IT-Based Management Summary

Group 06

11 12 2018

Forecasting and Probalistic Budgeting: Sales Volume Context (Learning with Case Studies)

Use Case

It is about Candle Manufacturing Inc. company, which produce three different candles like molded candles, solid candles and pulled candles. The company needs to setup the annual sales budget for the next year. To accomplish this, the traditional *time series-based forecasting* methods are applied and two new approaches has been introduced:
multinominal reggression-based
stochastic process-based forecasting of time series
To answer question about sales volumes that can expected for next year, the R software package are used as we can

- perform a traditional time series analysis and use the model for **time series-based forecasting** for the next year
- use timely intervals and perform a **regression-based forecasting**
- read monthly sales from transactional data
- perform a **stochastic process-based forecasting**
- derive year-end forecast in fixed-event form
- budget-forecast deviation with p-value to perform adjustments

Problem Statement

As there is uncertainity in business environment, the future predictation of sales volumes is also uncertain and time series-based approch forecast data with the help of historical data. It is not clear which time-based approch should be used in R to produce unbiased data. The two new approaches that are mentioned above allow additional forecast updating which are not possible in time series-based approches. Updating feature is very important in the fixed-event forecasting[1] context as fixed time period is considered over time leading to a successively reducing of the lead time.

Contribution

Traditional time series analysis covers the range between decomposition approaches, where non-stationary trends and seasonalities are included, and stationary ARIMA approaches. By introducing new modeling techniques in form of the multinomial regression-based and the stochastic processbased forecasting methods the time series modeling repertoire can be extended in an effective and easy to grasp way.

[1] In the management control the fixed-event forecasts are the year-end forecasts

Result
Multinomial regression-based and stochastic processbased forecasting are mathematically defined and statistically calibrated.

Research Methodology

The new artifacts are mathematically modeled and their applications are demonstrated in numerical examples.

Research literature

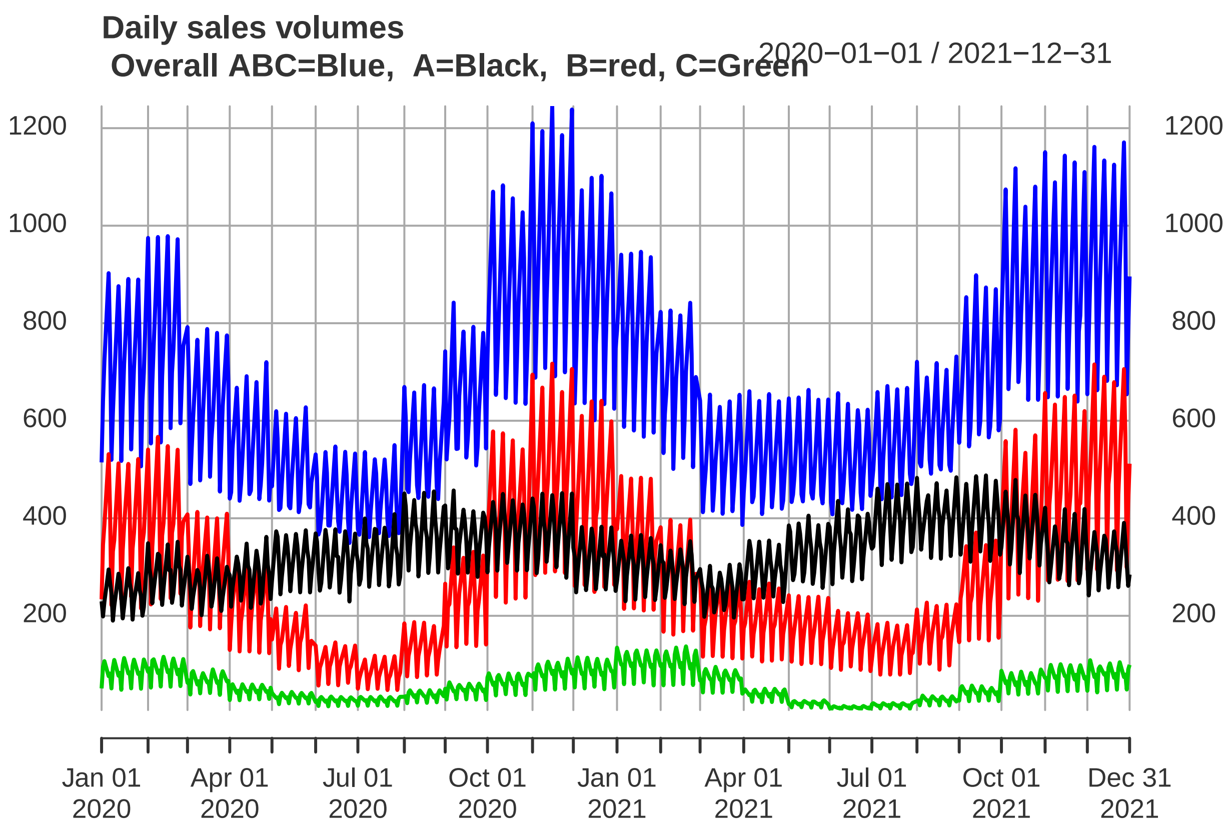
Hyndman Rob/Athanasopoulos George: Forecasting Principles and Practice Lawrence Michael/O'Connor Marcus: Sales forecasting updates: how good are they in practice?

