AstroML: Machine Learning for Astronomy

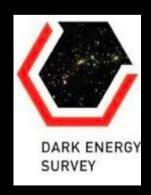
CIDU: 24 Oct 2012

Jake Vanderplas Andrew Connolly Zeljko Ivezic Alex Gray

Python is becoming a new standard tool in Astronomy, and will remain important for the foreseeable future











Machine Learning / Statistical Data Analysis tasks in Astronomy:

- Photometric Redshifts (Regression)
- Source Classification
- Dimensionality Reduction / Visualization
- Clustering
- N-point Statistics
- Period Finding
- Transient & Outlier Detection
- Density Estimation
- Matched Filtering
- Source Extraction
- Cross-matching

...

Machine Learning / Statistical Data Analysis tasks in Astronomy:

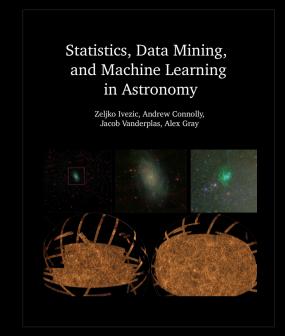
- Photometric Redshifts (Regression)
- Source Classification
- Dimensionality Reduction / Visualization
- Clust Every astronomer needs these sorts of
- N-pointools, and existing Python packages
- Period Fprovide an easy interface to many
- Transient & Outlier powerful algorithms.
- Density Estimation
- Matched Filtering
- Source Extraction
- Cross-matching

Statistics, Data Mining and Machine Learning in Astronomy

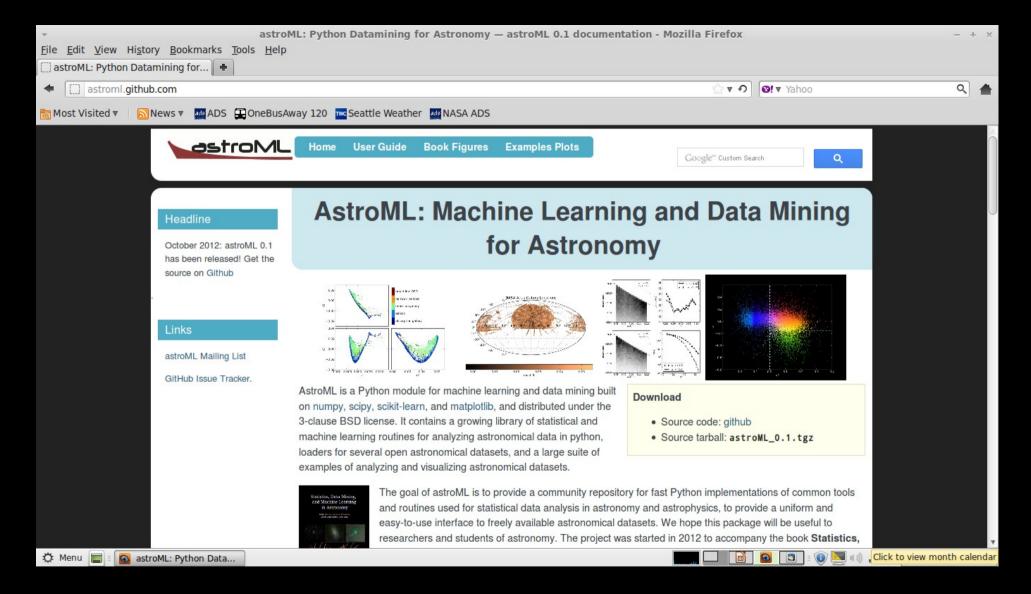
Zeljko Ivezic, Andrew Connolly, Jacob Vanderplas, Alex Gray

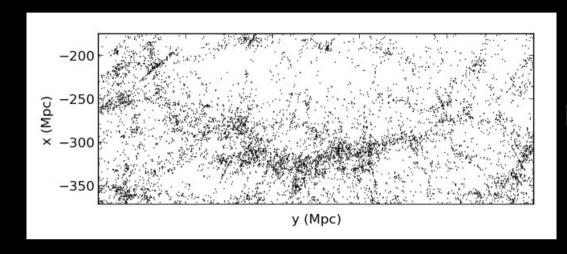
Princeton University Press, 2013

- Complete Practical guide to statistical analysis, data exploration, and machine learning
- Example-driven approach, using real data (SDSS, LIGO, LINEAR, WMAP, and others)
- All book figures and examples generated in python (matplotlib), with code available online – for free!
- Supporting python package: astroML
- Makes use of numpy, scipy, matplotlib, scikit-learn, pymc, healpy, and others where possible: limited code duplication

