Project 4 - Yulu

May 30, 2022

1 About Yulu

- 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, corporate offices, etc) 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 depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

The company wants to know which variables are significant in predicting the demand for shared electric cycles in the Indian market? How well those variables describe the electric cycle demands?

1.0.1 Column Profiling:

- datetime: datetime
- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- holiday: whether day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
- workingday: if day is neither weekend nor holiday is 1, otherwise is 0.
- 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
- temp: temperature in Celsius
- atemp: feeling temperature in Celsius
- humidity: humidity
- windspeed: wind speed
- casual: count of casual users
- registered: count of registered users

- count: count of total rental bikes including both casual and registered

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

[2]:
```python
df=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/
↪001/428/original/bike_sharing.csv?1642089089')
df.head()
```

[2]:
```
              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
```

[3]:
```python
df.shape
#There are 10886 rows and 12 columns in this dataset.
```

[3]: (10886, 12)

[4]:
```python
#The columns are
df.columns
```

[4]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

[5]:
```python
#Checking for null values
df.isna().sum()
#There are no null values in any of the columns
```

[5]:
```
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
```

[6]:
```
#Checking data types of columns
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
```

[7]:
```
#Changing data type of "datetime" column froom object to datetime64
df['datetime']=pd.to_datetime(df['datetime'])
df.dtypes
```

[7]:
```
datetime      datetime64[ns]
season                 int64
holiday                int64
workingday             int64
weather                int64
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
```

```
registered              int64
count                   int64
dtype: object
```

[8]:
```
#Checking no of categories in each column to find whether the column is␣
↪continuous or categorical
for column in df.columns:
    print('No. of categories in',column,':',df[column].nunique())
#We see that the categorical columns are season, holiday, workingday and␣
↪weather.
#We can consider the other columns as continuous.
```

```
No. of categories in datetime : 10886
No. of categories in season : 4
No. of categories in holiday : 2
No. of categories in workingday : 2
No. of categories in weather : 4
No. of categories in temp : 49
No. of categories in atemp : 60
No. of categories in humidity : 89
No. of categories in windspeed : 28
No. of categories in casual : 309
No. of categories in registered : 731
No. of categories in count : 822
```

[9]:
```
#Segregating categorical and continuous columns
categorical_columns=['season','holiday','workingday','weather']
continuous_columns=['temp','atemp', 'humidity', 'windspeed', 'casual',␣
↪'registered', 'count']
#datetime column is neither continuous nor categorical
```

[10]:
```
#Statistical Summary
df.describe()
```

[10]:

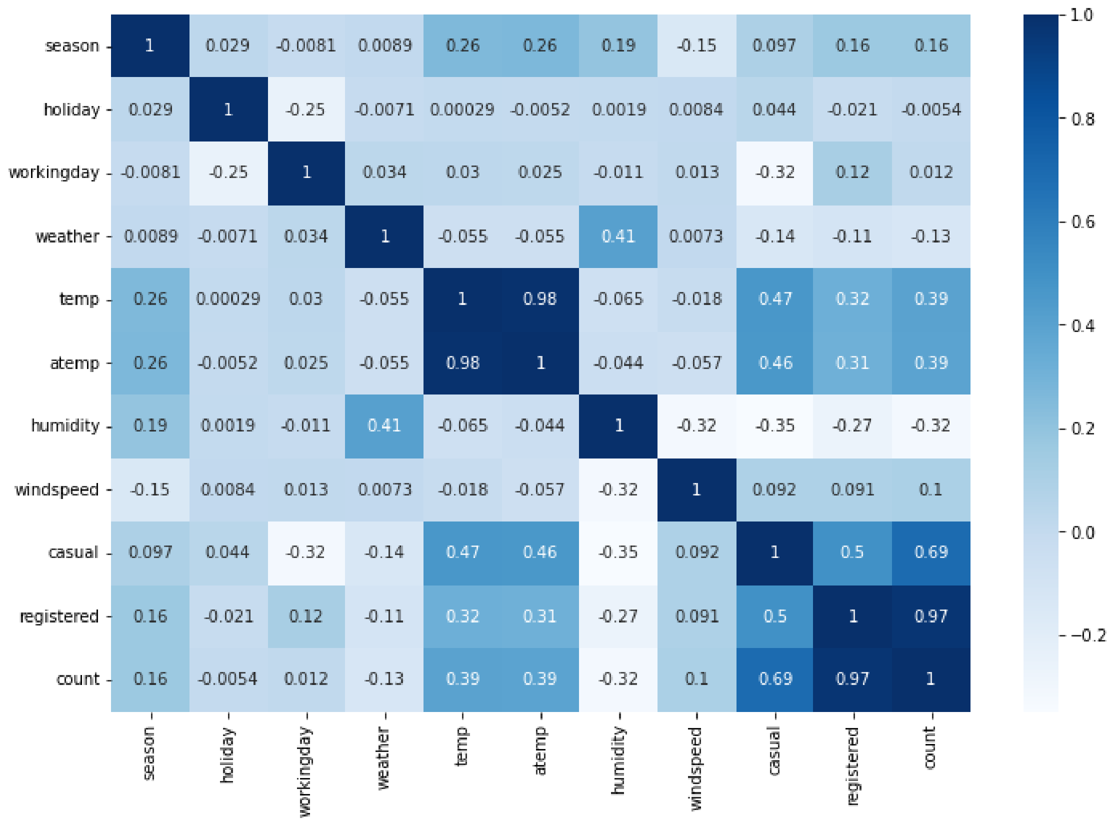
	season	holiday	workingday	weather	temp \
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000
mean	2.506614	0.028569	0.680875	1.418427	20.23086
std	1.116174	0.166599	0.466159	0.633839	7.79159
min	1.000000	0.000000	0.000000	1.000000	0.82000
25%	2.000000	0.000000	0.000000	1.000000	13.94000
50%	3.000000	0.000000	1.000000	1.000000	20.50000
75%	4.000000	0.000000	1.000000	2.000000	26.24000
max	4.000000	1.000000	1.000000	4.000000	41.00000

	atemp	humidity	windspeed	casual	registered \
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	23.655084	61.886460	12.799395	36.021955	155.552177

```
std         8.474601     19.245033      8.164537     49.960477    151.039033
min         0.760000      0.000000      0.000000      0.000000      0.000000
25%        16.665000     47.000000      7.001500      4.000000     36.000000
50%        24.240000     62.000000     12.998000     17.000000    118.000000
75%        31.060000     77.000000     16.997900     49.000000    222.000000
max        45.455000    100.000000     56.996900    367.000000    886.000000

              count
count  10886.000000
mean     191.574132
std      181.144454
min        1.000000
25%       42.000000
50%      145.000000
75%      284.000000
max      977.000000
```

[11]:
```python
#Finding correlation between the columns
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(),cmap='Blues',annot=True)
plt.show()
```



- From the heatmap, we see that the dependant column "count" has stronger correlation with registered, casual, temp, atemp and humidity.
- We can ignore the casual and registered column, since count = registered + casual.
- We can consider the column "temp" and not the column "atemp", since atemp is dependent on temp.

[12]:
```
#Adding new columns - Year,Month,Week,Week_day,Month_day
df['Year']=df['datetime'].dt.year
df['Month']=df['datetime'].dt.month_name()
df['Week_Day']=df['datetime'].dt.day_name()
df['Month_Day']=df['datetime'].dt.day
df['Hour']=df['datetime'].dt.hour
```

[13]:
```
#Dropping original "datetime" column, since it is no longer required
df.drop(columns='datetime',inplace=True)
```

[14]:
```
#Looking at the updated DataFrame
df.head(3)
```

[14]:
```
   season  holiday  workingday  weather  temp   atemp  humidity  windspeed  \
0       1        0           0        1  9.84  14.395        81        0.0
1       1        0           0        1  9.02  13.635        80        0.0
2       1        0           0        1  9.02  13.635        80        0.0

   casual  registered  count  Year    Month  Week_Day  Month_Day  Hour
0       3          13     16  2011  January  Saturday          1     0
1       8          32     40  2011  January  Saturday          1     1
2       5          27     32  2011  January  Saturday          1     2
```

- We have 5 more new categorical columns - 'Year','Month','Week','Week_Day','Month_Day'

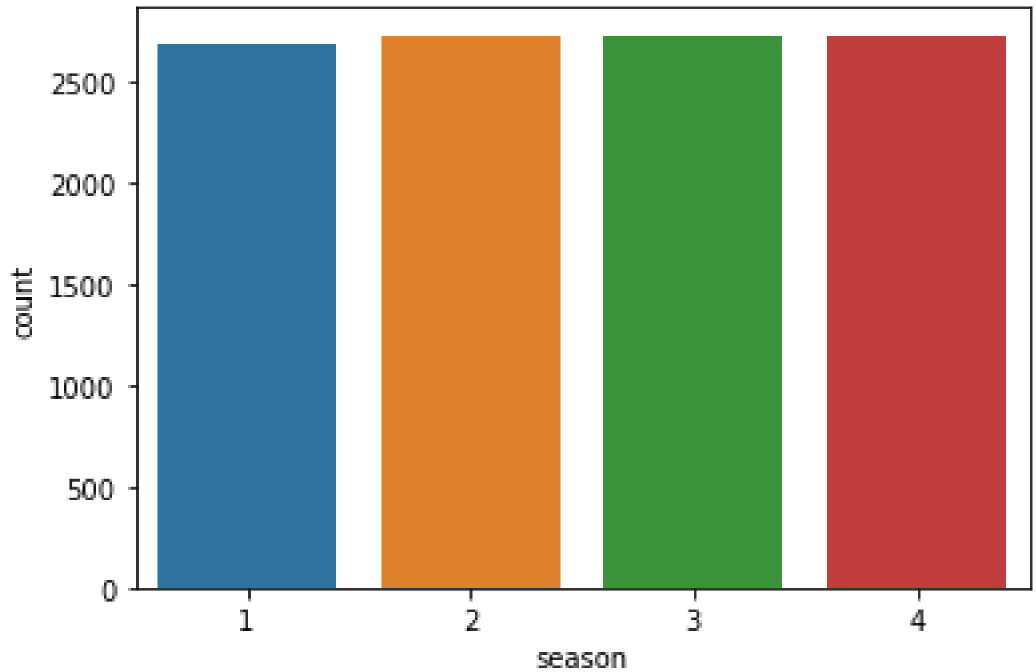
[ ]:
```

```

2 UNIVARIATE ANALYSIS

2.0.1 Analysis on Season column

[15]:
```
sns.countplot(data=df,x='season')
plt.show()
```



[16]:
```
print(df['season'].value_counts())
```

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

[17]:
```
print(df['season'].value_counts(normalize=True)*100)
```

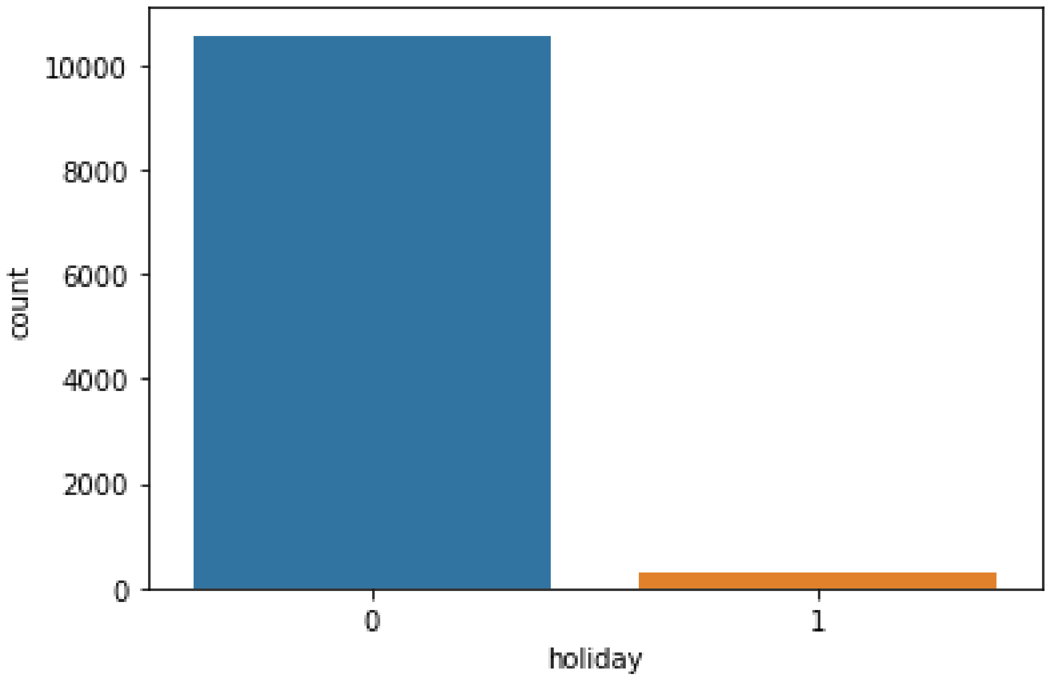
```
4    25.114826
2    25.105640
3    25.105640
1    24.673893
Name: season, dtype: float64
```

Inference - We see that we have almost equal data points for each of the 4 seasons.

[ ]:

2.0.2 Analysis on Holiday column

[18]:
```
sns.countplot(data=df,x='holiday')
plt.show()
```



[19]:
```
print(df['holiday'].value_counts())
```

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

[20]:
```
print(df['holiday'].value_counts(normalize=True)*100)
```

```
0    97.14312
1     2.85688
Name: holiday, dtype: float64
```

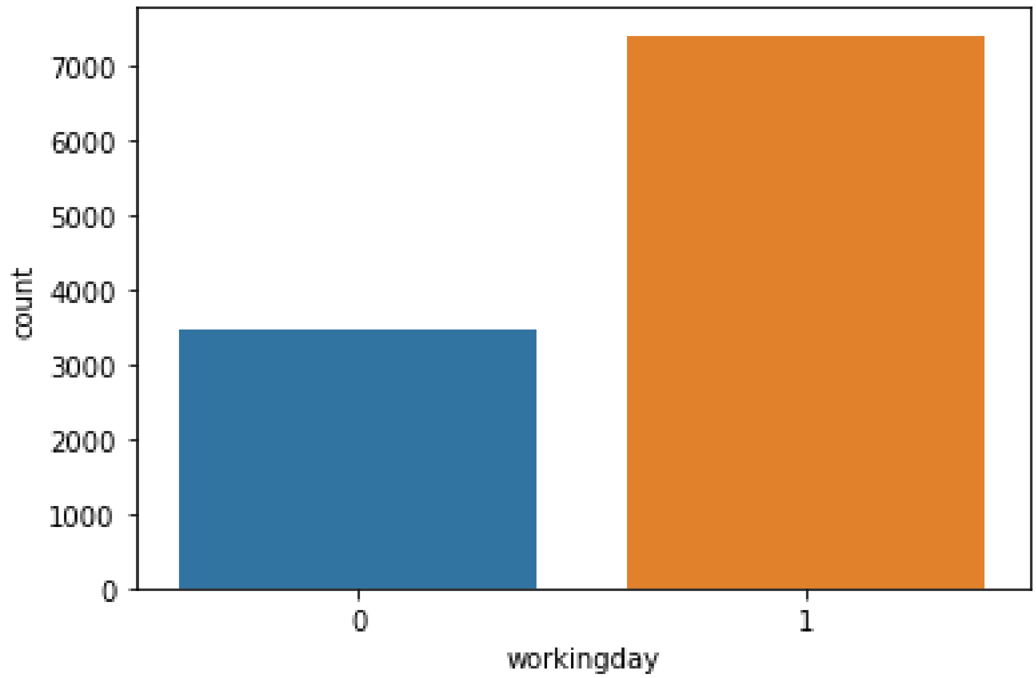
Inference - We see that we have very less data for holidays(value=1), which is expected because no of holdays in a year are very less in comparison to non-holidays.

[ ]:
```

```

2.0.3 Analysis on Working-Day column

[21]:
```
sns.countplot(data=df,x='workingday')
plt.show()
```



[22]:
```
print(df['workingday'].value_counts())
```

```
1    7412
0    3474
Name: workingday, dtype: int64
```

[23]:
```
print(df['workingday'].value_counts(normalize=True)*100)
```

```
1    68.087452
0    31.912548
Name: workingday, dtype: float64
```

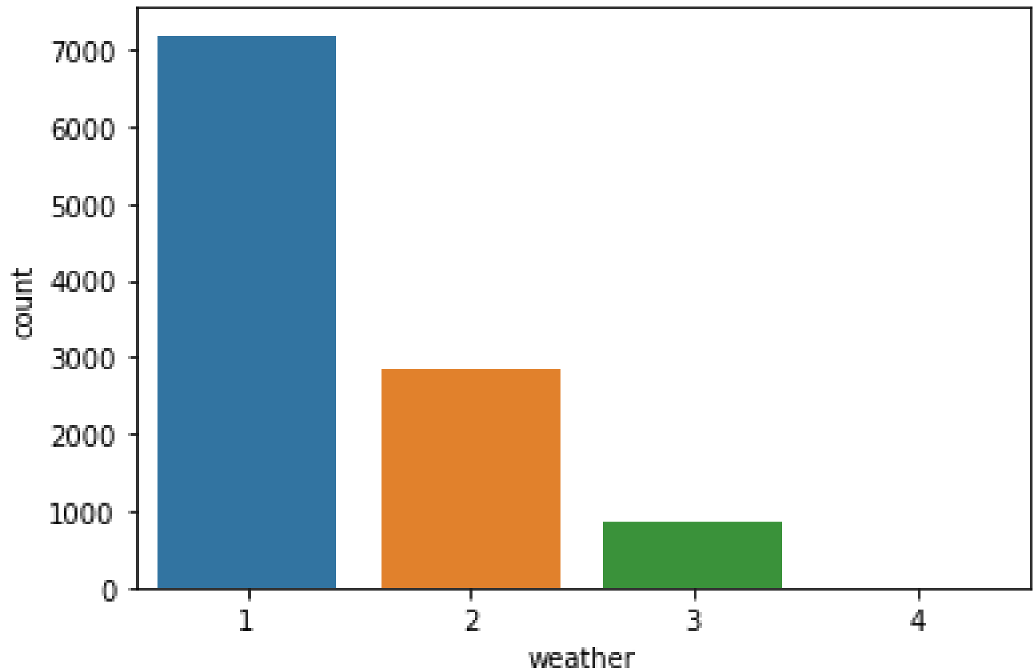
Inference - We see that we have more data for working-days(value=1), which is expected because no of working-days in a year are more in comparison to non-working days.

[ ]:
```

```

2.0.4 Analysis on Weather column

[24]:
```
sns.countplot(data=df,x='weather')
plt.show()
```



[25]:
```
print(df['weather'].value_counts())
```

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

[26]:
```
print(df['weather'].value_counts(normalize=True)*100)
```

```
1    66.066507
2    26.033437
3     7.890869
4     0.009186
Name: weather, dtype: float64
```

- 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

Inference - We see that we have less data for weather values 3 and 4. Probably this data is for a city that experiences very less snowfall and heavy rain.

