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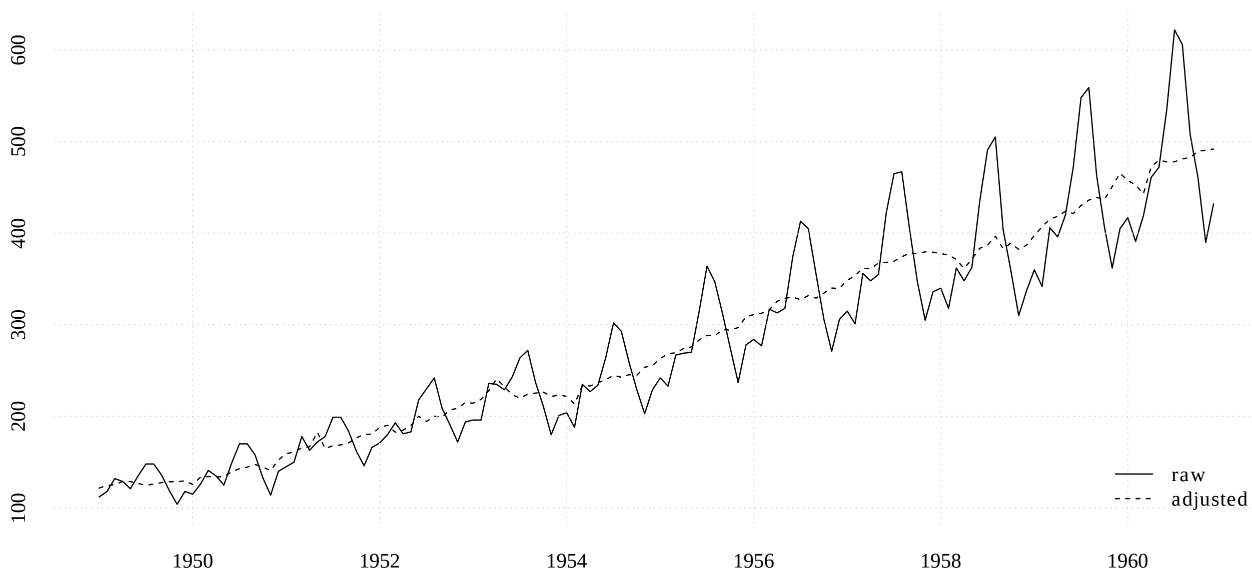
Abstract

An abstract of less than 150 words.

Overview

```
## Model:  seas(AirPassengers, x11 = "")
## View:   main
```



The X-11 method

The X-11 method is an iterative process, using appropriate moving averages to decompose a time series into trend/cycle, seasonal, and irregular components:

trend T_t long-term evolution of a time series

cycle C_t Smooth movement around the trend usually of longer period than the seasonal component. The X-11 method does not distinguish between trend and cycle and is usually refered to as trend/cycle component of a time series.

seasonal S_t Intra-year fluctuations repeated regularly year after year

irregular I_t Random fluctuations not explained by previous components

Additive vs Multiplicative Decomposition

Given an original time series X_t

Additive decomposition:

$$X_t = T_t + S_t + I_t$$

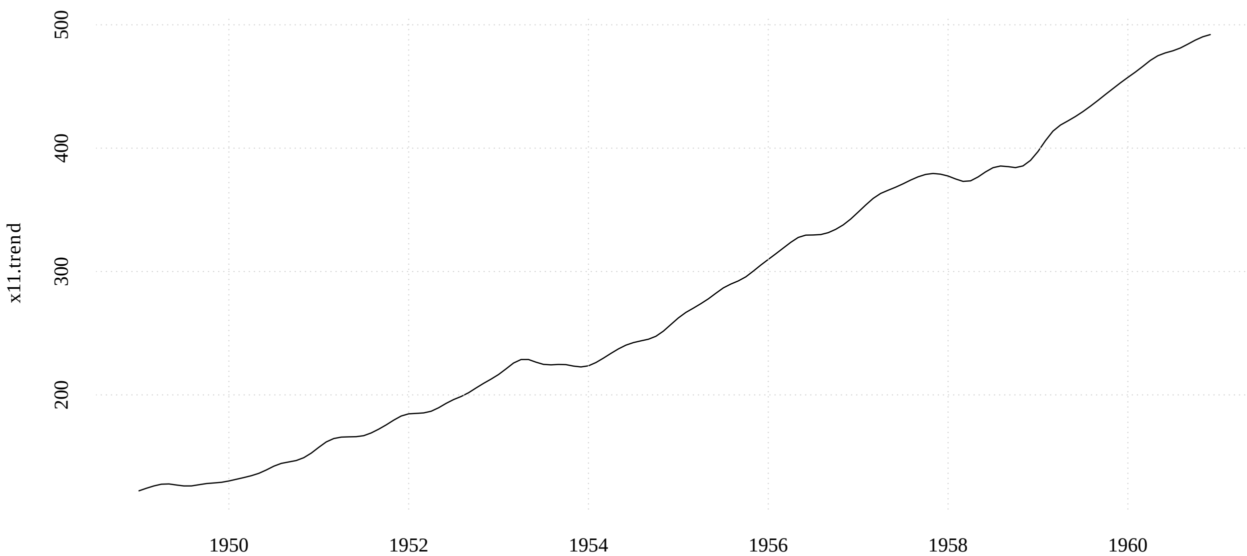
Multiplicitive decomposition:

