YULU - Business Case Study

Yulu is a Bangalore-based company that has partnered with Bajaj Auto to launch an electric bike-sharing program. Yulu electric two-wheelers bikes are co-designed and manufactured by Bajaj Company for Indian customers.

Yulu is a Mobile Application to find the closest vehicle available and being rented from the nearest Yulu Zone.Yulu operates in Bengaluru, Delhi, Gurugram, Mumbai, Pune, and Bhubaneswar with 18,000 single-seater vehicles across 2.5 million users.Yulu Bike is the state of the art and it runs in electric and designed for solo riding/ single person commuting and if 2 or more ppl are riding together the form faction and bike alignment is damaged to a great extent.

Problem Statement

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

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

Following are the analysis made in this notebook

- Count of registered and casual users by weather , holiday , season , workingday
- Casual vs registeres users count
- Rainy day vs clear day users count
- Windspeed vs user count
- Univariate , bivariate analysis
- Hypothesis testing - Chi-square , anova ,2 -sample t test
- Confidence interval
- Recommendations & Observations

In [29]:

```
#impoorting Libraties


import numpy as np
import numpy.random as rd
import pandas as pd
```

```python
import matplotlib.pyplot as plt
import plotly as pt
import plotly.express as px
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

%matplotlib inline
%config InlineBackend.figure_format ='retina'

#statastics
from scipy.stats import norm
from scipy import stats
from scipy.stats import chi2_contingency
```

In [30]:

```python
df=
pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/00
1642089089")
```

In [31]:

```python
# Printing first 5 rows in dataframe
df.head(5)
```

Out[31]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registere
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	1
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	3
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	2
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	1
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	

In [32]:

```python
# Shape of dataframe
df.shape
```

Out[32]:

```
(10886, 12)
```

In [33]:
```python
# Columns in yulu dataset
df.dtypes
```

Out[33]:
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

Data type of Datetime,Season,holiday,workingday,weather columns needs to be changed

In [34]:
```python
df['datetime'] = pd.to_datetime(df['datetime'])


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

In [35]:
```python
df.dtypes
```

Out[35]:
```
datetime      datetime64[ns]
season                object
holiday               object
workingday            object
weather               object
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
dtype: object
```

In [36]:
```python
# Finding any null values present in dataset
df.isnull().sum()
```

Out[36]:
```
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
```

No null values present in dataset

In [37]:
```
df.describe()
```

Out[37]:

	temp	atemp	humidity	windspeed	casual	registered	co
count	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.0000
mean	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.5741
std	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.1444
min	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.0000
25%	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.0000
50%	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.0000
75%	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.0000
max	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.0000

In [38]:
```
df.describe(include=["object"])
```

Out[38]:

	season	holiday	workingday	weather
count	10886	10886	10886	10886
unique	4	2	2	4
top	4	0	1	1
freq	2734	10575	7412	7192

We can see, sesaon , holiday , workingday , weather are the category columns present

In [39]:
```
#Category columns
category_columns=df.dtypes=="O"
cat_cols= category_columns[category_columns].index
cat_cols
```

Out[39]:
```
Index(['season', 'holiday', 'workingday', 'weather'], dtype='object')
```

In [40]:
```
#Numerical columns
numerical_columns=df.dtypes!="O"
num_cols= numerical_columns[numerical_columns].index
num_cols
```

Out[40]:
```
Index(['datetime', 'temp', 'atemp', 'humidity', 'windspeed', 'casual',
       'registered', 'count'],
      dtype='object')
```

We can see , 'temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count' are the numerical columns present

Value counts present- columnswise

In [41]:
```
columns = ['season', 'holiday', 'workingday', 'weather','registered',
'count', 'casual']
for col in columns:
  print("Value Counts in", col)
  print("")
  print(df[col].value_counts())
  print("")
```

```
Value Counts in season

4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64

Value Counts in holiday

0    10575
1      311
Name: holiday, dtype: int64

Value Counts in workingday

1    7412
0    3474
Name: workingday, dtype: int64

Value Counts in weather

1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64

Value Counts in registered

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

Value Counts in count
```

```
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

Value Counts in casual

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
```

Correlating in Heatmap

In [42]:

```
df_copy = df.copy().corr()
fig = px.imshow(df_copy, text_auto=True, width=1000, height=600)
fig.show()
```

In [ ]:

```

```

Univariate analysis

In [43]:

```
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.distplot(df[num_cols[index]], ax=axis[row, col], color ='red'
,kde=True)
        index += 1
plt.show()
```

Out[43]:

```
<AxesSubplot:xlabel='temp', ylabel='Density'>
```

Out[43]:

```
<AxesSubplot:xlabel='atemp', ylabel='Density'>
```

Out[43]:

