yulu-1

November 13, 2023

1 YULU BUSINESS CASE

[67]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
from scipy.stats import poisson
from scipy.stats import binom, ttest_ind,kstest, f_oneway,pearsonr,spearmanr,␣
↪shapiro, chi2_contingency
import scipy.stats as stats
import math
from statsmodels.graphics.gofplots import qqplot
```

Problem Statement: 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 depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

[24]:
```
df=pd.read_csv("/content/YULU.csv")
```

[25]:
```
df.head()
```

[25]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
3        75        0.0       3          10     13
```

```
4        75         0.0        0            1       1
```

[26]:
```
df.isna().sum()
```

[26]:
```
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
```

- data has no null values

---

[27]:
```
df.shape
```

[27]:
```
(10886, 12)
```

[28]:
```
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
```

[29]:
```
df.describe(include="all")
```

[29]:
```
                   datetime        season       holiday    workingday  \
count                 10886  10886.000000  10886.000000  10886.000000
unique                10886           NaN           NaN           NaN
top     2011-01-01 00:00:00           NaN           NaN           NaN
freq                      1           NaN           NaN           NaN
mean                    NaN      2.506614      0.028569      0.680875
std                     NaN      1.116174      0.166599      0.466159
min                     NaN      1.000000      0.000000      0.000000
25%                     NaN      2.000000      0.000000      0.000000
50%                     NaN      3.000000      0.000000      1.000000
75%                     NaN      4.000000      0.000000      1.000000
max                     NaN      4.000000      1.000000      1.000000

             weather         temp         atemp      humidity     windspeed  \
count   10886.000000  10886.00000  10886.000000  10886.000000  10886.000000
unique           NaN          NaN           NaN           NaN           NaN
top              NaN          NaN           NaN           NaN           NaN
freq             NaN          NaN           NaN           NaN           NaN
mean        1.418427     20.23086     23.655084     61.886460     12.799395
std         0.633839      7.79159      8.474601     19.245033      8.164537
min         1.000000      0.82000      0.760000      0.000000      0.000000
25%         1.000000     13.94000     16.665000     47.000000      7.001500
50%         1.000000     20.50000     24.240000     62.000000     12.998000
75%         2.000000     26.24000     31.060000     77.000000     16.997900
max         4.000000     41.00000     45.455000    100.000000     56.996900

              casual    registered         count
count   10886.000000  10886.000000  10886.000000
unique           NaN           NaN           NaN
top              NaN           NaN           NaN
freq             NaN           NaN           NaN
mean       36.021955    155.552177    191.574132
std        49.960477    151.039033    181.144454
min         0.000000      0.000000      1.000000
25%         4.000000     36.000000     42.000000
50%        17.000000    118.000000    145.000000
75%        49.000000    222.000000    284.000000
max       367.000000    886.000000    977.000000
```

[30]:
```
columns= ["season", "holiday","workingday","weather"]
df[columns]= df[columns].astype("object")
df["datetime"]=pd.to_datetime(df["datetime"])
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
```

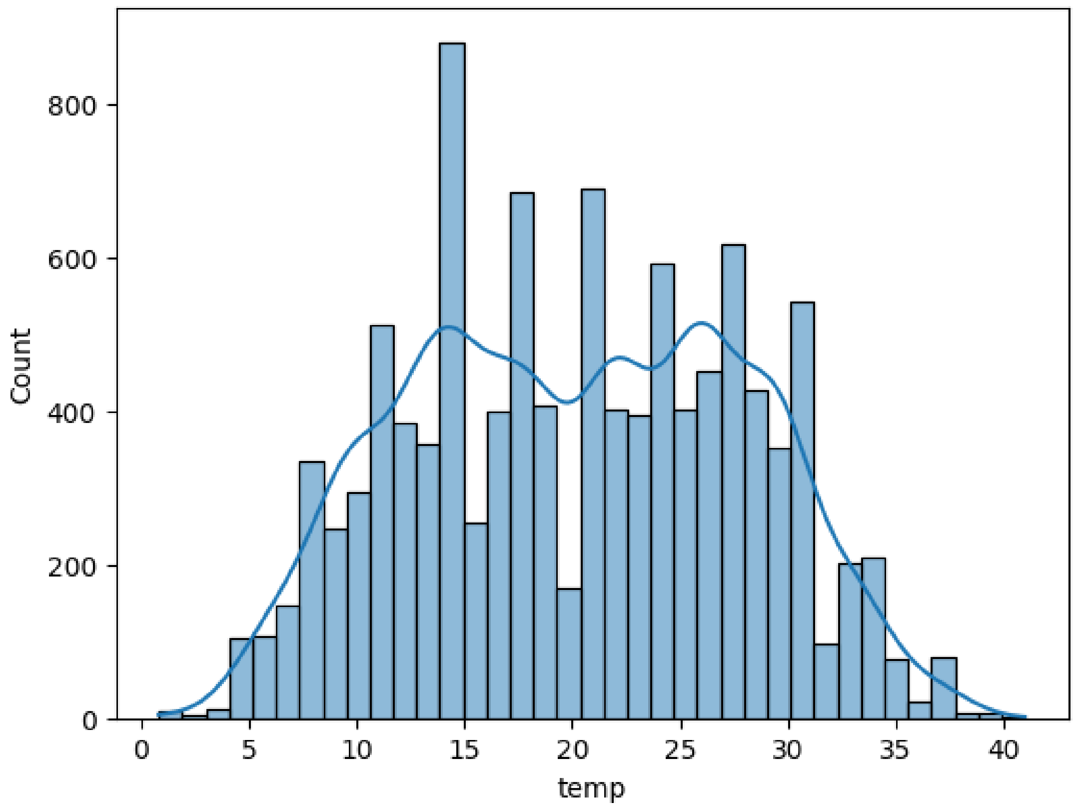
Converting numerical data to categorical data

---

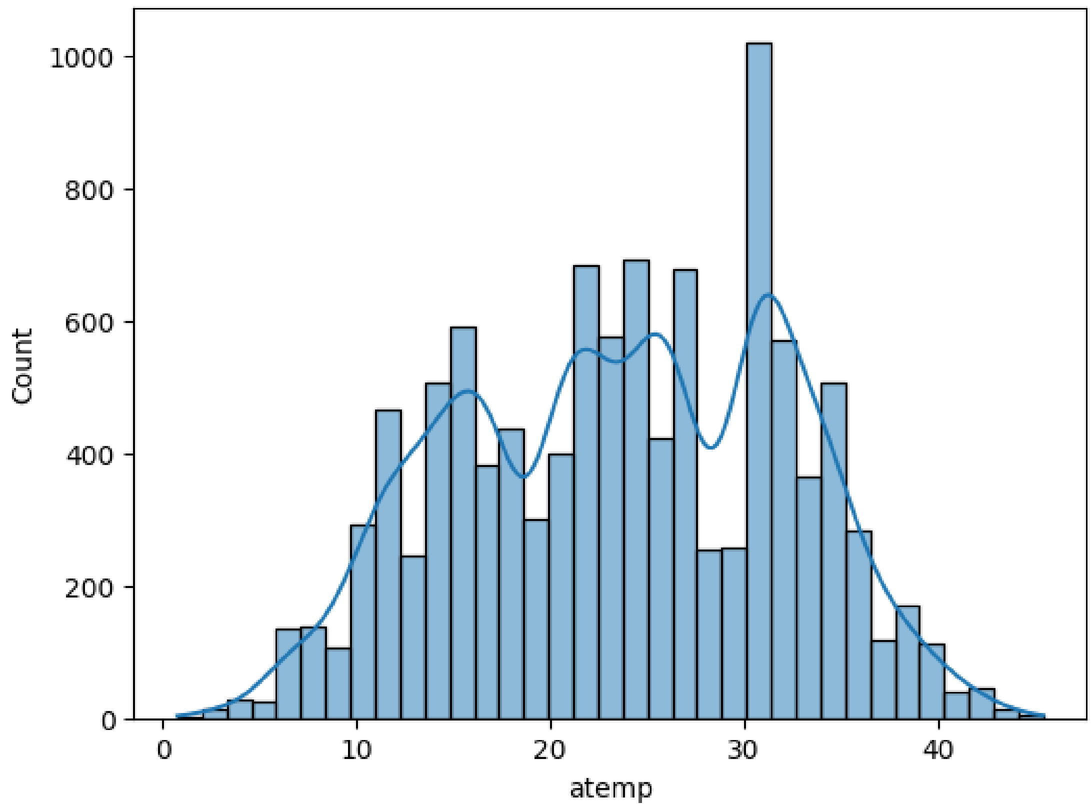
2 Univariate visual analysis

Visual anaylsis of continous data

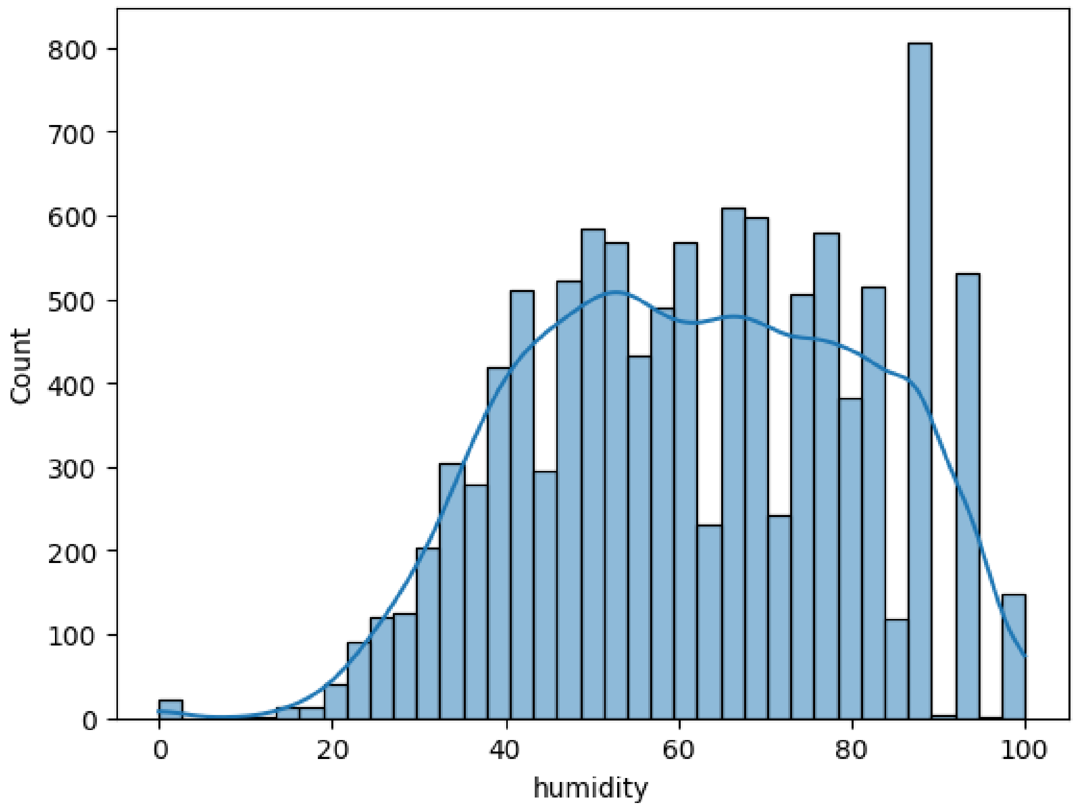
[31]:
```
for i in df.columns:
  if df[i].dtype==int or df[i].dtype==float   :
    sns.histplot(data= df, x=df[i], kde=True)
    plt.show()
```



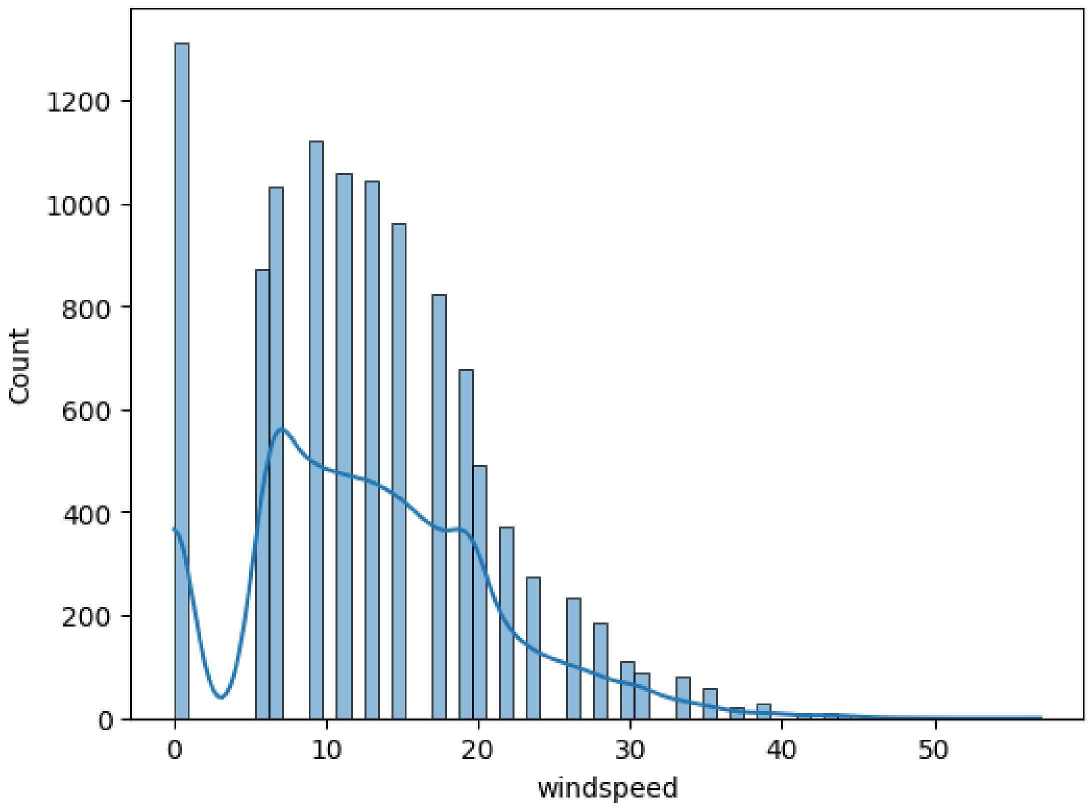
Count
temp
0
200
400
600
800
0
5
10
15
20
25
30
35
40

