In [2]:

```
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import statsmodels as sm
import statsmodels.formula.api as smf
from scipy.stats import t as tdist
from statsmodels.stats.outliers_influence import summary_table
get_ipython().magic(u'matplotlib inline')
```

In [3]:

```
os.getcwd()
```

Out[3]:

```
'/Users/sahiljain'
```

In [4]:

```
os.chdir("/Users/sahiljain/Downloads")
```

In [5]:

```
bikeShare = pd.read_csv('bike_share.csv')
```

In [6]:

```
# Let y = count, x1, x2, x3, x4 be temprature, humidity, windspeed, season
# and Weather respectively
y = bikeShare["count"]
x1 = bikeShare["temp"]
x2 = bikeShare["humidity"]
x3 = bikeShare["windspeed"]
x4 = bikeShare["season"]
x5 = bikeShare["weather"]
```

In [7]:

```
#(A) Fit a simple linear regression model relating count to temp.
# Formally test Beta_1 = 0 and beta_1 != 0.

# Linear model of count to temp.
lm = smf.OLS(y, sm.tools.tools.add_constant(x1),)
model1 = lm.fit()
model1.summary()
```

Out[7]:

OLS Regression Results

Dep. Variable:	count	**R-squared:**	0.156
Model:	OLS	**Adj. R-squared:**	0.156
Method:	Least Squares	**F-statistic:**	2006.
Date:	Tue, 26 Sep 2017	**Prob (F-statistic):**	0.00
Time:	17:00:47	**Log-Likelihood:**	-71125.
No. Observations:	10886	**AIC:**	1.423e+05
Df Residuals:	10884	**BIC:**	1.423e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-156.9856	7.945	-19.759	0.000	-172.560	-141.412
temp	5.0947	0.114	44.783	0.000	4.872	5.318

Omnibus:	1871.687	**Durbin-Watson:**	0.369
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3221.966
Skew:	1.123	**Prob(JB):**	0.00
Kurtosis:	4.434	**Cond. No.**	348.

In [8]:

```
# Calculating the parameters manually.
# Beta1_hat
beta1a_hat = np.corrcoef(x1,y)[0,1] * np.std(y) / np.std(x1)
beta1a_hat
```

Out[8]:

```
5.0947447119035711
```

In [9]:

```
# Beta0_hat
beta0a_hat = np.mean(y) - beta1a_hat * np.mean(x1)
beta0a_hat
```

Out[9]:

```
-156.98561782130787
```

In [10]:

```
# H0 : beta1 = 0 vs Ha : beta1 != 0
se_beta1a = model1.bse[1]
t = beta1a_hat /  se_beta1a
p_val1 = 2 * (1 - tdist.cdf(np.abs(t), df = 10884))
print("The p-value associated with Ho: beta1 = 0 is ", p_val1)
```

```
('The p-value associated with Ho: beta1 = 0 is ', 0.0)
```

In [20]:

```
# 95% Confindece Inteval for beta1
crit_val = tdist.ppf(0.975, df = 10884)
low_CI = beta1a_hat - crit_val*se_beta1a
upp_CI = beta1a_hat + crit_val*se_beta1a
print("The 95% confidence for beta1 is : ", low_CI, upp_CI)
```

```
('The 95% confidence for beta1 is : ', 4.8717449933595889, 5.3177444
304475534)
```

In [21]:

```
# Interpretaion : From the p-value which is 0, we will not reject the
# null hypothesis and the level of confidence in 99.5%. This means that
# variable windspeed is highly significant and bike rentals are
# significantly influenced by the temprature.
```

In [22]:

```
# (B) Fit a simple linear regression model relating count to humidity.
# Formally test Beta_1 = 0 and beta_1 != 0.

# Linear model of count to humidity
lm = smf.OLS(y, sm.tools.tools.add_constant(x2),)
model2 = lm.fit()
model2.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	count	**R-squared:**	0.101
Model:	OLS	**Adj. R-squared:**	0.101
Method:	Least Squares	**F-statistic:**	1219.
Date:	Tue, 26 Sep 2017	**Prob (F-statistic):**	2.92e-253
Time:	17:02:56	**Log-Likelihood:**	-71468.
No. Observations:	10886	**AIC:**	1.429e+05
Df Residuals:	10884	**BIC:**	1.430e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	376.4456	5.545	67.890	0.000	365.577	387.315
humidity	-2.9873	0.086	-34.915	0.000	-3.155	-2.820

Omnibus:	2068.515	**Durbin-Watson:**	0.351
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3709.739
Skew:	1.210	**Prob(JB):**	0.00
Kurtosis:	4.525	**Cond. No.**	218.

In [23]:

```
# Calculating the parameters manually

# Beta1_hat
beta1b_hat = np.corrcoef(x2,y)[0,1] * np.std(y) / np.std(x2)
beta1b_hat
```

Out[23]:

```
-2.9872685785344091
```

In [24]:

```
# Beta0_hat
beta0b_hat = np.mean(y) - beta1b_hat * np.mean(x2)
beta0b_hat
```

Out[24]:

```
376.44560833036167
```

In [25]:

```
# H0: beta1 = 0 vs Ha: beta1 != 0
se_beta1b = model2.bse[1]
t = beta1b_hat / se_beta1b
p_val2 = 2 * (1 - tdist.cdf(np.abs(t), df = 10884))
print("The p_value associated with Count vs humidity is ", p_val2)
```

```
('The p_value associated with Count vs humidity is ', 0.0)
```

In [27]:

```
# 95% Confindece Inteval for beta1
crit_val = tdist.ppf(0.975, df = 10884)
low_CI = beta1b_hat - crit_val*se_beta1b
upp_CI = beta1b_hat + crit_val*se_beta1b
print("The 95% confidence for beta1 is : ", low_CI, upp_CI)
```

```
('The 95% confidence for beta1 is : ', -3.1549769885633285, -2.81956
01685054896)
```

In [28]:

```
# Interpretation : From the p-value which is 2.92 * 10^-253 < 0,
# we will not reject the null hypothesis and the level of confidence
# in 99.5%. This means that variable humidity is highly significant and
# bike rentals are significantly influenced by the humidity.
```

In [29]:

```
# (C) Fit a simple linear regression model relating count to Windspeed.
# Formally test Beta_1 = 0 and beta_1 != 0.

