In [1]:
```
#Problem Statement

#Yulu is India's leading micro-mobility service provider, which offers unique vehicles for the daily commute.
#Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution
#through a user-friendly mobile app to enable shared, solo and sustainable commuting.

#Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas
#to make those first and last miles smooth, affordable, and convenient!

#Yulu has recently suffered considerable dips in its revenues.
#They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depend
#Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.
```

In [2]:
```
#Importing all important libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import ttest_ind, f_oneway,chi2_contingency
```

In [3]:
```
#Reading data
df=pd.read_csv("bike_sharing.csv")
```

In [4]:
```
#Checking how data looks like
df.head()
```

Out[4]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

In [5]:
```
#Checking Size of data
df.shape
```

Out[5]: (10886, 12)

In [6]:
```
#Checking data types of columns
df.info()

#Insights: dateime coulumn has object data type
```

```
<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
```

In [7]:
```
#Checking null counts
df.isna().sum()

#Insights: No Null Values found in records
```

Out[7]:
```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
dtype: int64
```

In [8]:
```
#Null values not found but there can be missing values
df1=pd.read_csv("bike_sharing.csv")
df1["datetime"]=pd.to_datetime(df1["datetime"])
df1["datetime"]=df1["datetime"].dt.time
df1["datetime"].value_counts()

#Insights:
#Total 456 days data we have but for few time frames no of readings are less than 456
#missing data is very less so we can go ahead with original data
```

Out[8]:
```
12:00:00    456
13:00:00    456
22:00:00    456
21:00:00    456
20:00:00    456
19:00:00    456
18:00:00    456
17:00:00    456
16:00:00    456
15:00:00    456
14:00:00    456
23:00:00    456
11:00:00    455
10:00:00    455
09:00:00    455
08:00:00    455
07:00:00    455
06:00:00    455
00:00:00    455
01:00:00    454
05:00:00    452
02:00:00    448
04:00:00    442
03:00:00    433
Name: datetime, dtype: int64
```

In [9]:
```
#Stastistical oveview of data
df.describe()
```

Out[9]:

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	c
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.00
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.57
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.14
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.00
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.00
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.00
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.00
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.00

In [10]:
```python
#unique attributes
df.nunique()
```

Out[10]:
```
datetime      10886
season            4
holiday           2
workingday        2
weather           4
temp             49
atemp            60
humidity         89
windspeed        28
casual          309
registered      731
count           822
dtype: int64
```

In [11]:
```python
#Finding out categorical variables
print("Different types of Seasons = ",df["season"].unique())
print("Different types of Workingday = ",df["workingday"].unique())
print("Different types of Weather = ",df["weather"].unique())

#Insights
#there are 4 types of seasons,     1:Spring 2:Summer 3:Fall 4:Winter

#there are 2 types of working day, 0:Not a working day 1:working day

#there are 4 types of weather:     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
```

```
Different types of Seasons =  [1 2 3 4]
Different types of Workingday =  [0 1]
Different types of Weather =  [1 2 3 4]
```

In [12]:
```python
#Converting continuous variables to categorical variables
df["humidity_bins"]=pd.cut(df["humidity"],5)
df["temp_bins"]=pd.cut(df["temp"],3)
df["windspeed_bins"]=pd.cut(df["windspeed"],6)
df.head()
```

Out[12]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	humidity_bins	temp_bins	windspeed_bins
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16	(80.0, 100.0]	(0.78, 14.213]	(-0.057, 9.499]
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]

In [13]:
```
#to do analysis on working days and season, we need day wise data
#step1: converting datetime column into only date
df["datetime"]=pd.to_datetime(df["datetime"])
df["datetime"]=df["datetime"].dt.date
df.head()
```

Out[13]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	humidity_bins	temp_bins	windspeed_bins
0	2011-01-01	1	0	0	1	9.84	14.395	81	0.0	3	13	16	(80.0, 100.0]	(0.78, 14.213]	(-0.057, 9.499]
1	2011-01-01	1	0	0	1	9.02	13.635	80	0.0	8	32	40	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
2	2011-01-01	1	0	0	1	9.02	13.635	80	0.0	5	27	32	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
3	2011-01-01	1	0	0	1	9.84	14.395	75	0.0	3	10	13	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]
4	2011-01-01	1	0	0	1	9.84	14.395	75	0.0	0	1	1	(60.0, 80.0]	(0.78, 14.213]	(-0.057, 9.499]

