Time Series Analysis: Problem Set - Week 8 (Tutorial and Computer Problems)

Attempt these questions before your class and discuss any issues with your tutor Go to your assigned tutorial class/Lab and record your attendance

1.

$$X_t = \sum_{j=0}^{\infty} \psi_j Z_{t-j}$$

(a) (i)

$$\hat{X}_{t+\ell} = E\left(X_{t+\ell}|X_t, X_{t-1}, \dots\right)$$

$$= E\left[\sum_{j=0}^{\infty} \psi_j Z_{t+\ell-j}|X_t, X_{t-1}, \dots\right]$$

$$= \sum_{j=\ell}^{\infty} \psi_j Z_{t+\ell-j}$$

$$= \sum_{j=0}^{\infty} \psi_{\ell+j} Z_{t-j}$$

(ii)

$$\epsilon_{t+\ell} = X_{t+\ell} - \hat{X}_{t+\ell}$$

$$= \sum_{j=0}^{\ell-1} \psi_j Z_{t+\ell-j}$$

$$\therefore Var(\epsilon_{t+\ell}) = \sigma^2 \sum_{j=0}^{\ell-1} \psi_j^2$$

(b) (i) Use the results: $\gamma_Z(0) = \sigma^2$ and $\gamma_Z(k) = 0, \ k \neq 0, \ -\pi < \omega < \pi$. Hence

$$f_Z(\omega) = \frac{1}{2\pi} \sum_{k=0}^{\infty} \gamma_Z(k) e^{-i\omega k}$$
$$= \frac{1}{2\pi}$$

- (ii) $f_X(\omega) = |\psi_j e^{-i\omega j}|^2 f_Z(\omega), -\pi < \omega < \pi.$
- 2. (i) $\alpha_1=1,\ \alpha_2=-0.5$ satisfy $|\alpha_2|<1,\ \alpha_2-\alpha_1<1$ and $\alpha_1+\alpha_2<1.$ Therefore, $\{X_t\}$ is stationary.
 - (ii) Let $E(X_t) = \mu$ for all t. Therefore,

$$\mu = \star + \mu - 0.5\mu \Rightarrow \star = 0.5\mu = 18$$

(iii)

$$\hat{x}_{t+1} = 18 + x_t - 0.5x_{t-1}$$

$$\therefore \hat{x}_{85} = 18 + x_{84} - 0.5x_{83} = 28.5$$

Therefore, a 90% FI for x_{t+1} is $\hat{x}_{t+1} \pm 1.645\hat{\sigma}$ or, in the case of t = 85,

$$\hat{x}_{85} \pm 1.645 \times 2 = (25.21, 31.79)$$

$$\hat{x}_{t+2} = 18 + \hat{x}_{t+1} - 0.5x_t$$

$$\therefore \hat{x}_{86} = 18 + \hat{x}_{85} - 0.5x_{84} = 32.25$$

We also have that the error is

$$\epsilon_{t+2} = X_{t+2} - \hat{X}_{t+2}$$

$$= X_{t+1} - \hat{X}_{t+1} + Z_{t+2}$$

$$= Z_{t+1} + Z_{t+2}$$

Therefore, $Var(\epsilon_{t+2}) = 2\sigma^2 = 8$. A 90% FI for x_{t+2} is $\hat{x}_{t+2} \pm 1.645\sqrt{8} = 32.25 \pm 4.653$.

3. (ia)

$$\hat{X}_{t+\ell} = E\left(X_{t+\ell}|Z_t, Z_{t-1}, \dots\right)$$

$$= E\left(50 + 0.5X_{t+\ell-1} + Z_{t+\ell} - 0.2Z_{t+\ell-1} - 0.1Z_{t+\ell-3}|Z_t, Z_{t-1}, \dots\right)$$

We have the cases of

$$\hat{X}_{t+\ell} = \begin{cases} 50 + 0.5X_t + 0.2Z_t - 0.1Z_{t-2} & ; \ell = 1\\ 50 + 0.5\hat{X}_{t+1} - 0.1Z_{t-1} & ; \ell = 2\\ 50 + 0.5\hat{X}_{t+2} - 0.1Z_t & ; \ell = 3 \end{cases}$$

(ib) It is clear that for $\ell \geq 4$,

$$\hat{X}_{t+\ell} = 50 + 0.5 \hat{X}_{t+\ell-1}$$

$$\Rightarrow \hat{X}_{t+\ell} - 100 = 0.5 \left[\hat{X}_{t+\ell-1} - 100 \right] \text{ since } E(X_t) = 100$$

Thus, as $\ell \to \infty$, $E\left(\hat{X}_{t+\ell-1} - 100 \to 0\right)$. In the long run, we always obtain the mean as our forecast. This is not very satisfactory. The model is good for short-term forecasting.

(ii) We are given

$$x_t = 109; x_{t-1} = 98; x_{t-2} = 90$$

 $\hat{x}_t = 108; x_{t-1} = 100; \hat{x}_{t-2} = 94$
 $z_t = 1; z_{t-1} = -2; z_{t-2} = -4$

We require the one-step forecast value using the model. Thus,

$$\hat{x}_{t+1} = 50 + 0.5x_t - 0.2z_t - 0.1z_{t-2}$$
$$= 50 + 0.5 - 0.2 \times 1 - 0.1 \times -4$$
$$= 104.7$$

