Timeseries analysis in R, in statistics time series, is one of the vast subjects, here we are going to analyze some basic functionalities with the help of R software.

The idea here is to how to start time series analysis in R. In this tutorial will go through different areas like decomposition, forecasting, clustering, and classification.

Cluster Analysis in R (https://finnstats.com/index.php/2021/04/20/cluster-analysis-in-r/)

Getting Time series data

```
data("AirPassengers")
AP <- AirPassengers
str(AP)
```

```
Time-Series [1:144] from 1949 to 1961: 112
118 132 129 121 135 148 148 136 119 ...
```

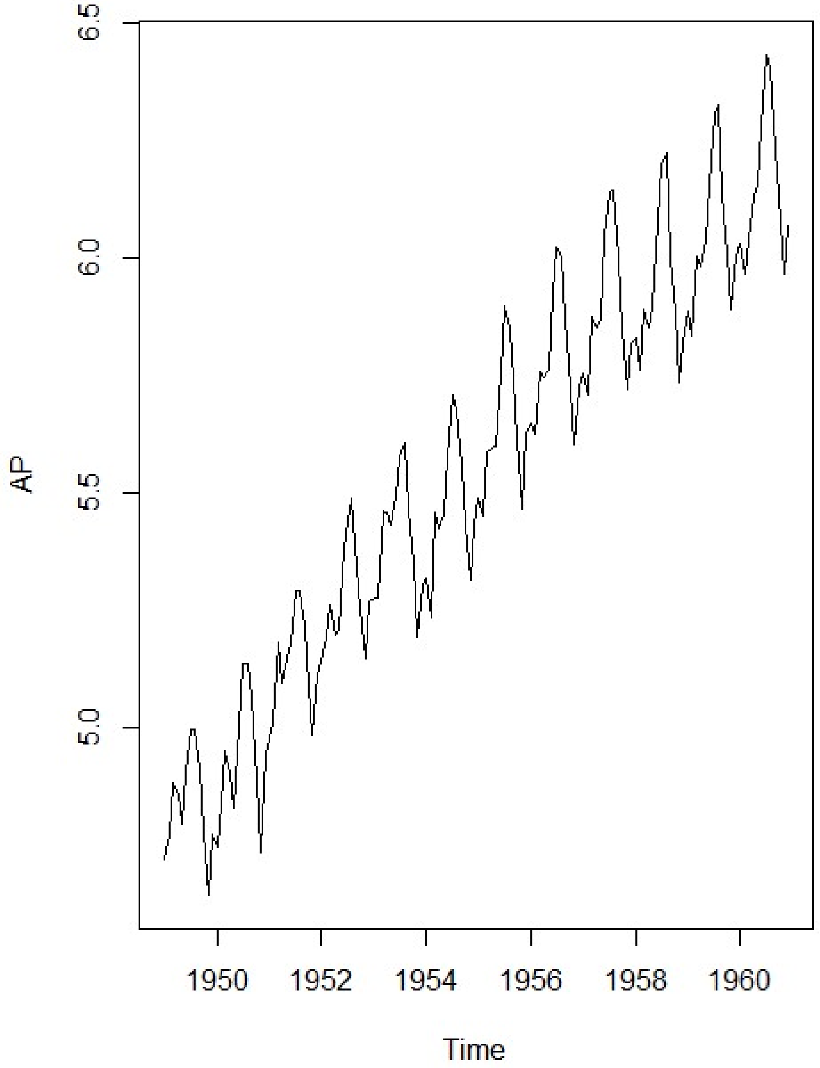
Year is starting from 1949 and ending with 1961 with 144 observations.

Now we need to convert the dataset into timeseries data.

```
ts(AP, frequency = 12, start=c(1949,1))
```

```
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov
Dec
1949 112 118 132 129 121 135 148 148 136 119
104 118
1950 115 126 141 135 125 149 170 170 158 133
114 140
1951 145 150 178 163 172 178 199 199 184 162
146 166
1952 171 180 193 181 183 218 230 242 209 191
172 194
1953 196 196 236 235 229 243 264 272 237 211
180 201
1954 204 188 235 227 234 264 302 293 259 229
203 229
1955 242 233 267 269 270 315 364 347 312 274
237 278
1956 284 277 317 313 318 374 413 405 355 306
271 306
1957 315 301 356 348 355 422 465 467 404 347
305 336
1958 340 318 362 348 363 435 491 505 404 359
310 337
1959 360 342 406 396 420 472 548 559 463 407
362 405
1960 417 391 419 461 472 535 622 606 508 461
390 432
```

```
plot(AP)
```

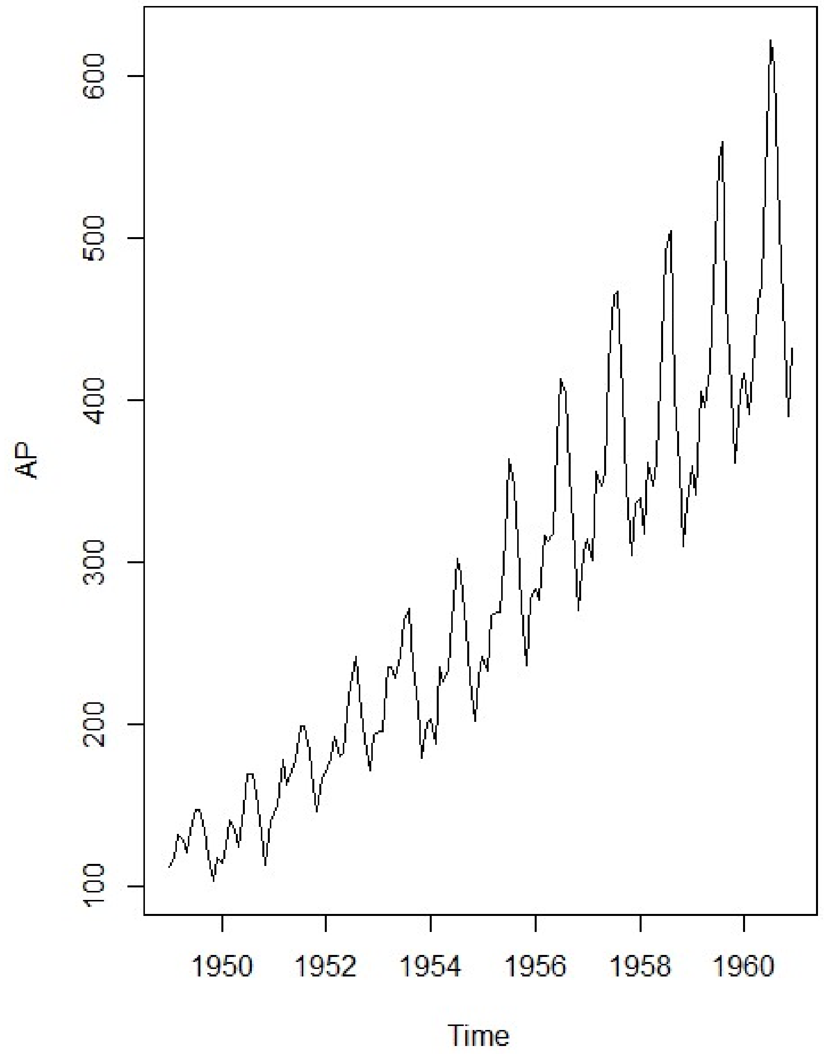


This data looks stationary and we can go for log transformation for nonstationary data.

