



Operational machine learning for the postprocessing of surface wind forecasts

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Forecasting winds at the local scale can be challenging due to the highly variable and complex nature of wind patterns, particularly in the case of complex terrain. In such cases, the accuracy of numerical weather prediction models (NWPs) is often limited by the quality of their initial conditions and their grid resolution. This is where the use of observational data through statistical postprocessing techniques can help to improve the quality of forecasts.

Statistical postprocessing is nowadays an established component in operational weather forecasting that is used to improve the accuracy, resolution, and calibration of NWP ensemble forecasts with historical observations. In recent years, machine learning techniques have shown great potential in the field of postprocessing, thanks to their ability to deal with increasingly large volumes of data, and the capacity to capture complex relationships between forecasts and observations that are not explicitly represented in traditional postprocessing methods.

To capitalize on machine learning for weather applications, and for it to gain acceptance and become a reliable technology for operational use, it is also crucial to consider the technical and engineering challenges that arise when implementing machine learning in a productive environment. MLOps, or Machine Learning Operations, is a set of practices that are used to manage and streamline the deployment, monitoring, and maintenance of machine learning models in production.

We will present our recent experience with the development and operationalization of a statistical postprocessing system based on the use of neural networks to predict the probability distribution of forecasts of surface winds. Following MLOps best practices, our framework aims to improve the reproducibility and automation of most common tasks in a machine learning-based system, such as efficient data loading and manipulation, the monitoring and visualization of prediction quality, and the automation of model training and deployment pipelines.

