In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm

from scipy.stats import ttest_1samp
from scipy.stats import chi2_contingency
from scipy.stats import f_oneway
from scipy.stats import ttest_ind,ttest_ind_from_stats
```

Problem Statement

We need to test the relationship of various variables with the count(no . of rented bicyles)

EDA

In [2]:

```
df=pd.read_csv(r"C://Users//bike_sharing.csv")
```

In [3]:

```
df
```

Out[3]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000
...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	26.0027
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	15.0013
10883	2012-12-19 21:00:00	4	0	1	1	13.94	15.910	61	15.0013
10884	2012-12-19 22:00:00	4	0	1	1	13.94	17.425	61	6.0032
10885	2012-12-19 23:00:00	4	0	1	1	13.12	16.665	66	8.9981

10886 rows × 12 columns

In [4]:

```
df.shape
```

Out[4]:

```
(10886, 12)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   datetime    10886 non-null  object 
 1   season      10886 non-null  int64  
 2   holiday     10886 non-null  int64  
 3   workingday  10886 non-null  int64  
 4   weather     10886 non-null  int64  
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64  
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64  
 10  registered  10886 non-null  int64  
 11  count       10886 non-null  int64  
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

Categorical Conversion

In [6]:

```
cols = ['season', "holiday", 'workingday',"weather"]
df[cols] = df[cols].astype('object')
```

In [7]:

```
df['datetime'] = pd.to_datetime(df['datetime'])
```

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 1   season      10886 non-null  object
 2   holiday     10886 non-null  object
 3   workingday  10886 non-null  object
 4   weather     10886 non-null  object
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: datetime64[ns](1), float64(3), int64(4), object(4)
memory usage: 1020.7+ KB
```

Missing Values

1. There seems to be no missing values

In [9]:

```
df.describe()
```

Out[9]:

	temp	atemp	humidity	windspeed	casual	registered
count	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177
std	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033
min	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000
25%	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000
50%	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000
75%	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000
max	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000

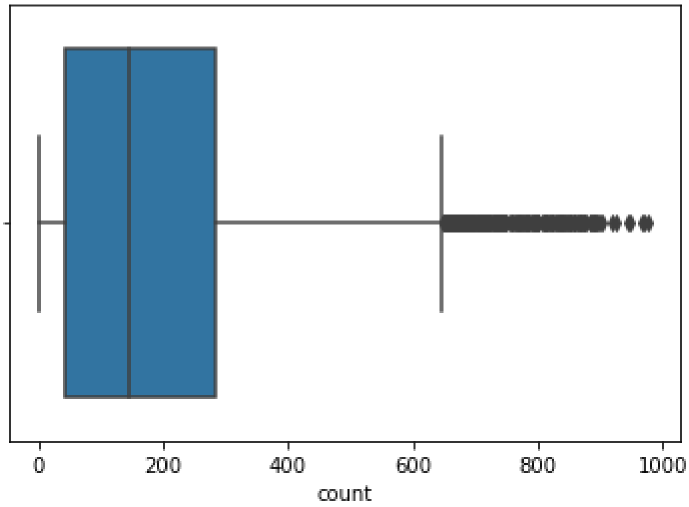
#OUTLIER DETECTION

In [10]:

```
sns.boxplot(x=df["count"])
```

Out[10]:

```
<AxesSubplot:xlabel='count'>
```



#OUTLIER TREATMENT

In [11]:

```
a=df["count"].quantile(0.75)
b=df["count"].quantile(0.25)
```

In [12]:

```
print(a,b)
```

```
284.0 42.0
```

In [13]:

```
iqr=a-b
iqr
```

Out[13]:

```
242.0
```

In [14]:

```
lower_lim= b-1.5*iqr
upper_lim=a+1.5*iqr
print(lower_lim,upper_lim)
```

```
-321.0 647.0
```

In [15]:

```
new_df_cap = df.copy()
```

In [16]:

```
new_df_cap['count'] = np.where(
    new_df_cap['count'] > upper_lim,upper_lim,np.where(new_df_cap['count'] < lower_lim,l
```

In [17]:

