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)
SM: Below are the findings
- Holiday: If the day is a holiday, it attracts more customers.
- Weekday: Wednesday & Saturday tends to contribute the highest in Count.
- Month: the count volume increased between April to Nov. It can be said that these months between these months are the seasonal period of the business.
- Season: W1_spring does the lowest in Count volume and W3_Fall does the highest in count volume.
- Weather Situation: Due to natural challenges in Rain & Snow, the count reduces but the count increases when the weather situation is Clear or Misty.
- Year: It is visible that business has grown in the year 2019 compared with 2018.

2. **Why is it important to use drop_first=True during dummy variable creation?** (2 mark)
SM: In the Dummy creation chapter, we learned whenever dummy creation is used we should drop one categorical variable from the dummy column creation.
i.e., if we have 10 values in one Categorical column, because of rule "K-1" we should be creating 9 dummy columns.
And using "drop_first=True", we can achieve that automatically as it skips the first dummy column creation.

3. **Looking at the pair plot among the numerical variables, which one has the highest correlation with the target variable?** (1 mark)
SM: Temp & TempFeelslike have the highest correlation with Count.

4. **How did you validate the assumptions of Linear Regression after building the model on the training set**? (3 marks)
SM: Validation performed with the below methods
- Using a distplot, it is visible that the error term is distributed normally.
- Using a heatmap, we verified there is no Multi Collinearity situation.
- Using multiple component and component-plus-residual (CCPR) plots, the Linear Relationship checks were performed.
- Using a scatter plot, a Homescedasticity check was performed and no pattern was found.
- With "print(lr_6.summary())", we got the Durbin-Watson value 2.085 to check the independence of Residual where no auto-correlation was noticed.

5. **Based on the final model, which are the top 3 features contributing significantly towards explaining the demand for shared bikes?** (2 marks)
SM: Top factors
- Temp
- Summer
- Sep

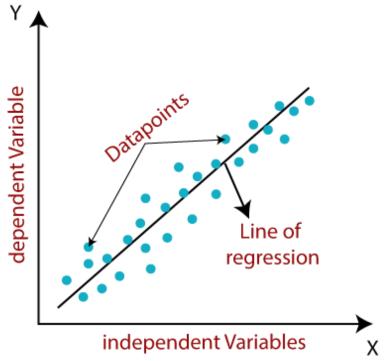
General Subjective Questions

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

Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. Linear regression makes predictions for continuous/real or numeric variables such as **sales, salary, age, product price**, etc.

Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable.

The linear regression model provides a sloped straight line representing the relationship between the variables. Consider the below image:



Mathematically, we can represent a linear regression as:

$$y= a_0+a_1x+ \varepsilon$$

Here,

Y= Dependent Variable (Target Variable)

X= Independent Variable (predictor Variable)

a0= intercept of the line (Gives an additional degree of freedom)

a1 = Linear regression coefficient (scale factor to each input value).

ε = random error

The values for the x and y variables are training datasets for Linear Regression model representation.

Linear regression can be further divided into two types of the algorithm:

Simple Linear Regression:

If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.

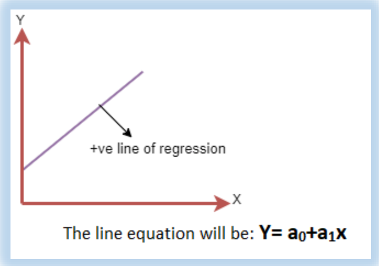
Multiple Linear regression:

If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear Regression.

Linear Regression Line: A linear line showing the relationship between the dependent and independent variables is called a regression line. A regression line can show two types of relationship:

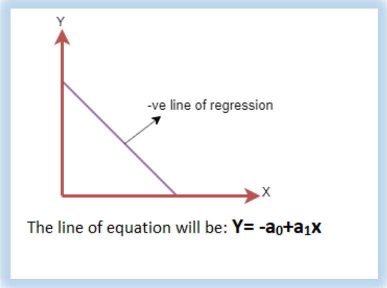
Positive Linear Relationship:

If the dependent variable increases on the Y-axis and the independent variable increases on X-axis, then such a relationship is termed a Positive linear relationship.



Negative Linear Relationship:

If the dependent variable decreases on the Y-axis and the independent variable increases on the X-axis, then such a relationship is called a negative linear relationship.



Finding the best fit line: When working with linear regression, our main goal is to find the best fit line that means the error between predicted values and actual values should be minimized. The best fit line will have the least error.

The different values for weights or the coefficient of lines (a0, a1) gives a different line of regression, so we need to calculate the best values for a0 and a1 to find the best fit line, so to calculate this we use cost function.

Cost function-

- The different values for weights or coefficient of lines (a0, a1) gives the different line of regression, and the cost function is used to estimate the values of the coefficient for the best fit line.

- Cost function optimizes the regression coefficients or weights. It measures how a linear regression model is performing.

- We can use the cost function to find the accuracy of the mapping function, which maps the input variable to the output variable. This **mapping function** is also known as Hypothesis function.

For Linear Regression, we use the **Mean Squared Error (MSE)** cost function, which is the average of squared error occurred between the predicted values and actual values. It can be written as:

For the above linear equation, MSE can be calculated as:

$$\text{MSE}= 1\frac{1}{N}\sum_{i=1}^{n}(y_i \; - (a_1x_i + a_0))^2$$

Where,

N=Total number of observation
Yi = Actual value
(a1xi+a0) = Predicted value.

Residuals: The distance between the actual value and predicted values is called residual. If the observed points are far from the regression line, then the residual will be high, and so cost function will high. If the scatter points are close to the regression line, then the residual will be small and hence the cost function.

Gradient Descent:

- Gradient descent is used to minimize the MSE by calculating the gradient of the cost function.
- A regression model uses gradient descent to update the coefficients of the line by reducing the cost function.
- It is done by a random selection of values of coefficient and then iteratively update the values to reach the minimum cost function.

Model Performance:

The Goodness of fit determines how the line of regression fits the set of observations. The process of finding the best model out of various models is called **optimization**. It can be achieved by below method:

R-squared method:

- R-squared is a statistical method that determines the goodness of fit.
- It measures the strength of the relationship between the dependent and independent variables on a scale of 0-100%.
- The high value of R-square determines the less difference between the predicted values and actual values and hence represents a good model.
- It is also called a coefficient of determination, or coefficient of multiple determination for multiple regression.

- It can be calculated from the below formula:

$$\text{R-squared}=\frac{\text{Explained variation}}{\text{Total Variation}}$$

Assumptions of Linear Regression

Below are some important assumptions of Linear Regression. These are some formal checks while building a Linear Regression model, which ensures to get the best possible result from the given dataset.

Linear relationship between the features and target:

Linear regression assumes the linear relationship between the dependent and independent variables.

Small or no multicollinearity between the features:

Multicollinearity means high-correlation between the independent variables. Due to multicollinearity, it may difficult to find the true relationship between the predictors and target variables. Or we can say, it is difficult to determine which predictor variable is affecting the target variable and which is not. So, the model assumes either little or no multicollinearity between the features or independent variables.

Homoscedasticity Assumption:

Homoscedasticity is a situation when the error term is the same for all the values of independent variables. With homoscedasticity, there should be no clear pattern distribution of data in the scatter plot.

Normal distribution of error terms:

Linear regression assumes that the error term should follow the normal distribution pattern. If error terms are not normally distributed, then confidence intervals will become either too wide or too narrow, which may cause difficulties in finding coefficients.

It can be checked using the q-q plot. If the plot shows a straight line without any deviation, which means the error is normally distributed.

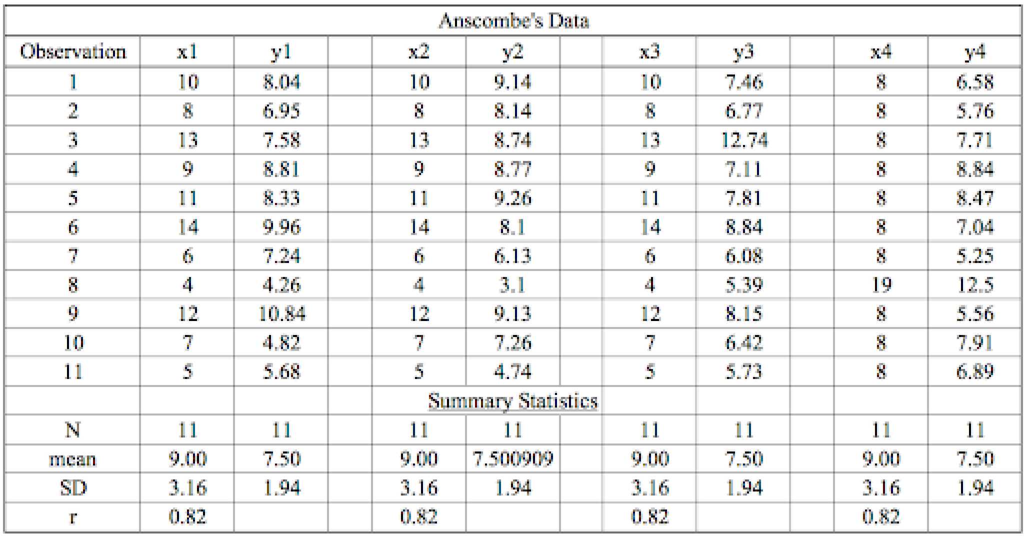
No autocorrelations:

The linear regression model assumes no autocorrelation in error terms. If there will be any correlation in the error term, then it will drastically reduce the accuracy of the model. Autocorrelation usually occurs if there is a dependency between residual errors.

2. **Explain Anscombe's quartet in detail**. (3 marks)
SM: Anscombe's Quartet can be defined as a group of four data sets which are nearly identical in simple descriptive statistics, but there are some peculiarities in the dataset that fools the regression model if built. They have very different distributions and appear differently when plotted on scatter plots.

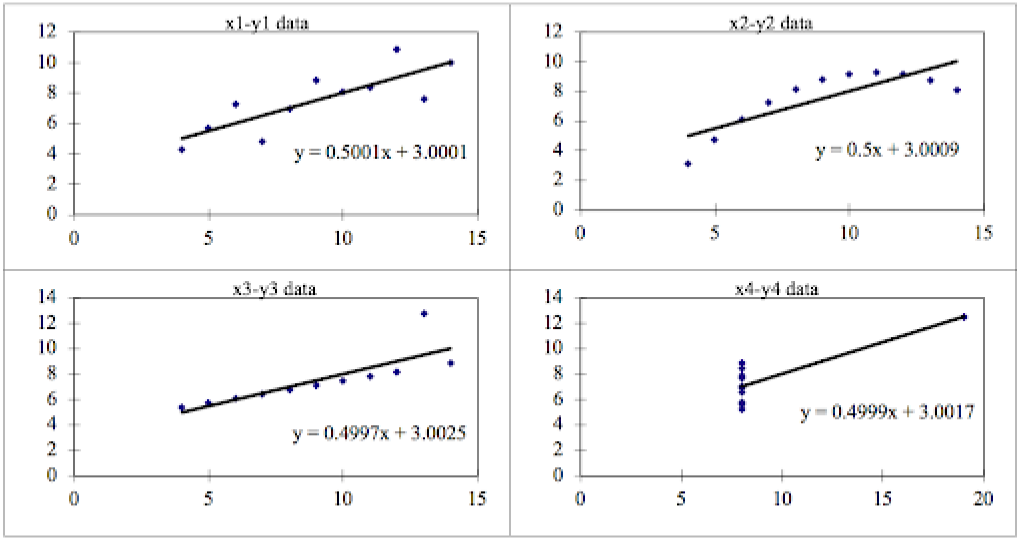
Purpose: Anscombe's quartet tells us about the importance of visualizing data before applying various algorithms to build models. This suggests the data features must be plotted to see the distribution of the samples that can help you identify the various anomalies present in the data (outliers, diversity 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.

Dataset:



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:



ANSCOMBE'S QUARTET FOUR DATASETS

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.

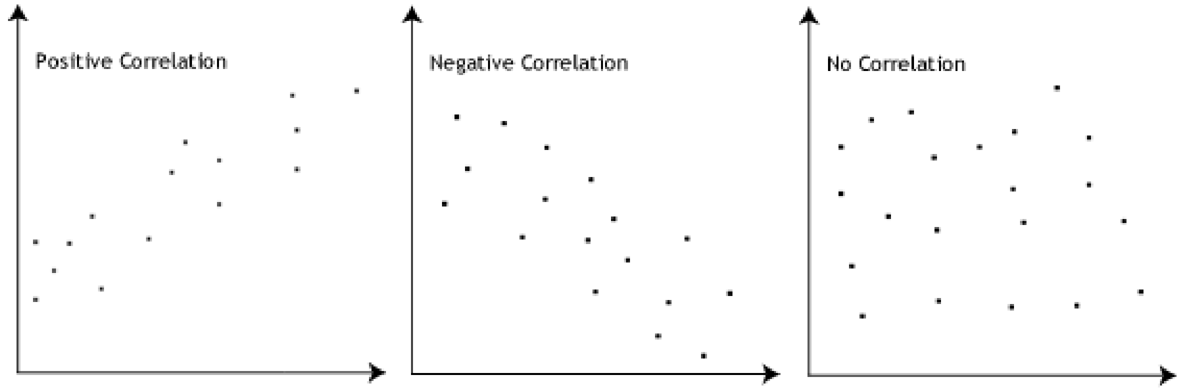
Data Set 4: shows the outliers involved in the data set, which also cannot be handled by the linear regression model.

As we 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?** (3 marks)

SM: 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:



4. **What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling?** (3 marks)
SM: 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 the feature scaling method, then it can consider the value 3000 meters 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 the same magnitudes and thus, tackle this issue.

Techniques to perform Feature Scaling

Consider the two most important ones:
Min-Max Normalization: This technique re-scales a feature or observation value with distribution value between 0 and 1.

$$X_{\text{new}} = \frac{X_i - \min(X)}{\max(x) - \min(X)}$$

Standardization: It is a very effective technique which re-scales a feature value so that it has distribution with 0 mean value and variance equals to 1.

$$X_{\text{new}} = \frac{X_i - X_{\text{mean}}}{\text{Standard Deviation}}$$

5. **You might have observed that sometimes the value of VIF is infinite. Why does this happen?** (3 marks)
SM: If there is perfect correlation, then VIF = infinity. This shows a 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.

An infinite VIF value indicates that the corresponding variable may be expressed exactly by a linear combination of other variables (which show an infinite VIF as well).

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

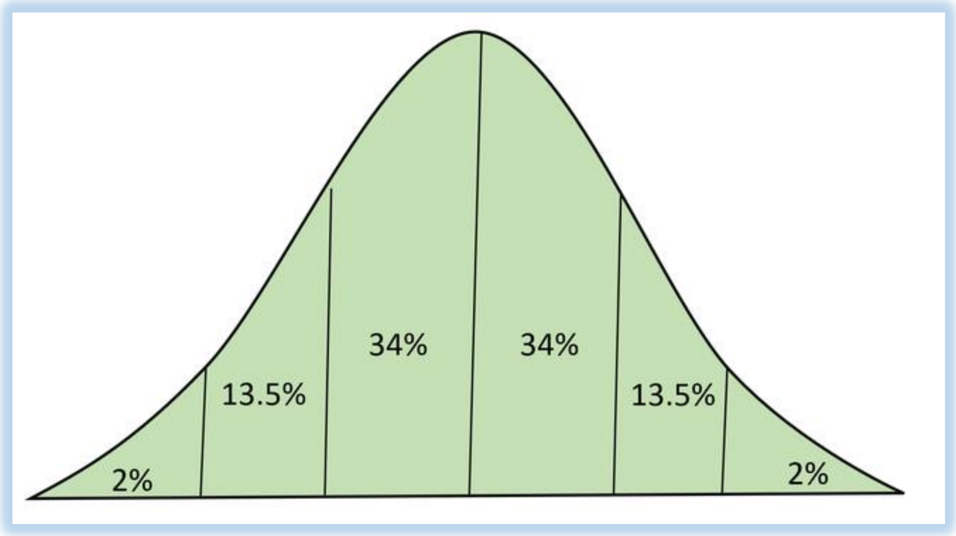
For the reference purpose, a 45% line is also plotted, if the samples are from the same population then the points are along this line.

Normal Distribution:

The normal distribution (aka Gaussian Distribution/ Bell curve) is a continuous probability distribution representing distribution obtained from the randomly generated real values.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Below is the portion of data representing different standard deviation



Usage:

The Quantile-Quantile plot is used for the following purpose:

- 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 behaviour.

Advantages 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.