```
Concept Used:

Bi-Variate Analysis
2-sample t-test: testing for difference across populations
ANNOVA
Chi-square

Project Flow:

Import the dataset and do usual exploratory data analysis steps like checking the
structure & characteristics of the dataset
Try establishing a relation between the dependent and independent variable (Dependent
“Count” & Independent: Workingday, Weather, Season etc)
Select an appropriate test to check whether:
Working Day has effect on number of electric cycles rented
No. of cycles rented similar or different in different seasons
No. of cycles rented similar or different in different weather
Weather is dependent on season (check between 2 predictor variable)
Set up Null Hypothesis (H0)
State the alternate hypothesis (H1)
Check assumptions of the test (Normality, Equal Variance). You can check it using
Histogram, Q-Q plot or statistical methods like levene’s test, Shapiro-wilk test.
Please continue doing the analysis even If some assumptions fail (levene’s test or
Shapiro-wilk test) but double check using visual analysis and report wherever necessary
Set a significance level (alpha)
Calculate test Statistics.
Decision to accept or reject null hypothesis.
Inference from the analysis


Define Problem Statement and perform Exploratory Data Analysis
Definition of problem (as per given problem statement with additional views)
Observations on shape of data, data types of all the attributes, conversion of categorical
attributes to 'category' (If required) , missing value detection, statistical summary.
Univariate Analysis (distribution plots of all the continuous variable(s)
barplots/countplots of all the categorical variables)
Bivariate Analysis (Relationships between important variables such as workday and count,
season and count, weather and count.
Illustrate the insights based on EDA
Comments on range of attributes, outliers of various attributes
Comments on the distribution of the variables and relationship between them
Comments for each univariate and bivariate plots
Hypothesis Testing :
2- Sample T-Test to check if Working Day has an effect on the number of electric cycles
rented
ANNOVA to check if No. of cycles rented is similar or different in different 1. weather 2.
season
Chi-square test to check if Weather is dependent on the season
```

In [234]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stat
import datetime as dt
```

In [235]:

```
df = pd.read_csv('bike_sharing.csv')
```

In [236]:

```
df.head(48)
```

Out[236]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3	13
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	32
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	27
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	10
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	1

In [237]:

```
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
```

Dataset is clean, There are no Null Values.

In [238]:

```
df.shape
```

Out[238]:

```
(10886, 12)
```

In [239]:

```
df.describe()
```

Out[239]:

	season	holiday	workingday	weather	temp	atemp	
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	108
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	1

In [240]:

```
df['datetime'] = df['datetime'].astype('datetime64[ns]')
```

In [241]:

```
df['day'] = df['datetime'].dt.day

df['month'] = df['datetime'].dt.month

df['hour'] = df['datetime'].dt.hour

df['year'] = df['datetime'].dt.year
```

In [242]:

```
df.head()
```

Out[242]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [273]:

```
day_df = df.groupby([df['day'],df['month'],df['year']])['count'].sum()
day_df = day_df.reset_index()
```

In [274]:

```
day_df
```

Out[274]:

	day	month	year	count
0	1	1	2011	985
1	1	1	2012	2294
2	1	2	2011	1360
3	1	2	2012	4579
4	1	3	2011	1851
...	...	...	...	...
451	19	10	2012	5424
452	19	11	2011	3663
453	19	11	2012	5499
454	19	12	2011	3403
455	19	12	2012	5267

456 rows × 4 columns

In [253]:

```
df['day'].unique()
```

Out[253]:

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19], dtype=int64)
```

we have data for 2 years they are 2011 and 2012 we have data for 12 month and 19 days for each month

In [260]:

```
column_list=list(df.columns)
col_len=len(column_list)
column_list
```

Out[260]:

```
['datetime',
 'season',
 'holiday',
 'workingday',
 'weather',
 'temp',
 'atemp',
 'humidity',
 'windspeed',
 'casual',
 'registered',
 'count',
 'day',
 'month',
 'hour',
 'year']
```

In [261]:

```
uniq = []
for i in range(col_len):
    uniq.append(df[column_list[i]].nunique())
x=zip(column_list,uniq)
for k,v in x:
    print(k +'  :  '+ str(v))
```

```
datetime  :  10886
season  :  4
holiday  :  2
workingday  :  2
weather  :  4
temp  :  49
atemp  :  60
humidity  :  89
windspeed  :  28
casual  :  309
registered  :  731
count  :  822
day  :  19
month  :  12
hour  :  24
year  :  2
```

we can see that season holiday and weather has less unique values, so we can change them into categorical columns

In [262]:

```
for i in range(len(uniq)):
    if uniq[i]<5:
        df[column_list[i]]=df[column_list[i]].astype('category')
```

In [263]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 1   season      10886 non-null  category
 2   holiday     10886 non-null  category
 3   workingday  10886 non-null  category
 4   weather     10886 non-null  category
 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
 12  day         10886 non-null  int64
 13  month       10886 non-null  int64
 14  hour        10886 non-null  int64
 15  year        10886 non-null  category
dtypes: category(5), datetime64[ns](1), float64(3), int64(7)
memory usage: 989.6 KB
```

In [264]:

```
df[['temp','atemp']].agg([min,max])
```

Out[264]:

	temp	atemp
min	0.82	0.760
max	41.00	45.455

In [265]:

```
(df['atemp']-df['temp']).describe()
```

Out[265]:

```
count    10886.000000
mean         3.424224
std          1.566612
min        -23.140000
25%          2.745000
50%          3.680000
75%          4.055000
max          8.045000
dtype: float64
```

There is no much difference between temp and atemp around 3.6 degrees.

In [266]:

```
df[['humidity','windspeed']].agg([min,max])
```

Out[266]:

	humidity	windspeed
min	0	0.0000
max	100	56.9969

In [267]:

```
df['wind_cat']=pd.cut(df['windspeed'],bins=[-1,0,3,7,12,18,24,31,38,46,54,63],labels=['Calm
```

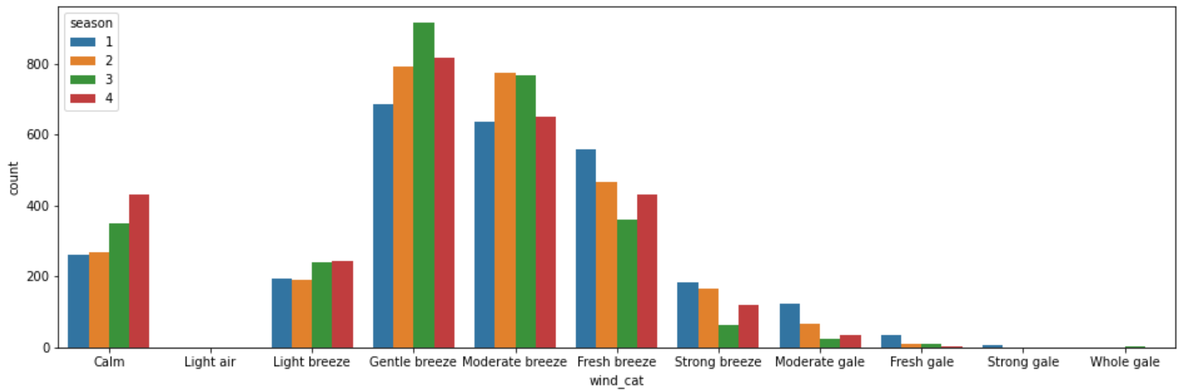
Units of the wind speed is not specified so assumed the wind speed in 'mph' and categorized the values. Above categorized the windspeed according to data present in [http://gyre.umeoce.maine.edu/data/gomoos/buoy/php/variable_description.php?variable=wind_2_speed (http://gyre.umeoce.maine.edu/data/gomoos/buoy/php/variable_description.php?variable=wind_2_speed)](http://gyre.umeoce.maine.edu/data/gomoos/buoy/php/variable_description.php?variable=wind_2_speed)

In [268]:

```
plt.figure(figsize=(16,5))
sns.countplot(x=df['wind_cat'],hue=df['season'])
```

Out[268]:

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



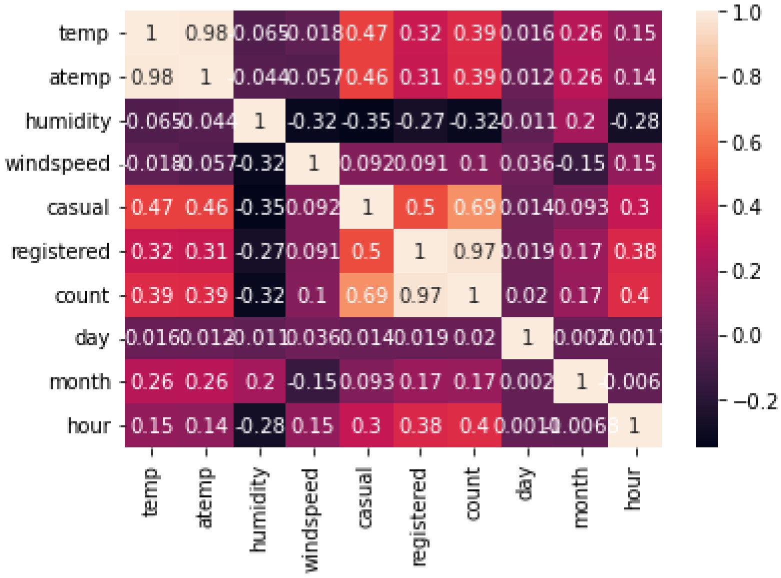
Wind speed for [0-3] mph is not present, and we can observe that data is right skewed because very few people travel during high wind speeds and most number of people travel during moderate wind speeds. From above plot we can say that-- on days which has wind speed less than 24mph people travels more.

In [269]:

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

Out[269]:

```
<AxesSubplot:>
```



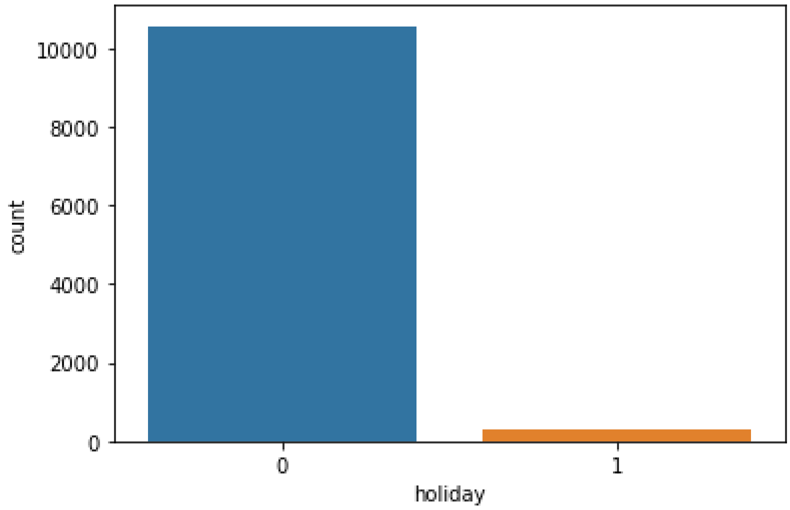
There is no significant insights from the heatmap

In [17]:

```
sns.countplot(x=df['holiday'])
```

Out[17]:

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



In [18]:

```
df['holiday'].value_counts()
```

Out[18]:

```
0    10575
1      311
Name: holiday, dtype: int64
```

from above we can say that most number of the rides were taken place on the non-holiday days considering 0 as not a holiday and 1 as a holiday

In [275]:

```
x=df['holiday'].value_counts()
x.index
```

Out[275]:

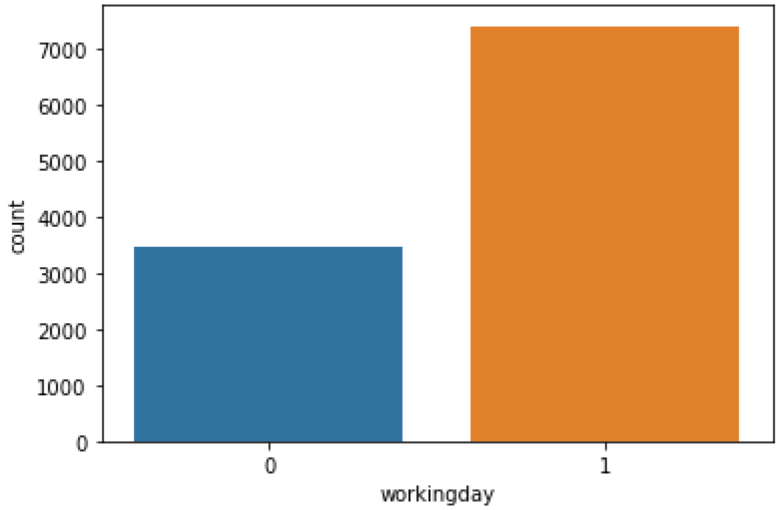
```
CategoricalIndex([0, 1], categories=[0, 1], ordered=False, dtype='category')
```

In [276]:

```
sns.countplot(x=df['workingday'])
```

Out[276]:

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



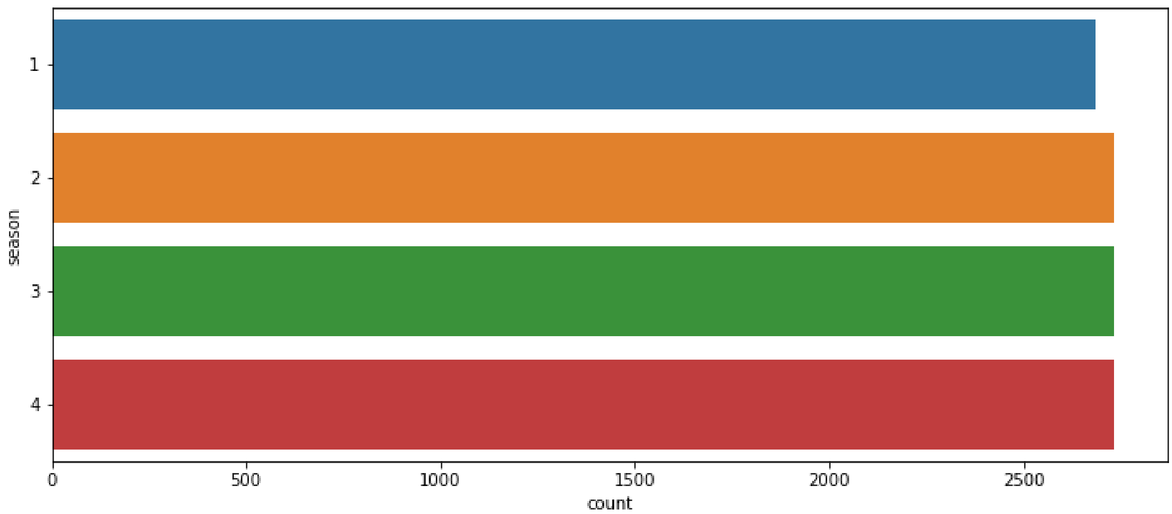
from above plots we can see that most of the rides are on working days compared to the holiday

In [278]:

```
plt.figure(figsize=(12,5))
sns.countplot(y=df['season'])
```

Out[278]:

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



In [279]:

```
df.season.value_counts()
```

Out[279]:

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

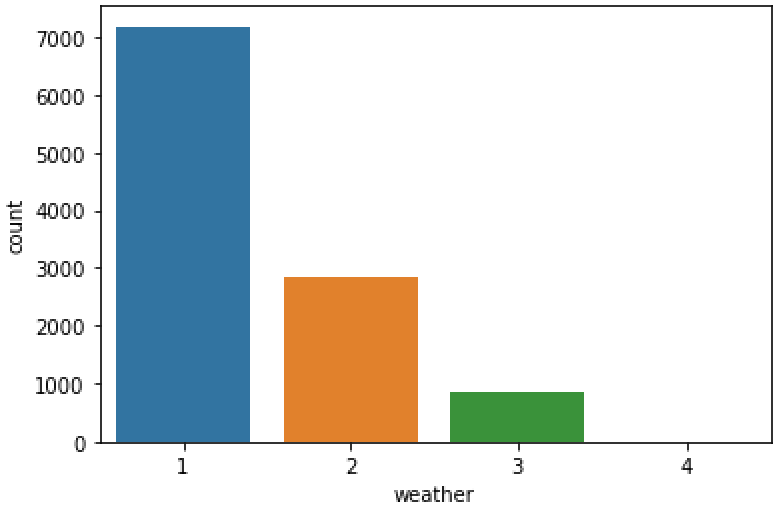
From above we can say that we have equal amount of data from all sesons

In [280]:

```
sns.countplot(x=df['weather'])
```

Out[280]:

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




```
1: Clear, Few clouds, partly cloudy, partly cloudy
2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog

Most of the people use yulu during when the weather condition is Clear, Few clouds, partly
cloudy, partly cloudy
```

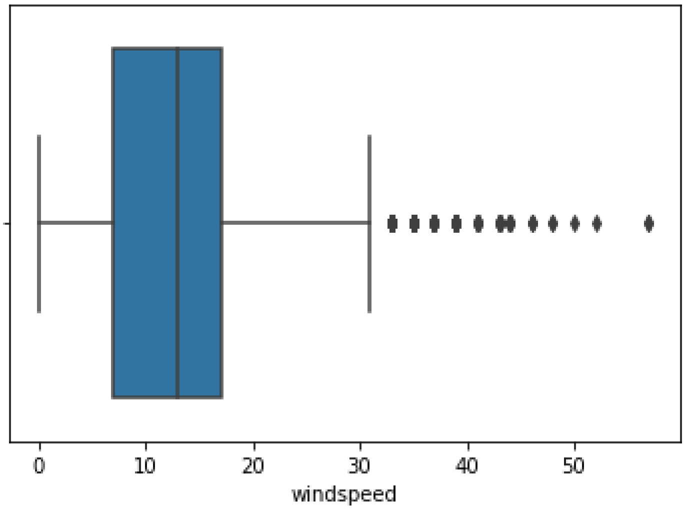
In [281]:

```
sns.boxplot(df['windspeed'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[281]:

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



There are more outliers in the wind speed

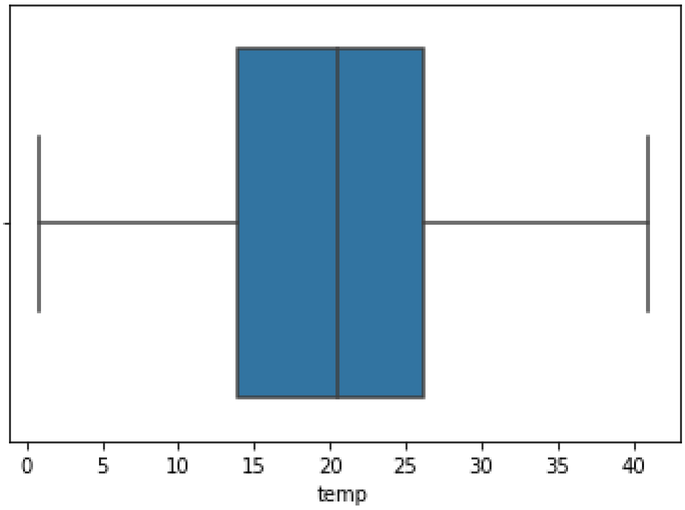
In [282]:

```
sns.boxplot(df['temp'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[282]:

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



No outliers in Temperature

In [283]:

```
df['weather'].value_counts()
```

Out[283]:

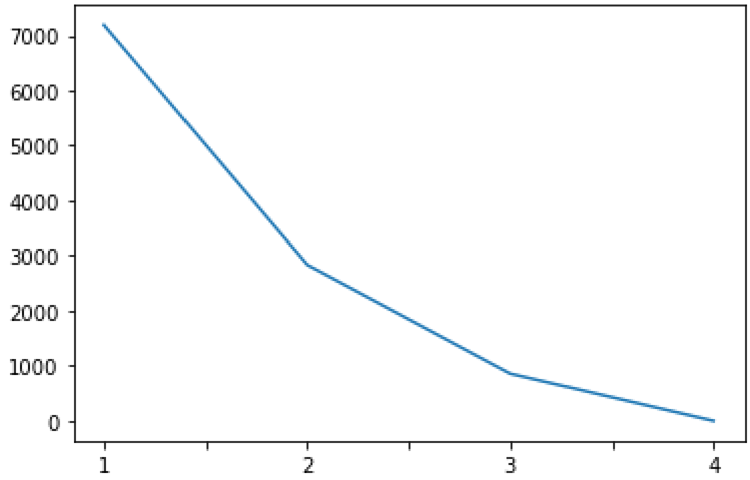
```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

In [284]:

```
df['weather'].value_counts().plot()
```

Out[284]:

```
<AxesSubplot:>
```



There is only one row data availale for weather type 4 we can consider it as an outlier

In [285]:

```
x=pd.DataFrame(df.groupby(df['weather'])['count'].sum())
x=x.reset_index()
x
```

Out[285]:

	weather	count
0	1	1476063
1	2	507160
2	3	102089
3	4	164

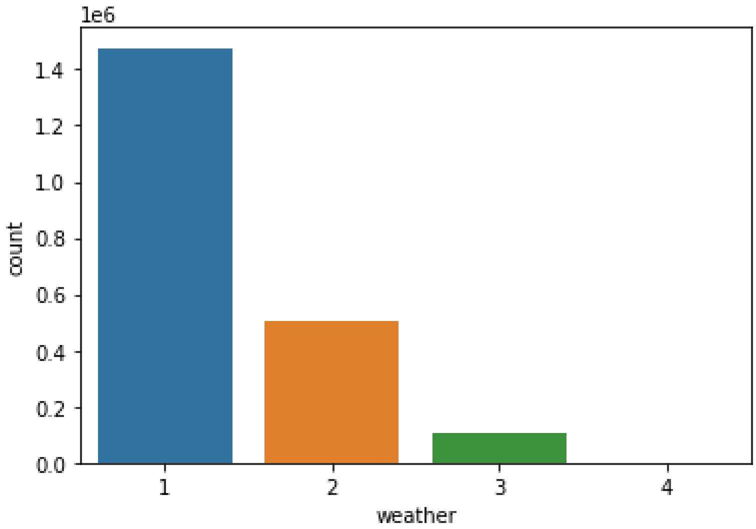
There are more number of rides taken place in weather condition 1 compared to other weathers.

