



LSST: Informatics and Statistics Research Challenges

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Outline

- Prelude
- Astroinformatics
- Example Application: The LSST Project
- Informatics & Statistics Challenge Problems
- Challenge Area: Distributed Data Mining
- Summary

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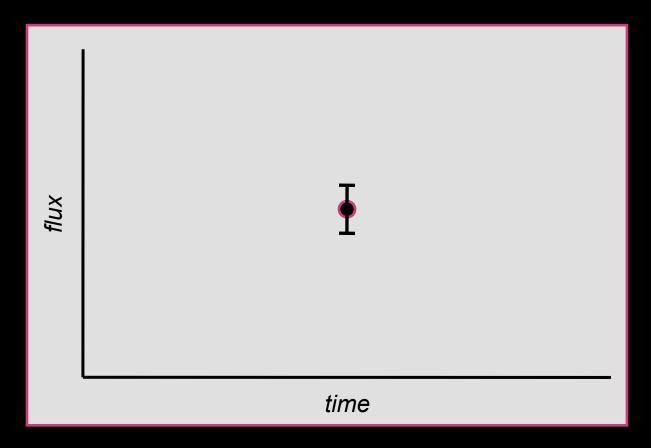
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Prelude

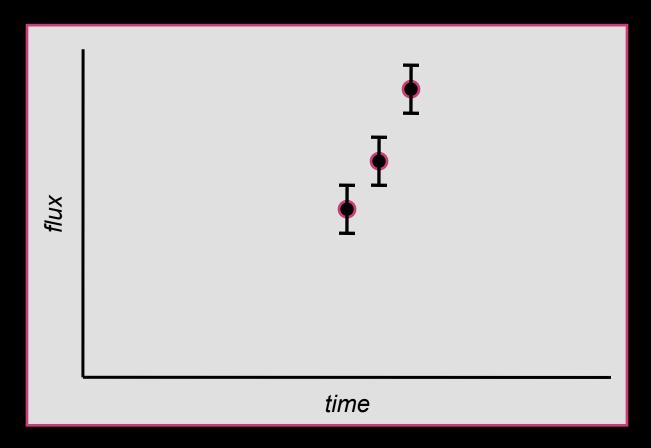
- LSST Challenge #1
- LSST Challenge #2
- The Data Flood
- Data-Enabled Science

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Characterize first! then Classify.

- Each night for 10 years LSST will obtain the equivalent amount of data that was obtained by the entire Sloan Digital Sky Survey
- My grad students will be asked to mine these data (~20 TB each night ≈ 40,000 CDs filled with data):

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Image: The CD Sea in Kilmington England (600,000 CDs)

- Each night for 10 years LSST will obtain the equivalent amount of data that was obtained by the entire Sloan Digital Sky Survey
- My grad students will be asked to mine these data (~20 TB each night ≈ 40,000 CDs filled with data):
 - A sea of CDs each and every day for 10 yrs
 - Cumulatively, a football stadium full of 200 million CDs after 10 yrs

Responding to the Data Flood

- Big Data is a national challenge and a national priority ... see August 9, 2010 announcement from OMB and OSTP @ http://www.aip.org/fyi (#87)
- More data is <u>not</u> just more data... more is different!
- Several national study groups have issued reports on the urgency of establishing scientific and educational programs to face the data flood challenges.
- Each of these reports has issued a call to action in response to the data avalanche in science, engineering, and the global scholarly environment.

Data Sciences: A National Imperative

- 1. National Academies report: Bits of Power: Issues in Global Access to Scientific Data, (1997) downloaded from http://www.nap.edu/catalog.php?record_id=5504
- 2. NSF (National Science Foundation) report: *Knowledge Lost in Information: Research Directions for Digital Libraries*, (2003) downloaded from http://www.sis.pitt.edu/~dlwkshop/report.pdf
- 3. NSF report: Cyberinfrastructure for Environmental Research and Education, (2003) downloaded from http://www.ncar.ucar.edu/cyber/cyberreport.pdf
- 4. NSB (National Science Board) report: Long-lived Digital Data Collections: Enabling Research and Education in the 21st Century, (2005) downloaded from http://www.nsf.gov/nsb/documents/2005/LLDDC report.pdf
- 5. NSF report with the Computing Research Association: Cyberinfrastructure for Education and Learning for the Future: A Vision and Research Agenda, (2005) downloaded from http://www.cra.org/reports/cyberinfrastructure.pdf
- 6. NSF Atkins Report: Revolutionizing Science & Engineering Through Cyberinfrastructure: Report of the NSF Blue-Ribbon Advisory Panel on Cyberinfrastructure, (2005) downloaded from http://www.nsf.gov/od/oci/reports/atkins.pdf
- 7. NSF report: The Role of Academic Libraries in the Digital Data Universe, (2006) downloaded from http://www.arl.org/bm~doc/digdatarpt.pdf
- 8. National Research Council, National Academies Press report: *Learning to Think Spatially,* (2006) downloaded from http://www.nap.edu/catalog.php?record_id=11019
- 9. NSF report: Cyberinfrastructure Vision for 21st Century Discovery, (2007) downloaded from http://www.nsf.gov/od/oci/ci_v5.pdf
- 10. JISC/NSF Workshop report on Data-Driven Science & Repositories, (2007) downloaded from http://www.sis.pitt.edu/~repwkshop/NSF-JISC-report.pdf
- 11. DOE report: Visualization and Knowledge Discovery: Report from the DOE/ASCR Workshop on Visual Analysis and Data Exploration at Extreme Scale, (2007) downloaded from http://www.sc.doe.gov/ascr/ProgramDocuments/Docs/DOE-Visualization-Report-2007.pdf
- 12. DOE report: Mathematics for Analysis of Petascale Data Workshop Report, (2008) downloaded from http://www.sc.doe.gov/ascr/ProgramDocuments/Docs/PetascaleDataWorkshopReport.pdf
- 13. NSTC Interagency Working Group on Digital Data report: *Harnessing the Power of Digital Data for Science and Society,* (2009) downloaded from http://www.nitrd.gov/about/Harnessing Power Web.pdf
- 14. National Academies report: Ensuring the Integrity, Accessibility, and Stewardship of Research Data in the Digital Age, (2009) downloaded from http://www.nap.edu/catalog.php?record_id=12615

Recent (March 2010) NSF working group: Data-Enabled Science (DES)

- DES group prepared a white paper of related challenges and recommendations to inform the NSF MPSAC (Mathematical & Physical Sciences directorate Advisory Committee).
- MPSAC may use the white paper as a source of ideas and information to advise NSF in DES areas.
- DES committee: 2 scientists each from Astronomy, Physics, Chemistry, Mathematics, Statistics, and Materials Science.

Some of the members of the NSF DES Working Group

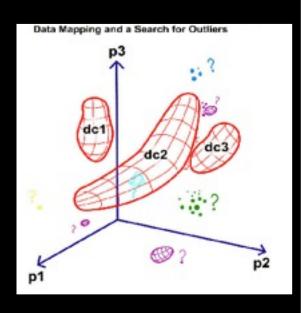
- Astronomy: Robert Hanisch, Kirk Borne
- Statistics: James Berger, Alan Karr
- Mathematical Sciences: David Keyes, ...
- Physics: Patrick Brady (LIGO as eventful astronomy), Harrison Prosper (LHC)
- Chemistry: Brooks Pate (Interstellar chemistry), ...
- Materials Science: Sharon Glotzer**, ...
- ** Chair of the committee that authored the 400-page "Glotzer Report" (2009) on data-intensive science, specifically simulation-based science & engineering. Reference: http://www.wtec.org/sbes/

Examples of Recommendations: Scientific Inference with Massive or

- Advances in fundamental mathematics and statistics are needed to provide the language, structure, and tools for many needed methodologies of data-enabled scientific inference.
 - Example 1: Exploitation of sparsity (e.g., out of a huge list of proteins, only an unknown few may be active in a particular metabolic process)
 - often hidden, discovered only with new mathematics involving harmonic analysis, approximation theory, numerical analysis and statistical theory;
 - led to compressed sensing.
 - Example 2: Machine learning in massive data sets
 - of late, an explosion in the utilization of nonparametric Bayes techniques
- Algorithmic advances in handling massive and complex data are crucial.
- Visualization (visual analytics) and citizen science (human computation or data processing) will play key roles.

Data-Enabled Science: Scientific KDD (Knowledge Discovery from Data)

- Characterize the known (clustering, unsupervised learning)
- Assign the new (classification, supervised learning)
- Discover the unknown (outlier detection, semi-supervised learning)



- Benefits of very large datasets:
 - best statistical analysis of "typical" events
 - automated search for "rare" events

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Astronomy: Data-Driven Science = Evidence-based Forensic Science



The Changing Landscape of Astronomical Research

- Past: 100's to 1000's of independent distributed heterogeneous data / metadata / information repositories.
- Today: Astronomical data are now accessible uniformly from <u>federated</u> distributed heterogeneous sources = the Virtual Observatory.
- Future: Astronomy is and will become even more data-intensive in the coming decade with the growth of massive data-producing sky surveys.
- Challenge: It will be prohibitively difficult to transport the data to the user application. Therefore

... SHIP THE CODE TO THE DATA!

