Statistics For Data Science(UE19CS203)

Analysis of bike rental dataset

Team Members:

Name	SRN
Nikhil VR	PES2UG19CS258
Mahantesh M	PES2UG19CS210

Abstract:

The bike sharing analysis is based on a dataset formed based on the study on bike rentals in the country of USA during the years of 2011and 2012.In the current generation where the society is very health conscious and concerned about the nature, the people avoiding the usage of motor transport has become a trend. This analysis is based on the climatic and temporal factors that help us in understanding the scenarios that favour the use of rental bikes among casual and registered riders.

Introduction:

Our field of study is concerned about the analysis of the bike rental count by casual and registered riders based on different factors. There are many factors that cause the variation in the count of bike rentals. The major factors that had the effect on the rental count were season, working days and weather situations. It is found that the behavior of renting bikes of the casual riders to the registered riders varied from each other. These varying factors are the epicenter where the study revolves around.

The dataset contains 14 columns and 732 rows. The main focus of the data analysis is to find the relation between the total bike rentals per day and the factors that might affect it .

Dataset:

The dataset used in this analysis is day.csv

Link- https://archive.ics.uci.edu/ml/datasets/Bike+Sharing+Dataset

It describes the following variables

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

- yr : year (0: 2011, 1:2012)

- mnth : month (1 to 12)

- hr : hour (0 to 23)

- holiday : weather day is holiday or not.

- weekday : day of the week

- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.

+ weathersit :

- 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 : Normalized temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-8, t_max=+39 (only in hourly scale)

- atemp: Normalized feeling temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-16, t_max=+50 (only in hourly scale)

- hum: Normalized humidity. The values are divided to 100 (max)

- windspeed: Normalized wind speed. The values are divided to 67 (max)

