Yulu - Case Study

Problem Statement

- 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
- Additional Views
  - From inferential statistics, Check the interdependence of features.
  - Predict variables based on climatic conditions of Indian Market

Installing Packages

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
import scipy.stats as stats
```

Loading Dataset

In [2]:

```
yulu = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/4

yulu.head()
```

Out[2]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casu
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	

In [3]:

```
yulu.dtypes
```

Out[3]:

```
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
```

- **All the features of dataset are continuous except datetime**

In [4]:

```
yulu.shape
```

Out[4]:

```
(10886, 12)
```

- **There are 10886 datapoints and 12 features**

Checking Null Values

In [5]:

```
yulu.isnull().sum()
```

Out[5]:

```
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
```

- **None of the columns contain any null values in the dataset**

Checking Duplicate Values

In [6]:

```
np.any(yulu.duplicated())
```

Out[6]:

```
False
```

- **There is no duplicates values found in our dataset**

In [7]:

```
cat_col = ["season", "holiday", "workingday", "weather"]

for i in cat_col:
    yulu[i] = yulu[i].astype("category")

yulu["datetime"] = pd.to_datetime(yulu["datetime"])
```

In [8]:

```
yulu.dtypes
```

Out[8]:

```
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
```

Statistical Summary

In [9]:

```
yulu.describe().T
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
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

- **Casual, Registered and Count features might contain outliers.**
- **As it can be oberseved from the summary there is significant difference between the mean and median of the above mentioned feature.**

In [10]:

```
yulu.describe(include = ["category"]).T
```

Out[10]:

	count	unique	top	freq
season	10886	4	4	2734
holiday	10886	2	0	10575
workingday	10886	2	1	7412
weather	10886	4	1	7192

- **Winter season is the top season as most of the customers take ride in that season particularily.**
- **Most of customer prefer to take ride in Clear, Few clouds and partly cloudy weather.**

Lets check the period of data available

In [11]:

```
yulu["datetime"].min()
```

Out[11]:

```
Timestamp('2011-01-01 00:00:00')
```

In [12]:

```
yulu["datetime"].max()
```

Out[12]:

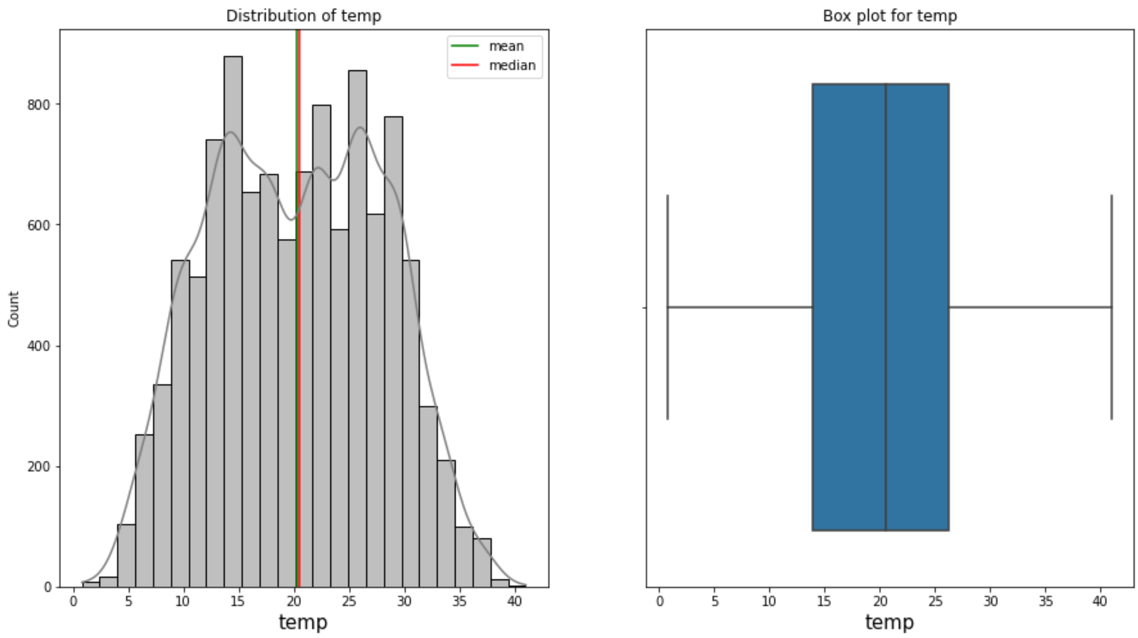
```
Timestamp('2012-12-19 23:00:00')
```

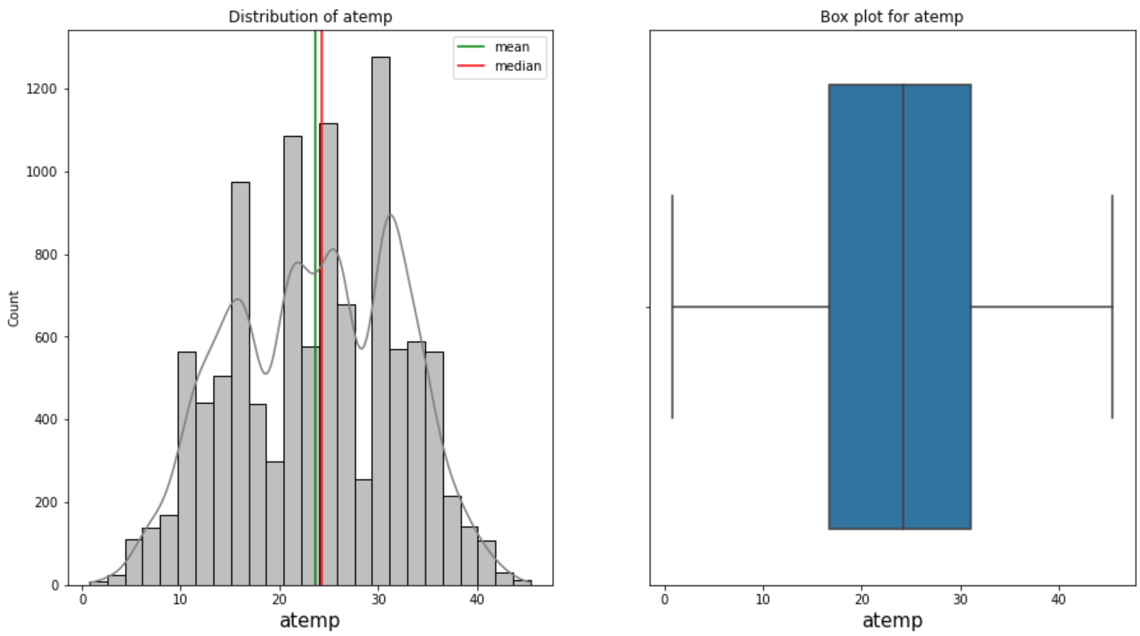
- **Data is available from 1st Jan 2011 till 19th Dec 2012**

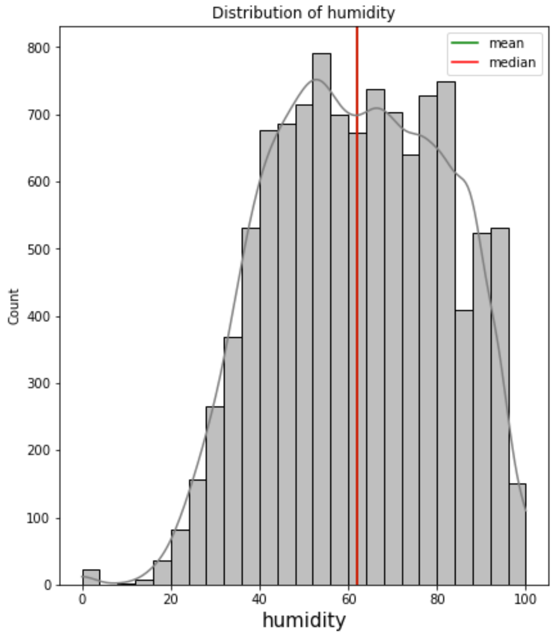
Univariate Analysis

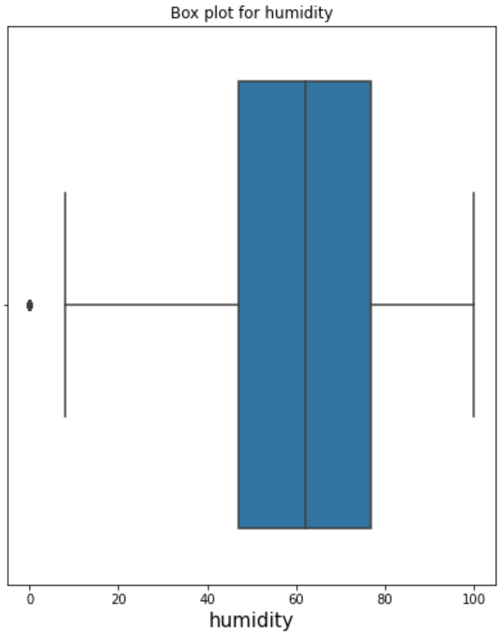
In [13]:

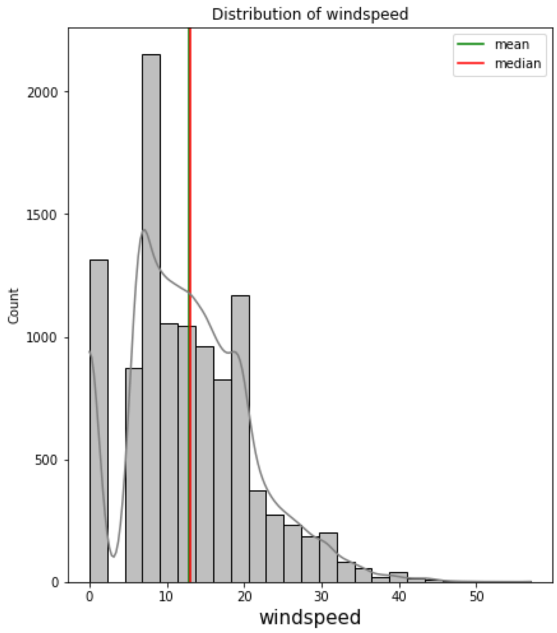
```
num_cat = ["temp", "atemp", "humidity", "windspeed", "casual", "registered", "count"]

for i in range(len(num_cat)):
    fig = plt.figure(figsize = (15, 8))

    ax1 = plt.subplot2grid((1, 2), (0, 0))
    ax1.set_title(f"Distribution of {num_cat[i]}")
    ax1.set_xlabel(ax1.get_xlabel(), fontsize = 15)
    ax1.axvline(yulu[num_cat[i]].mean(),color="green", label = "mean")
    ax1.axvline(yulu[num_cat[i]].median(),color="red", label = "median")
    ax1.legend(loc = "best")
    sns.histplot(data=yulu, x=num_cat[i], ax=ax1, bins=25, kde=True, color="gray")

    ax2 = plt.subplot2grid((1, 2), (0, 1))
    ax2.set_title(f"Box plot for {num_cat[i]}")
    ax2.set_xlabel(ax1.get_xlabel(), fontsize = 15)
    sns.boxplot(data = yulu, x=num_cat[i], ax=ax2)

plt.show()
```

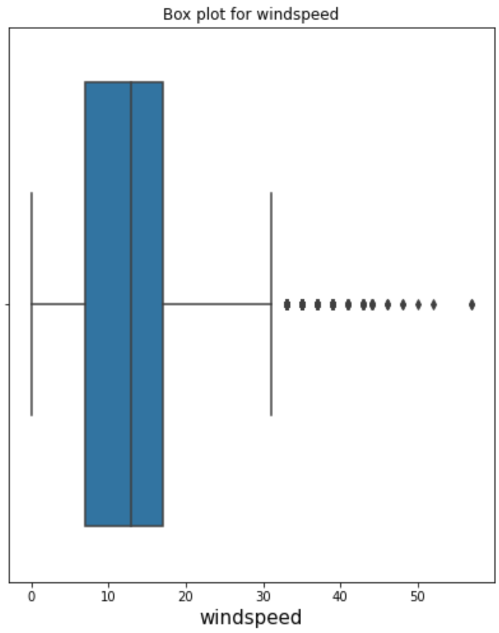


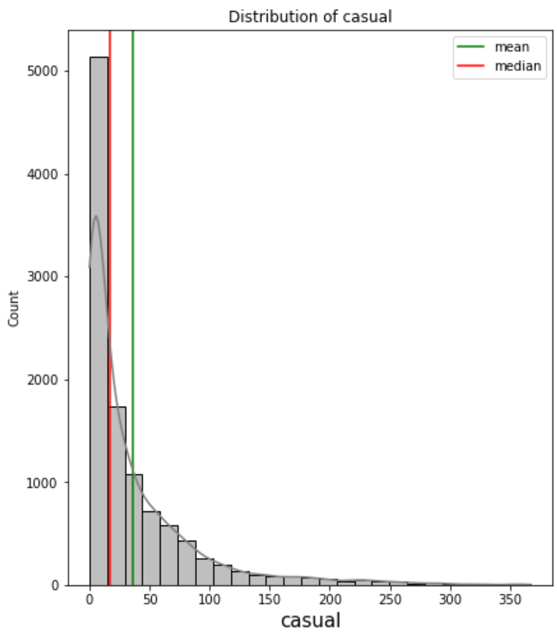


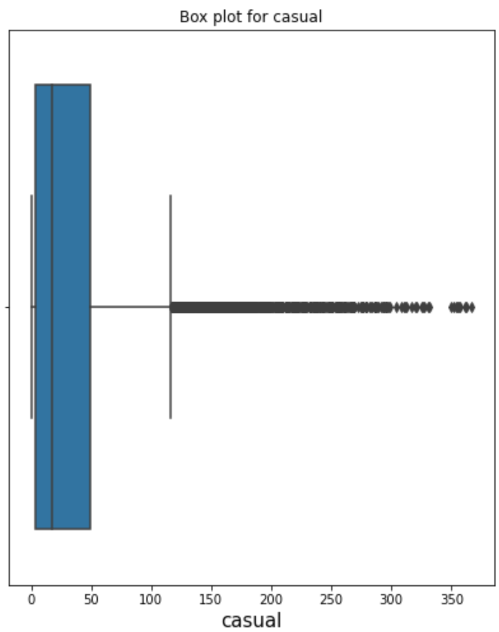

Distribution of humidity
mean
median
Count
humidity

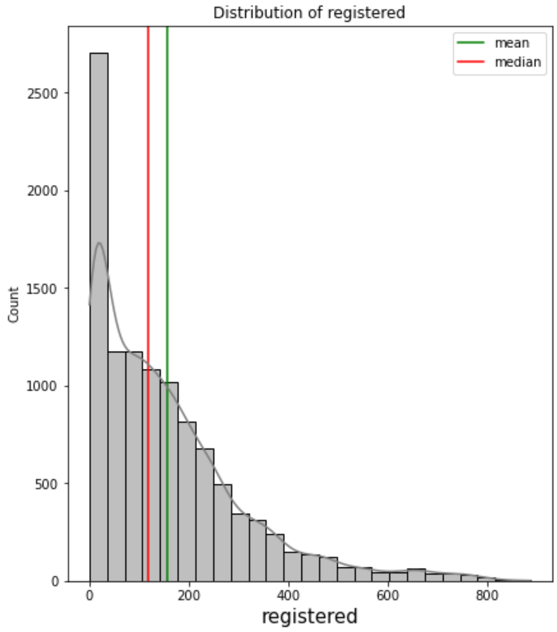

Box plot for humidity
humidity

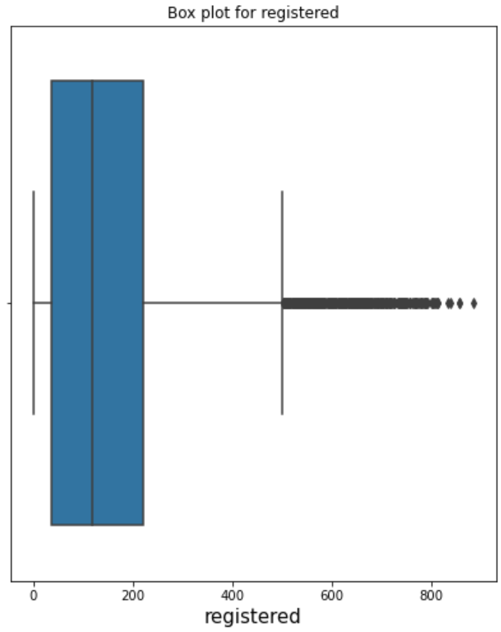

Distribution of windspeed
mean
median
Count
windspeed

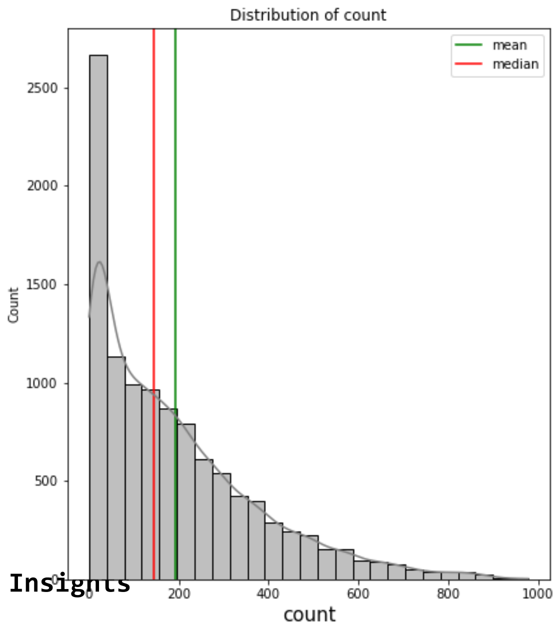

Box plot for windspeed
windspeed

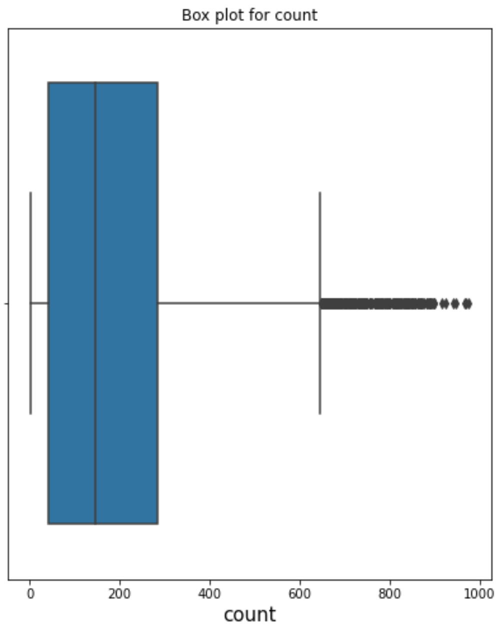

Distribution of casual
mean
median
Count
casual


Box plot for casual
casual







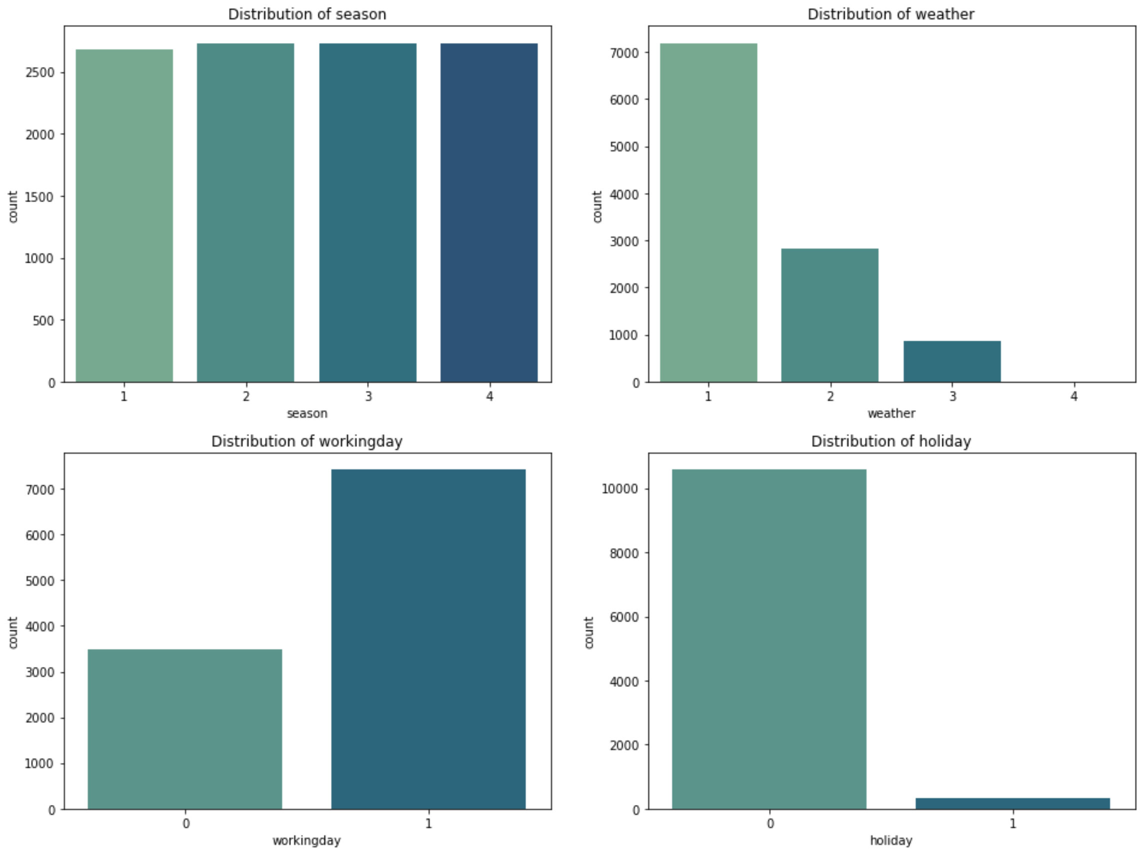


Insights

- **`casual`** , **`registered`** and **`count`** somewhat looks like **`Log Normal Distrinution`**
- **`temp`** , **`atemp`** and **`humidity`** looks like they follows the **`Normal Distribution`**
- **`windspeed`** follows the **`binomial distribution`**
- **`temp`** , **`atemp`** , **`windspeed`** & **`humidity`** don't contain any outliers as there is negligible difference in mean and median.
- Rest of the continous features contain outliers.

In [14]:

```
# countplot of each categorical column
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
cat_col = ["season", "weather", "workingday", "holiday"]

index = 0
for row in range(2):
    for col in range(2):
        axis[row, col].set_title(f"Distribution of {cat_col[index]}")
        sns.countplot(data=yulu, x=cat_col[index], ax=axis[row, col], palette="crest")
        index += 1

plt.show()
```



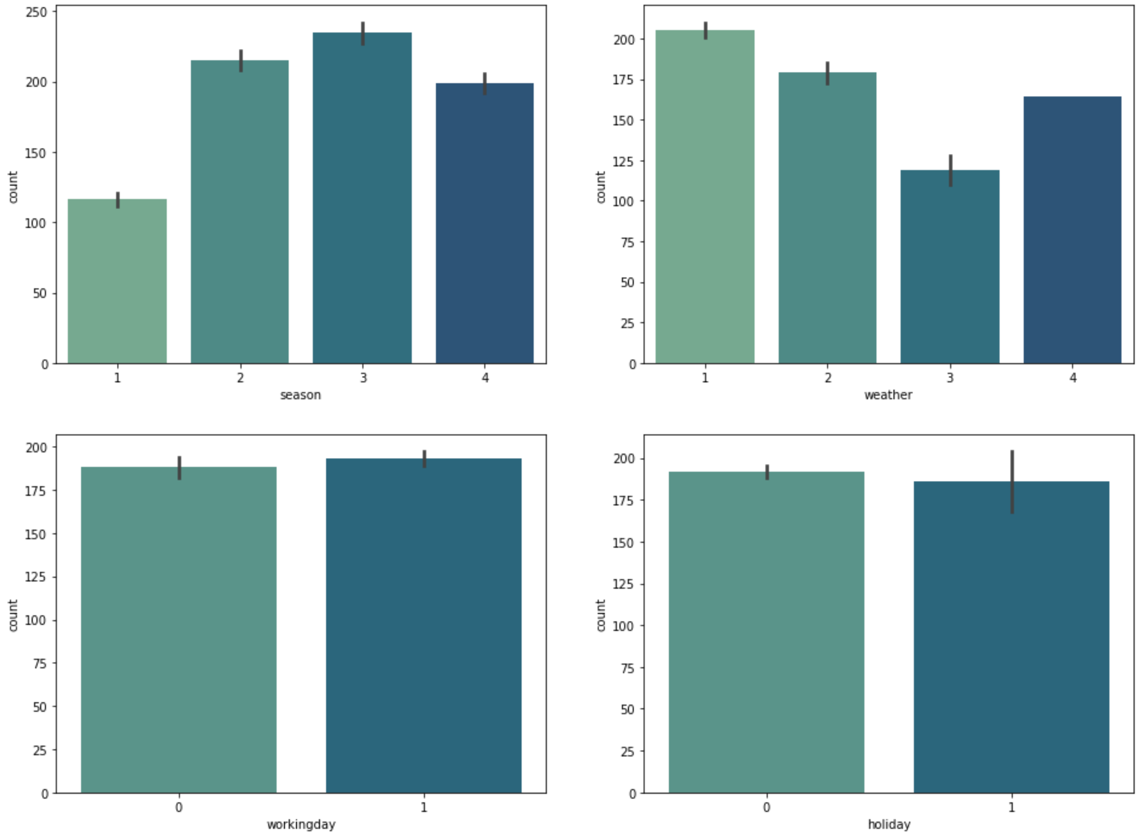
Insights

- Users book ride in all season equi-probabaly
- There is high demand of electric cycle in Clear, Few clouds, partly cloudy weather.
- There are around 3600 days which falls either on weekend or holiday.
- There is 3% days on which it was holiday.

Bivariate Analysis

In [15]:

```
# plotting categorical variables againt count using barplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(2):
        sns.barplot(data=yulu, x=cat_col[index], y='count', palette= "crest", ax=axis[ro
        index += 1

plt.show()
```

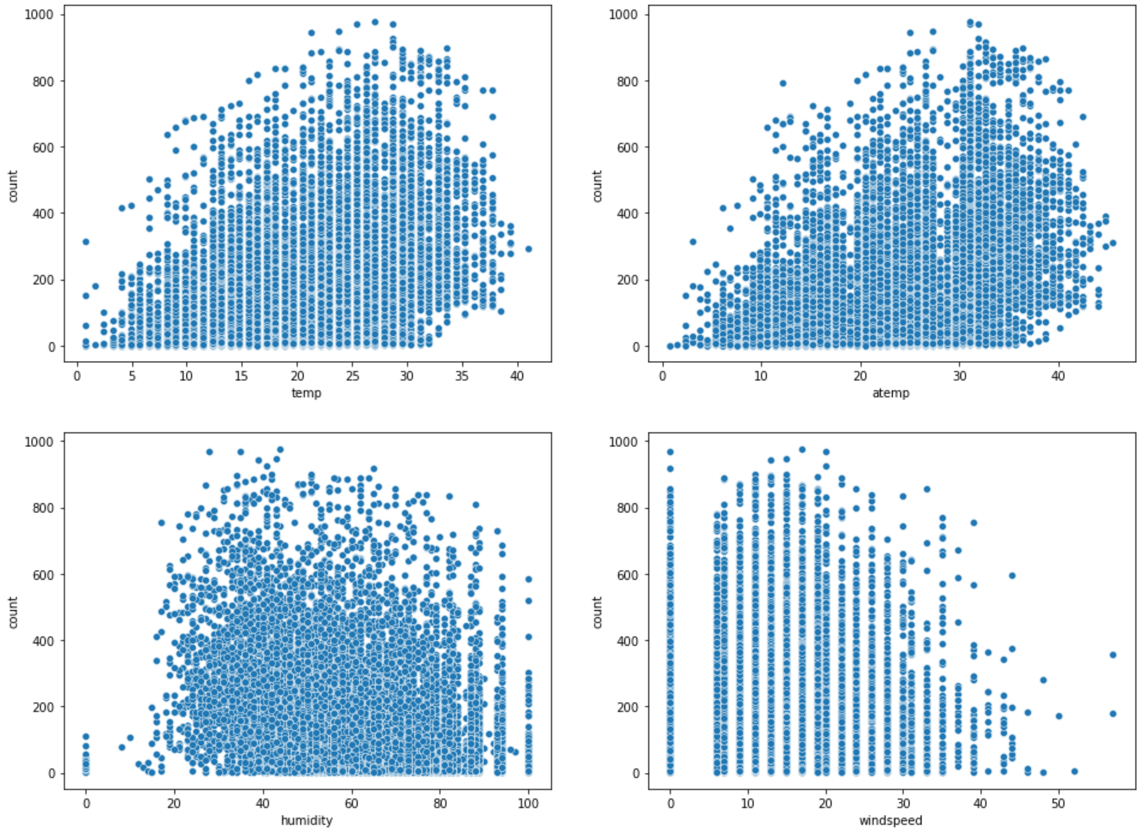


Insights

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

In [16]:

```
# plotting numerical variables againt count using scatterplot
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(2):
        sns.scatterplot(data=yulu, x=num_cat[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```



Insights

- 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.

Correlation Analysis

In [17]:

```
fig = plt.figure(figsize=(15,8))

sns.heatmap(yulu.corr(), cmap="Blues", annot = True, square=True)
plt.show()
```

Insights

- registered vs count, casual - count, temp - atemp, casual - registered. These features are highly correlated.

2. Hypothesis Testing

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

Step1 : Setting up Null and Alternate Hypothesis

- `Null Hypothesis (Ho)` : Working day has no effect on electric cycles being rented
- `Alternate Hypothesis (Ha)` : Working day has effect on electric cyles being rented

Step2: Selecting appropriate test

- Here we have two independent samples, we will use ttest_ind as it will be our two-tailed test.

Step3: Choosing Significance level

- `Significance level (alpha)` : 0.05

Step 4: Collect and Prepare Data

In [20]:

```
working_zero = yulu.loc[yulu["workingday"] == 0]["count"].values
working_one = yulu.loc[yulu["workingday"] == 1]["count"].values
```

- Lets check the variance of two dataset

In [21]:

```
np.var(working_zero)
```

Out[21]:

```
30171.346098942427
```

In [22]:

```
np.var(working_one)
```

Out[22]:

```
34040.69710674686
```

- The ratio of larger group to smaller group is less than 4:1. So we consider it as equi-variance

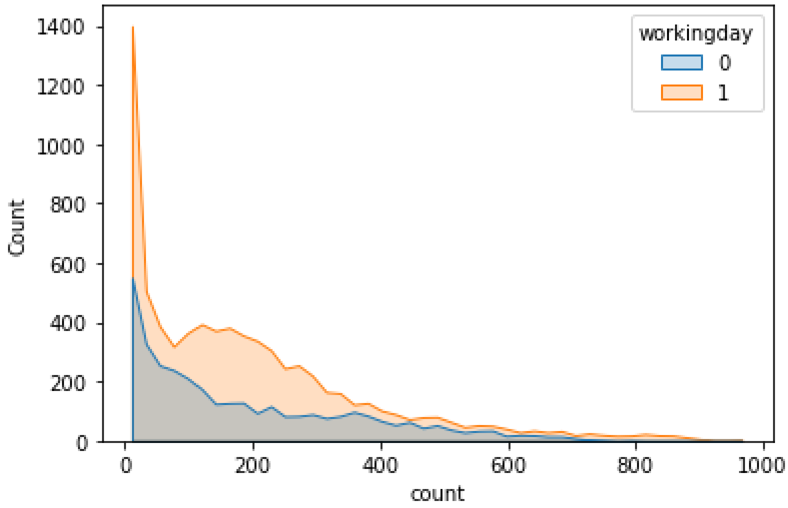
Lets verify this using histogram

In [31]:

```
sns.histplot(data = yulu, x = "count", hue = "workingday", element="poly")
```

Out[31]:

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



In [26]:

```
test_statistics, pvalue = stats.ttest_ind(a=working_one, b=working_zero, equal_var=True,
```

In [28]:

```
print(f"Test Statistics: {test_statistics} \npvalue: {pvalue}")
```

```
Test Statistics: 1.2096277376026694
pvalue: 0.22644804226361348
```

Step5: Taking Decision

In [29]:

```
if pvalue < 0.05:
    print("Reject Null Hypothesis (Ho)")
else:
    print("Fail to reject null hypothesis")
```

```
Fail to reject null hypothesis
```

Step6: Inference

- **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.**

2.2 `ANNOVA` to check if No. of cycles rented is similar or different in different
1. `weather`
2. `season`

Step1 : Setting up Null and Alternate Hypothesis

- **`Null Hypothesis (Ho)`** : Number of cycles rented is similar in different weather and season.
- **`Alternate Hypothesis (Ha)`** : Number of cycles rented is not similar in different weather and season.

Step2: Selecting Test

- **`Here we will using ANNOVA to test the hypothesis defined above`**

Step3: Choosing Significance level

- **`Significance Level (alpha):`** 0.05

Step4: Conduct and prepare test

In [37]:

```
# defining the data groups for the ANOVA

w1 = yulu[yulu['weather']==1]['count'].values
w2 = yulu[yulu['weather']==2]['count'].values
w3 = yulu[yulu['weather']==3]['count'].values
w4 = yulu[yulu['weather']==4]['count'].values

s5 = yulu[yulu['season']==1]['count'].values
s6 = yulu[yulu['season']==2]['count'].values
s7 = yulu[yulu['season']==3]['count'].values
s8 = yulu[yulu['season']==4]['count'].values

# conduct the one-way anova
t_stat, pvalue = stats.f_oneway(w1, w2, w3, w4, s5, s6, s7, s8)
```

In [39]:

```
print(f"Test Statistics: {t_stat}\npvalue: {pvalue}")
```

```
Test Statistics: 127.96661249562491
pvalue: 2.8074771742434642e-185
```

Step5: Taking Decision

In [40]:

```
if pvalue < 0.05:
    print("Reject null hypothesis (Ho)")
else:
    print("Fail to reject null hypothesis (Ha)")
```

```
Reject null hypothesis (Ho)
```

Step6: Inference

- **`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`**

2.3 Chi-square test to check if Weather is dependent on the season

Step1 : Setting up Null and Alternate Hypothesis

- **`Null Hypothesis (Ho)`** : Weather is independent of the season.
- **`Alternate Hypothesis (Ha)`** : Weather is not independent of the season.

Step2: Selecting Test

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

Step3: Choosing Significance level

- **`Significance Level (alpha):`** 0.05

Step4: Conduct and prepare test

In [44]:

```
# Lets create contigency table
season_weather = pd.crosstab(yulu["season"], yulu["weather"])
season_weather
```

Out[44]:

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

In [50]:

```
# Lets calculate expected value
chi_stat, p_value, dof, expected = stats.chi2_contingency(season_weather)

print("1. Chi_Stat : ", chi_stat)
print("2. p_value : ", p_value)
print("3. Degree of Freedom : ", dof)
print("4. Expected : ", expected)
```

```
1. Chi_Stat :  49.158655596893624
2. p_value :  1.549925073686492e-07
3. Degree of Freedom :  9
4. Expected :  [[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]]
```

Step5: Taking Decision

In [56]:

```
critical_val = stats.chi2.ppf(q=1-.05, df=dof)
print(f"critical value: {critical_val}")

if p_val <= .05:
    print("\nSince p-value is less than the alpha 0.05, We reject the Null Hypothesis. M
    Weather is dependent on the season.")
else:
    print("Since p-value is greater than the alpha 0.05, We do not reject the Null Hypot
```

```
critical value: 16.918977604620448

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

Step6: Inference

- **`Weather is dependent on the season`**

Inferences Related to All Hypothesis Testing Conducted

- We don't have the sufficient evidence to say that working day has effect on the number of cycles being rented.
- Number of cycles rented is not similar in different weather and season conditions
- Weather is dependent on the season.

Insights Based on EDA

- 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.

In [ ]:

```

```