Probabilistic Weather Forecasting

Tilmann Gneiting
Universität Heidelberg, Heidelberg, Germany
e-mail: `t.gneiting@uni-heidelberg.de`

Abstract

Operational probabilistic weather forecasts at leads times of days ahead depend on ensembles of numerical weather prediction (NWP) model runs. However, as ensemble forecasts tend to be biased and underdispersed, some form of statistical postprocessing is required, with Bayesian model averaging and nonhomogeneous regression being state of the art approaches for doing this. Challenges and opportunities for future work include postprocessing efforts for probabilistic forecasts of multivariate quantities, including the case of spatial, temporal and spatio-temporal weather trajectories.

Keywords: ensemble forecast, statistical postprocessing

1 Introduction

While weather forecasting has traditionally been viewed as a deterministic problem, with atmospheric scientists drawing on highly sophisticated numerical models of the atmosphere, the advent of ensemble prediction systems in the 1990s marks a radical change (Palmer 2002; Gneiting and Raftery 2005; Leutbecher and Palmer 2008). An ensemble forecast is a collection of numerical weather prediction (NWP) model integrations, typically on the order of 5 to 100, using slightly different initial conditions and/or model variants, with the output being a probabilistic forecast, providing an estimate of the uncertainty of the forecast, and ideally being interpretable as a random sample from the predictive distribution of future weather states. To give an example, Figure 1 shows three members of the University of Washington Mesoscale Ensemble (Grimit and Mass 2002) over Western North America and the Northeast Pacific Ocean.

2 Statistical postprocessing of ensemble weather forecasts

Statistical postprocessing techniques serve to improve the quality of NWP ensemble forecasts, as they seek to generate calibrated and sharp predictive distributions of future weather quantities (Gneiting, Balabdaoui and Raftery 2007). State of the art methods include the Bayesian model averaging (BMA) approach developed by Raftery et al. (2005), and the nonhomogeneous regression (NR) or ensemble model output statistics (EMOS) technique of Gneiting et al. (2005).

To fix the idea, let y denote the weather variable of interest, and write $x_1, \ldots, x_M$ for the corresponding M ensemble member forecasts. The NR/EMOS predictive distribution is a single parametric distribution of the general form

$$y \mid x_1, \ldots, x_M \sim f(y \mid x_1, \ldots, x_M),$$

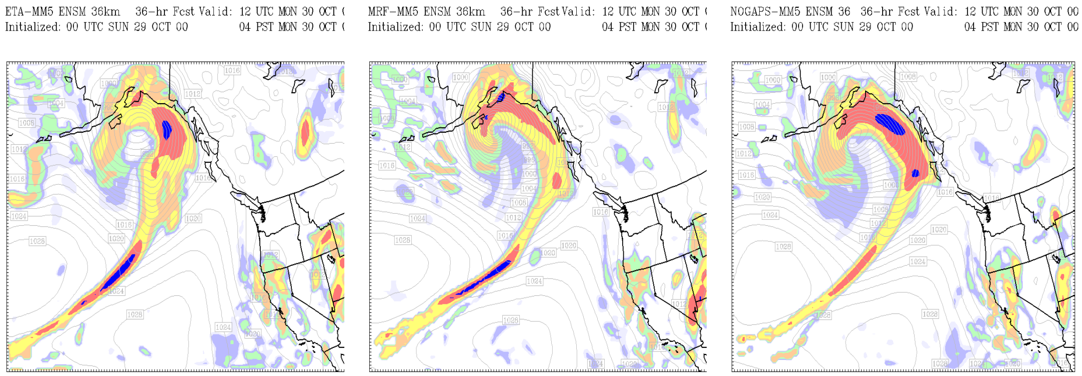

Figure 1: 36-hour ahead ensemble forecast valid October 30, 2000 over Western North America and the Northeast Pacific Ocean, with color representing quantitative precipitation. Three members of the University of Washington Mesoscale Ensemble (Grimit and Mass 2002) are shown.

where the left-hand side refers to the conditional distribution of the future weather quantity y, given the ensemble member forecasts $x_1, \ldots, x_M$ for y. On the right-hand side, f is a parametric density function, with the parameters depending on the ensemble values in suitable ways. For example, in the case of temperature or pressure, f is a normal or Gaussian density, where the mean is a bias corrected affine function of the ensemble mean and the variance is a dispersion-corrected affine function of the ensemble variance. In the case of a nonnegative quantity, such as wind speed or precipitation accumulation, or a power transformation thereof, f can be taken to be a truncated logistic, truncated normal or extreme value distribution (Wilks 2009; Thorarinsdottir and Gneiting 2010; Scheuerer 2013).

The BMA approach employs a mixture distribution of the general form

$$y \,|\, x_1, \ldots, x_M \sim \sum_{m=1}^{M} w_m \, g(y \,|\, x_m),$$

where $g(y|x_m)$ denotes a parametric density, often referred to as a kernel, that depends on the ensemble member forecast x_m in suitable ways, and where the mixture weights $w_1, \ldots, w_M$ are nonnegative and sum to 1. For example, $g(y|x_m)$ could be a normal density, where the mean is a bias corrected affine function of x_m and the variance is fixed at a certain value. The mixture weights $w_1, \ldots, w_m$ reflect the corresponding member's relative contributions to the predictive skill over a training period. In the case of temperature and pressure, the kernel g can be taken to be normal; in the case of wind speed and precipitation accumulation, gamma kernels can be employed (Sloughter et al. 2007; Sloughter, Gneiting and Raftery 2010)

3 Challenges and opportunities for future work

The aforementioned postprocessing techniques typically apply to a single weather variable at a single location and a single look-ahead time. However, in many types of applications it is critically important that dependencies in combined events, including the case of spatial, temporal and spatio-temporal weather scenarios, are properly accounted for. The celebrated theorem of Sklar (1959) demonstrates that standard approaches to statistical postprocessing can accommodate any type of joint dependence structure for combined events, provided that a suitable copula function is specified. If the dimension considered is small, or if specific structure can be exploited, such as temporal or spatial structure, parametric families of copulas can be fitted. For example, the approaches of Gel, Raftery and Gneiting (2004), Berrocal, Raftery and Gneiting (2007; 2008), Pinson et al. (2009), Schuhen, Thorarinsdottir and Gneiting (2012) and Möller, Lenkoski and Thorarinsdottir (2012) invoke Gaussian copulas. If the dimension is large and no specific structure can be exploited, one needs to resort to nonparametric approaches and empirical copulas (Schefzik, Thorarinsdottir and Gneiting 2013), by adopting multivariate rank order structure from historical weather records, as in the Schaake shuffle (Clark et al. 2004), or from the NWP ensemble at hand, as in the ensemble copula coupling approach (ECC; Schefzik, Thorarinsdottir and Gneiting 2013).

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