YULU BIZ CASE STUDY - HYPOTHESIS TESTING

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:

1. Which variables are significant in predicting the demand for shared electric cycles in the Indian market?
2. How well those variables describe the electric cycle demands

Concept Used:

1. Bi-Variate Analysis
2. 2-sample t-test: testing for difference across populations
3. ANNOVA
4. Chi-square

we need functions and methods to do all these analysis, so we must import Python libraries into our work notebook.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

To perform Hypothesis testing we need to import few test functions

```
from scipy.stats import ttest_ind,kstest
from scipy.stats import f_oneway,kruskal,chi2_contingency
```

To get the data into our work space we use the below code(to read csv files) and saving the whole set of data into a single variable(dataframe) which makes analysis easier

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089 -O yulu.csv
```

```
--2023-10-10 13:19:13--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 108.157.172.10, 108.157.172.176, 108.157.172.183, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|108.157.172.10|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 648353 (633K) [text/plain]
Saving to: ‘yulu.csv’

yulu.csv            100%[===================>] 633.16K  --.-KB/s    in 0.1s

2023-10-10 13:19:13 (6.08 MB/s) - ‘yulu.csv’ saved [648353/648353]
```

```
df = pd.read_csv('yulu.csv')
```

```
df.head()
```

TO ANALYSE THE BASIC METRICS

```
# TO GET NO. OF ROWS & COLUMNS:

df.shape

    (10886, 12)
```

```
# TO GET TOTAL ELEMENTS IN THE DATASET (i.e., the dot product of no. of rows & columns)

df.size

    130632
```

```
# To get index

df.index

    RangeIndex(start=0, stop=10886, step=1)
```

```
# TO GET THE NAMES OF THE COLUMNS

df.columns

    Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
           'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
          dtype='object')
```

```
# TO GET THE NAMES OF THE COLUMNS(alternate method)

df.keys()

    Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
           'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
          dtype='object')
```

```
# To get memory usage of each column

df.memory_usage()

    Index           128
    datetime      87088
    season        87088
    holiday       87088
    workingday    87088
    weather       87088
    temp          87088
    atemp         87088
    humidity      87088
    windspeed     87088
    casual        87088
    registered    87088
    count         87088
    dtype: int64
```

```
# TO GET THE TOTAL INFORMATION ABOUT THE DATASET.
# info function let us know the columns with their data types and no. of non-null values & the total memory usage


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
```

From the above analysis we get to know that except datetime which is an object all others are either integer or float

MISSING VALUE DETECTION

```
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
```

INFERENCE:

No missing values found

```
# To get the data type of each column

df.dtypes
```

```
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
```

STATISTICAL SUMMERY

```
df.describe()
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registe
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.00
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.55
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.03
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.00
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.00
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.00
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.00
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.00

Describe function returns the glimpse of the data with the statistical values from all over the data just to predict the normal ranges and average ranges to the particular elements. Note: It will display only the numerical values and return from the numerical values.

NOTE:

Here, season, weather, holiday, working day columns are categorical but considered as numerical.

```
df.describe(include=object)
```

	datetime
count	10886
unique	10886
top	2011-01-01 00:00:00
freq	1

INFERENCE:

1. Registered users are more than the casual users
2. There are days when there is zero casual users or even zero registered users have been recorded
3. Maximum - Windspeed is 56.996900 , Humidity = 100, Temperature is 41 degree celcius
4. There are 4 different seasons and 4 different weather conditions.

CONVERSION TO CATEGORICAL ATTRIBUTES:

Datatype of following attributes needs to changed to proper data type

1. datetime - to datetime
2. season - to categorical
3. holiday - to categorical
4. workingday - to categorical
5. 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('category')
```

```
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  category
 2   holiday     10886 non-null  category
 3   workingday  10886 non-null  category
 4   weather     10886 non-null  category
 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: category(4), datetime64[ns](1), float64(3), int64(4)
memory usage: 723.7 KB
```

NOTE:

The Dtype of datetime is now changed to datetime and season, weather, holiday, workingday are now changed to category

```
df.describe(include = 'category')
```

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

INFERENCE:

1. Among the 4 seasons, season 4 (winter) has more frequency than others but still their frequencies differs by very little margin
2. Among the 4 weeather, weather 1 has more frequency than others.

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

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

Splitting Datetime column into 2 seperate columns