```
new_df_cap
```

Out[17]:

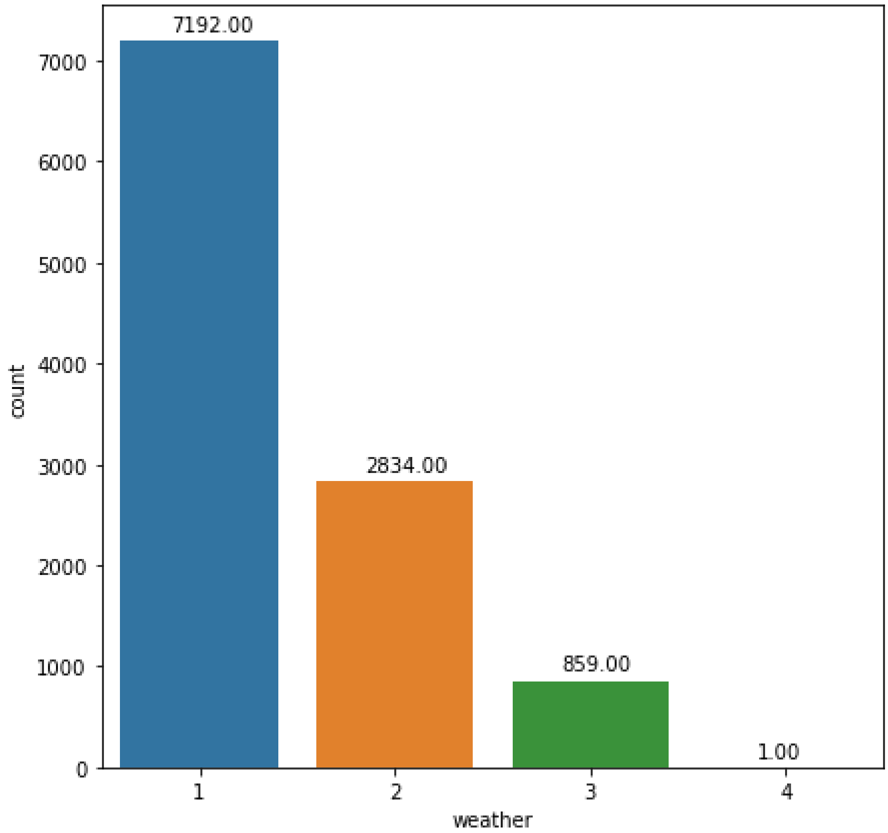
	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000
...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	26.0027
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	15.0013
10883	2012-12-19 21:00:00	4	0	1	1	13.94	15.910	61	15.0013
10884	2012-12-19 22:00:00	4	0	1	1	13.94	17.425	61	6.0032
10885	2012-12-19 23:00:00	4	0	1	1	13.12	16.665	66	8.9981

10886 rows × 12 columns

#UNIVARIATE ANALSYIS

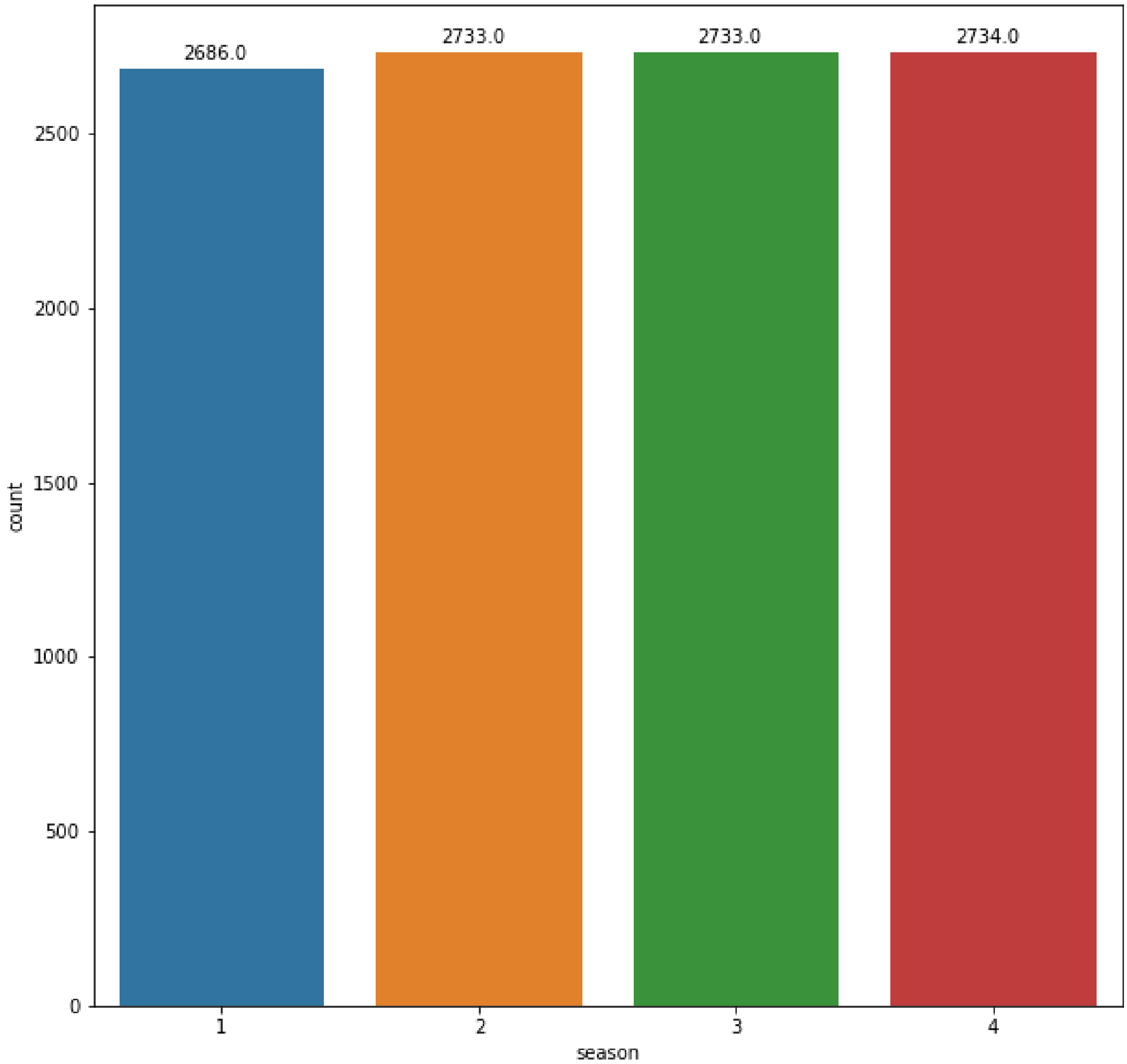
In [18]:

```
plt.figure(figsize=(7,7))
p=sns.countplot(x=new_df_cap["weather"])
for i in p.patches:
    plt.annotate("{:.2f}".format(i.get_height()),(i.get_x()+0.25,i.get_height()),xytext=
plt.show()
```



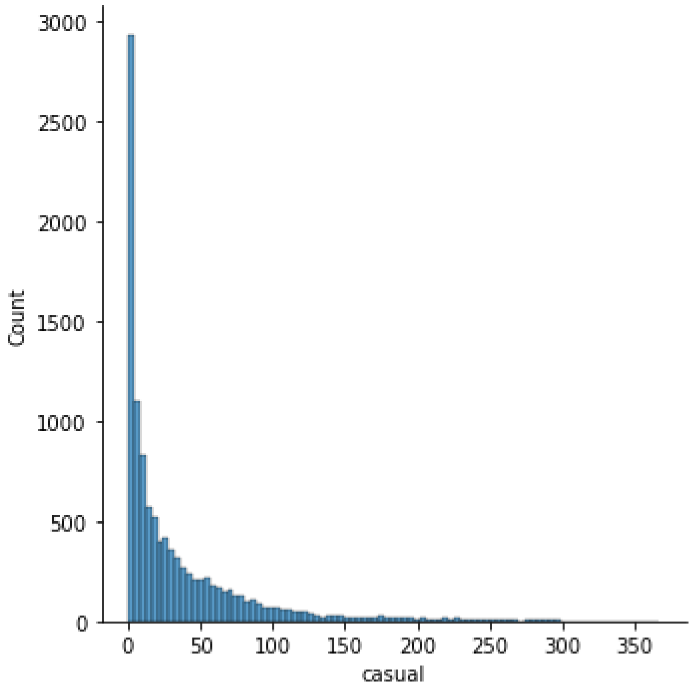
In [19]:

```
plt.figure(figsize=(10,10))
a=sns.countplot(x="season",data=new_df_cap)
for p in a.patches:
    a.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+0.01) ,x
plt.show()
```



In [20]:

```
sns.displot(x=new_df_cap["casual"])
plt.show()
```

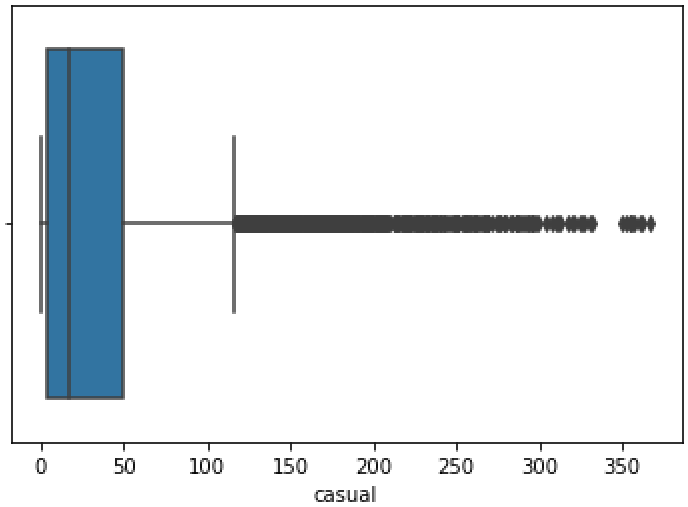


In [21]:

```
sns.boxplot(x=new_df_cap["casual"])
```

Out[21]:

<AxesSubplot:xlabel='casual'>



In [22]:

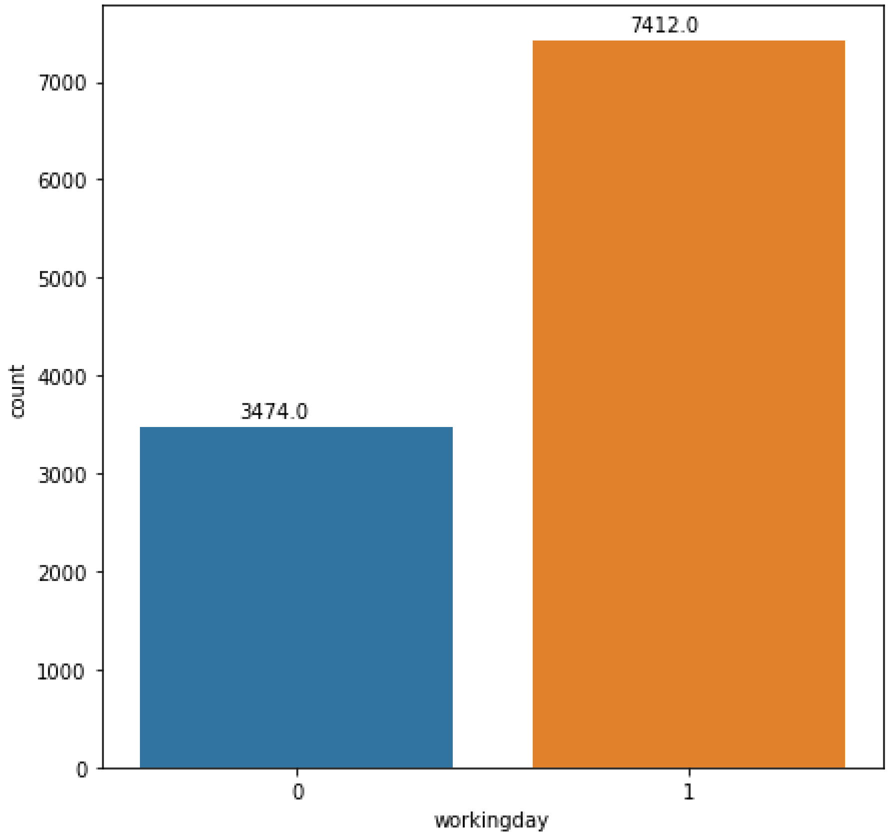
```
new_df_cap["season"].value_counts()
```

Out[22]:

```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

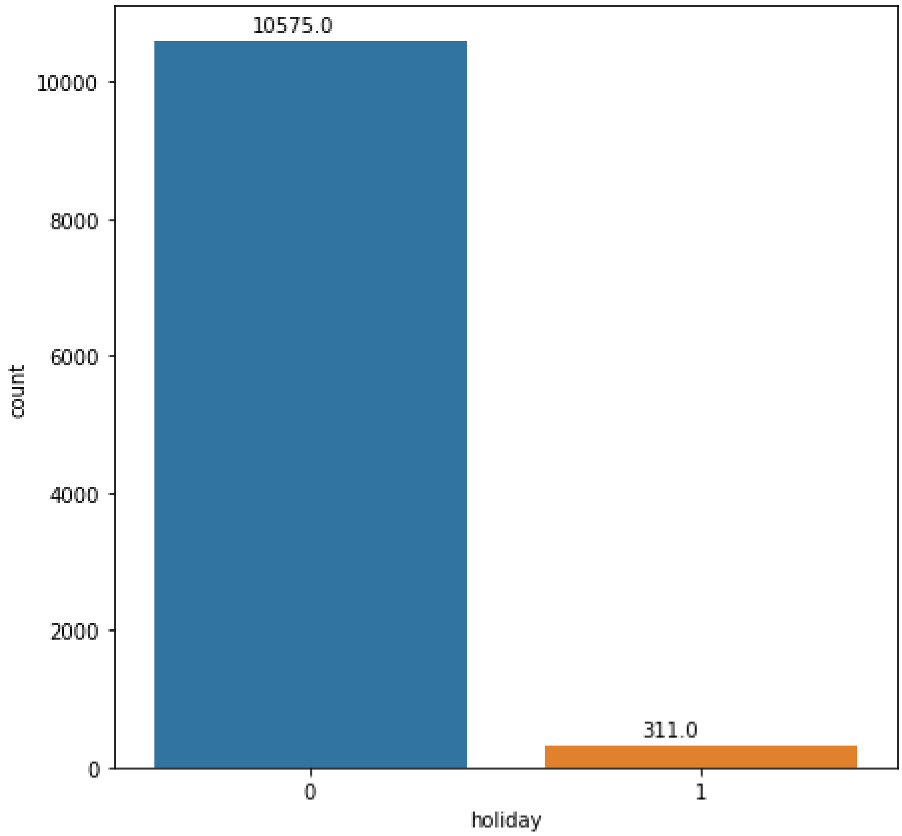
In [23]:

```
plt.figure(figsize=(7,7))
ax = sns.countplot(x="workingday", data=new_df_cap)

for p in ax.patches:
   ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+0.01) ,x
```



In [24]:

```
plt.figure(figsize=(7,7))
ax = sns.countplot(x="holiday", data=new_df_cap)

for p in ax.patches:
   ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+0.01) ,x
```



Observation

1. All the seasons have approx equal weightage in their occurences.
2. Most of the times the weather tended to be :- **Clear, Few clouds, partly cloudy, partly cloudy** followed by :- **Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist**
3. Casual No . of users have right skewed distribution i.e has a huge spread from 0-396 and large number of outliers .
4. working days:7412 & weekends or holidays : 3474
5. holidays:- 311 & non holidays : 10575

#CREATING BINS TO MAKE THE ANALYSIS EASIER

In [25]:

```
new_df_cap["humidity"]=pd.qcut(new_df_cap["humidity"],[0, .25, .5, .75, 1.],labels=["Low
```

In [26]:

```
new_df_cap["temp"]=pd.qcut(new_df_cap["temp"],[0, .25, .5, .75, 1.],labels=["very cold",
```

In [27]:

```
new_df_cap["atemp"]=pd.qcut(new_df_cap["atemp"],[0, .25, .5, .75, 1.],labels=["Low","Med
```

In [28]:

```
new_df_cap["windspeed"]=pd.qcut(new_df_cap["windspeed"],[0, .25, .5, .75, 1.],labels=["L
```

In [29]:

```
new_df_cap
```

Out[29]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	very cold	Low	Very high	Low
1	2011-01-01 01:00:00	1	0	0	1	very cold	Low	Very high	Low
2	2011-01-01 02:00:00	1	0	0	1	very cold	Low	Very high	Low
3	2011-01-01 03:00:00	1	0	0	1	very cold	Low	High	Low
4	2011-01-01 04:00:00	1	0	0	1	very cold	Low	High	Low
...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	cold	Medium	Medium	Very high
10882	2012-12-19 20:00:00	4	0	1	1	cold	Medium	Medium	High
10883	2012-12-19 21:00:00	4	0	1	1	very cold	Low	Medium	High
10884	2012-12-19 22:00:00	4	0	1	1	very cold	Medium	Medium	Low
10885	2012-12-19 23:00:00	4	0	1	1	very cold	Low	High	Medium

10886 rows × 12 columns

In [30]:

```
new_df_cap["windspeed"]
```

Out[30]:

```
0              Low
1              Low
2              Low
3              Low
4              Low
           ...
10881    Very high
10882         High
10883         High
10884          Low
10885       Medium
Name: windspeed, Length: 10886, dtype: category
Categories (4, object): ['Low' < 'Medium' < 'High' < 'Very high']
```

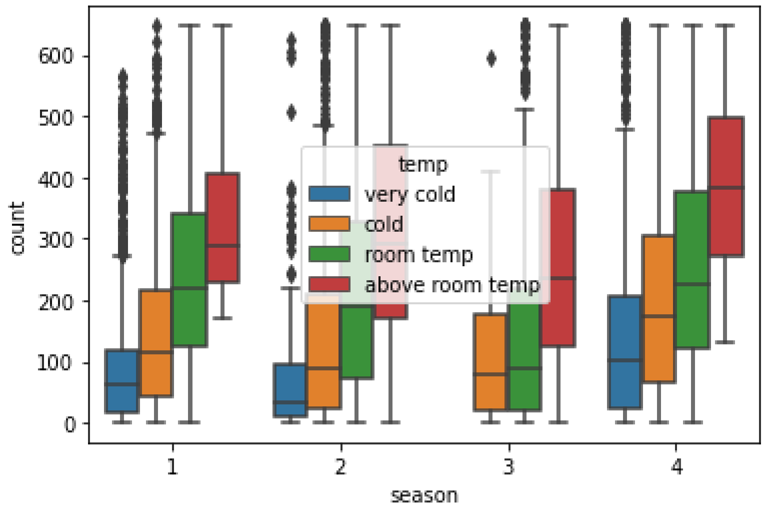
Bi-Variate Analysis

In [31]:

```
sns.boxplot(x="season",y="count",hue="temp",data=new_df_cap)
```

Out[31]:

```
<AxesSubplot:xlabel='season', ylabel='count'>
```

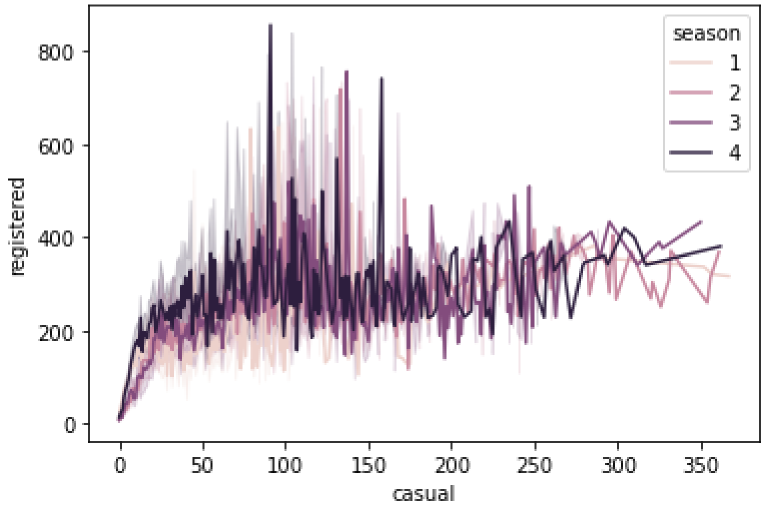


In [32]:

```
sns.lineplot(x="casual",y="registered",hue="season",data=new_df_cap)
```

Out[32]:

```
<AxesSubplot:xlabel='casual', ylabel='registered'>
```

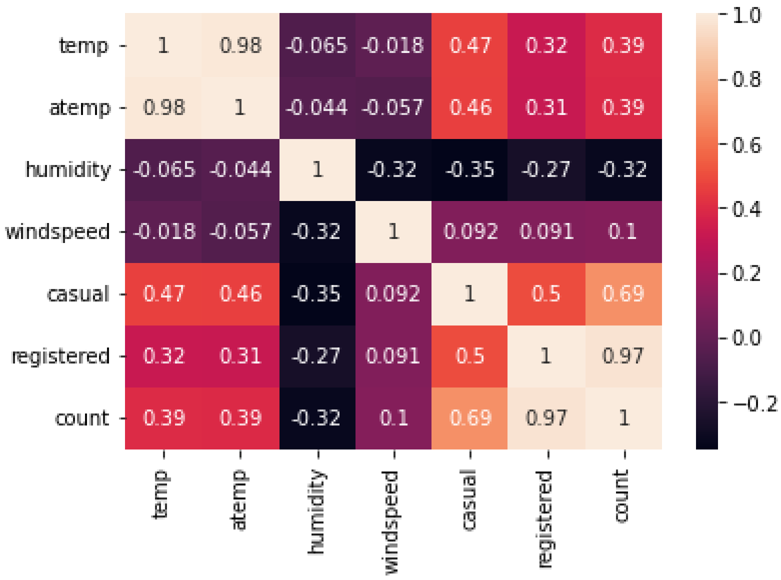


In [33]:

```
sns.heatmap(df.corr(),annot=True)
```

Out[33]:

```
<AxesSubplot:>
```

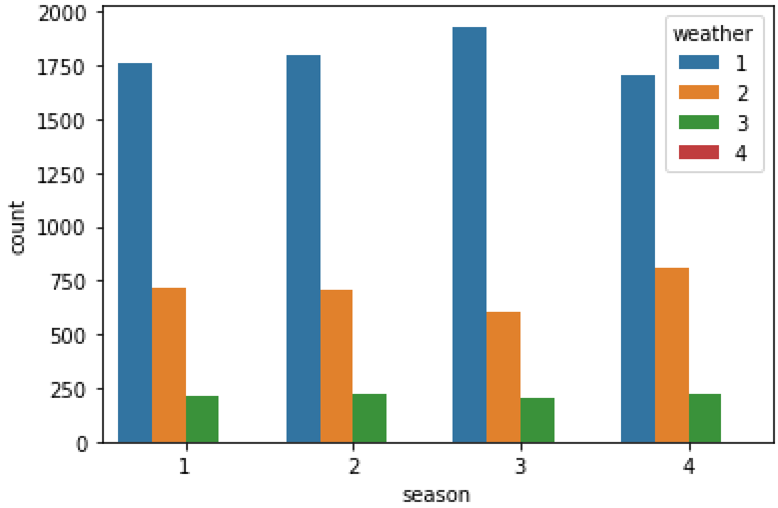


In [34]:

```
sns.countplot(x="season",hue="weather",data=new_df_cap)
```

Out[34]:

<AxesSubplot:xlabel='season', ylabel='count'>

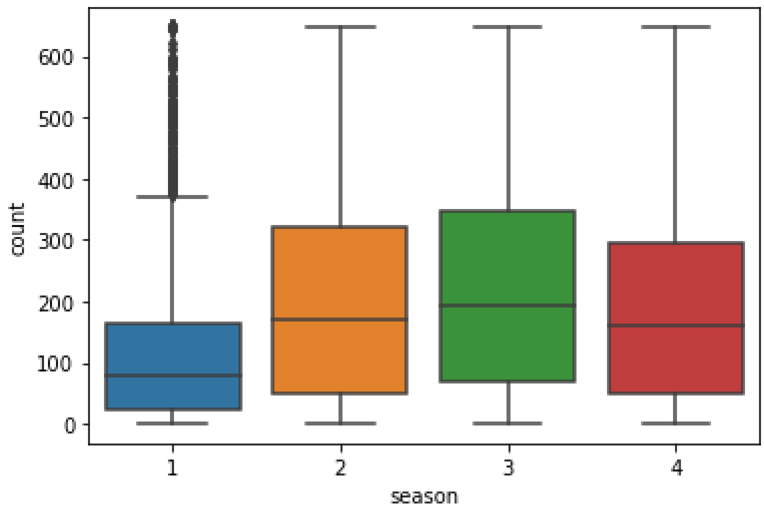


In [35]:

```
sns.boxplot(x="season",y="count",data=new_df_cap)
```

Out[35]:

<AxesSubplot:xlabel='season', ylabel='count'>

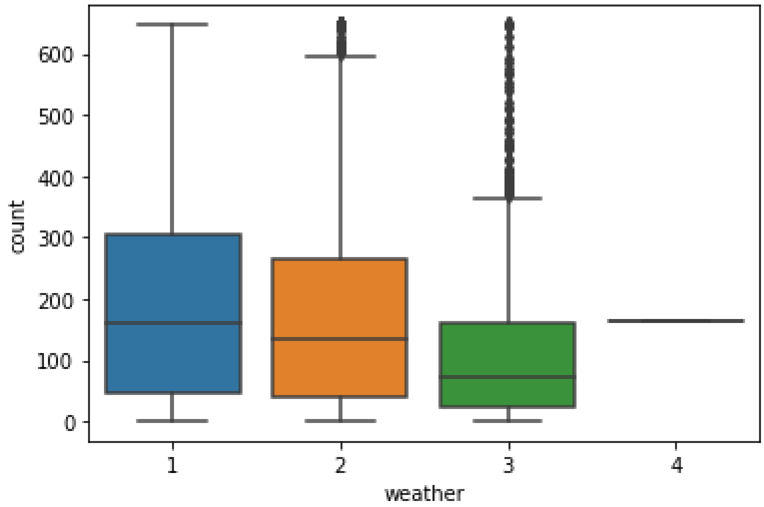


In [36]:

```
sns.boxplot(x="weather",y="count",data=new_df_cap)
```

Out[36]:

```
<AxesSubplot:xlabel='weather', ylabel='count'>
```

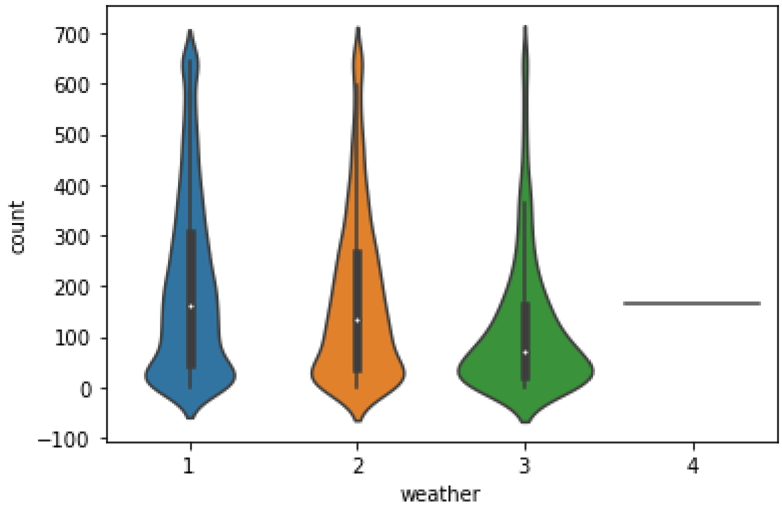


In [37]:

```
sns.violinplot(x="weather",y="count",data=new_df_cap)
```

Out[37]:

```
<AxesSubplot:xlabel='weather', ylabel='count'>
```

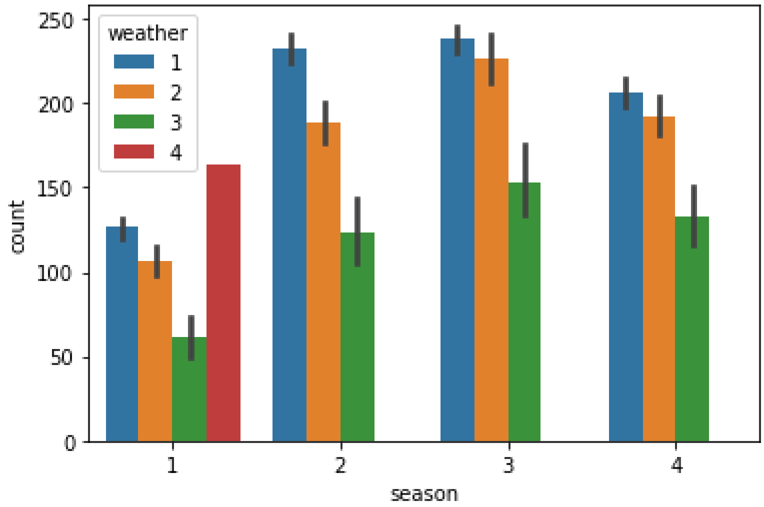


In [38]:

```
sns.barplot(x="season",y="count",hue="weather",data=new_df_cap)
```