- casual: count of casual users

- registered: count of registered users

- cnt: count of total rental bikes including both casual and registered

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   season      731 non-null    int64  
 1   yr          731 non-null    int64  
 2   mnth        731 non-null    object 
 3   holiday     731 non-null    int64  
 4   weekday     731 non-null    object 
 5   workingday  731 non-null    object 
 6   weathersit  731 non-null    int64  
 7   temp        731 non-null    float64
 8   atemp       731 non-null    float64
 9   hum         731 non-null    float64
 10  windspeed   731 non-null    float64
 11  casual      731 non-null    int64  
 12  registered  731 non-null    int64  
 13  cnt         731 non-null    int64  
dtypes: float64(4), int64(7), object(3)
memory usage: 80.1+ KB
```

In [6]:
```
df['season'].describe()
```

Out[6]:
```
count    731.000000
mean       2.496580
std        1.110807
min        1.000000
25%        2.000000
50%        3.000000
75%        3.000000
max        4.000000
Name: season, dtype: float64
```

In [7]:
```
df['yr'].describe()
```

Out[7]:
```
count    731.000000
mean       0.500684
std        0.500342
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
Name: yr, dtype: float64
```

In [8]:
```
df['mnth'].describe()
```

Out[8]:
```
count     731
unique     13
top         8
freq       60
Name: mnth, dtype: object
```

In [9]:
```
df['holiday'].describe()
```

Out[9]:
```
count    731.000000
mean       0.028728
std        0.167155
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
Name: holiday, dtype: float64
```

In [10]:
```
df['weekday'].describe()
```

Out[10]:
```
count     731
unique      8
top         1
freq      104
Name: weekday, dtype: object
```

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

Out[11]:
```
count    731.000000
mean       1.395349
std        0.544894
min        1.000000
25%        1.000000
50%        1.000000
75%        2.000000
max        3.000000
Name: weathersit, dtype: float64
```

In [12]:
```
df['temp'].describe()
```

Out[12]:
```
count    731.000000
mean       0.495385
std        0.183051
min        0.059130
25%        0.337083
50%        0.498333
75%        0.655417
max        0.861667
Name: temp, dtype: float64
```

In [13]:
```
df['atemp'].describe()
```

Out[13]:
```
count    731.000000
mean       0.474354
std        0.162961
min        0.079070
25%        0.337842
50%        0.486733
75%        0.608602
max        0.840896
Name: atemp, dtype: float64
```

In [14]:
```
df['hum'].describe()
```

Out[14]:
```
count    731.000000
mean       0.627894
std        0.142429
min        0.000000
25%        0.520000
50%        0.626667
75%        0.730209
max        0.972500
Name: hum, dtype: float64
```

In [16]:
```
df['casual'].describe()
```

Out[16]:
```
count     731.000000
mean      848.176471
std       686.622488
min         2.000000
25%       315.500000
50%       713.000000
75%      1096.000000
max      3410.000000
Name: casual, dtype: float64
```

In [17]:
```
df['registered'].describe()
```

Out[17]:
```
count     731.000000
mean     3656.172367
std      1560.256377
min        20.000000
25%      2497.000000
50%      3662.000000
75%      4776.500000
max      6946.000000
Name: registered, dtype: float64
```

In [18]:
```
df['cnt'].describe()
```

Out[18]:
```
count     731.000000
mean     4504.348837
std      1937.211452
min        22.000000
25%      3152.000000
50%      4548.000000
75%      5956.000000
max      8714.000000
Name: cnt, dtype: float64
```

Data Cleaning:

The data in its original form contained many null values which had to be replaced. These null values were replaced with mode of the variables.

Dataframe before cleaning:

In [4]:
```
df
```

Out[4]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.160446	331	654	985
1	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.248539	131	670	801
2	1	0	1	0	1	1	1	0.196364	0.189405	0.437273	0.248309	120	1229	1349
3	1	0	1	0	2	?	1	0.200000	0.212122	0.590435	0.160296	108	1454	1562
4	1	0	1	0	?	1	1	0.226957	0.229270	0.436957	0.186900	82	1518	1600
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
726	1	1	12	0	4	1	2	0.254167	0.226642	0.652917	0.350133	247	1867	2114
727	1	1	?	0	5	1	2	0.253333	0.255046	0.590000	0.155471	644	2451	3095
728	1	1	12	0	6	0	2	0.253333	0.242400	0.752917	0.124383	159	1182	1341
729	1	1	12	0	?	0	1	0.255833	0.231700	0.483333	0.350754	364	1432	1796
730	1	1	12	0	1	1	2	0.215833	0.223487	0.577500	0.154846	439	2290	2729

731 rows × 14 columns

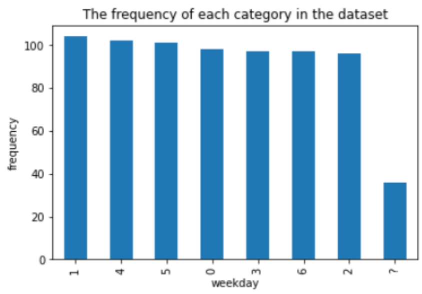
The Null values in the dataset were represented by ‘?’

In [21]:
```python
df.isin(['?']).sum(axis=0)
```

Out[21]:
```
season         0
yr             0
mnth          33
holiday        0
weekday       36
workingday    33
weathersit     0
temp           0
atemp          0
hum            0
windspeed      0
casual         0
registered     0
cnt            0
dtype: int64
```

In [24]:
```python
df['weekday'].value_counts().plot(kind='bar')
plt.xlabel('weekday')
plt.ylabel('frequency')
plt.title('The frequency of each category in the dataset')
```

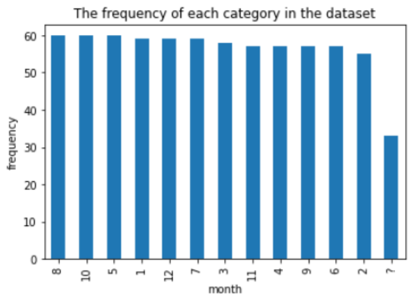
Out[24]:
```
Text(0.5, 1.0, 'The frequency of each category in the dataset')
```



In [25]:
```python
df["weekday"] = df["weekday"].replace(to_replace ="?",
                 value ="1")
```

In [22]:
```python
df['mnth'].value_counts().plot(kind='bar')
plt.xlabel('month')
plt.ylabel('frequency')
plt.title('The frequency of each category in the dataset')
```

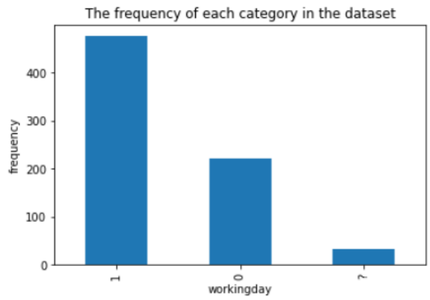
Out[22]:
```
Text(0.5, 1.0, 'The frequency of each category in the dataset')
```



In [23]:
```python
df["mnth"] = df["mnth"].replace(to_replace ="?",
                 value ="5")
```

