Yulu Business Case Study-Hypothesis Testing

```
[1] import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    import datetime as datetime
    from numpy import NaN, nan, NAN
    from scipy import stats
    import statsmodels.api as sm
    import warnings
    from scipy.stats import shapiro
    from scipy.stats import levene
    warnings.filterwarnings("ignore")
```

Loading data

```
bike_data = pd.read_csv('yulu bike sharing.txt')
bike_data
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	26.0027	7	329	336
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	15.0013	10	231	241
10883	2012-12-19 21:00:00	4	0	1	1	13.94	15.910	61	15.0013	4	164	168
10884	2012-12-19 22:00:00	4	0	1	1	13.94	17.425	61	6.0032	12	117	129
10885	2012-12-19 23:00:00	4	0	1	1	13.12	16.665	66	8.9981	4	84	88

10886 rows × 12 columns

```
bike_data.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
season	10886.0	2.506614	1.116174	1.00	2.0000	3.000	4.0000	4.0000
holiday	10886.0	0.028569	0.166599	0.00	0.0000	0.000	0.0000	1.0000
workingday	10886.0	0.680875	0.466159	0.00	0.0000	1.000	1.0000	1.0000
weather	10886.0	1.418427	0.633839	1.00	1.0000	1.000	2.0000	4.0000
temp	10886.0	20.230860	7.791590	0.82	13.9400	20.500	26.2400	41.0000
atemp	10886.0	23.655084	8.474601	0.76	16.6650	24.240	31.0600	45.4550
humidity	10886.0	61.886460	19.245033	0.00	47.0000	62.000	77.0000	100.0000
windspeed	10886.0	12.799395	8.164537	0.00	7.0015	12.998	16.9979	56.9969
casual	10886.0	36.021955	49.960477	0.00	4.0000	17.000	49.0000	367.0000
registered	10886.0	155.552177	151.039033	0.00	36.0000	118.000	222.0000	886.0000
count	10886.0	191.574132	181.144454	1.00	42.0000	145.000	284.0000	977.0000

```
bike_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
```



```
bike_data.shape
```

```
(10886, 12)
```

```
bike_data.isnull().any()
```

```
datetime      False
season        False
holiday       False
workingday    False
weather       False
temp          False
atemp         False
humidity      False
windspeed     False
casual        False
registered    False
count         False
dtype: bool
```

Activate Windows
Go to Settings to activate Windows.

```
bike_data.nunique()
```

```
datetime      10886
season            4
holiday           2
workingday        2
weather           4
temp             49
atemp            60
humidity         89
windspeed        28
casual          309
registered      731
count           822
dtype: int64
```

[10]
```
bike_data.duplicated().sum()
```

```
0
```

```
bike_data.dtypes
```

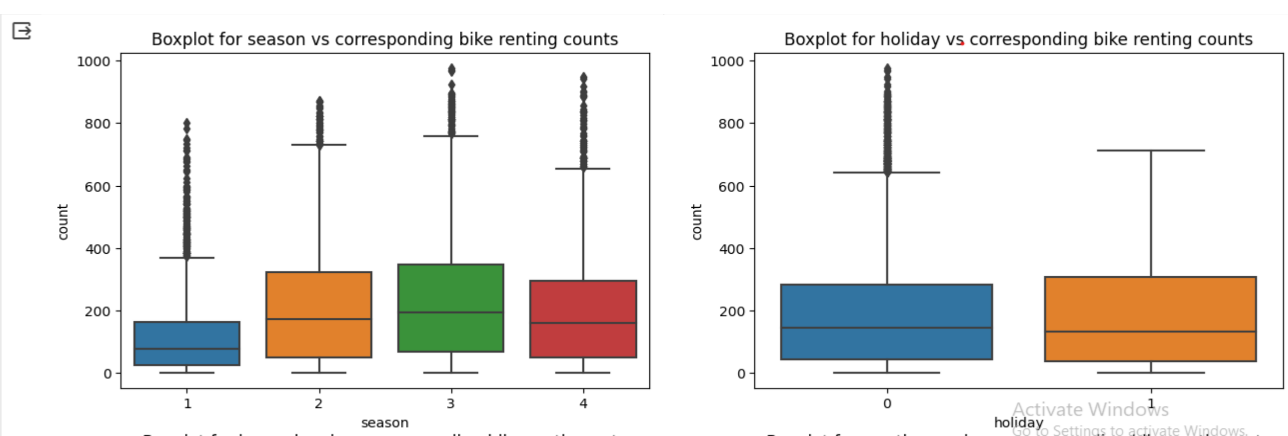
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

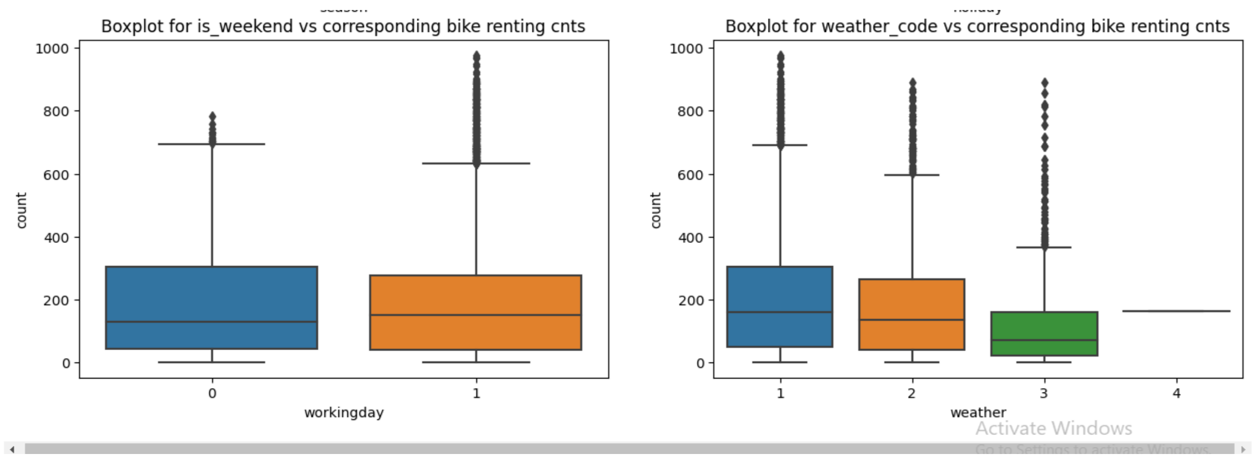
Insights

- There are 4 categorical features namely season, holiday, workingday, weather 7 numerical/continuos features and 1 datetime object. In total 12 independant features with 10886 rows.
- No missing data or null values present neither any duplicate row is there.

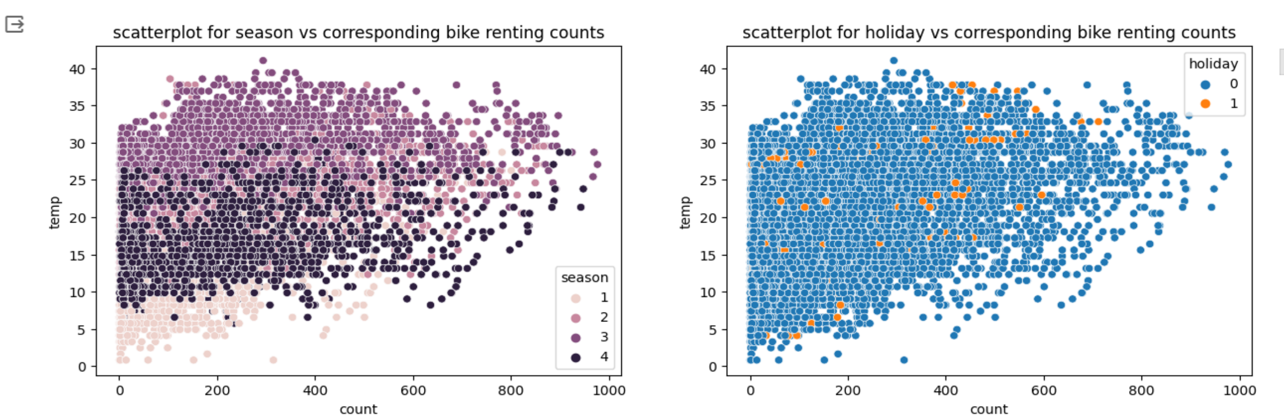
Outlier detections and removal

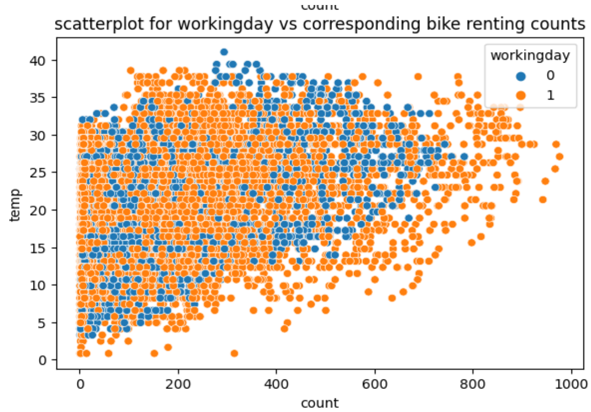
```
# Visualization before outlier removal
fig = plt.figure(figsize = (15,10))

ax1=fig.add_subplot(221)
sns.boxplot(x='season',y='count',data=bike_data)
ax1.set_title('Boxplot for season vs corresponding bike renting counts')

ax1=fig.add_subplot(222)
sns.boxplot(x='holiday',y='count',data=bike_data)
ax1.set_title('Boxplot for holiday vs corresponding bike renting counts')

ax1 = fig.add_subplot(223)
sns.boxplot(x = 'workingday', y = 'count', data = bike_data)
ax1.set_title('Boxplot for is_weekend vs corresponding bike renting cnts')

ax1 = fig.add_subplot(224)
sns.boxplot(x = 'weather', y = 'count', data = bike_data)
ax1.set_title('Boxplot for weather_code vs corresponding bike renting cnts')

plt.show()
```

