Internship proposal - 2023

Title: Can we simulate extreme heat waves in climate models using machine learning ?

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Supervisors

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Abstract

Since the pre-industrial era, the world has warmed by 1.1°C and the last IPCC report projects that it will keep warming if the emissions of greenhouse gasses continue to increase. One of the main and most societally relevant consequences of global warming is the changes in the distribution of meteo-climatic extreme events. Heat waves are among the most prominent of them, imposing terrible costs on societies and ecosystems [1]. Global warming shifts the distribution of temperatures towards higher values, therefore rendering extreme temperatures more likely – this is called the thermodynamic contribution. But global warming also modifies the general circulation of the atmosphere, which is the overall cause of extreme temperatures at the ground. This is called the dynamic contribution. Understanding the mechanisms by which global warming changes the dynamics leading to heat waves is however still an open question. The main difficulty associated with the study of heat waves, and extreme events in general, is their very nature: they are rare. Therefore, the data available to understand their dynamics is scarce. The solution to overcome this issue is to simulate the climate during very long periods of time in order to produce more extremes. However, this comes with a high computational cost. In recent years, methods have been developed to sample more effectively extreme events, using so-called rare event algorithms [2]. These methods usually rely on the parallel simulation of members and regular selection of the members which have the highest chance to reach extremes. Another approach consists of finding the optimal perturbations of the dynamics which would push the trajectory of the system towards extreme values [3]. Although this problem is mathematically well posed, it is very difficult to solve in practice for complex systems. The objective of the internship is to explore the use of machine learning techniques to find these optimal perturbations in a hierarchy of meteorological and climate relevant models. The proposed

approach to this problem is to employ a reinforcement learning strategy [4]. The machine learning model (the agent) would learn to find the optimal perturbations given the state of the system and the extremes one aims to reach. This approach has already been employed to control systems in fluid mechanics and can in principle be applied to sample extreme events [5]. Once these optimal perturbations are known, one can first simulate a large number of extremes and second investigate what are the properties of the perturbations to better understand the physical mechanisms leading to the extremes [6].

Work programme

The work proposed in the internship will apply to a hierarchy of meteorological and climate relevant dynamical models, beginning with the simplest ones. The first step will be to work with the Lorenz's system [7], which is a simple nonlinear system defined by three equations. The goal will be to validate the reinforcement learning procedure to simulate extremes of an observable on this system. This first step can consist in identifying and testing the implementation of several reinforcement algorithms. The student will have to compare their results, with a special concern regarding the computational cost. We will especially be interested to understand whether the algorithms can generalize at different starting points of the dynamical system. The second step will consist in applying this algorithm on a quasi-geostrophic model representing an approximation of the large-scale atmospheric circulation in the mid-latitudes [8]. For this system, the extremes of interest will be air or ground temperature and we will be interested in understanding the physical mechanisms sampled by the algorithms. Finally, if the results of the preceding steps are positive and there is still enough time, we will work with the intermediate complexity model PlaSim [9]. This model is a good approximation of an Earth System Model (ESM) while requiring a reasonable computational cost. The analysis of the physical mechanisms leading to extreme temperature events in this model will be of particular interest to our team.

Profile

We are seeking a motivated Master's student with a strong background in machine learning and data science (statistics, modeling). An experience with reinforcement learning algorithms would be a plus. Knowledge of general and geophysical fluid dynamics will make the internship more appealing but is absolutely not mandatory. Necessary concepts will be introduced during the internship.

Working conditions

The internship will take place mainly at LSCE in the ESTIMR team, in the Paris Saclay University with frequent exchanges at LPSM in Sorbonne University. The dates of the internship can be discussed with the student. The student will interact with PhD students, postdocs and engineers of the team. The student will receive a monthly gratification. Public transportation passes are reimbursed at 50%

References

[1] Horton, R. M., Mankin, J. S., Lesk, C., Coffel, E., & Raymond, C. (2016). A review of recent advances in research on extreme heat events. *Current Climate Change Reports*, *2*(4), 242-259.

[2] Bouchet, F., Rolland, J., & Wouters, J. (2019). Rare event sampling methods. *Chaos: An interdisciplinary journal of nonlinear science*, *29*(8), 080402.

[3] Grafke, T., & Vanden-Eijnden, E. (2019). Numerical computation of rare events via large deviation theory. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *29*(6), 063118.

[4] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

[5] Brunton, S. L., Noack, B. R., & Koumoutsakos, P. (2020). Machine learning for fluid mechanics. *Annual review of fluid mechanics*, *52*, 477-508.

[6] Plotkin, D. A., Webber, R. J., O'Neill, M. E., Weare, J., & Abbot, D. S. (2019). Maximizing simulated tropical cyclone intensity with action minimization. *Journal of Advances in Modeling Earth Systems*, *11*(4), 863-891.

[7] Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of atmospheric sciences*, *20*(2), 130-141.

[8] De Cruz, L., Demaeyer, J., & Vannitsem, S. (2016). The modular arbitrary-order ocean-atmosphere model: MAOOAM v1. 0. *Geoscientific Model Development*, *9*(8), 2793-2808.

[9] Fraedrich, K., Jansen, H., Kirk, E., Luksch, U., & Lunkeit, F. (2005). The Planet Simulator: Towards a user friendly model. *Meteorologische Zeitschrift*, *14*(3), 299-304.