In [287]:

```
sns.barplot(x=x['weather'],y=x['count'])
```

Out[287]:

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

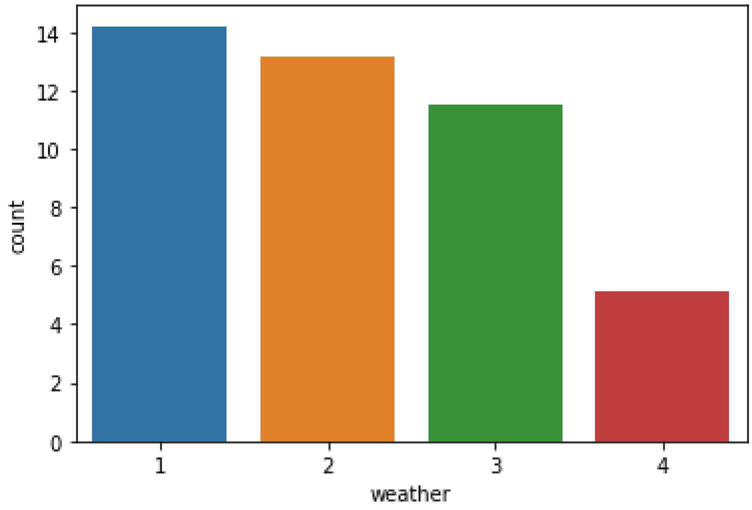


In [288]:

```
sns.barplot(x=x['weather'],y=np.log(x['count']))
```

Out[288]:

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



To get more visual understanding converted the data to log

In [289]:

```
x=pd.DataFrame(df.groupby(df['workingday'])['count'].sum())
x=x.reset_index()
x
```

Out[289]:

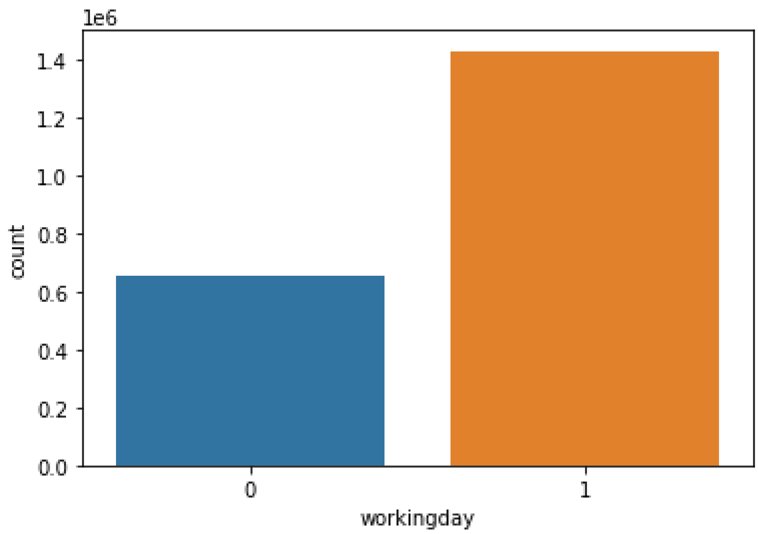
	workingday	count
0	0	654872
1	1	1430604

In [290]:

```
sns.barplot(x=x['workingday'],y=x['count'])
```

Out[290]:

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



More number of rides were taken place on working days compared to non working days considering 1 as working day and 0 as non working day

In [292]:

```
x=pd.DataFrame(df.groupby(df['season'])['count'].sum())
x=x.reset_index()
x
```

Out[292]:

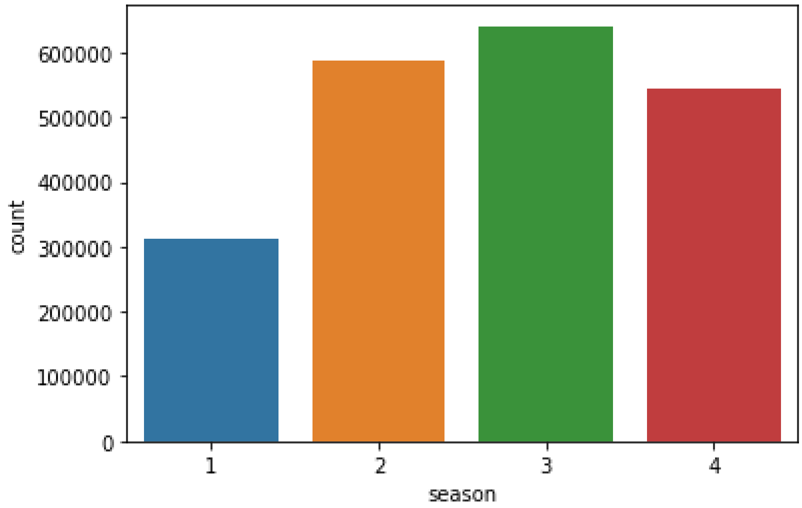
	season	count
0	1	312498
1	2	588282
2	3	640662
3	4	544034

In [35]:

```
sns.barplot(x=x['season'],y=x['count'])
```

Out[35]:

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



1: spring, 2: summer, 3: fall, 4: winter Less number of rides were taken place in spring season compared to other seasons and in fall season more number of rides were happened

In [297]:

```
x=pd.DataFrame(df.groupby(df['holiday'])['count'].sum())
x=x.reset_index()
x
```

Out[297]:

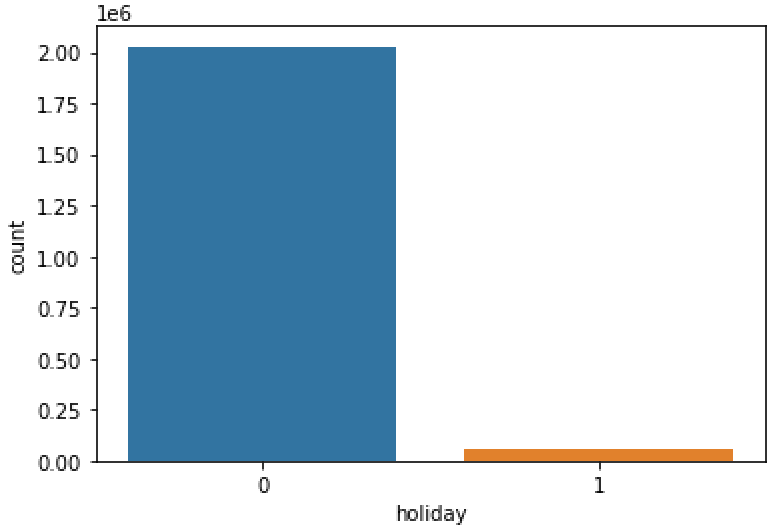
	holiday	count
0	0	2027668
1	1	57808

In [298]:

```
sns.barplot(x=x['holiday'],y=x['count'])
```

Out[298]:

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

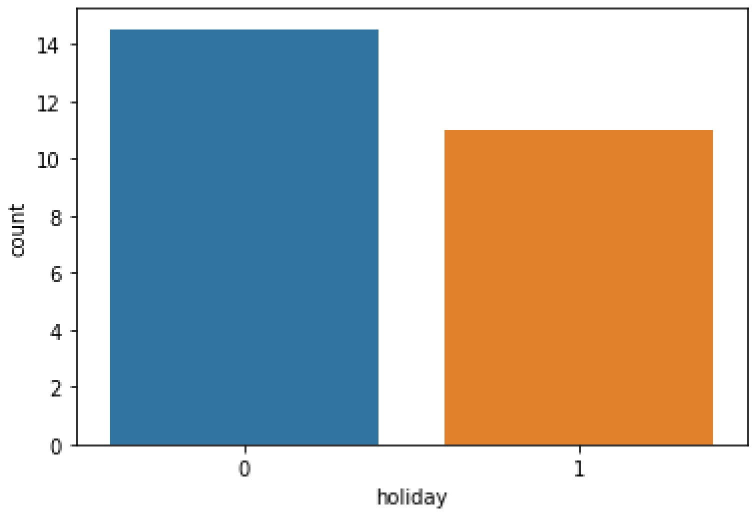


In [38]:

```
sns.barplot(x=x['holiday'],y=np.log(x['count']))
```

Out[38]:

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



Less number of rides were happened on holidays, we can infer that most of the people use Yulu to commute to workplaces.

In [301]:

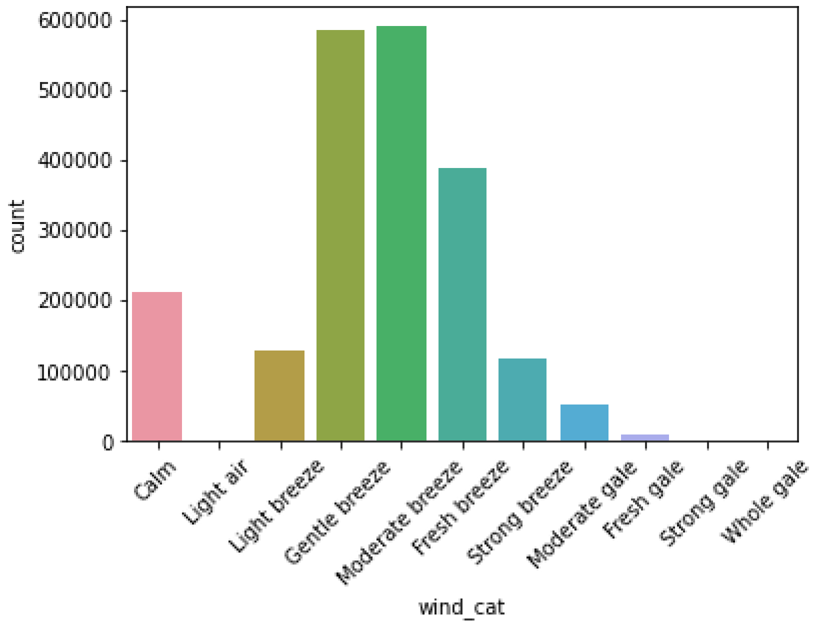
```
x=pd.DataFrame(df.groupby(df['wind_cat'])['count'].sum())
x=x.reset_index()
x
```

Out[301]:

	wind_cat	count
0	Calm	211526
1	Light air	0
2	Light breeze	128938
3	Gentle breeze	586141
4	Moderate breeze	590389
5	Fresh breeze	387342
6	Strong breeze	118882
7	Moderate gale	51007
8	Fresh gale	10053
9	Strong gale	659
10	Whole gale	539

In [302]:

```
g=sns.barplot(x=x['wind_cat'],y=x['count'])
g.set_xticklabels(labels = x['wind_cat'], rotation = 45)
plt.show()
```



Most of the rides takes place when there is Gentle,Moderate and fresh breeze. Users prefer Yulu when the climate is clear

In [ ]:

Working Day has effect on number of electric cycles rented

In [333]:

```
df.head()
```

Out[333]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [334]:

```
df['datetime'] = df['datetime'].astype('datetime64[ns]')
```

In [335]:

```
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  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: datetime64[ns](1), float64(3), int64(8)
memory usage: 1020.7 KB
```

In [336]:

```
df.head()
```

Out[336]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [338]:

```
df['day'] = df['datetime'].dt.day

df['month'] = df['datetime'].dt.month

df['hour'] = df['datetime'].dt.hour

df['year'] = df['datetime'].dt.year
```

In [339]:

```
x=pd.DataFrame(df.groupby([df['month'],df['year']])['count'].sum())
x=x.reset_index()
x
```

Out[339]:

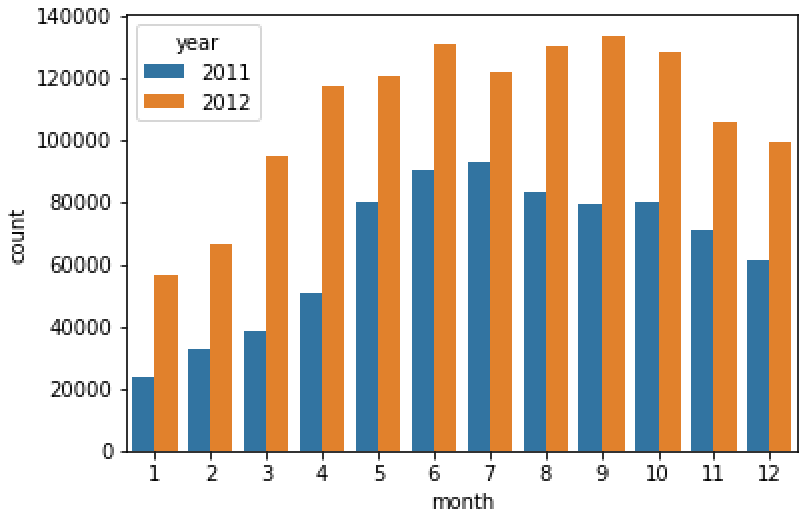
	month	year	count
0	1	2011	23552
1	1	2012	56332
2	2	2011	32844
3	2	2012	66269
4	3	2011	38735
5	3	2012	94766
6	4	2011	50517
7	4	2012	116885
8	5	2011	79713
9	5	2012	120434
10	6	2011	89776

In [340]:

```
sns.barplot(x=x['month'],y=x['count'],hue=x['year'])
```

Out[340]:

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



There is a potential increase of rides from 2011 to 2012 in every month.

In [345]:

```
x=pd.DataFrame(df.groupby(df['year'])['count'].sum())
x=x.reset_index()
x
```

Out[345]:

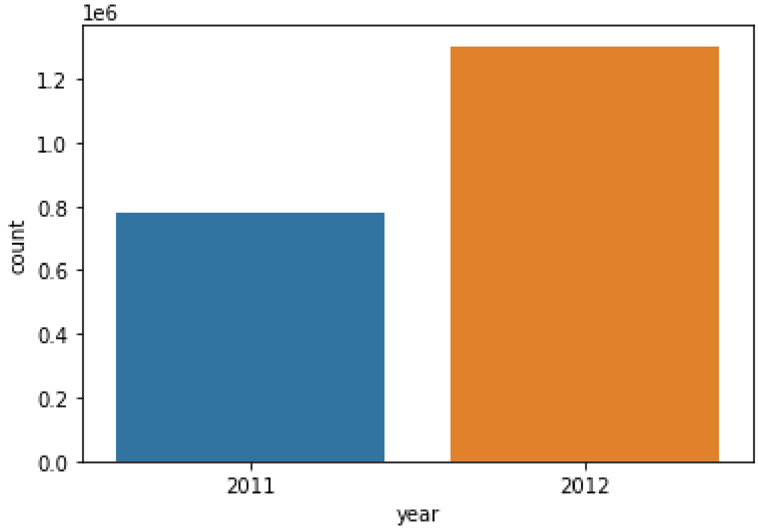
	year	count
0	2011	781979
1	2012	1303497

In [346]:

```
sns.barplot(x=x['year'],y=x['count'])
```

Out[346]:

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



number of rides in 2012 are increased compared to 2011

In [347]:

```
df.loc[df['workingday'] == 0].groupby([df['day'],df['month'],df['year']])['count'].sum()
```

Out[347]:

```
day  month  year
1    1      2011     985
            2012    2294
     4      2012    6041
     5      2011    3351
     7      2012    5531
                    ...
19   3      2011    3117
     5      2012    8294
     6      2011    4744
     8      2012    4549
     11     2011    3663
Name: count, Length: 145, dtype: int64
```

In [348]:

```
df.loc[df['workingday']==1].groupby([df['day'],df['month'],df['year']])['count'].sum()
```

Out[348]:

```
day  month  year
1    2      2011    1360
            2012    4579
     3      2011    1851
            2012    4990
     4      2011    2227
                    ...
19   10     2011    2424
            2012    5424
     11     2012    5499
     12     2011    3403
            2012    5267
Name: count, Length: 311, dtype: int64
```

Working Day has effect on number of electric cycles rented -- 2- Sample T-Test

Lets groupby the data by number of rides per each day and split them into working and not working days.

