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>>

- **Season 3 fall has highest demand for rental bikes**
- **I see that demand for next year has grown up**
- **Demand is continuously growing each month till June. The September month has highest demand and after September, demand is decreasing**
- **When there is a holiday, the demand has decreased.**
- **Weekday is not giving clear picture about demand.**
- **The clear weathersit has highest demand**
- **During September, bike sharing is more. During the year end and beginning, it is less, could be due to extreme weather conditions.**

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

Answer>>

It 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. Thus it will give n-1 dummies out of n discrete categorical levels by removing the first level.

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

Answer>>

'temp' and 'atemp' has the highest correlation with the target variable 'cnt'

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

Answer>>

- **By Residual Analysis**
- **Error Terms**
- **Linearity Check thru scatter plot drawing**
- **By checking Homoscedasticity**

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>>

- **R Squared**
- **P-value**
- **F – Statistic**

  Based on the model the 'holiday', 'temp' and 'hum' are top features those predict the demand of the shared bikes

General Subjective Questions

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

Answer>>

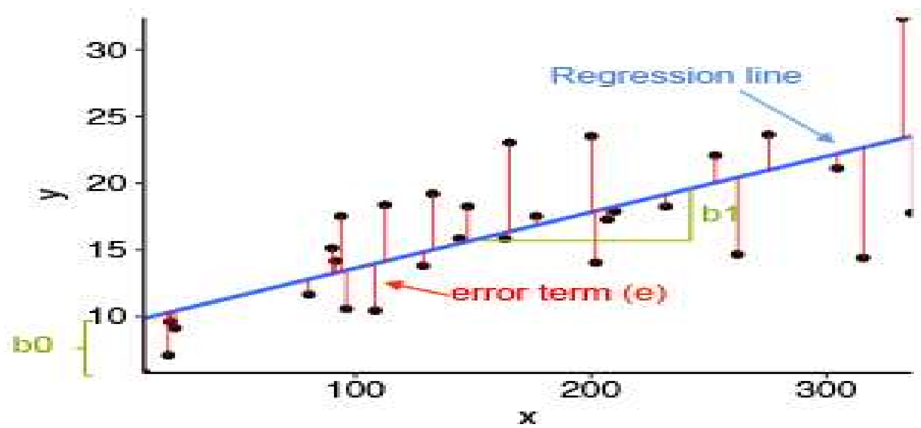
In the most simple words, Linear Regression is the supervised Machine Learning model in which the model finds the best fit linear line between the independent and dependent variable i.e it finds the linear relationship between the dependent(y) and independent variable(x).
Linear Regression is of two types: Simple and Multiple.
Simple Linear Regression is where only one independent variable is present and the model has to find the linear relationship of it with the dependent variable
Whereas, In Multiple Linear Regression there are more than one independent variables for the model to find the relationship.
Equation of Simple Linear Regression, where b_o is the intercept, b_1 is coefficient or slope, x is the independent variable and y is the dependent variable.

$$y = b_o + b_1x$$

Equation of Multiple Linear Regression, where bo is the intercept, $b_1,b_2,b_3,b_4\ldots,b_n$ are coefficients or slopes of the independent variables $x_1,x_2,x_3,x_4\ldots,x_n$ and y is the dependent variable.

$$y = b_o + b_1x_1 + b_2x_2 + b_3x_3 \ldots. + b_nx_n$$

A Linear Regression model's main aim is to find the best fit linear line and the optimal values of intercept and coefficients such that the error is minimized.
Error is the difference between the actual value and Predicted value and the goal is to reduce this difference.
Let's understand this with the help of a diagram.



$$y = b_o + b_1x$$

Image Source: Statistical tools for high-throughput data analysis

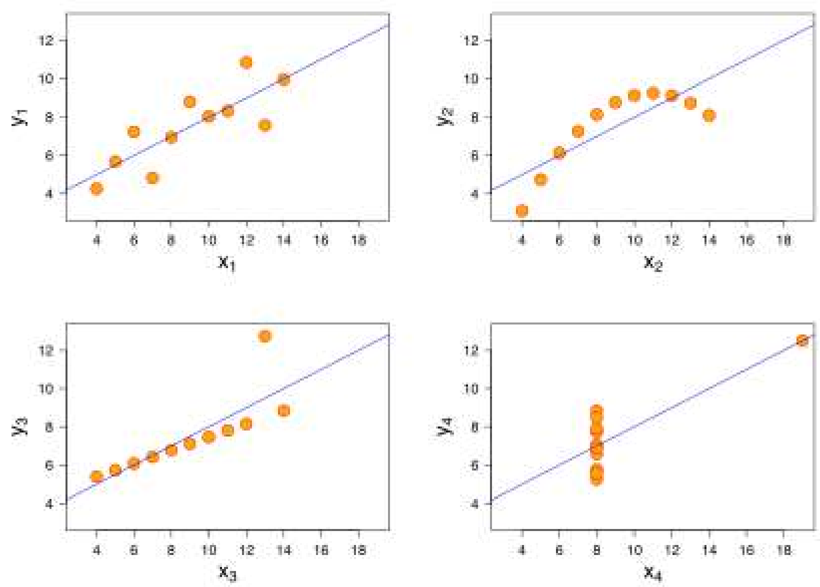
In the above diagram,

- x is our independent variable which is plotted on the x-axis and y is the dependent variable which is plotted on the y-axis.
- Black dots are the data points i.e the actual values.
- b_o is the intercept which is 10 and b_1 is the slope of the x variable.
- The blue line is the best fit line predicted by the model i.e the predicted values lie on the blue line.
- The vertical distance between the data point and the regression line is known as error or residual. Each data point has one residual and the sum of all the differences is known as the Sum of Residuals/Errors.

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

Answer>>

Anscombe's quartet comprises four data sets that have nearly identical simple descriptive statistics, yet have very different distributions and appear very different when graphed. Each dataset consists of eleven (*x*,*y*) points. They were constructed in 1973 by the statistician Francis Anscombe to demonstrate both the importance of graphing data when analyzing it, and the effect of outliers and other influential observations on statistical properties. He described the article as being intended to counter the impression among statisticians that "numerical calculations are exact, but graphs are rough."



For all four datasets:

Property	Value	Accuracy
Mean of *x*	9	exact

Sample variance of x : s^2_x	11	exact
Mean of y	7.50	to 2 decimal places
Sample variance of y : s^2_y	4.125	±0.003
Correlation between x and y	0.816	to 3 decimal places
Linear regression line	$y = 3.00 + 0.500x$	to 2 and 3 decimal places, respectively
Coefficient of determination of the linear regression :	0.67	to 2 decimal places

- The first scatter plot (top left) appears to be a simple linear relationship, corresponding to two variables correlated where y could be modelled as gaussian with mean linearly dependent on x.
- The second graph (top right); while a relationship between the two variables is obvious, it is not linear, and the Pearson correlation coefficient is not relevant. A more general regression and the corresponding coefficient of determination would be more appropriate.
- In the third graph (bottom left), the modelled relationship is linear, but should have a different regression line (a robust regression would have been called for). The calculated regression is offset by the one outlier which exerts enough influence to lower the correlation coefficient from 1 to 0.816.
- Finally, the fourth graph (bottom right) shows an example when one high-leverage point is enough to produce a high correlation coefficient, even though the other data points do not indicate any relationship between the variables.

The quartet is still often used to illustrate the importance of looking at a set of data graphically before starting to analyze according to a particular type of relationship, and the inadequacy of basic statistic properties for describing realistic datasets.

The datasets are as follows. The x values are the same for the first three datasets.

Anscombe's quartet

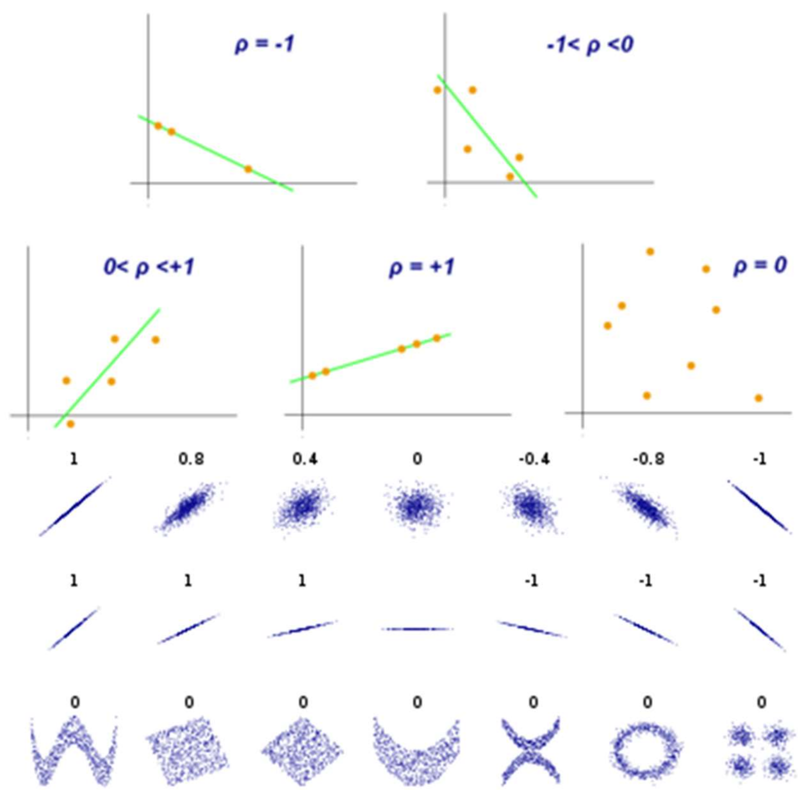
I		II		III		IV	
x	*y*	*x*	*y*	*x*	*y*	*x*	*y*
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	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

It is not known how Anscombe created his datasets. Since its publication, several methods to generate similar data sets with identical statistics and dissimilar graphics have been developed. One of these, the *Datasaurus Dozen*, consists of points tracing out the outline of a dinosaur, plus twelve other data sets that have the same summary statistics.

3. What is Pearson’s R? (3 marks)

Answer>>

Pearson's R, is a measure of linear correlation between two sets of data. It is the ratio between the covariance of two variables and the product of their standard deviations; thus, it is essentially a normalized measurement of the covariance, such that the result always has a value between −1 and 1. As with covariance itself, the measure can only reflect a linear correlation of variables, and ignores many other types of relationships or correlations. As a simple example, one would expect the age and height of a sample of teenagers from a high school to have a Pearson correlation coefficient significantly greater than 0, but less than 1 (as 1 would represent an unrealistically perfect correlation).



Several sets of (*x*, *y*) points, with the correlation coefficient of *x* and *y* for each set. The correlation reflects the strength and direction of a linear relationship (top row), but not the slope of that relationship (middle), nor many aspects of nonlinear relationships (bottom). N.B.: the figure in the center has a slope of 0 but in that case the correlation coefficient is undefined because the variance of *Y* is zero.

Pearson's correlation coefficient is the covariance of the two variables divided by the product of their standard deviations. The form of the definition involves a "product moment", that is, the mean (the first moment about the origin) of the product of the mean-adjusted random variables; hence the modifier *product-moment* in the name.

Pearson's correlation coefficient, when applied to a population, is commonly represented by the Greek letter *ρ* (rho) and may be referred to as the *population correlation coefficient* or the *population*

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

Answer>>

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

Normalization/Min-Max Scaling:
It brings all of the data in the range of 0 and 1.
sklearn.preprocessing.MinMaxScaler helps to implement normalization in python.

$$\text{MinMax Scaling: } x = \frac{x - min(x)}{max(x) - min(x)}$$

Standardization Scaling:

- Standardization replaces the values by their Z scores. It brings all of the data into a standard normal distribution which has mean (**μ**) zero and standard deviation one (**σ**).

$$\text{Standardisation: } x = \frac{x - mean(x)}{sd(x)}$$

- **sklearn.preprocessing.scale** helps to implement standardization in python.
- One disadvantage of normalization over standardization is that it **loses** some information in the data, especially about **outliers**.

It is important to note that **scaling just affects the coefficients** and none of the other parameters like **t-statistic, F-statistic, p-values, R-squared**, etc.

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.
The greater the VIF, the higher the degree of multicollinearity. In the limit, when multicollinearity is perfect (i.e., the regressor is equal to a linear combination of other regressors), the VIF tends to infinity.
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.