# Linear model between count vs windspeed.
lm = smf.OLS(y, sm.tools.tools.add_constant(x3), )
model3 = lm.fit()
model3.summary()
```

Out[29]:

OLS Regression Results

Dep. Variable:	count	**R-squared:**	0.010
Model:	OLS	**Adj. R-squared:**	0.010
Method:	Least Squares	**F-statistic:**	113.0
Date:	Tue, 26 Sep 2017	**Prob (F-statistic):**	2.90e-26
Time:	17:03:20	**Log-Likelihood:**	-71989.
No. Observations:	10886	**AIC:**	1.440e+05
Df Residuals:	10884	**BIC:**	1.440e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	162.7876	3.212	50.682	0.000	156.492	169.084
windspeed	2.2491	0.212	10.630	0.000	1.834	2.664

Omnibus:	2086.612	**Durbin-Watson:**	0.322
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3633.799
Skew:	1.247	**Prob(JB):**	0.00
Kurtosis:	4.338	**Cond. No.**	28.3

In [30]:

```
# Manually calculating the parametes.

# beta1_hat
beta1c_hat = np.corrcoef(x3,y)[0,1] * np.std(y) / np.std(x3)
beta1c_hat
```

Out[30]:

```
2.2490579173365712
```

In [31]:

```
# beta0_hat
beta0c_hat = np.mean(y) - beta1c_hat * np.mean(x3)
beta0c_hat
```

Out[31]:

```
162.78755033543703
```

In [33]:

```
# H0 : beta1 = 0 vs beta1 != 0
se_beta1c = model3.bse[1]
t = beta1c_hat / se_beta1c
p_val3 = 2 * (1 - tdist.cdf(np.abs(t), df = 10884))
print("The p-value associated with count vs windspeed is : ", p_val3)
```

```
('The p-value associated with count vs windspeed is : ', 0.0)
```

In [34]:

```
# 95% Confindece Inteval for beta1
crit_val = tdist.ppf(0.975, df = 10884)
low_CI = beta1c_hat - crit_val*se_beta1c
upp_CI = beta1c_hat + crit_val*se_beta1c
print("The 95% confidence for beta1 is : ", low_CI, upp_CI)
```

```
('The 95% confidence for beta1 is : ', 1.8343401065677059, 2.6637757
281054366)
```

In [35]:

```
# Interpretation : From the p-value which is 2.89 * 10^-26 < 0, we will
# not reject the null hypothesis and the level of confidence in 99.5%.
# This means that variable windspeed is highly significant and bike
# rentals are significantly influenced by the Windspeed.
```

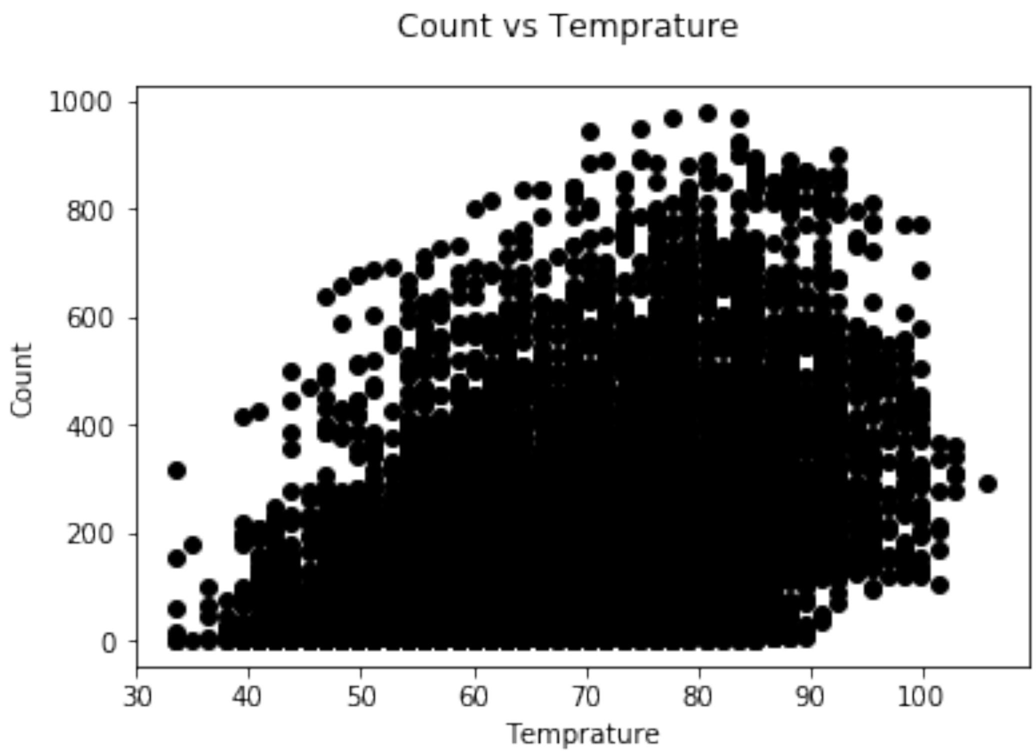
In [36]:

```
# (D) Construct three Scatter plots : (1) Count vs Temp
# (2) Count vs Humidity and (3) Count vs Windspeed. On all of these,
# plot the least squares line-of-best-fit, the 95% confindense interval
# and the 95% prediction interval.

