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.

How you can help here?

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

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns


from google.colab import files


uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving bike_sharing.txt to bike_sharing.txt
```

```
df = pd.read_csv('bike_sharing.txt')
```

```
df.head()
```

```
              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
```

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

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

```python
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
```

Datatype of following attributes needs to changed to proper data type

- **datetime** - to datetime

- **season** - to categorical
- **holiday** - to categorical
- **workingday** - to categorical
- **weather** - to categorical

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

```
         season  holiday  workingday  weather         temp
atemp  \
count   10886.0  10886.0     10886.0  10886.0  10886.00000
10886.000000
unique      4.0      2.0         2.0      4.0          NaN
NaN
top         4.0      0.0         1.0      1.0          NaN
NaN
freq     2734.0  10575.0      7412.0   7192.0          NaN
NaN
mean        NaN      NaN         NaN      NaN     20.23086
23.655084
std         NaN      NaN         NaN      NaN      7.79159
8.474601
min         NaN      NaN         NaN      NaN      0.82000
0.760000
25%         NaN      NaN         NaN      NaN     13.94000
16.665000
50%         NaN      NaN         NaN      NaN     20.50000
24.240000
75%         NaN      NaN         NaN      NaN     26.24000
31.060000
max         NaN      NaN         NaN      NaN     41.00000
45.455000

            humidity     windspeed        casual    registered
count
count   10886.000000  10886.000000  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       61.886460     12.799395     36.021955    155.552177
191.574132
```

```
std        19.245033      8.164537     49.960477    151.039033
181.144454
min         0.000000      0.000000      0.000000      0.000000
1.000000
25%        47.000000      7.001500      4.000000     36.000000
42.000000
50%        62.000000     12.998000     17.000000    118.000000
145.000000
75%        77.000000     16.997900     49.000000    222.000000
284.000000
max       100.000000     56.996900    367.000000    886.000000
977.000000
```

- There are no missing values in the dataset.
- **casual** and **registered** attributes might have outliers because their mean and median are very far away to one another and the value of standard deviation is also high which tells us that there is high variance in the data of these attributes.

```
# 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
```

There are no missing values present in the dataset.

```
# minimum datetime and maximum datetime
df['datetime'].min(), df['datetime'].max()

(Timestamp('2011-01-01 00:00:00'), Timestamp('2012-12-19 23:00:00'))

