STA2202H1: Time Series Analysis Assignment 1

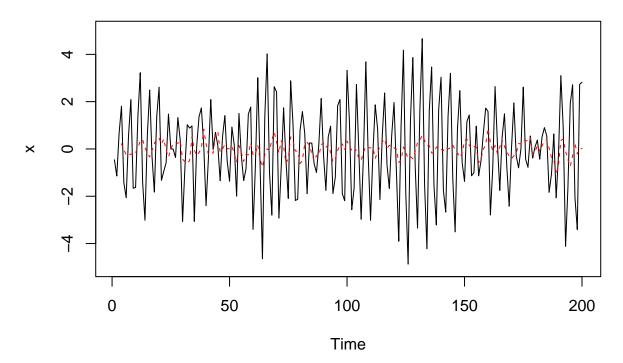
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$\mathbf{Q}\mathbf{1}$

```
set.seed(100)
# Simulate 200 observations from N(0,1); Gaussian white noise
w <- rnorm(220, 0, 1) # 20 extra to avoid startup problems
# Generate time series x_t using the second-order autoregression
x = filter(w, filter=c(0, -0.9), method="recursive")[-(1:20)] # remove the first 20
# Apply the moving average filter
v = filter(x, sides=1, filter=rep(1/4, 4)) # sides=1 for past values
# Plot x_t as a line
plot.ts(x, ylim=c(-5, 5), main="Autoregression model with the moving average filter")
# Superimpose the moving average filter v as a red dashed line
lines(v, col='red', lty=2)</pre>
```

Autoregression model with the moving average filter



Comment: After applying the moving average filter v_t , the generated time series data tends to be smooth with a relative constant variance by getting rid of the noise in the series.

 $\mathbf{Q2}$

(1) Show that the model can be written as $x_t = \delta t + \sum_{j=1}^t w_j$.

$$\begin{split} x_t &= \delta + x_{t-1} + w_t \\ &= \delta + (\delta + x_{t-2} + w_{t-1}) + w_t \\ &= 2\delta + x_{t-2} + w_{t-1} + w_t \\ &= 2\delta + (\delta + x_{t-3} + w_{t-2}) + w_{t-1} + w_t \\ &= 3\delta + x_{t-3} + w_{t-2} + w_{t-1} + w_t \\ &\dots \\ &= \delta t + x_0 + (w_1 + w_2 + \dots + w_{t-1} + w_t) \quad \text{ where } x_0 = 0 \\ &= \delta t + \sum_{j=1}^t w_j \end{split}$$

(2) Find the mean function and the autocovariance function of x_t .

The mean function of x_t

$$\mu_{x_t} = E(x_t) = E(\delta t + \sum_{j=1}^t w_j)$$

$$= E(\delta t) + \sum_{j=1}^t E(w_j)$$

$$= \delta t + 0$$

$$= \delta t$$

The autocovariance function of x_t

$$\begin{split} \gamma_x(s,t) &= Cov(x_s,x_t) \\ &= Cov(\delta s + \sum_{j=1}^s w_j, \delta t + \sum_{k=1}^t w_k) \\ &= \min\{s,t\}\sigma_w^2 \quad \text{because } w_t \text{ are uncorrelated random variables} \end{split}$$

(3) Show that x_t is not stationary.

Check condition 1: The expected value of x_t is $E(x_t) = \delta t$ from part (1), which is independent of time t only if there is no drift.

Check condition 2: WLOG, we can consider drift $\delta = 0$, then $x_t = \sum_{j=1}^t w_j$. The autocovaraince function is

$$\gamma(h) = Cov(x_t, x_{t+h}) = Cov(\sum_{j=1}^{t} w_j, \sum_{k=1}^{t+h} w_k) = min\{t, t+h\} \cdot \sigma_w^2 = t\sigma_w^2$$

, which is also dependent of time t.

Hence, x_t is not stationary.

