1 Define Problem Statement and perform Exploratory Data Analysis

1.1 Definition of problem

Yulu has recently suffered considerable dips in its revenues. They want to understand the factors affecting the demand for these shared electric cycles in the Indian market, like:

- 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

Try establishing a relation between the dependent and independent variables, to understand the factors on which the demand for these shared electric cycles depends. In the below data set 'count' is the dependent variable, whereas, variables like workingday, season , weather are independent variable.

In [124]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import chisquare, chi2, chi2_contingency
from scipy.stats import t, norm, ttest_1samp
from scipy.stats import ttest_ind
from scipy.stats import f_oneway
from scipy.stats import kruskal
from scipy.stats import pearsonr ,spearmanr
from scipy import stats
import statsmodels.api as sm
import statistics
from scipy.stats import poisson, binom
from scipy.stats import levene
```

In [125]:
```
df = pd.read_csv("yulu.csv")
```

In [126]:
```
df.head()
```

Out[126]:

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

1.2 Observations on shape of data, data types of all the attributes

In [127]:
```
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
```

In [128]:
```
df["date_time"] = pd.to_datetime(df["datetime"])
```

In [129]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 13 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         
 12  date_time   10886 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(3), int64(8), object(1)
memory usage: 1.1+ MB
```

Insight: The data contains 10886 rows and 12 columns. Most of the data is in int or float format, except for datetime which is in object format. SO created a new date_time column of datetime format

1.3 statistical summary , missing value detection

In [131]:
```
df.isna().sum()
```

Out[131]:
```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
date_time     0
dtype: int64
```

Insight: As can be seen from above therea are no missing value to deal with

In [132]:
```
df.describe()
```

Out[132]:

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	regist
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.00(
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.55
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.03
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.00(
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.00(
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.00(
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.00(
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.00(

In [133]:
```
df.describe(include=['object','datetime64'])
```

```
C:\Users\arghy\AppData\Local\Temp\ipykernel_32368\2229305108.py:1: FutureWarning: Treating datetime data as categor
ical rather than numeric in `.describe` is deprecated and will be removed in a future version of pandas. Specify `d
atetime_is_numeric=True` to silence this warning and adopt the future behavior now.
  df.describe(include=['object','datetime64'])
```

Out[133]:

	datetime	date_time
count	10886	10886
unique	10886	10886
top	2011-01-01 00:00:00	2011-01-01 00:00:00
freq	1	1
first	NaN	2011-01-01 00:00:00
last	NaN	2012-12-19 23:00:00

Insight: There is roughly 2 years worth of data and their respective statistical summary can be seen above.

In [135]:
```
df["season"].value_counts()
```

Out[135]:
```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

In [136]:
```
df["holiday"].value_counts()
```

Out[136]:
```
0    10575
1      311
Name: holiday, dtype: int64
```

In [137]:
```
df["workingday"].value_counts()
```

Out[137]:
```
1    7412
0    3474
Name: workingday, dtype: int64
```

In [138]:
```
df["weather"].value_counts()
```

Out[138]:
```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

In [139]:
```
df["casual"].value_counts()
```

Out[139]:
```
0      986
1      667
2      487
3      438
4      354
      ...
332      1
361      1
356      1
331      1
304      1
Name: casual, Length: 309, dtype: int64
```

In [140]:
```
df["registered"].value_counts()
```

Out[140]:
```
3      195
4      190
5      177
6      155
2      150
      ...
570      1
422      1
678      1
565      1
636      1
Name: registered, Length: 731, dtype: int64
```

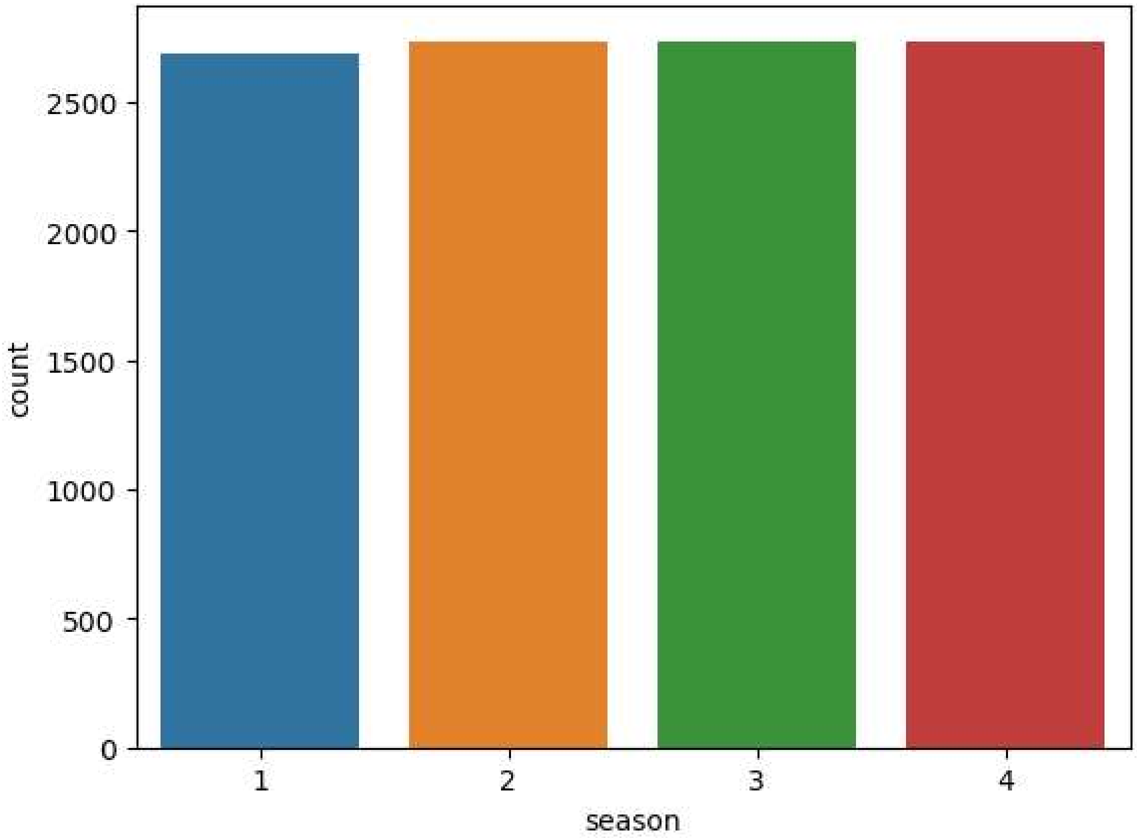
In [141]:
```
df["count"].value_counts()
```

Out[141]:
```
5      169
4      149
3      144
6      135
2      132
      ...
801      1
629      1
825      1
589      1
636      1
Name: count, Length: 822, dtype: int64
```

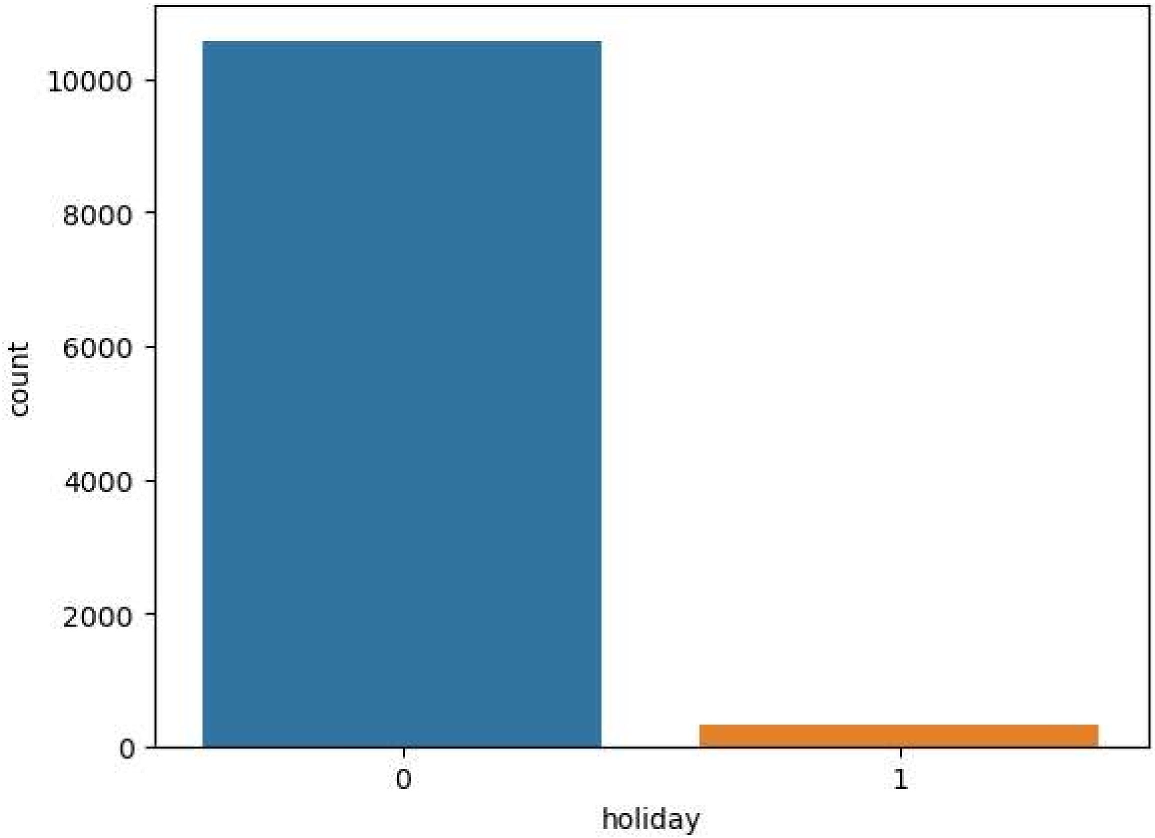
Insight: Season, holiday, working day and weather are categorical where as casual , registered and count are discrete variable.

1.4 Univariate Analysis

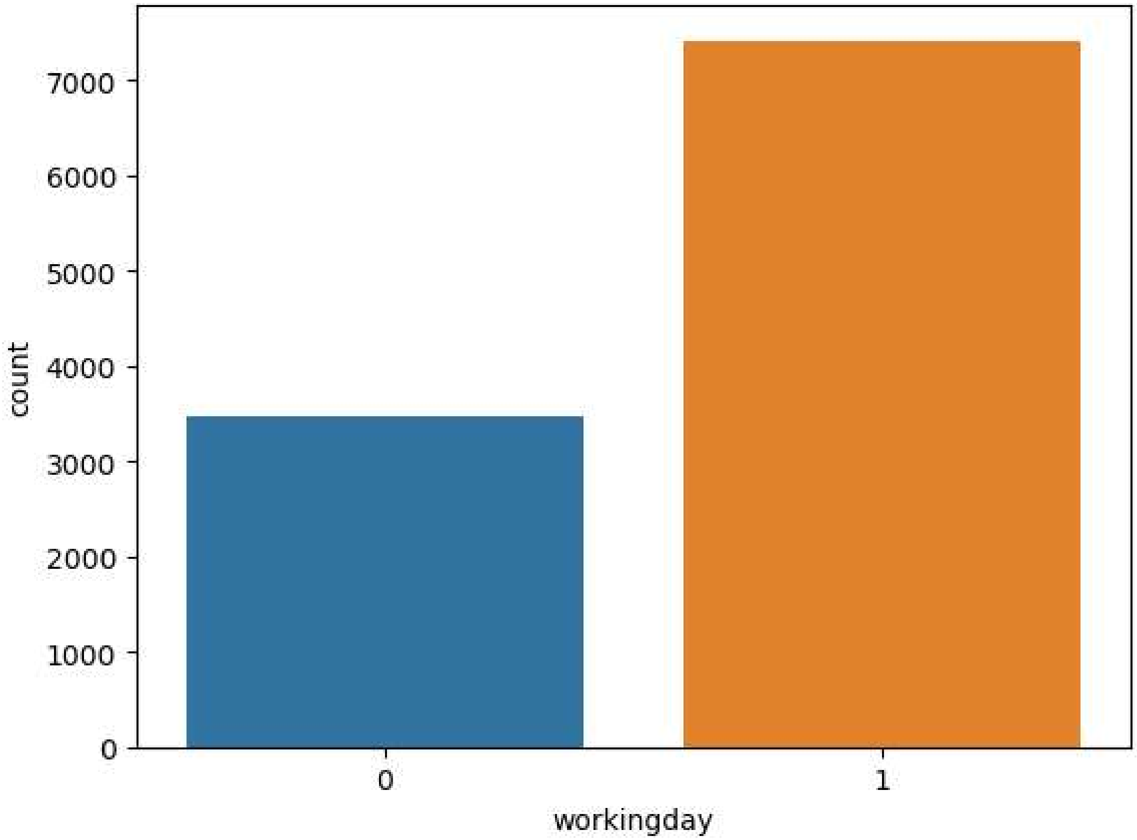
In [143]:
```
sns.countplot(x ='season', data = df)
plt.show()
```



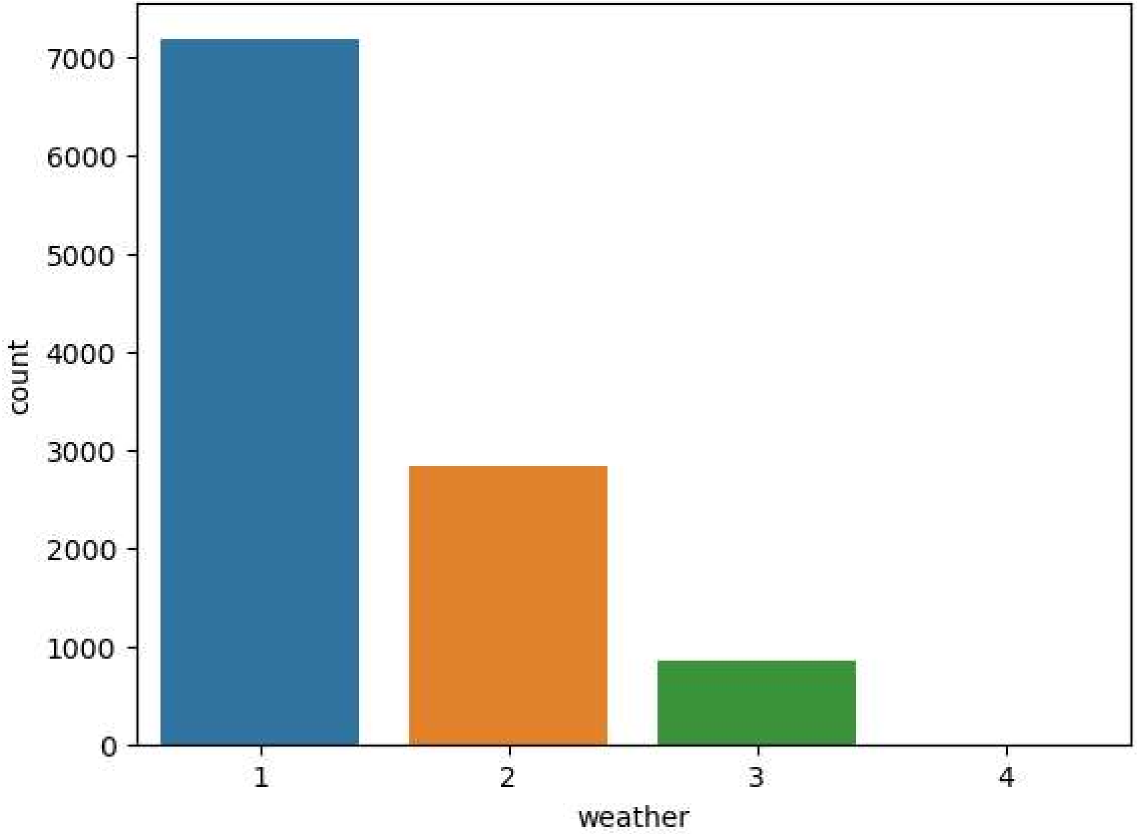
In [144]:
```
sns.countplot(x ='holiday', data = df)
plt.show()
```



In [145]:
```
sns.countplot(x ='workingday', data = df)
plt.show()
```



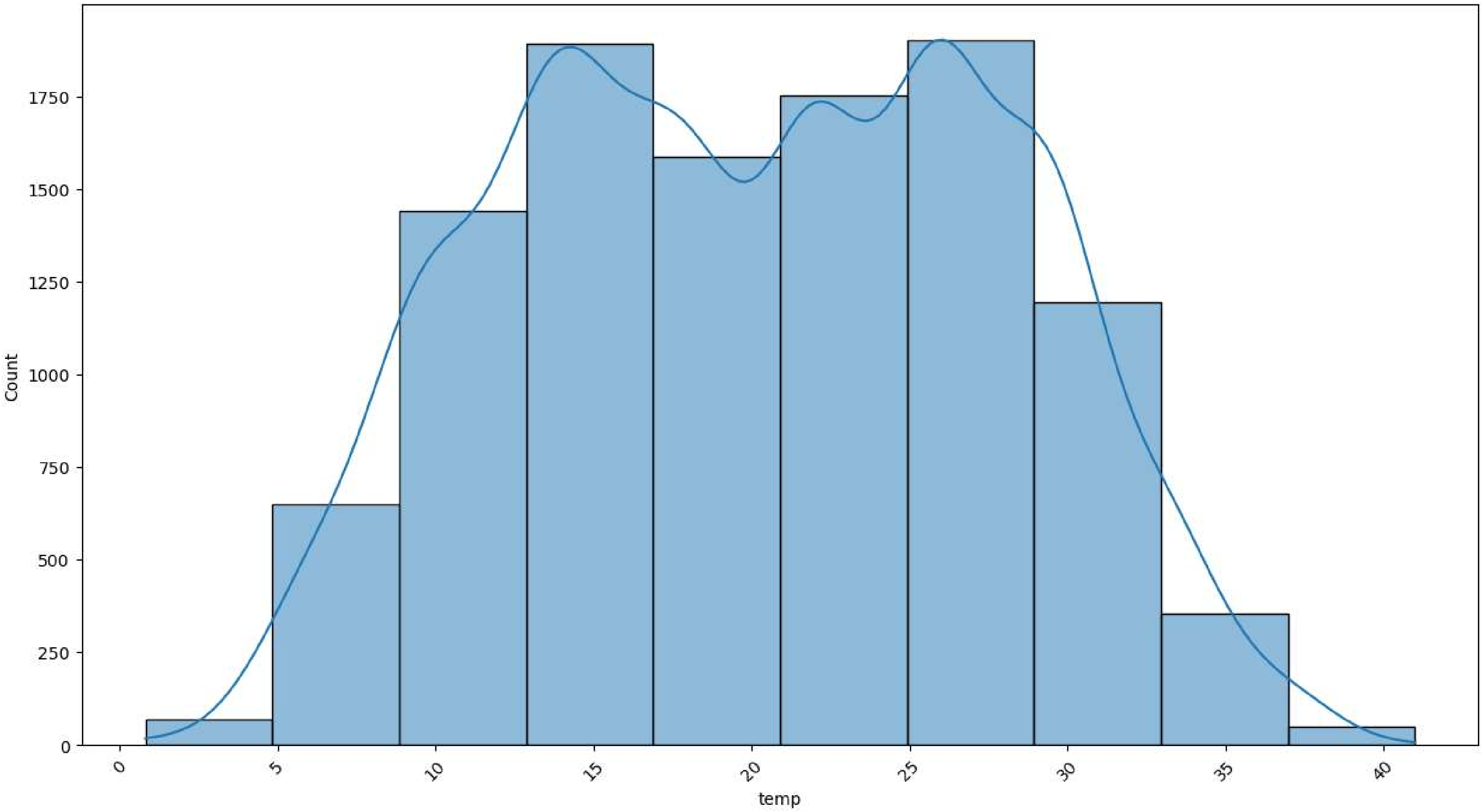
In [146]:
```
sns.countplot(x ='weather', data = df)
plt.show()
```



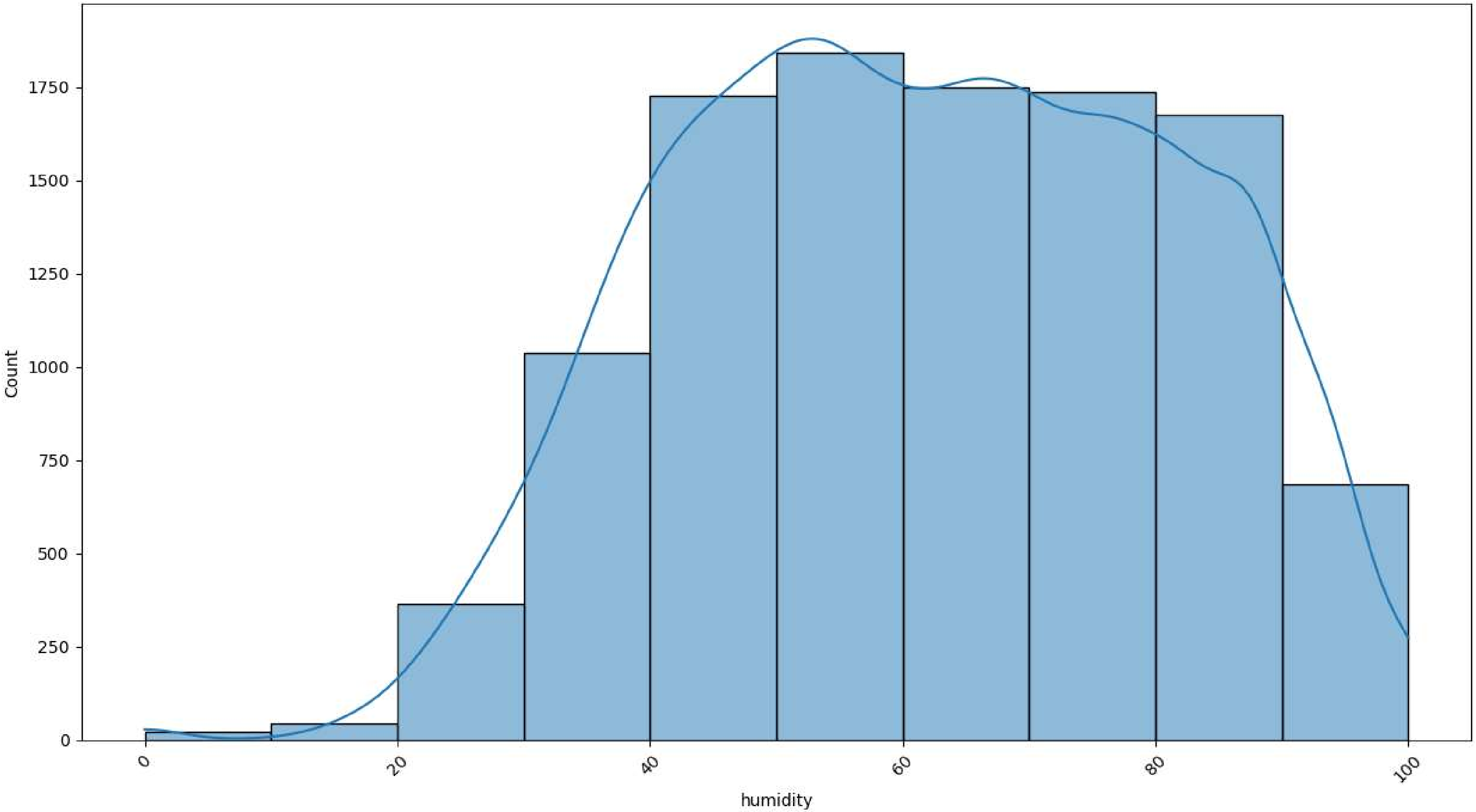
Insight: Seems like weather, holiday and workingday has some impact on the usage pattern. Working and non-holidays and weather type 1 has higher count

In [ ]:

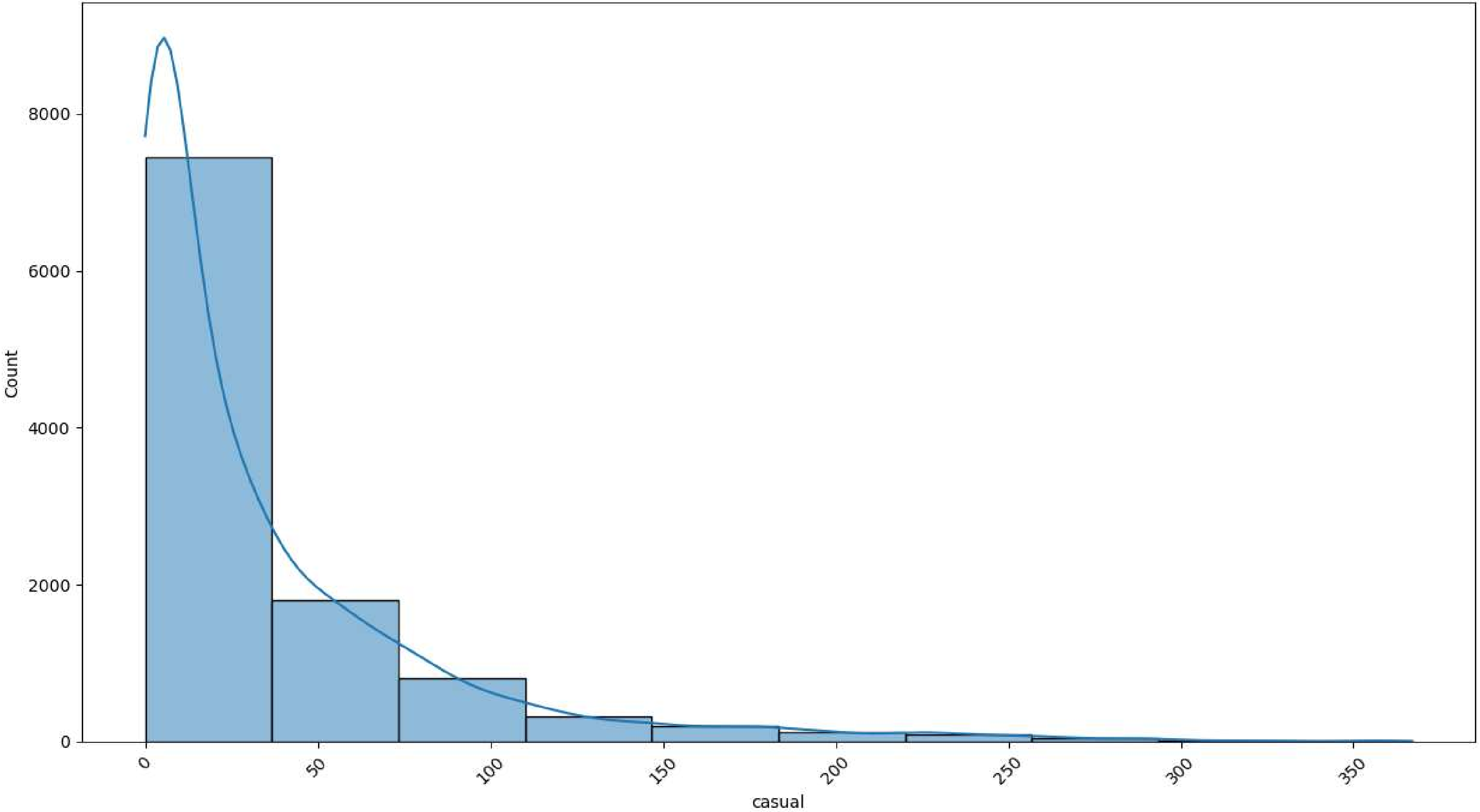
In [148]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(x="temp", bins=10, data = df, kde=True)
plt.show()
```



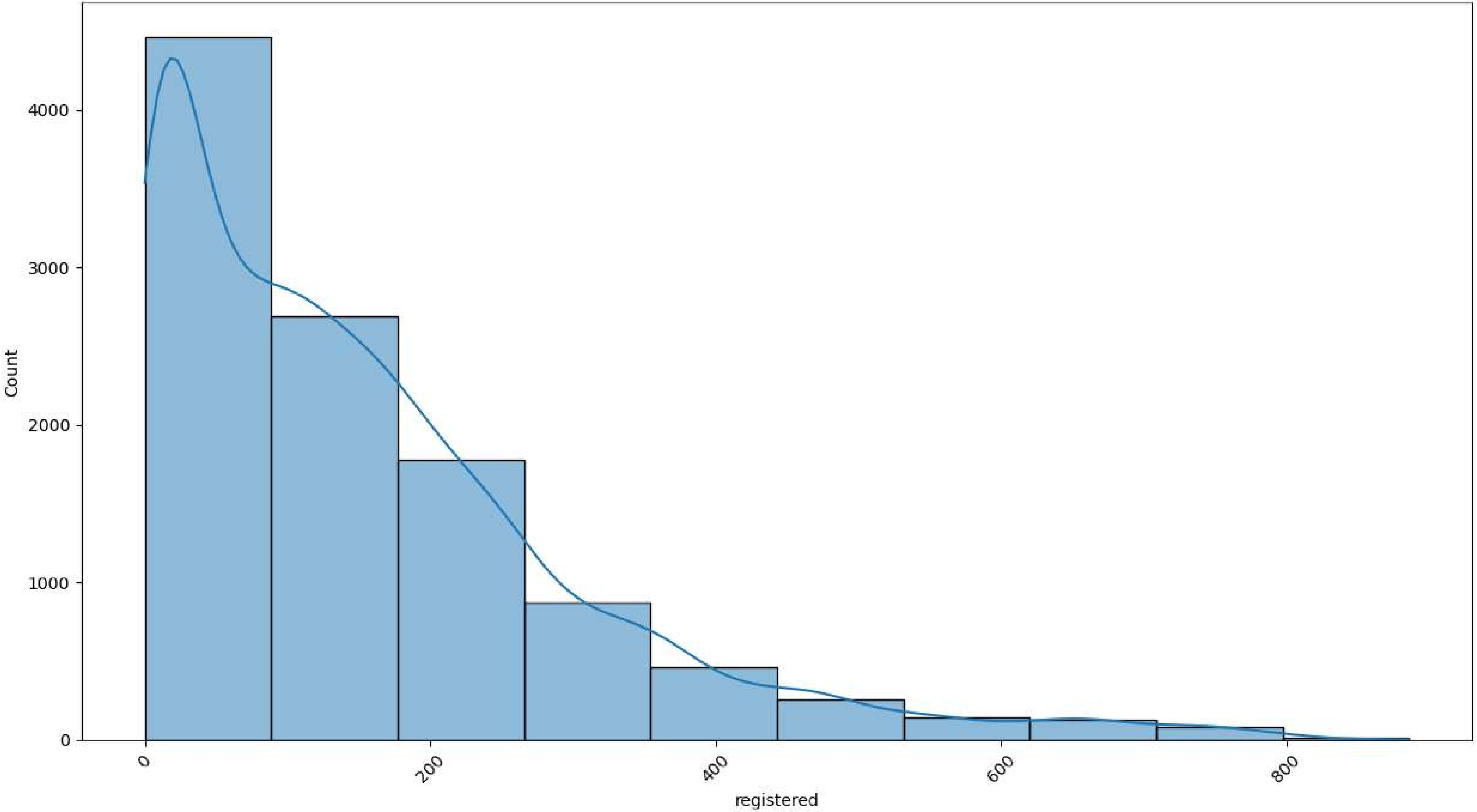
In [149]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(x="humidity", bins=10, data = df, kde=True)
plt.show()
```



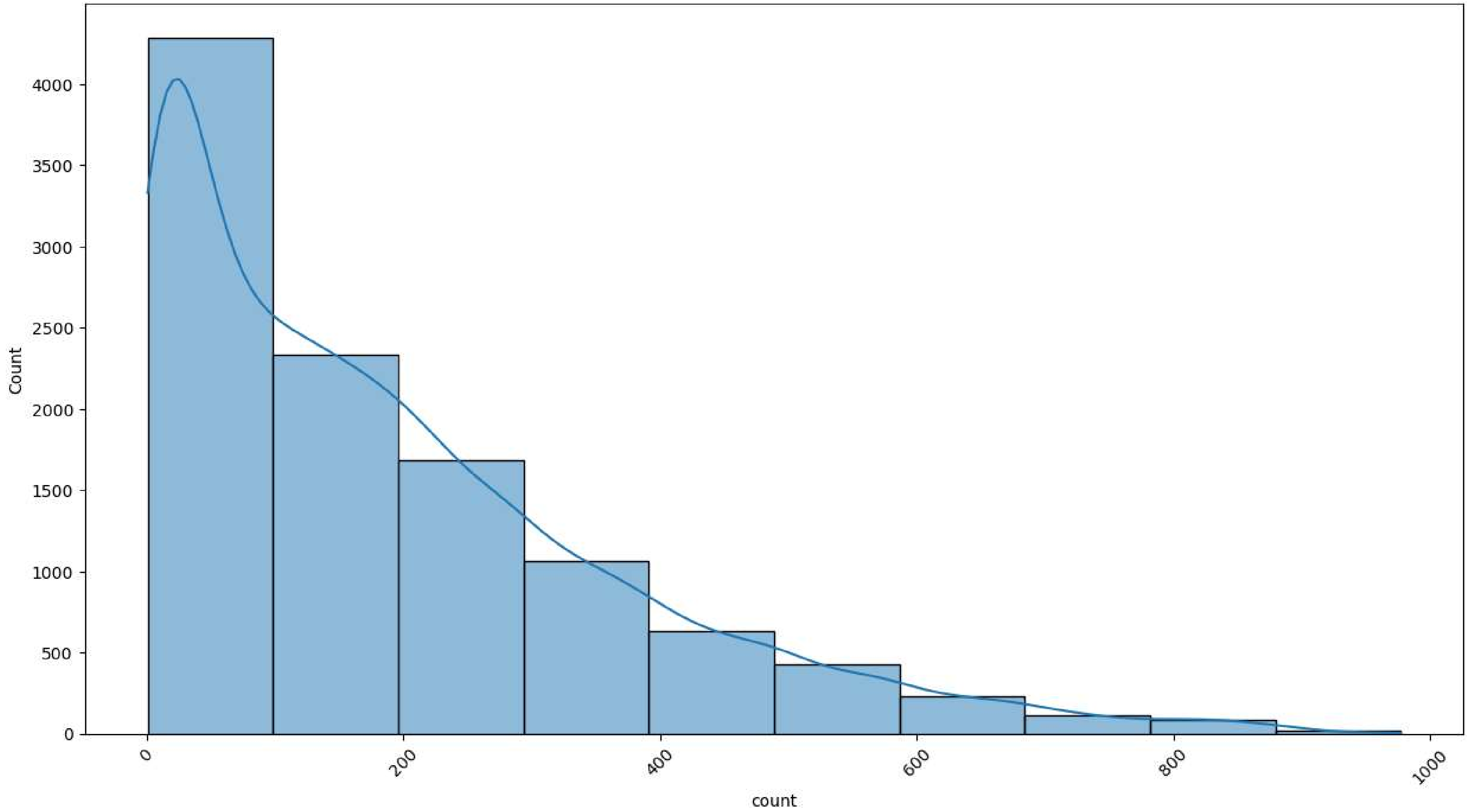
In [151]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(x="casual", bins=10, data = df, kde=True)
plt.show()
```



In [28]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(x="registered", bins=10, data = df, kde=True)
plt.show()
```



