Using machine learning to improve data assimilation for weather forecasting

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Data assimilation is at the core of weather forecasting, where it combines newly acquired observations with the latest model forecast to provide a statistically best estimate of the current atmospheric state. Data assimilation is founded in Bayesian statistics and in its variational form, used for example at the European Centre for Medium-range Weather Forecasts (ECMWF), it is solved by minimising a cost function similar to the loss function in machine learning. Hence there are exact mathematical equivalences between data assimilation and the process of training a machine learning algorithm. This gives opportunities for machine learning to help improve data assimilation and vice-versa. First, machine learning could help improve the performance of data assimilation algorithms, using machine learning surrogate models in place of current physically based models. These could provide extremely large ensembles of model forecasts or, given the fact that typical machine learning algorithms are differentiable, they could be used to help provide the gradients of the data assimilation cost function (in other words, they can provide the tangent linear and adjoint models needed for variational data assimilation). Second is the possibility to use machine learning to provide new models in areas where physically-based models are not available. Examples are to learn bias (mean error) corrections for models and observations, or to learn entirely new physical models. A big hope is to create observation forward models for applications where the physical equations are imperfectly known, particularly in the area of remote sensing the earth surface, with applications such as sea-ice, snow, soil moisture and surface windspeed. In the opposite direction, data assimilation approaches such as physically-based error quantification could also benefit machine learning applications in the earth sciences.