Removing Stellar Activity from RVs Using Artificial Intelligence

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Background

Since the first detection of an exoplanet around a sun-like star in 1995 (Mayor & Didier 1995), the radial velocity (RV) method has seen tremendous improvements. Currently, we are limited in RV measurement precision due to competing noise from stellar activity.

Heightening our sensitivity to signals from earth-analogue exoplanets requires thorough characterization of the stellar activity signals, such that we can automatically regress out their noise.

We propose a regression method that uses a deep convolutional neural network to characterize and regress out stellar variability signals, thereby increasing our sensitivity of detection, paving the way towards discovering more earth-mass exoplanets.

Methods

Radial Velocity (RV) method - exploits the gravitational pull a planet exerts on its host star which induces a radial velocity and red/blueshifts the starlight.

Convolutional Neural Networks (CNNs) - artificial intelligence algorithm that has revolutionized many complex tasks and is considered state-of-the art for shape recognition. CNNs require a training set.

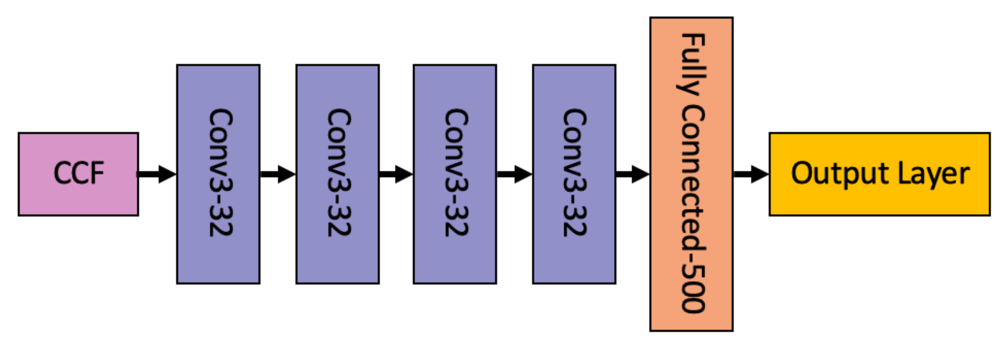

Figure 1: Convolutional Neural Network (CNN) Architecture- The architecture of our best-performing model. Conv stands for convolutional layers.

HARPS-N Solar Telescope – Our training set consists of 629 observations from the HARPS-N Solar Telescope spanning July 2015-2018. The HARPS-N spectrograph is a vacuum-enclosed cross-dispersed echelle spectrograph that has temperature and pressure stabilization.

Cross-Correlation Functions (CCFs) - As the host star moves away from us or towards us the average line spectrum is redshifted or blueshifted respectively. This average line spectrum is referred to as a Cross-Correlation Function (CCF). Besides radial velocities induced by planets, the shape of the CCF can also change based on stellar variability (Figure 1). We can train our neural network to recognize these shape changes in order to regress out stellar activity.

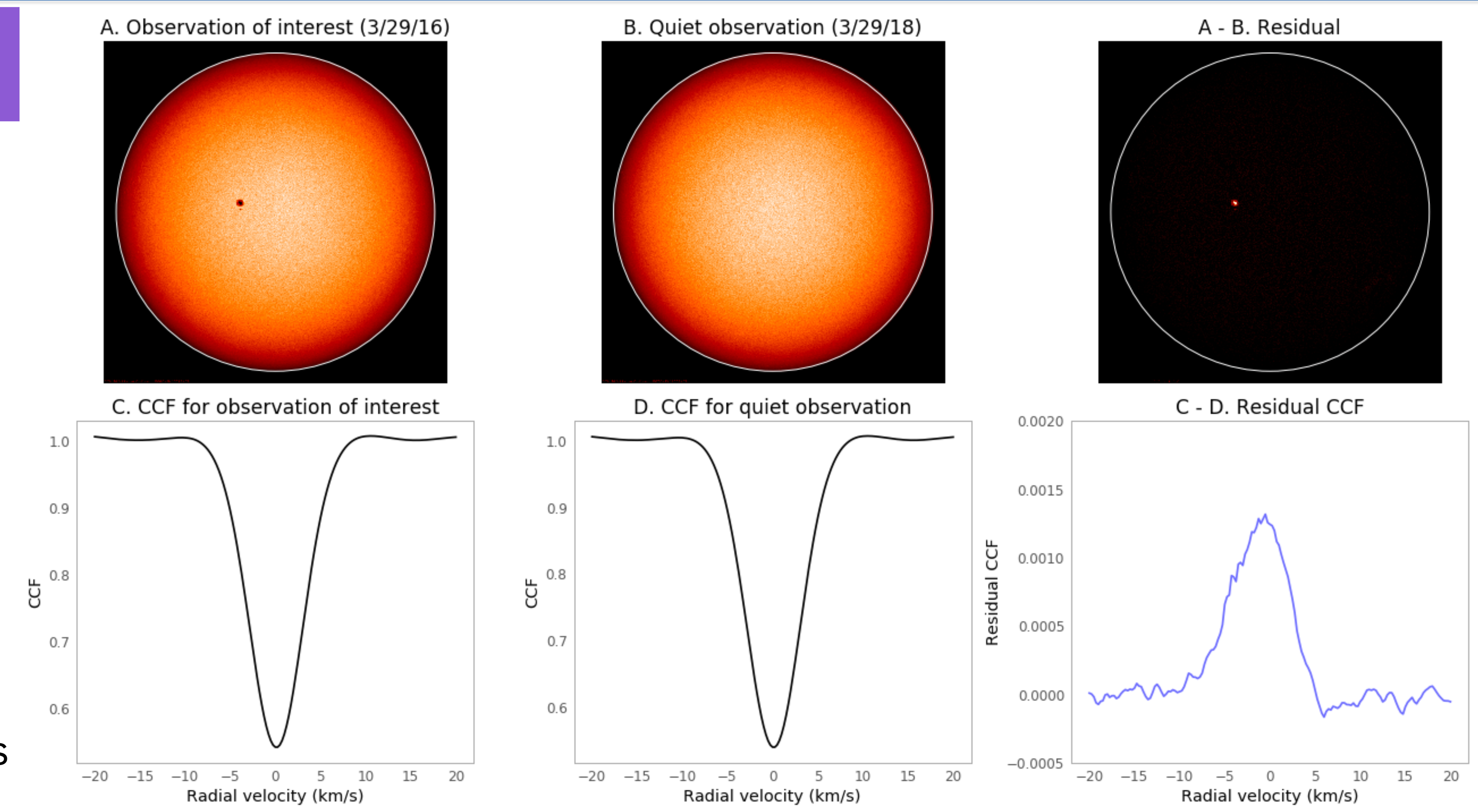

Figure 2: Residual CCFs– To highlight differences between CCFs, we subtract a quiet observation (B/D) from the observation of interest (A/C) to get the residuals (A-B/C-D).

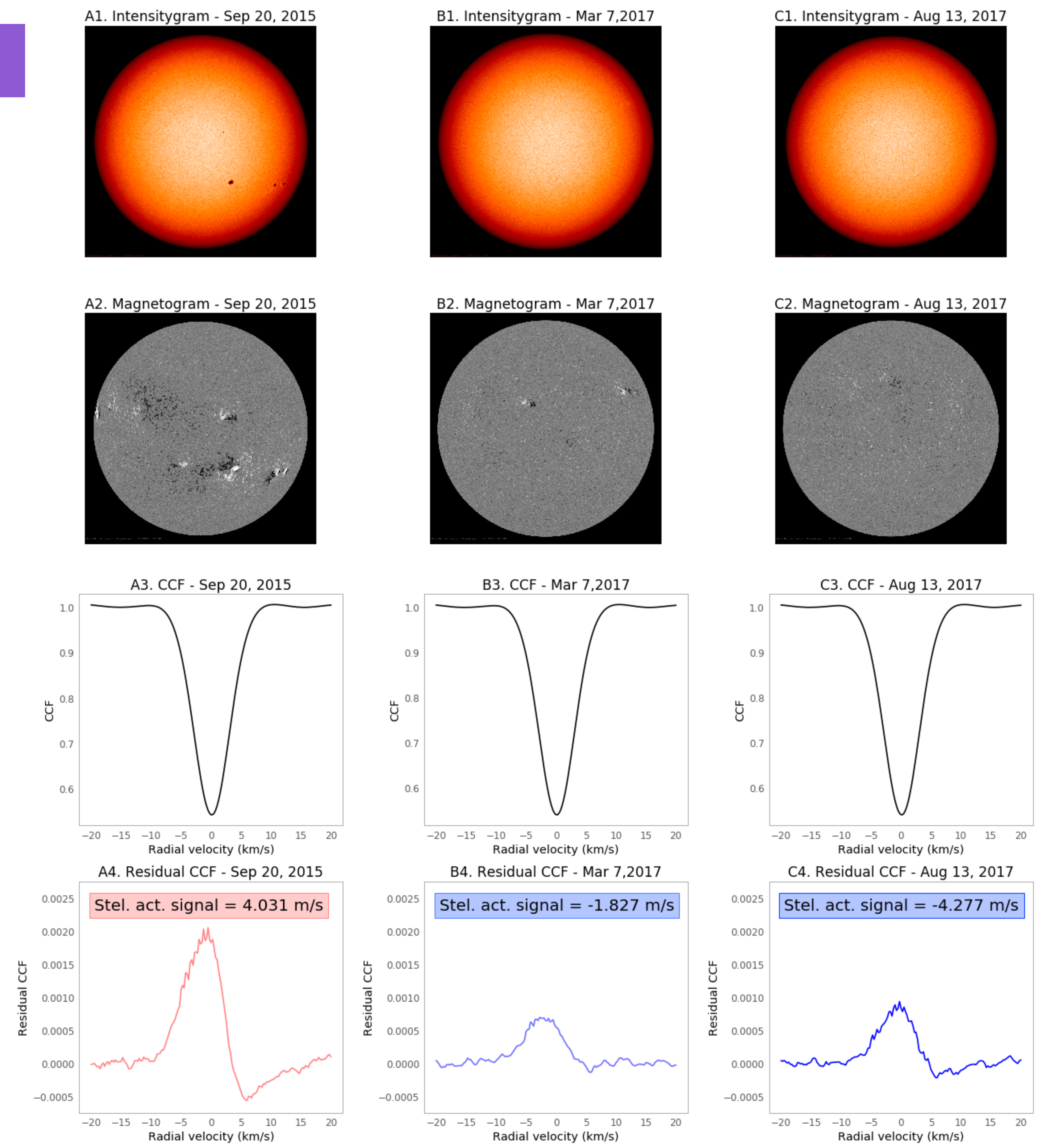

Figure 3: Cross-Correlation Functions and SDO observations – To illustrate how the CCF line shape (A4, B4, C4) corresponds to the inhomogeneities on the Sun's surface, we plot SDO images (A1-2, B1-2, C1-2) and CCFs from the same day.

Results

- In HARPS-N Solar Telescope data, our convolutional neural network can reduce the raw RV scatter from 1.512 m/s to 0.737 m/s (Figure 4, 5).
- In terms of planet detection, this improvement could allow observers to go from only being able to detect a gas giant of ~17$M_{\oplus}$ to becoming sensitive to a large rocky planet ~8.3$M_{\oplus}$. In this way, this work paves the way towards detecting smaller and smaller planets.

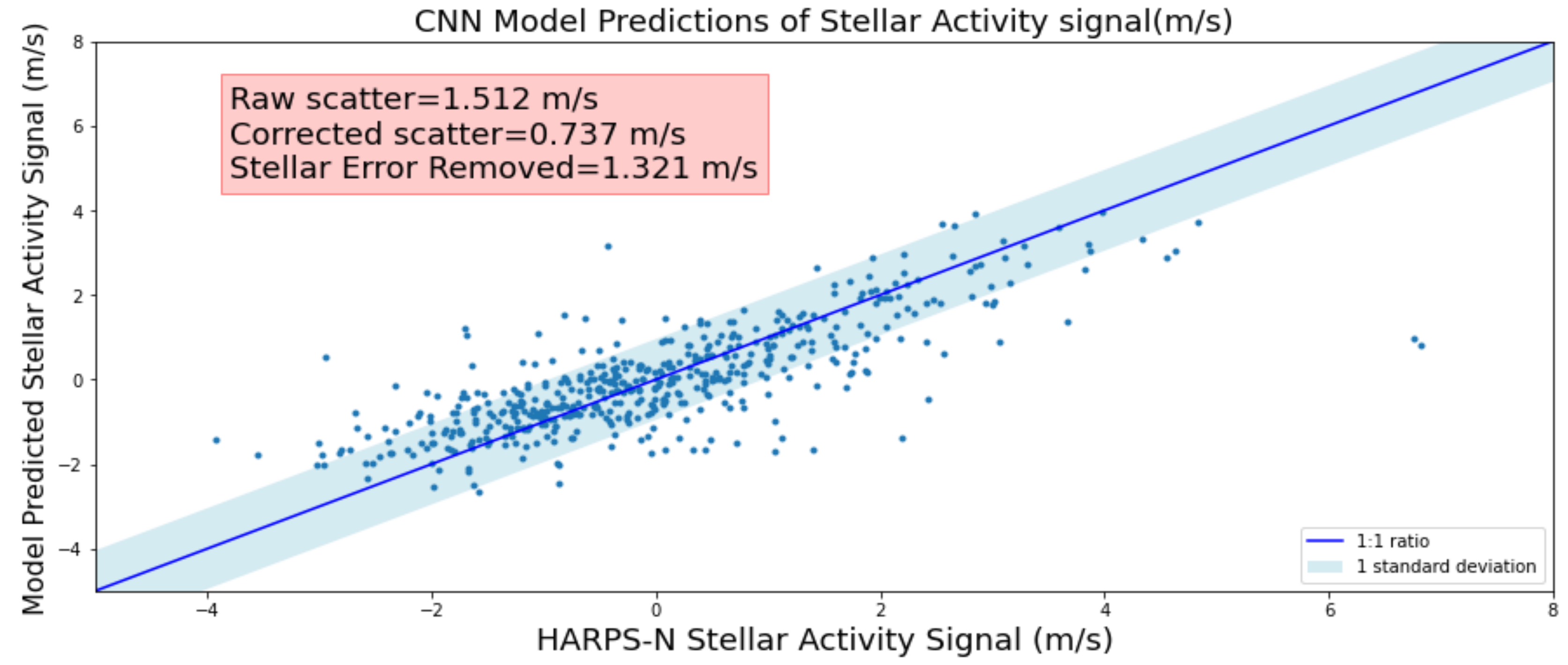

Figure 4: Convolutional Neural Network (CNN) predictions- Our CNN model can reduce the HARPS-N raw scatter from 1.5m/s to 0.737m/s by regressing out stellar activity signals based on the average line shape (CCF).

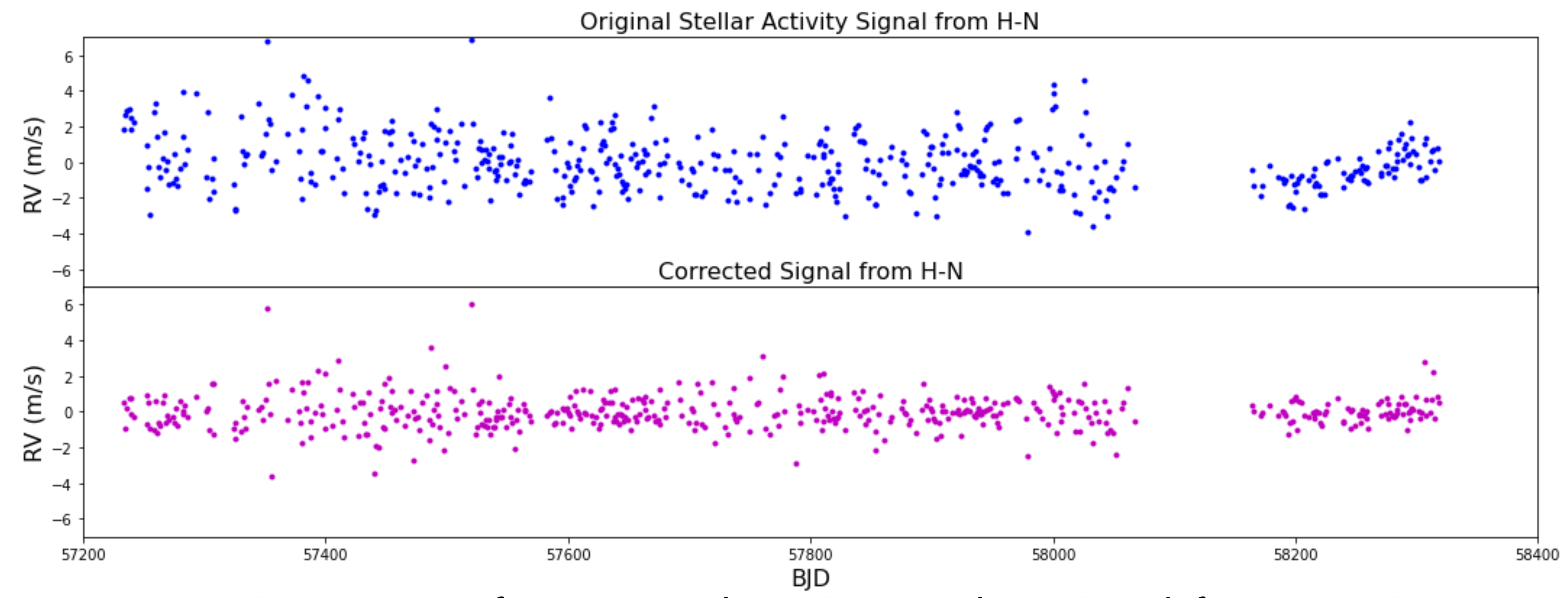

Figure 5: Comparison of Uncorrected vs. Corrected RV Signal from HARPS-N. a) Original Stellar Activity Signal (scatter: 1.512m/s). b) Corrected RV signal after regressing out stellar activity signals using CNN model (scatter: 0.737 m/s).

Future Directions

- To inject planet signals and further quantify how regressing out stellar activity improves our planet detection sensitivity
- Expand our technique to stars outside of our solar system

Acknowledgments

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References

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