

A hand with a silver ring on the ring finger is holding a black domino. In the background, a chain of black dominoes is arranged in a circle on a white surface. The text is overlaid on the right side of the image.

# **Analisis Data Deret Waktu**

Apa hubungan analisis deret waktu  
dengan ARIMA?

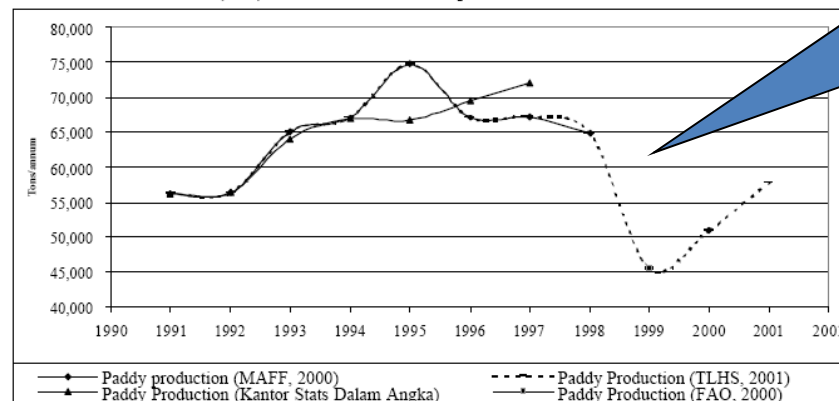
# Data Deret Waktu

“data yang diamati berdasarkan urutan waktu dengan rentang yang sama (jam, hari, minggu, bulan, tahun, dsb)”

Misalnya : data ekspor gula tahunan, data nilai tukar rupiah harian, dsb.

pertanian

Gambar 1: Perkiraan Produksi Padi Tahunan,  
(Ton) untuk Timor Lorosae pada tahun 1991-2001

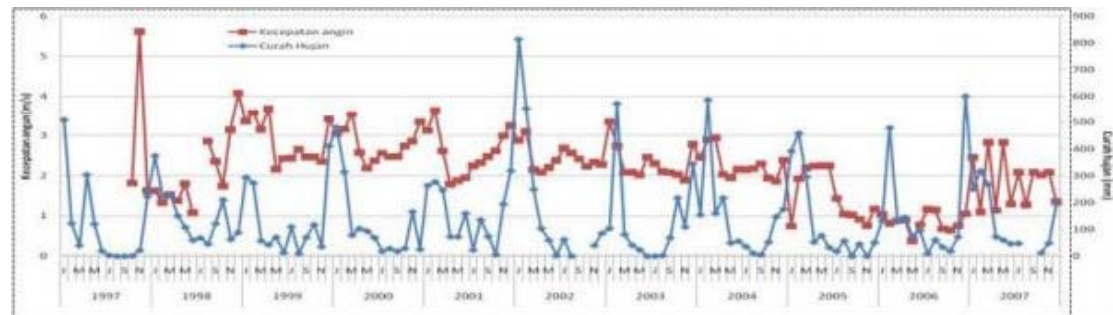


Data produksi  
beras tahunan

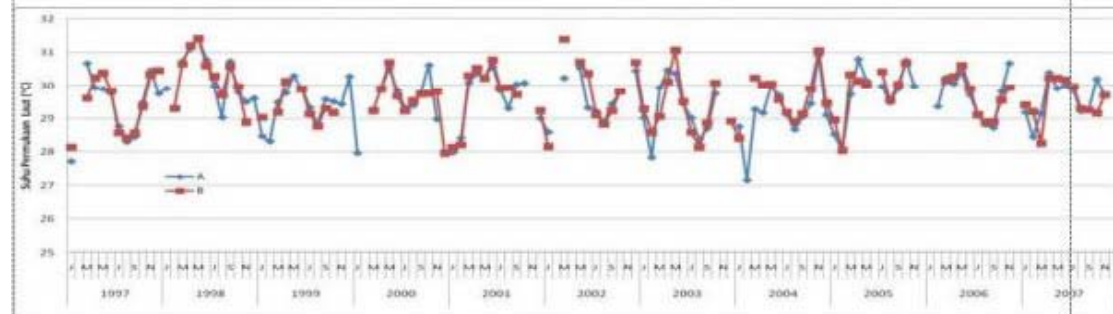


Sumber: Berbagai sumber, termasuk (i) Timor Lorosae Dalam Angka, Statistik Pertanian, angka-angka MAF (ii) Perkiraan untuk tahun 1995 dan 2001(iii) Susenas untuk data penduduk yang digunakan di

# Klimatologi



Gambar 3. Curah hujan dan kecepatan angin di Teluk Jakarta berdasarkan data stasiun BMG Tanjung Priok



Gambar 4. Variasi temporal suhu permukaan laut dari sensor AVHRR di Teluk Jakarta wilayah A dan B



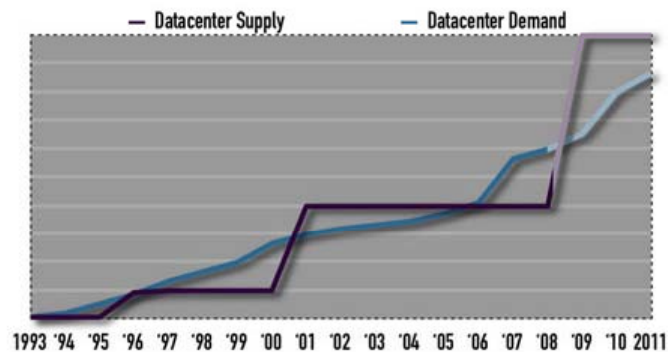
# Ekonomi



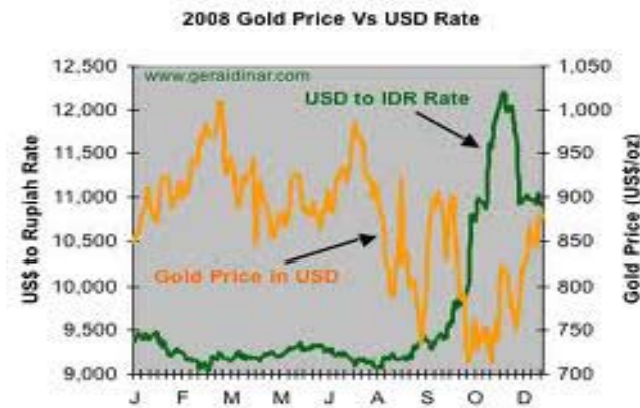
**Data keuangan**



**Data Stok Barang**



**Data supply demand**



**Data daya tukar nilai uang**

Kapan data didekati dengan metode deret waktu?

Kalau diduga kuat bahwa keragaman dalam data ada **faktor waktu yang dominan** (faktor-faktor lain yang mempengaruhi, juga dipengaruhi waktu)

# Data Deret Waktu

Data deret waktu secara teoritis ditulis sebagai:

$$y_t = b_1 z_1(t) + b_2 z_2(t) \dots + b_k z_k(t) + \varepsilon_k$$

dimana

$b_k$  = Parameter ke - k

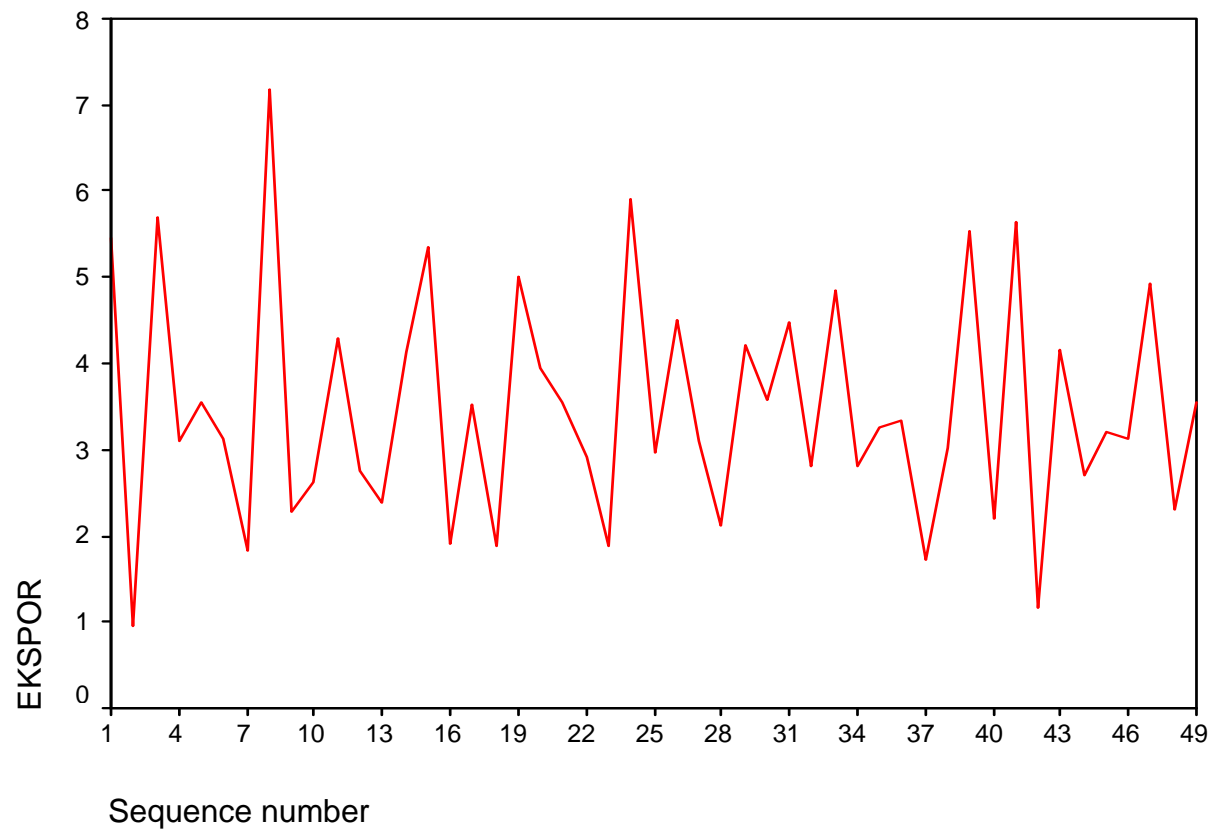
$z_k(t)$  = Fungsi Matematik ke - k pada t