In [349]:

```
count_not_working= pd.DataFrame(df.loc[df['workingday']==0].groupby([df['day'],df['month'],
```

In [350]:

```
count_not_working.shape
```

Out[350]:

```
(145, 1)
```

In [351]:

```
count_not_working=count_not_working.reset_index()
count_not_working=count_not_working.sort_values(by='count')
```

In [352]:

```
count_not_working
```

Out[352]:

	day	month	year	count
42	6	3	2011	605
116	16	4	2011	795
8	2	1	2011	801
62	9	1	2011	822
53	8	1	2011	959
...	...	...	...	...
45	6	10	2012	7965
11	2	6	2012	8120
66	9	9	2012	8227
141	19	5	2012	8294
111	15	9	2012	8714

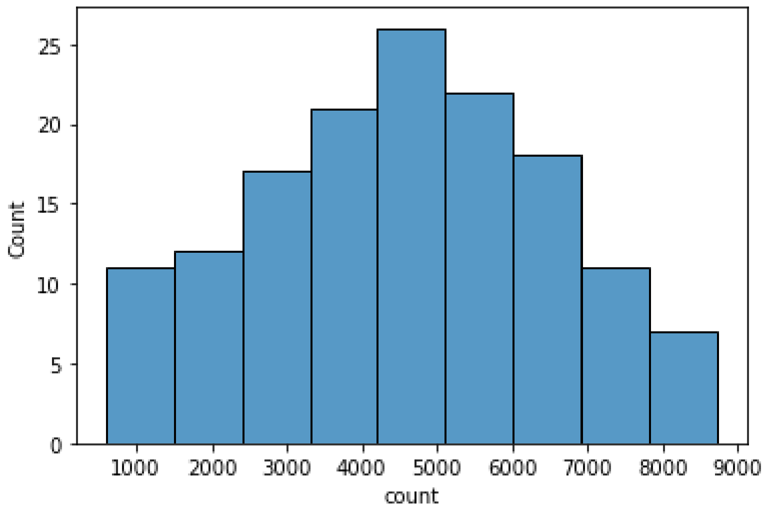
145 rows × 4 columns

In [353]:

```
sns.histplot(count_not_working['count'])
```

Out[353]:

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



Above we can see that data is normal and we are good to perform ttest on the data

In [320]:

```
count_working = pd.DataFrame(df.loc[df['workingday']==1].groupby([df['day'],df['month'],df[
```

In [98]:

```
count_working.head()
```

Out[98]:

			count
day	**month**	**year**	
1	**2**	**2011**	1360
		2012	4579
	3	**2011**	1851
		2012	4990
	4	**2011**	2227

In [100]:

```
count_working.shape
```

Out[100]:

(311, 1)

In [101]:

```
count_working=count_working.reset_index()
```

In [103]:

```
count_working.sort_values(by ='count')
```

Out[103]:

	day	month	year	count
151	10	3	2011	623
277	18	1	2011	683
113	7	12	2011	705
179	12	1	2011	1162
163	11	1	2011	1263
...	...	...	...	...
175	11	9	2012	7767
208	13	9	2012	7804
190	12	9	2012	7870
225	14	9	2012	8009
75	5	10	2012	8156

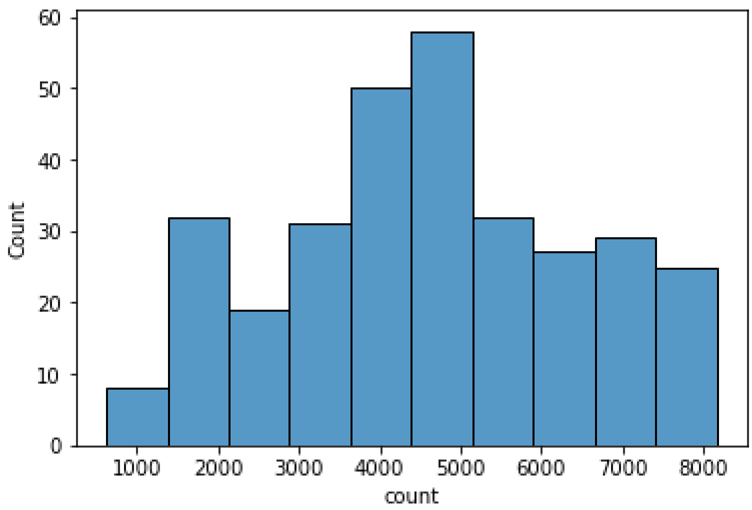
311 rows × 4 columns

In [173]:

```
sns.histplot(count_working['count'])
```

Out[173]:

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



This is almost similar to the normal distribution, lets make kstest to get clear idea about the means.

In [134]:

```
stat.kstest(count_not_working['count'],count_working['count'],'norm')
```

Out[134]:

```
KstestResult(statistic=0.06466348819159552, pvalue=0.7710689796479644)
```

we assume here the alpha as 0.05 and the pvalue > alpha , we can consider these two samples to perform ttest

In [177]:

```
stat.ttest_ind(count_working['count'].sample(80),count_not_working['count'].sample(80))
```

Out[177]:

```
Ttest_indResult(statistic=-1.5429234901059325, pvalue=0.12484983501298942)
```

```
Null Hypothesis : There is no effect of working days and non working days
Alternative Hypothesis : There is an effect of working days and non working days

alpha = 0.05
P value = 0.12

Since pvalue > alpha, it is failed to reject the null hypothesis, we can infer that there is no effect of
working day on the number of rides made per day.
```

No. of cycles rented similar or different in different seasons -- ANOVA

In [179]:

```
df['season'].unique()
```

Out[179]:

```
[1, 2, 3, 4]
Categories (4, int64): [1, 2, 3, 4]
```

In [191]:

```
season_1= pd.DataFrame(df.loc[df['season']==1].groupby([df['day'],df['month'],df['year']])[
```

In [192]:

```
season_1=season_1.reset_index()
season_1=season_1.sort_values(by='count')
```

In [193]:

```
season_1
```

Out[193]:

	day	month	year	count
34	6	3	2011	605
58	10	3	2011	623
102	18	1	2011	683
6	2	1	2011	801
48	9	1	2011	822
...	...	...	...	...
107	18	3	2012	5892
113	19	3	2012	6153
89	15	3	2012	6192
83	14	3	2012	6312
101	17	3	2012	7836

114 rows × 4 columns

In [ ]:

In [194]:

```
season_2= pd.DataFrame(df.loc[df['season']==2].groupby([df['day'],df['month'],df['year']])[
season_2=season_2.sort_values(by='count')
season_2
```

