Business Case: Yulu - Hypothesis Testing

About Yulu Yulu is India's leading micro-mobility service provider, which offers unique vehicles for the daily commute. Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution through a user-friendly mobile app to enable shared, solo and sustainable commuting.

Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas, corporate offices, etc) to make those first and last miles smooth, affordable, and convenient!

Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

https://drive.google.com/drive/folders/1fl9kl4n9_JM6248g0tk6hd6jvGiDh_M6?usp=sharing

In [1]:

```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from scipy.stats import f_oneway, kruskal # Numeric Vs categorical for many categories
from scipy.stats import ttest_ind # Numeric Vs categorical
from scipy.stats import shapiro # Test Gaussian (50 to 200 samples)
from scipy.stats import levene # Test variance
from scipy.stats import ks_2samp
from scipy.stats import norm
from scipy.stats import chi2_contingency , chisquare
from scipy.stats import ttest_1samp

from statsmodels.graphics.gofplots import qqplot
```

In [2]:

```python
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
pd.set_option("display.max_rows",50)
pd.set_option("display.max_columns",50)
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_14388\2873301260.py:1: DeprecationWarning: Importing display from IPython.core.display is deprecated since IPython 7.14, please import from IPython display
  from IPython.core.display import display, HTML
```

In [3]:
```python
df = pd.read_csv("yulu.csv")
df
```

Out[3]:

	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

shape of dataset

In [4]:
```python
df.shape
```

Out[4]:
```
(10886, 12)
```

In [5]:
```python
print(f"Number of rows: {df.shape[0]}\nNumber of columns: {df.shape[1]}")
```

```
Number of rows: 10886
Number of columns: 12
```

Dtype of each column

In [6]:
```
df.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
```

Datatype of following attributes needs to changed to proper data type

- datetime - to datetime
- season - to categorical
- holiday - to categorical
- workingdat - to categorical
- weather - to categorical

In [7]:
```
cat_cols = ['season','holiday','workingday','weather']
```

In [8]:
```
df["datetime"] = pd.to_datetime(df["datetime"])
```

In [9]:
```
for col in cat_cols:
    df[col] = df[col].astype('category')
```

In [10]:
```
df.dtypes
```

Out[10]:
```
datetime      datetime64[ns]
season              category
holiday             category
workingday          category
weather             category
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
dtype: object
```

In [11]:
```
df.describe()
```

Out[11]:

	temp	atemp	humidity	windspeed	casual	registered	count
count	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574132
std	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144454
min	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.000000
50%	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.000000
75%	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.000000
max	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.000000

In [12]:
```
df.describe(include="all")
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_14388\1985922364.py:1: FutureWarning: Treating datetime data as categorical rather than
numeric in `.describe` is deprecated and will be removed in a future version of pandas. Specify `datetime_is_numeric=True` to si
lence this warning and adopt the future behavior now.
  df.describe(include="all")
```

Out[12]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	co
count	10886	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.00
unique	10886	4.0	2.0	2.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	N
top	2011-01-01 00:00:00	4.0	0.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	N
freq	1	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	NaN	NaN	NaN	N
first	2011-01-01 00:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
last	2012-12-19 23:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
mean	NaN	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574
std	NaN	NaN	NaN	NaN	NaN	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144
min	NaN	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.00
25%	NaN	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.00
50%	NaN	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.00
75%	NaN	NaN	NaN	NaN	NaN	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.00
max	NaN	NaN	NaN	NaN	NaN	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.00

- casual and registered attributes might have outliers because their mean and median are very far away to one another and the valu of standard deviation is also high which tells us that there is high variance in the data of these attributes
- avg temperature is 20.23, max temperature is 41 and min temperature is 0
- avg humidity is 61.88, max humidity is 100 and min humidity is 0
- avg windspeed is 12.79, max windspeed is 56.99 and min windspeed is 0

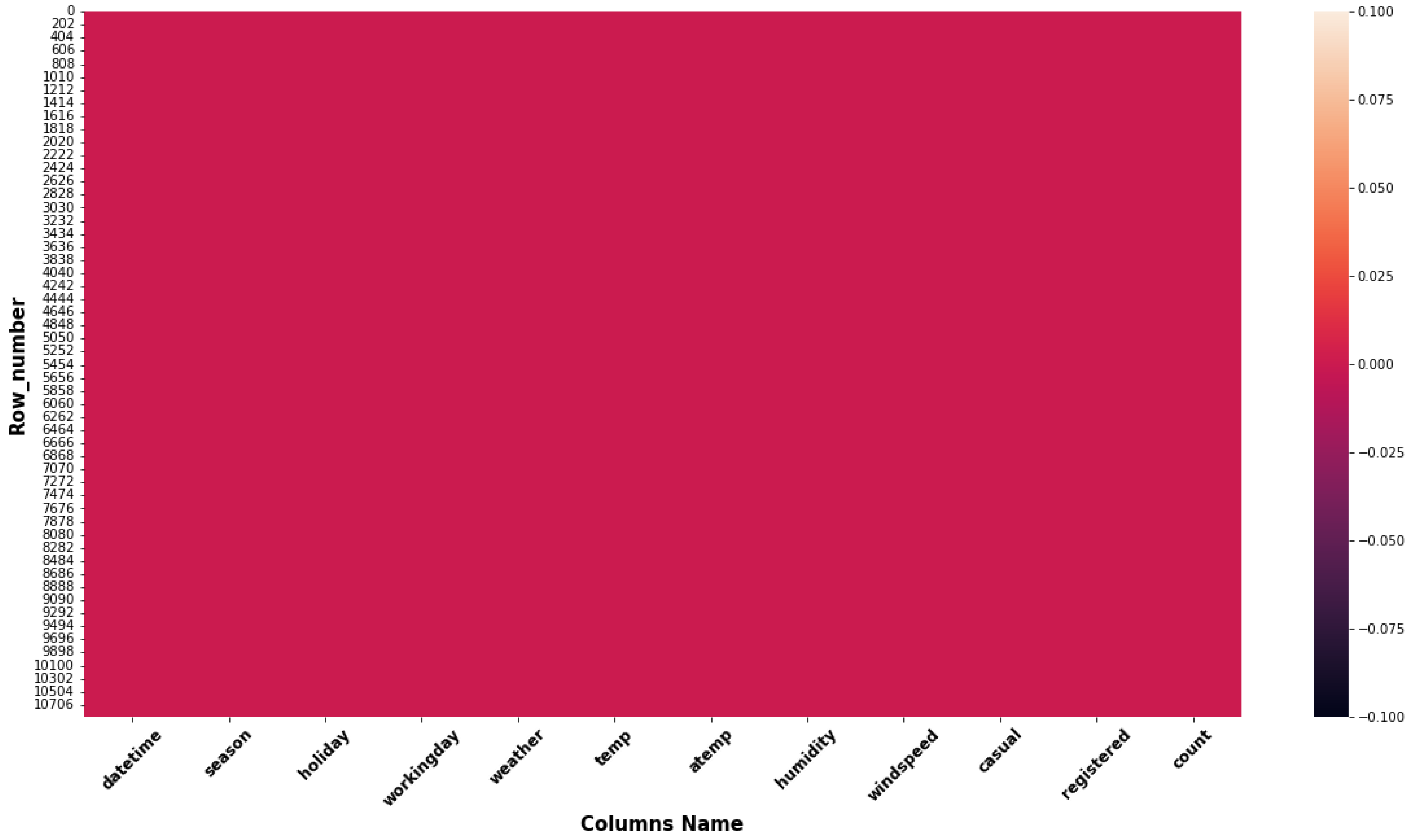
any null value

In [13]:
```
df.isna().sum()
```

Out[13]:
```
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
```

by using heatmap to show all null values

In [14]:
```
plt.figure(figsize=(20,10))
sns.heatmap(df.isnull())
plt.xlabel("Columns Name" , weight="bold" , fontsize=15)
plt.ylabel("Row_number" , weight="bold" , fontsize=15)
plt.xticks(rotation=45 , weight="bold",fontsize=12)
plt.show()
```



