Investigating cloud organizations using complementary approaches in self-supervision and geostationary satellite observations

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The representation of shallow trade wind cloud systems in climate models accounts for a significant inter-model spread in climate projections. Additionally, questions have been raised about how the changing climate will influence the frequency of occurrence of these cloud regimes. The mentioned points highlight the need to understand these cloud systems better and develop deep learning approaches to help us in this direction. Using two complementary neural networks in self-supervision (without human intervention), we investigate the representation learning of shallow clouds, which are often organized in large systems. The network's target is to learn the dimensionally reduced representations in a continuous space describing a cloud system spectrum and in a discrete space, aiming to identify distinct cloud systems in classes. Our primary intention for this approach is to develop a way in which every possible cloud system (extremes + transitions) could be well represented and studied further.

For this purpose, 50,000 GOES-ABI cloud optical depth images over North Atlantic trades from 2017 – 2021 covering the EUREC4A campaign study area are randomly cropped to 256 x 256 pixels and sorted or labeled by the machine. First, to establish our trust in neural network decisions, we visualize the network's focus in the activation space. We find that different self-attention heads of the neural network learn to focus on different semantics of the cloud system distribution. However, we find that different regularizations applied during the training of the network directly impact the representation learning of the cloud system. Targeting regional climate systems, we focus on two applications.

As a first application, we first investigate areas of the embedding/feature space characterized by high moisture conditions intruding into areas of high subsidence using ERA-5 profiles. Although organization-wise similar, we ask ourselves which are the key physical parameters that make the intrusion profiles differ from surrounding states. Aware that intrusions over trades can be more frequent during the change in subsidence, we analyze the temporal evolution of the intrusions in the feature space. As a second application, we investigate the physical properties of clouds in the different classes as identified by the neural network. Here, we are motivated to relate the net cloud radiative effect (Net-CRE) using Clouds and the Earth's Radiant Energy System (CERES) data using calculated cloud metrics and cloud physical properties of the discrete classes. As we show in our analyses that our network has learned to classify organizations in physical and visual ways, we outline applications of the network for data-driven discovery and process understanding. We highlight the characterization of transitional states between different extreme kinds of organization, which is currently unavailable by existing methods.