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? (3 marks)**

Answer: The below insight can be derived from analysing the categorical variable in the project

- **season**: Almost 32% of the bike booking were happening in season3 with a median of over 5000 booking (for the period of 2 years). This was followed by season2 & season4 with 27% & 25% of total booking. This indicates, season can be a good predictor for the dependent variable.
- **mnth**: Almost 10% of the bike booking were happening in the months 5,6,7,8 & 9 with a median of over 4000 booking per month. This indicates, mnth has some trend for bookings and can be a good predictor for the dependent variable.
- **weathersit**: Almost 67% of the bike booking were happening during 'weathersit1 with a median of close to 5000 booking (for the period of 2 years). This was followed by weathersit2 with 30% of total booking. This indicates, weathersit does show some trend towards the bike bookings can be a good predictor for the dependent variable.
- **holiday**: Almost 97.6% of the bike booking were happening when it is not a holiday which means this data is clearly biased. This indicates, holiday CANNOT be a good predictor for the dependent variable.
- **weekday**: weekday variable shows very close trend (between 13.5%-14.8% of total booking on all days of the week) having their independent medians between 4000 to 5000 bookings. This variable can have some or no influence towards the predictor. I will let the model decide if this needs to be added or not.
- **workingday**: Almost 69% of the bike booking were happening in 'workingday' with a median of close to 5000 booking (for the period of 2 years). This indicates, workingday can be a good predictor for the dependent variable.

2 . Why is it important to use drop_first=True during dummy variable creation? (2 mark)
Answer:
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.
Syntax -
drop_first: bool, default False, which implies whether to get k-1 dummies out of k categorical levels by removing the first level.
Let's say we have 3 types of values in Categorical column and we want to create dummy variable for that column. If one variable is not A and B, then It is obvious C. So we do not need 3rd variable to identify the C.

3. Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable? (1 mark)
Answer:
'temp' variable has 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? (3 marks)**
Answer:

1) **Normality of error terms**
   Error terms should be normally distributed

2) **Multicollinearity check**
   There should be insignificant multicollinearity among variables.

3) **Linear relationship validation**
   Linearity should be visible among variables

4) **Homoscedasticity**
   There should be no visible pattern in residual values.

5) **Independence of residuals**
   No auto-correlation

5) **Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes? (2 marks)**

Answer:
Below are the top 3 features contributing significantly towards explaining the demand of the shared bikes –

1) temp
2) Weather Situation 3
3) Year

General Subjective Questions

1. **Explain the linear regression algorithm in detail. (4 marks)**

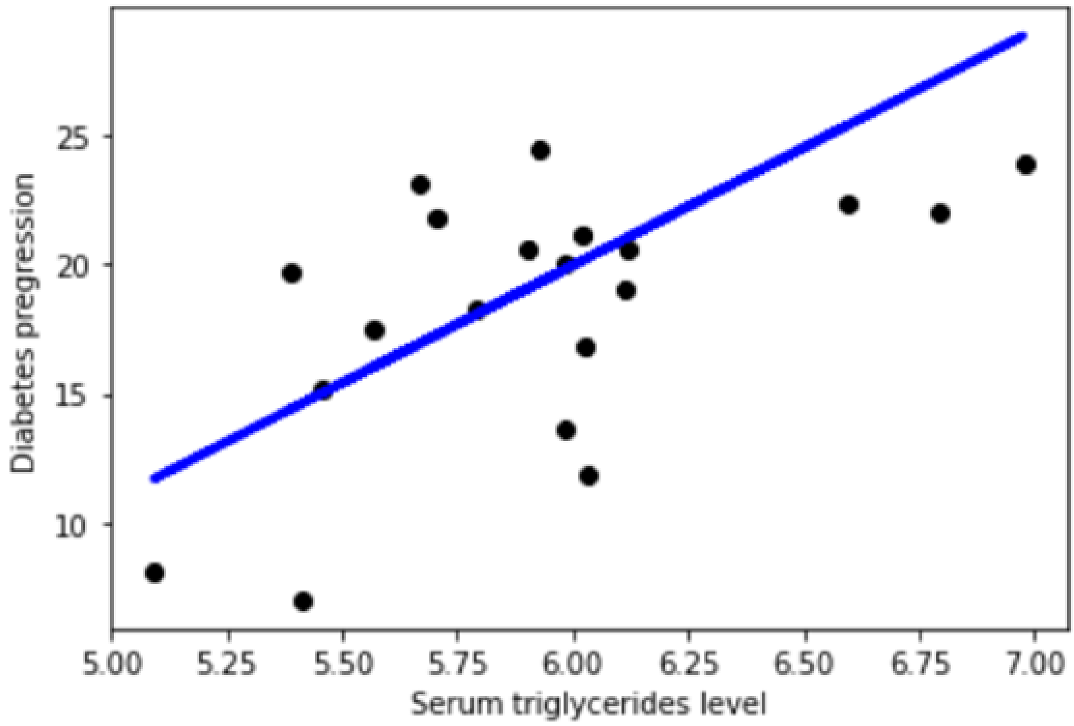
Answer:
Linear regression is a supervised machine learning method that is used by the Train Using AutoML tool and finds a linear equation that best describes the correlation of the explanatory variables with the dependent variable. This is achieved by fitting a line to the data using least squares. The line tries to minimize the sum of the squares of the residuals. The residual is the distance between the line and the actual value of the explanatory variable. Finding the line of best fit is an iterative process.

The following is an example of a resulting linear regression equation:

$$y = b_0 + b_1x_1 + b_2x_2 + \dots$$

In the example above, y is the dependent variable, and x_1, x_2, and so on, are the explanatory variables. The coefficients (b_1, b_2, and so on) explain the correlation of the explanatory variables with the dependent variable. The sign of the coefficients (+/-) designates whether the variable is positively or negatively correlated. b_0 is the intercept that indicates the value of the dependent variable assuming all explanatory variables are 0.

In the following image, a linear regression model is described by the regression line y = 153.21 + 900.39x. The model describes the relationship between the dependent variable, Diabetes pregression, and the explanatory variable, Serum triglycerides level. A positive correlation is shown. This example demonstrates a linear regression model with two variables. Although it is not possible to visualize models with more than three variables, practically, a model can have any number of variables.



A linear regression model helps in predicting the value of a dependent variable, and it can also help explain how accurate the prediction is. This is denoted by the R-squared and p-value values. The R-squared value indicates how much of the variation in the dependent variable can be explained by the explanatory variable and the p-value explains how reliable that explanation is. The R-squared values range between 0 and 1. A value of 0.8 means that the explanatory variable can explain 80 percent of the variation in the observed values of the dependent variable. A value of 1 means that a perfect prediction can be made, which is rare in practice. A value of 0 means the explanatory variable doesn't help at all in predicting the dependent variable. Using a p-value, you can test whether the explanatory variable's effect on the dependent variable is significantly different from 0.

2. **Explain the Anscombe's quartet in detail. (3 marks)**
Answer:

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

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

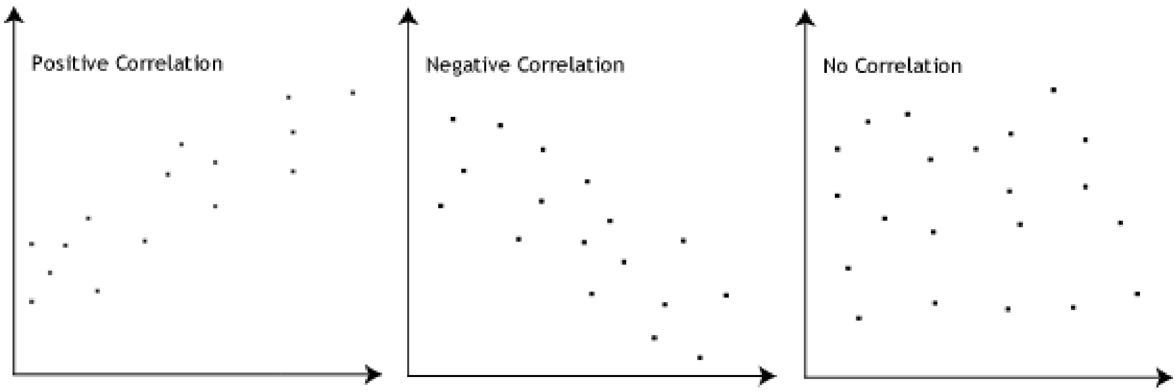
3. What is Pearson's R? (3 marks)

Answer

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).

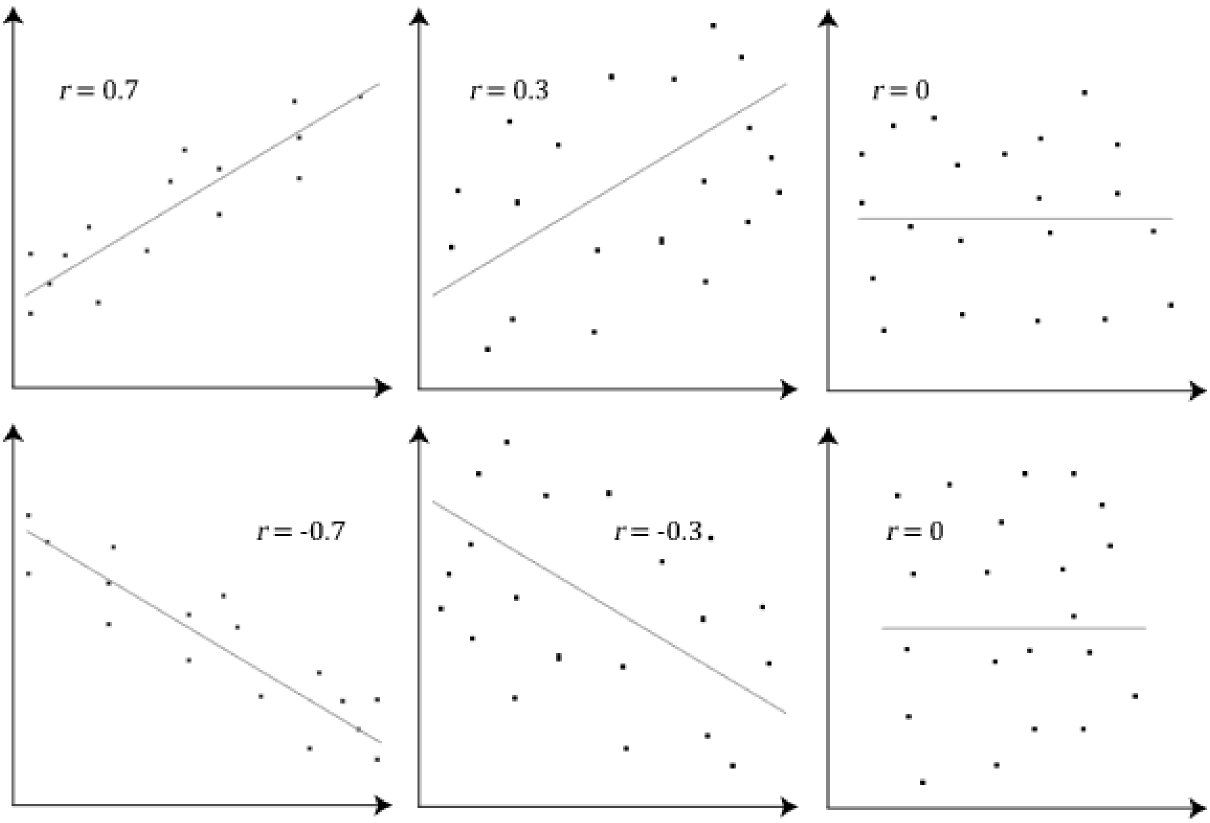
What values can the Pearson correlation coefficient take?

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:



How can we determine the strength of association based on the Pearson correlation coefficient?

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? (3 marks)**

Answer

Feature scaling is a data preprocessing technique used to transform the values of features or variables in a dataset to a similar scale. The purpose is to ensure that all features contribute equally to the model and to avoid the domination of features with larger values.

Feature scaling becomes necessary when dealing with datasets containing features that have different ranges, units of measurement, or orders of magnitude. In such cases, the variation in feature values can lead to biased model performance or difficulties during the learning process.

There are several common techniques for feature scaling, including standardization, normalization, and min-max scaling. These methods adjust the feature values while preserving their relative relationships and distributions.

By applying feature scaling, the dataset's features can be transformed to a more consistent scale, making it easier to build accurate and effective machine learning models. Scaling facilitates meaningful comparisons between features, improves model convergence, and prevents certain features from overshadowing others based solely on their magnitude.

Gradient Descent Based Algorithms

Machine learning algorithms like linear regression, logistic regression, neural network, PCA (principal component analysis), etc., that use gradient descent as an optimization technique require data to be scaled. Take a look at the formula for gradient descent below:

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

The presence of feature value X in the formula will affect the step size of the gradient descent. The difference in the ranges of features will cause different step sizes for each feature. To ensure that the gradient descent moves smoothly towards the minima and that the steps for gradient descent are updated at the same rate for all the features, we scale the data before feeding it to the model.

Having features on a similar scale can help the gradient descent converge more quickly towards the minima.

2. Distance-Based Algorithms

Distance algorithms like KNN, K-means clustering, and SVM(support vector machines) are most affected by the range of features. This is because, behind the scenes, **they are using distances between data points to determine their similarity.**

For example, let's say we have data containing high school CGPA scores of students (ranging from 0 to 5) and their future incomes (in thousands of Rupees):

	Student	CGPA	Salary '000
0	1	3.0	60
1	2	3.0	40
2	3	4.0	40
3	4	4.5	50
4	5	4.2	52

Since both the features have different scales, there is a chance that higher weightage is given to features with higher magnitudes. This will impact the performance of the machine learning algorithm; obviously, we do not want our algorithm to be biased towards one feature.

Therefore, we scale our data before employing a distance based algorithm so that all the features contribute equally to the result.

	Student	CGPA	Salary '000
0	1	-1.184341	1.520013
1	2	-1.184341	-1.100699
2	3	0.416120	-1.100699
3	4	1.216350	0.209657
4	5	0.736212	0.471728

The effect of scaling is conspicuous when we compare the Euclidean distance between data points for students A and B, and between B and C, before and after scaling, as shown below:

- Distance AB before scaling => $\sqrt{(40-60)^2+(3-3)^2}=20$
- Distance BC before scaling => $\sqrt{(40-40)^2+(4-3)^2}=1$
- Distance AB after scaling => $\sqrt{(1.1+1.5)^2+(1.18-1.18)^2}=2.6$
- Distance BC after scaling => $\sqrt{(1.1-1.1)^2+(0.41+1.18)^2}=1.59$

3. Tree-Based Algorithms

Tree-based algorithms, on the other hand, are fairly insensitive to the scale of the features. Think about it, a decision tree only splits a node based on a single feature. The decision tree splits a node on a feature that increases the homogeneity of the node. Other features do not influence this split on a feature.

So, the remaining features have virtually no effect on the split. This is what makes them invariant to the scale of the features!

What is Normalization?

Normalization is a data preprocessing technique used to adjust the values of features in a dataset to a common scale. This is done to facilitate data analysis and modeling, and to reduce the impact of different scales on the accuracy of machine learning models.

Normalization is a scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1. It is also known as Min-Max scaling.

Here's the formula for normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Here, Xmax and Xmin are the maximum and the minimum values of the feature, respectively.

- When the value of X is the minimum value in the column, the numerator will be 0, and hence X' is 0
- On the other hand, when the value of X is the maximum value in the column, the numerator is equal to the denominator, and thus the value of X' is 1
- If the value of X is between the minimum and the maximum value, then the value of X' is between 0 and 1

What is Standardization?

Standardization is another scaling method where 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.

Here's the formula for standardization:

$$X' = \frac{X - \mu}{\sigma}$$

μ is the mean of the feature values and σ is the standard deviation of the feature values. Note that, in this case, the values are not restricted to a particular range.

Now, the big question in your mind must be when should we use normalization and when should we use standardization? Let's find out!

The Big Question – Normalize or Standardize?

Normalization	Standardization
Rescales values to a range between 0 and 1	Centers data around the mean and scales to a standard deviation of 1
Useful when the distribution of the data is unknown or not Gaussian	Useful when the distribution of the data is Gaussian or unknown
Sensitive to outliers	Less sensitive to outliers
Retains the shape of the original distribution	Changes the shape of the original distribution
May not preserve the relationships between the data points	Preserves the relationships between the data points
Equation: (x – min)/(max – min)	Equation: (x – mean)/standard deviation

However, at the end of the day, the choice of using normalization or standardization will depend on your problem and the machine learning algorithm you are using. There is no hard and fast rule to tell you when to normalize or standardize your data. You can always start by fitting your model to raw, normalized, and standardized data and comparing the performance for the best results.

5. **You might have observed that sometimes the value of VIF is infinite. Why does this happen? (3 marks)**
Answer:
If there is perfect correlation, then VIF = infinity. 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 (R2) =1, which lead to 1/ (1-R2) infinity. To solve this 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. (3 marks)**
Answer:
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.