(4) Show that
$$\rho_x(t-1,t) = \sqrt{\frac{t-1}{t}} \to 1$$
 as $t \to \infty$.

$$\rho_x(t-1,t) = \frac{\gamma(t-1,t)}{\sqrt{\gamma(t-1,t-1)\gamma(t,t)}}$$

$$= \frac{(t-1)\sigma_w^2}{\sqrt{(t-1)\sigma_w^2 \cdot t\sigma_w^2}}$$

$$= \frac{(t-1)}{\sqrt{(t-1) \cdot t}}$$

$$= \sqrt{\frac{(t-1)^2}{(t-1) \cdot t}}$$

$$= \sqrt{\frac{t-1}{t}} = \sqrt{1 - \frac{1}{t}}$$

Then,
$$\lim_{t\to\infty} \{\rho_x(t-1,t)\} = \lim_{t\to\infty} \{\sqrt{1-\frac{1}{t}}\} = \sqrt{1-0} = 1.$$

That is, for large time t with lag h considerably less than t, $\rho_x(t-1,t)$ is nearly 1. This implies that the correlogram for this random walk with drift is characterised by positive autocorrelations with very slow decay down from unity.

(5) Suggest a transformation to make the series stationary, and prove that the transformed series is stationary.

We can take the first difference of x_t . Then,

$$z_{t} = x_{t} - x_{t-1}$$

$$= \delta + x_{t-1} + w_{t} - x_{t-1}$$

$$= \delta + w_{t}$$

Thus, the mean of z_t

$$E(z_t) = E\{\delta + w_t\}$$

$$= E(\delta) + E(w_t)$$

$$= \delta + 0$$

$$= \delta$$

, which is independent of t.

And the autocovariance function of z_t

$$\gamma(h) = Cov(z_t, z_{t+h})$$

$$= Cov(\delta + w_t, \delta + w_{t+h})$$

$$= \begin{cases} \sigma_w^2 & h = 0 \\ 0 & h \neq 0 \end{cases}$$
 because w_t are uncorrelated random variables

, which is also independent of t.

Hence, the transformed series z_t is stationary.

 $\mathbf{Q3}$

(1) Compute the sample autocorrelation function, $\hat{\rho}(h)$, at lags h = 0, 1, 2, and 3.

Here is a table of t, x_t , x_{t+1} , x_{t+2} , x_{t+3} .

t	x_t	x_t_1	x_t_2	x_t_3
1	24	20	25	31
2	20	25	31	30
3	25	31	30	32
4	31	30	32	37
5	30	32	37	33
6	32	37	33	40
7	37	33	40	38
8	33	40	38	NA
9	40	38	NA	NA
10	38	NA	NA	NA

The sample mean of these ten x_t values is $\bar{x} = 31$. Thus,

$$\begin{split} \hat{\rho}(0) &= \frac{\hat{\gamma}(0)}{\hat{\gamma}(0)} = 1 \\ \hat{\rho}(1) &= \frac{\hat{\gamma}(1)}{\hat{\gamma}(0)} = \frac{(24-31)(20-31)+(20-31)(25-31)+\ldots+(33-31)(40-31)+(40-31)(38-31)}{(24-31)^2+(20-31)^2+\ldots+(40-31)^2+(38-31)^2} \\ &= \frac{241}{378} \approx 0.638 \\ \hat{\rho}(2) &= \frac{\hat{\gamma}(2)}{\hat{\gamma}(0)} = \frac{(24-31)(25-31)+(20-31)(31-31)+\ldots+(37-31)(40-31)+(33-31)(38-31)}{378} \\ &= \frac{112}{378} \approx 0.296 \\ \hat{\rho}(3) &= \frac{\hat{\gamma}(3)}{\hat{\gamma}(0)} = \frac{(24-31)(31-31)+(20-31)(30-31)+\ldots+(32-31)(40-31)+(37-31)(38-31)}{378} \\ &= \frac{54}{378} \approx 0.143 \end{split}$$

(2) Test the null hypothesis.

Test the null hypothesis $H_0: \rho(1) = 0$ versus the alternative hypothesis $H_a: \rho(1) \neq 0$.

The t-test statistic is

$$t_{\rho(1)} = \frac{\hat{\rho}(1)}{\sigma_{\hat{\sigma}(1)}} = \frac{0.638}{1/\sqrt{10}} \approx 2.018$$

, which is greater than $z_{0.025} = 1.96 \approx 2$. Thus, we reject $H_0: \rho(1) = 0$ at a 5% level of significance.

(3) Use R and redo parts (1) and (2).

x <- c(24, 20, 25, 31, 30, 32, 37, 33, 40, 38)
Compute the sample autocorrelation function
acf(x, lag.max=3, plot=FALSE)</pre>

```
## Autocorrelations of series 'x', by lag
##
## 0 1 2 3
## 1.000 0.638 0.296 0.143

# Test the null hypothesis
n = 10 # sample size
t_statistic = 0.638/(1/sqrt(n)) # use 1/sqrt(n) to estimate the standard deviation
if (t_statistic > 1.96) {
   print("Reject the null hypothesis at a significance level of 5%")
} else {
   print("Do NOT reject the null hypothesis at a significance level of 5%")
}
```

$\mathbf{Q4}$

The autocovariance function of x_t is

$$\begin{split} \gamma(h) &= Cov(x_t, x_{t+h}) \\ &= Cov\{\frac{1}{3}(w_{t-1} + w_t + w_{t+1}), \frac{1}{3}(w_{t+h-1} + w_{t+h} + w_{t+h+1})\} \\ &= \frac{1}{9}Cov\{(w_{t-1} + w_t + w_{t+1}), (w_{t+h-1} + w_{t+h} + w_{t+h+1})\} \\ &= \left\{ \begin{array}{ll} \frac{3}{9}\sigma_w^2 & h = 0 \\ \frac{2}{9}\sigma_w^2 & h = \pm 1 \\ \frac{1}{9}\sigma_w^2 & h = \pm 2 \\ 0 & |h| > 2 \end{array} \right. \end{split}$$

Then the actual autocorrelation function ACF is

$$\rho(h) = \begin{cases} 1 & h = 0\\ \frac{2}{3} & h = \pm 1\\ \frac{1}{3} & h = \pm 2\\ 0 & |h| > 2 \end{cases}$$

(1) Simulation with n = 500.

```
set.seed(100)
# Simulate 500 observations from N(0,1); Gaussian white noise
w <- rnorm(502, 0, 1) # extra 2 to avoid startup problems
# Apply the moving average filter
x = filter(w, sides=2, filter=rep(1/3, 3))
x = head(x[-1], -1) # remove the first and last NA element
# Compute the sample ACF
acf(x, lag.max=20, plot=FALSE)
## Autocorrelations of series 'x', by lag
##
                      2
                            3
                                 4
                                           5
                                                        7
##
               1
                                                 6
   1.000 0.614 0.273 -0.103 -0.108 -0.125 -0.041 0.036
                                                            0.089
                                                                   0.005 -0.025
                     13
                           14
                                 15
                                       16
                                                 17
                                                        18
## -0.079 -0.088 -0.110 -0.072 -0.030 -0.022 -0.063 -0.054 -0.024
\#acf(x, laq.max=20, plot=TRUE)
```

Comparing the sample ACF to the actual ACF, we can find that the $\hat{\rho}(1) = 0.614$ and $\hat{\rho}(2) = 0.273$ are close to the actual ACF values $\frac{2}{3}$ and $\frac{1}{3}$, and the sample ACF values for lag h greater than 2 are around the actual ACF value of 0.

(2) Simulation with n = 50.

```
set.seed(100)
# Simulate 50 observations from N(0,1); Gaussian white noise
w <- rnorm(52, 0, 1) # extra 2 to avoid startup problems
# Apply the moving average filter
x = filter(w, sides=2, filter=rep(1/3, 3))
x = head(x[-1], -1) # remove the first and last NA element
# Compute the sample ACF
acf(x, lag.max=20, plot=FALSE)</pre>
```

```
##
## Autocorrelations of series 'x', by lag
##
##
        0
                1
                       2
                              3
                                      4
                                             5
                                                    6
                                                            7
                                                                   8
                                                                           9
                                                                                 10
    1.000
           0.416
                  0.237 -0.359 -0.290 -0.340 -0.031
                                                        0.123
                                                               0.258
##
                                                                      0.048 -0.078
##
       11
              12
                      13
                             14
                                     15
                                            16
                                                    17
                                                           18
                                                                  19
                                                                          20
## -0.385 -0.281 -0.366 -0.010
                                 0.016 0.278 0.137
                                                       0.140 -0.033
                                                                      0.032
\#acf(x, lag.max=20, plot=TRUE)
```

As the sample ACF results from the above two simulations show, when the number of observations n increases, the sample ACF values tend to be closer to the actual ACF values, that is, the empirical values tend to be closer to the theoretical values.

Q_5

(1) Show that this process is weak stationary.

$$\begin{aligned} x_t &= cos[2\pi(\frac{t}{12} + \phi)] \\ &= cos(\frac{\pi t}{6} + 2\pi\phi) \\ &= cos(\frac{\pi t}{6})cos(2\pi\phi) - sin(\frac{\pi t}{6})sin(2\pi\phi) \end{aligned}$$

Then, the mean

$$\begin{split} E(x_t) &= \cos(\frac{\pi t}{6}) \cdot E[\cos(2\pi\phi)] - \sin(\frac{\pi t}{6}) \cdot E[\sin(2\pi\phi)] \\ &= \cos(\frac{\pi t}{6}) \cdot \int_0^1 [\cos(2\pi\phi)] d\phi - \sin(\frac{\pi t}{6}) \cdot \int_0^1 [\sin(2\pi\phi)] d\phi \\ &= \cos(\frac{\pi t}{6}) \cdot \frac{1}{2\pi} [\sin(u)|_0^{2\pi}] - \sin(\frac{\pi t}{6}) \cdot \frac{1}{2\pi} [-\cos(u)|_0^{2\pi}] \\ &= \cos(\frac{\pi t}{6}) \cdot 0 - \sin(\frac{\pi t}{6}) \cdot 0 \\ &= 0 \end{split}$$

, which is independent of t.

And the autocovariance function

$$\begin{split} \gamma(h) &= Cov(x_t, x_{t+h}) = E(x_t x_{t+h}) \\ &= E\{cos(\frac{\pi t}{6} + 2\pi\phi) \cdot cos(\frac{\pi (t+h)}{6} + 2\pi\phi)\} \\ &= E\{\frac{1}{2} \cdot cos[\frac{\pi t}{6} + 2\pi\phi - \frac{\pi (t+h)}{6} - 2\pi\phi] + \frac{1}{2} \cdot cos[\frac{\pi t}{6} + 2\pi\phi + \frac{\pi (t+h)}{6} + 2\pi\phi]\} \\ &= \frac{1}{2} E\{cos(-\frac{\pi h}{6}) + cos[\frac{2\pi t + \pi h}{6} + 4\pi\phi]\} \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) + \frac{1}{2} E\{cos[\frac{2\pi t + \pi h}{6} + 4\pi\phi]\} \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) + \frac{1}{2} E\{cos(\frac{2\pi t + \pi h}{6}) cos(4\pi\phi) - sin(\frac{2\pi t + \pi h}{6}) sin(4\pi\phi)\} \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) + \frac{1}{2} \{cos(\frac{2\pi t + \pi h}{6}) \cdot \int_{0}^{1} [cos(4\pi\phi)] d\phi - sin(\frac{2\pi t + \pi h}{6}) \cdot \int_{0}^{1} [sin(4\pi\phi)] d\phi\} \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) + \frac{1}{2} \{cos(\frac{2\pi t + \pi h}{6}) \cdot 0 - sin(\frac{2\pi t + \pi h}{6}) \cdot 0\} \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) + 0 \\ &= \frac{1}{2} cos(\frac{\pi h}{6}) \end{split}$$

, which is independent of t.

Hence, the process x_t is weak stationary.

(2) Find its autocorrelation function.

From part (1), we can have $\gamma(0) = \frac{1}{2}cos(0) = \frac{1}{2}$.

Then, the autocorrelation function is

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \frac{\frac{1}{2}cos(\frac{\pi h}{6})}{\frac{1}{2}} = cos(\frac{\pi h}{6})$$