# Technical note on seasonal adjustment for Car sales

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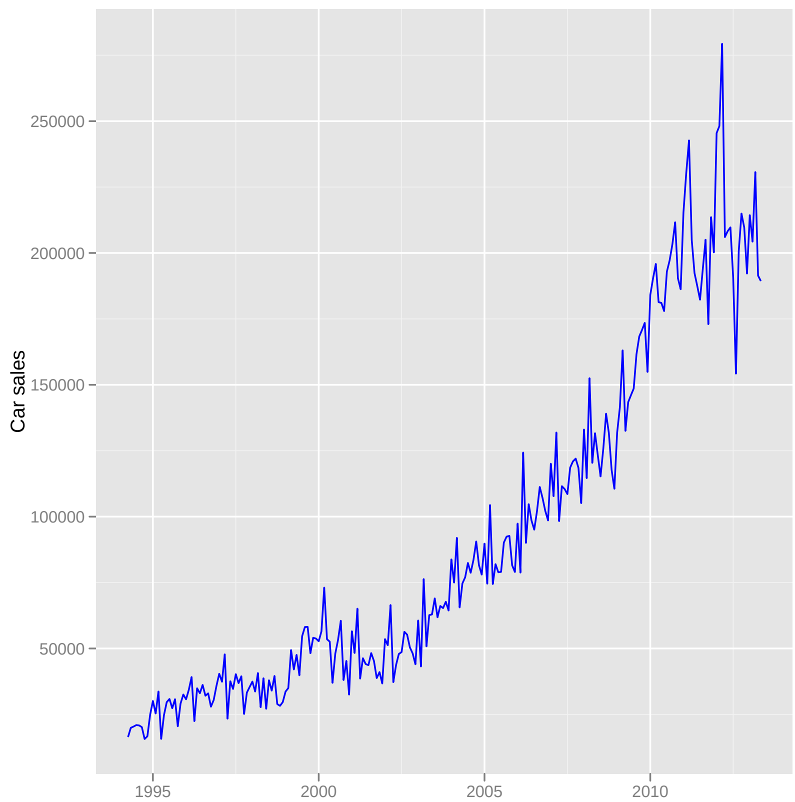
# 1 Car sales

We analyse the monthly data for car sales from April, 1994 onwards. Figure 1 below shows the original plot of the series. The plot shows seasonal peaks. In a non-seasonally adjusted series, it is difficult to discern a trend as the seasonal variations may mask the important characteristics of a time series.

**Figure 1** Car sales (Non seasonally adjusted)




# 2 Additive versus multiplicative seasonality

## 2.1 Seasonal dummy models

We rely on the seasonal dummy model to detect whether a series is additive or multiplicative. We use a simple approach and include a set of dummy variables to control for stable seasonality. This approach helps us assess the presence seasonal variations in a series. We can estimate:

$$y_t = \beta_0 + \beta_1 \text{Jan}_t + \beta_2 \text{Feb}_t + \beta_3 \text{Mar}_t + \beta_4 \text{Apr}_t + \beta_5 \text{May}_t + \beta_6 \text{Jun}_t$$

$$+\beta_7 \text{Jul}_t + \beta_8 \text{Aug}_t + \beta_9 \text{Sep}_t + \beta_{10} \text{Oct}_t + \beta_{11} \text{Nov}_t + \epsilon_t$$

where $\text{Jan}_t$, $\text{Feb}_t$ .... $\text{Nov}_t$ are dummy variables. In this formulation, December is the base month. The residual of the regression gives the seasonally adjusted series. We compare the standard deviation of the growth rate for the additive and log transformed regression and choose the one that is lower. In case of car sales, the standard deviation is lower for the log transformed series and we use multiplicative seasonal adjustment.

### 2.2 Slidingspans Diagnostic

X-12-Arima allows to check for the performance of additive and multiplicative seasonal adjustment through the slidingspans diagnostic. The slidingspans diagnostic is a measure of stability of the seasonally adjusted estimates. It applies the seasonal adjustment procedure to overlapping spans, with each span being adjusted as if it were a new series. If a month in a series belongs to more than two overslpping spans, the difference in the seasonally adjusted estimates in the different spans should not exceed 3%. If the difference is more than 3%, the month is flagged as unstable. We compare the number of months flagged as unstable through applying applying additive and multiplicative seasonal adjustment decomposition and find more unstable months through additive seasonal adjustment.

