

STREAMING ALGORITHMS FOR OPTIMAL COMBINATION OF IMAGES AND CATALOGS

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Processing Observations

- Take images on the mountain & process at home
 - ▣ IRAF, IDL, Python, PyRAF, ...
- Sloan Digital Sky Survey did single pass by design
 - ▣ The PHOTO pipeline
- The time-domain is different!

Goals

- From hundreds of visits, we need
 - ▣ High signal-to-noise ratio
 - ▣ Sharp images
 - ▣ Deep catalogs

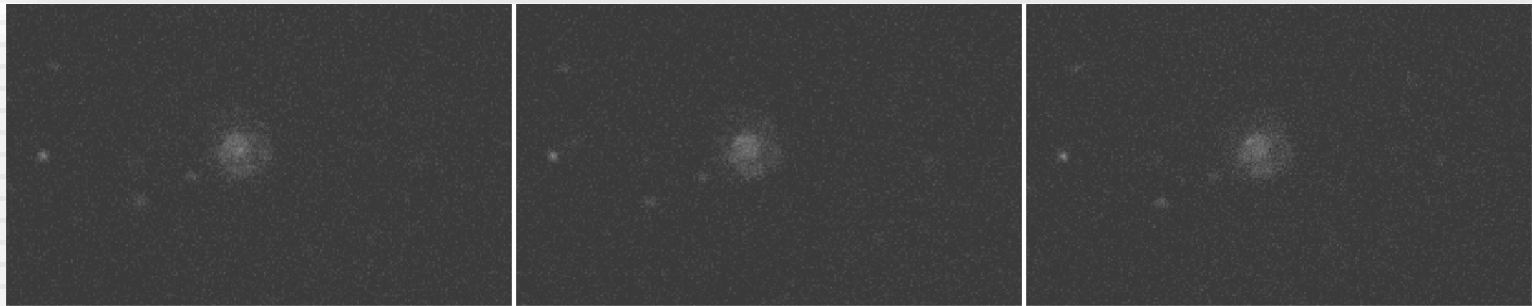
Traditionally

- Batches
 - ▣ Collect images of next release & combine them
 - ▣ Extract deep catalog & time series
- Long wait time & inefficient processing
 - ▣ Could we do it incrementally?

Outline

- Blind deconvolution of multi-epoch imaging
- On-the-fly catalogs for time-domain surveys

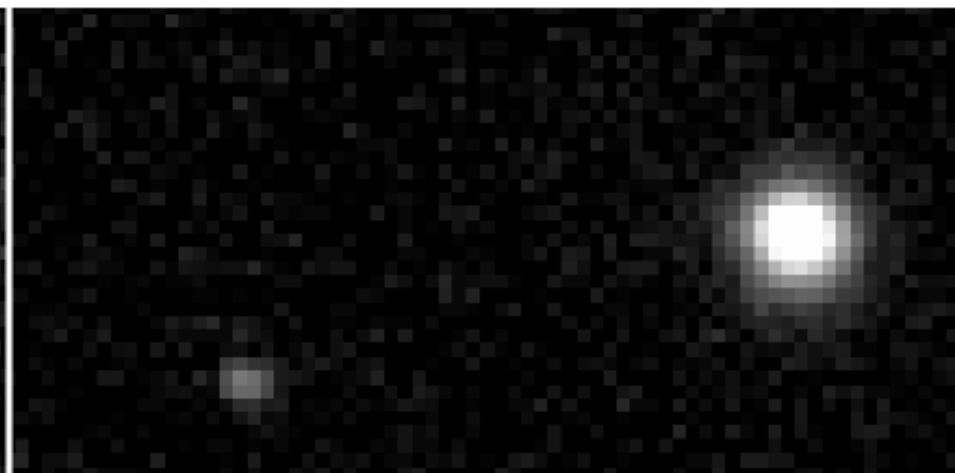
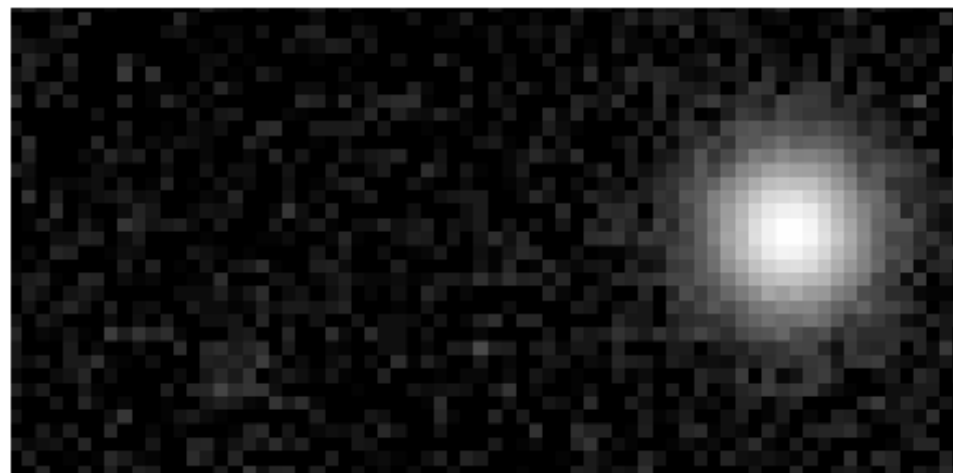
Combining Images



Current Methods

- Brute-force summing of images is incorrect
- Lucky imaging uses only the best images
- Convolve to worst acceptable PSF & coadd

Throwing away a lot of information!



Simple Model for Exposures

- Background image convolved with unknown point-spread function
- Plus the noise
- Solve for x ?

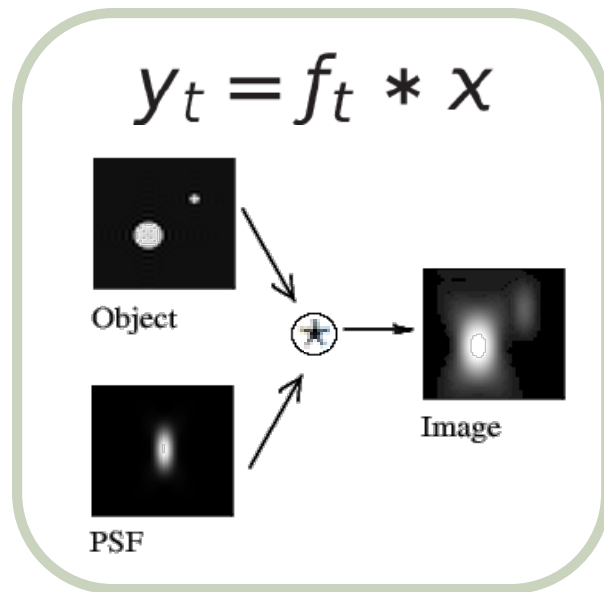


Image Deconvolution

- Correcting Hubble's optics & R-L deconvolution
 - ▣ See *White (1994), Starck+ (1994), Lauer (1994,2002), ...*
- Now it's different with hundreds of exposures
 - ▣ With different PSFs

Multiepoch Deconvolution

- We solve for background image & all the PSFs
 - ▣ Breaks the degeneracy of the single-image case
 - ▣ Iterative incremental approach
 - Solve for PSF of each incoming image
 - Update model image
 - Repeat until convergence

Computational Optics

- Elegant optimization
 - ▣ Richardson-Lucy updates for Poisson likelihood func
 - ▣ Gaussian yields similar updates

$$x_{t+1} = x_t \odot u_{t+1}$$

The devil is in the details!

