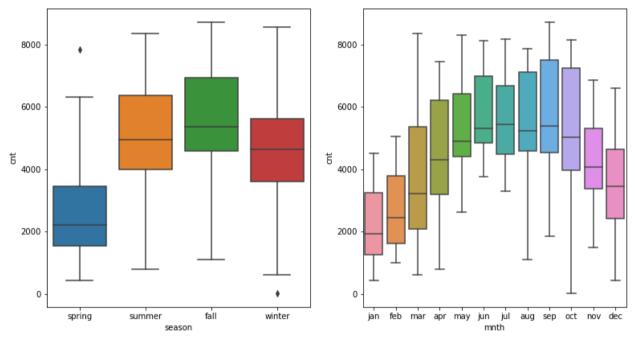
### **Assignment-based Subjective Questions**

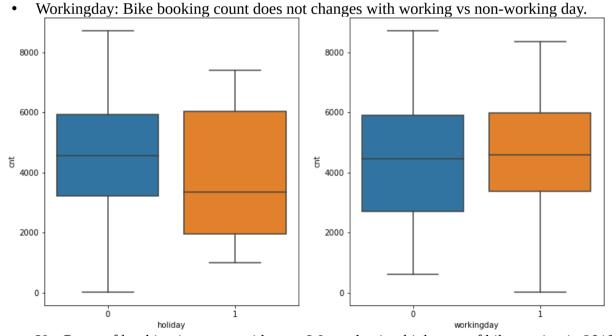
# 1. From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable? (3 marks)

Answer: We are having the following catagorical features in the dataset:

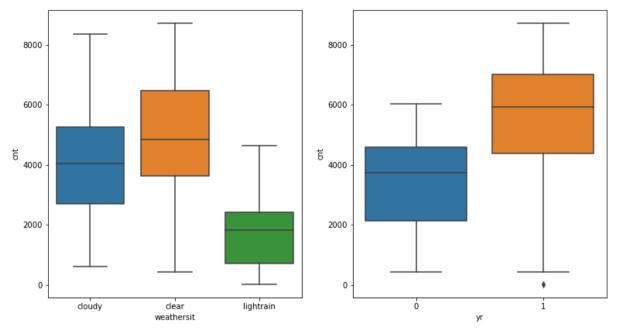
- Season: Counts of rented bikes depends on season, cnt increases in Fall and Summer season and it gets decreases with winter and spring
- mnth: Cnt varies with months as we are having higher booking with May, June, July, August, and September. And booking drcreases with Winters month.



• Holiday: Cnt depends on holiday. On non-holiday we are having higher cnt value.



 Yr: Count of booking increases with year. We are having higher no of bike renting in 2019 year compared to 2018.



• Weathersit: Weathersit affects the bike booking. Clear weather attracts the customers and have higher booking then cloudy and then light rain.

### 2. Why is it important to use drop\_first=True during dummy variable creation? (2 mark)

Answer: When we are converting the catagorical features to numeric feature. So that these can be scalarized. We break the single column into the all possible probable columns and fill the values between 0 and 1.

For example: We are having the following catagorical feature:

Season	
summer	
winter	
fall	
spring	

And it will be converted to following table:

summer	Winter	Fall	spring
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

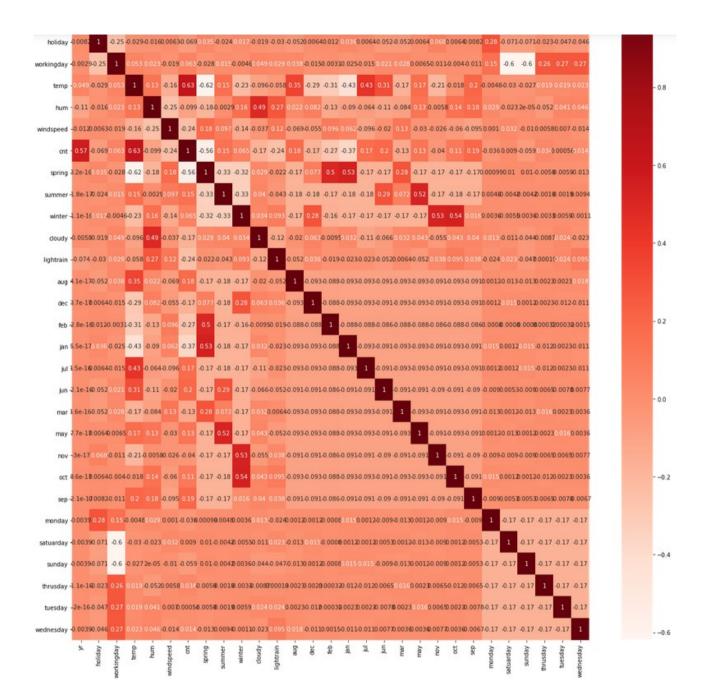
But we can extract the information with with 1 less column like if all the values are zero the we can assume it would be the final option and we can have the following table:

Winter	Fall	spring
0	0	0
1	0	0
0	1	0
0	0	1

As we can see 4 colums are reduced to 3 columns.

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

Answer: temp attribute is having the highest correlation with cnt (target variable) with 0.63 value.



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

**Answer:** We can validate the model on the following scenarios.

**a)** Low p-value --> p-value should be low (less then 0.05 is acceptable)

### OLS Regression Results

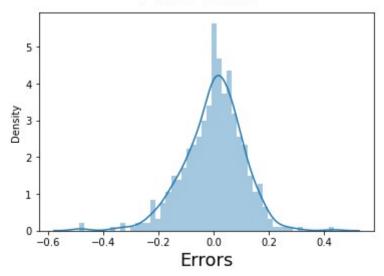
Dep. Variabl	e:		cnt R-	squared:		0.772
Model:			OLS Ad	j. R-squared:		0.767
Method:		Least Sq	uares F-	statistic:		187.7
Date:		Wed, 22 Dec	2021 Pro	ob (F-statist	ic):	4.31e-154
Time:		19:3	38:41 Log	g-Likelihood:		415.03
No. Observat	ions:		510 AI	C:		-810.1
Df Residuals	<b>:</b> :		500 BI	C:		-767.7
Df Model:			9			
Covariance 1	Type:	nonro	obust			
	coef	std err		t P> t	[0.025	0.975]
const	0.5723	0.013	43.029	9 0.000	0.546	0.598
yr	0.2486	0.010	25.83	0.000	0.230	0.268
windspeed	-0.2032	0.029	-6.94	0.000	-0.261	-0.146
spring	-0.2368		-16.51	0.000	-0.265	-0.209
winter	-0.0546	0.012	-4.589	9 0.000	-0.078	-0.031
cloudy	-0.0901	0.010	-8.79	0.000	-0.110	-0.070
lightrain	-0.2990		-10.279	9 0.000	-0.356	-0.242
jan	-0.1040		-5.09	7 0.000	-0.144	-0.064
sep	0.0862	0.018	4.76	4 0.000	0.051	0.122
sunday	-0.0465	0.014	-3.38	3 0.001	-0.074	-0.019
Omnibus:		47	7.207 Du	rbin-Watson:		1.996
Prob(Omnibus	s):			rque-Bera (J	3):	99.456
Skew:	-			ob(JB):	•	2.53e-22
Kurtosis:		4		nd. No.		8.67

**b)** Variance inflation factor (VIF) - VIF should be low (lesser then 5 is acceptable). as VIF = 1/(1-R-square)

	Features	VIF
1	windspeed	2.58
2	spring	2.12
0	yr	1.74
6	jan	1.59
4	cloudy	1.45
3	winter	1.37
8	sunday	1.15
7	sep	1.09
5	lightrain	1.08

c) Error Rate: Normalised Error rate with zero centralized.

### **Error Terms**



# 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:** Following features contribute the most:

- Light rain
- Yr
- Spring

## **General Subjective Questions**

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

**Answer:** Linear Regression is a supervised machine learning algorithm where the predicted output is continuous and has a constant slope. It's used to predict values within a continuous range, (e.g. sales, price) rather than trying to classify them into categories (e.g. cat, dog). There are two main types:

1. <u>Simple regression</u>: Simple linear regression uses traditional slope-intercept form, where *m* and *b* are the variables our algorithm will try to "learn" to produce the most accurate predictions. *X* represents our input data and *Y* represents our prediction.

$$y=mx+b$$

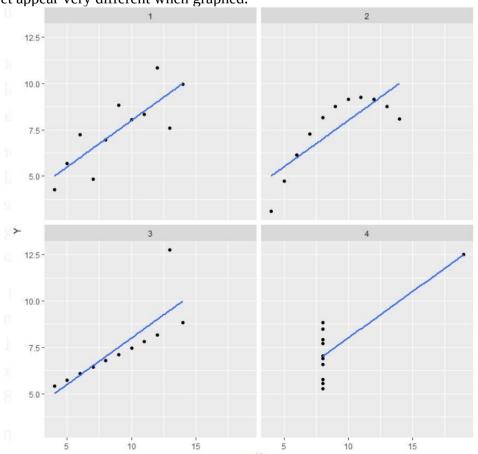
2. <u>Multivariable regression</u>: A more complex, multi-variable linear equation might look like this, where *W* represents the coefficients, or weights, our model will try to learn.

$$f(x,y,z) = w1x + w2y + w3z$$

For example: For sales predictions, these attributes might include a company's advertising spend on radio, TV, and newspapers.

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

**Answer:** Anscombe's quartet comprises four datasets that have nearly identical simple statistical properties, yet appear very different when graphed.



These above datasets have same Mean(x), std(x), Mean(y), std(y) and Cor(x,y) but their prediction are completely different.

**Conclusion:** It is strongly recommended to look at data first then start performing linear regression or any other analysis.