Using Mixture Density Networks to infer the interior structure of exoplanets

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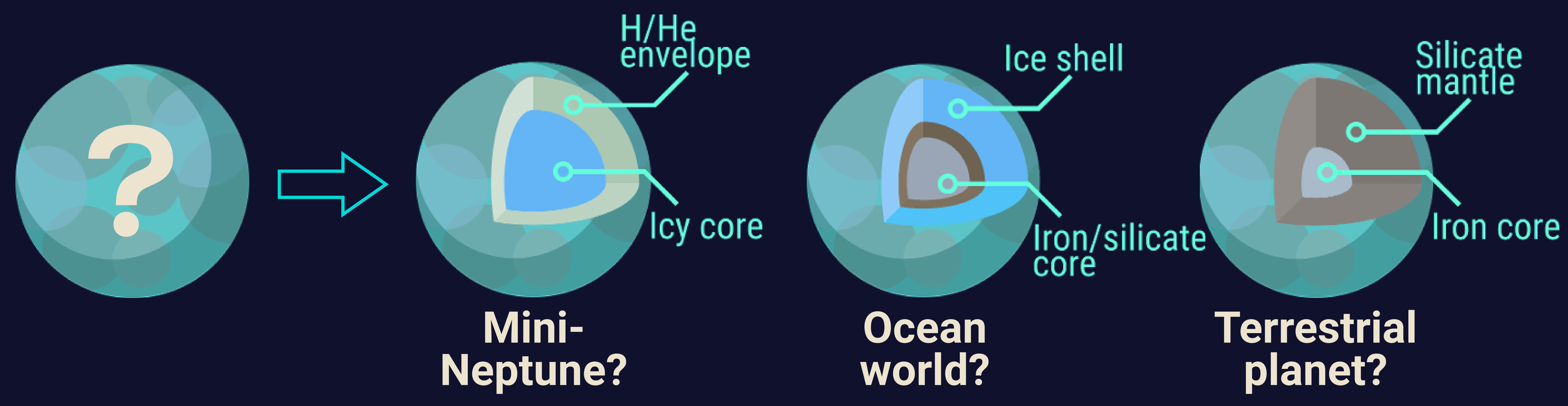
Exoplanet observations

For most exoplanets, only mass and radius can be measured. To understand these planets better, we need to know their interior structure.

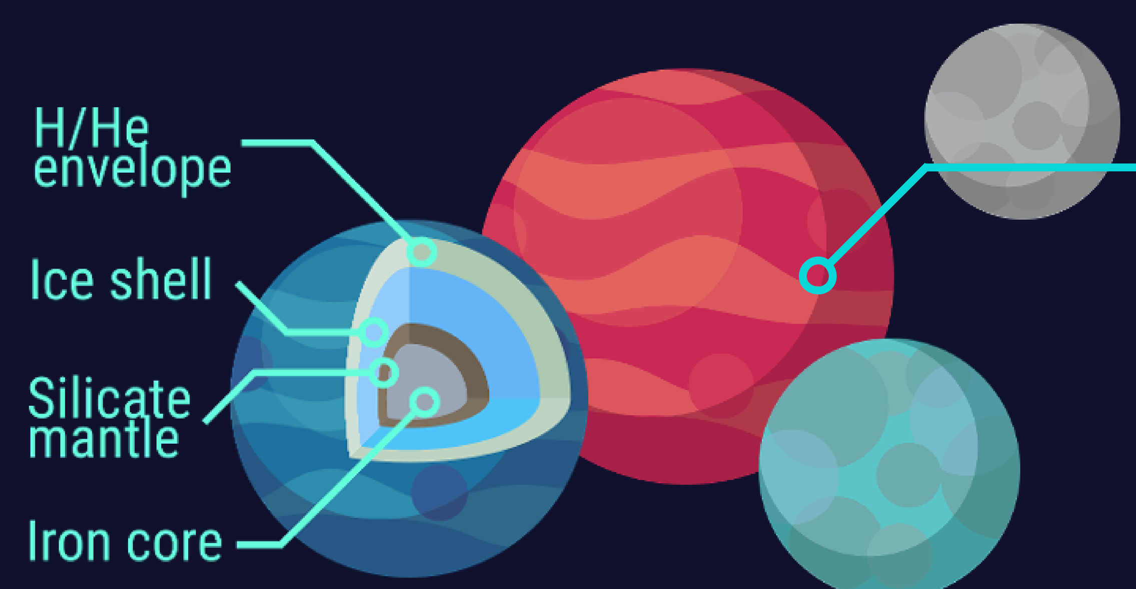


Interior structures

With only mass and radius, many solutions for the interior are possible[1]. To find all interior structures, we need to run thousands of interior models for a given planet. This can be computationally expensive and time consuming.

