Improvement on Exoplanet Detection Methods and Analysis via Gaussian Process Fitting Techniques

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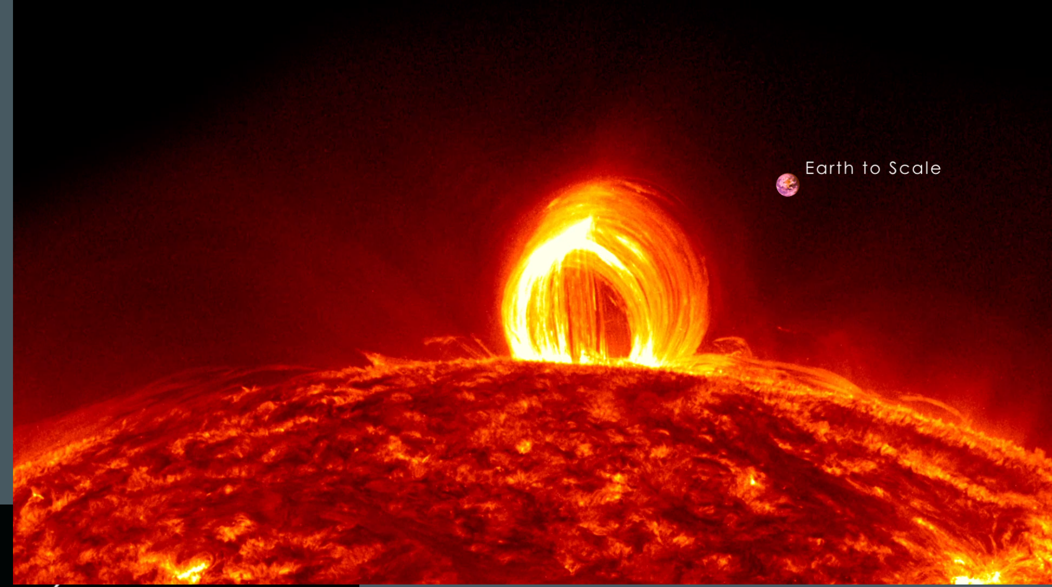
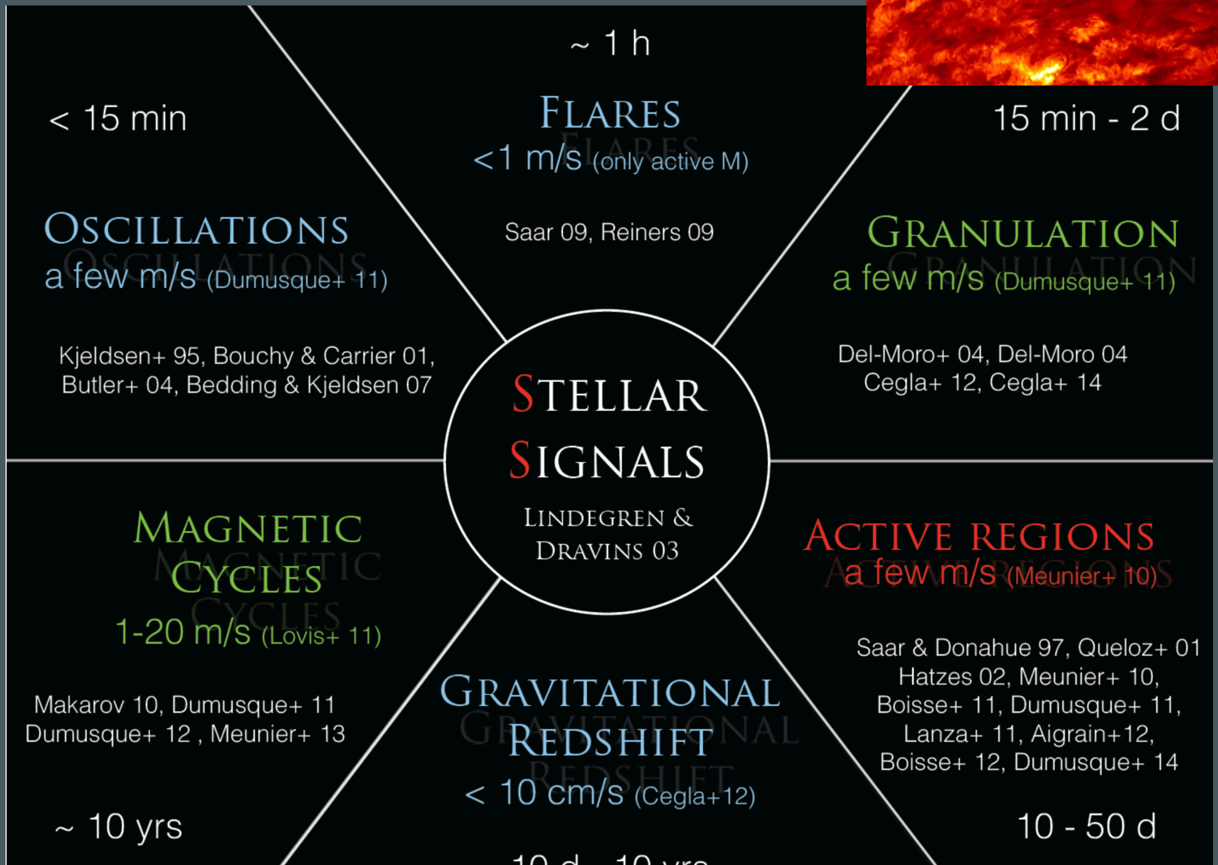
Motivation

- Finding (*small*) exoplanets proves difficult ... but possible!
- Existing problems include:
  - Our instrumentation isn't precise enough (*should be 10cm/s*).
  - Stellar activity of host stars complicate our readouts of planetary signals.

Stellar Activity Sources





credit: X. Dumusque

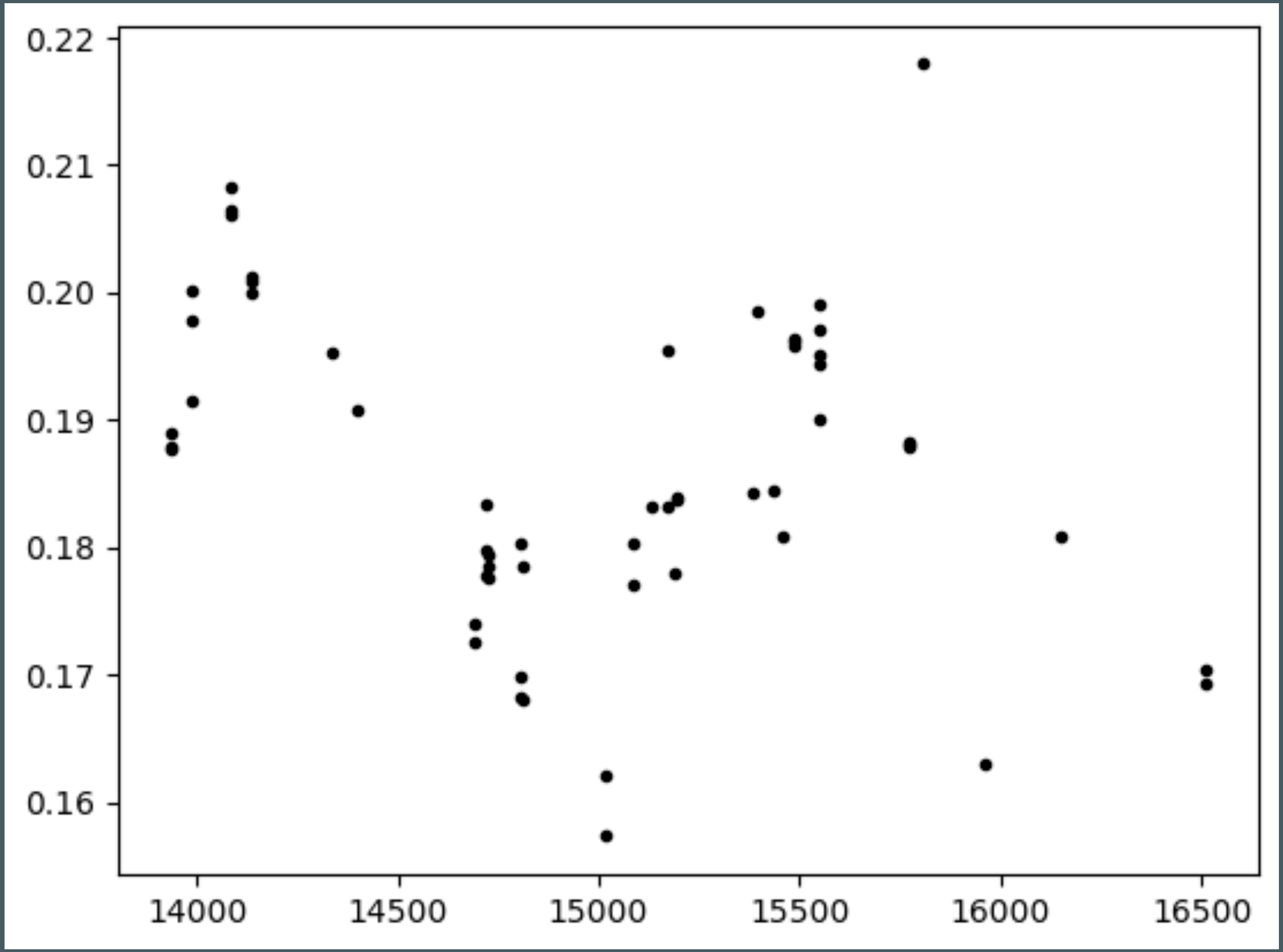
Solution

- Gaussian Process (GP) fits of stellar data.

Why?

- GP has proven itself successful in astrophysical and other fields.
- Ex: time series analyses to infer physical properties; exoplanet population; exoplanet detection via RV data.

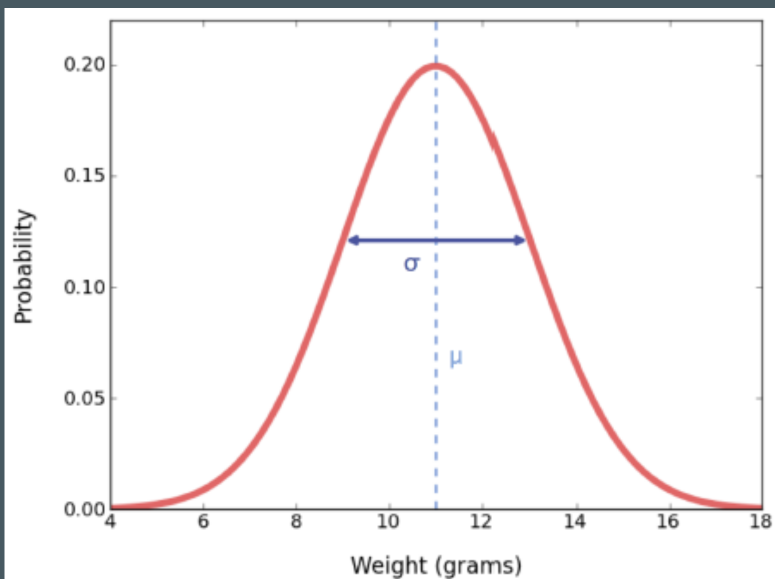
Example of Measurements

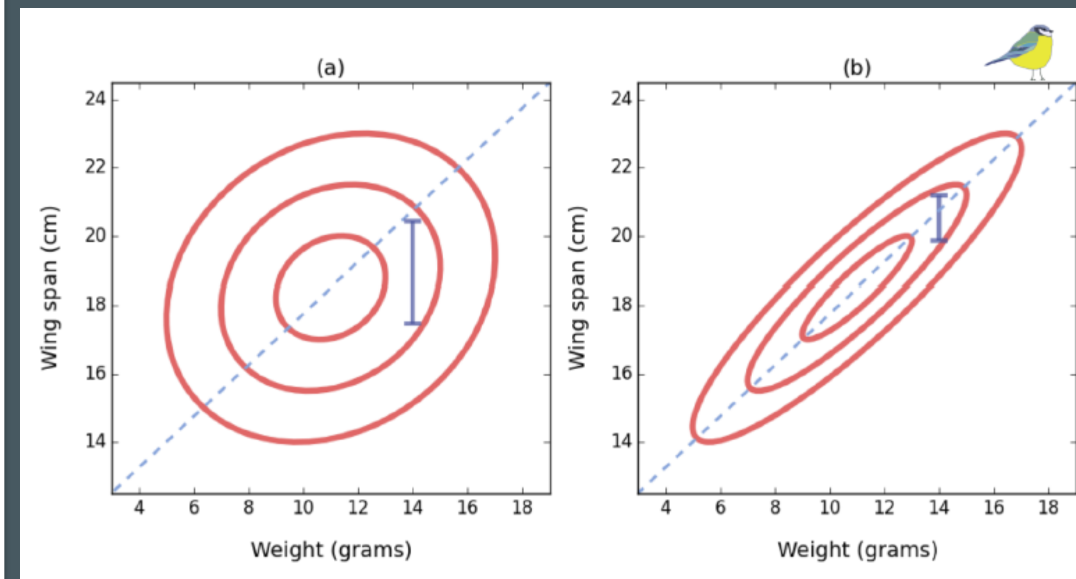


S_{HK} values

MJD (time)

What are Gaussian Processes?





$$P(y) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}$$

Standard deviation

Mean

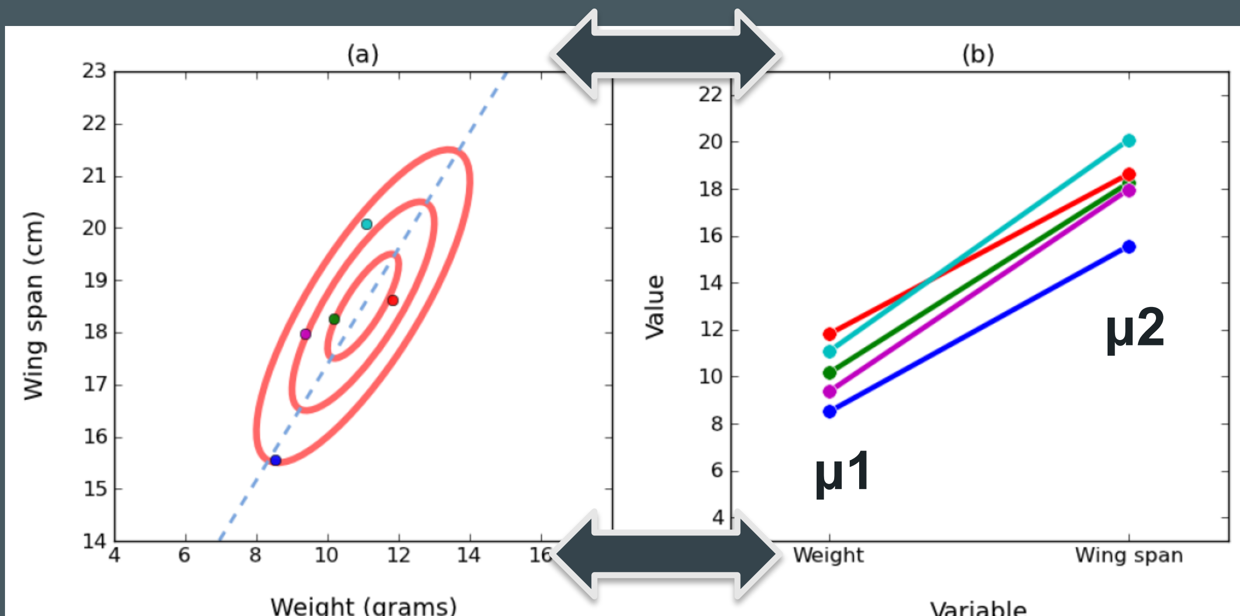
2 dimensional Gaussian

σ is now width of ellipse

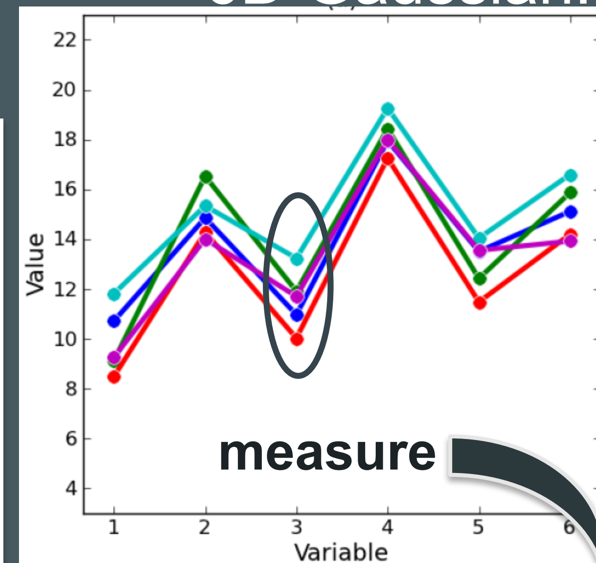
ellipses now centered on **μ**

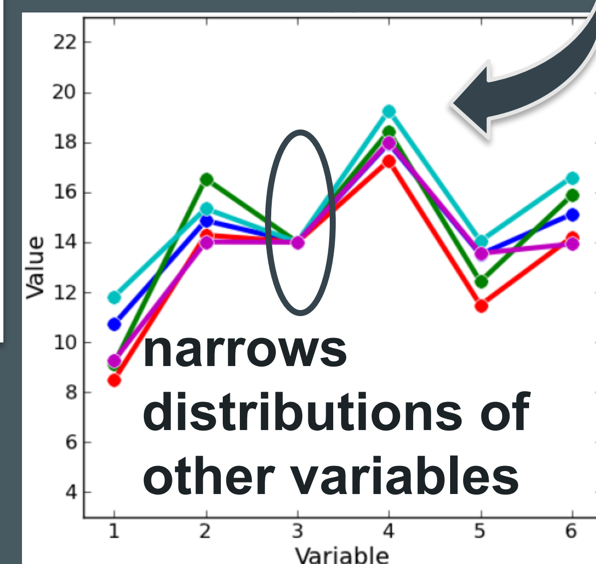
Figures from Raphaëlle Haywood's Ph.D. thesis

What are Gaussian Processes?



6D Gaussian!

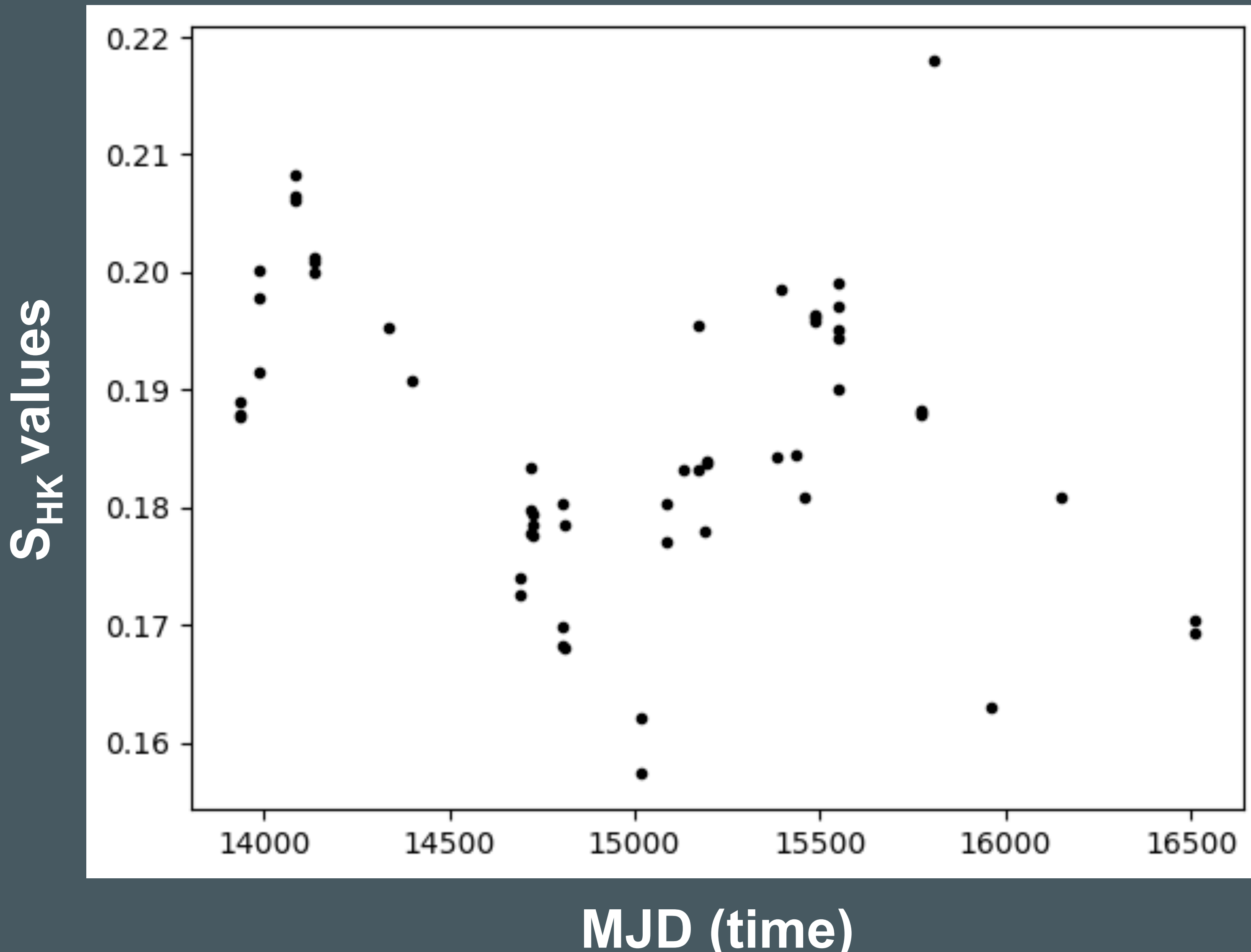




New way to represent 2D Gaussian:
5 samples from joint prior distribution of two variables

Figures from Raphaëlle Haywood's Ph.D. thesis

What are Gaussian Processes?

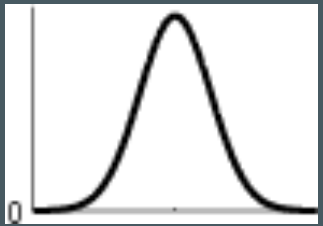


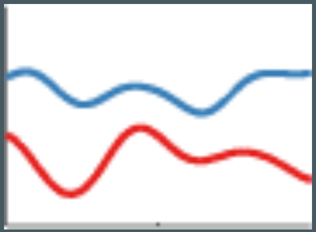
What are Gaussian Processes?

- Definition:
  - Function(s) of covariance amongst variables that change collectively.
- We use GP to measure correlation of our stellar data.
- Different GP’s affect the quality of your fits.
  - Difficulty is determining appropriate parameters and models.

