In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
```

In [2]:
```
yulu_df = pd.read_csv('bike_sharing.txt',delimiter=',')
yulu_df.head()
```

Out[2]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	re
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	

Defining Problem Statement and Analysing basic metrics

we have to find out that is the number of users using teh yulu bike rental service is effected because of holiday or season or weather etc using various hypothesis testing methods like ztest, chi-square test, Anova etc

In [3]:
```
yulu_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
```

from the above cell it is clear that except datetime column every other column is either in int or float and the datetime is in object(string) format

In [4]:
```
yulu_df.isna().sum()
```

Out[4]:
```
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
```

From the above cell it i scleatr that their are no missing values

In [5]:
```
yulu_df.describe()
```

Out[5]:

	season	holiday	workingday	weather	temp	atemp	hu
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.(
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.8
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.2
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.(
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.(
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.(
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.(
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.(

from the output of the above cell the mean of temp is 20.23 median is 20.50 and the max is 41 As teh mean and median are almost same and the 75% value and max vaalue are not that far we can say that teh data is not effected by outliers i.e., no sudden extreme temperaters recorded

the mean of humidity is 61.88 median is 62 and the max value is 100 so here also the mean and median are almost same and the 75% value and max value are close we can say that the data is not effected with outliers

the mean of causal bike renters is 36.02 and the median is 17 the 75% value is 49 and the max value is 367 as the mean and median are far and the 75% value and the max value are also far so we can conclude that their are outliers in this coulmn

the mean of registered users is 155.55 median iss 118 75% value is 222 and the max value is 886 the mean and median are almost close but the 75% and max are far so it is likely effected with some outliers

the mean of count iss 191.57 median is 145 75% value is 284 and the max value is 977 here the mean and median are far away and also the 75% value and max value are far away so the data is effected with outliers

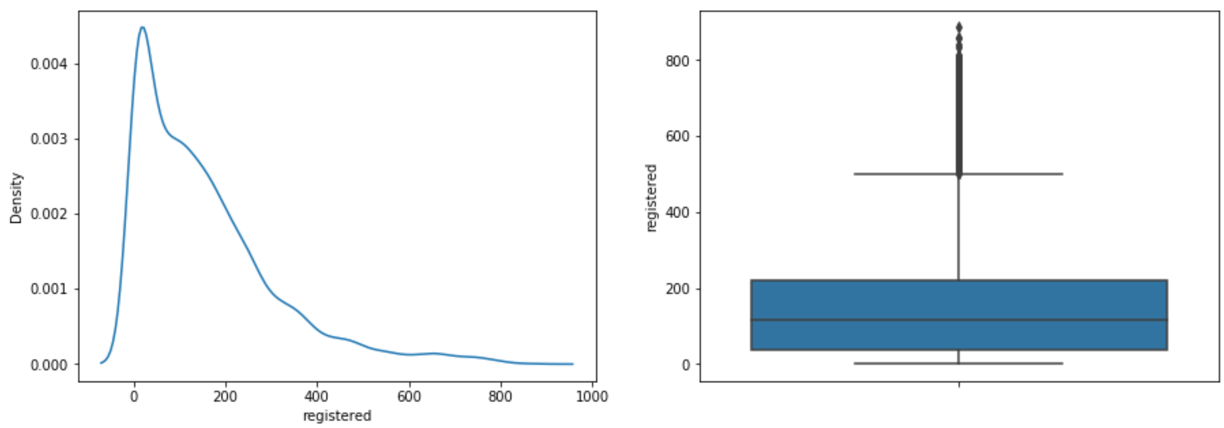
In [6]:
```python
yulu_df.describe(include='object')
```

Out[6]:

	datetime
count	10886
unique	10886
top	2012-06-07 21:00:00
freq	1

from the eabove cell output the datetime is not repeting

In [7]:
```python
plt.figure(figsize=(15,5))
plt.subplot(121)
sns.kdeplot(data=yulu_df,x='registered')
plt.subplot(122)
sns.boxplot(data=yulu_df,y='registered')
# plt.subplot(122)
plt.show()
```



the registered userd are exibiting right tailed dustribution as it is having some outliers it is even clena from the boxployt that their are outliers

In [8]:
```python
yulu_df.columns
```

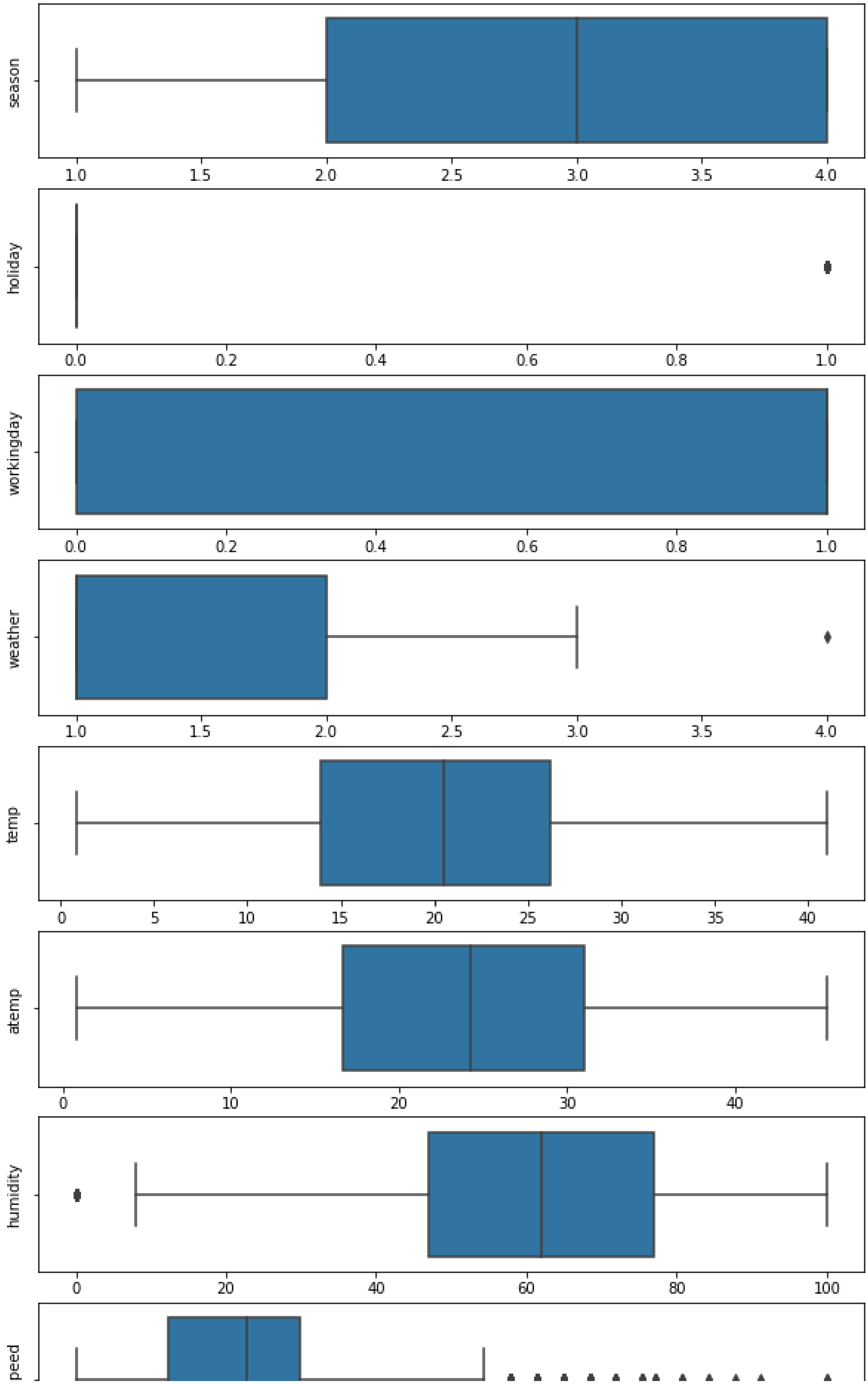
Out[8]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

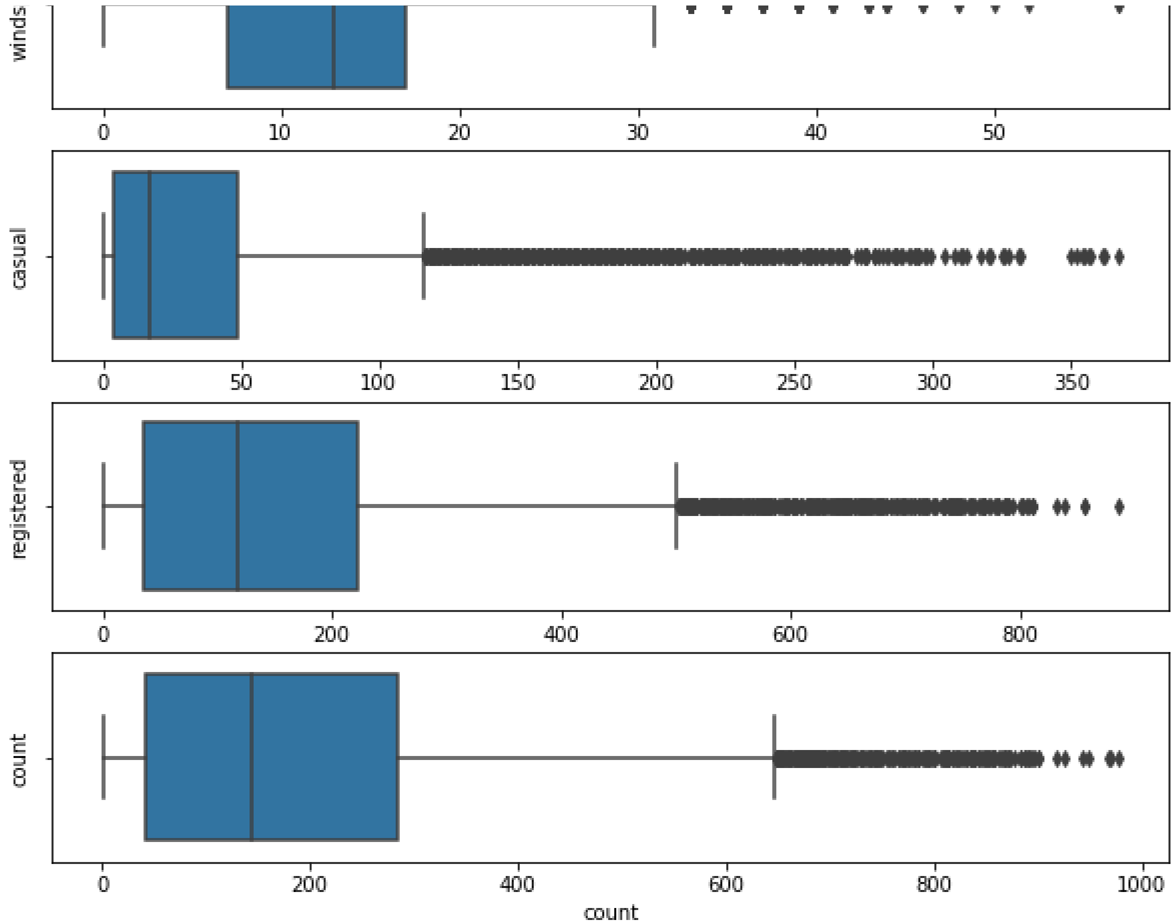
In [9]:
```python
yulu_df_no_datetime = yulu_df.drop('datetime',axis=1)
```

In [10]:
```
def all_plots(df):
    plt.figure(figsize=(10,25))
    for i in range(len(df.columns)):
        plt.subplot(11,1,i+1)
        sns.boxplot(data=df,x=df.columns[i])
        plt.ylabel(df.columns[i])
    plt.show()
```

The above function is used to plot the box plot of all the columns except datetime

In [11]:
```
all_plots(yulu_df_no_datetime)
```





the values which are above and below the viscures are called outliers

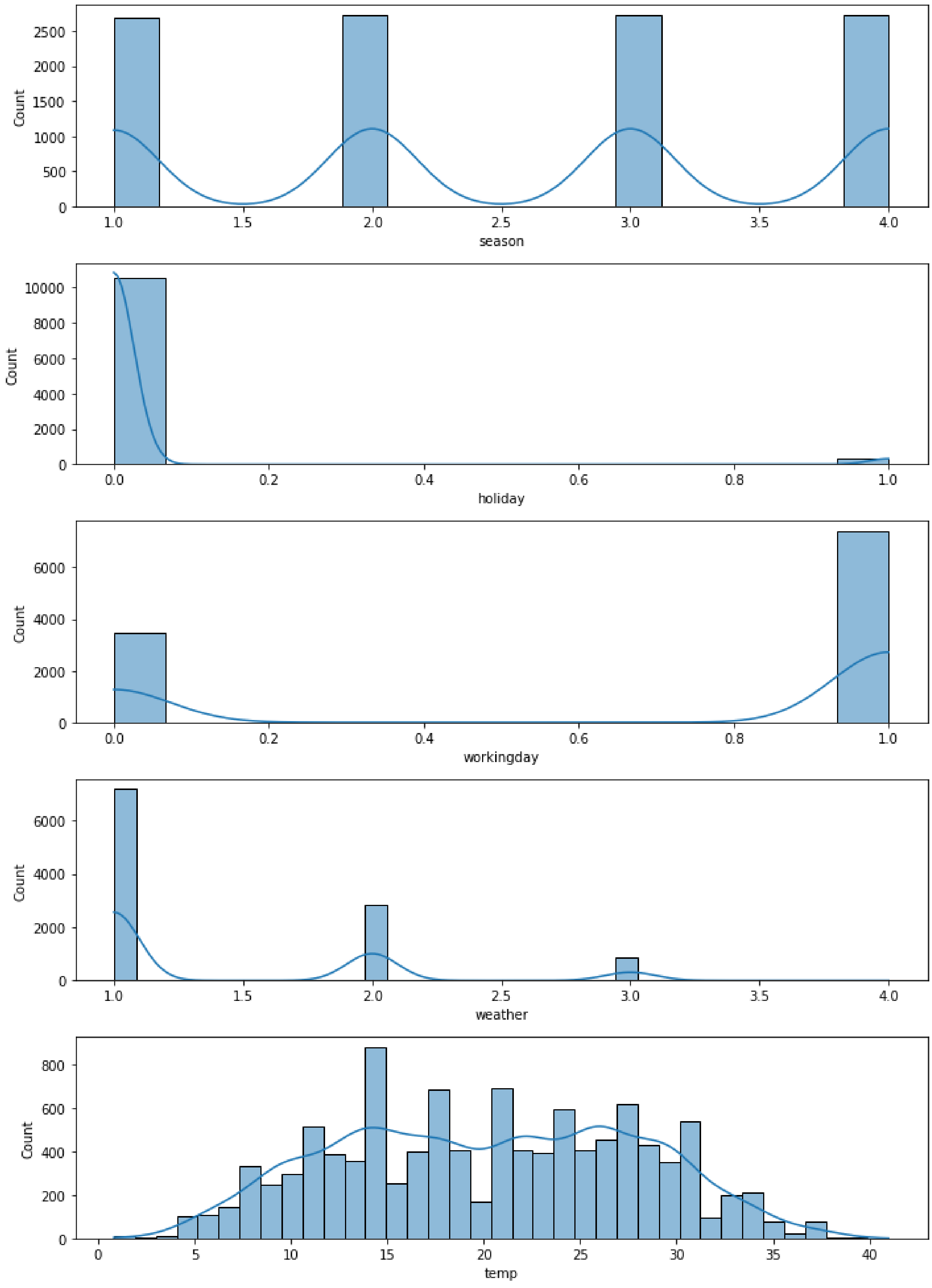
from the above plots we can observe that windspeed is having some outliers i.e., windspeed value above 33 aire considered outlier from the above boxplots

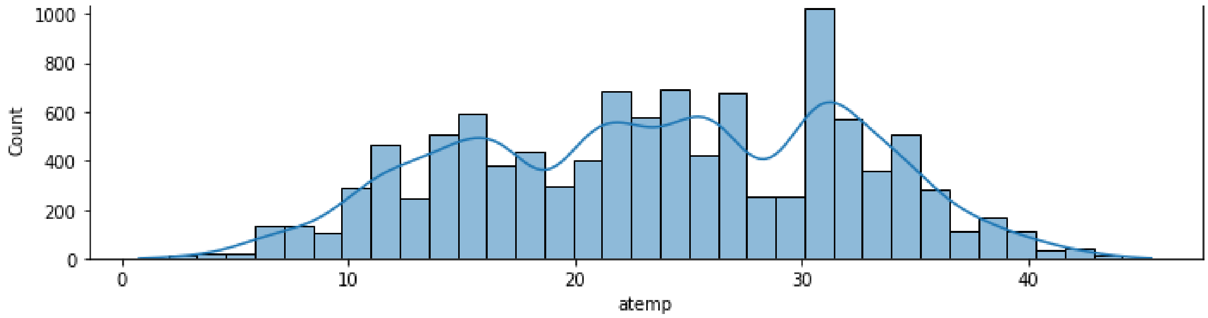
from the above plots we can observe that casual column ia also having a lot of outliers i.e., the value greaterthan 115 are considered outliers