```
df['date'] = df['datetime'].dt.date
df['time'] = df['datetime'].dt.time
```

```
df.sample()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	date	time
7970	2012-06-12 11:00:00	2	0	1	3	27.06	30.305	83	23.9994	8	57	65	2012-06-12	11:00:00

```
df.drop(['datetime'],axis = 1, inplace=True)
```

```
df.keys()
```

```
Index(['season', 'holiday', 'workingday', 'weather', 'temp', 'atemp',
       'humidity', 'windspeed', 'casual', 'registered', 'count', 'date',
       'time'],
      dtype='object')
```

```
# Accessing the rows with their iloc(integer location) values

df.iloc[:4]
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	date	time
0	1	0	0	1	9.84	14.395	81	0.0	3	13	16	2011-01-01	00:00:00
1	1	0	0	1	9.02	13.635	80	0.0	8	32	40	2011-01-01	01:00:00
2	1	0	0	1	9.02	13.635	80	0.0	5	27	32	2011-01-01	02:00:00
3	1	0	0	1	9.84	14.395	75	0.0	3	10	13	2011-01-01	03:00:00

```
# Accessing selected range of rows using external location values

df.loc[3:6]
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	date	time
3	1	0	0	1	9.84	14.395	75	0.0000	3	10	13	2011-01-01	03:00:00
4	1	0	0	1	9.84	14.395	75	0.0000	0	1	1	2011-01-01	04:00:00

```
# Accessing the specified columns for all rows using external location


df.loc[:,['workingday','count','date']]
```

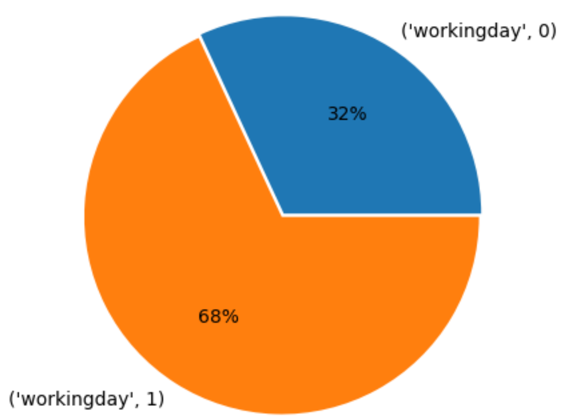
	workingday	count	date
0	0	16	2011-01-01
1	0	40	2011-01-01
2	0	32	2011-01-01
3	0	13	2011-01-01
4	0	1	2011-01-01
...	...	...	...
10881	1	336	2012-12-19
10882	1	241	2012-12-19
10883	1	168	2012-12-19
10884	1	129	2012-12-19
10885	1	88	2012-12-19

10886 rows × 3 columns

VISUAL ANALYSIS:

UNIVARIATE

```
workingday = ['workingday']

df1=df[workingday].melt().groupby(['variable','value'])[['value']].count()/len(df)

plt.pie(df1.value, labels=df1.index,explode=[0,0.02],autopct='%.0f%%')
plt.show()
```




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

```
1    7412
0    3474
Name: workingday, dtype: int64
```

INFERENCE:

The working day has more frequency than the holiday

Understanding the distribution of numerical attributes

```
# taking all the numerical columns names in an array

num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

# subplotting the graphs

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

# creating Histplot for every numerical attributes

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()
```

INFERENCE:

1. **Casual, Registered** and hence the **Count** somewhat looks like **Log Normal** Distribution
2. **Temp, atemp** and **humidity** looks like they follows the **Normal** Distribution
3. **Windspeed** follows the **Binomial** distribution

Analysing Categorical columns with countplot

```
cat_cols = ['season','holiday','workingday','weather']


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()
```

INFERENCE:

1. Data looks common as it should be like equal number of days in each season
2. More working days

3. Most frequent Weather is Clear, Few clouds, partly cloudy and the least one is Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog, obviously as this weather prevails noone will rent a bike

Predicting Outliers using BOXPLOT

```
# plotting box plots to detect outliers in the data

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.boxplot(y=df[num_cols[index]], ax=axis[row, col])
        index += 1

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

INFERENCE:

We can clearly observe that casual, registered and count have more outliers in the data whereas humidity has one outlier in the data

BIVARIATE ANALYSIS:

```
df['count'].max(), df['count'].min()
```

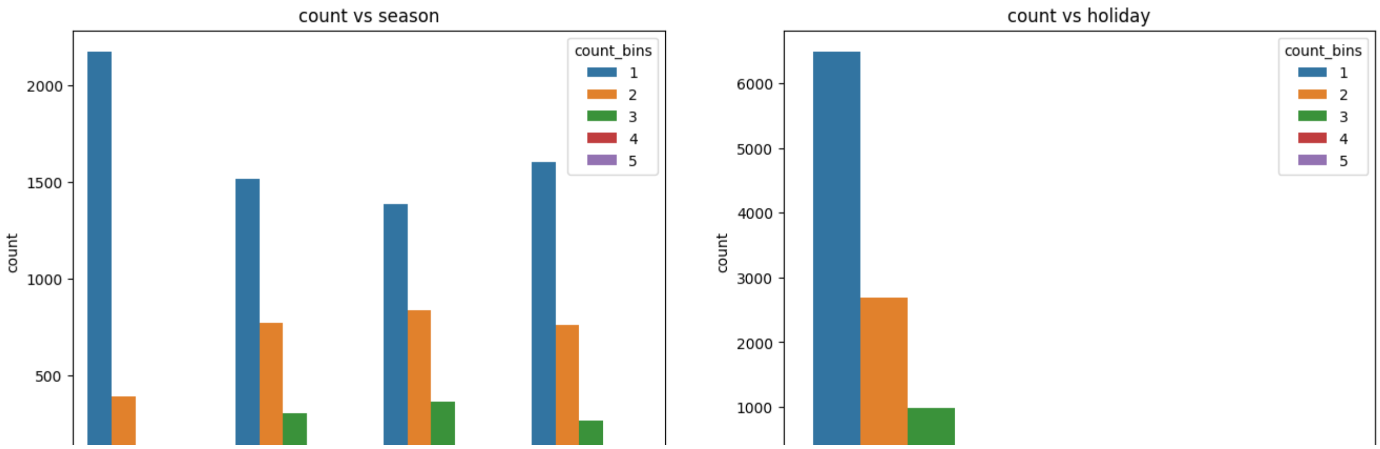
```
(977, 1)
```

```
bins = [0,200,400,600,800,1000]
labels = [1,2,3,4,5]

df['count_bins'] = pd.cut(df['count'],bins=bins, labels=labels)

df['count_bins'].value_counts()
```

```
1    6684
2    2759
3    1031
4     326
5      86
Name: count_bins, dtype: int64
```

Countplot of Categorical columns vs count

```
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],hue='count_bins', ax=axis[row,col])
    axis[row,col].set_title(f'count vs {cat_cols[index]}')
    index+=1
plt.show()
```



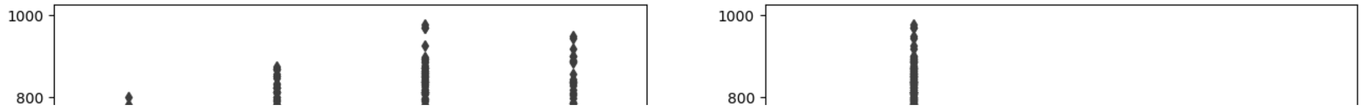
INFERENCE:

Visual analysis of all the categorical attributes with the count has been done.And from the result we observe,

1. Weather 4 has the least number of vehicles rented
2. Season 3 has more bikes rented

PREDICTING OUTLIERS USING BOXPLOT

```
# 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()
```

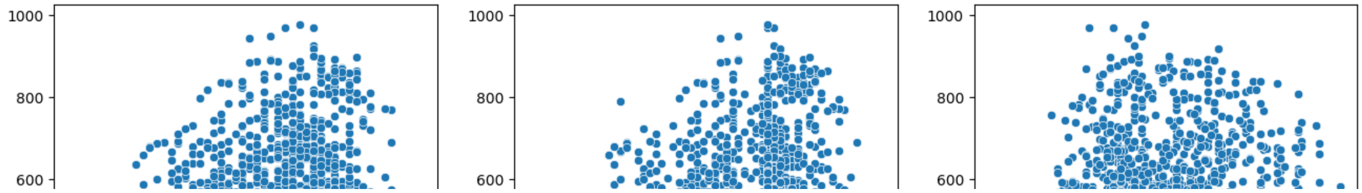


INFERENCE:

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

SCATTERPLOTS

```
# 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()
```



INFERENCE:

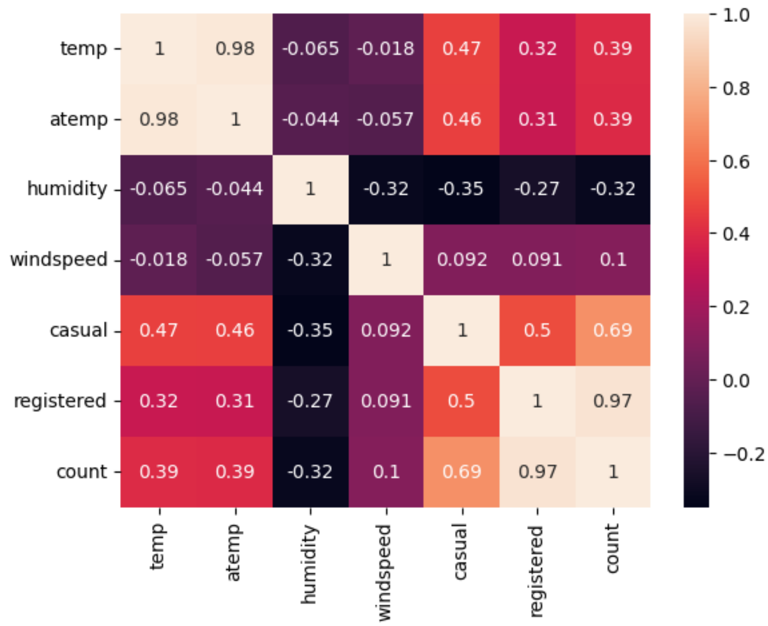
1. Whenever the **humidity < 20**, number of bikes rented is very very low.
2. Whenever the **temperature < 10**, number of bikes rented is less.
3. Whenever the **windspeed > 35**, number of bikes rented is less.
4. The number and the usage of **Registered** user also increased linearly

HEATMAPS

Correlation can be established only between two numerical columns

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

```
<ipython-input-64-7a3f2fbe6c0a>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  sns.heatmap(df.corr(),annot = True)
```



INFERENCE:

1. **Registered** users has **good** correaltion with count this implies that they contribute more towards count
2. **Humidity** has **negative** corrrelation with count
3. **Windspeed** and **Temperature** are **moderately** correlated with count

HYPOTHESIS TESTING:

1. Does working day has effect on number of electric cycles rented?

Since the test involve a **categorical** column and its **numerical** values ttest can be performed. Also, the two groups are independent of each other so we use **ttest_ind.**

2-SAMPLE TTEST

NULL HYPOTHESIS: (Ho) - **Working day** has **no effect** on number of electric cycles rented

ALTERNATE HYPOTHESIS: (Ha) - **Working day** has **an effect** on number of electric cycles rented

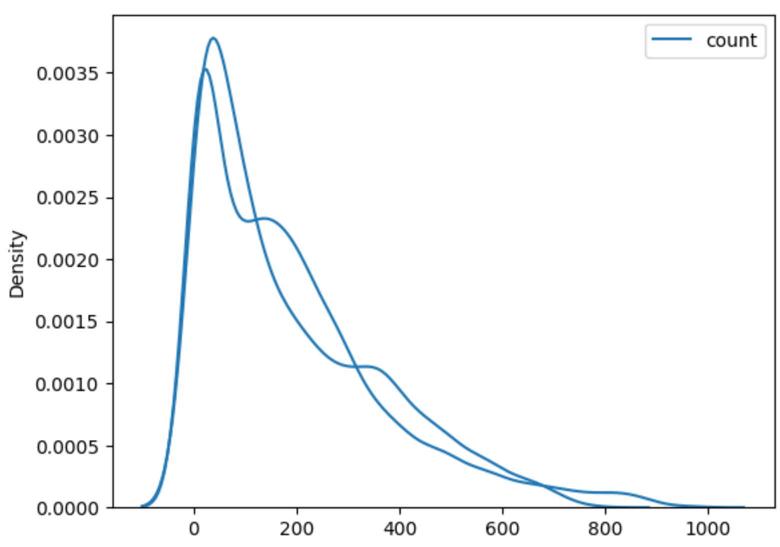
```
# For alpha =0.05 i.e., 95% confidence level