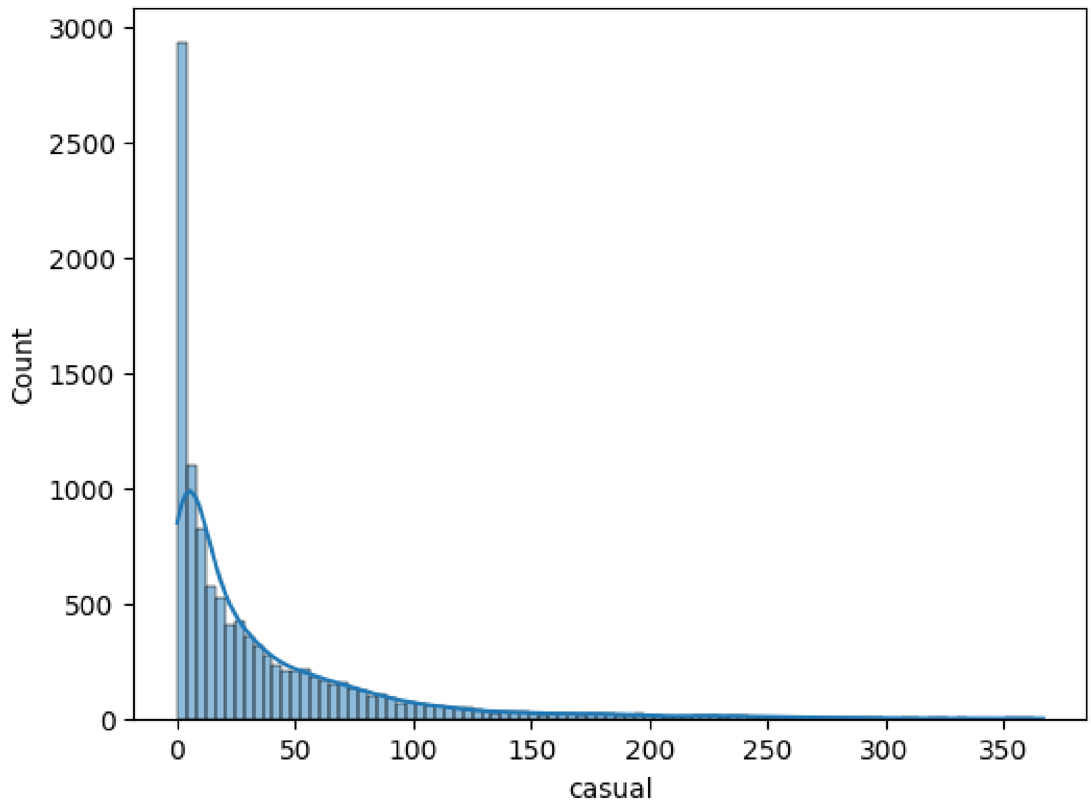


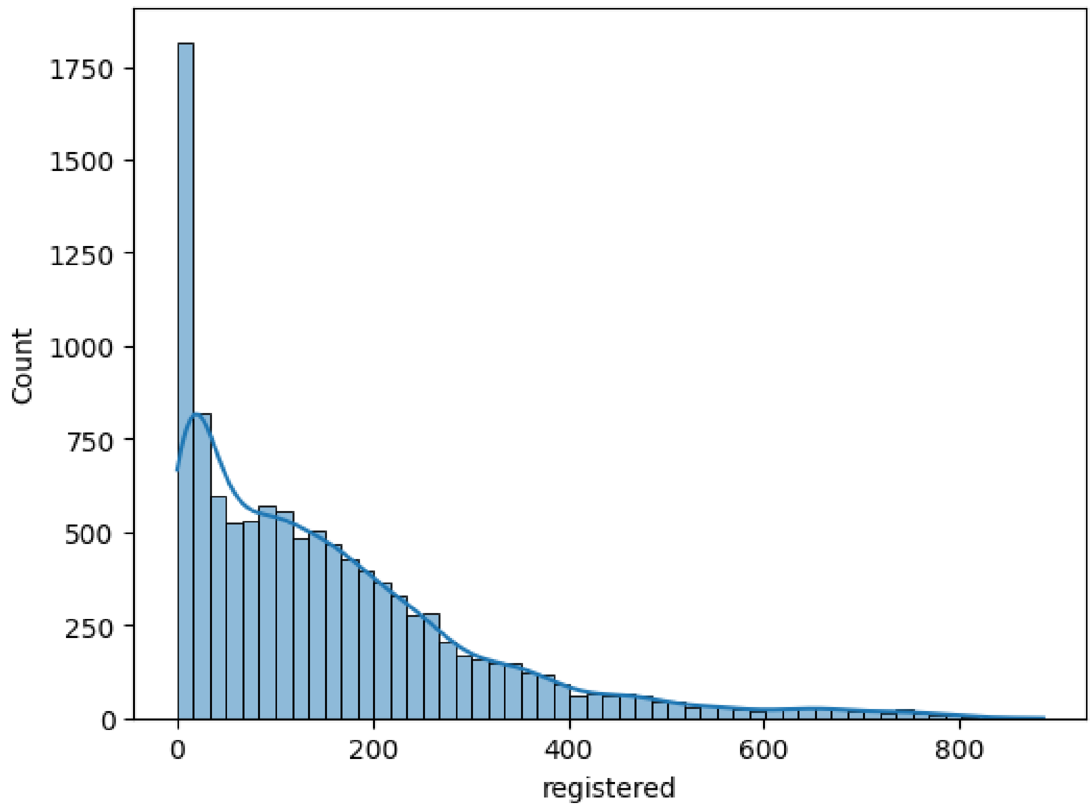
1000
800
600
400
200
0
Count
0
10
20
30
40
atemp



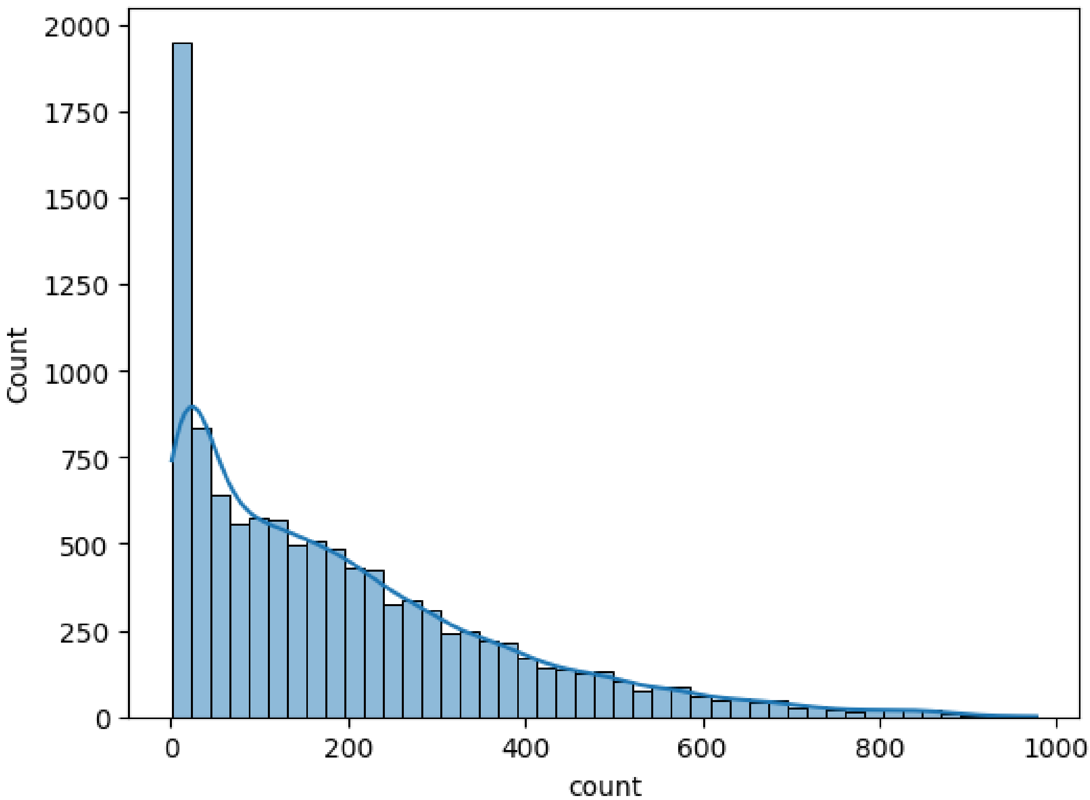
800
700
600
500
400
300
200
100
0
Count
0
20
40
60
80
100
humidity


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


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



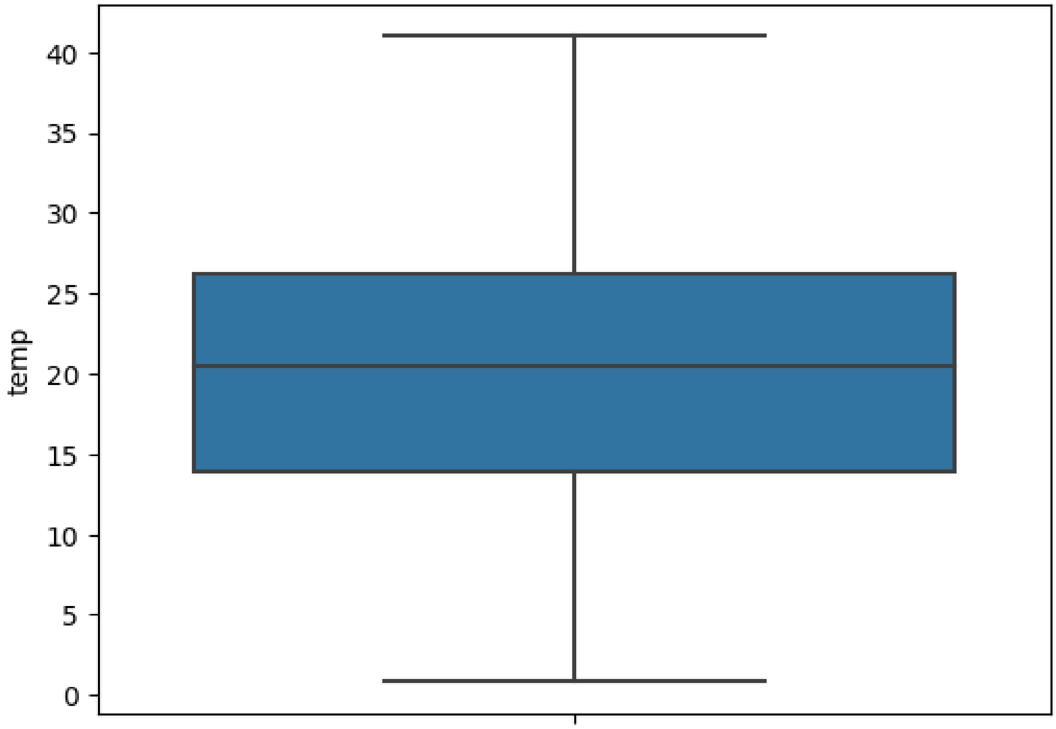
Count
1750
1500
1250
1000
750
500
250
0
0
200
400
600
800
registered



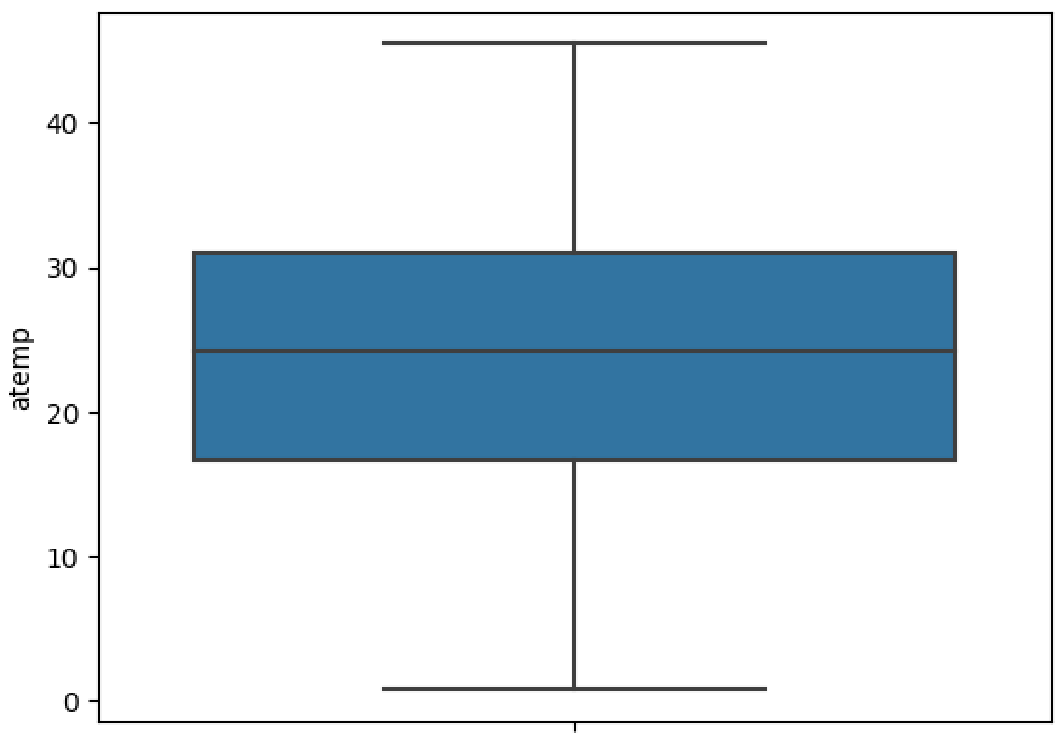
- From above plots we can say that temp, atemp and humidity follows normal distribution
- registered, casual and count follows log normal distribution

3 outlier detection

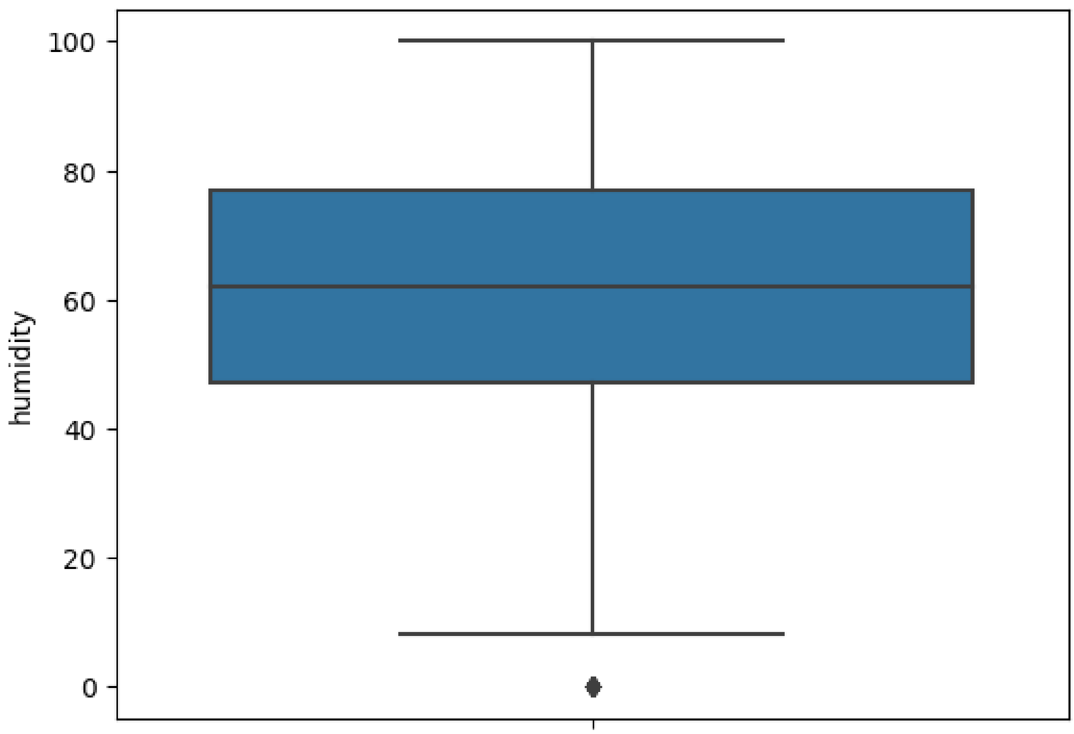
[64]:
```
for i in df.columns:
  if df[i].dtype==int or df[i].dtype==float    :
    sns.boxplot(y=df[i])
    plt.show()
```



