Yulu Business Case Study- Hypothesis Testing

The company wants to know:

```
Which variables are significant in predicting the demand for shared electric cycles in the Indian
How well those variables describe the electric cycle demands
```

Column Profiling:

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

```
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('bike_sharing.csv')
bike_data
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windsp
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0
...	...	...	...	...	...	...	...	...	...

```
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
```

```
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
```

```
bike_data.duplicated().sum()
```

```
0
```

```
bike_data.dtypes
```

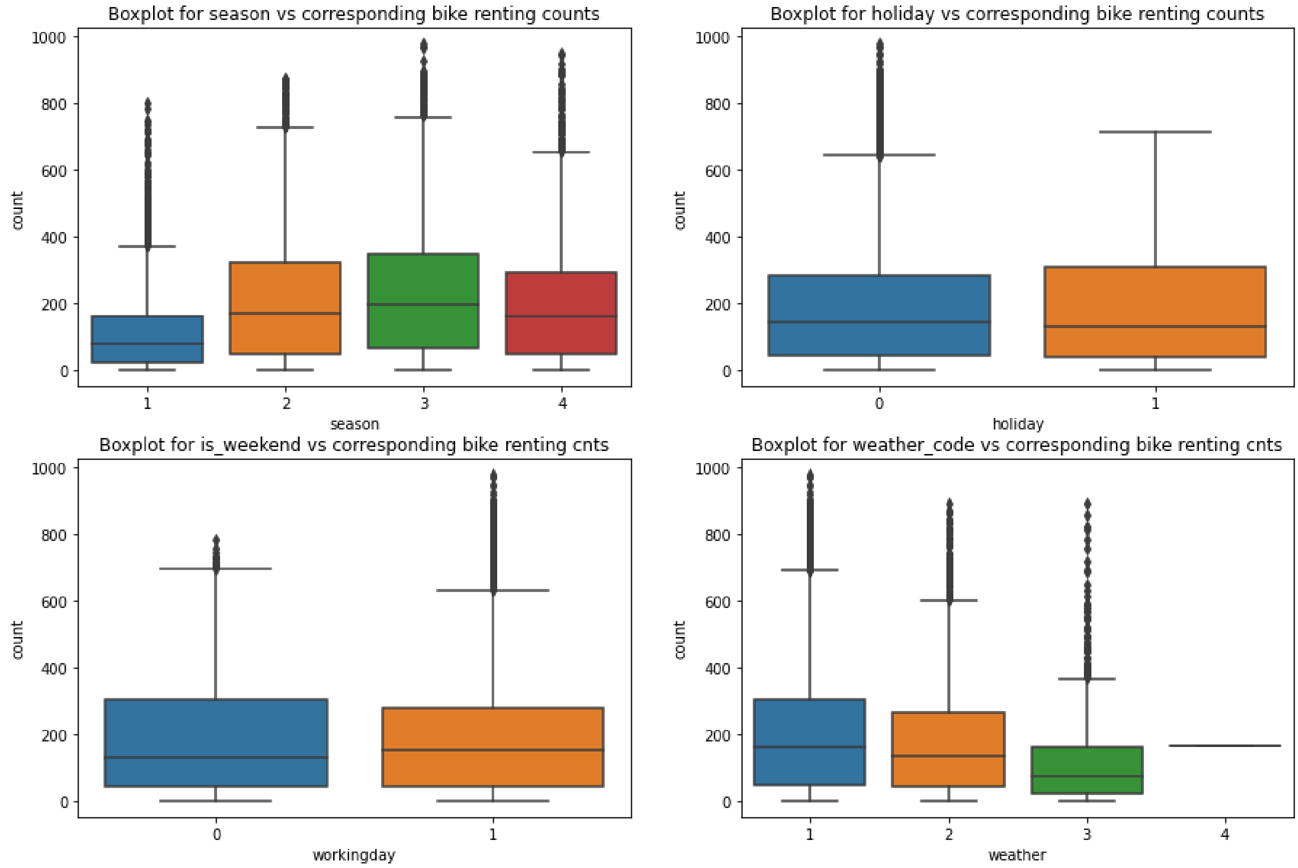
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

Insights

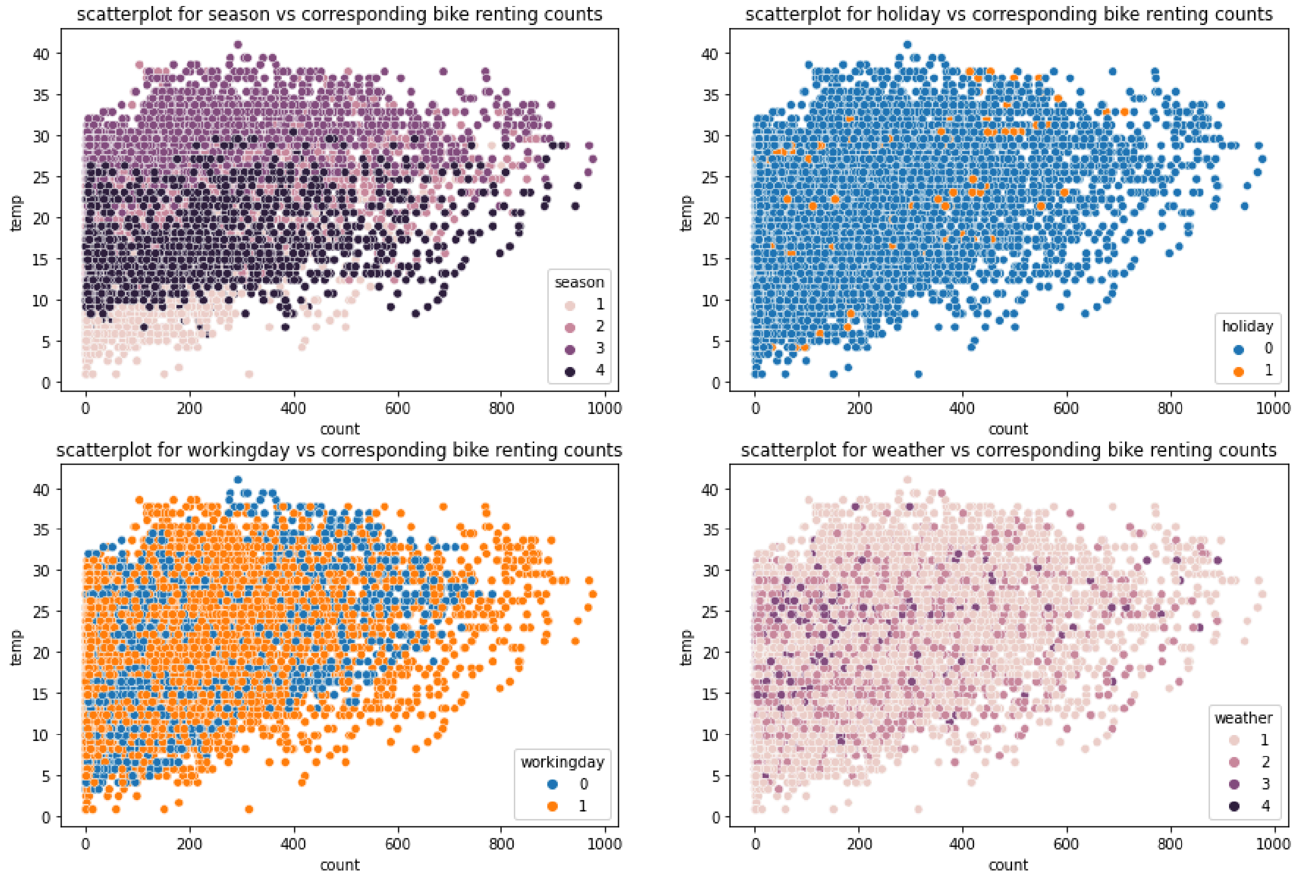
- There are 4 categorical features namely season, holiday, workingday, weather 7 numerical/continuos features and 1 datetime object. In total 12 independant features with 10886 rows.
- No missing data or null values present neither any duplicate row is there

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()
```




