A Typical User's Ground-Level Perspective on Machine Learning in Astronomy

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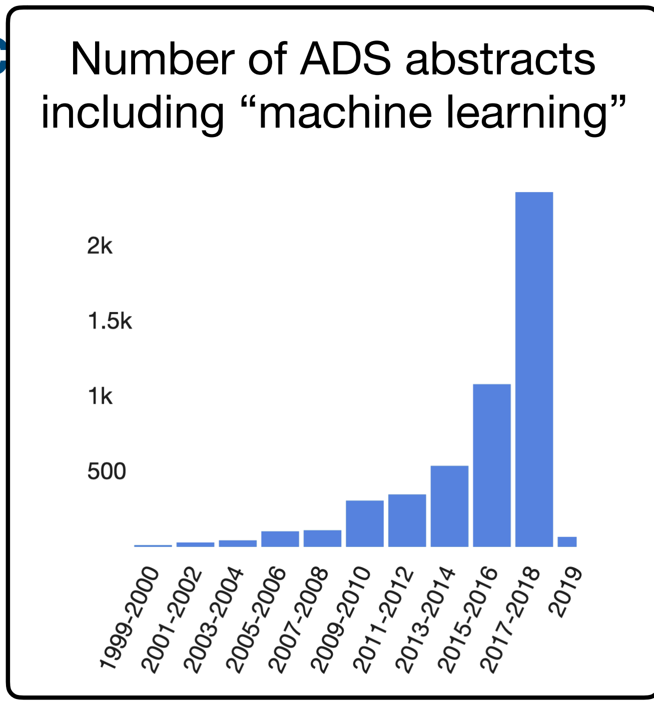
University of Washington

A Typical User's Ground-Level Perspective on Mac ronomy



Machine Learning is Boring*

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*normal, lots of people doing it.
And this is a good thing! (i.e. don't be scared!)

Most of our work isn't "big data"

(i.e. can run most algorithms on your laptop)

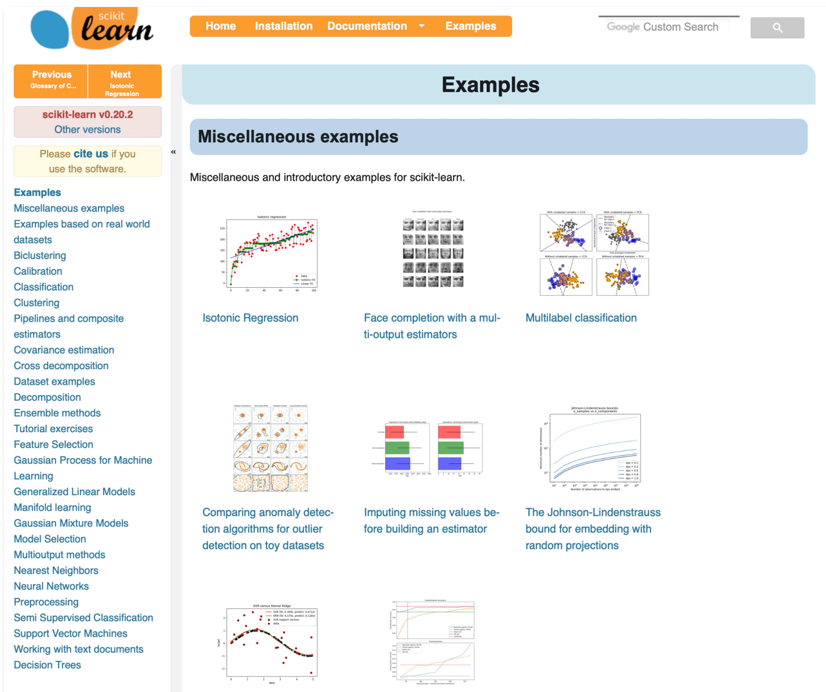
Yet sample size is big enough that
interesting/rare things can be found

Our data is becoming better suited for ML

- big datasets (Mario’s talk), especially Gaia!
- easier than ever to get data (Vizier/Xmatch, ADS, journals, Github, Zenodo…)
- value-added datasets for surveys (e.g. stellar parameters from SDSS)

ML is easier than ever to use

- robust, open source libraries available
- many programming languages
- many domain (astro) experts & workshops available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Examples
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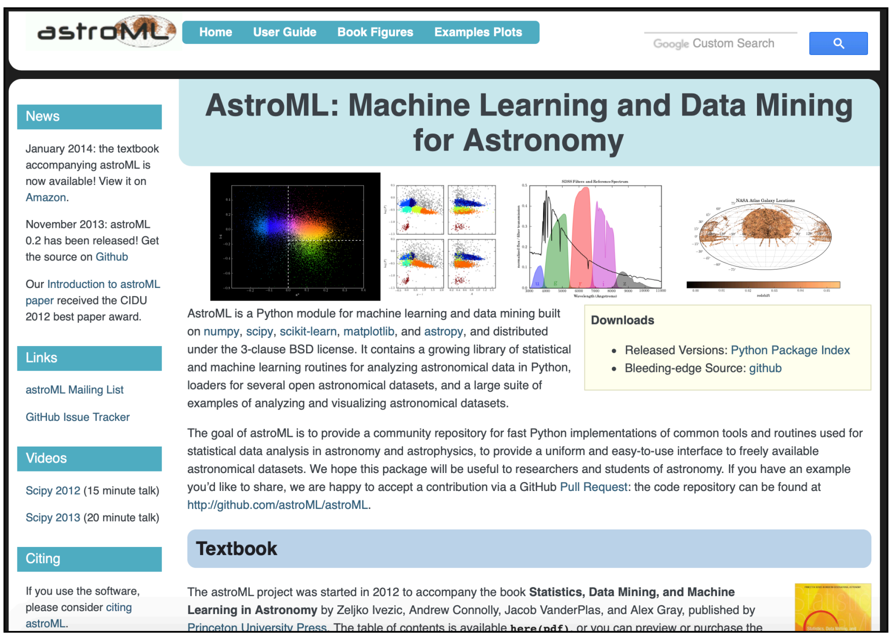
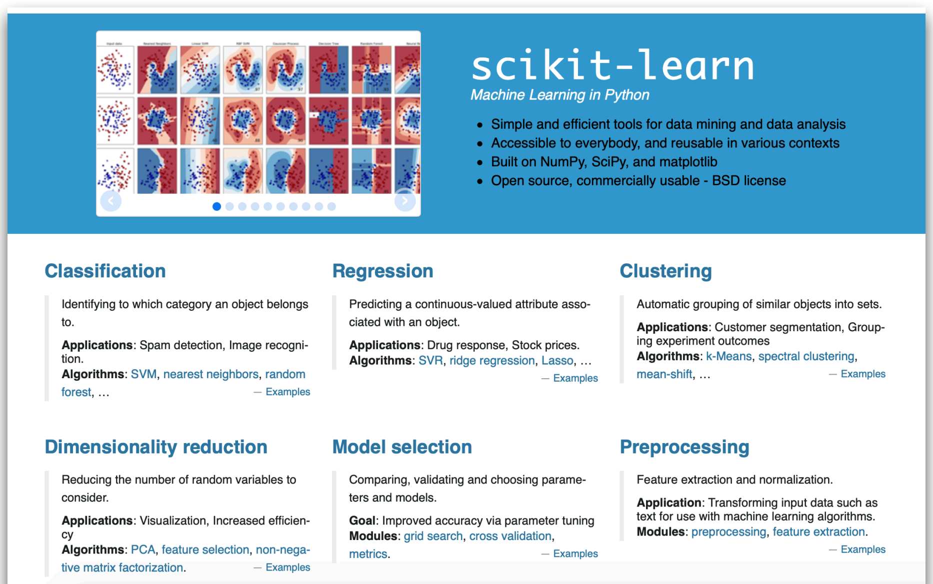
Miscellaneous and introductory examples for scikit-learn.
Isotonic Regression
Face completion with a multi-output estimators
Multilabel classification
Comparing anomaly detection algorithms for outlier detection on toy datasets
Imputing missing values before building an estimator
The Johnson-Lindenstrauss bound for embedding with random projections

also astroML!
(see Brigitta's talk later)