```
In [26]: df['workingday'].value_counts().plot(kind='bar')
         plt.xlabel('workingday')
         plt.ylabel('frequency')
         plt.title('The frequency of each category in the dataset')

Out[26]: Text(0.5, 1.0, 'The frequency of each category in the dataset')
```

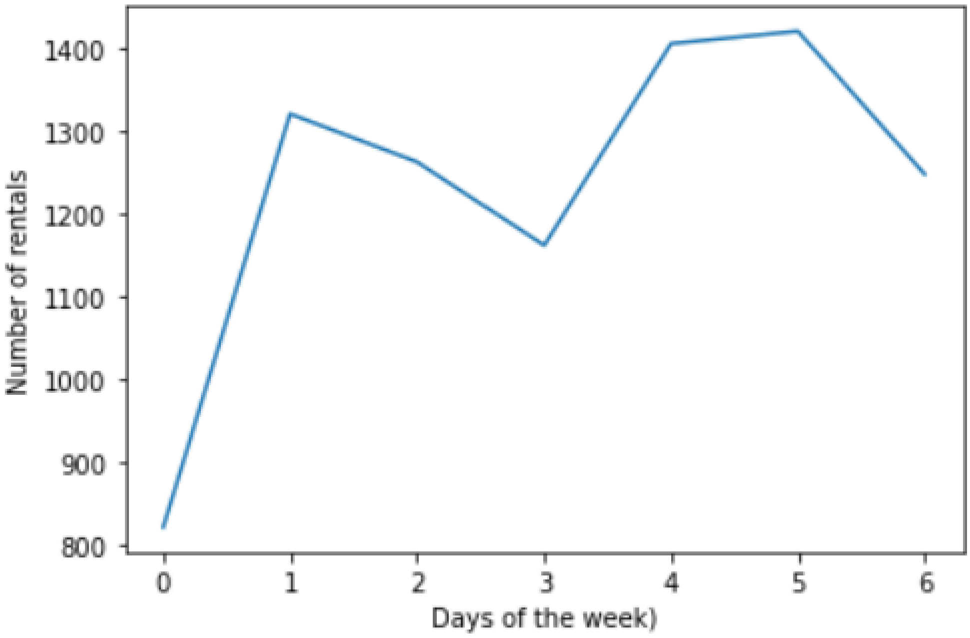



```
In [27]: df["workingday"] = df["workingday"].replace(to_replace ="?",
                           value ="1")
```

Exploratory Data Analysis:

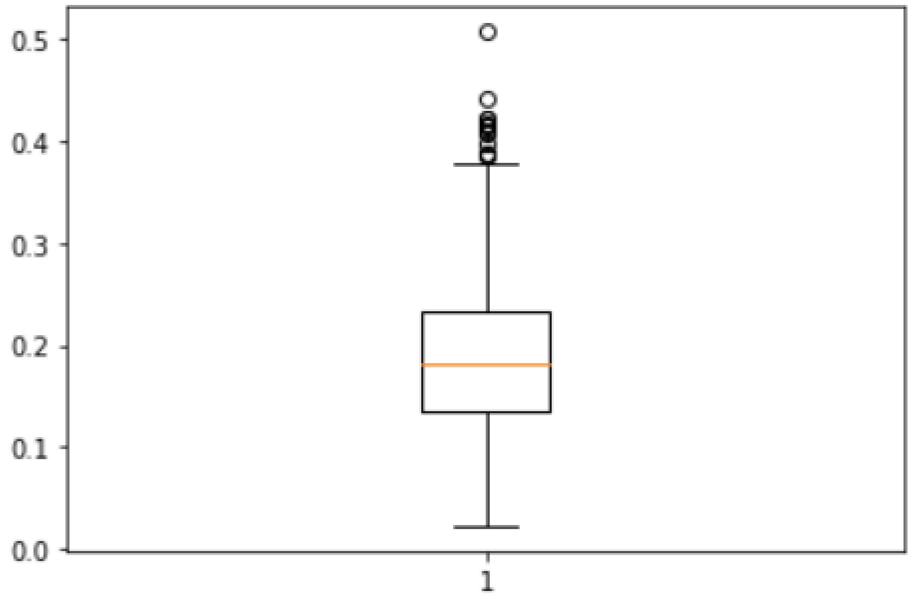
```
plt.plot(df["weekday"][8:15], df["cnt"][8:15])
plt.xlabel('Days of the week)')
plt.ylabel('Number of rentals')
```

```
Text(0, 0.5, 'Number of rentals')
```



In this plot we can visualize how the number of rentals changes with respect to what day of the week it is .

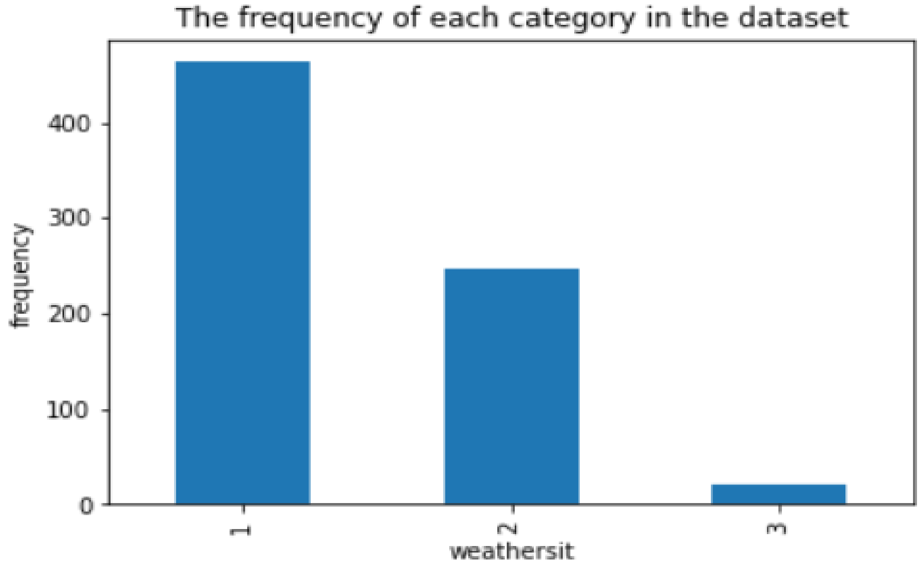
```
plt.boxplot(df["windspeed"])
plt.show()
```



This describes the outliers in the windspeed variable.

```
df['weathersit'].value_counts().plot(kind='bar')
plt.xlabel('weathersit')
plt.ylabel('frequency')
plt.title('The frequency of each category in the dataset')
```

```
Text(0.5, 1.0, 'The frequency of each category in the dataset')
```



This barplot describes the weather conditions and their frequency in the dataset .

Normalization and Standardization:

Normalization and standardization are done to change the values of numeric columns in the dataset to have a common scale, without distorting differences in the ranges of values.

In [35]:
```
import statistics
casmean = statistics.mean(df["casual"])
casvar = statistics.variance(df["casual"])
print(casmean,casvar)
```

```
848.1764705882352 471450.44141821115
```

In [36]:
```
regmean = statistics.mean(df["registered"])
regvar = statistics.variance(df["registered"])
print(regmean,regvar)
```

```
3656.172366621067 2434399.962029871
```

In [37]:
```
cntmean = statistics.mean(df["cnt"])
cntvar = statistics.variance(df["cnt"])
print(cntmean,cntvar)
```

```
4504.3488372093025 3752788.2082828926
```

Normalisation

In [52]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

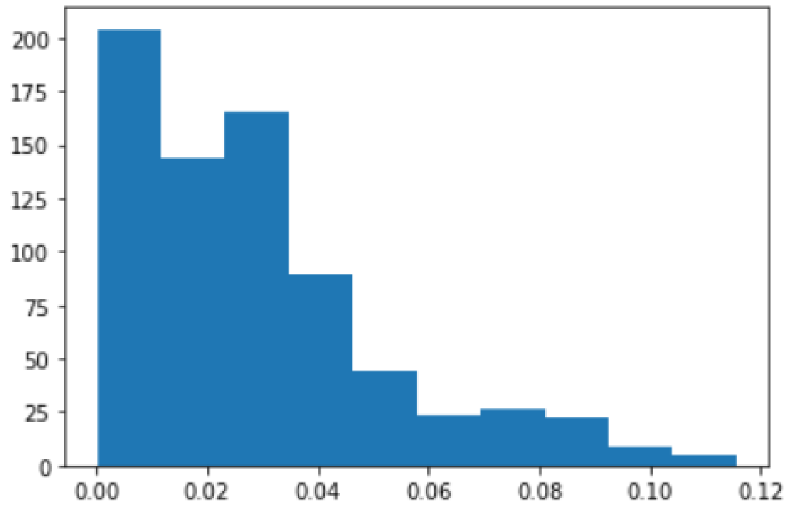
In [53]:
```
#cas normalised
norm_cas = preprocessing.normalize([newdf['casual']])
norm_cas_new = pd.DataFrame(norm_cas)
```

In [54]:
```
#registered normalised
norm_reg = preprocessing.normalize([newdf['registered']])
norm_reg_new = pd.DataFrame(norm_reg)
```

In [55]:
```
#count normalised
norm_cnt = preprocessing.normalize([newdf['cnt']])
norm_cnt_new = pd.DataFrame(norm_cnt)
```

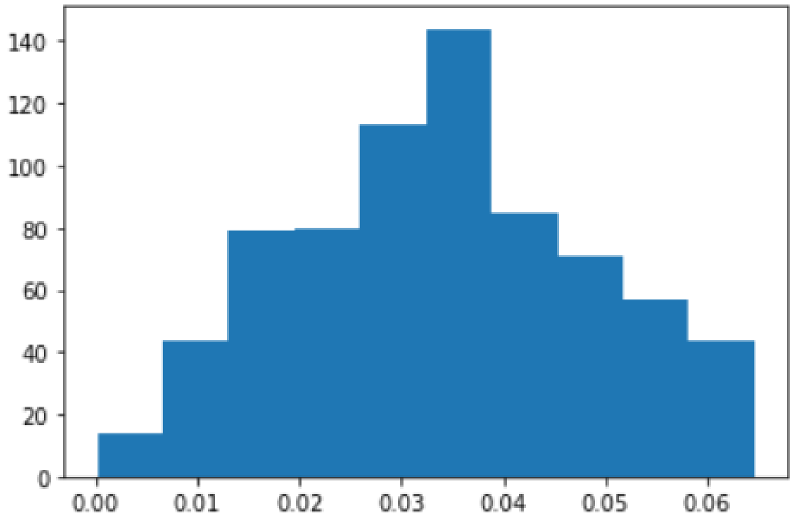
```
plt.hist(norm_cas_new)
```

```
(array([204., 144., 165.,  89.,  44.,  23.,  26.,  22.,   9.,   5.]),
 array([6.78046883e-05, 1.16217236e-02, 2.31756425e-02, 3.47295613e-02,
        4.62834802e-02, 5.78373991e-02, 6.93913180e-02, 8.09452369e-02,
        9.24991557e-02, 1.04053075e-01, 1.15606994e-01]),
 <a list of 10 Patch objects>)
```



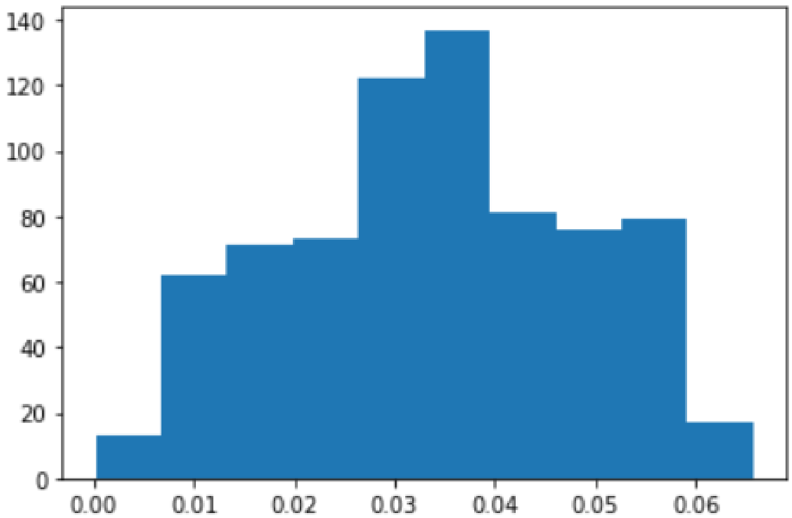
```
plt.hist(norm_reg_new)
```

```
(array([ 14.,  44.,  79.,  80., 113., 144.,  85.,  71.,  57.,  44.]),
 array([0.00018611, 0.00663097, 0.01307583, 0.01952069, 0.02596555,
        0.03241041, 0.03885528, 0.04530014, 0.051745  , 0.05818986,
        0.06463472]),
 <a list of 10 Patch objects>)
```



```
plt.hist(norm_cnt_new)
```

```
(array([ 13.,  62.,  71.,  73., 122., 137.,  81.,  76.,  79.,  17.]),
 array([0.00016597, 0.00672323, 0.01328049, 0.01983776, 0.02639502,
        0.03295228, 0.03950955, 0.04606681, 0.05262407, 0.05918133,
        0.0657386 ]),
 <a list of 10 Patch objects>)
```



Standardisation

In [59]:
```
#casual standardised
cas_train = newdf[["casual"]]
s_cas = scaler.fit_transform(cas_train)
print(s_cas.mean())
print(s_cas.var())
```

```
9.720146864023258e-17
1.0
```

In [60]:
```
 #registered standardised
reg_train = newdf[["registered"]]
s_reg = scaler.fit_transform(reg_train)
print(s_reg.mean())
print(s_reg.var())
```

```
7.776117491218607e-17
1.0
```

In [61]:
```
#count standardised
cnt_train = newdf[["cnt"]]
s_cnt = scaler.fit_transform(cnt_train)
print(s_cnt.mean())
print(s_cnt.var())
```

```
-1.1664176236827 91e-16
0.9999999999999999
```

Hypothesis:

```
In [84]: cntdf = df["cnt"]
         cntdf
```

```
Out[84]: 0       985
         1       801
         2      1349
         3      1562
         4      1600
                ...
         726    2114
         727    3095
         728    1341
         729    1796
         730    2729
         Name: cnt, Length: 731, dtype: int64
```

```
In [93]: sample_df = cntdf[300:400]
         sample_df
```

```
Out[93]: 300    3747
         301     627
         302    3331
         303    3669
         304    4068
                ...
         395    4509
         396    4579
         397    3761
         398    4151
         399    2832
         Name: cnt, Length: 100, dtype: int64
```

```
In [94]: cntdf.describe()
```

```
Out[94]: count     731.000000
         mean     4504.348837
         std      1937.211452
         min        22.000000
         25%      3152.000000
         50%      4548.000000
         75%      5956.000000
         max      8714.000000
         Name: cnt, dtype: float64
```

```
In [95]: sample_df.describe()
```

```
Out[95]: count     100.000000
         mean     3129.310000
         std       923.200261
         min       627.000000
         25%      2491.000000
         50%      3326.500000
         75%      3752.750000
         max      4579.000000
         Name: cnt, dtype: float64
```

Out of the 731 data values of count we consider 100 values for the sample size from 200 to 300.

Sample size = n = 100

Sample mean = Xbar = 3129

Std deviation of the sample = 923

```python
from scipy.stats import norm
from math import sqrt
#one sided hypothesis test(for smaller than in NULL hypothesis)
def one_sided_hypo(sample_mean, pop_mean, std_dev, sample_size, alpha):
    actual_z = abs(norm.ppf(alpha))
    hypo_z = (sample_mean - pop_mean) / (std_dev/sqrt(sample_size))
    print('actual z value :', actual_z)
    print('hypothesis z value :', hypo_z, '\n')
    if hypo_z >= actual_z:
        return True
    else:
        return False

alpha = 0.05
sample_mean = 3129
pop_mean = 4504
sample_size =  100
std_dev = 923

print('H0 : μ <=', pop_mean)
print('H1 : μ >', pop_mean)
print('alpha value is :', alpha, '\n')

reject = one_sided_hypo(sample_mean, pop_mean, std_dev, sample_size, alpha)
if reject:
    print('Reject NULL hypothesis')
else:
    print('Failed to reject NULL hypothesis')
```

```
H0 : μ <= 4504
H1 : μ > 4504
alpha value is : 0.05

actual z value : 1.6448536269514729
hypothesis z value : -14.897074756229687

Failed to reject NULL hypothesis
```

Since the hypothesis z value is much lesser than the actual z value, our null hypothesis is rejected.

Correlation:

Correlation

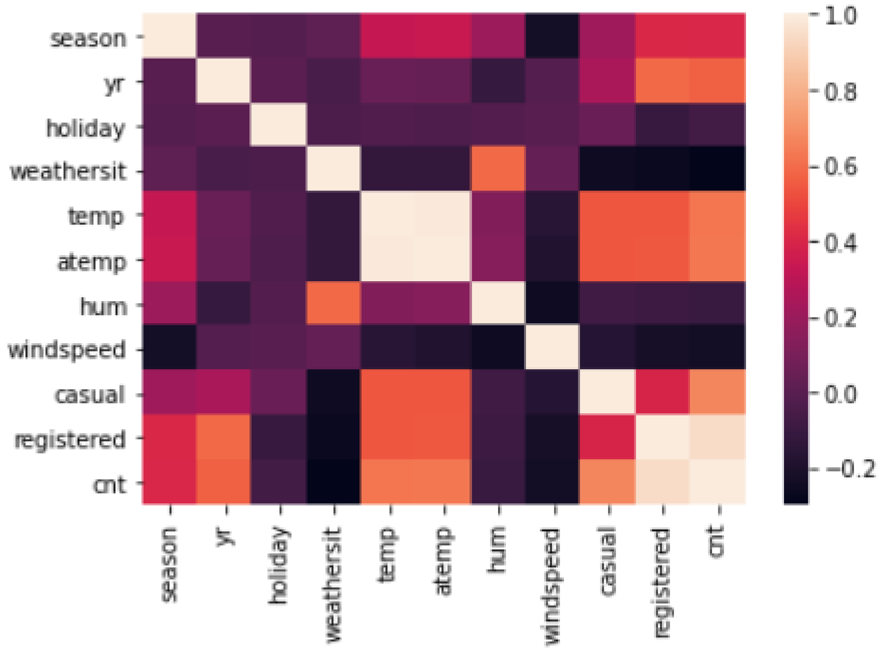
In [62]:
```python
corr = df.corr(method='pearson')
corr.head()
```

Out[62]:

	season	yr	holiday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
season	1.000000	-0.001844	-0.010537	0.019211	0.334315	0.342876	0.205445	-0.229046	0.210399	0.411623	0.406100
yr	-0.001844	1.000000	0.007954	-0.048727	0.047604	0.046106	-0.110651	-0.011817	0.248546	0.594248	0.566710
holiday	-0.010537	0.007954	1.000000	-0.034627	-0.028556	-0.032507	-0.015937	0.006292	0.054274	-0.108745	-0.068348
weathersit	0.019211	-0.048727	-0.034627	1.000000	-0.120602	-0.121583	0.591045	0.039511	-0.247353	-0.260388	-0.297391
temp	0.334315	0.047604	-0.028556	-0.120602	1.000000	0.991702	0.126963	-0.157944	0.543285	0.540012	0.627494

```
import seaborn as sns
sns.heatmap(corr) # this will give us a basic heat map
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b536e217c0>
```

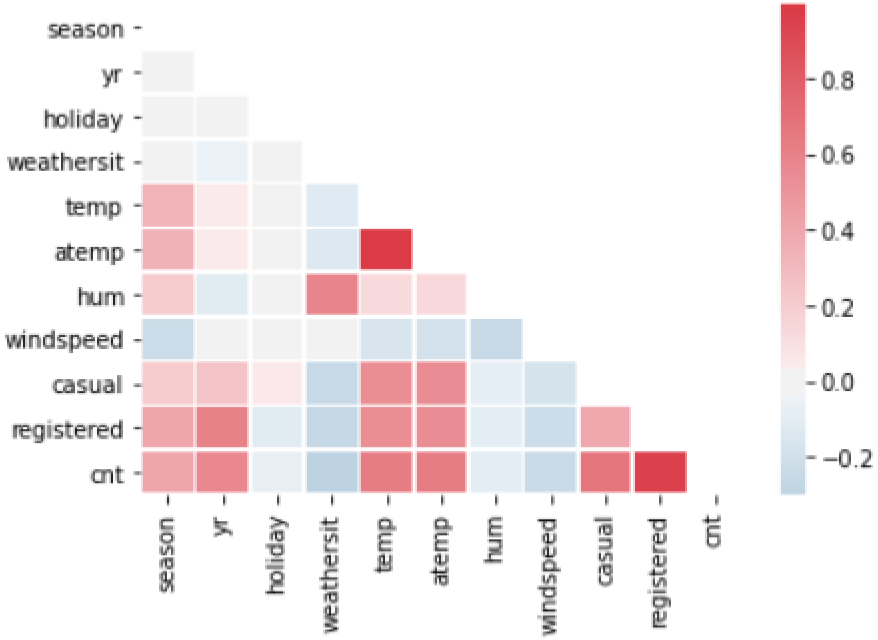



```
labels = {
    'season': 'season',
    'year': 'year',
    'holiday': 'holiday',
    'weathersit': 'weathersit',
    'temperature': 'temparature',
    'atemp': 'atemp',
    'humidity': 'humidity',
    'windspees': 'windspeed',
    'casual': 'casual',
    'registered': 'registered',
    'count': 'count'
}

corr = corr.rename(labels)
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
cmap = sns.diverging_palette(240, 10, as_cmap=True)

sns.heatmap(corr, mask=mask, linewidths=.5, cmap=cmap, center=0)
```

<matplotlib.axes._subplots.AxesSubplot at 0x1b536ee1d60>



Conclusion:

In general, it was seen that the number of registered users was overall higher compared to that of casual users. Specifically when classified by working days it was found that more number of registered bikes were rented on occasions when it was neither a weekend nor a holiday as compared to casual bike rentals which were more during situations (1) when it could have been a weekend or a holiday. This possibly helps us to have an understanding of purpose and type of bike rentals. Registered users might use bikes on a daily basis, example for work or other day to day activities where as casual bike rentals are associated with holiday and leisure.

The highest number of bike rentals were between the months of June and August, whereas the lowest number of bike rentals were between the months November and February. This gives us an indication about the role of corresponding seasons associated with these months. Irrespective of the type of bike rental the temperature (real) was equally correlated with both casual and registered rentals. However, one important thing to mention again is that the registered users were higher overall compared to casual users, hence the results could be biased or misleading, but overall it seems like temperature plays an important role for total count.