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?

Answer: From our analysis of categorical vs dependent variables we can observe below effect

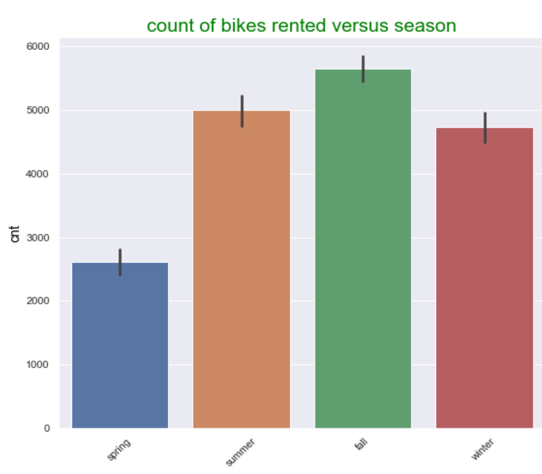
1. Count of Bikes rented is maximum during the Fall Season and least during the spring season

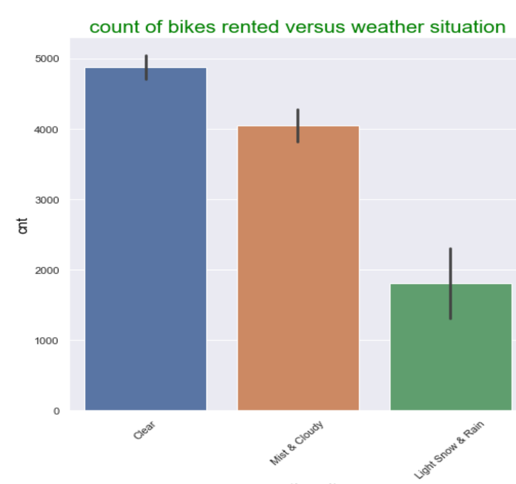
2. From the Month wise plot we can infer bike renting is maximum in June and least during the month of Jan.

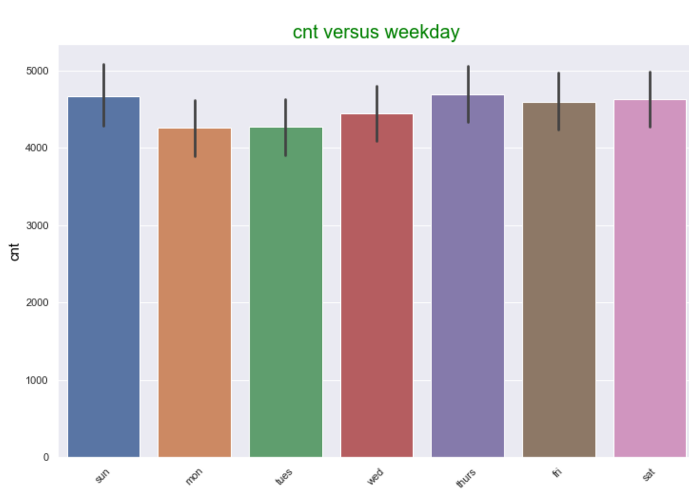
3. From the weather condition plot we can infer that most bikes are rented when weather conditions are Clear and least when it is light snow or light rain. Also no bikes are rented in case of heavy rains or snow.

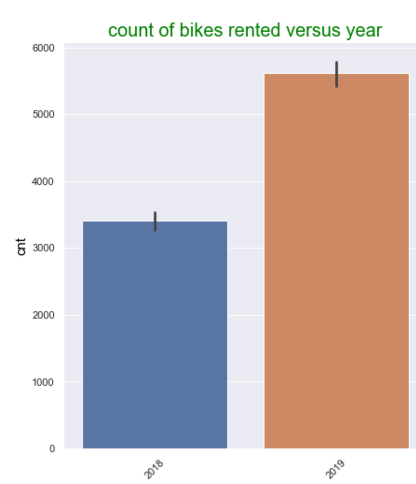
4. The count of bikes rented don't have significant difference for all days of week, however a little higher for sunday and thursday.