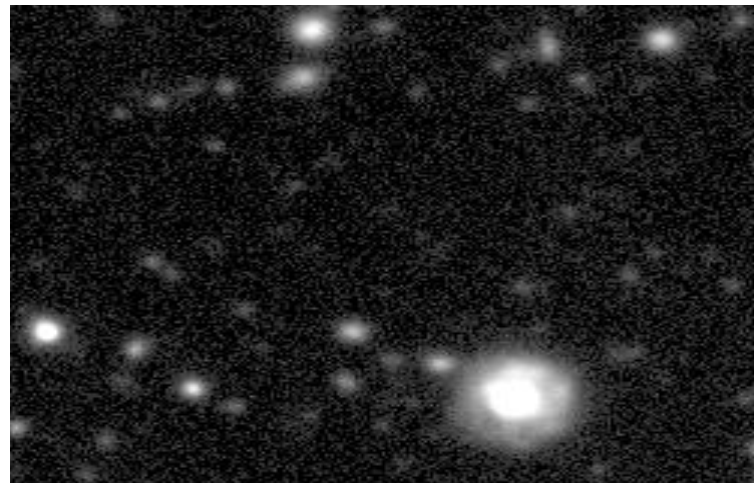
Priors & Likelihoods

- Stars are point sources
 - ▣ Regularization
- Modified likelihoods
 - ▣ Masking saturated & bad regions
 - ▣ Damped variants & robust stats
- Controlling convergence
 - ▣ Update clipping, ...

Coadded & Reconstructed

- Coadding
 - ▣ Brings out faint sources
 - ▣ But blurs the images
- We deconvolve
 - ▣ For high-res details

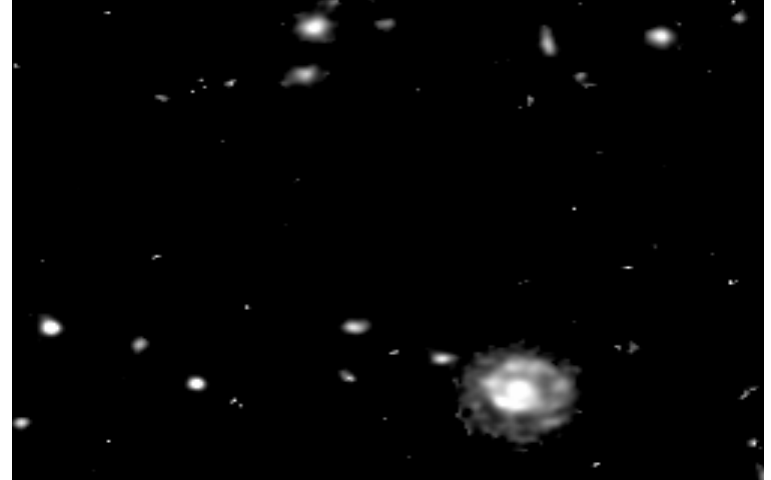
Coadded Image



Coadded & Reconstructed

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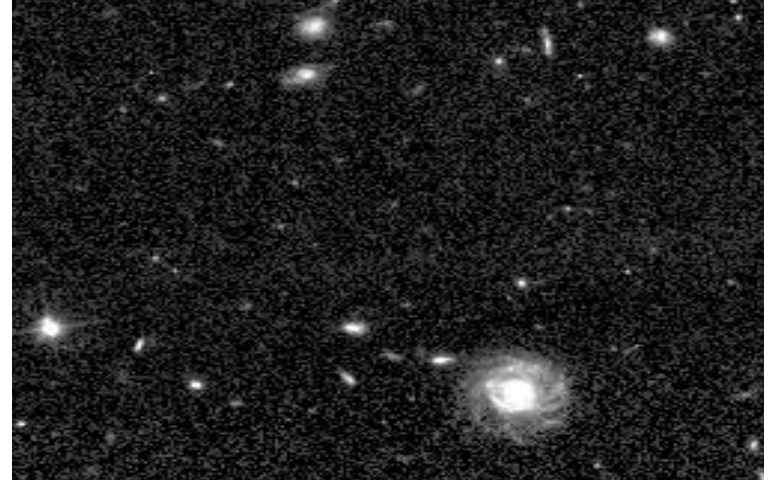
Deconvolved Image



Coadded & Reconstructed

- Coadding
 - ▣ Brings out faint sources
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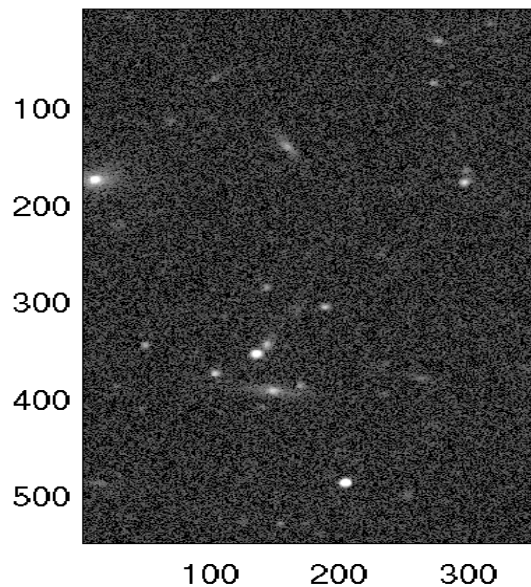
Hubble Image