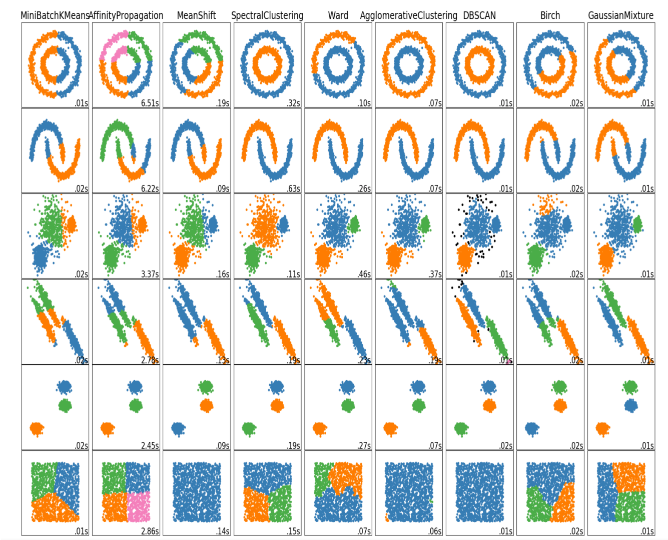


Problems that ML is good for:

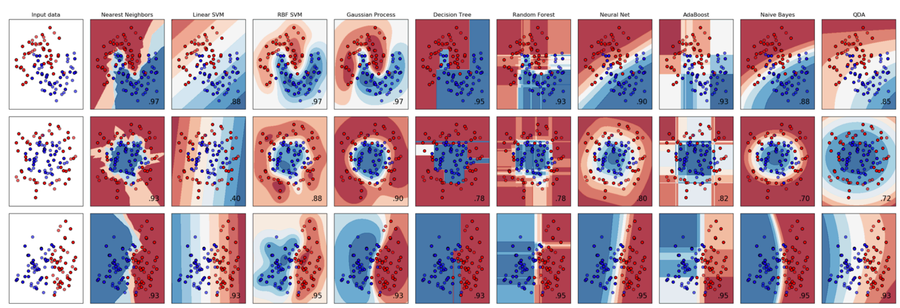


Each algorithm has specific use cases
(sometimes: just try them all!)

Clustering



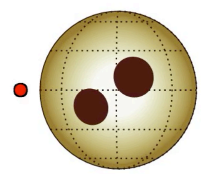
Classification

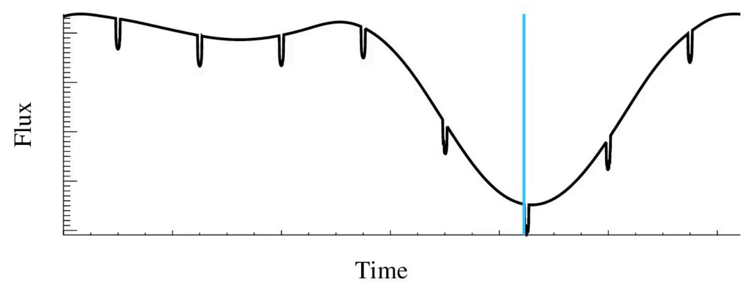


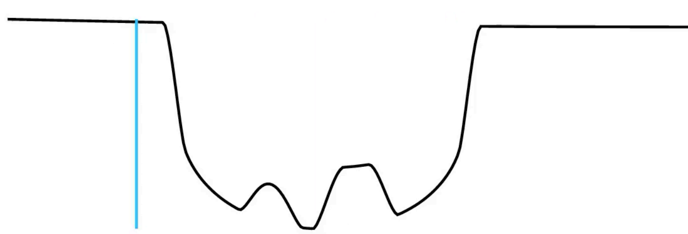
Goal: demonstrate 3 real problems that ML can be used for

Example 1: Clustering starspot evolution tracks

Kepler 17



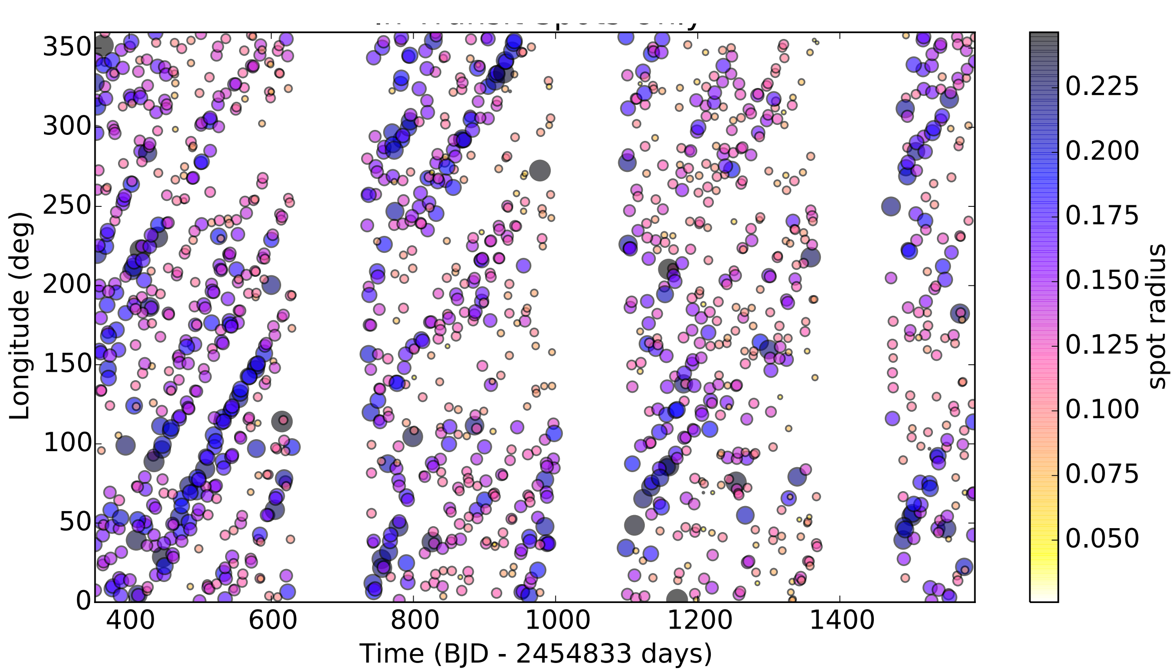




Davenport, Hebb, & Hawley (2015)

Example 1: Clustering starspot evolution tracks

Kepler 17



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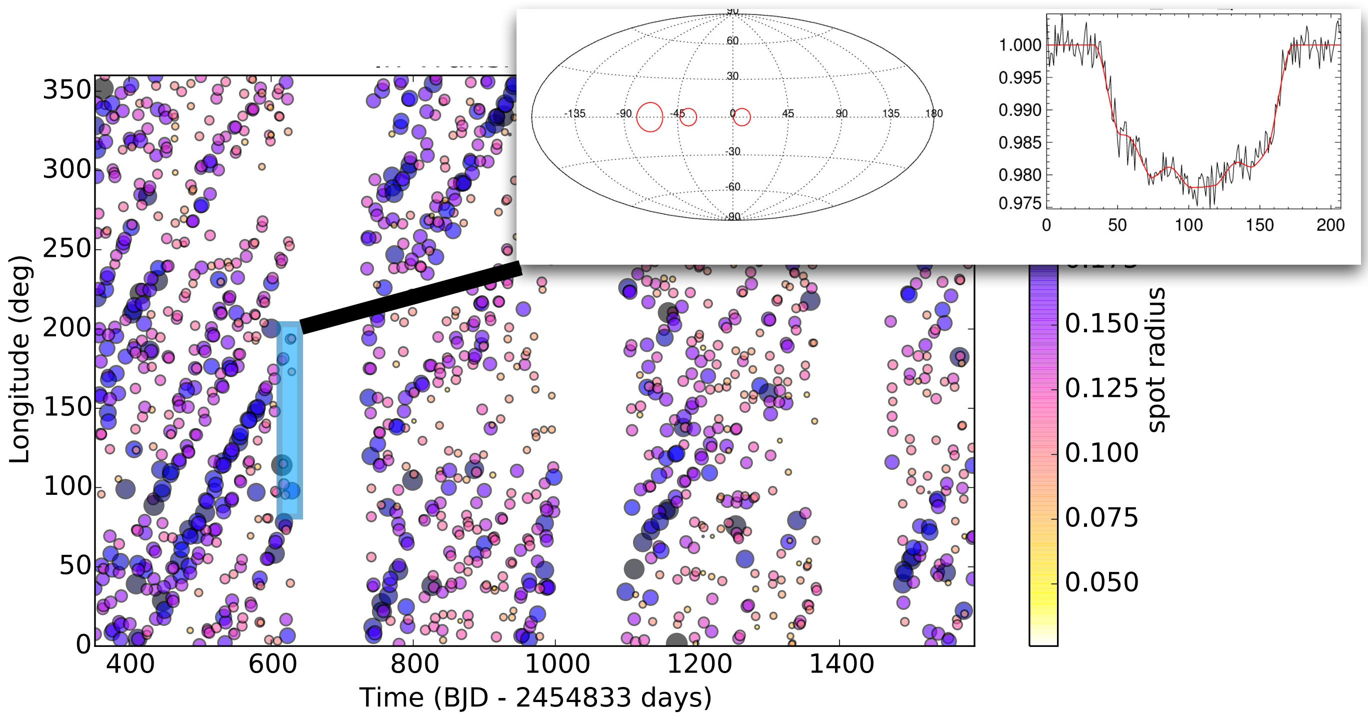
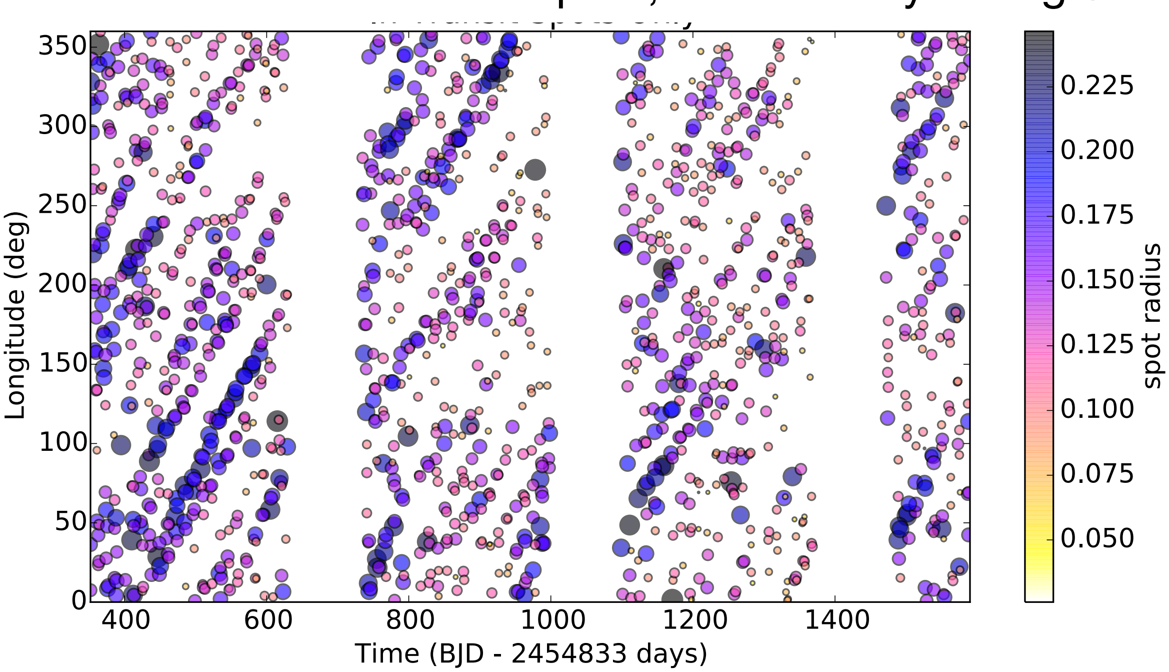


Example 1: Clustering starspot evolution tracks Kepler 17

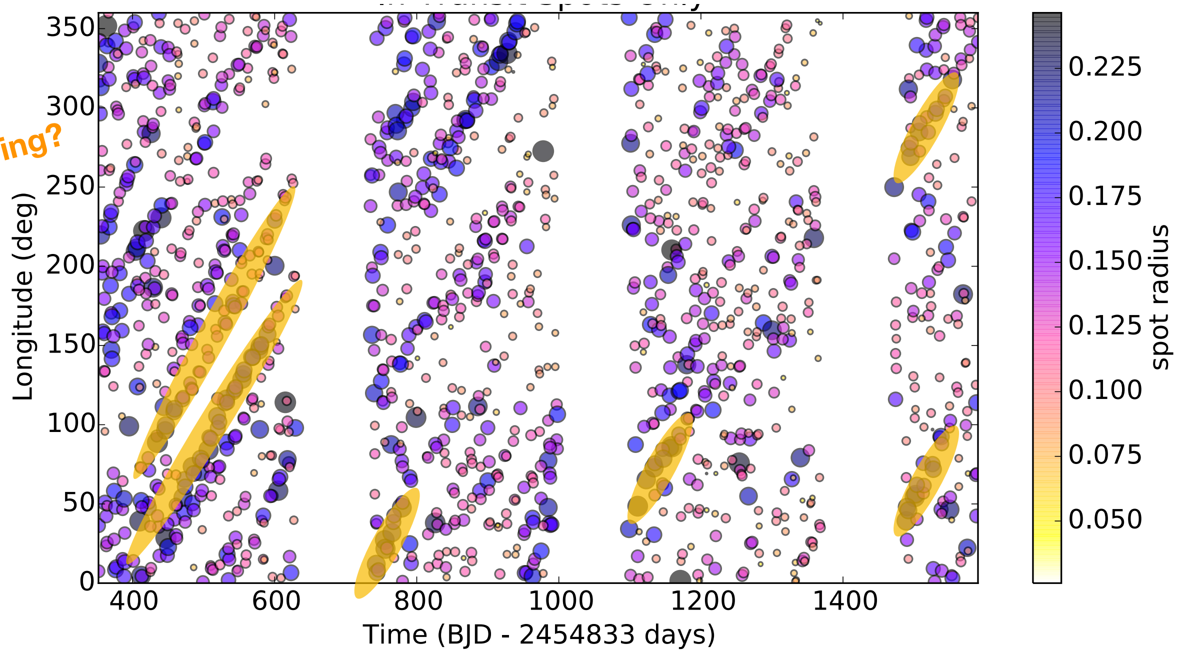
Question: Which tracks are starspots, how do they emerge/decay?



Example 1: Clustering starspot evolution tracks Kepler 17

Question: Which tracks are starspots, how do they emerge/decay?

Manual clustering?



