MONASH University

MONASH BUSINESS SCHOOL

Forecasting: principles and practice

Rob J Hyndman

2.3 Stationarity and differencing

Outline

Stationarity

Definition

If $\{y_t\}$ is a stationary time series, then for all s, the distribution of $(y_t, \ldots, y_{t+s})$ does not depend on t.

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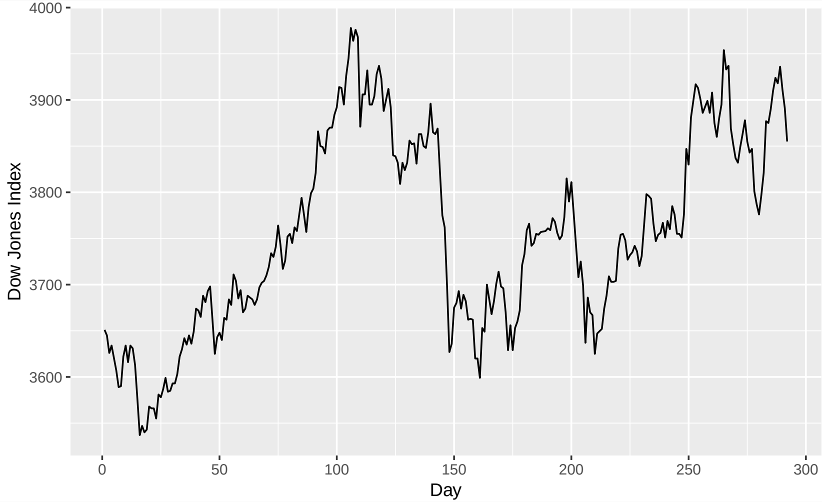
A **stationary series** is:

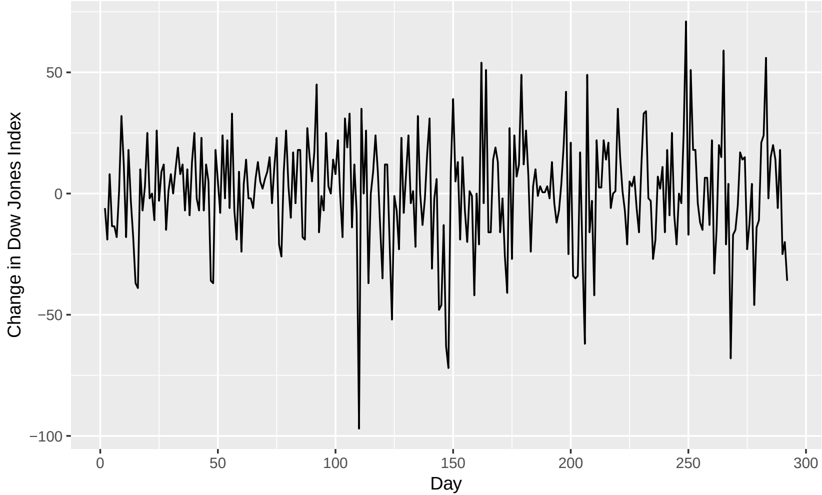
- roughly horizontal
- constant variance
- no patterns predictable in the long-term

Stationary?



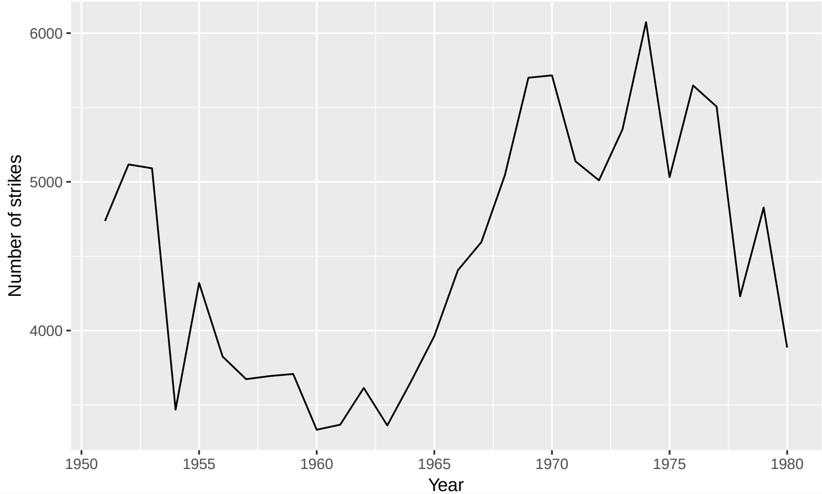
4000
3900
3800
3700
3600
Dow Jones Index
0
50
100
150
200
250
300
Day

Stationary?



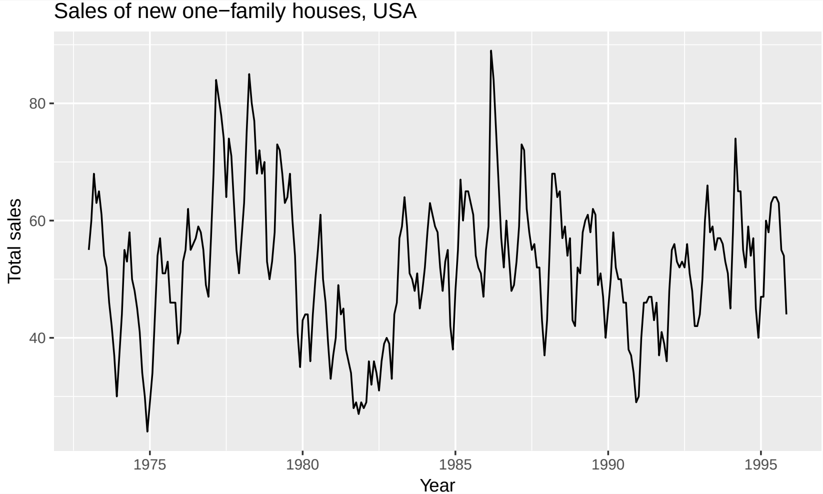
Change in Dow Jones Index
50
0
−50
−100
0
50
100
150
200
250
300
Day

Stationary?



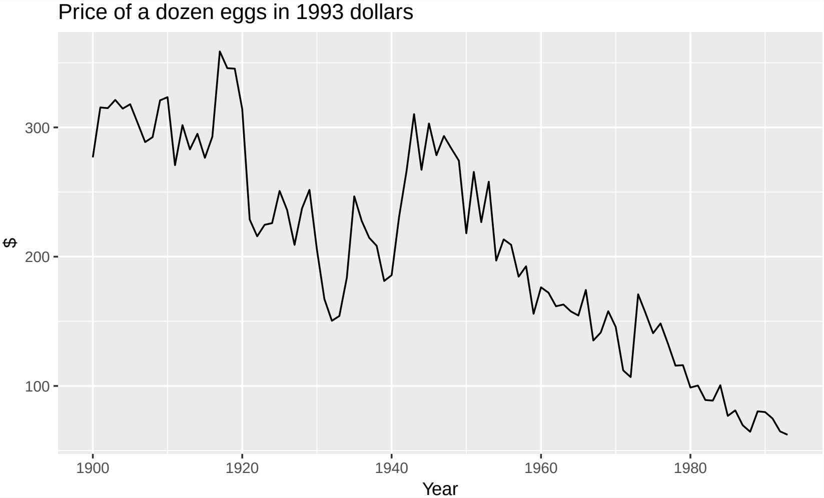
6000
5000
4000
Number of strikes
1950
1955
1960
1965
1970
1975
1980
Year

Stationary?



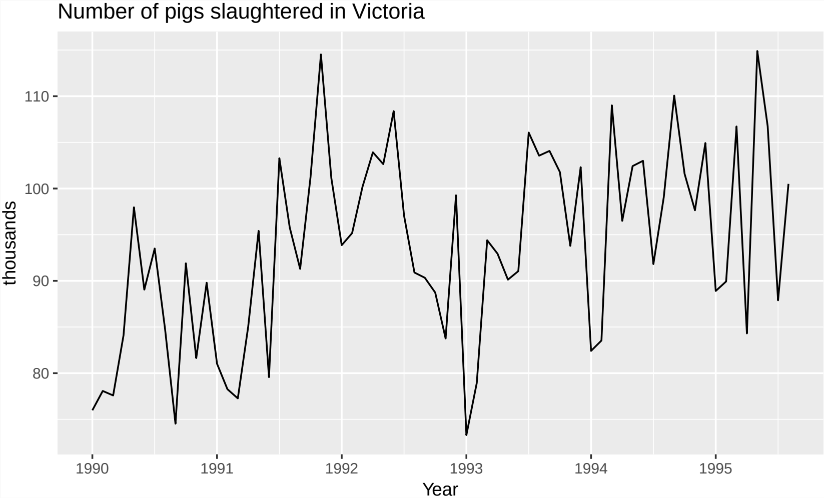
Sales of new one−family houses, USA
80
60
40
Total sales
1975
1980
1985
1990
1995
Year

Stationary?

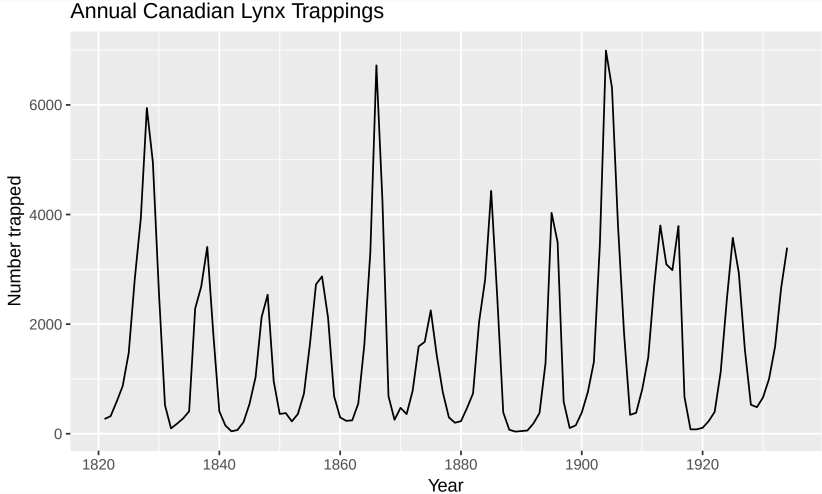


Price of a dozen eggs in 1993 dollars
$
300
200
100
1900
1920
1940
1960
1980
Year

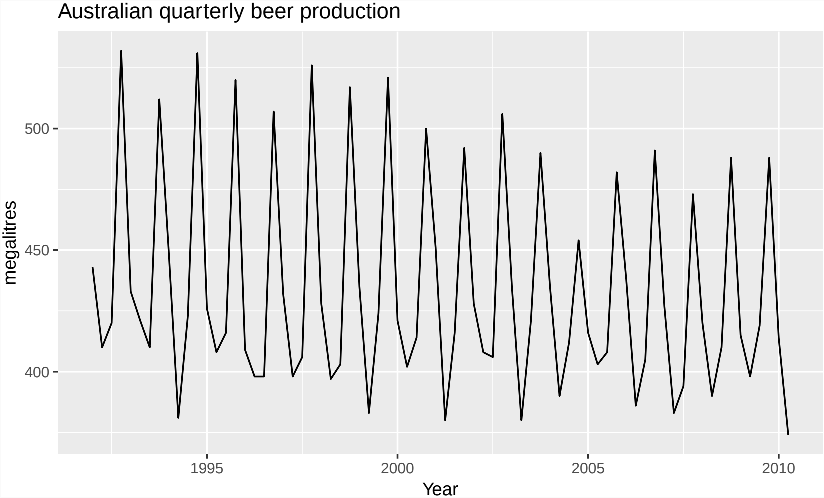
Stationary?


Number of pigs slaughtered in Victoria
thousands
110
100
90
80
1990
1991
1992
1993
1994
1995
Year

Stationary?


Annual Canadian Lynx Trappings
Number trapped
6000
4000
2000
0
1820
1840
1860
1880
1900
1920
Year

Stationary?


Australian quarterly beer production
megalitres
500
450
400
1995
2000
2005
2010
Year

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Transformations help to **stabilize the variance**.

For ARIMA modelling, we also need to **stabilize the mean**.

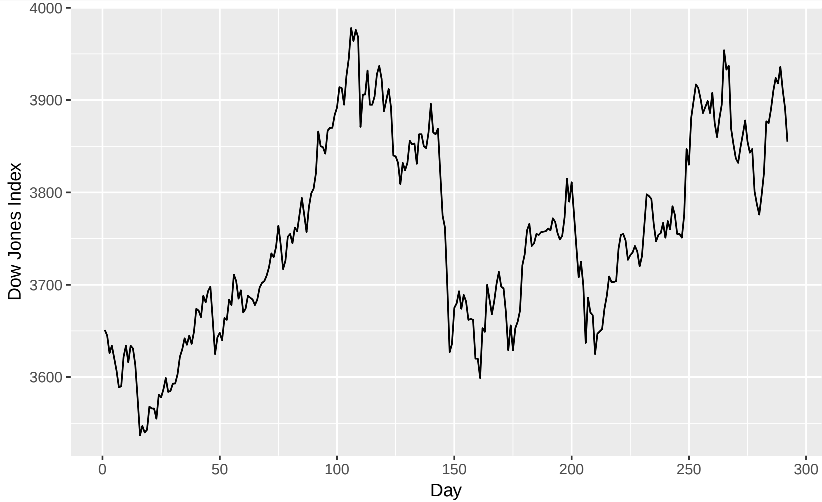
Non-stationarity in the mean

Identifying non-stationary series

- time plot.
- The ACF of stationary data drops to zero relatively quickly
- The ACF of non-stationary data decreases slowly.
- For non-stationary data, the value of r_1 is often large and positive.

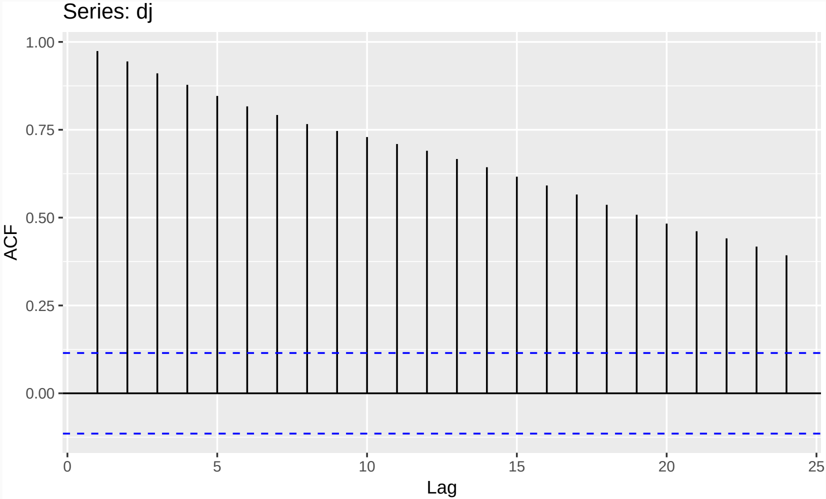
Example: Dow-Jones index

```r
autoplot(dj) + ylab("Dow Jones Index") + xlab("Day")
```



