

Gaussian Processes for Transmission Spectroscopy: Application to NICMOS and WFC3 observations of HD 189733

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Collaborators:

Oxford Astrophysics: S. Aigrain, T. Evans

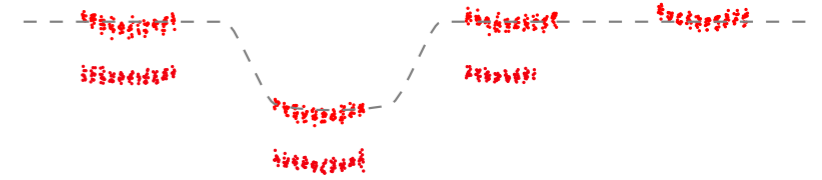
Oxford Information Engineering: S. Roberts, M. Osborne

Exeter: F. Pont, D. Sing

Transmission spectroscopy datasets

- Dataset consists of multiple light curves, in different wavelength channels.
- Systematics \gg Transmission signal
- Choice of model is crucial to the spectrum
- Simultaneous *auxiliary measurements*, which describe the state of the instrument.
- ‘Standard’ method is to model the baseline flux as a linear function of auxiliary measurements:

$$\mathbf{f} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon},$$



Why use a Gaussian process (GP) model?

- Using a non-parametric model makes fewer assumptions!
- GPs place a probability distribution over function space - this incorporates most commonly used functions.
- *Important, because often we have no physical justification to use a deterministic function of the systematics model.*

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Covariance matrix: defined by kernel function which uses the inputs \mathbf{X} , with parameter vector $\boldsymbol{\theta}$

Controls the systematics model and white noise

The Kernel function: Systematics + White Noise

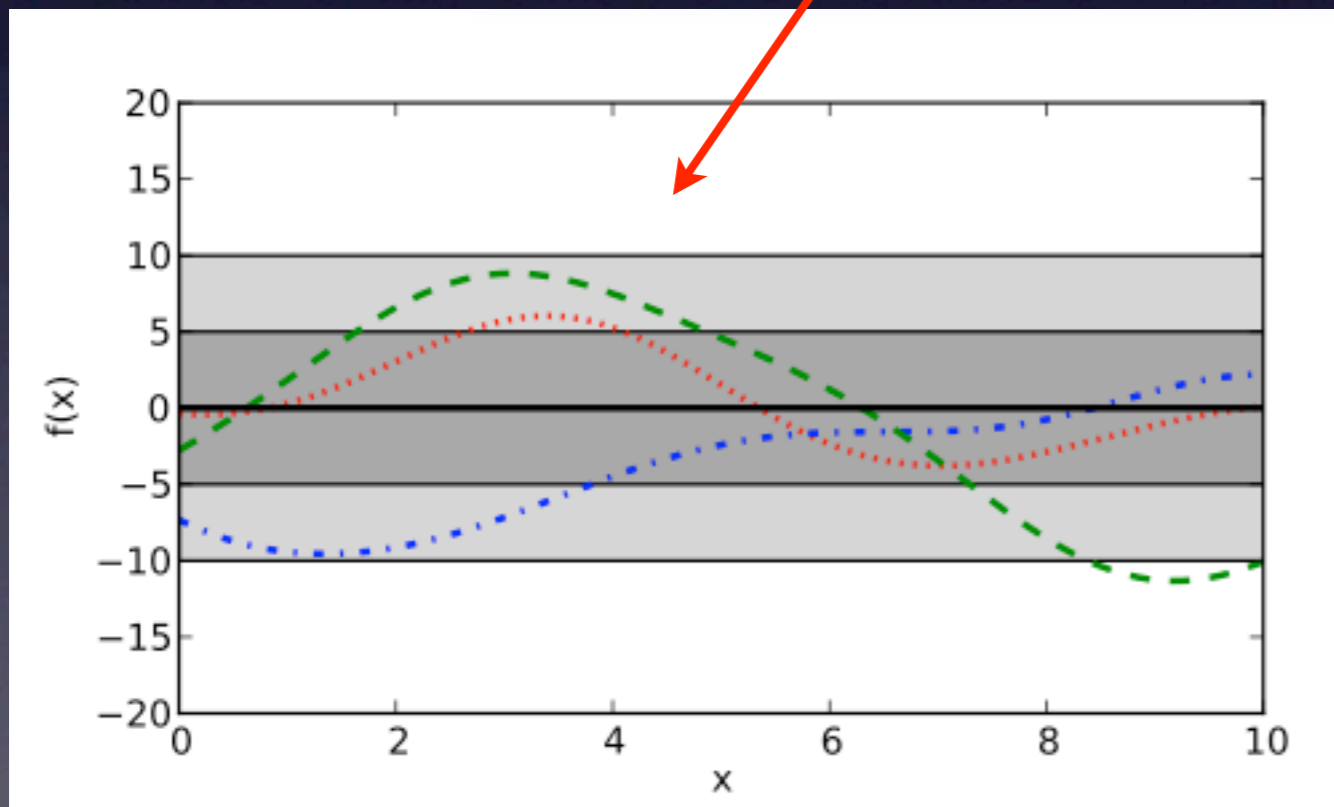
- Kernel function is a variation of the common squared exponential.

