

Take Home Test

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You are in charge of forecasting industrial output produced in the state of Armorica at the Federal Reserve Bank. Monthly industrial output data for Armorica has been provided to you in the spreadsheet.

```
setwd("~/Acads/MFE 2016/2nd Quarter/Empirical Methods in Finance/Week 5")
library(lubridate)
library(xlsx)
```

```
## Loading required package: rJava
```

```
## Loading required package: xlsxjars
```

```
library(xts)
```

```
## Loading required package: zoo
```

```
##
```

```
## Attaching package: 'zoo'
```

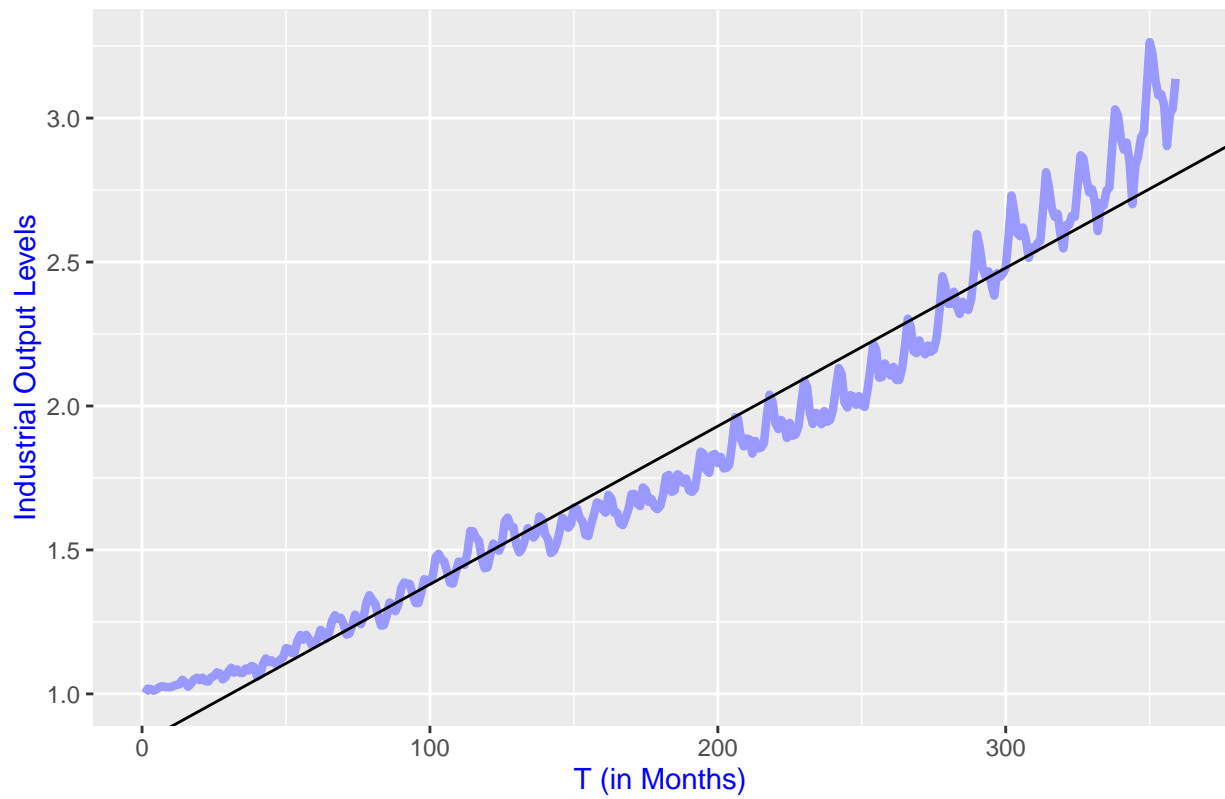
```
## The following objects are masked from 'package:base':
```

```
##
```

