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#LifeKoKaroLift

Post-Graduate Diploma in ML/AI

Course : Machine Learning

Lecture On : Timeseries

Instructor : Arihant Jain

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Today's Agenda

1. Introduction to time series and its components
2. Classical decomposition of a time series
3. Stationarity time series - ARMA Modelling
4. Time Series Differencing and ARIMA Modelling
5. Time Series smoothing

What is Time Series and Time Series Data ?

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A **time series** is a collection of observations of well-defined data items obtained through repeated measurements over time. The data points are indexed in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data. Examples of time series are heights of ocean tides, the daily closing value of the Dow Jones Industrial Average, etc

Time series data is data that is collected at different points in time. This is opposed to cross-sectional data which observes individuals, companies, etc. at a single point in time. Because data points in time series are collected at adjacent time periods there is potential for correlation between observations. This is one of the features that distinguishes time series data from cross-sectional data

Time Series Analysis

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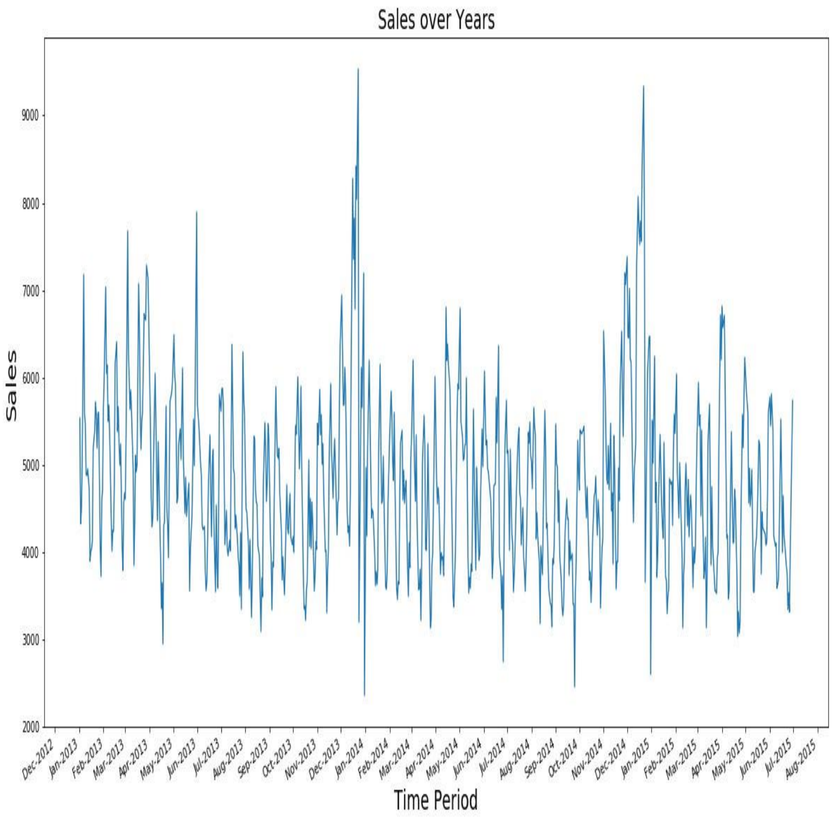
Time series analysis is a <u>statistical technique</u> that deals with time series data, or trend analysis. Time series data means that data is in a series of particular time periods or intervals. The data is considered in two types:

- Time series data: A set of observations on the values that a variable takes at different times
- Cross-sectional data: Data of one or more variables, collected at the same point in time.



Regression Vs Timeseries

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Regression	Time Series
1. In Regression it does not matter if we reshuffle the data.	1. Time Series consists time from before to the latest and they cannot be shuffled.
2. In Regression data points are independent.	2. In Time Series there is strong correlation between successive values.
3. Regression model predicts only on the basis of the values given.	3. Time Series not only depends on the values given, but also on depends on the sequence in which the values are given.