[ ]:

2.0.5 Analysis on Year, Month, Week_Day and Month_Day, Hour columns

[27]:
```
print('No Of Year Categories :',df['Year'].nunique())
print(df['Year'].value_counts())
```

```
No Of Year Categories : 2
2012    5464
2011    5422
Name: Year, dtype: int64
```

[28]:
```
print('No Of Month Categories :',df['Month'].nunique())
print(df['Month'].value_counts())
```

```
No Of Month Categories : 12
May          912
June         912
July         912
August       912
December     912
October      911
November     911
April        909
September    909
February     901
March        901
January      884
Name: Month, dtype: int64
```

[29]:
```
print('No Of Week_Day Categories :',df['Week_Day'].nunique())
print(df['Week_Day'].value_counts())
```

```
No Of Week_Day Categories : 7
Saturday     1584
Sunday       1579
Thursday     1553
Monday       1551
Wednesday    1551
Tuesday      1539
Friday       1529
Name: Week_Day, dtype: int64
```

[30]:
```
print('No Of Month_Day Categories :',df['Month_Day'].nunique())
print(df['Month_Day'].value_counts())
```

```
No Of Month_Day Categories : 19
1     575
9     575
17    575
```

```
5     575
16    574
15    574
14    574
13    574
19    574
8     574
7     574
4     574
2     573
12    573
3     573
6     572
10    572
11    568
18    563
Name: Month_Day, dtype: int64
```

[31]:

```
print('No Of Hour Categories :',df['Hour'].nunique())
print(df['Hour'].value_counts())
```

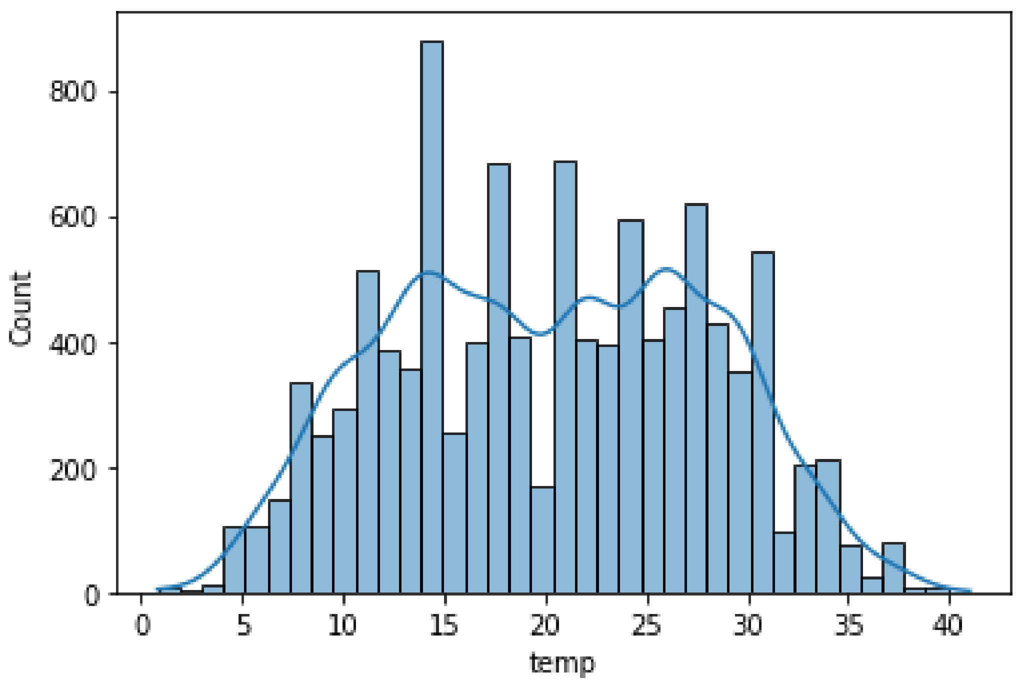
```
No Of Hour Categories : 24
12    456
13    456
22    456
21    456
20    456
19    456
18    456
17    456
16    456
15    456
14    456
23    456
11    455
10    455
9     455
8     455
7     455
6     455
0     455
1     454
5     452
2     448
4     442
3     433
Name: Hour, dtype: int64
```

Inference - We see that we have almost same number of data points for each category of year, month, month_day, week_day and hour. One observation is that we only have data for month_days from 1 to 19.

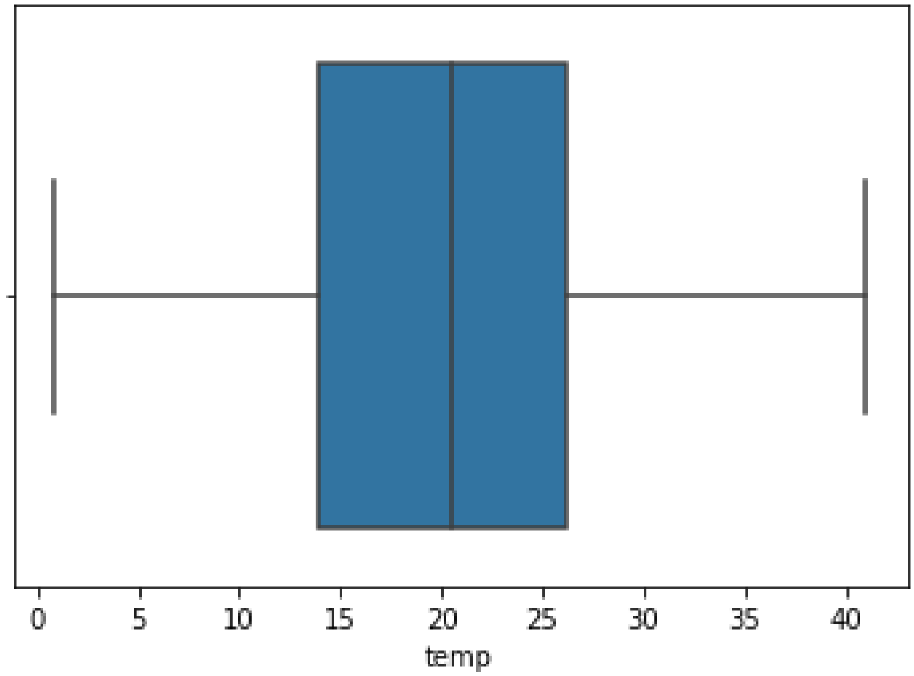
[ ]:

2.0.6 Analysis on Temp column

[32]:
```
sns.histplot(data=df,x='temp',kde=True)
plt.show()
```

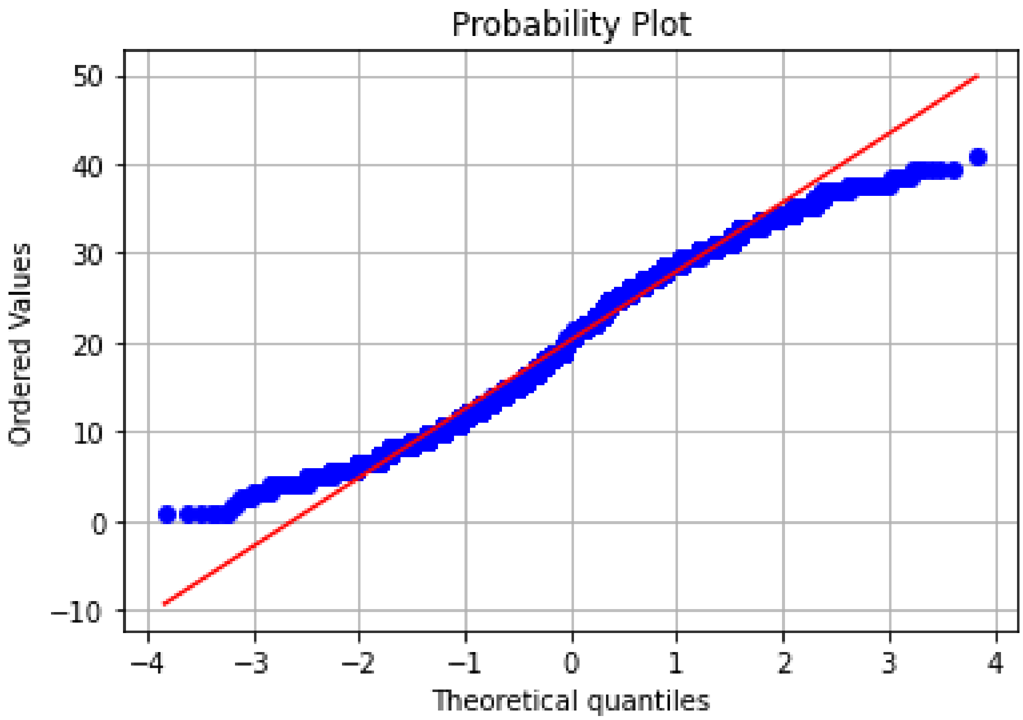


[33]:
```
sns.boxplot(data=df,x='temp')
plt.show()
```



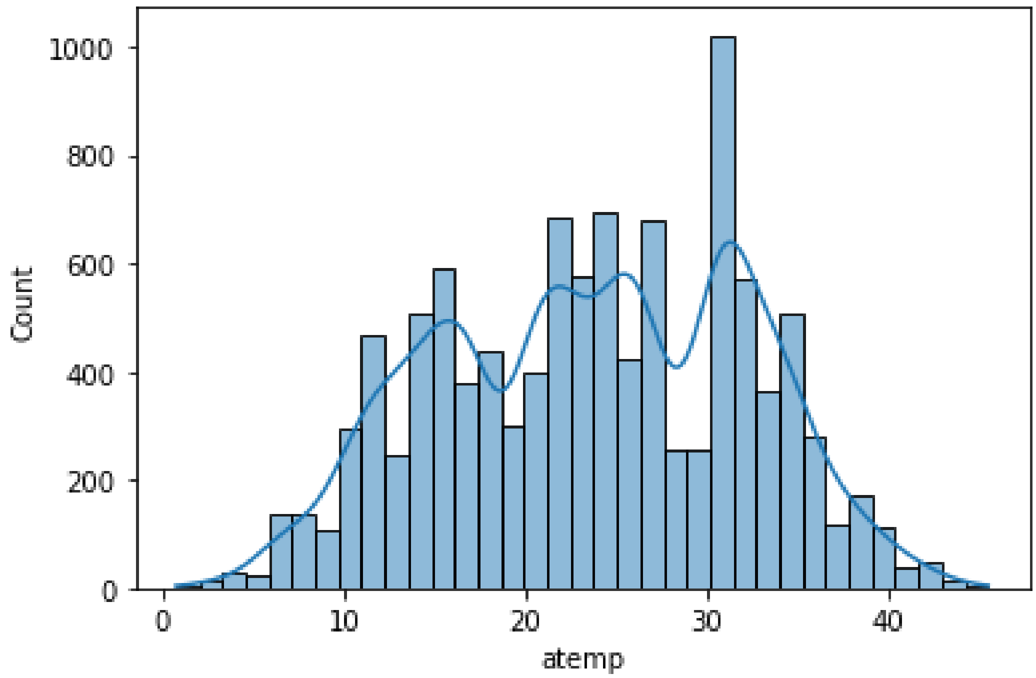
[34]:

```
#Checking if Temp column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['temp'],dist=stats.norm,plot=ax1)
plt.show()
#Temp column does not follow a normal distribution
```

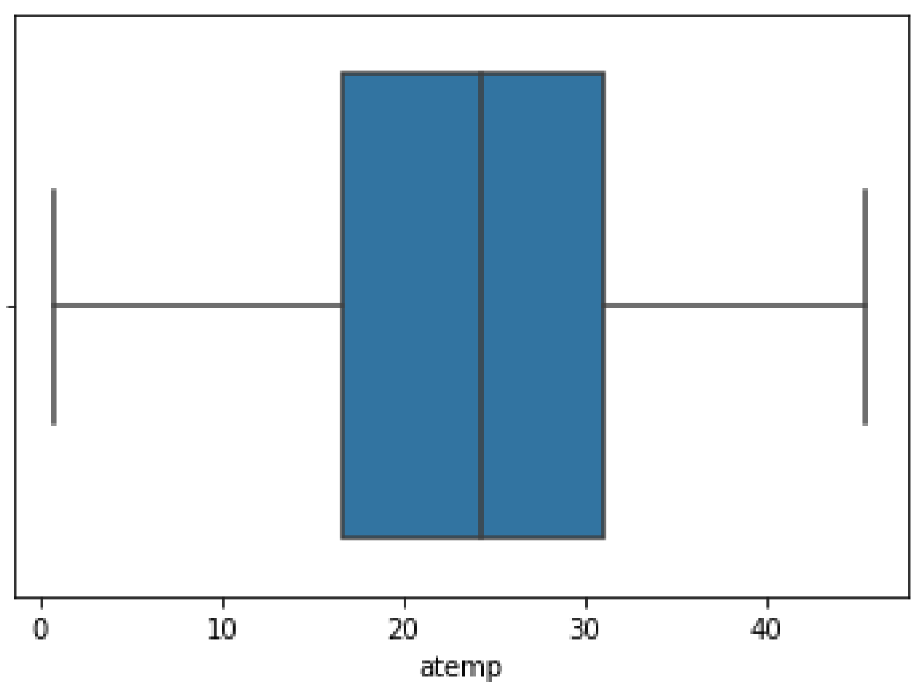


2.0.7 Analysis on A-Temp column

[35]:
```
sns.histplot(data=df,x='atemp',kde=True)
plt.show()
```

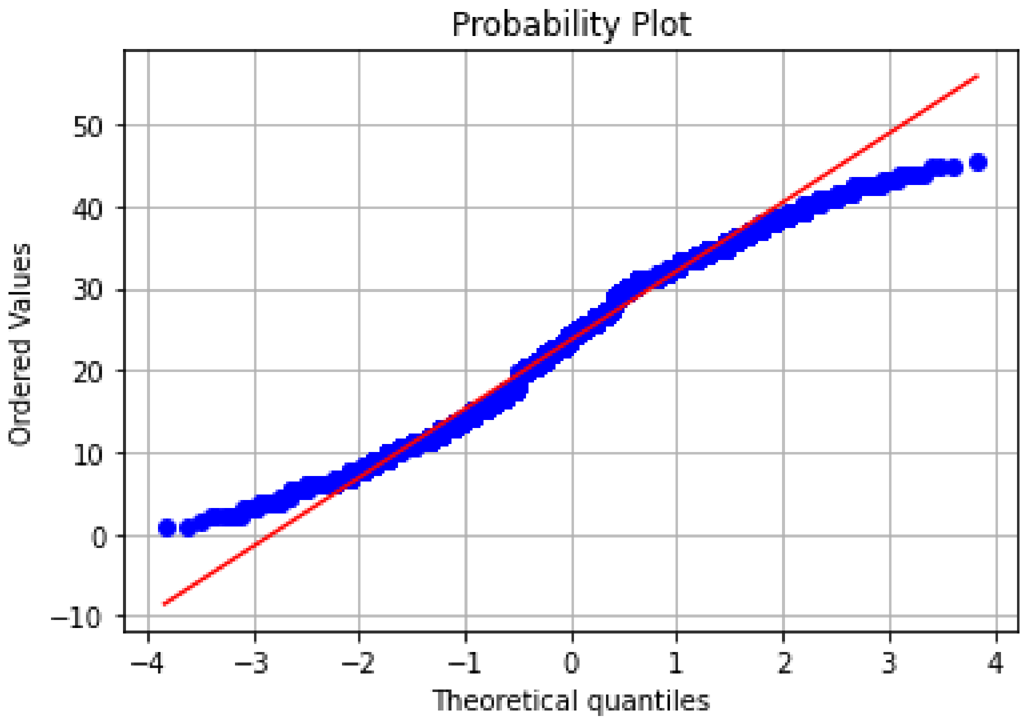


[36]:
```
sns.boxplot(data=df,x='atemp')
plt.show()
```



[37]:

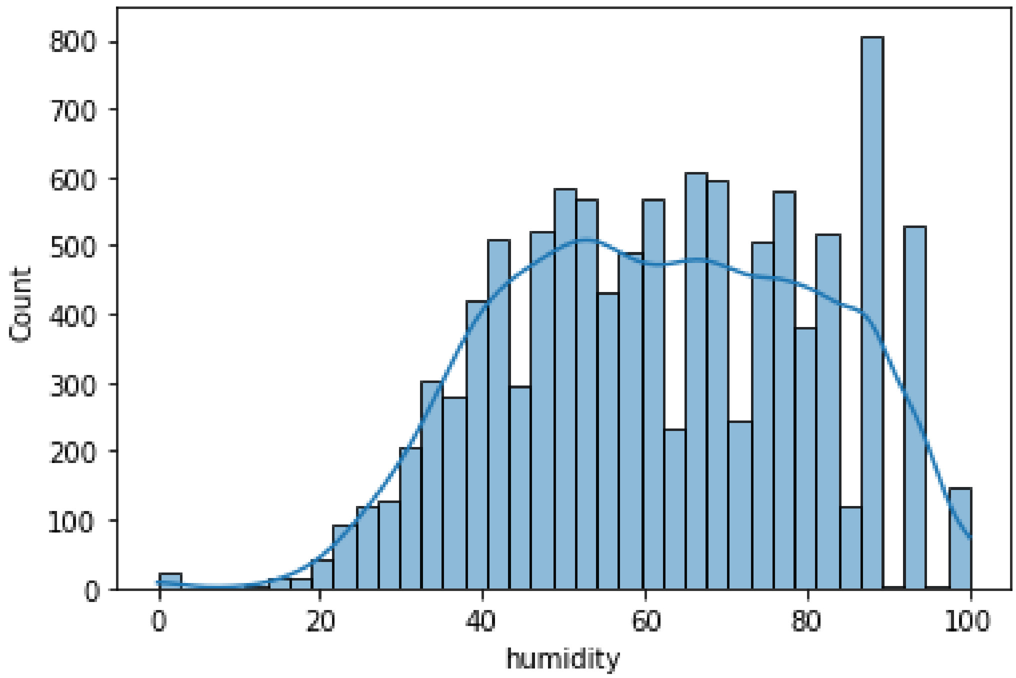
```
#Checking if A-Temp column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['atemp'],dist=stats.norm,plot=ax1)
plt.show()
#A-Temp column does not follow a normal distribution
```



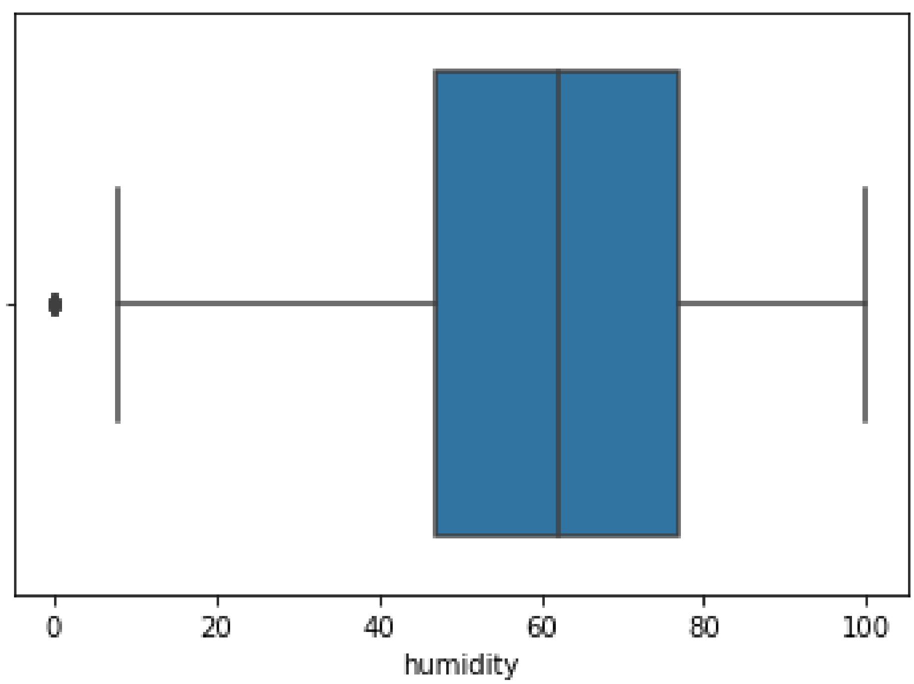
2.0.8 Analysis on Humidity column

[38]:

```
sns.histplot(data=df,x='humidity',kde=True)
plt.show()
```

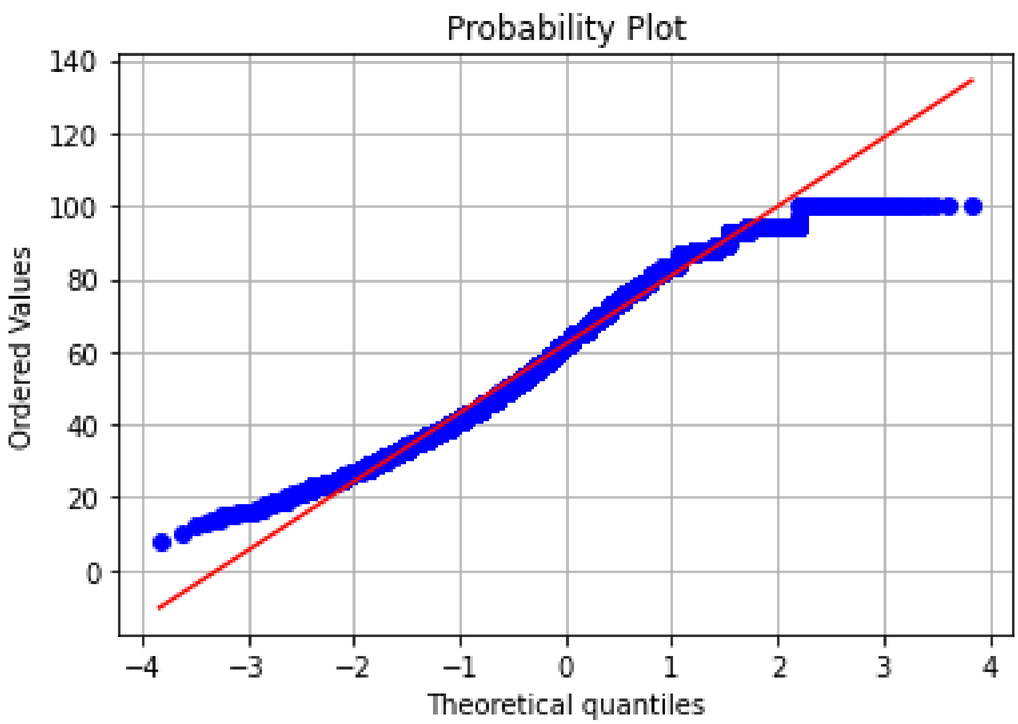


[39]:
```
sns.boxplot(data=df,x='humidity')
plt.show()
#We see that there are a few outliers in the left side.
```



