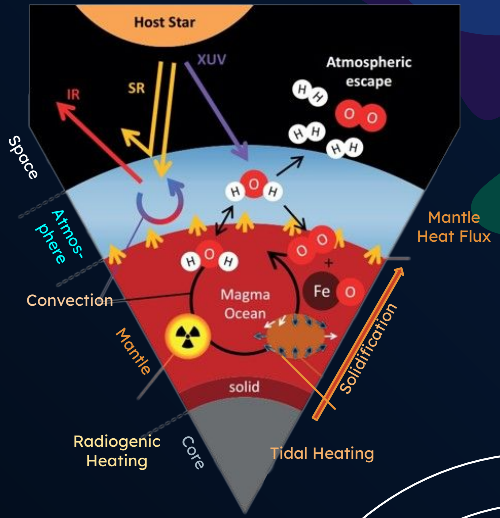
Studying the interior evolution of rocky exoplanets using machine learning

IDEA

To produce a surrogate machine learning model to study the interior evolution of rocky exoplanets using VPLanet within 0.1 to 4 M_E.



Goals achieved

1. Generated datasets - ✅
2. Understood Neural Networks - ✅
3. Applied NN suitable to our work (MLP) - ✅
   (RNN implementation remaining for next part)
4. Trained the model and test runs with MLP - ✅

Baselines implemented:

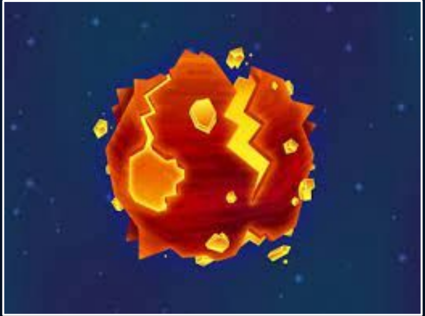
- Modeling minimal planet properties with minimal input parameters - ✅
- Taking insight of training performance and sensitivity of the model to the input parameters - ✅

Algorithms and libraries used: Multi-Layer Perceptron | Recurrent Neural Network | Sklearn

Relevant papers: VPLanet | MagmOc | ML for interior structure

Why to study planetary interiors?

- Terrestrial planets - provide solid or liquid surfaces for life
- Structure, compositions and morphology
- Heat transfer studies - mechanism and dynamics
- Volcanism and planet quakes
- Rotation and tidal locking
- Peculiar compositions (like metallic form of hydrogen)

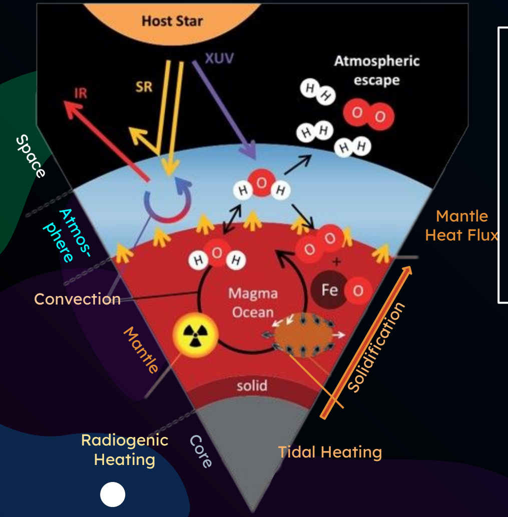


How does it link to atmospheres?

- The temperature and pressure profiles need to be consistent with the surface and interiors
- Study of gaseous interiors
- Surface-atmosphere interaction studies
- Time evolution of Earth’s atmosphere

Model - MagmOc - VPLanet

- Terrestrial planets simulated with possession of iron core, silicate mantle and water.
- Combined effects like stellar radiation, radioactive heating, tidal effects, atmospheric escape, etc. act on the planet.
- Melt solidifies due to the cooling, locking some amount of water in the solid rock.
- To restore the pressure equilibrium, water from the melt is then outgassed into the atmosphere