From Data-Driven to Data-

- Astronomy has always been a data-driven science
- It is now a data-intensive science: **Astroinformatics** 1
 - Data-oriented Astronomical Research = "the 4th Pa Characterize the known (clustering, unsupervised learning)
 - Assign the new (classification, supervised learning)
 Scientific KDD (Knowledge Discovery in Databases):
 Discover the unknown (outlier detection, semi-supervised learning)

 - Scientific Knowledge!
 - Benefits of very large datasets:
 - best statistical analysis of "typical" events
 - automated search for "rare" events

Astronomy Data Environment: Sky Surveys

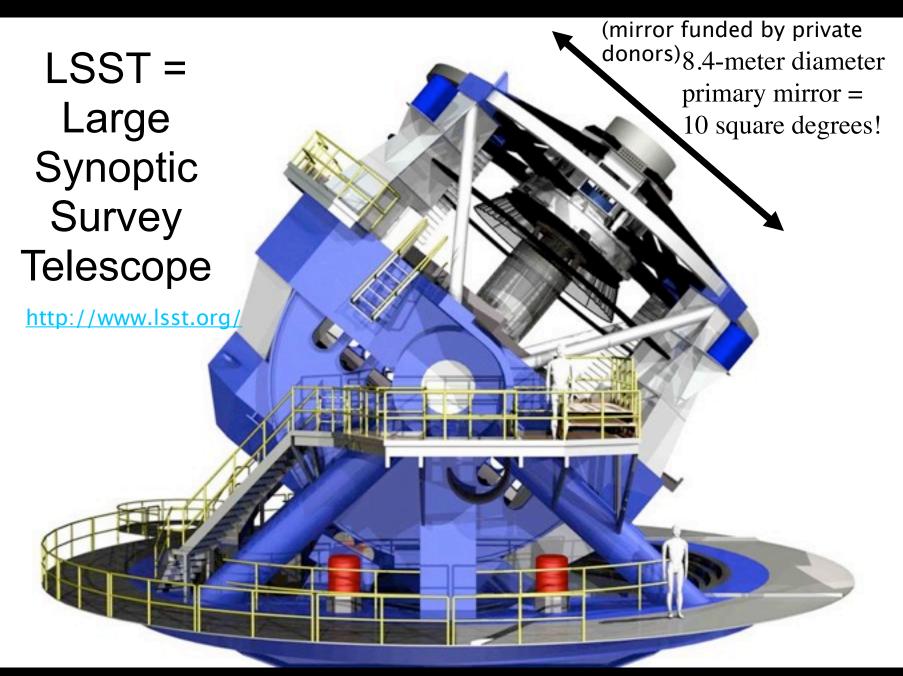
- To avoid biases caused by limited samples, astronomers now study the sky systematically = Sky Surveys
- Surveys are used to measure and collect data from all objects that are contained in large regions of the sky, in a systematic, controlled, repeatable fashion.
- These surveys include (... this is just a subset):
 - MACHO and related surveys for dark matter objects: ~ 1 Terabyte
 - Digitized Palomar Sky Survey: 3 Terabytes
 - 2MASS (2-Micron All-Sky Survey): 10 Terabytes
 - GALEX (ultraviolet all-sky survey): 30 Terabytes
 - Sloan Digital Sky Survey (1/4 of the sky): 40 Terabytes
 - and this one is just starting: Pan-STARRS: 40 Petabytes!
- Leading up to the big survey next decade:
 - LSST (Large Synoptic Survey Telescope): 100 Petabytes!

