GC33F-1206 The Climate Pocket: Tutorial on Building Fast Emulators in Climate Modeling.

Wednesday, 13 December 2023

17:10 - 21:30

Poster Hall A-C - South (Exhibition Level, South, MC)

Abstract

Decision-makers critically rely on climate models for understanding climate change and setting climate policies. These models however require inaccessible supercomputers. As a result, any task that requires multiple model runs, such as risk or sensitivity analyses, is expensive. In particular, interacting with climate models by querying many educational "what-if" scenarios, such as "what-if we plant 1 trillion trees", is too expensive.

The crux of the computational complexity is that the underlying differential equations have to be solved for every scenario or parameter update from scratch. Machine learning (ML) promises a paradigm shift: the idea behind ML-based ‚emulators‘ is to train ML models on large databases of simulated data. After training, the model has memorized how to solve the differential equations and can be quickly run for new parameter updates.

ML-based emulators have attracted attention in the Earth sciences by predicting weather in seconds rather than hours and in machine learning due to challenges in physical structure, high-dimensionality, and long-term stability. While there exists tutorials for emulating the weather (Pathak et al., 2022), emulating the climate poses different challenges. Specifically, physical-consistency and long-term stability are fundamental in developing emulators that have to extrapolate multiple years beyond the training data.

This tutorial will demonstrate an interactive climate emulator that can be used to explore „what-if“ climate policies via a jupyter notebook. Our goal is to introduce emulation to Earth and Machine Learning scientists and highlight its' pros and cons. Further, our tutorial is aimed to help Earth scientists adapt ML techniques for emulating their research and ML scientists to take on the challenges in climate data. Because every Earth science emulator will require different choices, our tutorial will focus on explaining those choices, e.g., when to use non-ML vs. ML and how to incorporate physical knowledge. The final model can be used to illustrate and explore climate policies.

Plain-language Summary

It is difficult to understand how exactly politics impact climate change. For example, would we have less heatwaves in the USA if the country would be powered by renewable energy? Most likely, yes, but even more important is to map the financial investment into renewables onto the reduction in heatwaves. In theory, those questions can be explored by Earth system models (ESMs) that predict the climate impacts as a result of future greenhouse gas emissions. In practice, approximations of ESMs such as En-ROADS are used to explore many policy scenarios, because full-scale climate models are too computationally expensive. Most recently, machine learning has promised a path towards better approximations of ESMs. This tutorial is a jupyter notebook that introduces such machine learning-based approximations of ESMs to Earth scientists and Machine Learning researchers.

First Author

L

Björn Lütjens

MIT

Authors

H
Lea M Hadzic
Palo Alto High School

N
Dava Newman
Massachusetts Institute of Technology

V
Mark Veillette
MIT Lincoln Laboratory

View Related