A NEURAL NETWORK BASED APPROACH TO MODELLING THE INTERNAL STRUCTURE OF TRANSITING ROCKY EXOPLANETS

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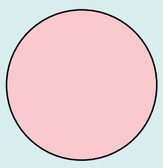
Introduction

Motivation

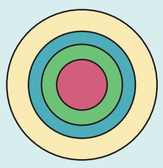
Analysis of the transiting rocky planets studied by ESA's **CH**aracterising **E**x**OP**lanet **S**atellite

CHEOPS

Objective



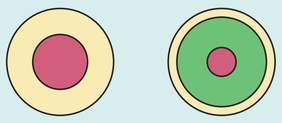
Observations:
- Mass
- Radius
- Stellar Properties



Internal Structure Parameters

Inherent degeneracy: Multiple structures can lead to the same mean density

Example:



Not possible to fully constrain internal structure parameters from observations

The Model

Internal Structure Model

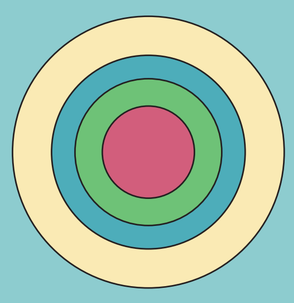
Developed by Haldemann et al. (in prep.), based on Dorn et al. (2015 and 2017, in Bern)

Input parameters
mass, luminosity, equilibrium temperature, layer mass fractions, core and mantle compositions

Solving planetary structure equations (Kippenhahn et al. 2012)

Output parameters
transit radius, layer thicknesses

- Iron Core
- Silicate Mantle
- Water
- H/He Atmosphere



Bayesian Inference Model

Input parameters

Stellar observables
mass, radius, equilibrium temperature, age, composition ([Si/H], [Mg/H], [Fe/H])

Planetary observables
mass, transit depth, period

Full Grid Approach

1. Sample from the stellar parameter space
2. For each planet in the system:
   a. Sample the internal structure parameters from the chosen priors
   b. Use the internal structure model to calculate the radius and therefore the likelihood
3. Accept the system based on the likelihood of its planets

Output parameters
Posterior of the internal structure parameters

Additional assumption:
Planetary composition matches stellar composition exactly
(e.g. Thiabaud et al. 2015)

Advantage:
Computation time only increases **linearly** with an added additional planet because we take advantage of the **high correlation** between planets in multiplanetary systems

Deep Neural Networks

Computational considerations when running the Bayesian inference model:

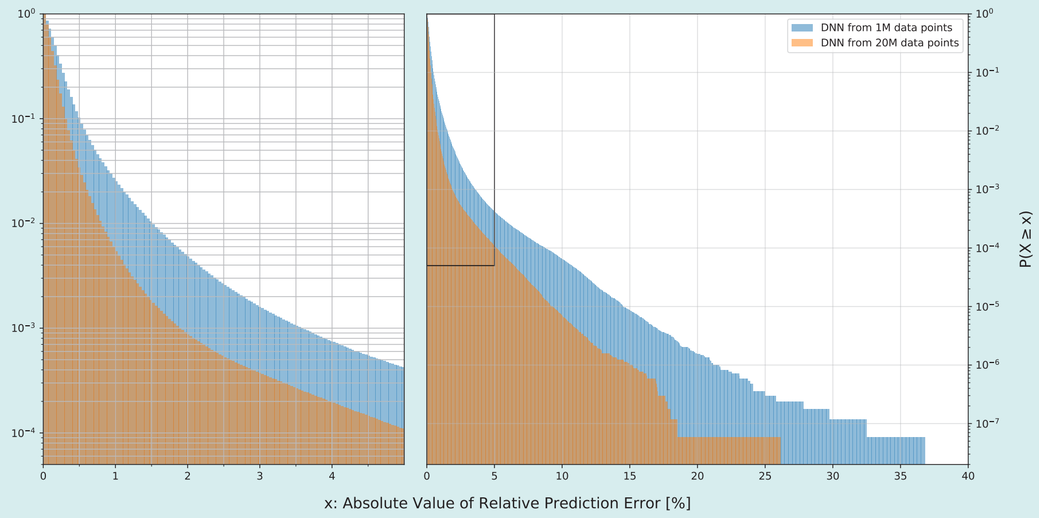
- Sampled stars: 12'000
- Sampled planetary systems per star: 8'000

→ 96 million sampled systems total

The internal structure model is too computationally expensive for this to be feasible.

Solution: Train a **Deep Neural Network**!

Training a DNN on the internal structure model
Evaluation of the trained DNN on test data:



Training data:
20M data points

Validation data:
2M data points

Test data:
15M data points

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References:
- Dorn, C., Khan, A., Heng, K., et al. 2015, A&A, 577, A83
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- Kippenhahn, R., Weigert, A. & Weiss, A. 2012, Stellar Structure and Evolution, 2nd edn., Astronomy and Astrophysics Library (Berlin Heidelberg: SpringerVerlag)
- Thiabaud, A., Marboeuf, U., Alibert, Y., Leya, I., & Mezger, K. 2015, A&A, 580, A30