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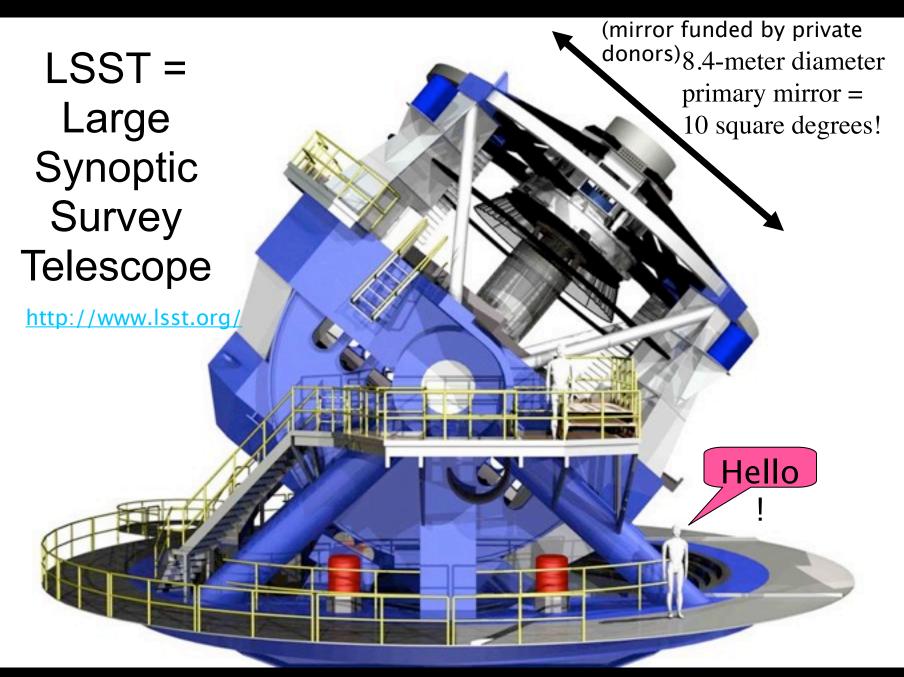
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LSST

 The highest-ranked ground-based astronomy facility for the next decade in the Astro2010 Decadal Survey Report



(design, construction, and operations of telescope, observatory, and data system: NSF)



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- Solar System Map (moving objects, NEOs, asteroids: census & tracking)
- Nature of Dark Energy (distant supernovae, weak lensing, cosmology)
- Optical transients (of all kinds, with alert notifications within 60 seconds)



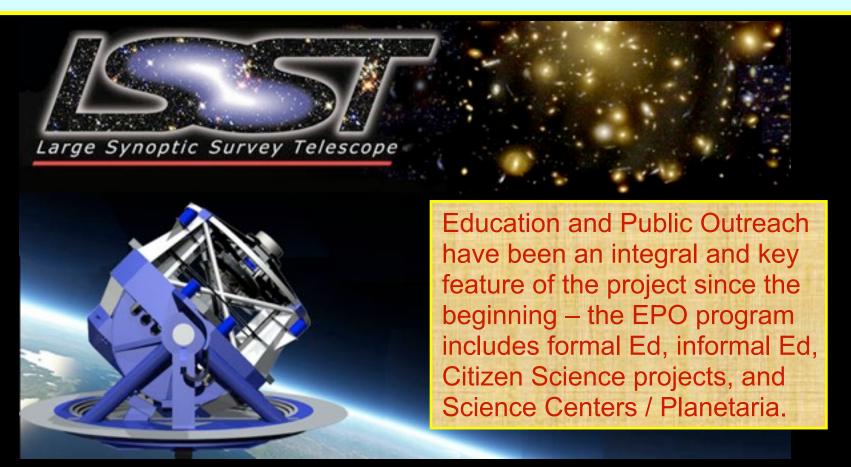
Cerro Pachon, Chile

LSST Observatory

- Where?

Observing Strategy: One pair of images every 40 seconds for each spot on the sky, then continue across the sky continuously every night for 10 years (2016-2026), with time domain sampling in log(time) intervals (to capture dynamic range of transients).

- LSST (Large Synoptic Survey Telescope):
 - Ten-year time series imaging of the night sky mapping the Universe!
 - 100,000 events each night anything that goes bump in the night!
 - Cosmic Cinematography! The New Sky! @ http://www.lsst.org/



The LSST focal plane array

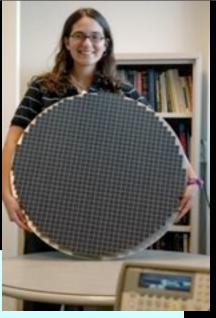
Camera Specs: (pending funding from the DOE) 201 CCDs @ 4096x4096 pixels each!

= 3 Gigapixels = 6 GB per image, covering 10 sq.degrees

= ~3000 times the area of one Hubble Telescope image

LSST Data Challenges

- Obtain one 6-GB sky image in 15 seconds
- Process that image in 5 seconds
- Obtain & process another co-located image for science validation within 20^s (= 15-second exposure + 5-second processing & slew)
- Process the 100 million sources in each image pair, catalog all sources, and generate worldwide alerts within 60 seconds (e.g., incoming killer asteroid)
- Generate 100,000 alerts per night (VOEvent messages)
- Obtain 2000 images per night
- Produce ~30 Terabytes per night
- Move the data from South America to US daily
- Repeat this every day for 10 years (2016-2026)
- Provide rapid DB access to worldwide community:
 - 100-200 Petabyte image archive
 - 20-40 Petabyte database catalog



1.93M

We proposed a new collaboration in 2009: Informatics and Statistical Sciences Collaboration (ISSC)

- We noted that there is one significant research area that is not represented in the original 10 teams.
 - That area is **Informatics and Statistics Research**:
 - Astroinformatics
 - Astrostatistics
- The Computer Science (data mining and machine learning) and Statistics research communities are becoming aware of and interested in LSST (astronomy data are abundant, interesting, and free).
 - The LSST data collection will be large and complex.

