```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
```

```
csv_path = "yulu dataset.txt"
df = pd.read_csv(csv_path, delimiter=",")
df.head()
```

	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

```
# no of rows amd columns in dataset
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")
```

```
# rows: 10886
# columns: 12
```

```
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
```

```
df['datetime'] = pd.to_datetime(df['datetime'])

cat_cols= ['season', 'holiday', 'workingday', 'weather']
for col in cat_cols:
    df[col] = df[col].astype('object')
```

```
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
```

```
df.iloc[:, 1:].describe(include='all')
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered
count	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
unique	4.0	2.0	2.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN
top	4.0	0.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN
freq	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177
std	NaN	NaN	NaN	NaN	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033
min	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000
25%	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000
50%	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000
75%	NaN	NaN	NaN	NaN	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000
max	NaN	NaN	NaN	NaN	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000

```
# detecting missing values in the dataset
df.isnull().sum()
```

```
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
```

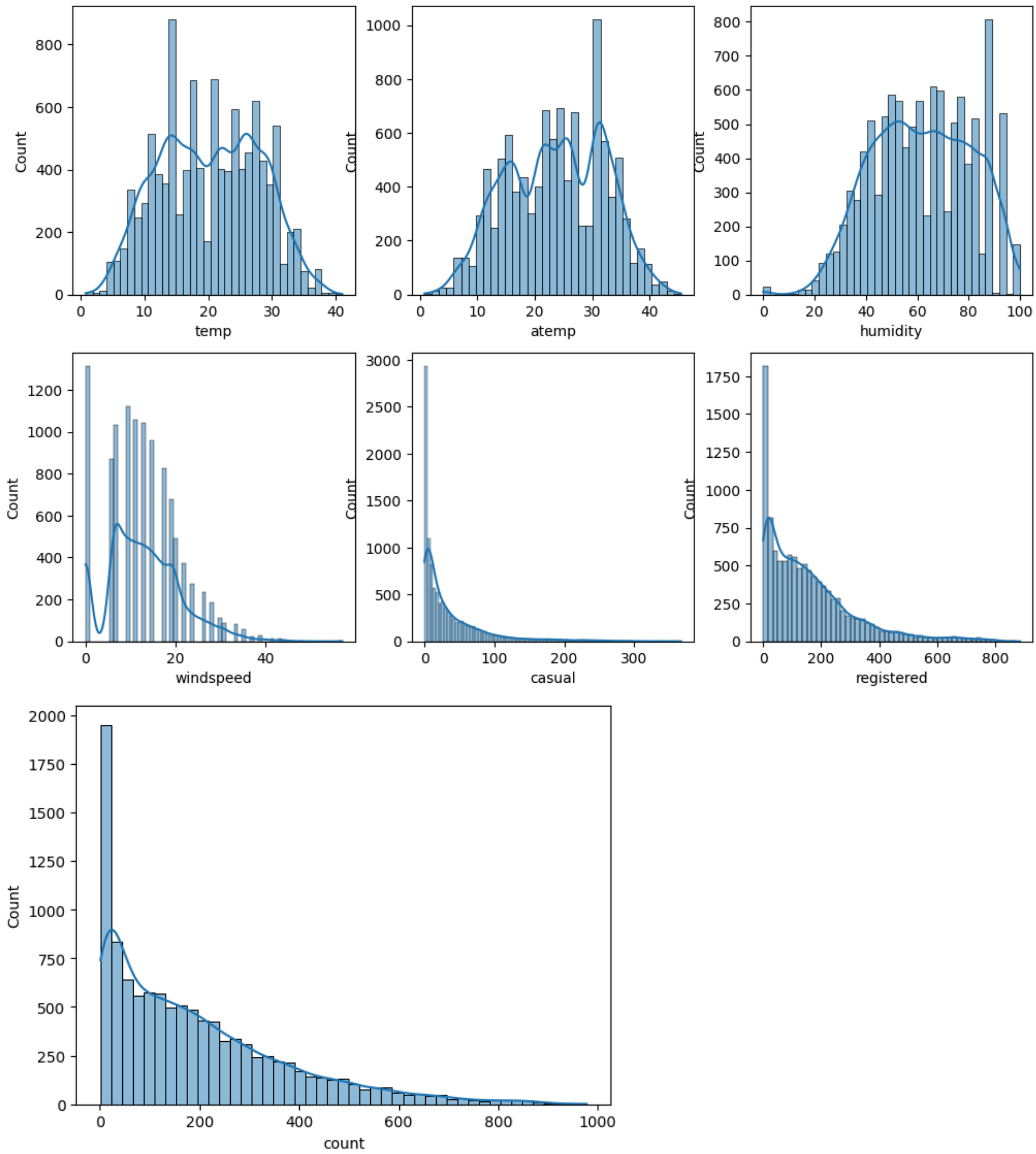
```
# minimum datetime and maximum datetime
print(df['datetime'].min(), df['datetime'].max())
# number of unique values in each categorical columns
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

```
2011-01-01 00:00:00 2012-12-19 23:00:00
```

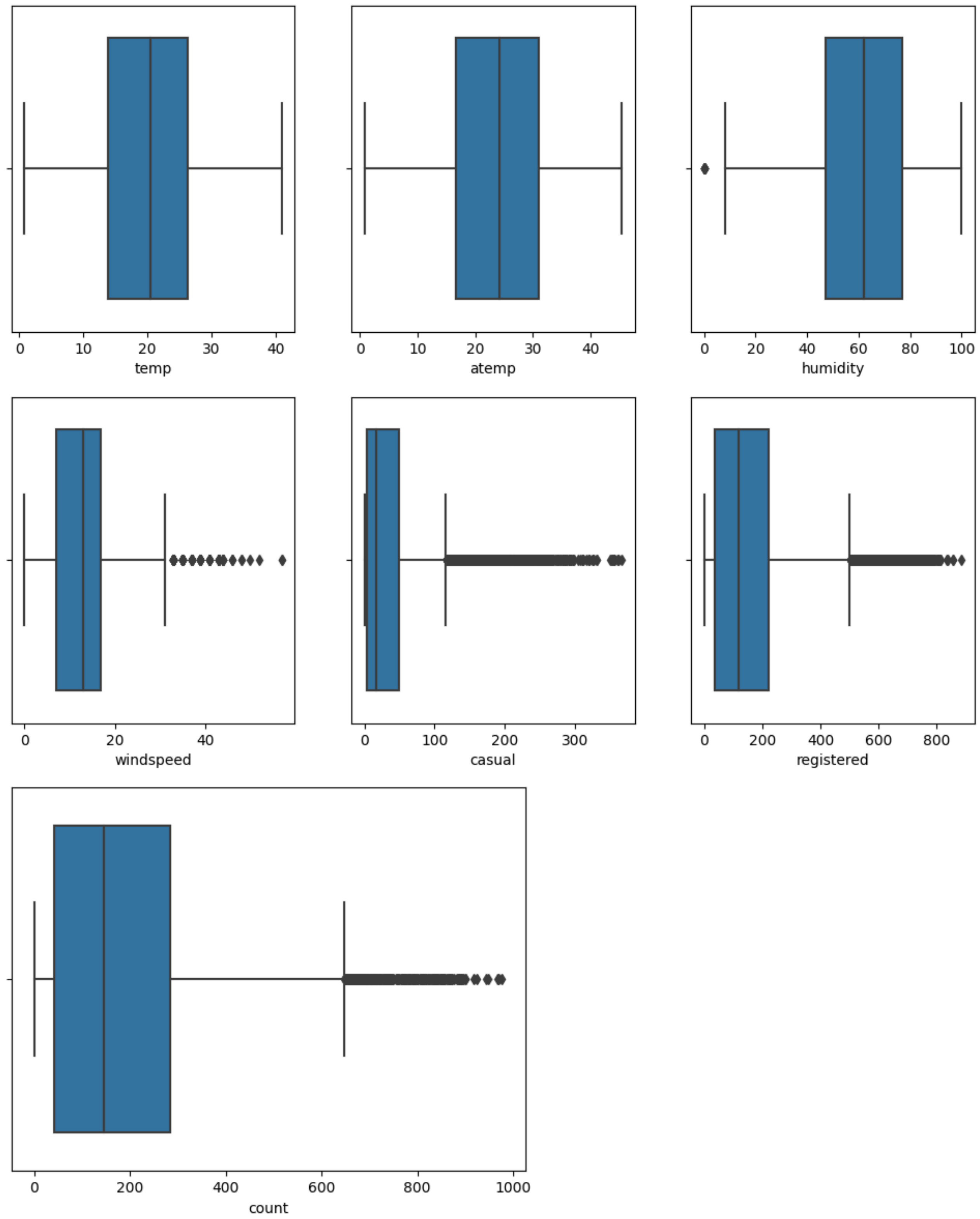
variable	value	value
holiday	**0**	10575
	1	311
season	**1**	2686
	2	2733
	3	2733
	4	2734
weather	**1**	7192
	2	2834
	3	859
	4	1
workingday	**0**	3474
	1	7412

```
# understanding the distribution for numerical variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 8))

index = 0
for row in range(2):
    for col in range(3):
        sns.histplot(df[num_cols[index]], ax=axis[row, col], kde=True)
        index += 1

plt.show()
```

