Yulu-Dataset@Dhanureddy

April 11, 2024

1 Yulu business case : Hypothesistesting

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.

Business problem:

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

So finding which variables majorily influence the demand for electric cycles is the task.

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

[ ]:
```
df = pd.read_csv("Yulu.csv")
```

[ ]:
```
df
```

[ ]:
```
               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]
```

Exploratory data analysis like checking for outliers and missing values if any

[ ]:
```
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
```

[ ]:
```
for column in df.columns:
  unique_values = df[column].nunique()
  print(column, ":", unique_values)
```

```
datetime : 10886
season : 4
holiday : 2
workingday : 2
weather : 4
temp : 49
atemp : 60
humidity : 89
windspeed : 28
casual : 309
registered : 731
count : 822
```

[ ]:
```
df.isna().isna().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
```

[ ]:
```
df.shape
```

[ ]:
```
(10886, 12)
```

[ ]:
```
summary = df.describe()
summary
```

[ ]:
```
             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
```

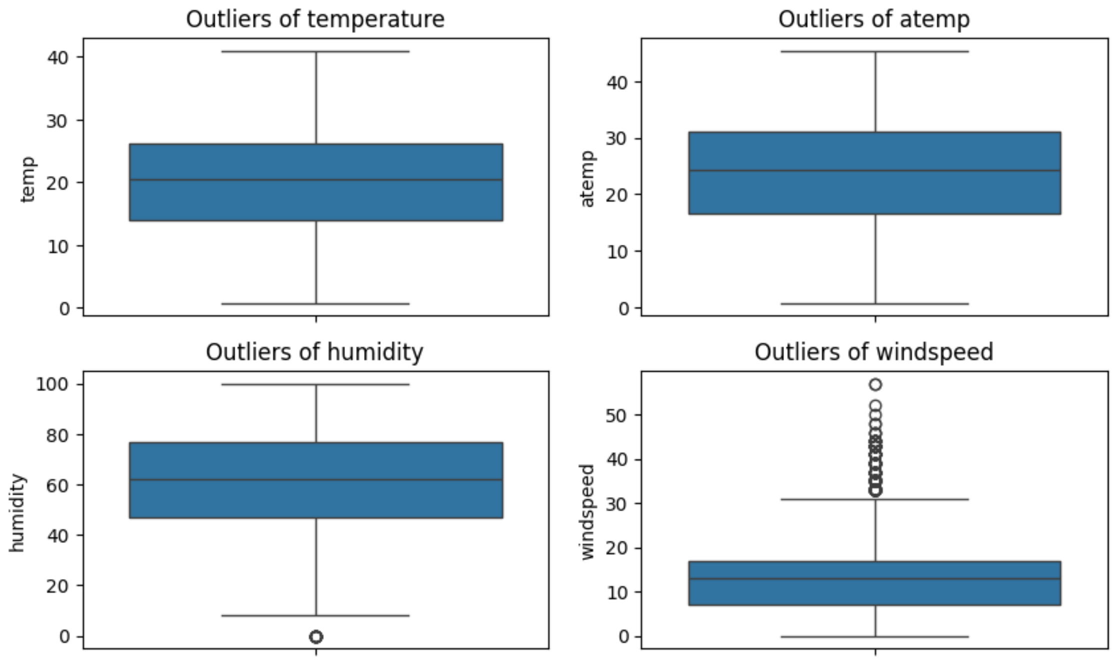
```
75%         4.000000      0.000000      1.000000      2.000000      26.24000
max         4.000000      1.000000      1.000000      4.000000      41.00000

                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
```

[ ]:

```python
plt.figure(figsize = (10, 6))
plt.subplot(2,2,1)
sns.boxplot(data = df.temp)
plt.title("Outliers of temperature")

plt.subplot(2,2,2)
sns.boxplot(data = df.atemp)
plt.title("Outliers of atemp")

plt.subplot(2,2,3)
sns.boxplot(data = df.humidity)
plt.title("Outliers of humidity")

plt.subplot(2,2,4)
sns.boxplot(data = df.windspeed)
plt.title("Outliers of windspeed")
```

[ ]:

```
Text(0.5, 1.0, 'Outliers of windspeed')
```



Setting boundaries to count for total outliers

[ ]:
```
Q1 = summary[["humidity", "windspeed"]].loc["25%"]
Q3 = summary[["humidity", "windspeed"]].loc["75%"]

IQR = Q3 - Q1
print(IQR)
```

```
humidity     30.0000
windspeed     9.9964
dtype: float64
```

[ ]:
```
lower_bound = Q1 - 1.5*IQR
upper_bound = Q3 + 1.5*IQR

bounds_df = pd.DataFrame({"LowerBound" : lower_bound, "UpperBound":␣
↪upper_bound})
print(bounds_df)
```

```
           LowerBound  UpperBound
humidity       2.0000    122.0000
windspeed     -7.9931     31.9925
```

[ ]:
```
humidity_outliers = df[(df["humidity"] < lower_bound["humidity"]) |␣
↪(df["humidity"] > upper_bound["humidity"])]
humidity_outliers
```

[ ]:

	datetime	season	holiday	workingday	weather	temp \
1091	2011-03-10 00:00:00	1	0	1	3	13.94
1092	2011-03-10 01:00:00	1	0	1	3	13.94
1093	2011-03-10 02:00:00	1	0	1	3	13.94
1094	2011-03-10 05:00:00	1	0	1	3	14.76
1095	2011-03-10 06:00:00	1	0	1	3	14.76
1096	2011-03-10 07:00:00	1	0	1	3	15.58
1097	2011-03-10 08:00:00	1	0	1	3	15.58
1098	2011-03-10 09:00:00	1	0	1	3	16.40
1099	2011-03-10 10:00:00	1	0	1	3	16.40
1100	2011-03-10 11:00:00	1	0	1	3	16.40
1101	2011-03-10 12:00:00	1	0	1	3	17.22
1102	2011-03-10 13:00:00	1	0	1	3	17.22
1103	2011-03-10 14:00:00	1	0	1	3	18.04
1104	2011-03-10 15:00:00	1	0	1	3	18.04
1105	2011-03-10 16:00:00	1	0	1	3	17.22
1106	2011-03-10 17:00:00	1	0	1	2	18.04
1107	2011-03-10 18:00:00	1	0	1	3	18.04
1108	2011-03-10 19:00:00	1	0	1	3	18.04
1109	2011-03-10 20:00:00	1	0	1	3	14.76
1110	2011-03-10 21:00:00	1	0	1	3	14.76
1111	2011-03-10 22:00:00	1	0	1	2	13.94
1112	2011-03-10 23:00:00	1	0	1	3	13.94

