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:

From the analysis of the categorical features of the given dataset, I've inferred below mentioned inferences.

- In 2019, we saw more bookings than in 2018, indicating growth.
- Clear weather attracts more bookings, and 2019 had more bookings in all weather conditions.
- Fall is the most popular season for bookings, with increases seen across all seasons in 2019.
- Thursday through Sunday are the busiest days for bookings.
- Despite being workdays, bookings still occur, though not as much as on holidays.
- Overall, 2019 showed a significant increase in bookings compared to the previous year, reflecting positive business progress.
- Demand for bikes continuously growing each month till June.
- After September, demand is decreasing.
- Demand is lesser on working day.
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2. Why is it important to use drop_first=True during dummy variable creation? (2 mark)
Answer:
When creating dummy variables from categorical data, setting drop_first=True is essential. This parameter **prevents multicollinearity**, where one predictor variable in a regression model can be predicted from the others.

- **Mitigation of Multicollinearity**
- **Enhanced Interpretability of Regression Coefficients**

Eliminating perfect multicollinearity is vital for accurately interpreting regression coefficients. When all levels of a categorical variable are included as predictors in the model, one level becomes redundant, rendering it impossible to estimate its unique effect on the dependent variable.

By dropping the first level of each categorical variable, you ensure that there's no perfect multicollinearity, where one dummy variable becomes a linear combination of the others. This not only aids in interpreting coefficients but also prevents issues like the "dummy variable trap," where including all levels of a categorical variable as predictors can hinder model performance and interpretation. Ultimately, drop_first=True enhances regression models by eliminating redundant information and improving their overall performance and interpretability.

This parameter ensures that one level of each categorical variable is dropped, creating n – 1 dummy variables for n categories.

Ultimately, using drop_first=True helps in improving the performance and interpretation of regression models by eliminating redundant information caused by perfect multicollinearity.

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

Answer:

'temp' variable has the highest correlation with the target variable.

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

Answer:

Residual Analysis has been done for validating of the Lineaar Regression assumptions, These assumption include:

- **Normality of Error Terms:** This assumption states that the error terms (residuals) should follow a normal distribution. It implies that most of the residuals should be clustered around zero
- **Multicollinearity:** Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated. So assumption states that there should not be any significant multicollinearity amongst the features.
- **Linearity:** Linearity assumes that the relationship between the independent variables and the dependent variable is linear. Residuals should be randomly scattered around zero when plotted against predicted values.
- **Homoscedasticity:** The variance of the errors should be constant across all levels of the independent variables. This assumption can be checked by plotting the residuals against the predicted values and ensuring that the spread of the residuals is consistent.
- **No Perfect Multicollinearity:** There should be no perfect multicollinearity among the independent variables, meaning that no independent variable should be a perfect linear function of other independent variables. This assumption can be assessed by calculating variance inflation factors (VIF) for each independent variable, with values below 5 typically considered acceptable.
- **Independence of Variables:** Independence of variables assumes that the predictor variables used in the regression model are not correlated with each other, meaning there should not be significant auto-correlation.

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,

- temp
- Light_snowrain
- year

General Subjective Questions

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

Linear regression may be defined as the statistical model that analyzes the linear relationship between a dependent variable with a 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.

And Linear regression can be extended to **Multi linear Regression** as well as shown below,

$$y = \beta 0 + \beta 1 \cdot x1 + \beta 2 \cdot x2 + \ldots + \beta n \cdot xn$$

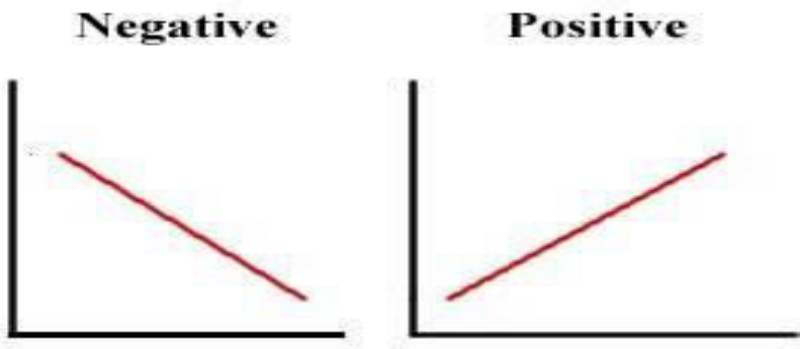
here, $x1, x2, \ldots, xn$ are independent variables and $\beta 1, \beta 2, \ldots, \beta n$ are their respective coefficients. Furthermore, the linear relationship can be positive or negative in nature as explained below−

Positive Linear Relationship:

A linear relationship will be called positive if both independent and dependent variables increase. It can be understood with the help of following graph

Negative Linear Relationship:

A linear relationship will be called positive if independent increases and dependent variable decreases. It can be understood with the help of following graph



The following are some assumptions about dataset that is made by Linear Regression model −

- **Normality of Error Terms:**
    - This assumption states that the error terms (residuals) should follow a normal distribution. It implies that most of the residuals should be clustered around zero
- **Multicollinearity:**
    - Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated. So assumption states that there should not be any significant multicollinearity amongst the features.
- **Linearity:**
    - Linearity assumes that the relationship between the independent variables and the dependent variable is linear. Residuals should be randomly scattered around zero when plotted against predicted values.
- **Homoscedasticity:**
    - Homoscedasticity refers to the assumption that the variance of the residuals should remain constant across all levels of the predictor variables. In simpler terms, there should not be any visible patterns in the residual plot.
- **Independence of Variables:**
    - Independence of variables assumes that the predictor variables used in the regression model are not correlated with each other, meaning there should not be significant auto-correlation.

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, and I must emphasize COMPLETELY, when they are graphed. Each graph tells a different story irrespective of their similar summary statistics,

Understanding Anscombe's Quartet

Anscombe's quartet is a set of four datasets that have nearly identical statistical properties but vastly different visual representations. This dataset was created by the statistician Francis Anscombe in 1973 to emphasize the importance of graphical exploration in data analysis and the potential pitfalls of relying solely on summary statistics.

The four datasets in Anscombe's quartet have the following characteristics:

Dataset I: It consists of linear relationships between the variables. The relationship is represented by a straight line, and the summary statistics (mean, variance, correlation coefficient) closely resemble those of a simple linear regression model.

Dataset II: It also has a linear relationship but with an outlier that significantly affects the correlation coefficient and regression line. Despite this outlier, the summary statistics remain similar to those of Dataset I.

Dataset III: This dataset exhibits a non-linear relationship. Although the data points are perfectly fitted by a simple linear regression model, the actual relationship is better captured by a

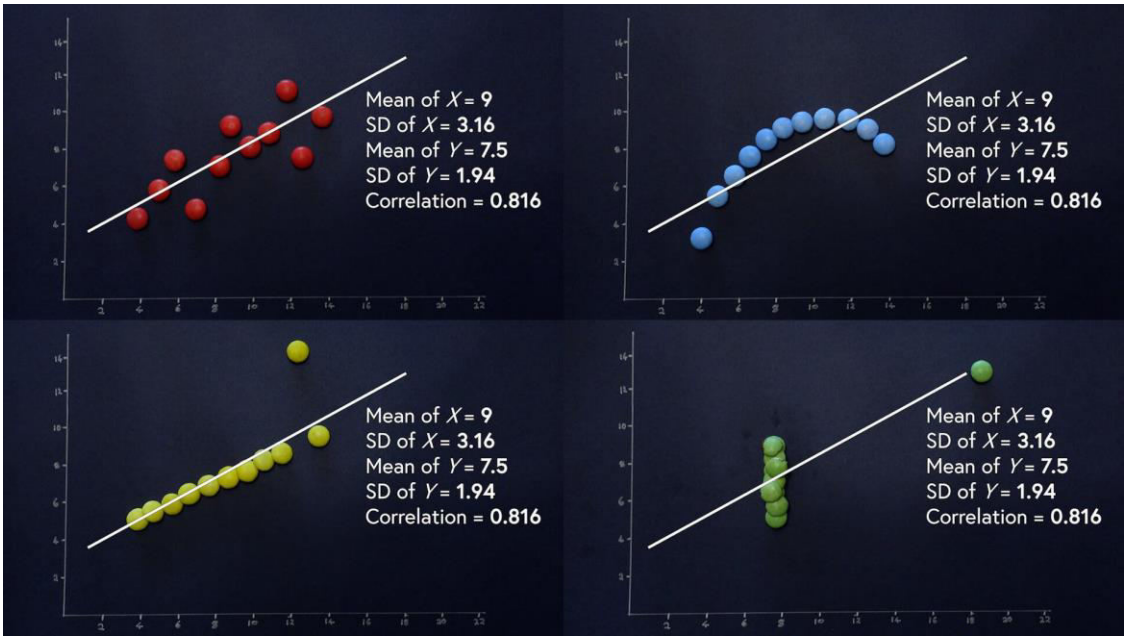
quadratic model. The summary statistics do not reveal this non-linearity.

Dataset IV: It contains an extreme outlier that exerts a disproportionate influence on the linear regression line. The outlier creates a high leverage point that affects the slope and intercept of the regression line.

By presenting these four datasets, Anscombe illustrated the limitations of relying solely on summary statistics such as mean, variance, and correlation coefficient. Despite having identical summary statistics, the datasets exhibit distinct patterns when visualized graphically. This highlights the importance of data visualization in understanding the underlying structure of the data and identifying potential outliers, non-linear relationships, and other anomalies that may not be apparent from summary statistics alone.

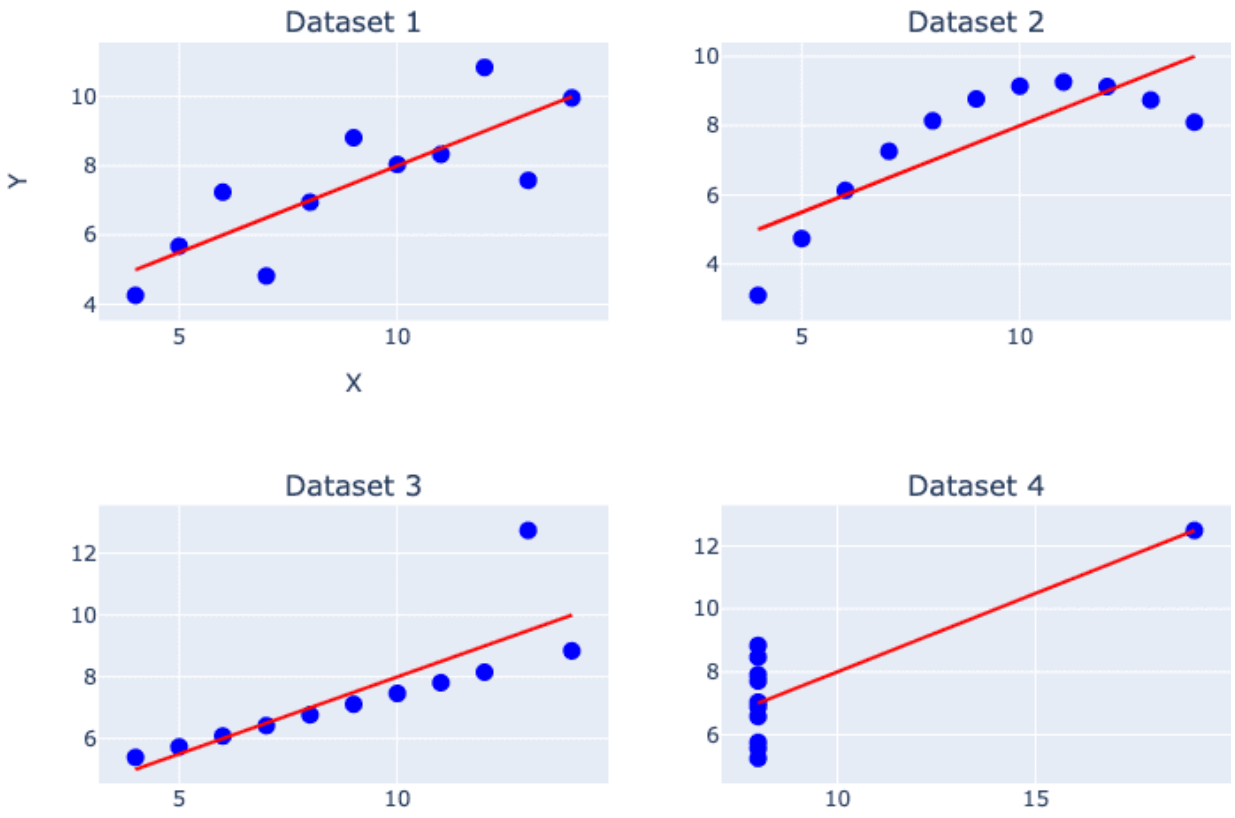
x1	y1	x2	y2	x3	y3	x4	y4
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.1	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.1	4.0	5.39	19.0	12.5
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

