

# Time Series Decomposition and Transforms

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# Transformations

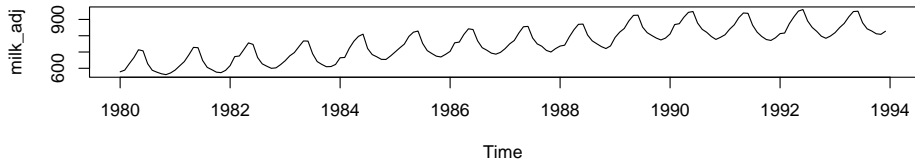
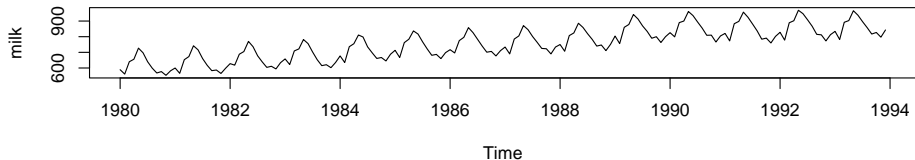
Trnasformation Are used to adjust historical data and often get a simple time series which are easier to model and lead to more accurate forecasts.

- Calendar adjustments
- Length of the month: since the different months of the year have different number of days and also because of leap year, one may adjust to the length of the month as follows:

$$W_t = \frac{X_t \times 365.25/12}{\text{no days in month } t}$$

- Number of working days
- Mathematical Transformations: to linearize the data and stabilize the variance- Box-Cox transformations (only positive data)

# Adjust for length of month: Monthly Milk Prod per cow



# Variance Stabilization - Box-Cox Transformations

To stabilize the variability over the series we use the Box-Cox transformations. A particular case is to log the data. Note that the multiplicative representation

$$y_t = T_t S_t R_t$$

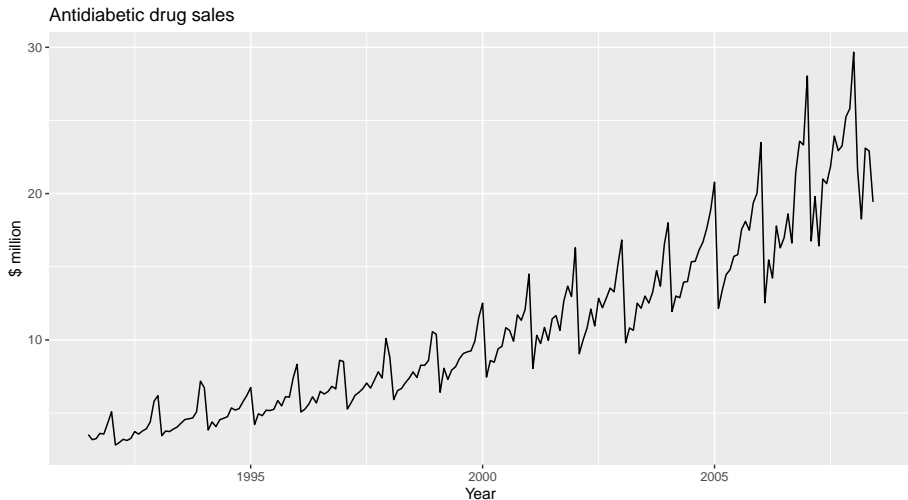
becomes

$$\log(y_t) = \log(T_t) + \log(S_t) + \log(R_t)$$

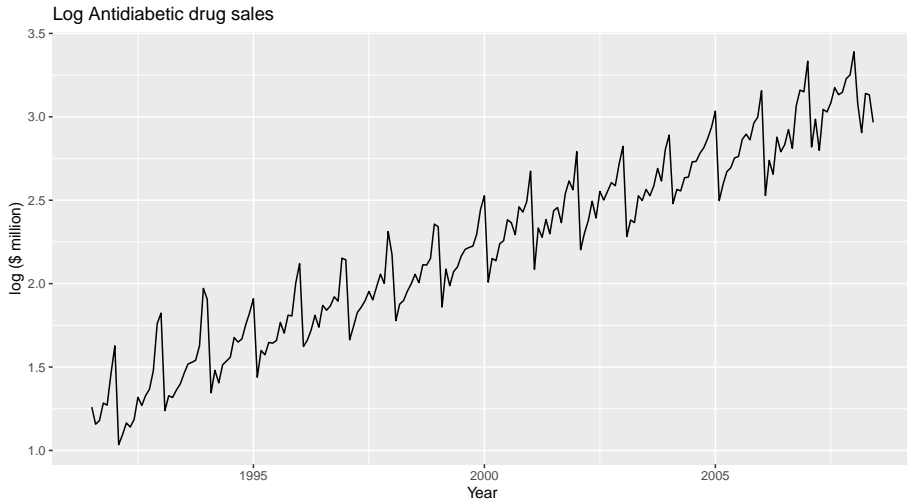
$$U_t = \begin{cases} \frac{X_t^\lambda - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \log X_t & \text{if } \lambda = 0 \end{cases}$$

These transforms are also used to improve approximation to normality (Gaussian distribution).

# Antidiabetic drug sales, a10



# Box-Cox (log) transform of a10



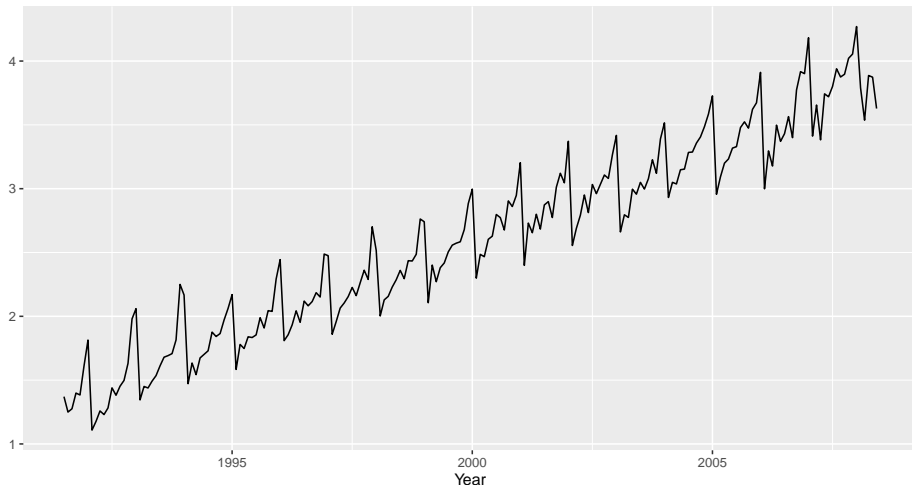
Now the variance is stable and the trend looks linear. Produce the season plots for the log data and comment.

# Finding the appropriate transform

To find the best Box-Cox transform - find  $\lambda$  that minimizes the variance.

```
## [1] 0.1313326
```

Box-Cox Antidiabetic drug sales



# Box-Cox Transform

- Log is the most used transformation
- When you model and forecast the transformed data then you need to back transform.
- Avoiding transforms is best



# Decomposition and filtering

- **Depending on the purpose of our study, our interest may be**

- ▶ the trend
- ▶ the seasonal component
- ▶ the random component
- ▶ all together

- **Approaches**

- ▶ Decomposition methods - estimate the trend /seasonal component
  - ★ with deterministic functions
  - ★ smooth functions- moving averages
  - ★ STL
- ▶ Filtering methods - Difference and Seasonal Difference

# Time Series Decomposition

- **Trend-Cycle**- aperiodic changes in level over time + **Seasonal** - (almost) periodic changes in level due to seasonal factors
- \*\*Additive decomposition

$$y_t = T_t + S_t + R_t$$

- ▶  $y_t$  data at time  $t$
- ▶  $T_t$  trend-cycle component at time  $t$
- ▶  $S_t$  seasonal component at time  $t$
- ▶  $R_t$  remainder component at time  $t$

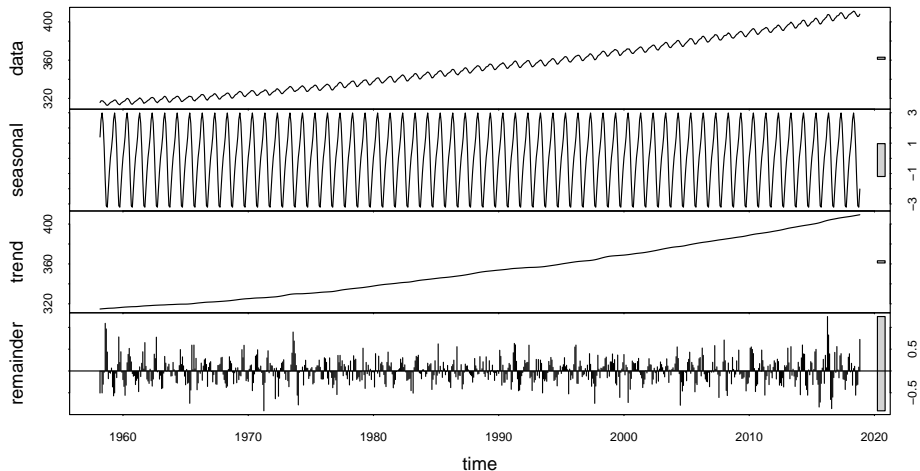
# Time Series Decomposition by Loess - STL

- The Seasonal Decomposition of Time Series by Loess is implemented in R in the `stl()` function
- Decomposes a time series into seasonal, trend and irregular components using loess
- Loess is a robust weighted regression smoothing method close to nearest neighbour regression
- The seasonal component is found by loess smoothing the seasonal sub-series (the series of all January values, ...)
- If `s.window = "periodic"` smoothing is effectively replaced by taking the mean
- The seasonal values are removed, and the remainder smoothed to find the trend
- The overall level is removed from the seasonal component and added to the trend component. This process is iterated a few times
- The remainder component is the residuals from the seasonal plus trend fit.

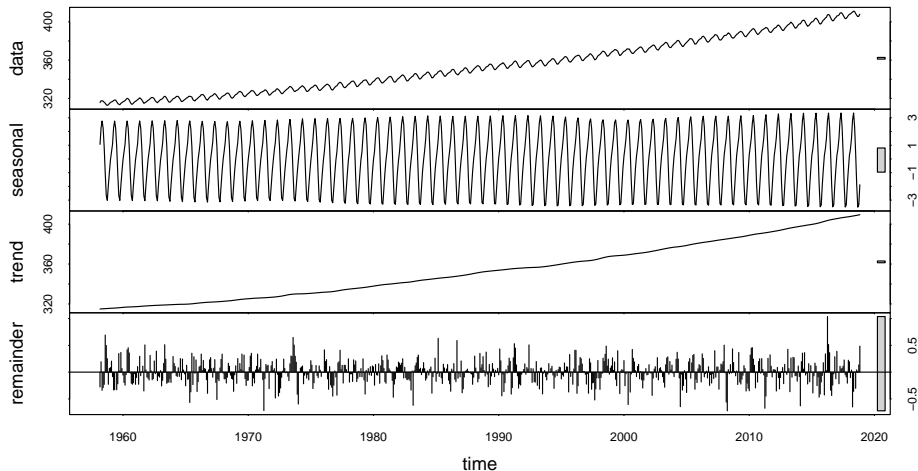
# STL decomposition

- Versatile and Robust
- Seasonal component allowed to change overtime and rate of change controlled by the user
- Smoothness of trend-cycle controlled by the user
- Optionally robust to outliers
- No calendar adjustments
- Only additive
- You need to log the data if multiplicative decomposition is needed

# STL decomposition of Cardox - fixed periodicity



# STL decomposition of Cardox - not fixed periodicity

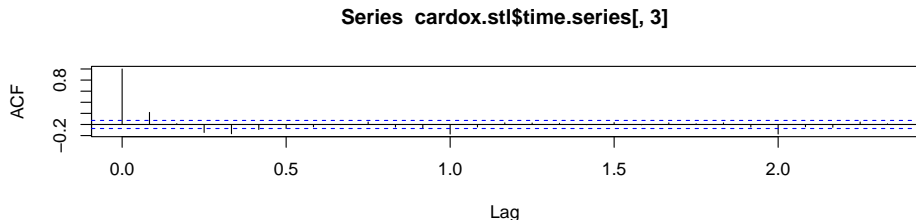
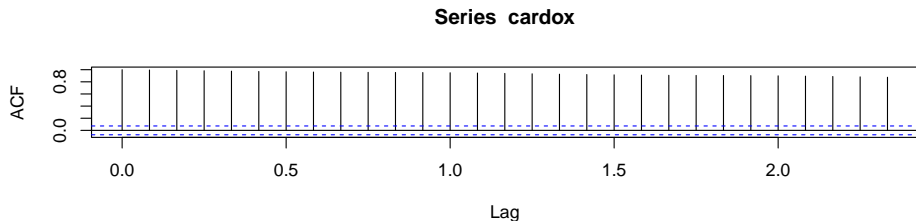


# STL components

```
head(cardox.stlper$time.series)
```

| ## |     |      | seasonal   | trend    | remainder   |
|----|-----|------|------------|----------|-------------|
| ## | Mar | 1958 | 1.4039091  | 314.8115 | -0.50536160 |
| ## | Apr | 1958 | 2.5512431  | 314.9140 | -0.01528735 |
| ## | May | 1958 | 2.9864460  | 315.0166 | -0.50308202 |
| ## | Jun | 1958 | 2.2977101  | 315.1059 | -0.30364134 |
| ## | Jul | 1958 | 0.6929085  | 315.1952 | -0.02813505 |
| ## | Aug | 1958 | -1.4385111 | 315.2765 | 1.09200191  |

# Investigate the correlation behaviour of the remainder.





## Some notation

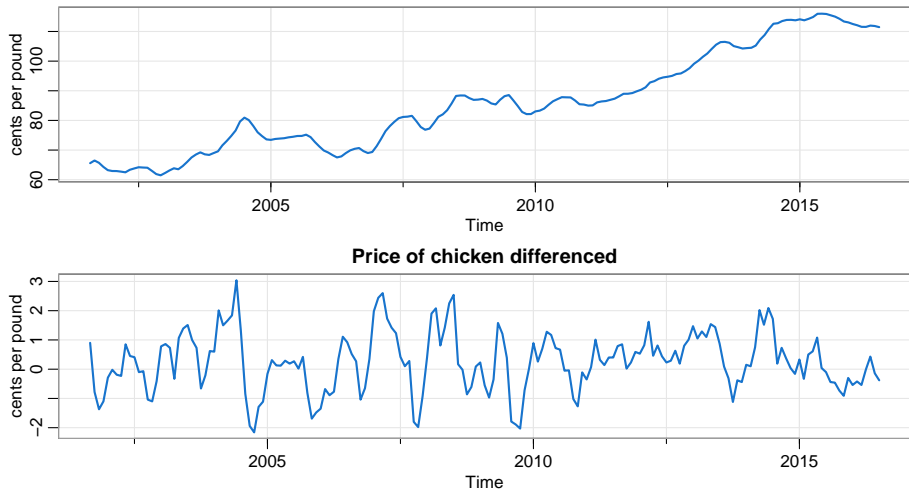
- $x_t$  denotes the observation at time  $t$
- $B$  is called the **backshift or lag** operator:  $Bx_t = x_{t-1}$
- $B^{12}x_t = x_{t-12}$
- $\nabla = 1 - B$  the **difference operator**:  
 $\nabla x_t = (1 - B)x_t = x_t - Bx_t = x_t - x_{t-1}$
- 

$$y_t = \nabla x_t = x_t - x_{t-1}$$

represents the increments or change of the variable  $x$  on consecutive time points

- Applying the difference operator is said **Differencing** and can help stabilise the mean of a time series by removing changes in the level of a time series and therefore eliminating (or reducing) trend

# The difference operator applied to the Monthly Price of Chicken

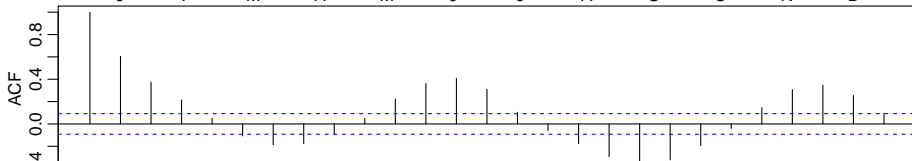
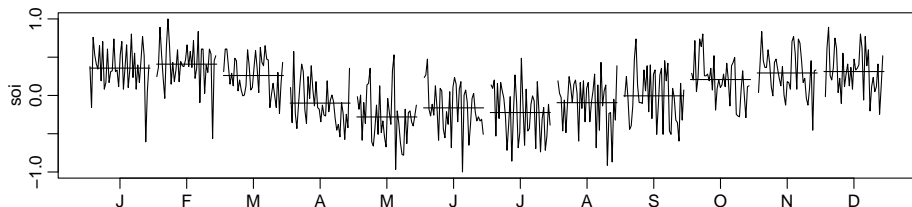
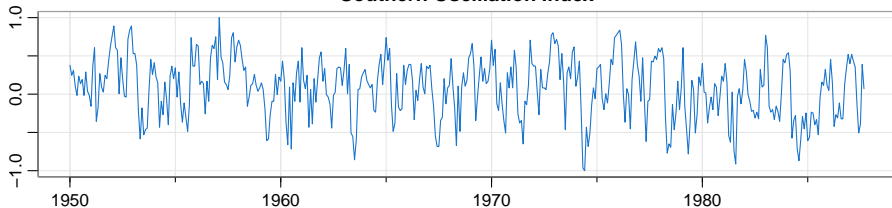


# Seasonal difference operator

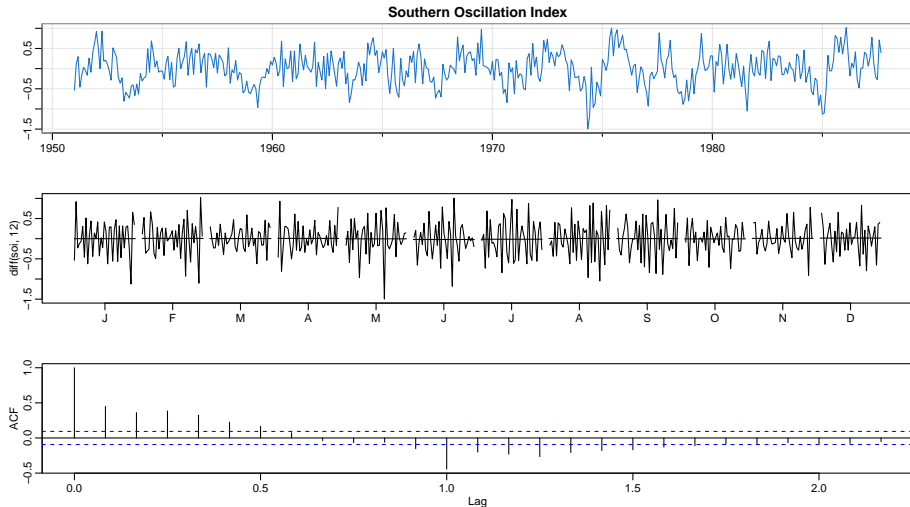
- Seasonal difference operator  $\nabla_S = 1 - B^S$ , where  $S$  is the seasonality
- $y_t = \nabla_S x_t = x_t - x_{t-S}$  represents the increments or change of the variable  $x$  over consecutive seasonal periods.
- If  $S = 12$  then  $y_t$  represents the increments from one year to the next
- Applying the seasonal difference operator can help stabilise the mean of a time series by removing changes in the level due to seasonality

# SOI (Southern Oscillation Index)

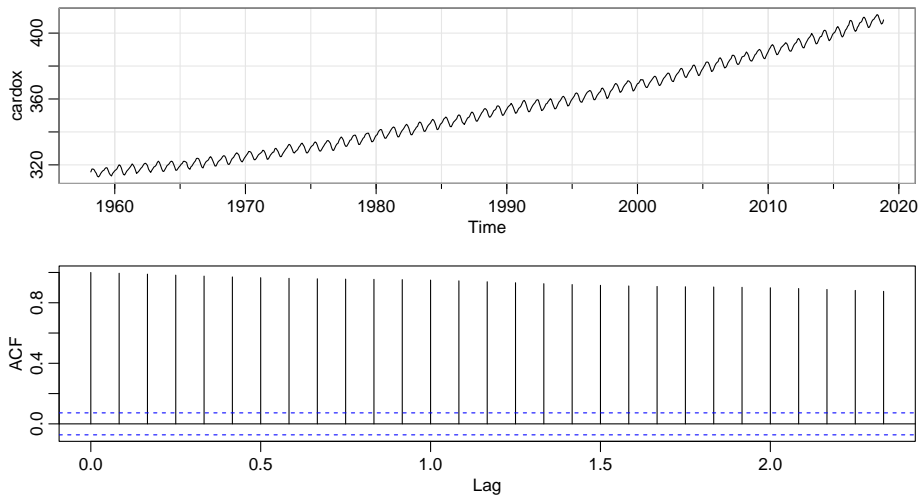
## Southern Oscillation Index



# Seasonally differenced SOI (Southern Oscillation Index)

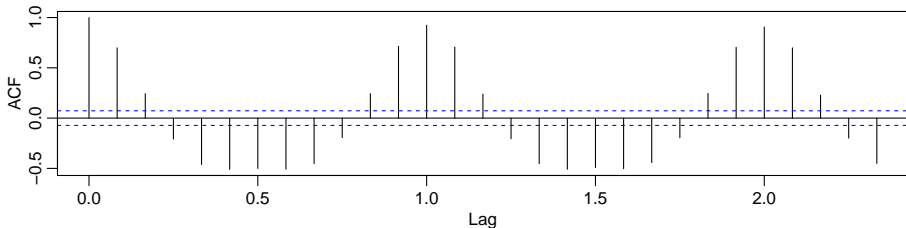
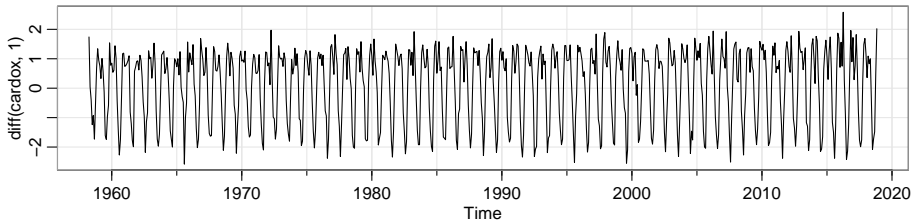


# Differencing time series with trend and seasonality



## Differencing time series with trend and seasonality - CARDOX

## 1 simple difference of Cardox

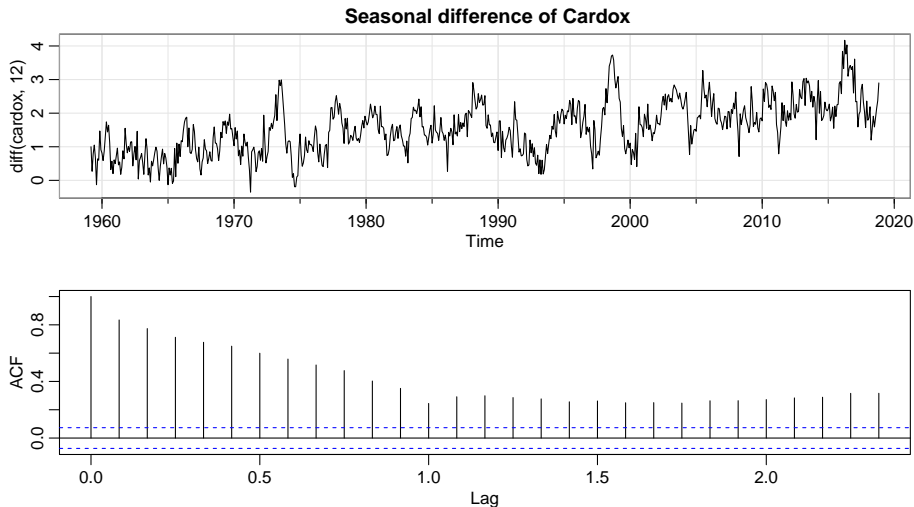


# Differencing time series with trend and seasonality - CARDOX

Simple differences, changes in carbon dioxide from month to month, show a seasonal cycle



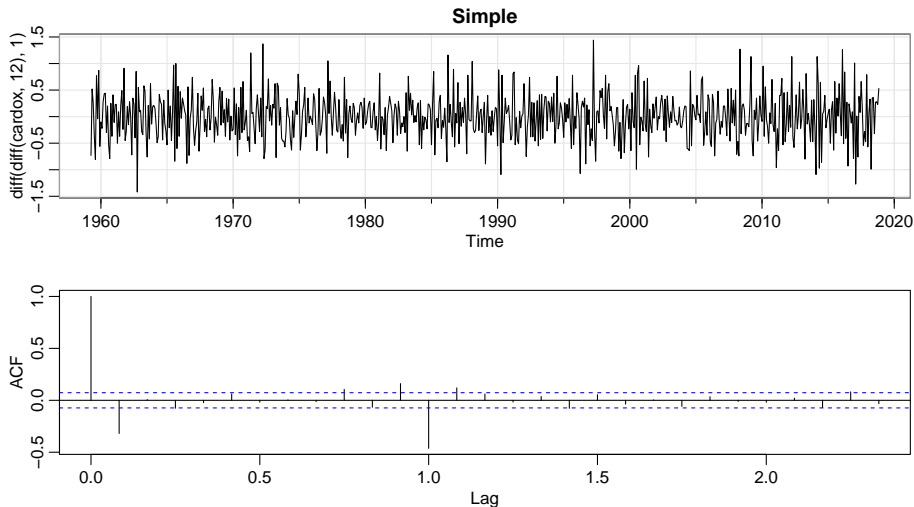
# Differencing time series with trend and seasonality - CARDOX



# Differencing time series with trend and seasonality

Seasonal differences, changes in carbon dioxide from one month to the same month next year , show some trend

# Differencing time series with trend and seasonality



# Differencing time series with trend and seasonality

- When we apply both operators, simple and seasonal the filtered data no longer presents trend or seasonality.
- Why is this important?