iness-case-yulu-hypothesis-testing

July 16, 2023

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.

[43]:
```python
import numpy as np
import pandas as pd

import os
for dirname, _, filenames in os.walk('https://d2beiqkhq929f0.cloudfront.net/
↪public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

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

[44]:
```python
csv_path = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/
↪428/original/bike_sharing.csv?1642089089"
df = pd.read_csv(csv_path, delimiter=",")
```

[45]:
```python
df.head()
```

[45]:
```
              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
```

[46]:
```python
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")
```

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

[47]:
```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

[48]:
```
df['datetime'] = pd.to_datetime(df['datetime'])

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

[49]:
```
df.iloc[:, 1:].describe(include='all')
```

[49]:
```
         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.

[50]:
```
df.isnull().sum()
```

[50]:
```
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.

[51]:
```python
df['datetime'].min(), df['datetime'].max()
```

[51]:
```
(Timestamp('2011-01-01 00:00:00'), Timestamp('2012-12-19 23:00:00'))
```

[52]:
```python
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

[52]:
```
                  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
```

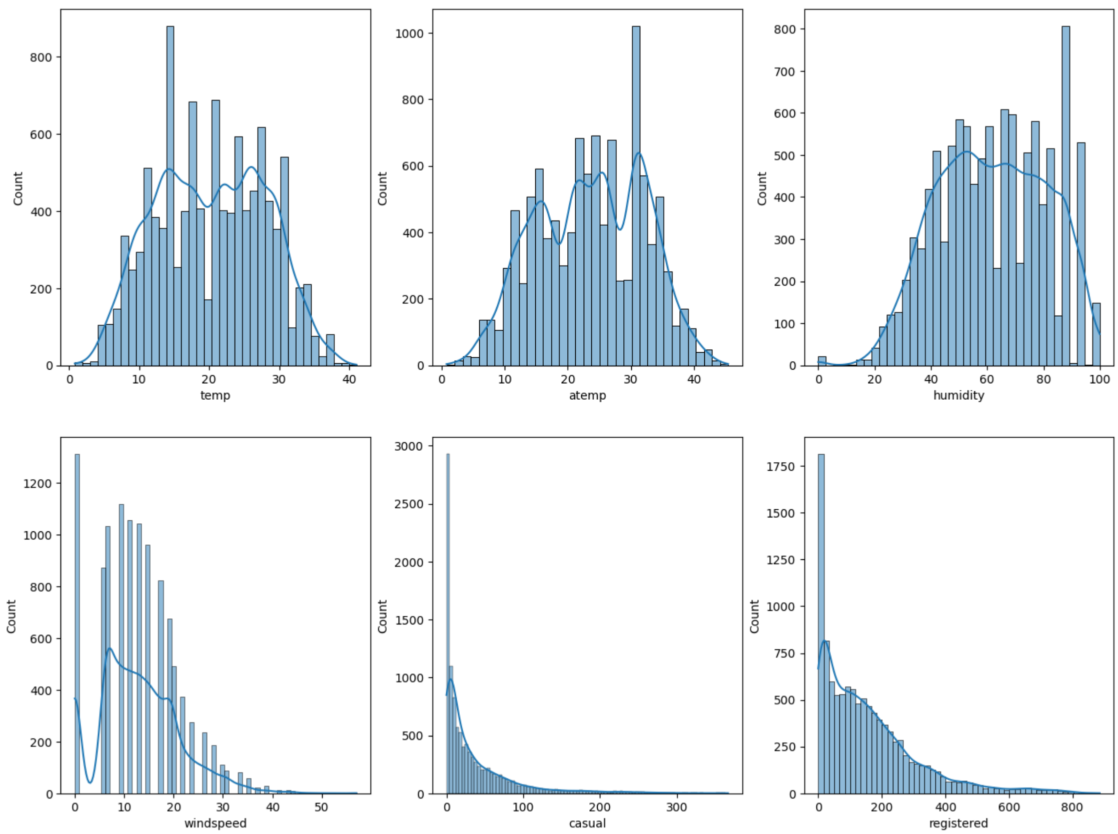
Univariate Analysis

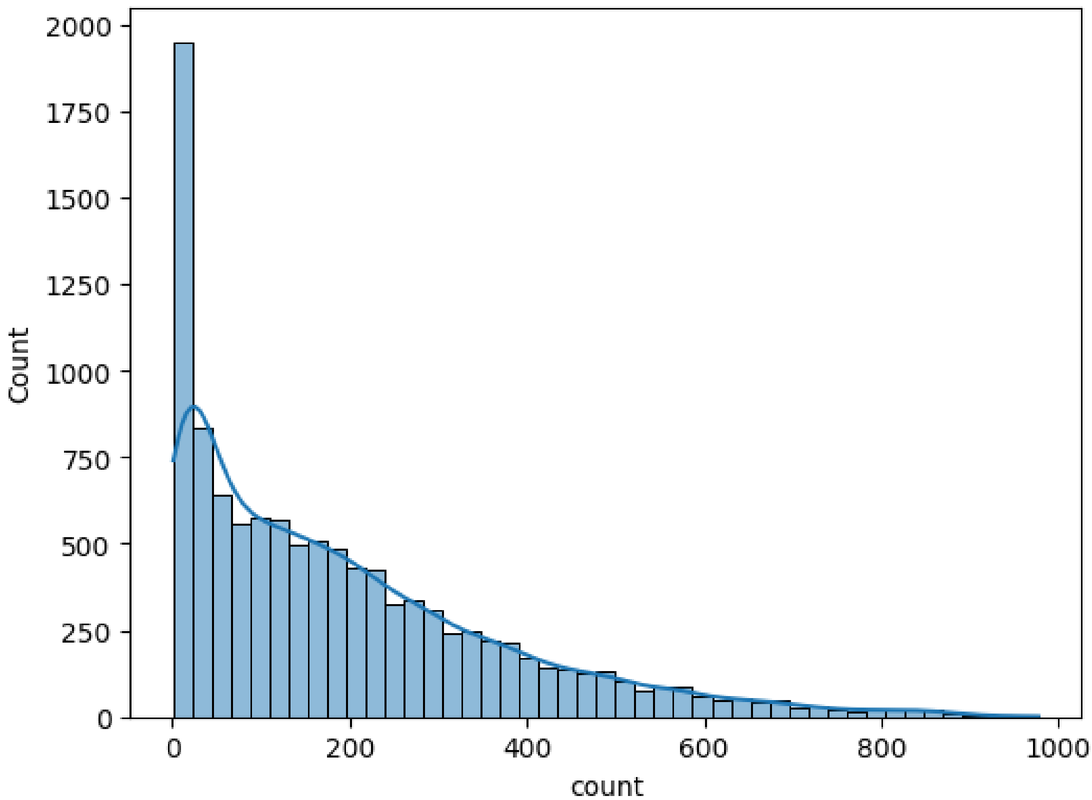
[53]:
```python
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual',␣
 ↪'registered','count']

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
Count
atemp
Count
humidity
Count
windspeed
Count
casual
Count
registered

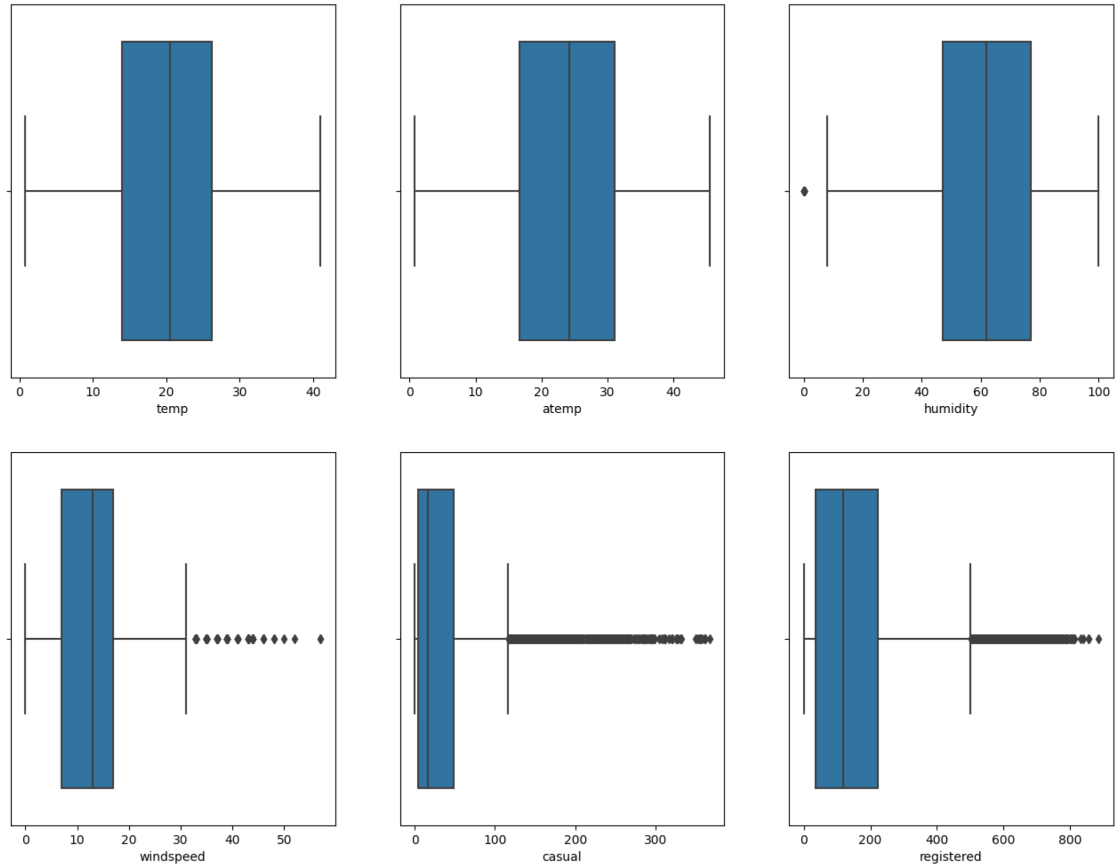


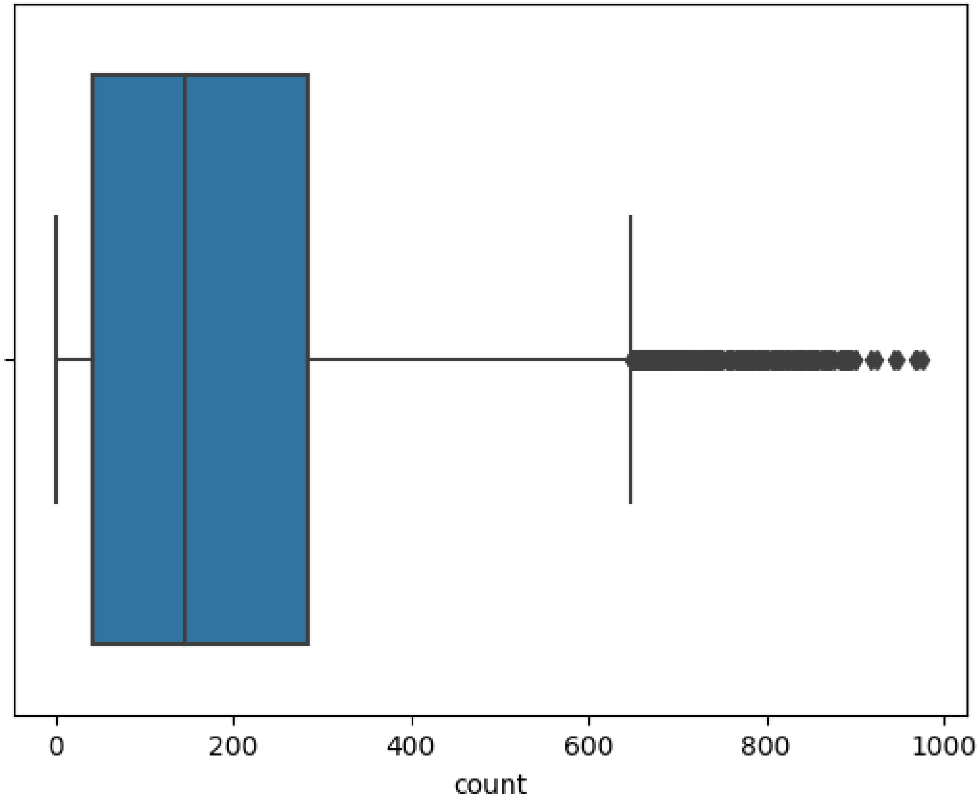
- casual, registered and count somewhat looks like Log Normal Distrinution
- temp, atemp and humidity looks like they follows the Normal Distribution
- windspeed follows the binomial distribution

[54]:
```
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

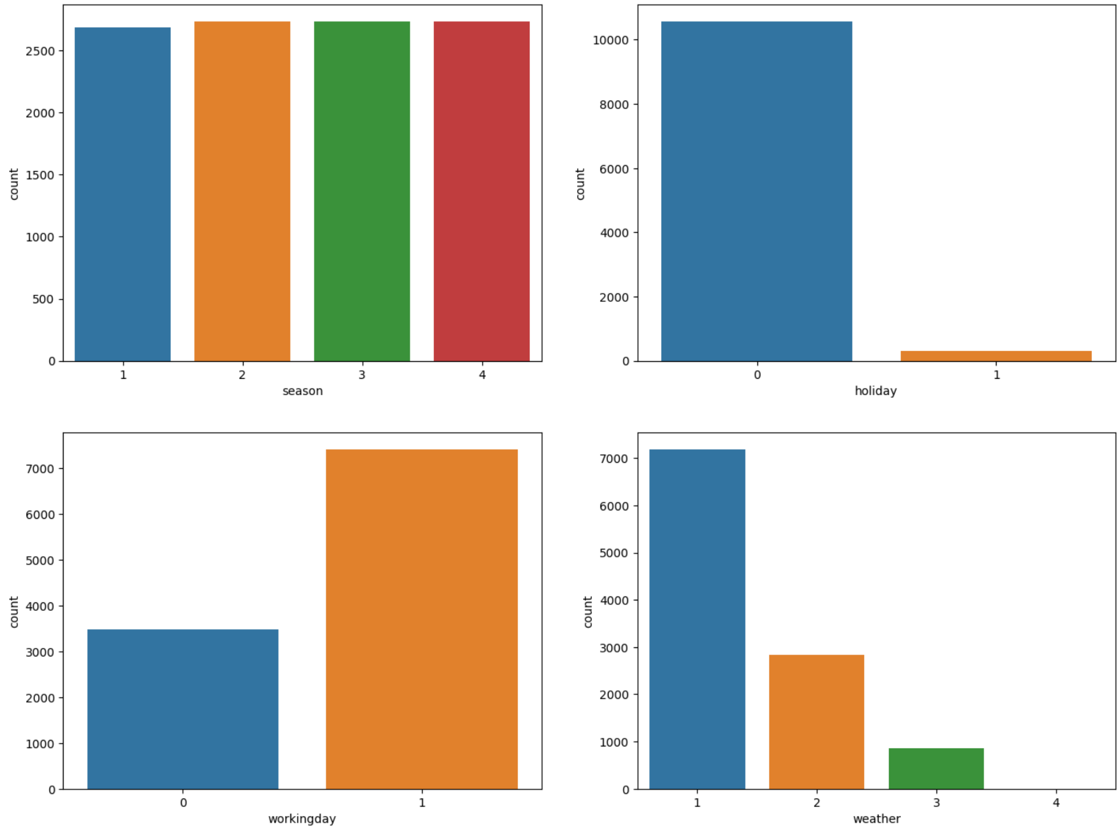


- Looks like humidity, casual, registered and count have outliers in the data.

[55]:
```
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()
```



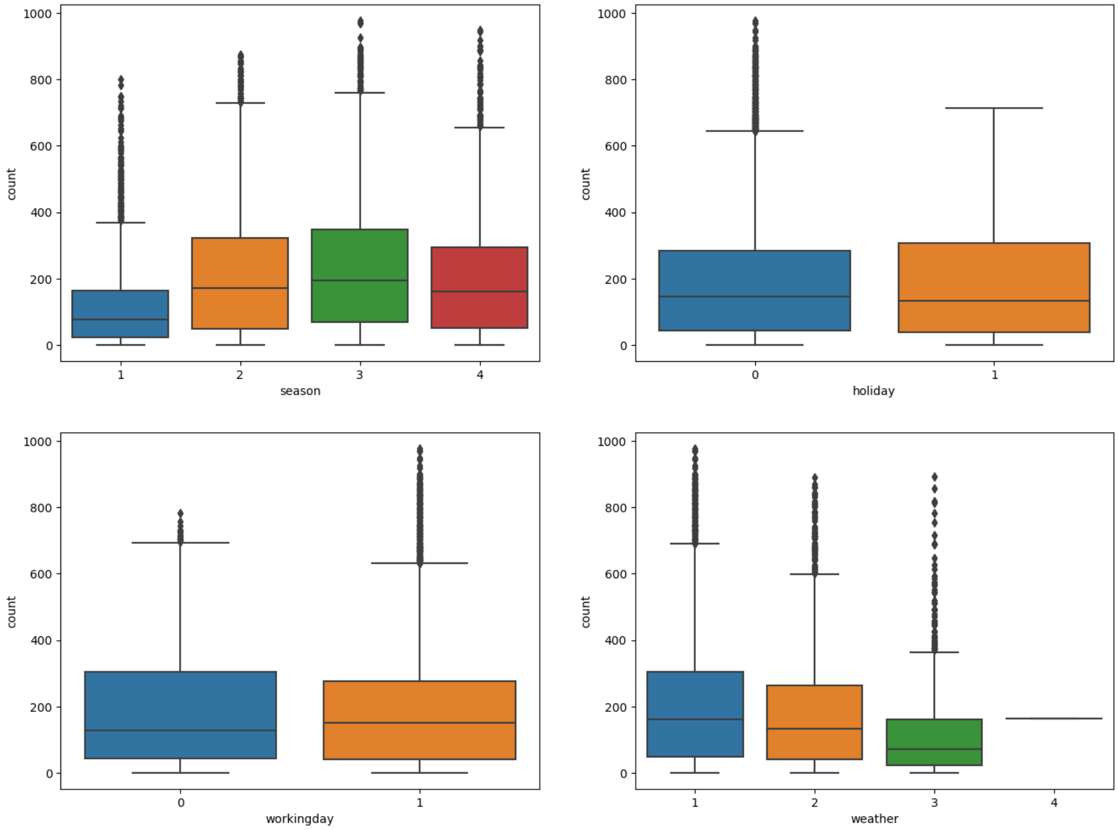
Data looks common as it should be like equal number of days in each season, more working days and weather is mostly Clear, Few clouds, partly cloudy, partly cloudy.

Bi-variate Analysis

[56]:
```
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()
```

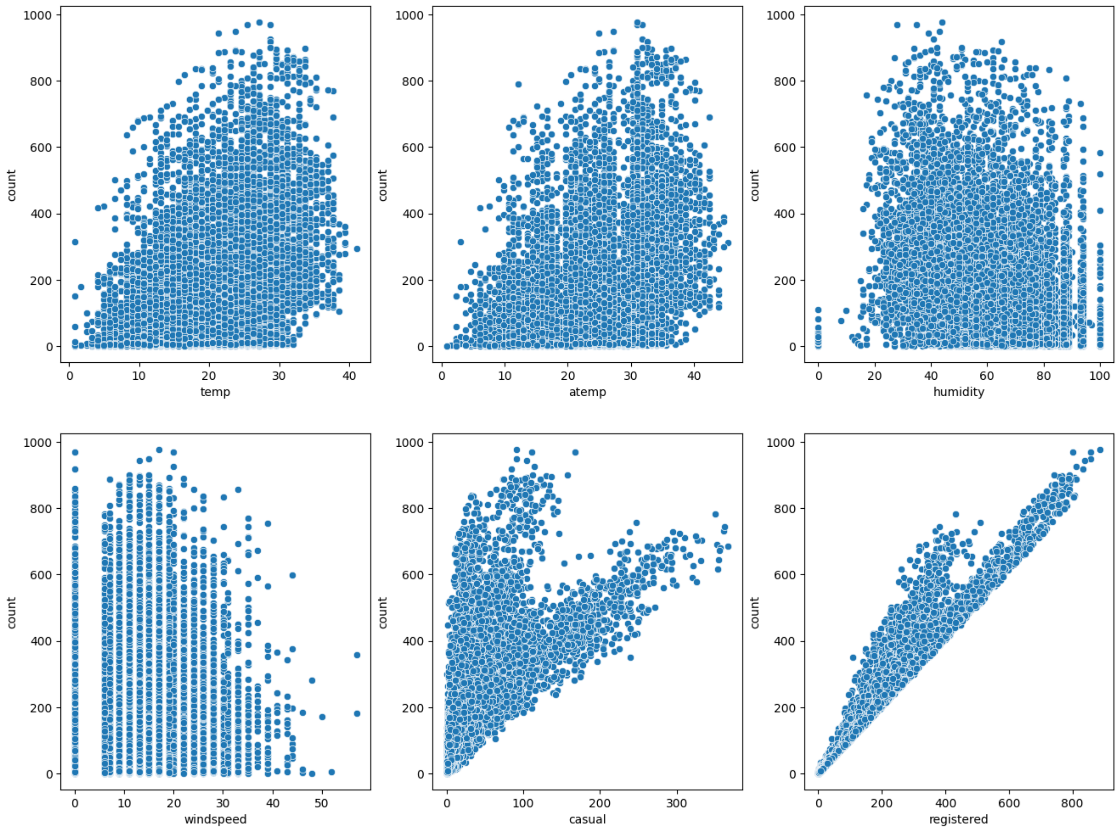


- In summer and fall seasons more bikes are rented as compared to other seasons.
- Whenever its a holiday more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is rain, thunderstorm, snow or fog, there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

[57]:
```
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.

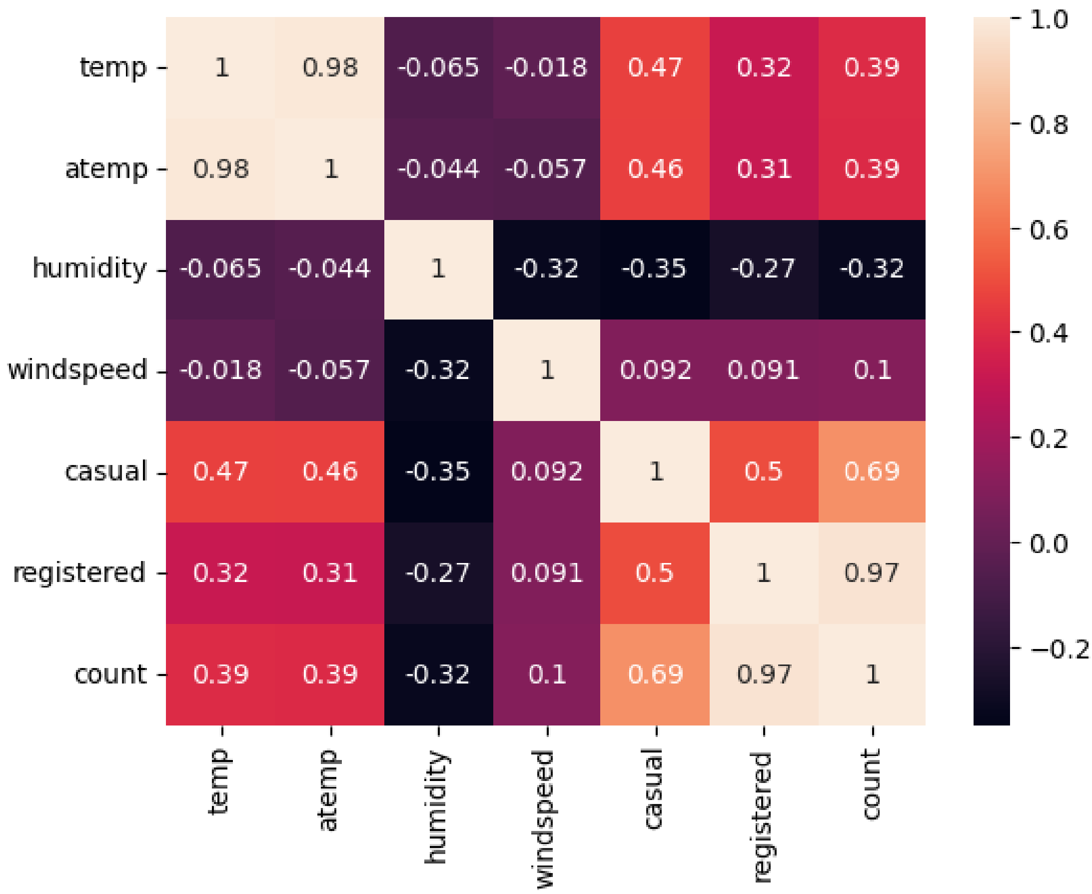
[58]:
```
df.corr()['count']
```

```
<ipython-input-58-c6e37b628cdf>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  df.corr()['count']
```

[58]:
```
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
```

[59]:
```
sns.heatmap(df.corr(), annot=True)
plt.show()
```

```
<ipython-input-59-6522c2b4e5f9>: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.

[60]:
```
data_table = pd.crosstab(df['season'], df['weather'])
print("Observed values:")
```

```
data_table
```

Observed values:

[60]:

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

[61]:
```
val = stats.chi2_contingency(data_table)
expected_values = val[3]
expected_values
```

[61]:
```
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]])
```

[62]:
```
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

[63]:
```python
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values

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

[63]:
```
(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

[64]:
```python
stats.ttest_ind(a=data_group1, b=data_group2, equal_var=True)
```

[64]:
```
Ttest_indResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348)
```

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

[65]:
```python
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
```

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

[65]: 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.