Capital Bike Share

March 24, 2019

0.1 Introduction

Bike sharing systems are a means of renting bicycles where the process of obtaining membership, rental, and bike return is automated via a network of kiosk locations throughout a city. Using these systems, people are able rent a bike from a one location and return it to a different place on an as-needed basis. Currently, there are over 500 bike-sharing programs around the world.

The data generated by these systems makes them attractive for researchers because the duration of travel, departure location, arrival location, and time elapsed is explicitly recorded. Bike sharing systems therefore function as a sensor network, which can be used for studying mobility in a city. In this competition, participants are asked to combine historical usage patterns with weather data in order to forecast bike rental demand in the Capital Bikeshare program in Washington, D.C.

Evaluation: Submissions are evaluated one the Root Mean Squared Logarithmic Error (RMSLE

0.1.1 Data

datetime - hourly date + timestamp
season - 1 = spring, 2 = summer, 3 = fall, 4 = winter
holiday - whether the day is considered a holiday
workingday - whether the day is neither a weekend nor holiday
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 - "feels like" temperature in Celsius
humidity - relative humidity
windspeed - wind speed
casual - number of non-registered user rentals initiated
registered - number of registered user rentals initiated
count - number of total rentals

Importing libraries

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from pandas.io.json import json_normalize
```

```
import scipy.stats as stats
import pylab
from numpy.random import seed
from numpy.random import randn
from scipy.stats import shapiro
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_log_error
%matplotlib inline
```

Importing datasets

```
In [2]: train = pd.read_csv("train.csv")
        test = pd.read_csv("test.csv")
```

```
In [3]: print(f'Shape of train dataset: {str(train.shape)}')
        print(f'Shape of test dataset: {str(test.shape)}')
```

```
Shape of train dataset: (10886, 12)
Shape of test dataset: (6493, 9)
```

```
In [4]: train.head()
```

```
Out[4]:               datetime  season  holiday  workingday  weather  temp   atemp  \
        0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
        1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
        2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
        3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
        4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

           humidity  windspeed  casual  registered  count
        0        81        0.0       3          13     16
        1        80        0.0       8          32     40
        2        80        0.0       5          27     32
        3        75        0.0       3          10     13
        4        75        0.0       0           1      1
```

```
In [5]: train.describe()
```

```
Out[5]:              season       holiday    workingday       weather         temp  \
        count  10886.000000  10886.000000  10886.000000  10886.000000  10886.00000
        mean       2.506614      0.028569      0.680875      1.418427     20.23086
        std        1.116174      0.166599      0.466159      0.633839      7.79159
        min        1.000000      0.000000      0.000000      1.000000      0.82000
        25%        2.000000      0.000000      0.000000      1.000000     13.94000
        50%        3.000000      0.000000      1.000000      1.000000     20.50000
        75%        4.000000      0.000000      1.000000      2.000000     26.24000
        max        4.000000      1.000000      1.000000      4.000000     41.00000
```

```
              atemp     humidity     windspeed        casual    registered  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
mean      23.655084     61.886460     12.799395     36.021955    155.552177
std        8.474601     19.245033      8.164537     49.960477    151.039033
min        0.760000      0.000000      0.000000      0.000000      0.000000
25%       16.665000     47.000000      7.001500      4.000000     36.000000
50%       24.240000     62.000000     12.998000     17.000000    118.000000
75%       31.060000     77.000000     16.997900     49.000000    222.000000
max       45.455000    100.000000     56.996900    367.000000    886.000000

              count
count  10886.000000
mean     191.574132
std      181.144454
min        1.000000
25%       42.000000
50%      145.000000
75%      284.000000
max      977.000000
```

In [6]:
```
def generateColumnInfo(df):
    cls = []
    nullCount = []
    nonNullCount = []
    nullsPct = []
    uniqCount = []
    dataType = []
    for i,col in enumerate(df.columns):
        cls.append(col)
        nullCount.append(df[col].isnull().sum())
        nonNullCount.append(len(df)-df[col].isnull().sum())
        nullsPct.append((df[col].isnull().sum())*(100)/len(df))
        uniqCount.append(df[col].nunique())
        dataType.append(df[col].dtype)

    column_info = pd.DataFrame(
        {'ColumnName': cls,
         'NullCount': nullCount,
         'NonNullCount': nonNullCount,
         'NullPercent': nullsPct,
         'UniqueValueCount': uniqCount,
         'DataType':dataType
        })
    return(column_info)
```

In [7]:
```
generateColumnInfo(train)
```

Out[7]:
```
    ColumnName  NullCount  NonNullCount  NullPercent  UniqueValueCount  \
0     datetime          0         10886          0.0             10886
```

```
1       season          0        10886         0.0                 4
2      holiday          0        10886         0.0                 2
3   workingday          0        10886         0.0                 2
4      weather          0        10886         0.0                 4
5         temp          0        10886         0.0                49
6        atemp          0        10886         0.0                60
7     humidity          0        10886         0.0                89
8    windspeed          0        10886         0.0                28
9       casual          0        10886         0.0               309
10  registered          0        10886         0.0               731
11       count          0        10886         0.0               822

   DataType
0    object
1     int64
2     int64
3     int64
4     int64
5   float64
6   float64
7     int64
8   float64
9     int64
10    int64
11    int64
```

In [8]:
```python
generateColumnInfo(test)
```

Out[8]:
```
  ColumnName  NullCount  NonNullCount  NullPercent  UniqueValueCount DataType
0   datetime          0          6493          0.0              6493   object
1     season          0          6493          0.0                 4    int64
2    holiday          0          6493          0.0                 2    int64
3 workingday          0          6493          0.0                 2    int64
4    weather          0          6493          0.0                 4    int64
5       temp          0          6493          0.0                49  float64
6      atemp          0          6493          0.0                65  float64
7   humidity          0          6493          0.0                79    int64
8  windspeed          0          6493          0.0                27  float64
```

Train contains 3 additional columns : casual, registered and count. There are no null values. We will start by converting the text column "datetime" to datetime type. We will extract the date related columns and drop the original column from the train set. We need to retain the datetime column on the test set as it is required to submit the results.

In [9]:
```python
train['date'] = pd.to_datetime(train['datetime'],format='%Y-%m-%d')
train.drop(['datetime'],axis=1,inplace=True)
train['date_year'],train['date_month'],train['date_day'],train['date_weekday'],train['
train['weekday_name'] = train['date'].dt.weekday_name
```

```
test['date'] = pd.to_datetime(test['datetime'],format='%Y-%m-%d')
test['date_year'],test['date_month'],test['date_day'],test['date_weekday'],test['date_
```

In [10]:
```
train.head()
```

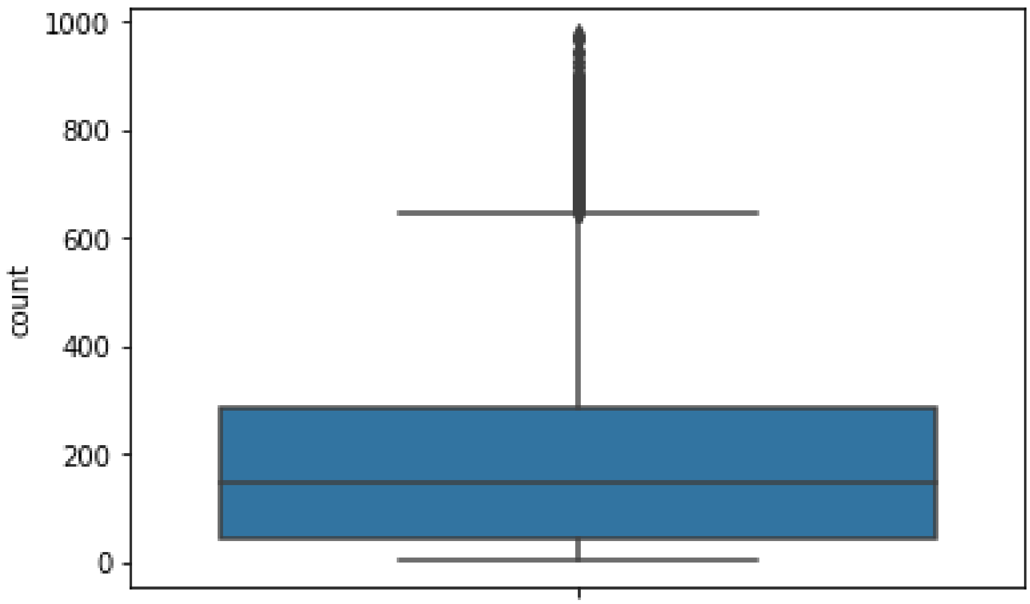
Out[10]:
```
   season  holiday  workingday  weather  temp   atemp  humidity  windspeed  \
0       1        0           0        1  9.84  14.395        81        0.0
1       1        0           0        1  9.02  13.635        80        0.0
2       1        0           0        1  9.02  13.635        80        0.0
3       1        0           0        1  9.84  14.395        75        0.0
4       1        0           0        1  9.84  14.395        75        0.0

   casual  registered  count                date  date_year  date_month  \
0       3          13     16 2011-01-01 00:00:00       2011           1
1       8          32     40 2011-01-01 01:00:00       2011           1
2       5          27     32 2011-01-01 02:00:00       2011           1
3       3          10     13 2011-01-01 03:00:00       2011           1
4       0           1      1 2011-01-01 04:00:00       2011           1

   date_day  date_weekday  date_hour weekday_name
0         1             5          0     Saturday
1         1             5          1     Saturday
2         1             5          2     Saturday
3         1             5          3     Saturday
4         1             5          4     Saturday
```

0.1.2 Distribution of dependant variable

We see many outliers (3ŒIQR) in the boxplot.

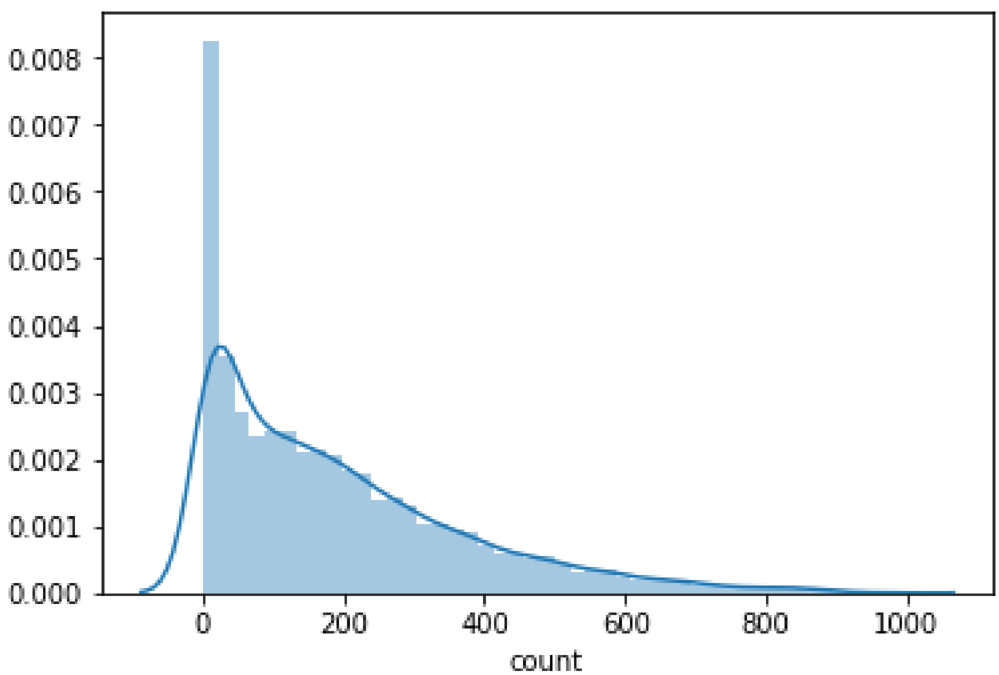
In [11]:
```
sns.boxplot(train['count'],orient='v')
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xfb0ed9470>
```

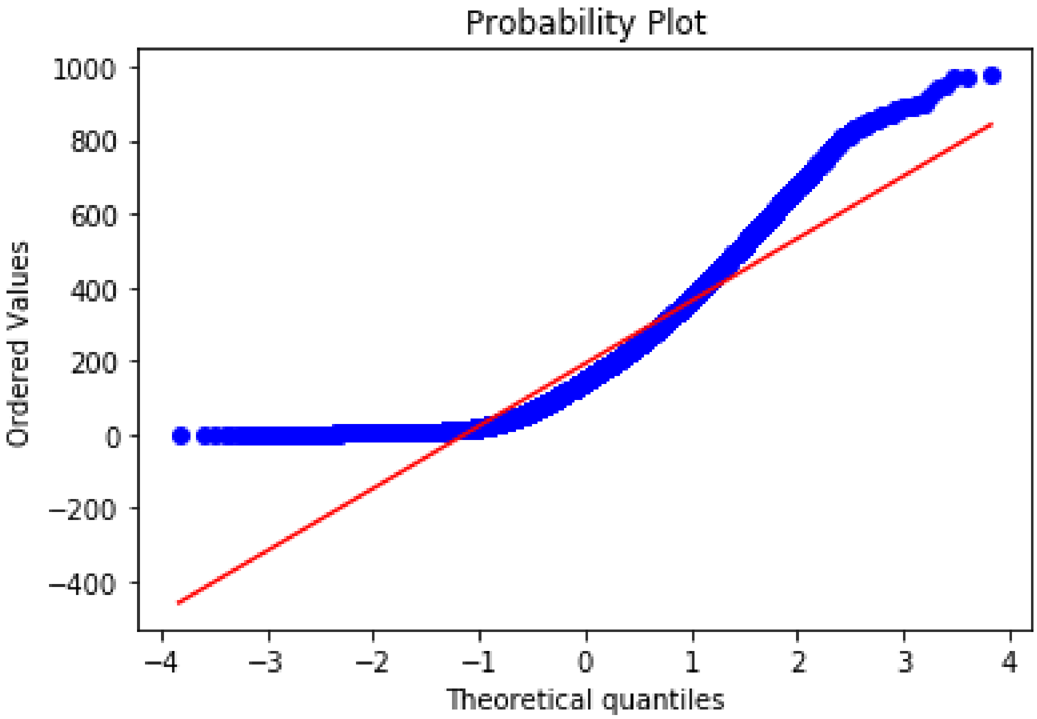


In [12]: sns.distplot(train['count'])

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xfb1219c18>



```
In [13]: measurements = np.random.normal(loc = 20, scale = 5, size=100)
         stats.probplot(train['count'], dist="norm", plot=pylab)
         pylab.show()
```



The 'count' variable has a right skew. Quantile-Quantile plot shows that it is not showing normal distribution. Shapiro-Wilk's test confirms this behavior.

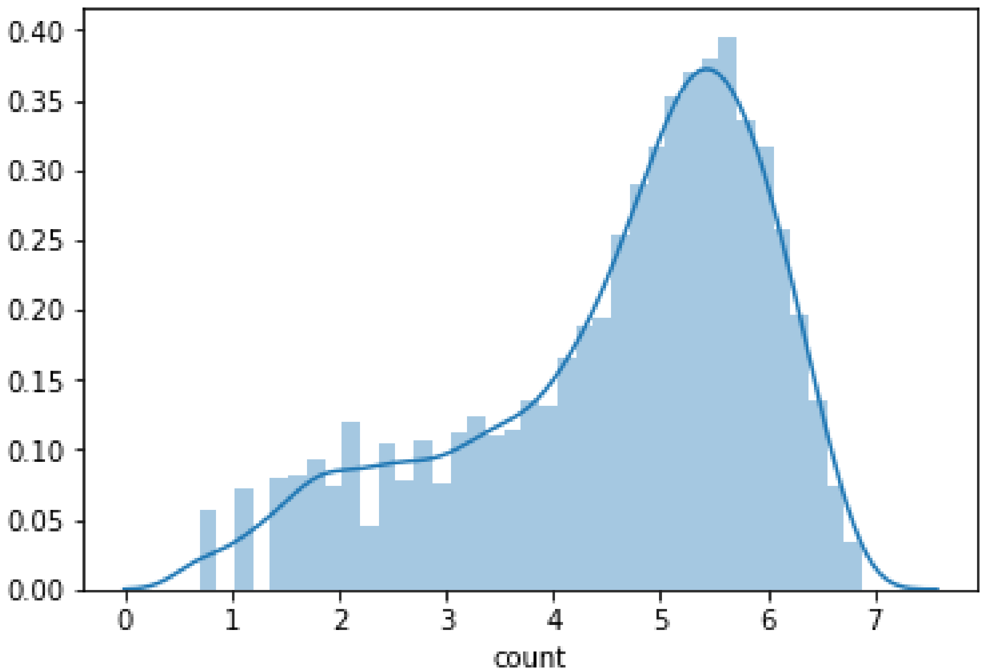
```
In [14]: #ShapiroWilk test
         stat, p = shapiro(train['count'])
         print('p=%.3f' % (p)) #Normal if p>0.1
```

```
p=0.000
```

```
D:\Anaconda\lib\site-packages\scipy\stats\morestats.py:1310: UserWarning: p-value may not be ac
  warnings.warn("p-value may not be accurate for N > 5000.")
```

Log transformation of the dependant variable improves the distribution. I will use the log transformation for statistical modeling.

```
In [15]: sns.distplot(np.log1p(train['count']))

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0xfb155d780>
```



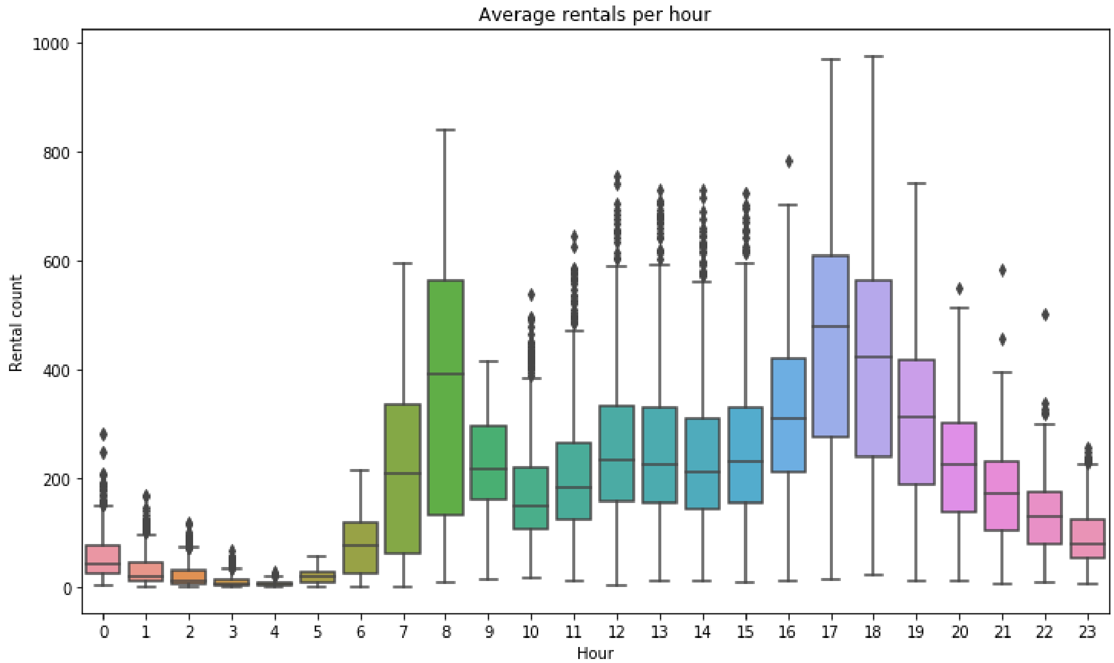
0.2 Exploratory data analysis (EDA)