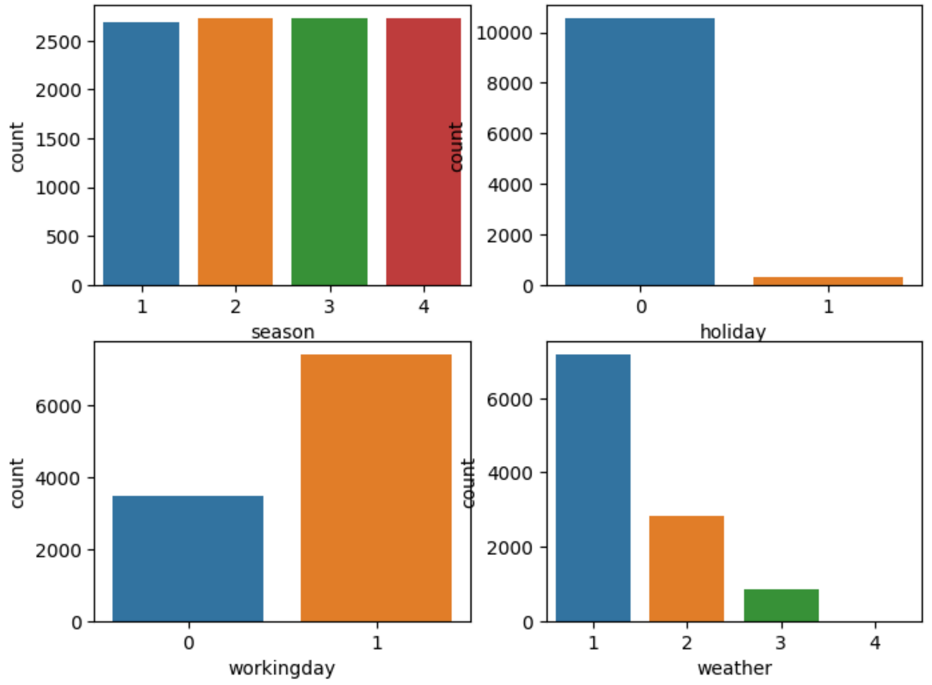
```
sns.histplot(df[num_cols[-1]], kde=True)
plt.show()
```



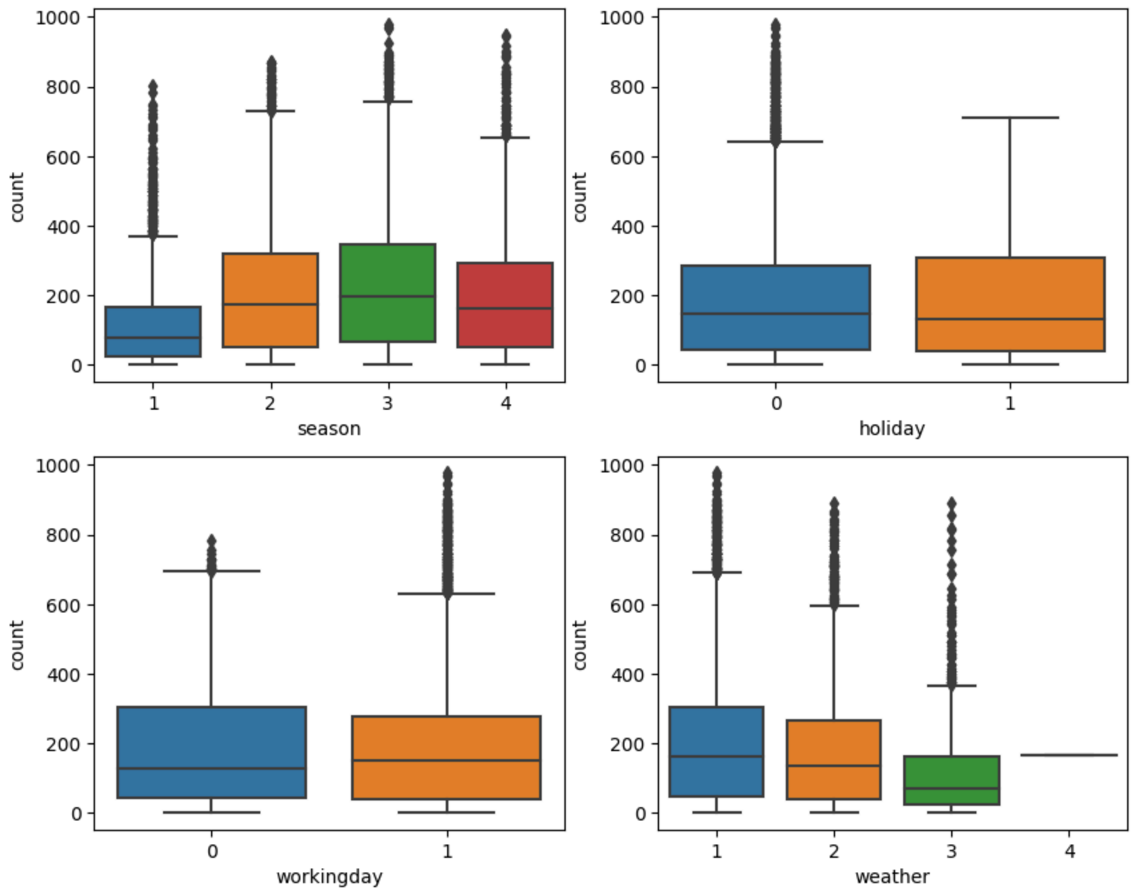

```
# plotting box plots to detect outliers in the data
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 9))

index = 0
for row in range(2):
    for col in range(3):
        sns.boxplot(x=df[num_cols[index]], ax=axis[row, col])
        index += 1

plt.show()
sns.boxplot(x=df[num_cols[-1]])
plt.show()
```




```
# countplot of each categorical column
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(8, 6))

index = 0
for row in range(2):
    for col in range(2):
        sns.countplot(data=df, x=cat_cols[index], ax=axis[row, col])
        index += 1

plt.show()
```

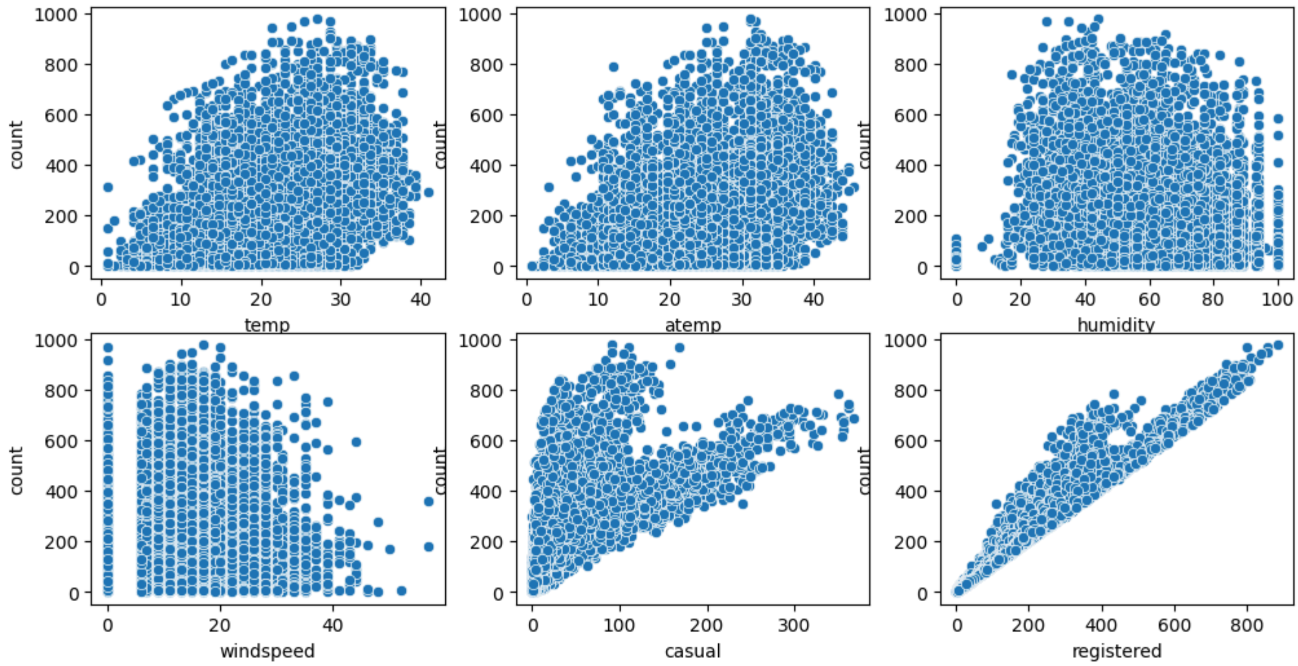



```
# plotting categorical variables againt count using boxplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))

index = 0
for row in range(2):
    for col in range(2):
        sns.boxplot(data=df, x=cat_cols[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```



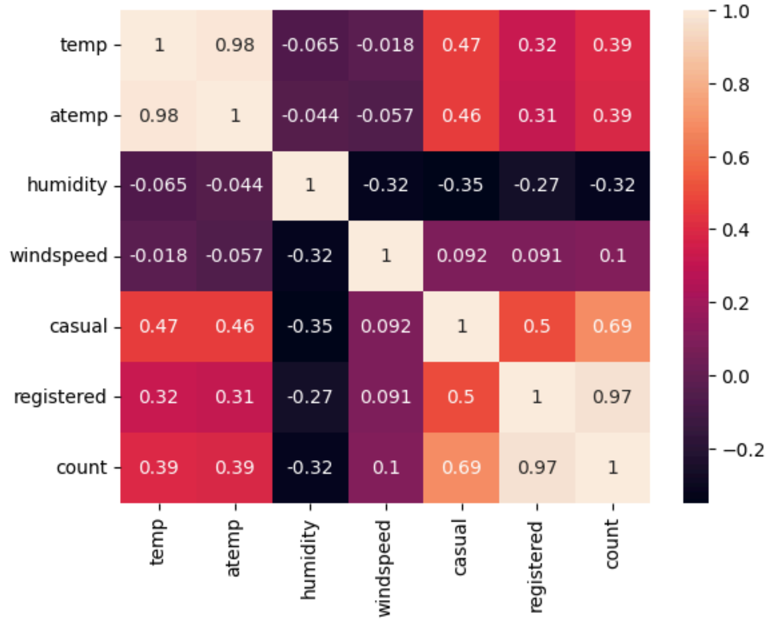

```
# plotting numerical variables againt count using scatterplot
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 6))

index = 0
```

```
for row in range(2):
    for col in range(3):
        sns.scatterplot(data=df, x=num_cols[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```




```
# understanding the correlation between count and numerical variables
df.corr()['count']
sns.heatmap(df.corr(), annot=True)
plt.show()
```

```
<ipython-input-22-b0729b22659f>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future
  df.corr()['count']
<ipython-input-22-b0729b22659f>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future
  sns.heatmap(df.corr(), annot=True)
```




```
data_table = pd.crosstab(df['season'], df['weather'])
print("Observed values:")
data_table
```

Observed values:

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

```
val = stats.chi2_contingency(data_table)
print(val)
expected_values = val[3]
print(expected_values)
nrows, ncols = 4, 4
dof = (nrows-1)*(ncols-1)
print("degrees of freedom: ", dof)
alpha = 0.05


chi_sqr = sum([(o-e)**2/e for o, e in zip(data_table.values, expected_values)])
chi_sqr_statistic = chi_sqr[0] + chi_sqr[1]
print("chi-square test statistic: ", chi_sqr_statistic)

critical_val = stats.chi2.ppf(q=1-alpha, df=dof)
print(f"critical value: {critical_val}")

p_val = 1-stats.chi2.cdf(x=chi_sqr_statistic, df=dof)
print(f"p-value: {p_val}")

if p_val <= alpha:
    print("\nSince p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning that\
    Weather is dependent on the season.")
else:
    print("Since p-value is greater than the alpha 0.05, We do not reject the Null Hypothesis")
```

```
Chi2ContingencyResult(statistic=49.158655596893624, pvalue=1.549925073686492e-07, dof=9, expected_freq=array([[1.77454639e+03, 6
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80625831e+03, 7.11754180e+02, 2.15736359e+02, 2.51148264e-01]]))
[[1.77454639e+03 6.99258130e+02 2.11948742e+02 2.46738931e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80625831e+03 7.11754180e+02 2.15736359e+02 2.51148264e-01]]
degrees of freedom:  9
chi-square test statistic:  44.09441248632364
critical value: 16.918977604620448
p-value: 1.3560001579371317e-06

Since p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning that    Weather is dependent on the season.
```

```
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values

print(np.var(data_group1), np.var(data_group2))
np.var(data_group2)// np.var(data_group1)
```

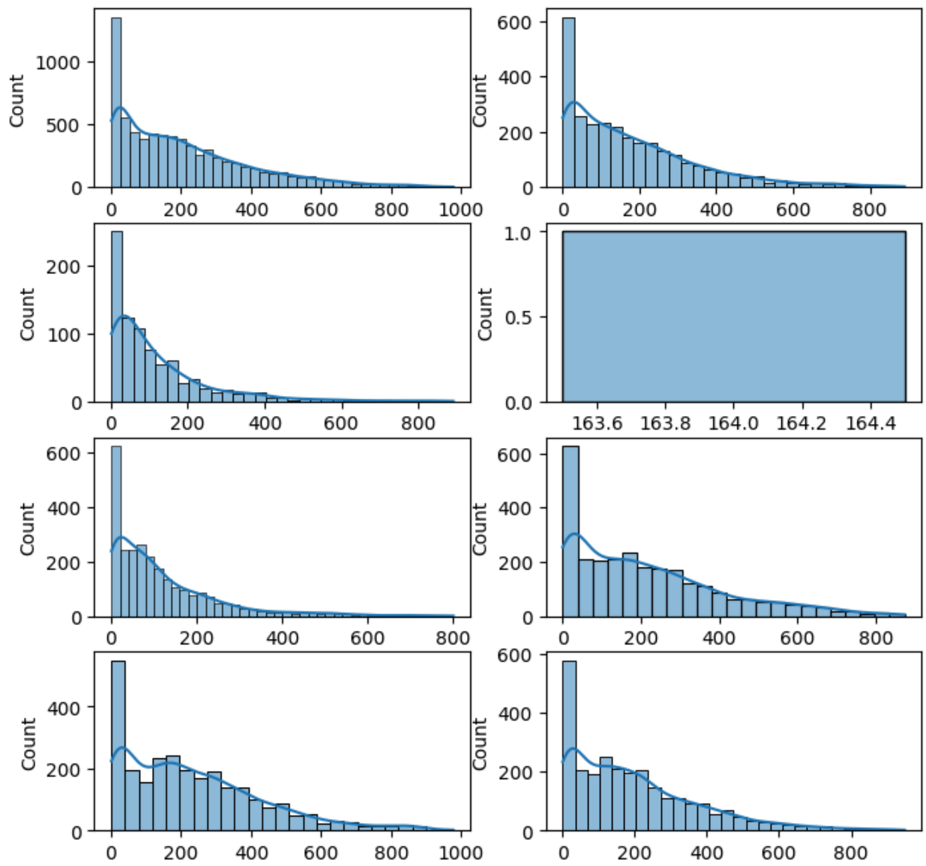
```
30171.346098942427 34040.69710674686
1.0
```

```
stats.ttest_ind(a=data_group1, b=data_group2, equal_var=True)
```

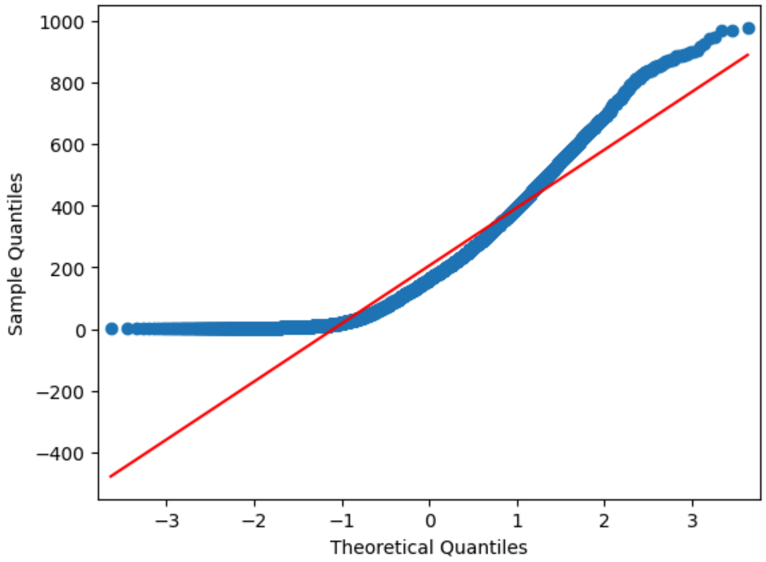
```
Ttest_indResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348)
```

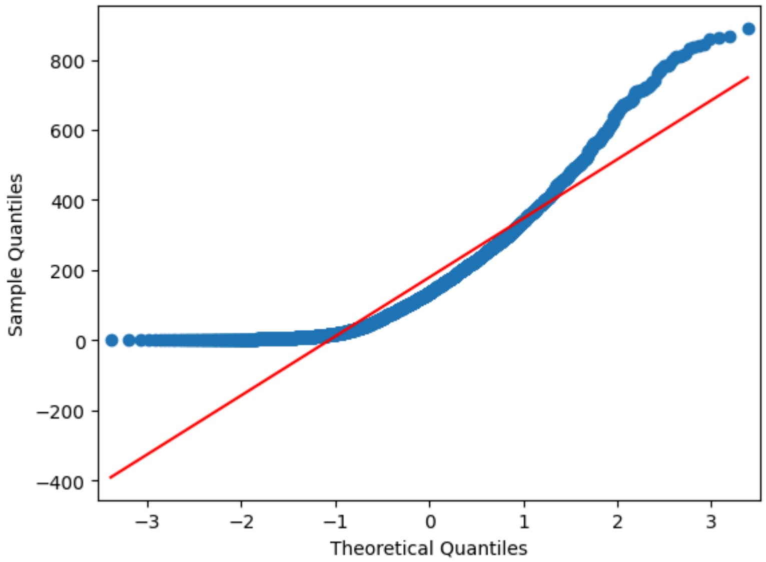
```
# defining the data groups for the ANOVA
from statsmodels.graphics.gofplots import qqplot
gp1 = df[df['weather']==1]['count'].values
gp2 = df[df['weather']==2]['count'].values
gp3 = df[df['weather']==3]['count'].values
gp4 = df[df['weather']==4]['count'].values

gp5 = df[df['season']==1]['count'].values
gp6 = df[df['season']==2]['count'].values
gp7 = df[df['season']==3]['count'].values
gp8 = df[df['season']==4]['count'].values
groups=[gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8]
```

