Business Case_ Yulu - Hypothesis Testing

June 21, 2024

1 Business Case: Yulu - Hypothesis Testing

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.

How you can help here?

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?

1.1 Importing libraries and Downloading dataset

[2]:
```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
from warnings import filterwarnings
filterwarnings('ignore')

# Downloading dataset
```

```
data = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
↪000/001/428/original/bike_sharing.csv?1642089089')
```

1.2 Basic Metrics

[ ]:
```
data.head()
```

[ ]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
3        75        0.0       3          10     13
4        75        0.0       0           1      1
```

[ ]:
```
data.shape
```

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

[ ]:
```
data.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
```

- datetime: datetime

- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- holiday: whether day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
- workingday: if day is neither weekend nor holiday is 1, otherwise is 0.
- weather:
  - 1: Clear, Few clouds, partly cloudy, partly cloudy
  - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
  - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
  - 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- 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

[ ]:
```
data.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
```

[ ]:
```
data.duplicated().sum()
```

[ ]:
```
0
```

We can see that there are no null values and no duplicate values

1.3 Exploratory Data Analysis

- Here Holiday data is included in the workingday column.
- Casual and Registered is summed to counts column.
- Also, temp and atemp gives us the similar info.
- So we can ignore these columns - holiday, casual, registered, temp

[31]:
```python
df = data.copy()

num_cols = ['atemp', 'humidity', 'windspeed', 'count']
cat_cols = ['season','weather', 'workingday']

# conversion of categorical attributes
df['season'] = df['season'].replace({1:'Spring',2:'Summer',3:'Fall',4:'Winter'})
df['weather'] = data['weather'].replace({1: 'Clear', 2: 'Cloudy', 3: 'Light␣
↪Rain', 4: 'Heavy Rain'})
df['workingday'] = df['workingday'].replace({0:'No',1:'Yes'})
df['holiday'] = df['holiday'].replace({0:'No',1:'Yes'})

# extrating months and days from datetime column
df['datetime'] = pd.to_datetime(df['datetime'])
df['month'] = df['datetime'].dt.month
df['weekday'] = df['datetime'].dt.weekday
df['month'] = df['month'].replace({1: 'January', 2: 'February', 3: 'March', 4:␣
↪'April', 5: 'May', 6: 'June', 7: 'July', 8: 'August', 9: 'September', 10:␣
↪'October', 11: 'November', 12: 'December'})
df['weekday'] = df['weekday'].replace({0: 'Monday', 1: 'Tuesday', 2:␣
↪'Wednesday', 3: 'Thursday', 4: 'Friday', 5: 'Saturday', 6: 'Sunday'})
df['datetime'] = df['datetime'].dt.strftime('%Y-%m-%d %H:%M:%S')
```

[32]:
```python
df.head()
```

[32]:
```
              datetime  season holiday workingday weather  temp   atemp  \
0  2011-01-01 00:00:00  Spring      No         No   Clear  9.84  14.395
1  2011-01-01 01:00:00  Spring      No         No   Clear  9.02  13.635
2  2011-01-01 02:00:00  Spring      No         No   Clear  9.02  13.635
3  2011-01-01 03:00:00  Spring      No         No   Clear  9.84  14.395
4  2011-01-01 04:00:00  Spring      No         No   Clear  9.84  14.395

   humidity  windspeed  casual  registered  count    month   weekday
0        81        0.0       3          13     16  January  Saturday
1        80        0.0       8          32     40  January  Saturday
2        80        0.0       5          27     32  January  Saturday
3        75        0.0       3          10     13  January  Saturday
4        75        0.0       0           1      1  January  Saturday
```

1.3.1 Statistical Analysis

[34]:
```python
df.describe()
```

[34]:
```
              temp         atemp      humidity     windspeed        casual  \
count  10886.00000  10886.000000  10886.000000  10886.000000  10886.000000
mean      20.23086     23.655084     61.886460     12.799395     36.021955
```

```
std        7.79159     8.474601    19.245033     8.164537    49.960477
min        0.82000     0.760000     0.000000     0.000000     0.000000
25%       13.94000    16.665000    47.000000     7.001500     4.000000
50%       20.50000    24.240000    62.000000    12.998000    17.000000
75%       26.24000    31.060000    77.000000    16.997900    49.000000
max       41.00000    45.455000   100.000000    56.996900   367.000000

         registered         count
count  10886.000000  10886.000000
mean     155.552177    191.574132
std      151.039033    181.144454
min        0.000000      1.000000
25%       36.000000     42.000000
50%      118.000000    145.000000
75%      222.000000    284.000000
max      886.000000    977.000000
```

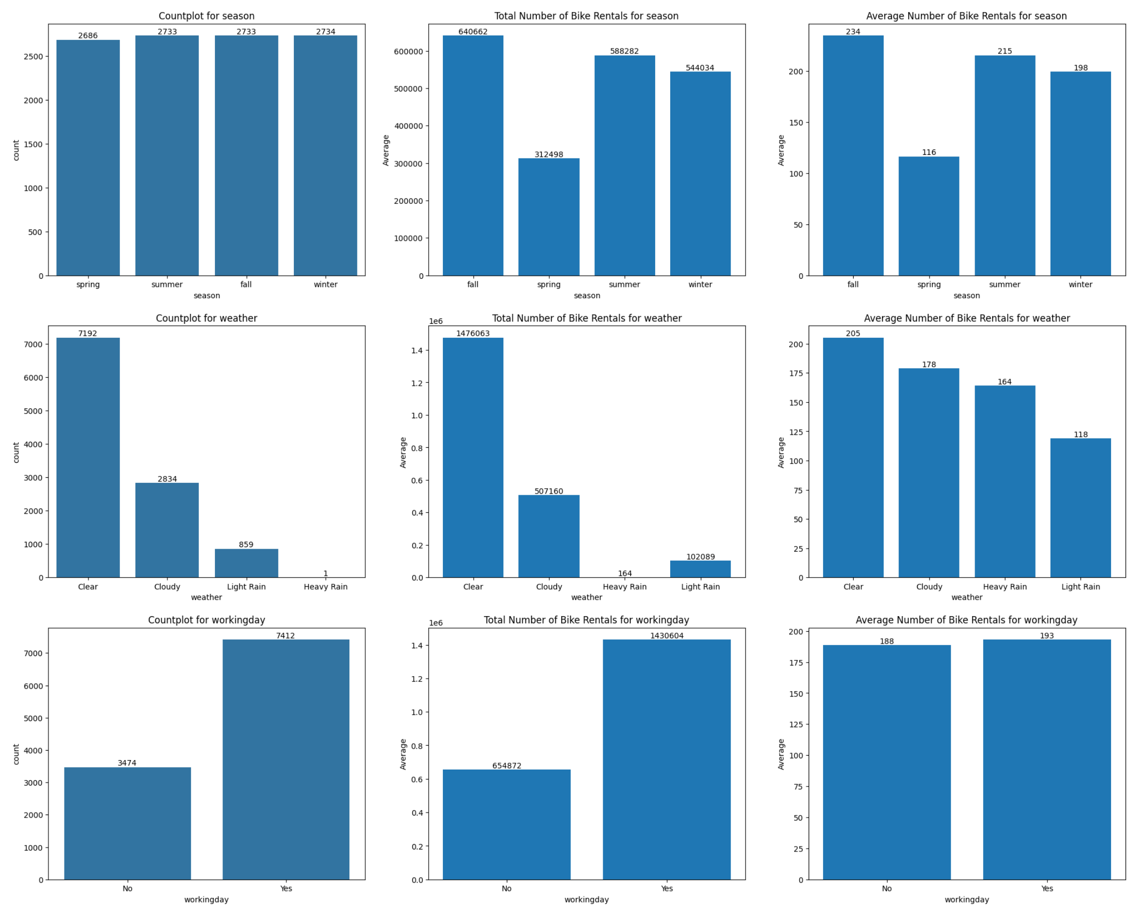
[35]:
```
df[cat_cols].describe()
```

[35]:
```
        season weather workingday
count    10886   10886      10886
unique       4       4          2
top     Winter   Clear        Yes
freq      2734    7192       7412
```

1.3.2 Analysis on categorical columns

[ ]:
```
# plots for categorical columns

plt.figure(figsize=(25, 20))

for i in cat_cols:
  plt.subplot(3, 3, cat_cols.index(i)*3+1)
  plt.title('Countplot for '+i)
  g = sns.countplot(df, x=i)
  for j in g.patches:
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=int(j.
↪get_height()), ha='center', va='bottom')

  plt.subplot(3, 3, cat_cols.index(i)*3+2)
  plt.title('Total Number of Bike Rentals for '+i)
  d = df.groupby(i)['count'].sum().reset_index()
  g = plt.bar(d[i],d['count'])
  plt.xlabel(i)
  plt.ylabel('Average')
  for j in g.patches:
```

```
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=int(j.
↪get_height()), ha='center', va='bottom')

  plt.subplot(3, 3, cat_cols.index(i)*3+3)
  plt.title('Average Number of Bike Rentals for '+i)
  d = df.groupby(i)['count'].mean().reset_index()
  g = plt.bar(d[i],d['count'])
  plt.xlabel(i)
  plt.ylabel('Average')
  for j in g.patches:
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=int(j.
↪get_height()), ha='center', va='bottom')

plt.show()
```

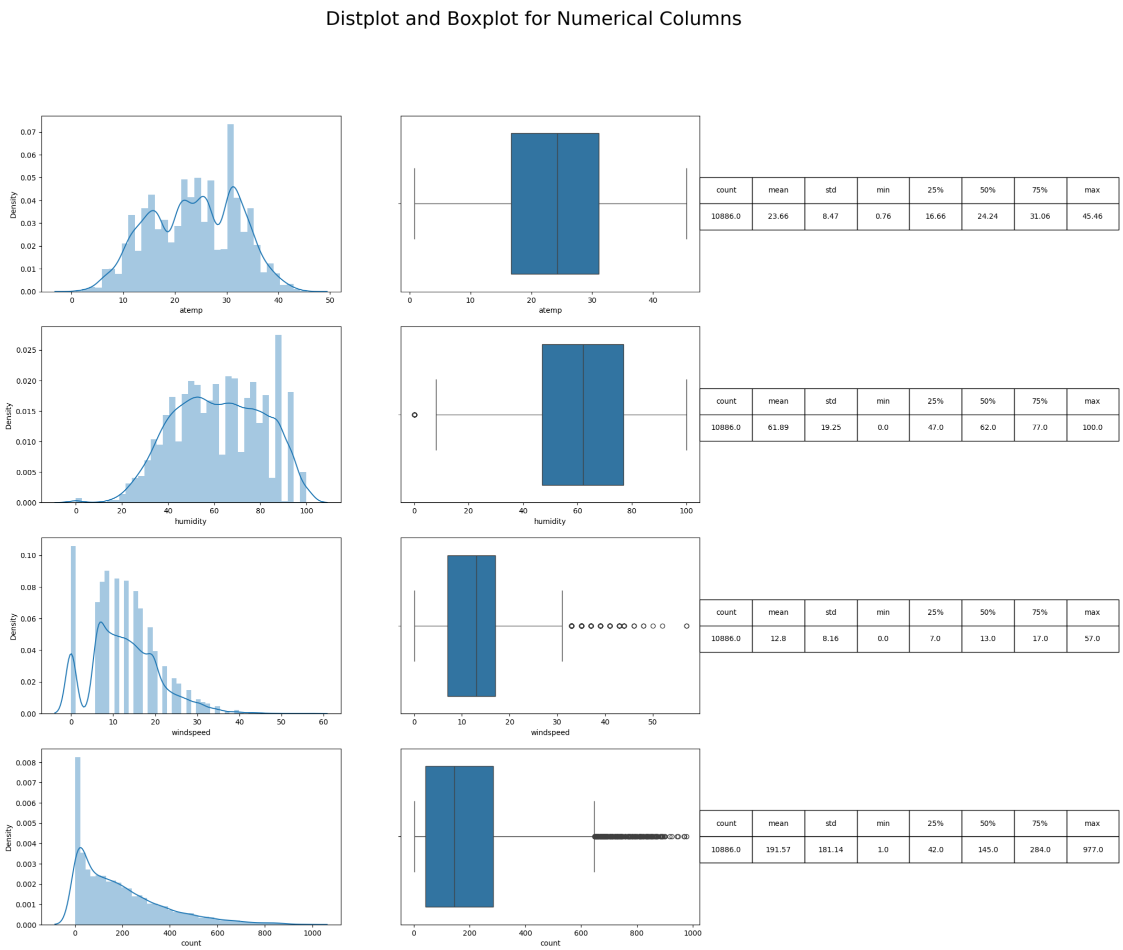


- There are more bike rentals on fall season with a total count of 640662 and an average of 234.
- There are more bike rentals on Clear weather with a total count of 1476063 and an average of 205.

- There are more bike rentals on working day but we can't find much difference on average.

1.3.3 Analysis on numerical columns

```
[ ]: # plots for Numerical columns

plt.figure(figsize=(25, 20)).suptitle('Distplot and Boxplot for Numerical␣
 ↪Columns', size=26)

for i in num_cols:
  plt.subplot(4, 3, num_cols.index(i)*3+1)
  g = sns.distplot(df[i], kde=True)

  plt.subplot(4, 3, num_cols.index(i)*3+2)
  g = sns.boxplot(x=df[i])

  plt.subplot(4, 3, num_cols.index(i)*3+3)
  statistics = df[i].describe().round(2)
  table = plt.table(colLabels=statistics.index, cellText=[statistics.values],␣
 ↪loc='center', cellLoc='center')
  table.scale(1.4,3)
  plt.axis('off')

plt.show()
```



count	mean	std	min	25%	50%	75%	max
10886.0	23.66	8.47	0.76	16.66	24.24	31.06	45.46

count	mean	std	min	25%	50%	75%	max
10886.0	61.89	19.25	0.0	47.0	62.0	77.0	100.0

count	mean	std	min	25%	50%	75%	max
10886.0	12.8	8.16	0.0	7.0	13.0	17.0	57.0

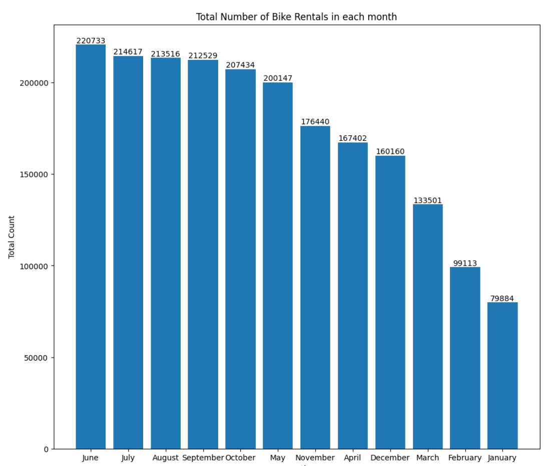
count	mean	std	min	25%	50%	75%	max
10886.0	191.57	181.14	1.0	42.0	145.0	284.0	977.0

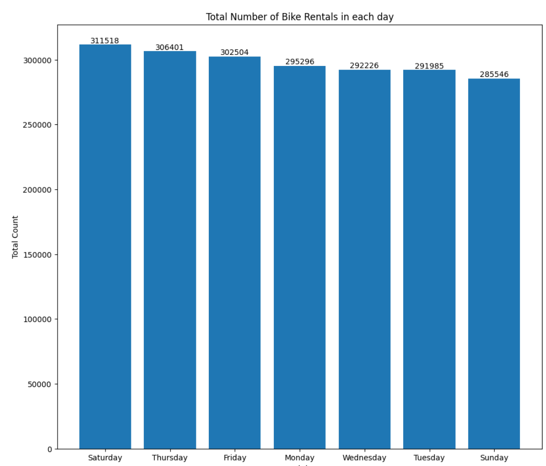
- The **atemp** column displays a wide range of apparent temperatures (0.76 to 45.455), with a mean of approximately 23.66 and moderate variability around the median of 24.24.
- The **humidity** column depicts a range of humidity values (0 to 100), with an average around 61.89. The distribution shows moderate variability, from 47 at the 25th percentile to 77 at the 75th percentile, indicating diverse humidity levels in the dataset.
- The **windspeed** column displays a range of wind speeds from 0 to 56.9979, with a mean of approximately 12.80.
- The **count** column reveals a wide range of total bike rental counts, varying from 1 to 977. The distribution is positively skewed, with a mean (191.57) greater than the median (145.0), indicating a concentration of lower values.

1.3.4 Analysis on months and days

[48]:
```
plt.figure(figsize=(25, 10))

plt.subplot(1,2,1)
plt.title('Total Number of Bike Rentals in each month')
```

```python
d = df.groupby('month')['count'].sum().reset_index().sort_values(by='count', ascending=False)
g = plt.bar(d['month'],d['count'])
plt.xlabel('month')
plt.ylabel('Total Count')
for j in g.patches:
  plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=int(j.get_height()), ha='center', va='bottom')

plt.subplot(1,2,2)
plt.title('Total Number of Bike Rentals in each day')
d = df.groupby('weekday')['count'].sum().reset_index().sort_values(by='count', ascending=False)
g = plt.bar(d['weekday'],d['count'])
plt.xlabel('weekday')
plt.ylabel('Total Count')
for j in g.patches:
  plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=int(j.get_height()), ha='center', va='bottom')
```





- June stands out as the peak month for bike rentals, with the highest count of 220733, followed closely by July and August.
- January, February, and March have notably lower bike rental counts, indicating potential off-peak periods, possibly influenced by colder weather or fewer outdoor activities.
- Saturday stands out as the peak day for bike rentals and also we can see that there is mo much difference in bike rentals among weekdays.

1.4 Correlation and Pair Plot

1.4.1 Heat Map

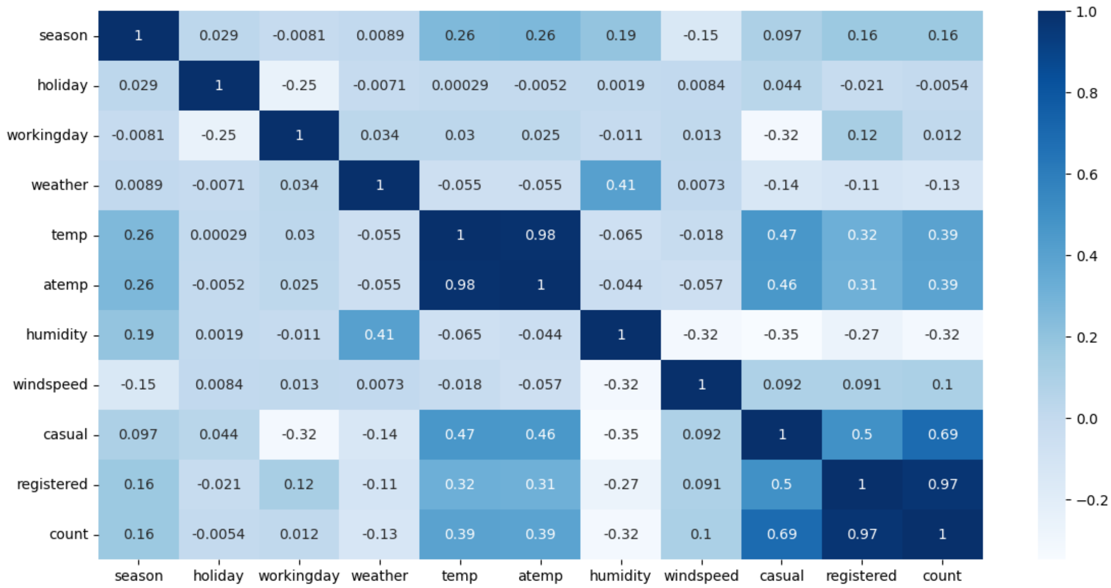
[ ]:
```
corr_df = data.corr(numeric_only=True)
corr_df
```

[ ]:

	season	holiday	workingday	weather	temp	atemp
season	1.000000	0.029368	-0.008126	0.008879	0.258689	0.264744
holiday	0.029368	1.000000	-0.250491	-0.007074	0.000295	-0.005215
workingday	-0.008126	-0.250491	1.000000	0.033772	0.029966	0.024660
weather	0.008879	-0.007074	0.033772	1.000000	-0.055035	-0.055376
temp	0.258689	0.000295	0.029966	-0.055035	1.000000	0.984948
atemp	0.264744	-0.005215	0.024660	-0.055376	0.984948	1.000000
humidity	0.190610	0.001929	-0.010880	0.406244	-0.064949	-0.043536
windspeed	-0.147121	0.008409	0.013373	0.007261	-0.017852	-0.057473
casual	0.096758	0.043799	-0.319111	-0.135918	0.467097	0.462067
registered	0.164011	-0.020956	0.119460	-0.109340	0.318571	0.314635
count	0.163439	-0.005393	0.011594	-0.128655	0.394454	0.389784

	humidity	windspeed	casual	registered	count
season	0.190610	-0.147121	0.096758	0.164011	0.163439
holiday	0.001929	0.008409	0.043799	-0.020956	-0.005393
workingday	-0.010880	0.013373	-0.319111	0.119460	0.011594
weather	0.406244	0.007261	-0.135918	-0.109340	-0.128655
temp	-0.064949	-0.017852	0.467097	0.318571	0.394454
atemp	-0.043536	-0.057473	0.462067	0.314635	0.389784
humidity	1.000000	-0.318607	-0.348187	-0.265458	-0.317371
windspeed	-0.318607	1.000000	0.092276	0.091052	0.101369
casual	-0.348187	0.092276	1.000000	0.497250	0.690414
registered	-0.265458	0.091052	0.497250	1.000000	0.970948
count	-0.317371	0.101369	0.690414	0.970948	1.000000

[ ]:
```
plt.figure(figsize=(14,7))
sns.heatmap(corr_df, annot=True, cmap='Blues')
plt.show()
```



count column seems to have ***positive*** correlation with **atemp** and and ***negative*** with **humidity**. We can see people go out with bike more when the temp is high and humidity is low.

1.4.2 Pair plot

```
[ ]: sns.pairplot(data, hue='workingday')
     plt.show()
```

```
Output hidden; open in https://colab.research.google.com to view.
```

1.5 Hypothesis Testing

1.5.1 Effect of Working Day on Bike Rentals

```
[ ]: df.groupby('workingday')['count'].mean()
```

```
[ ]: workingday
     No     188.506621
     Yes    193.011873
     Name: count, dtype: float64
```

Since this is categorical vs numerical having only 2 categorical fields, we can use 2 sample T-test

Null Hypothesis: Average number of bike rentals on the working day is same as the average number of bike rentals on the non-working day

Alternate Hypothesis: Average number of bike rentals on the working day is greater than the average number of bike rentals on the non-working day

[50]:
```python
# using 2 sample ttest
t_stat, p_val = stats.ttest_ind(df[df['workingday'] == 'Yes']['count'],
    df[df['workingday'] == 'No']['count'], alternative='greater')
```

[51]:
```python
H0 = 'Average number of bike rentals on the working day is same as the average
    number of bike rentals on the non-working day'
Ha = 'Average number of bike rentals on the working day is greater than the
    average number of bike rentals on the non-working day'
alpha = 0.05

print(f't-statistic: {t_stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')

if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
t-statistic: 1.2096277376026694
p-value: 0.11322402113180674
alpha: 0.05

Result: Failed to reject Null Hypothesis
Average number of bike rentals on the working day is same as the average number
of bike rentals on the non-working day
```

1.5.2 Effect of Season on Bike Rentals

[ ]:
```python
df.groupby('season')['count'].mean()
```

[ ]:
```
season
fall      234.417124
spring    116.343261
summer    215.251372
winter    198.988296
Name: count, dtype: float64
```

This is categorical vs numerical having 4 (more than 2) categorical fields, we can use one-way anova test if it follows anova assumptions or else we have to use krustal wallis test

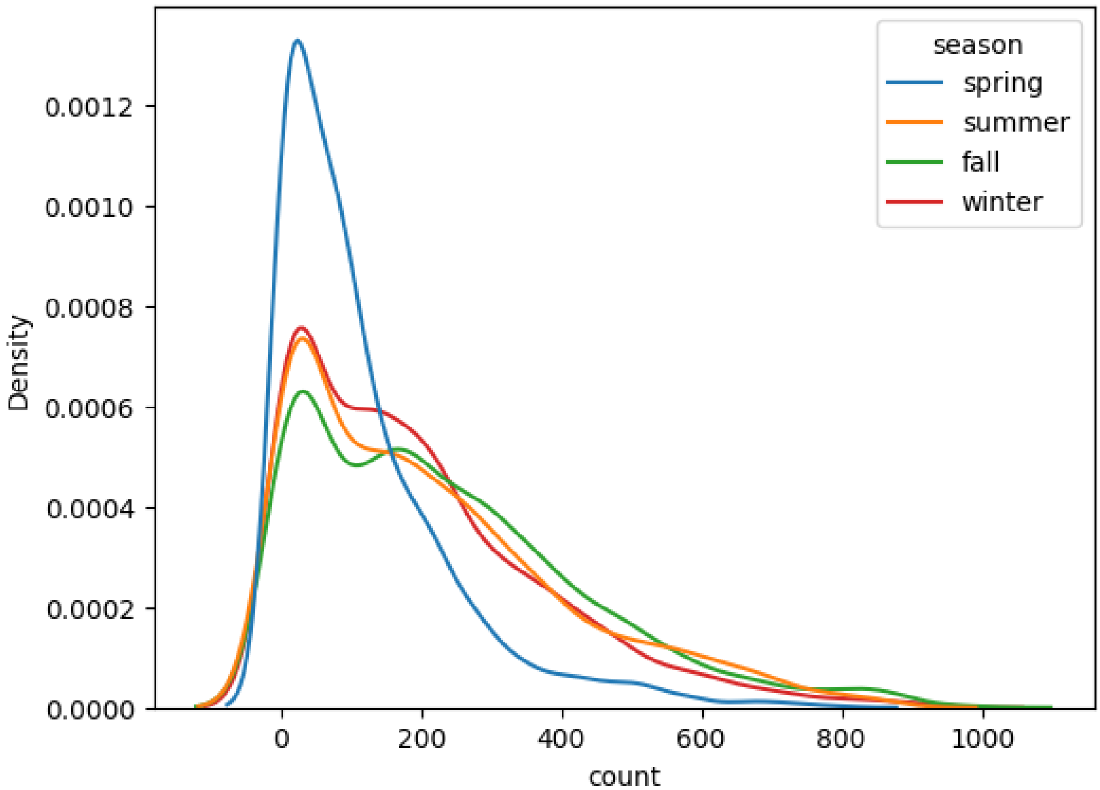
Assumptions of Anova:

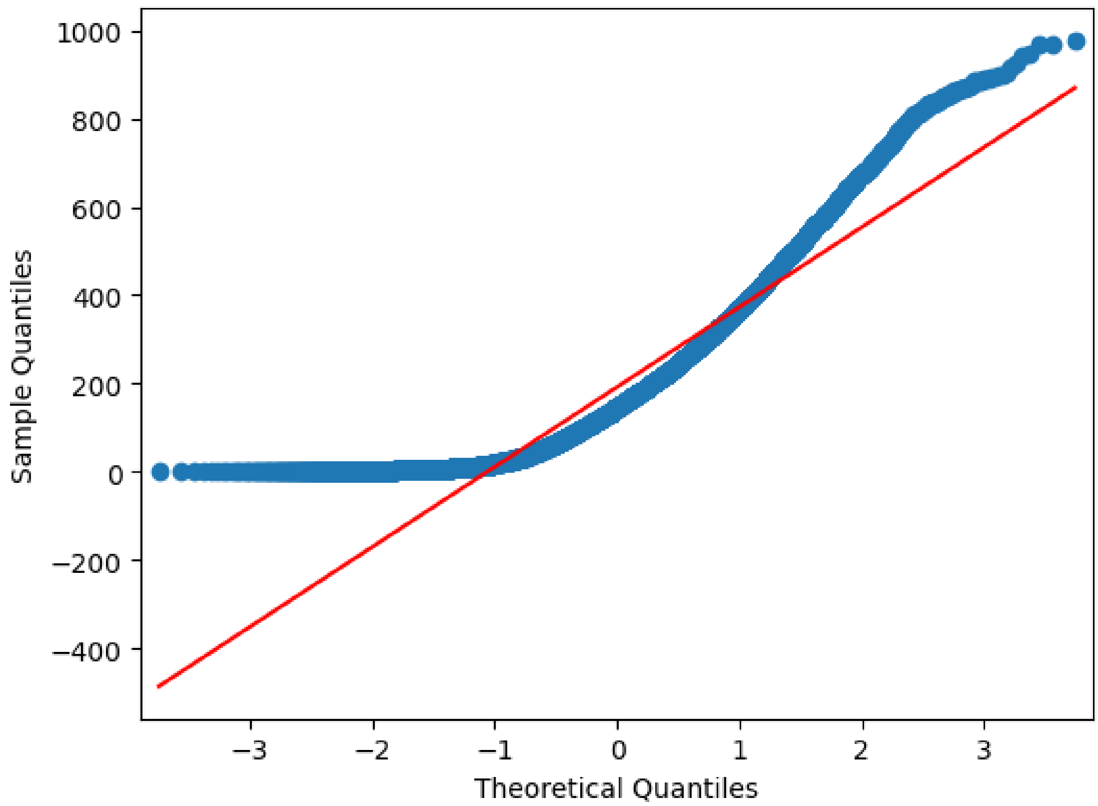
1. Data should follow a Gaussian distribution
2. Independent groups
3. Equal variance in all the groups

1. Normality Test

For this, curve test and qq-plot has to be used

[ ]:
```
# curve test
sns.kdeplot(df, x='count', hue='season')

# Q-Q plot
sm.qqplot(df['count'], line='s')

plt.show()
```





From the plots, it is clear that the data is not a normal distribution.

2. Independent groups

This condition is already satisfied since all seasons are independent of each other

3. Equal Variance Test

For this, levene test is used

[ ]:
```
H0 = 'Variance is same for all seasons'
Ha = 'Variance is not same for all seasons'

# levene test
alpha = 0.05
stat, p_val = stats.levene(df[df['season'] == 'spring']['count'],␣
  ↪df[df['season'] == 'summer']['count'], df[df['season'] == 'fall']['count'],␣
  ↪df[df['season'] == 'winter']['count'])

print(f'levene-statistic: {stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
```

```
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
levene-statistic: 187.7706624026276
p-value: 1.0147116860043298e-118
alpha: 0.05

Result: Reject Null Hypothesis
Variance is not same for all seasons
```

From this, we can say that variance is not same for all seasons and third assumption failed.

This data is not suitable to perform a ANOVA test since the first and third assumptions are not met.

So we have to try Kruskal Wallis Test

Kruskal Wallis Test **Null Hypothesis:** Average number of bike rentals is same for all the seasons.

Alternate Hypothesis: Average number of bike rentals is different for different seasons.

[ ]:
```
H0 = 'Average number of bike rentals is same for all the seasons'
Ha = 'Average number of bike rentals is different for different seasons'

# Kruskal wallis Test
alpha = 0.05
stat, p_val = stats.kruskal(df[df['season'] == 'spring']['count'],␣
 ↪df[df['season'] == 'summer']['count'], df[df['season'] == 'fall']['count'],␣
 ↪df[df['season'] == 'winter']['count'])

print(f'kruskal-statistic: {stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')

if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
kruskal-statistic: 699.6668548181988
p-value: 2.479008372608633e-151
alpha: 0.05
```

```
Result: Reject Null Hypothesis
Average number of bike rentals is different for different seasons
```

1.5.3 Effect of Weather on Bike Rentals

[ ]:
```
df.groupby('weather')['count'].mean()
```

[ ]:
```
weather
Clear          205.236791
Cloudy         178.955540
Heavy Rain     164.000000
Light Rain     118.846333
Name: count, dtype: float64
```

This is categorical vs numerical having 4 (more than 2) categorical fields, we can use one-way anova test if it follows anova assumptions or else we have to use krustal wallis test

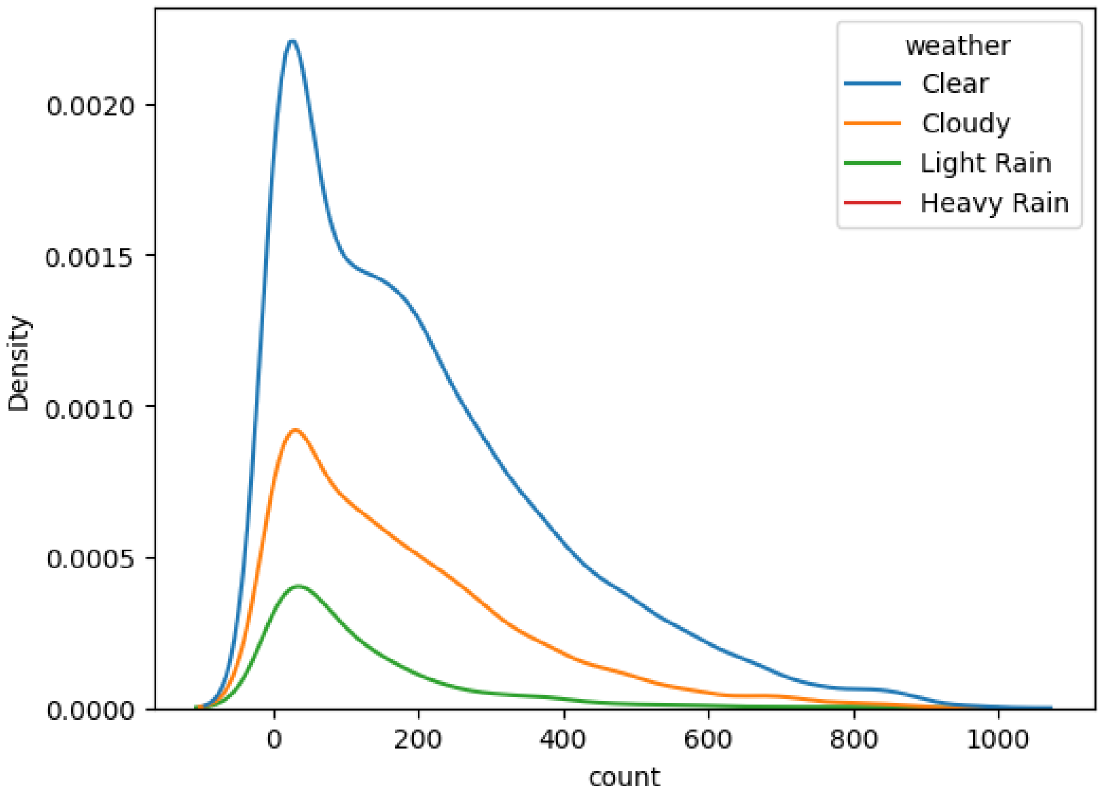
Assumptions of Anova:

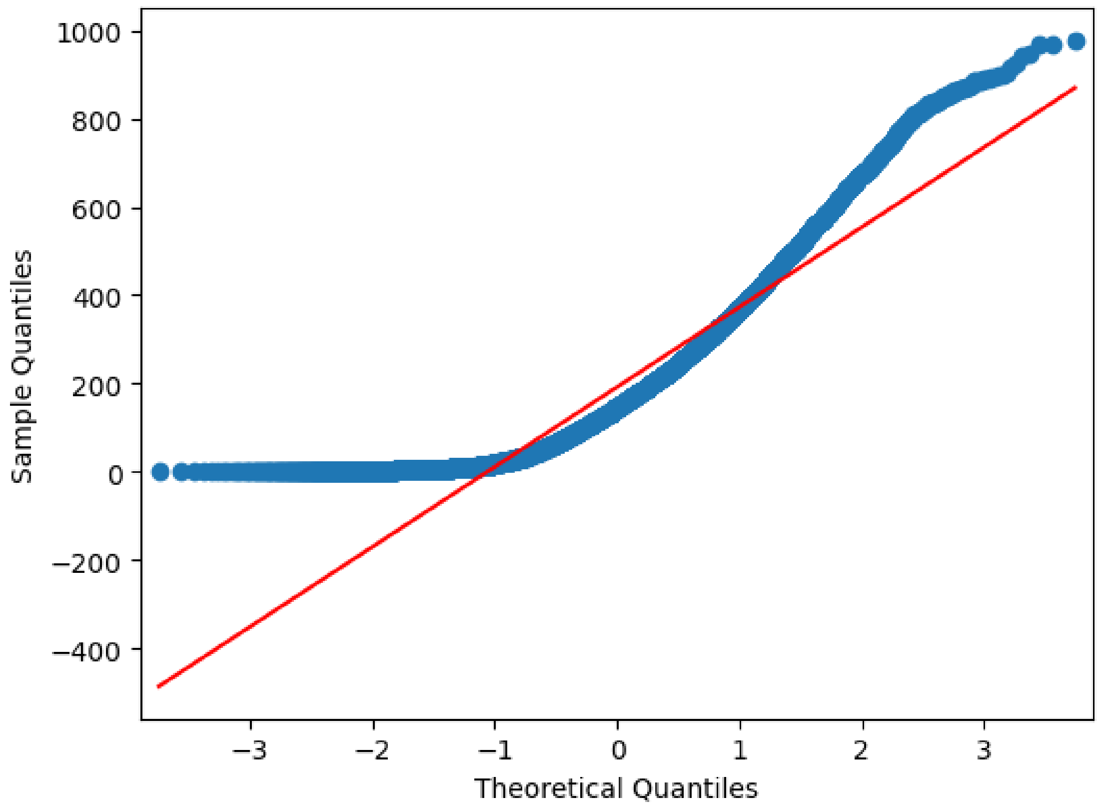
1. Data should follow a Gaussian distribution
2. Independent groups
3. Equal variance in all the groups

1. Normality Test

For this, curve test and qq-plot has to be used

[ ]:
```
# curve test
sns.kdeplot(df, x='count', hue='weather')

# Q-Q plot
sm.qqplot(df['count'], line='s')

plt.show()
```


weather
Clear
Cloudy
Light Rain
Heavy Rain
0.0020
0.0015
0.0010
0.0005
0.0000
Density
0
200
400
600
800
1000
count



From the plots, it is clear that the data is not a normal distribution.

2. Independent groups

This condition is already satisfied since all weather conditions are independent of each other

3. Equal Variance Test

For this, levene test is used

[ ]:
```
H0 = 'Variance is same for all weather conditions'
Ha = 'Variance is not same for all weather conditions'

# levene test
alpha = 0.05
stat, p_val = stats.levene(df[df['weather'] == 'Clear']['count'],␣
 ↪df[df['weather'] == 'Cloudy']['count'], df[df['weather'] == 'Heavy␣
 ↪Rain']['count'], df[df['weather'] == 'Light Rain']['count'])

print(f'levene-statistic: {stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
```

```
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
levene-statistic: 54.85106195954556
p-value: 3.504937946833238e-35
alpha: 0.05

Result: Reject Null Hypothesis
Variance is not same for all weather conditions
```

From this, we can say that variance is not same for all weather conditions and third assumption failed.

This data is not suitable to perform a ANOVA test since the first and third assumptions are not met.

So we have to try Kruskal Wallis Test

Kruskal Wallis Test **Null Hypothesis:** Average number of bike rentals is same for all weather conditions.

Alternate Hypothesis: Average number of bike rentals is different for different weather conditions.

[ ]:
```
H0 = 'Average number of bike rentals is same for all weather conditions'
Ha = 'Average number of bike rentals is different for different weather␣
 ↪conditions'

# Kruskal wallis Test
alpha = 0.05
stat, p_val = stats.kruskal(df[df['weather'] == 'Clear']['count'],␣
 ↪df[df['weather'] == 'Cloudy']['count'], df[df['weather'] == 'Heavy␣
 ↪Rain']['count'], df[df['weather'] == 'Light Rain']['count'])

print(f'kruskal-statistic: {stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')

if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
kruskal-statistic: 205.00216514479087
p-value: 3.501611300708679e-44
alpha: 0.05

Result: Reject Null Hypothesis
Average number of bike rentals is different for different weather conditions
```

1.5.4 Effect of Weather on Season

[ ]:
```python
ws_table = pd.crosstab(df['weather'], df['season'])
ws_table
```

[ ]:

season weather	fall	spring	summer	winter
Clear	1930	1759	1801	1702
Cloudy	604	715	708	807
Heavy Rain	0	1	0	0
Light Rain	199	211	224	225

This is categorical vs categorical, we can use chi-square test.

Null Hypothesis: Weather and Season are Independent

Alternate Hypothesis: Weather and Season are Dependent

[ ]:
```python
H0 = 'Weather and Season are Independent'
Ha = 'Weather and Season are Dependent'

# chi-square test
alpha = 0.05
stat, p_val= stats.chi2_contingency(ws_table)[0], stats.
 ↪chi2_contingency(ws_table)[1]

print(f'chi-statistic: {stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')

if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
chi-statistic: 49.15865559689363
p-value: 1.5499250736864862e-07
alpha: 0.05

Result: Reject Null Hypothesis
```

```
Weather and Season are Dependent
```

2 Insights

- There are more bike rentals on fall season.
- There are more bike rentals on Clear weather.
- There are more bike rentals on working day but we can't find much difference on average.
- June stands out as the peak month for bike rentals, followed closely by July and August.
- January, February, and March have notably lower bike rental counts, indicating potential off-peak periods, possibly influenced by colder weather or fewer outdoor activities.
- Saturday stands out as the peak day for bike rentals and also we can see that there is mo much difference in bike rentals among weekdays.
- count column has positive correlation with atemp and and negative with humidity. We can see people go out with bike more when the temp is high and humidity is low.
- Working day doesn't affect bike rentals i.e., Average number of bike rentals on the working day is same as the average number of bike rentals on the non-working day.
- Season affect bike rentals i.e., Average number of bike rentals is different for different seasons.
- Weather affect bike rentals i.e., Average number of bike rentals is different for different weather conditions.
- Weather and Season columns depends on each other.

3 Recommendations

- **Flexible Pricing Models:** Implement dynamic pricing models that adjust rental rates based on demand, season, and weather conditions to maximize revenue and utilization.
- **Inventory Management:** Ensure adequate availability of bikes during peak seasons and weekends. Conversely, optimize maintenance schedules during off-peak months to ensure bikes are ready for high-demand periods.
- **Fall Season Promotions:** Since there are more rentals in the fall, consider offering seasonal promotions such as discounts for long-term rentals or special deals for new customers.
- **Winter Incentives:** Given the lower rentals in January, February, and March, implement winter incentives like reduced prices, special bundled offers (e.g., bike rental plus hot beverage), or loyalty rewards for frequent renters.
- **Clear Weather Marketing:** Increase marketing efforts during clear weather days. Utilize weather forecasts to predict clear days and promote bike rentals through social media, email campaigns, and local advertising.
- **Rainy Day Discounts:** Offer discounts or incentives on rainy or less clear days to encourage rentals despite the weather conditions.

- **Weekend rider programs:** Develop weekend rental packages or extend Saturday operating hours to capitalize on the observed peak ridership on Saturdays.
- **Partner with Local Events:** Collaborate with local events, festivals, and outdoor activities during peak months and clear weather days to offer bike rentals as a convenient transportation option, thereby increasing visibility and rentals.
- **Surveys and Feedback:** Regularly gather feedback from customers about their preferences for seasons, weather conditions, and rental experiences to fine-tune strategies and improve service offerings.
- **Loyalty Programs:** Develop loyalty programs that reward frequent renters, especially targeting those who rent bikes during off-peak periods to encourage repeat business.