

Time Series Analysis

AR, MA and ARIMA Models

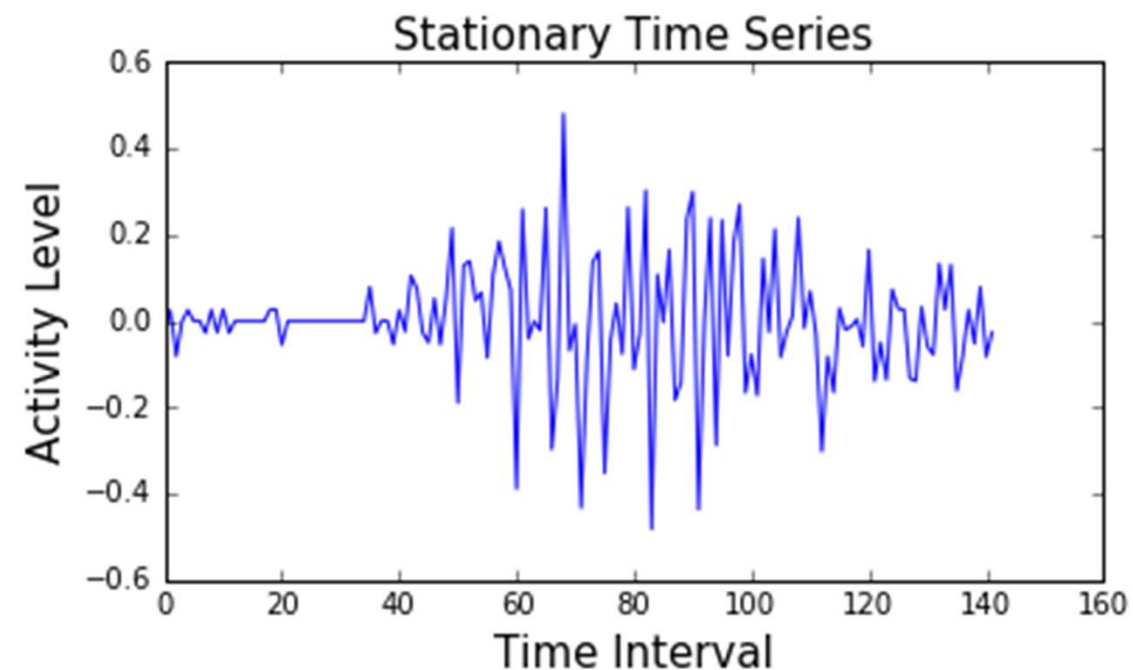
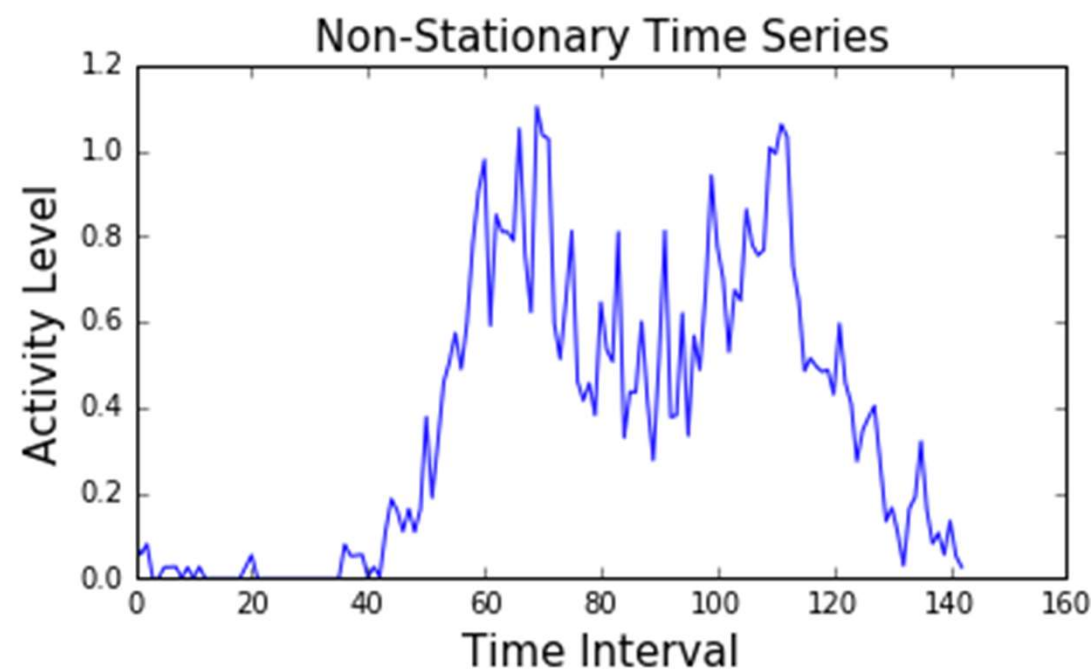
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Stationarity in Time Series

