

**Business Problem** 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?

Which variables from the data set will help you understand the demand for shared electric cycles in the Indian market?

How well will these variables help you understand the demand for shared electric cycles?

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
```

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

```
df.shape
(10886, 12)
```

```
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
```

```
df.head(5)
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0
2	2011-01-01 02:00:00	1	0	0	1	8.18	12.96	78	0.0
3	2011-01-01 03:00:00	1	0	0	1	7.36	12.295	76	0.0

```
##Checking for any null value
df.isnull().sum()
```

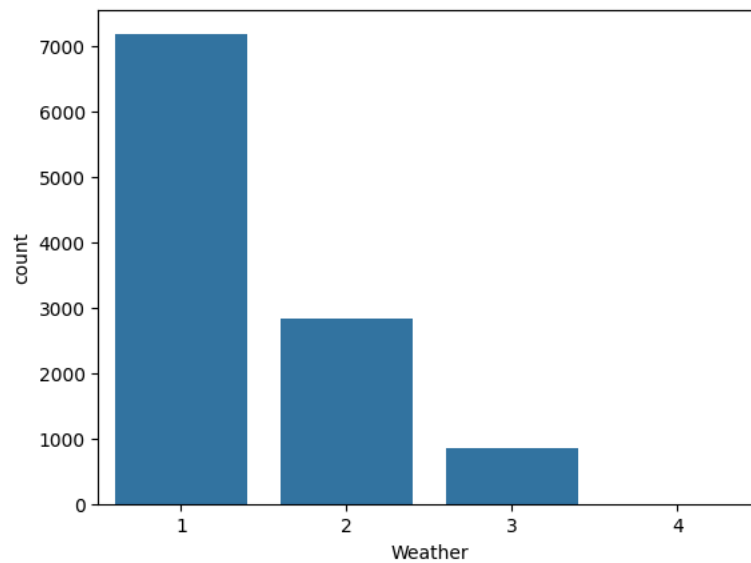
```
datetime    0
season      0
holiday     0
workingday  0
weather     0
temp        0
atemp       0
humidity    0
windspeed  0
casual      0
registered  0
count       0
dtype: int64
```

===== Univariate Analysis =====

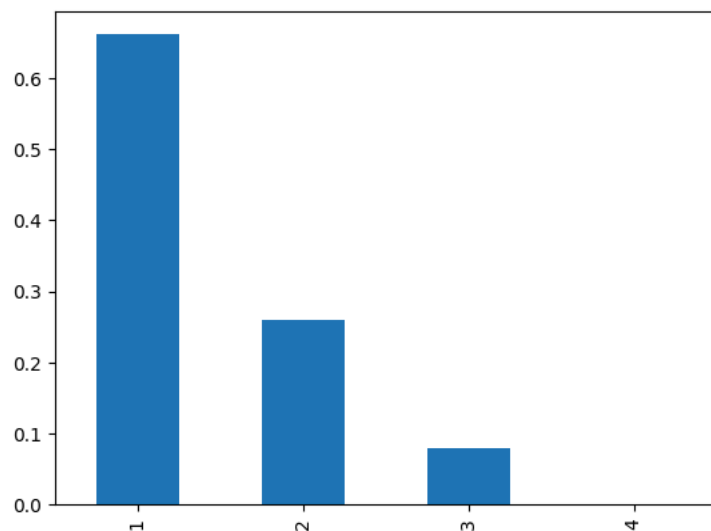
```
df.describe()
```

	season	holiday	workingday	weather	temp	after
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.65508
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.47460
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.76000
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.66500
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.24000
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.06000
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.45500

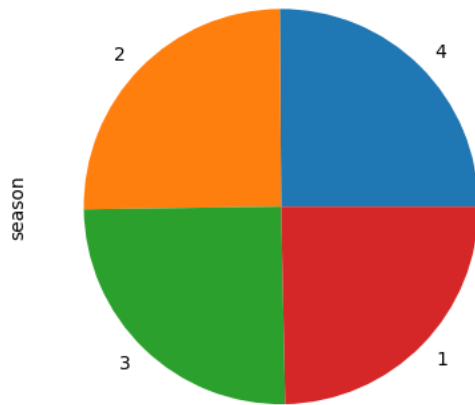
```
sns.countplot(x=df["weather"])
plt.xlabel("Weather")
plt.show()
```



```
df['weather'].value_counts(normalize=True).round(3).plot(kind = "bar")
plt.show()
```



```
df["season"].value_counts().plot(kind="pie")
plt.show()
```

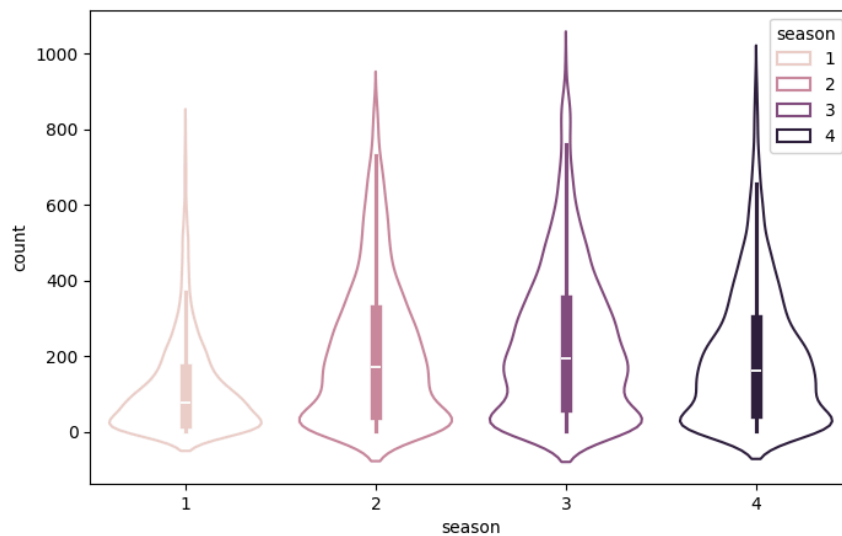


### Observation of Univariate Analysis

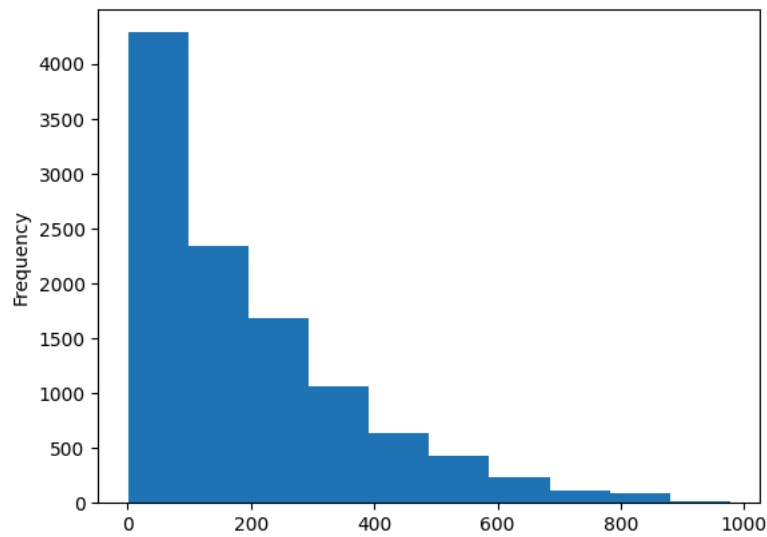
- weather category 1 has most number of values around 70 percent values
- 1. Clear, Few clouds, partly cloudy, partly cloudy
- season values are nearly equal for all seasons

### ✓ ++++++Bivariate Analysis++++++

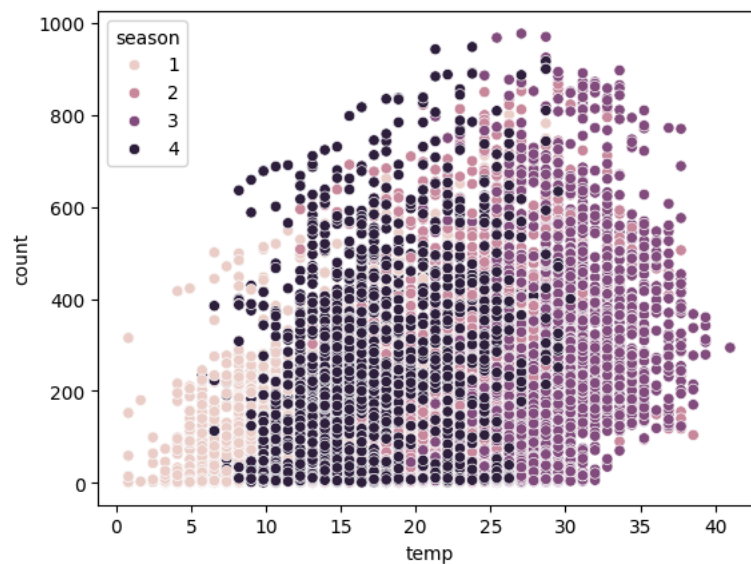
```
plt.figure(figsize=(8,5))
sns.violinplot(x = 'season', y = 'count', data = df,hue='season',fill=False)
plt.show()
```



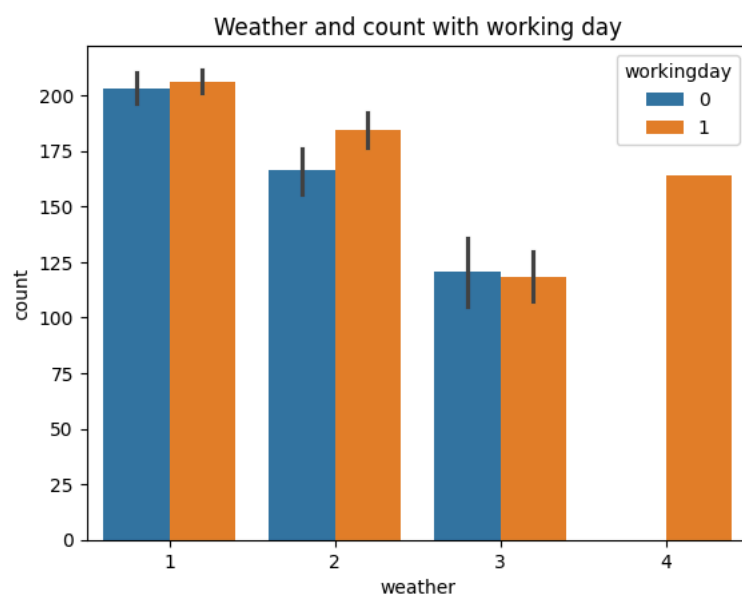
```
df["count"].plot(kind = "hist")
plt.show()
```



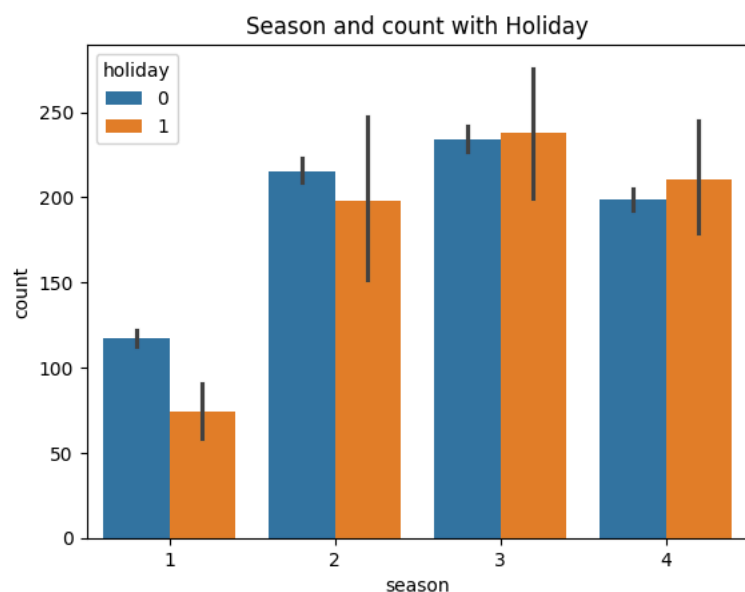
```
sns.scatterplot(data = df, x = "temp", y = "count", hue = "season")  
plt.show()
```



```
sns.barplot(x="weather", y="count",data=df, hue="workingday")  
plt.title("Weather and count with working day")  
plt.show()
```

