ACCELERATING RADIATIVE TRANSFER IN ATMOSPHERIC SIMULATIONS OF VENUS USING MACHINE LEARNED EMULATORS

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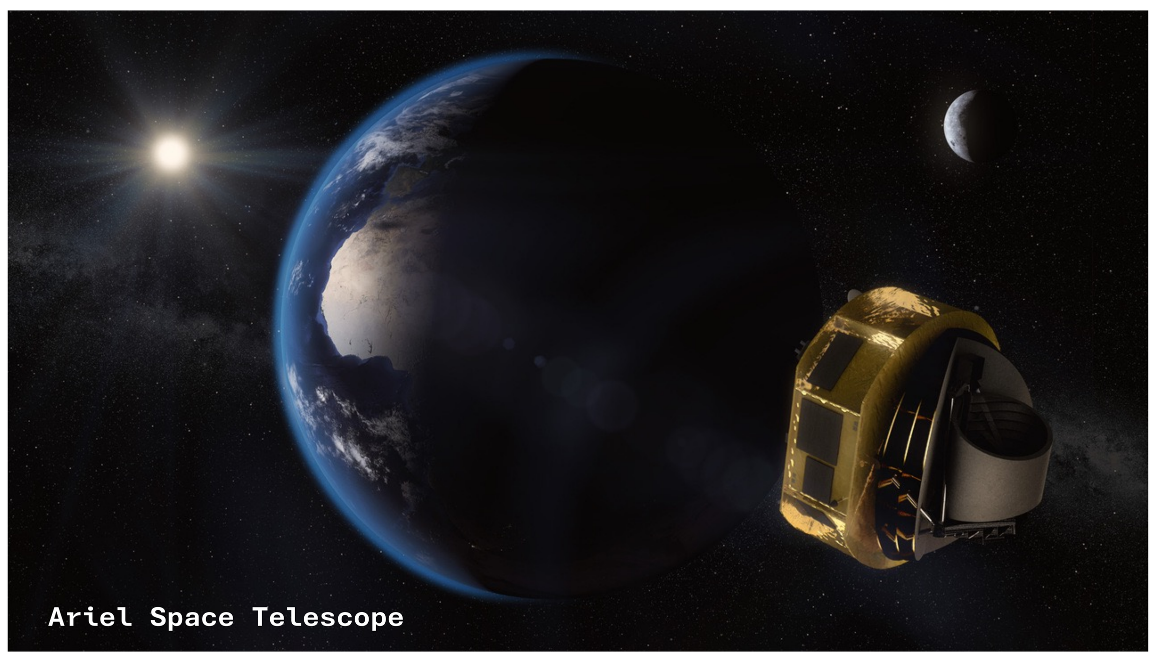
BIG PICTURE

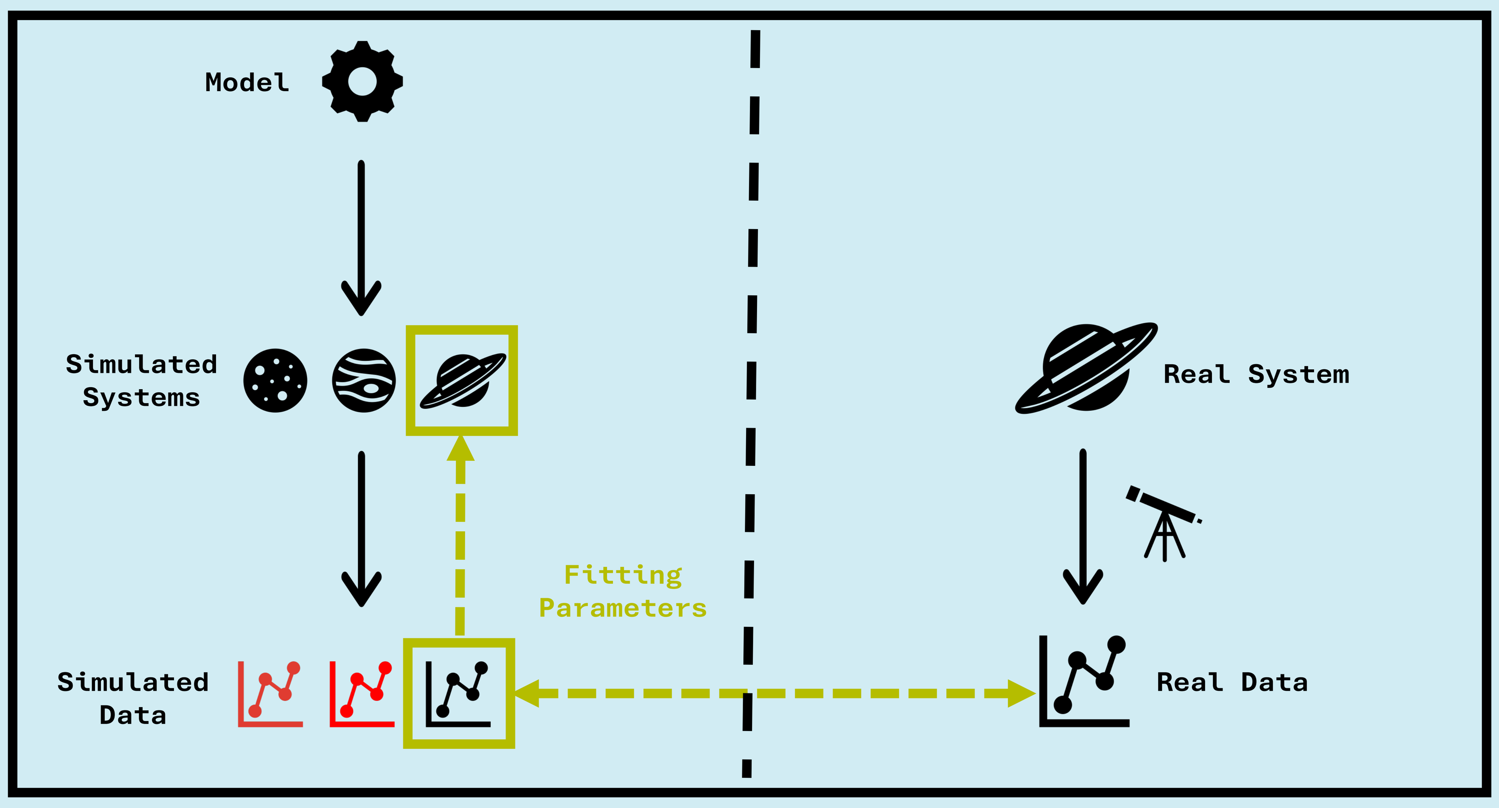
- **Why study exoplanets?** To address questions of life, habitability, planet formation, and to advance knowledge in climate science.
- **Ariel Space Telescope:** 3 year mission from 2029 to observe exoplanets
  - **Short mission:** Need to turn observation into fitted planetary parameters, *fast*, so we know which planets are interesting and should be re-observed
- **Fitting parameters to observations:** Use complicated forward models, which take of the order of *months* to run → this is too slow and will limit what we can learn from Ariel
- **Accelerating forward models:** Can accelerate components of forward model by replacing physical model with a machine-learned *emulator* (or *surrogate model*)

This work accelerates the radiative transfer component of a physical model, in the test-case of Venus



