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:
   Based on analysis with categorical columns using the boxplot and bar plot. Below are the few points, we could infer from the visualizations –
   - ✓ Fall season has attracted more booking and in each season the booking count has increased drastically from 2018 to 2019.
   - ✓ Trend increased starting of the year till mid of the year and then it started decreasing as we approached the end of year. Most of the bookings has been done during the months of May, June, July, Aug, Sep and Oct.
   - ✓ Clear weather attracted more bookings as noticed.
   - ✓ Wed, Thu, Fir and Sat had a greater number of bookings as compared to the start of the week.
   - ✓ On holidays, booking seems to be less in number which seems reasonable as on holidays, people may want to spend time at home and enjoy with family.
   - ✓ Year 2019 has higher Bike Rental than the year 2018, which shows good progress in terms of business.

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

   Answer:
   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.

Let's break it down:

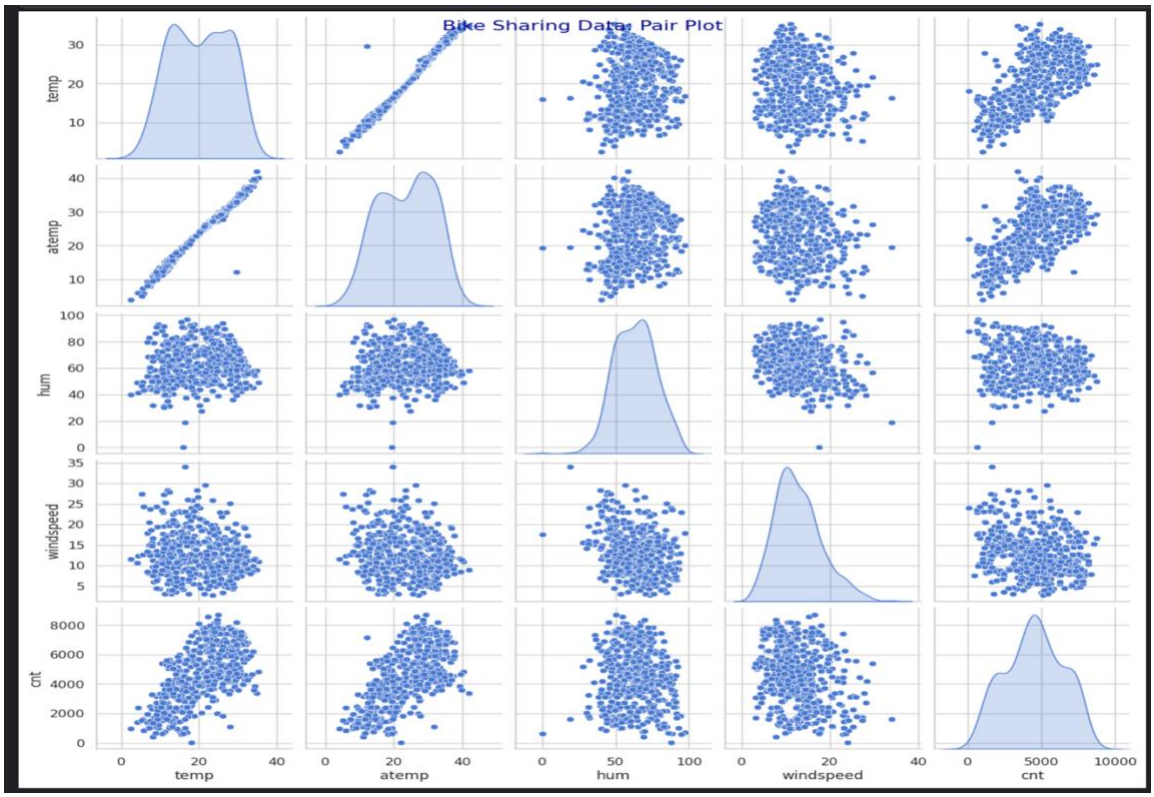
- **Dummy Variable Trap**: When creating dummy variables for categorical features, it's common to create one dummy variable for each level of the categorical variable. For example, if we have a categorical variable "Color" with three levels: Red, Green, and Blue, we might create dummy variables like `is_red`, `is_green`, and `is_blue`.

- **Multicollinearity**: However, including all dummy variables in the regression model without dropping one can lead to multicollinearity. This is because the presence of all dummy variables implies the value of the dropped dummy variable. For instance, if `is_red=0` and `is_green=0`, it implies that the color must be blue. Therefore, the information about one category can be derived from the others, leading to multicollinearity.

- **Drop First**: By using `drop_first=True`, we drop the first level of the categorical variable when creating dummy variables. This removes redundant information and helps to mitigate multicollinearity. It effectively eliminates one of the dummy variables, so each dummy variable becomes independent of the others.

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` variable has the highest correlation with the target variable `cnt`.