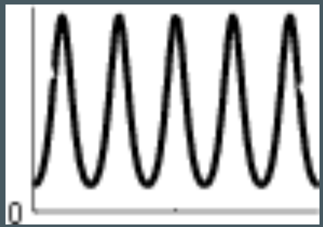
Kernels (covariance functions)

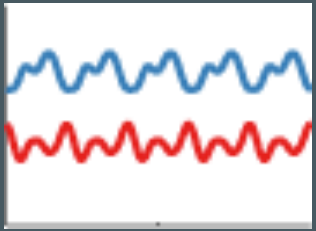
$$k_{\mathrm{SE}}(x, x') = \sigma^2 \exp\left(-\frac{(x-x')^2}{2\ell^2}\right)$$



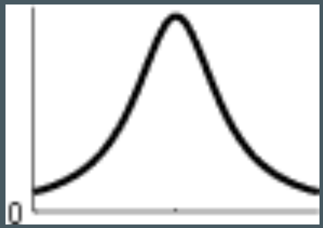


$$k_{\mathrm{Per}}(x, x') = \sigma^2 \exp\left(-\frac{2\sin^2(\pi|x-x'|/p)}{\ell^2}\right)$$





$$k_{\mathrm{RQ}}(x, x') = \sigma^2 \left(1 + \frac{(x-x')^2}{2\alpha\ell^2}\right)^{-\alpha}$$



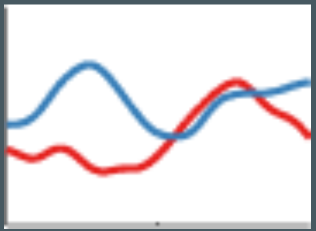
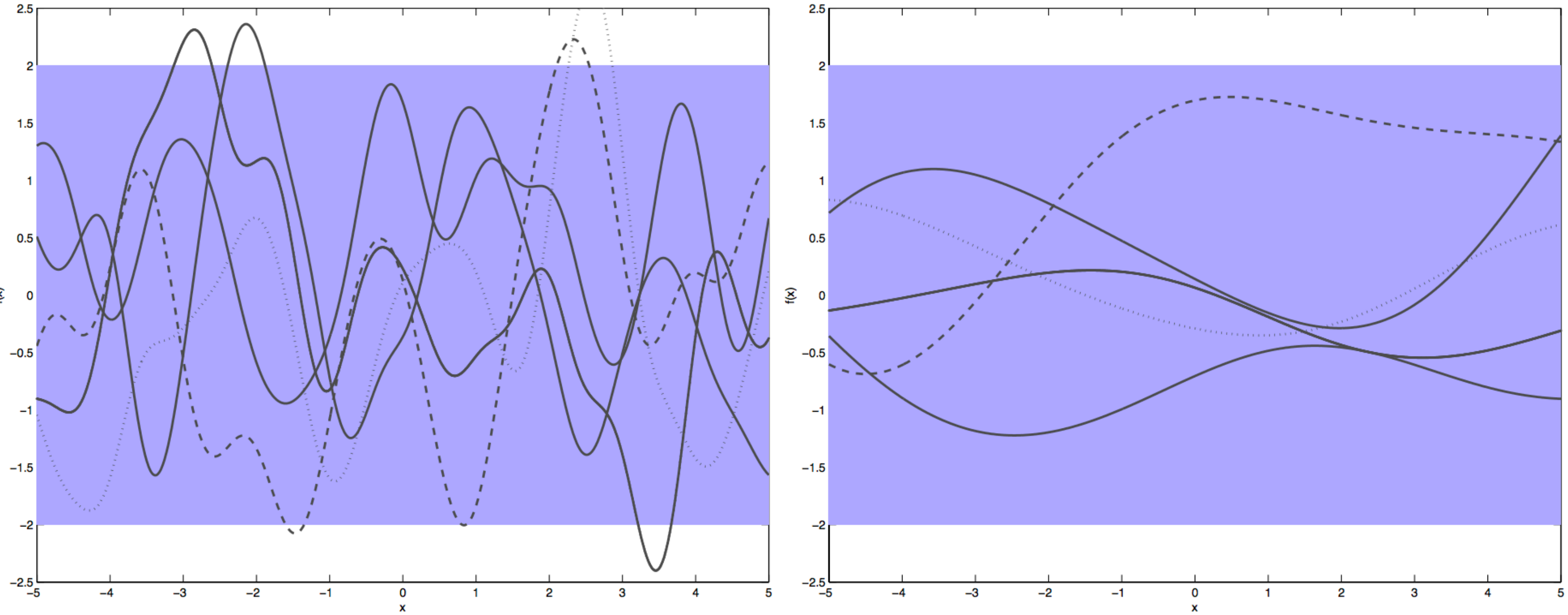


Photo Credit: David Duvenaud, "The Kernel Cookbook: Advice on Covariance functions"

Hyperparameters (what control kernels)



(a) small length scale **(b)** large length scale

Figure 2.4: Random samples from a Gaussian process prior with squared exponential covariance function. The left panel shows a small SE with small length scale value (0.5), whereas the right panel has a much larger value (3).

Photo Credit: Markus Schneider 's Thesis, "Learning from Demonstration with Gaussian Processes"

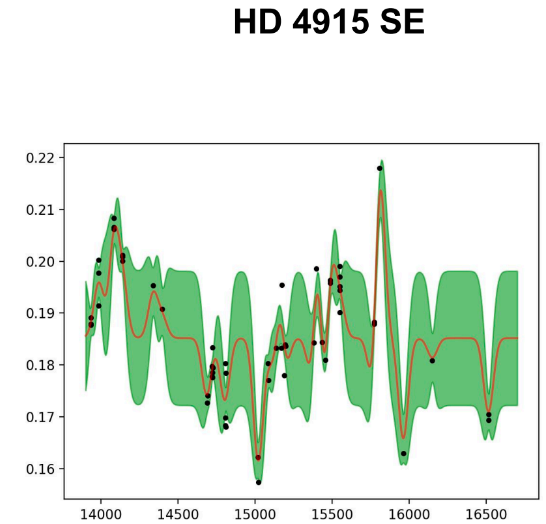
Methods

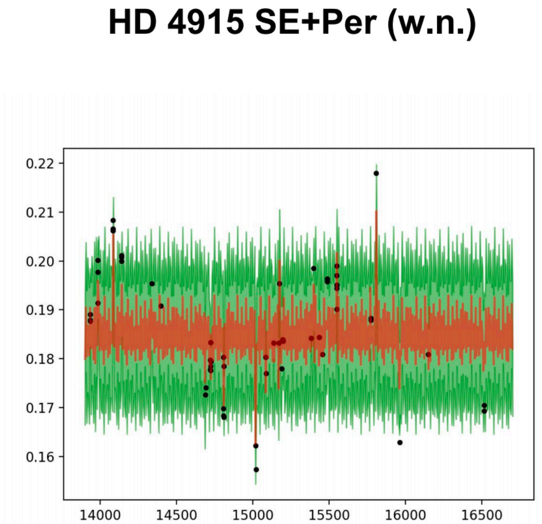
- Sample S-values (Ca II H and K measurements) of stars from Keck/HIRES.
- Apply GP to fit data and measure correlation.
- Adjust hyperparameters and/or consider alternative combination of kernels, until optimized.

