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# Explain the components of a time series data:

The components of time series are the various reasons and different factors which affect the values of each data point in a time series data, these are called the components of time series. There are various components of time series, some of them are shown below.

* The Long-Term movements
* The Short-Term movements
* Trends
* Seasonality, etc.

Long-Term Trends

Seasonal

Time series components

Short-Term Trends

Cyclic

Irregular trends

Figure 1 Time Series Components

# Explain the steps in Time Series Forecasting Process:

There are different time series models and every model has some wonderful functionalities and results. The purpose of time series models is to predict a specific series or event in the future, we all know that the future is unpredictable but these models help us predict the future based on the historical data we fed to these models to train on. The simplest steps to perform a time series forecasting is given below.

Choose Time series model

Splitting the data

Train the model

Evaluate the model

Perform forecasting

Figure 2 Time Series Forecasting process

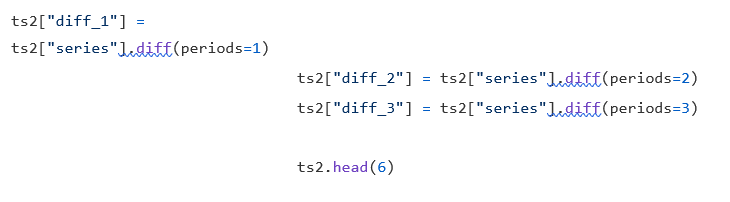
# Explain the stationarity of time series data. How do determine the stationarity?

As the name stationarity itself say those data points are stationary, in time series data, when the statistical properties of the data do not change over time, we say that the data is stationary. If the time series data is not stationary, then there are many ways and methods which is used to make the data stationary. For example, differencing the data helps us to transform the non-stationary data into stationary data.

There are various methods used to determine the stationarity in the data, for example, we sometimes split the data into two parts and then compare the mean and various of the data. If the mean and variance of the two partitioned data are different then it means that the data is non-stationary. There are other methods also like we perform the ADF tests and KPSS tests to check whether the data is stationary or not?

# Explain the methods for converting non-stationary time series data to stationary.

Many methods are used to transform the stationary data into stationary data. One of the simplest methods is called the Differencing method. In this method, we make the difference between all the data points and observations in our data. By using Pandas, we have a method called ‘diff()’ which takes the difference between the data points. The following code will change the non-stationary data into stationary data.



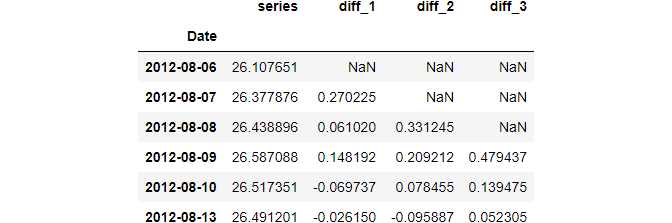


Figure 3 non-stationary data to stationary data [1].

# Explain the autocorrelation function for time series data and how to use it?

The autocorrelation function determines the gap between two observations. It checks the correlation of the same variables by checking the lag between two consecutive time intervals. This function is a statistical concept and is often known as the series correlation. With this function, we can easily determine the pattern of the data. For example, this function will correlate the prices of the US dollar by looking at the price of the previous day and the present day.

To use this function in Python, we will have to import it from a library called ‘statsmodels’, the function itself called the ‘plot\_acf’ which means plot autocorrelation function. This function works on the following formula.





Figure 4 autocorrelation function formula [2]

# Explain 3 error metrics used for measuring the performance of a time series, and forecasting model: their definitions, formulas, pros, and cons.

The Error metrics in any machine learning and data science project are very important, by using these metrics, we can see and judge the model we train very easily and efficiently. If we use the error metrics in the wrong way, it will affect the accuracy and optimization of the model. There are four major error metrics of time series, they are shown in the diagram below.

Error Metrics

Scale free error metrics

Relative error metrics

Percentage-Error metrics

Scale-dependent metrics

Figure Error metrics of Time series

The scale error metrics only work with units, for example, km, cm, dollar rate, etc of the fundamental data. These metrics are very easy to use and utilized. The scale-dependent metrics do not help compare different types of time series data because of their gauge reliance.



Figure Mean Squared Error (MSE) [3].

On the other hand, the percentage error metrics are highly scaled dependent and they can be used to compare different time series data because they are very scale-dependent. The weakest thing about percentage error metrics is that they can’t handle the zero values, if there are zero values in the time series data then these metrics will behave infinitely.



Figure Mean Absolute Percentage Error (MAPE) [3].

The relative error metrics are very useful in comparing the performance of the time series models against the performance of other standard models.



Figure Median Relative Absolute Error (MdRAE) [3].

# Explain the assumptions of a linear regression model.

The regression models draw the relationship between dependent variable Y with one or more than one independent variable. Based on different independent features, we have to predict only one feature and that feature will be a dependent.

The linear regression models have a total of four assumptions, they are given below.

**Normality**:

For any value of independent feature X, the value of dependent feature Y is equally distributed.

**Independence**: Here, the observations and data points are independent to each other.

**Homoscedasticity**: In this assumption, the variance is same for all the independent features X.

**Linearity**: this is the relationship between dependent and independent features based on the mean of Y.

Figure Assumptions of Linear regression models

# Explain the Exponential Smoothing (ES) algorithms: Simple, Double, and Triple ES. For what kind of time series data, each of these ES algorithms is suitable?

The Exponential Smoothing (ES) models are time series algorithms that deal with univariate data. These models are based on previous observations. It is the weighted sum of the previous past observations. The exponential smoothing algorithms have three main types, these types are explained below.

## Single Exponential Smoothing:

In time-series data, there are trends and seasonality in the data. The single exponential smoothing model only works on univariate data having no trends and no seasonality. These types of models only require one parameter which is often called the smoothing factor.

## Double Exponential Smoothing:

The double exponential smoothing algorithms are the next version of exponential smoothing models. These models deal with univariate data having trends. They have parameters like Alpha (a) and Beta (b).

## Triple Exponential Smoothing:

These models are also the extension of the Exponential Smoothing algorithms, the difference between triple exponential smoothing models and double exponential models is that the double exponential models work on univariate data having trends but the Triple exponential smoothing models work on univariate data having trends and seasonality both. In this model, a new parameter is added after Alpha, and Beta is Gamma.

# . Explain the assumptions of ARIMA models and Vector ARIMA models.

ARIMA also called the Autoregressive integrated moving average, is a machine learning model which is used for time series forecasting. This model helps us predict the future by forecasting future values. The assumptions of ARIMA models are given below:

* The ARIMA models work on stationary data, so the data should be stationary
* This model is a regression model which means that it’ll only work on a single feature, so the data should be univariate.
* The shift lever is none in this model
* No specific predictors are known
* No seasonal dummies and time anomalies
* Over time, the parameters of this model are constant
* The error process is also constant over time.

While on the other hand, the Vector ARIMA is the time series model which interacts with the active connection between variables. This model works on multivariate time series data. The assumptions of vector ARIMA are given below.

* At least two time series features are important
* These two time series features should influence each other
* Visualize data and check stationarity
* Data should be stationary

# Explain the assumptions of ARCH and GARCH models.

The ARCH and GARCH models are very useful in time series analysis. These models are highly in demand in the finance industry. These models are used for forecasting purposes and time series volatility.

The ARCH models also called the Autoregressive conditional heteroskedasticity measure the actual volatility and then forecast that volatility in the future. These models are dynamic, which means they are highly responsive to the change in data. The ARCH models are highly in demand and used by financial institutions by forecasting prices and other things in the future. There are different types of ARCH models and they are used to determine and analyze the data differently.

While the GARCH often called Generalized Autoregressive Conditional Heteroskedasticity is the model used in time series forecasting where the variance error is autocorrelated. These models are also used to forecast the volatility and forecast it in the future, the GARCH is used by the financial organizations to see the return volatility. These are highly used for forecasting the price of different products in the future.

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