Out[194]:

	day	month	year	count
90	16	4	2011	795
42	8	4	2011	1471
24	5	4	2011	1795
66	12	4	2011	2034
72	13	4	2011	2162
...	...	...	...	...
89	15	6	2012	7665
95	16	6	2012	7702
47	8	6	2012	7736
11	2	6	2012	8120
111	19	5	2012	8294

114 rows × 4 columns

In [195]:

```
season_3= pd.DataFrame(df.loc[df['season']==3].groupby([df['day'],df['month'],df['year']])[
season_3=season_3.sort_values(by='count')
season_3
```

Out[195]:

	day	month	year	count
46	8	9	2011	1842
40	7	9	2011	1996
34	6	9	2011	2710
28	5	9	2011	3351
52	9	9	2011	3544
...	...	...	...	...
105	18	8	2012	7865
71	12	9	2012	7870
83	14	9	2012	8009
53	9	9	2012	8227
89	15	9	2012	8714

114 rows × 4 columns

In [196]:

```
season_4= pd.DataFrame(df.loc[df['season']==4].groupby([df['day'],df['month'],df['year']])[
season_4=season_4.sort_values(by='count')
season_4
```

Out[196]:

	day	month	year	count
40	7	12	2011	705
92	16	11	2011	1817
66	12	10	2011	2416
108	19	10	2011	2424
0	1	10	2011	2429
...	...	...	...	...
61	11	10	2012	7570
13	3	10	2012	7572
55	10	10	2012	7691
31	6	10	2012	7965
25	5	10	2012	8156

114 rows × 4 columns

In [197]:

```
np.var(season_1['count'])
```

Out[197]:

```
2107165.9556786707
```

In [198]:

```
np.var(season_2['count'])
```

Out[198]:

```
2811640.8291782085
```

In [199]:

```
np.var(season_3['count'])
```

Out[199]:

```
2036263.220683286
```

In [200]:

```
np.var(season_4['count'])
```

Out[200]:

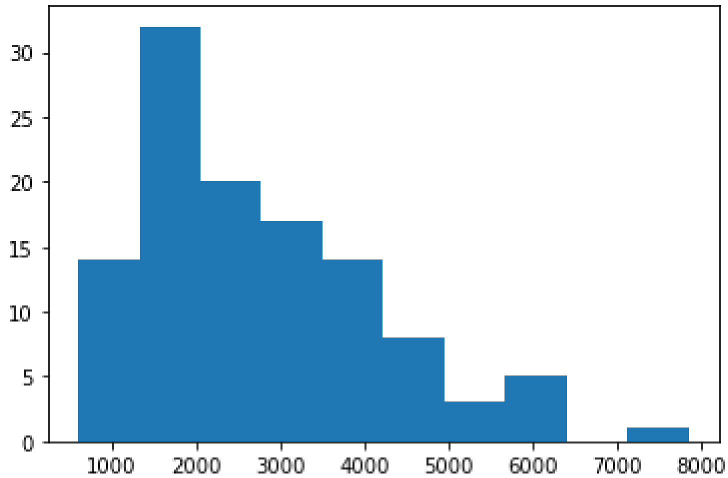
```
2147031.649738381
```

In [202]:

```
plt.hist(season_1['count'])
```

Out[202]:

```
(array([14., 32., 20., 17., 14.,  8.,  3.,  5.,  0.,  1.]),
 array([ 605. , 1328.1, 2051.2, 2774.3, 3497.4, 4220.5, 4943.6, 5666.7,
        6389.8, 7112.9, 7836. ]),
 <BarContainer object of 10 artists>)
```

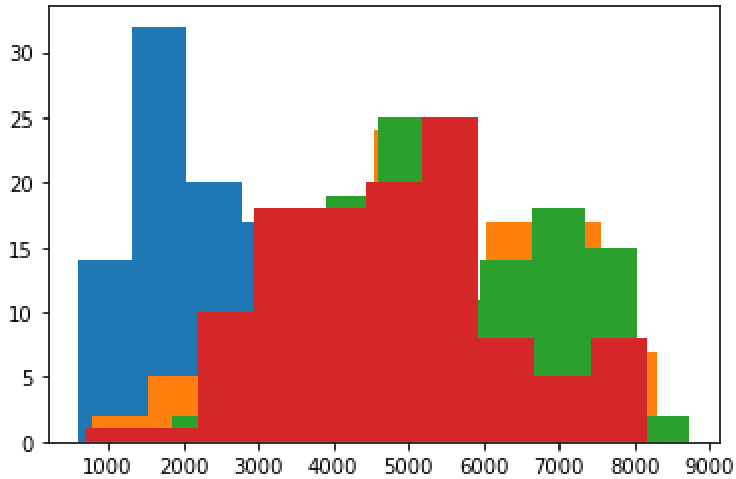


In [205]:

```
plt.hist(season_1['count'])
plt.hist(season_2['count'])
plt.hist(season_3['count'])
plt.hist(season_4['count'])
```

Out[205]:

```
(array([ 1.,  1., 10., 18., 18., 20., 25.,  8.,  5.,  8.]),
 array([ 705. , 1450.1, 2195.2, 2940.3, 3685.4, 4430.5, 5175.6, 5920.7,
        6665.8, 7410.9, 8156. ]),
 <BarContainer object of 10 artists>)
```



The samples are not normally distributed so we will test with levene's as it is performed for

In [207]:

```
stat.levene(season_1['count'],season_2['count'],season_3['count'],season_4['count'])
```

Out[207]:

```
LeveneResult(statistic=1.5071252673249398, pvalue=0.21194448921499898)
```

```
Null Hypothesis : The variances of each sample are equal
Alternate Hypothesis : The variances of atleast one sample differ.
alpha = 0.05
pvalue = 0.21

as pvalue > alpha , failed to reject the null hypothesis, so we can infer that the
variance of each sample are equal and we are good to perform anova on the samples.
```

In [208]:

```
stat.f_oneway(season_1['count'],season_2['count'],season_3['count'],season_4['count'])
```

Out[208]:

```
F_onewayResult(statistic=80.0504789788067, pvalue=1.506580502991204e-41)
```

```
Null Hypothesis : There is no difference between ride count of the seasons
Alternate Hypothesis : There is a significant difference between the ride count of the
seasons

alpha = 0.05
pvalue = 1.506580502991204e-41

alpha > pvalue

we have enough evidence to reject the null hypothesis and say that there is a diference
between the ride counts among the
seasons
```

No. of cycles rented similar or different in different weather -- ANOVA

In [209]:

```
df['weather'].uniqueue()
```

Out[209]:

```
[1, 2, 3, 4]
Categories (4, int64): [1, 2, 3, 4]
```

In [210]:

```
weather_1= pd.DataFrame(df.loc[df['weather']==1].groupby([df['day'],df['month'],df['year']]
weather_1=weather_1.sort_values(by='count')
weather_1
```

Out[210]:

	day	month	year	count
305	14	5	2012	2
226	11	1	2011	15
281	13	5	2011	20
186	9	3	2011	20
348	16	3	2011	27
...	...	...	...	...
267	12	9	2012	7870
34	2	6	2012	7881
197	9	9	2012	8103
111	5	10	2012	8156
420	19	5	2012	8294

434 rows × 4 columns

In [211]:

```
weather_2= pd.DataFrame(df.loc[df['weather']==2].groupby([df['day'],df['month'],df['year']]
weather_2=weather_2.sort_values(by='count')
weather_2
```

Out[211]:

	day	month	year	count
114	7	2	2012	5
65	4	6	2012	5
101	6	7	2012	7
204	12	7	2011	8
278	16	7	2012	11
...	...	...	...	...
116	7	5	2012	5228
221	13	7	2012	5429
139	8	8	2012	5497
162	9	10	2012	6000
121	7	8	2012	6031

346 rows × 4 columns

In [215]:

```
weather_3= pd.DataFrame(df.loc[df['weather']==3].groupby([df['day'],df['month'],df['year']]
weather_3=weather_3.sort_values(by='count')
weather_3
```

Out[215]:

	day	month	year	count
74	8	2	2011	1
42	4	8	2011	3
123	13	1	2012	3
63	7	1	2011	5
64	7	3	2011	6
...	...	...	...	...
68	7	9	2011	1591
185	19	10	2011	1803
15	1	10	2012	2043
25	2	9	2012	2139
27	2	10	2012	3941

187 rows × 4 columns

In [214]:

```
weather_4= pd.DataFrame(df.loc[df['weather']==4].groupby([df['day'],df['month'],df['year']]
weather_4=weather_4.sort_values(by='count')
weather_4
```

Out[214]:

	day	month	year	count
0	9	1	2012	164

In [ ]:

```

```

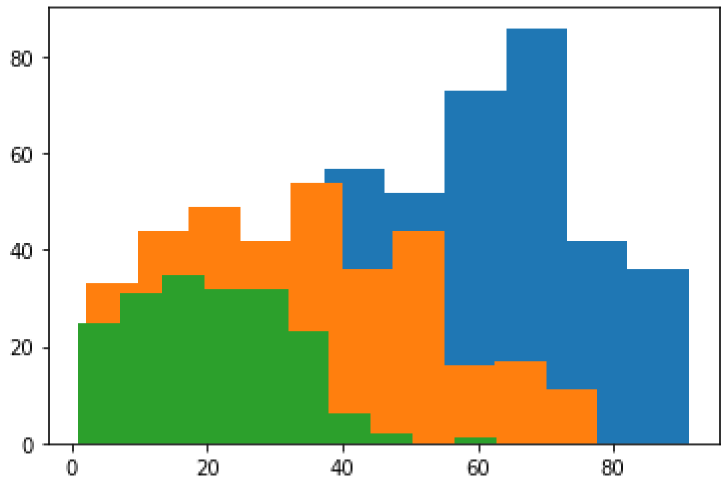
Removing the weather 4 as there is no much data in the weather 4 condition

In [293]:

```
plt.hist(np.sqrt(weather_1['count']))
plt.hist(np.sqrt(weather_2['count']))
plt.hist(np.sqrt(weather_3['count']))
# plt.hist(weather_4['count'])
```

Out[293]:

```
(array([25., 31., 35., 32., 32., 23.,  6.,  2.,  0.,  1.]),
 array([ 1.        ,  7.17773845, 13.35547689, 19.53321534, 25.71095379,
        31.88869223, 38.06643068, 44.24416912, 50.42190757, 56.59964602,
        62.77738446]),
 <BarContainer object of 10 artists>)
```



The data is not normally distributed so we need to perform levene's test.

In [294]:

```
stat.levene(np.sqrt(weather_1['count']),np.sqrt(weather_2['count']),np.sqrt(weather_3['coun
```

Out[294]:

```
LeveneResult(statistic=33.64696582500653, pvalue=7.495205135432121e-15)
```

```
Null Hypothesis : The variance of all the samples are equal
Alternative hypothesis : The variance of the samples are not equal

alpha = 0.05
pvalue = 7.495205135432121e-15

alpha > pvalue, so we can reject the null hypothesis that the variance of the samples are
not equal.
```

In [295]:

```
stat.f_oneway(weather_1['count'],weather_2['count'],weather_3['count'])
```

Out[295]:

```
F_onewayResult(statistic=244.75558358157312, pvalue=1.0951526874746051e-86)
```

```
Null Hypothesis : There a no change in the ride counts with change in weather
Alternative Hypothesis : There is a significant change of the ride counts with the change
in weather

alpha = 0.05
pvalue = 1.0951526874746051e-86

alpha > pvalue, hence we can reject the null hypothesis and continue with the alternative
hypothesis that there is a impact of
weather on the ride counts
```

Weather is dependent on season -- Chi-sq

In [220]:

```
#Contingency Table
contingency_table=pd.crosstab(df['weather'],df['season'])
print('contingency_table :-\n',contingency_table)
```

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

In [221]:

```
#Observed Values
Observed_Values = contingency_table.values
print("Observed Values :-\n",Observed_Values)
```

```
Observed Values :-
 [[1759 1801 1930 1702]
 [ 715  708  604  807]
 [ 211  224  199  225]
 [   1    0    0    0]]
```

In [222]:

```
b=stat.chi2_contingency(contingency_table)
Expected_Values = b[3]
print("Expected Values :-\n",Expected_Values)
```

```
Expected Values :-
 [[1.77454639e+03 1.80559765e+03 1.80559765e+03 1.80625831e+03]
 [6.99258130e+02 7.11493845e+02 7.11493845e+02 7.11754180e+02]
 [2.11948742e+02 2.15657450e+02 2.15657450e+02 2.15736359e+02]
 [2.46738931e-01 2.51056403e-01 2.51056403e-01 2.51148264e-01]]
```

In [223]:

```
#Degree of Freedom
no_of_rows=len(contingency_table.iloc[0:4,0])
no_of_columns=len(contingency_table.iloc[0,0:4])
df=(no_of_rows-1)*(no_of_columns-1)
print("Degree of Freedom:",df)
```

```
Degree of Freedom: 9
```

In [224]:

```
from scipy.stats import chi2
chi_square=sum([(o-e)**2./e for o,e in zip(Observed_Values,Expected_Values)])
chi_square_statistic=chi_square[0]+chi_square[1]
print("chi-square statistic:   ",chi_square_statistic)
```

```
chi-square statistic:    3.3970813914527893
```

In [226]:

```
#critical_value
critical_value=chi2.ppf(q=1-0.05,df=df)
print('critical_value:',critical_value)
```

```
critical_value: 16.918977604620448
```

In [228]:

```
#p-value
p_value=1-chi2.cdf(x=chi_square_statistic,df=df)
print('p-value:',p_value)
```

```
p-value: 0.9464543759349711
```

In [229]:

```
print('Significance level: 0.05')
print('Degree of Freedom: ',df)
print('chi-square statistic:',chi_square_statistic)
print('critical_value:',critical_value)
print('p-value:',p_value)
```

```
Significance level: 0.05
Degree of Freedom:  9
chi-square statistic: 3.3970813914527893
critical_value: 16.918977604620448
p-value: 0.9464543759349711
```

In [354]:

```
if p_value<=0.05:
    print("Reject H0,There is dependency on weather and season")
else:
    print("Retain H0,There is no dependency on weather and season")
```

```
Retain H0,There is no dependency on weather and season
```

Insights :

--> More number of rides were taken place on fall and summer.

--> More number of rides were taken place on fall and summer.
--> More number of rides were taken place on Gentle, Moderate and fresh breeze.
--> Less number of rides happened on holidays and more number of rides on working days.
--> Most of the people use yulu during when the weather condition is Clear, Few clouds, partly cloudy, partly cloudy

Recommendations :

--> As more number of rides are going to happen on fall and summer and we can make more bikes available during this season
    so that more people can make use of it.
--> Users prefer Yulu during the Gentle, moderate and fresh breeze time and during the working hours so that we can give
    some offers during the no working hours to make more use of Yulu and make availabity of bikes during the location
    for users to travel to work places.