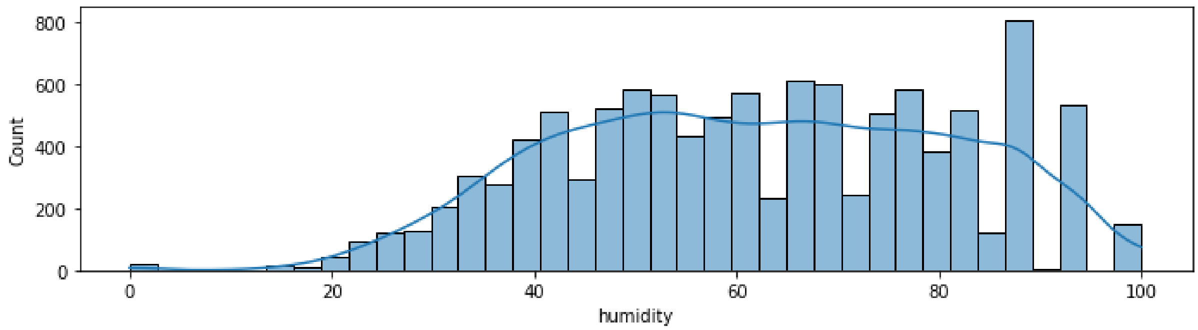
from the above plots we can observe that registered column is also having outliers i.e., values above 500 are considered outliers

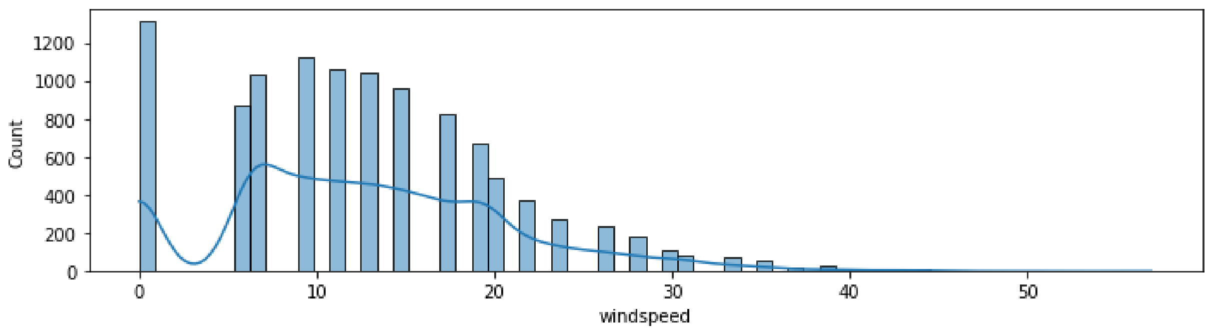
from the above plots we can observe that count column ia also having outliers i.e., values above 620 are considered outliers

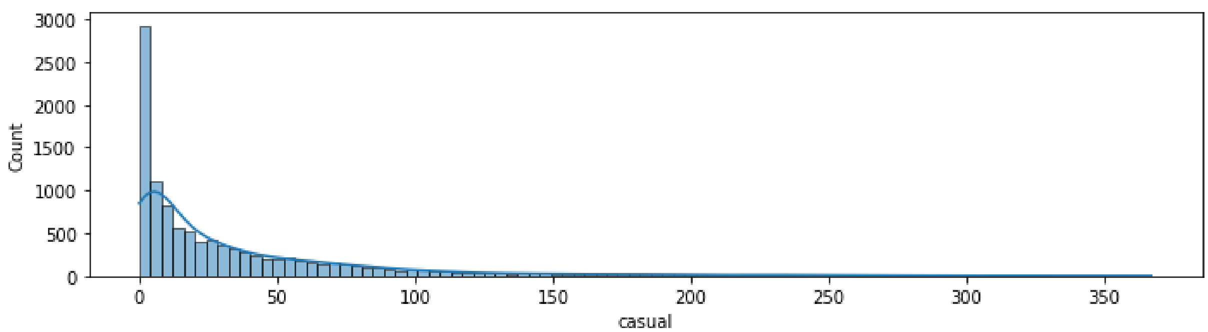
In [12]:
```python
fig, axes = plt.subplots(11,1,figsize=(10,30))
for col, ax in zip(yulu_df_no_datetime.columns,axes.ravel()):
    sns.histplot(data=yulu_df,x=col,ax=ax,kde=True)
    plt.xlabel(col)
fig.tight_layout()
plt.show()
```

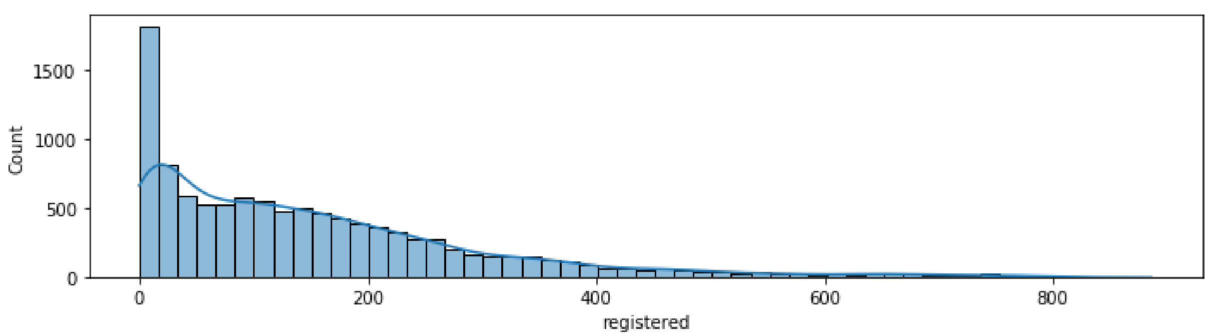


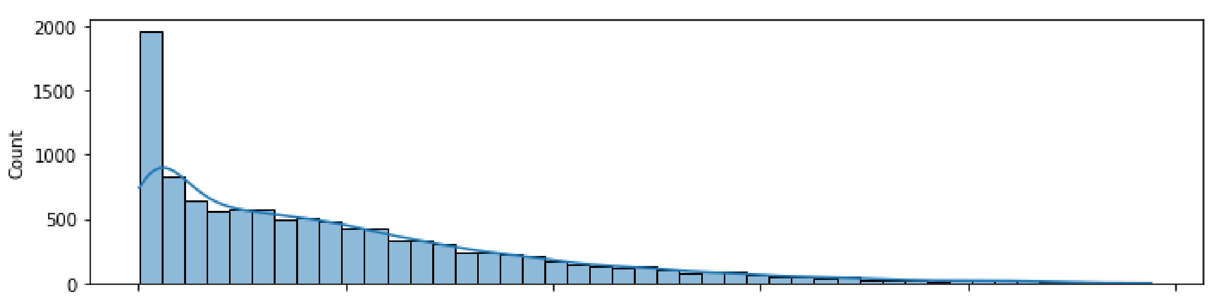

Count
0
200
400
600
800
1000
0
10
20
30
40
atemp

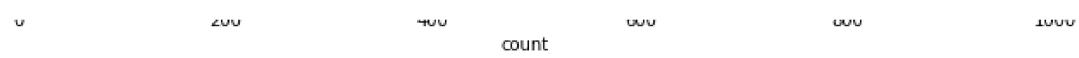

Count
0
200
400
600
800
0
20
40
60
80
100
humidity


Count
0
200
400
600
800
1000
1200
0
10
20
30
40
50
windspeed


Count
0
500
1000
1500
2000
2500
3000
0
50
100
150
200
250
300
350
casual


Count
0
500
1000
1500
0
200
400
600
800
registered


Count
0
500
1000
1500
2000
0
200
400
600
800
1000



from the above plots it is clear that casula registered and count all 3 columns follow right tailed distribution

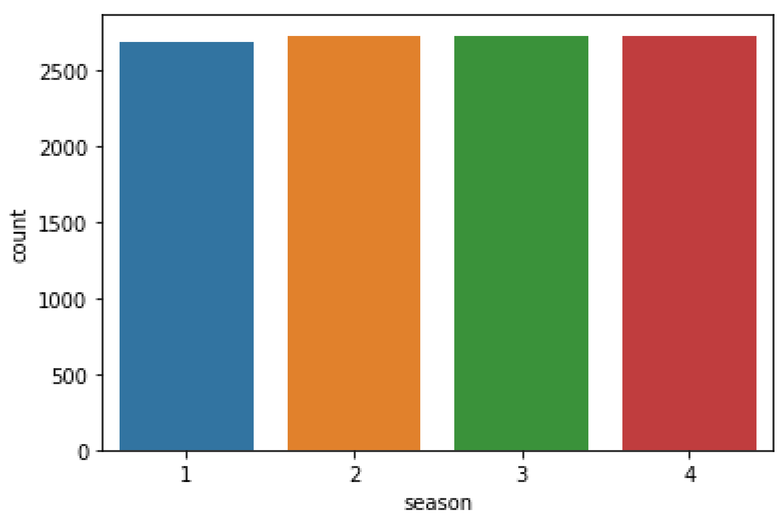
if the temp, atemp and humidity values are low then the bike rentel is high

In [13]:
```python
yulu_df.head()
```

Out[13]:

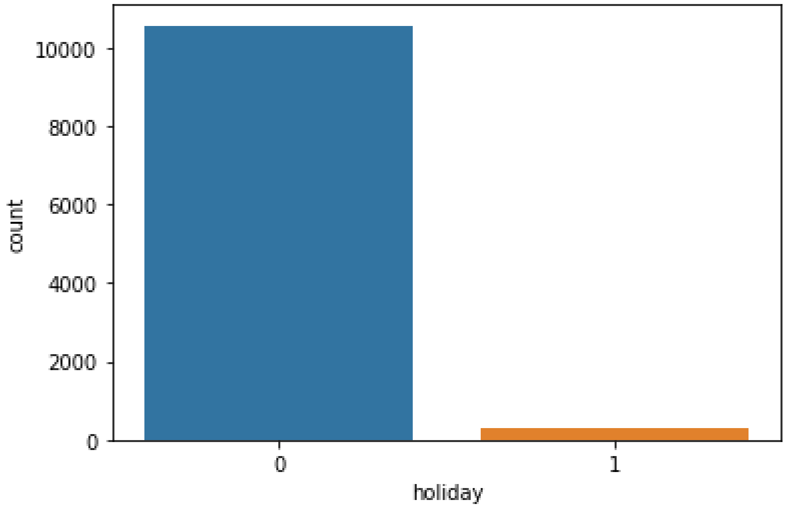
	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	re
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	
4	2011-01-01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

In [14]:
```python
sns.countplot(x=yulu_df['season'])
plt.show()
```



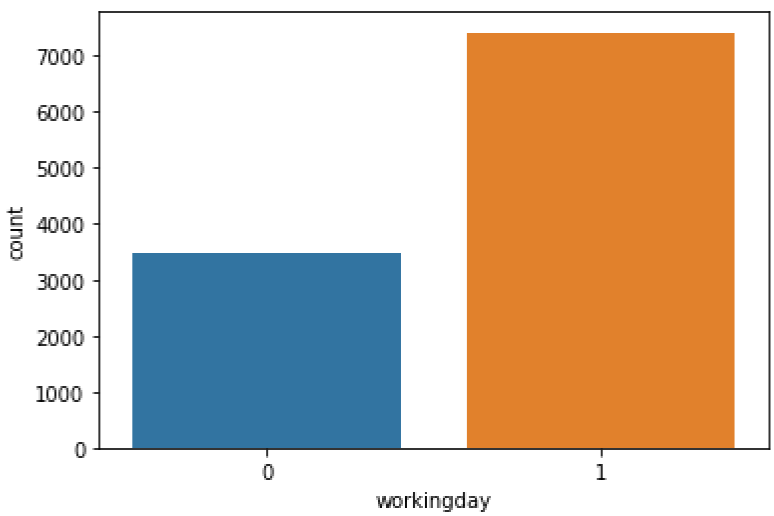
from the above countplot we can observe that irresspective of number of bike rents count is not effected because of season

In [15]:
```
sns.countplot(x=yulu_df['holiday'])
plt.show()
```



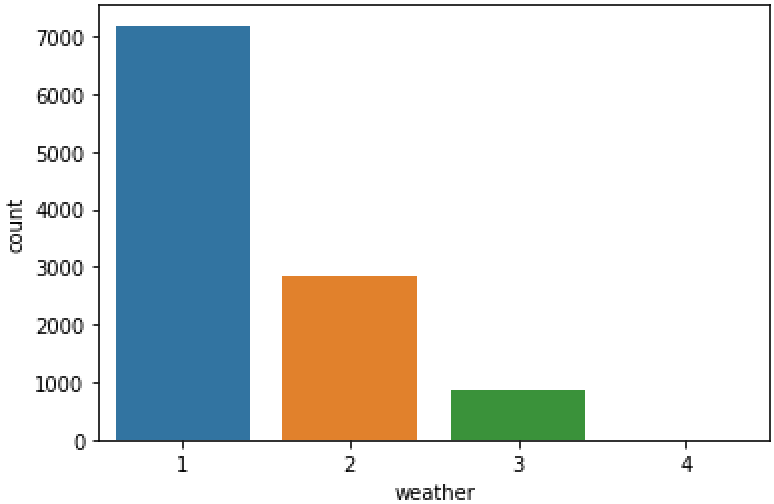
from the above countplot we can observe that bike rental is high in holidays and low in non holidays

In [16]:
```
sns.countplot(x=yulu_df['workingday'])
plt.show()
```



from the above countplot we can observe that bike rental is high on non working days when compatred to working days

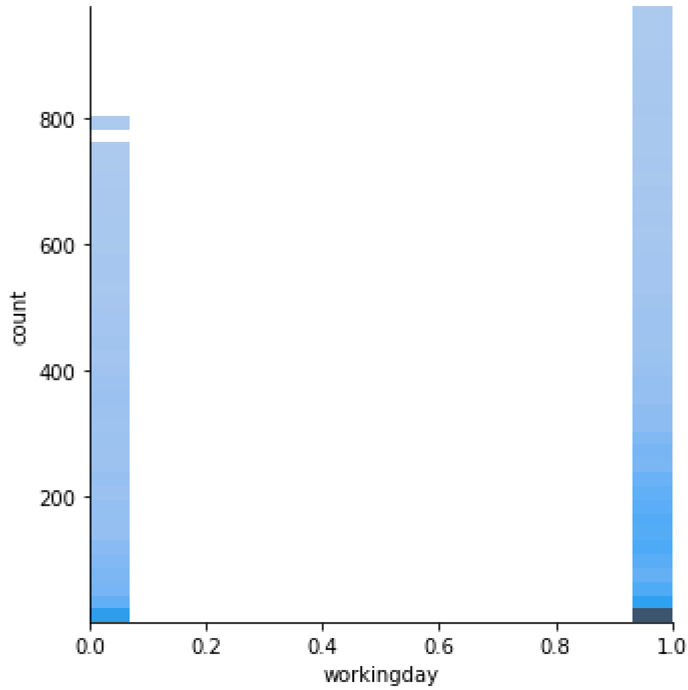
In [17]:
```
sns.countplot(x=yulu_df['weather'])
plt.show()
```



from the above countplot we can observe that weather of type 1 is having highest bike rentels followed by 2 and 3 and the weather 4 is having less than 1000 bikes rented

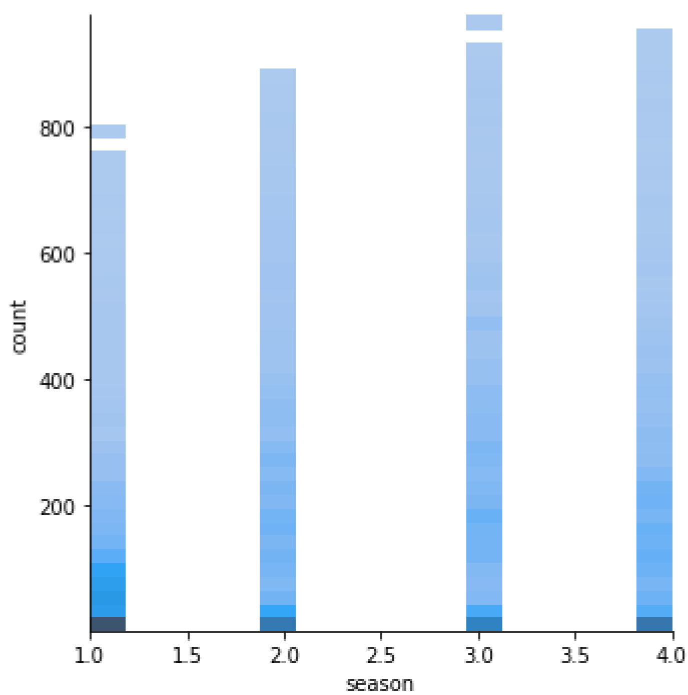
Bivariate Analysis.

In [18]:
```
sns.displot(x=yulu_df['workingday'],y=yulu_df['count'])
plt.show()
```



from the above displots we can observe that in working days more number of bikes are rented by the customers the most

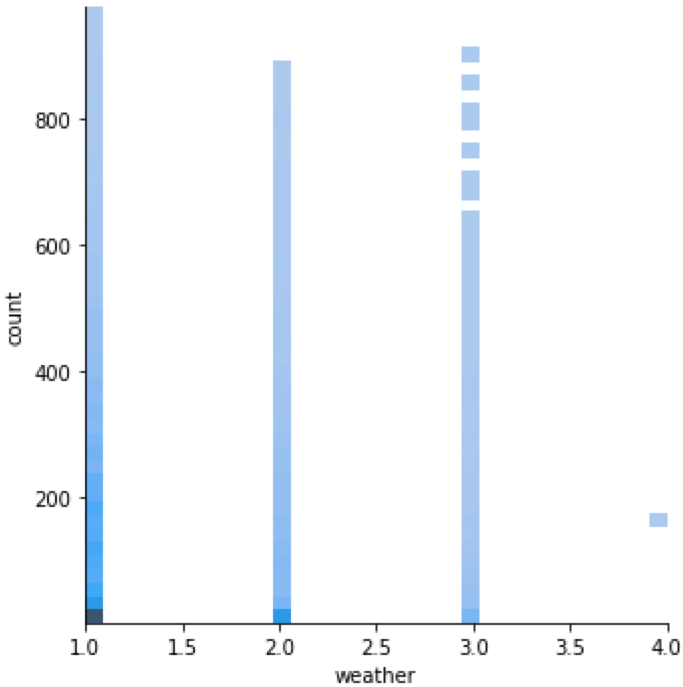
In [19]:
```
sns.displot(x=yulu_df['season'],y=yulu_df['count'])
plt.show()
```



from the above displot we can observe that season diessnot effect the bike renting

bike renting

In [20]:
```
sns.displot(x=yulu_df['weather'],y=yulu_df['count'])
plt.show()
```



from the above displot we caan observe that except weather value 4 nothing is effecting the bike rentel service

Hypothesis Testing

1. 2-sample z Test

AS the number of samples are large(>30) will be using Z-test insted of T-test and also the sample mean and the varience are known.

Assumptions of Z-test

1) The population mean and standerd deviation are finite. 2) Population standerd deviation are known.

Ho(Null hypothesis):-

(U1)Mean of number of yulu rental bikes rented by people on weekend or holiday(workingday = 0) is equal (U2)Mean of number of yulu rental bikes rented by people on non holiday or non weekend(workingday = 1)

U1 = U2

.

Ha(Alternate Hypothesis):-

(U1)Mean of number of yulu rental bikes rented by people on weekend or holiday(workingday = 0) is not equal (U2)Mean of number of yulu rental bikes rented by people on non holiday or non weekend(workingday = 1)

U1 != U2

.

alpha(significance level or type I error):-

considering 5% significance level

In [21]:
```
count_0 = yulu_df[yulu_df['workingday']==0]['count']
count_1 = yulu_df[yulu_df['workingday']==1]['count']
```

In [22]:
```
yulu_df['workingday'].value_counts()
```

Out[22]:
```
1    7412
0    3474
Name: workingday, dtype: int64
```

In [23]:
```
len(count_0),len(count_1)
```

Out[23]:
```
(3474, 7412)
```

In [24]:
```
np.mean(count_0),np.mean(count_1)
```

Out[24]:
```
(188.50662061024755, 193.01187263896384)
```

In [25]:
```
np.std(count_0),np.std(count_1)
```

Out[25]:
```
(173.69901006897658, 184.5012116674222)
```

the mean and the standerd deviation of the sample are finete so we can use ztest

In [26]:
```
zscore = (np.mean(count_0)-np.mean(count_1))/np.sqrt(np.var(count_0)/len(count_0)
```

In [27]:
```
zscore
```

Out[27]:
```
-1.2364033017261236
```

the tsetstatiscis value is -1.23

In [28]:
```
stats.norm.cdf(zscore)*2
```

Out[28]:
```
0.21630868945192083
```

we are multiplying with 2 because we are using 2 side ztest

the p-value is 0.216

below usisng statsmodels library

In [29]:
```
from statsmodels.stats.weightstats import ztest
```

In [30]:
```
ztest(count_0,count_1)
```

Out[30]:
```
(-1.2096277376026694, 0.22642176970306893)
```

Conclusion

As from the above cell output we observe that the test statistics is -1.20 and P-value is 0.2264 which is greater that 0.05 so we fail to reject the Null hypothesis.

2. Chi-square test

Test of independence(in this test we will be verifying are the 2 variables independent or not)

Assumptions of chi-square test

As Chi-square test is non-parameter test(i.e., it did not any assumptions).

Ho(Null hypothesis)

season and weather are independent

Ha(Alternate hypothesis)

season is dependent on weather

In [31]:
```
yulu_df.head()
```
Out[31]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	re
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	

alpha(significance level or type I error):-

considering 5% significance level

In [32]:
```
season_weather_crosstab = pd.crosstab(yulu_df['season'],yulu_df['weather'],margir
```

preparing contengency table using crosstab

In [33]:
```
season_weather_crosstab
```
Out[33]:

weather	1	2	3	4	All
season					
1	1759	715	211	1	2686
2	1801	708	224	0	2733
3	1930	604	199	0	2733
4	1702	807	225	0	2734
All	7192	2834	859	1	10886

In [34]:
```
season_weather_crosstab.columns
```
Out[34]:
```
Index([1, 2, 3, 4, 'All'], dtype='object', name='weather')
```

In [35]:
```
row = yulu_df['season'].unique()
column = yulu_df['weather'].unique()
```

In [36]:
```
row,column
```

Out[36]:
```
(array([1, 2, 3, 4], dtype=int64), array([1, 2, 3, 4], dtype=int64))
```

In [37]:
```
chi_square = 0
for i in row:
    for j in column:
        observed = season_weather_crosstab[i][j]
        expected = season_weather_crosstab[i]['All']*season_weather_crosstab['All
        chi_square += pow((observed-expected),2)/expected
```

calculating the test statistics value

In [38]:
```
pvalue = 1 -  stats.chi2.cdf(chi_square,(len(row)-1)*(len(column)-1))
```

In [39]:
```
pvalue
```

Out[39]:
```
1.5499250738404413e-07
```

In [40]:
```
chi_square,pvalue
```

Out[40]:
```
(49.15865559689362, 1.5499250738404413e-07)
```

Conclusion

As from the above cell output we observe that the test statistics(chi square) is 49.15 and P-value is 1.54*10^-7 which is far less that 0.05 so we reject the Null hypothesis.i.e., we accept the alternate hypothesis

Season is dependent on weather

3. Annova

Assumptions

Each group observations are qaussian(almost). Each group variance is almost the same.

Ho(Null hupothesis)

mean of number of cycles rented in different seasons are equal.

Ha(Alternate hypothesis)

mean of number of cycles rented in different seasons are not equal.

alpha(significance level or type I error):-

considering 5% significance level

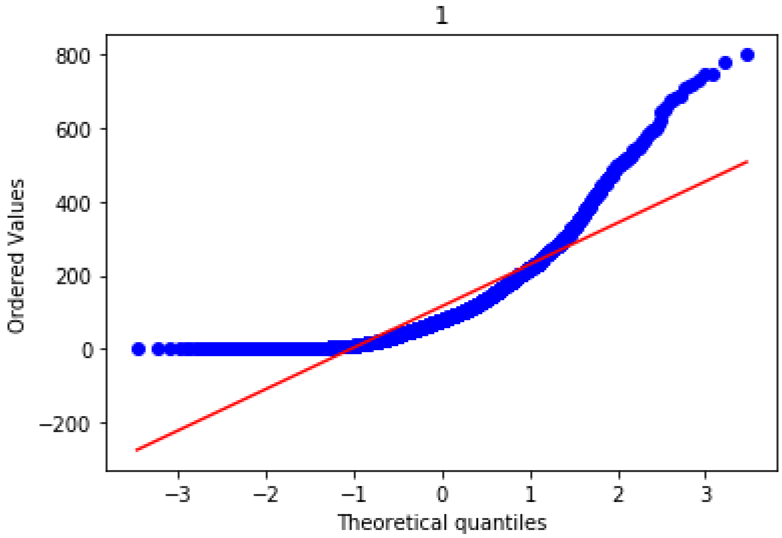
In [41]:
```
yulu_df.head()
```

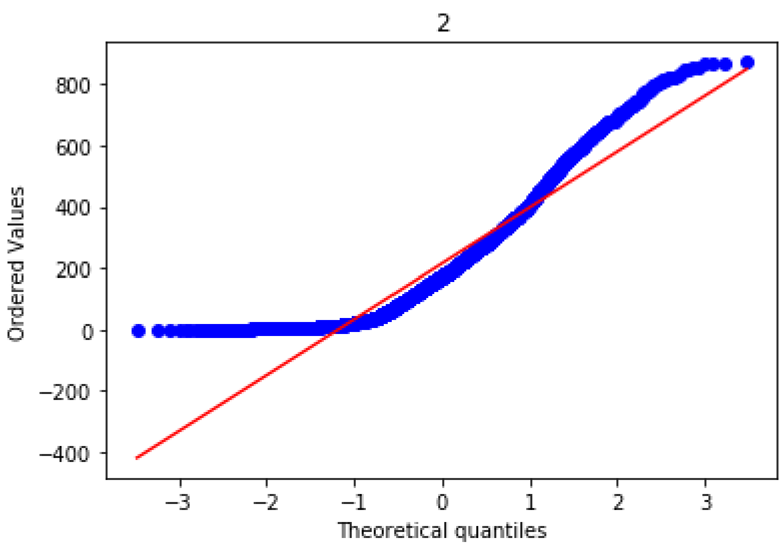
Out[41]:

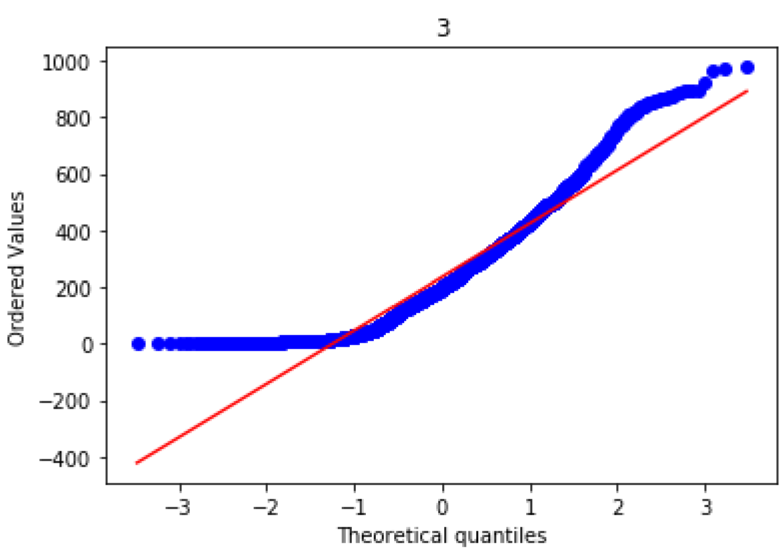
	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	re
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	
4	2011-01-01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

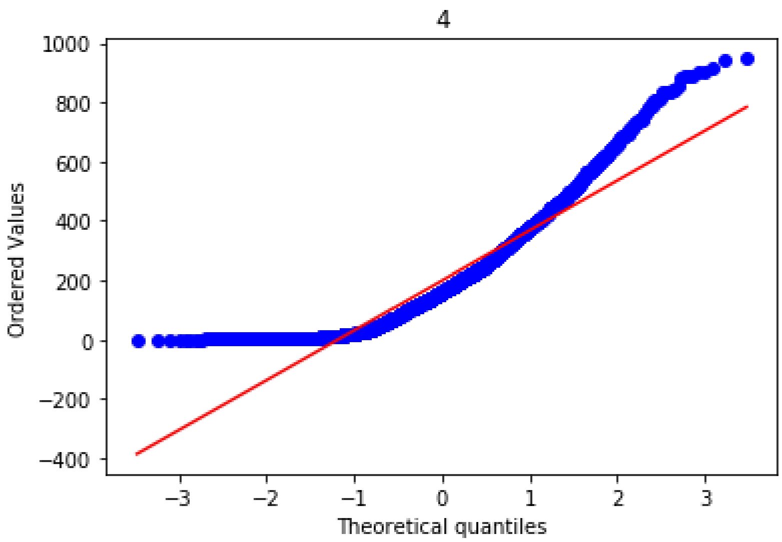
In [42]:
```
val = yulu_df['season'].unique()
```

In [43]:
```
for i in val:
    stats.probplot(yulu_df[yulu_df['season']==i]['count'],dist='norm',plot=plt)
    plt.title(i)
    plt.show()
```









from the above qqplots we can observe that the distribution is snot following normal so using boxcox transform to convert them to normal distribution(almost)

In [44]:
```
# import statsmodels.api as sm
# ax,_ = stats.boxcox(yulu_df[yulu_df['season']==1]['count'])
# sm.qqplot(ax,line='45',fit=True)
# plt.show()
```

In [45]:
```
boxcox_season_data = []
for i in val:
    boxcox_season_data.append(stats.boxcox(yulu_df[yulu_df['season']==i]['count']
```

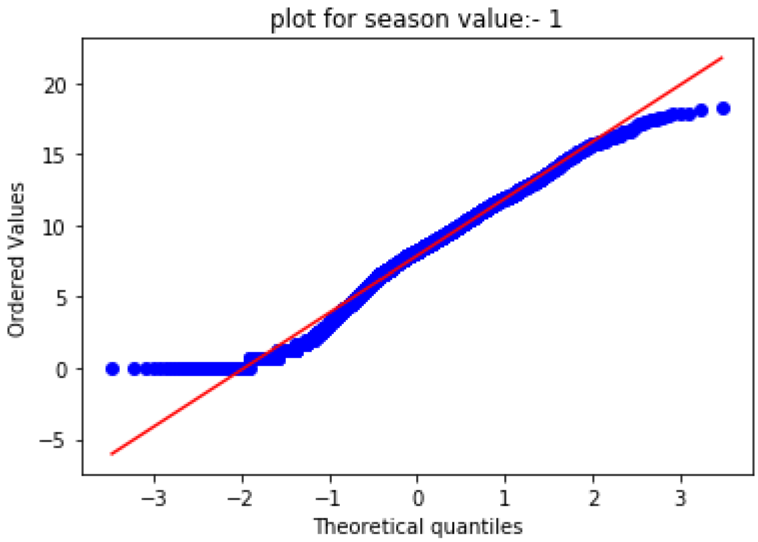
converting all the 4 season count values to boxcox

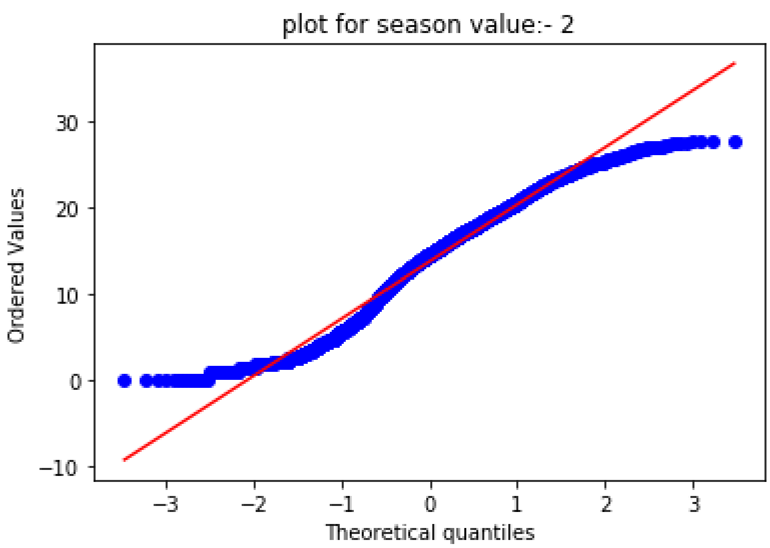
In [46]:
```
np.std(boxcox_season_data[0]),np.std(boxcox_season_data[1]),np.std(boxcox_season_
```

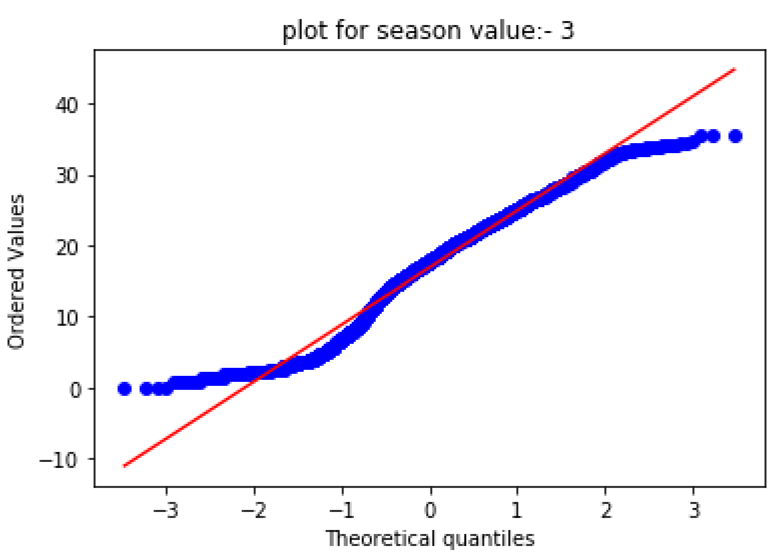
Out[46]:
```
(4.030523243229806, 6.684198954140307, 8.1292872980543, 6.513358363056977)
```

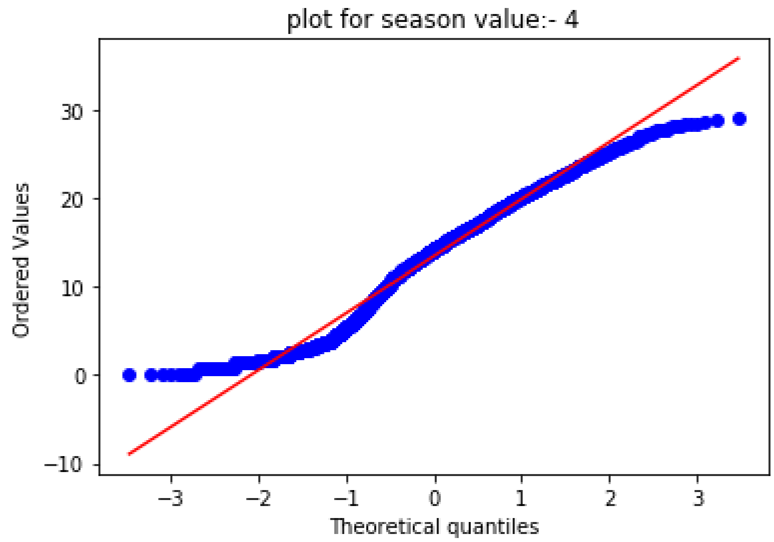
from the above we can observe that the standerd deviation of all the samples is almost same

In [47]:
```
for i in val:
#     ax,_ = stats.boxcox(yulu_df[yulu_df['season']==i]['count'])
    stats.probplot(boxcox_season_data[i-1],dist='norm',plot=plt)
    plt.title('plot for season value:- '+str(i))
    plt.show()
```









qqplots after applying boxcox transform is looking almost normal distribution

so the basic assumptions of anova are satisfied so applying anova

In [48]:
```
len(boxcox_season_data),len(val)
```
Out[48]:
```
(4, 4)
```

In [49]:
```
stats.f_oneway(boxcox_season_data[0],boxcox_season_data[1],boxcox_season_data[2],
```
Out[49]:
```
F_onewayResult(statistic=890.4936156746095, pvalue=0.0)
```

Conclusion

as the pvalue = 0.0 < 0.05 sos rejecting null hypothesis.

mean of number of cycles rented in different seasons are not equal.

Ho(Null hupothesis)

mean of number of cycles rented in different weather are equal.

Ha(Alternate hypothesis)

mean of number of cycles rented in different weather are not equal.

alpha(significance level or type I error):-

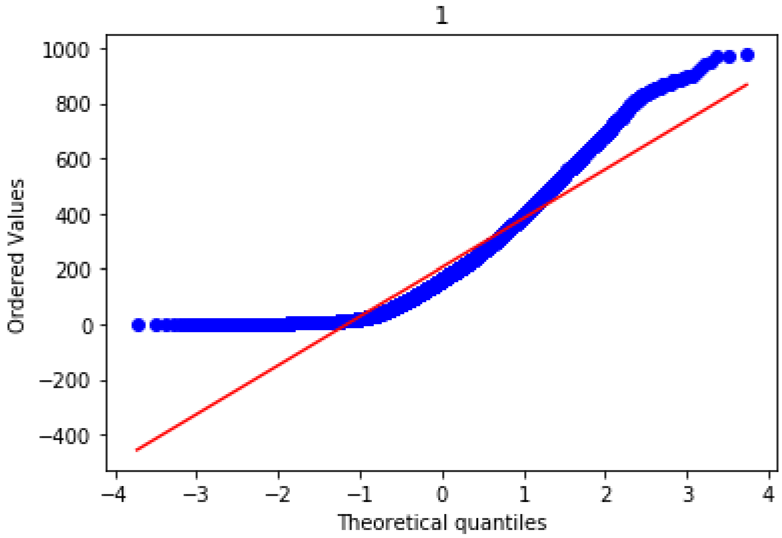
considering 5% significance level

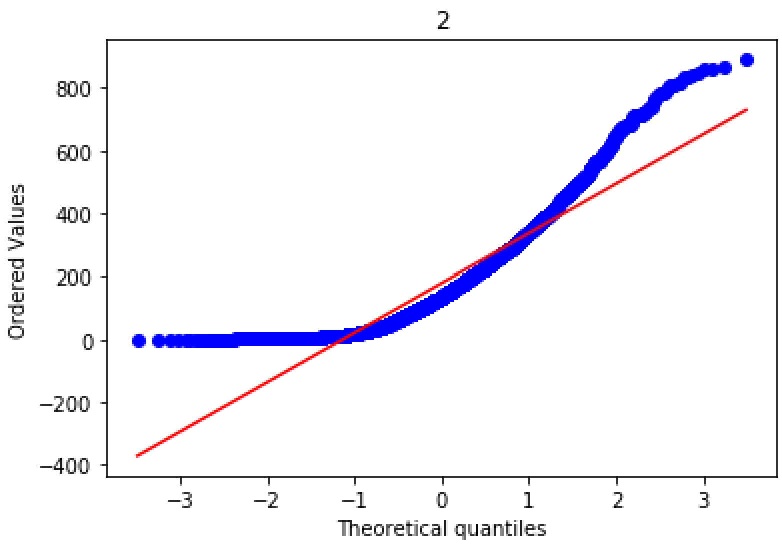
In [50]:
```
yulu_df['weather'].value_counts()
```

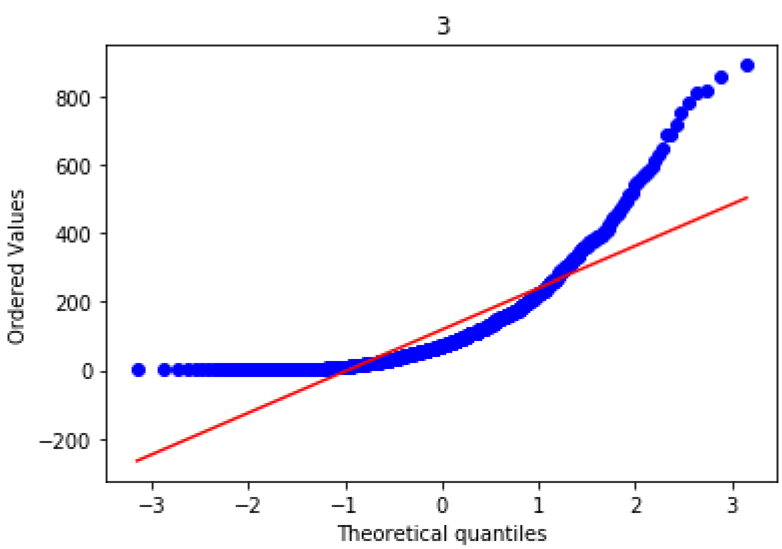
Out[50]:
```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

In [51]:
```
val = yulu_df['weather'].unique()
```

In [52]:
```
for i in val[:len(val)-1]:
    stats.probplot(yulu_df[yulu_df['weather']==i]['count'],dist='norm',plot=plt)
    plt.title(i)
    plt.show()
```







In [53]:
```
boxcox_weather_data = []
for i in val[:len(val)-1]:
    boxcox_weather_data.append(stats.boxcox(yulu_df[yulu_df['weather']==i]['count
```

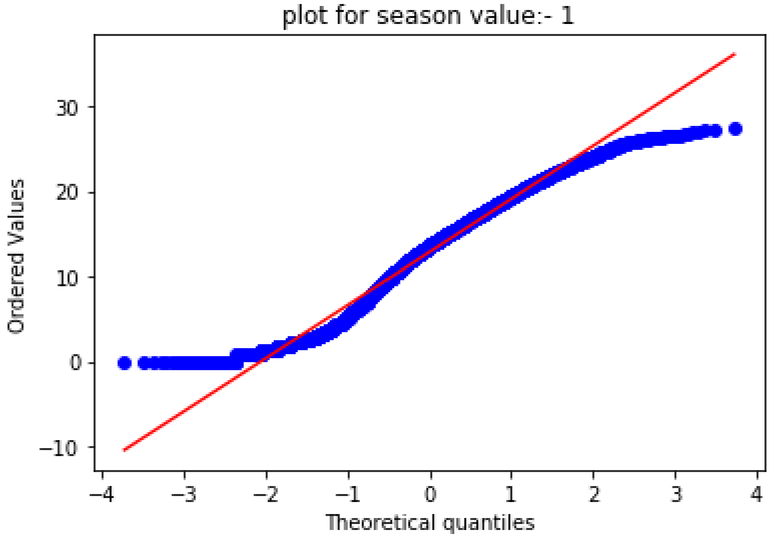
converting the non normal value to normal values using boxcox transform

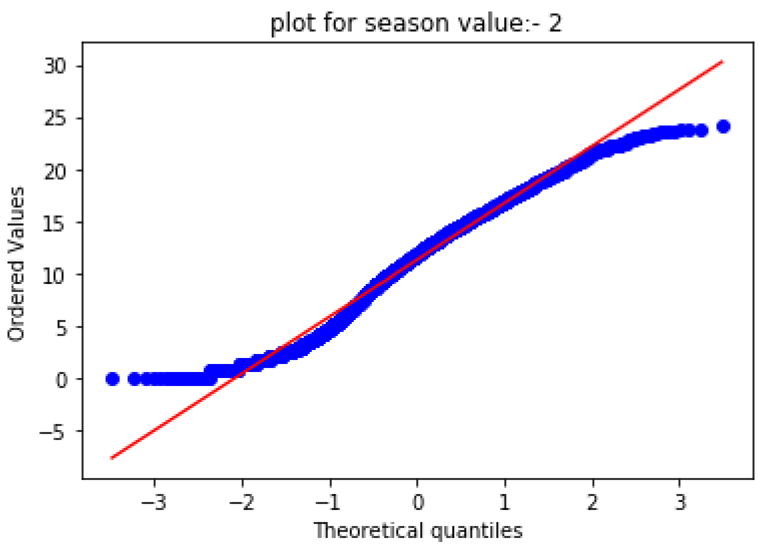
In [54]:
```
np.std(boxcox_weather_data[0]),np.std(boxcox_weather_data[1]),np.std(boxcox_weath
```

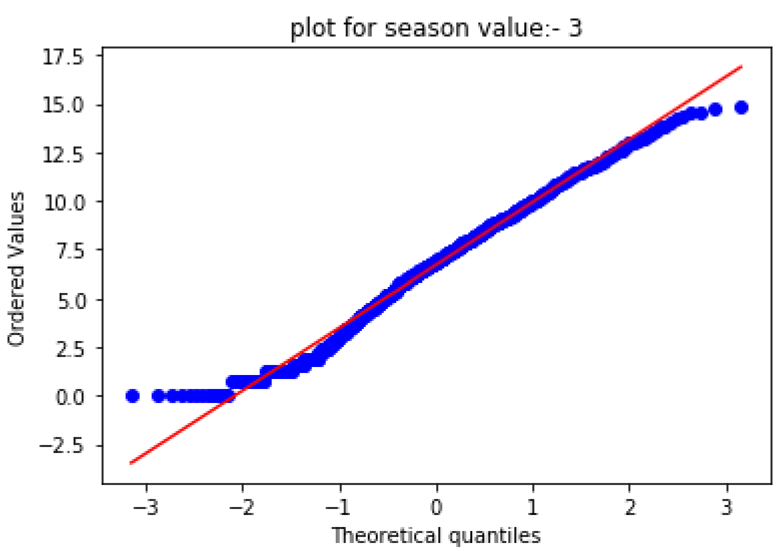
Out[54]:
```
(6.30925416386386, 5.479240814868601, 3.2364247999840274)
```

the standerd deviation of all the 3 samples are almost same

In [55]:
```
for i in val[:len(val)-1]:
    stats.probplot(boxcox_weather_data[i-1],dist='norm',plot=plt)
    plt.title('plot for season value:- '+str(i))
    plt.show()
```







from the qqplot it is clear that the samples follow normal distriibution after boxcox transform

so the basic asssumptions of Anova are followed by the samples

In [56]:
```
stats.f_oneway(boxcox_weather_data[0],boxcox_weather_data[1],boxcox_weather_data
```

Out[56]:
```
F_onewayResult(statistic=431.79686015294686, pvalue=3.4867243611236345e-181)
```

Conclusion

as the pvalue is 3.48*10^-181 <<<< 0.05 so rejecting Null hypothesis

mean of number of cycles rented in different weather are not equal.

In [ ]: