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)

The categorical variables found in the final model which help in determining the value of the dependent variable, demand **(cnt)** are **'season', 'mnth', 'weekday','weathersit', 'Yr', 'holiday'**

Weathersit : Summer and Winter
While the categorical variables season in summer and Winter do have considerable amount sees increase in bookings , whereas (weathersit_Mist & Cloudy , weathersit_Light Snow & Rain have negative coefficients indicate that an decrease in these values will lead to an decrease in the bike rentals

mnth : August and September
In the months of August and September there was considerable increase in the rental of bikes. And further months it shows the decreasing trend.

weekday: Saturday
More no of bookings were over the weekend(Saturday) compared to the start of the week.

Yr:2019
2019 shows more no of bookings compared to the 2018. Which shows growth in business.

holiday: During holiday there was very low no.of bookings . Maybe because people would be spending quality time with the family and celebrate indoors , rather than travelling.

This was inferred by looking at the coefficients of the variables in the final qualifying model.

The coefficients of the categorical variable in the qualifying model are

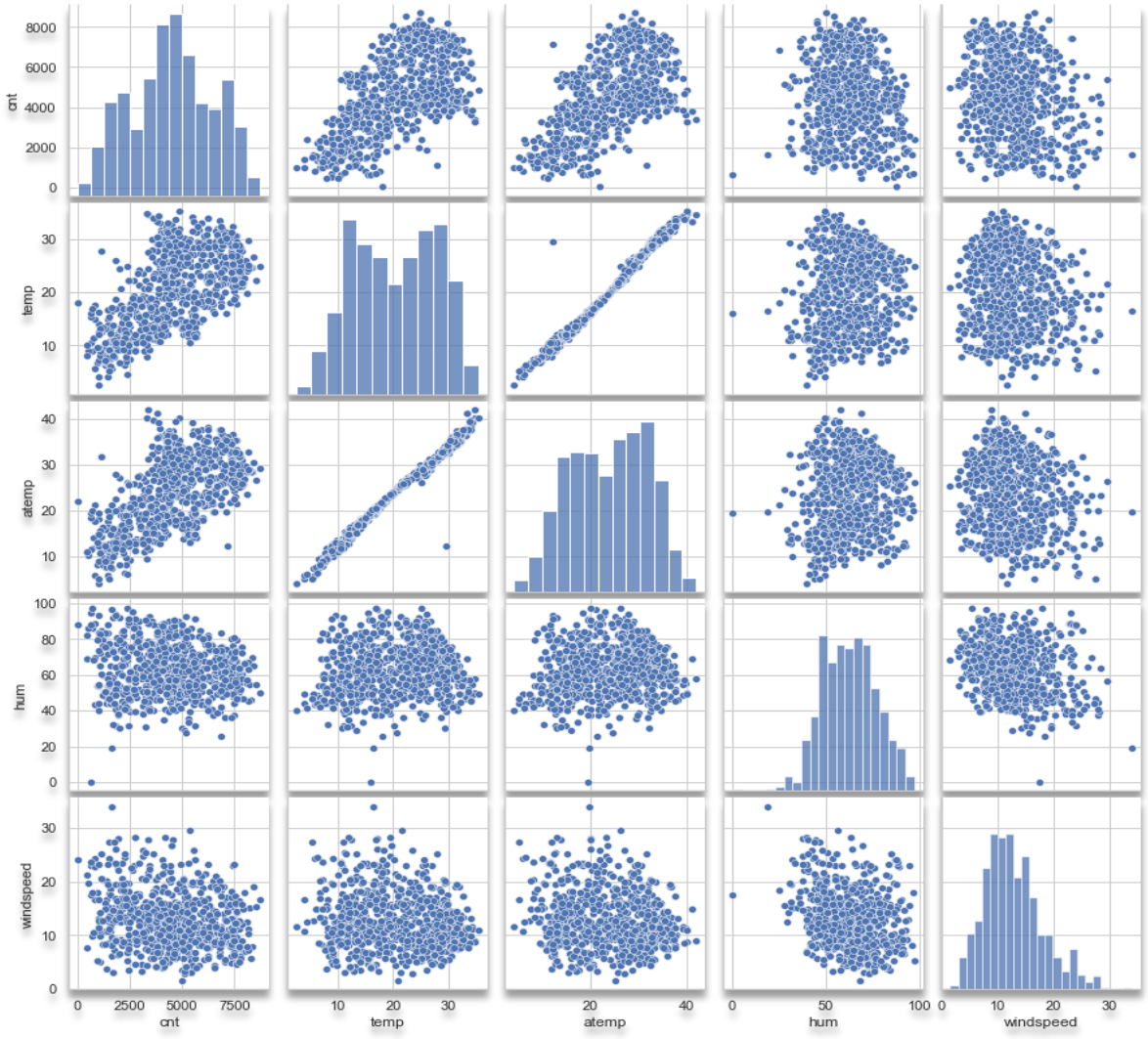
- season_Summer: 0.101995
- season_Winter: 0.148613
- mnth_Aug : 0.052332
- mnth_Sep: 0.119376
- weekday_Saturday: 0.052003
- yr: 0.228914
- workingday: 0.043346
- weathersit_Mist & Cloudy: -0.057896
- weathersit_Light Snow & Rain: -0.243111
- holiday: -0.058111