## 3 Steps in the seasonal adjustment procedure

Given that seasonality exists, it is important to model seasonality before the application of seasonal adjustment procedure. Seasonality in time series can be deterministic or stochastic. Stochastic seasonality can be stationary or non-stationary.

A visually appealing way of looking at the raw data is to plot the growth rates in each of the months across the years i.e the growth of April over March in each of the years from 1994 onwards. This gives us some idea of the presence of seasonal peaks, if any in the series.
The nature of seasonality can also be inferred intutively from the plot before the application of the testing procedures.

Presence of seasonal variations can be inferred from Figure 2, since the monthly means of growth rates across the years are not uniform.

### 3.1 Seasonal adjustment of car sales with X-12-ARIMA

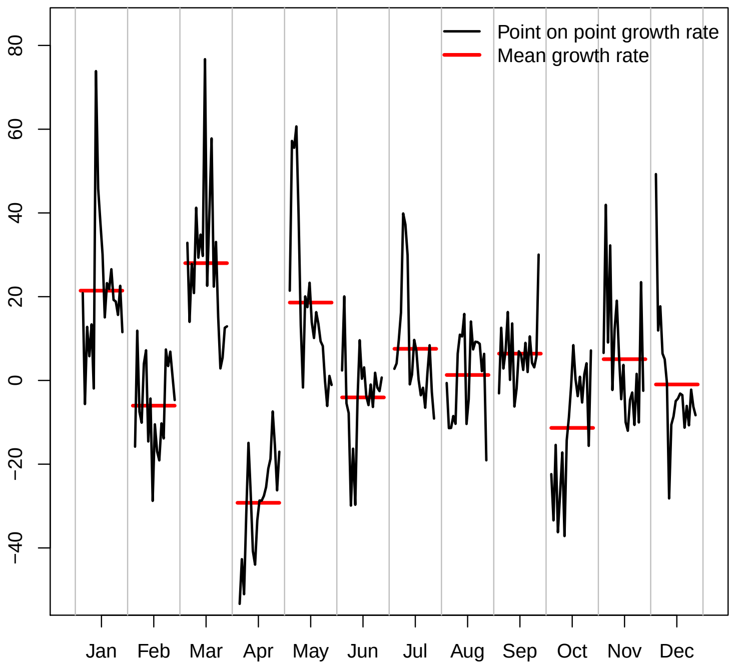
Seasonal adjustment is done with X-12-ARIMA method.

Figure 3 shows the non-seasonally and seasonally adjusted car sales. The plot reveals that the seasonal peaks are dampened after seasonal adjustment.

### 3.2 Diagnostic checks

After seasonal adjustment, a series of diagnostic checks are performed through relevant tests and quality assessment statistics.

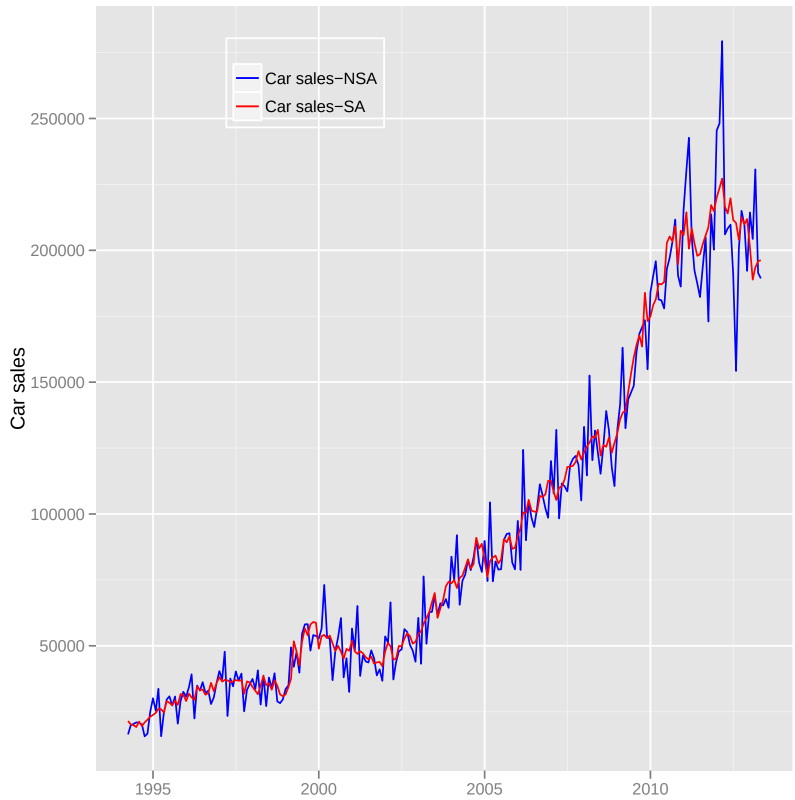
**Figure 2** Monthly growth rates across the years




