Using Deep Learning neural networks to predict the interior composition of exoplanets

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Using Deep Learning neural networks to predict the interior composition of exoplanets

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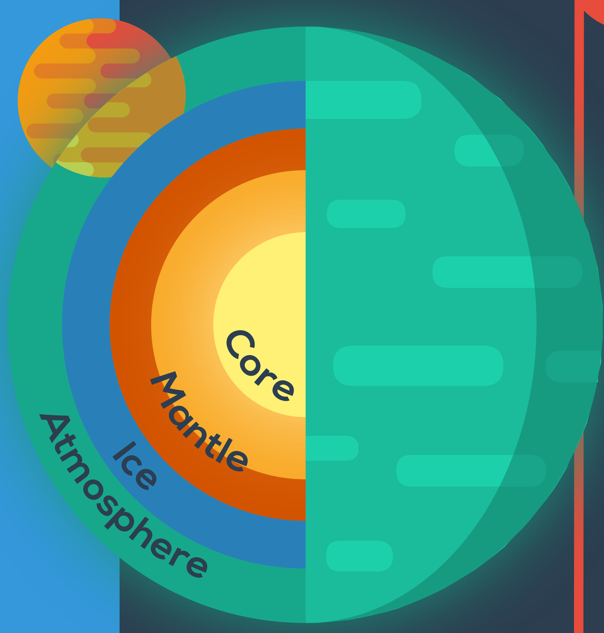
Motivation

- Very few observable parameters for exoplanets
- Solutions for interior structures are often degenerate [1]
- Many interior models need to be run to find all possible solutions
- **What observables do we need to break the degeneracies?**
- **Can we use machine learning to predict a planet's interior?**



Interior model

- Planet layers:
  - **Iron core**
  - **Silicate mantle**
  - **Ice**
  - **H/He atmosphere (solar-like)**
- Mass fractions constrained by model input
- Model output:
  - **Planet radius**
  - **Fluid Love number k_2** [2]
  - **Fe/Si ratio of planet** [3]

k_2 and Fe/Si

Fluid love number k_2

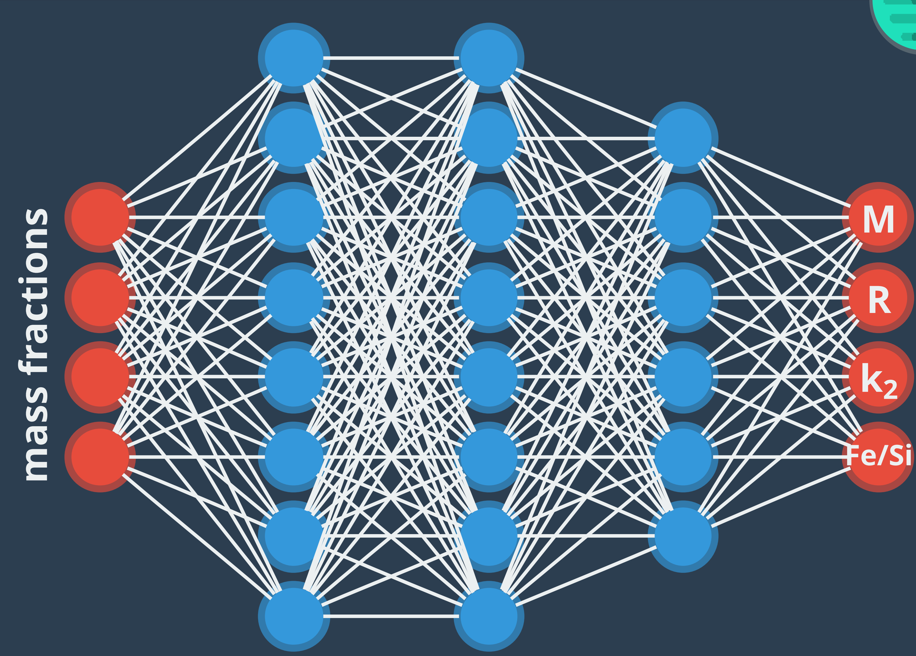
- **Measure of mass concentration in planet**
- Measurable from shape of the planet

Fe/Si ratio

- Mass ratio of iron to silicon in the planet
- **Indicator for core size**
- Potentially measurable in the host star

Neural Network

- Deep learning neural network with 3 hidden layers
- Up to four inputs:
  - **Planet mass M**
  - **Planet radius R**
  - **Fluid Love number k_2**
  - **Fe/Si ratio of planet**
- Predictions / Outputs:
  - **Mass fraction of each planetary layer**