In [14]:
```
#Checking how many days data we have
df.groupby("datetime").ngroups

#Insights
#we have total 456 days of data
```

Out[14]: 456

In [15]:
```
#grouping data
df_new=df.groupby(["datetime","season","workingday"])["count"].sum().reset_index()
df_new.head()
```

Out[15]:

	datetime	season	workingday	count
0	2011-01-01	1	0	985
1	2011-01-02	1	0	801
2	2011-01-03	1	1	1349
3	2011-01-04	1	1	1562
4	2011-01-05	1	1	1600

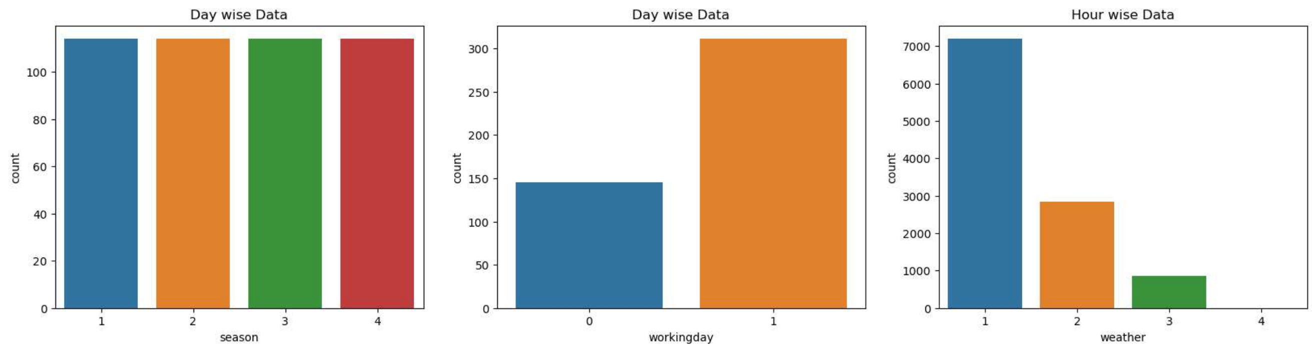
In [16]:
```
#Stastistical overview for new data
df_new.describe()

#Insights
#Count of total rental bikes per day. Mean and median dont have much difference (4573 and 4585 respectively)
```

Out[16]:

	season	workingday	count
count	456.000000	456.000000	456.000000
mean	2.500000	0.682018	4573.412281
std	1.119262	0.466204	1868.740135
min	1.000000	0.000000	605.000000
25%	1.750000	0.000000	3305.500000
50%	2.500000	1.000000	4585.500000
75%	3.250000	1.000000	5987.500000
max	4.000000	1.000000	8714.000000

In [17]:
```
#Graphocal Analysis
plt.figure(figsize=(20,10))
plt.subplot(2,3,1)
sns.countplot(data=df_new, x="season")
plt.title("Day wise Data")
plt.subplot(2,3,2)
sns.countplot(data=df_new, x="workingday")
plt.title("Day wise Data")
plt.subplot(2,3,3)
sns.countplot(data=df, x="weather")
plt.title("Hour wise Data")
```

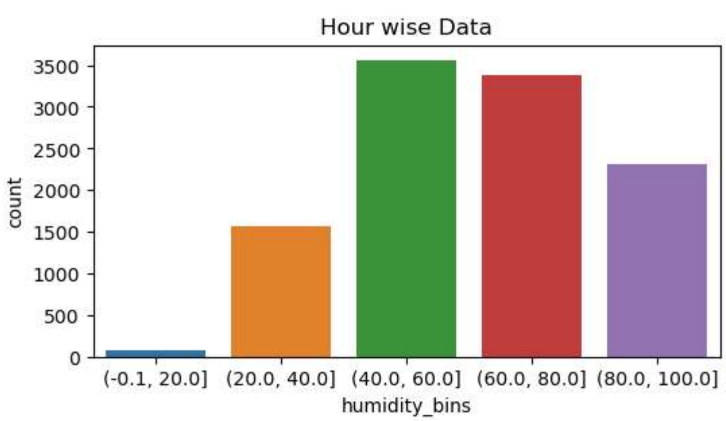
Out[17]:
```
Text(0.5, 1.0, 'Hour wise Data')
```



In [18]:
```
#humidity in city-hourly count and how much bikes rented
plt.figure(figsize=(6,3))
sns.countplot(data=df,x="humidity_bins")
plt.title("Hour wise Data")
humidity_wise_count=pd.DataFrame(df.groupby("humidity_bins")["count"].sum()).T
humidity_wise_count

#Figure show humidity distribution
#chart shows usage of bikes
```

Out[18]:

humidity_bins	(-0.1, 20.0]	(20.0, 40.0]	(40.0, 60.0]	(60.0, 80.0]	(80.0, 100.0]
count	14070	453412	786017	579255	252722



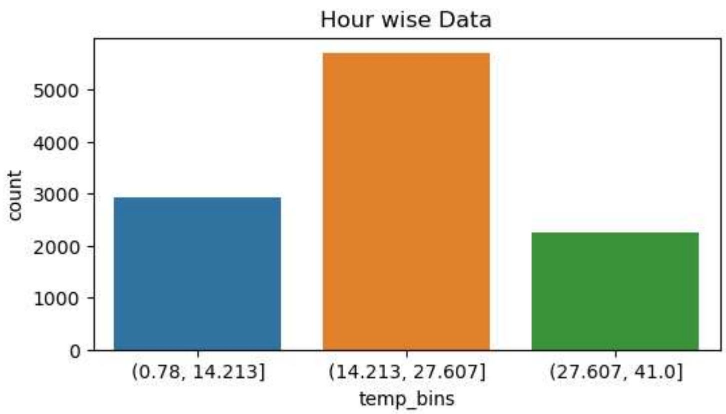
In [19]:
```
df["humidity_bins"].value_counts()
```

Out[19]:
```
(40.0, 60.0]     3564
(60.0, 80.0]     3382
(80.0, 100.0]    2302
(20.0, 40.0]     1560
(-0.1, 20.0]       78
Name: humidity_bins, dtype: int64
```

In [20]:
```
#insights
#Mostly humidity in city stays more than 40
#lets compare bikes rented per hours for humidity bins of 40-60, 60-80 and 80-100
#No of bikes/no of hours
print("Rented Bikes/hour for humidity between 40 and 60 =",786017//3564)
print("Rented Bikes/hour for humidity between 60 and 80 =",579255//3382)
print("Rented Bikes/hour for humidity between 80 and 100 =",252722//2302)

#insights: 40-60 hymidity is perfect weather for bike rental. as humidity increases less people prefer bikes
```

```
Rented Bikes/hour for humidity between 40 and 60 = 220
Rented Bikes/hour for humidity between 60 and 80 = 171
Rented Bikes/hour for humidity between 80 and 100 = 109
```

In [21]:
```
plt.figure(figsize=(6,3))
sns.countplot(data=df,x="temp_bins")
plt.title("Hour wise Data")
plt.show()
temp_wise_count=pd.DataFrame(df.groupby("temp_bins")["count"].sum()).T
temp_wise_count

#Figure show temperature distribution
#chart shows usage of bikes
```



Out[21]:

temp_bins	(0.78, 14.213]	(14.213, 27.607]	(27.607, 41.0]
count	301965	1114051	669460

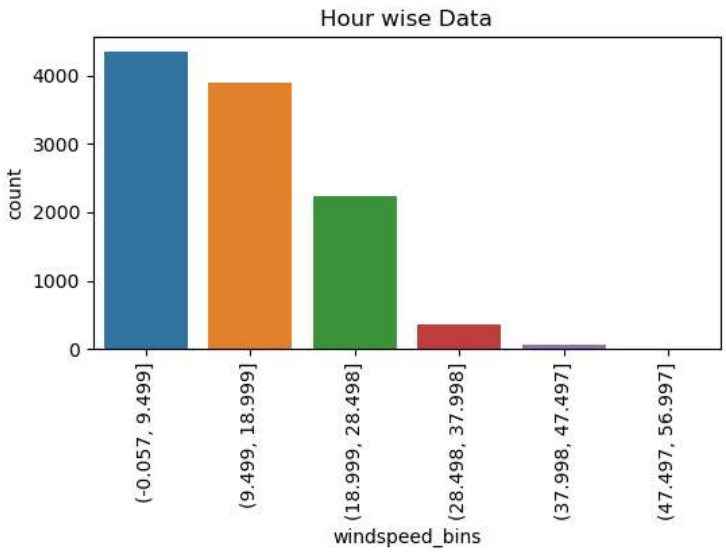
In [22]:
```
df["temp_bins"].value_counts()
```

Out[22]:
```
(14.213, 27.607]    5712
(0.78, 14.213]      2926
(27.607, 41.0]      2248
Name: temp_bins, dtype: int64
```

In [23]:
```
#insights
#Mostly temperature in city stays between 14 and 27
#lets compare bikes rented per hours for temperature bins
#No of bikes/no of hours
print("Rented Bikes/hour for temperature upto 14 =",301965//2926)
print("Rented Bikes/hour for temperature between 14 and 27 =",1114051//2926)
print("Rented Bikes/hour for temperature above 27=",669460//2248)

#insights: Ideal temp when people prefer bike is betwenn 14 and 27
#less people prefer bikes when its cold outside
```

```
Rented Bikes/hour for temperature upto 14 = 103
Rented Bikes/hour for temperature between 14 and 27 = 380
Rented Bikes/hour for temperature above 27= 297
```

In [24]:
```
plt.figure(figsize=(6,3))
sns.countplot(data=df,x="windspeed_bins")
plt.title("Hour wise Data")
plt.xticks(rotation=90)
plt.show()
windspeed_wise_count=pd.DataFrame(df.groupby("windspeed_bins")["count"].sum()).T
windspeed_wise_count


#Figure show windspeed distribution
#chart shows usage of bikes
```



Out[24]:

windspeed_bins	(-0.057, 9.499]	(9.499, 18.999]	(18.999, 28.498]	(28.498, 37.998]	(37.998, 47.497]	(47.497, 56.997]
count	712814	804180	482118	75113	10255	996

In [25]:
```
df["windspeed_bins"].value_counts()
```

Out[25]:
```
(-0.057, 9.499]     4339
(9.499, 18.999]     3884
(18.999, 28.498]    2236
(28.498, 37.998]     360
(37.998, 47.497]      61
(47.497, 56.997]       6
Name: windspeed_bins, dtype: int64
```

In [26]:
```
#insights
#Mostly Windspeed in city stays from 0-28.5
#lets compare bikes rented per hours for Windspeed bins 0-9.5, 9.5-19 and 19-28.5
#No of bikes/no of hours
print("Rented Bikes/hour for Windspeed upto 9.5 =",712814//4339)
print("Rented Bikes/hour for Windspeed between 9.5 and 19 =",804180//3884)
print("Rented Bikes/hour for Windspeed between 19 and 28.5=",482118//2236)

#insights: when windpeed is less than 9.5, comparitively less people rent bike
```

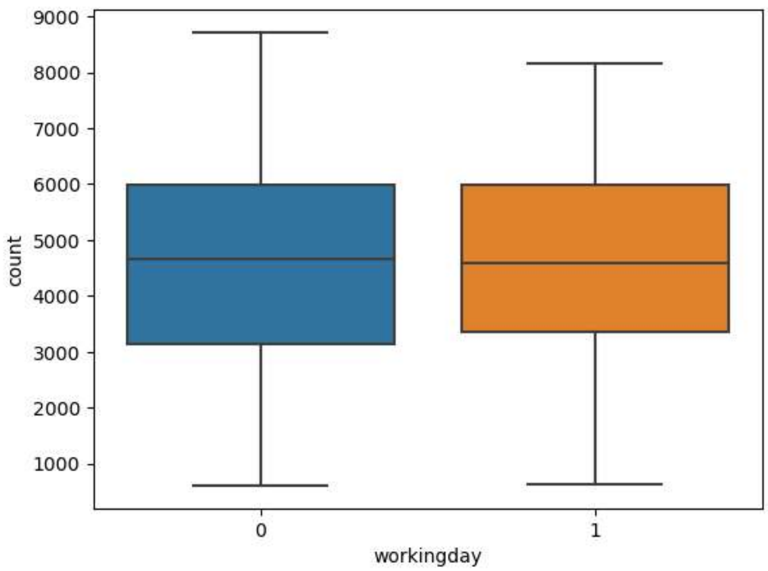
```
Rented Bikes/hour for Windspeed upto 9.5 = 164
Rented Bikes/hour for Windspeed between 9.5 and 19 = 207
Rented Bikes/hour for Windspeed between 19 and 28.5= 215
```

In [27]:
```
print("casual users demand/hour=",df["casual"].sum()//len(df["casual"]))
print("registered users demand/hour=",df["registered"].sum()//len(df["registered"]))

#insights
#registred user demand is more than casual
```

```
casual users demand/hour= 36
registered users demand/hour= 155
```

In [28]:
```
#Bivariate Analysis between No of vehicles and working day/non working day
sns.boxplot(data=df_new,x="workingday",y="count")

#Insights
#We can see there is not much difference in medians of both groups
#but based on above information we cant conclude no effect on No of vehicles rented if working or non working day
#we need to do 2t t test to check stastistically
```

Out[28]:
```
<AxesSubplot:xlabel='workingday', ylabel='count'>
```



In [29]:
```
#segregating samples for working day and non working day
df_workingday=df_new[df_new["workingday"]==1]
df_non_workingday=df_new[df_new["workingday"]==0]
```

In [30]:
```
#basic info about samples
print("Basic Stats about working Days data")
print("Mean for no of bikes rented on working days =",round(df_workingday["count"].mean()))
print("Std Deviation for no of bikes rented on working days =",round(df_workingday["count"].std()))
print("Total no of working days =",len(df_workingday))
print("")
print("Basic Stats about non working Days data")
print("Mean for no of bikes rented on non working days =",round(df_non_workingday["count"].mean()))
print("Std Deviation for no of bikes rented on non working days =",round(df_non_workingday["count"].std()))
print("Total no of non working days =",len(df_non_workingday))
```

```
Basic Stats about working Days data
Mean for no of bikes rented on working days = 4600
Std Deviation for no of bikes rented on working days = 1829
Total no of working days = 311

Basic Stats about non working Days data
Mean for no of bikes rented on non working days = 4516
Std Deviation for no of bikes rented on non working days = 1956
Total no of non working days = 145
```

In [31]:
```
#Checking if there is any effect on number of bikes rented based on if its working day or non working day

#Data we have: sample data
#Data we dont have: Population data
#As we dont have Population std deviation, we cant use Z test. 2 sample t test can be used in this case
#Sample size is more than 30 so t test will give similar results like z test

#Null Hypothesis: There is no effect of working days on No of bikes rented
#Alternate Hypothesis: No of bikes rented depends on if its a working day or not

#Test statistics: No of bikes rented per day
#Samples whoich we gonna use: df_workingday["counts"] and df_non_workingday["count"]
#significance level: 0.05
```

In [32]:
```
#performing T test and getting t stat and p value
t_stat_workingday,p_workingday=ttest_ind(df_non_workingday["count"],df_workingday["count"])
print("tstat=",t_stat_workingday)
print("p=",p_workingday)
```

```
tstat= -0.44477221614881995
p= 0.656696335987859
```

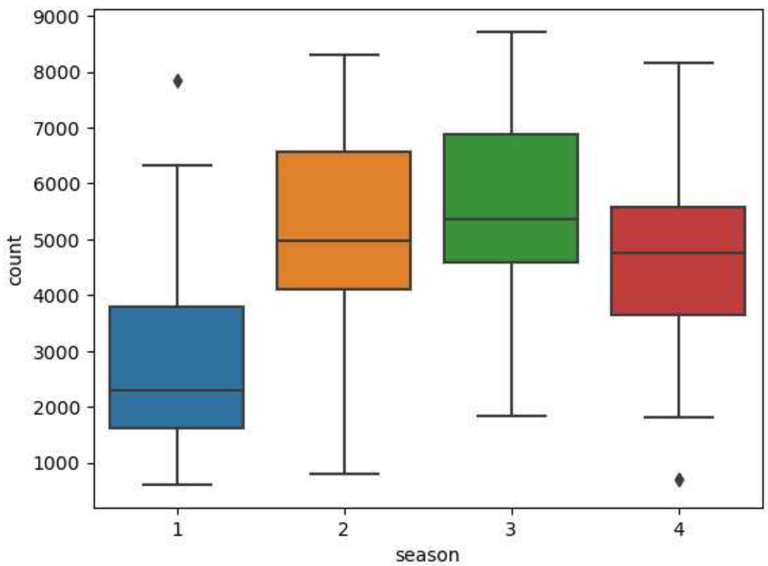
In [33]:
```
#Concluding 2 sample T test
if p_workingday<0.05:
    print("reject null hypothesis")
else:
    print("fail to reject null hypothesis")
```

```
fail to reject null hypothesis
```

In [34]:
```
#insights
#There is No EFFECT if day is working or not on no of bikes rented
```

In [35]:
```
#Bivariate Analysis between No of vehicles and working day/non working day
sns.boxplot(data=df_new,x="season",y="count")
```

Out[35]: <AxesSubplot:xlabel='season', ylabel='count'>



In [36]:
```
#segregating samples of different seasons
df_season1=df_new[df_new["season"]==1]
df_season2=df_new[df_new["season"]==2]
df_season3=df_new[df_new["season"]==3]
df_season4=df_new[df_new["season"]==4]
```

In [37]:
```python
#basic info about samples
print("Basic Stats about season1 data")
print("Mean for no of bikes rented on season1 =",round(df_season1["count"].mean()))
print("Std Deviation for no of bikes rented on season1 days =",round(df_season1["count"].std()))
print("Total no of season1 days =",len(df_season1))
print("")
print("Basic Stats about season2 data")
print("Mean for no of bikes rented on season2 =",round(df_season2["count"].mean()))
print("Std Deviation for no of bikes rented on season2 days =",round(df_season2["count"].std()))
print("Total no of season2 days =",len(df_season2))
print("")
print("Basic Stats about season3 data")
print("Mean for no of bikes rented on season3 =",round(df_season3["count"].mean()))
print("Std Deviation for no of bikes rented on season3 days =",round(df_season3["count"].std()))
print("Total no of season3 days =",len(df_season3))
print("")
print("Basic Stats about season4 data")
print("Mean for no of bikes rented on season4 =",round(df_season4["count"].mean()))
print("Std Deviation for no of bikes rented on season4 days =",round(df_season4["count"].std()))
print("Total no of season4 days =",len(df_season4))
print("")
```

```
Basic Stats about season1 data
Mean for no of bikes rented on season1 = 2741
Std Deviation for no of bikes rented on season1 days = 1458
Total no of season1 days = 114

Basic Stats about season2 data
Mean for no of bikes rented on season2 = 5160
Std Deviation for no of bikes rented on season2 days = 1684
Total no of season2 days = 114

Basic Stats about season3 data
Mean for no of bikes rented on season3 = 5620
Std Deviation for no of bikes rented on season3 days = 1433
Total no of season3 days = 114

Basic Stats about season4 data
Mean for no of bikes rented on season4 = 4772
Std Deviation for no of bikes rented on season4 days = 1472
Total no of season4 days = 114
```

In [38]:
```python
#Checking if there is any effect on number of bikes rented based on season
#Here we have 4 seasons. we need to check if no of bikes rented samples are statistically different for all 4 seasons
#here we are gonna compare more than 2 samples so Anova can be used

#Null Hypothesis: No of vehicles rented in all 4 seasons are same
#Alternate Hypothesis: No of vehicles rented in atleast 1 season is different than others

#Ftest is right tailed distribution which will tell us if samples are statistically significant or not by comparing p and alpha
#significance level: 0.05
```

In [39]:
```python
#performing Anova and getting f ratio and p values
f_ratio_season,p_season=f_oneway(df_season1["count"],df_season2["count"],df_season3["count"],df_season4["count"])

print("F-Ratio=",f_ratio_season)
print("P=",p_season)
```

```
F-Ratio= 80.0504789788067
P= 1.506580502991204e-41
```

In [40]:
```python
#Concluding Anova
if p_season<0.05:
    print("reject null hypothesis")
else:
    print("fail to reject null hypothesis")
```

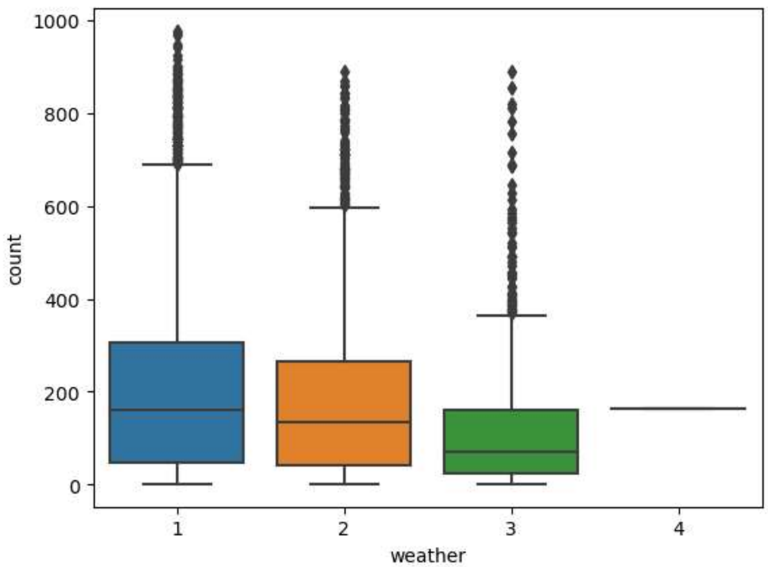
```
reject null hypothesis
```

In [41]:
```python
#Insights
#we are rejecting null hypothesis that all samples are same
#Number of bikes rented depends on season
```

In [42]:
```python
#for working days and season, data we used was per day
#weather may change during day,so will be using hour data to do statistical analysis of how weather influence No of bikes rentec
```

In [43]:
```
#Bivariate Analysis between No of vehicles and weather
sns.boxplot(data=df,x="weather",y="count")

#insights
#from graphs we can see there is difference in medians for no of bikes rented for all weathers
#we can also see outliers which are on higher side, will be ignoring for this analysis
#sample 4 data looks abnormal, will be investigating it
```

Out[43]: <AxesSubplot:xlabel='weather', ylabel='count'>



In [44]:
```
#segregating samples of different weathers
df_weather1=df[df["weather"]==1]
df_weather2=df[df["weather"]==2]
df_weather3=df[df["weather"]==3]
df_weather4=df[df["weather"]==4]
```

In [45]:
```
#basic info about samples
print("Basic Stats about weather1 data")
print("Mean for no of bikes rented on weather1 =",round(df_weather1["count"].mean()))
print("Std Deviation for no of bikes rented on weather1=",round(df_weather1["count"].std()))
print("Total no of weather1 hours =",len(df_weather1))
print("")
print("Basic Stats about weather2 data")
print("Mean for no of bikes rented on weather2 =",round(df_weather2["count"].mean()))
print("Std Deviation for no of bikes rented on weather2=",round(df_weather2["count"].std()))
print("Total no of weather2 hours =",len(df_weather2))
print("")
print("Basic Stats about weather3 data")
print("Mean for no of bikes rented on weather3 =",round(df_weather3["count"].mean()))
print("Std Deviation for no of bikes rented on weather3=",round(df_weather3["count"].std()))
print("Total no of weather3 hours =",len(df_weather3))
print("")
print("Basic Stats about weather4 data")
print("Mean for no of bikes rented on weather4 =",round(df_weather4["count"].mean()))
print("Total no of weather4 hours =",len(df_weather4))
```

```
Basic Stats about weather1 data
Mean for no of bikes rented on weather1 = 205
Std Deviation for no of bikes rented on weather1= 188
Total no of weather1 hours = 7192

Basic Stats about weather2 data
Mean for no of bikes rented on weather2 = 179
Std Deviation for no of bikes rented on weather2= 168
Total no of weather2 hours = 2834

Basic Stats about weather3 data
Mean for no of bikes rented on weather3 = 119
Std Deviation for no of bikes rented on weather3= 139
Total no of weather3 hours = 859

Basic Stats about weather4 data
Mean for no of bikes rented on weather4 = 164
Total no of weather4 hours = 1
```

In [46]:
```
#Checking if there is any effect on number of bikes rented based on weather
#Here we have 4 weather. we need to check if no of bikes rented samples are statistically different for all 4 weather
#here we are gonna compare more than 2 samples so Anova can be used

#Null Hypothesis: No of vehicles rented in all 4 weather are same
#Alternate Hypothesis: No of vehicles rented in atleast 1 weather is different than others

#Ftest is right tailed distribution which will tell us if samples are statistically significant or not by comparing p and alpha
#significance level: 0.05
```

In [47]:
```
#performing Anova and getting f ratio and p values
f_ratio_weather,p_weather=f_oneway(df_weather1["count"],df_weather2["count"],df_weather3["count"],df_weather4["count"])

print("F-Ratio=",f_ratio_weather)
print("P=",p_weather)
```

```
F-Ratio= 65.53024112793271
P= 5.482069475935669e-42
```

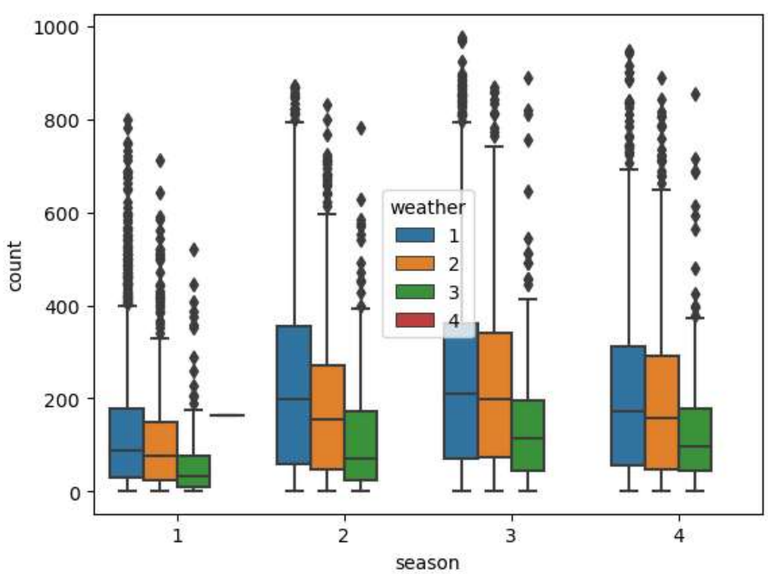
In [48]:
```
#Concluding Anova
if p_weather<0.05:
    print("reject null hypothesis")
else:
    print("fail to reject null hypothesis")
```

```
reject null hypothesis
```

In [49]:
```
#Insights
#we are rejecting null hypothesis that all samples are same
#Number of bikes rented depends on weather
```

In [50]:
```
#Bivariate Analysis between No of vehicles with weather and season

sns.boxplot(data=df, x="season", y="count", hue="weather")
```

Out[50]: <AxesSubplot:xlabel='season', ylabel='count'>



In [51]:
```
#season and weather both are categorical variables
#from diagram we can see there is some relation between by comparing medians
#to check stastistically we need to perfoem chi-square test
chi2_data=pd.crosstab(index=df["season"],columns=df["weather"])
chi2_data
```

Out[51]:

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 [52]:
```
#Chi-square test
#Null Hypothesis: Season and weather does not depend on each other
#Alternate Hypothesis: Season and weather depends on each other
#significance level=0.05
tstat_cat,P_cat,df_cat,exp=chi2_contingency(chi2_data)
print("tstat=",tstat_cat)
print("P=",P_cat)
```

```
tstat= 49.158655596893624
P= 1.549925073686492e-07
```

In [53]:
```
#Concluding Anova
if P_cat<0.05:
    print("reject null hypothesis")
else:
    print("fail to reject null hypothesis")
```

```
reject null hypothesis
```

In [54]:
```
#insights
#we fail to reject null hypothesis
#weather and season are dependednt on each other
```

In [55]:
```
#Collective insights

#we have hourly data for 456 days
#Overall count if we see then not much difference between mean and median of no of rental bikes.

#40-60 humidity is perfect weather for bike rental. As humidity increases less people prefer bikes.
#Ideal temp when people prefer bike is betwenn 14 and 27. less people prefer bikes when its cold outside
#When windspeed is less than 9.5, comparitively less people rent bike

#Registred user demand is more than casual
#number of vehicles rented is not influenced by if its working day or not working day

#number of vehicles rented is influenced by seasons
#season3 (fall) has highest demand
#season1 (spring) has lowest demand

#number of vehicles rented is influenced by weather
#weather1 (Clear, Few clouds, partly cloudy, partly cloudy) has highest demand
#weather3 has lowest demand(Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds)

#No of bikes rented depends on weather and season, also weather and season depends on each other
```

In [56]:
```
#recommendations

#Yulu should allocate some budget on weather forecasting as demand is highly dependent on such factors

#before fall season starts Yulu should make sure thta maintenance of all bikes and bike stastion is done and
#they are ready to tackle high demand during fall season
#spring season when demand is less, Yulu can focus on maintenance

#when windspeed is less, people dont prefer bikes. special discounts may increase the count

#when its cold people dont prefer bikes. Yulu can join hands with another startups which rents EV cars and divert customers
#who prefer cars rather than bike. in return they can get comission

#during less humid environment people dont prefer bikes, reason may be dehydration.
#yulu can provide drinks near bike stastions (collaboration with cold drink company sounds good for buissness)

#when weather is clear, demand is high so extra bikes can be kept in stick for such weather forecasting

#demand is more in registered customers, so focus should be convert casual user into registered by giving offers

#awareness aboout environment and EV is must. EV bike rallies on environment day soinds good idea to reach more people
```