Automatic time series forecasting

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Outline

- Motivation
- Exponential smoothing
- ARIMA modelling
- The forecast package

Motivation

- Common in manufacturing to have over one thousand product lines that need forecasting at least monthly.
- Forecasts are often required by people who do not know how to fit appropriate time series models.

Specifications

Automatic forecasting algorithms must

- determine an appropriate time series model
- estimate the parameters
- compute the forecasts with prediction intervals

Exponential smoothing

Reference



Makridakis, Wheelwright and Hyndman (1998) Forecasting: methods and applications, 3rd ed., Wiley: NY.

- Until recently, there has been no stochastic modelling framework incorporating likelihood calculation, prediction intervals, etc.
- Ord, Koehler & Snyder (JASA, 1997) and Hyndman, Koehler, Snyder and Grose (IJF, 2002) showed that all ES methods (including non-linear methods) are optimal forecasts from innovation state space models.

Pegels' (1969) taxonomy

Extended by Gardner (IJF 1985), Hyndman et al. (IJF 2002), and Taylor (IJF 2003).

		Seasonal Component				
	Trend	N	Α	M		
	Component	(None)	(Additive)	(Multiplicative)		
Ν	(None)	N,N	N,A	N,M		
Α	(Additive)	A,N	A,A	A,M		
A_d	(Additive damped)	A _d ,N	A_d , A	A _d ,M		
М	(Multiplicative)	M,N	M,A	M,M		
M_{d}	(Multiplicative damped)	M _d ,N	M_d ,A	M _d ,M		

General notation

$$\begin{array}{c} E \ T \ S \\ \uparrow \\ \hline \end{array}$$
 Error Trend Seasonal

Automatic forecasting

From Hyndman et al. (IJF, 2002):

- Apply each of 30 methods that are appropriate to the data. Optimize parameters and initial values using MLE (or some other criterion).
- Select best method using AIC:

$$AIC = -2\log(Likelihood) + 2p$$

where p = # parameters.

- Produce forecasts using best method.
- Obtain prediction intervals using underlying state space model.

Method performed very well in M3 competition.

ARIMA modelling

Conventional ARIMA forecasting

- calculate forecasts from the best fitting ARIMA model
- Not necessarily the best forecasting ARIMA model.
- Model identification either subjective and complex, or based on information criteria that may not give good forecasts.

Key ideas

- Fit ARIMA model to y_1, \ldots, y_t and forecast $y_{t+1|t}, \ldots, y_{t+h|t}$
- Calculate out-of-sample error $a_{t,i} = (y_{t+i} \hat{y}_{t+i|t})$
- Calculate average

$$MSE_i = \frac{1}{n-h-m+1} \sum_{t=m}^{n-h} a_{t,i}^2$$
 and $MSE = \frac{1}{h} \sum_{i=1}^{n} MSE_i$

 Choose model based on smallest MSE_i or smallest MSE.

Problem:

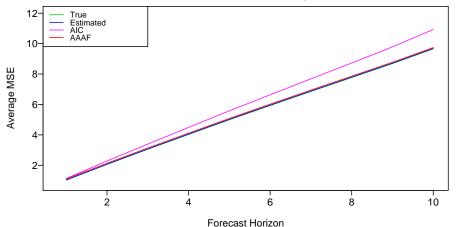
- Procedure involves fitting (n m)D model where D is the number of candidate models.
- Using nonlinear optimization is infeasible.

Solution:

- Estimate error series and fit all models using OLS regression.
- Kalman filter provides very fast updating of coefficients for each model.
- Algorithm involves D models passed through a Kalman filter.

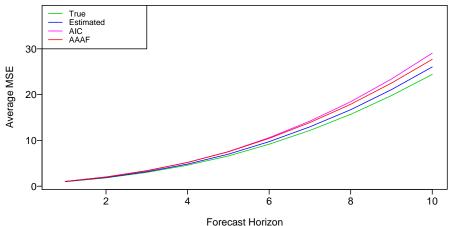
DGP: ARIMA(0,1,1)

No. of series 1000, with each length 100



DGP: ARIMA(2,1,2)

No. of series 1000, with each length 100



forecast() function

- Takes a time series as its main argument
- Returns forecasts from automatic ES algorithm.
- Yet to implement automatic ARIMA algorithm.
- Also has methods for objects of arima, HoltWinters and StructTS classes
- Calls predict() when appropriate.
- Output as class "forecast".

forecast class contains

- Original series
- Point forecasts
- Prediction interval
- Forecasting method used
- Residuals and other information

Methods applying to the forecast class:

- print
- plot
- summary

> forecast(beer)

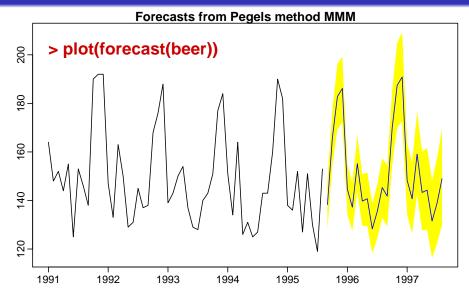
		Point	Forecast	Lo 80	H1 80
Sep	1995		138.2864	128.5376	148.2387
Oct	1995		165.8323	154.0843	177.8765
Nov	1995		182.7895	170.0695	195.9814
Dec	1995		186.1633	172.5645	199.7450
Jan	1996		144.6313	133.8904	155.3027
Feb	1996		137.2431	127.2945	147.7794
Mar	1996		155.1601	143.5184	166.8024
Apr	1996		139.7544	129.1742	150.2580

> summary(forecast(beer))

```
Forecast method: Pegels method MMM
Model Information:
  Pegels method MMM
  Smoothing parameters:
    alpha = 0.05
    beta = 0.399
    gamma = 0.05
          = 1
    phi
  Initial values:
    1 = 160.5127
    b = 0.9965
    s = 0.9652 \ 0.9152 \ 1.0322 \ 0.9294 \ 0.9328 \ 0.8479
        0.8965 0.9565 0.9314 1.1176 1.2275 1.2478
```

In-sample error measures:

ME MSE MAE MPE MAPE 0.693364420 65.159550580 6.476950267 0.001983306 0.044197349



- Automatic ES forecasting.
- Automatic ARIMA modelling using AIC.
- Forecasting intermittent demand data using Croston's method
- Forecasting using Theta method
- Includes 3003 time series from M3 competition.
- Includes 1001 time series from M competition.
- Includes 90 data sets from Makridakis,
 Wheelwright & Hyndman (1998)
- Available as compiled Windows binary from

http://www.robhyndman.info/Rlibrary/forecast/

Plan to upload to CRAN later this year.