

## Assignment-based Subjective Questions

**Question 1.** From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable? (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** <Your answer for Question 1 goes below this line> (Do not edit)

1. Bookings are steadily increasing from January to September, while bookings for November and December show a decreasing trend.
2. The fall season has more bookings compared to other seasons.
3. 2019 had more bookings than 2018, indicating that the business is increasing over the years, which is a good sign.
4. There is no clear indication from the holiday feature, whether it's a holiday or not, bookings remain the same
5. When the weather is clear, there are more bookings compared to when the weather is bad.
6. Bookings are steadily increasing from January to September for November and December bookings are in decreasing trend

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**Question 2.** Why is it important to use **drop\_first=True** during dummy variable creation? (Do not edit)

**Total Marks:** 2 marks (Do not edit)

**Answer:** <Your answer for Question 2 goes below this line> (Do not edit)

Dummy variables are used to represent **categorical** data in a format that can be understood by statistical models

Both statistical and machine learning models required numerical data. So we need to convert categorical data to numerical data.

**For ex:**

Let's say we have a feature called color: which has a 3 unique values, blue , red, orange. If we convert the color to number like {"blue":1, "red":2, "orange":3} we are adding implicit order like orange > red > blue but in real world scenarios which is not

Dummy variables will help in this kind of situation, like

Blue. Orange. Red

1	0	0
0	1	0
0	0	0

**Using** drop\_first we can avoid creating one more extra variable using k-1 variables we can represent k categorical features

In the above example If color is not blue and orange it is definitely Red

Blue Orange

1	0
0	1
0	0

Last row represents the red color.

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**Question 3.** Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable? (Do not edit)

**Total Marks:** 1 mark (Do not edit)

**Answer:** <Your answer for Question 3 goes below this line> (Do not edit)

temp has the highest correlation with the target 'cnt' variable.

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**Question 4.** How did you validate the assumptions of Linear Regression after building the model on the training set? (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** <Your answer for Question 4 goes below this line> (Do not edit)

- Normality of Error terms: The residual errors (difference between the actual and predicted) should be normally distributed
  - We need to check multicollinearity between the features, there should be minimal VIF (variance inflation factor) between the features.
  - Homoscedasticity: There should not be any homoscedasticity in residual values.
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**Question 5.** Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes? (Do not edit)

**Total Marks:** 2 marks (Do not edit)

**Answer:** <Your answer for Question 5 goes below this line> (Do not edit)

Top 3 features contributing significantly are:

1. Temp
  2. Winter season
  3. Year
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## General Subjective Questions

**Question 6.** Explain the linear regression algorithm in detail. (Do not edit)

**Total Marks:** 4 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

Linear regression defined as the statistical model that analyses the linear relationship between a dependent variable with given set of independent variables. Linear relationship between variables means that when the value of one or more independent variables will change (increase or decrease), the value of dependent variable will also change accordingly (increase or decrease).

Mathematically the relationship can be represented with the help of following equation –

$$Y = mX + c$$

Here, Y is the dependent variable we are trying to predict.

X is the independent variable we are using to make predictions.

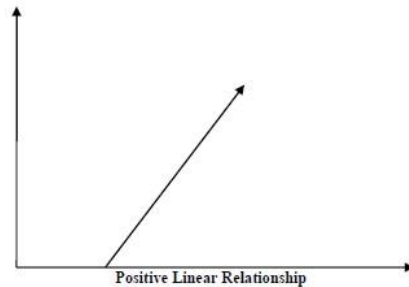
m is the slope of the regression line which represents the effect X has on Y

c is a constant, known as the Y-intercept. If  $X = 0$ , Y would be equal to c.

Furthermore, the linear relationship can be positive or negative in nature as explained below–

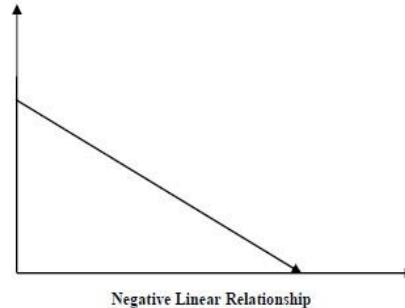
- Positive Linear Relationship:

- A linear relationship will be called positive if both independent and dependent variable increases. It can be understood with the help of following graph –



- Negative Linear relationship:

- A linear relationship will be called negative if independent increases and dependent variable decreases. It can be understood with the help of following graph –



Linear regression is of the following two types –

- Simple Linear Regression
- Multiple Linear Regression

Assumptions -

The following are some assumptions about dataset that is made by Linear Regression model –

- ✓ Multi-collinearity : Linear regression model assumes that there is very little or no multi-collinearity in the data. Basically, multi-collinearity occurs when the independent variables or features have dependency in them.
- ✓ Auto-correlation : Another assumption Linear regression model assumes is that there is very little or no auto-correlation in the data. Basically, auto-correlation occurs when there is dependency between residual errors.
- ✓ Relationship between variables Linear regression model assumes that the relationship between response and feature variables must be linear.

- ✓ Normality of error terms –
  - Error terms should be normally distributed
- ✓ Homoscedasticity : There should be no visible pattern in residual values.

**Question 7.** Explain the Anscombe's quartet in detail. (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

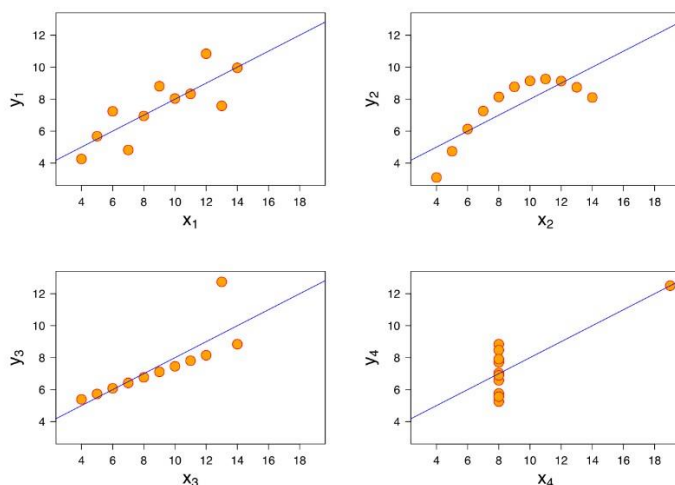
Anscombe's Quartet was developed by statistician Francis Anscombe. It comprises four datasets, each containing eleven (x, y) pairs. The essential thing to note about these datasets is that they share the same descriptive statistics. But things change completely, and I must emphasize COMPLETELY, when they are graphed. Each graph tells a different story irrespective of their similar summary statistics.

	I		II		III		IV	
	x	y	x	y	x	y	x	y
	10	8,04	10	9,14	10	7,46	8	6,58
	8	6,95	8	8,14	8	6,77	8	5,76
	13	7,58	13	8,74	13	12,74	8	7,71
	9	8,81	9	8,77	9	7,11	8	8,84
	11	8,33	11	9,26	11	7,81	8	8,47
	14	9,96	14	8,1	14	8,84	8	7,04
	6	7,24	6	6,13	6	6,08	8	5,25
	4	4,26	4	3,1	4	5,39	19	12,5
	12	10,84	12	9,13	12	8,15	8	5,56
	7	4,82	7	7,26	7	6,42	8	7,91
	5	5,68	5	4,74	5	5,73	8	6,89
SUM	99,00	82,51	99,00	82,51	99,00	82,50	99,00	82,51
AVG	9,00	7,50	9,00	7,50	9,00	7,50	9,00	7,50
STDEV	3,32	2,03	3,32	2,03	3,32	2,03	3,32	2,03

The summary statistics show that the means and the variances were identical for x and y across the groups:

- Mean of x is 9 and mean of y is 7.50 for each dataset.
- Similarly, the variance of x is 11 and variance of y is 4.13 for each dataset
- The correlation coefficient (how strong a relationship is between two variables) between x and y is 0.816 for each dataset

When we plot these four datasets on an x/y coordinate plane, we can observe that they show the same regression lines as well but each dataset is telling a different story:



- Dataset I appears to have clean and well-fitting linear models.
- Dataset II is not distributed normally.
- In Dataset III the distribution is linear, but the calculated regression is thrown off by an outlier.
- Dataset IV shows that one outlier is enough to produce a high correlation coefficient.

This quartet emphasizes the importance of visualization in Data Analysis. Looking at the data reveals a lot of the structure and a clear picture of the dataset.

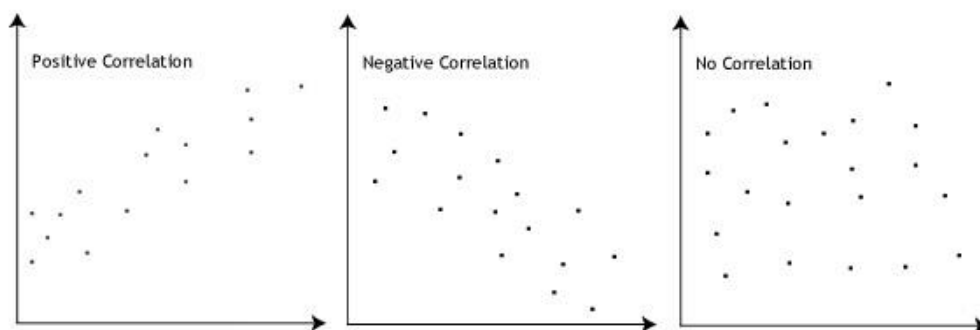
**Question 8.** What is Pearson's R? (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

Pearson's  $r$  is a numerical summary of the strength of the linear association between the variables. If the variables tend to go up and down together, the correlation coefficient will be positive. If the variables tend to go up and down in opposition with low values of one variable associated with high values of the other, the correlation coefficient will be negative.

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:



**Question 9.** What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling? (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

Feature Scaling is a technique to standardize the independent features present in the data in a fixed range. It is performed during the data pre-processing to handle highly varying magnitudes or values or units. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values.

Example: If an algorithm is not using feature scaling method then it can consider the value 3000

meter to be greater than 5 km but that's actually not true and in this case, the algorithm will give wrong predictions. So, we use Feature Scaling to bring all values to same magnitudes and thus, tackle this issue.

S.NO.	Normalized scaling	Standardized scaling
1.	Minimum and maximum value of features are used for scaling	Mean and standard deviation is used for scaling.
2.	It is used when features are of different scales.	It is used when we want to ensure zero mean and unit standard deviation.
3.	Scales values between [0, 1] or [-1, 1].	It is not bounded to a certain range.
4.	It is really affected by outliers.	It is much less affected by outliers.
5.	Scikit-Learn provides a transformer called MinMaxScaler for Normalization.	Scikit-Learn provides a transformer called StandardScaler for standardization.

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**Question 10.** You might have observed that sometimes the value of VIF is infinite. Why does this happen? (Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

If there is perfect correlation, then  $VIF = \infty$ . 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.

When the value of VIF is infinite it shows a perfect correlation between two independent variables. In the case of perfect correlation, we get R-squared ( $R^2$ ) = 1, which lead to  $1/(1-R^2)$  infinity. To solve this we need to drop one of the variables from the dataset which is causing this perfect multicollinearity.

**Question 11.** What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression.  
(Do not edit)

**Total Marks:** 3 marks (Do not edit)

**Answer:** Please write your answer below this line. (Do not edit)

The quantile-quantile (q-q) plot is a graphical technique for determining if two data sets come from populations with a common distribution.

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.

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