Machine Learning from End-user Database Annotations

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Outline

Talk will have 2 Practical Semantic Astronomy parts:

1)Astroinformatics for Eventful Astronomy

2)Machine Learning in the Galaxy Zoo Database

Part 1

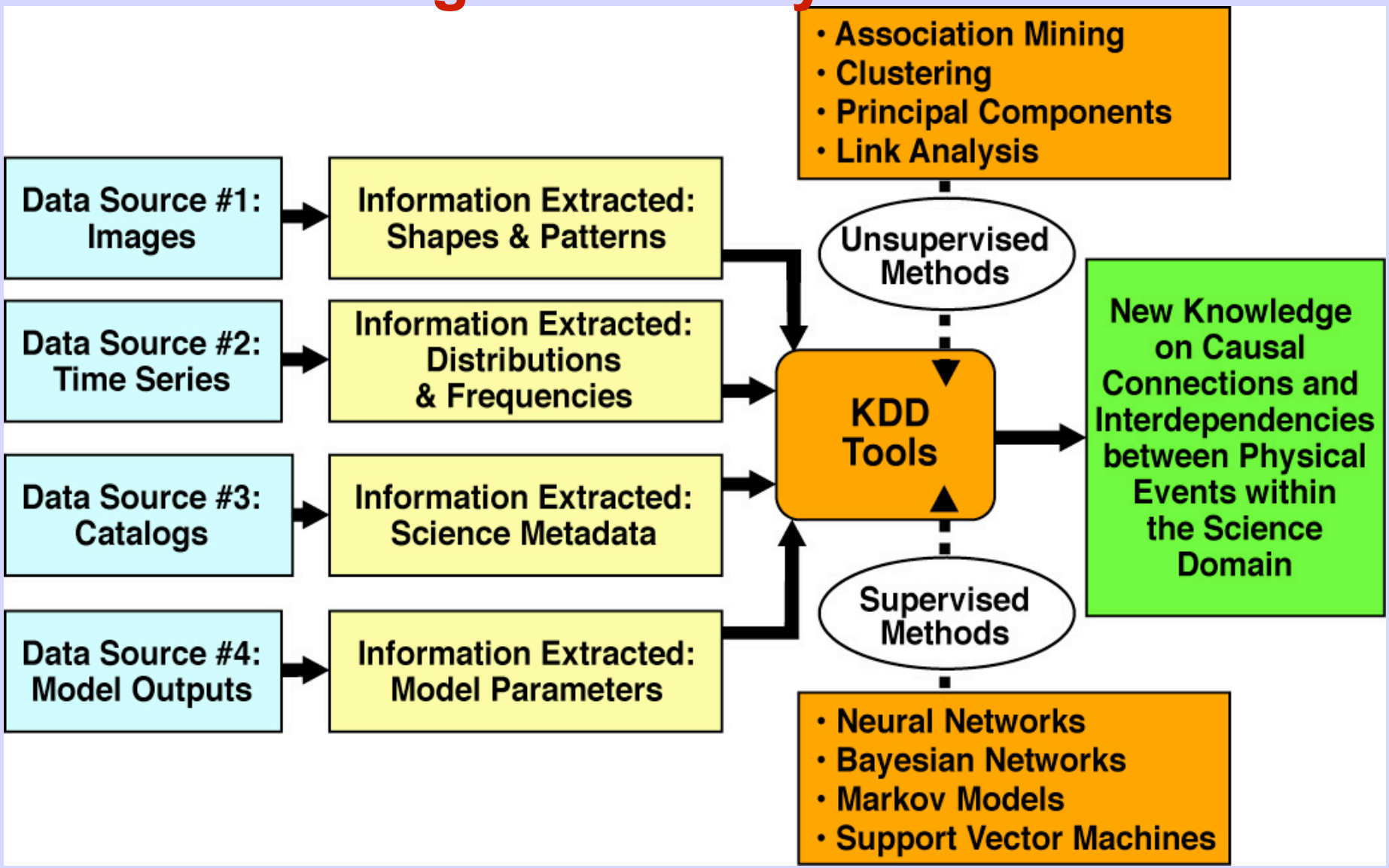
Astroinformatics for Eventful Astronomy

The LSST will represent a 10K-100K times increase in the VOEvent network traffic. This poses significant real-time classification demands on the event stream:

from data to knowledge!

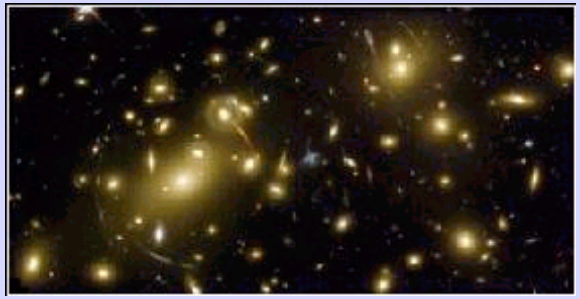
<u>from sensors to sense!</u>

Scientific KDD: Knowledge Discovery in Databases

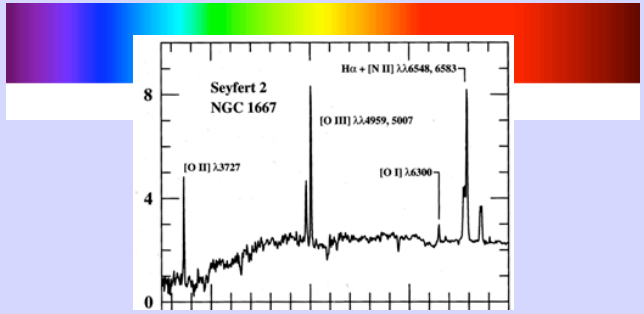


Astronomy Example

Data:



(a) Imaging data (ones & zeroes)



(b) Spectral data (ones & zeroes)

Information (catalogs / databases):

- Measure brightness of galaxies from image (e.g., 14.2 or 21.7)
- Measure redshift of galaxies from spectrum (e.g., 0.0167 or 0.346)

Knowledge:

Hubble Diagram ➡

Redshift-Brightness Correlation ➡

Redshift = Distance

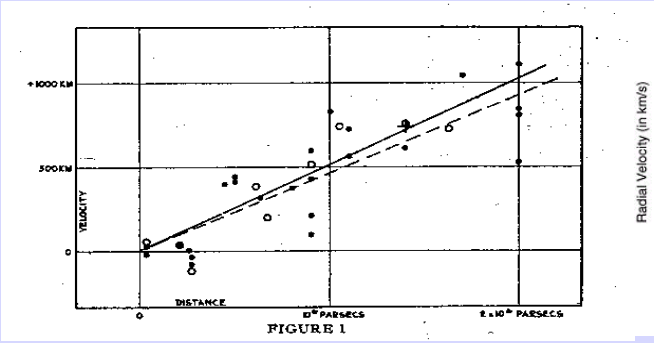
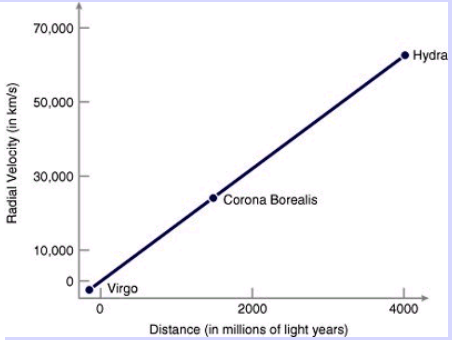
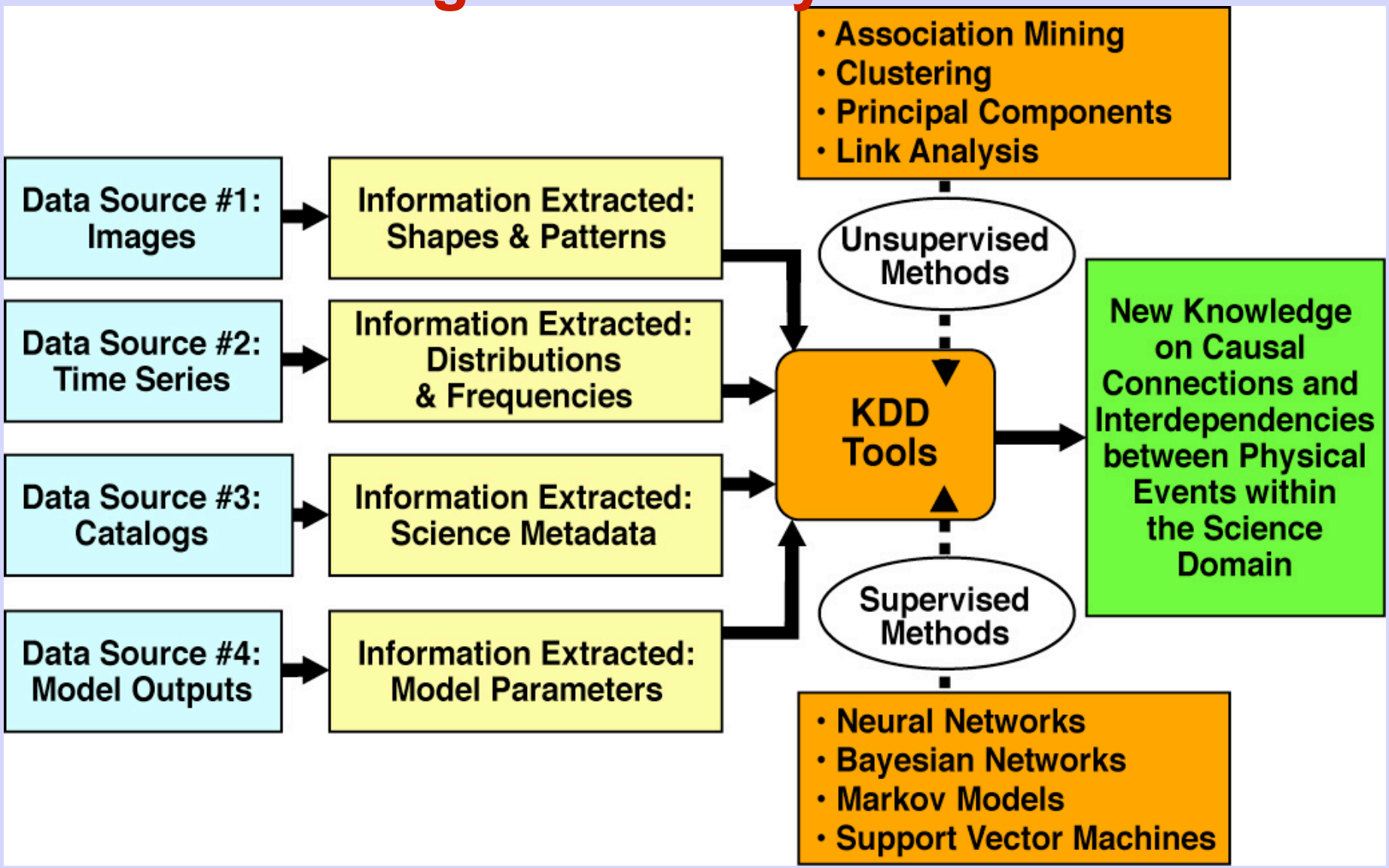


FIGURE 1

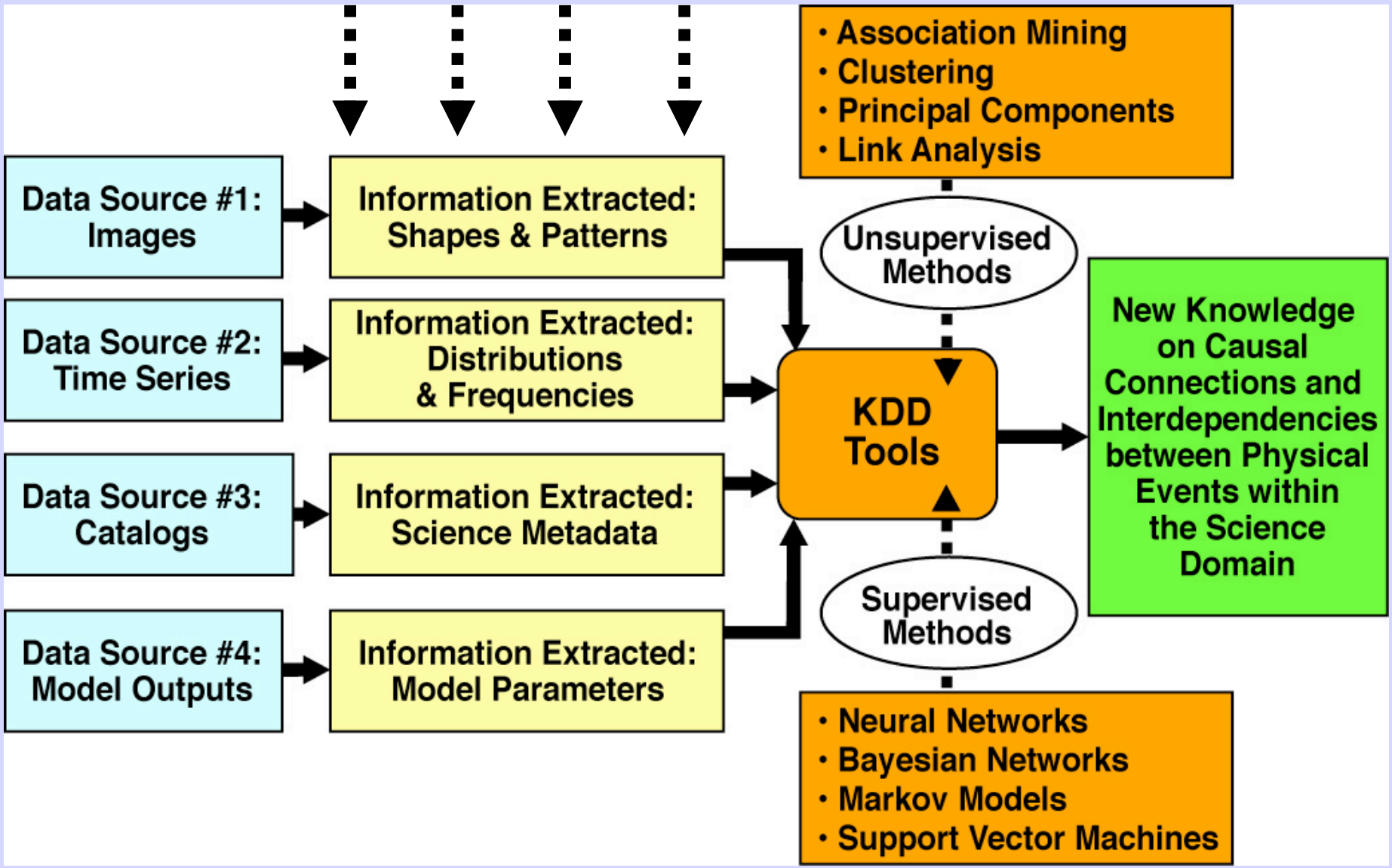


Understanding: the Universe is expanding!!

