Quantification of forecast uncertainty using neural networks

Maximiliano Sacco, Yicun Zhen, Pierre Tandeo, Juan Ruiz, Manuel Pulido

QUANTIFICATION OF FORECAST UNCERTAINTY USING NEURAL NETWORKS

Maximiliano Sacco[1], Yicun Zhen[2], Pierre Tandeo[2], Juan Ruiz[4,5], Manuel Pulido [6,5]

Abstract—**Uncertainty quantification in numerical weather and climate prediction is usually achieved using a Monte Carlo estimation (i.e., ensemble forecasting) of the forecast probability distribution function of the state of the system. In this work, we present a method for uncertainty quantification based on neural networks and using a likelihood-based loss function to train the network. This provides state dependent uncertainty estimation, without the need of integrating an ensemble of forecasts. The method is evaluated with a chaotic low-dimensional model in two scenarios: with stochastic errors only (SE) and systematic and stochastic errors (SSE).**

I. MOTIVATION

Uncertainty quantification in numerical weather and climate prediction is one of the main goals of ensemble forecasting approaches, which routinely provide an estimation of the state dependant uncertainty due to the errors in the initial conditions and in model formulation. This estimation comes at the cost of running the numerical model several times. Some studies have explored low cost approaches to estimate forecast uncertainty based on machine learning techniques. [1] designed a neural network that learned uncertainty quantification from an existing ensemble system. [2] and [3] estimated the uncertainty of a forecast system directly from the observations, using a new type of loss functions explicitly including the uncertainty in their formulation. In this work, we use a likelihood-based loss function to train a neural network as in [3], to incorporate both a correction in the systematic error component, and a quantification of the forecast uncertainty.

II. METHOD

The key to achieve a simultaneous estimation of the systematic error and the uncertainty associated with a forecast system is to incorporate the uncertainty in the formulation of the loss function. One possible way to achieve that is to define a cost function based on the likelihood of the observations given the forecast. Assuming that the error distribution is Gaussian, the likelihood can be expressed as a function of the forecast values and the forecast error standard deviations. In our implementation, optimal state-dependent values for both quantities are estimated through a neural network, whose input is the forecast produced by a numerical model. Moreover, in the implementation here proposed, instead of using observations (which are usually sparse in space and time as well as diverse in nature), we use the mean state of the system estimated using a data assimilation approach.

Corresponding author: M Sacco, msacco@gmail.com [1]National Meteorological Service of Argentina [2]IMT-Atlantique [3]Atmospheric and Oceanography Research Center (UBA-CONICET) [4]UMI-IFAECI (CNRS-UBA-CONICET) [5]$PhysicsDepartment - FACENA - UNNE$

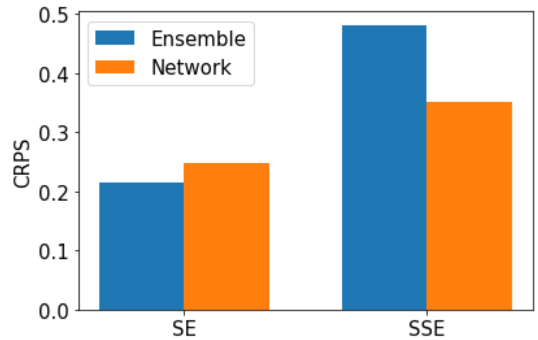

Fig. 1. The plot shows the Mean of the Continuous Ranked Probability Score computed over 3000 forecasts obtained with an ensemble of forecasts (blue) and with the neuronal network (orange) for both perfect (perf) and imperfect (imperf) model experiments.

III. EVALUATION

We evaluate the method using the Lorenz-96 chaotic low-dimensional model to simulate a numerical weather prediction system. Figure1 shows the continuous ranked probability score of the probabilistic forecast produced from a deterministic forecast combined with the neural network, and the one produced by an ensemble of forecasts under both SE and SSE scenarios. In the SE scenario, the ensemble method performs slightly better, with the neural network, being less expensive in terms of computation. In the SSE scenario, the neural network outperforms the ensemble approach. The advantage of the neural network approach is that it can capture both the stochastic and systematic components of model error.

REFERENCES

[1] S. Scher and G. Messori, “Predicting weather forecast uncertainty with machine learning,” *Quarterly Journal of the Royal Meteorological Society*, 10 2018.

[2] E. Camporeale, X. Chu, O. V. Agapitov, and J. Bortnik, “On the generation of probabilistic forecasts from deterministic models,” *Space Weather*, 2019.

[3] B. Wang, J. Lu, Z. Yan, H. Luo, T. Li, Y. Zheng, and G. Zhang, “Deep uncertainty quantification: A machine learning approach for weather forecasting,” 2018.