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Conditional normalizing flow for predicting the occurrence of rare extreme events on long time scales

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The socio-economic impacts of rare extreme events, such as droughts, are one of the main ways in which climate affects humanity. A key challenge is to quantify the changing risk of once-in-a-decade or even once-in-a-century events under global warming, while leaning heavily on comparatively short observation spans. The predictive power of classical statistical methods from extreme value theory (EVT) often remains limited to uncorrelated events with short return periods. This is mainly due to their strong assumption of an underlying exponential family distribution of the variable in question. Standard EVT is therefore at odds with the rich and large-scale correlations found in various surface climate parameters such as local temperatures, as well as the more complex shape of empirical distributions. Here, we turn to recent developments in machine learning, namely to conditional normalizing flows, which are flexible neural networks for modeling highly-correlated unknown distributions. Given a short time series, we show how such networks can model the posterior probability of events whose return periods are much longer than the observation span. The necessary correlations and patterns can be extracted from a paired set of inputs, i.e. time series, and outputs, i.e. return periods. To evaluate this approach in a controlled setting, we generate synthetic training data by sampling temporally autoregressive processes with a non-trivial covariance structure. We compare the results to a baseline analysis using EVT. In this work, we focus on the prediction of return periods of rare statistical events. However, we expect the same potential for a wide range of statistical measures, such as the power spectrum and rate functions. Future work should also investigate its applicability to compound and spatially extended events, as well as changing conditions under warming scenarios.