Assignment-based Subjective Questions

Q1) From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable?

- The demad of bike is less in the month of spring when compared with other seasons
- The demand bike increased in the year 2019 when compared with year 2018.
- Month Jun to Sep is the period when bike demand is high. The Month Jan is the lowest demand month.
- Bike demand is less in holidays in comparison to not being holiday.
- The demand of bike is almost similar throughout the weekdays.
- There is no significant change in bike demand with workign day and non working day.
- The bike demand is high when weather is clear and Few clouds however demand is less in case of Lightsnow and light rainfall. * * We do not have any dat for Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog , so we can not derive any conclusion. May be the company is not operating on those days or there is no demand of bike.

Q2) Why is it important to use **drop_first=True** during dummy variable creation?

The drop_first parameter specifies whether or not you want to drop the first category of the categorical variable you're encoding. By default, this is set to drop_first = False . This will cause get_dummies to create one dummy variable for every level of the input categorical variable.So to reduce the extra column creation during dummy variables we use drop_first=True.

Q3) Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable?

Temp has the highest correlation with cnt which is the target variable(After dropping the certain columns like atemp ,etc.)

Q4 How did you validate the assumptions of Linear Regression after building the model on the training set?

By doing Residual Analysis on y_train and y_train_predicted and then plotting distplot to check that normal distribution with mean is at zero and then plotting error terms with residul and y_train_predicted where we checked that residual plot is reasonably random and have reasonable constant variance(homoscedasticity)

Q5). Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes?

- Based on final model top three features contributing significantly towards explaining the demand are:

  1.Temperature (0.552)
  2.weathersit : Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds (-0.264)
  3.year (0.256)

General Subjective Questions

Q1) Explain the linear regression algorithm in detail.

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.
Mathematically we can represent as : **Y = B0+B1*X + E**

Where B0 = Intercept of line (Gives degree of freedom)
B1 = slope of line / Linear Regression Coefficient
E=Random Error
X = Predictor 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.

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 (B0, B1) gives a different line of regression, so we need to calculate the best values for B0 and B1 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 (B0,B1) 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.

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

- 2. Explain the Anscombe's quartet in detail.

Anscombe's quartet comprises four datasets that have nearly identical simple statistical properties, yet appear very different when graphed. Each dataset consists of eleven (x,y) points.

Simple understanding:

Once Francis John "Frank" Anscombe who was a statistician of great repute found 4 sets of 11 data-points in his dream and requested the council as his last wish to plot those points. Those 4 sets of 11 data-points are given below.

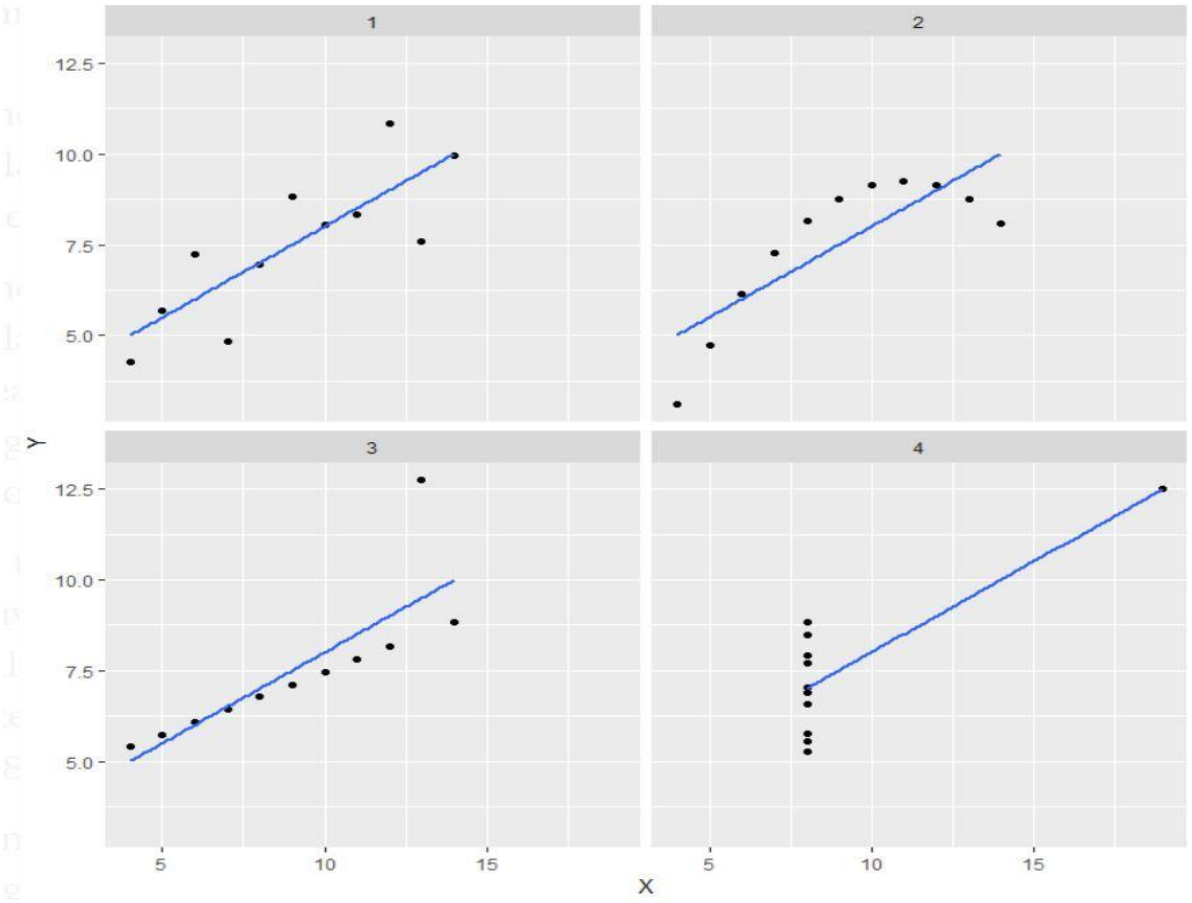
I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

After that, the council analyzed them using only descriptive statistics and found the mean, standard deviation, and correlation between x and y.

Summary

Set	mean(X)	sd(X)	mean(Y)	sd(Y)	cor(X,Y)
1	9	3.32	7.5	2.03	0.816
2	9	3.32	7.5	2.03	0.816
3	9	3.32	7.5	2.03	0.816
4	9	3.32	7.5	2.03	0.817

t is mentioned in the definition that Anscombe's quartet comprises four datasets that have nearly identical simple statistical properties, yet appear very different when graphed.



Explanation of this output:

- In the first one(top left) if you look at the scatter plot you will see that there seems to be a linear relationship between x and y.
- In the second one(top right) if you look at this figure you can conclude that there is a non-linear relationship between x and y.
- In the third one(bottom left) you can say when there is a perfect linear relationship for all the data points except one which seems to be an outlier which is indicated be far away from that line.
- Finally, the fourth one(bottom right) shows an example when one high-leverage point is enough to produce a high correlation coefficient.

Application:

The quartet is still often used to illustrate the importance of looking at a set of data graphically before starting to analyze according to a particular type of relationship, and the inadequacy of basic statistic properties for describing realistic datasets.

3. What is Pearson's R?

The Pearson correlation coefficient (r) is **the most common way of measuring a linear correlation**. It is a number between –1 and 1 that measures the strength and direction of the relationship between two variables. When one variable changes, the other variable changes in the same direction.
It is known by many names:

>Pearson's r

> Bivariate correlation

>Pearson product-moment correlation coefficient (PPMCC)

>The correlation coefficient

The Pearson correlation coefficient is a descriptive statistic, meaning that it summarizes the characteristics of a dataset. Specifically, it describes the strength and direction of the linear relationship between two quantitative variables.

Although interpretations of the relationship strength vary between disciplines, the table below gives general rules of thumb:

Pearson correlation coefficient (*r*) value	**Strength**	**Direction**
Greater than .5	Strong	Positive
Between .3 and .5	Moderate	Positive
Between 0 and .3	Weak	Positive
0	None	None
Between 0 and –.3	Weak	Negative
Between –.3 and –.5	Moderate	Negative
Less than –.5	Strong	Negative

When to use the Pearson correlation coefficient

The Pearson correlation coefficient (*r*) is one of several correlation coefficients that you need to choose between when you want to measure a correlation. The Pearson correlation coefficient is a good choice when **all** of the following are true:

- **Both variables are quantitative:** You will need to use a different method if either of the variables is qualitative.
- **The variables are normally distributed:** You can create a histogram of each variable to verify whether the distributions are approximately normal. It's not a problem if the variables are a little non-normal.
- **The data have no outliers:** Outliers are observations that don't follow the same patterns as the rest of the data. A scatterplot is one way to check for outliers—look for points that are far away from the others.
- **The relationship is linear:** "Linear" means that the relationship between the two variables can be described reasonably well by a straight line. You can use a scatterplot to check whether the relationship between two variables is linear.

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling?

What?

It 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?

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.*

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**).*

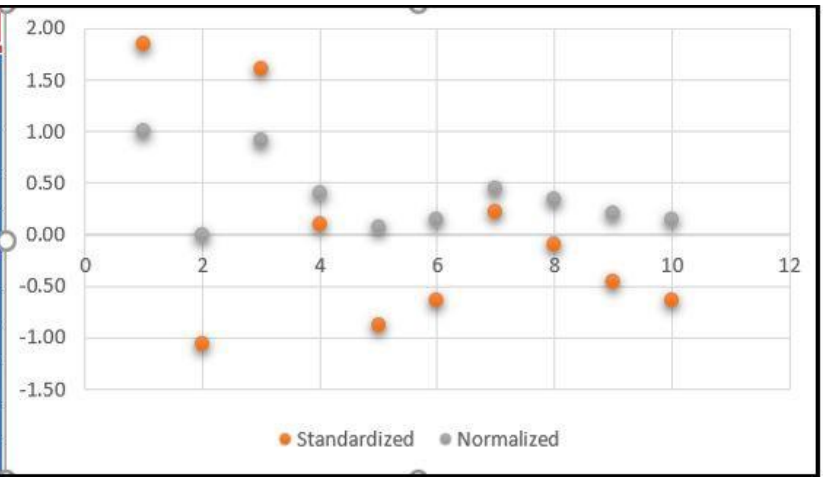
$$\text{Standardisation: } x = \frac{x - mean(x)}{sd(x)}$$

- ***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**.*

Example:

Below shows example of Standardized and Normalized scaling on original values.

Original	Standardized	Normalized
59	1.85	1.000
11	-1.06	0.000
55	1.61	0.917
30	0.09	0.396
14	-0.88	0.063
18	-0.64	0.146
32	0.21	0.438
27	-0.09	0.333
21	-0.46	0.208
18	-0.64	0.146



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

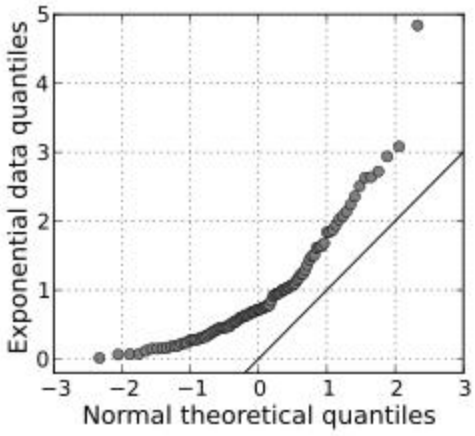
If there is perfect correlation, then VIF = infinity. This shows a perfect correlation between two independent variables. In the case of perfect correlation, we get R2 =1, which lead to 1/(1-R2) infinity. To solve this problem we need to drop one of the variables from the dataset which is causing this 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.

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.