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Probabilistic forecasting of heat waves with deep learning

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Extreme events such as storms, floods, cold spells and heat waves are expected to have an increasing societal impact with climate change. However the study of rare events is complicated due to computational costs of highly complex models and lack of observations. However, with the help of machine learning synthetic models for forecasting can be constructed and cheaper resampling techniques can be developed. Consequently, this may also clarify more regional impacts of climate change. .

In this work, we perform detailed analysis of how deep neural networks (DNNs) can be used in intermediate-range forecasting of prolonged heat waves of duration of several weeks over synoptic spatial scales. In particular, we train a convolutional neural network (CNN) on the 7200 years of a simulation of a climate model. As such, we are interested in probabilistic prediction (committor function in transition theory). Thus we discuss the proper forecasting scores such as Brier skill score, which is popular in weather prediction, and cross-entropy skill, which is based on information-theoretic considerations. They allow us to measure the success of various architectures and investigate more efficient pipelines to extract the predictions from physical observables such as geopotential, temperature and soil moisture. A priori, the committor is hard to visualize as it is a high dimensional function of its inputs, the grid points of the climate model for a given field. Fortunately, we can construct composite maps conditioned to its values which reveal that the CNN is likely relying on the global teleconnection patterns of geopotential. On the other hand, soil moisture signal is more localized with predictive capability over much longer times in future (at least a month). The latter fact relates to the soil-atmosphere interactions. One expects the performance of DNNs to greatly improve with more data. We provide quantitative assessment of this fact. In addition, we offer more details on how the undersampling of negative events affects the knowledge of the committor function. We show that transfer learning helps ensure that the committor is a smooth function along the trajectory. This will be an important quality when such a committor will be applied in rare event algorithms for importance sampling.

While DNNs are universal function approximators the issue of extrapolation can be somewhat problematic. In addressing this question we train a CNN on a dataset generated from a simulation without a diurnal cycle, where the feedbacks between soil moisture and heat waves appear to be significantly stronger. Nevertheless, when the CNN with the given weights is validated on a dataset generated from a simulation with a daily cycle the predictions seem to generalize relatively well, despite a small reduction in skill. This generality validates the approach.