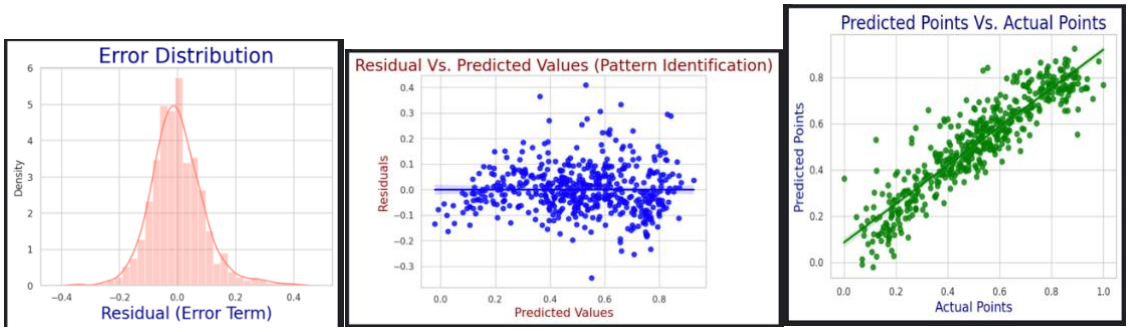
4. **How did you validate the assumptions of Linear Regression after building the model on the training set? (3 marks)**

Answer:
I have validated the assumption of Linear Regression Model based on below 5 assumptions -

- ✓ Normality of error terms
  - Error terms should be normally distributed in the histogram of the error terms and found that "Error Distribution" Is Normally Distributed Across 0
- ✓ Multicollinearity check
  - There should be insignificant multicollinearity among variables using VIF
- ✓ Linear relationship validation
  - Linearity should be visible among variables
- ✓ Homoscedasticity
  - There should be no visible pattern in residual values.

    we can see that variance is similar from both ends of the fitted line.

- ✓ Independence of residuals
  - We have used Residual Analysis to validate the assumptions of Linear Regression



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 on my model these are the **top 3 positive** features contributing significantly towards explaining the **demand** of the shared bikes –

- temp
- yr
- weather_winter

Below are the **top 3 negative** features contributing significantly towards explaining the **drop in demand** of the shared bikes –

- weathersit_bad
- windspeed
- holiday

General Subjective Questions

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

Answer:
Linear regression may be defined as the statistical model that analyses the linear relationship between a dependent variable with given set of independent variables.
It means that when the value of one or more independent variables changes (increase or decrease), the value of dependent variable will also change accordingly (increase or decrease).

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.

Linear regression is of the following two types −

- Simple Linear Regression
- Multiple Linear Regression

Assumptions -

The following are some assumptions about dataset that is made by Linear Regression model −

- ✓ Multi-collinearity –
  - Linear regression model assumes that there is very little or no multi-collinearity in the data. Basically, multi-collinearity occurs when the independent variables or features have dependency in them.
- ✓ Auto-correlation –
  - Another assumption Linear regression model assumes is that there is very little or no auto-correlation in the data. Basically, auto-correlation occurs when there is dependency between residual errors.
- ✓ Relationship between variables –
  - Linear regression model assumes that the relationship between response and feature variables must be linear.
- ✓ Normality of error terms –

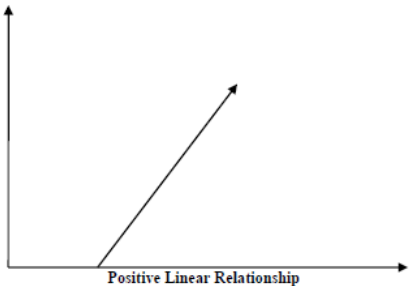
- Error terms should be normally distributed

✓ Homoscedasticity –

There should be no visible pattern in residual values.

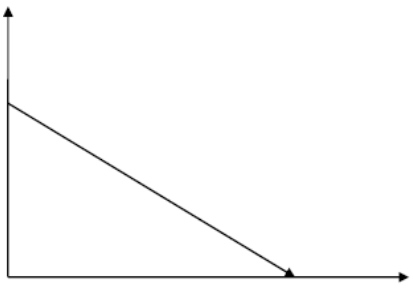
Furthermore, the linear relationship can be positive or negative in nature as explained below−

- Positive Linear Relationship:
  - A linear relationship will be called positive if both independent and dependent variable increases. It can be understood with the help of following graph –



Positive Linear Relationship

- Negative Linear relationship:
  - A linear relationship will be called positive if independent increases and dependent variable decreases. It can be understood with the help of following graph −



Negative Linear Relationship

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

Answer:

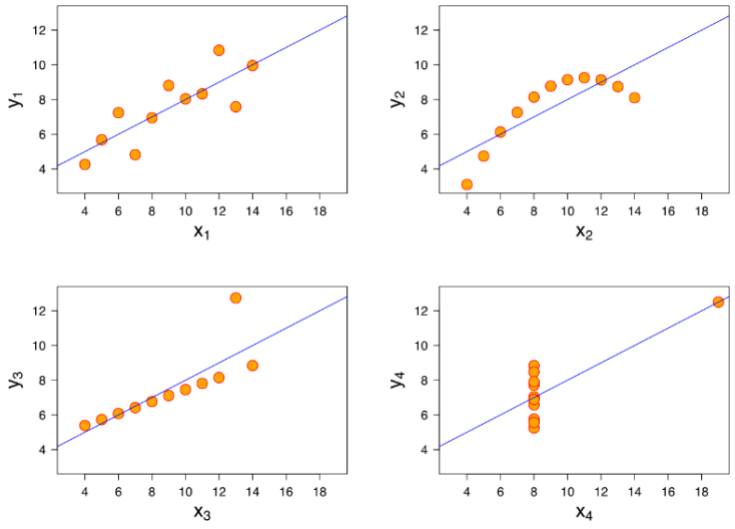
Anscombe's Quartet was developed by statistician **Francis Anscombe**. It comprises four datasets, each containing eleven (x, y) pairs. The essential thing to note about these datasets is that they share the same descriptive statistics. But things change completely, and I must emphasize COMPLETELY, when they are graphed. Each graph tells a different story irrespective of their similar summary statistics.

	I		II		III		IV	
	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
SUM	99,00	82,51	99,00	82,51	99,00	82,50	99,00	82,51
AVG	9,00	7,50	9,00	7,50	9,00	7,50	9,00	7,50
STDEV	3,32	2,03	3,32	2,03	3,32	2,03	3,32	2,03

The summary statistics show that the means and the variances were identical for x and y across the groups:

- Mean of x is 9 and mean of y is 7.50 for each dataset.
- Similarly, the variance of x is 11 and variance of y is 4.13 for each dataset
- The correlation coefficient (how strong a relationship is between two variables) between x and y is 0.816 for each dataset

When we plot these four datasets on an x/y coordinate plane, we can observe that they show the same regression lines as well, but each dataset is telling a different story:



- **Dataset I** appear to have clean and well-fitting linear models.
- **Dataset II** is not distributed normally.
- In **Dataset III** the distribution is linear, but the calculated regression is thrown off by an outlier.
- **Dataset IV** shows that one outlier is enough to produce a high correlation coefficient.

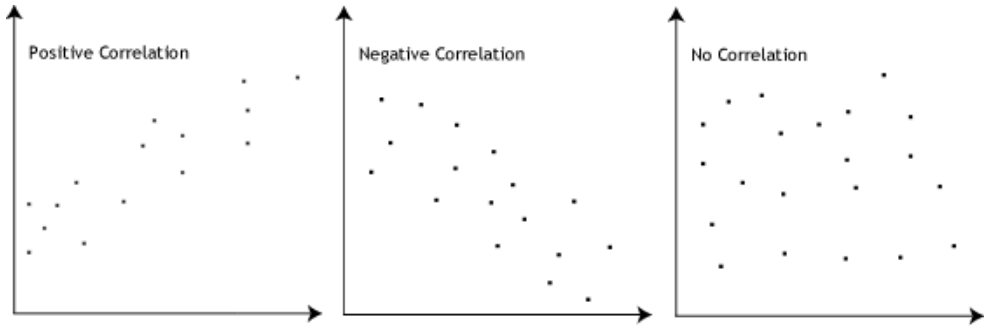
This quartet emphasizes the importance of visualization in Data Analysis. Looking at the data reveals a lot of the structure and a clear picture of the dataset.

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

Answer:
Pearson's r is a numerical summary of the strength of the linear association between the variables.

- If the variables tend to go up and down together, the correlation coefficient will be positive.
- If the variables tend to go up and down in opposition with low values of one variable associated with high values of the other, the correlation coefficient will be negative.

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)**

Answer:
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 feature scaling method, then it can consider the value 3000 meter to be greater than 5 km but that's not true, which may lead to the algorithm give

wrong predictions. So, we use Feature Scaling to bring all values to same magnitudes and thus, tackle this issue.

S.NO.	Normalized scaling	Standardized scaling
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.

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. If the VIF is 4, this means that the variance of the model coefficient is inflated by a factor of 4 due to the presence of multicollinearity.

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. To solve this 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:

The quantile-quantile (q-q) plot is a graphical technique for determining if two data sets come from populations with a common distribution.

The Q-Q plot is designed to help you visually compare the quantiles of your data to the quantiles of a theoretical distribution, which can reveal deviations from the expected distribution. a Q-Q plot is a valuable tool for assessing the distribution of data, especially in the context of linear regression. It helps evaluate the normality assumption, detect skewness and outliers, and guide model improvement if deviations are observed.

Use of Q-Q plot:

A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second dataset. By a quantile, we mean 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. A 45-degree reference line is also 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 of Q-Q plot:

When there are two data samples, it is often desirable to know if the assumption of a common distribution is justified. If so, then location and scale estimators can pool both data sets to obtain estimates of the common location and scale. If two samples do differ, it is also useful to gain some understanding of the differences.

The q-q plot can provide more insight into the nature of the difference than analytical methods such as the **chi-square** and **Kolmogorov-Smirnov 2-sample test**