Automatic time series forecasting

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Automatic forecasts of large numbers of univariate time series are often needed in business. It is common to have over one thousand product lines that need forecasting at least monthly. In these circumstances, an automatic forecasting algorithm is an essential tool. Automatic forecasting algorithms must determine an appropriate time series model, estimate the parameters and compute the forecasts. The most popular automatic forecasting algorithms are based on either exponential smoothing or ARIMA models.

Exponential smoothing

Although exponential smoothing methods have been around since the 1950s, a modelling framework incorporating procedures for model selection was not developed until relatively recently with the work of Ord et al. (1997) and Hyndman et al. (2002). In these (and other) papers, a class of state space models which underly all of the exponential smoothing methods has been developed. Exponential smoothing methods were originally classified by Pegels' (1969) taxonomy. This was later extended by Gardner (1985), modified by Hyndman et al. (2002), and extended again by Taylor (2003), giving a total of fifteen methods seen in the following table.

		Seasonal Component		
Trend Component		N (None)	A (Additive)	M (Multiplicative)
N	(None)	N,N	N,A	N,M
A	(Additive)	A,N	A,A	A,M
A_d	(Additive damped)	A_d,N	A_d,A	A_d,M
M	(Multiplicative)	M,N	M,A	M,M
M_d	(Multiplicative damped)	M_d,N	M_d,A	M_d,M

Some of these methods are better known under other names. For example, cell N,N describes the simple exponential smoothing (or SES) method, cell A,N describes Holt's linear method, and cell A_d,N describes the damped trend method. The additive Holt-Winters' method is given by cell A,A and the multiplicative Holt-Winters' method is given by cell A,M. The other cells correspond to less commonly used but analogous methods.

Hyndman et al. (2002) describes how each exponential smoothing method corresponds to two state space models, giving 30 models in total. They also discuss an automatic algorithm for identifying an appropriate exponential smoothing model in a general class of state space models. I will review an implementation of the Hyndman et al. (2002) algorithm in the `forecast` package for R.

ARIMA models

Automatic ARIMA modelling has a longer pedigree, but is not widely used because of the computational time involved. To my knowledge, no automatic ARIMA algorithms are currently available in existing R packages. Furthermore, existing automatic ARIMA methods are based on information criteria which aim to identify the "correct" model rather than find a good forecasting model. I will review the main existing approaches and describe a new algorithm for automatic ARIMA forecasting where the aim is to "select the model that produces the best forecast" rather than "calculate forecasts from the best model". Finally, I will discuss the implementation of this new algorithm in R.

References

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