```
<AxesSubplot:xlabel='humidity', ylabel='Density'>
```

Out[43]:

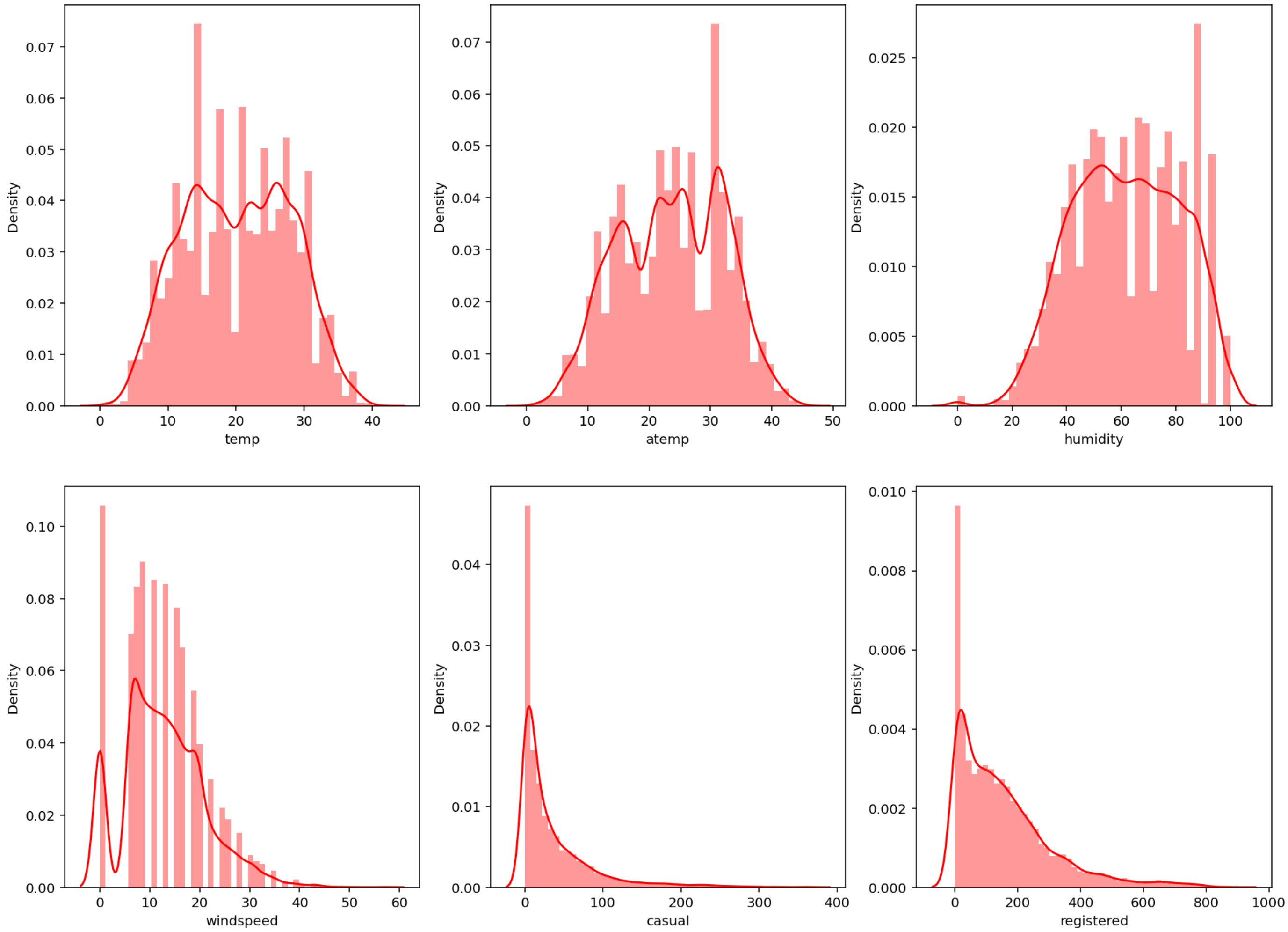
```
<AxesSubplot:xlabel='windspeed', ylabel='Density'>
```

Out[43]:

```
<AxesSubplot:xlabel='casual', ylabel='Density'>
```

Out[43]:

```
<AxesSubplot:xlabel='registered', ylabel='Density'>
```



In [44]:

```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(13, 8))

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

plt.show()
```

Out[44]:

```
<AxesSubplot:xlabel='season', ylabel='count'>
```

Out[44]:

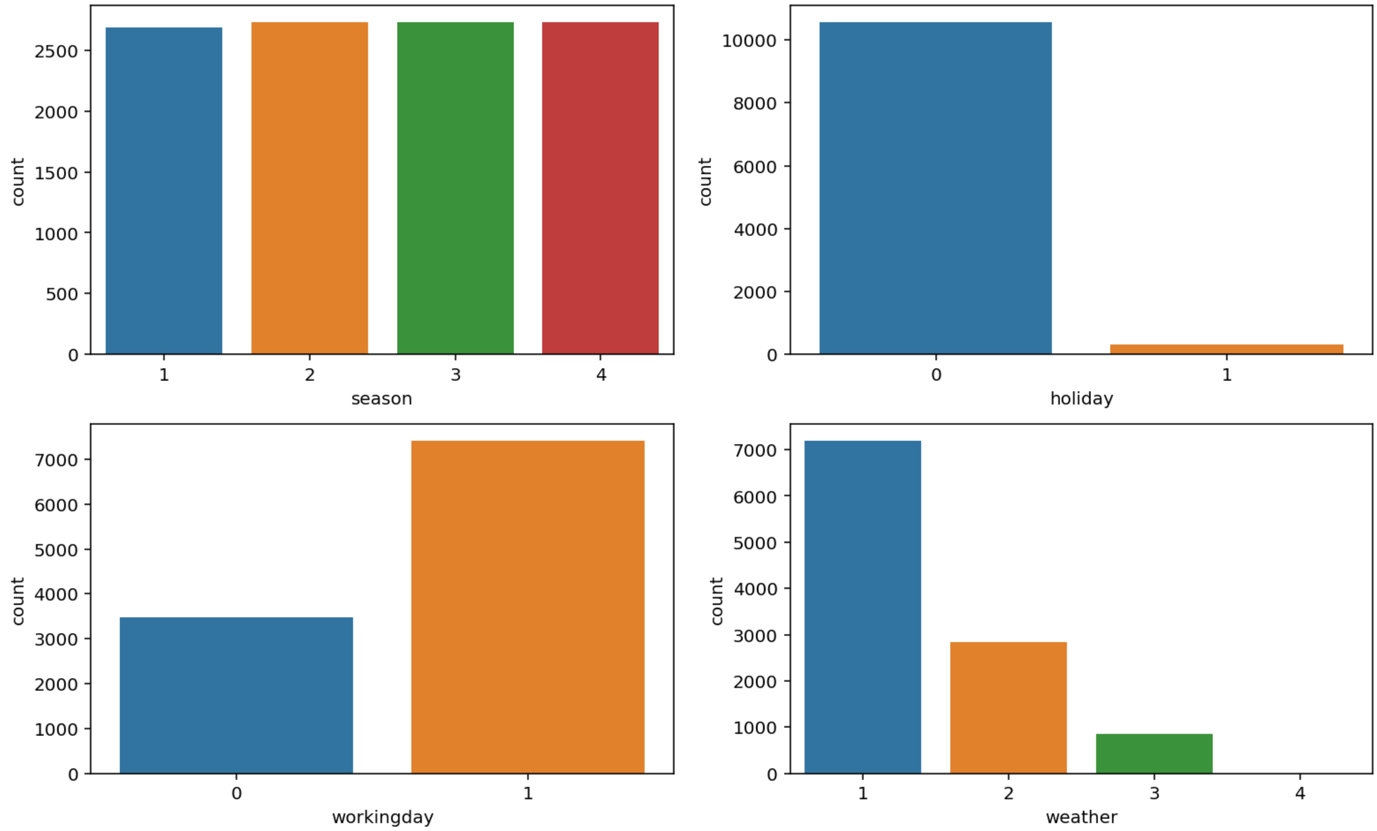
```
<AxesSubplot:xlabel='holiday', ylabel='count'>
```

Out[44]:

```
<AxesSubplot:xlabel='workingday', ylabel='count'>
```

Out[44]:

```
<AxesSubplot:xlabel='weather', ylabel='count'>
```



Insights:

Count represents the number of dataset present on those categories

- We can see ,that count is more on working day than holiday
- We can also see, that the overall count is huge in very cold
- Also we can see the same count of data present for all seasons
- And more working day data is present in dataset than holiday

In [45]:

```
#df['Product_Category'].nunique()
```

Bi-variate analysis

In [46]:

```
bins=[0,13.12,17.22,22.96,27.88,41.0]
group=["very cold","cold","cool/pleasant","hot","Very hot"]
df['temp_bin']=pd.cut(df['temp'],bins=bins,labels=group)

bins=[10,100,250,400,500,1000]
group=["very low","low","average","High","Very high"]
df['count_bin']=pd.cut(df['count'],bins=bins,labels=group)




#Casual customers - tempertatue wise
md=df[df['temp_bin']=='very cold']['casual'].sum()
td=df[df['temp_bin']=='cold']['casual'].sum()
```

```
sd=df[df['temp_bin']=='cool/pleasant']['casual'].sum()
fd=df[df['temp_bin']=='hot']['casual'].sum()
kd=df[df['temp_bin']=='Very hot']['casual'].sum()

data_dict1 = {'Count':[md,td,sd,fd,kd], 'temp': ["very
cold","cold","cool/pleasant","hot","Very hot"]}
df_b = pd.DataFrame(data=data_dict1, columns=['Count','temp'])
px.bar(data_frame=df_b, x="temp", y="Count", color="temp",
barmode="group",title="Total Casual customers rented yulu bike- temperature
category")
```

In [47]:

```
#Registered customers - temperature wise
md=df[df['temp_bin']=='very cold']['registered'].sum()
td=df[df['temp_bin']=='cold']['registered'].sum()
sd=df[df['temp_bin']=='cool/pleasant']['registered'].sum()
fd=df[df['temp_bin']=='hot']['registered'].sum()
kd=df[df['temp_bin']=='Very hot']['registered'].sum()

data_dict1 = {'Count':[md,td,sd,fd,kd], 'temp': ["very
cold","cold","cool/pleasant","hot","Very hot"]}
df_b = pd.DataFrame(data=data_dict1, columns=['Count','temp'])
```

```
px.bar(data_frame=df_b, x="temp", y="Count", color="temp",
barmode="group",title="Total Registered customers rented yulu bike-
temperature category")
```

Insights:

1. We can clearly see that , registered customers rented more number of bikes than casual
2. More number of bikes rented in very hot temperatures
3. Registered customers rented almost same number of bikes in cool/pleasant and hot temperatures
4. by casual customers, bike rented is very low in cold conditions

In [48]:

```
# registered customers mean on working and non working days
df.groupby("holiday")["registered"].mean()
print()
print()
df.groupby("holiday").mean()["casual"].plot.bar()
plt.ylabel("Mean count of casual customers")
plt.show
```

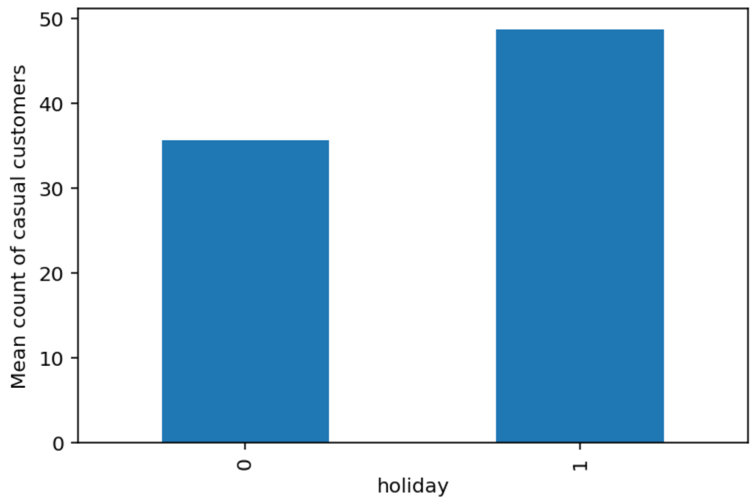
Out[48]:

```
holiday
0    156.094941
1    137.096463
Name: registered, dtype: float64
```

```
Out[48]: <AxesSubplot:xlabel='holiday'>
```

```
Out[48]: Text(0, 0.5, 'Mean count of casual customers')
```

```
Out[48]: <function matplotlib.pyplot.show(close=None, block=None)>
```



- We can observe , more mean on holiday than on not holiday days

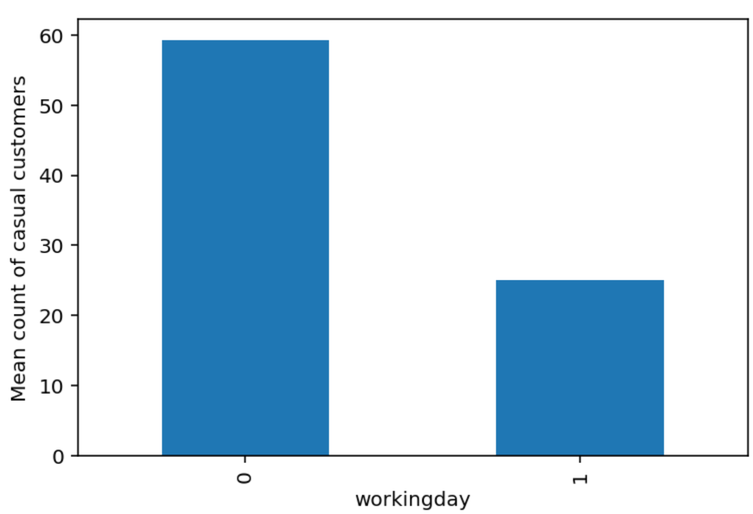
In [49]:
```
# Casual customers mean on working and non working days
df.groupby("workingday")["casual"].mean()
print()
print()
df.groupby("workingday").mean()["casual"].plot.bar()
plt.ylabel("Mean count of casual customers")
plt.show
```

```
Out[49]: workingday
0    59.308290
1    25.107663
Name: casual, dtype: float64
```

```
Out[49]: <AxesSubplot:xlabel='workingday'>
```

```
Out[49]: Text(0, 0.5, 'Mean count of casual customers')
```

```
Out[49]: <function matplotlib.pyplot.show(close=None, block=None)>
```



Mean is more on non working day than working day for casual and registered users

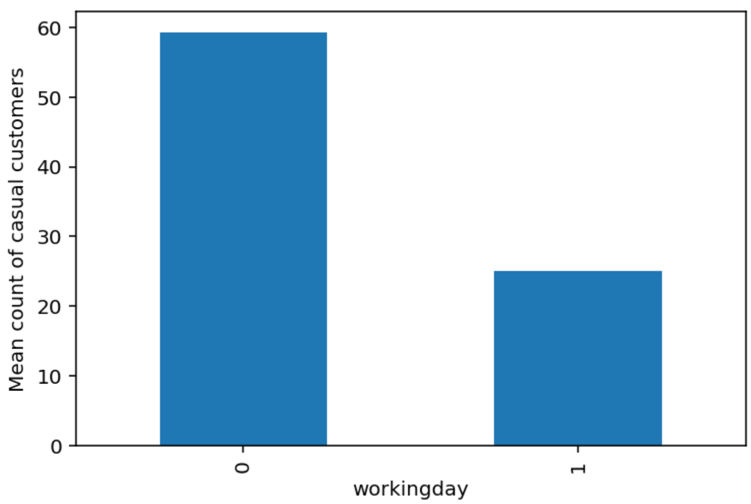
In [50]:
```
# registered customers mean on working and non working days
df.groupby("workingday")["registered"].mean()
print()
print()
df.groupby("workingday").mean()["casual"].plot.bar()
plt.ylabel("Mean count of casual customers")
plt.show
```

Out[50]:
```
workingday
0    129.198330
1    167.904209
Name: registered, dtype: float64
```

Out[50]: `<AxesSubplot:xlabel='workingday'>`

Out[50]: `Text(0, 0.5, 'Mean count of casual customers')`

Out[50]: `<function matplotlib.pyplot.show(close=None, block=None)>`



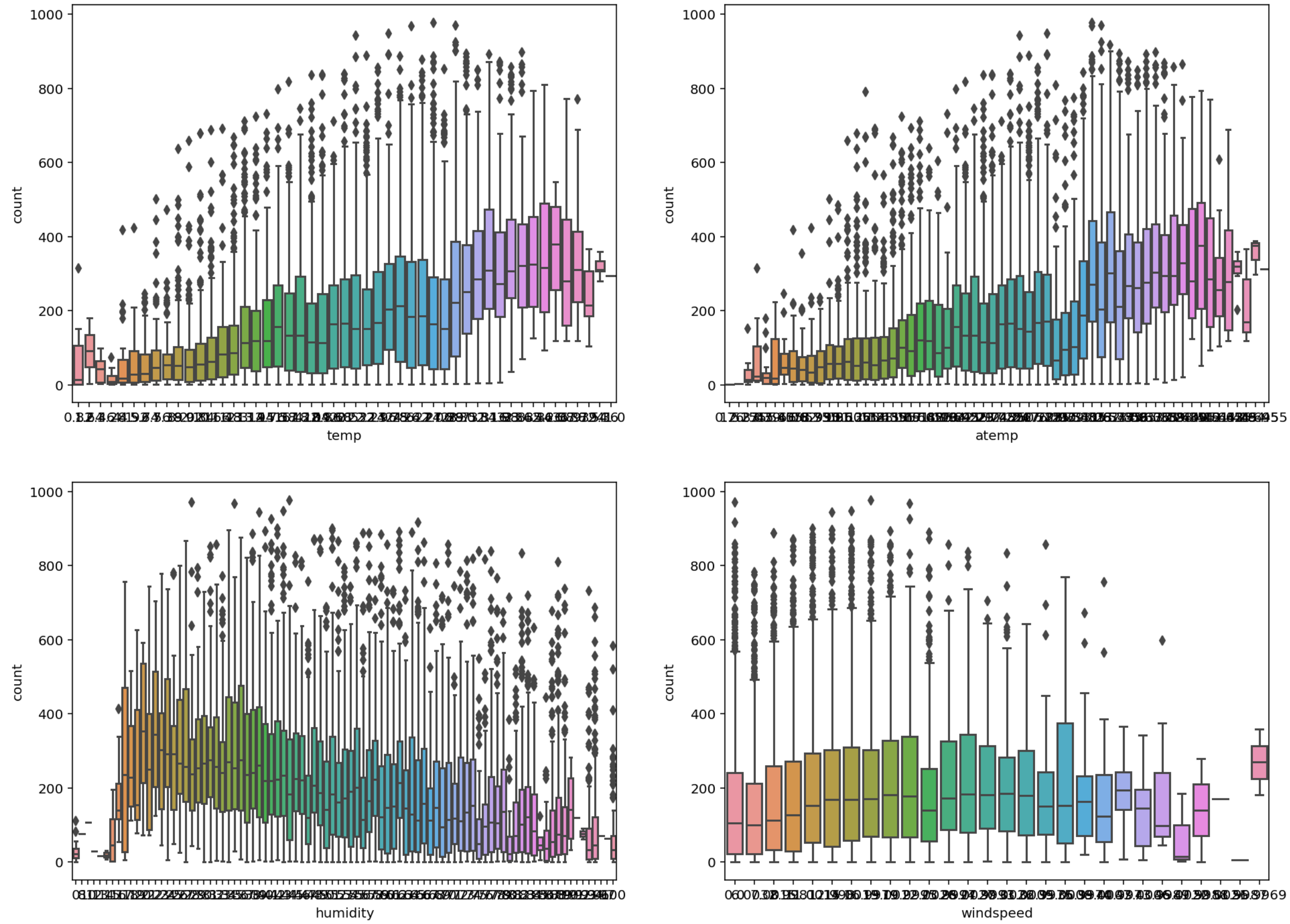
In [51]:
```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
cols= ['temp', 'atemp', 'humidity', 'windspeed','workingday','holiday']
index = 0
for row in range(2):
    for col in range(2):
        sns.boxplot(data=df, x=cols[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```

