Optimization in Supply Chain Management Project (Viva Questions)

Project Interview Questions

1.What is time series data and how does it differ from cross sectional data?

**A) Time series data is data that is measured using a sequence of certain points at times. The Dow Jones Index is an example of data that is measured using time series data, as the data collected is listed at a certain time each day. Line charts are used to plot time series data, and these enable the viewer of the data to analyze the data with ease, and to compare the differences between one set of data at a particular time and another set of data at a particular time.**

# 2.Can you explain the components of time series data?

**A) Time series data is everywhere around us, from financial data to weather forecasts. Understanding the components of a time series can help us better analyze and interpret the data. In this article, we will discuss the four main components of a time series: trend, seasonality, cyclicality, and randomness.**

**Tread Component: The trend component of a time series refers to the overall long-term behavior of the data. It is the gradual change in the level of the series over a long period of time. A trend can be upward, downward, or flat. For example, the trend of a stock price over several years can show an upward or downward trend, indicating the general direction of the stock’s value.**

**Seasonality Component: Seasonality is the repetitive pattern that occurs in a time series at fixed intervals, such as daily, weekly, or monthly. Seasonality can be caused by factors such as weather, holidays, or business cycles. For example, the demand for ice cream may increase during the summer months and decrease during the winter months, showing a seasonal pattern.**

**Cyclicality Component: Cyclicality refers to fluctuations in the data that are not predictable and not caused by seasonality. Cyclicality can be caused by factors such as economic cycles, political events, or technological changes. Cyclicality can be longer or shorter than seasonality, and its amplitude can vary. For example, the sales of automobiles may decrease during an economic recession and increase during an economic boom, showing cyclicality.**

# Randomness Component

**The randomness component of a time series refers to the fluctuations that are not predictable by any of the above components. It represents the unpredictable events that can occur in any time series, such as natural disasters, market crashes, or unexpected business events. Randomness can make it difficult to make predictions or draw conclusions from time series data.**

# Combining Components

**In practice, time series data can have a combination of all four components. It is important to understand the components of a time series to properly analyze and interpret the data. By decomposing a time series into its individual components, we can better understand the underlying patterns and trends in the data.**

**3) What are some common applications of time analysis and forecasting in business?**

* **Time series in Financial and Business Domain**
* **Time series in Medical Domain**
* **Time Series in Astronomy**
* **Time Series in Forecasting**
* **Time Series in Business Development**

## 4) How do you handle missing values in time series data?

1. **Missing Completely at Random (MCAR): In simple terms, MCAR means no relationship between the missing and already observed data. The probability of the missing data is entirely random and is not dependent on already observed data, i.e., P (Missing | Complete data) =p(Missing)**
2. **Missing at Random (MAR): A variable is missing at random if the probability of missingness depends only on the available information, i.e., P (Missing | Complete data) =p (Missing | Observed data) not at Random (MNAR): The probability of missingness, in this case, depends on the variable itself.**
3. **Missing not at Random (MNAR): The probability of missingness, in this case, depends on the variable itself.**

## 5) What is the stationarity in times series data, and why it is important?

**A)In mathematics and statistics, a stationary process is a stochastic process whose unconditional joint probability distribution does not change when shifted in time. Said more simply, we can slice up the time series data into equally sized chunks for a stationary time series and still get the same probability distribution.**

**There are multiple types of stationarity, which we’ll cover below. But for now, let’s understand the general concept of stationarity through visual exploration.**

## 6) What techniques can be used to make a time series data stationery?

**A)There are several techniques that can be used to make time series data stationary, depending on the nature and source of the non-stationarity. Some of the common techniques are:**

* **Differencing: This method involves taking the difference between successive observations of the data, which can remove the trend component and make the data more stationary. For example, if the original data is then the differenced data is *1*yt −yt−1.**
* **Seasonal decomposition: This method involves splitting the data into trend, seasonal, and residual components, and then removing or modeling the trend and seasonal components to obtain a stationary residual series.**
* **Log transformation: This method involves taking the natural logarithm of the data, which can reduce the trend component and stabilize the variance of the data. For example, if the original data is, then the log-transformed data is yt , then the log-transformed data is log (yt ). This can be done in Python using the np.log () function from the NumPy library.**

## 7) Explain the autoregressive (AR) model in time series forecasting?

**A) An autoregressive model is a type of time series model that assumes the current value of a variable depends on its previous values. In other words, what happened in the past can give us a clue about what might happen in the future. It’s like using historical data to forecast upcoming trends.**