In [29]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(x="count", bins=10, data = df, kde=True)
plt.show()
```



Insight: From the bucket sizes we can say that there is significantly more registered than casual rides

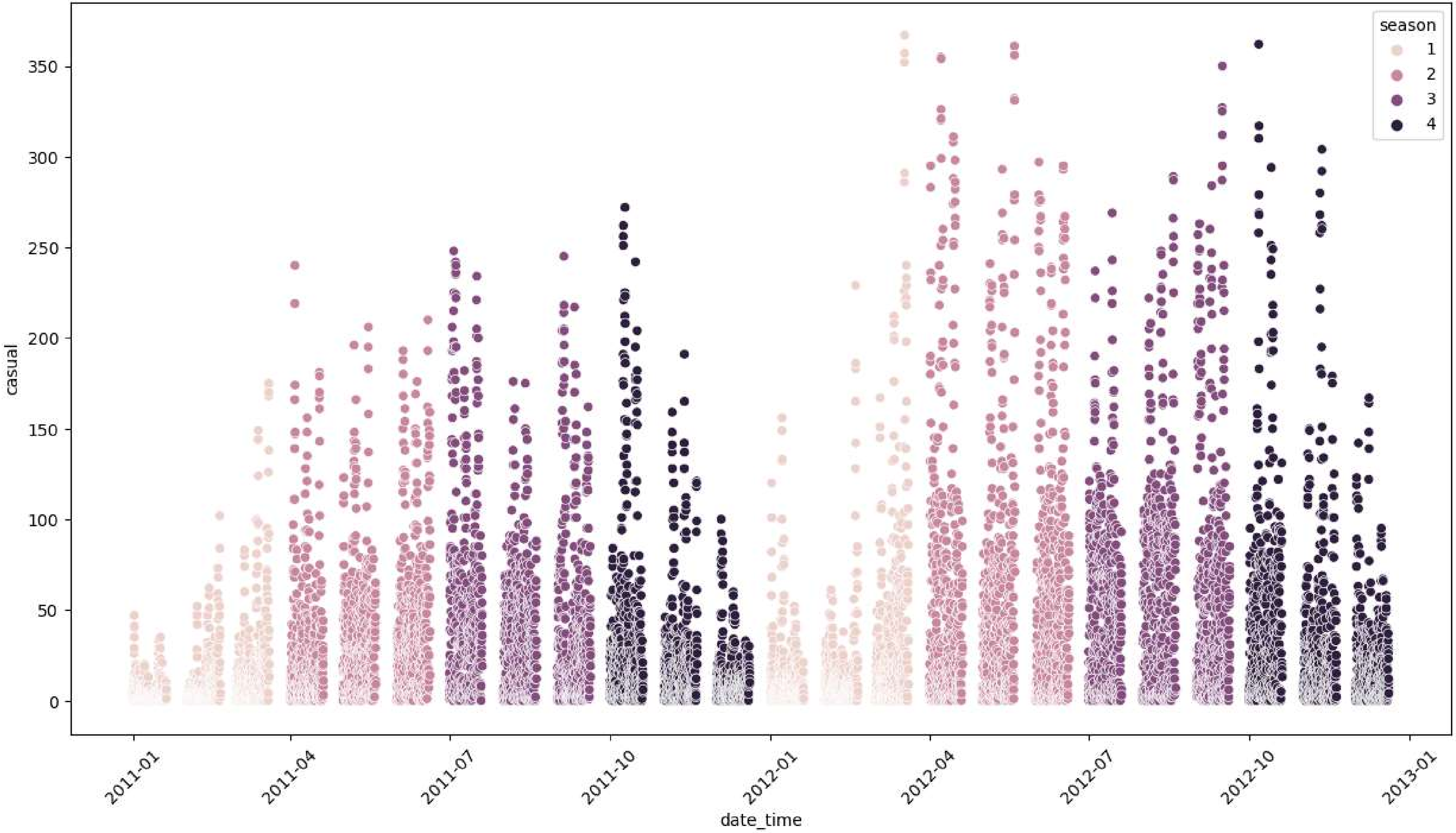
1.5 Bivariate Analysis

In [30]:
```
df.head()
```

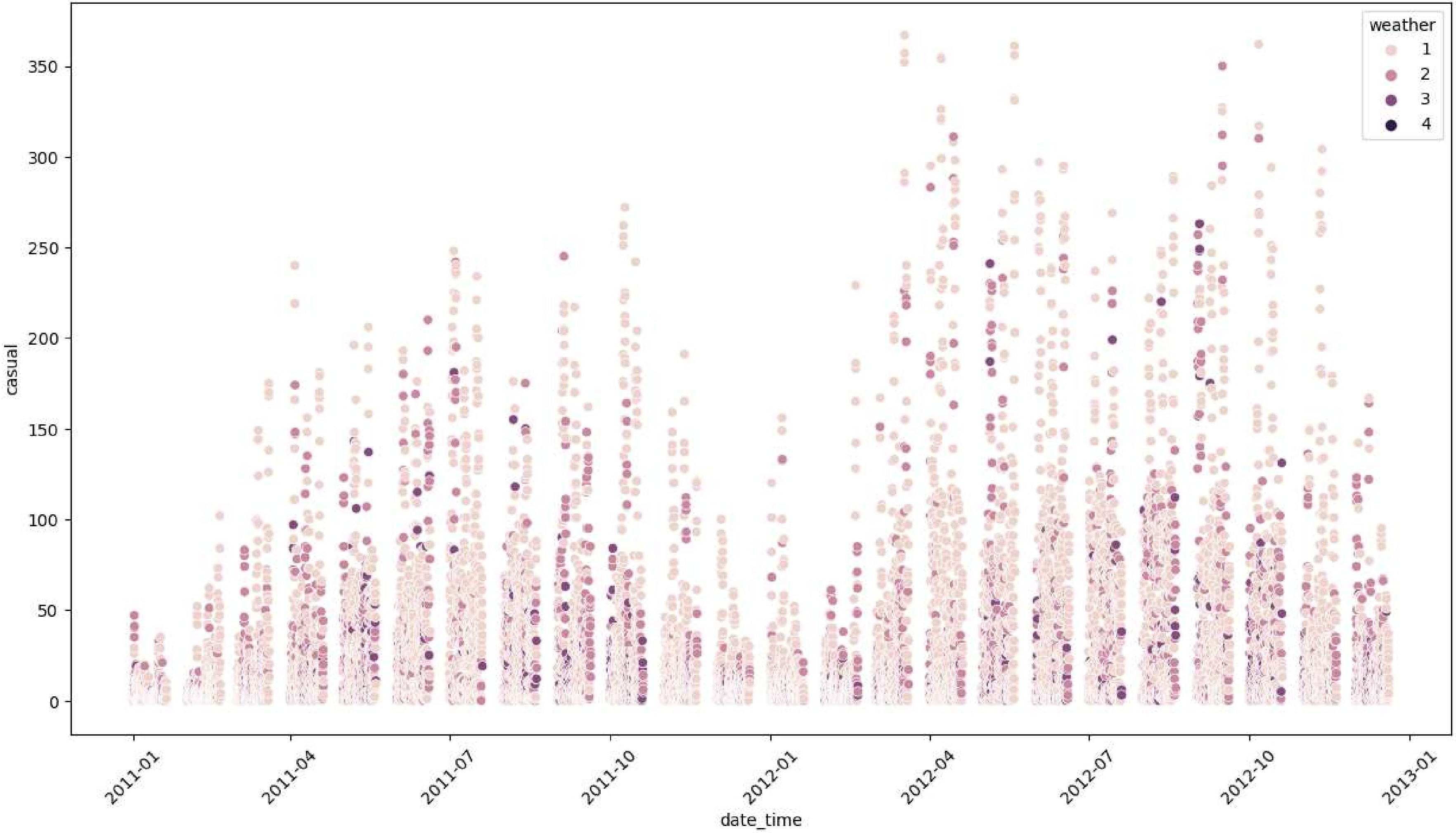
Out[30]:

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

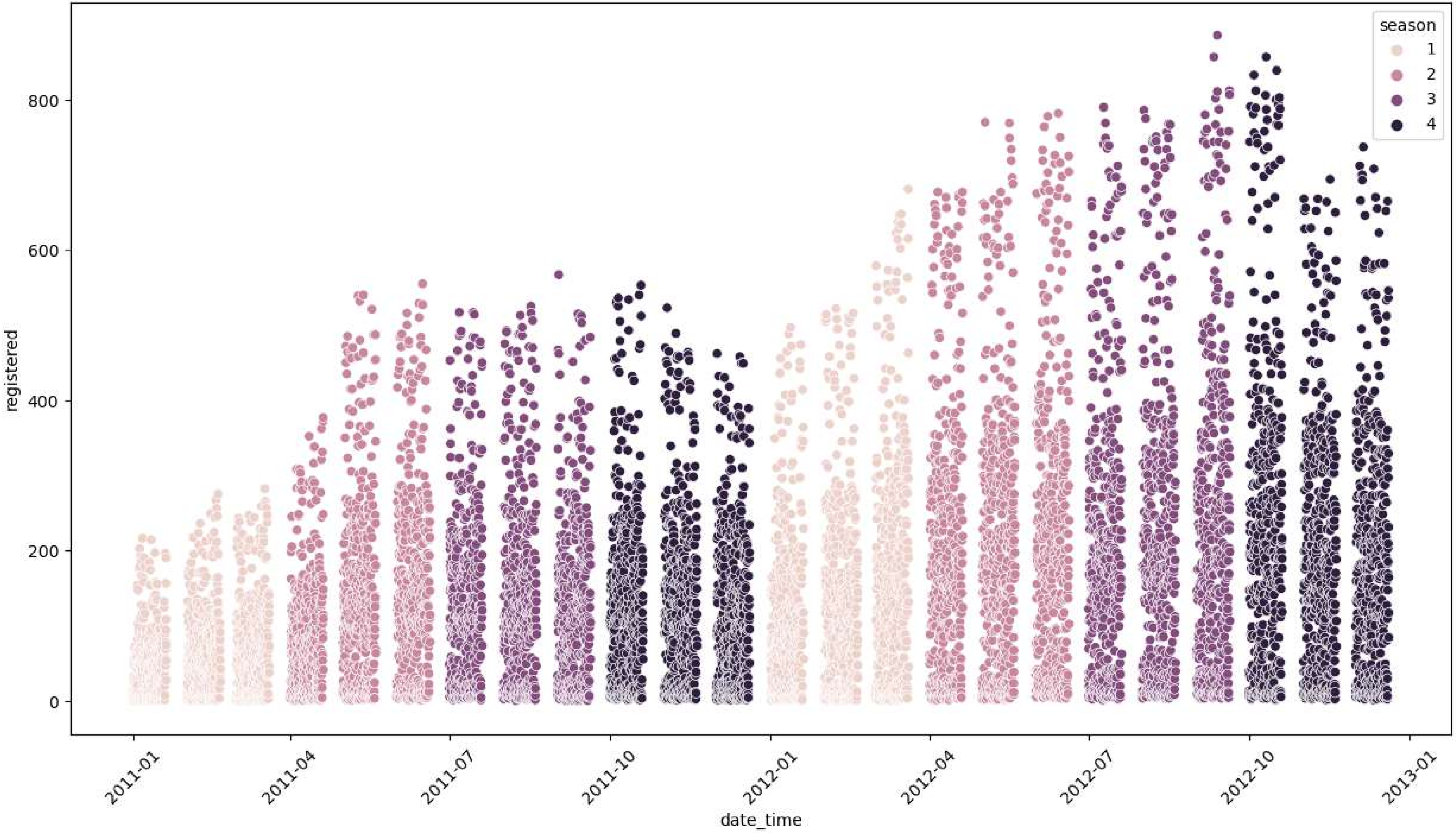
In [162]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.scatterplot(x = "date_time", y = "casual",data = df, hue= "season")
plt.show()
```



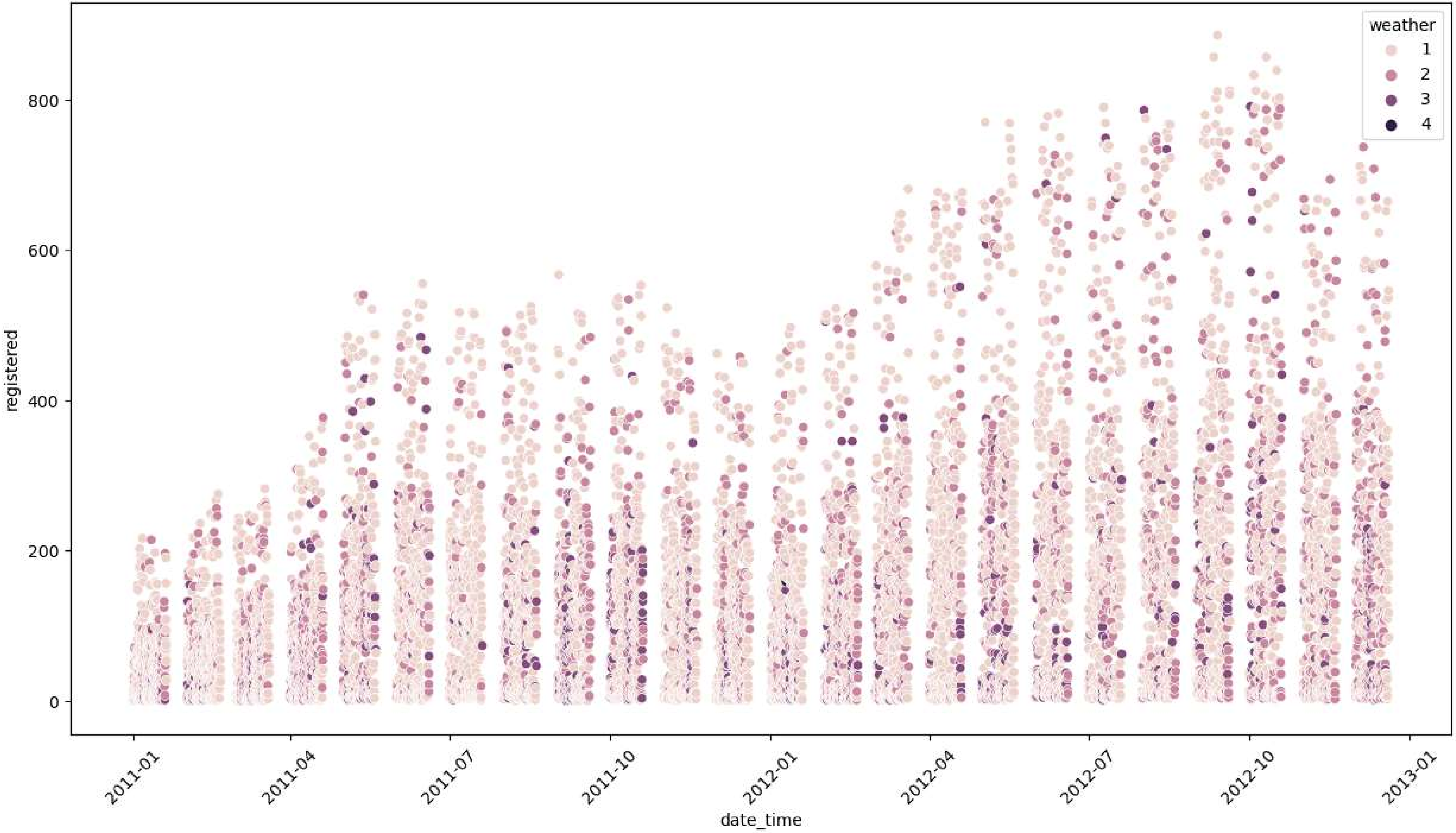
In [163]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.scatterplot(x = "date_time", y = "casual",data = df, hue= "weather")
plt.show()
```



In [164]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.scatterplot(x = "date_time", y = "registered",data = df,hue="season")
plt.show()
```

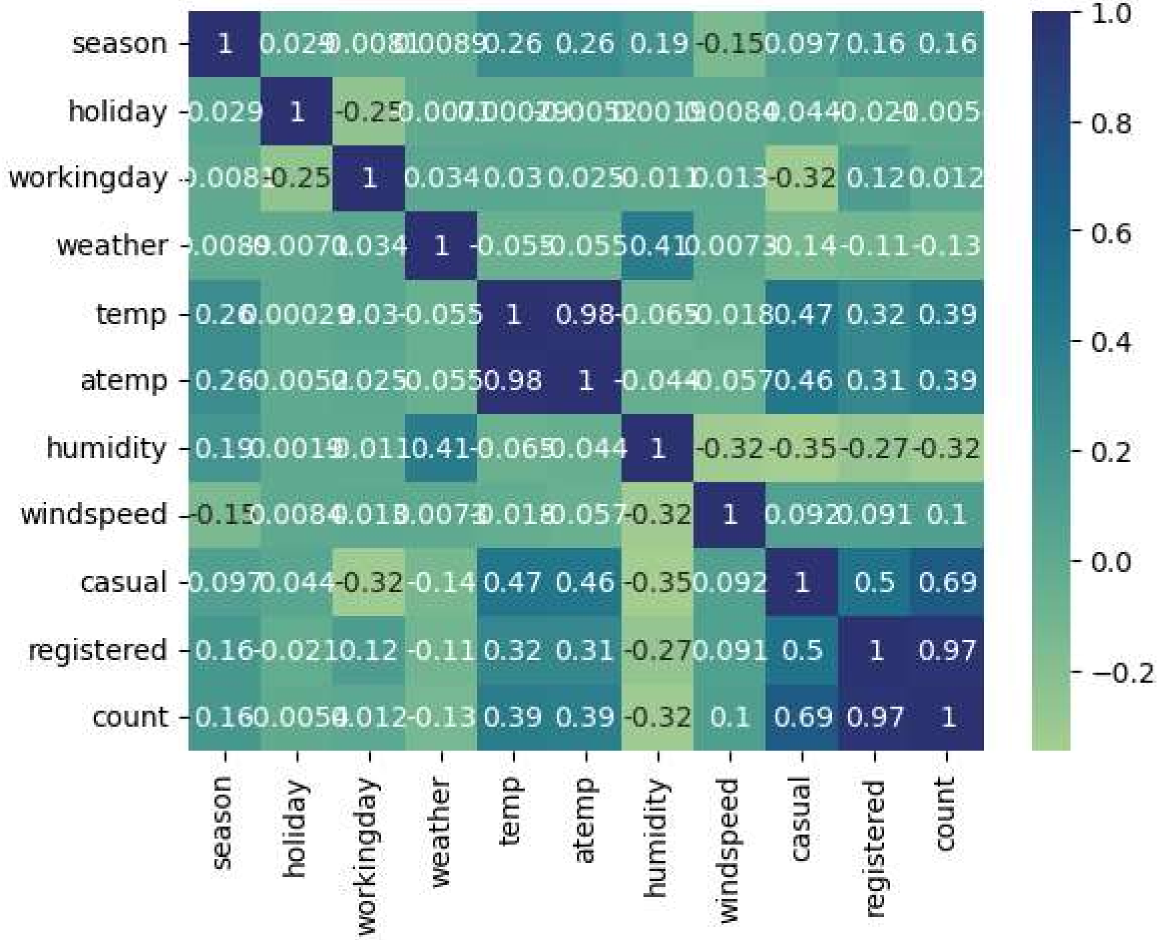


In [160]:
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.scatterplot(x = "date_time", y = "registered",data = df,hue="weather")
plt.show()
```



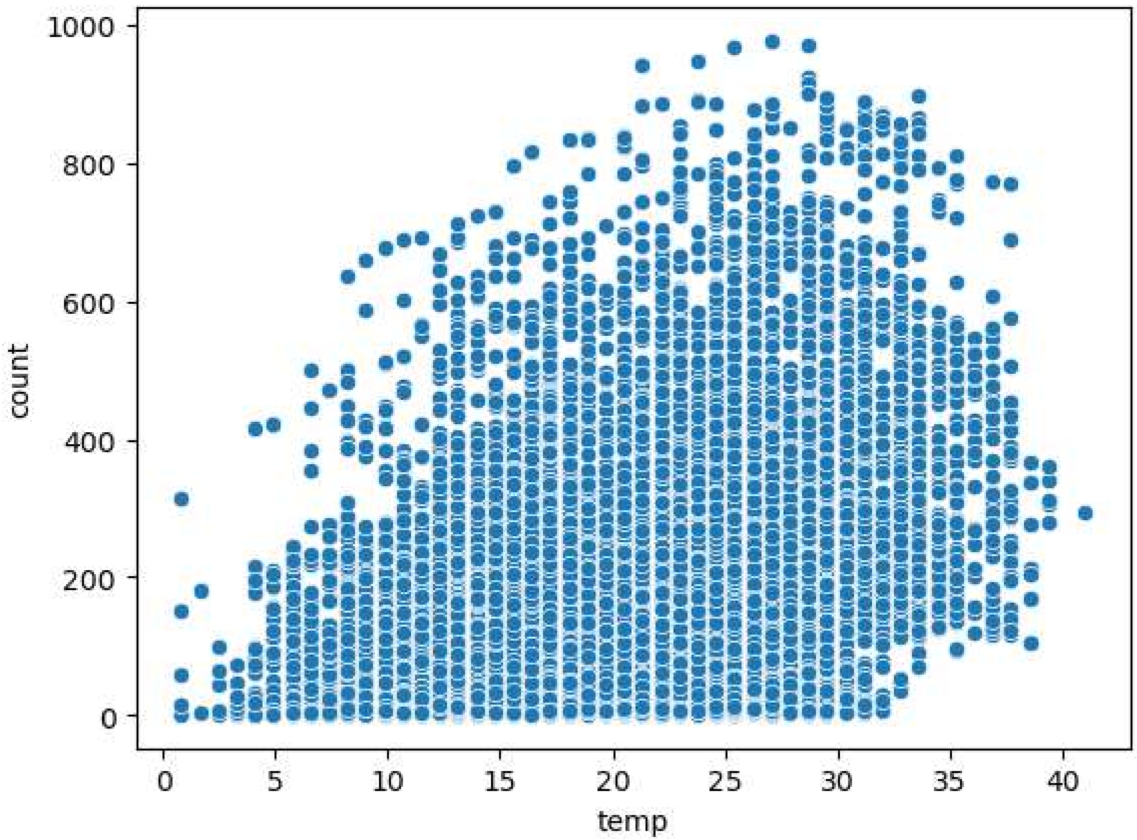
In [31]:
```
sns.heatmap(df.corr(),annot=True, cmap="crest")
```

Out[31]: <AxesSubplot:>



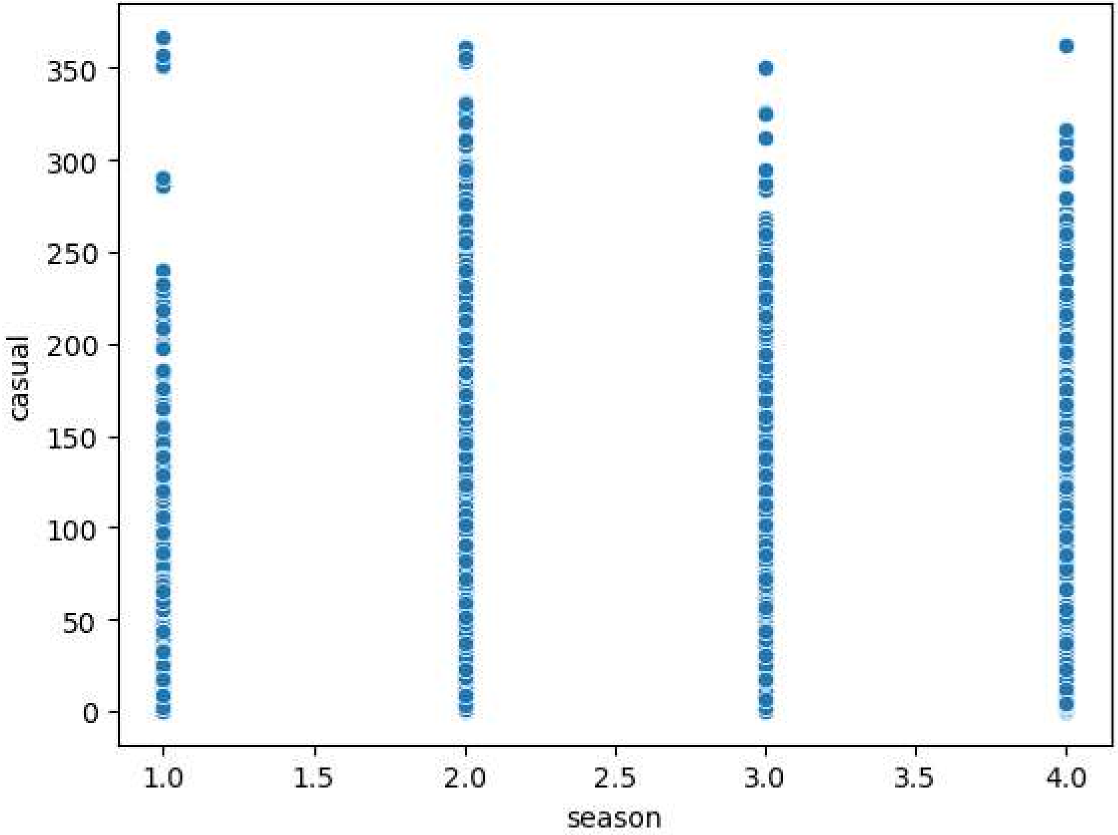
In [32]:
```
sns.scatterplot(x='temp',y='count',data=df)
```

Out[32]: <AxesSubplot:xlabel='temp', ylabel='count'>



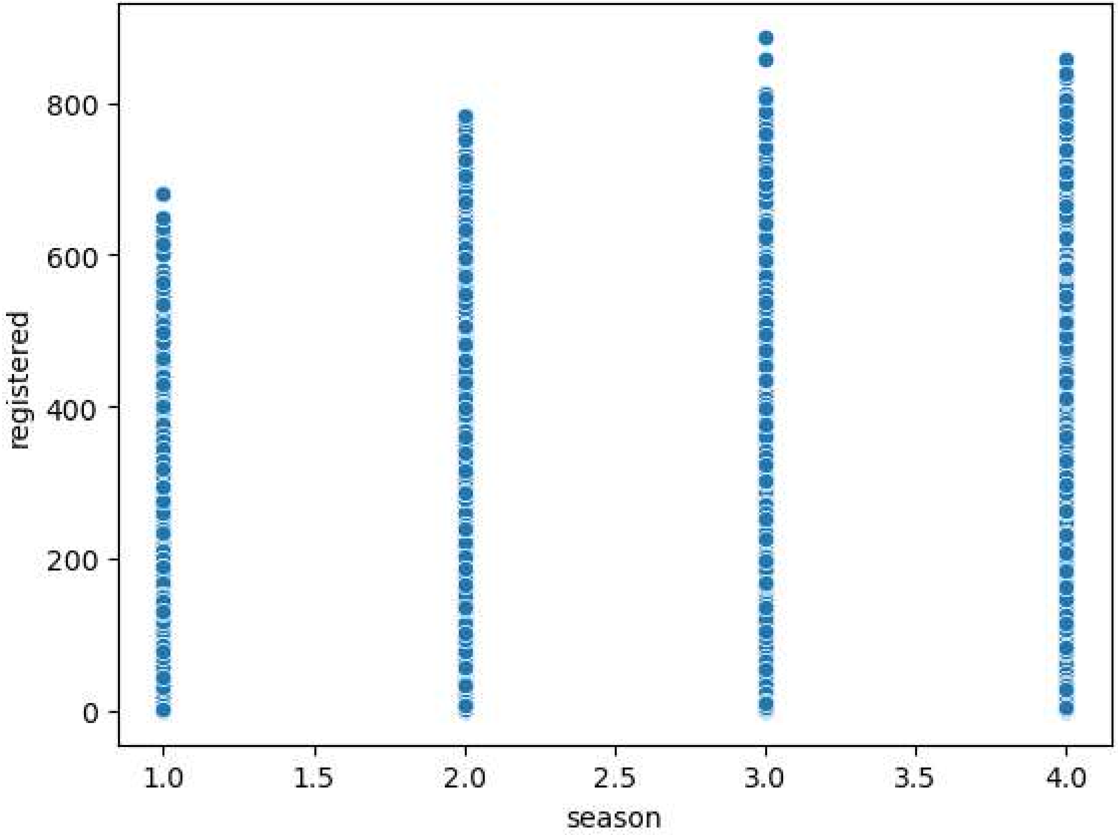
In [33]:
```
sns.scatterplot(x='season',y='casual',data=df)
```

Out[33]: <AxesSubplot:xlabel='season', ylabel='casual'>



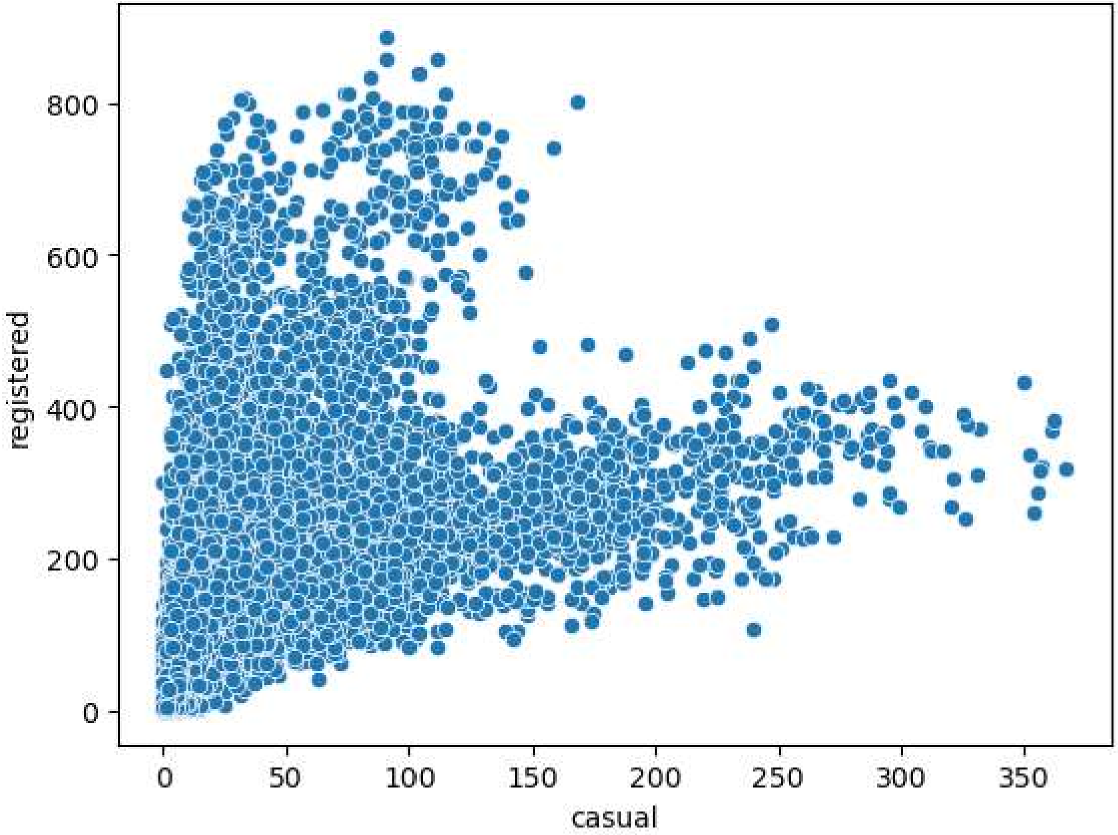
In [34]:
```
sns.scatterplot(x='season',y='registered',data=df)
```

Out[34]: <AxesSubplot:xlabel='season', ylabel='registered'>



In [35]:
```
sns.scatterplot(x='casual',y='registered',data=df)
```

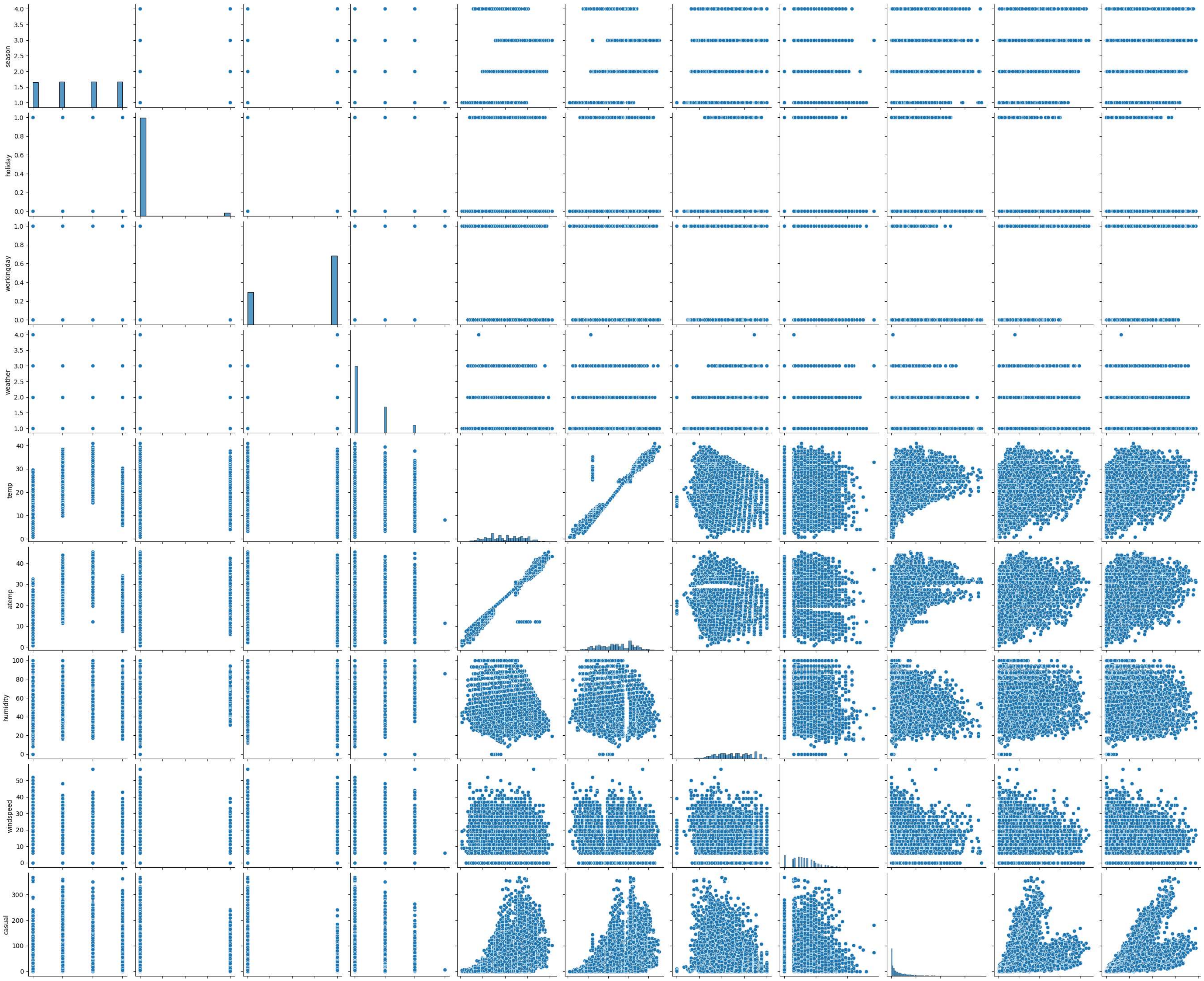
Out[35]: <AxesSubplot:xlabel='casual', ylabel='registered'>

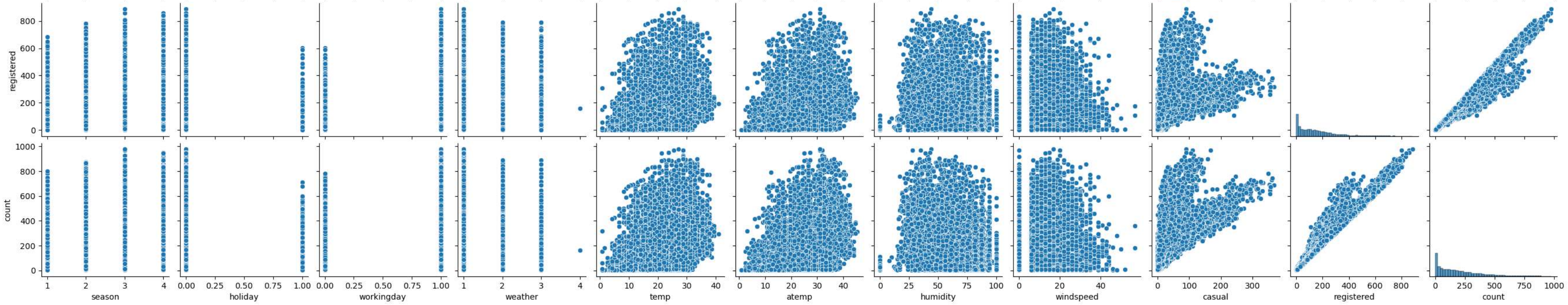


In [36]:
```
plt.figure(figsize=(8,8))
sns.pairplot(data=df.iloc[:, 1:])
```

Out[36]:
```
<seaborn.axisgrid.PairGrid at 0x2e2960ab7c0>
```