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

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

If we don't drop the first column then your dummy variables will be correlated. This may affect some models adversely and the effect is stronger when the cardinality is smaller. For example iterative models may have trouble converging and lists of variable importance may be distorted.

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



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

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

Following are the assumptions I have taken into consideration to validate of Linear Regression after building the mode on the training set:

- **Multicollinearity** Check on the variables (VIF values <0.05)
- **Residual Analysis on Error Terms :** If it is normally distributed and its mean is 0 . Linearity and independence of residuals
- **Homoscedasticity :** We checked if the residuals have constant variance.
- **R2 and Adjusted R2** : Checked R2 if the model is significant
  Train dataset R^2 : 0.846
  Train dataset Adjusted R^2 : 0.842
- **F- Statistics and Prob (F-statistic)** : This value helped to check the overall fir of the model.
  F-statistic: 210.2 Prob (F-statistic): 3.81e-192
  The F-Statistics value of 210.2 (which is greater than 1) and the p-value is almost 0 states that the overall model is significant

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

The top 3 features contributing significantly towards explaining the demand of the shared bikes are:

Variables	Coefficients
temp	0.5394
yr	0.2289
season_Winter	0.1486

General Subjective Questions

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

Linear Regression is a machine learning algorithm based on supervised learning. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables.

y = c + m * x ## Linear Equation

c=’constant

m = intercept

x = x variable / independent variable

y= target variable / dependent variable

Types of Linear Regression

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 independent variable increases on X-axis, then such a relationship is termed as a Positive linear relationship.

Linear Regression in Machine Learning

Negative Linear Relationship:

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

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

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.

It was constructed in 1973 by statistician Francis Anscombe to illustrate the importance of plotting the graphs before analyzing and model building, and the effect of other observations on statistical properties. There are these four data set plots which have nearly same statistical observations, which provides same statistical information that involves variance, and mean of all x,y points in all four datasets.

This tells us about the importance of visualising the data before applying various algorithms out there to build models out of them which suggests that the data features must be plotted in order to see the distribution of the samples that can help you identify the various anomalies present in the data like outliers, diversity of the data, linear separability of the data, etc. Also, the Linear Regression can be only be considered a fit for the data with linear relationships and is incapable of handling any other kind of datasets.

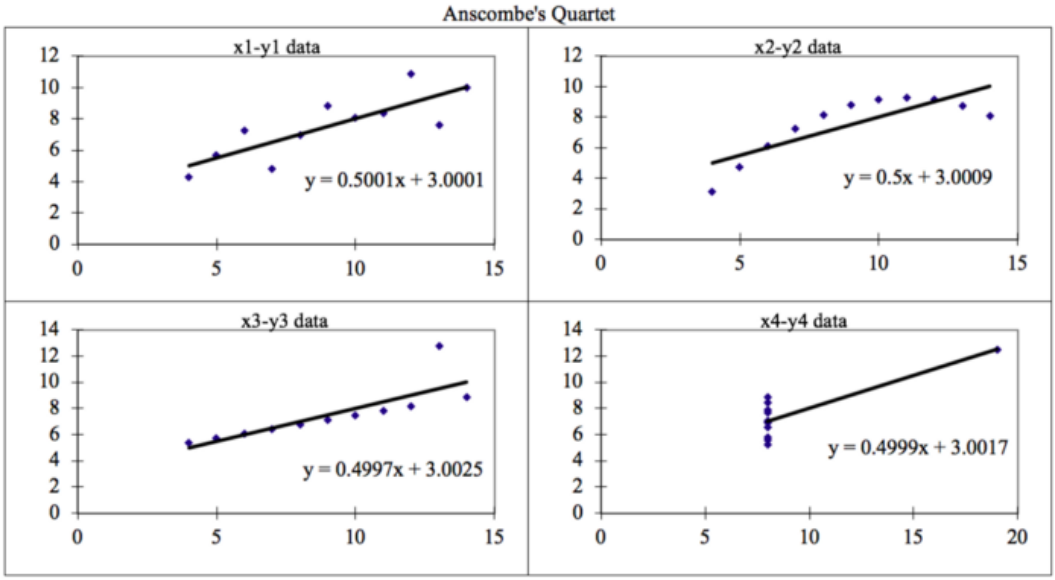
These four plots can be defined as follows:

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

The statistical information for all these four datasets are approximately similar and can be computed as follows:

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	

When these models are plotted on a scatter plot, all datasets generates a different kind of plot that is not interpretable by any regression algorithm which is fooled by these peculiarities and can be seen as follows:



The four datasets can be described as:

Dataset 1: this fits the linear regression model pretty well.

Dataset 2: this could not fit linear regression model on the data quite well as the data is non-linear.

Dataset 3: shows the outliers involved in the dataset which cannot be handled by linear regression model

Dataset 4: shows the outliers involved in the dataset which cannot be handled by linear regression model

Conclusion:

We have described the four datasets that were intentionally created to describe the importance of data visualisation and how any regression algorithm can be fooled by the same. Hence, all the important features in the dataset must be visualised before implementing any machine learning algorithm on them which will help to make a good fit model.

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

Pearson's correlation (also called Pearson's *R*) is a **correlation coefficient** commonly used in linear regression.

Pearson's correlation is the test statistics that measures the statistical relationship, or association, between two continuous variables. 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.

Assumptions:

Independent of case: Cases should be independent to each other.

Linear relationship: Two variables should be linearly related to each other. This can be assessed with a scatterplot: plot the value of variables on a scatter diagram, and check if the plot yields a relatively straight line.

Homoscedasticity: the residuals scatterplot should be roughly rectangular-shaped.

Properties:

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..

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.

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:

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).

High degree: If the coefficient value lies between ± 0.50 and ± 1, then it is said to be a strong correlation.

Moderate degree: If the value lies between ± 0.30 and ± 0.49, then it is said to be a medium correlation.

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? (3 marks)

Scaling 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.

Why is scaling performed?

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.
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.

Difference between normalized scaling and standardized scaling

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.

5. You might have observed that sometimes the value of VIF is infinite. Why does this happen? (3 marks)

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.

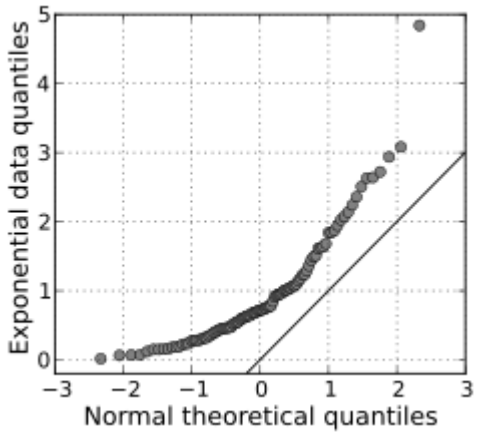
An infinite VIF value indicates that the corresponding variable may be expressed exactly by a linear combination of other variables (which show an infinite VIF as well).

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

Q-Q Plots (Quantile-Quantile plots) are plots of two quantiles against each other. A quantile is a fraction where certain values fall below that quantile. For example, the median is a

quantile where 50% of the data fall below that point and 50% lie above it. The purpose of Q Q plots is to find out if two sets of data come from the same distribution. A 45 degree angle is plotted on the Q Q plot; if the two data sets come from a common distribution, the points will fall on that reference line.

A Q Q plot showing the 45 degree reference line:



If the two distributions being compared are similar, the points in the Q–Q plot will approximately lie on the 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.

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.