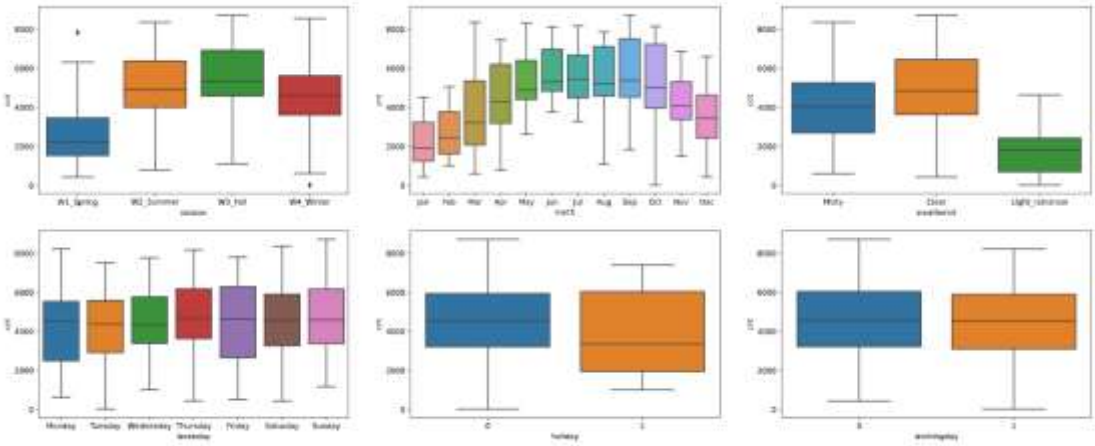
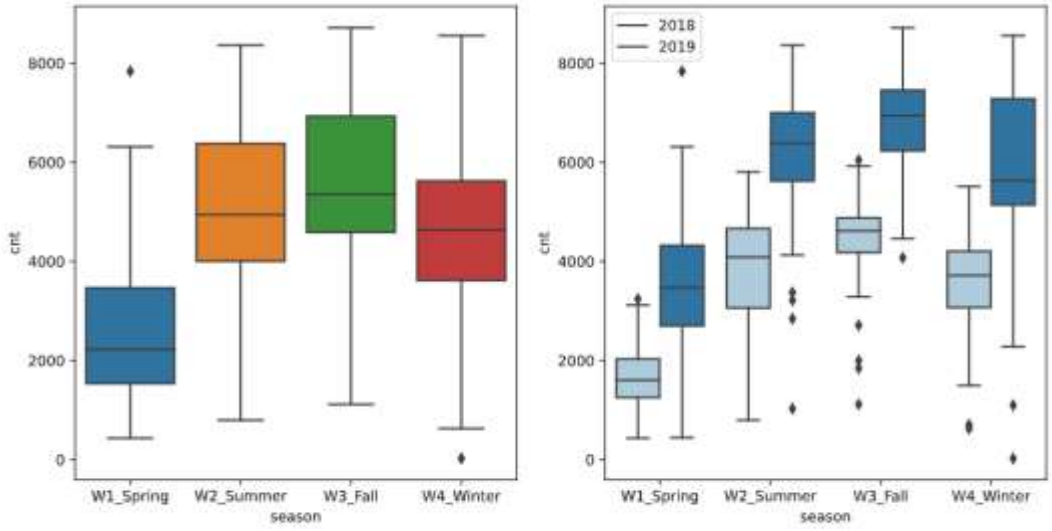
**Assignment-based Subjective Questions**

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



The plots above shows the relationship between categorical variables and a Target variable.

- Bike Rentals are more during the Fall season and then in summer
- Bike Rentals are more in the year 2019 compared to 2018
- Bike Rentals are more in partly cloudy weather
- Bike Rentals are more on Saturday ,Wednesday and Thursday




Almost 32% of the bike booking were happening in Fall with a median of over 5000 bookings (for two years). It is followed by Summer & Winter with 27% & 25% of total booking. It indicates that the season can be a good predictor of the dependent variable.

2. Why is it important to use **drop_ first =True** during dummy variable creation?
   we 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

   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.

3. Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable?
4. Bike rentals are more correlated to temperature
5. How did you validate the assumptions of Linear Regression after building the model on the training set?

Train R^2 : 0.826

Train Adjusted R^2 : 0.82

Test R^2: 0.8115

Test Adjusted R^2: 0.790564

Difference in R^2 between train and test: 1.5%

Difference in adjusted R^2 between Train and test: 3.15% which is less than 5%

Yes! Its a best model

We arrived at a very decent model for the the demand for shared bikes with the significant variables

We can see that temperature variable is having the highest coefficient 0.4914, which means if the temperature increases by one unit the number of bike rentals increases by 0.4914 units.

Similary we can see coefficients of other variables in the equation for best fitted line.

