In [1]:

```
! pip install matplotlib --upgrade
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) http
s://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pkg.de
v/colab-wheels/public/simple/)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-p
ackages (3.5.3)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/d
ist-packages (from matplotlib) (21.3)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-
packages (from matplotlib) (1.21.6)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.7/
dist-packages (from matplotlib) (3.0.9)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.
7/dist-packages (from matplotlib) (4.38.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/dis
t-packages (from matplotlib) (7.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python
3.7/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.
7/dist-packages (from matplotlib) (1.4.4)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist
-packages (from matplotlib) (0.11.0)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.
7/dist-packages (from kiwisolver>=1.0.1->matplotlib) (4.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-pac
kages (from python-dateutil>=2.7->matplotlib) (1.15.0)
```

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.

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

Dataset:

Dataset Link:
https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089 (https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089)

Column Profiling:

- datetime: datetime
- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- holiday: whether day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule (http://dchr.dc.gov/page/holiday-schedule))
- workingday: if day is neither weekend nor holiday is 1, otherwise is 0. weather:

  1: Clear, Few clouds, partly cloudy, partly cloudy

  2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist

  3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds

  4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp: temperature in Celsius
- atemp: feeling temperature in Celsius
- humidity: humidity
- windspeed: wind speed
- casual: count of casual users
- registered: count of registered users
- count: count of total rental bikes including both casual and registered

In [2]:

```
# Function for removing outliers after detection

def remove_outlier(df_in, col_name):
    q1 = df_in[col_name].quantile(0.25)
    q3 = df_in[col_name].quantile(0.75)
    iqr = q3-q1
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr
    df_out = df_in.loc[(df_in[col_name] > fence_low) & (df_in[col_name] < fence_high)]
    outlier_fraction = (len(df_in)-len(df_out))/len(df_in)
    if outlier_fraction > 0.0:
        fig, axes = plt.subplots(1, 1, sharex=True, figsize=(18,6))
        sns.boxplot(data=df_in, y=col_name)
        if outlier_fraction <= 0.10:
            fig.suptitle(f"Outliers constitute {round(outlier_fraction*100, 2)}% of dat
            plt.show()
            return df_out
        else:
            fig.suptitle(f"Outliers constitute significant amount of data ({round(outl
            plt.show()
            return df_in
    else:
        return df_in
```

1 Getting brief of data

1.1 Importing Libraries and fetching data into Dataframe

In [3]:

```
import warnings
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import io
warnings.filterwarnings('ignore')
```

In [4]:

```
csv_path = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/orig
df = pd.read_csv(csv_path, delimiter=",")
```

1.2 Inspecting First Few Rows of the DataFrame

In [5]:

```python
df.head(10)
```

Out[5]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casua
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0
5	2011-01-01 05:00:00	1	0	0	2	9.84	12.880	75	6.0032	0
6	2011-01-01 06:00:00	1	0	0	1	9.02	13.635	80	0.0000	2
7	2011-01-01 07:00:00	1	0	0	1	8.20	12.880	86	0.0000	1
8	2011-01-01 08:00:00	1	0	0	1	9.84	14.395	75	0.0000	1
9	2011-01-01 09:00:00	1	0	0	1	13.12	17.425	76	0.0000	8

In [6]:

```python
# Number of rows amd columns in dataset
print(f"# Number of Rows: {df.shape[0]} \n# Number of Columns: {df.shape[1]}")
```

```
# Number of Rows: 10886
# Number of Columns: 12
```

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

1.3 Data type and Non-NULL values

Let's look at the datatype and the number of non-null values in the Yulu dataframe

In [7]:

```
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
```

1.4 Type conversion

Datatype of following attributes needs to changed to proper data type

- **datetime** - to datetime
- **season** - to categorical
- **holiday** - to categorical
- **workingday** - to categorical
- **weather** - to categorical

In [8]:

```

df['datetime'] = pd.to_datetime(df['datetime'])

cat_cols= ['season', 'holiday', 'workingday', 'weather']
for col in cat_cols:
    df[col] = df[col].astype('object')
```

In [9]:

```
df.iloc[:, 1:].describe(include='all')
```

Out[9]:

	season	holiday	workingday	weather	temp	atemp	humidity	wi
count	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	1088
unique	4.0	2.0	2.0	4.0	NaN	NaN	NaN	
top	4.0	0.0	1.0	1.0	NaN	NaN	NaN	
freq	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	
mean	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	1
std	NaN	NaN	NaN	NaN	7.79159	8.474601	19.245033	
min	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	
25%	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	
50%	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	1
75%	NaN	NaN	NaN	NaN	26.24000	31.060000	77.000000	1
max	NaN	NaN	NaN	NaN	41.00000	45.455000	100.000000	5

1.5 Detecting missing values in the dataset

In [10]:

```

df.isnull().sum()
```

Out[10]:

```
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
```

- There are no missing values in the dataset.
- **casual** and **registered** attributes might have outliers because their mean and median are very far away to one another and the value of standard deviation is also high which tells us that there is high variance in the data of these attributes.

1.6 Data Mapping of Categorical Variables

- **season** - to categorical
- **holiday** - to categorical
- **workingday** - to categorical
- **weather** - to categorical

Also seggregating datetime values into day, date, hour, month, month name and year

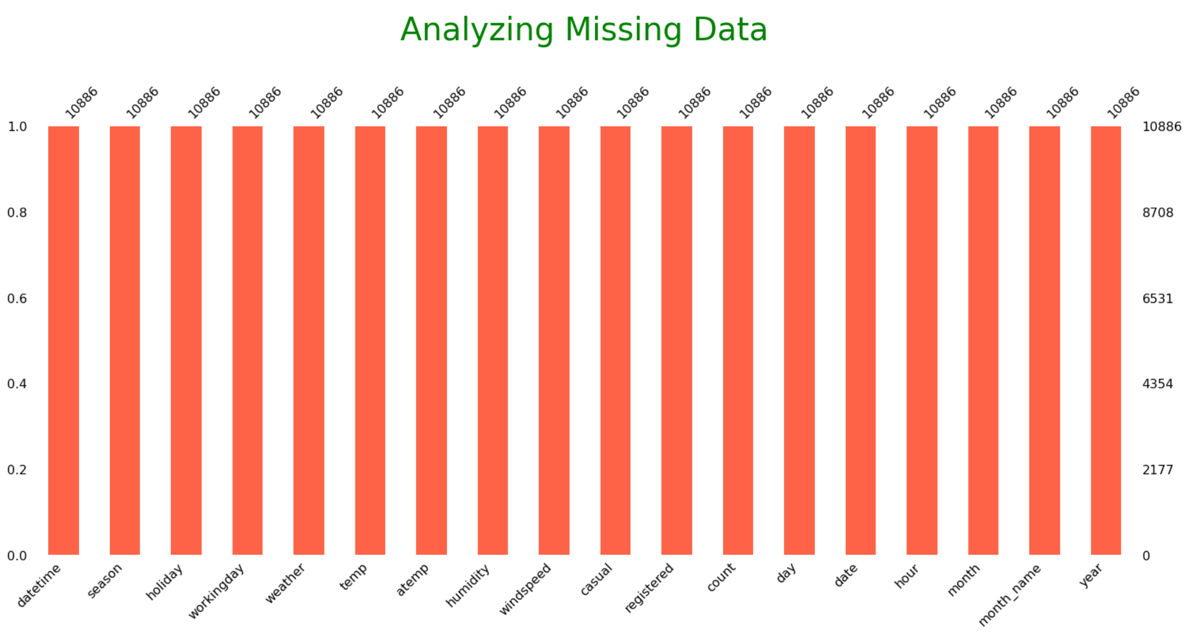
In [11]:

```
season_mapping = {1:'spring', 2:'summer', 3:'fall', 4:'winter'}
df["season"] = df["season"].map(lambda x: season_mapping[x])

holiday_mapping = {0:'no', 1:'yes'}
df["holiday"] = df["holiday"].map(lambda x: holiday_mapping[x])

working_day_mapping = {0:'no', 1:'yes'}
df["workingday"] = df["workingday"].map(lambda x: working_day_mapping[x])

weather_mapping = {1:'clear', 2:'partly_clear', 3:'rain', 4:'intense'}
df["weather"] = df["weather"].map(lambda x: weather_mapping[x])

df["day"]=df["datetime"].dt.day_name()
df["date"] = df["datetime"].dt.date
df["hour"] = df["datetime"].dt.hour
df["month"] = df["datetime"].dt.month
df["month_name"] = df["datetime"].dt.month_name()
df["year"] = df["datetime"].dt.year
```

1.7 Missing Number

In [12]:

```
msno.bar(df, color='tomato')
plt.title("\nAnalyzing Missing Data\n", fontsize=40, color="green")
plt.show()
```



2 Data Preprocessing

2.1 Summary Statistics of Dataset

2.1.1 Statistical summary about datetime data

In [13]:

```
df.describe(include = ['object','datetime64[ns]'])
```

Out[13]:

	datetime	season	holiday	workingday	weather	day	date	month_name
count	10886	10886	10886	10886	10886	10886	10886	10886
unique	10886	4	2	2	4	7	456	12
top	2011-01-01 00:00:00	winter	no	yes	clear	Saturday	2011-01-01	May
freq	1	2734	10575	7412	7192	1584	24	912
first	2011-01-01 00:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
last	2012-12-19 23:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN

2.1.2 Statistical summary about Numerical data

In [14]:

```
df.describe(include = ['int64','float64'])
```

Out[14]:

	temp	atemp	humidity	windspeed	casual	registered	
count	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	108
mean	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	1
std	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	1
min	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	
25%	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	
50%	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	1
75%	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	2
max	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	9

2.2 Minimum and maximum datetime

In [15]:

```

df['datetime'].min(), df['datetime'].max()
```

Out[15]:

```
(Timestamp('2011-01-01 00:00:00'), Timestamp('2012-12-19 23:00:00'))
```

The dataset has values between 1st Jan 2011 to 19th Dec 2012

2.3 Unique Values in each column

Before we move ahead, let's identify the number of unique values in each column

In [16]:

```
df.nunique()
```

Out[16]:

```
datetime      10886
season            4
holiday           2
workingday        2
weather           4
temp             49
atemp            60
humidity         89
windspeed        28
casual          309
registered      731
count           822
day               7
date            456
hour             24
month            12
month_name       12
year              2
dtype: int64
```

In [17]:

```
# number of unique values in each categorical columns
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

Out[17]:

		value
variable	**value**	
holiday	**no**	10575
	yes	311
season	**fall**	2733
	spring	2686
	summer	2733
	winter	2734
weather	**clear**	7192
	intense	1
	partly_clear	2834
	rain	859
workingday	**no**	3474
	yes	7412

2.4 Categorising Temperature And Humidity Levels and Windspeed column data :

In [18]:

```python
pd.DataFrame(df["atemp"].describe()).T
```

Out[18]:

	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 [19]:

```python
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 [20]:

```python
df["temperature"]=pd.Series(map(get_temp,df["atemp"]))
```

In [21]:

```python
pd.DataFrame(df["humidity"].describe()).T
```

Out[21]:

	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 [22]:

```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 [23]:

```python
df["gethumidity"]  = pd.Series(map(get_humidity,df["humidity"]))
```

In [24]:

```python
pd.DataFrame(df["windspeed"].describe()).T
```

Out[24]:

	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 [25]:

```python
df["windspeed_category"] = pd.qcut(df["windspeed"],8)
```

In [26]:

```python
df["windspeed_category"] = df["windspeed_category"].astype("object")
```

2.1.3 Statistical summary about categorical data

In [27]:

```python
df.describe(include=["object","category"])
```

Out[27]:

	season	holiday	workingday	weather	day	date	month_name	temperature	get
count	10886	10886	10886	10886	10886	10886	10886	10886	
unique	4	2	2	4	7	456	12	4	
top	winter	no	yes	clear	Saturday	2011-01-01	May	moderate	
freq	2734	10575	7412	7192	1584	24	912	4767	

Insights

- **Moderate level Temperature frequency is highest in given data**
- **70% humidty**
- **and most preferable windspeed 8-12**

2.5 Checking Duplicate Rows

Before we move ahead, let's identify if there are any duplicate rows

In [28]:

```
df.duplicated().any()
```

Out[28]:

```
False
```

So, there are no duplicate rows in the dataset

2.6 Correlation Matrix

In [29]:

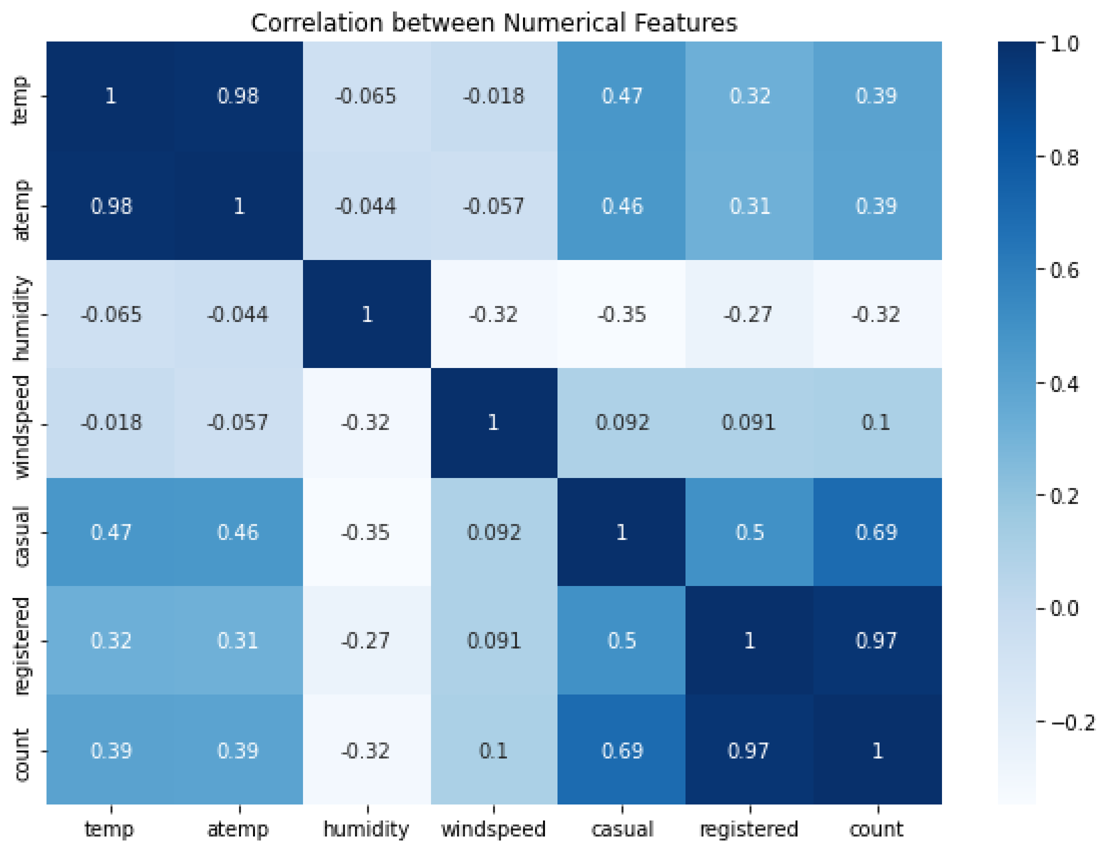
```
df[['temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']].corr()
```

Out[29]:

	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

In [30]:

```
### Heatmap (correlation between features)
plt.figure(figsize=(10,7))
sns.heatmap(df[['temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']].corr(),annot
plt.title("Correlation between Numerical Features")
plt.show()
```



	temp	atemp	humidity	windspeed	casual	registered	count
temp	1	0.98	-0.065	-0.018	0.47	0.32	0.39
atemp	0.98	1	-0.044	-0.057	0.46	0.31	0.39
humidity	-0.065	-0.044	1	-0.32	-0.35	-0.27	-0.32
windspeed	-0.018	-0.057	-0.32	1	0.092	0.091	0.1
casual	0.47	0.46	-0.35	0.092	1	0.5	0.69
registered	0.32	0.31	-0.27	0.091	0.5	1	0.97
count	0.39	0.39	-0.32	0.1	0.69	0.97	1

Insights

- 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 [31]:

```
df.sample(10)
```

Out[31]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
5888	2012-02-01 13:00:00	spring	no	yes	clear	18.86	22.725	47	15.0013
9131	2012-09-03 20:00:00	fall	yes	no	clear	29.52	34.090	76	7.0015
10134	2012-11-07 15:00:00	winter	no	yes	partly_clear	13.12	15.150	53	19.9995
9058	2012-08-19 19:00:00	fall	no	no	partly_clear	26.24	30.305	73	8.9981
10306	2012-11-14 20:00:00	winter	no	yes	clear	12.30	15.910	52	6.0032
10351	2012-11-16 17:00:00	winter	no	yes	clear	14.76	17.425	46	12.9980
2417	2011-06-08 15:00:00	summer	no	yes	clear	37.72	43.940	40	11.0014
4125	2011-10-03 22:00:00	winter	no	yes	partly_clear	16.40	20.455	82	0.0000
8383	2012-07-10 16:00:00	fall	no	yes	clear	32.80	36.365	43	15.0013
7726	2012-06-02 07:00:00	summer	no	no	clear	21.32	25.000	72	7.0015

10 rows × 21 columns

About the features :

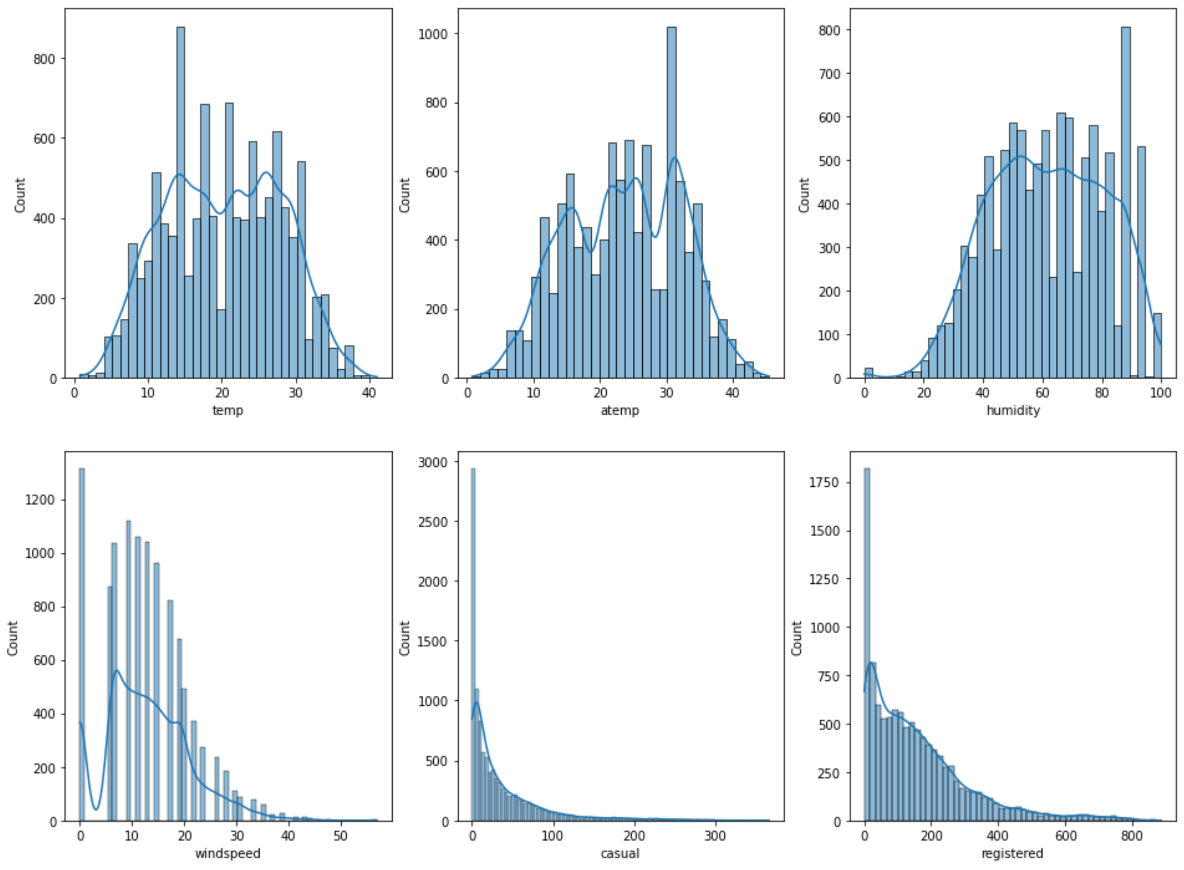
- **dependent variables** : count / registerd / casual
- **independent variables** : workingday / holiday / weather / seasons /temperature /humidity /windspeed

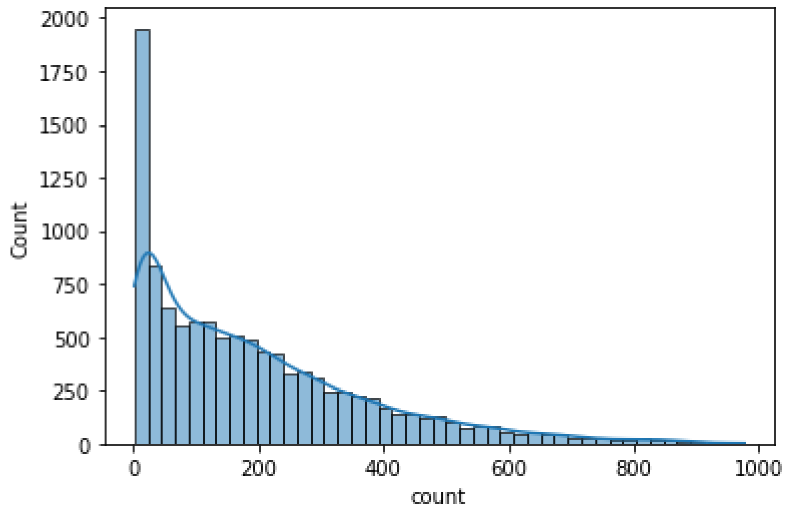
3 Univariate and Bivariate Analysis

3.1 Univariate Analysis

In [32]:

```python
# understanding the distribution for numerical variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 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()
```



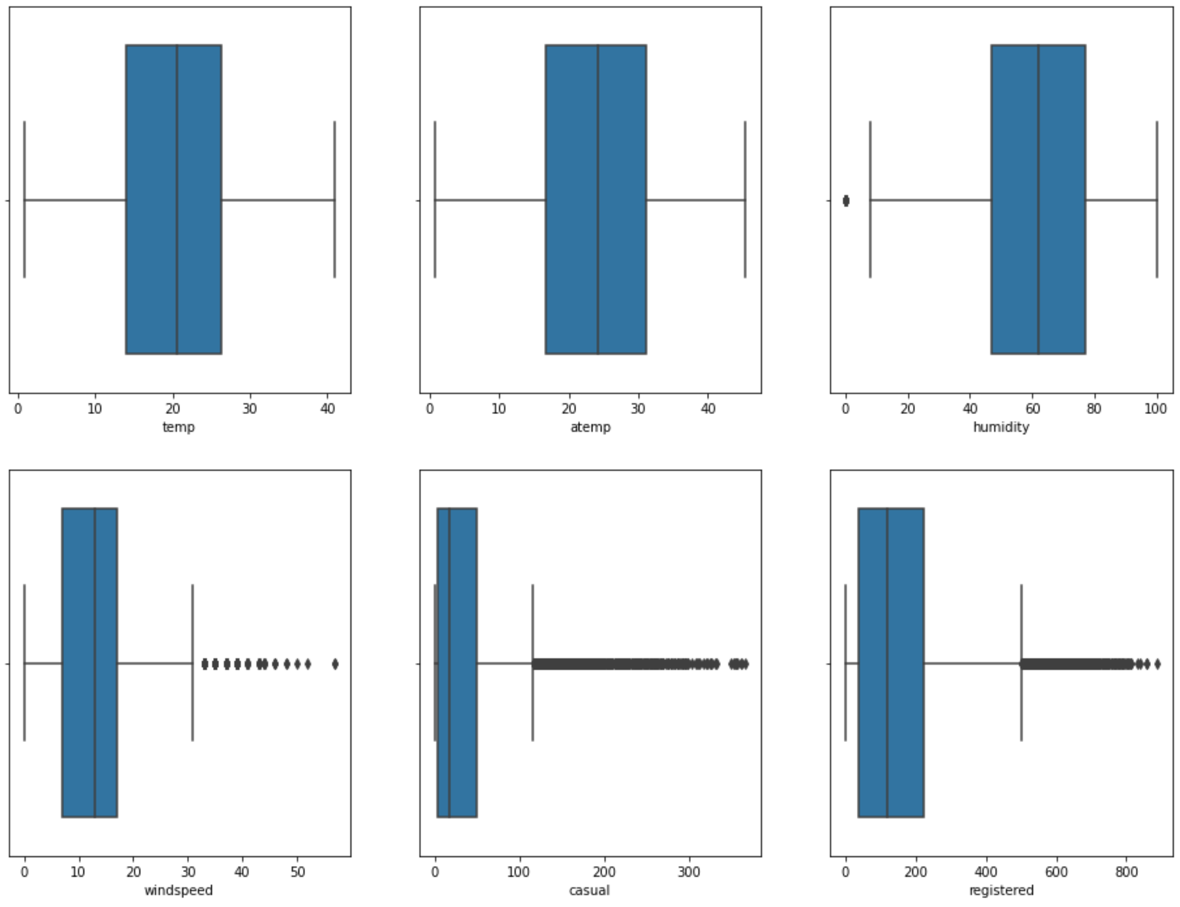


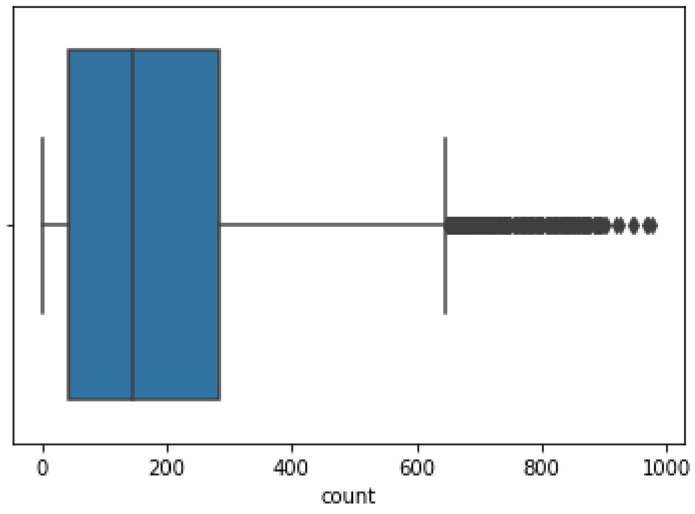
Insights:

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

In [33]:

```python
# plotting box plots to detect outliers in the data
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 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()
```





Looks like **humidity**, **casual**, **registered** and **count** have outliers in the data.

Outlier detection in Dataset :

In [34]:

```
# function for outlier detection
def detect_outliers(df):
    length_before = len(df)
    Q1 = np.percentile(df,25)
    Q3 = np.percentile(df,75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

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

```

In [35]:

```
rentedCyclesPerHour  = df["count"]
```

In [36]:

```
detect_outliers(rentedCyclesPerHour)
```

Out[36]:

```
'0.0278 % Outliers data from input data found'
```

Outlier treatment

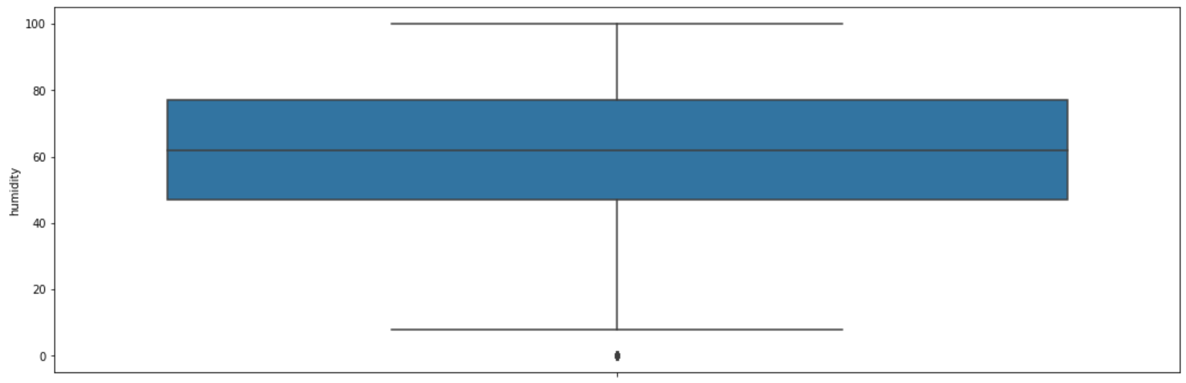
In [37]:

```
numeric_types = ['int64', 'float64']
get_columns_by_types = lambda df, types: [df.columns[index] for index in range(len(df.
```

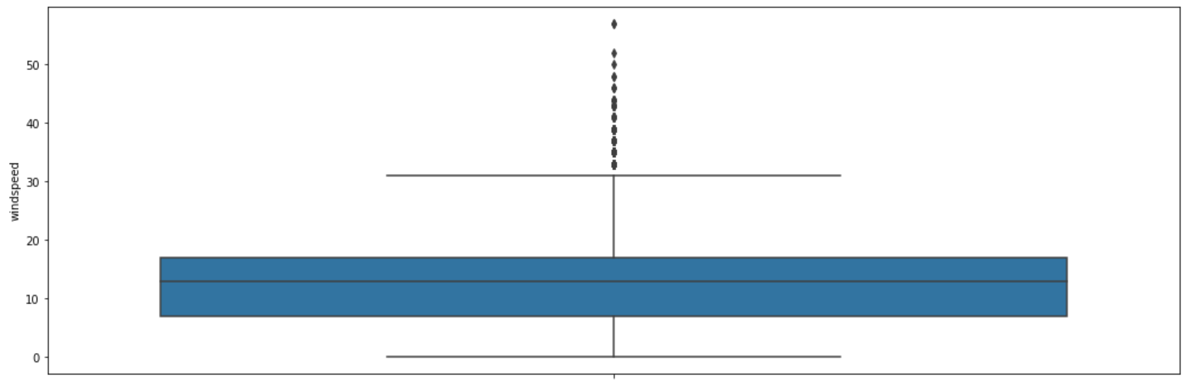
In [38]:

```
for column in get_columns_by_types(df, numeric_types):
    df = remove_outlier(df, column)
```

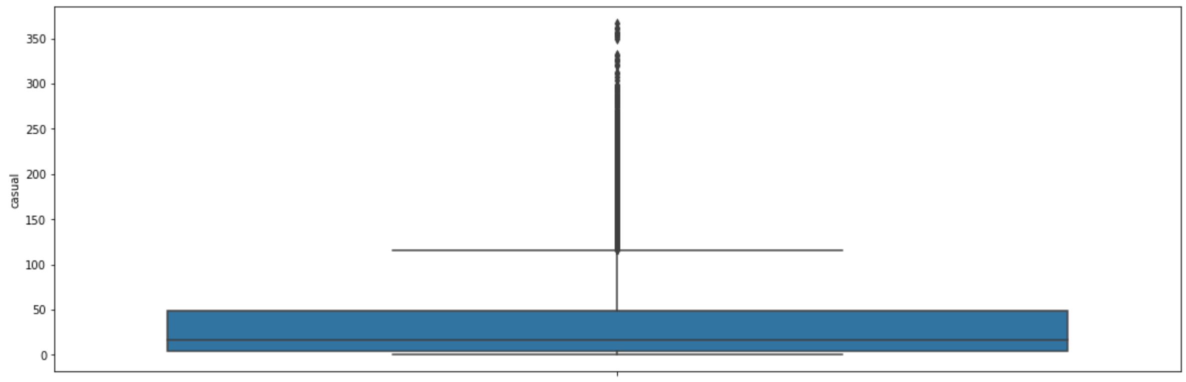
Outliers constitute 0.2% of data for column 'humidity'. Hence removing outliers.



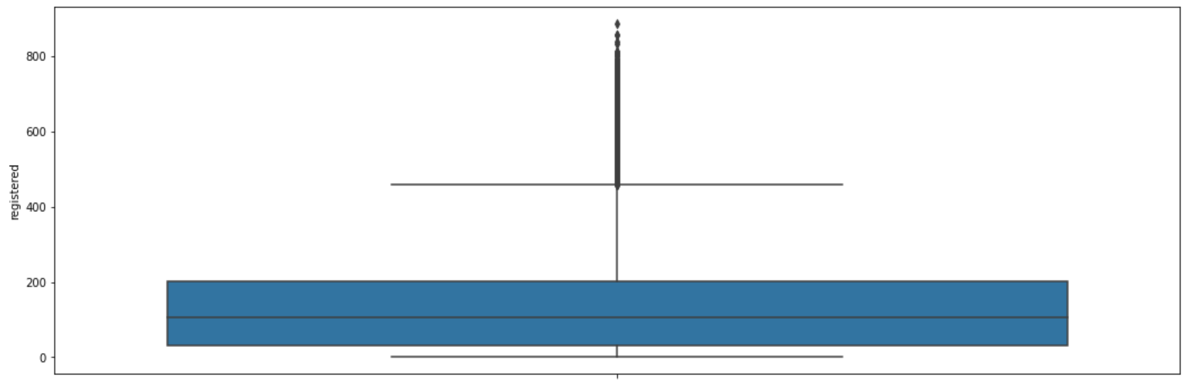
Outliers constitute 2.08% of data for column 'windspeed'. Hence removing outliers.



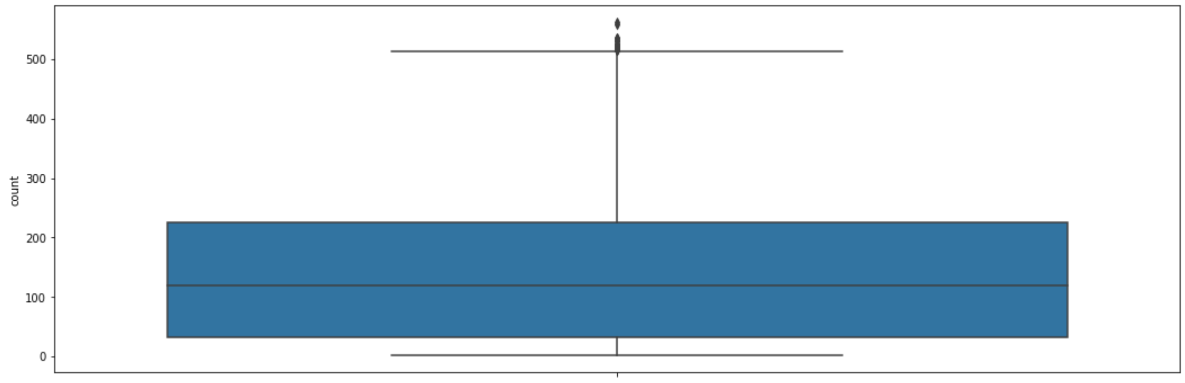
Outliers constitute 6.93% of data for column 'casual'. Hence removing outliers.



Outliers constitute 5.23% of data for column 'registered'. Hence removing outliers.



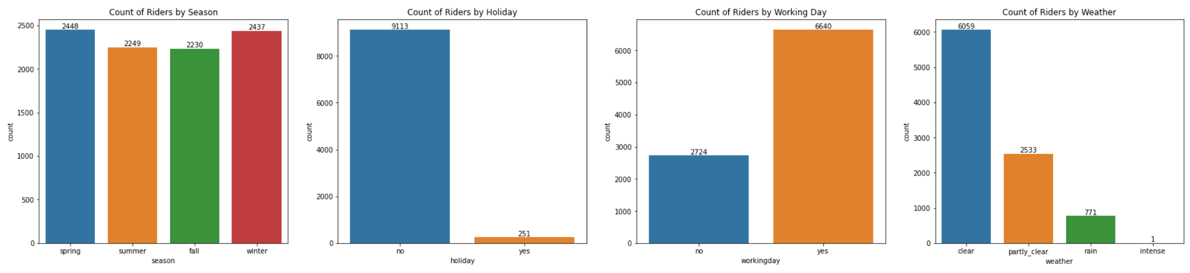
```
Outliers constitute 0.2% of data for column 'count'. Hence removing outliers.
```



3.1.1 Univariate Analysis for Categorical Columns

In [39]:

```python
fig,axes=plt.subplots(nrows=1, ncols=4, figsize=(30,6))
sns.countplot(x='season', data=df, ax=axes[0])
axes[0].bar_label(axes[0].containers[0])
axes[0].set_title('Count of Riders by Season')
sns.countplot(x='holiday', data=df, ax=axes[1])
axes[1].bar_label(axes[1].containers[0])
axes[1].set_title('Count of Riders by Holiday')
sns.countplot(x='workingday', data=df, ax=axes[2])
axes[2].bar_label(axes[2].containers[0])
axes[2].set_title('Count of Riders by Working Day')
sns.countplot(x='weather', data=df, ax=axes[3])
axes[3].bar_label(axes[3].containers[0])
axes[3].set_title('Count of Riders by Weather')
plt.show()
```



Insights:

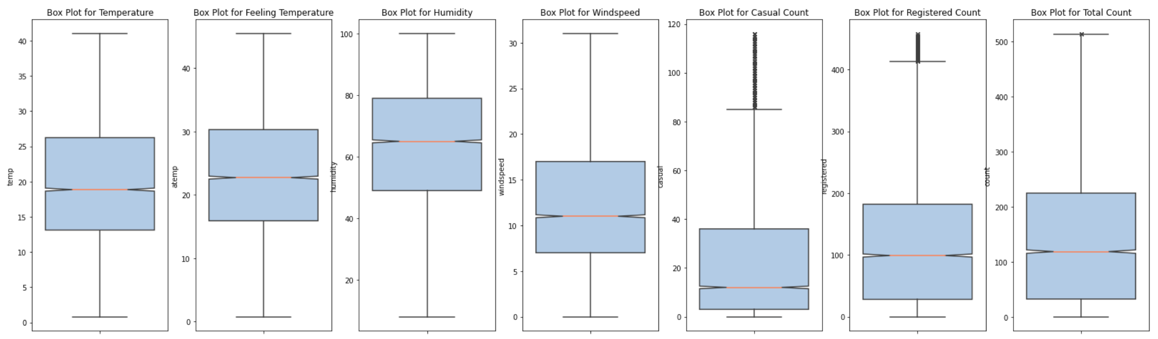
```
- The number of riders in all seasons is almost the same.
- More number of riders (97% of them) ride on non-holidays.
- More number of riders (68% of them) ride on working days.
- Nearly 92% of the riders ride on days when the weather is clear or partly clear.
```

Data looks common as it should be like equal number of days in each season, more working days and weather is mostly `Clear, Few clouds, partly cloudy, partly cloudy` .

3.1.2 Univariate Analysis for Continuous Columns

In [40]:

```python
fig,axes=plt.subplots(1,7,figsize=(28,8))
sns.boxplot(data=df, y="temp",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[0])
axes[0].set_title('Box Plot for Temperature')

sns.boxplot(data=df, y="atemp",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[1])
axes[1].set_title('Box Plot for Feeling Temperature')

sns.boxplot(data=df, y="humidity",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[2])
axes[2].set_title('Box Plot for Humidity')

sns.boxplot(data=df, y="windspeed",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[3])
axes[3].set_title('Box Plot for Windspeed')

sns.boxplot(data=df, y="casual",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[4])
axes[4].set_title('Box Plot for Casual Count')

sns.boxplot(data=df, y="registered",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[5])
axes[5].set_title('Box Plot for Registered Count')

sns.boxplot(data=df, y="count",
            notch=True, showcaps=True,
            flierprops={"marker": "x"},
            boxprops={"facecolor": (.4, .6, .8, .5)},
            medianprops={"color": "coral"}, ax = axes[6])
axes[6].set_title('Box Plot for Total Count')

plt.show()
```



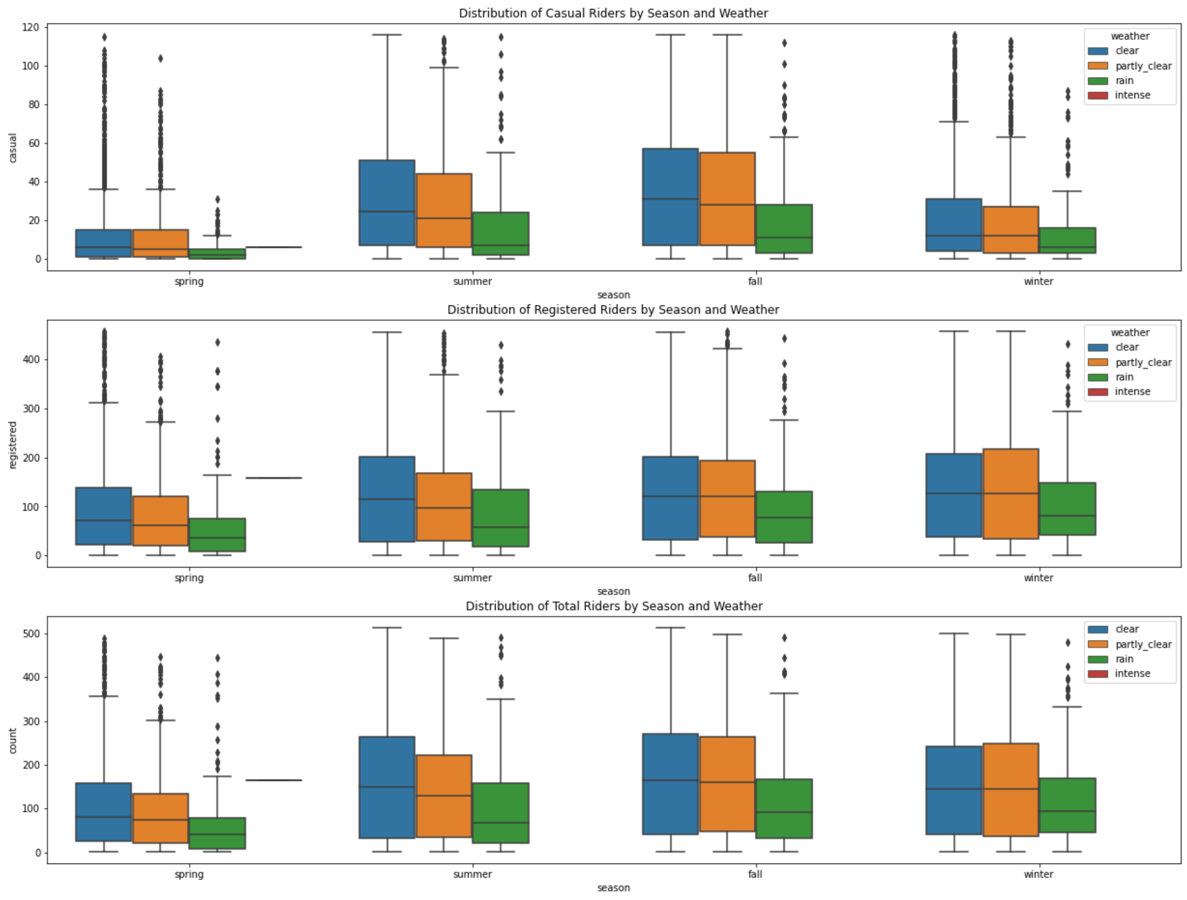
Insights:

- The mean and the median temperature in the dataset is approximately around 20°C.
- The mean and the median feeling temperature in the dataset is approximately around 24°C.
- The mean and the median humidity in the dataset is approximately around 62%.
- The windspeed is approximately around 13, with large number of outliers.
- There is a large number of outliers for casual, registered and total count of riders between 1st Jan 2011 to 19th Dec 2012. That could be due to the increase in the number of riders over this period. Let us investigate this with the help of time series analysis.

3.1.3 Distribution of Casual, Registered and Total Riders by Weather and Season

In [41]:

```python
fig,axes=plt.subplots(3,1,figsize=(21,16))

sns.boxplot(data=df, y="casual", x = 'season', hue = 'weather', ax=axes[0])
axes[0].set_title('Distribution of Casual Riders by Season and Weather')

sns.boxplot(data=df, y="registered", x = 'season', hue = 'weather', ax=axes[1])
axes[1].set_title('Distribution of Registered Riders by Season and Weather')

sns.boxplot(data=df, y="count", x = 'season', hue = 'weather', ax=axes[2])
axes[2].set_title('Distribution of Total Riders by Season and Weather')
plt.legend(loc='upper right')
plt.show()
```



Insights:

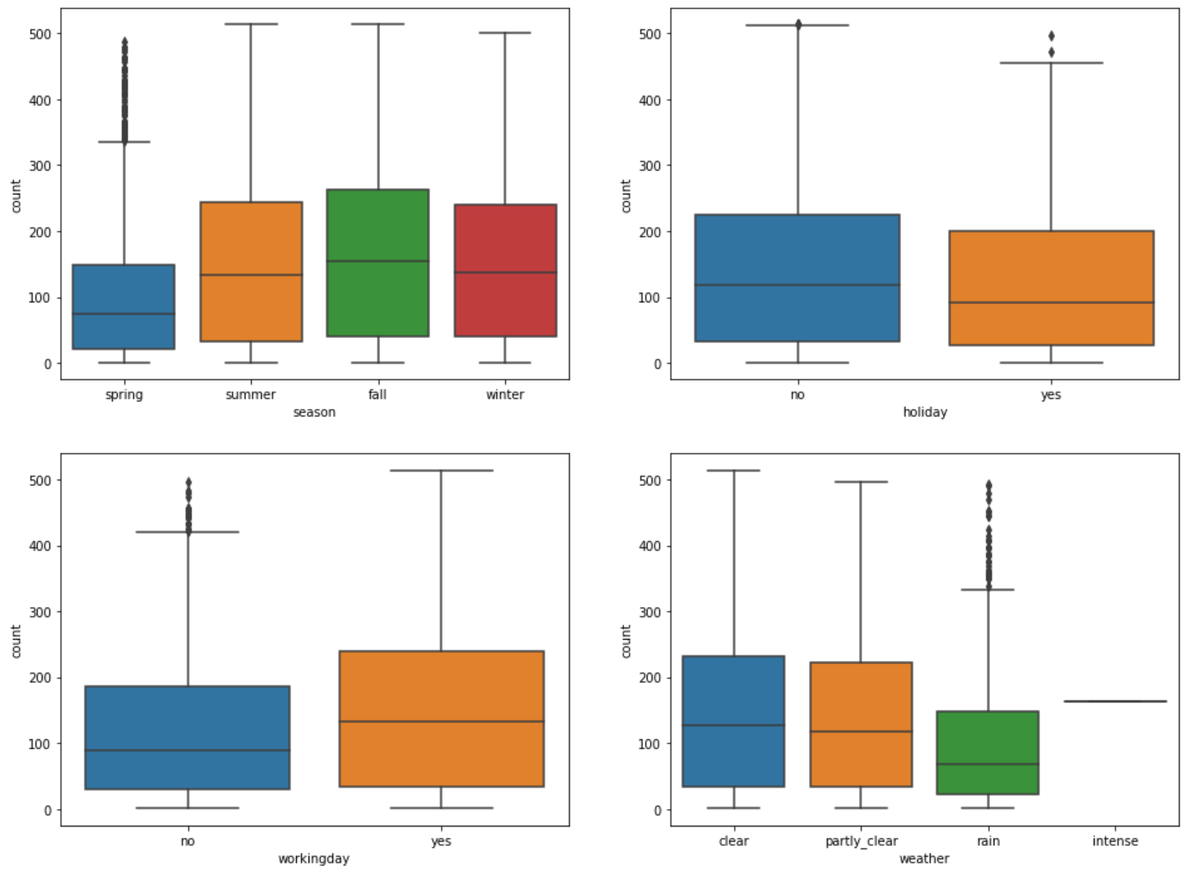
- The number of riders in every season is highest in clear and partly_clear weather

3.2 Bivariate Analysis

Plotting categorical variables againt count using boxplots

In [42]:

```python

fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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

plt.show()
```



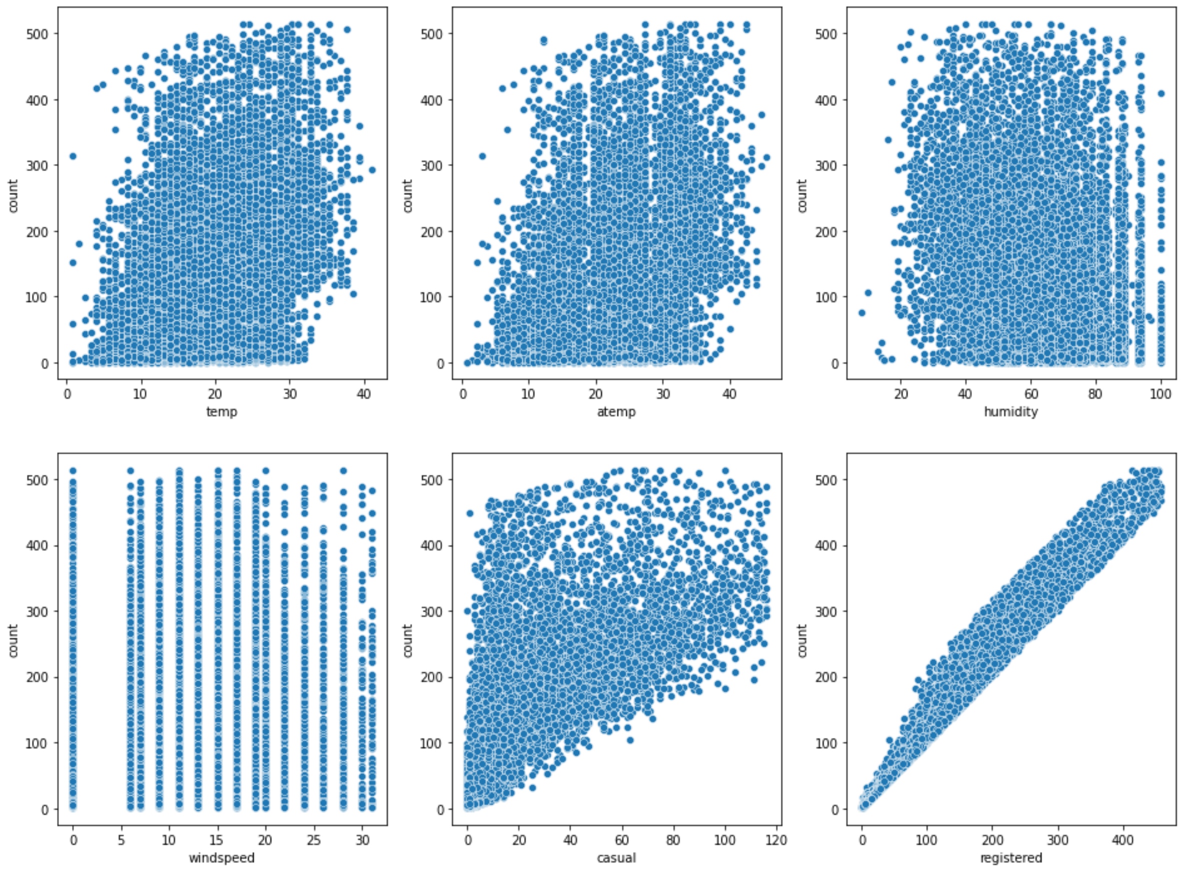
Insights:

- 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.

Plotting numerical variables againt count using scatterplot

In [43]:

```
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(3):
        sns.scatterplot(data=df, x=num_cols[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```



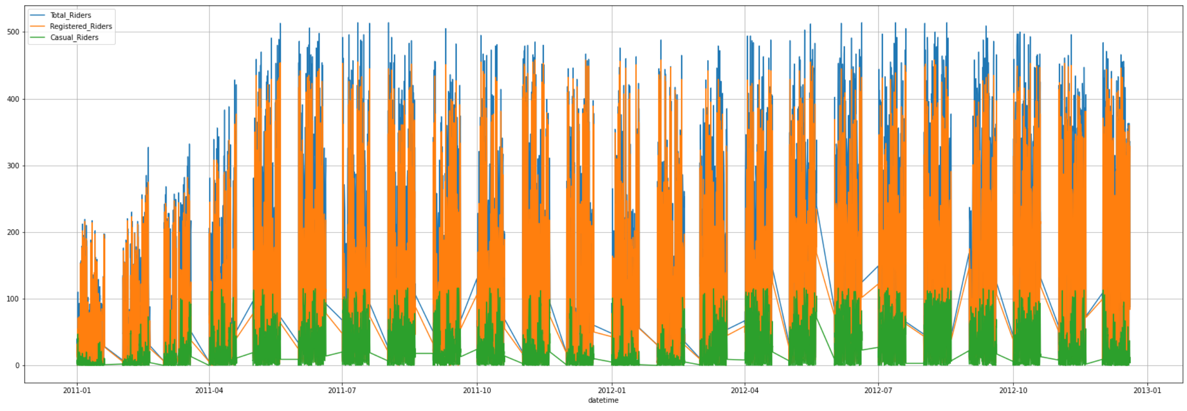
Insights:

- Whenever the humidity is less than 20, number of bikes rented is sparse
- 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.

3.2.1 Increase in Casual, Registered, and Total Riders over time

In [44]:

```
plt.figure(figsize=(30,10))
sns.color_palette('husl')
sns.lineplot(x = df['datetime'],y = df['count'].values)
sns.lineplot(x = df['datetime'],y = df['registered'].values)
sns.lineplot(x = df['datetime'],y = df['casual'].values)
plt.legend(['Total_Riders','Registered_Riders','Casual_Riders'])
plt.grid()
plt.show()
```



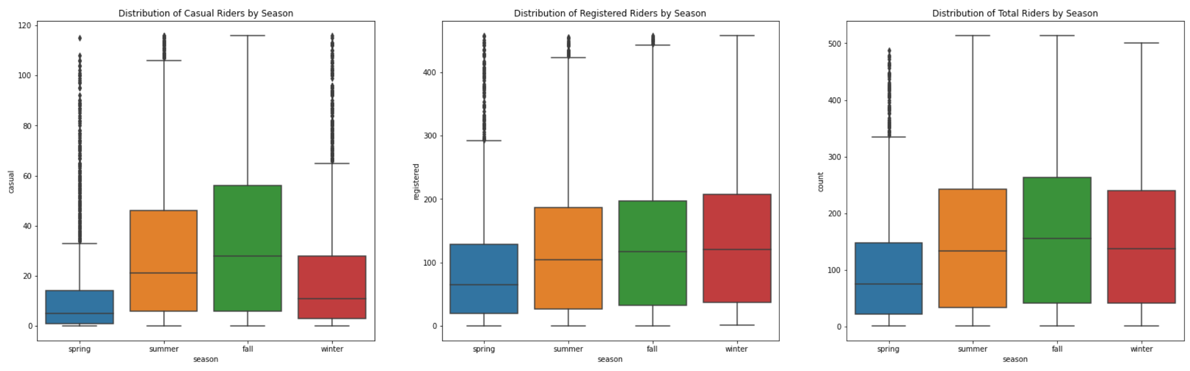
Insights:

- The number of casual, registered and total riders has increased considerably between 1st Jan 2011 to 19th Dec 2012.
- There is also a definite trend and seasonality as we can see increase in number of riders from spring to summer to fall and then a decrease in the number of riders in winter before rising again in spring next season.

3.2.2 Distribution of Casual, Registered and Total Riders by Season

In [45]:

```
fig,axes=plt.subplots(1,3,figsize=(28,8))

sns.boxplot(data=df, y="casual", x = 'season', ax=axes[0])
axes[0].set_title('Distribution of Casual Riders by Season')

sns.boxplot(data=df, y="registered", x = 'season', ax=axes[1])
axes[1].set_title('Distribution of Registered Riders by Season')

sns.boxplot(data=df, y="count", x = 'season', ax=axes[2])
axes[2].set_title('Distribution of Total Riders by Season')

plt.show()
```



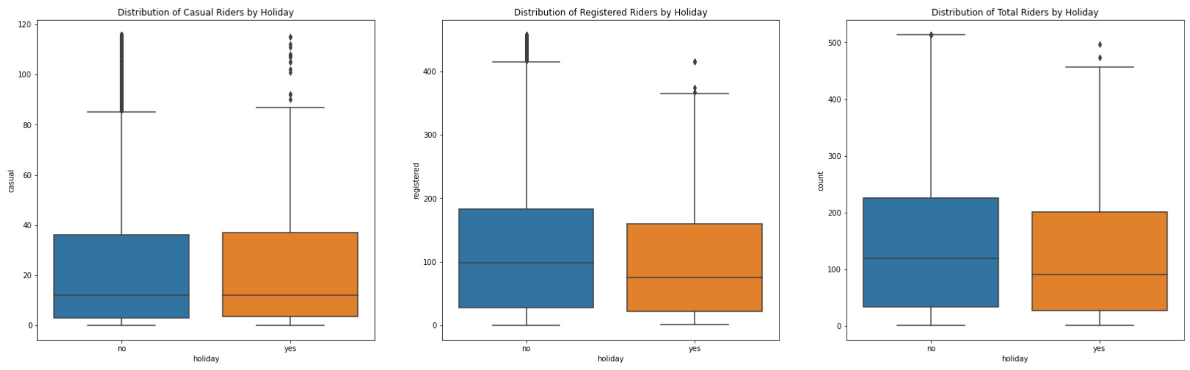
Insights:

- The median number of casual, registered and total riders is highest in fall and summer season followed by winter and spring season.

3.2.3 Distribution of Casual, Registered and Total Riders by Holiday

In [46]:

```python
fig,axes=plt.subplots(1,3,figsize=(28,8))

sns.boxplot(data=df, y="casual", x = 'holiday', ax=axes[0])
axes[0].set_title('Distribution of Casual Riders by Holiday')

sns.boxplot(data=df, y="registered", x = 'holiday', ax=axes[1])
axes[1].set_title('Distribution of Registered Riders by Holiday')

sns.boxplot(data=df, y="count", x = 'holiday', ax=axes[2])
axes[2].set_title('Distribution of Total Riders by Holiday')

plt.show()
```



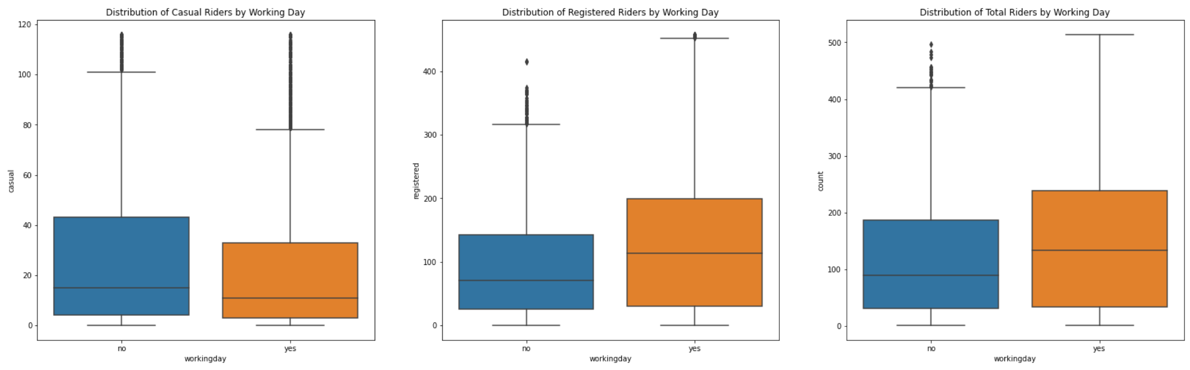
Insights:

- The median number of casual, registered and total riders is almost equal irrespective of whether it is a holiday or not.

3.2.4 Distribution of Casual, Registered and Total Riders by Working Day

In [47]:

```
fig,axes=plt.subplots(1,3,figsize=(28,8))

sns.boxplot(data=df, y="casual", x = 'workingday', ax=axes[0])
axes[0].set_title('Distribution of Casual Riders by Working Day')

sns.boxplot(data=df, y="registered", x = 'workingday', ax=axes[1])
axes[1].set_title('Distribution of Registered Riders by Working Day')

sns.boxplot(data=df, y="count", x = 'workingday', ax=axes[2])
axes[2].set_title('Distribution of Total Riders by Working Day')

plt.show()
```



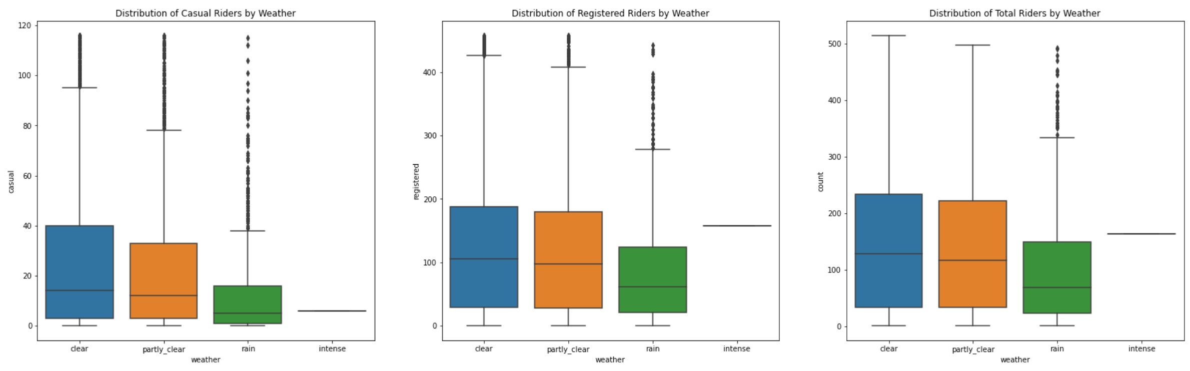
Insights:

- The median number of casual, registered and total riders is almost equal irrespective of whether it is a working day or not.

3.2.5 Distribution of Casual, Registered and Total Riders by Weather

In [48]:

```python
fig,axes=plt.subplots(1,3,figsize=(28,8))

sns.boxplot(data=df, y="casual", x = 'weather', ax=axes[0])
axes[0].set_title('Distribution of Casual Riders by Weather')

sns.boxplot(data=df, y="registered", x = 'weather', ax=axes[1])
axes[1].set_title('Distribution of Registered Riders by Weather')

sns.boxplot(data=df, y="count", x = 'weather', ax=axes[2])
axes[2].set_title('Distribution of Total Riders by Weather')

plt.show()
```



Insights:

```
- The median number of casual, registered and total riders is highest when the wea
ther is clear, followed by the number of casual, registered and total riders when
 the weather is partly_clear.
```

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

In [49]:

```python
registered_per_hour_median = df.groupby("hour")["registered"].median()
casual_per_hour_median = df.groupby("hour")["casual"].median()
```

In [50]:

```python
registered_per_hour_median = registered_per_hour_median.reset_index()
```

In [51]:

```python
casual_per_hour_median = casual_per_hour_median.reset_index()
```

In [52]:

```python
registered_per_hour_median["hour"]+= 1
```

In [53]:

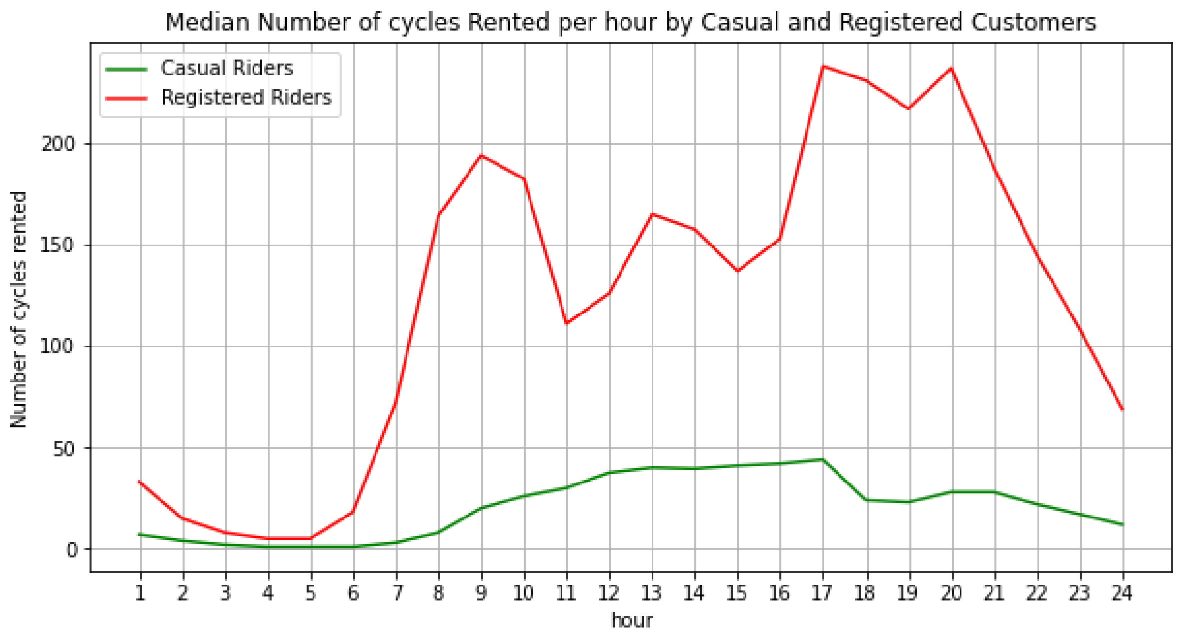
```
casual_per_hour_median["hour"]+= 1
```

In [54]:

```
median_count_perHr = registered_per_hour_median.merge(casual_per_hour_median,on="hour")
```

In [55]:

```
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("Median 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 [56]:

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

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

Out[56]:

```
16.301518856613765
```

In [57]:

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

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

Out[57]:

```
83.69848114338623
```

Insights

- **81% cycles had been rented by registered customers.**
- **19% cycles had been rented by casual customers.**

4 Correlation among different factors

In [58]:

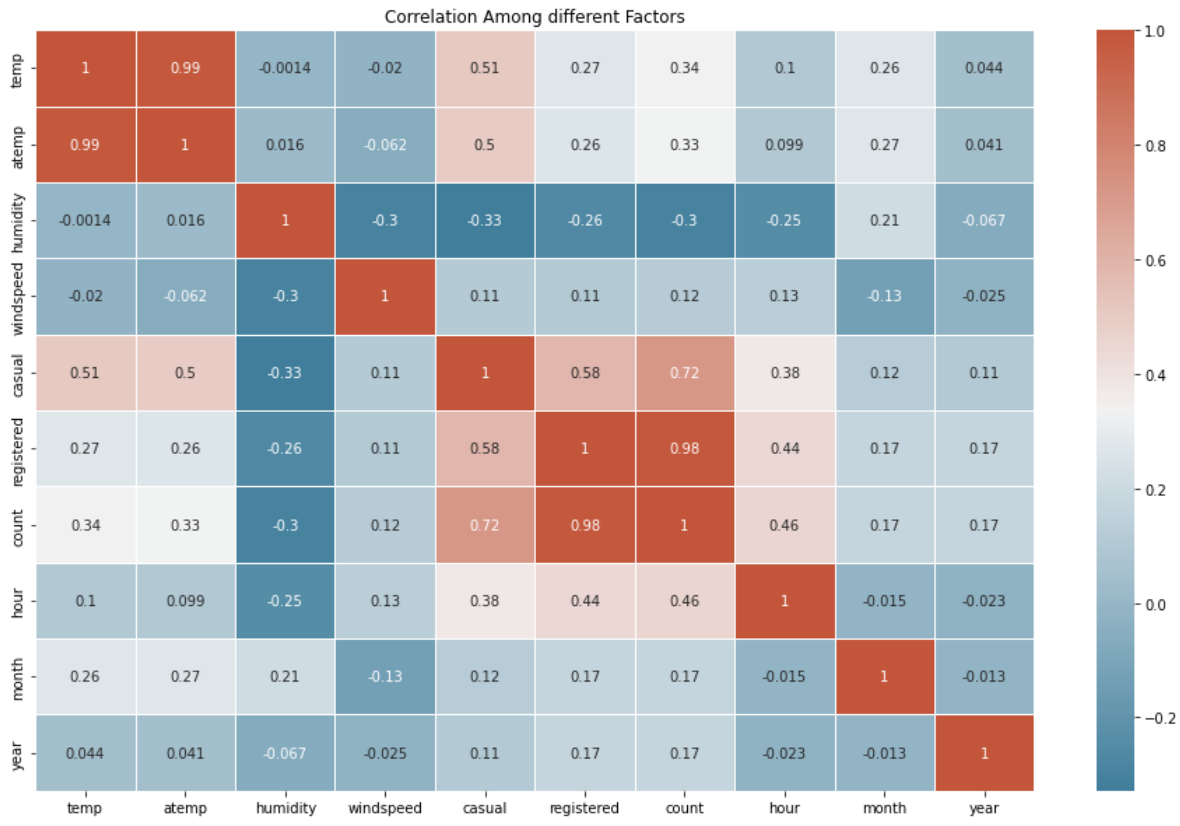
```
# Understanding the correlation between count and numerical variables
df.corr()['count']
```

Out[58]:

```
temp          0.337470
atemp         0.333909
humidity     -0.298090
windspeed     0.115870
casual        0.715850
registered    0.984471
count         1.000000
hour          0.459915
month         0.173165
year          0.170871
Name: count, dtype: float64
```

In [59]:

```python
yuluCorr = df.corr()
plt.figure(figsize=(16,10))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
plt.title('Correlation Among different Factors')
sns.heatmap(yuluCorr, annot=True, linewidths=.5, linecolor='white', cmap=cmap)
plt.show()
```



Insights:

- There is a very less correlation between {temperature, feeling temperature, humidity and windspeed} and {casual, registered and count} variables.
- There is a very strong correlation between temperature and feeling temperature.
- There is a very strong correlation between casual and total riders, as casual riders contribute to the total number of riders for Yulu.
- There is a very strong correlation between registered and total riders, as registered riders *contribute* to the total number of riders for Yulu.

5 Relationship between Dependent and Independent Variables

5.1 Effect of working day on number of electric cycles rented

Let us first set-up the hypothesis framework

Ho: Working Day has no effect on the number of electric cycles rented

H1: Working Day has effect on the number of electric cycles rented

Significance Level(α): 0.05 or 5%

Test Statistic: Two Sample T-test

In [60]:

```python
working_day_no = np.array(df[df.workingday == 'no']['count'])
working_day_yes = np.array(df[df.workingday == 'yes']['count'])
stats.ttest_ind(a=working_day_no, b=working_day_yes, equal_var=True)
```

Out[60]:

```
Ttest_indResult(statistic=-12.084616332054733, pvalue=2.2552148137228035e-3
3)
```

Insights:

```
- Since, pvalue(0.226) is greater than Significance Level(α) i.e 0.05, we fail to
 reject the null hypothesis that - working day has no effect on the number of elec
tric cycles rented.
- This implies that at 95% confidence level, the mean of number of riders on non-w
orking day is statistically not different from the mean number of riders on workin
g day.
```

5.2 Effect of holiday on number of electric cycles rented

Let us first set-up the hypothesis framework

Ho: Holiday has no effect on the number of electric cycles rented

H1: Holiday has effect on the number of electric cycles rented

Significance Level(α): 0.05 or 5%

Test Statistic: Two Sample T-test

In [61]:

```python
holiday_no = np.array(df[df.holiday == 'no']['count'])
holiday_yes = np.array(df[df.holiday == 'yes']['count'])
stats.ttest_ind(a=holiday_no, b=holiday_yes, equal_var=True)
```

Out[61]:

```
Ttest_indResult(statistic=2.026518727208322, pvalue=0.04273994729053667)
```

Insights:

```
- Since, pvalue(0.5736) is greater than Significance Level(α) i.e 0.05, we fail to
reject the null hypothesis that - holiday has no effect on the number of electric
 cycles rented.
- This implies that at 95% confidence level, the mean of number of riders on non-h
oliday is statistically not different from the mean number of riders on holiday.
```

5.3 Number of cycles rented similar or different in different seasons

Let us first set-up the hypothesis framework

Ho: Season has no effect on the number of electric cycles rented

H1: Season has effect on the number of electric cycles rented

Significance Level(α): 0.05 or 5%

Test Statistic: One Way ANOVA

In [62]:

```
season_spring = np.array(df[df.season == 'spring']['count'])
season_summer = np.array(df[df.season == 'summer']['count'])
season_fall = np.array(df[df.season == 'fall']['count'])
season_winter = np.array(df[df.season == 'winter']['count'])
```

Let us now calculate,

The degree of freedom(**dfn**) for different seasons, and

The degree of freedom(**dfd**) for all data points within different seasons

In [63]:

```
dfn = 3
dfd = len(season_spring) - 1 + len(season_summer) - 1 + len(season_fall) - 1 + len(seas
```

Critical Region at 95% confidence interval

In [64]:

```
from scipy.stats import f
critical_region = f.ppf(0.95, dfn=dfn, dfd=dfd)
print(f'The critical region for the hypothesis at 95% confidence interval: {critical_re
```

```
The critical region for the hypothesis at 95% confidence interval: 2.6058577
880302964
```

Let us now calculate the f-statistic based on data points

In [65]:

```
from scipy.stats import f_oneway

f_oneway(season_spring, season_summer, season_fall, season_winter)
```

Out[65]:

```
F_onewayResult(statistic=148.06214819202174, pvalue=9.583582124778882e-94)
```

Insights:

```
- Since, pvalue(6.164843386499654e-149) is lesser than Significance Level(α) i.e
 0.05, we reject the null hypothesis that - season has no effect on the number of
 electric cycles rented.
- This implies that at 95% confidence level, the mean of number of riders in diffe
rent seasons is statistically different for atleast one season.
```

5.4 Number of cycles rented similar or different in different weather

Let us first set-up the hypothesis framework

Ho: Weather has no effect on the number of electric cycles rented

H1: Weather has effect on the number of electric cycles rented

Significance Level(α): 0.05 or 5%

Test Statistic: One Way ANOVA

In [66]:

```
weather_clear = np.array(df[df.weather == 'clear']['count'])
weather_partly_clear = np.array(df[df.weather == 'partly_clear']['count'])
weather_rain = np.array(df[df.weather == 'rain']['count'])
weather_intense = np.array(df[df.weather == 'intense']['count'])
```

Let us now calculate,

The degree of freedom(**dfn**) for different weather, and

The degree of freedom(**dfd**) for all data points within different weather points

In [67]:

```
dfn = 3
dfd = len(weather_clear) - 1 + len(weather_partly_clear) - 1 + len(weather_rain) - 1 +
```

Critical Region at 95% confidence interval

In [68]:

```
from scipy.stats import f
critical_region = f.ppf(0.95, dfn=dfn, dfd=dfd)
print(f'The critical region for the hypothesis at 95% confidence interval: {critical_re
```

```
The critical region for the hypothesis at 95% confidence interval: 2.6058577
880302964
```

Let us now calculate the f-statistic based on data points

In [69]:

```
from scipy.stats import f_oneway

f_oneway(weather_clear, weather_partly_clear, weather_rain, weather_intense)
```

Out[69]:

```
F_onewayResult(statistic=37.2968446919463, pvalue=5.95629355789377e-24)
```

Insights:

```
- Since, pvalue(5.482069475935669e-42) is lesser than Significance Level(α) i.e 0.
05, we reject the null hypothesis that - weather has no effect on the number of el
ectric cycles rented.
- This implies that at 95% confidence level, the mean of number of riders in diffe
rent weather is statistically different for atleast one weather
```

5.5 Dependency of Weather on Seasons

Let us first set-up the hypothesis framework

Ho: Weather is independent on season

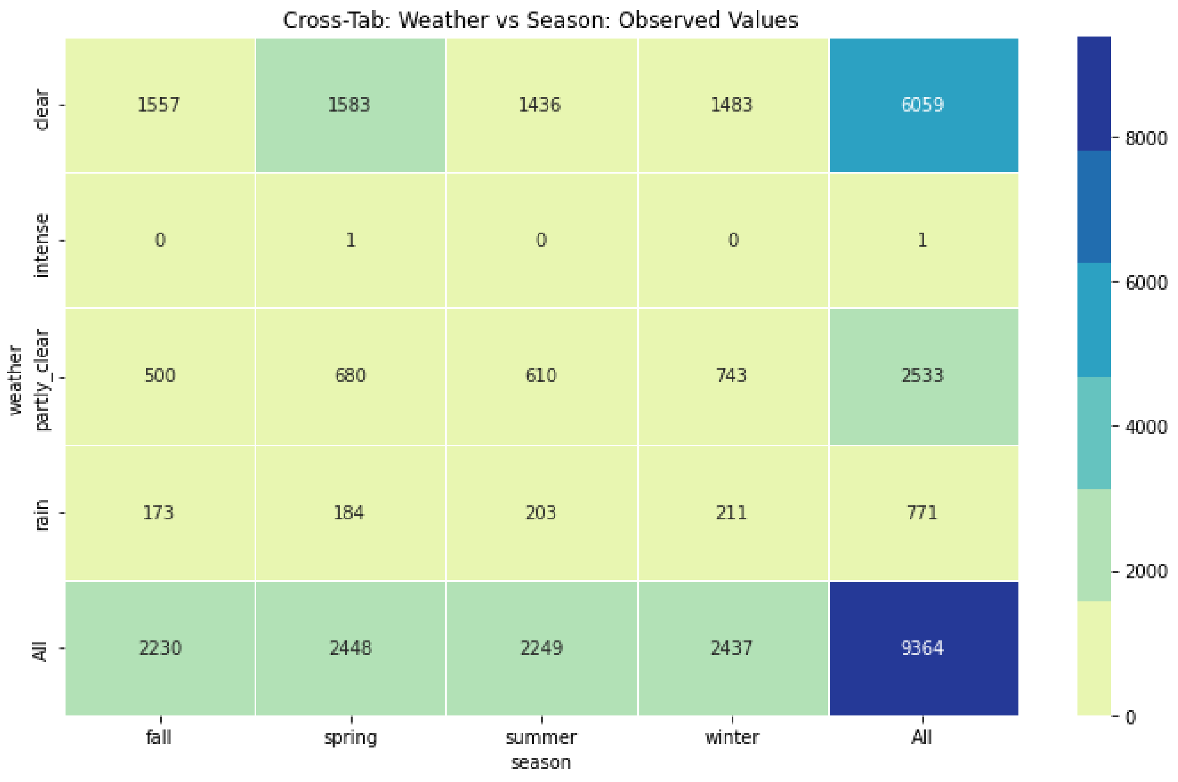
H1: Weather is dependent on season

Significance Level(α): 0.05 or 5%

Test Statistic: Chi-Square Test of Independence

In [70]:

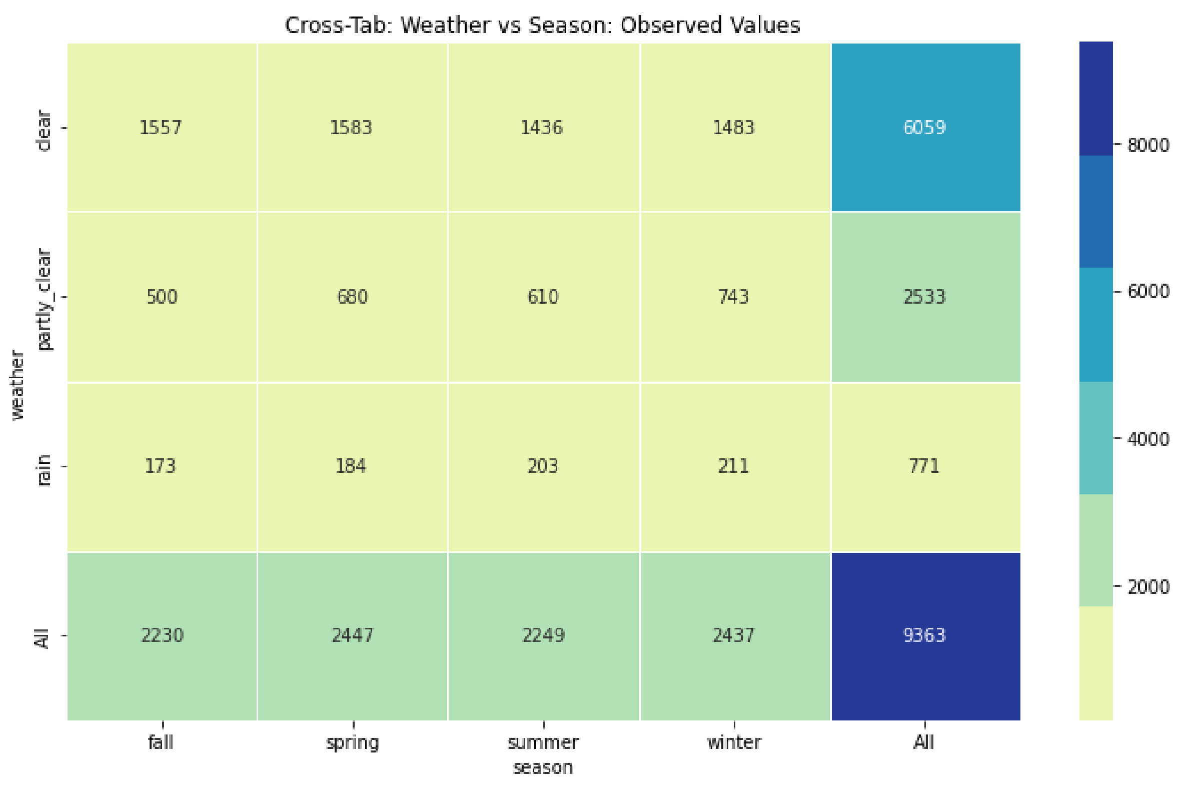
```python
df1 = pd.crosstab(index=df["weather"], columns=df["season"], margins=True)
colormap = sns.color_palette("YlGnBu")
plt.figure(figsize=(12,7))
plt.title('Cross-Tab: Weather vs Season: Observed Values')
sns.heatmap(df1, annot = True, fmt="d", linewidths=.5, linecolor='white', cmap=colormap
plt.show()
```



Please Note: We need to remove data points for intense weather conditions as for Chi-Square Test of Independence - The expected value inside each cell needs to be at least five in order for you to use this test.

In [71]:

```
df2 = df[df["weather"] != 'intense']
df2 = pd.crosstab(index=df2["weather"], columns=df2["season"], margins=True)
colormap = sns.color_palette("YlGnBu")
plt.figure(figsize=(12,7))
plt.title('Cross-Tab: Weather vs Season: Observed Values')
sns.heatmap(df2, annot = True, fmt="d", linewidths=.5, linecolor='white', cmap=colormap
plt.show()
```



Critical Region at 95% confidence interval

In [72]:

```
from scipy.stats import chi2
chi2.ppf(q=0.95, df=6)
print(f'The critical region for the hypothesis at 95% confidence interval: {critical_re
```

```
The critical region for the hypothesis at 95% confidence interval: 2.6058577
880302964
```

Let us now calculate the χ2-Statistic based on data points

In [73]:

```
from scipy.stats import chi2_contingency

observed = [[1930, 1759, 1801, 1702],
            [604, 715, 708, 807],
            [199, 211, 224, 225]]

chi2_contingency(observed)
```

Out[73]:

```
(46.101457310732485,
 2.8260014509929403e-08,
 6,
 array([[1805.76352779, 1774.04869086, 1805.76352779, 1806.42425356],
        [ 711.55920992,  699.06201194,  711.55920992,  711.81956821],
        [ 215.67726229,  211.8892972 ,  215.67726229,  215.75617823]]))
```

Insights:

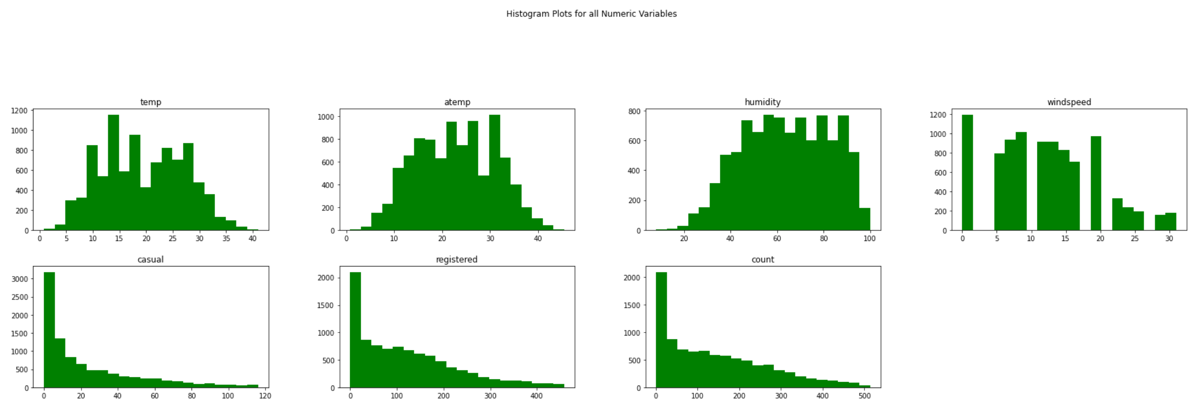
```
- Since, pvalue(2.8260014509929403e-08) is lesser than Significance Level(α) i.e
 0.05, we reject the null hypothesis that - weather is independent of season
- This implies that at 95% confidence level, weather is dependent on seasons.
```

6 Test of Normality

6.1 Histogram

In [74]:

```
yulu_cont = df[['temp','atemp','humidity','windspeed','casual','registered','count']]
yulu_cont.hist(layout = (5,4), color = 'green', figsize = (30,20), grid = False, bins =
plt.suptitle('Histogram Plots for all Numeric Variables')
plt.show()
```



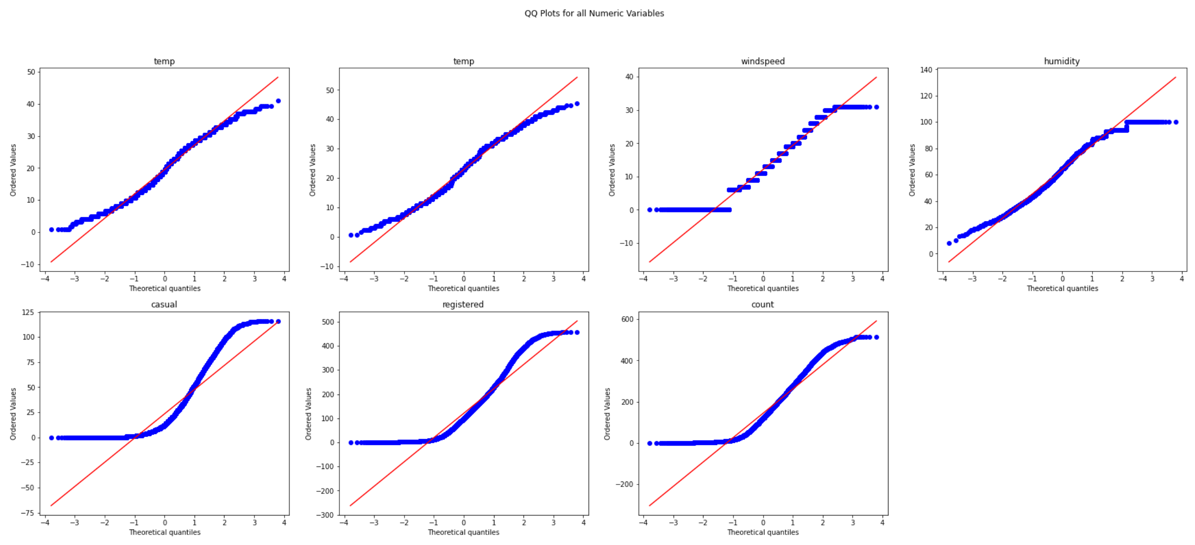
Insights

```
- We see from the above plot that the distribution of all the variables is skewed
 and hence are not normally distributed.
```

6.2 Q-Q Plot

In [75]:

```
import pylab
import scipy.stats as stats

plt.figure(figsize=(30,12))

ax1 = plt.subplot(241)
res = stats.probplot(yulu_cont['temp'], dist="norm", plot=plt)
ax1 = plt.title('temp')

ax2 = plt.subplot(242)
res = stats.probplot(yulu_cont['atemp'], dist="norm", plot=plt)
ax2 = plt.title('temp')

ax3 = plt.subplot(243)
res = stats.probplot(yulu_cont['windspeed'], dist="norm", plot=plt)
ax3 = plt.title('windspeed')

ax4 = plt.subplot(244)
res = stats.probplot(yulu_cont['humidity'], dist="norm", plot=plt)
ax4 = plt.title('humidity')

ax5 = plt.subplot(245)
res = stats.probplot(yulu_cont['casual'], dist="norm", plot=plt)
ax5 = plt.title('casual')

ax6 = plt.subplot(246)
res = stats.probplot(yulu_cont['registered'], dist="norm", plot=plt)
ax6 = plt.title('registered')

ax7 = plt.subplot(247)
res = stats.probplot(yulu_cont['count'], dist="norm", plot=plt)
ax7 = plt.title('count')

plt.suptitle('QQ Plots for all Numeric Variables')
plt.show()
```



Insights:

```
- From the QQ-Plot we observe that none of the variables is looking straight, henc
e showing deviation from normal distribution.
```

6.3 Levene's Test

6.3.1 Levene's Test for equality of variance for number of riders for 4 different seasons

Assumption:

```
Samples collected from the population are independent of each other

The population data is approximately normal in distribution
```

Setting up Hypothesis Framework

Ho: Variance is equal for all seasons

H1: Variance is not equal for all seasons (atleast one of the season has a variance different from the others)

Significance Level(α): 0.05 or 5%

Levene's Test-Statistic: As the data for all the seasons is skewed in distribution, we will use the median for test statistics.

In [76]:

```python
from scipy.stats import levene

levene(weather_clear, weather_partly_clear, weather_rain, center ='median')
```

Out[76]:

```
LeveneResult(statistic=58.591323761645285, pvalue=5.153228368533525e-26)
```

Insights:

```
- Since, pvalue(6.198278710731511e-36) is lesser than Significance Level(α) i.e 0.
05, we reject the null hypothesis that - Variance is equal for all seasons
- This implies that at 95% confidence level, Variance is not equal for all season
s, atleast one of the season has a variance different from the others
```

6.3.2 Levene's Test for equality of variance for number of riders for 4 different weather

Assumption:

```
Samples collected from the population are independent of each other

The population data is approximately normal in distribution
```

Setting up Hypothesis Framework

Ho: Variance is equal for all weathers

H1: Variance is not equal for all weathers (atleast one of the weather has a variance different from the others)

Significance Level(α): 0.05 or 5%

Levene's Test-Statistic: As the data for all the weathers is skewed in distribution, we will use the median for test statistics.

In [77]:

```python
from scipy.stats import levene

levene(season_spring, season_summer, season_fall, season_winter, center ='median')
```

Out[77]:

```
LeveneResult(statistic=134.92207742468392, pvalue=1.4156739715299946e-85)
```

Insight:

```
- Since, pvalue(1.0147116860043298e-118) is lesser than Significance Level(α) i.e
 0.05, we reject the null hypothesis that - Variance is equal for all weathers
- This implies that at 95% confidence level, Variance is not equal for all weather
s, atleast one of the weather has a variance different from the others.
```

6.3.3 Levene's Test for equality of variance for number of riders as per working day

Assumption:

```
Samples collected from the population are independent of each other

The population data is approximately normal in distribution
```

Setting up Hypothesis Framework

Ho: Variance is equal irrespective of working day or not

H1: Variance is not equal irrespective of working day or not

Significance Level(α): 0.05 or 5%

Levene's Test-Statistic: As the data for workingday or not is skewed in distribution, we will use the median for test statistics.

In [78]:

```python
from scipy.stats import levene

levene(working_day_no, working_day_yes, center ='median')
```

Out[78]:

```
LeveneResult(statistic=174.6581859409547, pvalue=1.604331056959309e-39)
```

Insights:

```
- Since, pvalue(0.9437823280916695) is greater than Significance Level(α) i.e 0.0
5, we fail to reject the null hypothesis that - Variance is equal irrespective of
 whether it is a working day or not.
- This implies that at 95% confidence level, Variance is equal irrespective of whe
ther it is a working day or not.
```

6.3.4 Levene's Test for equality of variance for number of riders as per holiday

Assumption:

```
Samples collected from the population are independent of each other

The population data is approximately normal in distribution
```

Setting up Hypothesis Framework

Ho: Variance is equal irrespective of holiday or not

H1: Variance is not equal irrespective of holiday or not

Significance Level(α): 0.05 or 5%

Levene's Test-Statistic: As the data for holiday is skewed in distribution, we will use the median for test statistics.

In [79]:

```python
from scipy.stats import levene

levene(np.array(df[df.holiday == 'no']['count']), np.array(df[df.holiday == 'yes']['cou
```

Out[79]:

```
LeveneResult(statistic=1.4686039727869589, pvalue=0.2255966689233179)
```

Insights:

```
- Since, pvalue(0.9991178954732041) is greater than Significance Level(α) i.e 0.0
5, we fail to reject the null hypothesis that - Variance is equal irrespective of
 whether it is a holiday or not.
- This implies that at 95% confidence level, Variance is equal irrespective of whe
ther it is a holiday or not.
```

6.4 Shapiro-Wilk Test

Shapiro-Wilk Test is used to test Normality.

Assumption: The sample is coming from a normal distribution

Setting up Hypothesis Framework

Ho: Sample comes from a normal distribution

H1: Sample is not coming from a population which is normally distributed

Significance Level(α): 0.05 or 5%

In [80]:

```python
from scipy.stats import shapiro

print('Insights:')
print(end = '\n')

for i in list(yulu_cont.columns):

  test_statistic, p_value = stats.shapiro(yulu_cont[i])

  print('****************************************************************************

  print(f'The test-statistic for {i} is {test_statistic} with p_value {p_value}')

  if p_value > 0.05:

    print('Hence at 95% confidence level, we fail to reject null hypothesis')
    print(f'Hence we can say that {i} is coming from normally distributed population')

  else:
    print('Hence at 95% confidence level, we reject null hypothesis')
    print(f'Hence we can say that {i} is not coming from normally distributed populatic

  print('****************************************************************************
  print(end = '\n')

```

```
Insights:

****************************************************************************
****************
The test-statistic for temp is 0.9806709885597229 with p_value 9.44563985663
9374e-34
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that temp is not coming from normally distributed populatio
n
****************************************************************************
****************

****************************************************************************
****************
The test-statistic for atemp is 0.9834496974945068 with p_value 1.3297287311
544133e-31
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that atemp is not coming from normally distributed populati
on
****************************************************************************
****************

****************************************************************************
****************
The test-statistic for humidity is 0.9798952341079712 with p_value 2.6224124
135481048e-34
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that humidity is not coming from normally distributed popul
ation
****************************************************************************
****************
```

```
****************************************************************************
****************
The test-statistic for windspeed is 0.9652013182640076 with p_value 1.453146
5075048353e-42
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that windspeed is not coming from normally distributed popu
lation
****************************************************************************
****************

****************************************************************************
****************
The test-statistic for casual is 0.818075954914093 with p_value 0.0
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that casual is not coming from normally distributed populat
ion
****************************************************************************
****************

****************************************************************************
****************
The test-statistic for registered is 0.9053951501846313 with p_value 0.0
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that registered is not coming from normally distributed pop
ulation
****************************************************************************
****************

****************************************************************************
****************
The test-statistic for count is 0.9148815274238586 with p_value 0.0
Hence at 95% confidence level, we reject null hypothesis
Hence we can say that count is not coming from normally distributed populati
on
****************************************************************************
****************
```

7 Insights & Recommendations:

7.1 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 sparse.
- 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.

Univariate analysis

- The number of riders in all seasons is almost the same.
- More number of riders (97% of them) ride on non-holidays.
- More number of riders (68% of them) ride on working days.

- Nearly 92% of the riders ride on days when the weather is clear or partly clear.
- The mean and the median temperature in the dataset is approximately around 20°C.
- The mean and the median feeling temperature in the dataset is approximately around 24°C.
- The mean and the median humidity in the dataset is approximately around 62%.
- The windspeed is approximately around 13, with large number of outliers.
- There is a large number of outliers for casual, registered and total count of riders between 1st Jan 2011 to 19th Dec 2012. That could be due to the increase in the number of riders over this period.

Bivariate analysis

- The number of casual, registered and total riders has increased considerably between 1st Jan 2011 to 19th Dec 2012.
- There is also a definite trend and seasonality as we can see increase in number of riders from spring to summer to fall and then a decrease in the number of riders in winter before rising again in spring next season.
- The median number of casual, registered and total riders is highest in fall and summer season followed by winter and spring season.
- The median number of casual, registered and total riders is almost equal irrespective of whether it is a holiday or not.
- The median number of casual, registered and total riders is almost equal irrespective of whether it is a working day or not.
- The median number of casual, registered and total riders is almost equal irrespective of whether it is a working day or not.
- The number of riders in every season is highest in clear and partly_clear weather

Correlation

- There is a very less correlation between {temperature, feeling temperature, humidity and windspeed} and {casual, registered and count} variables.
- There is a very strong correlation between temperature and feeling temperature.
- There is a very strong correlation between casual and total riders, as casual riders contribute to the total number of riders for Yulu.
- There is a very strong correlation between registered and total riders, as registered riders contribute to the total number of riders for Yulu.

General insights based on Statistical test

- 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 .

- The test-statistic for temp is 0.9806709885597229 with p_value 9.445639856639374e-34 Hence at 95% confidence level, we reject null hypothesis Hence we can say that temp is not coming from normally distributed population

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- The test-statistic for atemp is 0.9834496974945068 with p_value 1.3297287311544133e-31 Hence at 95% confidence level, we reject null hypothesis Hence we can say that atemp is not coming from normally distributed population

- The test-statistic for humidity is 0.9798952341079712 with p_value 2.6224124135481048e-34 Hence at 95% confidence level, we reject null hypothesis Hence we can say that humidity is not coming from normally distributed population

- The test-statistic for windspeed is 0.9652013182640076 with p_value 1.4531465075048353e-42 Hence at 95% confidence level, we reject null hypothesis Hence we can say that windspeed is not coming from normally distributed population

- The test-statistic for casual is 0.818075954914093 with p_value 0.0 Hence at 95% confidence level, we reject null hypothesis Hence we can say that casual is not coming from normally distributed population

- The test-statistic for registered is 0.9053951501846313 with p_value 0.0 Hence at 95% confidence level, we reject null hypothesis Hence we can say that registered is not coming from normally distributed population

- The test-statistic for count is 0.9148815274238586 with p_value 0.0 Hence at 95% confidence level, we reject null hypothesis Hence we can say that count is not coming from normally distributed population

7.2 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.
- As from 2 Sample T-test we have seen that holiday has no impact on the number of riders at 95% confidence level, Yulu should run similar promotional-campaigns/offers irrespective of whether it is a holiday or not.
- As from 2 Sample T-test we have seen that working day has no impact on the number of riders at 95% confidence level, Yulu should run similar promotional-campaigns/offers irrespective of whether it is a working day or not.
- As we have seen from Analysis of Variance(ANOVA), that mean number of riders is statistically different at 95% confidence level for different seasons, Yulu should have different strategies for different seasons. Yulu should try to increase the riders in the months of fall and winter when the number of riders goes down considerably and maximize capacity utilization of e-bikes in the months of summer and fall.
- As we have seen from Analysis of Variance(ANOVA), that mean number of riders is statistically different at 95% confidence level for different weathers, Yulu should have different strategies for different weathers. Yulu should try to maximize the capacity utilization of e-bikes when the weather is clear or partly clear.

- As we have seen from Chi-Square Test that weather is dependent on seasons at 95% confidence level. Yulu should maximize the capacity utilization or rides in every season when the weather is clear or partly_clear.
- Yulu should perform demand forecasting as we have seen that there is trend and seasonality in the data. Better demand forecasting will lead to better capacity utilization of e-bikes in different seasons.
- Yulu should also perform further investigation into the riders based on gender and age as insights into age bracket and gender would reveal a lot about the week on week capacity utilization on the type of customers preferring Yulu e-bikes.