Analisis Deret Waktu (STK 651)

Teknik Peramalan Melalui Pemulusan Data
(Bagian II)

Dr. Kusman Sadik, M.Si
Sekolah Pascasarjana Departemen Statistika IPB
Semester Genap 2017/2018
The most crucial issue in simple moving averages is the choice of the span, N.

A simple moving average will react faster to the changes if N is small.

This means that as N gets small, the variance of the moving average gets bigger.

This represents a dilemma in the choice of N. If the process is expected to be constant, a large N can be used whereas a small N is preferred if the process is changing.
Another approach to obtain a smoother that will react to process changes faster is to give geometrically decreasing weights to the previous observations. Hence an exponentially weighted smoother is obtained by introducing a discount factor $\theta$ as

$$
\sum_{t=0}^{T-1} \theta^t y_{T-t} = y_T + \theta y_{T-1} + \theta^2 y_{T-2} + \cdots + \theta^{T-1} y_1
$$

(4.3)
Please note that if the previous observations are to be discounted in a geometrically decreasing manner, then we should have $|\theta| < 1$. However, the smoother in Eq. (4.3) is not an average as the sum of the weights is

$$
\sum_{t=0}^{T-1} \theta^t = \frac{1 - \theta^T}{1 - \theta}
$$

(4.4)

and hence does not necessarily add up to 1. For that we can adjust the smoother in Eq. (4.3) by multiplying it by $(1 - \theta)/(1 - \theta^T)$. However, for large $T$ values, $\theta^T$ goes to zero and so the exponentially weighted average will have the following form:

$$
\tilde{y}_T = (1 - \theta) \sum_{t=0}^{T-1} \theta^t y_{T-t}
$$

$$
= (1 - \theta) \left( y_T + \theta y_{T-1} + \theta^2 y_{T-2} + \cdots + \theta^{T-1} y_1 \right)
$$

(4.5)
\[ \tilde{y}_T = (1 - \theta) \sum_{t=0}^{T-1} \theta^t y_{T-t} \]

\[ = (1 - \theta) \left( y_T + \theta y_{T-1} + \theta^2 y_{T-2} + \cdots + \theta^{T-1} y_1 \right) \]

This is called a simple or first-order exponential smoother.

An alternate expression in a recursive form for simple exponential smoothing is given by

\[ \tilde{y}_T = (1 - \theta) y_T + (1 - \theta) \left( \theta y_{T-1} + \theta^2 y_{T-2} + \cdots + \theta^{T-1} y_1 \right) \]

\[ = (1 - \theta) y_T + \theta (1 - \theta) \left( \tilde{y}_{T-1} + \theta y_{T-2} + \cdots + \theta^{T-2} y_1 \right) \]

\[ = (1 - \theta) y_T + \theta \tilde{y}_{T-1} \]
\[ \tilde{y}_T = (1 - \theta)y_T + \theta\tilde{y}_{T-1} \]

setting \( \lambda = 1 - \theta \),

\[ \tilde{y}_T = \lambda y_T + (1 - \lambda)\tilde{y}_{T-1} \quad (4.7) \]

In this representation the **discount factor**, \( \lambda \), represents the weight put on the last observation and \( (1 - \lambda) \) represents the weight put on the smoothed value of the previous observations.

Analogous to the size of the span in moving average smoothers, an important issue for the exponential smoothers is the choice of the discount factor, \( \lambda \). Moreover, from Eq. (4.7), we can see that the calculation of \( \tilde{y}_1 \) would require us to know \( \tilde{y}_0 \).
The Initial Value, $\tilde{y}_0$

Since $\tilde{y}_0$ is needed in the recursive calculations that start with $\tilde{y}_1 = \lambda y_1 + (1 - \lambda) \tilde{y}_0$, its value needs to be estimated. But from Eq. (4.7) we have

\[
\begin{align*}
\tilde{y}_1 &= \lambda y_1 + (1 - \lambda) \tilde{y}_0 \\
\tilde{y}_2 &= \lambda y_2 + (1 - \lambda) \tilde{y}_1 = \lambda y_2 + (1 - \lambda)(\lambda y_1 + (1 - \lambda) \tilde{y}_0) \\
&= \lambda (y_2 + (1 - \lambda) y_1) + (1 - \lambda)^2 \tilde{y}_0 \\
\tilde{y}_3 &= \lambda \left( y_3 + (1 - \lambda) y_2 + (1 - \lambda)^2 y_1 \right) + (1 - \lambda)^3 \tilde{y}_0 \\
&\vdots \\
\tilde{y}_T &= \lambda \left( y_T + (1 - \lambda) y_{T-1} + \cdots + (1 - \lambda)^{T-1} y_1 \right) + (1 - \lambda)^T \tilde{y}_0
\end{align*}
\]
The Initial Value, $\tilde{y}_0$

which means that as $T$ gets large and hence $(1 - \lambda)^T$ gets small, the contribution of $\tilde{y}_0$ to $\tilde{y}_T$ becomes negligible. Thus for large data sets, the estimation of $\tilde{y}_0$ has little relevance. Nevertheless, two commonly used estimates for $\tilde{y}_0$ are the following.

1. Set $\tilde{y}_0 = y_1$. If the changes in the process are expected to occur early and fast, this choice for the starting value for $\tilde{y}_T$ is reasonable.

2. Take the average of the available data or a subset of the available data, $\bar{y}$, and set $\tilde{y}_0 = \bar{y}$. If the process is at least at the beginning locally constant, this starting value may be preferred.
the independence and constant variance assumptions we have

\[
\text{Var}(\bar{y}_T) = \text{Var}\left(\sum_{t=0}^{\infty} (1 - \lambda)^t \cdot y_{T-t}\right)
\]

\[
= \lambda^2 \sum_{t=0}^{\infty} (1 - \lambda)^{2t} \text{Var}(y_{T-t})
\]

\[
= \lambda^2 \sum_{t=0}^{\infty} (1 - \lambda)^{2t} \text{Var}(y_T)
\]

\[
= \text{Var}(y_T) \lambda^2 \sum_{t=0}^{\infty} (1 - \lambda)^{2t}
\]

\[
= \frac{\lambda}{(2 - \lambda)} \text{Var}(y_T)
\]

Thus the question will be how much smoothing is needed. In the literature, \(\lambda\) values between 0.1 and 0.4 are often recommended and do indeed perform well in practice.
Peramalan

- Peramalan untuk satu waktu ke depan adalah:

\[ \hat{y}_{T+1} = \tilde{y}_T \]

- Karena pemulusan eksponensial sederhana adalah untuk data yang stasioner, maka ramalan untuk \( \tau \) waktu ke depan (\( \tau = 1, 2, 3, \ldots \)) adalah:

\[ \hat{y}_{T+\tau} = \tilde{y}_T \]
Ukuran Kebaikan Pemulusan

- Ukuran kebaikan pemulusan dapat menggunakan ukuran keakuratan peramalan seperti yang dibahas sebelumnya.
- Diantaranya adalah SSE, MSE, MAD, MSD, MPE, dan MAPE.
- Penghitungan nilai-nilai tersebut didasarkan pada nilai galat ramalan (forecast error), yaitu: 
  \[ e_t(1) = y_t - \hat{y}_t(t - 1) \]
- Misalnya 
  \[ MSE = \frac{1}{n} \sum_{t=1}^{n} [e_t(1)]^2 \] dan 
  \[ MAPE = \frac{1}{n} \sum_{t=1}^{n} |r e_t(1)| \]
Contoh

Berikut data profit bulanan (dalam milyar) suatu perusahaan di bidang ekspor impor selama 10 bulan terakhir.

a. Tentukan data termuluskan melalui teknik eksponensial sederhana dengan \( \lambda = 0.25 \). Kemudian buat time-series plotnya bersama dengan data asal.

b. Tentukan ramalan besarnya profit pada setiap satu waktu ke depan. Berapa ramalan profit pada bulan ke-11 dan ke-12?

<table>
<thead>
<tr>
<th>Bulan (t)</th>
<th>Profit (( Y_t ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
</tr>
<tr>
<td>4</td>
<td>22</td>
</tr>
<tr>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>16</td>
</tr>
<tr>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
</tr>
</tbody>
</table>
a. Tentukan data termuluskan melalui teknik eksponensial sederhana dengan $\lambda = 0.25$. Kemudian buat time-series plotnya bersama dengan data asal.

<table>
<thead>
<tr>
<th>Bulan (t)</th>
<th>$y_t$</th>
<th>$\tilde{y}_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11</td>
<td>15.05</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>15.79</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
<td>15.84</td>
</tr>
<tr>
<td>4</td>
<td>22</td>
<td>17.38</td>
</tr>
<tr>
<td>5</td>
<td>24</td>
<td>19.04</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>19.28</td>
</tr>
<tr>
<td>7</td>
<td>16</td>
<td>18.46</td>
</tr>
<tr>
<td>8</td>
<td>14</td>
<td>17.34</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>15.51</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>14.88</td>
</tr>
</tbody>
</table>

$\tilde{y}_0 = \bar{y}$
b. Tentukan ramalan besarnya profit pada setiap satu waktu ke depan. Berapa ramalan profit pada bulan ke-11 dan ke-12?

<table>
<thead>
<tr>
<th>Bulan (t)</th>
<th>$y_t$</th>
<th>$\tilde{y}_T$</th>
<th>Ramalan ($\hat{y}_{T+1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11</td>
<td>15.05</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>15.79</td>
<td>15.05</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
<td>15.84</td>
<td>15.79</td>
</tr>
<tr>
<td>4</td>
<td>22</td>
<td>17.38</td>
<td>15.84</td>
</tr>
<tr>
<td>5</td>
<td>24</td>
<td>19.04</td>
<td>17.38</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>19.28</td>
<td>19.04</td>
</tr>
<tr>
<td>7</td>
<td>16</td>
<td>18.46</td>
<td>19.28</td>
</tr>
<tr>
<td>8</td>
<td>14</td>
<td>17.34</td>
<td>18.46</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>15.51</td>
<td>17.34</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>14.88</td>
<td>15.51</td>
</tr>
<tr>
<td>11</td>
<td>-</td>
<td>14.88</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>-</td>
<td>14.88</td>
<td></td>
</tr>
</tbody>
</table>
Example 4.1

Consider the Dow Jones Index from June 1999 to June 2006 given in Figure 4.3. For first-order exponential smoothing we would need to address two issues as stated in the previous sections: how to pick the initial value $\tilde{y}_0$ and the smoothing constant $\lambda$. Following the recommendation in Section 4.2.2, we will consider the smoothing constants 0.2 and 0.4. As for the initial value, we will consider the first recommendation in Section 4.2.1 and set $\tilde{y}_0 = y_1$. Figures 4.5 and 4.6 show the

**FIGURE 4.6** The Dow Jones Index from June 1999 to June 2006 with first-order exponential smoothing with $\lambda = 0.4$. 
As an alternative estimate for the initial value, we can also use the average of the data between June 1999 and June 2001 since during this period the time series data appears to be stable. Figures 4.7 and 4.8 show the single exponential smoothing with the initial value equal to the average of the first 25 observations corresponding to the period between June 1999 and June 2001. Note that the choice of the initial value has very little effect on the smoothed values as time goes on.
Figure 4.7  The Dow Jones Index from June 1999 to June 2006 with first-order exponential smoothing with $\lambda = 0.2$ and $\bar{y}_0 = (\sum_{t=1}^{25} y_t)/25$ (i.e., initial value equal to the average of the first 25 observations).
FIGURE 4.8  The Dow Jones Index from June 1999 to June 2006 with first-order exponential smoothing with $\lambda = 0.4$ and $\tilde{y}_0 = (\sum_{t=1}^{25} y_t)/25$ (i.e., initial value equal to the average of the first 25 observations).
Pemulusan Eksponensial Ganda
(Second-Order Exponential Smoothing)

- *First-order exponential smoothing* hanya sesuai untuk data deret waktu yang stasioner.