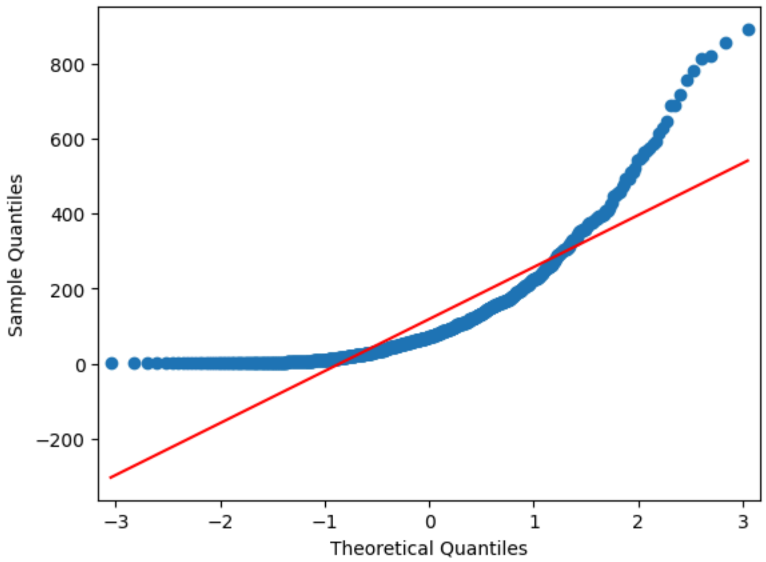
```
fig, axis = plt.subplots(nrows=4, ncols=2, figsize=(8, 8))

index = 0
for row in range(4):
    for col in range(2):
        sns.histplot(groups[index], ax=axis[row, col], kde=True)
        index += 1

plt.show()
```



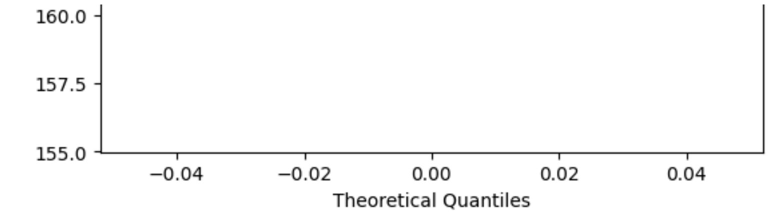

```
index = 0
for row in range(4):
    for col in range(2):
        qqplot(groups[index], line="s")
        index += 1

plt.show()
```

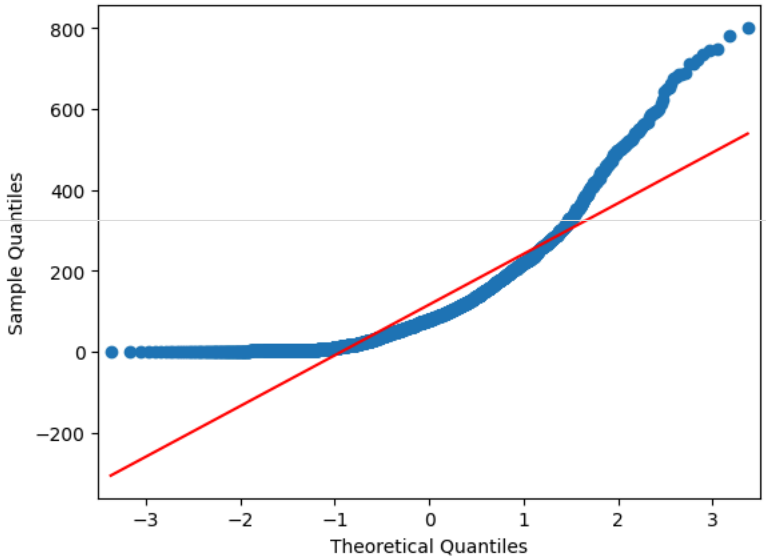

Sample Quantiles
Theoretical Quantiles

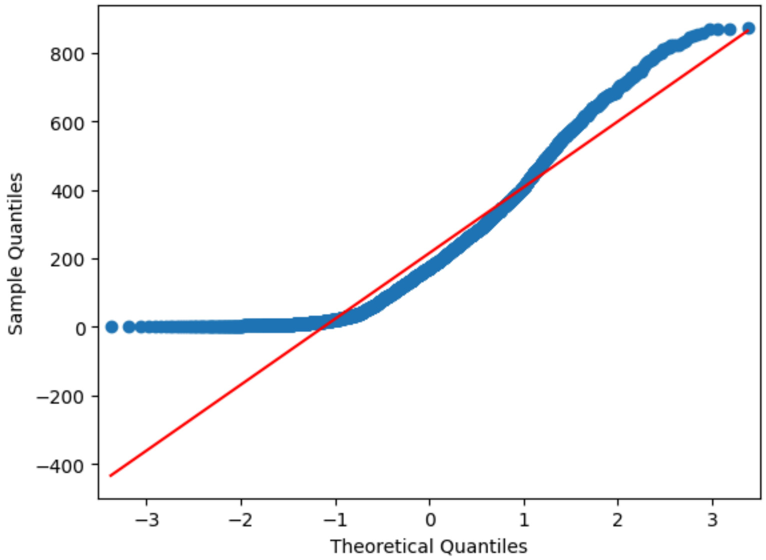

Sample Quantiles
Theoretical Quantiles

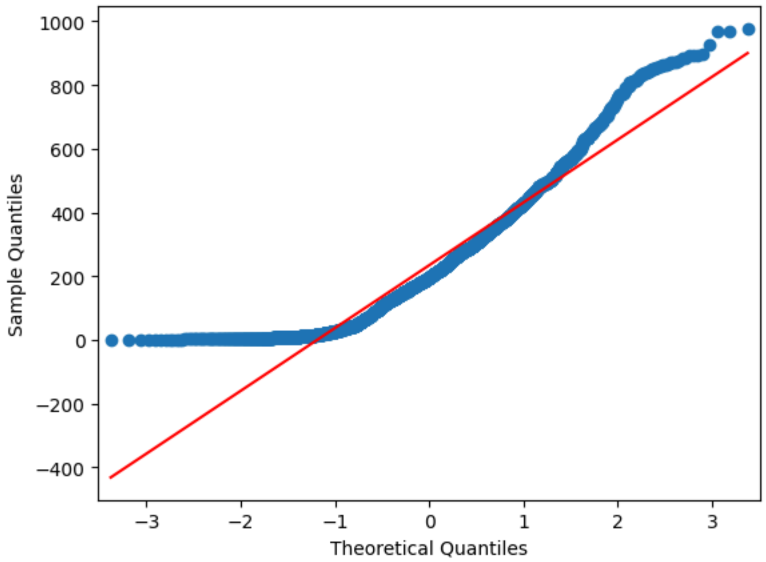

Sample Quantiles
Theoretical Quantiles

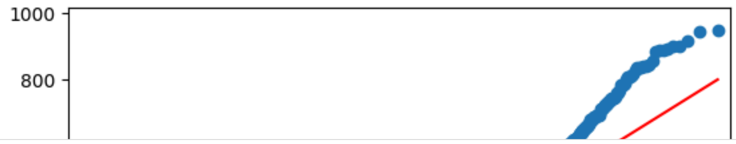

Sample Quantiles


160.0
157.5
155.0
−0.04
−0.02
0.00
0.02
0.04
Theoretical Quantiles


800
600
400
200
0
−200
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


1000
800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


1000
800

```
#Null Hypothesis: Variances is similar in different weather and season.

#Alternate Hypothesis: Variances is not similar in different weather and season.

#Significance level (alpha): 0.05
levene_stat, p_value = stats.levene(gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8)
print(p_value)
if p_value < 0.05:
    print("Reject the Null hypothesis.Variances are not equal")
else:
  print("Fail to Reject the Null hypothesis.Variances are  equal")
```

```
3.463531888897594e-148
Reject the Null hypothesis.Variances are not equal
```

```
#assumptions of ANOVA don't hold, we need Kruskal Wallis
kruskal_stat, p_value = stats.kruskal(gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8)
print("p_value===",p_value)
if p_value<0.05:
  print("Since p-value is less than 0.05, we reject the null hypothesis")
```

```
p_value=== 4.614440933900297e-191
Since p-value is less than 0.05, we reject the null hypothesis
```

Insights:

- Ride demand strongly depends on weather and season. Usage is highest during pleasant and dry conditions and lowest during rainy or extremely cold seasons.
- Temperature has a strong positive correlation with ride count. As temperature increases (up to a comfortable level), the number of rides also increases.
- Humidity and windspeed negatively affect ride demand. Riders avoid using bikes in humid or windy weather due to discomfort.
- Weekday and weekend ride counts are statistically similar. Indicates that people use Yulu for both commuting and leisure, ensuring consistent demand throughout the week.
- Variability in rides differs across weather and seasons. Ride counts fluctuate significantly between different weather and seasonal conditions.
- Significant differences exist in average rides across seasons and weather types. Demand is not uniform — some months and weather conditions generate much higher rentals.

Recommendations::

- Plan fleet allocation based on season and weather forecasts. Increase the number of bikes during dry, warm seasons and reduce during monsoons or cold months.
- Introduce dynamic pricing. Offer discounts during low-demand weather conditions and higher prices when demand peaks to balance usage.
- Schedule maintenance during low-demand periods. Perform bike servicing and battery replacements in rainy or cold seasons when rides are fewer.
- Maintain consistent weekday and weekend operations. Since usage is steady, ensure bike availability across all days to maximize revenue.
- Use predictive analytics for demand forecasting. Build models using weather, temperature, and season data to forecast future ride counts and optimize resource deployment.
- Enhance customer engagement. Notify users about favorable weather conditions or offer incentives for off-peak usage to increase ride frequency.
- Adopt sustainability-focused campaigns. Promote Yulu as an eco-friendly commuting option during high-demand seasons to boost ridership and brand image.

Start coding or generate with AI.

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