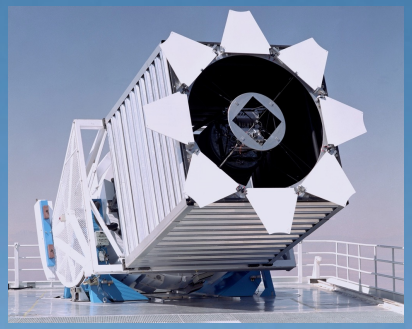
Uvod

LSST



SDSS

Analiza velikih baza podataka u fizici

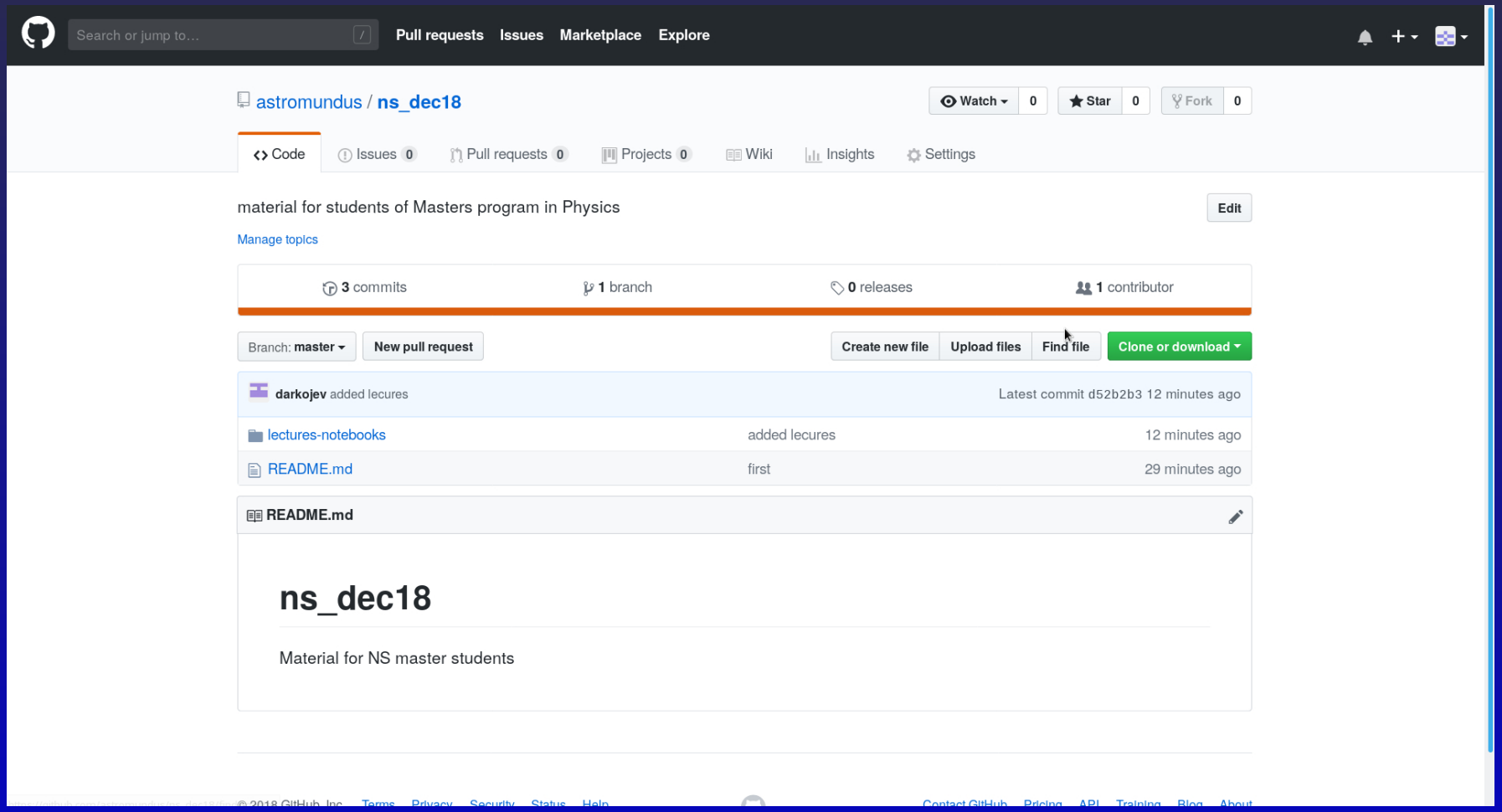
Darko Jevremović

Astronomical Observatory Belgrade

Outline

- Motivation for astrostatistics and this class
  - ever increasing data volume and complexity
  - sophisticated analysis, need for reproducibility
  - open-source approach
  - generally useful tools
- astroML
  - what is it?
  - what can you do with it?

Everything is on GitHub:
https://github.com/astromundus/ns_dec18.git



More (free!) 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

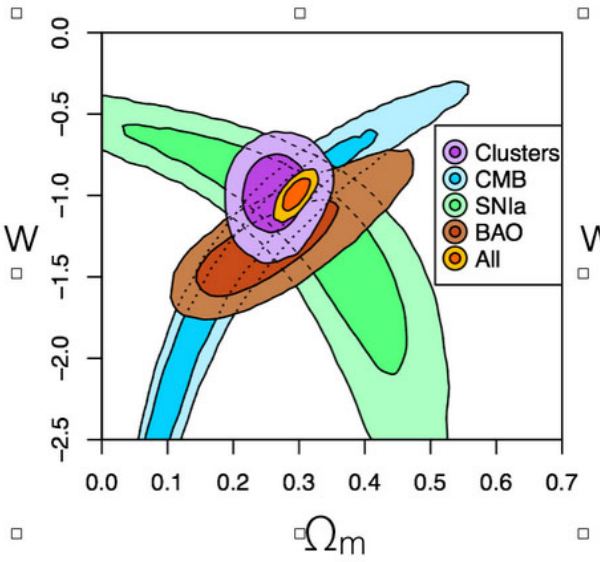
Python & Computers

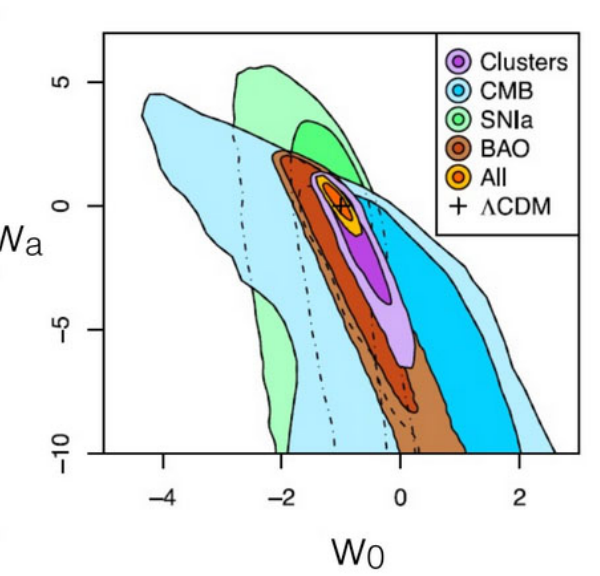
- We will be using Python 3 in this class. Python has become a de-facto standard for data analysis in astronomy (and beyond)
- It's best if you had Anaconda Python installed on your laptops when following along the examples in class.
    - You can work on homeworks at home.
- Macs and Linux will work. Bring your laptops along next time, we'll make sure you have everything installed.

Why Astrostatistics?

- More data, but mostly…
- More need, ***and the ability***, to properly analyze data

Rules of thumb and approximate statistics are often insufficient…





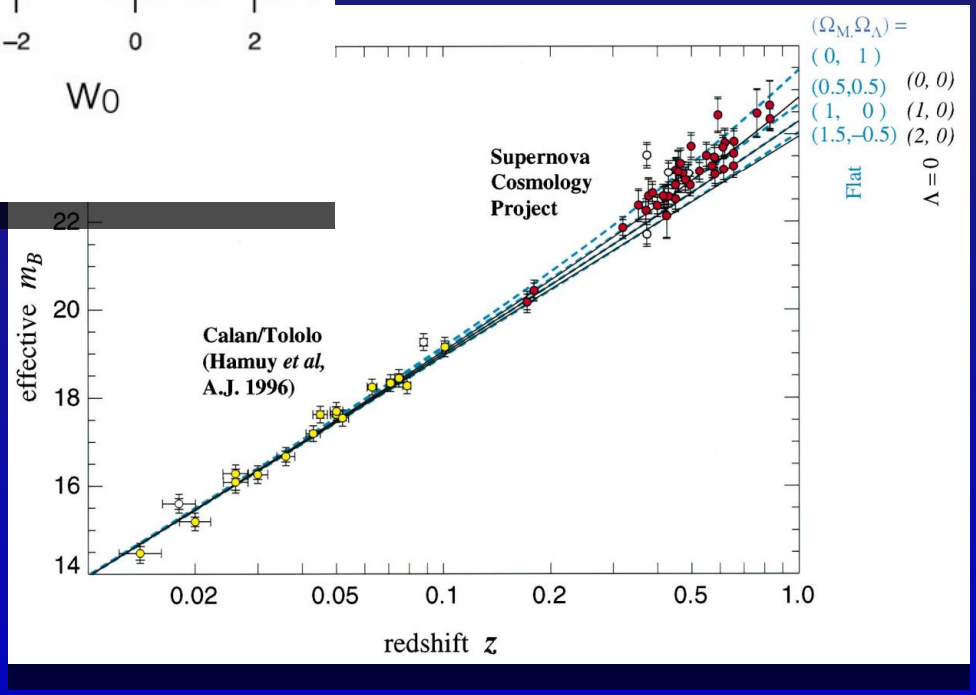
Mantz et al. 2015

The signals being measured today are typically *weak*; careful statistical analyses are required to detect and measure them.

Because we became more sophisticated in our data analysis, today we routinely perform measurements which would've been unthinkable 20 years ago.

Understanding the nature of Dark Energy ⤴

Discovery of Dark Energy ——>

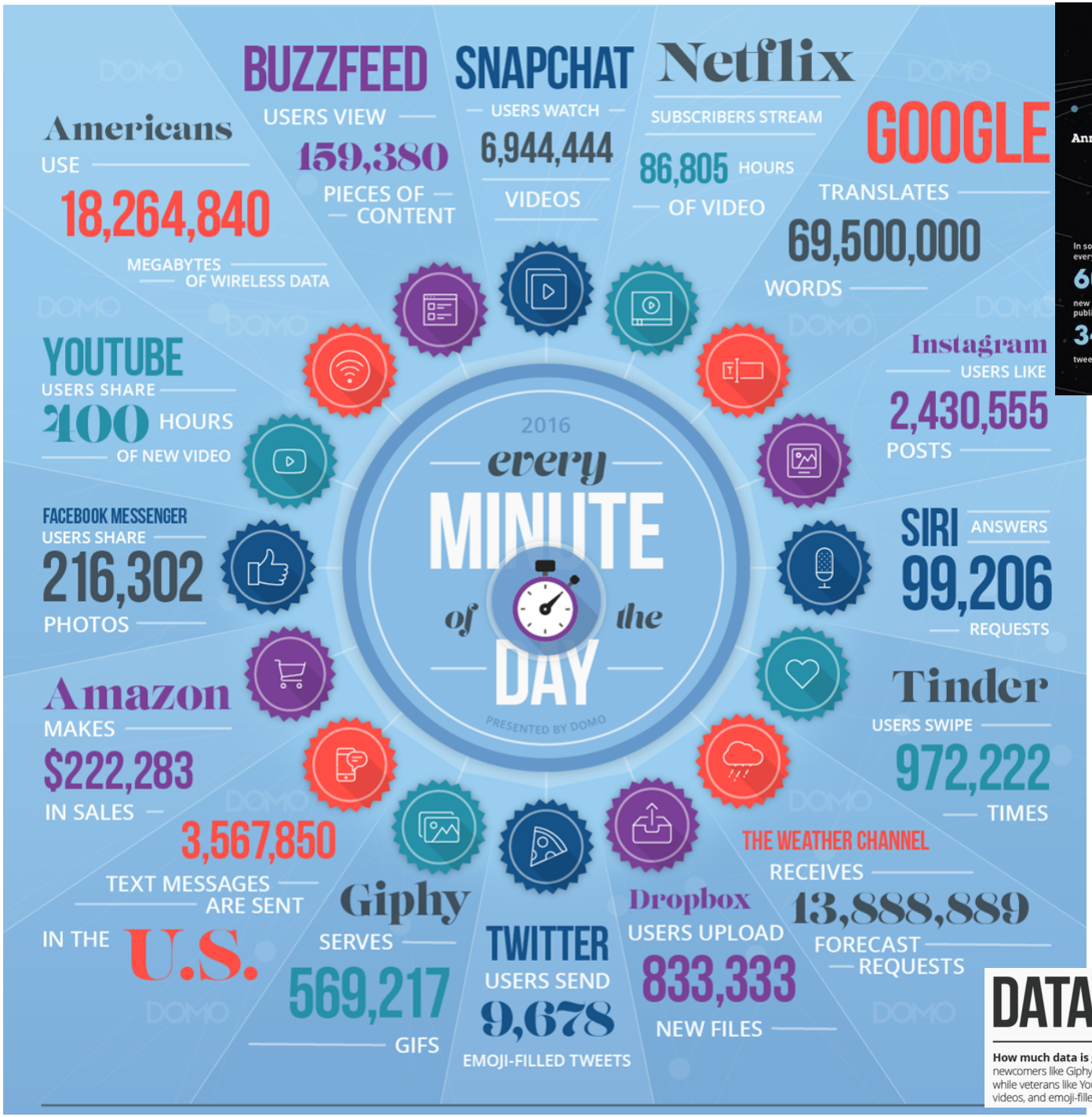


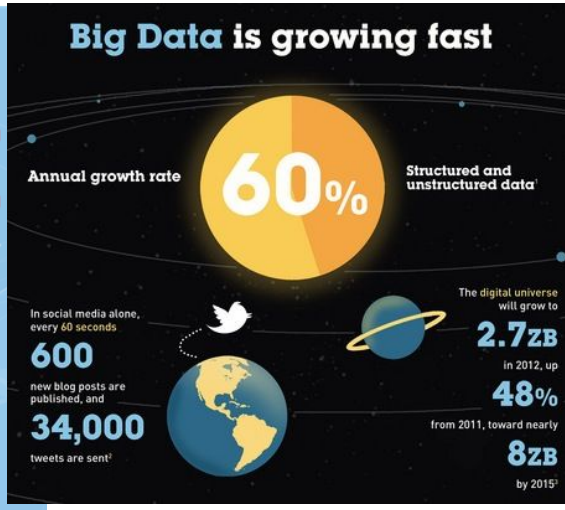
Also, they used to be too (computationally) expensive, but not any more!

Graph taken from Perlmutter et al., ApJ 517, 565 (1999)

The first Cray supercomputer at NCSA ⤴
(National Center for Supercomputing Applications)

Modern cell phone ⤴





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/

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!

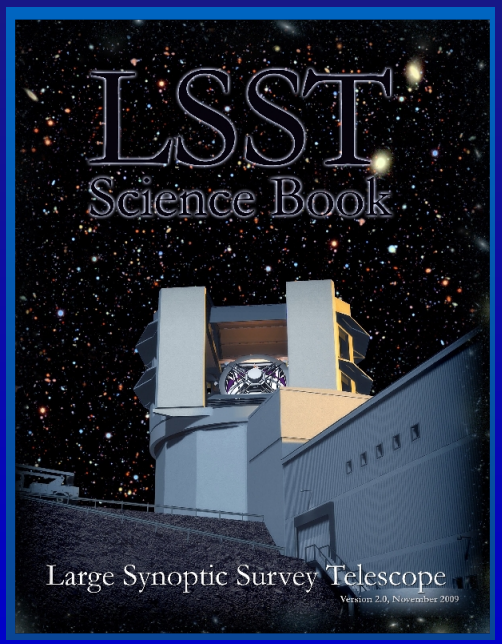
LSST Science Themes

- 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

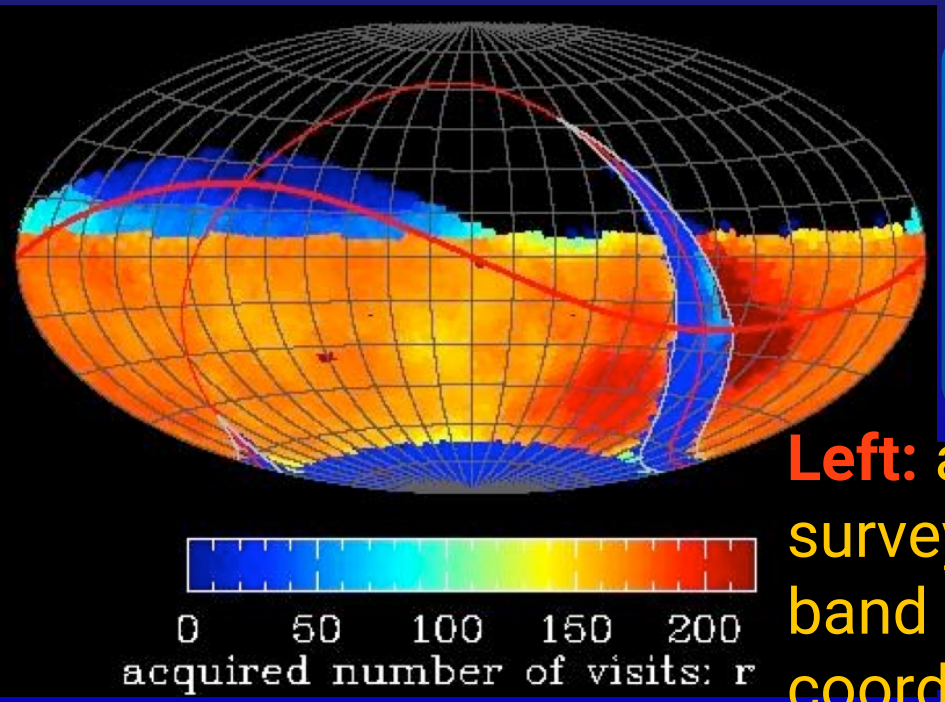
Summarizes LSST hardware, software, and observing plans, science enabled by LSST, and educational and outreach opportunities

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)

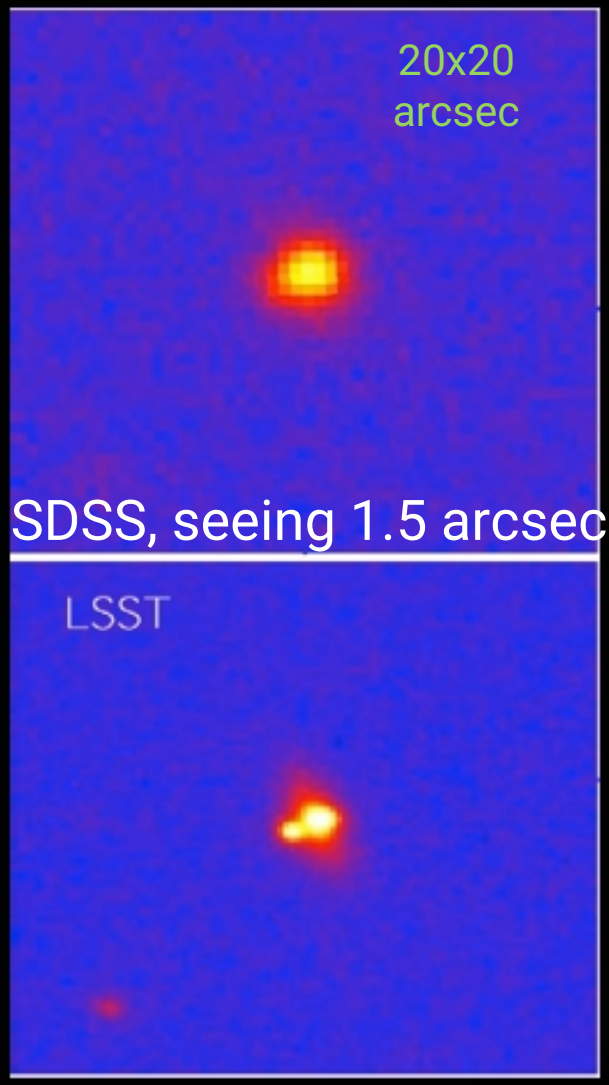
SDSS vs. LSST comparison: LSST=d(SDSS)/dt, LSST=SuperSDSS

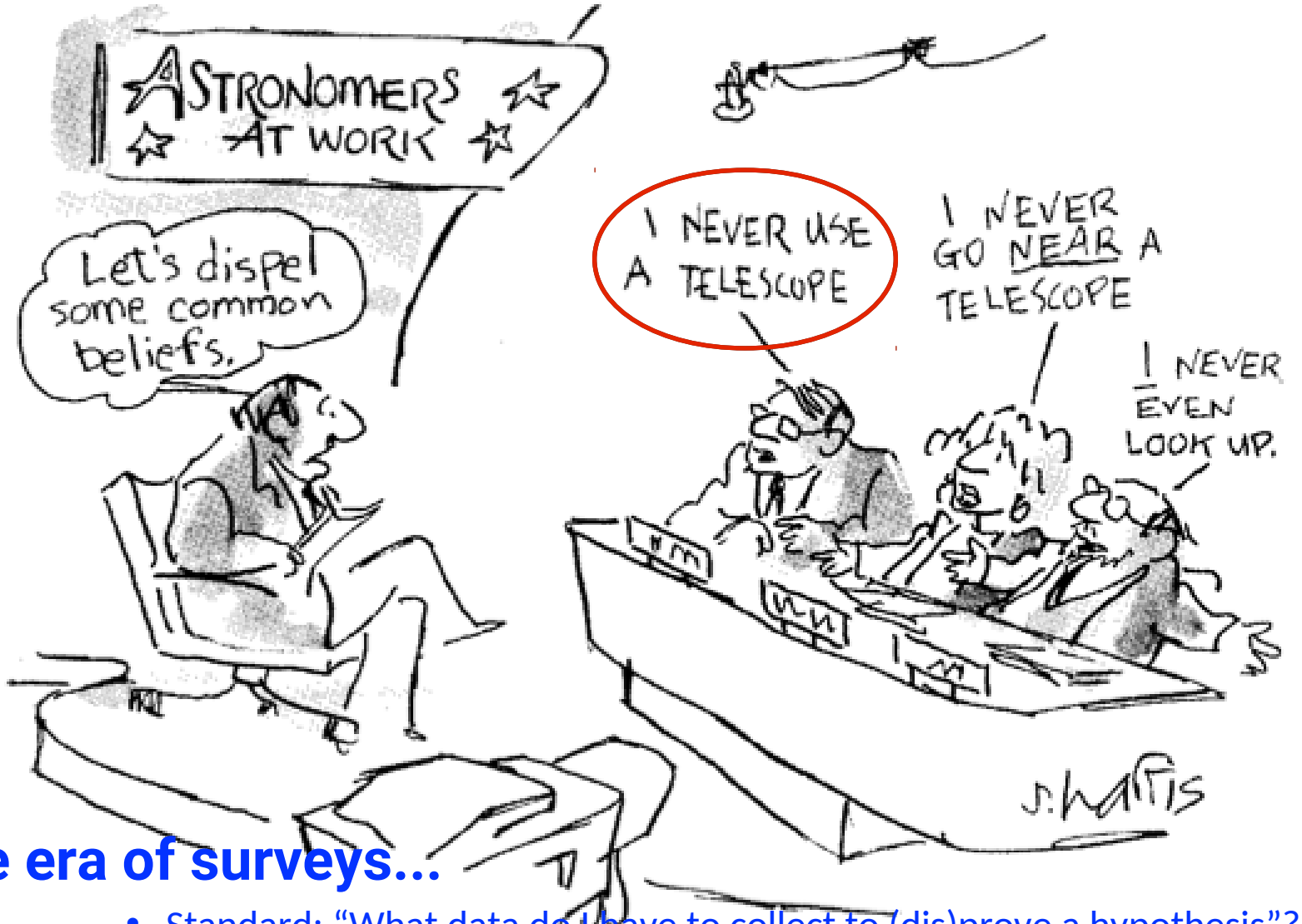
3x3 arcmin, gri

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

(almost) like LSST depth (but tiny area)

20x20 arcsec; lensed SDSS quasar (SDSS J1332+0347, Morokuma et al. 2007)





The era of surveys…

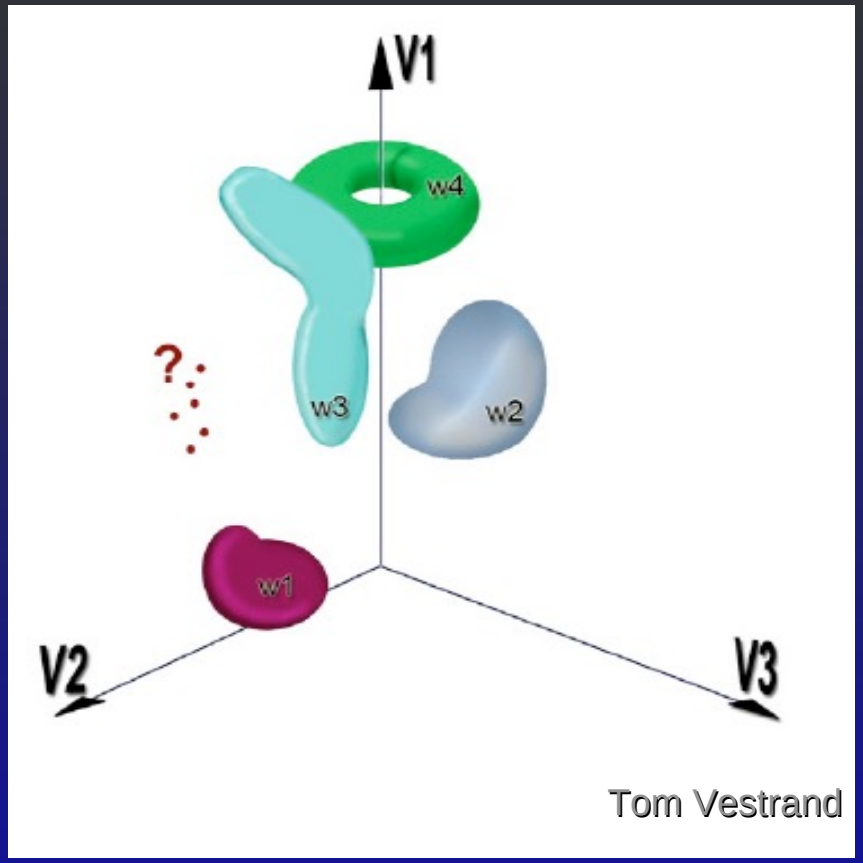
- Standard: "What data do I have to collect to (dis)prove a hypothesis"?
- Data-driven: "What theories can I test given the data I already have?"

Data analysis challenges in the era of Big Data

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

- Characterize the known (clustering)
- Assign the new (classification)
- Discover the unknown (outlier detection)



Benefits of very large data sets:

- best statistical analysis of “typical” events
- automated search for “rare” events

In this class, you will learn how to do all that.
Btw, it need not be an astronomical application!

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.

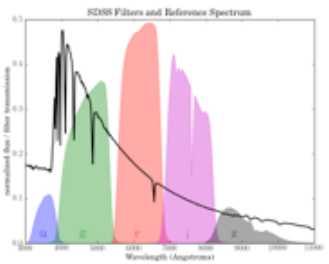
https://astrocompute.wordpress.com/2016/01/29/how-does-an-astronomer-become-a-data-scientist/

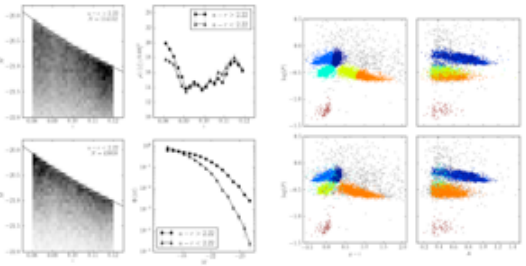
What to expect from this class

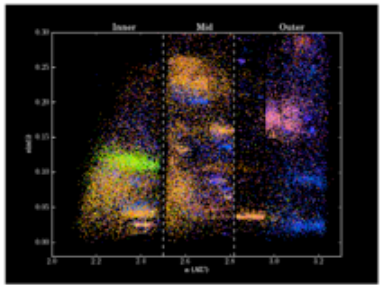
- **This class is not a computer science class**
- **This class is not a statistics class**
- **This class is not an astronomy class**
- **The main purpose of this class is to expose you to a combination of concepts and tools from the above fields so that you can "handle" your "data" (as in data & noise & models & understanding etc.). We want to demystify statistical methods and give you the practical tools to apply them.**
- **"Your data" can be big and small, astronomical or not, but most basic concepts and tools will have a general utility (e.g. histograms - which will be much more fun than you think!)**

AstroML (and Visualization)

AstroML: Machine Learning and Data Mining for Astronomy







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

The goal of astroML is to provide a community repository for fast Python implementations of common tools and routines used for statistical data analysis in astronomy and astrophysics, to provide a uniform and easy-to-use interface to freely available astronomical datasets. We hope this package will be useful to researchers and students of astronomy. The astroML project was started in 2012 to accompany the book **Statistics, Data Mining, and Machine Learning in Astronomy** by Zeljko Ivezic, Andrew Connolly, Jacob VanderPlas, and Alex Gray, to be published in late 2013. The table of contents is available here: **`here(pdf)`**.

User Guide

1. Introduction

- 1.1. Philosophy

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

Scipy 2012 (15 minute talk)

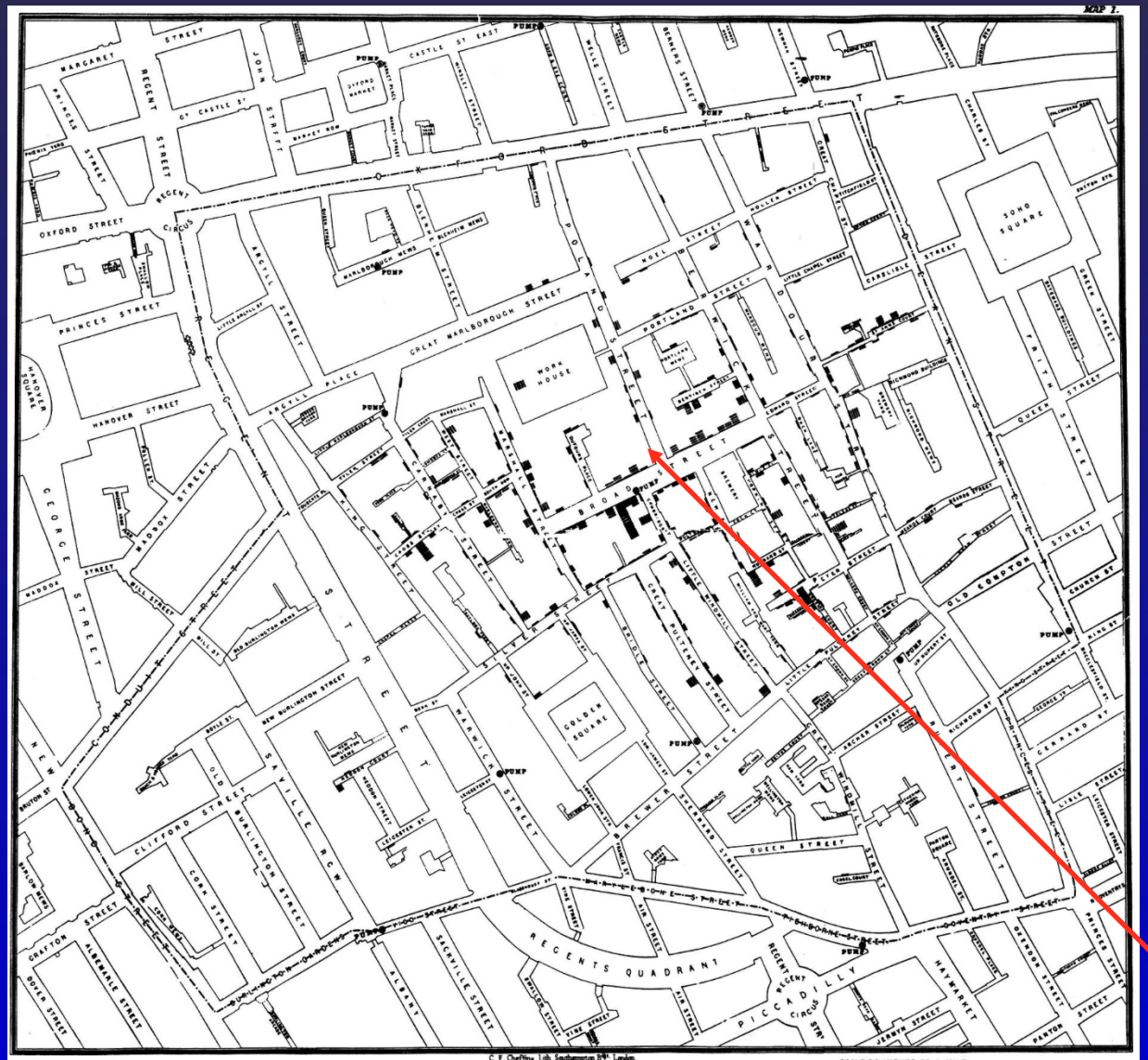
Citing

If you use the software, please consider citing astroML.

Open source!
www.astroML.org

Visualization of multi-dimensional correlations and search for patterns

"The greatest value of a picture is when it forces us to notice what we never expected to see." (John Tukey, 1977)



John Snow plotted the number of cholera deaths (black marks) in London in 1854 outbreak and realized that the deaths are clustered around the Broad Street pump: the cholera is spread by water!

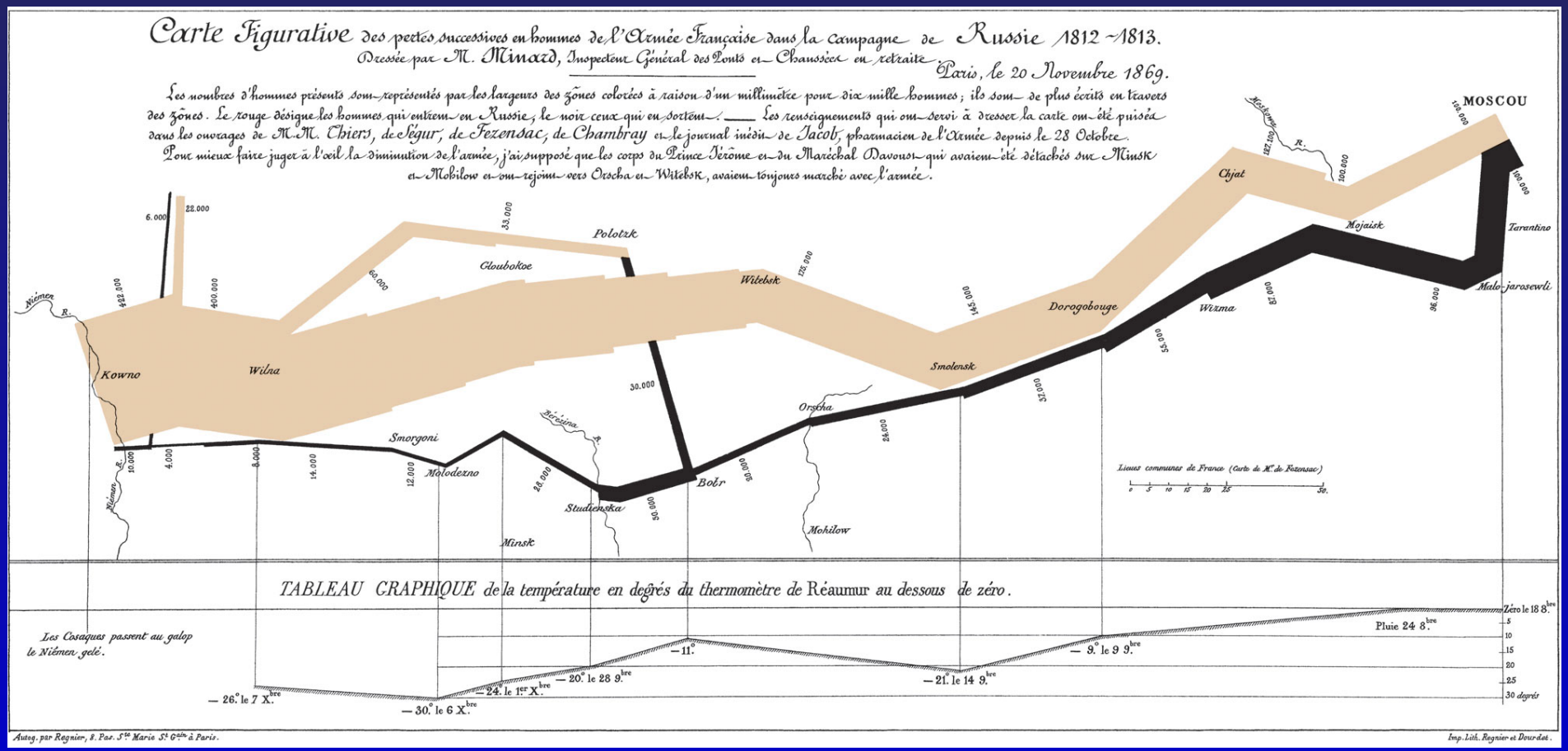
https://en.wikipedia.org/wiki/1854_Broad_Street_cholera_outbreak

The Broad Street pump

Visualization of multi-dimensional correlations and search for patterns

Napoleon's march on Moscow: 4-D data (2 positions, time, army size; also temperature and some other "metadata")

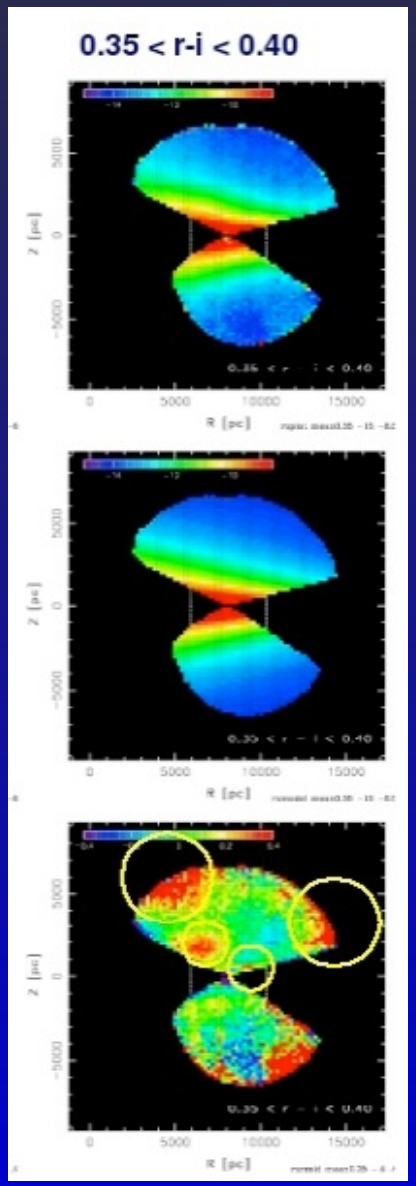
98% of soldiers perished… (visualization by Charles Minard)



https://upload.wikimedia.org/wikipedia/commons/2/29/Minard.png

Visualization of multi-dimensional correlations and search for patterns

"The greatest value of a picture is when it forces us to notice what we never expected to see." (John Tukey, 1977)