Scientific KDD: Knowledge Discovery in Databases



This is the Informatics Layer



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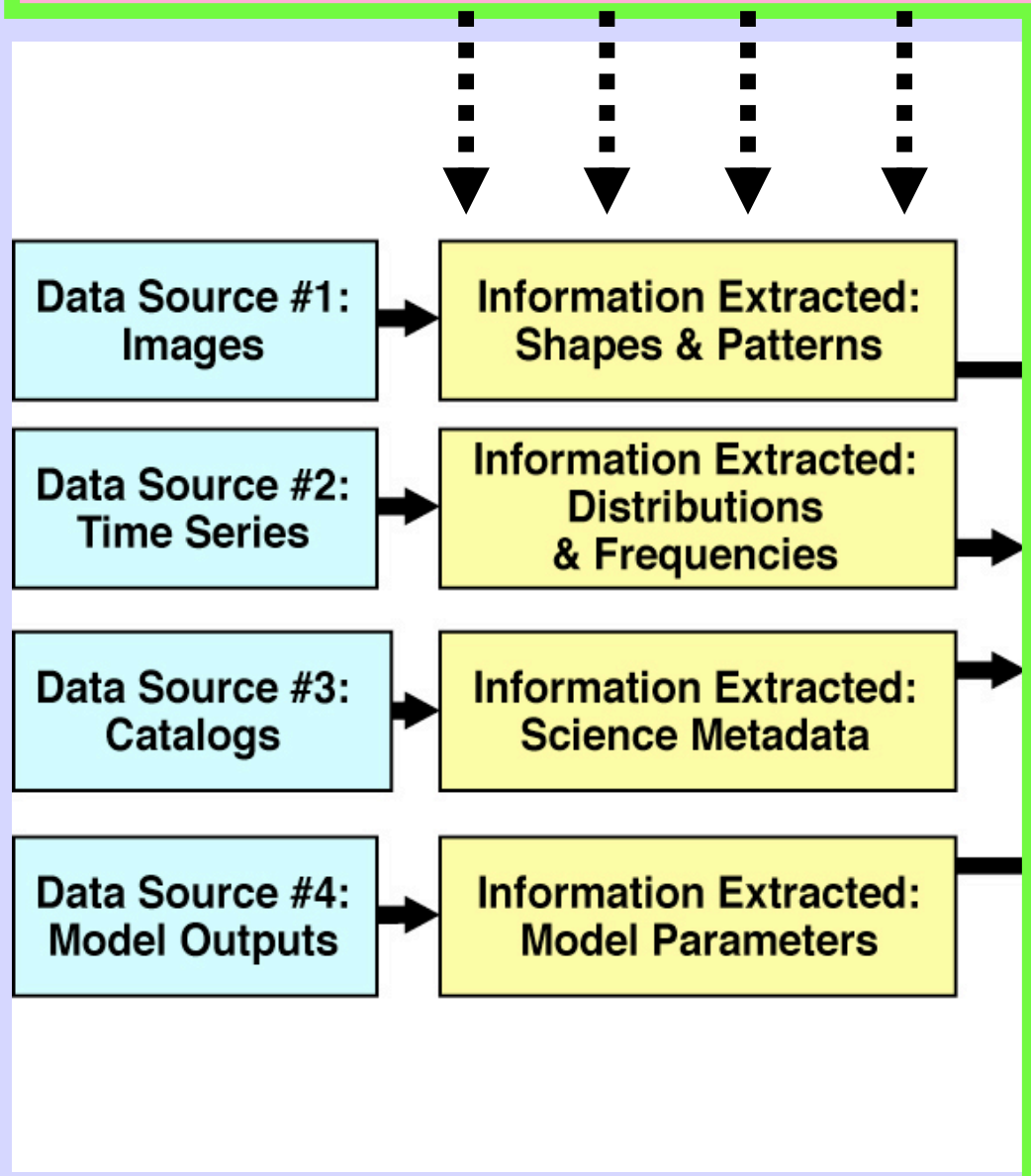


Informatics Layer:

- Provides standardized representations of the "information extracted" – for use in the KDD (data mining) layer.
- Standardization is not required (nor feasible) at the "data source" layer.
- The informatics is discipline-specific.
- Informatics enables KDD across large distributed heterogeneous scientific data repositories.

Astroinformatics for Eventful Astronomy

- Report discoveries back to the science database for community reuse
- Basic astronomical objects (informatics granules) are annotated ...
  - with follow-up observations of any kind
  - with new knowledge discovered
  - with common knowledge
  - with inter-relationships between objects and their properties
  - with concepts
  - with context
  - With assertions (e.g., classifications, concepts, quality flags, relationships, references, observational parameters, common knowledge, inter-connectivity with other objects)

    Semantics!
  - with experimental parameters
  - with observer / observatory descriptors

    Provenance (traceback)
- Enables knowledge-sharing and reuse

Astroinformatics for Eventful Astronomy

- In order to facilitate filtering and prioritization of events for rapid follow-up observations, a near real-time **characterization** provider of tags (end-user annotations) for each object and event is needed.

- The semantic integration of real-time survey data products with federated VO-accessible archival information resources will facilitate the sharing of knowledge-rich quantifiable astronomical features (event characterizations) to the research community.

- An astroinformatics-enabled characterization service for large sky surveys provides uniform tags, metadata, labels, terminology.

- Use cases of the characterization service include knowledge capture, annotation, data mining, & queries of distributed knowledgebases.

- The addition of human-provided annotations and semantic tagging, in structured form, will enhance and improve eventful astronomy research and worldwide astronomical knowledge.

Part 2

Machine Learning in the Galaxy Zoo Database

GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

ZOONIVERSE
REAL SCIENCE ONLINE

http://zooniverse.org/

Modes of Computing

- **Numerical Computation (*in silico*)**
  - Fast, efficient
  - Processing power is rapidly increasing
  - Model-dependent, subjective, only as good as your best hypothesis
- **Computational Intelligence**
  - Data-driven, objective (machine learning)
  - Often relies on human-generated training data
  - Often generated by a single investigator
  - Primitive algorithms
  - Not as good as humans on most tasks
- **Human Computation (*Carbon-based Computing*)**
  - Data-driven, objective (human cognition)
  - Creates training sets, Cross-checks machine results
  - Excellent at finding patterns, image classification
  - Capable of classifying anomalies that machines don't understand
  - Slow at numerical processing, low bandwidth, easily distracted

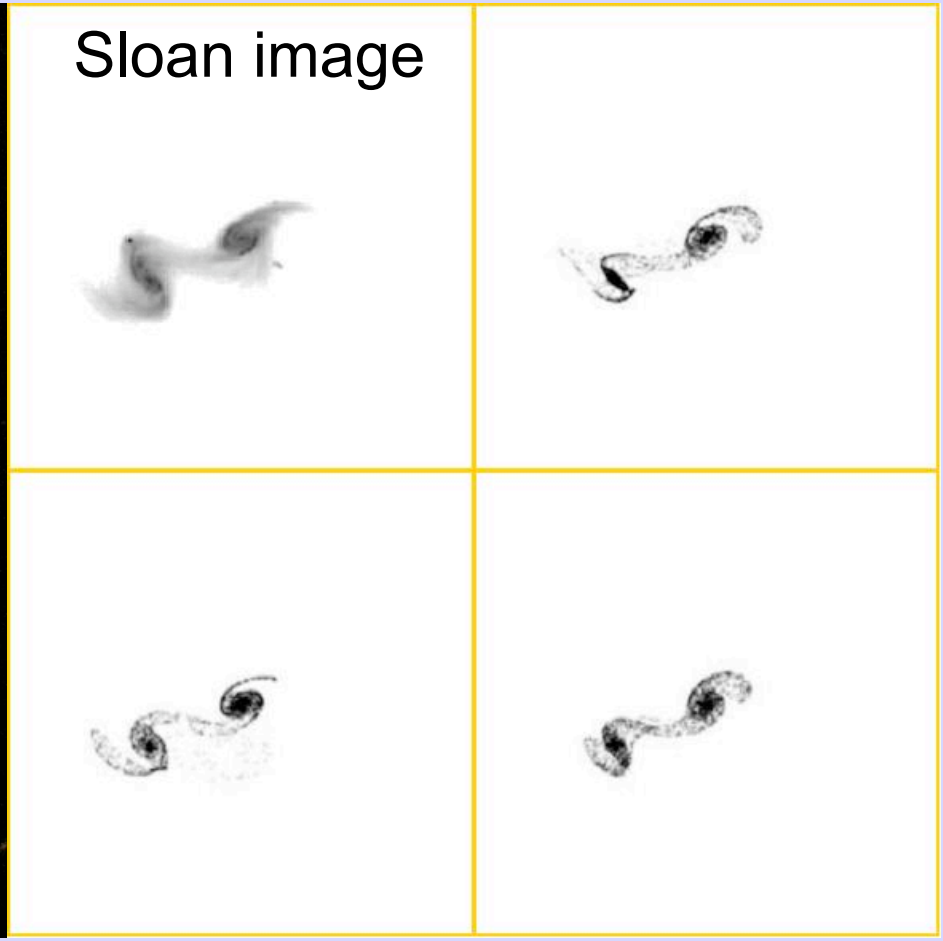
The Zooniverse: a Buffet of Zoos

http://zooniverse.org/

- Galaxy Zoo project (released July 2007):
  - http://www.galaxyzoo.org/
  - Classify galaxies (Spiral, Elliptical, Merger, or image artifact)
- Galaxy Merger Zoo (release November 2009)
  - http://mergers.galaxyzoo.org/
  - Run N-body simulations to find best model to match a real merger
  - One new merger every day
- The Hunt for Supernovae (released December 2009)
  - http://supernova.galaxyzoo.org/
  - Real-time event detection and classification
- Solar Storm Watch (released March 2010)
  - http://solarstormwatch.com/
  - Spot solar storms (CMEs) in near real-time

Merging/Colliding Galaxies are the building blocks of the Universe: **1 + 1 = 1**

Galaxy Mergers Zoo Gallery



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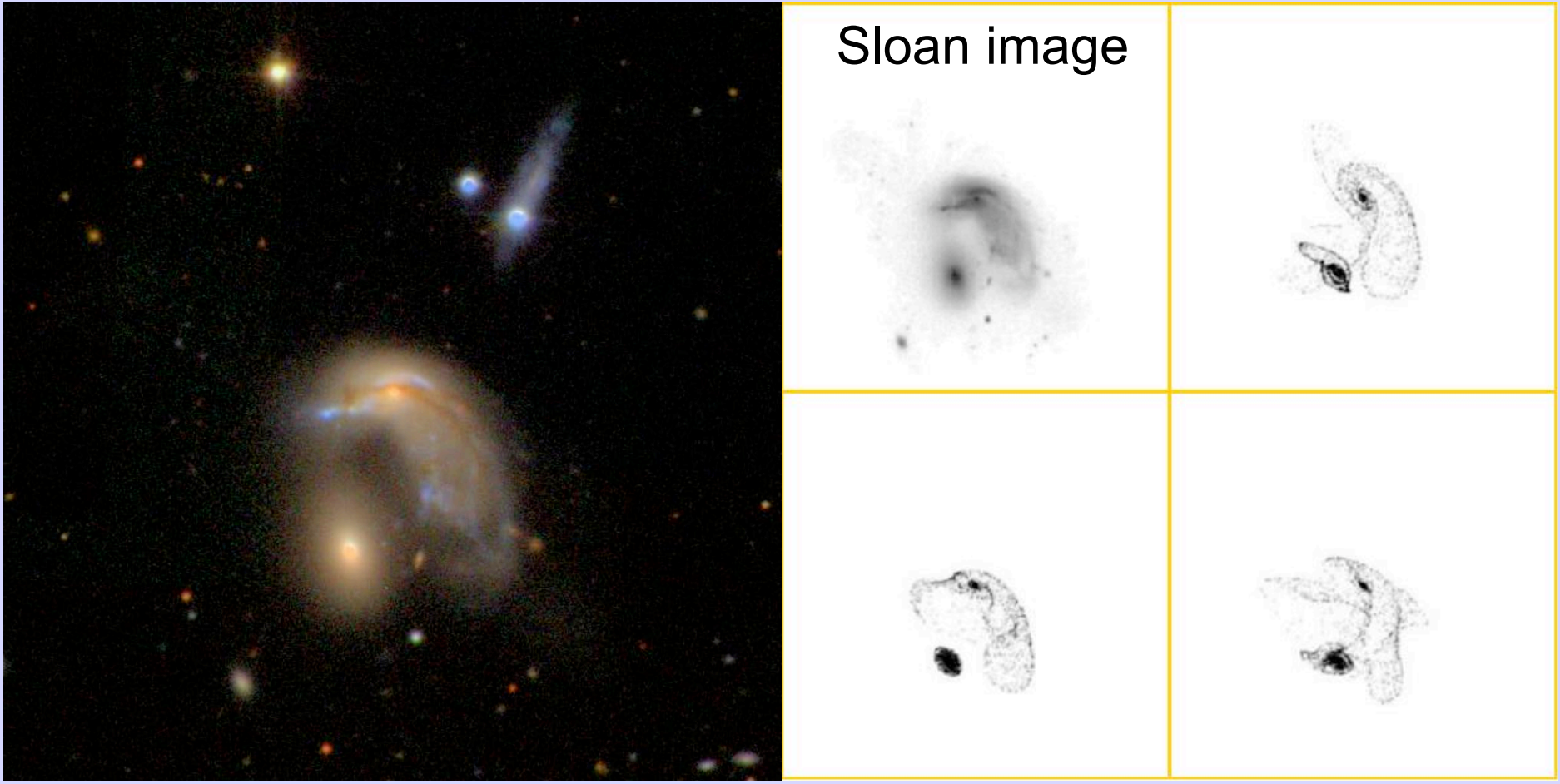
GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

Galaxy Mergers Zoo Gallery



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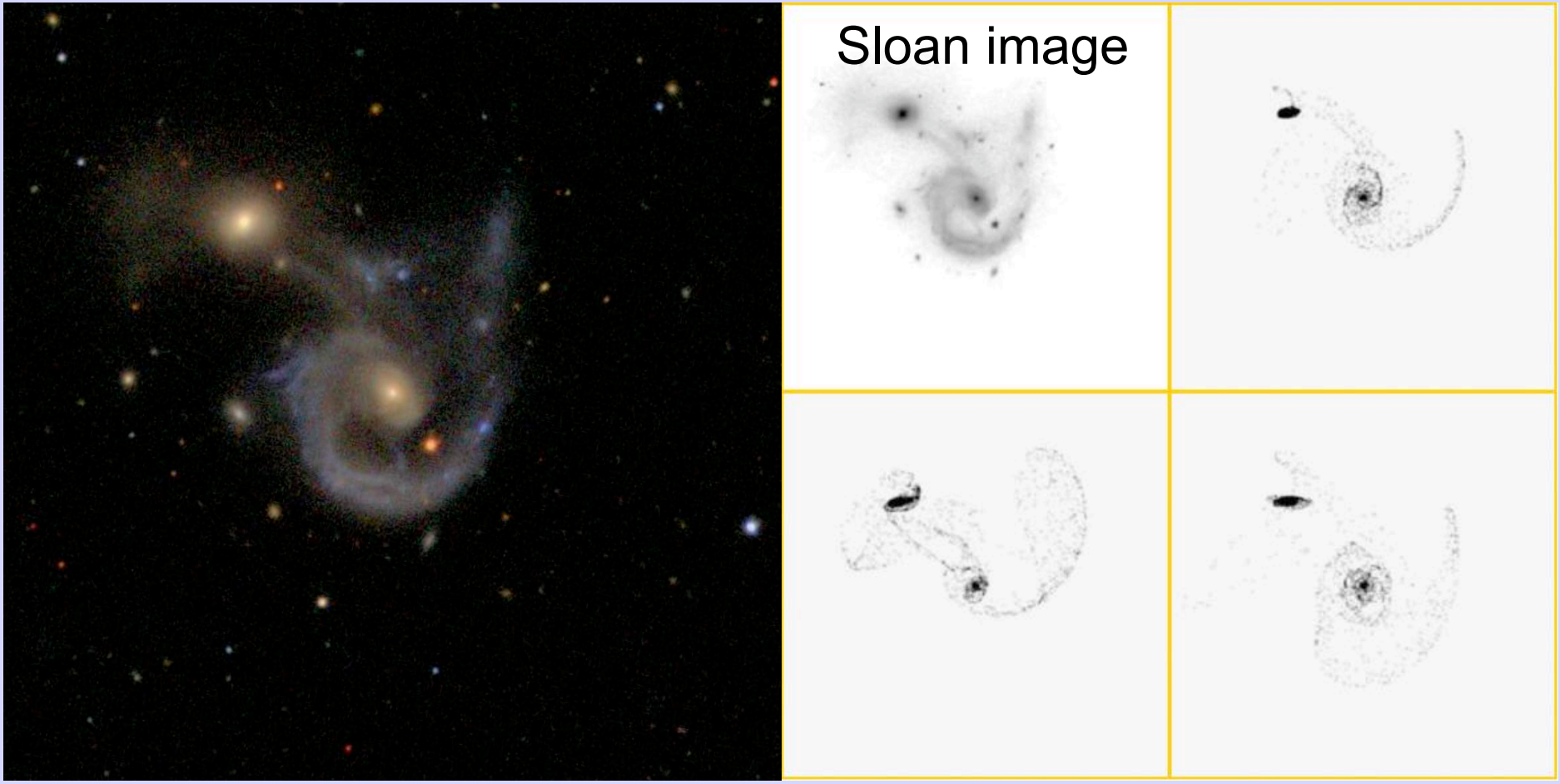
GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

Galaxy Mergers Zoo Gallery



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UNDERSTANDING COSMIC MERGERS

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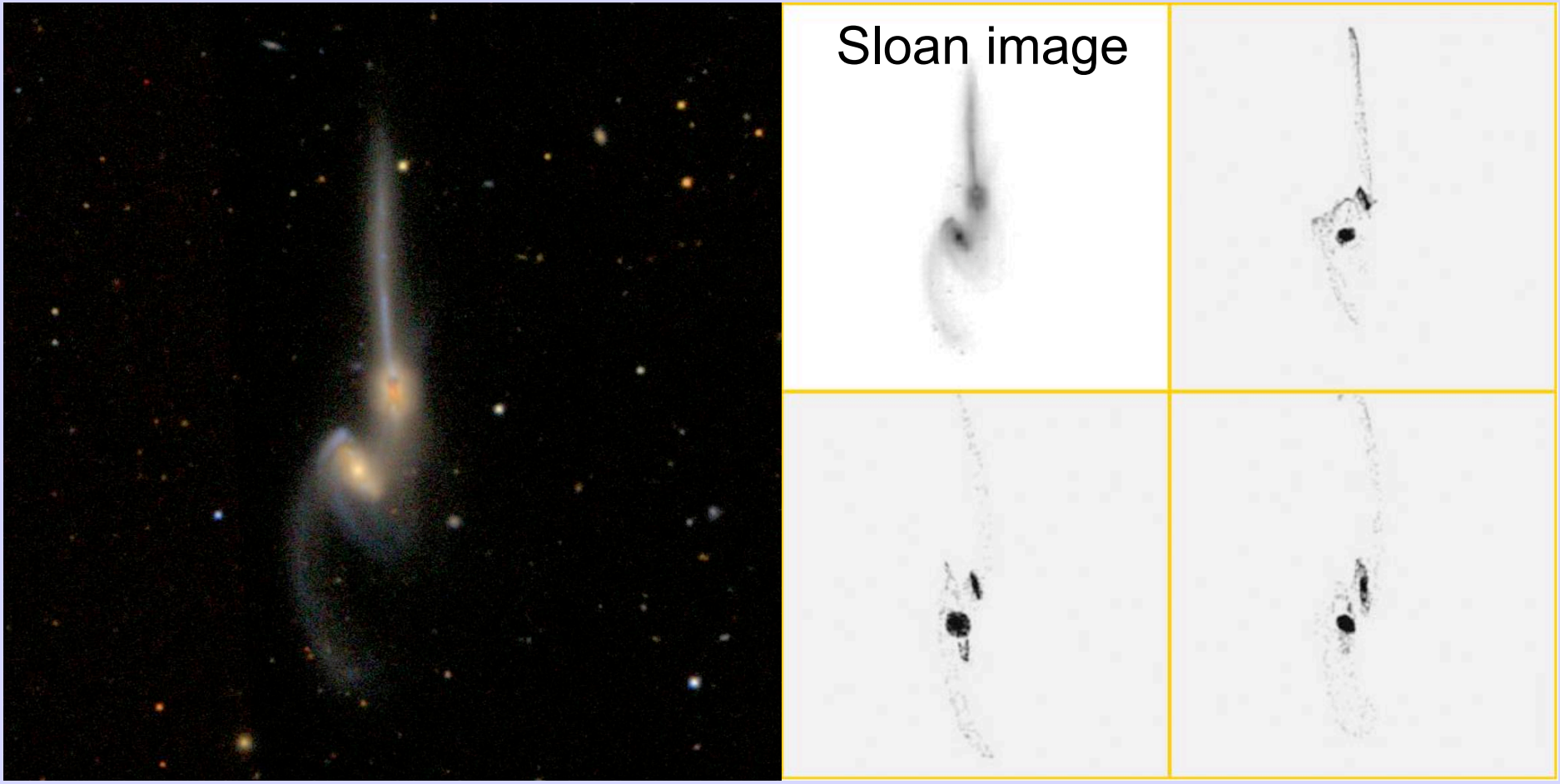

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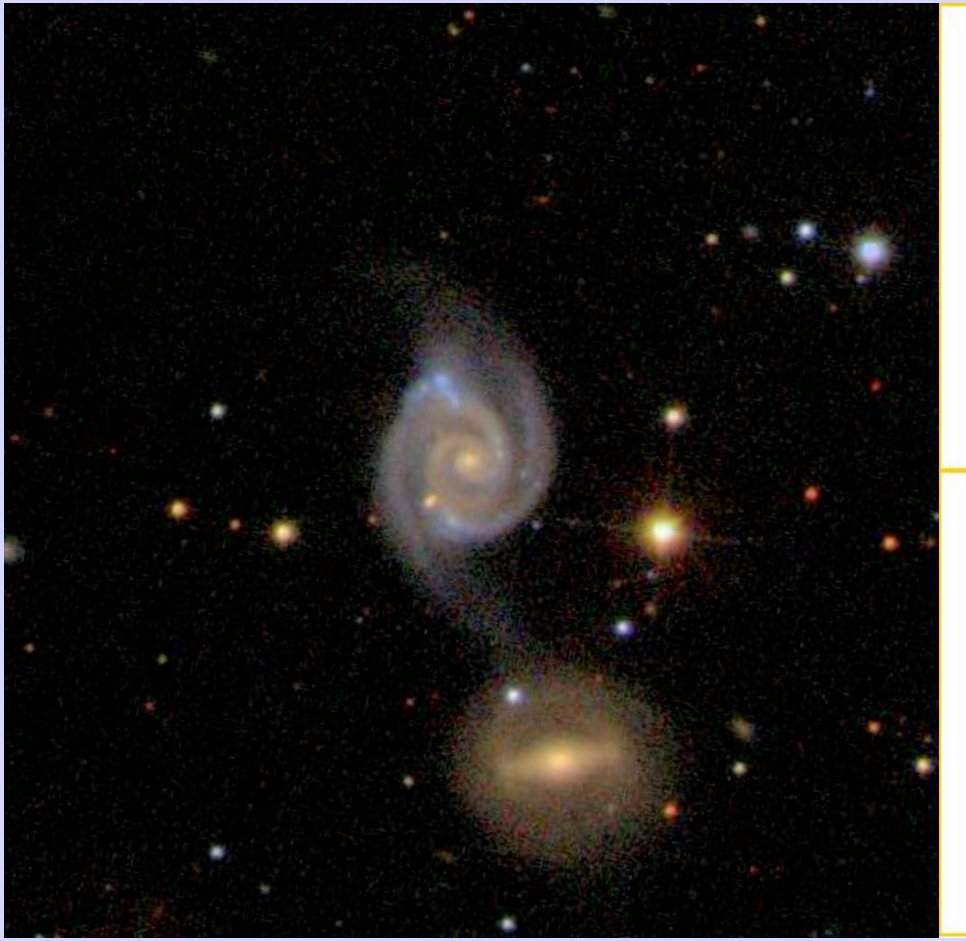

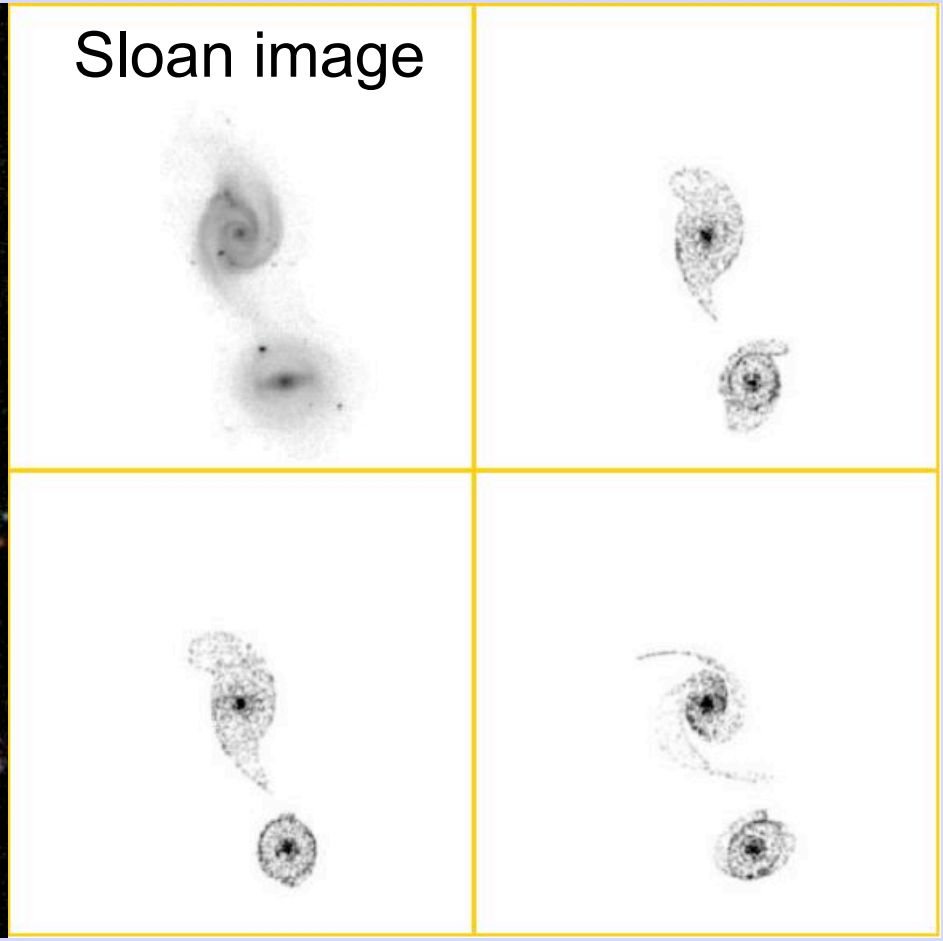

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GALAXY ZOO
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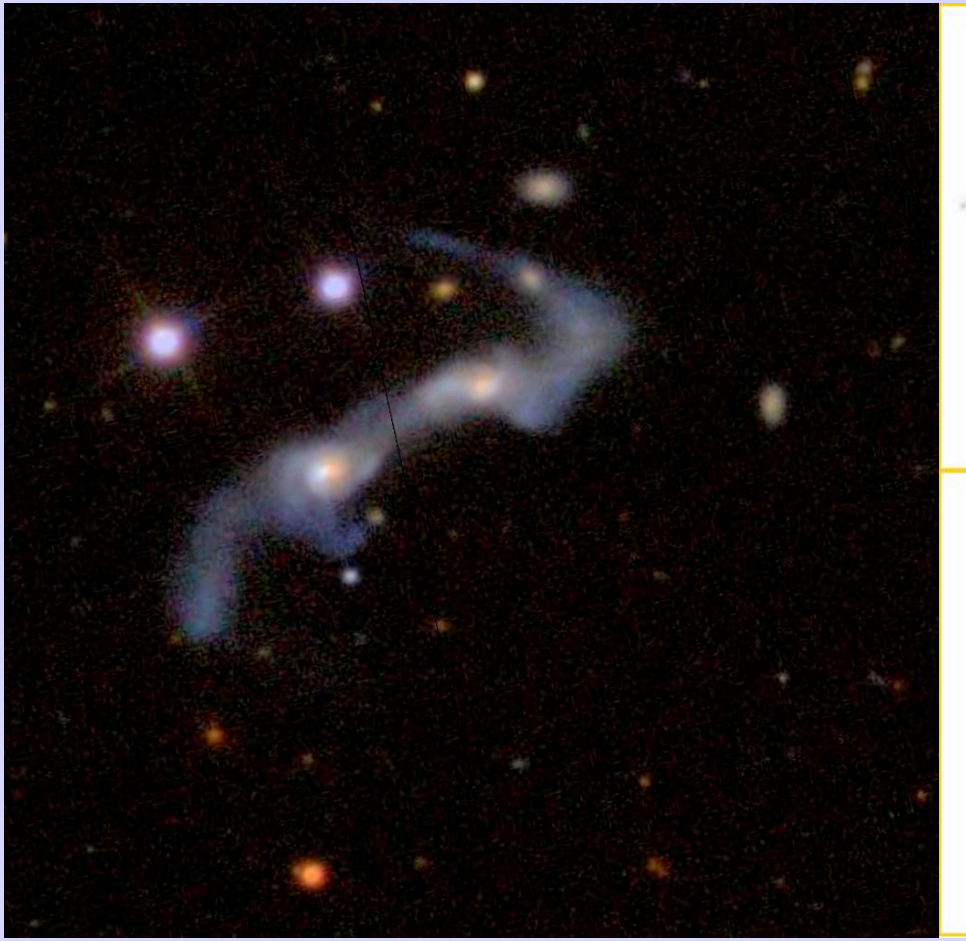
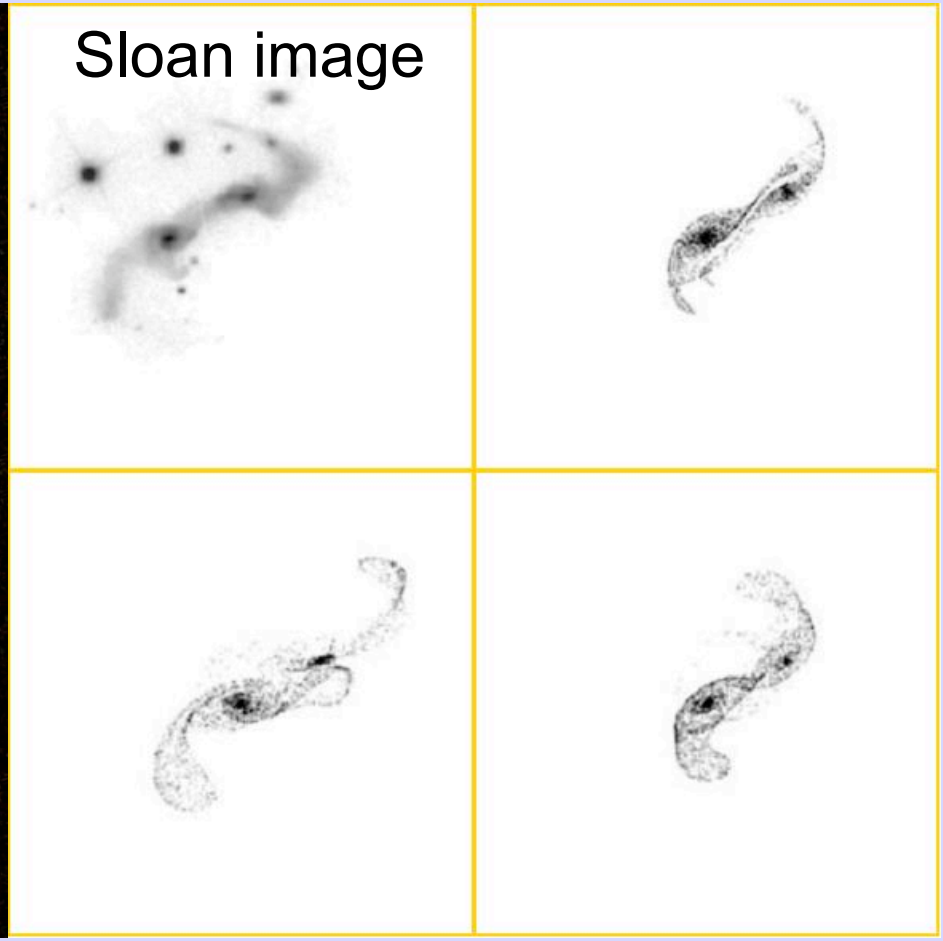
Galaxy Mergers Zoo Gallery





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GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

Tags produce a new data flood

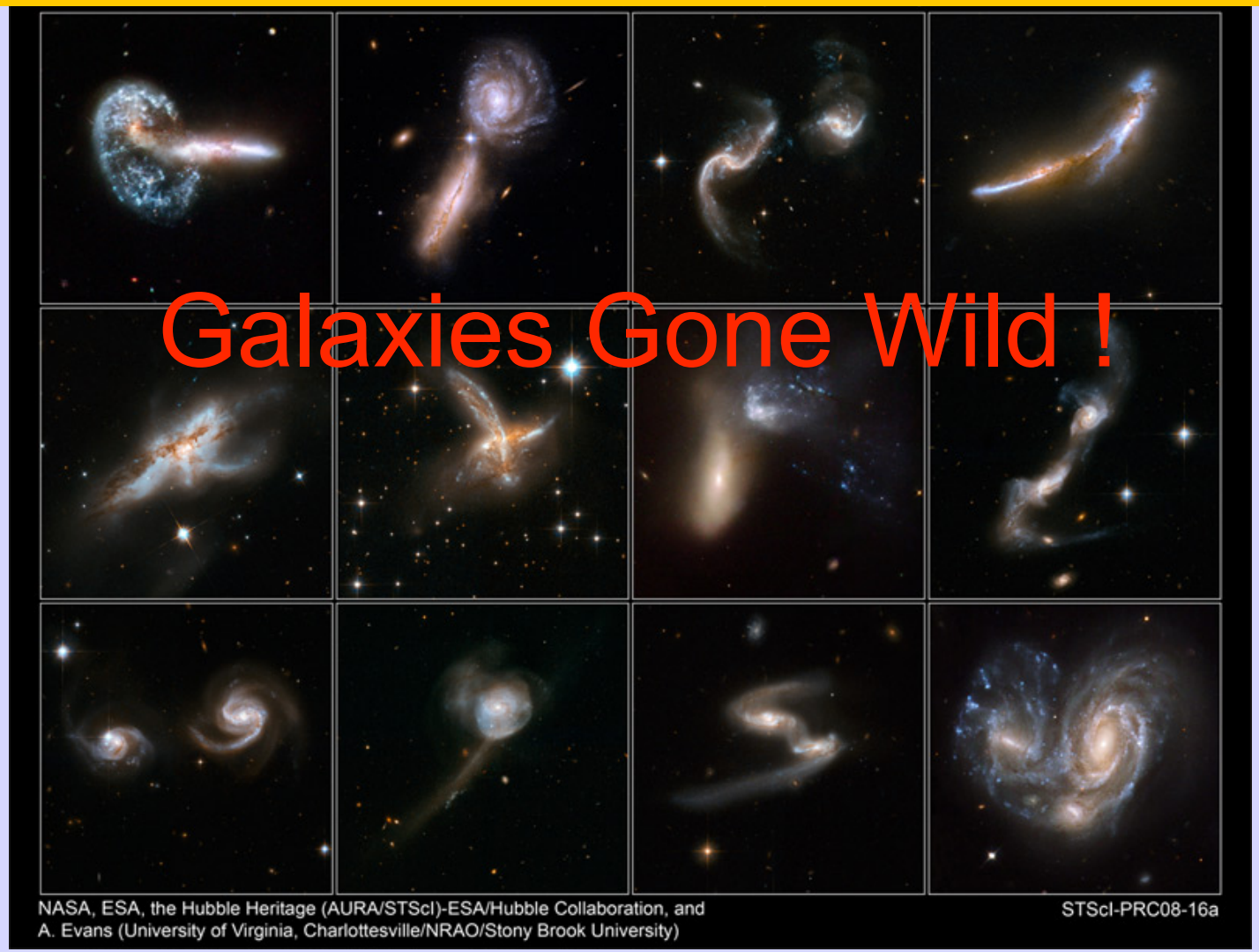
- **Tagging enables semantic data fusion & integration, and knowledge acquisition / representation / sharing.**
- User-contributed content adds **more** data to the data flood.
- Example – Galaxy Zoo project:
  - ~250,000 participants (*and growing*)
  - ~1 million galaxies have been labeled (classified)
  - ~200 million classifications have been collected
- Tagging is applicable to any data source, including document repositories – adding lightweight semantics to the data repository (taxonomies, folksonomies, annotations)
- Reference: *"TagLearner: A P2P Classifier Learning System from Collaboratively Tagged Text Documents",* Dutta, Zhu, Mahule, Kargupta, Borne, Lauth, Holz, & Heyer, 2009 ICDM paper.

Key Feature of Zooniverse:
Data mining from the volunteer-contributed labels

- Train the automated pipeline classifiers with:
  - Improved classification algorithms
  - Better identification of anomalies
  - Fewer classification errors
- Millions of training examples
- Hundreds of millions of class labels
- Statistics deluxe! …
  - Users (see paper: http://arxiv.org/abs/0909.2925)
  - Uncertainty quantification
  - Classification certainty vs. Classification dispersion

ZOONIVERSE
REAL SCIENCE ONLINE

First Case Study: test SDSS science catalog attributes to find which attributes correlate most strongly with user-classified mergers.



Sloan Science Database Attributes tested

Attribute	Description
$petroMag_{ug}$	Petrosian magnitude colors. A color was calculated for four independent pairs of bands in SDSS (u, g, r, i, z).
$petroRad_u * z$	Petrosian radius, transformed with redshift to be distance-independent.
$invConIndx_u$	Inverse concentration index. The ratio of the 50% Petrosian magnitude to the 90% Petrosian magnitude.
$isoRowcGrad_u * z$	Gradient of the isophotal row centroid, transformed with redshift to be distance-independent.
$isoColcGrad_u * z$	Gradient of the isophotal column centroid, transformed with redshift to be distance-independent.
$isoA_u * z$	Isophotal major axis, transformed with redshift to be distance-independent.
$isoB_u * z$	Isophotal minor axis, transformed with redshift to be distance-independent.
$isoAGrad_u * z$	Gradient of the isophotal major axis, transformed with redshift to be distance-independent.
$isoBGrad_u * z$	Gradient of the isophotal minor axis, transformed with redshift to be distance-independent.
$isoPhiGrad_u * z$	Gradient of the isophotal orientation, transformed with redshift to be distance-independent.
$texture_u$	Measurement of surface texture.
$lnLExp_u$	Log-likelihood of exponential profile fit.
$lnLDeV_u$	Log-likelihood of De Vaucouleurs profile fit.
$fracDev_u$	Fraction of the brightness profile explained by the De Vaucouleurs profile.

Results of Decision Tree Information Gain analysis

Attribute	Information Gain
$lnLExp_g$	0.10118
$texture_g$	0.07335
$lnLDeV_g$	0.06864
$petroMag_{gr}$	0.06626
$isoAGrad_u * z$	0.05729

Results of cluster separation analysis

Best Separation in Single Dimension	Best Separation Among 1014 Combinations
$isoAGrad_u * z$	$isoAGrad_u * z$
$petroRad_u * z$	$petroRad_u * z$
$texture_u$	$texture_u$
$isoA_z * z$	$isoA_z * z$
$lnLExp_u$	$lnLExp_u$
$lnLExp_g$	$lnLExp_g$
$isoA_u * z$	$petroRad_u * z$, $isoB_z * z$, $isoBGrad_u * z$, $lnLExp_g$
$isoB_z * z$	$isoAGrad_u * z$, $lnLExp_g$
$isoBGrad_u * z$	$petroRad_u * z$, $isoA_u * z$, $isoB_z * z$, $lnLExp_g$
$isoAGrad_z * z$	$isoAGrad_u * z$, $isoBGrad_u * z$, $lnLExp_g$

Summary Remarks

- These are just the first steps
- There is more to come
- We will seek involvement from Machine Learning community
- We will advise LSST project based on our results
- We anticipate using (requiring) lightweight semantics (folksonomies, taxonomies, …)
- Collecting annotations and tags in structured form (e.g., RDBMS) is essential for ease of retrieval and semantic data mining
- … and finally … my recommendation …

...

Party with your data !