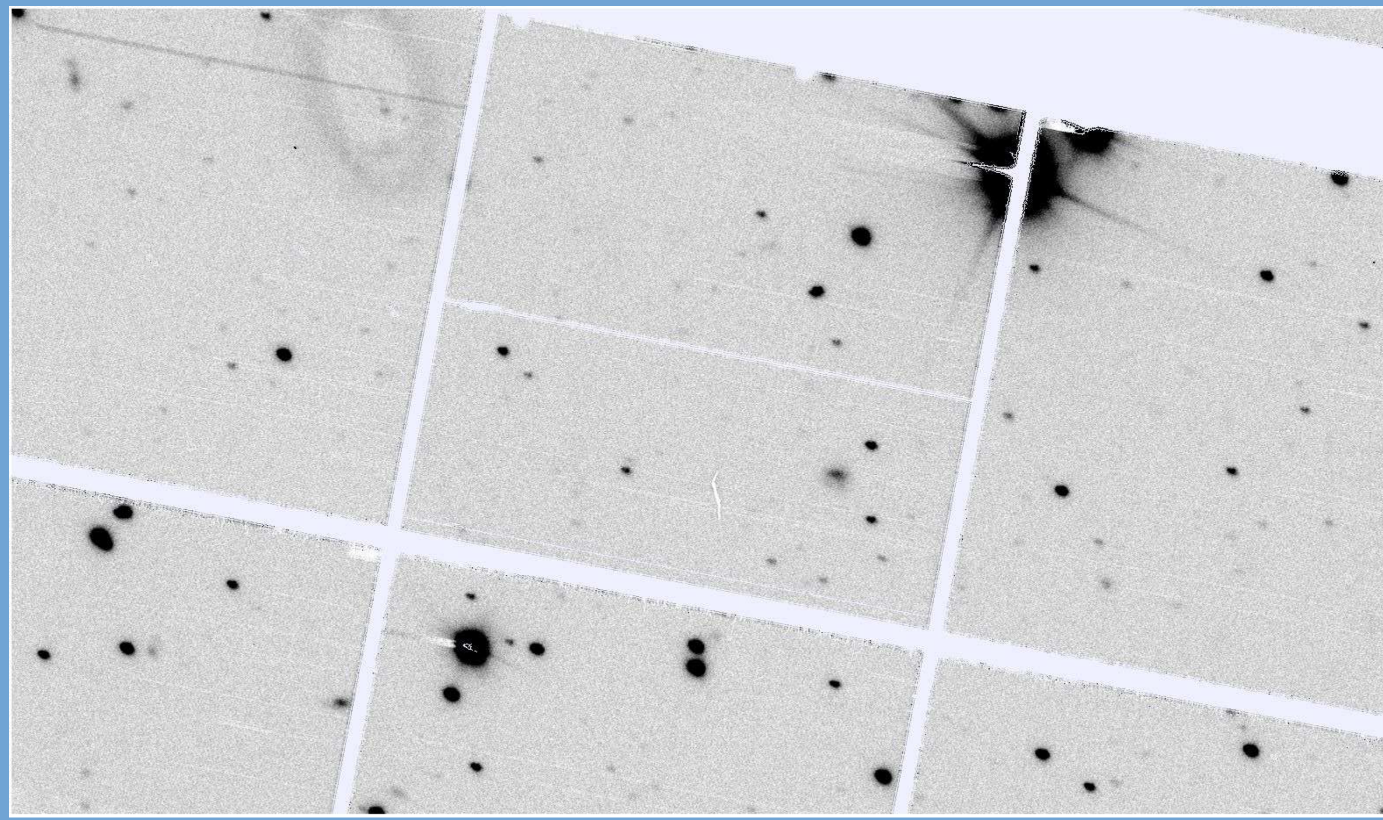

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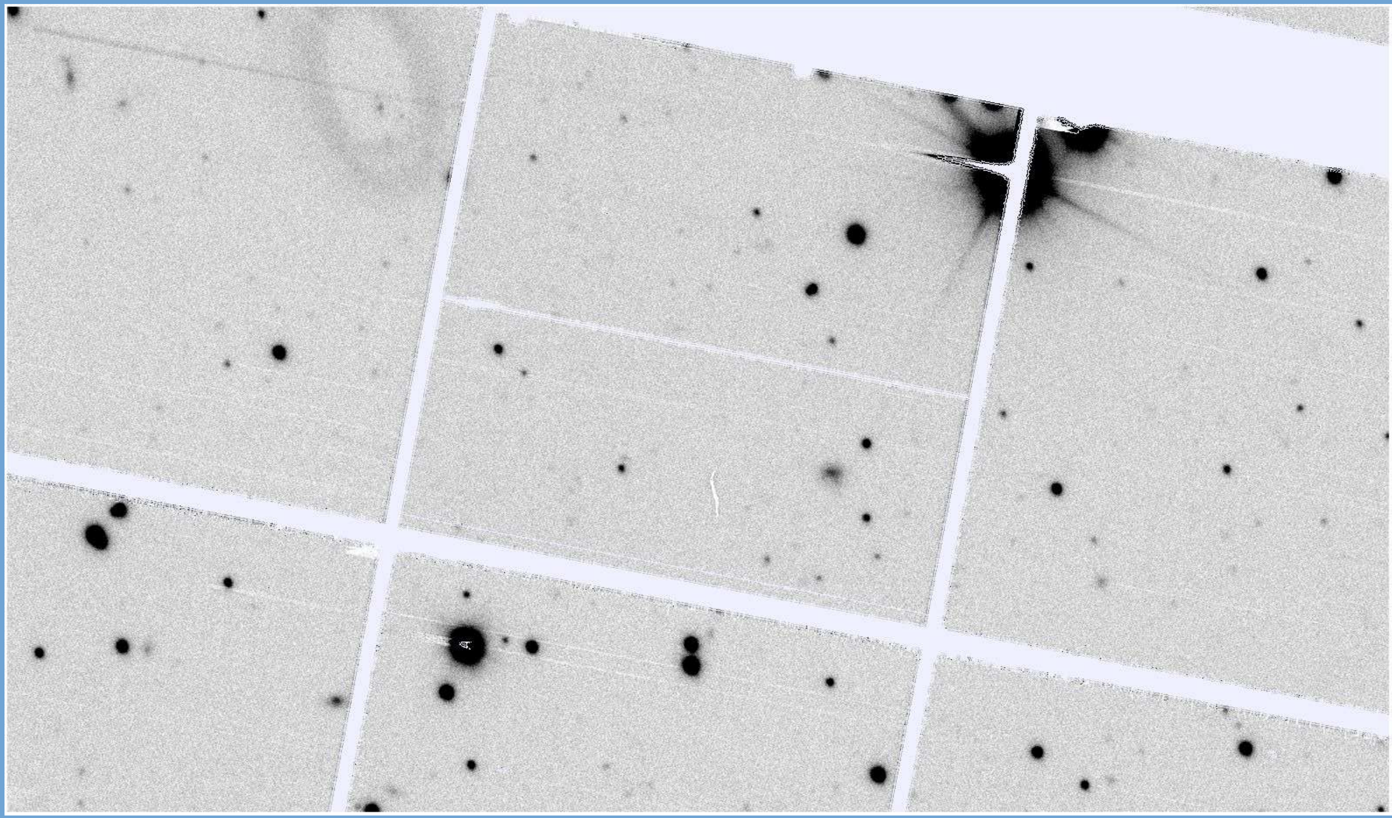