	atemp	humidity	windspeed	casual	registered	count
1091	15.910	0	16.9979	3	0	3
1092	15.910	0	16.9979	0	2	2
1093	15.910	0	16.9979	0	1	1
1094	17.425	0	12.9980	1	2	3
1095	16.665	0	22.0028	0	12	12
1096	19.695	0	15.0013	1	36	37
1097	19.695	0	19.0012	1	43	44
1098	20.455	0	15.0013	1	23	24
1099	20.455	0	11.0014	0	17	17
1100	20.455	0	16.9979	6	5	11
1101	21.210	0	15.0013	4	30	34
1102	21.210	0	15.0013	1	11	12
1103	21.970	0	19.9995	0	12	12
1104	21.970	0	15.0013	3	11	14
1105	21.210	0	16.9979	1	20	21
1106	21.970	0	26.0027	2	109	111
1107	21.970	0	23.9994	2	80	82
1108	21.970	0	39.0007	5	51	56
1109	16.665	0	22.0028	9	29	38
1110	17.425	0	15.0013	1	27	28
1111	16.665	0	8.9981	4	30	34
1112	17.425	0	6.0032	1	26	27

```
[ ]: windspeed_outliers = df[(df["windspeed"] < lower_bound["windspeed"]) |
     ↪(df["windspeed"] > upper_bound["windspeed"])]
     windspeed_outliers
```

```
[ ]:                   datetime  season  holiday  workingday  weather   temp  \
     175    2011-01-08 14:00:00       1        0           0        1   8.20
     178    2011-01-08 17:00:00       1        0           0        1   6.56
     194    2011-01-09 09:00:00       1        0           0        1   4.92
     196    2011-01-09 11:00:00       1        0           0        1   6.56
     265    2011-01-12 12:00:00       1        0           1        1   8.20
     …                      …     …       …           …        …     …
     10013  2012-11-02 14:00:00       4        0           1        2  16.40
     10154  2012-11-08 12:00:00       4        0           1        1  16.40
     10263  2012-11-13 01:00:00       4        0           1        3  18.04
     10540  2012-12-05 14:00:00       4        0           1        1  19.68
     10853  2012-12-18 15:00:00       4        0           1        1  18.86

             atemp  humidity  windspeed  casual  registered  count
     175     8.335        32    32.9975      12          83     95
     178     6.060        37    36.9974       5          64     69
     194     3.790        46    35.0008       0          19     19
     196     6.060        40    35.0008       2          47     49
     265     7.575        47    39.0007       3          52     55
     …         …       …         …     …          …     …
     10013  20.455        40    32.9975      63         199    262
     10154  20.455        24    32.9975      33         202    235
     10263  21.970        88    43.0006       0           5      5
     10540  23.485        33    32.9975      39         179    218
     10853  22.725        44    32.9975      28         218    246

     [227 rows x 12 columns]
```

Total_outliers count

```
[ ]: lower_outliers = (df[["humidity", "windspeed"]] < lower_bound).sum()
     upper_outliers = (df[["humidity", "windspeed"]] > upper_bound).sum()

     total_outliers = lower_outliers + upper_outliers

     outliers_count = pd.DataFrame({"LowerBoundary_Outliers": lower_outliers,
     ↪"UpperBoundary_Outliers": upper_outliers, "Total": total_outliers})
     print(outliers_count)
```

```
           LowerBoundary_Outliers  UpperBoundary_Outliers  Total
humidity                       22                       0     22
windspeed                       0                     227    227
```

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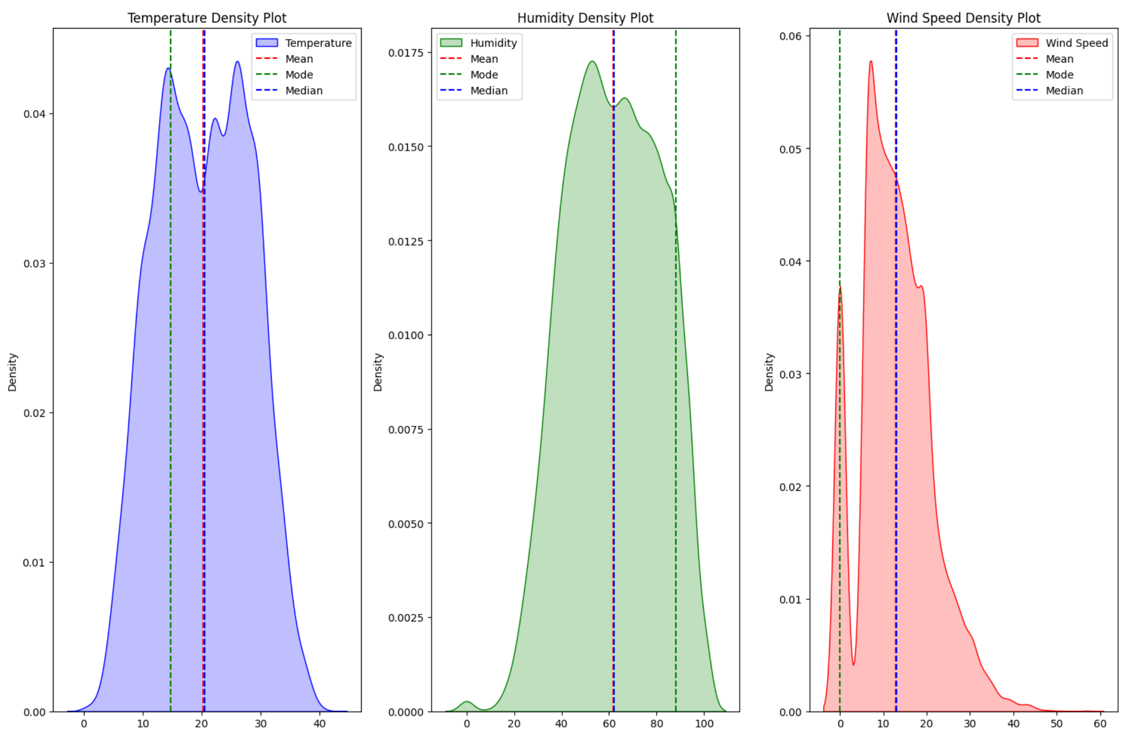
(Univariate Representation)

1. illustration of Density plots for three important continuous variables in the dataset

- The below plots define skewness of each variable

[ ]:
```
# Density plot for temp
plt.figure(figsize= (15,10))
plt.subplot(1, 3, 1)
sns.kdeplot(df['temp'], shade=True, color='blue', label='Temperature')
plt.axvline(df['temp'].mean(), color='r', linestyle='--', label='Mean')
plt.axvline(df['temp'].mode().values[0], color='g', linestyle='--',␣
↪label='Mode')
plt.axvline(df['temp'].median(), color='b', linestyle='--', label='Median')
plt.title('Temperature Density Plot')
plt.xlabel('Temperature')
plt.ylabel('Density')
plt.legend()


# Density plot for humidity
plt.subplot(1, 3, 2)
sns.kdeplot(df['humidity'], shade=True, color='green', label='Humidity')
plt.axvline(df['humidity'].mean(), color='r', linestyle='--', label='Mean')
plt.axvline(df['humidity'].mode().values[0], color='g', linestyle='--',␣
↪label='Mode')
plt.axvline(df['humidity'].median(), color='b', linestyle='--', label='Median')
plt.title('Humidity Density Plot')
plt.xlabel('Humidity')
plt.ylabel('Density')
plt.legend()

# Density plot for wind speed
plt.subplot(1, 3, 3)
sns.kdeplot(df['windspeed'], shade=True, color='red', label='Wind Speed')
plt.axvline(df['windspeed'].mean(), color='r', linestyle='--', label='Mean')
plt.axvline(df['windspeed'].mode().values[0], color='g', linestyle='--',␣
↪label='Mode')
plt.axvline(df['windspeed'].median(), color='b', linestyle='--', label='Median')
plt.title('Wind Speed Density Plot')
plt.xlabel('Wind Speed')
plt.ylabel('Density')
plt.legend()


plt.tight_layout()
```

```
<ipython-input-43-df5b22a3e34e>:4: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df['temp'], shade=True, color='blue', label='Temperature')
<ipython-input-43-df5b22a3e34e>:16: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df['humidity'], shade=True, color='green', label='Humidity')
<ipython-input-43-df5b22a3e34e>:27: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df['windspeed'], shade=True, color='red', label='Wind Speed')
```



Inference: In all the three distributions we have equal mean and median representing that the graphs might be pretty close to being symmetric around the central value.

