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:

I have done analysis on categorical columns using the boxplot and bar plot. Below are the few points we can infer from the visualization –

- season: Most of the bike booking were happening in summer and fall with a median of over 5000 booking. This indicates, season can be a good predictor for the dependent variable.
- month: Most bike booking was happening in the months May, June, July, Aug, Sep & Oct with a median of over 4000 booking per month. This indicates, month has some trend for bookings and can be a good predictor for the dependent variable.
- Weather sit: Most of the bike booking were happening during clear weather with a median of close to 5000 booking followed by cloudy with median above 4000.This indicate, weather sit does show some trend towards the bike bookings can be a good predictor for the dependent variable.
- holiday: Most of the bike booking were happening when it is not a holiday. This indicates, holiday can't be a good predictor for the dependent variable for increasing bookings.
- weekday: weekday variable shows very close trend having their independent medians between 4000 to 5000 bookings. This variable can have some or no influence towards the predictor.
- Working day: Almost 69% of the bike booking were happening in 'working day' with a median of close to 5000 booking (for the period of 2 years). This indicates, working day can be a good predictor for the dependent variable
- yr: 2019 is clearly a better year the bike booking. This indicates it could be useful.

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

While there are k levels in a categorical variable, it is tempting to create k dummy columns (or variables) to represent each level with a distinct column, it is important to consider the multi-collinearity issues which arise with that outlook towards dummy variable creation.

Multi-collinearity is an issue that arises while building an ML model if two or more variables carry the same amount or very similar information. This essentially affects the interpretability of the model.

If we create k dummy variables for k levels of categorical data, the kth variable contains no new information.

This is why it is important to use drop_first = True when we create dummy variables, to avoid multi-collinearity issues and maintain an interpretable model.

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

temp 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:**

While building the model, the Variance Inflation Factor was monitored closely to remove feature variables with very high correlation values to combat multi-collinearity and preserve the interpretability of the model.

- After training the model with a good number feature variables and after arriving at satisfying values for adjusted R-squared, AIC and BIC, the model was evaluated on a test set that was separated from the main dataset before beginning the analysis. Out of the 2 models, the qualifying model gave an R-squared value of 0.778 on the evaluation set.
- Another assumption of Linear Regression was tested by conducting a residual analysis on the error terms of the fitted data. The end result of the residual analysis was a normal distribution of the error terms, centered around 0.

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:**

The Top 3 features contributing significantly towards the demands of share bikes are:

 weathersit_Light_Snow (negative correlation).
 yr_2019 (Positive correlation).
 temp (Positive correlation).

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. Linear relationship between variables means that when the value of one or more independent variables will change (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.

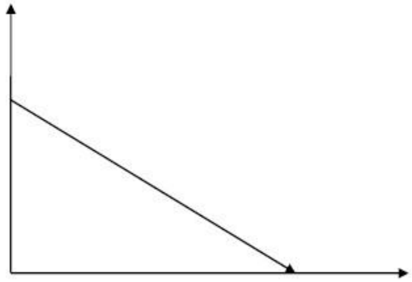
Furthermore, the linear relationship can be positive or negative in nature as explained below−

- 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 grap.

- 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

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

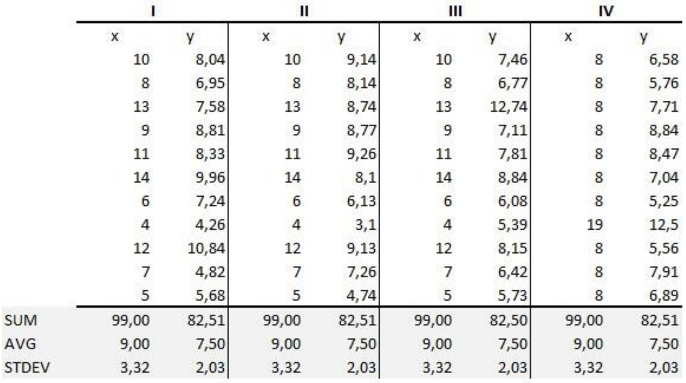
Homoscedasticity –

- There should be no visible pattern in residual values.

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.

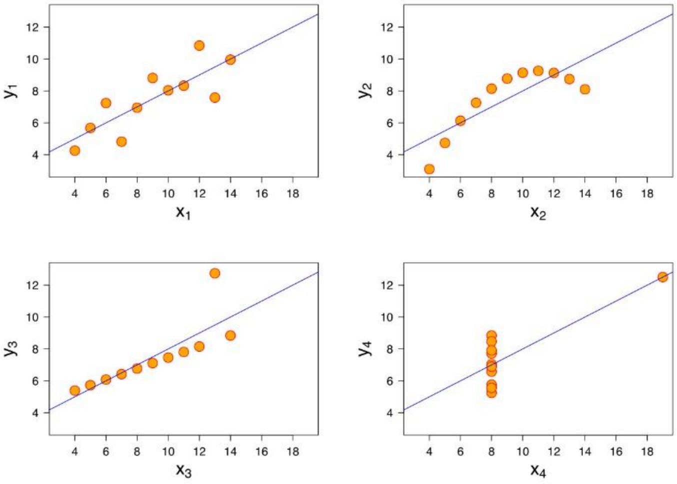


	I		II		III		IV	
	x	y	x	y	x	y	x	y
	10	8,04	10	9,14	10	7,46	8	6,58
	8	6,95	8	8,14	8	6,77	8	5,76
	13	7,58	13	8,74	13	12,74	8	7,71
	9	8,81	9	8,77	9	7,11	8	8,84
	11	8,33	11	9,26	11	7,81	8	8,47
	14	9,96	14	8,1	14	8,84	8	7,04
	6	7,24	6	6,13	6	6,08	8	5,25
	4	4,26	4	3,1	4	5,39	19	12,5
	12	10,84	12	9,13	12	8,15	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:



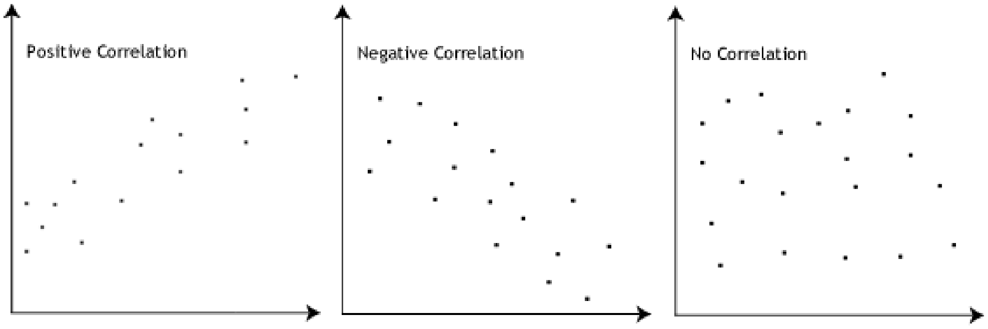
- Dataset I appears to have clean and well-fitting linear models.
- Dataset II is not distributed normally.
- In Dataset III the distribution is linear, but the calculated regression is thrown off by an outlier.
- Dataset IV shows that one outlier is enough to produce a high correlation coefficient.

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 actually not true and in this case, the algorithm will 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:

The formula for Variance Inflation Factor is

VIF = 1/1 – Ri^2

Where - The R-squared value of the fit between a feature variable as the dependent variable and the other feature variables as independent variables. When the Ri-squared value tends to 1, the denominator of the equation tends to zero, which in turn causes the value of the Variance Inflation Factor to tend to infinity.

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.

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