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Detection and Characterization of Climate Extremes with Deep Learning

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Over the past few years, the consequences of climate extremes have become increasingly concerning. According to IPCC projections (Intergovernmental Panel on Climate Change), such events are to keep increasing in frequency, intensity, and duration. We aim at characterizing those changes, depending on carbon emission scenarios. But the analysis of climate simulations requires a huge computational power: data are available at a daily frequency, at a global scale at a ~125km spatial resolution, and depend on each realization of different climate models and scenarios.

We propose a novel method, a deep learning model, to address such big geospatial data sets. The state of the art for climate extreme detection with Artificial Intelligence focuses on satellite imagery, past events, or short-term forecasting. It is less prolific for future events or simultaneous analysis of several climate models and scenarios. In 2020, Sinha et al. developed an anomaly detection model to spot avalanches in satellite images. She tackled the same issue as ours: an unsupervised anomaly detection problem, with numerous unlabeled pictures of both normal snow surfaces and avalanche deposits.

The algorithm is based on a Convolutional Variational AutoEncoder (CVAE), a Neural Network that learns in an unsupervised setup. It is fed with plenty of images, with a small proportion of abnormal images, and learns how to compress and reconstruct them. The network has no information about whether the image is an anomaly or not. At the end of the training phase, it does a good job reconstructing normal images, but it struggles (high reconstruction error) with unusual samples.

In our case, the model is trained for each season on observations of a specific climate variable (e.g. temperature), on a given geographical zone. It is then applied to projection data (IPCC scenarios) on the same variable for the same location. The output images and losses are then post-processed as time series to extract statistical characterizations of the events, such as their frequency, intensity, or duration. The results are validated with several members (realizations) of the same climate model, and compared with analytical indices over a historical sample.

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