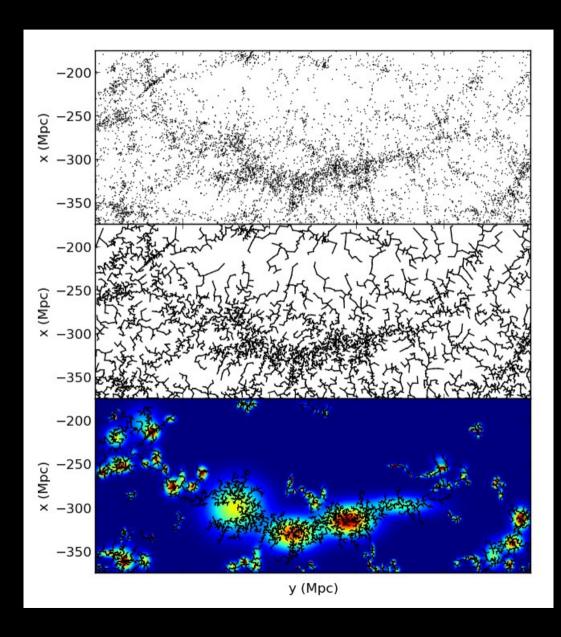


AstroML: Python Machine Learning for Astronomy





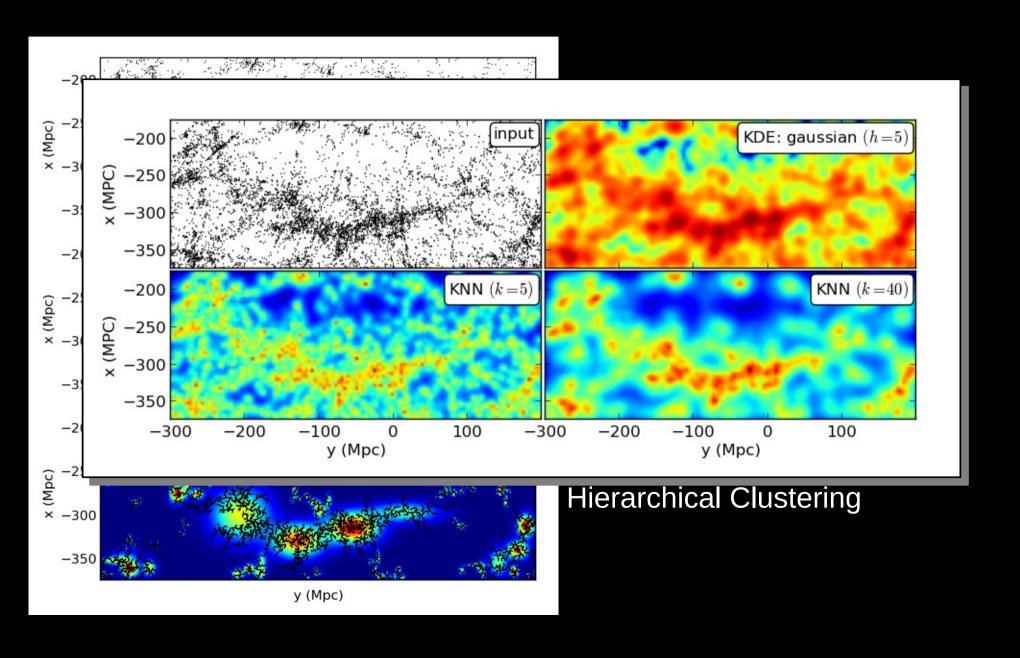
Projected Galaxy Locations

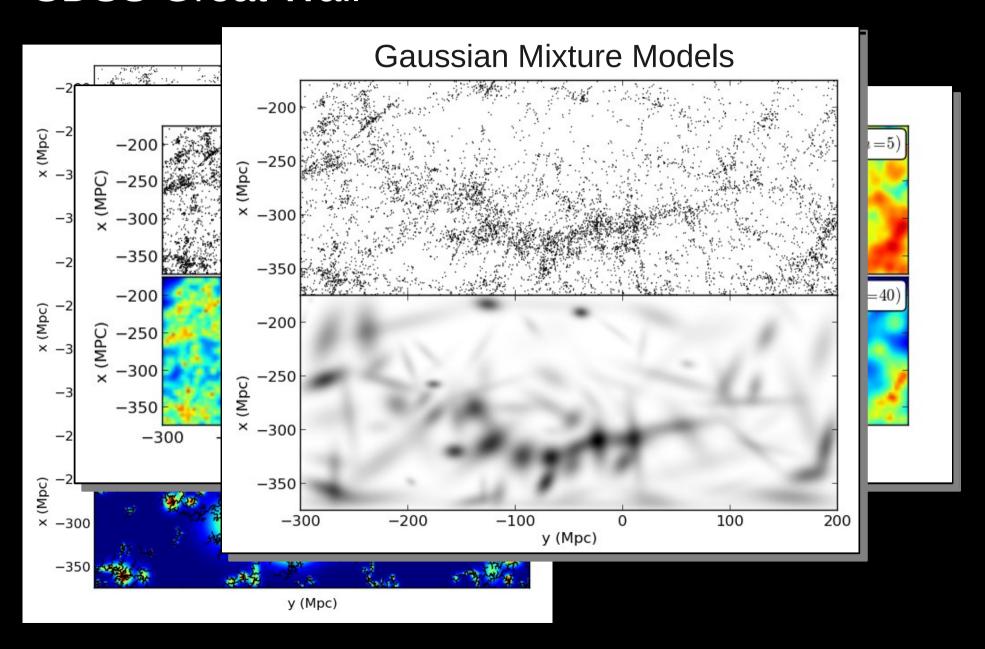


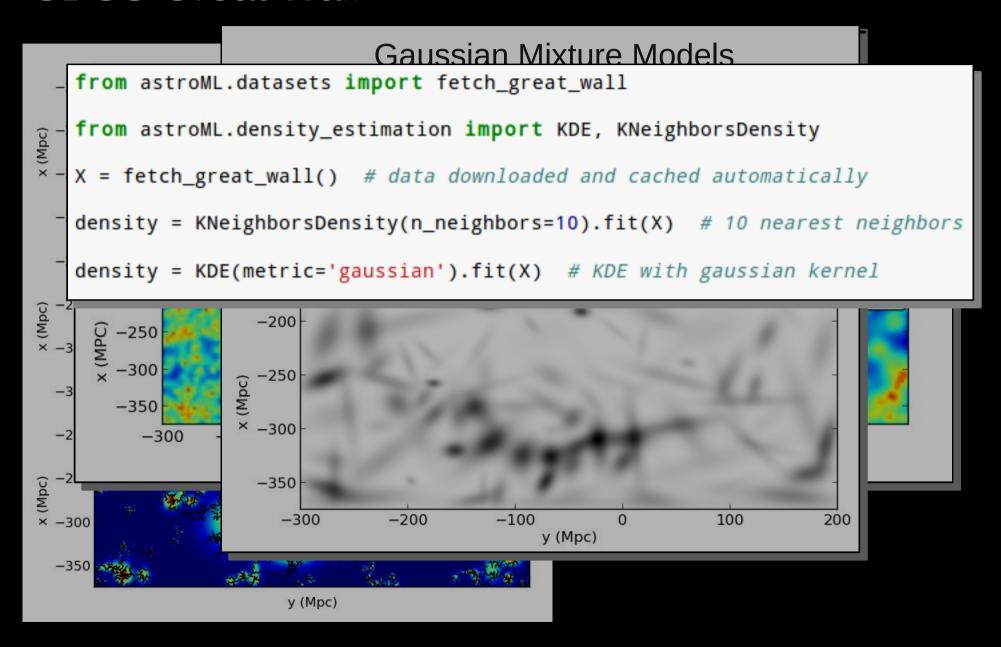
Projected Galaxy Locations

Minimum Spanning Tree

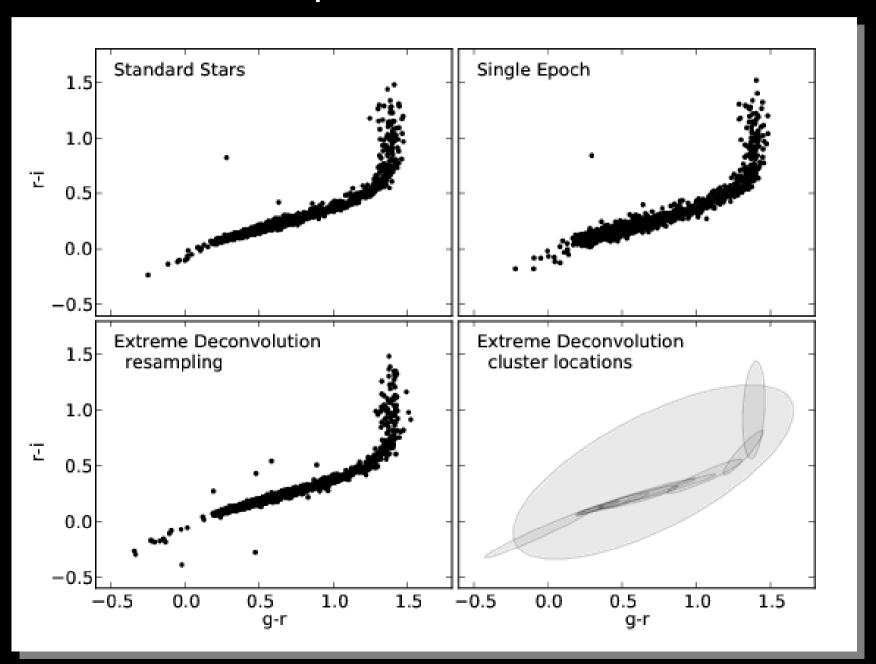
Hierarchical Clustering



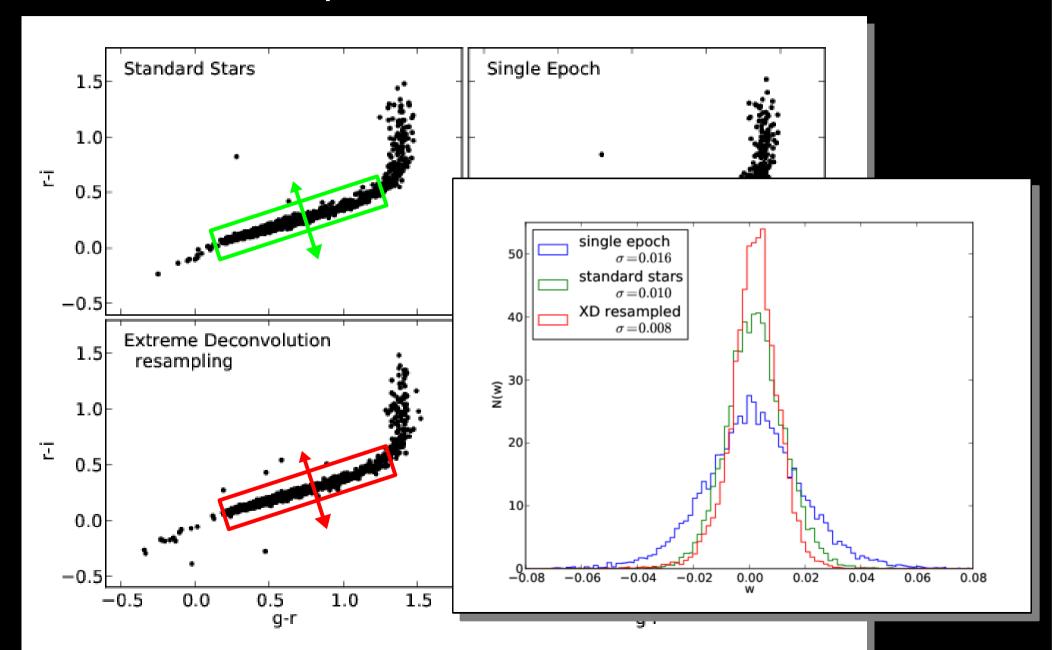




"Extreme Deconvolution" (GMM + errors): SDSS main sequence



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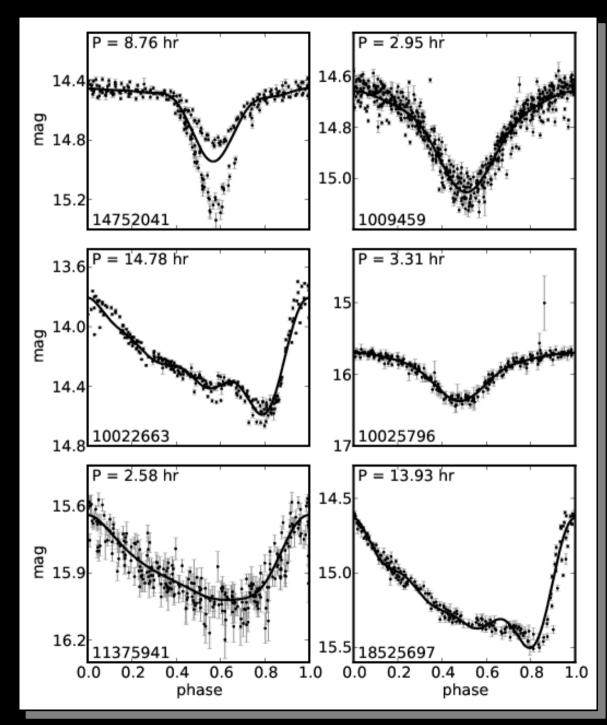


"Extreme Deconvolution" (GMM + errors): SDSS main sequence

```
Standard Stars
                                     Single Epoch
  from astroML.datasets import fetch_sdss_S82standards
 from astroML.density_estimation import XDGMM
 data = fetch sdss S82standards() # SDSS stripe 82 standard stars
 X = np.vstack([data['mmed_u'], data['mmed_g']]).T # u and g magnitudes
 Xerr = np.vstack([data['mrms_u'], data['mrms_g']]).T # u and g errors
 model = XDGMM(n_components=10).fit(X, Xerr) # fit the XD model
 density = model.sample(10000) # Sample 10000 deconvolved points
 1.0F
                                       20
 0.5
                                       10
0.01
-0.5
                                                           0.00
                                                                0.02
                                                                     0.04
                                                                          0.06
                                                                               0.08
          0.0
                 0.5
                       1.0
                              1.5
   -0.5
```

Lomb-Scargle Periodograms:

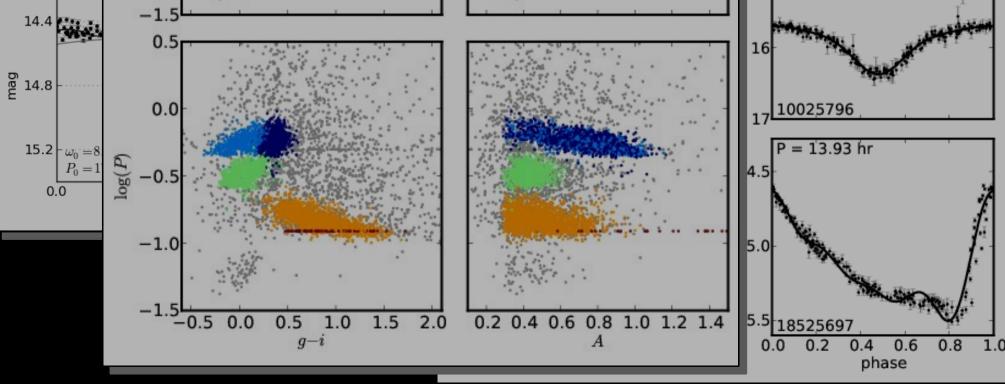
Light Curves



Lomb-Scargle Periodograms: **Light Curves** P = 8.76 hr P = 2.95 hr14. 14.8 15.0 mag 14.8 1009459 14752041 = 14.78 hr $P = 3.31 \, hr$ 15.2 $\omega_0 = 17.22$ $P_0 = 8.76 \text{ hours}$ 0.2 0.4 0.8 1.0 0.0 10022663 10025796 = 2.58 hr $P = 13.93 \, hr$ 15.2 $\mid \omega_0 = 8.61$ $P_0 = 17.52 \text{ hours}$ 14.5 0.2 0.8 1.0 0.4 0.6 0.0 phase 15.0 16.2 phase phase