# 1(a) Scatter plot of count vs temp.
fig1 = plt.figure()
plt.scatter(x1,y, c = "black")
fig1.suptitle("Count vs Temprature")
plt.ylabel("Count")
plt.xlabel("Temprature")
```

Out[36]:

```
<matplotlib.text.Text at 0x1135702d0>
```

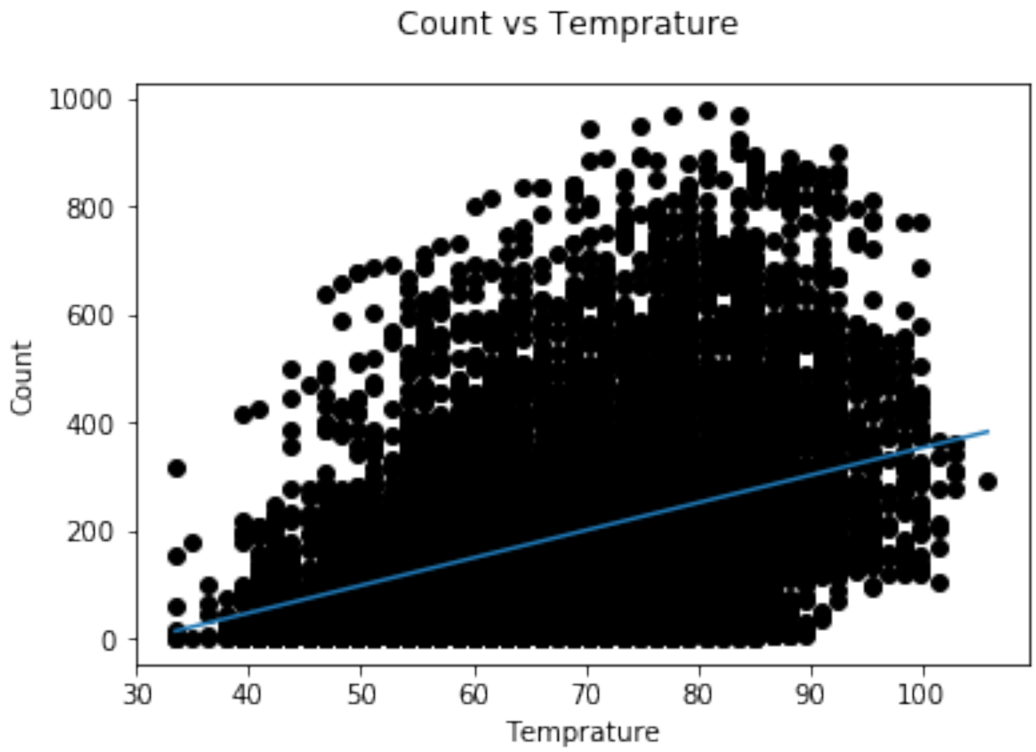


In [37]:

```
# 1(b) Scatter plot of count vs temp with line of best fit
fig1 = plt.figure()
plt.scatter(x1, y, c = "black")
fig1.suptitle("Count vs Temprature")
plt.ylabel("Count")
plt.xlabel("Temprature")
plt.plot(np.unique(x1), np.poly1d(np.polyfit(x1, y, 1))(np.unique(x1)))
```

Out[37]:

```
[<matplotlib.lines.Line2D at 0x113502210>]
```

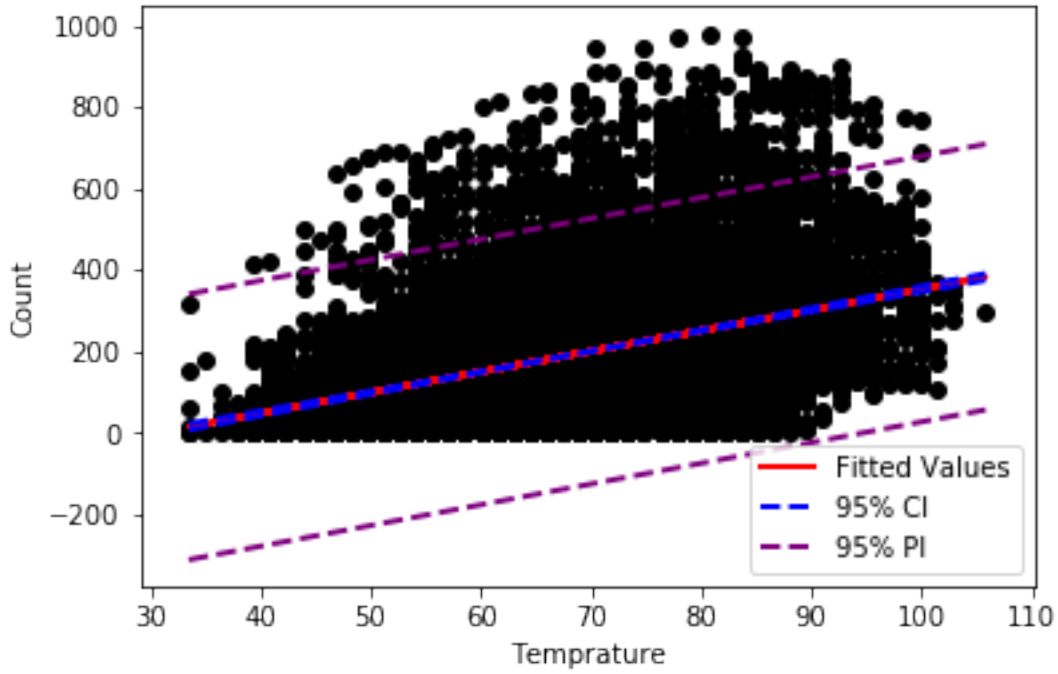


In [38]:

```
# 1(c) 95% Confidence interval and 95% prediction interval and
# plotting them on them scatter plot.

# Add the fitted line to the scatter plot
fitted_line, = plt.plot(x1, model1.predict(), '-', color = "red", linewidth = 2,
label = "Fitted Values")

# 95% CI and PI
beta0_hat = model1.params[0]
beta1_hat = model1.params[1]
sigma_hat = np.sqrt(model1.mse_resid)
n = bikeShare.shape[0]
sxx = n * np.var(x1)
xp = np.linspace(x1.min(), x1.max(), 100)
yp_hat = beta0_hat + beta1_hat * xp
se_mu0 = sigma_hat * np.sqrt((1/n) + ((xp-np.mean(x1))**2/sxx))
se_yp = sigma_hat * np.sqrt(1 + (1/n) + ((xp-np.mean(x1))**2/sxx))
crit_val = tdist.ppf(0.975, df = n-2)
ci_low = yp_hat - crit_val * se_mu0
ci_hi = yp_hat + crit_val * se_mu0
pi_low = yp_hat - crit_val * se_yp
pi_hi = yp_hat + crit_val * se_yp
plt.scatter(x1, y, c = "black")
fig1.suptitle("Count vs Temprature")
plt.ylabel("Count")
plt.xlabel("Temprature")
lowCI_line, = plt.plot(xp, ci_low, '--', color = "blue", linewidth = 2, label =
"95% CI")
uppCI_line, = plt.plot(xp, ci_hi, '--', color = "blue", linewidth = 2, label = "
95% CI")
lowPI_line, = plt.plot(xp, pi_low, '--', color = "purple", linewidth = 2, label
= "95% PI")
uppPI_line, = plt.plot(xp, pi_hi, '--', color = "purple", linewidth = 2, label =
"95% PI")
legend = plt.legend(handles = [fitted_line, lowCI_line, lowPI_line], loc = 4)
```

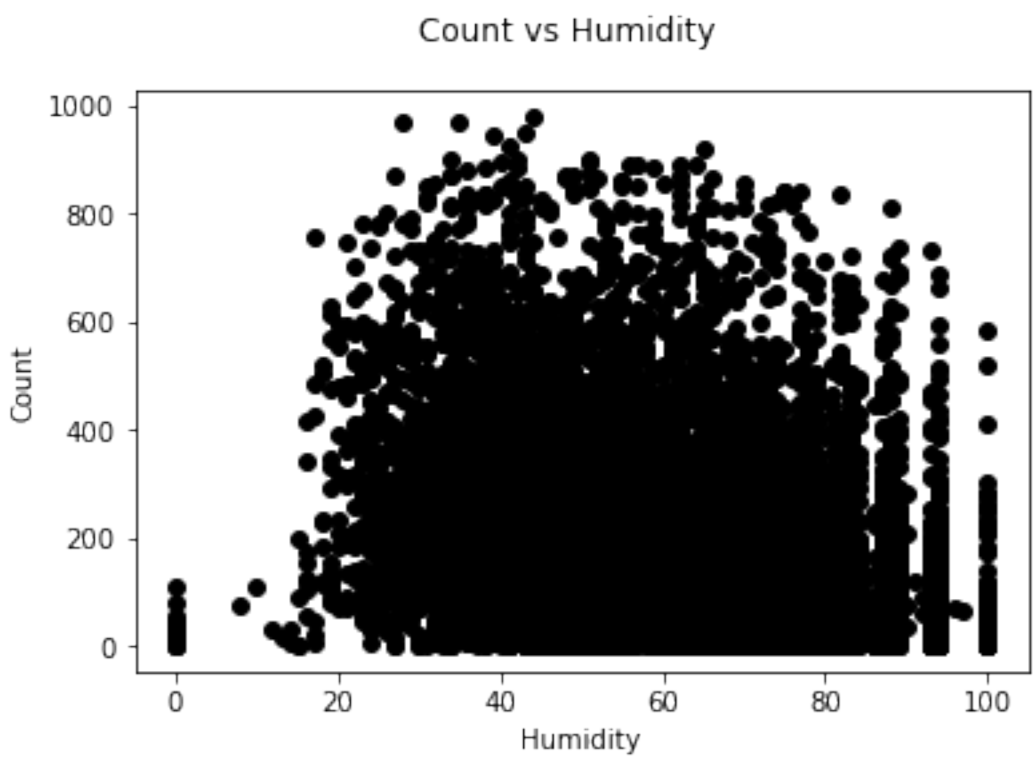


In [39]:

```
# 2(a) Scatter plot of Count vs Humidty
fig2 = plt.figure()
plt.scatter(x2,y, c = "black")
fig2.suptitle("Count vs Humidity")
plt.ylabel("Count")
plt.xlabel("Humidity")
```

Out[39]:

```
<matplotlib.text.Text at 0x1137cb390>
```

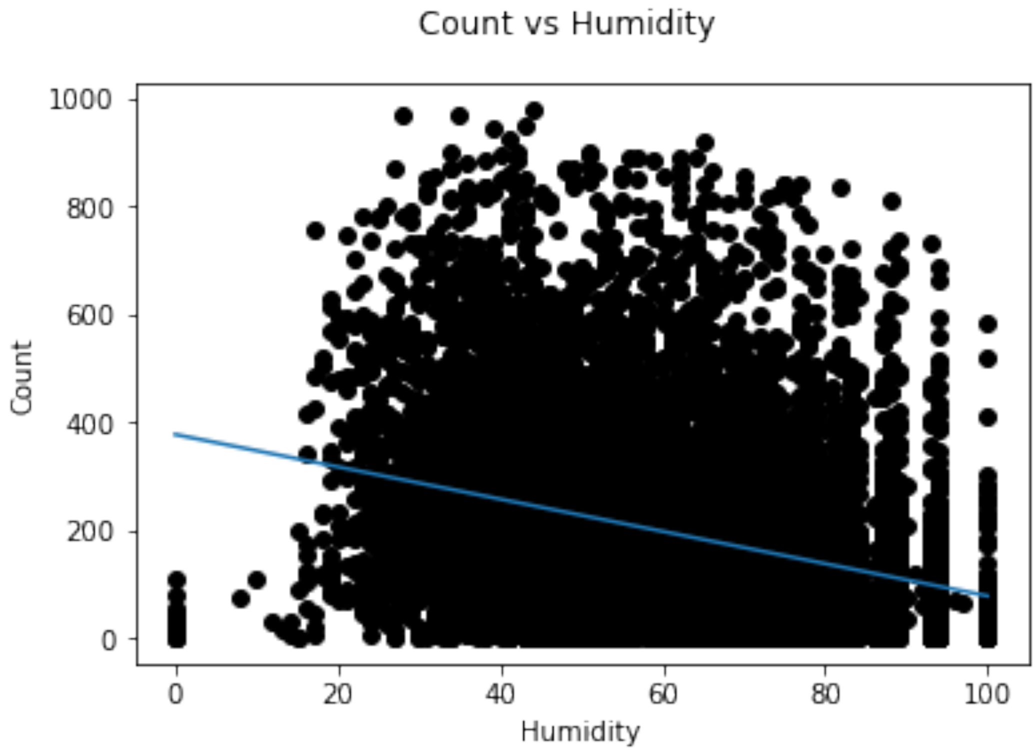


In [40]:

```
# 2(b) Line of best fit in Count vs Humidity
fig2 = plt.figure()
plt.scatter(x2, y, c = "black")
fig2.suptitle("Count vs Humidity")
plt.ylabel("Count")
plt.xlabel("Humidity")
plt.plot(np.unique(x2), np.poly1d(np.polyfit(x2, y, 1))(np.unique(x2)))
```

Out[40]:

```
[<matplotlib.lines.Line2D at 0x1136fcdd0>]
```

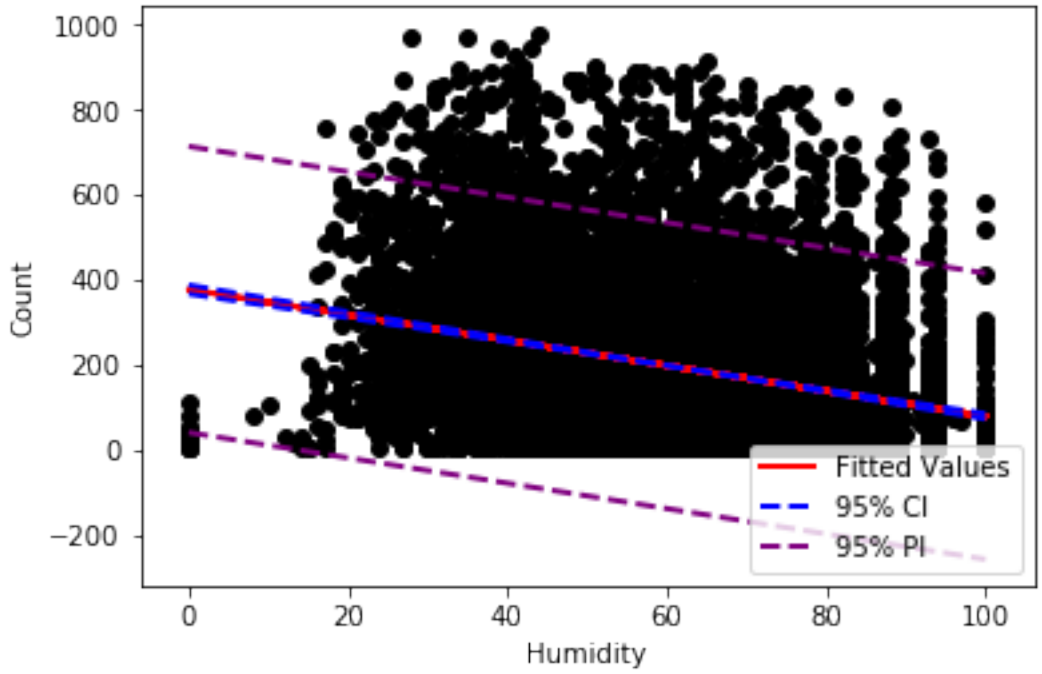


In [41]:

```
# 2(c) 95% Confidence interval and 95% prediction interval and
# plotting them on them scatter plot.