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

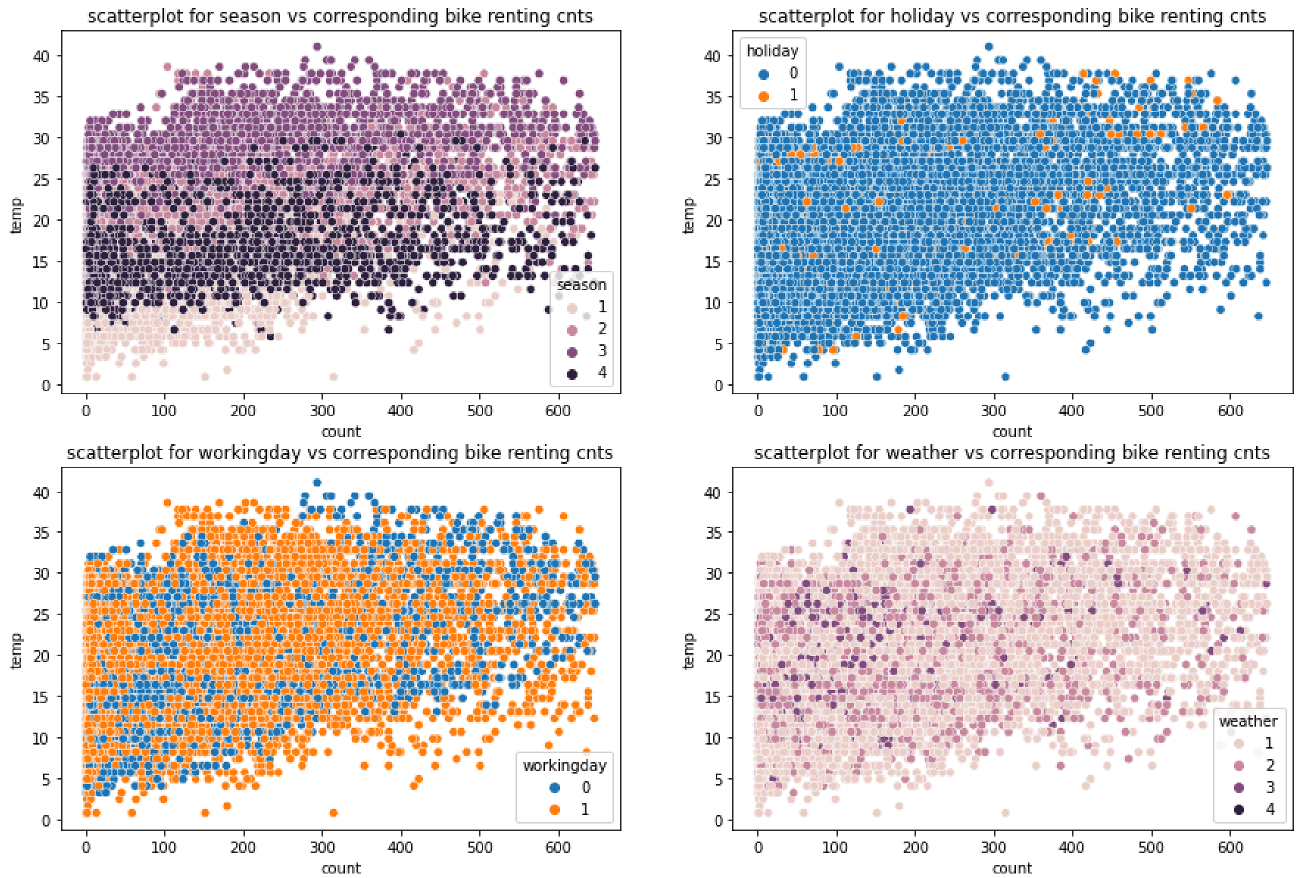
```
q1=bike_data['count'].quantile(0.25)
q3=bike_data['count'].quantile(0.75)
iqr=q3-q1
bike_data = bike_data[(bike_data['count'] >= q1 - 1.5*iqr) & (bike_data['count'] <= q3 +1
bike_data.shape
```

```
(10586, 12)
```

