620-374 Time Series & Forecasting Exercises
Assignment 4: Exercise 4
Assignment 5: Exercise 8
Assignment 6: Exercises 13 and 14

1. Spencer’s 15 point moving average is determined by the weights (to 3 sig. figs.):

\[-0.009 \quad -0.019 \quad -0.016 \quad 0.009 \quad 0.066 \quad 0.144 \quad 0.209 \quad 0.231 \quad 0.209 \quad 0.144 \quad 0.066 \quad 0.009 \quad -0.016 \quad -0.019 \quad -0.009\]

Demonstrate that it can be obtained as the composition of the following four moving averages (each is applied in turn).

\[
\begin{array}{cccc}
1/4 & 1/4 & 1/4 & 1/4 \\
1/4 & 1/4 & 1/4 & 1/4 \\
1/5 & 1/5 & 1/5 & 1/5 \\
\end{array}
\]

Hint: express each moving average in terms of a matrix operator.

2. Let \(a_1, \ldots, a_m\) be the weights for an \(m\) point moving average. Show that the condition

\[
\sum_{k=j \mod s} a_k = \frac{1}{s} \quad \text{for} \quad j = 0,1,\ldots, s - 1
\]

is necessary for the removal of an additive seasonal effect of period \(s\), in the sense that if it does not hold then we can always find a series for which the seasonal effect will not be removed.

3. Obtain sufficient conditions on the weights used for local regression smoothing to be independent of an additive seasonal effect of period \(s\).

4. The following time-series of monthly milk production per cow (in pounds) can be found at http://www-personal.buseco.monash.edu.au/~hyndman/forecasting/

Divide through by the number of days in a month to get daily milk production, and then decompose the time-series into trend/cycle, seasonal and residual (noise) components, and plot them.
5. The following time-series gives the inventory demand for product E15 over 24 months.

<table>
<thead>
<tr>
<th>Period</th>
<th>Observation</th>
<th>Period</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>143</td>
<td>13</td>
<td>206</td>
</tr>
<tr>
<td>2</td>
<td>152</td>
<td>14</td>
<td>193</td>
</tr>
<tr>
<td>3</td>
<td>161</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>4</td>
<td>139</td>
<td>16</td>
<td>207</td>
</tr>
<tr>
<td>5</td>
<td>137</td>
<td>17</td>
<td>218</td>
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<tr>
<td>6</td>
<td>174</td>
<td>18</td>
<td>229</td>
</tr>
<tr>
<td>7</td>
<td>142</td>
<td>19</td>
<td>225</td>
</tr>
<tr>
<td>8</td>
<td>141</td>
<td>20</td>
<td>204</td>
</tr>
<tr>
<td>9</td>
<td>162</td>
<td>21</td>
<td>227</td>
</tr>
<tr>
<td>10</td>
<td>180</td>
<td>22</td>
<td>223</td>
</tr>
<tr>
<td>11</td>
<td>164</td>
<td>23</td>
<td>242</td>
</tr>
<tr>
<td>12</td>
<td>171</td>
<td>24</td>
<td>239</td>
</tr>
</tbody>
</table>

Use Holt’s method (double exponential smoothing) to forecast period 25. Use values of 0.3 and 0.7 for the smoothing parameters $\alpha$ and $\beta$.

For $n = 0, 1, \ldots, 11$ use periods 1 to $12 + n$ to forecast period $13 + n$. Using the Mean Square Error (MSE) find better values of $\alpha$ and $\beta$. 
6. For the (deterministic) series

\[ X_t = t \text{ for } t = 0, 1, \ldots \]

what value of the smoothing parameter \( \alpha \) gives the best Exponential Smoothing forecast?

Now suppose that the \( X_t \) are independent and identically distributed (i.i.d.) \( N(0,1) \) random variables. What are the best lag and \( \alpha \) in this case?

Hint: if \( X \sim N(0,1) \), then the Minimum Variance Unbiased estimator of \( X \) is just 0.

7. Adaptive Response Rate Single Exponential Smoothing is a variant of Exponential Smoothing that continually adjusts the smoothing parameter \( \alpha \) to try and allow for changes in the trend.

Let \( X_t \) be our time series, \( F_t \) the forecast and \( \alpha_t \) the smoothing parameter at time \( t \). \( F_t \) is updated in the usual way

\[ F_{t+1} = \alpha_t X_t + (1 - \alpha_t) F_t \]

The smoothing parameter is defined in terms of the forecasting error \( E_t = X_t - F_t \). It is reduced if the forecasting error is “generally” unbiased (mean 0), which would happen if there little trend, and is increased otherwise. For some \( 0 < b < 1 \) we have

\[
\begin{align*}
A_{t+1} &= b E_t + (1 - b) A_{t+1} \\
M_{t+1} &= b |E_t| + (1 - b) M_{t+1} \\
a_{t+1} &= |A_t/M_t|
\end{align*}
\]

Apply this to the time series data from Question 5 and compare the results with those given by Holt’s method. Use \( b = 0.5 \).

8. There are many variants of the Holt-Winters method, depending upon whether there is no trend, a linear trend, an exponential trend, no seasonality, additive seasonality or multiplicative seasonality. All of them can be written in the following form, with smoothing parameters \( a \), \( b \) and \( c \)

\[
\begin{align*}
L_t &= a P_t + (1 - a) Q_t \quad \text{(level (seasonally adjusted))} \\
B_t &= b R_t + (1 - b) B_{t-1} \quad \text{(slope (seasonally adjusted))} \\
\Sigma_t &= c T_t + (1 - c) \Sigma_{t-s} \quad \text{(seasonality of period } s)\n\end{align*}
\]
Let \( X_t \) be our time series, for a linear trend and multiplicative seasonality we have

\[
P_t = \frac{X_t}{\sum_{t-s}} \quad \text{(seasonally adjusted observation)}
\]

\[
Q_t = L_{t-1} + B_{t-1} \quad \text{(projected level (seasonally adjusted))}
\]

\[
R_t = L_t - L_{t-1} \quad \text{(observed trend (seasonally adjusted))}
\]

\[
T_t = \frac{X_t}{L_t} \quad \text{(observed seasonal effect)}
\]

The \( m \) step ahead forecast is then

\[
F_{t+m} = (L_t + m B_t) \sum_{t+m-s}
\]

The following time series gives quarterly sales figures for a French company. It exhibits multiplicative seasonality.

<table>
<thead>
<tr>
<th>Period 1</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>362</td>
<td>385</td>
<td>432</td>
<td>341</td>
<td>382</td>
<td>409</td>
<td>498</td>
<td>387</td>
<td>473</td>
<td>513</td>
<td>582</td>
<td>474</td>
</tr>
<tr>
<td>Period 13</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
<td>23</td>
<td>24</td>
</tr>
<tr>
<td>Observation</td>
<td>544</td>
<td>582</td>
<td>681</td>
<td>557</td>
<td>628</td>
<td>707</td>
<td>773</td>
<td>592</td>
<td>627</td>
<td>725</td>
<td>854</td>
<td>661</td>
</tr>
</tbody>
</table>

Using initial values of 0.3 for each of the smoothing parameters, for \( n = 0, 1, \ldots, 11 \) forecast period \( 13 + n \) from periods 1 to 12 + \( n \). By trial and error (or otherwise) find values of \( a, b \) and \( c \) which reduce the MSE. What is your best forecast for period 25?

9. Suppose that we have a sequence of monthly observations \( X_t = (a + bt)S_t + \epsilon_t \), where \( S_t \) has period 12 and \( \epsilon_t \) is stationary.

Does the differencing operator \( \nabla_{12} \) make \( X_t \) stationary? Here \( \nabla_{12} X_t = X_t - X_{t-12} \). If not find a (combination of) differencing operators which does.
10. Let \( \{Z_t\}_{t=0}^{\infty} \) be a sequence of i.i.d. r.v.s with mean 0 and variance \( \sigma^2 \). Put

\[
X_t = Z_t + \theta Z_{t-1} \\
Y_t = Z_t + \frac{1}{\theta} Z_{t-1}
\]

Show that \( X_t \) and \( Y_t \) have the same autocorrelation function.

By rearranging the equations above, write \( Z_t \) as a linear combination of \( X_t, X_{t-1}, \ldots \) and as a linear combination of \( Y_t, Y_{t-1}, \ldots \). Show that in at most one case the coefficients are absolutely summable. (In this case we say that the model is invertible. It can be shown that there is at most one invertible model for any given autocorrelation function.)

11. Only answer this question if you know what a Markov chain is. Let \( X \) be a positive recurrent aperiodic discrete-time chain, with equilibrium distribution \( \pi \). Suppose that \( X \) is in equilibrium, that is \( P(X_t = x) = \pi(x) \). Show that \( X \) is stationary.

Note that Markov models and ARMA models do not overlap much.

For Questions 12 to 16 let \( \{Z_t\}_{t=0}^{\infty} \) be an i.i.d. sequence with mean \( \mu \) and variance \( \sigma^2 \).

12. Let \( \{X_t\}_{t=0}^{\infty} \) be the moving average (MA) process given by

\[
X_t = \sum_{k=0}^{m} \frac{1}{m+1} Z_{t-k}
\]

Show that the autocorrelation function of this process is

\[
\rho(k) = \begin{cases} 
(m+1-k)/(m+1) & \text{for } k = 0,1,\ldots,m \\
0 & \text{for } k > m
\end{cases}
\]

13. Find those values of \( a, b \geq 0 \) that make the following autoregressive (AR) process stationary

\[
X_t = aX_{t-1} + bX_{t-2} + Z_t.
\]

For \( a = 1/3 \) and \( b = 2/9 \) show that \( \{X_t\}_{t=0}^{\infty} \) has autocorrelation function
\[ \rho(k) = \frac{16}{21} \left( \frac{2}{3} \right)^k + \frac{5}{21} \left( -\frac{1}{3} \right)^k \text{ for } k = 0, 1, 2, \ldots \]

14. For each of the following models express the model in terms of the shift operator \( B \) acting on \( X_t \) and \( Z_t \) and then determine whether the model is stationary and/or invertible.

(a) \[ X_t = 0.3X_{t-1} + Z_t \]

(b) \[ X_t = Z_t - 1.3Z_{t-1} + 0.4Z_{t-2} \]

(c) \[ X_t = 0.5X_{t-1} + Z_t - 1.3Z_{t-1} + 0.4Z_{t-2} \]

What is the MA representation of model (a)?

15. Suppose that \( \{X_t\}_{t=0}^\infty \) is a stationary process and can be written as either \( X_t = \psi(B)Z_t \) or \( \pi(B)X_t = Z_t \), where \( B \) is the shift operator. We define the autocovariance generating function by

\[ \Gamma(s) = \sum_{k=-\infty}^{\infty} \gamma(k)s^k \]

where \( \gamma(k) = \text{Cov}(X_t, X_{t+k}) \). By equating coefficients of \( s^k \) show that

\[ \Gamma(s) = \sigma^2 \psi(s)\psi(1/s) = \frac{\sigma^2}{\pi(s)\pi(1/s)} \]

16. Find the partial autocorrelation of the AR(2) process \( X_t = \frac{1}{3}X_{t-1} + \frac{2}{9}X_{t-2} + Z_t \) (see Question 13).

17. The following is a realisation of a sequence of i.i.d. \( \text{N}(0,1) \) random variables, \( \{Z_t\}_{t=1}^{30} \).

