# Data Fusion at Scale in Astronomy

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#### Lots of Data, Many Sources

- World is exploding with data
- Data collection grows with Moore's law
  - Over 100 PB of astronomy data in 10 years
    - Pioneer in big data
    - Sloan Digital Sky Survey in house 35 TB
    - Large Synoptic Survey Telescope expected 60 PB<sup>1</sup>
  - Big data everywhere
    - Sciences: genomics, particle physics, astronomy
    - Industry: finance, social media, machine learning

# Making sense of it All

- Biggest challenges, extracting meaning
- Difficult to process, transfer and store
- Need new methods
  - Deal with lots of data
  - Scalable
  - Combine data, extract meaning.
- Parallel to Scale
  - GPUs and Clusters
  - Amdahl's Law

### Fusing Data at Scale

- Cross-Matching Astronomy Catalogs
- Optimal Image Coaddition
  - Sharpening Images, Doubling resolution
- Extracting Color from monochrome images

#### **Fusing Astronomy Catalogs**



#### Thesis Mork Divide, Conquer & Parallelize

- Pair of objects
  - Compute simple distance metric
- Challenge is in efficient Parallelism
  - Segments
  - Sorting/Thrust
  - Worker Jobs
  - Zones Algorithm<sup>1</sup>
  - Multi-GPU



<sup>1</sup> "There Goes the Neighborhood: Relational Algebra for Spatial Data Search" Gray, Szalay, Fekete (2004)



# **Unprecedented Speed**

- Optimization yields high matching performance
  - 50M × 150M in 50 seconds
  - 450M × 450M in 3 minutes vs 45mins !



"Faster catalog matching on Graphics Processing Units" M. Lee, T. Budavári (2017)

### Catalog Crossmatch

- Scientifically Important Problem
- Scalable Acceleration
  - Parallelized across multi-GPU
- 15x faster vs State of the Art
  - 3 minutes vs 45 minutes

### Observing the Sky

SDSS telescope at night by Patrick Galume

#### Multiple Exposures

Sloan Digital Sky Survey (SDSS)

- Stripe 82 has 70x coverage

Large Synoptic Survey Telescope (LSST)
 Will have 200x coverage



#### **Traditional Solutions**

- Lucky Imaging
  - Keep only the best/sharpest 1% of the images
- Coadding
  - Higher Signal-to-Noise Ratio
  - Worst acceptable blur (PSF)



#### **Traditional Solutions**

- Lucky Imaging
  - Keep only the best/sharpest 1% of the images



#### **Next-Generation Processing**

- Traditional methods are sub-optimal
  - Naive assumptions yield wrong results
- Computational Optics
  - Best possible signal-to-noise ratio
  - Sharper & deeper images
  - Higher resolution

#### **Computational Optics**

- Single frame solutions before
  - Correcting Hubble optics
  - Classic Richardson-Lucy deconvolution
    - White (1994), Starck+(1994), Fish+ (1995)
  - Limited by information in single frame
- Multiple frames provide new opportunities
  Breaks degeneracy of PSF and the "true" image

#### Linear Model for Exposures

- "true" image convolved with unknown PSF
- Plus some noise



• Solve for *x* 

... and f

### **Streaming Deconvolution**

- We solve for the underlying "true" image
- Gaussian likelihood function yields
  quadratic minimization

$$|y_t - Fx_t|^2$$

- Multiplicative updates
  - cf. Richardson-Lucy

$$x_{t+1} = x_t \odot \frac{F^T y_t}{F^T F x_t}$$

• Iterative approach:

Load next Observation Initialize new PSF

• Iterative approach:



• Iterative approach:



• Iterative approach:



The devil is in the details!

#### **Textbook Deconvolution**



Annis Coadd (2011)



unmodified deconv

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Annis Coadd (2011)

• Ringing artifacts



unmodified deconv

#### **Textbook Deconvolution**



Annis Coadd (2011)

unmodified deconv

- Ringing artifacts
- Speckled background



# **Robust Statistics**

- Quadratic cost function dominated by bad pixels
  - Poor convergence across image
- Apply Robust  $\rho(r)$ 
  - Quadratic for small residuals
  - Down-weights large
- Iterative re-weighting
  - Integrate with streaming





# **Careful Updates**

- Artifacts from nowhere
  - Large updates of tiny values
- Limit the influence of updates
  - E.g., no more than 2x



Update Image

Model Image



**Masking Pixels** 

• Ignore gaps as well as bad or saturated areas



• But we also solve for the missing areas!











MFBD + Robust + Update Clipping

#### **Super Resolution**

• Upscale and Downscale Operator



#### **Super Resolution**

- Upscale and Downscale Operator
- CFHTLS ~ 2x resolution of SDSS





# Super Resolution

- Upscale and Downscale Operator
- CFHTLS ~ 2x resolution of SDSS





### Performance

- Performance is important!
  - GPU-accelerated using pyCUDA
  - 140 images 2k by 2k: < 5 min
  - + Super Resolution, 4k by 4k: ~ 10 min
- Python, fast prototyping for experimentation
- Built Pipeline for processing Survey on MARCC

### Beyond the Optimal Coadd

- Combine multiple images
  - Increase quality: SNR
  - Increase clarity: deblurring
  - Increase resolution: Super Resolution
- Color estimation

#### **Differential Chromatic Refraction**



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#### **Differential Chromatic Refraction**





# DCR: Multiple PSFs

• Old model:

$$y_t = f_t * x + \epsilon_t$$

• Generalized model:



$$y_t = f'_t * x' + f''_t * x'' + \epsilon_t$$

subband 1

subband 2



# Simulate Observations

- LSST StarFast Simulator
- 2 Discrete wavelengths
- PSF of varying Zenith angle



subband 1



#### Sample Observations



# Thesis Wew Algorithm for Subbands

- Similar to MFBD
- Solving for multiple subband images



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#### subband 2 Observation









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subband 1 Recovered

#### subband 2 Observation



subband 2 Recovered











#### Noiseless – Flux Recovery



#### Introducing Noise



- 5 Observations
- 1 Realization



- 5 Observations
- 50 Realizations



- 15 Observations
- 50 Realizations





- 50 Observations
- 50 Realizations



#### **Positional Accuracy**

#### 0.06 0.06 0.06 0.06 5 input images 15 input images 50 input images 200 input images 0.05 0.05 0.05 0.05 0.04 0.04 0.04 0.04 Bias b 0.03 0.03 0.03 0.03 0.02 0.02 0.02 0.02 0.01 0.01 0.01 0.01 0.00 0.00 0.00 0.00 0 2 8 10 2 10 0 2 8 10 0 2 8 10 4 6 0 4 6 8 4 6 4 6 $f_1$ SNR $f_1 SNR$ $f_1$ SNR $f_1$ SNR

#### Position Bias of Coadd



### **Positional Accuracy**

#### Position Bias of Coadd



#### Position Bias of DCR Result



#### Realistic Simulation, 2 Sub-Bands

Monochrome Observation



#### Realistic Simulation, 2 Sub-Bands



#### **DCR** Deconvolution



#### Realistic Simulation, 2 Sub-Bands









#### Realistic Simulation, 3 Sub-Bands

Monochrome Observation



**DCR** Deconvolution



#### Realistic Simulation, 3 Sub-Bands

Simulated Ground Truth



**DCR** Deconvolution





# My Contributions

- Through:
  - Developing and implementing new algorithms
  - Advanced software and hardware
- Results:
  - Achieve high performance
  - Efficiently tackle big-data problems
  - Data fusion at scale!

#### Acknowledgments



Tamás Budavári



Alex Szalay



Randal Burns

#### Thank You

Any Questions?



#### **Zenith Angles**

