Hierarchical Multilevel Approaches of Forecast Combination

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Abstract. In this paper the approach of combining predictions is used to benefit from the advantages of forecasts predicting on different levels, to reduce the risks of high noise terms on low level predictions and overgeneralization on higher levels. The presented experimentally compared approaches of combining seasonal airline demand forecasts differ concerning input decomposition, multilevel structures, combination models and kinds of aggregation. Significant forecast improvements have been obtained when using multilevel, hierarchical structures.

1 Introduction

A typical approach to building a forecast model consists of a phase of data analysis, determination of a level of forecasting and history building, model creation, determination of appropriate preprocessing, parameter calibration and validation. The model, once built, is updated on a regular basis by model rebuilding or updating the history based on the most recent data. But even if the calibration has been done well, it is likely that the real relationship between given inputs and the values to predict is so complex that it can not be modelled perfectly. The input information is restricted to noisy data measured only for the hopefully most important influencing features and interpreted only at the current subspace representing the level of history building. The restriction of history pool and other parameter settings as well as a lot of preprocessing measures finally lead to a loss of information, too. This problem is becoming even more relevant if the underlying processes and data change over time and the chosen settings are not optimal any more.

To overcome the above mentioned problems there is a necessity for an approach which is not only taking into account the available information in a sophisticated manner but which is also able to adapt automatically to new situations.

We first discuss combining approaches which enable the modelling of complex functional relationships based on different less complex ones, but which also offer possibilities for adaptive parameter settings and preprocessing. Then the problem of choosing the level of forecasting and history building is investigated. We propose to extend the use of combination approaches to the combination of multilevel predictions and discuss related tasks. We finally

discuss experimental results which show a clear forecast improvement while using hierarchical multilevel combination strategies.

2 Combination Approaches

Forecast combination approaches are today a scientifically acknowledged procedure to model complex functional relationships in producing not one optimal forecast, but a number of forecasts and combining them for the final prediction. It can be considered as a black box where the inputs are individual forecasts and sometimes additional information and the output is a final forecast (see figure 1). The existing combination approaches are differing in

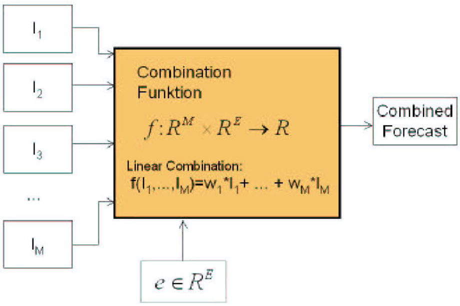

Fig. 1. Forecast Combination as a black box.

the description of the functional relationship which represents the black box. Beside the *simple average model*, which gives the same weight to all individual forecasts, there are two common groups of linear combination models, in which the relationship is a simple weighted linear sum of the individual forecasts and individual forecast performance is taken into account to calculate the weights. While *rank based models* describe forecast performance based on ranks of past performance without interpreting statistical properties of forecast errors, *variance / covariance based models* and *ordinary least squares regression based models* use error variance and covariance information to represent forecast performance. (for details see [1] and [2])

A more complex and flexible group of combination models are nonlinear combination models. There exist a wide variety of mostly application specific approaches. They differ in the selection of external input information as well as in the general approach. Typical nonlinear approaches include neural networks [3], (fuzzy) expert systems [4] or functional approaches.

At the beginning of the discussion related to combination approaches the scientists were surprised that combined forecasts outperformed individual forecasts. If it is possible to generate a combined forecast outperforming each