$$k(\mathbf{x}_n, \mathbf{x}_m) = \xi \exp \left(- \sum_{i=1}^K \eta_i (\mathbf{x}_{n,i} - \mathbf{x}_{m,i})^2 \right) + \delta_{nm} \sigma^2.$$

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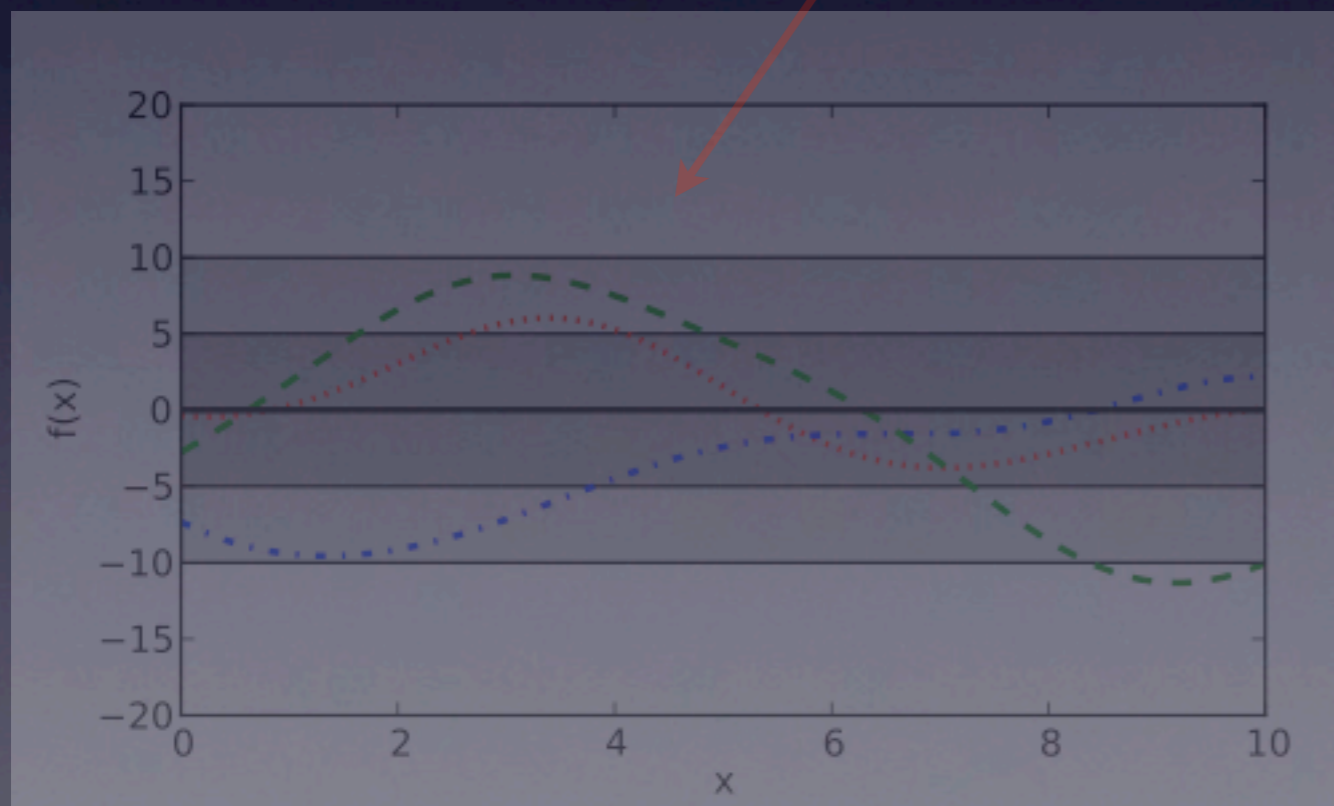
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Inverse length scale parameter for each input vector



