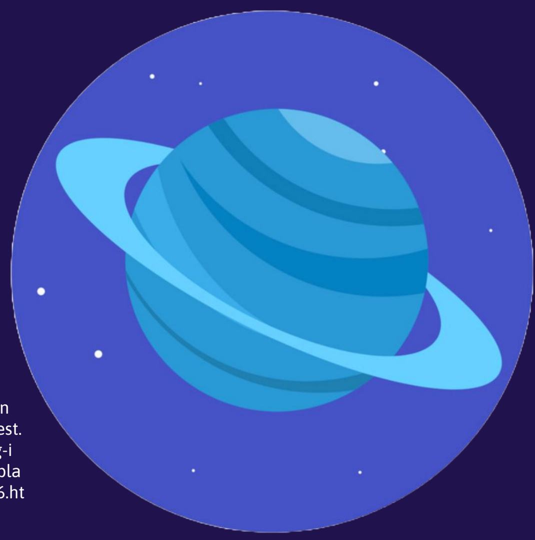
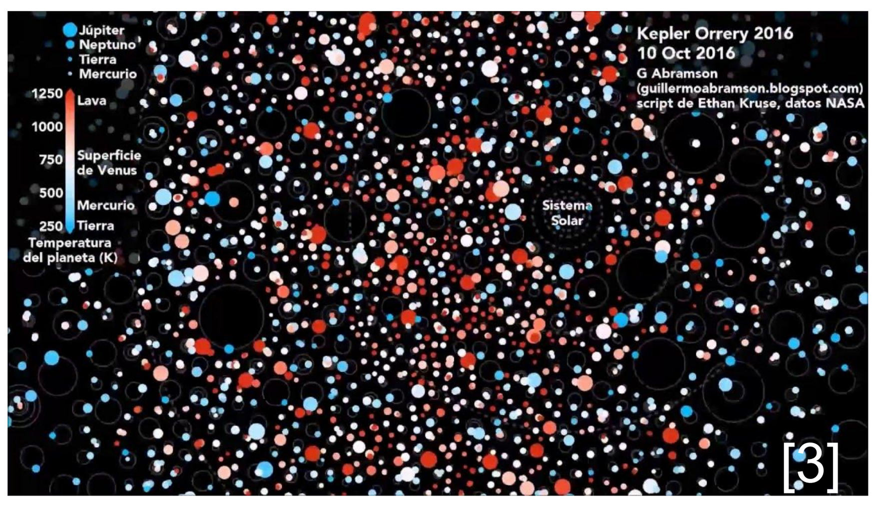
Star2Planet

Decoding and Predicting the Stellar Signatures of Planet Formation



INTRODUCTION

Thousands of exoplanets are known, yet the origins of their diversity remain unclear. Star2Planet links stellar chemistry and Galactic environment to planet formation and predicts planet-hosting stars using the insight.

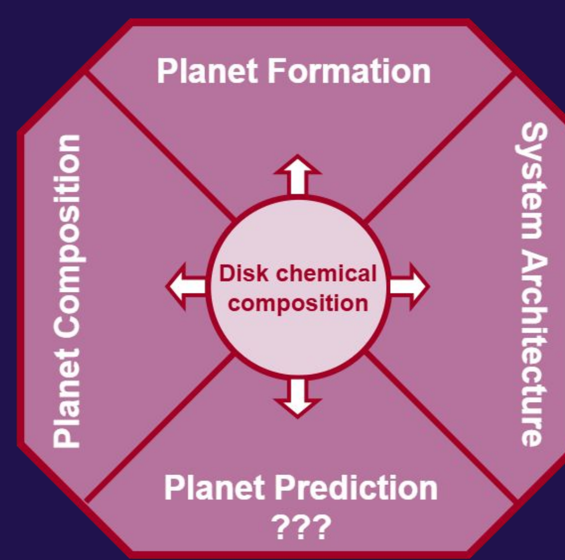


Guillermo Abramson. Kepler orrery 2016. Youtube. https://www.youtube.com/watch?v=AnY1Vl6BaYo

-> Why do some stars form planets while others do not?