Our approach

1. Compute set of planets with different interior structures covering a wide mass and radius range
2. Train a neural network to predict the interior structure based on mass and radius
3. Use network predictions instead of time-consuming forward models
4. Test with Solar System planets, where we have the most accurate data



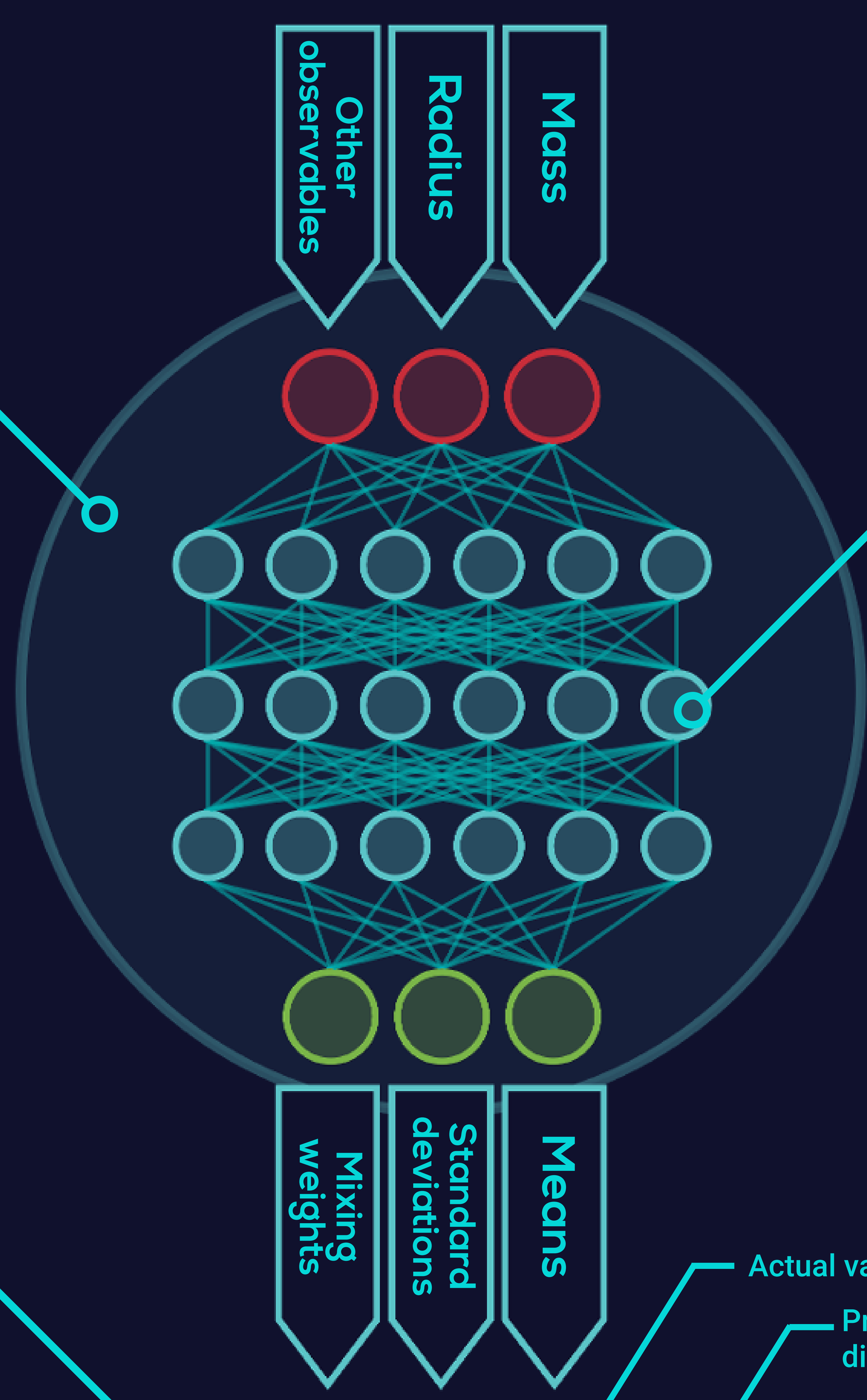
Training data

- 900 000 synthetic planets with random interior structures
- Each planet has:
  - Iron-rich core
  - Silicate mantle
  - High-pressure ice shell
  - H/He gas envelope (solar-like)
- Planet mass: 0.01 - 25 M_{Earth}
- 70% used for training
- 30% used for validation

Mixture Density Networks

A Mixture Density Network is similar to a conventional Neural Network, but instead of single target values it predicts continuous parameters in form of a mixture of normal distributions.

MDNs work well with inverse problems, where each input has multiple output values.

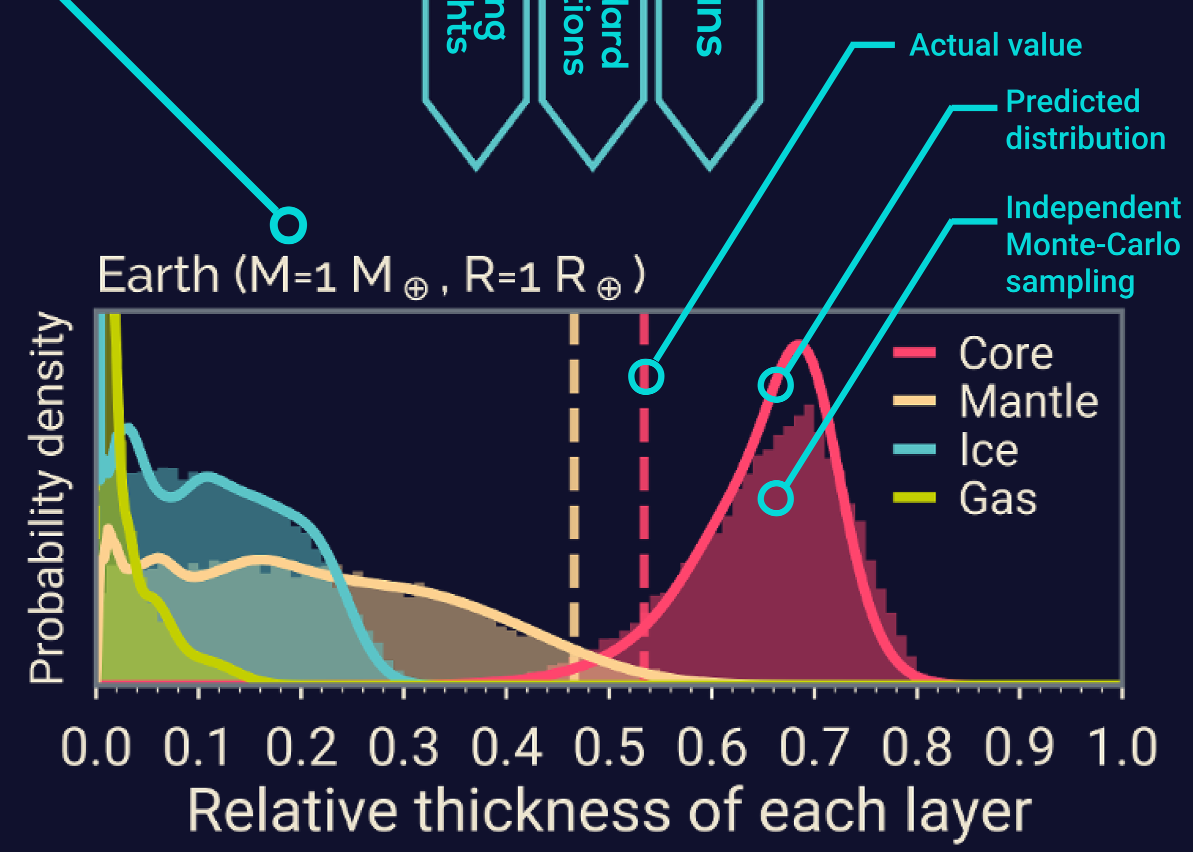


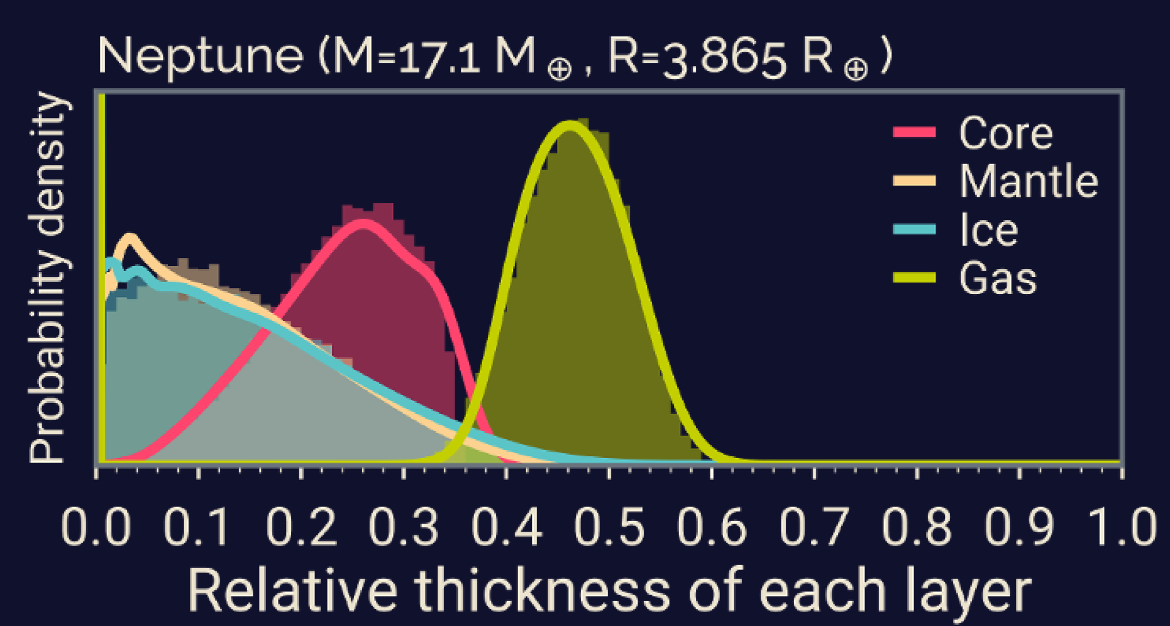
Network architecture

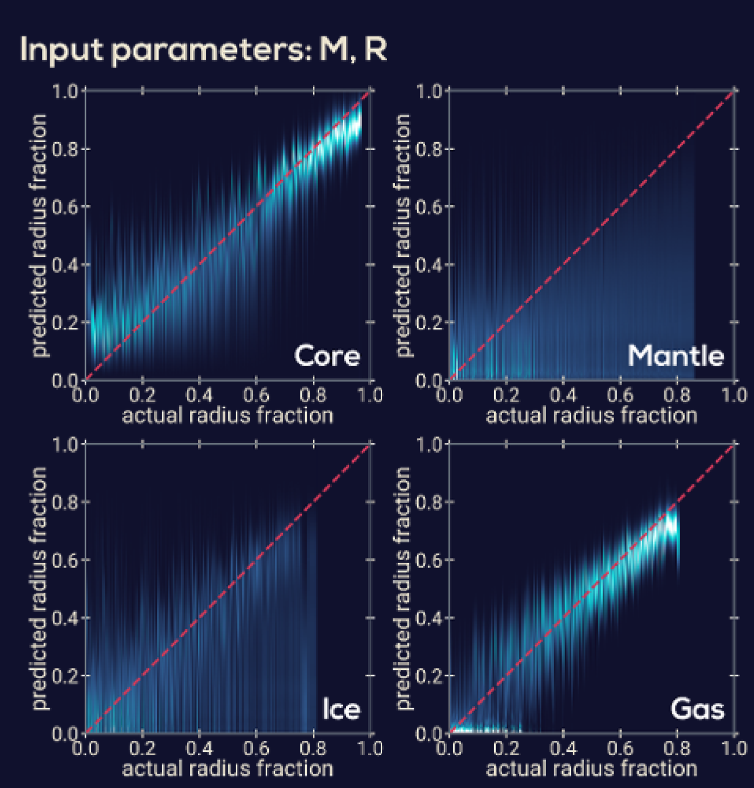
- 3 hidden layers with 512 neurons each
- Dropout layers before each hidden layer to improve robustness of model
- Outputs: Mixture density parameters

Results

- Predicted distributions align very well with distributions obtained by Monte-Carlo sampling the same prior distribution
- Predicted Earth:
  - Predominantly metal-rich/silicate planet
  - Thick ice shell possible
  - Small gas envelope possible
- Predicted Neptune:
  - Predominantly gaseous with small iron core
  - Ice and mantle not well constrained







Accuracy

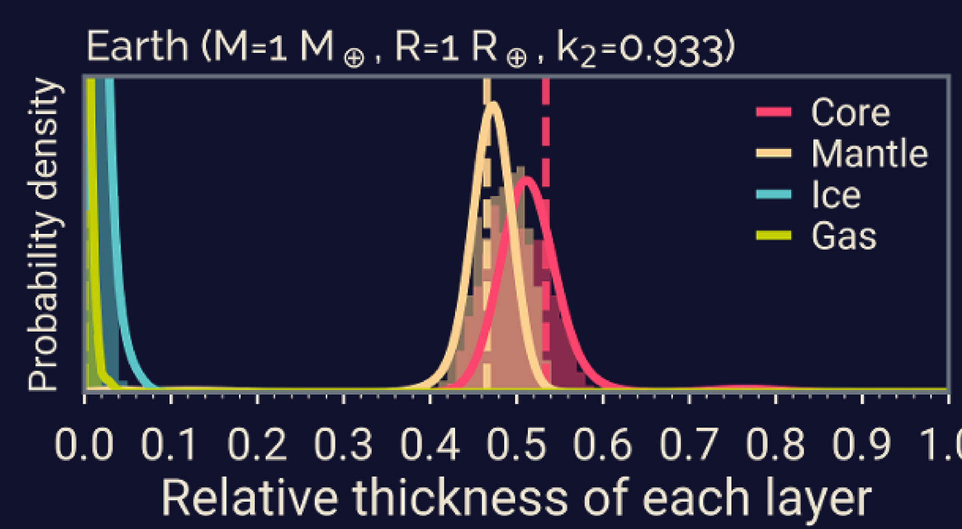
Each subplot shows the predicted layer thickness over the actual value from the validation data.

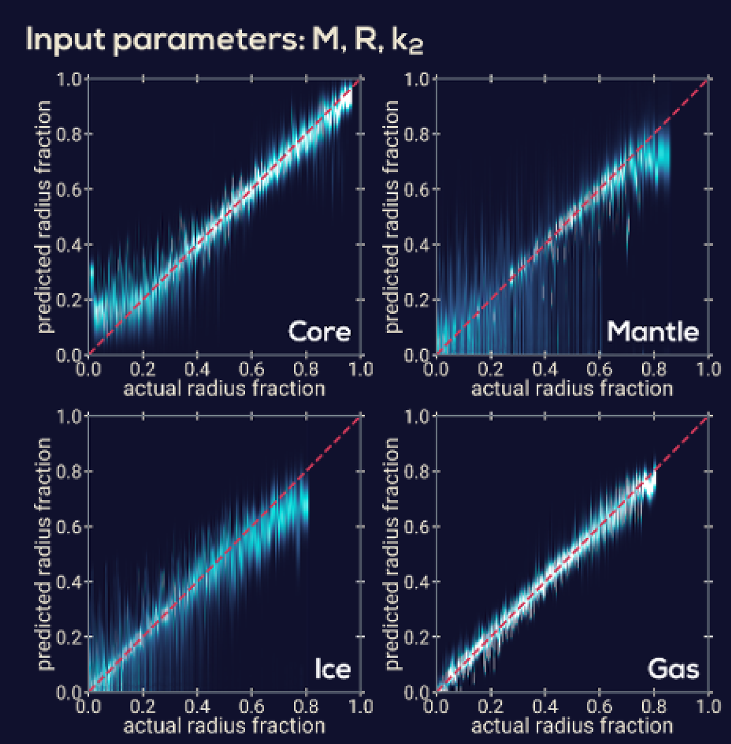
Predictions on the red line are well constrained

- Core and gas layers are fairly well constrained
- Mantle and ice layers can not be constrained well

Fluid Love number k_2

- k_2 is a measure of the mass concentration in the planet[3]
- Measurable from shape and dynamics of the planet[4]
- Using k_2 as additional input:
  - Interior structures constrained significantly better for all layers
  - Earth's interior predicted to within a few percent of the actual values





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