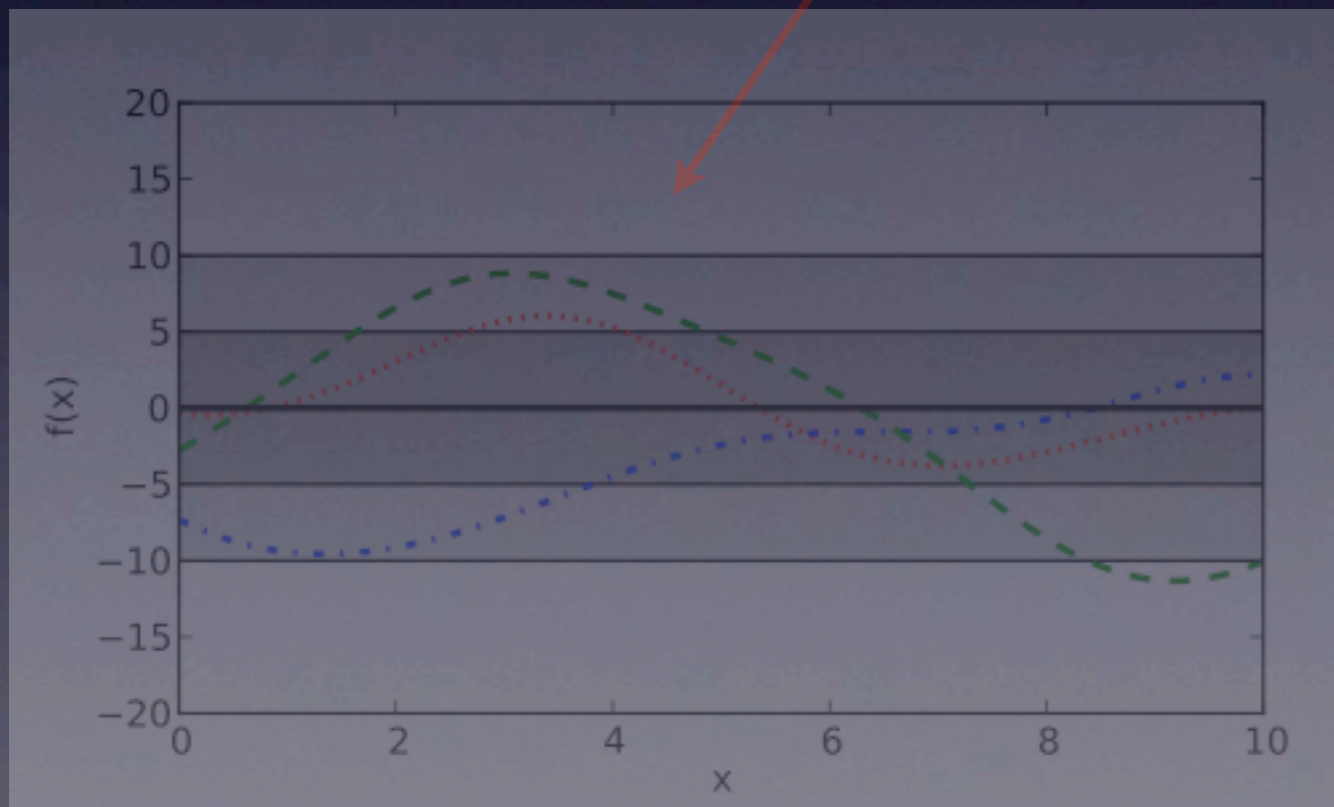
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Inverse length scale parameter for each input vector



White noise added to the diagonal

Probability distribution over smooth functions (but now multivariate!)

Inferring the Gaussian process parameters

- In a GP, the (marginal) likelihood function is multivariate Gaussian;

$$p(\mathbf{f} | \mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\phi}) = \mathcal{N} (T(\mathbf{t}, \boldsymbol{\phi}), \boldsymbol{\Sigma}(\mathbf{X}, \boldsymbol{\theta})) .$$

$$\mathcal{L}(\mathbf{r} | \mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\phi}) = \frac{1}{(2\pi)^{n/2} |\boldsymbol{\Sigma}|^{1/2}} \exp \left(-\frac{1}{2} \mathbf{r}^T \boldsymbol{\Sigma}^{-1} \mathbf{r} \right) ,$$

 (residuals | inputs, transit parameters, kernel parameters)

- Optimise with respect to the transit parameters and kernel (hyper-)parameters
or
- Explore the joint posterior distribution with MCMC (after multiplying by priors!)