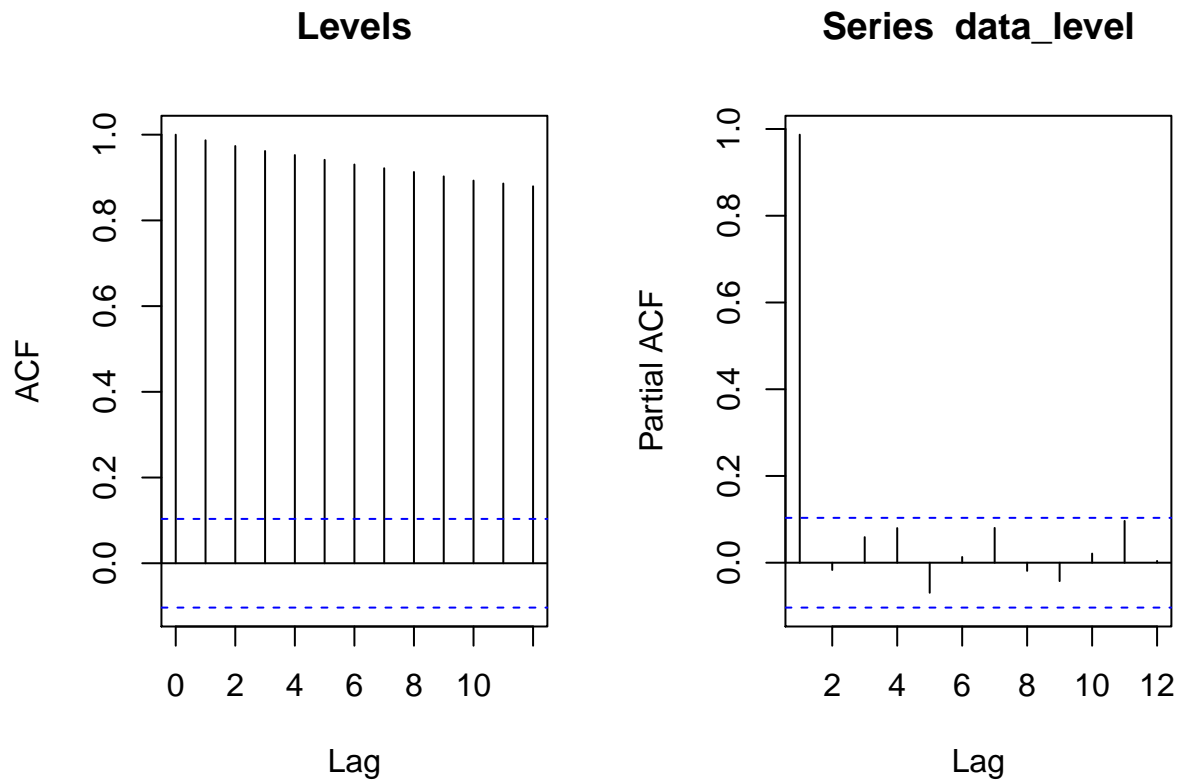
```
##      as.Date, as.Date.numeric
```

```
library(ggplot2)
data_level <- read.xlsx('open_book_data.xlsx', 'Sheet1')
t <- 1:length(data_level[,1])
colnames(data_level) <- "Levels"
reg <- lm(data_level[,1]~t)
c1 <- reg$coefficients[1]
m1 <- reg$coefficients[2]
logdata <- log(data_level)
reg2 <- lm(logdata[,1]~t)
c2 <- reg2$coefficients[1]
m2 <- reg2$coefficients[2]
y_diff <- diff(logdata[,1], lag=1)
diffdata <- data.frame(y_diff)
colnames(diffdata) <- "DiffLog"
t2 <- 1:length(diffdata[,1])
p1 <- ggplot(data_level, aes(x=t, y=data_level[,1])) + geom_line(color= '#9999FF', size=1.5) + ggtitle("
xlab("T (in Months)") + ylab("Industrial Output Levels") +
theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = elem
p1 + geom_abline(intercept = c1 , slope = m1)
```

Time Series Plot



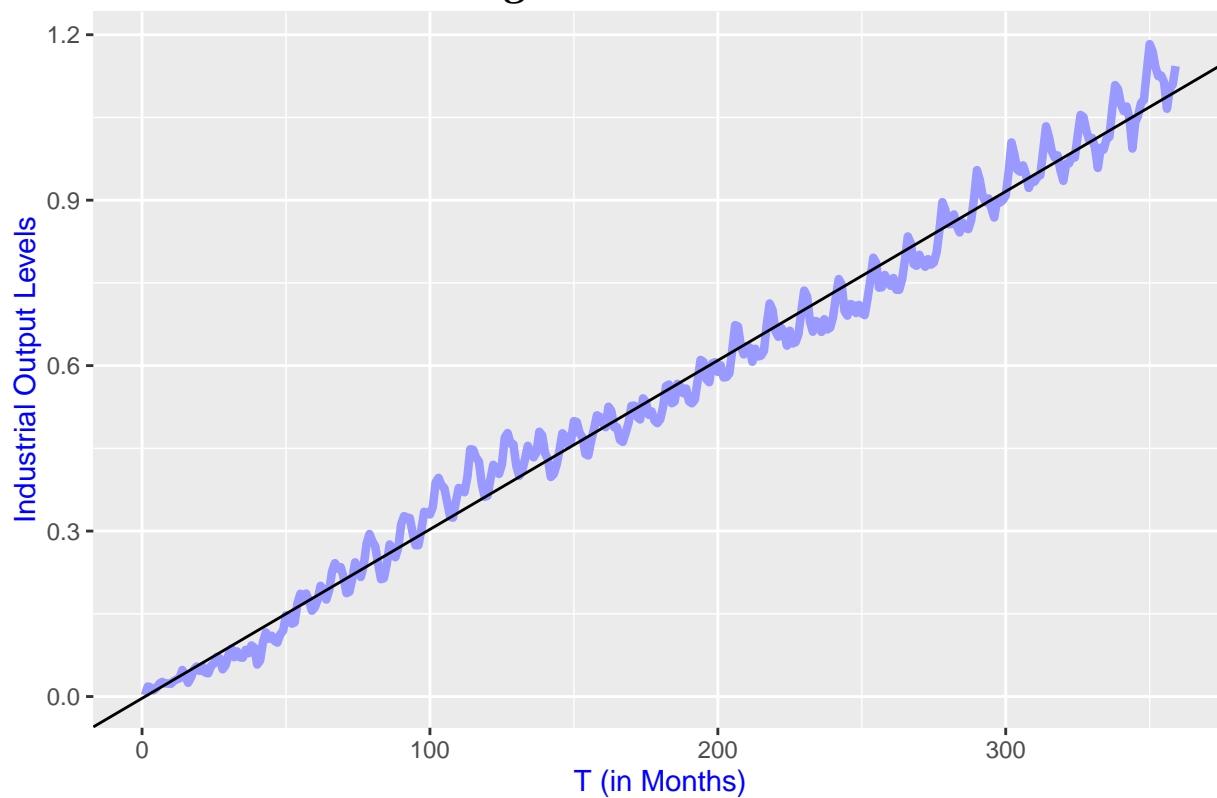
```
par(mfrow =c(1,2))  
acf(data_level,lag.max = 12)  
pacf(data_level,lag.max = 12)
```



