Plans to Estimate Adaptive Covariance Parameters Using a Neural Network

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There are plans at EMC to replace the covariances used for background error within the Real-Time Mesoscale Analysis (RTMA, de Pondeca *et al*., 2011) with a dynamically adaptive formulation based on compact-support beta distribution filters ("beta filters") embedded in a computationally efficient distributed multigrid algorithm (Purser *et al*. 2021). In the present operational two-dimensional formulation, the covariance is static, although possessing anisotropic and spatially inhomogeneous features tied to orography. But it uses recursive filters (Wu *et al*., 2002), which have proven to be difficult to parallelize efficiently. The inherently more efficient and more versatile multigrid beta filter (MGBF) covariances that we are extending into three dimensions offer us the opportunity to make these covariances adapt not only to fixed terrain, as is presently done, but also to the ambient flow conditions, and to the evident variability and uncertainty that we can deduce by exploiting the availability of ensembles of short forecasts. In order to make the connection between suitable diagnostics of the background field and ensemble on the one hand, and the covariance amplitude and anisotropy parameters on the other hand, we plan to employ the machine learning techniques of artificial neural networks (NN, Krasnopolsky 2013).

One problem we encounter is that the spatial shape of the covariance response is characterized not by independent scalar parameters, but by a tensor (an "aspect tensor") whose symmetry and positivity must be preserved. The ensemble-averaged outer-product of gradients of the fields formed by the departures of the ensemble members about their collective mean form a tensor which, when suitably mixed with a regularizing horizontally isotropic tensor and the result inverted, provides a tensor of the desired character, stretching the covariance response in the direction indicated by the ensemble. It is then the mixing weights (positive scalars) involved in this process that we can ask the NN to supply, as "outputs" in response to local atmospheric diagnostics, such as windiness, static stability, and ensemble variance, as well as fixed terrain diagnostics, that can be gathered as "inputs" to the NN. The covariance amplitude, i.e., the background error variance, for each analysis variable, is another set of parameters that we can ask a trained NN to provide in response to diagnostics from the background field and ensemble.

Another problem we must address is the "training" of the NN, which entails establishing a formal criterion that corresponds to an objective measure of the quality of the covariance estimate that the NN implies, over numerous archived cases. This needs to be set up in such a way that we can iteratively search for the combination of the very numerous internal weights of the NN that appear to optimize the choices of covariance parameters conditional on the characteristics of ambient flow and of the diagnosed variability within the ensemble. Fortunately, the products of nearby pairs of the observation innovations constitute unbiased (though obviously very noisy and sporadic) "measurements" of the covariance of these innovations. We can therefore use a weighted sum of the squares of the differences between a thinned subset of the products of innovation pairs, and the corresponding modeled covariance estimates, since these latter estimates only differ from the background error covariances by the addition of the small, and reasonably well known, diagonal covariance of the observation errors. It is the fact that the modeled covariances in the multigrid scheme are made up of additive quasi-Gaussian contributions, the beta filters, that will allow us to approximate these contributions by the true analytic Gaussians during the training phase of establishing the NN weights. It is important that the covariances be analytically differentiable with respect to their parameters, since the training process requires that the derivatives of the quality criterion be expressible explicitly with respect to the internal weights of the NN (through the "back-propagation" application of the chain rule) in order that these weights can be efficiently optimized. Once the NN has been successfully trained on a varied and representative archive of past cases, we believe we shall be able to implement a dynamically adaptive analysis for the RTMA using the multigrid beta filter approach, guided by the diagnostics we have available from the ensemble of short forecasts, from the background fields itself, and from the local topography.

References

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