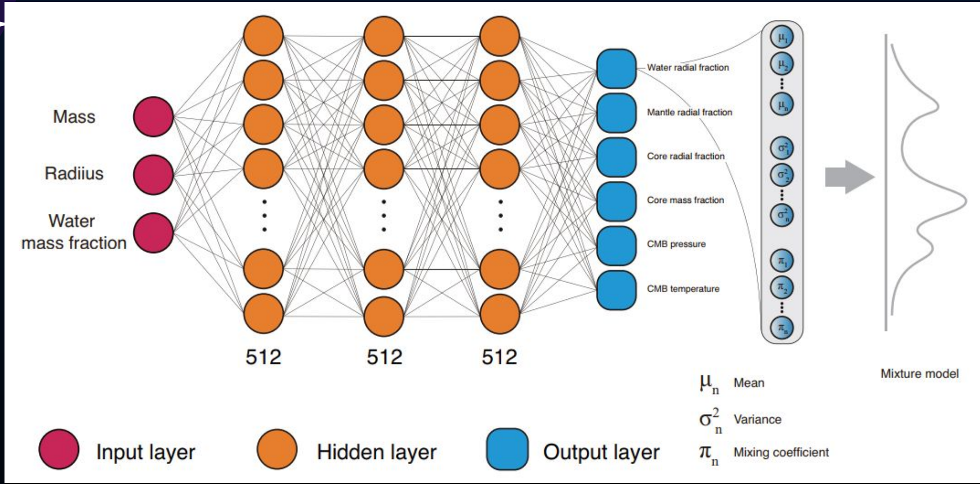


- In the atmosphere, water is lost into space due to photolysis.
- Hydrogen escapes, oxygen dissolves into the magma ocean where it oxidizes FeO to Fe_2O_3
- Remaining O_2 starts to build up in the atmosphere.

This variation of melt fraction, solidification time, mass of water and O_2 in solid and in magma oceans, pressure in the atmosphere as a function of evolution time has been studied in the package.

Study of rocky planet interiors using ML - *Zhao and Ni (2021, 2022)*

Used ML to predict the interior structure of rocky and gaseous exoplanets, i.e., thickness of each layer and solve for its density and pressure given the mass and radius of the planet to give the M-R variation using MDNs..



Mixture Density Networks (MDN) : A neural network in which a mixture of different distributions are used to model the output based upon the weights assigned by the algorithm.

A Gaussian MDN is used here. The mean, variance and mixing coefficient are calculated for each output property in order to get the final curve.

A 3-hidden-layer MDN was used with 3 inputs resulting in 6 outputs. Each hidden layer has 512 neurons.

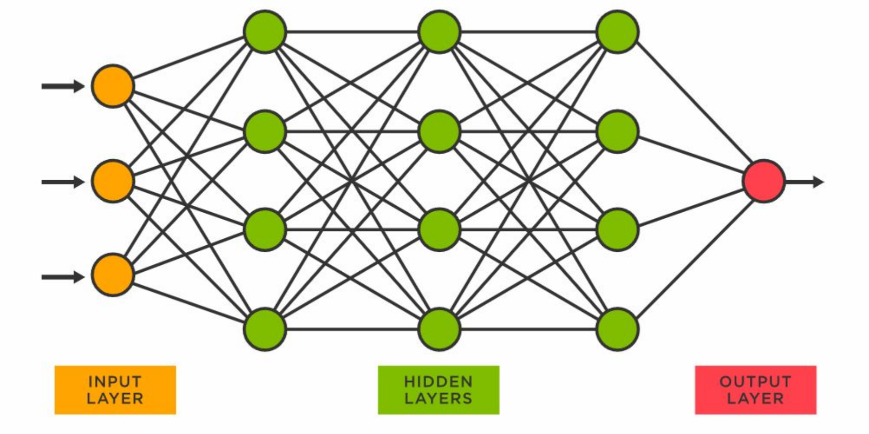
A total of 220,000 data points were used as the training dataset.

NEURAL NETWORKS

Why NNs are used in our model?

- The relationship between input and output parameter are very complicated. Ordinary algorithms like SVMs are less efficient for non-linear data.
- NNs provide much better results in terms of convergence and accuracy for both linear and non-linear data.

- Star mass
- Star planet distance
- Planet mass
- Planet radius
- Water mass



How various planetary properties will evolve over time

DATASET STRUCTURE

We divided our datasets into 3 parts in the following manner:

TRAPPIST-like Systems

- Star mass = {0.1, 0.2} solar mass
- Star-planet distance = {0.01, 0.03, 0.06} AU
- Planet mass = (0.5, 1..., 3.5, 4) earth mass
- Planet radius = For a constant density, constrained by mass
- Water mass = {1.0, 2.0} Terrestrial oceans

Earth-like Systems

- Star mass = {0.8, 1.0, 1.2} solar mass
- Star-planet distance = {0.1, 0.5, 1.0} AU
- Planet mass = (0.5, 1..., 3.5, 4) earth mass
- Planet radius = For a constant density, constrained by mass
- Water mass = {0.5, 1.0, 2.0} Terrestrial oceans

Combined dataset

This covers both Trappist and Earth like systems with intermediate values to accommodate permutations to model almost all Earth-sized exoplanets that can potentially host life.