Out[38]:

<AxesSubplot:xlabel='season', ylabel='count'>

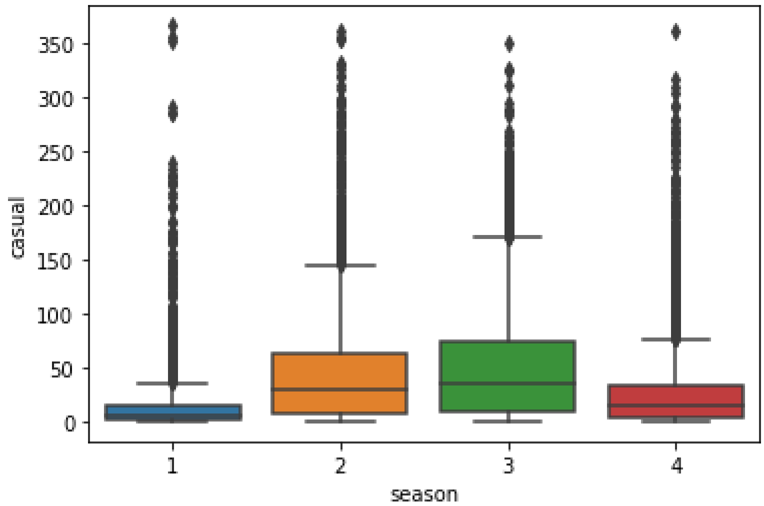


In [39]:

```
sns.boxplot(x="season",y="casual",data=new_df_cap)
```

Out[39]:

<AxesSubplot:xlabel='season', ylabel='casual'>

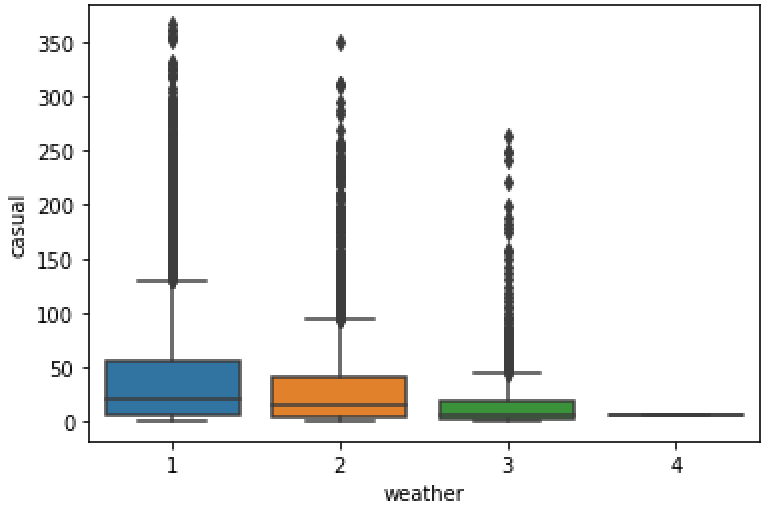


In [40]:

```
sns.boxplot(x="weather",y="casual",data=new_df_cap)
```

Out[40]:

```
<AxesSubplot:xlabel='weather', ylabel='casual'>
```

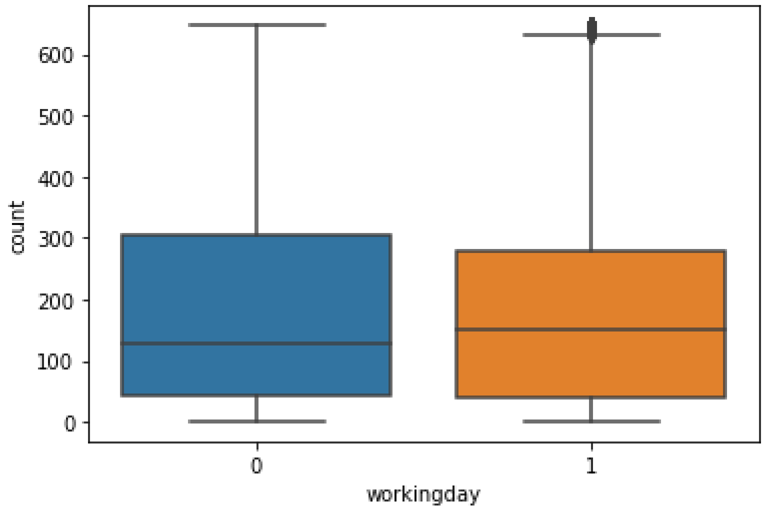


In [41]:

```
sns.boxplot(x="workingday",y="count",data=new_df_cap)
```

Out[41]:

```
<AxesSubplot:xlabel='workingday', ylabel='count'>
```

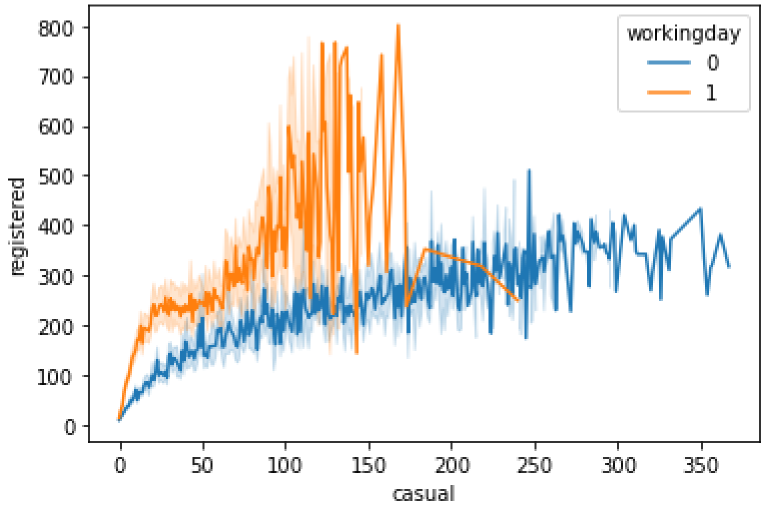


In [42]:

```
sns.lineplot(x="casual",y="registered",hue="workingday",data=new_df_cap)
```

Out[42]:

```
<AxesSubplot:xlabel='casual', ylabel='registered'>
```

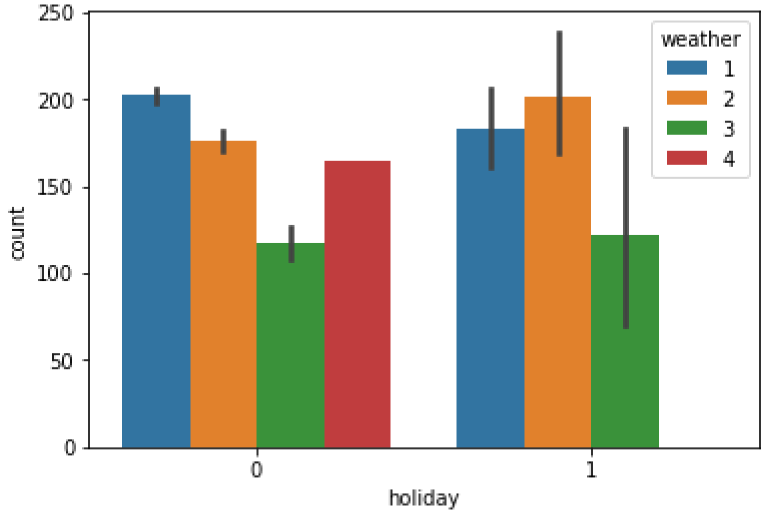


In [43]:

```
sns.barplot(x="holiday",y="count",hue="weather",data=new_df_cap)
```

Out[43]:

```
<AxesSubplot:xlabel='holiday', ylabel='count'>
```

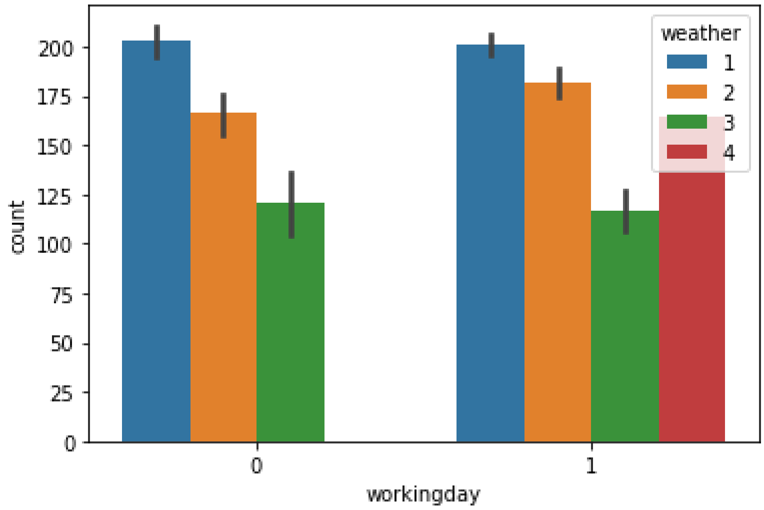


In [44]:

```
sns.barplot(x="workingday",y="count",hue="weather",data=new_df_cap)
```

Out[44]:

<AxesSubplot:xlabel='workingday', ylabel='count'>

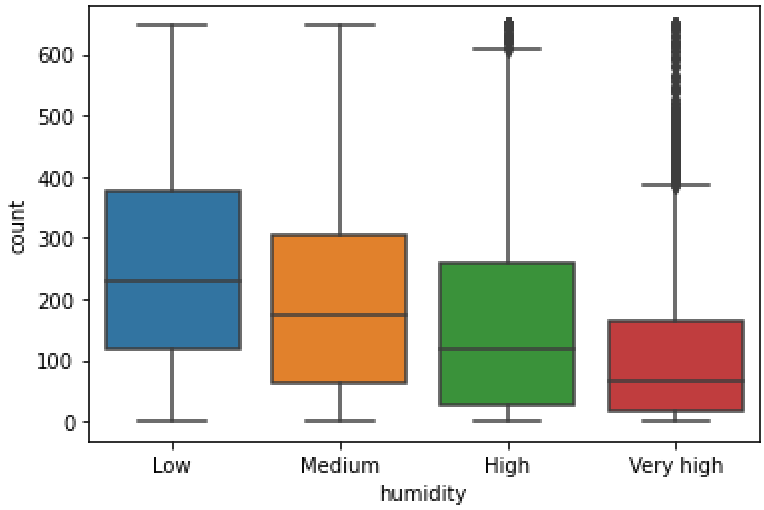


In [45]:

```
sns.boxplot(x="humidity",y="count",data=new_df_cap)
```

Out[45]:

<AxesSubplot:xlabel='humidity', ylabel='count'>

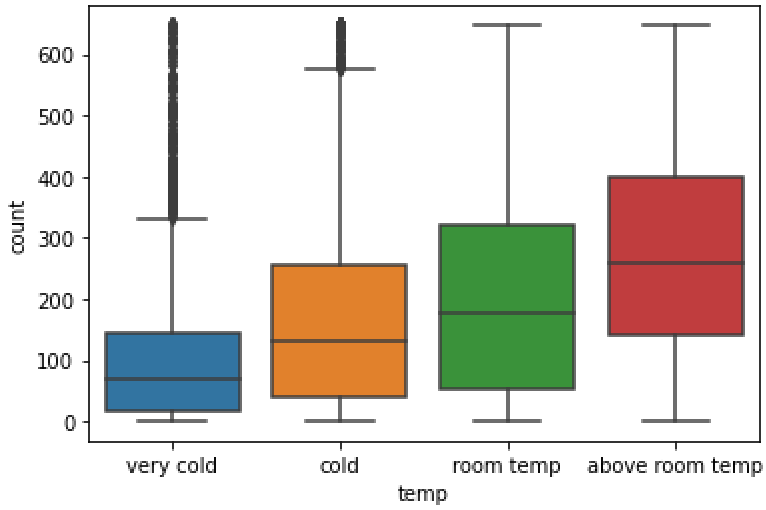


In [46]:

```
sns.boxplot(x="temp",y="count",data=new_df_cap)
```

Out[46]:

```
<AxesSubplot:xlabel='temp', ylabel='count'>
```



Observation

1. It is very clearly visible as the temperature rises FROM VERY COLD TO COLD to normal and above room temperatures , people prefer taking bicyles .
2. Whether it is Working Day or not does not greatly affect the number of rented bicyles i.e count
3. Also in every season , weather 1 is more preferred and more number of transaaction are there in weather 1 as more pleasnt weather
4. No. of biclyes rented are the **most** in 3rd Season , it has the greatest count .
5. **MEAN** No . of bicyles rented are the most in weather 1 :- i.e **Clear, Few clouds, partly cloudy, partly cloudy**
6. The distribtuion of rented cycles is concentraed at around 0-200 for all weathers.
7. It is seen that in every season , weather 1 is where most number of bicyles are rented .

Interesting Observation

1. One interesting thing :- in season 1 weather 4 comes out as an exception , will need more depth inlook .
2. Also one interesting fact is that the **total no of rented bicyles** is **not affected by working day** becasue **on holiday casual number of bicylce takes increase and compensate for loss in registred daily users .

Comments

1. There is strong correlation bw atemp and count .
2. There is strong correlation bw temp and count.
3. Humidity tends to reduce the the count of rented bicyles as it has negative correlation
4. Windspeed is negatively correlated to humidity .
5. weather 2 is more suitable if it happens to be a holiday and rented cycles demand increases . weather 2 is more in demand whether it is a holiday or working day .

6. As humidity varies , days with less humidity are more favourbale as compared to more humidity .

2 SAMPLE TTEST:-WORKINGDAY VS COUNT

1. - H0:- means of independent sample are same i.e working day does not affect
   - Ha:- means are different(2 tailed test) i.e working day affects
2. confidence levvel =99%
3. significance = 1-0.9 =0.01
4. alpha=0.01
5. test stattistic t

In [47]:

```
s1=300
s2=500
alpha=0.01
```

In [48]:

```
a=new_df_cap[new_df_cap["workingday"]==0].sample(s1)["count"]
a_mean=new_df_cap[new_df_cap["workingday"]==0].sample(s1)["count"].mean()
a_std=new_df_cap[new_df_cap["workingday"]==0].sample(s1)["count"].std()
```

In [49]:

```
b=new_df_cap[new_df_cap["workingday"]==1].sample(s2)["count"]
b_mean=new_df_cap[new_df_cap["workingday"]==1].sample(s2)["count"].mean()
b_std=new_df_cap[new_df_cap["workingday"]==1].sample(s2)["count"].std()
```

In [50]:

```
ttest_stat, p_value=ttest_ind_from_stats(a_mean,a_std,s1,b_mean,b_std,s2)
```

In [51]:

```
p_value
```

Out[51]:

```
0.7132331834791275
```

In [52]:

```
if p_value < alpha:
    print("Reject Null Hypothesis")
else:
    print("Fail to Reject Null Hypothesis")
```

```
Fail to Reject Null Hypothesis
```

ANOVA TEST :- SEASON VS COUNT

1. - H0:- means of independent sample are same i.e different season does not affect count no. of rented cycles
   - Ha:- means are different(2 tailed test) i.e different season affects no. of rented cycles

2. confidence level =99%
3. significance = 1-0.9 =0.01
4. alpha=0.01
5. test stattistic t

In [53]:

```
alpha=0.01
```

In [54]:

```
set_1=new_df_cap[new_df_cap["season"]==1]["count"]
set_2=new_df_cap[new_df_cap["season"]==2]["count"]
set_3=new_df_cap[new_df_cap["season"]==3]["count"]
set_4=new_df_cap[new_df_cap["season"]==4]["count"]
```

In [55]:

```
f_stat,p_value =f_oneway(set_1,set_2,set_3,set_4)
f_stat,p_value
```

Out[55]:

```
(243.33766355201303, 7.771506553957677e-153)
```

In [56]:

```
if p_value < alpha:
    print("Reject Null Hypothesis")
else:
    print("Fail to Reject Null Hypothesis")
```

```
Reject Null Hypothesis
```

ANOVA TEST :- WEATHER VS COUNT

1. - H0:- means of independent sample are same i.e different weather does not affect count no. of rented cycles
   - Ha:- means are different(2 tailed test) i.e different weather affects no. of rented cycles
2. confidence level =99%
3. significance = 1-0.9 =0.01
4. alpha=0.01
5. test stattistic :- F_ratio

In [57]:

```
dist_1=new_df_cap[new_df_cap["weather"]==1]["count"]
dist_2=new_df_cap[new_df_cap["weather"]==2]["count"]
dist_3=new_df_cap[new_df_cap["weather"]==3]["count"]
dist_4=new_df_cap[new_df_cap["weather"]==4]["count"]
```

In [58]:

```
f_stat, p_value=f_oneway(dist_1,dist_2,dist_3,dist_4)
f_stat, p_value
```

Out[58]:

```
(68.4116520342703, 8.034967610817961e-44)
```

In [59]:

```
if p_value < alpha:
    print("Reject Null Hypothesis")
else:
    print("Fail to Reject Null Hypothesis")
```

```
Reject Null Hypothesis
```

CHI-SQUARE TEST :- WEATHER VS SEASON

1. - H0:- means of independent sample are same i.e different seasons does not affect different weathers
   - Ha:- means are different(2 tailed test) i.e different seasons affects different weather
2. confidence level =99%
3. significance = 1-0.9 =0.01
4. alpha=0.01
5. test stattistic :- Chi2_statistic

In [60]:

```
data=pd.crosstab(index=new_df_cap["season"],columns=new_df_cap["weather"])
```

In [61]:

```
data
```

Out[61]:

weather	1	2	3	4
season				
1	1759	715	211	1
2	1801	708	224	0
3	1930	604	199	0
4	1702	807	225	0

In [62]:

```
chi_stat, p_value, dof, expected=chi2_contingency(data)
p_value
```

Out[62]:

```
1.549925073686492e-07
```

In [63]:

```
if p_value < alpha:
    print("Reject Null Hypothesis")
else:
    print("Fail to Reject Null Hypothesis")
```

```
Reject Null Hypothesis
```

INFERENCE

1. 2_sample Ttest :- working day does not affect the the number of rented bicyles hence we fail to reject null hypothesis(the means are same both when working day = 0 and working day =1)
2. ANOVA Test(count vs season):- Season does affect the number of rented bicyles , hence null hypothesis rejected .
3. ANOVA Test(count vs weather):- Weather does affect the number of rented bicycles , hence the null hypotheis rejected.
4. Chi_2 Test (season vs weather):- Weather and season are not dependent on each other .

RECOMMENDATIONS

1. We should focus more on increasing the inventory when days are more favorable for weather 1 .
2. On weekends aad holidays if weather forecasts predict category 2: we should be ready to supplement the demand .
3. Also when it is time for season 3, we should be ready to supplement the demand .
4. **On holidays , as casual users increase , there should be interesting competetions , meetups, trek, cyclothons to convert those casual to registered* *.
5. As there are more number of working days compared to holidays , the focus should be on more awareness campaigns about climate change , therrby increasing the use of our bikes .
6. On days with lower humidity and normal temperatures lie the golden opportunity to increase revenue
7. Windspeeds also will be favorable to manage the inventory if prior forecasts are available .