In [1]:
```python
#Importing the required libraries
import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns
%matplotlib inline
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn import metrics
import warnings
import os
```

In [2]:
```python
#Changing working directory
os.chdir('C:\\Users\\rakbansal\\Desktop\\Datasets\\Bike sharing')
```

In [3]:
```python
#Defining Column Names and reading in the file
columns= ['instant', 'date','season', 'year', 'month', 'hour','holiday', '
weekday', 'workingday', 'weather', 'temp', 'atemp', 'humidity', 'windspeed
', 'casual', 'registered', 'count']
hours= pd.read_csv("hour.csv")
hours.columns= columns
hours.head()
```

Out[3]:

	instant	date	season	year	month	hour	holiday	weekday	workingday	weather	temp	atemp
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.2879
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.2727
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.2727
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.2879
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.2879

In [4]:
```python
#Let's check the shape and other attributes of the dataset
hours.describe()
```

Out[4]:

	instant	season	year	month	hour	holiday	weekd
count	17379.0000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.0000
mean	8690.0000	2.501640	0.502561	6.537775	11.546752	0.028770	3.0036
std	5017.0295	1.106918	0.500008	3.438776	6.914405	0.167165	2.0057

min	1.0000	1.000000	0.000000	1.000000	0.000000	0.000000	0.0000
25%	4345.5000	2.000000	0.000000	4.000000	6.000000	0.000000	1.0000
50%	8690.0000	3.000000	1.000000	7.000000	12.000000	0.000000	3.0000
75%	13034.5000	3.000000	1.000000	10.000000	18.000000	0.000000	5.0000
max	17379.0000	4.000000	1.000000	12.000000	23.000000	1.000000	6.0000

In [5]:
```
#Let's check the shape
hours.shape
```

Out[5]:
```
(17379, 17)
```

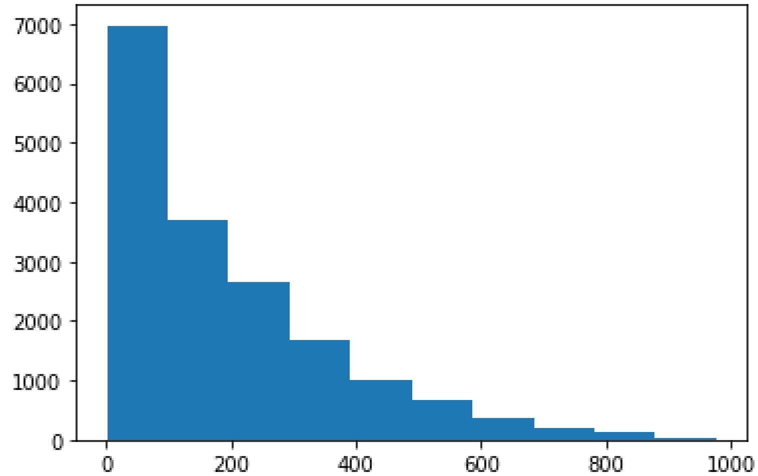
In [6]:
```
#Check if the data has any nulls
hours.isnull().sum()
```

Out[6]:
```
instant       0
date          0
season        0
year          0
month         0
hour          0
holiday       0
weekday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
dtype: int64
```

No nulls here! Let's begin exploring the variables now.

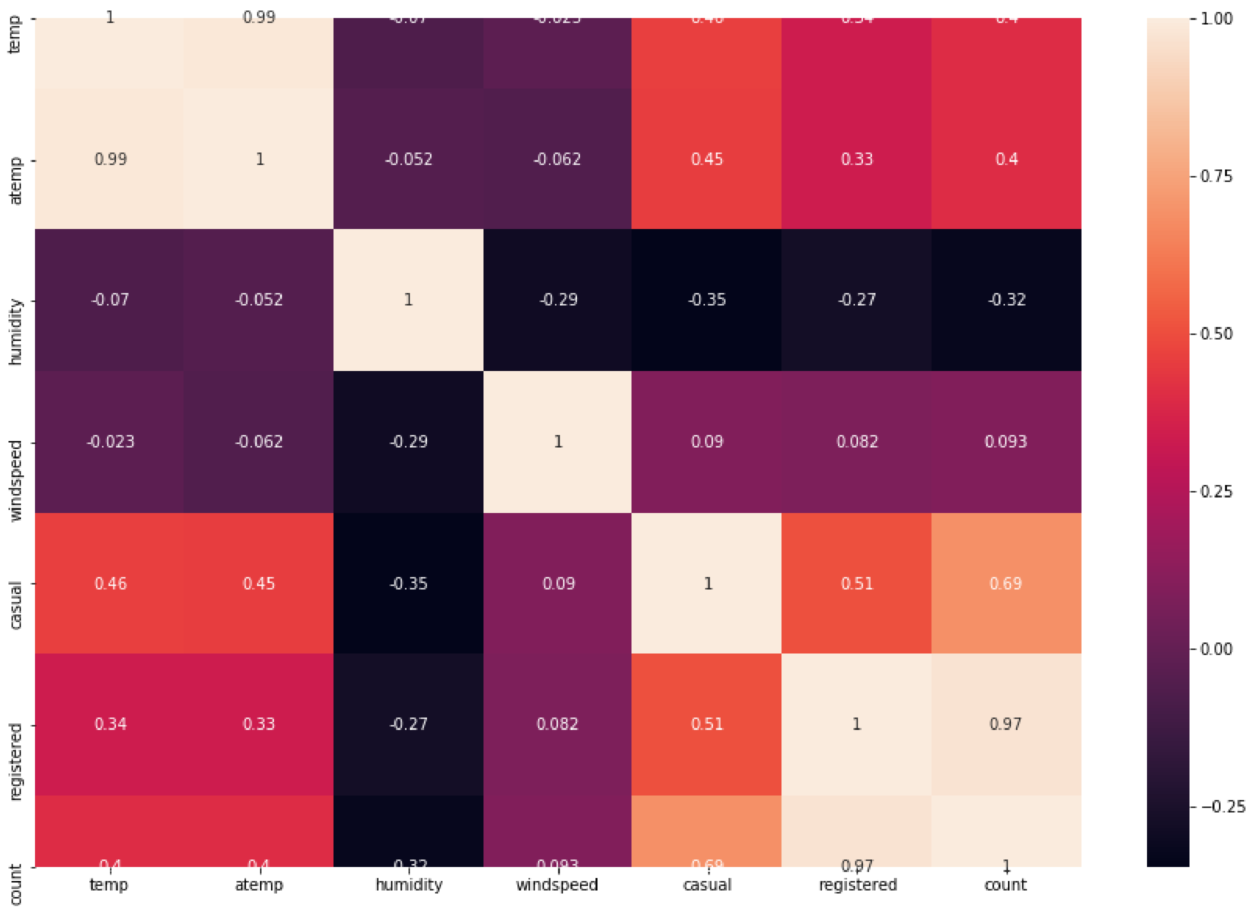
In [7]:
```
#Let's check the distribution of the dependent variable- Count
plt.hist(hours['count'])
```