Training data

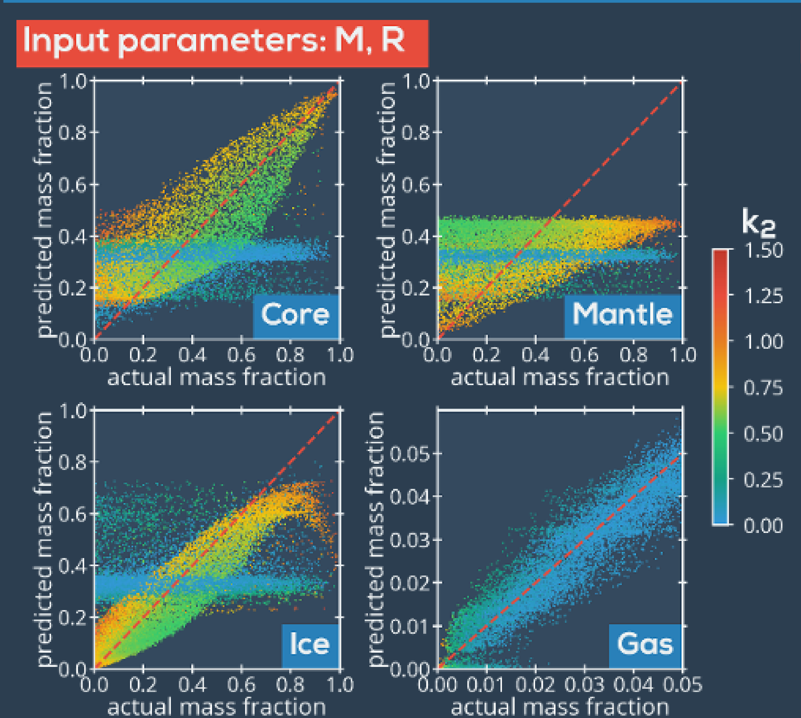
- Monte-Carlo sampling
- **200 000 planets with random mass fractions for each layer**
- Mass between 0 and 25 M_E
- 50% of planets are created with an atmosphere
- Data distribution:
  - **50% training**
  - **25% validation**
  - **25% error estimation**

Training Results

Each subplot shows the mass fractions predicted by the neural network over the actual mass fraction from the validation data.

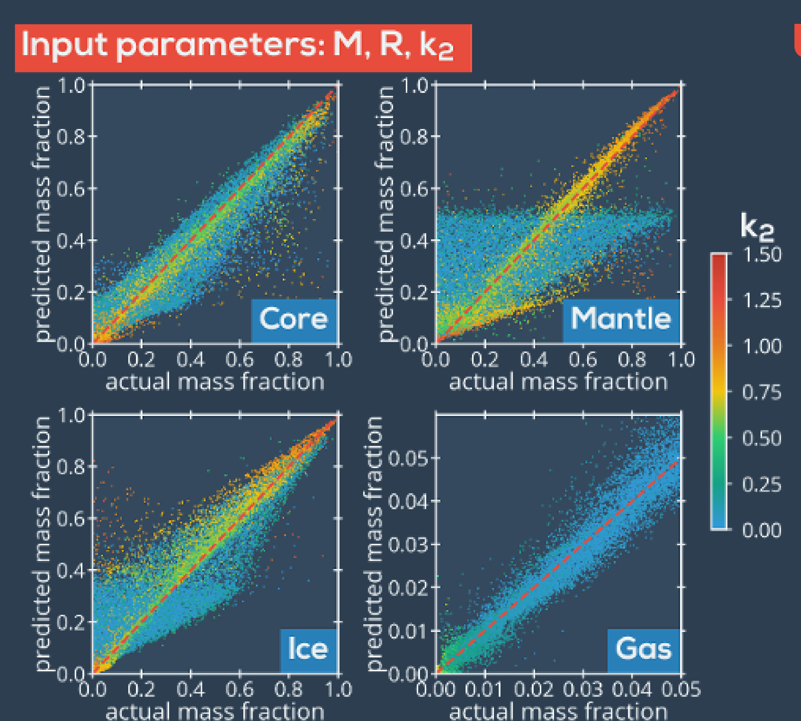
Points on the red diagonal line are accurately predicted.

Points are colored corresponding to the k_2 of the planet. Low values of k_2 correspond to extended atmospheres.



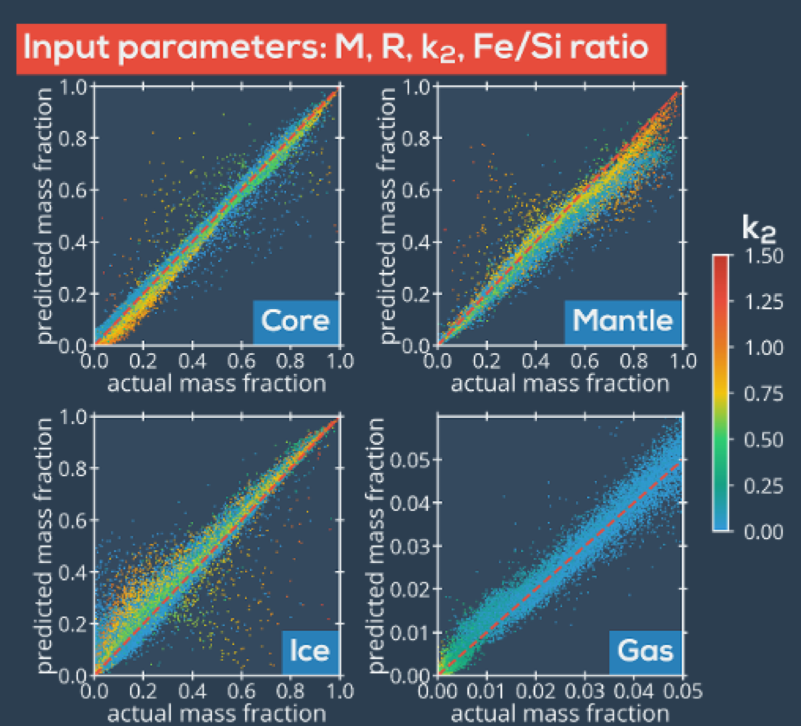
Using only mass and radius:

- Core and mantle not very well constrained
- **Atmosphere hides the interior structure**
  - Neural network guesses constant mass fractions for interior



Using mass, radius and k_2:

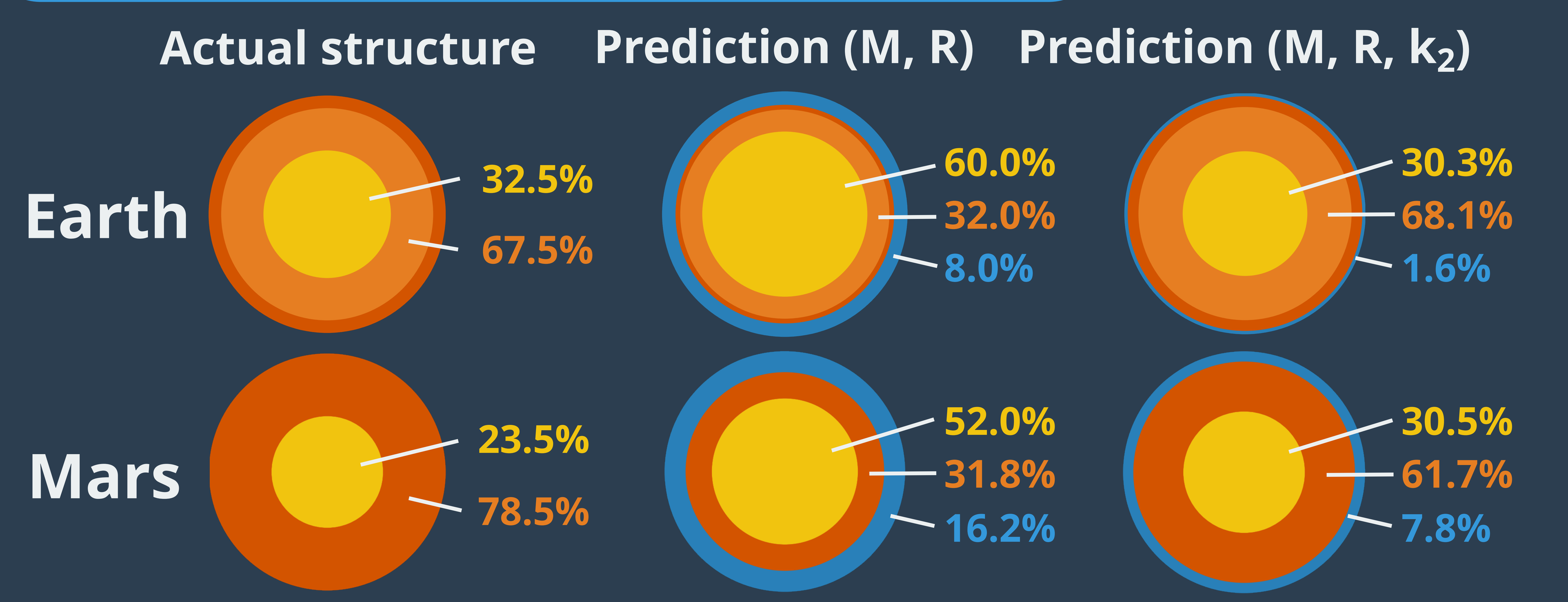
- **Interior well constrained for planets without atmosphere**
- Atmosphere still hides information about interior
  - Higher uncertainties
- **k_2 provides much better information about interior**



Using all inputs:

- **Interior well constrained for all planets**
- Degeneracy of models is nearly broken
- But: The exact Fe/Si ratio of the planet is needed.

Predictions for Solar System planets



Images are scaled to the radius of the respective planet

Results:

- **M, R:** Earth and Mars are predicted without an atmosphere, but with significant amounts of water. The neural network has too little information and picks a "generic", average planet which fits mass and radius.
- **M, R, k_2:** Earth is predicted very well with just a small ice layer. The prediction for Mars is close, but still a large amount of water fits all 3 input parameters. The use of k_2 gives more constrains on the interior structure.

Conclusion

- Our neural network predicts the full interior composition based on just a few inputs
- By changing the input parameters we can very quickly check how well these characterize the interior composition
- **Outlook:**
  - Error estimation using a second neural network
  - Testing more possible observables (e.g. Mg/Si ratio, Metallicity of the atmosphere...)

Acknowledgements

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References

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