AAEC 4484/ STAT(AAEC) 5484: Applied Economic Forecasting

Your Name Here

Homework #2 - Spring 2024

This assignment aims to enhance your understanding of time series and data patterns. It is intended to be straightforward.

Instructions:

- **Where necessary, please ensure that your graphs and visuals have proper titles and axis labels.**
- **Recall that you can use `help()` or `?seriesname` in your consoles to get general information on the dataset**.

Question 1: Basic Visualization of Time Series Data

i. Create time plots of the following time series: `Tobacco` from `aus_production`, `Lynx` from `pelt`, Intraday High prices (`High`) for `FB` from `gafa_stock`, `Demand` **for 2013** from `vic_elec`.

- Please use the `grid.arrange()` function from the `gridExtra` package to arrange your plots as a `2 x 2` grid.

ii. Briefly discuss any discernible pattern(s) you noticed in the data.

Question 2: Assessing (Potential) Seasonality

In our earlier class sessions, we explored the idea of drawing a random sample of data. The exercise below offers a practical demonstration.

We will pull a random sample of the `aus_retail` data set by selecting a random `Series ID`, according to our chosen seed. **Set a seed of your choice to ensure you generate your draw of the data.**

```r
# Remove the eval = FALSE argument from the code chunk to run your codes.

set.seed(xxxx) #Set this to your preferred seed
```

i. Use the `autoplot()`, `gg_season()`, `gg_subseries()`, and `ACF() %>% autoplot()` functions to explore possible seasonality in your chosen sample.

- Please use the `grid.arrange()` function from the `gridExtra` package to arrange your plots. **You are free to organize them however you wish.**
- **It might be useful to change the `lag_max` (how about to 3 years of data?) in the ACF to ensure that you can see a fair bit of the pattern in the correlogram.**

ii. What can you say about the series? Are there any seasonal patterns? Trends?

Question 3: White Noise

The `aus_livestock` series contains data on monthly "Meat production in Australia for human consumption".

i. Using the `filter()` function, extract the number of **Cows and heifers** slaughtered in **Tasmania**. Store this variable as `cows`.

ii. Produce the `autoplot()` of `cows` and its correlogram. **Comment on any pattern noticed in both.** Does this series look like white noise? **Explain your answer.**

iii. Now, using the `difference()` and `mutate()` functions, create a new column, `diff`, that computes the **month-to-month** changes (`lag = 1`) in your `cows` series. Store this new data as `d.cows`. *I would suggest using the head() command on your differenced series in the console to ensure that the `diff` column looks as you would expect.*

iv. Produce an `autoplot()` of `diff` along with the associated correlogram.

   a. Does the first differenced data now look like white noise?
   b. Did differencing remove any potential seasonality in the data?

Recall that a simple yes/no will not suffice. You will need to explain your conclusion.

v. Return to the `cows` series and again use the `difference()` and `mutate()` functions to create a new column called `diff12` that computes the **year-on-year** changes (`lag = 12`) in your `cows` series. Store this new data as `d12.cows`.

I would suggest using the `head(n = 14)` command on your `d12.cows` series in the console to ensure that the `diff12` column looks as you would expect.

vi. Produce an `autoplot` of `diff12` along with the associated correlogram.

   a. Does this new data, differenced at lag12, now look like white noise? **Recall that a simple yes will not suffice. You will need to explain your conclusion.**

   b. Did differencing remove all potential seasonality or trend in the data? If not, how would you solve this? **You are not required to do this. An intelligent answer based on the plots and your observations will suffice.**