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 analyzed the categorical variables using a Boxplot and inferred the following from it:

- Fall season seems to have attracted more bookings. Most of the bookings were made during the months of June, July, Aug, Sep and Oct. Sep being the highest grossing month.
- Since the booking count has increased drastically from 2018 to 2019, it seems that the business is doing well.
- Clear weather, not surprisingly, attracted more booking
- Thursdays and the end of the week seem to have a greater number of bookings.
- Fewer bookings during holidays
- Bookings seem to be stable regardless of whether its workday or weekend

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

Answer:

To avoid dummy variable trap we should always add one less (n-1) dummy variable than the total number of categories present in the categorical data (n) because the nth dummy variable is redundant as it carries no new information.

Imagine if we have 3 variables A, B, C. If both A and B are 0, we automatically understand C is 1. We don't necessarily need a dummy variable 'C'. It can be dropped. That's the basic idea after drop_first = True.

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

Answer:

The Variable 'temp' has the highest correlation of 0.63 with the Target variable.

4. How did you validate the assumptions of Linear Regression after building the model on the training set? (3 marks)

Answer:

I have validated the assumption of Linear Regression Model based on below 5 assumptions -

- Normality of error terms
  - Error terms should be normally distributed
- Multicollinearity check
  - There should be insignificant multicollinearity among variables.
- Linear relationship validation
  - Linearity should be visible among variables
- Homoscedasticity
  - There should be no visible pattern in residual values.
- Independence of residuals

- No autocorrelation

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:

Below are the top 3 features contributing significantly towards explaining the demand of the shared bikes –

- Temperature (temp)
- September (sep)
- Winter

General Subjective Questions

1. Explain the linear regression algorithm in detail. (4 marks)

Answer:

The overall idea of regression is to examine which variables are significant predictors of the outcome variable, and in what way do they–indicated by the magnitude and sign of the beta estimates–impact the outcome variable? These regression estimates are used to explain the relationship between one dependent variable and one or more independent variables. The simplest form of the regression equation with one dependent and one independent variable is defined by the formula y = c + b*x, where y = estimated dependent variable score, c = constant, b = regression coefficient, and x = score on the independent variable.

I) Single Linear Regression and **Multiple Linear Regression** are the two types of Linear Regressions.

II) A linear relationship can be **positive** or **negative** in nature as explained below−

A) Positive Linear Relationship: A linear relationship will be called positive if both independent and dependent variable increases.
B) Negative Linear relationship: A linear relationship will be called negative if independent variable increases and dependent variable decreases.

III) **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.

Three major uses for regression analysis are (1) determining the strength of predictors, (2) forecasting an effect, and (3) trend forecasting.

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

Answer:

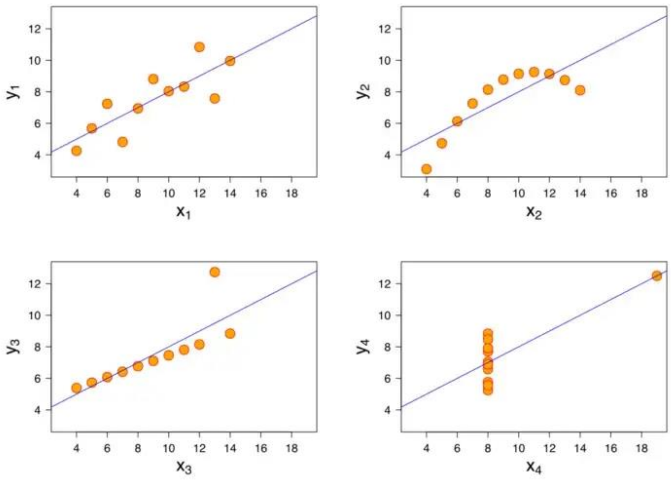
Anscombe's Quartet was developed by statistician Francis Anscombe. It comprises four datasets, each containing eleven (x,y) pairs. The essential thing to note about these datasets is that they share the same descriptive statistics. But things change completely, when they are graphed. Each graph tells a different story irrespective of their similar summary statistics.

Quartet's Summary Stats

The summary statistics show that the means and the variances were identical for x and y across the groups:

	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

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 :



1. **Dataset I** appears to have clean and well-fitting linear models.
2. **Dataset II** is not distributed normally.
3. In **Dataset III** the distribution is linear, but the calculated regression is thrown off by an outlier.
4. **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.

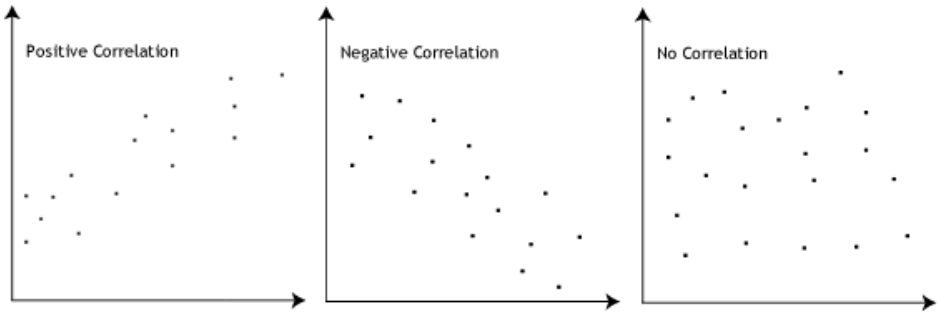
3. What is Pearson's R? (3 marks)

Answer:

In statistics, the Pearson correlation coefficient (PCC), also referred to as Pearson's r, the Pearson product-moment correlation coefficient (PPMCC), or the bivariate correlation, is a measure of linear correlation between two sets of data. It is the covariance of two variables, divided by the product of their standard deviations; thus it is essentially a normalized measurement of the covariance, such that the result always has a value between −1 and 1.

The Pearson's correlation coefficient varies between -1 and +1 where:

- r = 1 means the data is perfectly linear with a positive slope (i.e., both variables tend to change in the same direction)
- r = -1 means the data is perfectly linear with a negative slope (i.e., both variables tend to change in different directions)
- r = 0 means there is no linear association
- r > 0 < 5 means there is a weak association
- r > 5 < 8 means there is a moderate association
- r > 8 means there is a strong association



Pearson's formula:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Here,

- r=correlation coefficient
- xi =values of the x-variable in a sample
- x-bar=mean of the values of the x-variable
- yi=values of the y-variable in a sample
- y-bar=mean of the values of the y-variable

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling? (3 marks)

Answer:

Scaling 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 time, collected data set contains features highly varying in magnitudes, units and range. If scaling is not done, then algorithm only takes magnitude into 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.

A) 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.

$$\text{MinMax Scaling: } x = \frac{x - min(x)}{max(x) - min(x)}$$

B) 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?

(3 marks)

Answer:

If there is perfect correlation, then VIF = infinity. A large value of VIF indicates that there is a correlation between the variables. If the VIF is 4, this means that the variance of the model coefficient is inflated by a factor of 4 due to the presence of multicollinearity.

When the value of VIF is infinite, it shows a perfect correlation between two independent variables. In the case of perfect correlation, we get R-squared (R2) =1, which leads to 1/ (1-R2) infinity. To solve this, we need to drop one of the variables from the dataset which is causing this perfect multicollinearity.

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.

I) 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.

II) 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 tests.