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EnSOMble Forecasting: Leveraging Self-Organizing Maps for Tornado Threat Modeling

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Artificial neural networks such as self-organizing maps (SOMs) are a subset of machine learning that have only recently begun to figure prominently in the meteorological literature. These techniques are traditionally used to highlight meteorological patterns and scenarios that can be considered representative or “typical”, with the aim of bringing new perspectives to the physical interpretation of these scenarios.

In this proof-of-concept work, we bring SOMs to the arena of the National Severe Storms Laboratory-Weather Research and Forecasting (NSSL-WRF) ensemble, comprised of ten convection-allowing model runs that provided forecasters with high-resolution guidance from February 2014 through February 2018. By training a SOM with these four years of data, we generate clusters of two-dimensional maps of key environmental parameters for tornado occurrence. This enables forecasters to identify “failure modes”, wherein a particular ensemble member may be producing a particular pattern more or less frequently than seen in observations.

A benefit of SOMs is their intuitive output: by definition, the output of these SOMs resembles the input fields, which are maps of the tornadic near-storm environmental parameters with which forecasters are extremely familiar. The SOM output enables forecasters both to highlight the members of the ensemble that may be performing especially poorly and to accrue longer-term statistics about model strengths and weaknesses to enhance future model performance.

Through this proof-of-concept, we highlight the versatility of artificial neural networks and emphasize that they can also be used to provide meaningful insight into model skill and performance in extreme weather scenarios.