MONASH University

REVOLUTION ANALYTICS

Rob J Hyndman

Forecasting using R

12. Advanced methods

OTexts.com/fpp/2/5/

Outline

Cross-validation

Standard cross-validation

A more sophisticated version of training/test sets.

- Select one observation for test set, and use remaining observations in training set. Compute error on test observation.
- Repeat using each possible observation as the test set.
- Compute accuracy measure over all errors.
- Does not work normally for time series because we cannot use future observations to build a model.

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Time series cross-validation

Assume k is the minimum number of observations for a training set.

- Select observation $k+i$ for test set, and use observations at times $1, 2, \dots, k+i-1$ to estimate model. Compute error on forecast for time $k+i$.
- Repeat for $i = 0, 1, \dots, T-k$ where T is total number of observations.
- Compute accuracy measure over all errors.

Also called **rolling forecasting origin** because the origin $(k+i-1)$ at which forecast is based rolls forward in time.

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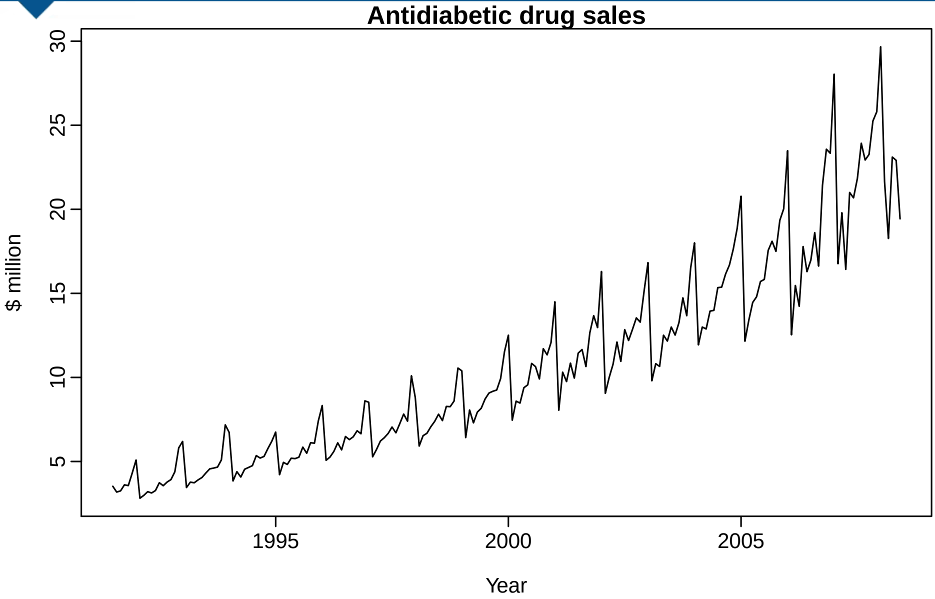
Example: Pharmaceutical sales



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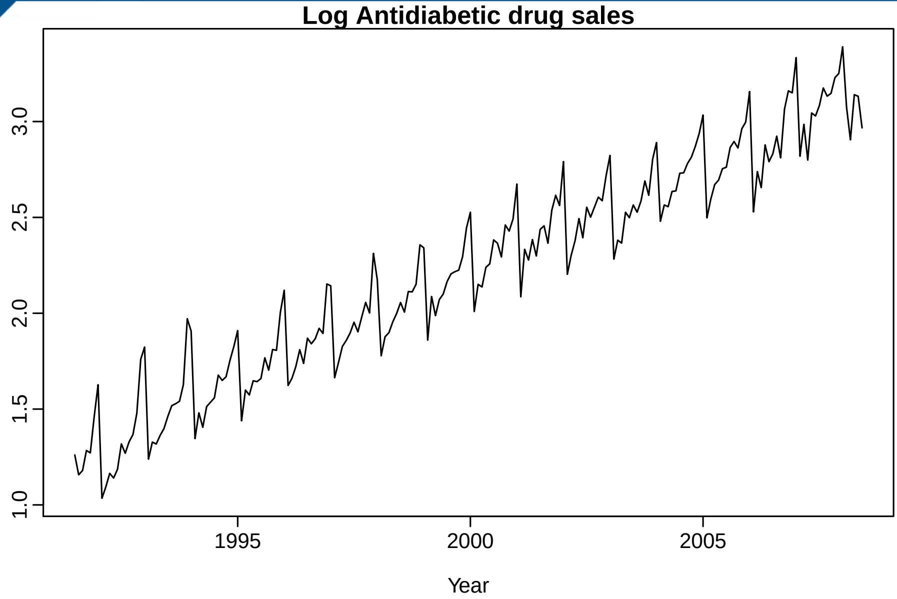

Example: Pharmaceutical sales

Which of these models is best?

