# Linear Regression Subjective Questions

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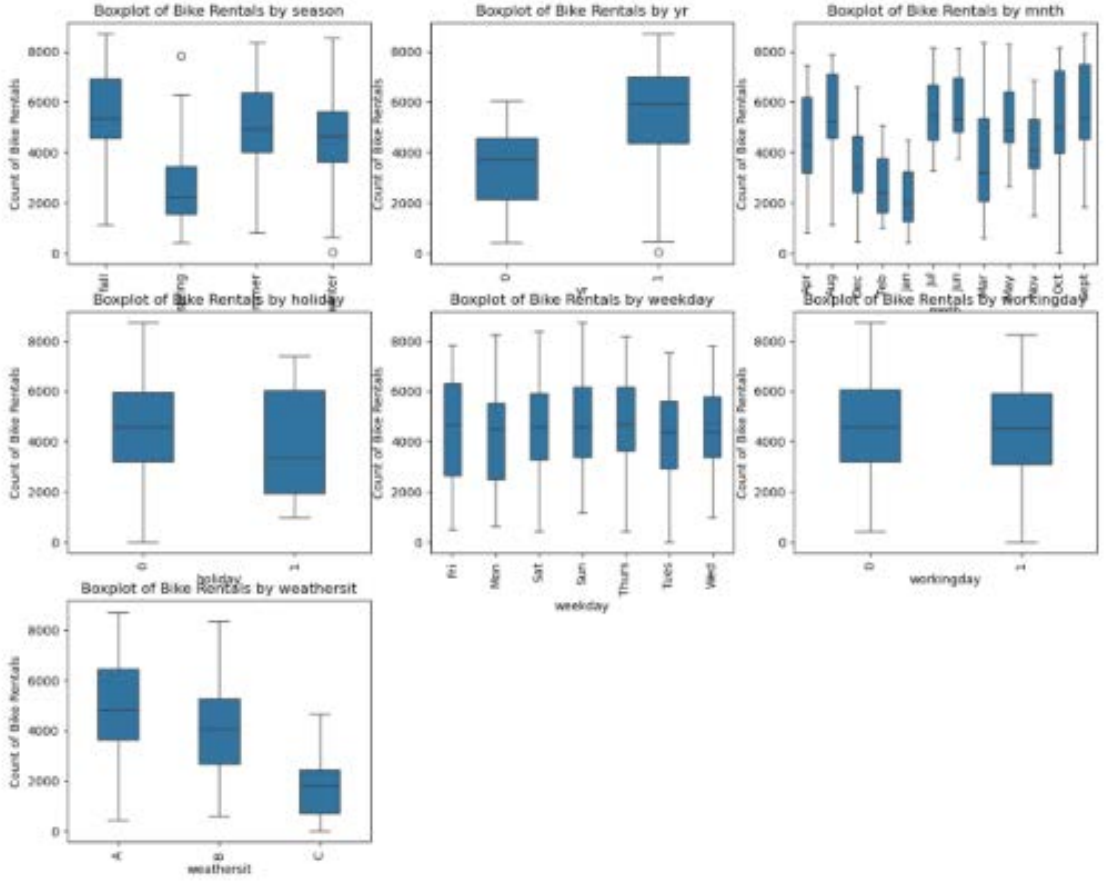
# Assignment-based Subjective Questions

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

Below are the few points we can infer from the visualization –

- During the fall season, bookings significantly increased, with a noticeable rise from 2018 to 2019.
- Most reservations were made in May through October, showing an upward trend from the beginning of the year to mid-year, followed by a decline towards year-end.
- Clear weather conditions naturally resulted in more bookings.
- Bookings were higher on Thursdays, Fridays, Saturdays, and Sundays compared to the beginning of the week.
- On non-holidays, the number of bookings decreased, which is expected as people prefer spending holidays at home with family.
- Bookings were almost equal on working days and non-working days.
- The year 2019 saw more bookings compared to the previous year, indicating positive business growth.



