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 Categorical variables analysis it is observed that for the seasons summer and fall and the months starting from March to September when the weather is clear the demand will increase.

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

   This will be done because that column can be represented as the combination of the other columns also if we keep all the columns it will introduce multicolinearity in the data. So to avoid this we will drop one of the columns of the dummy variable.
   Eg: Suppose Gender column has Male, Female as values then after creating dummies suppose if we remove Male dummy column then it can be represented as Female Dummy column where the Value of the column is Zero. If value is one then it will represent the actual Female data.

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

   temp (Temperature) and atemp(feeling temperature) both parameters is having highest correlation with target variable.

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

   1. Linear relationship is validated using partial residual plot represents the relationship between the predictor and the dependent variable while taking into account all the other variables.
   2. Multicollinearity check is done using heat map and vif values.
   3. No auto-correlation or independence is validated by Durbin-Watson (DW) statistic test

4. Homoscedasticity is validated by creating a scatter plot that shows residual vs fitted value. If the data points are spread across equally without a prominent pattern, it means the residuals have constant variance (homoscedasticity). Otherwise, if a funnel-shaped pattern is seen, it means the residuals are not distributed equally and depicts a non-constant variance (heteroscedasticity).
5. Normal distribution of error terms is validated using a Q-Q (Quantile-Quantile) plot. If the data points on the graph form a straight diagonal line, the assumption is met.

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

   Temp, summer and clear weather.

General Subjective Questions

1. Explain the linear regression algorithm in detail.

   Linear Regression is a machine learning algorithm based on **supervised learning**. It performs a **regression task**. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting.
   Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.

   Linear regression can be further divided into two types of the algorithm:
   Simple Linear Regression:
   If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.
   Multiple Linear regression:
   If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear Regression.

2. Explain the Anscombe's quartet in detail.

   Anscombe's Quartet can be defined as a group of four data sets which are **nearly identical in simple descriptive statistics**, but there are some peculiarities in the dataset that **fools the regression model** if built. They have very different distributions and **appear differently** when plotted on scatter plots.

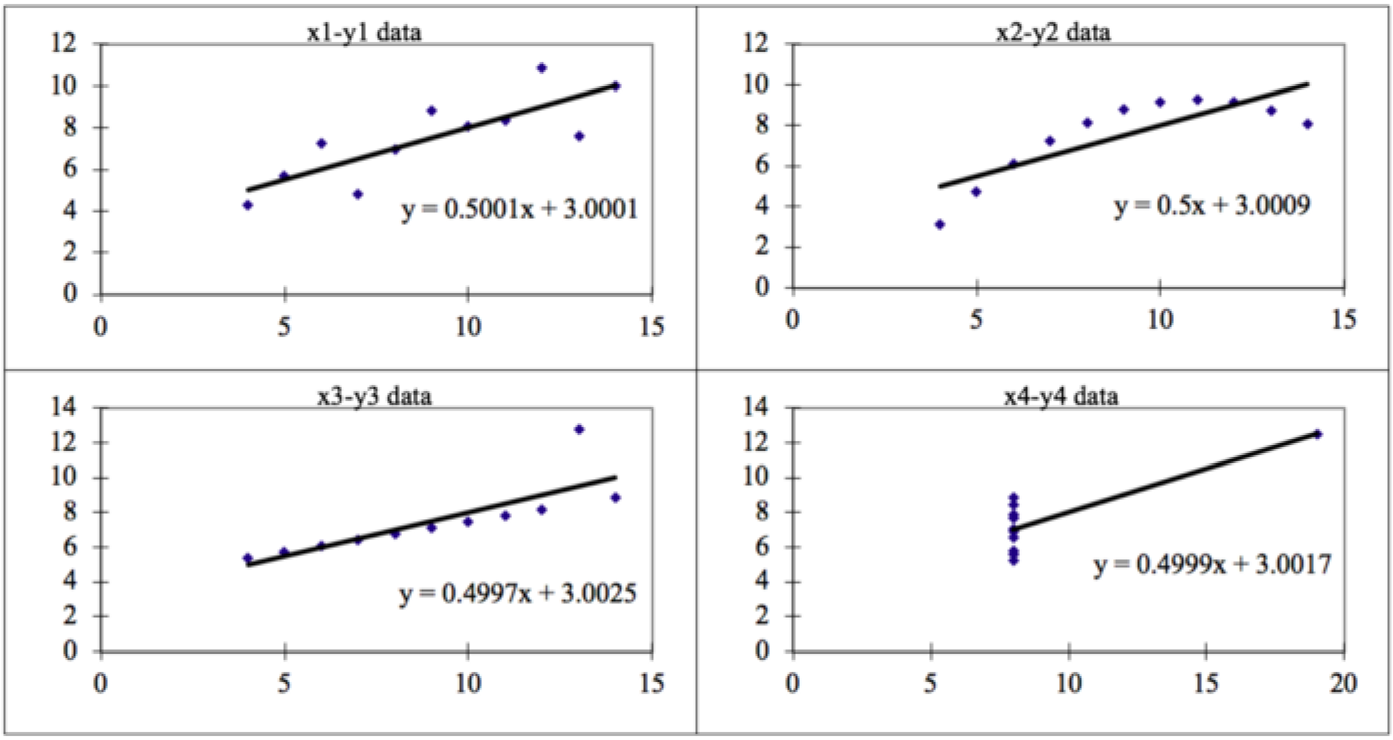
   It was constructed in 1973 by statistician Francis Anscombe to illustrate the importance of plotting the graphs before analyzing and model building, and the effect of other observations on statistical properties.
   This tells us about the importance of visualizing the data before applying various algorithms out there to build models out of them which suggests that the data features must be plotted in order to see the distribution of the samples that can help you identify the various anomalies present in the data like outliers, diversity of the data, linear separability of the data, etc. Also, the Linear Regression can be only be considered a fit for the **data with linear relationships** and is incapable of handling any other kind of datasets.
   These four plots can be defined as follows:

Anscombe's Data											
Observation	x1	y1		x2	y2		x3	y3		x4	y4
1	10	8.04		10	9.14		10	7.46		8	6.58
2	8	6.95		8	8.14		8	6.77		8	5.76
3	13	7.58		13	8.74		13	12.74		8	7.71
4	9	8.81		9	8.77		9	7.11		8	8.84
5	11	8.33		11	9.26		11	7.81		8	8.47
6	14	9.96		14	8.1		14	8.84		8	7.04
7	6	7.24		6	6.13		6	6.08		8	5.25
8	4	4.26		4	3.1		4	5.39		19	12.5
9	12	10.84		12	9.13		12	8.15		8	5.56
10	7	4.82		7	7.26		7	6.42		8	7.91
11	5	5.68		5	4.74		5	5.73		8	6.89

The statistical information for all these four datasets is approximately similar and can be computed as follows:

Anscombe's Data											
Observation	x1	y1		x2	y2		x3	y3		x4	y4
1	10	8.04		10	9.14		10	7.46		8	6.58
2	8	6.95		8	8.14		8	6.77		8	5.76
3	13	7.58		13	8.74		13	12.74		8	7.71
4	9	8.81		9	8.77		9	7.11		8	8.84
5	11	8.33		11	9.26		11	7.81		8	8.47
6	14	9.96		14	8.1		14	8.84		8	7.04
7	6	7.24		6	6.13		6	6.08		8	5.25
8	4	4.26		4	3.1		4	5.39		19	12.5
9	12	10.84		12	9.13		12	8.15		8	5.56
10	7	4.82		7	7.26		7	6.42		8	7.91
11	5	5.68		5	4.74		5	5.73		8	6.89
					Summary Statistics						
N	11	11		11	11		11	11		11	11
mean	9.00	7.50		9.00	7.500909		9.00	7.50		9.00	7.50
SD	3.16	1.94		3.16	1.94		3.16	1.94		3.16	1.94
r	0.82			0.82			0.82			0.82	

When these models are plotted on a scatter plot, all datasets generates a different kind of plot that is not interpretable by any regression algorithm which is fooled by these peculiarities and can be seen as follows:



The four datasets can be described as:

Dataset 1: this **fits** the linear regression model pretty well.

Dataset 2: this **could not fit** linear regression model on the data quite well as the data is non-linear.

Dataset 3: shows the **outliers** involved in the dataset which **cannot be handled** by linear regression model

Dataset 4: shows the **outliers** involved in the dataset which **cannot be handled** by linear regression model

Conclusion:

We have described the four datasets that were intentionally created to describe the importance of data visualization and how any regression algorithm can be fooled by the same. Hence, all the important features in the dataset must be visualized 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 or Pearson's correlation coefficient or Pearson's r is defined in statistics as the measurement of the strength of the relationship between two variables and their association with each other.
   The Pearson's correlation coefficient varies between -1 and +1 where:
   r = 1 means the data is perfectly linear with a positive slope (i.e., both variables tend to change in the same direction)
   r = -1 means the data is perfectly linear with a negative slope (i.e., both variables tend to change in different directions)
   r = 0 means there is no linear association

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 modeling. To solve this issue, we have to do scaling to bring all the variables to the same level of magnitude.

   The below table describes the difference between Normalization and Standardization.

Normalization	**Standardization**
Minimum and maximum value of features are used for scaling	Mean and standard deviation is used for scaling.
It is used when features are of different scales.	It is used when we want to ensure zero mean and unit standard deviation.
Scales values between [0, 1] or [-1, 1].	It is not bounded to a certain range.
It is really affected by outliers.	It is much less affected by outliers.
Scikit-Learn provides a transformer called MinMaxScaler for Normalization.	Scikit-Learn provides a transformer called StandardScaler for standardization.

Normalization	Standardization
This transformation squishes the n-dimensional data into an n-dimensional unit hypercube.	It translates the data to the mean vector of original data to the origin and squishes or expands.
It is useful when we don't know about the distribution	It is useful when the feature distribution is Normal or Gaussian.
It is a often called as Scaling Normalization	It is a often called as Z-Score Normalization.

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

   If there is perfect correlation, then VIF = infinity. This shows a perfect correlation between two independent variables. In the case of perfect correlation, we get R2 =1, which lead to 1/(1-R2) infinity. To solve this problem we need to drop one of the variables from the dataset which is causing this perfect multicolinearity.
   An infinite VIF value indicates that the corresponding variable may be expressed exactly by a linear combination of other variables (which show an infinite VIF as well).

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

   Quantile-Quantile (Q-Q) plot, is a graphical tool to help us assess if a set of data possibly came from some theoretical distribution such as a Normal, exponential or Uniform distribution. Also, it helps to determine if two data sets come from populations with a common distribution.
   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.
   Few advantages:
   a) It can be used with sample sizes also
   b) Many distributional aspects like shifts in location, shifts in scale, changes in symmetry, and the presence of outliers can all be detected from this plot.
   It is used to check following scenarios:
   If two data sets —
   i. come from populations with a common distribution
   ii. have common location and scale
   iii. have similar distributional shapes
   iv. have similar tail behavior

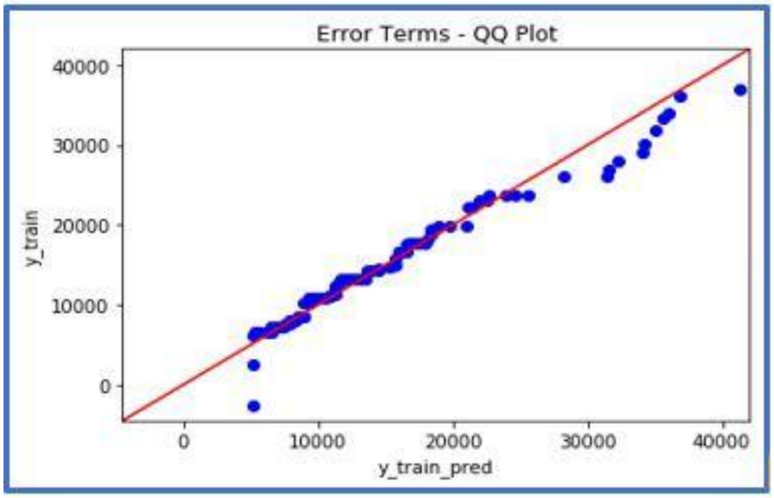
Interpretation:

A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second data set.

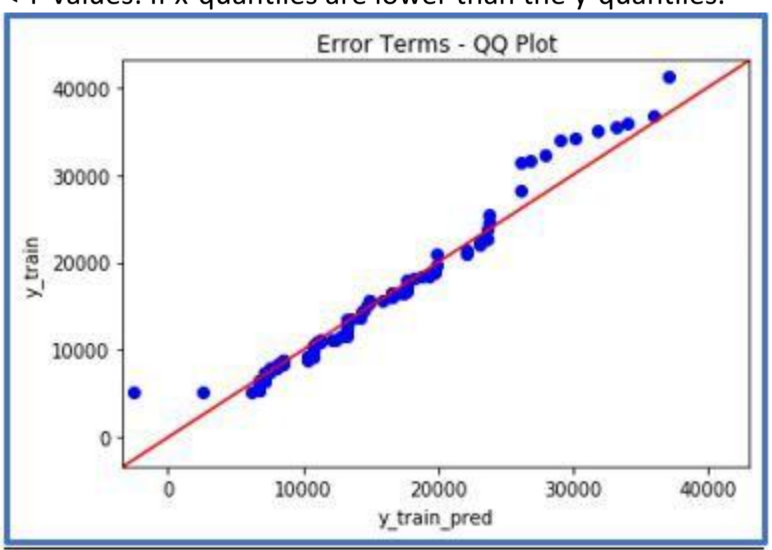
Below are the possible interpretations for two data sets.

a) Similar distribution: If all point of quantiles lies on or close to straight line at an angle of 45 degree from x -axis

b) Y-values < X-values: If y-quantiles are lower than the x-quantiles.



c) X-values < Y-values: If x-quantiles are lower than the y-quantiles.



d) Different distribution: If all point of quantiles lies away from the straight line at an angle of 45 degree from x -axis