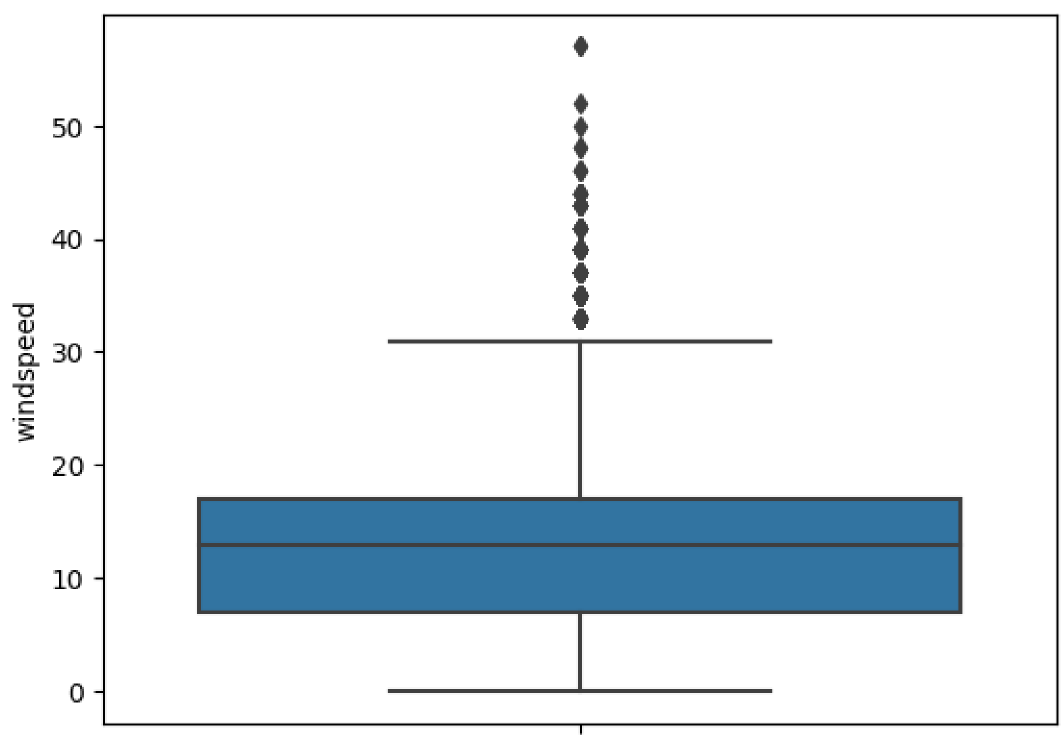
temp
0
5
10
15
20
25
30
35
40



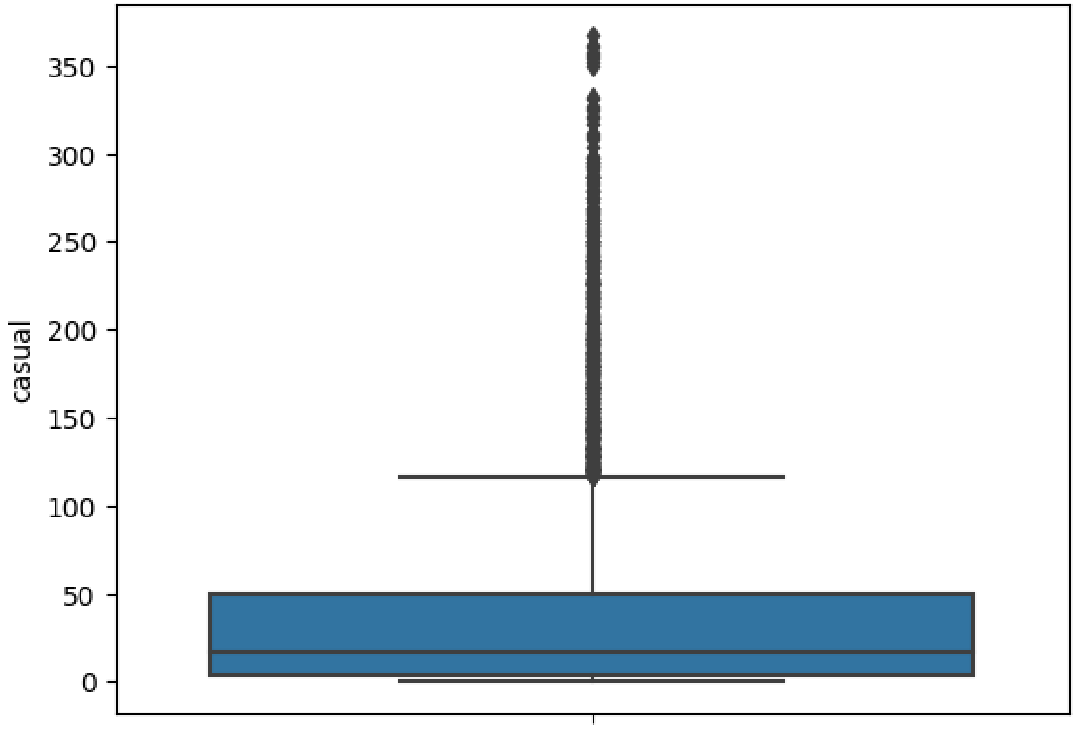
atemp
0
10
20
30
40

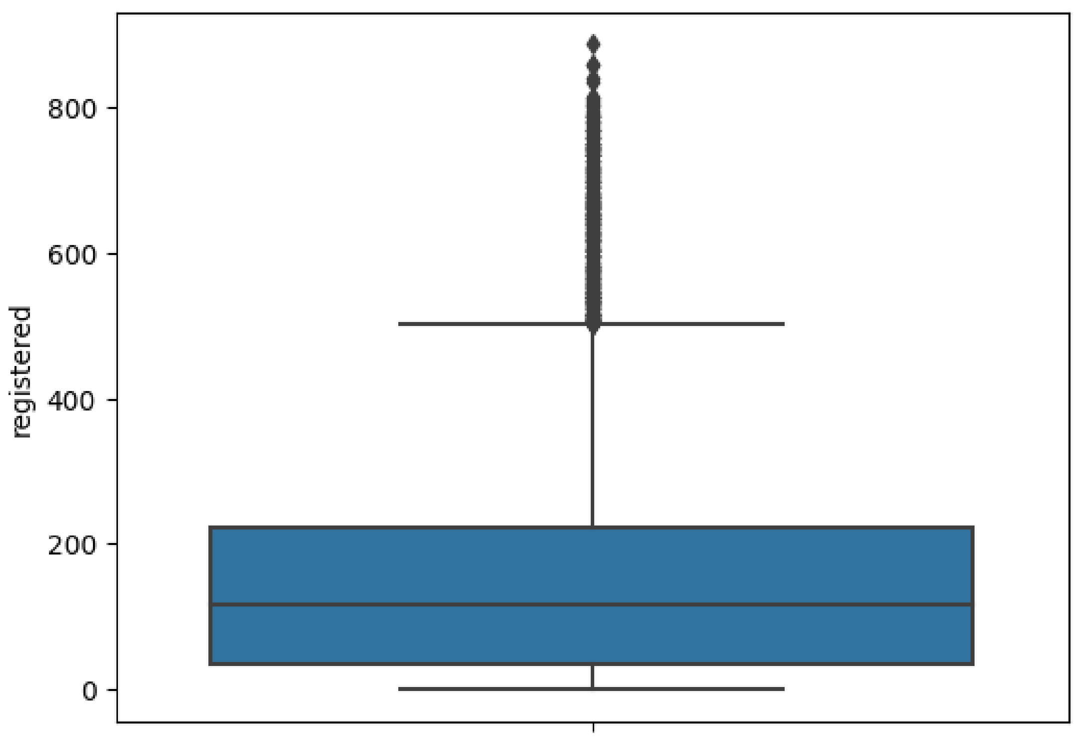


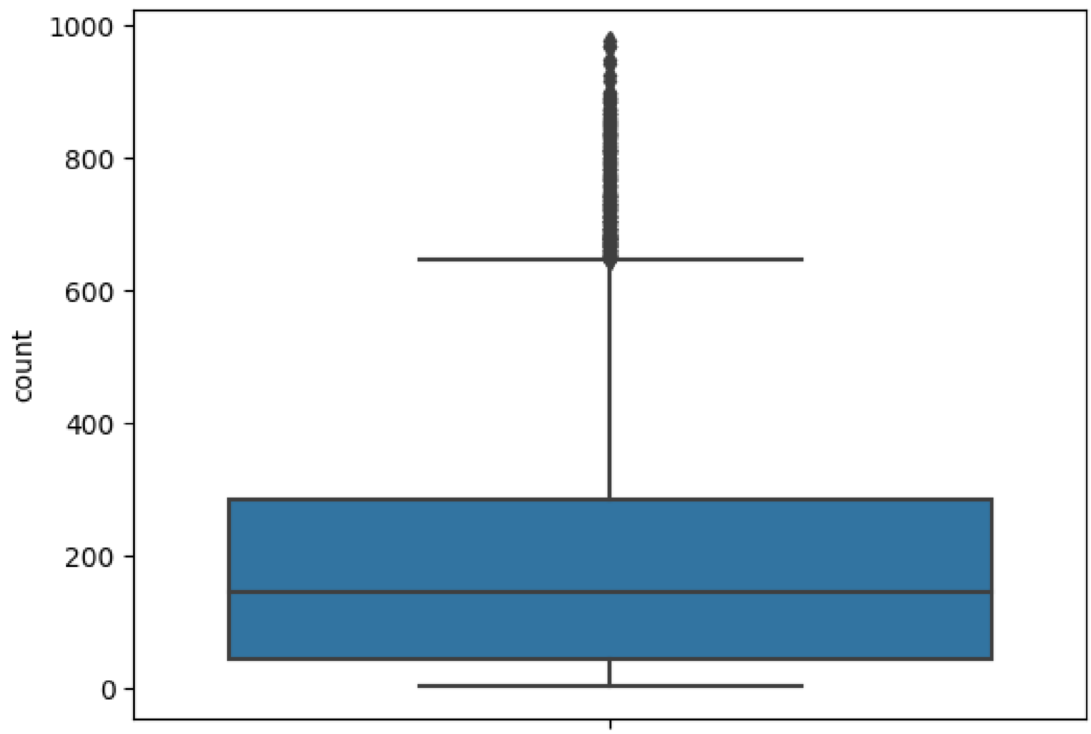
100
80
60
40
20
0
humidity



50
40
30
20
10
0
windspeed


casual
0
50
100
150
200
250
300
350

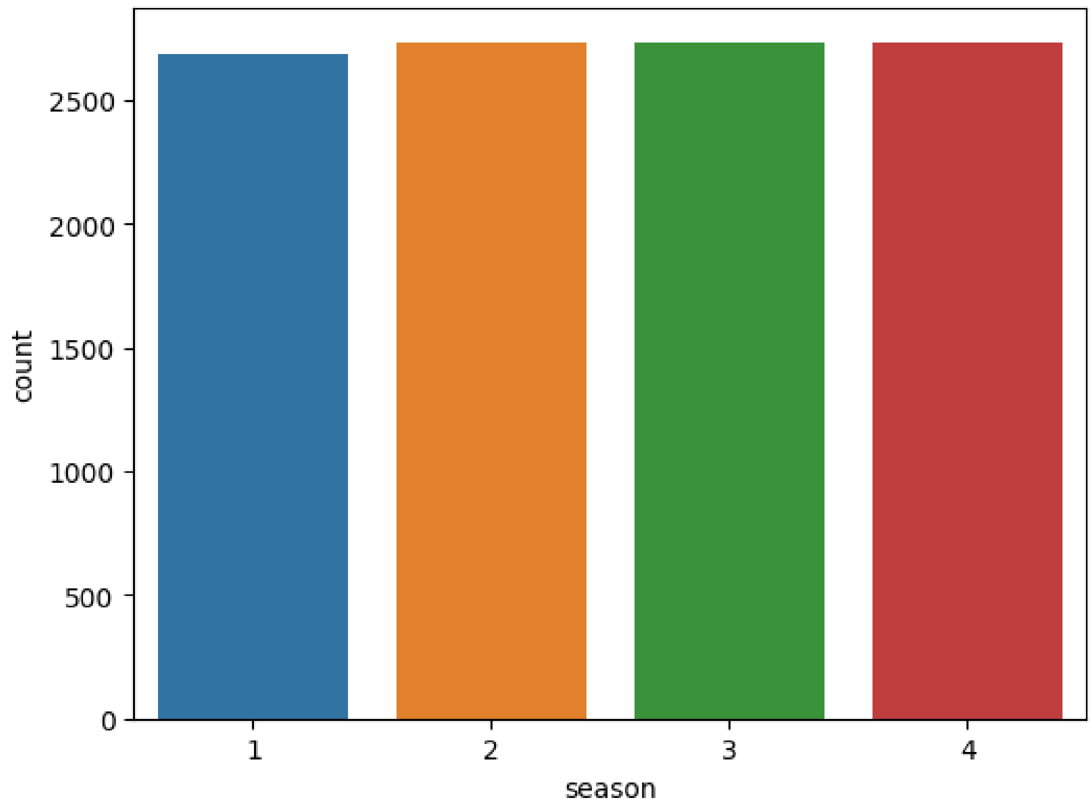

registered
0
200
400
600
800



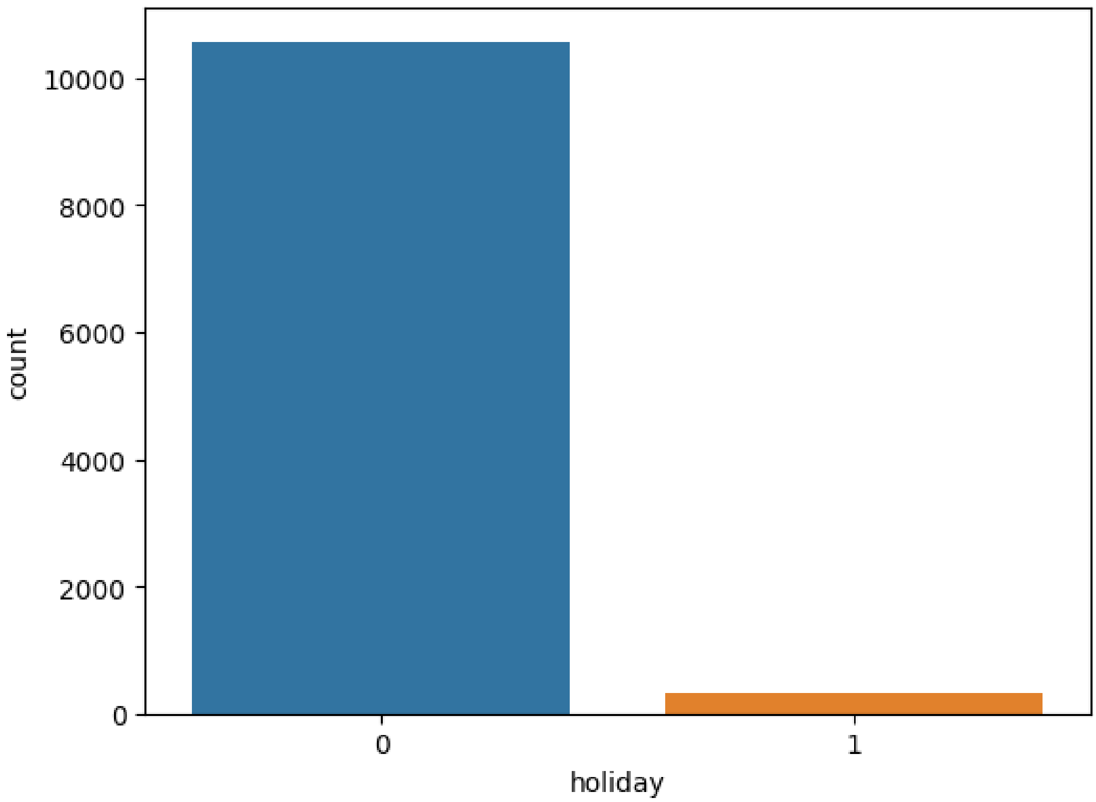
- humidity, casual, registered, count, windspeed has outliers

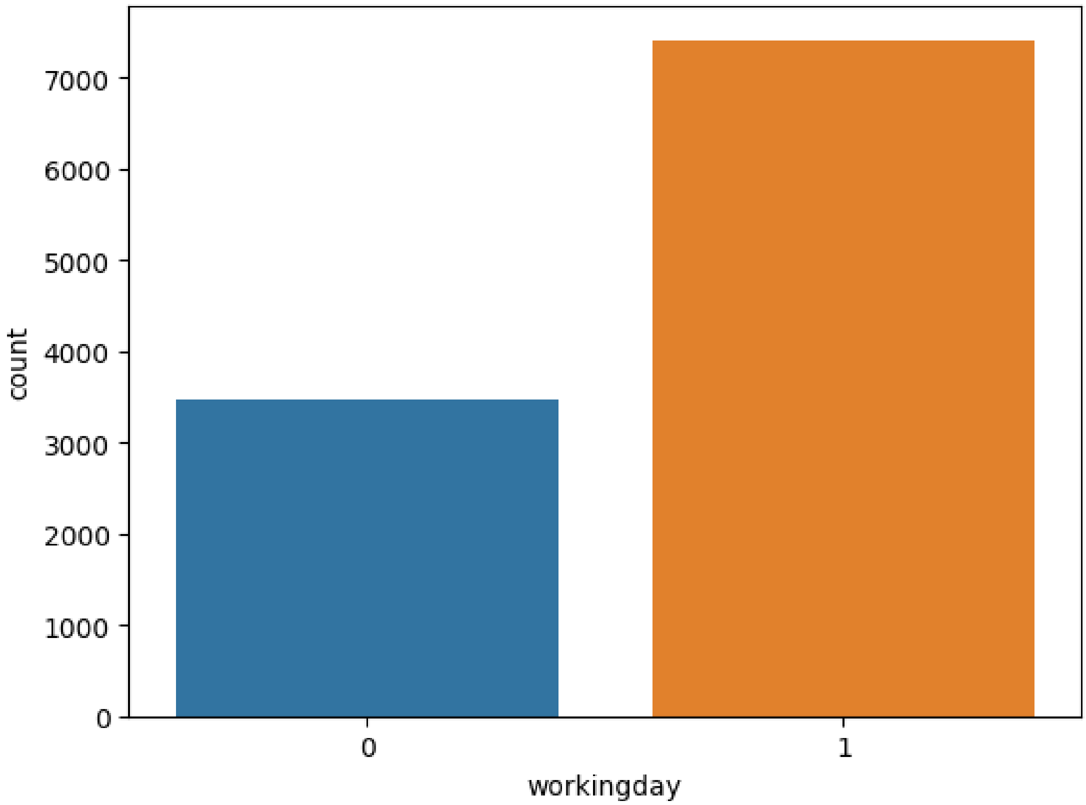
4 Visual analysis of categorical varaibles

[33]:
```
for i in df.columns:
  if df[i].dtype==object  :
    sns.countplot(data=df, x=df[i])
    plt.show()
```