$\varepsilon_k$  = Komponen Acak ke - k

## Karakteristik Data Deret Waktu

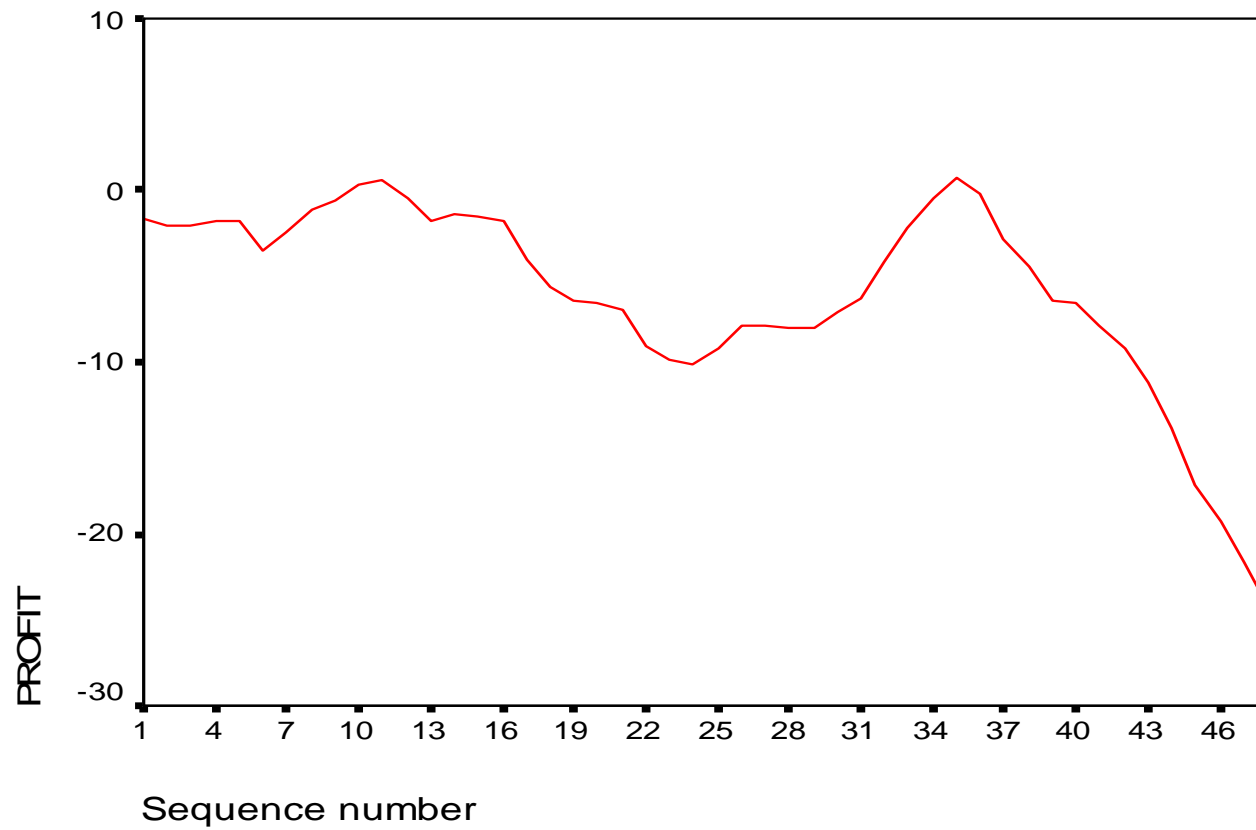
- Secara garis besar, data DW dibedakan menjadi dua, yaitu stasioner dan tidak stasioner
- Dikatakan stasioner apabila data DW memiliki nilai tengah (rataan) dan ragam (fluktuasi) yang konstan dari waktu ke waktu

## Contoh Data DW Stasioner





## Contoh Data DW Tidak Stasioner



## Pola Time Series Data

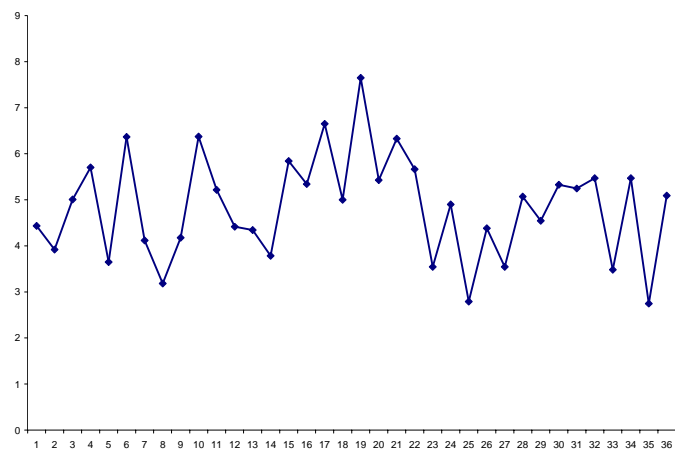
Secara garis besar pola data time series adalah:

- Pola Data Horizontal
  - Terjadi bila data berfluktuasi di sekitar rata-rata yang konstan.
  - Contoh: Data penjualan yang konstan
- Pola Data Musiman
  - Terjadi bilamana suatu deret dipengaruhi oleh faktor musiman (misalnya kuartal tahun tertentu, bulanan, atau hari-hari pada minggu tertentu)
  - Contoh: Data produksi tanaman

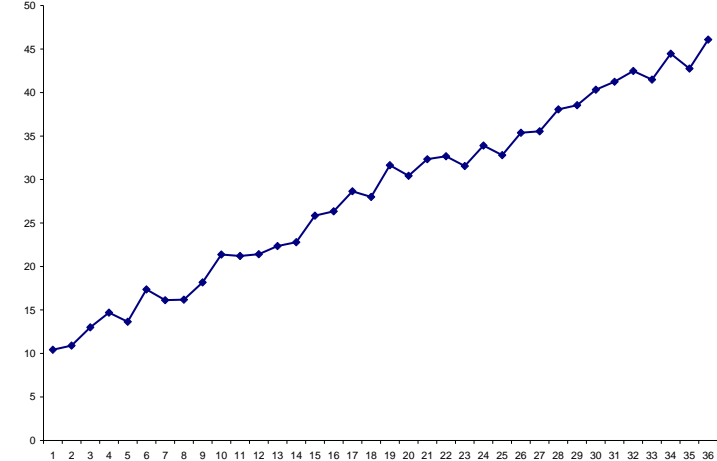
## Pola Time Series Data (contd)

- Pola Data Siklis
  - Terjadi bila data dipengaruhi oleh fluktuasi ekonomi jangka panjang seperti yang berhubungan dengan siklus bisnis.
  - Contoh: Penjualan mobil
- Pola Data Trend
  - Terjadi bilamana kenaikan atau penurunan sekuler jangka panjang dalam data
  - Contoh: GNP
- Pola Gabungan antara beberapa pola yang telah disebutkan diatas.