**To illustrate how AR models work, let’s consider a temperature dataset recording daily temperatures in a city. Our goal is to predict tomorrow’s temperature using an AR model.**

## The AR (1) Model

**The AR (1) model, with an order of 1, means we will only use the temperature from the previous day to predict the current day’s temperature. The model equation is:**

**Tomorrow’s temperature (Tomorrow) = β0 + β1 \* Today’s temperature (Today) + ε**

**In this equation:**  
**- Tomorrow represents the temperature we want to predict for tomorrow.**  
**- Today is the temperature recorded today (the value we know).**  
**- β0 and β1 are coefficients that the AR model calculates to make the prediction.**  
**- ε is an error term representing the difference between the predicted temperature and the actual temperature.**

## Model Coefficients and Today’s Temperature

**Suppose based on historical data, our AR (1) model finds the following values for the coefficients:**  
**- β0 = 2 (intercept term)**  
**- β1 = 0.7 (coefficient for today’s temperature)**

## Making the Prediction

**Now, we can use the AR (1) model to predict tomorrow’s temperature (Tomorrow):**

**Tomorrow = 2 + 0.7 \* 28 + ε**  
**T\_tomorrow = 2 + 19.6 + ε**  
**T\_tomorrow = 21.6 + ε**

## The Prediction

**The AR (1) model predicts that tomorrow’s temperature will be 21.6 degrees Celsius. However, keep in mind that the actual temperature might differ slightly due to the error term (ε), which accounts for unpredictable factors not considered by the model, such as sudden weather changes.**

**8) What is the moving average (MA) model in time series forecasting?**

**A) Moving Average Model: MA (q) The moving average model is a time series model that accounts for very short-run autocorrelation. It basically states that the next observation is the** **mean of every past observation. The order of the moving average model, q, can usually be estimated by looking at the ACF plot of the time series.**

## 9) Describe the autoregressive integrated moving average (ARMIA) model?

**A) An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses** [**time series data**](https://www.investopedia.com/terms/t/timeseries.asp) **to either better understand the data set or to predict future trends.**

**An autoregressive integrated moving average model is a form of** [**regression analysis**](https://www.investopedia.com/terms/r/regression.asp) **that gauges the strength of one dependent variable relative to other changing variables. The model's goal is to predict future securities or financial market moves by examining the differences between values in the series instead of through actual values.**

**An ARIMA model can be understood by outlining each of its components as follows:**

* [**Autoregression (AR)**](https://www.investopedia.com/terms/a/autoregressive.asp)**: refers to a model that shows a changing variable that regresses on its own lagged, or prior, values.**
* **Integrated (I)*:* represents the differencing of raw observations to allow the time series to become stationary (i.e., data values are replaced by the difference between the data values and the previous values).**
* [**Moving average (MA)**](https://www.investopedia.com/terms/m/movingaverage.asp)**: incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.**

**10) What is the difference between ARMIA and SARIMA models?**

**A) ARIMA and SARIMA are both algorithms for forecasting. ARIMA considers the past values (autoregressive, moving average) and predicts future values based on that. SARIMA similarly uses past values but also considers any seasonality patterns.**

**11) How do you choose the appropriate values for p, d, and q in ARMIA MODELING?**

**A) Choosing the appropriate values for the parameters p, d, and q in ARIMA (Autoregressive Integrated Moving Average) modeling is a crucial step in time series analysis. These parameters determine the order of the ARIMA model, which affects its ability to capture the underlying patterns in the data. Here's a step-by-step guide on how to choose these values:**

**1. \*\*Understand the Data\*\*: Start by gaining a deep understanding of your time series data. Examine the data visually by plotting it to identify any trends, seasonality, or irregular patterns. This visual inspection will help inform your choice of ARIMA parameters.**

**2. \*\*Stationarity\*\*: ARIMA models assume that the data is stationary, which means that its statistical properties (e.g., mean, variance) do not change over time. If your data is not stationary, you need to make it stationary by differencing (parameter d).**

**- \*\*d (Differencing Order) \*\*: Calculate the differencing order required to make the data stationary. This is the value of 'd' in ARIMA (p, d, q). Differencing involves subtracting each observation from the previous one (first-order differencing) or performing seasonal differencing if there is a seasonal component. You may need to apply differencing more than once until the data becomes stationary.**

**3. ACF and PACF: Use the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to identify potential values for p and q. These plots show the correlation between a time series and its lagged values at various lags.**

