Metamodeling Climate Trajectories Using Neural Networks

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Climate science heavily relies on large-scale models, such as those in the Coupled Model Intercomparison Project (CMIP6), which integrate complex physical, chemical, and biological processes to simulate past, present, and future climate scenarios. CMIP6, for instance, involves dozens of models and hundreds of simulations, each designed to capture different aspects of the Earth's climate system. However, the use of such large models comes with significant computational burdens, particularly as the number of state variables increases, leading to what is commonly referred to as the "curse of dimensionality."

In response, a wide range of simplified climate models aims to capture the essential dynamics of climate systems while reducing computational complexity. For example, FaIR uses four state variables for climate boxes and three for temperatures. Despite their reduced complexity, these models –basically a set of Ordinary Differential Equations – still face limitations in their numerical resolution, especially under uncertainties, as the number of grid points needed to calculate policy functions increases exponentially with the number of state variables.

This paper proposes the use of ReLU (Rectified Linear Unit) neural networks as an efficient tool to address these computational challenges by avoiding solving ODEs. Specifically, we propose an exponential parameterization of emission trajectories, which is particularly well-suited for approximating emission pathways stabilize over time (they tend to a limit representing a long-term equilibrium). Any function converging to zero at infinity can be decomposed into an exponential form (This is a well-known result of Ch. H. Müntz at 1914 and then studied by Laurent Schwartz at 1943). Economically, this also makes sense as Integrated Assessment Models (IAMs) such as DICE (Dynamic Integrated Climate Economic model) predict that carbon emissions asymptotically stabilize to zero through long term energy efficiency and recent SSPs (Shared Socio-economic Pathway) projections extending to 2500 are coherent with this prediction for emission trajectories. By leveraging this parameterization, we aim to approximate key climate trajectories (especially our QoI (Quantify of Interest): near-surface air temperature trajectory) with neural networks. Our approach decomposes the emission trajectories into Müntz coefficients and transforms the time domain to allow for a detailed regularity properties study of our QoI. Good regularity properties of our climate variables trajectories allows us to approximate them with neural network ensuring the accuracy and robustness of the approximation. This approach is supported by ReLU neural network convergence analysis research of Dmitry Yarotsky in 2017.

Our implementation involves three main steps: first, decomposing emission pathways (e.g. SSPs) into Muntz coefficients; second, generating temperature trajectory datasets based on these coefficients; and finally, train a ReLU neural network with these datasets. Once trained, our neural network is a powerful tool for (1) efficient evaluation of temperature trajectories and (2) sensitivity analysis of our QoI to emission pathways. Sensitivity analysis will provide valuable insights for emission pathway mitigation strategies in the context of climate change. Moreover, the methodology we propose is not limited to climate modeling and can be extended to a wide range of other high-dimensional problems.