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

```
300
```

```python
#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('bike_sharing.csv')
bike_datatime
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windsp
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0
...	...	...	...	...	...	...	...	...	...

```
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
```

```
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'].uniq
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19], dtype=int64)
```

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

```
array([ 5,  6,  7,  8,  9, 10,  3,  4, 11, 12], dtype=int64)
```

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

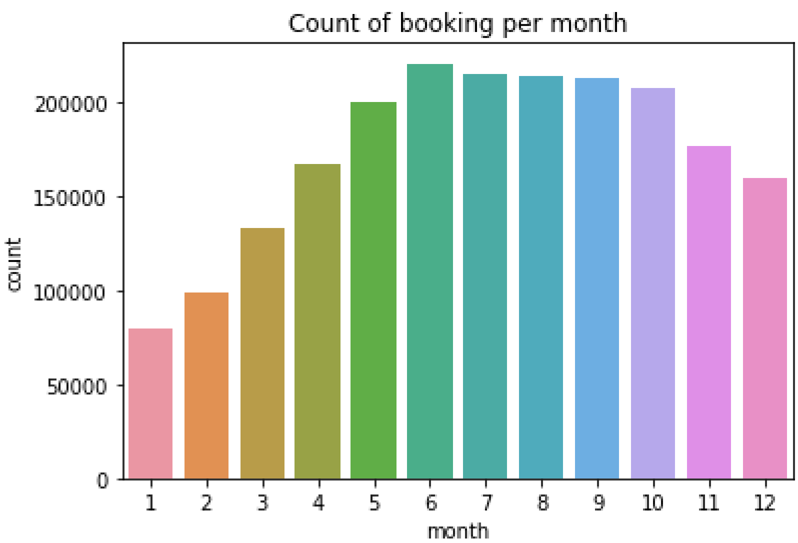
```
bike_dcopy['month'] = bike_dcopy['datetime'].dt.month
```

```
bike_dcopy.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0

```
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()
```

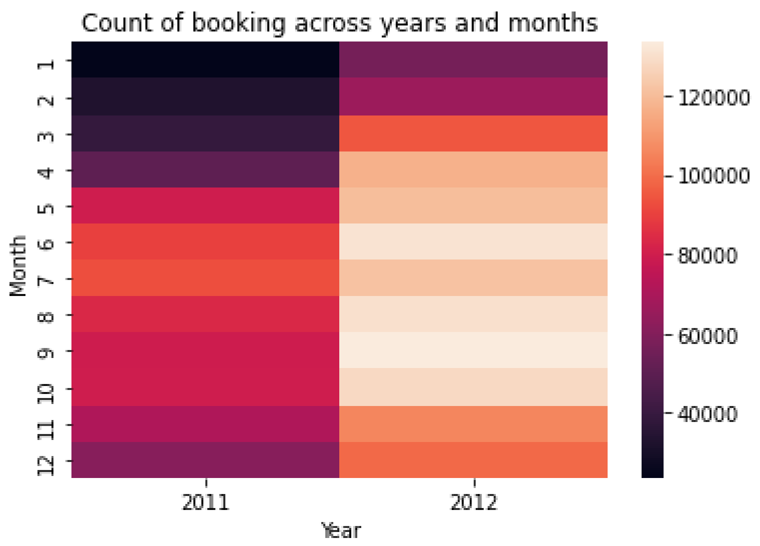

```
month_data = bike_dcopy.groupby(['month'])['count'].sum()
month_data = month_data.reset_index()
sns.barplot(x='month',y='count',data=month_data)
plt.title('Count of booking per month')
plt.show()
```



Insights

- Highest booking is in the month of june
- Almost same booking for the month of may,jully,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 monthwise 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

```
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()
```




```
#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
```

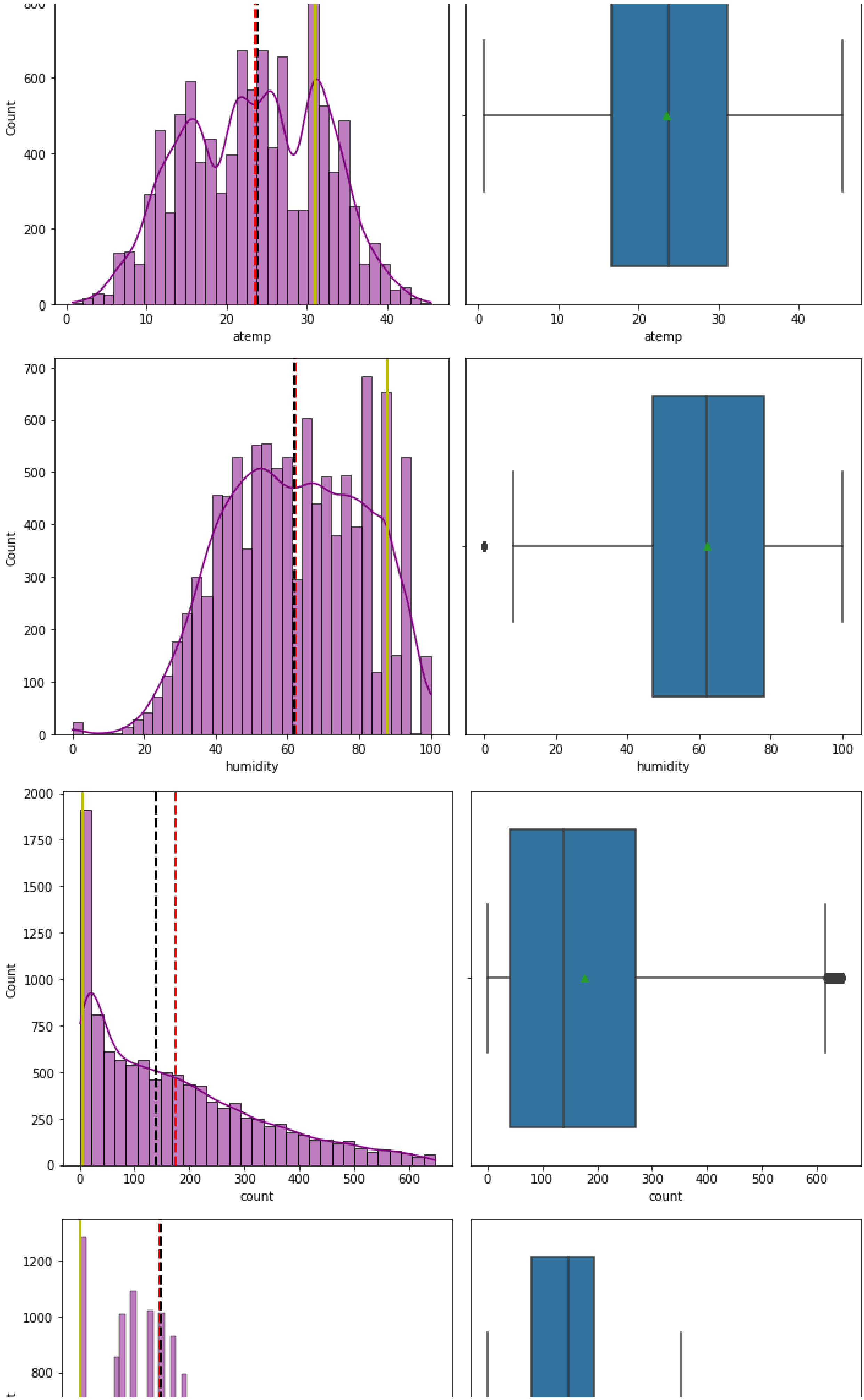
```
bike_data.columns
```

```
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.

```
#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
```

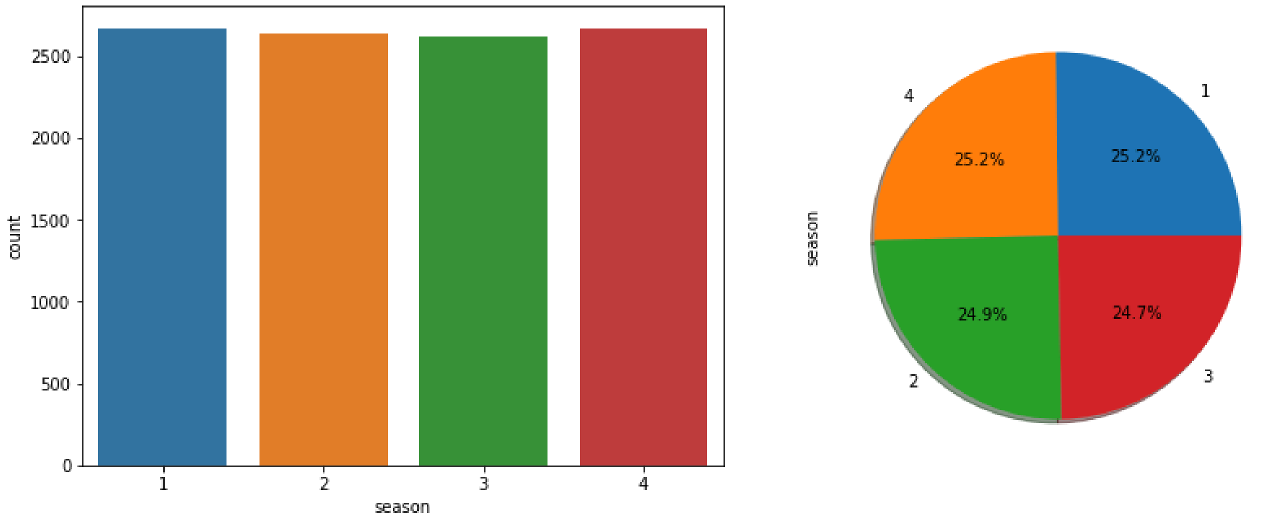
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

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

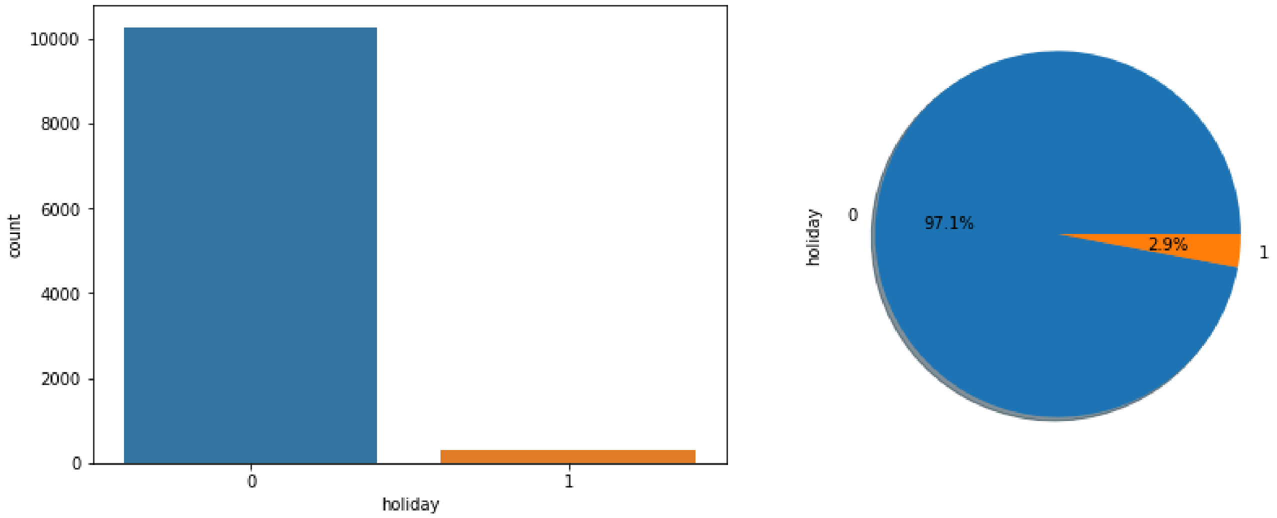
```
['season', 'holiday', 'workingday', 'weather']
```

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

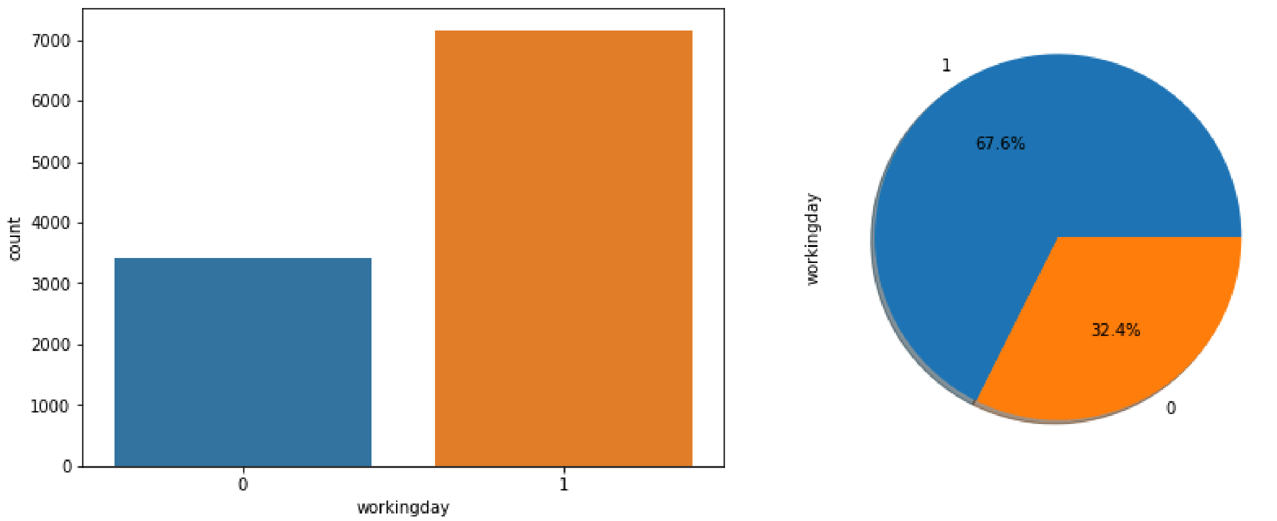
season wise sale



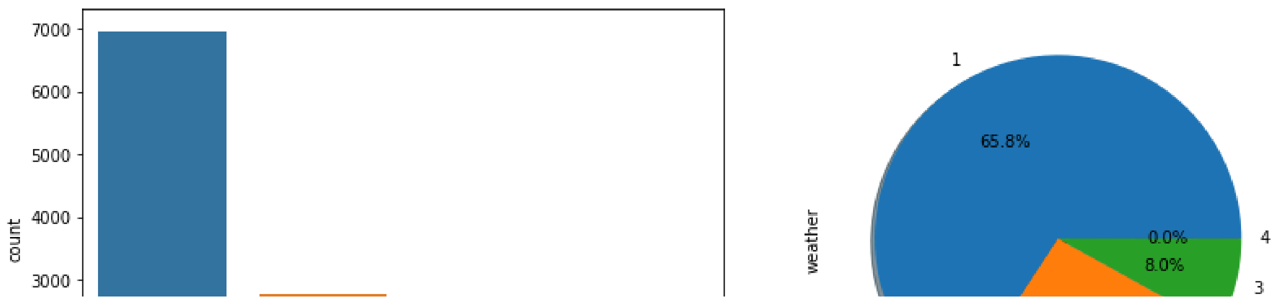
holiday wise sale

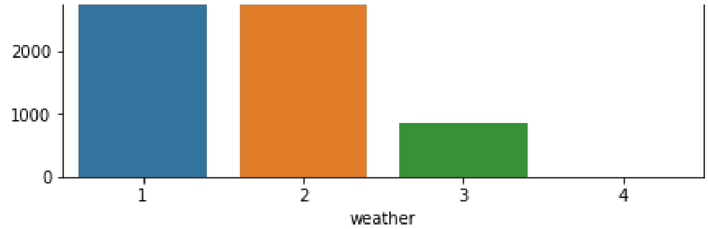


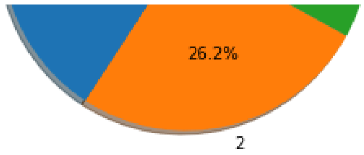
workingday wise sale



weather wise sale





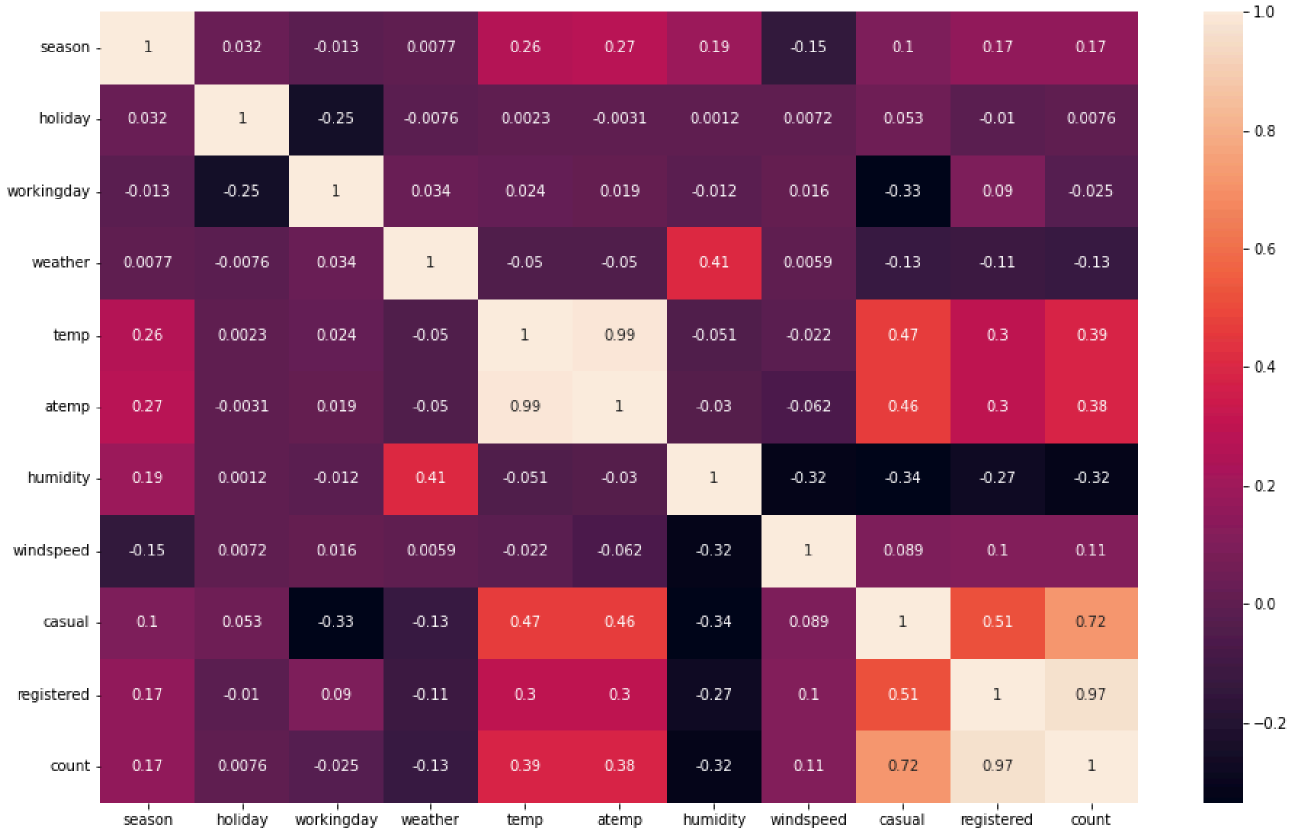


Insights

- For the weather (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog) number of users renting the bikesis much low and hence it;s 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 dont prefer to ride bikes
- During season (spring,summer,fall,winter) the count of renting the bikes is more or less

Correlation between bivariate analysis

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



Insights

- The Registered users has higher correlation as comapred to the casual user count
- The windspeed and season has very nearly zero positive correlation with the count which means, that means the windspeed and season didnt 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

```
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()
```

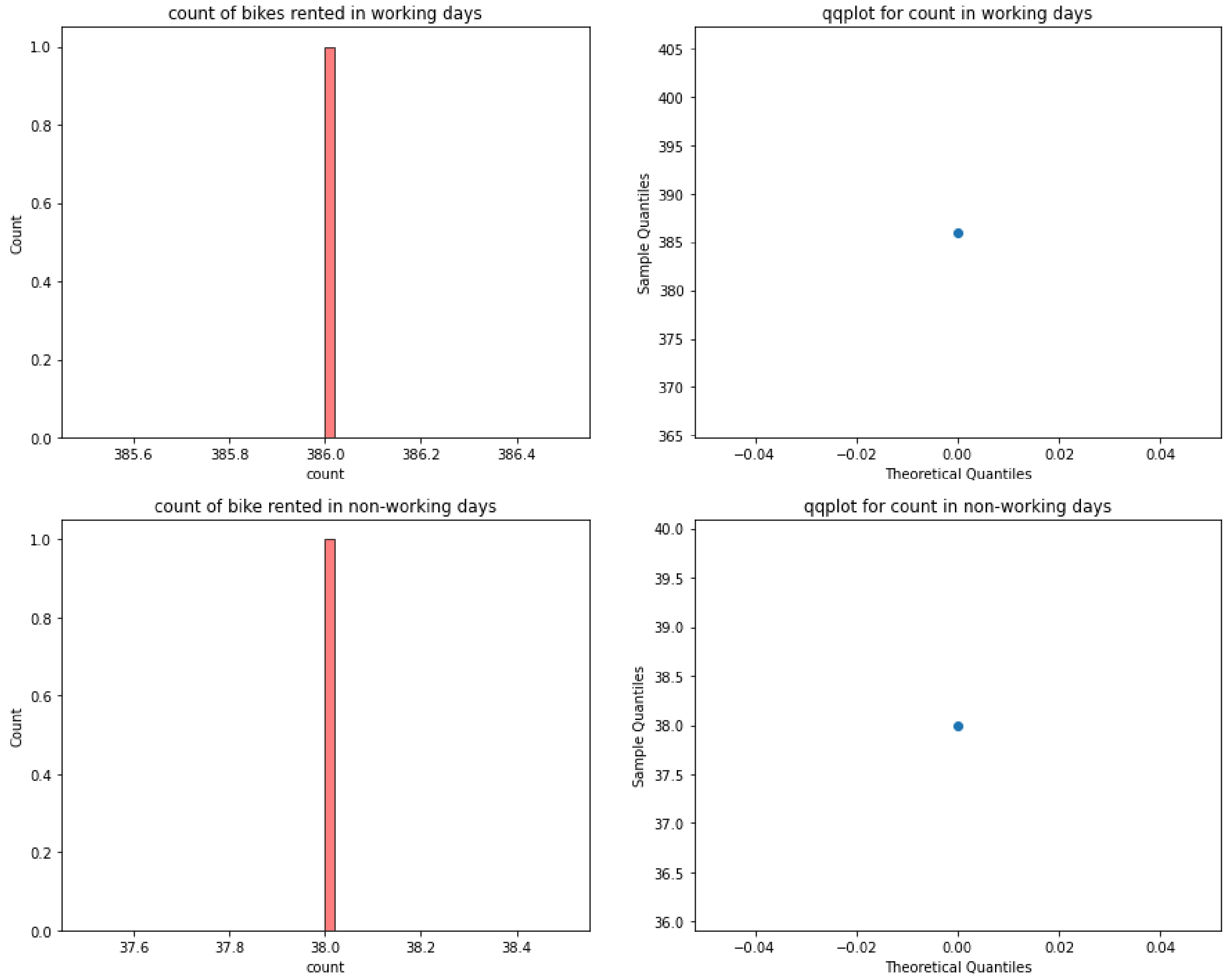
```
1    7161
0    3425
Name: workingday, dtype: int64
```

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