# number of unique values in each categorical columns
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()

                  value
variable   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
```

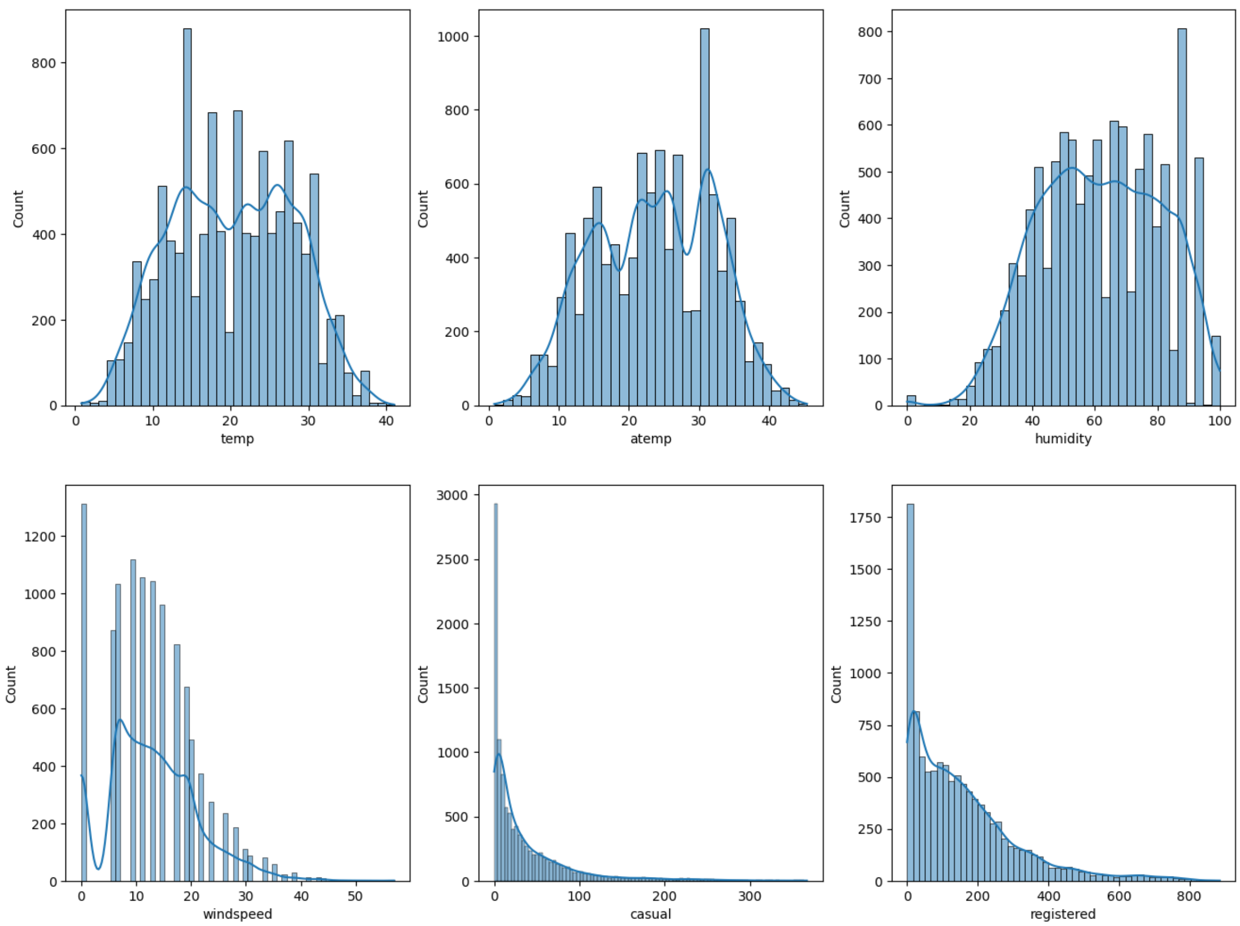
Univariate Analysis

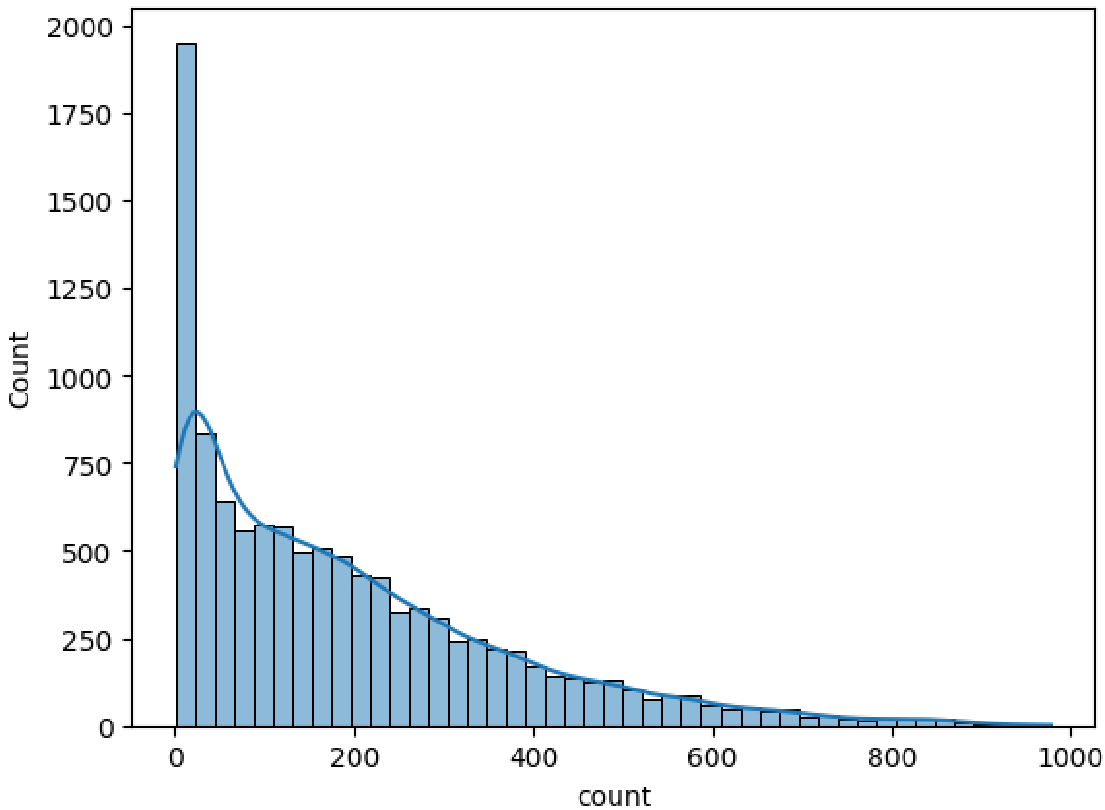
```
# understanding the distribution for numerical variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual',
'registered','count']

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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()
```


Count
temp
0 10 20 30 40
0 200 400 600 800
Count
atemp
0 10 20 30 40
0 200 400 600 800 1000
Count
humidity
0 20 40 60 80 100
0 100 200 300 400 500 600 700 800
Count
windspeed
0 10 20 30 40 50
0 200 400 600 800 1000 1200
Count
casual
0 100 200 300
0 500 1000 1500 2000 2500 3000
Count
registered
0 200 400 600 800
0 250 500 750 1000 1250 1500 1750

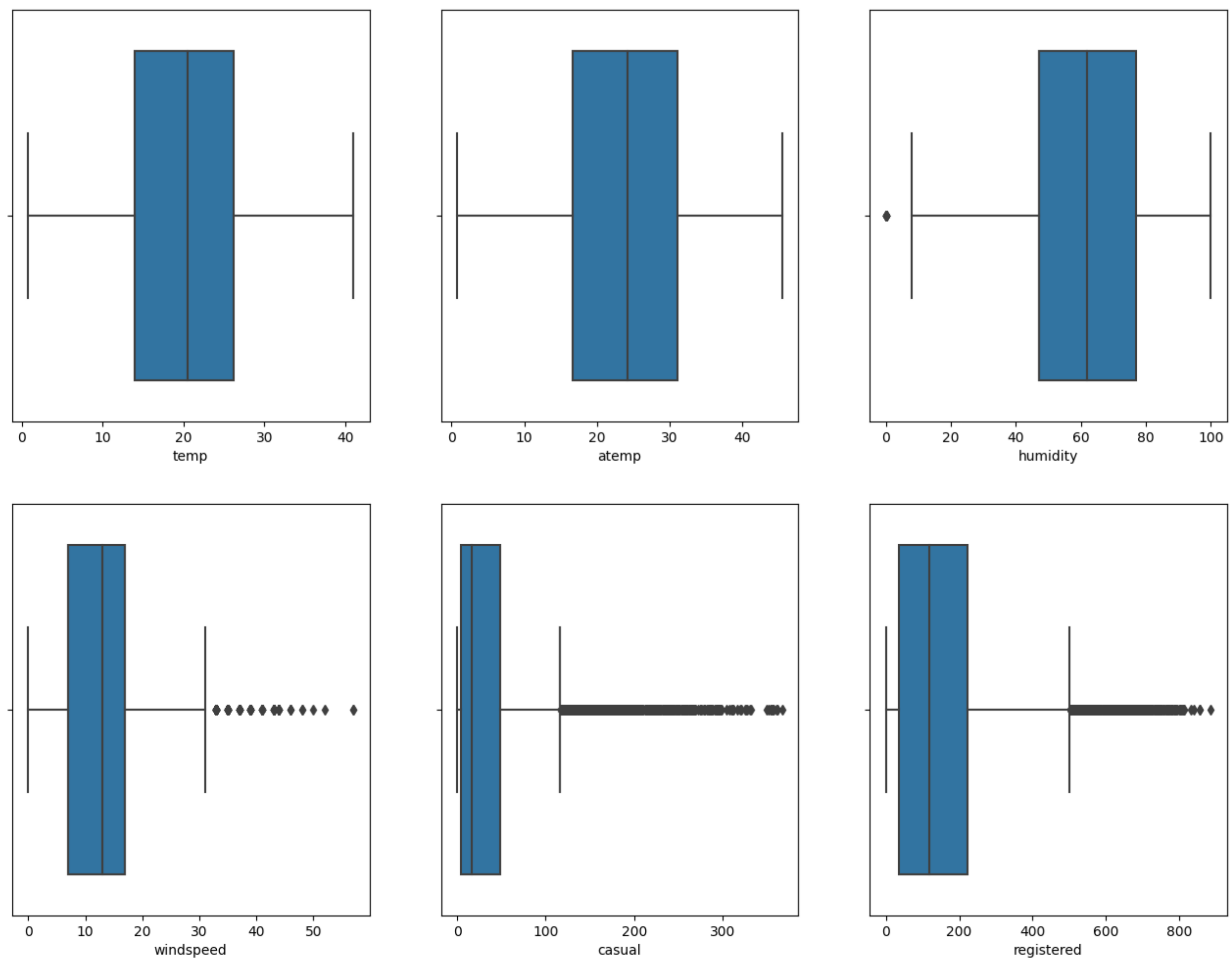


- **casual**, **registered** and **count** somewhat looks like **Log Normal Distrinution**
- **temp**, **atemp** and **humidity** looks like they follows the **Normal Distribution**
- **windspeed** follows the **binomial distribution**

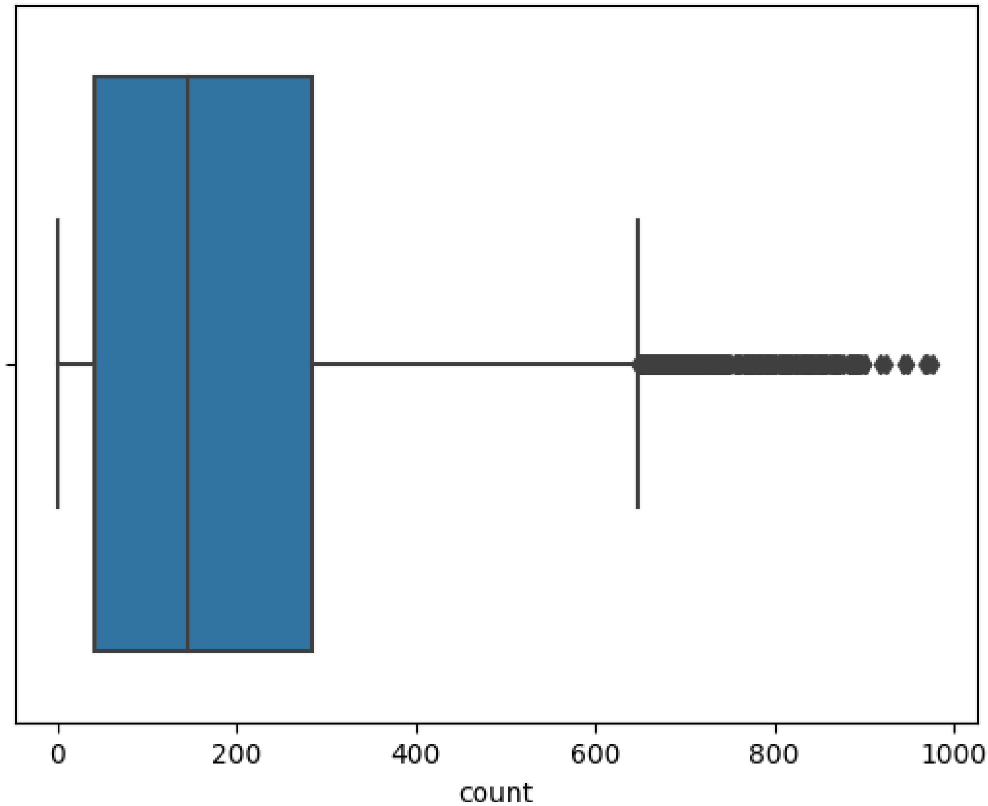
```
# plotting box plots to detect outliers in the data
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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()
```



0
10
20
30
40
temp
0
10
20
30
40
atemp
0
20
40
60
80
100
humidity
0
10
20
30
40
50
windspeed
0
100
200
300
casual
0
200
400
600
800
registered

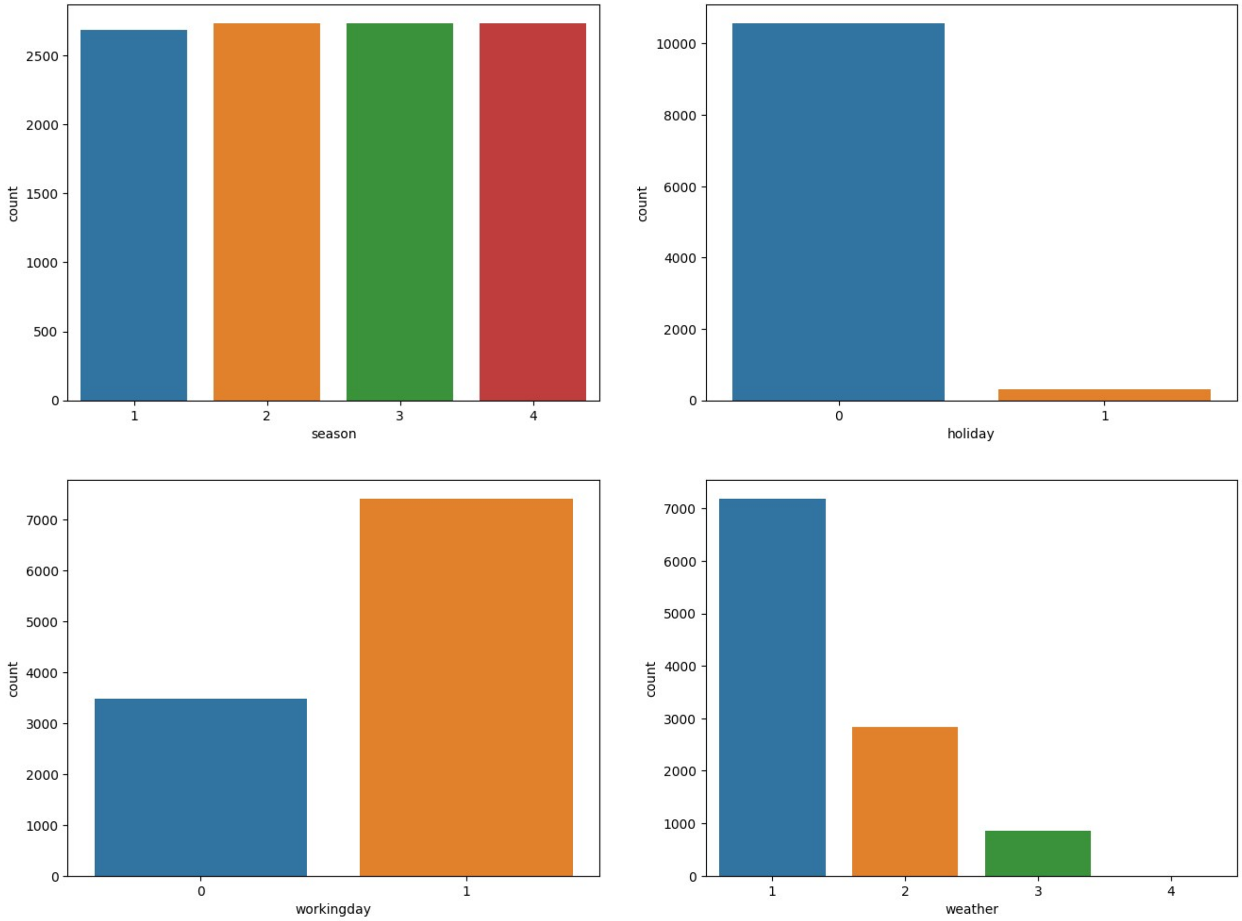


Looks like **humidity**, **casual**, **registered** and **count** have outliers in the data.

```
# countplot of each categorical column
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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()
```



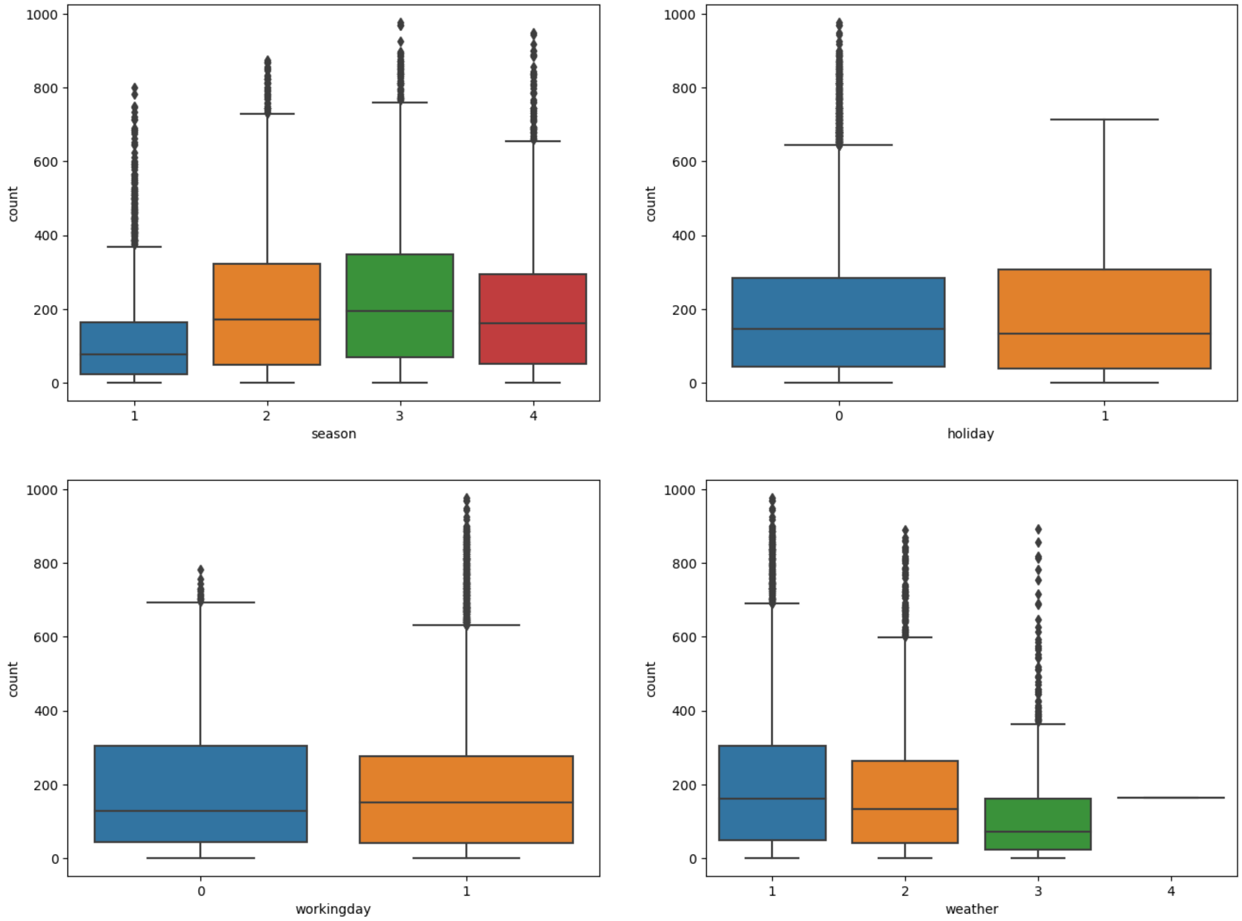
Data looks common as it should be like equal number of days in each season, more working days and weather is mostly `Clear, Few clouds, partly cloudy, partly cloudy`.

Bi-variate Analysis

```
# plotting categorical variables againt count using boxplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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()
```

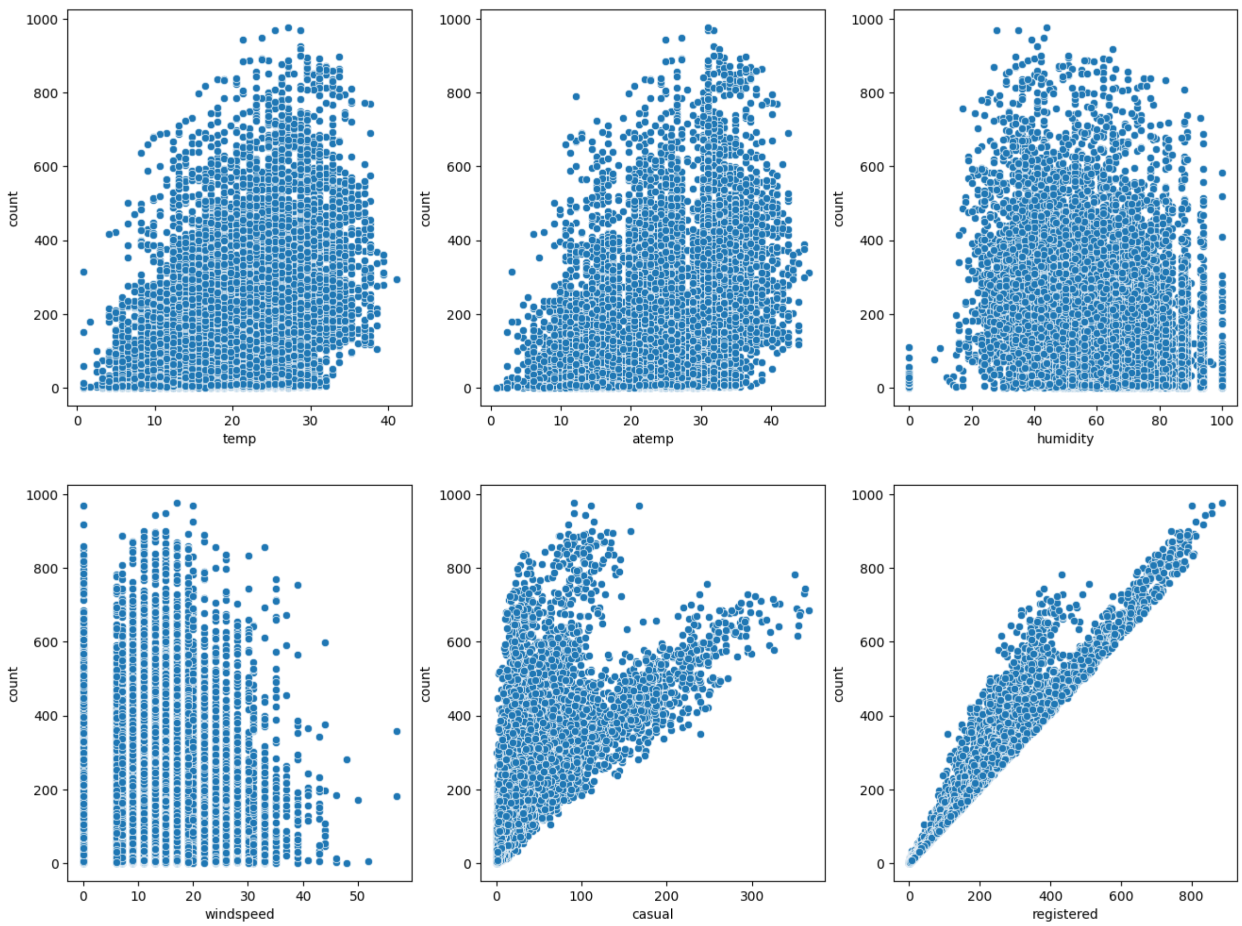


- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- Whenever its a **holiday** more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is **rain, thunderstorm, snow or fog**, there were less bikes were rented.

```
# plotting numerical variables againt count using scatterplot
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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()
```



- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

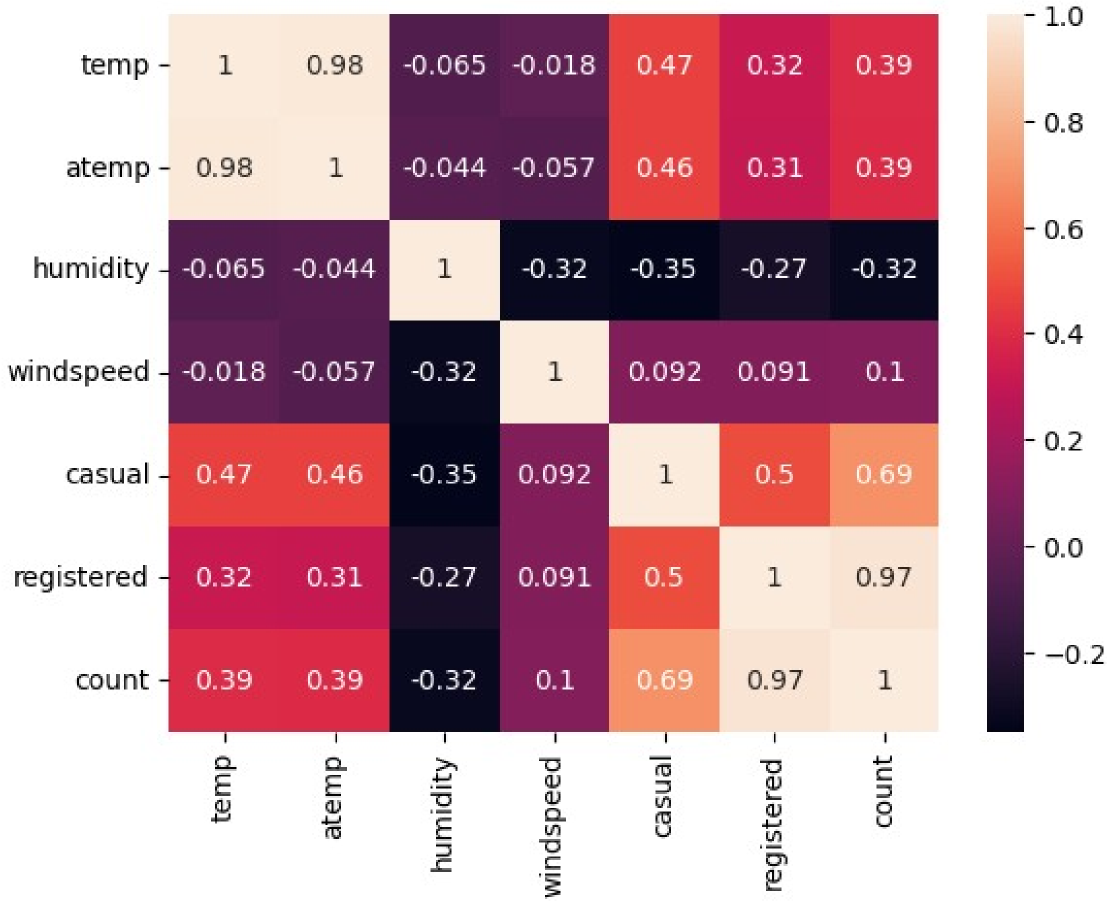
```
# understanding the correlation between count and numerical variables
df.corr()['count']

<ipython-input-17-85b774de02c3>:2: 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()['count']

temp          0.394454
atemp         0.389784
humidity     -0.317371
windspeed     0.101369
casual        0.690414
registered    0.970948
count         1.000000
Name: count, dtype: float64
```

```
sns.heatmap(df.corr(), annot=True)
plt.show()
```

```
<ipython-input-18-6522c2b4e5f9>: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)
```



Hypothesis Testing - 1

Null Hypothesis (H0): Weather is independent of the season

Alternate Hypothesis (H1): Weather is not independent of the season

Significance level (alpha): 0.05

We will use **chi-square test** to test hypyothesis defined above.

```
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)
expected_values = val[3]
expected_values

array([[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]])

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")

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.
```

Hypothesis Testing - 2

Null Hypothesis: Working day has no effect on the number of cycles being rented.

Alternate Hypothesis: Working day has effect on the number of cycles being rented.

Significance level (alpha): 0.05

We will use the **2-Sample T-Test** to test the hypothess defined above

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

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

```
(30171.346098942427, 34040.69710674686)
```

Before conducting the two-sample T-Test we need to find if the given data groups have the same variance. If the ratio of the larger data groups to the small data group is less than 4:1 then we can consider that the given data groups have equal variance.

Here, the ratio is 34040.70 / 30171.35 which is less than 4:1

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

```
TtestResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348,
df=10884.0)
```

Since pvalue is greater than 0.05 so we can not reject the Null hypothesis. We don't have the sufficient evidence to say that working day has effect on the number of cycles being rented.

Hypothesis Testing - 3

Null Hypothesis: Number of cycles rented is similar in different weather and season.

Alternate Hypothesis: Number of cycles rented is not similar in different weather and season.

Significance level (alpha): 0.05

Here, we will use the **ANOVA** to test the hypothess defined above

```
# defining the data groups for the ANOVA

gp1 = df[df['weather']==1]['count'].values
gp2 = df[df['weather']==2]['count'].values
gp3 = df[df['weather']==3]['count'].values
```

```python
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

# conduct the one-way anova
stats.f_oneway(gp1, gp2, gp3, gp4, gp5, gp6, gp7, gp8)
```

```
F_onewayResult(statistic=127.96661249562491,
pvalue=2.8074771742434642e-185)
```

Since p-value is less than 0.05, we reject the null hypothesis. This implies that Number of cycles rented is not similar in different weather and season conditions

Insights

- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- Whenever its a **holiday** more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is **rain, thunderstorm, snow or fog**, there were less bikes were rented.
- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

Recommendations

- In **summer** and **fall** seasons the company should have more bikes in stock to be rented. Because the demand in these seasons is higher as compared to other seasons.
- With a significance level of 0.05, **workingday** has no effect on the number of bikes being rented.
- In very low humid days, company should have less bikes in the stock to be rented.
- Whenever temprature is less than 10 or in very cold days, company should have less bikes.
- Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.