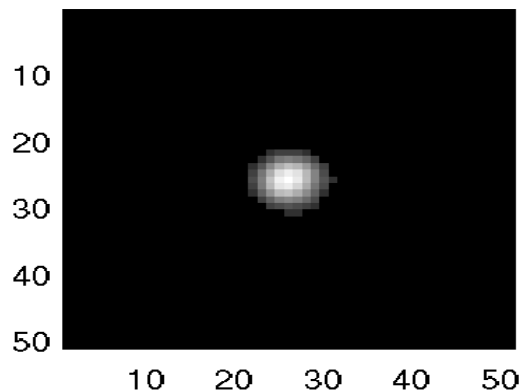
LSST ImSim

Work with Andy Connolly

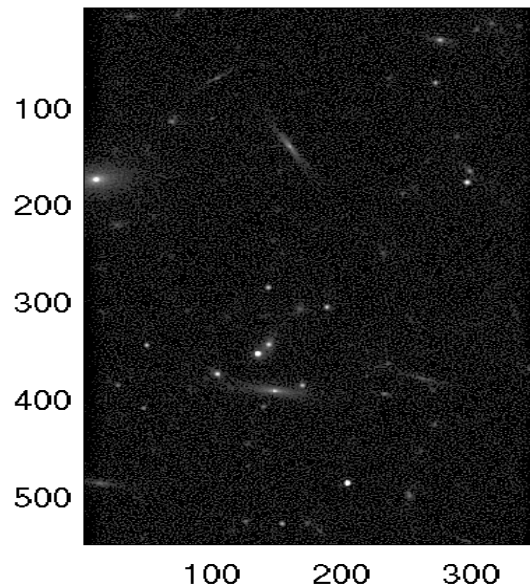
Observed 75|11



PSF20 0|20



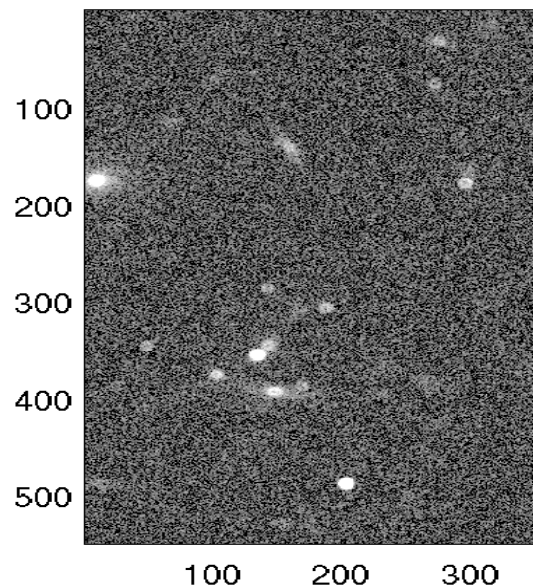
Estimated 28|75



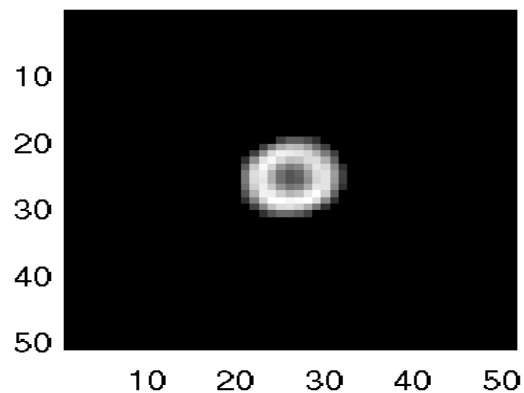
LSST ImSim

Work with Andy Connolly

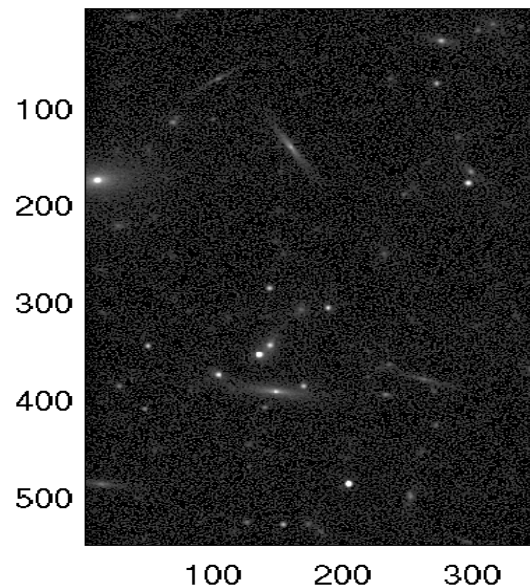
Observed 84|01



PSF20 0|20

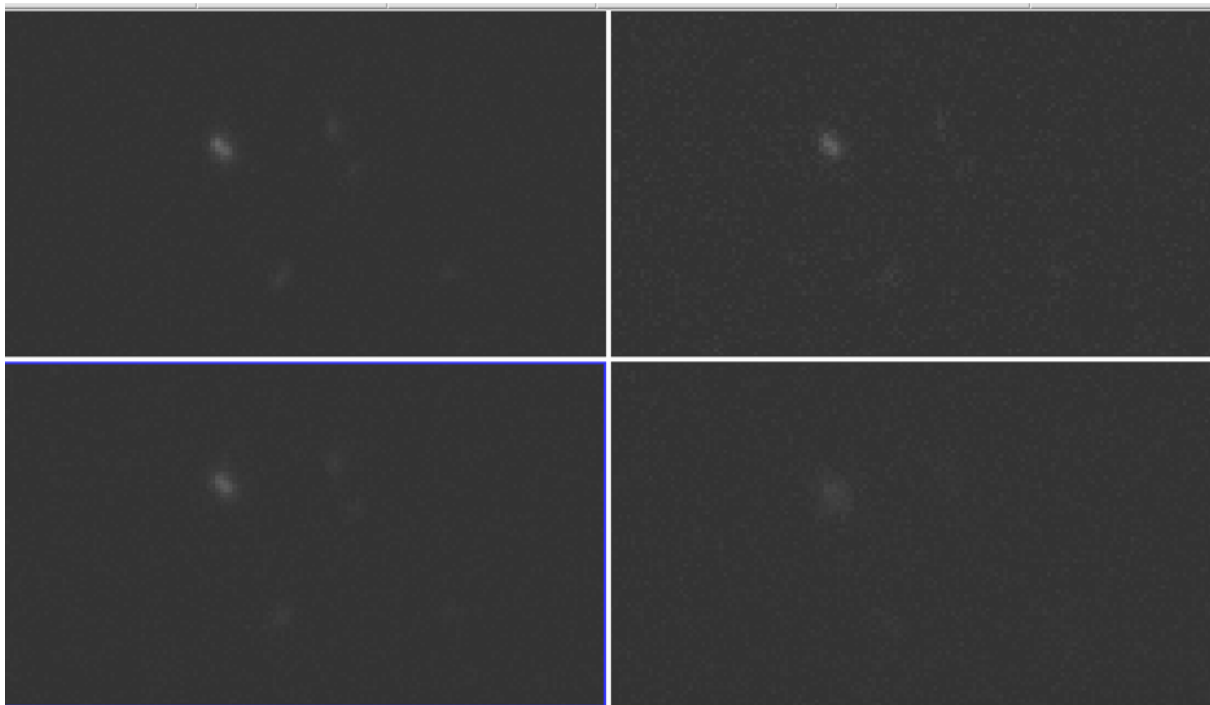