```
<Figure size 800x800 with 0 Axes>
```


season
holiday
workingday
weather
temp
atemp
humidity
windspeed
casual



Insight: From bivariate graphs

- Majority of the rides are dependent on weather type 1
- A large chunk of the rides happen on season type 3 and 4
- From heat map we can conclude that count and registered are heavily correlated. Which means more registration we have more ride count we get
- From scatter plot we can see that a high daily count is seen between temperature range 20 to 40

In [ ]:

1.6 insights based on EDA

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

Looking at the EDA some of the relations we can look at would be :

- Working Day has effect on number of electric cycles rented
- No. of cycles rented similar or different in different seasons
- No. of cycles rented similar or different in different weather
- Weather is dependent on season

2 Hypothesis Testing

2.1 Check if Working Day has an effect on the number of electric cycles rented

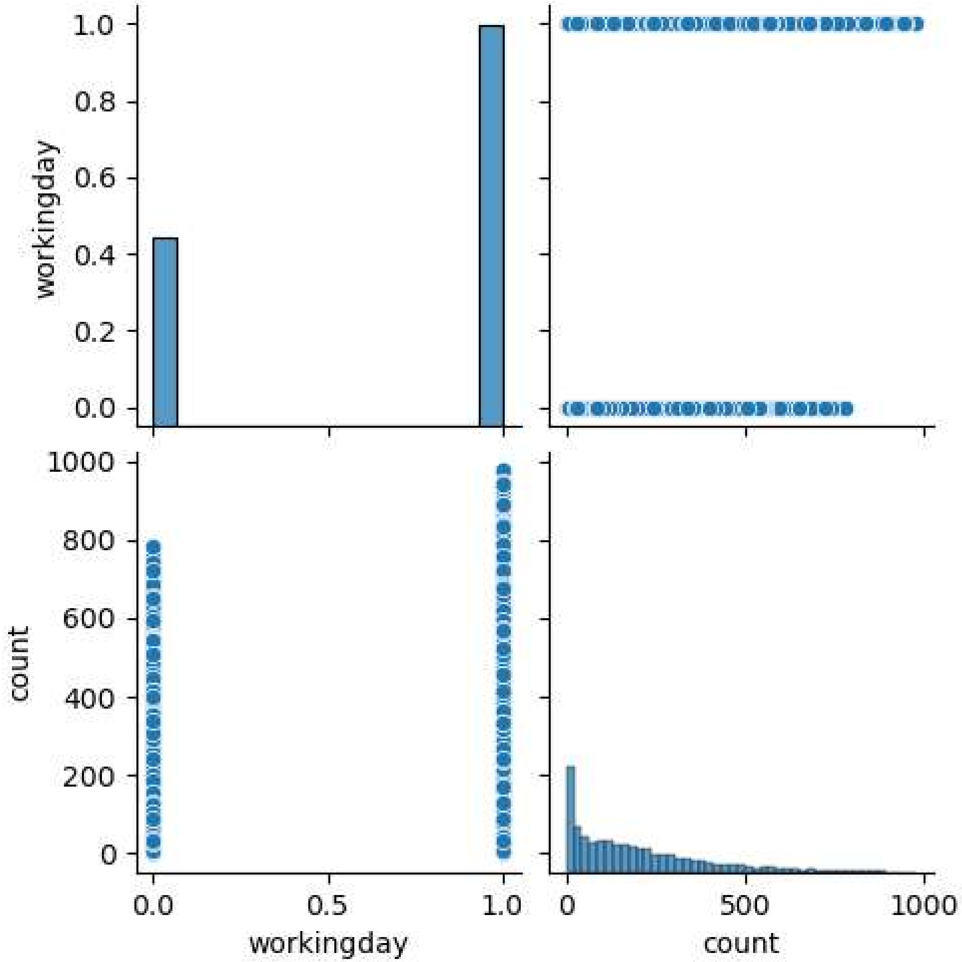
- Visual analysis
- Hypothesis formulation
- Select the appropriate test
- Check test assumptions
- Find the p-value
- Conclusion based on the p-value

2.1.1 Visual analysis

In [39]:
```
plt.figure(figsize=(8,8))
sns.pairplot(data=df.loc[:,["workingday","count"]])
```

Out[39]:
```
<seaborn.axisgrid.PairGrid at 0x2e29f2e7670>
```

```
<Figure size 800x800 with 0 Axes>
```



2.1.2 Hypothesis formulation

- H0 - average count on working and non-working days are same (null hypothesis)
- Ha - Average count on working days are higher than on non-working days. (Alternate Hypothesis)

2.1.3 Appropriate hypothesis test

- We can use a 2 sample T-test to find the relation between the means of count on working and non-working days

In [44]:
```
workingday_count = df.loc[df["workingday"]==1]["count"]
nonworkingday_count= df.loc[df["workingday"]==0]["count"]
```

In [58]:
```
workingday_count.info()
```

```
<class 'pandas.core.series.Series'>
Int64Index: 7412 entries, 47 to 10885
Series name: count
Non-Null Count  Dtype
--------------  -----
7412 non-null   int64
dtypes: int64(1)
memory usage: 115.8 KB
```

In [59]:
```
nonworkingday_count.info()
```

