National Aeronautics and Space Administration

Measuring Extreme Precision Radial Velocities (EPRVs) of Exoplanet-Hosting Stars in the Presence of Stellar Noise Using Deep Learning

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OBJECTIVE

Stellar variability has been known to be one of the largest contributors to Extreme Precision Radial Velocity (EPRV) noise for almost two decades (e.g., Rupprechet et al. 2004). Despite years of improvements in algorithms to mitigate stellar Radial Velocity (RV) jitter, it remains the largest barrier to RV precision for next-generation instruments such as ESPRESSO, EXPRES and NEID (Pepe et al. 2013, Jurgenson et al. 2016, Halverson et al. 2016). **We focused on using Deep Learning (DL) based neural networks to measure small planet-induced RVs in the presence of larger amplitude RV noise caused by stellar activity.**

Our goal is to develop a proof-of-concept DL-based approach to distinguish between planetary and stellar RV signals in the wavelength domain. Our work was split across two broad categories of work:

- Developing a data processing pipeline to process HARPS-North sun-as-a-star spectra (HARPS-N-S). The pipeline is capable of inducing a customizable planetary signal.
- Develop a baseline DL architecture to estimate planet-induced RVs in the HARPS-N-S data.

BACKGROUND

Statistical methodologies for mitigating stellar jitter in the wavelength domain are not limited by the cadence requirements of time-domain mitigation strategies, making them a versatile tool for mitigating stellar jitter for any observing cadence. Wavelength-domain methods attempt to leverage changes in spectral line shapes and/or differences between spectral lines that are caused by stellar activity. However, stellar RV noise can be caused by pulsations, granulation, convective blueshift inhibition, and spot/plage regions, and most wavelength-domain methods only model one or two of these effects (Figure 1). Neural networks, on the other hand, have the potential to model all effects simultaneously, at a greater level of complexity than previous algorithms by utilizing all of the available information in the spectra. Considering the variety of stellar phenomena which contribute to stellar RV noise, and the results of our past pilot study with similar data from Alpha Centauri B and de Beurs et al. (2020), we believe neural networks are well suited to this problem as they are able to capture the complex non-linear relationships between the spectral signatures of different kinds of stellar variability and RVs that are challenging for traditional EPRV approaches to capture.

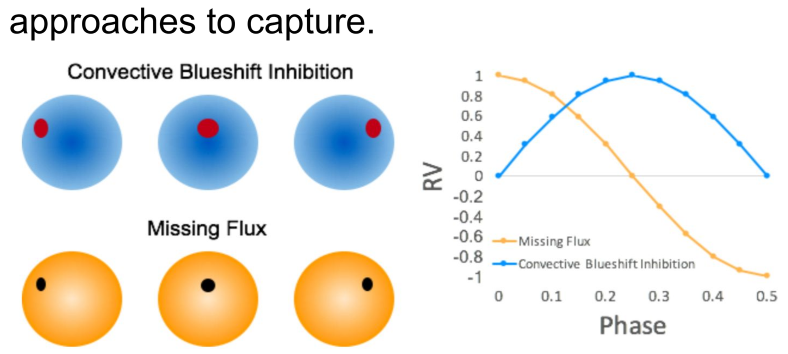

Figure 1. Left: Illustration of two spatial correlated sources of stellar RV jitter: convective blueshift inhibition from strong magnetic fields and rotational RV imbalance caused by missing flux in star spots. **Right:** Plot of the RV signals versus rotational phase corresponding to convective blueshift inhibition and missing flux.

