

Filtering stellar activity out from exoplanet observations with Gaussian processes

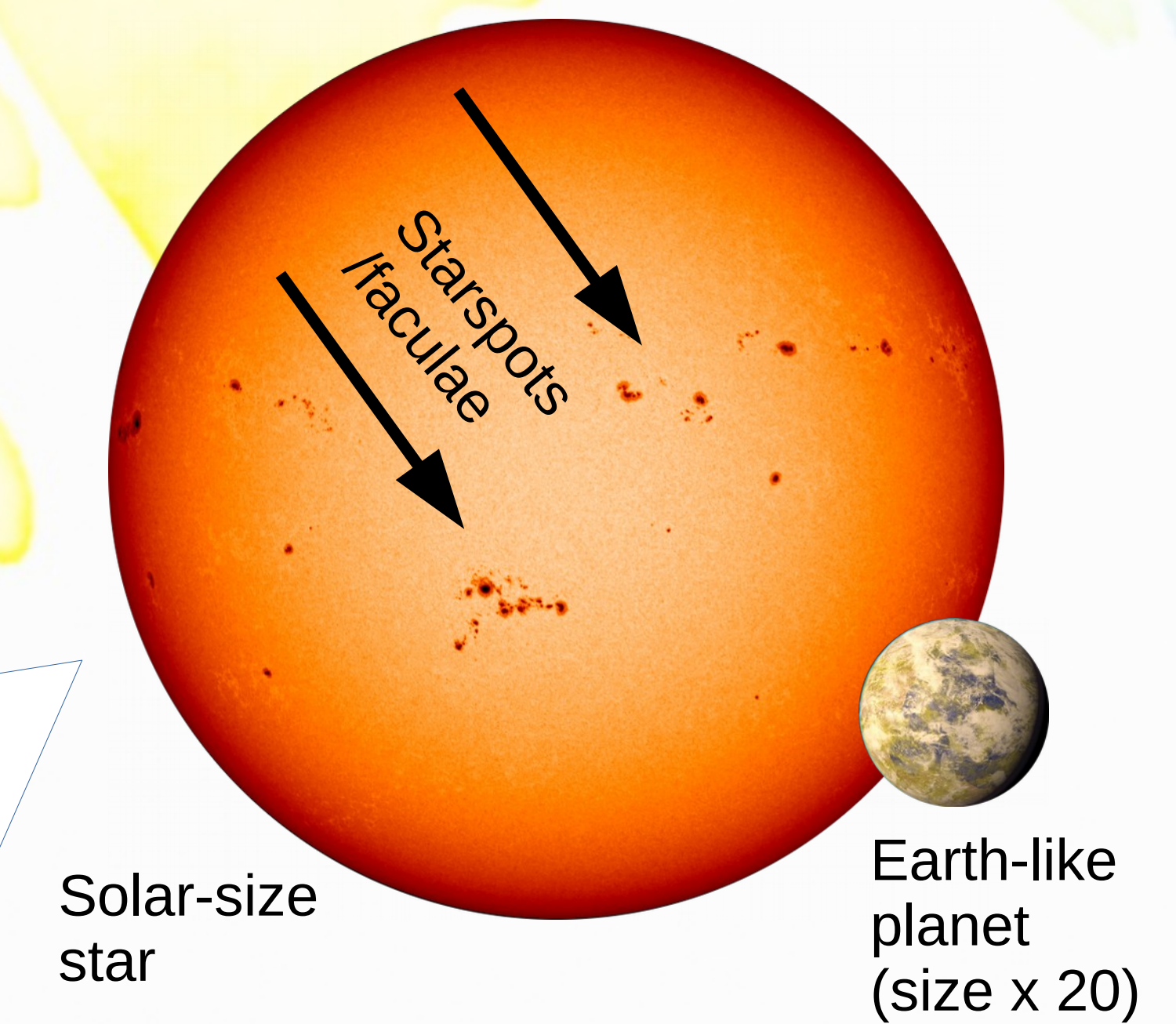
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Dynamo-driven stellar magnetic activity is one of the most problematic sources of contamination of the exoplanet signal, because of the stochastic behaviour of its manifestations, such as **starspots** and **faculae**.