However, mode was fluctuating denoting that continuous variables like "Temperature" and "Wind speed" are right skewed, meaning that the 'mode' was less than their 'mean'. Thus, its evident that data points from both variables (temperature and windspeed) have been majorily clusterd towards left side of the distribution and have some extreme values extending to the right side. But if we go deeper we can also observe that right skewness of Temperature variable was not that strong and pretty much resulting of being symmetric than rest of the other two.

Similarly, looking at the graph of "humidity", we can observe that 'mode' was much greater than 'mean' resulting into left skewness. Here, the data points have been majorily clustered towards right side of the dstribution and have some extreme values extending to the left side.

<——> <———————————————————————————————————>

2. Influence within each independent variables on total bike rentals

```
[ ]: total_rental_bikes_under_workingday = df.groupby("workingday")["count"].sum()
total_rental_bikes_under_workingday = total_rental_bikes_under_workingday.
 ↪reset_index(name = "sum_of_rental_bikes")
total_rental_bikes_under_workingday
```

[ ]:

	workingday	sum_of_rental_bikes
0	0	654872
1	1	1430604

```
[ ]: total_rental_bikes_under_weather = df.groupby("weather")["count"].sum()
total_rental_bikes_under_weather = total_rental_bikes_under_weather.
 ↪reset_index(name = "sum_of_rental_bikes")
total_rental_bikes_under_weather
```

[ ]:

	weather	sum_of_rental_bikes
0	1	1476063
1	2	507160
2	3	102089
3	4	164

```
[ ]: total_rental_bikes_under_season = df.groupby("season")["count"].sum()
total_rental_bikes_under_season = total_rental_bikes_under_season.
 ↪reset_index(name = "sum_of_rental_bikes")
total_rental_bikes_under_season
```

[ ]:

	season	sum_of_rental_bikes
0	1	312498
1	2	588282
2	3	640662
3	4	544034

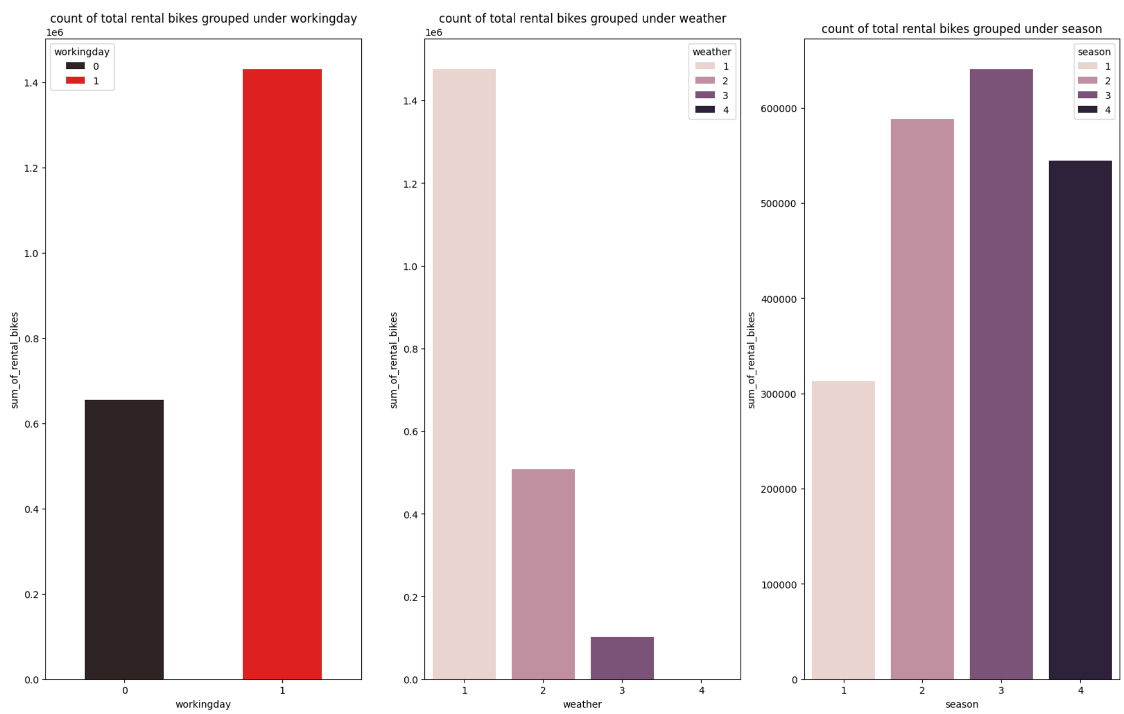
Bivariate realtionship of each independent variable

```
[ ]: plt.figure(figsize = (20, 12))
plt.subplot(1,3,1)
```

```
sns.barplot(data = total_rental_bikes_under_workingday, x = "workingday", y =␣
↪"sum_of_rental_bikes", hue = "workingday", color = "red", width = 0.5)
plt.title("count of total rental bikes grouped under workingday")

plt.subplot(1,3,2)
sns.barplot(data = total_rental_bikes_under_weather, x = "weather", y =␣
↪"sum_of_rental_bikes", hue = "weather")
plt.title("count of total rental bikes grouped under weather")

plt.subplot(1,3,3)
sns.barplot(data = total_rental_bikes_under_season, x = "season", y =␣
↪"sum_of_rental_bikes", hue = "season")
plt.title("count of total rental bikes grouped under season")
```

```
<ipython-input-47-89b9805fc4ed>:3: FutureWarning:

Setting a gradient palette using color= is deprecated and will be removed in
v0.14.0. Set `palette='dark:red'` for the same effect.

  sns.barplot(data = total_rental_bikes_under_workingday, x = "workingday", y =
"sum_of_rental_bikes", hue = "workingday", color = "red", width = 0.5)
```

[ ]: Text(0.5, 1.0, 'count of total rental bikes grouped under season')



Inference: From the above graphs we can conclude that, total count of bike rentals was pretty much higher in workingday than holiday; Total bike rentals count in weather category 1 is way higher than rest of other three weather patterns; And total bike rentals during season 3 is stood at top and then followed by season 2 and season 4.