FITTING ATMOSPHERES FROM OBSERVED DATA

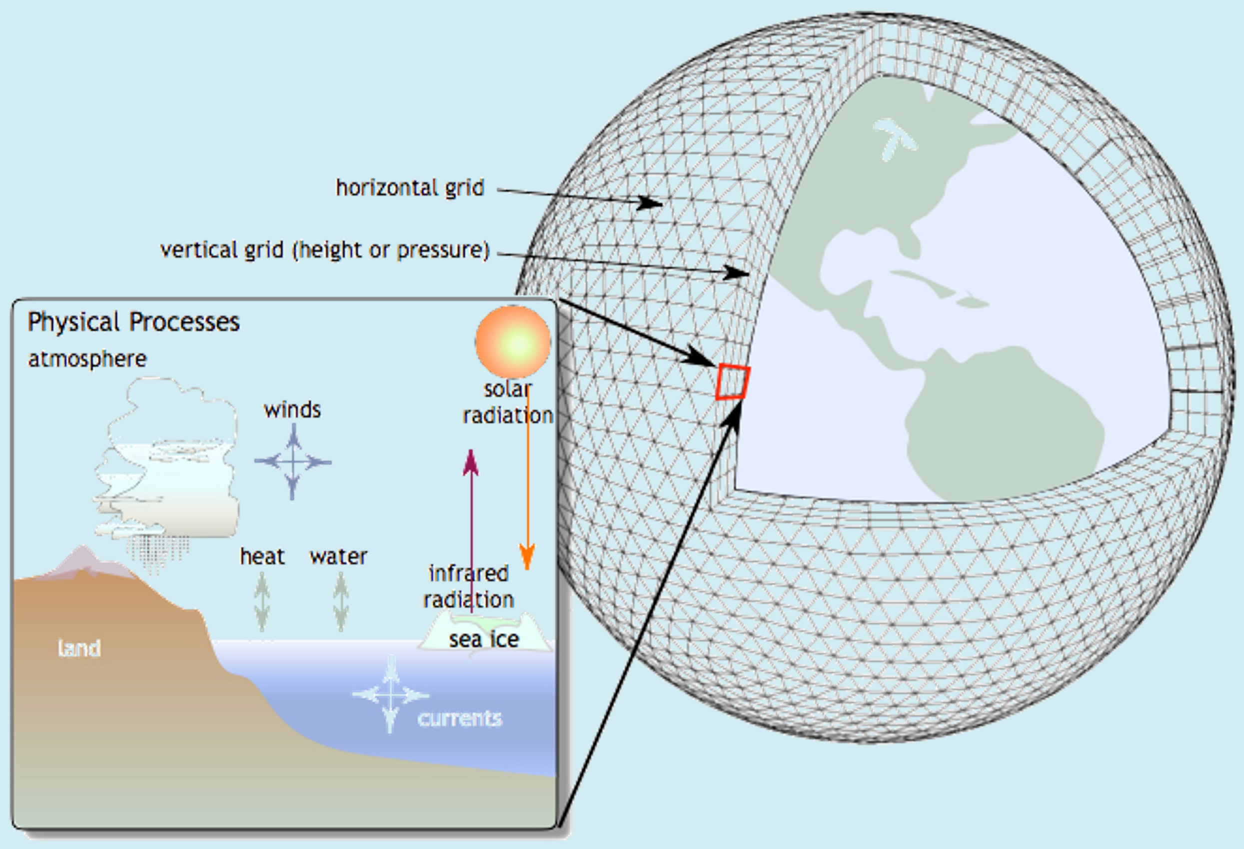
1. Simulation-Based Inference



2. Forward Models of Atmospheres

Planetary atmospheres are simulated using ***Global Circulation Models* (GCMs)*:*** these are mathematical models of the physical processes occurring in the atmosphere, such as the dynamics, radiative transfer, and chemical processes.

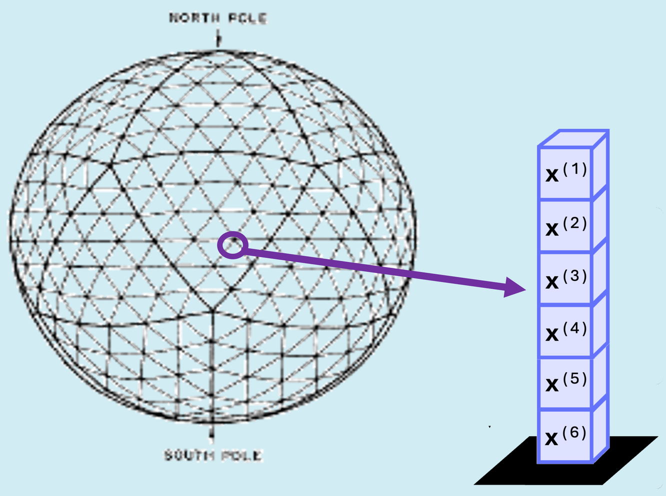
- Components of GCMs modelling different physical processes run in parallel
- Each component will solve physical equations across individual elements of a grid, over many timesteps until the model converges