What we know

- Planets are very **common and diverse** in the Galaxy.[1,2]
- **Chemistry shapes** planet formation, composition, and and even habitability.[3,4]



Correlations with disk metallicity. Created by student researcher using app.diagrams.net, 2025.

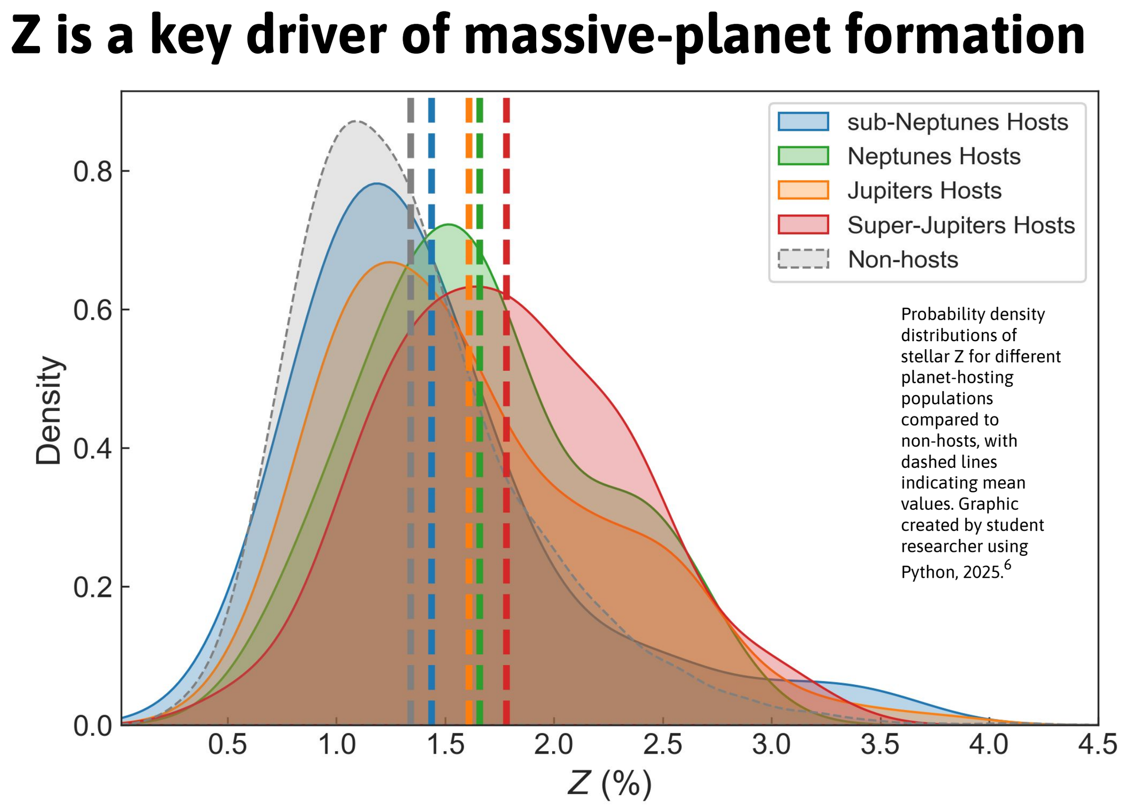
STUDY: Metallicity Controls Planet Formation & Architecture

Computed disk metallicity (Z) using a stoichiometric disk model[5] rather than using iron as a proxy for metallicity as often done previously

Planet Formation and Z

Neptune-, Jupiter-, and super-Jupiter hosts have **significantly higher Z** than non-hosts , while super-Earth hosts do not

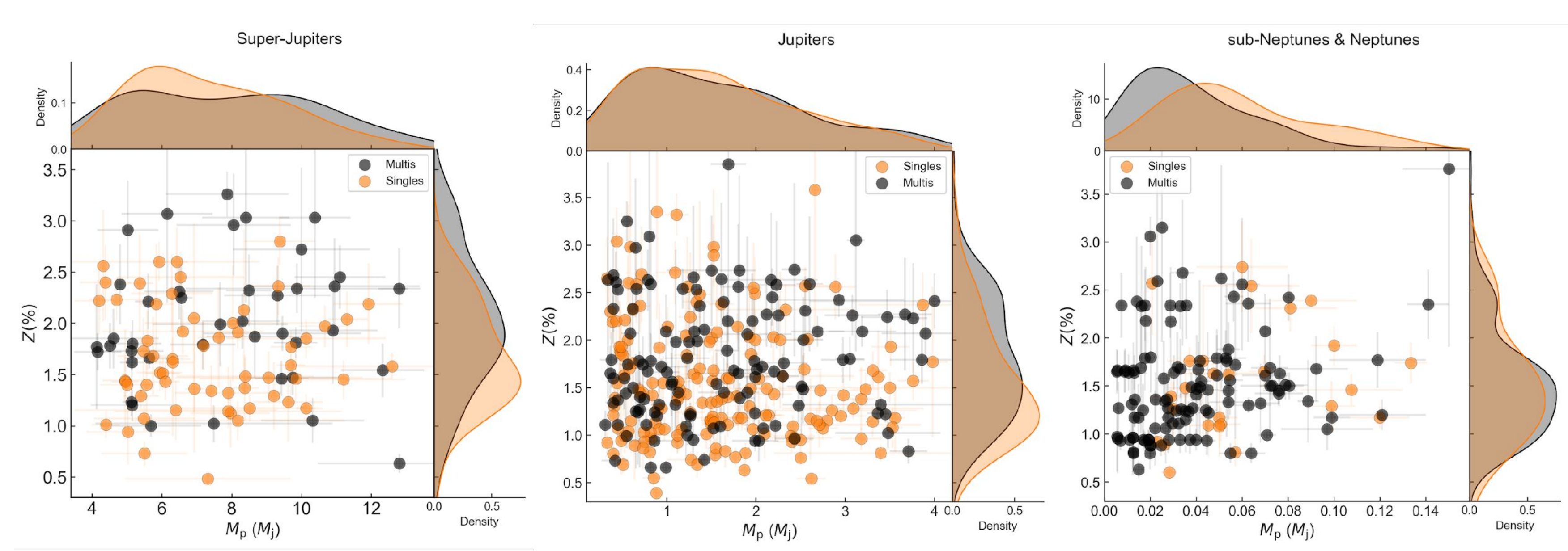
Z is a key driver of massive-planet formation



Probability density distributions of stellar Z for different planet-hosting populations compared to non-hosts, with dashed lines indicating mean values. Graphic created by student researcher using Python, 2025.[6]

Planet Multiplicity and Z

- **Low-mass planets:** multies and singles show statistically similar distributions of Z
- **High-mass planets:** multies form in higher-Z environments than singles
- **Z shapes giant-planet architectures**



Stellar Z versus planetary mass for multi-planet and single-planet systems. Created by student researcher using Python, 2025.[6]

❖ My findings **strongly support a single, dominant planet formation mechanism** (Core Accretion) for planet formation across the Galaxy.