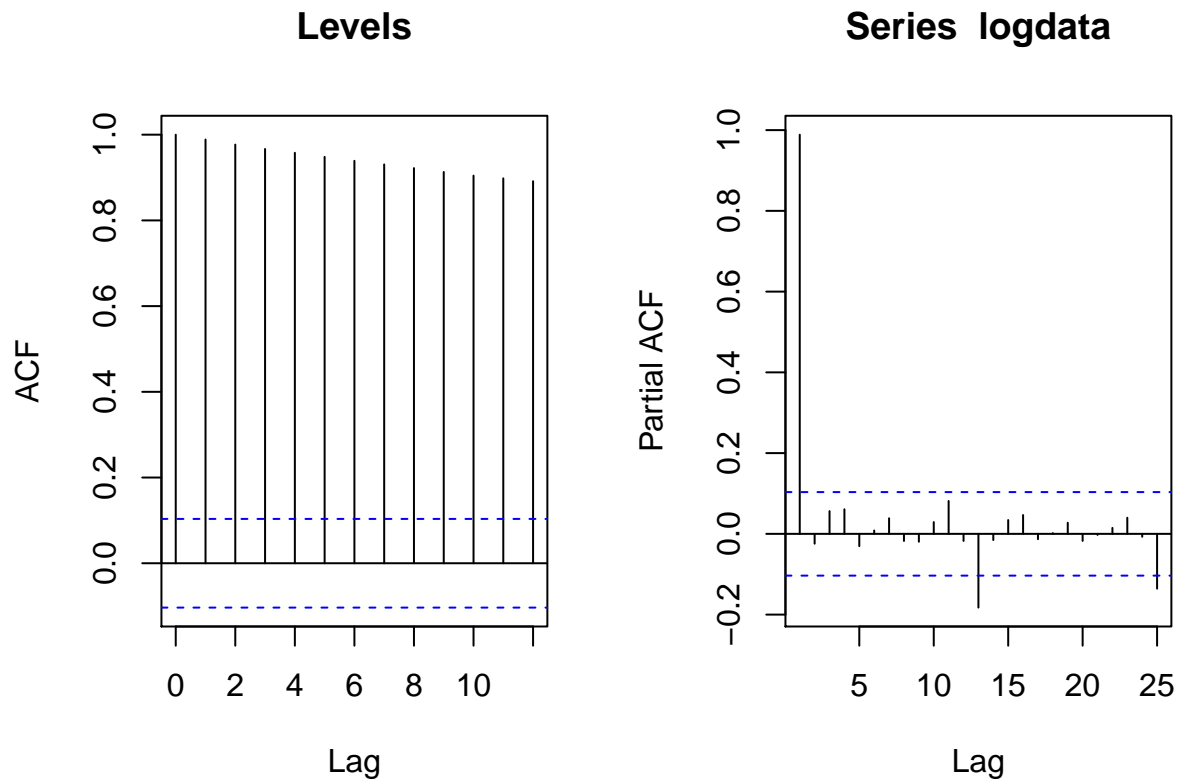
The time series plot of industrial data has $R^2 = 0.95$ a trend in data. The acf is significant and high. We can notice that the acf is decreasing very slowly (the series is not weak stationary). This can be shown from the graph of the time series which when fitted with straight line has high R^2 . Also, we do not have any conclusion from pacf. Thus levels data cannot be used to model the data. -> Log Levels

```
p2 <- ggplot(logdata,aes(x=t, y=logdata[,1])) + geom_line(color= '#9999FF', size=1.5) + ggtitle("Log Time Series") +
  xlab("T (in Months)") + ylab("Industrial Output Levels") +
  theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = element_text(family="Times", face="bold.italic", size=12))
p2+ geom_abline(intercept = c2 , slope = m2)
```

Log Time Series Plot



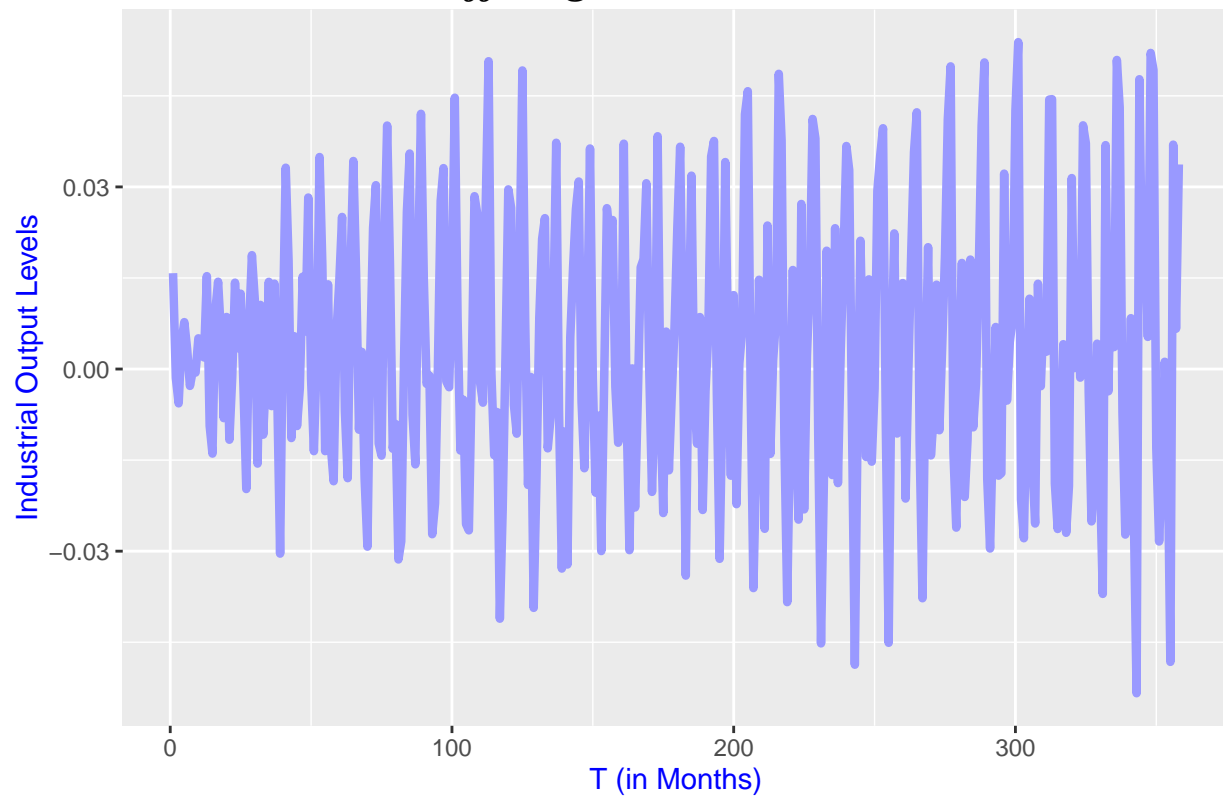
```
par(mfrow = c(1,2))  
acf(logdata,lag.max = 12)  
pacf(logdata)
```



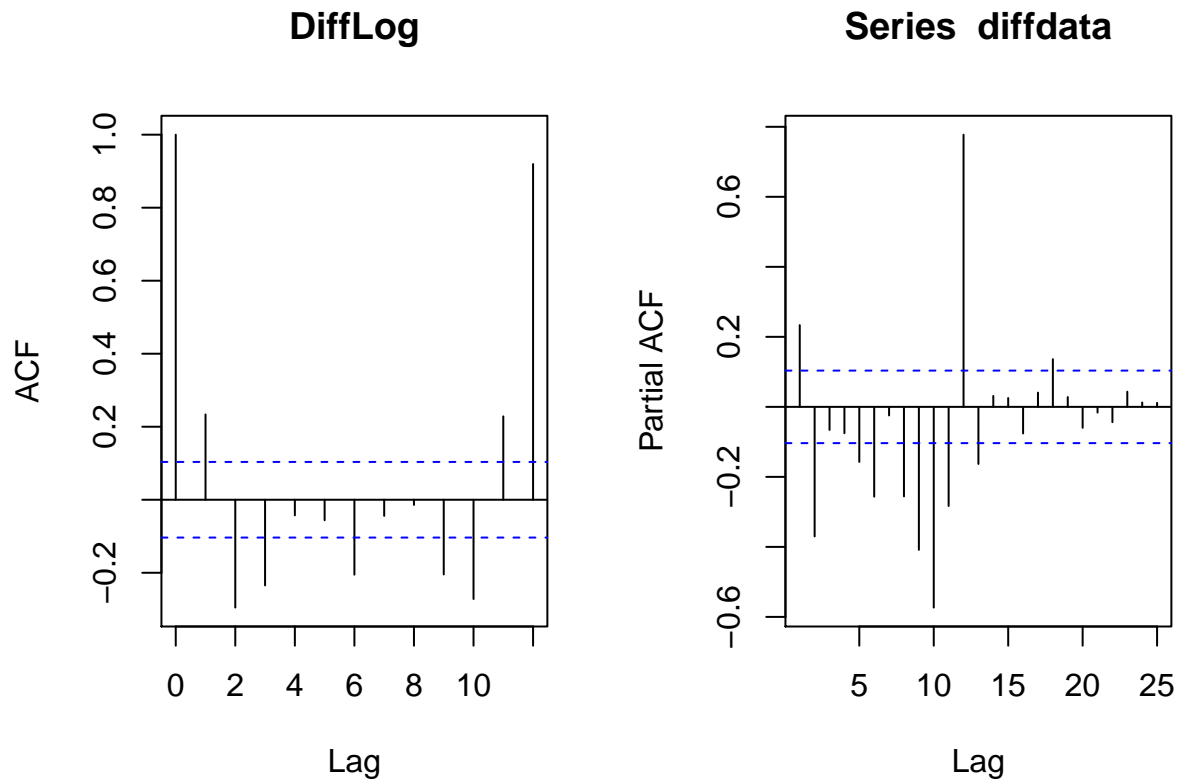
The above series fits the data better ($R^2 = 0.98$) than the Level. But still we find the trend (similar acf).
 The series is not weak stationary. -> Diff Log

```
ggplot(difffdata,aes(x=t2, y=difffdata[,1])) + geom_line(color= '#9999FF', size=1.5) + ggtitle("Diff Log T") +
  xlab("T (in Months)") + ylab("Industrial Output Levels") +
  theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = element_text(family="Times", face="bold.italic", size=18))
```

Diff Log Time Series Plot



```
par(mfrow = c(1,2))  
acf(diffdata, lag.max = 12)  
pacf(diffdata)
```

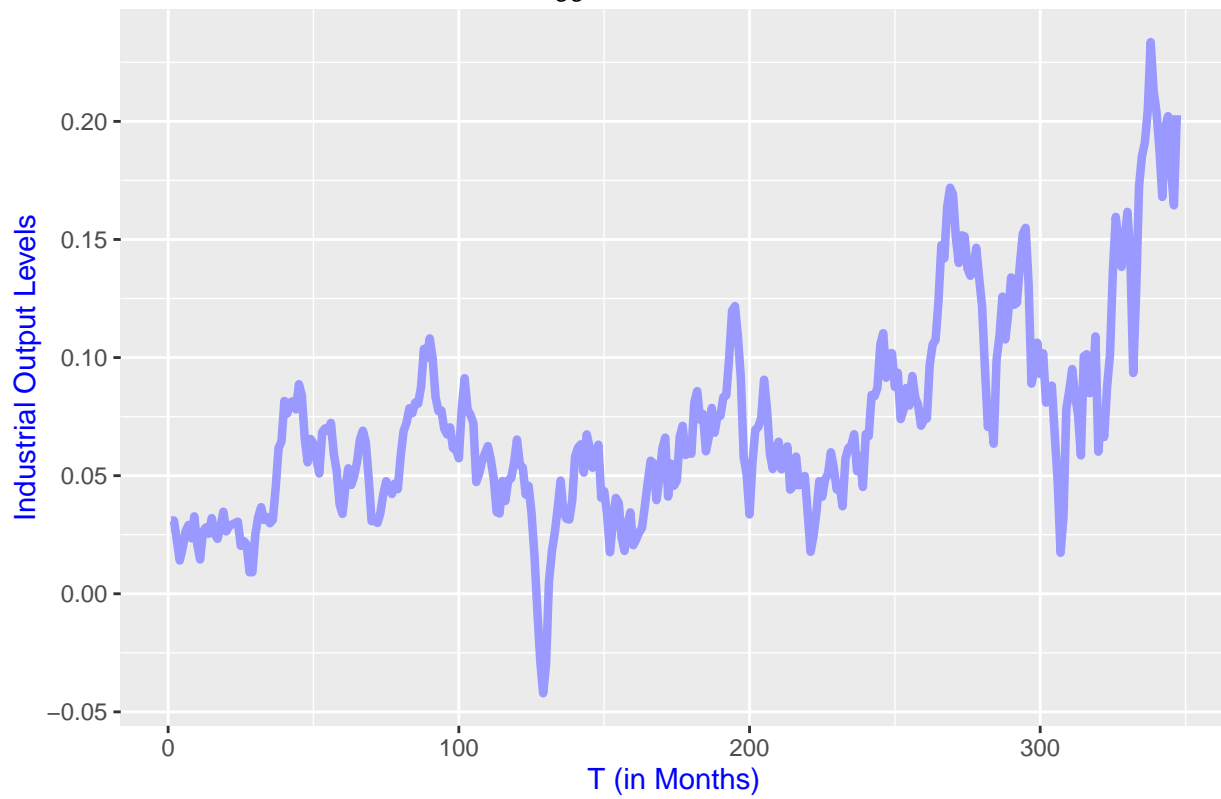


The diff log plot seems to have scattered. We can see that the trend is removed. But the series is significantly autocorrelated. -> Remove trend by taking 12th lag (removing seasonality).

```
y1 <- diff(data_level[,1],lag=12)
t3 <- 1:length(y1)
diff_12 <- data.frame(y1)

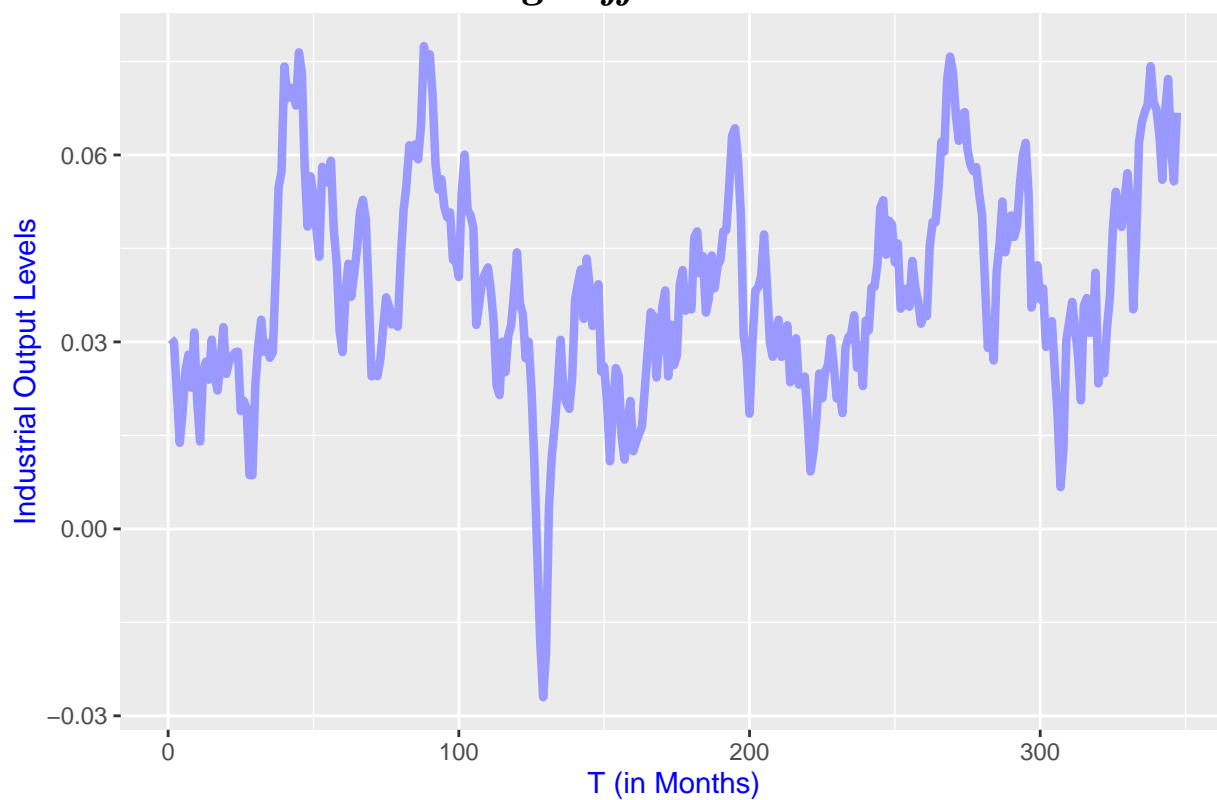
ggplot(diff_12,aes(x=t3, y=diff_12[,1])) + geom_line(color= '#9999FF', size=1.5) + ggtitle("12th Diff T") +
  xlab("T (in Months)") + ylab("Industrial Output Levels") +
  theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = c
```

12th Diff Time Series Plot

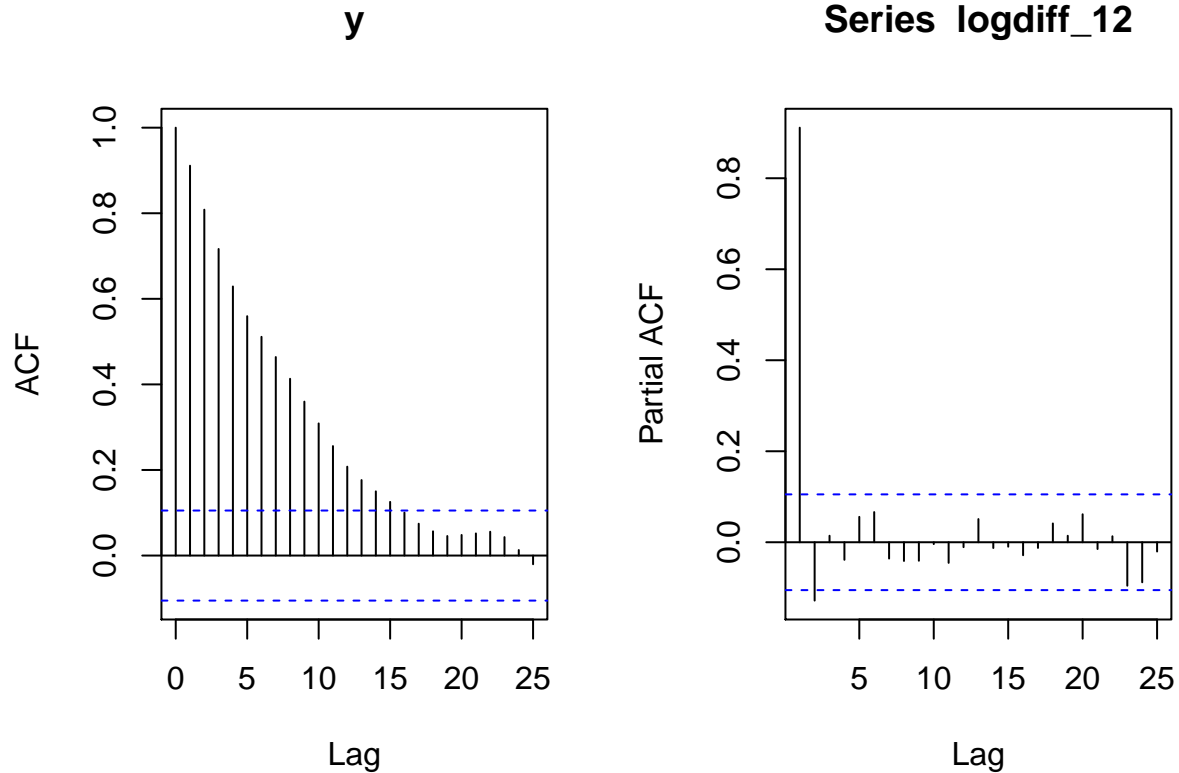


```
y<- diff(logdata[,1],lag=12)
logdiff_12 <- data.frame(y)
ggplot(logdiff_12,aes(x=t3, y=logdiff_12[,1])) + geom_line(color= '#9999FF', size=1.5) + ggtitle("12th Diff Time Series Plot") +
  xlab("T (in Months)") + ylab("Industrial Output Levels") +
  theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = element_text(family="Times", face="normal", size=12))
```


12th Log Diff Time Series Plot

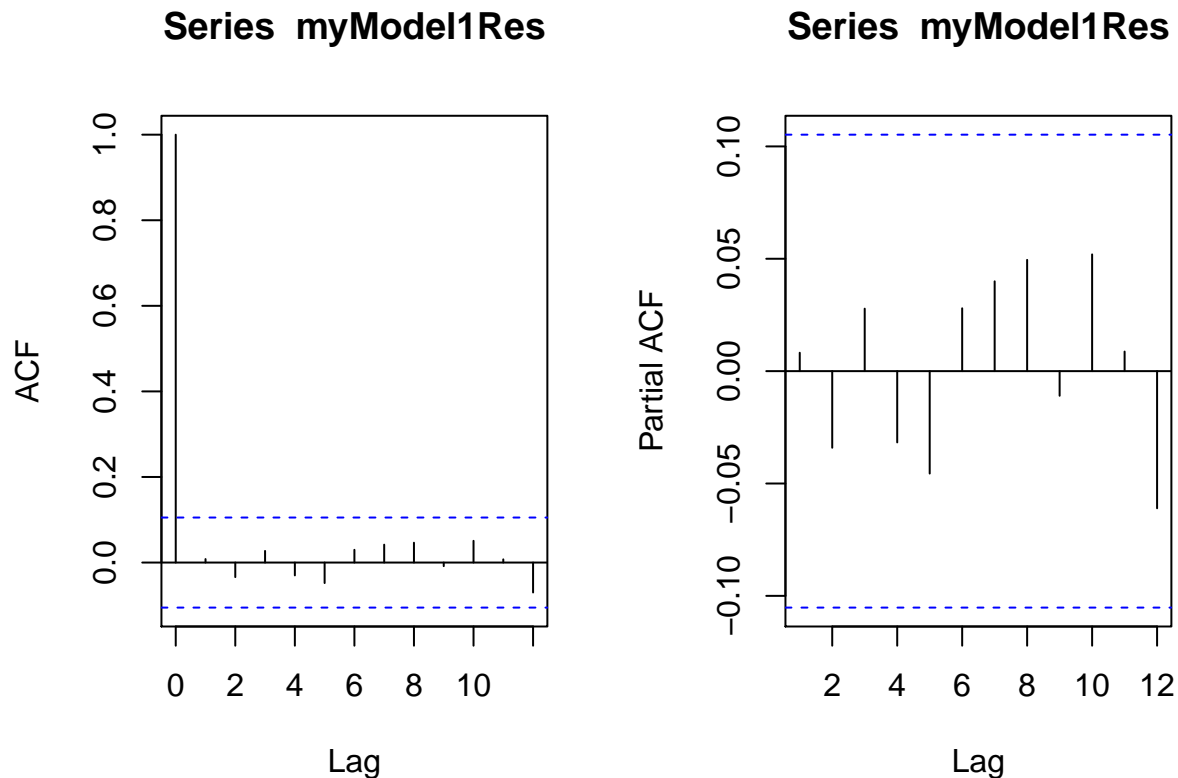


```
par(mfrow = c(1,2))  
acf(logdiff_12)  
pacf(logdiff_12)
```



Note that the 12th lag is taken for log data. Otherwise the series (for lag 12 at levels) is not stationary. The resulting time series has a significantly dropping acf. Also the pacf shows that there is no acf after 2nd lag(pacf =0 after second). Fitting AR(2) model

```
myModel1<-arima(logdiff_12, order=c(2,0,0))
myModel1Coef<-coef(myModel1)
myModel1Res<-residuals(myModel1)
par(mfrow = c(1,2))
acf(myModel1Res,lag.max = 12)
pacf(myModel1Res,lag.max = 12)
```



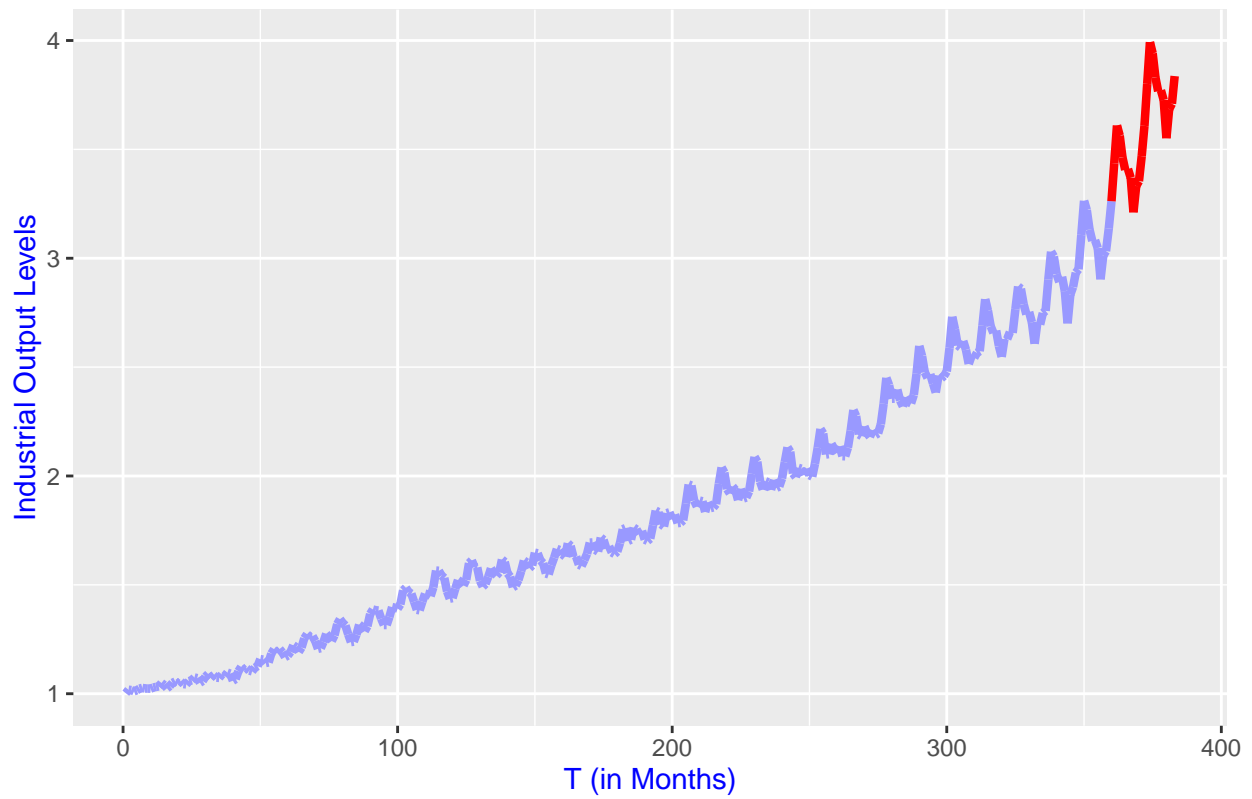
Our Model 1: AR(2,0,0) is a good fit for the data as the residuals are not correlated. Also, our model uses minimum number of parameters and hence is the best.

Forecast:

```
prediction_t <- 24
y_predict <- rep(0,prediction_t+2)
y_predict[1] <- logdiff_12[length(t3)-1,1]
y_predict[2] <- logdiff_12[length(t3),1]
for(i in 1:24){
  f <- y_predict[i+1]*as.numeric(myModel1Coef[1]) + y_predict[i]*as.numeric(myModel1Coef[2]) + as.numeric(myModel1Coef[3])
  y_predict[i+2] <- f
}
t0 <- length(logdata[,1])
logdata_prediction <- logdata[,1]
for(i in 1: prediction_t){
  logdata_prediction[t0+i] <- logdata_prediction[t0+i-12] + y_predict[t+2]
}

data_predict <- data.frame(exp(logdata_prediction))
t4 <- 1:length(data_predict[,1])
ggplot(data_predict,aes(x=t4, y=data_predict[,1])) + geom_line(color= ifelse(t4<=359, '#9999FF','red'),
  xlab("T (in Months)") + ylab("Industrial Output Levels") +
  theme(plot.title =element_text(family="Times", face="bold.italic", size=18) ) + theme(axis.title = c
```

Predicted Time Series Plot



The time series plot in red is the prediction. We used the prediction for log diff (see the for loop). From there we get the difference predicted. Add the pred to the log data $[t-12+1]$ and take exponential to get the graph.