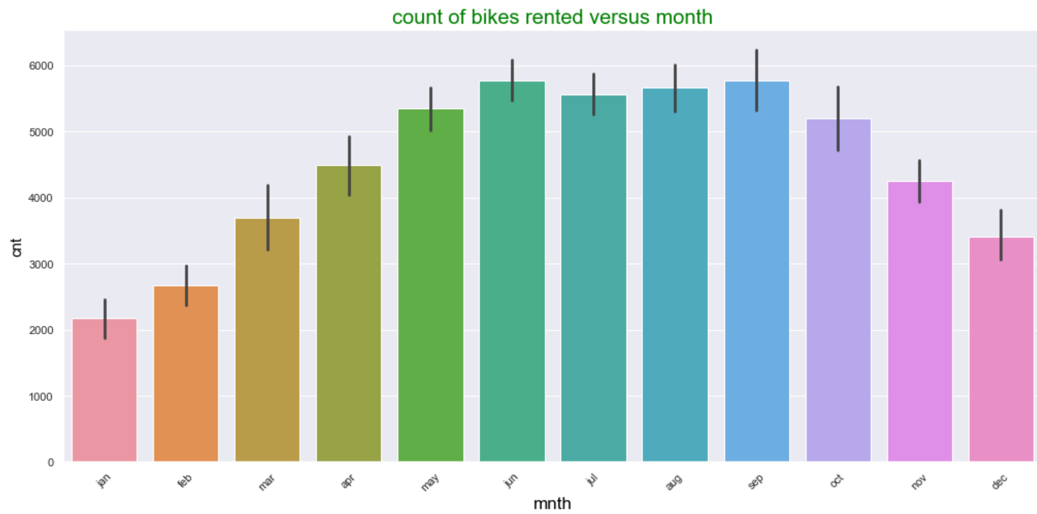
5. More bikes are rented in the year 2019 as compared to 2018.











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

Answer: If a categorical column has 2 levels, then the number of fields required to describe the data will be m-1, where m is the number of levels in a categorical column.

Eg: Gender has two categories male and female. When we use get_dummies over the gender column, It creates below values. Male column and female column are providing the same interpretation.

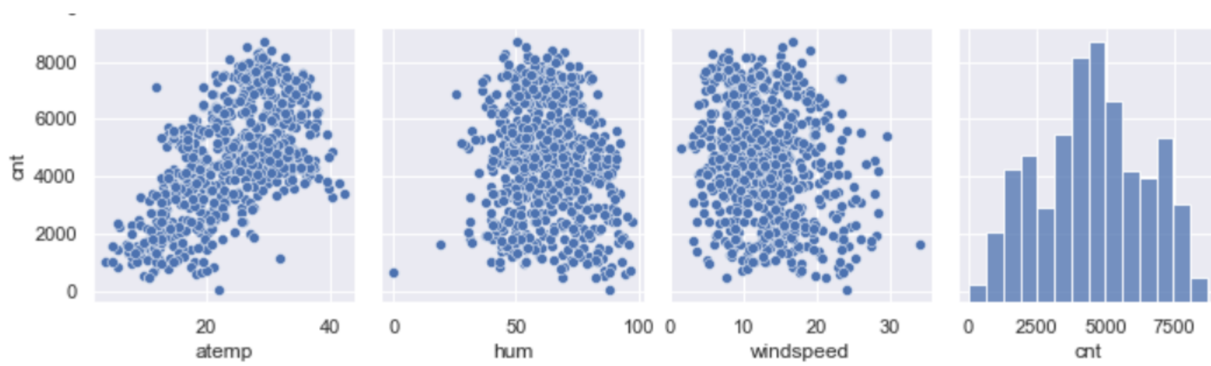
So any of the one column can be dropped as Gender can either be male or female i.e., if the male column would have value 0 that means the female will be 1 and vice-versa. Both of them having 0 value is not possible.

