# A formally motivated retrieval framework applied to the high-resolution APEX õ transmission spectrum of HD 189733 b

ATMOSPHERIC PHYSICS OF EXOPLANET



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#### Introduction **HD 189733 b** is a hot Jupiter ( $T_{eq} \approx 1200$ K) and is one of the most studied exoplanet to date. It is roughly 13% more massive and larger than Jupiter. It orbits a close K2 V star and has one of the highest TSM (≈ 770). However, in the literature, the values reported for the H<sub>2</sub>O abundance (-4 to -1.5 $\pm$ 0.5 log<sub>10</sub> MMR) and $V_{rest}$ (-8 to -2 $\pm$ 0.5 km/s) are inconsistent.

## **Objectives**

- Develop a formally motivated framework to retrieve high-resolution ground-based data.
- Use the framework on high-resolution data to characterize HD 189733 b's atmosphere.

## Log-likelihood function for HR data

#### Summarized demonstration

**Assumption 1**: the HR ground-based data can be represented as:

 $F = M_{\Theta} * D + N,$ 

petitRADTRANS 3

where D represents the instrumental deformations, as well as the telluric and stellar lines. All the terms above are 3D matrices (order, exp.,  $\lambda$ ). **Polyfit** divides the data by 2 polynomials fits (over  $\lambda$ , then over exposures).





**Groud-based observations** can benefit from higher resolving powers ( $R \approx$ 100,000) compared to space-based observations (e.g.  $R \leq 3000$  for the JWST). This allows for unambiguous species detections, and grants access to atmospheric kinematics ( $K_p$ ,  $V_{rest}$ ) from the Doppler effect. Bayesian inferences ("retrievals") are commonly performed to retrieve information such as species abundances, using the log-likelihood function:

$$\ln(L) = -\frac{1}{2} \sum \left(\frac{F - M_{\theta}}{U}\right)^2,$$

where F is the data,  $M_{\theta}$  is the forward model with parameters  $\theta$ , and U are the data uncertainties. For space-based observations,  $F \approx M_{\Theta} + N$ , where  $\Theta$  are the "true" parameters and N is the noise. In that case, calculating  $\ln(L)$  is straightforward. For ground-based observations, F contains deformations and telluric lines (D) not modelled in  $M_{\theta}$ . These are removed by a preparing pipeline, which deforms the spectrum (see Fig. 2).

### Methodology

- **CARMENES** "benchmark" data (0.96—1.71  $\mu$ m,  $R \approx 80,000$ , Fig. 3) from previous HD 189733 b observations (Alonso-Floriano et al. 2019).
- Upgraded version of the spectral modelling package **petitRADTRANS 3** (Mollière et al., 2019; Nasedkin et al., 2024; Blain et al. 2024 b), including a high-resolution retrieval framework (see Fig. 4).
- Preparing pipeline ("**Polyfit**") using 2<sup>nd</sup>-order polynomials to fit the data and to remove instrumental deformations as well as telluric and stellar lines.
- Nested sampling retrieval algorithm **MultiNest** (Feroz et al. 2009; Buchner et al., 2014).



Hence, its effect on the data is:

 $P_{\mathbf{R}}(F) \equiv F * \mathbf{R}_{F},$ 

where  $R_F$  ("preparing matrix") is the inverse of the product of the 2 fits. **Assumption 2**:  $R_F \approx A / D + B$ , where A and B represent the pipeline's imperfections. A depends only on  $M_{\Theta}$ , B depends on  $M_{\Theta}$ , D and N. **Assumption 3**:  $A/D \gg B$ , i.e., the pipeline has negligible residuals. **Assumption 4**: at the end of the retrieval,  $M_{\theta} \approx M_{\Theta} \ (\theta \rightarrow \Theta)$ .

With all the assumptions above, it can be shown that the log-likelihood function when using Polyfit-like pipelines is:

$$\ln(L) \approx -\frac{1}{2} \sum \left( \frac{P_{\rm R}(F) - P_{\rm R}(M_{\theta})}{U_{\rm R}} \right)^2,$$

where  $U_{\mathbf{R}} = U * |\mathbf{R}_{F}| * \sqrt{n}$  are the prepared data uncertainties and n is the product of the variance correction factors of the 2 fits. The above function is not valid when using e.g. SysRem (Tamuz et al., 2005), where the systematics are subtracted, not divided.



Pipeline biases can be inferred with a retrieval on *noiseless* data.



How does this step must be taken into account to perform a retrieval? Methods have been developed to tackle this issue (e.g. Brogi & Line 2019, Gibson et al., 2022), but they are not developed in a formal way.

Figure 4: Illustration of the model construction process. Steps 1—4 don't involve HR operations and are not represented. In the penultimate row, the spectra have been normalized over wavelengths for illustrative purposes. The bottom panel represents a forward model without modification.



#### $V_{\rm rest}$ and $T_0$ are **not degenerated**.

#### Results

CCF analysis on CARMENES data with Polyfit



### Results



### Results

Test retrieval on CARMENES data with SysREM

Radial velocity (km·s<sup>-1</sup>)





Figure 9: top row: sample of order #46 of the CARMENES prepared data. Bottom rows: posterior probability distributions for the CARMENES data, on all selected orders.

 $K_p = 165.71^{+29.30}_{-33.70}$ 

Figure 10: top row: (left) simulated data prepared with 1 SysREM pass and (right) a prepared forward model with 1 SysREM pass. Bottom: posterior probability distributions for the CARMENES data with 1 SysREM pass (on both the data and the forward models), on 46 selected orders

### Conclusion

- The retrieval and CCF results are consistent with each other, although the retrieval has smaller error bars and provides more details. Retrieval results for HD 189733 b are consistent with a super-solar metallicity, a sub-solar C/O ratio, and a significant spectral blueshift. Retrieved T is consistent with HST results (e.g., Tsiaras et al., 2018). Retrieving the mid-transit time is an important sanity check. The above framework and its demonstration are only valid for a subset
  - of preparing pipelines. Invalid frameworks may lead to biased results.

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