# Analyzing the Impacts of Stellar and Planetary Parameters to Exoplanet Habitability through Machine Learning

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## Introduction

Are there any planets other than Earth potentially habitable by humans? What factors affect habitability and how do they impact habitability? Seeking answers to these questions has been an active research field in astrophysics in the past decade.

In this study, we identified the most influential stellar and planetary parameters to exoplanet habitability and analyzed how they impact habitability through the lens of machine learning.

## Objectives

Build high-quality ML models (**Random Forest**, **XGBoost**) for exoplanet habitability prediction.

Perform analysis on the ML models through **SHAP** (**SH**apley **A**dditive ex**P**lanations) techniques to understand how stellar and planetary parameters impact exoplanet habitability.

## Dataset

The primary data sources for this study:

- Planetary Systems Composite Data @ **NASA Exoplanet Archive**: **5,834** confirmed exoplanets.
- Habitable World Catalog (**HWC**), PHL @ UPR Arecibo: **5,599** exoplanets.

The NASA dataset was joined with the HWC dataset. Then the `P_HABITABLE` data field from the HWC dataset to label the training data.

## Model Selection

Research in machine learning shows that tree-based models could be very effective for tabular dataset (on par with deep learning models). In this study, we chose to build **Random Forest** and **XGBoost** classifiers for exoplanet habitability prediction.

## Feature Engineering & Model Training

### Step 1: Data Downloading

- ***NASA Exoplanet Archive*** *(**5,834** exoplanets)*
- ***Habitable Worlds Catalog (HWC)****, PHL @ UPR Arecibo (**5,599** exoplanets)*

### Step 2: Feature Engineering

**Data Joining**

Join data from NASA and HWC.

Use `P-HABITABLE` data field from HWC to label training data.

**Data Cleaning**

* Filter out exoplanets with questionable status. (`pl_controv_flag`=1)

* Limit dataset to exoplanets. with **single-host stars**.

* Remove irrelevant features.

**Handling Missing Values**

* Remove features with ≥25% missing values.

* **Categorical**: fill missing values with **mode**.

* **Numerical**: fill missing values with Multivariate Imputation by Chained Equation (**MICE**).

**Converting Categorical Values**

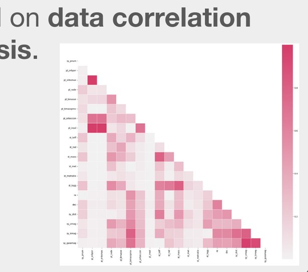
* **One-Hot Encoding** to convert categorical features into numerical values.

**Handling Data Imbalance**

* The dataset is highly imbalanced. Apply a combination of Synthetic Minority OVersampling Technique (**SMOTE**) and Edited Nearest Neighbors (**ENN**) techniques to oversample minorities and downsample majorities.

**Data Correlation Analysis**

Remove redundant features based on **data correlation analysis.**



**Min-Max Scalar**

Standardize value ranges to **[0.1]**

### Step 3: Model Training

* Randomly shuffle dataset, then split into train & test datasets for training & evaluation. Repeat 100 times. Use avg accuracy as the measure of model quality for the corresponding hyperparameters.

* Hyperparameter tuning through exhaustive search.

### Step 4: SHAP Analysis

* Feature importance analysis through **SHAP**.

* Perform analysis through **SHAP** to understand how the influential features impact the exoplanet habitability.

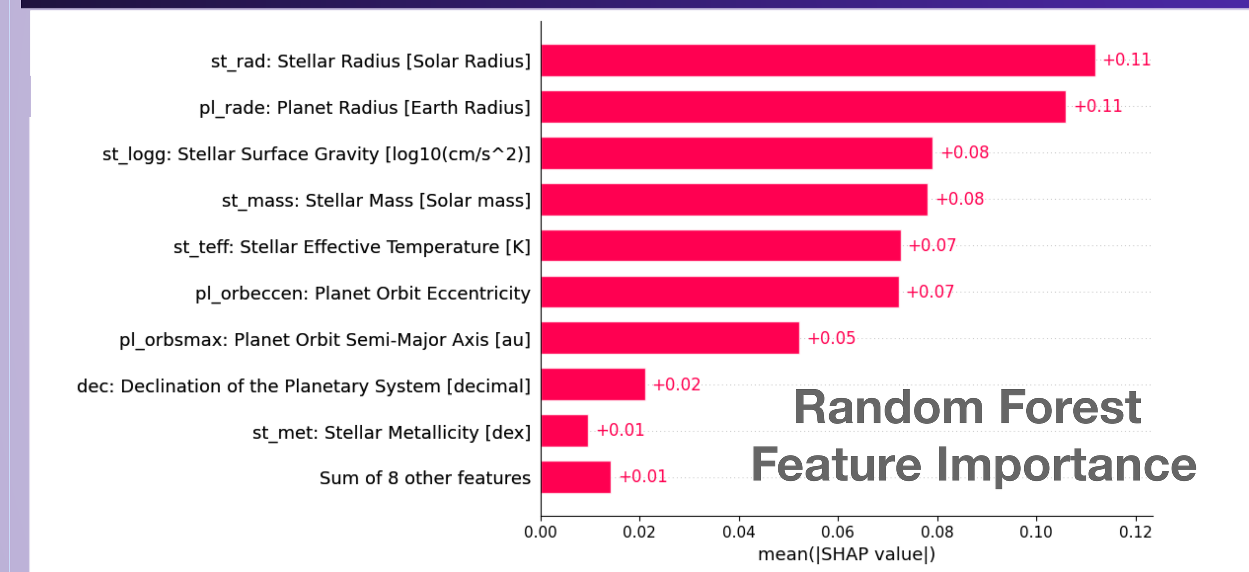
### Random Forest Model Evaluation

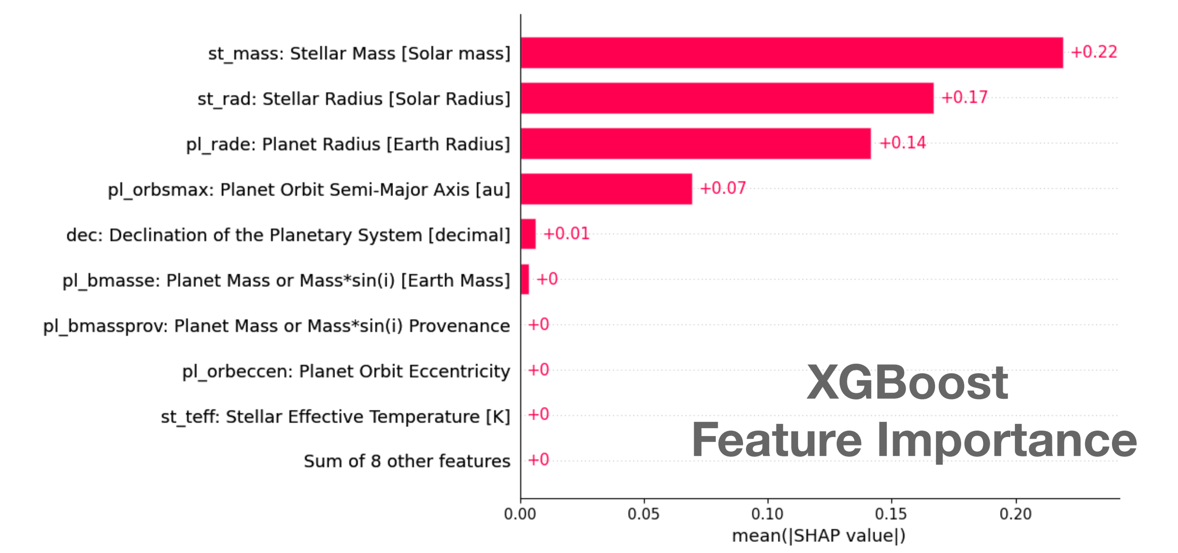
| Class | Random Forest | | |
|---|---|---|---|
| | Precision | Recall | F1 score |
| 1 (Habitable) | 0.96 | 0.94 | 0.95 |
| 0 (Non-Habitable) | 0.94 | 0.96 | 0.95 |

### XGBoost Model Evaluation

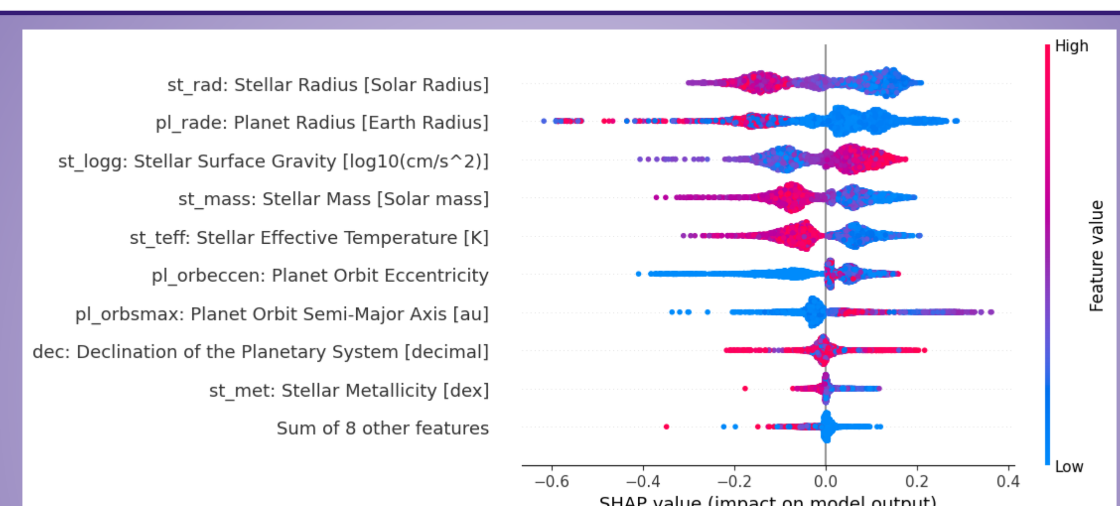
| Class | XGBoost | | |
|---|---|---|---|
| | Precision | Recall | F1 score |
| 1 (Habitable) | 0.94 | 0.97 | 0.95 |
| 0 (Non-Habitable) | 0.97 | 0.93 | 0.95 |

## SHAP Analysis

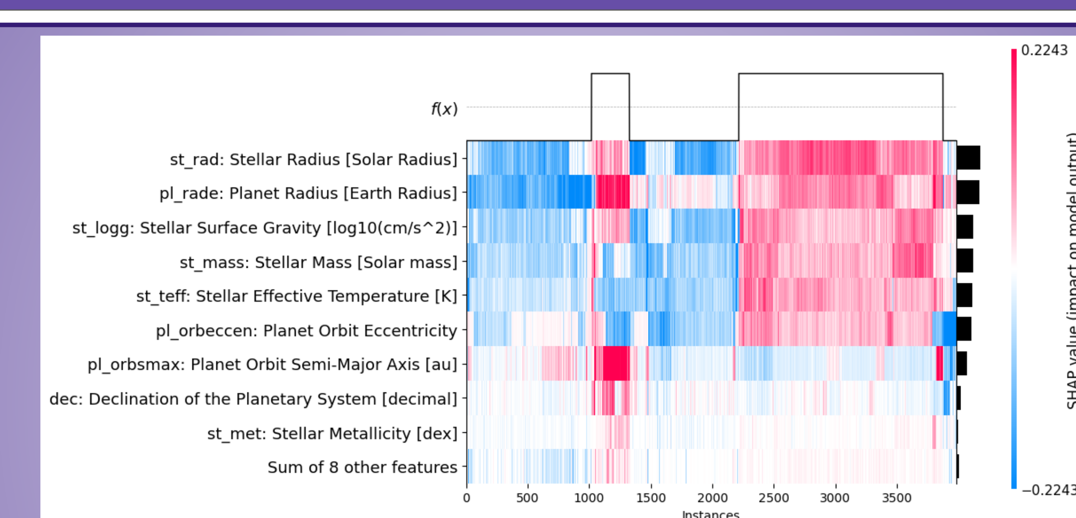



### Deep Dive on Random Forest through SHAP

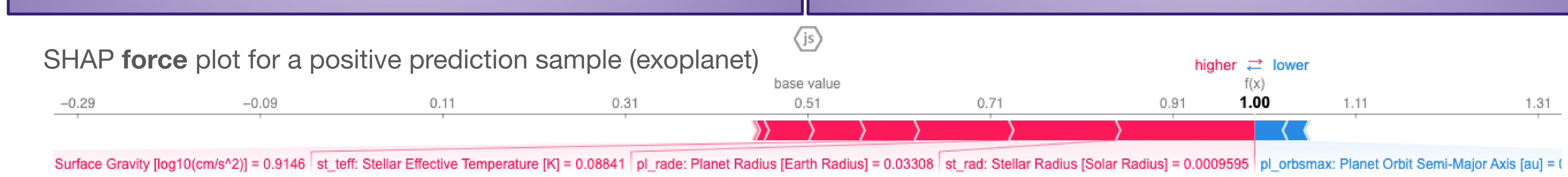


This SHAP **beeswarm** plot shows that relatively higher stellar radius, planet radius, stellar mass, and stellar effective temperatures contribute to habitability negatively, while relatively higher planet orbit semi-major axis contributes to habitability positively.

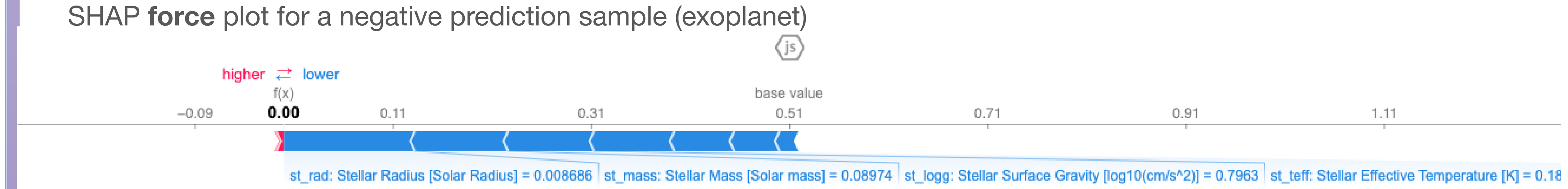


This SHAP **heatmap** plot groups samples (exoplanets) that have the same model predictions and the similar feature impacts together.

SHAP **force** plot for a positive prediction sample (exoplanet)

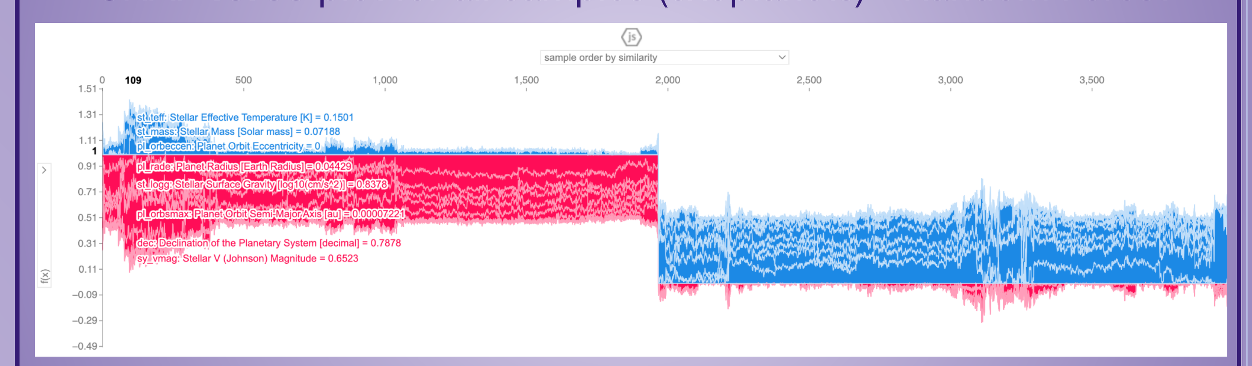


SHAP **force** plot for a negative prediction sample (exoplanet)

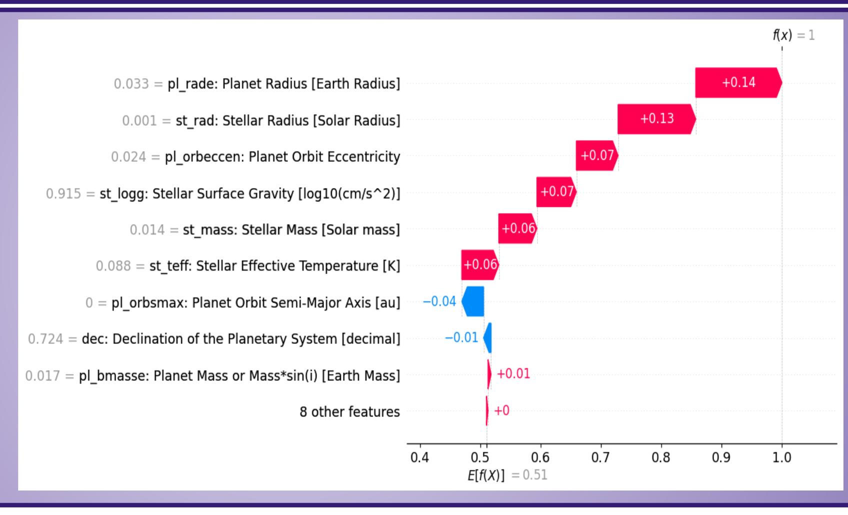


## More SHAP Analysis

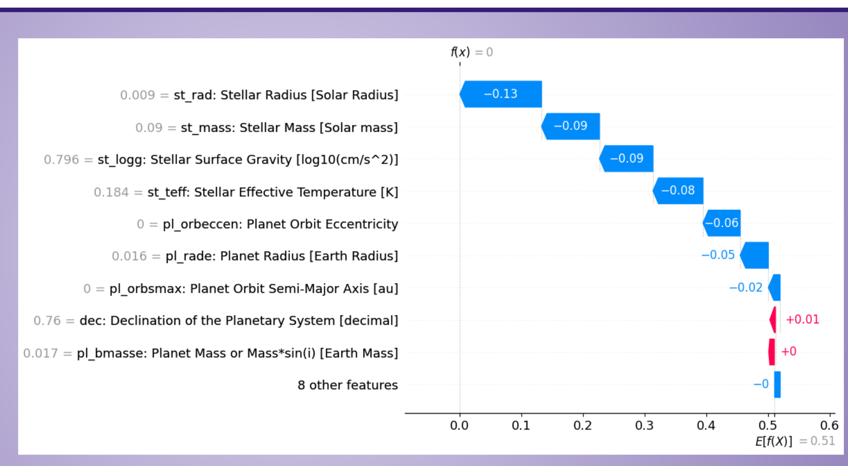
SHAP **force** plot for all samples (exoplanets) - Random Forest



SHAP **waterfall** plot for a positive prediction sample (exoplanet) - Random Forest



SHAP **waterfall** plot for a negative prediction sample (exoplanet) - Random Forest



## Conclusions

**Random Forest** and **XGBoost** models were trained to predict exoplanet habitability with high F1 scores at **0.95**.

Feature importance analysis through **SHAP** identified influential stellar and planetary parameters to habitability. Further **SHAP** analysis on those parameters showed that relatively higher stellar radius, stellar mass, stellar effective temperature, and planet radius have negative impacts on habitability, while relatively higher planet orbit semi-major has a positive impact.

This study demonstrated that machine learning techniques could be effective for both predicting exoplanet habitability and understanding how stellar and planetary parameters impact exoplanet habitability.

## Future Work

Train a **Neural Network** model for habitability prediction and SHAP analysis. Compare with tree-based models.

Study **Planetary Systems** as a whole to understand what planetary systems might be more likely to host habitable planets.