Session 2. ETSX: Explanatory variables

Demand Forecasting with the ADAM

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Contents

Introduction

While `es()` supports explanatory variables in the variable `xreg`, `adam()` has a more advanced functionality. So, we will use it starting from this task Load the packages `greybox` and `smooth`

```
library(greybox)
library(smooth)
```

ETSX

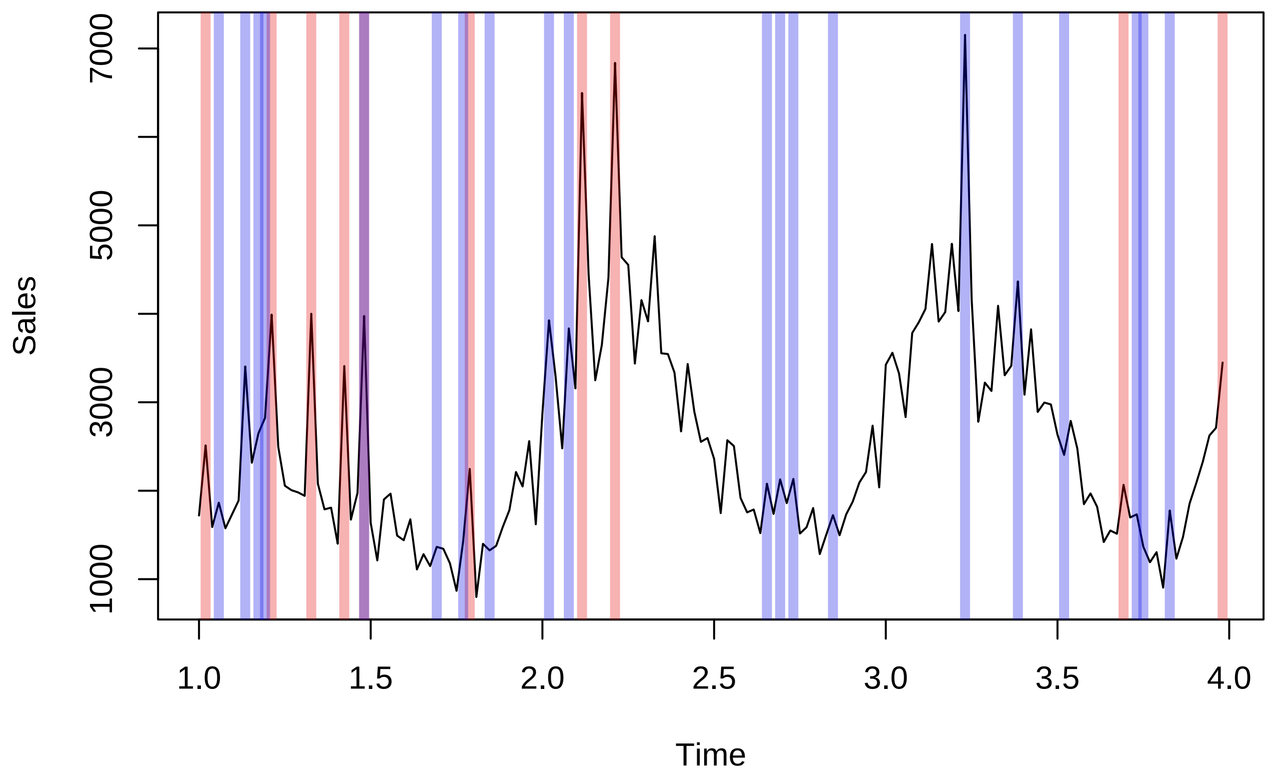
For this part of exercise we will use `PromoData`, weekly sales of a product with two types of promotions and price:

```
load("PromoData.Rdata")
```

We are interested in predicting sales for 13 weeks ahead, based on the data on price of product and planned promotions.

Produce plot of sales together with the promotions:

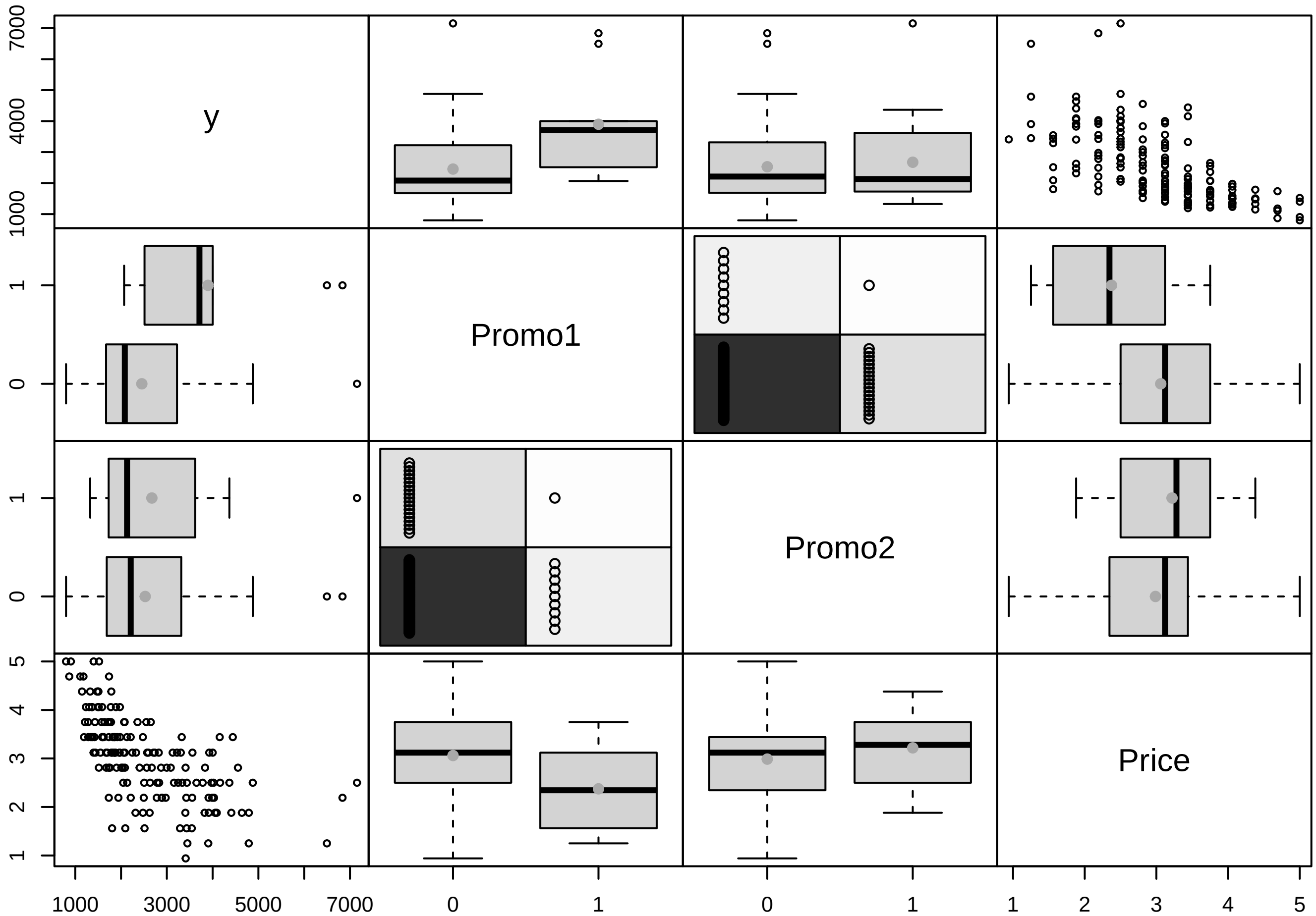
```
plot(PromoData$y, type="l", ylab="Sales")
abline(v=time(PromoData$y)[PromoData$Promo1==1],col=rgb(0.9,0,0,0.3),lwd=5)
abline(v=time(PromoData$y)[PromoData$Promo2==1],col=rgb(0,0,0.9,0.3),lwd=5)
```



Question What components do you see in the time series? Are the promotions influential?

In order to see the relations between the variables clearer, we can use the `spread()` function from the `greybox` package:

```
spread(PromoData)
```



It will produce different plots, depending on the types of variables.

Question What do you think about the relations between the variables?

Construct the ETS(A,N,N) model with both promotions as explanatory variables:

```
adam(PromoData, "ANN", formula=y~Promo1+Promo2, h=13, holdout=TRUE)
```

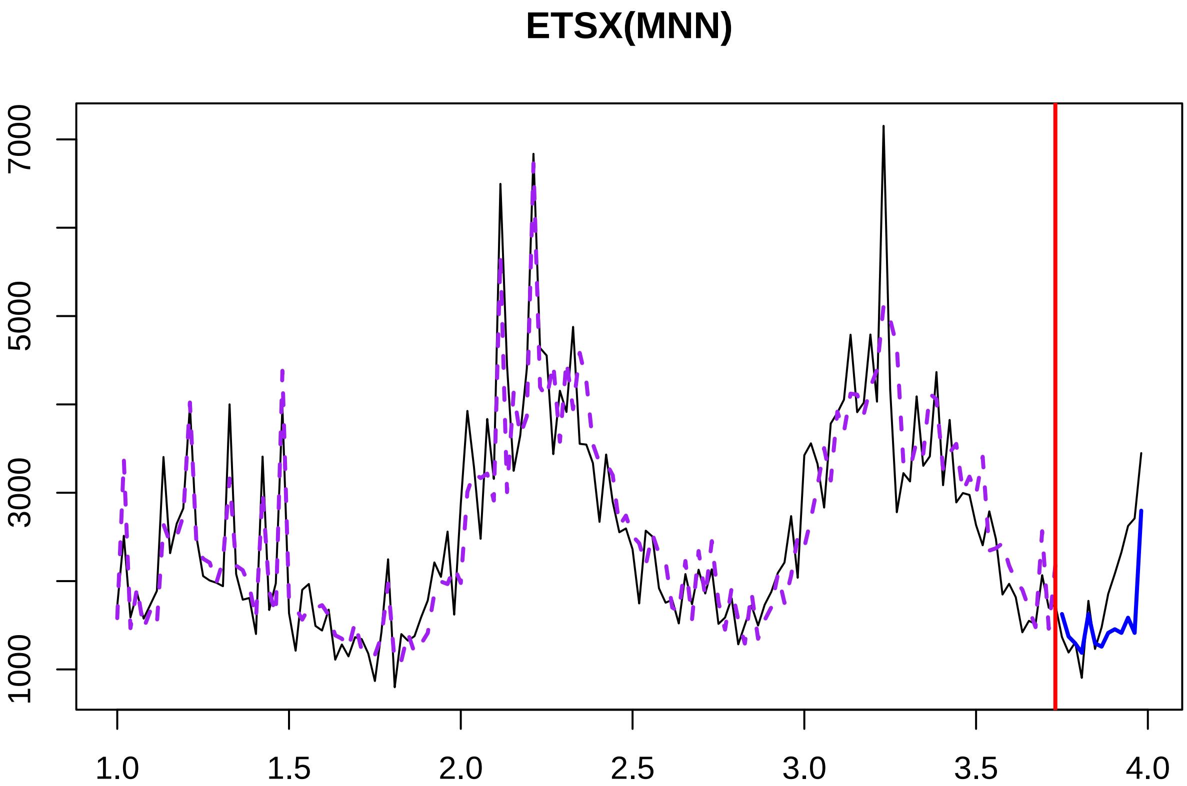
Compare the resulting model with the model with the multiplicative error:

```
adam(PromoData, "MNN", formula=y~Promo1+Promo2, h=13, holdout=TRUE)
```

Arguably, multiplicative model makes more sense in this context, because promotional uplifts should not be fixed, and should depend on the level of the series.

Now we add prices as explanatory variables:

```
adam(PromoData, "MNN", formula=y~., h=13, holdout=TRUE, silent=FALSE)
```



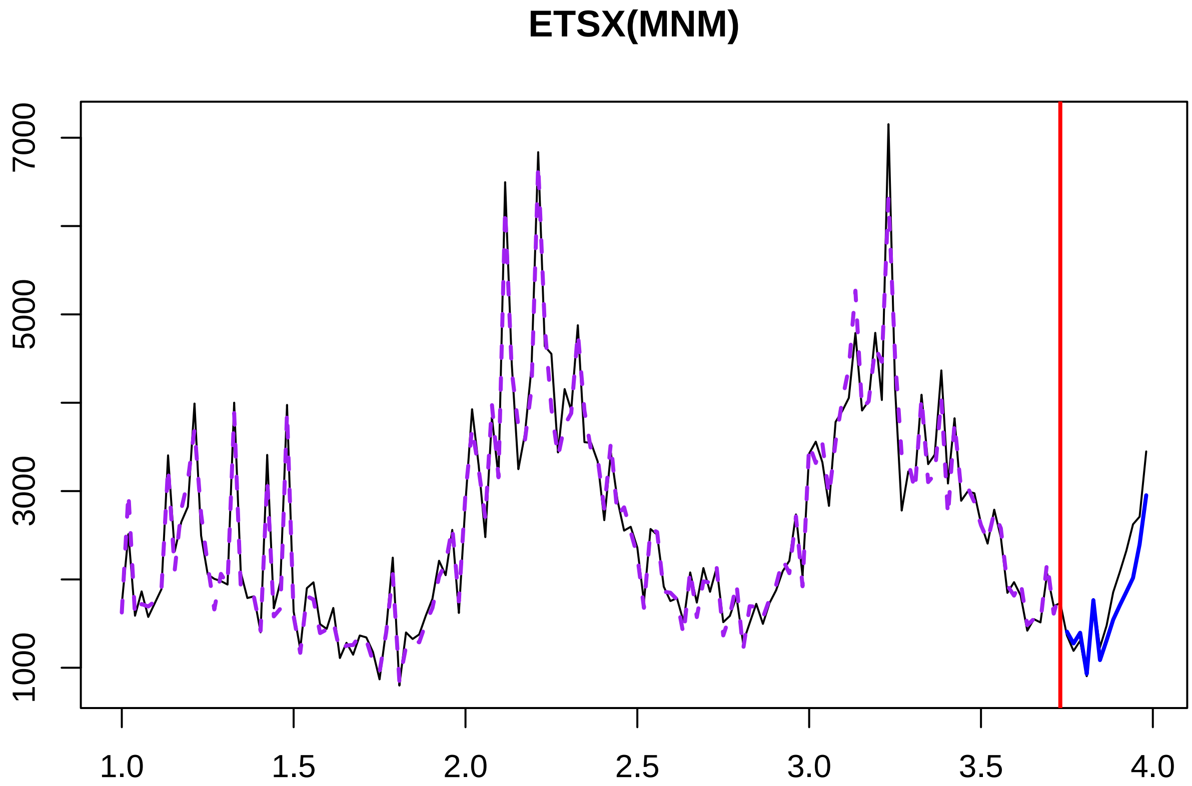

```
## Time elapsed: 0.18 seconds
## Model estimated using adam() function: ETSX(MNN)
## Distribution assumed in the model: Gamma
## Loss function type: likelihood; Loss function value: 1061.721
## Persistence vector g (excluding xreg):
##  alpha
## 0.5445
##
## Sample size: 143
## Number of estimated parameters: 6
## Number of degrees of freedom: 137
## Information criteria:
##      AIC     AICc      BIC     BICc
## 2135.442 2136.060 2153.220 2154.752
##
## Forecast errors:
## ME: 350.678; MAE: 472.22; RMSE: 611.808
## sCE: 174.817%; Asymmetry: 66.2%; sMAE: 18.108%; sMSE: 5.504%
## MASE: 0.747; RMSSE: 0.671; rMAE: 0.806; rRMSE: 0.846
```

Using the best model that we have so far, we can produce point forecasts and prediction intervals. If we want to do that for the next 13 weeks, we would need to tell function not to use holdout (`holdout=FALSE`) and provide values of variables `Promo1`, `Promo2` and `Price` in the `newdata` variable, otherwise the function will use last `h` in-sample values of the provided data (it will generate a warning about that):

```
promoModelMNN <- adam(PromoData, "MNN", formula=y~., h=13, holdout=FALSE)
forecast(promoModelMNN, h=13, interval="prediction") |>
    plot()
```

The previous models are missing an important component in the data - **seasonality**. In order to capture it, we will estimate ETSX(M,N,M) model telling the function that we deal with data with periodicity of 52 (`lags=52`):

```
promoModelMNM <- adam(PromoData, "MNM", lags=52, formula=y~., h=13, holdout=TRUE, silent=F)
```




```
promoModelMNM
```

