Contribution ID: **42** Type: **Oral presentation**

Deep Learning for Post-Processing Ensemble Weather Forecasts

Tuesday, 6 October 2020 17:30 (30 minutes)

Quantifying uncertainty in weather forecasts is critical, especially for predicting extreme weather events. This is typically accomplished with ensemble prediction systems, which consist of many perturbed numerical weather simulations, or trajectories, run in parallel. These systems are associated with a high computational cost and often involve statistical post-processing steps to inexpensively improve their raw prediction qualities. We propose a mixed model that uses only a subset of the original weather trajectories combined with a post-processing step using deep neural networks. These enable the model to account for non-linear relationships that are not captured by current numerical models or post-processing methods.

Applied to global data, our mixed models achieve a relative improvement in ensemble forecast skill (CRPS) of over 13%. Further, we demonstrate that this improvement is even more significant for extreme weather events on selected case studies. We also show that our post-processing can use fewer trajectories to achieve comparable results to the full ensemble. This can enable reduced computational costs for ensemble prediction systems or allow higher resolution trajectories to be run within operational deadlines, resulting in more accurate raw ensemble forecasts.

Thematic area

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

Primary authors: Mr GRÖNQUIST, Peter (ETH Zurich); Mr YAO, Chengyuan (ETH Zurich); Dr BEN-NUN, Tal (ETH Zurich); DRYDEN, Nikoli (ETH Zurich); DUEBEN, Peter (ECMWF); Dr LI, Shigang (ETH Zurich); Prof. HOEFLER, Torsten (ETH Zurich)

Presenter: DRYDEN, Nikoli (ETH Zurich)

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