# Add the fitted line to the scatter plot
fitted_line, = plt.plot(x2, model2.predict(), '-', color = "red", linewidth = 2,
label = "Fitted Values")

# 95% CI and PI
beta0_hat = model2.params[0]
beta1_hat = model2.params[1]
sigma_hat = np.sqrt(model2.mse_resid)
n = bikeShare.shape[0]
sxx = n * np.var(x2)
xp = np.linspace(x2.min(), x2.max(), 100)
yp_hat = beta0_hat + beta1_hat * xp
se_mu0 = sigma_hat * np.sqrt((1/n) + ((xp-np.mean(x2))**2/sxx))
se_yp = sigma_hat * np.sqrt(1 + (1/n) + ((xp-np.mean(x2))**2/sxx))
crit_val = tdist.ppf(0.975, df = n-2)
ci_low = yp_hat - crit_val * se_mu0
ci_hi = yp_hat + crit_val * se_mu0
pi_low = yp_hat - crit_val * se_yp
pi_hi = yp_hat + crit_val * se_yp
plt.scatter(x2, y, c = "black")
fig1.suptitle("Count vs Humidity")
plt.ylabel("Count")
plt.xlabel("Humidity")
lowCI_line, = plt.plot(xp, ci_low, '--', color = "blue", linewidth = 2, label =
"95% CI")
uppCI_line, = plt.plot(xp, ci_hi, '--', color = "blue", linewidth = 2, label = "
95% CI")
lowPI_line, = plt.plot(xp, pi_low, '--', color = "purple", linewidth = 2, label
= "95% PI")
uppPI_line, = plt.plot(xp, pi_hi, '--', color = "purple", linewidth = 2, label =
"95% PI")
legend = plt.legend(handles = [fitted_line, lowCI_line, lowPI_line], loc = 4)
```

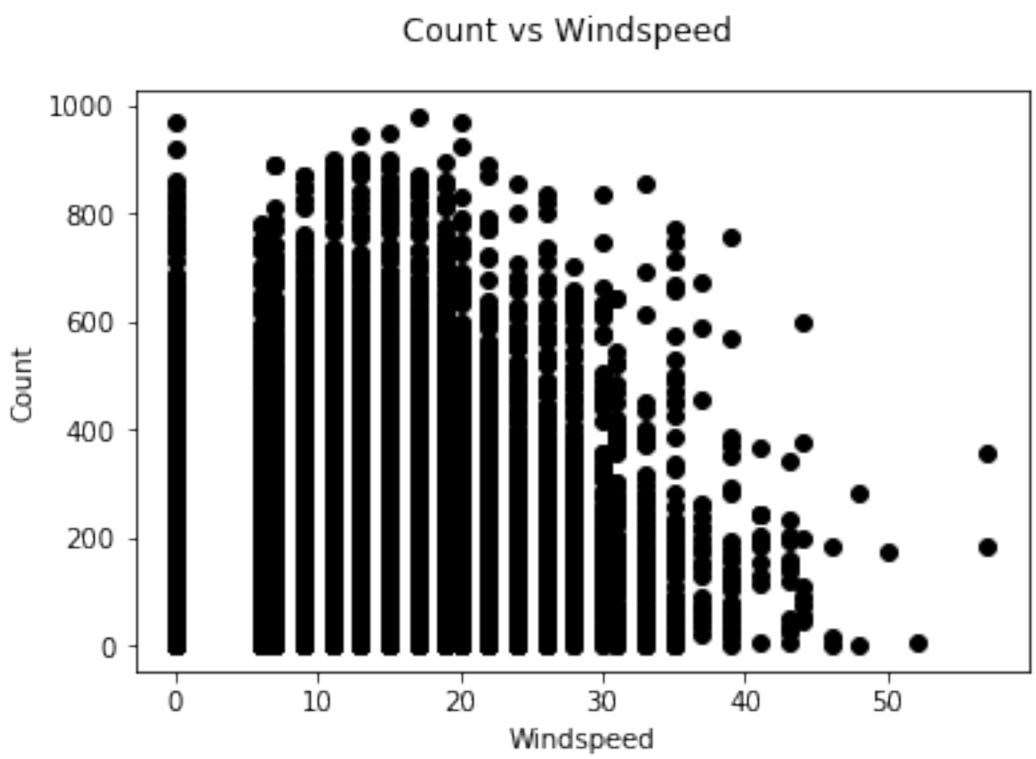


In [42]:

```
# 3(a) Scatter Plot for Count vs Windspeed
fig3 = plt.figure()
plt.scatter(x3,y, c = "black")
fig3.suptitle("Count vs Windspeed")
plt.ylabel("Count")
plt.xlabel("Windspeed")
```

Out[42]:

```
<matplotlib.text.Text at 0x113ae5550>
```

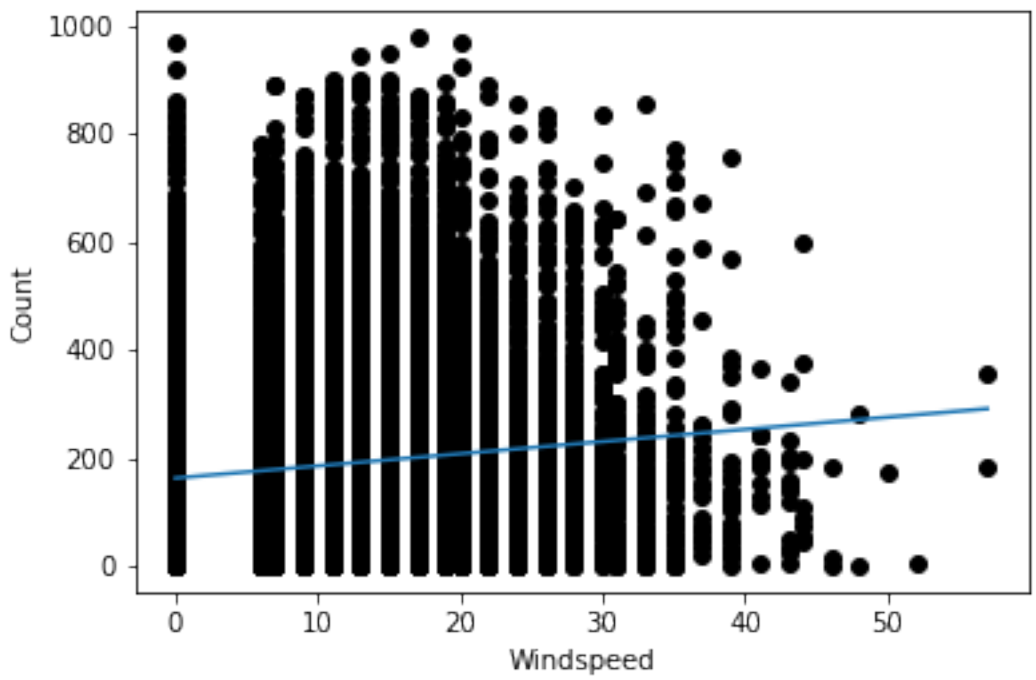


In [43]:

```
# 3(b) fig2 = plt.figure()
plt.scatter(x3, y, c = "black")
fig3.suptitle("Count vs Windspeed")
plt.ylabel("Count")
plt.xlabel("Windspeed")
plt.plot(np.unique(x3), np.poly1d(np.polyfit(x3, y, 1))(np.unique(x3)))
```

Out[43]:

```
[<matplotlib.lines.Line2D at 0x113d56690>]
```

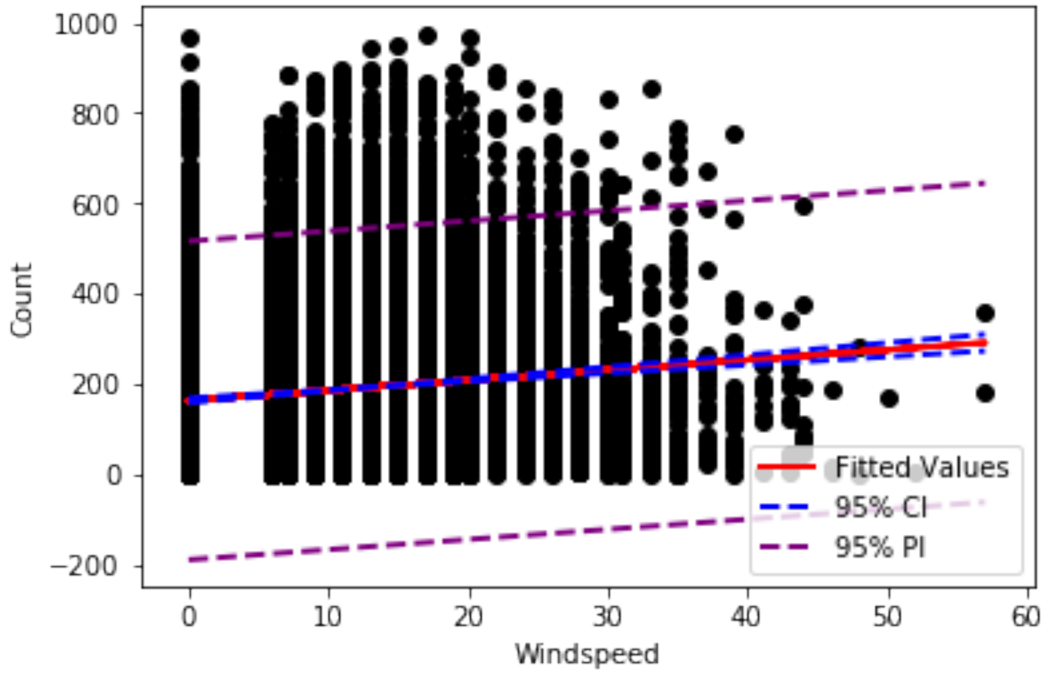


In [44]:

```
#3(c) 95% Confidence interval and 95% prediction interval and
# plotting them on them scatter plot.

# Add the fitted line to the scatter plot
fitted_line, = plt.plot(x3, model3.predict(), '-', color = "red", linewidth = 2,
label = "Fitted Values")

# 95% CI and PI
beta0_hat = model3.params[0]
beta1_hat = model3.params[1]
sigma_hat = np.sqrt(model3.mse_resid)
n = bikeShare.shape[0]
sxx = n * np.var(x3)
xp = np.linspace(x3.min(), x3.max(), 100)
yp_hat = beta0_hat + beta1_hat * xp
se_mu0 = sigma_hat * np.sqrt((1/n) + ((xp-np.mean(x3))**2/sxx))
se_yp = sigma_hat * np.sqrt(1 + (1/n) + ((xp-np.mean(x3))**2/sxx))
crit_val = tdist.ppf(0.975, df = n-2)
ci_low = yp_hat - crit_val * se_mu0
ci_hi = yp_hat + crit_val * se_mu0
pi_low = yp_hat - crit_val * se_yp
pi_hi = yp_hat + crit_val * se_yp
plt.scatter(x3, y, c = "black")
fig1.suptitle("Count vs Windspeed")
plt.ylabel("Count")
plt.xlabel("Windspeed")
lowCI_line, = plt.plot(xp, ci_low, '--', color = "blue", linewidth = 2, label =
"95% CI")
uppCI_line, = plt.plot(xp, ci_hi, '--', color = "blue", linewidth = 2, label = "
95% CI")
lowPI_line, = plt.plot(xp, pi_low, '--', color = "purple", linewidth = 2, label
= "95% PI")
uppPI_line, = plt.plot(xp, pi_hi, '--', color = "purple", linewidth = 2, label =
"95% PI")
legend = plt.legend(handles = [fitted_line, lowCI_line, lowPI_line], loc = 4)
```



In [60]:

```
# (E) Using you're results form part (d) predict the number of bike
# rentals in hours for which
# (i) The outside temprature is 80 degrees fahrenheit
# (ii) The wind speed in 15 mph
# (iii) The relative humidity is 100%

# (i) When the outside temprature is 80
X1i = 80
Y1i = -156.9856 + 5.09475*X1i
Y1i
```

Out[60]:

```
250.59440000000004
```

In [64]:

```
# (ii) When the windspeed in 15
X3i = 15
Y3i = 162.7879 + 2.249*X3i
Y3i
```

Out[64]:

```
196.5229
```

In [65]:

```
#(iii) When relative humidity
X2i = 100
Y2i = 376.4450 - 2.9872*X2i
Y2i
```

Out[65]:

```
77.72499999999997
```

In [66]:

```
# (F) Fit a linear regression model relation count to season using
# automated functions.

reg1 = smf.ols('y ~ C(x4)', data = bikeShare).fit()
reg1.summary()
```

Out[66]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.061
Model:	OLS	**Adj. R-squared:**	0.061
Method:	Least Squares	**F-statistic:**	236.9
Date:	Tue, 26 Sep 2017	**Prob (F-statistic):**	6.16e-149
Time:	17:33:18	**Log-Likelihood:**	-71701.
No. Observations:	10886	**AIC:**	1.434e+05
Df Residuals:	10882	**BIC:**	1.434e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	116.3433	3.387	34.352	0.000	109.704	122.982
C(x4)[T.2]	98.9081	4.769	20.740	0.000	89.560	108.256
C(x4)[T.3]	118.0739	4.769	24.758	0.000	108.726	127.422
C(x4)[T.4]	82.6450	4.769	17.331	0.000	73.298	91.992

Omnibus:	1896.059	**Durbin-Watson:**	0.337
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3190.509
Skew:	1.156	**Prob(JB):**	0.00
Kurtosis:	4.299	**Cond. No.**	4.82

In [67]:

```
# From the model we can see that all of the season's catergorical
# variables are highly significant. Regression equation will look
# something like this :
# Y = 116.343 + 98.908X1 + 118.074X2 + 82.645X3, where Beta0 is 116.343
# and beta1 = 98.908, beta2 = 118.075, beta3 = 82.645. When it'll
# be spring season there will 116.343 rentals per day/hour where as
# number of rental increases in fall season, declines in summer and
# winter. Expected value in all of the seasons will looks as follows :

# (1) Y_spring = Beta0 = 116.343
# (2) Y_summer = Beta0 + Beta2X2 = 116.343 + 98.908*X2
# (3) Y_fall = Beta0 + Beta3X3 = 116.343 + 118.074*X3
# (4) Y_winter = Beta0 + Beta4X4 = 116.343 + 82.645*X4
```

In [68]:

```
# (G) Fit a linear regression model relation count to weather using automated
# functions.

reg2 = smf.ols('y ~ C(x5)', data = bikeShare).fit()
reg2.summary()
```

Out[68]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.018
Model:	OLS	**Adj. R-squared:**	0.017
Method:	Least Squares	**F-statistic:**	65.53
Date:	Tue, 26 Sep 2017	**Prob (F-statistic):**	5.48e-42
Time:	17:33:22	**Log-Likelihood:**	-71948.
No. Observations:	10886	**AIC:**	1.439e+05
Df Residuals:	10882	**BIC:**	1.439e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	205.2368	2.117	96.936	0.000	201.087	209.387
C(x5)[T.2]	-26.2813	3.982	-6.599	0.000	-34.087	-18.475
C(x5)[T.3]	-86.3905	6.482	-13.328	0.000	-99.096	-73.685
C(x5)[T.4]	-41.2368	179.567	-0.230	0.818	-393.221	310.748

Omnibus:	2029.021	**Durbin-Watson:**	0.329
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3492.480
Skew:	1.221	**Prob(JB):**	0.00
Kurtosis:	4.319	**Cond. No.**	109.

In [69]:

```
# From the model we can see that most of the variables are highly
# significant apart from 4 which is stormy. Regression equation will
# look something like this :
# Y = 205.237 - 26.281X1 - 86.390X2 - 41.237X3, where Beta0 is 205.237
# and beta1 = -26.281, beta2 = -86.390, beta3 = -41.237. When it'll
# be nice/sunny weather there will 205.237 rentals per day/hour where
# as number of rental decreases in cloudy weather, declines even more in
# stormy and rainy. Expected value in all of the weather's will looks as
# follows :

# (1) Y_spring = Beta0 = 205.237
# (2) Y_summer = Beta0 + Beta2X2 = 205.237 - 26.281*X2
# (3) Y_fall = Beta0 + Beta3X3 = 205.237 - 86.390*X3
# (4) Y_winter = Beta0 + Beta4X4 = 205.237 - 41.237*X4
```