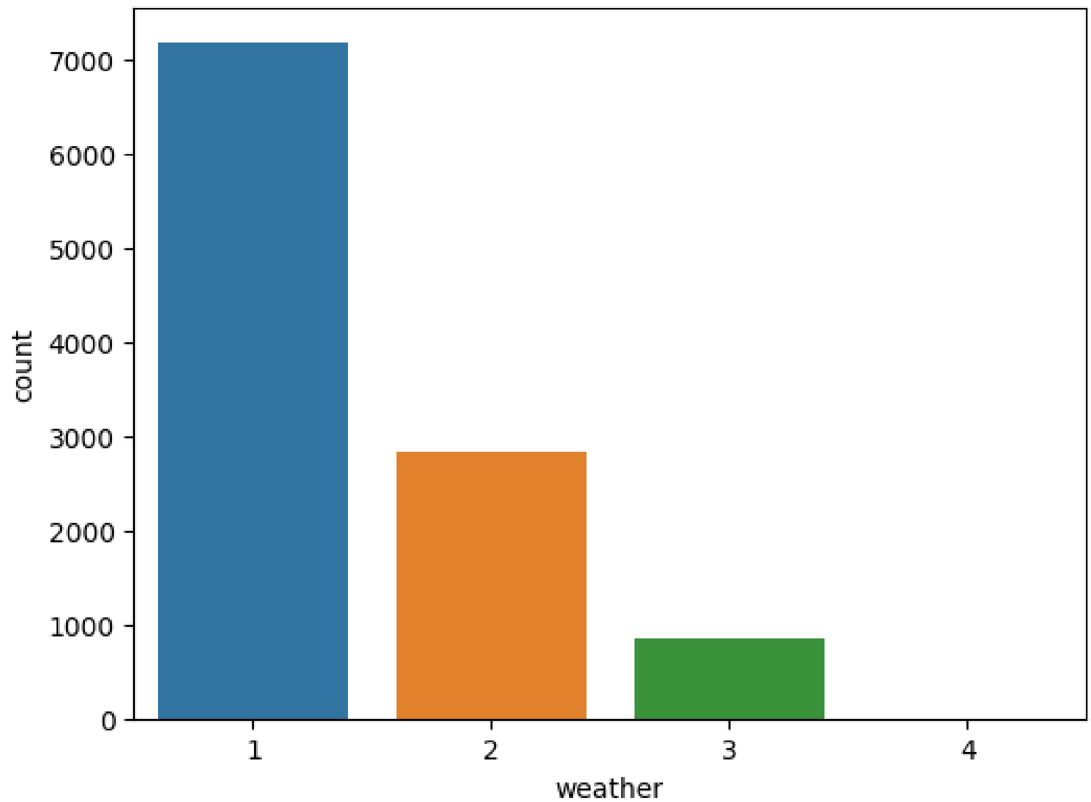


2500
2000
1500
1000
500
0
count
1
2
3
4
season


10000
8000
6000
4000
2000
0
count
0
1
holiday



7000
6000
5000
4000
3000
2000
1000
0
count
0
1
workingday

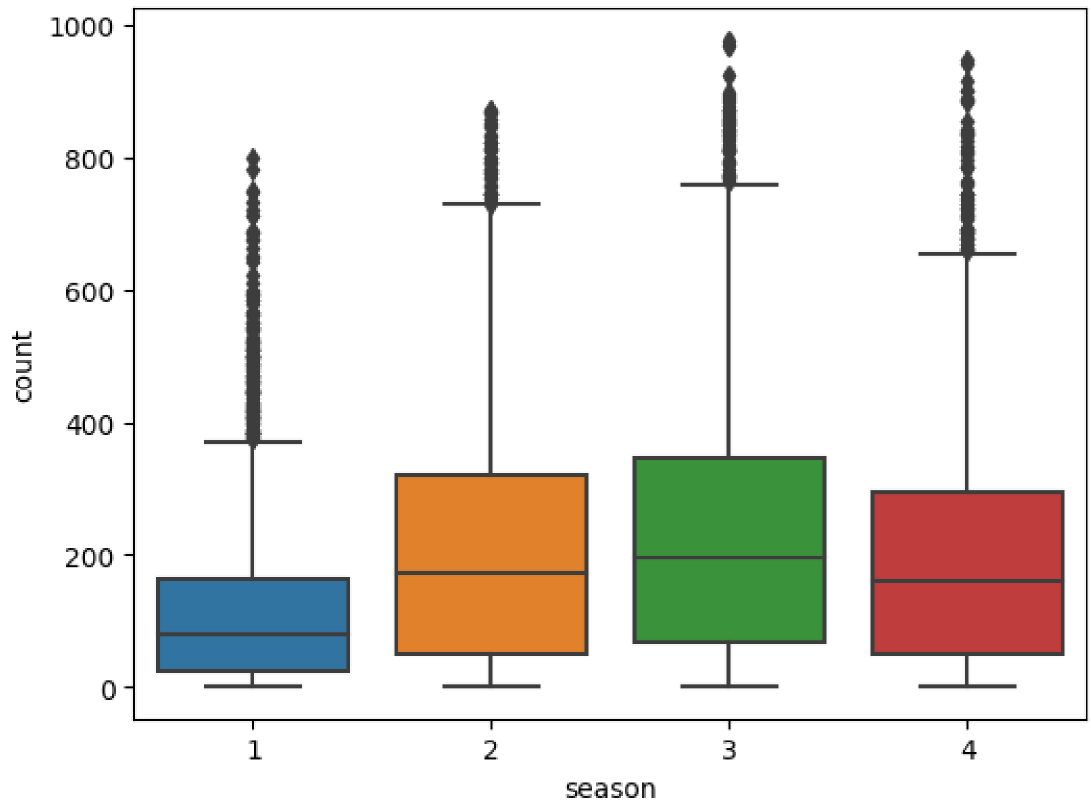


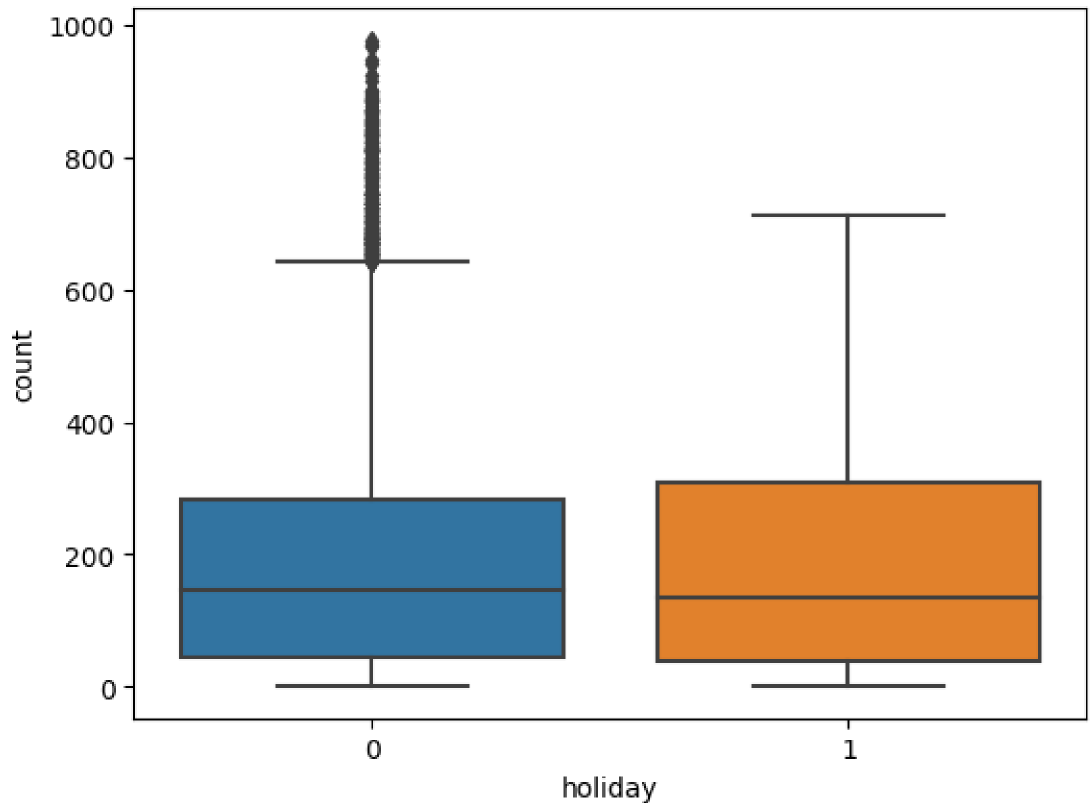
- data resembles real world data as it has more working days than holidays, equal number of days in all seasons and most of the days are clear

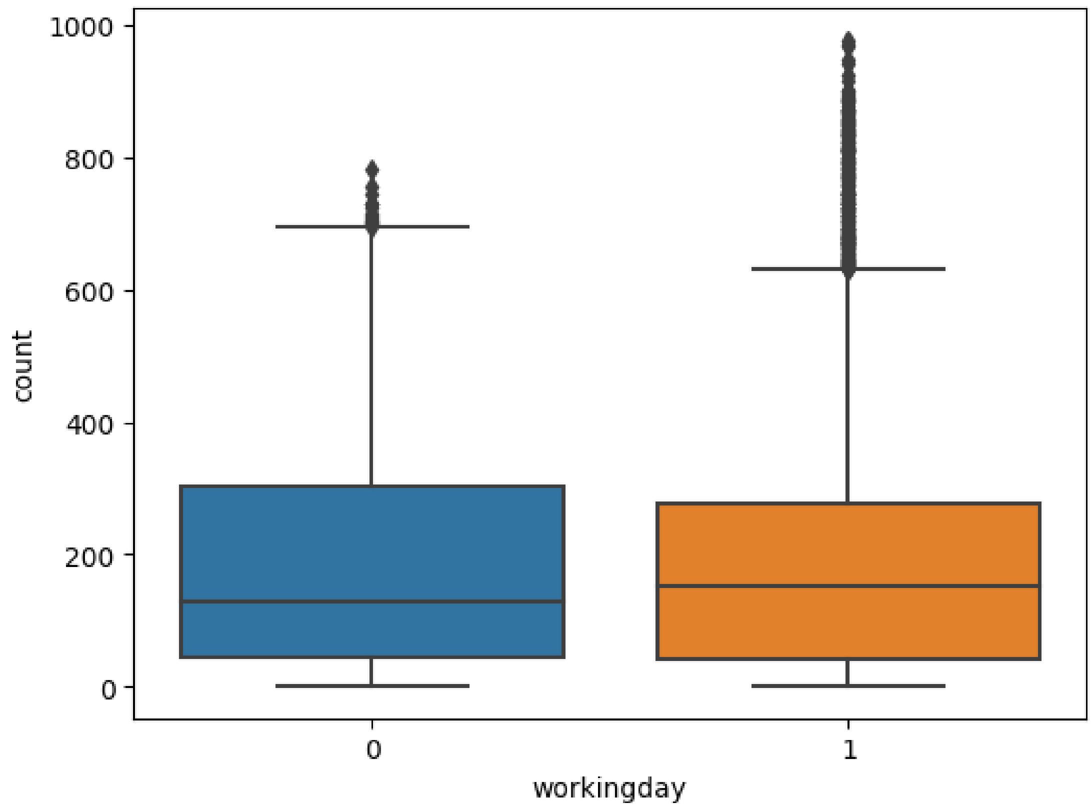
5 Bivariate analysis

Count VS categorical variables using boxplot

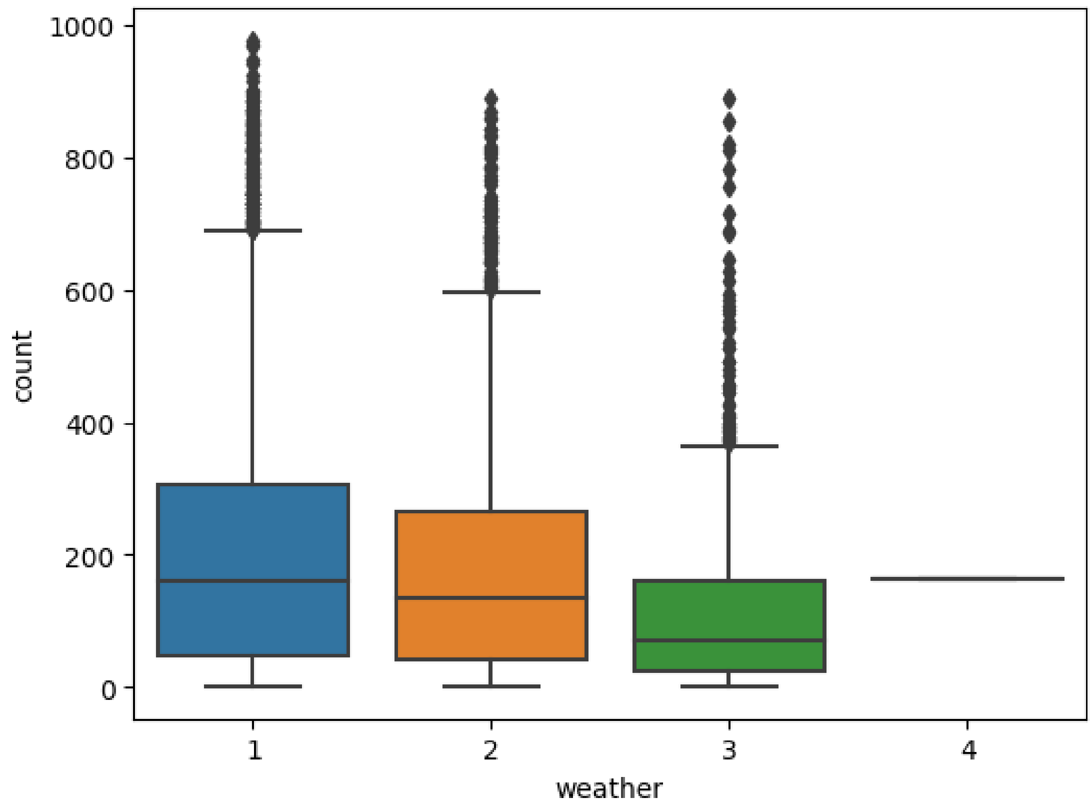
[34]:
```
for j in df.columns:
  if df[j].dtype==object:
    sns.boxplot(x=df[j],y=df["count"])
    plt.show()
```


1000
800
600
400
200
0
count
1
2
3
4
season


1000
800
600
400
200
0
count
0
1
holiday



1000
800
600
400
200
0
count
0
1
workingday



- More number of bikes are booked in fall followed by summer, winter and least bikes are booked in spring
- More number of bikes are booked on holidays
- More number of bikes are booked on clear weather days and least are booked on heavy rainfall days

6 Correlation between numerical variables

[35]:
```
df.corr()
```

```
<ipython-input-35-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  df.corr()
```

[35]:
```
               temp     atemp  humidity  windspeed    casual  registered  \
temp       1.000000  0.984948 -0.064949  -0.017852  0.467097    0.318571
atemp      0.984948  1.000000 -0.043536  -0.057473  0.462067    0.314635
humidity  -0.064949 -0.043536  1.000000  -0.318607 -0.348187   -0.265458
windspeed -0.017852 -0.057473 -0.318607   1.000000  0.092276    0.091052
```