The forecast error is

$$\epsilon_{t+1} = X_{t+1} - \hat{X}_{t+1} = Z_{t+1}$$

Therefore, $Var\left(\epsilon_{t+1}\right) = 1$ and a 95% FI for X_{t+1} is

$$104.7 \pm 1.96 or (102.74, 106.66)$$

4. We have that

$$\gamma_0 = (1 + 0.7^2) \times 1.5^2 = 3.3525$$

 $\gamma_1 = (0.7) \times 1, 5^2 = 1.575$
 $\gamma_k = 0, \ k \ge 2.$

Therefore,

$$f_X(\omega) = \frac{1}{2\pi} \left[\gamma_0 + 2 \sum_{j=1}^{\infty} \gamma_j \cos(\omega_j) \right]$$
$$= \frac{1}{2\pi} \left[\gamma_0 + 2\gamma_1 \cos(\omega) \right]$$
$$= \frac{1}{2\pi} \left[3.3525 + 3.15 \cos(\omega) \right].$$

and

$$f_X^*(\omega) = \frac{f_X(\omega)}{\gamma_0} = \frac{1}{2\pi \times 3.3535} [3.3525 + 3.15\cos(\omega)]$$

(ii) Use calculus to sketch.

Computer Exercise Computer Exercise: Submit your answers to Q3 by 11.59 on Monday 11 April

1. (i) x=scan()

(ii) d1=diff(x) ts.plot(d1) acf(d1) pacf(d1)

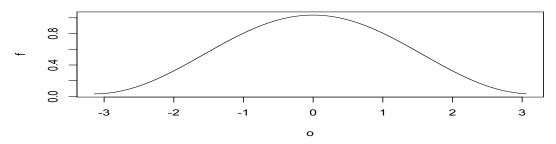
The series look non-stationary with a trend.

(iii) d2=diff(d1) ts.plot(d2) acf(d2) pacf(d2)

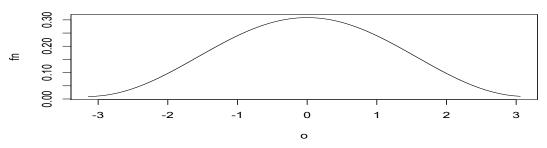
The series in d2 looks stationary.

- (iv) d=2 is the best value for d.
- (v) ts.plot(d2)
 acf(d2)
 pacf(d2)
- 2. (i) o=c(-32:32)/10 # to create a vector for omega OR o= seq(-pi,pi,0.1)
 s2=1.5^2 # variance of the noise
 f=(3.3525+3.15*cos(o))/(2 pi) # take from Q4
 plot(o,f, type="l", main="sdf of MA(1)")

sdf of MA(1)



normalised sdf of MA(1)



```
3.
   (i) fit1=arima(d2, order=c(1,0,0))
       fit1
       Call:
       arima(x = d2, order = c(1, 0, 0))
       Coefficients:
       ar1 intercept
       0.7318
                0.0045
       s.e. 0.0483
                      0.0045
       sigma^2 estimated as 0.0002977: log likelihood = 522.5, aic = -1038.99
       fit2=arima(d2, order=c(2,0,0))
       fit2
       arima(x = d2, order = c(2, 0, 0))
       Coefficients:
       ar1 ar2 intercept
       0.564 0.2293 0.0043
       s.e. 0.069 0.0692 0.0056
       sigma^2 estimated as 0.0002819: log likelihood = 527.84, aic = -1047.67
       fit3=arima(d2, order=c(3,0,0))
       fit3
       Call:
       arima(x = d2, order = c(3, 0, 0))
       Coefficients:
                     ar3 intercept
           ar2
       0.6275 0.3843 -0.2754 0.0045
       s.e. 0.0680 0.0766 0.0681 0.0043
       sigma^2 = 535.67, aic = -1061.35
       fit4=arima(d2, order=c(0,0,3))
       fit4
```

```
Call:
arima(x = d2, order = c(0, 0, 3))
Coefficients:
ma1 ma2 ma3 intercept
0.5341 0.6813 0.3719 0.0045
s.e. 0.0608 0.0564 0.0580 0.0030
sigma^2 estimated as 0.0002709: log likelihood = 531.58, aic = -1053.15
fit5=arima(d2, order=c(1,0,2))
fit5
Call:
arima(x = d2, order = c(1, 0, 2))
Coefficients:
                                                                      ma2 intercept
ar1 ma1
0.6810 -0.1112 0.4202 0.0044
s.e. 0.0716 0.0794 0.0757 0.0046
sigma^2 estimated as 0.0002539: log likelihood = 537.99, log likeliho
```

(ii) The model with the smallest AIC value is ARIMA(1,2) for the data in d2. The constant can be dropped out since its se is 0.0046 and the t-ratio is 0.957 (small). The fitted model is

$$Y_t = 0.6810Y_{t-1} + Z_t - 0.1112Z_{t-1} + 0.4202Z_{t-2}, Var(Z_t) = 0.0002593$$

```
(iii) tsdiag(fit1)
    tsdiag(fit2)
    tsdiag(fit3)
    tsdiag(fit4)
    tsdiag(fit5)
```

Largest p-values for the GOF statistic is for fit5. This confirms the ARMA(1,2) as the best model.

```
forecast=predict(fit5,n.ahead=5,se.fit=T)
forecast

$pred
Time Series:
Start = 199
End = 203
Frequency = 1
[1] 0.012828029 0.012496967 0.009917557 0.008160866 0.006964485

$se
Time Series:
Start = 199
End = 203
Frequency = 1
[1] 0.01593570 0.01834138 0.02241245 0.02406806 0.02479846
```

```
(v) ts.plot(cbind(forecast$pred, forecast$se), lty=c(1,2))
legend("topleft", c("Forecast Values", "---SEs"))
```

```
(vi) ts.plot(cbind(forecast$pred,forecast$pred+1.96*forecast$se, forecast$pred,forecast$pred-1.96*forecast$se),
    lty=c(1,2,3))
    legend("bottomleft", c("Forecast Values", "---UL", "---LL"))
```