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Machine learning-based uncertainty quantification for data assimilation: a simple model experiment

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Quantifying forecast uncertainty is a key aspect of state-of-the-art data assimilation systems which has a large impact on the quality of the analysis and then the following forecast. In recent years, most operational data assimilation systems incorporate state-dependent uncertainty quantification approaches based on 4-dimensional variational approaches, ensemble-based approaches, or their combination. However, these quantifications of state-dependent uncertainties have a large computational cost. Machine learning techniques consist of trainable statistical models that can represent complex functional dependencies among different groups of variables. In this work, we use a fully connected two hidden layer neural network for the state-dependent quantification of forecast uncertainty in the context of data assimilation. The input to the network is a set of three consecutive forecasted states centered at the desired lead time and the network's output is a corrected forecasted state and an estimation of its uncertainty. We train the network using a loss function based on the observation likelihood and a large database of forecasts and their corresponding analysis. We perform observing system simulation experiments using the Lorenz 96 model as a proof-of-concept and for an evaluation of the technique in comparison with classic ensemble-based approaches.

Results show that our approach can produce state-dependent estimations of the forecast uncertainty without the need for an ensemble of states (at a much lower computational cost), particularly in the presence of model errors. This opens opportunities for the development of a new type of hybrid data assimilation system combining the capabilities of machine learning and ensembles.