Timeseries analysis in R

Log transform

```
AP <- log(AP)
plot(AP)
```



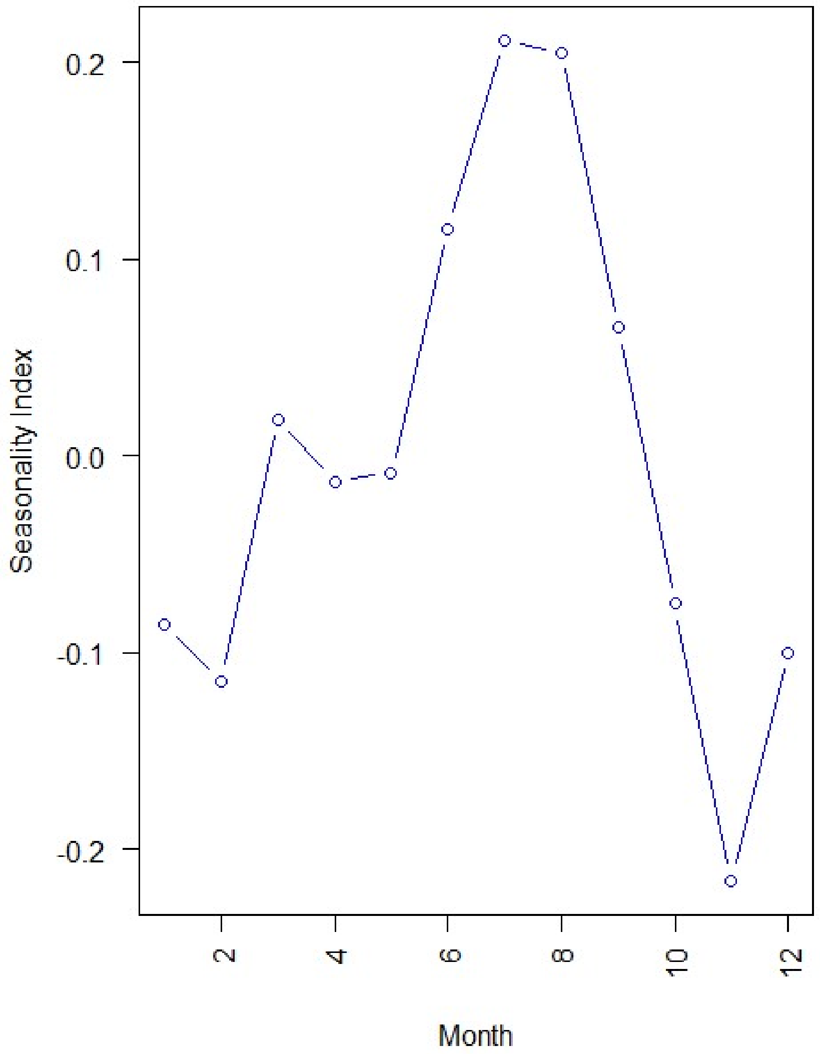
Decomposition of additive time series

[Major components of time series](https://finnstats.com/index.php/2021/02/16/components-of-time-series-analysis/) (https://finnstats.com /index.php/2021/02/16/components-of-time-series-analysis/)

```
decomp <- decompose(AP)
decomp$figure
```

```
[1] -0.085815019 -0.114412848  0.018113355
-0.013045611 -0.008966106  0.115392997
0.210816435  0.204512399  0.064836351
-0.075271265 -0.215845612 -0.100315075
```

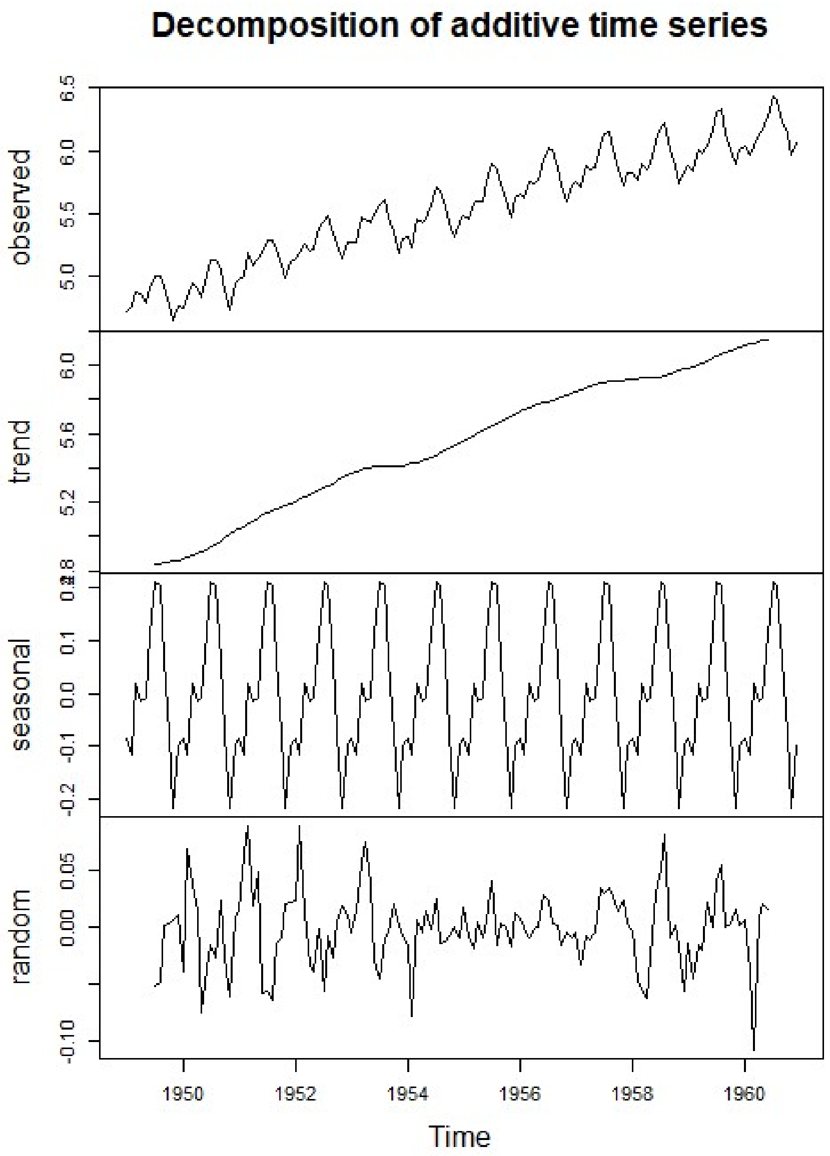
```
plot(decomp$figure,
     type = 'b',
     xlab = 'Month',
     ylab = 'Seasonality Index',
     col = 'blue',
     las = 2)
```



In this dataset currently in log form, Month 11 showing -20% downside, and Month 7 and 8 showing 20% upper side.

[Tidyverse tricks in R (https://finnstats.com/index.php/2021/04/02/tidyverse-in-r/)](https://finnstats.com/index.php/2021/04/02/tidyverse-in-r/)

```
plot(decomp)
```



Basically, the time series split into three component trend, seasonal and random.

Forecasting

ARIMA – Autoregressive Integrated Moving Average

```
library(forecast)
model <- auto.arima(AP)
model
```

```
Series: AP
ARIMA(0,1,1)(0,1,1)[12]
Coefficients:
          ma1     sma1
      -0.4018  -0.5569
s.e.   0.0896   0.0731
sigma^2 estimated as 0.001371:  log
likelihood=244.7
AIC=-483.4   AICc=-483.21   BIC=-474.77
```

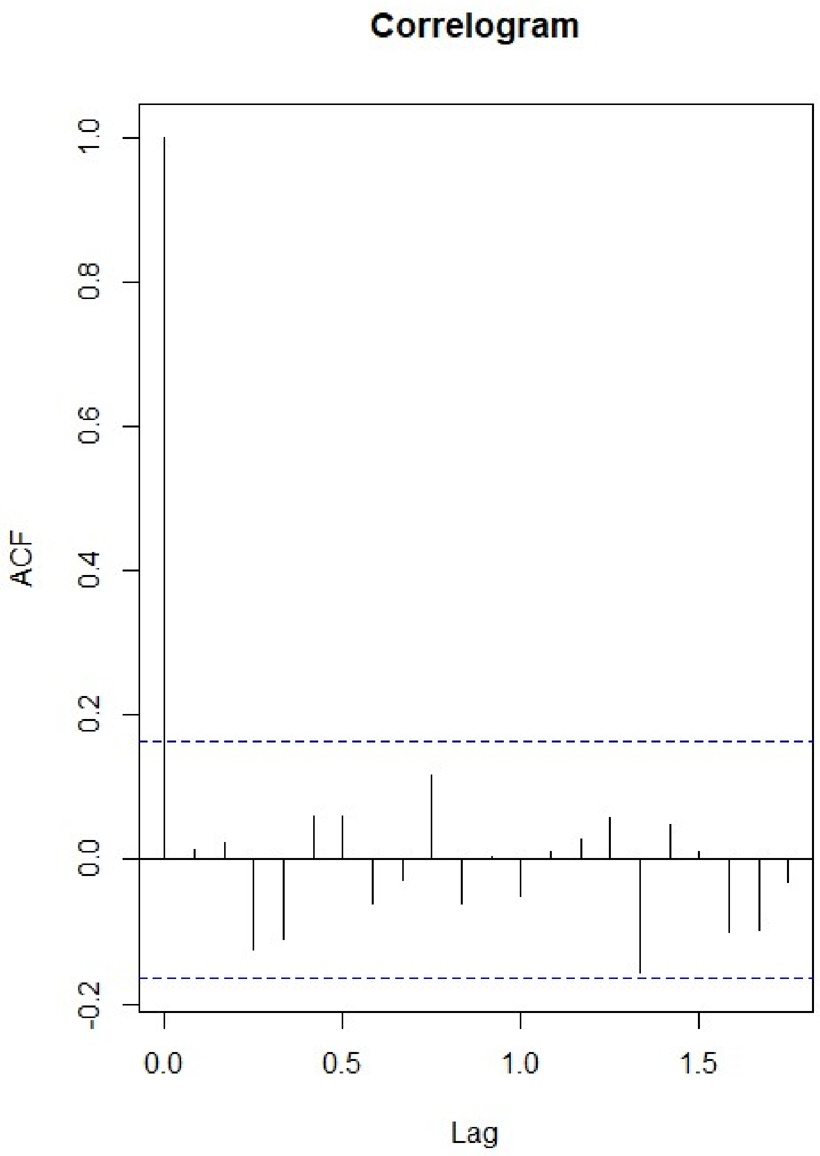
AIC and BIC will help us to choose the best time series model.

[Repeated Measures of ANOVA in R (https://finnstats.com/index.php/2021/04/06/repeated-measures-of-anova-in-r/)](https://finnstats.com/index.php/2021/04/06/repeated-measures-of-anova-in-r/)

ACF and PACF plots

It is always looking into ACF and PACF when we are dealing with time series data.

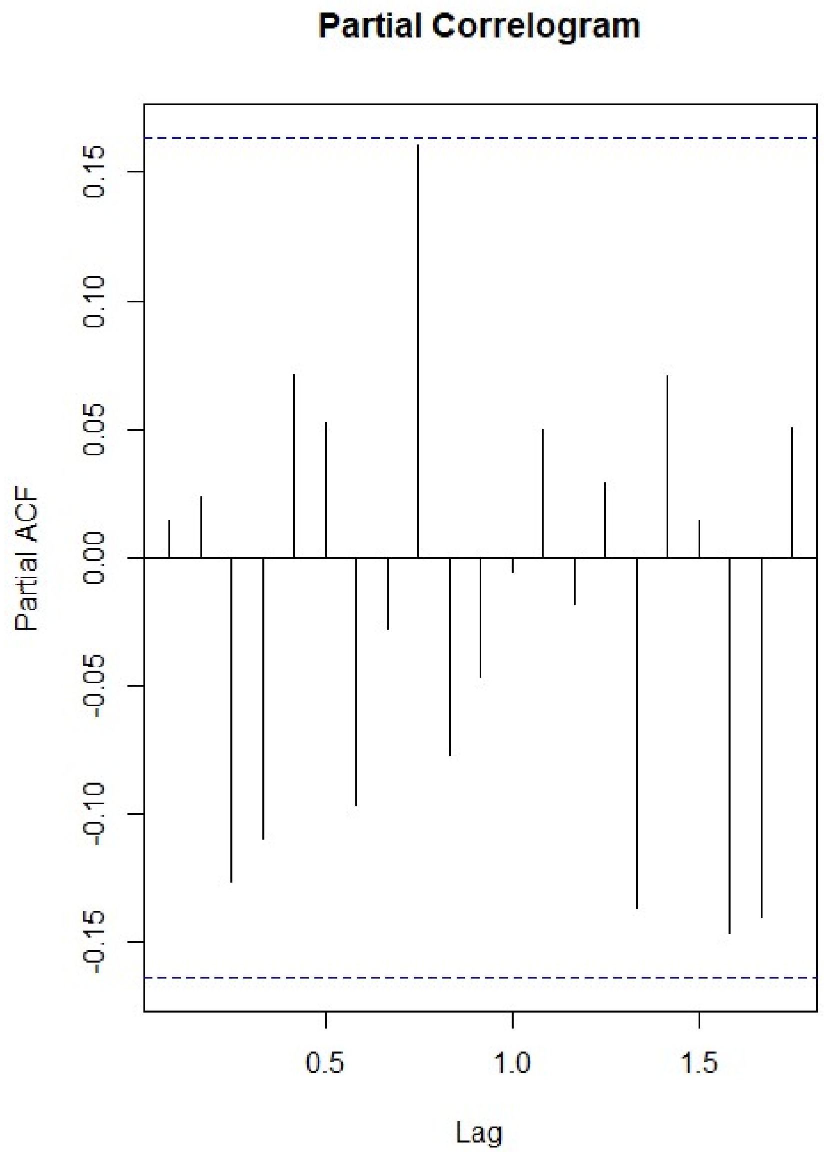
```
acf(model$residuals, main = 'Correlogram')
```



The dotted lines are significant bounds. A log 0 its crossing the significance bound.

Within 1 and 1.5 its just touching the significance bounds

```
pacf(model$residuals, main = 'Partial
Correlogram' )
```



In this case all the lags are within significant bounds.

Deep Neural Network in R (https://finnstats.com/index.php/2021/04/10/neural-network-in-r/)

Ljung-Box test

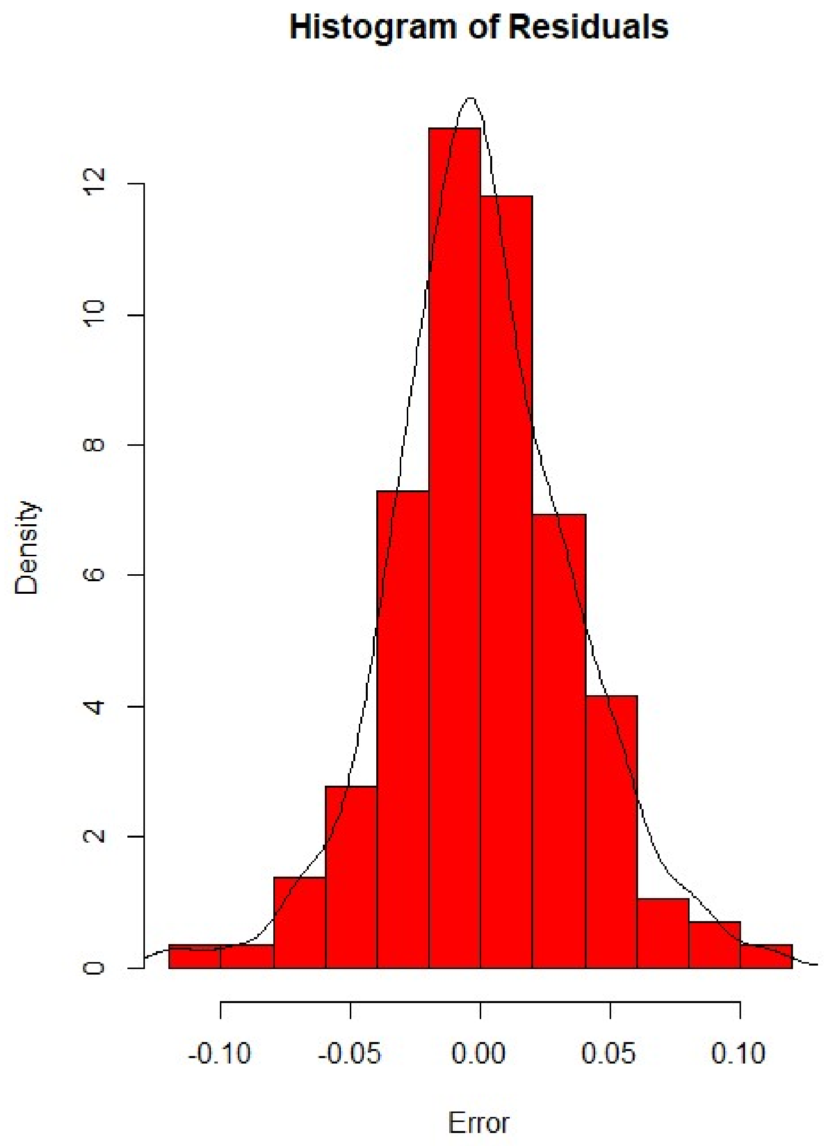
```
Box
lag
typ
=
'Lj
Box
```

```
Box-Ljung test
data:  model$residuals
X-squared = 17.688, df = 20, p-value =
0.6079
```

No significant difference was observed that indicates autocorrelation observed at lag 1 and 1.5 may be due to random chance.

Residual plot

```
hist(model$residuals,
     col = 'red',
     xlab = 'Error',
     main = 'Histogram of Residuals',
     freq = FALSE)
lines(density(model$residuals))
```

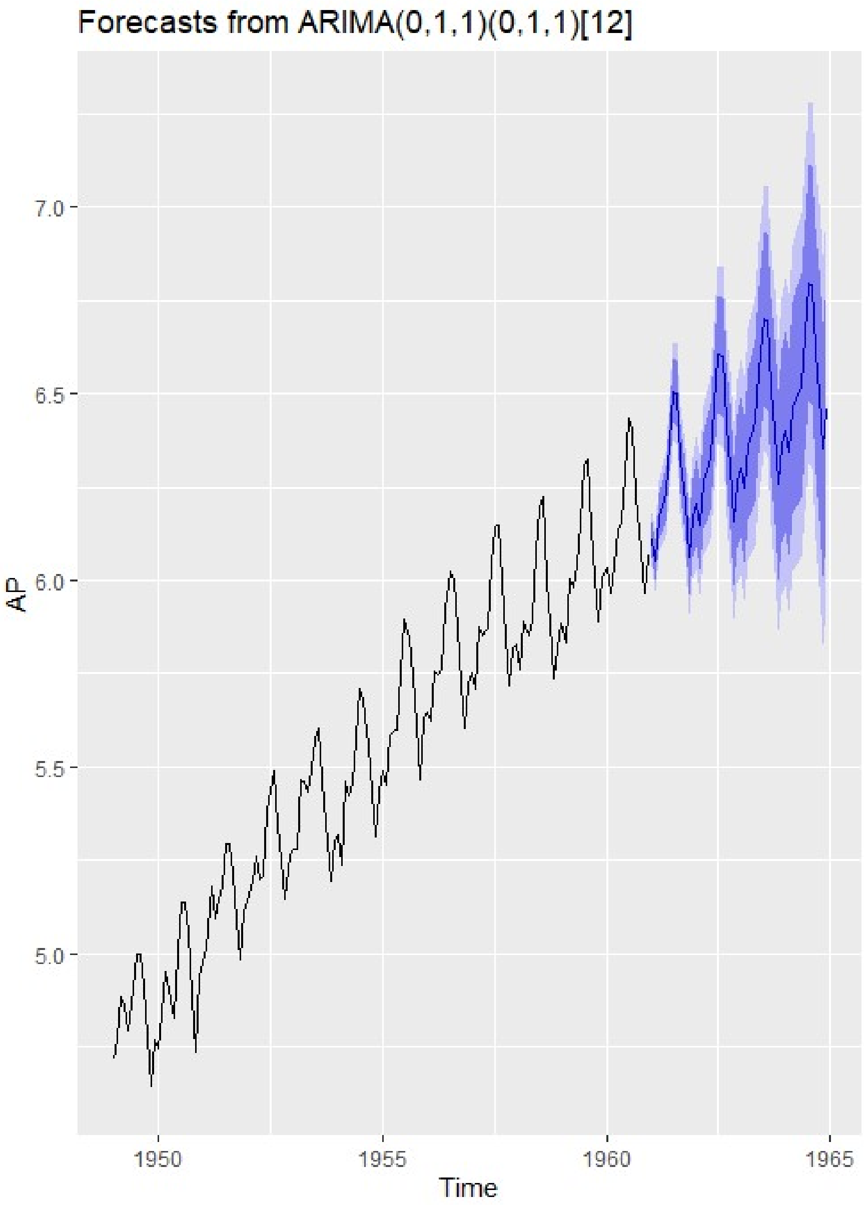


Most of the values are concentrated at 0 and look normal distribution, same indicates there is no series problem with the existing model.

[Linear optimization in R (https://finnstats.com/index.php/2021/04/12/linear-optimization-using-r/)](https://finnstats.com/index.php/2021/04/12/linear-optimization-using-r/)

Forecast

```
f <- forecast(model, 48)
library(ggplot2)
autoplot(f)
```




```
accuracy(f)
                          ME          RMSE
MAE          MPE        MAPE        MASE
ACF1
Training set 0.0005730622 0.03504883
0.02626034 0.01098898 0.4752815 0.2169522
0.01443892
```

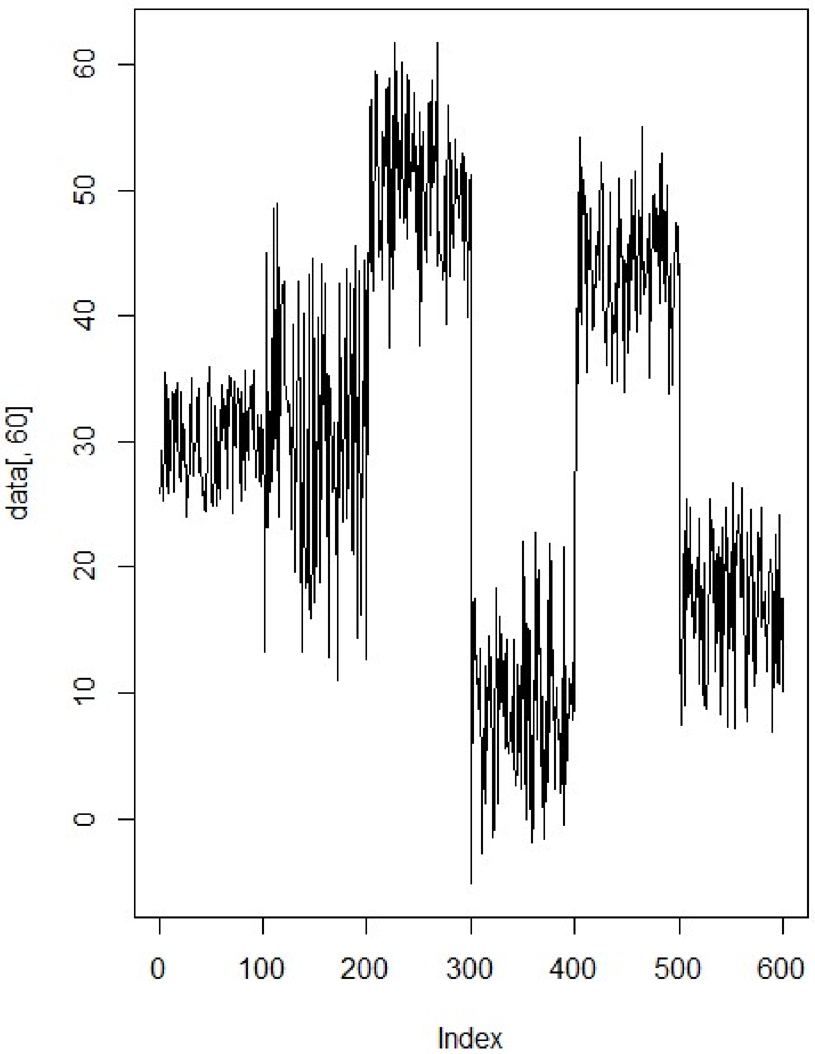
Time-series clustering

Getting Data for Cluster Analysis

The dataset you can access from **here (https://github.com/finnstats/finnstats/blob/main/synthetic_control.data.txt)**

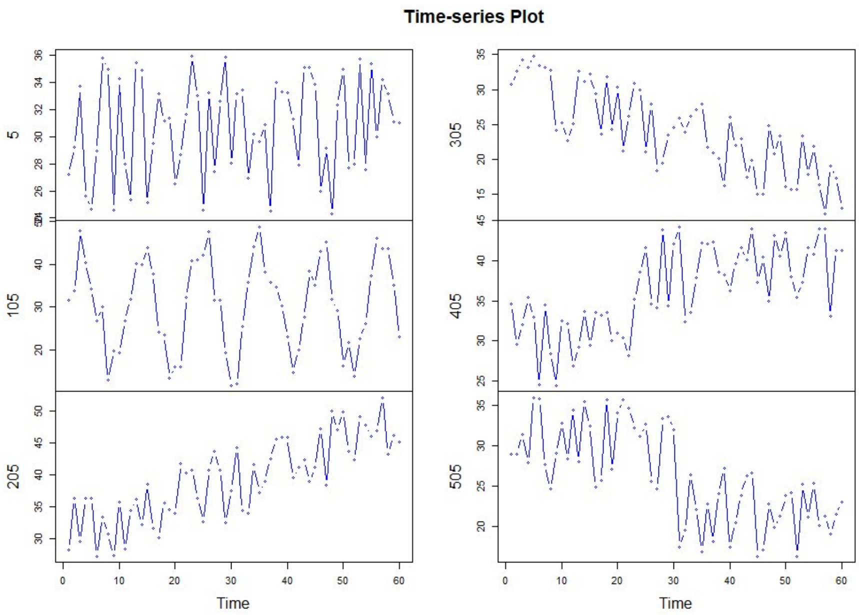
```
data <- read.table("D:/RStudio
/TimeseriesAnalysis
/synthetic_control.data.txt", header = F,
sep = "")
str(data)
'data.frame': 600 obs. of  60 variables:
```

```
plot(data[,60], type = 'l')
```



```
j <- c(5, 105, 205, 305, 405, 505)
sample <- t(data[j,]) plot.ts(sample,

main = "Time-series Plot",
col = 'blue',
type = 'b')
```



Data preparation

```
n <- 10
s <- sample(1:100, n)
i <- c(s,100+s, 200+s, 300+s, 400+s, 500+s)
d <- data[i,]
str(d)
```

```
pattern <- c(rep('Normal', n),
             rep('Cyclic', n),
             rep('Increasing trend', n),
             rep('Decreasing trend', n),
             rep('Upward shift', n),
             rep('Downward shift', n))
```

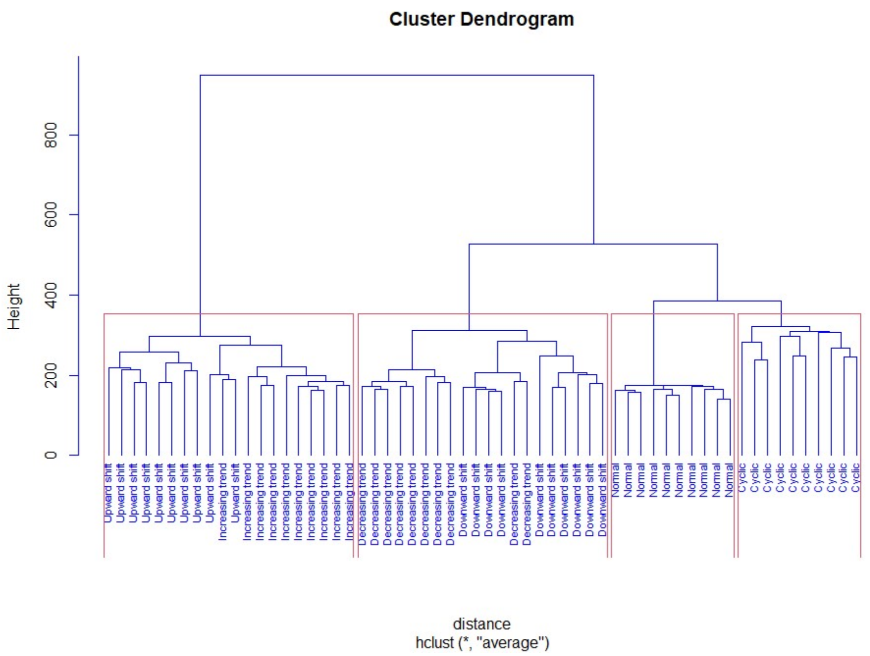
Calculate distances

[Market Basket Analysis in R (https://finnstats.com/index.php/2021/04/16/market-basket-analysis-in-r/)](https://finnstats.com/index.php/2021/04/16/market-basket-analysis-in-r/)

```
library(dtw)
distance <- dist(d, method = "DTW")
```

Hierarchical clustering

```
hc <- hclust(distance, method = 'average')
plot(hc,
     labels = pattern,
     cex = 0.7,
     hang = -1,
     col = 'blue')
rect.hclust(hc, k=4)
```



Time series classification

Data preparation

```
pattern100 <- c(rep('Normal', 100),
                rep('Cyclic', 100),
                rep('Increasing trend', 100),
                rep('Decreasing trend', 100),
                rep('Upward shift', 100),
                rep('Downward shift', 100))
newdata <- data.frame(data, pattern100)
str(newdata)
newdata$pattern100<-factor(newdata$pattern100)
```

Classification with decision tree

```
library(party)
tree <- ctree(pattern100~., newdata)
```

Classification performance

```
tab <- table(Predicted = predict(tree,
newdata), Actual = newdata$pattern100)
```

```
Actual
Predicted          Cyclic Decreasing trend
Downward shift Increasing trend Normal
  Cyclic              97
0             3                0      0
  Decreasing trend      0
99             8                0      0
  Downward shift        0
1            89                0      0
  Increasing trend      2
0             0               96      0
  Normal                1
0             0                0    100
  Upward shift          0
0             0                4      0
                  Actual
Predicted          Upward shift
  Cyclic                    0
  Decreasing trend          0
  Downward shift            0
  Increasing trend          6
  Normal                    4
  Upward shift             90
```

```
sum(diag(tab))/sum(tab)
0.9516667
```

This indicates classification is above 95% accurate.