Out[51]: `<AxesSubplot:xlabel='temp', ylabel='count'>`

Out[51]: `<AxesSubplot:xlabel='atemp', ylabel='count'>`

Out[51]: `<AxesSubplot:xlabel='humidity', ylabel='count'>`

Out[51]: `<AxesSubplot:xlabel='windspeed', ylabel='count'>`



In [ ]:

```

```

Crosstabs

In [52]:

```
# Cross tab for count_bin / working day
pd.crosstab(df['count_bin'],columns=df['workingday'], margins=True)
print()
print()
totalcount=pd.crosstab(df['count_bin'],columns=df['workingday'],
normalize='index')
totalcount.plot(kind='bar',figsize=(10,7))
plt.xlabel("count")
plt.ylabel("")
plt.show()
```

Out[52]:

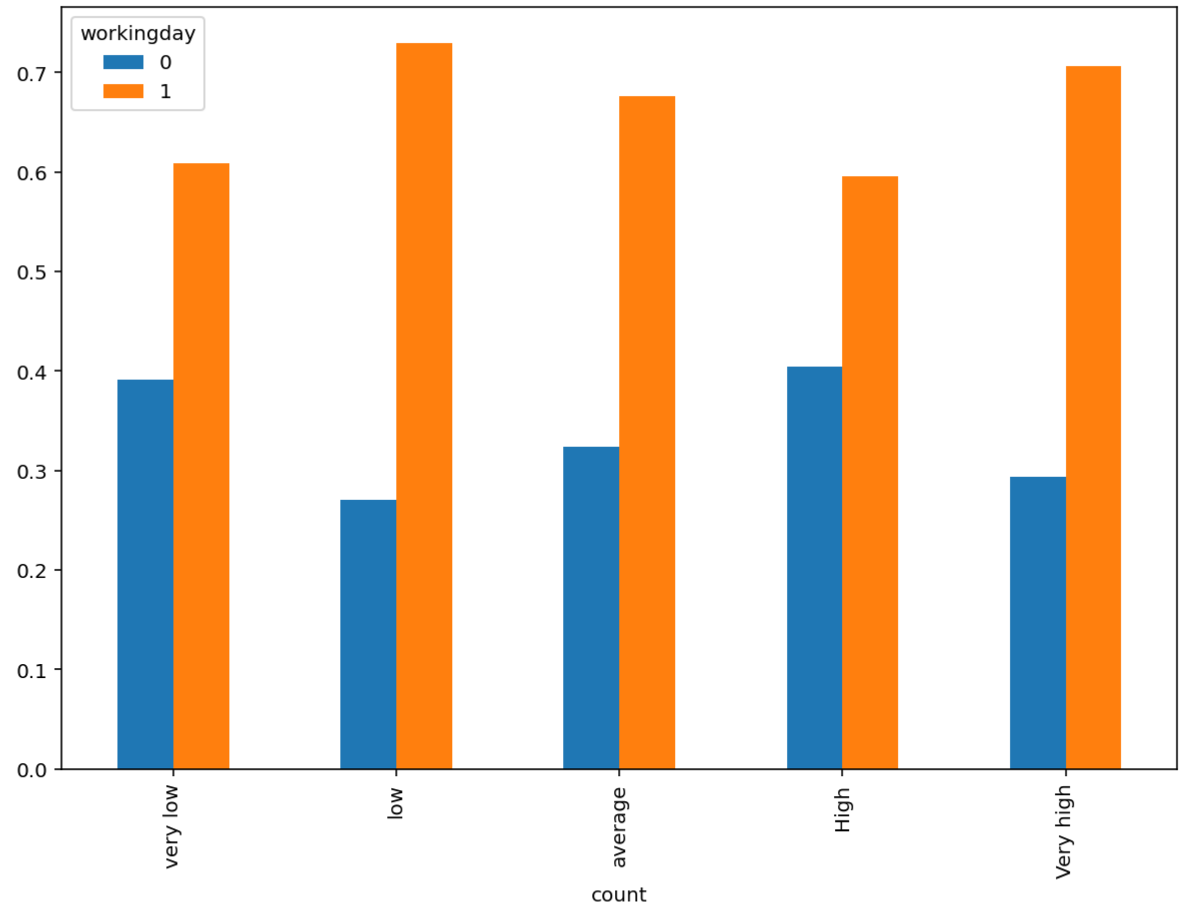
workingday count_bin	0	1	All
very low	1213	1886	3099
low	895	2415	3310
average	584	1221	1805
High	261	385	646

Very high	234	563	797
All	3187	6470	9657

Out[52]: <AxesSubplot:xlabel='count_bin'>

Out[52]: Text(0.5, 0, 'count')

Out[52]: Text(0, 0.5, '')



In [53]:

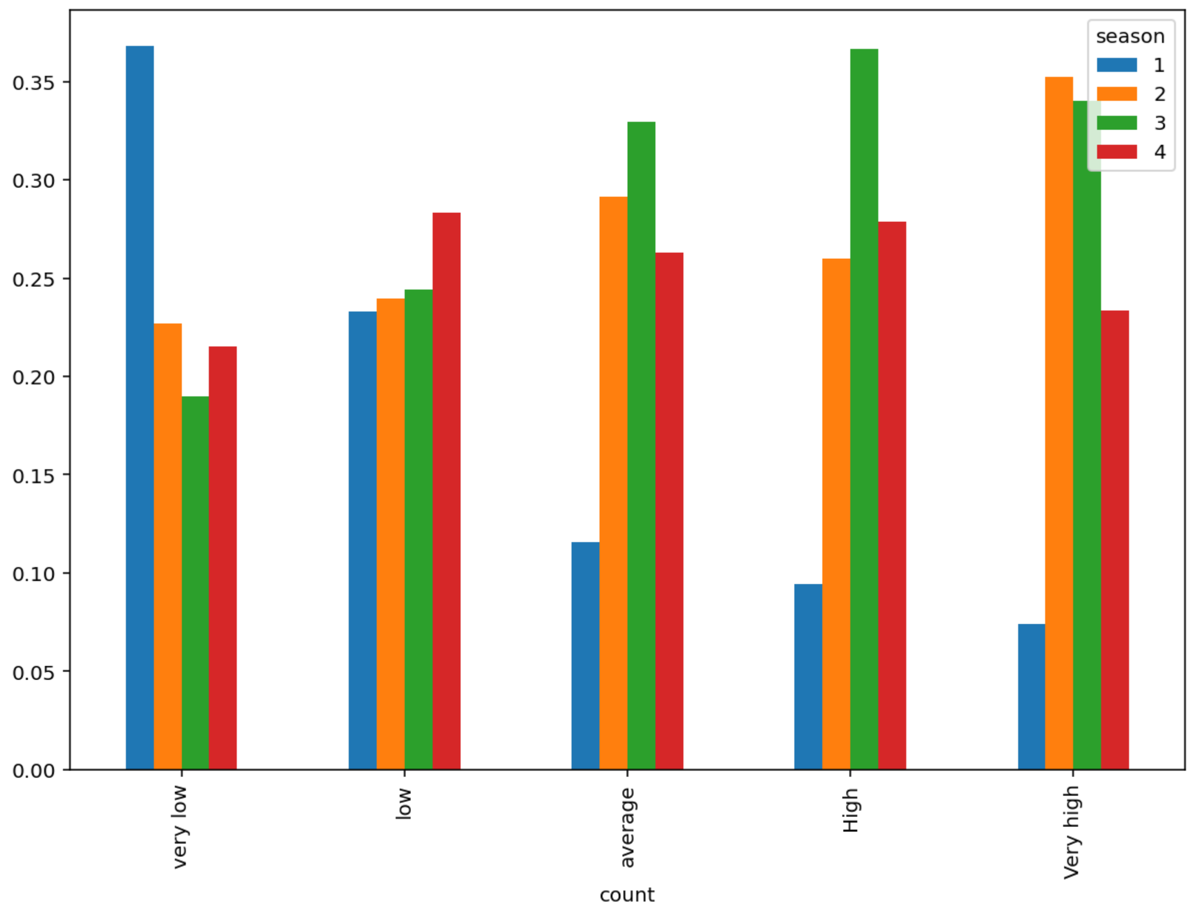
```
# Cross tab for count_bin / season
pd.crosstab(df['count_bin'],columns=df['season'], margins=True)
print()
print()
totalcount=pd.crosstab(df['count_bin'],columns=df['season'],
normalize='index')
totalcount.plot(kind='bar',figsize=(10,7))
plt.xlabel("count")
plt.ylabel("")
plt.show()
```

Out[53]:

season	1	2	3	4	All
count_bin					
very low	1141	703	588	667	3099
low	771	793	809	937	3310
average	209	526	595	475	1805

High	61	168	237	180	646
Very high	59	281	271	186	797
All	2241	2471	2500	2445	9657

Out[53]:
```
<AxesSubplot:xlabel='count_bin'>
```
Out[53]:
```
Text(0.5, 0, 'count')
```
Out[53]:
```
Text(0, 0.5, '')
```



In [54]:
```
# Cross tab for count_bin / temperature bin
pd.crosstab(df['count_bin'],columns=df['temp_bin'], margins=True)
print()
print()
totalcount=pd.crosstab(df['count_bin'],columns=df['temp_bin'],
normalize='index')
totalcount.plot(kind='bar',figsize=(10,7))
plt.xlabel("count")
plt.ylabel("")
plt.show()
```

Out[54]:

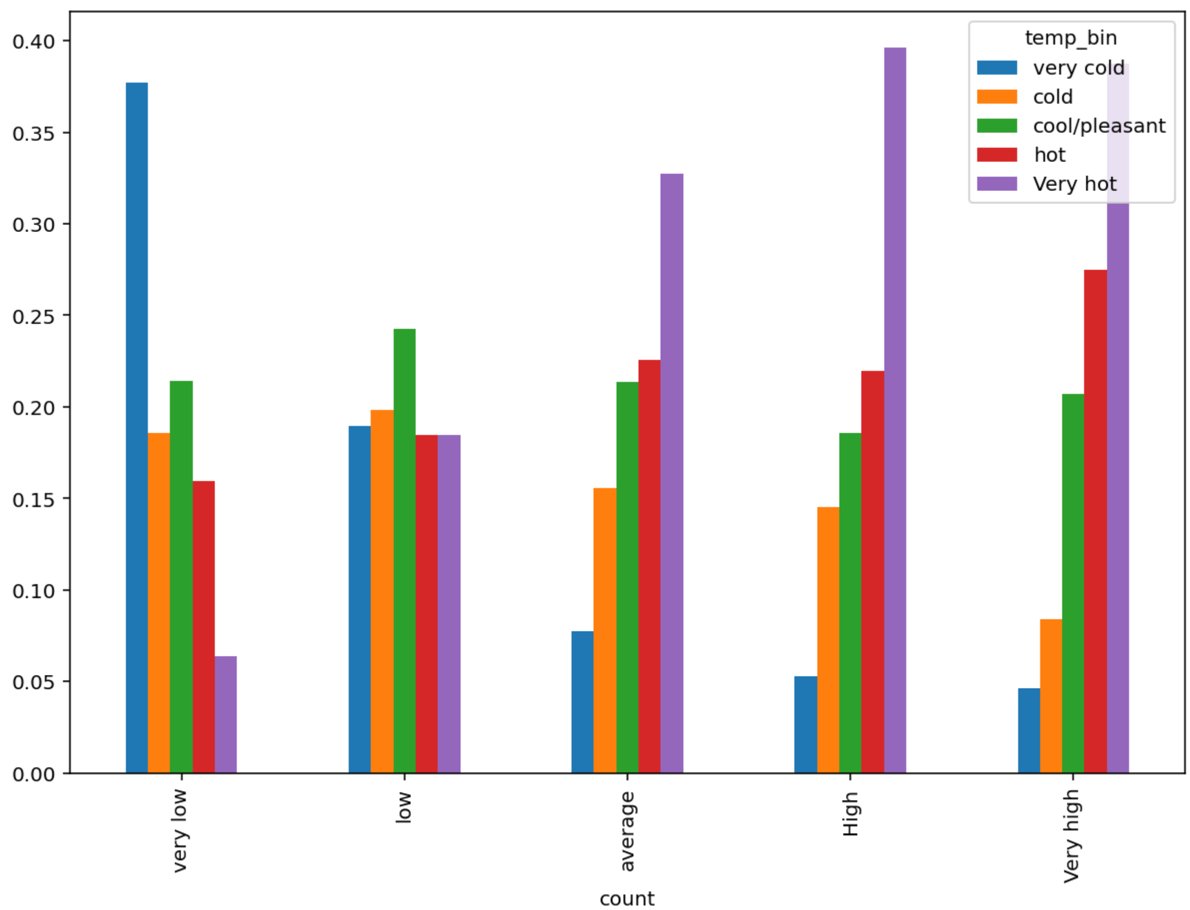
temp_bin	**very cold**	**cold**	**cool/pleasant**	**hot**	**Very hot**	**All**
count_bin						
very low	1168	576	664	494	197	3099
low	627	657	803	611	612	3310

average	140	281	386	407	591	1805
High	34	94	120	142	256	646
Very high	37	67	165	219	309	797
All	2006	1675	2138	1873	1965	9657

Out[54]:
```
<AxesSubplot:xlabel='count_bin'>
```

Out[54]:
```
Text(0.5, 0, 'count')
```

Out[54]:
```
Text(0, 0.5, '')
```



Insights:

- We can see very low temperatures has more count on very cold temperature
- Count is very on season 1
- Count is quite low on working day , ie) below average

Confidence interval- 95% on Season,workingday,temp_bins

In [ ]:
```

```

In [55]:
```
sample_size = 100
collect_sample_means_working = []
collect_sample_means_Notworking=[]
```

```python
collect_sample_means_clearweather=[]
collect_sample_means_rainweather=[]  #Light rain,thunderstorm

for person in range(1000):
    sample_mean_working = df[df['workingday']==1]
["count"].sample(sample_size).mean()
    collect_sample_means_working.append(sample_mean_working)

    sample_mean_notworking = df[df['workingday']==0]
["count"].sample(sample_size).mean()
    collect_sample_means_Notworking.append(sample_mean_notworking)

    sample_mean_clearweather = df[df['weather']==1]
["count"].sample(sample_size).mean()
    collect_sample_means_clearweather.append(sample_mean_clearweather)

    sample_mean_rainweather = df[df['weather']==3]
["count"].sample(sample_size).mean()
    collect_sample_means_rainweather.append(sample_mean_rainweather)

# Collecting a random sample mean
m_working = collect_sample_means_working[0]
m_notworking = collect_sample_means_Notworking[0]
m_clearweather = collect_sample_means_working[0]
m_rainweather = collect_sample_means_Notworking[0]
```

In [56]:

```python
#95% confidence - z values
Zl= norm.ppf(0.025)
Zr= norm.ppf(0.975)

#workingday vs nonworking day
workingday_mean=round(df[df['workingday']==1]['count'].mean(),2)
notworkingday_mean=round(df[df['workingday']==0]['count'].mean(),2)

left = m_working + Zl * workingday_mean / np.sqrt(sample_size)
right = m_working + Zr * workingday_mean / np.sqrt(sample_size)
print(f"\n95% confidence that the population mean of bikes rented on working
day is in [{np.round(left,2)}, {np.round(right,2)}]")

left = m_nonworking + Zl * notworkingday_mean / np.sqrt(sample_size)
right = m_nonworking + Zr * notworkingday_mean / np.sqrt(sample_size)
print(f"\n95% confidence that the population mean bikes rented on Non-working
day is in [{np.round(left,2)}, {np.round(right,2)}]")
```

```
#weather - 1-clear vs 3-raining
clearweather_mean=round(df[df['weather']==1]['count'].mean(),2)
rainweather_mean=round(df[df['weather']==4]['count'].mean(),2)

left = m_clearweather + Zl * clearweather_mean / np.sqrt(sample_size)
right = m_clearweather + Zr * clearweather_mean / np.sqrt(sample_size)
print(f"\n95% confidence that the population mean of bikes rented on clear weather day is in [{np.round(left,2)}, {np.round(right,2)}]")

left = m_rainweather + Zl * rainweather_mean / np.sqrt(sample_size)
right = m_rainweather + Zr * rainweather_mean / np.sqrt(sample_size)
print(f"\n95% confidence that the population mean bikes rented on rainy day is in [{np.round(left,2)}, {np.round(right,2)}]")
```

```
95% confidence that the population mean of bikes rented on working day is in [159.13, 23
4.79]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Input In [56], in <cell line: 13>()
     10 right = m_working + Zr * workingday_mean / np.sqrt(sample_size)
     11 print(f"\n95% confidence that the population mean of bikes rented on working day
 is in [{np.round(left,2)}, {np.round(right,2)}]")
---> 13 left = m_nonworking + Zl * notworkingday_mean / np.sqrt(sample_size)
     14 right = m_nonworking + Zr * notworkingday_mean / np.sqrt(sample_size)
     15 print(f"\n95% confidence that the population mean bikes rented on Non-working da
y is in [{np.round(left,2)}, {np.round(right,2)}]")

NameError: name 'm_nonworking' is not defined
```

