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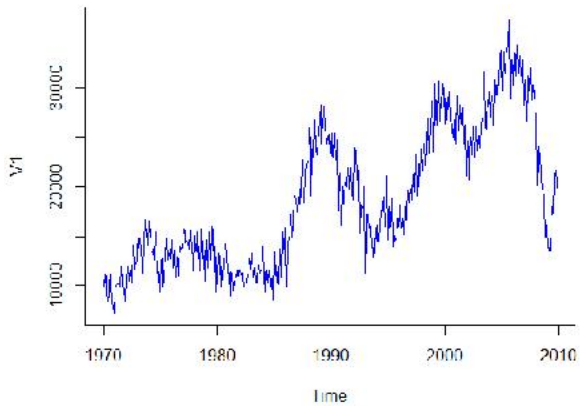
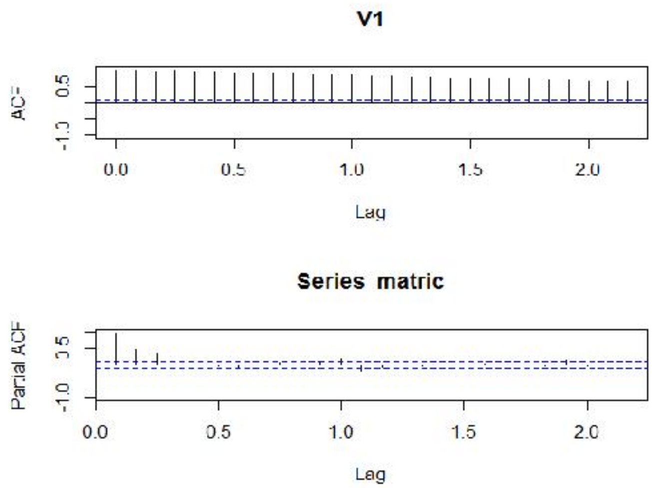
Practical Assignment 1 – SERIES TEMPORALES (Time Series)

Series 1

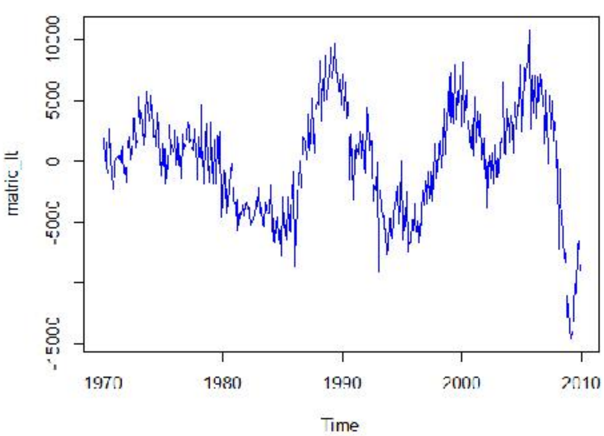
File: "matric.dat" Number of vehicles registered in Catalonia.
Monthly data for 1970.1 to 2009.12. Source: General Directorate of Traffic

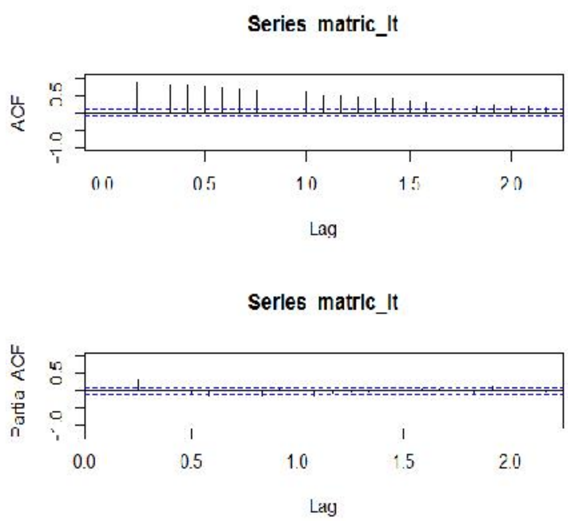




The above pictures are showing the original plot of the "matric.dat" data. By looking at the Plot, ACF and Partial ACF, the time series is non-stationary; which shows that the time series is increasing approximately linearly with time.

<u>Transformation of data </u>– Liner Trend

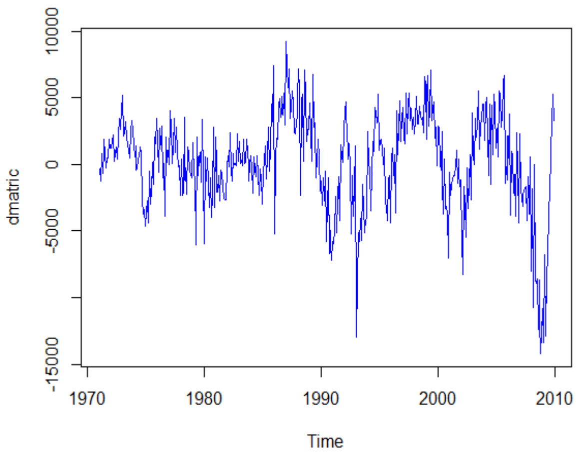


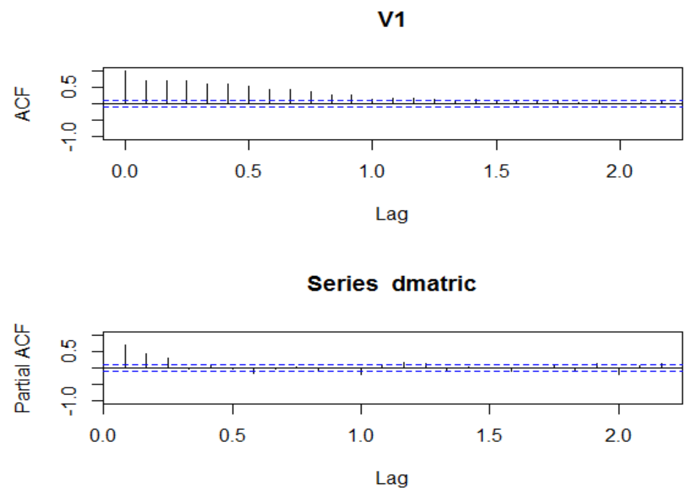


The above pictures are showing a liner
transformation plot of the data. In many situations, it is desirable or necessary to transform a time series data set before using the sophisticated methods.

The ACF shows that the de-treading of data but it still needs a little more observation because in ACF lags do not tail off quickly. So, we need to apply the first difference before selecting a model.

Difference





The above pictures are showing a first difference plot of the data with the ACF and Partial ACF to show a better view of the data. ACF shows that the data tail off very well and no seasonality exists.

Estimation

Looking at the first difference of the data, we can see clearly see that Partial ACF shows a 3 lag tail off. So, we need to selected a AR(3) and moving average smoothing MA(1) on the data. Apply the ARMA model ARMA(3,1)

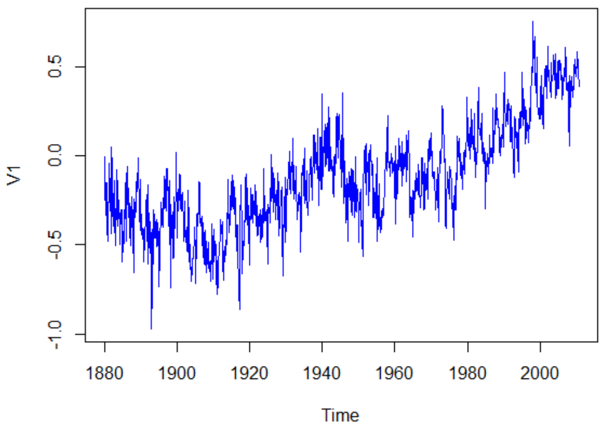
Note: There are other possible ARMA models that we can select.

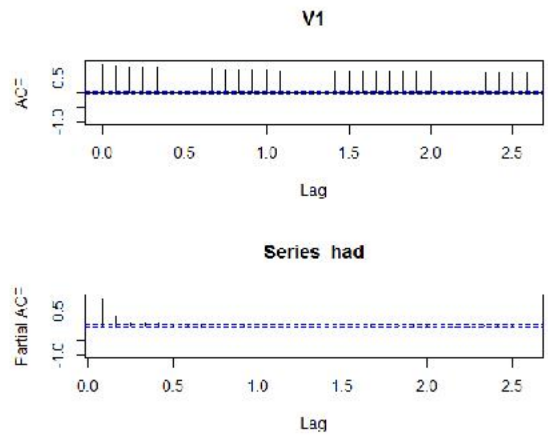
Below show the ARMA model selected for this time series.

```
> model<-arima(dmatric,c(3,0,1))
> model

Call:
arima(x = dmatric, order = c(3, 0, 1))

Coefficients:
         ar1     ar2     ar3     ma1  intercept
      0.1609  0.3572  0.3265  0.1182   258.0758
s.e.  0.1779  0.0815  0.0810  0.1903   753.0819

sigma^2 estimated as 5388311:  log likelihood = -4291.63,  aic = 8595.26
```

Series 2

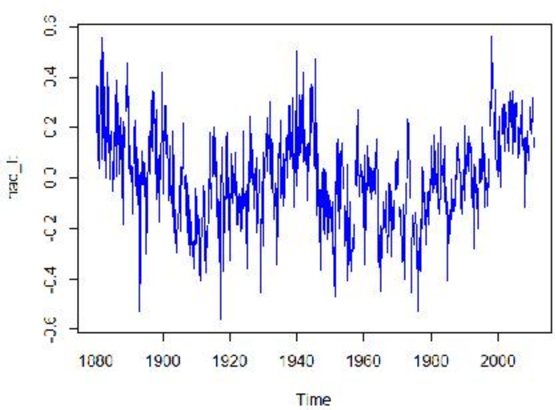
File: "had.dat"
"Anomaly" in global mean temperature (difference relative to a reference value set in analyzes of climate change). Monthly data from 1880.1 to 2009.9. Source: Hadley Centre of the UK Met Office

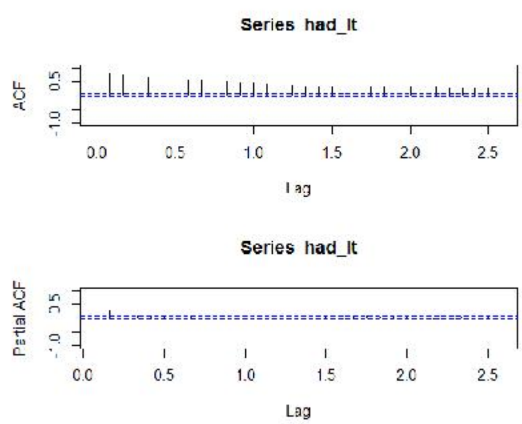




The above pictures are showing the original plot of the "had.dat" data. By looking at the Plot, ACF and Partial ACF, the time series is non-stationary and seasonality; which shows that the time series is increasing approximately linearly with time and seasonal component within the data.

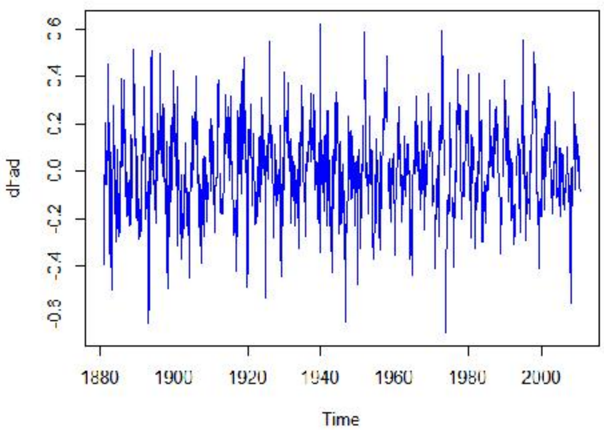
<u>Transformation of data</u> – Liner Trend

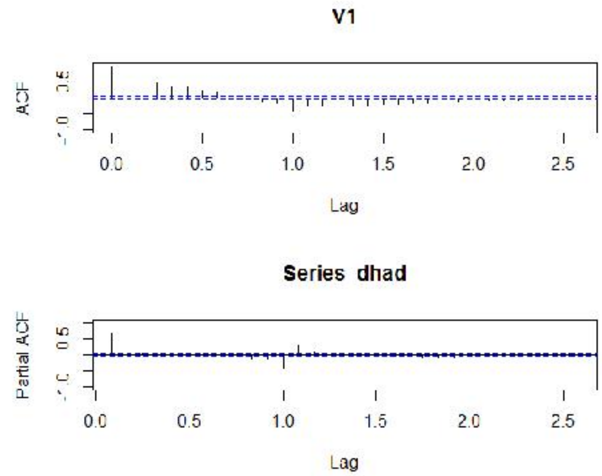




The above pictures are showing a liner transformation plot of the data. In many situations, it is desirable or necessary to transform a time series data set before using the sophisticated methods. The ACF shows that the de-treading of data but it still needs a little more observation because in ACF lags do not tail off quickly. So, we need to apply the first difference before selecting a model.