**- \*\*p (Autoregressive Order) \*\*: The lag value where the PACF plot crosses the significance threshold for the first time can suggest the value of 'p.' It indicates the number of autoregressive terms to include in the model.**

**- \*\*q (Moving Average Order): The lag value where the ACF plot crosses the significance threshold for the first time can suggest the value of 'q.' It represents the number of moving average terms to include in the model.**

**4. \*\*Model Selection\*\*: Create several candidate ARIMA models with different combinations of p, d, and q values. Use statistical metrics like AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), or out-of-sample performance to evaluate and compare the models. The model with the lowest AIC or BIC is often preferred.**

**5. \*\*Check Residuals\*\*: After fitting the model, check the residuals for autocorrelation and heteroscedasticity (changing variance). Residuals should ideally be white noise with no significant autocorrelation.**

**6. \*\*Validate the Model\*\*: Use validation techniques such as hold-out samples or cross-validation to assess the model's out-of-sample performance and ensure it generalizes well.**

**7. \*\*Refinement\*\*: If the initial model does not perform well or if the residuals show patterns, consider refining the model by adjusting the values of p, d, and q and repeating the modeling process.**

**8. \*\*Forecasting\*\*: Once you have a satisfactory ARIMA model, you can use it for forecasting future values of the time series.**

**The process of selecting p, d, and q values may involve some trial and error, especially when dealing with complex and noisy time series data. It's essential to combine statistical analysis with domain knowledge to make informed decisions about the appropriate parameters for your ARIMA model.**

**12) What is seasonality in time series data and how do you handle it in forecasting?**

**A) Seasonality in time series data refers to recurring and predictable patterns or fluctuations that occur at regular intervals within the data. These patterns typically repeat over a fixed time period, such as daily, weekly, monthly, or annually. Seasonality can be caused by various factors, including weather, holidays, economic cycles, and other recurring events.**

**Handling seasonality in time series forecasting is crucial because it can significantly impact the accuracy of your predictions. Here are some common approaches to address seasonality in time series forecasting:**

**1. \*\*Differencing (d)\*\*:**

**- One of the fundamental techniques to handle seasonality is to difference the data. This involves subtracting the time series from its lagged version at a fixed seasonal lag.**

**- For example, if you have monthly data and there is an annual seasonality pattern, you can differentiate the data by subtracting the value from the same month in the previous year. This typically results in a stationary time series, making it amenable to standard forecasting techniques like ARIMA.**

**2. \*\*Seasonal Decomposition\*\*:**

**- Seasonal decomposition techniques separate a time series into its trend, seasonal, and residual components. Common methods include additive and multiplicative decomposition.**

**- Once the decomposition is done, you can model and forecast each component separately.**

**- Additive Decomposition: Original Data = Trend + Seasonal + Residual**

**- Multiplicative Decomposition: Original Data = Trend \* Seasonal \* Residual**

**3. \*\*Seasonal Models\*\*:**

**- Some time series forecasting methods are specifically designed to handle seasonality. Seasonal methods include Seasonal Exponential Smoothing, Seasonal ARIMA (SARIMA), and TBATS (Trigonometric Seasonal Decomposition of Time Series).**

**- SARIMA, for instance, extends the ARIMA model by incorporating seasonal autoregressive and moving average terms. It explicitly models both the seasonal and non-seasonal components.**

**4. \*\*Fourier Transforms\*\*:**

**- Fourier transforms can be used to analyze and filter out the seasonal component from the time series data. This technique decomposes the time series into different frequency components, allowing you to isolate and model the seasonality.**

**5. \*\*Calendar Adjustments\*\*:**

**- If your time series data is influenced by calendar events like holidays or weekdays, you can create calendar-adjusted variables that account for these effects. This can be particularly useful for daily or weekly data.**

**6. \*\*Machine Learning Models\*\*:**

**- Machine learning algorithms like Random Forests, Gradient Boosting, and neural networks can be trained to capture seasonality patterns. These models can automatically learn and adapt to the data's seasonal behavior.**

**7. \*\*Exogenous Variables\*\*:**

**- If you have access to external data that may influence seasonality (e.g., temperature for sales of ice cream), you can include these exogenous variables in your forecasting model to improve its accuracy.**

**8. \*\*Rolling Forecasts\*\*:**

**- For long-term forecasts, you can apply rolling forecasts, where you periodically update your model with new data and adjust your seasonal component estimates accordingly.**

**13) What is the purpose of the Box- Jenkins methodology in time series Analysis?**   
**A) The Box-Jenkins methodology, also known as the Box-Jenkins approach or Box-Jenkins method, is a widely used framework in time series analysis for modeling and forecasting univariate time series data. This methodology was developed by George Box, Gwilym Jenkins, and Gregory Reinsel, and it primarily serves the following purposes:**

**1. Modeling: The primary purpose of the Box-Jenkins methodology is to model the underlying structure of a time series data set. Time series data typically exhibit patterns such as trends, seasonality, and autocorrelation (dependence on past observations), and the methodology aims to capture these patterns accurately.**

**2. Forecasting: Once a suitable model is developed, it can be used for forecasting future values of the time series. This is crucial in various fields like finance, economics, and operations management for making informed decisions based on future predictions.**

**3. Identification: The Box-Jenkins approach involves a systematic process of identifying the appropriate mathematical model for a given time series. This includes identifying the order of differencing (d), autoregressive (AR) and moving average (MA) components, and any seasonal components (SARIMA). This identification step helps in selecting the most appropriate model structure.**

**4. Estimation: Once the model structure is identified, the next step is to estimate the model parameters. This involves fitting the model to the historical data using various estimation techniques, such as maximum likelihood estimation (MLE), to obtain the best-fitting parameters.**

**5. Diagnostics: After parameter estimation, the methodology involves a thorough diagnostic analysis to assess the adequacy of the model. Diagnostic tests and graphical checks are performed to ensure that the model adequately captures the data's characteristics and does not violate key assumptions.**

**6. Model Selection: Box-Jenkins allows for the comparison of different models to determine which one provides the best fit to the data. This is often done using criteria like AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion), which balance model complexity and goodness of fit.**

**7. Model Validation: The methodology emphasizes the importance of validating the chosen model by assessing its performance on out-of-sample data. This helps ensure that the model's forecasting accuracy is reliable.**

**8. Monitoring and Updating: Time series data can change over time due to various factors, and the Box-Jenkins methodology encourages the monitoring of model performance and periodic updating as needed to maintainaccurate forecasts.**

**14) Explain the concept of ACF (Auto Correlation Function) and PACF (Partial Auto Correlation function) in time series analysis?**

1. **In time series analysis, the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) are two important tools used to understand and model the dependencies or correlations between observations in a time series. These functions help in identifying the appropriate order of autoregressive (AR) and moving average (MA) terms when building a time series model, such as an ARIMA (Autoregressive Integrated Moving Average) model.**

1. Auto-Correlation Function (ACF): - The ACF measures the correlation between a time series and its own lagged values at various time lags. - It quantifies the relationship between an observation at a given time point and its past observations at different time intervals. - The ACF is represented as a plot of correlation coefficients against the time lag.

- The ACF can be used to identify the order of the MA (Moving Average) component in an ARIMA model. If the ACF shows a significant spike at a particular lag and then rapidly drops off, it suggests the presence of an MA term at that lag.

2. Partial Auto-Correlation Function (PACF):

**The PACF, on the other hand, measures the correlation between a time series and its own lagged values while controlling for the correlations at shorter lags.**

**- It helps to isolate the direct relationship between observations at different time intervals, removing the influence of shorter lags.**

**- The PACF is represented as a plot of correlation coefficients against the time lag, like the ACF.**

- **The PACF is particularly useful for identifying the order of the AR (Autoregressive) component in an ARIMA model. If the PACF shows a significant spike at a particular lag and then drops to zero, it suggests the presence of an AR term at that lag.**

**Here's a step-by-step process of how ACF and PACF can be used in time series analysis:**

**ACF Analysis:**

* **Calculate the ACF for the time series data at various lags.**
* **Examine the ACF plot to identify significant spikes or correlations at different lags.**
* **Significant spikes at certain lags may indicate potential MA terms in the model.**

**PACF Analysis:**

* **Calculate the PACF for the same time series data.**
* **Examine the PACF plot to identify significant spikes or correlations at different lags.**
* **Significant spikes at certain lags may indicate potential AR terms in the model.**

**Model Identification:**

* **Based on the significant spikes observed in both the ACF and PACF plots, you can make an initial determination of the order of AR and MA terms in your time series model.**
* **This initial identification is often used as a starting point for fitting various candidate models and further fine-tuning.**

**15) How do you access the goodness of an Arima model?**

**A) Evaluating the goodness of fit of an ARIMA (Autoregressive Integrated Moving Average) model is crucial to determine how well the model captures the underlying patterns and structures in the time series data. Several methods and metrics can be used to assess the quality and appropriateness of an ARIMA model:**

**Residual Analysis**:

* **Examine the residuals (the differences between the observed values and the predicted values) of the ARIMA model.**
* **A good ARIMA model should result in residuals that are approximately white noise, which means they are uncorrelated, have constant mean (zero), and constant variance.**
* **Plot the ACF and PACF of the residuals to check for any remaining autocorrelation. There should be no significant spikes in these plots.**
* **Use statistical tests such as the Ljung-Box test to formally test for the absence of autocorrelation in the residuals.**

**Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE)**:

* **Calculate these metrics to quantify the overall accuracy of the model's point forecasts.**
* **Lower values of MAE, MSE, and RMSE indicate better model fit, as they represent smaller errors between the model's predictions and the actual data.**

**Mean Absolute Percentage Error (MAPE)**:

* **MAPE is a percentage-based error metric that measures the average relative error of the model's forecasts.**
* **It is useful for understanding the accuracy of the model in terms of the scale of the data.**
* **Smaller MAPE values indicate better accuracy.**

**AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion)**:

* **These are information criteria used for model selection and comparison.**
* **Lower AIC and BIC values suggest a better trade-off between model complexity and goodness of fit.**
* **You can compare multiple ARIMA models with different orders to select the one with the lowest AIC or BIC**.

**Visual Inspection:**

* **Plot the observed values and the model's forecasts on the same graph to visually assess how well the model captures the data's patterns, trends, and seasonality.**
* **Look for any discrepancies between the model's forecasts and the actual data.**

**Out-of-Sample Forecasting:**

* **Assess the model's performance by comparing its forecasts to actual data that was not used during the model fitting process (out-of-sample data).**
* **Calculate accuracy metrics (e.g., MAE, MSE, RMSE) for the out-of-sample forecasts to evaluate the model's predictive ability.**

**Cross-Validation:**

* **Perform cross-validation by splitting the data into multiple training and testing subsets.**
* **Fit the ARIMA model to each training subset and evaluate its performance on the corresponding testing subset.**
* **This helps assess how well the model generalizes to unseen data.**

**Forecast Accuracy Plots:**

* **Plot forecast accuracy over time to visualize how well the model performs at different forecast horizons.**
* **You can use metrics like MAE, MSE, RMSE, or MAPE to create these plots.**

**Back testing**:

* **If you have access to additional data beyond your initial modeling period, you can back test the ARIMA model by comparing its historical forecasts to actual outcomes.**

**16) What is the Ljung –Box test, and how is it used in times series analysis?**

1. **The Ljung-Box test is a statistical test used in time series analysis to assess whether a given time series is a white noise or exhibits significant autocorrelation at various lags. Here's a brief explanation of its purpose and usage:**

**The primary purpose of the Ljung-Box test is to determine if there is any remaining serial correlation (autocorrelation) in the residuals of a time series model after fitting a model to the data. In other words, it helps in checking whether the model adequately captures the temporal dependencies in the data.**

**Model Validation: After fitting a time series model (e.g., ARIMA or GARCH) to historical data, you compute the residuals (the differences between observed values and predicted values). The Ljung-Box test is then applied to these residuals.**

**Null Hypothesis: The test involves formulating a null hypothesis that there is no significant autocorrelation in the residuals of the model (i.e., the residuals are white noise). The alternative hypothesis is that there is autocorrelation.**

**Test Statistic: The Ljung-Box test computes a test statistic based on the autocorrelations of the residuals at different lags. This statistic follows a chi-squared distribution under the null hypothesis.**

**Critical Values: You compare the test statistic to critical values from the chi-squared distribution to determine whether to reject the null hypothesis. If the test statistic is larger than the critical value at a chosen significance level (e.g., 0.05), you reject the null hypothesis, indicating the presence of significant autocorrelation.**

**Interpretation: If the null hypothesis is rejected, it suggests that the model's residuals still contain systematic patterns, indicating that the model may not adequately capture the underlying temporal structure of the data. In such cases, you may need to refine the model.**

**17) Can you discuss the concept of white noise in time series data?**

* **A) Random: Each data point is independent of the others and is generated from a random process.**
* **Constant Mean: The mean (average) of the data remains constant over time.**
* **Constant Variance: The variance (spread) of the data points remains constant over time.**
* **No Autocorrelation: There is no systematic pattern or correlation between data points at different time steps; the autocorrelation at all lags is close to zero.**
* **In essence, white noise represents pure randomness and serves as a benchmark for comparison when analyzing time series data. It is often used to test the hypothesis that a given time series exhibits meaningful patterns or structure beyond what would be expected by random chance. If a time series is white noise, it lacks any predictable or exploitable information. In contrast, deviations from white noise suggest the presence of underlying patterns or relationships that can be explored and modeled in time series analysis.**

**18) What is exponential smoothing, and when is it commonly used in forecasting?**

**A)Exponential smoothing is a popular time series forecasting method used to make predictions based on past observations, giving more weight to recent data while exponentially decreasing the importance of older data. It is commonly used in forecasting when there is an expectation that recent data points are more relevant and informative for predicting future values.**

**Purpose: Exponential smoothing is used to forecast future values in a time series by assigning exponentially decreasing weights to past observations. The method helps capture trends and seasonality in the data.**

**Mathematical Formula: At its core, exponential smoothing involves computing a weighted average of past observations, where more recent observations receive higher weights. The formula typically looks like this:**

**Forecast at time *�+1t*+1 = *�×α*× Observation at time *�t* + *(1−�) ×*(1−*α) ×* Forecast at time *�t***

**Here, *�α* (alpha) is the smoothing parameter, which determines the weight assigned to the most recent observation.**

**Common Usage: Exponential smoothing is commonly used in various forecasting scenarios, such as sales forecasting, demand forecasting, and financial forecasting. It is particularly useful when there is a belief that recent data carries more predictive power than older data, and when there may be underlying trends or seasonality in the time series.**

**Types: There are different variations of exponential smoothing, including Simple Exponential Smoothing, Holt's Linear Exponential Smoothing, and Holt-Winters Exponential Smoothing, each suited for different types of time series data with varying levels of trend and seasonality.**

**19) Describe the holt winters method for time series forecasting?**

**A) The Holt-Winters method is a time series forecasting technique that extends simple exponential smoothing and Holt's linear exponential smoothing to account for seasonality.**

**The Holt-Winters method is used for time series forecasting when there are trends and seasonality patterns in the data. It provides forecasts that capture both the underlying trend and seasonal variations.**

* **It considers three main components in a time series:**
* **Level (L):Represents the smoothed value of the series without trend or seasonality.**
* **Trend (T):Represents the slope or direction of the series.**
* **Seasonality (S):Represents the recurring patterns or seasonal variations within the data.**
* **The Holt-Winters method involves recursive calculations of these components, with separate equations for each component. It uses three sets of equations: one for updating the level, one for updating the trend, and one for updating the seasonality.**
* **To make forecasts, the method combines these components to project future values while considering the trend and seasonality. The final forecast is the sum of the level, trend, and seasonality components.**
* **There are different variations of the Holt-Winters method, including additive and multiplicative versions, depending on whether the seasonality is constant or proportional over time.**

## 20) What is the difference between additives and multiplicative seasonality in time series forecasting?

### A) Additive Seasonality

I**n additive seasonality, seasonal fluctuations are added to the trend and error components of the time series.**

**The forecasting model for additive seasonality is typically expressed as:**

**Forecast = Level + Trend + Seasonality + Error**

**Additive seasonality is appropriate when the seasonal fluctuations are relatively constant in magnitude over time.**

**Use additive seasonality when seasonal fluctuations have a consistent, fixed magnitude.**

**Example:If you're forecasting quarterly sales, and each quarter you expect to see a consistent increase or decrease in sales, regardless of the overall trend, additive seasonality may be a good fit.**

*Multiplicative Seasonality*

**In multiplicative seasonality, seasonal fluctuations are multiplied by the trend and error components of the time series.**

**The forecasting model for multiplicative seasonality is typically expressed as:**

**Forecast = Level \* Trend \* Seasonality \* Error**

**the seasonal component is multiplied with the level, trend, and error terms.**

**Multiplicative seasonality is appropriate when the magnitude of seasonal fluctuations is proportional to the level of the time series. This means that as the level of the series increases or decreases, the seasonal effect also scales accordingly.**

**Use multiplicative seasonality when the seasonal fluctuations are proportional to the level of the time series.**

**Example: If you're forecasting monthly electricity consumption, and the seasonal effect becomes more pronounced as overall consumption increases during hot summer months, multiplicative seasonality may be more suitable.**