Out[7]:
```
(array([6972., 3705., 2659., 1660.,  987.,  663.,  369.,  188.,  139.,
          37.]),
 array([  1. ,   98.6, 196.2, 293.8, 391.4, 489. , 586.6, 684.2, 781.8,
        879.4, 977. ]),
 <a list of 10 Patch objects>)
```



It doesn't look normally distributed and has a right skew/positive skew. We can modify it later during the variable transformation phase.

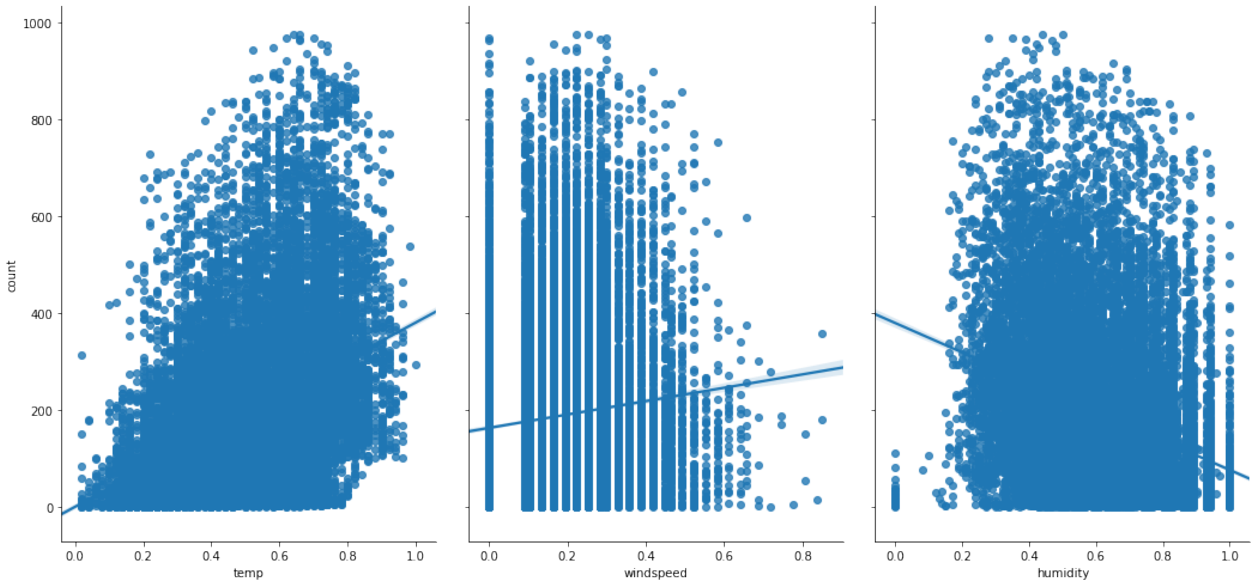
In [8]:
```
#Let's see how other numerical variables are related to the count variable
num_features= hours[['temp', 'atemp', 'humidity', 'windspeed', 'casual', '
registered', 'count']]
plt.figure(figsize=(15,10))
correlation= num_features.corr()
sns.heatmap(correlation, annot= True)
plt.show();
```



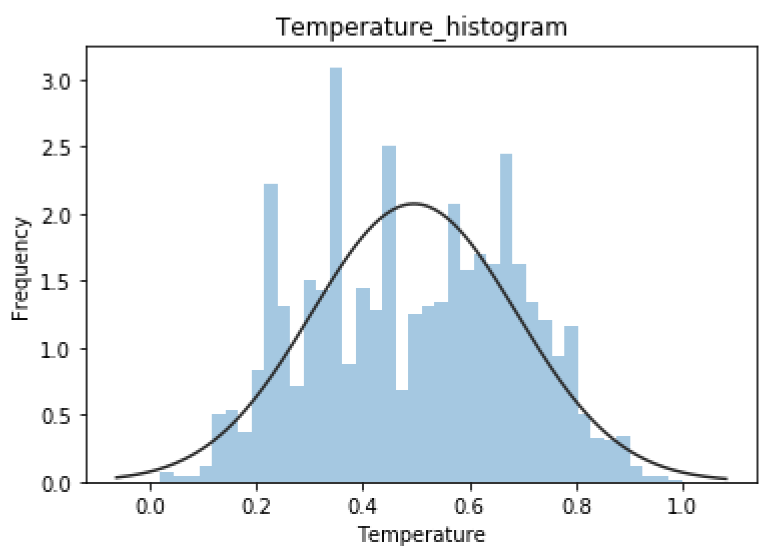
Casual and Registred users do appear to have high correlation to the dependent 'count' variable but that is because count is a summation of both these categories. So, we will ignore this relationship. Another thing to note here is the high correlation between 'temp' and 'atemp' which can introduce multicollinearity in the model. Therefore, we will only consider one varible 'temp' in the model.

