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)

Ans:

Answer : Observations from above boxplots for categorical variables:

The year box plots indicates that more bikes are rent during 2019.

The season box plots indicates that more bikes are rent during fall season.

The working day and holiday box plots indicate that more bikes are rent during normal working days than on weekends or holidays.

The month box plots indicates that more bikes are rent during september month.

The weekday box plots indicates that more bikes are rent during saturday.

The weathersit box plots indicates that more bikes are rent during Clear, Few clouds, Partly cloudy weather.

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.
- Let's say we have 3 types of values in Categorical column and we want to create dummy variable for that column. If one variable is not furnished and semi furnished, then It is obvious unfurnished. So we do not need 3rd variable to identify the unfurnished.

Value	Indicator Variable	
Furnishing Status	furnished	semi-furnished
furnished	1	0
semi-furnished	0	1
unfurnished	0	0

Hence if we have categorical variable with n-levels, then we need to use n-1 columns to represent the dummy variables.

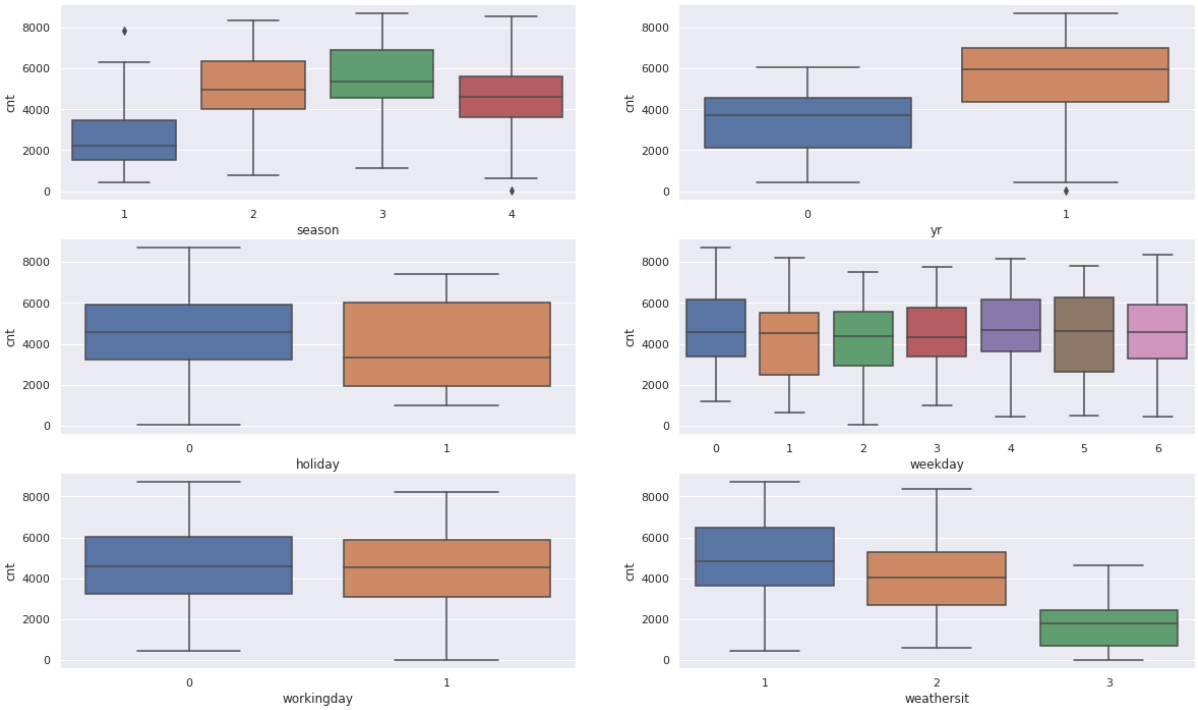
3. Looking at the pair-plot among the numerical variables, which one has the highest correlation

with the target variable? (1 mark)

By looking at the pair plot temp variable has the highest (0.63) correlation with target variable 'cnt'.