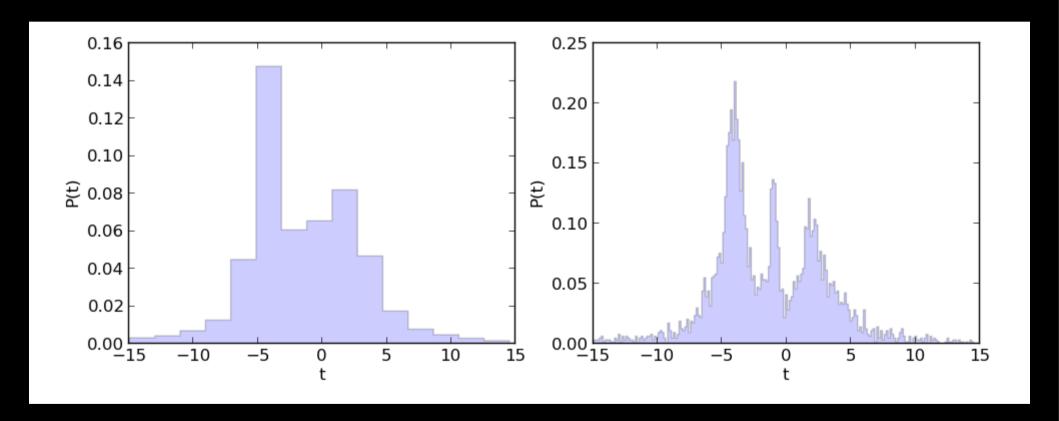
Lomb-Scargle Periodograms: **Light Curves** P = 8.76 hr= 2.95 hr 0.0 B 14.8 1009459 $P = 3.31 \, hr$ 15.2 $\omega_0 = 1$ 0.0 0.0 10025796 P = 13.93 hr15.2 -1.00.8 phase

Lomb-Scargle Periodograms: **Light Curves** P = 8.76 hr $P = 2.95 \, hr$ from astroML.datasets import fetch_LINEAR_sample from astroML.time_series import lomb_scargle data = fetch_LINEAR_sample() # LINEAR is a database of time-domain observations t, y, dy = data[14752041].TP_LS = lomb_scargle(t, y, dy, omega) 0.5 ရာ 14.8 17 10025796 0.0 $15.2 \mid \omega_0 = 8$ P = 13.93 hr



The problem with histograms: choosing the bin width.

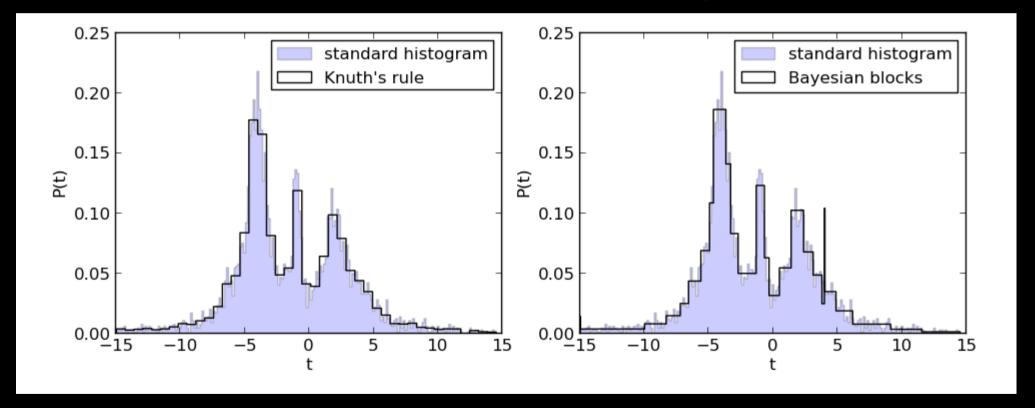
These show the same data set: how do we choose the right binning?

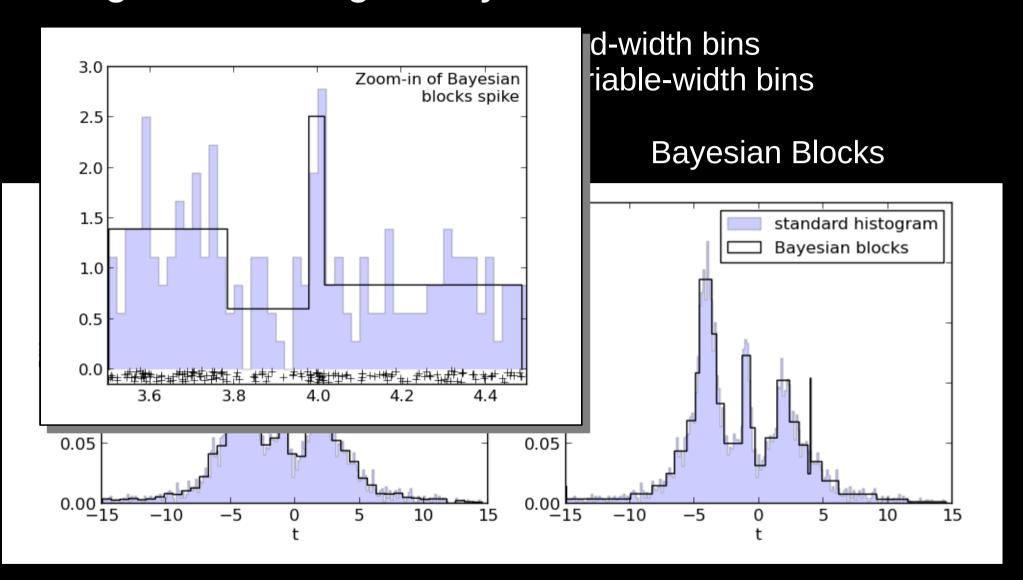


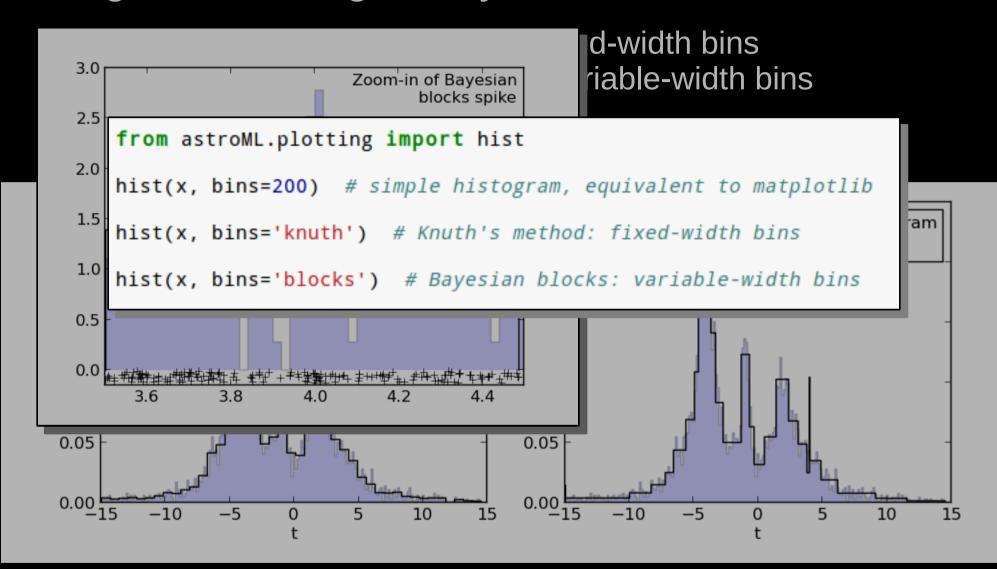
Knuth's Method: optimization over fixed-width bins Bayesian blocks: optimization over variable-width bins

Knuth's Method

Bayesian Blocks







The Vision:

- Reproducible Research: provide a standard repository for sharing well-tested algorithms
- Coherent & well-written examples using real data: useful for both education and research
- Speed-up data exploration: examples require a minimal amount of code (typically ~10 lines)
- Move tested, useful code upstream for use in other fields.
 A few examples:
 - Ball Tree & two-point statistics (scikit-learn 0.10)
 - Minimum Spanning Tree (scipy 0.11)
 - binned_statistics (scipy 0.11)
 - Bayesian blocks in matplotlib?
 - Extreme Deconvolution in scikit-learn?

Thank You

http://astroML.github.com