Application of Time Series

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Time Series

- Election Forecast
- Supply Chain Forecasting
- Advertising spend
- Web traffic
- Government Predictions
- Budget Forecast
- Turnover/Sales Prediction
- Bookings forecasting
- Science & Engineering
- Econometrics GDP, Inflation
- Earthquake prediction
- signal processing
- Health management
- mathematical finance
- Economic Growth
- Control engineer
- Weather Forecast
- Medicine
- Astronomy
- Healthcare Diagnosis
- Biomedical Monitoring
- Trading Market

Components of Time Series

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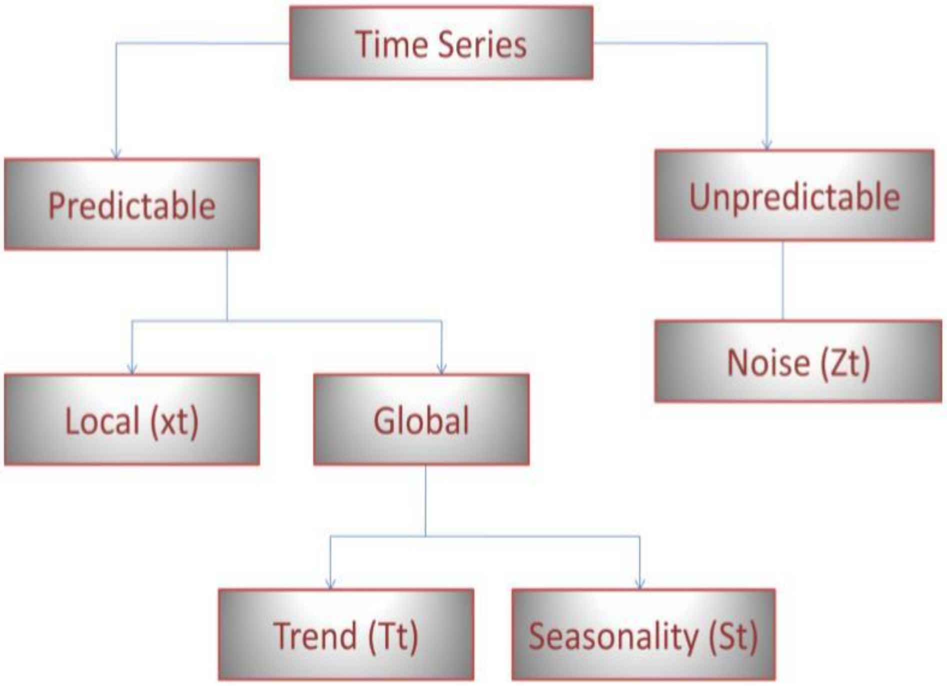

Source – dataanalyticsedge.com

Local Predictable part (Xt)

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Local predictable part consists of auto regressive behavior. It shows how time series is influenced by its immediate past.

$$X_t = a + bX_{t-1} + cX_{t-2}$$

If we know few time stamps immediately preceding time, we can predict the time series values.

Example: Give yesterday's price we can predict today's price but not price after a year

Global Predictable part

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In Global predictable part the present time series does not depend on the immediate past.

Example: Temperature in January does not depend on the December or November temperature.

This Global predictable part consists of two parts Trend and Seasonality.

Trend: Trend refers to any pattern that talks about the overall increase or decrease in the values

Seasonality: Seasonality refers to a repeating pattern of values seen in the data