$$X_t = T_t \cdot S_t \cdot I_t$$

How is this X-11 decomposition performed?

Estimate a trend

```
## Model:  seas(AirPassengers, x11 = "")
## View:   x11.trend
```



We omit the specific choice of weights for each moving average [to learn more about this see another "story"] and instead will refer to a moving averages by whether or not they estimate a trend (trend moving average) or a seasonal component (seasonal moving average)

Apply trend Moving Average

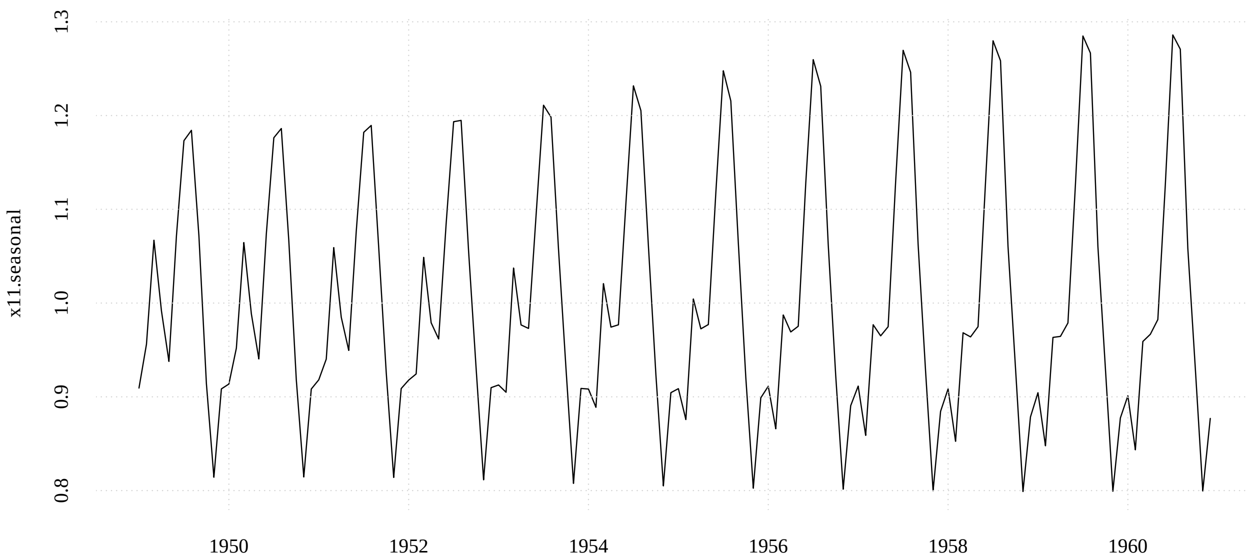
The first component that gets estimated is the trend/cycle component. It gets estimated by applying a moving average filter speficially for trends. An example of an estimated trend/cycle component is displayed at the right.

After Estimating Trent T_t Subtract it!

Here inlies the main concept of the X-11 method. By subtracting off our first estimate of the trend we in effect have a series that is free of long-term movement. The only remaining movement should be either seasonal or irregular.

Estimate seasonal component in the de-trended series

```
## Model:  seas(AirPassengers, x11 = "")
## View:   x11.seasonal
```



Recall we have a detrended series that has just had the estimated trend removed. Again we omit the detail of exactly how a seasonal moving average filter looks and acts.

Notice the *detrended* series is void of long term drift and is centered roughly around zero

Apply Seasonal Moving Average Filter

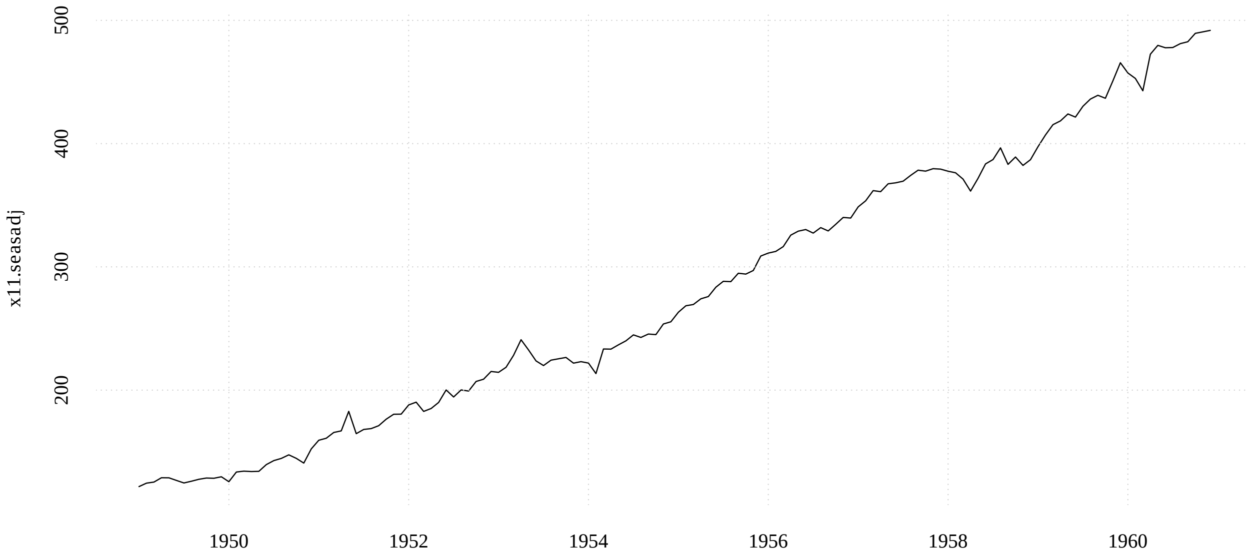
The second component that will be estimated is the seasonal component. An example of the estimated seasonal component (estimated from the de-trended series) is displayed at the right

We also have the Irregular series now too

By subtracting the newly estimated seasonal component from the de-trended series, we have in essence an original estimate of the irregular component.

Now we have our inital estimates

```
## Model:  seas(AirPassengers, x11 = "")
## View:   x11.seasadj
```



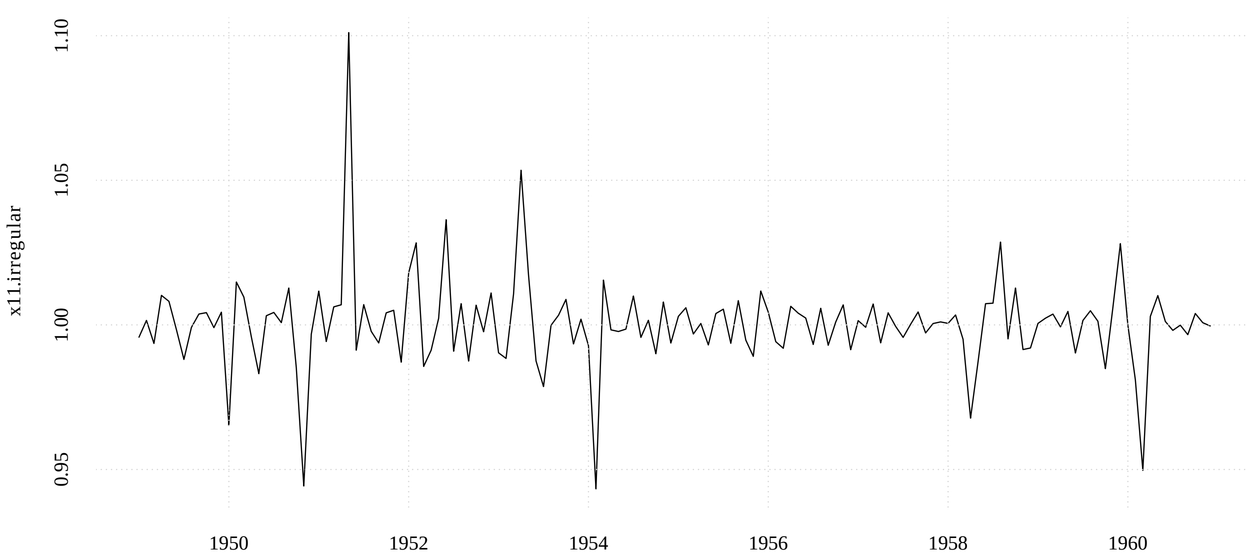
The first run through the X-11 moving average filters provides us with initial estimates of the trend, seasonal and irregualar components of our original time series

First Estimate of Seasonally Adjusted Series From these estimated

components, the first estimate of the seasonally adjusted series is given as: $A_t = \widehat{T}_t + \widehat{I}_t$

Estimate extreme values

```
## Model:  seas(AirPassengers, x11 = "")
## View:   x11.irregular
```



The irregular estimates give us a first glimpse into identifying extreme values and other regression typ effects…

Now estimate any nessesary regression effects

Since we have removed all trend and seasonallity, what is left are the irregular components. From these estimated values we can identify extremes and outliers. The irregular values are plotted along with some outliers idetified.

There are other effects that can be found from estimated irregular series. This includes trading day (TD) and holiday effects.

Trading Day effects

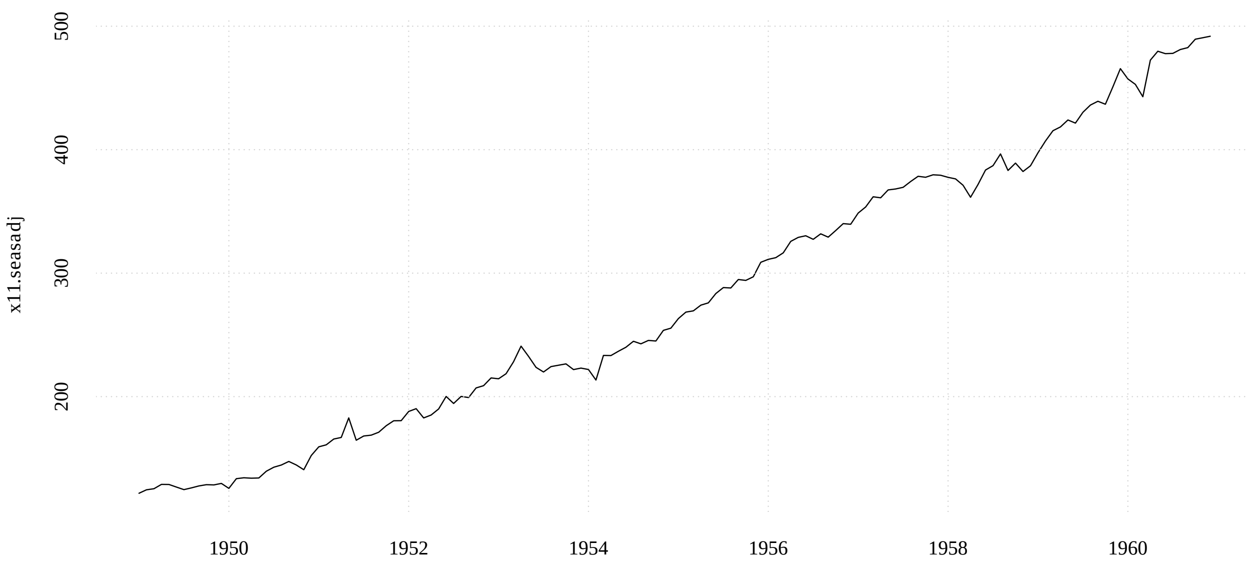
Measures the impact of the day-of-the-week composition of a month. For example, January 2016 will have 5 Fridays, 5 Saturdays, and 5 Sundays. While January 2013 had 4 Fridays, 4 Saturdays and 4 Sundays. This can have a dramatic effect on a seasonal adjustment

Moving Holiday Effects

Holidays that occur at the same time every year will be included in the seasonal component estimates. However, some holidays effect a time series and move from month-to-month e.g.) Easter which can call March or April depending on the calendar

Now iterate the method

```
## Model:  seas(AirPassengers, x11 = "")
## View:   x11.seasadj
```



The beauty of the X11 method is through iteration comes improved estimates of each trend, seasonal and irregular components.

A "less seasonal" trend

By construction of the moving average filters, the first estimates of the seasonally adjusted series A_t, MUST have less sesaonality than the original series X_t.

Repeat previous methodology on A_t

1. Estimate trend: use a trend moving average filter

2. Estimate seasonal and irregular: use seasonal moving average filter

3. Identify Extreme observation and calendar effects