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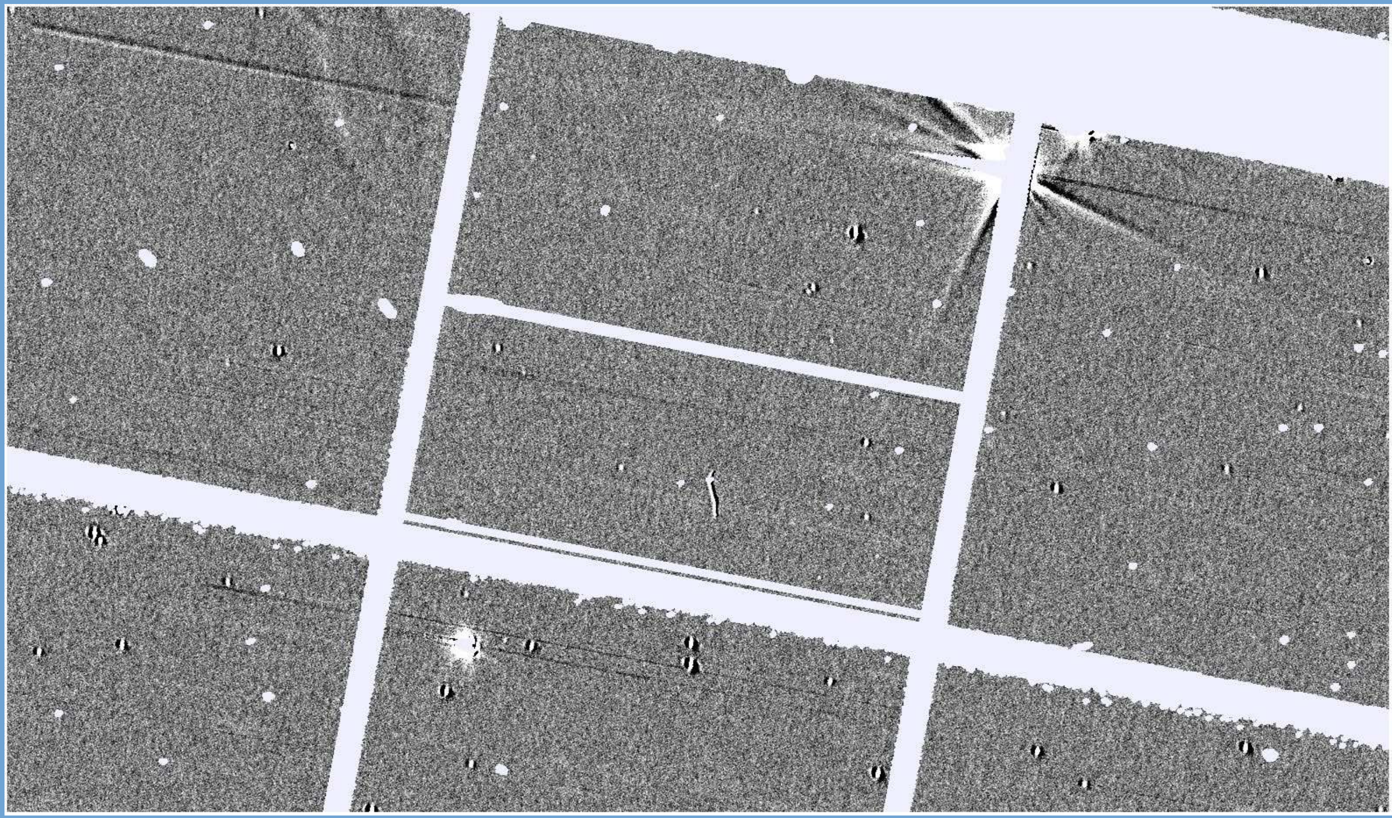

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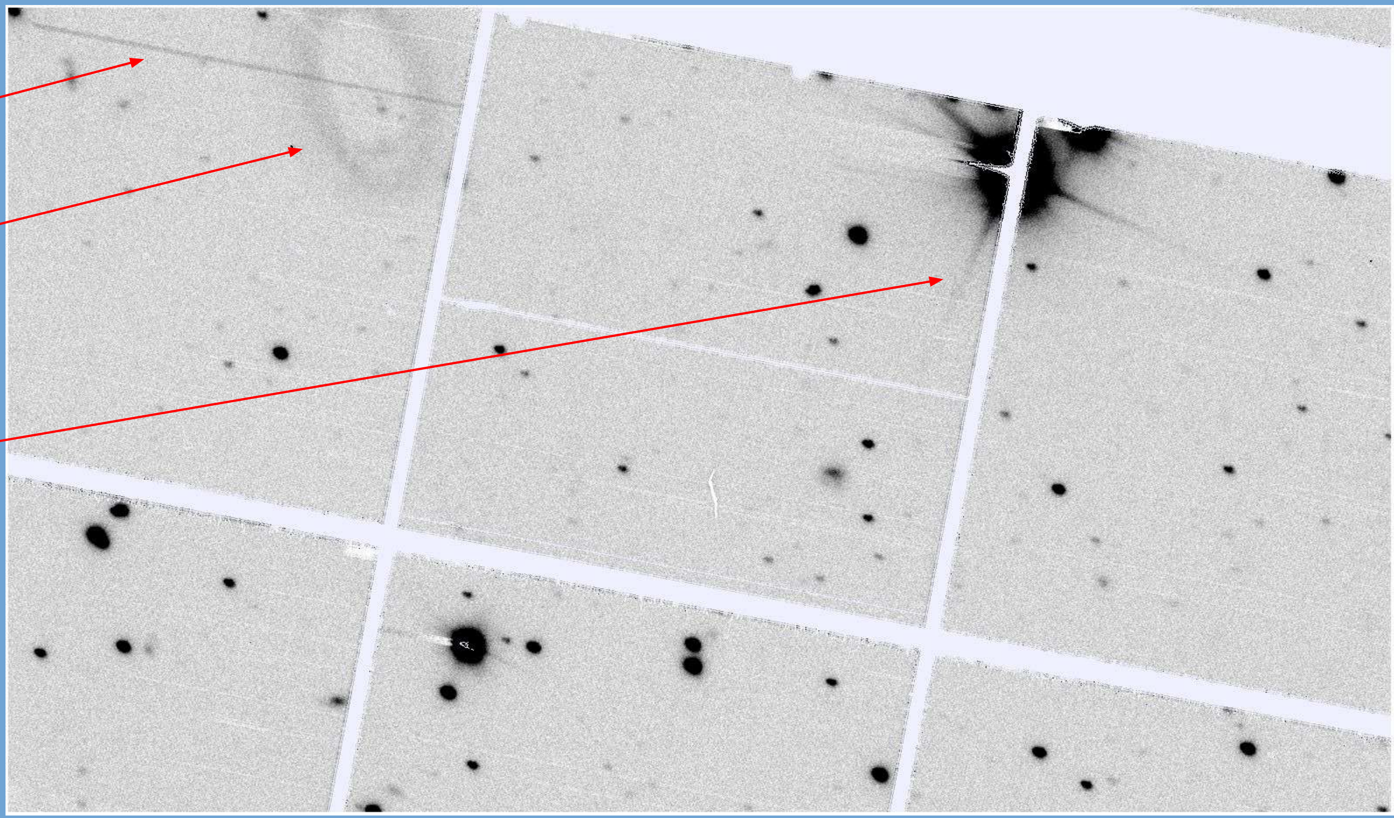

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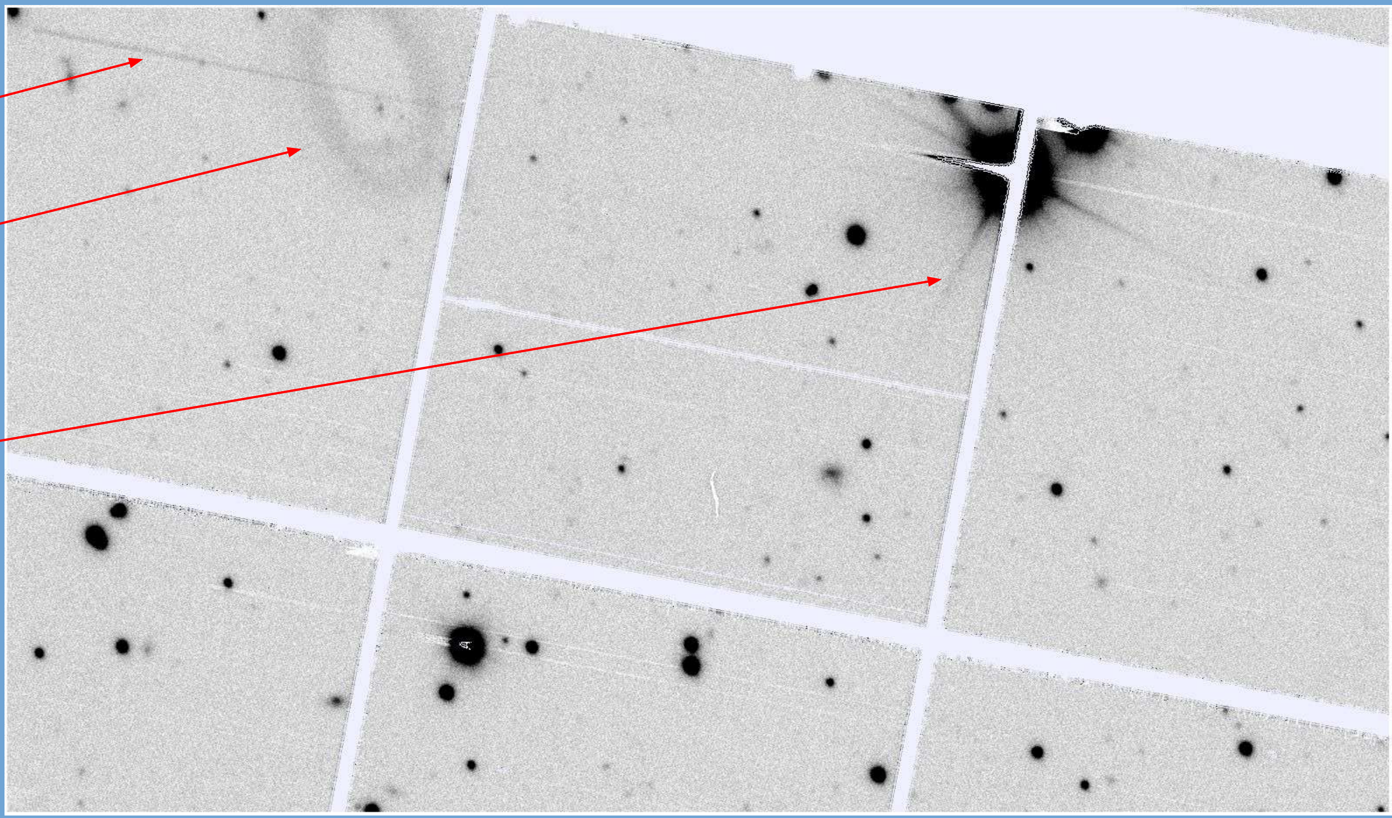