Time Series With Trend and Seasonality

Imp Components of Time Series

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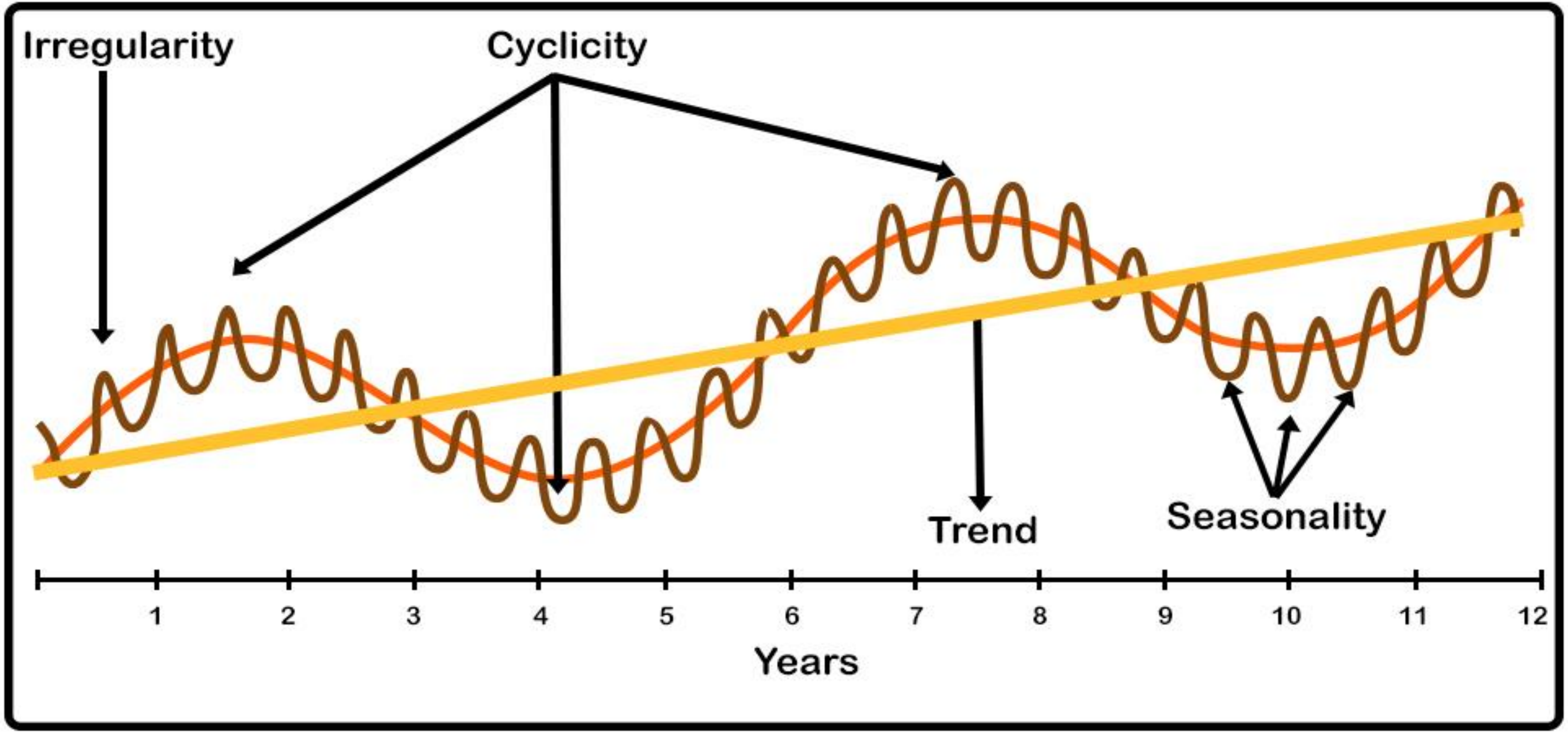

Classical decomposition of a time series

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Additive & Multiplicative Model

let’s understand what the analysis features of a Time Series are –

- **Level**: is the average value in the series

- **Trend**: is the increasing or decreasing value in the series

- **Seasonality**: is the repeating the short-term cycle in the series

- **Noise**: is the random variation in the series.

Additive & Multiplicative Models

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The Additive Model

It is a model of data in which the effects of the individual factors are differentiated and added to model the data.

y(t) = Level + Trend + Seasonality + Noise

In the additive model, the behavior is linear where changes over time are consistently made by the same amount, like a linear trend. In this situation, the linear seasonality has the same amplitude and frequency.