```
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 =
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, colc
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()
```



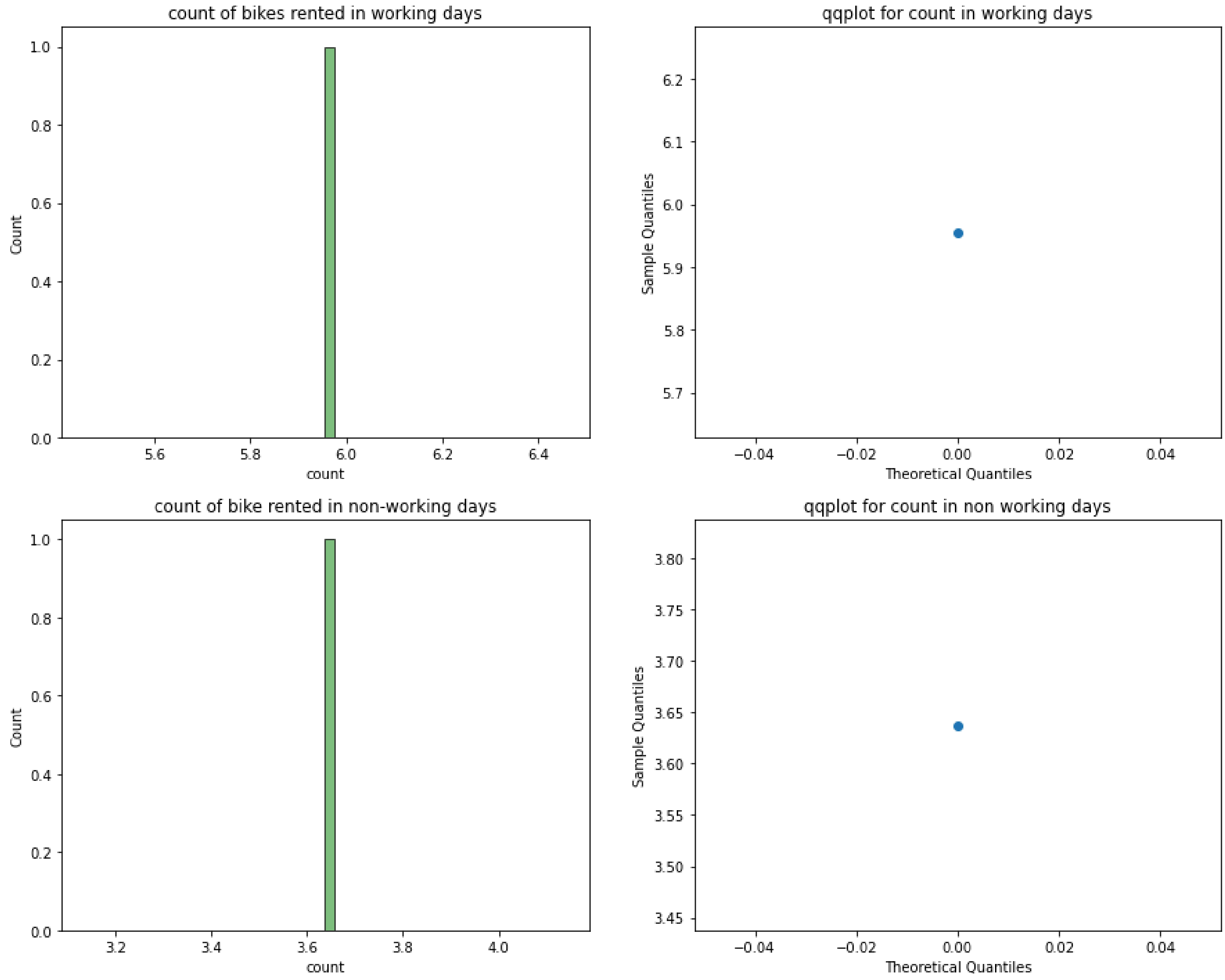

```
t_test, p_value = stats.ttest_ind(working_data['count'],non_working_data['count'],
                                  alternative='greater', equal_var = False)
t_test, p_value
```

```
(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, colc
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,
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()
```




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

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

```
(nan, nan)
```

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

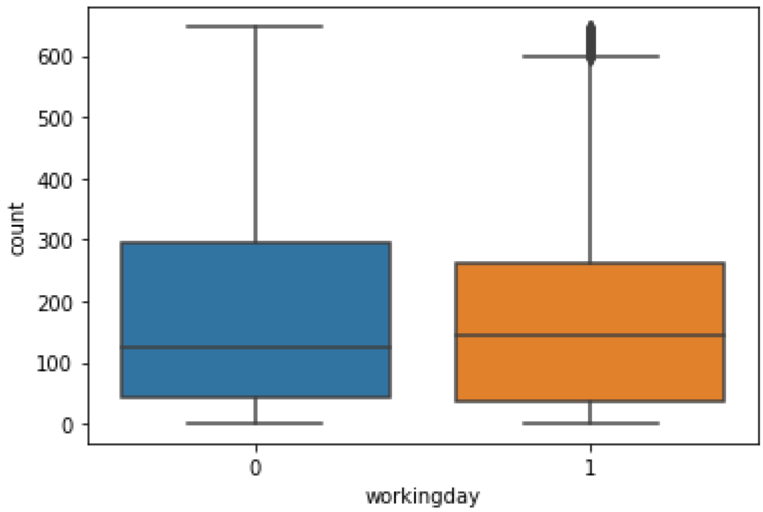
```
htResult(p_value)
```

```
Fail to Reject NULL HYPOTHESIS
```

```
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

```
contigency_table = pd.crosstab(bike_data.weather,bike_data.season,margins=True,margins_na
contigency_table
```

season	1	2	3	4	Total
weather					
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	1	2	3	4	Row_total
weather					
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
        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

Insights

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

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

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

```
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_na
contigency_table
```

season	1	2	3	4	Total
weather					
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
        exp.at[x,y]=float(v)
exp = exp.iloc[[0,1,2,3,4], [0,1,2,3]]
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

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

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

```
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]]))
```

```
alpha = 0.05
if p_value >= alpha:
    print('We fail to reject the Null Hypothesis Ho and thus we can conclude that smokers
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

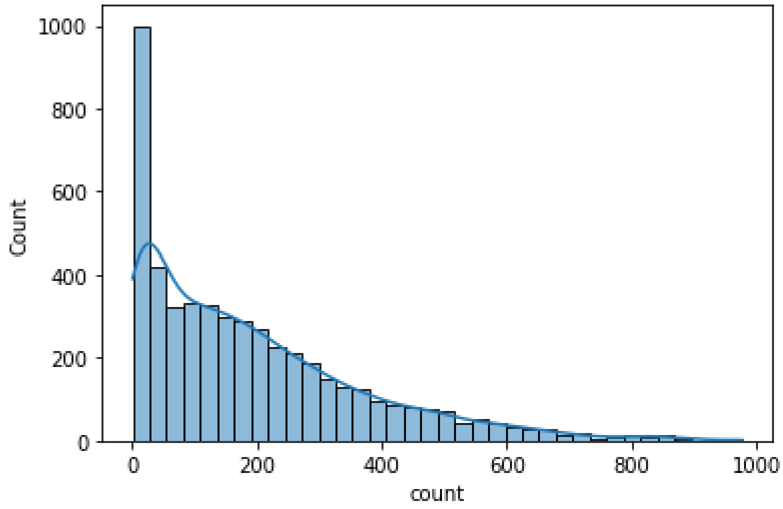
```
bike_dcopy['weather'].value_counts()
```

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

```
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')
```

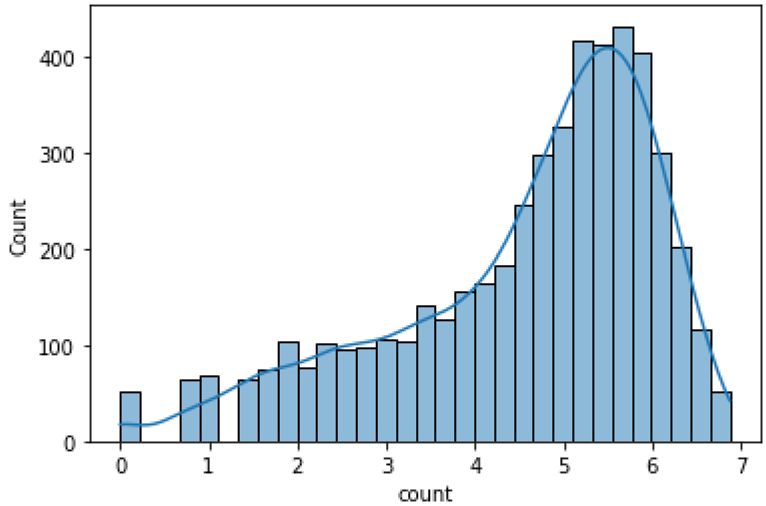
```
sns.histplot(bike_dcopy['count'].sample(5000), kde = True)
```

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




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

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




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

```
ShapiroResult(statistic=0.8756839036941528, pvalue=0.0)
```

Insights

- Even after taking log the distribution is not normal.

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

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

```
1    7192
2    2834
3     859
```