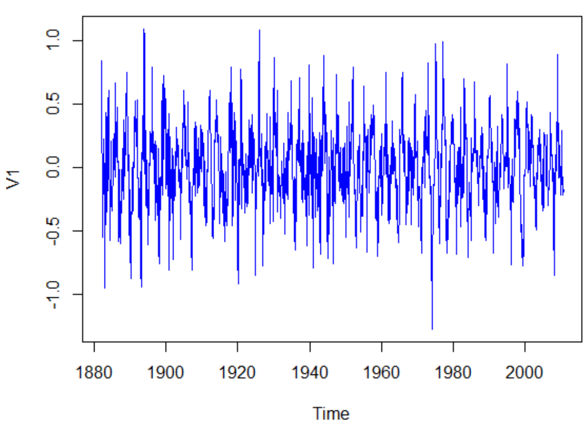
Difference

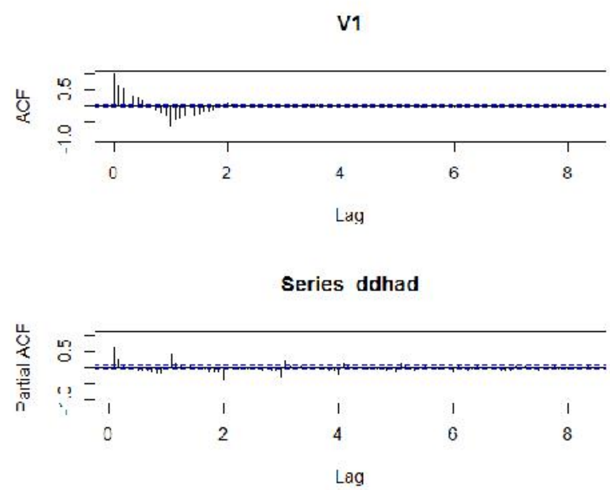




The above pictures are showing a first difference plot of the data with the ACF and Partial ACF to show a better view of the data. They show that the data tail off very well but seasonality exists.

Seasonal Difference





The above pictures are showing a seasonal difference plot of the data with the ACF and Partial ACF at lag=100 to show a better view of the data. They show that the data and seasonality tail off very quickly. This serves as a good transformation to select an ARMA model.

Estimation

Looking at the first difference of the data, we can see clearly see that Partial ACF shows a 2 lag tail off. So, we need to selected a AR(2) and moving average smoothing MA(1) on the data. Apply the ARMA model ARMA(2,1)

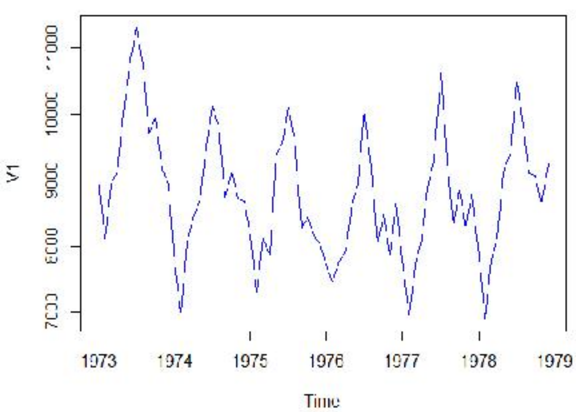
Note: There are other possible ARMA models that we can select.

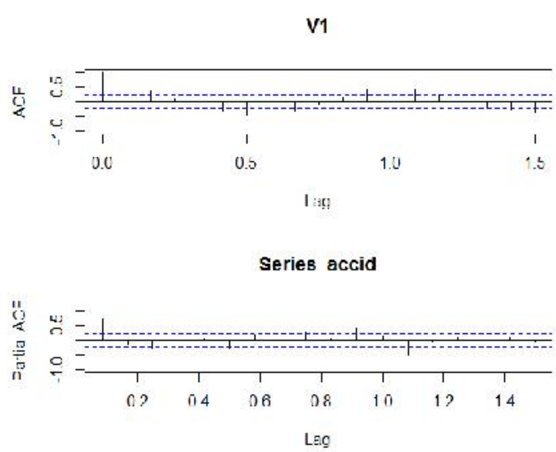
Below show the ARMA model selected for this time series.

```
> model2<-arima(ddhad,c(2,0,1))
> model2

Call:
arima(x = ddhad, order = c(2, 0, 1))

Coefficients:
         ar1     ar2      ma1  intercept
      0.6207  0.1334  -0.1465     0.0012
s.e.  0.1011  0.0672   0.1009     0.0211

sigma^2 estimated as 0.05736:  log likelihood = 15.57,  aic = -21.14
```

Series 3

File: "accidents.dat"
Deaths in road accidents in the US. Monthly data from 1973.1 to 1978.12





The above pictures are showing the original plot of the "accidents.dat" data. By looking at the Plot, ACF and Partial ACF, the time series is stationary; which shows that the time series is not changing with time. We can also say that it is a good selection of a white noise in our plot.

Estimation

Looking at the original data, we can see clearly see that Partial ACF shows a 1 lag tail off. So, we need to selected a AR(1) and moving average smoothing MA(1) on the data. Apply the ARMA model - ARMA(1,1)

Note: There are other possible ARMA models that we can select.

Below show the ARMA model selected for this time series.

```
> model3<-arima(accid,c(1,0,1))
> model3

Call:
arima(x = accid, order = c(1, 0, 1))

Coefficients:
         ar1     ma1  intercept
      0.6228  0.1677  8810.5605
s.e.  0.1158  0.1347   236.4644

sigma^2 estimated as 440533:  log likelihood = -570.37,  aic = 1148.74
```