Bike Sharing Assignment

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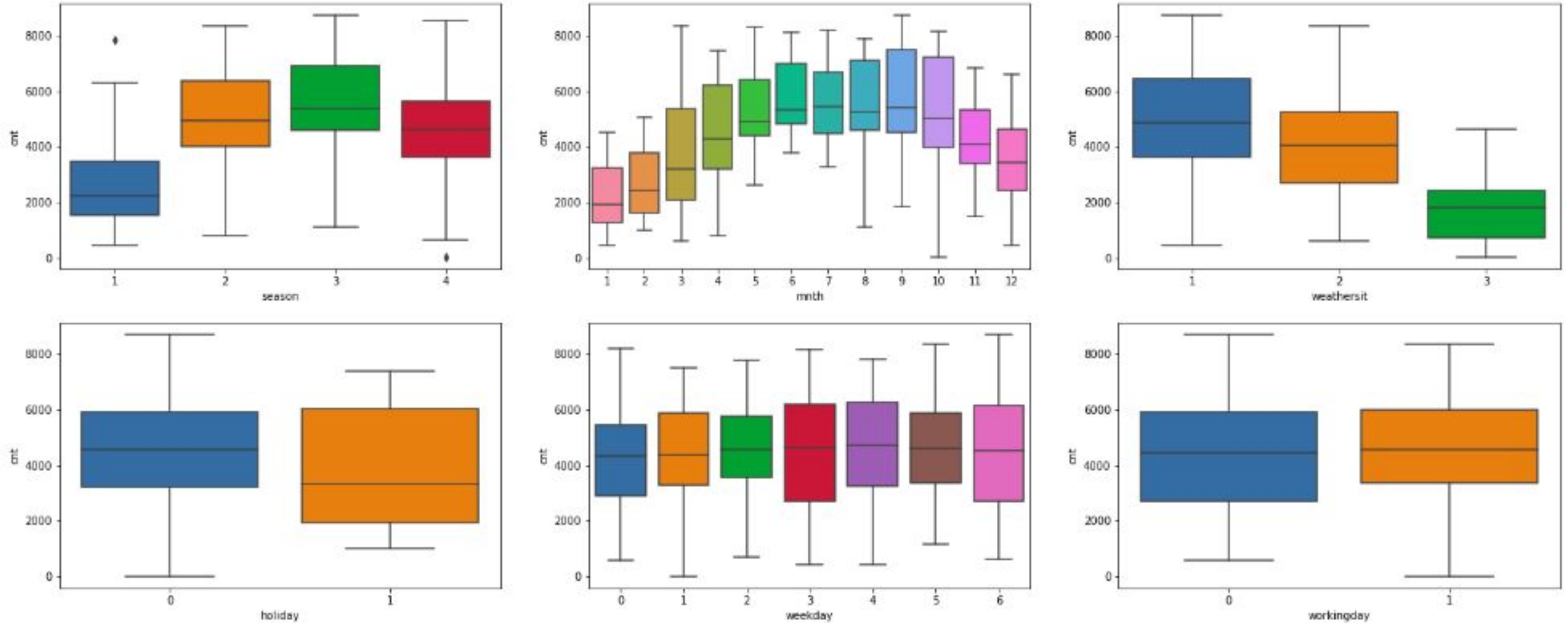
From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable?

There were 6 categorical variables in the dataset. I used Box plot (refer the fig to next slide) to study their effect on the dependent variable (‘cnt’) . The inference that I 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.

```
plt.figure(figsize=(25, 10))
plt.subplot(2,3,1)
sns.boxplot(x = 'season', y = 'cnt', data = bike)
plt.subplot(2,3,2)
sns.boxplot(x = 'mnth', y = 'cnt', data = bike)
plt.subplot(2,3,3)
sns.boxplot(x = 'weathersit', y = 'cnt', data = bike)
plt.subplot(2,3,4)
sns.boxplot(x = 'holiday', y = 'cnt', data = bike)
plt.subplot(2,3,5)
sns.boxplot(x = 'weekday', y = 'cnt', data = bike)
plt.subplot(2,3,6)
sns.boxplot(x = 'workingday', y = 'cnt', data = bike)
plt.show()
```



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.