1. Linear model with trend and seasonal dummies applied to log data.
2. ARIMA model applied to log data
3. ETS model applied to original data

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- Set $k = 48$ as minimum training set.
- Forecast 12 steps ahead based on data to time $k + i - 1$ for $i = 1, 2, \dots, 156$.
- Compare MAE values for each forecast horizon.

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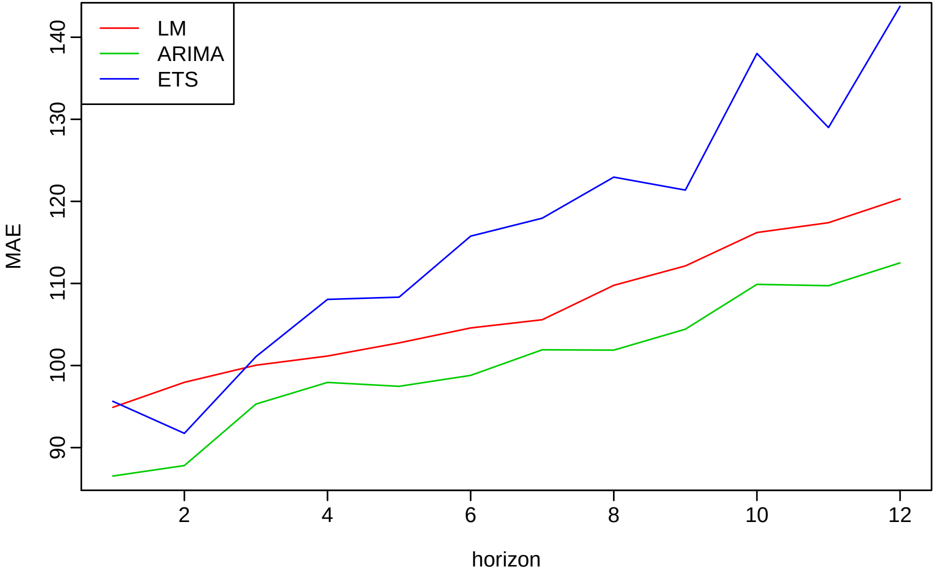

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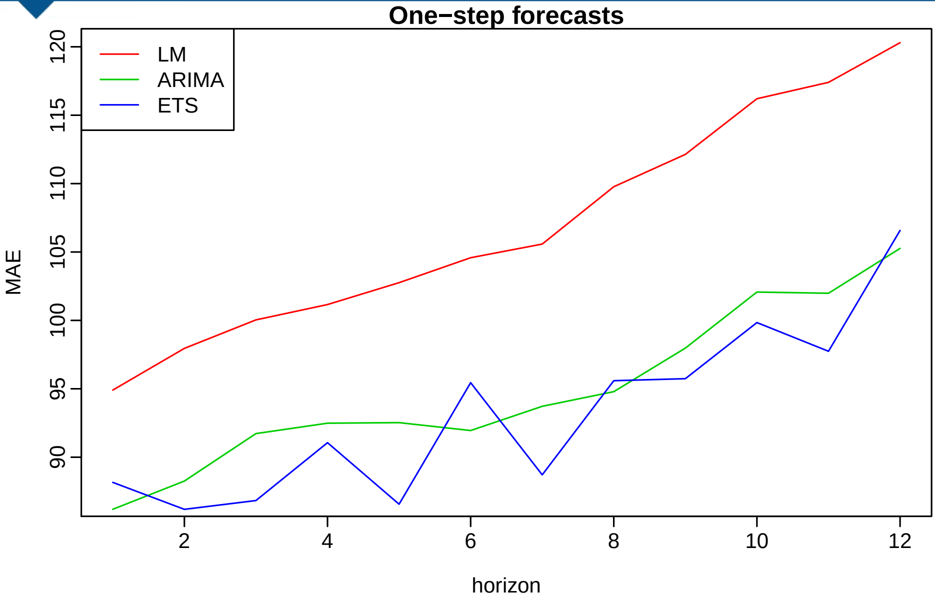