METHODOLOGY

ALGORITHM USED: MULTILAYER PERCEPTRON

NUMBER OF HIDDEN LAYERS: 3

NODES IN EACH LAYER: 16

ACTIVATION FUNCTION: *RELU* with *ADAM* optimiser

PARAMETERS MODELLED

1. Mantle Potential Temperature
2. Net flux coming out of the atmosphere
3. Pressure of water in the atmosphere
4. Mass of water in the magma ocean and the atmosphere combined
5. mass of O_2 in the magma ocean and the atmosphere combined
6. the mass of H_2 escaping into space

[INPUT FOR THE MLP]

A row of every output files generated from VPlanet

Trained to predict

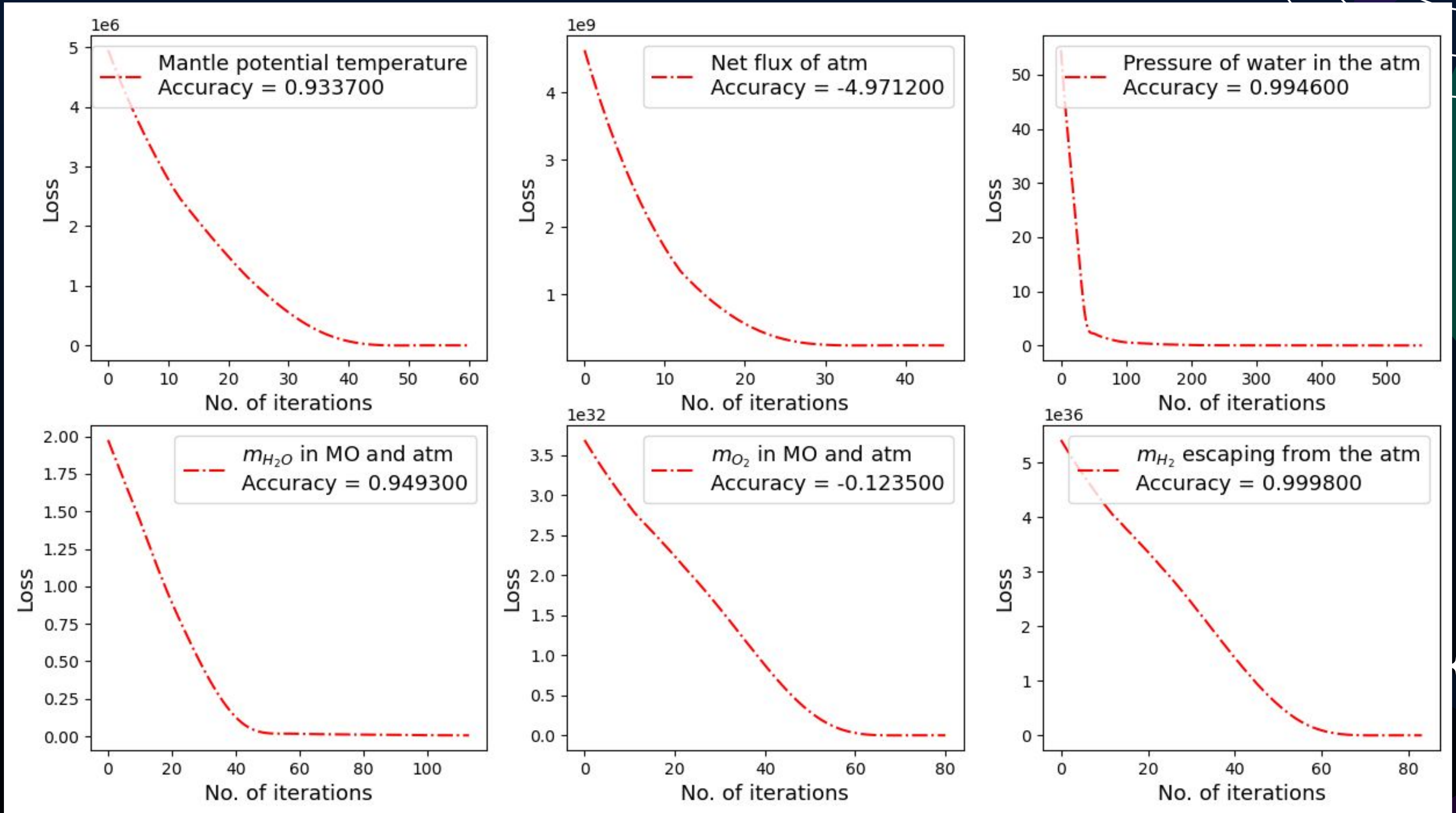
The following row for every output file from VPlanet

[OUTPUT OF THE MLP]

We ran the model to predict the second row (evolution after first time step) and 11th row and compared the results.