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

The Pair-Plot tells us that there is a LINEAR RELATION between 'temp','atemp' and 'cnt

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

lr6 model coefficient values

- const 0.084143
- yr 0.230846
- workingday 0.043203
- temp 0.563615
- windspeed -0.155191
- season_2 0.082706
- season_4 0.128744
- mnth_9 0.094743
- weekday_6 0.056909
- weathersit_2 -0.074807
- weathersit_3 -0.306992

F Statistics

F-Statistics is used for testing the overall significance of the Model: Higher the F-Statistics, more significant the Model is.

- F-statistic: 233.8
- Prob (F-statistic): 3.77e-181

The F-Statistics value of 233 (which is greater than 1) and the p-value of '~0.0000' states that the overall model is significant

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

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.

Explain the linear regression algorithm in detail.

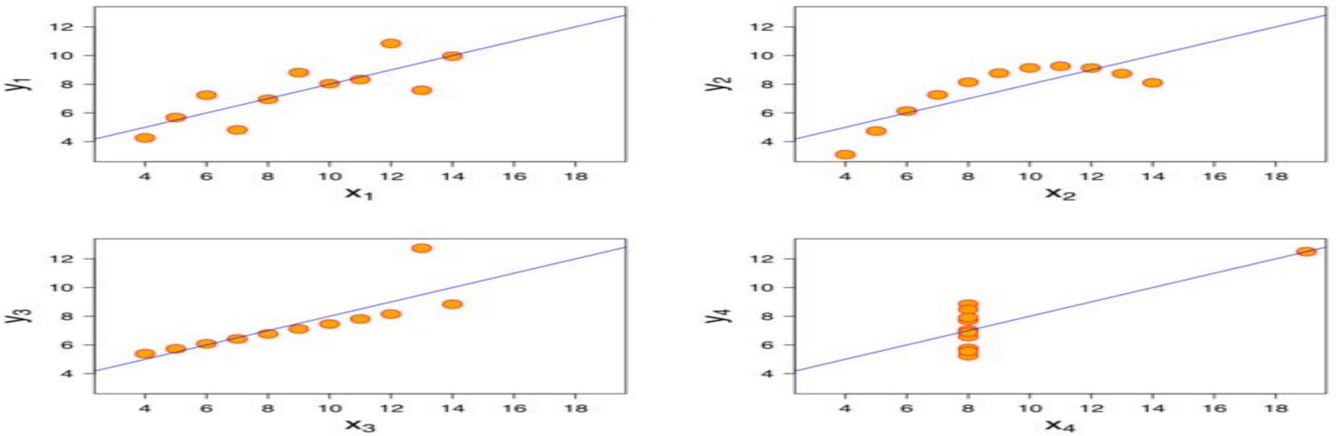
Linear regression may be defined as the statistical model that analyzes the linear relationship between a dependent variable with given set of independent variables. Linear relationship between variables means that when the value of one or more independent variables will change (increase or decrease),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

Mathematically the relationship can be represented with the help of following equation

$$Y = c + MX$$

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 change completely, and I must emphasize **COMPLETELY,** when they are graphed. Each graph tells 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. 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.

What is Pearson’s R?

The Pearson product-moment correlation coefficient (or Pearson correlation coefficient, for short) is a measure of the strength of a linear association between two variables and is denoted by r. Basically, a Pearson product-moment correlation attempts to draw a line of best fit through the data of two variables, and the Pearson correlation coefficient, 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).

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.

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

If all the independent variables are orthogonal to each other, then VIF = 1.0. 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. This would mean that that standard error of this coefficient is inflated by a factor of 2 (square root of variance is the standard deviation). The standard error of the coefficient determines the confidence interval of the model coefficients. If the standard error is large, then the confidence intervals may be large, and the model coefficient may come out to be non-significant due to the presence of multicollinearity. A general rule of thumb is that if VIF > 10 then there is multicollinearity.

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.

It can be used with sample sizes also.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.

If 2 datasets come from populations with a common distribution and have common location and scale and have similar distributional shapes