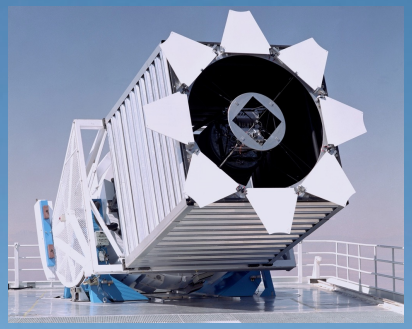
Lecture 0: Introduction

Željko Ivezić, Department of Astronomy, University of Washington

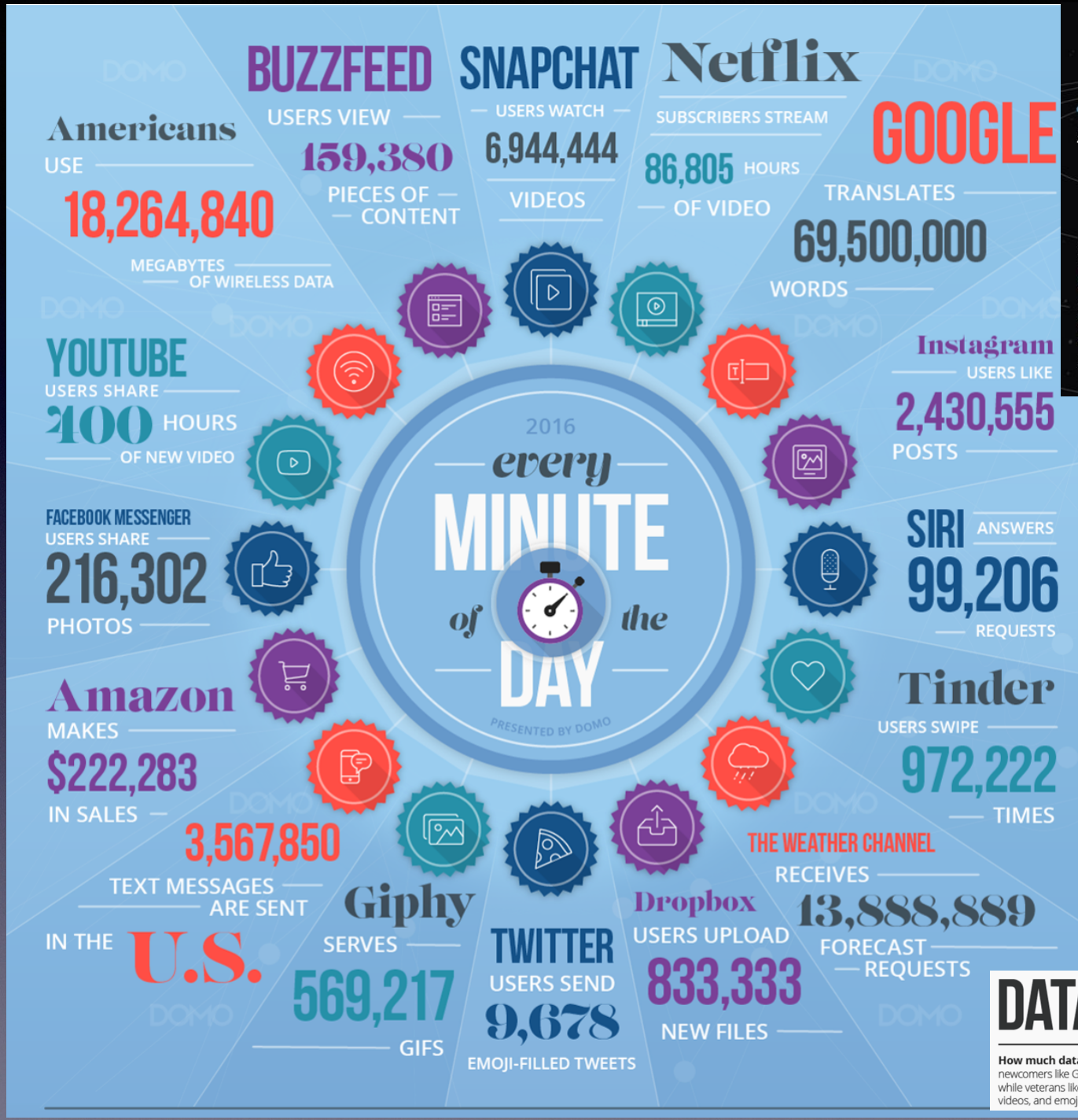
LSST

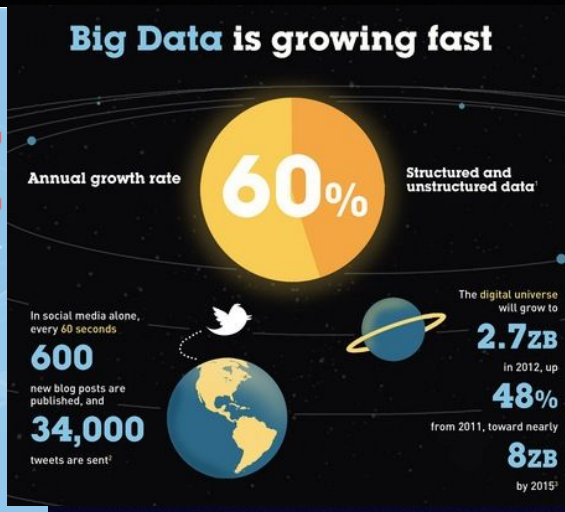


SDSS

Outline

- Big Data in astronomy
- What is LSST and why should you care?
- Motivation for astroML
  - ever increasing data volume and complexity
  - sophisticated analysis, need for reproducability
  - open-source approach
  - generally useful tools





DATA NEVER SLEEPS 4.0

How much data is generated every minute? In the fourth annual edition of Data Never Sleeps, newcomers like Giphy and Facebook Messenger illustrate the rise of our multimedia messaging obsession, while veterans like Youtube and Snapchat highlight our insatiable appetite for video. Just how many GIFs, videos, and emoji-filled Tweets flood the internet every minute? See for yourself below.

Sky Survey Projects	Data Volume
DPOSS (The Palomar Digital Sky Survey)	3 TB
2MASS (The Two Micron All-Sky Survey)	10 TB
GBT (Green Bank Telescope)	20 PB
GALEX (The Galaxy Evolution Explorer)	30 TB
SDSS (The Sloan Digital Sky Survey)	40 TB
SkyMapper Southern Sky Survey	500 TB
PanSTARRS (The Panoramic Survey Telescope and Rapid Response System)	~ 40 PB expected
LSST (The Large Synoptic Survey Telescope)	~ 200 PB expected
SKA (The Square Kilometer Array)	~ 4.6 EB expected

Zhang & Zhao (2015): http://datascience.codata.org/articles/10.5334/dsj-2015-011/

"Ask Not What Data You Need To Do Your Science, Ask What Science You Can Do With Your Data."

The era of surveys...

- Standard: "What data do I have to collect to (dis)prove a hypothesis"?
- Data-driven: "What theories can I test given the data I already have?"

Alternative Careers: Leveraging your Astronomy Degree for Data Science

by Ben Cook | Jun 1, 2016 | Career Navigation, Personal Experiences | 0 comments

Big Data in Astronomy

Alongside the recent explosion of "Big Data" into the public consciousness, there has been a similar transition into the age of "Big Astronomy". Astronomers have always been adept at drawing conclusions using advanced statistics and data analysis. Now, with the advent of extremely large simulations like Illustris and surveys like the upcoming LSST, astronomers are increasingly gaining experience in dealing with datasets vastly larger than could ever hope to fit on a single computer.

For early career astronomers looking for advice, I think you can do no better than look at the posts made by Jessica Kirkpatrick, who obtained a PhD in Astronomy and then became a data scientist at Microsoft/Yammer, and I understand she has since taken a position as Director of Data Science at the education start-up InstaEDU.

The term "Data Scientist" is extraordinarily broad. For example, the post "What is a Data Scientist?" describes some of the Data Analyst roles a Data Scientists may play:

- Derive business insight from data.
- Work across all teams within an organization.
- Answer questions using analysis of data.
- Design and perform experiments and tests.
- Create forecasts and models.
- Prioritize which questions and analyses are actionable and valuable.
- Help teams/executives make data-driven decisions.
- Communicate results across the company to technical and non-technical people.

https://astrocompute.wordpress.com/2016/01/29/how-does-an-astronomer-become-a-data-scientist/

LSST in one sentence:

An optical/near-IR survey of half the sky in ugrizy bands to r~27.5 based on ~800 visits over a 10-year period:

More information at www.lsst.org and arXiv:0805.2366

A catalog of 20 billion stars and 20 billion galaxies with exquisite photometry, astrometry and image quality!

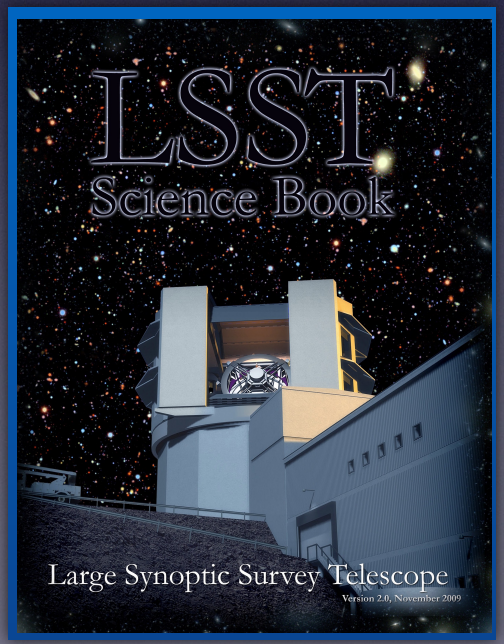
LSST Science Themes

- Dark matter, dark energy, cosmology (spatial distribution of galaxies, gravitational lensing, supernovae, quasars)
- Time domain (cosmic explosions, variable stars)
- The Solar System structure (asteroids)
- The Milky Way structure (stars)

LSST Science Book: arXiv:0912.0201

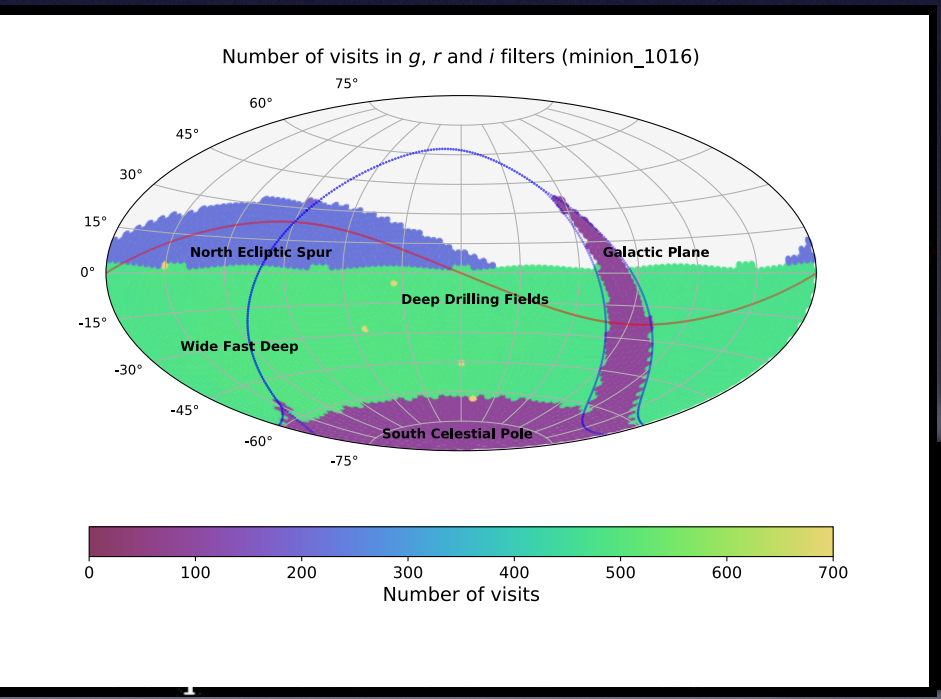
Summarizes LSST hardware, software, and observing plans, science enabled by LSST, and educational and outreach opportunities

245 authors, 15 chapters, 600 pages



Basic idea behind LSST: **a uniform sky survey**

- 90% of time will be spent on a uniform survey: every 3-4 nights, the whole observable sky will be scanned twice per night
- after 10 years, half of the sky will be imaged about 1000 times (in 6 bandpasses, ugrizy): a digital color movie of the sky
- ~100 PB of data: about a billion 16 Mpix images, enabling **measurements for 40 billion objects**



LSST in one sentence:
An optical/near-IR survey of half the sky in ugrizy bands to r~27.5 (36 nJy) based on 825 visits over a 10-year period: deep wide fast.

Left: a 10-year simulation of LSST survey: the number of visits in the r band (Aitoff projection of eq. coordinates)

SDSS
gri
3.5'x3.5'
r~22.5

HSC
gri
3.5'x3.5'
r~27

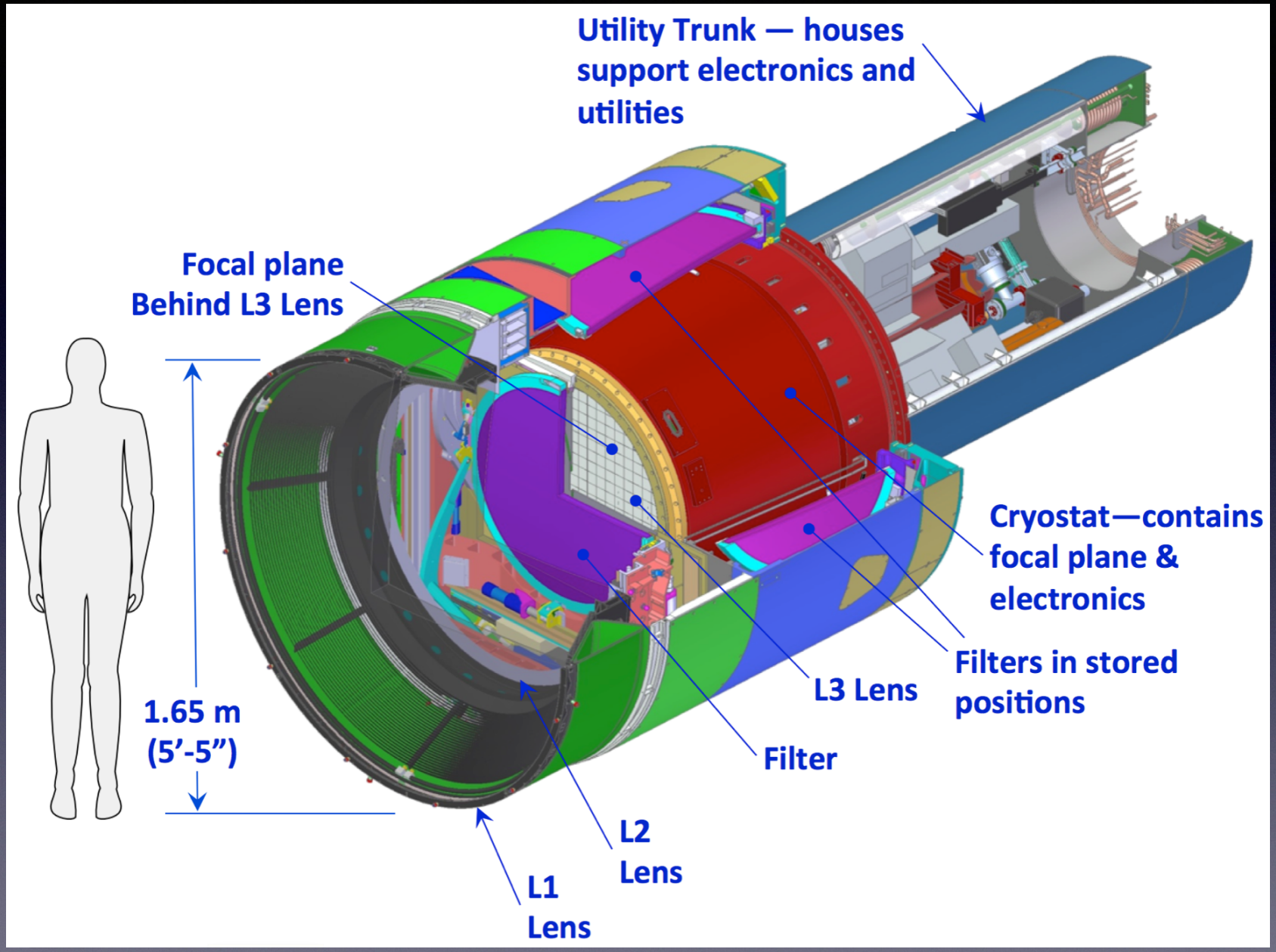
3 arcmin is 1/10 of the full Moon's diameter

like LSST depth (but tiny area)

LSST will deliver 5 million such images

Telescope Mount Assembly before going from Spain to Chile

LSST camera



The largest astronomical camera: 2800 kg, 3200 Megapix

Large Synoptic Survey Telescope

LSST Operations: Sites & Data Flows

French Site

Satellite Processing Center

Data Release Production

Long-term Storage (copy 3)

Archive Site

Archive Center

Alert Production

Data Release Production

Calibration Products Production

EPO Infrastructure

Long-term Storage (copy 2)

Data Access Center

Data Access and User Services

HQ Site

Science Operations

Observatory Management

Education & Public Outreach

Base Site

Base Center

Long-term storage (copy 1)

Data Access Center

Data Access & User Services

Summit Site

Telescope & Camera

Data Acquisition

Crosstalk Correction

Mar 10, 2019

First light: 2021
Operations: 2022

Some obvious points…

- **Ever increasing data volume and complexity**
  - SDSS is ~30 TB; LSST will be one SDSS per night, or a total of >100 PB of data (40 billion objects); of course, also Gaia and many other surveys
  - who and how will do the required data analysis?
- **Sophisticated analysis, need for reproducability**
  - with the increasing data complexity, analysis becomes more complex, too; what do we do in case of disagreement?
- **Open-source approach improves efficiency**
  - we are not data starved any more!
  - the bottleneck for new results is in human resources (as in “grad students and postdocs”) and analysis tools
  - nobody has an unlimited budget; collaborate and share!

Data analysis challenges in the era of Big Data

1) Large data volume (petabytes)

2) Large numbers of objects (billions)

3) Highly multi-dimensional spaces (thousands)

4) Unknown statistical distributions

5) Time-series data (irregular sampling)

6) Heteroscedastic errors, truncated, censored and missing data

7) Unreliable quantities (e.g. unknown systematics and random errors)

The bottleneck is not any more data availability but instead our ability to extract useful and reliable information from data.

- Some tools and methods…
  - Correlation coefficients (many dimensions, missing data)
  - The bootstrap and the jackknife methods
  - Maximum Likelihood Method
  - The goodness of fit and model selection
  - Bayesian statistics
  - Markov Chain Monte Carlo methods
  - Regression (“fitting”, LSQ, outliers, regularization)
  - Density estimation (“multi-dimensional histograms”)
  - Clustering (kernel, parametric)
  - Classification (supervised and unsupervised, active learning)
  - Dimensionality Reduction (PCA, ICA, LLE and friends)
  - Time-series analysis (periodogram, stochastic processes)

Some tools and methods…

- Correlation coefficients (many dimensions, missing data)
- The bootstrap and the jackknife methods
- Maximum Likelihood Method
- The goodness of fit and model selection
- Bayesian statistics
- Markov Chain Monte Carlo methods
- Regression ("fitting", LSQ, outliers, regularization)
- Density estimation ("multi-dimensional histograms")
- Clustering (kernel, parametric)
- Classification (supervised and unsupervised, active learning)
- Dimensionality Reduction (PCA, ICA, LLE and friends)
- Time-series analysis (periodogram, stochastic processes)

These topics are not typically taught to astronomers in graduate school.
Mario Jurić: "Astrostatistics and astroinformatics are the new calculus!"

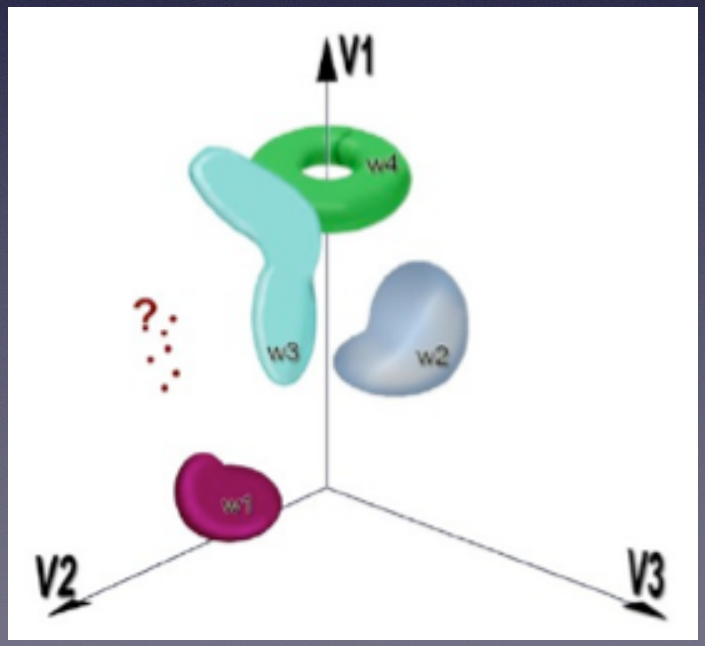
Some tools and methods…

- Correlation coefficients (many dimensions, missing data)
- The bootstrap and the jackknife methods
- Maximum Likelihood Method
- The goodness of fit and model selection
- Bayesian statistics
- Markov Chain Monte Carlo methods
- Regression ("fitting", LSQ, outliers, regularization)
- Density estimation ("multi-dimensional histograms")
- Clustering (kernel, parametric)
- Classification (supervised and unsupervised, active learning)
- Dimensionality Reduction (PCA, ICA, LLE and friends)
- Time-series analysis (periodogram, stochastic processes)

Statistical analysis of a massive LSST dataset

- A large (100 PB) database and sophisticated analysis tools: for each of 40 billion objects there will be about 1000 measurements (each with a few dozen measured parameters)

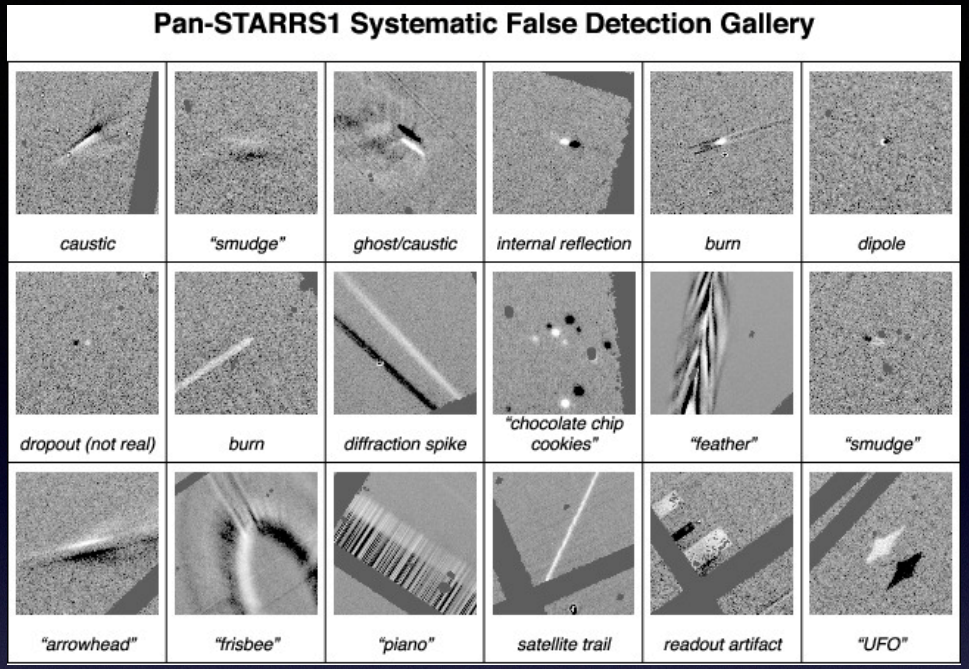
Data mining and machine learning:

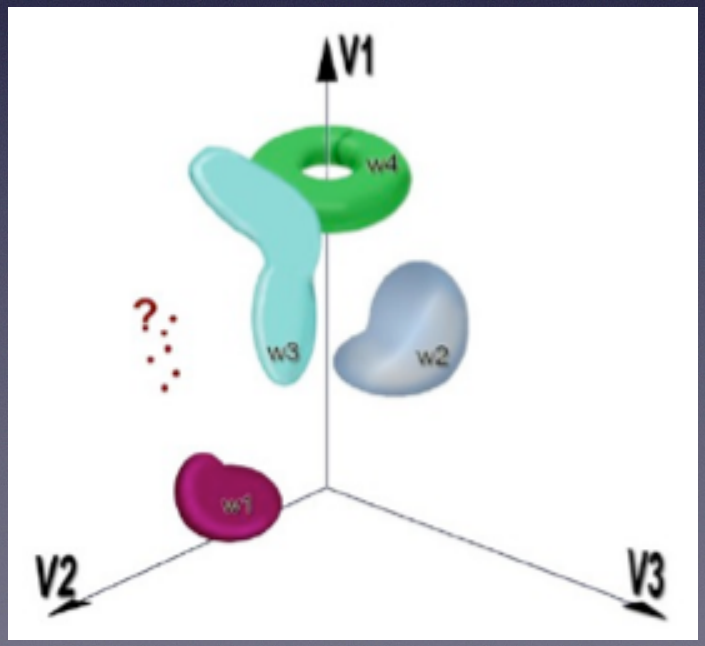


- 10,000-D space with 40 billion points
- Characterization of known objects
- Classification of new populations
- Discoveries of unusual objects

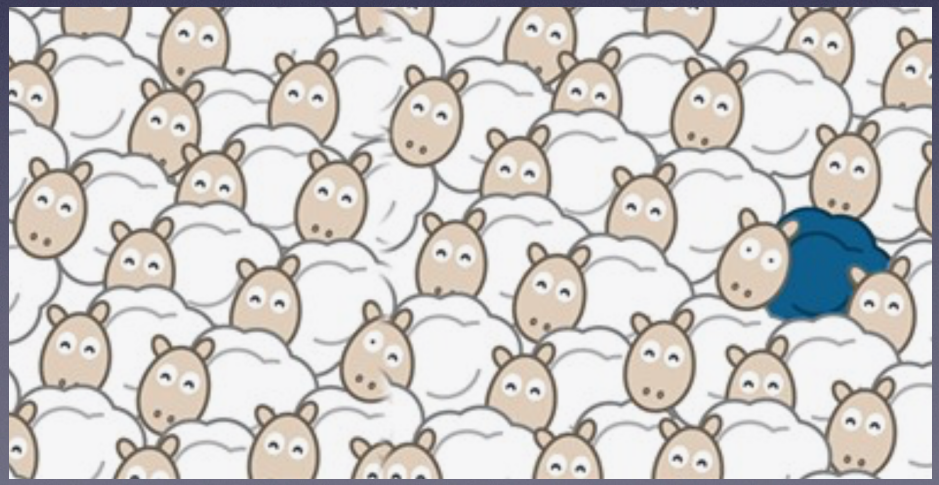
Clustering, classification, outliers

It is often not straightforward to identify alerts worth following: need to first reject instrumental artefacts, and then **classify** astrophysical sources to select those that are "most interesting"





Clustering, classification, outliers…



Selected topics (where work is needed)

1) Interpretation of spectral energy distributions (SEDs)

2) Spatial correlations

3) Moving objects

4) Variable objects

Everything I'd like to do with LSST data, but don't know (yet) how

For more details: Ivezić, Connolly & Jurić 2016, arXiv:1612.04772

5) Systematic measurement uncertainties

6) Astrophysical simulations and astrophysical systematics

7) LSST System Enhancements

8) New algorithms in LSST

Main work areas:
- astronomical digital image processing
- statistical modeling and analysis
- data mining and machine learning
- high performance computing

astroML Home User Guide Book Figures Examples Plots

Google™ Custom Search

AstroML: Machine Learning and Data Mining for Astronomy

News

October 2012: astroML 0.1 has been released! Get the source on Github

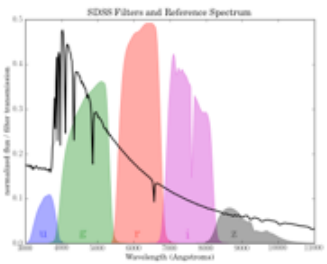
Our Introduction to astroML paper received the CIDU 2012 best paper award.

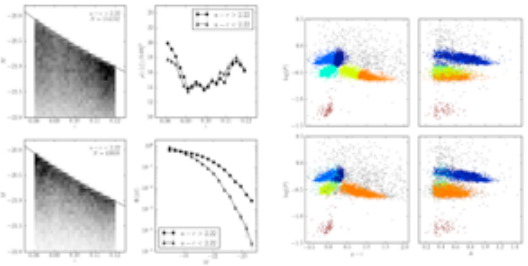
Links

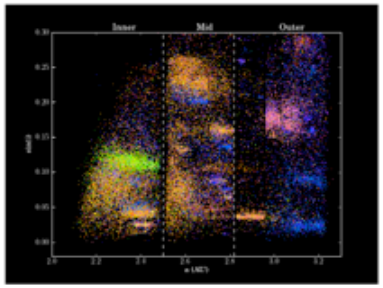
astroML Mailing List

GitHub Issue Tracker

Videos







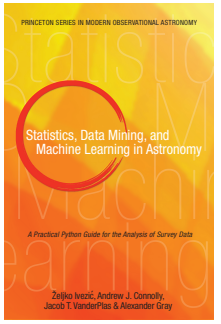
AstroML is a Python module for machine learning and data mining built on numpy, scipy, scikit-learn, and matplotlib, and distributed under the 3-clause BSD license. It contains a growing library of statistical and machine learning routines for analyzing astronomical data in python, loaders for several open astronomical datasets, and a large suite of examples of analyzing and visualizing astronomical datasets.

Downloads

- Released Versions: Python Package Index
- Bleeding-edge Source: github

How do we efficiently train our astronomy students to use sophisticated methods from statistics, data mining and machine learning?

mon tools
and easy-
esearchers
istics,
anderPlas,



User Guide

1. Introduction

- 1.1. Philosophy

Open source!
www.astroML.org

Updated edition available soon (Dec 3, 2019)

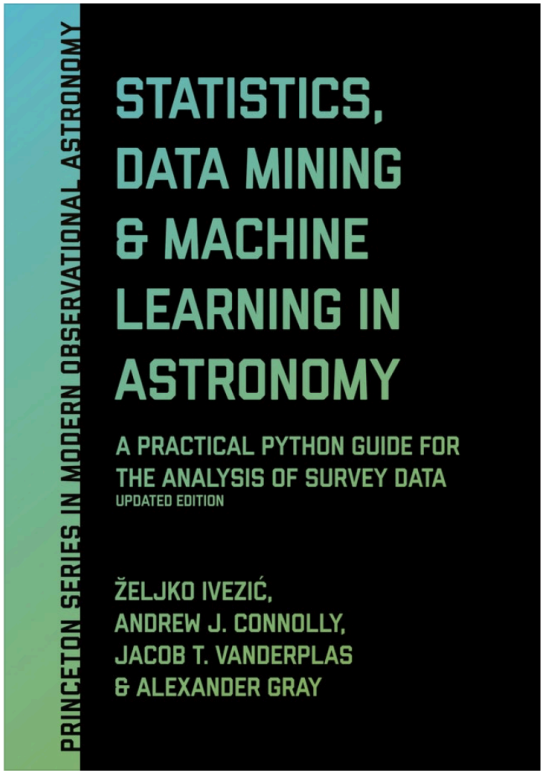
https://press.princeton.edu/books/hardcover/9780691198309/statistics-data-mining-and-machine-learning-in-astronomy

Expanded with new sections on deep learning methods, hierarchical Bayes modeling, and approximate Bayesian computation (and updated astroML from python2 to python3).

Physics & Astronomy

Statistics, Data Mining, and Machine Learning in Astronomy: *A Practical Python Guide for the Analysis of Survey Data, Updated Edition*

Željko Ivezić, Andrew J. Connolly, Jacob T. VanderPlas, and Alexander Gray



Hardcover

Price: $85.00 / £70.00
ISBN: 9780691198309
Published: 12/03/2019
Copyright: 2020
Pages: 560
Size: 7 x 10 in.

More

ebook

Buy This

Download Cover

Share

Overview Author(s) Reviews [1]

Textbook Figures

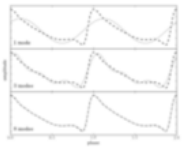
This section makes available the source code used to generate every figure in the book *Statistics, Data Mining, and Machine Learning in Astronomy*. Many of the figures are fairly self-explanatory, though some will be less so without the book as a reference. The table of contents of the book can be seen **here(pdf)**.

Figure Contents

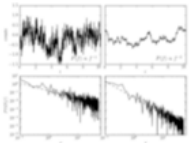
Each chapter links to a page with thumbnails of the figures from the chapter.

Chapter 10: Time Series Analysis

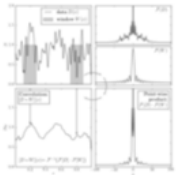
This chapter covers the analysis of both periodic and non-periodic time series, for both regularly and irregularly spaced data.



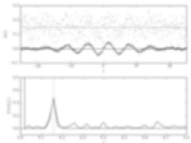
Fourier Reconstruction of RR-Lyrae Templates



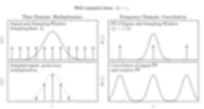
Generating Power-law Light Curves



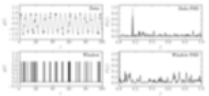
Plot a Diagram explaining a Convolution



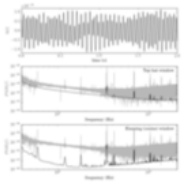
Fast Fourier Transform Example



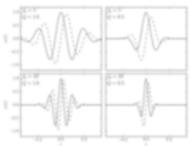
The effect of Sampling



The effect of Sampling



Plot the power spectrum of the LIGO big dog event

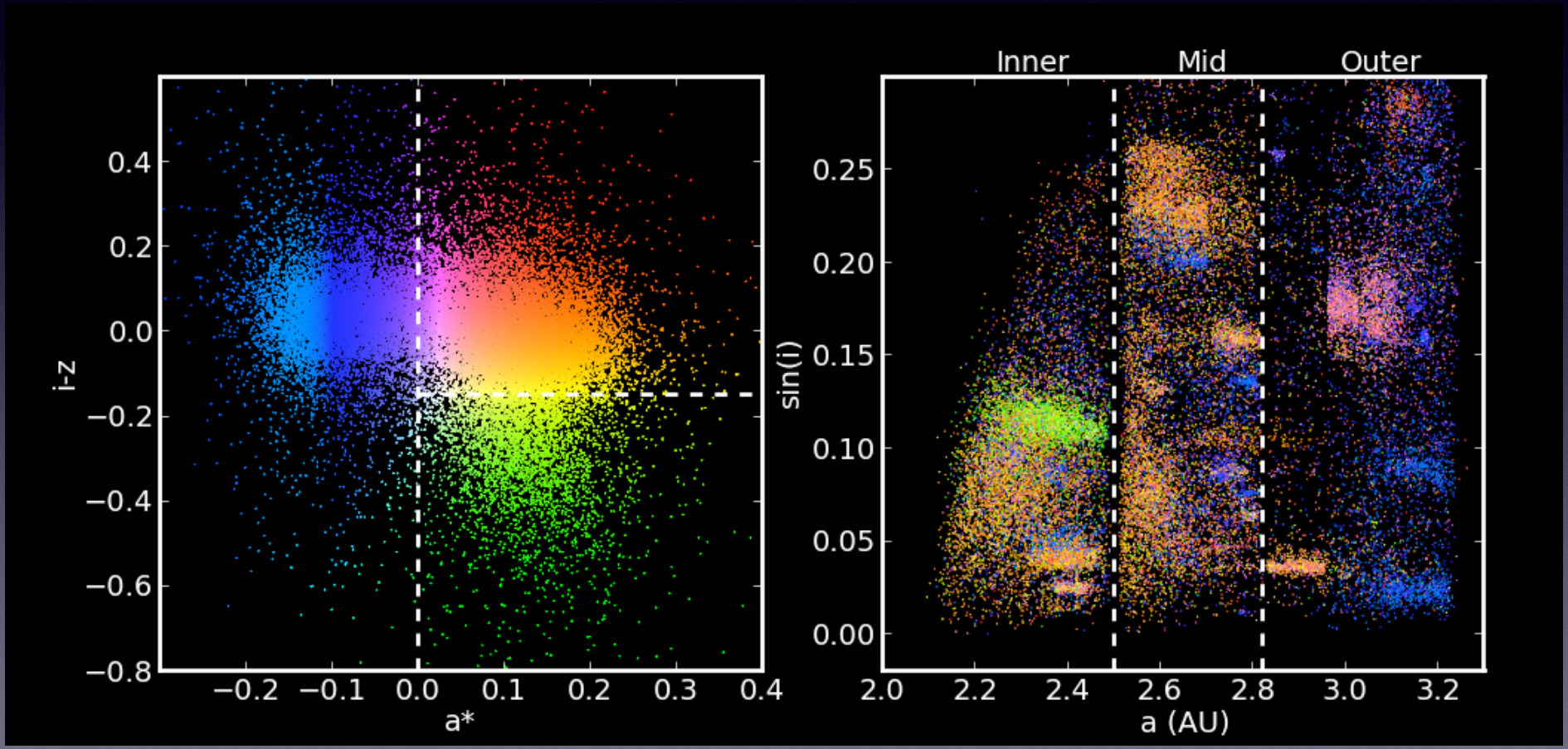


Examples of Wavelets

You can make this plot from scratch in <1 hour!

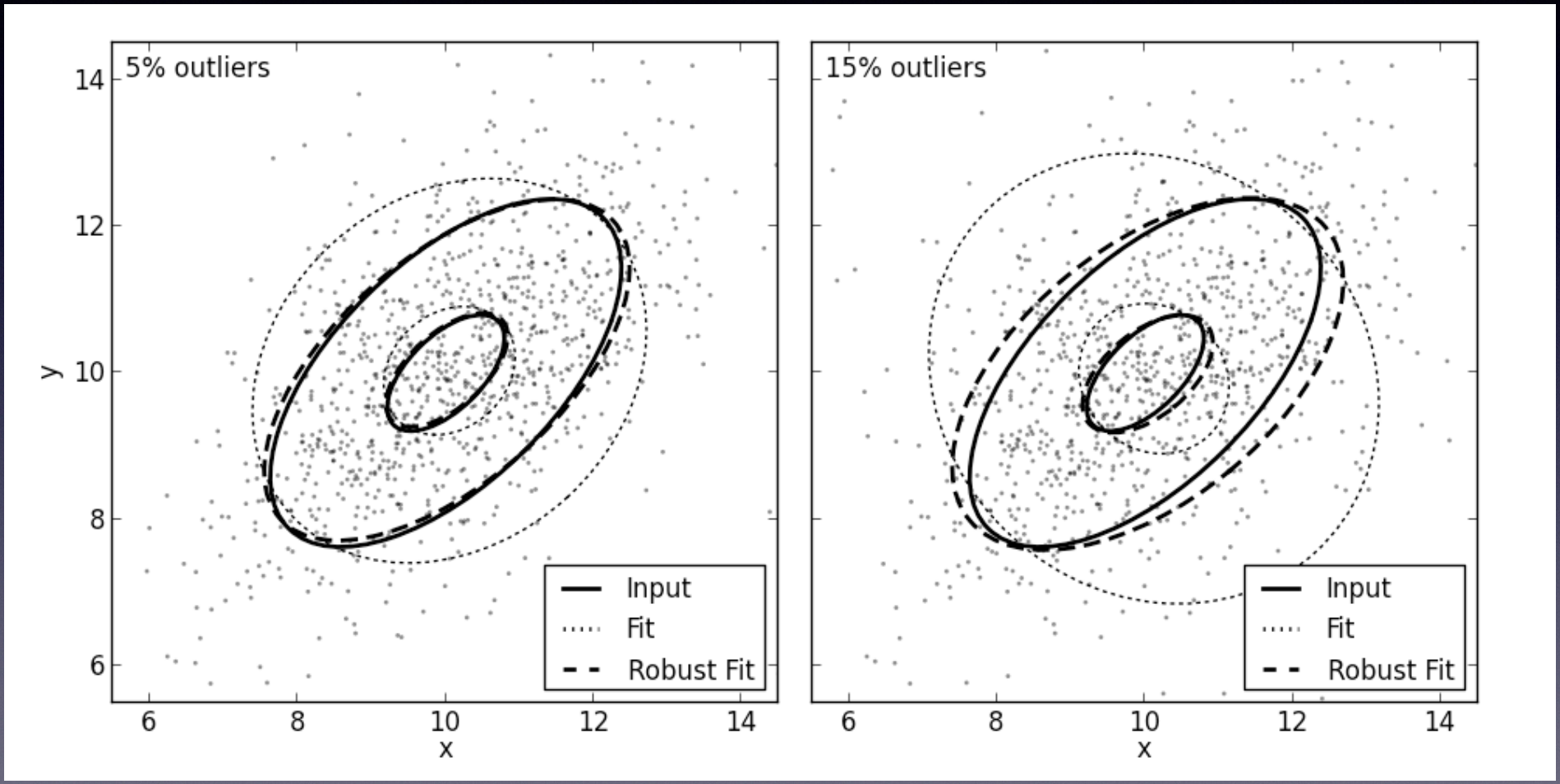
Example: SDSS asteroids

Visualization of 4-dimensional correlations



- **Robust parameters for a 2-dimensional gaussian**

standard methods are not robust to outliers



If you feel uneasy with git and/or python/jupyter, please peruse

https://github.com/uw-astr-324-s17/astr-324-s17/blob/master/notebooks/Week-1-Thu.ipynb

Additional Resources:

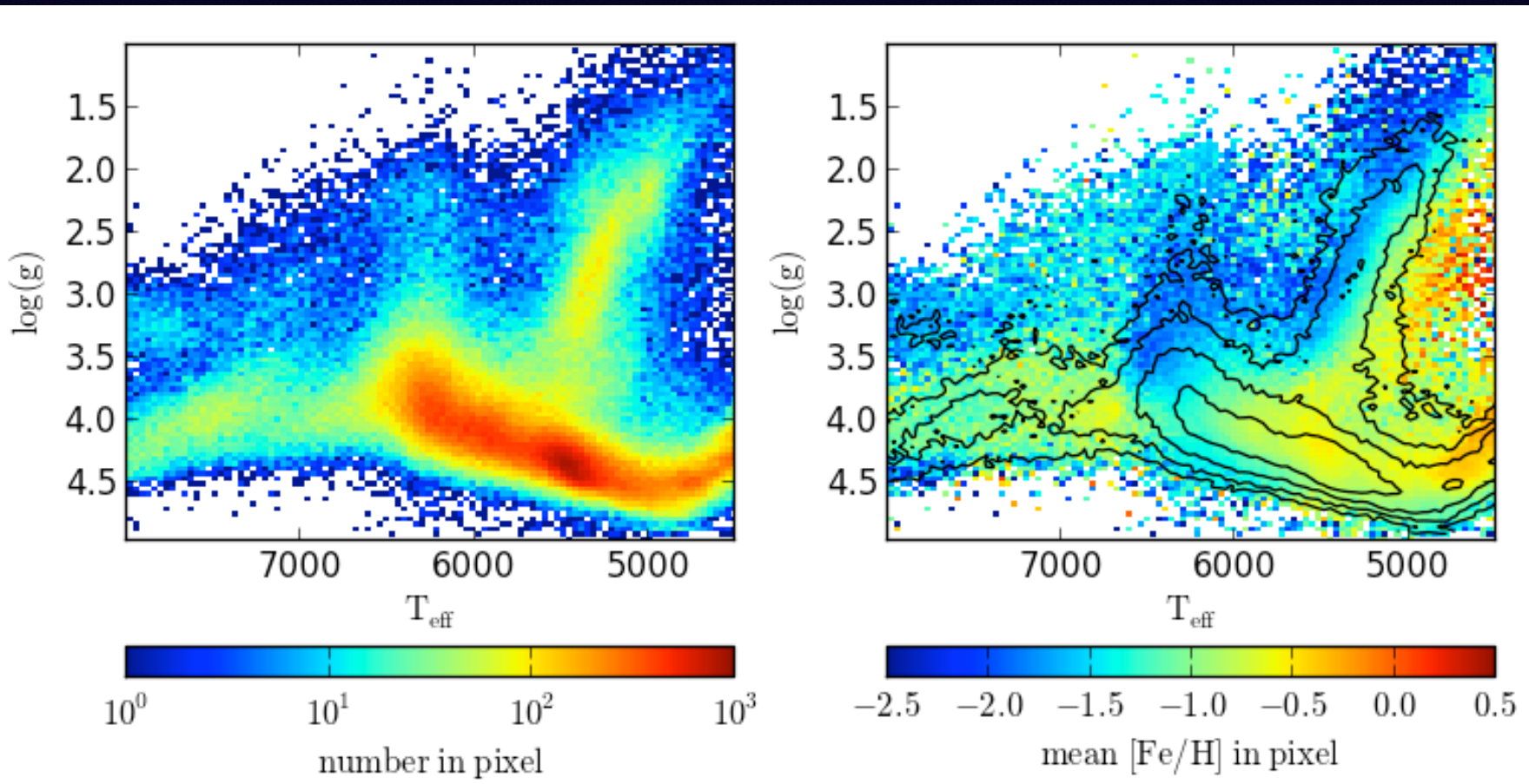
- E-Science 2015 seminar on python: https://github.com/uwescience/python-seminar-2015
  Includes introduction to python, git, matplotlib and pandas.
- Big Data in Astronomy: Hands-on with Large Surveys (Astr 597, by Mario Juric) https://github.com/mjuric/astr597b_wi16
  excellent lectures on python, numpy, github, matplotlib, databases
- Scikit-learn Tutorial by Jake VanderPlas
  https://github.com/jakevdp/sklearn_tutorial

Even more resources:

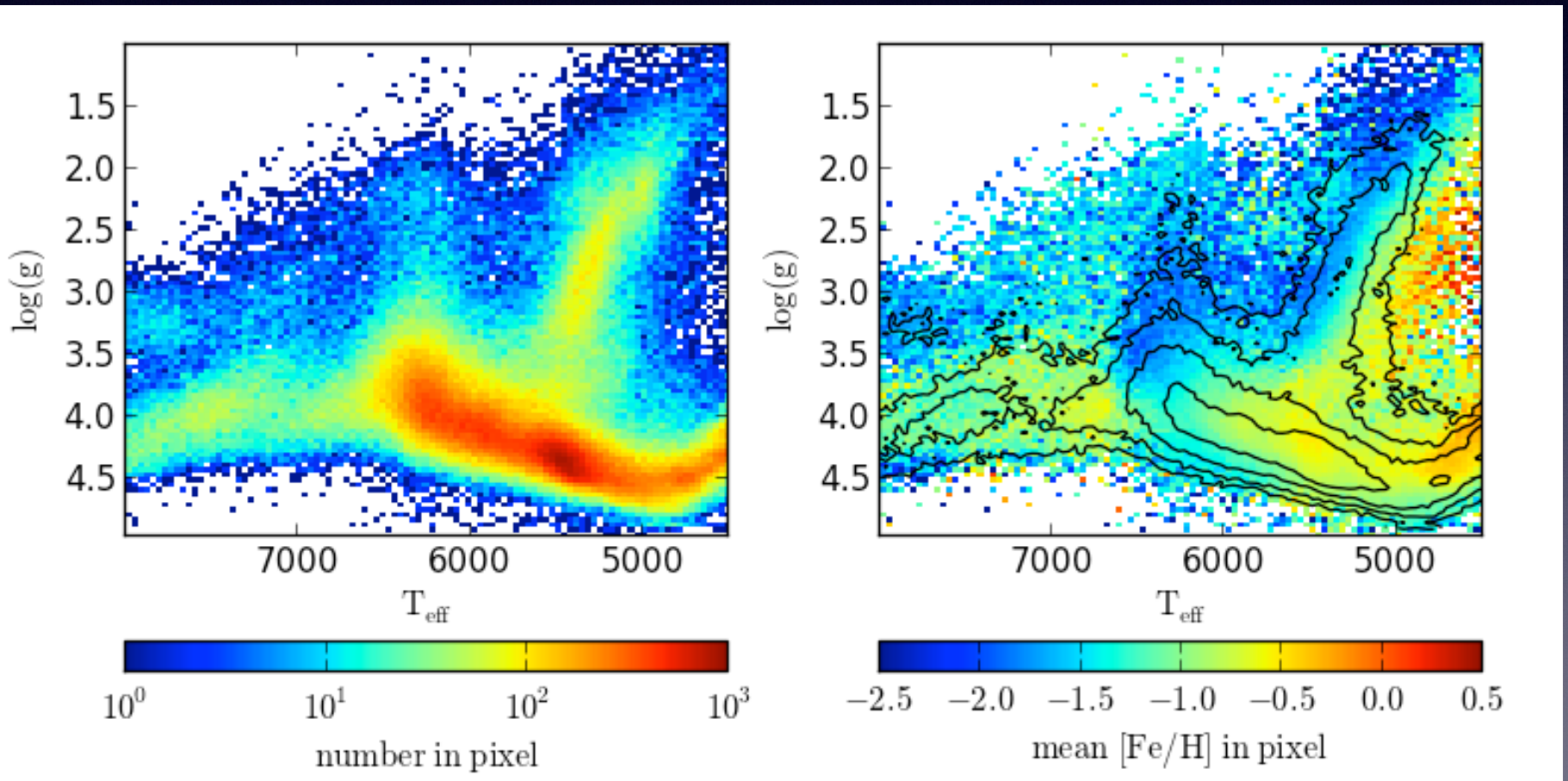
- Concise “handbook”: *Notes on statistics for physicists* by Orear, http://www.astro.washington.edu/users/ivezic/Teaching/Astr507/orear.pdf
- A great book: *Probability Theory: The Logic of Science* by Jaynes, http://bayes.wustl.edu/etj/prob/book.pdf
- A book about python and data science by Jake VanderPlas: https://github.com/jakevdp/PythonDataScienceHandbook
- An intro class by Gordon Richards (Drexel University): https://github.com/gtrichards/PHYS_T480
- An advanced class by Phil Marshall (Stanford University): https://github.com/KIPAC/StatisticalMethods
- LSST Data Science Fellowship Program: https://github.com/LSSTC-DSFP/LSSTC-DSFP-Sessions
- TED talk “The best stats you’ve ever seen” by Hans Rosling: http://ls.st/0dt

- A simple example of astroML use:
  a Hess diagram coded by a third quantity
- Hess diagram is astronomical term for pixelated color-magnitude diagram, where each pixel is coded to display the number of objects in it (also known as “two-dimensional histogram”)

- **A Hess diagram coded by a third quantity**
- Here we plot a measure of the star's surface gravity strength vs. effective temperature (both estimated from a spectrum obtained by SDSS); the left panel shows the count of stars in each pixel



- Of course, the pixels don't have to be coded by the number of objects in it - we can use instead any other statistic (the mean, median, scatter, etc): the right panel shows the mean metallicity [Fe/H] by color and the same counts as in the left panel, but now using contours



AstroML testing

https://github.com/carmensg/IAA_School2019
/blob/master/lectures/Day3-ZeljkoIvezic/notebooks/astroMLtesting.ipynb

Slide Type: Slide

```
! curl -O https://raw.githubusercontent.com/astroML/astroML/master/examples/datasets/plot_SDSS_SSPP.py
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100  3049  100  3049    0     0   9292      0 --:--:-- --:--:-- --:--:-- 12147
```

Slide Type: -

```
%matplotlib inline
%run ./plot_SDSS_SSPP.py
```