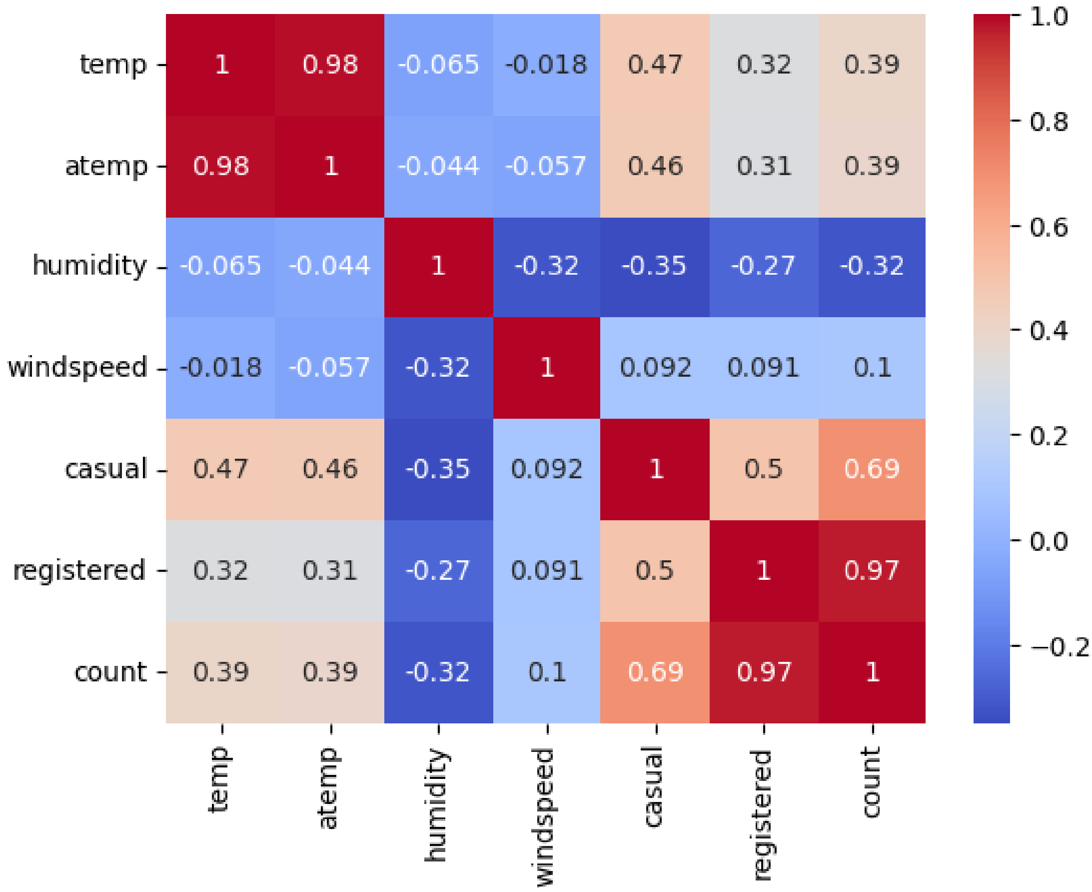
```
casual      0.467097  0.462067 -0.348187   0.092276  1.000000    0.497250
registered  0.318571  0.314635 -0.265458   0.091052  0.497250    1.000000
count       0.394454  0.389784 -0.317371   0.101369  0.690414    0.970948

               count
temp        0.394454
atemp       0.389784
humidity   -0.317371
windspeed   0.101369
casual      0.690414
registered  0.970948
count       1.000000
```

[36]:

```python
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
```

```
<ipython-input-36-0a3cd13aeaf5>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
```

[36]: <Axes: >



7 Try establishing a relation between the dependent and independent variable (Dependent "Count" & Independent: Workingday, Weather, Season etc)

8 Count VS Workingday

[37]:
```
df.groupby("workingday").mean()
```

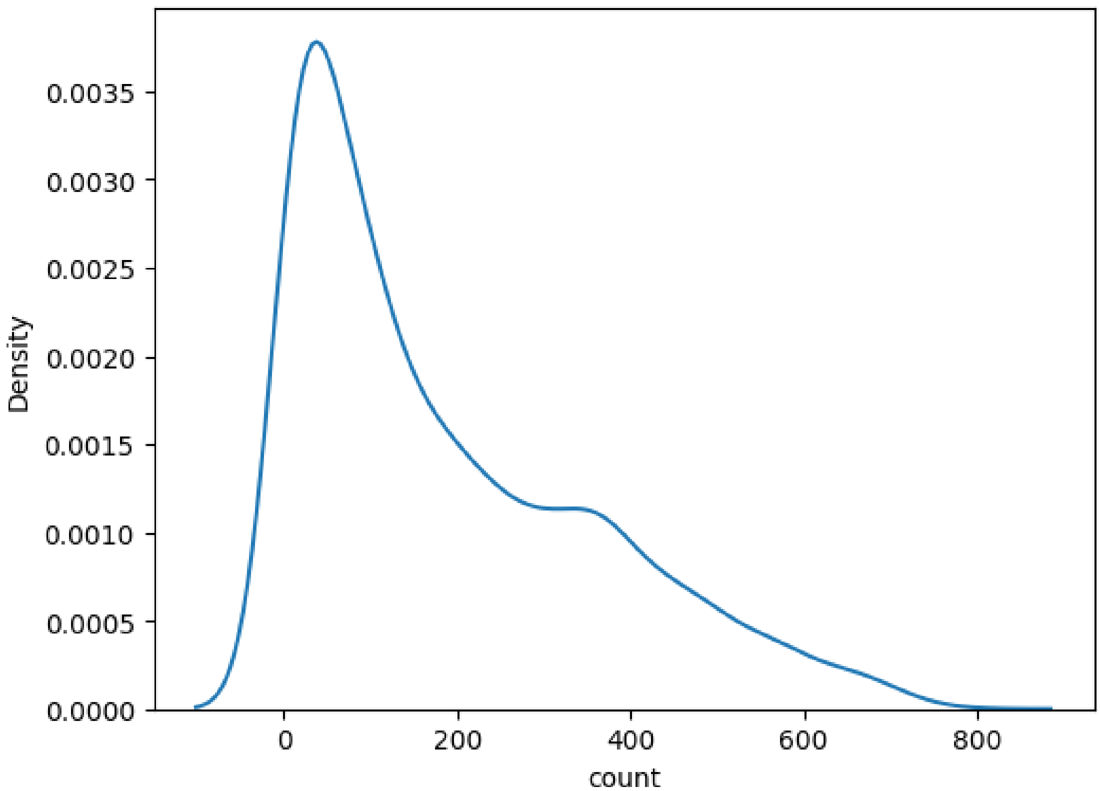
```
<ipython-input-37-d3490184e13c>:1: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.mean is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  df.groupby("workingday").mean()
```

[37]:
```
                 temp      atemp   humidity  windspeed     casual  registered  \
workingday
0           19.889839  23.349837  62.192286  12.639916  59.308290  129.198330
```

```
1             20.390696   23.798153   61.743119   12.874143   25.107663   167.904209

                   count
workingday
0             188.506621
1             193.011873
```

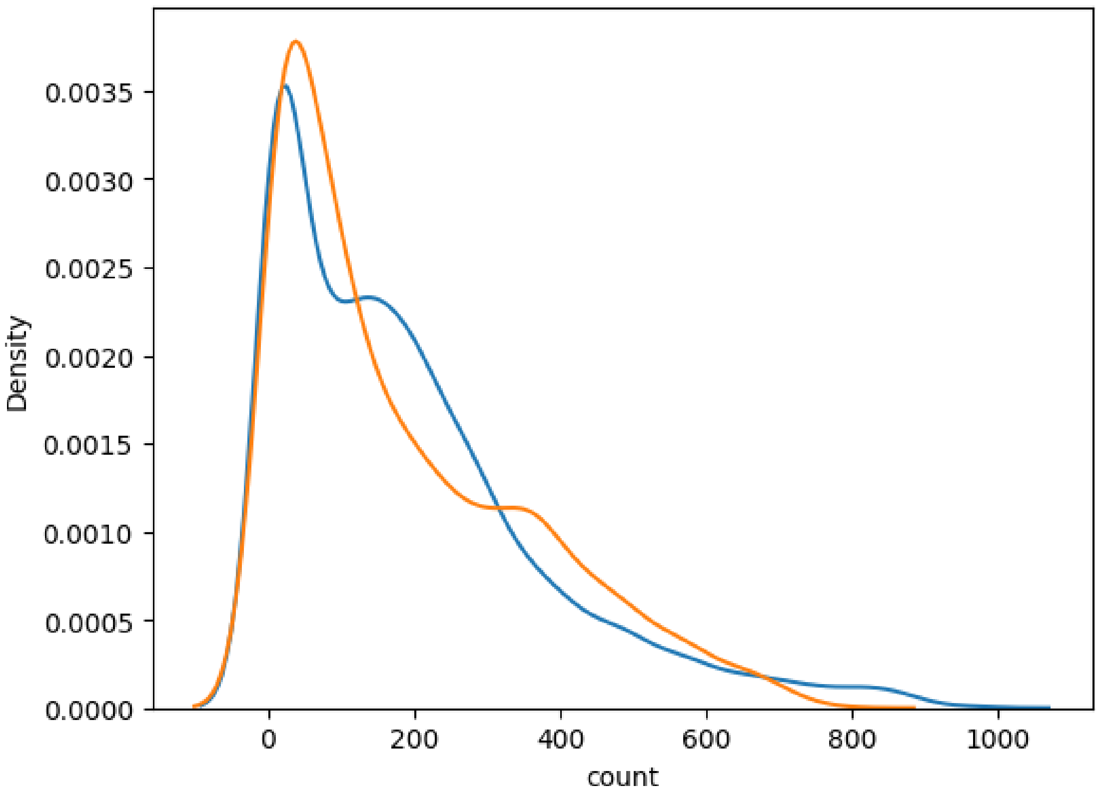
[38]:
```python
a=df.loc[df["workingday"]==0]["count"]
sns.kdeplot(a)
```

[38]: <Axes: xlabel='count', ylabel='Density'>



[39]:
```python
b=df.loc[df["workingday"]==1]["count"]
sns.kdeplot(b)
sns.kdeplot(a)
```

[39]: <Axes: xlabel='count', ylabel='Density'>



[40]:
```
kstest(a,b)
```

[40]:
```
KstestResult(statistic=0.05570196737090361, pvalue=8.003959300341833e-07,
statistic_location=125, statistic_sign=1)
```

The number of bikes booked on a workingday and non working day are not normal distribution as per KS-test

[41]:
```
Ho="Number of bikes booked does not depend on workingay or not"
Ha="Number of bikes booked depend on workingay or not"

t_stat,p_value=ttest_ind(a,b,alternative="two-sided")
print("t_stat : ",t_stat)
print("p_value : ",p_value)
alpha= 0.05
if p_value < alpha :
 print("Reject Ho")
else :
 print("Fail to Reject Ho")
```

```
t_stat :  -1.2096277376026694
p_value :  0.22644804226361348
```

```
Fail to Reject Ho
```

- data of number of bikes booked on working and non workingday are not a normal distribution as per KS test.
- However if we perform ttest to check whether they are dependent or independent we can see that number of bikes booked is does not depend on workingday or non working day

9 Count VS Weather

[42]:
```python
df.groupby("weather").sum()
```

```
<ipython-input-42-05a0e0d3221c>:1: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.sum is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  df.groupby("weather").sum()
```

[42]:
```
              temp       atemp  humidity   windspeed  casual  registered  \
weather
1        147846.82  172565.755    407907  92723.1626  289900     1186163
2         55587.80   65387.220    195831  34517.8506   87246      419914
3         16790.32   19544.905     69872  12087.2020   14983       87106
4             8.20      11.365        86      6.0032       6         158

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

[43]:
```python
df_weather1=df.loc[df["weather"]==1]["count"]
df_weather2=df.loc[df["weather"]==2]["count"]
df_weather3=df.loc[df["weather"]==3]["count"]
df_weather4=df.loc[df["weather"]==4]["count"]
```

[44]:
```python
Ho= "Number of bikes booked does not depend on weather"
Ha= "Number of bikes booked depends on weather"
f_stat,p_value=f_oneway(df_weather1,df_weather2,df_weather3,df_weather4)
print("f_stat : ",f_stat)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print(f"Conclusion : {Ha}")
else:
 print("Interpretation : Fail to Reject Ho")
```

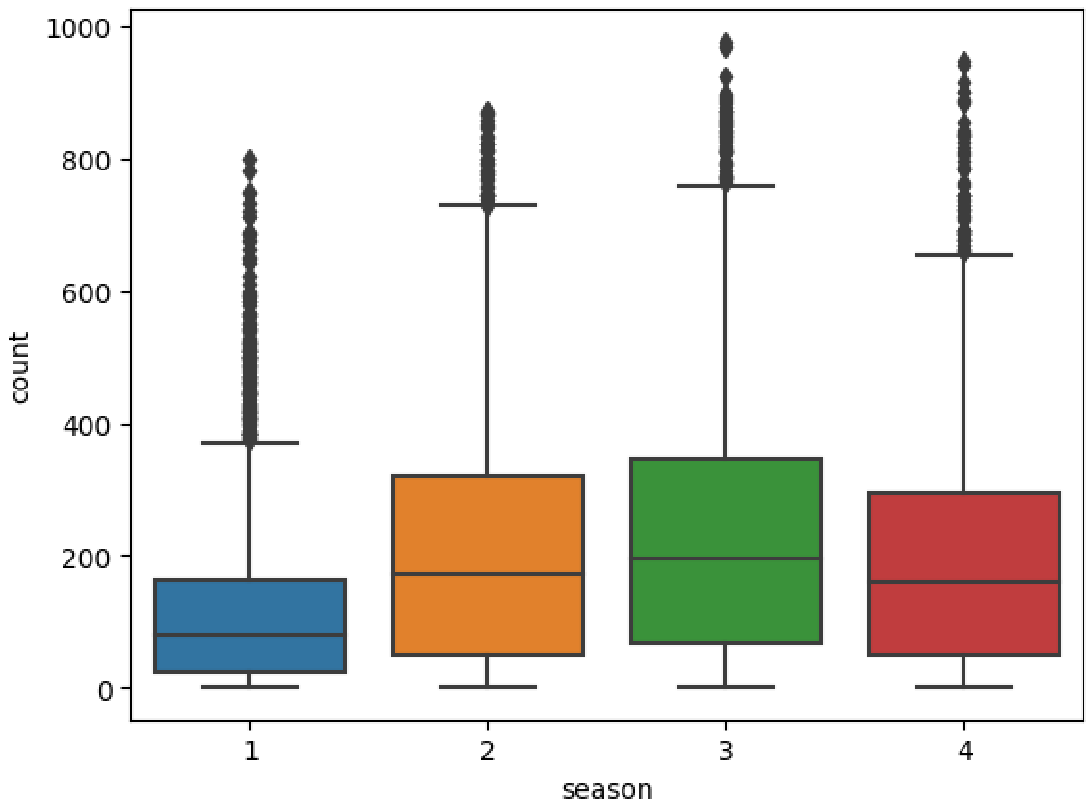
```
f_stat :  65.53024112793271
p_value :  5.482069475935669e-42
Interpretation : Reject Ho
Conclusion : Number of bikes booked depends on weather
```

- Clearly after performing ANOVA test on COUNT and Weather we can see that number of bikes booked depend on weather

10 Count VS Season

[45]:
```
sns.boxplot(x="season", y="count", data=df)
```

[45]:
```
<Axes: xlabel='season', ylabel='count'>
```



[46]:
```
df_season1=df.loc[df["season"]==1]["count"]
df_season2=df.loc[df["season"]==2]["count"]
df_season3=df.loc[df["season"]==3]["count"]
df_season4=df.loc[df["season"]==4]["count"]
```

[47]:
```
Ho= "Number of bikes booked does not depend on season"
Ha= "Number of bikes booked depends on season"
```