<table>
<thead>
<tr>
<th>( t )</th>
<th>( Z_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td>1</td>
<td>1.38</td>
</tr>
<tr>
<td>2</td>
<td>0.53</td>
</tr>
<tr>
<td>3</td>
<td>1.58</td>
</tr>
<tr>
<td>4</td>
<td>1.32</td>
</tr>
<tr>
<td>5</td>
<td>1.04</td>
</tr>
<tr>
<td>6</td>
<td>0.33</td>
</tr>
<tr>
<td>7</td>
<td>-0.20</td>
</tr>
<tr>
<td>8</td>
<td>1.90</td>
</tr>
<tr>
<td>9</td>
<td>0.72</td>
</tr>
<tr>
<td>10</td>
<td>-0.27</td>
</tr>
<tr>
<td>11</td>
<td>-1.43</td>
</tr>
<tr>
<td>12</td>
<td>-1.15</td>
</tr>
<tr>
<td>13</td>
<td>-0.07</td>
</tr>
<tr>
<td>14</td>
<td>1.69</td>
</tr>
<tr>
<td>15</td>
<td>0.28</td>
</tr>
<tr>
<td>16</td>
<td>0.01</td>
</tr>
<tr>
<td>17</td>
<td>0.94</td>
</tr>
<tr>
<td>18</td>
<td>-2.10</td>
</tr>
<tr>
<td>19</td>
<td>0.09</td>
</tr>
<tr>
<td>20</td>
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</tr>
<tr>
<td>21</td>
<td>1.76</td>
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<tr>
<td>22</td>
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<td>25</td>
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<tr>
<td>26</td>
<td>-1.03</td>
</tr>
<tr>
<td>27</td>
<td>-1.71</td>
</tr>
<tr>
<td>28</td>
<td>1.18</td>
</tr>
<tr>
<td>29</td>
<td>-0.59</td>
</tr>
<tr>
<td>30</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Use them to generate realisations of the following sequences. In each case plot the series and (using suitable software) plot the sample autocorrelation and sample partial autocorrelation.

(a) The AR(1) sequence \( X_t = 0.6X_{t-1} + Z_t \), with \( X_0 = 0 \).

(b) The MA(1) sequence \( X_t = Z_t + 0.6Z_{t-1} \), with \( Z_0 = 0 \).

(c) The AR(2) sequence \( X_t = -0.8X_{t-1} + 0.3X_{t-2} + Z_t \), with \( X_0 = X_{-1} = 0 \).

(d) The MA(2) sequence \( X_t = Z_t + 0.8Z_{t-1} - 0.3Z_{t-2} \), with \( Z_0 = Z_{-1} = 0 \).

(e) The ARMA(1,1) sequence \( X_t = 0.6X_{t-1} + Z_t + 0.6Z_{t-1} \), with \( X_0 = 0 \) and \( Z_0 = 0 \).

18. The following time-series gives a particular manufacturer’s stock level of Evaporated and Sweet Condensed Milk over the period Jan 1971 to Dec 1980.

![Stock Level Chart](http://www-personal.buseco.monash.edu.au/~hyndman/forecasting/)

The original data can be found at http://www-personal.buseco.monash.edu.au/~hyndman/forecasting/

Calculate the autocorrelation function (acf) and partial autocorrelation function (pacf) for this series.

The data clearly has (additive) seasonality with period 12. Apply a lag 12 differencing to remove the seasonality and recalculate the acf and pacf.
There is some indication of a (local) trend. Apply a further lag 1 differencing to remove any trend and recalculate the acf and pacf. Does the series look stationary now? Suggest a model for the differenced series.

Express your model (including differencing) using the shift operator $B$.

19. The following time series gives the sheep population in England and Wales from 1867 to 1939.

![Time series graph](image)

The original data can be found at http://www-personal.buseco.monash.edu.au/~hyndman/forecasting/

There appears to be a linear trend. Accordingly apply a lag 1 differencing then calculate the acf and pacf.

Fit an AR(p) model to the differenced data. Use it to forecast ahead a further 3 years.
20. The following time series gives the net generation of electricity in the U.S.A. for the period Jan 1985 to Oct 1996.

The original data can be found at http://www-personal.buseco.monash.edu.au/~hyndman/forecasting/

Fit an ARIMA model to this data and use it to forecast ahead 24 months.

Check that the residuals resemble white noise by calculating their acf.

The seasonality looks like it could be multiplicative. Accordingly take logs of the original data and repeat your analysis. How do your new forecasts compare to the old ones?

If you wish to check your forecasts against the real thing, more recent data is available from http://www.eia.doe.gov/emeu/mer/elect.html