Example 1: Clustering starspot evolution tracks

Kepler 17

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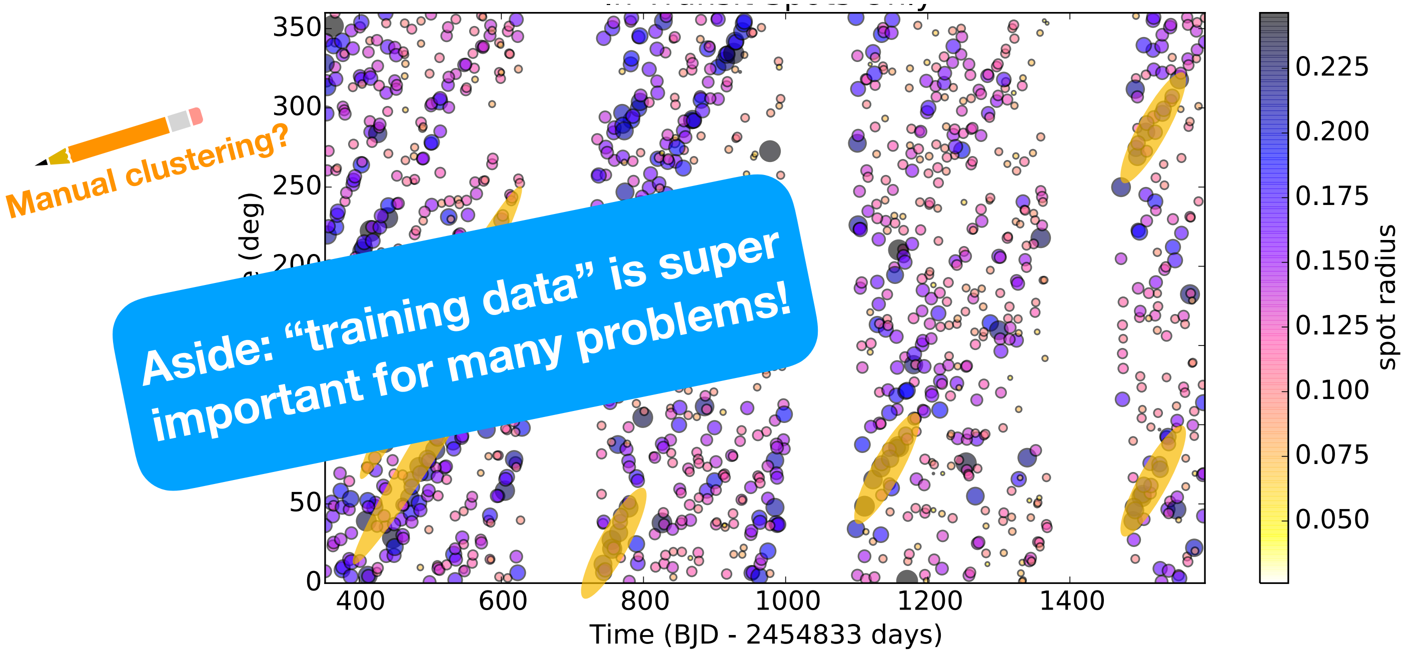

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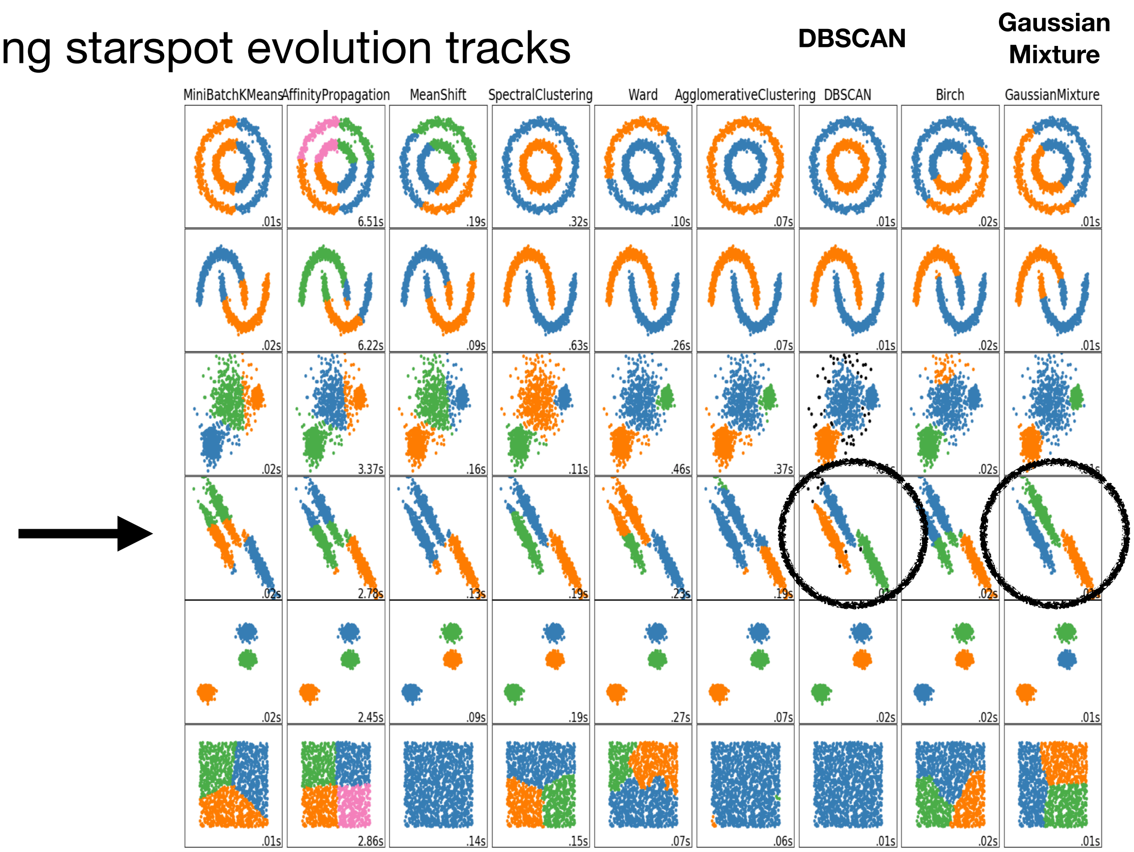
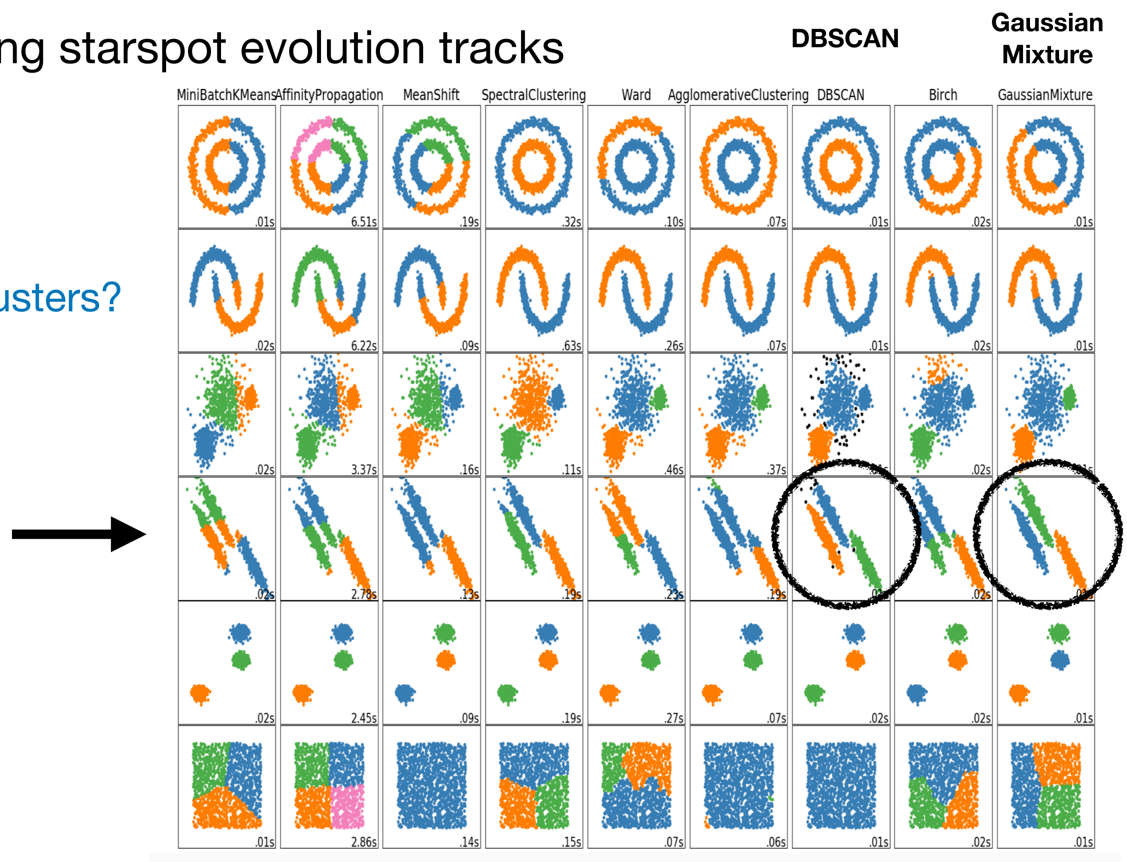


Example 1: Clustering starspot evolution tracks

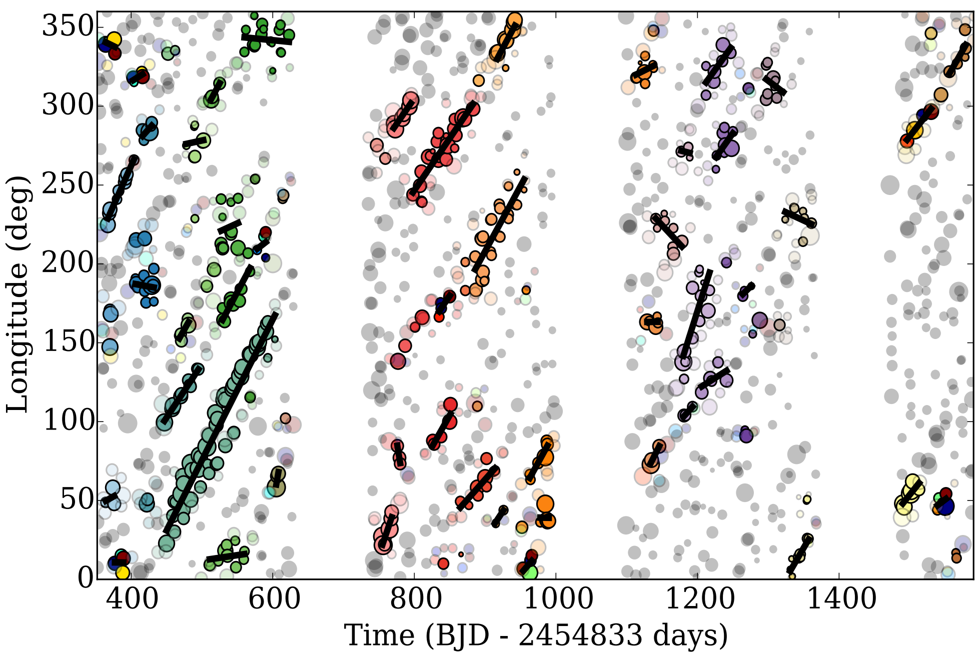
need to predefine Nclusters?



Example 1: Clustering starspot evolution tracks

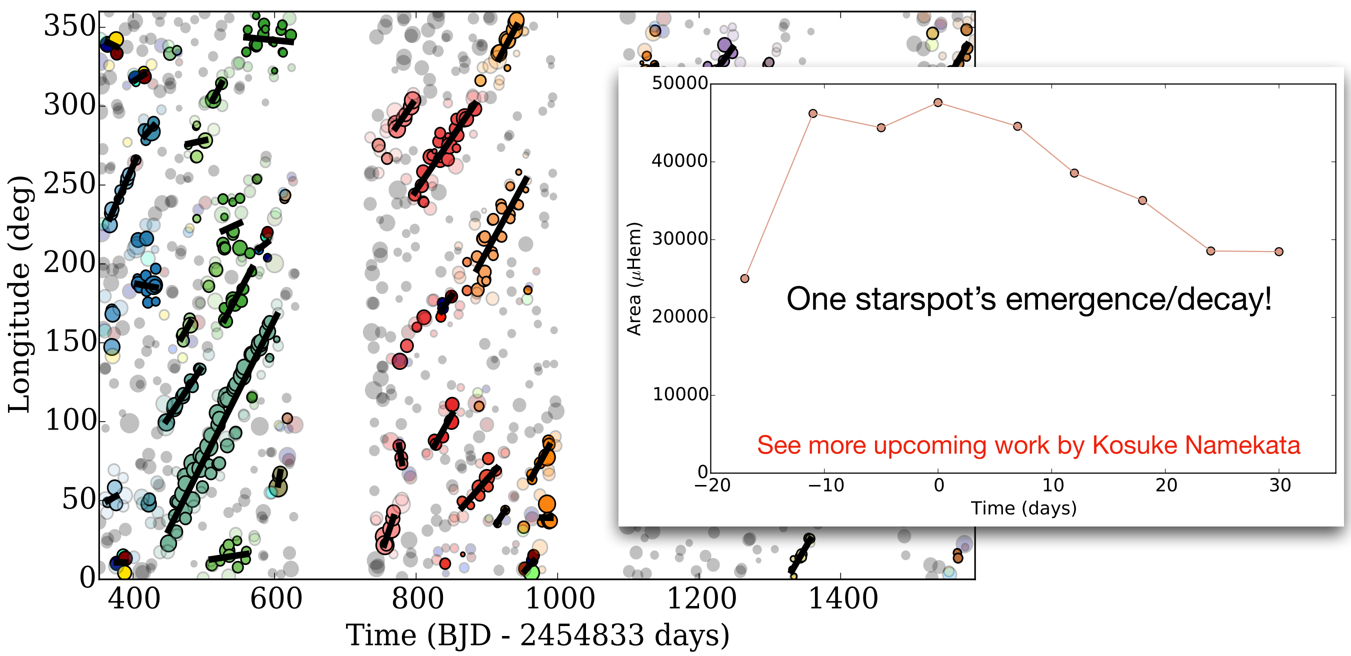
Kepler 17

DBSCAN: Density-based spatial clustering of applications with noise



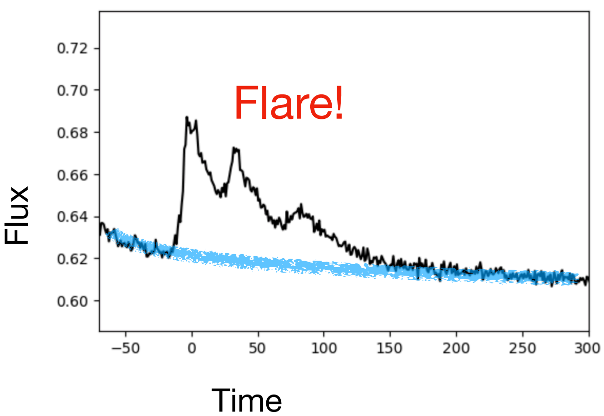
Example 1: Clustering starspot evolution tracks — Kepler 17

DBSCAN: Density-based spatial clustering of applications with noise



Example 2: Modeling a complex stellar flare

Question: Is there (quasi-) sinusoidal behavior in the flare decay?



https://github.com/RileyWClarke/QPP-GP

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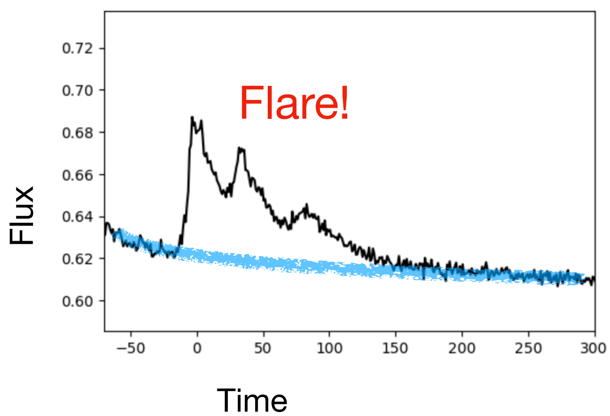

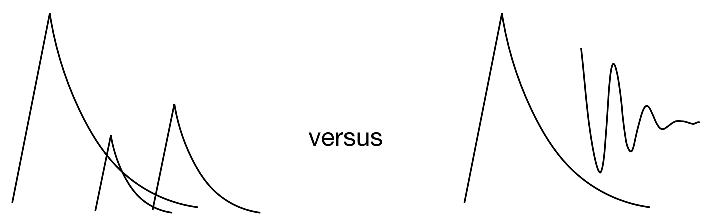

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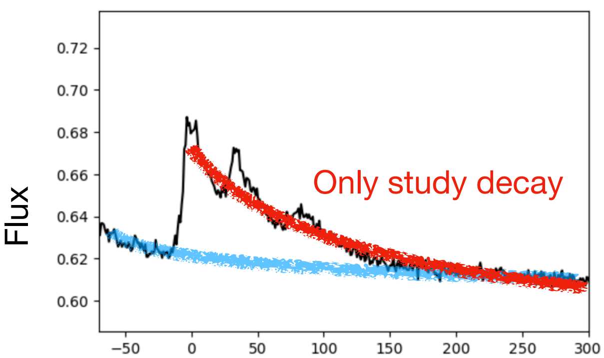

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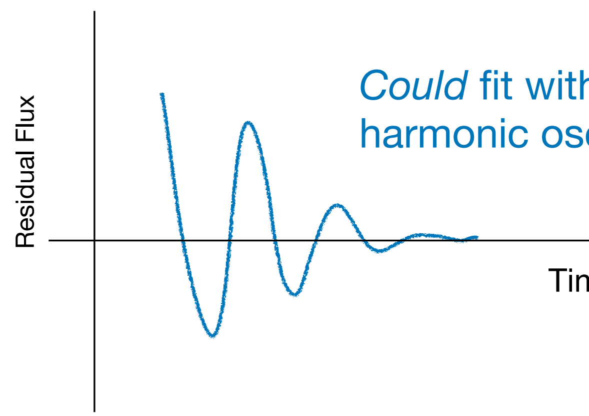

Could fit with a damped harmonic oscillator

Difficult to classify sinusoidal vs. stochastic, & strict vs quasi sinusoid

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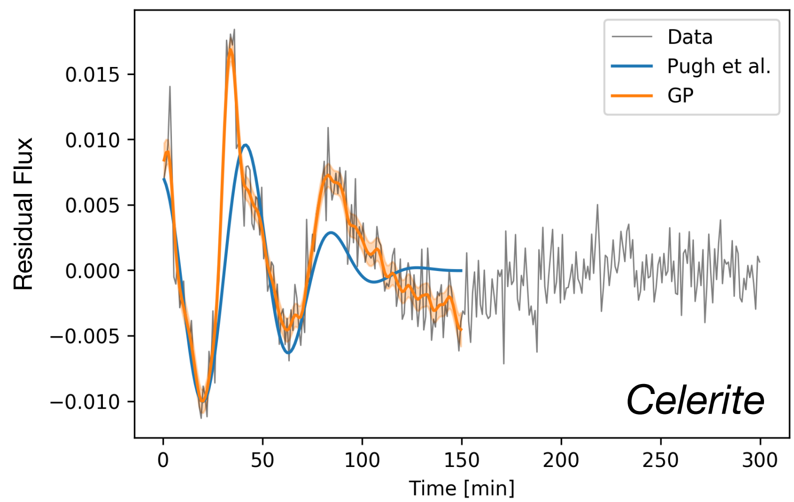
Example 2: Modeling a complex stellar flare

Gaussian Process



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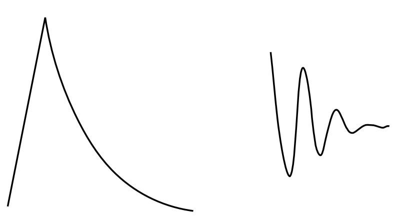
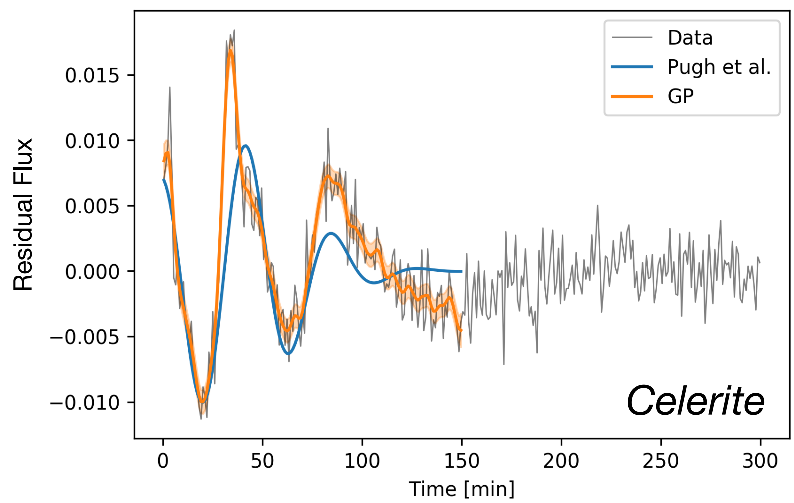
Example 2: Modeling a complex stellar flare

Gaussian Process

Use an exponential +
simple-harmonic-oscillator *kernel*





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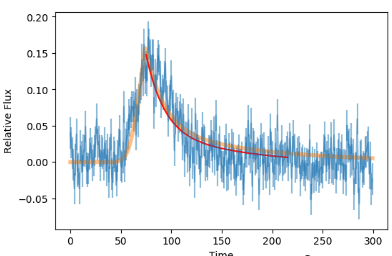
Example 2: Modeling a complex stellar flare