workingday_1 = df[df['workingday']==1][['count']]

workingday_0 = df[df['workingday']==0][['count']]

t_stat, p_value = ttest_ind(workingday_1['count'], workingday_0['count'])

print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Working day has an effect on number of electric cycles rented')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Working day has no effect on number of electric cycles rented')
```

```
p_value :  0.22644804226361348
FAIL TO REJECT Ho
INFERENCE - Working day has no effect on number of electric cycles rented
```

INFERENCE:

Whether its a working day or not the number of bikes rented is **not affected**

```
sns.kdeplot(workingday_1)
sns.kdeplot(workingday_0)
plt.show()
```



INFERRENCE:

The **kdeplot** vividly shows that the graphs of both the groups are almost the **same distribution** and they have **almost same mean.** so ttest is reliable in this case.

```
workingday_0.mean(), workingday_1.mean()
```

```
(count    188.506621
 dtype: float64,
```

```
count    193.011873
dtype: float64)
```

2. Does weather has effect on number of electric cycles rented?

As the test has to be performed between **more than 2 categorical** groups we prefer **ANNOVA**

ANNOVA

NULL HYPOTHESIS: (Ho) - **Weather** has **no effect** on number of electric cycles rented

ALTERNATE HYPOTHESIS: (Ha) - **Weather** has **an effect** on number of electric cycles rented

```
weather_1 = df[df['weather']==1]['count']
weather_2 = df[df['weather']==2]['count']
weather_3 = df[df['weather']==3]['count']
weather_4 = df[df['weather']==4]['count']
```

```
# For alpha =0.05 i.e., 95% confidence level
```

```
f_stat, p_value = f_oneway(weather_1, weather_2, weather_3, weather_4)
print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Weather has an effect on number of electric cycles rented')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Weather has no effect on number of electric cycles rented')
```

```
p_value :  5.482069475935669e-42
REJECT Ho
INFERENCE - Weather has an effect on number of electric cycles rented
```

INFERENCE:

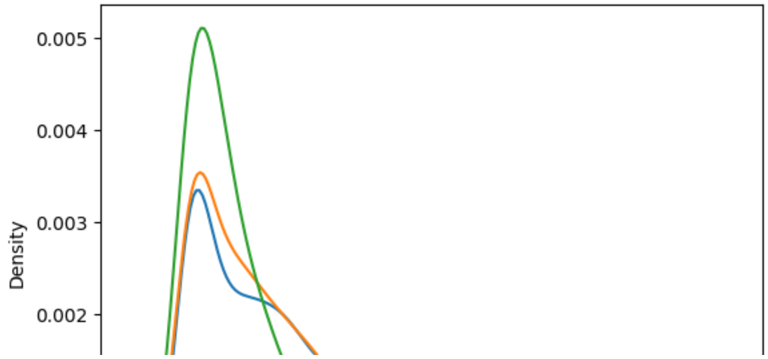
Weather has **an effect** on the number of vehicles to be rented

ASSUMPTION OF ANNOVA:

1. Distribution follows **Gaussian**
2. All samples are **independent**
3. **Equal variance** among different groups

```
sns.kdeplot(weather_1)
sns.kdeplot(weather_2)
sns.kdeplot(weather_3)
sns.kdeplot(weather_4)
```

```
<ipython-input-12-9199e072790a>:4: UserWarning: Dataset has 0 variance; skipping density estimate. Pass `warn_singular=False` to disable
  sns.kdeplot(weather_4)
<Axes: xlabel='count', ylabel='Density'>
```




```
weather_1.var(), weather_2.var() ,weather_3.var(), weather_4.var()
```

```
(35328.79846268022, 28347.248993301797, 19204.77589271419, nan)
```

INFERENCE:

Since there is **no equal variance** among the groups we cant just rely on Annova. so to **check the reliability** of Annova we perform **Kruskal** test

KRUSKAL TEST

```
# For alpha =0.05 i.e., 95% confidence level


kruskal_stat, p_value = kruskal(weather_1, weather_2, weather_3, weather_4)
print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Weather has an effect on number of electric cycles rented')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Weather has no effect on number of electric cycles rented')
```

```
p_value :  3.501611300708679e-44
REJECT Ho
INFERENCE - Weather has an effect on number of electric cycles rented
```

INFERENCE:

Kruskal test also confirms that **Weather** has **an effect** on the number of vehicles rented

```
weather_grouped = pd.DataFrame(df.groupby('weather')['count'].sum())

sns.barplot(data = weather_grouped, x=weather_grouped.index, y='count')
```

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

Visual confirmation of the fact that weather has effect on the number of vehicles to be rented

3. Does season has effect on number of electric cycles rented?

As the test has to be performed between **more than 2 categorical** groups we prefer **ANNOVA**

ANNOVA

NULL HYPOTHESIS: (Ho) - **Season** has **no effect** on number of electric cycles rented

ALTERNATE HYPOTHESIS: (Ha) - **Season** has **an effect** on number of electric cycles rented

```
season_1 = df[df['season']==1]['count']
season_2 = df[df['season']==2]['count']
season_3 = df[df['season']==3]['count']
season_4 = df[df['season']==4]['count']
```

```
# For alpha =0.05 i.e., 95% confidence level
```

```
f_stat, p_value = f_oneway(season_1, season_2, season_3, season_4)
print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Season has an effect on number of electric cycles rented')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Season has no effect on number of electric cycles rented')
```

```
p_value :  6.164843386499654e-149
REJECT Ho
INFERENCE - Season has an effect on number of electric cycles rented
```

INFERENCE:

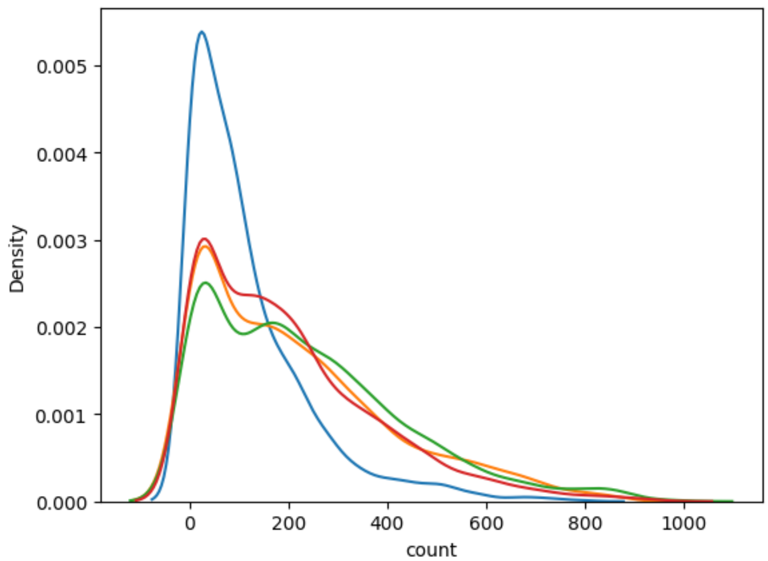
Season has **an effect** on the number of vehicles to be rented

ASSUMPTION OF ANNOVA:

1. Distribution follows **Gaussian**
2. All samples are **independent**
3. **Equal variance** among different groups

```
sns.kdeplot(season_1)
sns.kdeplot(season_2)
sns.kdeplot(season_3)
sns.kdeplot(season_4)
```

```
<Axes: xlabel='count', ylabel='Density'>
```




```
season_1.var(), season_2.var() ,season_3.var(), season_4.var()
```

```
(15693.568533717144, 36867.01182553242, 38868.517012662865, 31549.720316669307)
```

INFERENCE:

Since there is **no equal variance** among the groups we cant just rely on Annova. so to **check the reliability** of Annova we perform **Kruskal** test

KRUSKAL TEST

