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A hyper-ensemble forecast of surface drift

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The prediction of surface drift of water is an important task, with applications such as marine transport, pollutant dispersion, and search-and-rescue activities. However, it is also very challenging, because it depends on ocean models that (usually) do not completely accurately represent wind-induced current, that do not include wave-driven currents, etc. However, the real surface drift depends on all present physical phenomena, which moreover interact in complex ways.

Furthermore, although each of these factors can be forecasted by deterministic models, the latter all suffer from limitations, resulting in imperfect predictions. In the present study, we try and predict the drift of buoys launched during the DART06 (Dynamics of the Adriatic sea in Real-Time 2006) and MREA07 (Maritime Rapid Environmental Assessment 2007) sea trials, using the so-called hyper-ensemble technique: different models are combined in order to minimize departure from independent observations during a training period. The obtained combination is then used in forecasting mode.

We review and try out different hyper-ensemble techniques, such as the simple ensemble mean, least-squares weighted linear combinations, and techniques based on data assimilation, which dynamically update the model's weights in the combination when new observations become available. We show that the latter methods alleviate the need of a priori fixing the training length.

When the forecast period is relatively short, the discussed methods lead to much smaller forecasting errors compared with individual models (at least 3 times smaller), with the dynamic methods leading to the best results. When many models are available, errors can be further reduced by removing colinearities between them by performing a principal component analysis. At the same time, this reduces the amount of weights to be determined.

In complex environments, the skill of individual models may vary over time periods smaller than the desired forecasting period. In these cases, a simpler method such as a fixed linear combination or a simple ensemble mean may lead to the smaller forecast errors.
In any case, the dynamic methods allow to estimate a characteristic time during which the model weights are more or less stable, which allows predicting how long the obtained combination will be valid in forecasting mode, and hence to choose which hyper-ensemble method one should use.