Method

- Analysis
  - GP Fits
  - Corner Plots
  - Likelihood

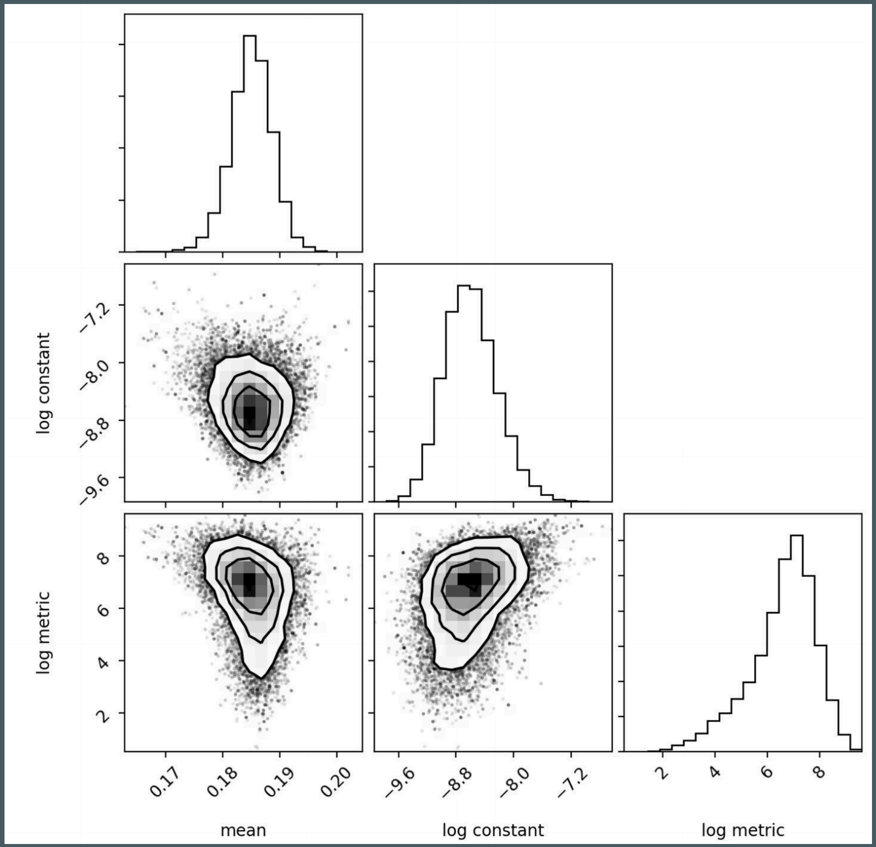
Qualitative GP Fits





Bryce Van Ross, August 26, 2017

Corner Plots



Bryce Van Ross, August 26, 2017

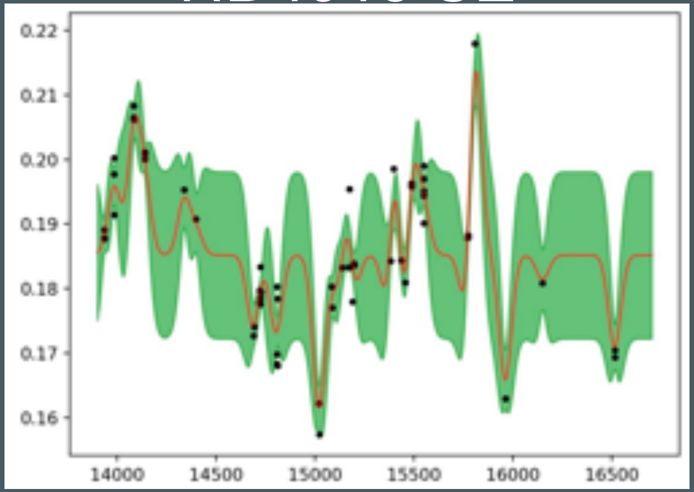
Likelihood

BIC= ln(sample size)*parameters+(max log likelihood)

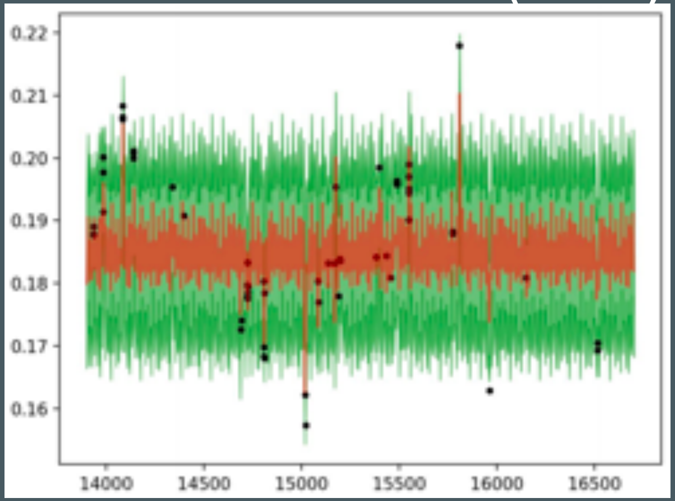
Star, Kernel (White Noise)	Fun Value	BIC	Delta BIC
HD4915, SE	-197.654	-383.179	0
HD4915, SE (White Noise)	-197.654	-379.136	4.043
HD4915, Per	-186.594	-357.016	26.163
HD4915, Per (White Noise)	-187.684	-355.153	28.026
HD4915, SE+Per	-181.964	-339.670	43.509
HD4915, SE+Per (White Noise)	-173.01	-317.719	65.460
HD4915, RQ	-198.388	-380.604	2.575
HD4915, RQ (White Noise)	-198.388	-376.561	6.618
HD4915, SE+Per+RQ	-198.967	-361.547	21.632
HD4915, SE+Per+RQ (White Noise)	-198.927	-357.423	25.755
HD10700, SE	-2677.292	-5334.680	119.253
HD10700, SE (White Noise)	-2706.79	-5387.041	66.892
HD10700, Per	-2492.059	-4957.579	496.354
HD10700, Per (White Noise)	-2593.152	-5153.131	300.803
HD10700, SE+Per	-2677.292	-5314.776	139.157
HD10700, SE+Per (White Noise)	-2677.292	-5308.142	145.792
HD10700, RQ	-2740.236	-5453.933	.000
HD10700, RQ (White Noise)	-2740.236	-5447.299	6.635
HD10700, SE+Per+RQ	-2677.292	-5294.872	159.061
HD10700, SE+Per+RQ (White Noise)	-2752.542	-5438.738	15.196
HD154345, SE	-654.593	-1293.145	49.253
HD154345, SE (White Noise)	-654.593	-1287.798	54.600
HD154345, Per	-536.803	-1052.218	290.180
HD154345, Per (White Noise)	-539.691	-1052.646	959.219
HD154345, SE+Per	-668.098	-1304.113	38.284
HD154345, SE+Per (White Noise)	-654.593	-1271.756	70.641
HD154345, RQ	-681.893	-1342.398	.000
HD154345, RQ (White Noise)	-681.893	-1337.050	5.347
HD154345, SE+Per+RQ	-682.329	-1316.534	25.864
HD154345, SE+Per+RQ (White Noise)	-692.065	-1330.659	11.739

Results

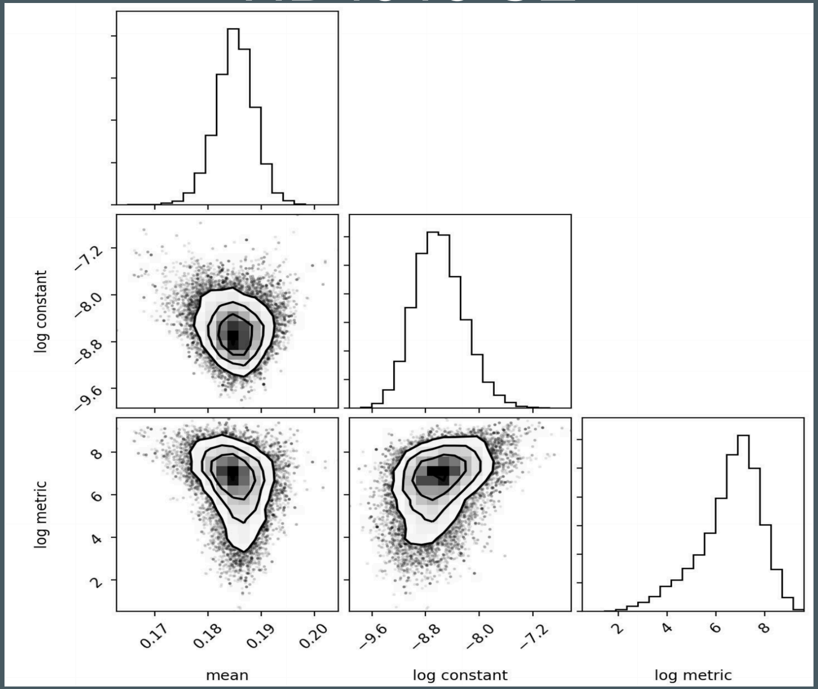
HD4915 SE



HD4915 SE+Per (w.n.)



HD4915 SE

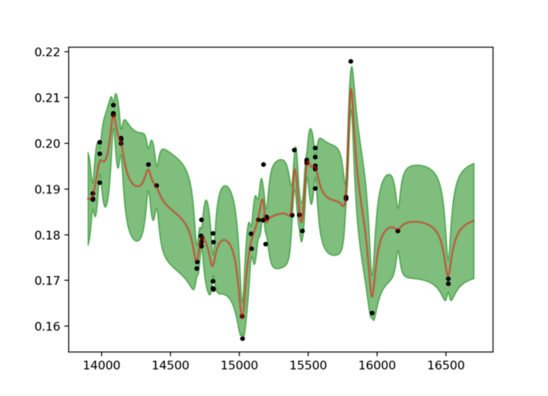


Bayesian Information Criterion (BIC):

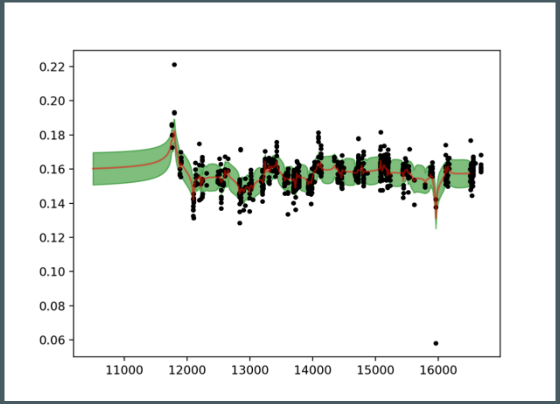
ln(sample size)*parameters + max log likelihood

What's the Best Fit?