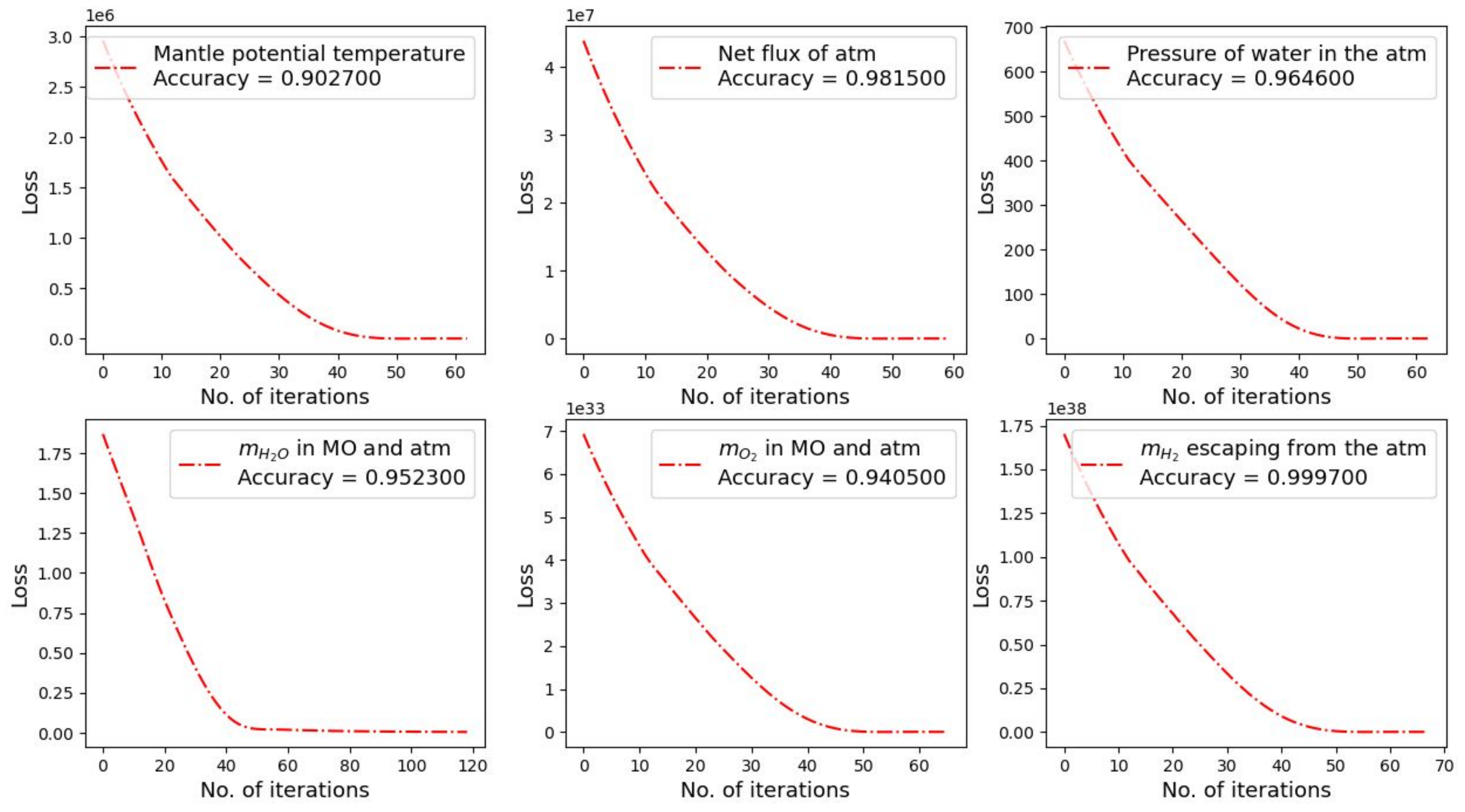
RESULTS

MLP was used to predict the second row of the evolution series given the five input parameters and the first row of the time-series.



Negative accuracy represents imperfect correlation between parameters.

RESULTS



Upon training to predict the 11th row given the 10th row, the accuracy improved significantly.

FUTURE PLAN

- The complete plan is to develop a model that gets the five input parameters and predict the evolution over the entire timescale of the planet.
- We plan to train the model using MLP to predict the first few rows and proceed with RNN thereafter.
- Exploring other NN algorithms if required.
- The next step would be to apply the complete model on dataset (3) and achieve higher accuracy.
- Thereafter we may explore for a more detailed dataset varying more input parameters (that have been fixed to Earth-like values presently).

Chandan Kumar Sahu
Maitrey Sharma
School of Physical Sciences, NISER