```
<class 'pandas.core.series.Series'>
Int64Index: 3474 entries, 0 to 10813
Series name: count
Non-Null Count  Dtype
--------------  -----
3474 non-null   int64
dtypes: int64(1)
memory usage: 54.3 KB
```

2.1.4 Check test assumptions:

- Independence: working and non-working days are independent of each other
- Random Sampling: assuming that the data is selected from raw data set which is naturally normal
- Homogeneity of varience : checked below
- Normality of data : checked below
- Significance level set to 5%

Homogeneity of variance

In [52]:
```
np.var(workingday_count)
```

Out[52]:
```
34040.697106746935
```

In [49]:
```
np.var(nonworkingday_count)
```

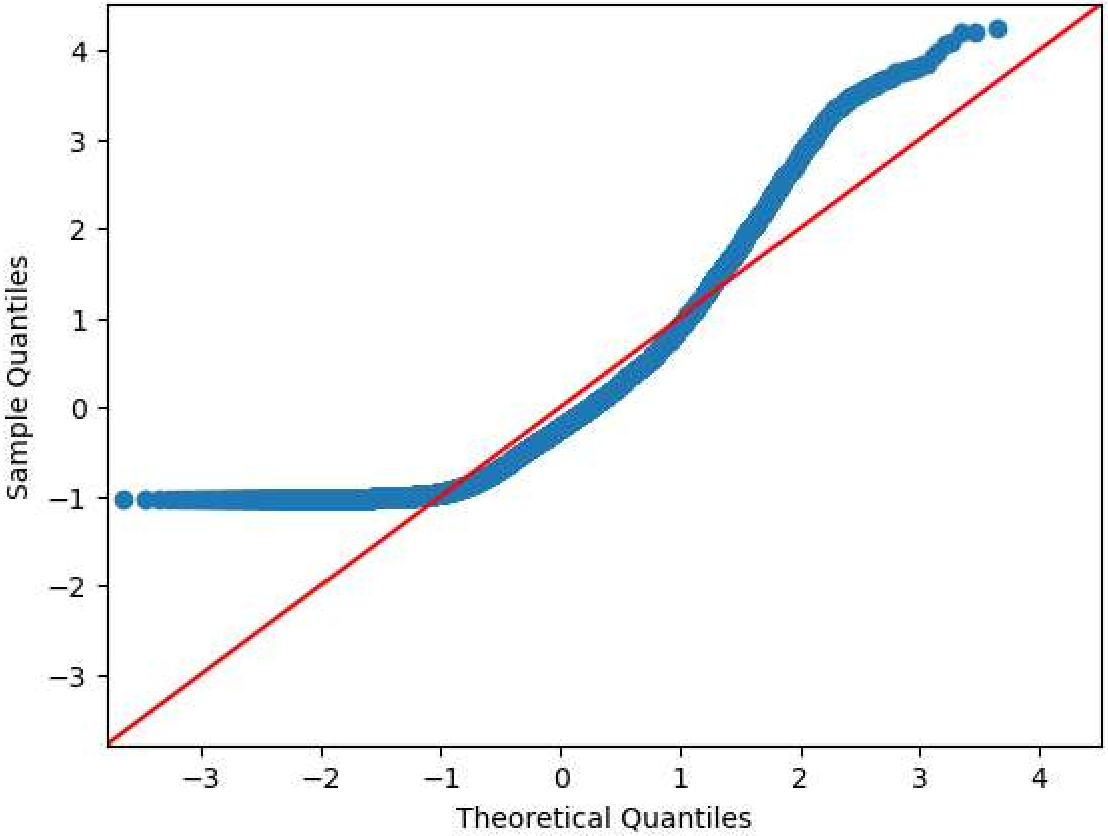
Out[49]:
```
30171.34609894243
```

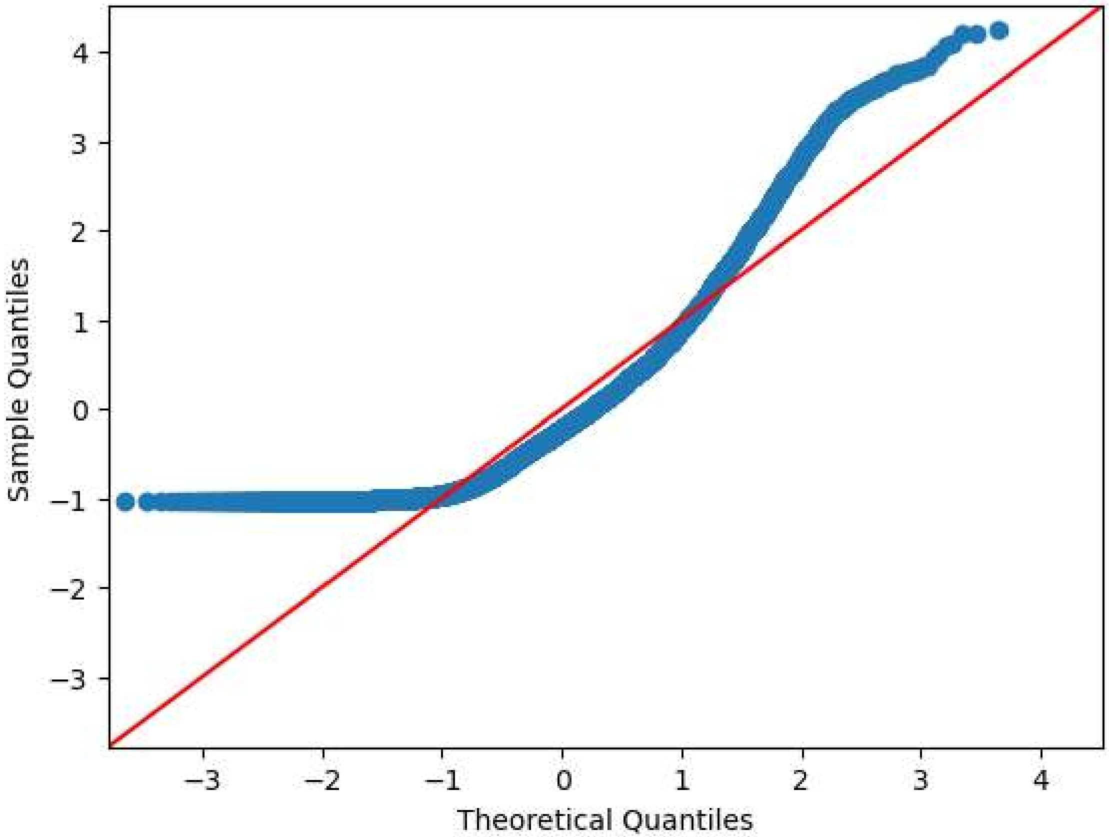
Conclusion: As can be seen the variance of the 2 samples are close enough, so we can say that variences are homogeneous

Normality of data:

In [56]:
```
sm.qqplot(workingday_count,line='45',fit=True,dist=stats.norm)
```

Out[56]:

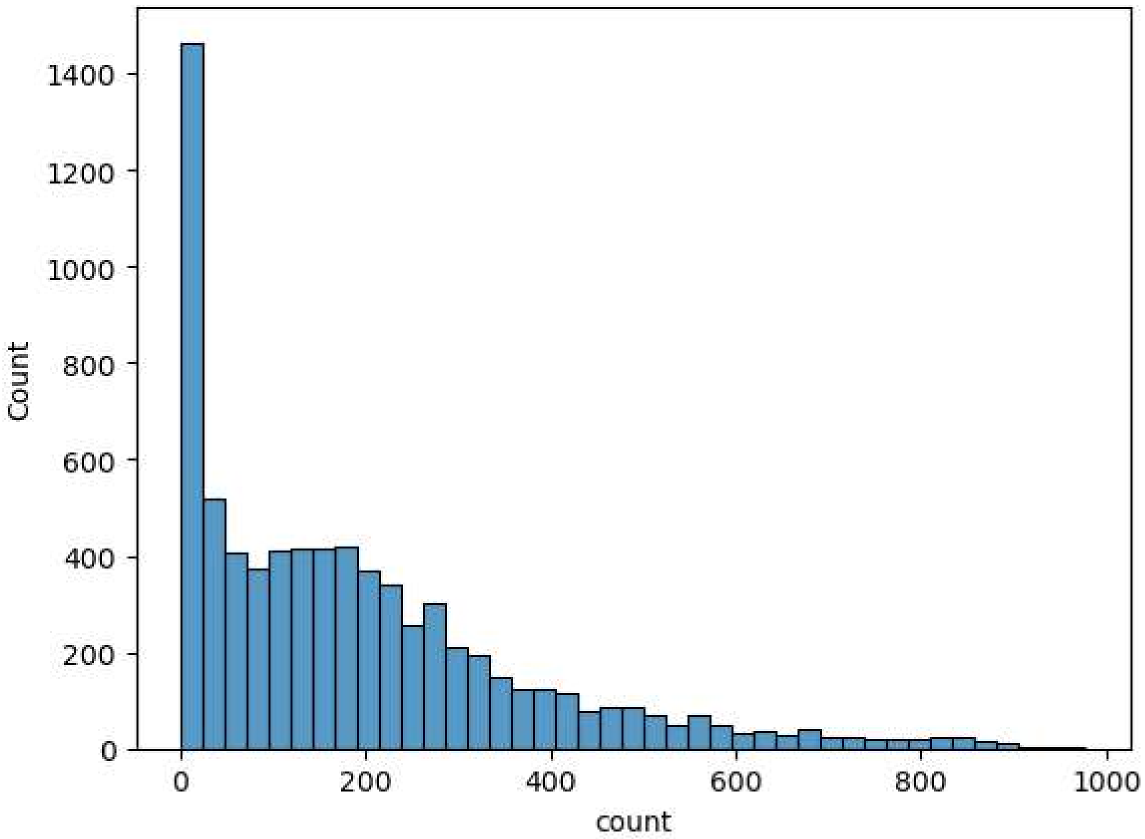




Sample Quantiles
Theoretical Quantiles
4
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3
4

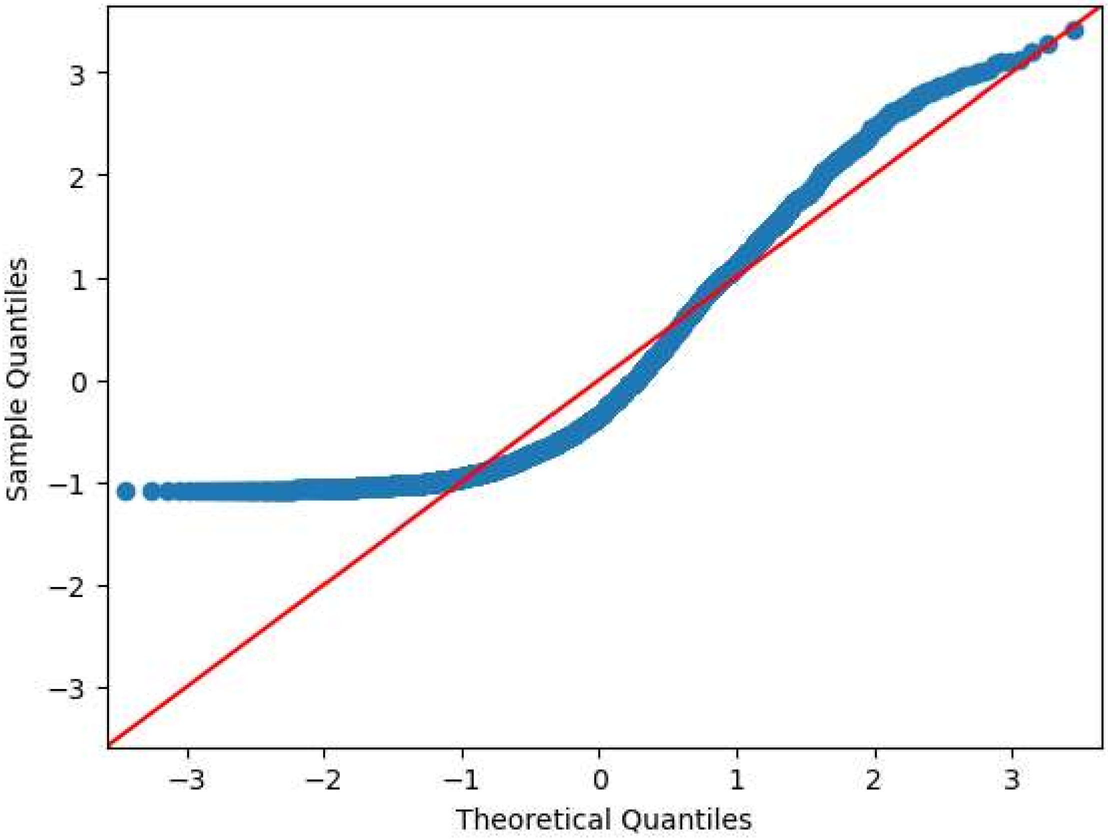
In [60]:
```
sns.histplot(workingday_count)
```

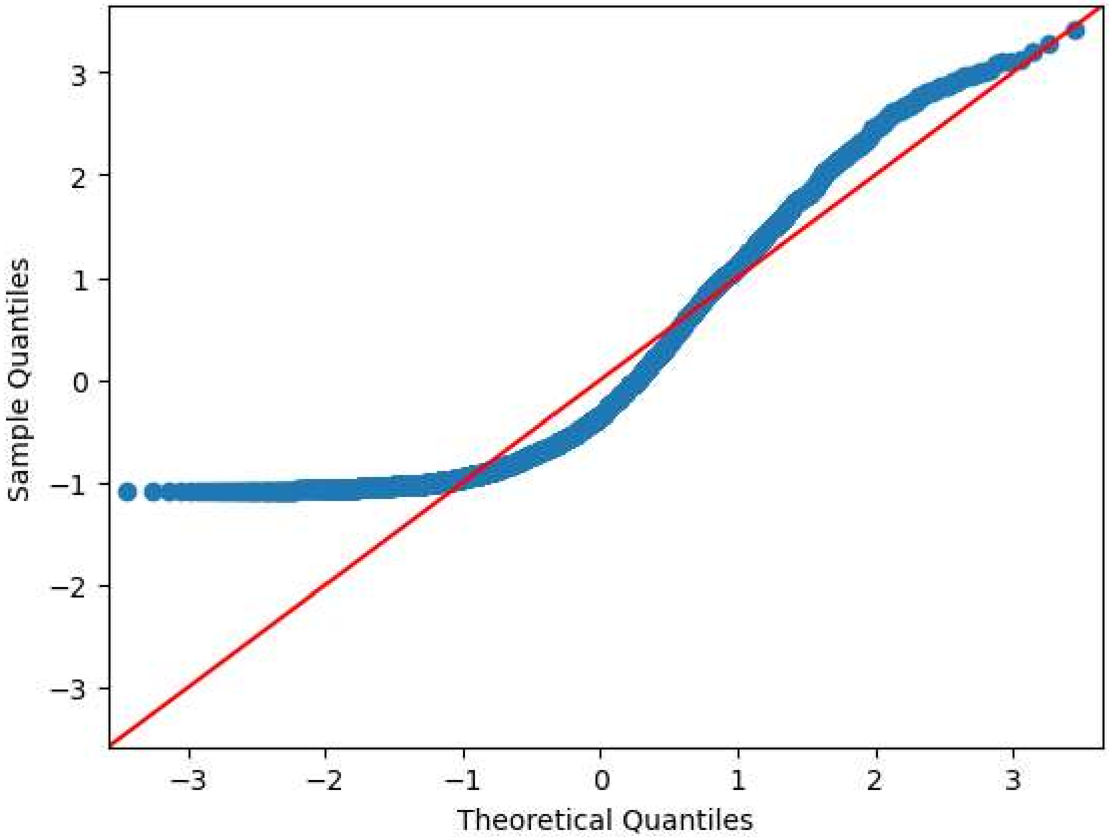
Out[60]: <AxesSubplot:xlabel='count', ylabel='Count'>



In [82]:
```
sm.qqplot(nonworkingday_count,line='45',fit=True,dist=stats.norm)
```

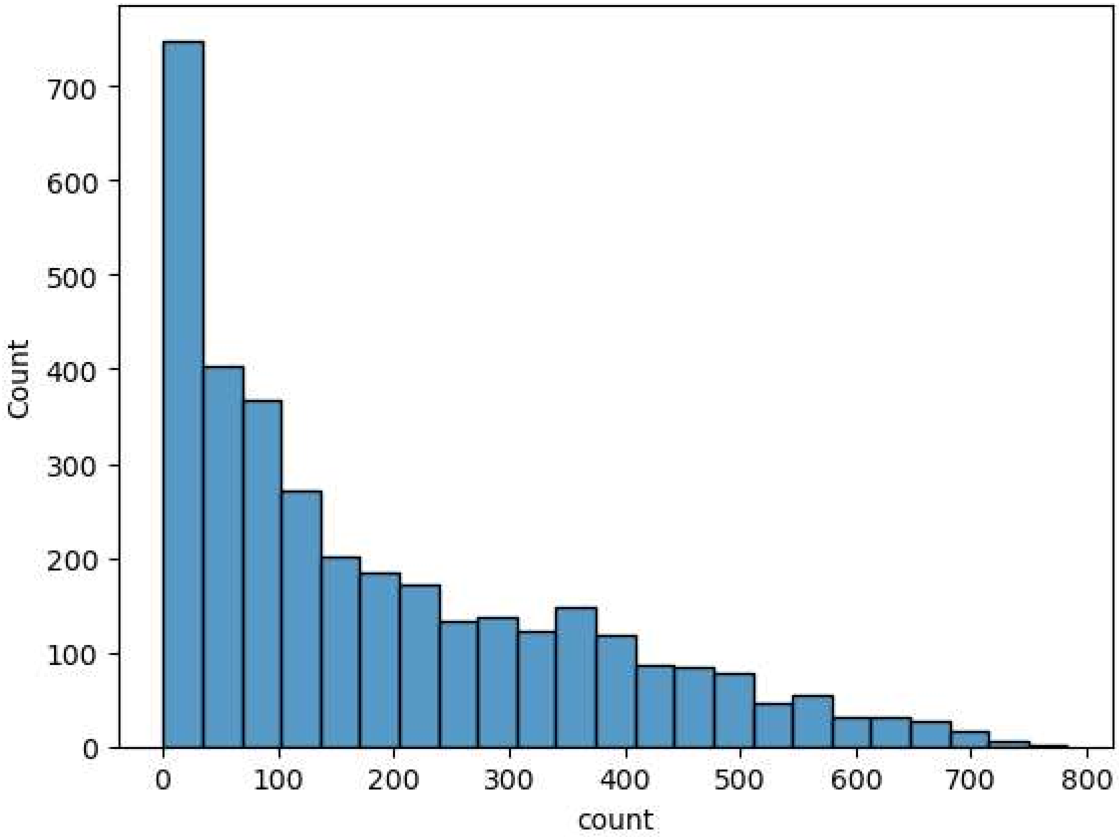
Out[82]:




Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3

In [61]:
```
sns.histplot(nonworkingday_count)
```

Out[61]: <AxesSubplot:xlabel='count', ylabel='Count'>



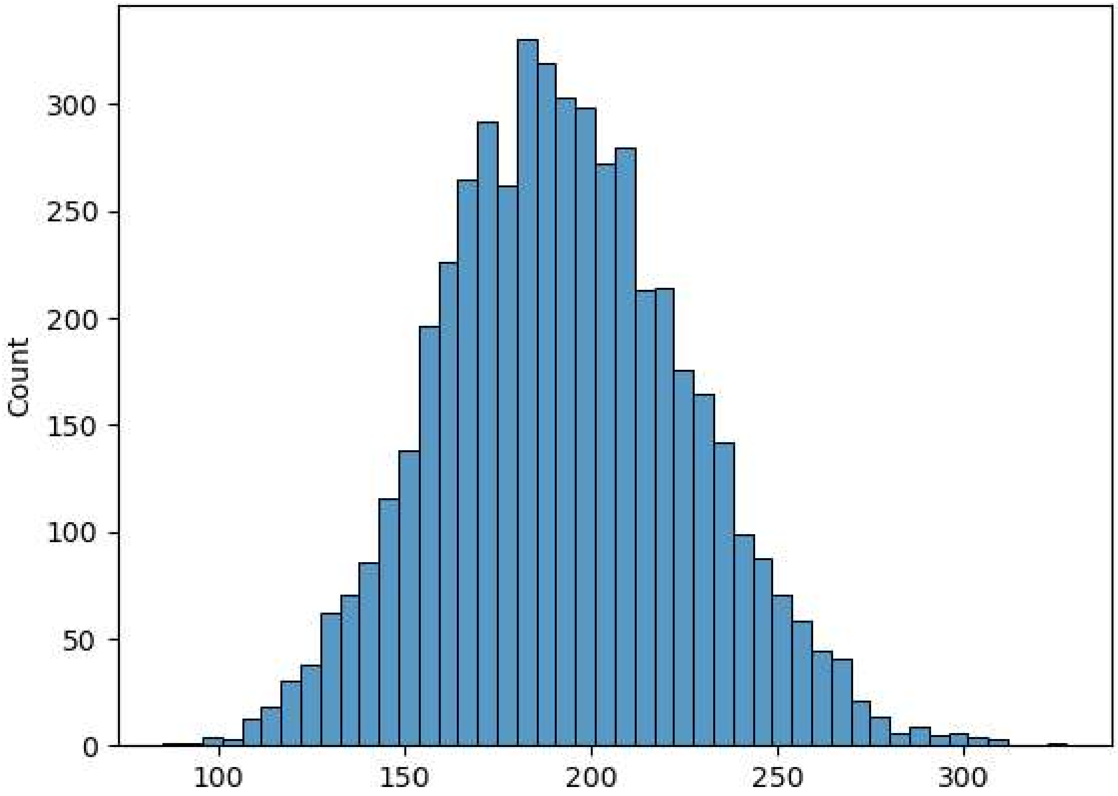
Insight: As can be seen the raw data is clearly not normally distributed. SO we will do random sampling to check if we can apply CLT

In [83]:
```
#sampling for workingday count
wkd_30 = [np.mean(workingday_count.sample(30)) for i in range(5000) ]
# limitting sampling to 6000 since my computer is hanging up with higher count
```

In [87]:

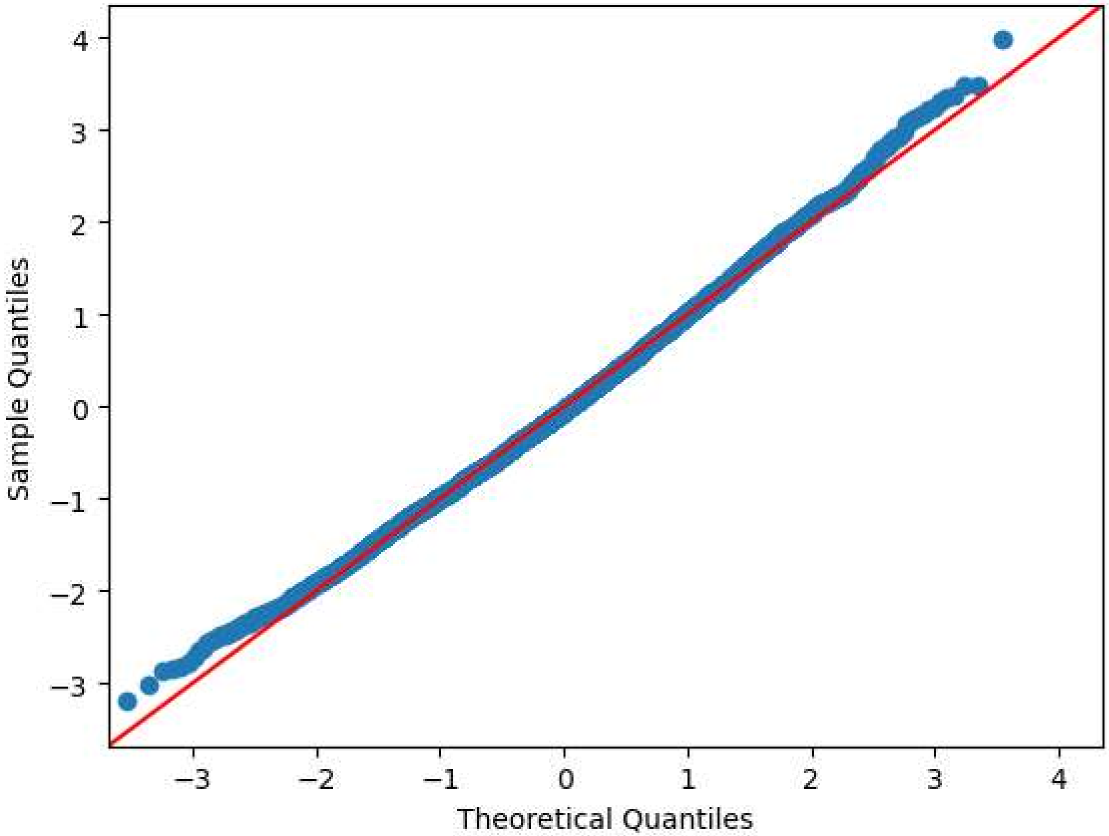
```
sns.histplot(wkd_30)
```

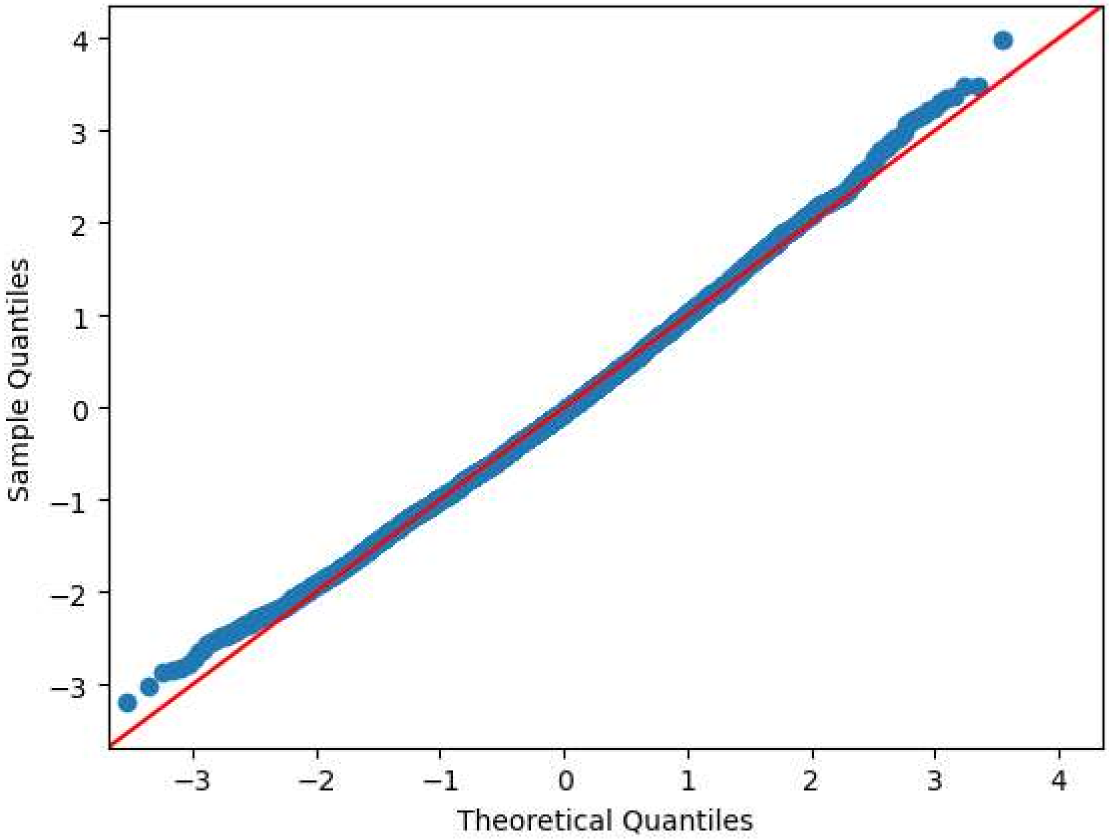
Out[87]: <AxesSubplot:ylabel='Count'>



In [88]:
```
wkd_30_df = pd.Series(wkd_30)
sm.qqplot(wkd_30_df,line='45',fit=True,dist=stats.norm)
```

Out[88]:

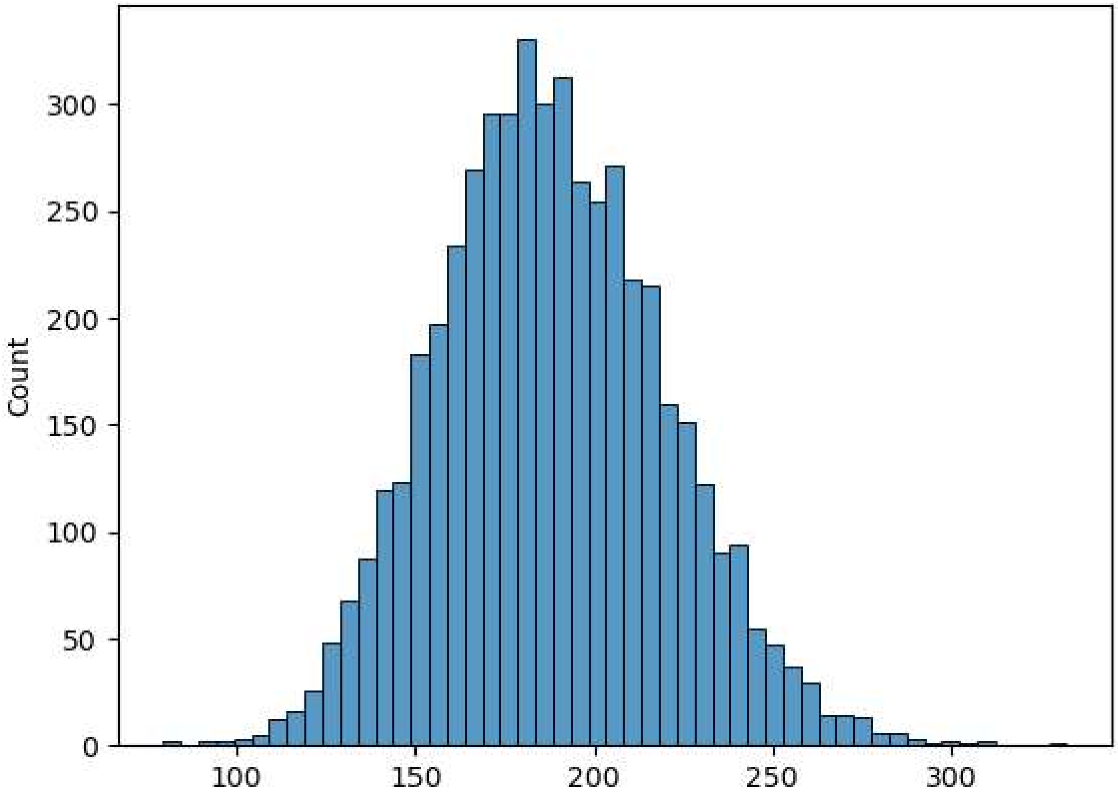




In [84]:
```
#sampling for non-workingday count
nwkd_30 = [np.mean(nonworkingday_count.sample(30)) for i in range(5000) ]
# limitting sampling to 6000 since my computer is hanging up with higher count
```

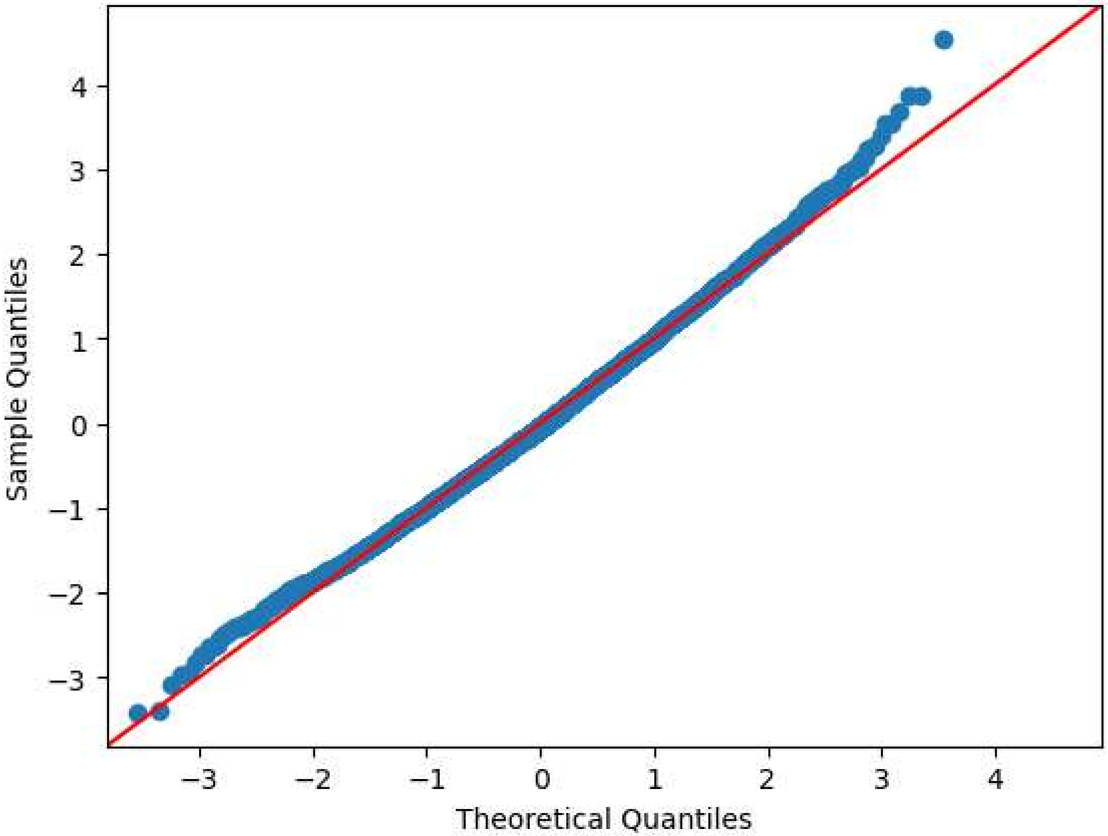
In [85]:
```
sns.histplot(nwkd_30)
```

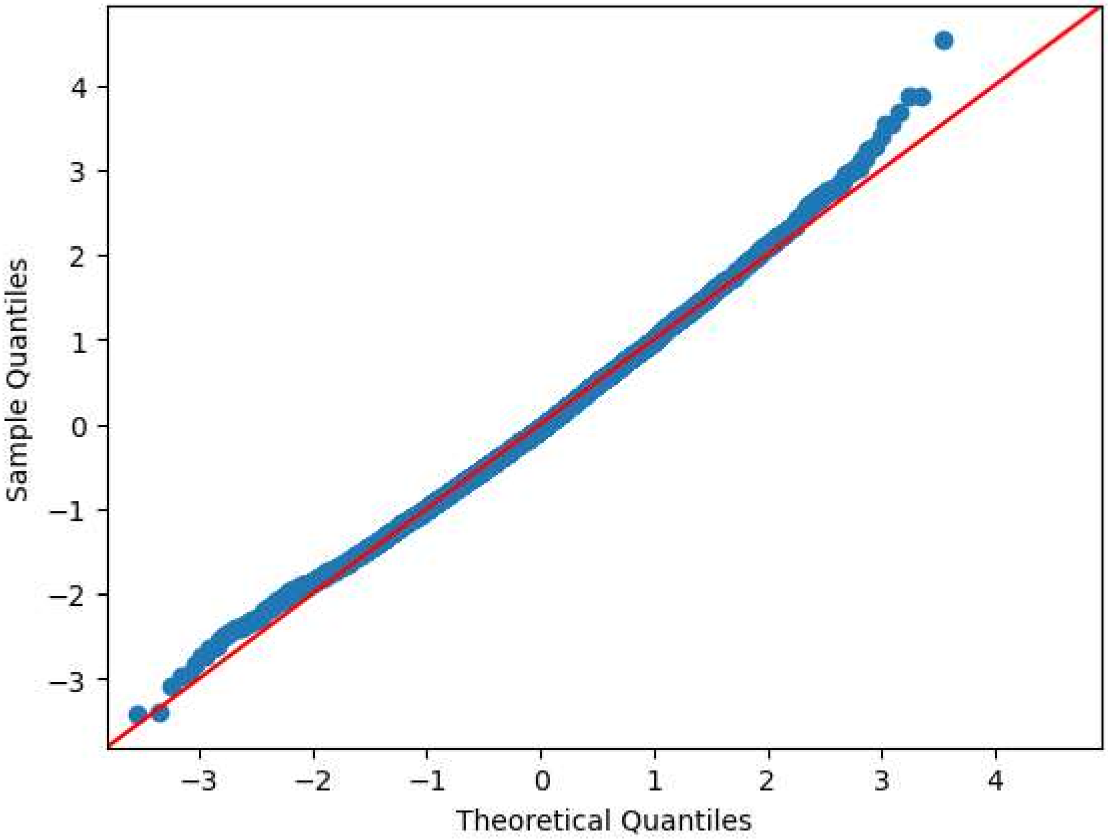
Out[85]: <AxesSubplot:ylabel='Count'>



In [89]:
```
nwkd_30_df = pd.Series(nwkd_30)
sm.qqplot(nwkd_30_df,line='45',fit=True,dist=stats.norm)
```

Out[89]:





Conclusion: after random sampling we can conclude that the 2 samples are now normally distributed. so we can apply T-test to these samples

2.1.5 Performing 2 sample t-test and finding the p-value

H0 - average count on working and non-working days are same (null hypothesis)

Ha - Average count on working days are higher than on non-working days. (Alternate Hypothesis)

if p-value is less than seignificance level of 5% we reject the null hypothesis

In [92]:
```
stat , pvalue = ttest_ind(wkd_30_df, nwkd_30_df, alternative = "greater")
pvalue
```

Out[92]:
```
3.09394292198298930e-12
```

2.1.6 Conclusion based on the pvalue

In [93]:
```
if pvalue < 0.05:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

Insight: we can reject the null hypothesis and conclude that the average count on working days are higher than non-working days.

2.2 Check if No. of cycles rented is similar or different in different 1. weather 2. season

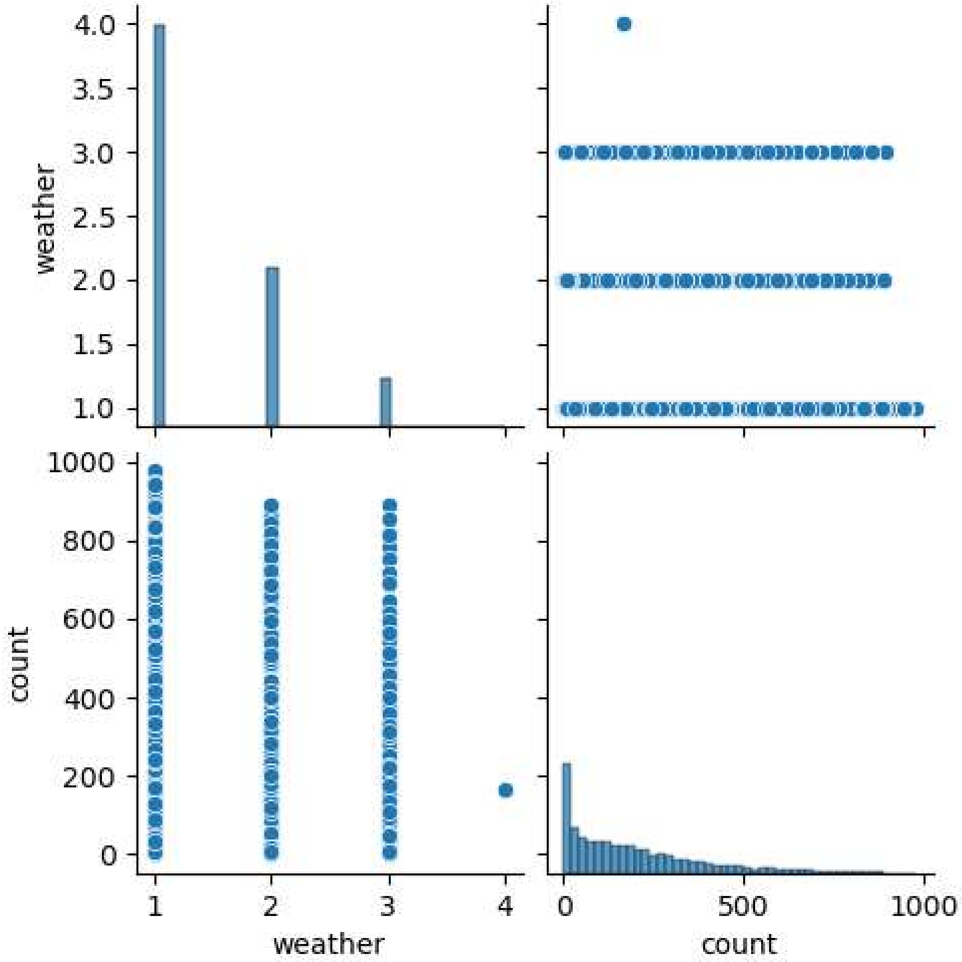
- Visual analysis
- Hypothesis formulation
- Select the appropriate test
- Check test assumptions
- Find the p-value
- Conclusion based on the p-value

2.2.1 Visual Analysis

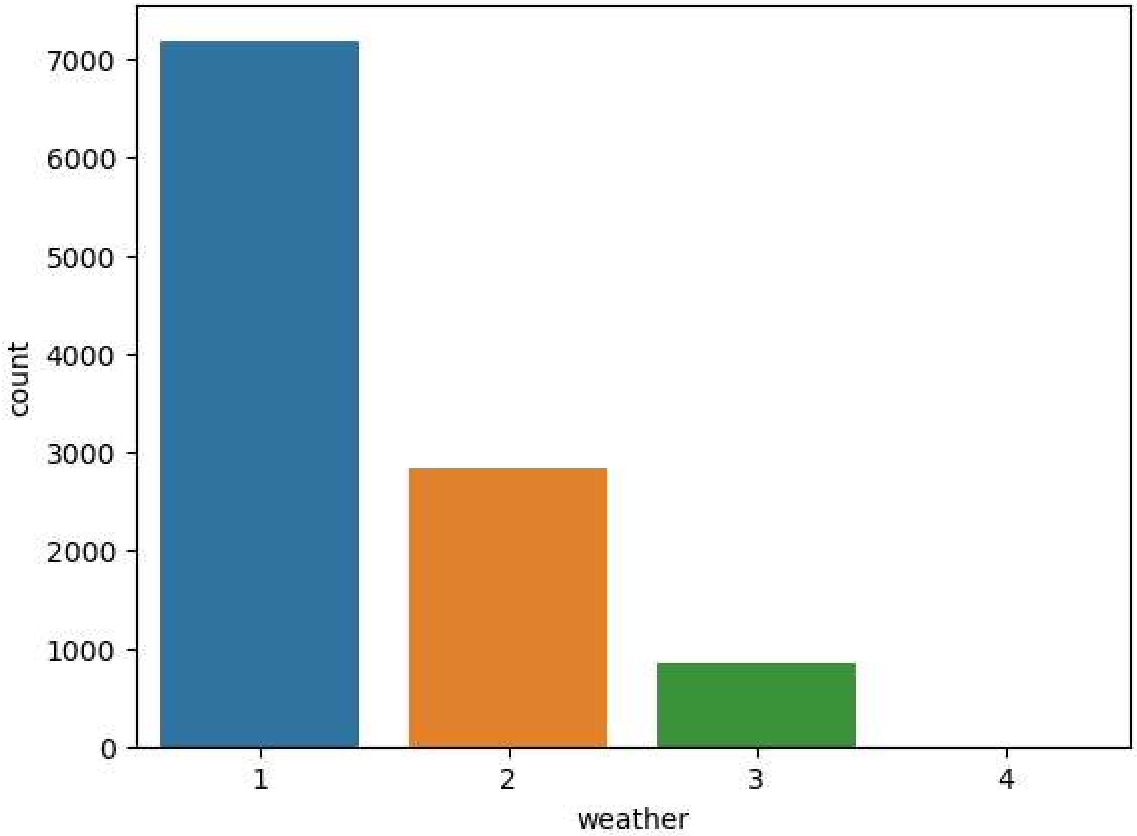
In [94]:
```
plt.figure(figsize=(8,8))
sns.pairplot(data=df.loc[:,["weather","count"]])
```

Out[94]:
```
<seaborn.axisgrid.PairGrid at 0x2e2a5c64910>
```

```
<Figure size 800x800 with 0 Axes>
```



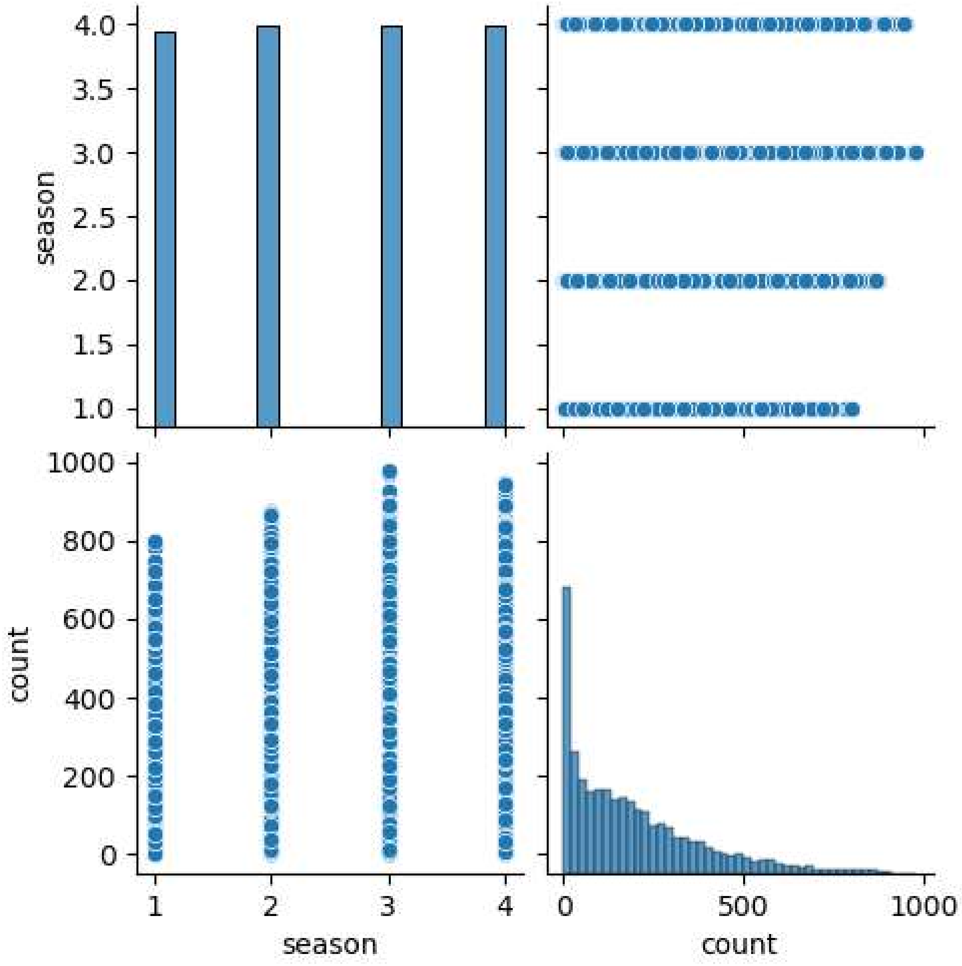
In [95]:
```
sns.countplot(x ='weather', data = df)
plt.show()
```



In [96]:
```
plt.figure(figsize=(8,8))
sns.pairplot(data=df.loc[:,["season","count"]])
```

Out[96]: <seaborn.axisgrid.PairGrid at 0x2e2aa2a0310>

<Figure size 800x800 with 0 Axes>



2.2.2 Hypothesis formulation

In [100]:
```
df.groupby("weather")["count"].mean()
```

Out[100]:
```
weather
1    205.236791
2    178.955540
3    118.846333
4    164.000000
Name: count, dtype: float64
```

H0 - Mean count across all weather are same (null hypothesis)

Ha - Mean count across all weather are different (alternate hypothesis)

2.2.3 Appropriate test

- We can use ANOVA in this case to check if weather has any effect on mean count

In [101]:
```
df.groupby("season")["count"].mean()
```

Out[101]:
```
season
1    116.343261
2    215.251372
3    234.417124
4    198.988296
Name: count, dtype: float64
```

H0 - Mean count across all seasons are same (null hypothesis)

Ha - Mean count across all seasons are different (alternate hypothesis)

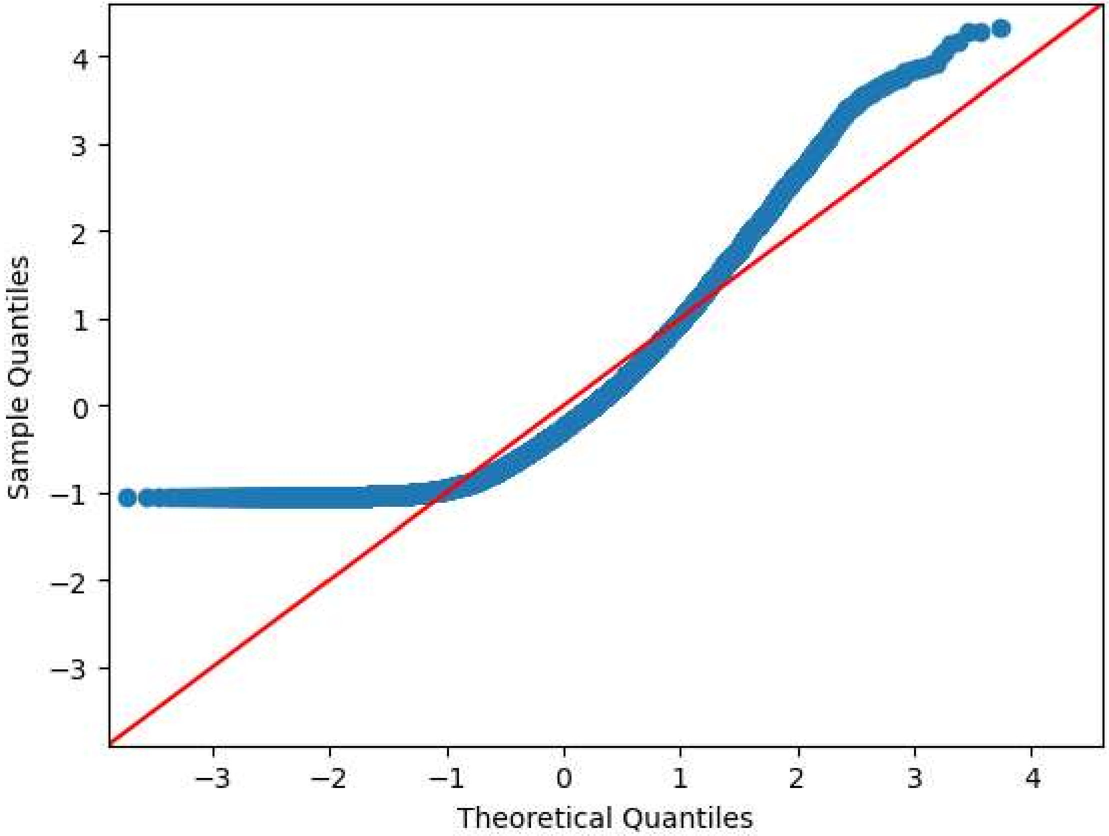
Appropriate test: We can use ANOVA in this case to check if weather has any effect on mean count, only if the assumptions are satisfied , else we need to use the Kruskal Wallis test.

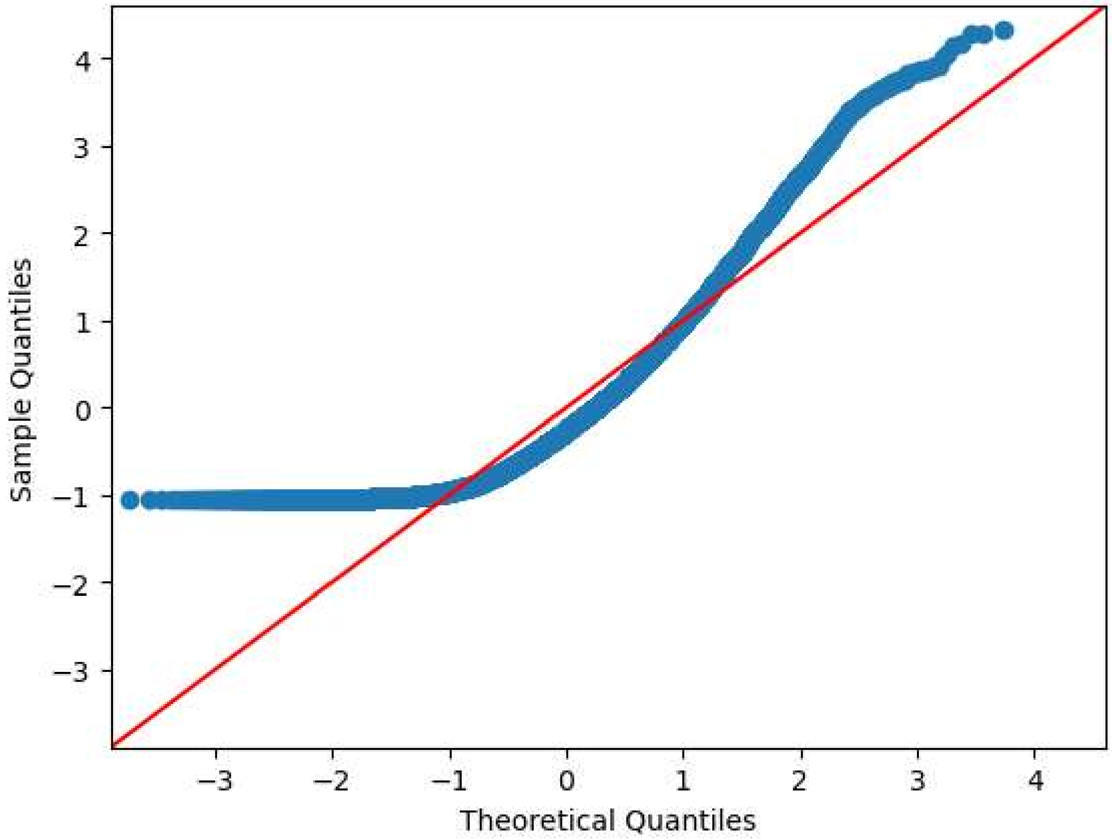
2.2.4 Check test assumptions

Assumption 1: each sample is taken from a normally distributed population

In [102]:
```
sm.qqplot(df["count"],line='45',fit=True,dist=stats.norm)
```

Out[102]:





Assumption 2: Each season / weather data is independent of each other

Assumption 3: Variance should be close between different groups, we can perform Leven's test for this

In [103]:
```
season1_count = df.loc[df["season"]==1]["count"]
season2_count = df.loc[df["season"]==2]["count"]
season3_count = df.loc[df["season"]==3]["count"]
season4_count = df.loc[df["season"]==4]["count"]
```

In [105]:
```
weather1_count = df.loc[df["weather"]==1]["count"]
weather2_count = df.loc[df["weather"]==2]["count"]
weather3_count = df.loc[df["weather"]==3]["count"]
weather4_count = df.loc[df["weather"]==4]["count"]
```

In [106]:
```
w_stats, p_value = levene(season1_count, season2_count,season3_count,season4_count, center='mean')
p_value
```

Out[106]:
```
5.725941205064937e-134
```

In [108]:
```
# H0- Variance among group is equal
# Ha-Variance among group is not equal

alpha = 0.05
if p_value < alpha:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

In [109]:
```
w_stats, p_value = levene(weather1_count, weather2_count,weather3_count,weather4_count, center='mean')
p_value
```

Out[109]:
```
1.889180918625458e-39
```

In [110]:
```
# H0- Variance among group is equal
# Ha-Variance among group is not equal

alpha = 0.05
if p_value < alpha:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

Conclusion: the source data is not normal and the variance among group are not equal. So we cannot use ANOVA rather we will have to use kruskal Wallis test in this case.

2.2.5 Find the p_value

In [111]:
```
stat, p_value = kruskal(season1_count, season2_count,season3_count,season4_count)
p_value
```

Out[111]:
```
2.479008372608633e-151
```

In [112]:
```
alpha = 0.05
if p_value < alpha:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

In [113]:
```
stat, p_value = kruskal(weather1_count, weather2_count,weather3_count,weather4_count)
p_value
```

Out[113]:
```
3.501611300708679e-44
```

In [114]:
```
alpha = 0.05
if p_value < alpha:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

2.2.6 Conclusion based on p_value

Insight:

- The p-value was too low after the kruskal test and we had to reject the null hypothesis. So we can conclude that the mean count is different for different season
- The p-value was too low after the kruskal test and we had to reject the null hypothesis. So we can conclude that the mean count is different for different weathers

2.3 Check if Weather is dependent on the season

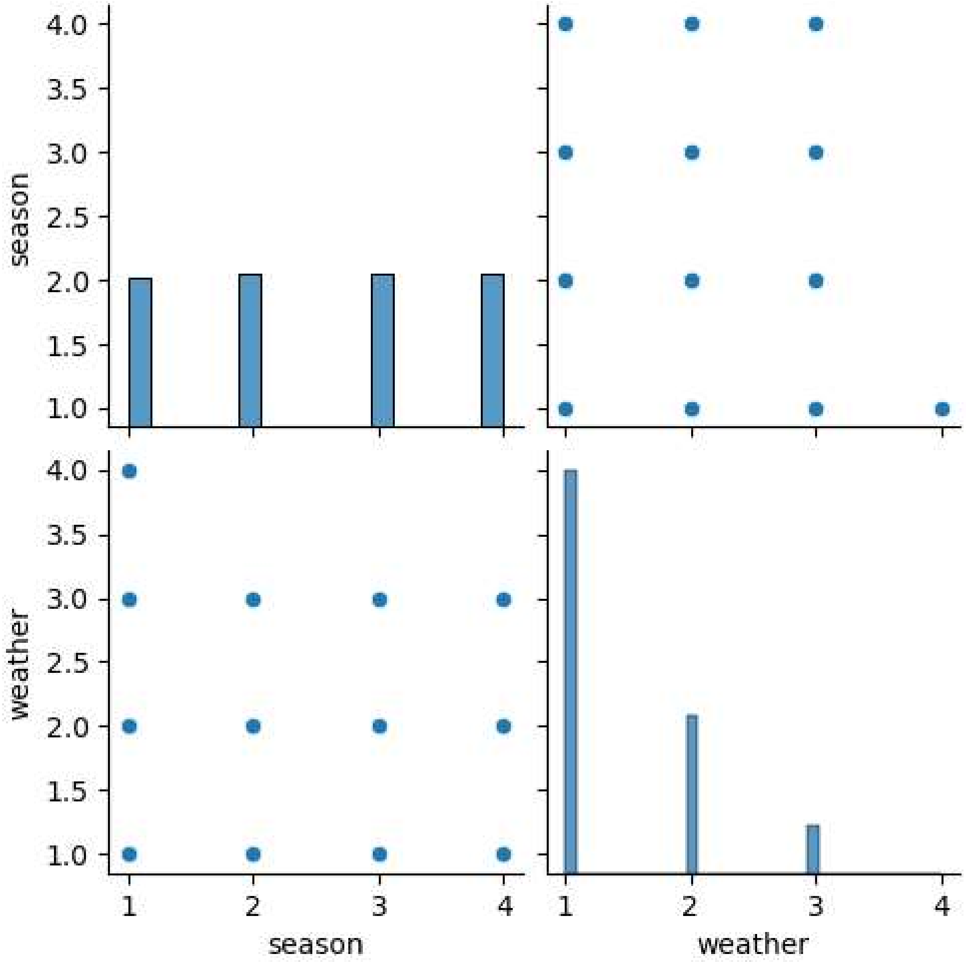
- Visual analysis
- Hypothesis formulation
- Select the appropriate test
- Check test assumptions
- Find the p-value
- Conclusion based on the p-value

2.3.1 Visual Analysis

In [115]:
```
plt.figure(figsize=(8,8))
sns.pairplot(data=df.loc[:,["season","weather"]])
```

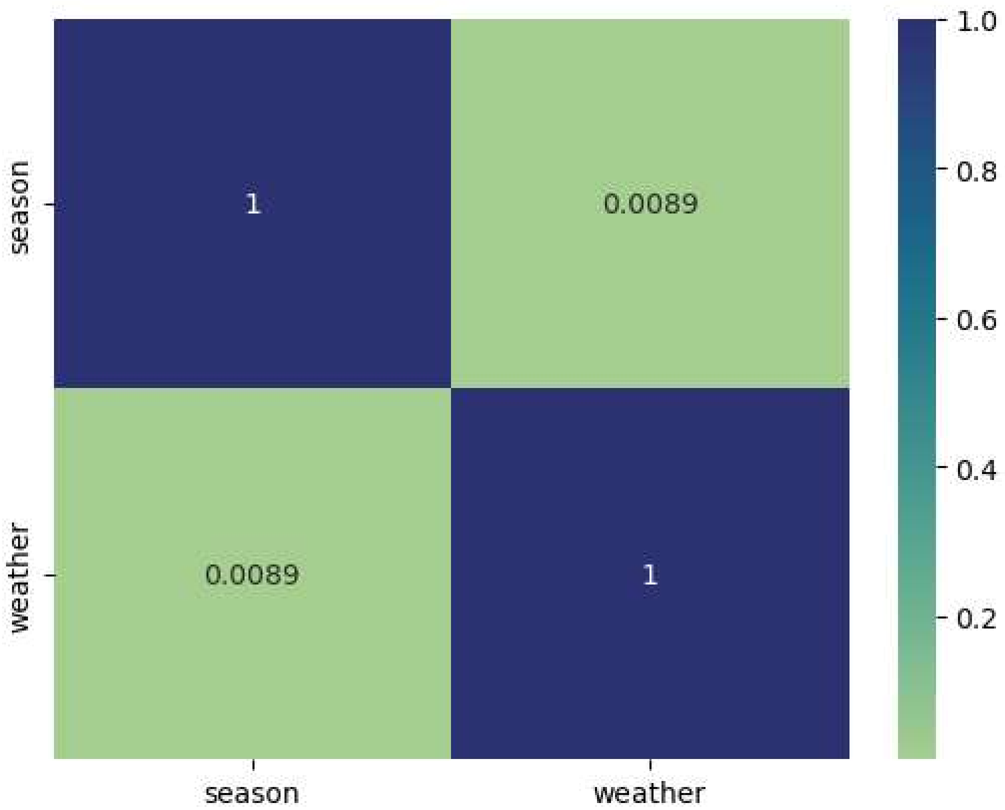
Out[115]:
```
<seaborn.axisgrid.PairGrid at 0x2e2a563d040>
```

```
<Figure size 800x800 with 0 Axes>
```



In [116]:
```
sns.heatmap(df.loc[:,["season","weather"]].corr(),annot=True, cmap="crest")
```

Out[116]: <AxesSubplot:>



Insight: Looking at the above graphical data it seems like weather and season are not dependent on each other

2.3.2 Hypothesis formulation

H0- Weather is in-dependent of season (null hypothesis)

Ha- Weather is dependent on season (alternate hypothesis)

2.3.3 Appropriate test

Since both the features, season and weather are categorical in nature it seems like Chisquared test will be most appropriate for this scenario

2.3.4 Check test Assumptions

- Variables are categorical: yes both season and weather are categorical
- Observations are independent : yes the observations are independent of each other
- Each cell is mutually exclusive: yes each cell is mutually exclusive

- Expected value in each cell is greater than 5 (at least in 80% of cells) : perform crosstab to check below

In [118]:
```
weather_season =pd.crosstab(df['weather'], df['season'])
```

In [119]:
```
weather_season
```

Out[119]:

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

As can be seen roughly 80% of the cells have value greater than 5. So this satisfies the chi-squared assumption

2.3.5 Find p_value

In [120]:
```
chi_stat, p_value, df, freq = chi2_contingency(weather_season)
p_value
```

Out[120]:
```
1.5499250736864862e-07
```

In [121]:
```
alpha = 0.05
if p_value < alpha:
    print("Reject H0")


else :
    print("cannot reject H0")
```

```
Reject H0
```

2.3.6 Conclusion based on p_value

Insight: Since the p-value is very low we reject the null hypothesis and we can conclude that weather and season are not independent.

3 Inference from the analysis

- we can conclude that average count on working days are higher than non-working days.
- we can conclude that the mean count is different for different season
- we can conclude that the mean count is different for different weathers
- we can conclude that weather and season are not independent

In [ ]: