Deep Learning for Post-processing Ensemble Weather and Subseasonal Prediction

Yuejian Zhu[1], Vijay Tallapragada[1], M.M. Nageswararao[2]

[1]EMC/NCEP/NWS/NOAA,

[2]UCAR visiting scientist at EMC

Statistical post-processing can dramatically improve the quality of forecast products; it has been discussed in the literature for many decades. Early weather forecasts were sometimes adjusted based on a technique known as the “perfect-prog” method, which required no training data from the dynamical model. The Kalman Filter (or decaying average; Cui et al. 2006; 2012) method began to be used for NCEP daily operation in 2008 when accumulating the model bias in real-time could be removed to adjust the ensemble forecast. Since generating ensemble reforecasts, the more complicated corrections can be made to ensemble forecasts with the combination of large consistent reforecast training data and decaying average real-time biases to incorporate corrections for typical overconfidence in raw ensemble forecasts (Guan et al 2015). The frequency match method (FMM, Zhu and Luo 2015) has been implemented to calibrate probabilistic quantitative precipitation forecasts (PQPF) when considering a non-Gaussian distribution for precipitation.

Artificial neural networks (ANN) or deep machine learning (DML) models became practically applicable due to rapidly increasing computational power. The ANN/DML methods are used in a wide range of post-processing approaches for weather and sub-seasonal to seasonal prediction in order to extract some key representative features from a set of raw forecast data or reforecasts. These representative features can then be used to infer new outcomes based on new information entering the machine learning algorithm. Relied on the 30 years of NCEP GEFSv12 reforecasts, various applications through DML (or ANN) have been examined to compare other useful statistical post-processing methods. In this study, use of ANN/DML for the following complexities (or usage) will be discussed, 1). For non-gaussian distribution forecast elements, such as precipitation; 2). Extreme forecast elements and 2nd-moment calibration, such as heavy rainfall, heatwaves etc.; and 3). Training samples dependency, such as reforecast frequency, ensemble size, and spatial/temporal correlations of training samples. Finally, we summarize our work toward future GEFS reforecast configuration, improve forecast reliability from weather to sub-seasonal time scale, and implement new skillful products for the stakeholders and users.

Keywords: Statistical post-processing, Extremes, Deep Machine learning, NCEP GEFSv12 reforecast