Assignment-based Subjective Questions

1. From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable?

There are set of variables whose values are in number format but they are categorical variables. After convert them into categorical form, we found below information.

- Bike sharing customers are more in heavy rain and summer season. It gets reduced in winter season and more reduced in spring.
- Bike sharing customers are more in year 2019 than 2018.
- there is not much effect on working day and non-working day. Also not much effect on holiday and non-holiday.

2. Why is it important to use drop_first=True during dummy variable creation?

drop_first=True is important to use, as it helps in reducing the extra column created during dummy variable creation. Hence it reduces the correlations created among dummy variables.

3. Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable?

- temp and atemp has higher co-relation with target variable.

4. How did you validate the assumptions of Linear Regression after building the model on the training set?

Linear Regression makes certain assumptions about the data and provides predictions based on that. Naturally, if we don’t take care of those assumptions Linear Regression will penalise us with a bad model.
We will take a dataset and try to fit all the assumptions and check the metrics and compare it with the metrics in the case that we hadn’t worked on the assumptions.

5. Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes?

1. Season -Weathersit – Windspeed Based on manual but this doesn’t look linear
2. Yr – spring – Nov Based on RFE

General Subjective Questions

1. Explain the linear regression algorithm in detail.

Linear regression is a type of machine-learning algorithm that learns from the labelled datasets and maps the data points to the most optimized linear functions. which can be used for prediction on new datasets.

It computes the linear relationship between a dependent variable and one or more independent features. When the number of the independent feature, is 1 then it is known as Univariate Linear regression, and in the case of more than one feature, it is known as multivariate linear regression.

There are two main types of Linear Regression.

1. **Simple Linear Regression**

   This is the simplest form of linear regression, and it involves only one independent variable and one dependent variable. The equation for simple linear regression is:

   $y = \beta_0 + \beta_1 X$

   where:

   - Y is the dependent variable
   - X is the independent variable
   - β0 is the intercept
   - β1 is the slope

2. Multiple Linear Regression

   This involves more than one independent variable and one dependent variable. The equation for multiple linear regression is:

   $y = \beta_0 + \beta_1 X + \beta_2 X + \ldots\ldots\ldots\beta_n X$

   where:

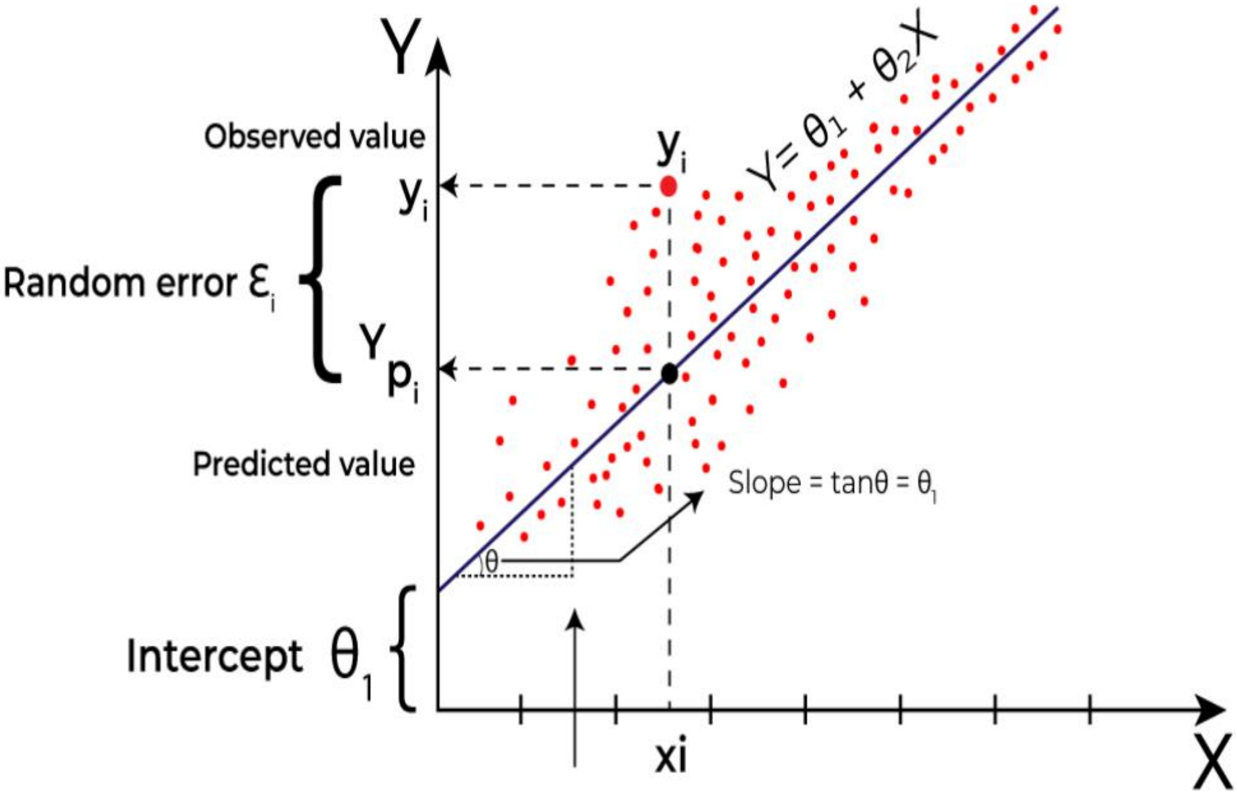
   - Y is the dependent variable
   - X1, X2, …, Xp are the independent variables
   - β0 is the intercept
   - β1, β2, …, βn are the slopes

The goal of the algorithm is to find the best Fit Line equation that can predict the values based on the independent variables.

In regression set of records are present with X and Y values and these values are used to learn a function so if you want to predict Y from an unknown X this learned function can be used. In regression we have to find the value of Y, So, a function is required that predicts continuous Y in the case of regression given X as independent features.

Our primary objective while using linear regression is to locate the best-fit line, which implies that the error between the predicted and actual values should be kept to a minimum. There will be the least error in the best-fit line.

The best Fit Line equation provides a straight line that represents the relationship between the dependent and independent variables. The slope of the line indicates how much the dependent variable changes for a unit change in the independent variable(s).

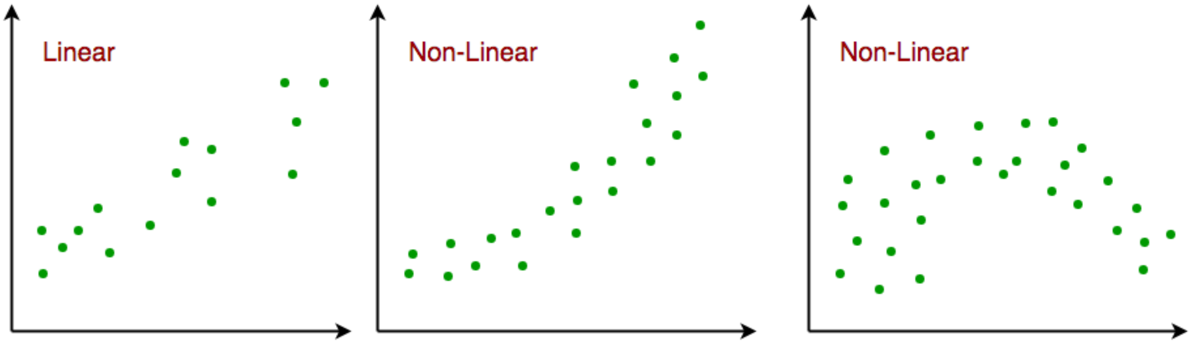


Here Y is called a dependent or target variable and X is called an independent variable also known as the predictor of Y. There are many types of functions or modules that can be used for regression. A linear function is the simplest type of function. Here, X may be a single feature or multiple features representing the problem.

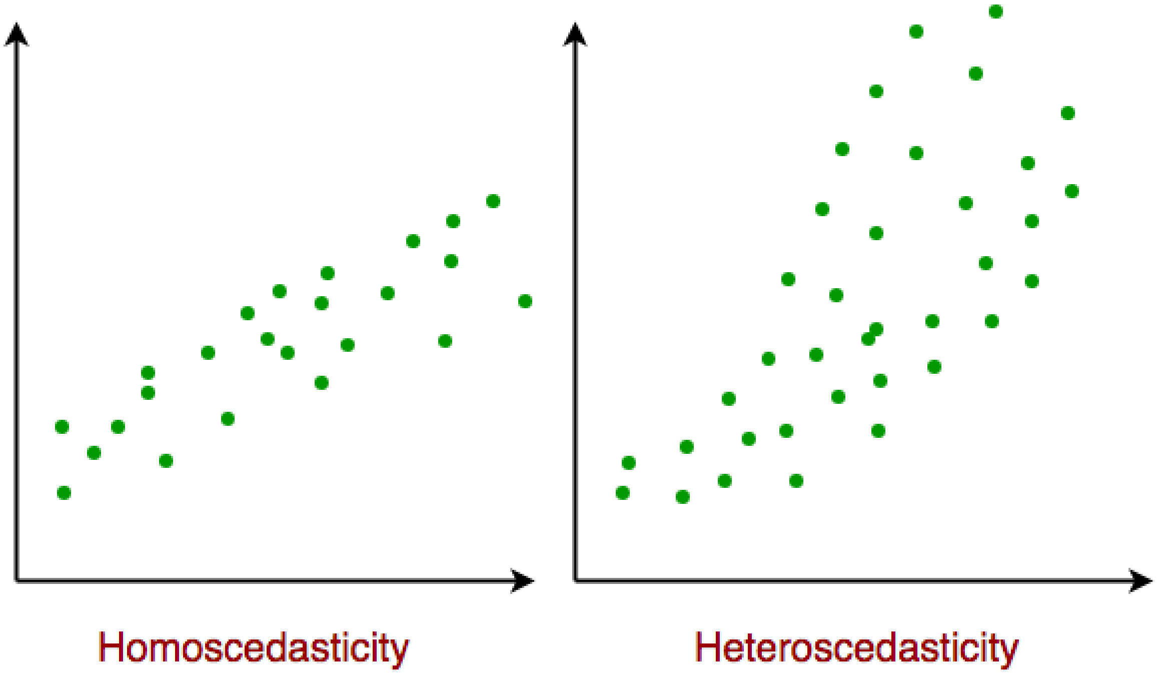
Assumptions of Simple Linear Regression

Linear regression is a powerful tool for understanding and predicting the behaviour of a variable, however, it needs to meet a few conditions in order to be accurate and dependable solutions.

1. **Linearity**: The independent and dependent variables have a linear relationship with one another. This implies that changes in the dependent variable follow those in the independent variable(s) in a linear fashion. This means that there should be a straight line that can be drawn through the data points. If the relationship is not linear, then linear regression will not be an accurate model.



2. **Independence**: The observations in the dataset are independent of each other. This means that the value of the dependent variable for one observation does not depend on the value of the dependent variable for another observation. If the observations are not independent, then linear regression will not be an accurate model.
3. **Homoscedasticity**: Across all levels of the independent variable(s), the variance of the errors is constant. This indicates that the amount of the independent variable(s) has no impact on the variance of the errors. If the variance of the residuals is not constant, then linear regression will not be an accurate model.



Homoscedasticity

Heteroscedasticity

4. **Normality**: The residuals should be normally distributed. This means that the residuals should follow a bell-shaped curve. If the residuals are not normally distributed, then linear regression will not be an accurate model.

<u>**Assumptions of Multiple Linear Regression**</u>

For Multiple Linear Regression, all four of the assumptions from Simple Linear Regression apply. In addition to this, below are few more:

1. **No multicollinearity**: There is no high correlation between the independent variables. This indicates that there is little or no correlation between the independent variables. Multicollinearity occurs when two or more independent variables are highly correlated with each other, which can make it difficult to determine the individual effect of each variable on the dependent variable. If there is multicollinearity, then multiple linear regression will not be an accurate model.
2. **Additivity:** The model assumes that the effect of changes in a predictor variable on the response variable is consistent regardless of the values of the other variables. This assumption implies that there is no interaction between variables in their effects on the dependent variable.
3. **Feature Selection:** In multiple linear regression, it is essential to carefully select the independent variables that will be included in the model. Including irrelevant or redundant variables may lead to overfitting and complicate the interpretation of the model.
4. **Overfitting:** Overfitting occurs when the model fits the training data too closely, capturing noise or random fluctuations that do not represent the true underlying relationship between variables. This can lead to poor generalization performance on new, unseen data.

Multicollinearity is a statistical phenomenon that occurs when two or more independent variables in a multiple regression model are highly correlated, making it difficult to assess the individual effects of each variable on the dependent variable.

- **Correlation Matrix:** Examining the correlation matrix among the independent variables is a common way to detect multicollinearity. High correlations (close to 1 or -1) indicate potential multicollinearity.
- **VIF (Variance Inflation Factor):** VIF is a measure that quantifies how much the variance of an estimated regression coefficient increases if your predictors are correlated. A high VIF (typically above 10) suggests multicollinearity.

2. Explain the Anscombe's quartet in detail.

Anscombe's quartet comprises a set of four datasets, having identical descriptive statistical properties in terms of means, variance, R-squared, correlations, and linear regression lines but having different representations when we scatter plots on a graph.

The datasets were created by the statistician Francis Anscombe in 1973 to demonstrate the importance of visualizing data and to show that summary statistics alone can be misleading.

The four datasets that make up Anscombe's quartet each include 11 x-y pairs of data. When plotted, each dataset seems to have a unique connection between x and y, with unique variability patterns and distinctive correlation strengths. Despite these variations, each dataset has the same summary statistics, such as the same x and y mean and variance, x and y correlation coefficient, and linear regression line.

Anscombe's quartet is used to illustrate the importance of exploratory data analysis and the drawbacks of depending only on summary statistics. It also emphasizes the importance of using data visualization to spot trends, outliers, and other crucial details that might not be obvious from summary statistics alone.

3. What is Pearson's R?

Correlation coefficients are used to measure how strong a relationship is between two variables There are several types of correlation coefficient, but the most popular is PEARSON'S correlation. **Pearson's correlation** (also called Pearson's *R*) is a **correlation coefficient** commonly used in linear regression. The full name is the **Pearson Product Moment Correlation (PPMC)**. It shows the linear relationship between two sets of data.

Potential problems with Pearson correlation.

The PPMC is not able to tell the difference between dependent variables and independent variables. For example, if you are trying to find the correlation between a high calorie diet and diabetes, you might find a high correlation of .8. However, you could also get the same result with the variables switched around. In other words, you could say that diabetes causes a high calorie diet. That obviously makes no sense. Therefore, as a researcher you have to be aware of the data you are plugging in. In addition, the PPMC will not give you any information about the slope of the line; it only tells you whether there is a relationship.

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling?

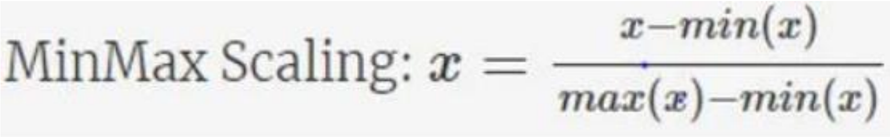
Scaling is a step of data Pre-Processing which is applied to independent variables to normalize the data within a particular range. It also helps in speeding up the calculations in an algorithm.

Most of the times, collected data set contains features highly varying in magnitudes, units and range. If scaling is not done then algorithm only takes magnitude in account and not units hence incorrect modelling. To solve this issue, we have to do scaling to bring all the variables to the same level of magnitude.

scaling just affects the coefficients and none of the other parameters like **t-statistic, F-statistic, p-values, R-squared**, etc.

Normalization/Min-Max Scaling:

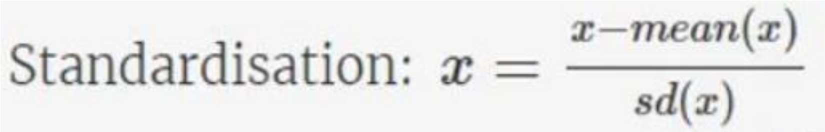
It brings all of the data in the range of 0 and 1. **sklearn.preprocessing.MinMaxScaler** helps to implement normalization in python.



$$\text{MinMax Scaling: } x = \frac{x - min(x)}{max(x) - min(x)}$$

Standardization Scaling:

Standardization replaces the values by their Z scores. It brings all of the data into a standard normal distribution which has mean (**μ**) zero and standard deviation one (**σ**).



$$\text{Standardisation: } x = \frac{x - mean(x)}{sd(x)}$$

- **sklearn.preprocessing.scale** helps to implement standardization in python.
- One disadvantage of normalization over standardization is that it **loses** some information in the data, especially about **outliers**.

5. You might have observed that sometimes the value of VIF is infinite. Why does this happen?

An infinite value of VIF for a given independent variable indicates that it can be perfectly predicted by other variables in the model.

$$VIF_1 = \frac{1}{1 - R^2}$$

Infinite VIF happens when the value of R is either +1 or -1.

In our bike sharing assignment, you can see temp and atemp having corelation 1. Both are perfectly predicted by other variables in the model and VIF comes to be infinite.

6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression.

Q Q Plots (Quantile-Quantile plots) are plots of two quantilesagainst each other. A quantile is a fraction where certain values fall below that quantile. For example, the median is a quantile where 50% of the data fall below that point and 50% lie above it. The purpose of Q Q plots is to find out if two sets of data come from the same distribution. A 45 degree angle is plotted on the Q Q plot; if the two data sets come from a common distribution, the points will fall on that reference line.

This helps in a scenario of linear regression when we have training and test data set received separately and then we can confirm using Q-Q plot that both the data sets are from populations with same distributions.