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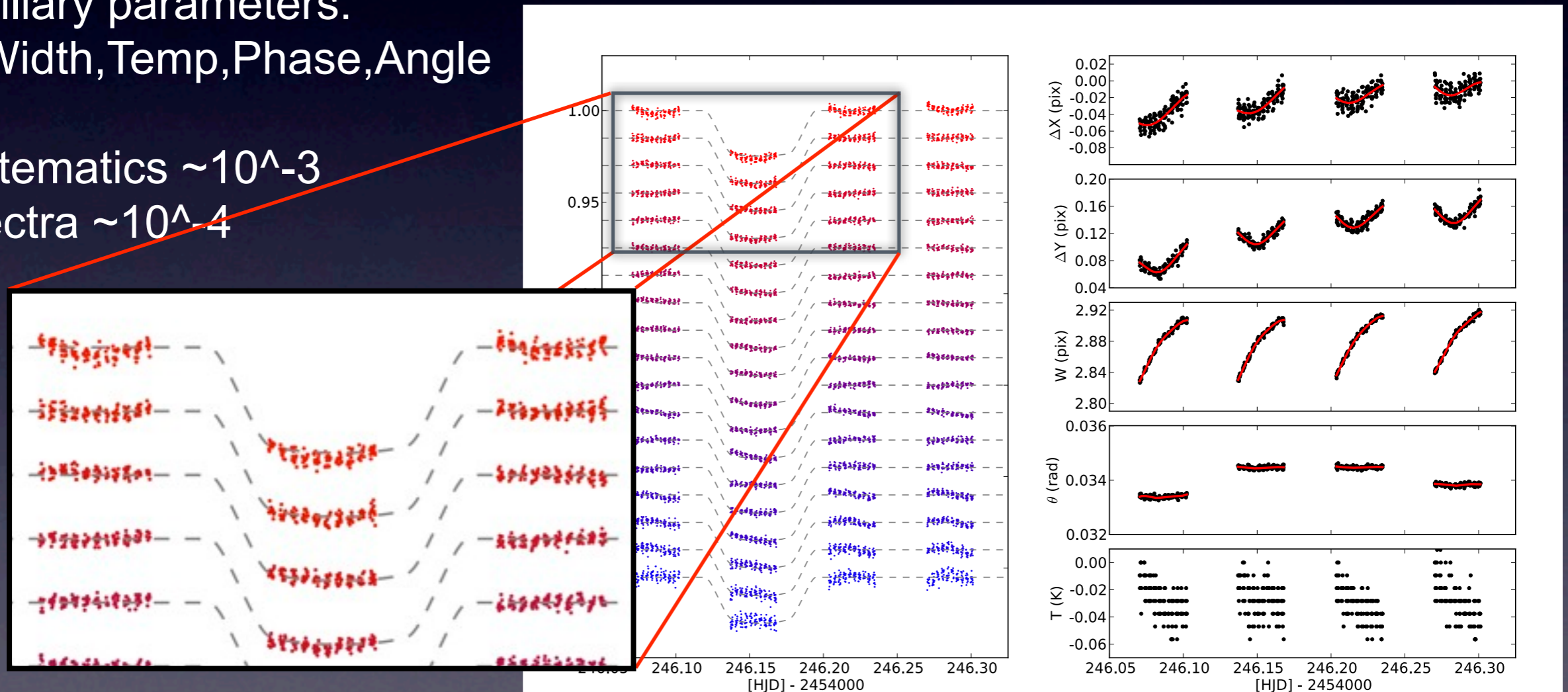
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Inverse covariance matrix requires
 $O(n^3)$ calculations!!