APPROACH

1. HARPS-N-S is subjected to a series of pre-processing steps that place it on a normalized wavelength spectral grid, during which small planet-induced RV signals are injected into the spectra and represents our target for the neural network to predict.
2. Training, validation, and test splits - given our application of supervised learning is focused in the wavelength domain and utilizes a single spectra per training input, we determined there to be less of a need to apply sequential, time-based, splits. However, we recognize the benefit of continuous windows of observations when defining the splits and developed code to produce non-overlapping, sequential, splits.
3. Rescaling is applied to the planet-induced RVs (outputs), and dimensionality reduction is applied to the normalized wavelength spectra (inputs). Due to the increase in size of a single HARPS-N-S spectra, many in-memory approaches to dimensionality reduction were infeasible with HPC. This was solved by iteratively fitting PCA, via incremental principal components analysis.
4. Neural network architectures are explored and built. The focus was not to fully optimize the network architecture, but to find something that generalized sufficiently well.
5. Networks are trained using the training data.
6. Network's performance is evaluated using the validation data and error analysis ensues.
7. Modifications to the network architecture are performed to alleviate any glaring issues. Steps 2-6 are repeated to allow the modified network to be retrained with any updates.
   a. Updates to the pre-processing of HARPS-N-S data were necessary as the team's understanding of the data progressed. Each update to the complete HARPS-N-S data was followed by executing steps 1-6.
8. The final network is selected and is scored on the test split.

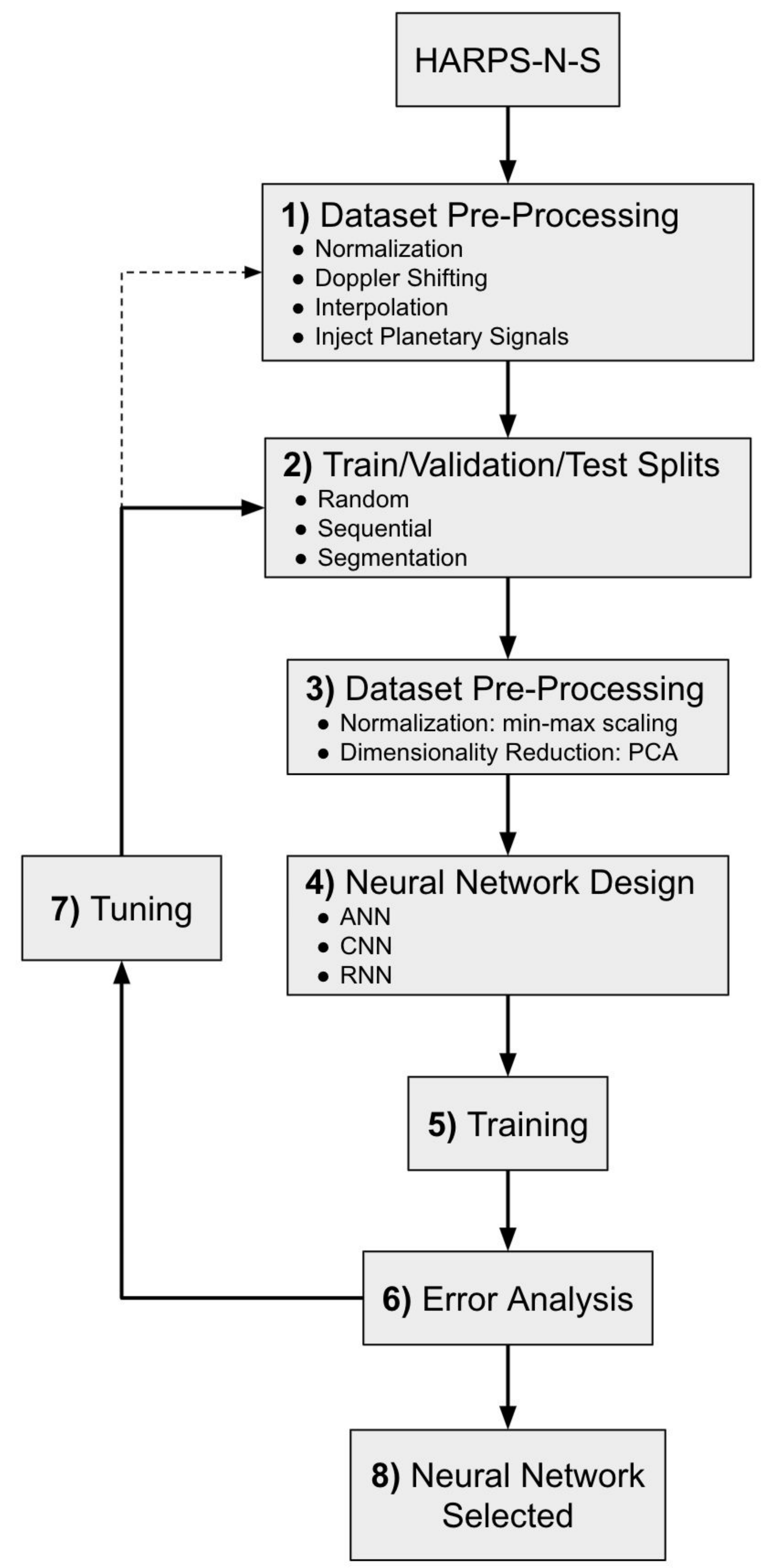

Figure 2. High-level process that employed for much of the work covered by this project.

RESULTS

Data Processing Pipeline: Resulting from this iterative process, we were able to create a data processing pipeline that allows the team to generate new planetary RV datasets, for both HARPS-N-S and HARPS-ACB (Figure 3). The ability to generate varying planetary RV datasets will enable further experimentation and the development of more robust DL-based approaches for this problem.

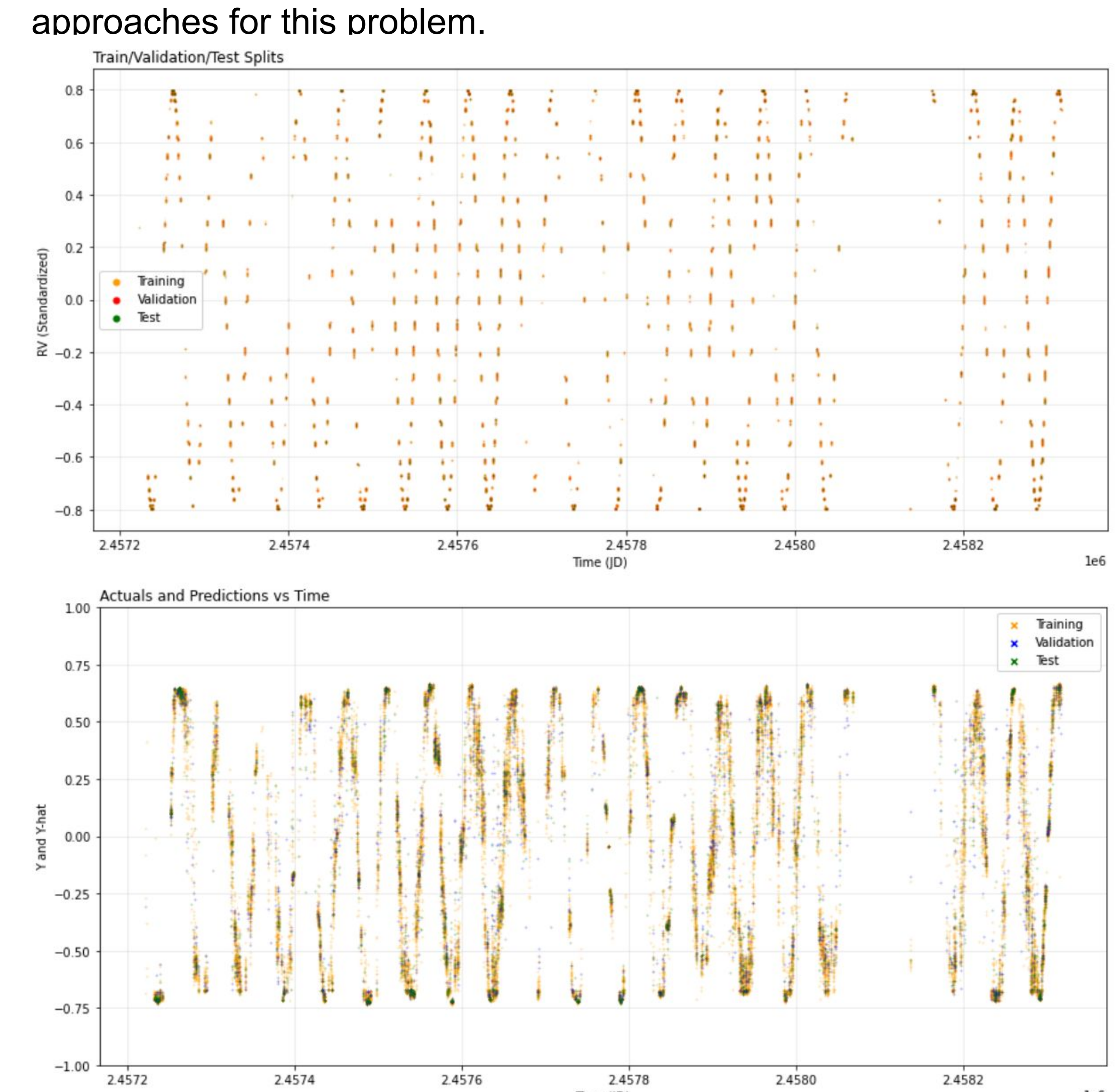

Figure 4. The upper plot shows a 80 cm/s planet-induced RV signal that has been injected into HARPS-N-S. The lower plot shows the recovered (predicted) RV signal. Coloring is based on training (80%), validation (10%), and test (10%) splits.

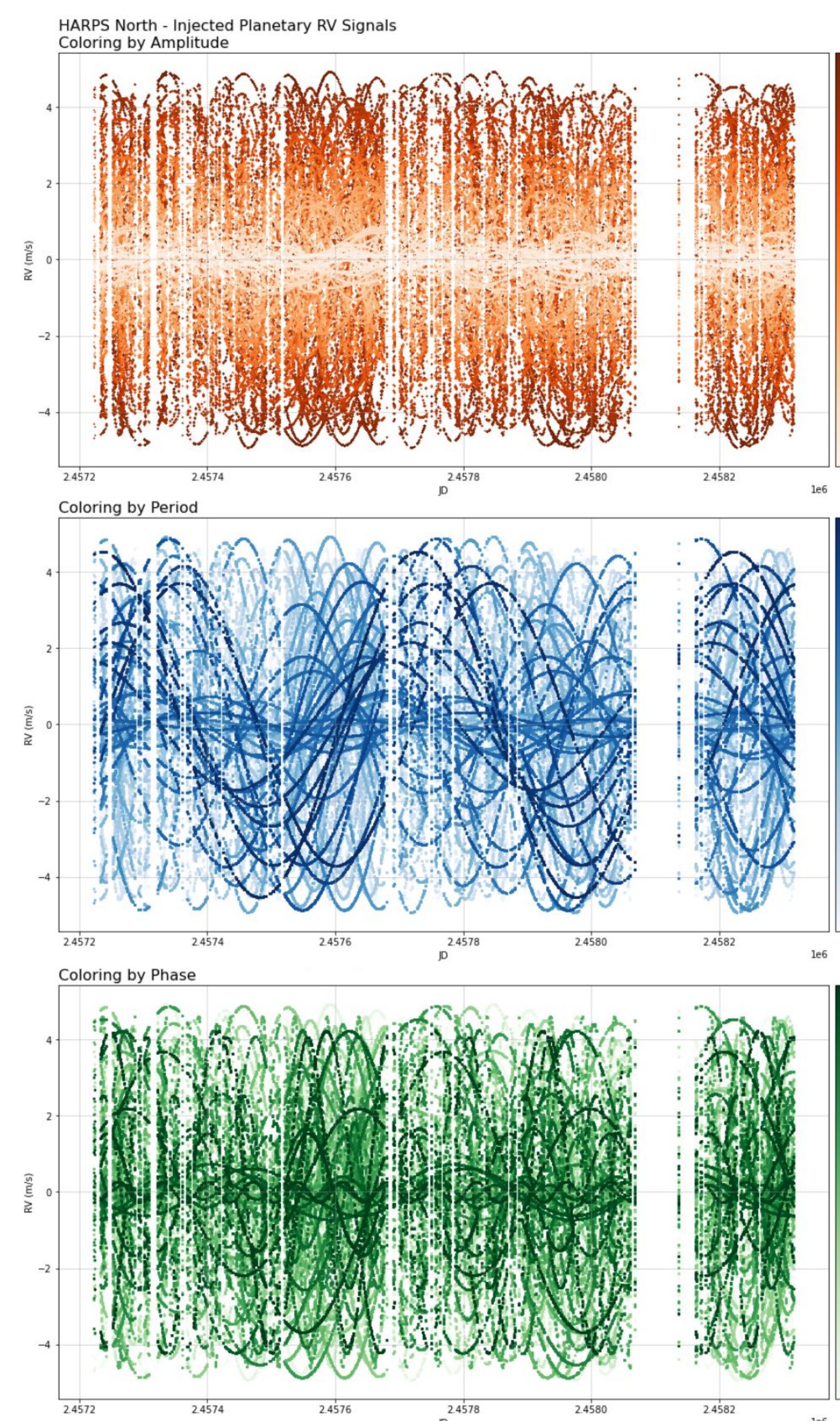

Figure 3. Varying planetary RV signals resulting from the pipeline - HARPS-ACB displayed in this example. RVs are the same across the three plots, but coloring is used to highlight the differences in RV signal characteristics.

Network In addition, the team developed code to perform the end-to-end training of neural networks on these data. The code exposes parameters up-front, allowing for quick and readable experimentation when modifying approaches to dimensionality reduction, network architecture, network hyperparameters, and the number of input planetary datasets, allowing the team to run multiple experiments, expanding our understanding of the feasibility of strategies for modeling planetary RV signals. Our baseline HARPS-N-S architecture was trained and evaluated on randomized train (80%), validation (10%), and test (10%) splits for a planet-induced RV signal of 0.8 m/s (Figure 4). The network was able to recover the planetary RV signal with a RMSE of 0.168 m/s on the training split; validation RMSE of 0.2131 m/s; test RMSE of 0.2099 m/s (Figure 4 and 5). The slightly higher validation RMSE, compared to the train RMSE, indicates some overfitting, while the loss curves did show fairly good generalization.

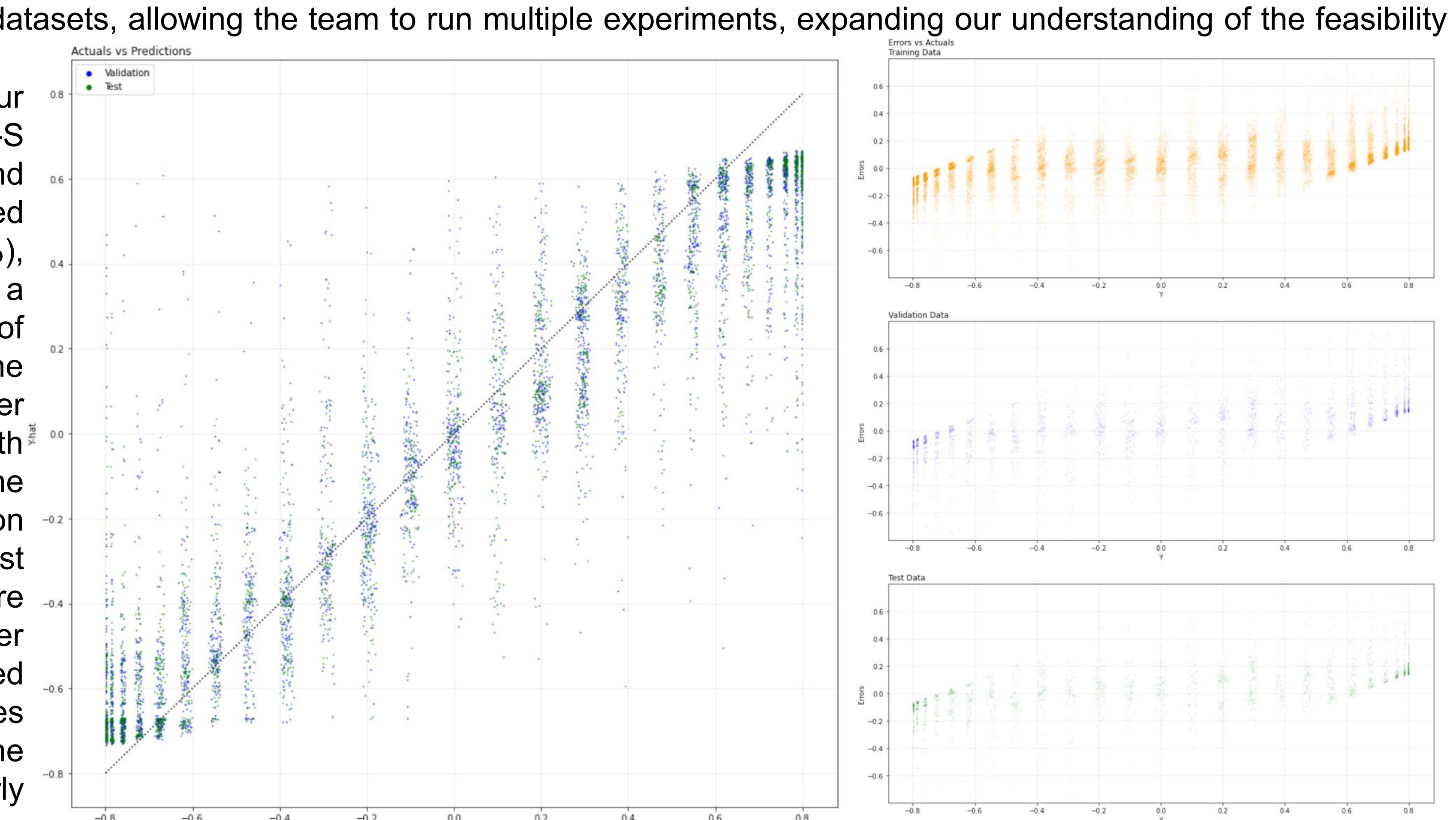

Figure 5. The upper plot shows a 80 cm/s planet-induced RV signal that has been injected into HARPS-N-S. The lower plot shows the recovered (predicted) RV signal. Coloring is based on training (80%), validation (10%), and test (10%) splits.

SIGNIFICANCE

The research was an initial step in enhancing the field of EPRV data reduction by providing the EPRV community with a proof-of-concept method for substantially mitigating stellar RV jitter in the wavelength-domain, as well as allowing us to begin understanding the data requirements for neural networks in distinguishing between planetary and stellar activity RVs.

The pre-processing and baseline DL pipelines from this research showed promising results in terms of the applicability of deep learning to predict EPRVs for any star. This pilot study greatly aided in preparing and succeeding with both the NASA ROSES-EPRV as well as the Topical R&TD proposals, strengthening JPL's position in the EPRV domain, one of the primary objectives of this proposal.

As methods for mitigating stellar RV jitter improve, the EPRV community will be able to apply these methods to measure more precise masses for small, rocky planets like earth. This work forms a basis for improved EPRV observations that could boost the efficiency of upcoming missions like HabEx that plan to directly image habitable exoplanets by ~50 % (R. Morgan, EPRV working group report), which would improve our chance of detecting biosignatures and propel forward the search for extraterrestrial life.

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