

# Milestone 1: Data Collection, Description, and Preprocessing Strategy

## Dataset Description

### Data Source

The primary dataset is sourced from the **NASA Exoplanet Archive (Planetary Systems Table)**. This is a public astronomical archive containing data on all confirmed exoplanets.

- **Total Raw Observations:** ~39,000 rows
- **Unique Confirmed Planets:** ~6,100 planets
- **Format:** CSV (Comma Separated Values)

## The "Duplicate" Nature of Astronomical Data

The raw dataset contains approximately 39,000 entries for only 6,100 planets. This is because the archive records **historical scientific publications**. If a specific planet (e.g., *Kepler-186 f*) has been observed by five different research teams over a decade, it appears five times in the dataset with slightly different measurement values.

For Machine Learning purposes, treating these rows as independent data points would introduce **Data Leakage** and **Bias**. Therefore, a critical part of our data description involves defining the "Best Representative Row" for each planet.

## Feature (Selected Attributes)

From the 280+ columns available in the raw data, we have selected the following features based on their relevance to planetary habitability physics.

### Planetary Parameters

Feature Name (Raw)	Standardized Name	Unit	Description
pl_name	planet_name	String	Unique identifier for the exoplanet.
pl_rade	radius_earth	Earth Radii (\$R_{E}\$)	The radius of the planet compared to Earth. Crucial for determining if a planet is rocky or gaseous.

Feature Name (Raw)	Standardized Name	Unit	Description
pl_masse	mass_earth	Earth Masses (\$M_E\$)	The mass of the planet. Determines gravity and atmosphere retention.
pl_orbper	orbital_period	Days	Time taken to complete one orbit around the host star.
pl_orbsmax	semimajor_axis	AU	Average distance from the star. Determines the thermal environment.
pl_eqt	eq_temp_k	Kelvin (\$K\$)	Theoretical equilibrium temperature of the planetary surface.
pl_dens	density	\$g/cm^3\$	Bulk density, used to infer composition (Iron, Rock, Water, Gas).

Stellar Parameters

Feature Name (Raw)	Standardized Name	Unit	Description
hostname	host_star_name	String	Name of the host star.
st_teff	star_temp_k	Kelvin (\$K\$)	Effective surface temperature of the star.
st_lum	star_luminosity	log(Solar)	Total energy output of the star relative to the Sun.
st_spectype	star_spectype	String	Spectral classification (e.g., G2V, M3). Indicates star age, size, and radiation stability.

Data Cleaning & Deduplication

Allowing multiple rows for the same planet violates this assumption and causes the model to memorize specific planets rather than learning generalizable physics.

Implementation:

- Completeness Sorting:** We calculate the number of **NaN** (missing) values for every row.
- Selection:** For every unique planet name, we retain only the row with the **least missing data**.
- Result:** The dataset is reduced from ~39,000 observations to ~6,100 unique, high-quality planetary profiles.

Missing Data Handling (Imputation Strategy)

Astronomical data often suffers from missing values due to observational limitations (e.g., Mass is harder to measure than Radius).

### Physics-Based Recovery (Unit Conversion)

Before statistical imputation, we recover real data stored in alternative units. The NASA archive often stores data in "Jupiter Units" when "Earth Units" are missing.

- **Formula:**  $\text{Radius}_{\text{Earth}} \approx 11.209 \times \text{Radius}_{\text{Jupiter}}$
- **Formula:**  $\text{Mass}_{\text{Earth}} \approx 317.8 \times \text{Mass}_{\text{Jupiter}}$
- This will give us more ground real values of the dataset

### Statistical Imputation

For remaining gaps, we use **Median Imputation**.

- **Why:** Exoplanet data is heavily right-skewed (power-law distribution). The Mean is sensitive to outliers (massive gas giants), whereas the Median provides a robust central tendency for typical planets.

## Outlier Detection & Handling

Outliers are often errors to be removed. In Exoplanetary Science, outliers are often **real, massive objects** (Hot Jupiters, Brown Dwarfs).

- **Lower Bound (Physics Floor):** We enforce strict physical limits. Values  $\leq 0$  for Mass, Radius, or Temperature are removed as they represent measurement errors.
- **Upper Bound (No Capping):** We explicitly **do not** remove or cap massive planets.
  - A planet with  $100 M_E$  is physically valid. Removing it would bias the model against gas giants.
  - So, We use robust scaling methods (see Section 3.5) to handle these large values without deleting them.

## Feature Engineering

We derive new "synthetic" features that combine multiple physical parameters to give the ML model stronger signals regarding habitability.

### 1. Habitability Score (ESI Proxy):

- A calculated index based on the geometric mean of a planet's similarity to Earth in terms of Radius and Temperature.
- *Formula:*  $\text{Score} = \sqrt[0.57]{(1 - \frac{R - R_{\oplus}}{R + R_{\oplus}})} \times (1 - \frac{T - 288}{T + 288})^{1.07}$

### 2. Stellar Compatibility:

- Maps Spectral Types (O, B, A, F, G, K, M) to a numerical score.
- G and K stars (Sun-like) receive high scores (1.0 - 0.9). M stars (volatile red dwarfs) receive medium scores. O/B stars (short-lived) receive low scores.

### 3. Orbital Stability:

- A logarithmic interaction feature between Orbital Period and Semi-Major Axis to represent the orbital dynamics of the system.

## Categorical Encoding & Feature Scaling

### Encoding:

- **Feature: `star_class`** (derived from **`star_spectype`**).
- **One-Hot Encoding.**
- **Justification:** Spectral types are nominal categories without a strict linear ordinal relationship suitable for regression.

### Scaling:

- **RobustScaler.**
- Standard scalers (Z-score) use Mean and Variance. Because we retained massive "Monster" planets (outliers), the Mean is distorted. **RobustScaler** uses the Median and Interquartile Range (IQR), ensuring that Earth-like planets are scaled appropriately even in the presence of massive Gas Giants.

## Target Variable Creation

Since "Habitability" is not a direct column in the raw data, we generate a ground-truth label for supervised learning.

- **Label: `habitable_binary`** (0 or 1).
- **Criteria (Conservative):**
  1. **Radius:**  $0.5 R_{\oplus}$  to  $1.6 R_{\oplus}$  (Likely Rocky Surface).
  2. **Temperature:**  $200 K$  to  $330 K$  (Potential for Liquid Water).

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## Conclusion

The preprocessing pipeline outlined above transforms raw, noisy, and duplicated astronomical data into a clean, physics-compliant dataset.