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?

- From the data set given, analysing the **Month** Variable, it is observed that the most of the bike booking were happening in the months 5 to 9 months with a median above 4000 booking per month. This indicates, month has some trend for bookings and can be a good predictor for the dependent variable.
- Analysing the **weathersit** with target variable, most of the bike booking were happening during weathersit = Clear with a median close to 5000 booking. This was followed by other weather situations. This indicates, weather situation also can be a good predictor for the dependent variable.
- Analysing the **workingday** variable, most of the bike booking were happening in 'workingday' with a median close to 5000.This indicates, working day can be a good predictor for the dependent variable
- Analysing the **season** variable, most of the bike booking were happening in season3 with a median of above 5000 booking. Season summer and season winter with good number of bookings. This indicates, season can be a good predictor for the dependent variable.

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

If we did **not use drop_first=True** while creating dummy variables it will create dummy variables for all the categories in the column. For ex: take Weekday, in our data set week day has 0 to 6 values correspondingly

0: 'sunday', 1: 'monday', 2: 'tuesday', 3: 'wednesday', 4: 'thursday', 5: 'friday', 6: 'saturday'

Now if we don't use drop_first = True, it will create all the 7 columns in the data set for week day.

If we use **drop_first = True**, we can get only 6 columns except **WeekDay_Sunday**, as we don't need this in data set, if it is not there also we can analyse it by looking all the other columns i.e, if all the columns has a zero value then obviously it is Sunday.

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

Temp (temperature)

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

I have validated the assumption of Linear Regression after the building the model on the training set through residual analysis

- Verifying the Linear relationship between x and y can be done with pair plot. It is easy verify the Linearity on the plot.
- Multicollinearity: This can be verified using the VIF values, as a rule of thumb, VIFs values above 5 are generally indicators of multicollinearity
- Error Terms are normally distributed: using QQ Plot or dist plots, if the QQ plot shows a straight line then it is normally distributed.

- Homoscedasticity: residual plot, verify that the variance of the error terms is constant across the values of the dependent variable.

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

- **Temperature (temp)** has a coefficient value of 0.5499 - indicated that a unit increase in temp variable increases the bike hire numbers by 0.5499 units.
- **Season Winter** has a coefficient value of 0.1318 indicated that, a unit increase in winter season variable increases the bike hire numbers by 0.1318 units.
- **Year (yr)** has coefficient value of 0.2331 indicated that a unit increase in yr variable increases the bike hire numbers by 0.2331 units

General Subjective Questions:

1. Explain the linear regression algorithm in detail.

Linear regression is finding the best linear relationship between the independent and dependent variables. It is mostly done by the Sum of Squared Residuals Method.

Linear regression is one of the very basic forms of machine learning algorithms where we can train a model to predict the behaviour of the data based on some variables.

In Linear Regression, whenever X is increasing Y is also increasing or vice versa that means they have a correlation or there will be a linear downward relationship.

One example for that could be that the police department is running a campaign to reduce the number of robberies, in this case, the graph will be linearly downward.

Linear regression is used to predict a quantitative response Y from the predictor variable X.

Mathematically, we can write a linear regression equation be like below:

$$Y = mx + c$$

Where m and c given by the formulas:

m is slope of the line,

c is the y intercept of the line

Assumption of Linear Regression is:

- There **is a linear Relationship between dependant and independent** variables
- Error values (ε) are normally distributed for any given value of X that **means Error terms are normally distributed around zero.**
- Constant variance assumption: It is assumed that the residual terms have the variance, σ2, this assumption is also known as the assumption of homogeneity or **homoscedasticity.**
- **Independent error assumption**: residual terms are independent of each other, i.e. their pair-wise covariance is zero.
- The independent variables are linearly independent of each other, i.e**. there is no multicollinearity in the data.**

Use Cases of Linear Regression:

- Prediction of trends and Sales targets: To predict how industry is performing or how many sales targets industry may achieve in the future.
- Price Prediction: LR is used in price prediction – we can predict the change in price of product.
- Risk Management: LR is used in Risk Management in the financial and insurance sector.

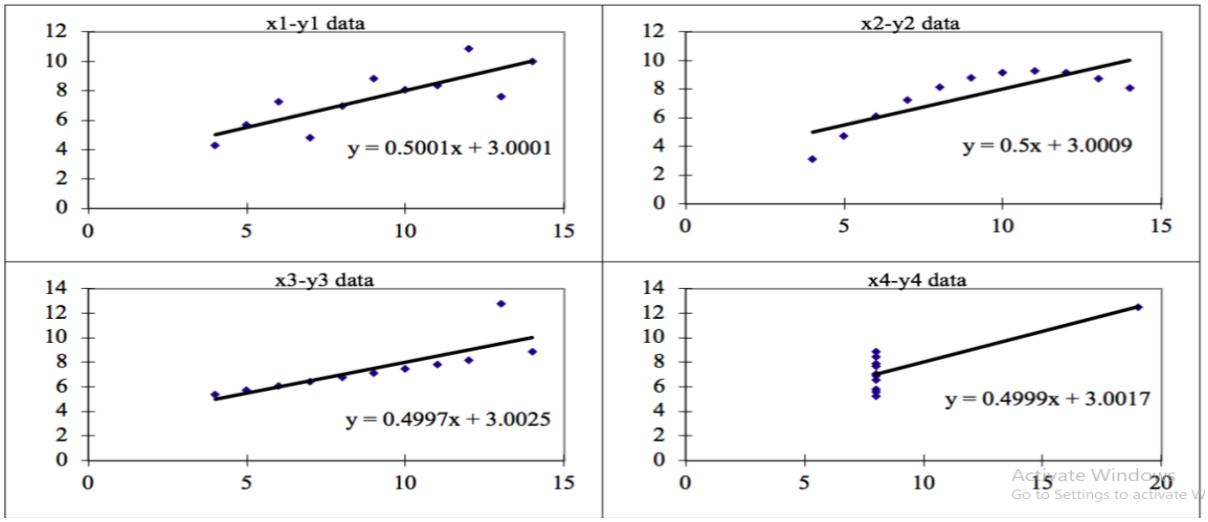
2. Explain the Anscombe's quartet in detail?

Ancombe's Quartet tells us the importance of data visualization before applying any algorithm to the data set.

This can be defined by four data sets having 11 data points each, which are nearly identical. Even though these data points looks identical but it appear differently when plot scatter plots. The Four Datasets looks like:

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

You can see the plots below.



When we observe the four data set scatter plots,

Data set 1 – fits **Data set 1** the Linear Regression model pretty well, **Data Set 2** – could not fits the LR model as the data is non Linear. **Data set 3 and 4** have outliers involved in the data set which cannot be handled by Linear Regression Model

These datasets are created intentionally to describe the importance of data visualisation and how any regression algorithm can be fooled by the same. Hence, all the important features in the dataset must be visualised before implementing any machine learning algorithm on them which will help to make a good fit model.

3. What is Pearson's R?

Pearson correlation coefficient will calculates the strength of a linear association between two variables that means change in the one variable where the other variable changes and this is denoted by r.

What does the Pearson correlation coefficient test do?

It seeks to draw a line through the data of two variables to show their relationship. The relationship can be measured with the calculator of Pearson correlation coefficient. This linear relationship can either be positive or negative

For example:

- **Positive linear relationship: T**he income of a person increases as his/her experience increases.
- **Negative linear relationship:** If the vehicle speed is increases, then time taken to travel decreases, and vice versa.

Pearson correlation coefficient formula:

$$r = \frac{N\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{[N\Sigma x^2 - (\Sigma x)^2][N\Sigma y^2 - (\Sigma y)^2]}}$$

Where:

- N = the number of pairs of scores
- Σxy = the sum of the products of paired scores
- Σx = the sum of x scores
- Σy = the sum of y scores
- Σx2 = the sum of squared x scores
- Σy2 = the sum of squared y scores

It is the covariance of two variables, divided by the product of their standard deviations and the result always **has a value between −1 and 1**. This measure can only reflect a linear correlation of variables, and ignores many other types of relationship or correlation.

Correlation coefficient formulas are used to find how strong a relationship is between data. The formulas return a value between -1 and 1, where:

- 1 indicates a strong positive relationship.
- -1 indicates a strong negative relationship.
- A result of zero indicates no relationship at all.

Pearson's correlation coefficient formula, when applied to a population is:

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} \quad \text{(Eq.1)}$$

cov is the covariance , σ_X Is the standard deviation of X and

σ_Y is the standard deviation of Y

The formula for p can be expressed in terms of mean and expectation.

$$\operatorname{cov}(X,Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$$

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

Scaling:
Scaling is the pre-processing applied to independent variables to normalize the data with in a particular range and also helps in speeding up the calculations.

For Ex: one feature is in KG's and the other is in grams, the other one is in litres etc. Here scaling is performed to normalize the all the units.

Why is scaling performed?

Often, the data set contains most varying units, magnitudes and range. If we have such data and if we not done scaling then it will only takes the magnitude in account and not units hence the incorrect model will build. To resolve this we will use scaling to bring all the variables to the same level of magnitude and units.

Scaling only effects the coefficients but not the other parameters.

Normalization/Min-Max Scaling:
It is a technique that the values are shifted or rescaled and is ranging between 0 and 1 known as min – max scaling. That means it brings all the data within 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:
It is another technique in which the values are centered around the mean with a unit standard deviation. This means that the mean of the attribute becomes zero and the resultant distribution has a unit standard deviation.
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.

Disadvantage of Min-max scaling over standardization: Normalization lose the information of outliers.

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

- VIF = infinity is indicates that there is perfect correlation between the two independent variables.
- If such cases are arrived, we get R2 = 1, which leads to 1/(1-R2) = 1/0 = infinity.

- To solve this problem we need to drop one of the variable which causes the perfect correlation i.e. multicollinearity
- This infinite value of VIF indicates that the corresponding varibale can be expressed by Linear Combination of the other variables.

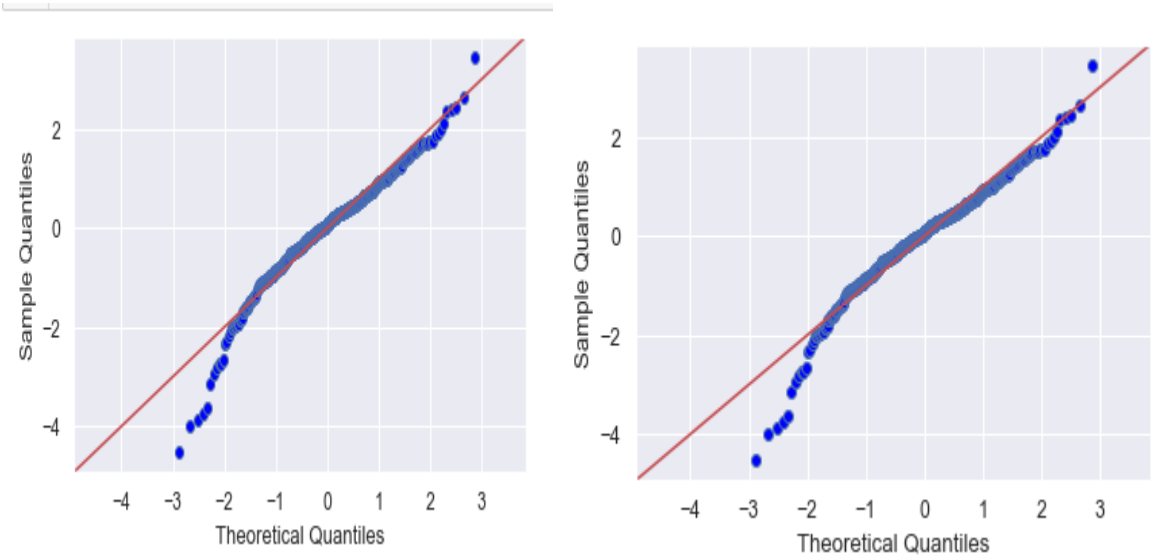
6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression?

Q Q Plots (Quantile-Quantile plots) are the plots of two quantiles against each other.

A quantile is a fraction where certain values fall below that quantile
For ex: 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 a scenario of linear regression we can analyse that error terms are normally distributed
IQQ plots are used to check the following scenarios:

- If two data sets, come from populations with a common distribution
- If two data sets have common location and scale
- If two data sets have similar distributional shapes
- If two data sets have similar tail behaviour

QQ plot looks like:



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