General subjective

1. Explain the linear regression algorithm in detail.

Regression is a method of modelling a target value based on independent predictors. This method is mostly used for forecasting and finding out cause and effect relationship between variables. Regression techniques mostly differ based on the number of independent variables and the type of relationship between the independent and dependent variables.

Simple linear regression is a type of regression analysis where the number of independent variables is one and there is a linear relationship between the independent(x) and dependent(y) variable. The red line in the above graph is referred to as the best fit straight line. Based on the given data points, we try to plot a line that models the points the best. The line can be modelled based on the linear equation shown below.

```
y = a_0 + a_1 * x      ## Linear Equation
```

The motive of the linear regression algorithm is to find the best values for a_0 and a_1

Linear regression is a **linear model**, e.g. a model that assumes a linear relationship between the input variables (x) and the single output variable (y). More specifically, that y can be calculated from a linear combination of the input variables (x).

When there is a single input variable (x), the method is referred to as **simple linear regression**. When there are **multiple input variables**, literature from statistics often refers to the method as multiple linear regression.

Different techniques can be used to prepare or train the linear regression equation from data, the most common of which is called **Ordinary Least Squares**. It is common to therefore refer to a model prepared this way as Ordinary Least Squares Linear Regression or just Least Squares Regression.

For example, in a simple regression problem (a single x and a single y), the form of the model would be:

$$y = B0 + B1*x$$

In higher dimensions when we have more than one input (x), the line is called a plane or a hyper-plane. The representation therefore is the form of the equation and the specific values used for the coefficients (e.g. B0 and B1 in the above example).

It is common to talk about the complexity of a regression model like linear regression. This refers to the number of coefficients used in the model.

When a coefficient becomes zero, it effectively removes the influence of the input variable on the model and therefore from the prediction made from the model (0 * x = 0). This becomes relevant if you look at regularization methods that change the learning algorithm to reduce the complexity of regression models by putting pressure on the absolute size of the coefficients, driving some to zero.

2. Explain the Anscombe's quartet in detail

   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.

3. What is Pearson's R?

Pearson r correlation: Pearson r correlation is the most widely used correlation statistic to measure the degree of the relationship between linearly related variables. For example, in the stock market, if we want to measure how two stocks are related to each other, Pearson r correlation is used to measure the degree of relationship between the two. The point-biserial correlation is conducted with the Pearson correlation formula except that one of the variables is dichotomous. The following formula is used to calculate the Pearson r correlation:

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

rxy = Pearson r correlation coefficient between x and y
n = number of observations
xi = value of x (for ith observation)
yi = value of y (for ith observation)

Types of research questions a Pearson correlation can examine:

Is there a statistically significant relationship between age, as measured in years, and height, measured in inches?

Is there a relationship between temperature, measured in degrees Fahrenheit, and ice cream sales, measured by income?

Is there a relationship between job satisfaction, as measured by the JSS, and income, measured in dollars?

Assumptions

For the Pearson r correlation, both variables should be normally distributed (normally distributed variables have a bell-shaped curve). Other assumptions include linearity and homoscedasticity. Linearity assumes a straight line relationship between each of the two variables and homoscedasticity assumes that data is equally distributed about the regression line.

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. **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:

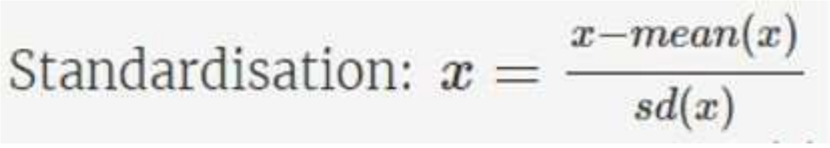
- *It brings all of the data in the range of 0 and*

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.

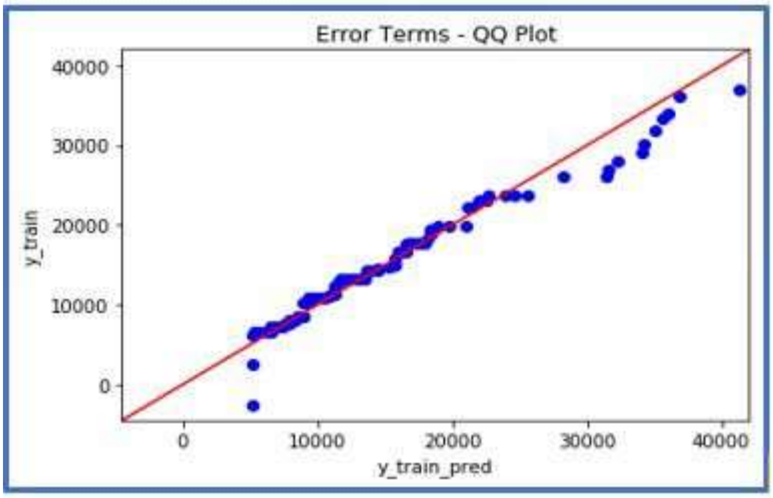
5. You might have observed that sometimes the value of VIF is infinite. Why does this happen?
An infinite VIF value indicates that the corresponding variable may be expressed exactly by a linear combination of other variables (which show an infinite VIF as well).

- n linear regression collinearity can make coefficient unstable
  - There will not be any issue in prediction accuracy but coefficients would be less reliable and p-value would be more
  - Correlation coefficients help us detect correlation between pairs but not the multiple correlation x1 = 2*x3 + 4*x7
  - PCA is one thing, we don’t want to transform variable to keep interpretability intact
  - We want some way to reduce dimensions
- 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

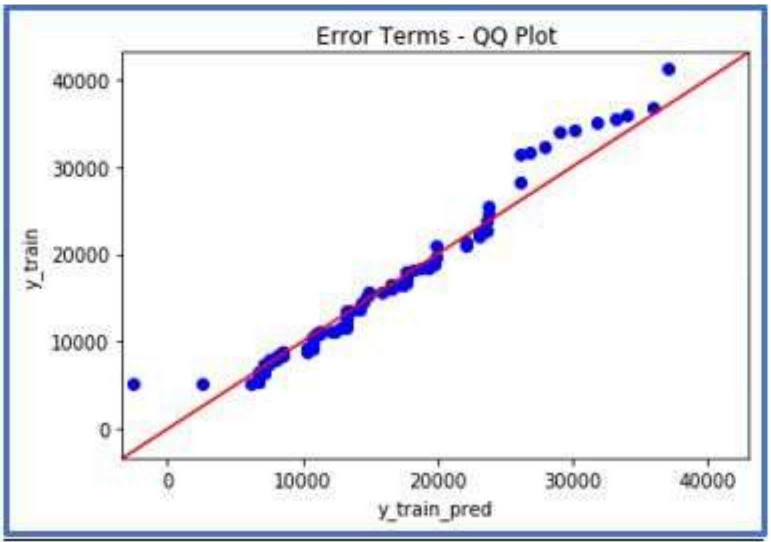
6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression.

  - *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.*

- *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.*



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

Assignment based—

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

The inference that We could derive were:

- season: Almost 32% of the bike booking were happening in season3 with a median of over 5000 booking (for the period of 2 years). This was followed by season2 & season4 with 27% & 25% of total booking. This indicates, season can be a good predictor for the dependent variable.
- mnth: Almost 10% of the bike booking were happening in the months 5,6,7,8 & 9 with a median of over 4000 booking per month. This indicates, mnth has some trend for bookings and can be a good predictor for the dependent variable.
- weathersit: Almost 67% of the bike booking were happening during 'weathersit1 with a median of close to 5000 booking (for the period of 2 years). This was followed by weathersit2 with 30% of total booking. This indicates, weathersit does show some trend towards the bike bookings can be a good predictor for the dependent variable.
- holiday: Almost 97.6% of the bike booking were happening when it is not a holiday which means this data is clearly biased. This indicates, holiday CANNOT be a good predictor for the dependent variable.
- weekday: weekday variable shows very close trend (between 13.5%-14.8% of total booking on all days of the week) having their independent medians between 4000 to 5000 bookings. This variable can have some or no influence towards the predictor. I will let the model decide if this needs to be added or not.
- workingday: Almost 69% of the bike booking were happening in 'workingday' with a median of close to 5000 booking (for the period of 2 years). This indicates, workingday can be a good predictor for the dependent variable

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

- 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

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

Using the pair plot, we could see there is a linear relation between temp and atemp variable with the predictor ‘cnt’.

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

1. ## **Error terms are normally distributed with mean zero (not X, Y)**

- A) **Residual Analysis Of Training Data**

```
 y_train_pred = lr6.predict(X_train_lm6)
res = y_train-y_train_pred
# Plot the histogram of the error terms
fig = plt.figure()
sns.distplot((res), bins = 20)
fig.suptitle('Error Terms', fontsize = 20)              # Plot heading
plt.xlabel('Errors', fontsize = 18)                     # X-label
```

### Insights
- From the above histogram, we could see that the Residuals are normally distributed. Hence our assumption for Linear Regression is valid.

B) **## There is a linear relationship between X and Y**

```
bike_new=bike_new[[ 'temp', 'atemp', 'hum', 'windspeed','cnt']]

sns.pairplot(bike_num, diag_kind='kde')
plt.show()
```

## Insight
- Using the pair plot, we could see there is a linear relation between temp and atemp variable with the predictor ‘cnt’.

c)

## There is No Multicollinearity between the predictor variables

```
# Check for the VIF values of the feature variables.

from statsmodels.stats.outliers_influence import variance_inflation_factor


# Create a dataframe that will contain the names of all the feature variables and their respective VIFs

vif = pd.DataFrame()

vif['Features'] = X_train_new.columns

vif['VIF'] = [variance_inflation_factor(X_train_new.values, i) for i in range(X_train_new.shape[1])]

vif['VIF'] = round(vif['VIF'], 2)

vif = vif.sort_values(by = "VIF", ascending = False)

vif
```

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

As per our final Model, the top 3 predictor variables that influences the bike booking are:

- **Temperature (temp)** - A coefficient value of ‘0.5636’ indicated that a unit increase in temp variable increases the bike hire numbers by 0.5636 units.
- **Weather Situation 3 (weathersit_3)** - A coefficient value of ‘-0.3070’ indicated that, w.r.t Weathersit1, a unit increase in Weathersit3 variable decreases the bike hire numbers by 0.3070 units.
- **Year (yr)** - A coefficient value of ‘0.2308’ indicated that a unit increase in yr variable increases the bike hire numbers by 0.2308 units.

So, it's suggested to consider these variables utmost importance while planning, to achive maximum Booking

The next best features that can also be considered are

season_4: - A coefficient value of ‘0.128744’ indicated that w.r.t season_1, a unit increase in season_4 variable increases the bike hire numbers by 0.128744 units.

windspeed: - A coefficient value of ‘-0.155191’ indicated that, a unit increase in windspeed variable decreases the bike hire numbers by 0.155191 units.

NOTE:
The details of weathersit_1 & weathersit_3
weathersit_1: Clear, Few clouds, Partly cloudy, Partly cloudy
weathersit_3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
The details of season1 & season4
season1: spring
season4: winter