- There are no missing value in tha dataset

By extracting 'hour','month','year' data from datetime column we will be able to

In [15]:
```
df["hour"] = df["datetime"].dt.hour
df["month"] = df["datetime"].dt.month
df["year"] = df["datetime"].dt.year
```

convert hour into category

In [16]:
```
df["TimeSlot"] = df["hour"].apply(lambda x: "Dawn" if x<=4 else ("Early Morning"
                                                              if x<=9 else ("Noon"
                                                                       if x<=16 else ("Late Evening"
                                                                                 if x<=21 else "Night"))))
```

find how many unique value in column

season

In [29]:
```
df["season"].unique()
```

Out[29]:
```
[1, 2, 3, 4]
Categories (4, int64): [1, 2, 3, 4]
```

In season there is four unique value

- 1: spring
- 2: summer
- 3: fall
- 4: winter

holiday

In [30]:
```
df["holiday"].unique()
```

Out[30]:
```
[0, 1]
Categories (2, int64): [0, 1]
```

workingday

In [32]:
```
df["workingday"].unique()
```

Out[32]:
```
[0, 1]
Categories (2, int64): [0, 1]
```

In workingday there is two unique value

- 0: Holiday, weekend
- 1: working day

weather

In [33]:
```
df["weather"].unique()
```

Out[33]:
```
[1, 2, 3, 4]
Categories (4, int64): [1, 2, 3, 4]
```

In weather there is four unique value

- 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

Understanding the distribution of the data for the qualitative attributes:

In [28]:
```
df[cat_cols].melt().groupby(["variable","value"])[["value"]].count()
```

Out[28]:

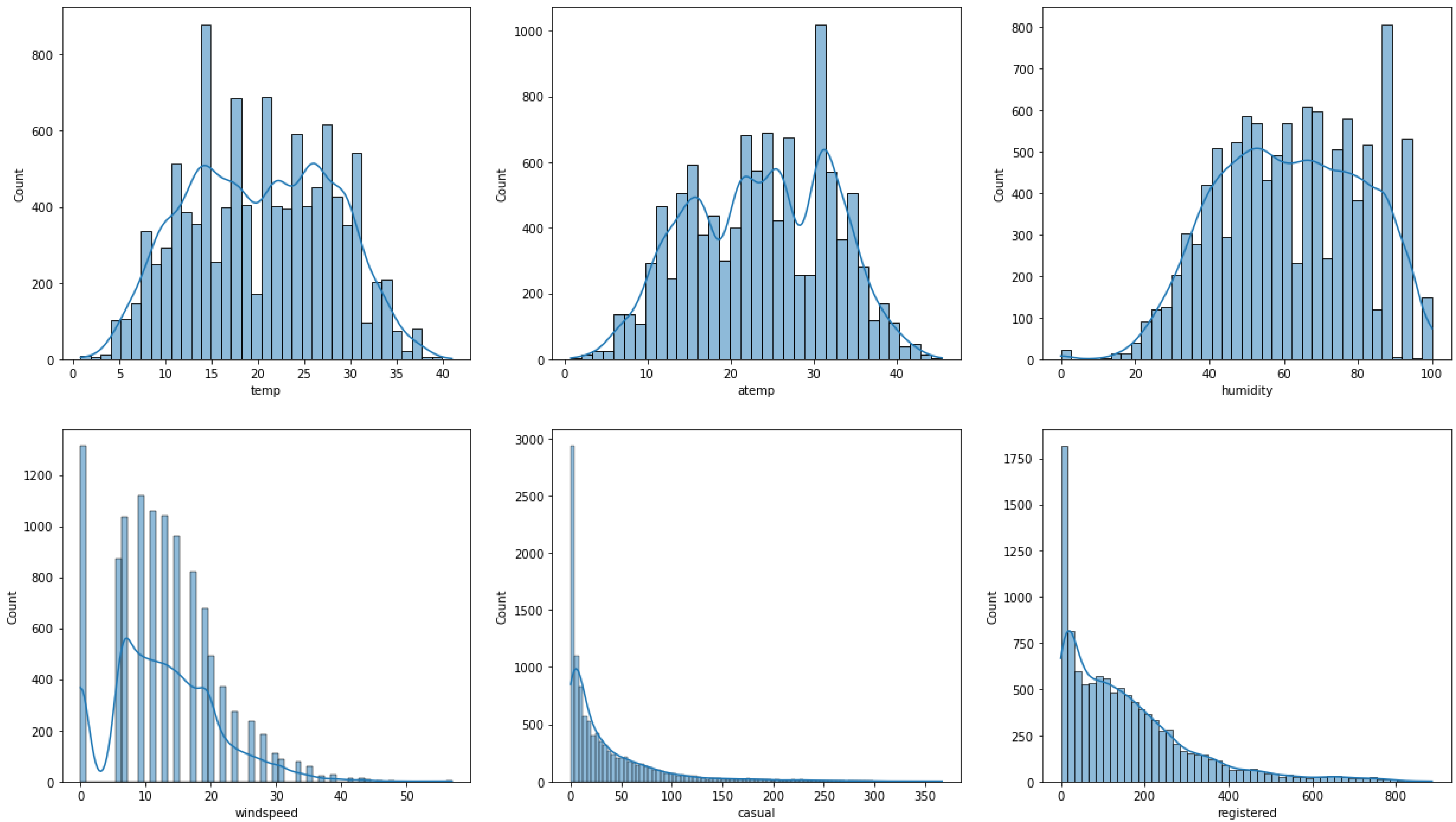
variable	value	value
holiday	0	10575
	1	311
season	1	2686
	2	2733
	3	2733
	4	2734
weather	1	7192
	2	2834
	3	859
	4	1
workingday	0	3474
	1	7412

Univariate Analysis

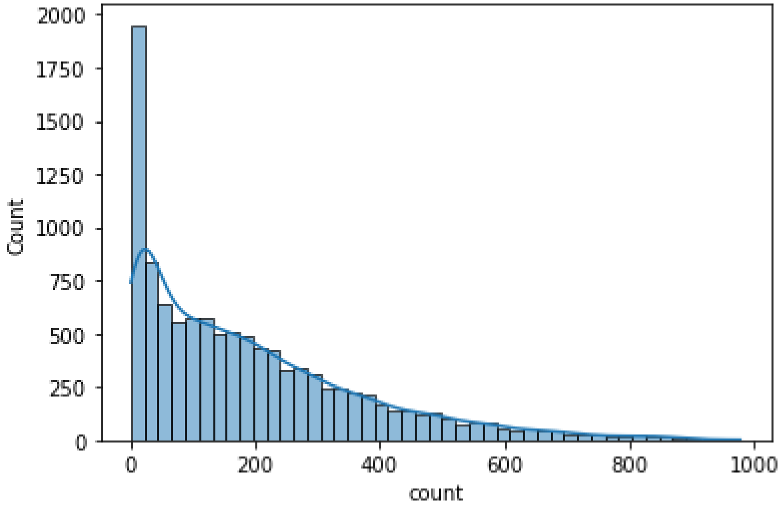
In [18]:

```
num_cols = ['temp','atemp','humidity','windspeed','casual','registered','count']
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(21, 12))

index=0
for row in range(2):
    for col in range(3):
        sns.histplot(df[num_cols[index]] , ax=axis[row,col] , kde=True)
        index+=1
plt.show()
sns.histplot(df[num_cols[-1]] , kde=True)
plt.show
```



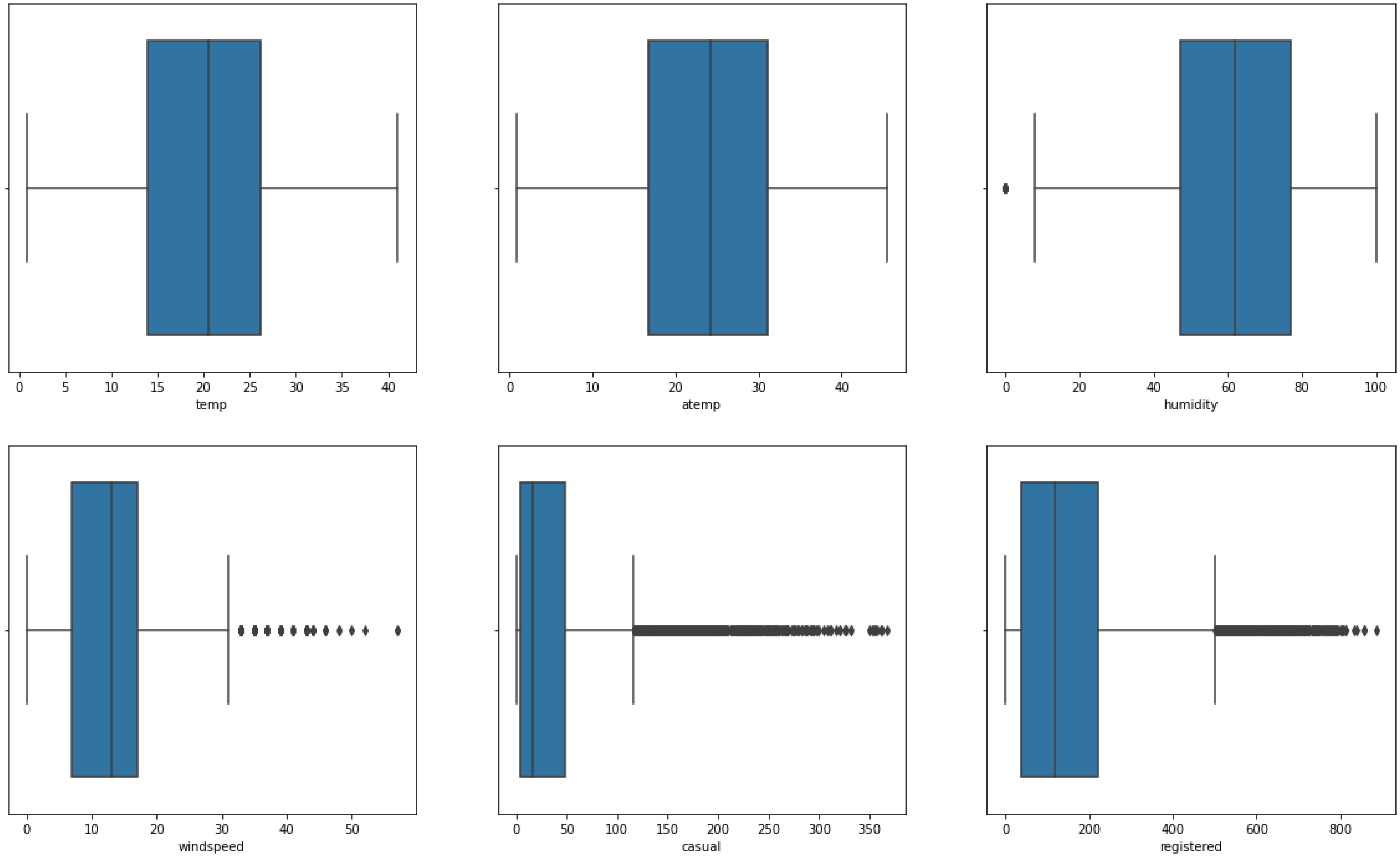

```
Out[18]: <function matplotlib.pyplot.show(close=None, block=None)>
```



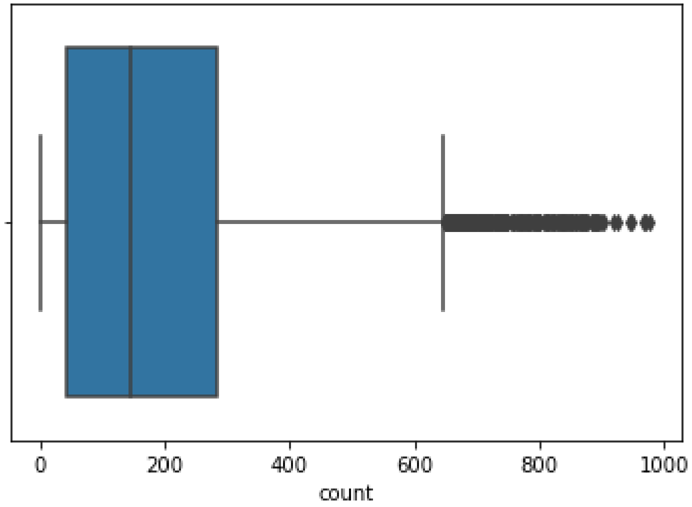
- **casual, registered and count** somewhat looks like **Log Normal Distribtion**
- **temp, atemp and humidity** looks like they follows the **Normal distribution**
- **windspeed** follows the **binomial distribution**

In [19]:
```
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(20, 12))

index=0
for row in range(2):
    for col in range(3):
        sns.boxplot(x=df[num_cols[index]] , ax=axis[row,col])
        index+=1
plt.show()
sns.boxplot(x=df[num_cols[-1]])
plt.show()
```



0 5 10 15 20 25 30 35 40
temp
0 10 20 30 40
atemp
0 20 40 60 80 100
humidity
0 10 20 30 40 50
windspeed
0 50 100 150 200 250 300 350
casual
0 200 400 600 800
registered

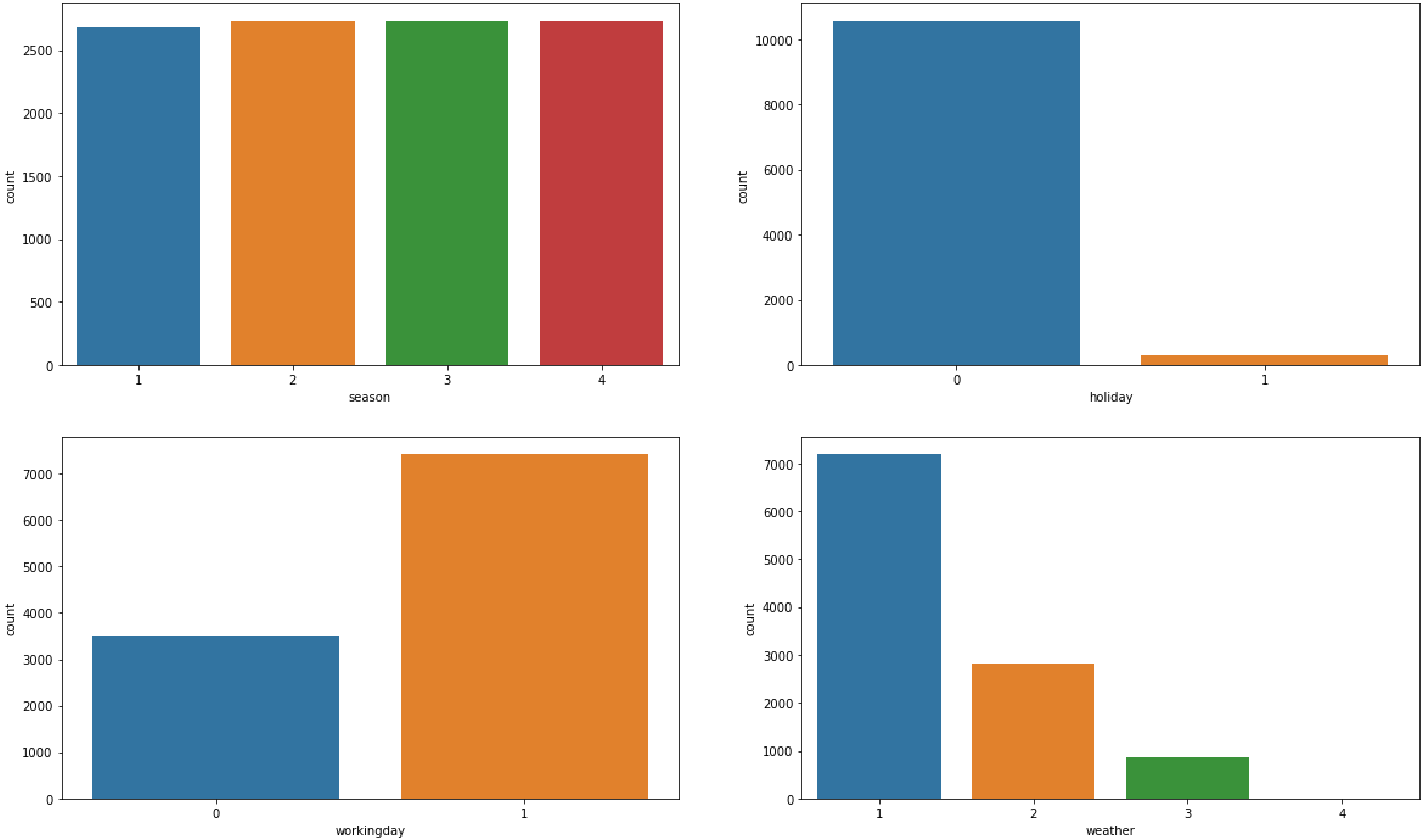


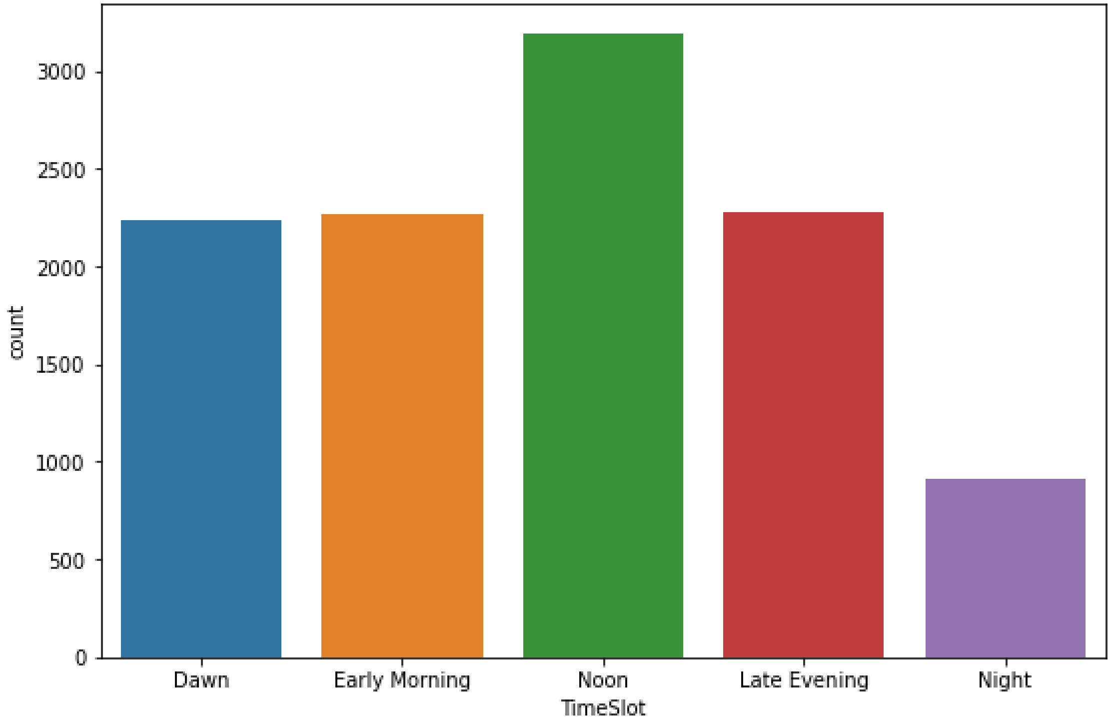
- **temp, atemp** has not outliers in the data
- **humidity and windspeed** has some outliers in the data
- **casual, registered and count** has more outliers in the data

In [20]:

```
num_cat_cols=['season','holiday','workingday','weather','TimeSlot']
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(20, 12))

index=0
for row in range(2):
    for col in range(2):
        sns.countplot(x=df[num_cat_cols[index]] , ax=axis[row,col])
        index+=1
plt.show()
plt.figure(figsize=[9,6])
sns.countplot(x=df[num_cat_cols[-1]])
plt.show()
```


count
season
count
holiday
count
workingday
count
weather



- In every season people love to ride equal
- most of people ride on **working day**
- When Weather is clear, few **clouds, partly, cloudy, partly cloudy** morpeople ride and use bike
- most of people rented bike on **noon time**

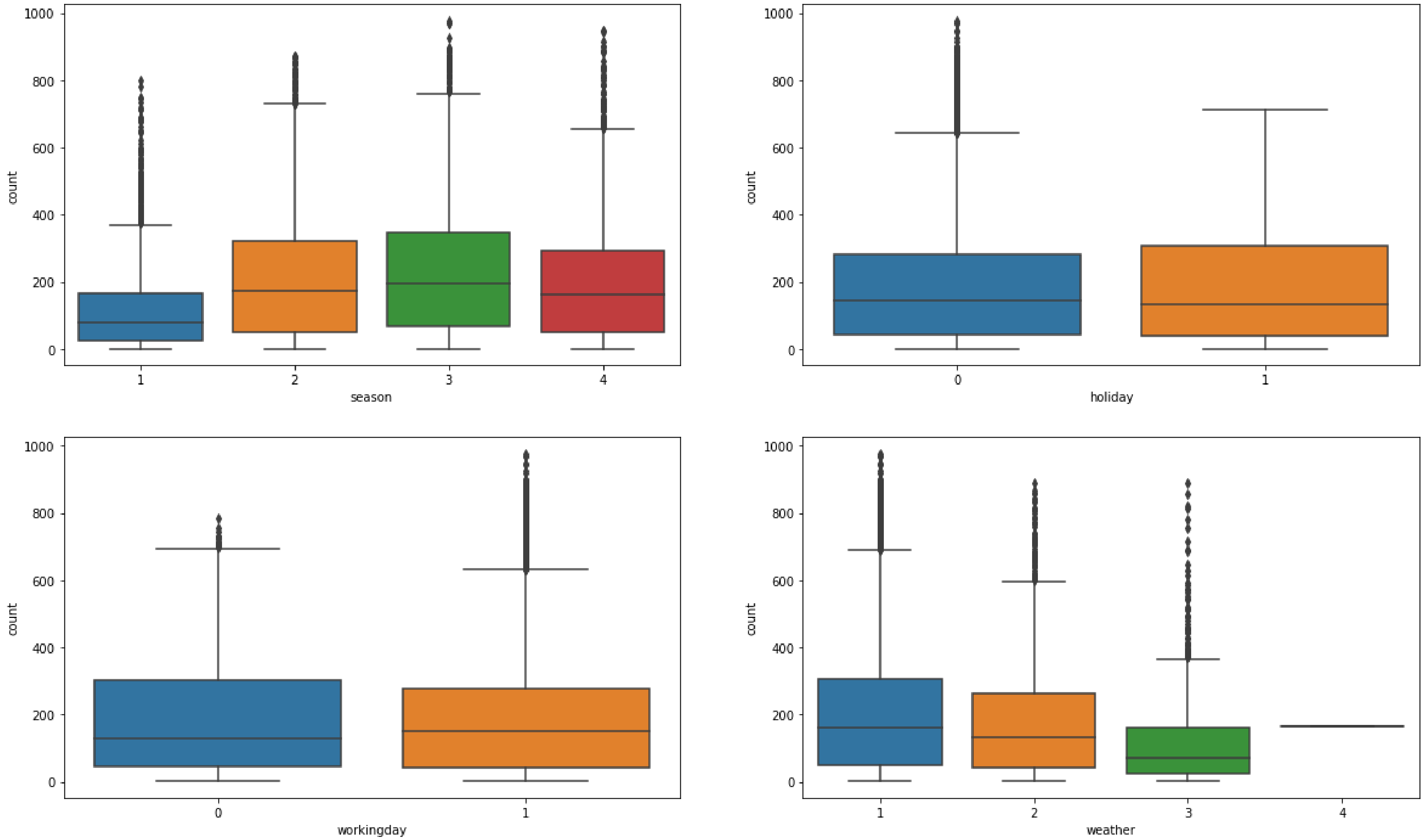
Bi-variate Analysis

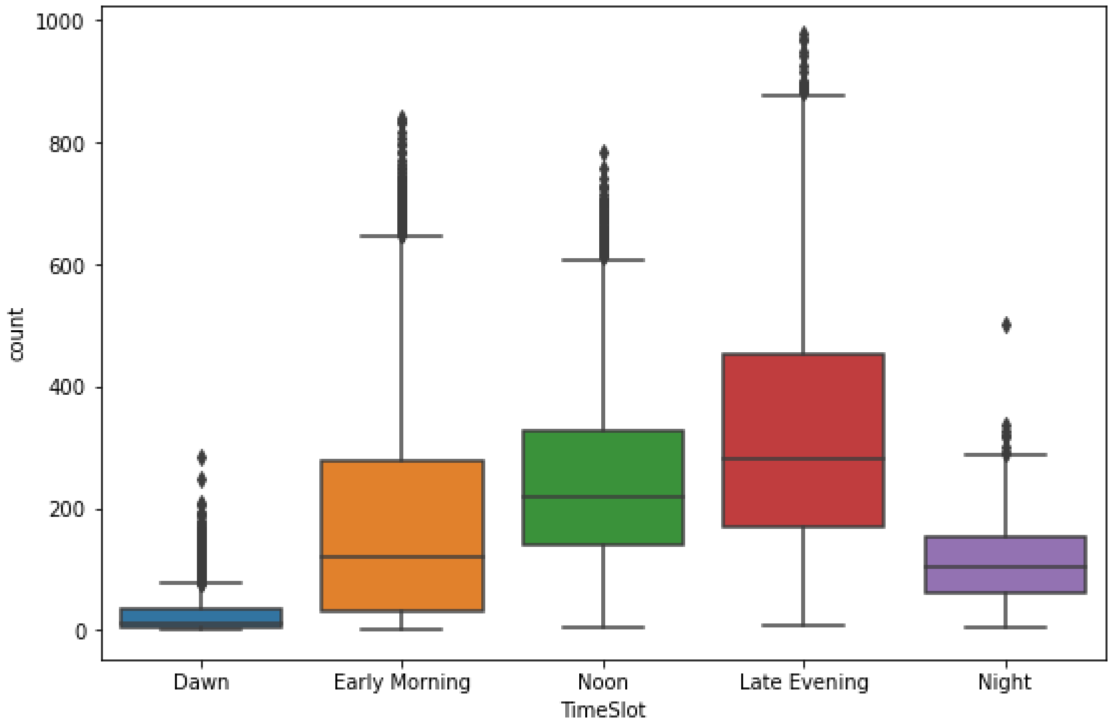
In [21]:

```
num_cat_cols=['season','holiday','workingday','weather','TimeSlot']
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(20, 12))

index=0
for row in range(2):
    for col in range(2):
        sns.boxplot(x=df[num_cat_cols[index]] ,y=df['count'], ax=axis[row,col])
        index+=1
```

```
plt.show()
plt.figure(figsize=[9,6])
sns.boxplot(x=df[num_cat_cols[-1]],y=df['count'])
plt.show()
```

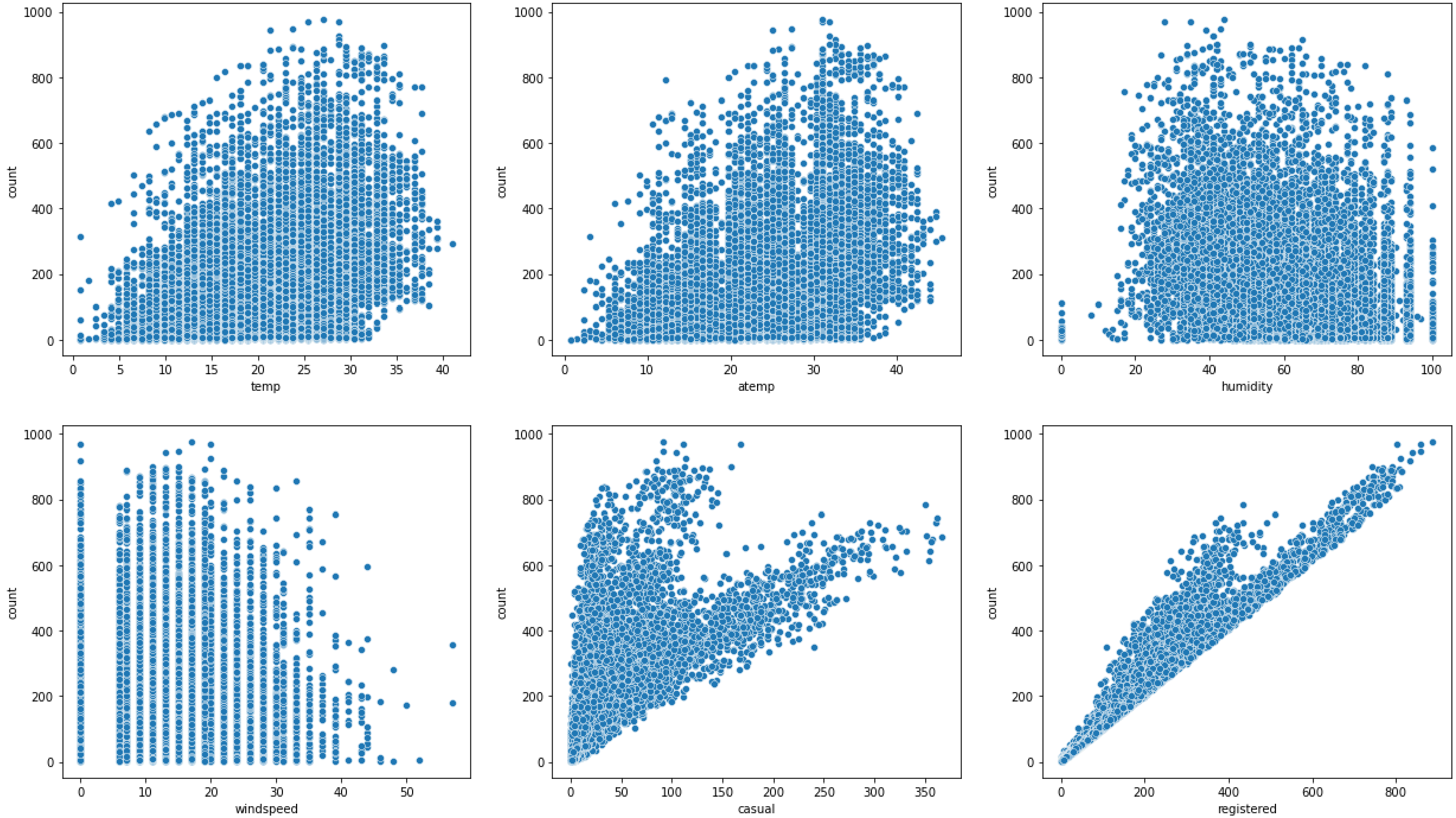




- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- Whenever its a **holiday** more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is **rain, thunderstorm, snow or fog**, there were less bikes were rented.
- Most people rented bike in **late Evening**

In [22]:
```
num_cols = ['temp','atemp','humidity','windspeed','casual','registered','count']
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(21, 12))

index=0
for row in range(2):
    for col in range(3):
        sns.scatterplot(x=df[num_cols[index]] ,y=df[num_cols[-1]] ,ax=axis[row,col])
        index+=1
plt.show()
```



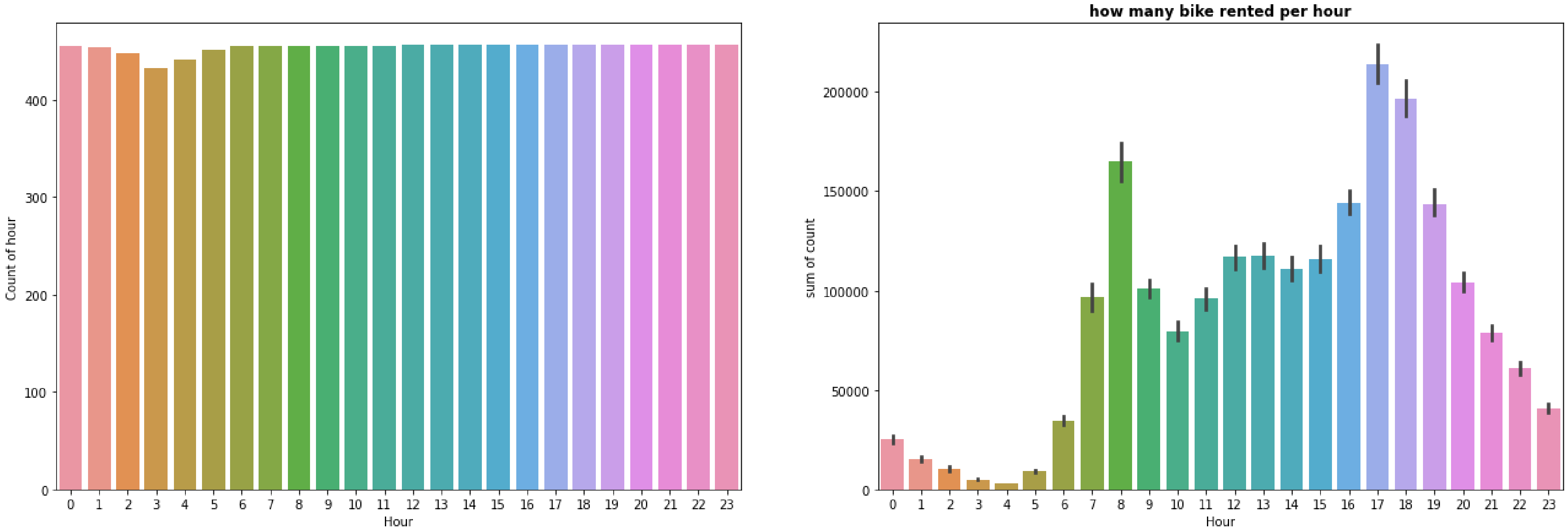
- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

when most of customer rented bike?

In [64]:
```
plt.figure(figsize=[22,7])

plt.subplot(1,2,1)
sns.countplot(data=df , x="hour")
plt.xlabel("Hour" )
plt.ylabel("Count of hour" )

plt.subplot(1,2,2)
sns.barplot(data=df , x="hour" , y='count' , estimator=sum)
plt.xlabel("Hour" )
plt.ylabel("sum of count" )
plt.title("how many bike rented per hour",weight='bold')
plt.show()
```

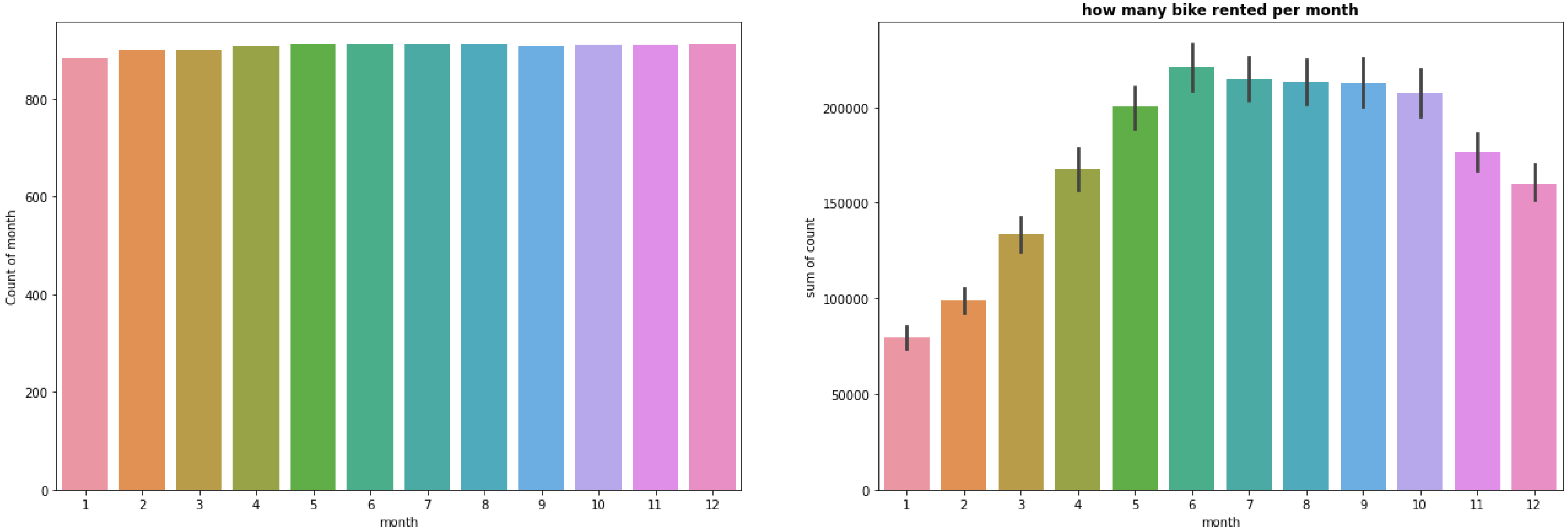


In [65]:
```
plt.figure(figsize=[22,7])

plt.subplot(1,2,1)
sns.countplot(data=df , x="month")
plt.xlabel("month" )
plt.ylabel("Count of month" )

plt.subplot(1,2,2)
```

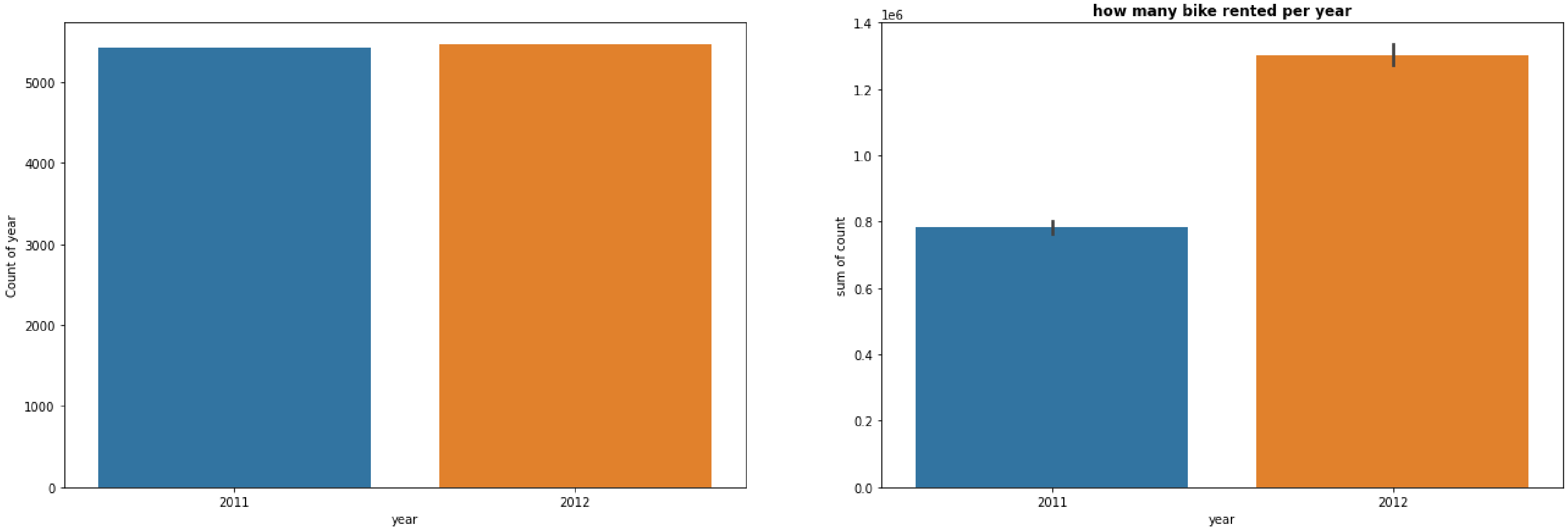
```
sns.barplot(data=df , x="month" , y='count' , estimator=sum)
plt.xlabel("month" )
plt.ylabel("sum of count" )
plt.title("how many bike rented per month",weight='bold')
plt.show()
```



In [66]:
```
plt.figure(figsize=[22,7])

plt.subplot(1,2,1)
sns.countplot(data=df , x="year")
plt.xlabel("year" )
plt.ylabel("Count of year" )

plt.subplot(1,2,2)
sns.barplot(data=df , x="year" , y='count' , estimator=sum)
plt.xlabel("year" )
plt.ylabel("sum of count" )
plt.title("how many bike rented per year",weight='bold')
plt.show()
```

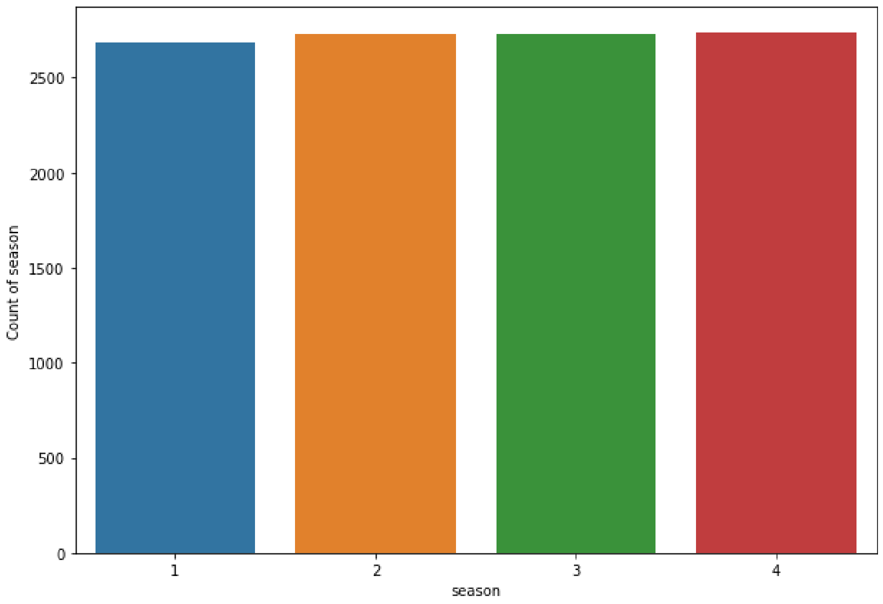


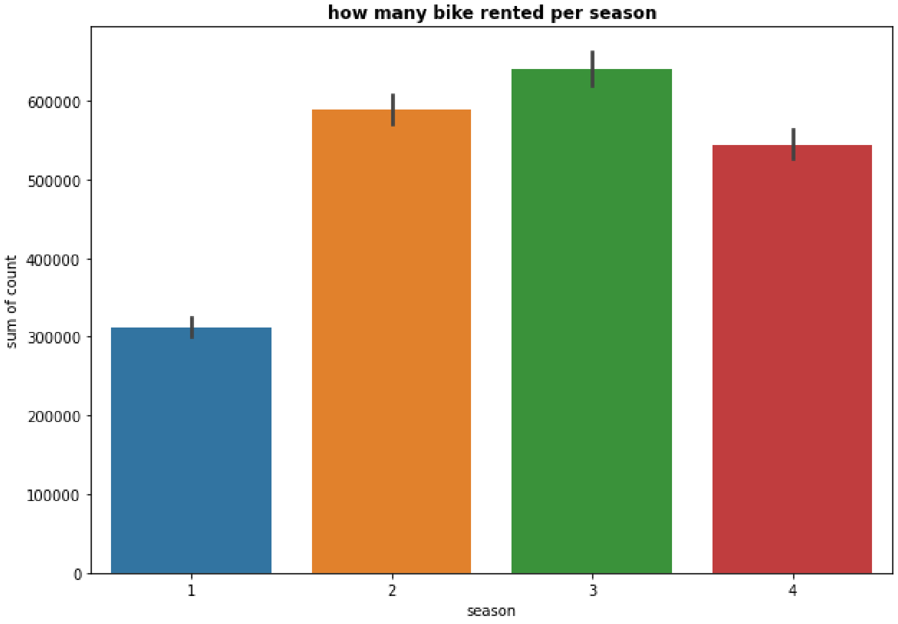
In [67]:

```
plt.figure(figsize=[22,7])

plt.subplot(1,2,1)
sns.countplot(data=df , x="season")
plt.xlabel("season" )
plt.ylabel("Count of season" )

plt.subplot(1,2,2)
sns.barplot(data=df , x="season" , y='count' , estimator=sum)
plt.xlabel("season" )
plt.ylabel("sum of count" )
plt.title("how many bike rented per season",weight='bold')
plt.show()
```



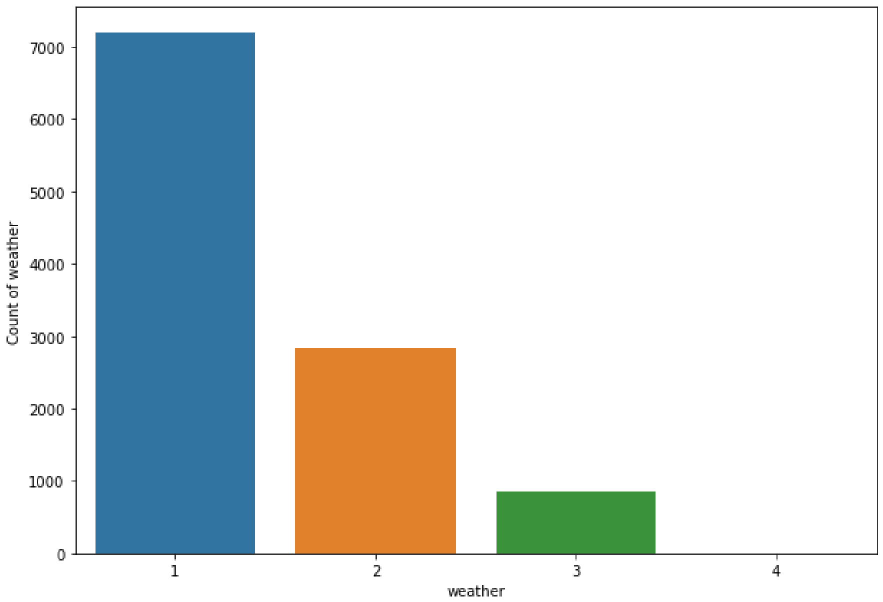


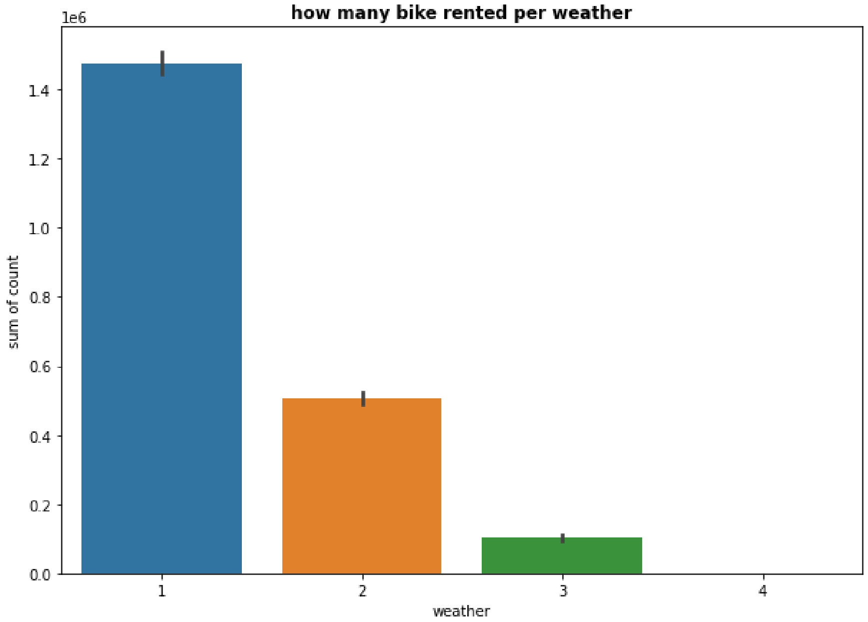
In [68]:

```
plt.figure(figsize=[22,7])

plt.subplot(1,2,1)
sns.countplot(data=df , x="weather")
plt.xlabel("weather" )
plt.ylabel("Count of weather" )

plt.subplot(1,2,2)
sns.barplot(data=df , x="weather" , y='count' , estimator=sum)
plt.xlabel("weather" )
plt.ylabel("sum of count" )
plt.title("how many bike rented per weather",weight='bold')
plt.show()
```





Correlation between variables

In [69]:

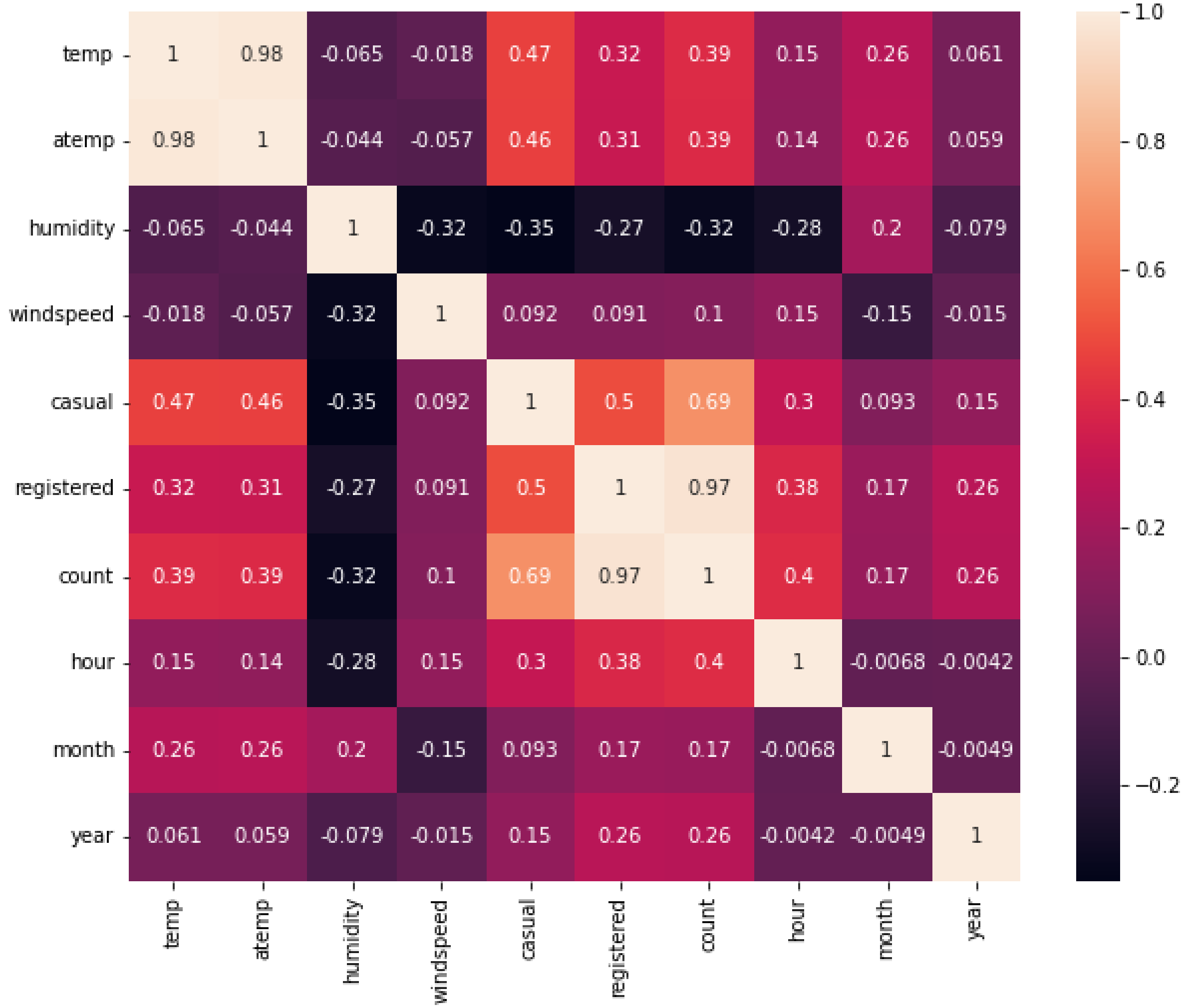
```
df.corr()["count"]
```

Out[69]:

```
temp          0.394454
atemp         0.389784
humidity     -0.317371
windspeed     0.101369
casual        0.690414
registered    0.970948
count         1.000000
hour          0.400601
month         0.166862
year          0.260403
Name: count, dtype: float64
```

In [71]:

```
plt.figure(figsize=[10,8])
sns.heatmap(df.corr(),annot=True)
plt.show()
```



Find length of outliers

In [75]:
```
Q1 = np.percentile(df["count"],25)
Q3 = np.percentile(df["count"],75)
```

In [97]:

```
IQR = Q3-Q1
upper_fence = Q3+(IQR*1.5)
lower_fence = max(0,Q1-(IQR*1.5))
```

In [98]:

```
print("Interquartile range is ",IQR)
print("Upper fence is {0} \nLower fence is {1}".format(upper_fence,lower_fence))
```

```
Interquartile range is  242.0
Upper fence is 647.0
Lower fence is 0
```

In [101…

```
outlier_df = df[(df["count"]>upper_fence) | (df["count"]<lower_fence)]
outlier_df
```

Out[101]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	hour	month	year	TimeSlot
6611	2012-03-12 18:00:00	1	0	1	2	24.60	31.060	43	12.9980	89	623	712	18	3	2012	Late Evening
6634	2012-03-13 17:00:00	1	0	1	1	28.70	31.820	37	7.0015	62	614	676	17	3	2012	Late Evening
6635	2012-03-13 18:00:00	1	0	1	1	28.70	31.820	34	19.9995	96	638	734	18	3	2012	Late Evening
6649	2012-03-14 08:00:00	1	0	1	1	18.04	21.970	82	0.0000	34	628	662	8	3	2012	Early Morning
6658	2012-03-14 17:00:00	1	0	1	1	28.70	31.820	28	6.0032	140	642	782	17	3	2012	Late Evening
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
10678	2012-12-11 08:00:00	4	0	1	2	13.94	15.150	61	19.9995	16	708	724	8	12	2012	Early Morning
10702	2012-12-12 08:00:00	4	0	1	2	10.66	12.880	65	11.0014	18	670	688	8	12	2012	Early Morning
10726	2012-12-13 08:00:00	4	0	1	1	9.84	11.365	60	12.9980	24	655	679	8	12	2012	Early Morning
10846	2012-12-18 08:00:00	4	0	1	1	15.58	19.695	94	0.0000	10	652	662	8	12	2012	Early Morning
10870	2012-12-19 08:00:00	4	0	1	1	9.84	12.880	87	7.0015	13	665	678	8	12	2012	Early Morning

300 rows × 16 columns

length of outlier

In [102…
```
len(outlier_df)
```

Out[102]:
```
300
```

Hypothesis Testing

Hypothesis Testing 1

2- Sample T-Test

- to check if Working Day has an effect on the number of electric cycles rented

Null Hypothesis: Working day has no effect on the number of cycles being rented.

Alternate Hypothesis: Working day has effect on the number of cycles being rented.

Significance level (alpha): 0.05

We will use the **2-Sample T-Test** to test the hypothess defined above

In [130…
```
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values
statistic , p_value = ttest_ind(a=data_group1, b=data_group2)
if p_value>=0.05:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject to fail Null hypothesis")
else:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject Null hypothesis \naccept alternate hypothesis")
```

```
statistic value is -1.2096277376026694,
pvalue is 0.22644804226361348
Reject to fail Null hypothesis
```

Since pvalue is greater than 0.05 so we can not reject the Null hypothesis. We don't have the sufficient evidence to say that working day has effect on the number of cycles being rented.

Hypothesis Testing 2

Null Hypothesis: Number of cycles rented is similar in different weather and season.

Alternate Hypothesis: Number of cycles rented is not similar in different weather and season.

Significance level (alpha): 0.05

Here, we will use the **ANOVA** to test the hypothess defined above

In [117…

```
# defining the data groups for the ANOVA

weather_1 = df[df['weather']==1]['count'].values
weather_2 = df[df['weather']==2]['count'].values
weather_3 = df[df['weather']==3]['count'].values
weather_4 = df[df['weather']==4]['count'].values

season_1 = df[df['season']==1]['count'].values
season_2 = df[df['season']==2]['count'].values
season_3 = df[df['season']==3]['count'].values
season_4 = df[df['season']==4]['count'].values
```

conduct the one-way anova of weather

In [129…

```
statistic , p_value = f_oneway(weather_1,weather_2,weather_3,weather_4)
if p_value>=0.05:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject to fail Null hypothesis")
else:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject Null hypothesis \naccept alternate hypothesis")
```

```
statistic value is 65.53024112793271,
pvalue is 5.482069475935669e-42
Reject Null hypothesis
accept alternate hypothesis
```

conduct the one-way anova of season

In [131…

```
statistic , p_value = f_oneway(season_1,season_2,season_3,season_4)
if p_value>=0.05:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject to fail Null hypothesis")
else:
    print(f"statistic value is {statistic}, pvalue is {p_value}\nReject Null hypothesis \naccept alternate hypothesis")
```

```
statistic value is 236.94671081032106, pvalue is 6.164843386499654e-149
Reject Null hypothesis
accept alternate hypothesis
```

conduct the one-way anova of season and weather

In [132…

```
statistic , p_value = f_oneway(weather_1,weather_2,weather_3,weather_4,season_1,season_2,season_3,season_4)
if p_value>=0.05:
    print(f"statistic value is {statistic}, \npvalue is {p_value}\nReject to fail Null hypothesis")
else:
    print(f"statistic value is {statistic}, pvalue is {p_value}\nReject Null hypothesis \naccept alternate hypothesis")
```

```
statistic value is 127.96661249562491, pvalue is 2.8074771742434642e-185
Reject Null hypothesis
accept alternate hypothesis
```

Since p-value is less than 0.05, we reject the null hypothesis. This implies that Number of cycles rented is not similar in different weather and season conditions

Hypothesis Testing 3

Null Hypothesis (H0): Weather is independent of the season

Alternate Hypothesis (H1): Weather is dependent of the season

Significance level (alpha): 0.05

We will use **chi-square test** to test hypyothesis defined above.

In [136…

```
data_table = pd.crosstab(df['season'], df['weather'] )
print("Observed values:")
data_table
```

```
Observed values:
```

Out[136]:

weather season	1	2	3	4
1	1759	715	211	1
2	1801	708	224	0
3	1930	604	199	0
4	1702	807	225	0

In [140…

```
statistic, p_value, dof, array = chi2_contingency(data_table)
statistic , p_value = f_oneway(weather_1,weather_2,weather_3,weather_4,season_1,season_2,season_3,season_4)
if p_value>=0.05:
    print(f"statistic value is {statistic}, \npvalue is {p_value}, \nDegree of freedom is {dof},\narray is {array}\nReject to fa
else:
    print(f"statistic value is {statistic}, \npvalue is {p_value}, \nDegree of freedom is {dof},\narray is {array}\nReject Null l
```

```
statistic value is 127.96661249562491,
pvalue is 2.8074771742434642e-185,
Degree of freedom is 9,
array is [[1.77454639e+03 6.99258130e+02 2.11948742e+02 2.46738931e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80625831e+03 7.11754180e+02 2.15736359e+02 2.51148264e-01]]
Reject Null hypothesis
accept alternate hypothesis
```

Since p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning that Weather is dependent on the season.

Insights

- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- Whenever its a **holiday** more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.

- Whenever there is **rain, thunderstorm, snow or fog**, there were less bikes were rented.

- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

Recommendations

- In **summer** and **fall** seasons the company should have more bikes in stock to be rented. Because the demand in these seasons is higher as compared to other seasons.
- With a significance level of 0.05, **workingday** has no effect on the number of bikes being rented.
- In very low humid days, company should have less bikes in the stock to be rented.
- Whenever temprature is less than 10 or in very cold days, company should have less bikes.
- Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.

https://drive.google.com/drive/folders/1fl9kl4n9_JM6248g0tk6hd6jvGiDh_M6?usp=sharing