Additive & Multiplicative Models

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The Multiplicative Model

In this situation, trend and seasonal components are multiplied and then added to the error component. It is not linear, can be exponential or quadratic and represented by a curved line as below:

y(t) = Level * Trend * Seasonality * Noise

Different from the additive model, the multiplicative model has an increasing or decreasing amplitude and/or frequency over time.

Additive vs Multiplicative

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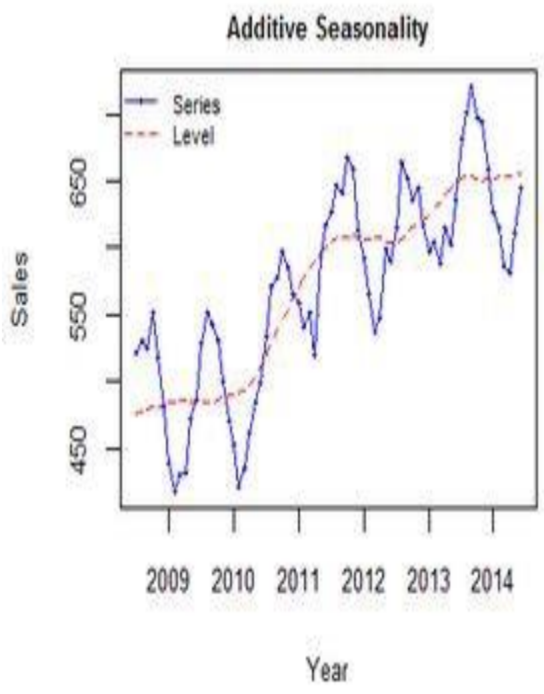

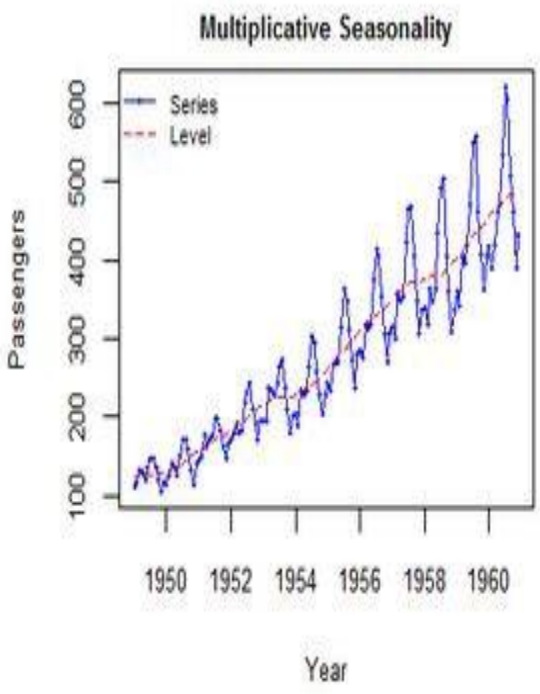

Source: https://goo.gl/szKmgo

Defining Stationarity in a time series

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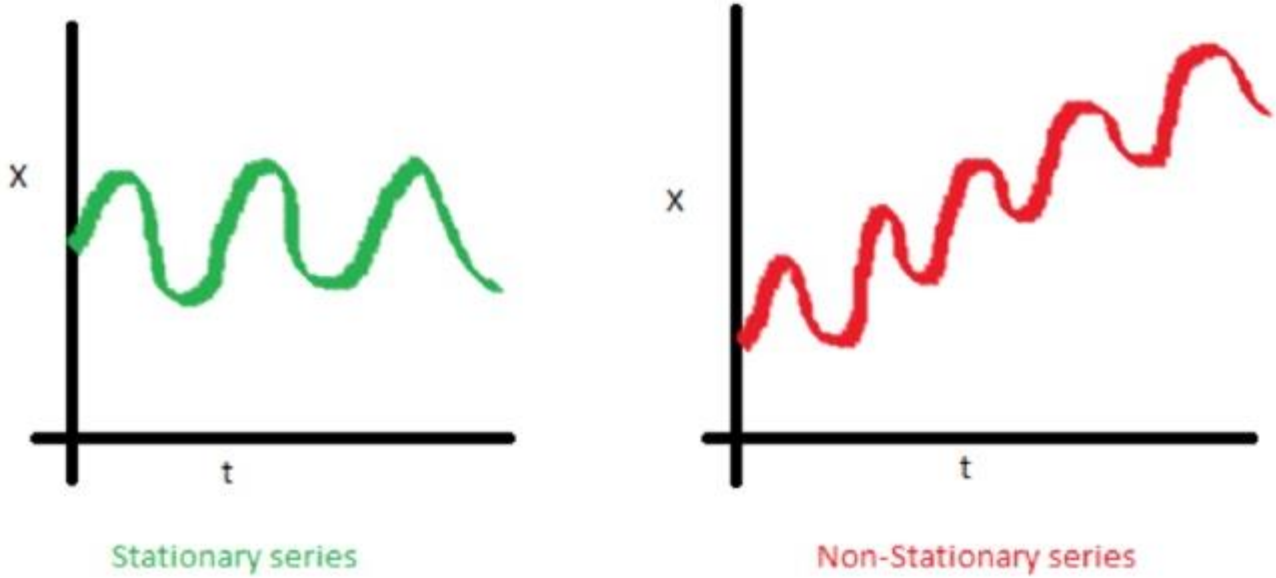
In the most intuitive sense, stationarity means that the statistical properties of a process generating a time series do not change over time. **A stationary series is one in which the properties – mean, variance and covariance, do not vary with time.**

It does not mean that the series does not change over time, just that the *way* it changes does not itself change over time.

linear function - The value of a linear function changes as x grows, but the *way* it changes remains constant — it has a constant slope; one value that captures that rate of change.

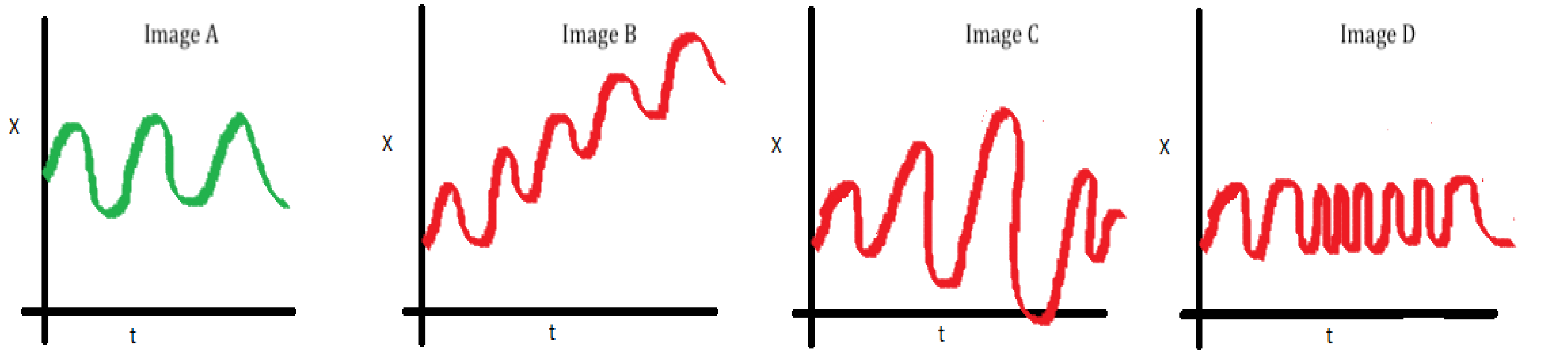
Stationary and Non-Stationary Series



Stationarity Continues .

The Principles of Stationarity

Time-Dependent Mean | Time-Dependent Variance | Time-Dependent Covariance



Stationary series | Non-Stationary series | Non-Stationary series | Non-Stationary series

Different Methods to Check Stationarity

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statistical tests like the unit root stationary tests. Unit root indicates that the statistical properties of a given series are not constant with time, which is the condition for stationary time series.

Suppose we have a time series :
$y_t = a*y_{t-1} + \varepsilon_t$

where y_t is the value at the time instant t and ε_t is the error term.

In order to calculate y_t we need the value of y_{t-1}, which is :
$y_{t-1} = a*y_{t-2} + \varepsilon_{t-1}$

If we do that for all observations, the value of y_t will come out to be:
$y_t = a^n*y_{t-n} + \Sigma\varepsilon_{t-i}*a^i$

If the value of a is 1 (unit) in the above equation, then the predictions will be equal to the y_{t-n} and sum of all errors from t-n to t, which means that the variance will increase with time. This is knowing as unit root in a time series. We know that for a stationary time series, the variance must not be a function of time. The unit root tests check the presence of unit root in the series by checking if value of a=1.

Methods to Check Stationarity -
1. ADF Test
2. KPSS Test

ADF Test

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ADF (Augmented Dickey Fuller) Test

The Dickey Fuller test is one of the most popular statistical tests. It can be used to determine the presence of unit root in the series, and hence help us understand if the series is stationary or not.

The null and alternate hypothesis of this test are:

Null Hypothesis: The series has a unit root (value of a =1)

Alternate Hypothesis: The series has no unit root

If we fail to reject the null hypothesis, we can say that the series is non-stationary

Test for stationarity: If the test statistic is less than the critical value, we can reject the null hypothesis (aka the series is stationary). When the test statistic is greater than the critical value, we fail to reject the null hypothesis (which means the series is not stationary)

KPSS Test

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KPSS test for checking the stationarity of a time series (slightly less popular than the Dickey Fuller test)

- The null and alternate hypothesis for the KPSS test are opposite that of the ADF test

null hypothesis as the process is trend stationary, to an alternate hypothesis of a unit root series.

Null Hypothesis: The process is trend stationary

Alternate Hypothesis: The series has a unit root (series is not stationary)

Test for stationarity: If the test statistic is greater than the critical value, we reject the null hypothesis (series is not stationary). If the test statistic is less than the critical value, if fail to reject the null hypothesis (series is stationary).

How to Make Series Stationary ?

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In order to use time series forecasting models, it is necessary to convert any non-stationary series to a stationary series first.

Making a Time Series Stationary –

- Differencing
- Seasonal Differencing
- Log transform

Making a Time Series Stationary

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Differencing

In this method, we compute the difference of consecutive terms in the series. Differencing is typically performed to get rid of the varying mean. Mathematically, differencing can be written as:

$$y_t' = y_t - y_{(t-1)} \quad \textit{where } y_t \textit{ is the value at a time } t$$

Seasonal Differencing

In seasonal differencing, instead of calculating the difference between consecutive values, we calculate the difference between an observation and a previous observation from the same season. For example, an observation taken on a Wednesday will be subtracted from an observation taken on the previous Wednesday .

$$y_t' = y_t - y_{(t-n)}$$

Transformation

Transformation are used to stabilize the non-constant variance of a series. Common transformation methods include power transform, square root, and log transform.

Time Series Forecasting

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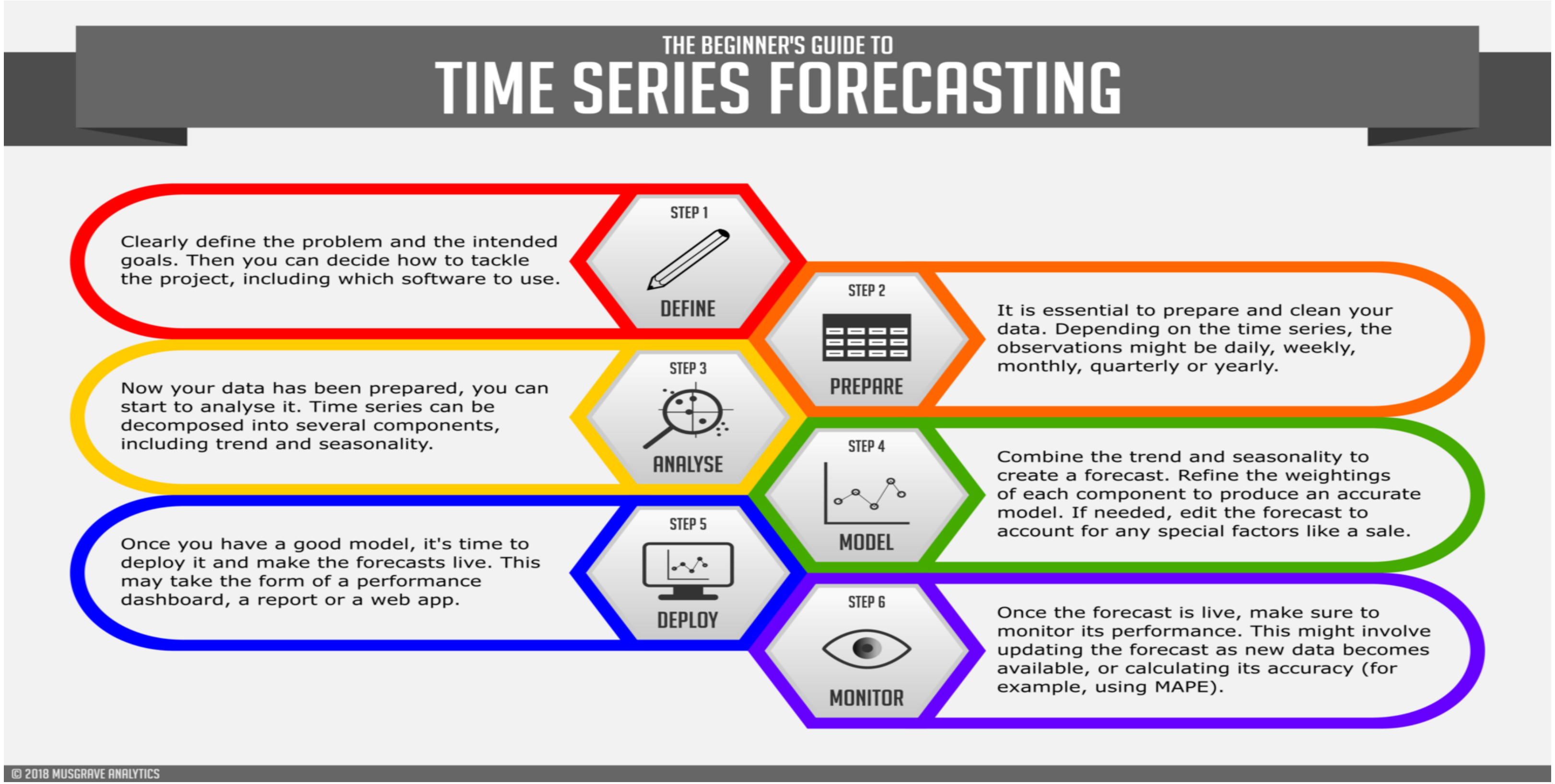

Source - musgraveanalytics

ARMA Modelling

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ARMA models are commonly used in time series modeling. In ARMA model, AR stands for auto-regression and MA stands for moving average.

AR or MA are not applicable on non-stationary series

In case you get a non stationary series, you first need to stationarize the series (by taking difference / transformation) and then choose from the available time series models.

Auto-Regressive Time Series Model

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The Autoregressive Model, or AR model for short, relies only on past period values to predict current ones. It's a linear model, where current period values are a sum of past outcomes multiplied by a numeric factor. We denote it as AR(p), where "p" is called the order of the model and represents the number of lagged values we want to include.

x(t) = alpha * x(t – 1) + error (t)

This equation is known as *AR(1) formulation*. The numeral one (1) denotes that the next instance is solely dependent on the previous instance. The alpha is a coefficient to minimize the error function.

Examples – GDP Forecast

Moving Average Time Series Model

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Let's suppose that "r" is some time-series variable, like returns. Then, a simple Moving Average (MA) model looks like this:

$$r_t = c + \theta_1 \epsilon_{t-1} + \epsilon_t$$

ARIMA Model

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An ARIMA model is a class of statistical models for analyzing and forecasting time series data. It explicitly caters to a suite of standard structures in time series data, and as such provides a simple yet powerful method for making skillful time series forecasts.

ARIMA is an acronym that stands for Autoregressive Integrated Moving Average. It is a generalization of the simpler Autoregressive Moving Average and adds the notion of integration.

•AR: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations

•I: Integrated. The use of differencing of raw observations (e.g. subtracting an observation from an observation at the previous time step) 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

Parameters

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The parameters of the ARIMA model are defined as follows:

•**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

What Is Exponential Smoothing?

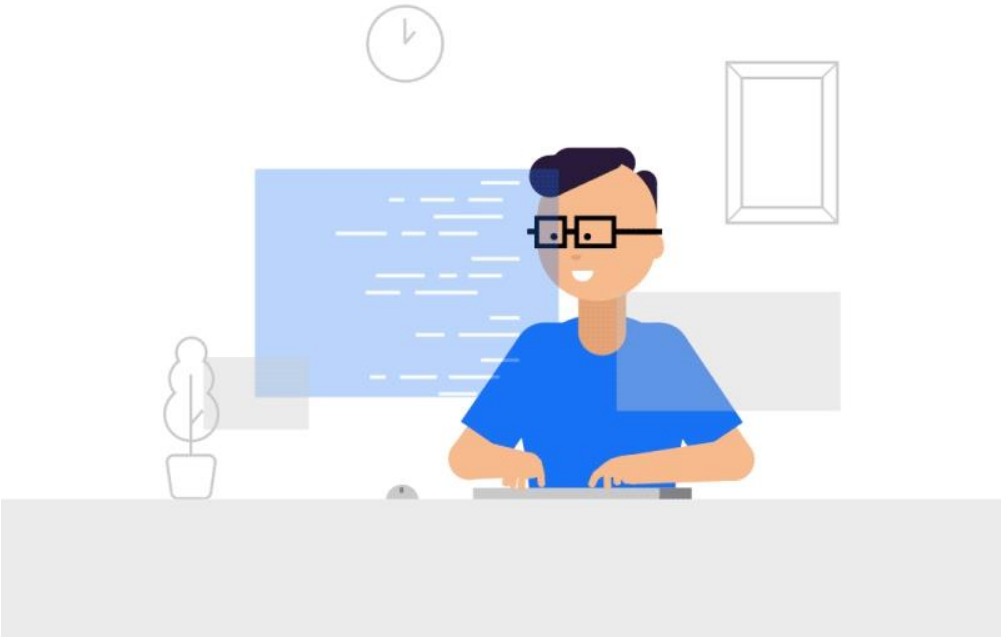
Exponential smoothing is a time series forecasting method for univariate data

Time series methods like the Box-Jenkins ARIMA family of methods develop a model where the prediction is a weighted linear sum of recent past observations or lags.
Exponential smoothing forecasting methods are similar in that a prediction is a weighted sum of past observations, but the model explicitly uses an exponentially decreasing weight for past observations.

Specifically, past observations are weighted with a geometrically decreasing ratio.

Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation the higher the associated weight.

Let’s see an example



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Thank You !