The new LSST ISSC research team

- In discussing the data-related research challenges posed by LSST, we identified several research areas:
 - Statistics
 - Data & Information Visualization
 - Data mining (machine learning)
 - Data-intensive computing & analysis
 - Large-scale scientific data management
- These areas represent Statistics and the science of Informatics (Astroinformatics) = Data-intensive Science = the 4th Paradigm of Scientific Research

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Informatics

 These areas represent Statistics and the science of Informatics (Astroinformatics) = Data-intensive Science = the 4th Paradigm of Scientific Research

The LSST ISSC Research Team

- Chairperson: K.Borne, GMU
- Core team: 3 astronomers + 2 =
 - K.Borne (scientific data mining in astronomy)
 - Eric Feigelsen, Tom Loredo (astrostatistics)
 - Jogesh Babu (statistics)
 - Alex Gray (computer science, data mining)
- Full team: ~30 scientists
 - ~60% astronomers
 - ~30% statisticians

Full list of team members:

http://www.lsstcorp.org/strausstest/StraussTest2.php

- ~10% data mining, machine learning computer scientists
- Original ISSC proposal: 50+ co-signers, only half were astronomers

Some key astronomy problems that require informatics and statistical techniques ... Astroinformatics & Astrostatistics!

- Probabilistic Cross-Matching of objects from different catalogues
- The distance problem (e.g., Photometric Redshift estimators)
- Star-Galaxy separation; QSO-Star separation
- Cosmic–Ray Detection in images
- Supernova Detection and Classification
- Morphological Classification (galaxies, AGN, gravitational lenses, ...)
- Class and Subclass Discovery (brown dwarfs, methane dwarfs, ...)
- Dimension Reduction = Correlation Discovery
- Learning Rules for improved classifiers
- Classification of massive data streams
- Real-time Classification of Astronomical Events
- Clustering of massive data collections

ISSC "current topics"

- Advancing the field = Community-building:
 - Astroinformatics + Astrostatistics (several workshops this year!!)
 - Education, education, education! (Citizen Science, undergrad+grad ed...)
- LSST Event Characterization vs. Classification
- Sparse time series and the LSST observing cadence
- Challenge Problems, such as the Photo-z challenge and the Supernova Photometric Classification challenge
- Testing algorithms on the LSST simulations: images/catalogs PLUS observing cadence – can we recover known classes of variability?
- Generating and/or accumulating training samples of numerous classes (especially variables and transients)
- Proposing a mini-survey during the science verification year (Science Commissioning):
 - e.g., high-density and evenly-spaced observations of extragalactic and Galactic test fields are obtained, to generate training sets for variability classification and assessment thereof
- Science Data Quality Assessment (SDQA): R&D efforts to support LSST Data Management team

LSST Level 3 Products from ISSC (TBD)

- Training sets for classification of various classes of variability or transient behavior
- Comparison samples of statistically robust classes of objects (non-transients), for use in evaluating the LSST object catalog
- Algorithms: e.g., for statistical analysis, time series analysis, photo-z estimation, star-galaxy separation, outlier (surprise) detection, data mining, ...
- Results from precursor experiments on LSST event classification and characterization – training sets, results, algorithms, recommended cadences, etc.

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The clustering problem:

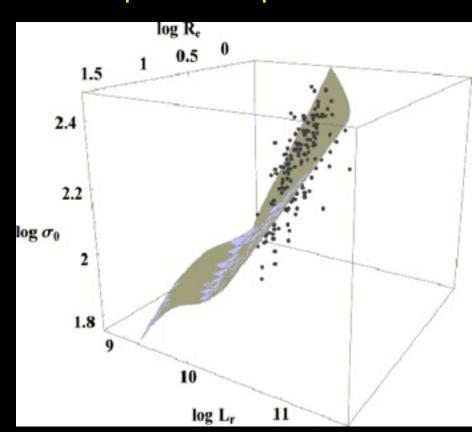
- Finding clusters of objects within a data set
- What is the significance of the clusters (statistically and scientifically)?
- What is the optimal algorithm for finding friends-offriends or nearest neighbors?
 - N is >10¹⁰, so what is the most efficient way to sort?
 - Number of dimensions ~ 1000 therefore, we have an enormous subspace search problem
- Are there pair-wise (2-point) or higher-order (N-way) correlations?
 - N is >10¹⁰, so what is the most efficient way to do an N-point correlation?
 - algorithms that scale as N²logN won't get us there

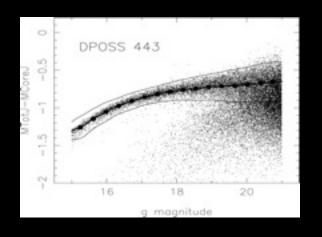
Outlier detection: (unknown unknowns)

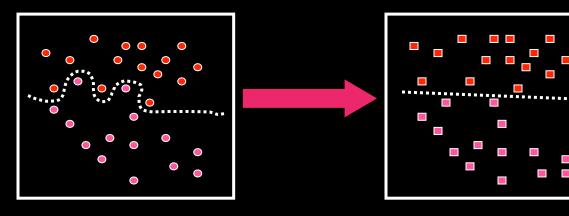
- Finding the objects and events that are outside the bounds of our expectations (outside known clusters)
- These may be real scientific discoveries or garbage
- Outlier detection is therefore useful for:
 - Novelty Discovery *is my Nobel prize waiting?*
 - Anomaly Detection is the detector system working?
 - Data Quality Assurance is the data pipeline working?
- How does one optimally find outliers in 10³-D parameter space? or in interesting subspaces (in lower dimensions)?
- How do we measure their "interestingness"?

The dimension reduction problem:

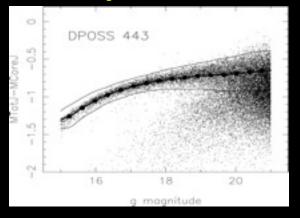
- Finding correlations and "fundamental planes" of parameters
- Number of attributes can be hundreds or thousands
 - The Curse of High Dimensionality!
- Are there combinations
 (linear or non-linear functions) of observational parameters that correlate strongly with one another?
- Are there eigenvectors or condensed representations (e.g., basis sets) that represent the full set of properties?

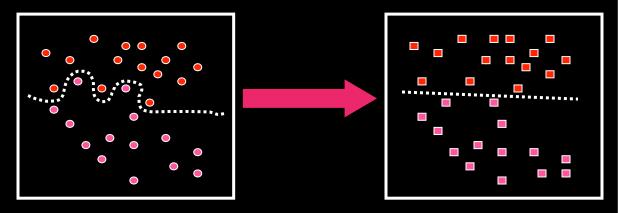




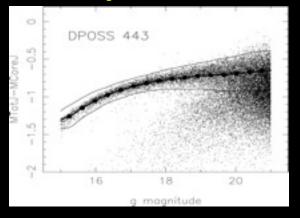


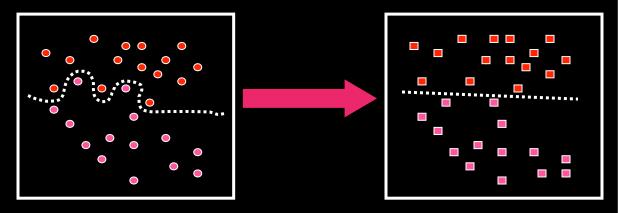
- The superposition / decomposition problem:
 - Finding distinct clusters (Classes of Object) among objects that overlap in parameter space



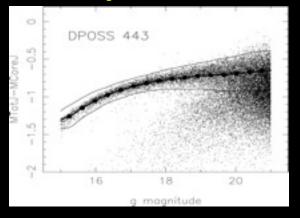


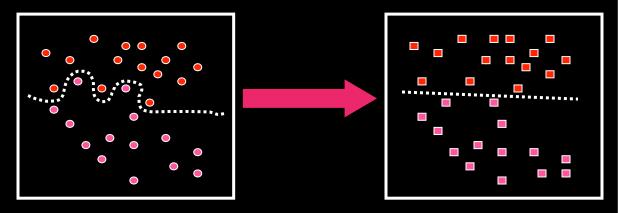
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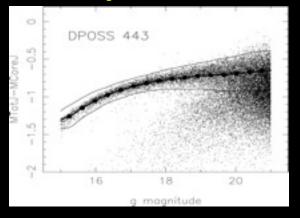


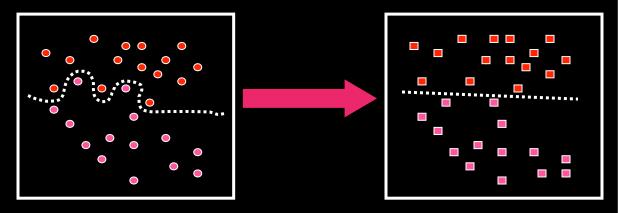
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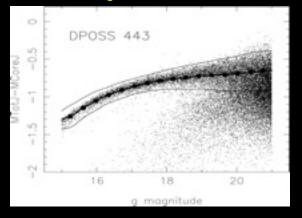


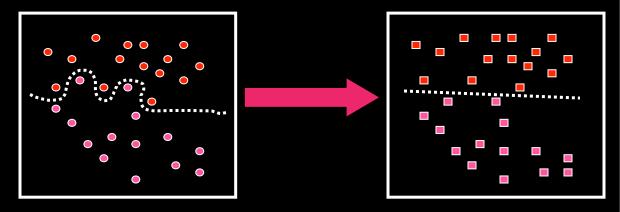
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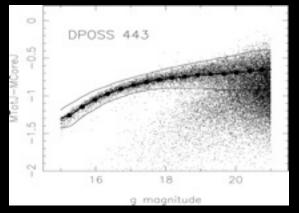


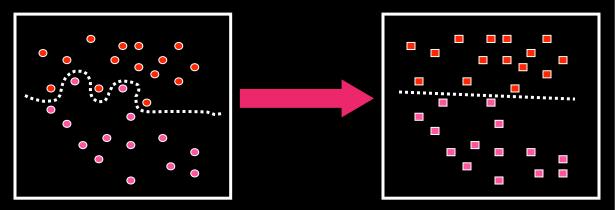
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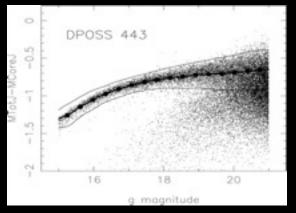
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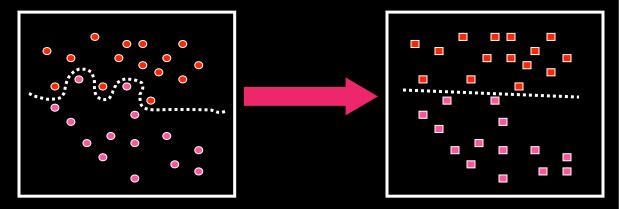




– What if there are 10¹¹ objects that overlap in a 10³-D parameter space?

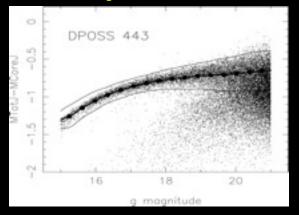
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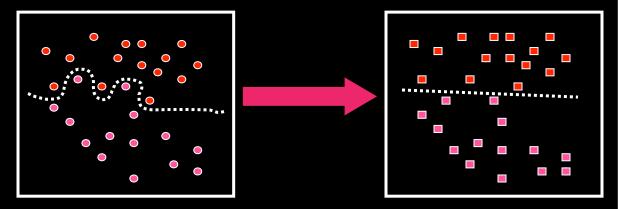




- What if there are 10¹⁰ objects that overlap in a 10³-D parameter space?
- What is the optimal way to separate and extract the different unique classes of objects?

- The superposition / decomposition problem:
 - Finding distinct clusters (Classes of Object) among objects that overlap in parameter space

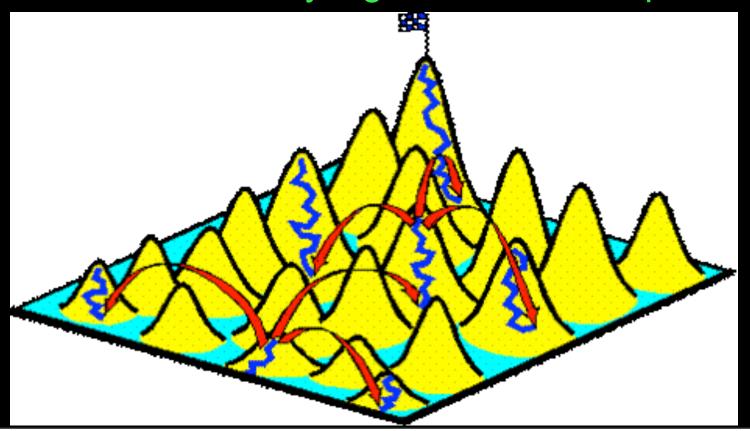




- What if there are 10¹⁰ objects that overlap in a 10³-D parameter space?
- What is the optimal way to separate and extract the different unique classes of objects?
- How are constraints applied?

