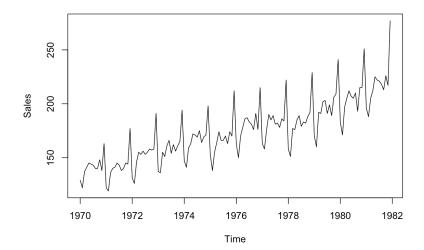
3.4

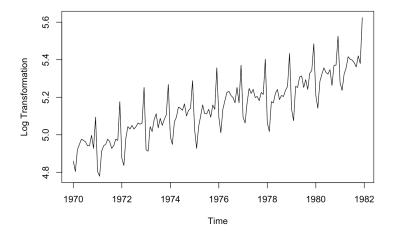
```
# 3.4

SALES <- read.table("SALES.TXT",header=T)
Sales <- ts(SALES$Sales,frequency=12, start=1970)
# This plot shows the monthly sale volume
plot(Sales)</pre>
```



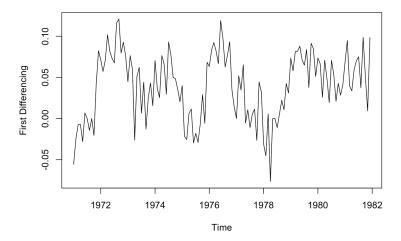
The Log transformation removed the increasing variance, now study the plot below, we can see that the variance is likely to be a constant.

```
# Apply log transformation to remove the increasing variance
log_transform <- log(Sales)
plot(log_transform, ylab='Log Transformation')</pre>
```



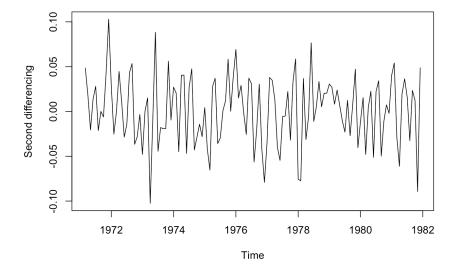
Next, use diff() function to remove the linear trend of the model, we have the result below. This is not stationary, but indeed does not have linear trend as the original.

```
# First differencing removed the linear trend of the time-serie model
sale_diff <- diff(log_transform, lag=12)
ts.plot(sale_diff, ylab="First Differencing")
```



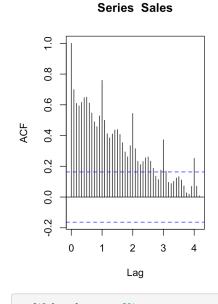
Then differencing again to remove the seasonality, the result below is really close to white-noise (strictly stationary). Hence this is the final time series model.

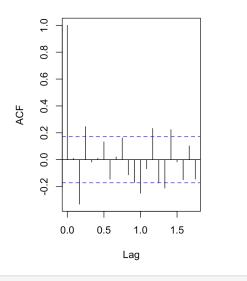
```
# Second differencing removed the seasonality, so the model looks better and
# really close to the stationary model
second_diff <- diff(sale_diff, lag=2)
plot(second_diff, ylab="Second differencing")</pre>
```



Now compare to the ACF/PACF of the original, we see that even though there is still a very small amount of lag with significant (level of 5%) but is much lesser than the original.

```
par(mfrow=c(1,2))
acf(Sales, lag.max = 50)
acf(second_diff, main='Final')
```





Final

pacf(Sales, lag.max = 50)
pacf(second_diff, main='Final')

