



National Aeronautics and
Space Administration

AI/ML Models and Tools for Processing and Analysis of Observational Data from the Habitable Worlds Observatory

Megan Ansdell

NASA Headquarters
HWO AI/ML Working Group Co-chair

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Thanks to this 🌟Team: Ehsan Gharib-Nezhad (NASA/ARC)*, Virisha Timmaraju (JPL), Bruce Dean (GSFC), Aquib Moin (UAE), Cecilia Garraffo (Harvard/CfA), Mark Moussa (GSFC), Gioia Rau (NSF), Mario Damiano (JPL), Gautier Bardi (JPL), Victoria Da Poian (GSFC), Hamed Valizadegan (ARC), Mahdi Habibi, Emily Mader (ARC), Miguel Martinho (NASA/ARC), Wenli Mo (JHU), Niki Parenteau (ARC), Steven Dillmann (Stanford)

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Key Science Objectives & Potential Impact

1. Data Processing

- Background subtraction
- Artifacts removal
- Saturation
- Source detection & validation
- Noise reduction

2. Atmospheric Characterization

- Biomarker retrieval
- Identify & quantify key absorbers
- Atmospheric compositions
- Thermal structure
- Recover physical parameters from spectra
- Degeneracy among these parameters

3. Tools and Pipelines

- Open-source tools, platforms and ecosystems for AI/ML deployment.
- Interfaces, integrations & IDEs.
- Online tutorials and examples to deploy the models

4. Wavefront Sensing and Control

- Autonomous global alignment/segment ID
- Deep-learning-enhanced image stacking
- Real-time multi-field error corrections
- Autonomous wavefront maintenance
- Generative AI for novel WFSC strategies

Objective 1: Atmospheric Characterization

- **Generative adversarial networks** for *molecular signature detection and atmospheric properties inference* (Zingales and Waldmann, 2018)
- **Deep belief neural networks** for *identification of molecular absorbers responsible for spectral signatures* (Waldmann et al., 2016)
- **Convolutional-based neural networks** for *prediction of extrasolar atmospheric parameters* (Gharib-Nezhad et al., 2024)
- **Convolutional-based neural networks and self-organizing maps** for *classification of planet candidates using photometry data* from missions like Kepler, K2, and TESS (Armstrong et al., 2016; Ansdell et al 2018, Valizadegan et al., 2022&23)
- **Neural network framework** for *sampling of high-dimensional parameter spaces* (Hammad et al., 2023)
- **Simulation-based Inference for Exoplanet Atmospheric Retrieval using Normalizing FLOWS** (Aubin et al. 2023)
- **Local Interpretable Model-Agnostic Explanations (XAI)** to *provide understanding about which spectral absorption lines are most influential towards a given atmospheric parameter prediction*

Slide: Thanks to Miguel Martinho (ARC), Cecilia Garraffo (Harvard/CfA)



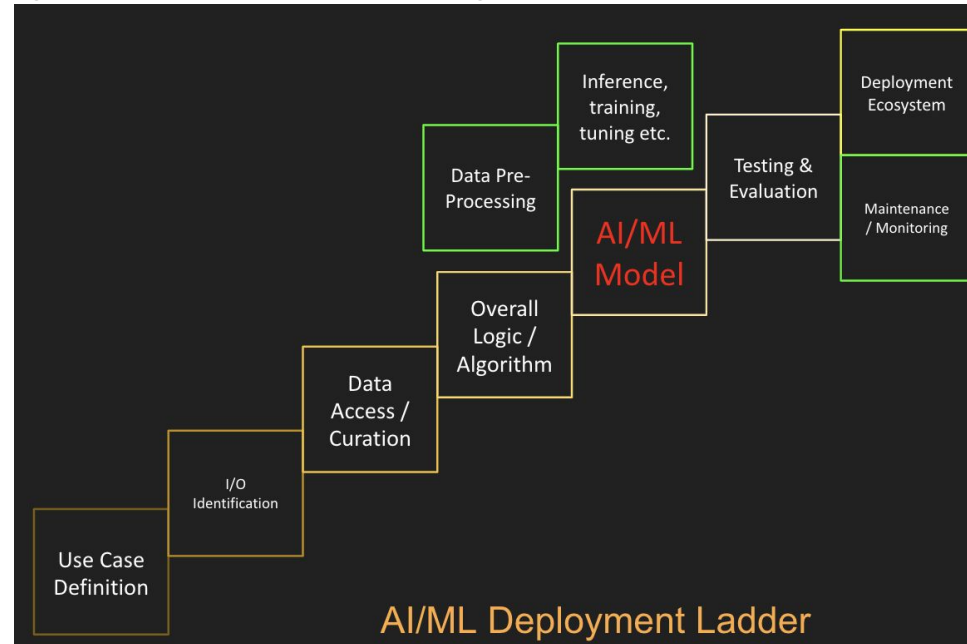
Objective 2: Integrating AI/ML into Wavefront Sensing & Control