Implementation

Task 1

Importing and analyzing daily sales data and plotting of xSD01.xts

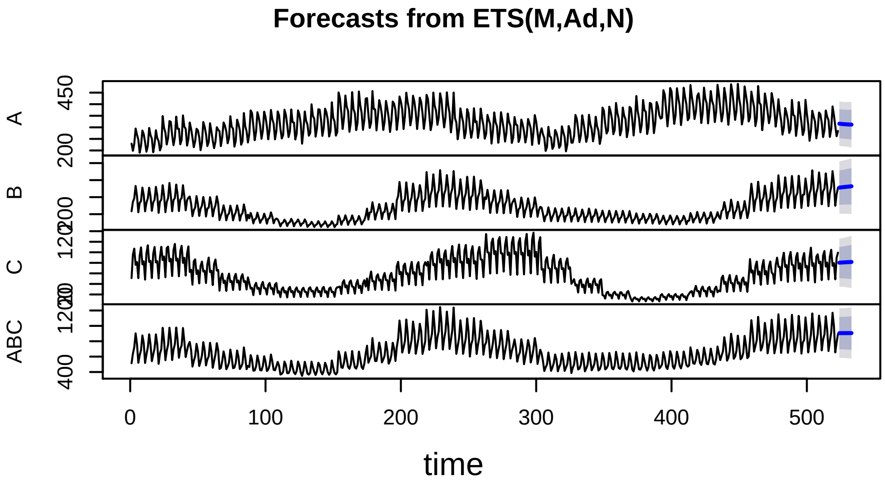
```
library(xts)
## Warning: package 'xts' was built under R version 3.4.4
## Loading required package: zoo
## Warning: package 'zoo' was built under R version 3.4.4
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
xSD01.xts<-readRDS("DataCMI")
str(xSD01.xts)
## Warning in format.POSIXlt(as.POSIXlt(x), ...): unknown timezone 'zone/tz/
## 2018g.1.0/zoneinfo/Europe/Vienna'
## An 'xts' object on 2020-01-01/2021-12-31 containing:
##   Data: num [1:523, 1:4] 230 199 228 295 269 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:4] "A" "B" "C" "ABC"
##   Indexed by objects of class: [Date] TZ: UTC
##   xts Attributes:
##  NULL
plot(xSD01.xts, main="Daily sales volumes \n Overall ABC=Blue,  A=Black,  B=red, C=Green")
```



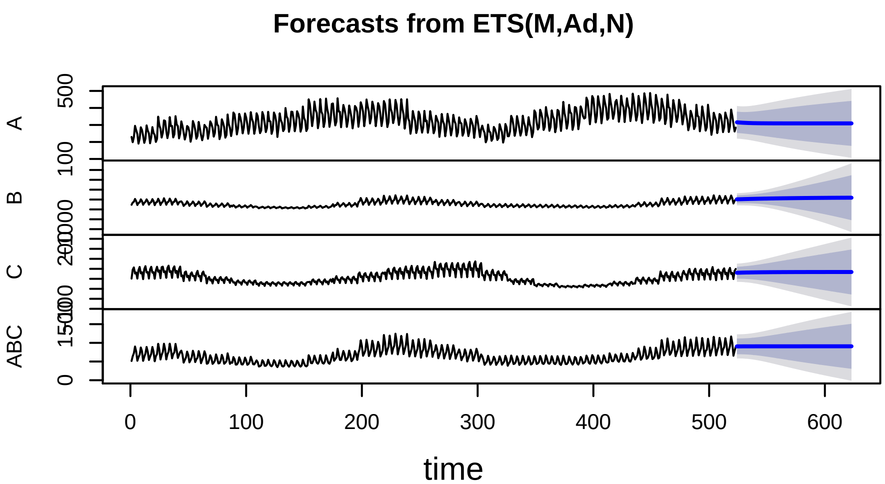
Task 2

Forecasting daily sales volumes by using automated procedures in forecasting packages

```
library(forecast)
## Warning: package 'forecast' was built under R version 3.4.4
plot(forecast(as.ts(xSD01.xts)))
```




```
plot(forecast(as.ts(xSD01.xts),100))
```




```
xSD01.fc<-forecast(as.ts(xSD01.xts),100)
attributes(xSD01.fc)
## $names
## [1] "forecast" "method"
##
## $class
## [1] "mforecast"
```

```
xSD01.fc$method
```

```
##              A              B              C            ABC
## "ETS(M,Ad,N)" "ETS(M,Ad,N)" "ETS(M,Ad,N)" "ETS(M,Ad,N)"
```

```
xSD01.fc$method
```

```
##              A              B              C            ABC
```

```
## "ETS(M,Ad,N)" "ETS(M,Ad,N)" "ETS(M,Ad,N)" "ETS(M,Ad,N)"
```

Interpretation: Planning horizon (plan period) of 100 days already shows exploding uncertainties of ABC, B and C

Task 3

Including additional (predictable) variables into the TS data set

```
xSD01Ext.xts<-NULL # Extracting date information from xts-object
xSD01Ext.xts<-xSD01.xts
xSD01Ext.xts$Year<-as.factor(format(index(xSD01.xts),"%Y"))
xSD01Ext.xts$Quarter<-as.factor(quarters(index(xSD01.xts)))
xSD01Ext.xts$Month<-format(index(xSD01.xts),"%m")
xSD01Ext.xts$wDay<-format(index(xSD01.xts),"%u")
```

Task 4

Performing numeric regressions Numeric regression: Regressing daily sales volumes against numeric variables

```
xSD01ABC.svlm <- NULL # Single variable linear model (svlm)
xSD01ABC.svlm <- lm(ABC~wDay,xSD01Ext.xts)
summary(xSD01ABC.svlm)
```

```
##
## Call:
## lm(formula = ABC ~ wDay, data = xSD01Ext.xts)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -285.28 -138.50  -41.32  126.29  492.94
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  802.001     18.156  44.172   <2e-16 ***
## wDay         -50.055      5.466  -9.157   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 176.7 on 521 degrees of freedom
## Multiple R-squared:  0.1386, Adjusted R-squared:  0.137
## F-statistic: 83.85 on 1 and 521 DF,  p-value: < 2.2e-16
```

Task 5

Performing multinomial regressions Multinomial (factor) regression: Regressing daily sales volumes against categorical variables

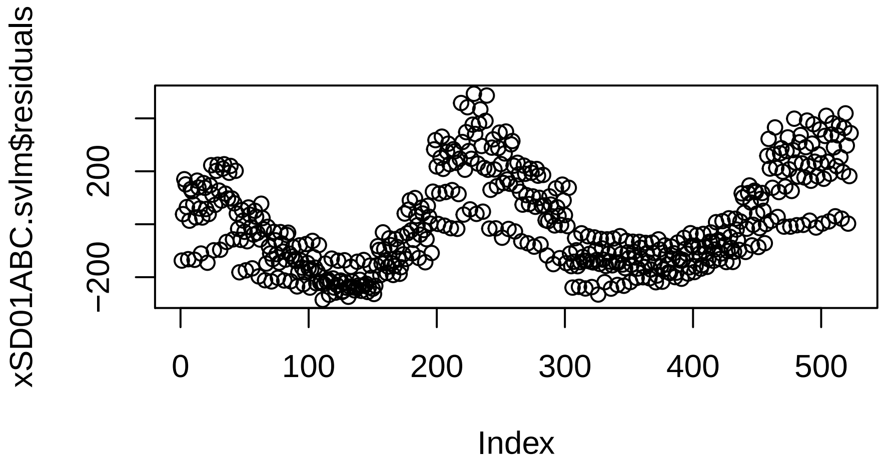
```
xSD01ABC.sflm <- NULL # Single factor linear model (sflm)
xSD01ABC.sflm <- lm(ABC~as.factor(wDay),xSD01Ext.xts)
summary(xSD01ABC.sflm)
```

```
##
## Call:
## lm(formula = ABC ~ as.factor(wDay), data = xSD01Ext.xts)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -301.14 -133.00  -25.36  122.85  423.19
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)        821.70      15.55  52.844  < 2e-16 ***
## as.factor(wDay)2  -113.65      21.99  -5.168 3.38e-07 ***
## as.factor(wDay)3  -301.69      21.94 -13.752  < 2e-16 ***
## as.factor(wDay)4  -250.92      21.94 -11.438  < 2e-16 ***
## as.factor(wDay)5  -182.33      21.94  -8.311 8.38e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 158.6 on 518 degrees of freedom
## Multiple R-squared:  0.3103, Adjusted R-squared:  0.305
## F-statistic: 58.26 on 4 and 518 DF,  p-value: < 2.2e-16
```

```
attributes(xSD01ABC.sflm)
```

```
## $names
##  [1] "coefficients"  "residuals"     "effects"       "rank"
##  [5] "fitted.values" "assign"        "qr"            "df.residual"
##  [9] "contrasts"     "xlevels"       "call"          "terms"
## [13] "model"
##
## $class
## [1] "lm"
```

```
plot(xSD01ABC.svlm$residuals) # Plotting svlm & sflm residuals
```




```
plot(xSD01ABC.sflm$residuals)
```