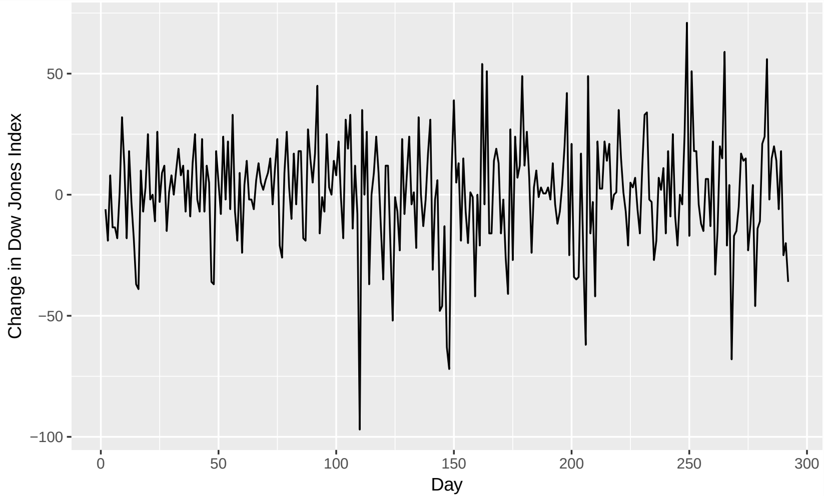
Example: Dow-Jones index

```r
ggAcf(dj)
```



Example: Dow-Jones index

```r
autoplot(diff(dj)) +
  ylab("Change in Dow Jones Index") + xlab("Day")
```



Example: Dow-Jones index

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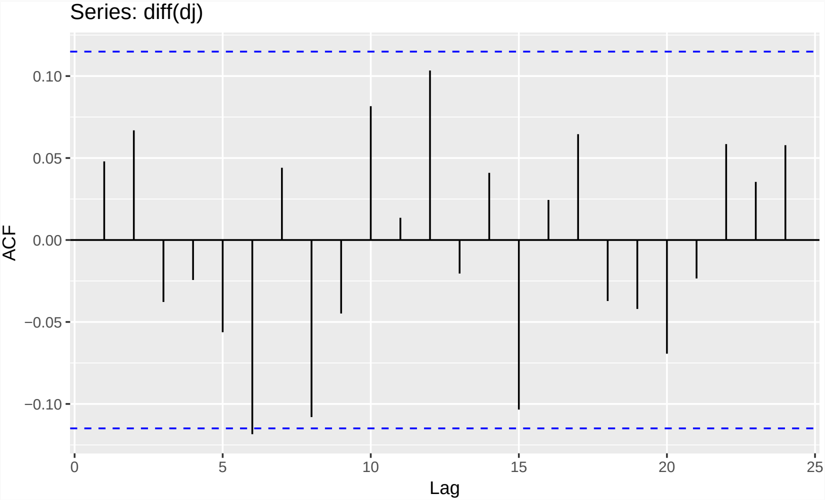

Outline

Differencing

- Differencing helps to **stabilize the mean**.
- The differenced series is the *change* between each observation in the original series: $y'_t = y_t - y_{t-1}$.
- The differenced series will have only $T - 1$ values since it is not possible to calculate a difference y'_1 for the first observation.

Second-order differencing

Occasionally the differenced data will not appear stationary and it may be necessary to difference the data a second time:

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$$\begin{aligned} y''_t &= y'_t - y'_{t-1} \\ &= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\ &= y_t - 2y_{t-1} + y_{t-2}. \end{aligned}$$

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- y''_t will have $T - 2$ values.
- In practice, it is almost never necessary to go beyond second-order differences.

Seasonal differencing

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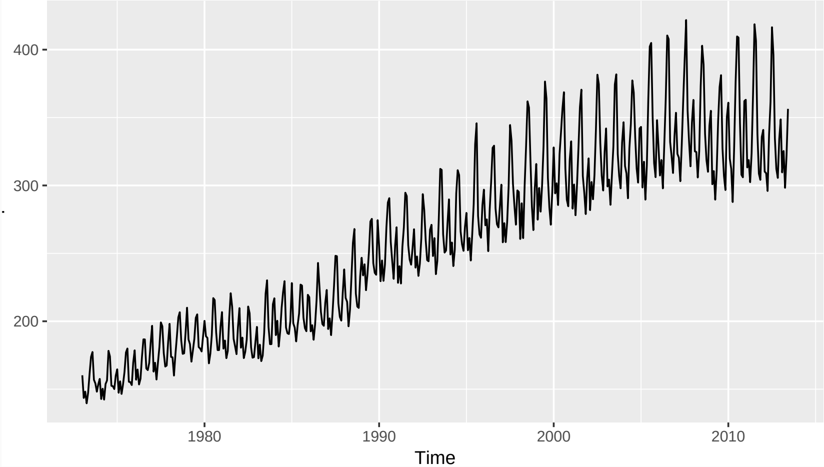
where m = number of seasons.

- For monthly data $m = 12$.
- For quarterly data $m = 4$.

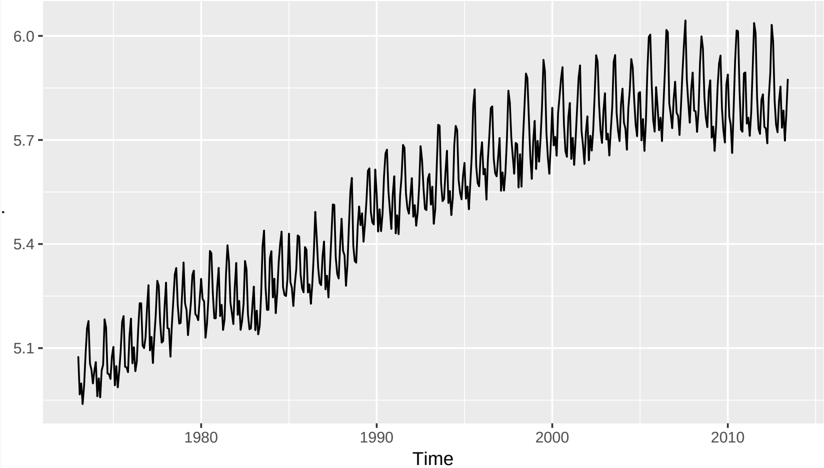
Electricity production

```r
usmelec %>% autoplot()
```



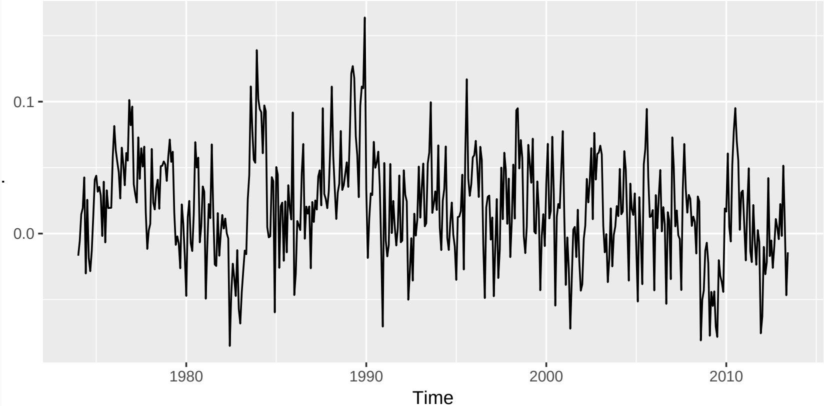
Electricity production

```
usmelec %>% log() %>% autoplot()
```



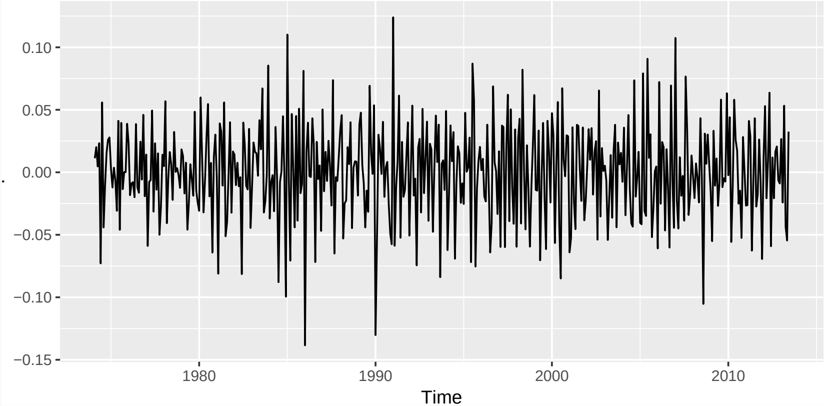
Electricity production

```
usmelec %>% log() %>% diff(lag=12) %>%
  autoplot()
```