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

Setting **drop_first = True** is crucial because it eliminates the extra column generated during the creation of dummy variables, thereby reducing the correlations among them.

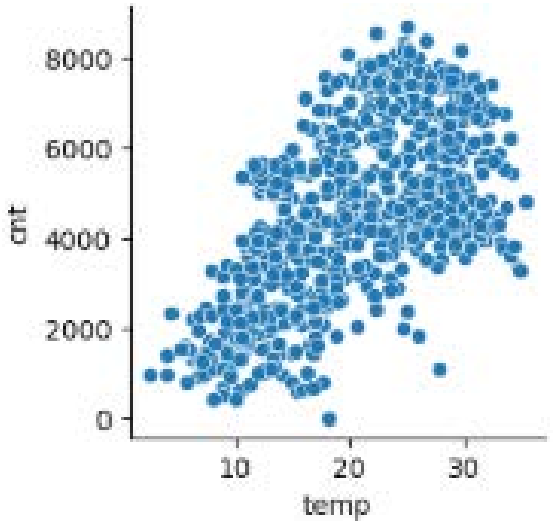
**Syntax:**

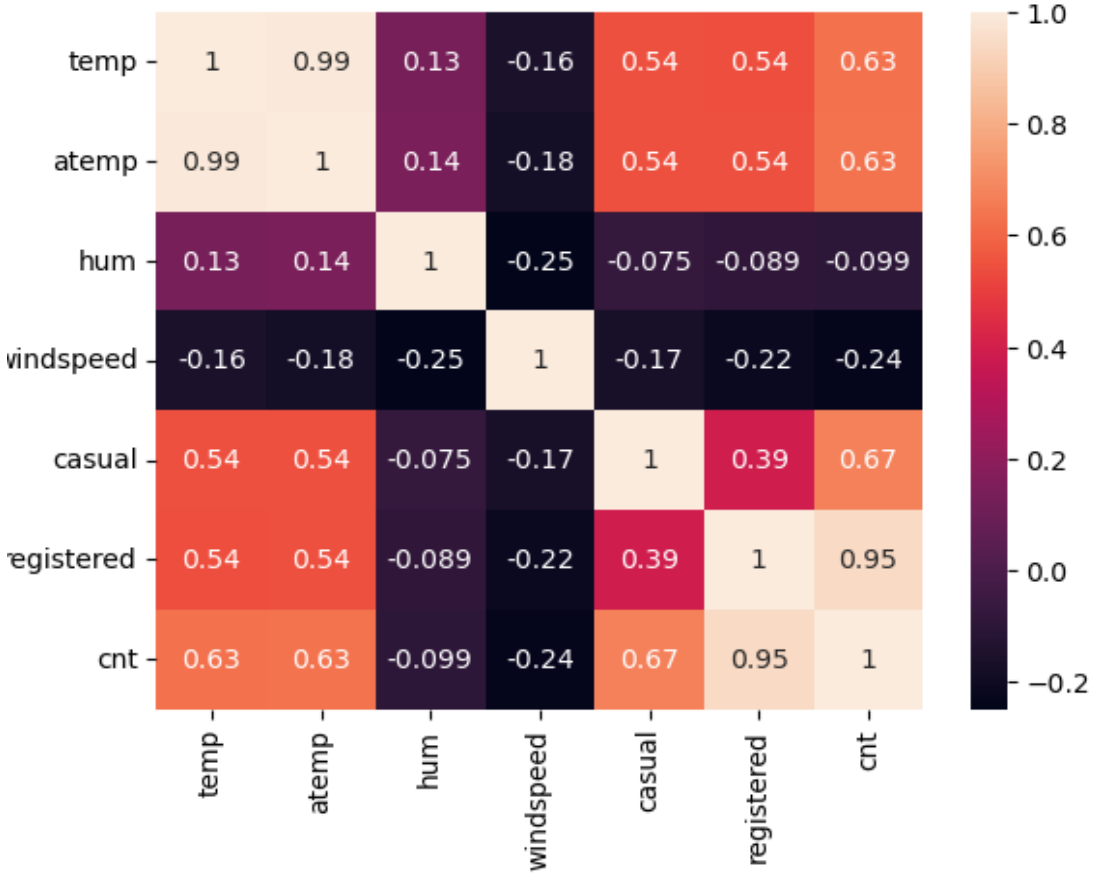
- drop_first: bool, default is False. This parameter decides whether to generate $k-1$ dummy variables from k categorical levels by removing the first level.