We also see there are some variables with negative coefficients, A negative coefficient suggests that as the independent variable increases, the dependent variable tends to decrease. We have spring, mist cloudy , light snow variables with negative coefficient. The coefficient value signifies how much the mean of the dependent variable changes given a one-unit shift in the independent variable while holding other variables in the model constant.

(3 marks)

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

- A US bike-sharing provider BoomBikes can focus more on Temperature
- We can see demand for bikes was more in 2019 than 2018, so just focus as there is increase in 2019 and might be facing dips in their revenues due to the ongoing Corona pandemic and by the time it reduces the things will be better
- Can focus more on Summer & Winter season, August, September month, Weekends, Working days as they have good influence on bike rentals.
- We can see spring season has negative coefficients and negatively correlated to bike rentals. So we can give some offers there to increase the demand
- Now seeing to weathersit variable, we have got negative coefficients for Mist +cloudy and Lightsnow weather... And yes we can give offers

(2 marks)

**General Subjective Questions**

1. Explain the linear regression algorithm in detail.

   Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. For example, a modeler might want to relate the weights of individuals to their heights using a linear regression model.

   A linear regression line has an equation of the form ***Y = a + bX***, where ***X*** is the explanatory variable and ***Y*** is the dependent variable. The slope of the line is ***b***, and ***a*** is the intercept (the value of ***y*** when ***x*** = 0). It involves following steps:

**Least-Squares Regression**

The most common method for fitting a regression line is the method of least-squares. This method calculates the best-fitting line for the observed data by minimizing the sum of the squares of the vertical deviations from each data point to the line (if a point lies on the fitted line exactly, then its vertical deviation is 0). Because the deviations are first squared, then summed, there are no cancellations between positive and negative values.

**Outliers and Influential Observations**

After a regression line has been computed for a group of data, a point which lies far from the line (and thus has a large residual value) is known as an ***outlier***. Such points may represent erroneous data, or may indicate a poorly fitting regression line. If a point lies far from the other data in the horizontal direction, it is known as an ***influential observation***. The reason for this distinction is that these points have may have a significant impact on the slope of the regression line.

**Residuals**

Once a regression model has been fit to a group of data, examination of the residuals (the deviations from the fitted line to the observed values) allows the modeler to investigate the validity of his or her assumption that a linear relationship exists.

**Extrapolation**

**Lurking Variables**

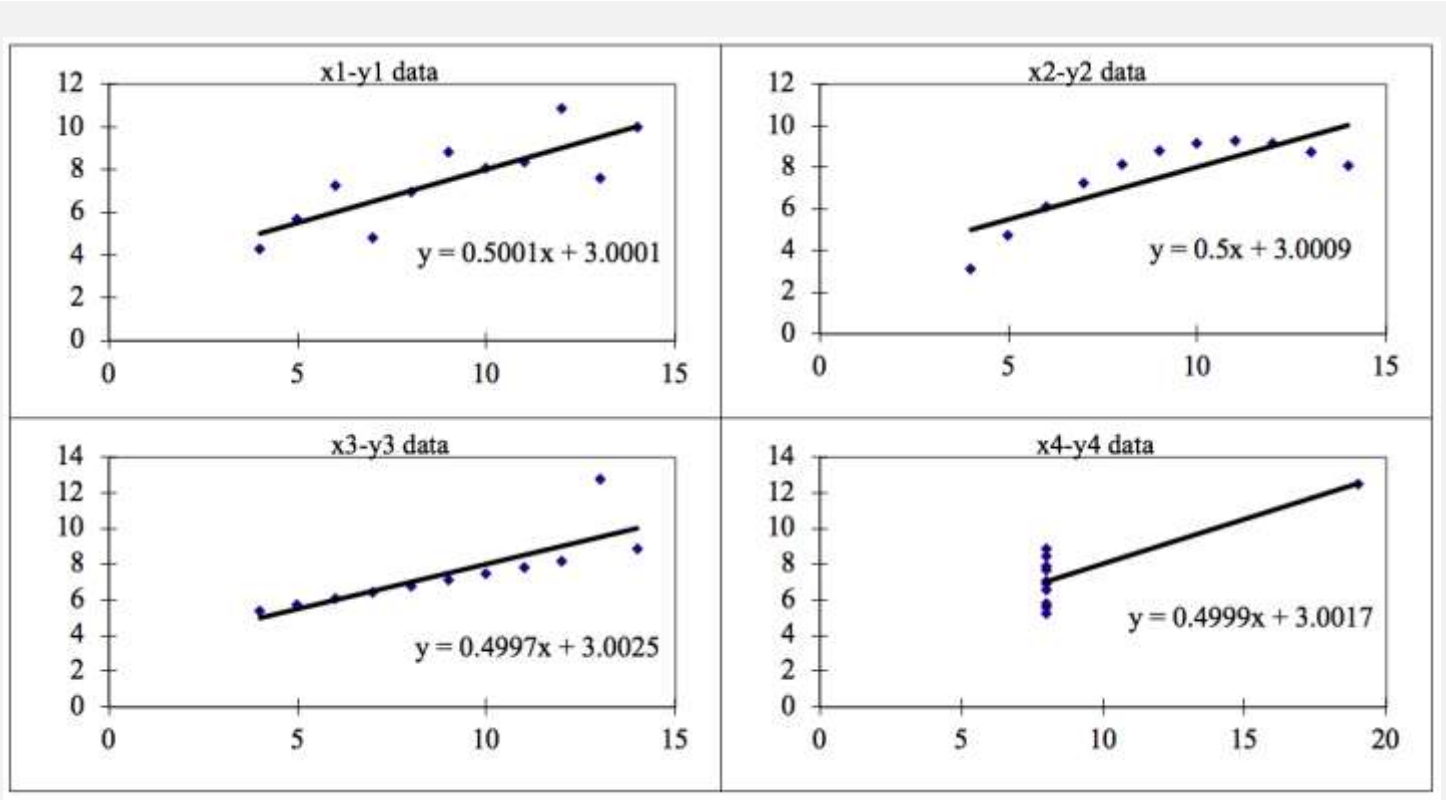
2. Explain the Anscombe's quartet in detail. (3 marks)

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.

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.

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:



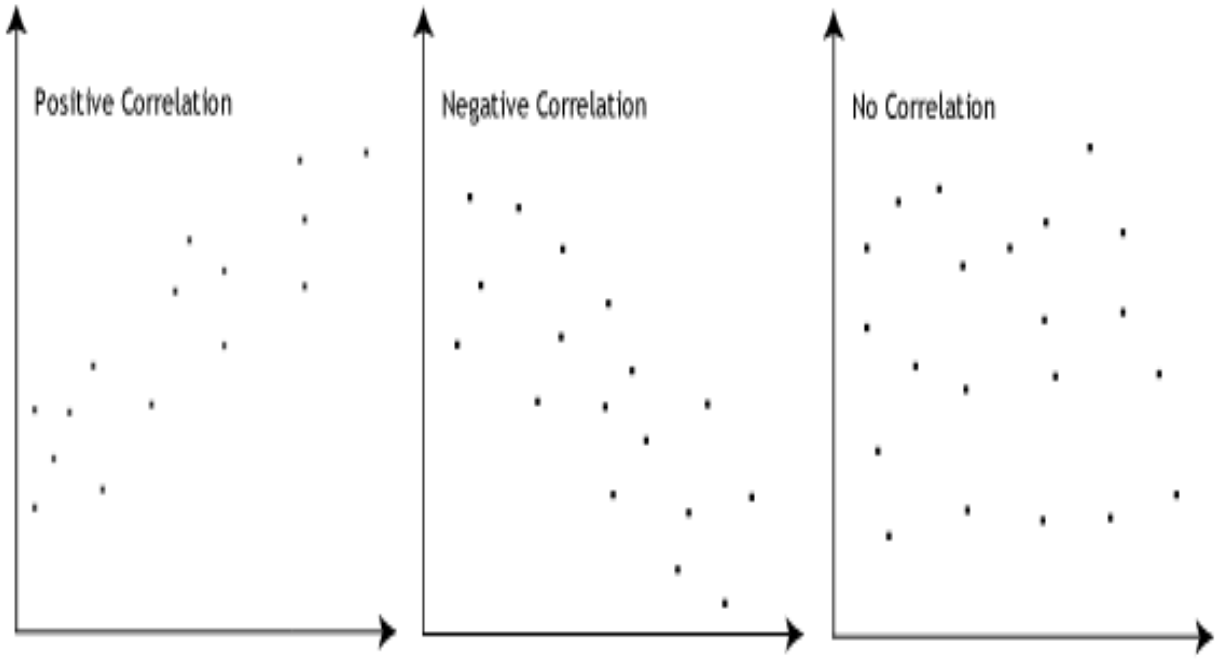

The four datasets can be described as:**Dataset 1:** this **fits** the linear regression model pretty well.**Dataset 2:** this **could not fit** linear regression model on the data quite well as the data is non-linear.**Dataset 3:** shows the **outliers** involved in the dataset which **cannot be handled**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

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

*r*, indicates how far away all these data points are to this line of best fit (i.e., how well the data points fit this new model/line of best fit).

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:




the two variables have to be measured on either an interval or ratio scale. However, both variables do not need to be measured on the same scale (e.g., one variable can be ratio and one can be interval)

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

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.

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**.

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

- In VIF, each feature is regression against all other features. If R2 is more which means this feature is correlated with other features. [0]
  - VIF = 1 / (1 – R2)
  - When R2 reaches 1, VIF reaches infinity
- We try to remove features for which VIF > 5
- R2 reaches the 1 because all the points lies in the linear line .So the R2 value will tend to 1
  This indicates that Co-efficient is more corelated

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

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.

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