LEARN: Developing Machine Learning model

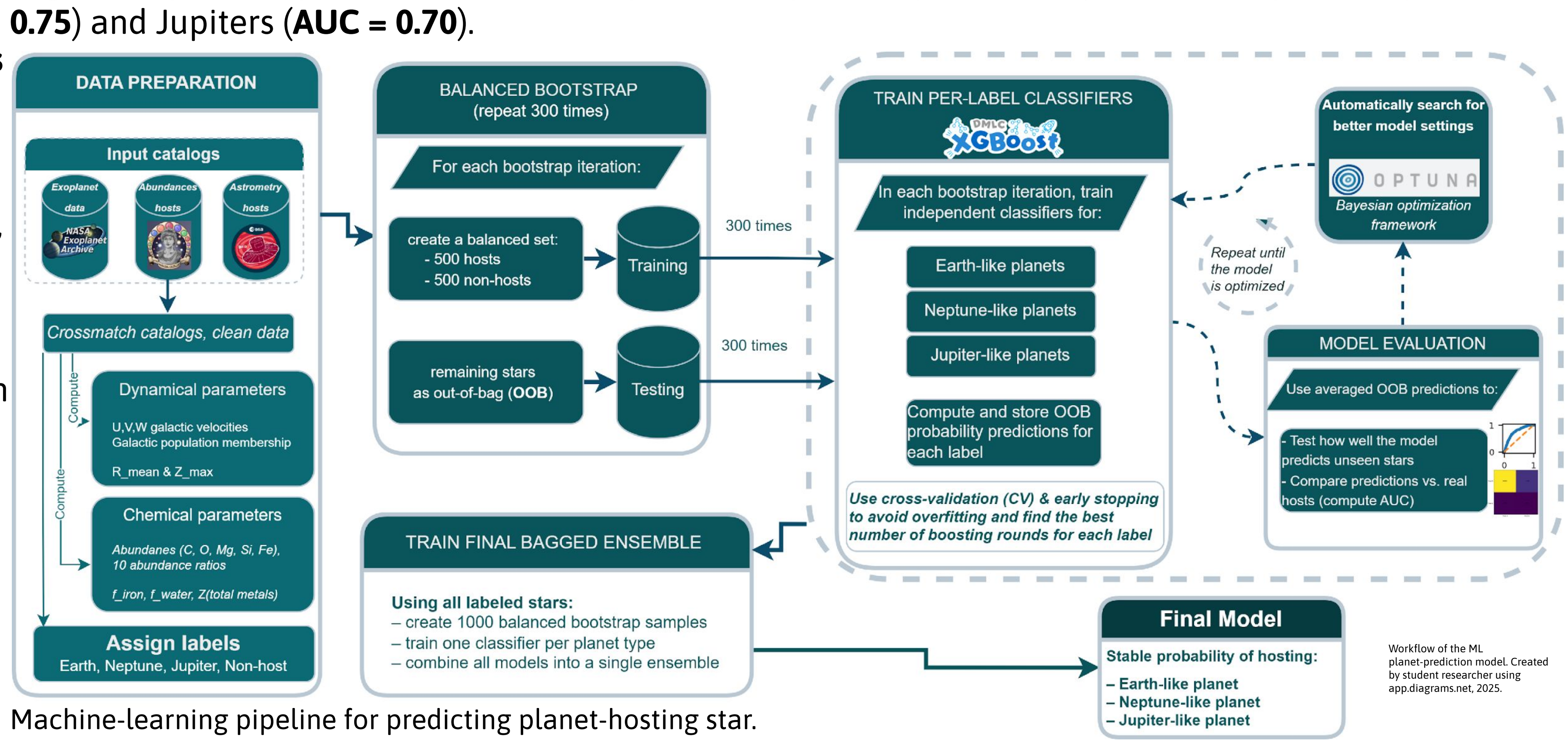
Planet formation is **regulated by disk chemistry** and the birth environment of stars, **encoded in Galactic kinematics**

Protoplanetary disk properties are computed using a stoichiometric disk model based on key elements (C, O, Mg, Si, Fe).

- Because C and O abundances are often unavailable, I developed an ensemble ML model to predict them from Fe, Mg, and Si. Oxygen: 0.07 dex (R^2 = 0.74). Carbon: 0.06 dex (R^2 = 0.86)

Stellar Galactic kinematics are computed to probe the Galactic environment's impact on planet formation.[7]

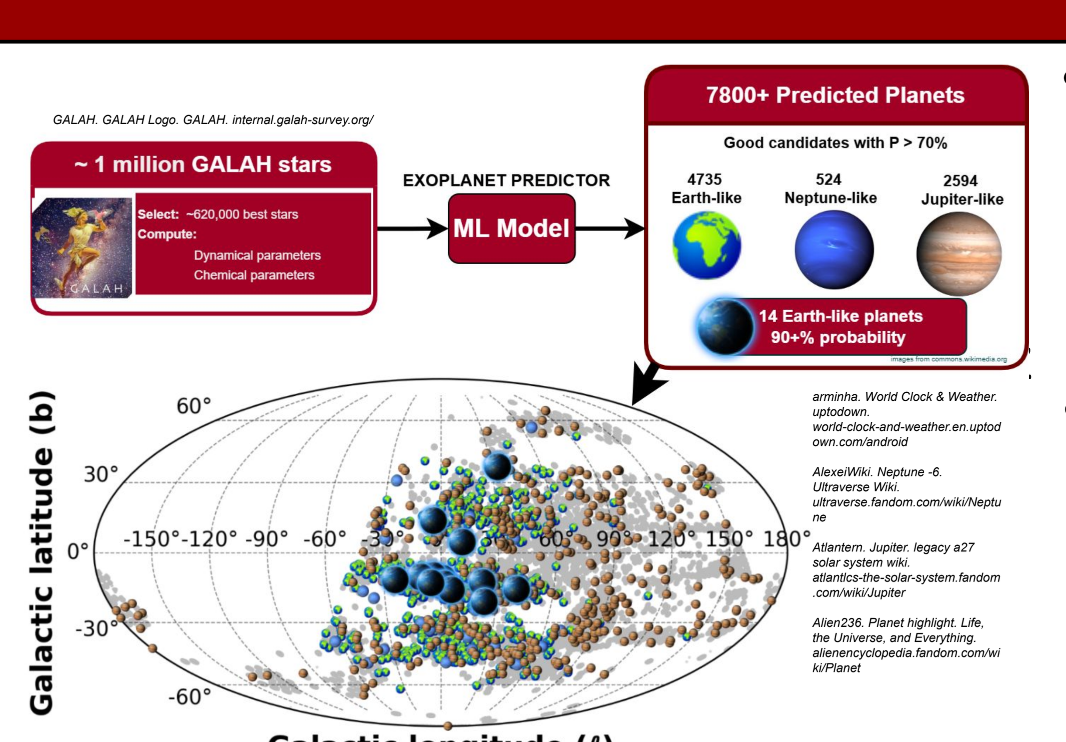
Highest separability was achieved for Neptune-like planets (**AUC = 0.78**), followed by Earths (**AUC = 0.75**) and Jupiters (**AUC = 0.70**).



Machine-learning pipeline for predicting planet-hosting star.

Workflow of the ML planet-prediction model. Created by student researcher using app.diagrams.net, 2025.

PREDICT: New Worlds



Spatial distribution of ML-predicted Earth-, Neptune-, and Jupiter-like planet-host candidates in the GALAH sample, shown in Galactic longitude and latitude. Created by student researcher using Python and app.diagrams.net, 2025.

- **Identified 7,853 planet-hosting stars** in GALAH with **over 70% probability.**
  - ➢ **14 of them Earth like** with over 90% probability.
- Low-mass and high-mass planets show **distinct Galactic distributions.**
  - ➢ This **suggests differing planet-formation environments** across the Galaxy.

CONCLUSIONS & IMPACTS

- ➢ **Disk chemistry is the primary driver of planetary diversity.**
- ➢ **Planet formation is dominated by Core Accretion.**
- ➢ **Indirect stellar observations can predict host stars**
- ➢ **Different Galactic environments give rise to different planetary populations**

Broader impacts

- **Advances a unified, chemistry-based theory of planet formation**
- **Provides mission-ready targets for PLATO (ESA), Roman (NASA), and other future surveys**

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