In [9]:
```
#Let's see the distribution visually
sns.pairplot(num_features, x_vars= ['temp', 'windspeed', 'humidity'], y_va
rs= 'count', height= 7, aspect=0.7, kind= 'reg')
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x1030ea90>

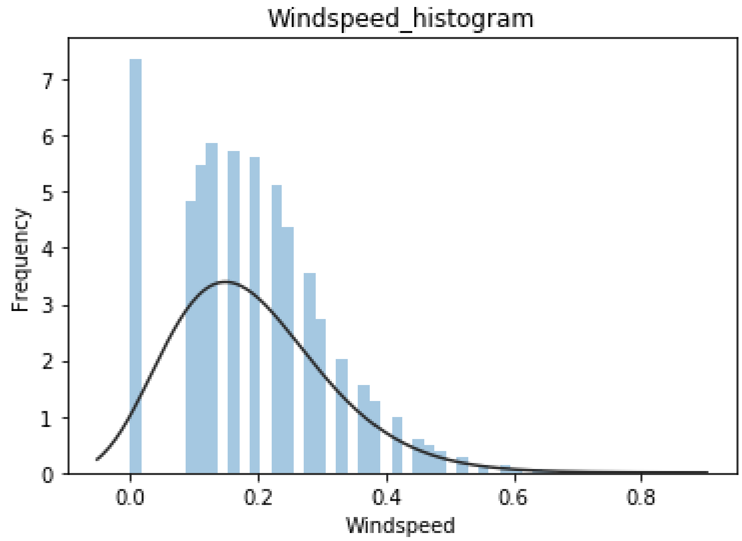


In [10]:
```
#Let's take a look at their distributions individually and check if they a
re normally distributed
#Checking for normality of num features
temp= num_features[['temp']]
sns.distplot(temp, kde=False, fit=stats.gamma)
plt.xlabel('Temperature')
plt.ylabel('Frequency')
plt.title("Temperature_histogram")
plt.show()
```



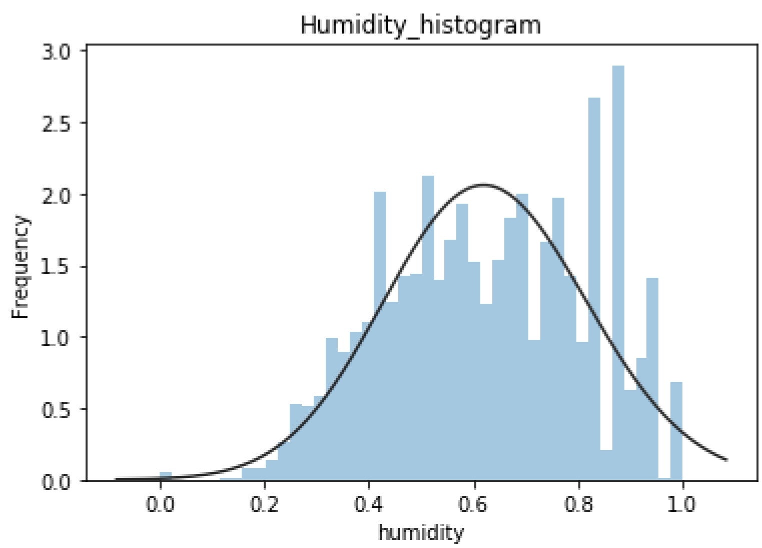
In [11]:
```
windspeed= num_features[['windspeed']]
```

```
sns.distplot(windspeed, kde=False, fit=stats.gamma)
plt.xlabel('Windspeed')
plt.ylabel('Frequency')
plt.title("Windspeed_histogram")
plt.show()
```



In [12]:

```
humidity= num_features[['humidity']]
sns.distplot(humidity, kde=False, fit=stats.gamma)
plt.xlabel('humidity')
plt.ylabel('Frequency')
plt.title("Humidity_histogram")
plt.show()
```



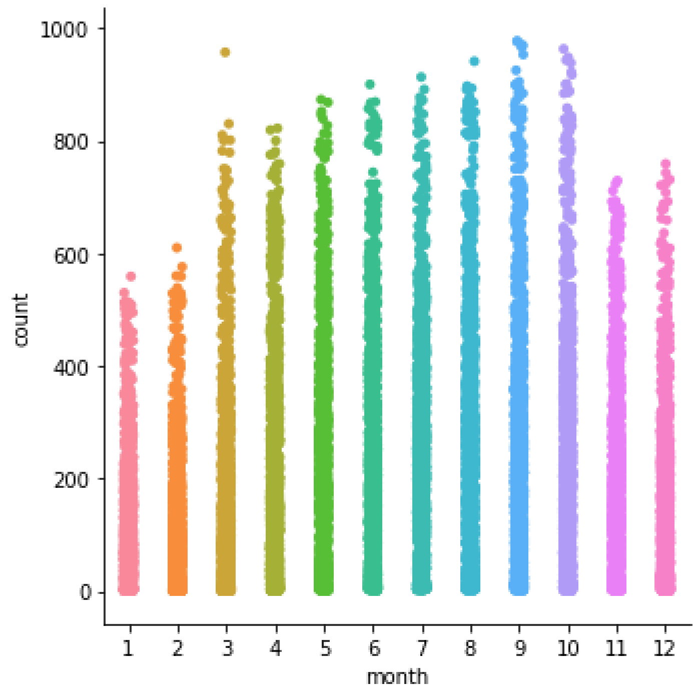
Windspeed and humidity do have a certain degree of skewness to right and left. We will have to transform these variables before including them in the model.

In [13]:

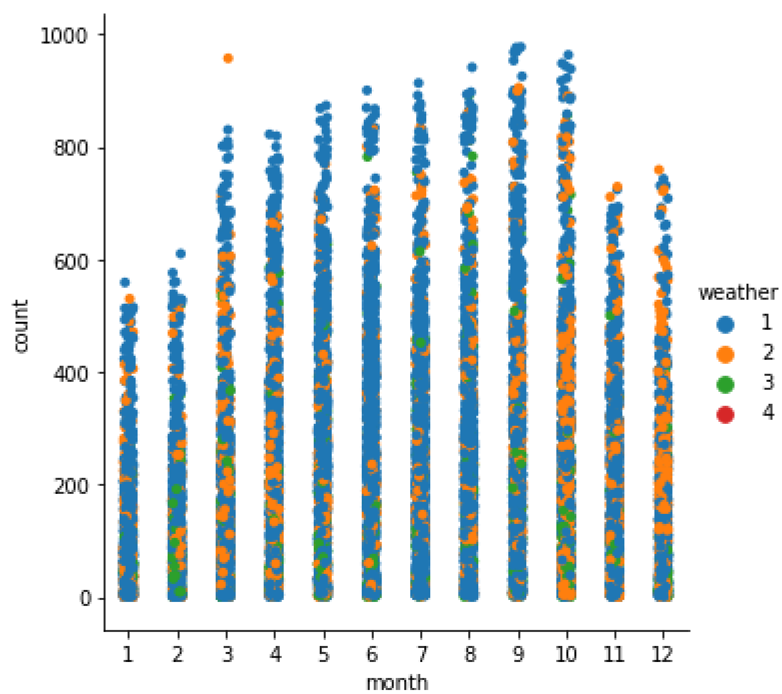
```
#Time to move to categorical variables now
sns.catplot(x='month', y= 'count',data= hours)
```

Out[13]:

```
<seaborn.axisgrid.FacetGrid at 0x3098810>
```

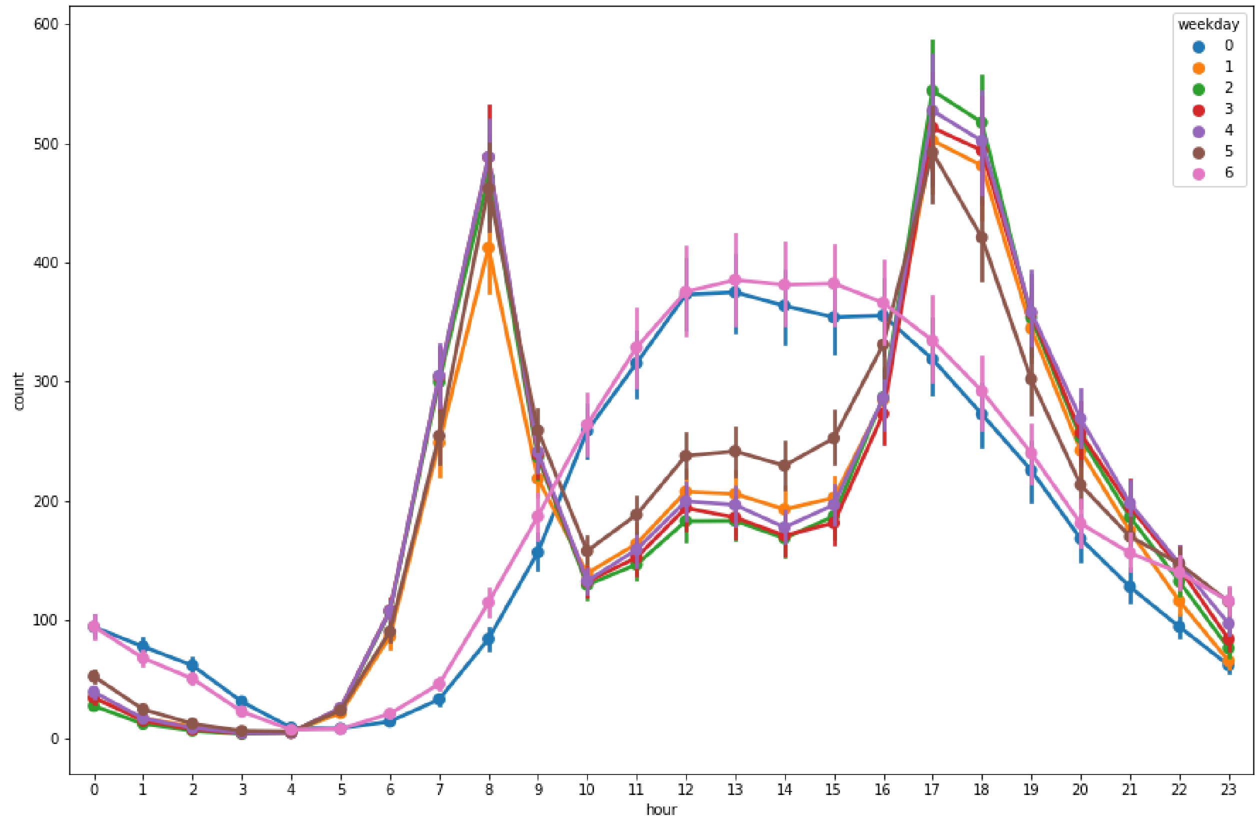


In [14]:
```
sns.catplot(x='month', y= 'count', hue= 'weather', data= hours)
```
Out[14]: <seaborn.axisgrid.FacetGrid at 0x7549f50>



As expected, weather-1 or clear days see maximum usage of bike rentals.

In [15]:
```
plt.figure(figsize=(15,10))
sns.pointplot(x= 'hour', y= 'count', hue= 'weekday', join= True, data= hou
rs)
plt.show()
```



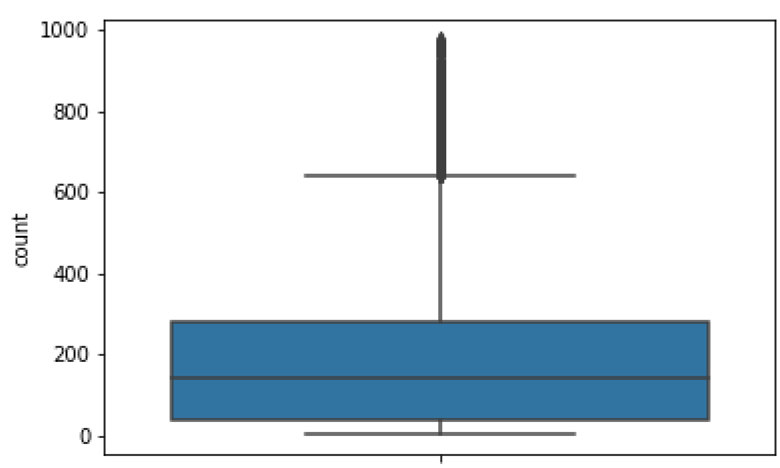
Two things can be observed from this chart:

1. Bike rentals peak during 6-8 am and 4-7 pm on weekdays which can be attributed to those being office commute hours.
2. The weekends see demand rise during afternoon hours which is when people go out.

Now that basic exploration is completed, let's take a look at outliers and see if we have any!

In [16]:
```
#Box-Plot for Count variable
sns.boxplot(data=hours,y="count")
```

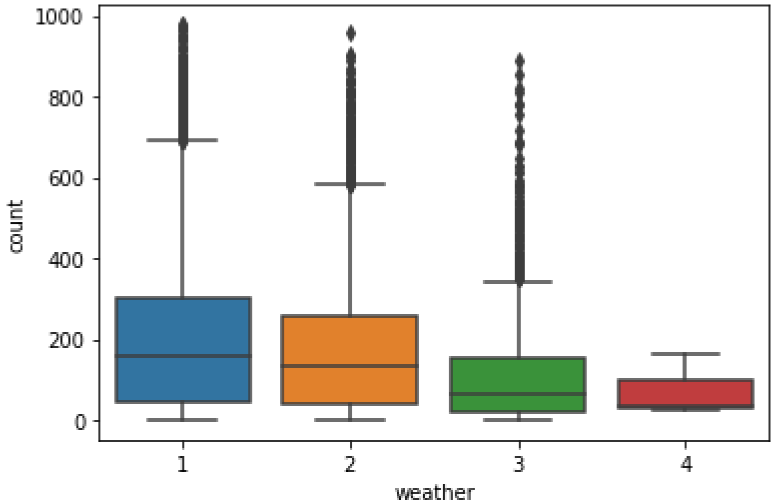
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x307b110>



In [17]:
```
#Box-Plot for weather
```

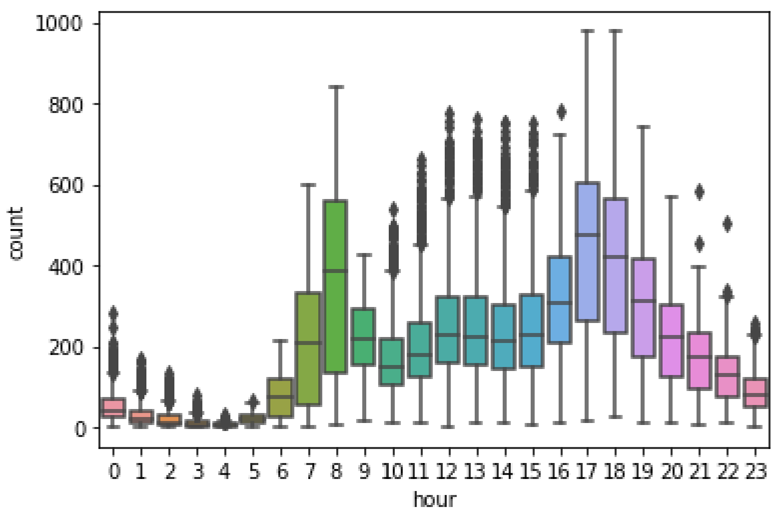
```
sns.boxplot(data=hours,y="count",x="weather")
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x121ce7f0>



In [18]:
```
#Box-plot for hours
sns.boxplot(data=hours,y="count",x="hour")
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x119dda90>



It looks like there are plenty of outliers that lie beyond the Inter-Quartlie Rangle (IQR). We will remove them using the IQR method i.e. any observation lying outside 1.5*IQR will be treated as an outlier and removed from the final dataset.

Let's first modify the dataset a bit and convert categorical variables into actual categories as well as get rid of integer 0 and 1 values in them.

In [19]:
```
#Filling in values for relevant features: all other featutes are already i
n the form of dummies
#or will not be used in the model due to multicollinearity.
hours['season']= hours.season.map({1: "Spring", 2 : "Summer", 3 : "Fall",
4 :"Winter" })
hours['weather']= hours.weather.map({1: "Clear and Cloudy",\
                                     2 : "Mist and Cloudy", \
```

```
                                                 3 : "Light Snow and rain, thunders
trom", \
                                                 4 :"Heavy Rain and thunderstrom an
d ice pallets " })
hours.head()
```

Out[19]:

	instant	date	season	year	month	hour	holiday	weekday	workingday	weather	temp	atemp
0	1	2011-01-01	Spring	0	1	0	0	6	0	Clear and Cloudy	0.24	0.2879
1	2	2011-01-01	Spring	0	1	1	0	6	0	Clear and Cloudy	0.22	0.2727
2	3	2011-01-01	Spring	0	1	2	0	6	0	Clear and Cloudy	0.22	0.2727
3	4	2011-01-01	Spring	0	1	3	0	6	0	Clear and Cloudy	0.24	0.2879
4	5	2011-01-01	Spring	0	1	4	0	6	0	Clear and Cloudy	0.24	0.2879

In [20]:

```
#Now coerce the remaining categories into factors
cat_features= ["hour","weekday","month","season","weather","holiday","work
ingday"]
hours_modified= hours.astype({'hour': 'category', 'weekday': 'category', '
month': 'category', 'season': 'category', 'weather': 'category', 'holiday'
:'category', 'workingday':'category'})
```

In [21]:

```
#Let's check the data types of these variables now
hours_modified.dtypes
```

Out[21]:

```
instant          int64
date            object
season        category
year             int64
month         category
hour          category
holiday       category
weekday       category
workingday    category
weather       category
temp           float64
atemp          float64
humidity       float64
windspeed      float64
casual           int64
registered       int64
count            int64
dtype: object
```

In [22]:
```python
#standardize the numerical features as they are in different units, have o
utliers and skewed distributions
#Getting column names
num_features= hours[['temp', 'humidity', 'windspeed', 'count']]

#Create the Scaler object
scaler = preprocessing.StandardScaler()

# Fit your data on the scaler object
scaled_df = scaler.fit_transform(num_features)
scaled_df = pd.DataFrame(scaled_df, columns= ['Temp_s', 'Humidity_s', 'Win
dspeed_s', 'Count_s'])
```

In [23]:
```python
#Finally join them all and make a single DF
hours_new= hours_modified[['hour','workingday', 'weather', 'season']]
training= pd.concat([hours_new, scaled_df], axis=1)
training.head()
```

Out[23]:

	hour	workingday	weather	season	Temp_s	Humidity_s	Windspeed_s	Count_s
0	0	0	Clear and Cloudy	Spring	-1.334648	0.947372	-1.553889	-0.956339
1	1	0	Clear and Cloudy	Spring	-1.438516	0.895539	-1.553889	-0.824022
2	2	0	Clear and Cloudy	Spring	-1.438516	0.895539	-1.553889	-0.868128
3	3	0	Clear and Cloudy	Spring	-1.334648	0.636370	-1.553889	-0.972879
4	4	0	Clear and Cloudy	Spring	-1.334648	0.636370	-1.553889	-1.039037

Time to get rid of outliers from the standardized dataset. As mentioned earlier, we will be using the Inter-quartile Range. Another, option is to use standard deviation as a cut-off point and remove observations that lie above/below 3*SD.

In [24]:
```python
#Define 25th and 75th percentile.
q25 = training.Count_s.quantile(0.25)
q75 = training.Count_s.quantile(0.75)
iqr = q75 - q25
print('Percentiles: 25th=%.3f, 75th=%.3f, IQR=%.3f' % (q25, q75, iqr))
# calculate the cutoff point
cut_off = iqr * 1.5
lower, upper = q25 - cut_off, q75 + cut_off
# identify outliers
outliers = [x for x in training.Count_s if x < lower or x > upper]
print('Identified outliers: %d' % len(outliers))
#Removing outliers
outliers_removed = training.loc[(training.Count_s >= lower) & (training.Co
unt_s <= upper)]
print('Non-outlier observations: %d' % len(outliers_removed))
```

```
Percentiles: 25th=-0.824, 75th=0.505, IQR=1.329
Identified outliers: 505
Non-outlier observations: 16874
```

In [25]:
```
training_df= pd.get_dummies(outliers_removed)
training_df.shape
```

Out[25]:
```
(16874, 38)
```

This completes Data exploration and data preparation and start with training the dataset. Here's what we will be performing:

1. OLS Regression with Scikit Learn
2. Linear Regression with Cross Validation
3. OLS Regression with Statsmodel for better clarity
4. Regularization with the help of Ridge Regresion
5. Regression with Random Forest.

For all techniques, we will be judging the quality of the model based on Root Mean Square Error(RMSE).

In [26]:
```
#divide data into features (X) and target variable(y)
X= training_df.drop(['Count_s'], axis=1)
y= training_df['Count_s']

#Splitting into train and test- 70% for training and 30% for testing
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=2,
test_size=0.3)

#Print their shapes
print("shape of training data:", X_train.shape, "\nShape of test data:", X
_test.shape, "\nShape of training label:", y_train.shape, "\nShape of test
 label:", y_test.shape)
```

```
shape of training data: (11811, 37)
Shape of test data: (5063, 37)
Shape of training label: (11811,)
Shape of test label: (5063,)
```

Let's try a basic Linear Regression and see how it performs.

In [27]:
```
#Running the reg- import the library
from sklearn.linear_model import LinearRegression

#instantiate the model
linreg= LinearRegression()

#Fit the model
model= linreg.fit(X_train, y_train)
```

In [28]:
```
#Let's predict on the test set
y_pred= linreg.predict(X_test)
```

In [29]:
```
#Take a look at basic parameters like Coefficients, R-squared and errors
print ('The intercept is:',linreg.intercept_ , '\nThe coeff values are:',
linreg.coef_)
```

```
The intercept is: -4268458437573.1934
The coeff values are: [ 2.52206857e-01 -8.81525713e-02 -3.18195264e-02  7.
21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  3.88777631e+12
  3.88777631e+12 -1.42361754e+11 -1.42361754e+11 -1.42361754e+11
 -1.42361754e+11  4.50847106e+11  4.50847106e+11  4.50847106e+11
  4.50847106e+11]
```

In [30]:
```
#MAE- Mean Absolute Error: Mean of absolute value of errors. Simplest metr
ic to check quality of a model
print (metrics.mean_absolute_error(y_test, y_pred))
```

```
0.3982578821809484
```

In [31]:
```
#MSE- Mean Squared Error: Mean of squared errors. It's a bit harder to int
erpret than MAE
print (metrics.mean_squared_error(y_test, y_pred))
```

```
0.2855755379718704
```

In [32]:
```
#RMSE: Root MSE. Same as MSE but easier to interpret as it's in terms of Y
. It also minimizes large errors.
print (np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

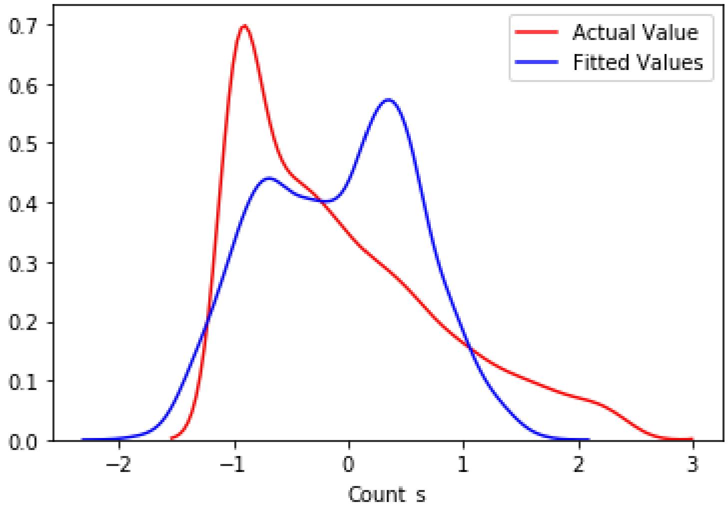
```
0.5343926814355436
```

In [33]:
```
#R squared- how much of variance is explained by this model
linreg.score(X,y)
```

Out[33]:
```
0.6254504832242752
```

In [34]:
```
#Plotting actual vs predicted outputs
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1
)
```

Out[34]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13a018b0>
```



The first thing to note here is that co-efficient values are huge even though we get an acceptable RMSE. But let's re-run the model using cross-validation and see if it helps us acheive better results.

Regression using Cross-Validation

In [35]:
```
#Using cros validation-importing the libraries
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics

#Applying it on the model now
scores = cross_val_score(model, X, y, cv=7)
print ("Cross val scores:",scores)
```

```
Cross val scores: [-1.1875049   0.57972909  0.61194794  0.42369965  0.5449
597   0.54267842
  0.51665607]
```

In [37]:
```
#CV of 5 gives good results, so we will use that
# Make cross validated predictions
predictions = cross_val_predict(model, X, y, cv=5)
```

In [38]:
```
print ('The intercept is:',model.intercept_ , '\nThe coeff values are:', m
odel.coef_)
```

```
The intercept is: -4268458437573.1934
The coeff values are: [ 2.52206857e-01 -8.81525713e-02 -3.18195264e-02  7.
21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  7.21967793e+10
  7.21967793e+10  7.21967793e+10  7.21967793e+10  3.88777631e+12
  3.88777631e+12 -1.42361754e+11 -1.42361754e+11 -1.42361754e+11
 -1.42361754e+11  4.50847106e+11  4.50847106e+11  4.50847106e+11
  4.50847106e+11]
```

In [39]:
```
#Let's check the RMSE
print (np.sqrt(metrics.mean_squared_error(y, predictions)))
```

```
0.6022063233429561
```

Even cross- validation doesn't show much improvement. Let's see what's happening here using another library called 'Statsmodel' that gives a nice detailed summary of the fitted model.

Regression with Statsmodels

In [40]:
```
#using Statsmodels
import statsmodels.api as sm
X = sm.add_constant(X) # adding a constant
model2 = sm.OLS(y, X).fit()
predictions = model2.predict(X)

print_model = model2.summary()
print(print_model)
```

```
                            OLS Regression Results                            
==========================================================================================
====
Dep. Variable:                Count_s   R-squared:                             0
.626
Model:                            OLS   Adj. R-squared:                        0
.625
Method:                 Least Squares   F-statistic:                           8
04.9
Date:                Sun, 10 Nov 2019   Prob (F-statistic):                    
0.00
Time:                        13:41:34   Log-Likelihood:                      -12
997.
No. Observations:               16874   AIC:                               2.607
e+04
Df Residuals:                   16838   BIC:                               2.634
e+04
Df Model:                          35                                         

Covariance Type:            nonrobust                                         

==========================================================================================
==============================================
                                                            coef    std err      
          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
----------------------------------------------
const                                                 -1.116e+11   2.25e+11      
     -0.495      0.620   -5.54e+11     3.3e+11
Temp_s                                                    0.2585      0.008      
     30.888      0.000       0.242       0.275
Humidity_s                                               -0.0883      0.006      
    -14.029      0.000      -0.101      -0.076
Windspeed_s                                              -0.0270      0.004
```

```
     -6.160      0.000      -0.036      -0.018
hour_0                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_1                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_2                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_3                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_4                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_5                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_6                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_7                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_8                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_9                                                 -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_10                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_11                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_12                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_13                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_14                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_15                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_16                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_17                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_18                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_19                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_20                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_21                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_22                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
hour_23                                                -1.998e+09   2.79e+10
     -0.072      0.943   -5.68e+10    5.28e+10
workingday_0                                           -6.483e+10   7.61e+11
     -0.085      0.932   -1.56e+12    1.43e+12
workingday_1                                           -6.483e+10   7.61e+11
     -0.085      0.932   -1.56e+12    1.43e+12
weather_Clear and Cloudy                                9.064e+10   9.25e+11
      0.098      0.922   -1.72e+12     1.9e+12
weather_Heavy Rain and thunderstrom and ice pallets     9.064e+10   9.25e+11
      0.098      0.922   -1.72e+12     1.9e+12
```

```
weather_Light Snow and rain, thunderstrom                 9.064e+10   9.25e+11
      0.098      0.922   -1.72e+12     1.9e+12
weather_Mist and Cloudy                                   9.064e+10   9.25e+11
      0.098      0.922   -1.72e+12     1.9e+12
season_Fall                                               8.783e+10    1.1e+11
      0.802      0.423   -1.27e+11    3.02e+11
season_Spring                                             8.783e+10    1.1e+11
      0.802      0.423   -1.27e+11    3.02e+11
season_Summer                                             8.783e+10    1.1e+11
      0.802      0.423   -1.27e+11    3.02e+11
season_Winter                                             8.783e+10    1.1e+11
      0.802      0.423   -1.27e+11    3.02e+11
==========================================================================
====
Omnibus:                     1326.302   Durbin-Watson:                   0
.487
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2247
.000
Skew:                           0.587   Prob(JB):
0.00
Kurtosis:                       4.348   Cond. No.                     2.36
e+15
==========================================================================
====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The smallest eigenvalue is 7.27e-27. This might indicate that there ar
e
strong multicollinearity problems or that the design matrix is singular.
```

```
c:\users\rakbansal\appdata\local\programs\python\python37_32\lib\site-pack
ages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is depreca
ted and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

As we saw earlier, the co-efficients are huge, the p-values are not significant and the adjusted R-squared doesn't explain the variance in the model. Let's see if this is because of multicollinearity and check the Varinace Inflation Factor (VIF) of the features. By a rule of thumb, any variable with VIF greater than 10 is prone to multicollinearity.

In [41]:

```
#Calculating VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
df= training_df
X = add_constant(df)
pd.Series([variance_inflation_factor(X.values, i)
               for i in range(X.shape[1])],
              index=X.columns)
```

```
c:\users\rakbansal\appdata\local\programs\python\python37_32\lib\site-pack
ages\statsmodels\regression\linear_model.py:1636: RuntimeWarning: divide b
y zero encountered in double_scalars
  return 1 - self.ssr/self.centered_tss
```

```
Out[41]: const                                                      0.000000e+00
         Temp_s                                                     3.317569e+00
         Humidity_s                                                 1.810741e+00
         Windspeed_s                                                1.164215e+00
         Count_s                                                    2.673075e+00
         hour_0                                                     5.414617e+06
         hour_1                                                     1.291465e+06
         hour_2                                                     8.926025e+07
         hour_3                                                     9.842016e+08
         hour_4                                                     4.513899e+05
         hour_5                                                     4.639483e+08
         hour_6                                                     4.666725e+10
         hour_7                                                     2.457869e+05
         hour_8                                                     1.051975e+09
         hour_9                                                     9.331393e+05
         hour_10                                                    1.527133e+08
         hour_11                                                    1.622488e+08
         hour_12                                                    9.977968e+06
         hour_13                                                    1.967225e+07
         hour_14                                                    1.006481e+07
         hour_15                                                    4.252423e+08
         hour_16                                                    2.309645e+07
         hour_17                                                    1.209418e+07
         hour_18                                                    8.689941e+07
         hour_19                                                    2.125583e+06
         hour_20                                                    2.974623e+08
         hour_21                                                    3.306312e+08
         hour_22                                                    5.909236e+07
         hour_23                                                    4.396430e+09
         workingday_0                                               1.377004e+06
         workingday_1                                               4.514246e+07
         weather_Clear and Cloudy                                   3.671741e+05
         weather_Heavy Rain and thunderstrom and ice pallets        1.460477e+11
         weather_Light Snow and rain, thunderstrom                  1.615280e+09
         weather_Mist and Cloudy                                    2.692515e+08
         season_Fall                                                2.655599e+05
         season_Spring                                              1.677967e+05
         season_Summer                                              1.331026e+07
         season_Winter                                              1.100937e+06
         dtype: float64
```