<————————————————————————————————————> <———————————————————————————————————>

3. Tests conducted to esatblish relationship between means of rental bikes usage across three individual independent variables.

(i) Indpendent two sample T_test vs two sample Z_test results on determining "workingday vs holiday" affect on count variable.

```
[ ]: from statsmodels.stats import weightstats as stests
     from scipy.stats import ttest_ind

     working_day_count = df[df["workingday"] == 1]["count"]
     holiday_day_count = df[df["workingday"] == 0]["count"]
```

```
[ ]: # H0: The mean rental bikes usage difference between working-days and holidays␣
      ↪is equal
     # H1: The mean rental bikes usage difference between working-days and holidays␣
      ↪is not equal

     alpha = 0.05
     z_stat, p_value = stests.ztest(working_day_count, holiday_day_count, value = 0,␣
      ↪alternative = "two-sided")
     print("z_stat :", z_stat, ",", "p_value :", p_value)

     print("<------------------------------------------>")

     if p_value < alpha:
       print("reject the null hypothesis : There is significant mean difference of␣
      ↪rental bikes usage between working-days and holidays")
     else:
       print("unable to reject null hypothesis : This high difference might also␣
      ↪exist under the assumption of null hypothesis being true")
```

```
z_stat : 1.2096277376026694 , p_value : 0.22642176970306893
<------------------------------------------>
unable to reject null hypothesis : This high difference might also exist under
the assumption of null hypothesis being true
```

```
[ ]: # H0: The mean rental bikes usage difference between working-days and holidays␣
      ↪is equal
     # H1: The mean rental bikes usage difference between working-days and holidays␣
      ↪is not equal

     alpha = 0.05
```

```
t_stat, p_value = ttest_ind(working_day_count, holiday_day_count, alternative =␣
↪"two-sided")
print("t_stat :", t_stat, ",", "p_value :", p_value)

print("<---------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of␣
↪rental bikes usage between working-days and holidays")
else:
  print("unable to reject null hypothesis : This high difference might also␣
↪exist under the assumption of null hypothesis being true")
```

```
t_stat : 1.2096277376026694 , p_value : 0.22644804226361348
<---------------------------------------->
unable to reject null hypothesis : This high difference might also exist under
the assumption of null hypothesis being true
```

Inference: By using both t_test and z_test for evaluating the affect of workingday on total bike retals, we can conclude from both the tests that there was no influence or significant mean difference resulting within the groups because, p_value was much higher than alpha level; meaning we do not have sufficient evidence to claim that there was a difference beyond what could occur by random chance.

……………………………………………….

……………………………………………….

……………………………………………….

(ii) Determining whether means of bikes rentals usage around different seasons are equal or not.

(a) I am Using levene and shapiro to conduct tests of normality and equality of variance between different seasonal conditions in order to validate whether to conduct Anova or not.

[ ]:
```
spring = df[df["season"] == 1]["count"]
summer = df[df["season"] == 2]["count"]
fall = df[df["season"] == 3]["count"]
winter = df[df["season"] == 4]["count"]
```

[ ]:
```
from scipy.stats import shapiro
from scipy.stats import levene
alpha = 0.05

## under shapiro test,
# H0: The data is normally distributed
# H1: The data is not normally distributed

## under levene test,
# H0: The variances are equal across seasons
```

```
# H1: The variances are different acorss seasons


stat1, p_value1 = shapiro(spring)
stat2, p_value2 = shapiro(summer)
stat3, p_value3 = shapiro(fall)
stat4, p_value4 = shapiro(winter)

print("stat1 :", stat1, "p_value1 :", p_value1)
print("stat2 :", stat2, "p_value2 :", p_value2)
print("stat3 :", stat3, "p_value3 :", p_value3)
print("stat4 :", stat4, "p_value4 :", p_value4)

if p_value1 < alpha or p_value2 < alpha or p_value3 < alpha or p_value4 < alpha:
  print("reject the null hypothesis : There is no normality in the seasons␣
 ↪rental bike usage")
else:
  print("unable to reject null hypothesis : There is normality in the seasons␣
 ↪rental bike usage")

print("<---------------------->")
print("<---------------------->")

l_stat, p_value = levene(spring, summer, fall, winter)
print("l_stat :", l_stat, "p_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is no equality in variances between␣
 ↪seasons rental bike usage")
else:
  print("unable to reject null hypothesis : There is equality in variances␣
 ↪between seasons rental bike usage")
```

```
stat1 : 0.8087388873100281 p_value1 : 0.0
stat2 : 0.900481641292572 p_value2 : 6.039093315091269e-39
stat3 : 0.9148160815238953 p_value3 : 1.043458045587339e-36
stat4 : 0.8954644799232483 p_value4 : 1.1301682309549298e-39
reject the null hypothesis : There is no normality in the seasons rental bike
usage
<---------------------->
<---------------------->
l_stat : 187.7706624026276 p_value : 1.0147116860043298e-118
<----------------------------------------->
reject the null hypothesis : There is no equality in variances between seasons
rental bike usage
```

—-> As normality and equality of variance using shapiro & levene tests on season varible was not satisfied; we now use "kruskal", an alternative to Anova.

```
[ ]: from scipy.stats import kruskal
     alpha = 0.05

     # HO: The means of rental bikes usage of different seasons are equal
     # H1: The means of rental bikes usage of differnet seasons are not equal

     k_stat, p_value = kruskal(spring, summer, fall, winter)
     print("k_stat :", k_stat, ",", "p_value :", p_value)

     print("<----------------------------------------->")

     if p_value < alpha:
       print("reject the null hypothesis : There is significant mean difference of␣
      ↪rental bikes usage between different seasons")
     else:
       print("unable to reject null hypothesis : This high difference might also␣
      ↪exist under the assumption of null hypothesis being true")
```

```
k_stat : 699.6668548181988 , p_value : 2.479008372608633e-151
<----------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different seasons
```

Infernece: By using kruskal, we can come to a conclusion that bikes usage was fluctuating across all the four seasons. There was no equality between them. Does finding and focussing on particular top two seasons by conducting futher hypothesis testing and framing right strategies which caters to them should ultimately benefit the long term prosperity of business.

(b) Repeated the same above process by considering only registered users

```
[ ]: re_spring = df[df["season"] == 1]["registered"]
     re_summer = df[df["season"] == 2]["registered"]
     re_fall = df[df["season"] == 3]["registered"]
     re_winter = df[df["season"] == 4]["registered"]
```

```
[ ]: from scipy.stats import shapiro
     from scipy.stats import levene
     alpha = 0.05

     ## under shapiro test,
     # HO: The data is normally distributed
     # H1: The data is not normally distributed

     ## under levene test,
     # HO: The variances are equal across seasons
     # H1: The variances are different acorss seasons
```

```python
stat1, p_value1 = shapiro(re_spring)
stat2, p_value2 = shapiro(re_summer)
stat3, p_value3 = shapiro(re_fall)
stat4, p_value4 = shapiro(re_winter)

print("stat1 :", stat1, "p_value1 :", p_value1)
print("stat2 :", stat2, "p_value2 :", p_value2)
print("stat3 :", stat3, "p_value3 :", p_value3)
print("stat4 :", stat4, "p_value4 :", p_value4)

if p_value1 < alpha or p_value2 < alpha or p_value3 < alpha or p_value4 < alpha:
  print("reject the null hypothesis : There is no normality in the seasons␣
 ↪rental bike usage")
else:
  print("unable to reject null hypothesis : There is normality in the seasons␣
 ↪rental bike usage")

print("<---------------------->")
print("<---------------------->")

l_stat, p_value = levene(re_spring, re_summer, re_fall, re_winter)
print("l_stat :", l_stat, "p_value :", p_value)

print("<---------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is no equality in variances between␣
 ↪seasons rental bike usage")
else:
  print("unable to reject null hypothesis : There is equality in variances␣
 ↪between seasons rental bike usage")
```

```
stat1 : 0.8068912625312805 p_value1 : 0.0
stat2 : 0.875313401222229 p_value2 : 2.598007352858211e-42
stat3 : 0.8749604225158691 p_value3 : 2.352780121601368e-42
stat4 : 0.8786174654960632 p_value4 : 6.565083305361768e-42
reject the null hypothesis : There is no normality in the seasons rental bike
usage
<---------------------->
<---------------------->
l_stat : 116.3420701074739 p_value : 3.696231945833219e-74
<---------------------------------------->
reject the null hypothesis : There is no equality in variances between seasons
rental bike usage
```

[ ]:
```python
from scipy.stats import kruskal
alpha = 0.05

# HO: The means of rental bikes usage of different seasons are equal
# H1: The means of rental bikes usage of differnet seasons are not equal

k_stat, p_value = kruskal(re_spring, re_summer, re_fall, re_winter)
print("k_stat :", k_stat, ",", "p_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of␣
↪rental bikes usage between different seasons")
else:
  print("unable to reject null hypothesis : This high difference might also␣
↪exist under the assumption of null hypothesis being true")
```

```
k_stat : 542.9283509737561 , p_value : 2.3698212326776174e-117
<----------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different seasons
```

Inference: Similar results or patterns were observed in registered users when compared them to that of Total users.

……………………………………………….

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(iii) Determining whether means of different seasons bikes usage are equal or not.

(a) I am Using levene and shapiro to conduct tests of normality and equality of variance between different weather patterns in order to validate whether to conduct Anova or not.

[ ]:
```python
weather_category_1 = df[df["weather"] == 1]["count"]
weather_category_2  = df[df["weather"] == 2]["count"]
weather_category_3 = df[df["weather"] == 3]["count"]
weather_category_4  = df[df["weather"] == 4]["count"]
```

[ ]:
```python
#Assumption: Weather category 4 is not included beacause there is no bike usage␣
↪data related to it
## under shapiro test,
# HO: The data is normally distributed
# H1: The data is not normally distributed

## under levene test,
# HO: The variances are equal across seasons
```

```python
# H1: The variances are different acorss seasons


stat1, p_value1 = shapiro(weather_category_1)
stat2, p_value2 = shapiro(weather_category_2)
stat3, p_value3 = shapiro(weather_category_3)

print("stat1 :", stat1, "p_value1 :", p_value1)
print("stat2 :", stat2, "p_value2 :", p_value2)
print("stat3 :", stat3, "p_value3 :", p_value3)

if p_value1 < alpha or p_value2 < alpha or p_value3 < alpha:
  print("reject the null hypothesis : There is no normality in the rental bike usage of different weather conditions")
else:
  print("unable to reject null hypothesis : There is normality in the rental bike usage of different weather conditions")

print("<---------------------->")
print("<---------------------->")

l_stat, p_value = levene(weather_category_1, weather_category_2, weather_category_3)
print("l_stat :", l_stat, "p_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is no equality in variances between rental bike usage based on different weather conditions")
else:
  print("unable to reject null hypothesis : There is equality in variances between rental bike usage based on different weather conditions")
```

```
stat1 : 0.8909230828285217 p_value1 : 0.0
stat2 : 0.8767687082290649 p_value2 : 9.781063280987223e-43
stat3 : 0.7674332857131958 p_value3 : 3.876090133422781e-33
reject the null hypothesis : There is no normality in the rental bike usage of
different weather conditions
<---------------------->
<---------------------->
l_stat : 81.67574924435011 p_value : 6.198278710731511e-36
<----------------------------------------->
reject the null hypothesis : There is no equality in variances between rental
bike usage based on different weather conditions
```

```
/usr/local/lib/python3.10/dist-packages/scipy/stats/_morestats.py:1882:
UserWarning: p-value may not be accurate for N > 5000.
```

```
warnings.warn("p-value may not be accurate for N > 5000.")
```

—-> As normality and equality of variance using shapiro & levene tests on weather patterns variable was not satisfied; we now use "kruskal", an alternative to Anova.

```
[ ]: # H0: The means of rental bikes usage of different weathers patterns are equal
# H1: The means of rental bikes usage of differnet weathers patterns are not␣
↪equal

k_stat, p_value = kruskal(weather_category_1, weather_category_2,␣
↪weather_category_3, weather_category_4)
print("k_stat :", k_stat, ",", "p_value :", p_value)

print("<---------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of␣
↪rental bikes usage between different weather patterns")
else:
  print("unable to reject null hypothesis : This high difference might also␣
↪exist under the assumption of null hypothesis being true")
```

```
k_stat : 205.00216514479087 , p_value : 3.501611300708679e-44
<---------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different weather patterns
```

Infernece: By using kruskal, we can come to a conclusion that bikes usage was fluctuating across all the four weather patterns. There was no equality between them. Does finding and focussing on particular top two weather conditions by conducting futher hypothesis testing and framing right strategies which caters to them should ultimately benefit the long term prosperity of business.

(b) Repeated the same above process by considering only registered users

```
[ ]: re_weather_category_1 = df[df["weather"] == 1]["registered"]
re_weather_category_2  = df[df["weather"] == 2]["registered"]
re_weather_category_3 = df[df["weather"] == 3]["registered"]
re_weather_category_4  = df[df["weather"] == 4]["registered"]
```

```
[ ]: #Assumption: Weather category 4 is not included beacause there is no bike usage␣
↪data related to it
## under shapiro test,
# H0: The data is normally distributed
# H1: The data is not normally distributed

## under levene test,
# H0: The variances are equal across seasons
# H1: The variances are different acorss seasons
```

```python
stat1, p_value1 = shapiro(re_weather_category_1)
stat2, p_value2 = shapiro(re_weather_category_2)
stat3, p_value3 = shapiro(re_weather_category_3)

print("stat1 :", stat1, "p_value1 :", p_value1)
print("stat2 :", stat2, "p_value2 :", p_value2)
print("stat3 :", stat3, "p_value3 :", p_value3)

if p_value1 < alpha or p_value2 < alpha or p_value3 < alpha:
  print("reject the null hypothesis : There is no normality in the rental bike␣
↪usage of different weather conditions")
else:
  print("unable to reject null hypothesis : There is normality in the rental␣
↪bike usage of different weather conditions")

print("<---------------------->")
print("<---------------------->")

l_stat, p_value = levene(re_weather_category_1, re_weather_category_2,␣
↪re_weather_category_3)
print("l_stat :", l_stat, "p_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is no equality in variances between␣
↪rental bike usage based on different weather conditions")
else:
  print("unable to reject null hypothesis : There is equality in variances␣
↪between rental bike usage based on different weather conditions")
```

```
stat1 : 0.8689420223236084 p_value1 : 0.0
stat2 : 0.8497174382209778 p_value2 : 1.401298464324817e-45
stat3 : 0.7499492168426514 p_value3 : 4.471773824247394e-34
reject the null hypothesis : There is no normality in the rental bike usage of
different weather conditions
<---------------------->
<---------------------->
l_stat : 51.13604558028773 p_value : 7.86334408573682e-23
<----------------------------------------->
reject the null hypothesis : There is no equality in variances between rental
bike usage based on different weather conditions
```

[ ]:
```python
# HO: The means of rental bikes usage of different weathers patterns are equal
# H1: The means of rental bikes usage of differnet weathers patterns are not␣
↪equal
```

```
k_stat, p_value = kruskal(re_weather_category_1, re_weather_category_2,␣
 ↪re_weather_category_3, re_weather_category_4)
print("k_stat :", k_stat, ",", "p_value :", p_value)

print("<---------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of␣
 ↪rental bikes usage between different weather patterns")
else:
  print("unable to reject null hypothesis : This high difference might also␣
 ↪exist under the assumption of null hypothesis being true")
```

```
k_stat : 173.90759520169638 , p_value : 1.8239836388365876e-37
<---------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different weather patterns
```

Inference: Similar results or patterns were observed in registered users when compared them to that of Total users.

<———————————————————————————> <——————————————————————————>

4. Even though assumptiosns like normality and equality of variance do not satisfy for variables like "season" and "weather" to conduct Anova; But still let us consider conducting it for identifying the changes that we could observe in p_values.

(i) (a)Conducting Anova for seasons to check the difference between the groups

```
[ ]: from scipy.stats import f_oneway

alpha = 0.05

# H0: The means of bikes usage between different seasons would be equal
# H1: The means of bikes usage between different seasons would be not equal

spring = df[df["season"] == 1]["count"]
summer = df[df["season"] == 2]["count"]
fall = df[df["season"] == 3]["count"]
winter = df[df["season"] == 4]["count"]

f_stat, p_value = f_oneway(spring, summer, fall, winter)
print("f_stat :", f_stat, ",", "P_value :", p_value)

print("<---------------------------------------->")

if p_value < alpha:
```

```
  print("reject the null hypothesis : There is significant mean difference of␣
↪rental bikes usage between different seasons")
else:
  print("unable to reject null hypothesis : This high difference might also␣
↪exist under the assumption of null hypothesis being true")
```

```
f_stat : 236.94671081032106 , P_value : 6.164843386499654e-149
<---------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different seasons
```

(b) Repeating the same test for only registered users

[ ]:
```
re_spring = df[df["season"] == 1]["registered"]
re_summer = df[df["season"] == 2]["registered"]
re_fall = df[df["season"] == 3]["registered"]
re_winter = df[df["season"] == 4]["registered"]

f_stat, p_value = f_oneway(re_spring, re_summer, re_fall, re_winter)
print("f_stat :", f_stat, ",", "P_value :", p_value)

print("<---------------------------------------->")
if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of␣
↪rental bikes usage between different seasons")
else:
  print("unable to reject null hypothesis : This high difference might also␣
↪exist under the assumption of null hypothesis being true")
```

```
f_stat : 167.97539126005708 , P_value : 1.8882994650328087e-106
<---------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different seasons
```

Infernece: Though the P-values are more significant and lower; ultimately contributing to reject the null hypothesis, but still they cannot be categorized as right numbers becasue the assumptions like normality and equality of variance between groups was not observed.

……………………………………………………..

……………………………………………………..

……………………………………………………..

(ii) (a) Conducting Anova for weather patterns to check the difference between the groups

[ ]:
```
# H0: The means of bikes usage between different weather patterns would be equal
# H1: The means of bikes usage between different weather patterns would be not␣
↪equal
```

```python
alpha = 0.05

weather_category_1 = df[df["weather"] == 1]["count"]
weather_category_2  = df[df["weather"] == 2]["count"]
weather_category_3 = df[df["weather"] == 3]["count"]
weather_category_4  = df[df["weather"] == 4]["count"]

f_stat, p_value = f_oneway(weather_category_1,  weather_category_2 , weather_category_3, weather_category_4)
print("f_stat :", f_stat, ",", "P_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of rental bikes usage between different weather patterns")
else:
  print("unable to reject null hypothesis : This high difference might also exist under the assumption of null hypothesis being true")
```

```
f_stat : 65.53024112793271 , P_value : 5.482069475935669e-42
<----------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
bikes usage between different weather patterns
```

(b) Repeating the same test for only registered *users*

[ ]:
```python
re_weather_category_1 = df[df["weather"] == 1]["registered"]
re_weather_category_2  = df[df["weather"] == 2]["registered"]
re_weather_category_3 = df[df["weather"] == 3]["registered"]
re_weather_category_4  = df[df["weather"] == 4]["registered"]

f_stat, p_value = f_oneway(re_weather_category_1,  re_weather_category_2 , re_weather_category_3, re_weather_category_4)
print("f_stat :", f_stat, ",", "P_value :", p_value)

print("<----------------------------------------->")

if p_value < alpha:
  print("reject the null hypothesis : There is significant mean difference of rental bikes usage between different weather patterns")
else:
  print("unable to reject null hypothesis : This high difference might also exist under the assumption of null hypothesis being true")
```

```
f_stat : 48.93397612585586 , P_value : 2.0932747272621856e-31
<----------------------------------------->
reject the null hypothesis : There is significant mean difference of rental
```

```
bikes usage between different weather patterns
```

Infernece: Though the P-values were more significant and lower; ultimately contributing to reject the null hypothesis, but still they cannot be categorized as right numbers becasue the assumptions like normality and equality of variance between groups was not observed.

<————————————————————————————————————> <———————————————————————————————————————>

5. Conducting chisquare test of independence to check whether there is any dependency between season and weather patterns

```
[ ]: from scipy.stats import chi2_contingency

# H0: There is independency between season and weather
# H1: There is dependency between season and weather

# Construct a contingency table
contingency_table = pd.crosstab(df.season, df.weather)
print(contingency_table)

print("<--------------------------------->")
print("<--------------------------------->")

# Perform chi-square test of independence
chi2, p_value, dof, expected_values = chi2_contingency(contingency_table)

# Print results
print("Chi-square statistic:", chi2)
print("p-value:", p_value)
print("Degrees of freedom:", dof)
print("Expected frequencies table:")
print(expected_values)

print("<--------------------------------->")

# Interpret the results
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant association␣
 ↪between weather and season (dependency exists).")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪association between weather and season (independency exists).")
```

```
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
<---------------------------------->
<---------------------------------->
Chi-square statistic: 49.158655596893624
p-value: 1.549925073686492e-07
Degrees of freedom: 9
Expected frequencies table:
[[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]]
<---------------------------------->
Reject the null hypothesis: There is a significant association between weather
and season (dependency exists).
```

Infernece: We all know that weather depends upon season. It's only based on season, weather conditions alter and change. Yet, In very rare instances we tend to observe certain deviations in weather patterns not corroborating with the season, however still majority of weather conditions are fluctuating beacause of changes in seasons.

And now, the same kind of dependency relationship was also observed in this dataset between season and weather categories.

<————————————————————————————> <————————————————————————————————>

6. Conducting advance Hypothesis (ols) and spearmen rank corr for continuous and independent variables vs one dependent variable "count"

—> Asumptiosn of normality and equality of variance do not satisfy, but still conducting ols test.

Continuous variables

```
[ ]: import statsmodels.api as sm
     from statsmodels.formula.api import ols
```

(i) count vs humidity

```
[ ]: test = ols('count ~ C(humidity)', data = df).fit()

     anova_table = sm.stats.anova_lm(test, typ = 1)

     print(anova_table)
```

```
                  df        sum_sq        mean_sq         F          PR(>F)
C(humidity)     88.0  4.651380e+07  528565.886167  18.37038  4.163831e-258
Residual     10797.0  3.106591e+08   28772.725358       NaN            NaN
```

```
[ ]: from scipy.stats import spearmanr
```

```
# H0: There is no correlation between count and humidity
# H1: There is correlation between count and humidity

# Calculating Spearman's rank correlation coefficient
spearman_corr, p_value = spearmanr(df['count'], df['humidity'])

print("Spearman's rank correlation coefficient:", spearman_corr)
print("P-value:", p_value)

print("<--------------------------------->")

if p_value < alpha:
    print("Reject the null hypothesis: There is a significant correlation␣
↪between count and humidity.")
else:
    print("Fail to reject the null hypothesis: There is is no correlation␣
↪between count and humidity")
```

```
Spearman's rank correlation coefficient: -0.3540491220175611
P-value: 0.0
<--------------------------------->
Reject the null hypothesis: There is a significant correlation between count and
humidity.
```

Inference: If we observe the negative corr betweeen humidity and count variable, it was more or less evident that less humid conditions will be favourable to increase the demand for our shared rental cycles

But still the negative corr, was not that strong; meaning that there are other important variables which could be also affecting the count varible.

(ii) count vs atemp

[ ]:
```
test = ols('count ~ C(atemp)', data = df).fit()

anova_table = sm.stats.anova_lm(test, typ = 1)

print(anova_table)
```

```
                df         sum_sq       mean_sq          F  PR(>F)
C(atemp)      59.0   6.479027e+07  1.098140e+06   40.66064     0.0
Residual   10826.0   2.923826e+08  2.700745e+04        NaN     NaN
```

[ ]:
```
# H0: There is no correlation between count and atemp
# H1: There is correlation between count and atemp

# Calculating Spearman's rank correlation coefficient
spearman_corr, p_value = spearmanr(df['count'], df['atemp'])
```

```
print("Spearman's rank correlation coefficient:", spearman_corr)
print("P-value:", p_value)

print("<---------------------------------->")

if p_value < alpha:
    print("Reject the null hypothesis: There is a significant correlation␣
 ↪between count and atemp.")
else:
    print("Fail to reject the null hypothesis: There is is no correlation␣
 ↪between count and atemp")
```

```
Spearman's rank correlation coefficient: 0.40656175392045846
P-value: 0.0
<---------------------------------->
Reject the null hypothesis: There is a significant correlation between count and
atemp.
```

Inference: Observing the spermen rank corr between count and atemp variables, it was more or less evident that there was a positive relationship between the variables; meaning if atemp was increasing, then there was also a slight increase in cycles demand, but for real assessment we have to consider even some other variables for making a reliable conclusion.

(iii) count vs windspeed

[ ]:
```
test = ols('count ~ C(windspeed)', data = df).fit()

anova_table = sm.stats.anova_lm(test, typ = 1)

print(anova_table)
```

```
                   df        sum_sq        mean_sq         F        PR(>F)
C(windspeed)     27.0  6.767861e+06  250661.511834  7.767247  7.529783e-30
Residual      10858.0  3.504051e+08   32271.601847       NaN           NaN
```

[ ]:
```
# H0: There is no correlation between count and windspeed
# H1: There is correlation between count and windspeed

# Calculating Spearman's rank correlation coefficient
spearman_corr, p_value = spearmanr(df['count'], df['windspeed'])

print("Spearman's rank correlation coefficient:", spearman_corr)
print("P-value:", p_value)

print("<---------------------------------->")

if p_value < alpha:
```

```
    print("Reject the null hypothesis: There is a significant correlation␣
↪between count and windspeed.")
else:
    print("Fail to reject the null hypothesis: There is is no correlation␣
↪between count and windspeed")
```

```
Spearman's rank correlation coefficient: 0.1357773747113304
P-value: 5.9015220272171205e-46
<-------------------------------->
Reject the null hypothesis: There is a significant correlation between count and
windspeed.
```

Inference: Observing the relationship between windspeed and count variables, we can comment that there was a negligible positive relationship; However the effect of this result was not relaible and impactful. Thus, we can conclude that the wind speed has less impact on cycles demand than other continuous variables.

Overall Inference: Here, we could observe that p_value in every continuous variable was less than alpha level, thus this signifies that they do have an influence on rental bike usage. Though these stats will not give us the full picture of how much actual influence they have, but still combinely they might stand a great number vice versa to independent variables like season, weather and workingday.

To get a full picture, looking at f-stat, and overall p_value statistic by combining all three variables gives us the true picture.

……………………………………………….. ……………………………………………….. ………………………………………………..

Independent variables

[ ]:
```
alpha = 0.05

# H0: There is no relationship betweeen dependent and independent variables
# H1: There is a signifiant relationship between dependent and independent␣
↪varibales

test = ols('count ~ C(workingday) * C(weather) * C(season)', data = df).fit()

print(test.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  count   R-squared:                       0.082
Model:                            OLS   Adj. R-squared:                  0.080
Method:                 Least Squares   F-statistic:                     40.20
Date:                Wed, 20 Mar 2024   Prob (F-statistic):          6.26e-180
Time:                        07:13:15   Log-Likelihood:                -71582.
No. Observations:               10886   AIC:                         1.432e+05
Df Residuals:                   10861   BIC:                         1.434e+05
Df Model:                          24
```

```
Covariance Type:            nonrobust
================================================================================
=====================================
                                                         coef    std err
t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-------------------------------------
Intercept                                            122.1722      7.437
16.427      0.000     107.593     136.751
C(workingday)[T.1]                                     6.6844      8.956
0.746      0.455     -10.872      24.240
C(weather)[T.2]                                      -34.4377     13.440
-2.562      0.010     -60.783      -8.093
C(weather)[T.3]                                      -81.8341     21.925
-3.732      0.000    -124.811     -38.857
C(weather)[T.4]                                       17.5717     86.930
0.202      0.840    -152.828     187.971
C(season)[T.2]                                       120.2102     10.466
11.486      0.000      99.695     140.726
C(season)[T.3]                                       123.0778     10.184
12.085      0.000     103.115     143.041
C(season)[T.4]                                        75.4700     10.177
7.416      0.000      55.522      95.418
C(workingday)[T.1]:C(weather)[T.2]                    22.1677     16.409
1.351      0.177      -9.997      54.332
C(workingday)[T.1]:C(weather)[T.3]                    24.7990     26.858
0.923      0.356     -27.847      77.445
C(workingday)[T.1]:C(weather)[T.4]                    17.5717     86.930
0.202      0.840    -152.828     187.971
C(workingday)[T.1]:C(season)[T.2]                    -14.8682     12.598
-1.180      0.238     -39.563       9.827
C(workingday)[T.1]:C(season)[T.3]                     -9.1473     12.318
-0.743      0.458     -33.294      14.999
C(workingday)[T.1]:C(season)[T.4]                     12.0898     12.511
0.966      0.334     -12.435      36.614
C(weather)[T.2]:C(season)[T.2]                       -14.2405     18.992
-0.750      0.453     -51.469      22.988
C(weather)[T.3]:C(season)[T.2]                       -31.1064     35.176
-0.884      0.377    -100.057      37.844
C(weather)[T.4]:C(season)[T.2]                     -5.957e-14   6.24e-14
-0.954      0.340   -1.82e-13    6.28e-14
C(weather)[T.2]:C(season)[T.3]                        -3.8023     19.495
-0.195      0.845     -42.016      34.411
C(weather)[T.3]:C(season)[T.3]                        24.7091     31.639
0.781      0.435     -37.309      86.727
C(weather)[T.4]:C(season)[T.3]                      1.342e-16   1.28e-14
0.010      0.992    -2.5e-14    2.53e-14
C(weather)[T.2]:C(season)[T.4]                        23.5641     19.202
```

```
1.227      0.220     -14.075      61.203
C(weather)[T.3]:C(season)[T.4]                            26.6267     34.432
0.773      0.439     -40.865      94.119
C(weather)[T.4]:C(season)[T.4]                           3.29e-15    1.4e-14
0.236      0.814   -2.41e-14    3.06e-14
C(workingday)[T.1]:C(weather)[T.2]:C(season)[T.2]   -20.3205     23.198
-0.876      0.381     -65.792      25.152
C(workingday)[T.1]:C(weather)[T.3]:C(season)[T.2]   -23.4659     40.855
-0.574      0.566    -103.548      56.617
C(workingday)[T.1]:C(weather)[T.4]:C(season)[T.2]          0          0
nan        nan            0            0
C(workingday)[T.1]:C(weather)[T.2]:C(season)[T.3]    15.8199     23.802
0.665      0.506     -30.837      62.477
C(workingday)[T.1]:C(weather)[T.3]:C(season)[T.3]   -68.8315     38.581
-1.784      0.074    -144.458       6.795
C(workingday)[T.1]:C(weather)[T.4]:C(season)[T.3]          0          0
nan        nan            0            0
C(workingday)[T.1]:C(weather)[T.2]:C(season)[T.4]   -29.9963     23.163
-1.295      0.195     -75.399      15.407
C(workingday)[T.1]:C(weather)[T.3]:C(season)[T.4]   -53.5890     40.286
-1.330      0.183    -132.557      25.379
C(workingday)[T.1]:C(weather)[T.4]:C(season)[T.4]          0          0
nan        nan            0            0
==============================================================================
Omnibus:                     1856.007   Durbin-Watson:                   0.354
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3125.932
Skew:                           1.130   Prob(JB):                         0.00
Kurtosis:                       4.334   Cond. No.                     1.42e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.09e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Inference: The combined summary table of independent variables denotes that there was significant difference between seasons, weather patterns, workingday and 'Count' variable.

We have very low 'p_value' than alpha and high 'f_stat' contributing to difference of means within each indepdent variable.

[ ]:
```
# H0: There is no relationship betweeen dependent and independent variables
# H1: There is a signifiant relationship between dependent and independent
  ↪varibales

test = ols('count ~ C(workingday) * C(weather) * C(season)', data = df).fit()
```

```python
anova_table = sm.stats.anova_lm(test, typ = 3)

print(anova_table)

print("<---------------------------------------->")

alpha = 0.05

if p_value < alpha:
    print("Reject the null hypothesis: There is a significant association␣
 ↪between independent and dependent variables (dependency exists).")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪association between the independent and dependent variables (independency␣
 ↪exists).")

print("<---------------------------------------->")
print("<---------------------------------------->")
```

```
                                          sum_sq       df           F  \
Intercept                           8.149616e+06      1.0  269.830911
C(workingday)                       1.682331e+04      1.0    0.557014
C(weather)                          5.304915e+05      3.0    5.854796
C(season)                           5.562554e+06      3.0   61.391401
C(workingday):C(weather)            7.052205e+04      3.0    0.778320
C(workingday):C(season)             1.636489e+05      3.0    1.806119
C(weather):C(season)                3.037499e+05      9.0    1.117450
C(workingday):C(weather):C(season)  3.859605e+05      9.0    1.419891
Residual                            3.280313e+08  10861.0         NaN

                                          PR(>F)
Intercept                           6.502632e-60
C(workingday)                       4.554820e-01
C(weather)                          5.443133e-04
C(season)                           2.374949e-39
C(workingday):C(weather)            5.058838e-01
C(workingday):C(season)             1.436722e-01
C(weather):C(season)                3.491036e-01
C(workingday):C(weather):C(season)  2.025818e-01
Residual                                     NaN
<---------------------------------------->
Reject the null hypothesis: There is a significant association between
independent and dependent variables (dependency exists).
<---------------------------------------->
<---------------------------------------->
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:1896:
ValueWarning: covariance of constraints does not have full rank. The number of
```

```
constraints is 9, but rank is 6
  warnings.warn('covariance of constraints does not have full '
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:1896:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 9, but rank is 6
  warnings.warn('covariance of constraints does not have full '
```

[1]:
```
!pip install nbconvert
```

```
Requirement already satisfied: nbconvert in /usr/local/lib/python3.10/dist-
packages (6.5.4)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (4.9.4)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (4.12.3)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (6.1.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (0.7.1)
Requirement already satisfied: entrypoints>=0.2.2 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.4)
Requirement already satisfied: jinja2>=3.0 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (3.1.3)
Requirement already satisfied: jupyter-core>=4.7 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (5.7.2)
Requirement already satisfied: jupyterlab-pygments in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (2.1.5)
Requirement already satisfied: mistune<2,>=0.8.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.8.4)
Requirement already satisfied: nbclient>=0.5.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.10.0)
Requirement already satisfied: nbformat>=5.1 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (5.10.3)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (24.0)
Requirement already satisfied: pandocfilters>=1.4.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (1.5.1)
Requirement already satisfied: pygments>=2.4.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (2.16.1)
Requirement already satisfied: tinycss2 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (1.2.1)
Requirement already satisfied: traitlets>=5.0 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (5.7.1)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core>=4.7->nbconvert)
(4.2.0)
```