```
f_stat,p_value=f_oneway(df_season1,df_season2,df_season3,df_season4)
print("f_stat : ",f_stat)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print(f"Conclusion : {Ha}")
else:
 print("Interpretation : Fail to Reject Ho")
```

```
f_stat :  236.94671081032106
p_value :  6.164843386499654e-149
Interpretation : Reject Ho
Conclusion : Number of bikes booked depends on season
```

- Clearly after performing ANOVA test on COUNT and Season we can see that number of bikes booked depend on season

11 Count VS Holiday

[48]:
```
df_holiday= df[df["holiday"]==1]["count"]
df_noholiday= df[df["holiday"]==0]["count"]
```

[49]:
```
kstest(df_holiday, df_noholiday)
```

[49]:
```
KstestResult(statistic=0.048058805196384724, pvalue=0.4735777551913273,
statistic_location=352, statistic_sign=-1)
```

[50]:
```
Ho="Number of bikes booked does not depend on holidays"
Ha="Number of bikes booked depend on holiday"

t_stat,p_value=ttest_ind(df_holiday,df_noholiday,alternative="two-sided")
print("t_stat : ",t_stat)
print("p_value : ",p_value)
alpha= 0.05
if p_value < alpha :
 print("Reject Ho")
 print(f"Conclusion : {Ha}")
else :
 print("Fail to Reject Ho")
 print(f"Conclusion : {Ho}")
```

```
t_stat :  -0.5626388963477119
p_value :  0.5736923883271103
Fail to Reject Ho
Conclusion : Number of bikes booked does not depend on holiday or not
```

- Number of bikes booked does not depend on holiday

12 Temperature VS Count

[51]:
```
df["temp"].max()
```

[51]:
```
41.0
```

[52]:
```
df["temp"].min()
```

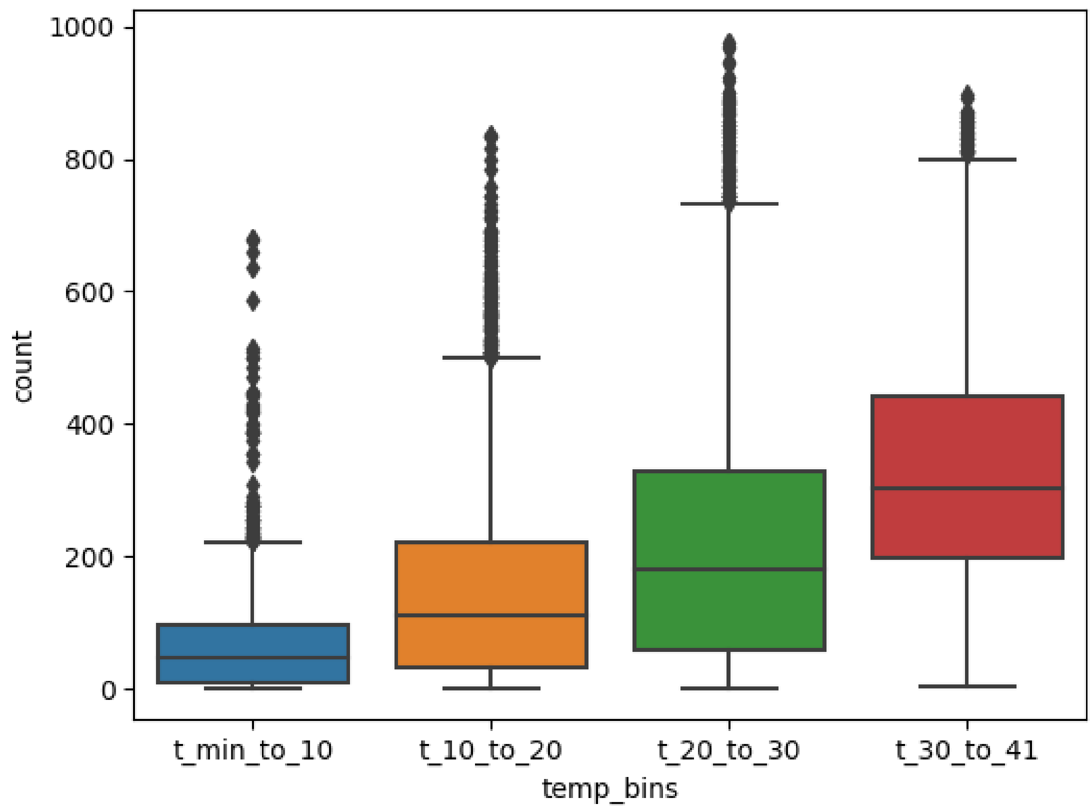
[52]:
```
0.82
```

[53]:
```
bins= [df["temp"].min(),10,20,30,df["temp"].max()]
labels= ["t_min_to_10","t_10_to_20", "t_20_to_30", "t_30_to_41"]
df["temp_bins"]= pd.cut(df["temp"],bins=bins,labels=labels)
df.head()
```

[53]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count    temp_bins
0        81        0.0       3          13     16  t_min_to_10
1        80        0.0       8          32     40  t_min_to_10
2        80        0.0       5          27     32  t_min_to_10
3        75        0.0       3          10     13  t_min_to_10
4        75        0.0       0           1      1  t_min_to_10
```

[54]:
```
sns.boxplot(x="temp_bins", y="count", data=df)
```

[54]:
```
<Axes: xlabel='temp_bins', ylabel='count'>
```



[55]:
```
df_t_min_to_10= df[df["temp_bins"]=="t_min_to_10"]["count"]
df_t_10_to_20= df[df["temp_bins"]=="t_10_to_20"]["count"]
df_t_20_to_30= df[df["temp_bins"]=="t_20_to_30"]["count"]
df_t_30_to_41= df[df["temp_bins"]=="t_30_to_41"]["count"]
```

[56]:
```
Ho= "Number of bikes booked does not depend on temperature"
Ha= "Number of bikes booked depends on temperature"
f_stat,p_value=f_oneway(df_t_min_to_10,df_t_10_to_20,df_t_20_to_30,df_t_30_to_41)
print("f_stat : ",f_stat)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print(f"Conclusion : {Ha}")
else:
 print("Interpretation : Fail to Reject Ho")
 print(f"Conclusion : {Ho}")
```

```
f_stat :  647.7741989440545
p_value :  0.0
Interpretation : Reject Ho
```

```
Conclusion : Number of bikes booked depends on temperature
```

- Number of bikes booked depends on temperature
- less number of bikes are booked when temperature is below 10 *More number of bikes are booked when temperature is in between 20 to 30

13 Temp VS atemp correlation

test to check whether data is normally distributed

Wilkin-Shapiro test

[57]:
```
shapiro(df["temp"])
```

```
/usr/local/lib/python3.10/dist-packages/scipy/stats/_morestats.py:1882:
UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

[57]:
```
ShapiroResult(statistic=0.9804227352142334, pvalue=4.577117001754969e-36)
```

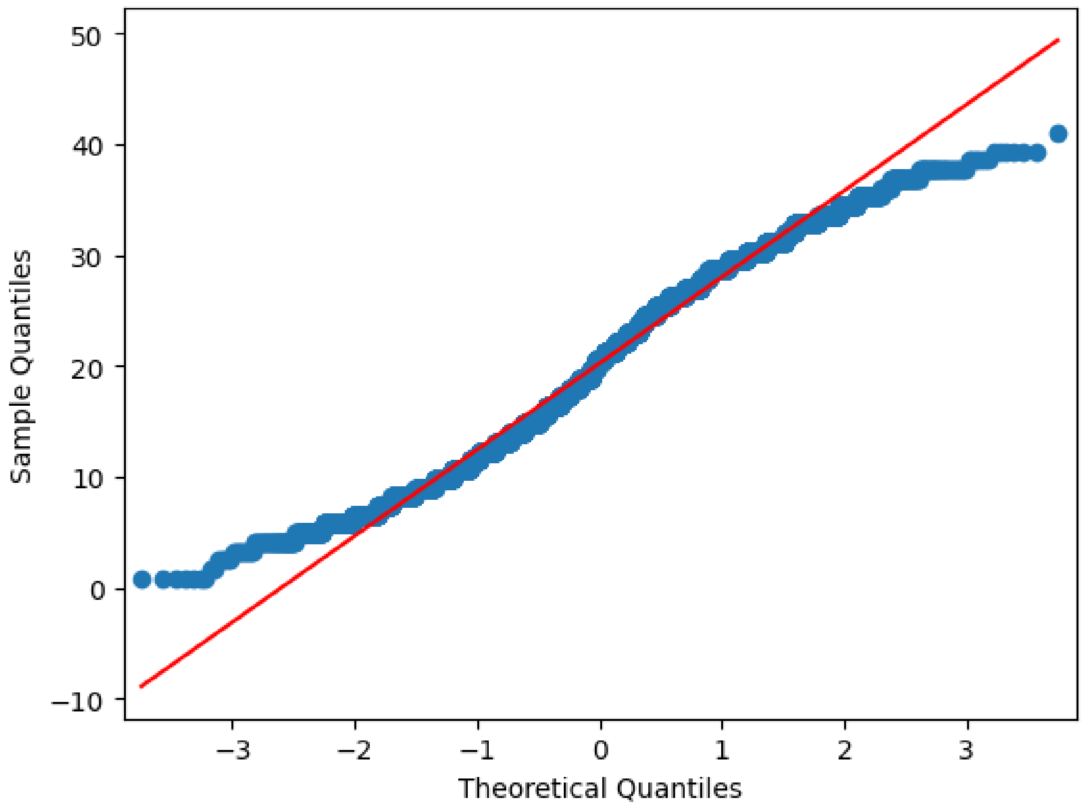
[58]:
```
shapiro(df["atemp"])
```

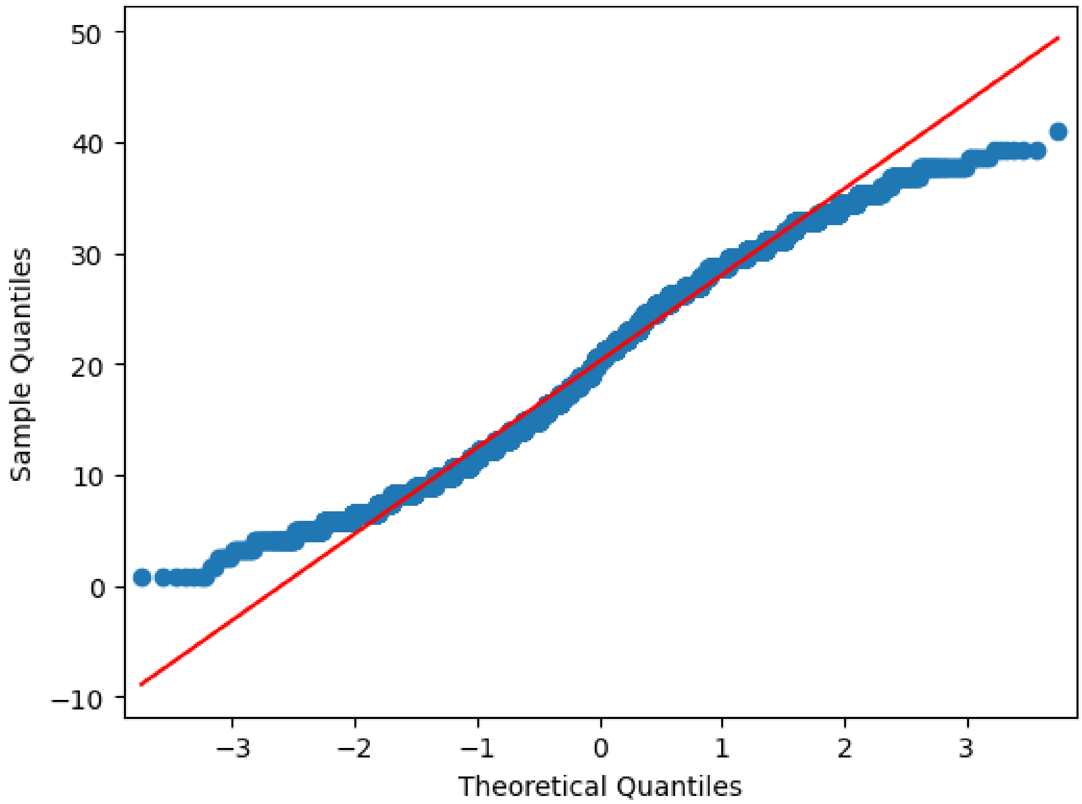
[58]:
```
ShapiroResult(statistic=0.9815532565116882, pvalue=3.35599504562436e-35)
```

Q-Q Plot

[59]:
```
qqplot(df["temp"], line="s")
```

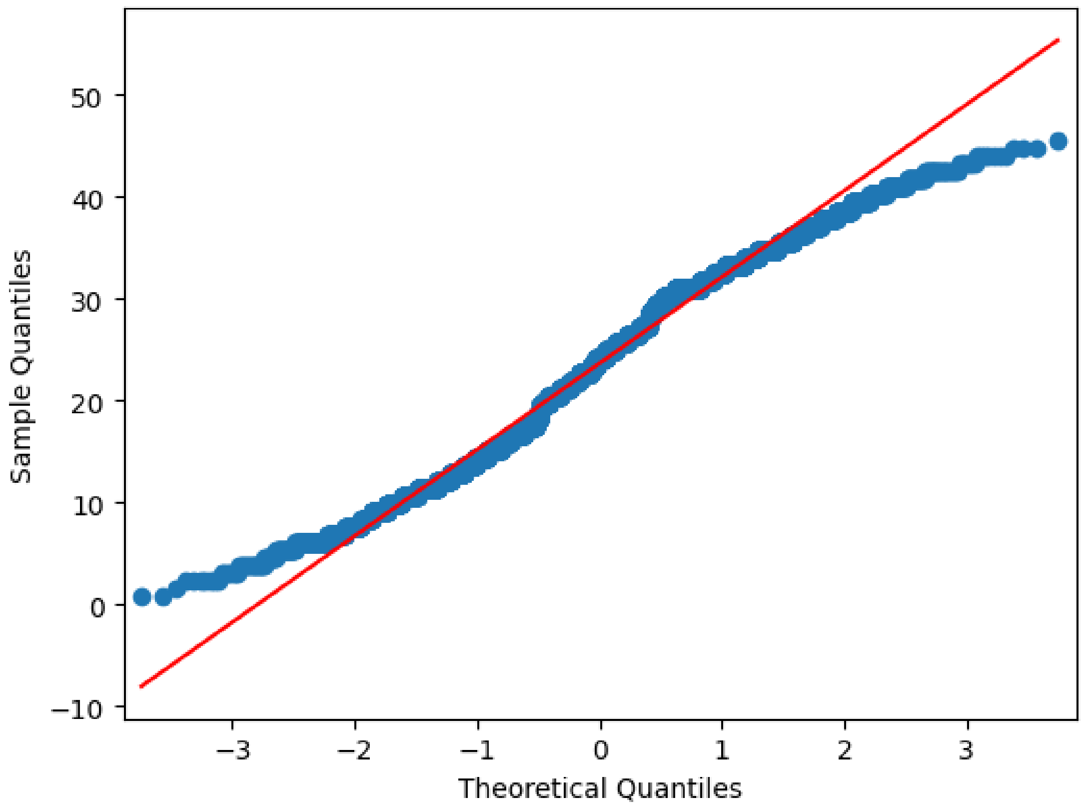
[59]:

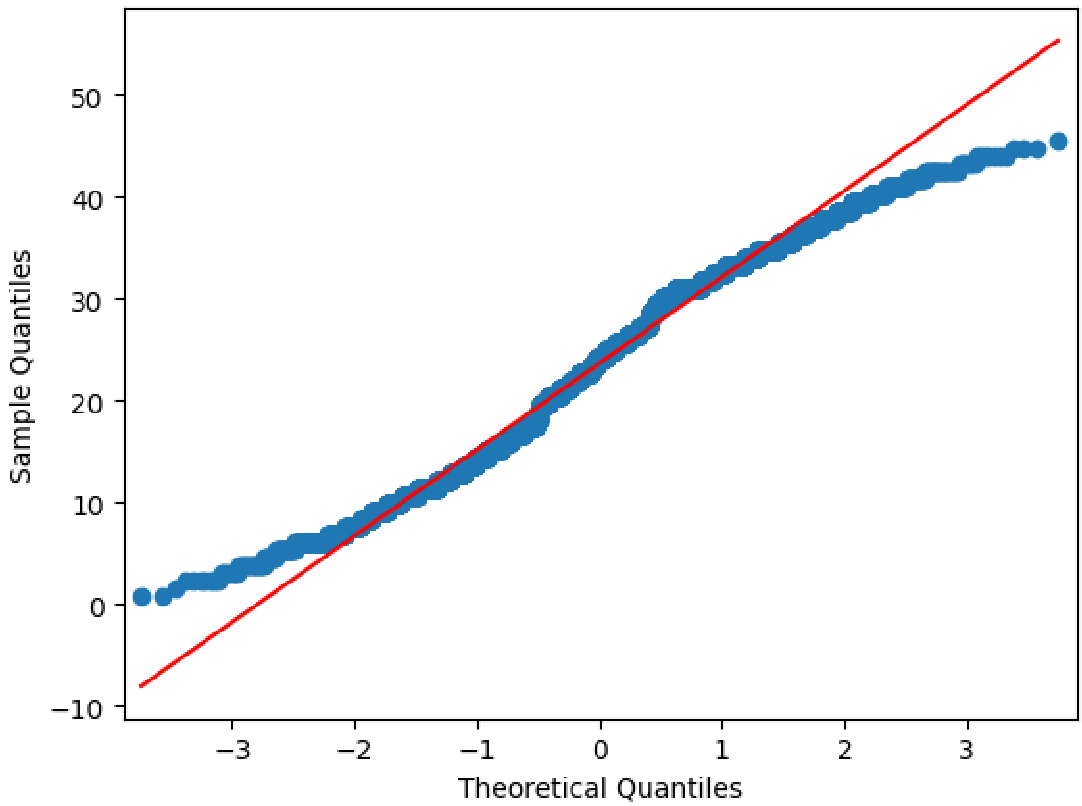

Sample Quantiles
Theoretical Quantiles
50
40
30
20
10
0
−10
−3
−2
−1
0
1
2
3




```
[60]: qqplot(df["atemp"], line="s")
```

[60]:

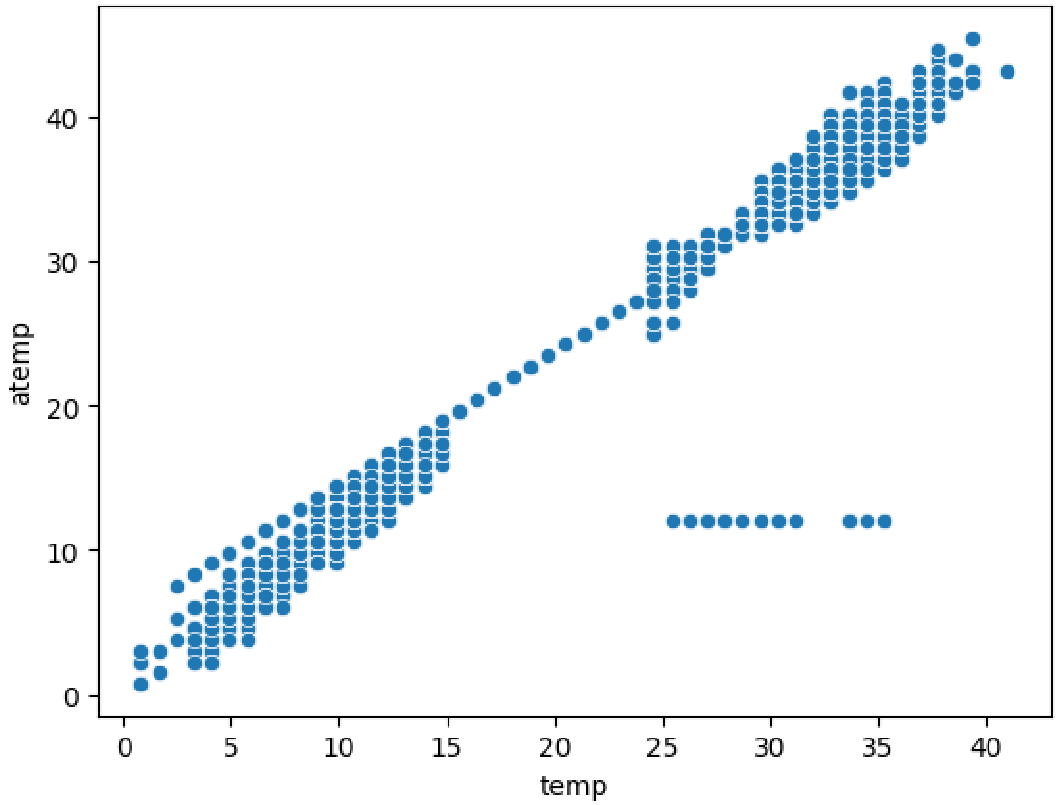

Sample Quantiles
Theoretical Quantiles
50
40
30
20
10
0
−10
−3
−2
−1
0
1
2
3



scatte plot to check linearity of data

[61]:
```
sns.scatterplot(x=df["temp"], y=df["atemp"])
```

[61]: <Axes: xlabel='temp', ylabel='atemp'>



[62]:
```
Ho= "temp and atemp are not related"
Ha= "temp and atemp are related"
corr_coeff,p_value=spearmanr(df["temp"],df["atemp"])
print("corr_coeff : ",corr_coeff)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print(f"Conclusion : {Ha}")
else:
 print("Interpretation : Fail to Reject Ho")
```

```
corr_coeff :  0.9871284684480133
p_value :  0.0
Interpretation : Reject Ho
Conclusion : temp and atemp are related
```

- Temp and atemp are positively correlated

14 Season VS Weather

[65]:
```
df_season_weather= pd.crosstab(columns=df["season"], index=df["weather"])
df_season_weather
```

[65]:

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

[68]:
```
# Ho : Season Doesn't affect weather( Independant)
# Ha :  Season affects weather( Dependant)
chi_stat,p_value,dof,expected=chi2_contingency(df_season_weather)
print("chi_stat : ",chi_stat)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print("Conclusion : Season affects weather( Dependant)")
else:
 print("Interpretation : Fail to Reject Ho")
```

```
chi_stat :  49.15865559689363
p_value :  1.5499250736864862e-07
Interpretation : Reject Ho
Conclusion : Season affects weather( Dependant)
```

- Season and Weather are dependent

15 Count VS Datetime

[72]:
```
df_0_to_8= df.loc[(df["datetime"].dt.time >=pd.to_datetime("00:00:00").time())
 ↪& (df["datetime"].dt.time <= pd.to_datetime("07:59:59").time() )]["count"]
df_8_to_16= df.loc[(df["datetime"].dt.time >=pd.to_datetime("08:00:00").time())
 ↪& (df["datetime"].dt.time <= pd.to_datetime("15:59:59").time() )]["count"]
df_16_to_24= df.loc[(df["datetime"].dt.time >pd.to_datetime("16:00:00").time())
 ↪& (df["datetime"].dt.time <= pd.to_datetime("23:59:59").time() )]["count"]

print(f"No. of bikes booked between 00:00 to 08:00 are {df_0_to_8.sum()}")
print(f"No. of bikes booked between 08:00 to 16:00 are {df_8_to_16.sum()}")
print(f"No. of bikes booked between 16:00 to 23:59 are {df_16_to_24.sum()}")
```

```
No. of bikes booked between 00:00 to 08:00 are 199243
No. of bikes booked between 08:00 to 16:00 are 902983
No. of bikes booked between 16:00 to 23:59 are 838984
```

[73]:
```
Ho= "Number of bikes booked does not depend on time"
Ha= "Number of bikes booked depends on time"
f_stat,p_value=f_oneway(df_16_to_24,df_8_to_16,df_0_to_8)
print("f_stat : ",f_stat)
print("p_value : ",p_value)
alpha = 0.05
if p_value< alpha:
 print("Interpretation : Reject Ho")
 print(f"Conclusion : {Ha}")
else:
 print("Interpretation : Fail to Reject Ho")
 print(f"Conclusion : {Ho}")
```

```
f_stat :  1992.1392781061618
p_value :  0.0
Interpretation : Reject Ho
Conclusion : Number of bikes booked depends on time
```

- Number of bikes booked depends on time
- During mid night that is from 00:00 to 08:00 less number of bikes are booked compared to the rest of the day

16 Recommendations

- More number of bikes should be available during fall and summer to increase profits *During heavy rainfall weather conditions,company has to concentrate on marketing strategies or has to utilize that time to keep the vehicles charged, as very low number of bikes are booked* During clear weather conditions more number bikes should be made available *Workigday or holiday does not impact on number of bikes booked
- More number should be available between 08:00 to 23:59 as that is the peak time for bookings