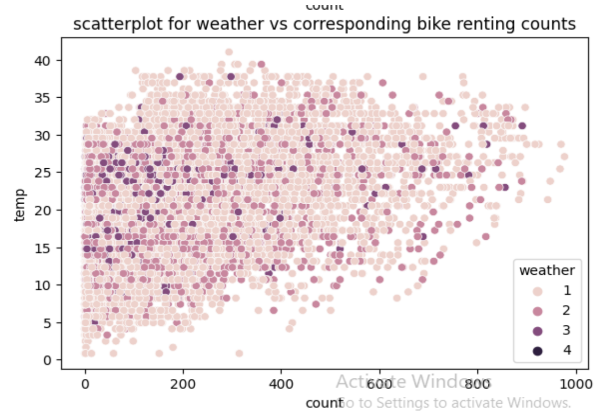





```
fig = plt.figure(figsize = (15,10))

ax1 = fig.add_subplot(221)
sns.scatterplot(x = 'count', y = 'temp',data = bike_data, hue ='season' )
ax1.set_title('scatterplot for season vs corresponding bike renting counts')

ax1 = fig.add_subplot(222)
sns.scatterplot(x ='count', y = 'temp', data = bike_data, hue ='holiday')
ax1.set_title('scatterplot for holiday vs corresponding bike renting counts')

ax1 = fig.add_subplot(223)
sns.scatterplot(x = 'count', y = 'temp',data = bike_data, hue ='workingday')
ax1.set_title('scatterplot for workingday vs corresponding bike renting counts')

ax1 = fig.add_subplot(224)
sns.scatterplot(x = 'count',y = 'temp',data = bike_data, hue ='weather')
ax1.set_title('scatterplot for weather vs corresponding bike renting counts')

plt.show()
```







[14]
```
# Taking backup of original data before removing outliers
bike_dcopy = bike_data.copy()
```

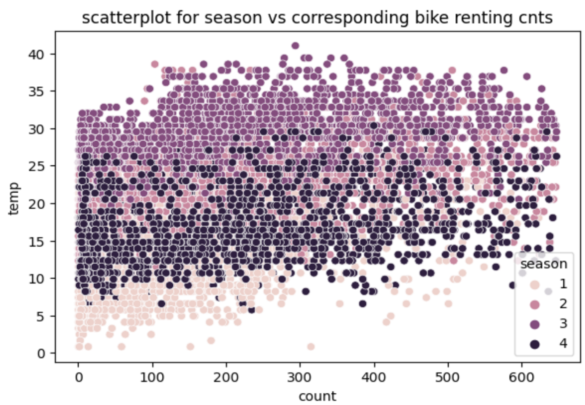
```
q1=bike_data['count'].quantile(0.25)
q3=bike_data['count'].quantile(0.75)
iqr=q3-q1
bike_data = bike_data[(bike_data['count'] >= q1 - 1.5*iqr) & (bike_data['count'] <= q3 +1.5*iqr)]
bike_data.shape
```

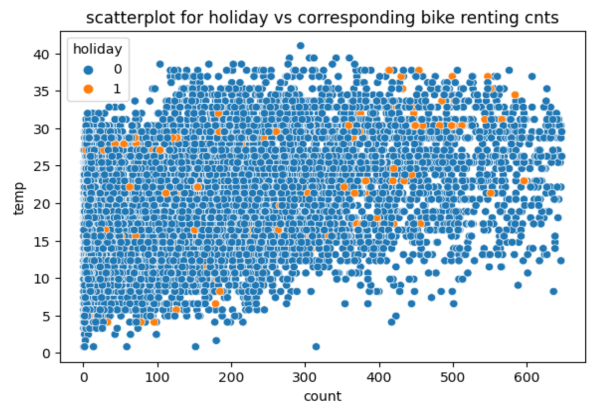
```
(10586, 12)
```

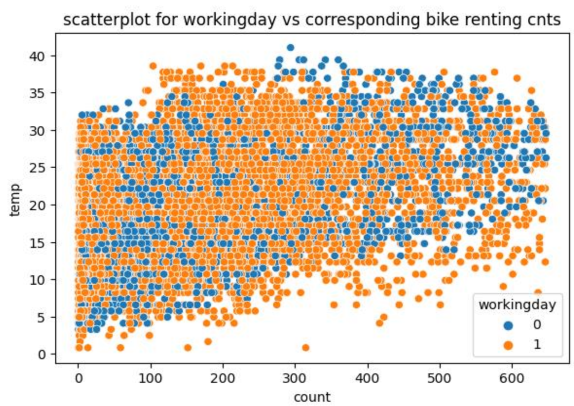
```
bike_dcopy.shape[0] - bike_data.shape[0]
```

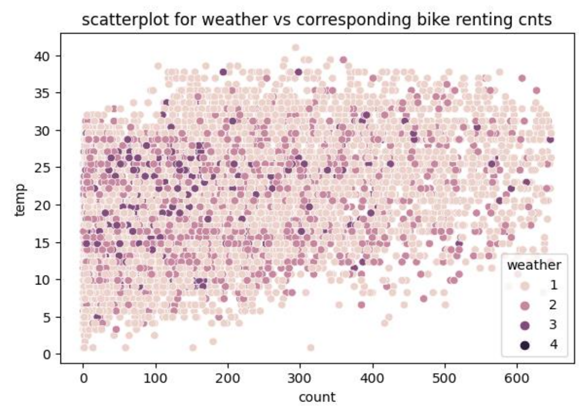
```
300
```

[18]
```
#Visualization after removing outliers
fig = plt.figure(figsize = (15,10))

ax1 = fig.add_subplot(221)
sns.scatterplot(x = 'count', y = 'temp',data = bike_data, hue ='season' )
ax1.set_title('scatterplot for season vs corresponding bike renting cnts')

ax1 = fig.add_subplot(222)
sns.scatterplot(x ='count', y = 'temp', data = bike_data, hue ='holiday')
ax1.set_title('scatterplot for holiday vs corresponding bike renting cnts')

ax1 = fig.add_subplot(223)
sns.scatterplot(x = 'count', y = 'temp',data = bike_data, hue ='workingday')
ax1.set_title('scatterplot for workingday vs corresponding bike renting cnts')

ax1 = fig.add_subplot(224)
sns.scatterplot(x = 'count',y = 'temp',data = bike_data, hue ='weather')
ax1.set_title('scatterplot for weather vs corresponding bike renting cnts')

plt.show()
```









Insights

- After dealing with the outliers, total of 300 rows are removed out off 10886 from the dataset, As we can see from the above scatterplot, the data now looks more clean.

Univariate and Bivariate analysis

```
#creating a new dataframe for indexing timestamp
bike_datatime = pd.read_csv('yulu bike sharing.txt')
bike_datatime
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	26.0027	7	329	336
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	15.0013	10	231	241
10883	2012-12-19 21:00:00	4	0	1	1	13.94	15.910	61	15.0013	4	164	168
10884	2012-12-19 22:00:00	4	0	1	1	13.94	17.425	61	6.0032	12	117	129
10885	2012-12-19 23:00:00	4	0	1	1	13.12	16.665	66	8.9981	4	84	88

10886 rows × 12 columns

[21]
```
bike_dcopy["datetime"].sort_values()
```

```
0        2011-01-01 00:00:00
1        2011-01-01 01:00:00
2        2011-01-01 02:00:00
3        2011-01-01 03:00:00
4        2011-01-01 04:00:00
                ...
10881    2012-12-19 19:00:00
10882    2012-12-19 20:00:00
10883    2012-12-19 21:00:00
10884    2012-12-19 22:00:00
10885    2012-12-19 23:00:00
Name: datetime, Length: 10886, dtype: object
```

[22]
```
bike_dcopy['datetime'] = pd.to_datetime(bike_dcopy['datetime'])

bike_dcopy['year'] = bike_dcopy['datetime'].dt.year
bike_dcopy['month'] = bike_dcopy['datetime'].dt.month
bike_dcopy['day'] = bike_dcopy['datetime'].dt.day
```