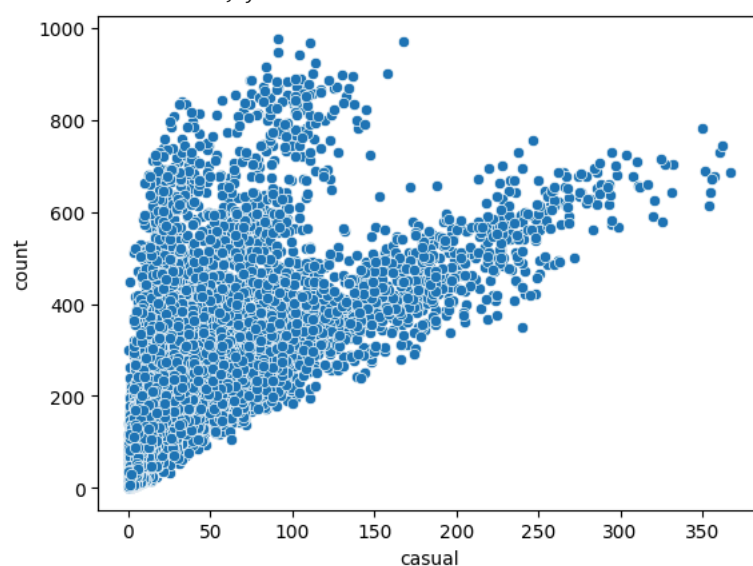


```
sns.barplot(x="season", y="count",data=df, hue="holiday")
plt.title("Season and count with Holiday")
plt.show()
```



```
sns.scatterplot(x="casual", y="count",data=df)
```

<Axes: xlabel='casual', ylabel='count'>

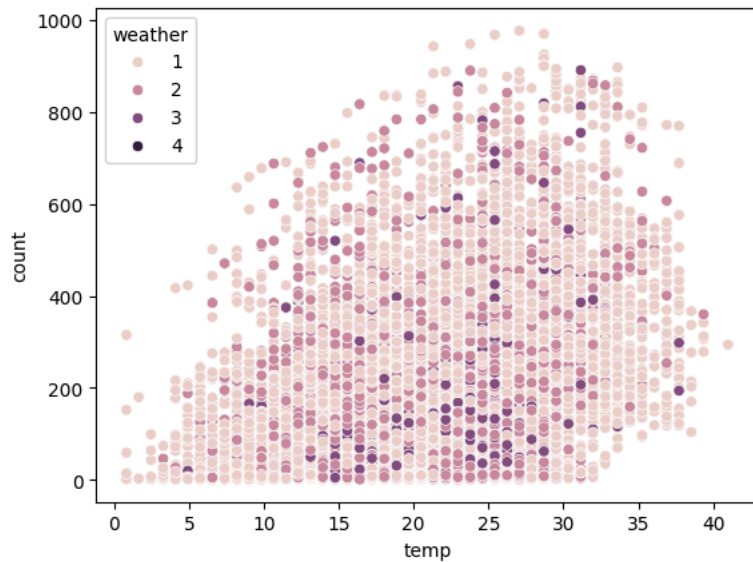


### Observation

1. Weather day 1 has most bikes rented (1: Clear, Few clouds, partly cloudy, partly cloudy)
2. Season Fall has most number of counts and spring has least
3. No users on holidays in Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog weather conditions
4. weather category 1 has equal users on holidays and workdays

## ✓ Getting a bird eye view of some data

```
sns.scatterplot(data = df, x = "temp", y = "count", hue = "weather")
plt.show()
```



## ✓ \* Objective 1

### 2 sample Test

To determine whether holiday and working day has any effect on number of bikes rented

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

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

```
workinday_rent_count = df["count"].loc[df["workingday"] == 0]
holiday_rent_count = df["count"].loc[df["workingday"] == 1]
```

**Null Hypothesis** Ho is working day and holiday has no effect on number of bikes rented

Ho = holiday and working day are same

i.e. Ho => number of bikes rented on holiday are same as number of bikes rented on working day

**Alternate Hypothesis** Ha => number of bikes rented on holiday are not same as number of bikes rented on working day

using 2 sample test

Keeping full sample size as is as larger sample size assures us a near normal distribution

```
samp1=workinday_rent_count
samp2=holiday_rent_count
alpha=0.05

zscore,p_value= ztest(samp1,samp2,alternative='two-sided')
print(p_value)
if p_value < alpha:
    print("Reject Ho:there is no similarity in count of bikes rented in different weathers")
else:
    print("Failed to reject H0/Accept Ho:Working day and holiday has no effect on number of bikes rented ")

0.22642176970306893
Failed to reject H0/Accept Ho:Working day and holiday has no effect on number of bikes rented
```

**Observation** We accept number of bikes rented on holiday are same as number of bikes rented on working day, i.e null hypothesis

note: There is a risk in considering the values of this test as very correct as we have not taken the normal sample distribution for 2 sample test and not cross checked with assumptions of the test (Normality, Equal Variance).

## ✓ Objective 2

### Chi-square

Test to check if Weather is dependent on the season

Weather:

- 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

season:

- 1. spring
- 2. summer
- 3. fall
- 4. winter

Hypothesis

Null Hypothesis "Ho"

Weather and season are independent or No relation

Alternate hypoothesis "Ha"

variables weather and season are dependent or significant relationship

Ho is variables are independent

Ha is variables are dependent

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

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

```
df["season"].value_counts()

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

Contingency table

```
pd.crosstab(index=df['weather'],columns=df["season"],margins=True)
```

season	1	2	3	4	All
weather					
1	1759	1801	1930	1702	7192
2	715	708	604	807	2834
3	211	224	199	225	859
4	1	0	0	0	1
All	2686	2733	2733	2734	10886

```
from scipy.stats import chi2_contingency

# defining the table
data = [[1759, 715, 211, 1], [1801, 708, 224, 0], [1930, 604, 199, 0], [1702, 807, 225, 0]]
stat, p, dof, expected = chi2_contingency(data)
print(p)
print(expected)

1.549925073686492e-07
[[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]]
```

```
alpha = 0.05
p

if p < alpha:
    print("Reject Ho. Accept Ha")
else:
    print("Accept Ho, fail to reject the null hypothesis")

    Reject Ho. Accept Ha
```

**Observation** We have Rejected null hypothesis and accepted Alternate hypothesis

Variables weather and season are **dependent** and will affect the each other values resulting changes in count in rented bikes

```
=====
=
```

- Objective 3

1. ANNOVA to check if No. of cycles rented is similar or different in different weathers To check whether "Weather" has any effect on number of bikes rented

**Hypothesis Null Hypothesis** "Ho" :-Bikes rented in all weather are similar

**Alternate hypothesis** "Ha" :-Number of Bikes rented in all weather are different

```
## stats model library
from scipy.stats import f_oneway
```

Weather

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 Pellets + Thunderstorm + Mist, Snow + Fog

```
df.weather.value_counts()
```

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

```
cat_1 = df.loc[df['weather'] == 1]['count'].values
cat_2 = df.loc[df['weather'] == 2]['count'].values
cat_3 = df.loc[df['weather'] == 3]['count'].values
cat_4 = df.loc[df['weather'] == 4]['count'].values
```

```
# f_oneway(cat_1, cat_2, cat_3, cat_4)
```

```
statistic,p_value=f_oneway(cat_1, cat_2, cat_3, cat_4)
print(statistic)
print(p_value)
```

```
65.53024112793271
5.482069475935669e-42
```

```
alpha=0.05
if p_value < alpha:
    print("Reject Ho:- Number of Bikes rented in all weather are different")
else:
    print("Accept Ho:-Bikes rented in all weather are similar")

    Reject Ho:- Number of Bikes rented in all weather are different
```

**Observation**

As we **reject the NULL Hypothesis**: Means yulu need to have different policies for different weather conditions as these are not working. same policies for all weather won't work.