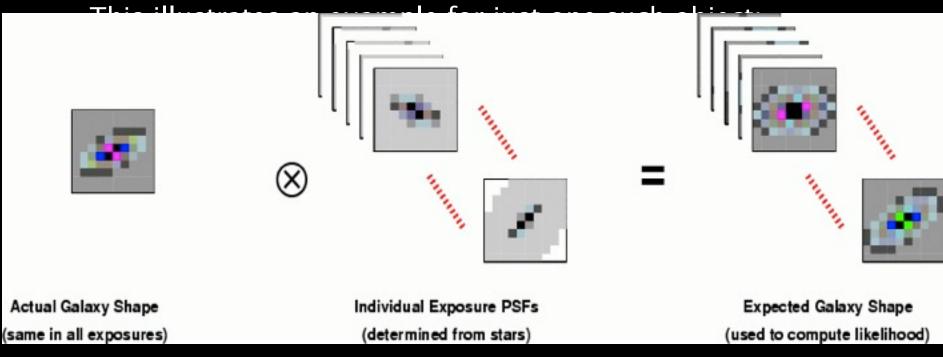
The optimization problem:

 Finding the optimal (best-fit, global maximum likelihood) solution to complex multivariate functions over very high-dimensional spaces



Example: Beyond Exascale Computational & Data Science

• Find the optimal <u>simultaneous</u> solution for 20,000,000,000 objects' shapes across 2000 image planes, each of which has 201x4096x4096 pixels ... 10²³ floating-point operations!



References:

http://universe.ucdavis.edu/docs/MultiFit-ADASS.pdf

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Why Distributed Data Mining (DDM)? Because ...

... many great scientific discoveries have come from inter-comparisons of diverse data sources:

- Quasars
- Gamma-ray bursts
- Ultraluminous IR galaxies
- X-ray black-hole binaries
- Radio galaxies

- . .

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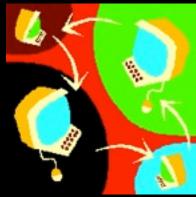
- . . .

Distributed Data

- Distributed data are the norm (across people, institutions, projects, agencies, nations, ...)
- Data are usually heterogeneous (e.g., databases, images, catalogs, file systems, web interfaces, document libraries, binary, text, structured, unstructured, ...)
- Scientists want to query and to mine these data (= 2 different user scenarios)
- Virtual Observator ementations enable data discontinued integration, but do not yet factories







Distributed Data Mining (DDM)

- DDM comes in 2 types:
 - 1. Distributed Mining of Data
 - 2. Mining of Distributed Data
- Type 1 requires sophisticated algorithms that operate with data in situ ...
 - Ship the Code to the Data
- Type 2 takes many forms, with data being centralized (in whole or in partitions) or data remaining in place at distributed sites
- References: http://www.cs.umbc.edu/~hillol/DDMBIB/
 - C. Giannella, H. Dutta, K. Borne, R. Wolff, H. Kargupta. (2006). Distributed Data Mining for Astronomy Catalogs. Proceedings of 9th Workshop on Mining Scientific and Engineering Datasets, as part of the SIAM International Conference on Data Mining (SDM), 2006. [http://www.cs.umbc.edu/~hillol/PUBS/Papers/Astro.pdf]
 - H. Dutta, C. Giannella, K. Borne and H. Kargupta. (2007). Distributed Top-K Outlier Detection from Astronomy Catalogs using the DEMAC System. Proceedings of the SIAM International Conference on Data Mining, Minneapolis, USA, April 2007. [http://www.cs.umbc.edu/~hillol/PUBS/Papers/sdm07.pdf]

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Data Science Challenge Areas in Astronomy over the next 10 years — addressable by Astroinformatics

- Scalability of statistical, computational, & data mining algorithms to peta- and exa- scales
- Algorithms for optimization of simultaneous multi-point fitting across massive multi-dimensional data cubes
- Multi-resolution, multi-pole, fractal, hierarchical methods and structures for exploration of condensed representations of petascale databases
- Petascale analytics for visual exploratory data analysis of massive databases (including feature detection, pattern & interestingness discovery, correlation mining, clustering, class discovery, eigen-monitoring, dimension reduction)
- Indexing and associative memory techniques (trees, graphs, networks) for highly-dimensional petabyte databases
- Rapid query and search algorithms for petabyte databases

Astroinformatics Research paper available!

Addresses the data science challenges, research agenda, application areas, use cases, and recommendations for the new science of *Astroinformatics*.

Borne (2010): "Astroinformatics: Data-Oriented Astronomy Research and Education", Journal of Earth Science Informatics, vol. 3, pp. 5-17.

See also http://arxiv.org/abs/0909.3892

State of the Profession position paper, submitted to the Astro2010 Decadal Survey 3/15/2009

Astroinformatics: A 21st Century Approach to Astronomy

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