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?

Ans: Below inferences can be drawn from the analysis of the categorical variables with respect to their effect on the dependent variable:

I. season vs cnt: It can be seen that during the Fall season the demand of shared bikes is the most, followed by Summer and winter and its lowest during the Spring season.

II. yr vs cnt: The demand for shared bikes is higher in the year 2019 than in 2018.

III. holiday vs cnt: median value is more when it is not a holiday but the IQR is wider in case it's a holiday.

IV. workingday vs cnt: median is higher when it is a working day but the IQR is wider in case when it's not a workingday.

V. weathersit vs cnt: demand is higher in clear weather.

VI. mnth vs cnt: demand is higher during the month of September.

VII. weekday vs cnt: demand is higher on Thursday and Friday.

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

Ans: It is important to use drop_first=True during dummy variable creation because otherwise it will produce redundant data which may affect our model. It simply creates (K-1) number of columns if a categorical column has K number of category. Suppose we want to do a dummy encoding for a column "Profession" which has "Employed", "Unemployed" and "Student" as its category. If drop_first=False i.e. if the first column is not dropped then it will create three different columns for "Employed", "Unemployed" and "Student". This may cause multicollinearity in the model. But if drop_first=True then only two columns will be created which are "Employed" and "Unemployed".

When "Employed" column has 1 and "Unemployed" as 0 it denotes that the profession is "Employed".

when "Employed" column has 0 and "Unemployed" as 1 it denotes that the profession is '"Unemployed"

and if both are 0 then it denotes "Student".

Employed	Unemployed	Profession is :
1	0	Employed
0	1	Unemployed
0	0	Student

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

Ans: Looking at the pair plot, it can be seen that '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?

Ans: here are the assumptions and how they are verified in the training set

Assumption	How they are checked
1. Error Terms are normally distributed	A plot was plotted of the residuals to check if the errors are normally distributed with a mean equal to zero.
2. Error Terms are independent of each other	The residuals are plotted against the predicted training data. As there was no particular pattern, we can conclude the error terms are independent
3. Homoscedasticity	After checking the residuals are independent, the **Goldfeld Quandt Test** was run to check for homoscedasticity. The null hypothesis was failed to be rejected as it has high p-Value which proved there is Homoscedasticity present.
4. There is linear relationship between predictor and predicted variable	Scatter plot was plotted to check the linearity
5. There is no multicollinearity	VIF values were checked to be under 5

5. Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes?

Ans: Based on the final model the top 3 features are:

1. Temp (positive significance, co-efficient value: 0.478)
2. Light_Snow&Rain_weather (negative significance, co-efficient value: -0.285)
3. Year (positive significance, co-efficient value: 0.234)

GENERAL SUBJECTIVE QUESTIONS

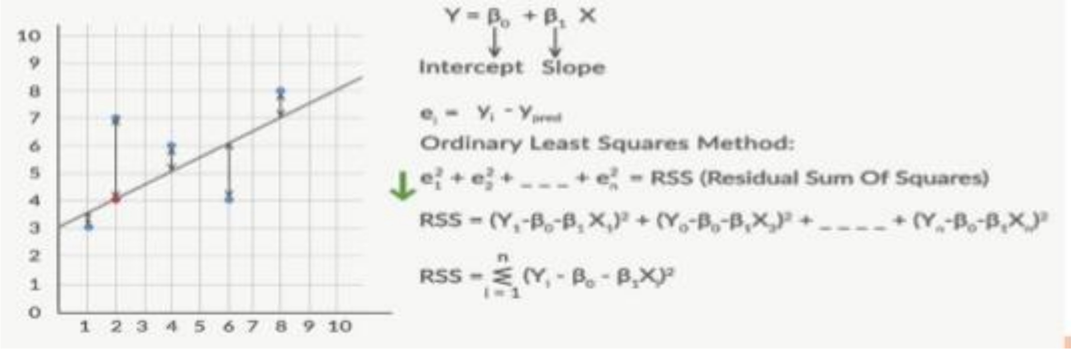
1. Explain the linear regression algorithm in detail.

Ans: Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. There are two types of Linear Regression:

- Simple Linear Regression: relationship between only one predictor variable and one target variable.
- Multiple Linear Regression: relationship between more than one predictor variable and a target variable

In the first step a scatter plot is plotted between the dependent and the independent variable. A best fit is tried to fit in the scatter plot. The standard equation of this line for simple linear regression is given by the expression of $\mathbf{y = \beta_0 + \beta_1 x}$, where β_0 is the y-intercept and β_1 is the slope of the line that actually means the change in y that takes place due to the unit change in x. For multiple linear regression, the equation of the line is **y =** $\boldsymbol{\beta_0}$**+** $\boldsymbol{\beta_1 x_1}$ **+** $\boldsymbol{\beta_2 x_2}$ **+ …… +** $\boldsymbol{\beta_p x_p}$, where x_1, x,…, x_p are the predictor variables.

The best-fit line is found by minimising the expression of RSS (Residual Sum of Squares) which is equal to the sum of squares of the residual for each data point in the plot. Residuals for any data point is found by subtracting predicted value of dependent variable from actual value of dependent variable:



$Y = \beta_0 + \beta_1 X$

Intercept Slope

$e_i = Y_i - Y_{pred}$

Ordinary Least Squares Method:

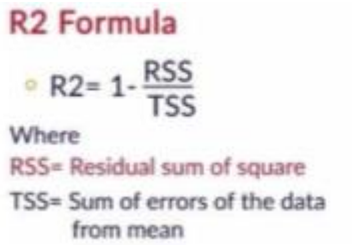
$e_1^2 + e_2^2 + \_\_\_ + e_n^2$ = RSS (Residual Sum Of Squares)

$RSS = (Y_1-\beta_0-\beta_1 X_1)^2 + (Y_0-\beta_0-\beta_1 X_2)^2 + \_\_\_\_ + (Y_n-\beta_0-\beta_1 X_n)^2$

$RSS = \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X)^2$

The strength of the linear regression model can be assessed using 2 metrics: 1. R² or Coefficient of Determination 2. Residual Standard Error (RSE)

R2 provides a measure of how well actual outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model, i.e. expected outcomes. So, the higher the R-squared, the better the model fits your data.



R2 Formula

- $R2 = 1 - \frac{RSS}{TSS}$

Where

RSS= Residual sum of square

TSS= Sum of errors of the data from mean

PreProcessing of the Data: This step is required before the splitting of the data. The Data is first cleaned, all unnecessary columns are removed. Categorical variables are treated with dummy encoding and all the continuous variables are scaled: either by the method of standardisation or normalisation.

Splitting of Train and Test Sets: The entire dataset is divided two parts- Training and Test Set. The data is divided in the ratio of 70% Training and 30% Test data or in the ratio of 80-20 percent ratio.

Adjusted R²: In case of multiple linear regression, we check the adjusted R-squared value instead of the simple R-squared as adjusted R-squared penalizes the model if it keeps on adding redundant variables whereas R-squared only increases as we add more variables.

Model Building: Model is built using feature selection. The various methods for optimal feature selection:

1. Try all possible combinations (2p models for p features)

    - Time consuming and practically unfeasible
2. Manual Feature Elimination
    - Build model
    - Drop features that are least helpful in prediction (high p-value)
    - Drop features that are redundant (using correlations, VIF, usually >5)
    - Rebuild model and repeat
3. Automated Approach
    - Recursive Feature Elimination (RFE)
    - Forward/Backward/Stepwise Selection based on AIC

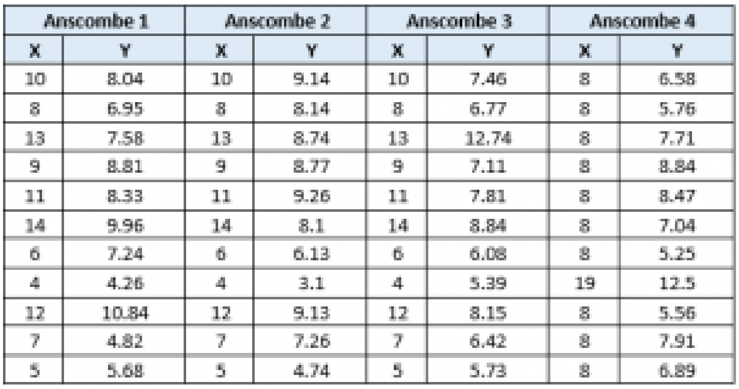
It is generally recommended that we follow a balanced approach, i.e., use a combination of automated (coarse tuning) + manual (fine tuning) selection in order to get an optimal model.

After performing these steps, we need to do a residual analysis of the train data where by the assumptions of linear regression, we need to make check if the error terms are normally distributed and homoscedastic.

Next, We make predictions on the test set using the final model that we have built with the train set. If we get a R-squared value for the plot of the actual Y and the predicted Y, around the R-squared value we got in our final regression model using the training set, we can say that our model is a fine predictor of our unknown test set and we can go forward with that model. The coefficients we use for our model equation are the coefficients we obtain from the final regression on our training set.

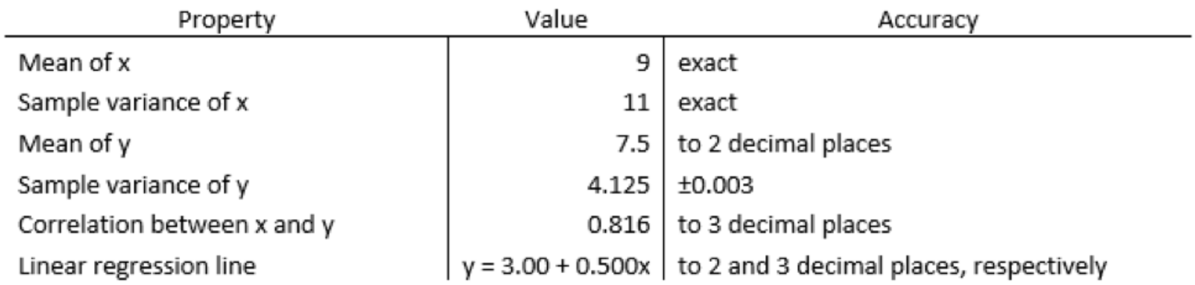
2. Explain the Anscombe's quartet in detail

Ans: The statistician France Anscombe constructed the Anscombe dataset in 1973. Anscombe created the dataset to show the importance of visualizing data and also to highlight how outliers can have an effect on the statistical findings of a dataset. Anscombe's Quartet consists of four data sets, that when examined have nearly the identical statistical properties, yet when graphed the datasets tell a very different story. Each of the datasets in the quartet consists of 11 (x,y) points:



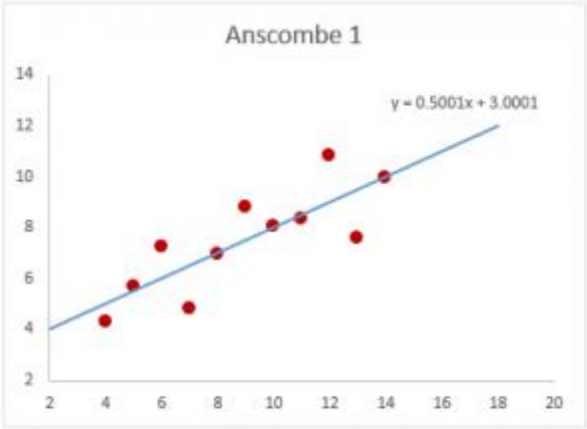
Anscombe 1		Anscombe 2		Anscombe 3		Anscombe 4	
X	Y	X	Y	X	Y	X	Y
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.1	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.1	4	5.39	19	12.5
12	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

Each Dataset in the quartet consists of the following statistical analysis:

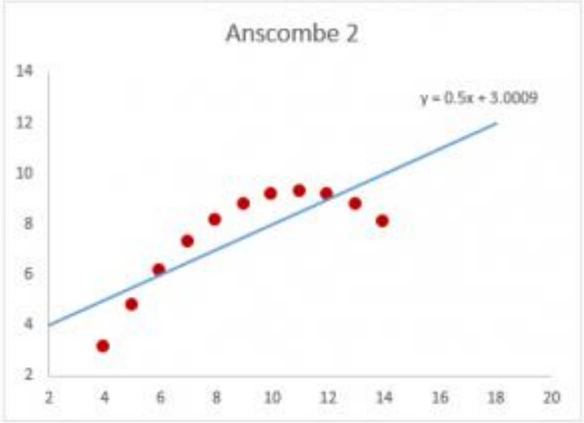


Property	Value	Accuracy
Mean of x	9	exact
Sample variance of x	11	exact
Mean of y	7.5	to 2 decimal places
Sample variance of y	4.125	±0.003
Correlation between x and y	0.816	to 3 decimal places
Linear regression line	y = 3.00 + 0.500x	to 2 and 3 decimal places, respectively

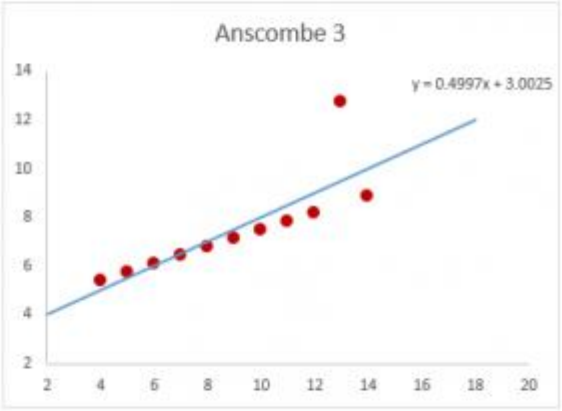
Anscombe 1 – This graph shows a simple linear positive relationship. It is what we would expect to see, assuming a normal distribution.



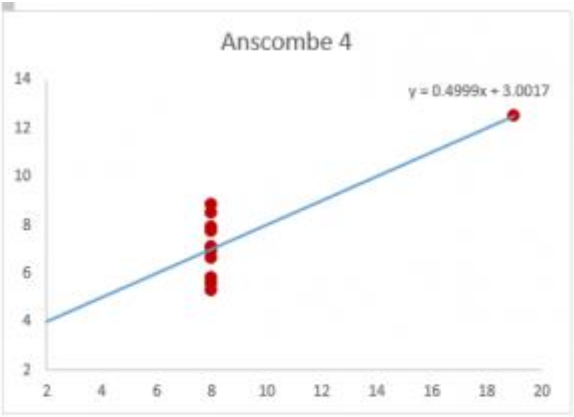
Anscombe 2 – This graph does not appear to be normally distributed. We can however see a relationship between the 2   variables, it appears to be quadratic or parabolic, but it is not linear.



Anscombe 3 – This graph is showing a clear outlier in the dataset. The data points, with the exception of the outlier are showing what appears to be perfect linear relationship, but because of the outlier the value of the correlation coefficient has been reduced from 1 to 0.816.



Anscombe 4 – In this graph we can see that the value of x stays constant with the exception of one outlier. This outlier has created the same correlation coefficient as the other datasets, which is a high correlation, however the relationship between the two variables is not linear.



3. What is Pearson's R?

Ans: Pearson's R also known as the Pearson's Correlation constant, measures the strength of the linear association between two continuous variables X and Y. It is known as the best method of measuring the association between variables of interest because it is based on the method of covariance. It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship. The coefficient varies between -1 and +1. The formula is as follows:

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

r_{xy} = Pearson r correlation coefficient between x and y
n = number of observations
x_i = value of x (for i^{th} observation)
y_i = value of y (for i^{th} observation)

Assumptions:

1. Both variables should be normally distributed i.e the normal distribution describes how the values of a variable are distributed

2. There should be no significant outliers as Pearson's R is very sensitive to outliers, which can have a very large effect on the line of best fit and the Pearson correlation coefficient.
3. Each variable should be continuous.
4. The two variables have a linear relationship.
5. The observations are paired observations. That is, for every observation of the independent variable, there must be a corresponding observation of the dependent variable.
6. Homoscedasticity: the residuals scatterplot should be roughly rectangular-shaped

Properties:
1. Limit: Coefficient values can range from +1 to -1, where +1 indicates a perfect positive relationship, -1 indicates a perfect negative relationship, and a 0 indicates no relationship exists..
2. Pure number: It is independent of the unit of measurement. For example, if one variable's unit of measurement is in inches and the second variable is in quintals, even then, Pearson's correlation coefficient value does not change.
3. Symmetric: Correlation of the coefficient between two variables is symmetric. This means between X and Y or Y and X, the coefficient value of will remain the same.

Degree of correlation:
1. Perfect: If the value is near ± 1, then it said to be a perfect correlation: as one variable increases, the other variable tends to also increase (if positive) or decrease (if negative).
2. High degree: If the coefficient value lies between ± 0.50 and ± 1, then it is said to be a strong correlation.
3. Moderate degree: If the value lies between ± 0.30 and ± 0.49, then it is said to be a medium correlation.
4. Low degree: When the value lies below + .29, then it is said to be a small correlation.
No correlation: When the value is zero.

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling?
Ans: Scaling is a technique to standardize the independent features present in the data in a fixed range. In data processing, it is also known as data normalization and is generally performed during the data preprocessing step.
Reason: While working with a model, it is important to scale the features to a range which is centered around zero. This is done so that the variance of the features are in the same range. If a feature's variance is orders of magnitude more than the variance of other features, that particular feature might dominate other features in the dataset.

Normalized Scaling vs Standardised Scaling:
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.
Standardization is another scaling technique 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.

- Normalization is good to use when you know that the distribution of your data does not follow a Gaussian distribution. This can be useful in algorithms that do not assume any distribution of the data like K-Nearest Neighbors and Neural Networks.
- Standardization, on the other hand, can be helpful in cases where the data follows a Gaussian distribution. However, this does not have to be necessarily true. Also, unlike normalization, standardization does not have a bounding range. So, even if you have outliers in your data, they will not be affected by standardization.

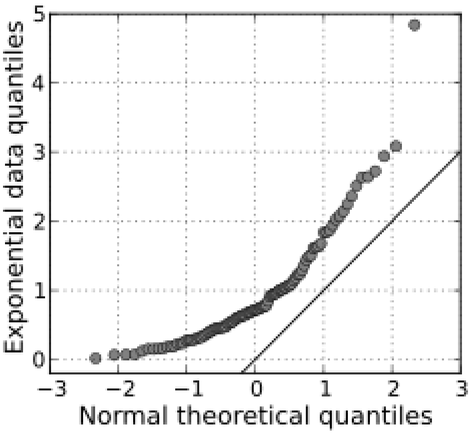
5. You might have observed that sometimes the value of VIF is infinite. Why does this happen?
Ans: **Variance inflation factor** *(VIF)* signifies the extent of correlation between one predictor and the other predictors in a model. It is used for checking collinearity/multicollinearity among the predictor variables. Higher values signify that it is difficult to impossible to assess accurately the contribution of predictors to a model. The formula for VIF is as follows:

$$VIF = \frac{1}{1 - R^2}$$

where R-squared value signifies extent to which a predictor is correlated with the other predictor variables in a linear regression. 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). This happens when R^2 value becomes 1.

6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression.
Ans: The quantile-quantile (q-q) plot is a graphical technique for determining if two data sets come from populations with a common distribution. 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, it is meant that 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.

Use: A 45-degree reference line is 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: 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 a more powerful approach to do this than the common technique of comparing histograms of the two samples, but requires more skill to interpret. 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. 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.