As expected, there is a lot of multicollinearity in the dataset and the model looks like it's overfitting. There are three ways to deal with overfitting:

1. Regularization
2. Bagging
3. Boosting

In this model,we will be testing two of these techniques- Regularization using 'Ridge Regression' and Bagging using 'Random Forests'.

Ridge Regression

Ridge Regression can be used to make better predictions as it introduces a small amount of bias in the model. It penalizes huge coefficients by a factor called lambda.

In [42]:
```
#Import the library
from sklearn.linear_model import Ridge

#Instantiate the model
rr = Ridge(alpha=100)

#Train the model
rr.fit(X_train, y_train)

#Predict and check RMSE
pred_test_rr= rr.predict(X_test)
print(np.sqrt(metrics.mean_squared_error(y_test,pred_test_rr)))
```

```
0.5436164496658877
```

In [43]:
```
#R-squared
print(metrics.r2_score(y_test, pred_test_rr))
```

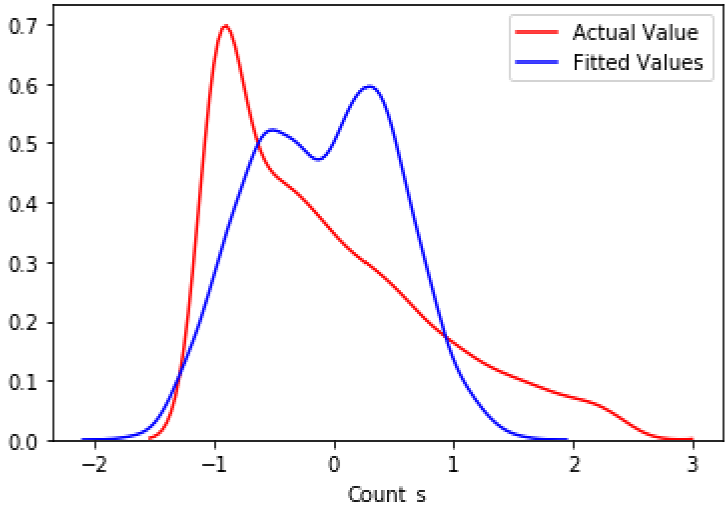
```
0.6098918249676489
```

In [44]:
```
#Let's see if it solved the huge co-efficient problem
print ('The intercept is:',rr.intercept_ , '\nThe coeff values are:', rr.c
oef_)
```

```
The intercept is: -0.1283918774090986
The coeff values are: [ 0.28601948 -0.13178739 -0.02171695 -0.49740693 -0.
58283648 -0.60919522
 -0.64955875 -0.66192185 -0.58944844 -0.3197872   0.31345687  0.58231779
  0.24074691 -0.01630499  0.06747211  0.21181461  0.14086963  0.11200584
  0.14034121  0.43505685  0.79714864  0.70925803  0.54820555  0.18787761
 -0.01463619 -0.18548433 -0.35999128 -0.00168351  0.00168351  0.07444821
  0.00174525 -0.15309925  0.07690578 -0.09462143 -0.10223874  0.0304828
  0.16637737]
```

In [45]:
```
#Plotting actual vs predicted outputs
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(pred_test_rr, hist=False, color="b", label="Fitted Values" ,
ax=ax1)
```

Out[45]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x138b0f70>
```



Random Forests

Ridge regression did a good job with dealing with the overfitting problem but it also introduced high bias and variance. Let's see if Random Forest can provide better results.

In [46]:
```
#Regression with Random Forest
from sklearn.ensemble import RandomForestRegressor
rfreg = RandomForestRegressor(n_estimators = 200)
rfreg.fit(X_train, y_train)
```

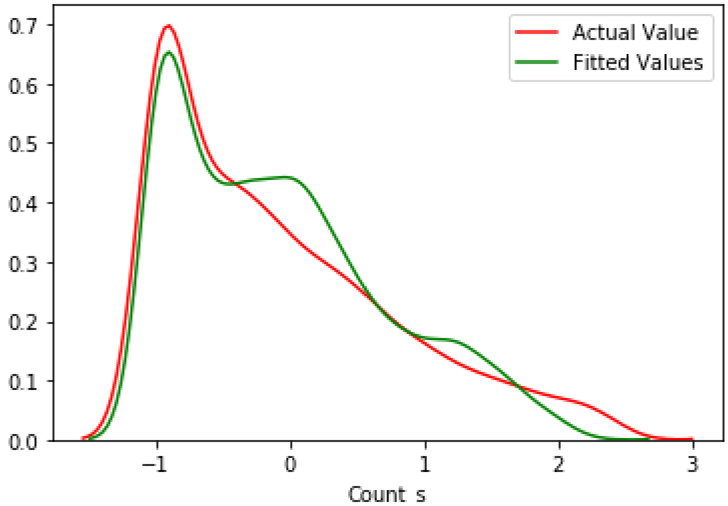
Out[46]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=200,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

In [47]:
```
#Make Predictions
pred= rfreg.predict(X_test)

#Check RMSE
print('RMSE:', np.sqrt(metrics.mean_squared_error((y_test),(pred))))

score = rfreg.score(X_test, pred)
print(score)
```

```
RMSE: 0.37835776372798674
1.0
```

In [48]:
```
#Visualize the fitted vs original values
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(pred, hist=False, color="g", label="Fitted Values" , ax=ax1)
```

Out[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13fbdb30>
```


Actual Value
Fitted Values
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−1
0
1
2
3
Count_s