(B.) Visualising Categorical Variables:

```
plt.figure(figsize=(20, 12))
plt.subplot(3,2,1)
sns.boxplot(x = 'season', y = 'cnt', data = bb)
plt.subplot(3,2,2)
sns.boxplot(x = 'yr', y = 'cnt', data = bb)
plt.subplot(3,2,3)
sns.boxplot(x = 'holiday', y = 'cnt', data = bb)
plt.subplot(3,2,4)
sns.boxplot(x = 'weekday', y = 'cnt', data = bb)
plt.subplot(3,2,5)
sns.boxplot(x = 'workingday', y = 'cnt', data = bb)
plt.subplot(3,2,6)
sns.boxplot(x = 'weathersit', y = 'cnt', data = bb)
plt.show()
```



4. How did you validate the assumptions of Linear Regression after building the model on the

training set? (3 marks)

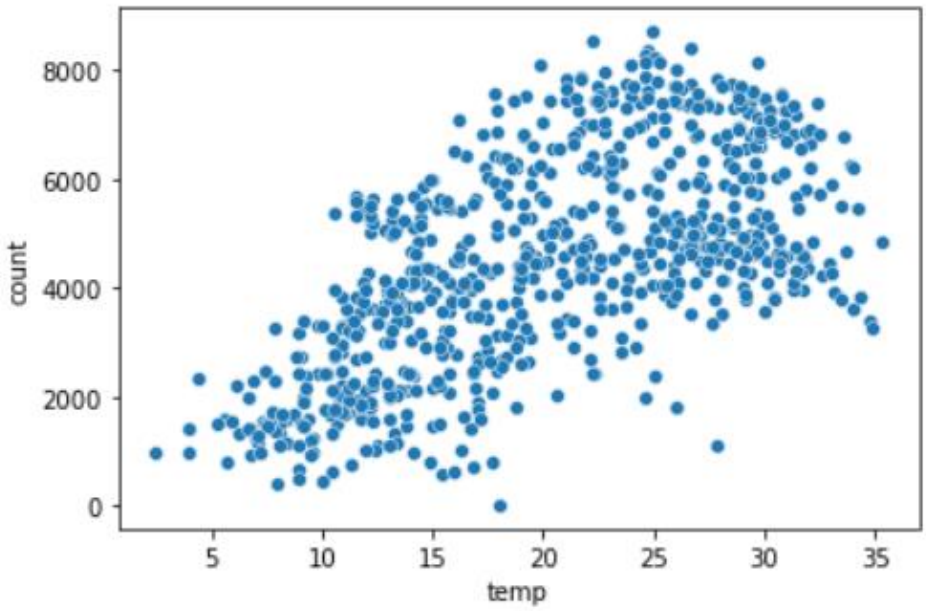
Answer:

1. **Linear Relationship between the features and target:**

According to this assumption there is linear relationship between the features and target.Linear regression captures only linear relationship.This can be validated by plotting a scatter plot between the features and the target