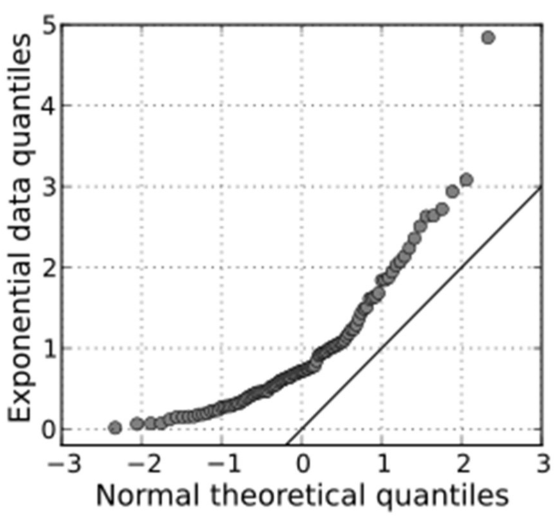
6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression. (3 marks)
Answer>> Definition:

A Q–Q plot (quantile-quantile plot) is a probability plot, a graphical method for comparing two probability distributions by plotting their *quantiles* against each other. A point (x, y) on the plot corresponds to one of the quantiles of the second distribution (y-coordinate) plotted against the same quantile of the first distribution (x-coordinate). This defines a parametric curve where the parameter is the index of the quantile interval.

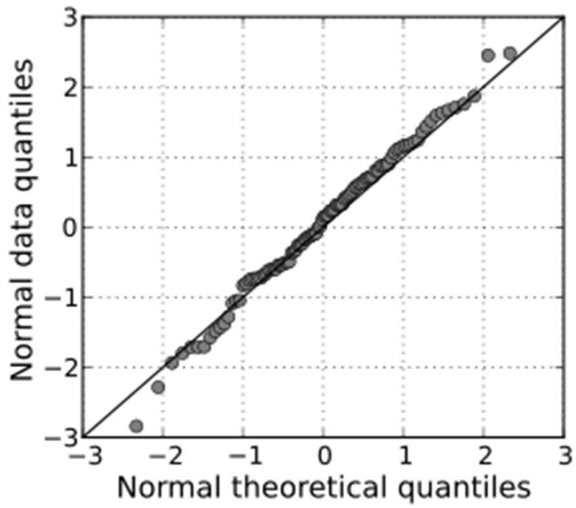
If the two distributions being compared are similar, the points in the Q–Q plot will approximately lie on the identity line $y = x$. If the distributions are linearly related, the points in the Q–Q plot will approximately lie on a line, but not necessarily on the line $y = x$. Q–Q plots can also be used as a graphical means of estimating parameters in a location-scale family of distributions.

Use:

A Q–Q plot is used to compare the shapes of distributions, providing a graphical view of how properties such as location, scale, and skewness are similar or different in the two distributions. Q–Q plots can be used to compare collections of data, or theoretical distributions. The use of Q–Q plots to compare two samples of data can be viewed as a non-parametric approach to comparing their underlying distributions. A Q–Q plot is generally more diagnostic than comparing the samples' histograms, but is less widely known. Q–Q plots are commonly used to compare a data set to a theoretical model. This can provide an assessment of goodness of fit that is graphical, rather than reducing to a numerical summary statistic. Q–Q plots are also used to compare two theoretical distributions to each other. Since Q–Q plots compare distributions, there is no need for the values to be observed as pairs, as in a scatter plot, or even for the numbers of values in the two groups being compared to be equal.



A normal Q–Q plot of randomly generated, independent standard exponential data, (X ~ Exp(1)). This Q–Q plot compares a sample of data on the vertical axis to a statistical population on the horizontal axis. The points follow a strongly nonlinear pattern, suggesting that the data are not distributed as a standard normal (X ~ N(0,1)). The offset between the line and the points suggests that the mean of the data is not 0. The median of the points can be determined to be near 0.7



A normal Q–Q plot comparing randomly generated, independent standard normal data on the vertical axis to a standard normal population on the horizontal axis. The linearity of the points suggests that the data are normally distributed.

Importance:

A Q-Q plot helps to compare the sample distribution of the variable at hand against any other possible distributions graphically.

Understanding the distribution of a variable(s) is one of the first and foremost tasks done while exploring a dataset. One way to test the distribution of continuous variables graphically is via a Q-Q plot. These plots come in handy in the case of parametric tests as they insist on the assumption of normality even though they can be used for any underlying distribution.