- Apabila data deret waktu tidak stasioner (mengandung trend) dapat menggunakan *second-order exponential smoothing*. 
Pemulusan Eksponensial Ganda
(Second-Order Exponential Smoothing)

\[
\tilde{y}_T^{(1)} = \lambda y_T + (1 - \lambda) \tilde{y}_{T-1}^{(1)}
\]

\[
\tilde{y}_T^{(2)} = \lambda \tilde{y}_T^{(1)} + (1 - \lambda) \tilde{y}_{T-1}^{(2)}
\]

where \(\tilde{y}_T^{(1)}\) and \(\tilde{y}_T^{(2)}\) denote the first- and second-order smoothed exponentials we have an estimate of \(y_T\) as

\[
\hat{y}_T = 2\tilde{y}_T^{(1)} - \tilde{y}_T^{(2)}
\]
Example 4.2

Consider the U.S. Consumer Price Index (CPI) from January 1995 to December 2004 in Table 4.2. Figure 4.13 clearly shows that the data exhibits a linear trend. To smooth the data, following the recommendation in Section 4.2, we can use single exponential smoothing with $\lambda = 0.3$ as given in Figure 4.14.

As we expected, the exponential smoother does a very good job in capturing the general trend in the data and provides a less jittery (smooth) version of it. However, we also notice that the smoothed values are consistently below the actual values. Hence there is an apparent bias in our smoothing. To fix this problem we have two choices: use a bigger $\lambda$ or second-order exponential smoothing. The former will lead to less smooth estimates and hence defeat the purpose. For the latter, however, we can use $\lambda = 0.3$ to calculate $\tilde{y}_T^{(1)}$ and $\tilde{y}_T^{(2)}$ as given in Table 4.3.
FIGURE 4.14 Single exponential smoothing of the U.S. Consumer Price Index (with $\tilde{y}_0 = y_1$).
FIGURE 4.16  The double exponential smoothing of the U.S. Consumer Price Index (with $\alpha = 0.3$ and $\gamma = 0.3$).
### TABLE 4.3  Second-Order Exponential Smoothing of the U.S. Consumer Price Index (with $\lambda = 0.3$, $\tilde{y}_0^{(1)} = y_1$, and $\tilde{y}_0^{(2)} = \tilde{y}_1^{(1)}$)

<table>
<thead>
<tr>
<th>Date</th>
<th>$y_t$</th>
<th>$\tilde{y}_T^{(1)}$</th>
<th>$\tilde{y}_T^{(2)}$</th>
<th>$\hat{y}_T = 2\tilde{y}_T^{(1)} - \tilde{y}_T^{(2)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan-1995</td>
<td>150.3</td>
<td>150.300</td>
<td>150.300</td>
<td>150.300</td>
</tr>
<tr>
<td>Feb-1995</td>
<td>150.9</td>
<td>150.480</td>
<td>150.354</td>
<td>150.606</td>
</tr>
<tr>
<td>Mar-1995</td>
<td>151.4</td>
<td>150.756</td>
<td>150.475</td>
<td>151.037</td>
</tr>
<tr>
<td>Apr-1995</td>
<td>151.9</td>
<td>151.099</td>
<td>150.662</td>
<td>151.536</td>
</tr>
<tr>
<td>May-1995</td>
<td>152.2</td>
<td>151.429</td>
<td>150.892</td>
<td>151.967</td>
</tr>
<tr>
<td>:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nov-2004</td>
<td>191.0</td>
<td>190.041</td>
<td>188.976</td>
<td>191.106</td>
</tr>
<tr>
<td>Dec-2004</td>
<td>190.3</td>
<td>190.119</td>
<td>189.319</td>
<td>190.919</td>
</tr>
</tbody>
</table>
Some time series data exhibit cyclical or seasonal patterns that cannot be effectively modeled using the polynomial model.

The exponential smoothing techniques that can be used in modeling seasonal time series.

The methodology was originally introduced by Holt and Winters and is generally known as Winters' method.

The seasonal adjustment is made to the linear trend model. Two types of adjustments are suggested additive and multiplicative.
Model Musiman Aditif

\[ y_t = L_t + S_t + \varepsilon_t \]

where \( L_t \) represents the linear trend component and can in turn be represented by \( \beta_0 + \beta_1 t \); \( S_t \) represents the seasonal adjustment with \( S_t = S_{t+s} = S_{t+2s} = \cdots \) for \( t = 1, \ldots, s - 1 \), where \( s \) is the length of the period of the cycles; and the \( \varepsilon_t \) are assumed to be uncorrelated with mean 0 and constant variance \( \sigma^2_{\varepsilon} \).
Model Musiman Multiplikatif

\[ y_t = L_t S_t + \varepsilon_t \]

where \( L_t \) represents the linear trend component and can in turn be represented by \( \beta_0 + \beta_1 t \); \( S_t \) represents the seasonal adjustment with \( S_t = S_{t+s} = S_{t+2s} = \cdots \) for \( t = 1, \ldots, s - 1 \), where \( s \) is the length of the period of the cycles; and the \( \varepsilon_t \) are assumed to be uncorrelated with mean 0 and constant variance \( \sigma^2_\varepsilon \).
Perbedaan Aditif dan Multiplikatif


Metode Pemulusan Winters
(Musiman Aditif dan Multiplikatif)

Silakan baca : Montgomery, et.al. 2008 (hlm. 210 – 217)
# Simple Exponential Smoothing (SES)

# Data bisa di download di: http://robjhyndman.com/tsdldata/hurst/precip1.dat
# contains total annual rainfall in inches for London,
# from 1813-1912 (original data from Hipel and McLeod, 1994).

library("forecast")
library("TTR")
library("graphics")

hujan <- scan("1-precip1.dat.txt", skip=1)
hujan.ts <- ts(hujan, start=c(1813))

# 1. Exponential Smoothing : nilai alpha tertentu

hujan.ses <- HoltWinters(hujan.ts, alpha = 0.25, beta=FALSE, gamma=FALSE)

hujan.ses
hujan.ses$SSE
hujan.ses$fitted

plot(hujan.ses)
points(hujan.ts)
# Ramalan untuk 5 waktu ke depan

library("forecast")
hujan.ramal <- forecast.HoltWinters(hujan.ses, h=5)

hujan.ramal
plot(hujan.ramal)

# 2. Exponential Smoothing : alpha optimum

hujan.ses <- HoltWinters(hujan.ts, beta=FALSE, gamma=FALSE)

hujan.ses
hujan.ses$SSE
hujan.ses$fitted

plot(hujan.ses)
points(hujan.ts)
Smoothing parameters:
alpha: 0.25
beta : FALSE
gamma: FALSE

> hujan.ses$SSE
[1] 2033.499

> hujan.ses$fitted
Time Series:
Start = 1814
End = 1912
Frequency = 1

   xhat  level
1814 23.56000 23.56000
1815 24.18750 24.18750
1816 23.60562 23.60562
...
1910 24.59185 24.59185
1911 24.78389 24.78389
1912 24.78541 24.78541
Garis Merah: Data termuluskan (alpha = 0.25)
Keluaran Program R: (3)

> hujan.ramal

Point Forecast  Lo 80  Hi 80  Lo 95  Hi 95
1913  25.55906  19.72224  31.39588  16.63242  34.48570
1914  25.55906  19.54261  31.57551  16.35769  34.76043
1916  25.55906  19.19854  32.08482  15.83148  35.28664
1917  25.55906  19.03330  32.08482  15.57877  35.53935

Call:
HoltWinters(x = hujan.ts, beta = FALSE, gamma = FALSE)

Smoothing parameters:
  alpha: 0.02412151  # alpha-optimum
beta : FALSE
gamma: FALSE

> hujan.ses$SSE  # SSE terkecil akibat alpha optimum
[1] 1828.855
Holt-Winters dalam Program R

- Fungsi `HoltWinters (alpha = …, beta=…, gamma=…)` dalam program R merupakan fungsi umum untuk pemulusan eksponensial.
- Misalnya, pemulusan eksponensial sederhana (SES) merupakan kasus khusus pada fungsi `HoltWinters` dengan `beta=FALSE` dan `gamma=FALSE`.
- Data yang mengandung tren (`beta`) dan musiman (`gamma`) dapat menggunakan `HoltWinters` untuk berbagai nilai `beta` dan `gamma` termasuk nilai optimumnya.
# Metode Holt-Winters

# Data bisa di download di: http://robjhyndman.com/tsdldata/data/fancy.dat
# contains monthly sales for a souvenir shop at a beach resort town
# in Queensland, Australia, for January 1987-December 1993,
# (original data from Wheelwright and Hyndman, 1998)

library("forecast")
library("TTR")
library("graphics")

souv <- scan("3-fancy.dat.txt")
souv.ts <- ts(souv, frequency=12, start=c(1987,1))
logsouv.ts <- log(souv.ts)
ts.plot(logsouv.ts)
points(logsouv.ts)

# Holt-Winters
logsouv.hw <- HoltWinters(logsouv.ts)
logsouv.hw
plot(logsouv.hw)
points(logsouv.ts)

logsouv.hw$SSE
logsouv.hw$fitted
# Ramalan untuk 3 musim ke depan (h = 3x12 = 36)

```
library("forecast")
logsouv.ramal <- forecast.HoltWinters(logsouv.hw, h=36)
logsouv.ramal
plot.forecast(logsouv.ramal)
```
### Keluaran Program R: (1)

```r
Call:
HoltWinters(x = logsouv.ts)

**Smoothing parameters:**  # Nilai optimum
- alpha: 0.413418
- beta: 0
- gamma: 0.9561275

```r
call$logsov.hw$SSE
[1] 2.011491
```

```r
call$logsov.hw$fitted
    xhat level trend season
Jan 1988  7.587087 8.410417 0.02996319 -0.853292804
Feb 1988  8.420498 8.538312 0.02996319 -0.147776883
Mar 1988  8.820034 8.624325 0.02996319  0.165746136
Apr 1988  8.469533 8.681279 0.02996319 -0.241709002
```

```r
.
.
.
Oct 1993 10.273731 10.226692 0.02996319  0.017075769
Nov 1993 10.704981 10.282382 0.02996319  0.392635166
Dec 1993 11.520598 10.330996 0.02996319  1.159639123
```
Keluaran Program R: (2)

Garis Merah : Data termuluskan
### Point Forecast

<table>
<thead>
<tr>
<th>Month</th>
<th>Value</th>
<th>Lower 80%</th>
<th>Upper 80%</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
</table>
Keluaran Program R: (4)

4.1 Consider the time series data shown in Table E4.1.

a. Make a time series plot of the data.

b. Use simple exponential smoothing with $\lambda = 0.2$ to smooth the first 40 time periods of this data. How well does this smoothing procedure work?

c. Make one-step-ahead forecasts of the last 10 observations. Determine the forecast errors.

- Selesaikan pertanyaan poin (a) s.d. (c) menggunakan Excel.
- Selesaikan pertanyaan poin (a) s.d. (c) menggunakan Program R.
- Apa kesimpulan Anda?
Tugas Praktikum: (2)

2. Exercises 4.31 (Montgomery, hlm. 228).

4.31 Montgomery et al. [1990] give four years of data on monthly demand for a soft drink. These data are given in Table E4.5.

a. Make a time series plot of the data and verify that it is seasonal. Why do you think seasonality is present in these data?

b. Use Winters’ multiplicative method for the first three years to develop a forecasting method for this data. How well does this smoothing procedure work?

c. Make one-step-ahead forecasts of the last 12 months. Determine the forecast errors. How well did your procedure work in forecasting the new data?

- Selesaikan pertanyaan poin (a) s.d. (c) menggunakan Program R.

- Apa kesimpulan Anda?
Pustaka

Catatan Kuliah

Bisa di-download di

kusmansadik.wordpress.com
Terima Kasih