In essence, Anscombe's quartet serves as a cautionary tale, reminding analysts to complement statistical analysis with graphical exploration to gain a more comprehensive understanding of the data and to avoid drawing erroneous conclusions based solely on summary statistics.



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

When we plot these four datasets on an x/y coordinate plane, we can observe that they showthe same regression lines as well but each dataset is telling a different story:



- 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.

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.

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

Answer:

Pearson's correlation coefficient (often denoted as Pearson's r) is a statistical measure that quantifies the strength and direction of a linear relationship between two continuous variables. It assesses the linear association between two variables, indicating how much one variable changes when the other changes, assuming a linear relationship between them. The closer r is to 1 or -1, the stronger the linear relationship. A value closer to 0implies a weaker linear relationship.

Key points about Pearson's correlation coefficient:

Resulting Range: The value of r ranges between -1 and 1.

- $r = 1$ implies a perfect positive linear relationship.
- $r = -1$ implies a perfect negative linear relationship.
- $r = 0$ means no linear relationship exists between the variables.

Direction:

- Positive r values indicate a positive linear relationship (both variables increase or decrease together).
- Negative r values indicate a negative linear relationship (one variable increases while the other decreases).

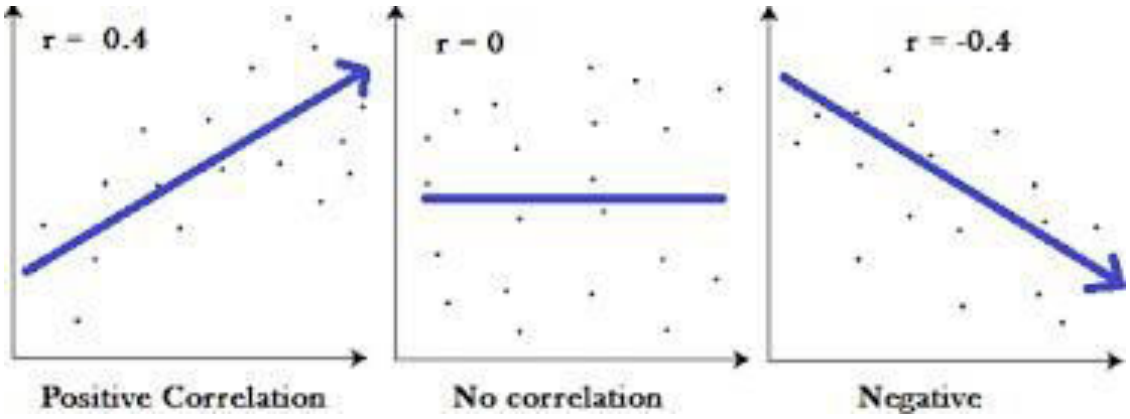
Assumptions: Pearson's r assumes a linear relationship between variables and is sensitive to outliers and non-linear patterns.

The formula for Pearson's correlation coefficient between two variables X and Y with n points is:

$$r = \frac{\Sigma(X - \overline{X})(Y - \overline{Y})}{\sqrt{\Sigma(X - \overline{X})^2 \Sigma(Y - \overline{Y})^2}}$$

Here, $\overline{X}$ and $\overline{Y}$ represent the means of variables X and Y respectively.

Pearson's r is widely used in various fields like statistics, social sciences, finance, and more to measure the strength and direction of linear relationships between variables.



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

Answer:

Scaling in data analysis refers to adjusting the range or distribution of data to ensure that different features or variables have comparable scales. It's done for several reasons:

Consistent Comparison: Scaling helps in comparing features that have different units or scales. For instance, if one feature ranges from 0 to 1000 and another from 0 to 1, the one with larger values might dominate the analysis. Scaling brings them to a common scale for fair comparison.

Algorithm Performance: Many machine learning algorithms, like SVM, K-nearest neighbors, and neural networks, are sensitive to the scale of input features. Scaling helps these algorithms converge faster and prevents features with larger scales from disproportionately influencing the model.

Normalization and standardization are two common scaling techniques:

4. 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. The occurrence of infinite values for the Variance Inflation Factor (VIF) typically arises due to perfect multicollinearity among the predictor variables in a regression model. Perfect multicollinearity occurs when one or more independent variables in the model can be perfectly predicted by a linear combination of other independent variables. This leads to numerical instabilities and makes it impossible to estimate the VIF for the affected variable(s) accurately. If the VIF is 3, this means that the variance of the model coefficient is inflated by a factor of 3 due to the presence of multicollinearity. When the value ofVIF 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 $\frac{1}{1-r^2}$ infinity. To solve this we need to drop one of the variables from the dataset which is causing this perfectmulticollinearity.

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

(3 marks)

Answer:

A Q-Q (quantile-quantile) plot is a graphical technique used to assess whether a dataset follows a particular probability distribution, such as the normal distribution. It compares the quantiles of the dataset against the quantiles of a theoretical distribution.

Here's how it works:

1. Quantiles: Quantiles are points taken at regular intervals from a cumulative distribution function (CDF). For example, the median is a quantile that divides the data into two equal parts.

2. Constructing a Q-Q Plot: In a Q-Q plot, the quantiles of the dataset are plotted against the quantiles of a theoretical distribution. If the data matches the theoretical distribution, the points in the Q-Q plot should roughly fall along a straight line.

The use and importance of a Q-Q plot in linear regression are as follows:

1. Assumption Checking: In linear regression, several assumptions are made about the data, including the assumption of normality of residuals (errors). The Q-Q plot helps in checking if the residuals follow a normal distribution. If the residuals are normally distributed, the points in the Q-Q plot will roughly form a straight line.

2. Detecting Departures from Normality: If the Q-Q plot shows a departure from a straight line (e.g., if the points deviate significantly from the line), it suggests that the residuals might not follow a normal distribution. This departure could indicate issues like outliers, skewness, or heavy-tailed distributions in the residuals.

3. Model Validity: Assessing the normality of residuals is crucial in linear regression because violating the assumption of normally distributed errors might affect the validity of statistical inferences and predictions made by the model.

In summary, a Q-Q plot is a valuable tool in linear regression analysis as it helps to visually examine whether the residuals adhere to the assumption of normality. This assessment is important for understanding the reliability of the regression model and the accuracy of its predictions.