By using **drop_first=True** drops the first resulting column (Male)

Gender	Male	Female
Male	1	0
Female	0	1

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

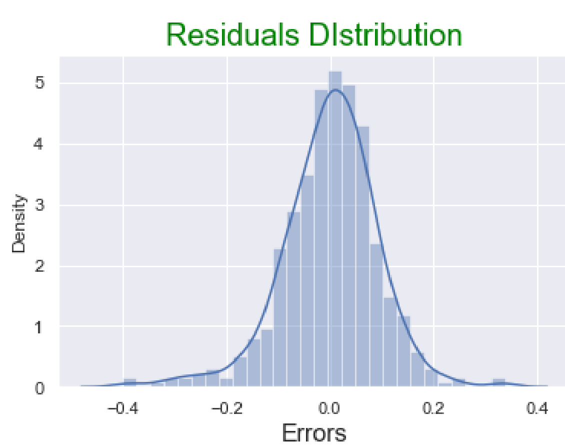
Answer: The variable atemp - Adjusted Temp has the highest correlation with total bike count- cnt (Target Variable)

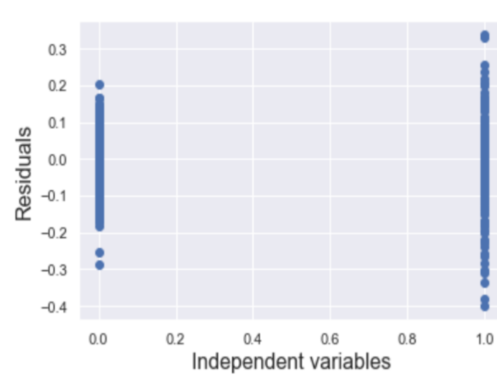


4. How did you validate the assumptions of Linear Regression after building the model on the training set?

Answer: Assumption of linear regression after building the model can be validated by residual analysis.

- Checked if the error terms are normally distributed using a histogram plot
- Checked for any kind of patterns between residuals and independent variable using scatter plot.





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

Answer: The top three features that have significantly explained the target variable - Adjusted the demand of the shared bikes are as follows:

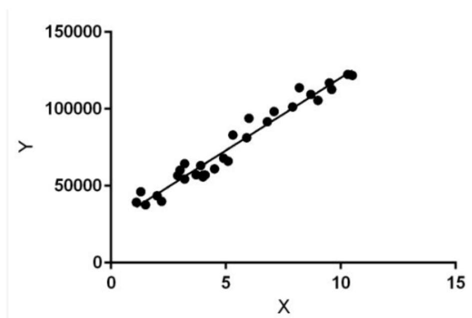
1) **atemp**: feeling temperature in Celsius
2) **yr** : year 2018 or 2019
3) **winter** : one of the categories of season

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1275	0.017	7.429	0.000	0.094	0.161
yr	0.2334	0.008	27.867	0.000	0.217	0.250
holiday	-0.0934	0.027	-3.513	0.000	-0.146	-0.041
atemp	0.5370	0.024	22.850	0.000	0.491	0.583
windspeed	-0.1319	0.026	-5.132	0.000	-0.182	-0.081
summer	0.0990	0.011	8.750	0.000	0.077	0.121
winter	0.1311	0.011	12.114	0.000	0.110	0.152
aug	0.0679	0.017	4.065	0.000	0.035	0.101
sep	0.1209	0.017	7.226	0.000	0.088	0.154
light_snow&rain	-0.2760	0.025	-10.953	0.000	-0.326	-0.227
mist&cloudy	-0.0822	0.009	-9.184	0.000	-0.100	-0.065

General Subjective Questions

1. Explain the linear regression algorithm in detail.

Answer: Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.

In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

$$y = \theta_1 + \theta_2.x$$

While training the model we are given :

x: input training data (univariate – one input variable(parameter))

y: labels to data (supervised learning)

When training the model – it fits the best line to predict the value of y for a given value of x. The model gets the best regression fit line by finding the best θ1 and θ2 values.

θ1: intercept

θ2: coefficient of x

Once we find the best θ1 and θ2 values, we get the best fit line. So when we are finally using our model for prediction, it will predict the value of y for the input value of x.

2. Explain the Anscombe's quartet in detail.

Answer: 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. These four plots can be defined as follows:

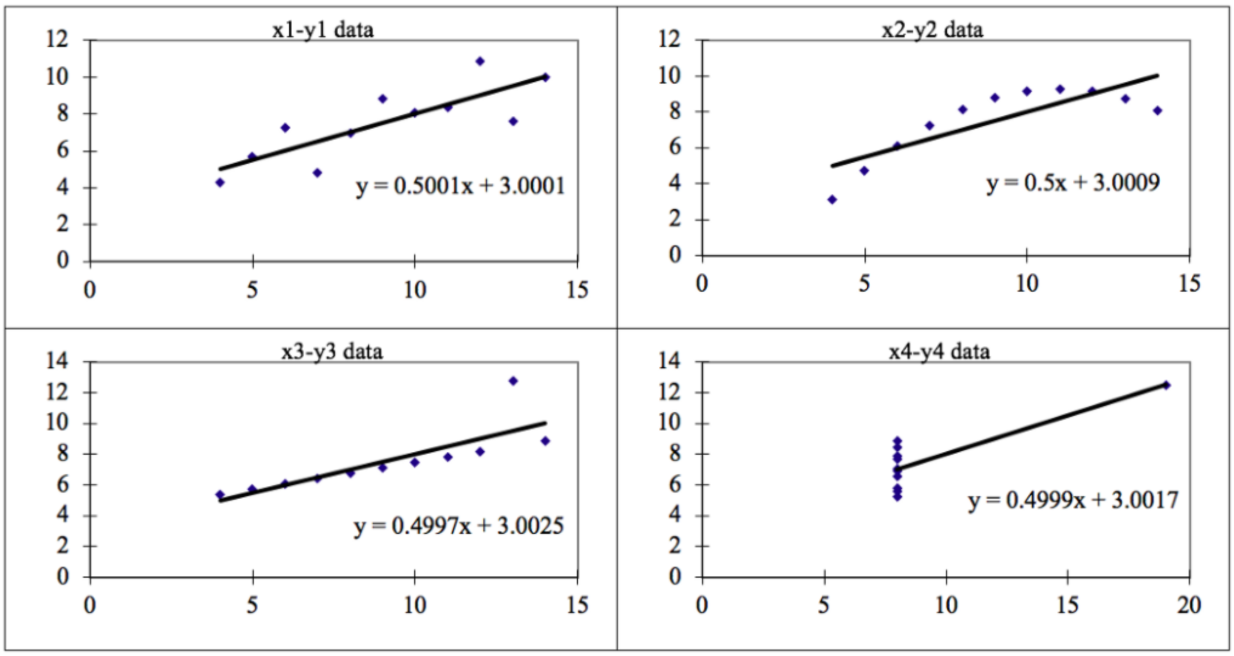
Anscombe's Data											
Observation	x1	y1		x2	y2		x3	y3		x4	y4
1	10	8.04		10	9.14		10	7.46		8	6.58
2	8	6.95		8	8.14		8	6.77		8	5.76
3	13	7.58		13	8.74		13	12.74		8	7.71
4	9	8.81		9	8.77		9	7.11		8	8.84
5	11	8.33		11	9.26		11	7.81		8	8.47
6	14	9.96		14	8.1		14	8.84		8	7.04
7	6	7.24		6	6.13		6	6.08		8	5.25
8	4	4.26		4	3.1		4	5.39		19	12.5
9	12	10.84		12	9.13		12	8.15		8	5.56
10	7	4.82		7	7.26		7	6.42		8	7.91
11	5	5.68		5	4.74		5	5.73		8	6.89

Image by Author

The statistical information for all these four datasets are approximately similar and can be computed as follows:

Anscombe's Data											
Observation	x1	y1		x2	y2		x3	y3		x4	y4
1	10	8.04		10	9.14		10	7.46		8	6.58
2	8	6.95		8	8.14		8	6.77		8	5.76
3	13	7.58		13	8.74		13	12.74		8	7.71
4	9	8.81		9	8.77		9	7.11		8	8.84
5	11	8.33		11	9.26		11	7.81		8	8.47
6	14	9.96		14	8.1		14	8.84		8	7.04
7	6	7.24		6	6.13		6	6.08		8	5.25
8	4	4.26		4	3.1		4	5.39		19	12.5
9	12	10.84		12	9.13		12	8.15		8	5.56
10	7	4.82		7	7.26		7	6.42		8	7.91
11	5	5.68		5	4.74		5	5.73		8	6.89
					Summary Statistics						
N	11	11		11	11		11	11		11	11
mean	9.00	7.50		9.00	7.500909		9.00	7.50		9.00	7.50
SD	3.16	1.94		3.16	1.94		3.16	1.94		3.16	1.94
r	0.82			0.82			0.82			0.82	

When these models are plotted on a scatter plot, all datasets generates a different kind of plot that is not interpretable by any regression algorithm which is fooled by these peculiarities and can be seen as follows:



Dataset 1: this fits the linear regression model pretty well.