- **AI/ML techniques can automate** the *global alignment and segment identification* of HWO's segmented primary mirror, significantly reducing human intervention.
- **Deep learning models can** achieve sub-pixel accuracy in *image stacking and fine phasing*, enhancing precision and efficiency in the commissioning process.
- **Real-time AI-driven correction can** manage multi-field wavefront errors, ensuring ongoing *optimal telescope performance* under varying conditions.
- **Multi-layer neural networks enable** both coarse and fine *wavefront adjustments*, maintaining diffraction-limited performance without substantial manual oversight.
- **Generative AI and reinforcement learning methods** can discover new, more efficient configurations and strategies for *optical alignment* and correction.
- **Challenges include** ensuring AI solutions translate effectively to real-world conditions and *optimizing onboard computational resources* for *real-time control*.



Objective 3: Ecosystems and Platforms for AI/ML Development and Deployment

- **Interfacing, hosting, operationalization and maintenance of AI/ML models** to adoption of an integrated AI/ML deployment and production framework.
- **AI/ML Deployment Ladder** for building a holistic, systematic & end-to-end AI/ML deployment scheme to facilitate HWO data processing & analysis.
- **Open-source & proprietary tools, platforms & ecosystems**



Habitable Worlds Observatory AI/ML for Data Processing & Analysis Task Group

Case Study 1:

Detecting Earth-analogs orbiting Sun-like HWO targets with Extreme Precision Radial Velocities (EPRVs)

Virisha Timmaraju

Team: Hamsa Shwetha Venkataram, Sam Halverson, Ian Colwell, Alex Wise

Deep Learning-based Measurement of Planetary Radial Velocities in the Presence of Stellar Variability, Colwell et. al., The Astronomical Journal (Accepted)



Overview

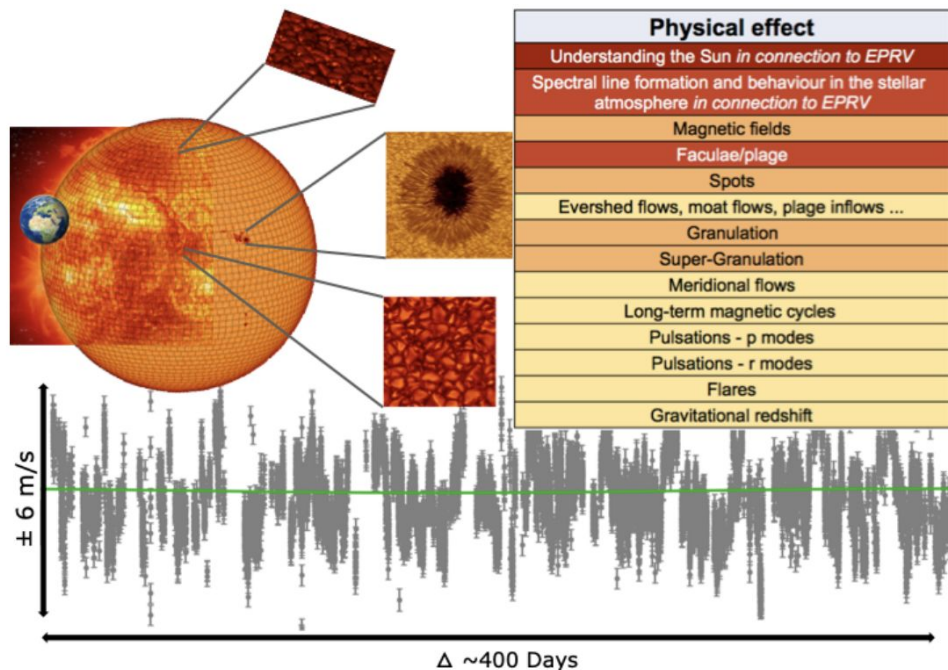
Motivation: The largest noise source in the error budgets of RV instruments is stellar activity. It masquerades as an exoplanet, leading to false detections of Earth analogs and poor mass measurements. The challenge lies in extending neural networks to be applicable across new instruments and stellar targets, given their training specific to solar data.

Capability: A transfer learning model that can adapt the learned complex interactions between multiple activity types in solar data and predict planetary radial velocities for other target stars.

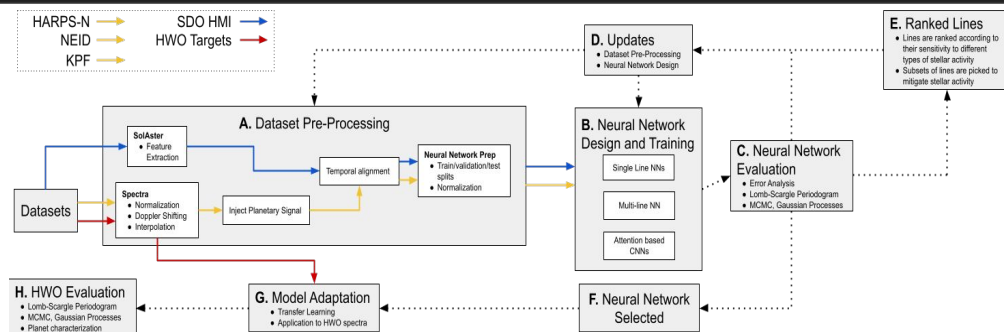
Use-Case: HARPS and NEID instrument data. NEID standard stars: HD 3651, Sig Dra, and Tau Ceti chosen for their minimal RV noise. These are also on the HWO mission star list.

Impact: Substantially reduce the error in planet-induced RV signal recovery across diverse stellar targets, thereby improving the accuracy of exoplanet detection and characterization.

Stellar Activity (Credit: EPRV WG Report)

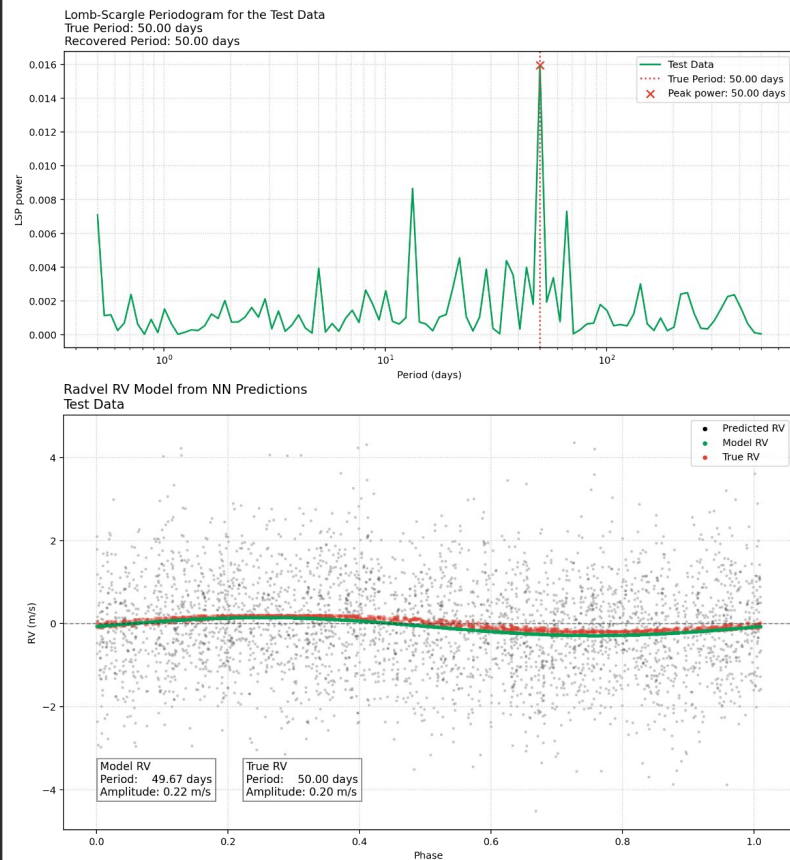


Technical Overview



Enhancing Stellar Characterization: The Role of Transfer Learning

1. CNN trained on HARPS-N Solar (HARPS-N-S) results in a RMSE of **1.2 m/s**
2. CNN can recover a **0.2 m/s** injected planetary RV signal in HARPS-N-S
3. Preliminary work showed that the CNN trained on HARPS-N-S can recover a 5.0 m/s injected planetary RV signal in HARPS Alpha Cen B without any retraining on Alpha Cen B.
4. Garraffo et al. (2021) showed that transfer learning improved stellar characterization accuracy from 88.8% to 97.8% with just 100 epochs of retraining on real observational data.



The Role of EPRV in Supporting HWO Mission Goals

- **Stellar Jitter Limits Detection:** Stellar noise below 1 m/s currently prevents reliable detection of Earth-mass exoplanets around Sun-like stars.
- **Critical for Earth-Like Planet Detection:** Achieving <10 cm/s precision is necessary to detect and measure masses of Earth analogs.
- **Improves Survey Efficiency:** Prior knowledge of planet orbits through EPRV allows HWO to conduct its exoplanet survey faster and more effectively.
- **Informs Mission Design:** Progress in EPRV or astrometry precision directly impacts the mission's architecture and observational strategy.

Habitable Worlds Observatory

AI/ML for Data Processing & Analysis Task Group

Case Study 2:

TelescopeML: Deep Learning suite of models and PyPI Package to enable modeling extrasolar Atmospheres

Key Objectives:

- Trained CNN models for low-resolution brown dwarf analysis.
- Python PyPI package for re-training CNNs on synthetic datasets.
- Online tutorials and open-source GitHub code for extended functionality.

Ehsan (Sam) Gharib-Nezhad
NASA Ames Research Center (BEARI)

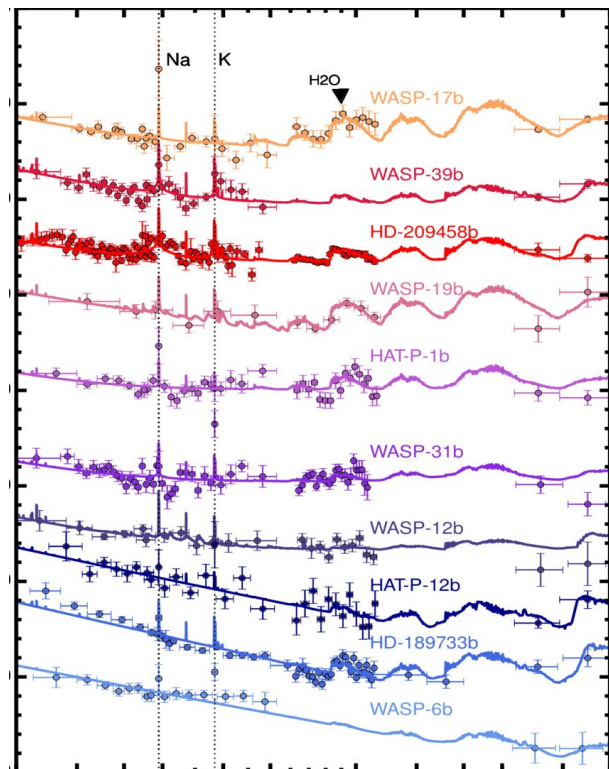
Thanks to this 🌟 Team: Natasha Batalha (STT), Hamed Valizadegan(TI), Miguel Martinho(TI), Ben Lew(STA), Mahdi Habibi (U. Düsseldorf), Gopal Nukula (intern), Vidgat Parishia (intern)

Gharib-Nezhad, Batalha, Valizadeh et al + 2024a TelescopeML-I, *Journal of Open Source Software* ([link](#))
Gharib-Nezhad, Valizadeh, Batalha, et. al. + 2024b TelescopeML-II, *The Astrophysical Journal* (Accepted)

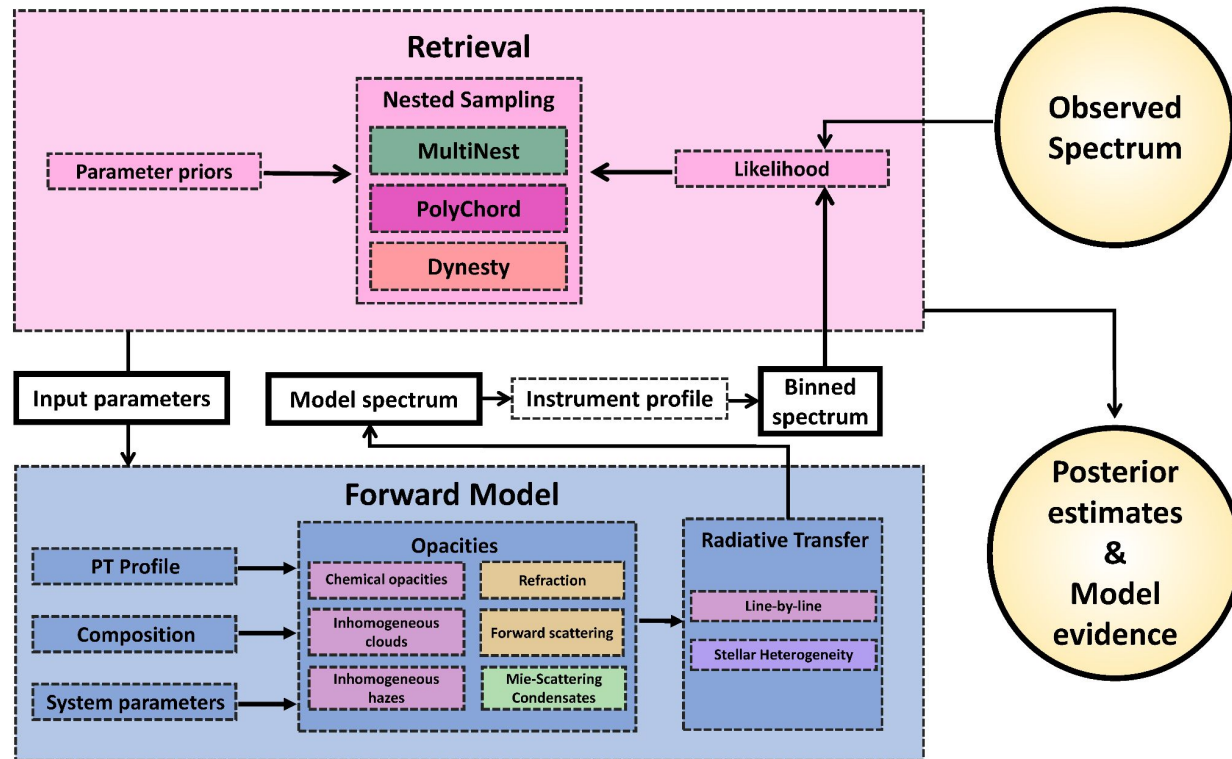


From Observation to Characterization

Forward and Retrieval are two traditional radiative transfer atmospheric modeling approaches that utilize synthetic data to infer atmospheric parameters such as mixing ratio, temperature, and gravity.



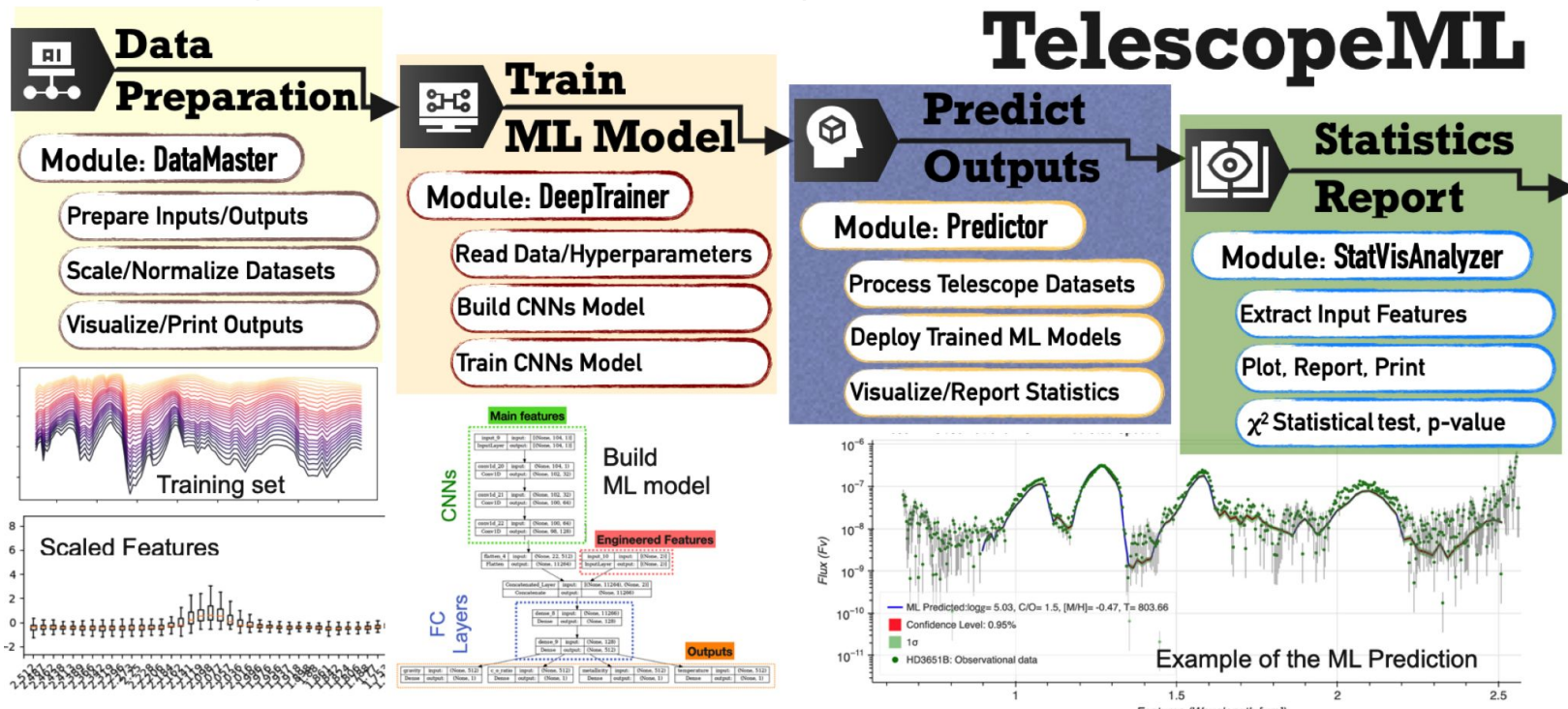
Goyal et al. 2017 MNRAS



Luis Welbanks

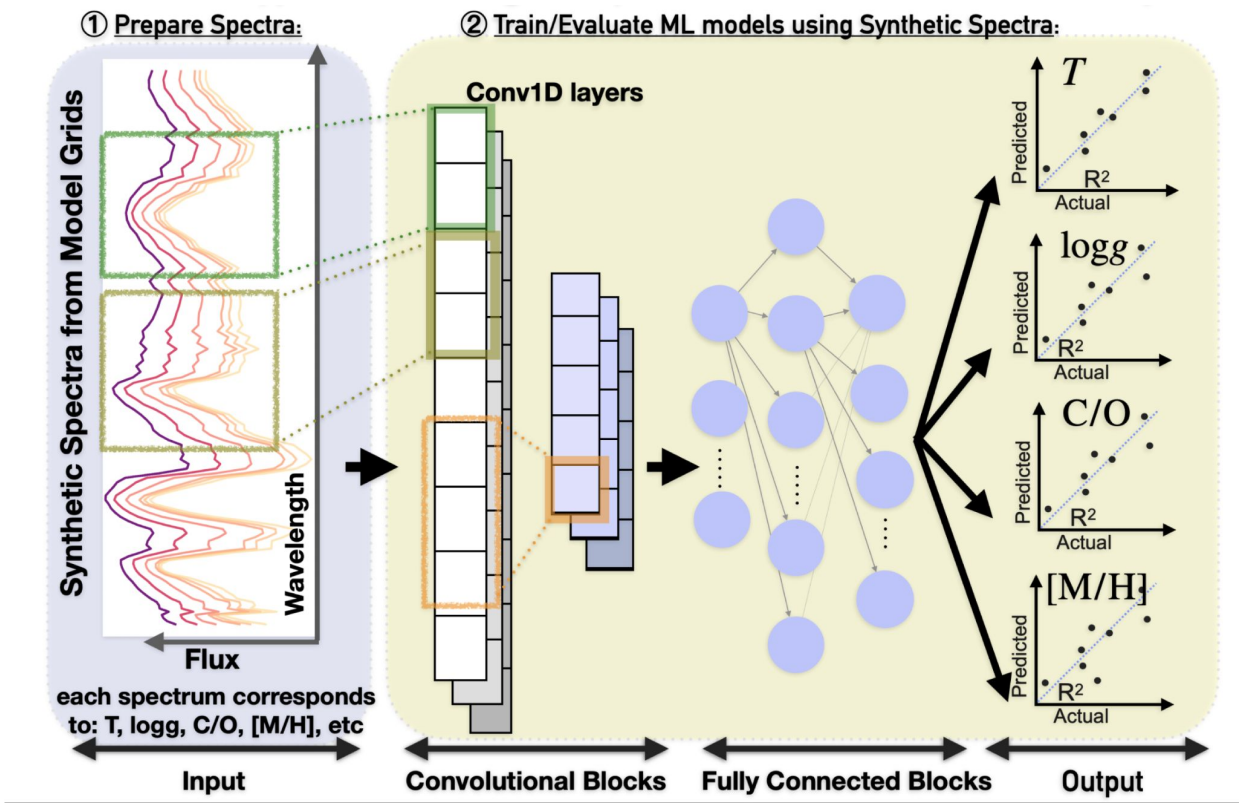
TelescopeML package For Atmospheric Characterizing

Reproducible, inclusive, accessible are three key core concepts in developing this package. All trained ML models, Python modules, synthetic datasets, and Jupyter notebook examples are made publicly available to enable further implementation of deep neural networks on observational spectra.