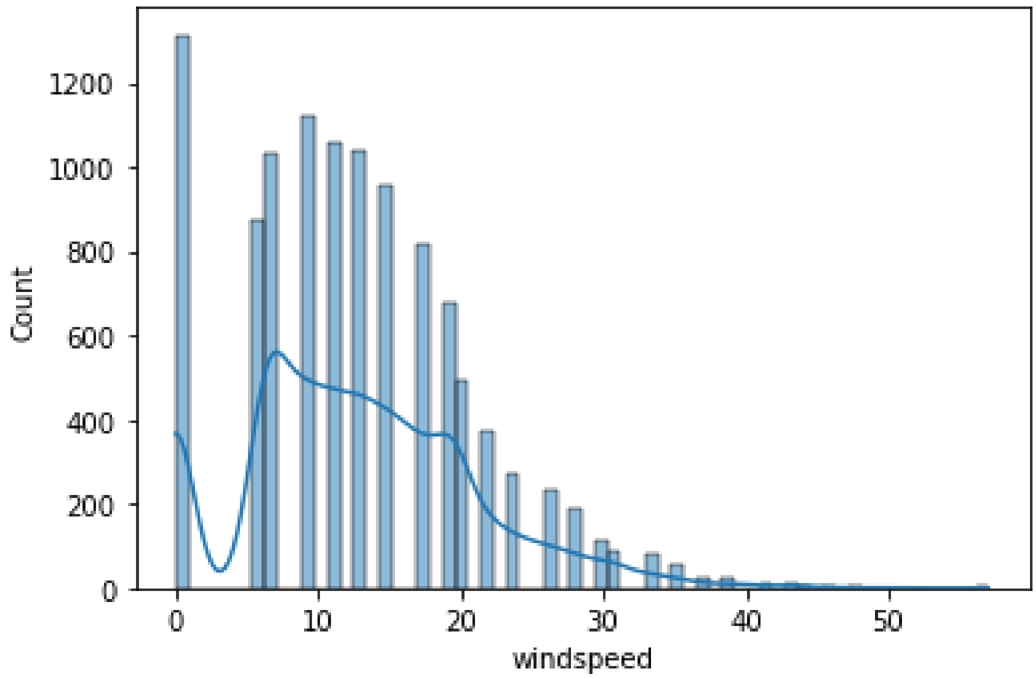
[40]:
```
#Since there are a few outliers in the humidity column, therefore we can remove␣
↪them.
q1=np.percentile(df['humidity'],25)
q3=np.percentile(df['humidity'],75)
iqr=q3-q1
df=df[(df['humidity']>q1-1.5*iqr)]
```

[41]:
```
#Checking if Humidity column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['humidity'],dist=stats.norm,plot=ax1)
plt.show()
#Humidity column does not follow a normal distribution
```

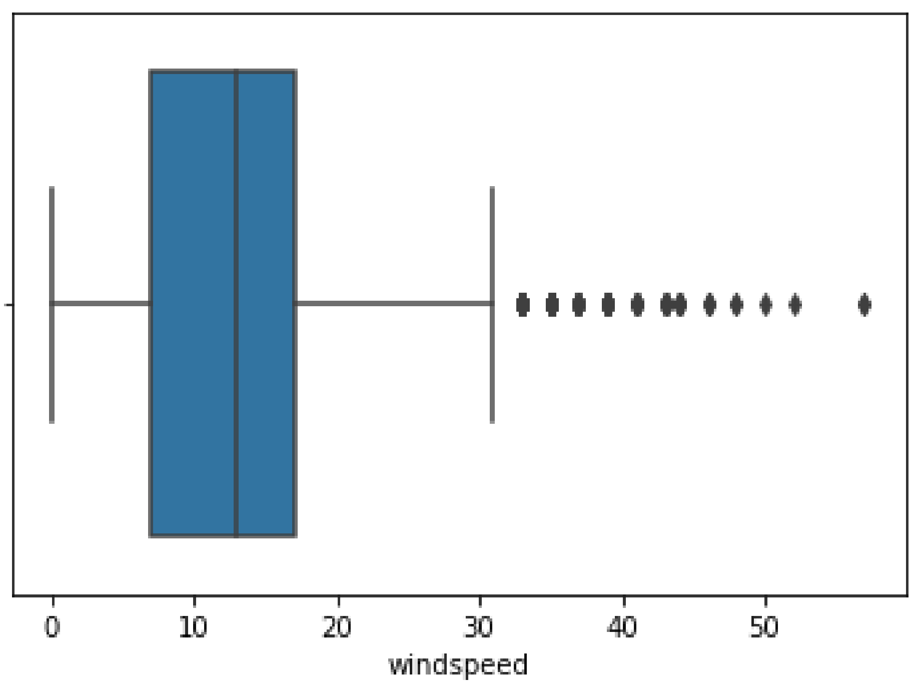


2.0.9 Analysis on Windspeed column

[42]:
```
sns.histplot(data=df,x='windspeed',kde=True)
plt.show()
```

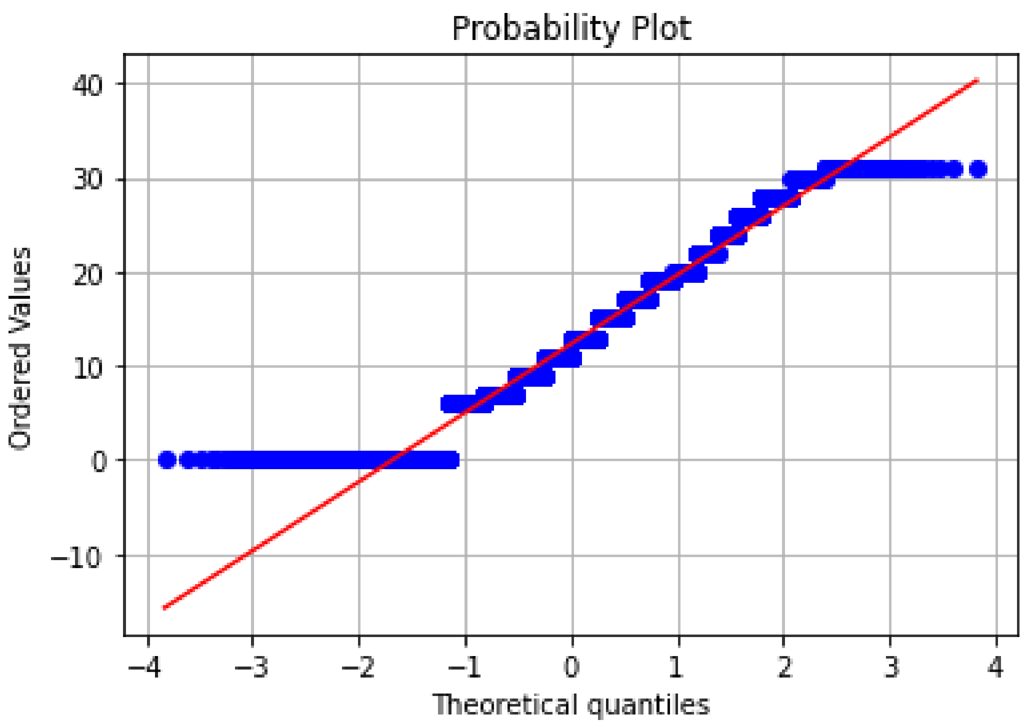


[43]:
```
sns.boxplot(data=df,x='windspeed')
plt.show()
#We see that there are some outliers in the right side.
```



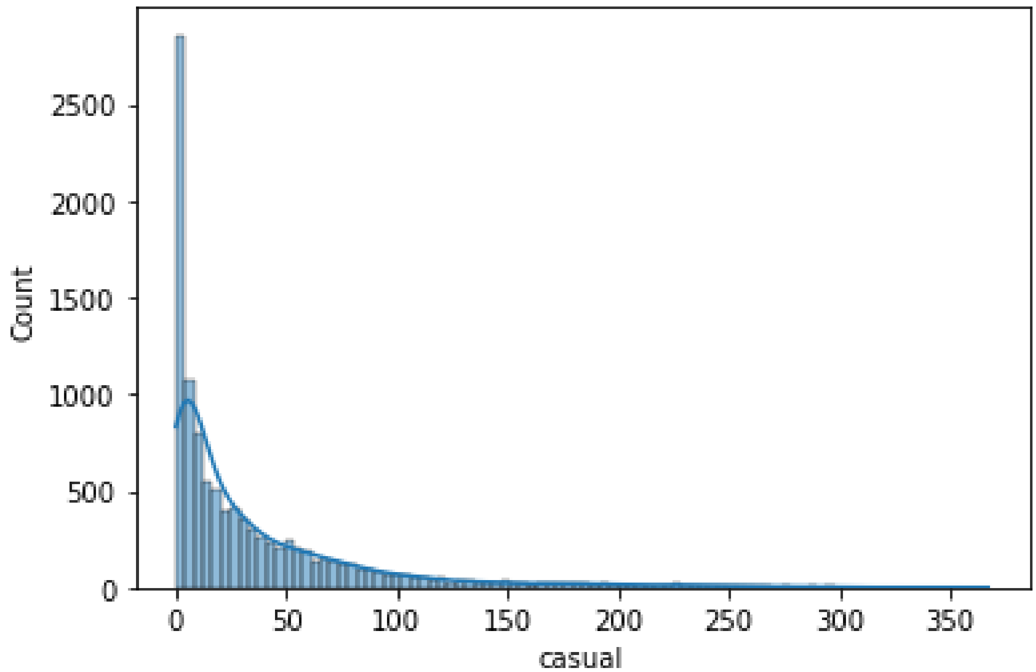
[44]:
```
#Since there are a few outliers in the windspeed column, therefore we can␣
↪remove them.
q1=np.percentile(df['windspeed'],25)
q3=np.percentile(df['windspeed'],75)
iqr=q3-q1
df=df[(df['windspeed']<q3+1.5*iqr)]
```

[45]:
```
#Checking if Windspeed column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['windspeed'],dist=stats.norm,plot=ax1)
plt.show()
#Windspeed column does not follow a normal distribution
```



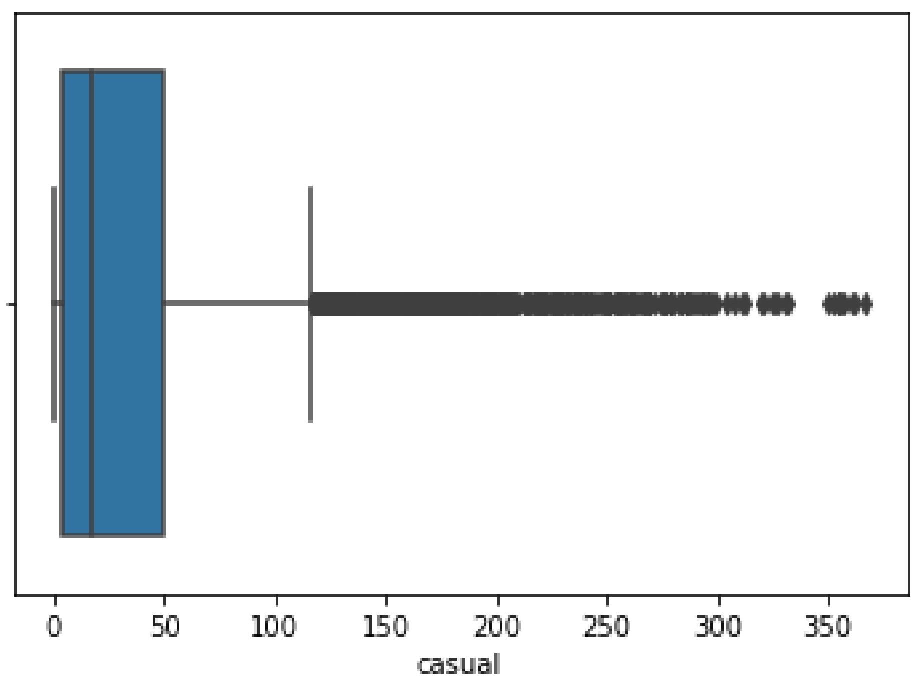
2.0.10 Analysis on Casual column

[46]:
```
sns.histplot(data=df,x='casual',kde=True)
plt.show()
#It is right skewed
```



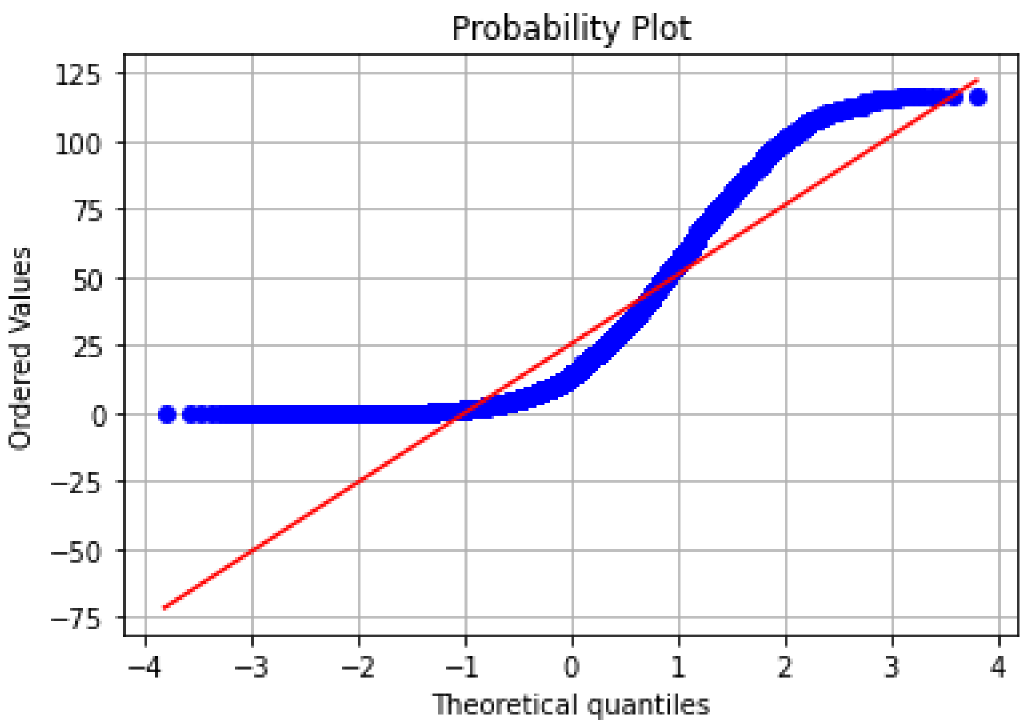
[47]:

```
sns.boxplot(data=df,x='casual')
plt.show()
#We see that there are a lot of outliers in the right side.
```



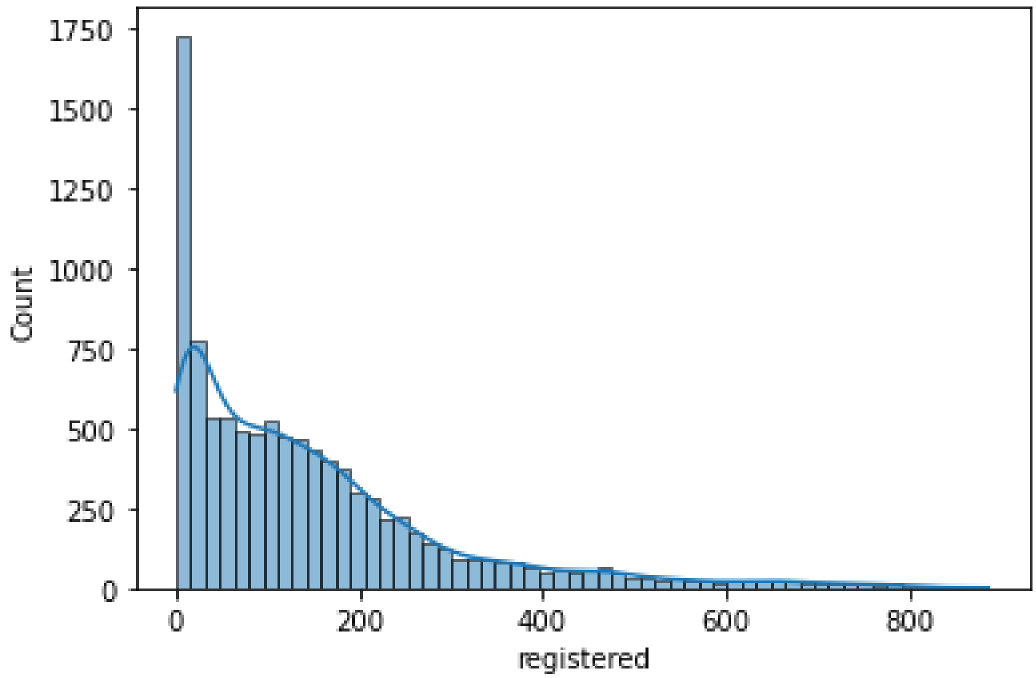
```
[48]: #Since there are a few outliers in the casual column, therefore we can remove␣
      ↪them.
      q1=np.percentile(df['casual'],25)
      q3=np.percentile(df['casual'],75)
      iqr=q3-q1
      df=df[(df['casual']<q3+1.5*iqr)]
```

```
[49]: #Checking if Casual column follows a normal distribution
      fig,ax1=plt.subplots()
      plt.grid()
      stats.probplot(x=df['casual'],dist=stats.norm,plot=ax1)
      plt.show()
      #Casual column does not follow a normal distribution
```

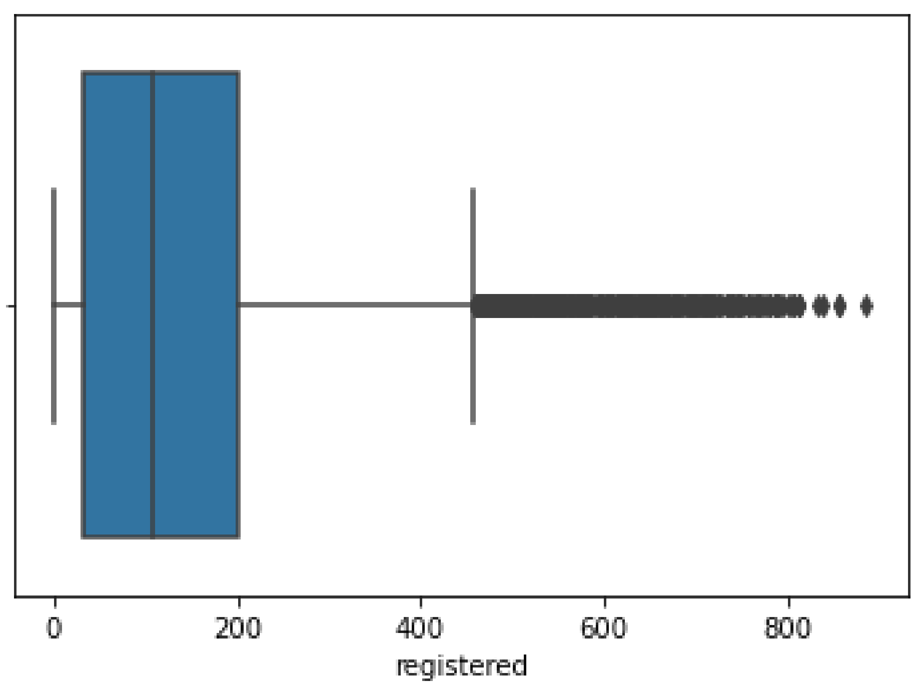


2.0.11 Analysis on Registered column

```
[50]: sns.histplot(data=df,x='registered',kde=True)
      plt.show()
      #It is ritgh skewed
```

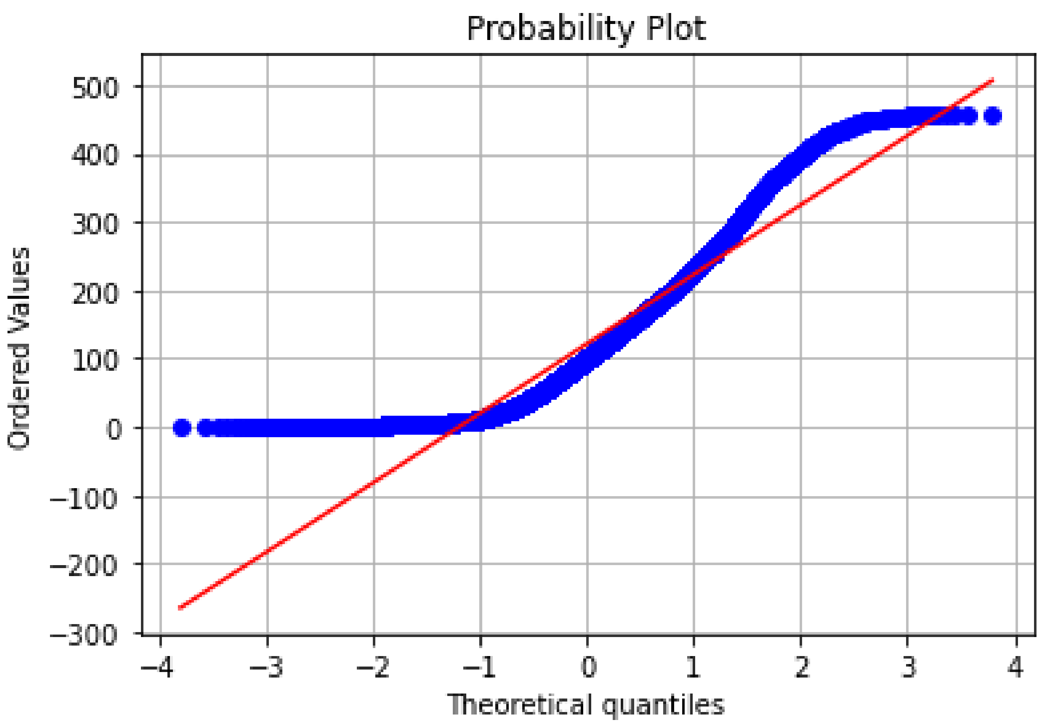


[51]:
```
sns.boxplot(data=df,x='registered')
plt.show()
#We see that there are a lot of outliers in the right side.
```



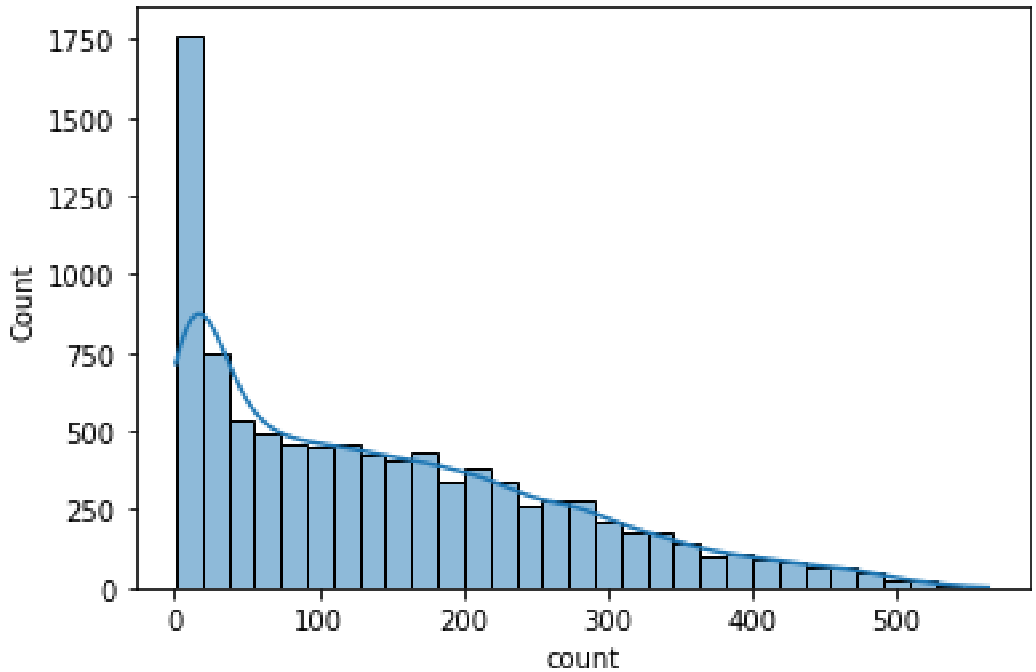
[52]:
```
#Since there are a few outliers in the Registered column, therefore we can␣
↪remove them.
q1=np.percentile(df['registered'],25)
q3=np.percentile(df['registered'],75)
iqr=q3-q1
df=df[(df['registered']<q3+1.5*iqr)]
```

[53]:
```
#Checking if Registered column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['registered'],dist=stats.norm,plot=ax1)
plt.show()
#Registered column does not follow a normal distribution
```

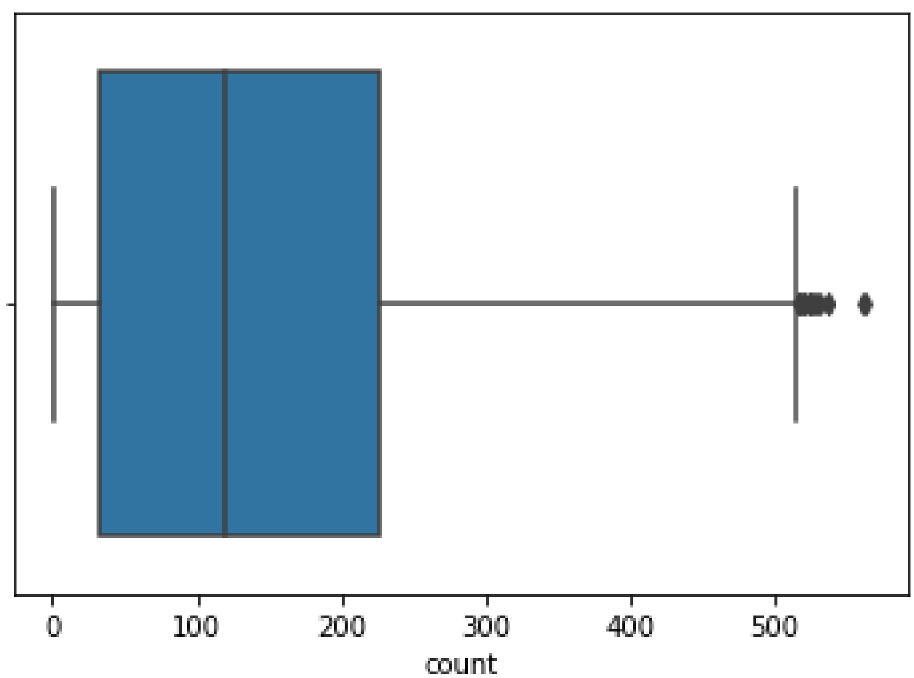


2.0.12 Analysis on Count column

[54]:
```
sns.histplot(data=df,x='count',kde=True)
plt.show()
#It is right skewed.
```



[55]:
```
sns.boxplot(data=df,x='count')
plt.show()
#We see that there are a lot of outliers in the right side.
```

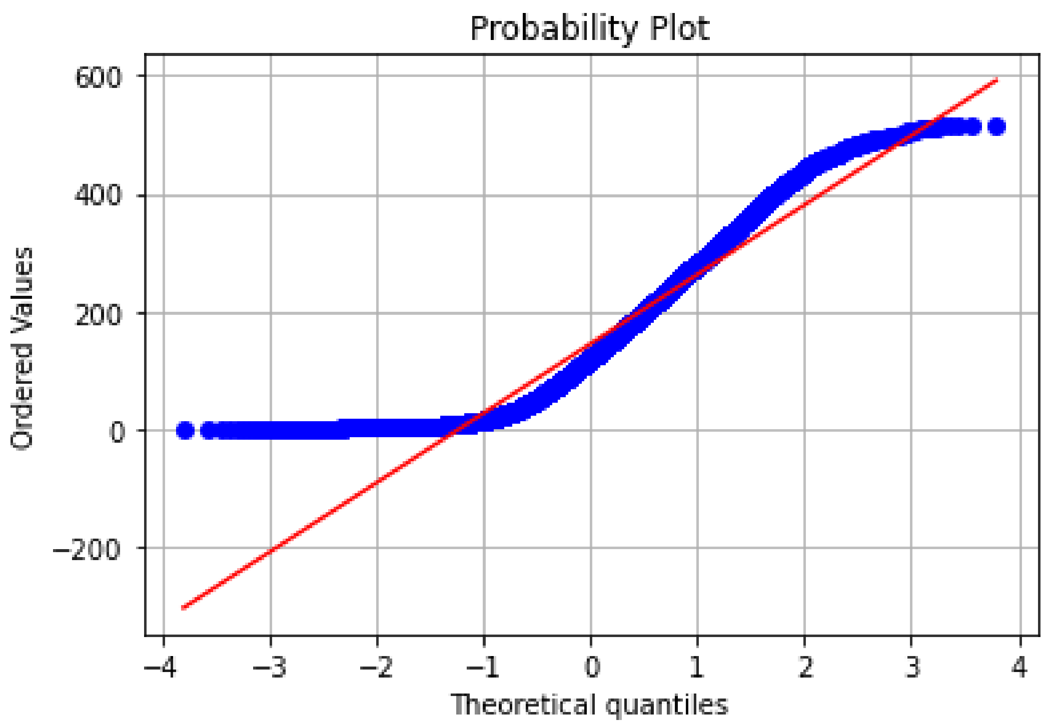


[56]:

```
#Since there are a few outliers in the Count column, therefore we can remove␣
↪them.
q1=np.percentile(df['count'],25)
q3=np.percentile(df['count'],75)
iqr=q3-q1
df=df[(df['count']<q3+1.5*iqr)]
```

[57]:

```
#Checking if Count column follows a normal distribution
fig,ax1=plt.subplots()
plt.grid()
stats.probplot(x=df['count'],dist=stats.norm,plot=ax1)
plt.show()
#Count column does not follow a normal distribution
```

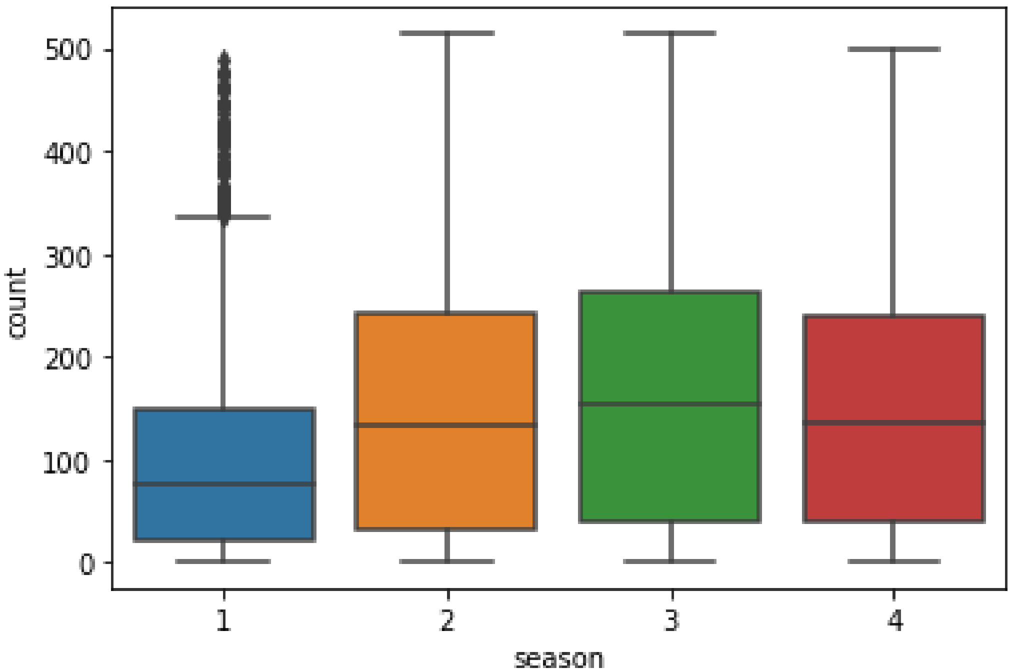


[ ]:

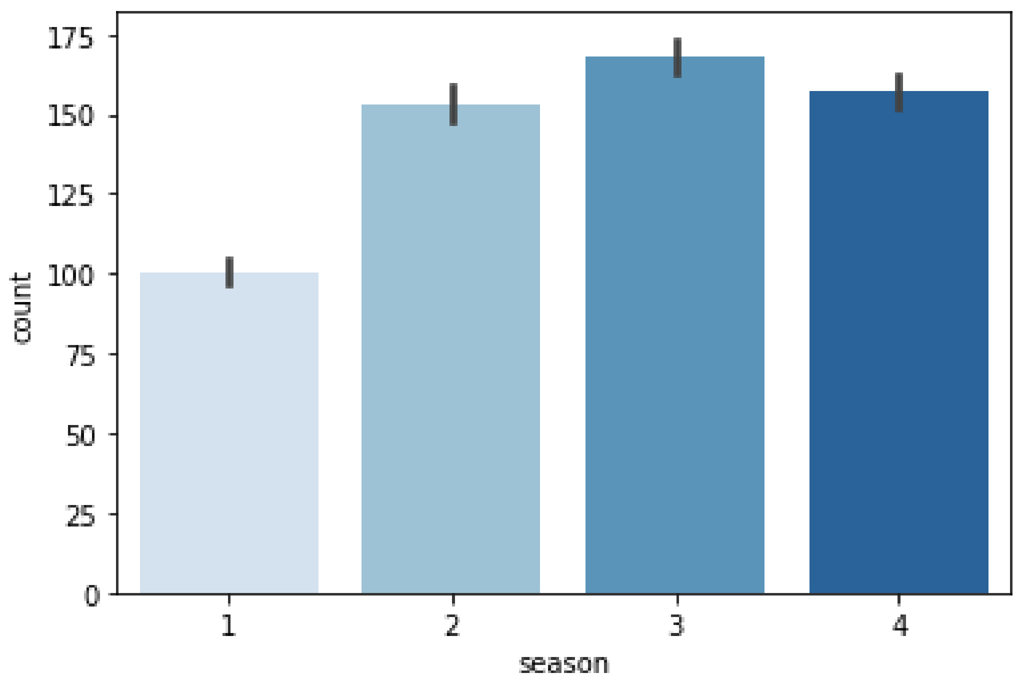
3 Bi-Variate Analysis.

3.0.1 Season And Count

[58]:
```
sns.boxplot(data=df,x='season',y='count')
plt.show()
```



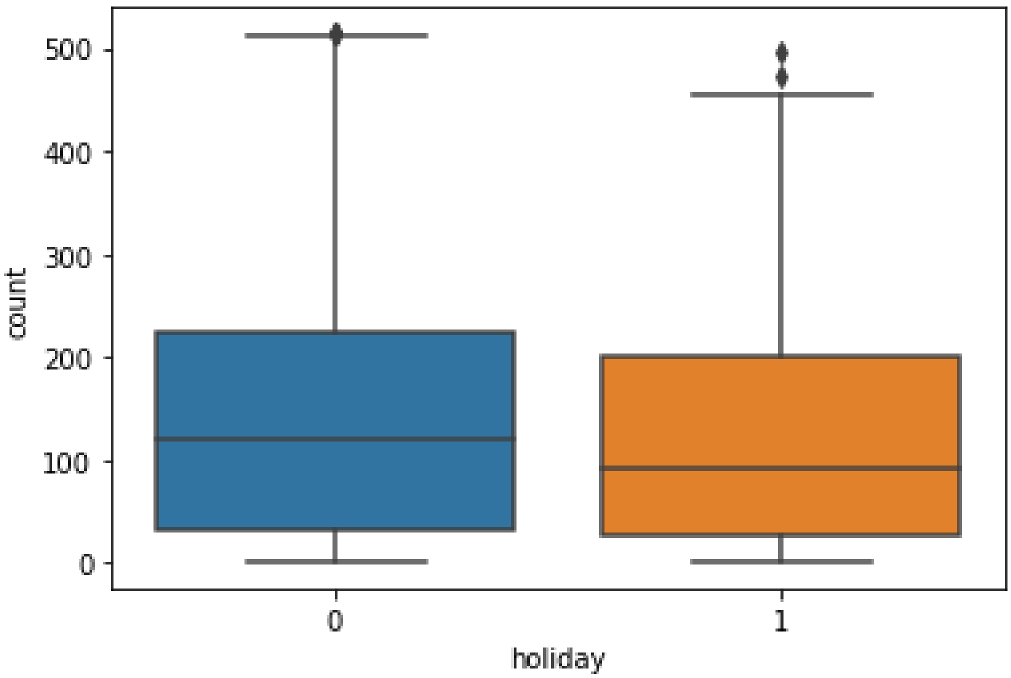
[59]:
```
sns.barplot(data=df,x='season',y='count',palette='Blues')
plt.show()
```



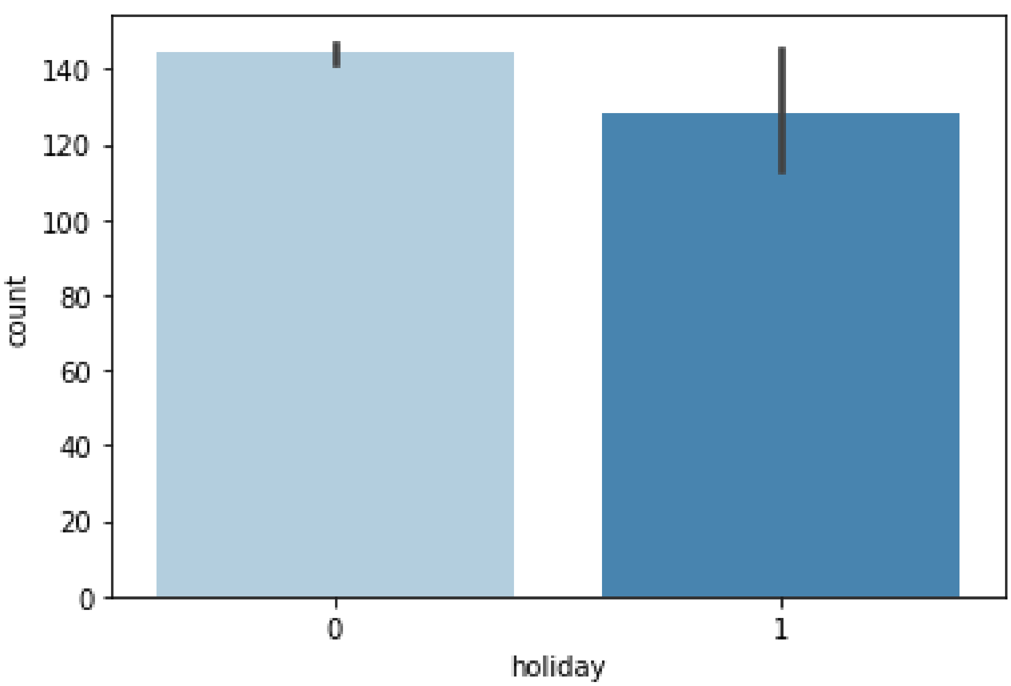
Inference - The mean count of electric cycles rented is highest for season 3 and lowest for season 1.

3.0.2 Holiday And Count

[60]:
```
sns.boxplot(data=df,x='holiday',y='count')
plt.show()
```



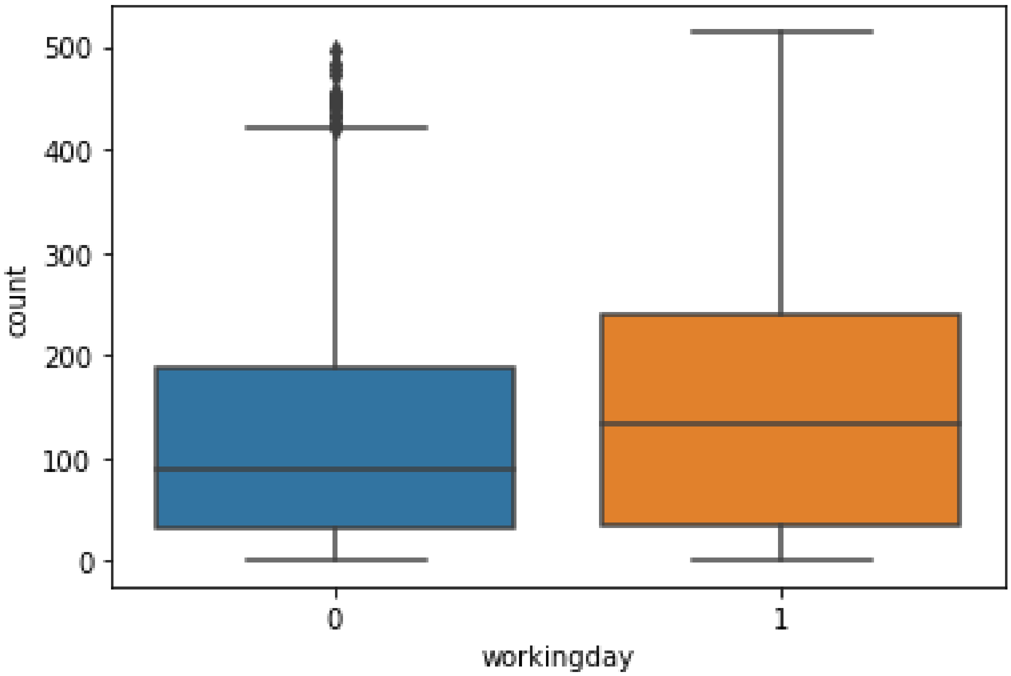
[61]:
```
sns.barplot(data=df,x='holiday',y='count',palette='Blues')
plt.show()
```



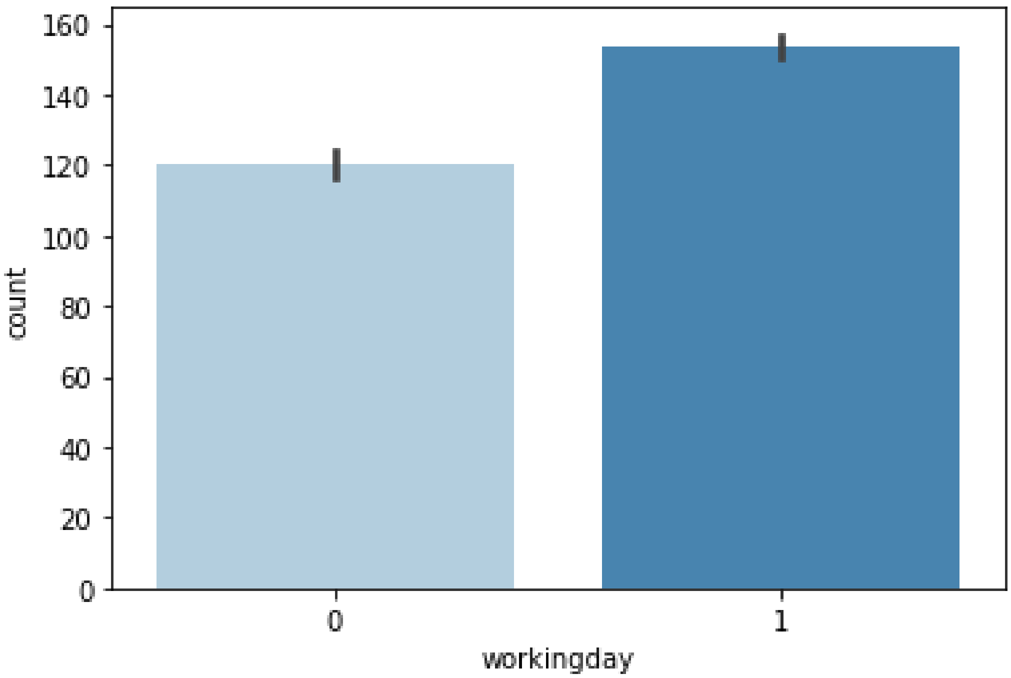
Inference - The mean count of electric cycles rented for non-holidays is more than holidays.

3.0.3 Working-Day And Count

[62]:
```
sns.boxplot(data=df,x='workingday',y='count')
plt.show()
```



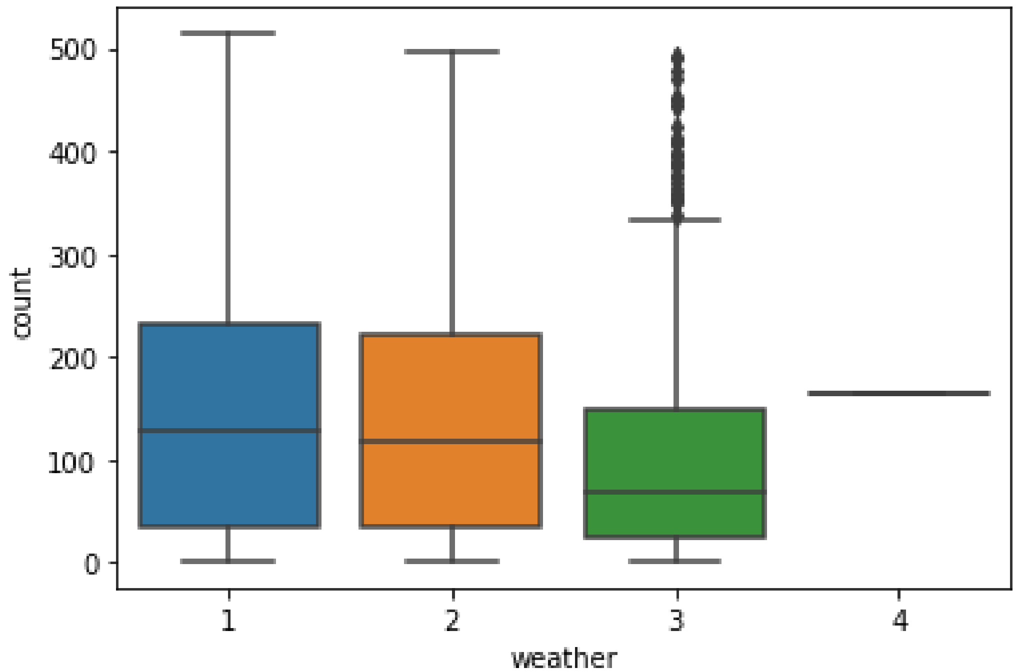
[63]:
```
sns.barplot(data=df,x='workingday',y='count',palette='Blues')
plt.show()
```



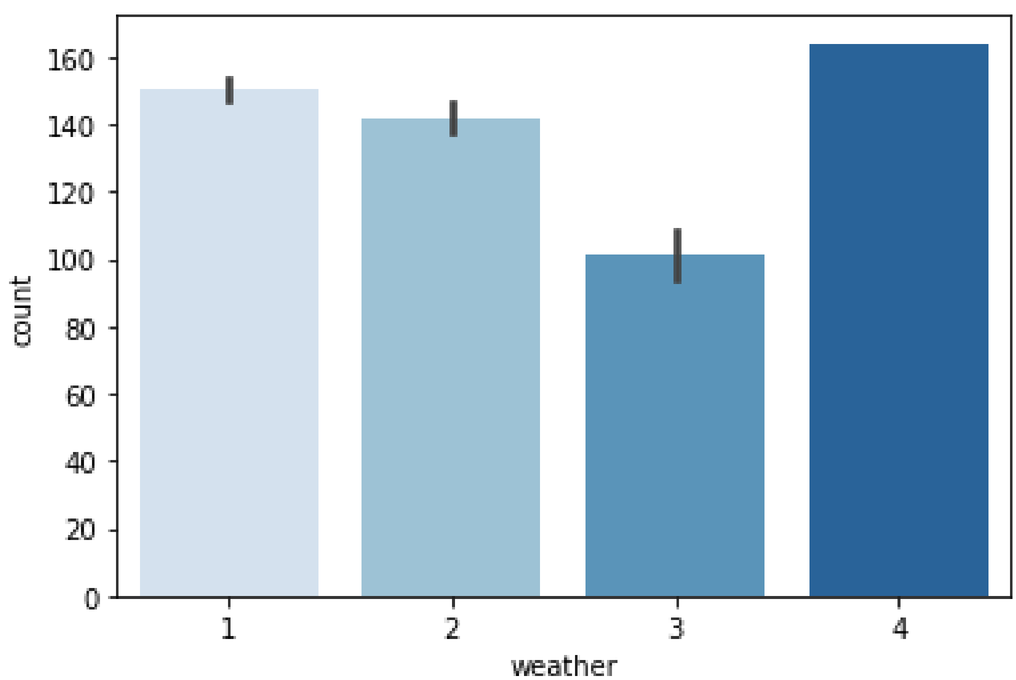
Inference - The mean count of electric cycles rented for working-days is more than non working-days.

3.0.4 Weather And Count

[64]:
```
sns.boxplot(data=df,x='weather',y='count')
plt.show()
```



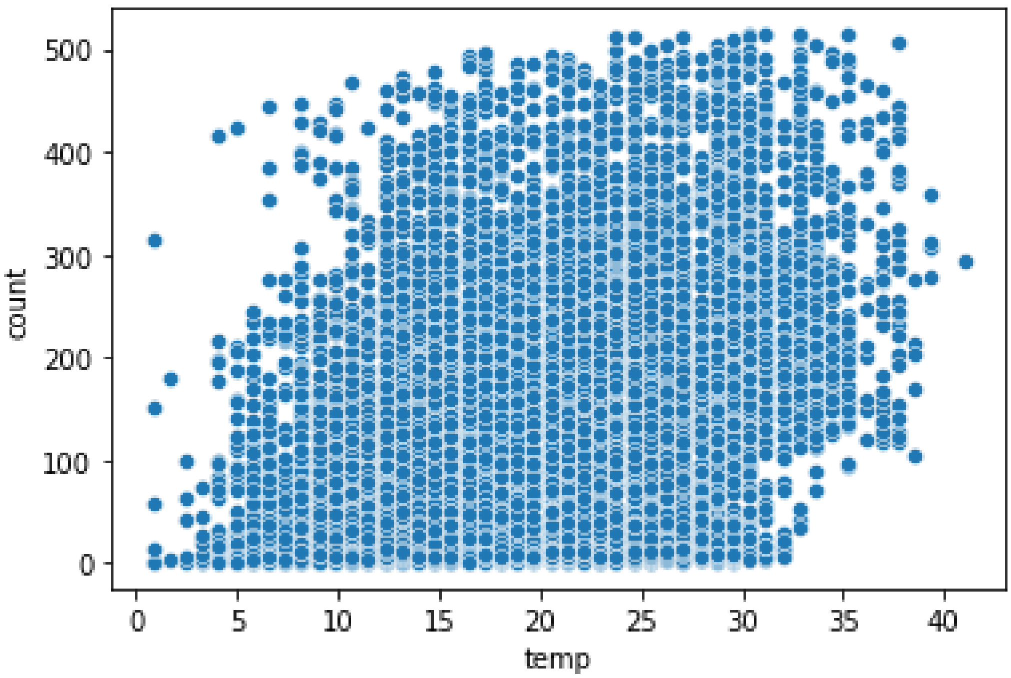
[65]:
```
sns.barplot(data=df,x='weather',y='count',palette='Blues')
plt.show()
```



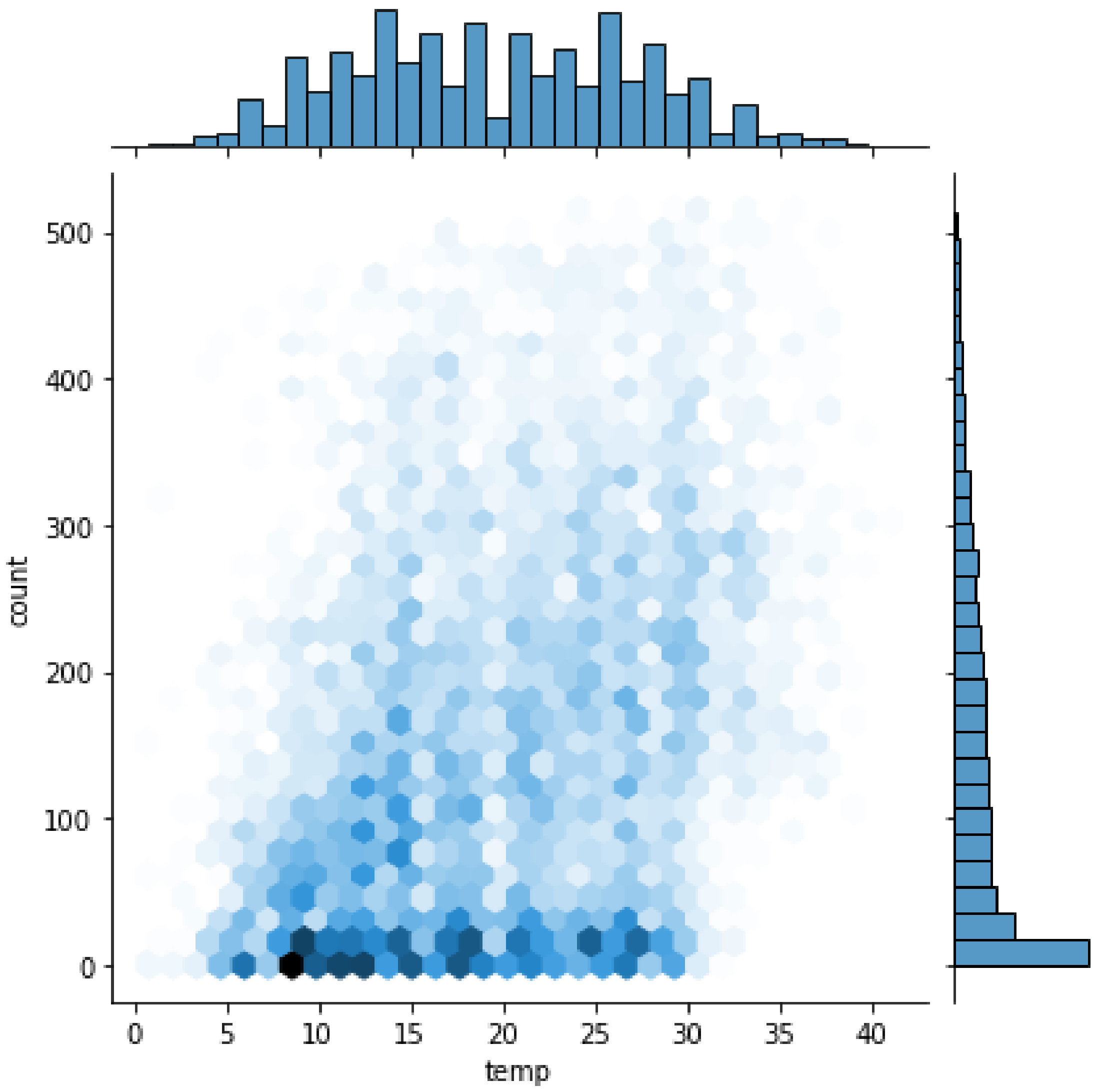
Inference - We saw earlier that we juist have 1 data point for weather 4, hence we can ignore it. The mean and median count of electric cycles rented is greater for weather 1 and weather2.

3.0.5 Temp And Count

[66]:
```
sns.scatterplot(data=df,x='temp',y='count')
plt.show()
```



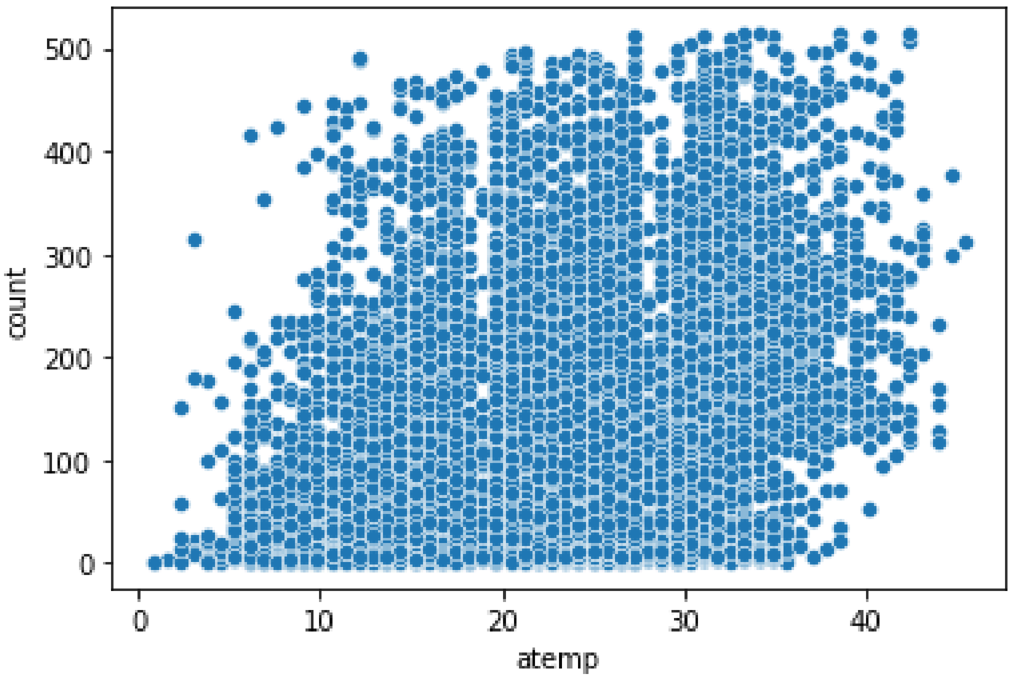
[67]:
```
sns.jointplot(data=df,x='temp',y='count',kind='hex')
plt.show()
```



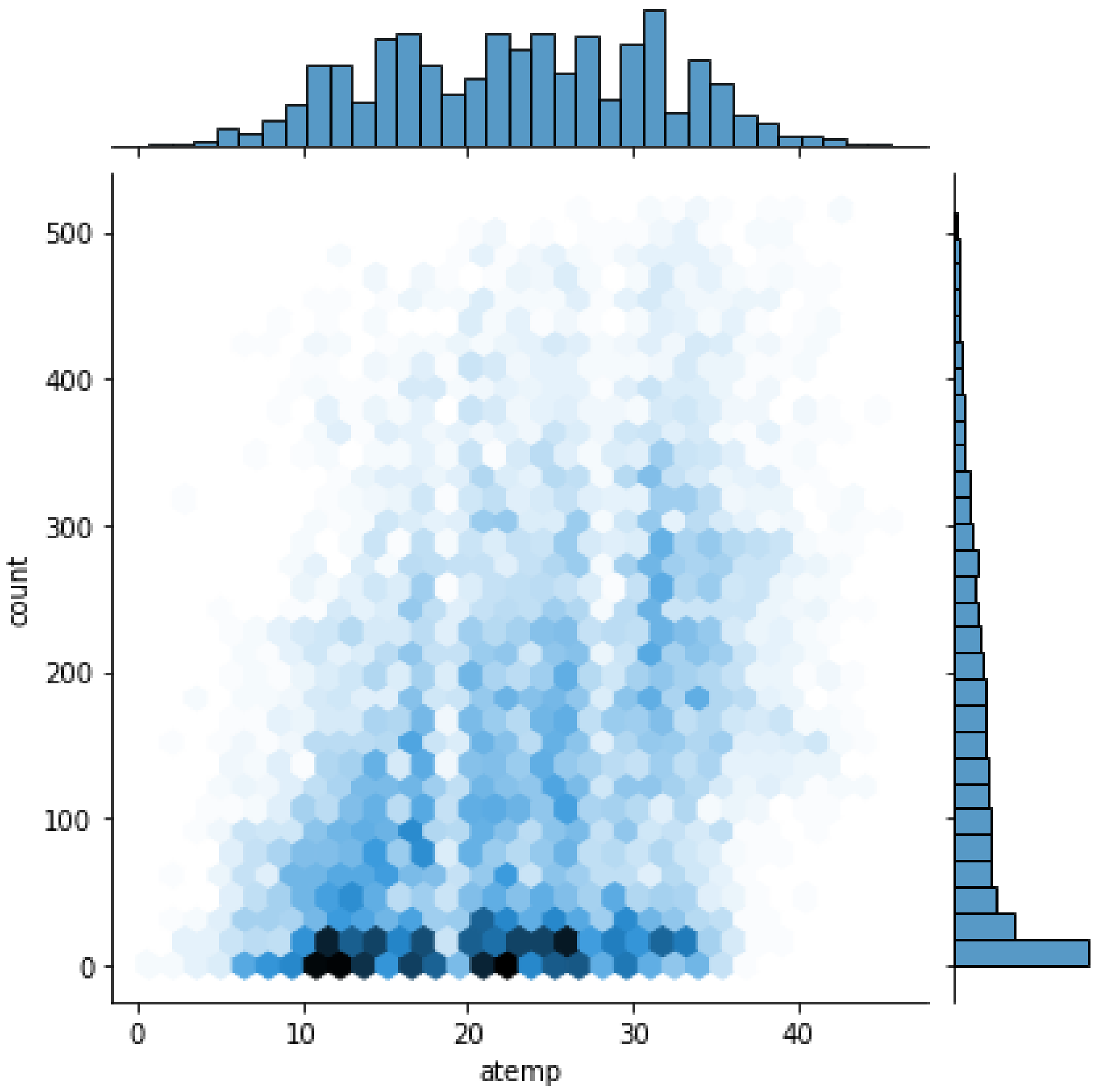
Inference - We can conclude that count and temp do not have a linear relationship.

3.0.6 A-Temp And Count

[68]:
```
sns.scatterplot(data=df,x='atemp',y='count')
plt.show()
```



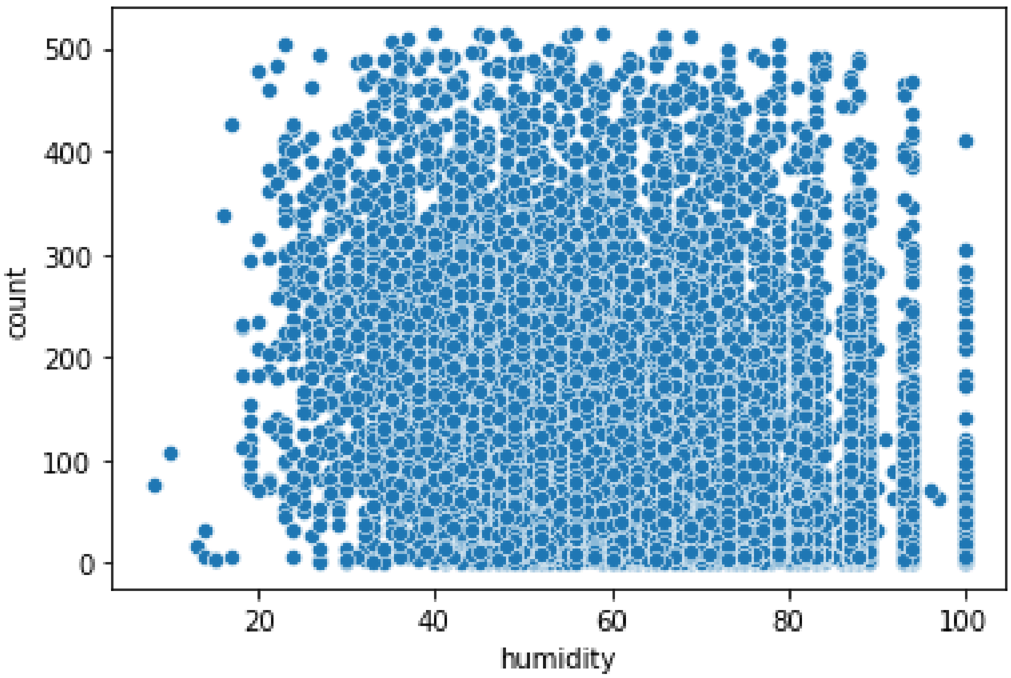
[69]:
```
sns.jointplot(data=df,x='atemp',y='count',kind='hex')
plt.show()
```



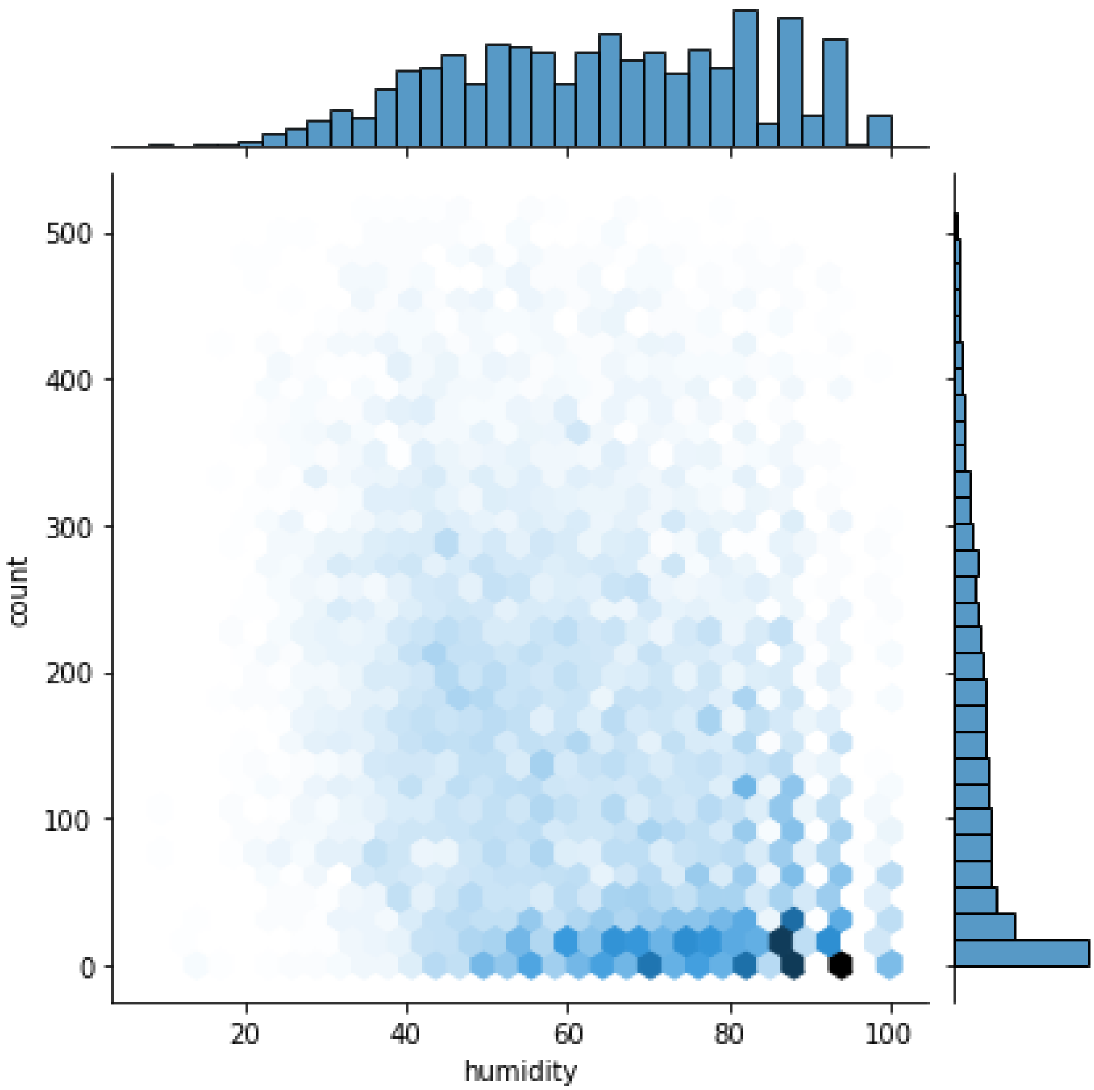
Inference - We can conclude that count and a-temp do not have a linear relationship.

3.0.7 Humidity And Count

[70]:
```
sns.scatterplot(data=df,x='humidity',y='count')
plt.show()
```



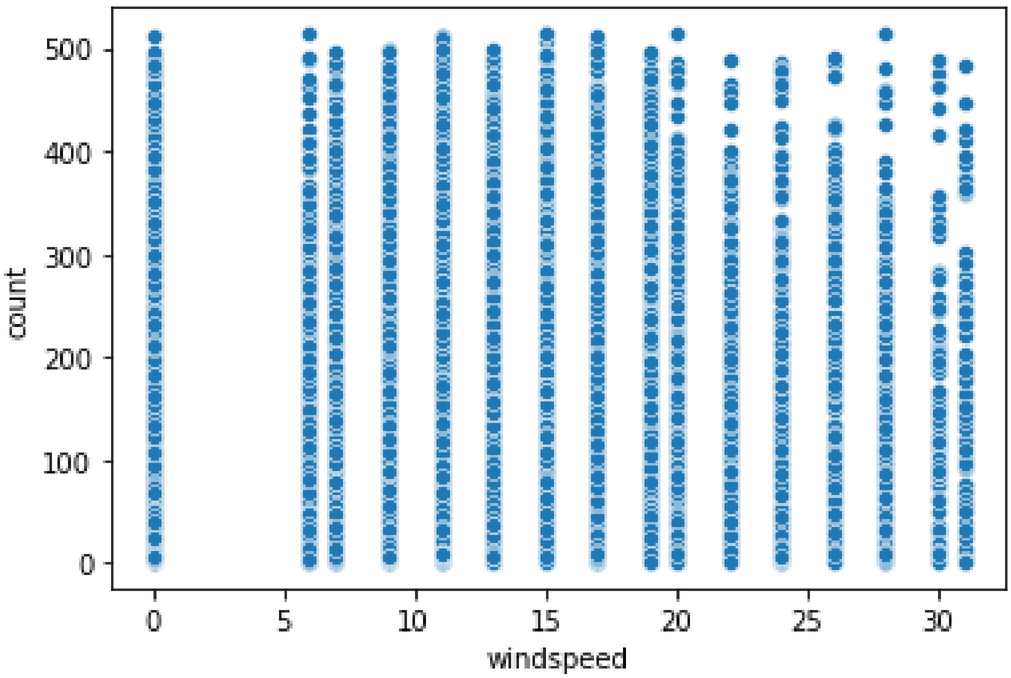
[71]:
```
sns.jointplot(data=df,x='humidity',y='count',kind='hex')
plt.show()
```



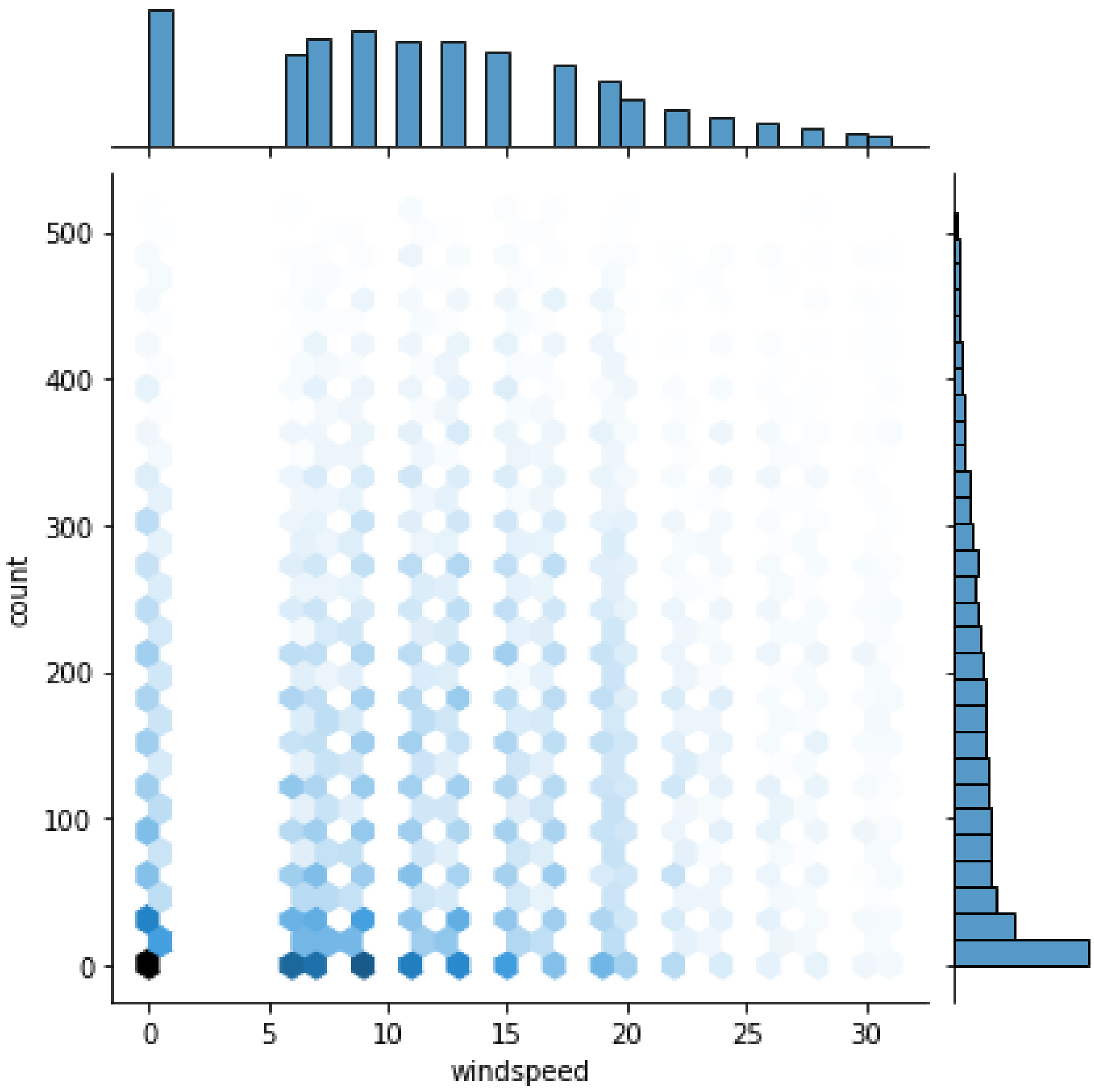
Inference - We can conclude that count and humidity do not have a linear relationship.

3.0.8 Windspeed And Count

[72]:
```
sns.scatterplot(data=df,x='windspeed',y='count')
plt.show()
```



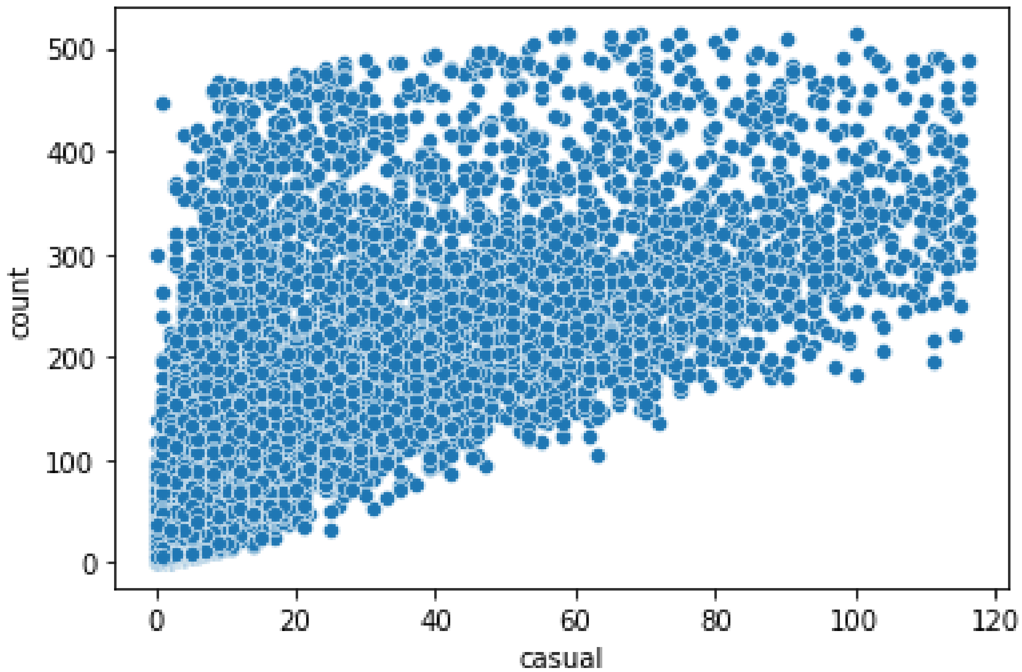
[73]:
```
sns.jointplot(data=df,x='windspeed',y='count',kind='hex')
plt.show()
```



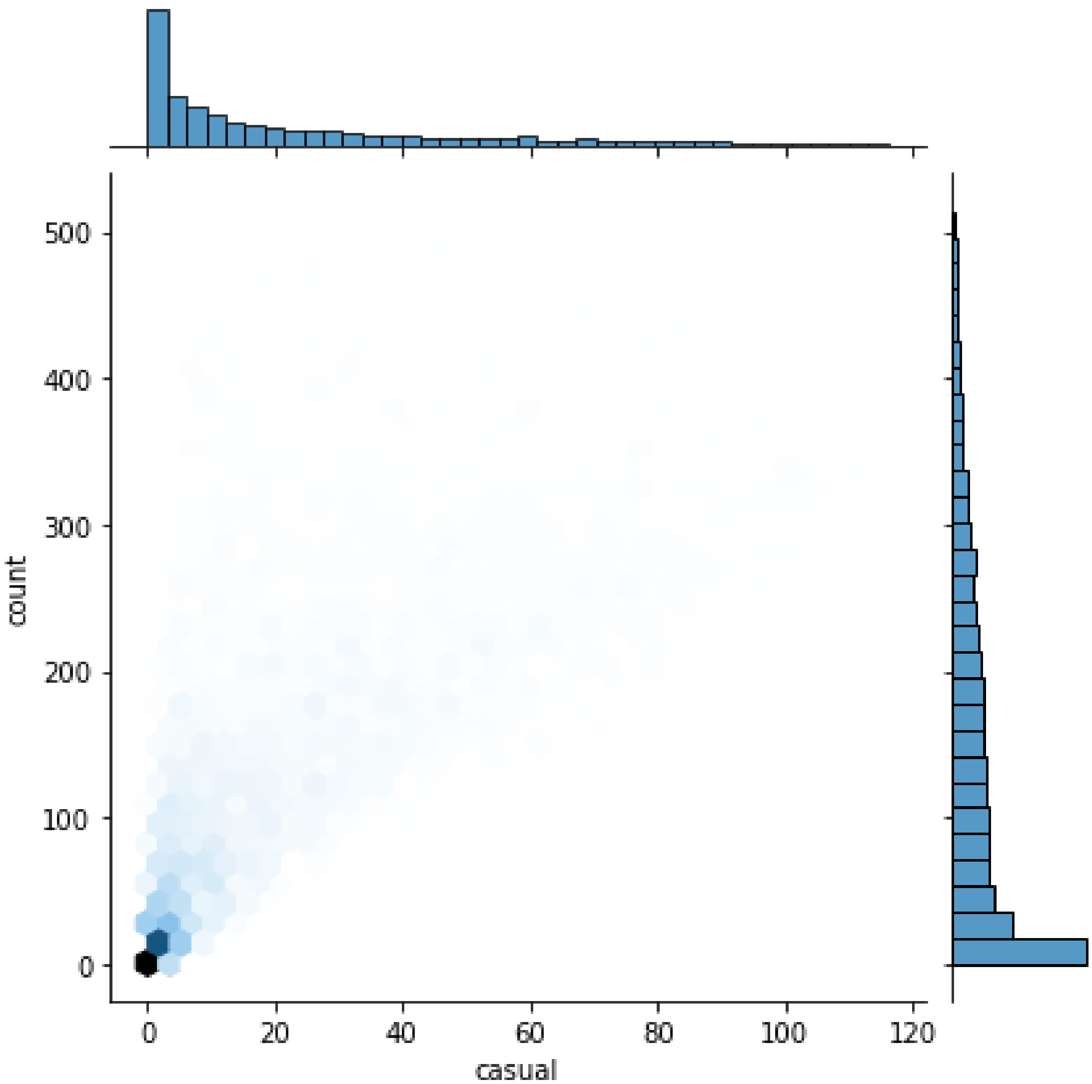
Inference - We can conclude that count and windspeed do not have a linear relationship.

3.0.9 Casual And Count

[74]:
```
sns.scatterplot(data=df,x='casual',y='count')
plt.show()
```



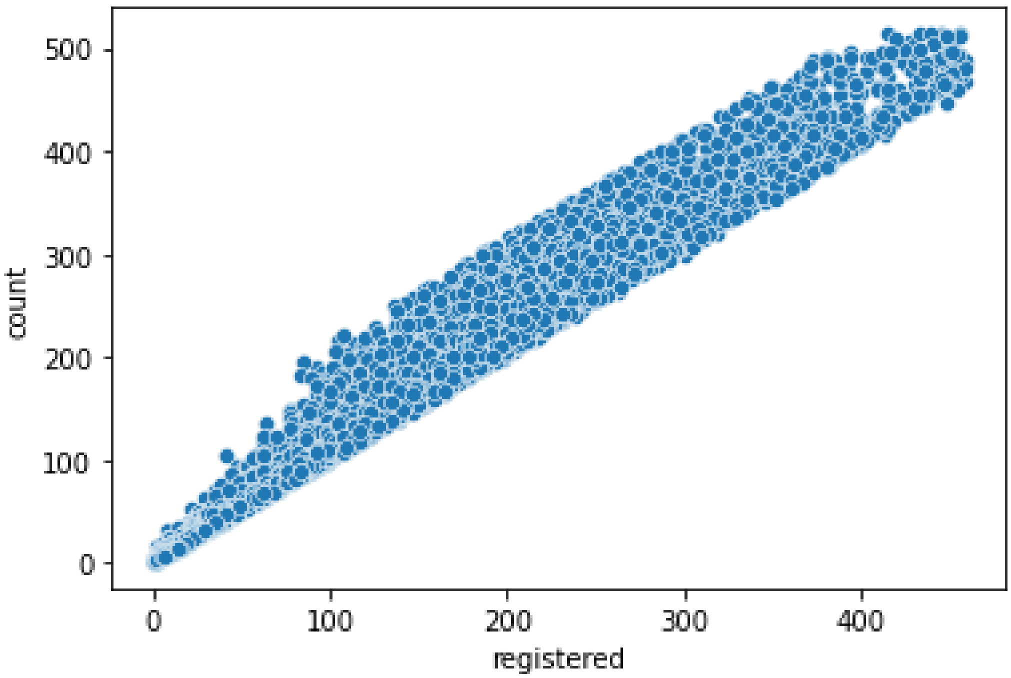
[75]:
```
sns.jointplot(data=df,x='casual',y='count',kind='hex')
plt.show()
```



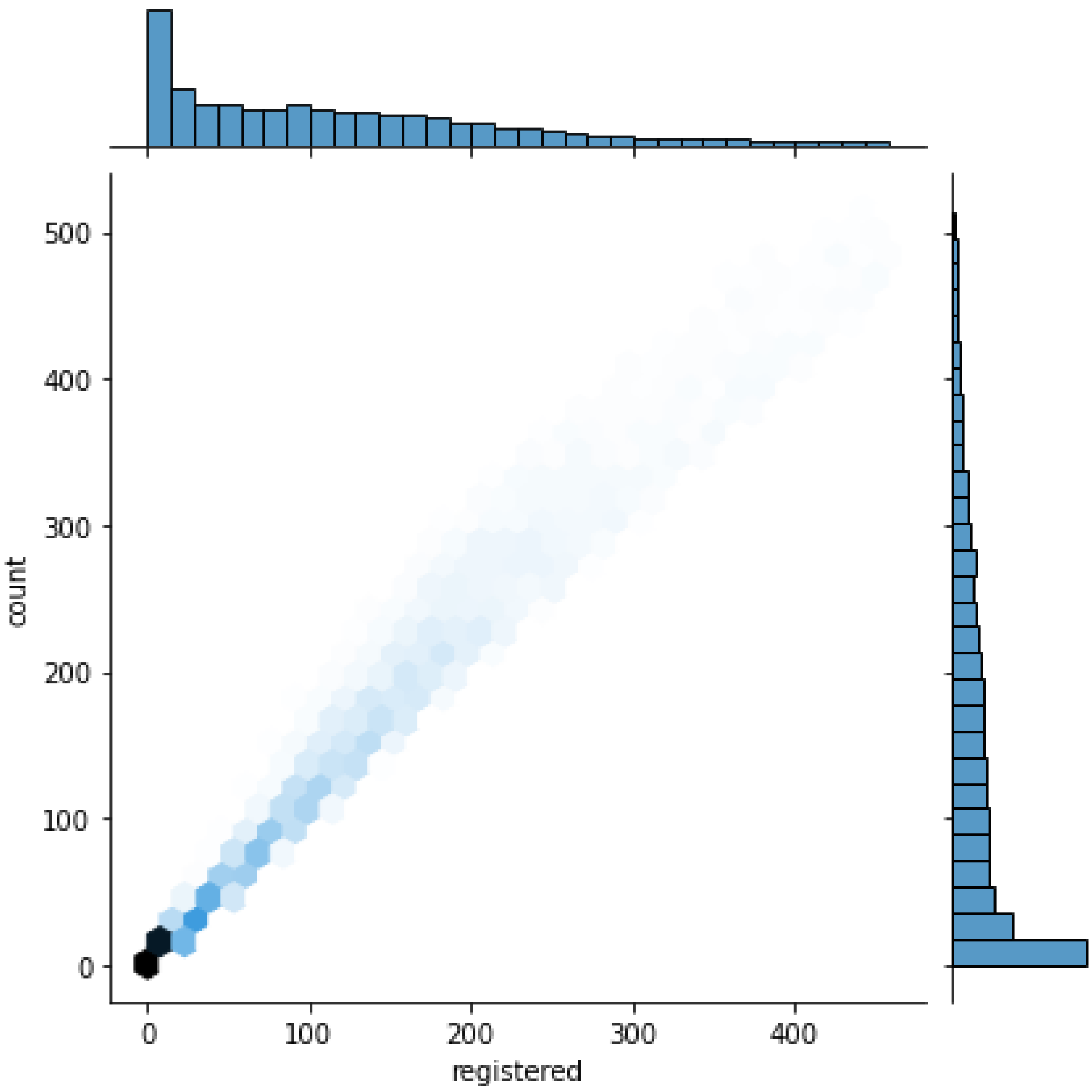
Inference - We can observe that count and casual have a positive relationship, but it is not perfectly linear. Also this relationship is expected since count = registered + casual.

3.0.10 Registered And Count

[76]:
```
sns.scatterplot(data=df,x='registered',y='count')
plt.show()
```



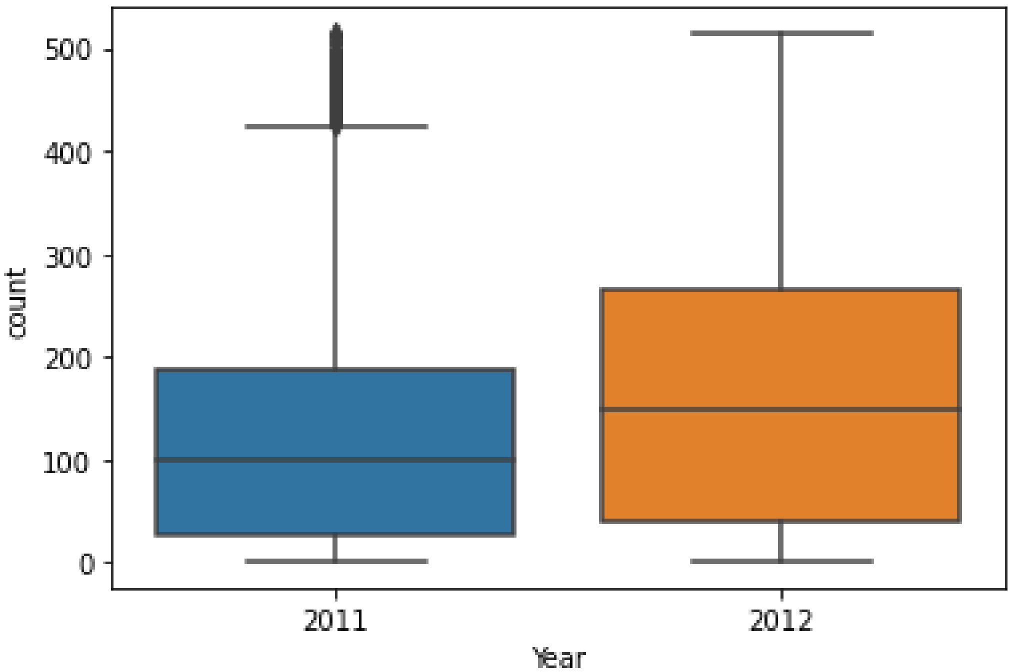
[77]:
```
sns.jointplot(data=df,x='registered',y='count',kind='hex')
plt.show()
```



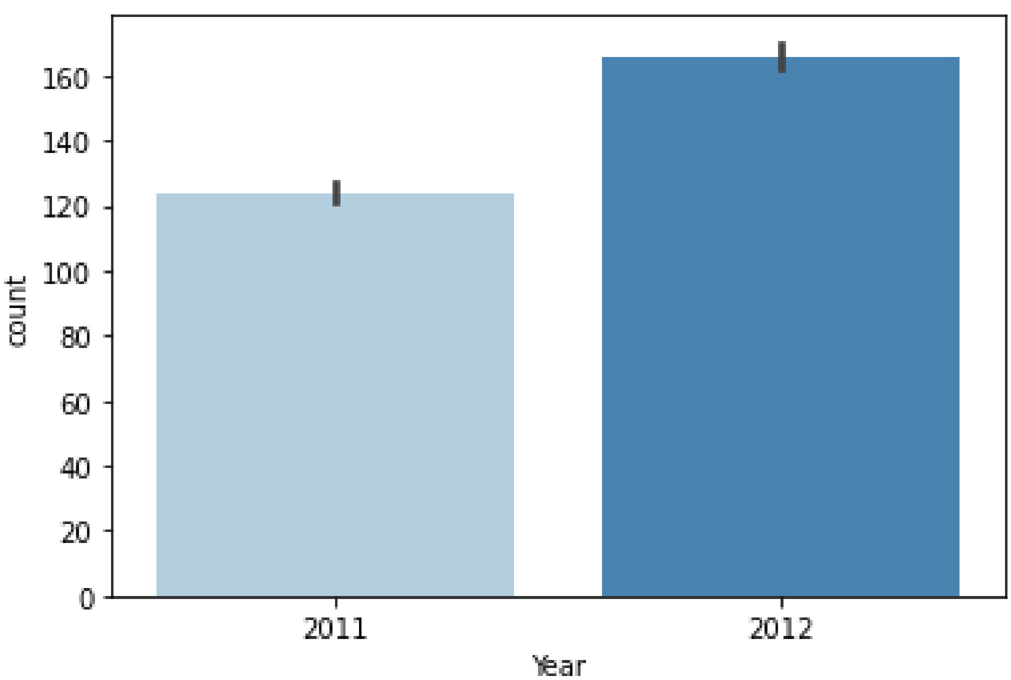
Inference - We can observe that count and registered have a positive linear relationship, but it is not perfectly linear. Also this relationship is expected since count = registered + casual.

3.0.11 Year And Count

[78]:
```
sns.boxplot(data=df,x='Year',y='count')
plt.show()
```



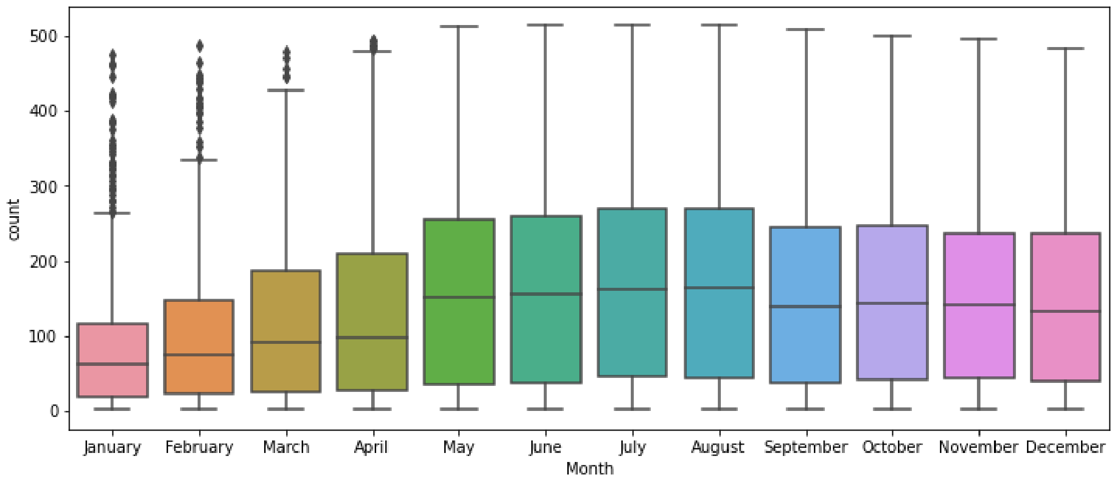
[79]:
```
sns.barplot(data=df,x='Year',y='count',palette='Blues')
plt.show()
```



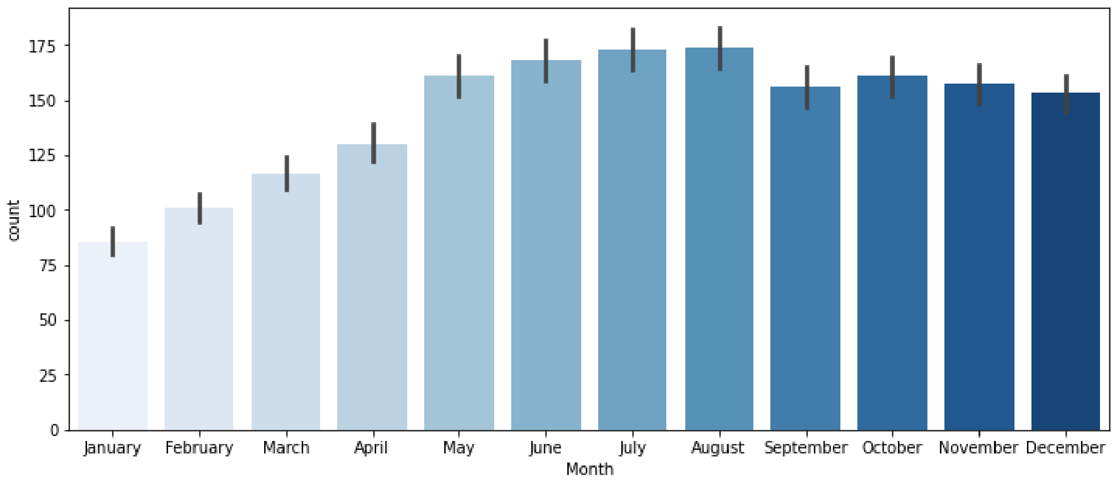
Inference - We observe that the mean and median count of electric cycles is rented is more in 2012 than 2011.

3.0.12 Month And Count

[80]:
```
plt.figure(figsize=(12,5))
sns.boxplot(data=df,x='Month',y='count')
plt.show()
```



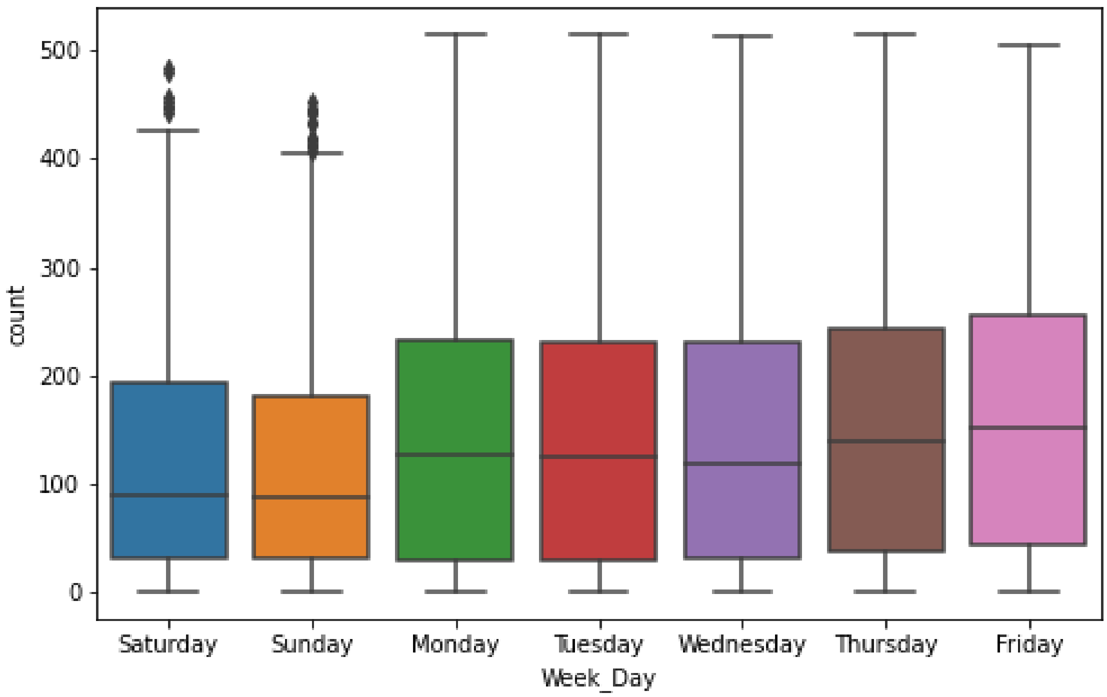
[81]:
```
plt.figure(figsize=(12,5))
sns.barplot(data=df,x='Month',y='count',palette='Blues')
plt.show()
```



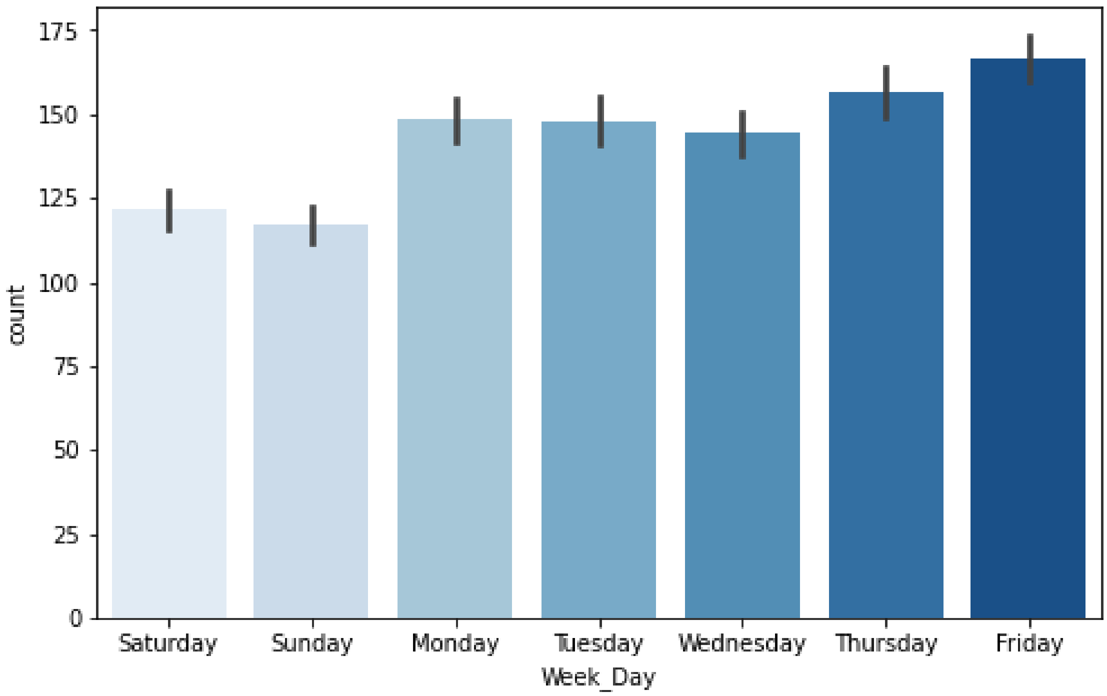
Inference - We can observe that mean and median count of cycles rented is maximum for the middle 4 months and minimum for the first 4 months.

3.0.13 Week_day And Count

[82]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=df,x='Week_Day',y='count')
plt.show()
```



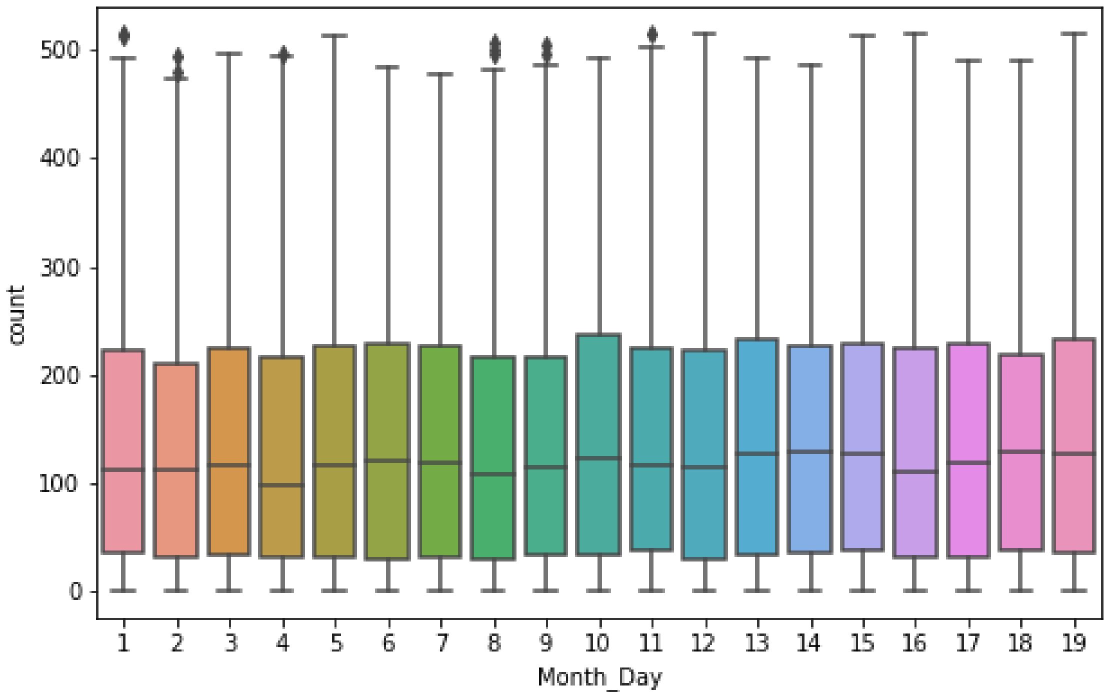
[83]:
```
plt.figure(figsize=(8,5))
sns.barplot(data=df,x='Week_Day',y='count',palette='Blues')
plt.show()
```



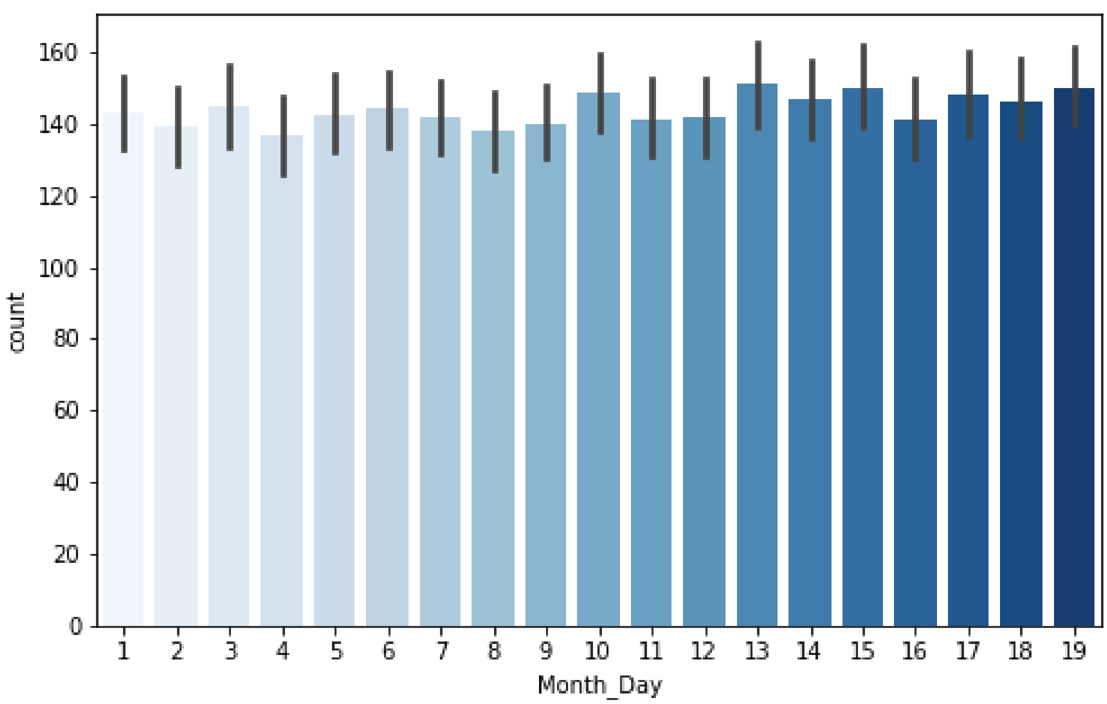
Inference - We can observe that mean and median count of cycles rented is maximum for Friday and minimum for Sunday and Saturday.

3.0.14 Month_Day And Count

[84]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=df,x='Month_Day',y='count')
plt.show()
```



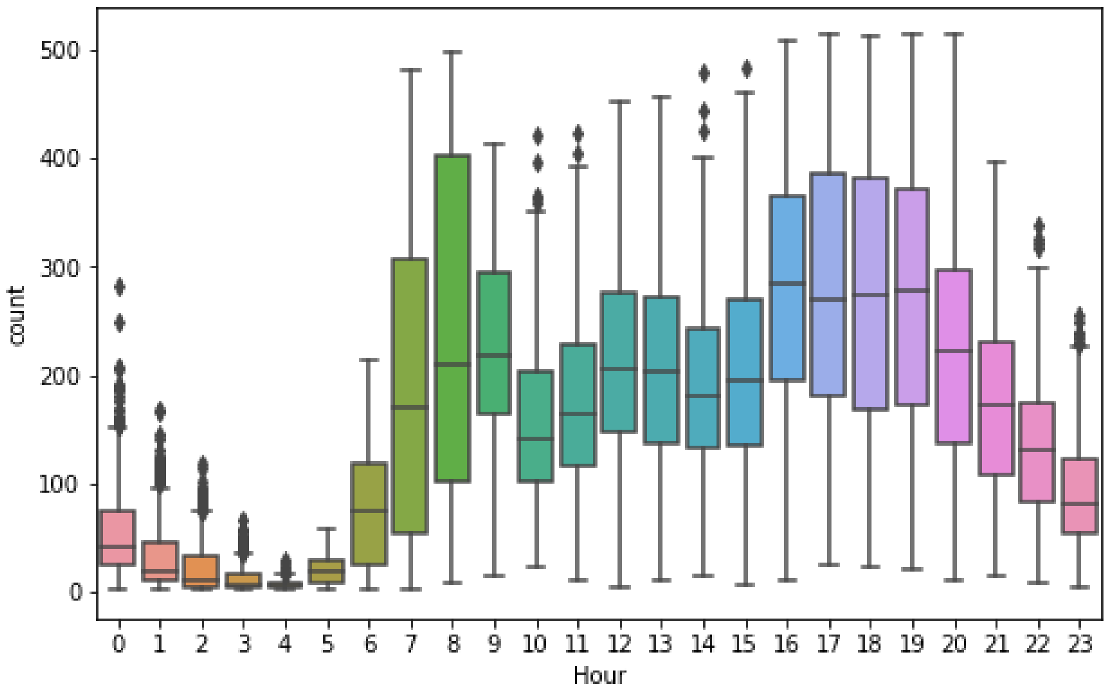
[85]:
```
plt.figure(figsize=(8,5))
sns.barplot(data=df,x='Month_Day',y='count',palette='Blues')
plt.show()
```



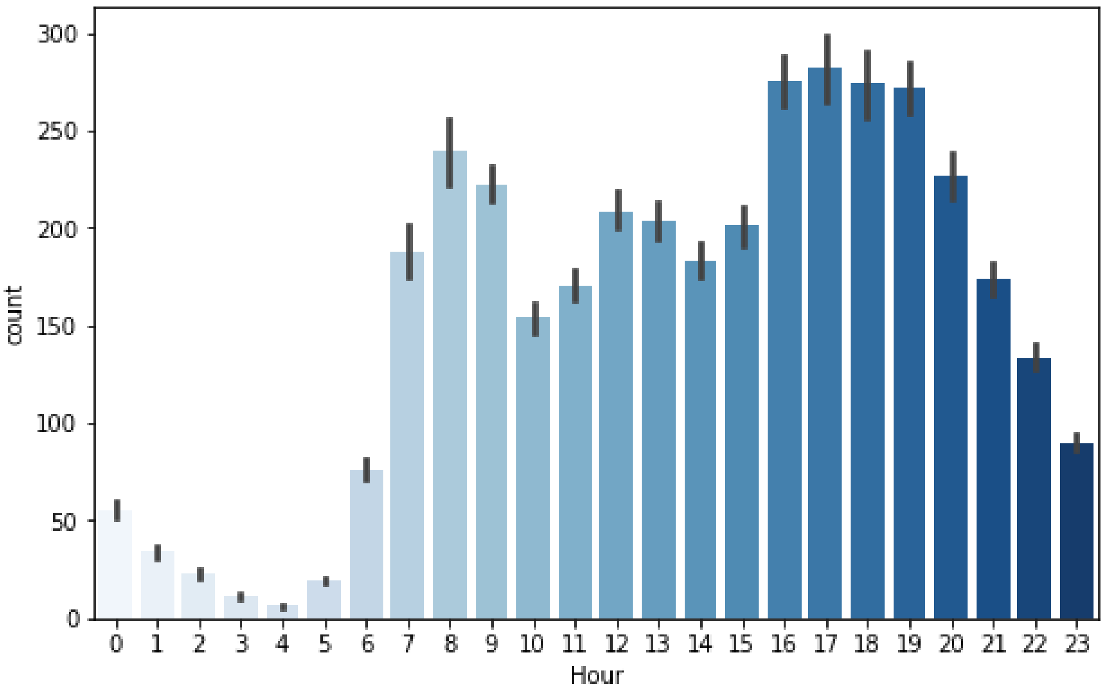
Inference - We can observe that mean and median count of cycles rented is almost same for all month_days.

3.0.15 Hour And Count

[86]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=df,x='Hour',y='count')
plt.show()
```



[87]:
```
plt.figure(figsize=(8,5))
sns.barplot(data=df,x='Hour',y='count',palette='Blues')
plt.show()
```



Inference - We can observe that mean and median count of cycles rented is minimum from 12 AM to 6 AM, and maximum for 4 PM to 8 PM.

[ ]:

4 Hypothesis Testing

-

4.0.1 1) To check if Working-Day has an effect on the number of electric cycles rented.

[88]:
```
#Lets check the different categories of working day
df['workingday'].unique().tolist()
```

[88]: [0, 1]

[89]:
```
#Lets segregate the two datasets
working_day_0 = df.loc[df['workingday']==0,'count']
working_day_1 = df.loc[df['workingday']==1,'count']
```

[90]:
```
#Lets check the length of both datasets.
print(len(working_day_0),len(working_day_1))
```

```
2724 6640
```

-

  We can perform a 2 sample independent t-test to verify whether working-day has an effect on the number of electric cycles rented, since the population mean and standard deviation are unknown.

- Null Hypothesis : Working-Day has no effect on number of electric cycles rented, which can be represented as : Mean number of cycles sold for category zero is same as mean number of cycles sold for category one : Mean(Category 0) = Mean(Category 1).
- Alternative Hypothesis : Working-Day has an effect on number of electric cycles rented, which can be represented as : Mean number of cycles sold for category zero is not same as mean number of cycles sold for category one : Mean(Category 0) != Mean(Category 1).

4.0.2 Assumptions:

- Population mean and sigma are finite.
- Observations are random and finite.

[91]:
```
alpha = 0.05
t_value,p_value=stats.ttest_ind(working_day_0,working_day_1)
print('p-value for two tailed test is {}'.format(p_value))
print()

if p_value<=alpha:
    print('Conclusion - Since p-value({}) <= alpha({})'.format(p_value,alpha))
    print('We reject the null hypothesis H0.')
    print('So we can conclude that the working-day has an effect on the mean␣
 ↪number of cycles sold.')

else:
    print('Conclusion - Since p-value({}) > alpha({})'.format(p_value,alpha))
    print('We cannot reject the null hypothesis H0.')
    print('So we can conclude that the working-day has no effect on the mean␣
 ↪number of cycles sold.')
```

```
p-value for two tailed test is 2.2552148137228035e-33

Conclusion - Since p-value(2.2552148137228035e-33) <= alpha(0.05)
We reject the null hypothesis H0.
So we can conclude that the working-day has an effect on the mean number of
cycles sold.
```

[ ]:

```

```

-

4.0.3 2) To check if Holiday has an effect on the number of electric cycles rented.

[92]:

```
#Lets check the different categories of holiday
df['holiday'].unique().tolist()
```

[92]: [0, 1]

[93]:

```
#Lets segregate the two datasets
holiday_0 = df.loc[df['holiday']==0,'count']
holiday_1 = df.loc[df['holiday']==1,'count']
```

[94]:

```
#Lets check the length of both datasets.
print(len(holiday_0),len(holiday_1))
```

```
9113 251
```

-

We can perform a 2 sample independent t-test to verify whether holiday has an effect on the number of electric cycles rented, since the population mean and standard deviation are unknown.

- Null Hypothesis : Holiday has no effect on number of electric cycles rented, which can be represented as : Mean number of cycles sold for holiday zero is same as mean number of cycles sold for holiday one : Mean(Holiday 0) = Mean(Holiday 1).
- Alternative Hypothesis : Holiday has an effect on number of electric cycles rented, which can be represented as : Mean number of cycles sold for Holiday zero is not same as mean number of cycles sold for Holiday one : Mean(Holiday 0) != Mean(Holiday 1).

4.0.4 Assumptions:

- Population mean and sigma are finite.
- Observations are random and finite.

[95]:

```
alpha = 0.05
t_value,p_value=stats.ttest_ind(holiday_0,holiday_1)
print('p-value for two tailed test is {}'.format(p_value))
```

```
print()

if p_value<=alpha:
    print('Conclusion - Since p-value({}) <= alpha({})'.format(p_value,alpha))
    print('We reject the null hypothesis H0.')
    print('So we can conclude that the Holiday has an effect on the mean number␣
 ↪of cycles sold.')

else:
    print('Conclusion - Since p-value({}) > alpha({})'.format(p_value,alpha))
    print('We cannot reject the null hypothesis H0.')
    print('So we can conclude that the Holiday has no effect on the mean number␣
 ↪of cycles sold.')
```

```
p-value for two tailed test is 0.04273994729053667

Conclusion - Since p-value(0.04273994729053667) <= alpha(0.05)
We reject the null hypothesis H0.
So we can conclude that the Holiday has an effect on the mean number of cycles
sold.
```

[ ]:

-

4.0.5 3) To check if no. of cycles rented is similar or different for different Weather categories

[96]:
```
#Lets check the different categories of weather
df['weather'].unique().tolist()
```

[96]: [1, 2, 3, 4]

[97]:
```
#Lets segregate the two datasets
weather_1 = df.loc[df['weather']==1,'count']
weather_2 = df.loc[df['weather']==2,'count']
weather_3 = df.loc[df['weather']==3,'count']
weather_4 = df.loc[df['weather']==4,'count']
```

[98]:
```
#Lets check the length of both datasets.
print(len(weather_1),len(weather_2),len(weather_3),len(weather_4))
```

```
6059 2533 771 1
```

-

  We can perform a One-Way ANOVA test to verify whether Weather has an effect on the number of electric cycles rented, since the no. of categories are more than 2.

- Null Hypothesis : Weather has no effect on the number of electric cycles rented, which can be represented as : There is no difference between the mean number of cycles sold for the different weather categories.
- Alternative Hypothesis : Weather has an effect on the number of electric cycles rented, which can be represented as : There is difference between the mean number of cycles sold for the different weather categories.

4.0.6 Assumptions:

- Variance of each group is almost same.
- Observations are random and finite.

[99]:
```
alpha = 0.05
f_value, p_value = stats.f_oneway(weather_1,weather_2,weather_3,weather_4)
print('p-value for two tailed test is {}'.format(p_value))
print()

if p_value<=alpha:
    print('Conclusion - Since p-value({}) <= alpha({})'.format(p_value,alpha))
    print('We reject the null hypothesis H0.')
    print('So we can conclude that the Weather has an effect on the mean number␣
 ↪of cycles sold.')

else:
    print('Conclusion - Since p-value({}) > alpha({})'.format(p_value,alpha))
    print('We cannot reject the null hypothesis H0.')
    print('So we can conclude that the Weather has no effect on the mean number␣
 ↪of cycles sold.')
```

```
p-value for two tailed test is 5.95629355789377e-24

Conclusion - Since p-value(5.95629355789377e-24) <= alpha(0.05)
We reject the null hypothesis H0.
So we can conclude that the Weather has an effect on the mean number of cycles
sold.
```

[ ]:

-

4.0.7 4) To check if no. of cycles rented is similar or different for different Season categories

[100]:
```
#Lets check the different categories of season
df['season'].unique().tolist()
```

[100]:
```
[1, 2, 3, 4]
```

[101]:
```
#Lets segregate the two datasets
season_1 = df.loc[df['season']==1,'count']
season_2 = df.loc[df['season']==2,'count']
season_3 = df.loc[df['season']==3,'count']
season_4 = df.loc[df['season']==4,'count']
```

[102]:
```
#Lets check the length of both datasets.
print(len(season_1),len(season_2),len(season_3),len(season_4))
```

```
2448 2249 2230 2437
```

-

We can perform a One-Way ANOVA test to verify whether Season has an effect on the number of electric cycles rented, since the no. of categories are more than 2.

- Null Hypothesis : Season has no effect on the number of electric cycles rented, which can be represented as : There is no difference between the mean number of cycles sold for the different Season categories.
- Alternative Hypothesis : Season has an effect on the number of electric cycles rented, which can be represented as : There is difference between the mean number of cycles sold for the different Season categories.

4.0.8 Assumptions:

- Variance of each group is almost same.
- Observations are random and finite.

[103]:

```
alpha = 0.05
f_value, p_value = stats.f_oneway(season_1,season_2,season_3,season_4)
print('p-value for two tailed test is {}'.format(p_value))
print()

if p_value<=alpha:
    print('Conclusion - Since p-value({}) <= alpha({})'.format(p_value,alpha))
    print('We reject the null hypothesis H0.')
    print('So we can conclude that the Season has an effect on the mean number␣
 ↪of cycles sold.')

else:
    print('Conclusion - Since p-value({}) > alpha({})'.format(p_value,alpha))
    print('We cannot reject the null hypothesis H0.')
    print('So we can conclude that the Season has no effect on the mean number␣
 ↪of cycles sold.')
```

```
p-value for two tailed test is 9.583582124778882e-94

Conclusion - Since p-value(9.583582124778882e-94) <= alpha(0.05)
We reject the null hypothesis H0.
So we can conclude that the Season has an effect on the mean number of cycles
sold.
```

[ ]:

```

```

-

4.0.9 5) To check if Weather is dependent on Season

[104]:

```
#Lets check the different categories of Season
df['season'].unique().tolist()
```

[104]: [1, 2, 3, 4]

[105]:

```
#Lets check the different categories of Weather
df['weather'].unique().tolist()
```

[105]: [1, 2, 3, 4]

-

We can perform a Chi-Square test to determine whether "Weather" And "Season" are indepedent or dependent on each other, since both are categorical data.

- Null Hypothesis : Weather has no relationship with Season : Weather and Season are independent of each other.
- Alternative Hypothesis : Weather has relationship with Season : Weather and Season are dependent on each other.

4.0.10 Assumptions:

- Since it is a non-parametric test, therefore there is no assumption about the population.

[106]:
```
alpha = 0.05
stat, p_value, dof, expected = stats.chi2_contingency(pd.
 ↪crosstab(df['weather'],df['season']))
print('p-value for two tailed test is {}'.format(p_value))
print()

if p_value<=alpha:
    print('Conclusion - Since p-value({}) <= alpha({})'.format(p_value,alpha))
    print('We reject the null hypothesis H0.')
    print('So we can conclude that Weather and Season are dependent on each␣
 ↪other.')

else:
    print('Conclusion - Since p-value({}) > alpha({})'.format(p_value,alpha))
    print('We cannot reject the null hypothesis H0.')
    print('So we can conclude that Weather and Season are independent of each␣
 ↪other.')
```

```
p-value for two tailed test is 7.37899576712981e-08

Conclusion - Since p-value(7.37899576712981e-08) <= alpha(0.05)
We reject the null hypothesis H0.
So we can conclude that Weather and Season are dependent on each other.
```

[ ]:
```

```