Store Sales Forecasting

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The Carlson Department Store suffered heavy damage when a hurricane struck on August 31. The store was closed for four months (September through December), and Carlson is now involved in a dispute with its insurance company about the amount of lost sales during the time the store was closed. Two key issues must be resolved: (1) the amount of sales Carlson would have made if the hurricane had not struck. (2) whether Carlson is entitled to any compensation for excess sales due to increased business activity after the storm. More than $8 billion in federal disaster relief and insurance money came into the county, resulting in increased sales at department stores and numerous other businesses. The Table below gives Carlson's sales data for the 48 months preceding the storm. It also reports the total sales for the 48 months preceding the storm for all department stores in the county, as well as the total sales in the county for the four months the Carlson Department Store was closed. Carlson's managers asked you to analyze the data and develop estimates of the lost sales at the Carlson Department Store for the months of September through December. They also asked you to determine whether a case can be made for excess storm-related sales during the same period. If such a case can be made, Carlson is entitled to compensation for excess sales it would have earned in addition to ordinary sales.

```r
library(expsmooth)
```

```
## Loading required package: forecast
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
## Registered S3 methods overwritten by 'forecast':
##   method             from
##   fitted.fracdiff    fracdiff
##   residuals.fracdiff fracdiff
```

```r
library(forecast)


data_csv <- read.csv('sales_data.csv')

store_data_csv <- data_csv['Store.data']
county_data_csv <- data_csv['County.data']
```

Convert data frame to time series format

```
store_data_ts <- ts(store_data_csv[1:52,], frequency = 12, start = c(2012, 9))
store_data_ts
```

```
##       Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec
## 2012                                         1.71 1.90 2.74 4.20
## 2013 1.45 1.80 2.03 1.99 2.32 2.20 2.13 2.43 1.90 2.13 2.56 4.16
## 2014 2.31 1.89 2.02 2.23 2.39 2.14 2.27 2.21 1.89 2.29 2.83 4.04
## 2015 2.31 1.99 2.42 2.45 2.57 2.42 2.40 2.50 2.09 2.54 2.97 4.35
## 2016 2.56 2.28 2.69 2.48 2.73 2.37 2.31 2.23   NA   NA   NA   NA
```

```
county_data_ts_plot <- ts(county_data_csv[1:52,], frequency = 12, start = c(2012, 9))
county_data_ts_plot
```

```
##        Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep   Oct   Nov   Dec
## 2012                                                  55.8  56.4  71.4 117.6
## 2013  46.8  48.0  60.0  57.6  61.8  58.2  56.4  63.0  57.6  53.4  71.4 114.0
## 2014  46.8  48.6  59.4  58.2  60.6  55.2  51.0  58.8  49.8  54.6  65.4 102.0
## 2015  43.8  45.6  57.6  53.4  56.4  52.8  54.0  60.6  47.4  54.6  67.8 100.2
## 2016  48.0  51.6  57.6  58.2  60.0  57.0  57.6  61.8  69.0  75.0  85.2 121.8
```

```
county_data_ts <- ts(county_data_csv[1:48,], frequency = 12, start = c(2012, 9))
county_data_ts
```

```
##        Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep   Oct   Nov   Dec
## 2012                                                  55.8  56.4  71.4 117.6
## 2013  46.8  48.0  60.0  57.6  61.8  58.2  56.4  63.0  57.6  53.4  71.4 114.0
## 2014  46.8  48.6  59.4  58.2  60.6  55.2  51.0  58.8  49.8  54.6  65.4 102.0
## 2015  43.8  45.6  57.6  53.4  56.4  52.8  54.0  60.6  47.4  54.6  67.8 100.2
## 2016  48.0  51.6  57.6  58.2  60.0  57.0  57.6  61.8
```

Forecast store sales using exponential smoothing

```
ets_fit_store <- ets(store_data_ts)
```

```
## Warning in ets(store_data_ts): Missing values encountered. Using longest
## contiguous portion of time series
```

```
summary(ets_fit_store)
```

```
## ETS(A,N,A)
##
## Call:
##  ets(y = store_data_ts)
##
##   Smoothing parameters:
```

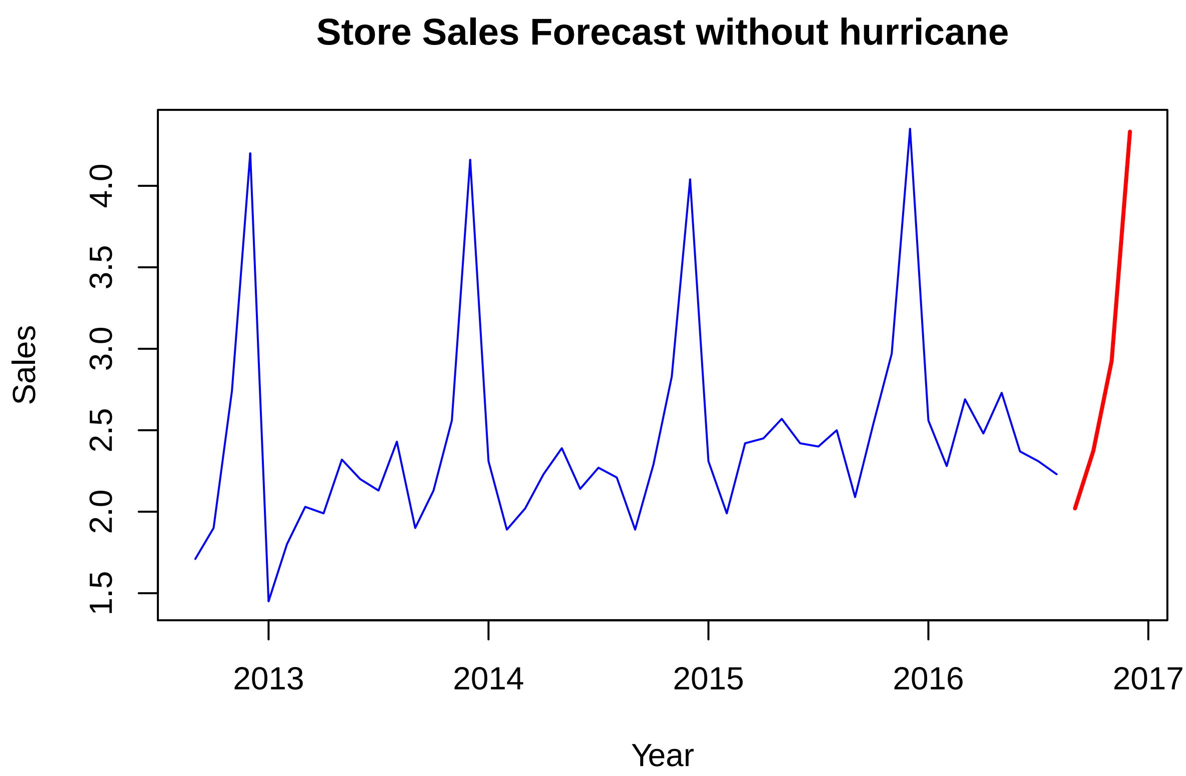
```
##     alpha = 0.2204
##     gamma = 1e-04
##
##   Initial states:
##     l = 2.2435
##     s = -0.1222 -0.1907 -0.1625 0.0458 -0.1413 -0.1598
##            -0.445 -0.2387 1.7733 0.3664 -0.1862 -0.539
##
##   sigma:  0.1817
##
##      AIC     AICc      BIC
## 35.55089 50.55089 63.61890
##
## Training set error measures:
##                      ME      RMSE       MAE       MPE     MAPE      MASE
## Training set 0.02983186 0.1529294 0.1161052 0.8325261 5.198752 0.6146747
##                      ACF1
## Training set -0.001237759
```

```r
pred_store_sales_without_hurricane <- forecast(ets_fit_store, h = 4)

pred_store_sales_without_hurricane
```

```
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Sep 2016       2.020107 1.787240 2.252974 1.663967 2.376246
## Oct 2016       2.372952 2.134495 2.611409 2.008264 2.737640
## Nov 2016       2.925468 2.681550 3.169386 2.552427 3.298509
## Dec 2016       4.332404 4.083144 4.581665 3.951193 4.713615
```

```r
plot(store_data_ts, col="blue", xlab="Year", ylab="Sales", main="Store Sales Forecast without hurricane
lines(pred_store_sales_without_hurricane$mean, col = 'red', lwd = 2)
```



Forecast county sales without hurricane

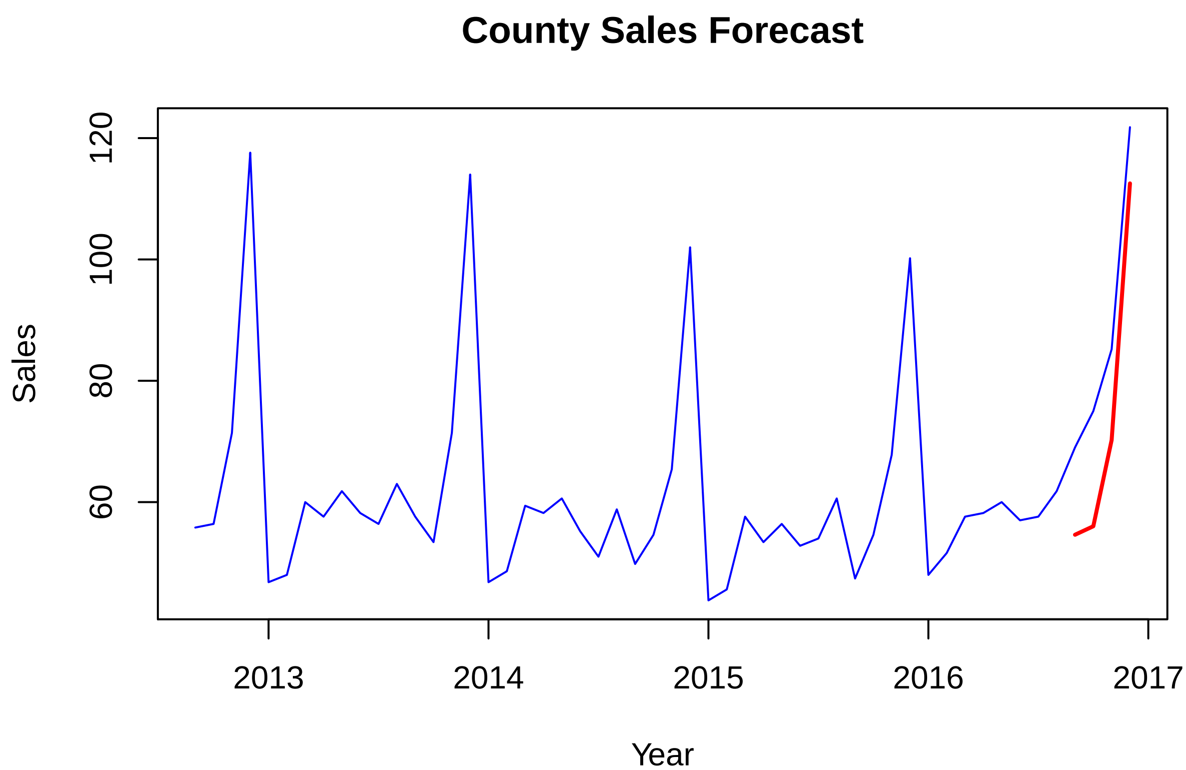
```r
ets_fit_county <- ets(county_data_ts)
ets_fit_county
```

```
## ETS(M,N,M)
##
## Call:
##  ets(y = county_data_ts)
##
##   Smoothing parameters:
##     alpha = 0.2896
##     gamma = 2e-04
##
##   Initial states:
##     l = 61.8311
##     s = 0.9966 0.9056 0.9131 0.9735 0.943 0.9706
##            0.7985 0.7692 1.8142 1.1323 0.903 0.8804
##
##   sigma:  0.0443
##
##      AIC     AICc      BIC
## 291.452 306.452 319.520
```

```r
pred_county_without_hurricane <- forecast(ets_fit_county, h = 4)
pred_county_without_hurricane
```

```
##          Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
## Sep 2016       54.61294  51.51457  57.71132  49.87438  59.35151
## Oct 2016       56.01602  52.70717  59.32488  50.95557  61.07648
## Nov 2016       70.23764  65.93084  74.54444  63.65096  76.82433
## Dec 2016      112.53414 105.38978 119.67850 101.60779 123.46050
```

```r
plot(county_data_ts_plot, col="blue", xlab="Year", ylab="Sales", main="County Sales Forecast", type='l'
lines(pred_county_without_hurricane$mean, col = 'red', lwd = 2)
```



Forecast store sales with hurricane

```r
county_sales_without_hurricane <- pred_county_without_hurricane$mean
county_sales_without_hurricane
```

```
##            Sep       Oct       Nov       Dec
## 2016  54.61294  56.01602  70.23764 112.53414
```

```r
store_sales_without_hurricane <- pred_store_sales_without_hurricane$mean
store_sales_without_hurricane
```

```
##           Sep      Oct      Nov      Dec
## 2016 2.020107 2.372952 2.925468 4.332404
```

```r
county_sales_with_hurricane <- ts(county_data_csv[49:52,], frequency = 12, start = c(2016, 9))
county_sales_with_hurricane
```

```
##        Sep   Oct   Nov   Dec
## 2016  69.0  75.0  85.2 121.8
```

```r
county_sales_ratio <- county_sales_with_hurricane/county_sales_without_hurricane
county_sales_ratio
```

```
##           Sep      Oct      Nov      Dec
## 2016 1.263437 1.338903 1.213025 1.082338
```

```r
store_sales_with_hurricane <- store_sales_without_hurricane * county_sales_ratio

store_sales_with_hurricane
```

```
##           Sep      Oct      Nov      Dec
## 2016 2.552277 3.177152 3.548665 4.689127
```

Store sales forecast if there was no hurricane

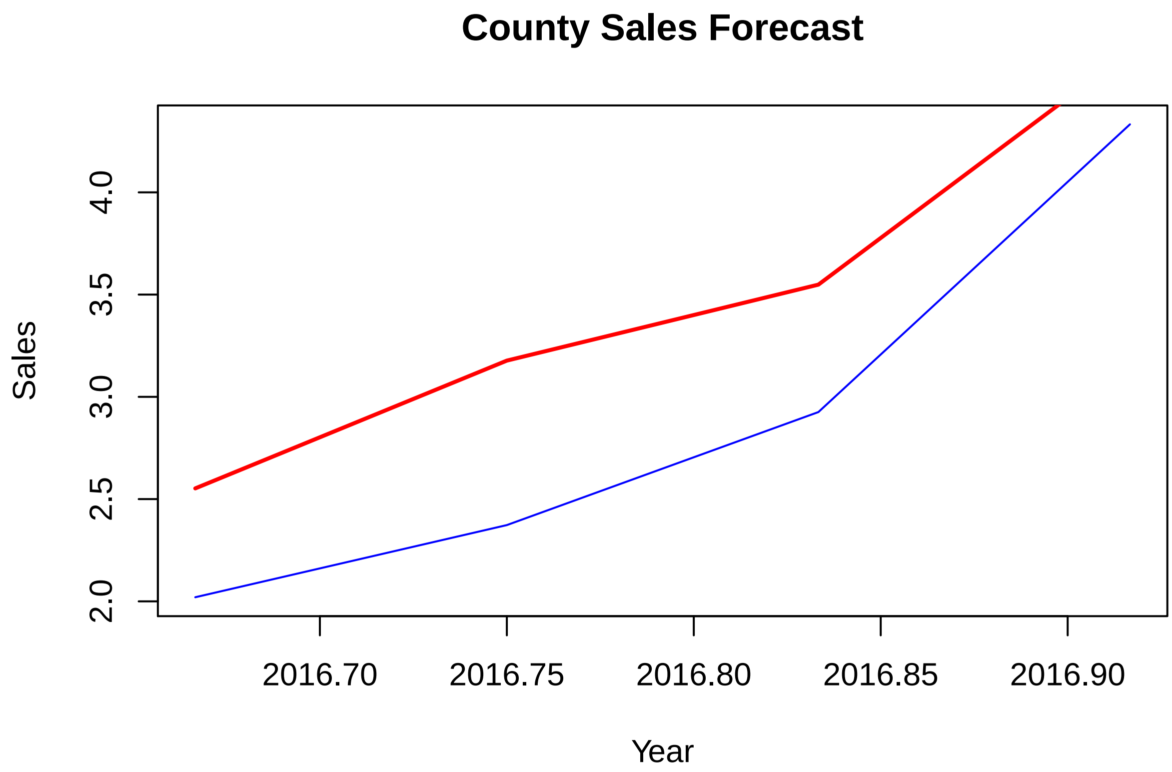
```r
store_sales_without_hurricane
```

```
##           Sep      Oct      Nov      Dec
## 2016 2.020107 2.372952 2.925468 4.332404
```

```r
#store sales forecast if shop made sales after the hurricane
store_sales_with_hurricane
```

```
##           Sep      Oct      Nov      Dec
## 2016 2.552277 3.177152 3.548665 4.689127
```

```r
plot(store_sales_without_hurricane, col="blue", xlab="Year", ylab="Sales", main="County Sales Forecast"
lines(store_sales_with_hurricane, col = 'red', lwd = 2)
```



Conclusion

The shop would have made increased sales if it was functional after the hurricane as observed in the above values.

Hence, Carlson stores is entitled to compensation for excess sales due to increased business activity after the storm.