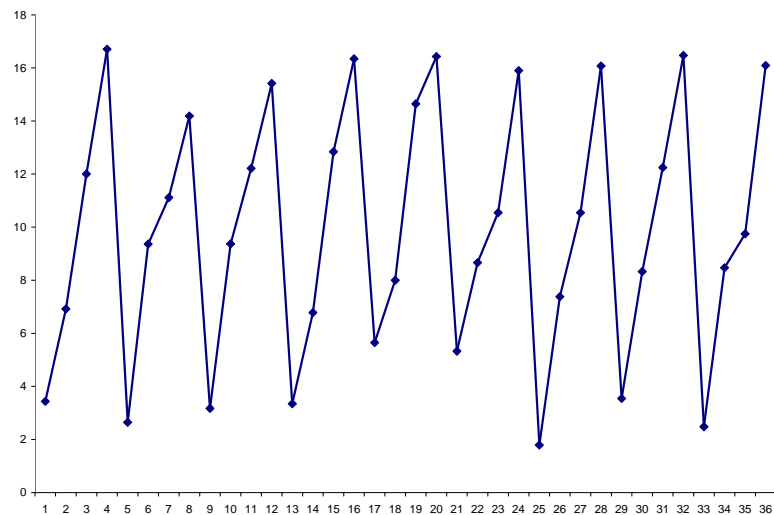
# Pola Data Time Series



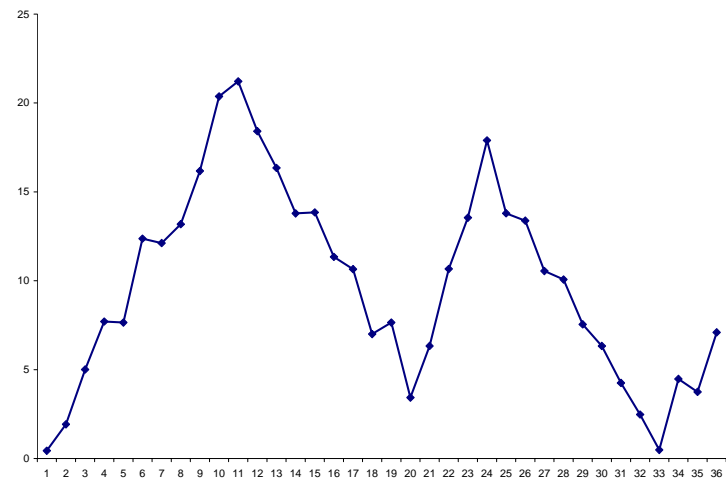
**Konstan**



**Trend**



**Seasonal**



**Cyclic**

# Dekomposisi Data Deret Waktu

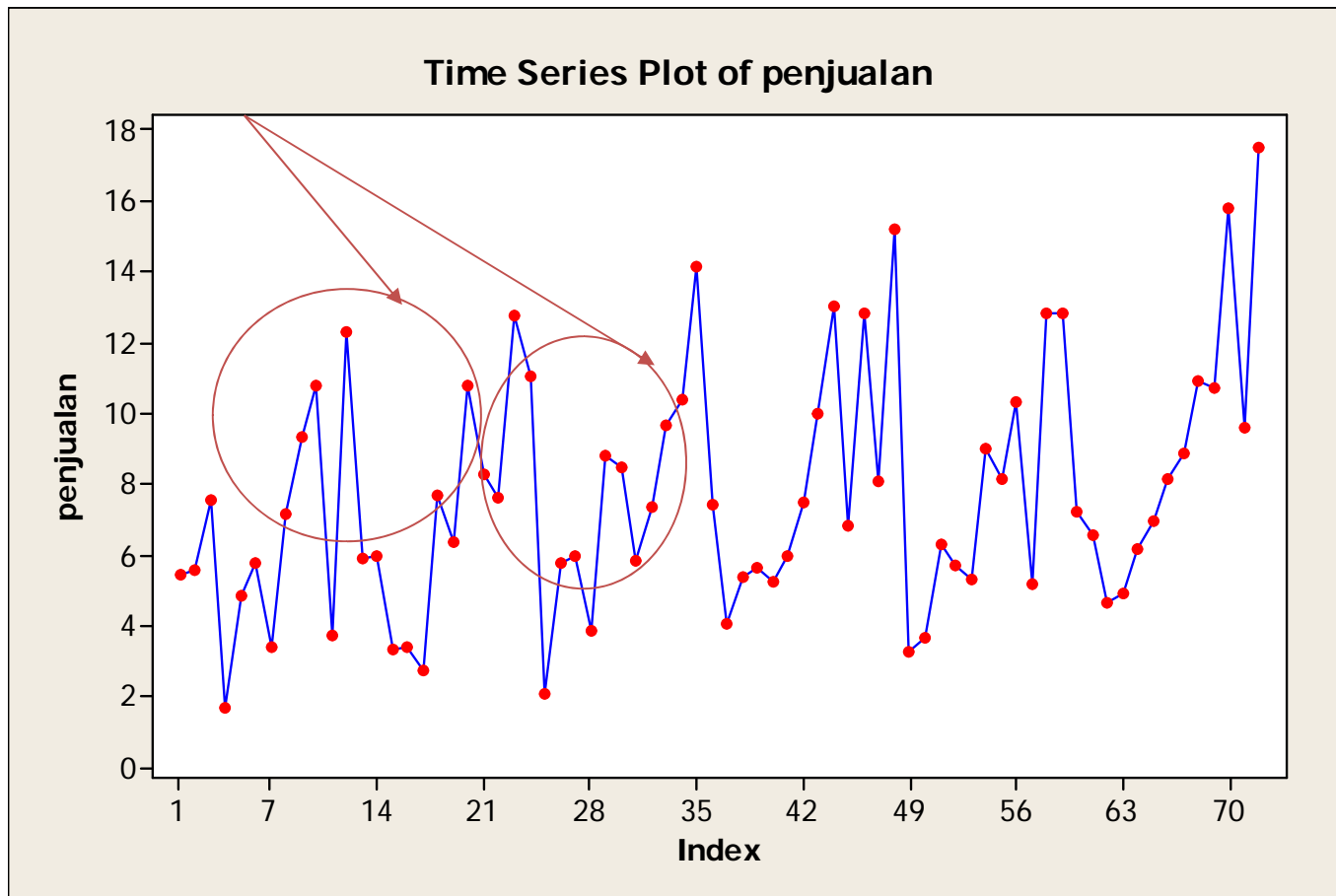
- Data deret waktu terdiri atas 3 komponen:
  - Komponen Musiman
  - Komponen tren dan siklik
  - Komponen sisaan (containing anything else in the time series).
- Model Aditif  $Y_t = S_t + T_t + E_t$ ,  
dengan:
  - $y_t$  = data periode  $t$ ,
  - $S_t$  = komponen musiman periode  $t$ ,
  - $T_t$  = komponen tren-siklik periode  $t$
  - $E_t$  = komponen sisaan (or irregular or error) period  $t$ .
- Model Multiplikatif  $Y_t = S_t \times T_t \times E_t$ .



# Plot Deret Waktu

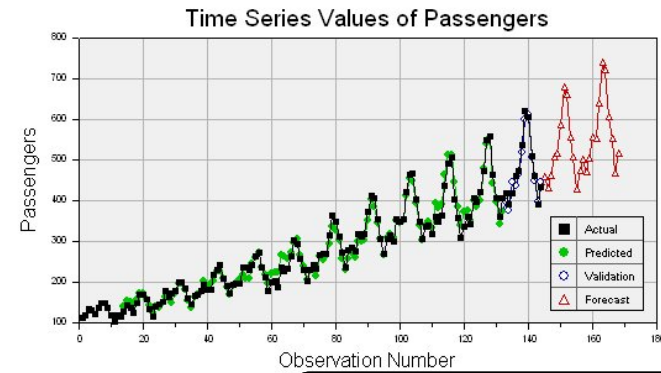
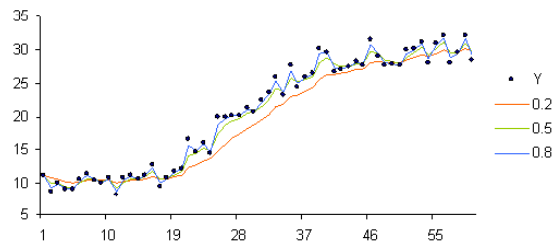
Time Series plot sangat penting untuk melihat pola data deret waktu yang akan kita analisa lebih lanjut.

Dibawah ini adalah contoh data deret waktu penjualan yang memiliki pola musiman.



# Ruang Lingkup Analisis Deret Waktu

Pemuluan

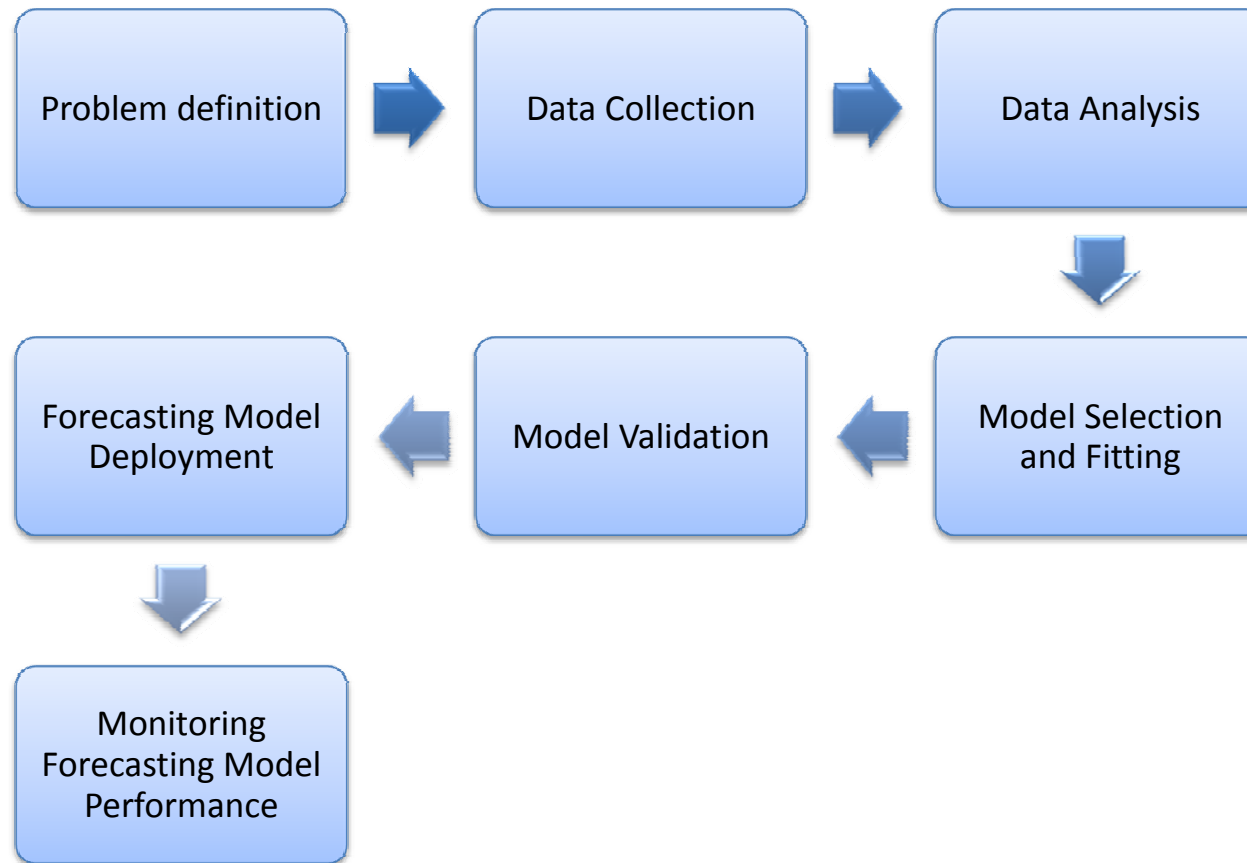


Peramalan

$$X_t = c + \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i}$$

Pemodelan

# Proses Peramalan



# Forecasting Types



**QUALITATIVE**



**QUANTATIVE**

# Qualitative Methods

Qualitative forecasting techniques are subjective, **based on the opinion** and judgment of consumers, experts; they are appropriate when past data are not available.

Predicting the impact of gasoline price if and when it hits rp. 10.000/ltr.





# Quantitative methods

- Quantitative forecasting models are used to forecast future data as a function of past data; they are appropriate when past data are available.




# When Can One Do Quantitative Forecasting?

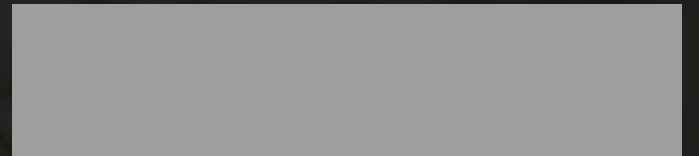
1. Information about the past is available.
2. This information is available in the form of numerical data
3. *Assumption of continuity*: It can be assumed that some aspects of the past pattern will continue into the future.

Continuity assumption is also need for qualitative forecasting





# Model for Non- Stationary Time Series



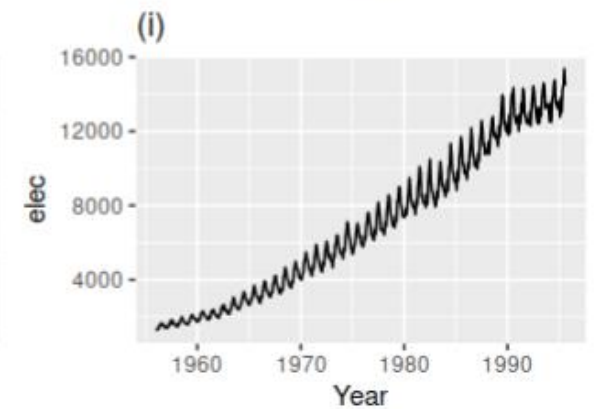
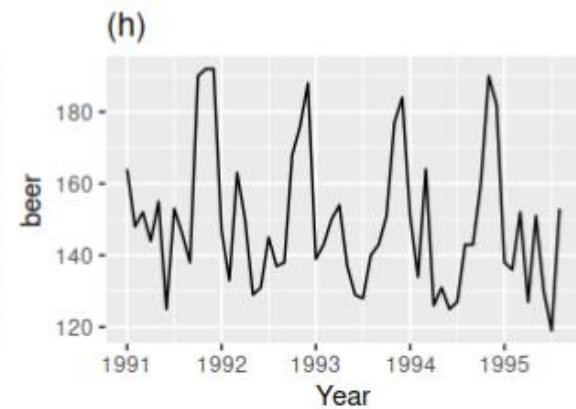
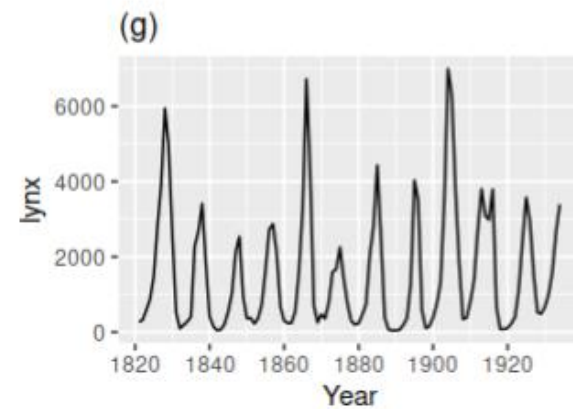
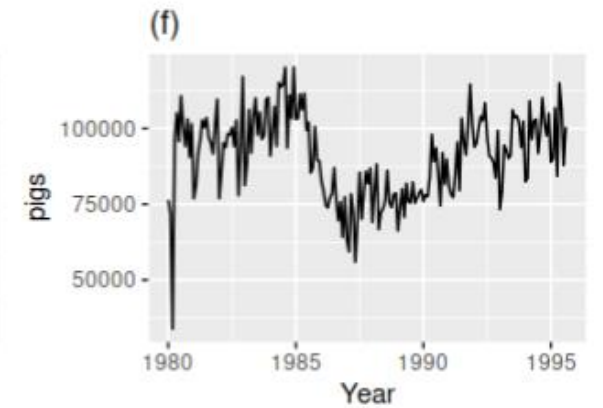
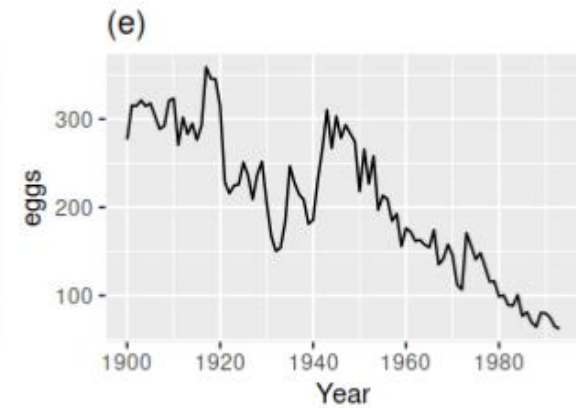
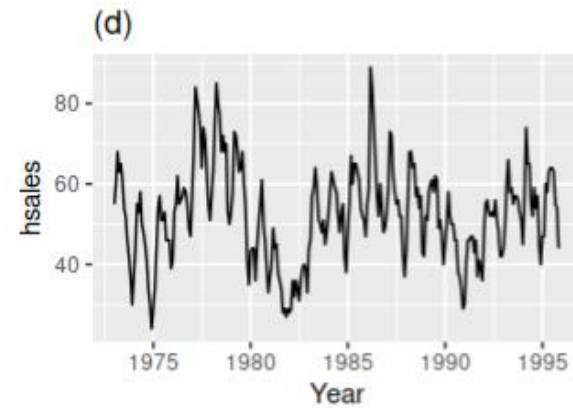
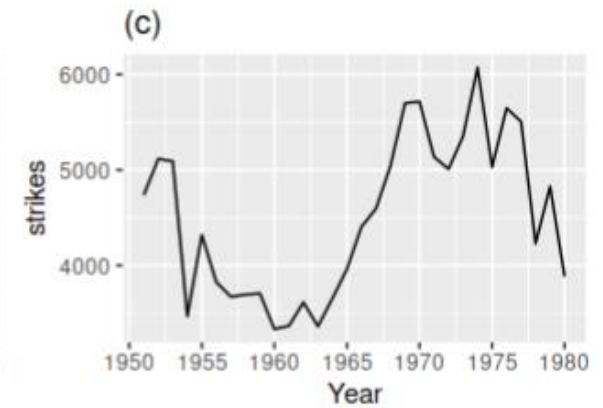
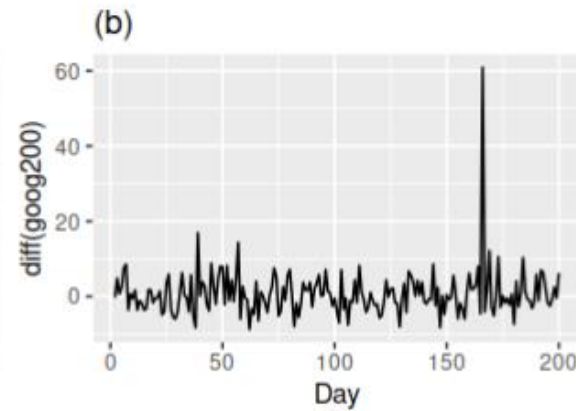
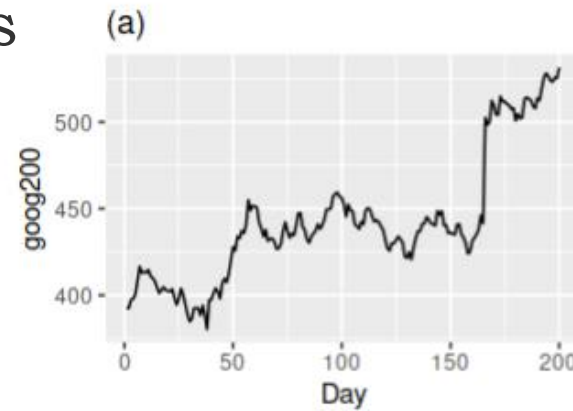
# Outline

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- Differencing
- ARIMA Model

# Which of these series are stationary?

- (a) Google stock price for 200 consecutive days;
- (b) Daily change in the Google stock price for 200 consecutive days;
- (c) Annual number of strikes in the US;
- (d) Monthly sales of new one-family houses sold in the US;
- (e) Annual price of a dozen eggs in the US (constant dollars);
- (f) Monthly total of pigs slaughtered in Victoria, Australia;
- (g) Annual total of lynx trapped in the McKenzie River district of north-west Canada;
- (h) Monthly Australian beer production;
- (i) Monthly Australian electricity production





We normally restrict autoregressive models to stationary data, in which case some constraints on the values of the parameters are required.

- For an AR(1) model:  $-1 < \phi_1 < 1$ .
- For an AR(2) model:  $-1 < \phi_2 < 1$ ,  $\phi_1 + \phi_2 < 1$ ,  $\phi_2 - \phi_1 < 1$ .

The invertibility constraints for other models are similar to the stationarity constraints.

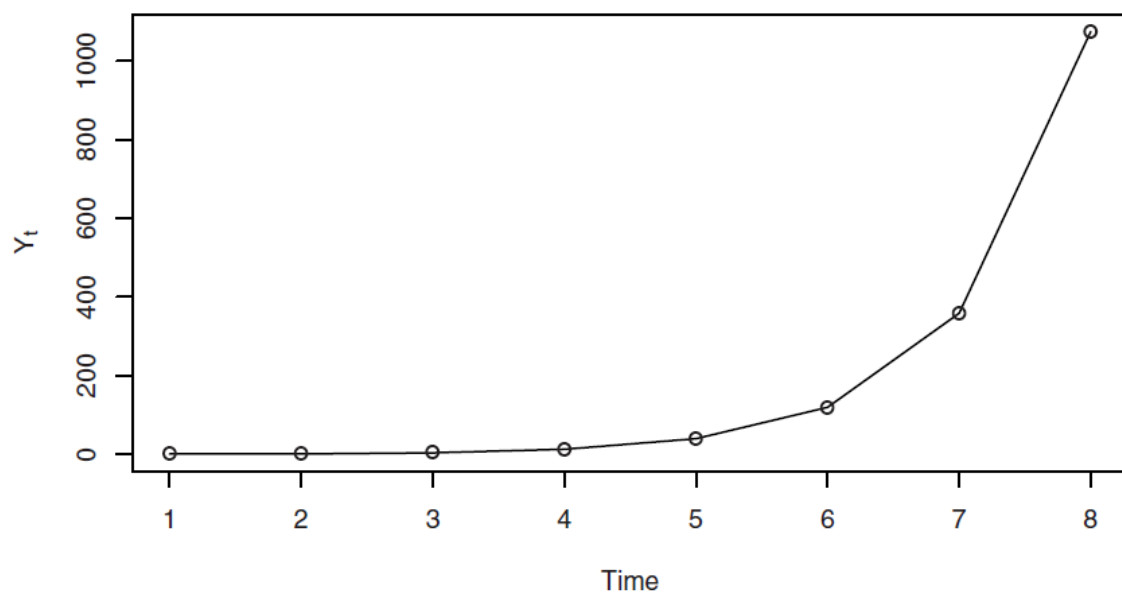
- For an MA(1) model:  $-1 < \theta_1 < 1$ .
- For an MA(2) model:  $-1 < \theta_2 < 1$ ,  $\theta_2 + \theta_1 > -1$ ,  $\theta_1 - \theta_2 < 1$ .

$$Y_t = 3Y_{t-1} + e_t \quad e_t \sim iid(0, \sigma_e^2)$$

Iterating into the past as we have done before yields

$$Y_t = e_t + 3e_{t-1} + 3^2e_{t-2} + \dots + 3^{t-1}e_1 + 3^tY_0 \quad Y_0 = 0$$

An Explosive "AR(1)" Series



Simulation of the Explosive "AR(1) Model"  $Y_t = 3Y_{t-1} + e_t$

$t$	1	2	3	4	5	6	7	8
$e_t$	0.63	-1.25	1.80	1.51	1.56	0.62	0.64	-0.98
$Y_t$	0.63	0.64	3.72	12.67	39.57	119.33	358.63	1074.91

$$Var(Y_t) = \frac{1}{8}(9^t - 1)\sigma_e^2$$

and

$$Cov(Y_t, Y_{t-k}) = \frac{3^k}{8}(9^{t-k} - 1)\sigma_e^2$$

respectively. Notice that we have

$$Corr(Y_t, Y_{t-k}) = 3^k \left( \frac{9^{t-k} - 1}{9^t - 1} \right) \approx 1 \quad \text{for large } t \text{ and moderate } k$$

# Differencing

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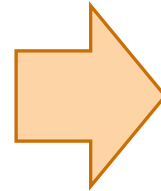
$$AR(1) : Y_t = \phi Y_{t-1} + e_t \quad e_t \sim iid(0, \sigma_e^2)$$

if  $|\phi| \geq 1$ , the AR(1) is non stationary model

Suppose  $\phi = 1$

$$\begin{aligned} Y_t &= Y_{t-1} + e_t \\ Y_t - Y_{t-1} &= e_t \\ \nabla^1 Y_t &= e_t \end{aligned}$$

$$\begin{aligned} E(\nabla^1 Y_t) &= E(e_t) = 0 \\ Var(\nabla^1 Y_t) &= Var(e_t) = \sigma_e^2 \end{aligned}$$



Stationary model

# Differencing

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Backshift ( $B$ ) :

$$B(Y_t) = Y_{t-1}$$

$$B^2(Y_t) = Y_{t-2}$$

$$B^k(Y_t) = Y_{t-k}$$

Backward ( $\nabla$ ) :

$$\nabla = 1 - B$$

$$\nabla^2 = (1 - B)^2 = (1 - 2B - B^2)$$

$$\nabla Y_t = (1 - B)Y_t = Y_t - Y_{t-1}$$

$$\nabla^2 Y_t = (1 - B)^2 Y_t = (1 - 2B - B^2)Y_t = Y_t - 2Y_{t-1} + Y_{t-2}$$

# ARIMA Models

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A time series  $\{Y_t\}$  is said to follow an **integrated autoregressive moving average** model if the  $d$ th difference  $W_t = \nabla^d Y_t$  is a stationary ARMA process. If  $\{W_t\}$  follows an ARMA( $p, q$ ) model, we say that  $\{Y_t\}$  is an ARIMA( $p, d, q$ ) process. Fortunately, for practical purposes, we can usually take  $d = 1$  or at most 2.

Consider then an ARIMA( $p, 1, q$ ) process. With  $W_t = Y_t - Y_{t-1}$ , we have

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

or, in terms of the observed series,

$$\begin{aligned} Y_t - Y_{t-1} = & \phi_1 (Y_{t-1} - Y_{t-2}) + \phi_2 (Y_{t-2} - Y_{t-3}) + \cdots + \phi_p (Y_{t-p} - Y_{t-p-1}) \\ & + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \end{aligned}$$



# ARIMA Models

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$$Y_t - Y_{t-1} = \phi_1(Y_{t-1} - Y_{t-2}) + \phi_2(Y_{t-2} - Y_{t-3}) + \cdots + \phi_p(Y_{t-p} - Y_{t-p-1}) \\ + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

which we may rewrite as

$$Y_t = (1 + \phi_1)Y_{t-1} + (\phi_2 - \phi_1)Y_{t-2} + (\phi_3 - \phi_2)Y_{t-3} + \cdots \\ + (\phi_p - \phi_{p-1})Y_{t-p} - \phi_p Y_{t-p-1} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

We call this the **difference equation form** of the model.

Notice that it appears to be an ARMA( $p + 1, q$ ) process

# The IMA(1,1) Model

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$$d = 1, q = 1$$

$$Y_t = Y_{t-1} + e_t - \theta e_{t-1}$$



$Y_t$  is Non-stationary process

$$Y_t - Y_{t-1} = e_t - \theta e_{t-1}$$

$$W_t = e_t - \theta e_{t-1}$$



$W_t$  is stationary process

# The IMA(2,2) Model

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$$d = 2, q = 2$$

$$Y_t = 2Y_{t-1} - Y_{t-2} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \quad \longrightarrow \quad Y_t \text{ is Non-stationary process}$$

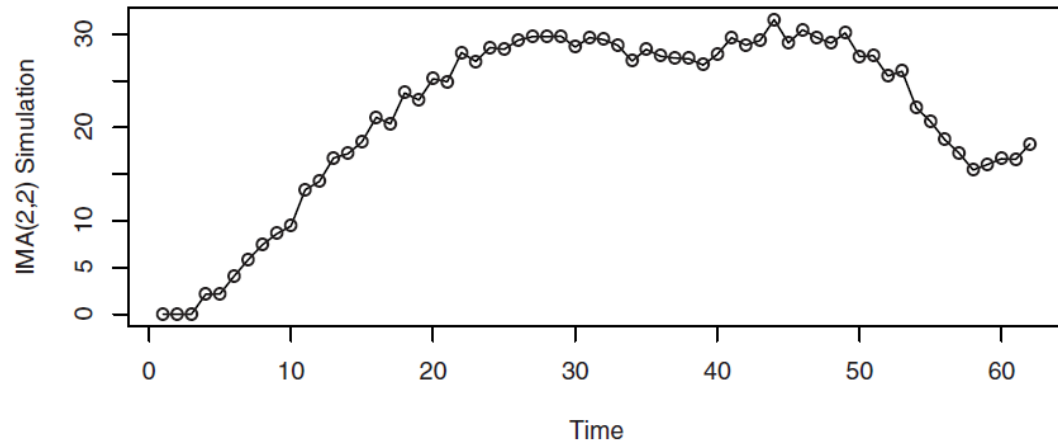
$$Y_t - 2Y_{t-1} + Y_{t-2} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$

$$\nabla^2 Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$

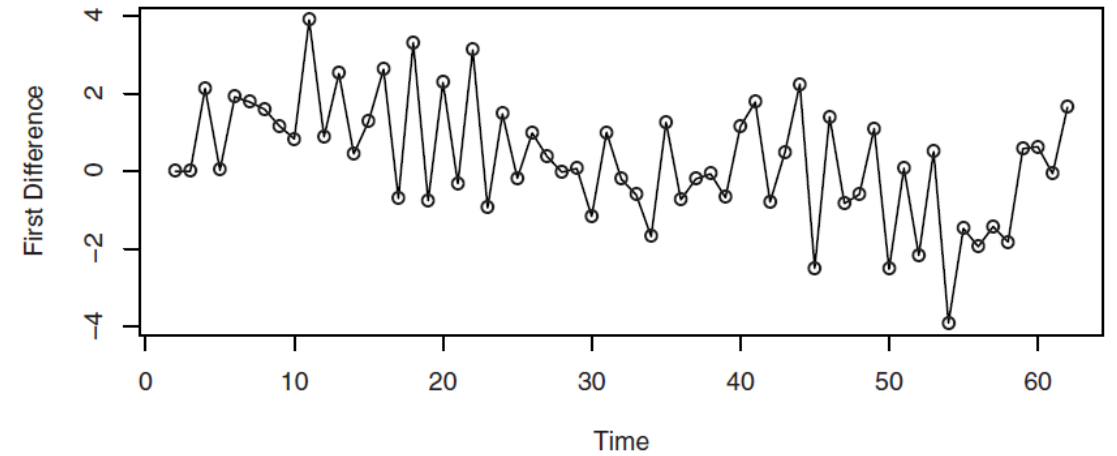
$$W_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \quad \longrightarrow \quad W_t \text{ is stationary process}$$

# The IMA(2,2) Model

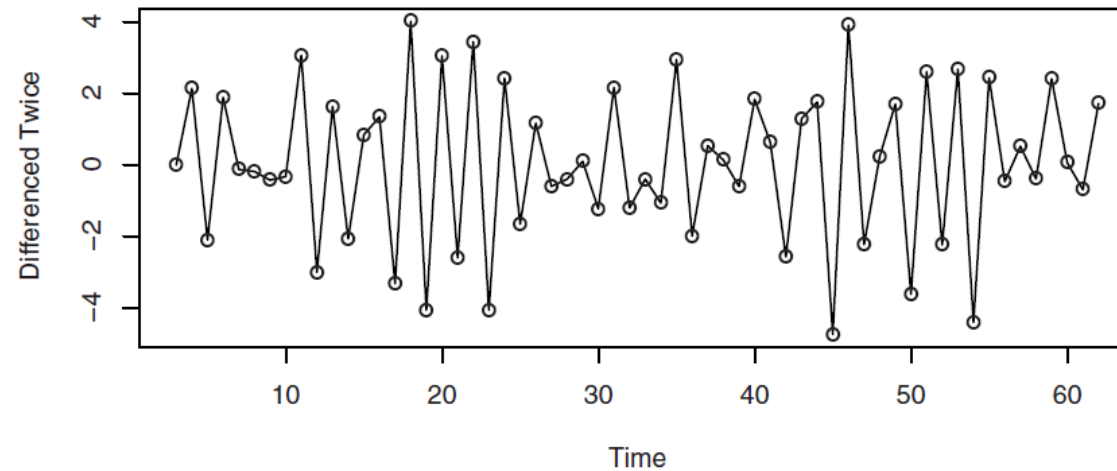
Simulation of an IMA(2,2) Series with  $\theta_1 = 1$  and  $\theta_2 = -0.6$



First Difference of the Simulated IMA(2,2) Series



Second Difference of the Simulated IMA(2,2) Series



# The ARI(1,1) Model

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$$p = 1, d = 1$$

$$\nabla Y_t = \phi \nabla Y_{t-1} + e_t$$



$\nabla Y_t$  is stationary process

$$Y_t - Y_{t-1} = \phi(Y_{t-1} - Y_{t-2}) + e_t$$

$$Y_t = (1 + \phi)Y_{t-1} - \phi Y_{t-2} + e_t$$



$Y_t$  is Non-stationary  
process

# ARIMA Models

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$$\text{ARIMA}(0, 0, 1) : Y_t = e_t - \theta e_{t-1}$$

$$\text{ARIMA} (1,1,0) : \nabla Y_t = \phi \nabla Y_{t-1} + e_t$$

$$\text{ARIMA}(0, 1, 1) : \nabla Y_t = e_t - \theta e_{t-1}$$

$$\text{ARIMA} (0,2,2) : \nabla^2 Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$

$$\text{ARIMA}(1, 0, 0) : Y_t = \phi Y_{t-1} + e_t$$

$$\text{ARIMA} (1,1,1) : \nabla Y_t = \phi \nabla Y_{t-1} + e_t - \theta_1 e_{t-1}$$

# Exercise

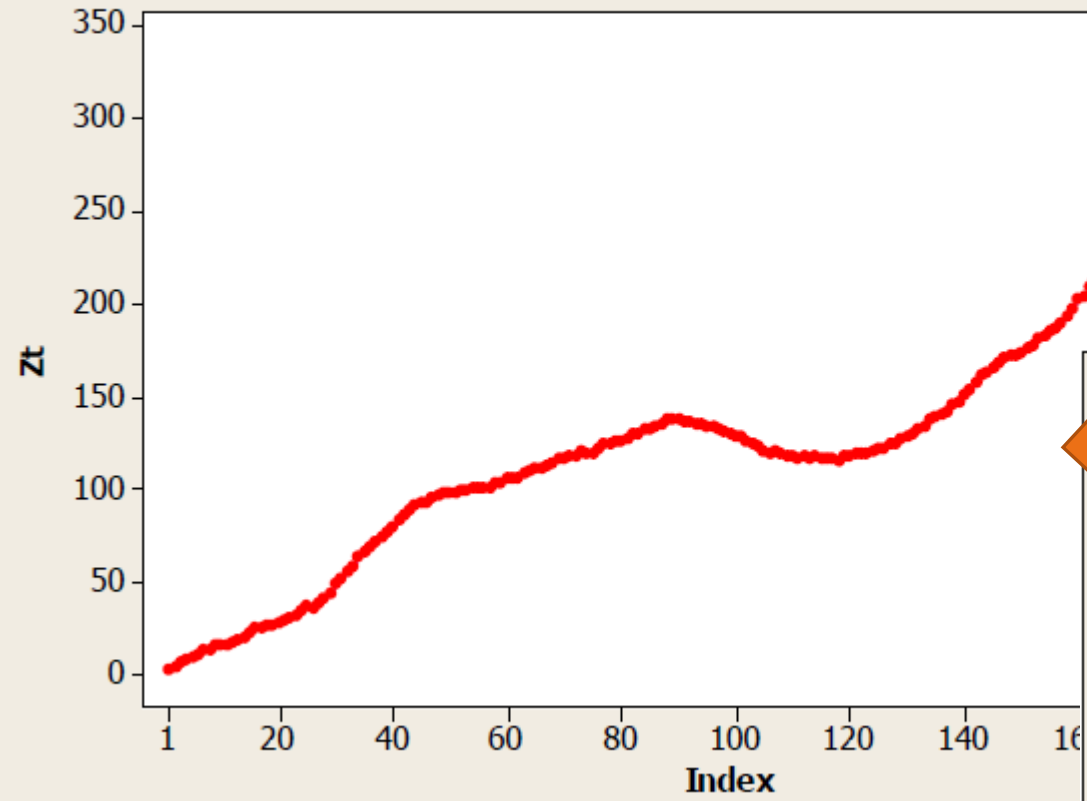
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Consider the process  $Y_t = Y_{t-1} + e_t + \frac{1}{4}e_{t-1}$

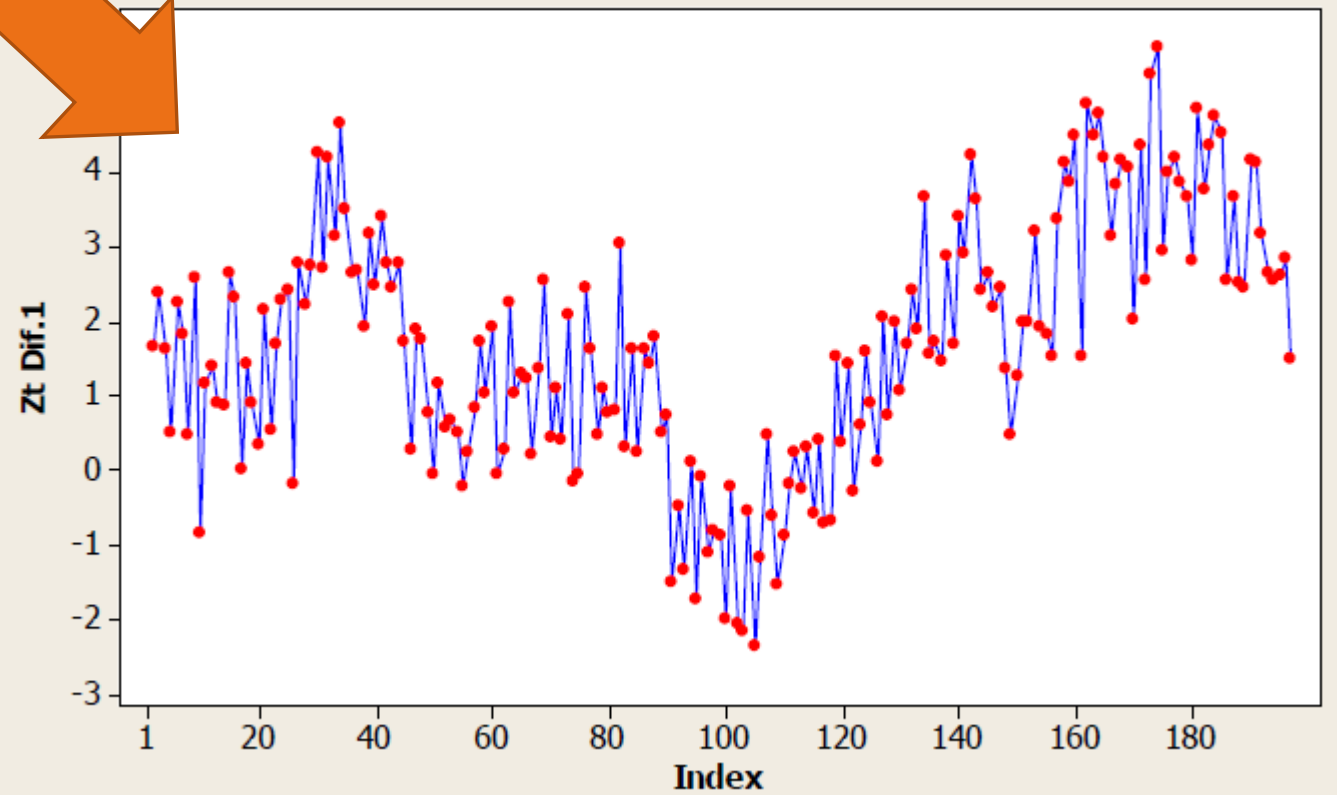
Is the process invertible?

Is the process stationary?

**Zt - ARIMA(0, 2, 1)**

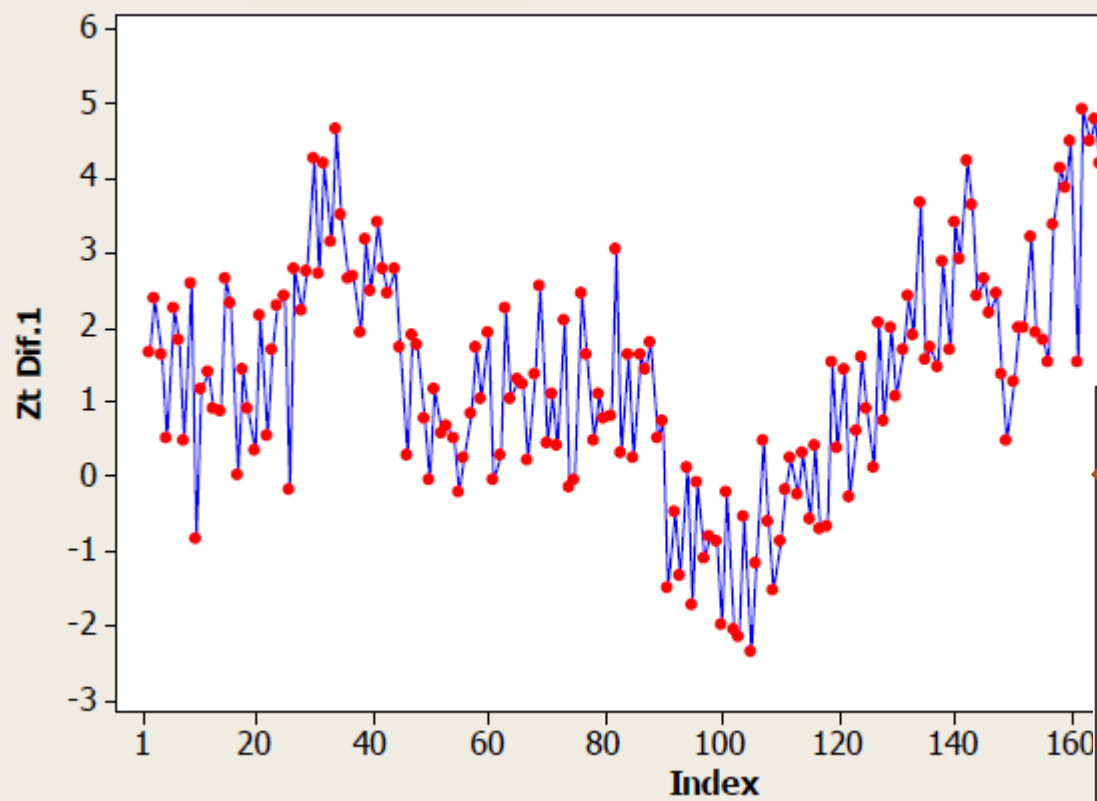


**Zt (Differencing Ordo 1)**

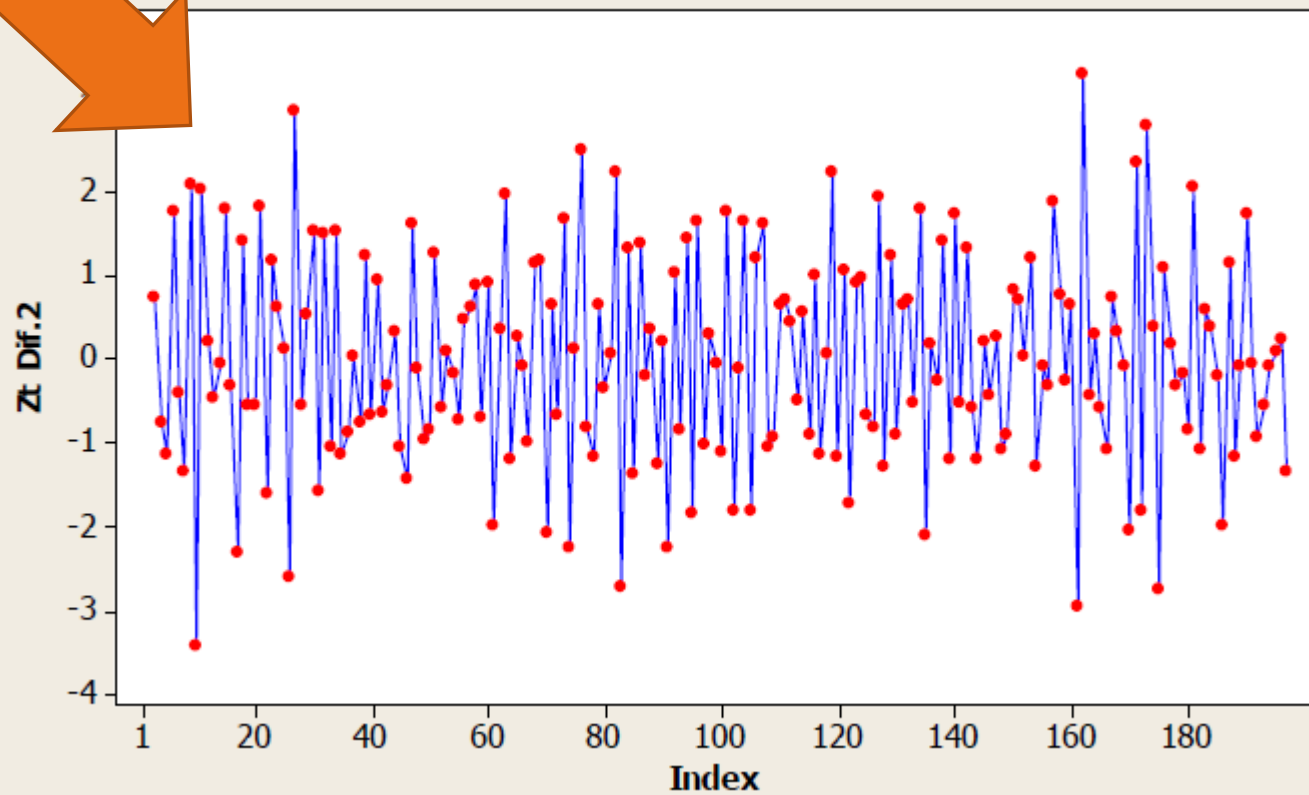




**Zt (Differencing Ordo 1)**



**Zt (Differencing Ordo 2)**



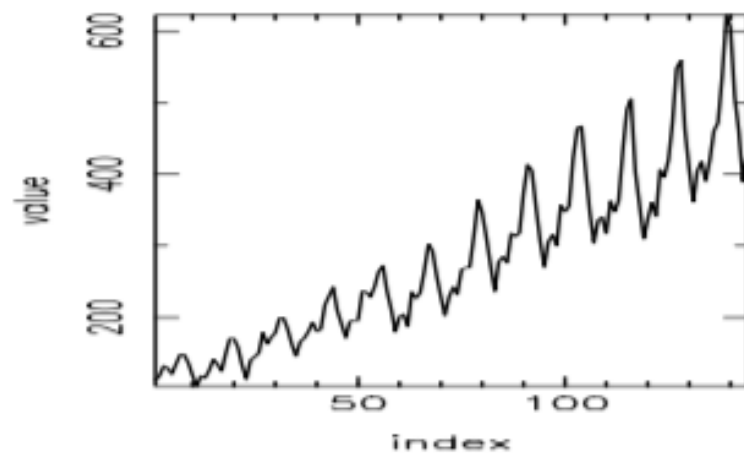
# Other Transformations

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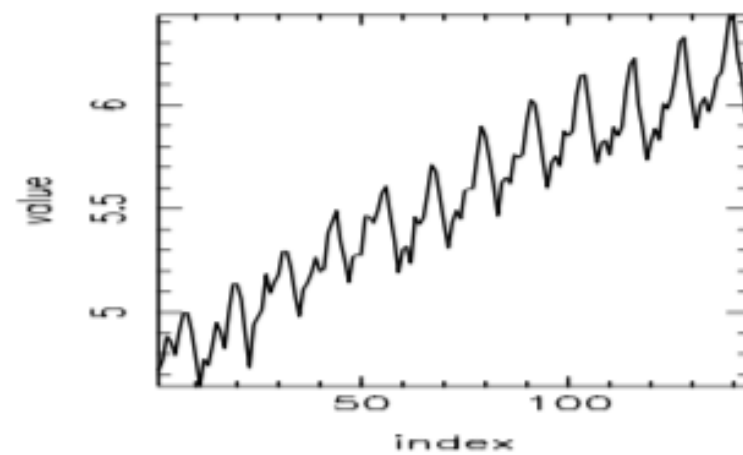
- ❑ We have seen how differencing can be a useful transformation for achieving stationarity.
- ❑ However, the other transformation is also a useful method for achieving stationarity.

Common Box-Cox Transformations	
Lambda	Suitable Transformation
-2	$Y^{-2} = 1/Y^2$
-1	$Y^{-1} = 1/Y^1$
-0.5	$Y^{-0.5} = 1/(\text{Sqrt}(Y))$
0	$\log(Y)$
0.5	$Y^{0.5} = \text{Sqrt}(Y)$
1	$Y^1 = Y$
2	$Y^2$

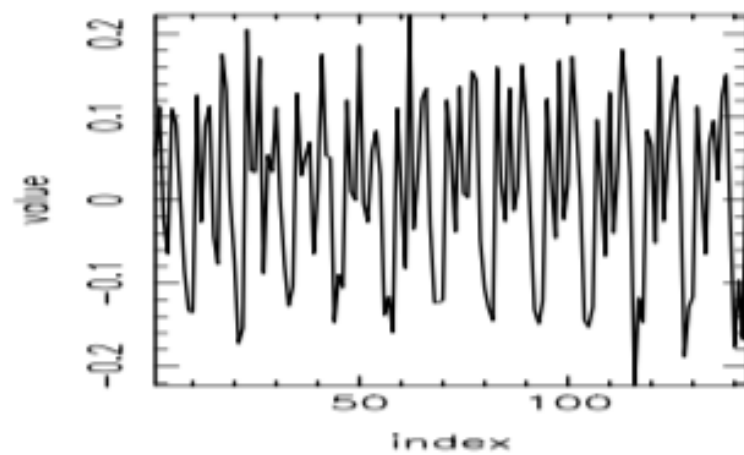
Airline data



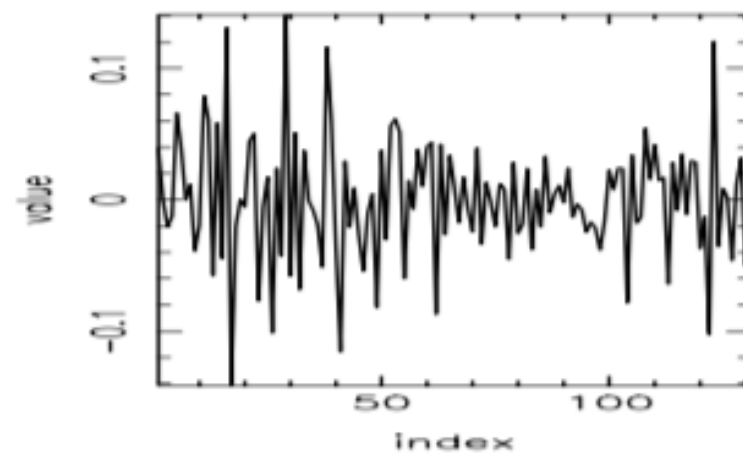
Log airline data



1st diff log airline



1st, 12th Diff log airline data



# The next meetings

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- Model Specification
- Parameter estimation
- Model Diagnostic
- Forecasting

# Thanks

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