In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import figure
import warnings
warnings.filterwarnings('ignore')
import statsmodels.api as sm
from scipy.stats import norm
from scipy.stats import t
import plotly.express as px
```

In [ ]:

About the project and Problem Statement :

In [ ]:

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.

`The company wants to know:`

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

Column Profiling:

- datetime: datetime
- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- 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

In [ ]:

In [2]:
```
df = pd.read_csv("bike_sharing.txt")
```

In [3]:
```
data = df.copy()
```

 # shape of the data :

In [4]:
```
data.shape
```

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

In [5]:
```
data.head(10)
```

Out[5]:

	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
5	2011-01-01 05:00:00	1	0	0	2	9.84	12.880	75	6.0032	0	1	1
6	2011-01-01 06:00:00	1	0	0	1	9.02	13.635	80	0.0000	2	0	2
7	2011-01-01 07:00:00	1	0	0	1	8.20	12.880	86	0.0000	1	2	3
8	2011-01-01 08:00:00	1	0	0	1	9.84	14.395	75	0.0000	1	7	8
9	2011-01-01 09:00:00	1	0	0	1	13.12	17.425	76	0.0000	8	6	14

10886 Records of bike Rented (each record shows howmany bikes were rented during that hour of the day.)

In [6]:
```
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
```

In [7]:
```
data.isna().sum()
```

Out[7]:
```
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
```

no null values detected

In [8]:
```
data.columns
```

Out[8]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

unique values per columns:

In [9]:
```
data.nunique()
```

Out[9]:
```
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
```

In [ ]:

In [ ]:

In [ ]:

workingday: except weekend or holiday is 1, offday : 0.

weather :

- weather changed to
  1. : Clear, Few clouds, partly cloudy, partly cloudy (clear)
  2. : Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist (cloudy)
  3. : Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds (little rain)
  4. : Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog (heavey rain)

Pre-processing data :

In [10]:
```
data["weather"].replace({1:"Clear",
                       2:"Cloudy",
                       3:"Little Rain",
                       4:"Heavy Rain"},inplace=True)
data["season"].replace({1:"Spring",
                       2:"Summer",
                       3:"Fall",
                       4:"Winter"},inplace=True)
data["workingday"].replace({1:"Yes",
                           0:"No"},inplace=True)
data["datetime"] = pd.to_datetime(data["datetime"])
data["holiday"].replace({1:"Yes",
                           0:"No"},inplace=True)
data["day"]=data["datetime"].dt.day_name()
data["date"] = data["datetime"].dt.date
data["hour"] = data["datetime"].dt.hour
data["Month"] = data["datetime"].dt.month
data["Month_name"] = data["datetime"].dt.month_name()
data["year"] = data["datetime"].dt.year
```

Describing Statistical summery of Independent Numerical Features :

Categorising Temperature And Humidity Levels and Windspeed column data :

In [11]:
```
pd.DataFrame(data["atemp"].describe()).T
```

Out[11]:

	count	mean	std	min	25%	50%	75%	max
atemp	10886.0	23.655084	8.474601	0.76	16.665	24.24	31.06	45.455

In [12]:
```
def get_temp(temp):
    if temp <= 12 : return "very low"
    elif temp > 12 and temp < 24 : return "low"
    elif temp >= 24  and temp < 35 :  return "moderate"
    elif temp >= 35 : return "high"
```

In [13]:
```
data["temperature"]=pd.Series(map(get_temp,data["atemp"]))
```

In [ ]:
```
```

In [14]:
```
pd.DataFrame(data["humidity"].describe()).T
```

Out[14]:

	count	mean	std	min	25%	50%	75%	max
humidity	10886.0	61.88646	19.245033	0.0	47.0	62.0	77.0	100.0

In [15]:
```python
def get_humidity(H):
    if 0 <= H <= 10:
        return "10%"
    elif 11 <= H <= 20:
        return "20%"
    elif 21 <= H <= 30:
        return "30%"
    elif 31 <= H <= 40:
        return "40%"
    elif 41 <= H <= 50:
        return "50%"
    elif 51 <= H <= 60:
        return "60%"
    elif 61 <= H <= 70:
        return "70%"
    elif 71 <= H <= 80:
        return "80%"
    elif 81 <= H <= 90:
        return "90%"
    elif 91 <= H <= 100:
        return "100%"
```

In [16]:
```python
data["gethumidity"]  = pd.Series(map(get_humidity,data["humidity"]))
```

In [17]:
```python
pd.DataFrame(data["windspeed"].describe()).T
```

Out[17]:

	count	mean	std	min	25%	50%	75%	max
windspeed	10886.0	12.799395	8.164537	0.0	7.0015	12.998	16.9979	56.9969

In [18]:
```python
data["windspeed_category"] = pd.qcut(data["windspeed"],8)
```

In [19]:
```python
data["windspeed_category"] = data["windspeed_category"].astype("object")
```

Data information :

In [20]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   datetime           10886 non-null  datetime64[ns]
 1   season             10886 non-null  object
 2   holiday            10886 non-null  object
 3   workingday         10886 non-null  object
 4   weather            10886 non-null  object
 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
 12  day                10886 non-null  object
 13  date               10886 non-null  object
 14  hour               10886 non-null  int64
 15  Month              10886 non-null  int64
 16  Month_name         10886 non-null  object
 17  year               10886 non-null  int64
 18  temperature        10886 non-null  object
 19  gethumidity        10886 non-null  object
 20  windspeed_category  10886 non-null  object
dtypes: datetime64[ns](1), float64(3), int64(7), object(10)
memory usage: 1.7+ MB
```

statistical summery about categorical data :

In [21]:
```
data.describe(include=["object","category"])
```

Out[21]:

	season	holiday	workingday	weather	day	date	Month_name	temperature	gethumidity	windspeed_category
count	10886	10886	10886	10886	10886	10886	10886	10886	10886	10886
unique	4	2	2	4	7	456	12	4	10	8
top	Winter	No	Yes	Clear	Saturday	2011-01-01	May	moderate	70%	(-0.001, 6.003]
freq	2734	10575	7412	7192	1584	24	912	4767	1845	2185

Moderate level Temperature frequency is highest in given data

70% humidty

and most preferable windspeed 8-12

In [22]:
```
correlations = data[['temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']].corr().unstack()
```

Correlation Matrix :

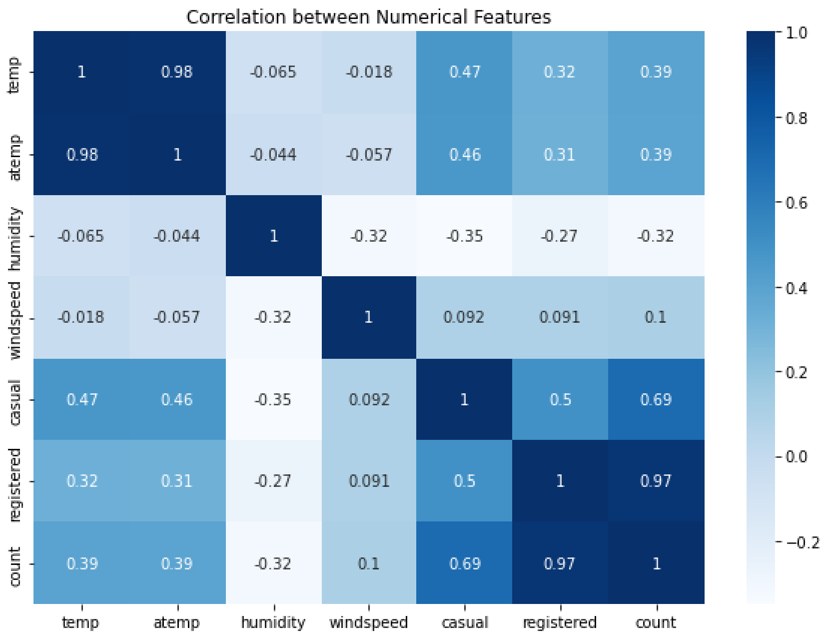
In [23]:
```
data[['temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']].corr()
```

Out[23]:

	temp	atemp	humidity	windspeed	casual	registered	count
temp	1.000000	0.984948	-0.064949	-0.017852	0.467097	0.318571	0.394454
atemp	0.984948	1.000000	-0.043536	-0.057473	0.462067	0.314635	0.389784
humidity	-0.064949	-0.043536	1.000000	-0.318607	-0.348187	-0.265458	-0.317371
windspeed	-0.017852	-0.057473	-0.318607	1.000000	0.092276	0.091052	0.101369
casual	0.467097	0.462067	-0.348187	0.092276	1.000000	0.497250	0.690414
registered	0.318571	0.314635	-0.265458	0.091052	0.497250	1.000000	0.970948
count	0.394454	0.389784	-0.317371	0.101369	0.690414	0.970948	1.000000

Heatmap (correlation between features)

In [24]:
```
plt.figure(figsize=(10,7))
sns.heatmap(data[['temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']].corr(),annot=True,cmap = "Blues")
plt.title("Correlation between Numerical Features")
plt.show()
```



Correlation between Temperature and Number of Cycles Rented for all customers : 0.39

Correlation between Temperature and Number of Cycles Rented for casual subscribers : 0.46

Correlation between Temperature and Number of Cycles Rented for registered subscribers : 0.31

Correlation between Temperature and Number of Cycles Rented for registered subscribers : 0.31

Humidity has a negative correlation with the number of cycles rented which is -0.32

Pre-processed Data Sample :

In [25]:
```
data.sample(10)
```

Out[25]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	...	count	day	date	hour	Month	Month_name	year	temperature	gethumidity	windspeed_category
4218	2011-10-07 19:00:00	Winter	No	Yes	Clear	22.96	26.515	52	0.0000	51	...	294	Friday	2011-10-07	19	10	October	2011	moderate	60%	(-0.001, 6.003]
3408	2011-08-11 22:00:00	Fall	No	Yes	Clear	28.70	32.575	48	0.0000	34	...	157	Thursday	2011-08-11	22	8	August	2011	moderate	50%	(-0.001, 6.003]
381	2011-01-17 09:00:00	Spring	Yes	No	Cloudy	6.56	7.575	47	15.0013	8	...	47	Monday	2011-01-17	9	1	January	2011	very low	50%	(12.998, 15.001]
89	2011-01-04 21:00:00	Spring	No	Yes	Clear	9.02	13.635	64	0.0000	0	...	48	Tuesday	2011-01-04	21	1	January	2011	low	70%	(-0.001, 6.003]
5349	2011-12-16 23:00:00	Winter	No	Yes	Cloudy	12.30	15.150	49	8.9981	4	...	75	Friday	2011-12-16	23	12	December	2011	low	50%	(7.002, 8.998]
90	2011-01-04 22:00:00	Spring	No	Yes	Clear	9.02	12.880	64	6.0032	1	...	35	Tuesday	2011-01-04	22	1	January	2011	low	70%	(-0.001, 6.003]
5865	2012-01-19 14:00:00	Spring	No	Yes	Clear	9.84	11.365	44	12.9980	15	...	119	Thursday	2012-01-19	14	1	January	2012	very low	50%	(8.998, 12.998]
1548	2011-04-10 09:00:00	Summer	No	No	Cloudy	15.58	19.695	94	8.9981	31	...	81	Sunday	2011-04-10	9	4	April	2011	low	100%	(7.002, 8.998]
763	2011-02-15 05:00:00	Spring	No	Yes	Clear	9.02	9.090	32	31.0009	0	...	4	Tuesday	2011-02-15	5	2	February	2011	very low	40%	(22.003, 56.997]
2833	2011-07-06 23:00:00	Fall	No	Yes	Clear	27.88	31.820	83	15.0013	20	...	98	Wednesday	2011-07-06	23	7	July	2011	moderate	90%	(12.998, 15.001]

10 rows × 21 columns

In [ ]:

About the features :

dependent variables : count / registerd / casual

independent variables : workingday / holiday / weather / seasons /temperature /humidity /windspeed.

In [ ]:

Outlier detection in Dataset :

In [26]:
```
def detect_outliers(data):
    length_before = len(data)
    Q1 = np.percentile(data,25)
    Q3 = np.percentile(data,75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

    length_after = len(data[(data>lowerbound)&(data<upperbound)])
    return f"{np.round((length_before-length_after)/length_before,4)} % Outliers data from input data found"
```

In [27]:
```
rentedCyclesPerHour  = data["count"]
```

In [ ]:

In [28]:
```
detect_outliers(rentedCyclesPerHour)
```

Out[28]: '0.0278 % Outliers data from input data found'

In [ ]:

Number of cycles rented by : casual users and registered users

Average Number of Cycles rented by `Casual vs Registered Subscribes` :

In [29]:
```
registered_per_hour_median = data.groupby("hour")["registered"].median()
casual_per_hour_median = data.groupby("hour")["casual"].median()
```

In [30]:
```
registered_per_hour_median = registered_per_hour_median.reset_index()
```

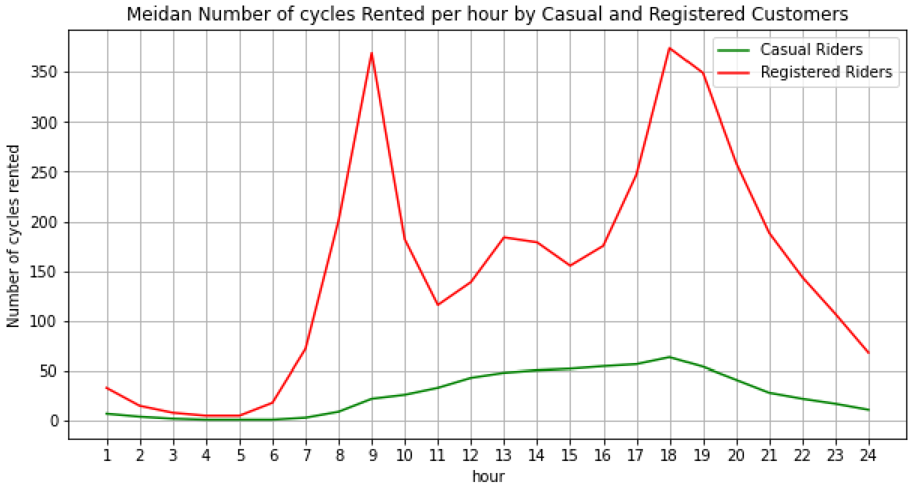
In [31]:
```
casual_per_hour_median = casual_per_hour_median.reset_index()
```

In [32]:
```
casual_per_hour_median["hour"]+= 1
```

In [33]:
```
registered_per_hour_median["hour"]+= 1
```

In [34]:
```
median_count_perHr = registered_per_hour_median.merge(casual_per_hour_median,on="hour")
```

In [35]:
```
plt.figure(figsize=(10,5))
sns.lineplot(x = median_count_perHr["hour"],
             y = median_count_perHr["casual"],color="g",legend='auto')
sns.lineplot(x = median_count_perHr["hour"],
             y = median_count_perHr["registered"],color="r",legend='auto')
plt.legend(["Casual Riders","Registered Riders"])
plt.title("Meidan Number of cycles Rented per hour by Casual and Registered Customers")
plt.grid()
plt.xticks(np.arange(1,25,1))
plt.ylabel("Number of cycles rented")
plt.show()
```



From above linplot :

- **registered customers seems to be using rental cycles mostly for work-commute purposes.**
- **registered cycle counts seems to be much higher than the casual customers.**

In [36]:
```
print("Casual Users (in %) :")
(data["casual"].sum()/data["count"].sum())*100
```

```
Casual Users (in %) :
```

Out[36]:
```
18.8031413451893
```

In [37]:
```
print("Registered Users (in %) : ")
(data["registered"].sum()/data["count"].sum())*100
```

```
Registered Users (in %) :
```

Out[37]:
```
81.1968586548107
```

81% cycles had been rented by registered customers.

19% cycles had been rented by casual customers.

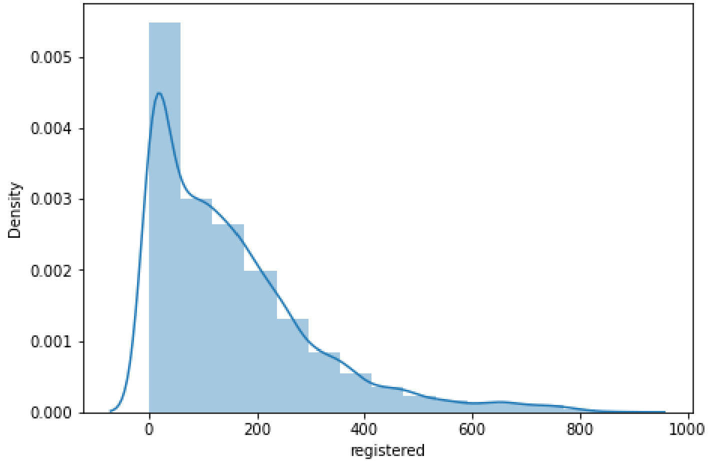
Using Bootrsapping : Confidence Interval of Mean Number of cycles Rented by Casual And Registered Customers :

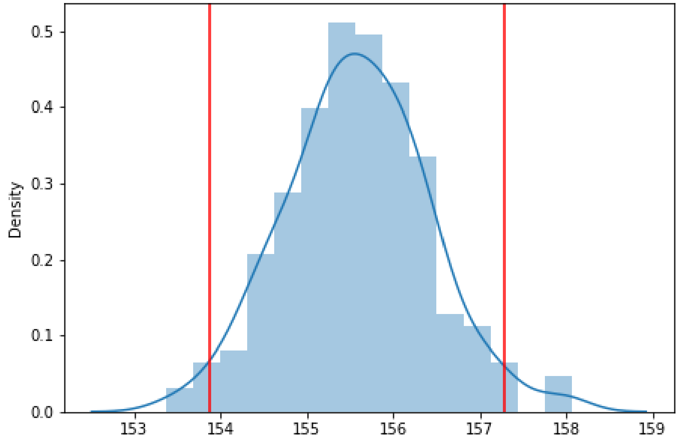
In [38]:
```python
def Confidence_Interval_Bootstrapping(data, confidence=95 , sample_size = 30000,trials = 200):


    '''
    data : array
    confidence level : Required Confidence Level
    Sample Size  : length of Sample Size
    Trials : How many times we take sample sample from data.
    '''
    print("Data Distribution before Sampling/Bootstrap:  Data Distribution After Sampling/Bootstraping")


    bootstrapped_mean= np.empty(trials)

    for i in range(trials):
        btssample = data.sample(n=sample_size,replace=True)
        bootstrapped_mean[i] = np.mean(btssample)

    print()
    sample_mean = np.mean(bootstrapped_mean)
    sample_std = np.std(data)
    standard_error = sample_std/np.sqrt(sample_size)
    talfa_by2 = t.ppf((1-((1-(confidence)/100)/2)),df = sample_size-1)
    margin_of_error = talfa_by2*standard_error
    print("sample mean :",sample_mean)
    print("sample standard deviation :",sample_std)
    print("sample size: ",sample_size)
    plt.figure(figsize=(16,5))
    plt.subplot(121)
    sns.distplot(data,bins = 15)

    plt.subplot(122)

    sns.distplot(bootstrapped_mean,bins = 15)

    lower_ = sample_mean - margin_of_error
    upper_ = sample_mean + margin_of_error
    CI = (lower_,upper_)

    plt.axvline(x = lower_,c = "r")
    plt.axvline(x = upper_,c = "r")
    plt.show()



    print("Confidence Interval : ",CI)
```

Confidence Interval of Average Number of Cycles Rented by Registered Customers

In [39]:
```
Confidence_Interval_Bootstrapping(data["registered"])
```

```
Data Distribution before Sampling/Bootstrap:  Data Distribution After Sampling/Bootstraping

sample mean : 155.58265333333333
sample standard deviation : 151.03209561628552
sample size:  30000
```



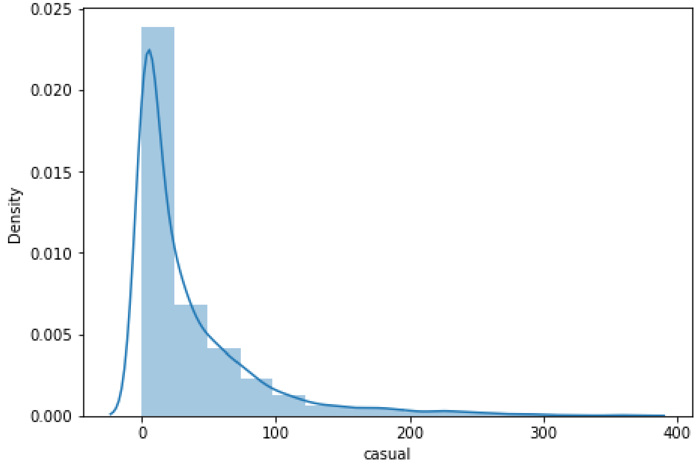


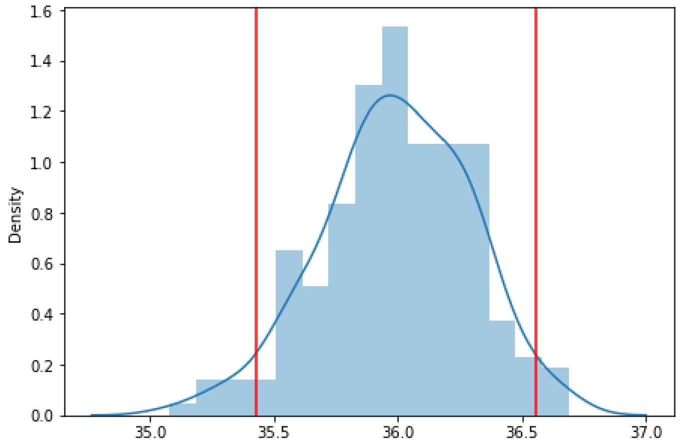

```
Confidence Interval :  (153.87352672766121, 157.29177993900544)
```

Confidence Interval of Average Number of Cycles Rented by Casual Customers

In [40]:
```
Confidence_Interval_Bootstrapping(data["casual"])
```

```
Data Distribution before Sampling/Bootstrap:  Data Distribution After Sampling/Bootstraping

sample mean : 35.99225833333333
sample standard deviation : 49.95818180763136
sample size:  30000
```






```
Confidence Interval :  (35.426915865230676, 36.55760080143599)
```

In [ ]:

In [ ]:

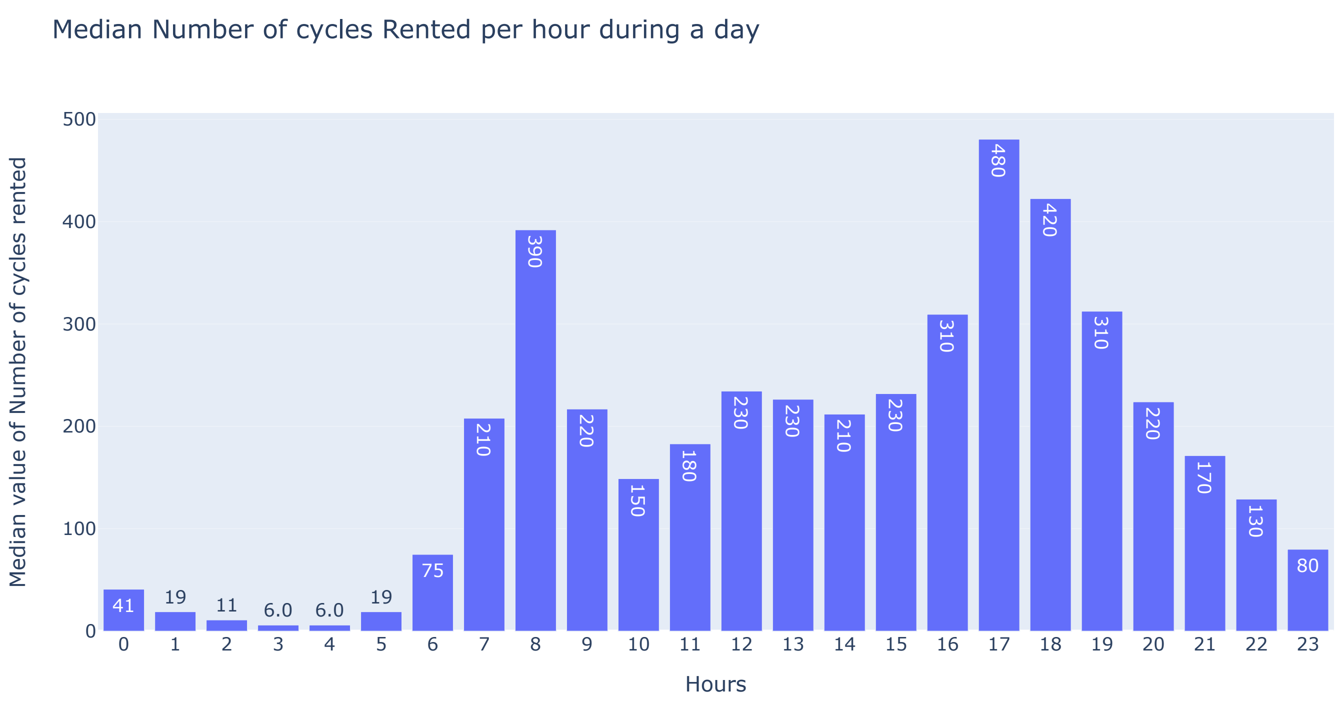
In [ ]:

In [ ]:

Hourly median number of cycles rented during the day :

In [41]:

```
fig = px.bar(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,text_auto='.2s',
              labels={
                     "x": "Hours",
                     "y": "Median value of Number of cycles rented",}
             ,title="Median Number of cycles Rented per hour during a day"
            )
fig.update_layout(
    xaxis = dict(
        tickmode = 'linear',
        tick0 = 0,
        dtick = 1
    )
)


fig.show()
```



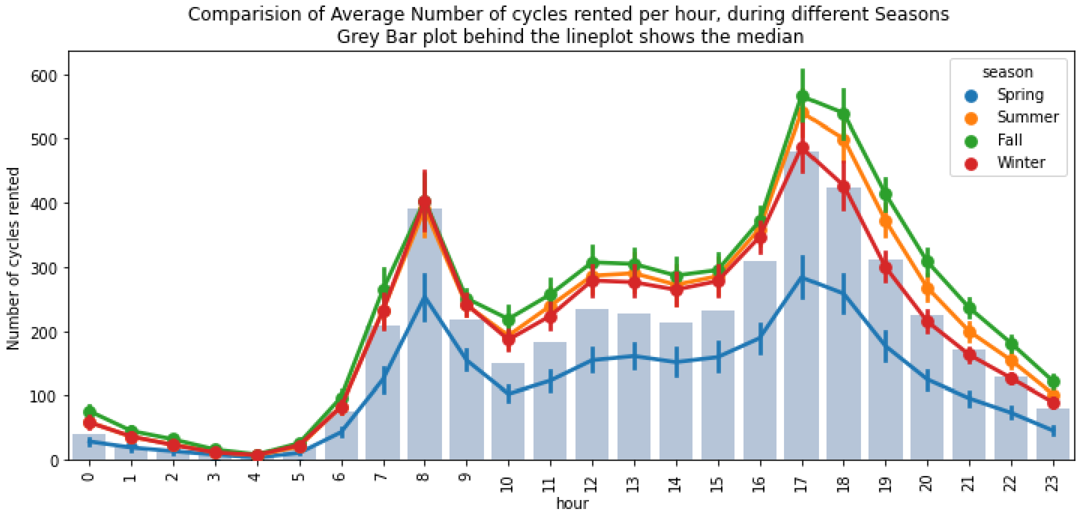
- **from above bar chart :**
- **shows the median value of number of cycles were rented during perticular hour of the day.**
- **Median of number of cycles rented are higher during morning 7 to 9 am to evening 4 to 8pm .**

In [ ]:

Effect of seasons on number of cycles rented during hours :

In [ ]:

In [42]:
```
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,
            color="lightsteelblue")
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["season"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, during different Seasons \nGrey Bar plot behind the lineplot shows the median")
plt.xticks(rotation = 90)
plt.ylabel("Number of cycles rented")
plt.show()
```



during the morning 7-9am and afternoon 4pm to 7pm , the cycles rent counts is increasing.

during the spring season , looks like people prefer less likely to rent the cycle.

In [ ]:

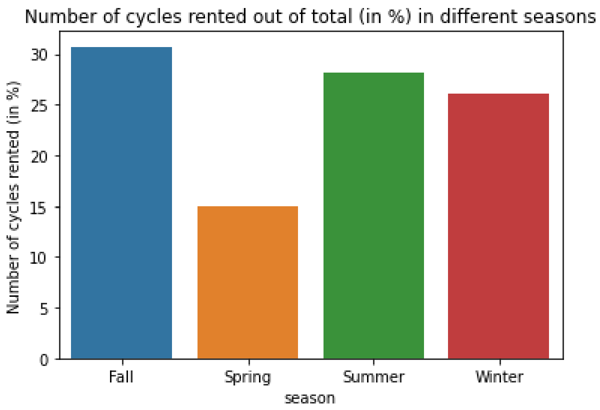
Number of cycles rented during differnet seasons (in %) :`

In [43]:
```
season_wise_rent_percentage = data.groupby("season")["count"].sum()/np.sum(data["count"])*100
```

In [44]:
```
season_wise_rent_percentage
```

Out[44]:
```
season
Fall      30.720181
Spring    14.984493
Summer    28.208524
Winter    26.086802
Name: count, dtype: float64
```

In [45]:
```
sns.barplot(x= season_wise_rent_percentage.index,
           y = season_wise_rent_percentage)
plt.ylabel("Number of cycles rented (in %)")
plt.title("Number of cycles rented out of total (in %) in different seasons")
plt.show()
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

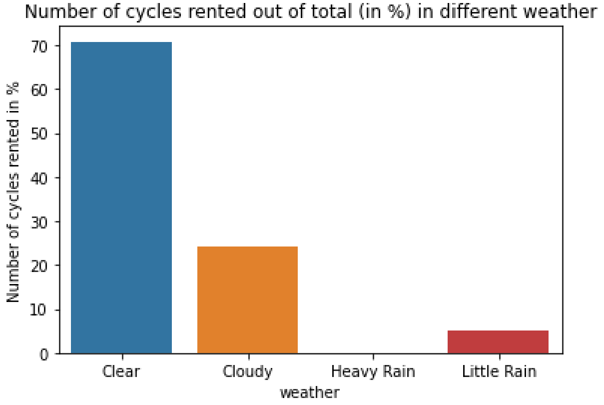
In [ ]:

weather effect on cycle rental median counts hourly :

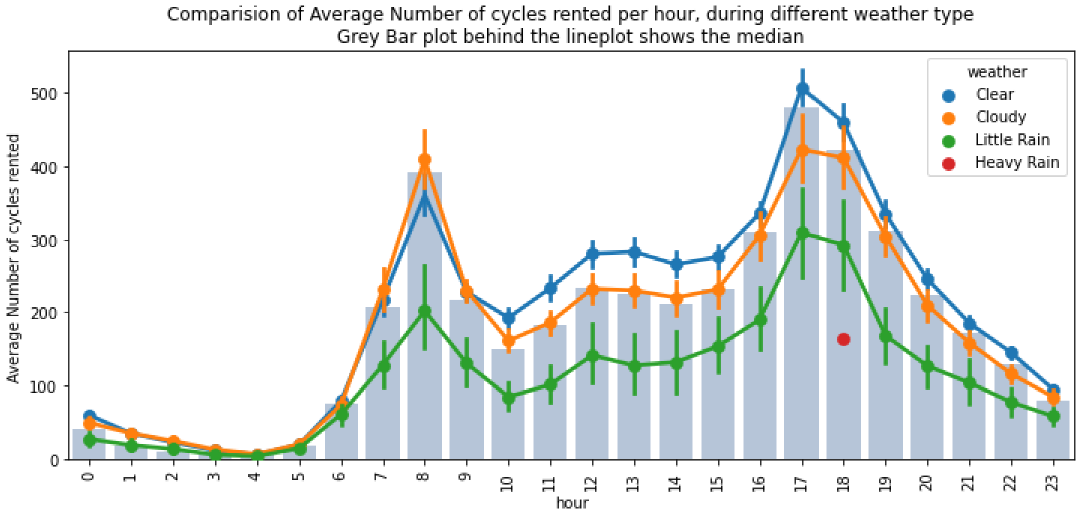
In [46]:
```
weather_wise_rent_percentage = data.groupby("weather")["count"].sum()/np.sum(data["count"])*100
weather_wise_rent_percentage
```

Out[46]:
```
weather
Clear          70.778230
Cloudy         24.318669
Heavy Rain      0.007864
Little Rain     4.895237
Name: count, dtype: float64
```

In [47]:
```
sns.barplot(x= weather_wise_rent_percentage.index,
            y = weather_wise_rent_percentage)
plt.title("Number of cycles rented out of total (in %) in different weather")

plt.ylabel("Number of cycles rented in %")
plt.show()
```



In [48]:
```
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,
            color="lightsteelblue")
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["weather"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, during different weather type\nGrey Bar plot behind the lineplot shows the median")

plt.xticks(rotation = 90)
plt.ylabel("Average Number of cycles rented")
plt.show()
```



70% of the cycles were rented when it was clear weather.

24% when it was cloudy weather .

during rainy weather , only around 5% of the cycles were rented.

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```

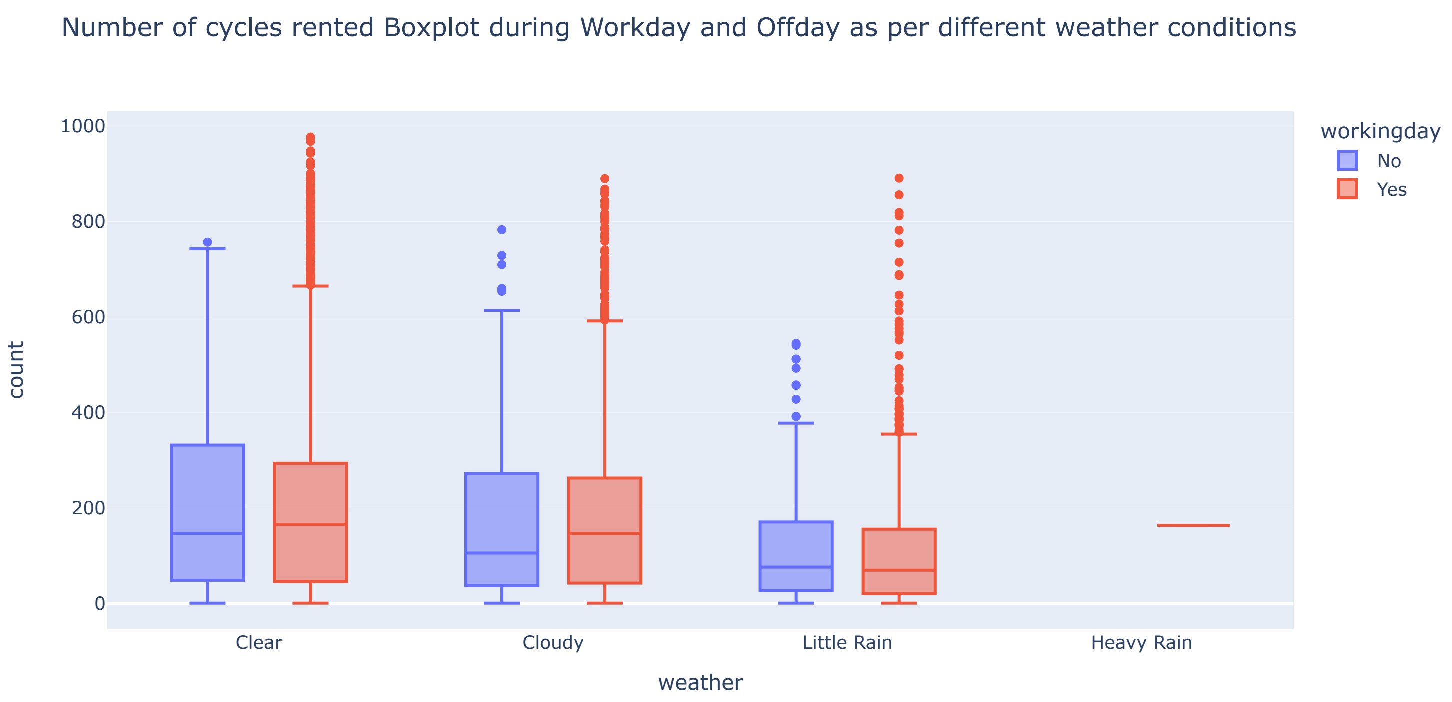
```
In [ ]:
```

DISTRIBUTIONS and Comparision of number of cycles rented during working days and off day , across different seasons.

- **Boxplot - distribution of number of bike rented , during different weather as per workingday or not!**

```
In [ ]:
```

In [49]:
```
fig = px.box(data, x="weather", y="count", color="workingday",
            title="Number of cycles rented Boxplot during Workday and Offday as per different weather conditions")

fig.show()
```

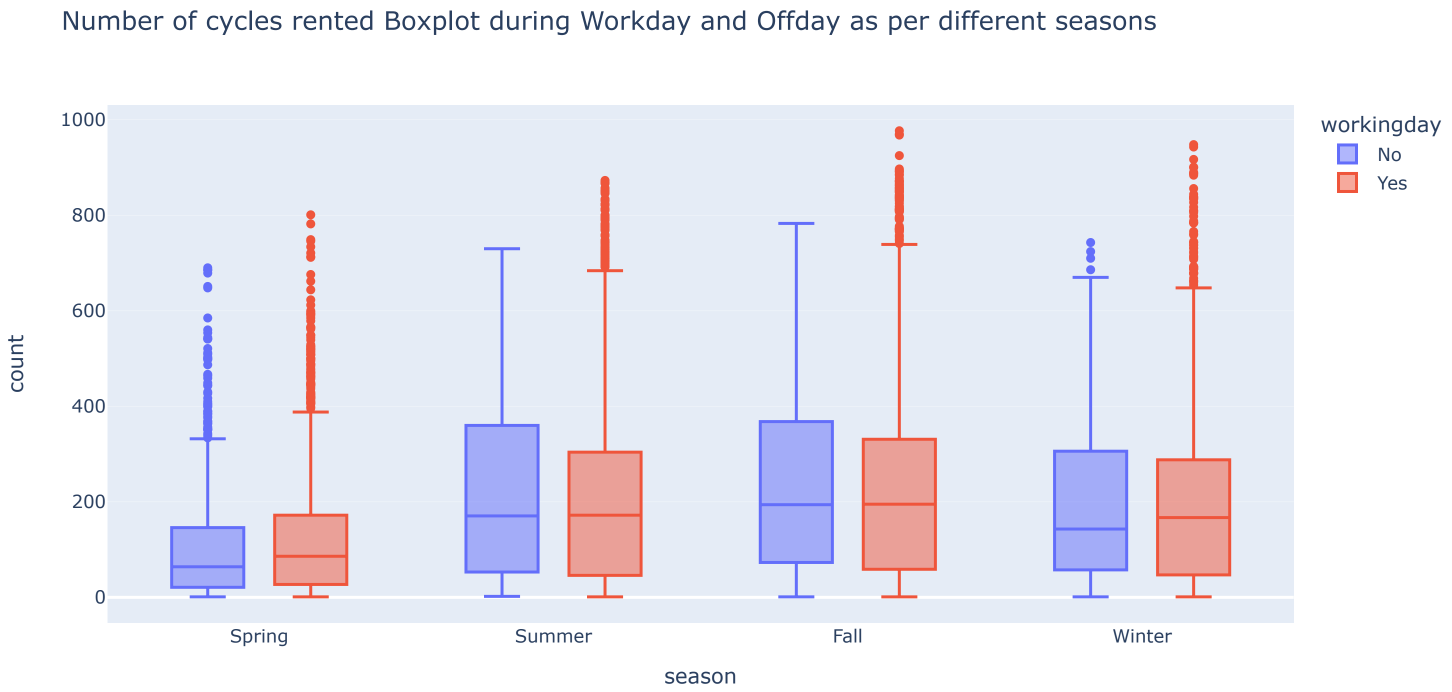


from above boxplot, we can say , there's no significant activity during heavy rain weather.

High activity during clear and cloudy weather.

- **Boxplot - distribution of number of bike rented , during different seasons as per workingday or not!**

In [50]:
```
fig = px.box(data, x="season", y="count", color="workingday",
             title="Number of cycles rented Boxplot during Workday and Offday as per different seasons")
fig.show()
```

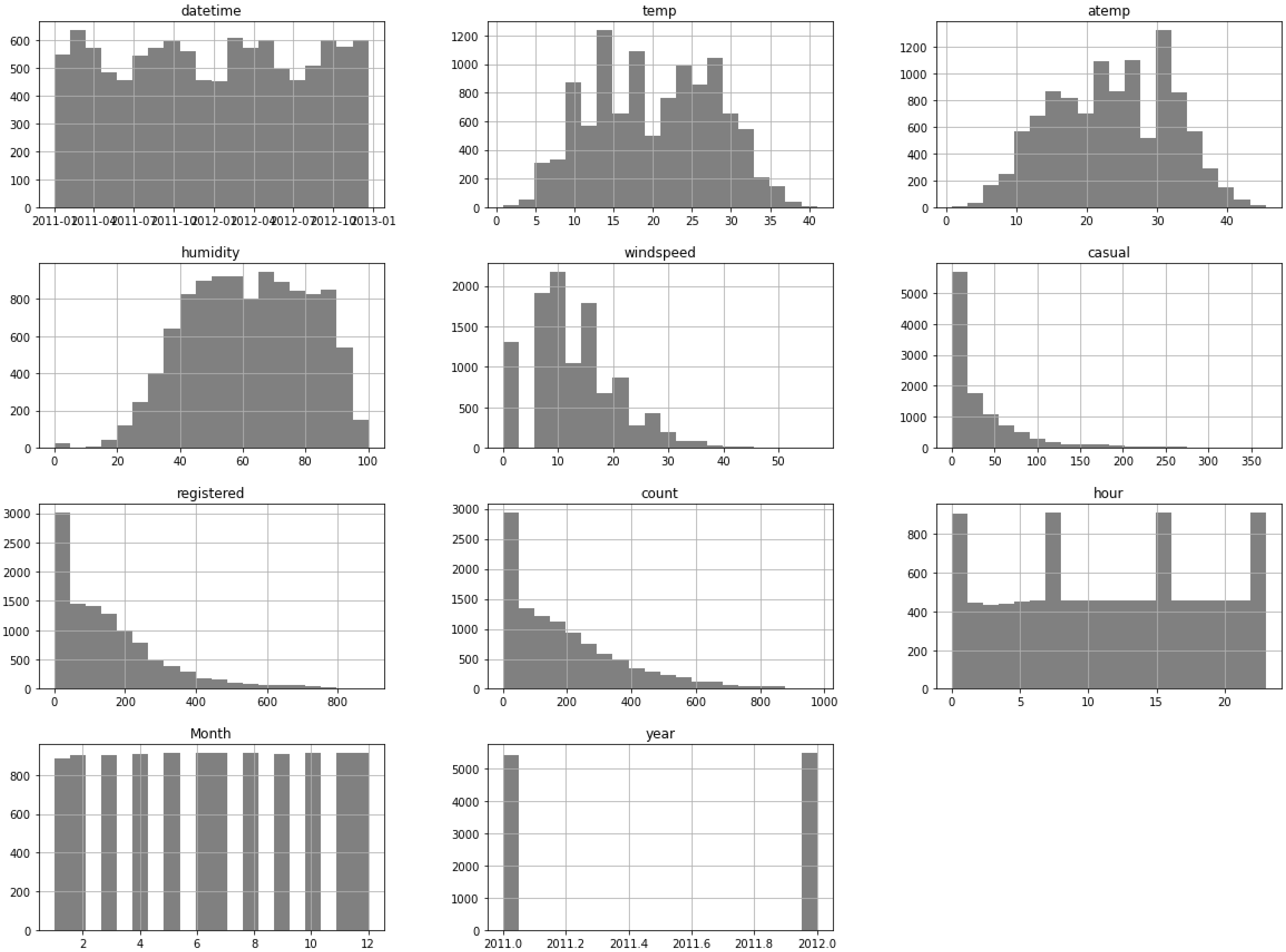


during spring season , number of bike rented were lower than summer and fall.

overview on distributions of Numerical Features :

In [51]:

```
data.hist(bins=20,figsize=(20,15),color='grey')
plt.show()
```



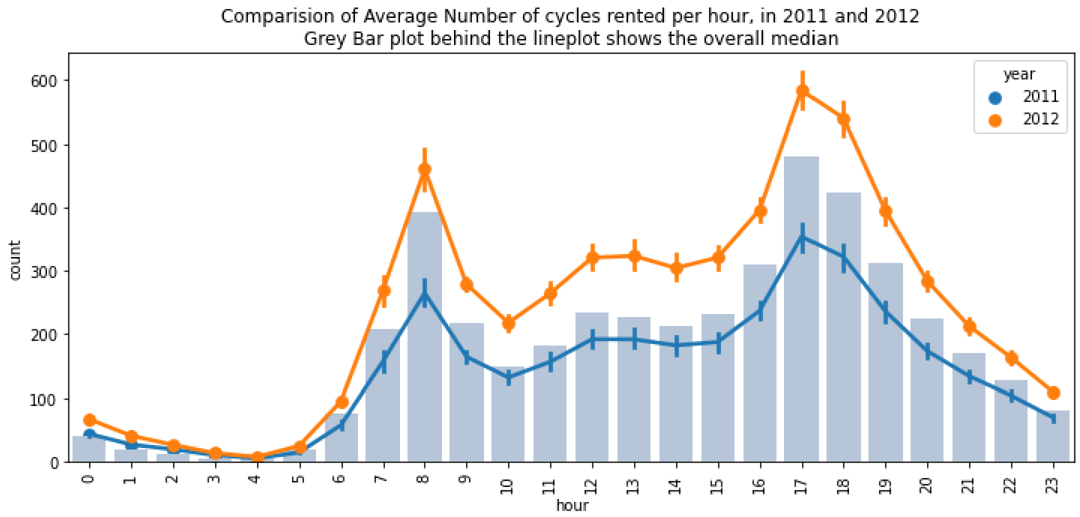
From above distribution plots of number of bikes rented , are not normally distributed.

- also that there are outliers in the data and overall distributions are heavily right skewed .

- data need to be tranformed for hypothesis test calculations further.

Yearly difference in number of bike rental :

In [52]:
```
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,
            color="lightsteelblue")
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["year"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, in 2011 and 2012\nGrey Bar plot behind the lineplot shows the overall median")
plt.xticks(rotation = 90)
plt.show()
```



hourly average bike rented in year 2011 and 2012

In [ ]:

In [53]:
```
data.groupby("year")["count"].median()
```

Out[53]:
```
year
2011    111.0
2012    199.0
Name: count, dtype: float64
```

In [54]:
```
(((199-111)/111))*100
```

Out[54]:
```
79.27927927927928
```

from 2011 , there's 79.27% hike in hourly median number of bike rental.

In [55]:
```
data.groupby("year")["casual"].median()
```

Out[55]:
```
year
2011    13.0
2012    20.0
Name: casual, dtype: float64
```

In [56]:
```
data.groupby("year")["registered"].median()
```

Out[56]:
```
year
2011     91.0
2012    161.0
Name: registered, dtype: float64
```

In [57]:
```
(((161-91)/91))*100
```

Out[57]:
```
76.92307692307693
```

in registered customers , 76% hike in hourly median cycle rental from 2011 to 2012.

in 2011 , median number of hourly rental were 13 , and in 2012 , its 20. -

In [ ]:

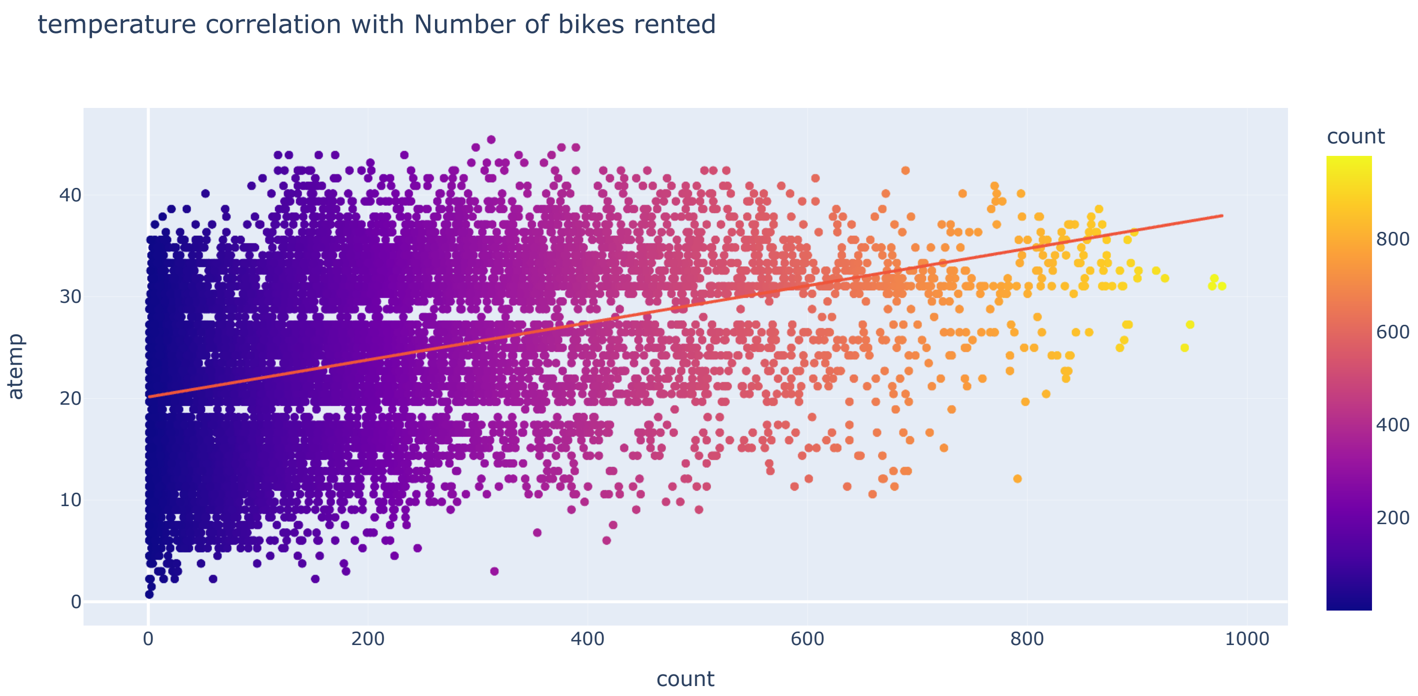
In [ ]:

In [ ]:

In [ ]:

Number and cycles rented and temperature correlation :

In [58]:
```
fig = px.scatter(data, x="count", y="atemp",  color="count", trendline="ols",
                title="temperature correlation with Number of bikes rented")
fig.show()
```



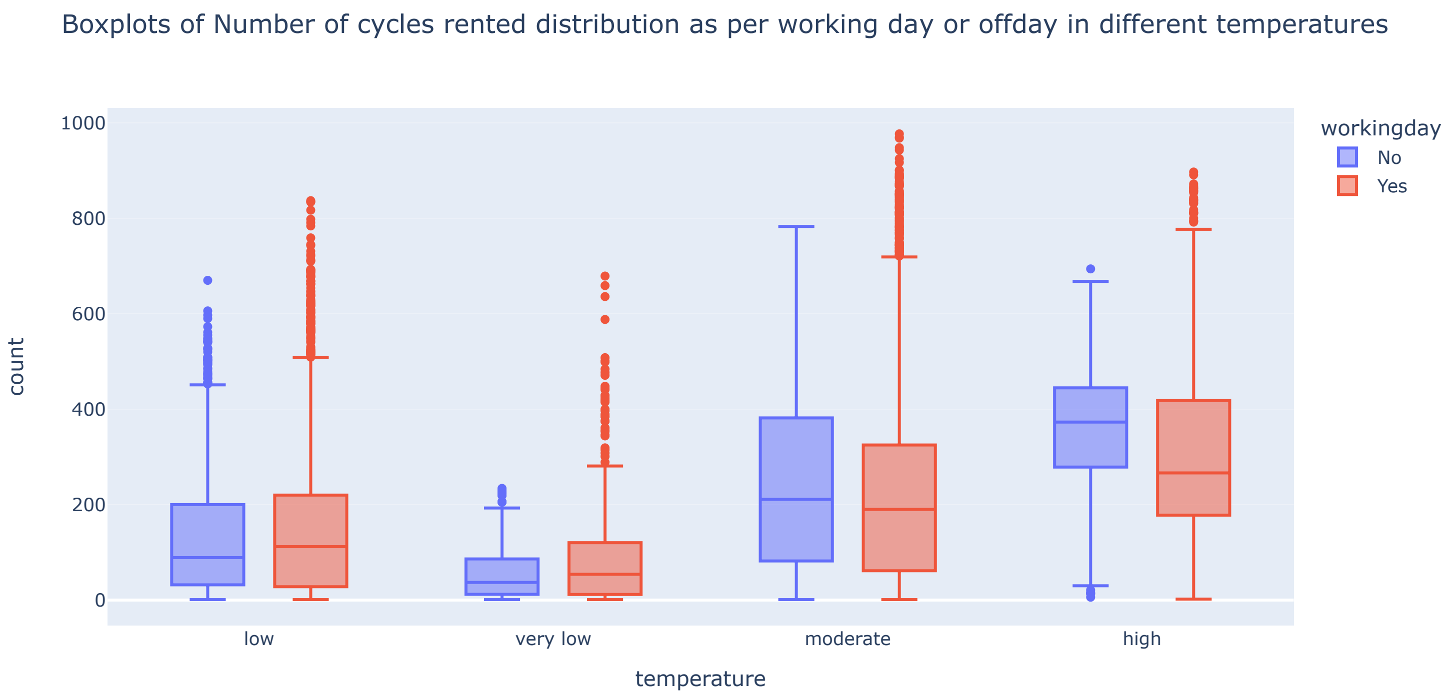
- **from scatter plot , there's a positive correlation across temperature and number of bikes rented.**

- **After categorising the temperature as low, verylow, moderate, high :**

In [59]:
```
data["temperature"].value_counts()
```

Out[59]:
```
moderate    4767
low         4318
very low    1014
high         787
Name: temperature, dtype: int64
```

In [60]:
```
fig = px.box(data, x="temperature", y="count", color="workingday",
             title= "Boxplots of Number of cycles rented distribution as per working day or offday in different temperatures")
fig.show()
```



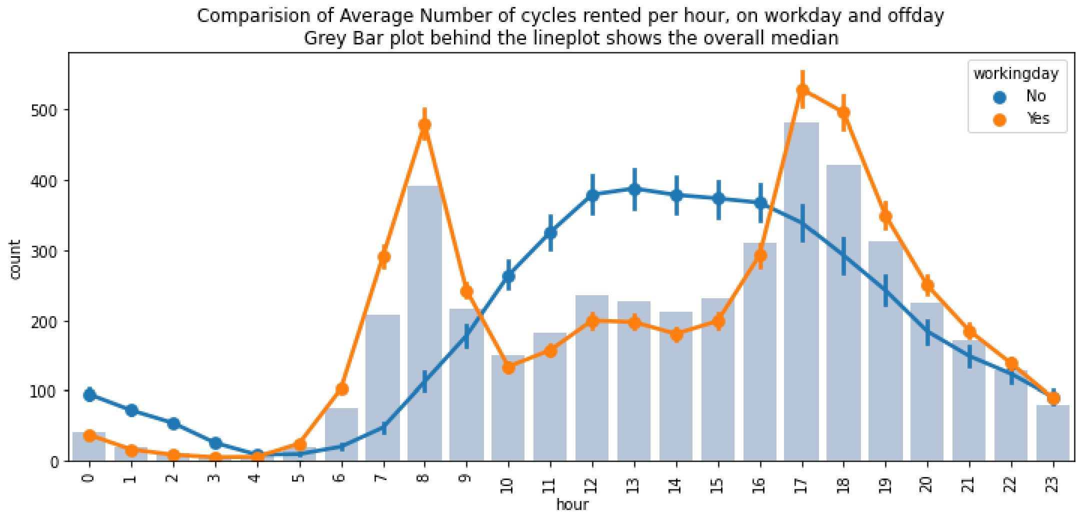
from above boxplot :

number of bike rented during moderate to high temerature is significantly higher than lower temperature.

In [ ]:

offday vs working day number of cycles rented trend during a day :

In [61]:
```
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,
            color="lightsteelblue")
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["workingday"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, on workday and offday\nGrey Bar plot behind the lineplot shows the overall median")

plt.xticks(rotation = 90)
plt.show()
```



number of cycles rented changed as per working day and off-day . trend is opposit.

on off days , number of cycles rented increases during the day time ! which is opposite of during working days.

from above plot it looks like, working day count of cycle rented seems to be higher than offday! lets do a AB test : weather mean of rented cycled on working day and offdays are same or not !

In [ ]:

hourly median number of cycles rented during

In [62]:
```
data.groupby("workingday")["count"].median()
```

Out[62]:
```
workingday
No     128.0
Yes    151.0
Name: count, dtype: float64
```

hourly average number of cycles rented during

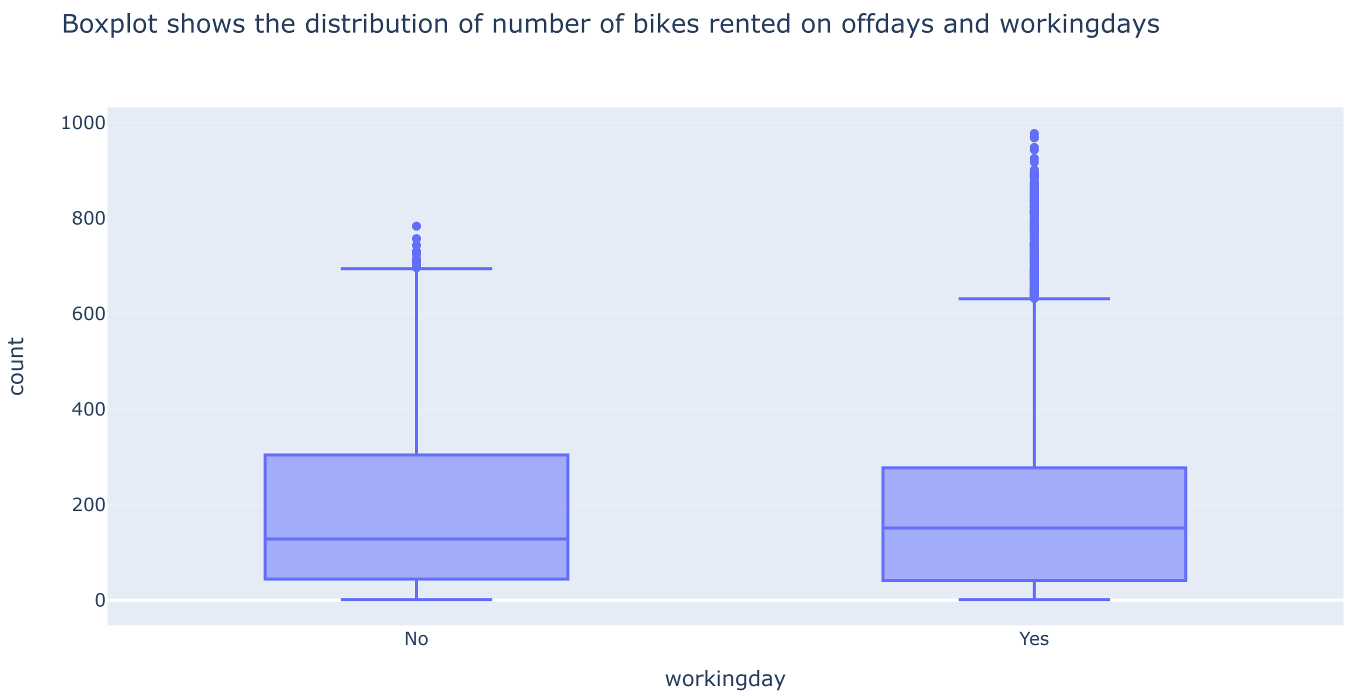
In [63]:
```
data.groupby("workingday")["count"].mean()
```

Out[63]:
```
workingday
No     188.506621
Yes    193.011873
Name: count, dtype: float64
```

In [ ]:

Boxplot : number of bikes rented during working day and off-day :

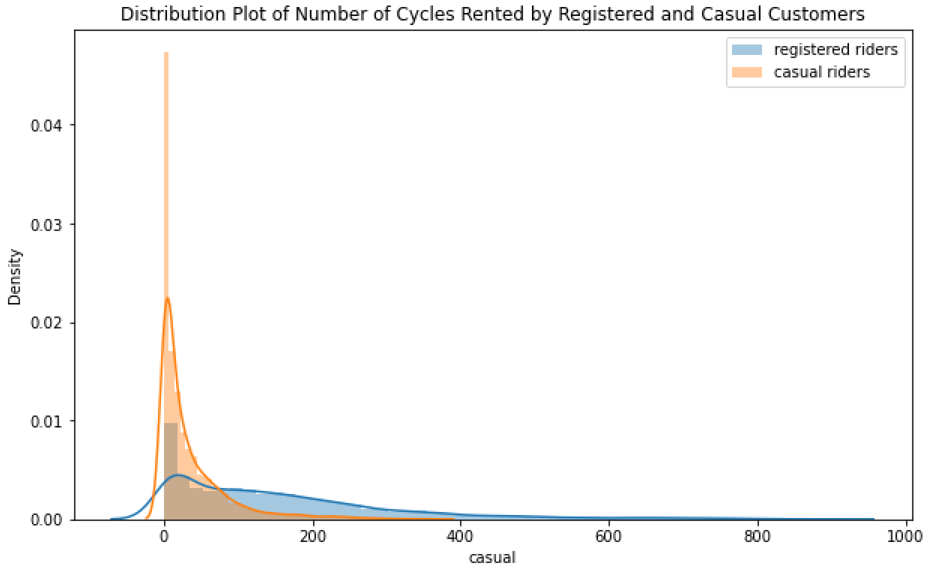
In [64]:
```
fig = px.box(data, x="workingday", y="count",
            title="Boxplot shows the distribution of number of bikes rented on offdays and workingdays")
fig.show()
```



- **from above boxplot ,**
- **distributions of hourly number of bike rented during working day and off day seems similar .**
- **though there are more outliers in workinday category.**

Distribution Plot of Number of Cycles Rented by Registered and Casual Customers

In [65]:
```
plt.figure(figsize=(10,6))

sns.distplot(data["registered"], label = "registered riders")
sns.distplot(data["casual"], label = "casual riders")
plt.title("Distribution Plot of Number of Cycles Rented by Registered and Casual Customers")
plt.legend()
plt.show()
```



testing if mean number of electric cycles rented on workday is equal to on offday !

t-test :

If working day and offday has an effect on the number of electric cycles rented.

distribution of number of bikes rented as per working day or offday (in percentages)

In [66]:
```
data.groupby("workingday")["count"].sum()/np.sum(data["count"])*100
```

Out[66]:
```
workingday
No     31.40156
Yes    68.59844
Name: count, dtype: float64
```

In [67]:
```
workingday = data.loc[data["workingday"]=="Yes"]["count"]
offday = data.loc[data["workingday"]=="No"]["count"]
```

- Establishing Hypothesis :

```
H0: average # of cycles rented on workingdays   =   average # of cycles rented on offday
Ha: average # of cycles rented on workingdays  !=   average # of cycles rented on offday
```

In [68]:
```
m1 = np.mean(workingday)
n1 = len(workingday)
s1 = np.std(workingday,ddof = 1)

m2 = np.mean(offday)
n2 = len(offday)
s2 = np.std(offday,ddof = 1)
```

In [69]:
```
m1,m2,m1-m2
```

Out[69]:
```
(193.01187263896384, 188.50662061024755, 4.505252028716285)
```

calulating Test Statistic :

In [70]:
```
T_observed =(m1-m2)/(np.sqrt(((s1**2)/n1)+((s2**2)/n2)))
T_observed
```

Out[70]:
```
1.236258041822322
```

p-Value :

In [71]:
```
p_value = 2*(1-stats.t.cdf(T_observed,n1+n2-2))
p_value
```

Out[71]:
```
0.2163893399034813
```

Extream Critical Value

In [72]:
```
T_critical = stats.t.ppf(0.975,n1+n2-2)
T_critical
```

Out[72]:
```
1.9601819678713073
```

In [73]:
```
p_value > 0.05
```

Out[73]:
```
True
```

In [74]:
```
-T_critical <  T_observed < T_critical
```

Out[74]:
```
True
```

we failed to reject null Hypothesis

mean of number of cycles rented on

working days are equal as the cycles rented on offdays.

In [ ]:

In [ ]:

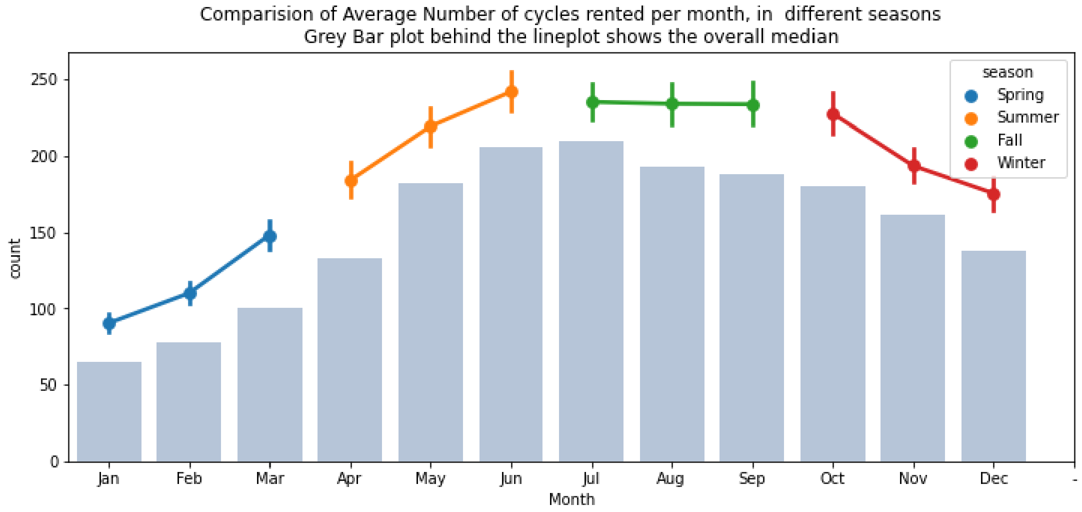
In [ ]:

In [ ]:

In [ ]:

Month and season wise , effect on median and average number of cycles rented .

In [75]:
```python
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("Month")["count"].median(),
           x = data.groupby("Month")["count"].median().index,
           color="lightsteelblue")
sns.pointplot(x = data["Month"],
              y= data["count"],
              hue=data["season"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per month, in  different seasons\nGrey Bar plot behind the lineplot shows the overall median")

plt.xticks([0,1,2,3,4,5,6,7,8,9,10,11,12],["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec","-"])

plt.show()
```



cycle rental counts decreased during winter season and opering spring seaosn .

During Summer season , count increase and stays a constant till pre-winter season .

From May to November the number of cycles rented are increasing

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

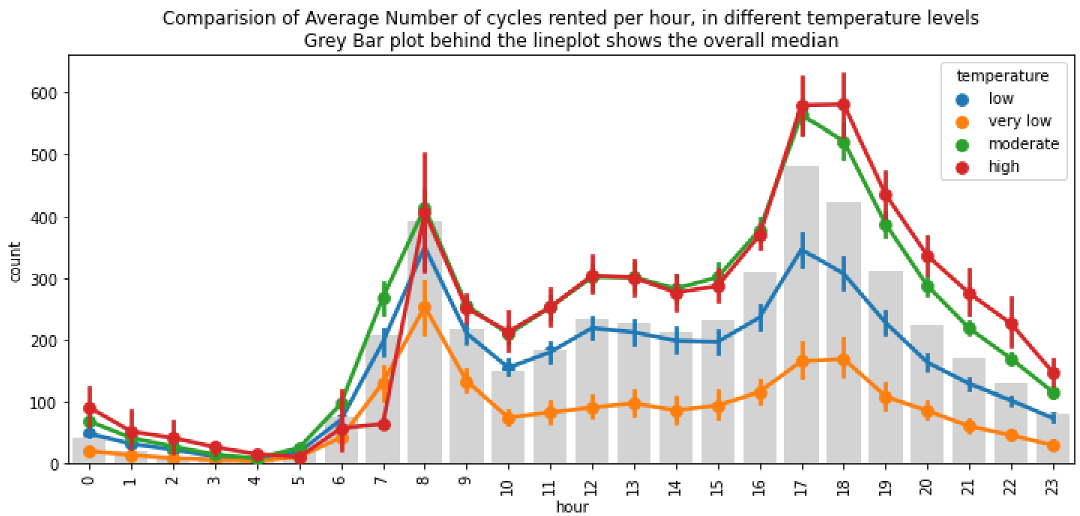
temperature effect on cycle rental

In [ ]:

In [76]:
```
temperature_wise_rent_percentage = data.groupby("temperature")["count"].sum()/np.sum(data["count"])*100
temperature_wise_rent_percentage
```

Out[76]:
```
temperature
high        12.487269
low         30.172248
moderate    53.538617
very low     3.801866
Name: count, dtype: float64
```

In [77]:
```
plt.figure(figsize=(12,5))
sns.barplot(y = data.groupby("hour")["count"].median(),
           x = data.groupby("hour")["count"].median().index,
            color="lightgrey")
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["temperature"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, in different temperature levels\nGrey Bar plot behind the lineplot shows the overall median")

plt.xticks(rotation = 90)
plt.show()
```



Average Number of Bikes rented are higher in moderate to high temperature.

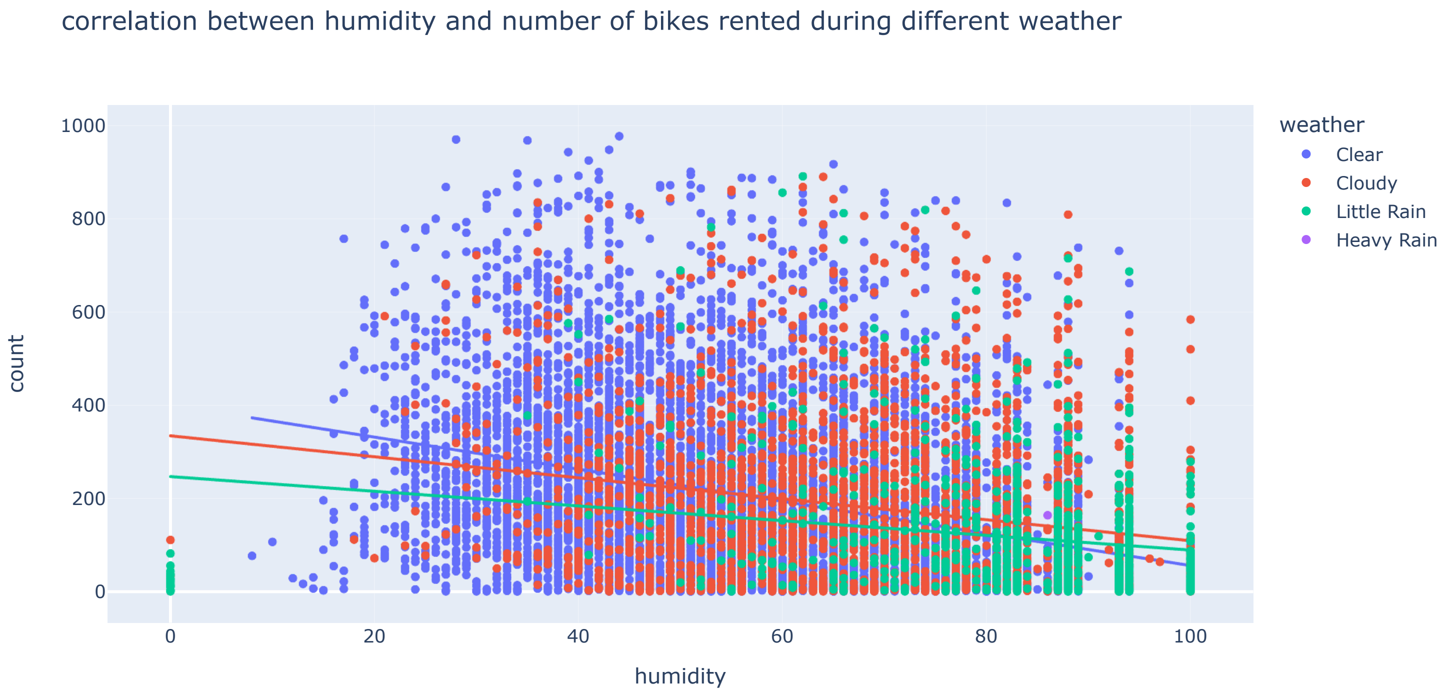
which decreases when temperature is low to very low!

In [ ]:

In [ ]:

humidity vs count

In [78]:
```
fig = px.scatter(data, y="count", x="humidity",  color="weather", trendline="ols",
                title=" correlation between humidity and number of bikes rented during different weather")
fig.show()
```



Scatter plot above , shows kind of a negative correlation , between humidity and number of bikes rented. After Categorising Humidity level , we can see

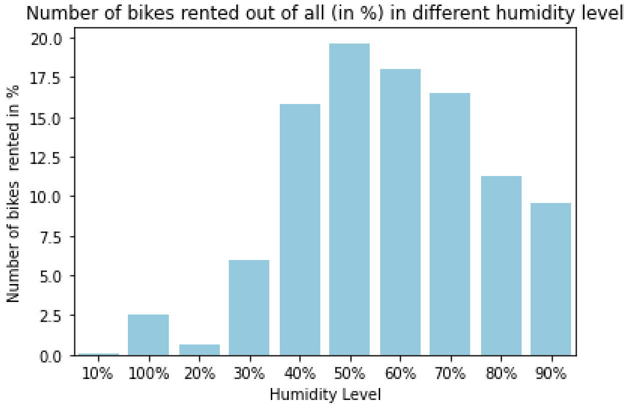
In [79]:
```
humidity_wise_rent_percentage = data.groupby("gethumidity")["count"].sum()/np.sum(data["count"])*100
humidity_wise_rent_percentage
```

Out[79]:
```
gethumidity
10%      0.038696
100%     2.565314
20%      0.635970
30%      5.942528
40%     15.798887
50%     19.659541
60%     18.030512
70%     16.507215
80%     11.268459
90%      9.552879
Name: count, dtype: float64
```

Counts are increasing from humidity level of 40% to 70% .

40 to 70% humidity level seems to be most comfortable for cycling.

In [80]:
```
sns.barplot(x= humidity_wise_rent_percentage.index,
           y = humidity_wise_rent_percentage,color="skyblue")
plt.title("Number of bikes rented out of all (in %) in different humidity level")
plt.ylabel("Number of bikes  rented in %")
plt.xlabel("Humidity Level")
plt.show()
```



In [ ]:

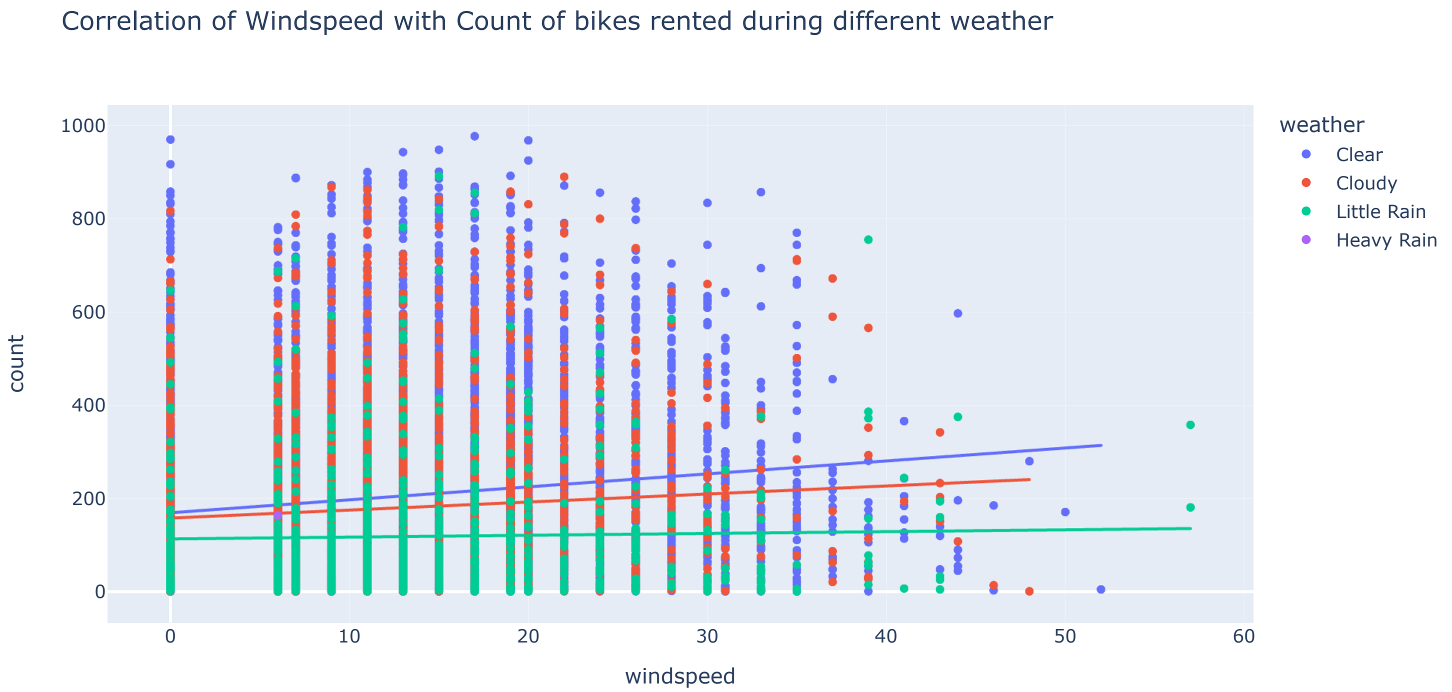
In [ ]:

In [ ]:

In [ ]:

Windspeed vs count :

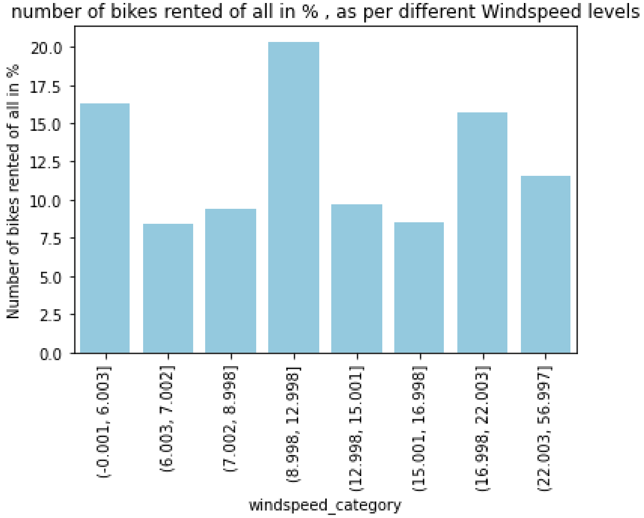
In [81]:
```
fig = px.scatter(data, y="count", x="windspeed",  color="weather", trendline="ols",
                title= "Correlation of Windspeed with Count of bikes rented during different weather")
fig.show()
```



In [82]:
```
windspeed_wise_rent_percentage = data.groupby("windspeed_category")["count"].sum()/np.sum(data["count"])*100
windspeed_wise_rent_percentage
```

Out[82]:
```
windspeed_category
(-0.001, 6.003]     16.325482
(6.003, 7.002]       8.421435
(7.002, 8.998]       9.433002
(8.998, 12.998]     20.356743
(12.998, 15.001]     9.715336
(15.001, 16.998]     8.488901
(16.998, 22.003]    15.682703
(22.003, 56.997]    11.576398
Name: count, dtype: float64
```

In [83]:
```
sns.barplot(x= windspeed_wise_rent_percentage.index,
           y = windspeed_wise_rent_percentage,color="skyblue")
plt.title("number of bikes rented of all in % , as per different Windspeed levels")
plt.ylabel("Number of bikes rented of all in %")
plt.xticks(rotation =90)
plt.show()
```



from above, plot:

windspeed are categorised in different groups .

Windspeed increases , the number of bike rented are decreases.

Most often windspeed is 8 to 24.

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Test for Independence between few categorical features. :

In [ ]:

In [ ]:

If Weather is dependent on the season

chi-square test : for independence :

weather and season are categorical variables

> **for dependency : chi square test :**

> **H0: weather and seasons are independent**

> **Ha: weather and seasons are dependent**

In [84]:
```
temp_data = data[data["weather"].isin(["Little Rain","Clear","Cloudy"])]
```

In [85]:
```
observed = pd.crosstab(index = temp_data["season"],
           columns = temp_data["weather"],
            values= temp_data["count"],
           aggfunc=np.sum
           )
```

In [86]:
```
observed
```

Out[86]:

weather	Clear	Cloudy	Little Rain
season			
Fall	470116	139386	31160
Spring	223009	76406	12919
Summer	426350	134177	27755
Winter	356588	157191	30255

In [ ]:

In [87]:
```
row_sum = np.array(np.sum(observed,axis = 1))
col_sum = np.array(np.sum(observed,axis = 0))
```

In [ ]:

In [88]:
```
pd.crosstab(index = temp_data["season"],
           columns = temp_data["weather"],
               values= temp_data["count"],
           aggfunc=np.sum,
            margins=True         )
```

Out[88]:

weather	Clear	Cloudy	Little Rain	All
season				
Fall	470116	139386	31160	640662
Spring	223009	76406	12919	312334
Summer	426350	134177	27755	588282
Winter	356588	157191	30255	544034
All	1476063	507160	102089	2085312

In [89]:
```
expected = []
for i in row_sum:
    expected.append((i*col_sum)/np.sum(np.sum(observed,axis = 0)))
expected
```

Out[89]:
```
[array([453484.88557396, 155812.72247031,  31364.39195574]),
 array([221081.86259035,  75961.44434981,  15290.69305984]),
 array([416408.3330293 , 143073.60199337,  28800.06497733]),
 array([385087.91880639, 132312.23118651,  26633.8500071 ])]
```

In [90]:
```
expected = pd.DataFrame(expected,columns=observed.columns)
```

In [91]:
```
expected.index = observed.index
```

In [92]:
```
expected
```

Out[92]:

weather	Clear	Cloudy	Little Rain
season			
Fall	453484.885574	155812.722470	31364.391956
Spring	221081.862590	75961.444350	15290.693060
Summer	416408.333029	143073.601993	28800.064977
Winter	385087.918806	132312.231187	26633.850007

In [93]:
```
T_observed = np.sum(np.sum(((observed-expected)**2)/expected))
```

In [94]:
```
T_observed
```

Out[94]: 10838.372332480216

In [95]:
```
df = (len(observed)-1)*(len(observed.columns)-1)
```

In [96]:
```
T_critical = stats.chi2.ppf(0.95,df)
T_critical
```

Out[96]: 12.591587243743977

In [97]:
```
p_value = 1-stats.chi2.cdf(T_observed,df)
p_value
```

Out[97]: 0.0

In [98]:
```
if T_observed > T_critical:
    print("Reject Null Hypothesis : \nWeather and Season are dependent variables")
else:
    print("Failed to Reject Null Hypothesis :\nWeather and Season are independent Variables")
```

```
Reject Null Hypothesis :
Weather and Season are dependent variables
```

From ChiSquare test of independece :

We reject Null hyothesis as independence:

Conclude that weather and seasons are Dependent Features.

In [99]:
```
# using library
```

In [100]:
```
stats.chi2_contingency(observed)
```

Out[100]:
```
(10838.372332480214,
 0.0,
 6,
 array([[453484.88557396, 155812.72247031,  31364.39195574],
        [221081.86259035,  75961.44434981,  15290.69305984],
        [416408.3330293 , 143073.60199337,  28800.06497733],
        [385087.91880639, 132312.23118651,  26633.8500071 ]]))
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [101]:
```
def chi2Test_of_independence(table):
    print(table)
    observed = table.fillna(0)
    row_sum = np.array(np.sum(observed,axis = 1))
    col_sum = np.array(np.sum(observed,axis = 0))
    expected = []
    for i in row_sum:
        expected.append((i*col_sum)/np.sum(np.sum(observed,axis = 0)))
    expected = pd.DataFrame(expected,columns=observed.columns)

    expected.index = observed.index
    print()
    print((expected))
    T_observed = np.sum(np.sum(((observed-expected)**2)/expected))
    df = (len(observed)-1)*(len(observed.columns)-1)
    T_critical = stats.chi2.ppf(0.95,df)
    p_value = 1-stats.chi2.cdf(T_observed,df)
    print("T_statistic : ",np.round(T_observed,3),"\np_value : ",p_value)
    if T_observed > T_critical:
        print("Reject Null Hypothesis")
    else:
        print("Failed to Reject Null Hypothesis")
```

If weather and temperature are dependent :

for dependency : chi square test :

H0: weather and temperature are independent

Ha: weather and temperature are dependent

In [102]:
```
observed_temp_weather = pd.crosstab(index=temp_data["weather"],
           columns= temp_data["temperature"],
                                   values=temp_data["casual"],
                                   aggfunc=np.sum)
```

In [103]:
```
chi2Test_of_independence(observed_temp_weather)
```

```
temperature   high    low  moderate  very low
weather
Clear        52538  56379    177592      3391
Cloudy       11496  23163     51780       807
Little Rain   1726   3249      9869       139

temperature          high           low       moderate     very low
weather
Clear        48616.205381  61207.181565  176870.279678  3206.333375
Cloudy       14631.146791  18420.426916   53229.473683   964.952610
Little Rain   2512.647828   3163.391519    9141.246638   165.714015

T_statistic :  2979.804
p_value :  0.0
Reject Null Hypothesis
```

"Weather and Ttemperature are dependent variables"

In [104]:
```
# using library , varifying implementation with library results.
```

In [105]:
```
stats.chi2_contingency(observed_temp_weather)
```

Out[105]:
```
(2979.8035003021923,
 0.0,
 6,
 array([[4.86162054e+04, 6.12071816e+04, 1.76870280e+05, 3.20633337e+03],
        [1.46311468e+04, 1.84204269e+04, 5.32294737e+04, 9.64952610e+02],
        [2.51264783e+03, 3.16339152e+03, 9.14124664e+03, 1.65714015e+02]]))
```

If Weather and Humidity Level are dependent :

for dependency : chi square test :

H0: weather and Humidity are independent

Ha: weather and Humidity are dependent

In [106]:
```
chi2Test_of_independence(pd.crosstab(index=temp_data["weather"],
           columns= temp_data["gethumidity"],
                                    values=temp_data["casual"],
                                  aggfunc=np.sum
                                   ))
```

```
gethumidity   10%    100%     20%      30%      40%      50%      60%  \
weather
Clear        35.0   635.0  4374.0  26879.0  68726.0  69117.0  53398.0
Cloudy        6.0  2385.0    51.0   3236.0   7090.0  13370.0  15420.0
Little Rain  40.0  1681.0     NaN      NaN    357.0    925.0   1099.0

gethumidity      70%      80%      90%
weather
Clear        38241.0  19202.0   9293.0
Cloudy       20060.0  13803.0  11825.0
Little Rain   2499.0   4355.0   4027.0

gethumidity        10%         100%          20%           30%           40%  \
weather
Clear        59.883100  3475.437675  3271.391557  22263.945028  56314.510531
Cloudy       18.021942  1045.940101   984.532003   6700.379951  16947.967526
Little Rain   3.094959   179.622224   169.076439   1150.675020   2910.521943

gethumidity           50%           60%           70%           80%  \
weather
Clear        61666.285330  51689.465202  44949.289647  27620.155612
Cloudy       18558.595136  15556.050641  13527.580975   8312.342520
Little Rain   3187.119535   2671.484157   2323.129378   1427.501868

gethumidity           90%
weather
Clear        18589.636319
Cloudy        5594.589204
Little Rain    960.774477

T_statistic :  75755.823
p_value :  0.0
Reject Null Hypothesis
```

From the dependency test :

we can conclude that weather and humidity are dependent features.

In [ ]:

In [ ]:

checking if the distribution of number of cycles rented are similar in different weather.

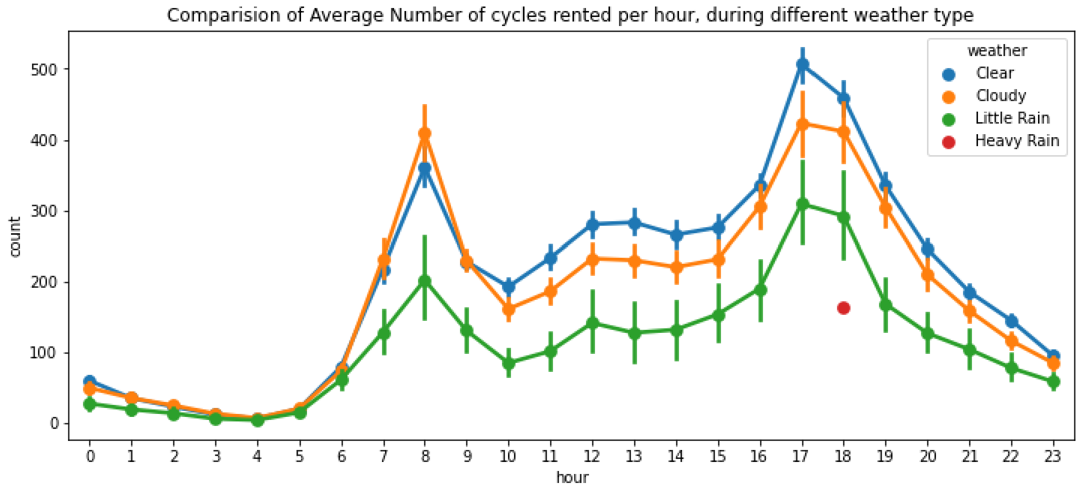
If Average No. of cycles rented is similar or different in different weather

In [ ]:

In [107]:
```
data["weather"].unique()
```

Out[107]: array(['Clear', 'Cloudy', 'Little Rain', 'Heavy Rain'], dtype=object)

In [108]:
```
plt.figure(figsize=(12,5))
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["weather"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, during different weather type")
plt.show()
```



- **we have 4 different weather here, to check if there's significant differnece between 4 weathers , we can perform anova test :**

H0: population mean of number of cycles rented in different seaons are same

Ha: population mean of number of cycles rented in different seaons are different

In [ ]:

In [ ]:

In [109]:
```
Clear = data.loc[data["weather"]=="Clear"]["count"]
Cloudy = data.loc[data["weather"]=="Cloudy"]["count"]
Little_Rain = data.loc[data["weather"]=="Little Rain"]["count"]
Heavy_Rain = data.loc[data["weather"]=="Heavy Rain"]["count"]
```

In [110]:
```
len(Clear),len(Cloudy),len(Little_Rain),len(Heavy_Rain)
```

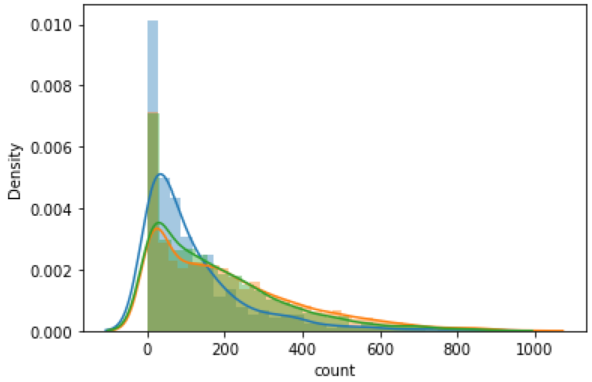
Out[110]:
```
(7192, 2834, 859, 1)
```

- **Heavy rain weather has only 1 record , exlcuding Heavy Rain weather from the test :**

checking the distribution before applying test :

In [111]:
```
sns.distplot((Little_Rain))
sns.distplot((Clear))
sns.distplot((Cloudy))
```

Out[111]:
```
<AxesSubplot:xlabel='count', ylabel='Density'>
```

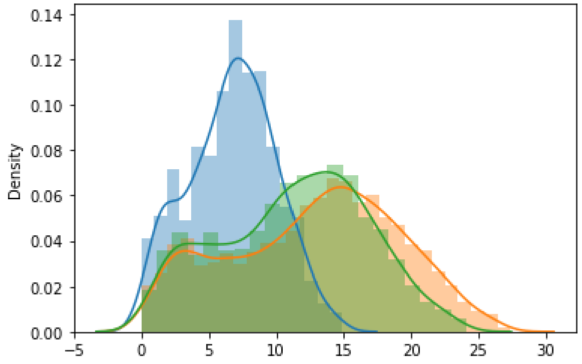


since the data is nomally distributed , assumption for anova test breaks.

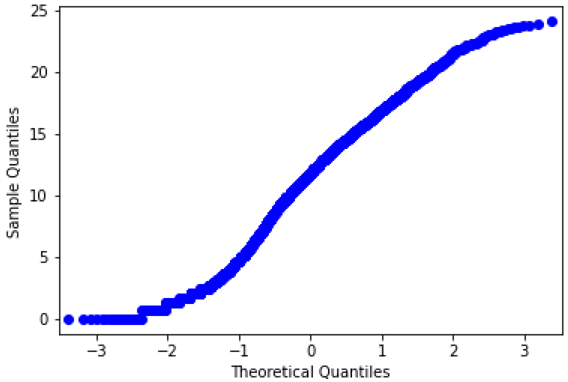
applying Boxcox transformation and checking the distribution .

In [112]:
```
sns.distplot(stats.boxcox(Little_Rain)[0])
sns.distplot(stats.boxcox(Clear)[0])
sns.distplot(stats.boxcox(Cloudy)[0])
```

Out[112]: <AxesSubplot:ylabel='Density'>



In [113]:
```
sm.qqplot((stats.boxcox(Cloudy)[0]))
plt.show()
```



Testing if data is significantly normally distributed

In [114]:
```
stats.anderson(Clear,dist="norm"),stats.anderson(Cloudy,dist="norm"),stats.anderson(Little_Rain,dist="norm")
```

Out[114]:
```
(AndersonResult(statistic=209.40911708071326, critical_values=array([0.576, 0.656, 0.787, 0.917, 1.091]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])),
 AndersonResult(statistic=90.59885984506218, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])),
 AndersonResult(statistic=54.80752275061889, critical_values=array([0.573, 0.653, 0.783, 0.914, 1.087]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])))
```

Since the datasets for tests, are not normally distributed, and having significance varinace between weathers ,

we cannot perform anova test .

we can use non parametric test : Kruskal Wallis test :

In [115]:
```
kr  = data[["weather","count"]]
```

In [116]:
```
kr = kr[kr["weather"].isin(['Clear', 'Cloudy', 'Little Rain'])]
```

In [117]:
```
kr["rank"] = kr["count"].rank()
```

In [118]:
```
rank_sum = kr.groupby("weather")["rank"].sum()
rank_sum = rank_sum.astype("int64")
rank_sum
```

Out[118]:
```
weather
Clear          40752899
Cloudy         14990213
Little Rain     3503943
Name: rank, dtype: int64
```

In [119]:
```
N = len(kr)
N
```

Out[119]:
```
10885
```

In [120]:
```
degree_of_freedom = kr["weather"].nunique()-1
degree_of_freedom
```

Out[120]:
```
2
```

In [121]:
```
H = ((12/(N*(N+1)))*(np.sum(((rank_sum**2)/(kr.groupby("weather")["rank"].count()))))-(3*(N+1))
H
```

Out[121]:
```
204.95101790400076
```

In [122]:
```
p_value = 1-stats.chi2.cdf(205.073,degree_of_freedom)
p_value
```

Out[122]:
```
0.0
```

In [123]:
```
H_critical = stats.chi2.ppf(0.95,2)
H_critical
```

Out[123]:
```
5.991464547107979
```

H statistic from Kruskal Wallis test , is higher than the Critical Value ,

p_value is smaller than significant value 0.05 ,

we reject Null Hypothesis.

Hence we conclude that the Population mean number of cycles rented across different weather are not same.

In [124]:
```
# using library :
```

In [125]:
```
Clear = data.loc[data["weather"]=="Clear"]["count"]
Cloudy = data.loc[data["weather"]=="Cloudy"]["count"]
Little_Rain = data.loc[data["weather"]=="Little Rain"]["count"]
```

In [126]:
```
stats.kruskal(Clear,Cloudy,Little_Rain)
```

Out[126]:
```
KruskalResult(statistic=204.95566833068537, pvalue=3.122066178659941e-45)
```

In [ ]:

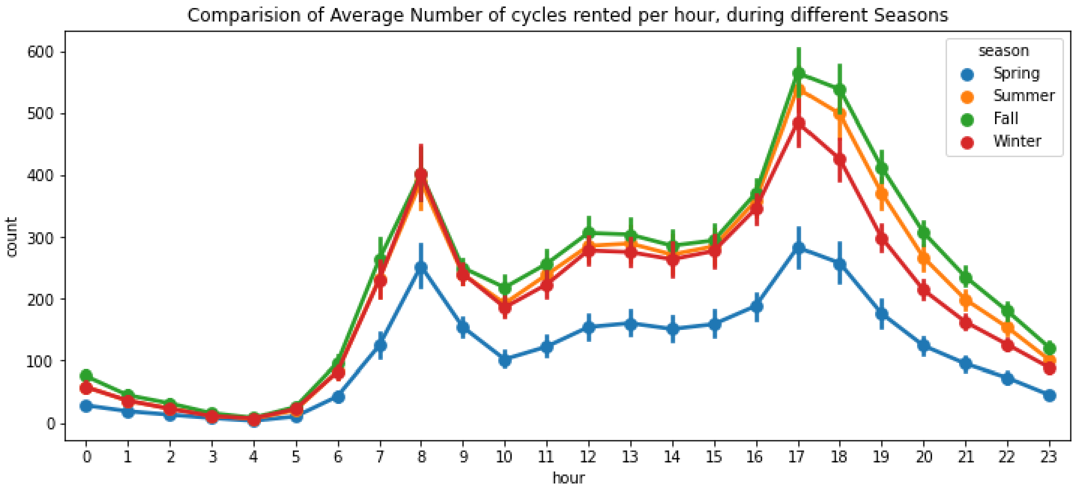
In [ ]:

In [ ]:

In [ ]:

If No. of cycles rented is similar or different in different seasons

In [127]:
```
plt.figure(figsize=(12,5))
sns.pointplot(x = data["hour"],
              y= data["count"],
              hue=data["season"],
              ci=95)
plt.title("Comparision of Average Number of cycles rented per hour, during different Seasons")
plt.show()
```



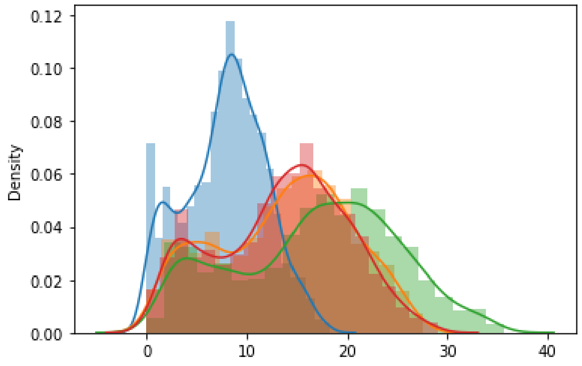
In [128]:
```
Spring = data.loc[data["season"]=="Spring"]["count"]
Summer = data.loc[data["season"]=="Summer"]["count"]
Fall = data.loc[data["season"]=="Fall"]["count"]
Winter = data.loc[data["season"]=="Winter"]["count"]
```

In [129]:
```
len(Spring),len(Summer),len(Fall),len(Winter)
```

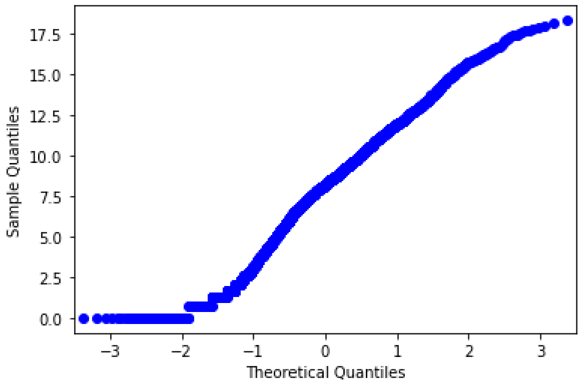
Out[129]: (2686, 2733, 2733, 2734)

In [130]:
```
sns.distplot(stats.boxcox(Spring)[0])
sns.distplot(stats.boxcox(Summer)[0])
sns.distplot(stats.boxcox(Fall)[0])
sns.distplot(stats.boxcox(Winter)[0])
```

Out[130]: <AxesSubplot:ylabel='Density'>



In [131]:
```
sm.qqplot((stats.boxcox(Spring)[0]))
plt.show()
```



Testing if data is significantly normally distributed

In [132]:
```
stats.anderson(Spring,dist="norm"),stats.anderson(Summer,dist="norm"),stats.anderson(Fall,dist="norm"),stats.anderson(Winter,dist="norm")
```

Out[132]:
```
(AndersonResult(statistic=134.99126589743582, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])),
 AndersonResult(statistic=73.98826756049903, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])),
 AndersonResult(statistic=54.3859876350034, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])),
 AndersonResult(statistic=70.89794313022367, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_level=array([15. , 10. ,  5. ,  2.5,  1. ])))
```

Since the datasets for tests, are not normally distributed, and having significance varinace between all seaons ,

we cannot perform anova test .

we can use non parametric test : Kruskal Wallis test :

In [ ]:

In [133]:
```
kr  = data[["season","count"]]
kr["rank"] = kr["count"].rank()
rank_sum = kr.groupby("season")["rank"].sum()
rank_sum = rank_sum.astype("int64")
N = len(kr)
degree_of_freedom = kr["season"].nunique()-1
H = ((12/(N*(N+1)))*(np.sum(((rank_sum**2)/(kr.groupby("season")["rank"].count())))))-(3*(N+1))
H
```

Out[133]: 699.6499424783542

In [134]:
```
p_value = 1-stats.chi2.cdf(205.073,degree_of_freedom)
p_value
```

Out[134]: 0.0

In [135]:
```
H_critical = stats.chi2.ppf(0.95,degree_of_freedom)
H_critical
```

Out[135]: 7.814727903251179

In [136]:
```
H > H_critical
```

Out[136]: True

H statistic from Kruskal Wallis test , is higher than the Critical Value , p_value is smaller than significant value 0.05 ,

we reject Null Hypothesis.

Hence we conclude that the Population mean number of cycles rented across different Seasons are not same.

In [137]:
```
Spring = data.loc[data["season"]=="Spring"]["count"]
Summer = data.loc[data["season"]=="Summer"]["count"]
Fall = data.loc[data["season"]=="Fall"]["count"]
Winter = data.loc[data["season"]=="Winter"]["count"]

stats.kruskal(Spring,Summer,Fall,Winter)
```

Out[137]: KruskalResult(statistic=699.6668548181988, pvalue=2.479008372608633e-151)

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Inferences and Recommendations :

- There is a positive Correlation between Temperature and Number of cycles rented.
- Demand increases with the rise in the temperature from modate to not very high.
- As per shows in the chats in the file , till certain level of humidity level , demand increases , when humidity is too low or very high , there are very few observations.
- Humidity level , 40% to 70% highest records have been observed.

- As per hourly average number of cycles rented by registered and casual customer plots ,
- Registered Customers seems to be using rental cycles mostly for work commute purposes.

- registered customers are much higher than the casual customers. 81% customers are Registered and 19% only are casual riders. Which is good thing for a consistent business. Though it is recommended to introduce more go-to offers and strategical execution to attract more casual riders, that further increase chances of converting to consistent users.
- Confidence interval of average number of cycles rented by registered customers is (153,157) and casual customers is (35,37).

- Demand for cycles increases during the rush hours specifically during working days , from morning 7 to 9 am and in evening 4 to 8pm.
- on off days demands are higher from 10 am to evening 7pm.
- Though it is concluded from statistical tests, that demand on weekdays and off-days are similar. We can say demand is equal with 95% confidene.

- During spring season , customers prefer less likely to rent cycle. demand increases in summer and fall season.
- From May to October, demand is increasing .

- During clear and cloudy weather demand is higher than in rainy weather.

- in 2012 , there's 180% hike in demand , from 2011.
- in registered customers , its been 176% hike , where casual customers in 2013 were average 13 to in 2012 are 20.

- **statistical test results shows,**
- average number of cycles rented during working days and off days are significantly similar.
- weather and seasons are dependent.
- Weather and temperature , Weather and humidity level are also dependent .
- There's significance difference in demand during different weather and seasons .

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: