# yulu-hypothesis-testing-case-study

June 21, 2024

## 1 Problem Statement

To help Yulu increase their revenues for their bike sharing platform, Specifically determine: - 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]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy as sp
import seaborn as sns
```

#### 1.0.1 Identification of variables and data types:

[2]:
```python
df = pd.read_csv('yulu.txt')
```

[3]:
```python
df
```

[3]:
```
                  datetime  season  holiday  workingday  weather   temp  \
0      2011-01-01 00:00:00       1        0           0        1   9.84
1      2011-01-01 01:00:00       1        0           0        1   9.02
2      2011-01-01 02:00:00       1        0           0        1   9.02
3      2011-01-01 03:00:00       1        0           0        1   9.84
4      2011-01-01 04:00:00       1        0           0        1   9.84
…                      …       …        …           …        …      …
10881  2012-12-19 19:00:00       4        0           1        1  15.58
10882  2012-12-19 20:00:00       4        0           1        1  14.76
10883  2012-12-19 21:00:00       4        0           1        1  13.94
10884  2012-12-19 22:00:00       4        0           1        1  13.94
10885  2012-12-19 23:00:00       4        0           1        1  13.12

        atemp  humidity  windspeed  casual  registered  count
0      14.395        81     0.0000       3          13     16
1      13.635        80     0.0000       8          32     40
2      13.635        80     0.0000       5          27     32
3      14.395        75     0.0000       3          10     13
4      14.395        75     0.0000       0           1      1
```

```
…       …        …        …      …          …     …
10881   19.695        50     26.0027        7          329     336
10882   17.425        57     15.0013       10          231     241
10883   15.910        61     15.0013        4          164     168
10884   17.425        61      6.0032       12          117     129
10885   16.665        66      8.9981        4           84      88

[10886 rows x 12 columns]
```

[4]:
```
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
```

[5]:
```
df.describe()
```

[5]:
```
             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
```

### 1.0.2 Check for Null Values

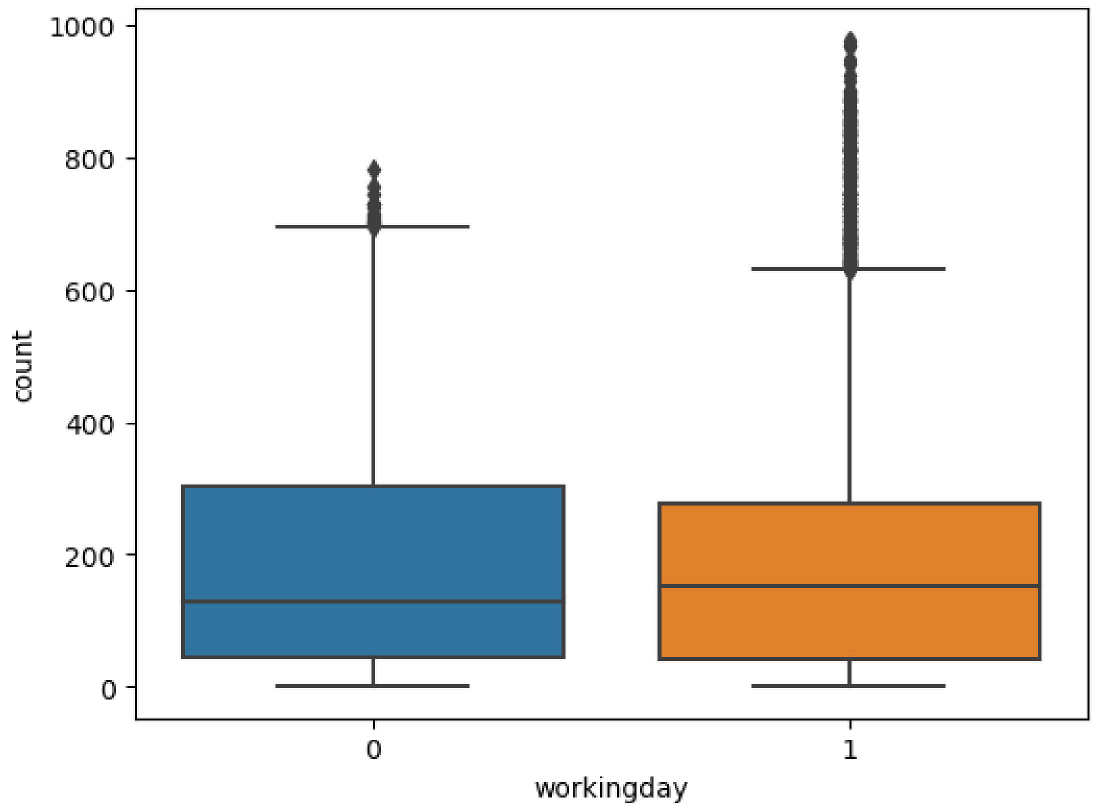
[6]:
```
df.isnull().sum()/len(df)*100
```

[6]:
```
datetime      0.0
season        0.0
holiday       0.0
workingday    0.0
weather       0.0
temp          0.0
atemp         0.0
humidity      0.0
windspeed     0.0
casual        0.0
registered    0.0
count         0.0
dtype: float64
```

## 1.1 Analysing the effect of Work Day on bike renting

**Graphical Analysis**

[7]:
```
sns.boxplot(data=df,x='workingday',y='count')
plt.show()
```




### 1.1.1 Outlier Treatment - Work Day

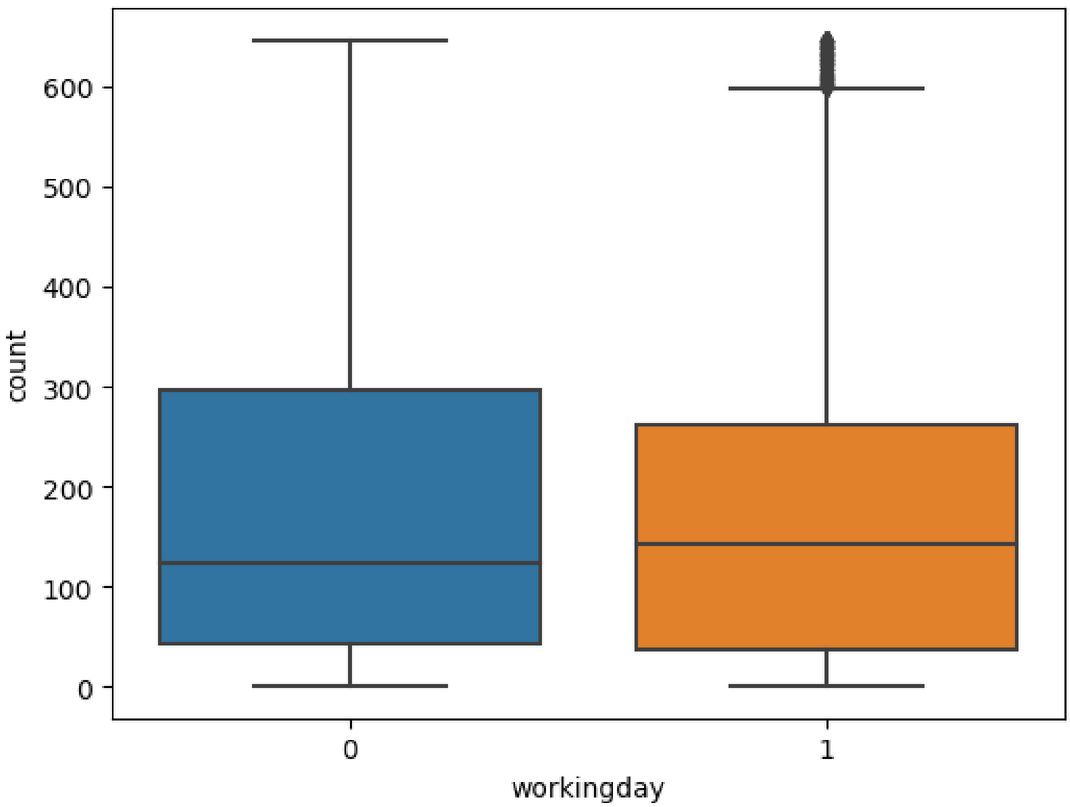
[8]:
```
q1 = df['count'].quantile(0.25)
```

[9]:
```
q3 = df['count'].quantile(0.75)
```

[10]:
```
iqr = q3 - q1
```

[11]:
```
df = df[(df['count'] > (q1 - 1.5*iqr)) & (df['count'] < (q3 + 1.5*iqr))]
```

[12]:
```
sns.boxplot(data=df,x='workingday',y='count')
plt.show()
```




Visually there is no significant impact of working day on the count of bikes hired. We test the same using hypothesis testing.

## 1.2 Hypothesis Testing - Work Day

### 1.2.1 Step 1 : Define Null and Alternate Hypothesis

H0(Null Hypothesis) : Count on weekday = Count on Weekend

HA(Alternative Hypothesis) : Count on weekday > Count on Weekend.

### 1.2.2 Step 2 : Select Appropriate test

This is a one-tailed test concerning two population means from two independent populations. As the population standard deviations are unknown, the two sample independent t-test will be the appropriate test for this problem.

### 1.2.3 Step 3 : Decide the significance level

If nothing specific mentioned, we pick significance level = 0.05

### 1.2.4 Step 4 : Prepare the data

[13]:
```
df['workingday'].value_counts()
```

[13]:
```
workingday
1    7161
0    3422
Name: count, dtype: int64
```

[14]:
```
weekday=df[df['workingday']==1]['count'].sample(3422)
weekend=df[df['workingday']==0]['count'].sample(3422)
```

[15]:
```
weekday.std()
```

[15]:
```
150.51821247116226
```

[16]:
```
weekend.std()
```

[16]:
```
163.7821664607603
```

As the sample standard deviations are different, the population standard deviations may be assumed to be different.

**Perform t-test to get the probability that bike rented on weekday is same as that of weekend**

[17]:
```
from scipy.stats import ttest_ind
t_test, p_value= ttest_ind(weekday, weekend, equal_var=False,␣
↪alternative='greater')
```

[18]:
```
p_value
```

[18]:
```
0.9868094841530048
```

- As the p-value 0.954672 is greater than level of significance, we fail to reject the null hypothesis, that - bike rented count on weekday = rented count on Weekend.
- Hence we assume that bike rented count on weekday is same as rented count on Weekend

## 1.3 Is the demand for cycles same for all weather conditions

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

**Non Graphical analysis**

[19]:
```
df['weather'].value_counts()
```

[19]:

```
weather
1    6962
2    2770
3     850
4       1
Name: count, dtype: int64
```

**Outlier treatment - Remove Weather type 4, as there is only one value in it**

[20]:

```python
df = df[~(df['weather']==4)]
```

[21]:

```python
df['weather'].value_counts()
```

[21]:

```
weather
1    6962
2    2770
3     850
Name: count, dtype: int64
```

[22]:

```python
w1=df[df['weather']==1]['count'].sample(850)
w2=df[df['weather']==2]['count'].sample(850)
w3=df[df['weather']==3]['count'].sample(850)
```

[23]:

```python
df.groupby(['weather'])['count'].describe()
```

[23]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| weather | | | | | | | | |
| 1 | 6962.0 | 187.131140 | 161.333785 | 1.0 | 45.0 | 153.0 | 286.0 | 646.0 |
| 2 | 2770.0 | 166.117690 | 146.992422 | 1.0 | 39.0 | 130.0 | 254.0 | 646.0 |
| 3 | 850.0 | 111.862353 | 121.233389 | 1.0 | 23.0 | 70.5 | 157.0 | 646.0 |

### 1.3.1 Step 1 : Define Null and Alternate Hypothesis

- H0: Bikes rented is same in all weathers
- Ha: Bikes rented count is not same for all weathers
- alpha = 0.05

### 1.3.2 Step 2 : Select Appropriate Test

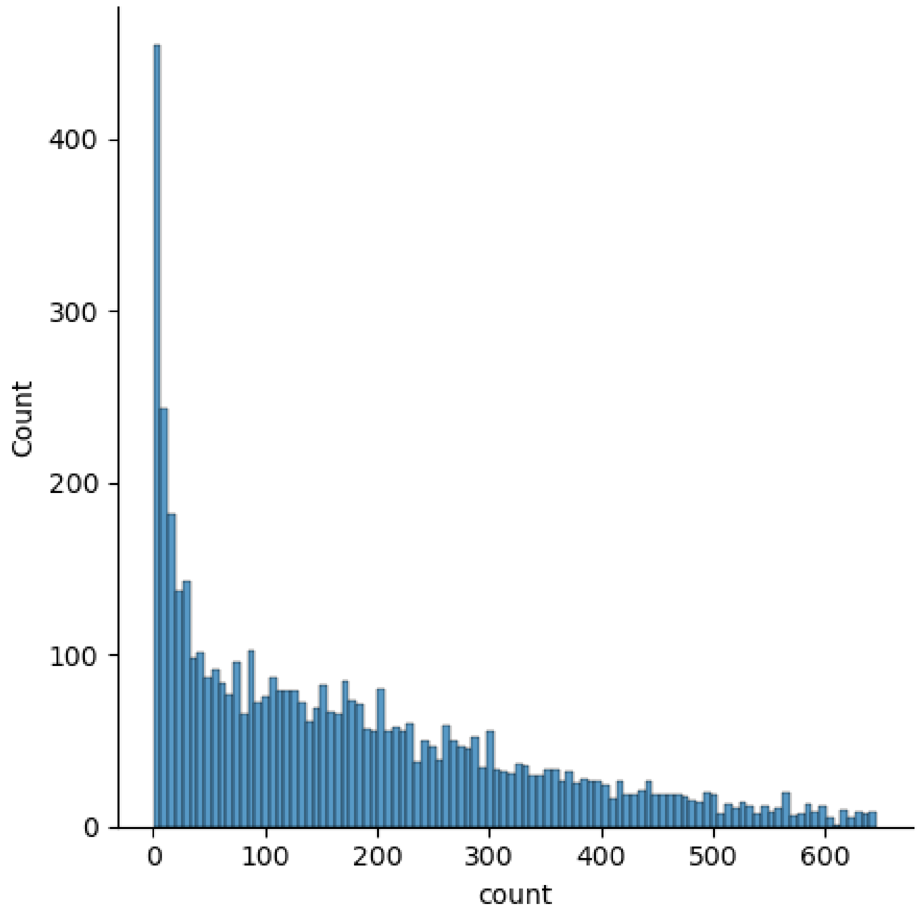
This is a problem, concerning three population means. **One-way ANOVA** could be the appropriate test here provided normality and equality of variance assumptions are verified. - For testing of normality, `Shapiro-Wilk's test` is applied to the response variable. - For equality of variance, `Levene test` is applied to the response variable.

**Shapiro-Wilk's Test : Test for Normal distribution of inputs:**

- H0 : Count follows Normal distribution
- HA : Count does not follow Normal Distribution

[24]:
```
sns.displot(df['count'].sample(4999), bins=100)
plt.show()
```

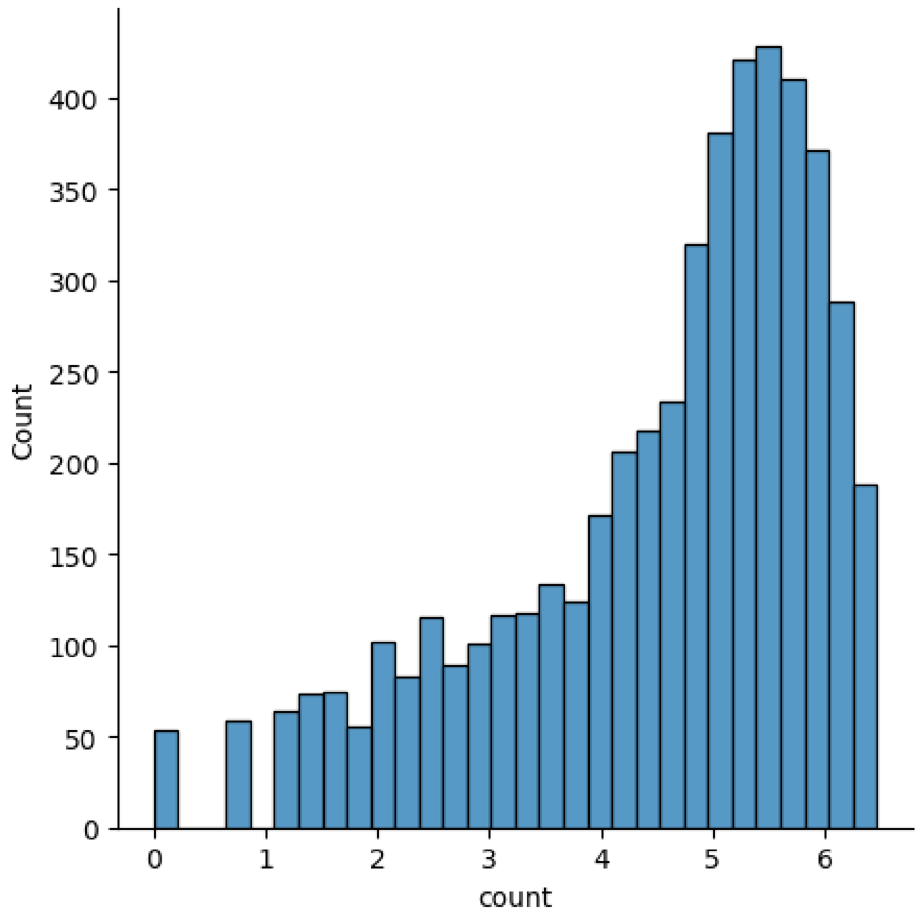
```
C:\Users\vinut\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




The input does not look normal. So, use a transformation : `log normal transformation` to check if input follows Normal distribution.

[25]:
```
sns.displot(np.log(df['count'].sample(4999)))
plt.show()
```

```
C:\Users\vinut\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




The input is still left skewed and does not follow Normal distribution. However, verify using Shapiro Wilk test

[26]:
```
from scipy.stats import shapiro
#null - series is normal
#alter- not normal
w, p_value=shapiro(df['count'].sample(4999))
```

[27]:
```
p_value
```

[27]: 0.0

As p-value is less than significance value, so we can reject the null hypothesis that count data is a normal distributed data.

Now, use levene test for test of variance

[28]:
```
#levene test
#null- equal variance
```

```
#alter- not equal var
from scipy.stats import levene
statistic, p_val= levene(w1,w2,w3)
```

[29]:
```
p_val
```

[29]: 1.1461769344474315e-21

p-value is very low and less than significance level, hence we conclude that the variances are not same.

Both the input assumptions fail for ANOVA. Yet we go ahead with our analysis using ANOVA.

[30]:
```
from scipy.stats import f_oneway
test,p_val=f_oneway(w1,w2,w3)
```

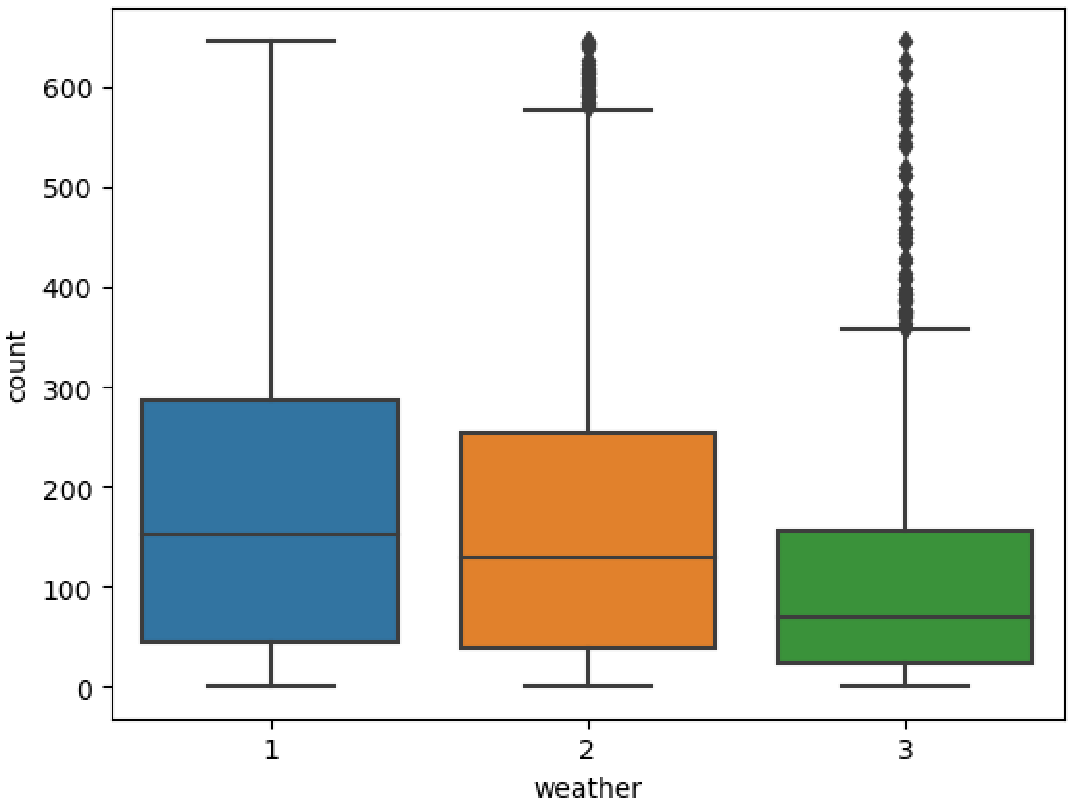
[31]:
```
p_val
```

[31]: 6.281741611916107e-26

Since the p_val is very low, we reject the null hypothesis that weather has no effect on bike sharing

[32]:
```
# Graphical analysis - Weather v/s count
```

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




Bikes are least rented in weather 3

### 1.4 Effect of season on bike renting

[34]:
```
df['season'].value_counts()
```

[34]:
```
season
1    2669
4    2664
2    2633
3    2616
Name: count, dtype: int64
```

## 2 Hypothesis testing - Season

We select ANOVA because we have more than two inputs to compare - H0: Bikes rented is same in all seasons - Ha: Bikes rented count is not same for all seasons

1: spring, 2: summer, 3: fall, 4: winter

From previous analysis, the Normality test already failed for input data. Now, test for variance using Lavene's test

[35]:
```
s1=df[df['season']==1]['count'].sample(2685)
s2=df[df['season']==2]['count'].sample(2685)
s3=df[df['season']==3]['count'].sample(2685)
s4=df[df['season']==4]['count'].sample(2685)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[35], line 1
----> 1 s1=df[df['season']==1]['count'].sample(2685)
      2 s2=df[df['season']==2]['count'].sample(2685)
      3 s3=df[df['season']==3]['count'].sample(2685)

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:5858, in NDFrame.
↪sample(self, n, frac, replace, weights, random_state, axis, ignore_index)
   5855 if weights is not None:
   5856     weights = sample.preprocess_weights(self, weights, axis)
-> 5858 sampled_indices = sample.sample(obj_len, size, replace, weights, rs)
   5859 result = self.take(sampled_indices, axis=axis)
   5861 if ignore_index:

File ~\anaconda3\Lib\site-packages\pandas\core\sample.py:151, in sample(obj_len ␣
↪size, replace, weights, random_state)
    148     else:
    149         raise ValueError("Invalid weights: weights sum to zero")
--> 151 return random_state.choice(obj_len, size=size, replace=replace,␣
↪p=weights).astype(
    152     np.intp, copy=False
    153 )

File mtrand.pyx:984, in numpy.random.mtrand.RandomState.choice()

ValueError: Cannot take a larger sample than population when 'replace=False'
```

[ ]:
```
#levene test
#null- equal variance
#alter- not equal var

test, p_val= levene(s1,s2,s3,s4)
```

[ ]:
```
p_val
```

p-value is very low, hence we conclude that the variances are not same

Both the input assumptions fail for ANOVA. Yet we go ahead with our analysis using ANOVA

[ ]:
```
from scipy.stats import f_oneway
test,p_val=f_oneway(s1,s2,s3,s4)
```

[36]:
```
p_val
```

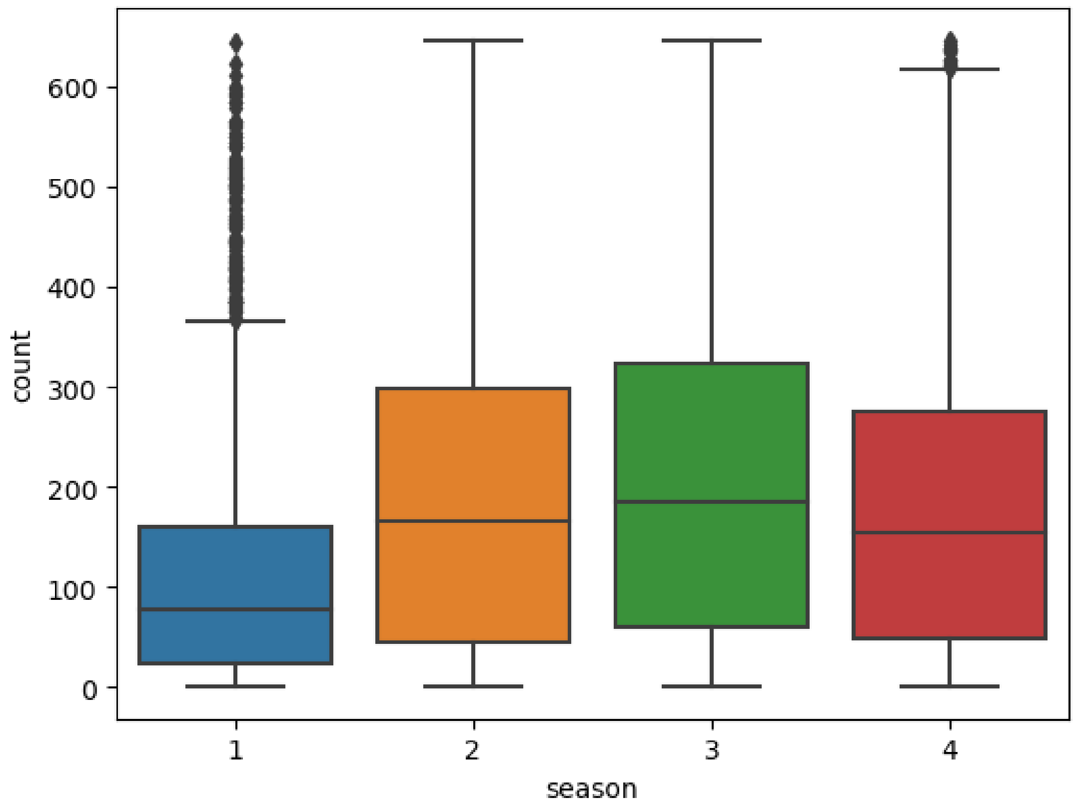
[36]: 6.281741611916107e-26

Since the p_val is very low, we reject the null hypothesis that season has no effect on bike sharing

[37]:
```
# Graphical analysis - season v/s count
```

[38]:
```
sns.boxplot(data=df,x='season',y='count')
```

[38]: <Axes: xlabel='season', ylabel='count'>




We see that sales are high in season 2 and 3, next best seson is 4, 1 is the season for least rented bikes

# 3 Check if weather is dependent on season

# 4 Hypothesis testing - Independence test - Chi-square

We select Chi-sqaure test for independence because

- H0: No association between weather and season

- Ha: Weather is dependent on season, for bike count

[39]:
```
subs_table = pd.
 ↪crosstab(index=df['season'],columns=df['weather'],values=df['count'],␣
 ↪aggfunc='sum')
subs_table
```

[39]:

| weather | 1 | 2 | 3 |
|---|---|---|---|
| season | | | |
| 1 | 212386 | 75694 | 12919 |
| 2 | 366757 | 121426 | 26973 |
| 3 | 401955 | 120789 | 27883 |
| 4 | 321709 | 142237 | 27308 |

[40]:
```
_, p_val, _, _ = sp.stats.chi2_contingency(subs_table)
```

[41]:
```
p_val
```

[41]: 0.0

The probability obtained for test of independence is 0. We reject the null hypothesis. Weather and season are dependent

# 5 Business Insights based on Visual Analysis and Hypothesis Testing

- Workday has no effect on Bike Sharing
- Weather has an effect on bike sharing and bikes are least rented in weather 3
- Season has an effect on bike sharing and bikes are least rented in season 1
- Weather and season are dependent - weather 1 and season 2, weather 1 and season 3 - indicate high bike rented count

# 6 Recommendation to Yulu

- Give equal priority to weekend and weekdays for renting bike
- Descale operations in weather 3
- Descale operations in season 1.
- Upscale operations in teh following combinations: Weather 1 and season2; Weather 1 and season 3. Happy renting!

[ ]:

[ ]:

[ ]: