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?

   Please find the below analysis on analysis of the categorical variables from the dataset using box plots:

   - June, July, Aug, Sep and Oct had high demands for the bike
   - Holiday had less demand in average, maybe because less people going out
   - 2019 had a significant demand compared to 2018
   - Summer and Fall had more demand then Spring and Winter

2. Why is it important to use **drop_first=True** during dummy variable creation?
   - It helps in reducing extra variable creation during dummy variables creation
   - It helps in reducing correlations among dummy variables

3. Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable?
   - We can see temp and atemp having the highest correlation with the target variable

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

   Below points were taken care for Linear Regression:

   - Checking p-value for each feature which should be less than 0.05
   - Checking VIF value for each feature should be definitely less than 10 but between 5 and 10 also be checked (Valid VIFs are generally less than 5)
   - Error rates should be normally distributed

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

   Top 3 features contributing are:

   - temp
   - winter
   - light snow rain

General Subjective Questions

1. Explain the linear regression algorithm in detail.

   Linear regression is a type of supervised machine learning algorithm that 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.

   Assumption for Linear Regression Model

   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.

   Linearity: The independent and dependent variables have a linear relationship with one another.

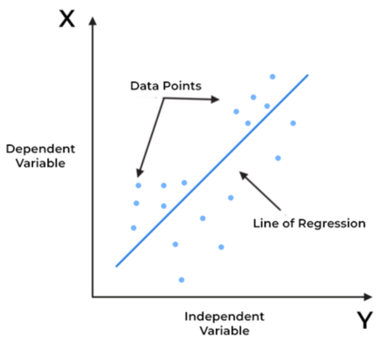
   Independence: The observations in the dataset are independent of each other.

   Homoscedasticity: Across all levels of the independent variable(s), the variance of the errors is constant.

   Normality: The residuals should be normally distributed.

   No multicollinearity: There is no high correlation between the independent variables.

   A sloped straight line represents the linear regression model with equation y = mx + c.



Best Fit Line for a Linear Regression Model

   In the above figure,

   X-axis = Independent variable

   Y-axis = Output / dependent variable

   Line of regression = Best fit line for a model

Here, a line is plotted for the given data points that suitably fit all the issues. Hence, it is called the 'best fit line.' The goal of the linear regression algorithm is to find this best fit line seen in the above figure.

There are two main types of linear regression:

Simple Linear Regression: This is the simplest form of linear regression, and it involves only one independent variable and one dependent variable

Multiple Linear Regression: This involves more than one independent variable and one dependent variable.

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.

2. Explain the Anscombe's quartet in detail.

Anscombe's quartet is a group of four data sets that are nearly identical in simple descriptive statistics, but there are peculiarities that fool the regression model once you plot each data set. As you can see, the data sets have very different distributions so they look completely different from one another when you visualize the data on scatter plots.

Purpose of Anscombe's quartet:

Anscombe's quartet tells us about the importance of visualizing data before applying various algorithms to build models. This suggests the data features must be plotted to see the distribution of the samples that can help you identify the various anomalies present in the data (outliers, diversity of the data, linear separability of the data, etc.). Moreover, the linear regression can only be considered a fit for the data with linear relationships and is incapable of handling any other kind of data set.

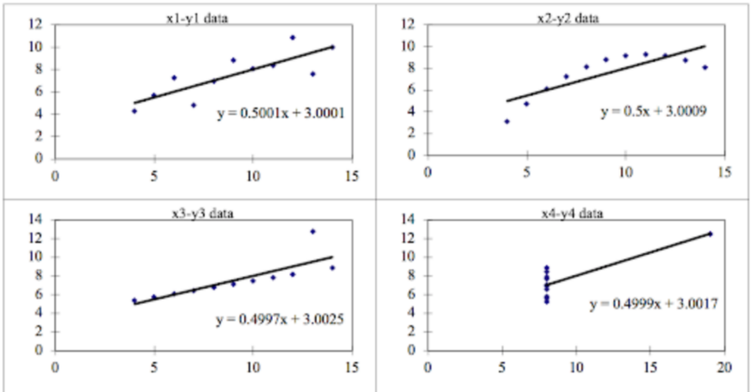
We can define these four plots as follows:

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 these four data sets are approximately similar. We can compute them 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	

However, when these models are plotted on a scatter plot, each data set generates a different kind of plot that isn't interpretable by any regression algorithm, as you can see below:



We can describe the four data sets as:

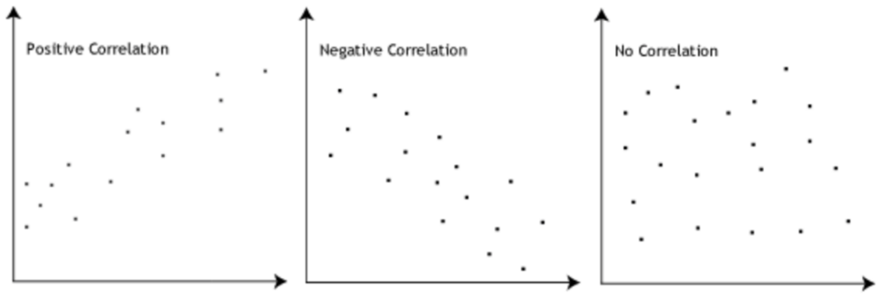
- Dataset 1 – Fits the linear regression model pretty well
- Dataset 2 – Cannot fit the linear regression model because the data is non-linear
- Dataset 3 – Shows the outliers involved in the dataset which cannot be handled by the linear regression model
- Dataset 4 - Shows the outliers involved in the dataset which also cannot be handled by the linear regression model

As you can see, Anscombe's quartet helps us to understand the importance of data visualization and how easy it is to fool a regression algorithm. So, before attempting to interpret and model the data or implement any machine learning algorithm, we first need to visualize the data set in order to help build a well-fit model.

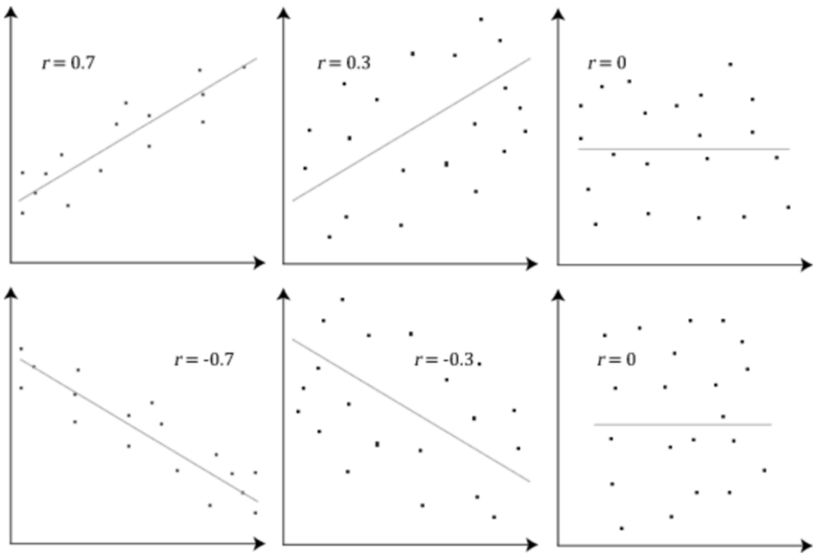
3. What is Pearson's R?

The Pearson product-moment correlation coefficient (or Pearson correlation coefficient, for short) is a measure of the strength of a linear association between two variables and is denoted by *r*. Basically, a Pearson product-moment correlation attempts to draw a line of best fit through the data of two variables, and the Pearson correlation coefficient, *r*, indicates how far away all these data points are to this line of best fit (i.e., how well the data points fit this new model/line of best fit).

The Pearson correlation coefficient, *r*, can take a range of values from +1 to -1. A value of 0 indicates that there is no association between the two variables. A value greater than 0 indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 indicates a negative association; that is, as the value of one variable increases, the value of the other variable decreases. This is shown in the diagram below:



The stronger the association of the two variables, the closer the Pearson correlation coefficient, *r*, will be to either +1 or -1 depending on whether the relationship is positive or negative, respectively. Achieving a value of +1 or -1 means that all your data points are included on the line of best fit – there are no data points that show any variation away from this line. Values for *r* between +1 and -1 (for example, *r* = 0.8 or -0.4) indicate that there is variation around the line of best fit. The closer the value of *r* to 0 the greater the variation around the line of best fit. Different relationships and their correlation coefficients are shown in the diagram below:



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

   Feature scaling is a method used to normalize the range of independent variables or features of data. In data processing, it is also known as data normalization and is generally performed during the data pre-processing step.

   Example — if you have multiple independent variables like age, salary, and height; With their range as (18–100 Years), (25,000–75,000 Euros), and (1–2 Meters) respectively, feature scaling would help them all to be in the same range, for example- centered around 0 or in the range (0,1) depending on the scaling technique.

Hence, **Scaling the data can help to balance the impact of all variables on the distance calculation and can help to improve the performance of the algorithm**. In particular, several ML techniques, such as neural networks, require that the input data to be normalized for it to work well.

Normalized scaling and Standardized scaling are the 2 types of scaling techniques.

Normalized Scaling	Standardized Scaling
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.
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.

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

   A variance inflation factor (VIF) is a measure of the amount of multicollinearity in regression analysis. Multicollinearity exists when there is a correlation between multiple independent variables in a multiple regression model. This can adversely affect the regression results. Thus, the variance inflation factor can estimate how much the variance of a regression coefficient is inflated due to multicollinearity.

   VIF is infinite means there is perfect correlation. A large value of VIF indicates that there is a correlation between the variables. If the VIF is 4, this means that the variance of the model coefficient is inflated by a factor of 4 due to the presence of multicollinearity. This would mean that that standard error of this coefficient is inflated by a factor of 2 (square root of variance is the standard deviation).

   Also, it shows 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 multicollinearity.

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

   The quantile-quantile plot is a graphical method for determining whether two samples of data came from the same population or not. A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second data set. By a quantile, we mean the fraction (or percent) of points below the given value.

Use of Q-Q plot:
A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second dataset. By a quantile, we mean the fraction (or percent) of points below the given value. That is, the 0.3 (or 30%) quantile is the point at which 30% percent of the data fall below and 70% fall above that value. A 45-degree reference line is also plotted. If the two sets come from a population with the same distribution, the points should fall approximately along this reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two data sets have come from populations with different distributions.

Importance of Q-Q plot:
When there are two data samples, it is often desirable to know if the assumption of a common distribution is justified. If so, then location and scale estimators can pool both data sets to obtain estimates of the common location and scale. If two samples do differ, it is also useful to gain some understanding of the differences. The q-q plot can provide more insight into the nature of the difference than analytical methods such as the chi-square and Kolmogorov-Smirnov 2-sample tests.