```
In [16]: #creating additional dataframe for EDA
         byUserType = train.drop(['count'],axis=1)
         byUserType = pd.melt(byUserType,id_vars = ['season', 'holiday', 'workingday', 'weathe
                'humidity', 'windspeed', 'date',
                'date_year', 'date_month', 'date_day', 'date_weekday', 'date_hour',
                'weekday_name'],value_vars = ['casual', 'registered'],var_name='user_type',valu
```

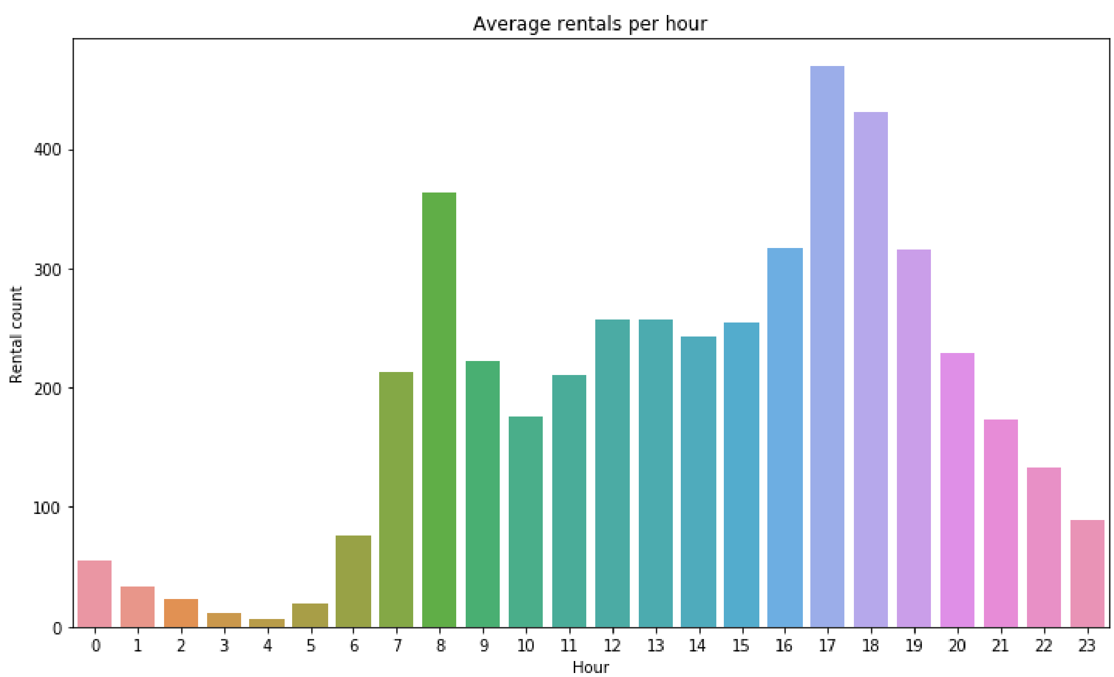
I will analyze each column in this section. I will start with the date/time based columns.

0.2.1 Date Columns

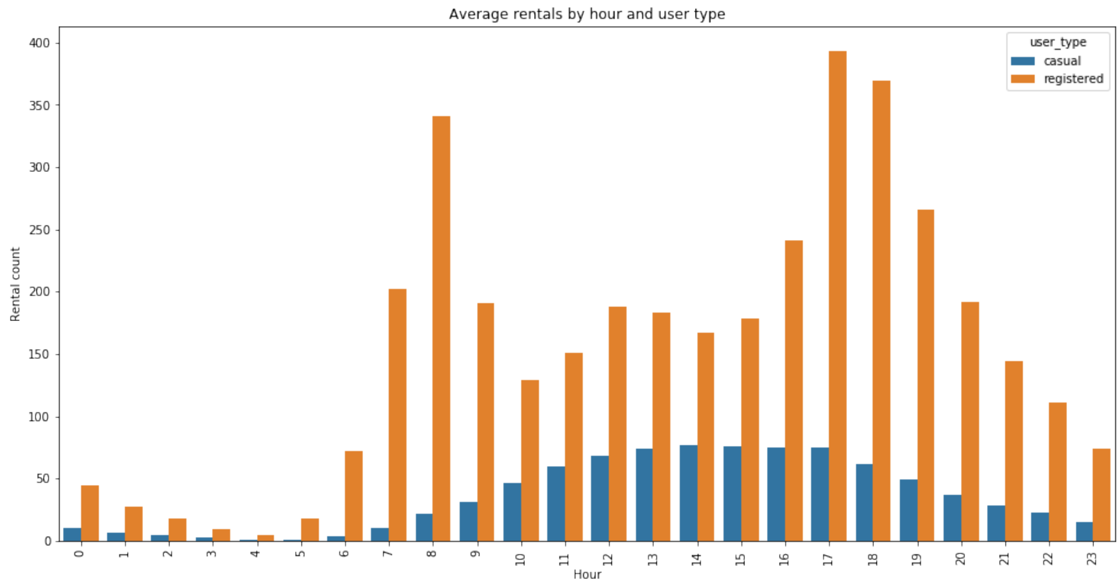
```
In [17]: plt.figure(figsize=(12,7))
         sns.boxplot(data=train, x='date_hour',y='count')
         plt.title('Average rentals per hour')
         plt.xlabel('Hour')
         plt.ylabel('Rental count')
         plt.show()
```



In [18]:
```
plt.figure(figsize=(12,7))
sns.barplot(data=train,x='date_hour',y='count',ci=None)
plt.title('Average rentals per hour')
plt.xlabel('Hour')
plt.ylabel('Rental count')
plt.show()
```



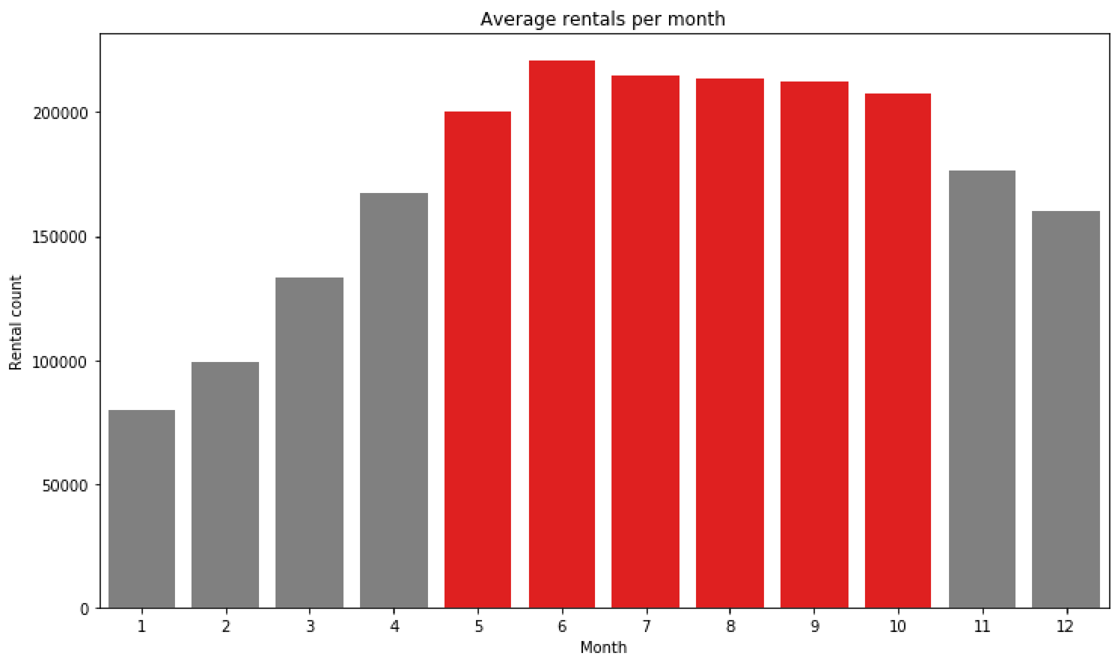
```
In [19]: plt.figure(figsize=(16,8))
         plt.xticks(rotation=90)
         ax = sns.barplot(data=byUserType,x='date_hour',y='user_count',hue='user_type',ci=None)
         plt.title('Average rentals by hour and user type')
         plt.xlabel('Hour')
         plt.ylabel('Rental count')
         plt.show()
```



Demand is relatively high between 7am-9am and 4pm-7pm. This high demand is fueled by registered users. The demand from casual users is high between 11am-5pm. This could be attributed to the visitors and it coincides with the timings of major tourist attractions in the DC area.

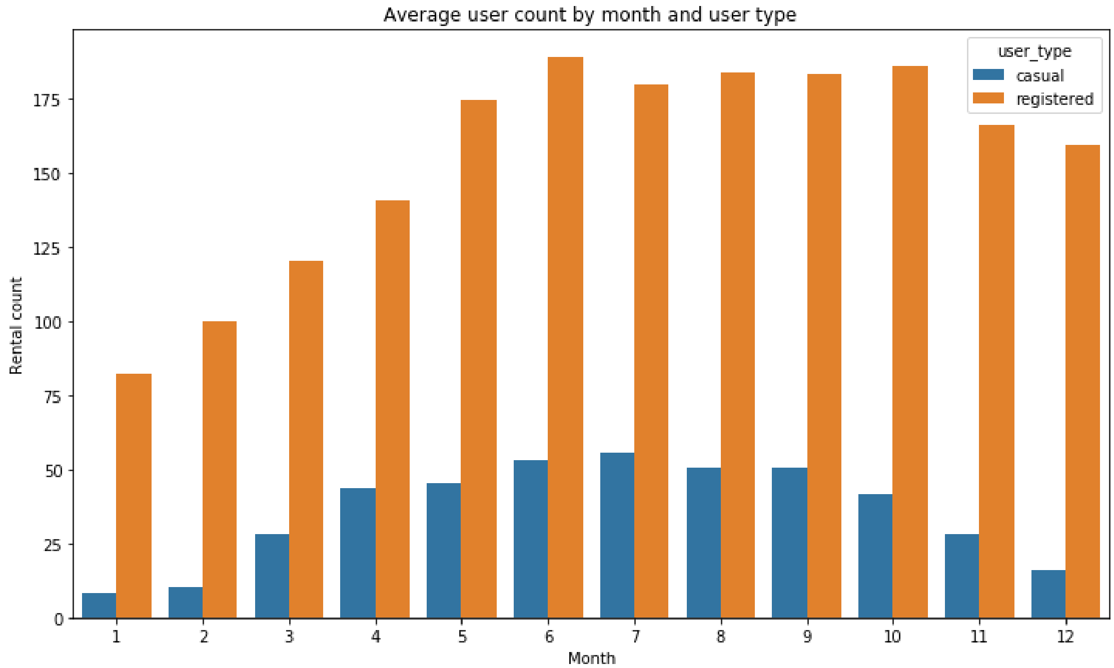
```
In [20]: plt.figure(figsize=(12,7))
         countByMonth = train.groupby(['date_month'],as_index=False).sum()[['date_month','coun
         ids = countByMonth['date_month']
         values = countByMonth['count']
         plt.figure(figsize=(12,7))
         clrs = ['grey' if (x < 180000) else 'red' for x in values ]
         sns.barplot(x=ids,y=values,ci=None,palette=clrs)
         plt.title('Average rentals per month')
         plt.xlabel('Month')
         plt.ylabel('Rental count')
         plt.show()
```