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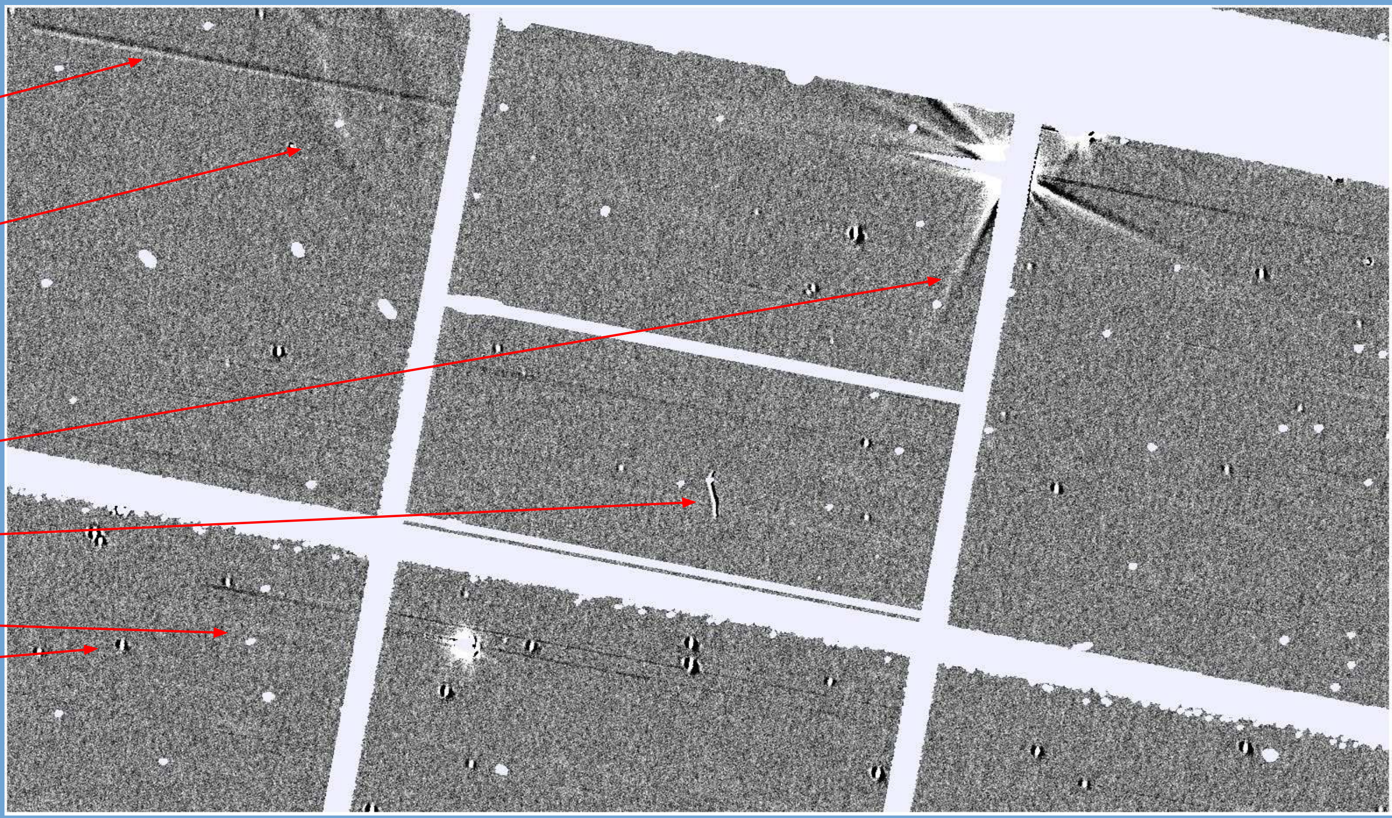

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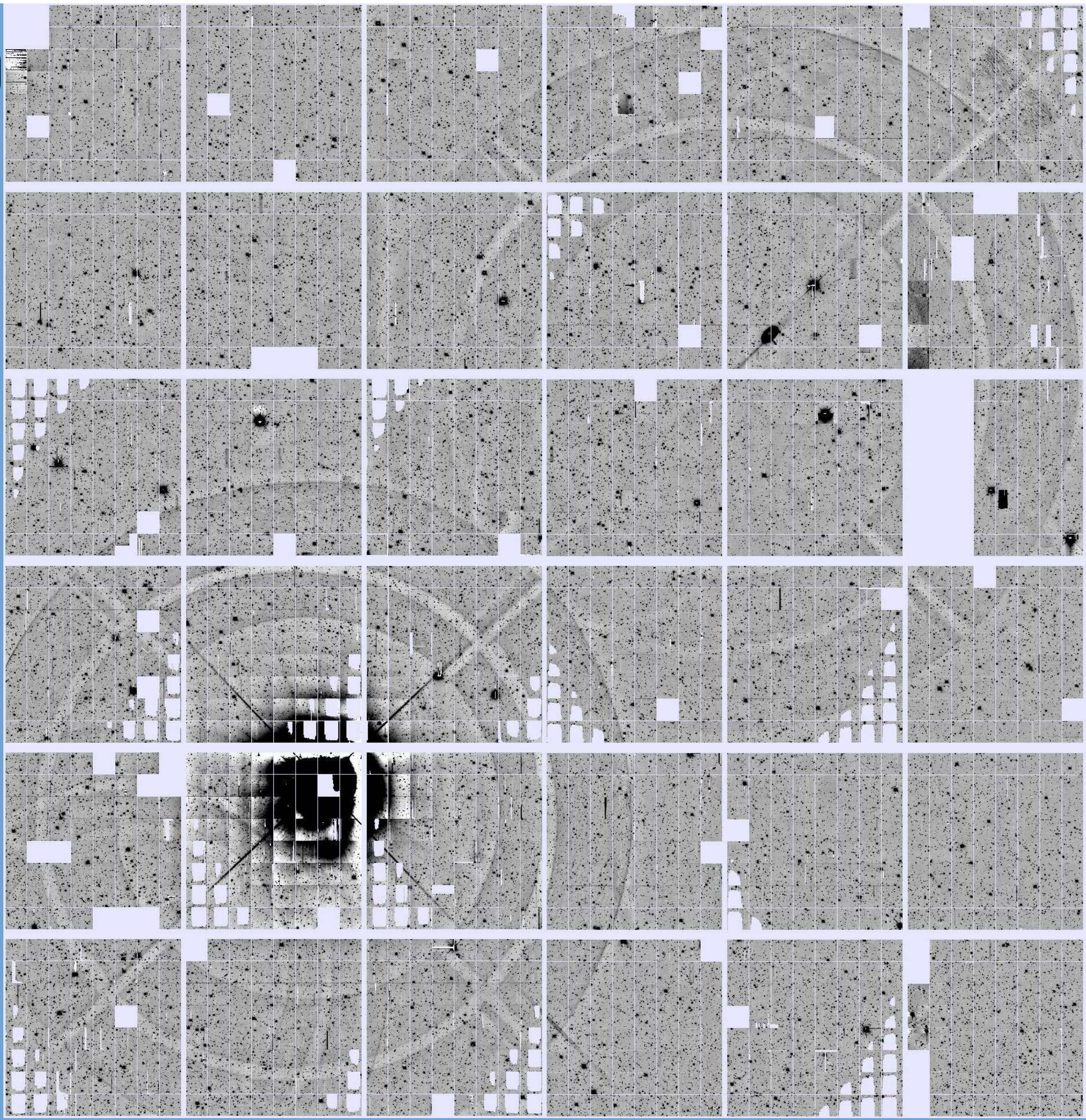