■ What is Stationarity

- In the most intuitive sense, stationarity means that the **statistical property** (mainly mean and variance) of a process generating time series do not change over time.
- It does not mean that the series does not change over time, just that the *way* it changes does not itself change over time.

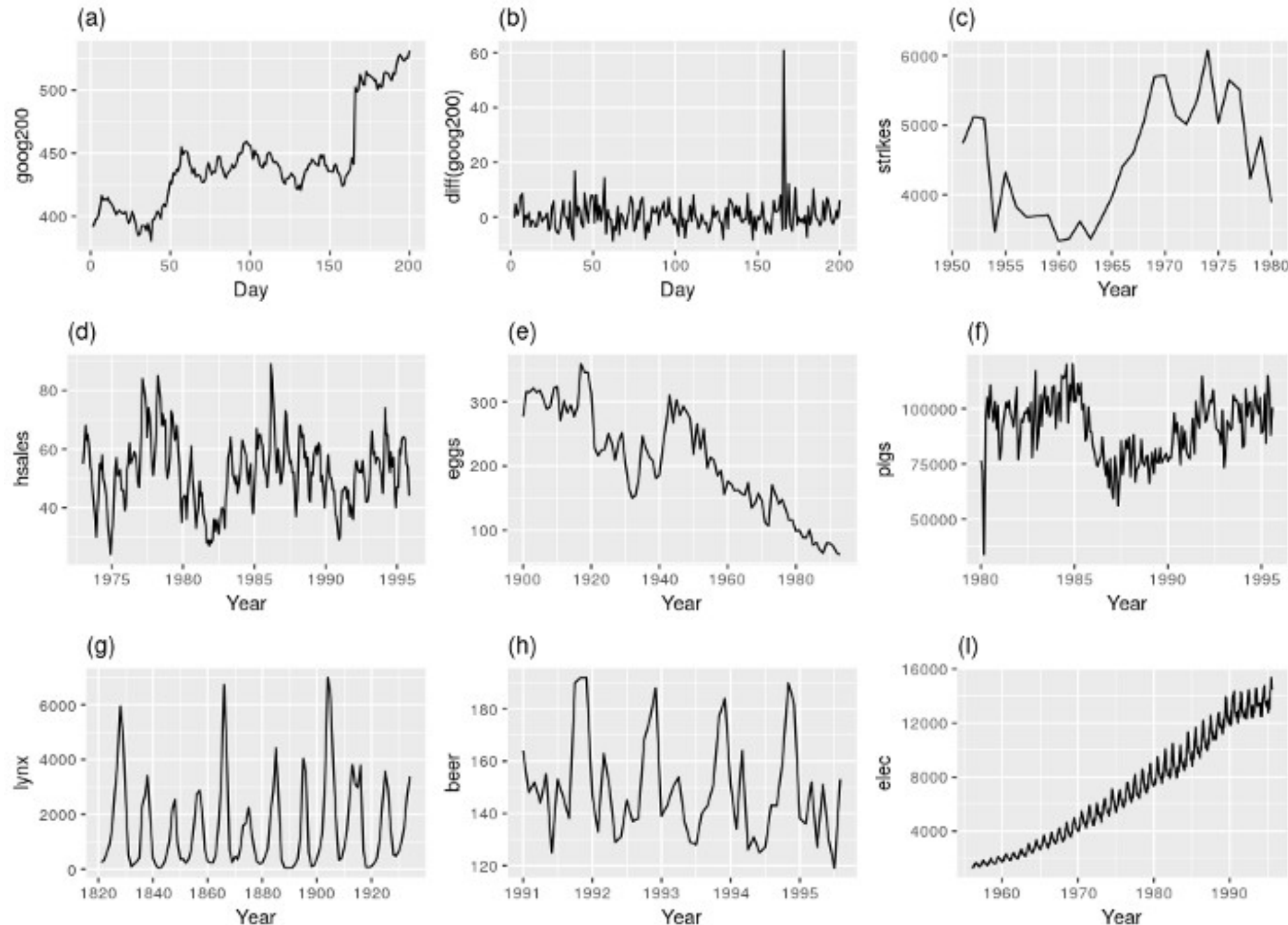


■ Why is it important

- Stationary data are much more simpler to analyse and model. Hence, for time series analysis and modelling if a series is non-stationary we make them stationary by differencing.

