Graduate Certificate in AI for Renewable Energy Forecasting

Time Series Analysis and Forecasting

Autoregressive (AR) model: A time series model that uses the past values of the series to predict future values. The AR model assumes that the current value of the series depends on a linear combination of its past p values and a white noise error term.

Autocorrelation: The correlation between a time series and a lagged version of itself. Autocorrelation measures the strength and direction of the linear relationship between the observations at different time lags.

Box-Cox transformation: A data transformation technique used to stabilize the variance and improve the normality of a time series. The Box-Cox transformation involves taking the power transformation of the series using a parameter lambda, which is estimated from the data.

C Cyclical component: A component of a time series that exhibits a regular pattern of ups and downs over time. Cyclical patterns have a duration of more than one year and less than the entire length of the series.

Cross-validation: A technique used to evaluate the performance of a time series model by dividing the data into training and validation sets. The model is trained on the training set and then tested on the validation set to assess its ability to generalize to new data.

Decomposition: The process of breaking down a time series into its underlying components, such as trend, seasonality, and cyclical patterns. Decomposition helps to identify the sources of variation in the series and to develop appropriate models for forecasting.

Dickey-Fuller test: A statistical test used to determine whether a time series is stationary or non-stationary. The test involves estimating a regression model with a lagged difference of the series as the dependent variable and testing the hypothesis that the coefficient of the lagged difference is equal to zero.

Exponential smoothing: A time series forecasting method that uses a weighted average of the past observations to predict future values. Exponential smoothing assigns higher weights to more recent observations and lower weights to older observations.

Forecast error: The difference between the actual value of a time series and the forecast value. Forecast errors can be used to evaluate the performance of a time series model and to improve its accuracy.

Holt-Winters method: A time series forecasting method that extends exponential smoothing to include trend and seasonality components. The Holt-Winters method uses three smoothing parameters to estimate the level, trend, and seasonal components of the series.

Integrated (I) model: A time series model that involves differencing the series to achieve stationarity. The I model is used when the series exhibits a stochastic trend or a unit root.

MA (Moving Average) model: A time series model that uses a weighted average of past error terms to predict future values. The MA model assumes that the current value of the series depends on a linear combination of past error terms and a white noise error term.

Moving average smoothing: A data smoothing technique that involves taking the average of a moving window of observations in a time series. Moving average smoothing helps to reduce the noise and variability in the series and to highlight the underlying patterns.

Multivariate time series: A time series that consists of multiple interdependent series. Multivariate time series analysis involves modeling the relationships between the series and using the information from all series to improve the accuracy of the forecasts.

Non-seasonal component: A component of a time series that does not exhibit a regular pattern of ups and downs over time. Non-seasonal components include trend, cyclical patterns, and irregular fluctuations.

Partial autocorrelation: The correlation between a time series and a lagged version of itself, after controlling for the effects of the intervening lags. Partial autocorrelation measures the direct relationship between the observations at different time lags.

Random walk model: A time series model that assumes that the future values of the series are equal to the current value plus a random error term. The random walk model is a special case of the ARIMA model with zero lagged differences and zero moving average terms.

Regression analysis: A statistical method used to model the relationship between a dependent variable and one or more independent variables. Regression analysis can be used to identify the factors that influence a time series and to develop predictive models.

Seasonal component: A component of a time series that exhibits a regular pattern of ups and downs over time, with a fixed frequency. Seasonal patterns have a duration of one year or less and are usually related to external factors such as weather, holidays, or business cycles.

Seasonal difference: The difference between a value in a time series and the corresponding value in the previous year. Seasonal differencing is used to remove seasonal patterns from a time series and to achieve stationarity.

Seasonal index: A measure of the strength and direction of the seasonal pattern in a time series. The seasonal index is calculated as the ratio of the seasonal mean to the overall mean, and it is usually expressed as a percentage.

Seasonal naive forecast: A forecasting method that uses the last observed value of a seasonal time series as the forecast for the next period. The seasonal naive forecast is a simple and intuitive method that is often used as a benchmark for more complex forecasting models.

Seasonality: A pattern of ups and downs in a time series that repeats at regular intervals over time. Seasonality is usually related to external factors such as weather, holidays, or business cycles.

SARIMA (Seasonal Autoregressive Integrated Moving Average) model: An extension of the ARIMA model that includes seasonal components. The SARIMA model involves differencing the series to achieve stationarity, modeling the autoregressive and moving average components, and incorporating the seasonal differences and seasonal moving average components.

Stationarity: A property of a time series that implies that the statistical properties of the series, such as the mean, variance, and autocorrelation, are constant over time. Stationary time series are easier to model and to forecast than non-stationary series.

Trend: A pattern of ups and downs in a time series that persists over time and does not repeat at regular intervals. Trends can be either deterministic or stochastic, and they can be modeled using various techniques such as linear regression or exponential smoothing.

Trend component: A component of a time series that exhibits a persistent pattern of ups and downs over time. The trend component reflects the underlying direction or tendency of the series and can be either deterministic or stochastic.

TS (Time Series) data: Data that are collected over time and that exhibit a pattern of variation. TS data can be univariate or multivariate, and they can be modeled using various techniques such as regression analysis, exponential smoothing, or ARIMA models.

Unit root: A characteristic of a time series that implies that the series is non-stationary and that its variance increases over time. A unit root can be detected using the Dickey-Fuller test and can be removed by differencing the series.

Variance: A measure of the dispersion or spread of a time series. The variance is the average of the squared differences between the observations and the mean of the series.

White noise: A random process that consists of uncorrelated and identically distributed error terms. White noise is used as a building block for time series models and as a benchmark for evaluating their performance.

Y Yellow phase: A term used in the context of renewable energy forecasting to denote the period of high solar irradiance and low wind speeds during the day. The yellow phase is a critical period for renewable energy systems, as it determines the peak production and the need for storage or backup capacity.