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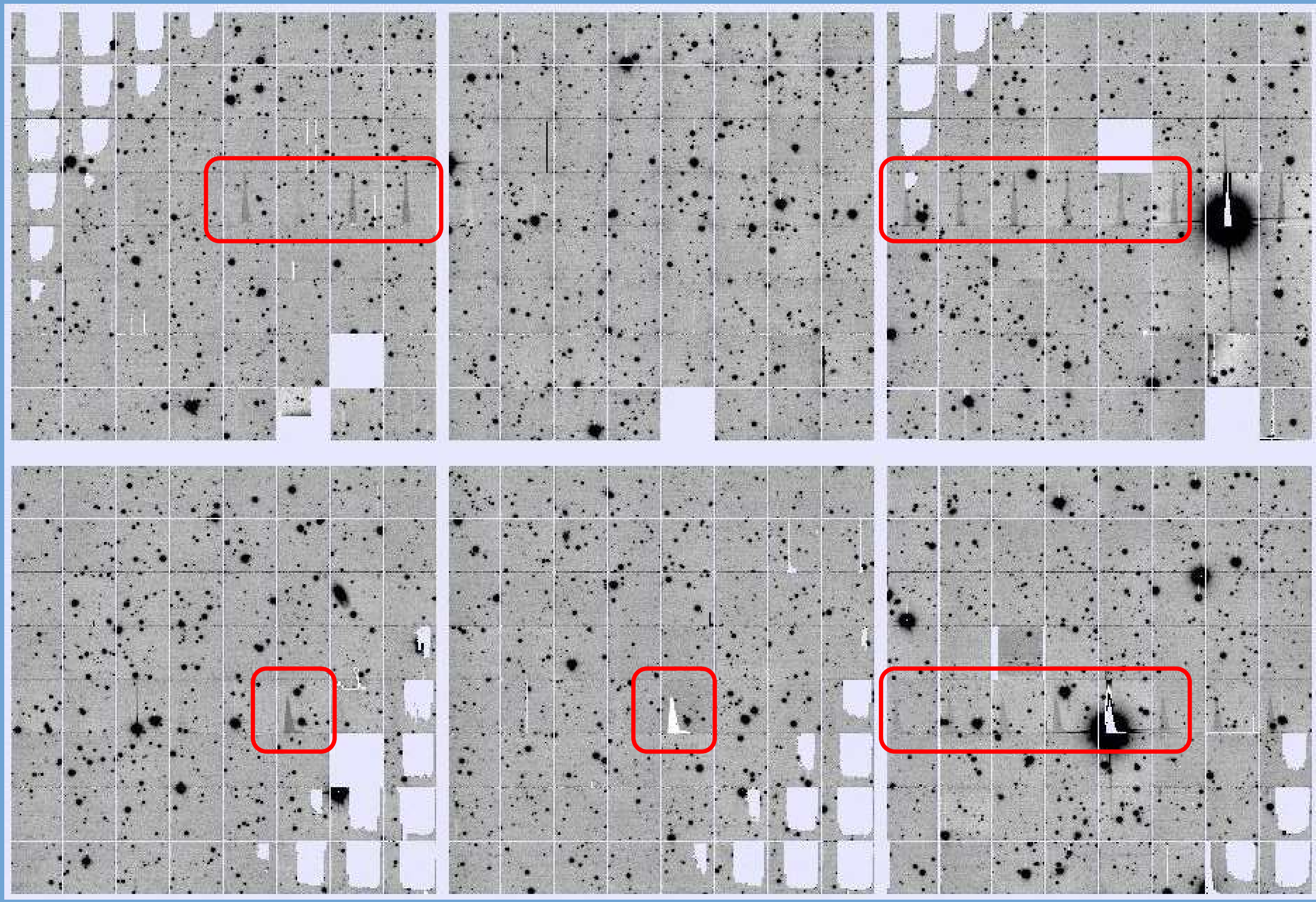
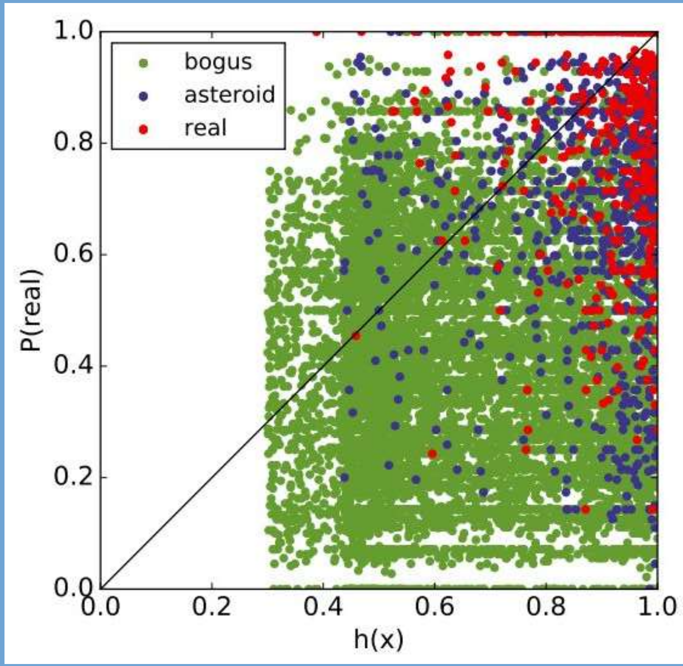


Garbage Rejection : Pan-STARRS Asteroid Science

- Statistics used in Pan-STARRS IPP -> MOPS cuts
  - second moments (Mxx, Myy)
  - flux & S/N in both positive and negative images
  - number of masked & unmasked pixels in diff image
  - positive and negative pixel values in diff image
- Cuts based on collection of false positives, known asteroids
  - Reduce false positive by 70% - 90%
- Raw false positive rate is > 99% - 99.9%
  - ***we rely heavily on human vetting for asteroids***
  - ~20,000 - 40,000 detections vetted ***per night***