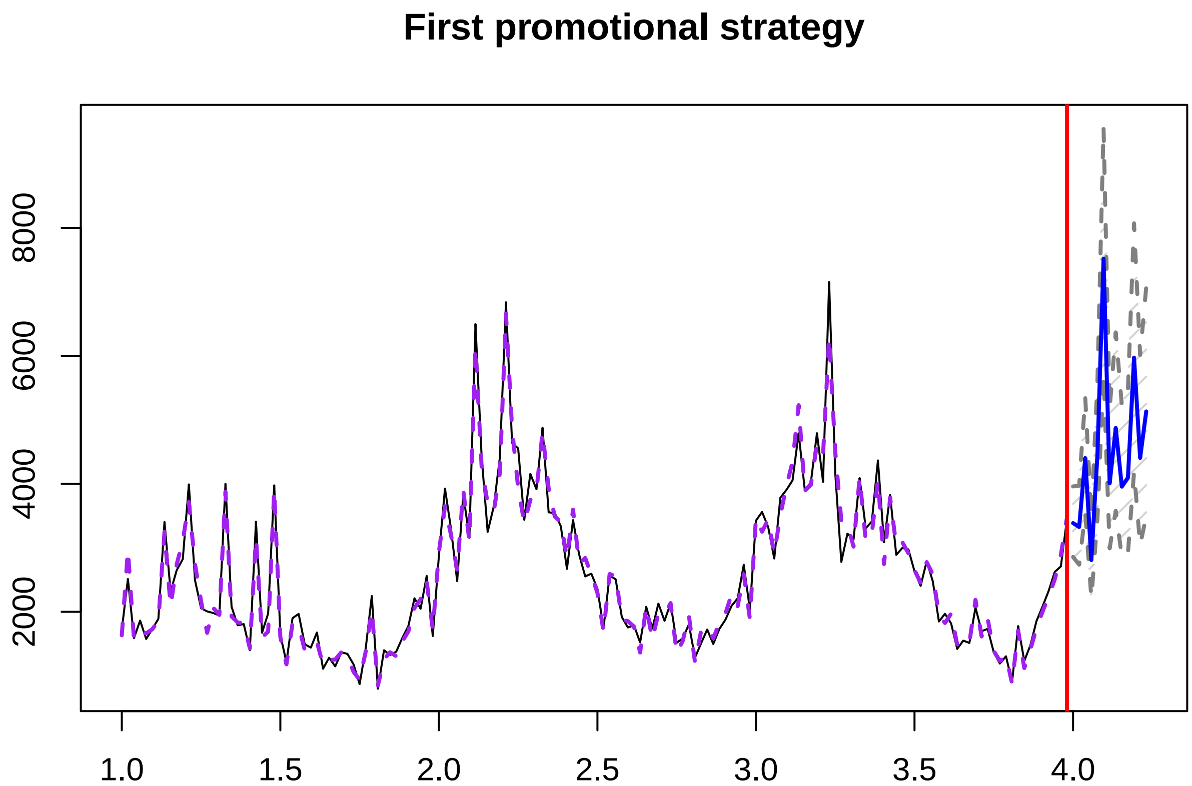
```
## Time elapsed: 1.33 seconds
## Model estimated using adam() function: ETSX(MNM)
## Distribution assumed in the model: Gamma
## Loss function type: likelihood; Loss function value: 929.116
## Persistence vector g (excluding xreg):
##  alpha  gamma
## 0.5761 0.0000
##
## Sample size: 143
## Number of estimated parameters: 58
## Number of degrees of freedom: 85
## Information criteria:
##      AIC     AICc      BIC     BICc
## 1974.232 2055.708 2146.077 2348.254
##
## Forecast errors:
## ME: 203.686; MAE: 241.532; RMSE: 308.393
## sCE: 101.54%; Asymmetry: 74.7%; sMAE: 9.262%; sMSE: 1.399%
## MASE: 0.382; RMSSE: 0.338; rMAE: 0.412; rRMSE: 0.426
```

As we see from the output (AICc, holdout error measures - whatever you prefer) and the figure above, the ETSX(M,N,M) is more suitable for this data than the ETSX(M,N,N).

In a similar manner, we can fit a model with a trend or allow function to select the most appropriate one (in terms of AIC). But for demonstration purposes, ETSX(M,N,M) should suffice.

Now that we selected the model, we can forecast what sales we will have with different sets of promotions/values of price. The following code provides just an example, feel free to experiment in your own time:

```
# Refit the model
promoModelMNM <- adam(PromoData, "MNM", lags=52, formula=y~., h=13, holdout=FALSE)
# Create new data
# We can decide which promotions to have in the next 13 weeks
# And we can see how changes in price will impact our forecast
promoNewdata <- data.frame(Promo1=c(0,0,0,0,0,1,0,0,0,0,0,0,0),
                           Promo2=c(0,0,1,0,1,1,0,0,0,0,1,0,0),
                           Price=rep(2.8, 13))
# Produce forecast with the prediction interval
forecast(promoModelMNM, newdata=promoNewdata, h=13, interval="prediction") |>
    plot(main="First promotional strategy")
```



Task Take 5 minutes to experiment with different promotional and pricing strategies to see how they impact the forecast.

Finally, `adam()` supports variables selection via information criteria, which is triggered via `regressors="select"` and an adaptation mechanism of the parameters of explanatory variables (dynamic ETSX) via `regressors="adapt"`. We suggest you investigating these features on your own.

Additional materials

For some additional examples on ETS implemented in `smooth` run:

```
vignette("adam","smooth")
```

Some additional resources on exponential smoothing:

1. ETS in the blog of Ivan Svetunkov;
2. Chapter 10 of ADAM;
3. Posts on the functions in smooth package;
4. Posts of Nikos Kourentzes on exponential smoothing.