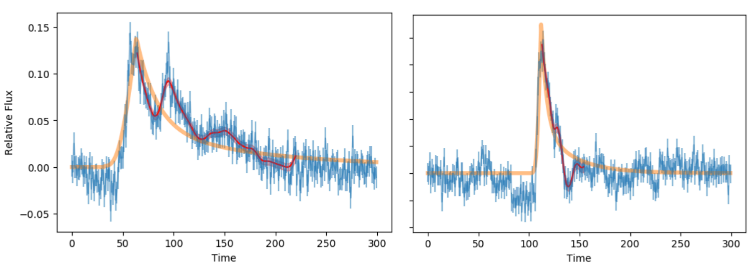
Gaussian Process

No Period



Objective search

Candidate Periods



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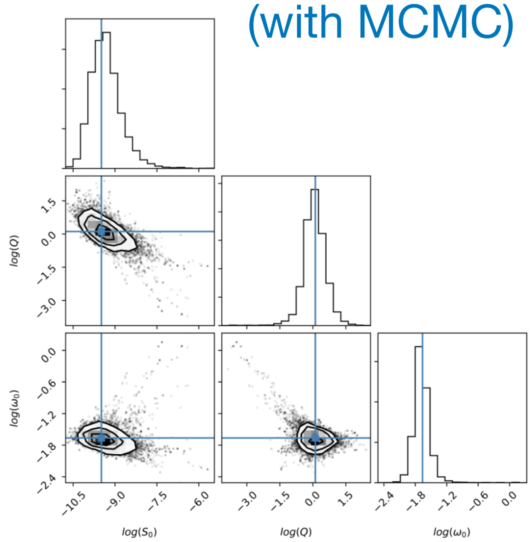
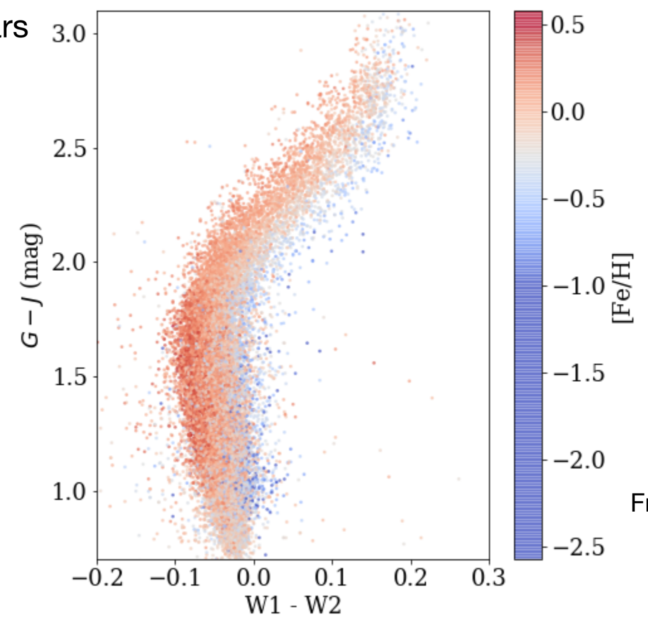
Robust uncertainties!
(with MCMC)



Example 3: Modeling photometric metallicities

Observation: [Fe/H] gradient in stars

Gaia DR2 + (WISE + 2MASS) + APOGEE



[3.4] - [4.6]

From APOGEE

https://github.com/jradavenport/ingot/

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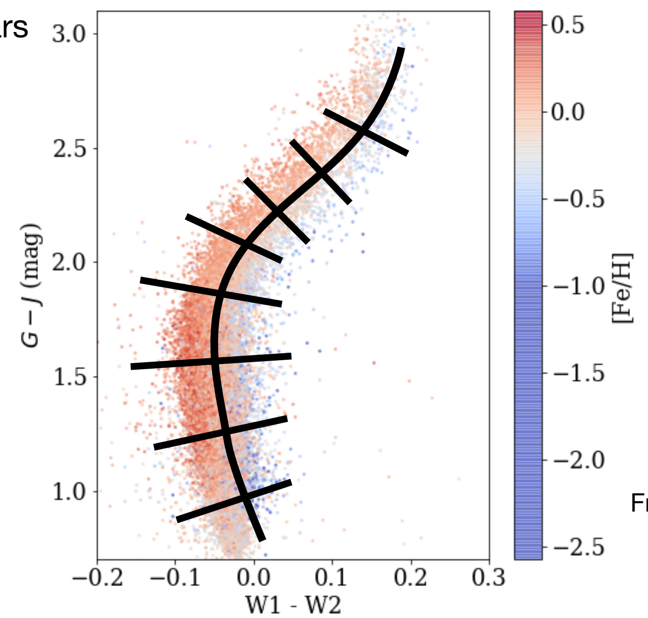
Observation: [Fe/H] gradient in stars

We could build a complex polynomial or spline model



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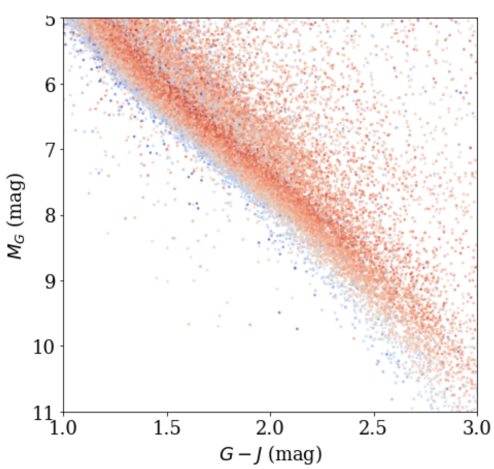
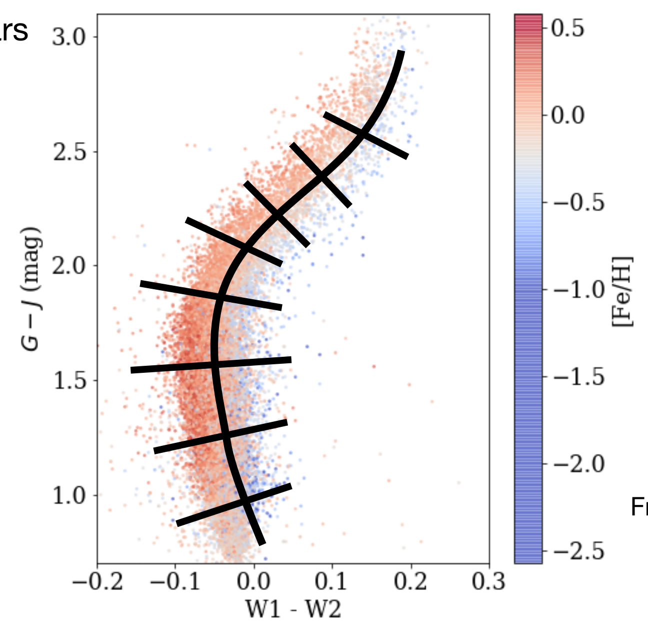
Tedious, and difficult to add additional dimensions!





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jradavenport

Example 3: Modeling photometric metallicities

Or use a simple, flexible ML model!

Observation: [Fe/H] gradient in stars

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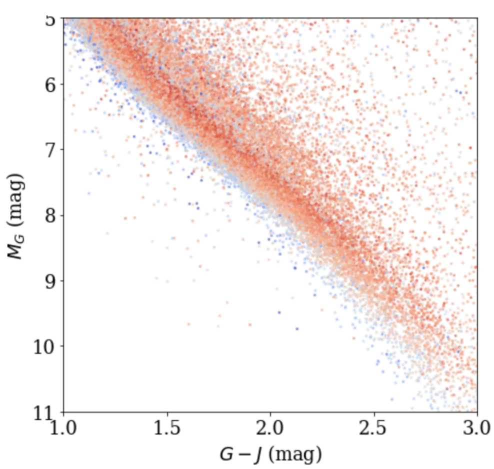

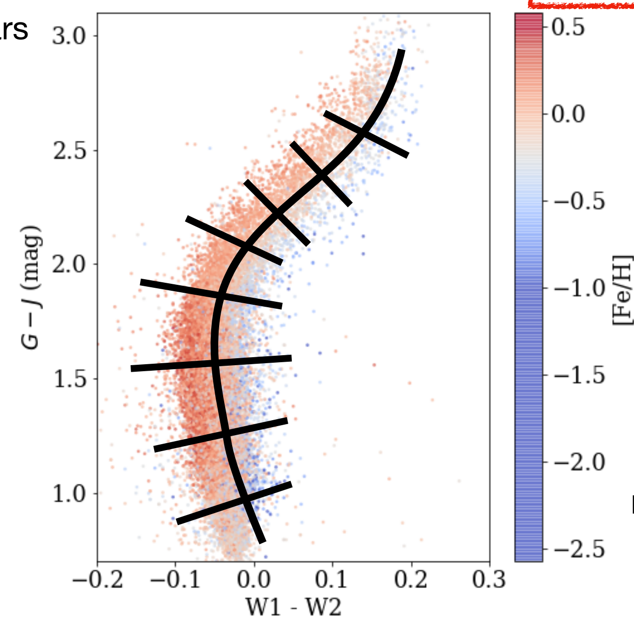

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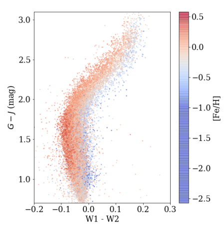
Example 3: Modeling photometric metallicities

KNearestNeighbors

Xdata = (*G-J*, W1-W2)
Ydata = [Fe/H]

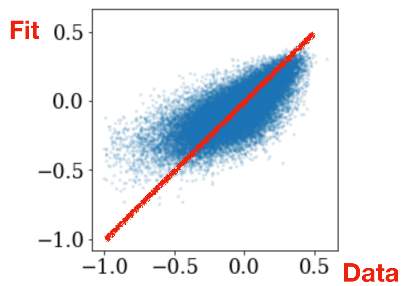



```
In [43]: model = KNeighborsRegressor(n_neighbors=5)

         model.fit(Xdata, Ydata)
         newY = model.predict(Xdata)

         plt.figure(figsize=(4,4))
         plt.scatter(Ydata, newY, s=3, alpha=0.14)
         # plt.xlim(-.5,.5)
         plt.ylim(plt.xlim())

Out[43]: (-1.0819262972727413, 0.6647018304720514)
```



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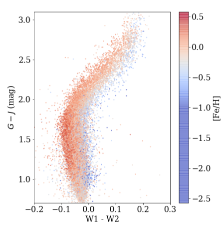


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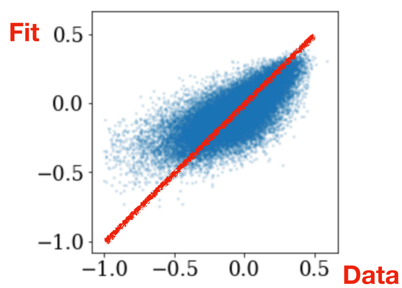
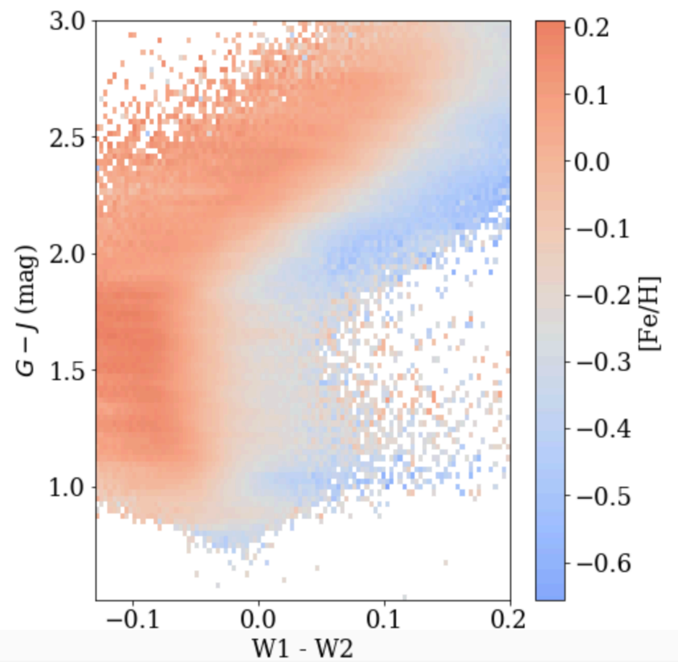


Example 3: Modeling photometric metallicities

KNearestNeighbors

<u>Result</u>: a simple to use "surface", no tweaking for shape/order, extend to addtional dimensions easily

1 Million new stars with no spectra



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KNearestNeighbors

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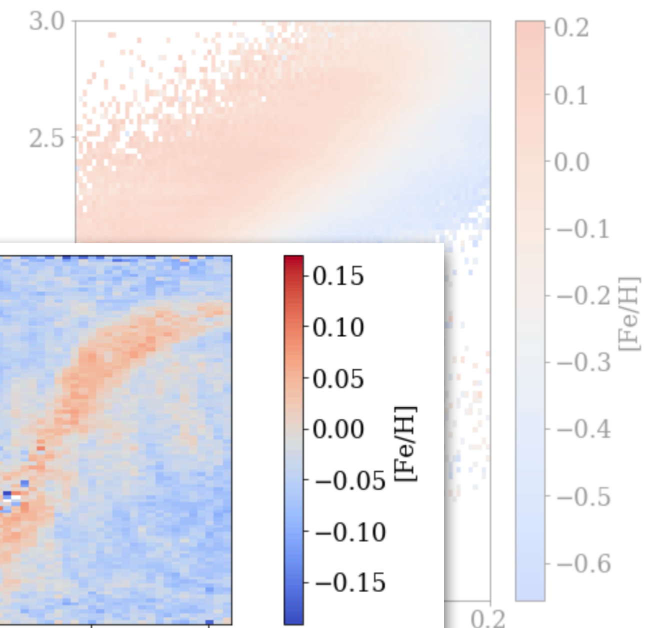

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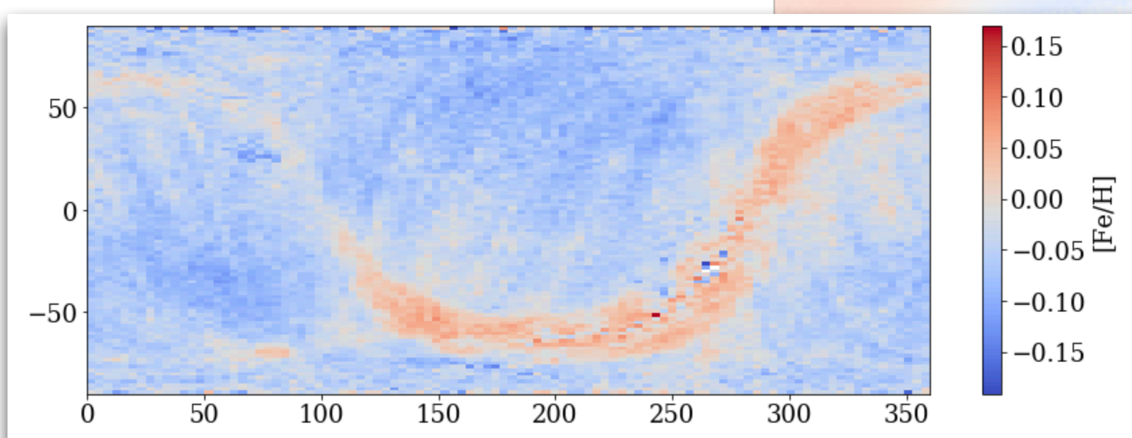

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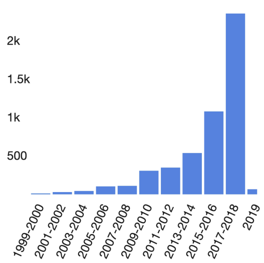
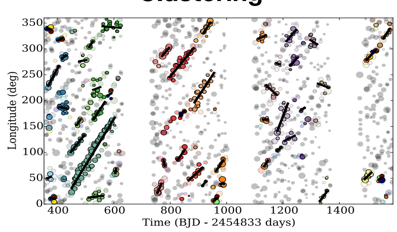
Conclusions

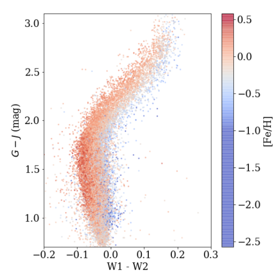


ML is easier and more “boring” than ever!

Clustering



Regression



GP’s