For example, if a categorical column has three values, and we create dummy variables for this column, we only need two out of the three dummy variables. If a variable isn't A or B, it must be C. Therefore, the third dummy variable isn't necessary to identify C.

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

From the correlation analysis, the pair plot, and heatmap, the variable temp seems to have the highest correlation with the target variable cnt.



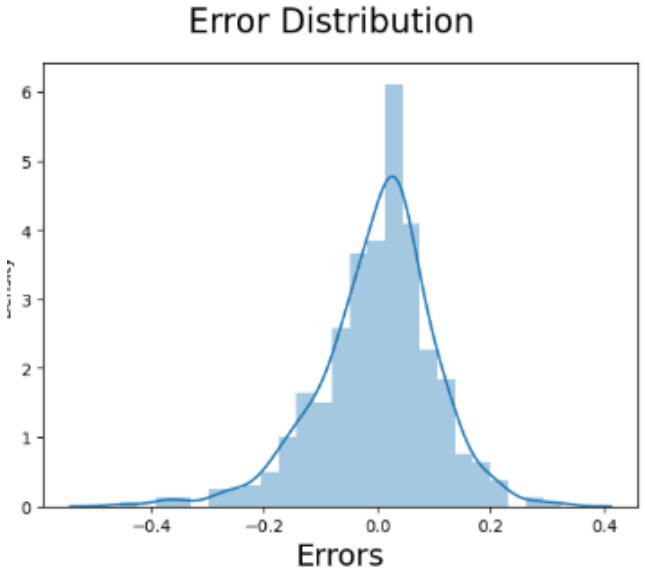



# 4. How did you validate the assumptions of Linear Regression after building the model on the training set?

Linear regression models are validated based on the following assumptions-

- There should be a linear relationship between target and predictor variables
- Error terms should be normally distributed with mean zero.
- Error terms should be independent of each other
- Error terms should be exhibiting homoscedasticity.
- There is no strong correlation between the predictors.

I have used scatter plot of predictors to validate linear relationship , distplot of error terms for validating the error terms, heatmap and VIF to validate there is no multicollinearity between the predictors.




| | Features | VIF |
|---|---|---|
| 1 | temp | 3.95 |
| 2 | windspeed | 3.72 |
| 0 | yr | 2.03 |
| 3 | season_spring | 1.49 |
| 4 | mnth_Jul | 1.26 |
| 5 | weathersit_C | 1.04 |

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

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

- Year
- Temperature in Celsius(temp)
- Windspeed

# General Subjective Questions

# 1.Explain the linear regression algorithm in detail.

Linear regression may be defined as the statistical model that analyses the linear relationship between a dependent variable with given set of independent variables. Linear relationship between variables means that when the value of one or more independent variables will change (increase or decrease), the value of dependent variable will also change accordingly (increase or decrease).

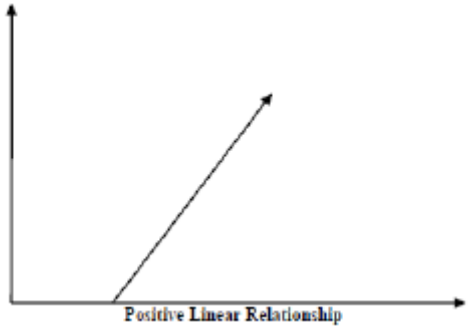
Mathematically the relationship can be represented with the help of following equation − **Y = mX + c**

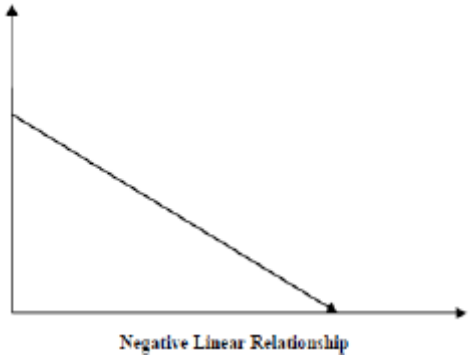
Here, Y is the dependent variable we are trying to predict. X is the independent variable we are using to make predictions. m is the slope of the regression line which represents the effect X has on Y c is a constant, known as the Y-intercept. If X = 0, Y would be equal to c

Furthermore, the linear relationship can be positive or negative in nature as explained below−

**Positive Linear Relationship**: A linear relationship will be called positive if both independent and dependent variable increases.

**Negative Linear relationship**: A linear relationship will be called positive if independent increases and dependent variable decreases.



Linear regression is of the following two types −

- Simple Linear Regression
- Multiple Linear Regression

**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.

# 2.**Explain the Anscombe's quartet in detail.**

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 tell a f=different story when they are graphed.

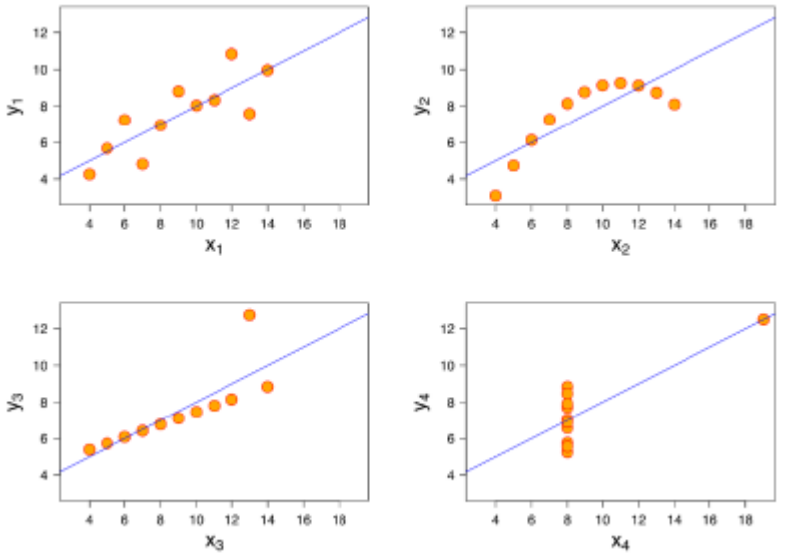
The summary statistics show that the means and the variances were identical for x and y across the groups:

- Mean of x is 9 and mean of y is 7.50 for each dataset.
- Similarly, the variance of x is 11 and variance of y is 4.13 for each dataset
- The correlation coefficient (how strong a relationship is between two variables) between x and y is 0.816 for each dataset

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 irrespective of their similar summary statistics.

- Dataset I appears to have clean and well-fitting linear models.
- Dataset II is not distributed normally.
- In Dataset III the distribution is linear, but the calculated regression is thrown off by an outlier.
- Dataset IV shows that one outlier is enough to produce a high correlation coefficient.

| | 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 |



# 3.**What is Pearson's R?**

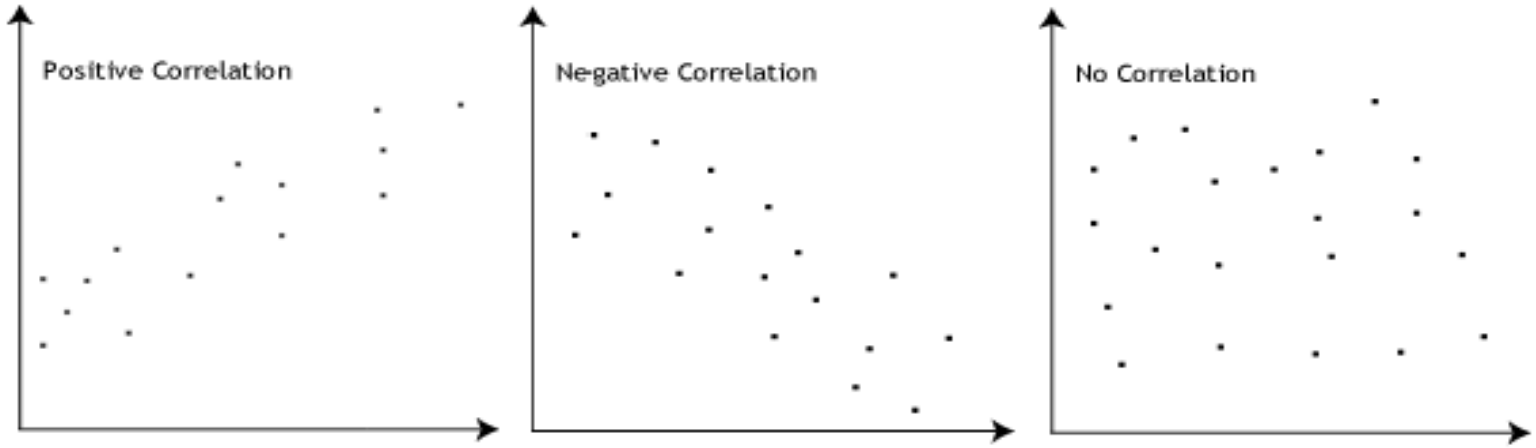
Pearson's r is a numerical summary of the strength of the linear association between the variables. If the variables tend to go up and down together, the correlation coefficient will be positive. If the variables tend to go up and down in opposition with low values of one variable associated with high values of the other, the correlation coefficient will be negative.

$$r = Cov(X,Y) / \sigma x \, \sigma y$$

- Covariance measures how X and Y vary together

- $\sigma x \, \sigma y$ : Standard deviations of X and Y

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:



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

Feature Scaling is a technique to standardize the independent features present in the data in a fixed range. It is performed during the data pre-processing to handle highly varying magnitudes or values or units. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values. Example**:** If an algorithm is not using feature scaling method then it can consider the value 3000 meter to be greater than 5 km but that's actually not true and in this case, the algorithm will give wrong predictions. So, we use Feature Scaling to bring all values to same magnitudes and thus, tackle this issue.

| Normalized scaling | Standardized scaling |
|---|---|
| Minimum and maximum value of features are used for scaling | Mean and standard deviation is used for scaling. |
| It is used when features are of different scales. | It is used when we want to ensure zero mean and unit standard deviation. |
| Scales values between [0, 1] or [-1, 1]. | It is not bounded to a certain range. |
| It is really affected by outliers. | It is much less affected by outliers. |
| Scikit-Learn provides a transformer called MinMaxScaler for Normalization. | Scikit-Learn provides a transformer called StandardScaler for standardization. |

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

An infinite value for the Variance Inflation Factor (VIF) typically indicates a problem of perfect multicollinearity among the predictor variables in a regression model

**Causes of Infinite VIF**

1. **Perfect Multicollinearity** : When one predictor variable is a perfect linear combination of one or more other predictor variables in the model, perfect multicollinearity occurs. This means that there is a direct, exact linear relationship between the predictors.

**Example**: If you have a variable a that is exactly twice the value of another variable b,there is perfect multicollinearity between a and b.

**2. Dummy Variable Trap** : This happens when dummy variables are created for categorical variables without dropping one category. Including all categories as dummy variables causes perfect multicollinearity since one dummy variable can be exactly predicted by the others.

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 lead 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.

The quantile-quantile (q-q) plot is a graphical technique for determining if two data sets come from populations with a common distribution.

**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.

**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.