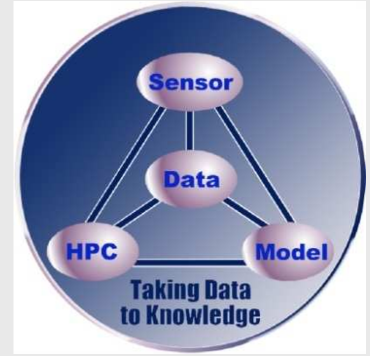

Conquering the Astronomical Data Flood through Machine Learning and Citizen Science

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http://spacs.gmu.edu/

The Problem: Big Data is a Big Challenge

LSST big data challenge #1

- **Each night** for 10 years LSST will obtain roughly the equivalent amount of data that was obtained by the entire Sloan Digital Sky Survey
- Our grad students will be asked to mine these data (~20 TB each night ≈ 40,000 CDs filled with data):
  - *A truckload of CDs each and every day for 10 yrs*
  - *Cumulatively, a football stadium full of 100 million CDs after 10 yrs*

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  - *A truckload of CDs each and every day for 10 yrs*
  - *Cumulatively, a football stadium full of 100 million CDs after 10 yrs*
- The challenge is to find the new, the novel, the interesting, and the surprises (the unknown unknowns) within all of these data.
- *Yes, more is most definitely different !*

LSST big data challenge # 2

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Characterize first !
(Unsupervised Learning)

Classify later.

Characterization includes …

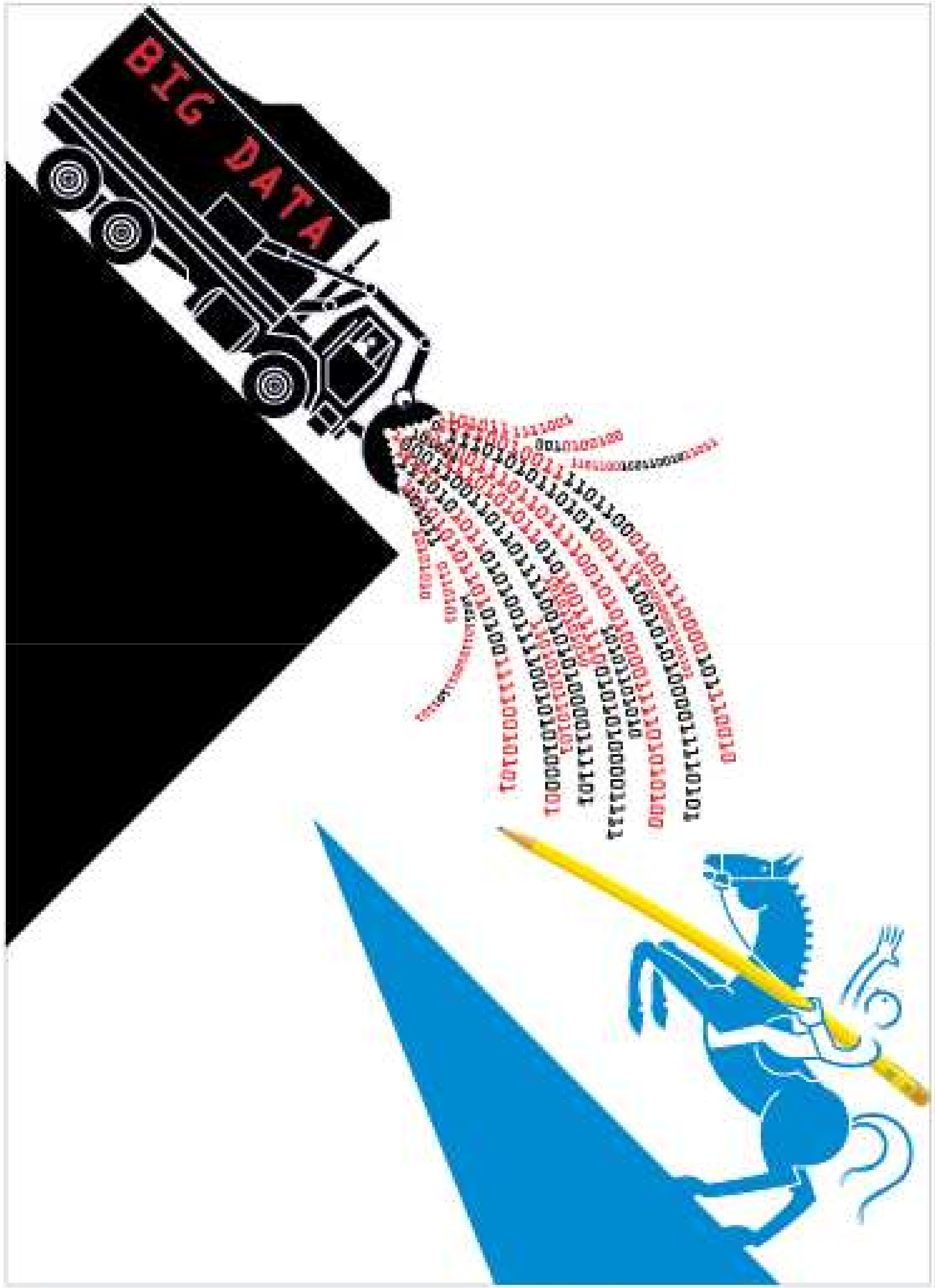
- Feature Detection and Extraction:
  - Identifying and describing features in the data
    - via machine algorithms or human inspection (including the potentially huge contributions from Citizen Science)
  - Extracting feature descriptors from the data
  - Curating these features for search, re-use, & discovery
  - Finding other parameters and features from other archives, other databases, other information sources – and using those to help characterize (ultimately classify) each new event.

Data-driven Discovery (Unsupervised Learning)
i.e., What can I do with characterizations?

1. Class Discovery – Clustering
2. Principal Component Analysis – Dimension Reduction
3. Outlier (Anomaly / Deviation / Novelty) Detection – Surprise Discovery
4. Link Analysis – Association Analysis – Network Analysis
5. and more.

The Promise: Big Data leads to Big Insights and New Discoveries

http://kdd2012.sigkdd.org/

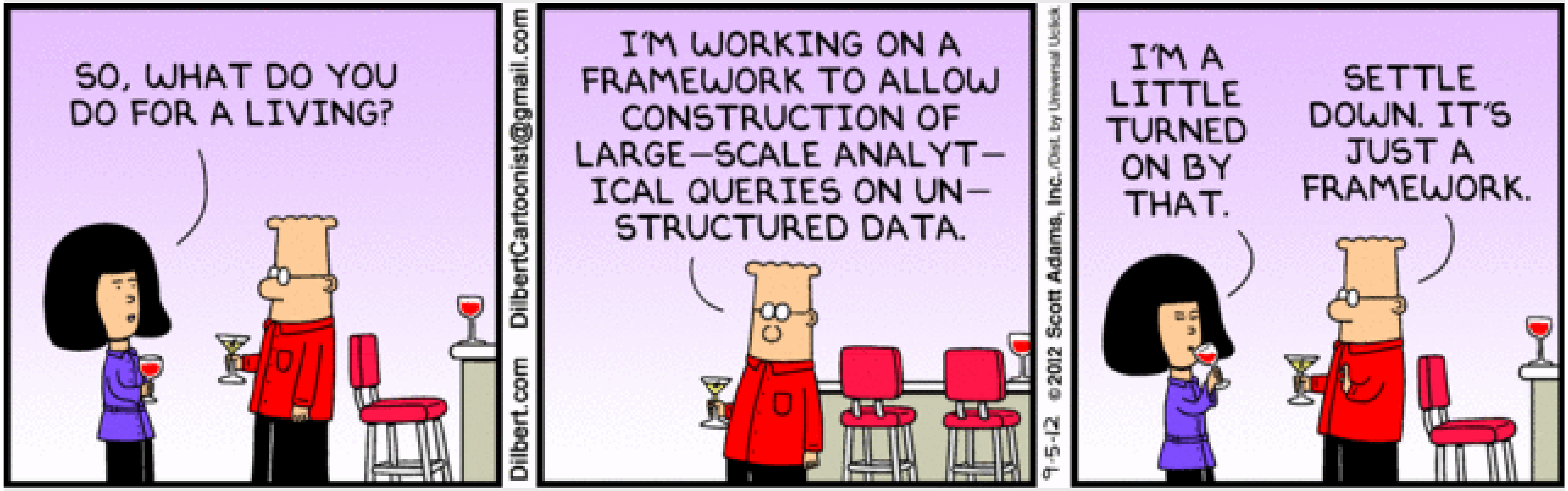


Scary News:

Big Data is taking us to a Tipping Point

http://bit.ly/HUqmu5

Good News: Big Data is Sexy

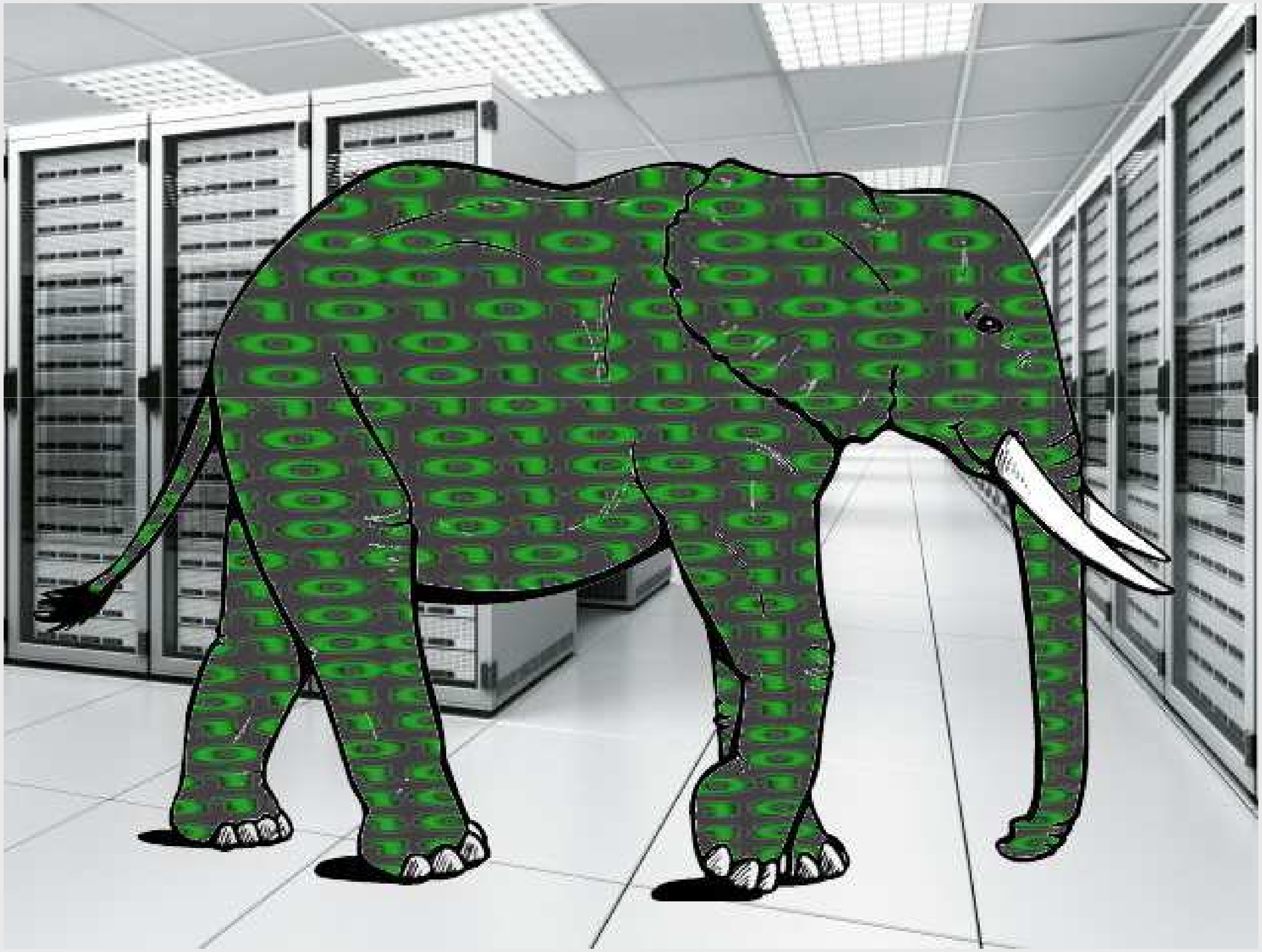


http://dilbert.com/strips/comic/2012-09-05/

There are many technologies associated with Big Data

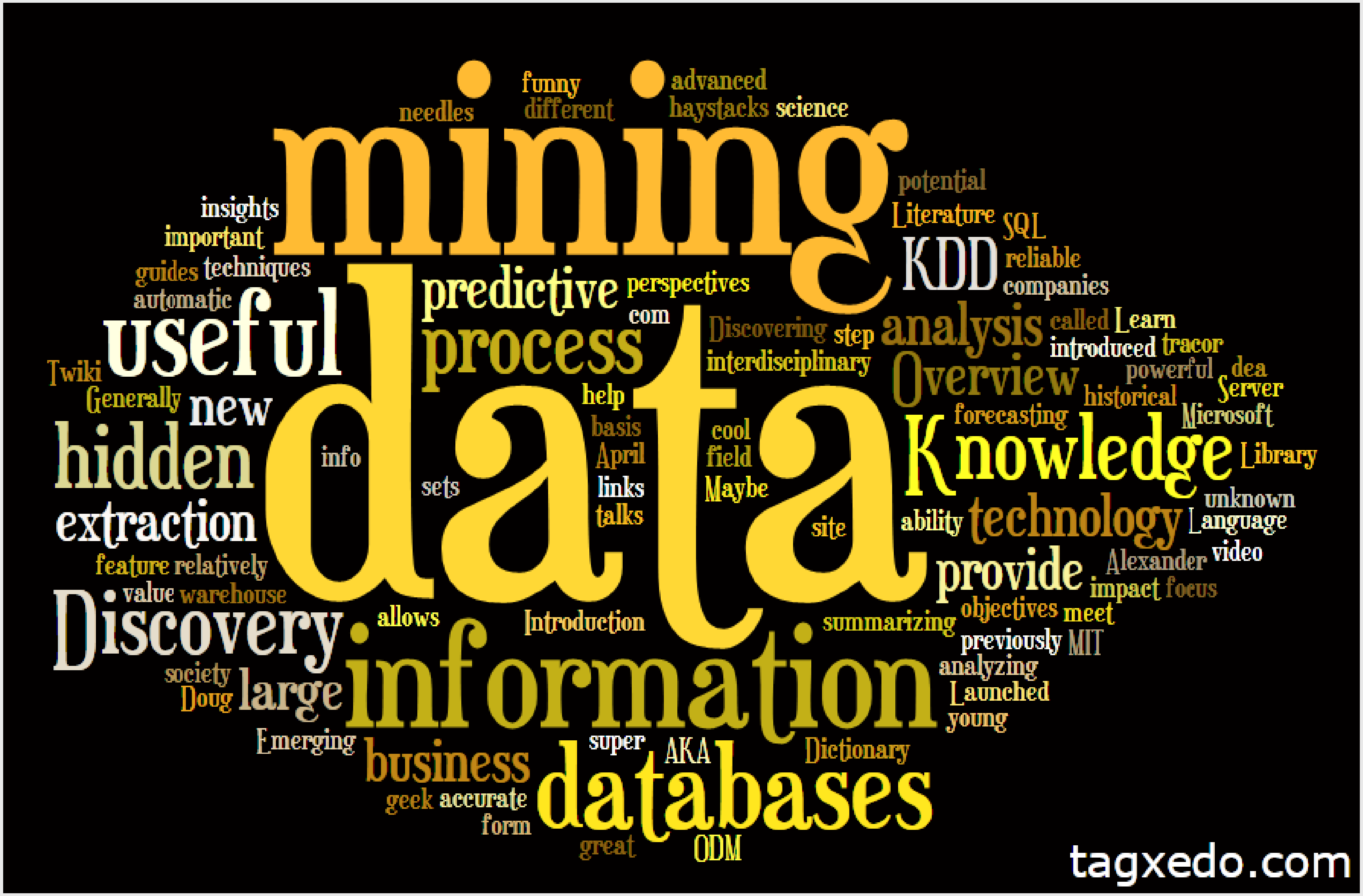
http://siliconangle.com/blog/2012/07/13/big-data-nightmares/

One approach to Big Data: Hadoop and Map/Reduce (Computational Science)

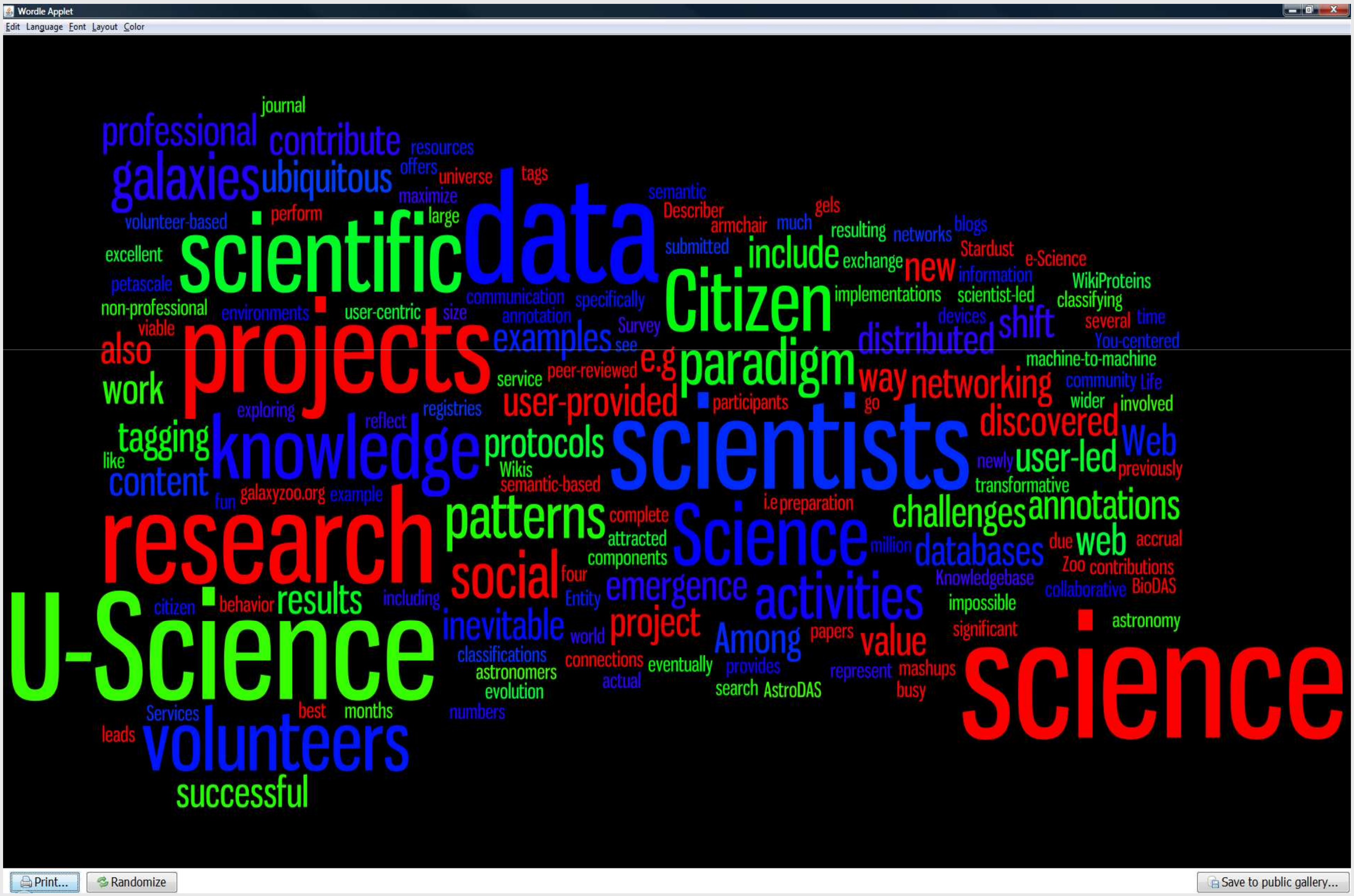


http://www.bigdatabytes.com/wp-content/uploads/2012/01/big-data.jpg

Another approach to Big Data:
Data Science (Informatics)



A third approach to Big Data:
Citizen Science (crowdsourcing)



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

Galaxy Zoo: example of Citizen Science (crowdsourcing)

http://astrophysics.gsfc.nasa.gov/outreach/podcast/wordpress/index.php/2010/10/08/saras-blog-be-a-scientist/

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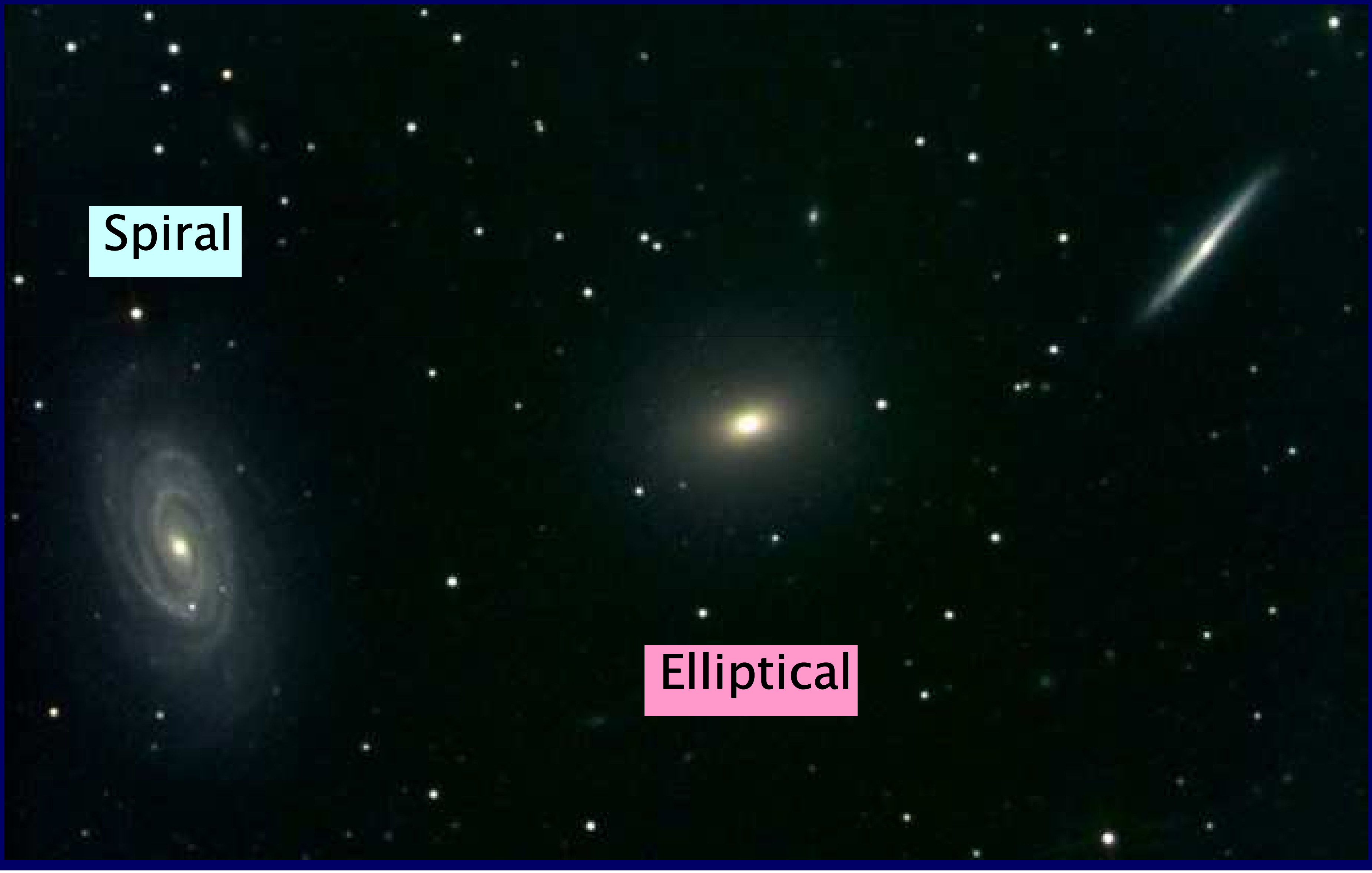
There are 2 main types of galaxies in the Universe: Spiral & Elliptical (plus there are some peculiar & irregular galaxies)

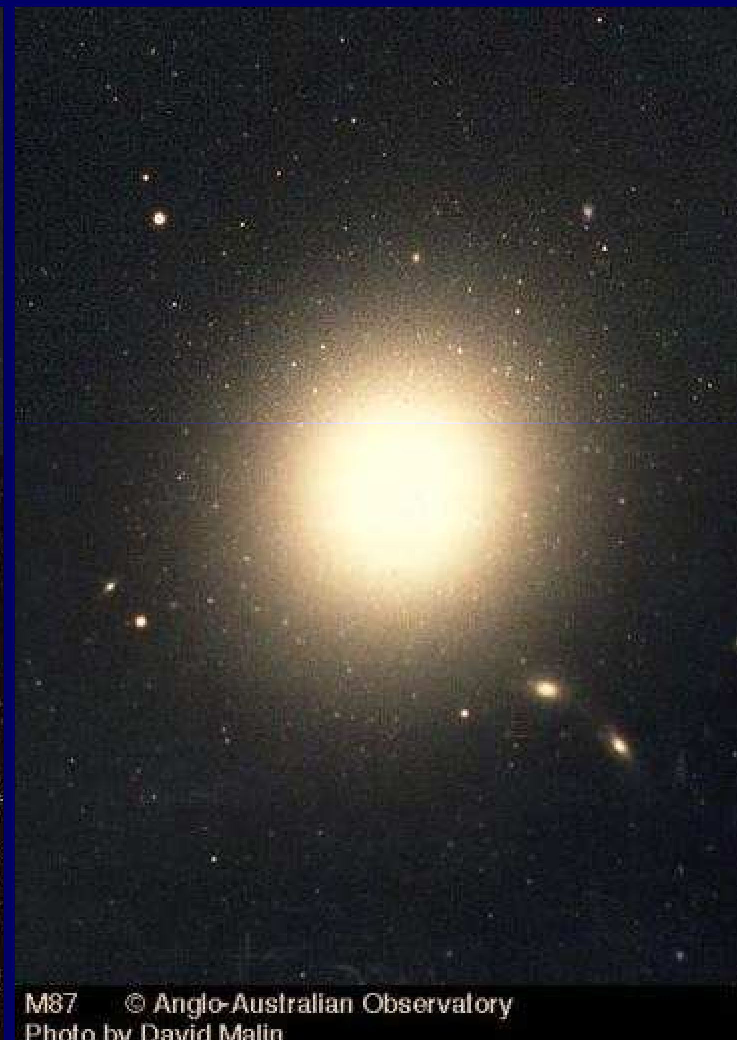


Gallery of Elliptical Galaxies

M32

M59

M87

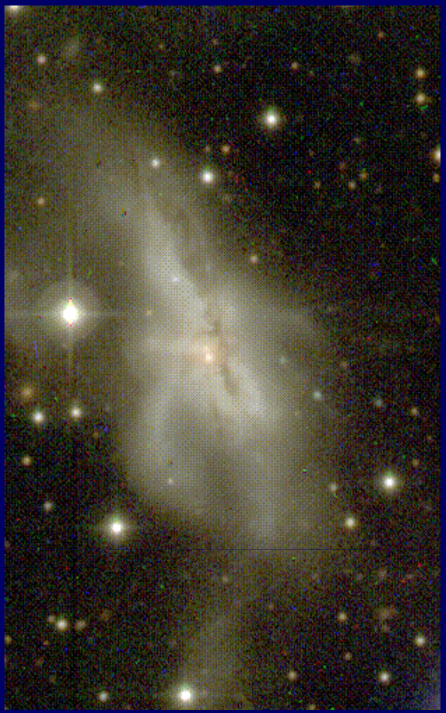


M105

M110=NGC205

Gallery of Face-on Spiral Galaxies

There are lots of Peculiar Galaxies also !



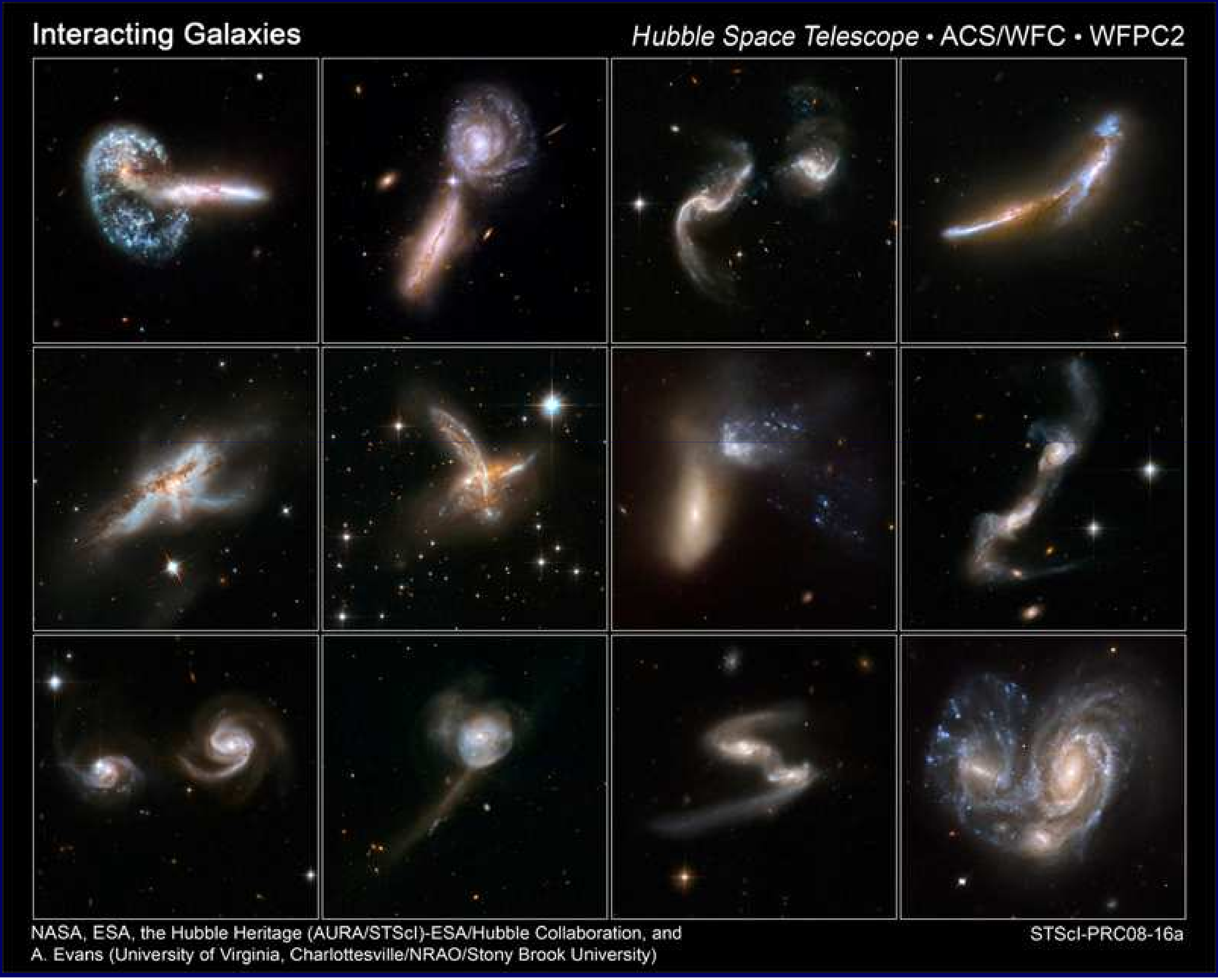
There are lots of things you can do with these peculiar galaxies …

- Spell your name in galaxies @
- http://writing.galaxyzoo.org

k i r k   b o r n e

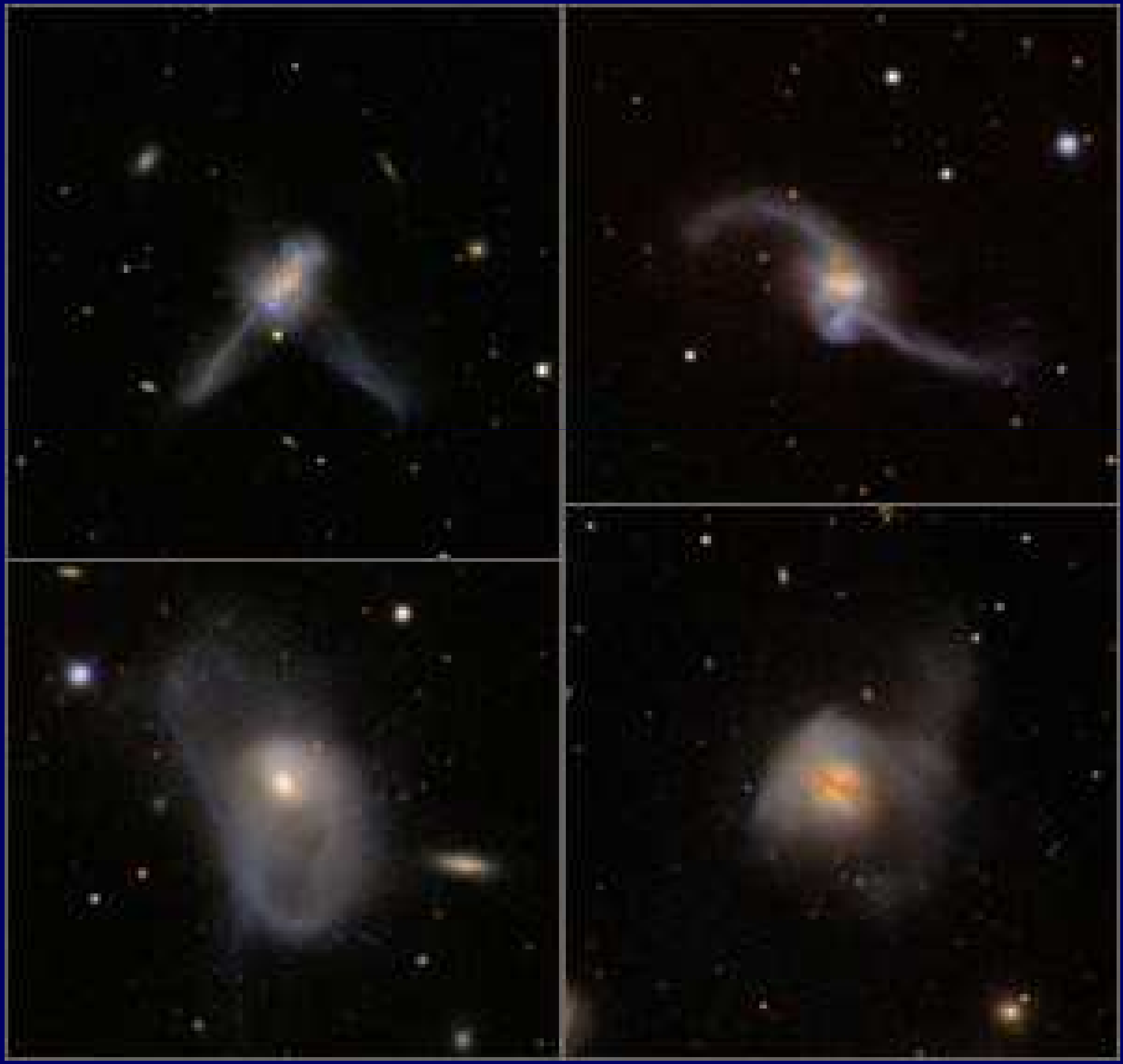
Galaxies Gone Wild !

Colliding and Merging Galaxies = Interacting Galaxies

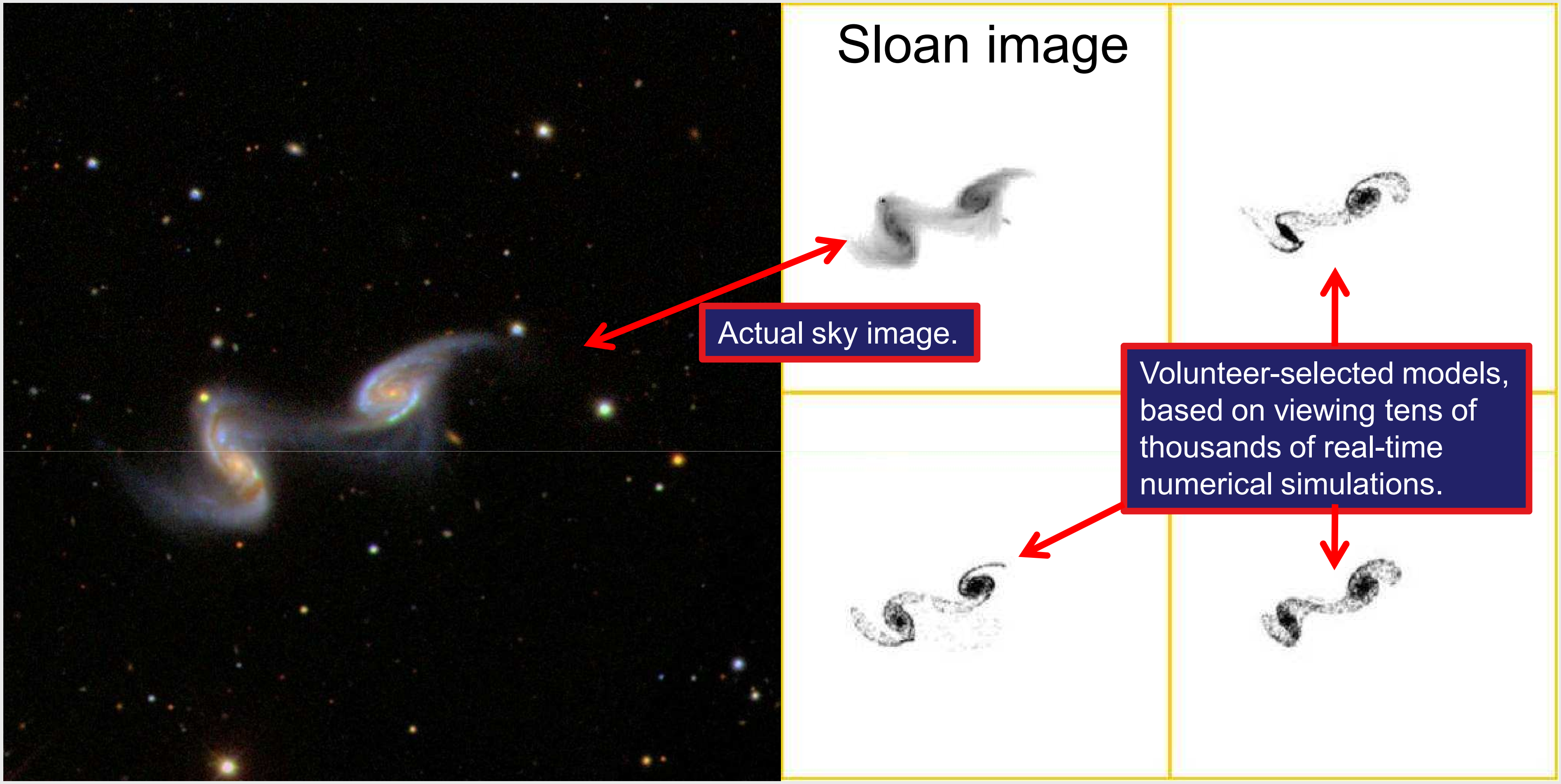


Colliding and Merging Galaxies = Interacting Galaxies

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



Galaxy Mergers Zoo Gallery



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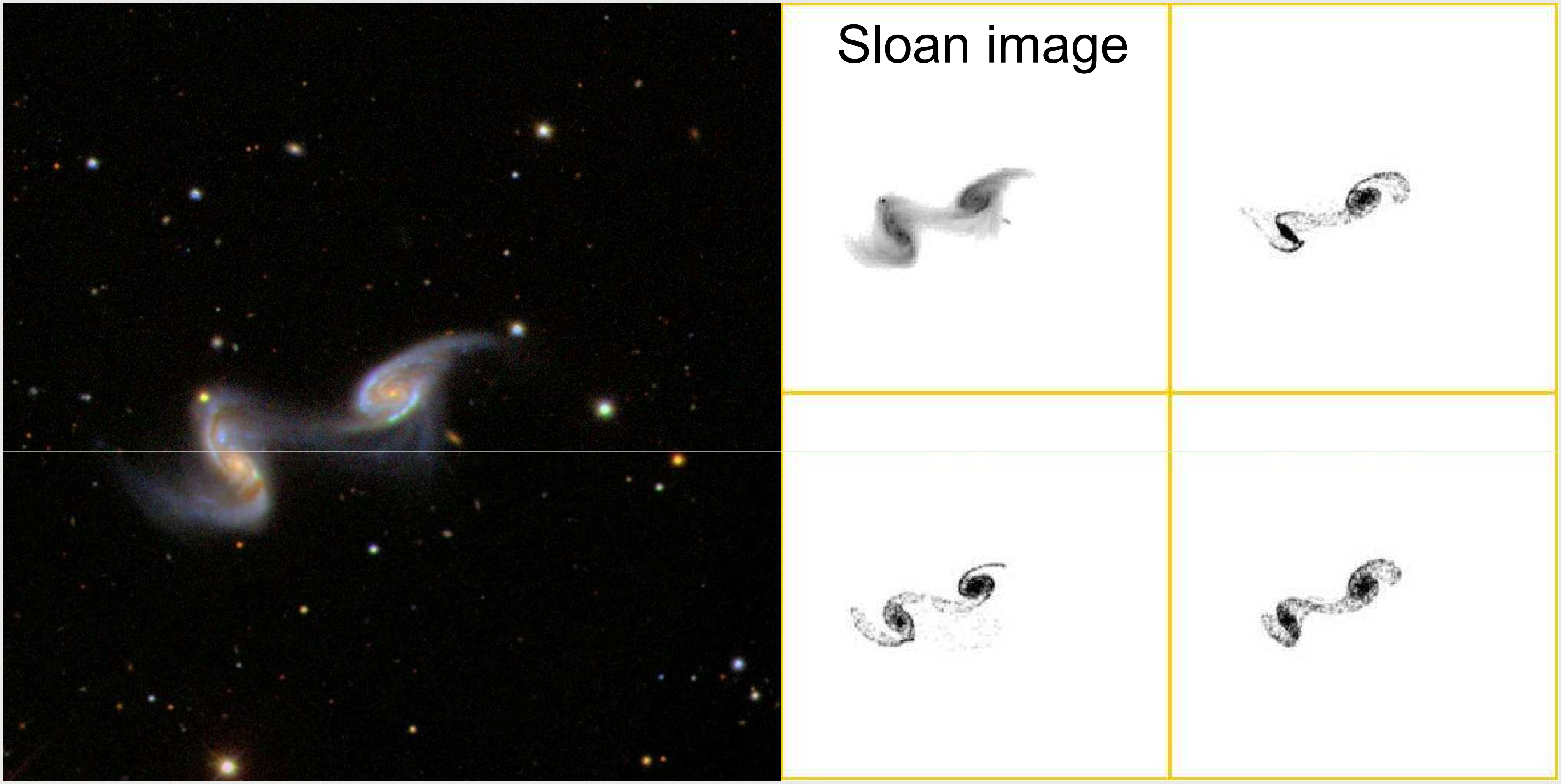
GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

Galaxy Mergers Zoo Gallery



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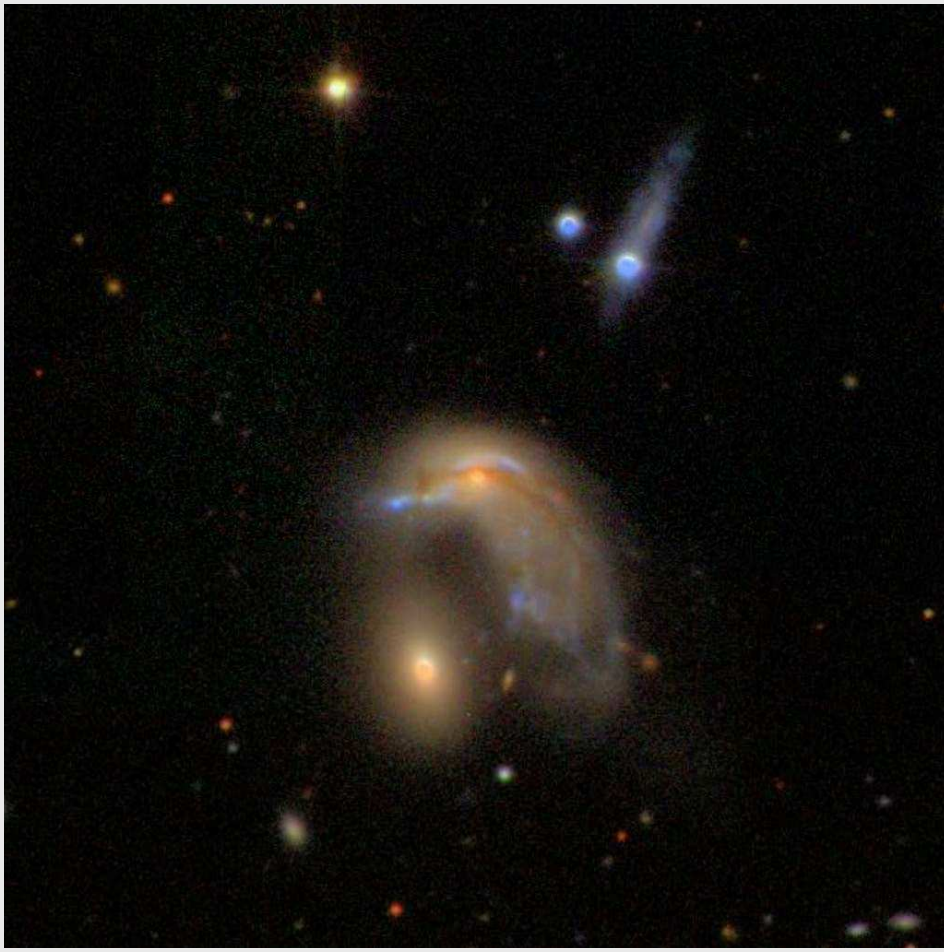

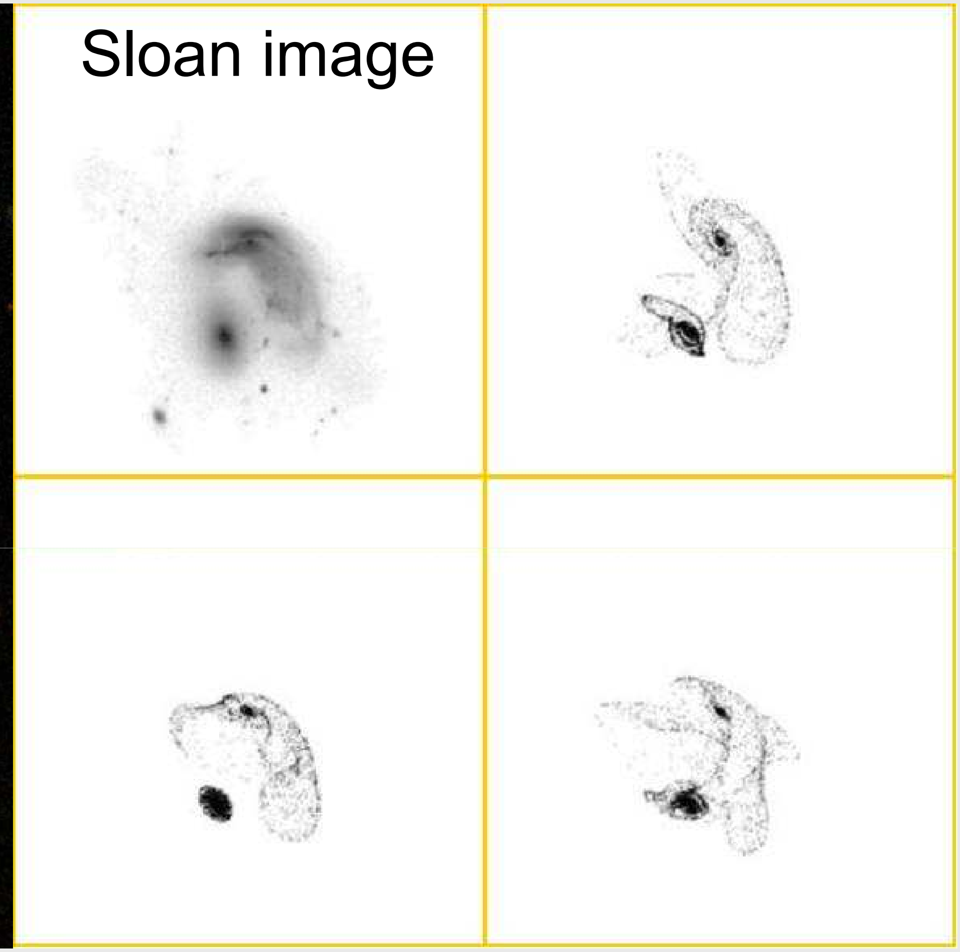

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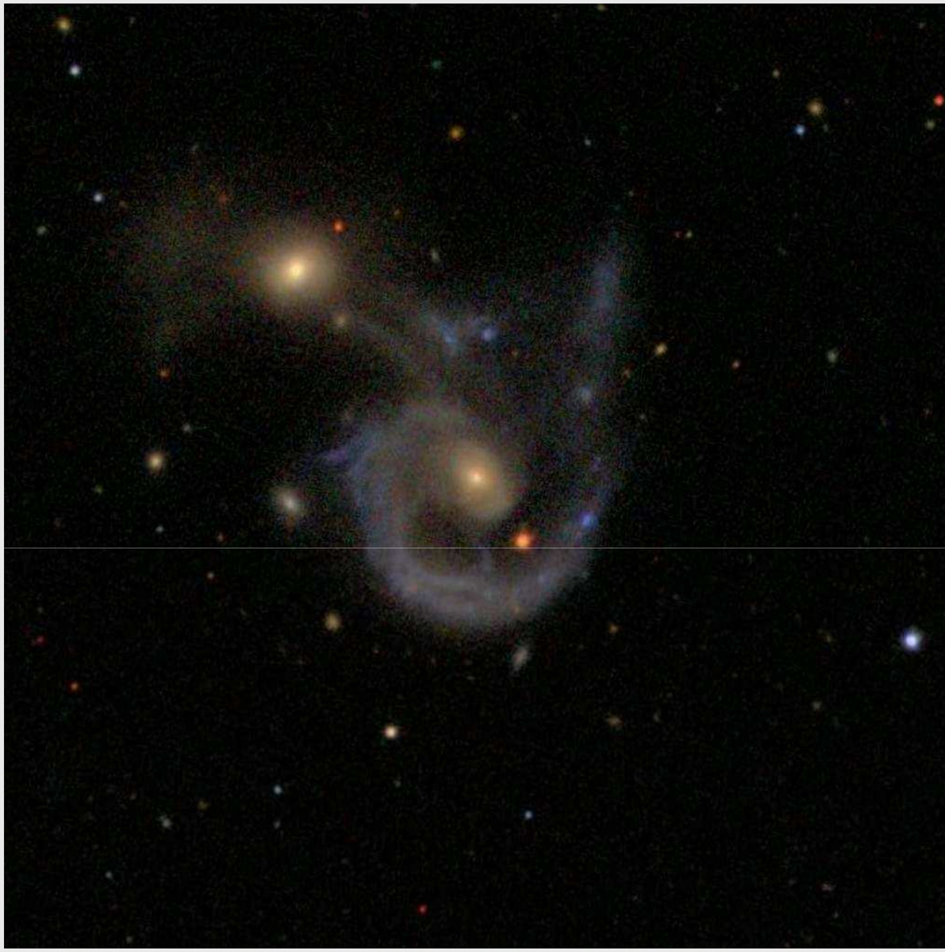

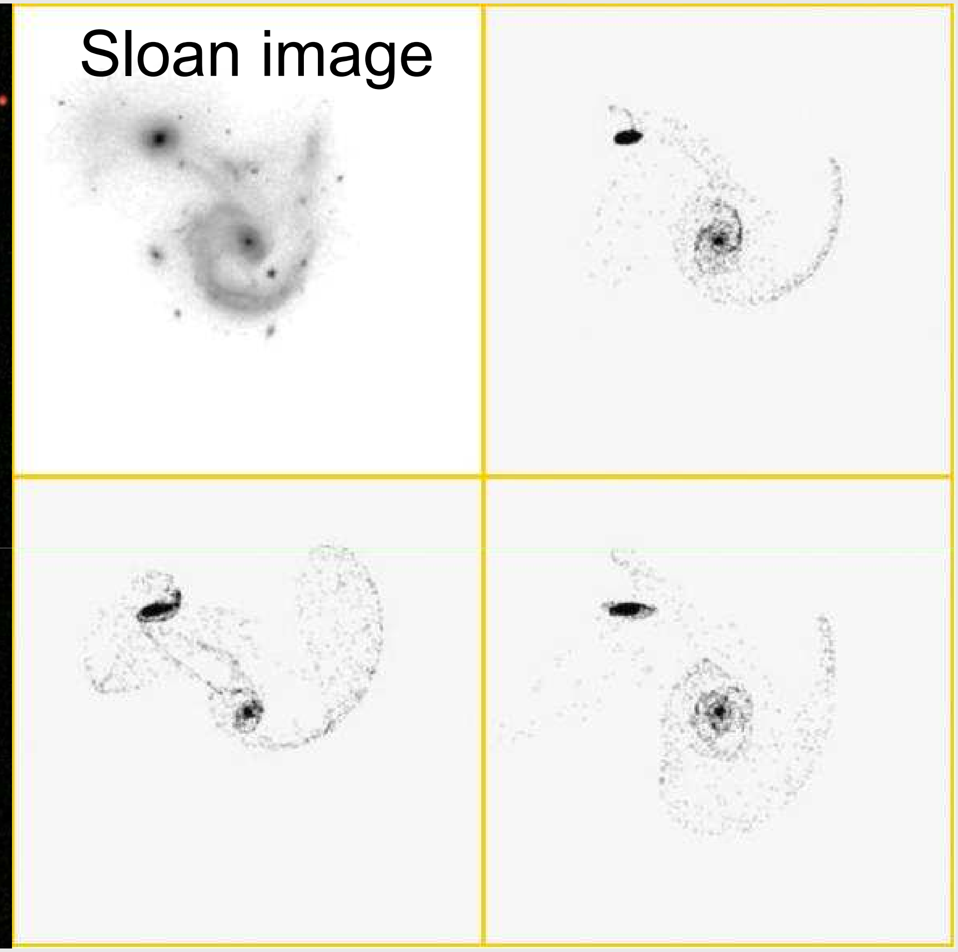

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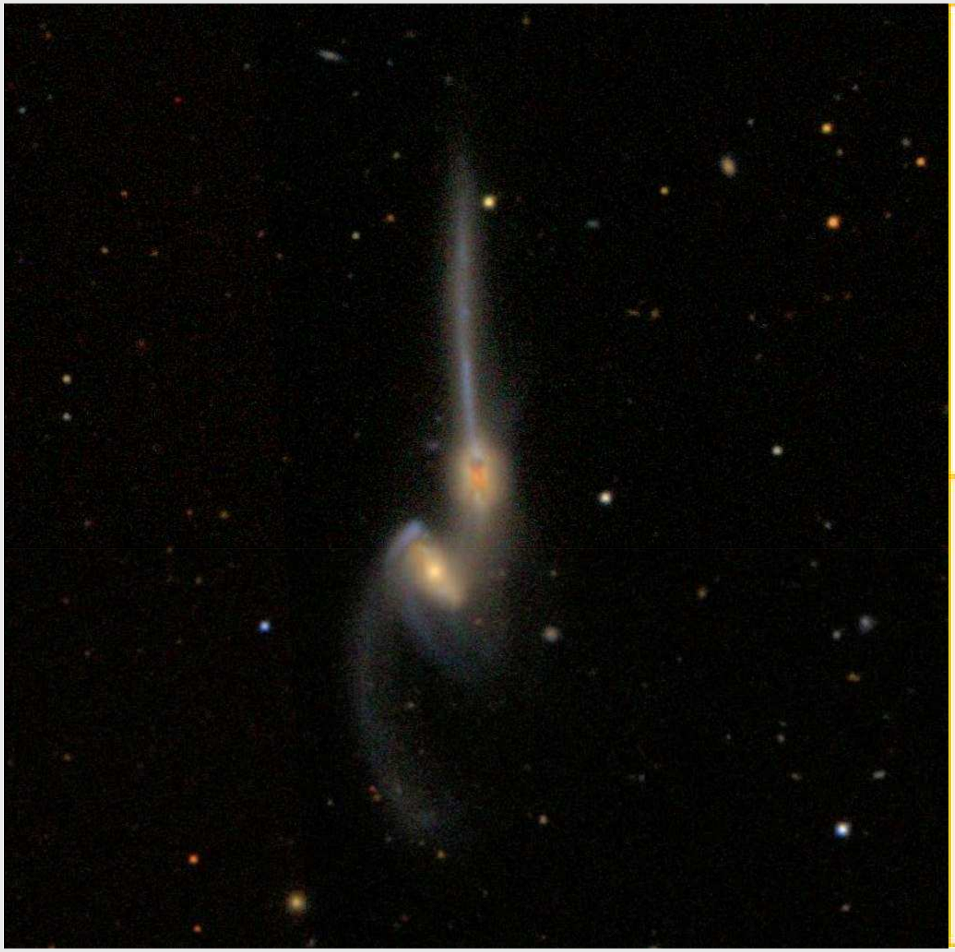

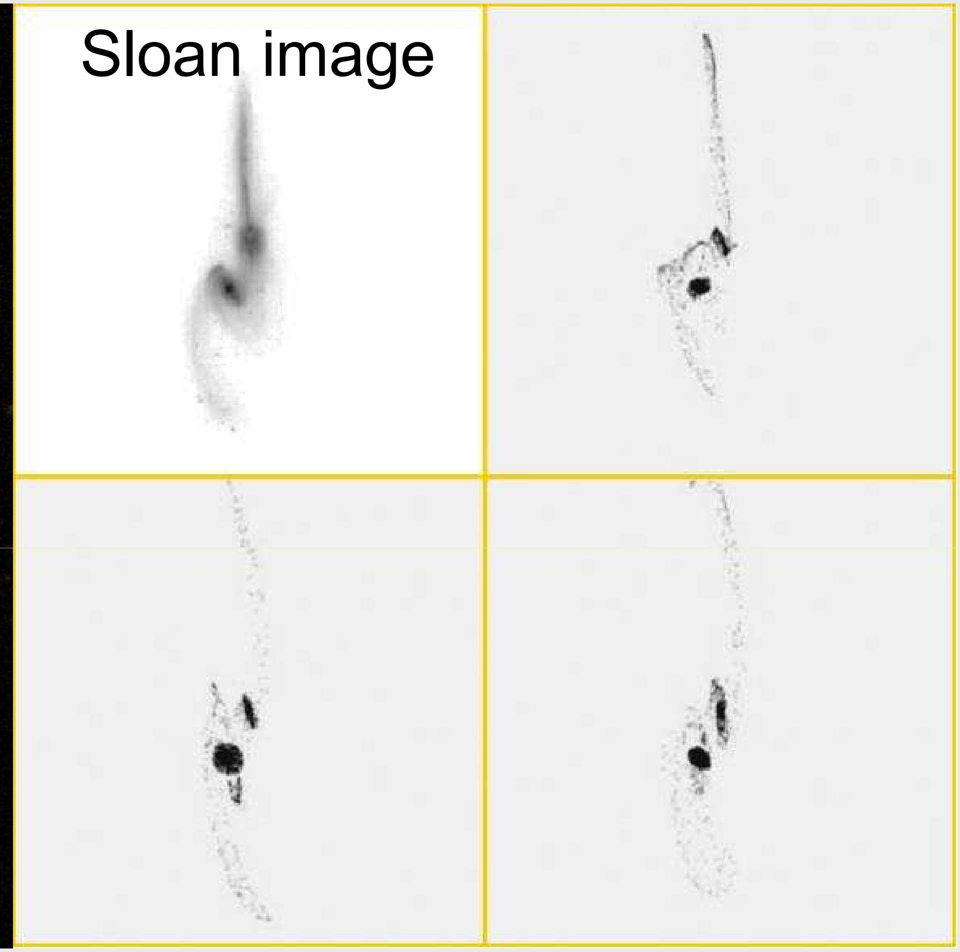

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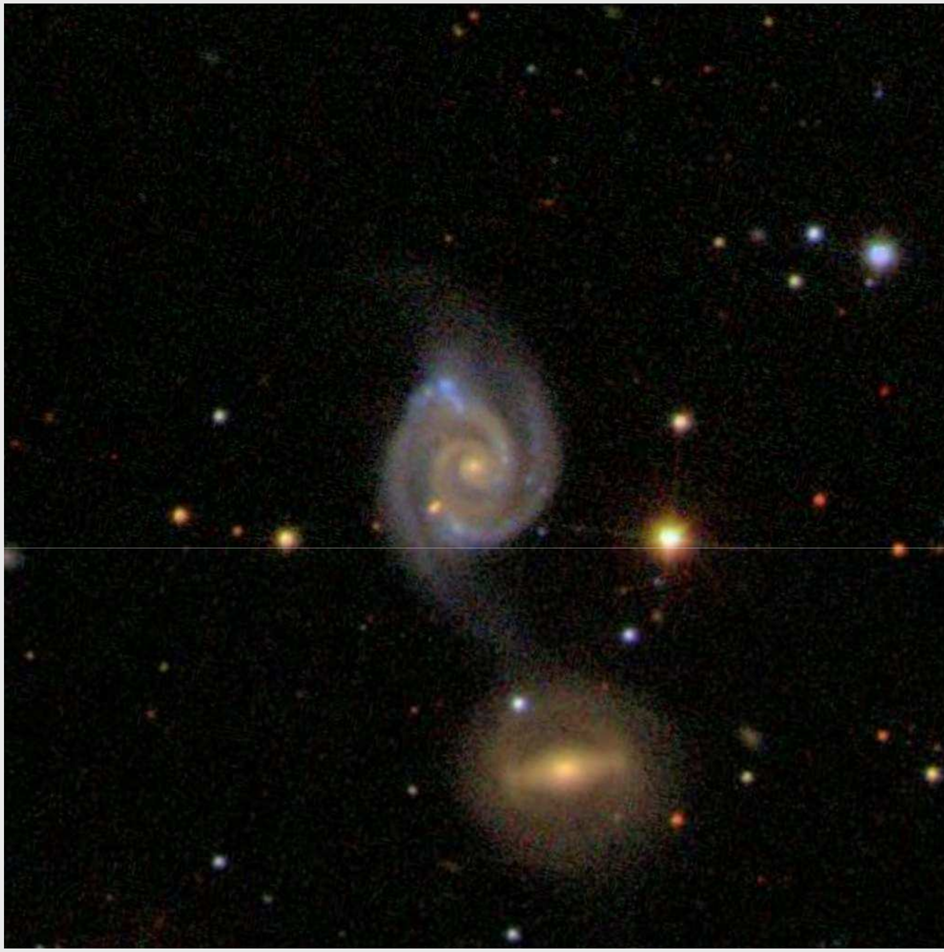

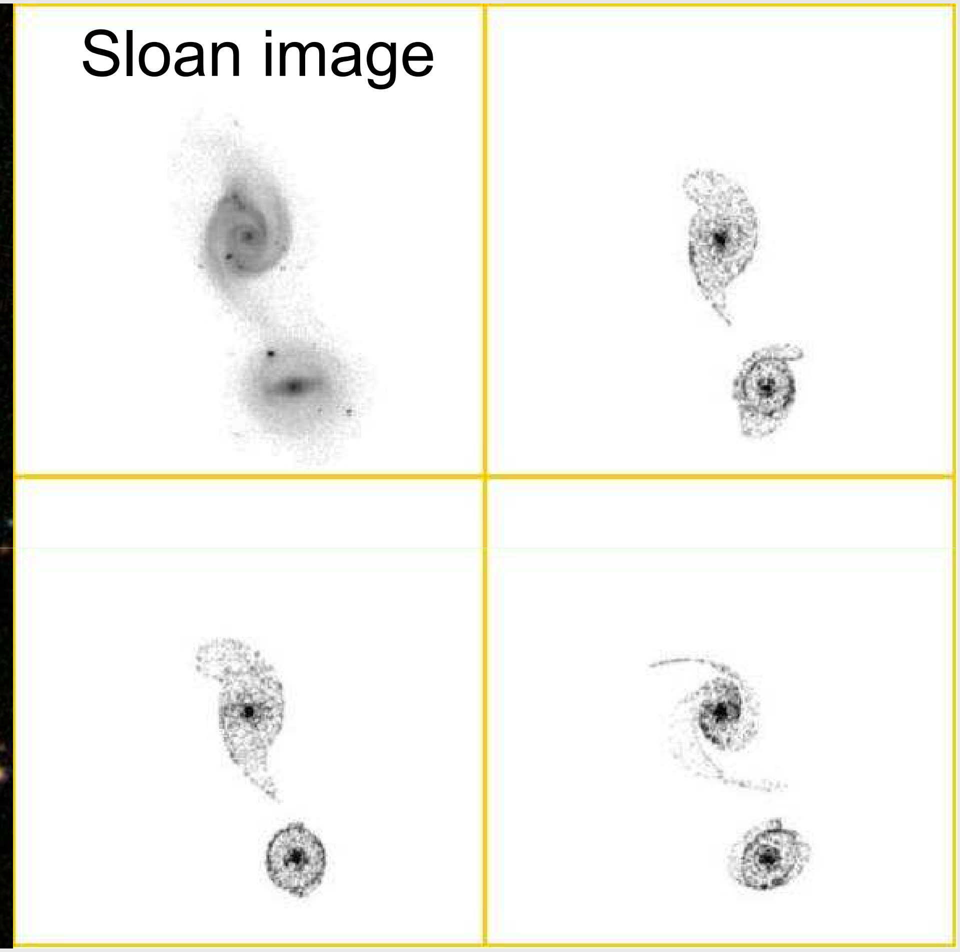

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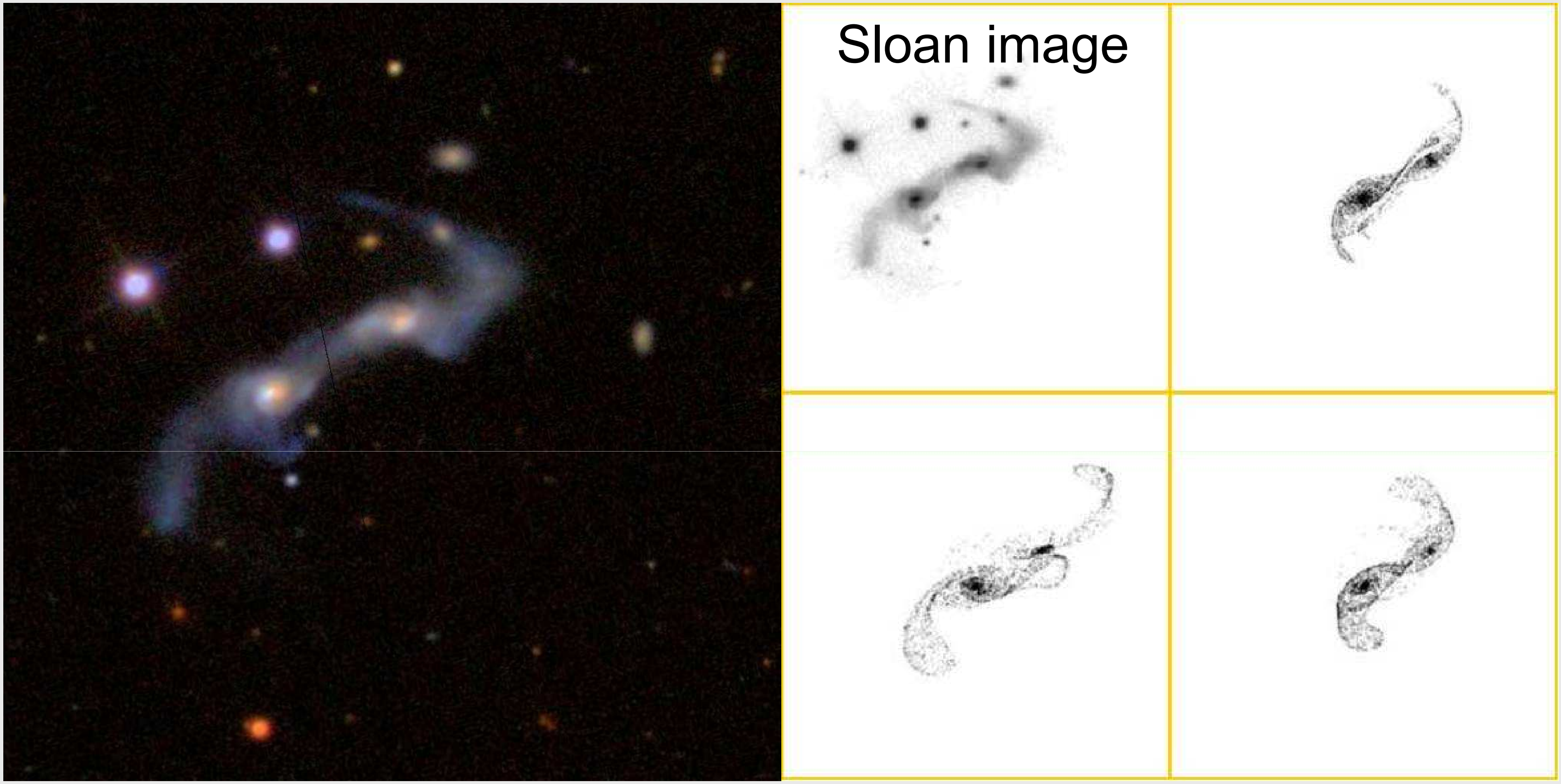
GALAXY ZOO
UNDERSTANDING COSMIC MERGERS

Galaxy Mergers Zoo Gallery



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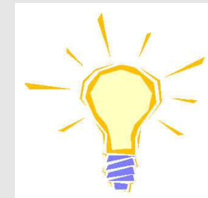
Key Feature of Zooniverse:
Data mining from the volunteer-contributed labels

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

ZOONIVERSE
REAL SCIENCE ONLINE

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)
  - with experimental parameters
  - with observer / observatory descriptors

Semantics!

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.

Responding to Big Data in Science

- ***X-Informatics*** (*e.g.,* X = Bio, Geo, Astro, …):
  - addresses the scientific data lifecycle challenges in the era of Big Data and data-intensive science …
  - via data science techniques for indexing, accessing, searching, fusing, integrating, mining, and analyzing massive data repositories.
  - Includes automatic (autonomous) tagging and annotation

- ***Citizen Science*** (user-guided, informatics-powered):
  - Human computation (*e.g.,* tagging, labeling, classification)
    - characterized by enormous cognitive capacity and pattern recognition efficiency (carbon-based computing)
  - Semantic e-Science **and** Volunteer Citizen Science
  - Tagging everything, everywhere: ***Analytics in the Cloud***

Astroinformatics and Citizen Science: Resistance is futile, you will be assimilated