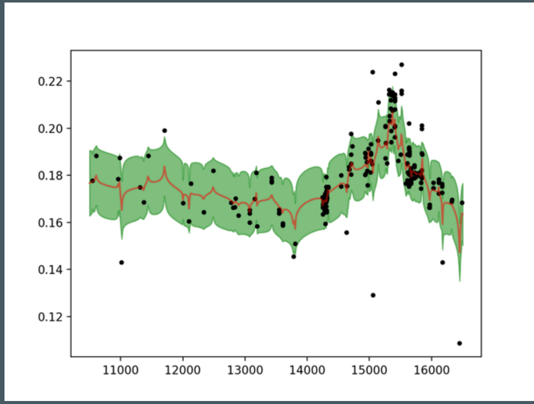
HD4915 RQ

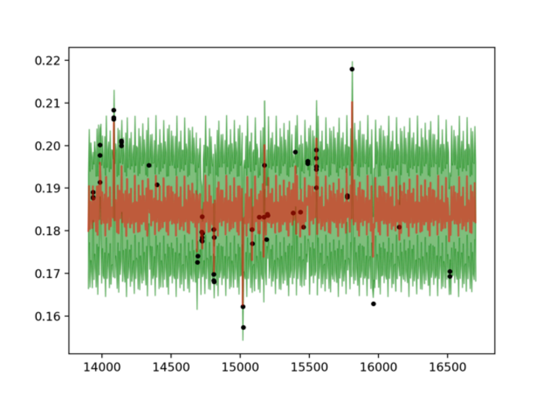


HD10700 RQ

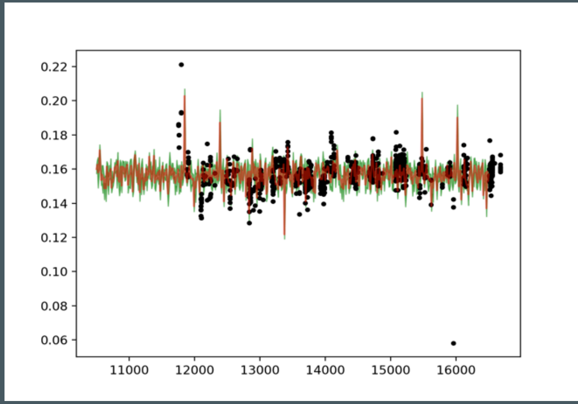


HD154345 RQ

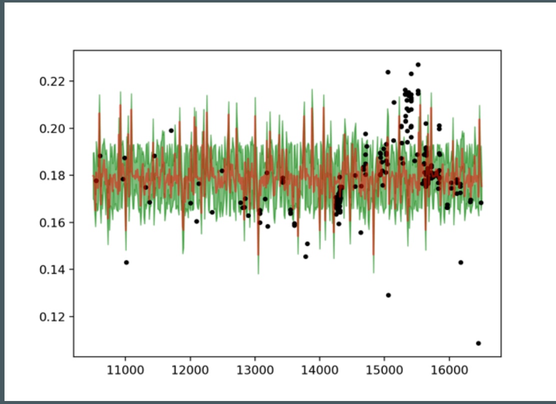




HD4915 SE+Per (w. noise)



HD10700 Per



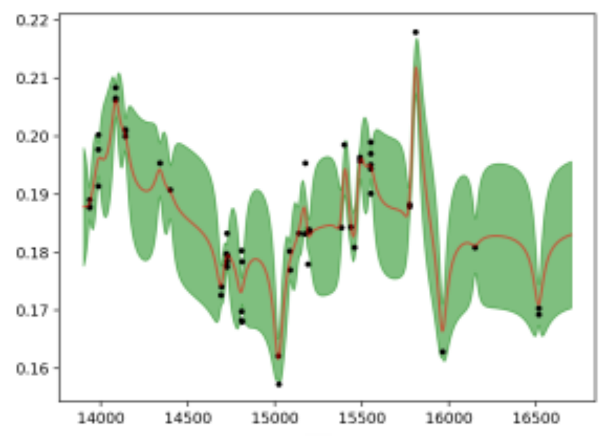
HD154345 Per (w. noise)

Bryce Van Ross, 09/19/17

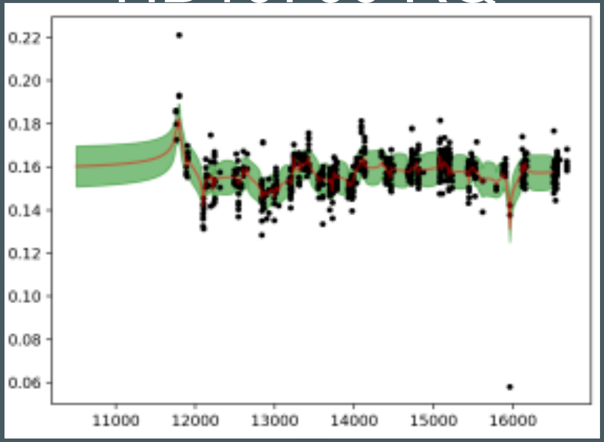
Conclusions Thus Far

- Per and Per(w. noise) fit the data poorly.
- RQ, RQ(w. noise), and SE+Per+RQ(w. noise) are likely the best kernels.
- Hyperparameters need reevaluation, but some are well constrained.

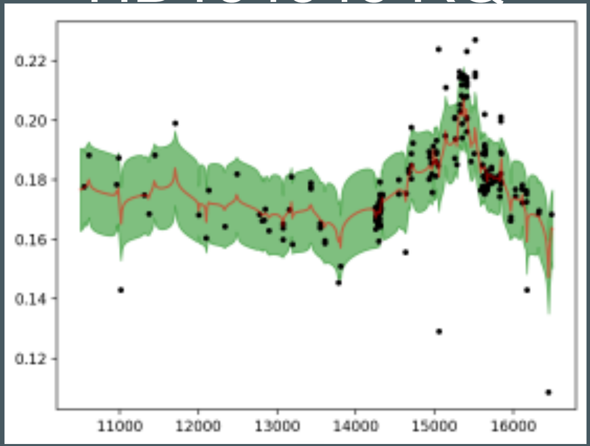
HD4915 RQ



HD10700 RQ



HD154345 RQ



Next Steps

- Can we infer the same results with H-alpha?
- Apply to RV data of same stars
  - **Method 1:** Subtract our stellar fit from RV model, then fit residuals using Keplerian parameters.
  - **Method 2:** Simultaneously unite our stellar fit with Keplerian.
  - Interpret Keplerian parameters.
- GP fits to the stellar activity data not well constrained? Maybe need more observations to reliably remove the stellar activity signal, reveal real planetary signals in RVs.

Acknowledgements

Further Questions?

Feel free to email me at:

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