Contribution ID: **63** Type: **Oral presentation**

Machine Learning for Applied Weather Prediction

Tuesday, 6 October 2020 16:30 (30 minutes)

Weather forecasting has progressed from being a very human-intensive effort to now being highly enabled by computation. The first big advance was in terms of numerical weather prediction (NWP), i.e., integrating the equations of motion forward in time with good initial conditions. But the more recent improvements have come from applying machine-learning (ML) techniques to improve forecasting and to enable large quantities of machine-based forecasts.

One of the early successes of the use of AI in weather forecasting was the Dynamical Integrated foreCast (DICast®) System. DICast builds on several concepts that mimic the human forecasting decision process. It leverages the NWP model output as well as historical observations at the site for the forecast. It begins by correcting the output of each NWP model according to past performance. DICast then optimizes blending of the various model outputs, again building on the past performance record. DICast has been applied to predict the major variables of interest (such as temperature, dew point, wind speed, irradiance, and probability of precipitation) at sites throughout the world. It is typical for DICast to outperform the best individual model by 10-15%. One advantage of DICast is that it can be trained on a relatively limited dataset (as little as 30 to 90 days) and updates dynamically to include the most recent forecast information. The gridded version of this system, the Graphical Atmospheric Forecast System (GRAFS) can interpolate forecasts to data-sparse regions.

DICast and other machine-learning methods have been applied by the National Center for Atmospheric Research (NCAR) to various needs for targeted weather forecasts. Such applications include hydrometeorological forecasting for agricultural decision support; forecasting road weather to enhance the safety of surface transportation; forecasting movement of wildland fires; and predicting wind, and solar power for utilities and grid operators to facilitate grid integration. NCAR has found AI/ML to be an effective for postprocessing for these and many applications and it has become part of any state-of-the-science forecasting system.

An example of using multiple AI methods for targeted forecasts is predicting solar power production. AI methods are used in both Nowcasting and in forecasting for Day-Ahead grid integration. DICast is one of the methods that blends input from multiple forecast engines. For the very short ranges, NCAR developed a regime-based solar irradiance forecasting system. This system uses k-means clustering to identify cloud regimes, then applies a neural network to each regime separately. This system was shown to out-predict other methods that did not utilize regime separation. NCAR is currently designing a comprehensive wind and solar forecasting system for desert regions that combines NWP with machine-learning approaches. For the first few hours, ML approaches leverage historical and real-time data. DICast improves on the NWP forecasts. The meteorological variables are converted to power using a model regression tree. The Analog Ensemble ML approach further improves the forecast and provides probabilistic information. This systems approach that leverages the best of NWP with ML shows success at providing a seamless forecast across multiple time scales for use-inspired applications.

Thematic area

1. Machine Learning for Product development - Including NWP Post-processing, Non-linear Ensemble Averaging, Development of new NWP Products

Primary author: Dr HAUPT, Sue Ellen (National Center for Atmospheric Research)

Presenter: Dr HAUPT, Sue Ellen (National Center for Atmospheric Research)

Session Classification: Session 3 (cont.) and Session 4: ML for Data Assimilation and ML for Product Development

Track Classification: ECMWF-ESA Workshop on Machine Learning for Earth System Observation and Prediction