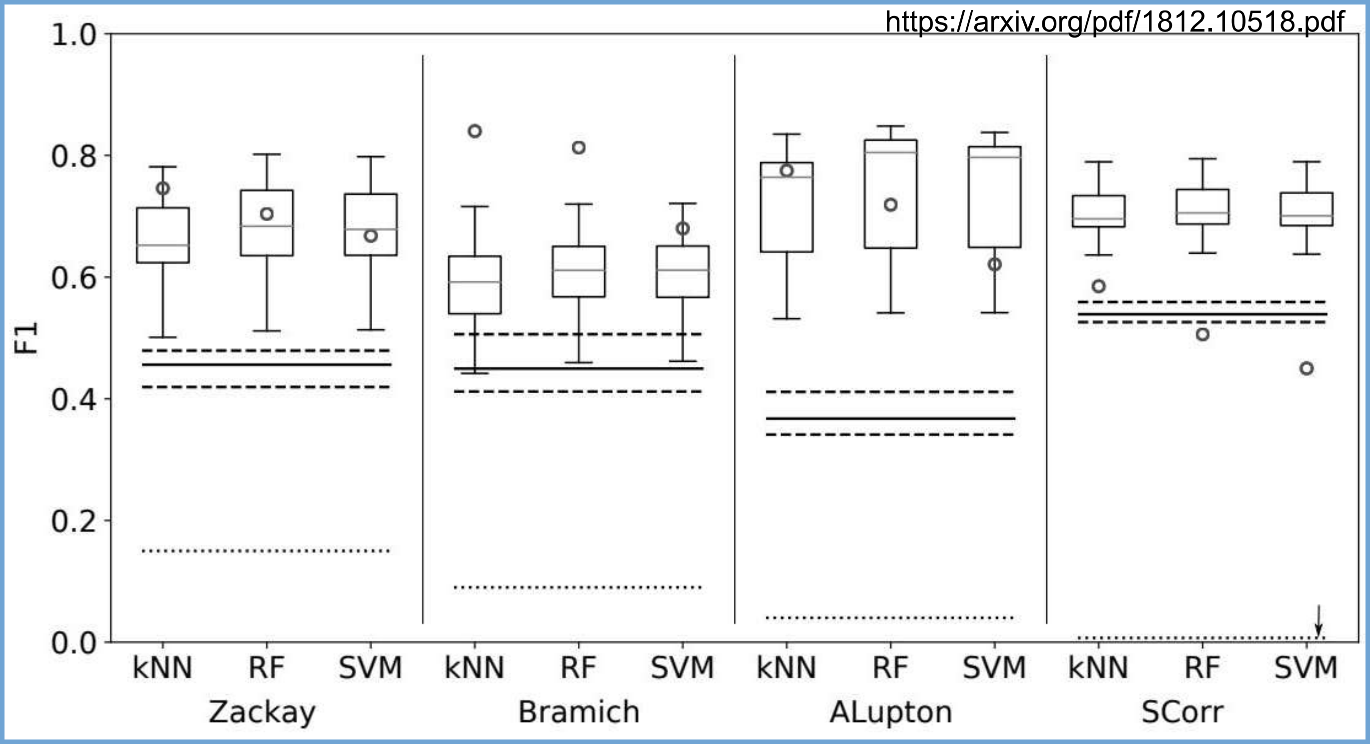
Garbage Rejection : Pan-STARRS Transient Science

- Initial cut based on source statistics
- Machine learning classifier(s) on pixels
  - Wright et al 2015 : Medium-Deep field data
    - compared NNet, Random Forest, SVM
    - settled on Random Forest based on tests
      - Purity: 99%, Missed Detection Rate: 6.2%
  - Wright et al 2017 : individual exposures
    - Convolutional NNet for initial classification
      - Purity: 42%, Missed Detection Rate: < 1%
    - Human vetting by Supernova Hunters
      - ~20,000 - 30,000 classifications of ~6000 detections ***per week***
    - Final selection based on combined score

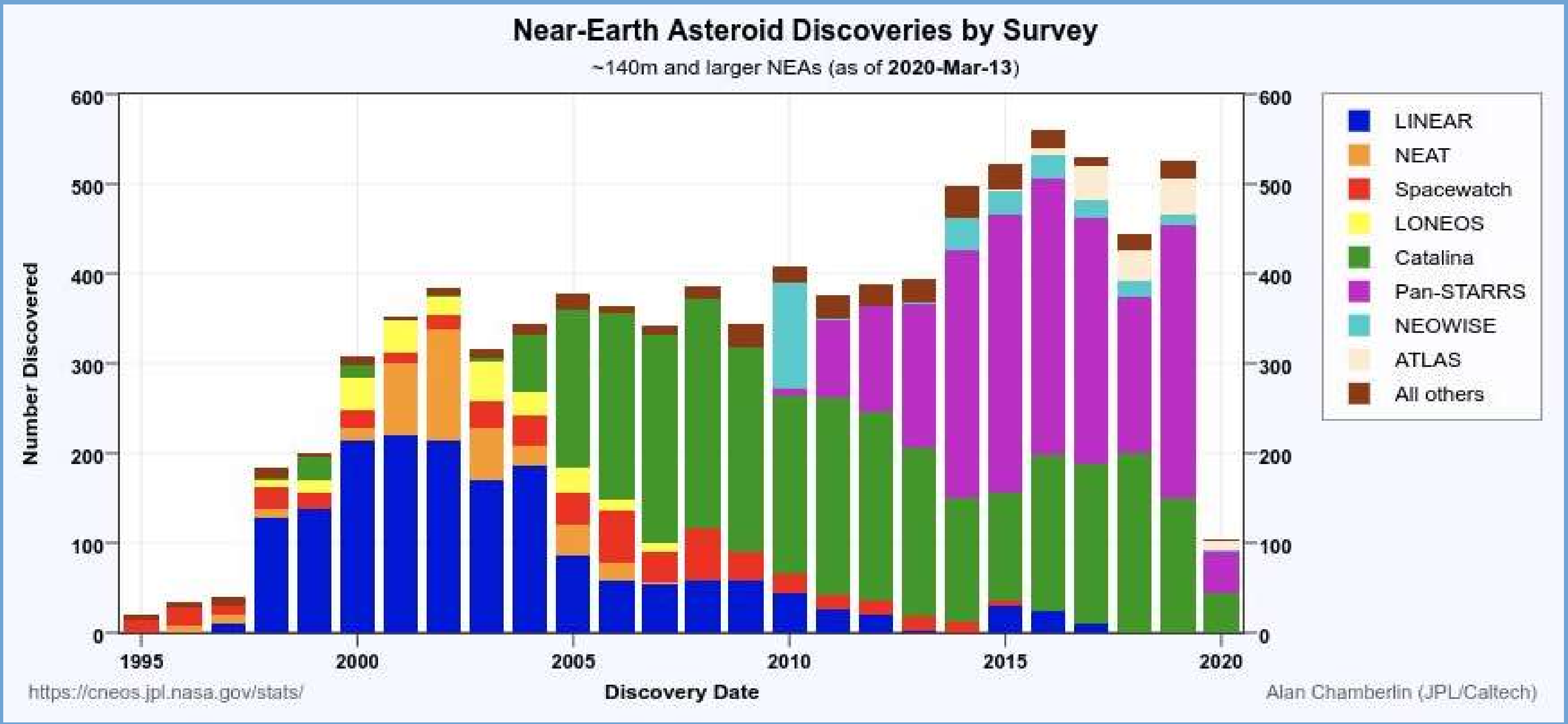


Sanchez et al 2019 : Comparison of techniques

- circles : real data
- horizontal lines : results pre-ML classification
- whiskers : ranges for simulation results with ML classifications



Classification & Follow-up



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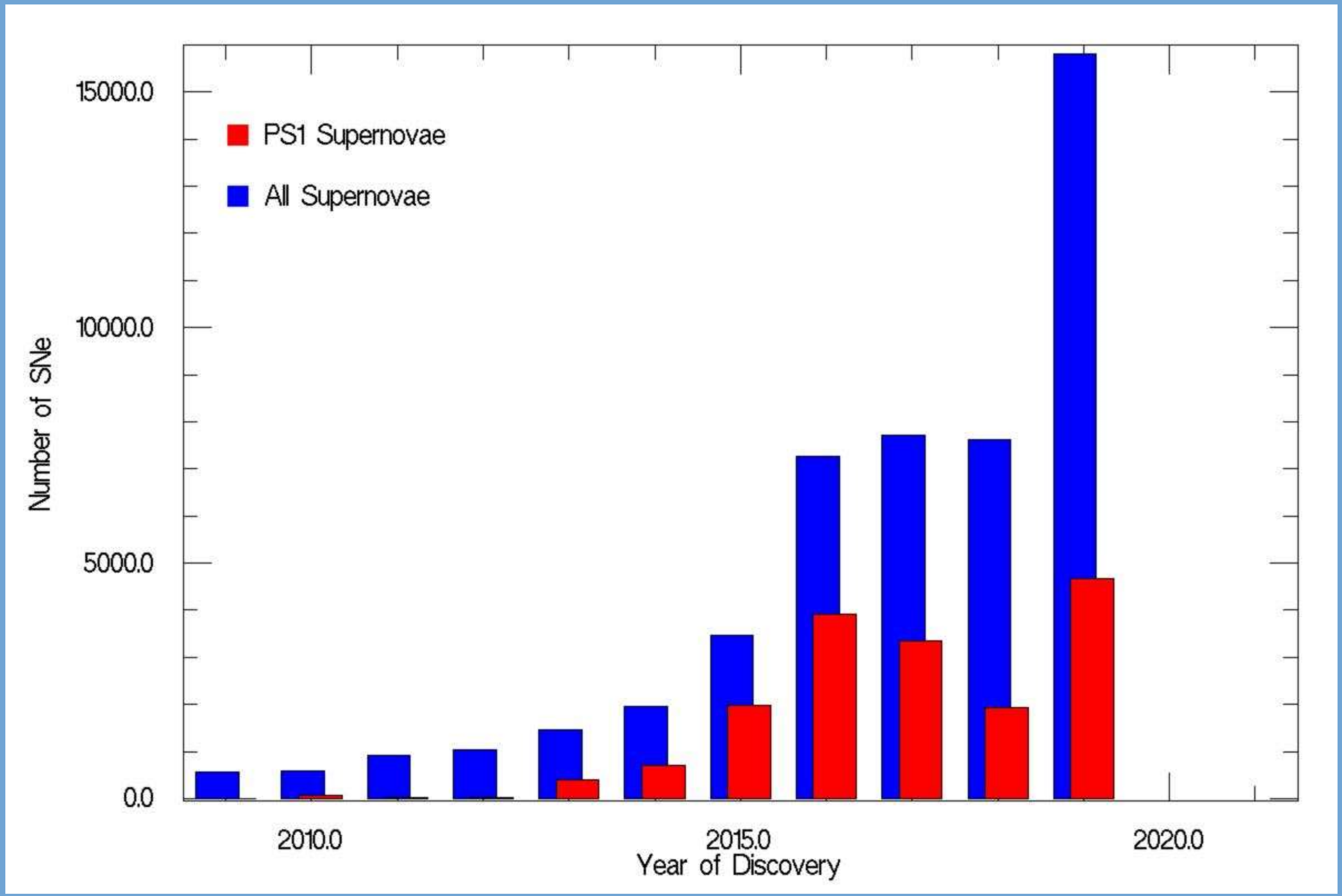

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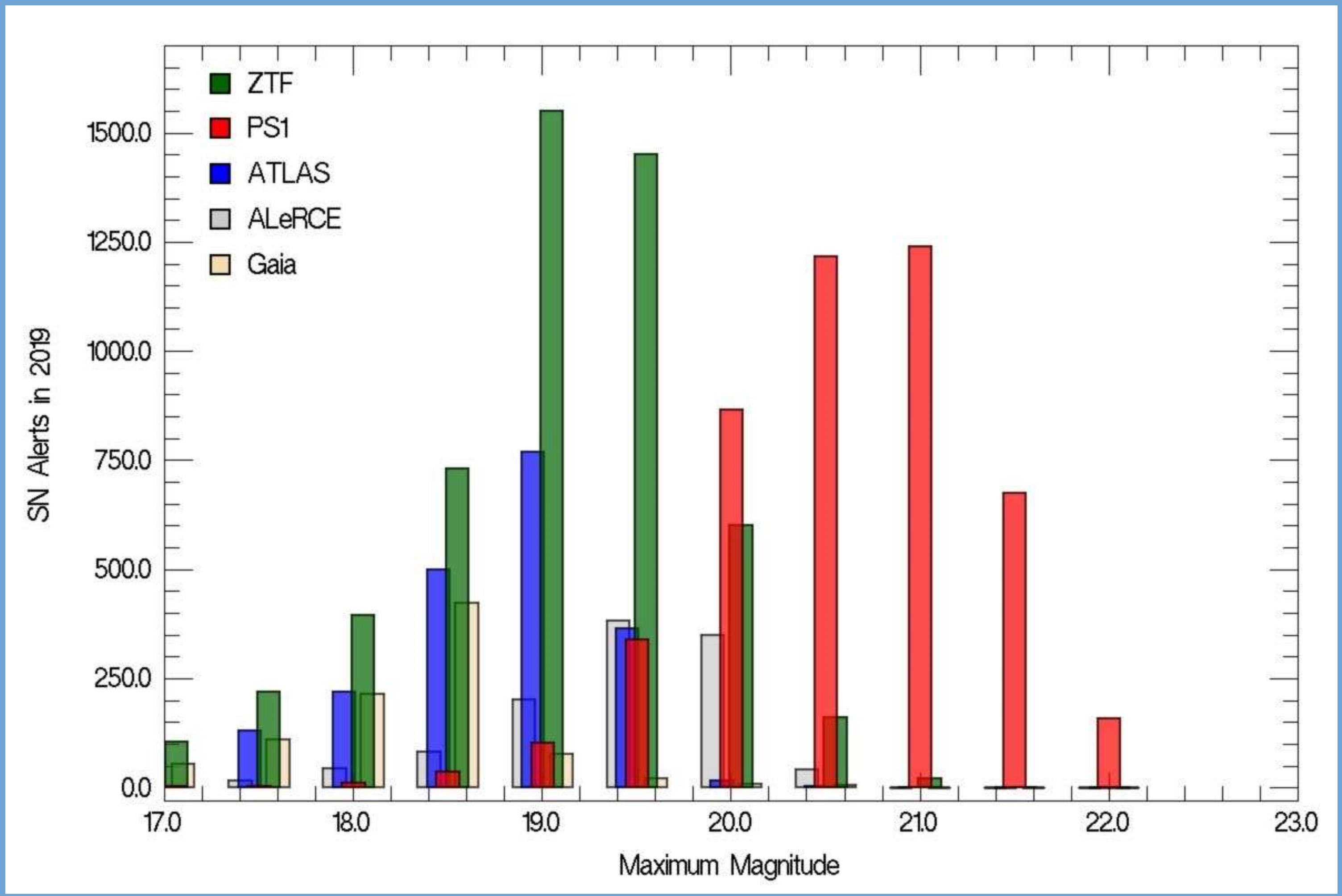

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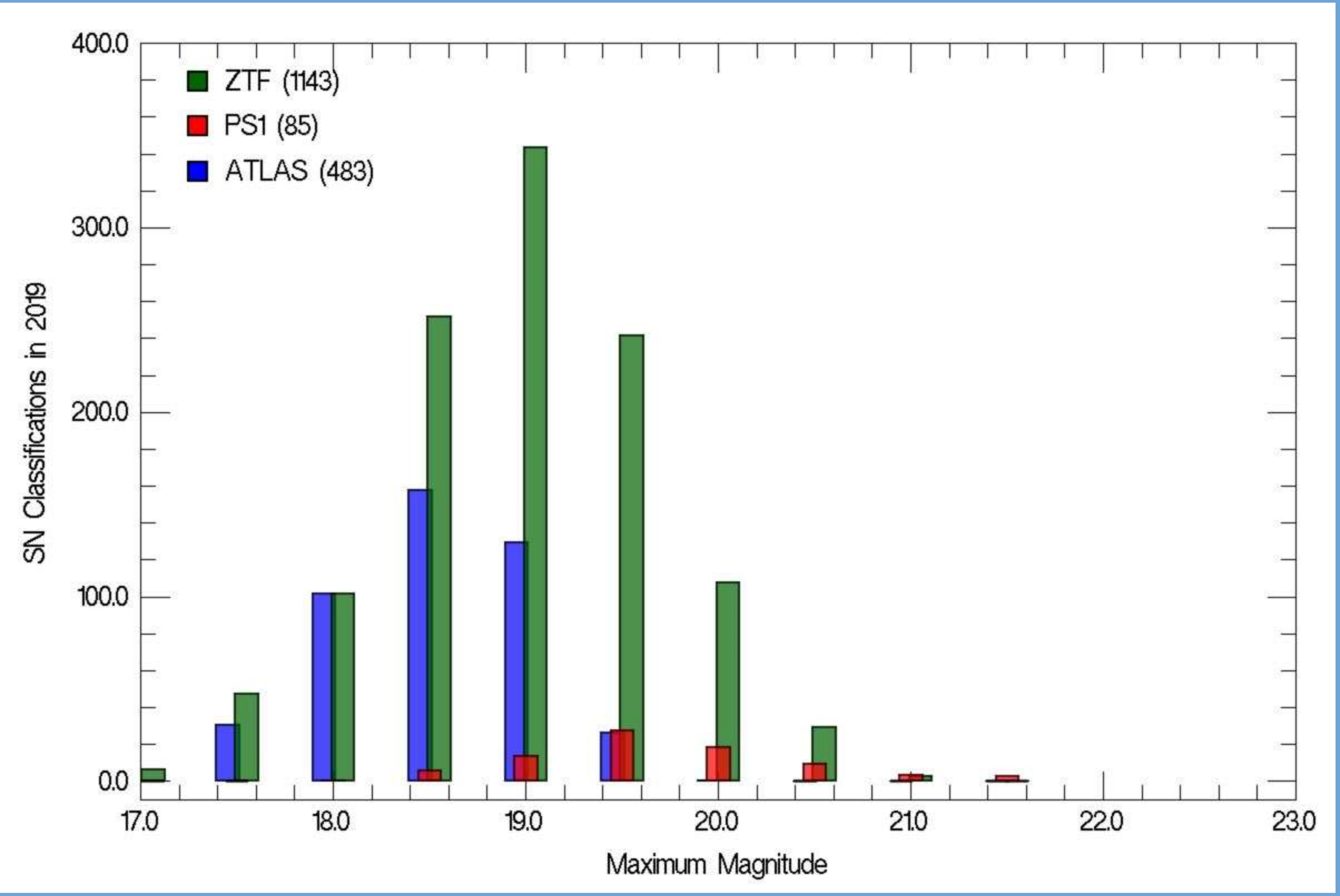

Conclusions & Lessons Learned

- Template quality matters a lot
- Image differencing is sensitive to tuning
- Cross-convolution was critical for
  - warp-warp subtractions
  - improving image quality vs infrequent template updates
- Mask / eliminate artifacts as much as possible
- Machine learning is helping but human vetting is still needed
- Triage targets for science follow-up