```
#####
```



## 2. ANNOVA to check if No. of cycles rented is similar or different in different seasons

To check whether "seasons" has any effect on number of bikes rented

**Hypothesis** Null Hypothesis "Ho" :-Bikes rented in all seasons are similar

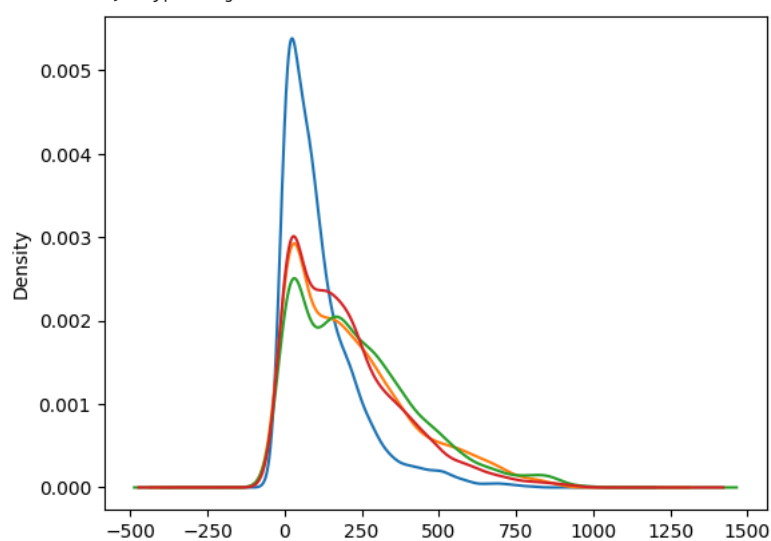
**Alternate hypothesis "Ha"**:-number of Bikes rented in all seasons are different

```
df["season"].value_counts()
```

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

```
df.groupby('season')['count'].plot(kind='kde')
```

```
season
1    Axes(0.125,0.11;0.775x0.77)
2    Axes(0.125,0.11;0.775x0.77)
3    Axes(0.125,0.11;0.775x0.77)
4    Axes(0.125,0.11;0.775x0.77)
Name: count, dtype: object
```



```
sea_cat_1=df.loc[df['season']==1]['count'].values
sea_cat_2=df.loc[df['season']==2]['count'].values
sea_cat_3=df.loc[df['season']==3]['count'].values
sea_cat_4=df.loc[df['season']==4]['count'].values
```

```
statistic,p_value=f_oneway(sea_cat_1, sea_cat_2, sea_cat_3, sea_cat_4)
print(statistic)
print(p_value)
```

```
236.94671081032106
6.164843386499654e-149
```

```
alpha=0.05
if p_value < alpha:
    print("Reject Ho:- Number of Bikes rented in all season are different")
else:
    print("Accept Ho:-Bikes rented in all season are similar")

    Reject Ho:- Number of Bikes rented in all season are different
```

## Observation

As we reject the NULL Hypothesis :This means we need to have different policies for different seasons. same policies for al seasons won't work

## ✓ Insights and Recommendations

Insights

- working day and holiday has no effect on number of bikes rented Note: There is a risk in considering the values of this test as very correct as we have not taken the normal sample distribution for 2 sample test and not cross checked with assumptions of the test (Normality, Equal Variance).

Variables like weather and seasons are dependent variables

- Variables like weather and seasons are **dependent** variables
- Anova test on weather has given us insight of weather has effect on number of bikes rented, number of Bikes rented in all seasons are different.