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 –

Below are the inferences –

- Fall seems to have more booking as compared to other seasons.
- Jun, July, Aug, Sep & October has more number of booking of ride.
- More number of usage is in Clear weather
- More number of booking are in holidays which is obvious
- There is little drop in booking in working day as compared to non working day.
- Booking increase in 2019 as compared to 2018

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

Answer –

drop_first = True help in reducing the extra column created during dummy values creation. So, if there are n levels in categorial feature then it will help to create n-1 dummy variables. First variable which is dropped can be easily identified by looking remaining n-1 columns

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

Answer –

'temp' has highest correlation

4. How did you validate the assumptions of Linear Regression after building the model on the training set? (3 marks)

Answer –

Below are the validation done –

1. Linearity: Pair plot shows linear relationship between independent & target variable
2. Independence: No autocorrelation via scatterplot
3. Homoscedasticity: No definite pattern (like linear or quadratic or funnel shaped) obtained from the scatter plot
4. Normality: The errors follow a normal distribution.
5. No multicollinearity: Variables are not highly correlated. It is done using VIF.

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 top 3 features -

1. Yr
2. Spring
3. Light_snowrain

General Subjective Questions

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

Answer –

Linear regression is an algorithm that provides a linear relationship between an independent variable and a dependent variable to predict the outcome of future events. It is a statistical method used in data science and machine learning for predictive analysis.

The independent variable is also the predictor or explanatory variable that remains unchanged due to the change in other variables. However, the dependent variable changes with fluctuations in the independent variable. The regression model predicts the value of the dependent variable, which is the response or outcome variable being analyzed or studied.

There are 2 types -
Simple Linear Regression
Multiple Linear Regression

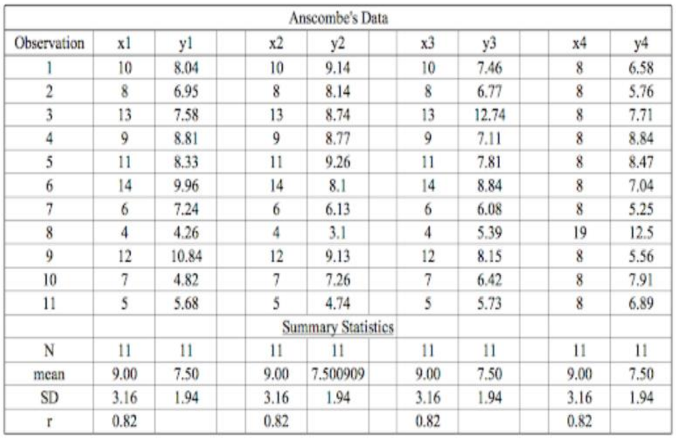
Mathematically the relationship can be represented with the help of following equation −
Y = mX + c
Here, Y is the dependent variable we are trying to predict.
X is the independent variable we are using to make predictions.
m is the slope of the regression line which represents the effect X has on Y
c is a constant, known as the Y-intercept. If X = 0, Y would be equal to c.

Assumption -

1. Linearity: The relationship between the dependent and independent variables is linear.
2. Independence: The observations are independent of each other.
3. Homoscedasticity: The variance of the errors is constant across all levels of the independent variables.
4. Normality: The errors follow a normal distribution.
5. No multicollinearity: The independent variables are not highly correlated with each other.

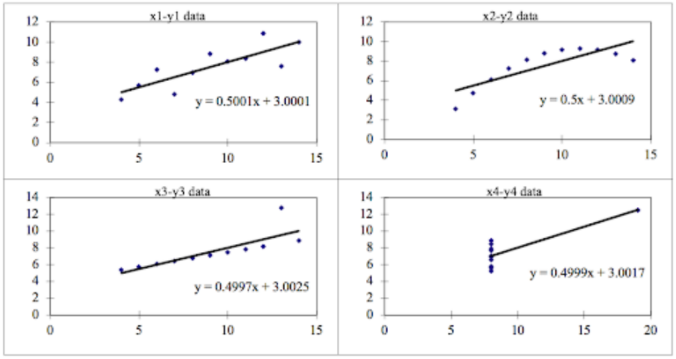
2. Explain the Anscombe's quartet in detail. (3 marks)

Answer – Anscombe's quartet was constructed in 1973 by statistician Francis Anscombe to illustrate the importance of plotting data before you analyze it and build your model. These four data sets have nearly the same statistical observations, which provide the same information (involving variance and mean) for each x and y point in all four data sets. However, when you plot these data sets, they look very different from one another.



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:



- Data Set 1: fits the linear regression model pretty well.
- Data Set 2: cannot fit the linear regression model because the data is non-linear.
- Data Set 3: shows the outliers involved in the data set, which cannot be handled by the linear regression model.
- Data Set 4: shows the outliers involved in the data set, which also cannot be handled by the linear regression model.

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 mode

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

Answer –

The Pearson correlation coefficient (r) is the most common way of measuring a linear correlation. It is a number between –1 and 1 that measures the strength and direction of the relationship between two variables.

If it is in between 0 and 1 : Positive correlation
When one variable changes, the other variable changes in the same direction.

If it is 0 : No correlation
There is no relationship between the variables.

If it is between 0 and –1 : Negative Correlation
When one variable changes, the other variable changes in the opposite direction.

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling? (3 marks)

Answer –

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

Feature scaling is employed for a number of purposes:

- Scaling guarantees that all features are on a comparable scale and have comparable ranges. This process is known as feature normalisation. This is significant because the magnitude of the features has an impact on many machine learning techniques. Larger scale features may dominate the learning process and have an excessive impact on the outcomes. You can avoid this problem and make sure that each feature contributes equally to the learning process by scaling the features.
- Algorithm performance improvement: When the features are scaled, several machine learning methods, including gradient descent-based algorithms, distance-based algorithms (such k-nearest neighbours), and support vector machines, perform better or converge more quickly. The algorithm’s performance can be enhanced by scaling the features, which can hasten the convergence of the algorithm to the ideal outcome.
- Preventing numerical instability: Numerical instability can be prevented by avoiding significant scale disparities between features. Examples include distance calculations or matrix operations, where having features with radically differing scales can result in numerical overflow or underflow problems. Stable computations are ensured and these issues are mitigated by scaling the features.
- Scaling features makes ensuring that each characteristic is given the same consideration during the learning process. Without scaling, bigger scale features could dominate the learning, producing skewed outcomes. This bias is removed through scaling, which also guarantees that each feature contributes fairly to model predictions.

S.NO.	Normalization	Standardization
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.
6.	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.
7.	It is useful when we don’t know about the distribution	It is useful when the feature distribution is Normal or Gaussian.
8.	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? (3 marks)
Answer –

If all the independent variables are orthogonal to each other, then VIF = 1.0. If there is perfect correlation, then VIF = infinity. A large value of VIF indicates that there is a correlation between the variables.

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.

6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression. (3 marks)

Answer –
The QQ plot, or quantile-quantile plot, is a graphical tool to help us assess if a set of data plausibly came from some theoretical distribution such as a normal or exponential. A QQ plot is a scatterplot created by plotting two sets of quantiles against one another. If both sets of quantiles came from the same distribution, we should see the points forming a line that's roughly straight.

Importance of Q-Q plot

- Since Q-Q plot is like probability plot. So, while comparing two datasets the sample size need not to be equal.
- Since we need to normalize the dataset, so we don’t need to care about the dimensions of values.
- Determine whether two samples are from the same population.
- Whether two samples have the same tail.
- Whether two samples have the same distribution shape.
- Whether two samples have common location behavior.