Understanding what do the cloud regimes look like rather than what they are: from a bottom to top approach in AI

Dwaipayan Chatterjee[1], Hartwig Deneke[2], Susanne Crewell[1]
[1]Institute for Geophysics and Meteorology, University of Cologne, Cologne, Germany (dchatter@uni-koeln.de)
[2]Leibniz Institute for Tropospheric Research, Leipzig, Germany

The resolution of geostationary satellites is continuously improving, enabling new insights into clouds' complex structure and organization. Recent research shows preliminary causality between cloud organization, cloud feedbacks, and climate sensitivity. Therefore, how cloud systems organize is important for the local climate and strongly connects to the Earth's response to warming through cloud system feedback.

Our work aims to understand the structure and organization of cloud systems by exploiting the self-learning capability of a deep neural network and using high-resolution cloud optical depth images. The neural network utilizes deep clustering and non-parametric instance-level discrimination for decision-making at any learning stage.

We want the neural network (NN) to understand the connections between cloud scenes and generalize from a machine learning perspective. In doing so in the past, we have seen -

- Crowd-sourcing projects for labeling observe a subjectivity on cloud system boundary and disagreement because of sub-cloud systems within a dominant cloud organization. All this indicates that, by nature, the categories are fluidic.
- Therefore, a top-down approach, i.e., a supervised training network with fixed labels, fixes the semantic categories that the network can find and learn. In that way, the machine is forced to memorize the cloud semantic relations, setting up limitations for our model to understand the not-so-fixed relations.

Taking inspiration from recent developments in computer vision for pattern analysis of uncurated images and from the above discussion, we think for earth system data, especially for passive observation of cloud structure and organization , the machine must learn what it is like? instead of "what it is?" Our NN architecture could learn this "likelihood of closeness" from the available data itself, i.e., using a bottom to top approach where the network learns the choice of task from the data.

The data augmentation in the data pipeline, multi-clustering of the dense vectors, and Multilayer perceptron projection at the end of the Convolutional Neural Network (CNN) help the network learn a better representation of images. By bringing data augmentation such as random crops in our case, we discourage memorization and encourage generalization.

Unlike most studies, our neural network is trained over the central European domain, characterized by strong land surface type and topography variations. The satellite data is post-processed and retrieved at a higher spatio-temporal resolution (2 km,5 min), equivalent to the future Meteosat Third Generation satellite.

We show how recent advances in deep learning networks are used to understand the cloud's physical properties in temporal and spatial scales. We avoid the noise and bias obtained from human labeling in a purely data-driven approach. We demonstrate explainable artificial intelligence (XAI), which helps gain trust for the neural network's performance. We visualize the cloud organization's different regions that correspond to any decision of interest by the neural network. We use K-nearest neighbors to find similar cloud structures at different time scales.

A thorough quantified evaluation is done on two spatial domains and two-pixel configurations (128x128,64x64). We examine the uncertainty associated with distinct machine-detected cloud-pattern categories using an independent hierarchal - agglomerative algorithm. Therefore the work also explores the uncertainties related to the automatic machine-detected patterns and how they vary with different cloud classification types.