Dataset 2: this could not fit linear regression model on the data quite well as the data is non-linear.

Dataset 3: shows the outliers involved in the dataset which cannot be handled by linear regression model

Dataset 4: shows the outliers involved in the dataset which cannot be handled by linear regression model

We have described the four datasets that were intentionally created to describe the importance of data visualisation and how any regression algorithm can be fooled by the same. Hence, all the important features in the dataset must be visualised before implementing any machine learning algorithm on them which will help to make a good fit model.

3. What is Pearson’s R?

Answer: Pearson’s R is a numerical summary of the strength of the linear association between the variables. It varies between -1 and +1. 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 = 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

Below, is the formula to calculate Pearson’s R for a given dataset.

$$r = \frac{N\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{[N\Sigma x^2 - (\Sigma x)^2][N\Sigma y^2 - (\Sigma y)^2]}}$$

Where:

N	=	number of pairs of scores
Σxy	=	sum of the products of paired scores
Σx	=	sum of x scores
Σy	=	sum of y scores
Σx^2	=	sum of squared x scores
Σy^2	=	sum of squared y scores

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

Answer: 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.
It is extremely important to rescale the variables so that they have a comparable scale. If we don't have comparable scales, then some of the coefficients as obtained by fitting the regression model might be very large or very small as compared to the other coefficients.
Normalized scaling means to scale a variable to have values between 0 and 1, while standardized scaling refers to transform data to have a mean of zero and a standard deviation of 1.

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

Answer: It directly indicates that the particulate variable has severe collinearity. Also, the corresponding variable can be expressed as a linear combination of other variables. In other words, squared multiple correlation of any predictor variable with the other predictors approaches unity.

VIF= 1/1-rsquare=1/1-1 =inf

When rsquare is one VIF equals to infinity

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

Answer: 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

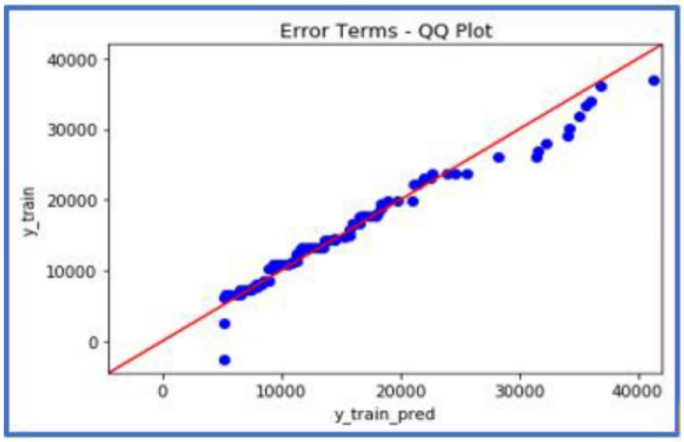
Interpretation:

A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second data set.

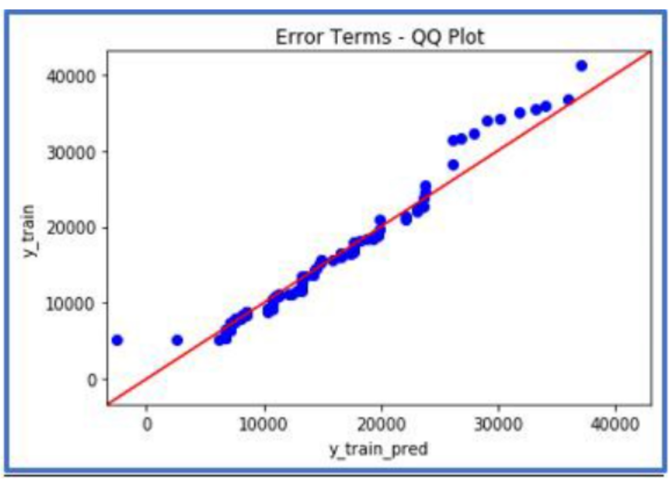
Below are the possible interpretations for two data sets.

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.



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