Estimated 10|84

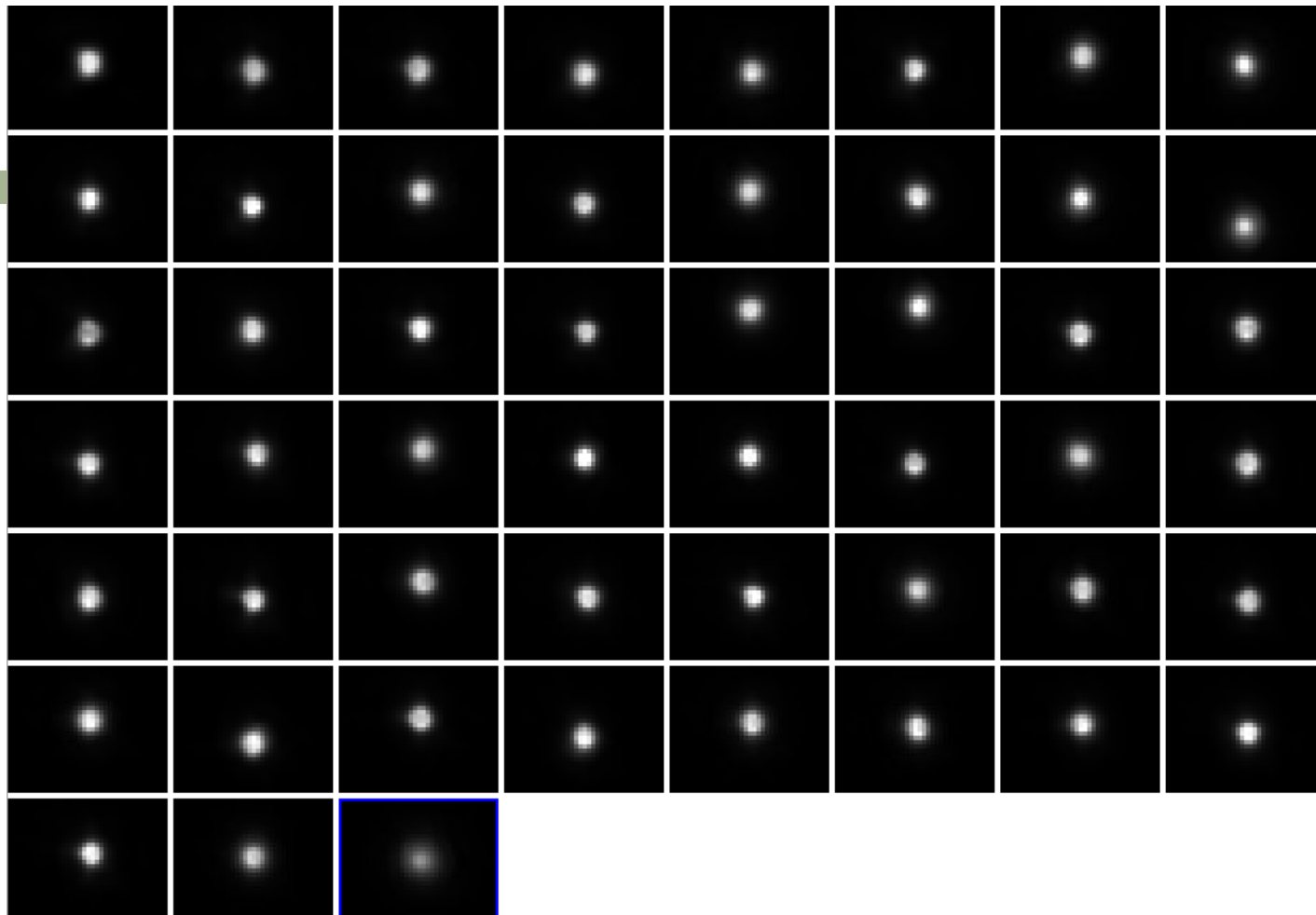


SDSS Stripe 82

- Single-epoch samples



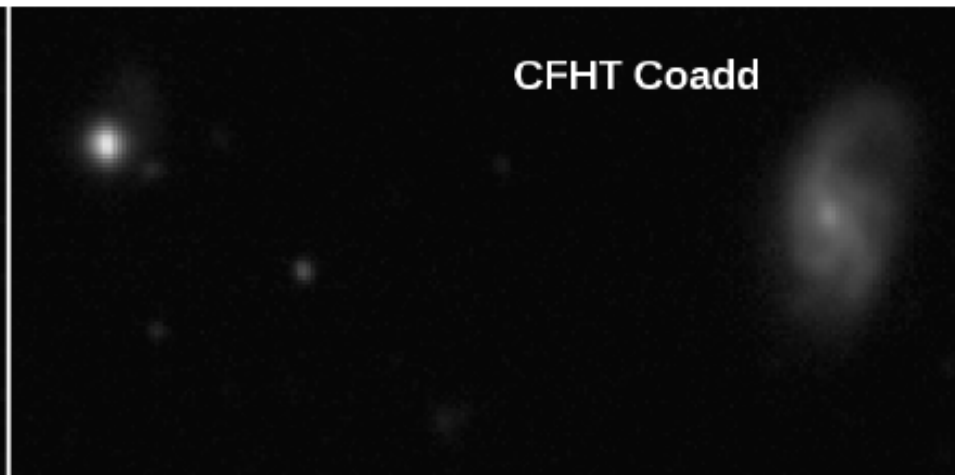
PSFs



S82 Coadd



CFHT Coadd



Our Result

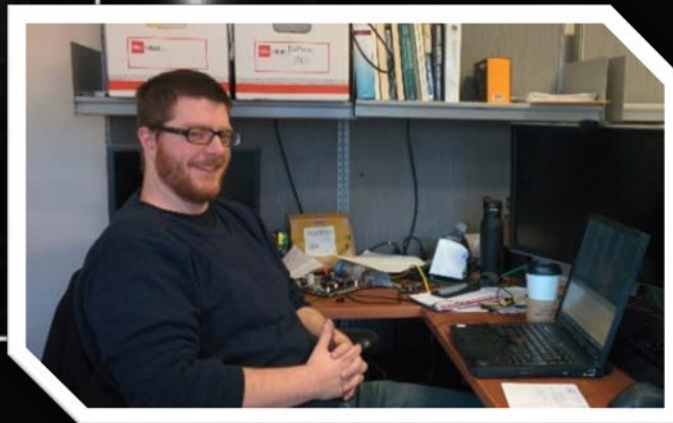


Our Result SR



S82 Coadd

CFHT Coadd



Our Result

Result SR

Matthias Lee

Beyond Pretty Pictures

- Statistical comparison to ground truth
 - ▣ To deeper exposures
 - ▣ To LSST ImSim

Tools and Future Work

- Fast GPU implementation in Python + CUDA
- Include sky background solution
- Source extraction from results
- Need pipeline code
- Get more science out!

[Funded by NSF AAG]

Alternatively on Catalogs?

- Coadd images & perform forced photometry
 - ▣ Ideal but registration tricky, processing slow, ...
- Extract source lists from each image
 - ▣ Combine source lists into a catalog

Need to dig in the noise to go deep!

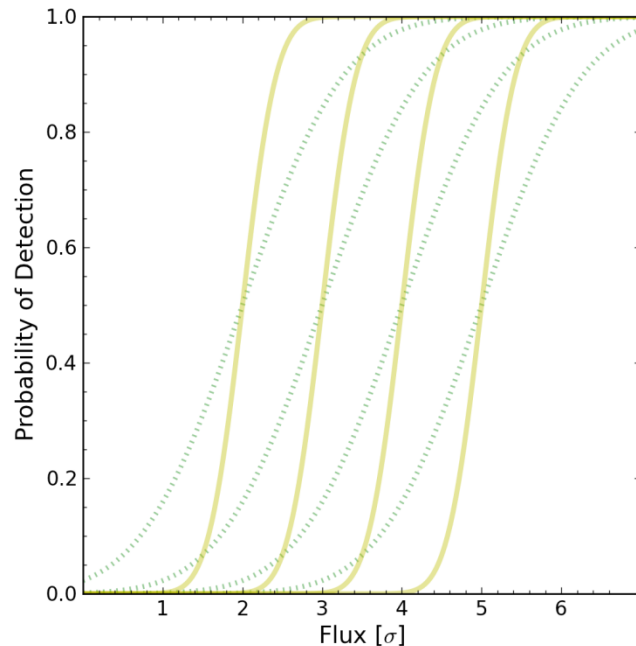
Detection Probability

- Measured flux is true + normal error $f_i = f + \epsilon_i$
- Probability of detection

$$P_f \equiv P(f_i > f_D | f) = \frac{1}{2} \operatorname{erfc} \left(\frac{f_D - f}{\sigma \sqrt{2}} \right)$$

Detection Probability

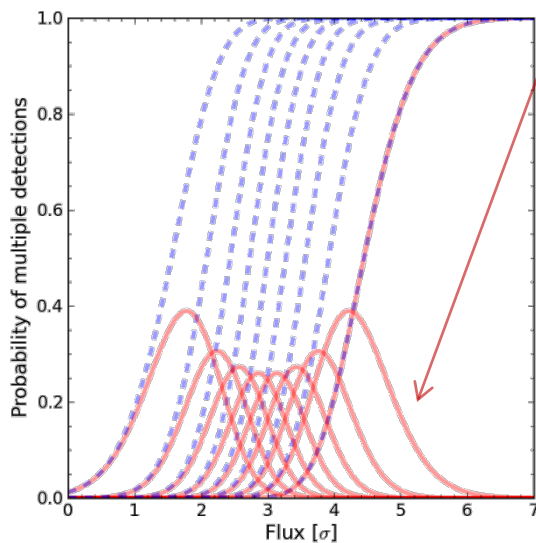
- Measured flux is true + normal error $f_i = f + \epsilon_i$
- Probability of detection
 - As a function of the true flux →
 - Thresholds at 2-, 3-, 4- & 5 σ
 - Sharper for 9-way **stacks**



Detection Probability

□ Multiple exposures

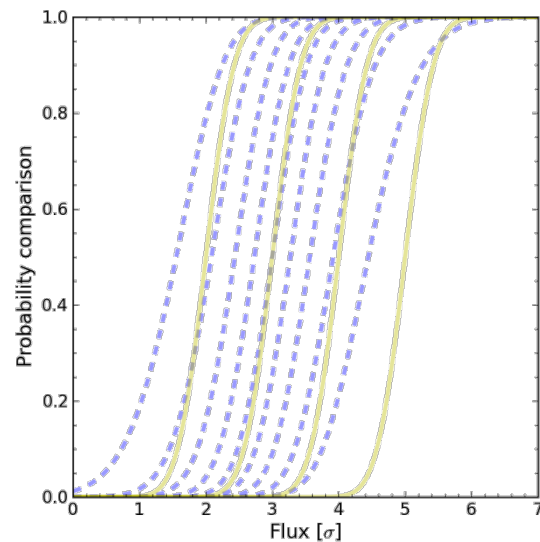
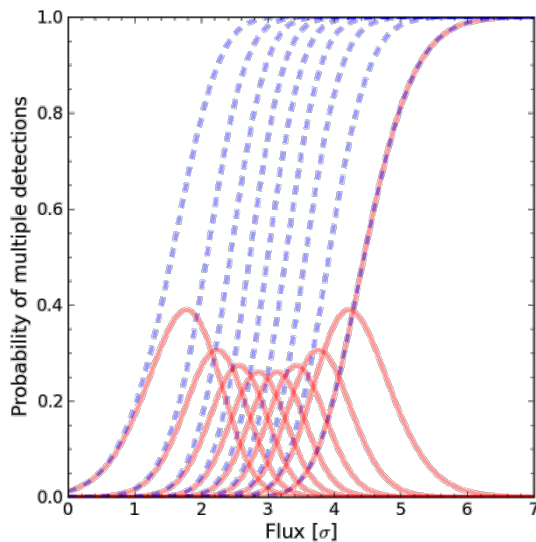
■ Binomial $P(n|k, f) = \binom{k}{n} P_f^n (1 - P_f)^{k-n}$



Detection Probability

Multiple exposures

Binomial $P(n|k, f) = \binom{k}{n} P_f^n (1 - P_f)^{k-n}$



What is a Real Source?

- Is it “real” or just “noise” ?
 - ▣ Bayesian hypothesis testing

$$B = \frac{L_{\text{real}}}{L_{\text{noise}}}$$

We weed out the noise as we go!

Summary

- Processing on streams of data
 - ▣ Linear scaling and monitoring of results
- Multiepoch deconvolution works
 - ▣ GPU speed makes this practical
- On-the-fly catalog aggregation

Incremental approaches that scale