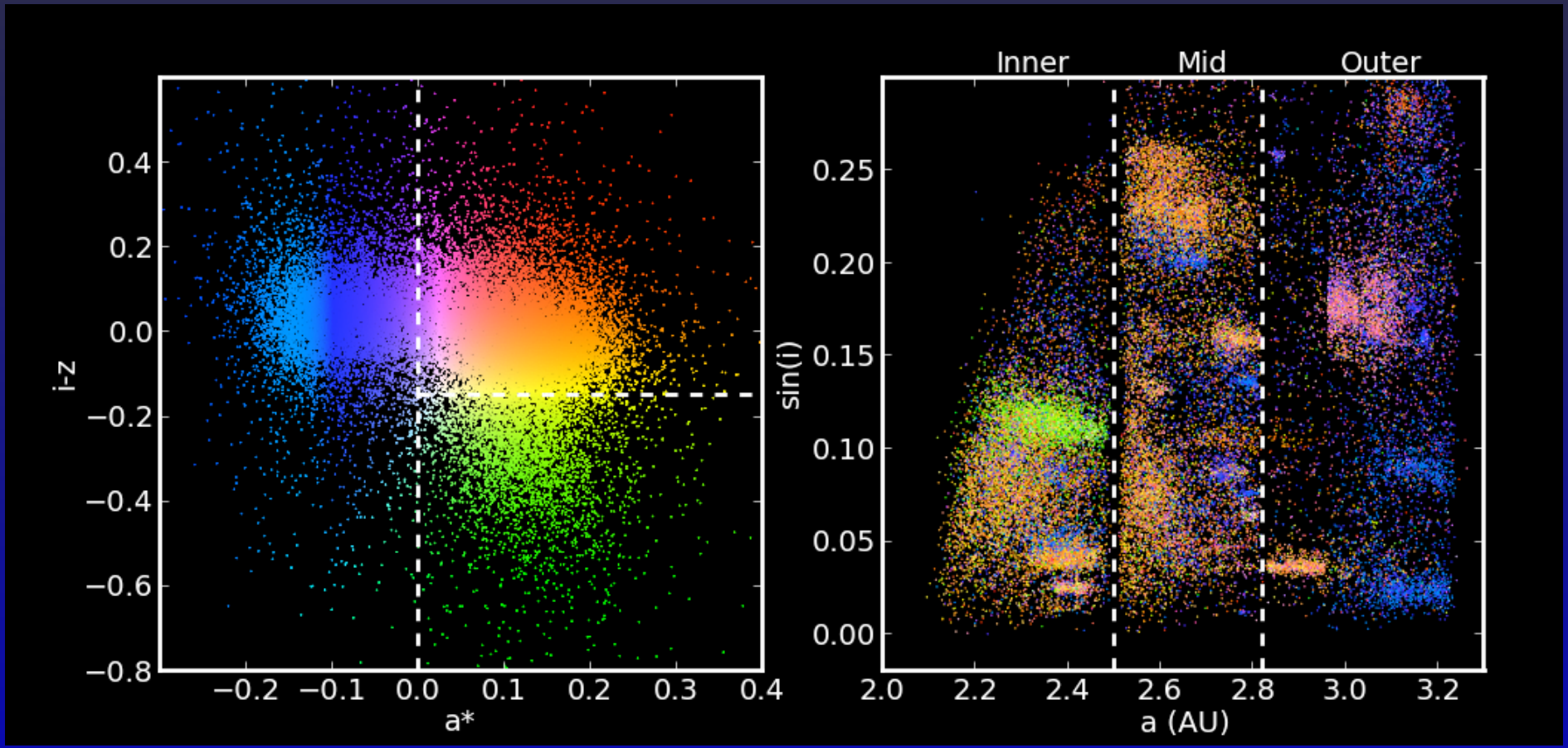


- An example from Jurić et al. (2008): our Galaxy grew by cannibalizing nearby smaller neighbors
- Four-dimensional data: stellar color, apparent magnitude, position on the sky (RA, Dec)
- Step 1: derive three dimensional positions and bin the data in cylindrical coordinates
- Step 2: fit a (relatively complicated) model
- Step 3: subtract the best-fit model from data
- We will learn about all these steps in this class.

You will be able to make this plot yourself!

Ivezic et al. (2002)

Visualization of 4-dimensional correlations



Homework #1 is based on this example

Previous: Stellar Paramete... | Next: Mercator Project... | Up: Chapter 1: Intro...

SDSS Stripe 82 Moving Object Catalog

This documentation is for astroML **version 0.2**

This page

SDSS Stripe 82 Moving Object Catalog

Links

astroML Mailing List

GitHub Issue Tracker

Videos

Scipy 2012 (15 minute talk)

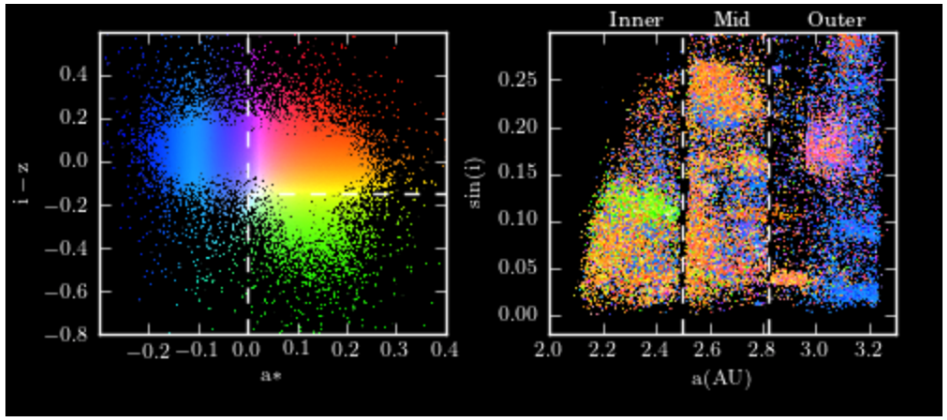
Scipy 2013 (20 minute talk)

Citing

If you use the software, please consider citing astroML.

Figure 1.12.

A multicolor scatter plot of the properties of asteroids from the SDSS Moving Object Catalog (cf. figure 1.8). The left panel shows observational markers of the chemical properties of the asteroids: two colors a* and i-z. The right panel shows the orbital parameters: semimajor axis a vs. the sine of the inclination. The color of points in the right panel reflects their position in the left panel. This plot is similar to that used in figures 3-4 of Parker et al 2008.



Code output:

Python source code:

```
# Author: Jake VanderPlas
# License: BSD
#   The figure produced by this code is published in the textbook
#   "Statistics, Data Mining, and Machine Learning in Astronomy" (2013)
#   For more information, see http://astroML.github.com
#   To report a bug or issue, use the following forum:
#    https://groups.google.com/forum/#!forum/astroml-general
import numpy as np
from matplotlib import pyplot as plt
```

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)**.

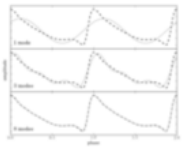
Figure Contents

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

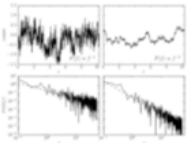
- Chapter 1: Introduction
- Chapter 2: Fast Computation and Massive Datasets
- Chapter 3: Probability and Statistical Distributions
- Chapter 4: Classical Statistical Inference
- Chapter 5: Bayesian Statistical Inference
- Chapter 6: Searching for Structure in Point Data
- Chapter 7: Dimensionality and its Reduction
- Chapter 8: Regression and Model Fitting
- Chapter 9: Classification
- Chapter 10: Time Series Analysis
- Appendix

Chapter 10: Time Series Analysis

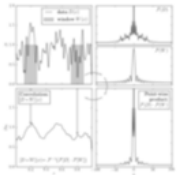
This chapter covers the analysis of both periodic and non-periodic time series, for both regularly and irregularly spaced data.



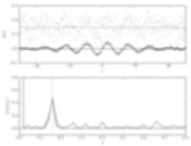
Fourier Reconstruction of RR-Lyrae Templates



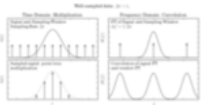
Generating Power-law Light Curves



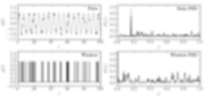
Plot a Diagram explaining a Convolution



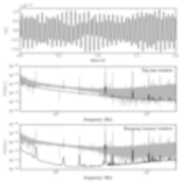
Fast Fourier Transform Example



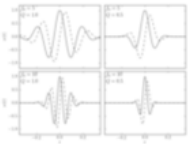
The effect of Sampling



The effect of Sampling



Plot the power spectrum of the LIGO big dog event

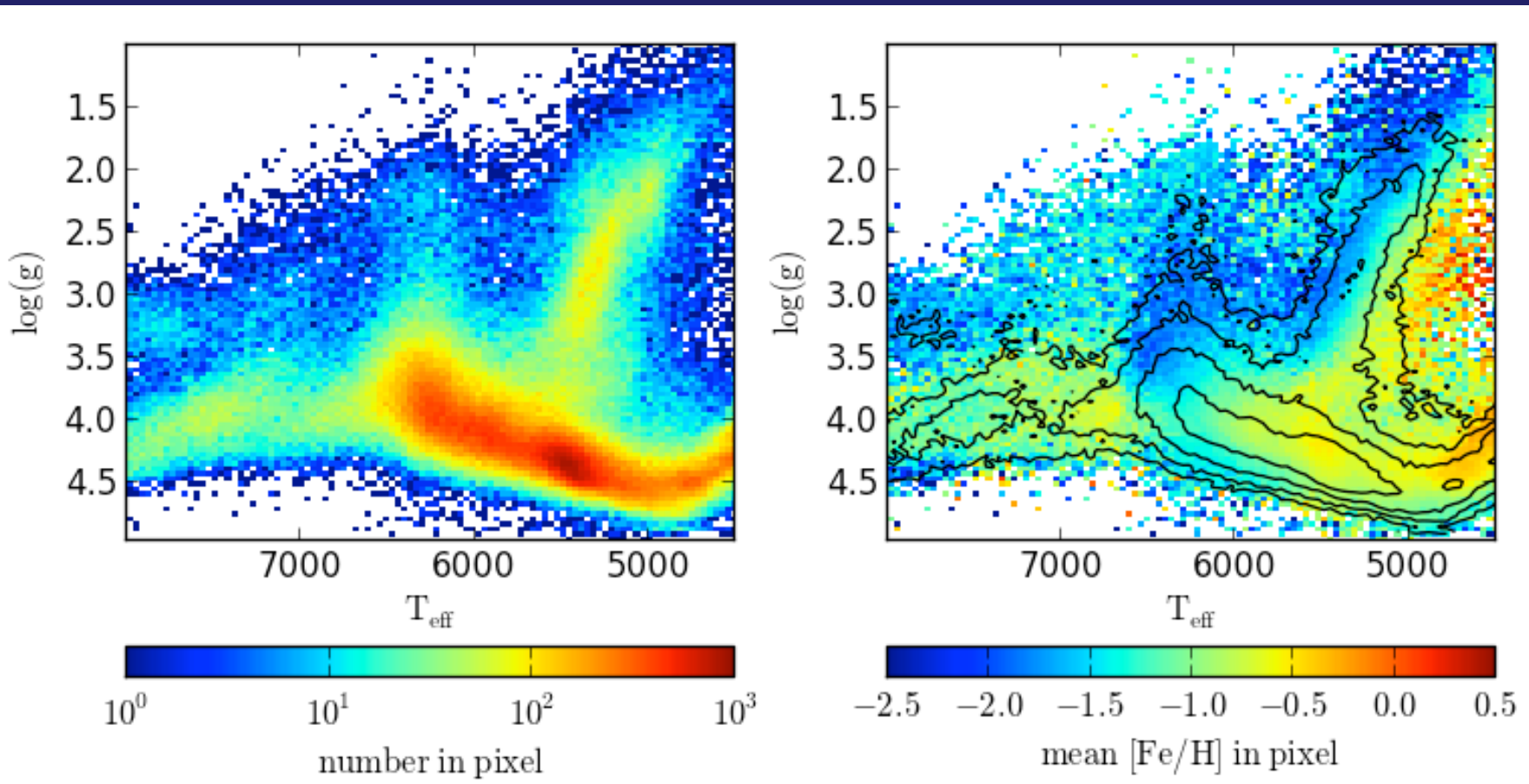


Examples of Wavelets

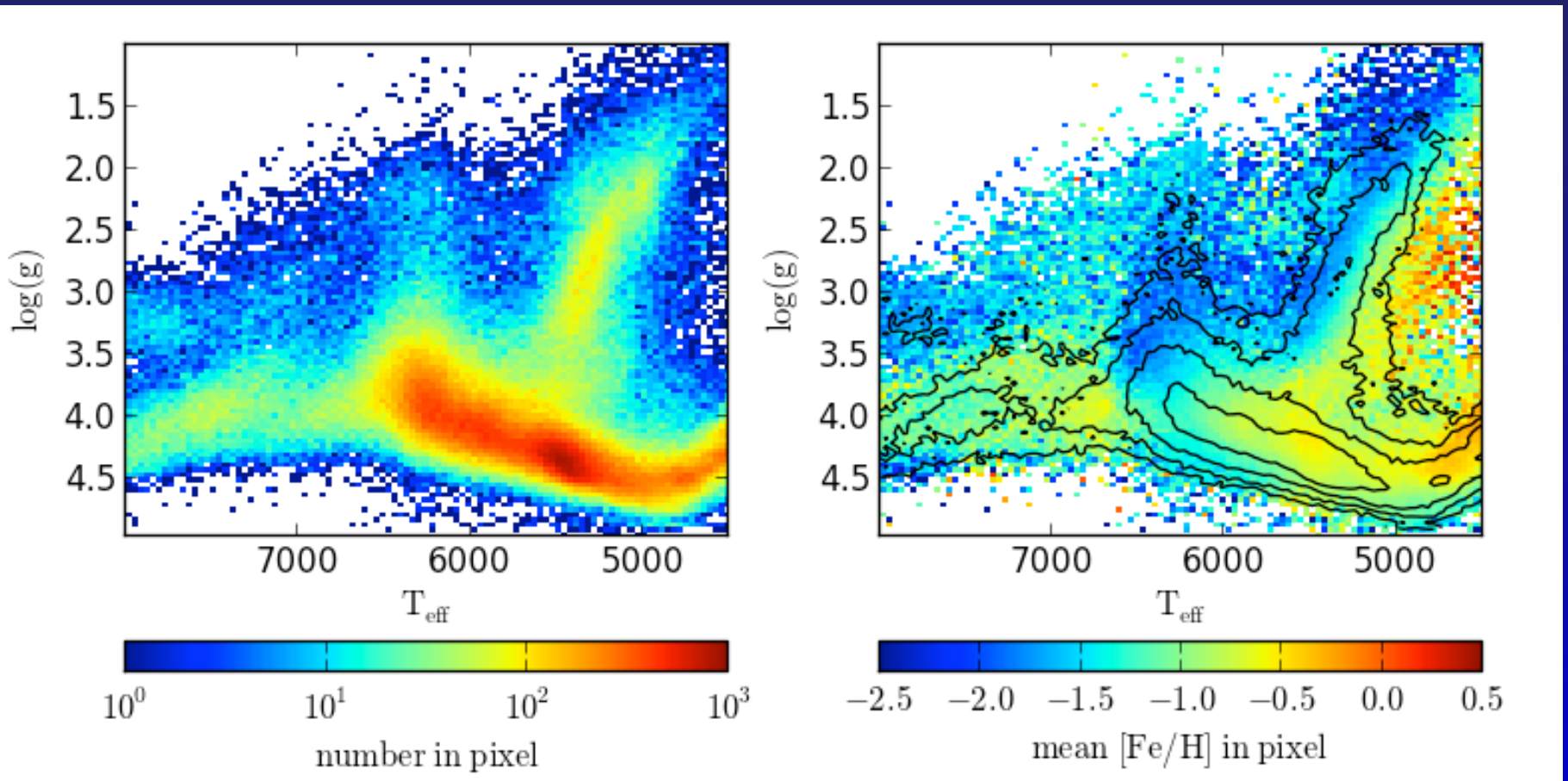
- https://github.com/astroML/astroML_figures
- $BOOK/book_figures/chapter1/fig_moving_objects_multicolor.py

```
def compute_color(mag_a, mag_i, mag_z, a_crit=-0.1):
    """
    Compute the scatter-plot color using code adapted from
    TCL source used in Parker 2008.
    """
    # define the base color scalings
    R = np.ones_like(mag_i)
    G = 0.5 * 10 ** (-2 * (mag_i - mag_z - 0.01))
    B = 1.5 * 10 ** (-8 * (mag_a + 0.0))

    # enhance green beyond the a_crit cutoff
    G += 10. / (1 + np.exp((mag_a - a_crit) / 0.02))

    # normalize color of each point to its maximum component
    RGB = np.vstack([R, G, B])
    RGB /= RGB.max(0)

    # return an array of RGB colors, which is shape (n_points, 3)
    return RGB.T


#------------------------------------------------------------
# Fetch data and extract the desired quantities
data = fetch_moving_objects(Parker2008_cuts=True)
mag_a = data['mag_a']
mag_i = data['mag_i']
mag_z = data['mag_z']
a = data['aprime']
sini = data['sin_iprime']

# dither: magnitudes are recorded only to +/- 0.01
mag_a += -0.005 + 0.01 * np.random.random(size=mag_a.shape)
mag_i += -0.005 + 0.01 * np.random.random(size=mag_i.shape)
mag_z += -0.005 + 0.01 * np.random.random(size=mag_z.shape)

# compute RGB color based on magnitudes
color = compute_color(mag_a, mag_i, mag_z)

#------------------------------------------------------------
# set up the plot
fig = plt.figure(figsize=(5, 2.2), facecolor='k')
fig.subplots_adjust(left=0.1, right=0.95, wspace=0.3,
                    bottom=0.2, top=0.93)
```

- **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



- $astroMLdir/astroML/stats/_binned_statistic.py

```
def binned_statistic(x, values, statistic='mean',
                     bins=10, range=None):
    """
    Compute a binned statistic for a set of data.

    This is a generalization of a histogram function.  A histogram divides
    the space into bins, and returns the count of the number of points in
    each bin.  This function allows the computation of the sum, mean, median,
    or other statistic of the values within each bin.

    Parameters
    ----------
    x : array_like
        A sequence of values to be binned.
    values : array_like
        The values on which the statistic will be computed.  This must be
        the same shape as x.
    statistic : string or callable, optional
        The statistic to compute (default is 'mean').
        The following statistics are available:

          * 'mean' : compute the mean of values for points within each bin.
            Empty bins will be represented by NaN.
          * 'median' : compute the median of values for points within each
            bin. Empty bins will be represented by NaN.
          * 'count' : compute the count of points within each bin.  This is
            identical to an unweighted histogram.  `values` array is not
            referenced.
          * 'sum' : compute the sum of values for points within each bin.
            This is identical to a weighted histogram.
          * function : a user-defined function which takes a 1D array of
            values, and outputs a single numerical statistic. This function
            will be called on the values in each bin.  Empty bins will be
            represented by function([]), or NaN if this returns an error.

    bins : int or sequence of scalars, optional
        If `bins` is an int, it defines the number of equal-width
```

- $astroMLdir/astroML/stats/_binned_statistic.py

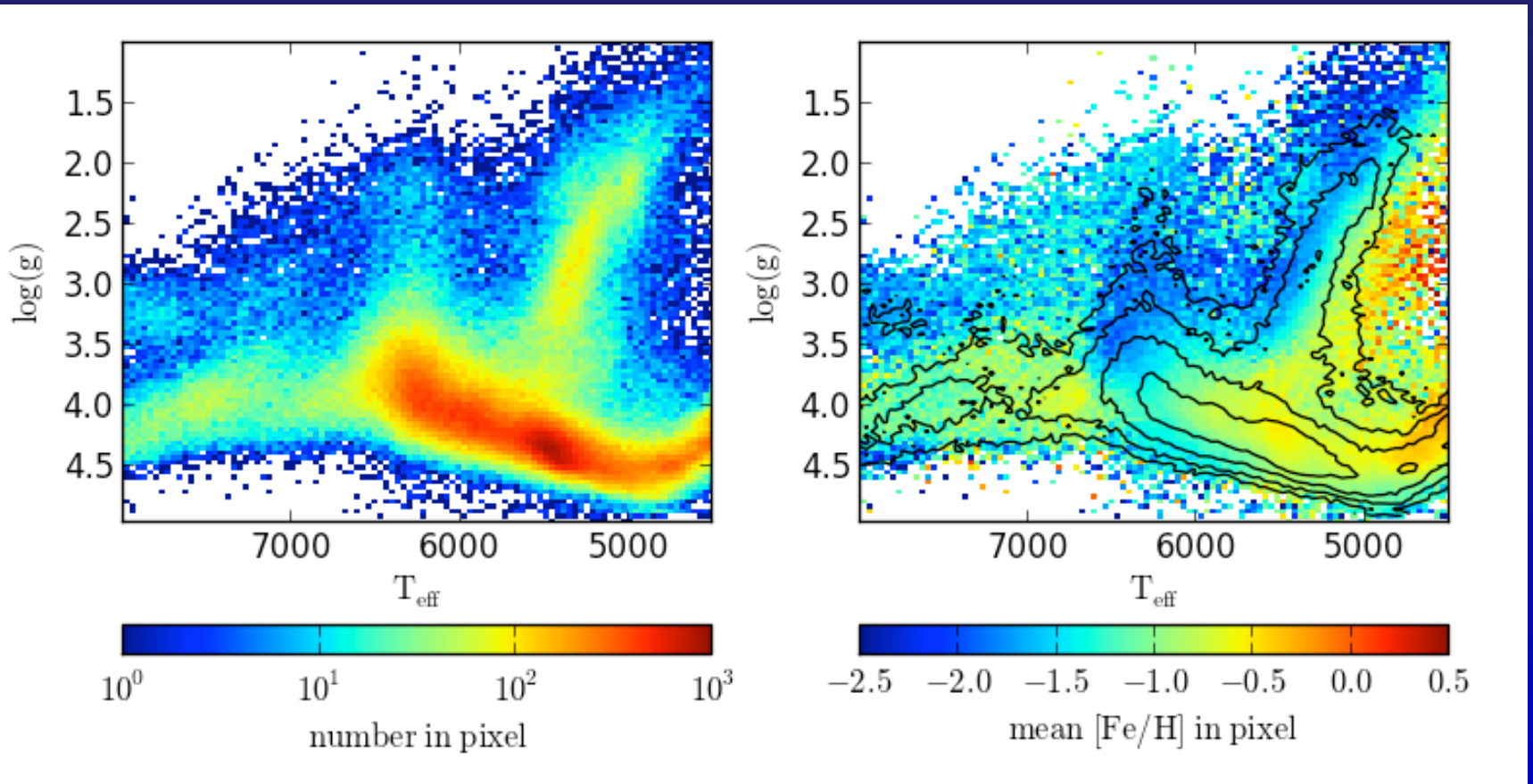
```
def binned_statistic(x, values, statistic='mean',
                     bins=10, range=None):
    """
    Compute a binned statistic for a set of data.

    This is a generalization of a histogram function.  A histogram divides
    the space into bins, and returns the count of the number of points in
    each bin.  This function allows the computation of the sum, mean, median,
    or other statistic of the values within each bin.

    Parameters
    ----------
    x : array_like
        A sequence of values to be binned.
    values : array_like
```

```
#------------------------------------------------------------
# Plot the results using the binned_statistic function
from astroML.stats import binned_statistic_2d
N, xedges, yedges = binned_statistic_2d(Teff, logg, FeH,
                                        'count', bins=100)

FeH_mean, xedges, yedges = binned_statistic_2d(Teff, logg, FeH,
                                               'mean', bins=100)
```

- $astroMLdir/astroML/stats/_binned_statistic.py

```
    bins : int or sequence of scalars, optional
        If `bins` is an int, it defines the number of equal-width
```

- make this plot by running
  %run $astroMLdir/examples/datasets/plot_SDSS_SSPP.py
- now, let's look at the code and change something, for example, let's only select stars with 15 < rpsf < 16
  find line 23: data = data[(rpsf > 15) & (rpsf < 19)]
  and change 19 to 16, save and then rerun…



- make this plot by running
  %run $astroMLdir/examples/datasets/plot_SDSS_SSPP.py
- now, let's look at the code and change something, for example, let's only select stars with 15 < rpsf < 16
  find line 23: data = data[(rpsf > 15) & (rpsf < 19)]
  and change 19 to 16, save and then rerun…