Photometric and spectroscopic spurious signals with a similar amplitude as the planetary signal hamper the detection and characterization of Earth-like planets.

Machine-learning **Gaussian processes (GP)** regression algorithms have become a standard approach to tackle at least part of this issue. The flexibility of this method allows the treatment of stellar noise as correlated signal.

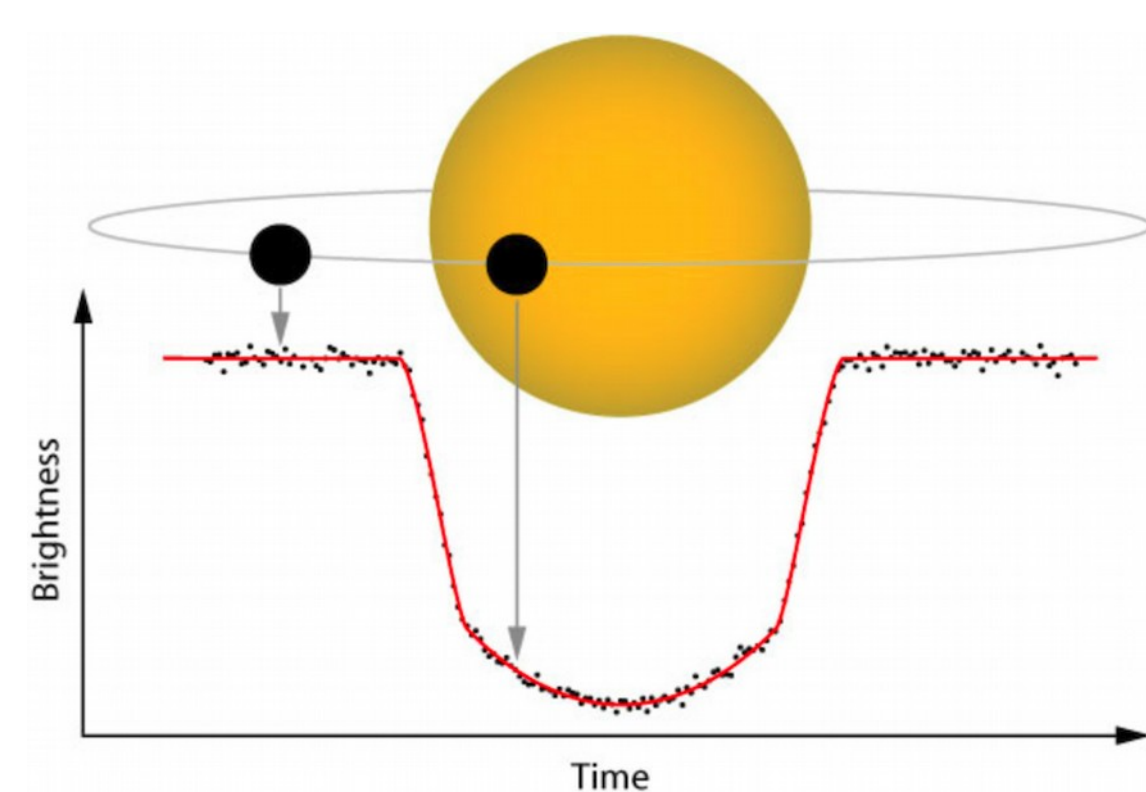
Our team is active in the application of this technique to exoplanet detection and characterization.



Impact on planetary transits

In-transit and out-of-transit starspot signals lead to incorrect transit depth measurements (up to a few thousand ppm).

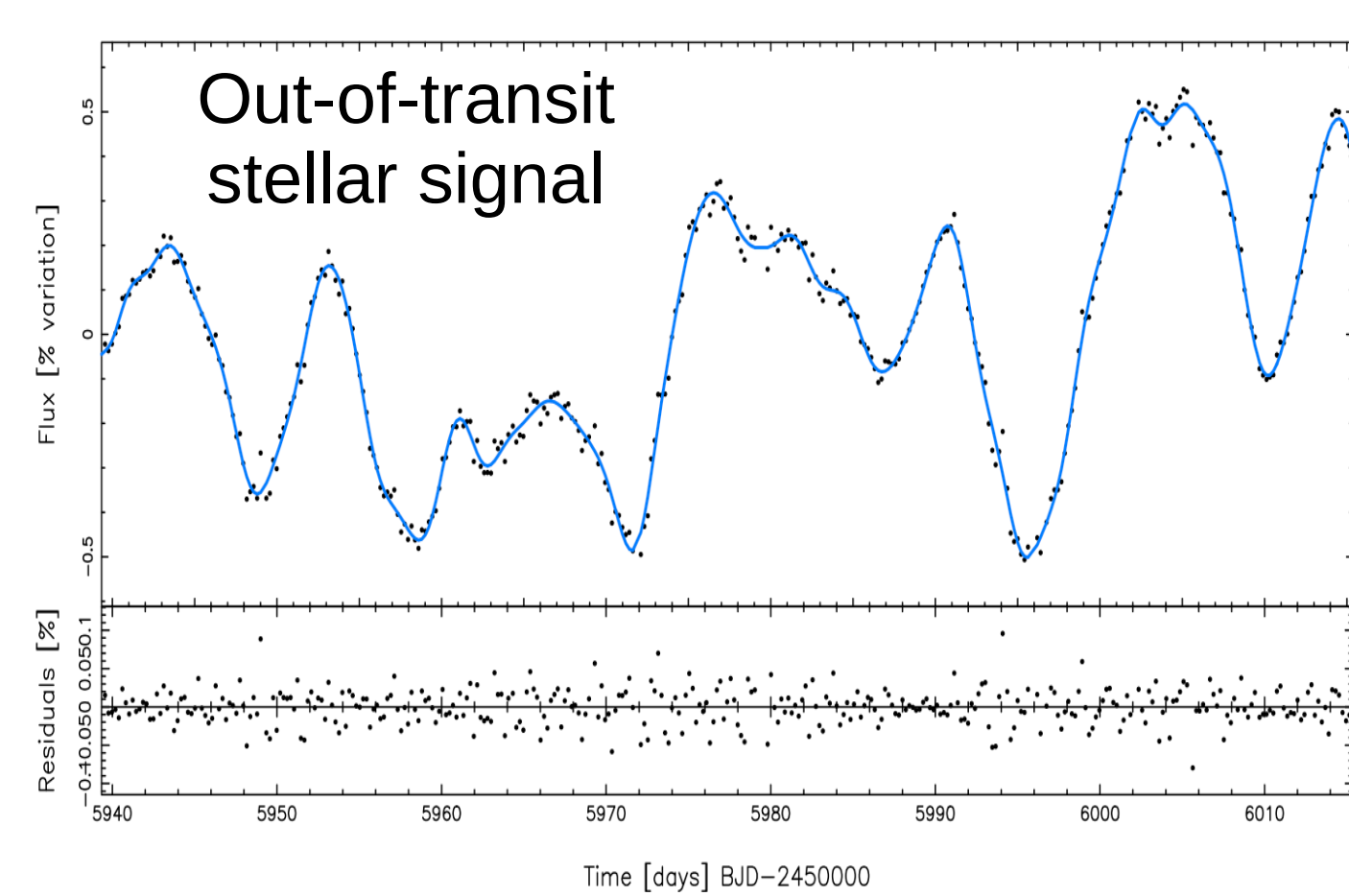
➔ Measurements of planet radii and atmospheric absorption features are affected (e.g. Alonso+2008, Silva-Valio+2010, Pont+2008, McCullough+2014 were among the first to report this problem).