```
# For alpha =0.05 i.e., 95% confidence level
```

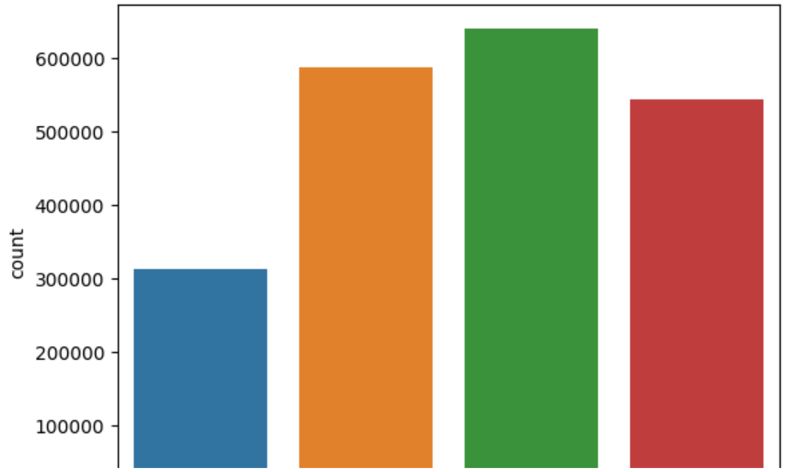
```
kruskal_stat, p_value = kruskal(season_1, season_2, season_3, season_4)
print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Season has an effect on number of electric cycles rented')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Season has no effect on number of electric cycles rented')
```

```
p_value :  2.4790083726086633e-151
REJECT Ho
INFERENCE - Season has an effect on number of electric cycles rented
```

INFERENCE:

Kruskal test also confirms that **Season** has **an effect** on the number of vehicles rented

```
season_grouped = pd.DataFrame(df.groupby('season')['count'].sum())
sns.barplot(data=season_grouped,x=season_grouped.index,y='count')
plt.xticks(range(4),['spring','summer','fall','winter'])
plt.show()
```



Visual confirmation of the fact that Season has effect on the number of vehicles to be rented

4. Is Weather dependent on Season ?

Comparing **two categorical** columns involving their **frequency**, so we need to perform **chi-square test**

CHI-SQUARE TEST

NULL HYPOTHESIS: (Ho) - **Weather** is **independent** of **Season**

ALTERNATE HYPOTHESIS: (Ha) - **Weather** is **dependent** on **Season**

```
pd.crosstab(df['weather'],df['season'])
```

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

```
# For alpha =0.05 i.e., 95% confidence level


chi_stat,p_value,dof,exp = chi2_contingency(pd.crosstab(df['weather'],df['season']))

print('p_value : ',p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Weather and Season are Dependent')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Weather and Season are Independent')
```

```
p_value :  1.5499250736864862e-07
REJECT Ho
INFERENCE - Weather and Season are Dependent
```

INFERENCE:

Weather and **Season** are two columns which **Depend** on each other

EXTRA BITS:

1. Whether the number of casual users depend on temperature ?

```
chi_stat,p_value,dof,exp = chi2_contingency(pd.crosstab(df['temp'],df['casual']))

print('p_value : ', p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Temperature and number of Casual users are Dependent')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Temperature and number of Casual users are Independent')
```

```
p_value :  1.7731490661070978e-237
REJECT Ho
INFERENCE - Temperature and number of Casual users are Dependent
```

2. Whether the number of registered users depend on temperature ?

```
chi_stat,p_value,dof,exp = chi2_contingency(pd.crosstab(df['temp'],df['registered']))

print('p_value : ', p_value)

alpha = 0.05

if p_value < alpha:
  print('REJECT Ho')
  print('INFERENCE - Temperature and number of Registered users are Dependent')

else:
  print('FAIL TO REJECT Ho')
  print('INFERENCE - Temperature and number of Registered users are Independent')
```

```
p_value :  0.99943702404443
FAIL TO REJECT Ho
INFERENCE - Temperature and number of Registered users are Independent
```

INFERENCE:

It is Statistically proved that,

1. Number of **Casual** users are **dependent** on **Temperature**
2. Number of **Registered** users are **independent** of **Temperature**

Insights:

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

Recommendations:

1. 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.
2. With a significance level of 0.05, workingday has no effect on the number of bikes being rented.
3. In very **low humid** days, company should have **less bikes** in the stock to be rented. so, maintainance of the bikes like repair works can be done.
4. Whenever temprature is less than 10 or in very cold days, company should have less bikes.
5. Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.