Can Artifical Intelligence help us understand how planets evolve?

Unravelling the interior evolution of terrestrial planets using Machine Learning

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In Short

- The mantle of rocky planets behaves like a highly viscous fluid over geological time scales.
- Key parameters and initial conditions to the non-linear partial differential equations governing mantle flows are poorly known.
- Machine Learning (ML) can help us invert observations to constrain these parameters. We propose generating ∼60000 simulations in 2020 to train ML algorithms.
- Preliminary results show promise for building reliable forward surrogate models and inverting observables to generate admissible solution spaces.

Studying how rocky planets like Mercury, Venus, the Earth and Mars evolve over billions of years requires modelling mantle convection, the main driver of planetary evolution. Mantle rocks subjected to high temperature and pressure, but still well below their melting point, behave like a highly viscous fluid over geological time scales (millions to billions of years). The physics of the mantle can thus be quantified by solving equations of conservation of mass, momentum and energy for an extremely viscous fluid. These non-linear partial differential equations are typically solved numerically using sophisticated fluid dynamics codes like GAIA [1].

The parameters and initial conditions governing mantle convection are poorly known. However, certain outputs of the simulations can be "observed" (directly or indirectly) via remote-sensing or in situ measurements performed by spacecraft missions. These observations can help constrain key parameters and initial conditions, thus elucidating the basic physics and evolution of planets. Such inference can be approached either as a *forward problem*, by testing several parameter combinations looking for those that match the observables best, or as an *inverse problem*, by directly calculating the parameters from given observables.

There are two main challenges upon scanning high-dimensional parameter spaces. First, it is computationally expensive to solve the fluid equations for several parameter combinations. Hence, it is desirable to learn a mapping from parameters to observables that can rapidly generate a large number of samples. Second, this is an ill-posed problem as different combinations of parameters can lead to the same observable (i.e. the solution to the inverse problem is non-unique). Therefore, it is important to robustly identify all possible solutions and not just one.

To address the first challenge, we propose finding a "low-dimensional" alternative to fully dynamic 2D or 3D simulation that doesn't loose the complexity of the flow. We will thus use Neural Networks (NNs) to find mappings from several parameters to simple 1D temperature profiles. To this end, we will use both-steady-state and fully time-dependent simulations of the thermal and convective evolution of the mantle. We will then build parametrized models from the former and direct evolution models from the latter by treating time as another variable. Such *surrogate models* will be the first of their kinds in the mantle convection community.

The second challenge of studying high-dimensional, ill-posed inverse problems has recently been addressed to some extent using ML in a handful of geophysics papers. For example, [4] showed that mantle convection can be studied as a pattern recognition problem using Mixture Density Networks (MDN) [3]. We will use MDNs to systematically quantify the degree to which different observables and their combinations can help constrain the parameters governing the thermal evolution of Mars.

Fig. 1 illustrates our approach to using ML in this project. As a proof of concept, we generated a small dataset of approximately 1000 Mars-like simulations based on a setup similar to that of [2]. We solved the partial differential equations of mantle convection with our in-house C++ code GAIA [1], which uses a finite-volume discretization on a fixed Voronoi grid in arbitrary geometries.

We use Neural Networks (NN) to determine the non-linear mappings between certain inputs and outputs. In a fully connected NN, the input nodes are connected to the output nodes via neurons in so-called "hidden layers". Each connection is quantified by an adjustable weight, which is optimised over several iterations by back-propagating the error in the NN prediction.Based on this concept, for the *forward problem*, we compare 1D, laterally-averaged temperature profiles predicted by a trained NN with those derived from 2D simulations carried out with

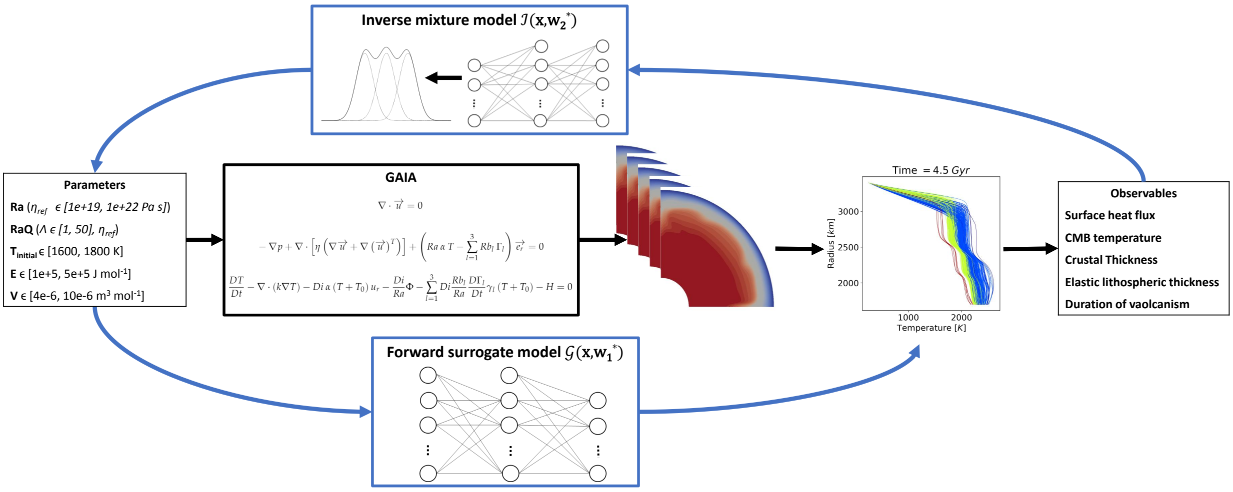

Figure 1: *Illustration of our strategy for using machine learning to study mantle convection both as a forward and inverse problem.*

GAIA that were never used in any part of the training, development, or validation of the network. Fig. 2 shows that the accuracy of NN predictions increases with the amount of data. For the *inverse problem*, we employed MDNs to calculate how model parameters can be retrieved by combining different observables. We found that increasing the number of simulation samples can help tightening constraints on multiple parameters, which strengthens the importance of using HLRN system to generate a large dataset of convection simulations.

The interdisciplinary field of ML and mantle convection simulations is still in its infancy. Yet, using these algorithms to build complex forward surrogates and to exhaustively analyze high-dimensional parameter-observable spaces in an inverse manner has clear potential to drastically improve our understanding of how rocky planets evolve.

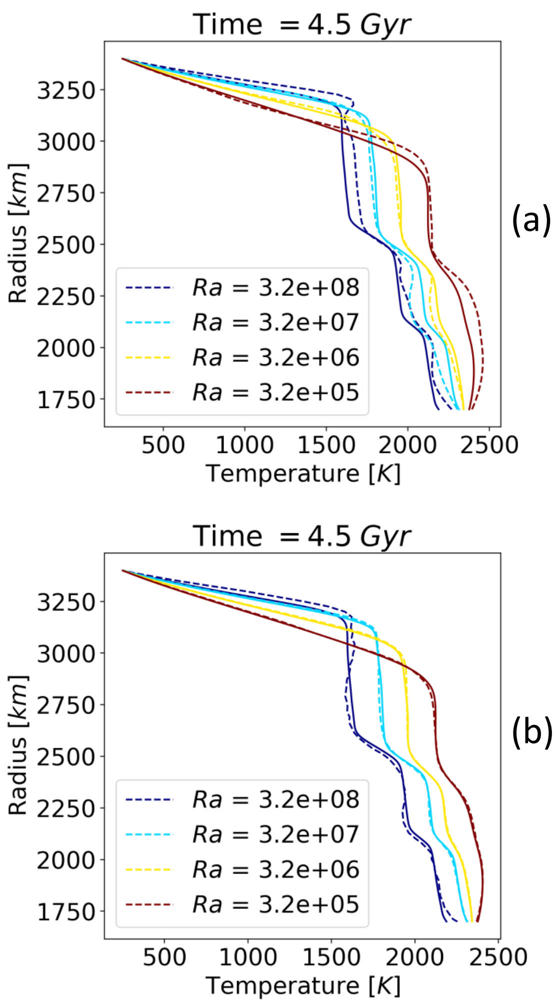

Figure 2: *Comparison of 1D temperature profiles predictions from NN (dashed lines) with those of GAIA simulations (solid lines) for different values of the Rayleigh number Ra, a non-dimensional parameter that quantifies the vigor of convection. Predictions from a NN trained with 80% of a) 30 simulations and b) 1000 simulations.*

WWW

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More Information

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