Machine-learning inference of the interior structure of low-mass exoplanets

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We explore the application of machine-learning, based on mixture density neural networks (MDNs), to the interior characterization of low-mass exoplanets up to 25 Earth masses constrained by mass, radius, and fluid Love number $k_2$. MDNs are a special subset of neural networks, able to predict the parameters of a Gaussian mixture distribution instead of single output values, which enables them to learn and approximate probability distributions. With a dataset of 900,000 synthetic planets, consisting of an iron-rich core, a silicate mantle, a high-pressure ice shell, and a gaseous H/He envelope, we train an MDN using planetary mass and radius as inputs to the network. We show that the MDN is able to infer the distribution of possible thicknesses of each planetary layer from mass and radius of the planet. This approach obviates the time-consuming task of calculating such distributions with a dedicated set of forward models for each individual planet.

The fluid Love number $k_2$ bears constraints on the mass distribution in the planets' interior and will be measured for an increasing number of exoplanets in the future. Adding $k_2$ as an input to the MDN significantly decreases the degeneracy of possible interior structures.