Yulu

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!

Problem Statement

Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

Yulu 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

---

1 ▶ Import the required Libraries

```
# Importing required libraries -
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
from scipy.stats import ttest_ind # T-test for independent samples
from scipy.stats import shapiro # Shapiro-Wilk's test for Normality
from scipy.stats import levene # Levene's test for Equality of Variance
from scipy.stats import f_oneway # One-way ANOVA
from scipy.stats import chi2_contingency # Chi-square test of independence
```

```
import warnings
warnings.simplefilter('ignore')
```

```
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

link = 'https://drive.google.com/file/d/1o94fXnmvrx6jRgI6S-SeZ3tfnKjCDY0i/view?usp=sharing'

id = link.split("/")[-2]

downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('bike_sharing.csv')
```

```
df = pd.read_csv('bike_sharing.csv')
df.head()
```

	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
	2011-01-								

Exploratory Data Analysis

a. Examine dataset structure, characteristics, and statistical summary.

```
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
```

```
# Shape of the dataset -
print("No. of rows : ", df.shape[0])
print("No. of columns : ", df.shape[1])
```

```
No. of rows :  10886
No. of columns :  12
```

```
df.describe()
```

	season	holiday	workingday	weather	temp	atem
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.00000
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

```
# checking data types
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
```

Insights 🐾 the datatypes of all columns expect Datetime is integer or float. The Datatime column is a object.

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

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

b. Identify missing values and perform Imputation using an appropriate method.

```
#checking null values
df.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
```

After looking at the dataset provided, we can say that there are no null values in the sample provided. So, there is no need of missing value treatment.

c. Identify and remove duplicate records.

```
df.duplicated().sum()
```

```
0
```

```
def dist_check(df, col_name):
  print("Unique values : ", df[col_name].unique())
  print("Value counts : ")
  print(df[col_name].value_counts())
```

```
col_list = ['workingday',   'holiday',  'weather', 'season']
for col in col_list:
  print(col, " -")
  dist_check(df, col)
  print("\n")
```

```
workingday  -
Unique values :  [0 1]
Value counts :
workingday
1    7412
0    3474
Name: count, dtype: int64


holiday  -
Unique values :  [0 1]
Value counts :
holiday
0    10575
1      311
Name: count, dtype: int64


weather  -
Unique values :  [1 2 3 4]
Value counts :
weather
1    7192
2    2834
3     859
4       1
Name: count, dtype: int64


season  -
Unique values :  [1 2 3 4]
Value counts :
season
4    2734
2    2733
3    2733
1    2686
Name: count, dtype: int64
```

After looking at the dataset provided, we can say that there are duplicate values in the sample provided. So, there is no need of drop duplicate treatment.

Column Profiling:

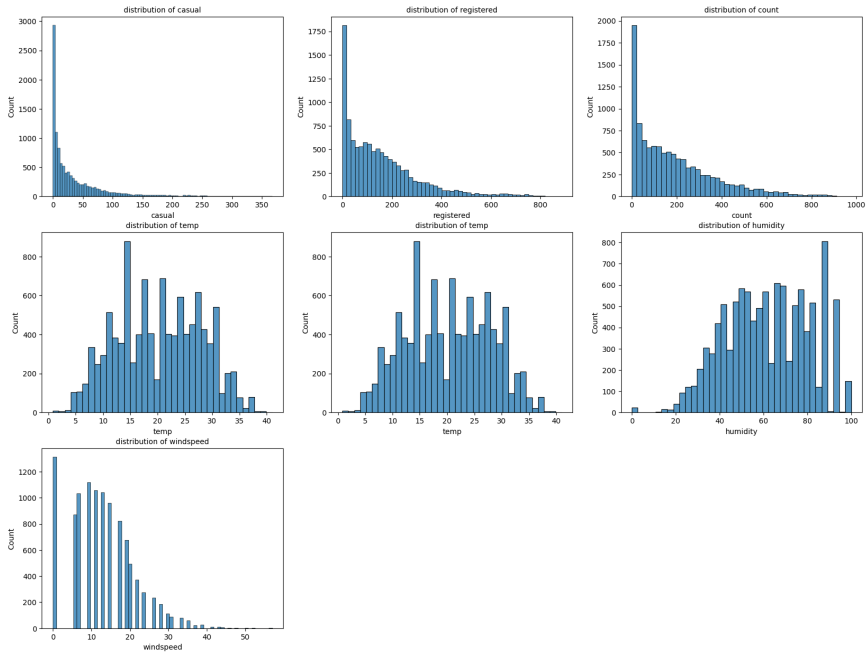
- datetime: datetime
- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- holiday : whether day is a holiday or not
- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.
- weather:
- 1: Clear, Few clouds, partly cloudy
- 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
- 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
- 4: Heavy Rain + Ice Pellets + Thunderstorm + Mist, Snow + Fog
- temp: temperature in Celsius
- atemp: feeling temperature in Celsius
- humidity: humidity
- windspeed: wind speed
- casual: count of casual users
- registered: count of registered users
- count: count of total rental bikes including both casual and registered

Univariate Analysis

d. Analyze the distribution of Numerical & Categorical variables, separately

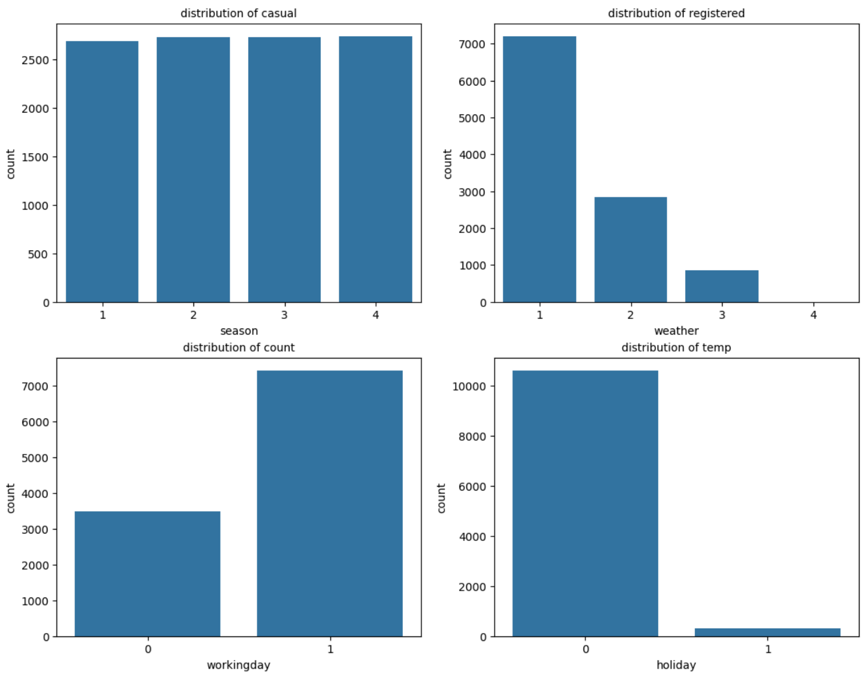
```
# Checking the distribution of the continous variables
plt.figure(figsize=(20,15))
plt.suptitle("Checking the distribution of the continous variables",fontsize=20)
plt.subplot(3,3,1)
sns.histplot(df, x = "casual")
plt.title("distribution of casual",fontsize=10)

plt.subplot(3,3,2)
sns.histplot(df, x = "registered")
plt.title("distribution of registered",fontsize=10)

plt.subplot(3,3,3)
sns.histplot(df, x = "count")
plt.title("distribution of count",fontsize=10)

plt.subplot(3,3,4)
sns.histplot(df, x = "temp")
plt.title("distribution of temp",fontsize=10)

plt.subplot(3,3,5)
sns.histplot(df, x = "temp")
plt.title("distribution of temp",fontsize=10)

plt.subplot(3,3,6)
sns.histplot(df, x = "humidity")
plt.title("distribution of humidity",fontsize=10)

plt.subplot(3,3,7)
sns.histplot(df, x = "windspeed")
plt.title("distribution of windspeed",fontsize=10)

plt.show()
```

Checking the distribution of the continous variables



- registered and total rides looks RIGHT SKEWED. This data needs to be treated. We can try taking log of the same and check if it forms log normal distribution or not.
- temp, atemp and humidity looks normally distributed but we need to apply proper checks to it before reaching the conclusion.
- Windspeed looks right skewed, if there is less windspeed then more rides are happening. This data also needs to be checked for normality by taking log.

```
plt.figure(figsize=(13,10))
plt.subplot(2,2,1)
sns.countplot(data = df, x = "season")
plt.title("distribution of casual",fontsize=10)

plt.subplot(2,2,2)
sns.countplot(data = df, x = "weather")
plt.title("distribution of registered",fontsize=10)

plt.subplot(2,2,3)
sns.countplot(data = df, x = "workingday")
plt.title("distribution of count",fontsize=10)

plt.subplot(2,2,4)
sns.countplot(data = df, x = "holiday")
plt.title("distribution of temp",fontsize=10)

plt.show()
```

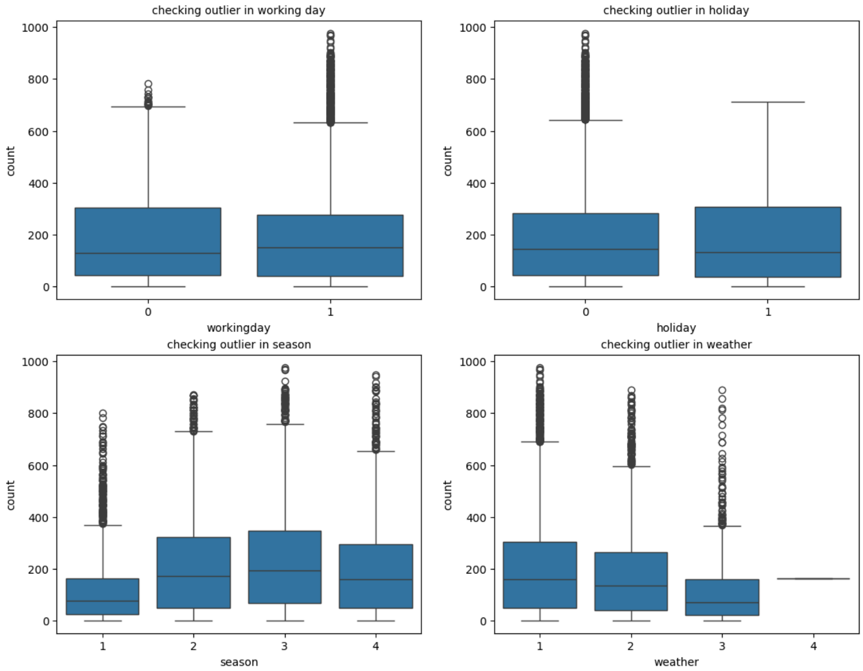


- A count plot for season shows that alll seasons have same distribution of bike rides. There is no prefered season as such.
- We can say that weather is considerably one of the factors affecting bike rides. When the weather is Clear, Few clouds, partly cloudy, partly cloudy there are more rides while when the weather is Heavy Rain, Ice Pallets, Thunderstorm, Mist, Snow or Fog then hardly any rides are booked.
- On working day, people prefer taking rides more than non working days .
- On holidays, people don't seem to use the services much .

e. Check for Outliers and deal with them accordingly.

Bivariate Analysis

```
plt.figure(figsize=(13,10))
plt.subplot(2,2,1)
sns.boxplot(data = df, x = "workingday", y ="count")
plt.title("checking outlier in working day",fontsize=10)

plt.subplot(2,2,2)
sns.boxplot(data = df, x = "holiday", y ="count")
plt.title("checking outlier in holiday",fontsize=10)

plt.subplot(2,2,3)
sns.boxplot(data = df, x = "season", y ="count")
plt.title("checking outlier in season",fontsize=10)

plt.subplot(2,2,4)
sns.boxplot(data = df, x = "weather", y ="count")
plt.title("checking outlier in weather",fontsize=10)

plt.show()
```



- The median of working day and non working day seem almost similar. There are more outliers on the working day.
- The median of holiday and non holiday seem almost similar. There are more outliers on non holiday. We can say that the holiday column and working day column are vice versa.
- The medians of season 2 - Summer and 3 - Fall is little bit more than 4 - Winter. The least median is of 1 - Spring. All the seasons are seeing some outliers.
- Looking at the weather and bike ride relationship, the adverse weather 4 - Heavy rains is expected to see least bike ride bookings while weather 1
  clear weather and 2 - Mist and cloudy have similar medians.

  The median of weather 3 - Light snow, rain is little lower than the 1st and 2nd weather.

. Remove/Clip existing outliers as necessary.

```
# unique values in each column
for i in df.columns:
  print(i,' : ',df[i].nunique())
```

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

```
# # 3.
# # Outlier Treatment using IQR (not needed but, we can do it) -

#q1 = df['count'].quantile(0.25)
#q3 = df['count'].quantile(0.75)
#iqr = q3-q1

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

#print("No. of rows : ", df.shape[0])
```

Outlier treatment using np.clip()

```
df_copy = df.copy()

# cliping the data np.clip() between the 5 percentile and 95 percentile
cols=['workingday','holiday','season','weather']
for col in cols:

  percentile = df_copy[col].quantile([0.05,0.95]).values
  df_copy[col] = np.clip(df_copy[col], percentile[0], percentile[1])
print("No. of rows : ", df_copy.shape[0])
```

```
No. of rows :  10502
```

2. Try establishing a Relationship between the Dependent and Independent Variables.

```
# dropping datetime column since its an object
df_corr = df_copy.drop(['datetime'], axis=1)
df_corr.corr()
```

	season	holiday	workingday	weather	temp	atemp	humidity	w
season	1.000000	NaN	-0.013043	0.008808	0.265315	0.271787	0.195919	·
holiday	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
workingday	-0.013043	NaN	1.000000	0.032134	0.027040	0.021993	-0.016988	
weather	0.008808	NaN	0.032134	1.000000	-0.047737	-0.048406	0.404451	
temp	0.265315	NaN	0.027040	-0.047737	1.000000	0.985847	-0.047441	·
atemp	0.271787	NaN	0.021993	-0.048406	0.985847	1.000000	-0.026657	·
humidity	0.195919	NaN	-0.016988	0.404451	-0.047441	-0.026657	1.000000	·
windspeed	-0.150028	NaN	0.016716	0.007914	-0.023029	-0.064081	-0.319781	
casual	0.104915	NaN	-0.320807	-0.123741	0.474008	0.469316	-0.328495	
registered	0.166013	NaN	0.089811	-0.107327	0.304362	0.301952	-0.273570	
count	0.166137	NaN	-0.022473	-0.124045	0.388402	0.385047	-0.320078	

i. Plot a Correlation Heatmap and draw insights.

```
fig, ax = plt.subplots(figsize=(10,8))
sns.heatmap(df_corr.corr(), cmap="YlGnBu", annot=True)
plt.show()
```

Insights 🐾 **The positive value of correlation between Temprature and Count indicate that bicycle rentals sligthly depend on temperature also.**

from the correlation we can verify some logical points:

- feeling temperature or aparent temprature and temp are highly correlated, because they are most of the times approximately the same have a very small dreference
- count, causal, registered are all correlated to each other because all of them

```
# Dropping highly correlated columns -
dfn = df_corr.drop(columns=['casual', 'registered', 'atemp'])
```

Aggregating the total no. of bike rides based on the given factors -

```
# 1. Workingday -
pd.DataFrame(dfn.groupby('workingday')['count'].describe())
```

workingday	count	mean	std	min	25%	50%	75%	max
0	3392.0	177.003538	158.964897	1.0	42.0	123.0	290.0	614.0
1	7110.0	169.720394	147.844592	1.0	37.0	141.0	259.0	613.0

```
# 2. Holiday -
pd.DataFrame(dfn.groupby('holiday')['count'].describe())
```

holiday	count	mean	std	min	25%	50%	75%	max
0	10502.0	172.072748	151.55623	1.0	39.0	136.0	266.0	614.0

```
# 3. Season -
pd.DataFrame(dfn.groupby('season')['count'].describe())
```

season	count	mean	std	min	25%	50%	75%	max
1	2668.0	112.404798	116.055038	1.0	23.75	78.0	161.0	612.0
2	2597.0	189.621871	159.160385	1.0	42.00	161.0	291.0	614.0
3	2592.0	206.568287	159.658486	1.0	58.00	183.5	318.0	614.0
4	2645.0	181.224575	150.473489	1.0	48.00	153.0	272.0	613.0

```
# 4. Weather -
pd.DataFrame(dfn.groupby('weather')['count'].describe())
```

weather	count	mean	std	min	25%	50%	75%	max
1	6894.0	182.759646	155.973226	1.0	44.0	151.0	282.0	614.0
2	2759.0	164.258427	144.296961	1.0	39.0	129.0	253.0	614.0
3	849.0	110.687868	118.605718	1.0	23.0	70.0	157.0	613.0

3. Check if there any significant difference between the no. of bike rides on Weekdays and Weekends?

Hypothesis Testing

a.) Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1) :

```
Ho : Working day has no effect on the number of electric cycles rented

Ha: Working day has an effect
```

b.) Select an appropriate test -

```
2- Sample T-Test
```

Scenario 1: Working day effect

```
df_working_day = df[dfn["workingday"] == 1]
mean_working_day = df_working_day["count"].mean()

df_non_working_day = df[dfn["workingday"] == 0]
mean_non_working_day = df_non_working_day["count"].mean()

print("Mean of Working day :", mean_working_day)
print("Mean of Non Working day :", mean_non_working_day)
```

```
Mean of Working day : 169.72039381153306
Mean of Non Working day : 177.00353773584905
```

c. Set a significance level ▶ Alpha : 0.05 (Taking 0.05 as the significance value, ie., 95 % Confidence)

Test_statistic : Mean of count of bicycles rented

Right Tailed test : Mean of working day greater than mean of non working day is tested

d. Calculate test Statistics / p-value

```
from scipy.stats import ttest_ind,  ttest_1samp
alpha =0.05
t_stat, p_val = ttest_ind(df_working_day["count"], df_non_working_day["count"], alternative = "greater")

print(f'Test_statistic :{t_stat}, p-value : {p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
Test_statistic :-2.3033547323374934, p-value : 0.989360832205484
Fail to Reject Null Hypothesis
```

e. Decide whether to accept or reject the Null Hypothesis.

Insights ▶
Result of ttest on Working day data - The slight difference in mean is not significant to reject the Null Hypothesis. So, we Fail to Reject H0 and believe that the rides on working day and non working day are similar.

Scenario 2 : Holiday Effect

Ho : Holiday has no effect on the number of electric cycles rented

Ha: Holiday has an effect

Alpha : 0.05 (Taking 0.05 as the significance value, ie., 95 % Confidence)

Test_statistic : Mean of count of bicycles rented

```
df_holiday = df[df["holiday"] == 1]
mean_holiday = df_holiday["count"].mean()

df_non_holiday = df[dfn["holiday"] == 0]
mean_non_holiday = df_non_holiday["count"].mean()

print("Mean of Holiday :", mean_holiday)
print("Mean of Non Holiday :", mean_non_holiday)
```

```
Mean of Holiday : 182.58899676375404
Mean of Non Holiday : 172.07274804799087
```

```
t_stat, p_val = ttest_ind(df_holiday["count"], df_non_holiday["count"], alternative = "greater")

print(t_stat, p_val)

if(p_val < 0.05):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
1.1993188349501058 0.11521514172223637
Fail to Reject Null Hypothesis
```

Insights ▶ : Result of ttest on Holiday data - The slight difference in mean is not significant to reject the Null Hypothesis.

So, we Fail to Reject H0 and believe that the rides on holiday and a non holiday are similar.

4. Check if the demand of bicycles on rent is the same for different Weather conditions?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1) Scenario 1 : Weather Effect

Ho : Weather has no effect on the number of electric cycles rented

Ha: Weather has an effect

Alpha : 0.05 (Taking 0.05 as the significance value, ie., 95 % Confidence)

```
df_weather_1 = df[dfn["weather"] == 1]
mean_weather_1 = df_weather_1["count"].mean()

df_weather_2 = df[dfn["weather"] == 2]
mean_weather_2 = df_weather_2["count"].mean()

df_weather_3 = df[dfn["weather"] == 3]
mean_weather_3 = df_weather_3["count"].mean()

df_weather_4 = df[df["weather"] == 4]
mean_weather_4 = df_weather_4["count"].mean()

print("Mean of Weather 1 (Clear, Few clouds, partly cloudy, partly cloudy) :", mean_weather_1)
print("Mean of Weather 2 (Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist) :", mean_weather_2)
print("Mean of Weather 3 (Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds) :", mean_weather_3)
print("Mean of Weather 4 (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog) :", mean_weather_4)
```

```
Mean of Weather 1 (Clear, Few clouds, partly cloudy, partly cloudy) : 182.75964606904554
Mean of Weather 2 (Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist) : 164.25842696629215
Mean of Weather 3 (Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds) : 110.68786808009423
Mean of Weather 4 (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog) : 164.0
```

b. Select an appropriate test -

Performing ANOVA test to check if No. of cycles rented is similar or different in- Different Weather and Different Season

```
alpha=0.05

f_stat, p_val = f_oneway(df_weather_1["count"], df_weather_2["count"], df_weather_3["count"], df_weather_4["count"])

print(f'test statistic : {f_stat}, p-value : {p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 61.343443940764686, p-value : 2.6151472403438144e-39
Reject Null Hypothesis
```

As we can see above, the p value is extremely less than significance value - (alpha - 0.05). So, we Reject the Null Hypothesis which said that the mean of all weathers is same.

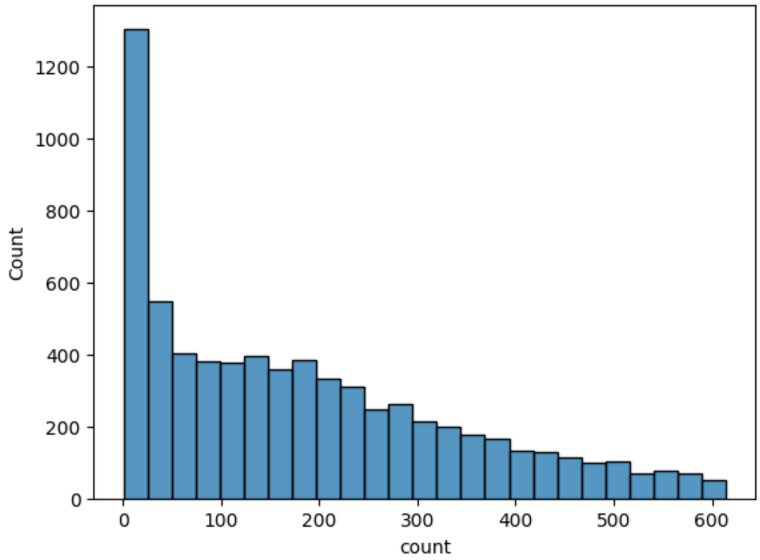
Insights ▶ **We can strongly say that Weather has a extreme effect on number of bicycles rented.**

c. Check assumptions of the test

i. Normality : Checking if the Weather data is Gaussian or not

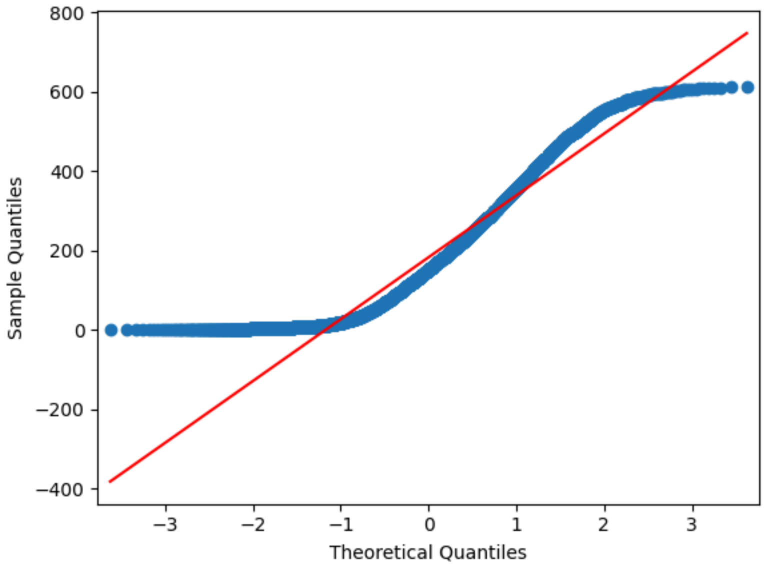
```
from scipy.stats import norm
from scipy.stats import shapiro, kstest
from statsmodels.graphics.gofplots import qqplot

sns.histplot(df_weather_1, x = "count")
```

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



As per histplot , our data is right skewed

```
qqplot(df_weather_1["count"], line = "s")
plt.show()
```



According to qq plot data is not gaussian , its not normal distribution.

Shapiro - wilk test

```
#Ho: Data is Gaussian

# Ha: Data is not Gaussion
weather_1_subset = df_weather_1["count"].sample(100)

test_stat, p_val = shapiro(weather_1_subset)

print(f'test_statistics :{test_stat}, p-value :  {p_val}')


if(p_val < 0.05):
  print("Reject Null Hypothesis")
  print('Data is not Gaussian')
else:
  print("Fail to Reject Null Hypothesis")
  print('Data is Gausian')
```

```
test_statistics :0.919511079788208, p-value :  1.3259934348752722e-05
Reject Null Hypothesis
Data is not Gaussian
```

According to the Shapiro test, Weather data provided is not Gaussian.

KS test

```
# Ho: Data is Gaussian

# Ha: Data is not Gaussian
test_stat, p_val = kstest(weather_1_subset, norm.cdf, args=(weather_1_subset.mean(), weather_1_subset.std()))

print(f'test_statistics : {test_stat}, p-value : {p_val}')

if(p_val < 0.05):
  print("Reject Null Hypothesis")
  print('Data is not Gaussian')
else:
  print("Fail to Reject Null Hypothesis")
  print('Data is Gaussian')
```

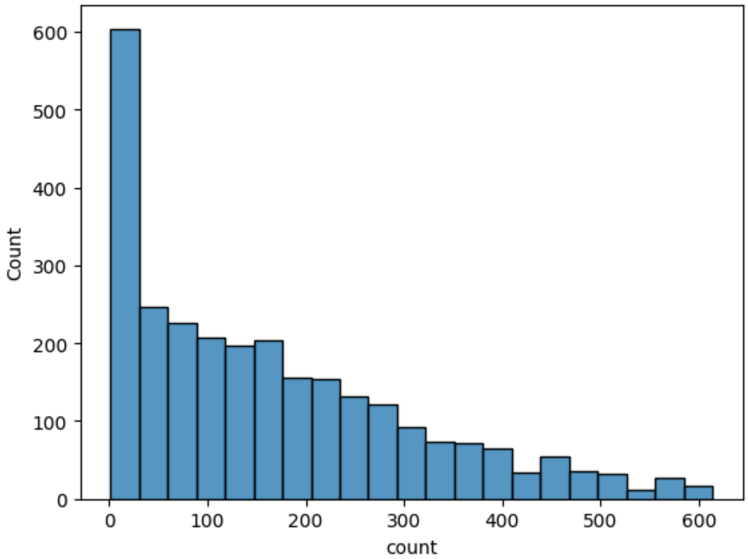
```
test_statistics : 0.12146311524079045, p-value : 0.09613459581743294
Fail to Reject Null Hypothesis
Data is Gaussian
```

According to the KS test, Weather data provided is not Gaussian.

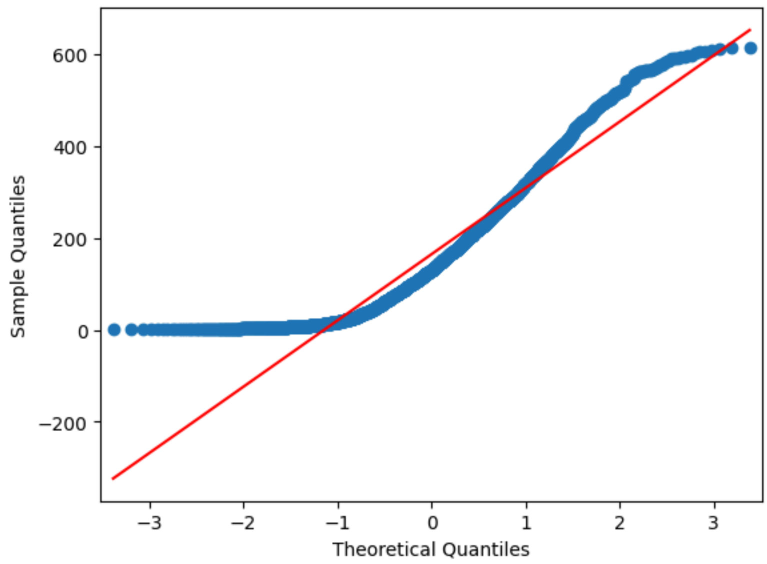
Weather 2

```
sns.histplot(df_weather_2, x = "count")
```

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




```
qqplot(df_weather_2["count"], line = "s")
plt.show()
```



Shapiro - wilk test

```
# Ho: Data is Gaussian

# Ha: Data is not Gaussian
alpha=0.05
weather_2_subset = df_weather_2["count"].sample(100)

test_stat, p_val = shapiro(weather_2_subset)

print(f'test_statistics : {test_stat}, p-value :{p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
  print('Data is not Gaussian')
else:
  print("Fail to Reject Null Hypothesis")
  print('Data is Gaussian.')
```

```
test_statistics : 0.8918999433517456, p-value :5.996824938847567e-07
Reject Null Hypothesis
Data is not Gaussian
```

According to shapiro wilk test , our data is not Gaussian ,means its not normal distribution.

KS-test

```
# Ho: Data is Gaussian

# Ha: Data is not Gaussian
alpha=0.05

test_stat, p_val = kstest(weather_2_subset, norm.cdf, args=(weather_2_subset.mean(), weather_2_subset.std()))

print(f'test statistics :{test_stat}, p-value :  {p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
  print("Data is not Gaussian")
else:
  print("Fail to Reject Null Hypothesis")
  print("Data is Gaussian.")
```

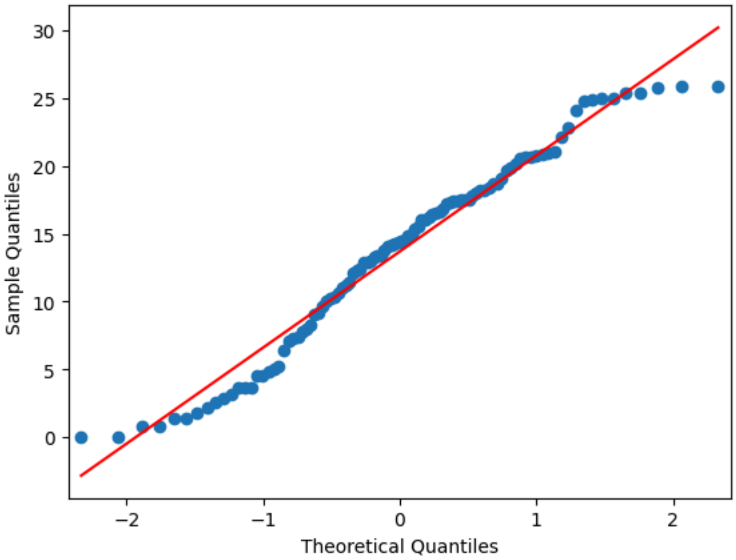
```
test statistics :0.13069636214331282, p-value :  0.05983858598089448
Fail to Reject Null Hypothesis
Data is Gaussian.
```

Insights ▶ After applying Qqplot, Shapiro test and KS test, Weather 2 data still doesn't follow Gaussian.

Boxcox

To solve this problem, using Boxcox over the sample data of weather 2

```
from scipy.stats import boxcox

transformed_data_weather_2 = boxcox(weather_2_subset)[0]

qqplot(transformed_data_weather_2, line = "s")
plt.show()
```




```
# shapiro wilk test
alpha=0.05
test_stat, p_val = shapiro(transformed_data_weather_2)

print(f'test statitic :{test_stat}, p-value : {p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statitic :0.9641795754432678, p-value : 0.008075983263552189
Reject Null Hypothesis
```

```
#KS test
alpha=0.05
test_stat, p_val = kstest(transformed_data_weather_2, norm.cdf, args=(transformed_data_weather_2.mean(), transformed_data_weather_2.std(

print(f'test statistic : {test_stat}, p-value : {p_val}')

if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

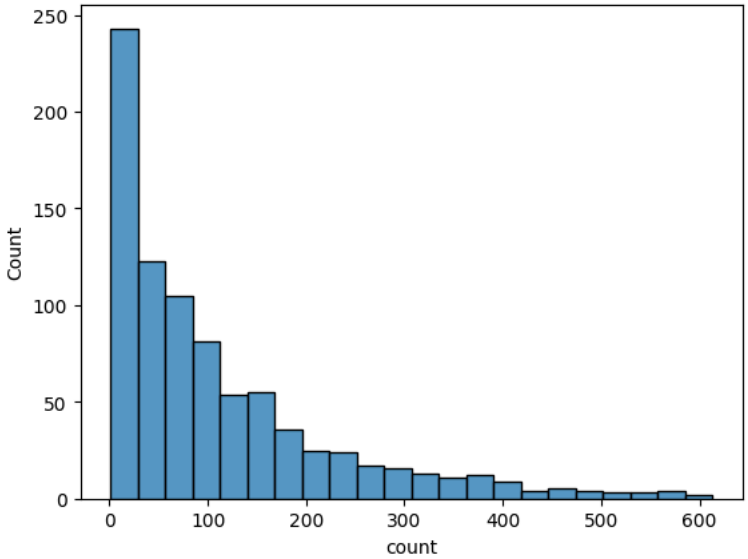
```
test statistic : 0.07420194067883706, p-value : 0.6137509085739272
Fail to Reject Null Hypothesis
```

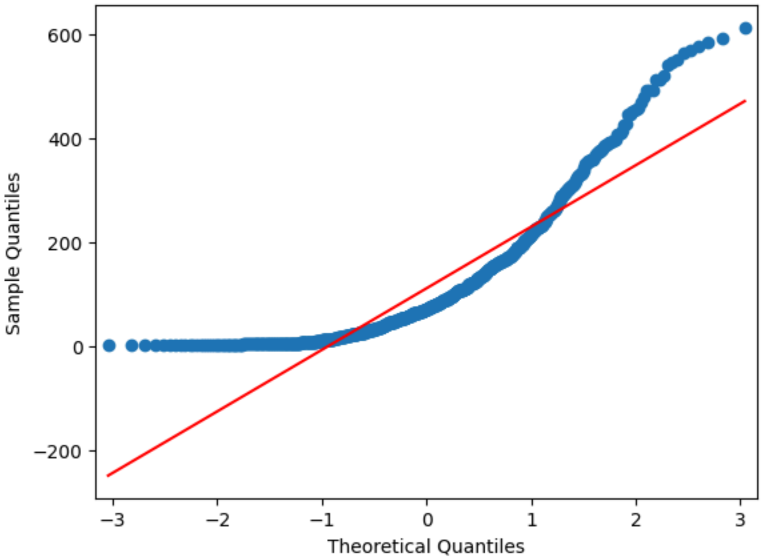
Conclusion : If one test says that the data is Gaussian then we continue to believe that the data is Gaussian. Here, the transformed data now follows Gaussian distribution.

Weather 3

```
sns.histplot(df_weather_3, x = "count")


qqplot(df_weather_3["count"], line = "s")
plt.show()
weather_3_subset = df_weather_3["count"].sample(100)


test_stat, p_val = shapiro(weather_3_subset)

print("Shapiro Test: ")
```

```
print(f'test statistic value :{test_stat}, p-value :  {p_val}')


if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
test_stat, p_val = kstest(weather_3_subset, norm.cdf, args=(weather_3_subset.mean(), weather_3_subset.std()))

print("--" * 50)
print("KS Test: ")
print(f'test statistics : {test_stat}, p-value : {p_val}')


if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```



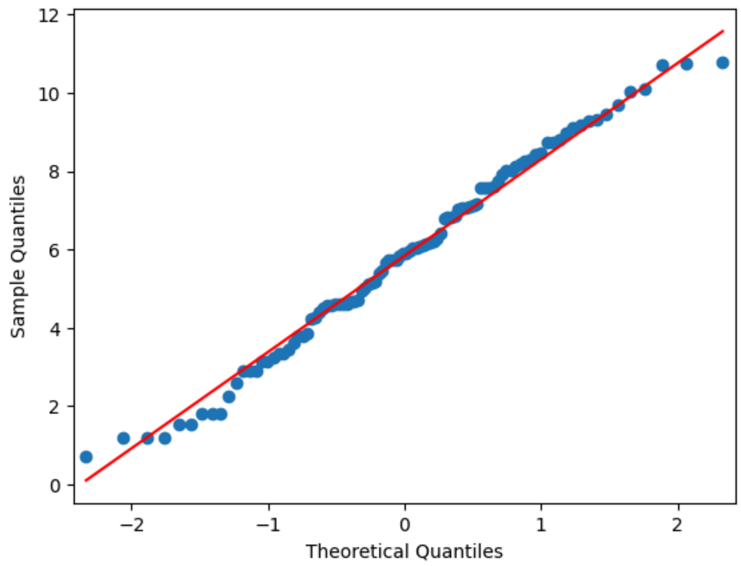



```
Shapiro Test:
test statistic value :0.7803515791893005, p-value :  6.443273692369189e-11
Reject Null Hypothesis
----------------------------------------------------------------------------------------------------
KS Test:
test statistics : 0.20378978438939455, p-value : 0.0004057020308314053
Reject Null Hypothesis
```

Weather 3 follows same pattern as weather 2. The data is not Gaussian.

Applying boxcox to make it Gaussian.

```
from scipy.stats import boxcox

alpha=0.05
transformed_data_weather_3 = boxcox(weather_3_subset)[0]


qqplot(transformed_data_weather_3, line = "s")
plt.show()
test_stat, p_val = shapiro(transformed_data_weather_3)

print("Shapiro Test: ")
print(f'test statistics : {test_stat}, p-value : {p_val}')


if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
test_stat, p_val = kstest(transformed_data_weather_3, norm.cdf, args=(transformed_data_weather_3.mean(), transformed_data_weather_3.std(

print("--"*50)
print("KS test: ")
print(f'test statitics : {test_stat}, p-value : {p_val}')


if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```




```
Shapiro Test:
test statistics : 0.983907163143158, p-value : 0.26420244574546814
Fail to Reject Null Hypothesis
------------------------------------------------------------------------------------
KS test:
test statitics : 0.04932073235604906, p-value : 0.9581695303646064
Fail to Reject Null Hypothesis
```

After applying boxcox for Weather 3, the data is now transformed to Gaussian distribution

5. Check if the demand of bicycles on rent is the same for different Seasons?

Ho : Season has no effect on the number of electric cycles rented

Ha: Season has an effect

Alpha : 0.05 (Taking 0.05 as the significance value, ie., 95 % Confidence)

Test_statistic : Mean of count of bicycles rented

```
df_season_1 = df[df["season"] == 1]
mean_season_1 = df_season_1["count"].mean()

df_season_2 = df[df["season"] == 2]
mean_season_2 = df_season_2["count"].mean()

df_season_3 = df[df["season"] == 3]
mean_season_3 = df_season_3["count"].mean()

df_season_4 = df[df["season"] == 4]
mean_season_4 = df_season_4["count"].mean()

print("Mean of season 1 (Spring) :", mean_season_1)
print("Mean of season 2 (Summer) :", mean_season_2)
print("Mean of season 3 (Fall) :", mean_season_3)
print("Mean of season 4 (Winter) :", mean_season_4)
```

```
Mean of season 1 (Spring) : 112.4047976011994
Mean of season 2 (Summer) : 189.62187139006545
Mean of season 3 (Fall) : 206.56828703703704
Mean of season 4 (Winter) : 181.22457466918715
```

```
from scipy.stats import f_oneway
alpha =0.05
f_stat, p_val = f_oneway(df_season_1["count"], df_season_2["count"], df_season_3["count"], df_season_4["count"])

print(f_stat, p_val)

if(p_val < alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
209.17107132721443 8.775683191212859e-132
Reject Null Hypothesis
```

As we can see above, the p value is extremely less than significance value - (alpha - 0.05). So, we Reject the Null Hypothesis which said that the mean of all seasons is same.

We can strongly say that Seasons have an extreme effect on number of bicycles rented.

---

6. Check if the Weather conditions are significantly different during different Seasons?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1)

```
Ho : Weather is not dependent on Season
Ha: Weather is dependent on Season
```

b. Select an appropriate test

```
Chi-square test
```

c. Create a Contingency Table against ‘Weather’ & ‘Season’ columns

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

season weather	1	2	3	4	All
1	1743	1689	1822	1640	6894
2	713	686	576	784	2759
3	211	222	194	221	848
4	1	0	0	0	1
All	2668	2597	2592	2645	10502

d. Set a significance level and Calculate the test Statistics / p-value

```
Alpha : 0.05 (Taking 0.05 as the significance value, ie., 95 % Confidence)
```

```
 #    H0 : Weather is not dependent on Season
  #    Ha: Weather is dependent on Season
alpha =0.05
from scipy.stats import chi2_contingency
chi_stat, p_val, dof, expected = chi2_contingency(weather_season)

print(f'chi-stats value : {chi_stat}, p-value :  {p_val}, degree of freedom : {dof}, expected value: {expected}')

if(p_val <alpha):
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
chi-stats value : 47.02070298259308, p-value :  6.759649418996184e-05, degree of freedom : 16, expected value: [[1.75139897e+03 1.7(
  6.89400000e+03]
 [7.00915254e+02 6.82262712e+02 6.80949153e+02 6.94872881e+02
  2.75900000e+03]
 [2.15431727e+02 2.09698724e+02 2.09294991e+02 2.13574557e+02
  8.48000000e+02]
 [2.54046848e-01 2.47286231e-01 2.46810131e-01 2.51856789e-01
  1.00000000e+00]
 [2.66800000e+03 2.59700000e+03 2.59200000e+03 2.64500000e+03
  1.05020000e+04]]
Reject Null Hypothesis
```

After applying the chi2_contigency test, we observe that the p value is very less in comparision to alpha(0.05), so we can say that the Weather is dependent on Season.

Conclusion :

```
 * Yulu is facing losses because of lower demand of electric bicycles as
    seen in the data provided above.

* The factors analysed above were demand on a working day, holiday, across
   different seasons, different weather conditions and temparature.

* It is seen that the demand is higher on clear weather days as people
  tend to enjoy riding bicycles on those days.

* While it is very difficult for people to ride an electric vehicle during
  rain, snow, heavy wind, etc. so the demand is very low during that time.

* Seasons also have a similar effect like weather.

* Holiday or working day doesn't have much effect on the rides. People
  prefer it during both.
```

Recommendations : 🐾

As the issues of less bicycle rentals are happening due to the climatic conditions so I would like to recommend the following -

- Yulu should reduce the rate/price when the weather or season is not favourable. Usually all other transports, increase their pricing so this can be one attraction.
- Yulu should try to offer some protection options like in rainy season assure customers that it is safe to ride a electric vehicle and have some safety equipments like raincoats, helmets, etc available with the bicycle.
- Yulu should offer exiciting packages/deals during office hours on workdays so that people try to use bicycles instead of buses/cars.
- Yulu should also try to advertise itself as Environment safe company and try to lure people towards environment protection.
- On holidays, discounts can be offered for multiple bicycle bookings by one account as usually friends and family groups plan to go out and if discount is offered it might attract them.
- During high temprature, the probablility of using bicycle is low, so they can also make some refreshing stations where people can get some drink and rest for a while if they are travelling far.

```
Start coding or generate with AI.
```