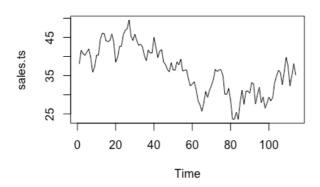
# **Assignment 5**

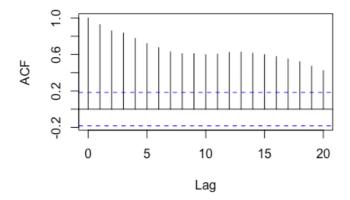
## Question 4

First, we plot the time series and its ACF:

## **Plot of Sales**



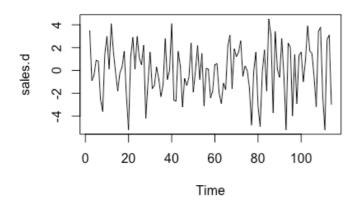
# Series sales.ts



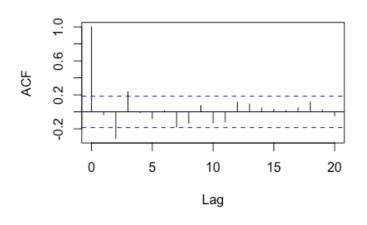
Both plots suggest that the series are not stationary.

There is no particular well-defined trend. The trend term appears to be linear. We use technique of differencing to obtain stationary time series.

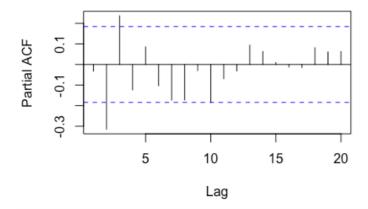
## Plot of Differenced Sales



## Series sales.d



# Series sales.d



After differencing once we see from the plots of residuals that they look stationary and fairly uncorrelated except at lags 2 and 3. We should try to fit ARIMA (3,1,0), ARIMA (0,1,3), ARIMA (2,1,1) models.

For ARIMA (3,1,0) we get:

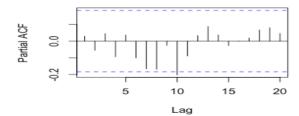
# Call: arima(x = sales.ts, order = c(3, 1, 0), method = "ML")

## Coefficients:

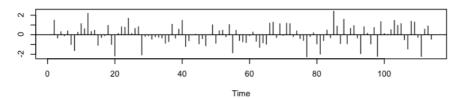
ar1 ar2 ar3 0.0413 -0.3167 0.2500 s.e. 0.0922 0.0875 0.0923

 $sigma^2$  estimated as 4.576: log likelihood = -246.48, aic = 500.96

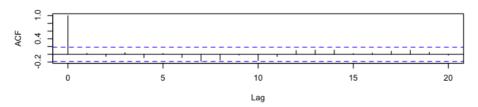
## Series sales.ar3\$residuals



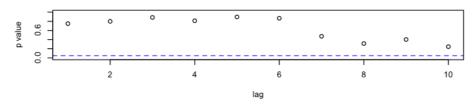
#### Standardized Residuals



#### **ACF of Residuals**



#### p values for Ljung-Box statistic



# For ARIMA (0,1,3) we get:

#### Call:

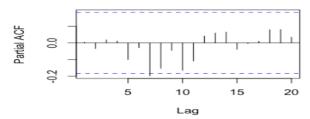
arima(x = sales.ts, order = c(0, 1, 3), method = "ML")

## Coefficients:

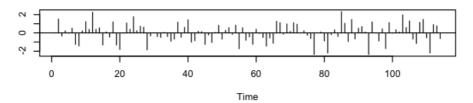
ma1 ma2 ma3 0.0847 -0.3427 0.2502 s.e. 0.0935 0.0888 0.1113

sigma^2 estimated as 4.468: log likelihood = -245.22, aic = 498.44

#### Series sales.ma3\$residuals



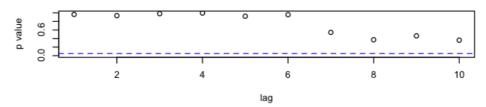
## Standardized Residuals



## **ACF of Residuals**



# p values for Ljung-Box statistic



# For ARIMA (2,1,1) model we get:

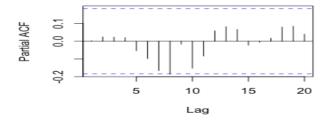
Call: arima(x = sales.ts, order = c(2, 1, 1), method = "ML")

Coefficients:

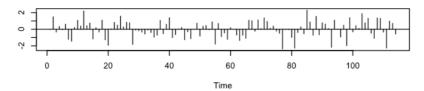
ar1 ar2 ma1 -0.6131 -0.3489 0.7029 .e. 0.1453 0.0979 0.1420

sigma^2 estimated as 4.447: log likelihood = -244.94, aic = 497.88

## Series sales.arma21\$residuals



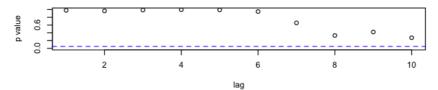




#### **ACF of Residuals**



#### p values for Ljung-Box statistic



If we compare the plots for all 3 models we see that ARIMA (2,1,1) model passes the WN test. Whereas for AR (3) model in SPACF plot there is a spike at lag 10, and for MA (3) model there is a spike at lag 7 in SPACF plot. Also, if we compare AIC values of the 3 models, we see that ARIMA (2,1,1) model has the lowest AIC. Hence, we choose ARIMA (2,1,1) to make the forecasts and we get:

```
> sales.pred

$pred

Time Series:

Start = 115

End = 120

Frequency = 1

[1] 35.01178 36.11269 35.46852 35.47930 35.69747 35.55995

$se

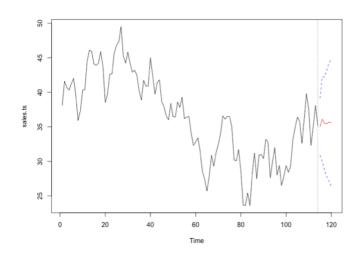
Time Series:

Start = 115

End = 120

Frequency = 1

[1] 2.108821 3.119094 3.438072 3.929344 4.373361 4.710523
```



```
## Question 4
mypath = "/Users/safurasuleymanovs/Desktop/4B/Stat/A5/"
data.set ="sales2.txt"
sales.y = scan(paste(mypath,data.set,sep=""))
sales.ts = ts(scan(paste(mypath,data.set,sep="")))
plot(sales.ts, main="Plot of Sales")
acf(sales.ts)
sales.d = diff(sales.ts)
plot(sales.d, type="I", main = "Plot of Differenced Sales")
acf(sales.d)
pacf(sales.d)
sales.ar3 <- arima(sales.ts,order=c(3,1,0),method="ML")</pre>
pacf(sales.ar3$residuals)
tsdiag(sales.ar3)
sales.ma3 <- arima(sales.ts,order=c(0,1,3),method="ML")</pre>
pacf(sales.ma3$residuals)
tsdiag(sales.ma3)
sales.arma21 <- arima(sales.ts,order=c(2,1,1),method="ML")</pre>
pacf(sales.arma21$residuals)
tsdiag(sales.arma21)
sales.pred <- predict(sales.arma21,n.ahead=6,se.fit=TRUE)</pre>
u <- sales.pred$pred + 1.96*sales.pred$se
I <- sales.pred$pred - 1.96*sales.pred$se
plot(sales.ts,xlim=c(1,120),type="l",xlab="Time")
lines(sales.pred$pred,col="red")
lines(u,col='blue',lty='dashed')
lines(l,col='blue',lty='dashed')
abline(v=114,lty="dotted")
```