Deep Learning for Ensemble Forecasting

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2. Focal Area
(2) Predictive modeling through the use of AI techniques and AI-derived model components and the use of AI and other tools to design a prediction system comprising a hierarchy of models

3. Science Challenge
While both climate and weather forecast systems have continued to improve due to substantial efforts to improve computational capabilities, observations, and numerical models, the atmosphere is a chaotic system, and this puts a fundamental limit on our ability to make predictions. Forecasts made by high-resolution models initialized with only slightly different atmospheric states can quickly diverge. Quantifying uncertainty in forecasts is essential to adequately understand them and to make the best-informed policy decisions particularly when it comes to hydrology, extreme weather (including extreme precipitation events), and climate.

Currently, forecast uncertainty at the time of prediction is assessed using ensemble systems. These systems initialize multiple forecast models with slightly different initial states or different representations of atmospheric physics and use the spread of the resulting predictions to estimate uncertainty. Additionally, the ensemble mean is typically more predictive than a single deterministic forecast. Ensemble forecasts come at extreme computational cost that limits their potential applications: typical ensembles involve 5-100 members that each use the computational resources of running a single forecast model. Nonetheless, quantifying forecast uncertainty is valuable enough that many of the world's premier weather forecasting agencies (NOAA [1] and ECMWF [2] for instance) provide operational ensemble weather forecasts. Ensembles have recently been applied to climate modeling [3] where the need for assessing confidence in climate predictions is critical, and thus the need for informing ensemble details for climate is also critical. Ensembles also have potential for use in sensitivity studies as a way to isolate changes associated with the chaotic nature of the system from changes associated with a variable of interest. More efficient methods for accurately generating ensemble spread and improving the overall ensemble forecast would be a boon for weather forecasting, climate modeling, and our understanding of atmospheric dynamics and processes.

Recently, deep convolutional neural networks have been demonstrated as very effective for many tasks in the field of atmospheric science including forecasting [4], satellite retrievals [5], downscaling/super resolution [6], atmospheric state classification, and many others. They have also been successfully applied as post-processing for ensemble forecasts [7,8]. These machine learning tools are particularly well suited for problems that involve very large, gridded datasets where complex non-linear relationships must be learned, and more conventional methods may not be up to the task. They could be a powerful tool for predicting forecast uncertainty or estimating likely ensemble spread using fewer ensemble members and for understanding parameters and conditions that lead to growth of uncertainty in predictions. A Deep Learning (DL) based approach to ensemble modeling and uncertainty estimation has the potential for massive computational savings for existing ensemble systems and would allow for

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ensemble-like uncertainty estimation in weather and climate studies that would otherwise not have the resources for this type of analysis. In addition to this huge computational savings, a system that can estimate model uncertainty combined with explainable AI techniques such as layer-wise relevance propagation [9,10], would allow for more sophisticated understanding of where model spread is introduced in ensemble simulations. These methods would allow model uncertainty to be interrogated in ways that traditional ensembles cannot with the goal of understanding the model states and variables that lead to large uncertainties.

4. Rationale

Ensemble forecasting is currently done at a massive computational cost, but is necessary to understand uncertainty and the spread of possible outcomes in weather and climate predictions and to account for the chaotic nature of the atmosphere. Furthermore, current understanding of the variables and model states that lead to rapid growth in uncertainty is limited. This is particularly important when forecasting extreme weather and precipitation events which have substantial human and economic impacts. Deep-learning has the potential to revolutionize the way ensemble modeling and uncertainty estimation is done:

- Several techniques exist to interrogate neural networks and have been demonstrated as powerful exploratory data analysis tools for meteorological data [9]. DL-based ensemble systems can leverage explainable AI techniques to understand the key variables and meteorological conditions that lead to high uncertainty in forecasts.
- Replacing or enhancing existing ensemble systems with a DL approach would lead to huge computational savings (a DL-based ensemble system might only require 1/2 - 1/50 of the computational resources).
- Improved efficiency could result in significant power savings. While deep learning research is itself computationally expensive, power used by DL projects is dwarfed by the power consumption of the supercomputers used for ensemble modeling. We estimate the power used by the CESM large ensemble project [3], a single study, to be about 220MWh, enough to run a 4-GPU cluster typical of deep learning studies for about 20-years. Even a modest performance improvement for ensemble modeling systems would make such a deep-learning project worthwhile.
- This reduction in computational requirements would allow resources to be re-tasked towards other important elements of modeling, for instance increases in model resolution and better representation of model physics. Improved models and better representation of forecast uncertainty created by freed up resources can improve weather and climate risk assessment and aid in making important policy decisions. In particular, improved uncertainty estimates for extreme weather events like extreme precipitation and flooding would have a large impact.
- Cheaper ensembles would make uncertainty estimation accessible for climate and weather studies that would otherwise be resource limited. Ensemble modeling is very useful for such studies because it allows the chaotic variability of the atmosphere to be isolated from changes of interest. For instance, ensemble means for climate projections can isolate temperature changes due to the long-term climate forcing from the semi-random yearly to decadal scale temperature variability that occurs in individual model realizations.

Ultimately, such a project will have the most significant impact if performance improvements achieved through deep learning are available to, and are implemented by, many modeling centers. Therefore we recommend making any resulting code open source and ensuring that pre-trained deep-learning models are publicly available for download.

5. Narrative

Recently, deep learning and Convolutional Neural Networks (CNNs) have been demonstrated as powerful tools for various tasks related to atmospheric data, particularly in the areas of modeling, remote sensing, and pattern recognition/clustering. Deep learning has the potential to revolutionize how ensemble forecasting is done, which could lead to massive computational savings, incorporation of uncertainty estimates in studies and forecasts where they were previously not feasible, better understanding of extreme weather and climate forecasts and impacts, and new approaches to investigate how high-uncertainty regions develop and propagate in models. This problem could be approached in several different ways:

1. Uncertainty estimation as a post-processing step: Given an initial, final, and some intermediate states from a single model run, task a DL-model with estimating the likely distribution of ensemble members had an ensemble forecast been run, by estimating the moments of the distributions of the prognostic variables for instance.
2. Time-integrated approach: run a DL-model alongside a forecast model during integration and estimate the increase in forecast uncertainty with each time-step. This may be more reasonable than (1) because the DL model is only tasked with estimating changes over a much smaller time-window.
3. Hybrid approach: Use a DL-model to inform an ensemble forecast by identifying likely bifurcation points or high-uncertainty regions and dynamically adding and removing ensemble members with the goal of significantly reducing the number of members required for a useful forecast.
4. Mix of (1) and (3): develop an AI model to add ensemble members when a rapid increase in uncertainty is deemed likely alongside another model that predicts uncertainty for each member.
5. Given a small set of ensemble members, use adversarial learning to generate plausible final states for additional ensemble members without running full forecasts for them.
6. Use a DL-based ensemble to merge uncertainty information from model runs at multiple resolutions. For instance, by estimating uncertainty for a high-resolution model using an ensemble of lower resolution or lower complexity models.

The result of research in this area would be the development of machine-learning and AI based techniques for estimating forecast uncertainty. This would be a significant shift from how this problem has historically been approached using model ensembles and could substantially reduce the computational cost of uncertainty estimates and improve our understanding of how uncertainty develops in weather and climate prediction. This can result in freed computational resources for other important modeling tasks, improved understanding of how uncertainty develops in models, uncertainty estimates for modeling tasks where such estimates are typically not possible due to limited resources, and improved/additional uncertainty estimates for extreme weather and precipitation events or climate forecasts.

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