Detecting the stationarity in Time Series

■ Visualization



$$s(t) = .180 \quad 165 \quad 110 \quad 115 \quad 120 \dots$$

$$s(t-1) = \dots \quad 160 \quad 105 \quad 110 \quad 115 \dots$$

$$5 \quad 5 \quad 5 \quad 5 \dots$$

- (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.

$$\frac{s(t) - s(t-1)}{s(t) - s(t-1)}$$

Detecting the stationarity in Time Series

- **Statistical Tests**

- Sometimes identifying the stationarity of a time series can't be done just by visualizing it.
- Hence, we need to perform [Statistical Tests](#) in order to check if the time series is stationary.

- **The Dickey Fuller Tests**

- The [Dickey-Fuller](#) test was the first statistical test developed to test the null hypothesis that a unit root is present in an autoregressive model of a given time series, and that the process is thus not stationary. The original test treats the case of a simple lag-1 AR model.

- **The KPSS Tests**

- Another prominent test for the presence of a unit root is the [KPSS test](#). [Kwiatkowski et al, 1992]
Conversely to the Dickey-Fuller family of tests, the null hypothesis assumes stationarity around a mean or a linear trend, while the alternative is the presence of a unit root.

There are other tests to determine the stationarity of time series models.

Auto-Regressive Models

- **Intuition**

- Auto-Regressive models are based on the idea that current value of the series, X_t , can be explained as a **linear combination** of p past values $X_{t-1}, X_{t-2}, \dots, X_{t-p}$, together with a **random residual error** (**white noise**) in the same series.

- **Definition**

- An auto-regressive model of order p , abbreviated as $AR(p)$ is of the form:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \phi_3 X_{t-3} + \dots + \phi_p X_{t-p} + \epsilon_t = \sum_{i=1}^p \phi_i X_{t-i} + \epsilon_t$$

Where X_t is a stationary and ϵ_t is random residual error (usually modelled by normal distribution with zero mean) and $\phi_1, \phi_2, \dots, \phi_p$ ($\phi_p \neq 0$) are model parameters. The hyperparameter p represents the length of the “direct look back” in the series (i.e. how many past time stamps we want to look into). p is usually determined by model validation methods.

Auto-Regressive Models

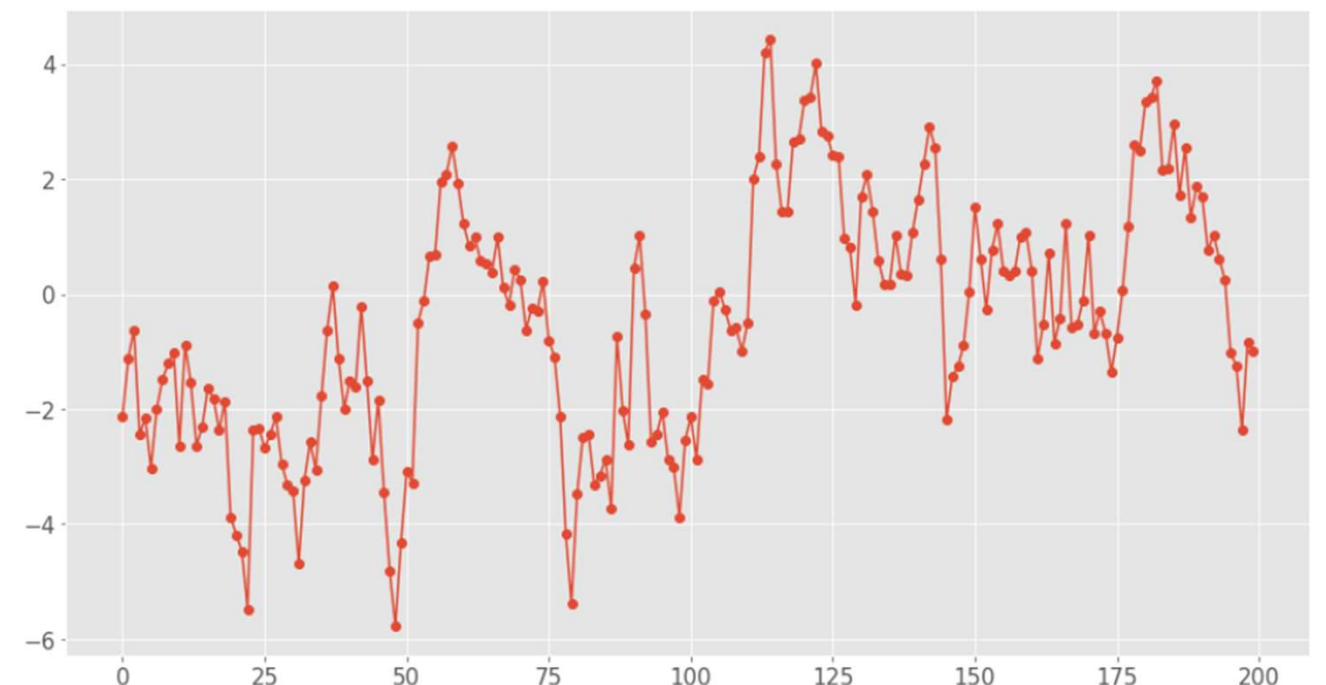
- The simplest of AR process is $AR(0)$, which has no dependence between the terms. In fact, $AR(0)$ is just random residual error (also called [white noise](#)).
- $AR(1)$ can be given by $X_t = \phi_1 X_{t-1} + \epsilon_t$
 - Only the previous term in the process and the noise term contribute to the output.
 - If $|\phi_1|$ is close to 0, then the process still looks like a white noise.
 - If $\phi_1 < 0$, X_t tends to oscillate between positive and negative values.
 - If $\phi_1 = 1$ then the process is equivalent to a random walk.

- Simulated $AR(1)$ process: $X_t = 0.9X_{t-1} + \epsilon_t$

Mean: $E[X_t] = 0$

Variance: $Var(X_t) = \frac{\sigma_\epsilon^2}{(1 - \phi_1^2)}$

Where, σ_ϵ^2 is the variance of noise.



Moving Average (MA) Models

- The name might be misleading but moving average models should not be confused with the [moving average smoothing](#).
- **Motivation**
 - Recall that in *AR* models, current observation X_t is regressed using the previous / past observations like: $X_{t-1}, X_{t-2}, \dots, X_{t-p}$ plus an error term: ϵ_t (also called noise) at current time point.
 - One problem of *AR* model is the ignorance of the correlated noise structures (which is unobservable) in the time series.
 - In other words, the imperfectly predictable terms in the current time ϵ_t , and previous steps $\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_{t-q}$ are also informative for predicting observations.
- **Definition**
 - A moving average model of order q , abbreviated as $MA(q)$ is of the form:

$$X_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} + \dots + \theta_q \epsilon_{t-q} = \epsilon_t + \sum_{j=1}^q \theta_j \epsilon_{t-j}$$

Where $\theta_q \neq 0$

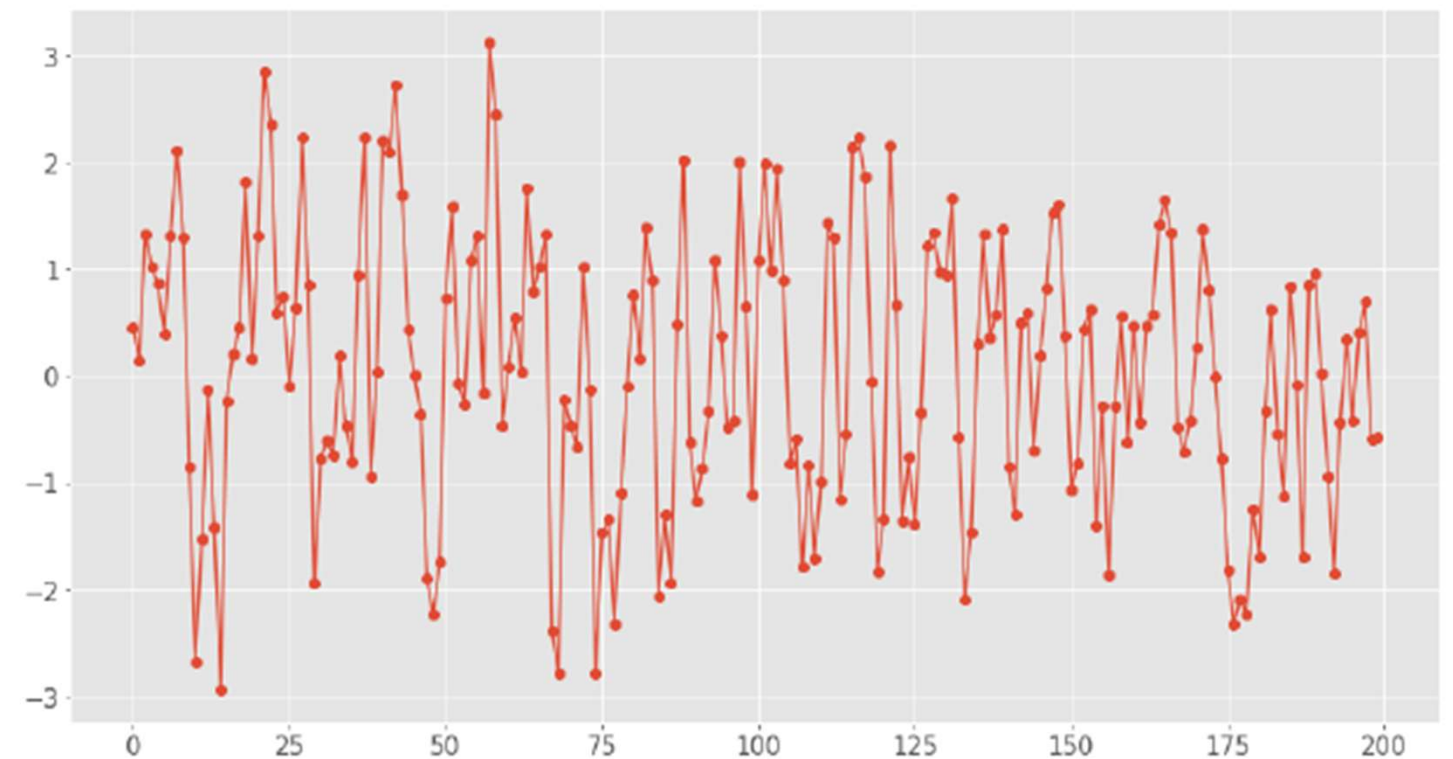
Moving Average (MA) Models

- Although the equation of moving average (*MA*) model looks like a regression model, the difference is that the ϵ_t is not observable.
- Contrary to *AR* model, finite *MA* model is always stationary. (Yes, *AR* process can be non-stationary, for example: random walk)
- Finite *MA* models are stationary because the observation is just a weighted moving average over past forecast errors.
- Simulated *MA*(1) process: $X_t = \epsilon_t + 0.8 \epsilon_{t-1}$

Mean: $E[X_t] = 0$

Variance: $Var(X_t) = \sigma_\epsilon^2(1 + \theta_1^2)$

Where, σ_ϵ^2 is the variance of noise.



ARMA Models

- **Intuition**

- Auto-Regressive and Moving Average models can be combined together to form ARMA models.

- **Definition**

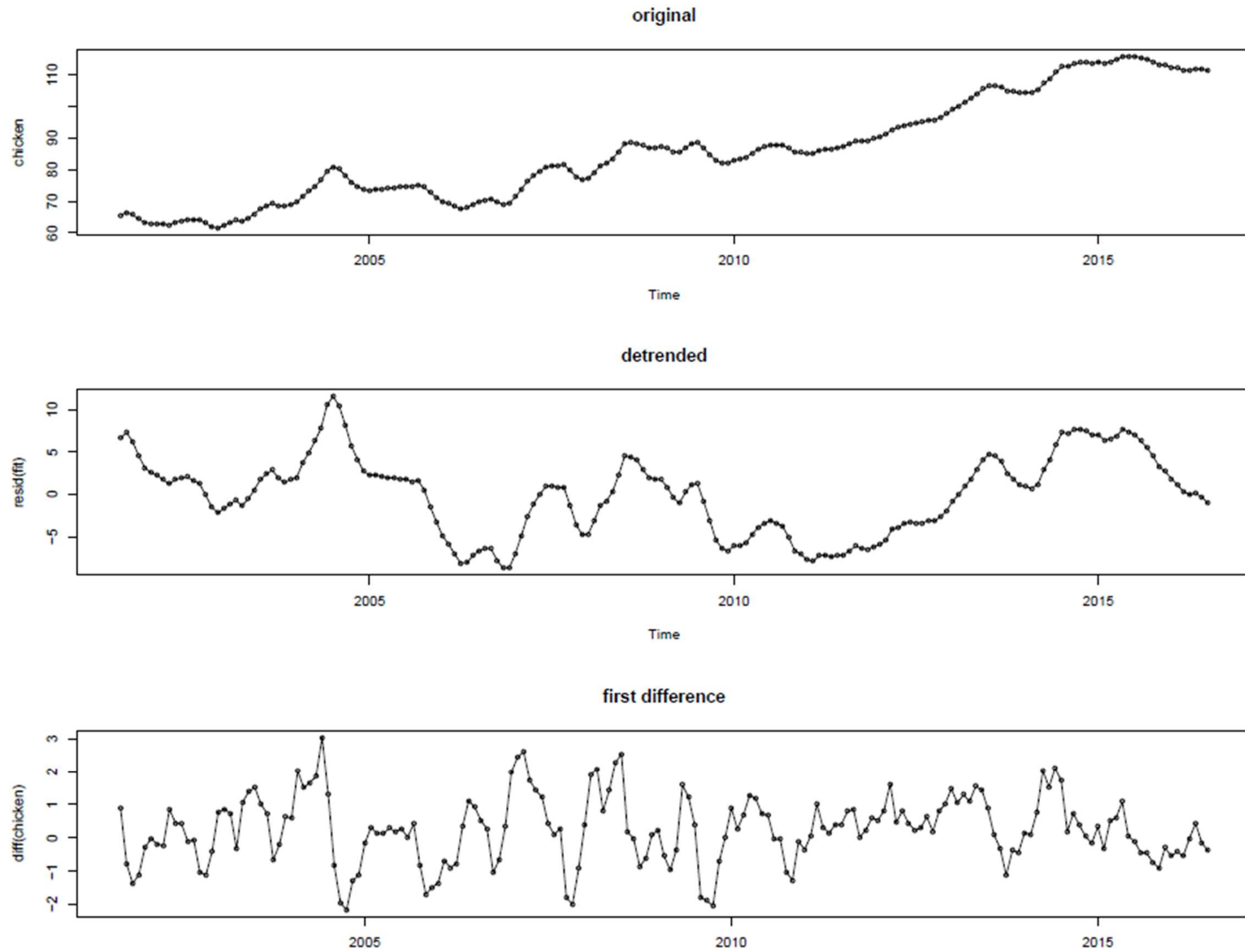
- A time series $\{X_t ; t = 0, \pm 1, \pm 2, \dots\}$ is $ARMA(p, q)$ if it is stationary and

$$X_t = \epsilon_t + \sum_{i=1}^p \phi_i X_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j}$$

Where $\phi_p \neq 0$ and $\theta_q \neq 0$

- One limitation of ARMA models is the stationarity condition.
- In many situations, time series can be thought of as being composed of two components, a non-stationary trend series and a zero-mean stationary series. The strategies to **stationarize** time series models are:
 - **Detrending:** Subtract with an estimate for trend and deal with residual.
 - **Differencing:** Take the difference of the time series, often those are stationary.

Detrending and Differencing



ARIMA Model

ARIMA is an acronym that stands for **A**uto-**R**egressive **I**ntegrated **M**oving **A**verage.

Specifically,

- **AR** *Autoregression*. A model that uses the dependent relationship between an observation and some number of **lagged observations**.
- **I** *Integrated*. The use of **differentencing** of raw observations in order to make the time series stationary.
- **MA** *Moving Average*. A model that uses the dependency between an observation and a **residual error** from a moving average model applied to lagged observations.
- Each of these components are explicitly specified in the model as a parameter.
- Note that **AR** and **MA** are two widely used **linear models** that work on stationary time series, and **I** is a **preprocessing procedure** to “stationarize” time series if needed.

ARIMA Model

A standard notation is used of ARIMA (p, d, q) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used.

- p The number of lag observations included in the model, also called the **lag order**.
- d The number of times that the raw observations are differenced, also called the **degree of differencing**.
- q The size of the moving average window, also called the **order of moving average**.
- A value of **0** can be used for a parameter, which indicates to not use that element of the model.
- In other words, ARIMA model can be configured to perform the function of an ARMA model, and even a simple AR, I, or MA model.

Thank You