```
np.sort(bike_dcopy[bike_dcopy['count'] >= bike_dcopy['count'].quantile(0.75)]['day'].unique())
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19])
```


[24]
```
bike_dcopy[bike_dcopy['count'] >= bike_dcopy['count'].quantile(0.95)]['month'].unique()
```

```
array([ 5,  6,  7,  8,  9, 10,  3,  4, 11, 12])
```

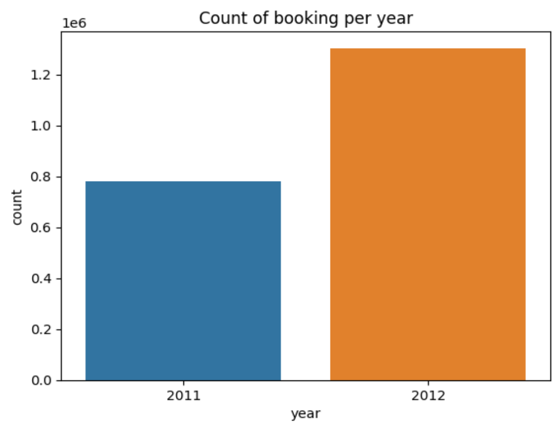
[25]
```
bike_dcopy['year'] = bike_dcopy['datetime'].dt.year
```

[26]
```
bike_dcopy['month'] = bike_dcopy['datetime'].dt.month
```

[27]
```
bike_dcopy.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	year	month	day
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16	2011	1	1
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40	2011	1	1
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32	2011	1	1
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13	2011	1	1
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1	2011	1	1

```
year_data = bike_dcopy.groupby(['year'])['count'].sum()
year_data = year_data.reset_index()
sns.barplot(x='year',y='count',data=year_data)
plt.title('Count of booking per year')
plt.show()
```




```
month_data = bike_dcopy.groupby(['month'])['count'].sum()
month_data = month_data.reset_index()
sns.barplot(x='month',y='count',data=month_data)
plt.title('Count of booking per month')
plt.show()
```

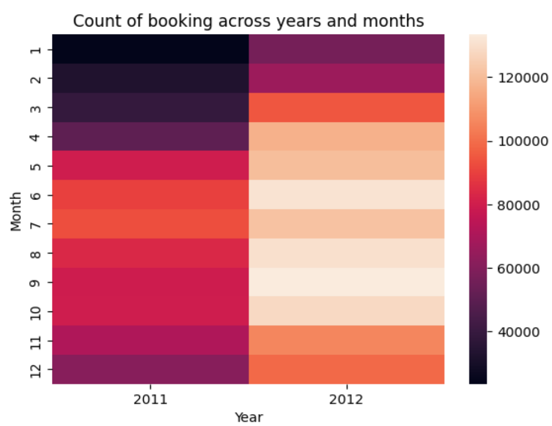
Insights

- Highest booking is in the month of june.
- Almost same booking for the month of may, july, august, september, octomber and gradually decreasing for the rest of the month.

- The count is less during the cold months (November, December, January and February), where due to cold people prefer not to ride cycle.
- As we can see from the month-wise bar plot, the demand for the bikes at the starting of the month is quite low as compared to the months from march 2012 onwards. There's a drop in the middle owing to cold and winter season.
- Almost every months has the same number of bookings.

```
[30] mon_year_data = bike_dcopy.groupby(['year','month'])['count'].sum()
     mon_year_data = pd.DataFrame(mon_year_data)
     mon_year_data.reset_index(inplace = True)
     myy = mon_year_data.pivot('month','year','count').fillna(0)
```

```
sns.heatmap(myy)
plt.title('Count of booking across years and months')
plt.xlabel('Year')
plt.ylabel('Month')
plt.show()
```




```
[32] #Univariate analysis for numerical/continuos variables
     def num_feat(col_data):
         fig,ax = plt.subplots(nrows=1,ncols=2,figsize=(10,5))
         sns.histplot(col_data, kde=True, ax=ax[0], color = 'purple')
         ax[0].axvline(col_data.mean(), color='r', linestyle='--',linewidth=2)
         ax[0].axvline(col_data.median(), color='k', linestyle='dashed', linewidth=2)
         ax[0].axvline(col_data.mode()[0],color='y',linestyle='solid',linewidth=2)
         sns.boxplot(x=col_data, showmeans=True, ax=ax[1])
         plt.tight_layout()
```

```
bike_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10586 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   datetime    10586 non-null  object 
 1   season      10586 non-null  int64  
 2   holiday     10586 non-null  int64  
 3   workingday  10586 non-null  int64  
 4   weather     10586 non-null  int64  
 5   temp        10586 non-null  float64
 6   atemp       10586 non-null  float64
 7   humidity    10586 non-null  int64  
 8   windspeed   10586 non-null  float64
 9   casual      10586 non-null  int64  
 10  registered  10586 non-null  int64  
 11  count       10586 non-null  int64  
dtypes: float64(3), int64(8), object(1)
memory usage: 1.0+ MB
```



```
bike_data.columns
```

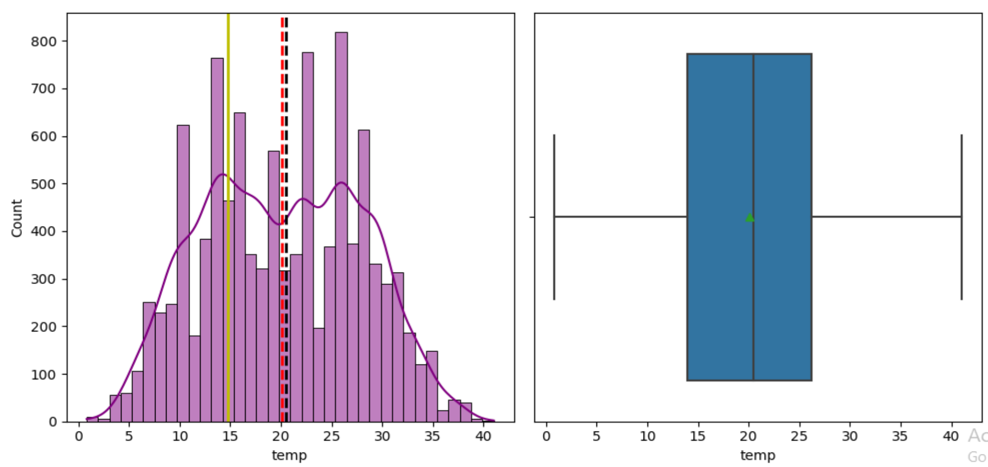
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

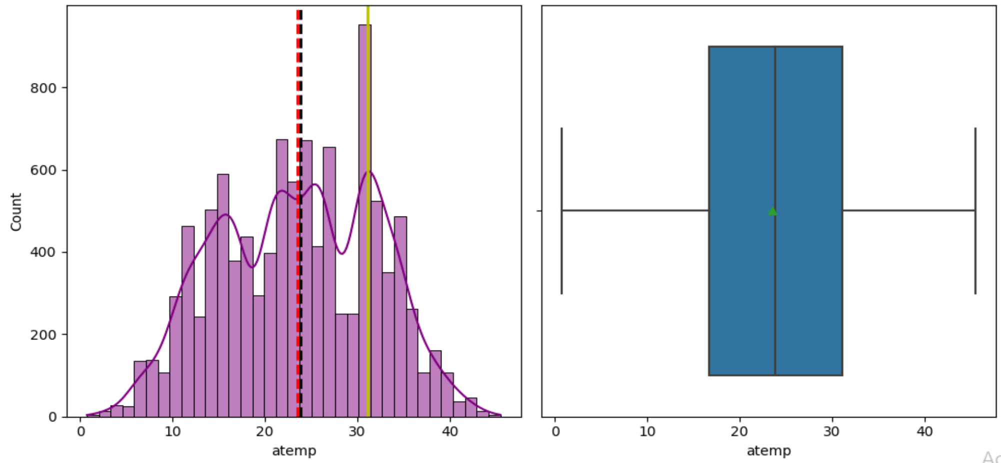


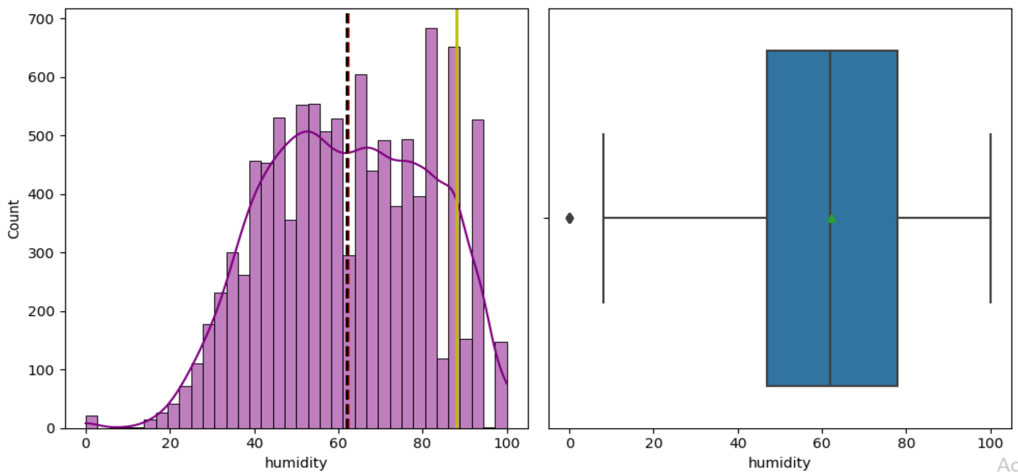
```
num_cols = ['temp','atemp','humidity','count','windspeed']
num_cols
```

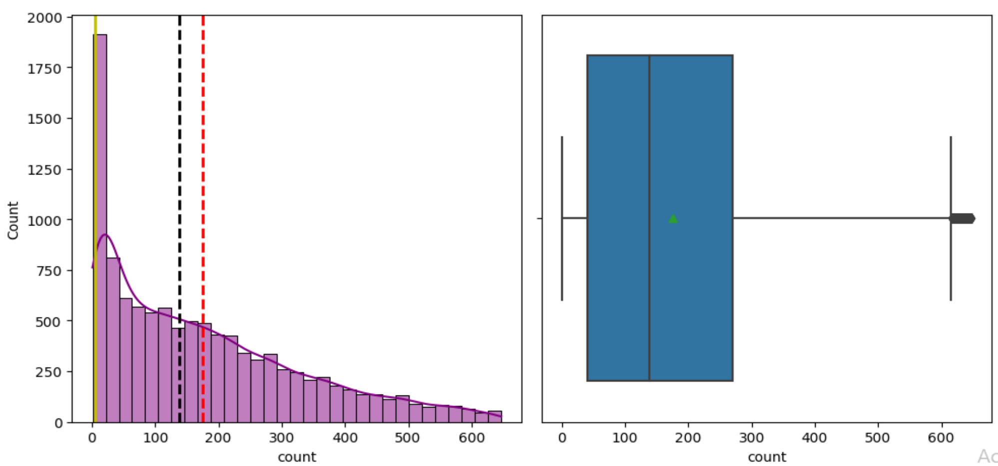
```
['temp', 'atemp', 'humidity', 'count', 'windspeed']
```

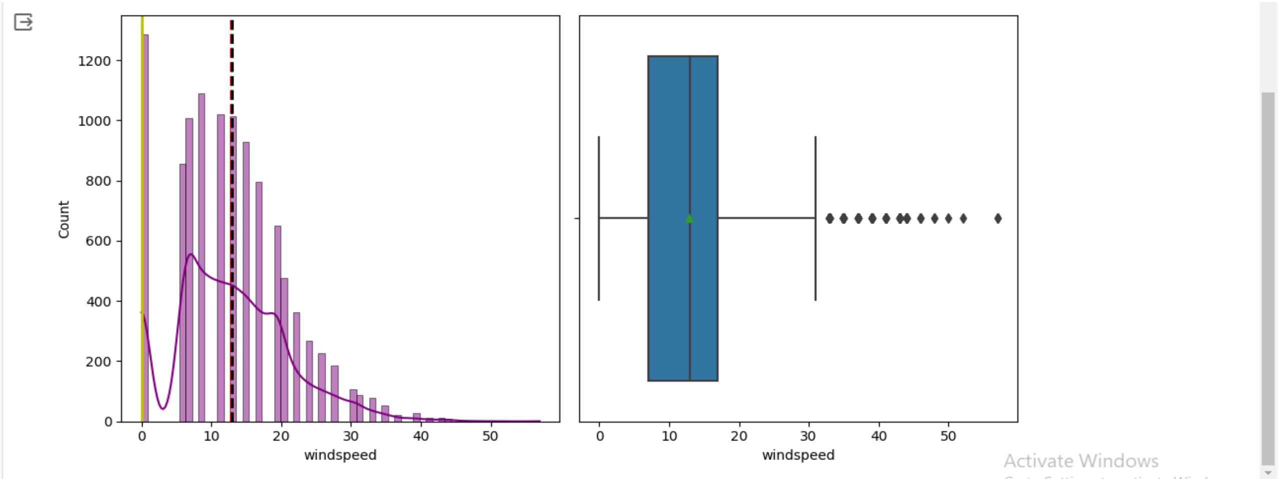
```
for i in num_cols:
    num_feat(bike_data[i])
```




Count
atemp
atemp


Count
humidity
humidity


Count
count
count



Insights

- There are outliers in the windspeed and casual users which tells us that, the windspeed is not uniform.
- The exponential decay curve for the count tells us that, as the users renting bikes increases the frequency decreases.

```
[37] #EDA on Univariate Categorical variables
     def cat_feat(col_data):
         fig,ax = plt.subplots(nrows=1,ncols=2,figsize=(12,5))
         fig.suptitle(col_data.name+' wise sale',fontsize=15)
         sns.countplot(col_data,ax=ax[0])
         col_data.value_counts().plot.pie(autopct='%1.1f%%',ax=ax[1], shadow = True)
         plt.tight_layout()
```

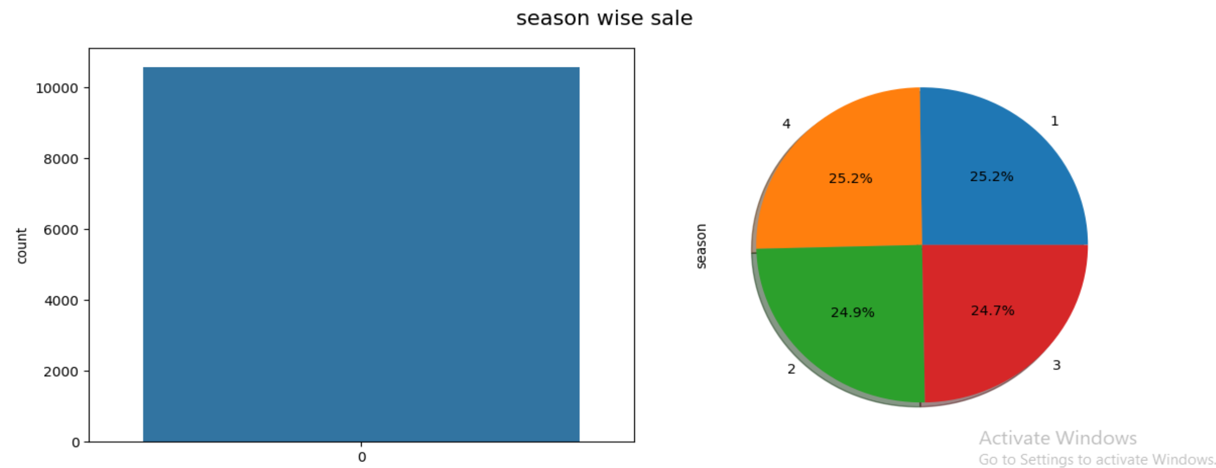
```
bike_data.columns
```

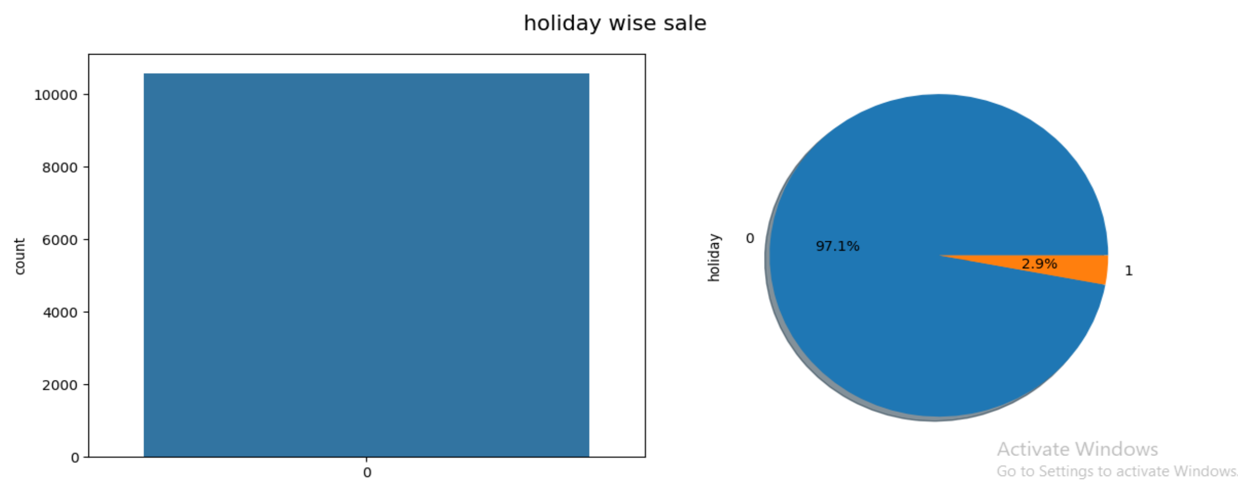
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

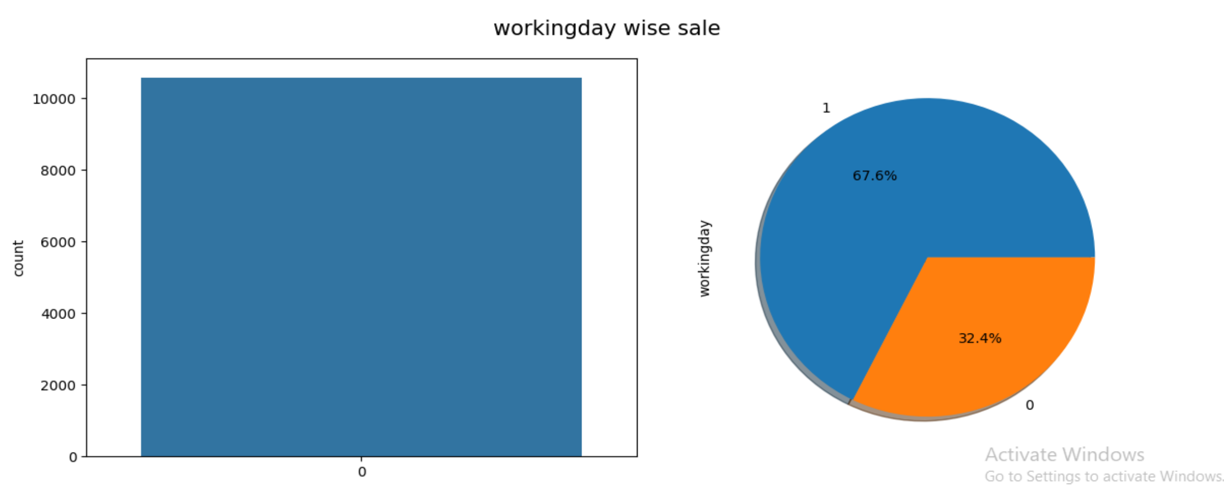
```
[39] cat_cols = ['season', 'holiday', 'workingday', 'weather']
     cat_cols
```

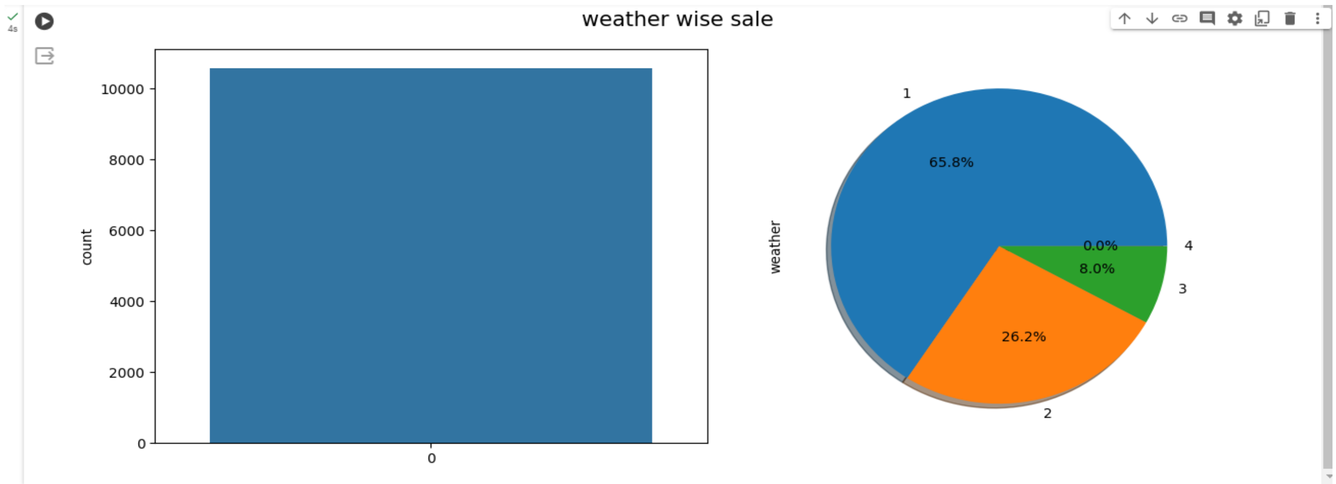
```
['season', 'holiday', 'workingday', 'weather']
```

```python
for i in cat_cols:
    cat_feat(bike_data[i])
```







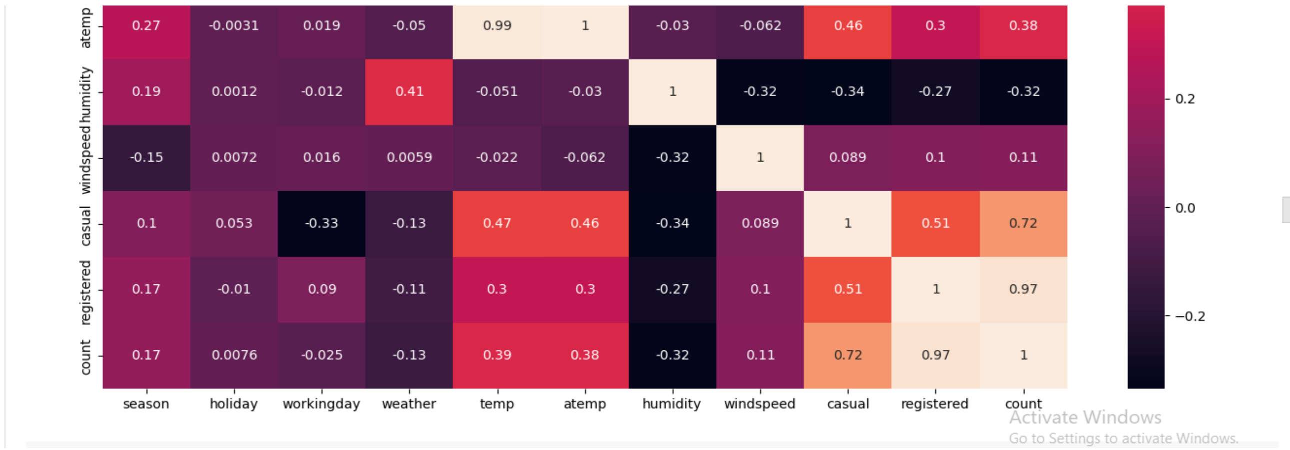


Insights

- For the weather (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog) number of users renting the bikes is much low and hence it is good to drop the feature while doing the further tests.
- When weather is good (Clear, Few clouds, partly cloudy, partly cloudy) people tend to rent more bikes.
- Count of renting the bikes on working day is much higher than non-working day.
- During Holidays people do not prefer to ride bikes
- During season (spring, summer, fall, winter) the count of renting the bikes is more or less.

Correlation between bivariate analysis

```
[41] plt.figure(figsize = (16, 10))
     sns.heatmap(bike_data.corr(),annot=True)
     plt.show()
```



Insights

- The Registered users has higher correlation as compared to the casual user count.
- The wind speed and season has very nearly zero positive correlation with the count which means, that means the wind speed and season did not have any affect on the bike renting.
- temp and atemp has moderate correlation with the count. People tend to go out on bright sunny day when the temp is normal whereas during the harsh condition such as during too hot or too cold there is a drop in the renting the bike.
- When its holiday, user count is considerably low but when its working day user count is moderately high.

2 Sample T-Test

```
[42] bike_data.shape

(10586, 12)
```

```
bike_data['workingday'].value_counts(normalize = True) * 100

1    67.645947
0    32.354053
Name: workingday, dtype: float64
```

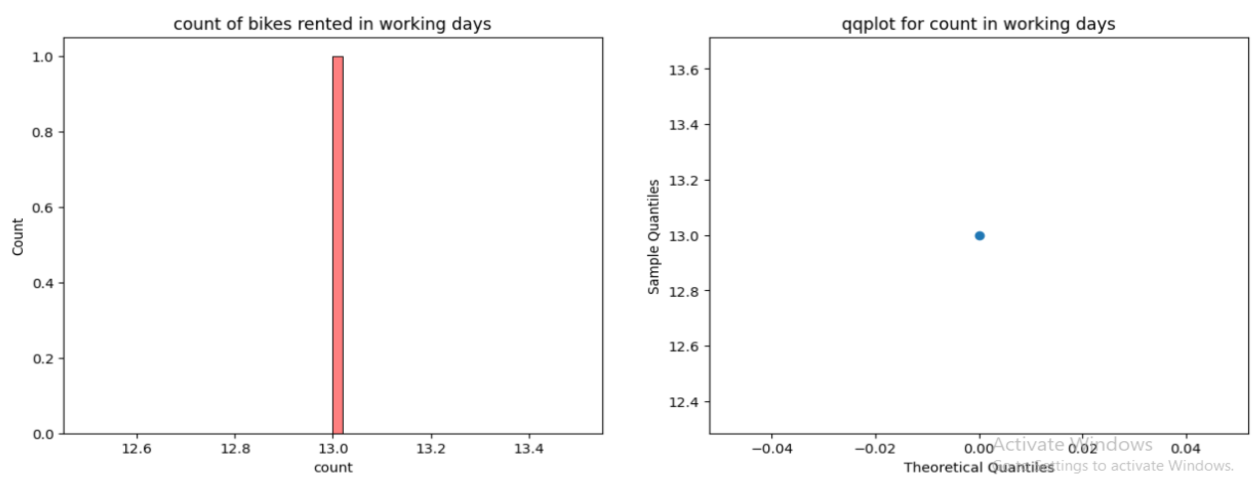
```
bike_data['workingday'].value_counts()

1    7161
0    3425
Name: workingday, dtype: int64
```

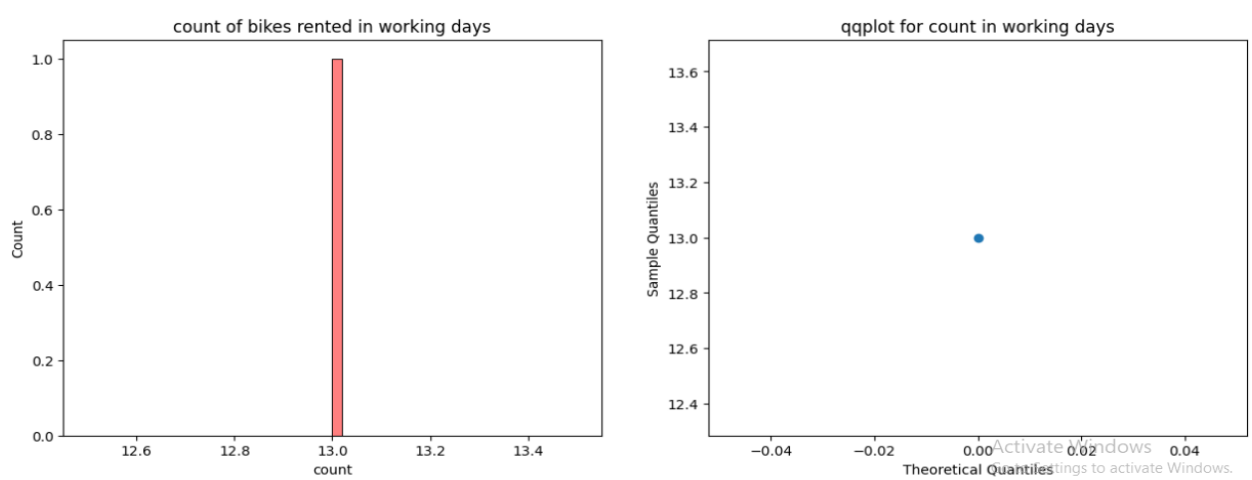
```
[45] working_data = bike_data[bike_data['workingday'] == 1].sample(replace = False)
     non_working_data = bike_data[bike_data['workingday'] == 0].sample(replace = False)
```

```
[46] round(working_data['count'].std()**2,2), round(non_working_data['count'].std()**2 ,2)
```

```
(nan, nan)
```

```
fig = plt.figure(figsize = (15,12))

ax1 = fig.add_subplot(221)
sns.histplot(data = working_data, x = 'count' , bins = 50, kde = True, ax = ax1, color = 'red')
ax1.set_title('count of bikes rented in working days')

ax2 = fig.add_subplot(222)
sm.qqplot(working_data['count'], line = 's', ax = ax2)
ax2.set_title('qqplot for count in working days')

ax3 = fig.add_subplot(223)
sns.histplot(data = non_working_data, x = 'count' , bins = 50, kde = True, ax = ax3, color = 'red')
ax3.set_title('count of bike rented in non-working days')

ax4 = fig.add_subplot(224)
sm.qqplot(non_working_data['count'], line = 's', ax = ax4)
ax4.set_title('qqplot for count in non-working days')

plt.show()
```



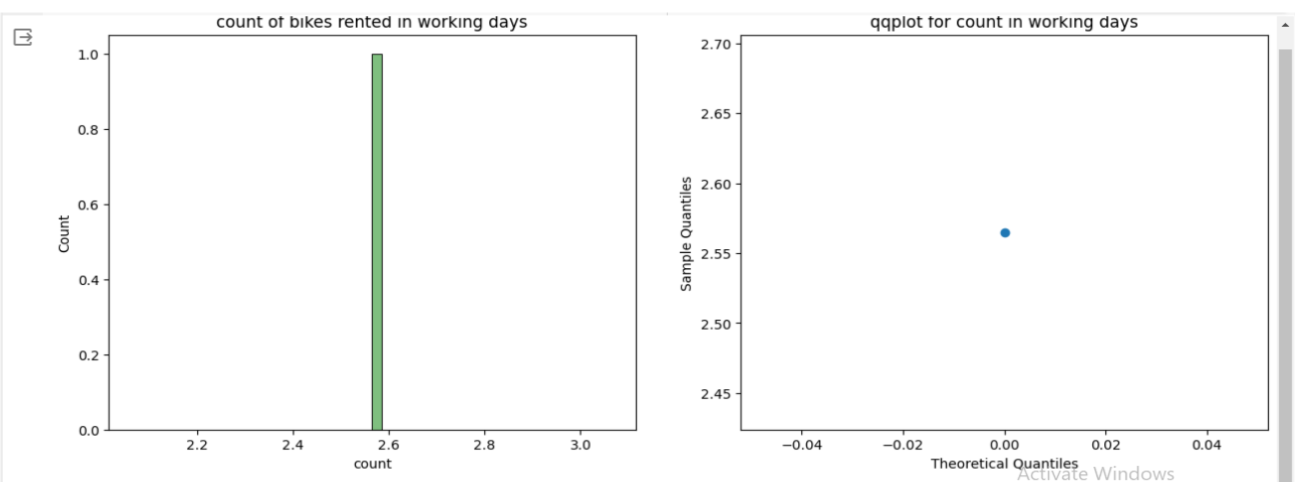


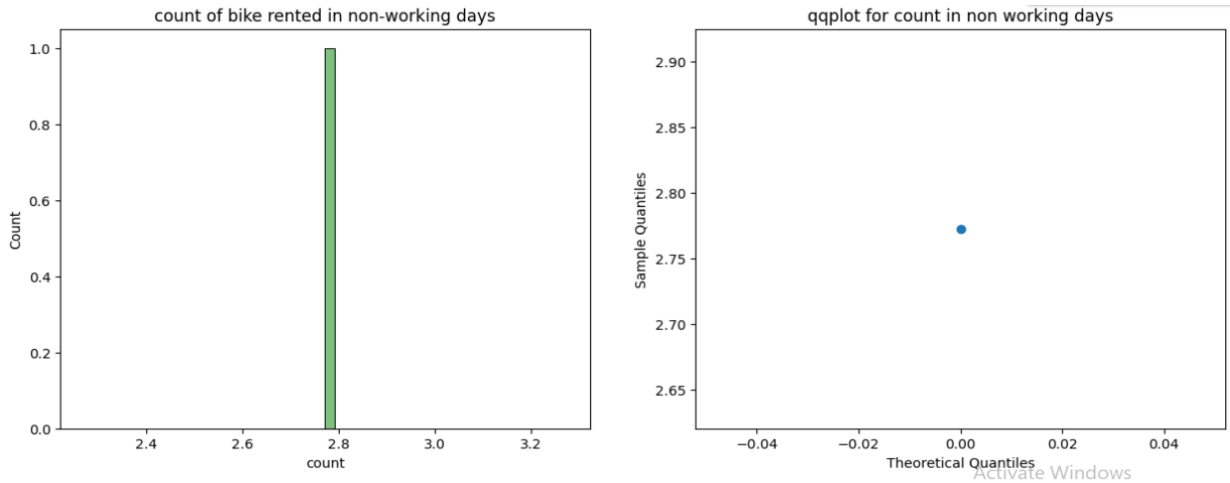
```
[48] t_test, p_value = stats.ttest_ind(working_data['count'],non_working_data['count'],
                                      alternative='greater', equal_var = False)
     t_test, p_value

     (nan, nan)
```

Insights

- As we are getting nan values and the distribution is also not in the normal form which violates the conditions for 2 sample test, Hence we reject the null hypothesis.
- We got the p-Value as nan which should be p-Value<alpha(0.05), so after trying with the log to reject the null hypothesis.

```
fig = plt.figure(figsize = (15,12))

ax1 = fig.add_subplot(221)
sns.histplot(data = np.log(working_data['count']) , bins = 50, kde = True, ax = ax1, color = 'green')
ax1.set_title('count of bikes rented in working days')

ax2 = fig.add_subplot(222)
sm.qqplot(np.log(working_data['count']), line = 's', ax = ax2)
ax2.set_title('qqplot for count in working days')

ax3 = fig.add_subplot(223)
sns.histplot(data = np.log(non_working_data['count']) , bins = 50, kde = True, ax = ax3, color  = 'green')
ax3.set_title('count of bike rented in non-working days')

ax4 = fig.add_subplot(224)
sm.qqplot(np.log(non_working_data['count']), line = 's', ax = ax4)
ax4.set_title('qqplot for count in non working days')

plt.show()
```






```
[50] sample_w_log = np.log(working_data['count'])
     sample_nw_log = np.log(non_working_data['count'])
```

```
[51] statistic,p_value = stats.ttest_ind(sample_w_log,sample_nw_log , alternative = 'greater')
     statistic,p_value
```

```
(nan, nan)
```

```
[52] def htResult(p_value):
         significance_level = 0.05
         if p_value <= significance_level:
             print('Reject NULL HYPOTHESIS')
         else:
             print('Fail to Reject NULL HYPOTHESIS')
```

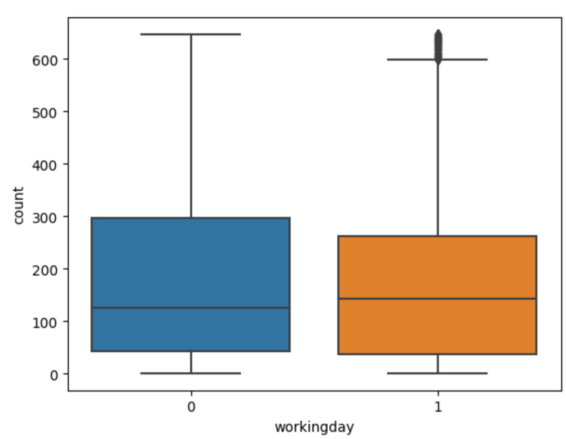
```
[53] htResult(p_value)
```

```
Fail to Reject NULL HYPOTHESIS
```

```
[54] stats.levene(sample_w_log, sample_nw_log, center='median')
```

```
LeveneResult(statistic=nan, pvalue=nan)
```

```
sns.boxplot(x='workingday', y='count', data=bike_data)
plt.show()
```



Insights

- We are getting the p value as nan, so we are failing to reject the null hypothesis.

Chi Square

```
[56] contigency_table = pd.crosstab(bike_data.weather,bike_data.season,margins=True,margins_name='Total')
contigency_table
```

season / weather	1	2	3	4	Total
1	1744	1721	1843	1657	6965
2	714	690	579	787	2770
3	211	223	195	221	850
4	1	0	0	0	1
Total	2670	2634	2617	2665	10586

```
contigency_table = contigency_table.rename(columns = {'Total':'Row_total'})
contigency_table
```

season / weather	1	2	3	4	Row_total
1	1744	1721	1843	1657	6965
2	714	690	579	787	2770
3	211	223	195	221	850
4	1	0	0	0	1
Total	2670	2634	2617	2665	10586


```
[58] n = contigency_table.at["Total", "Row_total"]
exp=contigency_table.copy()
for x in exp.index[0:-1]:
    for y in exp.columns[0:-1]:
        v= (((contigency_table.at[x, "Row_total"]) * (contigency_table.at["Total", y]))/n ).round(2)
        exp.at[x,y]=float(v)

exp = exp.iloc[[0,1,2,3,4], [0,1,2,3]]
exp
```

season / weather	1	2	3	4
1	1756.71	1733.03	1721.84	1753.42
2	698.65	689.23	684.78	697.34
3	214.39	211.50	210.13	213.99
4	0.25	0.25	0.25	0.25
Total	2670.00	2634.00	2617.00	2665.00

Insights

- Weather has expeted counts less than 5, so we will drop it.

```
[59] bike_data['weather'].value_counts()
```

```
1    6965
2    2770
3     850
4       1
Name: weather, dtype: int64
```

```
[60] bike_data['season'].value_counts()
```

```
1    2670
4    2665
2    2634
3    2617
Name: season, dtype: int64
```

```
bike_data=bike_data[~(bike_data['weather']==10.0)]
bike_data['weather'].value_counts()
```

```
1    6965
2    2770
3     850
4       1
Name: weather, dtype: int64
```



```
contigency_table = pd.crosstab(bike_data.weather,bike_data.season,margins=True,margins_name='Total')
contigency_table
```

season / weather	1	2	3	4	Total
1	1744	1721	1843	1657	6965
2	714	690	579	787	2770
3	211	223	195	221	850
4	1	0	0	0	1
Total	2670	2634	2617	2665	10586

Insights

- Weather has expected counts less than 5 so again we will drop it.

```
contigency_table = contigency_table.rename(columns = {'Total':'Row_total'})
contigency_table
```

season / weather	1	2	3	4	Row_total
1	1744	1721	1843	1657	6965
2	714	690	579	787	2770
3	211	223	195	221	850
4	1	0	0	0	1
Total	2670	2634	2617	2665	10586

```
n = contigency_table.at["Total", "Row_total"]
exp=contigency_table.copy()
for x in exp.index[0:-1]:
    for y in exp.columns[0:-1]:
        v= (((contigency_table.at[x, "Row_total"]) * (contigency_table.at["Total", y]))/n ).round(2)
        exp.at[x,y]=float(v)

exp = exp.iloc[[0,1,2,3,4], [0,1,2,3]]
exp
```

season	1	2	3	4
weather				
1	1756.71	1733.03	1721.84	1753.42
2	698.65	689.23	684.78	697.34
3	214.39	211.50	210.13	213.99
4	0.25	0.25	0.25	0.25
Total	2670.00	2634.00	2617.00	2665.00

```
weather_code_season_dep = pd.crosstab(bike_data['weather'], bike_data['season'])
weather_code_season_dep
```

season	1	2	3	4
weather				
1	1744	1721	1843	1657
2	714	690	579	787
3	211	223	195	221
4	1	0	0	0


```
[66] stat, p_value, dof, expected = stats.chi2_contingency(weather_code_season_dep)
     stat, p_value, dof, expected
     #stat, p, dof, expected
```

```
(47.17309400137371,
 3.643774770920206e-07,
 9,
 array([[1.75671169e+03, 1.73302569e+03, 1.72184064e+03, 1.75342197e+03],
        [6.98649159e+02, 6.89229171e+02, 6.84780843e+02, 6.97340828e+02],
        [2.14386926e+02, 2.11496316e+02, 2.10131305e+02, 2.13985452e+02],
        [2.52219913e-01, 2.48819195e-01, 2.47213301e-01, 2.51747591e-01]]))
```

```
[67] alpha = 0.05
     if p_value >= alpha:
         print('We fail to reject the Null Hypothesis Ho and thus we can conclude that smokers proportion is not significantly different in different regions"')
     else:
         print('We reject the Null Hypothesis Ho')
```

```
We reject the Null Hypothesis Ho
```


Insights

- We can reject null hypothesis as we have enough number of proofs to reject null hypothesis. So, it seems like weather and season are dependent on each other.

Annova

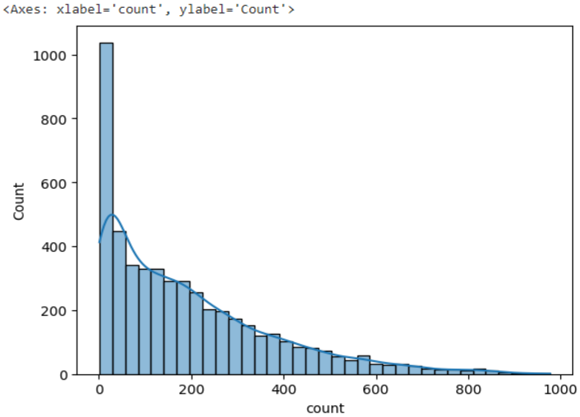
```
[68] bike_dcopy['weather'].value_counts()
```

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

```
[69] def normality_check(series, alpha=0.05):
         _, p_value = shapiro(series)
         print(f'p value = {p_value}')
         if p_value >= alpha:
             print('We fail to reject the Null Hypothesis Ho')
         else:
             print('We reject the Null Hypothesis Ho')
```

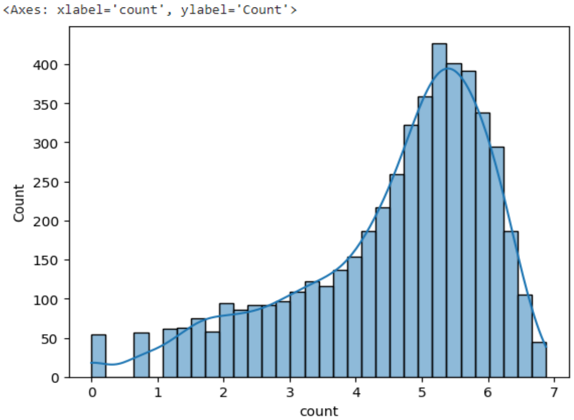
```
sns.histplot(bike_dcopy['count'].sample(5000), kde = True)
```

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




```
[71] sns.histplot(np.log(bike_dcopy['count'].sample(5000)), kde = True)
```

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




```
[72] stats.shapiro(bike_dcopy['count'].sample(5000))
```

```
ShapiroResult(statistic=0.8811339139938354, pvalue=0.0)
```

Insights

- Even after taking log the distribution is not normal.

```
[73] bike_dcopy=bike_dcopy[~(bike_dcopy['weather']==10.0) ]
     bike_dcopy=bike_dcopy[~(bike_dcopy['weather']==26.0) ]
```

```
[74] bike_dcopy['weather'].value_counts()
```

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

```
[75] normality_check(bike_dcopy['weather'].sample(1400, replace = True))
```

```
p value = 0.0
We reject the Null Hypothesis Ho
```

```
[76] bike_dcopy.groupby(['weather'])['count'].describe()
```

weather	count	mean	std	min	25%	50%	75%	max
1	7192.0	205.236791	187.959566	1.0	48.0	161.0	305.0	977.0
2	2834.0	178.955540	168.366413	1.0	41.0	134.0	264.0	890.0
3	859.0	118.846333	138.581297	1.0	23.0	71.0	161.0	891.0
4	1.0	164.000000	NaN	164.0	164.0	164.0	164.0	164.0

```
[ ] def variance_check(series1, series2, series3,series4,series5, alpha=0.05):
        _, p_value = levene(series1, series2, series3)
        print(f'p value = {p_value}')
        if (p_value >= alpha).all():
            print('We fail to reject the Null Hypothesis Ho')
        else:
            print('We reject the Null Hypothesis Ho')
```

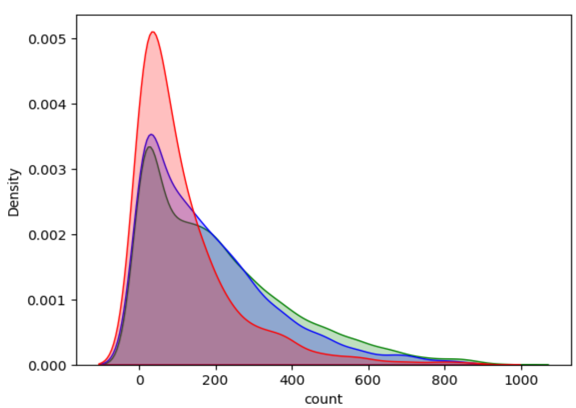


```
[78] series1 = bike_dcopy[bike_dcopy['weather'] == 1]['count']
     series2 = bike_dcopy[bike_dcopy['weather'] == 2]['count']
     series3 = bike_dcopy[bike_dcopy['weather'] == 3]['count']
     series4 = bike_dcopy[bike_dcopy['weather'] == 4]['count']
     series5 = bike_dcopy[bike_dcopy['weather'] == 7]['count']
```

```
[79] variance_check(series1, series2, series3,series4,series5)
```

```
p value = 6.198278710731511e-36
We reject the Null Hypothesis Ho
```

```
sns.kdeplot(series1,color = 'green',shade='green')
sns.kdeplot(series2,color = 'blue',shade = 'blue')
sns.kdeplot(series3,color = 'red',shade = 'red')
sns.kdeplot(series4,color = 'yellow',shade = 'yellow')
sns.kdeplot(series5,color = 'orange',shade = 'orange')
plt.show()
```



Activate Windows
Go to Settings to activate Windows.

```
[81] stat,p = stats.f_oneway(bike_dcopy[bike_dcopy['weather'] == 1]['count'],
                        bike_dcopy[bike_dcopy['weather'] == 2]['count'],
                        bike_dcopy[bike_dcopy['weather'] == 3]['count'],
                       bike_dcopy[bike_dcopy['weather'] == 4]['count'],
                       bike_dcopy[bike_dcopy['weather'] == 7]['count'])
stat,p

(nan, nan)
```

```
test, p_val= stats.levene(bike_dcopy[bike_dcopy['weather'] == 1]['count'],
                        bike_dcopy[bike_dcopy['weather'] == 2]['count'],
                        bike_dcopy[bike_dcopy['weather'] == 3]['count'],
                       bike_dcopy[bike_dcopy['weather'] == 4]['count'],
                       bike_dcopy[bike_dcopy['weather'] == 7]['count'])
test, p_val

(nan, nan)
```


Insights

- As we are getting nan values for both the test and P value where P-value<alpha(0.05) and we cant predict the value of p, we reject HO, thus we can say that count of bikes differ with a change in weather.

Checking for season

```
bike_dcopy['season'].value_counts()

4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

```
[84] bike_dcopy.groupby(['season'])['count'].describe()
```

season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

```
[85] stat,p = stats.f_oneway(bike_dcopy[bike_dcopy['season'] == 1]['count'],
                        bike_dcopy[bike_dcopy['season'] == 2]['count'],
                        bike_dcopy[bike_dcopy['season'] == 3]['count'],
                       bike_dcopy[bike_dcopy['season'] == 4]['count'],
                       bike_dcopy[bike_dcopy['season'] == 7]['count'])
stat,p

(nan, nan)
```

Activate Windows
Go to Settings to activate Windows.

```
[86] test, p_val= stats.levene(bike_dcopy[bike_dcopy['season'] == 1]['count'],
                        bike_dcopy[bike_dcopy['season'] == 2]['count'],
                        bike_dcopy[bike_dcopy['season'] == 3]['count'],
                       bike_dcopy[bike_dcopy['season'] == 4]['count'],
                       bike_dcopy[bike_dcopy['season'] == 7]['count'])
test, p_val

(nan, nan)
```

Insights

- As we are getting nan values for both the test and P value where P-value<alpha(0.05) and we can not predict the value of p, we reject Ho, thus we can say that count of bikes differ with a change in weather.

Recommendations and Insights

- There are 4 categorical features namely season, holiday, working day, weather 7 numerical/continuos features and 1 date time object. In total 12 independent features with 10886 rows.
- No missing data or null values present neither any duplicate row is there
- After dealing with the outliers, total of 300 rows are removed out off 10886 from the dataset, As we can see from the above scatterplot, the data now looks more clean
- Highest booking is in the month of june.
- Almost same booking for the month of may, july, august, september, octomber and gradually decreasing for the rest of the month.
- The count is less during the cold months (November, December, January and February), where due to cold people prefer not to ride cycle.
- As we can see from the month-wise bar plot, the demand for the bikes at the starting of the month is quite low as compared to the months from march 2012 onwards. There's a drop in the middle owing to cold and winter season.
- Almost every months has the same number of bookings
- There are outliers in the wind speed and casual users which tells us that, the wind speed is not uniform.
- The exponential decay curve for the count tells us that, as the users renting bikes increases the frequency decreases.
- For the weather (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog) number of users renting the bikes is much low and hence it is good to drop the feature while doing the further tests.

- When weather is good (Clear, Few clouds, partly cloudy, partly cloudy) people tend to rent more bikes
- Count of renting the bikes on working day is much higher than non-working day.
- During Holidays people don not prefer to ride bikes.
- During season (spring, summer, fall, winter) the count of renting the bikes is more or less.
- The Registered users has higher correlation as compared to the casual user count.
- The wind speed and season has very nearly zero positive correlation with the count which means, that means the wind speed and season did not have any affect on the bike renting.
- temp and atemp has moderate correlation with the count. People tend to go out on bright sunny day when the temp is normal whereas during the harsh condition such as during too hot or too cold there is a drop in the renting the bike.
- When its holiday, user count is considerably low but when its working day user count is moderately high.
- Weather has expected counts less than 5, so we will drop it.
- We are getting the p value as nan, so we are failing to reject the null hypothesis.
- Weather has expected counts less than 5 so again we will drop it.
- We can reject null hypothesis as we have enough number of proofs to reject null hypothesis, So it seems like weather and season are dependent on each other.
- Even after taking log the distribution is not normal
- As we are getting nan values for both the test and P value where P-value<alpha(0.05) and we can not predict the value of p, we reject HO, thus we can say that count of bikes differ with a change in weather.
- As we are getting nan values for both the test and P value where P-value<alpha(0.05) and we can not predict the value of p, we reject Ho, thus we can say that count of bikes differ with a change in weather.

2 Sample T-Test

- The distribution is not normal which violates conditions for conducting 2 sample t test. Also the varaince of the samples is unequal. Hence we will do log-transformation
- We got a p-value nan which we can not predict whether greater than or less than 0.05 and hence we can say that we can accept the null hypothesis. We will confirm after log - transformation as well.
- After taking log, we still can not get a near normal distribution with inequal variance. So we can calculate the p-value and test-statistics.
- **<u>Conclusion</u>** : As the p value is nan we failed to reject the null hypothesis.

In order to conclude, we can say that the major factors affecting the count of bikes rented are season and weather. The working and non working days can't be considered as a significant factor in predicting the future of rental business. At the same time, the business team must focus on the months other than winter months for increasing the bike parking zones as during the winter months of (Nov, Dec, Jan, Feb), theres's a considerable dip in the count. So the team can utilize these months for serving some other purpose such as renting electric cars, etc which can be a comfortable means for commute in cold.