

gollum: An intuitive programmatic and visual interface for precomputed synthetic spectral model grids

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Summary

The spectra of stars, brown dwarfs, and planets are complex and information-rich. Complexity can be reduced by distilling spectra down to their fundamental stellar parameters: effective temperature, surface gravity, and iron abundance, and sometimes others such as alpha element abundance, carbon-to-oxygen ratio, or sedimentation efficiency of clouds. To a first order, these control the appearance of stellar and substellar spectra. Synthetic spectral models mimic stellar spectra across a grid of these fundamental parameters. Due to the computational constraints of modeling stellar and substellar spectra, model grids have high resolution in the spectral axis (wavelength coordinates) but are coarsely sampled over fundamental stellar parameters. Comparing these grids to data has been a challenge due to the large number of model grids, their size, their coarse sampling, and their dimensionality, making the relation between fundamental stellar parameters and spectral appearance somewhat unintuitive at times. This motivates the development of an intuitive, performant interface allowing astronomers to explore numerous model grids and compare them to data.

Statement of need

gollum is a Python package for intuitive analysis and visualization of precomputed synthetic spectra. Its API is designed to have modules dedicated to each model grid it supports, with each module then containing classes for both individual spectra and bulk grid access. The programmatic interface to spectral analysis uses method-chaining to make gollum code very readable, taking inspiration from frameworks like lightkurve (Lightkurve Collaboration et al., 2018). The visual interface in the form of interactive dashboards powered by bokeh (Bokeh Development Team, 2018) sports low-latency sliders and toggles. This allows users to tweak both fundamental stellar parameters and extrinsic parameters such as radial velocity and rotational broadening, building their intuition. gollum's modularity allows for a wide range of model grids to potentially be supported, and its performance is optimized with libraries such as numpy, scipy, astropy, and specutils to allow for quick loading and processing of large amounts of data (Astropy Collaboration et al., 2022; Earl et al., 2023; Harris et al., 2020; Virtanen et al., 2020).

gollum appeals to use cases ranging from entry-level astronomers to seasoned researchers with its combination of intuition-building and performance. The framework has been demonstrated on high-resolution spectra of brown dwarfs from Keck-NIRSPEC using bdxda (Kimani-Stewart

et al., 2021), has experimental support for starspots, used in `acdc` (Cao et al., 2022), and its programmatic interface has been used in the analysis of IGRINS spectra with `plotspec` (Kaplan, 2023). It interoperates with `muler` (Gully-Santiago et al., 2022), a similar framework designed for observed data from échelle spectrographs, and can also be used for flux calibration and empirical telluric correction. `gollum`'s programmatic interface is being used to create an extension to the `blase` framework (Gully-Santiago & Morley, 2022; Shankar & Gully-Santiago, 2023) that will allow for inference of fundamental stellar parameters from observed spectra using interpretable machine learning and interpolation techniques, taking inspiration from other frameworks such as `starfish` (Czekala et al., 2015) that also specialize in spectroscopic inference. `gollum` currently supports PHOENIX, Sonora Bobcat, and Sonora Diamondback, model grids, and implementations for other model grids such as `CoolTLUSTY` and `Sonora Elf Owl` are in progress (Husser et al., 2013; Lacy & Burrows, 2023; Marley et al., 2021; Morley et al., 2024; Mukherjee et al., 2024).

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