Accounting for activity-induced RV variations through Gaussian-process regression

Stellar activity or Earth-mass planet?

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How will we overcome the stellar activity barrier?

By learning about the physical processes at play on the surfaces of stars







By learning about the physical processes at play on the surfaces of stars

See tomorrow







Treat activity-induced RV variations as (correlated) "noise"

Baluev (2012), Tuomi et al. (2012), Haywood et al. (2014), Rajpaul et al. (2015), Faria et al. (2016), Anglada-Escudé et al. (2016), Mortier et al. (2016), López-Morales et al. (2016), Grunblatt et al. (2017) and many others.



Gaussian process fit to RV data

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Note: I am talking about rotation-modulated signals arising from surface features.



Gaussian process fit to RV data







Time

• In radial-velocity (RV) time-series:

Planet signals: periodic and coherent

Activity signals:

quasi-periodic and non-coherent

• white noise correlated noise \rightarrow chi2 log \mathcal{L}

• In radial-velocity (RV) time-series:

Planet signals: periodic and coherent **Activity signals:** quasi-periodic and non-coherent

• white noise correlated noise \rightarrow chi2 log \mathcal{L}

• Activity-induced RV variations are a signature of the intrinsic magnetic behaviour of a star. All observables, eg. the lightcurve, R'_{HK} index, FWHM,... share a common frequency structure and similar covariance properties.

All data points are completely independent of each other



All data points are completely independent of each other



Data points are correlated with each other



Data points are correlated with each other



Covariance matrix



Rotation-modulated activity: quasi-periodic variations



Lightcurve

Rotation-modulated activity: quasi-periodic variations



 $\mathbf{K}_{i,j} = k (t_i, t_j)$



 $\mathbf{K}_{i,j} = k \ (t_i, t_j)$



Typical Kepler lightcurves of FGKs stars



Corresponding autocorrelation functions (ACFs)











$$k(t,t') = \eta_1^2 \cdot \exp\left[-\frac{(t-t')^2}{2\eta_2^2} - \frac{2\sin^2\left(\frac{\pi(t-t')}{\eta_3}\right)}{\eta_4^2}\right]$$













Determining the hyperparameters



- Can "train" the GP on an auxiliary dataset, eg. the lightcurve (Haywood et al. 2014, Grunblatt et al. 2015), the spectroscopic indicators like FWHM, BIS (Rajpaul et al. 2015), in some cases even the RVs themselves (Faria et al. 2016)
- Can "fix" the hyperparameter values using Gaussian priors, based on prior knowledge/analysis (López-Morales et al. 2016)

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López-Morales, Haywood, Giles et al. (2016)







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Maximize likelihood function to determine best-fit parameters and uncertainties, eg. via MCMC procedure:

$$\ln \mathcal{L} = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln(\det \mathbf{K}) - \frac{1}{2}\left(\underline{y} - \underline{\mu}\right)^T \mathbf{K}^{-1}(\underline{y} - \underline{\mu})$$

n: number of RV observations

$$y = \text{RV}$$

 $\mu = \text{model}$
 $\mathbf{K}_{i,j} = k(t, t') = \eta_1^2 \cdot \exp\left[-\frac{(t-t')^2}{2\eta_2^2} - \frac{2\sin^2\left(\frac{\pi(t-t')}{\eta_3}\right)}{\eta_4^2}\right]$



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Use priors for stellar rotation and active region lifetime derived from *Kepler* lightcurve Place strong prior on η₄



Lightcurve amplitude (mag)











Synthetic stellar surface



Synthetic stellar surface



Reconstructed lightcurve



-0.015 -0.01

85×10-3

Delta Delta

0.01

0.015

-0.01

0.01

0-0

Synthetic stellar surface



Band centre wavelength [A] = 5500.

Reconstructed surface map





A lightcurve, or an RV curve, will only ever show 2-3 peaks per stellar rotation. This is equivalent to $\eta_4 \approx 0.5$.

$$k(t,t') = \eta_1^2 \cdot \exp\left[-\frac{(t-t')^2}{2\eta_2^2} - \frac{2\sin^2\left(\frac{\pi(t-t')}{\eta_3}\right)}{\eta_4^2}\right]$$



Kepler-21b in the mass-radius diagram



Adapted from López-Morales et al. (2016)

• GPs are just like any other statistics tool: garbage in, garbage out! Choice of covariance function/hyperparameters is crucial. Must think carefully of physical phenomena/instrumental sources to be accounted for.

• Precision \neq accuracy

• There is only so much data can tell you Degeneracies produced by disc-averaged measurements. Must think about observing strategy. See Friday

• Statistics do not tell you about the nature of a signal.

For more on GPs: see online lectures/code by Dan Foreman-Mackey, among many others — just ask me! rhaywood@cfa.harvard.edu