#### COMPUTATIONAL STATISTICS IN ASTRONOMY: NOW AND SOON

Tamás Budavári / The Johns Hopkins University

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## **Recording Observations**

Tamás Budavári



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#### Multicolor Universe



#### **Eventful Universe**





#### Trends in Astronomy

## Exponential growth of data Moore's law in detectors





## Sloan Digital Sky Survey

Cosmic Genome Project 2001-2010

- **500M** rows, 400+ cols ~ 18TB
- 30TB of images from 30 CCDs
- Software revolution in astro

Astronomers learn SQL

Cannot look at the data anymore



#### **The New Generations**

Large Synoptic Survey Telescope [OPTICAL]
 3 trillion rows, 200+ attributes, 100+ tables ~ 30PB
 60PB of images, 3.2 Gpix cam

Square Kilometer Array [RADIO]
 Processing limited



#### **Data-Intensive Science**

- The Fourth Paradigm Jim Gray
  - Phenomenology
  - Calculus
  - Simulations
  - eScience









## Keeping Up?

Image processing
 Catalog extraction
 O(n)

What is difficult?
 O(n log n)
 O(n<sup>2</sup>), ...

#### More is Different

Lots of opportunities
 Lots of challenges
 Lots of problems

- New approaches
- New algorithms
- New tools

#### New computers

#### Do More at the Data

Statistics on remote resources
 Fine-tune SQL Server for astronomy
 Analyses in and driven by SQL

SDSS catalog archive and more
 GALEX, HLA, UKIDSS, PanSTARRS, ...



**C**#



**Open SkyQuery** 

Images of RC3 Galaxies

**Object Cross-ID** 

CasJobs

Teachers

Links to other projects

Powered by Microsoft

Sample SQL Queries

Details of SDSS Data



#### SDSS Query / CasJobs

**MyDB** 

Help		Tools	Query	History
M	yDB		- Loc	al Only 🔽
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	1	10	roomba	
	20	10	stat	
	11	24	test1	

#### Tamas Budavari 's MyDB

Groups

#### 20,992 kB of 100,000 kB used

Import

From this page you can get various information about the contents of both your MyDB and shared tables within your groups. Click the left table links to get information about a specific table, such as rows, columns or size. From the table pages you can also perform various table-specific tasks, such as:

Profile

Queues

SkyServer

Logout

budavari

Output

- Download a table
- Mangage your group tables
- Rename a table
- Drop a table

Sizes are approximations only.

*Row counts are approximations only. For exact value run a count. There's always some overhead, even empty MyDB's take up space. Group tables do not count towards your MyDB size limit.* 

#### Contact

Name: v3\_5\_16 \$ ,\$Revision: 1.64 \$, Last modified: Tuesday, January 27, 2009 at 3:19:32 PM

## **Storing Simulations**

- Millennium Run (MPA)
  - 10 billion particles, 64 snapshots
  - FoF groups and merger trees
- Millennium XXL
  - 300 billion particles
- MultiDark Bolshoi
- Turbulence simulations (JHU)
   1024<sup>4</sup> grid, 27TB



## **Storing Simulations**

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## **Observing Simulations**



#### **Fast Searches**

Map space-filling curves to database indices
 Hierarchical Triangular Mesh – on the unit sphere
 Peano-Hilbert / Morton curves – in 3D
 Combine with query shapes
 Build from primitives



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Map space-filling curves to database indices
 Hierarchical Triangular Mesh – on the unit sphere
 Peano-Hilbert / Morton curves – in 3D
 Combine with query shapes

Build from primitives



# Millennium XXI



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## **Understanding Subtleties**

#### Interactive visualization of 27TB of turbulence sim





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Dynamical federation of archives

🛐 Google Calendar 🛛 🗙 🔇	) astroML: Python Datamini: × 🕼 Open SkyQuery ×		x
← → C ③ openskyquery.r	et/Sky/SkySite/browse/Browse.aspx	🛣 🖌 🕓	٩
National Virtual Observatory	Open SkyQuery Simple Query Advanced Query Import Data Tutorial Help Contact Us	Hosted By JOHNS HOPKINS UNIVERSITY	
Nodes Rosat 0 (*) PLS 0 (*) SDSS 0 (*) SDSSDR2 0 (*) SDSSDR3 0 (*) SDSSDR5 0 (*) SDSSDR5 0 (*) SDSSDR5 0 (*) SDSSDR6 0 (*) SDSSDR6 0 (*) SDSSDR6 0 (*) SDSSDR6 0 (*) SDSSDR5	Build       Edit       Submit         SELECT o.obild, o.ra,      dec, o.r, o.type,      doild, t.ra, t.dec         FROM       SDSS:PhotoPrimary o, TWOMASS:PhotoPrimary t         WHERE XMATCH(o, t) < 3.5 AND	Sample Queries XMatch/Region 2 XMatch/Region 2 Three Node Match 0 Brown Dwarf Search 0 MyData XMatch (upload) 0 Xmatch 1: (upload) 0 ABELL Xmatch (upload) 0 Single Node Query 0 Single Node Join 0	

#### **Cross-Identification**

#### One of the most fundamental analysis steps

## What is the Right Question?

- Cross-identification is a hard problem
  - Computationally, Scientifically & Statistically
  - Need symmetric *n*-way solution
  - Need reliable quality measure



#### □ Same or not?

Distance threshold? Maximum likelihood?

## Modeling the Astrometry

# Astrometric precision A simple function

Where on the sky?Anywhere really...

 $p(\vec{x}|\vec{m}, M)$ 



#### Same or Not?

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#### The Bayes factor $B(H, K|D) = \frac{p(D|H)}{p(D|K)}$ $D = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$ *H*: all observations of the same object at *m*

#### $\mathbf{S}_{\Box}$ K: might be from separate objects at $\{m_i\}$

#### Same or Not?

The Bayes factor  

$$B(H,K|D) = \frac{p(D|H)}{p(D|K)} \qquad D = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$$

$$H: \text{ all observations of the same object at } m$$

$$p(D|H) = \int p(\vec{m}|H) \prod_{i=1}^n p_i(\vec{x}_i|\vec{m}, H) d^3m$$
On the sky
$$K: \text{ might be from separate objects at } \{m_i\}$$
Astrometry

#### Same or Not?

**B**The Bayes factor
$$B(H, K|D) = \frac{p(D|H)}{p(D|K)}$$
 $D = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$ **B** $H$ : all observations of the same object at  $m$  $p(D|H) = \int p(\vec{m}|H) \prod_{i=1}^{n} p_i(\vec{x}_i|\vec{m}, H) d^3m$ **On the skyAstrometry** $p(D|K) = \prod_{i=1}^{n} \left\{ \int p(\vec{m}_i|K) p_i(\vec{x}_i|\vec{m}_i, K) d^3m_i \right\}$ 

#### Normal Distribution

□ Astrometric precision:  $w = 1/\sigma^2$ 

□ Fisher distribution:  $N(\vec{x}|w, \vec{m}) = \frac{w \,\delta(|\vec{x}| - 1)}{4\pi \sinh w} \exp(w \,\vec{m} \vec{x})$ □ Analytic results:

$$B(H, K|D) = \frac{\sinh w}{w} \prod_{i=1}^{n} \frac{w_i}{\sinh w_i}, \quad w = \left| \sum_{i=1}^{n} w_i \vec{x}_i \right|$$

For high accuracies:  
$$= 2^{n-1} \frac{\prod w_i}{\sum w_i} \exp\left\{-\frac{\sum_{i < j} w_i w_j \psi_{ij}^2}{2\sum w_i}\right\}$$

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#### Analytic Results

Normal distribution
 Flat and spherical
 Gauss and Fisher

□ 2-way results  $B = \frac{2}{\sigma_1^2 + \sigma_2^2} \exp\left\{-\frac{\psi^2}{2(\sigma_1^2 + \sigma_2^2)}\right\}$ 

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#### From Priors to Posteriors

#### Posterior probability from prior & Bayes factor

$$P(H|D) = \left[1 + \frac{1 - P(H)}{BP(H)}\right]^{-1}$$

# Prior probability of a match Like dice in a bag: 1/N and N<sup>1-n</sup> In general?



#### From Priors to Posteriors

Different selections **Nearby** / Distant **Red** / Blue But only 1 number.  $\frac{N_{\star}}{\neg_{N_{i}}}$  $P_0$ 



#### Self-Consistent Estimates

TB &

Szalay (2008)

# Prior has an unknown fudge-factor Educated guess P(H|D) = [1 + (1 - P(H))/(B P(H))]^{-1} Or solve for it:

$$\sum_{i=1}^{n} P(H) = N_{\star}$$

$$\sum_{i=1}^{n} P(H|D) = N_{\star}$$

#### Works in General

- Simulations *Heinis, TB, Szalay (2009)* Demo performance
- □ Proper motion Kerekes, TB+ (2010)
  - Unknown velocities
- □ Matching events TB (2011)
  - E.g., supernovae in time



## SkyQuery – the new generation!

Dynamic federation of astronomy databases
 Query the collection as if they were one

The 3<sup>rd</sup> generation tool coming this fall
 Cluster of machines running partitioned jobs
 Proper probabilistic exec with variable errors

#### Almost pure standard SQL

SELECT p.ObjID, p.RA, p.Dec, s.BestObjID, s.SpecObjID, s.RA, s.Dec INTO xtest FROM SDSSDR7:PhotoObjAll AS p CROSS JOIN SDSSDR7:SpecObjAll AS s WHERE p.RA BETWEEN Ø AND 5 AND p.Dec > -9999

AND s.Dec > -9999

AND s.RA > -9999

#### Almost pure standard SQL

SELECT p.ObjID, p.RA, p.Dec, s.BestObjID, s.SpecObjID, s.RA, s.Dec INTO xtest FROM SDSSDR7:PhotoObjAll AS p CROSS JOIN SDSSDR7:SpecObjAll AS s



WHERE

p.RA BETWEEN 0 AND 5 AND p.Dec > -9999 AND s.Dec > -9999 AND s.RA > -9999

#### Almost pure standard SQL

Added XMATCH
 Verifiable
 Flexible

```
SELECT p.ObjID, p.RA, p.Dec,
       s.BestObjID, s.SpecObjID, s.RA, s.Dec
INTO xtest
FROM SDSSDR7:PhotoObjAll AS p
    CROSS JOIN SDSSDR7:SpecObjAll AS s
XMATCH BAYESIAN AS x
    MUST p ON Point(p.RA, p.Dec), 0.1
    MUST s ON Point(s.RA, s.Dec), 0.1
    HAVING LIMIT 1e3
WHERE
    p.RA BETWEEN Ø AND 5
    AND p.Dec > -9999
    AND s.Dec > -9999
    AND s.RA > -9999
```

Sky	Query				u	sername: dobos   acco	unt   log ou
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Che	eck Submit Output:		٢	ask name:			
1	SELECT p.ObjID, p	.RA, p.De	ec,				*
2	s.BestObjI	D, s.Spec	:ObjID, s.R	A, s.Dec			
3	INTO xtest						
4	FROM SDSSDR7:Phot	oObjAll A	NS p				
5	CROSS JOIN SD	SSDR7:Spe	cObjAll AS	S			
6	XMATCH BAYESIAN A	S X					
7	MUST p ON Poi	nt(p.RA,	p.Dec), 0.	1, 0.1, 0.1			=
8	MUST s ON Poi	nt(s.RA,	s.Dec), 0.	1, 0.1, 0.1			
9	HAVING LIMIT	1e3					
10	WHERE						
11	p.RA BETWEEN	0 AND 5					
12	AND p.Dec > -	9999					
13	AND s.Dec > -	9999					
14	AND s.RA > -9	999					-

## Only the first steps...

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Different geometries

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- Resolved sources have shapes: galaxies, etc.
- Varies as a function of wavelength



#### Science is Interactive

#### Science is Interactive

#### Tamás Budavári

#### "Too much to be accurate"

By the time you do the calculations, the answer may have changed...



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#### Science is Interactive

#### "Too much to be accurate"

By the time you do the calculations, the answer may have changed...

- Randomized algorithms
  - Improving answers over time
  - Rethink the basic methods



## Principal Component Analysis

#### Principal directions

- Directions of largest variations
- Eigenproblem of covariances
- Singular Value Decomposition

Problems

- Needs lots of memory
- Only need largest ones
- Very sensitive to outliers



#### Streams of Data

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#### Mean

$$\mu = \frac{1}{N} \sum_{n=1}^{N} x_n$$
$$\mu_n = \frac{n-1}{n} \mu_{n-1} + \frac{1}{n} x_n$$

 $\boldsymbol{\mu} = \boldsymbol{\gamma} \boldsymbol{\mu}_{\text{prev}} + (1 - \boldsymbol{\gamma}) \boldsymbol{x}$ 

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#### Streams of Data



#### Covariance

$$C = \gamma C_{\text{prev}} + (1 - \gamma) y y^{\text{T}}$$

$$y = x - \mu_{\text{prev}}$$

 $\boldsymbol{\mu} = \gamma \boldsymbol{\mu}_{\text{prev}} + (1 - \gamma)\boldsymbol{x}$ 

#### **Iterative evaluation!**

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#### **Streaming PCA**

#### Initialization

Eigensystem of a small, random subset

Truncate at p largest eigenvalues

#### Incremental updates

- Mean and the low-rank A matrix
- SVD of A yields new eigensystem

#### Randomized algorithm!

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 $C \approx E_p \Lambda_p E_p^{\mathrm{T}}$ 

$$C \approx \gamma E_p \Lambda_p E_p^{\mathrm{T}} + (1 - \gamma) \mathbf{y} \mathbf{y}^{\mathrm{T}}$$
$$\approx A A^{\mathrm{T}}$$

#### **Robust PCA**

- PCA minimizes σ<sub>RMS</sub> of the residuals r = y Py
   Quadratic formula: Σr<sup>2</sup> extremely sensitive to outliers
- We optimize a robust M-scale σ<sup>2</sup> (Maronna 2005)
   Implicitly given by

$$\frac{1}{N}\sum_{n=1}^{N}\rho\left(\frac{r_{n}^{2}}{\sigma^{2}}\right) = \delta \qquad \qquad \mu = \left(\sum w_{n}x_{n}\right) / \left(\sum w_{n}\right) \\ C = \sigma^{2}\left[\sum w_{n}(x_{n} - \mu)(x_{n} - \mu)^{\mathrm{T}}\right] / \left(\sum w_{n}r_{n}^{2}\right)$$

□ Fits in with the iterative method (TB+ 2009)

## Galaxy Spectra

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#### Galaxy Spectra

High SNR eigenfunctions
 Sign of robustness



#### Galaxy Spectra

- High SNR eigenfunctions
   Sign of robustness
- □ It makes a difference





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#### Synthetic Streams

- 3D Gaussian rotated into 50D
   Stretches: 7, 6, 5
   Total Var = 110
- Plotting square roots of the top 5 eigenvalues

#### Streaming Classic PCA



Eigen Val 0 Eigen Val 1 Eigen Val 2 Eigen Val 3 Eigen Val 4 Outliers

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#### With Outliers

□ Adding 0.1% outliers  $\Box \sigma = 100$  in each bin Outliers take over the PCs Instability, no convergence

**Streaming Classic PCA** 



Eigen Val 0 Eigen Val 1 Eigen Val 2 Eigen Val 3 Eigen Val 4

## **Robust Algorithm**

Outliers under controlMarked on top

Initialized with SVD
 On a set of 100 vectors

Streaming Robust PCA



Eigen Val 0 Eigen Val 1 Eigen Val 2 Eigen Val 3 Eigen Val 4 Outliers

#### Comparison

□ Classic

Robust



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Sparsity

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# Important wavelengths Cf., the Lick indices

(RE)DISCOVER ASTRONOMY!



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## Time Domain (the new window)

- Online aggregation of survey data
  - Learning the night sky from a series of images
    - Correcting for atmospheric distortions
  - Finding transient events
- Online federation of event streams
- Online outlier detection new discoveries!

#### Uncertainties

- No data points
- Measurements with errors

#### **Inverse Problems**

- Bayesian inference but computational bottlenecks
  - High dimensional models w/ empirical priors
  - Non-parameteric?
- Deconvolution with degeneracies
  - Aided by physics
- Photometric inversion

**TB (2009)** 
$$p(\boldsymbol{\xi}|\boldsymbol{y}_q, M) = \int d\boldsymbol{x} \ p(\boldsymbol{\xi}|\boldsymbol{x}) \ p(\boldsymbol{x}|\boldsymbol{y}_q, M)$$



## Trends in Computing

## New Limitation is Energy!

- Power to compute the same thing?
   CPU is 10× less efficient than a digital signal processor
   DSP is 10× less efficient than a custom chip
- New design: multicores with slower clocks
   But the interconnect is expensive
   Need simpler components

## **Emerging Architectures**

Andrew Chien: 10×10 to replace the 90/10 rule
 Custom modules on chip, cf. SoC in cellphones



## **Emerging Architectures**

Andrew Chien: 10×10 to replace the 90/10 rule
 Custom modules on chip, cf. SoC in cellphones



Statistics on a specialized units, e.g., codecs?

## GPUs Evolved to be General Purpose

- Virtual world: simulation of real physics
   C for CUDA and OpenCL with lots of libraries
- 512 cores ~25k threads running 1 billion/sec
- Old algorithms built on wrong assumption
  - Today processing is free but memory is slow

#### New programming paradigm!

## Integrated with Databases

# Scientific computations on the GPU Driven remotely from SQL User-Defined Functions



#### **Baryon Acoustic Oscillations**

- 600 trillion galaxy pairs
   Correlation function:
- C for CUDA on GPUs
  - SPATIAL STATISTICS!



## Matching on GPUs

Recent Github release Multi-GPU implementation □ Search in 5" – great perf! NVIDIA GTX 480 1.5GB 29Mx29M in 11 seconds C2050 Teslas 400M×150M in 3 minutes

[dat] 1 [tmr] Load: 12.776000 [tmr] Copy: 0.452000 [tmr] Sort: 2.605000 [tmr] Lmts: 0.000000 [tmr] Back: 0.499000 [tmr] Splt: 0.921000 [dat] 2 [tmr] Load: 10.296000 [tmr] Copy: 0.453000 [tmr] Sort: 2.823000 [tmr] Lmts: 0.000000 [tmr] Back: 0.499000 [tmr] Splt: 0.905000 [tmr] Cop2: 0.671000 [tmr] Mtch: 10.998000 [tmr] Etch: 0.265000 [tmr] Main: 47.876000 [res] 587727177914515631 587727177914515631 587727177914515580 587727177914515580 587727177914515797 587727177914515797 587727177914581686 587727177914581686

C:\>CuXmatch.exe dr7.bin 29000000 dr7.bin 29000000 5 5 4

[dbg] n zones: 129600



Astronomy has always been data-driven
 Data-intensive for decades (since SDSS)
 Need new approaches and algorithms
 But prototypes are not enough to scale
 Many promising directions to explore

#### Perfect timing for the SAMSI Big Data Program!