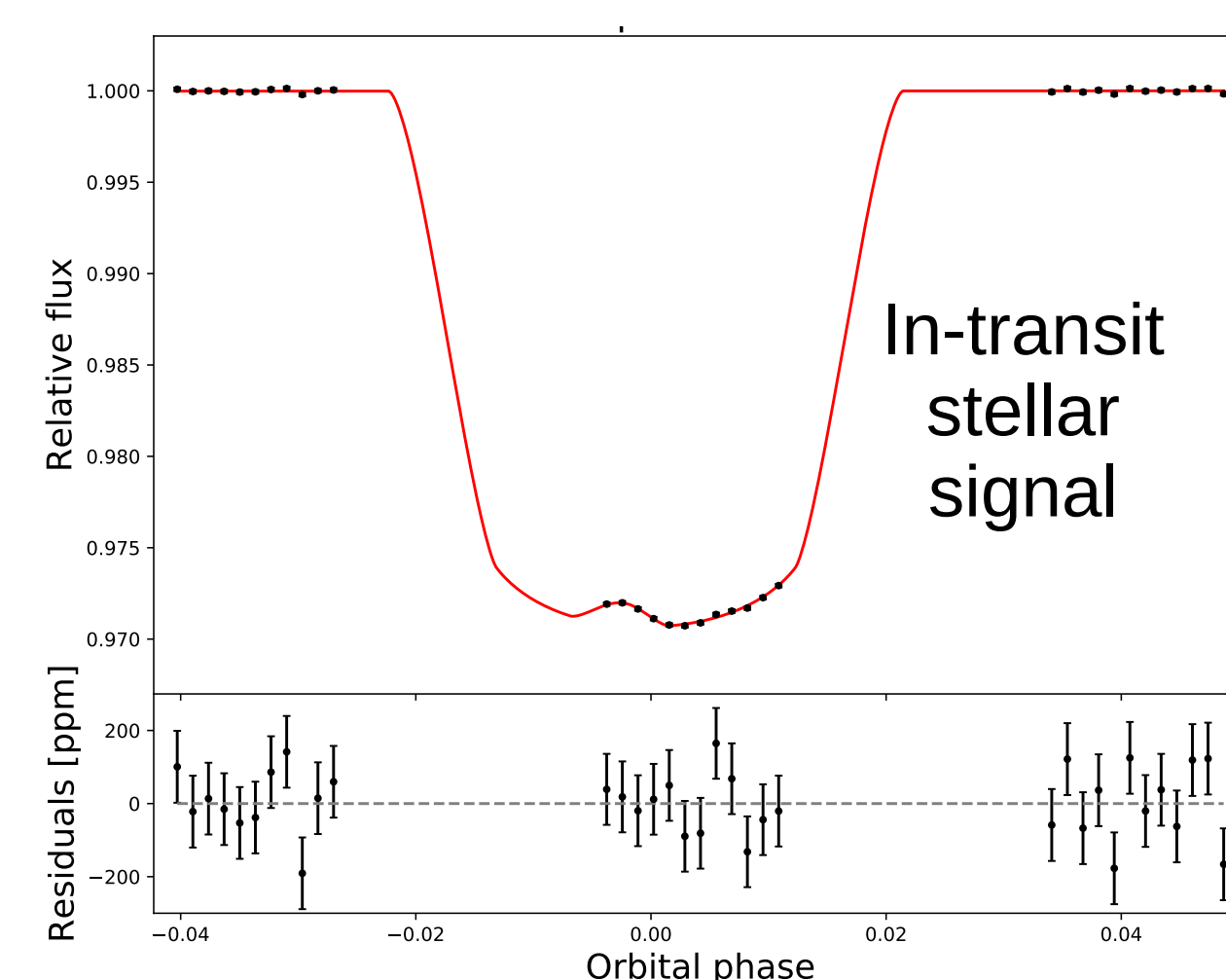
This is the ideal photometric transit shape, where

$$\text{Transit depth} \propto \left(\frac{R_{\text{planet}}}{R_{\text{star}}} \right)^2$$

But what we see is this:



Haywood+2014



Bruno+2018

With **GP**, the stellar activity signal is treated as correlated noise.

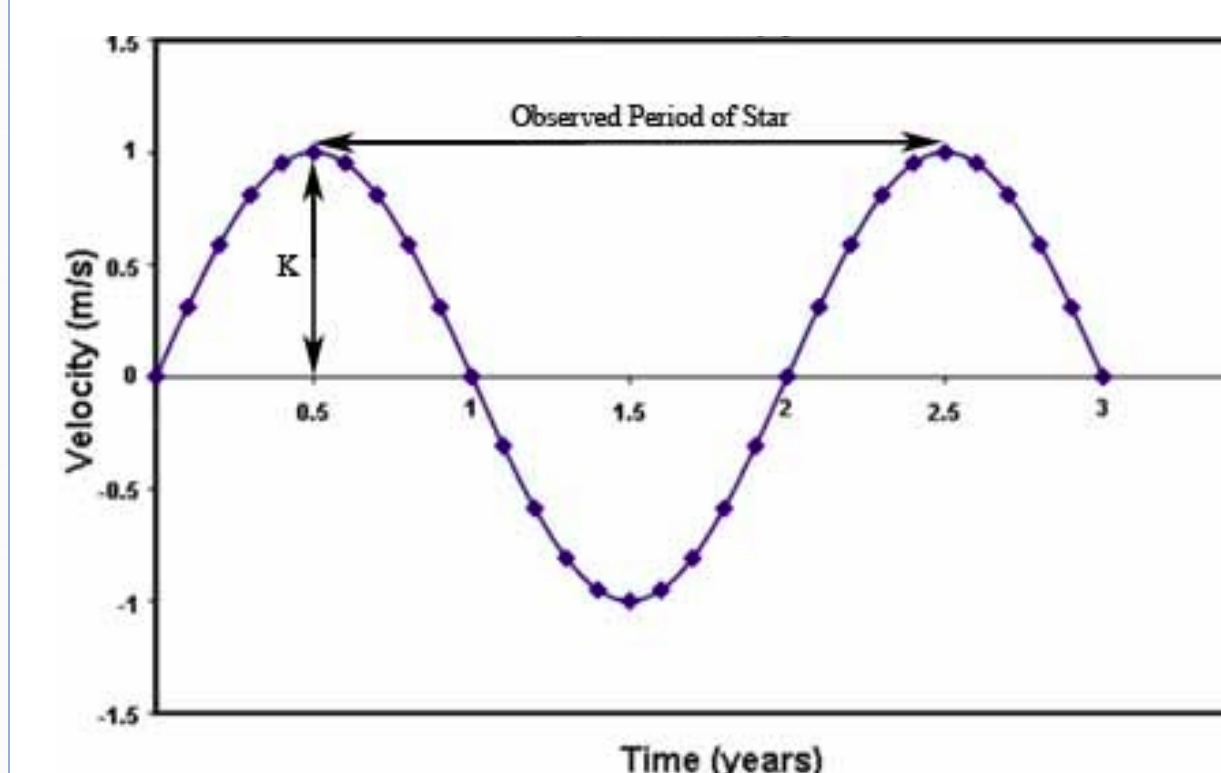
- Photometry can be **corrected for both occulted and non-occulted starspots**.
- Long-term photometric variations can be used to reduce the impact of starspots on transmission spectra (e.g. Alam+2018, Bruno+2019, submitted).
- Stellar activity can be corrected altogether with instrumental effects (Gibson+2014).
- GP can be included in pipelines for space-borne observatories (Aigrain+2016).
- Well-tested kernels (e.g. squared exponential/Matérn) are able to represent starspot evolution, while **traditional methods require the data set to be cut in a few days-long segments** (e.g. Lanza+2009, Bruno+2016).

However, **GP cannot find for us important physical constraints** for the modelling of the host star. An example is the starspot-to-faculae ratio, which is crucial to understand the stellar baseline level and therefore the amount of transit depth correction.

Impact on radial velocities (RV)

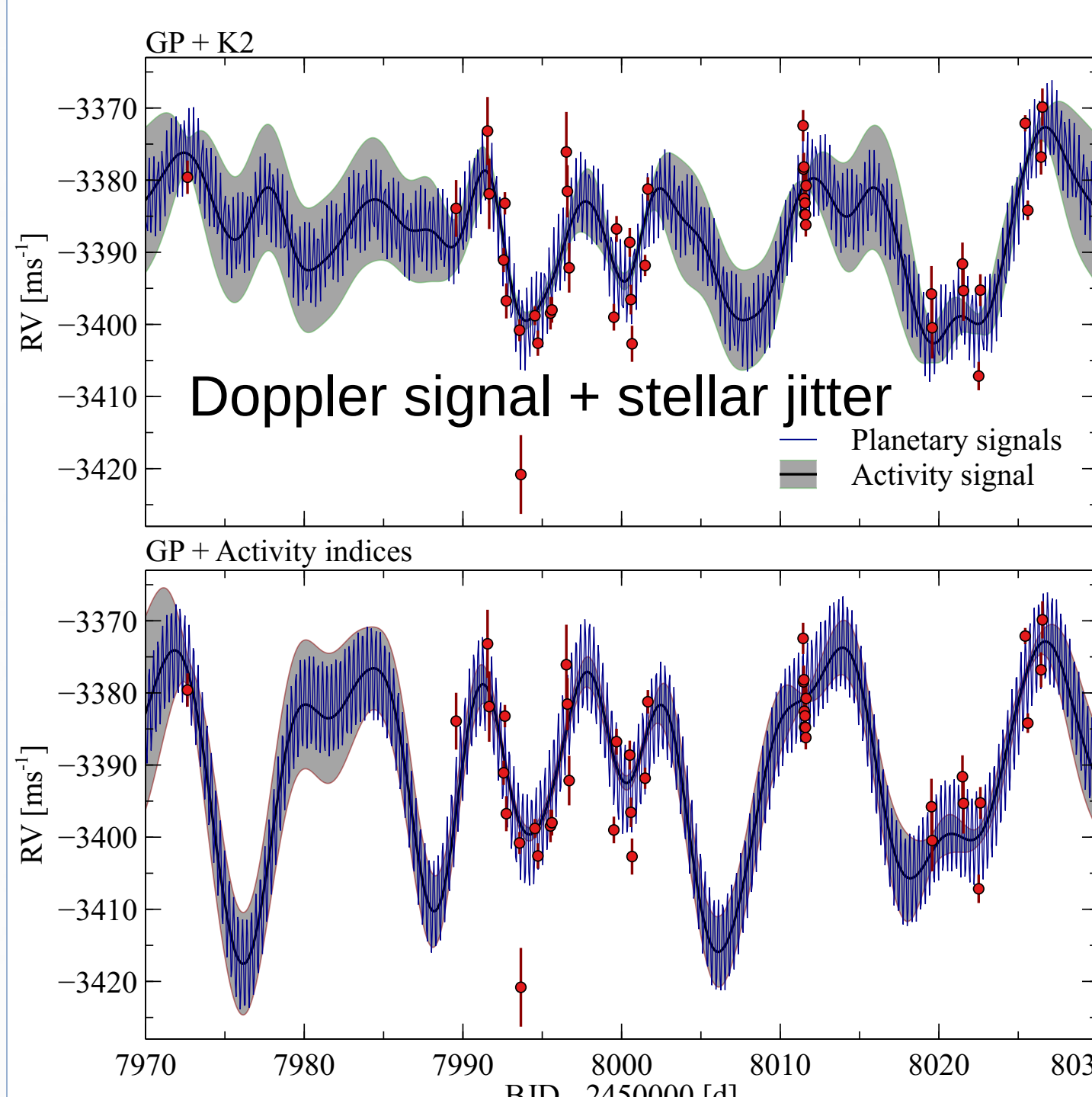
Spots and faculae have different spectral features from the rest of the star. As the star rotates, these are Doppler-shifted to the observer and introduce spurious RV variations (or RV jitter) possibly larger than the planetary signal (e.g. Queloz+2009).

➔ The detection of planets around young and/or active stars can be challenging, as well as their mass determination.



Radial velocity model curve: K is the radial velocity semi-amplitude.

$$K \propto m_{\text{planet}} (M_{\text{star}} + m_{\text{planet}})^{-2/3} P^{-1/3}$$



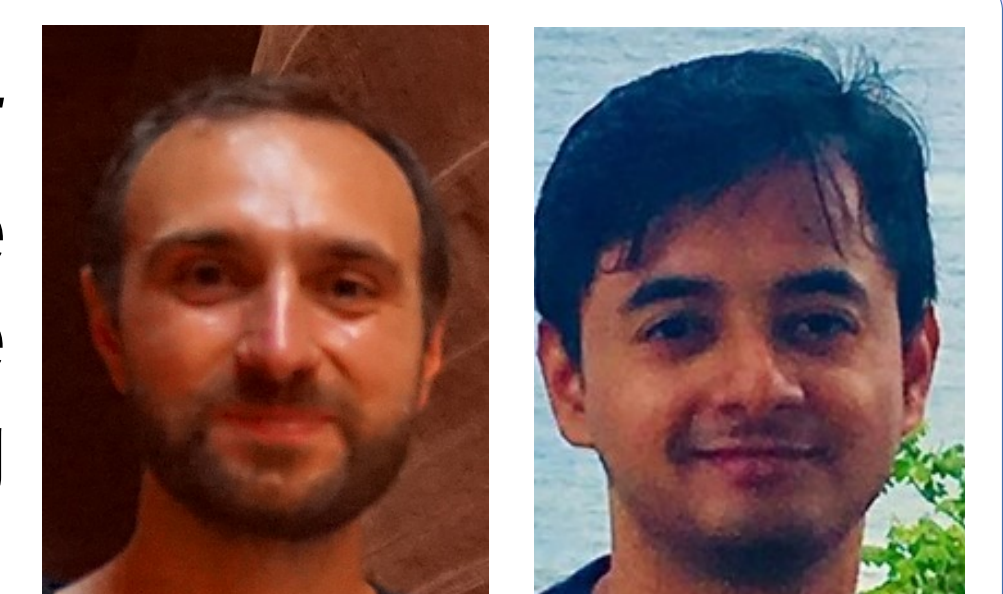
Malavolta+2018

- Keplerian signals produced by one or more planets are affected by stellar jitter coming from stellar spots, plages and supergranulation (~1m/s amplitude, Meunier+2019).
- **GP** are used in our GAPS collaboration to **filter the stellar signal out** and determine reliable planetary masses.
- Quasi-periodic covariance kernels are used to represent the stellar activity signal (Haywood+2014, Rajpaul+2015).

- Spectroscopic activity indices or photometry can be coupled to RV to get better constraints on the stellar activity signal (e.g. Malavolta+2018).
- **Satisfying parametric formulations that connect photometric and activity-induced RV signals are still lacking** (e.g. Aigrain+2011, Haywood+2014).



We'd like to have a chat about classification algorithms to recognize features in time series and the plausible performance of other machine learning algorithms to tackle stellar activity signals.



References

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Acknowledgments

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