yulu_hypothesis_testing

November 25, 2023

0.1 Import libraries and data

[ ]:
```
import os
from pathlib import Path
import pandas as pd
pd.set_option('display.max_columns', 500)
import numpy as np
import statsmodels.api as sm
import scipy.stats as stats
import pylab as py

import seaborn as sns
import matplotlib.pyplot as plt
```

[ ]:
```
yulu_data = pd.read_csv('bike_sharing.txt')
```

[ ]:
```
yulu_data.shape
```

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

[ ]:
```
yulu_data
```

[ ]:
```
                  datetime  season  holiday  workingday  weather   temp  \
0      2011-01-01 00:00:00       1        0           0        1   9.84
1      2011-01-01 01:00:00       1        0           0        1   9.02
2      2011-01-01 02:00:00       1        0           0        1   9.02
3      2011-01-01 03:00:00       1        0           0        1   9.84
4      2011-01-01 04:00:00       1        0           0        1   9.84
…                        …     …       …           …       …     …
10881  2012-12-19 19:00:00       4        0           1        1  15.58
10882  2012-12-19 20:00:00       4        0           1        1  14.76
10883  2012-12-19 21:00:00       4        0           1        1  13.94
10884  2012-12-19 22:00:00       4        0           1        1  13.94
10885  2012-12-19 23:00:00       4        0           1        1  13.12

        atemp  humidity  windspeed  casual  registered  count
0      14.395        81     0.0000       3          13     16
1      13.635        80     0.0000       8          32     40
```

```
2      13.635      80    0.0000      5         27     32
3      14.395      75    0.0000      3         10     13
4      14.395      75    0.0000      0          1      1
…        …      …       …      …        …     …
10881  19.695      50   26.0027      7        329    336
10882  17.425      57   15.0013     10        231    241
10883  15.910      61   15.0013      4        164    168
10884  17.425      61    6.0032     12        117    129
10885  16.665      66    8.9981      4         84     88

[10886 rows x 12 columns]
```

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.

0.2 EDA

0.3 Univariate Analysis

[ ]:
```
yulu_data.columns
```

[ ]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

[ ]:
```
yulu_data.isnull().sum()
```

[ ]:
```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
```

```
registered    0
count         0
dtype: int64
```

[ ]:
```python
yulu_data['datetime'] = pd.to_datetime(yulu_data['datetime'])
yulu_data['date'] = yulu_data['datetime'].dt.date
yulu_data['year'] = yulu_data['datetime'].dt.year
yulu_data['month'] = yulu_data['datetime'].dt.month
yulu_data['day'] = yulu_data['datetime'].dt.day
yulu_data['hour'] = yulu_data['datetime'].dt.hour
yulu_data['week'] = yulu_data['datetime'].dt.week
```

```
/tmp/ipykernel_16250/3721930838.py:7: FutureWarning: Series.dt.weekofyear and
Series.dt.week have been deprecated. Please use Series.dt.isocalendar().week
instead.
  yulu_data['week'] = yulu_data['datetime'].dt.week
```

[ ]:
```python
# 2 years of data
yulu_data['datetime'].min(), yulu_data['datetime'].max()
```

[ ]:
```
(Timestamp('2011-01-01 00:00:00'), Timestamp('2012-12-19 23:00:00'))
```

[ ]:
```python
yulu_data['date'].nunique()
```

[ ]:
```
456
```

[ ]:
```python
yulu_data.groupby(['season'])['date'].nunique()
```

[ ]:
```
season
1    114
2    114
3    114
4    114
Name: date, dtype: int64
```

[ ]:
```python
yulu_data.groupby(['holiday'])['date'].nunique()
```

[ ]:
```
holiday
0    443
1     13
Name: date, dtype: int64
```

[ ]:
```python
yulu_data.groupby(['workingday'])['date'].nunique()
```

[ ]:
```
workingday
0    145
1    311
Name: date, dtype: int64
```

[ ]:
```
yulu_data.groupby(['weather'])['date'].nunique()
```

[ ]:
```
weather
1    434
2    346
3    187
4      1
Name: date, dtype: int64
```

[ ]:
```
for col in ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered',␣
 ↪'count']:
    print("column: ", col)
    display(yulu_data[col].describe(percentiles=[0.1,0.9]))
    print("=="*50)
```

```
column:  temp

count    10886.00000
mean        20.23086
std          7.79159
min          0.82000
10%          9.84000
50%         20.50000
90%         30.34000
max         41.00000
Name: temp, dtype: float64

================================================================================
====================
column:  atemp

count    10886.000000
mean        23.655084
std          8.474601
min          0.760000
10%         12.120000
50%         24.240000
90%         34.090000
max         45.455000
Name: atemp, dtype: float64

================================================================================
====================
column:  humidity

count    10886.000000
mean        61.886460
std         19.245033
min          0.000000
10%         37.000000
```

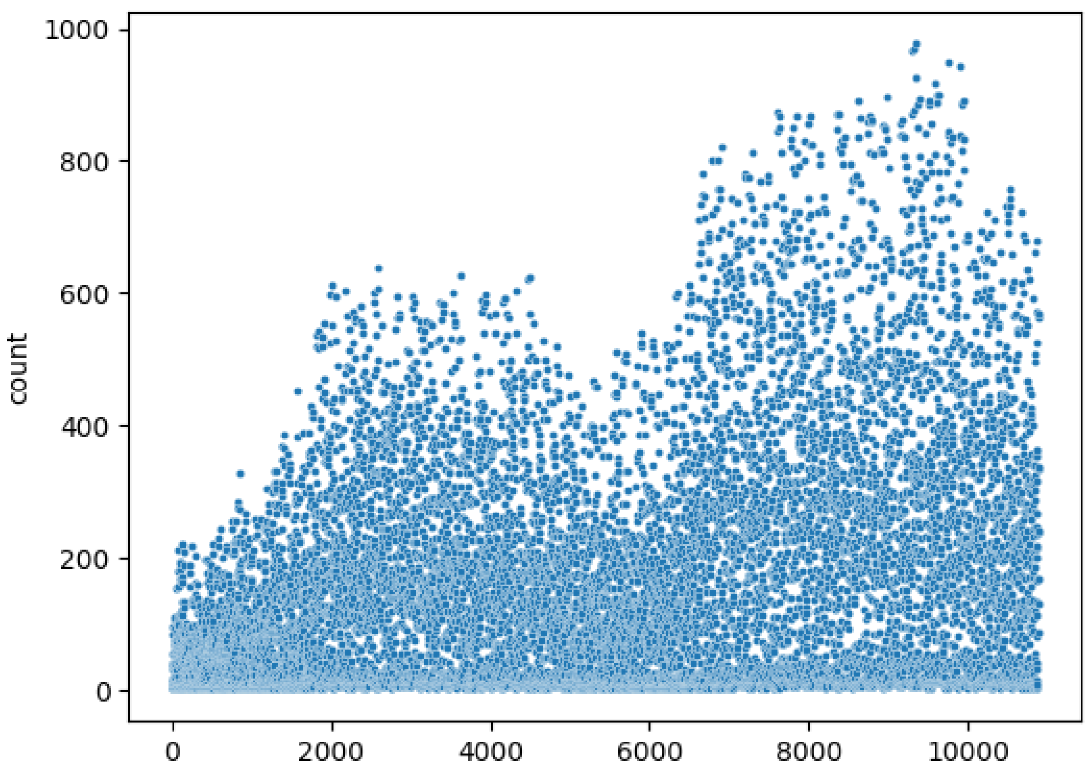
```
50%         62.000000
90%         88.000000
max        100.000000
Name: humidity, dtype: float64
================================================================================
====================
column:  windspeed
count    10886.000000
mean        12.799395
std          8.164537
min          0.000000
10%          0.000000
50%         12.998000
90%         23.999400
max         56.996900
Name: windspeed, dtype: float64
================================================================================
====================
column:  casual
count    10886.000000
mean        36.021955
std         49.960477
min          0.000000
10%          1.000000
50%         17.000000
90%         94.000000
max        367.000000
Name: casual, dtype: float64
================================================================================
====================
column:  registered
count    10886.000000
mean       155.552177
std        151.039033
min          0.000000
10%          7.000000
50%        118.000000
90%        354.000000
max        886.000000
Name: registered, dtype: float64
================================================================================
====================
column:  count
```

```
count    10886.000000
mean       191.574132
std        181.144454
min          1.000000
10%          9.000000
50%        145.000000
90%        452.000000
max        977.000000
Name: count, dtype: float64

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

0.4 Relationship with dependent variable: count (Bivariate Analysis)

[ ]:
```
sns.scatterplot(yulu_data['count'], s=10)
```

[ ]: <AxesSubplot: ylabel='count'>

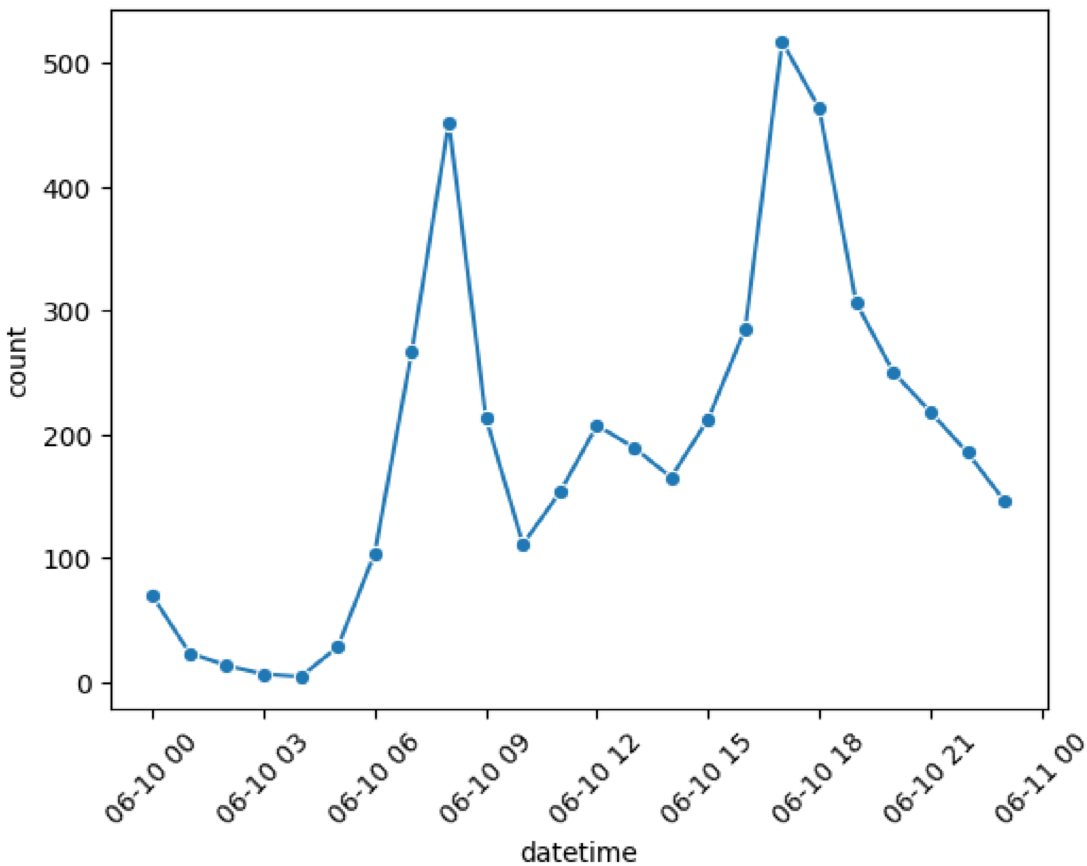


[ ]:
```
random_date = np.random.choice(yulu_data['date'])
random_date
```

[ ]: datetime.date(2011, 6, 10)

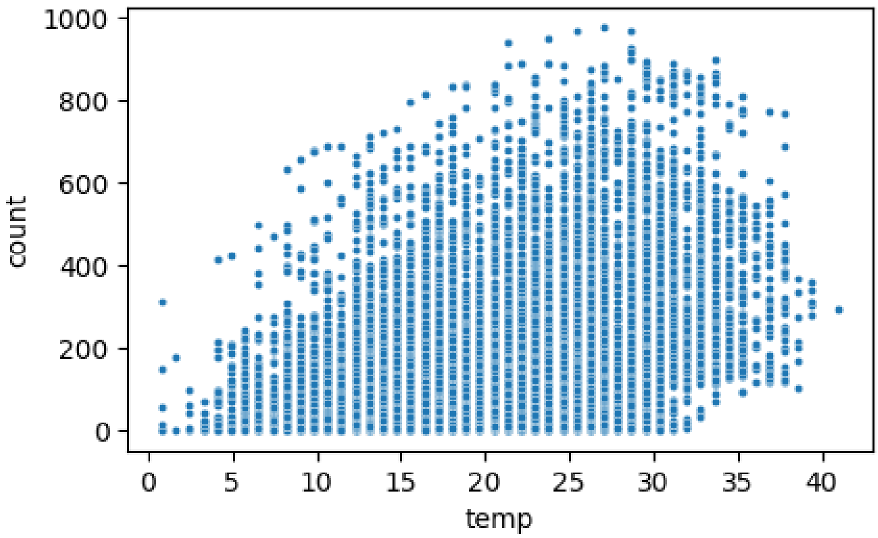
[ ]:
```
sns.lineplot(yulu_data[yulu_data['date']==pd.Timestamp(random_date)].
↪set_index('datetime')['count'], marker='o')
plt.xticks(rotation=45)
plt.show()
```

```
/tmp/ipykernel_16250/2179937167.py:1: FutureWarning: Comparison of Timestamp
with datetime.date is deprecated in order to match the standard library
behavior. In a future version these will be considered non-comparable. Use 'ts
== pd.Timestamp(date)' or 'ts.date() == date' instead.
  sns.lineplot(yulu_data[yulu_data['date']==pd.Timestamp(random_date)].set_index
('datetime')['count'], marker='o')
```

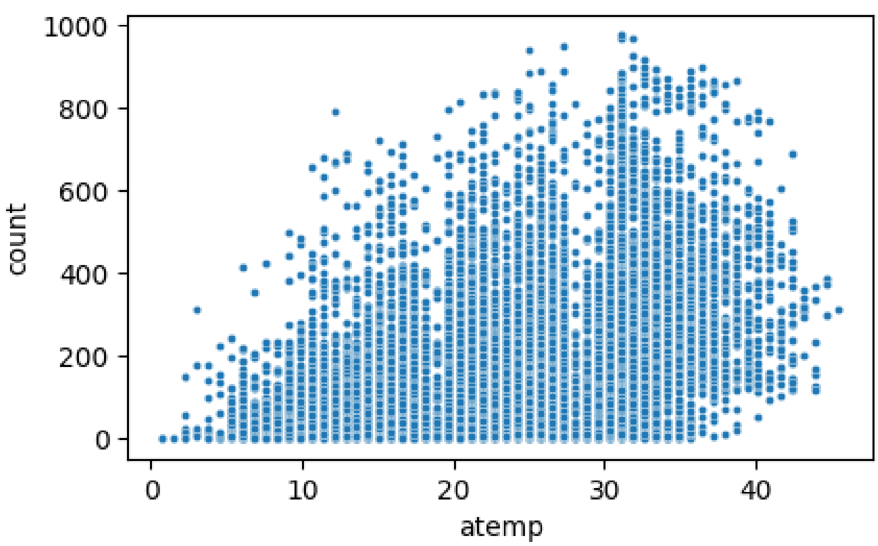


[ ]:
```
for col in ['temp', 'atemp', 'humidity', 'windspeed']:
    print(f"column: {col}")
    plt.figure(figsize=(5,3))
    sns.scatterplot(yulu_data, x=col, y='count', s=10)
    plt.show()
    print("=="*50)
```

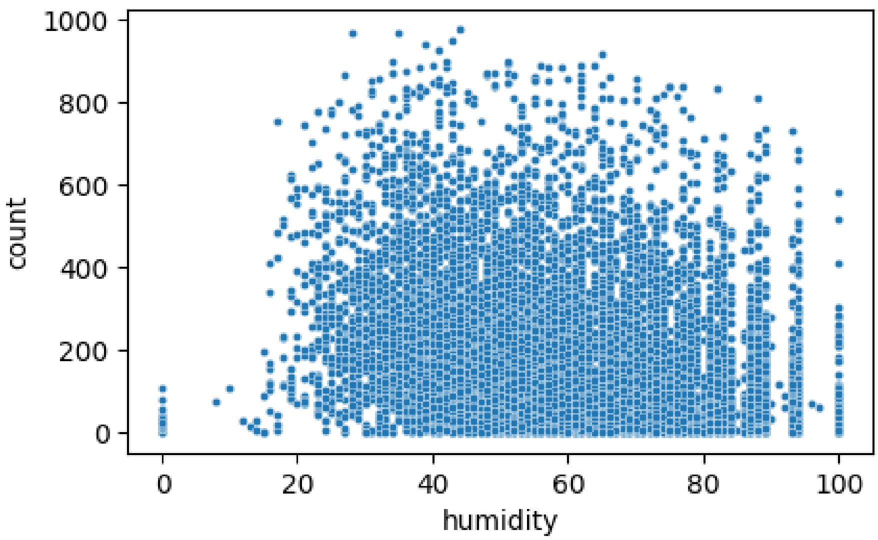
```
column: temp
```



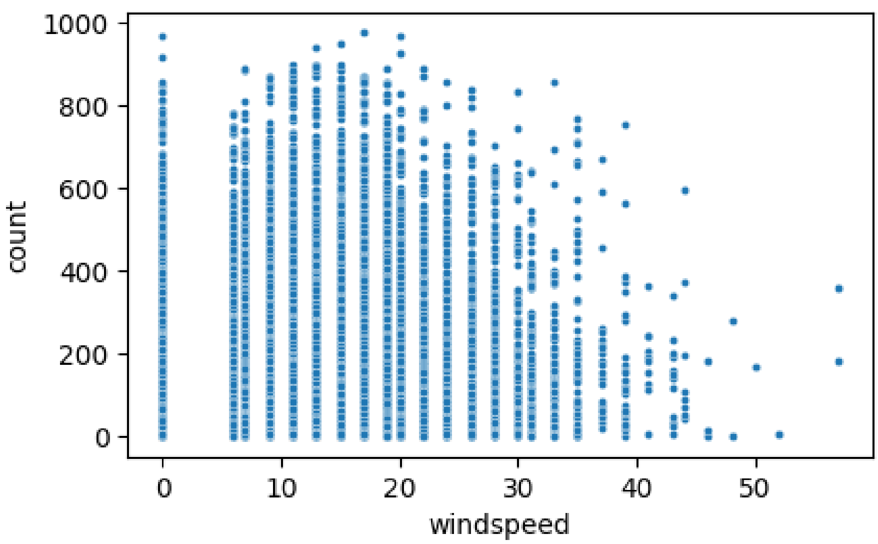

```
================================================================================
====================
column: atemp
```




```
================================================================================
====================
column: humidity
```




```
================================================================================
====================
column: windspeed
```




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

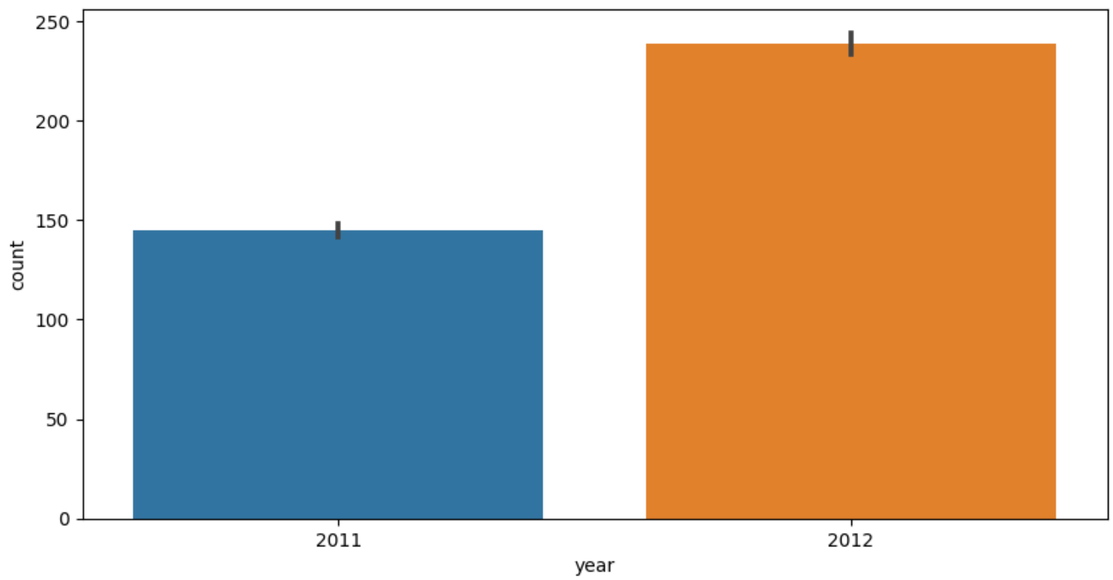
Drop columns with humidity==0

[ ]:
```
yulu_data[yulu_data['humidity']==0].shape
```

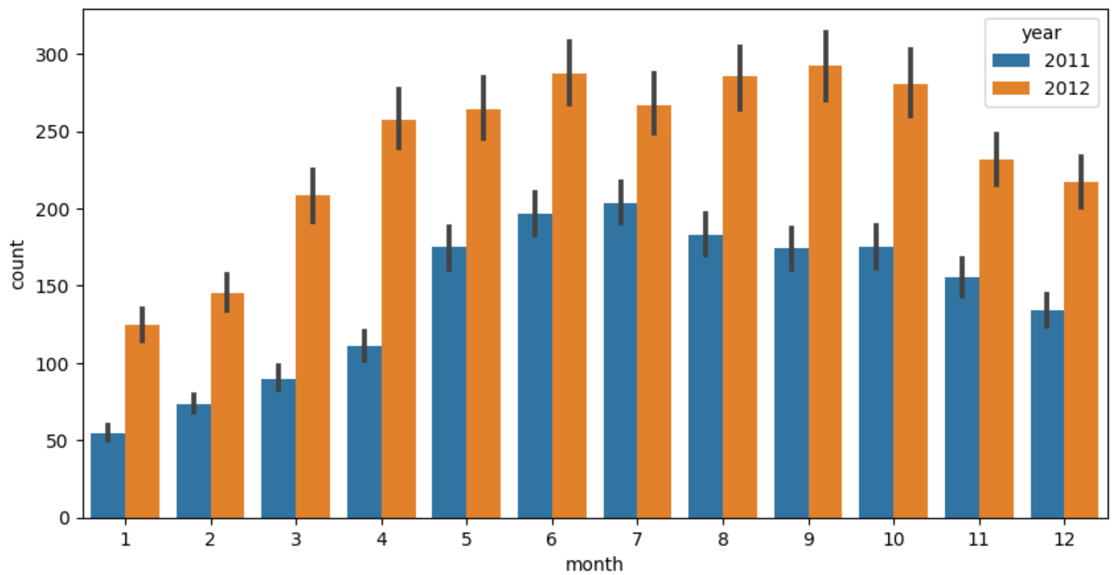
[ ]: (22, 18)

[ ]:
```
yulu_data = yulu_data[yulu_data['humidity']!=0].reset_index(drop=True)
```

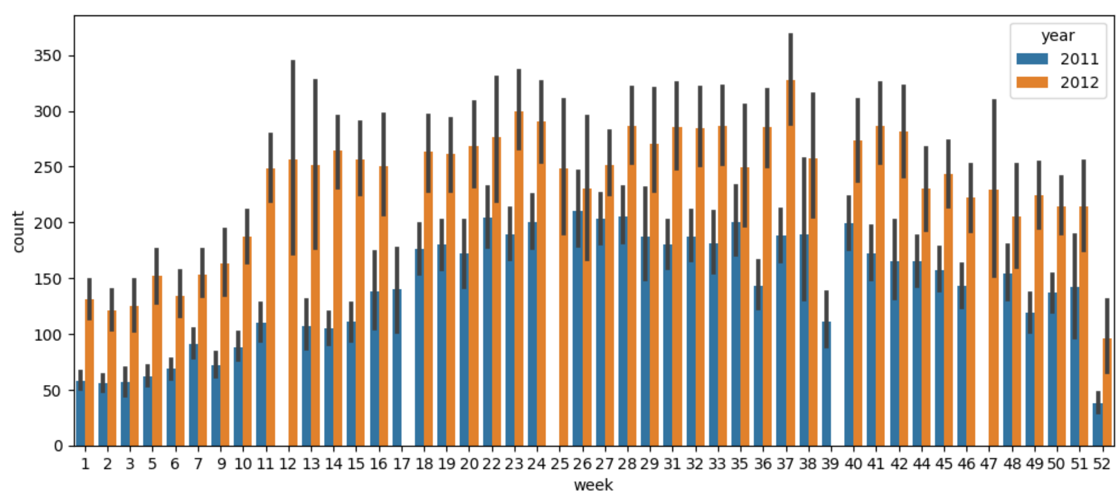
[ ]:
```
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='year', y='count')
plt.show()
```



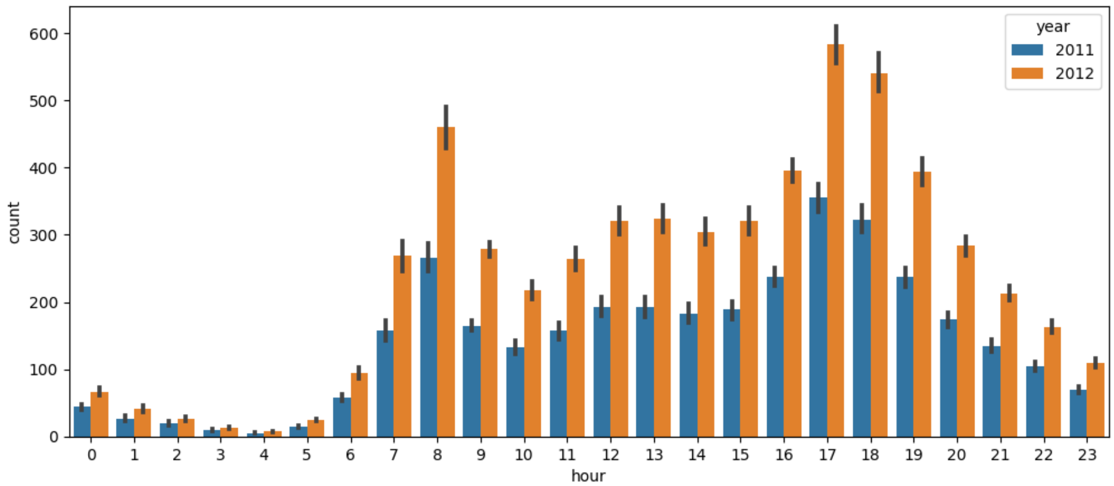
[ ]:
```
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='month', y='count', hue='year')
plt.show()
```



[ ]:
```
plt.figure(figsize=(12,5))
sns.barplot(yulu_data, x='week', y='count', hue='year')
plt.show()
```



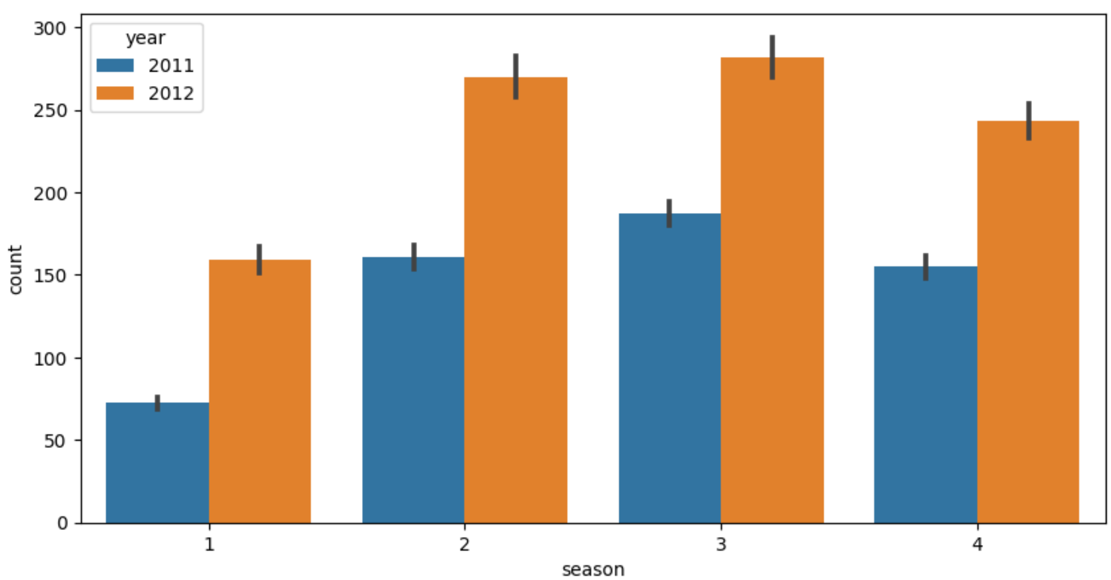
[ ]:
```
plt.figure(figsize=(12,5))
sns.barplot(yulu_data, x='hour', y='count', hue='year')
plt.show()
```



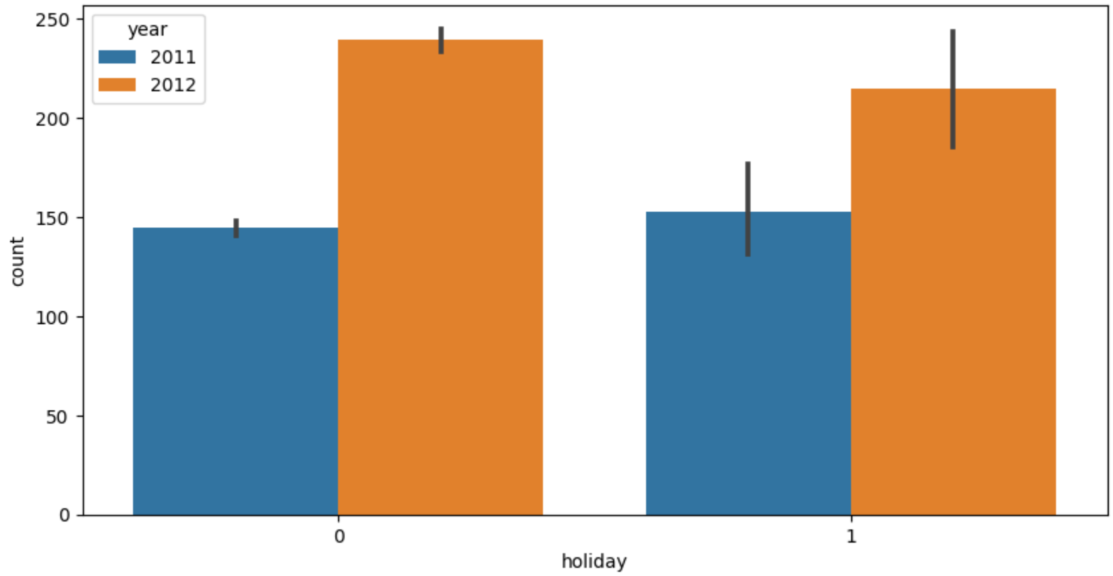
[ ]:
```
yulu_data.columns
```

[ ]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count',
       'date', 'year', 'month', 'day', 'hour', 'week'],
      dtype='object')
```

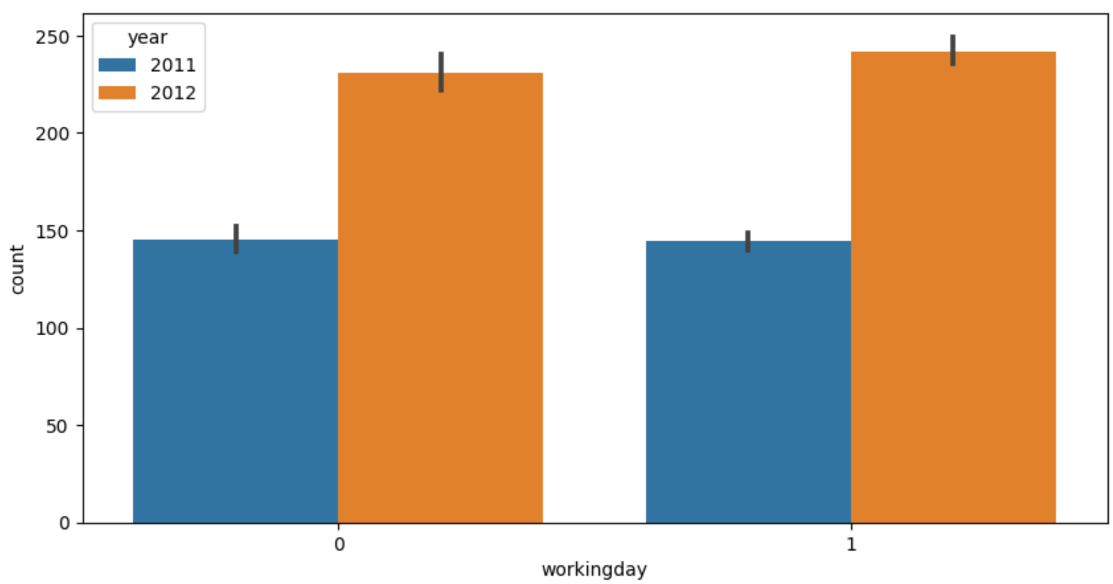
[ ]:
```
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='season', y='count', hue='year')
plt.show()
```



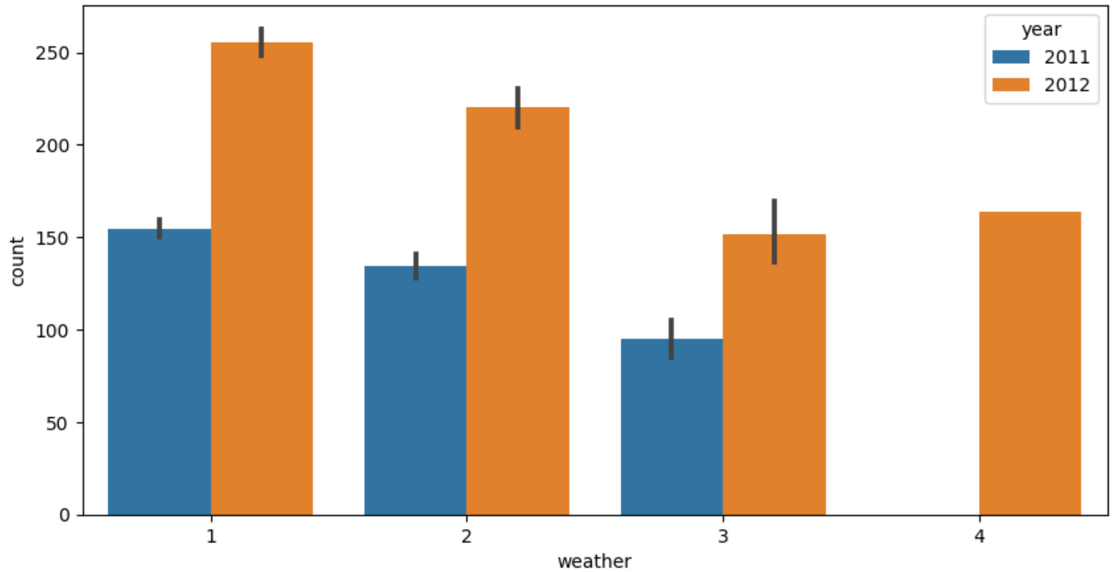
[ ]:
```python
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='holiday', y='count', hue='year')
plt.show()
```



[ ]:
```python
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='workingday', y='count', hue='year')
plt.show()
```



[ ]:
```python
plt.figure(figsize=(10,5))
sns.barplot(yulu_data, x='weather', y='count', hue='year')
plt.show()
```

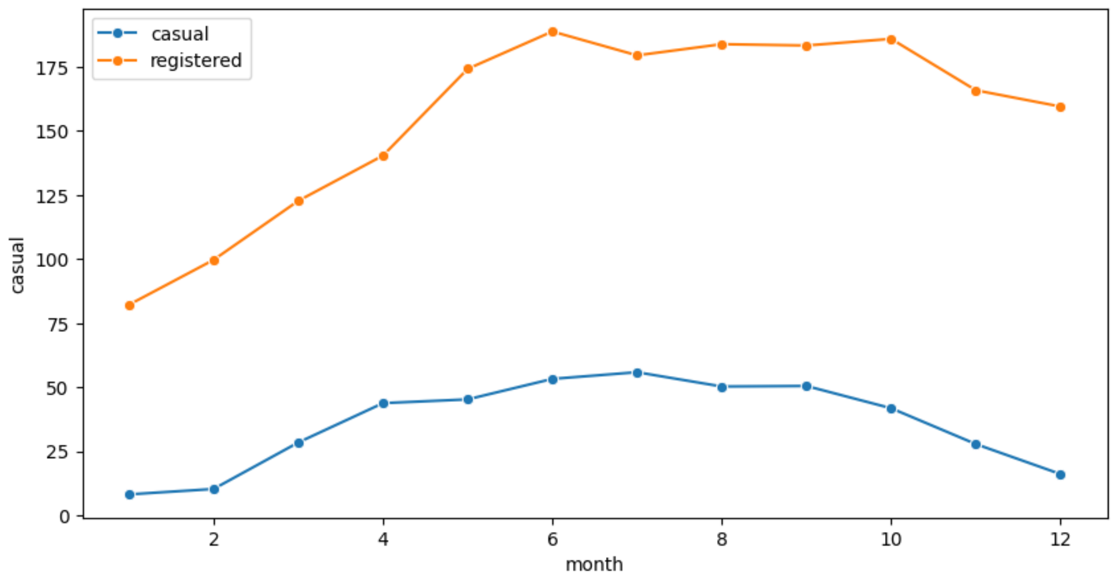


[ ]:
```python
yulu_data.groupby("month")[['casual', 'registered']].mean().reset_index()
```

[ ]:

	month	casual	registered
0	1	8.203620	82.162896
1	2	10.318535	99.684795
2	3	28.452787	122.716724
3	4	43.798680	140.361936
4	5	45.268640	174.190789
5	6	53.260965	188.770833
6	7	55.862939	179.462719
7	8	50.296053	183.822368
8	9	50.496150	183.309131
9	10	41.807903	185.891328
10	11	27.829857	165.847420
11	12	16.118421	159.495614

[ ]:
```python
plt.figure(figsize=(10,5))
sns.lineplot(yulu_data.groupby("month")[['casual', 'registered']].mean().
 ↪reset_index(), x='month', y='casual', marker='o', label="casual")
sns.lineplot(yulu_data.groupby("month")[['casual', 'registered']].mean().
 ↪reset_index(), x='month', y='registered', marker='o', label="registered")
plt.show()
```



Numerical values (to quantify observations)

[ ]:
```
yulu_data.groupby(['year'])['count'].mean()
```

[ ]:
```
year
2011    144.695556
2012    238.560944
Name: count, dtype: float64
```

[ ]:
```
yulu_data[yulu_data['month'].isin([5,6,7,8])]['count'].mean(),␣
 ↪yulu_data[~yulu_data['month'].isin([5,6,7,8])]['count'].mean()
```

[ ]:
```
(232.73382675438597, 171.26385809312637)
```

[ ]:
```
yulu_data[yulu_data['hour'].isin([7,8,9,17,18,19])]['count'].mean(),␣
 ↪yulu_data[~yulu_data['month'].isin([7,8,9,17,18,19])]['count'].mean()
```

[ ]:
```
(336.11294462779614, 177.61542245726233)
```

[ ]:
```
tmp = yulu_data.groupby(['year', 'season']).agg({'count': 'mean'})
tmp["count_shift"] = tmp["count"].shift(1)
tmp["% increase"] = (tmp["count"]-tmp["count_shift"])/tmp["count"]*100
tmp[['count','% increase']].fillna(0)
```

[ ]:
```
                    count  % increase
year season
2011 1          72.642583    0.000000
     2         160.940746   54.863772
     3         186.994872   13.933070
```

```
      4        154.787125  -20.807769
2012 1        159.476889    2.940717
      2        269.601757   40.847237
      3        281.735380    4.306745
      4        243.189466  -15.850158
```

[ ]:
```
yulu_data.groupby(['holiday'])['count'].mean().to_frame()
```

[ ]:
```
              count
holiday
0        192.082346
1        185.877814
```

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

[ ]:
```
                 count
workingday
0           188.506621
1           193.502165
```

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

[ ]:
```
              count
weather
1        205.236791
2        179.030720
3        121.109654
4        164.000000
```

[ ]:
```
yulu_data.groupby(['weather'])[['casual','registered','count']].mean()
```

[ ]:
```
            casual  registered       count
weather
1        40.308676  164.928115  205.236791
2        30.805085  148.225636  179.030720
3        17.810489  103.299166  121.109654
4         6.000000  158.000000  164.000000
```

0.5 Insights:

1. Is there an increase in rentals from 2011 to 2012? -> **An increase in rental counts: 144 to 232 from 2011 to 2012**
2. Are rental counts are high during certain months? -> **From months May to Aug, avg rental counts are 232, compared 170 for the rest of the year**
3. Is there an increased usage of rentals during certain hours of the day? -> **During morning and evenings hours, avg rental counts are 335 compared to 177 during the rest of hours**

4. Is there an increase in rentals during particular season of the year? -> **Rentals are high(40-60% increase usage) during summer, fall, and winter season than during spring season**
5. Is there an increase in rentals during holiday? -> No substantial increase
6. Is there an increase in rentals during working day? -> No substantial increase
7. Is there an increase in rentals during a particular weather? -> **Casual rentals are high(avg: 35) when the weather is clear and misty**

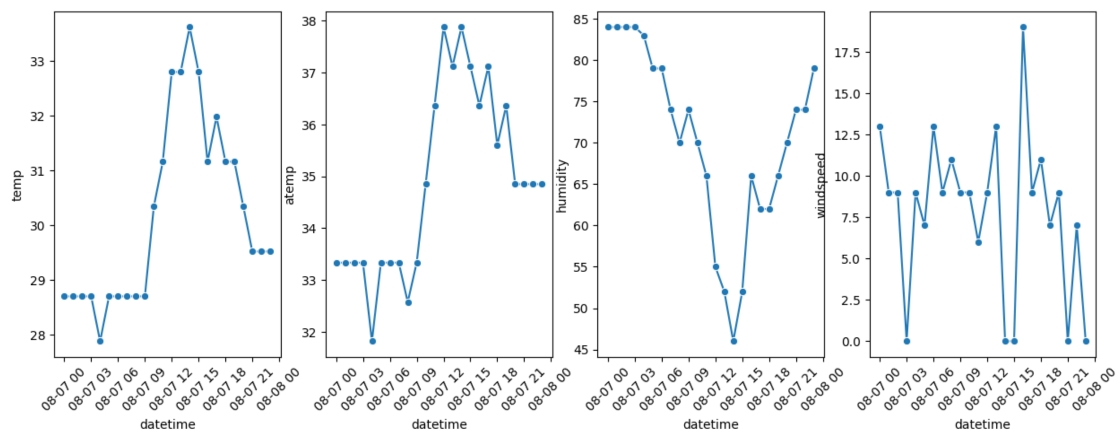
All these intuitional insights can be validated using hypothesis testing

0.6 Understanding continuous variables

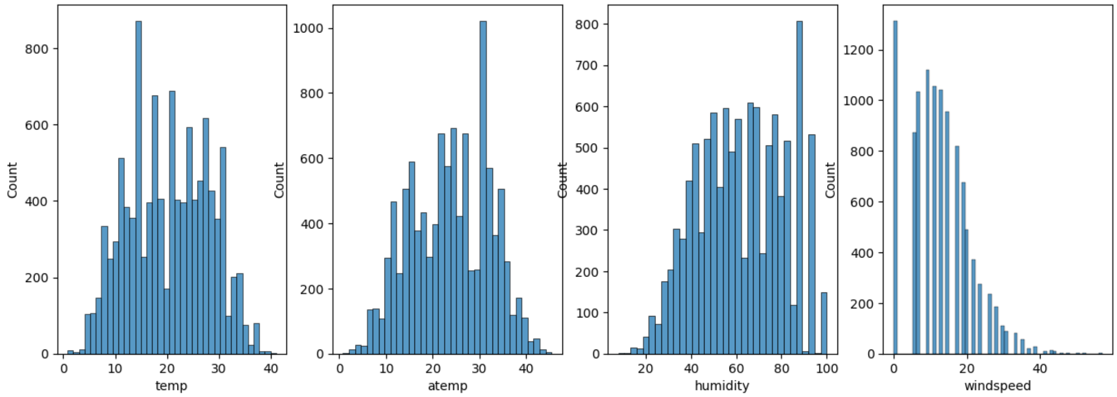
[ ]:
```
random_date = np.random.choice(yulu_data['date'])
random_date
```

[ ]:
```
datetime.date(2012, 8, 7)
```

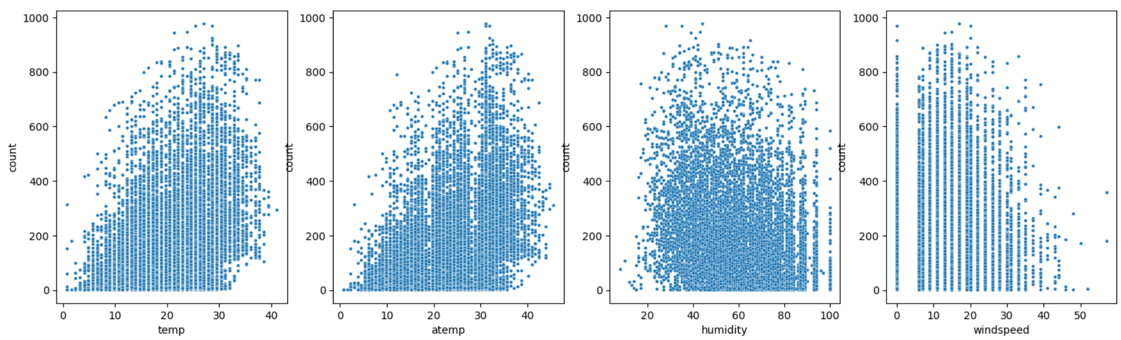
[ ]:
```
plt.figure(figsize=(15, 5))
for i, col in enumerate(['temp', 'atemp','humidity', 'windspeed']):
    # print(i+1, col)
    plt.subplot(1, 4, i+1)
    sns.lineplot(yulu_data[yulu_data['date']==random_date].
 ↪set_index('datetime')[col], marker='o')
    plt.xticks(rotation=45)
plt.show()
```



[ ]:
```
plt.figure(figsize=(15, 5))
for i, col in enumerate(['temp', 'atemp', 'humidity','windspeed']):
    # print(i+1, col)
    plt.subplot(1, 4, i+1)
    sns.histplot(data=yulu_data, x=col)
plt.show()
```



[ ]:
```
plt.figure(figsize=(18, 5))
for i, col in enumerate(['temp', 'atemp', 'humidity', 'windspeed']):
    # print(f"column: {col}")
    plt.subplot(1, 4, i+1)
    sns.scatterplot(yulu_data, x=col, y='count', s=10)
plt.show()
```



0.7 Hypothesis Testing

0.7.1 Tests performed:

1. **QQ plots/Probability plots**
2. **Shapiro-Wilk Test**
3. **Levene Test**
4. **Anderson-Darling Test**
5. **Kolmogorov-Smirnoff Test**
6. **ANOVA**
7. **Chi-square Test**
8. **Mann-Whitney U Test**
9. **Kruskal-Willis H Test**

Let us understand significance and assumptions of each tests

1. **QQ plots/Probability plots**: A Q-Q (quantile-quantile) plot is a graphical tool used in statistics to assess whether a dataset follows a particular theoretical distribution. The Q-Q plot compares the quantiles of the observed data to the quantiles of a specified distribution.
2. **Shapiro-Wilk test**: The Shapiro-Wilk test is a statistical test used to assess whether a given sample comes from a normally distributed population. It is a popular test for normality, and it is particularly useful when dealing with smaller sample sizes.
3. **Anderson-Darling test**: The Anderson–Darling test is a statistical test of whether a given sample of data is drawn from a given probability distribution. In its basic form, the test assumes that there are no parameters to be estimated in the distribution being tested, in which case the test and its set of critical values is distribution-free. It is a modification of the Kolmogorov-Smirnov test and places more emphasis on the tails of the distribution.
4. **Kolmogorov-Smirnoff test**: The Kolmogorov-Smirnov (K-S) test is a `non-parametric` test used to assess whether a sample follows a specific distribution, typically the null hypothesis that it comes from a standard uniform distribution or another specified theoretical distribution. The K-S test is applicable to a wide range of distributional comparisons and is often used for testing the assumption of normality.
5. **Levene test**: The Levene test tests the null hypothesis that all input samples are from populations with equal variances.
6. **ANOVA**: The significance of ANOVA lies in its ability to determine whether there are statistically significant differences in the means of three or more groups.
7. **Chi-square test**: Chi-Square test is a statistical test used to determine if there is a significant association between two `categorical variables`. It is applicable when the data consists of counts or frequencies in different categories and is often used to analyze data in contingency tables.
8. **Mann-Whitney U test**: The Mann-Whitney U test, also known as the Wilcoxon rank-sum test, is a `non-parametric test` used to compare two independent groups when the dependent variable is ordinal or continuous but not normally distributed. It assesses whether there is a significant difference between the distributions of two independent samples. The test is often used as an alternative to the independent samples t-test when the assumptions of normality are violated.
9. **Kruskal-Wallis H test**: The Kruskal-Wallis H test is a `non-parametric` test used to determine if there are any statistically significant differences between three or more independent groups when the dependent variable is ordinal or continuous but not normally distributed. It is an extension of the Mann-Whitney U test for comparing more than two groups
10. **Fisher's Exact Test**
11. **Cramer's V**

[ ]:
```
## significance level
```

[ ]:
```
alpha = 0.05
```

0.8 Hypothesis 1: Working Day has effect on number of electric cycles rented

Ho: Working day does not have any effect on rentals Ha: Working day does have effect on rentals

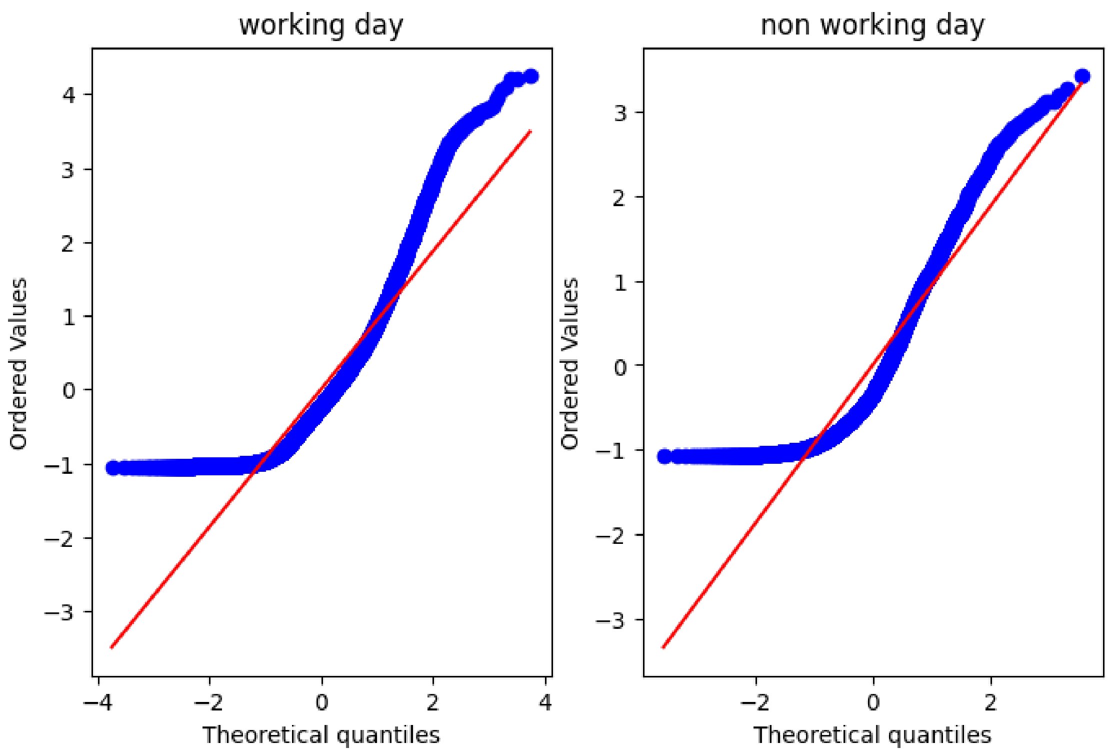
[ ]:
```python
yulu_data.groupby(['workingday']).agg({'count':['mean', 'median', 'count']})
```

[ ]:
```
                  count
                   mean median count
workingday
0            188.506621  128.0  3474
1            193.502165  151.0  7390
```

[ ]:
```python
workingday_df = yulu_data[yulu_data['workingday']==1].copy().
    ↪reset_index(drop=True)
non_workingday_df = yulu_data[yulu_data['workingday']==0].copy().
    ↪reset_index(drop=True)
```

0.8.1 QQ plots

[ ]:
```python
plt.figure(figsize=(8,5))
plt.subplot(1,2,1)
stats.probplot((workingday_df['count']-workingday_df['count'].mean())/
    ↪workingday_df['count'].std(), dist="norm", plot=py)
plt.title("working day")

plt.subplot(1,2,2)
stats.probplot((non_workingday_df['count']-non_workingday_df['count'].mean())/
    ↪non_workingday_df['count'].std(), dist="norm", plot=py)
plt.title("non working day")
py.show()
```



Insights: Distributions do not follow normal distribution We cannot use two sampled T-test since the normality is not followed

Since QQ plots show us, the samples do not follow normal distribution, I will skip other normality tests

In the cases, QQ plots gave us confidence about normality, we can bolster our claim by using the below tests to determine normality

We can use any of the following tests for normality:

1. Shapiro-Wilk
2. Anderson-Darling
3. Kolmogorov-Smirnoff

0.8.2 Levene Test

[ ]:
```
# standardizing the data before performing test
res = stats.levene((workingday_df['count']-workingday_df['count'].mean())/
↪workingday_df['count'].std(),
                    (non_workingday_df['count']-non_workingday_df['count'].
↪mean())/non_workingday_df['count'].std(),
                    center='mean')
# res.statistic, res.pvalue
```

```
print('test statistic: ', res.statistic)
if res.pvalue < alpha:
    print("we reject null hypothesis, -> samples do not have equal variances")
else:
    print("we accept null hypothesis, -> samples have equal variances")
```

```
test statistic:  23.173008405967
we reject null hypothesis, -> samples do not have equal variances
```

Insights: It can be sensitive to distributions which do not follow normality

0.8.3 Mann-Whitney U Test

[ ]:
```
res = stats.mannwhitneyu(workingday_df['count'],
                         non_workingday_df['count'],
                         alternative='two-sided'
                        )
print(f"mann whitney test \n   1. test statistic: {res.statistic}\n   2. p␣
 ↪value: {res.pvalue}")
test_statistic = res.statistic
p_value = res.pvalue
if p_value < alpha:
    print("we reject null hypothesis, distributions are not same")
else:
    print("we accept null hypothesis, distribution are same")
print("=="*100)
```

```
mann whitney test
   1. test statistic: 12855953.5
   2. p value: 0.898106954713987
we accept null hypothesis, distribution are same
================================================================================
================================================================================
========================================
```

Insights: Working day has no effect on bike rentals

0.9 Hypothesis 2: No. of cycles rented are similar in different seasons

Ho: No of cycles rented are same in different seasons Ha: No of cycles rented are different in different seasons

[ ]:
```
yulu_data.groupby(['season']).agg({'count':['mean', 'median']})
```

[ ]:
```
              count
               mean median
season
1        117.070195   79.0
```

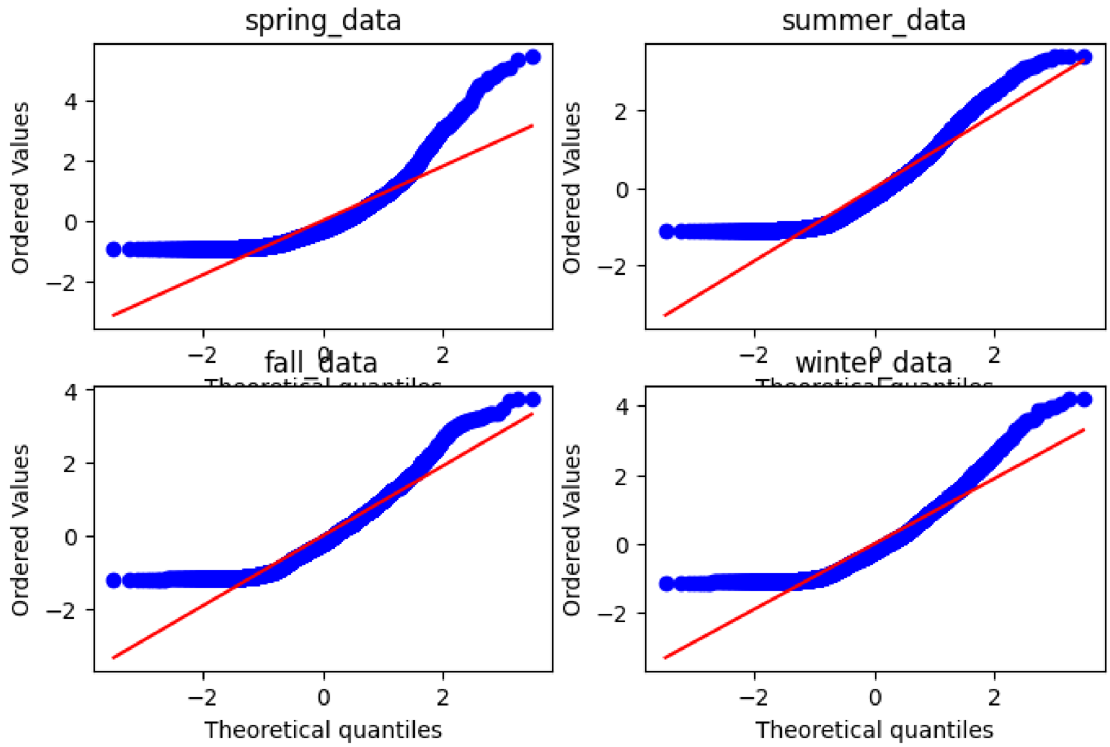
```
2       215.251372  172.0
3       234.417124  195.0
4       198.988296  161.0
```

[ ]:
```python
spring_data = yulu_data[yulu_data['season']==1].copy().reset_index(drop=True)
summer_data = yulu_data[yulu_data['season']==2].copy().reset_index(drop=True)
fall_data = yulu_data[yulu_data['season']==3].copy().reset_index(drop=True)
winter_data = yulu_data[yulu_data['season']==4].copy().reset_index(drop=True)

print(spring_data.shape, summer_data.shape, fall_data.shape, winter_data.shape)
```

```
(2664, 18) (2733, 18) (2733, 18) (2734, 18)
```

0.9.1 QQ plots

[ ]:
```python
plt.figure(figsize=(8,5))
plt.subplot(2,2,1)
stats.probplot((spring_data['count']-spring_data['count'].mean())/
 ↪spring_data['count'].std(), dist="norm", plot=py)
plt.title("spring_data")

plt.subplot(2,2,2)
stats.probplot((summer_data['count']-summer_data['count'].mean())/
 ↪summer_data['count'].std(), dist="norm", plot=py)
plt.title("summer_data")

plt.subplot(2,2,3)
stats.probplot((fall_data['count']-fall_data['count'].mean())/
 ↪fall_data['count'].std(), dist="norm", plot=py)
plt.title("fall_data")

plt.subplot(2,2,4)
stats.probplot((winter_data['count']-winter_data['count'].mean())/
 ↪winter_data['count'].std(), dist="norm", plot=py)
plt.title("winter_data")
py.show()
```



Insights: Distributions do not follow normal distribution

We cannot use Mann-Whitney U Test since it compares only two independent groups, we will use an extension of the test i.e. Kruskal-Wallis H Test

0.9.2 Kruskal-Wallis H Test

```
[ ]: res = stats.kruskal(spring_data['count'],
                         summer_data['count'],
                         fall_data['count'],
                         winter_data['count']
                         )
     print(f"kruskal wallis h test \n   1. test statistic: {res.statistic}\n   2. p␣
      ↪value: {res.pvalue}")
     test_statistic = res.statistic
     p_value = res.pvalue
     if p_value < alpha:
         print("we reject null hypothesis, samples' distributions are not same")
     else:
         print("we accept null hypothesis, samples' distribution are same")
     print("=="*100)
```

```
kruskal wallis h test
   1. test statistic: 683.7552982442343
   2. p value: 6.98952539470282e-148
we reject null hypothesis, samples' distributions are not same
================================================================================
================================================================================
========================================
```

Insights: Bikes rentals are different during different seasons

0.10 Hypothesis 3: No. of cycles rented are similar in different weather

Ho: No of cycles rented are same in different weather Ha: No of cycles rented are different in different weather

[ ]:
```
yulu_data.groupby(['weather']).agg({'count':['mean', 'median']})
```

[ ]:

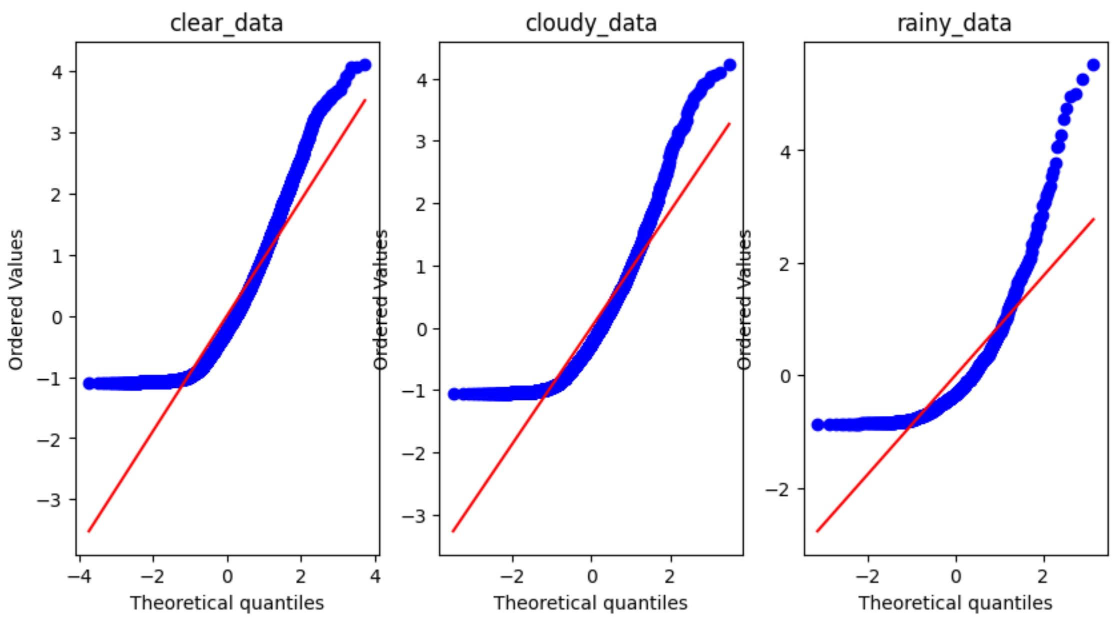
	count	
	mean	median
weather		
1	205.236791	161.0
2	179.030720	134.0
3	121.109654	75.0
4	164.000000	164.0

[ ]:
```
clear_data = yulu_data[yulu_data['weather']==1].copy().reset_index(drop=True)
cloudy_data = yulu_data[yulu_data['weather']==2].copy().reset_index(drop=True)
rainy_data = yulu_data[yulu_data['weather']==3].copy().reset_index(drop=True)
stormy_data = yulu_data[yulu_data['weather']==4].copy().reset_index(drop=True)

print(clear_data.shape, cloudy_data.shape, rainy_data.shape, stormy_data.shape)
```

```
(7192, 18) (2832, 18) (839, 18) (1, 18)
```

[ ]:
```
plt.figure(figsize=(10,5))
plt.subplot(1,3,1)
stats.probplot((clear_data['count']-clear_data['count'].mean())/
 ↪clear_data['count'].std(), dist="norm", plot=py)
plt.title("clear_data")

plt.subplot(1,3,2)
stats.probplot((cloudy_data['count']-cloudy_data['count'].mean())/
 ↪cloudy_data['count'].std(), dist="norm", plot=py)
plt.title("cloudy_data")

plt.subplot(1,3,3)
stats.probplot((rainy_data['count']-rainy_data['count'].mean())/
 ↪rainy_data['count'].std(), dist="norm", plot=py)
```

```
plt.title("rainy_data")

py.show()
```



Insights: Distributions do not follow normal distribution

0.10.1 Kruskal-Wallis H Test

[ ]:
```
res = stats.kruskal(clear_data['count'],
                    cloudy_data['count'],
                    rainy_data['count']
                    )
print(f"kruskal wallis h test \n   1. test statistic: {res.statistic}\n   2. p␣
 ↪value: {res.pvalue}")
test_statistic = res.statistic
p_value = res.pvalue
if p_value < alpha:
    print("we reject null hypothesis, samples' distributions are not same")
else:
    print("we accept null hypothesis, samples' distribution are same")
print("=="*100)
```

```
kruskal wallis h test
   1. test statistic: 188.76467195433247
   2. p value: 1.0239347824645635e-41
we reject null hypothesis, samples' distributions are not same
================================================================================
```

==

Insights: **Bikes rentals are different during different weather**

0.11 Hypothesis 4: Weather is dependent on season (check between 2 predictor variable)

Ho: Weather is independent of season Ha: Weather is dependent on season

[ ]:
```
yulu_data['weather'].value_counts(normalize=True), yulu_data['season'].
 ↪value_counts(normalize=True)
```

[ ]:
```
(1    0.662003
 2    0.260677
 3    0.077228
 4    0.000092
 Name: weather, dtype: float64,
 4    0.251657
 2    0.251565
 3    0.251565
 1    0.245214
 Name: season, dtype: float64)
```

[ ]:
```
yulu_data[['weather', 'season']].corr()
```

[ ]:

	weather	season
weather	1.000000	0.015426
season	0.015426	1.000000

For categorical variables, we can use Chi-square tests to check for independence

[ ]:
```
res = stats.chisquare(yulu_data['weather'],
                      yulu_data['season']
                     )
print(f"chi square test \n   1. test statistic: {res.statistic}\n   2. p value:␣
 ↪{res.pvalue}")
test_statistic = res.statistic
p_value = res.pvalue
if p_value < alpha:
    print("we reject null hypothesis, distributions are dependent")
else:
    print("we accept null hypothesis, distribution are independent")
print("=="*100)
```

```
chi square test
   1. test statistic: 9965.916666666668
   2. p value: 0.9999999998046497
we accept null hypothesis, distribution are independent
```

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

Insights: Weather is independent of season

0.12 Hypothesis 5: Is there an increase in rentals from 2011 to 2012?

Ho: No increase in rentals Ha: Increase in rentals

[ ]:
```
yulu_data.groupby(['year'])['count'].mean().to_frame()
```

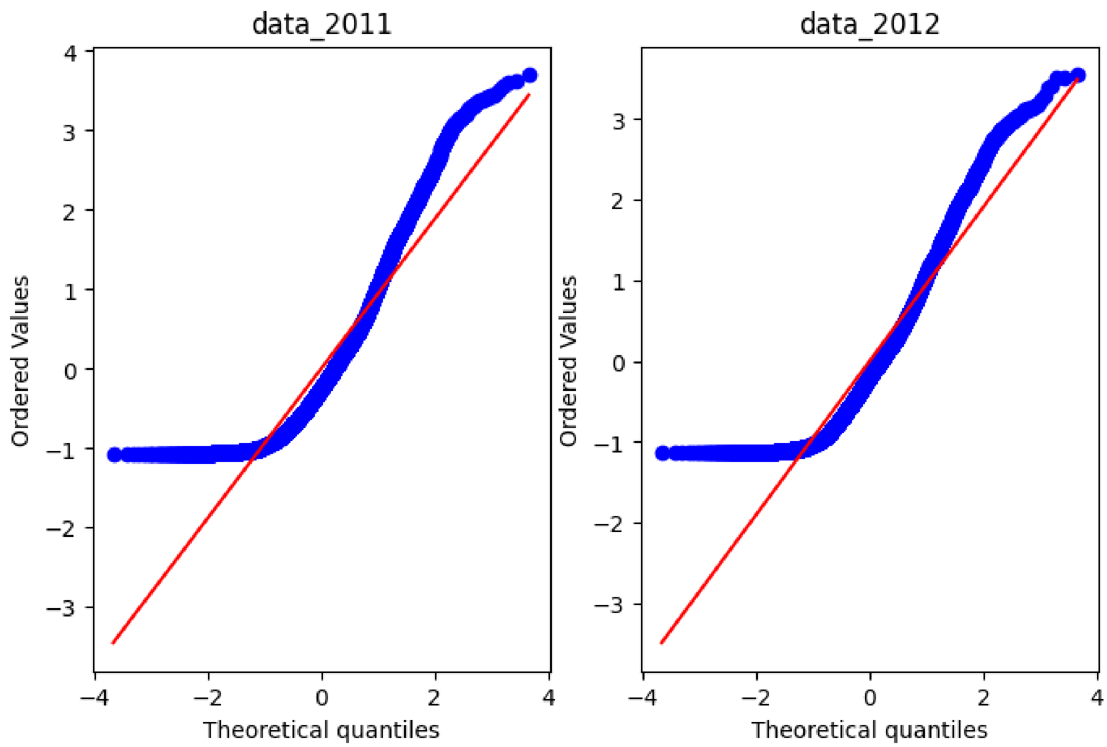
[ ]:
```
            count
year
2011   144.695556
2012   238.560944
```

[ ]:
```
data_2011 = yulu_data[yulu_data['year']==2011].copy().reset_index(drop=True)
data_2012 = yulu_data[yulu_data['year']==2012].copy().reset_index(drop=True)

print(data_2011.shape, data_2012.shape)
```

```
(5400, 18) (5464, 18)
```

0.12.1 QQ plots

[ ]:
```
plt.figure(figsize=(8,5))
plt.subplot(1,2,1)
stats.probplot((data_2011['count']-data_2011['count'].mean())/
 ↪data_2011['count'].std(), dist="norm", plot=py)
plt.title("data_2011")

plt.subplot(1,2,2)
stats.probplot((data_2012['count']-data_2012['count'].mean())/
 ↪data_2012['count'].std(), dist="norm", plot=py)
plt.title("data_2012")
py.show()
```



Insights: Distributions do not follow normal distribution

0.12.2 Mann-Whitney U Test

```
[ ]: res = stats.mannwhitneyu(data_2011['count'],
                             data_2012['count'],
                             alternative='two-sided'
                            )
     print(f"mann whitney test \n   1. test statistic: {res.statistic}\n   2. p␣
      ↪value: {res.pvalue}")
     test_statistic = res.statistic
     p_value = res.pvalue
     if p_value < alpha:
         print("we reject null hypothesis, distributions are not same")
     else:
         print("we accept null hypothesis, distribution are same")
     print("=="*100)
```

```
mann whitney test
   1. test statistic: 11038930.0
   2. p value: 2.688188065648264e-114
we reject null hypothesis, distributions are not same
================================================================================
```

==
==

Insights: Rentals increased in 2012 compared to 2011

0.13 Hypothesis 6: Are rental counts are different during may-aug months?

Ho: Rentals are not different Ha: Rentals are same

[ ]:
```
may_aug_data = yulu_data[yulu_data['month'].isin([5,6,7,8])].copy().
  ↪reset_index(drop=True)
rest_year_data = yulu_data[~yulu_data['month'].isin([5,6,7,8])].copy().
  ↪reset_index(drop=True)

print(may_aug_data.shape)
print(rest_year_data.shape)
```

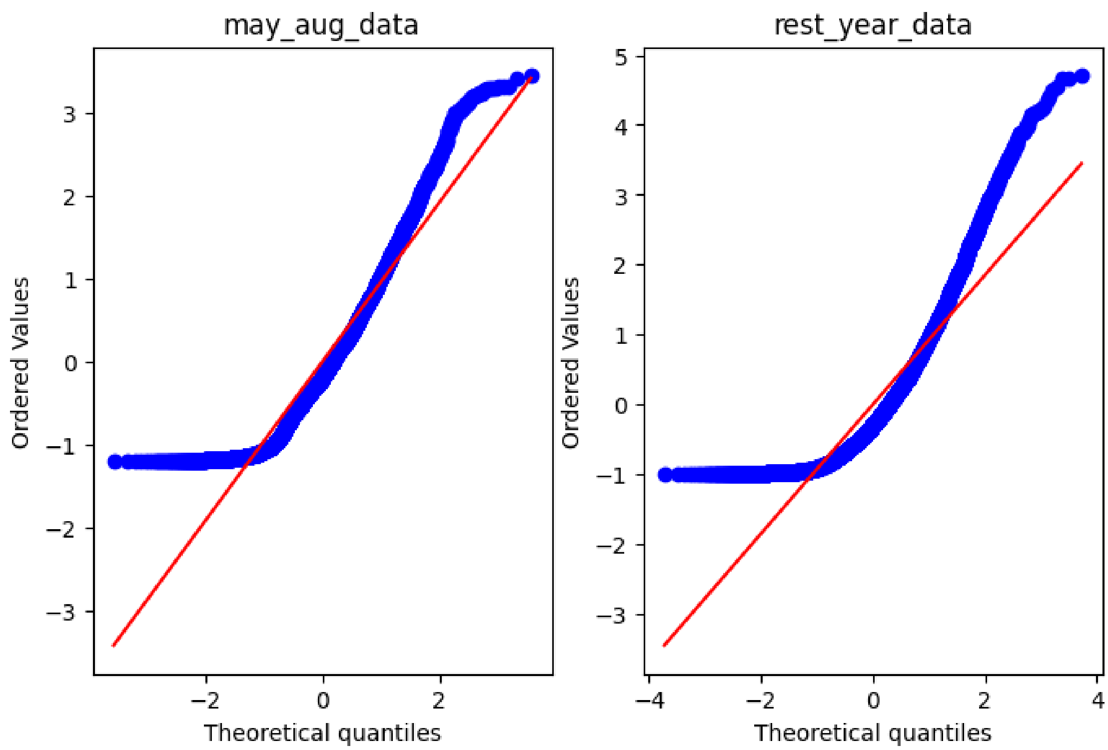
```
(3648, 18)
(7216, 18)
```

[ ]:
```
may_aug_data['count'].mean(), rest_year_data['count'].mean()
```

[ ]:
```
(232.73382675438597, 171.26385809312637)
```

0.13.1 QQ plots

[ ]:
```
plt.figure(figsize=(8,5))
plt.subplot(1,2,1)
stats.probplot((may_aug_data['count']-may_aug_data['count'].mean())/
  ↪may_aug_data['count'].std(), dist="norm", plot=py)
plt.title("may_aug_data")

plt.subplot(1,2,2)
stats.probplot((rest_year_data['count']-rest_year_data['count'].mean())/
  ↪rest_year_data['count'].std(), dist="norm", plot=py)
plt.title("rest_year_data")
py.show()
```



Insights: Distributions do not follow normal distribution

0.13.2 Mann-Whitney U Test

[ ]:
```
res = stats.mannwhitneyu(may_aug_data['count'],
                         rest_year_data['count'],
                         alternative='two-sided'
                        )
print(f"mann whitney test \n   1. test statistic: {res.statistic}\n   2. p␣
 ↪value: {res.pvalue}")
test_statistic = res.statistic
p_value = res.pvalue
if p_value < alpha:
    print("we reject null hypothesis, distributions are not same")
else:
    print("we accept null hypothesis, distribution are same")
print("=="*100)
```

```
mann whitney test
   1. test statistic: 15815103.5
   2. p value: 3.4110287438067357e-66
we reject null hypothesis, distributions are not same
================================================================================
```

==
==

Insights: Rentals are higher(different) during the May-Aug period

```
[ ]:
```