### 3.2.1 Validation of the automodel choice by X-12-ARIMA

A test of validation of the auto model choice by X-12-ARIMA is the randomness of residuals of the fitted ARIMA model. The Ljung-Box test is conducted on the residuals of the fitted ARIMA model to check whether or not the residuals are white noise. The ACFs of the residuals are plotted to check for randomness. Figure 4 reveals that the residuals are white noise.

**Figure 3** Car sales (NSA and SA)




### 3.2.2 Presence of identifiable seasonality

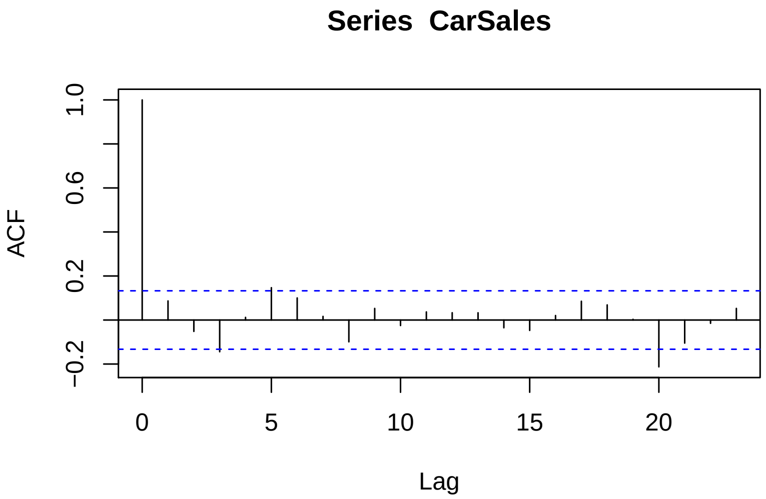
The statistic M7 shows the amount of moving seasonality present relative to stable seasonality. It shows the combined result for the test of stable and moving seasonality in the series. A value lesser than 1 is desirable to show identifiable seasonality in the series. The value of M7 for car production is 0.498 .

*Car sales series show identifiable seasonality on the basis of the M7 statistic.*

# 4 Spectral representation

Figure 5 shows the spectral plot of the growth rate of the unadjusted and seasonally adjusted series. Spectral plot, an important tool of the frequency domain analysis shows the portion of variance contributed by cycles of different frequencies.
The x-axis represent frequency from 0 to pi (3.14). The seasonal frequencies are pi/6 (0.52 on the x-axis), pi/3 (1.04 on the x-axis) , pi/2 (1.57 on the x-axis), 2pi/3 (2.09 on the x-axis) and 5 pi/6 (2.6 on the x-axis). In terms of periods (months); they are 12 months, 6 months, 4 months, 3 months and 2.4 months.
The figure at the lower panel shows that peaks at seasonal frequencies are eliminated after seasonal adjustment. For example the peaks at 1.04, 2.09 and 2.6 corresponding to 6 months,

**Figure 4** ACF of residuals




3 months and 2.4 months respectively, are eliminated after seasonal adjustment. Other peaks seen in the lower panel of the figure are not at seasonal frequencies.

**Figure 5** Car sales spectral plot (NSA and SA)