Electricity production

```
usmelec %>% log() %>% diff(lag=12) %>%
  diff(lag=1) %>% autoplot()
```



Electricity production

- Seasonally differenced series is closer to being stationary.
- Remaining non-stationarity can be removed with further first difference.

If $y'_t = y_t - y_{t-12}$ denotes seasonally differenced series, then twice-differenced series is

$$\begin{aligned} y^*_t &= y'_t - y'_{t-1} \\ &= (y_t - y_{t-12}) - (y_{t-1} - y_{t-13}) \\ &= y_t - y_{t-1} - y_{t-12} + y_{t-13}\,. \end{aligned}$$

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- it makes no difference which is done first—the result will be the same.
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Seasonal differencing

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It is important that if differencing is used, the differences are interpretable.

Interpretation of differencing

- first differences are the change between **one observation and the next**;
- seasonal differences are the change between **one year to the next**.

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But taking lag 3 differences for yearly data, for example, results in a model which cannot be sensibly interpreted.

Outline

Unit root tests

Statistical tests to determine the required order of differencing.

1. Augmented Dickey Fuller test: null hypothesis is that the data are non-stationary and non-seasonal.
2. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test: null hypothesis is that the data are stationary and non-seasonal.
3. Other tests available for seasonal data.

KPSS test

```
library(urca)
summary(ur.kpss(goog))
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 7 lags.
##
## Value of test-statistic is: 10.72
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

KPSS test

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## critical values 0.347 0.463  0.574 0.739
```

```r
ndiffs(goog)
```

```
## [1] 1
```

Automatically selecting differences

STL decomposition: $y_t = T_t + S_t + R_t$

Seasonal strength $F_s = \max\left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(S_t+R_t)}\right)$

If $F_s > 0.64$, do one seasonal difference.

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If $F_s > 0.64$, do one seasonal difference.

```
usmelec %>% log() %>% nsdiffs()
```

```
## [1] 1
```

```
usmelec %>% log() %>% diff(lag=12) %>% ndiffs()
```

```
## [1] 1
```

Outline

Lab Session 14

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Backshift notation

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$$B(By_t) = B^2 y_t = y_{t-2} \, .$$

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$$B(By_t) = B^2y_t = y_{t-2} \,.$$

For monthly data, if we wish to shift attention to "the same month last year," then B^{12} is used, and the notation is $B^{12}y_t = y_{t-12}$.

Backshift notation

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$$y'_t = y_t - y_{t-1} = y_t - By_t = (1 - B)y_t \ .$$

Note that a first difference is represented by $(1 - B)$.

Similarly, if second-order differences (i.e., first differences of first differences) have to be computed, then:

$$y''_t = y_t - 2y_{t-1} + y_{t-2} = (1 - B)^2 y_t \ .$$

Backshift notation

- Second-order difference is denoted $(1-B)^2$.
- *Second-order difference* is not the same as a *second difference*, which would be denoted $1-B^2$;
- In general, a dth-order difference can be written as
$$(1-B)^d y_t.$$
- A seasonal difference followed by a first difference can be written as
$$(1-B)(1-B^m)y_t\ .$$

Backshift notation

The "backshift" notation is convenient because the terms can be multiplied together to see the combined effect.

$$\begin{aligned}(1-B)(1-B^m)y_t &= (1-B-B^m+B^{m+1})y_t \\ &= y_t - y_{t-1} - y_{t-m} + y_{t-m-1}.\end{aligned}$$

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For monthly data, $m = 12$ and we obtain the same result as earlier.