Example: Pharmaceutical sales

```
k <- 48
n <- length(a10)
mae1 <- mae2 <- mae3 <- matrix(NA,n-k-12,12)
for(i in 1:(n-k-12))
{
  xshort <- window(a10,end=1995+(5+i)/12)
  xnext <- window(a10,start=1995+(6+i)/12,end=1996+(5+i)/12)
  fit1 <- tslm(xshort ~ trend + season, lambda=0)
  fcast1 <- forecast(fit1,h=12)
  fit2 <- auto.arima(xshort,D=1, lambda=0)
  fcast2 <- forecast(fit2,h=12)
  fit3 <- ets(xshort)
  fcast3 <- forecast(fit3,h=12)
  mae1[i,] <- abs(fcast1[['mean']]-xnext)
  mae2[i,] <- abs(fcast2[['mean']]-xnext)
  mae3[i,] <- abs(fcast3[['mean']]-xnext)
}
plot(1:12,colMeans(mae1),type="l",col=2,xlab="horizon",ylab="MAE",
     ylim=c(0.58,1.0))
lines(1:12,colMeans(mae2),type="l",col=3)
lines(1:12,colMeans(mae3),type="l",col=4)
legend("topleft",legend=c("LM","ARIMA","ETS"),col=2:4,lty=1)
```

Variations on time series cross validation

- Keep training window of fixed length.

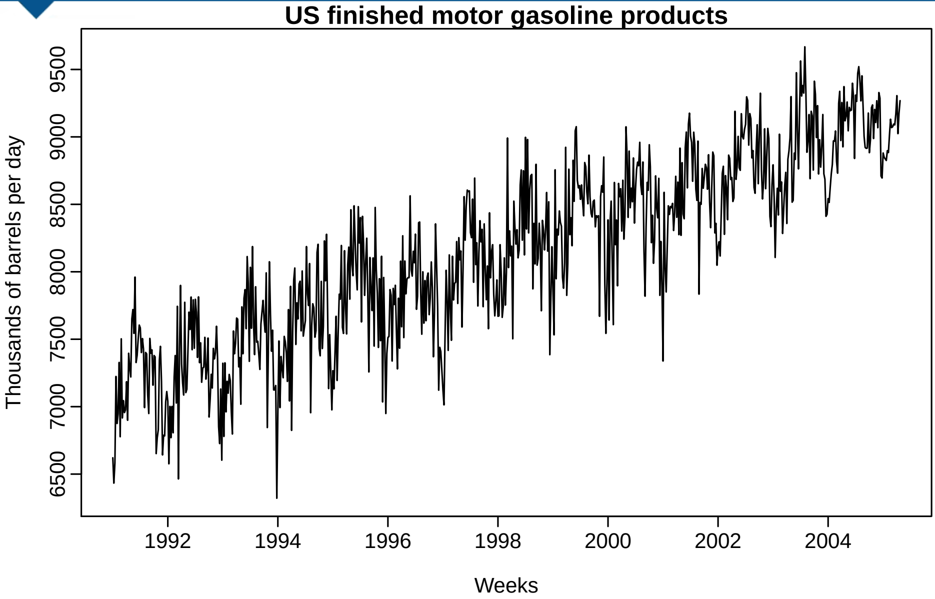
```
xshort <- window(a10,start=i+1/12,end=1995+(5+i)/12)
```

- Compute one-step forecasts in out-of-sample period.

```
for(i in 1:(n-k))
{
  xshort <- window(a10,end=1995+(5+i)/12)
  xlong <- window(a10,start=1995+(6+i)/12)
  fit2 <- auto.arima(xshort,D=1, lambda=0)
  fit2a <- Arima(xlong,model=fit2)
  fit3 <- ets(xshort)
  fit3a <- ets(xlong,model=fit3)
  mae2a[i,] <- abs(residuals(fit3a))
  mae3a[i,] <- abs(residuals(fit2a))
}
```

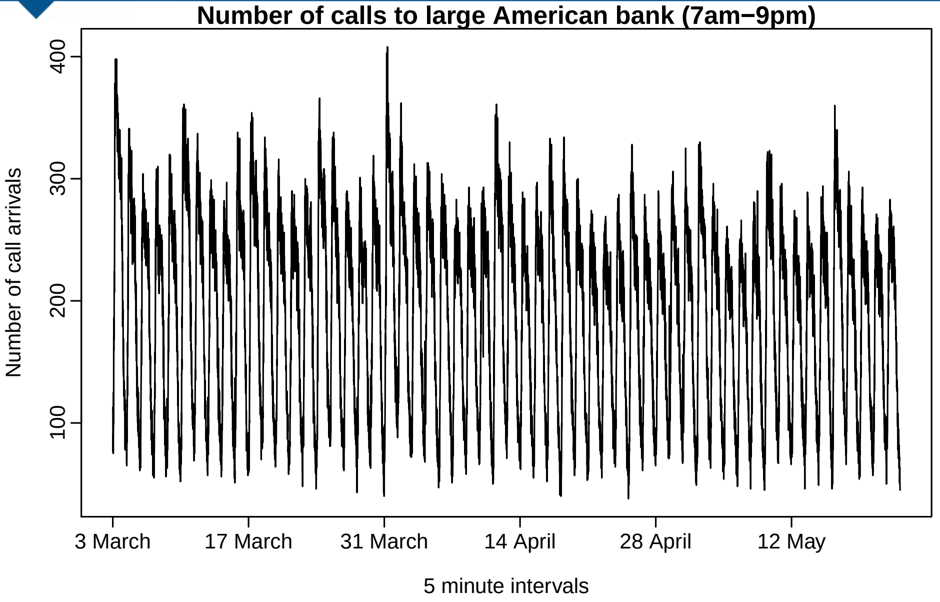
Outline

Examples

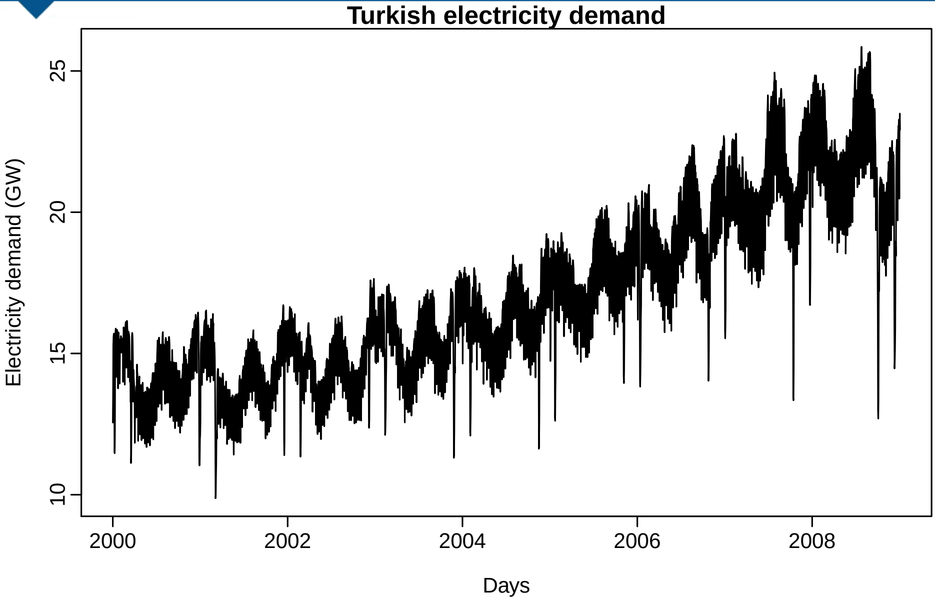


US finished motor gasoline products
Thousands of barrels per day
9500
9000
8500
8000
7500
7000
6500
1992
1994
1996
1998
2000
2002
2004
Weeks

Examples


Number of calls to large American bank (7am−9pm)
Number of call arrivals
100
200
300
400
3 March
17 March
31 March
14 April
28 April
12 May
5 minute intervals

Examples


Turkish electricity demand
Electricity demand (GW)
10
15
20
25
2000
2002
2004
2006
2008
Days

TBATS model

TBATS

Trigonometric terms for seasonality
Box-Cox transformations for heterogeneity
ARMA errors for short-term dynamics
Trend (possibly damped)
Seasonal (including multiple and non-integer periods)

TBATS model

$$y_t = \text{observation at time } t$$

$$y_t^{(\omega)} = \begin{cases} (y_t^\omega - 1)/\omega & \text{if } \omega \neq 0; \\ \log y_t & \text{if } \omega = 0. \end{cases}$$

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^{M} s_{t-m_i}^{(i)} + d_t$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t$$

$$d_t = \sum_{i=1}^{p} \phi_i d_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)}$$

$$\begin{aligned} s_{j,t}^{(i)} &= s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t \\ s_{j,t}^{(i)} &= -s_{j,t-1}^{(i)} \sin \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos \lambda_j^{(i)} + \gamma_2^{(i)} d_t \end{aligned}$$

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M seasonal periods

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global and local trend

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ARMA error

Fourier-like seasonal terms

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TBATS

Trigonometric

Box-Cox

ARMA

Trend

Seasonal

Box-Cox transformation

M seasonal periods

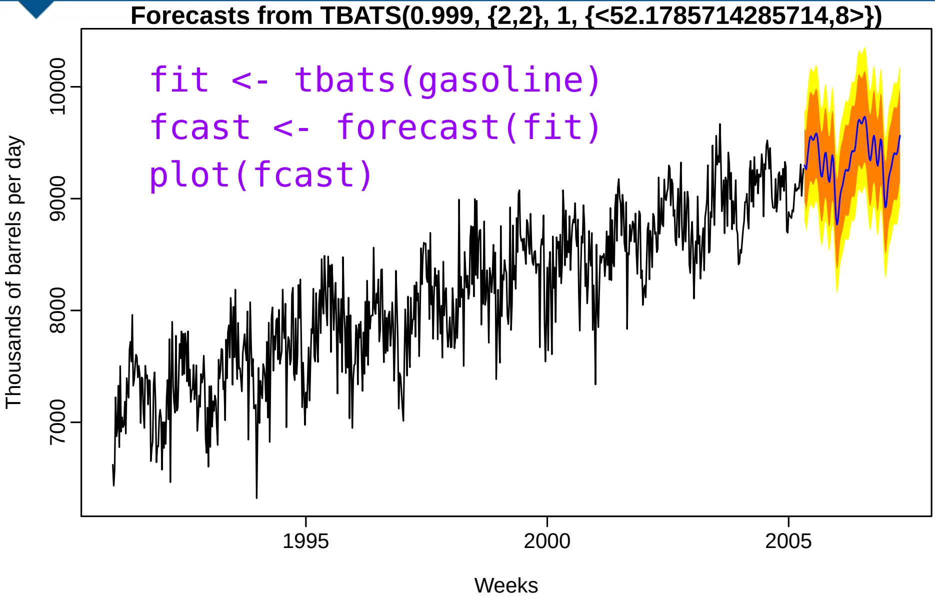
global and local trend

ARMA error

Fourier-like seasonal terms

Examples

```r
fit <- tbats(gasoline)
fcast <- forecast(fit)
plot(fcast)
```



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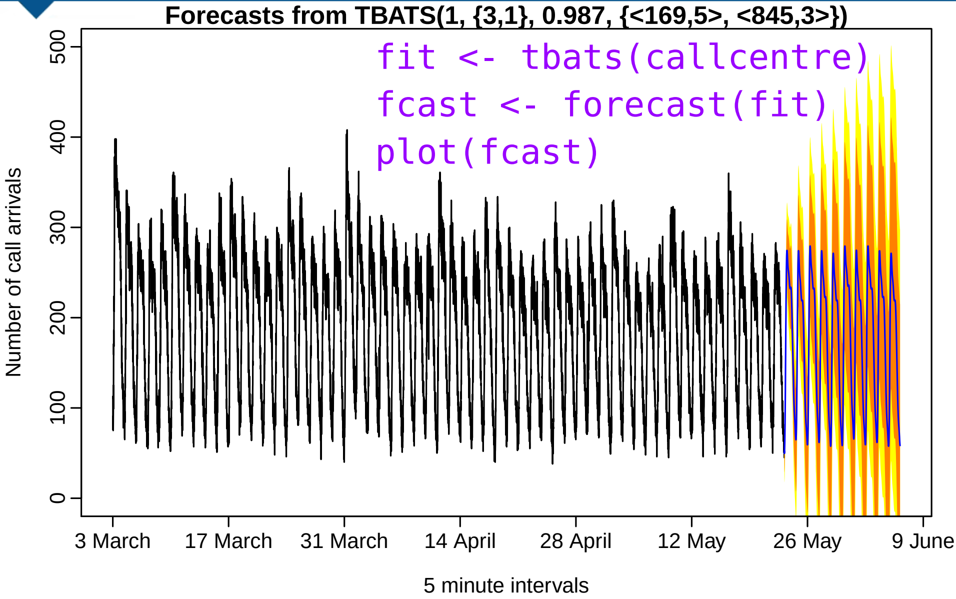
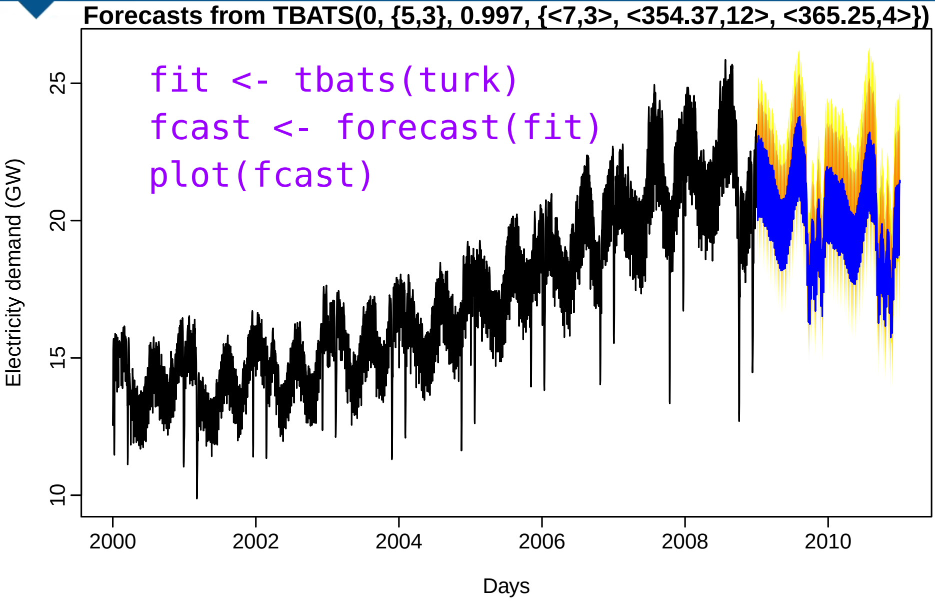

Forecasts from TBATS(1, {3,1}, 0.987, {<169,5>, <845,3>})
fit <- tbats(callcentre)
fcast <- forecast(fit)
plot(fcast)
Number of call arrivals
0
100
200
300
400
500
3 March
17 March
31 March
14 April
28 April
12 May
26 May
9 June
5 minute intervals

Examples


Forecasts from TBATS(0, {5,3}, 0.997, {<7,3>, <354.37,12>, <365.25,4>})
fit <- tbats(turk)
fcast <- forecast(fit)
plot(fcast)
Electricity demand (GW)
10
15
20
25
2000
2002
2004
2006
2008
2010
Days

Outline

Forecasting proportions

Simple approach

- Use a logit transformation on proportions: $f(u) = \log\left(\frac{u}{1-u}\right)$
- Then build model and back-transform the forecasts.

More complicated:

- Let y_t be a binary variable (e.g., water quality above some threshold value on day t).

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- Use a generalized linear model with a latent autocorrelated process. e.g., $\Pr(y_t) = f^{-1}(\alpha + \beta x_t + u_t)$ where x_t is a vector of predictors and u_t is a correlated process.
- Theory and methodology not well developed and very little software available.
- b1ld and gee packages allows some simple correlation structures.

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CASE STUDY 1: Paperware company

Problem: Want forecasts of each of hundreds of items. Series can be stationary, trended or seasonal. They currently have a large forecasting program written in-house but it doesn't seem to produce sensible forecasts. They want me to tell them what is wrong and fix it.

CASE STUDY 1: Paperware company

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- They employ no statisticians and want the program to produce forecasts automatically.

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Methods currently used

A 12 month average

C 6 month average

E straight line regression over last 12 months

G straight line regression over last 6 months

H average slope between last year’s and this year’s values.
(Equivalent to differencing at lag 12 and taking mean.)

I Same as H except over 6 months.

K I couldn’t understand the explanation.

CASE STUDY 2: PBS

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The **Pharmaceutical Benefits Scheme** (PBS) is the Australian government drugs subsidy scheme.

- Many drugs bought from pharmacies are subsidised to allow more equitable access to modern drugs.
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Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost $800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from $220 to $22 after it was listed on the PBS.

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CASE STUDY 2: PBS

- In 2001: $4.5 billion budget, under-forecasted by $800 million.
- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- Although monthly data available for 10 years, data are aggregated to annual values, and only the first three years are used in estimating the forecasts.
- All forecasts being done with the FORECAST function in MS-Excel!

Problem: How to do the forecasting better?

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CASE STUDY 3: Airline

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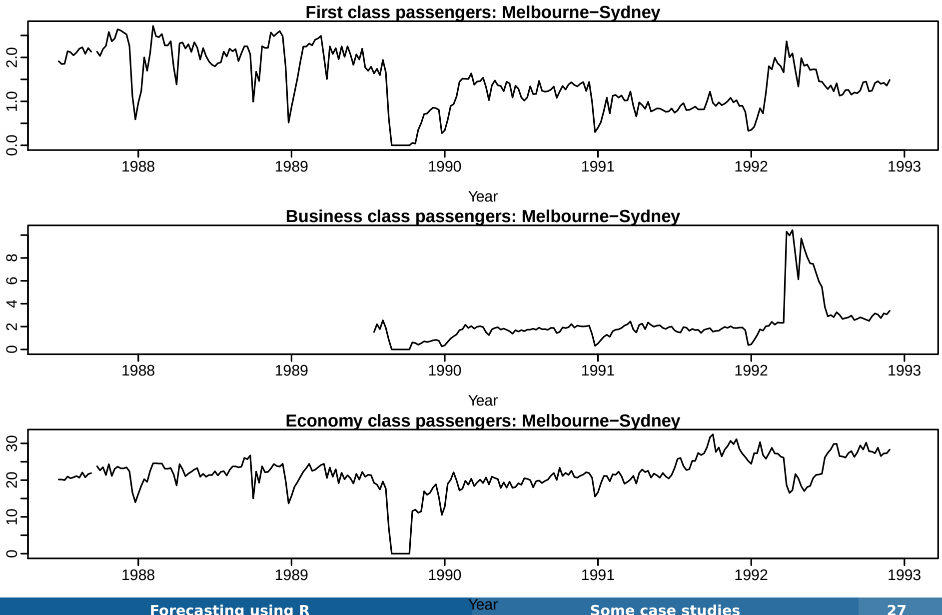

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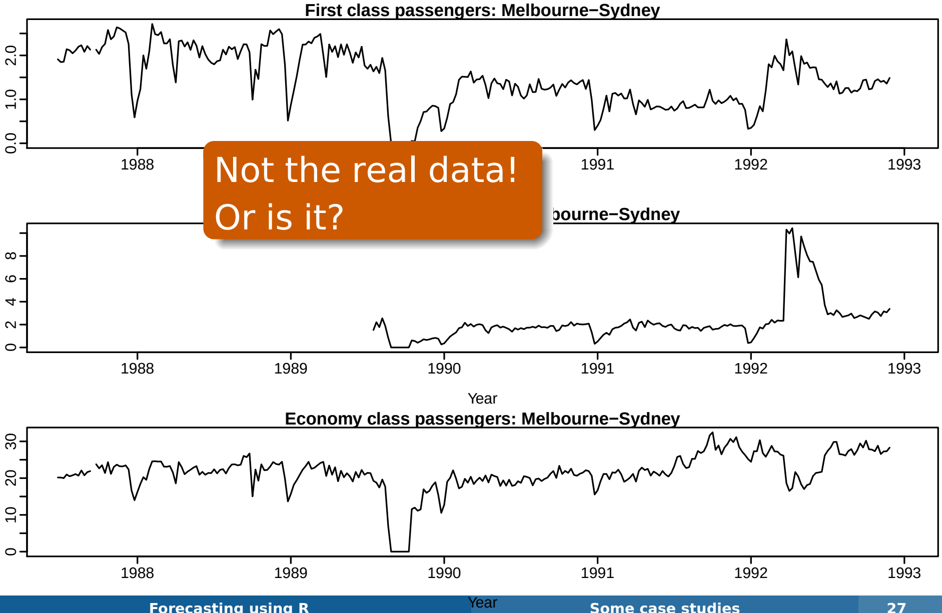

Not the real data!

Or is it?

CASE STUDY 3: Airline

Problem: how to forecast passenger traffic on major routes.

Additional information

- They can provide a large amount of data on previous routes.
- Traffic is affected by school holidays, special events such as the Grand Prix, advertising campaigns, competition behaviour, etc.
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Outline

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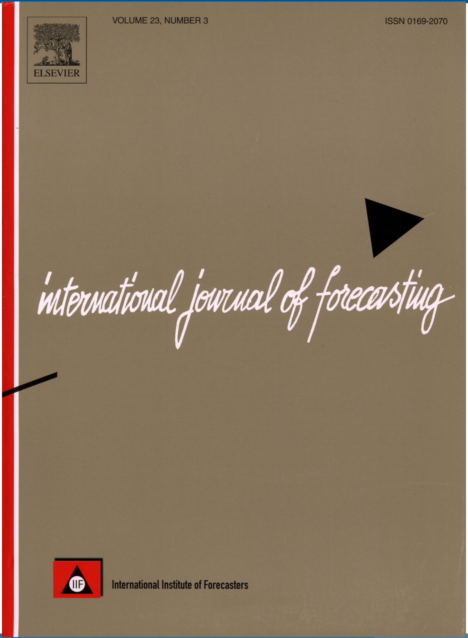

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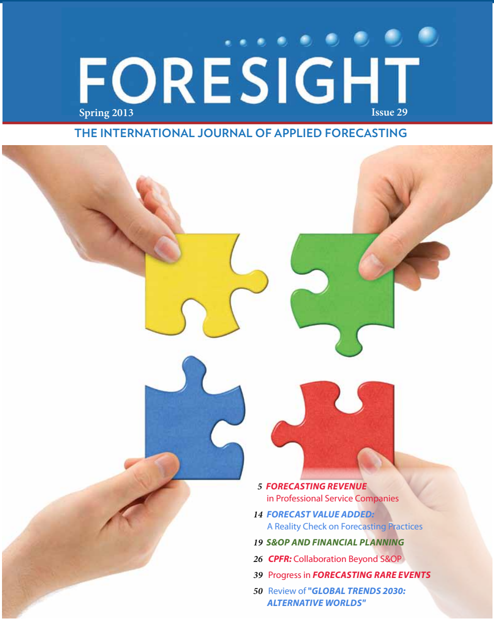

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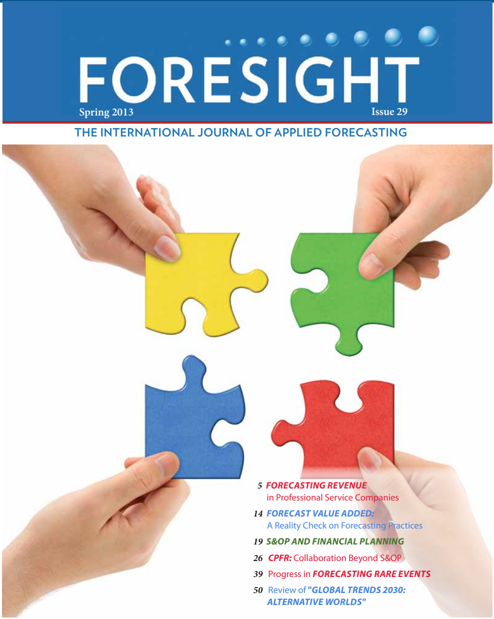
Links to all of the above at **www.forecasters.org**.



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