NICMOS transmission spectroscopy of HD 189733

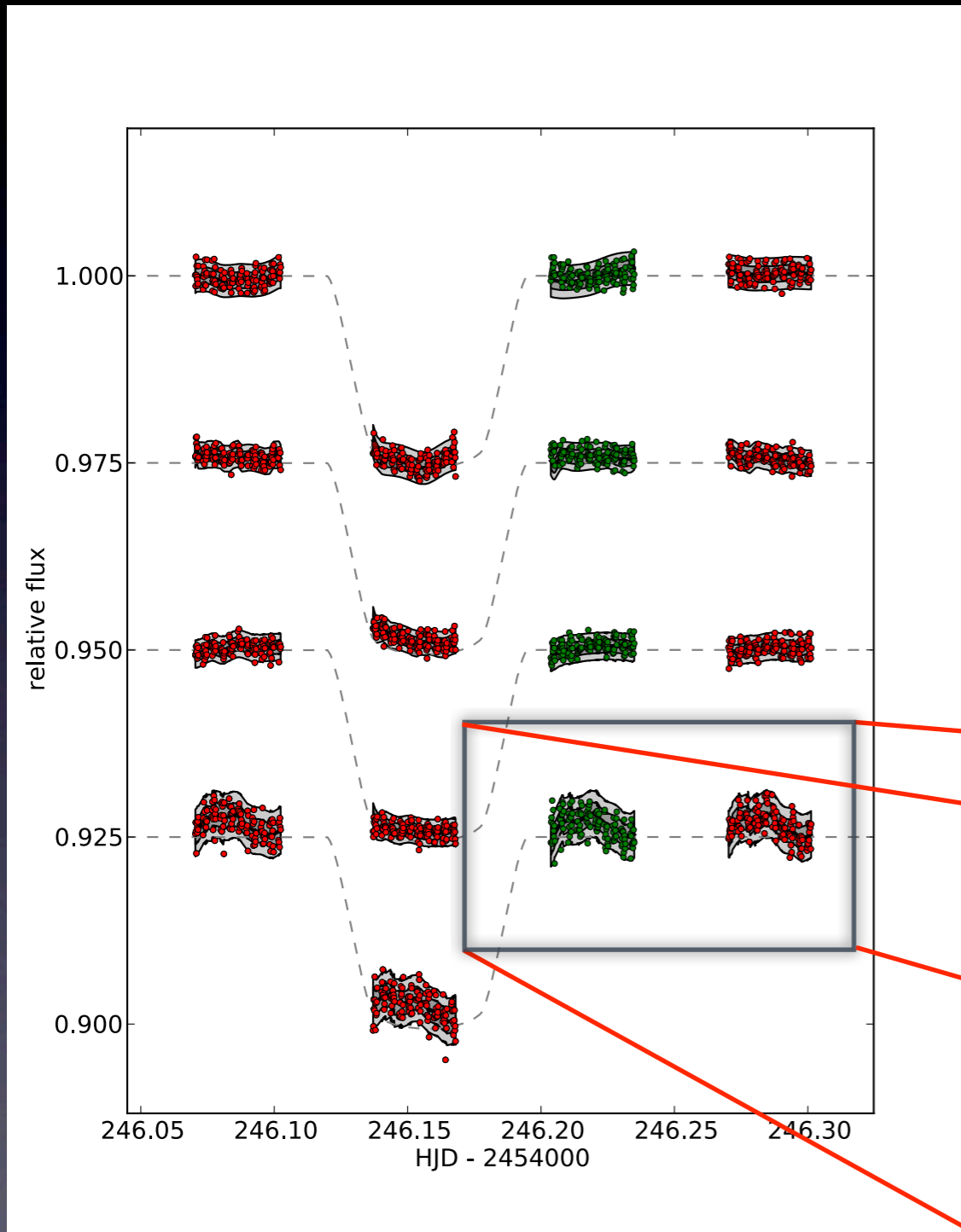
- First analysed by Swain, Vasisht & Tinetti (2008). Consists of 18 light curves from 1.4 to 2.5 μm (CH_4 , H_2O)
- Reanalysed by Gibson, Pont & Aigrain (2011).
- Auxiliary parameters:
X, Y, Width, Temp, Phase, Angle
- Systematics $\sim 10^{-3}$
Spectra $\sim 10^{-4}$



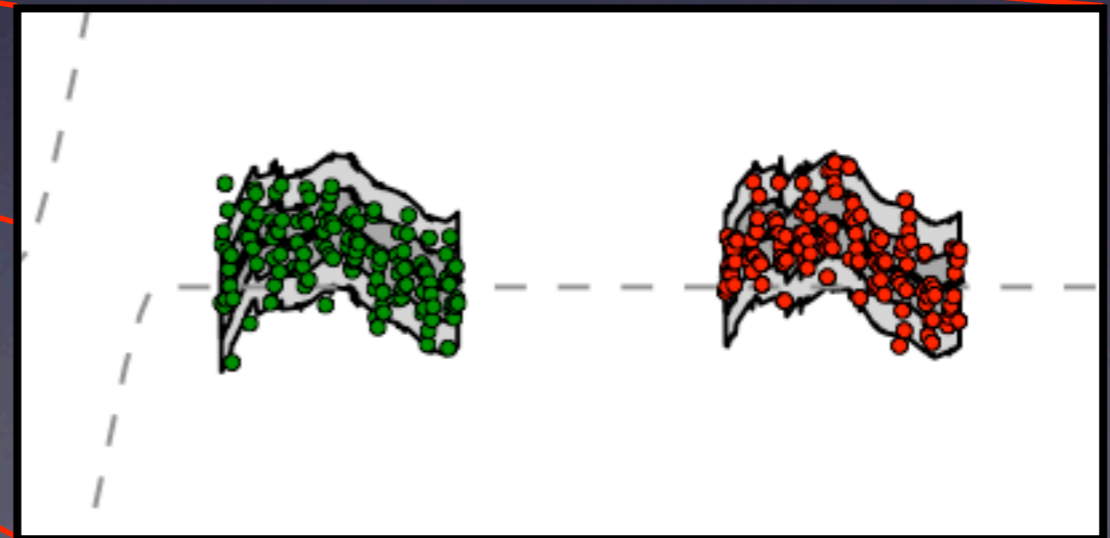
Gibson, Pont & Aigrain (2011)

NICMOS transmission spectroscopy of HD 189733

Gibson et al. (submitted)

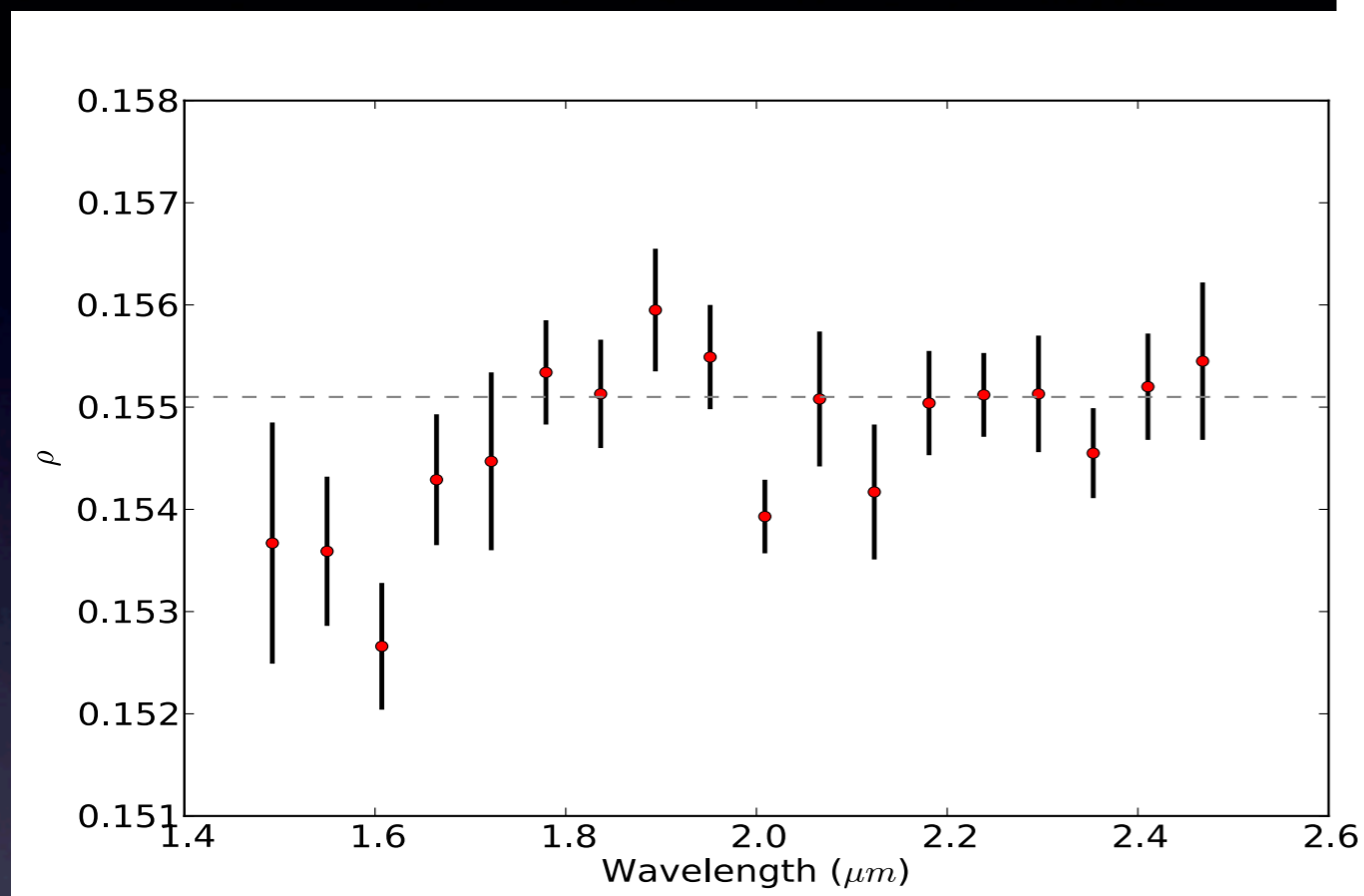


- GP model 'trained' on red points only
- Predictive distribution made for green points (from input X)
- 1 and 2 sigma GP predictive distribution shown



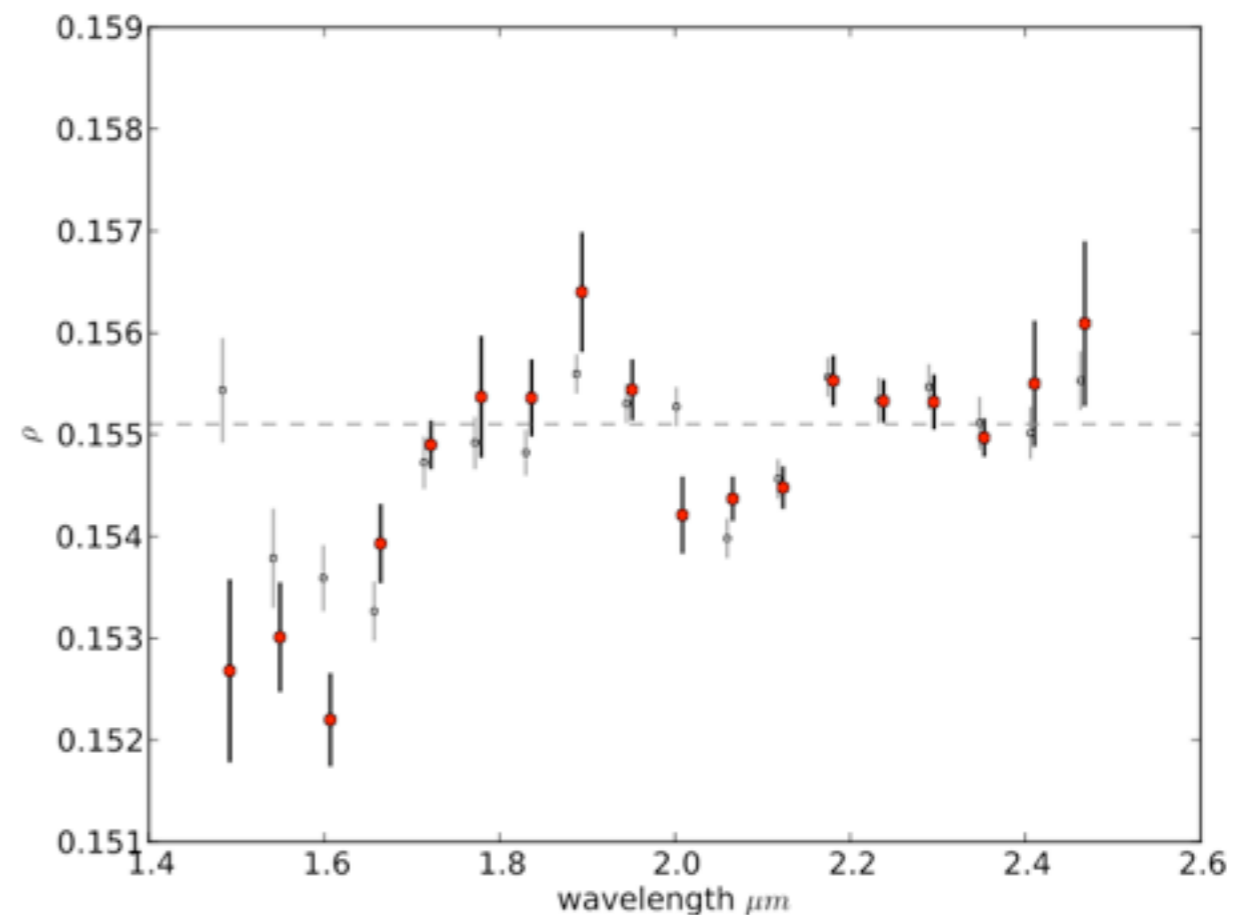
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Gaussian process model

Gibson, Pont & Aigrain (2011)



Linear basis functions

- This shows the linear basis function model is not sufficient to explain the NICMOS systematics.

Gaussian processes for transmission spectroscopy

- Paper will appear on astro-ph tonight!

A Gaussian process framework for modelling instrumental systematics: application to transmission spectroscopy

N. P. Gibson^{1*}, S. Aigrain¹, S. Roberts², T. M. Evans¹, M. Osborne² and F. Pont³

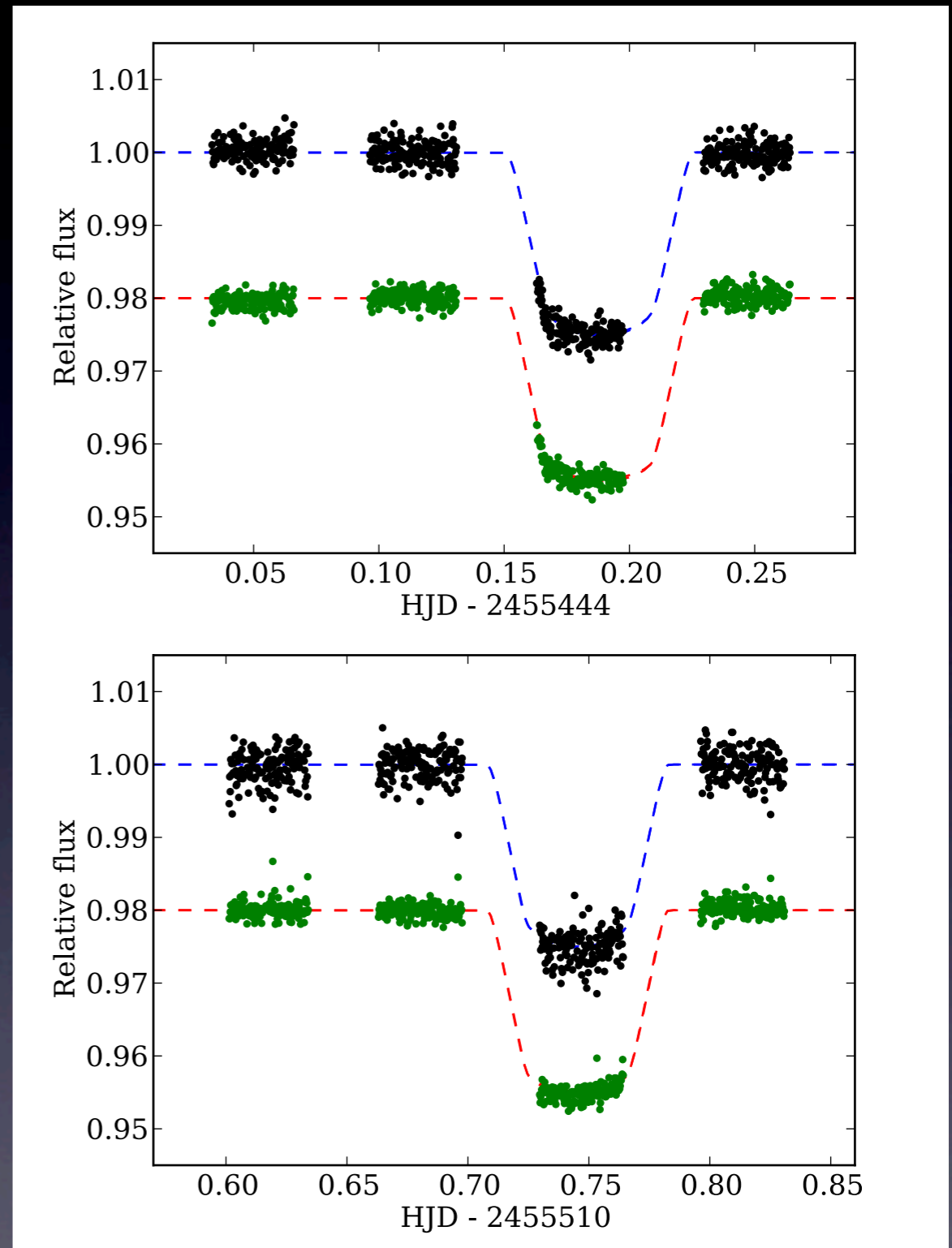
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³*School of Physics, University of Exeter, Exeter, EX4 4QL, UK*

WFC3 transmission spectroscopy of HD 189733

- G141 grism - Idea was to bridge the gap between ACS and NICMOS data
- 2 transits observed
- Light curves at ~ 1.1 and $1.6 \mu\text{m}$
- GP type-II max likelihood only
- Analysis on-going...



Gibson et al. (in prep)

WFC3 transmission spectroscopy of HD 189733