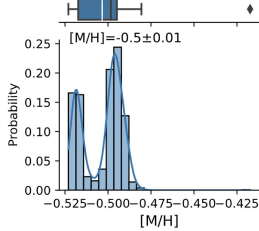
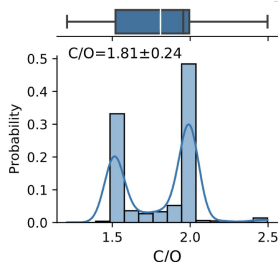
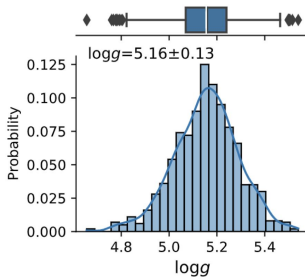
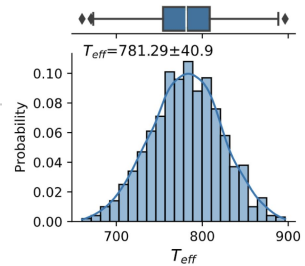
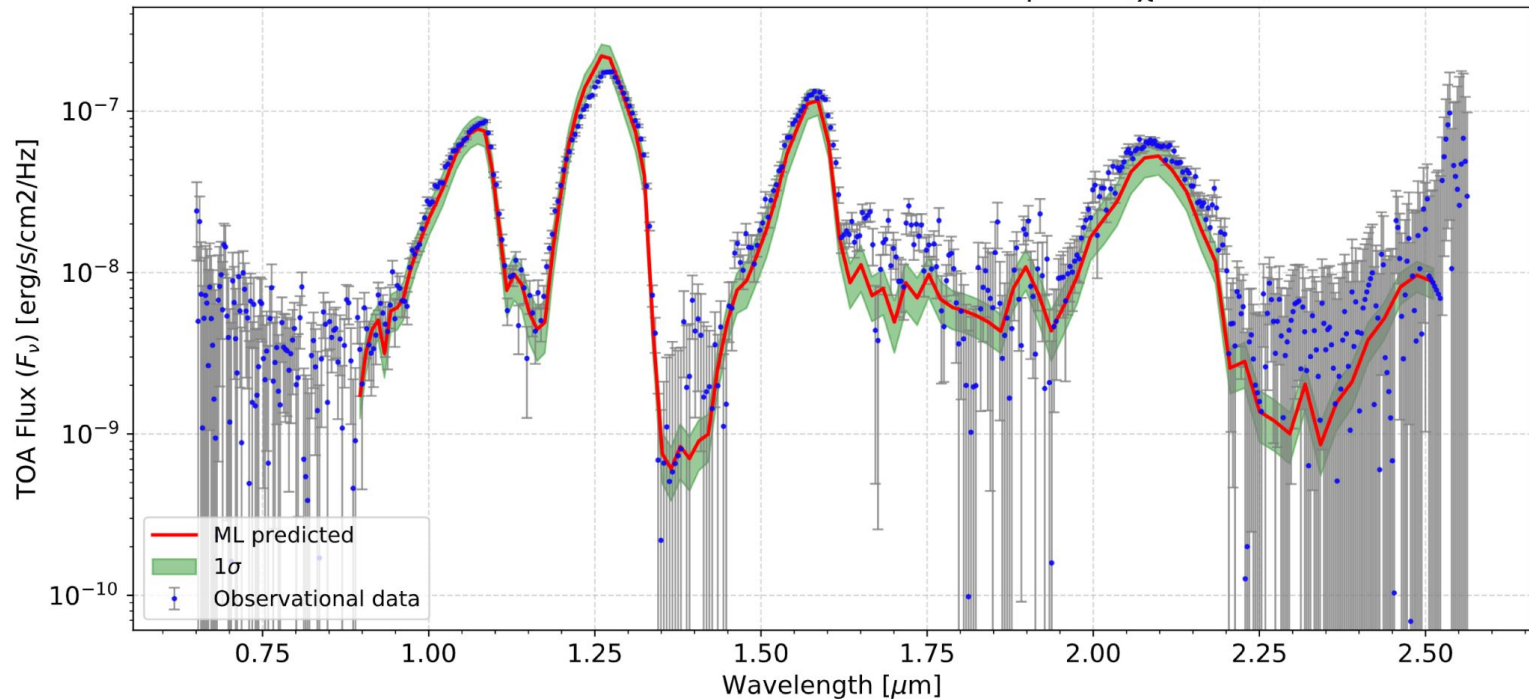
CNN Architecture:

Synthetic Spectra to Atmospheric Prediction: Example of the CNN architecture



Benchmark HD 3651B: Observational vs. ML Predicted [1/2]

Example of deploying the trained CNN model on a late-type T dwarf, HD 3651B by accounting for observational uncertainty in the fluxes (shown in the histogram)



Benchmark HD 3651B:

Literature vs ML Predicted [2/2]