```
<Figure size 864x504 with 0 Axes>
```

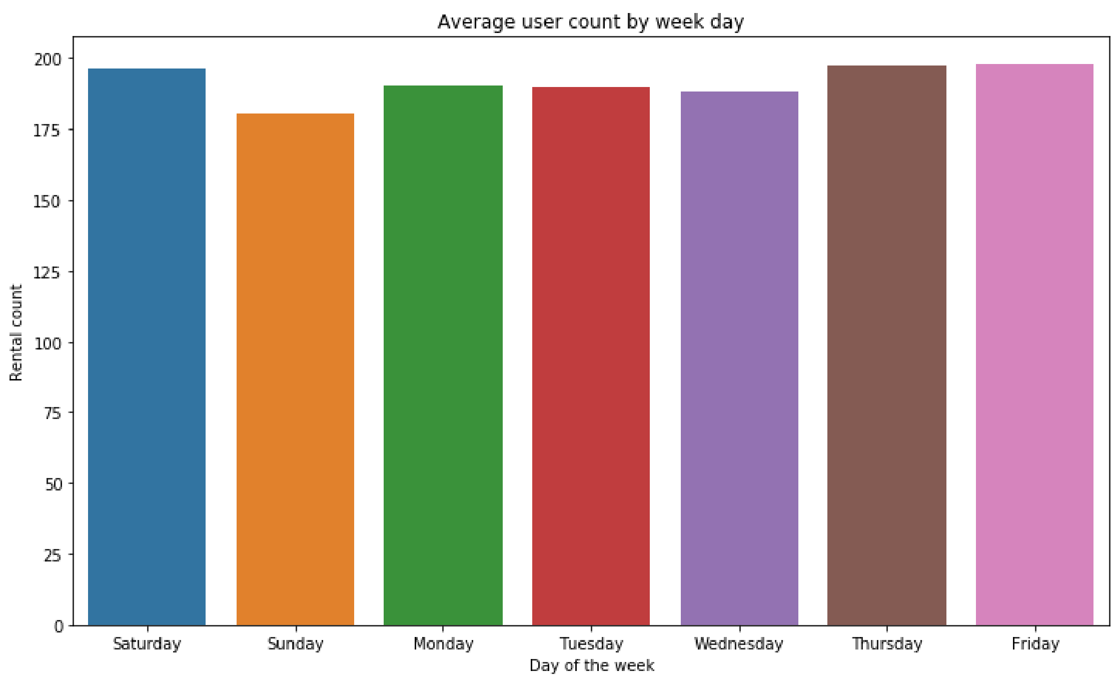


Demand is high during the summer months (May to October). Both registered and casual riders show the same behavior.

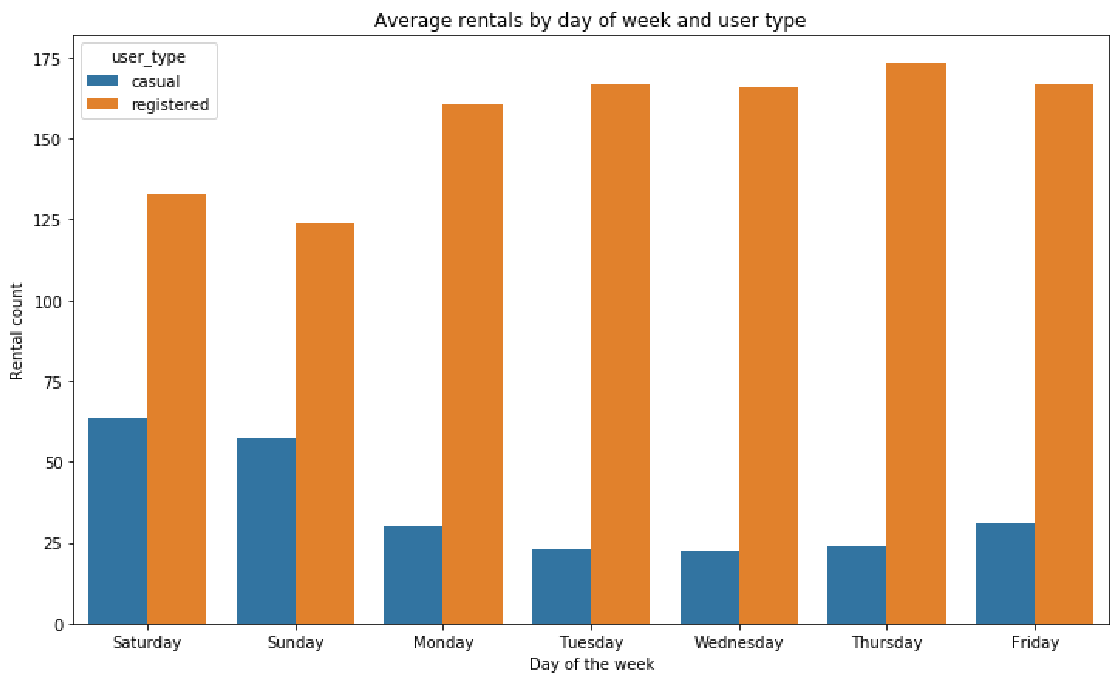
```
In [21]: plt.figure(figsize=(12,7))
         sns.barplot(data=byUserType,x='date_month',y='user_count',hue='user_type',ci=None)
         plt.title('Average user count by month and user type')
         plt.xlabel('Month')
         plt.ylabel('Rental count')
         plt.show()
```




```
In [22]: plt.figure(figsize=(12,7))
         sns.barplot(data=train,x='weekday_name',y='count',ci=None)
         plt.title('Average user count by week day')
         plt.xlabel('Day of the week')
         plt.ylabel('Rental count')
         plt.show()
```

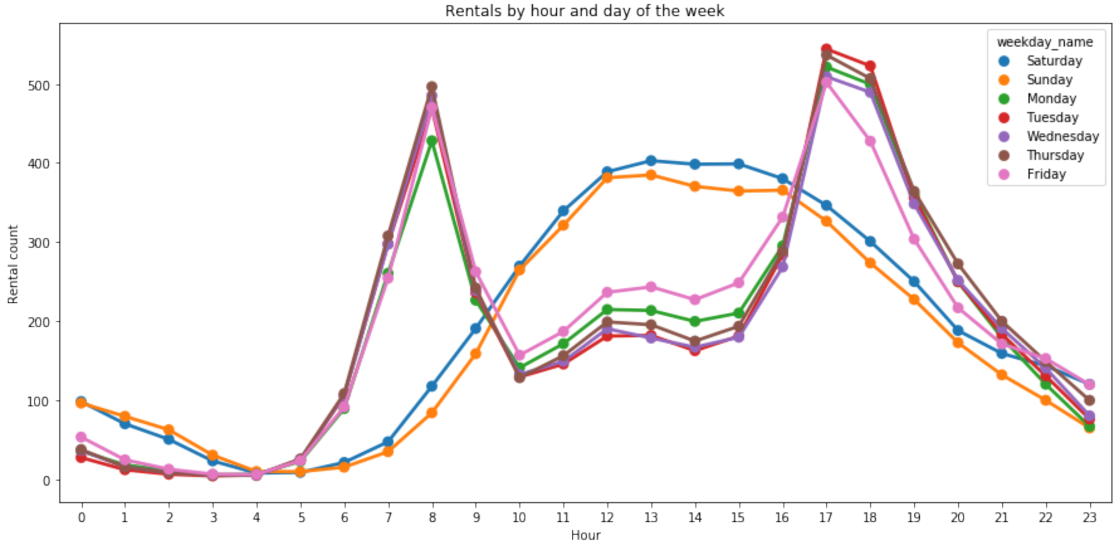


In [23]:
```
plt.figure(figsize=(12,7))
sns.barplot(data=byUserType,x='weekday_name',y='user_count',hue='user_type',ci=None)
plt.title('Average rentals by day of week and user type')
plt.xlabel('Day of the week')
plt.ylabel('Rental count')
plt.show()
```



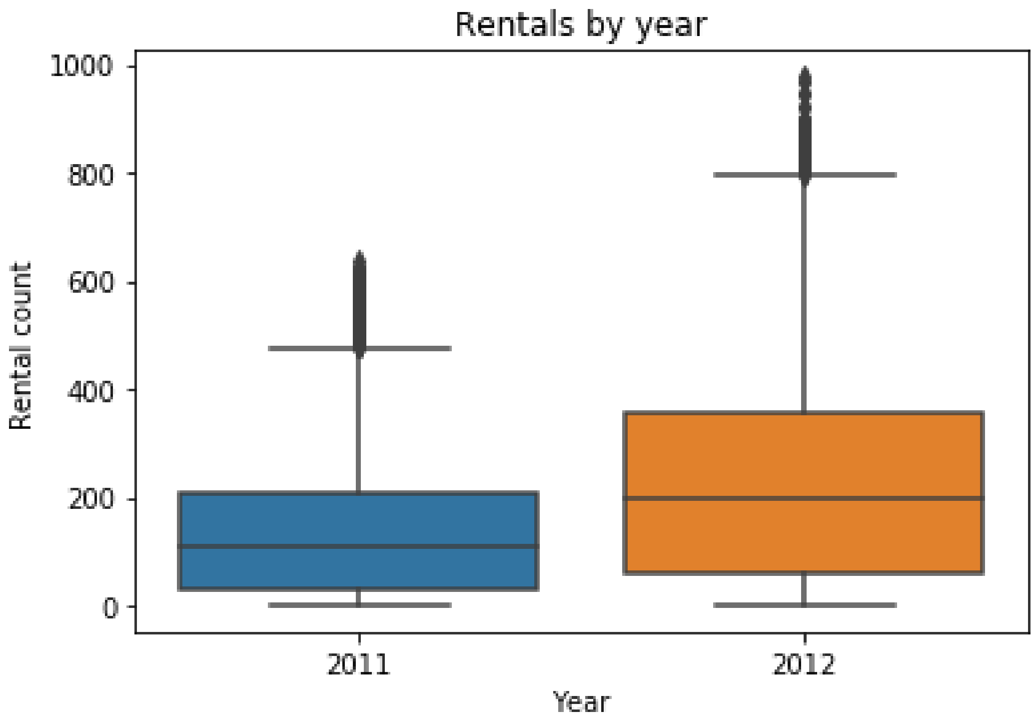
- Demand from registered users is higher on weekdays.
- Demand from casual users is higher on weekends.

In [24]:
```
plt.figure(figsize=(15,7))
sns.pointplot(data=train,x='date_hour',y='count',hue='weekday_name',ci=None)
plt.title('Rentals by hour and day of the week')
plt.xlabel('Hour')
plt.ylabel('Rental count')
plt.show()
```

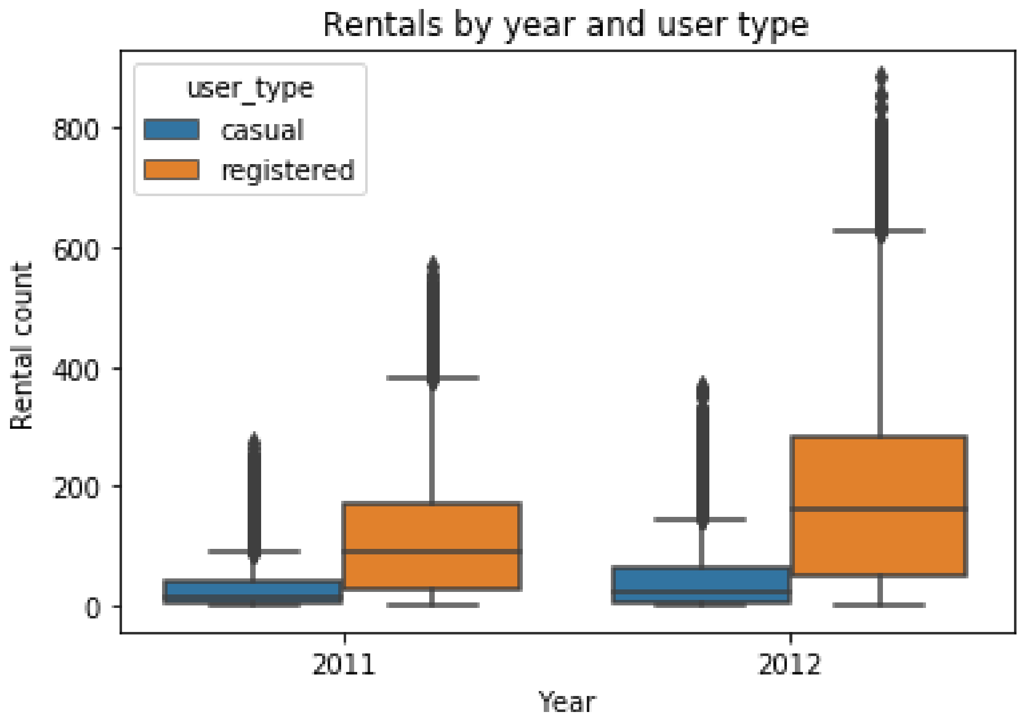


- There is a significant difference in the demand between weekdays and weekends.
- On weekdays, the peak demand is during commuting hours (7am-9am) and (4pm-7pm).
- On weekends, the peak demand is betwwen noon and 4pm.

In [25]:
```
sns.boxplot(data=train,x='date_year',y='count')
plt.title('Rentals by year')
plt.xlabel('Year')
plt.ylabel('Rental count')
plt.show()
```



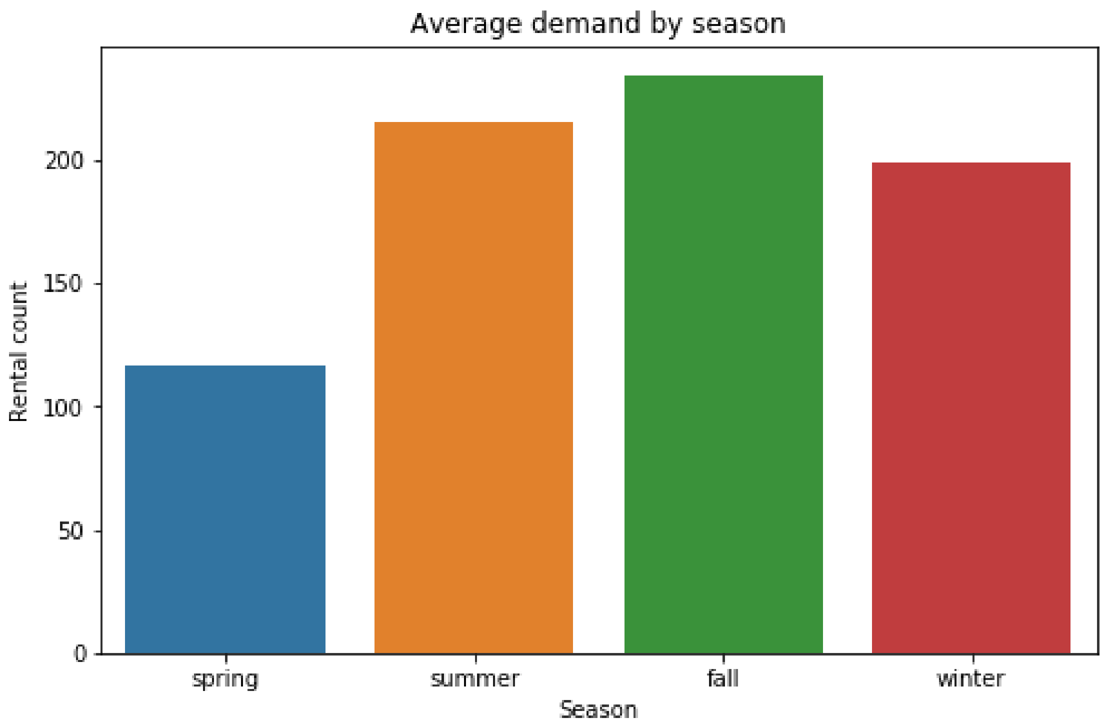

```
In [26]: sns.boxplot(data=byUserType,x='date_year',y='user_count',hue="user_type")
         plt.title('Rentals by year and user type')
         plt.xlabel('Year')
         plt.ylabel('Rental count')

Out[26]: Text(0,0.5,'Rental count')
```



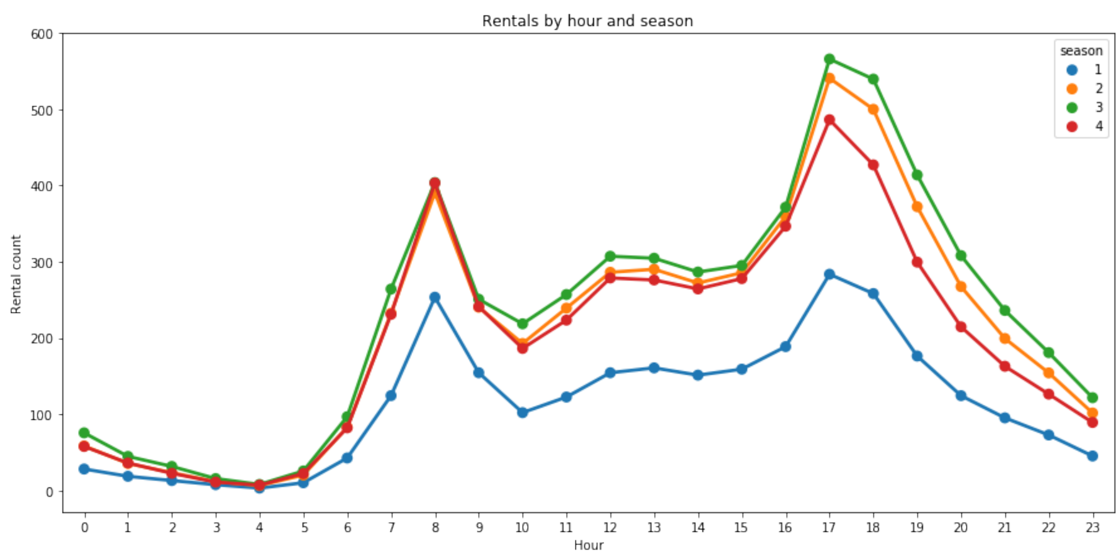
0.2.2 Season

```
In [27]: plt.figure(figsize=(8,5))
         sns.barplot(data=train,x='season',y='count',ci=None)
         ax = plt.axes()
         plt.xticks(rotation=0)
         ax.set_xticklabels(['spring','summer','fall','winter'])
         plt.title('Average demand by season')
         plt.xlabel('Season')
         plt.ylabel('Rental count')
         plt.show()
```

```
D:\Anaconda\lib\site-packages\matplotlib\cbook\deprecation.py:107: MatplotlibDeprecationWarning
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

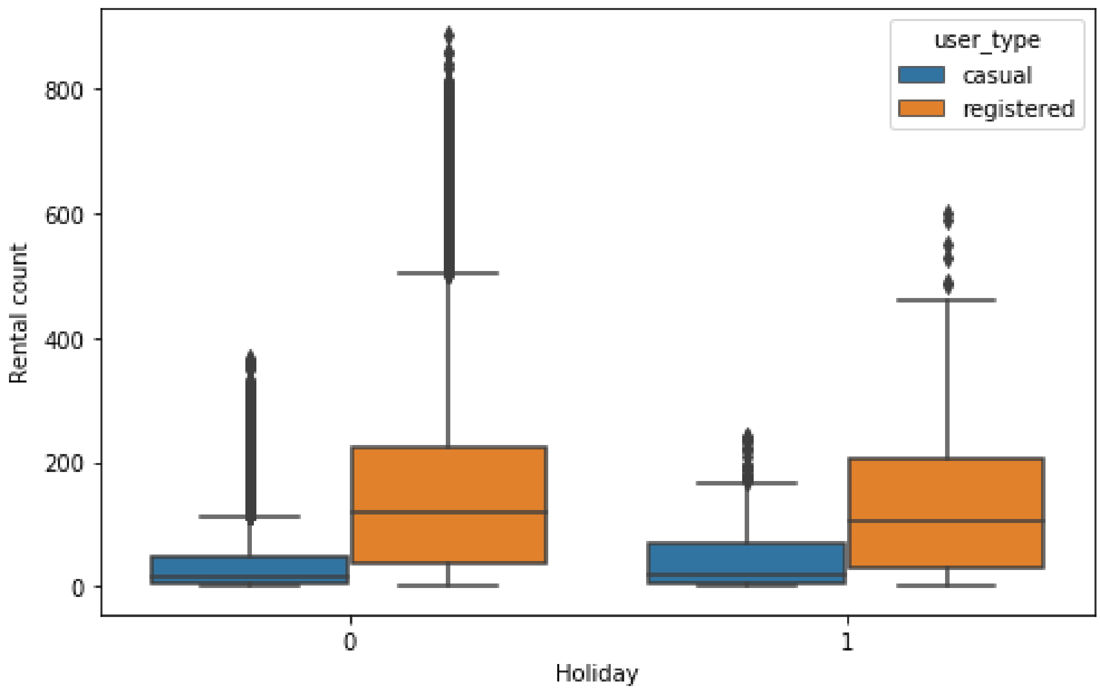



```
In [28]: plt.figure(figsize=(15,7))
         g = sns.pointplot(data=train,x='date_hour',y='count',hue='season',ci=None)
         plt.title('Rentals by hour and season')
         plt.xlabel('Hour')
         plt.ylabel('Rental count')
         plt.show()
```

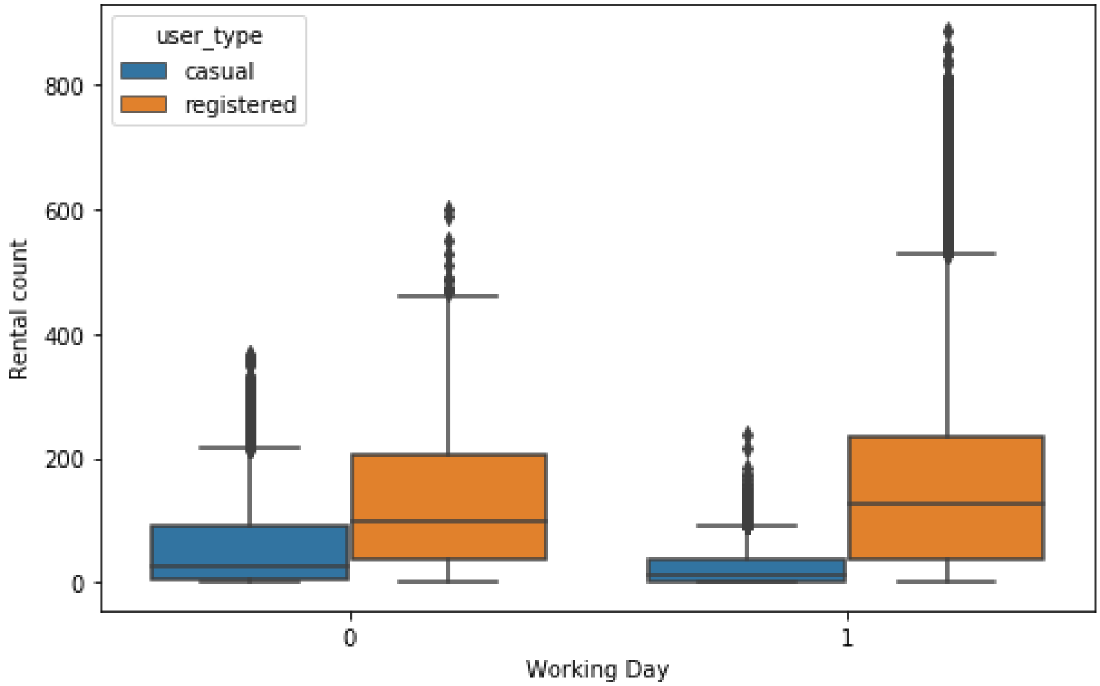


0.2.3 Holiday and Working Days

In [29]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=byUserType,x='holiday',y='user_count',hue='user_type')
plt.xlabel('Holiday')
plt.ylabel('Rental count')
plt.show()
```



In [30]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=byUserType,x='workingday',y='user_count',hue='user_type')
plt.xlabel('Working Day')
plt.ylabel('Rental count')
plt.show()
```

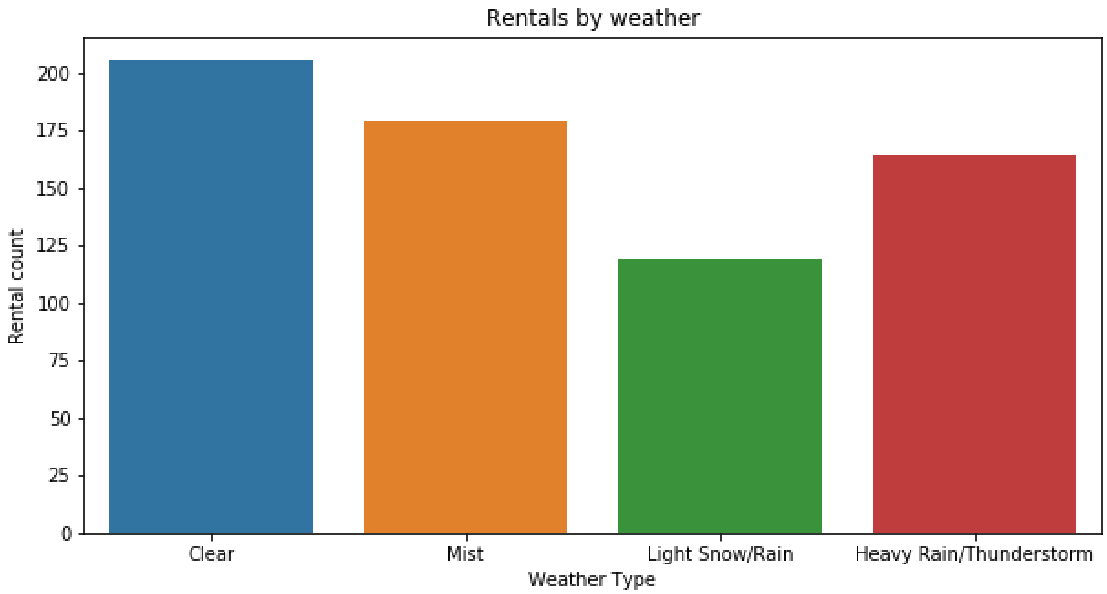


- Demand from registered users is higher during working days
- Demand from casual users is higher during hilidays

0.2.4 Weather

In [31]:
```
plt.figure(figsize=(10,5))
sns.barplot(data=train,x='weather',y='count',ci=None)
plt.title('')
ax = plt.axes()
plt.xticks(rotation=0)
ax.set_xticklabels(['Clear','Mist','Light Snow/Rain','Heavy Rain/Thunderstorm'])
plt.title('Rentals by weather')
plt.xlabel('Weather Type')
plt.ylabel('Rental count')
plt.show()
```

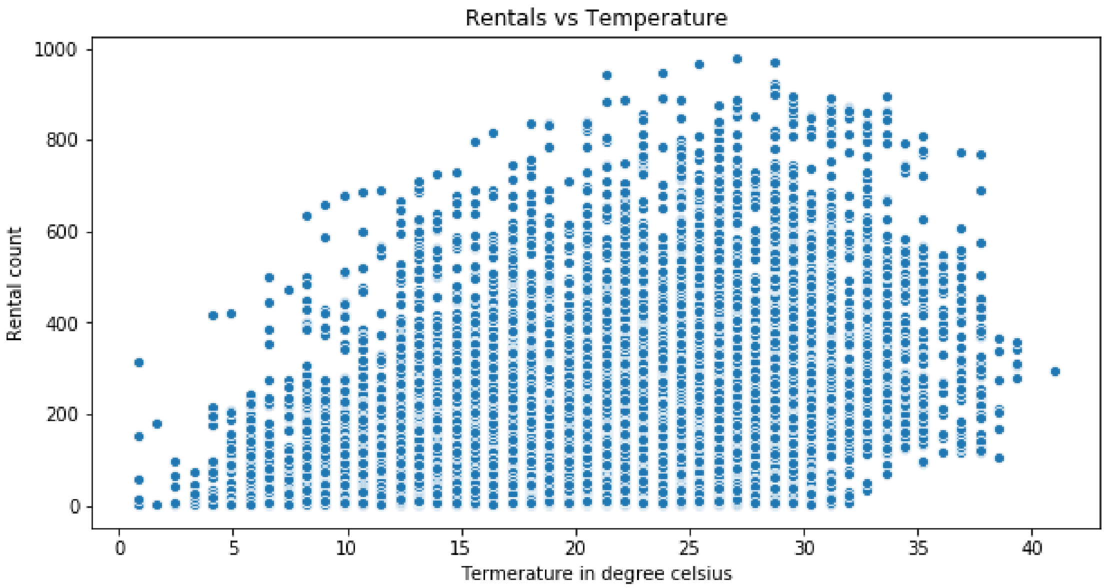
```
D:\Anaconda\lib\site-packages\matplotlib\cbook\deprecation.py:107: MatplotlibDeprecationWarning
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



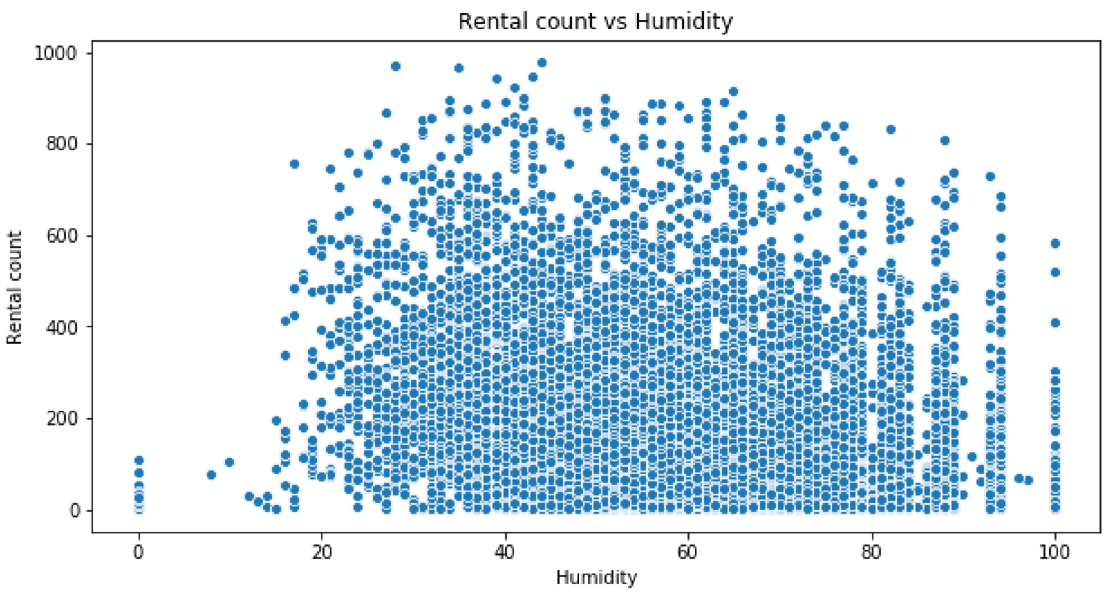
- People prefer to rent bikes during good weather.
- Interestingly, there is higher demand during Heavy Rains and Thunderstorms than during light rain or snow.

0.2.5 Temperature

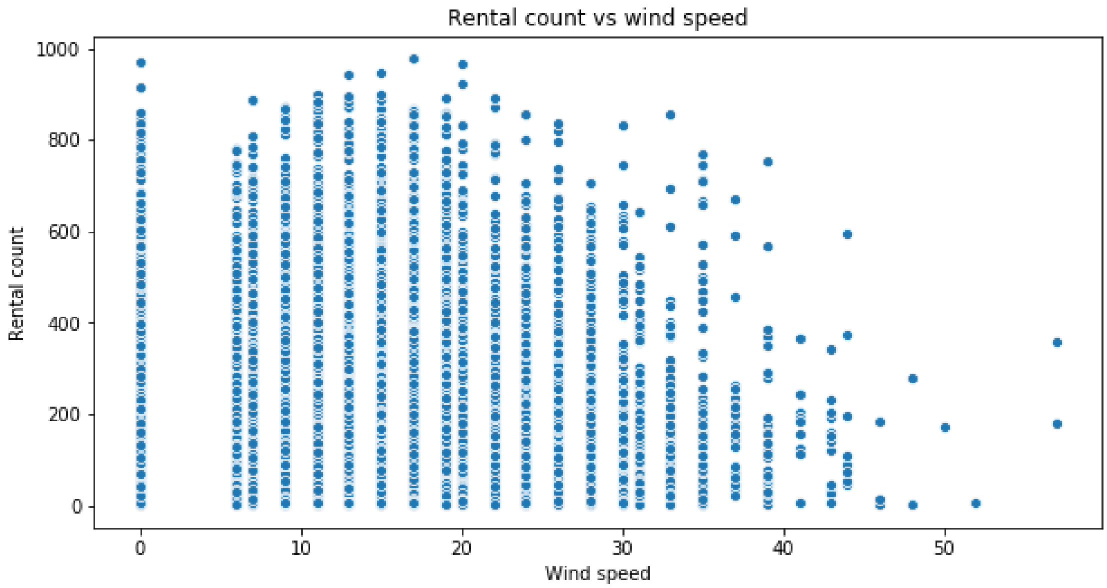
```
In [32]: plt.figure(figsize=(10,5))
         sns.scatterplot(data=train,x='temp',y='count',ci=None)
         plt.title('Rentals vs Temperature')
         plt.xlabel('Termerature in degree celsius')
         plt.ylabel('Rental count')
         plt.show()
```




```
In [33]: plt.figure(figsize=(10,5))
         sns.scatterplot(data=train,x='humidity',y='count',ci=None)
         plt.title('Rental count vs Humidity')
         plt.xlabel('Humidity')
         plt.ylabel('Rental count')
         plt.show()
```



```
In [34]: plt.figure(figsize=(10,5))
         sns.scatterplot(data=train,x='windspeed',y='count',ci=None)
         plt.title('Rental count vs wind speed')
         plt.xlabel('Wind speed')
         plt.ylabel('Rental count')
         plt.show()
```




```
In [35]: train.drop(['weekday_name'],inplace=True,axis=1)
```

0.3 Feature Engineering

```
In [36]: generateColumnInfo(train)
```

Out[36]:

	ColumnName	NullCount	NonNullCount	NullPercent	UniqueValueCount	\
0	season	0	10886	0.0	4	
1	holiday	0	10886	0.0	2	
2	workingday	0	10886	0.0	2	
3	weather	0	10886	0.0	4	
4	temp	0	10886	0.0	49	
5	atemp	0	10886	0.0	60	
6	humidity	0	10886	0.0	89	
7	windspeed	0	10886	0.0	28	
8	casual	0	10886	0.0	309	
9	registered	0	10886	0.0	731	
10	count	0	10886	0.0	822	
11	date	0	10886	0.0	10886	
12	date_year	0	10886	0.0	2	
13	date_month	0	10886	0.0	12	

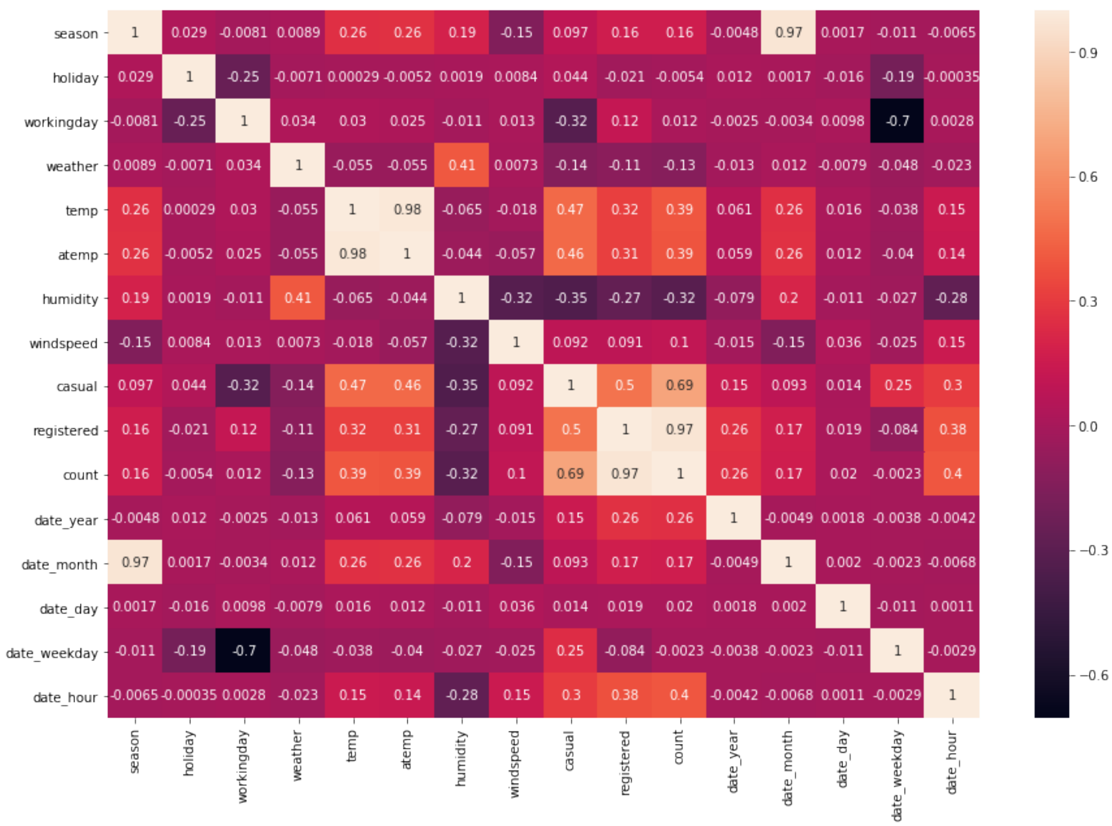
```
14       date_day          0        10886          0.0                19
15   date_weekday          0        10886          0.0                 7
16      date_hour          0        10886          0.0                24

          DataType
0            int64
1            int64
2            int64
3            int64
4          float64
5          float64
6            int64
7          float64
8            int64
9            int64
10           int64
11  datetime64[ns]
12           int64
13           int64
14           int64
15           int64
16           int64
```

In [37]:
```
generateColumnInfo(test)
```

Out[37]:
```
      ColumnName  NullCount  NonNullCount  NullPercent  UniqueValueCount  \
0       datetime          0          6493          0.0              6493
1         season          0          6493          0.0                 4
2        holiday          0          6493          0.0                 2
3     workingday          0          6493          0.0                 2
4        weather          0          6493          0.0                 4
5           temp          0          6493          0.0                49
6          atemp          0          6493          0.0                65
7       humidity          0          6493          0.0                79
8      windspeed          0          6493          0.0                27
9           date          0          6493          0.0              6493
10     date_year          0          6493          0.0                 2
11    date_month          0          6493          0.0                12
12      date_day          0          6493          0.0                12
13  date_weekday          0          6493          0.0                 7
14     date_hour          0          6493          0.0                24

          DataType
0           object
1            int64
2            int64
3            int64
4            int64
```

```
5          float64
6          float64
7            int64
8          float64
9   datetime64[ns]
10           int64
11           int64
12           int64
13           int64
14           int64
```

In [38]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(train.corr(),annot=True)
plt.show()
```



- Date_hour shows the highes correlation with count.
- There is a very high co-relation between season and date_month and temp and atemp.
- I will drop season and atemp columns to avoid multicollinearity.

In [39]:
```python
train.drop(['season','atemp'],inplace=True,axis=1)
test.drop(['season','atemp'],inplace=True,axis=1)
```

One hot encoding "weather"

```
In [40]: train = pd.get_dummies(train, columns=['weather'], prefix=['weather_'])
         test = pd.get_dummies(test, columns=['weather'], prefix=['weather_'])
```

The date column is no longer required.

```
In [41]: train.drop('date',inplace=True,axis=1)
         test.drop('date',inplace=True,axis=1)

In [42]: train['date_year'] = train['date_year'].astype("category")
         train['date_month'] = train['date_month'].astype("category")
         train['date_day'] = train['date_day'].astype("category")
         train['date_weekday'] = train['date_weekday'].astype("category")
         train['date_hour'] = train['date_hour'].astype("category")
```

0.4 Statistical Modeling

```
In [43]: X = train.drop(['count','casual','registered'],axis=1)
         y = train['count']

In [44]: X_train,X_valid, y_train,y_valid = train_test_split(X,y, test_size=0.3,random_state=1

In [45]: res_alg = ['Random Forest','SVR','KNN','GBR','LR']
         res_rmsle = []

In [46]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.svm import SVR
         from sklearn.ensemble import GradientBoostingRegressor
         from sklearn.neighbors import KNeighborsRegressor
         from sklearn.linear_model import LinearRegression
         from sklearn.model_selection import GridSearchCV

In [47]: #Random forest
         rfModel = RandomForestRegressor()
         rfModel.fit(X_train,np.log1p(y_train))
         rfPred = rfModel.predict(X_valid)
         np.sqrt(mean_squared_log_error(np.exp(rfPred),y_valid))
         res_rmsle.append(np.sqrt(mean_squared_log_error(np.exp(rfPred),y_valid)))

In [48]: #Support vector regression
         svrModel = SVR()
         svrModel.fit(X_train,np.log1p(y_train))
         svrPred = svrModel.predict(X_valid)
         res_rmsle.append(np.sqrt(mean_squared_log_error(np.exp(svrPred),y_valid)))

In [49]: #K-nearest neighbors
         knnModel = KNeighborsRegressor()
         knnModel.fit(X_train,np.log1p(y_train))
         knnPred = knnModel.predict(X_valid)
         res_rmsle.append(mean_squared_log_error(np.exp(knnPred),y_valid))
```

```
In [50]: #Gradient boosting regressor
         gbModel = GradientBoostingRegressor()
         gbModel.fit(X_train,np.log1p(y_train))
         gbPred = gbModel.predict(X_valid)
         gbPred = pd.DataFrame(gbPred)
         gbPred = gbPred[0].apply(lambda x:0.0 if x<0 else x)
         res_rmsle.append(np.sqrt(mean_squared_log_error(np.exp(gbPred),y_valid)))
```

```
In [51]: #Linear regression
         lrModel = LinearRegression()
         lrModel.fit(X_train,np.log1p(y_train))
         lrPred = lrModel.predict(X_valid)
         lrPred = pd.DataFrame(lrPred)
         lrPred = lrPred[0].apply(lambda x:0.0 if x<0 else x)
         res_rmsle.append(np.sqrt(mean_squared_log_error(np.exp(lrPred),y_valid)))
```

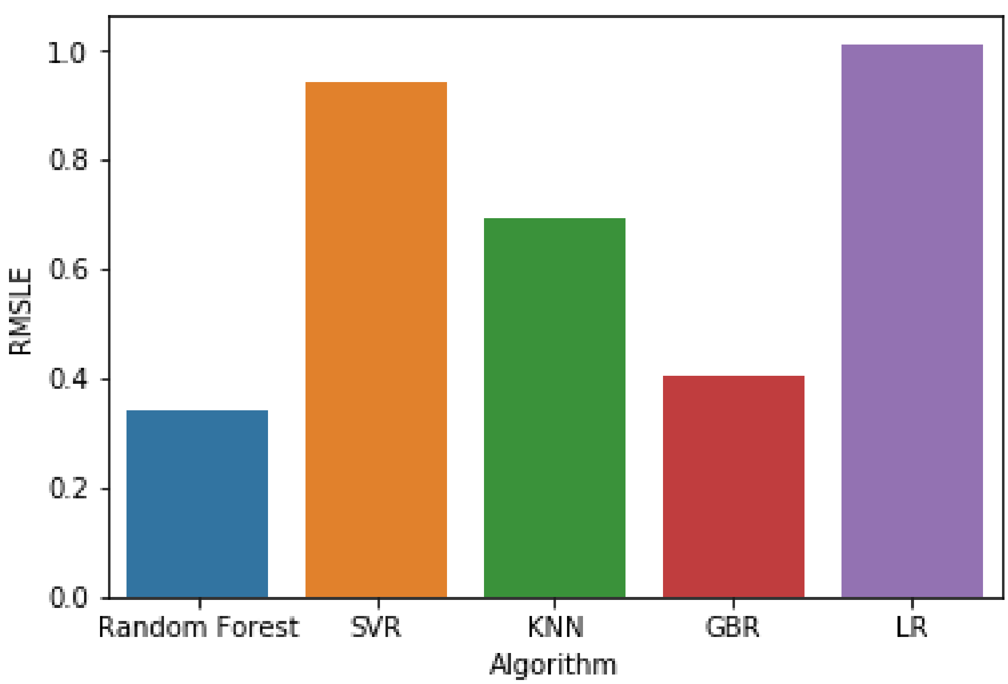
```
In [52]: results = pd.DataFrame({'Algorithm':res_alg,'RMSLE':res_rmsle})
         results.sort_values('RMSLE')
```

Out[52]:

	Algorithm	RMSLE
0	Random Forest	0.338849
3	GBR	0.405260
2	KNN	0.691466
1	SVR	0.942840
4	LR	1.011953

```
In [53]: sns.barplot(data=results,x='Algorithm',y='RMSLE')
```

```
Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0xfb2ec5e80>
```



Random forest gives the lowest RMSLE value. In the next section, I will tune the hyperparameters of the random forest model.

0.5 Tuning

0.5.1 Random Search

I will define a grid of hyperparameters and use Scikit-Learn's RandomizedSearchCV method to randomly sample from the grid, performing K-Fold CV with each combination of values. RandomizedSearchCV will not try every combination, but selects at random to sample a wide range of values.K-Fold CV reduces overfitting. I will try adjusting the following set of hyperparameters:

- n_estimators = number of trees in the foreset
- max_features = max number of features considered for splitting a node
- max_depth = max number of levels in each decision tree
- min_samples_split = min number of data points placed in a node before the node is split
- min_samples_leaf = min number of data points allowed in a leaf node
- bootstrap = method for sampling data points (with or without replacement)

```
In [54]: n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
         max_features = ['auto', 'sqrt']
         max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
         max_depth.append(None)
         min_samples_split = [2, 5, 10]
         min_samples_leaf = [1, 2, 4]
         bootstrap = [True, False]
```

```
In [55]: random_grid = {'n_estimators': n_estimators,
                        'max_features': max_features,
                        'max_depth': max_depth,
                        'min_samples_split': min_samples_split,
                        'min_samples_leaf': min_samples_leaf,
                        'bootstrap': bootstrap}
```

```
In [56]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [57]: rf = RandomForestRegressor()
         rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_i
```

```
In [58]: rf_random.fit(X_train,np.log1p(y_train))
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  7.1min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 11.4min finished
```

```
Out[58]: RandomizedSearchCV(cv=3, error_score='raise',
                   estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=N
                    max_features='auto', max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=1, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                    oob_score=False, random_state=None, verbose=0, warm_start=False),
                   fit_params=None, iid=True, n_iter=100, n_jobs=-1,
                   param_distributions={'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400,
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score='warn', scoring='neg_mean_squared_log_error',
                   verbose=1)
```

```
In [59]: rf_random.best_params_
```

```
Out[59]: {'bootstrap': True,
          'max_depth': 100,
          'max_features': 'auto',
          'min_samples_leaf': 1,
          'min_samples_split': 2,
          'n_estimators': 1400}
```

0.5.2 Grid Search CV

Now that we know the range for each hyperparameter, I will fine tune the hyperparameters with GridSearchCV. GridSearchCV will perform KFold Cross validation on each combination.

```
In [60]: param_grid = {
             'bootstrap': [True],
             'max_depth': [100,120,150],
             'max_features': ['auto'],
             'min_samples_leaf': [1,2],
             'min_samples_split': [2,3,4],
             'n_estimators': [500,800,1000 ]
         }
```

```
In [61]: from sklearn.model_selection import GridSearchCV
```

```
In [62]: rf = RandomForestRegressor()
         rf_grid = GridSearchCV(estimator =rf,param_grid=param_grid,scoring='neg_mean_squared_l
```

```
In [63]: rf_grid.fit(X_train,np.log1p(y_train))
         pred=rf_grid.predict(X_valid)
```

```
Fitting 3 folds for each of 54 candidates, totalling 162 fits


[Parallel(n_jobs=1)]: Done 162 out of 162 | elapsed: 29.6min finished
```

```
In [64]: print((np.sqrt(mean_squared_log_error(np.exp(pred),y_valid))))
```

```
0.317396652773138
```

Tuning has led to a decrease in the RMSLE value. Let us look at the final hyperparameters:

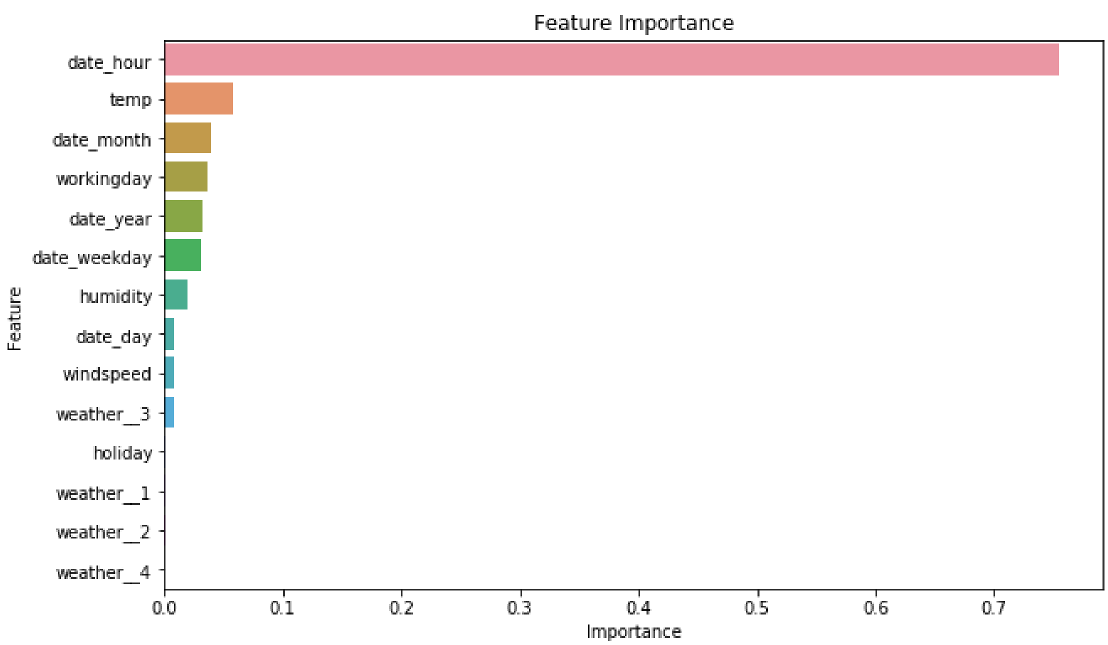
```
In [65]: rf_grid.best_params_
```

```
Out[65]: {'bootstrap': True,
          'max_depth': 150,
          'max_features': 'auto',
          'min_samples_leaf': 1,
          'min_samples_split': 3,
          'n_estimators': 800}
```

```
In [67]: f_imp = pd.DataFrame({'Feature':X_train.columns,'Importance':rf_grid.best_estimator_.i
```

```
In [68]: plt.figure(figsize=(10,6))
         sns.barplot(data=f_imp.sort_values(by='Importance',ascending=False),x='Importance',y=
         plt.title('Feature Importance')
```

```
Out[68]: Text(0.5,1,'Feature Importance')
```



0.6 Generate predictions on Test

```
In [69]: testPred=rf_grid.predict(test.drop('datetime',axis=1))
         testPred= np.exp(testPred)
         d={'datetime':test['datetime'],'count':testPred}
         ans=pd.DataFrame(d)
         ans.to_csv('answer.csv',index=False)
```