Test the statistics signifoicance of created bin

Hypothesis Testing - 1 - chi2_square test

- Null Hypothesis (H0): Weather is independent of the season
- Alternate Hypothesis (H1): Weather is not independent of the season
- Statastic Significance level (alpha): 0.05

In [ ]:

```
## season vs weather

data_corr = pd.crosstab(df['season'], df['weather'])
p_val= chi2_contingency(data_corr)[1]
print("P-value::",p_val)
if p_val <= 0.05:
    print("Since p-value is less than the alpha-value 0.05, We reject the Null Hypothesis. This tells that season and weather is dependent on each
```

```
other")
else:
    print("p-value is greater than the alpha 0.05, We do not reject the Null Hypothesis")
```

P-value is less then alpha - 0.05 , We reject the Null Hypothesis (Ho). This implies that Weather is dependent on the season.

Similarly we can test for other features as well

In [ ]:

```
 # H0: The two features not dependent (independent)
# Ha : Two features are dependent

#p-value > alpha - accept-h0 - independent
#p-value < alpha -reject h0- dependent



#chi2_contingency returns - chi stat, p value, df, expected freq
alpha = 0.05
columns=['season','workingday','holiday',"temp_bin","weather"]
for cols in columns:
    s= pd.crosstab(df[cols], df["count_bin"])
    print(cols,"vs Count")
    print("*"*10)
    print(s)
    print()
    print("--"*25)
    p_val = chi2_contingency(s)[1]
    print(cols,":::::  P-Val::::",p_val)
    print("--"*25)
    if p_val <= alpha:
      print("Since p-value is less than alpha . we reject❌ null hypothesis. ie)", cols,"and count- these two features are dependent✅")
      print()
    else:
      print("P-value is high , we fail to reject hypothesis✅ . ie)",cols,"and count- these two features are not dependent❌")
```

Insights:

As we see,

- temp_bin and count are dependent
- holiday and count
- working day and count

- season and count

all these features are dependent

Hypothesis testing 2 - 2-sample T test

This is a method used to test whether the unknown population means of two groups are equal or not.

A two-sample t-test is used to analyze the results from A/B tests. Randomly sampled from two normal populations and the two independent groups have equal variances.

In [ ]:

```
# Working day vs non-working day
df_nonwork = df[df['workingday']==0]['count'].values
df_work = df[df['workingday']==1]['count'].values

#finding ratio
(np.var(df_nonwork)/np.var(df_work))
```

In [ ]:

```
# 2- sample t test
stats.ttest_ind(a=df_nonwork, b=df_work, equal_var=True)
```

We see , tha variances of two data is almost equal , and less, we proceeded with 2-sample t test , and as a result , we get p-value less than 0.05(alpha value)

Since pvalue is greater than 0.05 .We can not reject the Null hypothesis. this implies that working day has no direct effect on the number of yulu bikes being rented.

In [ ]:

```
#holiday vs not holiday
df_notholiday = df[df['holiday']==0]['count'].values
df_holiday = df[df['holiday']==1]['count'].values

np.var(df_notholiday), np.var(df_holiday)
```

Since variance is not equal or almost equal , we cannot proceed with 2-sample t test for holiday and count

Hypothesis Testing -3 - Anova

In [ ]:

```
w1 = df[df['weather']==1]['count'].values
w2 = df[df['weather']==2]['count'].values
w3 = df[df['weather']==3]['count'].values
w4 = df[df['weather']==4]['count'].values

s1 = df[df['season']==1]['count'].values
s2 = df[df['season']==2]['count'].values
```

```
s3 = df[df['season']==3]['count'].values
s4 = df[df['season']==4]['count'].values
```

In [ ]:
```
# Anova test
stats.f_oneway(w1, w2, w3, w4, s1, s2, s3, s4)
```

As we see in above test result , p-value is less than 0.05,

we reject the null hypothesis. This states that no of yulu bikes rented is not similar/statastical in different weather and season conditions , mentioned in data.

In [ ]:
```
## temperature vs count

t1 = df[df['temp_bin']=="very cold"]['count'].values
t2 = df[df['temp_bin']=="cold"]['count'].values
t3 = df[df['temp_bin']=="cool/pleasant"]['count'].values
t4 = df[df['temp_bin']=="hot"]['count'].values
t5 = df[df['temp_bin']=="Very hot"]['count'].values
```

In [ ]:
```
stats.f_oneway(t1,t2,t3,t4,t5)
```

P-values is less than 0.05 , and the features are not similar in different temperatures

Observations

As analysed in dataset , we can come with following observations

- We can see , there is only one data available for heavy rainy day,
- In heat map , we can see season ,weather is correlated
- We also see, working day has more number of bikes rented than non working day
- On weather 1 has more number of bikes rented
- Whenever , there is heavy rain, the bikes rented is low
- On very hot day , there are more count of bikes rented and less bikes on very cold climate
- Also more mean count on holidays than non holiday days
- Also we can see , the 95% confidence interval for working day is in (142,217)
- And Confidence interval 95% for rainy weather is [161.13, 225.41]
- In hypothesis test , we can find that season and weather are not dependent
- Also season , working day , holiday , temp_bin are also dependent to count of bikes being rented
- Humidity less than 20 , the count of bikes being rented falls to very low

Recommendations

1. In rainy weather , less bikes are rented , this can be increased by promotional Offers
2. Working day and non working day , there is much difference in renting the bikes , this can increased

3. During cold weather , company should have less bikes available , and this can decrease the maintenance cost on those seasonal weather
4. In very low humid days, company should have less bikes in the stock to be rented.
5. And the same , in case of thunderstorms and heavy rain , since , on those days , people wouldn’t prefer to go out. Company should bring less bikes for rent.
6. When windspeed is high , company should have less bikes for renting.