```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr
from scipy.stats import spearmanr
from scipy.stats import probplot
from scipy.stats import ttest_ind
from scipy.stats import ttest_rel
from scipy.stats import chi2, chisquare, chi2_contingency
from scipy.stats import f_oneway, levene
import statsmodels.api as sm
from scipy.stats import shapiro
import warnings
warnings.filterwarnings('ignore')

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

```python
data.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

# Changing data type od date
data['datetime'] = pd.to_datetime(data.datetime)

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  datetime64[ns]
 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: datetime64[ns](1), float64(3), int64(8)
memory usage: 1020.7 KB

for i in data.columns[1:5]:
    data[i] = data[i].astype('category')

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  datetime64[ns]
 1   season      10886 non-null  category
 2   holiday     10886 non-null  category
 3   workingday  10886 non-null  category
 4   weather     10886 non-null  category
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
```

```
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: category(4), datetime64[ns](1), float64(3), int64(4)
memory usage: 723.7 KB
```

```python
# Checking null values in dataframe
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
```

```python
# Checking duplicated values in dataframe
data.duplicated().sum()
```

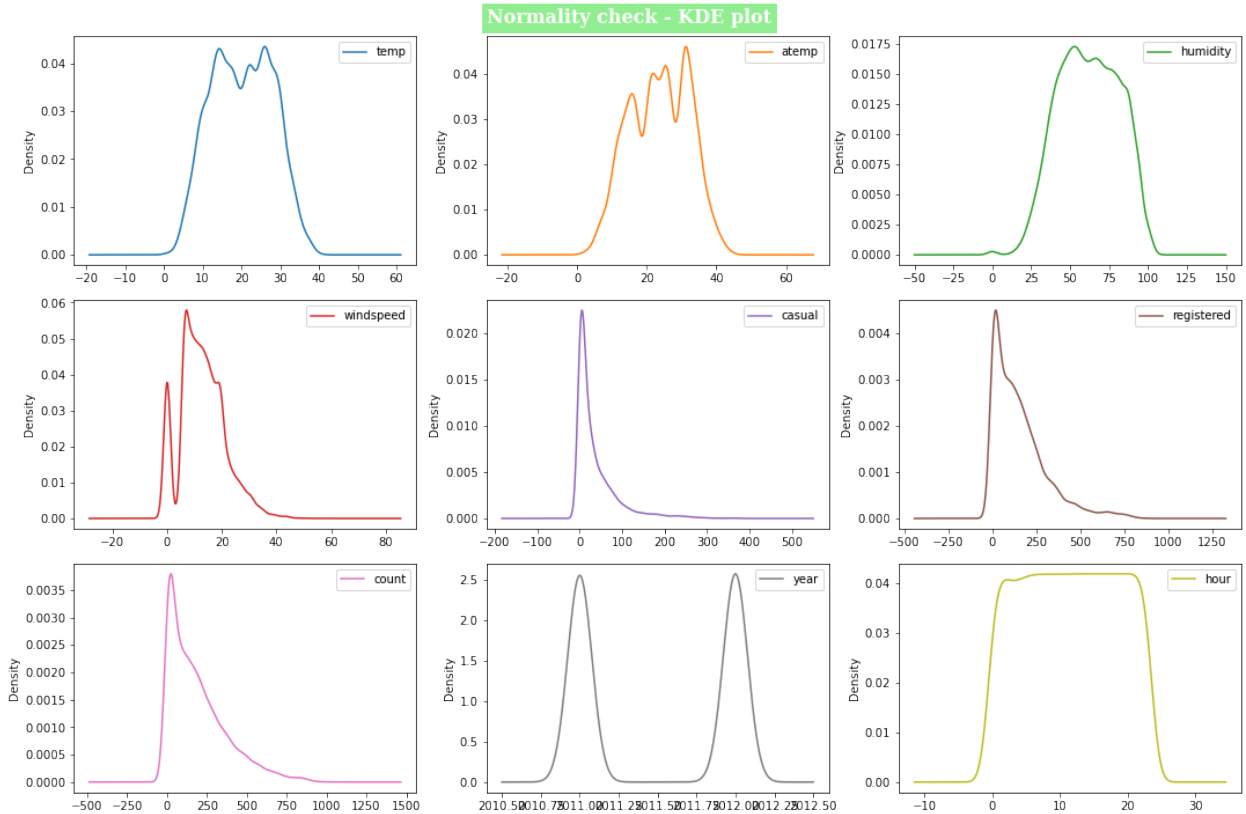
```
0
```

```python
data.describe().T
```

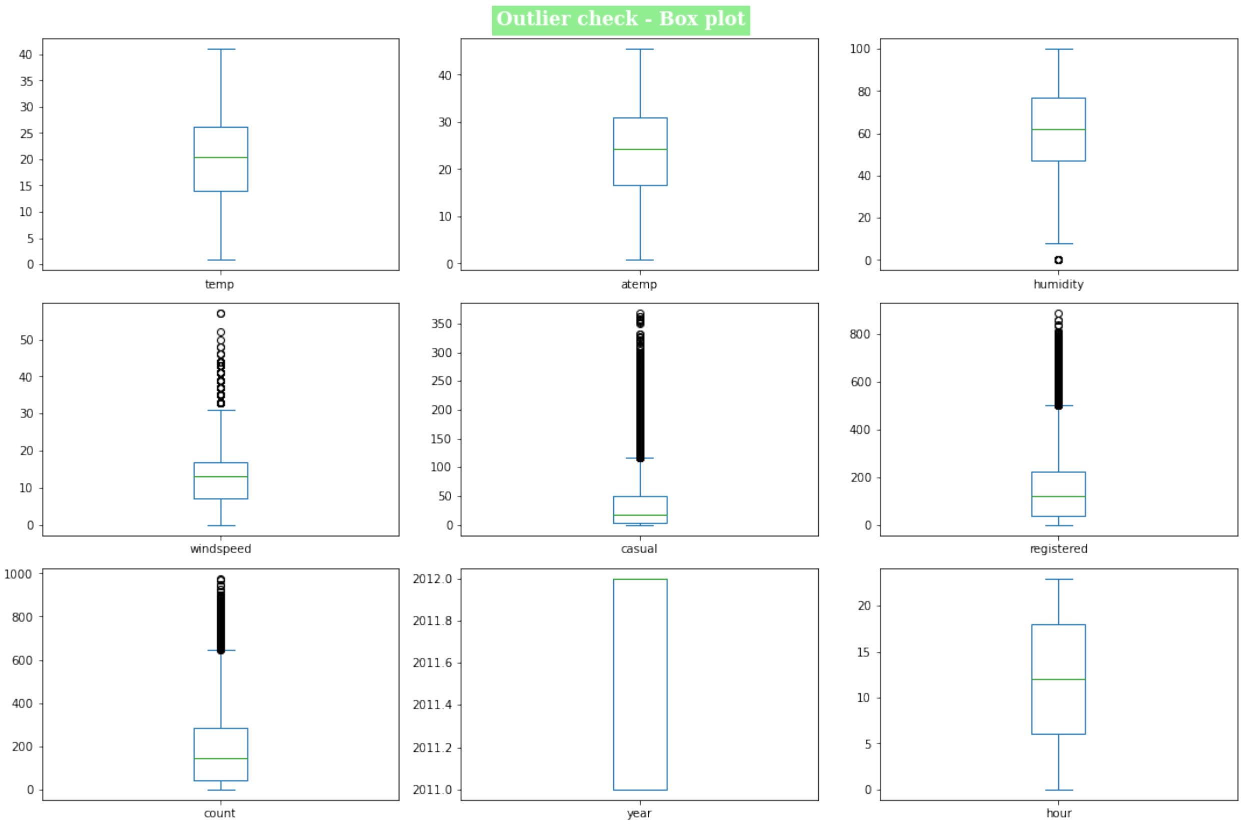
```
              count        mean         std   min      25%      50%
75%  \
temp        10886.0   20.230860    7.791590  0.82  13.9400   20.500
26.2400
atemp       10886.0   23.655084    8.474601  0.76  16.6650   24.240
31.0600
humidity    10886.0   61.886460   19.245033  0.00  47.0000   62.000
77.0000
windspeed   10886.0   12.799395    8.164537  0.00   7.0015   12.998
16.9979
casual      10886.0   36.021955   49.960477  0.00   4.0000   17.000
49.0000
registered  10886.0  155.552177  151.039033  0.00  36.0000  118.000
222.0000
count       10886.0  191.574132  181.144454  1.00  42.0000  145.000
284.0000

                 max
temp         41.0000
```

```
atemp          45.4550
humidity      100.0000
windspeed      56.9969
casual        367.0000
registered    886.0000
count         977.0000
```

```
data['year'] = data['datetime'].dt.year
data['month'] = data['datetime'].dt.month
data['hour'] = data['datetime'].dt.hour
data['month'] = data['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'})
data['day'] = data['datetime'].dt.day_name()


plt.rcParams['figure.figsize'] = [15, 10]

# Collect columns that are 'int64' or 'float64' dtype
numeric_cols = [col for col in data.columns if data[col].dtype in
['int64', 'float64']]

# Plot KDE for each numeric column
data[numeric_cols].plot(kind='kde', subplots=True, layout=(3, 3),
sharex=False)

# Set the overall title for the entire figure
plt.suptitle('Normality check - KDE plot', fontsize=16,
fontfamily='serif', fontweight='bold', backgroundcolor='lightgreen',
color='w')

plt.tight_layout()  # Adjust the layout to make room for the suptitle
plt.show()
```




```python
plt.rcParams['figure.figsize'] = [15, 10]
# Plot KDE for each numeric column
data[numeric_cols].plot(kind='box', subplots=True, layout=(3, 3),
sharex=False)

# Set the overall title for the entire figure
plt.suptitle('Outlier check - Box plot', fontsize=16,
fontfamily='serif', fontweight='bold', backgroundcolor='lightgreen',
color='w')

plt.tight_layout()  # Adjust the layout to make room for the suptitle
plt.show()
```



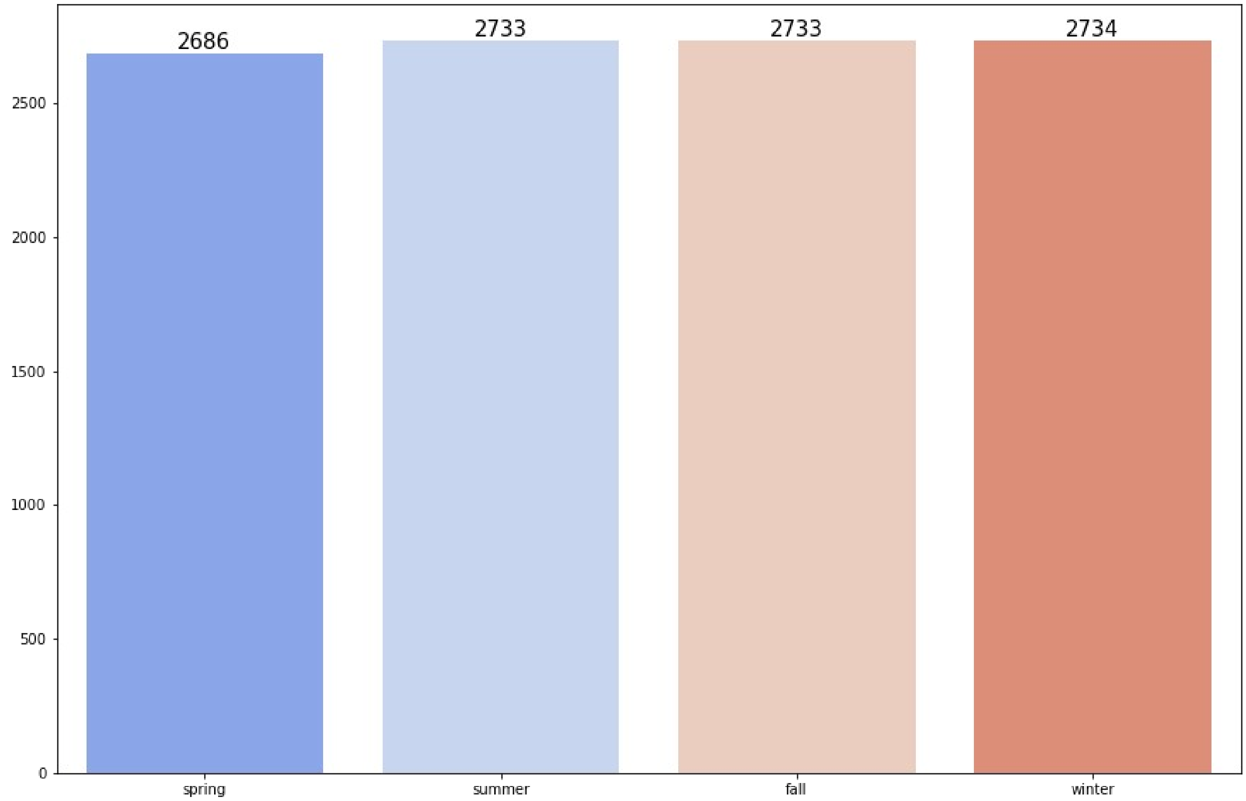

```python
# Map numerical values to season names
season_mapping = {1: 'spring', 2: 'summer', 3: 'fall', 4: 'winter'}
data['season'] = data['season'].map(season_mapping)
data
```

```
                  datetime  season holiday workingday weather   temp
atemp  \
0     2011-01-01 00:00:00  spring       0          0       1   9.84
14.395
1     2011-01-01 01:00:00  spring       0          0       1   9.02
13.635
2     2011-01-01 02:00:00  spring       0          0       1   9.02
13.635
3     2011-01-01 03:00:00  spring       0          0       1   9.84
14.395
4     2011-01-01 04:00:00  spring       0          0       1   9.84
14.395
...                   ...     ...     ...        ...     ...    ...
...
10881 2012-12-19 19:00:00  winter       0          1       1  15.58
19.695
10882 2012-12-19 20:00:00  winter       0          1       1  14.76
17.425
10883 2012-12-19 21:00:00  winter       0          1       1  13.94
15.910
```

```
10884 2012-12-19 22:00:00  winter       0          1        1  13.94
17.425
10885 2012-12-19 23:00:00  winter       0          1        1  13.12
16.665

       humidity  windspeed  casual  registered  count  year     month
hour  \
0            81     0.0000       3          13     16  2011   January
0
1            80     0.0000       8          32     40  2011   January
1
2            80     0.0000       5          27     32  2011   January
2
3            75     0.0000       3          10     13  2011   January
3
4            75     0.0000       0           1      1  2011   January
4
...         ...        ...     ...         ...    ...   ...       ...
...
10881        50    26.0027       7         329    336  2012  December
19
10882        57    15.0013      10         231    241  2012  December
20
10883        61    15.0013       4         164    168  2012  December
21
10884        61     6.0032      12         117    129  2012  December
22
10885        66     8.9981       4          84     88  2012  December
23

             day
0       Saturday
1       Saturday
2       Saturday
3       Saturday
4       Saturday
...          ...
10881  Wednesday
10882  Wednesday
10883  Wednesday
10884  Wednesday
10885  Wednesday

[10886 rows x 16 columns]
```

```
# Season wise count
season = data.season.value_counts()
ax = sns.barplot(x = season.index, y = season.values, palette =
'coolwarm')
```

```
ax.bar_label(ax.containers[0], fontsize=15)
plt.show()
```




```
data.workingday.value_counts()
```

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

```
data.weather.value_counts()
```

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

```
# Mapping holiday
holiday_mapped = {0: 'Not_holiday', 1: 'Holiday'}
data['holiday'] = data['holiday'].map(holiday_mapped)
data
```

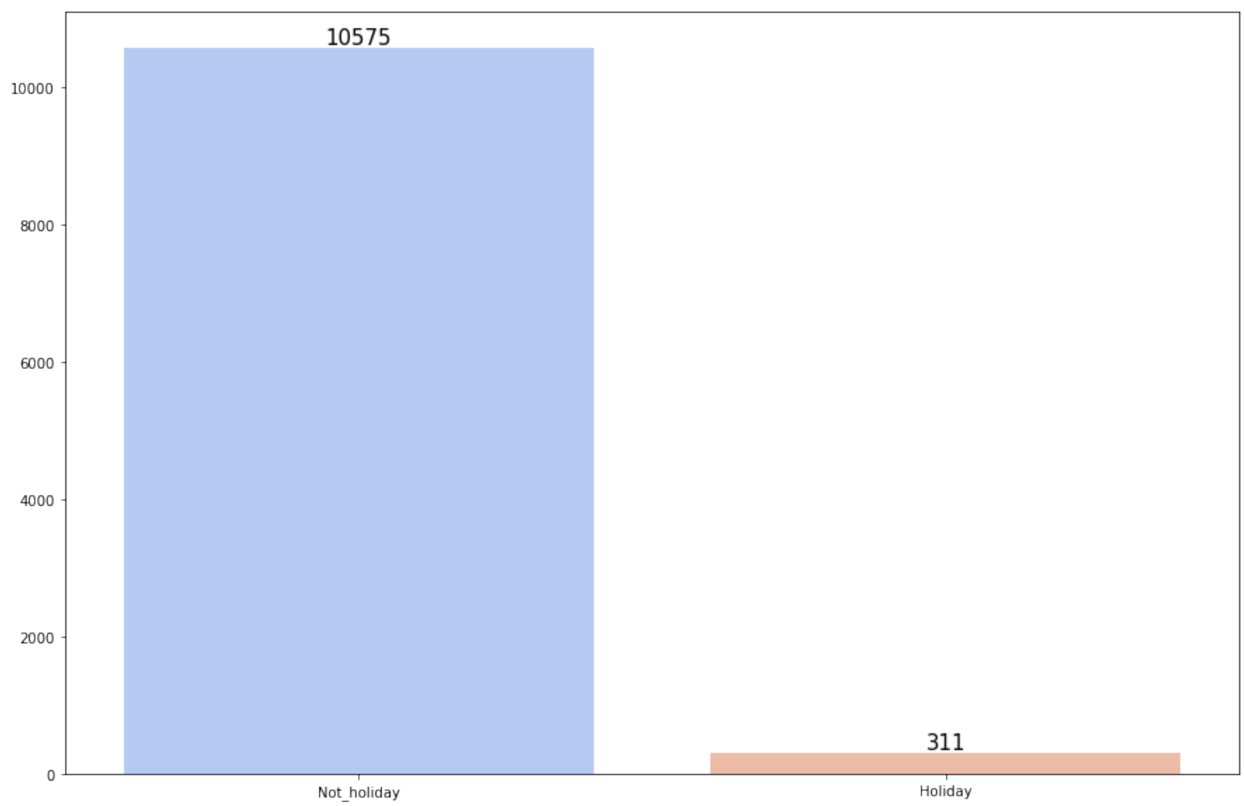
```
                 datetime  season      holiday workingday weather
temp  \
0     2011-01-01 00:00:00  spring  Not_holiday          0       1
```

```
9.84
1     2011-01-01 01:00:00  spring  Not_holiday          0       1
9.02
2     2011-01-01 02:00:00  spring  Not_holiday          0       1
9.02
3     2011-01-01 03:00:00  spring  Not_holiday          0       1
9.84
4     2011-01-01 04:00:00  spring  Not_holiday          0       1
9.84
...                   ...     ...          ...        ...     ...    .
..
10881 2012-12-19 19:00:00  winter  Not_holiday          1       1
15.58
10882 2012-12-19 20:00:00  winter  Not_holiday          1       1
14.76
10883 2012-12-19 21:00:00  winter  Not_holiday          1       1
13.94
10884 2012-12-19 22:00:00  winter  Not_holiday          1       1
13.94
10885 2012-12-19 23:00:00  winter  Not_holiday          1       1
13.12

        atemp  humidity  windspeed  casual  registered  count  year
month  \
0      14.395        81     0.0000       3          13     16  2011
January
1      13.635        80     0.0000       8          32     40  2011
January
2      13.635        80     0.0000       5          27     32  2011
January
3      14.395        75     0.0000       3          10     13  2011
January
4      14.395        75     0.0000       0           1      1  2011
January
...       ...       ...        ...     ...         ...    ...   ...
...
10881  19.695        50    26.0027       7         329    336  2012
December
10882  17.425        57    15.0013      10         231    241  2012
December
10883  15.910        61    15.0013       4         164    168  2012
December
10884  17.425        61     6.0032      12         117    129  2012
December
10885  16.665        66     8.9981       4          84     88  2012
December

       hour       day
0         0  Saturday
```

```
1          1   Saturday
2          2   Saturday
3          3   Saturday
4          4   Saturday
...      ...        ...
10881     19  Wednesday
10882     20  Wednesday
10883     21  Wednesday
10884     22  Wednesday
10885     23  Wednesday

[10886 rows x 16 columns]
```

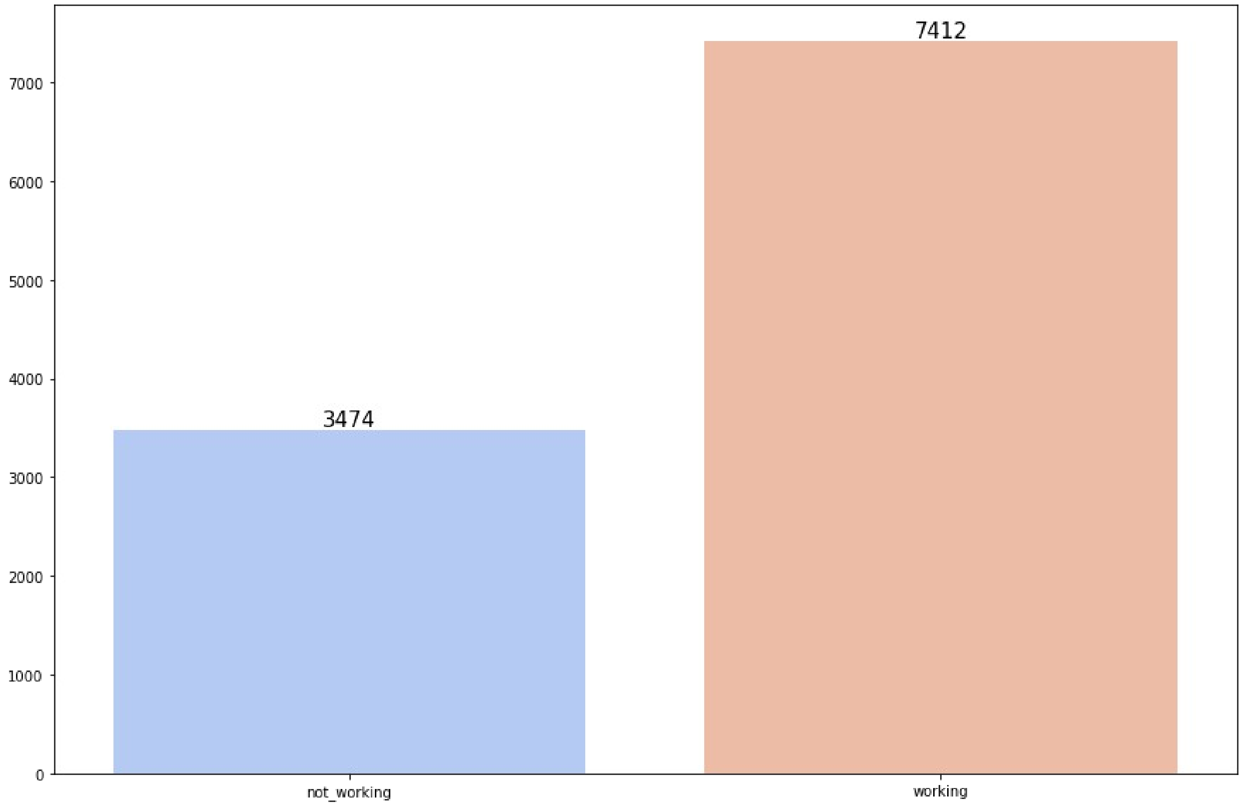
```
holiday = data.holiday.value_counts()
ax = sns.barplot(x = holiday.index, y = holiday.values, palette =
'coolwarm')
ax.bar_label(ax.containers[0], fontsize=15)
```

```
[Text(0, 0, '10575'), Text(0, 0, '311')]
```

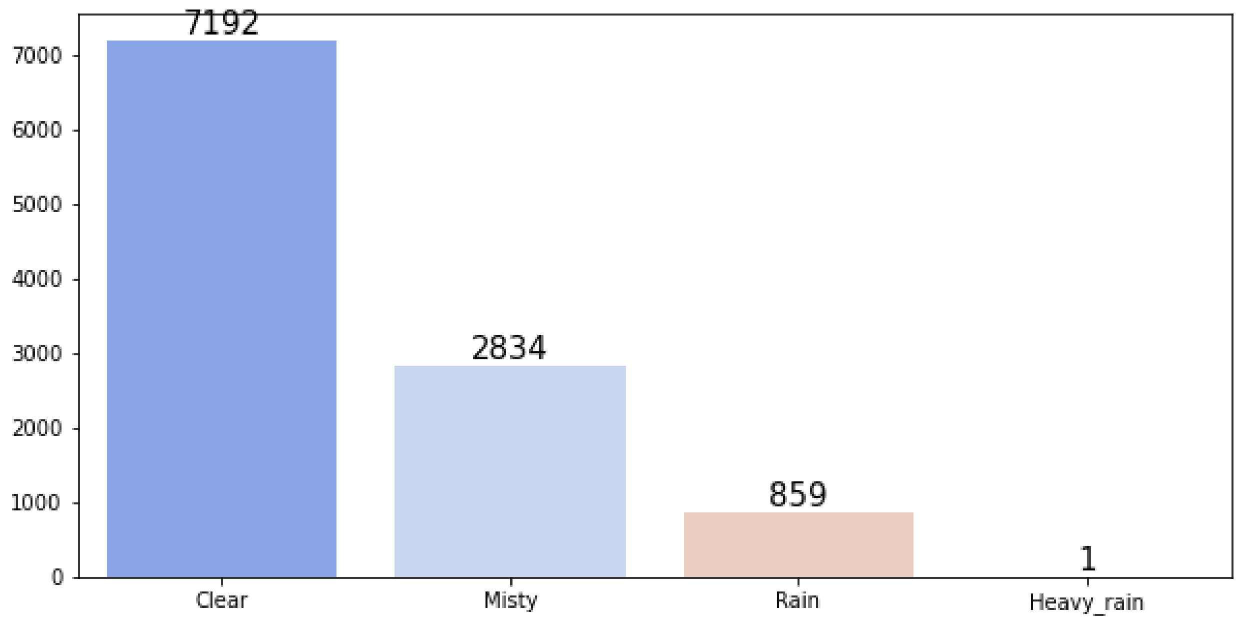



```
workingday_mapped = {1: 'working', 0: 'not_working'}
data['workingday'] = data['workingday'].map(workingday_mapped)

working = data.workingday.value_counts()
ax = sns.barplot(x = working.index, y = working.values, palette =
```

```
'coolwarm')
ax.bar_label(ax.containers[0], fontsize=15)

[Text(0, 0, '3474'), Text(0, 0, '7412')]
```

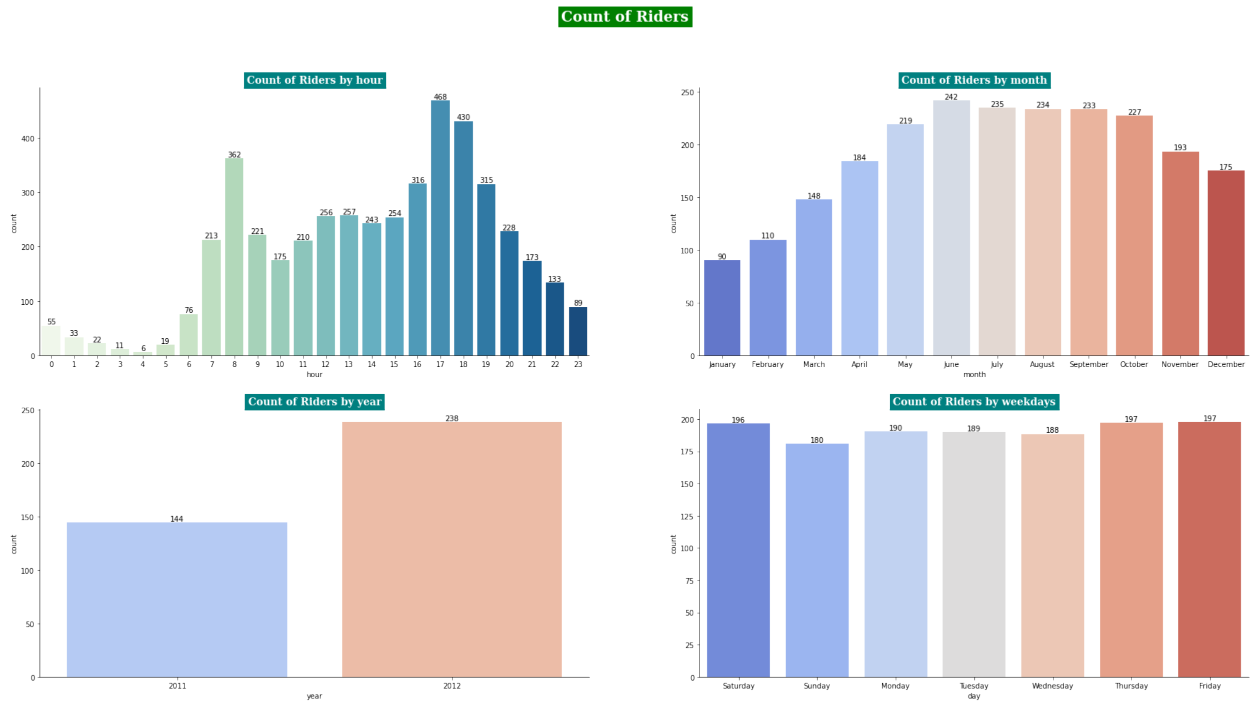



```
weather_mapped = {1: 'Clear', 2: 'Misty', 3: 'Rain', 4: 'Heavy_rain'}
data['weather'] = data['weather'].map(weather_mapped)

plt.figure(figsize = (10, 5))
weather = data.weather.value_counts()
ax = sns.barplot(x= weather.index, y= weather.values, palette =
'coolwarm')
ax.bar_label(ax.containers[0], fontsize=15)
plt.show()
```

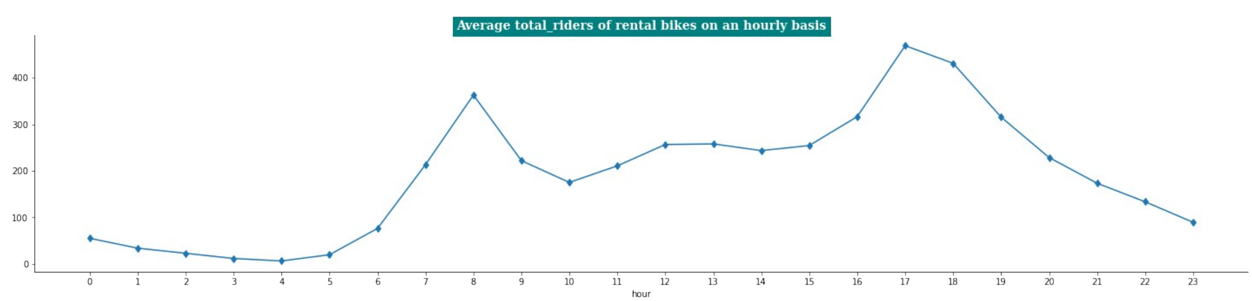



```
data.dtypes

datetime      datetime64[ns]
season              category
holiday             category
workingday          category
weather             category
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
year                   int64
month                 object
hour                   int64
day                   object
dtype: object

# for _ in data.columns[5:]:
#         print(f'Value_counts of the column {_} are :-
{data[_].value_counts().to_frame().reset_index()}')
#         print()
#         print('-'*140)
#         print()

# Count of riders

plt.figure(figsize=(30,15))
plt.suptitle('Count of
```

```
Riders',fontsize=20,fontfamily='serif',fontweight='bold',backgroundcol
or='green',color='w')

plt.subplot(221)
b=sns.barplot(data=data, x="hour", y="count",palette='GnBu',ci=None)
b.bar_label(b.containers[0],fmt='%d') # %d-int
plt.title('Count of Riders by
hour',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor
='teal',color='w')

plt.subplot(222)
b=sns.barplot(data=data, x="month",
y="count",palette='coolwarm',ci=None)
b.bar_label(b.containers[0], label_type='edge',fmt='%d')
plt.title('Count of Riders by
month',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolo
r='teal',color='w')

plt.subplot(223)
b=sns.barplot(data=data, x="year",
y="count",palette='coolwarm',ci=None)
b.bar_label(b.containers[0], label_type='edge',fmt='%d')
plt.title('Count of Riders by
year',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor
='teal',color='w')

plt.subplot(224)
b=sns.barplot(data=data, x="day",
y="count",palette='coolwarm',ci=None)
b.bar_label(b.containers[0], label_type='edge',fmt='%d')
plt.title('Count of Riders by
weekdays',fontsize=14,fontfamily='serif',fontweight='bold',backgroundc
olor='teal',color='w')
sns.despine()

plt.show()
```

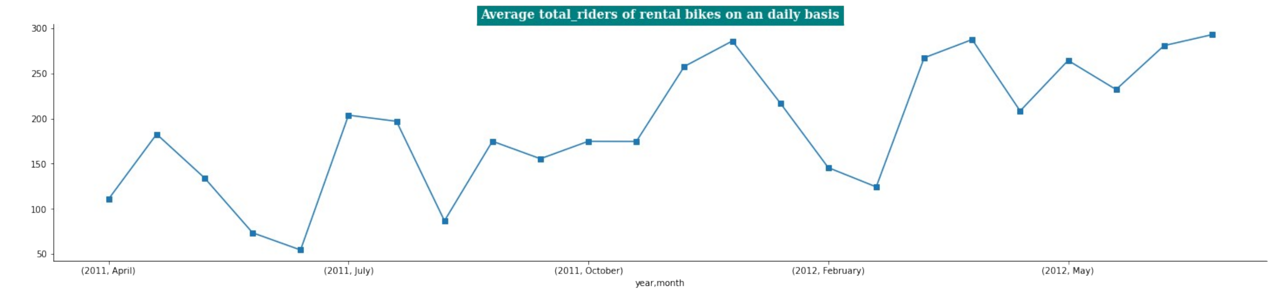



```
# Count by hourly basis

plt.figure(figsize = (25,5))
plt.title("Average total_riders of rental bikes on an hourly basis"
          ,fontsize=14,fontfamily='serif',fontweight='bold',background
color='teal',color='w')
data.groupby('hour')['count'].mean().plot(kind = 'line', marker = 'd')
plt.xticks(np.arange(0, 24))
sns.despine()
plt.show()
```



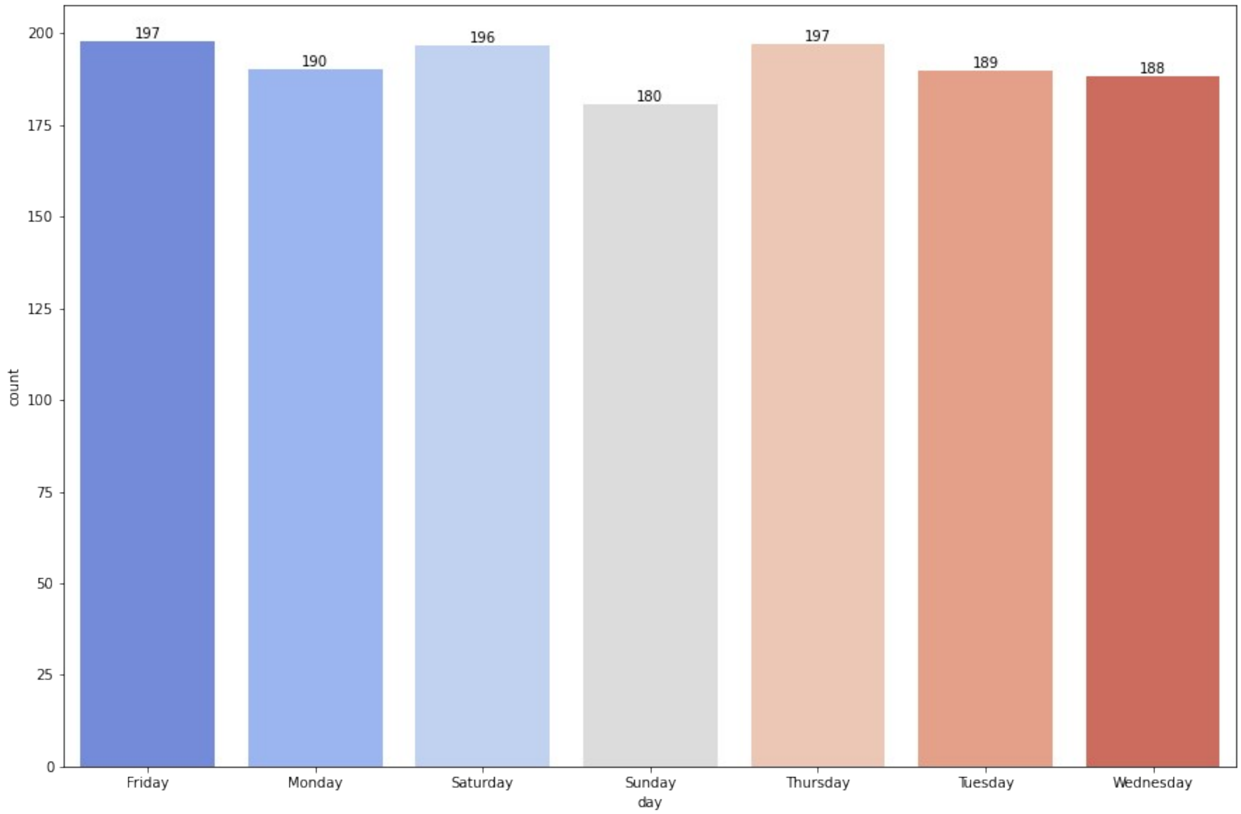

```
plt.figure(figsize = (25,5))
plt.title("Average total_riders of rental bikes on an daily basis"
          ,fontsize=14,fontfamily='serif',fontweight='bold',background
color='teal',color='w')
data.groupby(['year','month'])['count'].mean().plot(kind = 'line',
marker = 's')
sns.despine()
```

```
plt.show()
```




```
day_cnt_riders=data.groupby('day')
['count'].mean().to_frame().reset_index()
display(day_cnt_riders)
b = sns.barplot(x= 'day', y= 'count', data = day_cnt_riders, palette =
'coolwarm')
b.bar_label(b.containers[0], label_type='edge',fmt='%d')
plt.show()
```

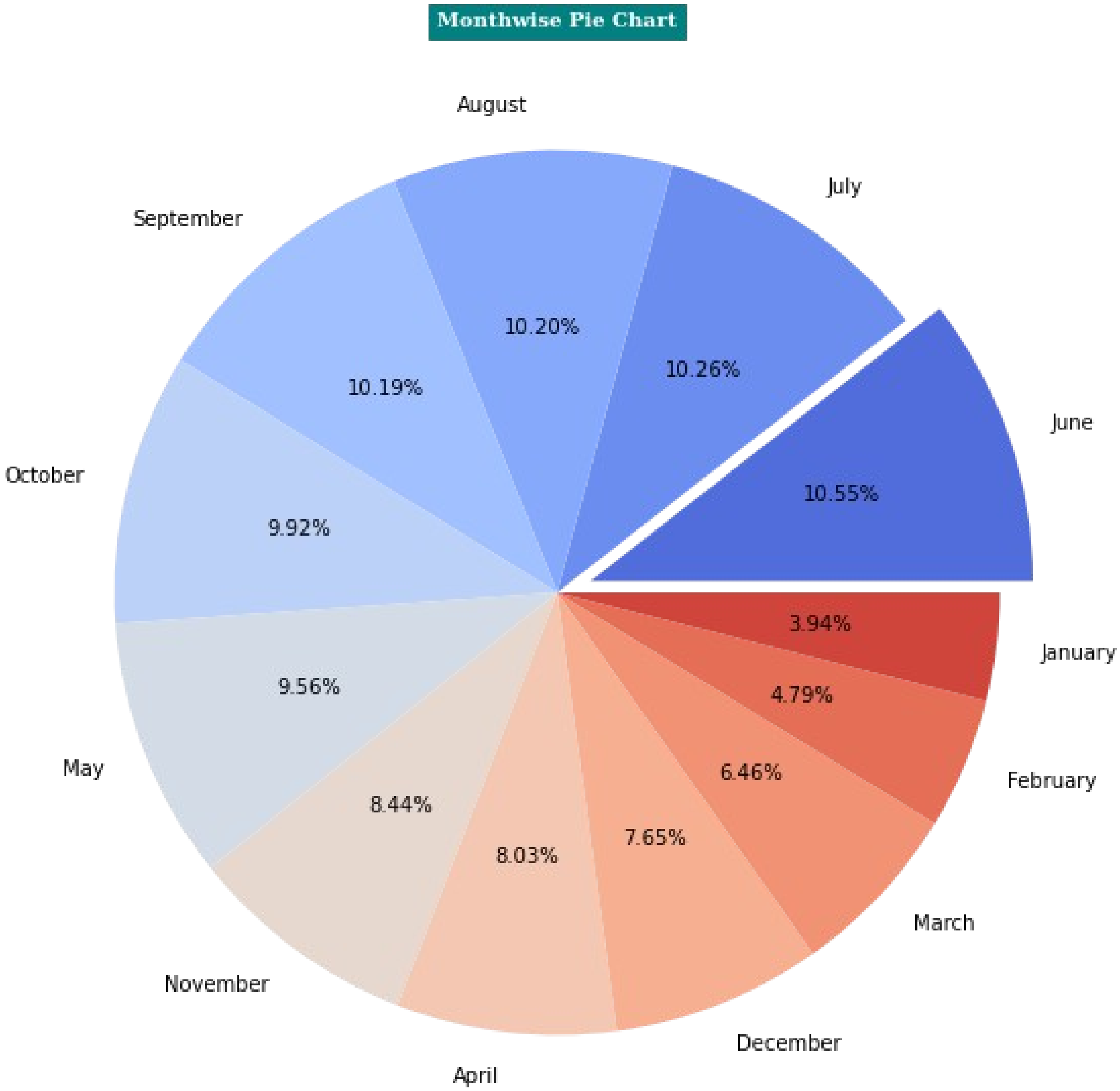
	day	count
0	Friday	197.844343
1	Monday	190.390716
2	Saturday	196.665404
3	Sunday	180.839772
4	Thursday	197.296201
5	Tuesday	189.723847
6	Wednesday	188.411348




```
monthwise_cnt = data.groupby('month')
['count'].mean().sort_values(ascending=False).to_frame().reset_index()
display(monthwise_cnt)
colors = sns.color_palette('coolwarm', len(monthwise_cnt))
plt.pie(data=monthwise_cnt,
x=monthwise_cnt['count'],labels=monthwise_cnt['month'],colors =
colors,
        explode=(0.08,0,0,0,0,0,0,0,0,0,0,0), autopct='%0.2f%%')
plt.title('Monthwise Pie
Chart',fontsize=10,fontfamily='serif',fontweight='bold',backgroundcolo
r='teal',color='w')
```

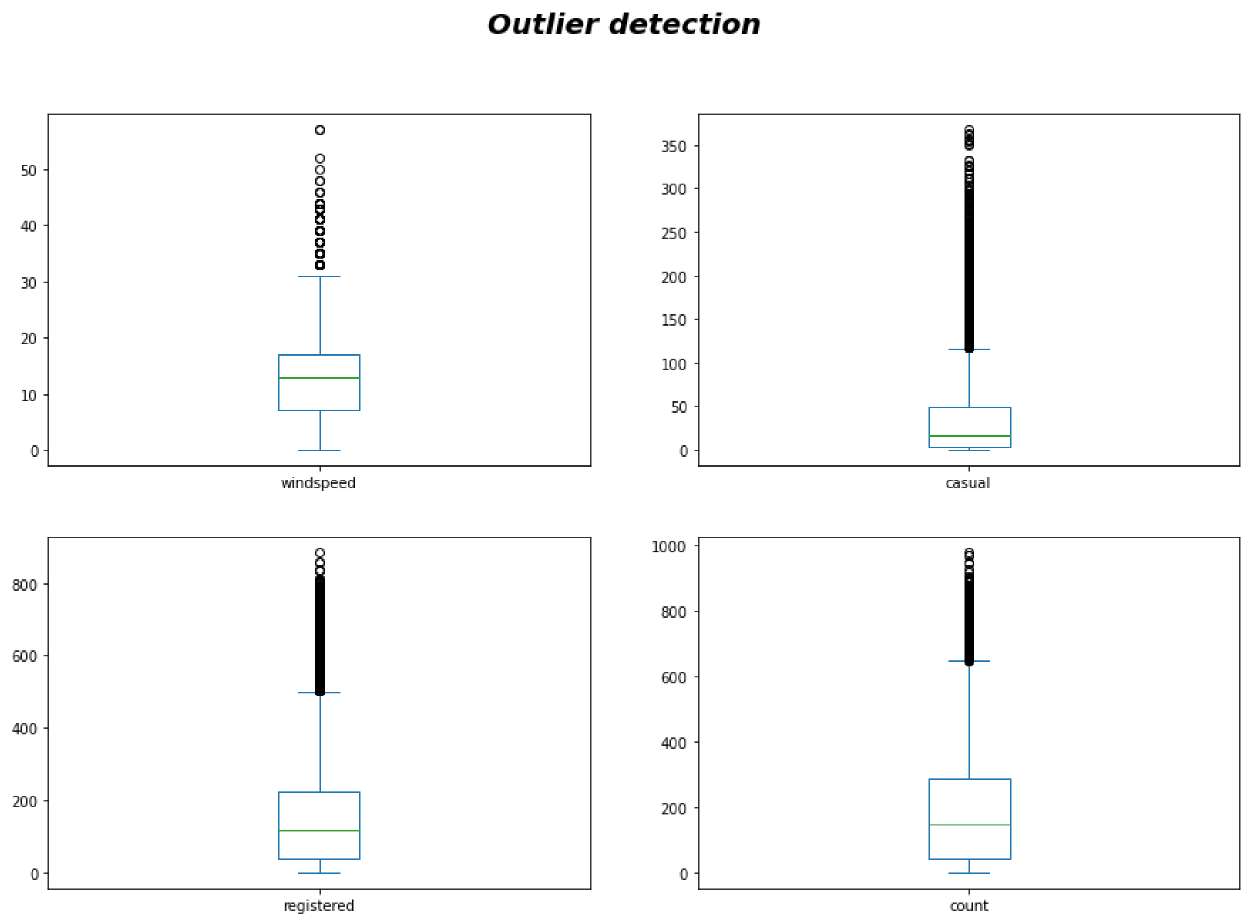
	month	count
0	June	242.031798
1	July	235.325658
2	August	234.118421
3	September	233.805281
4	October	227.699232
5	May	219.459430
6	November	193.677278
7	April	184.160616
8	December	175.614035
9	March	148.169811
10	February	110.003330
11	January	90.366516

```
Text(0.5, 1.0, 'Monthwise Pie Chart')
```



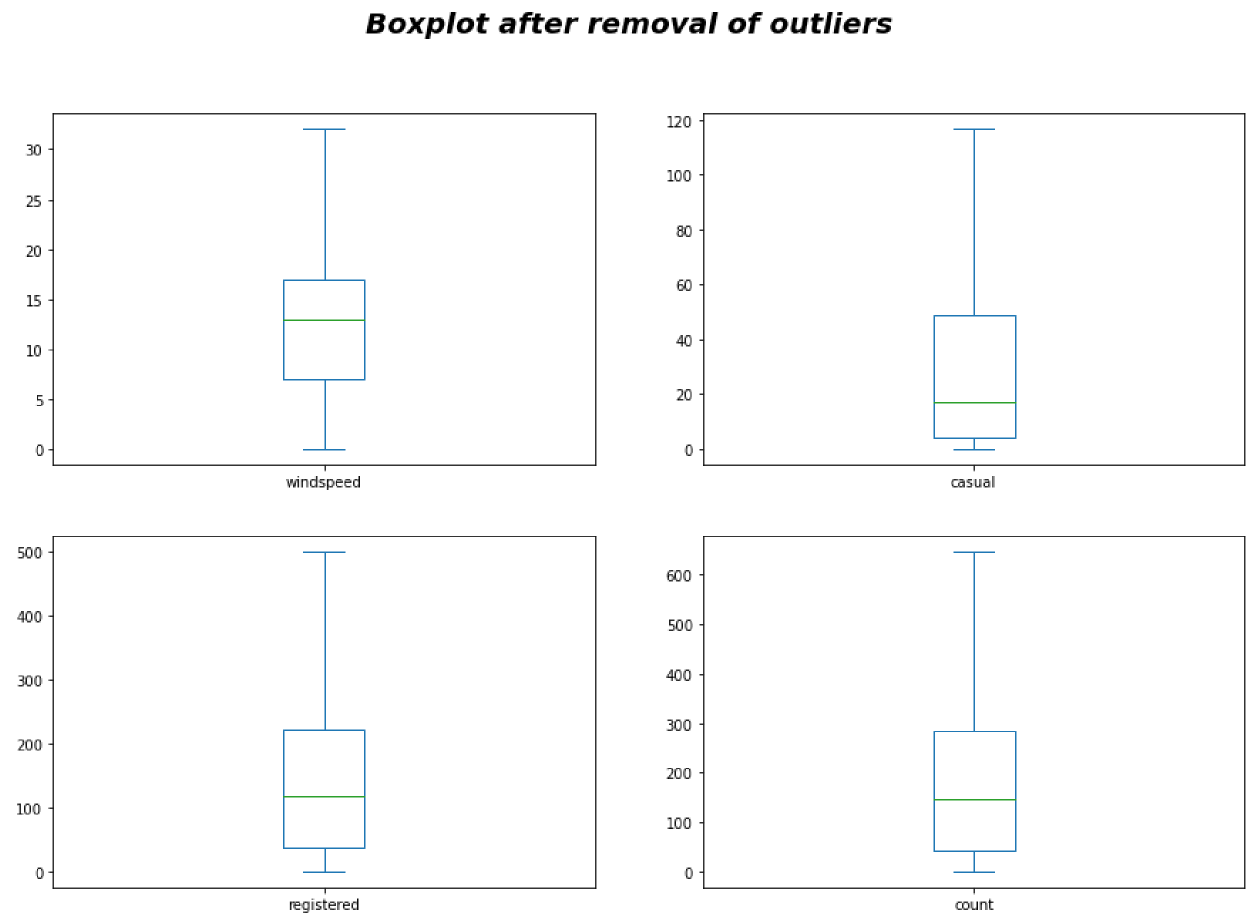

```
# Outlier detection
plt.figure(figsize = (12, 4))
data_outlier = data.iloc[:, 8:12]
plt.rcParams['figure.figsize'] = [15, 10]
data_outlier.plot(kind = 'box', subplots = True, layout = (2,2),
sharex = False)
plt.suptitle('Outlier detection', fontsize = 20, fontweight = 'bold',
fontstyle = 'italic')
plt.show()
```

```
<Figure size 864x288 with 0 Axes>
```




```
# Outlier removal using IQR method for each column
for col in data_outlier.columns:
    Q1 = data_outlier[col].quantile(0.25)
    Q3 = data_outlier[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - IQR * 1.5
    upper_bound = Q3 + IQR * 1.5
    data_outlier[col] = data_outlier[col].clip(lower=lower_bound,
upper=upper_bound)

print('After removing outliers')


# Box plot of the clipped data
plt.rcParams['figure.figsize'] = [15, 10]
data_outlier.plot(kind='box', subplots=True, layout=(2, 2),
sharex=False)
plt.suptitle('Boxplot after removal of outliers', fontsize=20,
```

```
fontweight='bold', fontstyle='italic')
plt.show()

After removing outliers
```




```
# Correlation

data_numeric = data.select_dtypes(include=np.number)

for col in data_numeric.columns:
    pearson_coef, _ = pearsonr(data_numeric[col],
data_numeric['count'])
    spearman_coef, _ = spearmanr(data_numeric[col],
data_numeric['count'])

    if spearman_coef > 0:
        if spearman_coef > 0.5:
            print('There is Strong Positive correlation between
total_riders and', col,
                  '- pearson-corrcoef: ', np.round(pearson_coef, 2))
            print('There is Strong Positive correlation between
```

```
total_riders and', col,
                  '- spearman-corrcoef: ', np.round(spearman_coef, 2))
        else:
            print('There is Weak Positive correlation between
total_riders and', col,
                  '- pearson-corrcoef: ', np.round(pearson_coef, 2))
            print('There is weak Positive correlation between
total_riders and', col,
                  '- spearman-corrcoef: ', np.round(spearman_coef, 2))
    elif spearman_coef == 0:
        print('There is No correlation between total_riders and', col,
              '- pearson-corrcoef: ', np.round(pearson_coef, 2))
        print('There is No correlation between total_riders and', col,
              '- spearman-corrcoef: ', np.round(spearman_coef, 2))
    else:
        if spearman_coef < -0.5:
            print('There is Strong Negative correlation between
total_riders and', col,
                  '- pearson-corrcoef: ', np.round(pearson_coef, 2))
            print('There is Strong Negative correlation between
total_riders and', col,
                  '- spearman-corrcoef: ', np.round(spearman_coef, 2))
        else:
            print('There is Weak Positive correlation between
total_riders and', col,
                  '- pearson-corrcoef: ', np.round(pearson_coef, 2))
            print('There is weak Positive correlation between
total_riders and', col,
                  '- spearman-corrcoef: ', np.round(spearman_coef, 2))
    print()
    print('*' * 50)
```

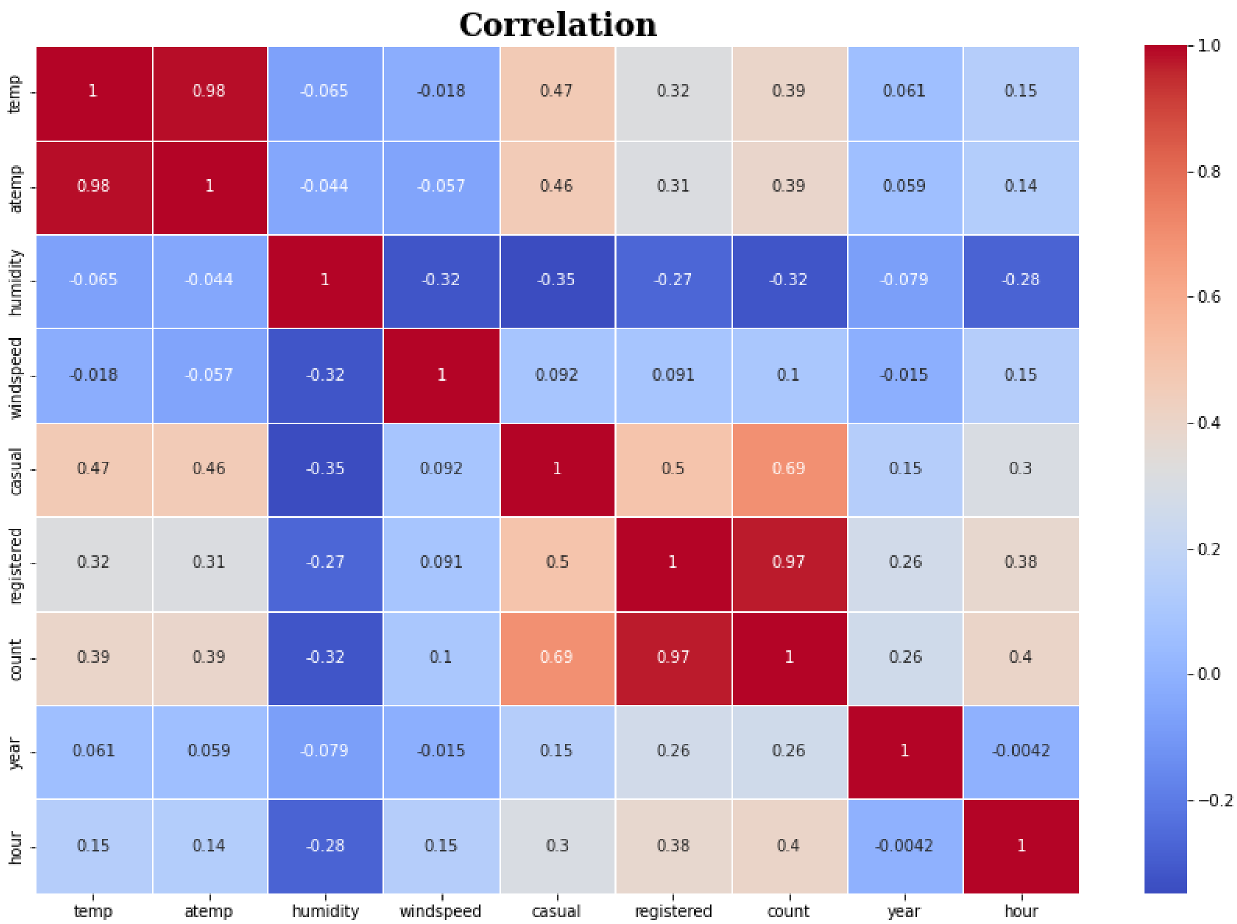
```
There is Weak Positive correlation between total_riders and temp -
pearson-corrcoef:  0.39
There is weak Positive correlation between total_riders and temp -
spearman-corrcoef:  0.41

**************************************************
There is Weak Positive correlation between total_riders and atemp -
pearson-corrcoef:  0.39
There is weak Positive correlation between total_riders and atemp -
spearman-corrcoef:  0.41

**************************************************
There is Weak Positive correlation between total_riders and humidity -
pearson-corrcoef:  -0.32
There is weak Positive correlation between total_riders and humidity -
spearman-corrcoef:  -0.35

**************************************************
```

```
There is Weak Positive correlation between total_riders and windspeed
- pearson-corrcoef:  0.1
There is weak Positive correlation between total_riders and windspeed
- spearman-corrcoef:  0.14

**************************************************
There is Strong Positive correlation between total_riders and casual -
pearson-corrcoef:  0.69
There is Strong Positive correlation between total_riders and casual -
spearman-corrcoef:  0.85

**************************************************
There is Strong Positive correlation between total_riders and
registered - pearson-corrcoef:  0.97
There is Strong Positive correlation between total_riders and
registered - spearman-corrcoef:  0.99

**************************************************
There is Strong Positive correlation between total_riders and count -
pearson-corrcoef:  1.0
There is Strong Positive correlation between total_riders and count -
spearman-corrcoef:  1.0

**************************************************
There is Weak Positive correlation between total_riders and year -
pearson-corrcoef:  0.26
There is weak Positive correlation between total_riders and year -
spearman-corrcoef:  0.22

**************************************************
There is Strong Positive correlation between total_riders and hour -
pearson-corrcoef:  0.4
There is Strong Positive correlation between total_riders and hour -
spearman-corrcoef:  0.52

**************************************************
```

```
corr_df =  data.corr()
display(corr_df)
plt.figure(figsize=(15,10))
sns.heatmap(data.corr(), annot=True, linewidth=.5,cmap='coolwarm')
plt.yticks()
plt.title('Correlation',fontfamily='serif',fontweight='bold',fontsize=
20)
plt.show()
```

```
                temp     atemp  humidity  windspeed    casual
registered  \
temp        1.000000  0.984948 -0.064949  -0.017852  0.467097
0.318571
```

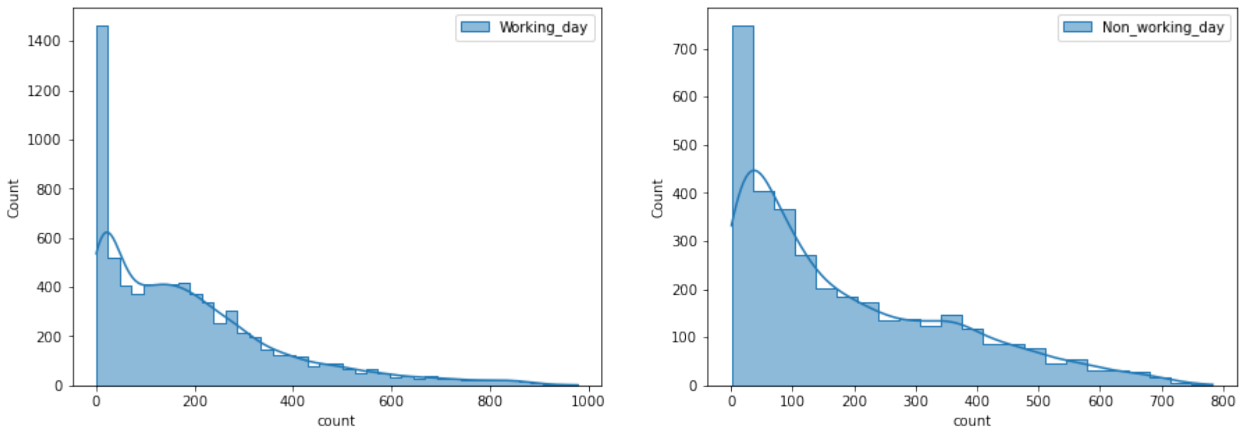
```
atemp        0.984948  1.000000 -0.043536  -0.057473  0.462067
0.314635
humidity    -0.064949 -0.043536  1.000000  -0.318607 -0.348187    -
0.265458
windspeed   -0.017852 -0.057473 -0.318607   1.000000  0.092276
0.091052
casual       0.467097  0.462067 -0.348187   0.092276  1.000000
0.497250
registered   0.318571  0.314635 -0.265458   0.091052  0.497250
1.000000
count        0.394454  0.389784 -0.317371   0.101369  0.690414
0.970948
year         0.061226  0.058540 -0.078606  -0.015221  0.145241
0.264265
hour         0.145430  0.140343 -0.278011   0.146631  0.302045
0.380540

               count      year      hour
temp        0.394454  0.061226  0.145430
atemp       0.389784  0.058540  0.140343
humidity   -0.317371 -0.078606 -0.278011
windspeed   0.101369 -0.015221  0.146631
casual      0.690414  0.145241  0.302045
registered  0.970948  0.264265  0.380540
count       1.000000  0.260403  0.400601
year        0.260403  1.000000 -0.004234
hour        0.400601 -0.004234  1.000000
```



Question: If there any significant difference between the no. of bike rides on Weekdays and Weekends?

```
weekday = data[data.workingday == 'working']['count']
weekend = data[data.workingday == 'not_working']['count']

plt.figure(figsize= (15, 5))
plt.suptitle("Normality check - Histplot",fontsize=16,fontweight="bold")
plt.subplot(121)
sns.histplot(weekday, kde= True, element = 'step',label = 'Working_day')
plt.legend()
plt.subplot(122)
sns.histplot(weekend, kde = True, element = 'step', label = 'Non_working_day')
plt.legend()

<matplotlib.legend.Legend at 0x1f24cf834f0>
```

Normality check - Histplot

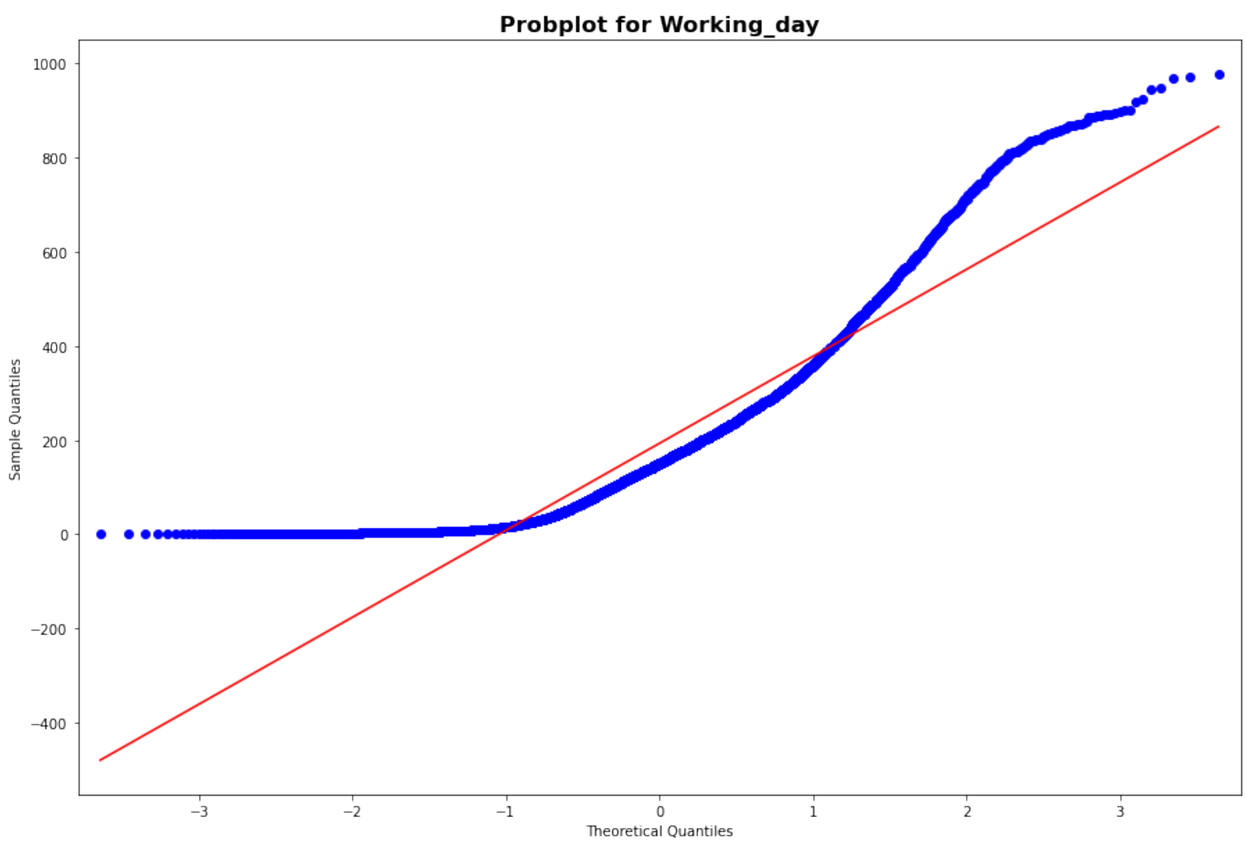


Does not follow normal distribution

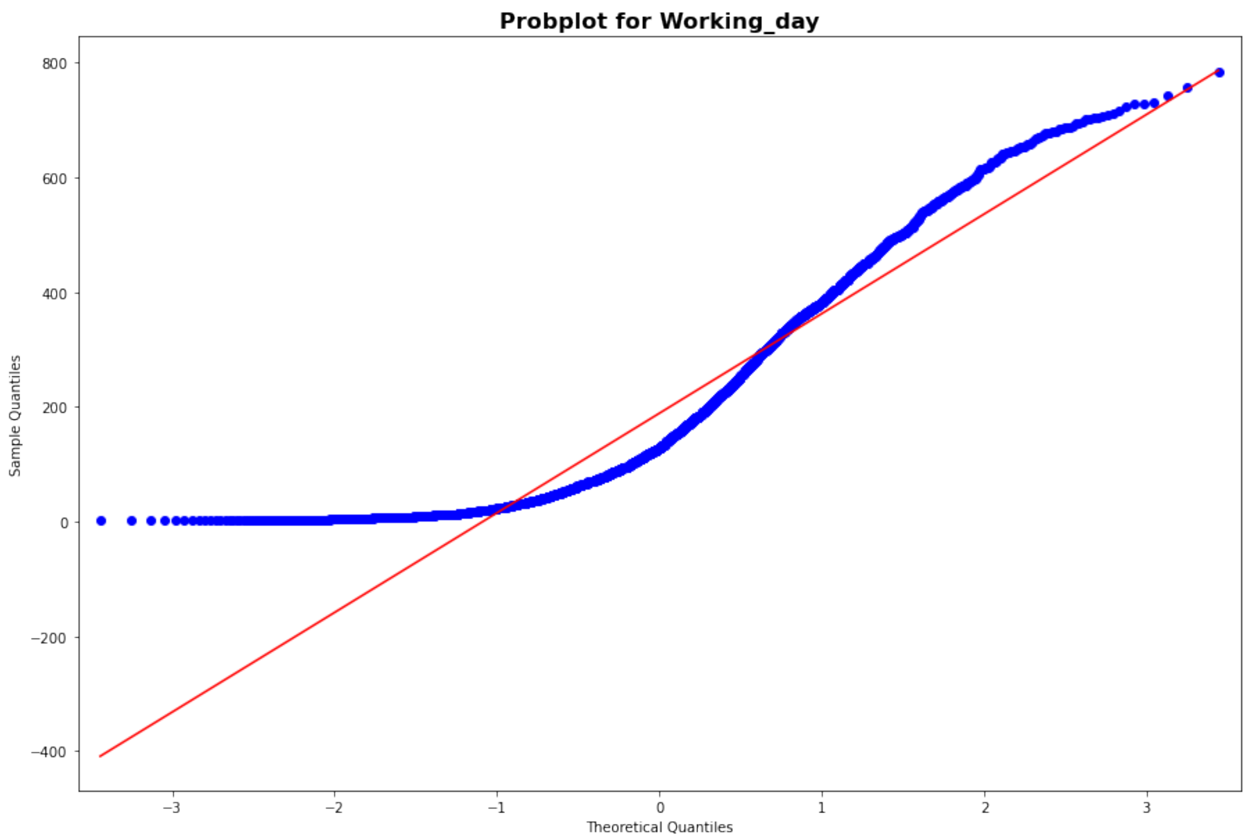
```
plt.figure(figsize = (7, 4))
sm.qqplot(weekday, line = 's')
plt.title('Probplot for Working_day', fontsize = 16, fontweight =
'bold')
```

```
Text(0.5, 1.0, 'Probplot for Working_day')
```

```
<Figure size 504x288 with 0 Axes>
```



```
sm.qqplot(weekend, line = 's')
plt.title('Probplot for Working_day', fontsize = 16, fontweight =
'bold')

Text(0.5, 1.0, 'Probplot for Working_day')
```



Shapiro- Wilk test

H0: Data is Gaussian

Ha: Data is not Gaussian

```
shapiro_stat , p_val = shapiro(weekday)
print(f"shapiro_stat : {shapiro_stat} , p_value : {p_val}")

if p_val < 0.05:
    print('weekday does not follow normal distribution')
else:
    print('Weekday follows a normal distribution')

shapiro_stat : 0.8702576160430908 , p_value : 0.0
weekday does not follow normal distribution

shapiro_stat , p_val = shapiro(weekend)
print(f"shapiro_stat : {shapiro_stat} , p_value : {p_val}")
```

```
if p_val < 0.05:
    print('Weekend data does not follow normal distribution')
else:
    print('Weekend data follows a normal distribution')
```

```
shapiro_stat : 0.8852126598358154 , p_value : 4.203895392974451e-45
Weekend data does not follow normal distribution
```

H0: There is no significance difference between no of bike rides on weekdays and weekends.

Ha: There is significance difference between no of bike rides on weekdays and weekends.

```
t_stat, p_val = ttest_ind(weekday, weekend)
if p_val < 0.05:
    print('Reject H0')
    print('There is significance difference between no of bike rides
on weekdays and weekends.')
else:
    print('Fail to reject H0')
    print('There is no significance difference between no of bike
rides on weekdays and weekends.')
```

```
Fail to reject H0
There is no significance difference between no of bike rides on
weekdays and weekends.
```

Insight

There is no significance difference between no of bike rides on weekdays and weekends.

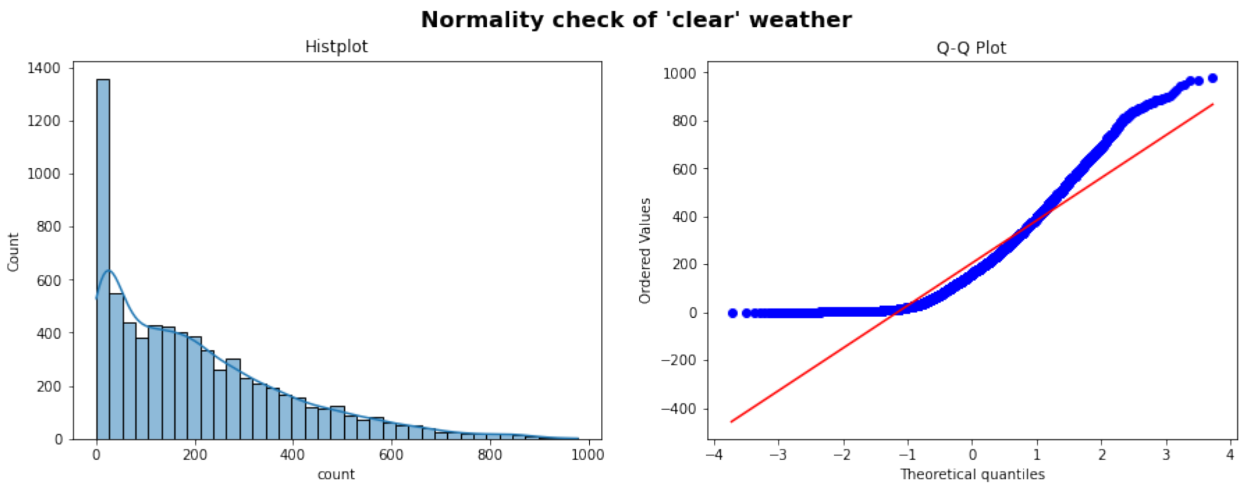
Question: if the demand of bicycles on rent is the same for different Weather conditions?

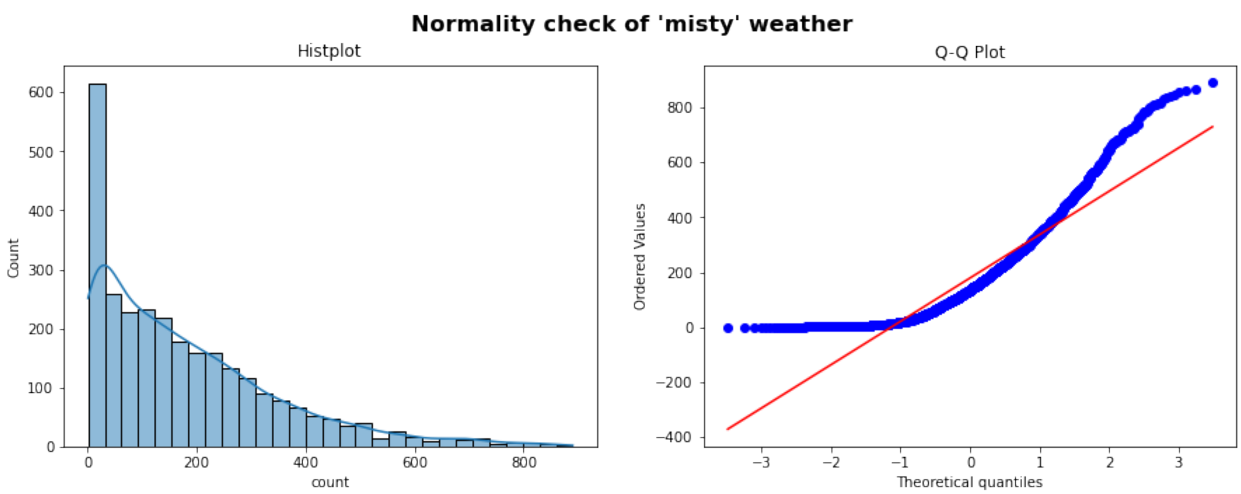
H0: The demand of bicycles on rent is the same for different Weather conditions

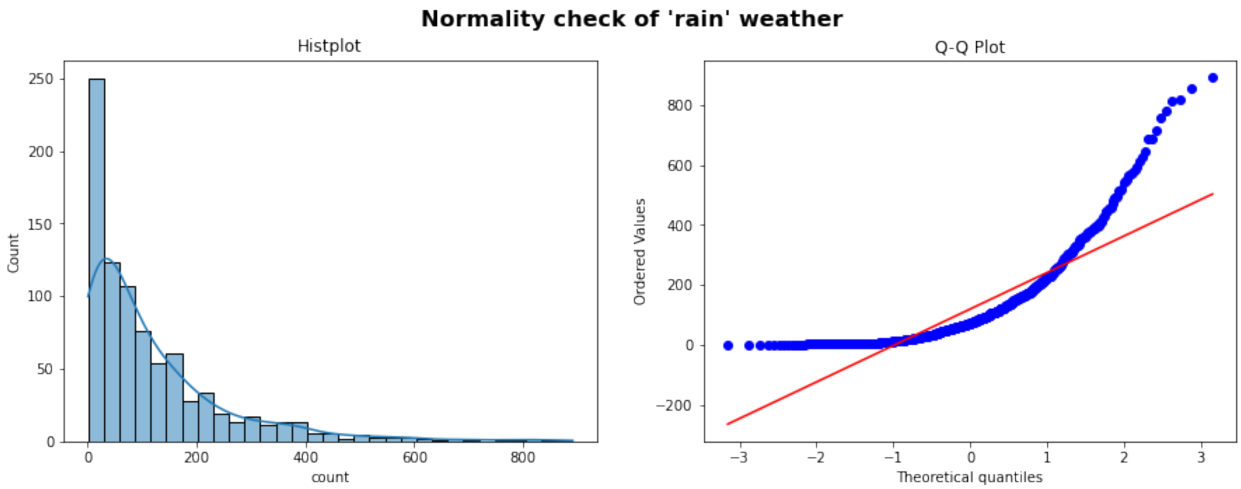
Ha: The demand of bicycles on rent is not same for different Weather conditions

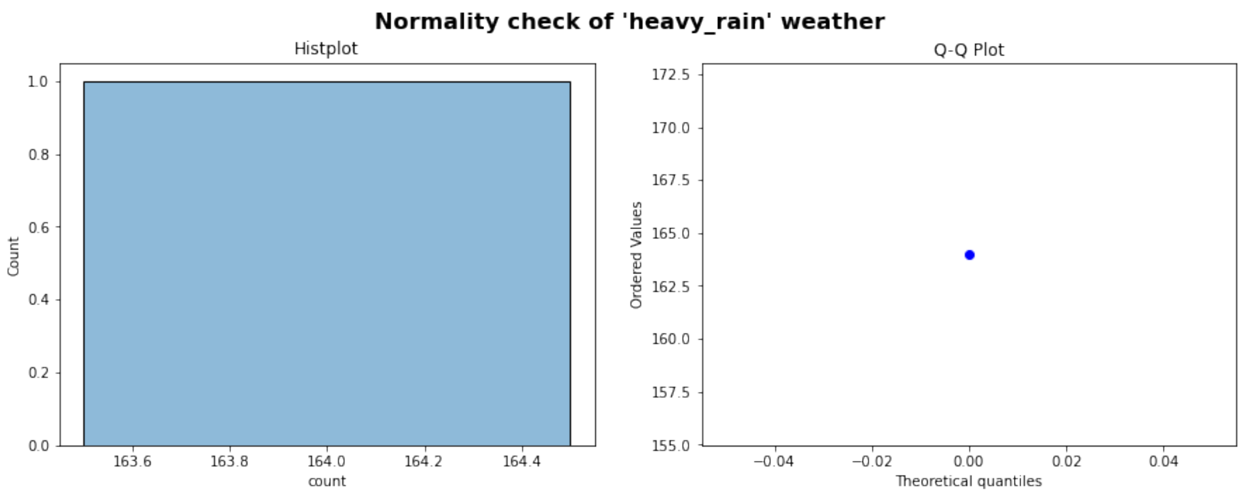
```
clear = data[data.weather == 'Clear']['count']
misty = data[data.weather == 'Misty']['count']
rain = data[data.weather == 'Rain']['count']
heavy_rain = data[data.weather == 'Heavy_rain']['count']

weather = {'clear': clear, 'misty': misty, 'rain': rain, 'heavy_rain':
heavy_rain}
for col, Data in weather.items():
    plt.figure(figsize = (15, 5))
    plt.subplot(121)
```

```
    plt.suptitle(f'Normality check of \'{col}\' weather',
fontsize=16,fontweight="bold")
    sns.histplot(Data, kde = True)
    plt.title('Histplot')

    plt.subplot(122)
    probplot(Data, dist='norm', plot=plt)
    plt.title('Q-Q Plot')

    plt.show()
```










```
# Shapiro - Wilk Test
weather = {'clear': clear, 'misty': misty, 'rain': rain}
for col, Data in weather.items():
        shapiro_stat , p_val = shapiro(Data)
        print(f"shapiro_stat : {shapiro_stat} , p_value : {p_val}")

        if p_val < 0.05:
            print(f'{col}  weather does not follow normal 
distribution')
        else:
            print(f'{col}  weather follows a normal distribution')
        print('-'* 70)
```

```
shapiro_stat : 0.8909225463867188 , p_value : 0.0
clear  weather does not follow normal distribution
----------------------------------------------------------------------
shapiro_stat : 0.8767688274383545 , p_value : 9.781063280987223e-43
misty  weather does not follow normal distribution
----------------------------------------------------------------------
```

```
shapiro_stat : 0.7674333453178406 , p_value : 3.876134581802921e-33
rain  weather does not follow normal distribution
----------------------------------------------------------------------
```

Equality Varience

```
H0: Groups have equal variances
Ha: Groups have different variances

levene_stat, p_value = levene(clear,misty,rain)

print('Levene_stat : ', levene_stat)
print('p-value : ', p_value)

if p_value < 0.05:
    print('Reject H0')
    print('Groups have different variances')
else:
    print('Fail to reject H0')
    print('Groups have equal variances')

Levene_stat :  81.67574924435011
p-value :  6.198278710731511e-36
Reject H0
Groups have different variances
```

Given weather condition have different variances

Assumption for f test are failing here, still we have applied the test, as per instruction

```
# F test
f_stat, p_val = f_oneway(clear, misty, rain, heavy_rain)
print(f'f_stat: {f_stat}')
print(f'p value: {p_val}')
if p_val < 0.05:
    print('Reject H0')
    print('The demand of bicycles on rent is not same for different
Weather conditions')
else:
    print('Fail to reject H0')
    print('The demand of bicycles on rent is  same for different
Weather conditions')

f_stat: 65.53024112793271
p value: 5.482069475935669e-42
Reject H0
The demand of bicycles on rent is not same for different Weather
conditions
```

Insights

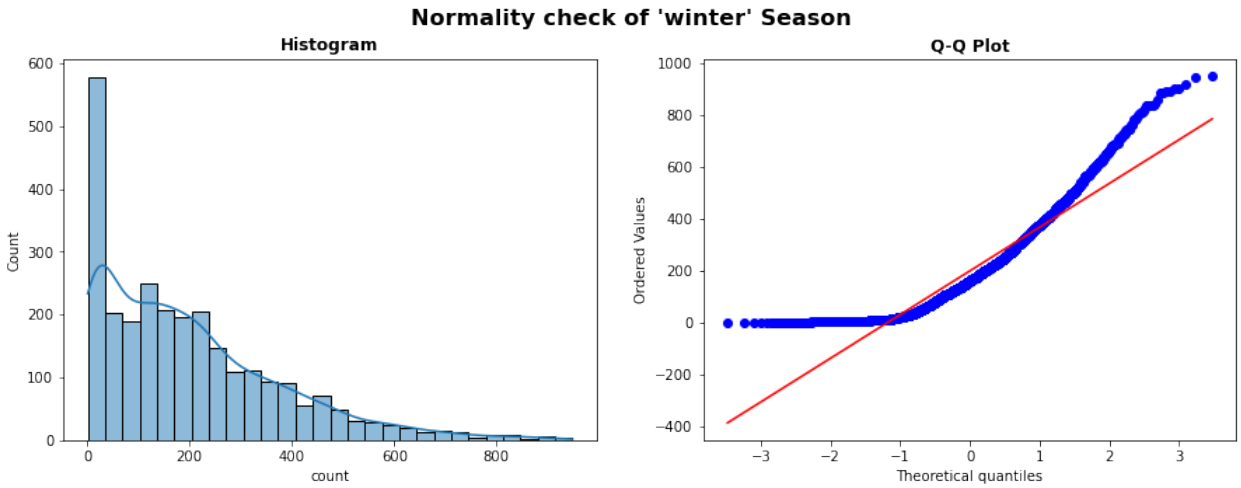
The demand of bicycles on rent is not same for different Weather conditions

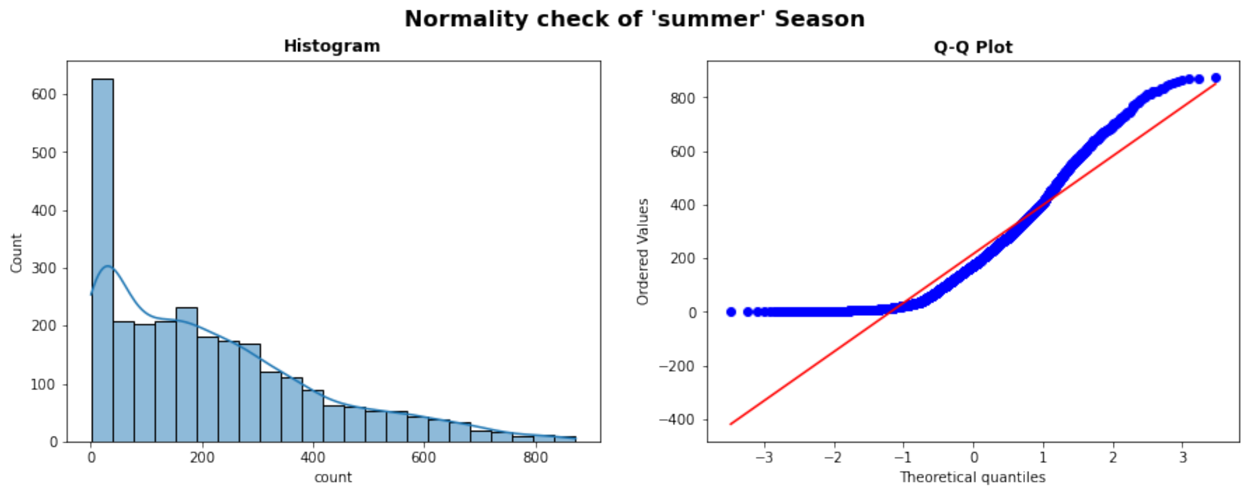
Question: if the demand of bicycles on rent is the same for different Seasons?

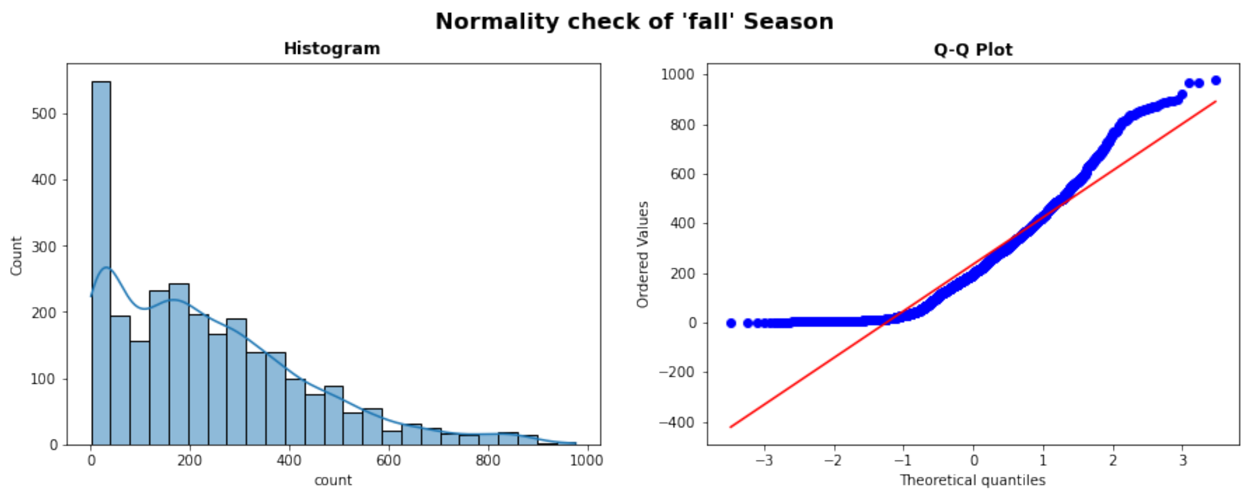
H0: The demand of bicycles on rent is the same for different Seasons

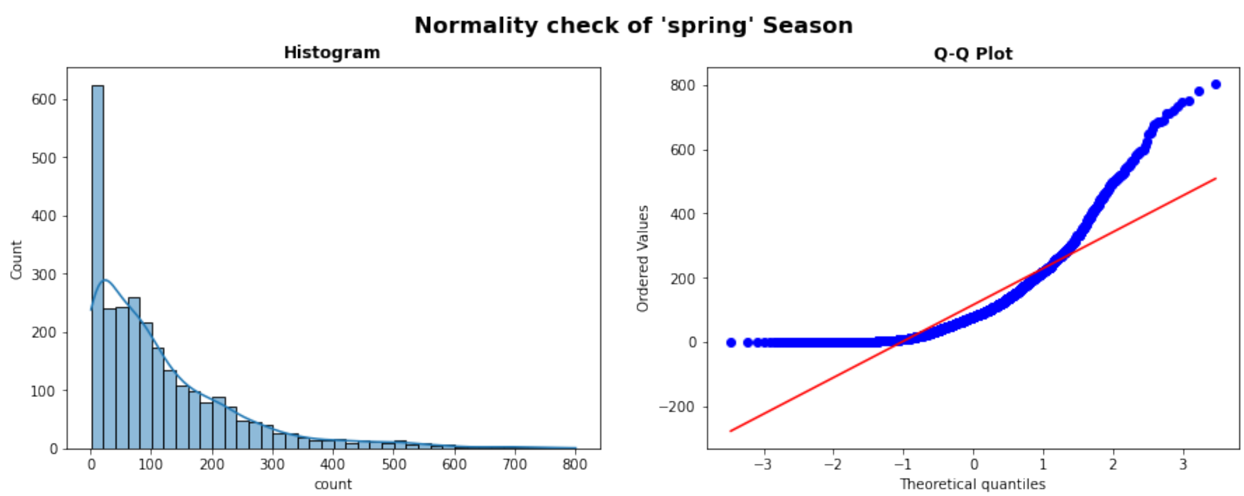
Ha: The demand of bicycles on rent is different for different Seasons

```
winter = data[data.season == 'winter']['count']
summer = data[data.season == 'summer']['count']
fall = data[data.season == 'fall']['count']
spring = data[data.season == 'spring']['count']

seasons = {'winter': winter, 'summer': summer, 'fall': fall, 'spring':
spring}
for col, Data in seasons.items():
    plt.figure(figsize = (15, 5))
    plt.suptitle(f'Normality check of \'{col}\'
Season',fontsize=16,fontweight="bold")
    plt.subplot(121)
    sns.histplot(Data, kde = True)
    plt.title('Histogram', fontweight = 'bold')

    plt.subplot(122)
    probplot(Data, dist='norm', plot=plt)
    plt.title('Q-Q Plot', fontweight = 'bold')
    plt.show()
```










```
# Shapiro - Wilk Test
seasons = {'winter': winter, 'summer': summer, 'fall': fall, 'spring':
spring}
for col, Data in seasons.items():
```

```
        shapiro_stat , p_val = shapiro(Data)
        print(f"shapiro_stat : {shapiro_stat} , p_value : {p_val}")

        if p_val < 0.05:
            print(f'{col}  season does not follow normal 
distribution')
        else:
            print(f'{col}  season follows a normal distribution')
        print('-'* 70)
```

```
shapiro_stat : 0.8954642415046692 , p_value : 1.130082751748606e-39
winter  season does not follow normal distribution
----------------------------------------------------------------------
shapiro_stat : 0.9004815220832825 , p_value : 6.038716365804366e-39
summer  season does not follow normal distribution
----------------------------------------------------------------------
shapiro_stat : 0.9148167371749878 , p_value : 1.0437229694698105e-36
fall  season does not follow normal distribution
----------------------------------------------------------------------
shapiro_stat : 0.8087379336357117 , p_value : 0.0
spring  season does not follow normal distribution
----------------------------------------------------------------------
```

Equality Varience

H0: Groups have equal variances

Ha: Groups have different variances

```
levene_stat, p_value = levene(winter, summer, fall, spring)

print('Levene_stat : ', levene_stat)
print('p-value : ', p_value)

if p_value < 0.05:
    print('Reject H0')
    print('Groups have different variances')
else:
    print('Fail to reject H0')
    print('Groups have equal variances')
```

```
Levene_stat :  187.7706624026276
p-value :  1.0147116860043298e-118
Reject H0
Groups have different variances
```

```
f_stat, p_val = f_oneway(winter, summer, fall, spring)
print('p value: ',  p_val)
print('F Statistics: ', f_stat)
if p_val < 0.05:
```

```
    print('Reject H0')
    print('The demand of bicycles on rent is different for different 
Seasons')
else:
    print('Fail to reject H0')
    print('The demand of bicycles on rent is the same for different 
Seasons')

p value:  6.164843386499654e-149
F Statistics:  236.94671081032104
Reject H0
The demand of bicycles on rent is different for different Seasons
```

Insight

The demand of bicycles on rent is different for different Seasons

Question: if the Weather conditions are significantly different during different Seasons?

H0: Weather are independent of seasons

Ha: Weather are dependent of seasons

```
weather_season = pd.crosstab(data.weather, data.season)
weather_season
```

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

```
chi_stat , p_value , dof , expected = chi2_contingency(weather_season)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)
print("dof : ",dof)
print("expected : ",expected)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("Weather is dependent on season")
else:
    print("Fail to Reject Ho")
    print("Weather is independent on season")
```

```
chi_stat :  49.15865559689363
p_value :  1.5499250736864862e-07
dof :  9
expected :  [[1.77454639e+03 1.80559765e+03 1.80559765e+03
1.80625831e+03]
 [6.99258130e+02 7.11493845e+02 7.11493845e+02 7.11754180e+02]
 [2.11948742e+02 2.15657450e+02 2.15657450e+02 2.15736359e+02]
 [2.46738931e-01 2.51056403e-01 2.51056403e-01 2.51148264e-01]]
Reject Ho
Weather is dependent on season
```

Insights

Weather is dependent on season

Insights

1. Maximum bike rentals occur during winter, while the minimum is observed in spring.
2. Clear weather is associated with the highest bike rental counts, whereas rentals sharply decrease in rain, misty, snow, or fog. Humidity, windspeed, temperature and weather are correlated with season and impacts the count of bike rented.
3. Bike rentals peak during the day, decline through the night, indicating a pattern fluctuation.
4. Less rentals on holidays and weekends, with a demand increase on non-working days.
5. Casual riders dominate on weekends, while registered users are more active on working days.
6. The hourly rental count shows impressive annual growth from 2011 to 2012.
7. January to March sees the lowest rental counts, and a distinctive daily trend shows peak usage during the afternoon.
8. Clear and partly_cloudy weather correlates with higher rental counts, while extreme weather conditions have limited data representation.
9. ANOVA tests confirm statistically significant impacts of seasons and weather on bike rentals.
10. Working days vs. holidays have limited impact according to a 2-sample t-test.
11. ChiSquare confirms that the Weather is dependent on the Seasons.

Recommandations

1. Leverage seasonal patterns by implementing targeted marketing during peak seasons (winter). Introduce seasonal incentives and exclusive packages to drive higher demand.
2. Optimize resource utilization by implementing dynamic time-based pricing. Adjust rental rates to encourage bike usage during off-peak hours, enhancing accessibility.
3. Collect more data on extreme weather conditions to understand user behavior. Consider specialized bike models or safety measures for different weather scenarios.
4. Launch weather-specific promotional campaigns focusing on clear and partly cloudy conditions. Introduce weather-based discounts to attract more users during favorable weather.
5. Fine-tune inventory levels based on monthly demand patterns. Avoid overstocking during low-demand months and ensure sufficient bikes during peak periods.
6. Provide amenities like umbrellas or rain jackets to enhance customer comfort. Elevate the overall biking experience, contributing to positive customer feedback.
7. Partner with weather services for real-time updates in marketing campaigns. Showcase ideal biking conditions through app integration, appealing to weather-specific preferences.
8. Conduct thorough seasonal bike maintenance to prevent breakdowns. Ensure optimal bike performance, enhancing customer satisfaction.
9. Encourage customer feedback to identify areas for improvement. Customize services based on insights, exceeding customer expectations.