## Electric\_Production\_Forecasting

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```
## Electric Production Analysis and Forecasting
#Loading Electric Production Dataset
dataset=read.csv("Electric_Production.csv")
#Getting Quick overview of Data Set Structure and contents
head(dataset)
##
         DATE IPG2211A2N
## 1 1/1/1985
              72.5052
## 2 2/1/1985
              70.6720
## 3 3/1/1985 62.4502
## 4 4/1/1985 57.4714
## 5 5/1/1985
                55.3151
## 6 6/1/1985
                58.0904
tail(dataset)
##
           DATE IPG2211A2N
## 392 8/1/2017 108.9312
## 393 9/1/2017
                 98.6154
## 394 10/1/2017
                   93.6137
## 395 11/1/2017
                  97.3359
## 396 12/1/2017 114.7212
## 397 1/1/2018
                 129.4048
#total Entries
print(paste("Total Entries :-",nrow(dataset)))
## [1] "Total Entries :- 397"
#Time Series Indexing
temp<-dataset["IPG2211A2N"]</pre>
rownames(temp)<-dataset$DATE</pre>
dataset=temp
#Counting Missing Values
sum(is.na(dataset))
```

**##** [1] 0

```
library(timeSeries)

## Loading required package: timeDate

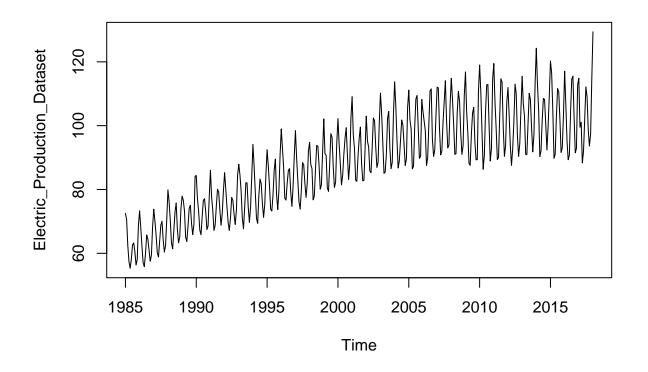
## ## Attaching package: 'timeSeries'

## The following objects are masked from 'package:graphics':

## lines, points

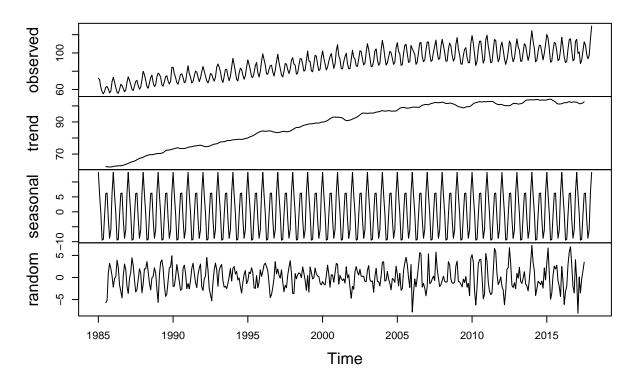
#data set to Time Series Object

Electric_Production_Dataset=ts(dataset$IPG2211A2N,start=c(1985,1),frequency=12)
plot(Electric_Production_Dataset)
```

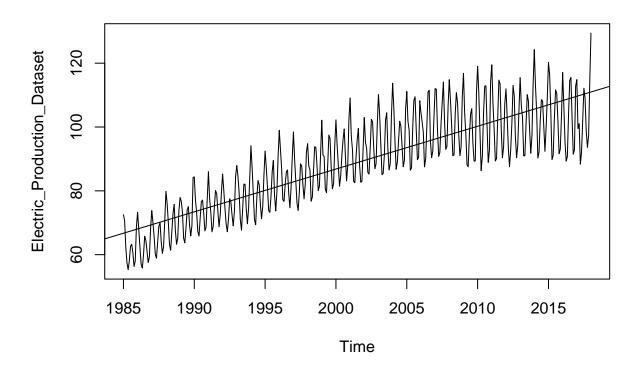


#Since as from the Graph Plotted above we can say that the Electric\_Production\_Dataset is Additive in n decompose\_data=decompose(Electric\_Production\_Dataset, "additive") plot(decompose\_data)

## **Decomposition of additive time series**



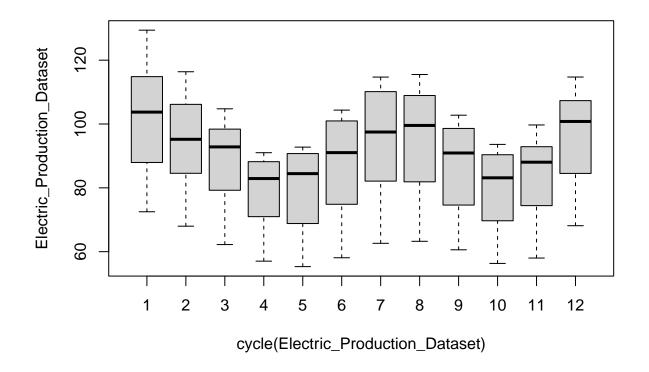
```
#Plotting Trend Line
plot(Electric_Production_Dataset)
abline(reg=lm(Electric_Production_Dataset~time(Electric_Production_Dataset)))
```



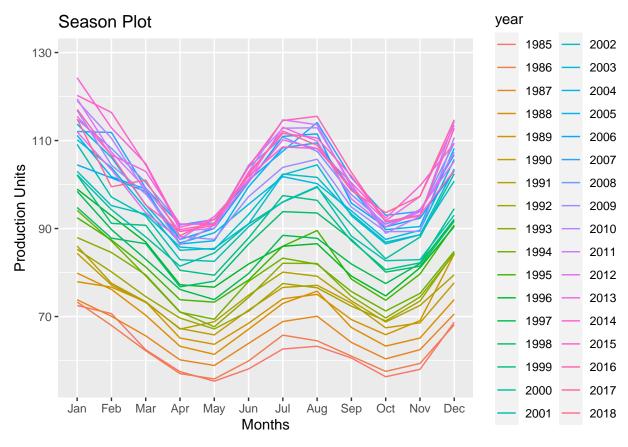
```
#Creating boxplot with cycle()
boxplot(Electric_Production_Dataset~cycle(Electric_Production_Dataset))

#Plotting Seasonl Plot
library(forecast)

## Registered S3 method overwritten by 'quantmod':
## method from
## as.zoo.data.frame zoo
```



ggseasonplot(Electric\_Production\_Dataset,ylab="Production Units",xlab="Months",main="Season Plot")

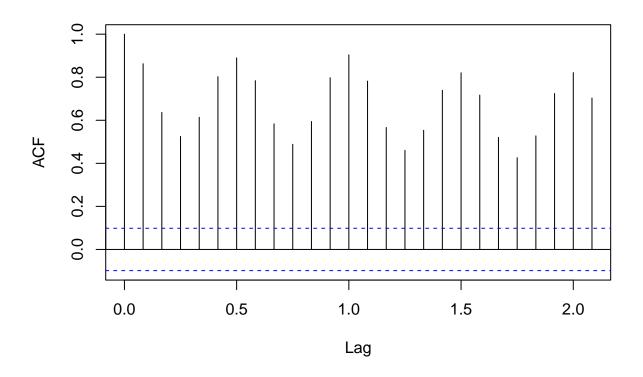


```
#Checking Satationarity
library(tseries)
adf.test(Electric_Production_Dataset)

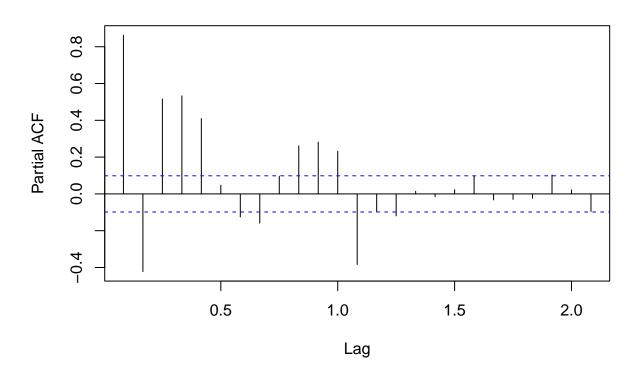
## Warning in adf.test(Electric_Production_Dataset): p-value smaller than printed
## p-value

##
## Augmented Dickey-Fuller Test
##
## data: Electric_Production_Dataset
## Dickey-Fuller = -5.139, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
```

```
#adf test says that the Series is Stationary so Plotting ACF
acf(Electric_Production_Dataset)
```

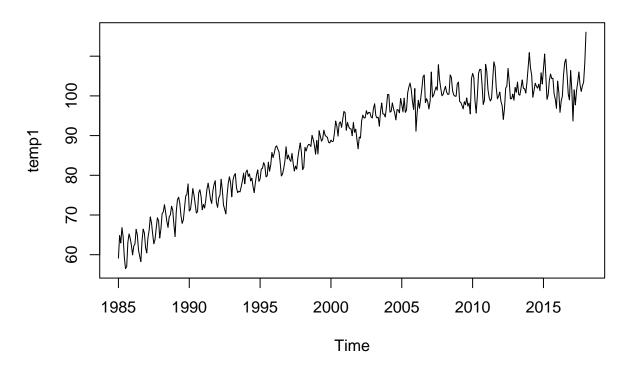


pacf(Electric\_Production\_Dataset)



```
#acf and pacf showing non Stationarity, So from above We concluded that the Electric_Production_Dataset
#Removing Seasonality for making dataset stationary
temp=stl(Electric_Production_Dataset,'per')
temp1=seasadj(temp)
plot(temp1,main="Removed Seasonality")
```

#### **Removed Seasonality**



```
Electric_Production_Dataset=temp1

adf.test(Electric_Production_Dataset)

##

## Augmented Dickey-Fuller Test

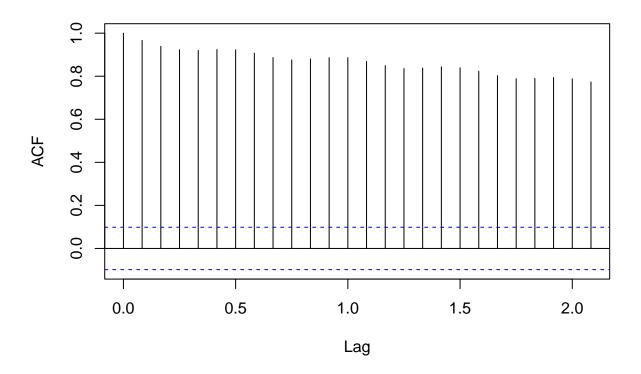
##

## data: Electric_Production_Dataset

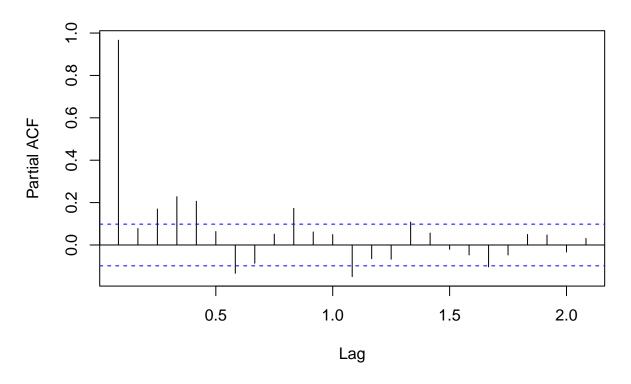
## Dickey-Fuller = -3.1667, Lag order = 7, p-value = 0.09376

## alternative hypothesis: stationary

#adf test says that the Series is Stationary so Plotting ACF and PACF
acf(Electric_Production_Dataset)
```

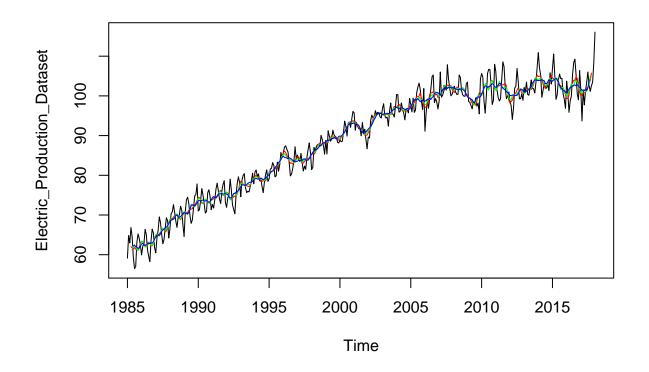


pacf(Electric\_Production\_Dataset)



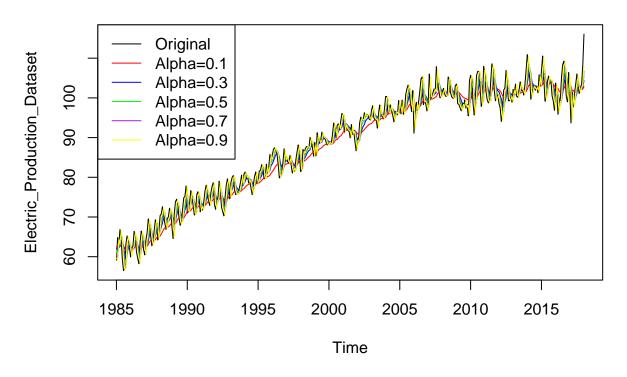
```
#Dataset is Stationarized

# Plotting Simple Moving Average with 7,9,11 intervals
plot(Electric_Production_Dataset)
sm1<-ma(Electric_Production_Dataset,order=7)
lines(sm1,col="red")
sm2<-ma(Electric_Production_Dataset,order=9)
lines(sm2,col="green")
sm3<-ma(Electric_Production_Dataset,order=11)
lines(sm3,col="blue")</pre>
```



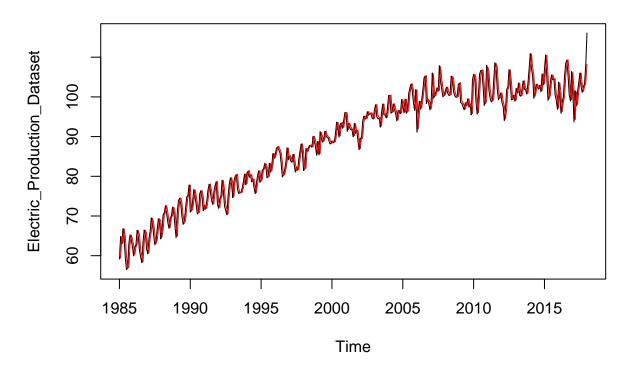
```
#applying single exponential smothing with Different values of alpha
plot(Electric_Production_Dataset,main="Single Exponential Smoothing")
legend("topleft",c("Original","Alpha=0.1","Alpha=0.3","Alpha=0.5","Alpha=0.7","Alpha=0.9"),lty=c(1,1,1,model1=ets(Electric_Production_Dataset,model="ANN",alpha = 0.1)
lines(model1$fitted,col="red")
model2=ets(Electric_Production_Dataset,model="ANN",alpha = 0.3)
lines(model2$fitted,col="blue")
model3=ets(Electric_Production_Dataset,model="ANN",alpha = 0.5)
lines(model3$fitted,col="green")
model4=ets(Electric_Production_Dataset,model="ANN",alpha = 0.7)
lines(model4$fitted,col="purple")
model5=ets(Electric_Production_Dataset,model="ANN",alpha = 0.9)
lines(model5$fitted,col="yellow")
```

### **Single Exponentioal Smoothing**



#### forecast(model5,11) Hi 80 ## Point Forecast Lo 80 Lo 95 Hi 95 ## Feb 2018 115.2265 111.5321 118.9208 109.57645 120.8765 ## Mar 2018 115.2265 110.2562 120.1967 107.62515 122.8278 ## Apr 2018 115.2265 109.2466 121.2063 106.08112 124.3718 115.2265 108.3844 122.0685 104.76250 125.6904 ## May 2018 ## Jun 2018 115.2265 107.6193 122.8336 103.59238 126.8605 ## Jul 2018 115.2265 106.9245 123.5284 102.52965 127.9233 ## Aug 2018 115.2265 106.2834 124.1695 101.54924 128.9037 ## Sep 2018 115.2265 105.6853 124.7676 100.63456 129.8183 ## Oct 2018 115.2265 105.1226 125.3303 99.77393 130.6790 ## Nov 2018 115.2265 104.5896 125.8633 98.95876 131.4941 ## Dec 2018 115.2265 104.0820 126.3709 98.18254 132.2704 #applying Double exponential smothing with default values plot(Electric\_Production\_Dataset, main="Double Exponentioal Smoothing") model=ets(Electric\_Production\_Dataset, model = "AAN") lines(model\$fitted,col="red")

#### **Double Exponentioal Smoothing**

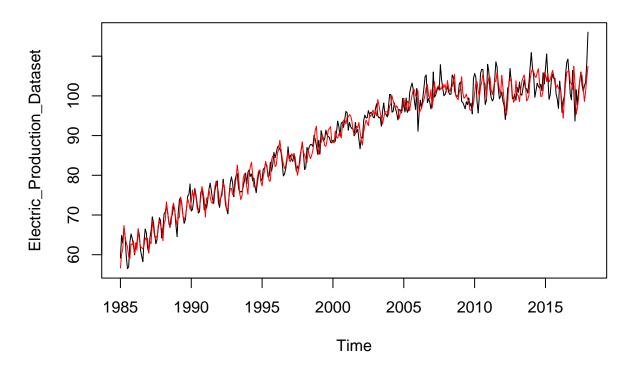


# forecast(model,11) ## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95

```
## Feb 2018
                  115.7194 112.0214 119.4173 110.06385 121.3749
## Mar 2018
                  115.8586 110.7815 120.9356 108.09390 123.6232
## Apr 2018
                  115.9977 109.8430 122.1524 106.58494 125.4105
                  116.1369 109.0668 123.2071 105.32407 126.9498
## May 2018
## Jun 2018
                  116.2761 108.3960 124.1562 104.22451 128.3277
## Jul 2018
                  116.4153 107.8009 125.0297 103.24069 129.5899
## Aug 2018
                  116.5545 107.2635 125.8454 102.34514 130.7638
## Sep 2018
                  116.6936 106.7720 126.6153 101.51979 131.8675
## Oct 2018
                  116.8328 106.3181 127.3475 100.75199 132.9136
## Nov 2018
                  116.9720 105.8959 128.0481 100.03252 133.9115
## Dec 2018
                  117.1112 105.5006 128.7217 99.35434 134.8680
```

```
#applying Triple exponential smothing with default values
plot(Electric_Production_Dataset,main="Triple Exponential Smoothing")
model=ets(Electric_Production_Dataset,model = "AAA")
lines(model$fitted,col="red")
```

## **Triple Exponentioal Smoothing**



#### forecast(model,11)

```
Hi 95
##
            Point Forecast
                              Lo 80
                                       Hi 80
                                                 Lo 95
## Feb 2018
                  108.7064 105.3132 112.0996 103.5170 113.8958
## Mar 2018
                  109.0455 105.3226 112.7683 103.3519 114.7391
## Apr 2018
                  106.6135 102.5877 110.6392 100.4566 112.7703
## May 2018
                  108.8240 104.5165 113.1316 102.2362 115.4118
## Jun 2018
                  112.0553 107.4832 116.6274 105.0628 119.0477
## Jul 2018
                  114.1676 109.3453 118.9899 106.7926 121.5426
## Aug 2018
                  112.7656 107.7054 117.8258 105.0267 120.5045
## Sep 2018
                  110.9931 105.7055 116.2806 102.9064 119.0797
## Oct 2018
                  109.1904 103.6848 114.6960 100.7703 117.6105
## Nov 2018
                  109.5343 103.8189 115.2497 100.7933 118.2753
## Dec 2018
                  112.3817 106.4637 118.2996 103.3310 121.4323
```