CONAN: A Python package for modeling lightcurve and radial velocity data of exoplanetary systems

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Summary

`CONAN` (COde for exoplaNet ANalysis) is an open-source Python package to perform comprehensive analyses of exoplanetary systems. It provides a unified Bayesian framework to simultaneously analyze diverse exoplanet datasets to derive global system parameters. `CONAN` allows to consistently model photometric transit light curves, occultations, phase curves, and radial velocity measurements, while detrending each dataset with any combination of parametric, sinusoidal, Gaussian Processes, and spline models.

Statement of need

Detecting and characterizing exoplanets, planets orbiting stars other than our Sun, is a major focus area of astronomical research. This endeavor increasingly relies on heterogeneous datasets spanning multiple epochs, observing techniques, instruments, and wavelengths. As such, robustly estimating the physical and orbital properties of planets routinely requires the simultaneous modeling of the different signals, while dealing with the unique systematics of each instrument and the time-dependent impact of stellar variability.

`CONAN` is designed to address these needs with a number of key features:

- Multi-dataset analysis: Seamless analysis of combined lightcurve (LC) and radial velocity (RV) datasets from various instruments.

- Multiplanet support: Simultaneous fit to multiple planets in a single system.

- Comprehensive photometric modeling: Robust modeling of transits, occultations, and phase curves, including effects such as ellipsoidal variations and Doppler beaming (see Model definition).

- Modeling time- and wavelength-dependent signals: Analysis of light curves with transit timing variations (TTVs) and transit depth variations (transmission spectroscopy).

- Flexible baseline and noise modeling: Selection of one or combination of polynomial, sinusoidal, multi-dimensional Gaussian Processes (GP), and spline functions for data detrending.

- Extensible and customizable modeling: Users can easily incorporate new LC and RV models or modify default ones to suit specific needs, e.g., modeling the transit of non-spherical planets, Rossiter–McLaughlin signals, or even non-planetary signals.

- Robust Bayesian inference: Parameter estimation and/or model comparison via nested sampling with `dynesty` (Speagle, 2020) or Markov-Chain Monte Carlo sampling with emcee(D. Foreman-Mackey et al., 2013).

- Derivation of priors on limb darkening coefficients: Derive priors for the quadratic limb darkening coefficients (Kipping, 2013) from the stellar parameters using `ldtk` (Parviainen & Aigrain, 2015).

- Automated selection of parametric model parameters: Uses the Bayesian Information Criterion to suggest best combination of cotrending basis vectors for the analysis of time-series data.

- Science data download: Built-in support for downloading data from various instruments (including TESS, CHEOPS, Kepler, and K2) and also system parameters from NASA Exoplanet Archive.

- Quick result visualization and manipulation: Instant plot of the best-fit model and a result object that can be easily manipulated for customized analysis. A sample of an instant plot obtained from a `CONAN` fit is shown in Figure 1.
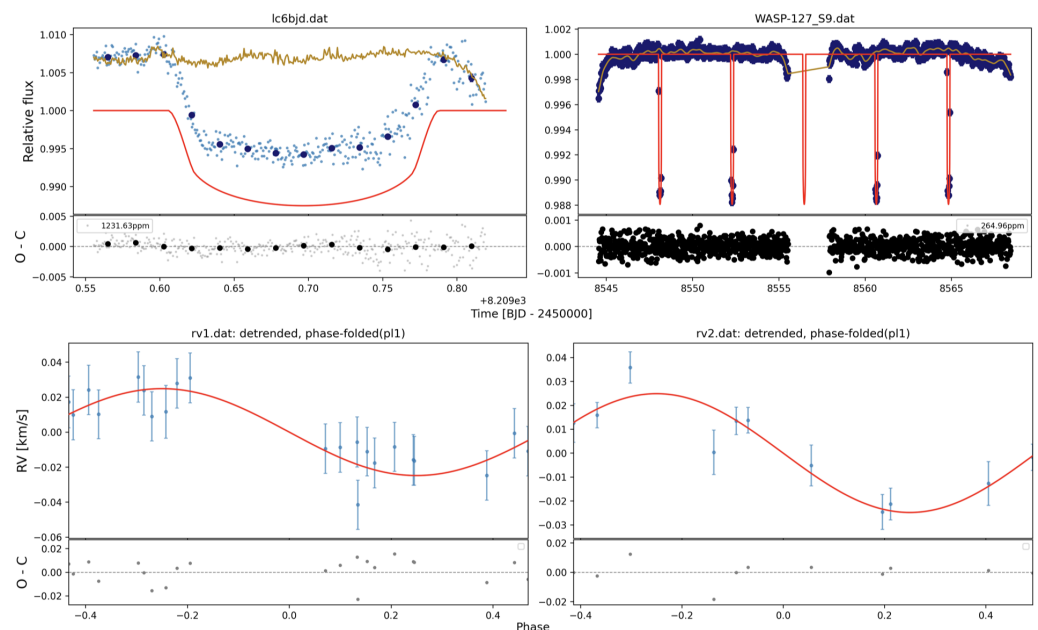

Figure 1: An example of joint fit to transit and RVs of WASP-127 b. The top panels show the best-fit models to the ground-based (left) and TESS (right) undetrended lightcurves. The transit model is shown in red, while the detrending baseline model is shown in gold (left: parametric model; right: GP). The bottom panels show the best-fit RV model overplotted on the detrended and phasefolded data. The details of the fit can be found in the online documentation.

State of the field

There are similar tools to `CONAN` for performing joint fit to exoplanet data, each with its own strengths and limitations. Some of these include `Juliet`(Espinoza et al., 2019), PyOrbit (Malavolta, 2016), exoplanet(Daniel Foreman-Mackey et al., 2021), `Pyaneti`(Barragán et al., 2019), ExoFAST(Eastman et al., 2013). One of the main strengths of `CONAN` compared to these tools is its capability to fit a wider variety of planetary signals. None of these publicly available tools can model full-orbit phasecurves of exoplanets using different phase functions. Notably, `CONAN` allows the user to define the custom model they would like to use in fitting the data, opening up practically unlimited use cases for `CONAN`. Additionally, `CONAN`'s capability to automatically select the best cotrending basis vectors for a dataset makes it especially well-suited to modeling extensive sets of ground-based observations, substantially reducing manual model selection effort.

The full documentation can be accessed at https://conan-exoplanet.readthedocs.io

Software design

`CONAN` is designed with modularity, extensibility, and computational efficiency as core principles. The software architecture comprises several interconnected components that enable flexible analysis of exoplanet data while maintaining ease of use. The package follows an object-oriented design centered around three primary data container classes: `lc_obj` for photometric data, `rv_obj` for radial velocity data, and `fit_obj` for managing analysis configurations and parameters. These classes provide a unified interface for handling heterogeneous datasets from multiple instruments while preserving metadata and allowing custom preprocessing. Users interact with the package primarily through high-level functions (`load_lightcurves`, `load_rvs`, `fit_setup`, `run_fit`) that abstract the underlying complexity while permitting fine-grained control when needed. The modeling framework is divided into distinct, composable components. This modular design allows users to enable or disable specific physical effects based on their data characteristics, or to supply custom model functions that seamlessly integrate with the existing framework.

Computational efficiency is achieved through strategic use of compiled extensions (Fortran or Numba-accelerated Python functions), vectorized NumPy operations, and parallel processing for both data likelihood calculations and sampling. The software scales efficiently from single-planet, single-dataset analyses to complex multi-planet, multi-instrument campaigns. Checkpointing and resumable sampling are also supported to facilitate long-running analyses.

`CONAN` supports two complementary workflows: an interactive Python API for exploratory analysis and scripting, and a configuration-file-based interface (supporting both YAML and custom .dat formats) for reproducible batch processing. The configuration system allows complete specification of data sources, model components, priors, and sampling parameters, enabling analyses to be launched via command-line or Python with minimal code. Automatic data acquisition from archives (TESS, CHEOPS, Kepler, K2, NASA Exoplanet Archive) and built-in visualization capabilities reduce the overhead of common tasks.

Research impact statement

`CONAN` was first introduced in (Lendl et al., 2017), and has had significant research impact in the exoplanet field while its user base is steadily growing. It started first as a tool to model ground-based observations from the swiss Euler telescope but has now grown to support data from various observing instruments, including space-based. It is being actively developed to be flexible in incorporating the community needs as data-analyis methods improve. `CONAN` has been for exoplanet data analysis in over 20 peer-reviewed publications [e.g.; Psaridi et al. (2023); Petit dit de la Roche et al. (2024); Seidel et al. (2025)] with more than 650 citations.

AI usage disclosure

No generative AI was used in the development of this software, or the writing of this manuscript.

Acknowledgements

(D. Foreman-Mackey et al., 2017), `spleaf` (Delisle et al., 2020), `lightkurve` (Lightkurve Collaboration et al., 2018), `numpy` (Harris et al., 2020), `ldtk` (Parviainen & Aigrain, 2015). We thank the developers of these packages for their work.

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