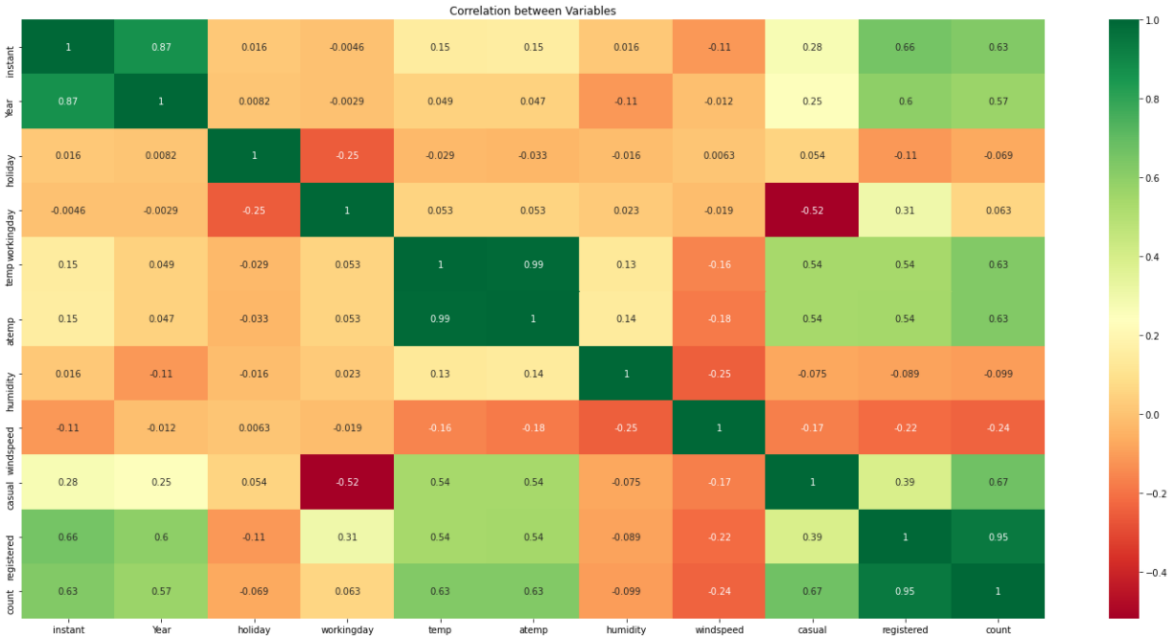
Ex:2)222

```
#scatter plot for temperature to count
sns.scatterplot(x='temp',y='count' ,data=bike)
plt.show()
```



2) 2.Little or no Multicollinearity between the features:

Multicollinearity is a state of very high inter-correlations or inter-associations among the independent variables.It is therefore a type of disturbance in the data if present weakens the statistical power of the regression model.Pair plots and heatmaps(correlation matrix) can be used for identifying highly correlated features.



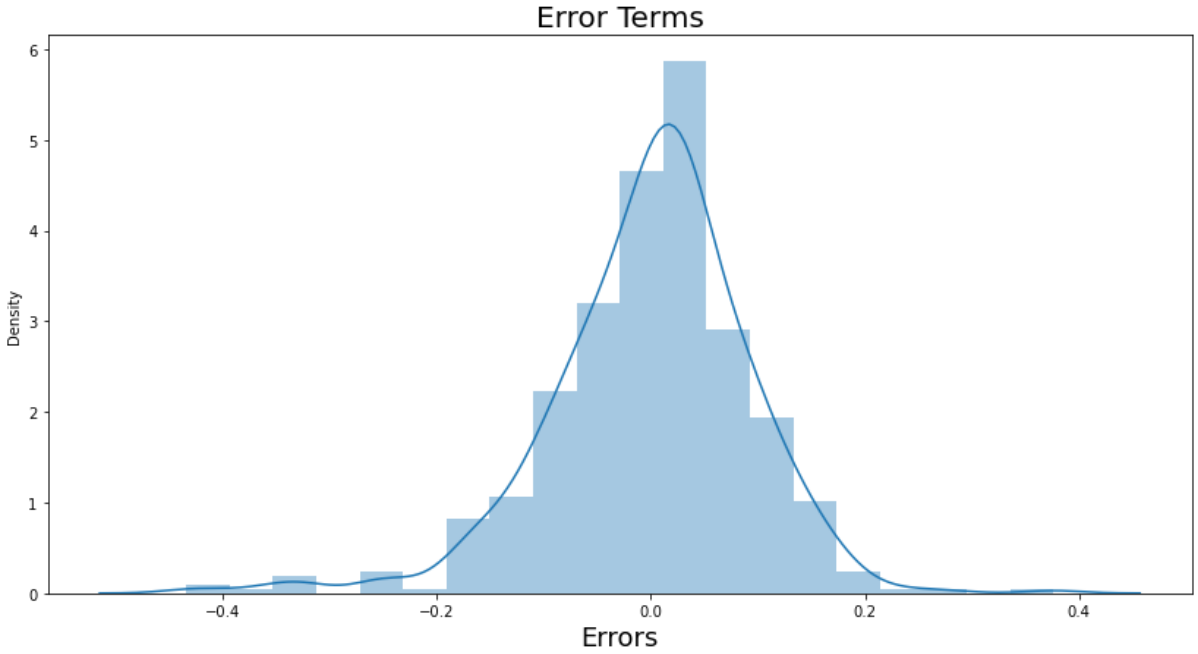
3) 3.Homoscedasticity Assumption:

Homoscedasticity describes a situation in which the error term (that is, the “noise” or random disturbance in the relationship between the features and the target) is the same across all values of the independent variables.A scatter plot of residual values vs predicted values is a goodway to check for homoscedasticity.There should be no clear pattern in the distribution and if there is a specific pattern,the data is heteroscedastic.

4.Normal distribution of error terms:

The fourth assumption is that the error(residuals) follow a normal distribution.However, a less widely known fact is that, as sample sizes increase, the normality assumption for the residuals is not needed. More precisely, if we consider repeated sampling from our population, for large sample sizes, the distribution (across repeated samples) of the ordinary least squares estimates of the regression coefficients follow a normal distribution. As a consequence, for moderate to large sample sizes, non-normality of residuals should not

adversely affect the usual inferential procedures. This result is a consequence of an extremely important result in statistics, known as the central limit theorem.



5.Little or No autocorrelation in the residuals:

Autocorrelation occurs when the residual errors are dependent on each other.The presence of correlation in error terms drastically reduces model's accuracy.This usually occurs in time series models where the next instant is dependent on previous instant.

```
#Building a model
X_train_lm5= sm.add_constant(X_train_new5)
lm5=sm.OLS(y_train,X_train_lm5).fit()
print(lm5.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  count   R-squared:                       0.826
Model:                            OLS   Adj. R-squared:                  0.822
Method:                 Least Squares   F-statistic:                     236.7
Date:                Wed, 16 Feb 2022   Prob (F-statistic):          3.10e-182
Time:                        19:52:10   Log-Likelihood:                 484.63
No. Observations:                 510   AIC:                            -947.3
Df Residuals:                     499   BIC:                            -900.7
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0902      0.030      2.964      0.003       0.030       0.150
```

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 :

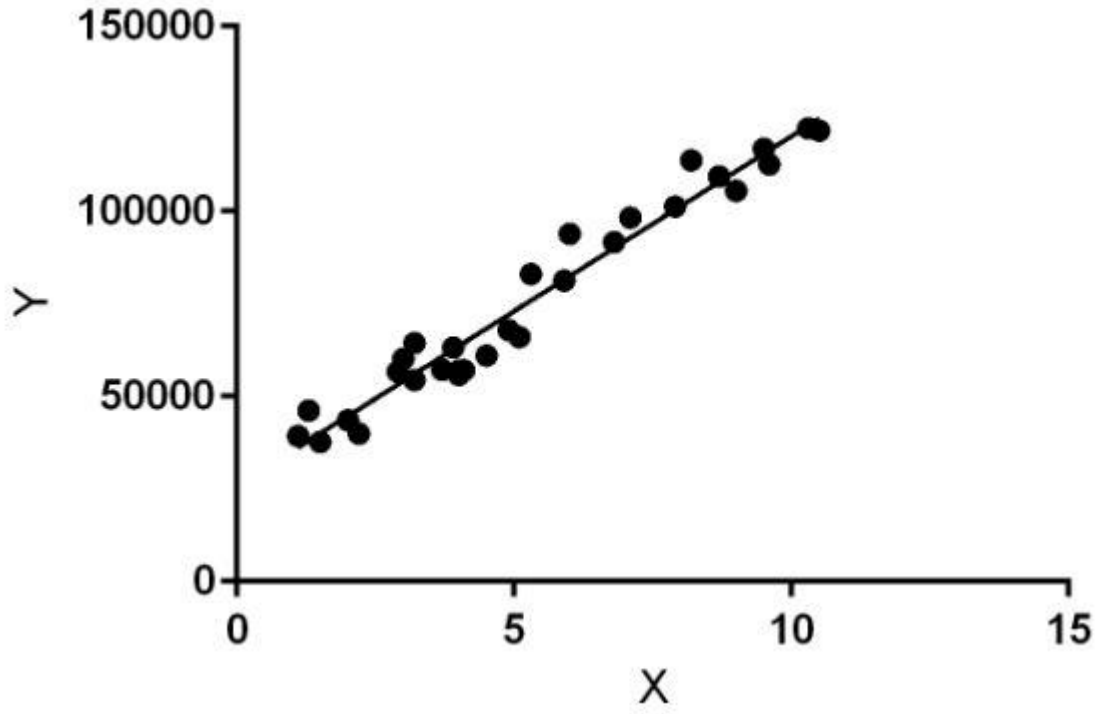
The Top 3 features contributing significantly towards the demands of share bikes are:

- 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)**
   Ans:

Linear Regression is a machine learning algorithm based on **supervised learning**. It performs a **regression task**. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.
In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Hypothesis function for Linear Regression :

$$y = \theta_1 + \theta_2.x$$

While training the model we are given :
x: input training data (univariate – one input variable(parameter))
y: labels to data (supervised learning)
When training the model – it fits the best line to predict the value of y for a given value of x. The model gets the best regression fit line by finding the best θ_1 and θ_2 values.
θ_1: intercept
θ_2: coefficient of x
Once we find the best θ_1 and θ_2 values, we get the best fit line. So when we are finally using our model for prediction, it will predict the value of y for the input value of x.
How to update θ_1 and θ_2 values to get the best fit line ?
Cost Function (J):
By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ_1 and θ_2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y).

$$minimize \frac{1}{n} \sum_{i=1}^{n} (pred_i - y_i)^2$$

$$J = \frac{1}{n} \sum_{i=1}^{n} (pred_i - y_i)^2$$

Cost function(J) of Linear Regression is the **Root Mean Squared Error (RMSE)** between predicted y value (pred) and true y value (y).
Gradient Descent
To update θ_1 and θ_2 values in order to reduce Cost function (minimizing RMSE value) and achieving the best fit line the model uses Gradient Descent. The idea is to start with random θ_1 and θ_2 values and then iteratively updating the values, reaching minimum cost.

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

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**

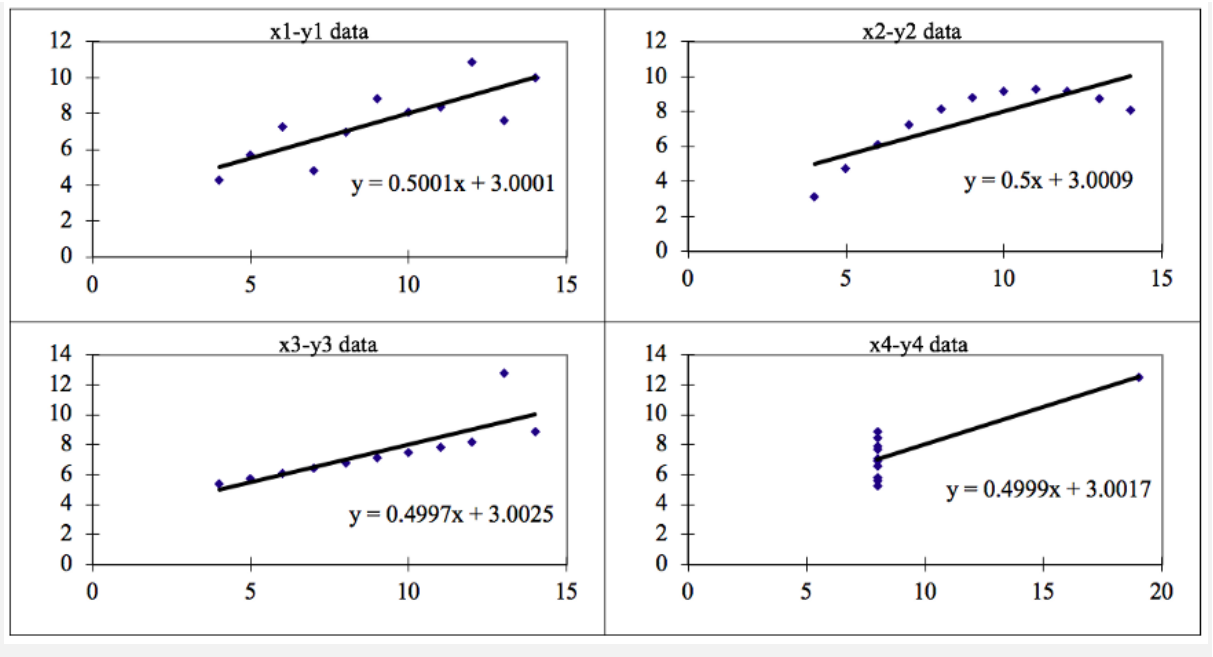
regression model if built. They have very different distributions and **appear differently** when plotted on scatter plots.

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

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:

1. **Dataset 1:** this **fits** the linear regression model pretty well.
2. **Dataset 2:** this **could not fit** linear regression model on the data quite well as the data is non-linear.
3. **Dataset 3:** shows the **outliers** involved in the dataset which **cannot be handled** by linear regression model
4. **Dataset 4:** shows the **outliers** involved in the dataset which **cannot be handled** by linear regression model

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

Ans:

Pearson's Correlation Coefficient

In Statistics, the Pearson's Correlation Coefficient is also referred to as **Pearson's r, the Pearson product-moment correlation coefficient (PPMCC), or bivariate correlation**. It is a

statistic that measures the linear correlation between two variables. Like all correlations, it also has a numerical value that lies between -1.0 and +1.0.

Whenever we discuss correlation in statistics, it is generally Pearson's correlation coefficient. However, it cannot capture nonlinear relationships between two variables and cannot differentiate between dependent and independent variables.

Pearson's correlation coefficient is the covariance of the two variables divided by the product of their standard deviations. The form of the definition involves a "product moment", that is, the mean (the first moment about the origin) of the product of the mean-adjusted random variables; hence the modifier product-moment in the name.

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

and standardized scaling? (3 marks)

Ans:

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**).*

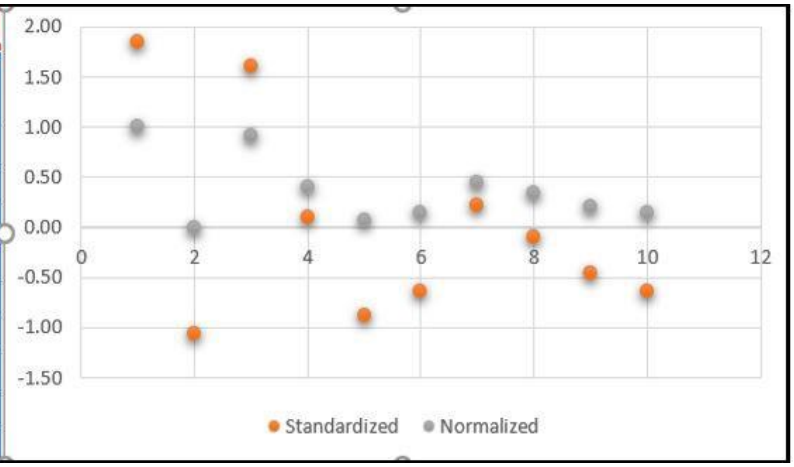
$$\text{Standardisation: } x = \frac{x - mean(x)}{sd(x)}$$

- ***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



4. **You might have observed that sometimes the value of VIF is infinite. Why does this happen?**
   Ans:

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).

(3 marks)

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

(3 marks

Ans:

Quantile-Quantile (Q-Q) plot, is a graphical tool to help us assess if a set of data plausibly came from some theoretical distribution such as a Normal, exponential or Uniform distribution. Also, it helps to determine if two data sets come from populations with a common distribution.

This helps in a scenario of linear regression when we have training and test data set received separately and then we can confirm using Q-Q plot that both the data sets are from populations with same distributions.

Few advantages:

a) It can be used with sample sizes also

b) Many distributional aspects like shifts in location, shifts in scale, changes in symmetry, and the presence of outliers can all be detected from this plot.

It is used to check following scenarios:

If two data sets —

i. come from populations with a common distribution

ii. have common location and scale

iii. have similar distributional shapes

iv. have similar tail behavior

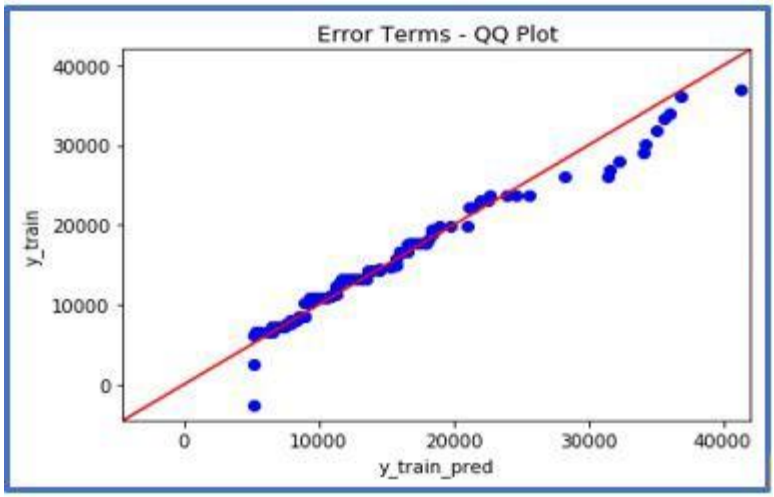
Interpretation:

A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second data set.

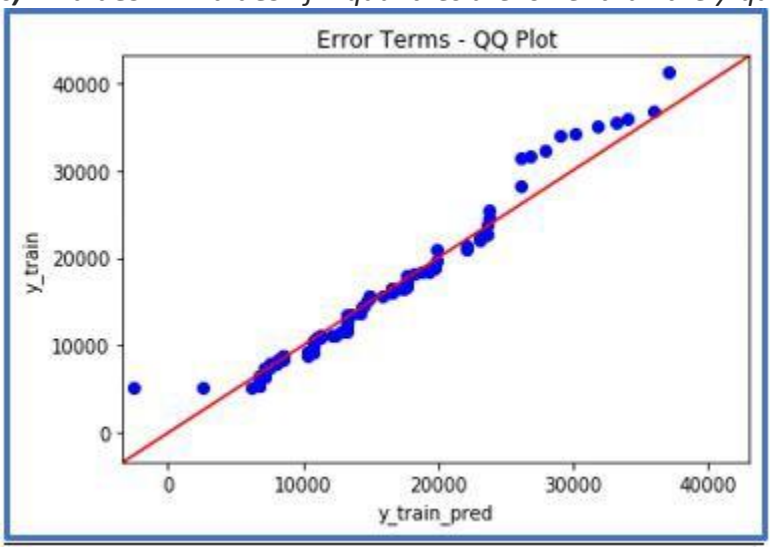
Below are the possible interpretations for two data sets.

*a) **Similar distribution**: If all point of quantiles lies on or close to straight line at an angle of 45 degree from x -axis*

*b) **Y-values < X-values:** If y-quantiles are lower than the x-quantiles.*



***c) X-values < Y-values:** If x-quantiles are lower than the y-quantiles.*



*d) **Different distribution:** If all point of quantiles lies away from the straight line at an angle of 45 degree from x -axis*