Assignment #1
ETS Laboratory

Due: Tuesday, Oct 7, before 11:59pm
(40 pts. Total)

The data set `RSGCSN.csv` includes monthly retail sales of grocery stores in the US from January 1992 through August 2017 expressed in millions of US dollars.
Source: https://fred.stlouisfed.org/series/RSGCSN

Issue the following commands to load the data and convert it into an appropriate time series object:

```
library(fpp)
library(dplyr)
#
# Read csv file and make it a time series
RS <- read.csv("RSGCSN.csv") %>%
  select(-DATE) %>%
  ts(start= c(1992,1), frequency=12)
```

In this assignment we will focus on long term forecast as it is appropriate for aggregate planning and/or facilities planning.

In this assignment we are interested in obtaining a 5years+ forecast (68 months to be precise) of the size of the grocery store market in the US, and we want that forecast in monthly intervals (not just annual sales) because we are interested in peak (not just average) capacity requirements. Such a forecast is useful if you are preparing an infrastructure plan for a grocery store chain for example. This forecast is useful to make projections about number of new stores to open, number of distribution centers and their capacity, personnel and other infrastructure decisions.

In this assignment we will learn to use the `ets(…)` function to fit and analyze exponential smoothing models. Before proceeding to fit a model we examine and divide the data into two sets; a training set `tr` to fit the models and a testing (or hold-out) data set `te` to assess the out-of-sample performance of the models. This is accomplished with the following code:

```
tr <- window(RS, end=c(2011,12))
te <- window(RS, start=c(2012,1))
plot(RS)
abline(v=c(2011,12), col="grey")
```

1. (5 pts.) Holt-Winters Model Analysis: part I:

    - Use the `ets(…)` function to fit a Holt-Winters exponential smoothing model to the sales data. Leave up to the `ets(…)` function to decide if a damping parameter is necessary (i.e., do not specify the `damped` directive. Call this model `f.HW`, and report the model details including the optimized value of each of the constants and smoothing parameters required by the model, the AIC, $AICc$ and BIC values, as well as the in-sample fitting indicators.

- Use the `forecast(…)` function to obtain a 68-month-ahead forecast, name this forecast `fc.HW` and plot it (i.e. call the `plot(fc.HW)` function); overlay on this plot the actual sales observed during this testing period (i.e. call the function `points(te, col="red", pch=19)` to overlay the testing data).

- Reproduce the plot again, but now zooming on the forecasting period. To do this, include the `xlim` and `ylim` parameters in the initial plot call (i.e., use `plot(fc.HW, xlim=c(2009,2018), ylim=c(40000,60000) )` to focus the plot on the forecast period). No change is necessary for the `points(…)` call. For the rest of this assignment **include the above values for the `xlim` and `ylim` parameters in every forecast plot in Questions 1 through 7.**

- Calculate the in-sample and out-of-sample fit statistics. You can obtain the in-sample and out-of-sample fit metrics comparison by calling the function `accuracy(fc.HW, te)`

- Based on your analysis above, discuss the forecast bias and compare the out-of-sample MAE with the MAE that you would obtain if you used the naïve forecasting method. What do you think is driving the poor model performance? Examine carefully the MAE of the naïve forecasting method over the 68-month-ahead forecasting horizon. Which model/method would you choose for forecasting?

2. (5 pts.) Holt-Winters Model Analysis: part II:

- Optimize the parameters of a Holt-Winters model disallowing damping of growth (i.e., use the `damped=FALSE` directive in the call to the `ets(…)` function). Call the fitted model `f.HW2`, and report the model details including the optimized value of each of the constants and smoothing parameters required by the model, the AIC, $AICc$ and BIC values, as well as the in-sample fitting indicators.

- Obtain a 68-month-ahead forecast, name this forecast `fc.HW2` and plot it.

- Calculate the in-sample and out-of-sample fit statistics of the `fc.HW2` forecast.

- As in Question 1, based on your analysis above, discuss the forecast bias and compare the out-of-sample MAE of `fc.HW`, `fc.HW2` and the naïve forecast? Discuss also the confidence interval cone of both models. What do you suspect is making the cone of `fc.HW2` much larger? Which of the models analyzed thus far would you choose for forecasting? Why?

3. (5 pts) Automatic/Optimized ETS Model Selection:

    - Now we call the `ets(…)` function using the `model="ZZZ"` directive to optimize the model selection including multiplicative models (i.e., set the `restrict=FALSE` option). Call the fitted model `f.O`, and report the model details, the AIC, $AICc$ and BIC values, as well as the in-sample fitting indicators.
    - Obtain a 68-month-ahead forecast, name this forecast `fc.O` and plot it.
    - Calculate the in-sample and out-of-sample fit statistics of the `fc.O` forecast.
    - Compare the out-of-sample MAE of fc.HW, fc.HW2, fc.O and the naïve forecast? Compare the $AICc$ and BIC of models f.HW, f.HW2 and f.O. Which of the models analyzed thus far would you choose for forecasting? Why?

4. (5 pts) Automatic/Optimized model using BoxCox-Transformed Data:

    - Select the best value of the "lambda" parameter for the BoxCox transformation over the training set tr, and then use the `ets(…)` function to optimize the model selection as you did in Question 3. Call the fitted model `fB.O`, and report the model details, the AIC, $AICc$ and BIC values, as well as the in-sample fitting indicators.
    - Obtain a 68-month-ahead forecast, name this forecast `fBc.O` and plot it.
    - Calculate the in-sample and out-of-sample fit statistics of the `fBc.O` forecast.
    - Compare the in-sample and out-of-sample MAE of `fBc.O, fc.O` and the naïve forecast? Which of the models analyzed thus far would you choose for forecasting? Why?

5. (5 pts) Optimized model with damping using BoxCox-Transformed Data:

    - Using the best value of "lambda" (i.e., the same you used in Question 4), and set `damped=TRUE` in the `ets(…)` function. Name the fitted model `fB.OD` and report the model details and metrics.
    - Obtain a 68-month-ahead forecast, name this forecast `fBc.OD` and plot it.
    - Calculate the in-sample and out-of-sample fit statistics of the `fBc.OD` forecast.

- Compare the in-sample and out-of-sample MAE of `fBc.OD, fBc.O, fc.O` and the naïve forecast? Why do you think the damping constant is not helping? Which of these three models would you choose for forecasting?

6. (5 pts) In an effort to improve forecasts, in this question we want to assess the value of old information and discard the oldest segment of the information that does not have predictive value. To this end code and execute the following:

   Evaluate the selection of a moving training set starting from 1992, 1993, etc all the way to starting in 2006, but in each case keep the end of the training set fixed at December of 2011. For each starting year:

   - Select the value of the Box "lambda" for each training set
   - Obtain an optimized model using all the ETS-options that you consider pertinent based on your analysis in previous questions.
   - Extract the in-sample RMSE
   - Select the best starting year for the training set
   - Report the lowest RMSE and the starting year the generates it
   - Create a "reduced" training set starting the year you identified above, and terminating in December of 2011. Name this reduced training set `trr`.
   - Explain why we cannot use the $AICc$ or BIC criteria to select the best starting year for the training data set in the procedure described above.

7. (5 pts) Fitting a model on the reduced training dataset:

   - Figure out the best value of the BoxCox lambda value for the reduced training data set `trr`, and fit the best ETS model to this data. Report the model parameters and metrics. Name this model `f`.

   - Obtain a 68-month-ahead forecast, name this forecast `fc` and plot it.

   - Calculate the in-sample and out-of-sample fit statistics of the `fc` forecast.

   - Is the in-sample $AICc$ for model `f.O` comparable with the in-sample $AICc$ for model `f`? Explain.

   - Is the in-sample $MASE$ for model `f.O` comparable with the in-sample $MASE$ for model `f`? Explain.

   - Is the out-of-sample $RMSE$ for model `fc.O` comparable with the out-of-sample $RMSE$ for model `fc`? Explain. Is the `fc` forecast truly an out-of-sample forecast? Explain.

8. (5 pts.) Aggregate Sales Forecast for 2017—2022:

- Next we need to prepare a monthly sales forecast through December 2022. To this end we first set the training set to include all the data starting from the year we selected in Question 6 through August 2017. Select the ETS model you analyzed in Question 7, and fit the best parameters to that model. Name the resulting model `ff`.

- Compare the in-sample fit statistics of `ff` with those of model `f`.

- Obtain a 64-month-ahead forecast, name this forecast `ffc` and plot it (this time do not include the `xlim` and `ylim` limits on the forecast plot.

- Based on your analysis what would you estimate the out-of-sample (i.e., the actual) $MAPE$ be over the next five years? How about the out-of-sample (actual) $RMSE$?