3. Radiative Transfer Component of GCMs

- Radiative Transfer is the physical process of **energy transport** by **electromagnetic radiation**
- Atmospheric models consider radiation incident from:
  1. The host star
  2. Geothermal emission from the planetary surface

  and model the interaction of this radiation with atmospheric constituents (absorption, emission, scattering)



Model Assumptions:

- Atmospheres are modelled as a collection of atmospheric columns which <u>do not interact with each other</u>
- Flux is modelled to <u>only move upwards or downwards</u> (*"The two-stream approximation")*
- Cloud profiles are <u>fixed</u> across time

Model inputs and outputs:

- **Inputs:** density (ρ), pressure (p) and temperature (T)
- **Outputs:** Upward flux, downward flux

ACCELERATING FORWARD MODELS USING MACHINE LEARNING

Why Machine Learning?

- **Numerically solving physical equations is <u>slow</u>**: Global circulation models are notoriously computationally expensive and slow to run, with some taking of the order of months to run until convergence.
- **<u>Faster GCMs are needed to enable scientific inference</u>**: code optimisation can only get us so far; we need to reduce the complexity of the computations, without compromising the accuracy of the output

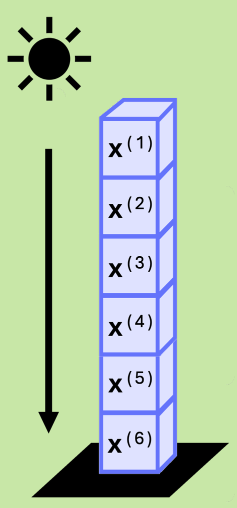
Machine Learning Emulators

How can we use machine learning for our task?

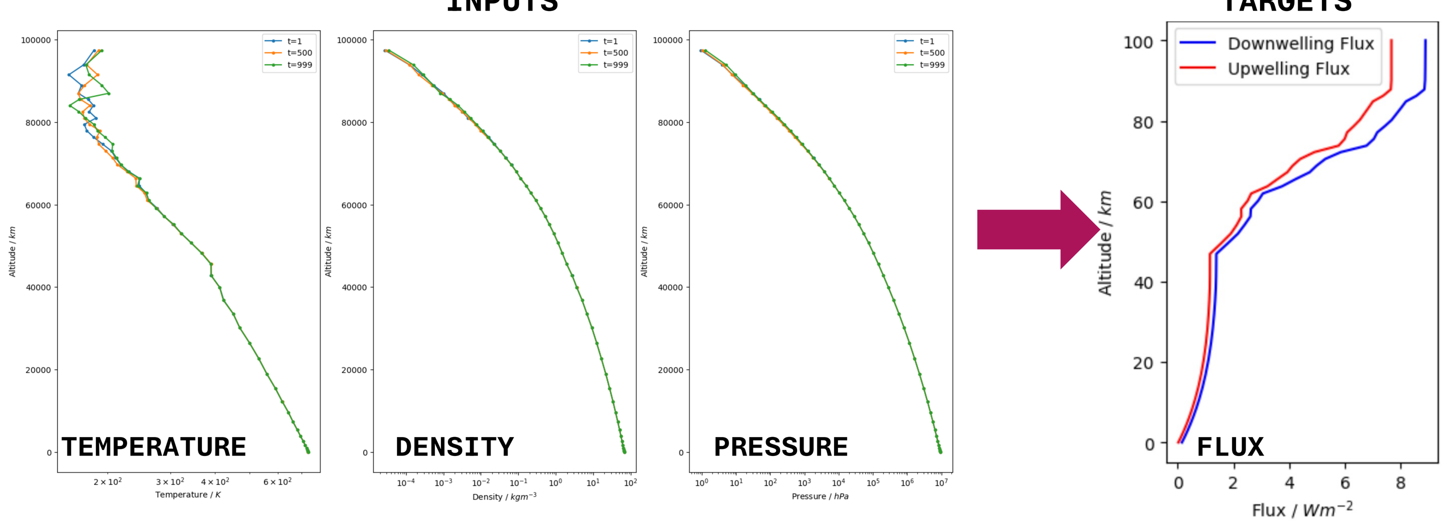
- **Machine learning emulators** or ***surrogate models*** are models trained under the *supervised* objective of mapping a set of inputs to a (set of) specified target(s).
- Given a set of inputs, an emulator will retrieve **roughly the same output** compared to the physically-based numerical model, but from **a less intensive route of computations**

Choosing Model Architecture

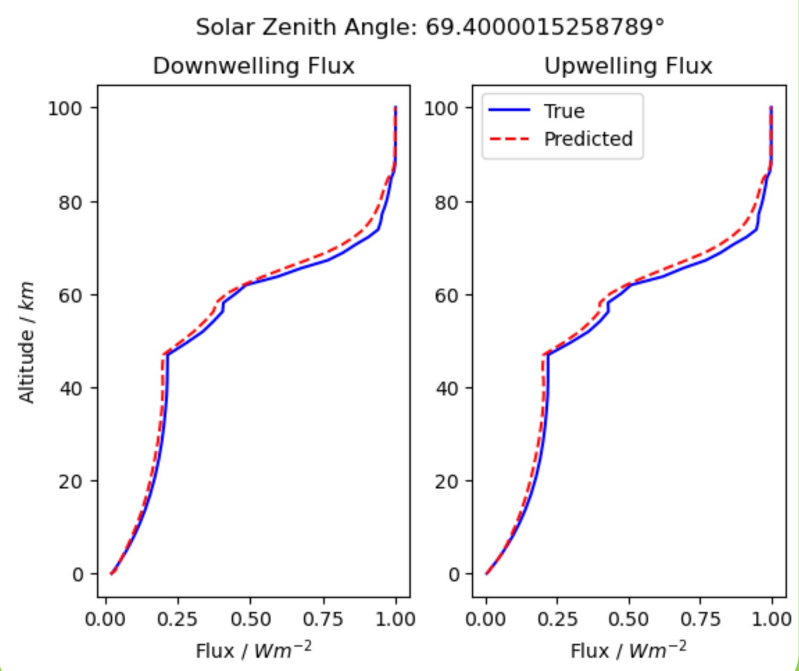
- **Spatial structure matters in our data:** electromagnetic flux flows from the top of an atmospheric column to the bottom
- **Certain algorithms incorporate this structure:** Choosing architectures with relevant assumptions of the structure of the data can guide the learning process to utilise information contained within this structure



Data



Model Performance



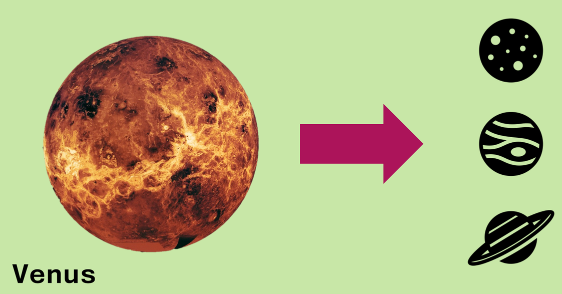
Previous Work in this Field

The past couple of years have seen the development of deep learning (DL) surrogate models for components of numerical weather prediction (NWP) models, specifically of Earth's climate.

- *Yao et al (2023)* tested a broad range of DL architectures for creating surrogate models for the radiative transfer component of NWP models of Earth
- Earth-based models are trained on observed data
- This work can inform our approach for developing emulators of (exo)planet atmospheric models

Trajectory of this Work

- This work differs from previous work in that it uses simulated data instead of real observations, and covers a different area of parameter space (Venus).
- The future of this work would be to generalise these models to (exo)planets covering a broader range of parameter-space.



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