Carolina_CrimeRate_Linear_Model

September 19, 2018

1 Linear Model on North Carolina Crime Rate Dataset (Part II)

1.1 Objective:

To use insights from EDA to develop a suitable **linear model with crmrte as the dependent variable** and explain the various aspects of the model.

1.2 Actionable Observations from EDA

1) The **density and urban variable** has highest correlation with crime rate.

2) But, density and urban variable **seems to be highly correlated**, which is obvious, because urban areas are densely populated. Hence, there is a **high chance of multicollinearity** between density and urban features. We wll use linear regression to sort out this question.

3) The feature, 'urban' has a correlation of 0.62 with crime rate, but whether the correlation is because 'urban' has very high correlation with 'density' is yet to be known.

4) A combination of density and location (west/ central/ urban) can help aid crime rate prediction.

5) Wage columns, wfed & wtrd are positively correlated to 'density' feature. This can be intuitively understood as the **weekly wages would be higher in urban areas.**

6) Some of the **"wage features" are positively correlated**, as the wage increase/ decrease in one domain would certainly influence the other.

7) wtrd & wfir are positively correlated to wfed & wloc. Also, wfir and wtrd have moderate correlation with each other.

8) There are **6 strongly correlated values** with Crime Rate: crmrte, density, urban, wfed, taxpc, wtrd.

2 Load Input Data

In [61]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LinearRegression
```

```python
from sklearn import metrics

# Load crime_v2.csv into a pandas dataFrame.
crimeData = pd.read_csv("crime_v2.csv")

# (Q) how many data-points and features?
print (crimeData.shape)

# See the input data.
crimeData.head(5)
# Identified the columns have header information.
```

```
(91, 25)
```

Out[61]:

```
   county  year    crmrte    prbarr   prbconv   prbpris  avgsen     polpc  \
0       1    87  0.035604  0.298270  0.527596  0.436170    6.71  0.001828
1       3    87  0.015253  0.132029  1.481480  0.450000    6.35  0.000746
2       5    87  0.012960  0.444444  0.267857  0.600000    6.76  0.001234
3       7    87  0.026753  0.364760  0.525424  0.435484    7.14  0.001530
4       9    87  0.010623  0.518219  0.476563  0.442623    8.22  0.000860

    density      taxpc    ...           wtuc        wtrd        wfir  \
0  2.422633  30.993681    ...     408.724487  221.270065  453.172211
1  1.046332  26.892078    ...     376.254181  196.010101  258.564972
2  0.412766  34.816051    ...     372.208435  229.320892  305.944061
3  0.491557  42.947586    ...     397.690125  191.172012  281.065094
4  0.546948  28.054739    ...     377.312561  206.821487  289.312469

         wser        wmfg        wfed        wsta        wloc       mix  \
0  274.177460  334.540008  477.579987  292.089996  311.910004  0.080169
1  192.307693  300.380005  409.829987  362.959992  301.470001  0.030227
2  209.697220  237.649994  358.980011  331.529999  281.369995  0.465116
3  256.721435  281.799988  412.149994  328.269989  299.029999  0.273622
4  215.193329  290.890015  377.350006  367.230011  342.820007  0.060086

    pctymle
0  0.077871
1  0.082607
2  0.072115
3  0.073537
4  0.070698

[5 rows x 25 columns]
```

3 Data Cleaning

In [62]:
```
# Data Cleaning based on EDA
# Last row with special character fixed in input data.

# Removing the wage outlier row based on observation from EDA
crimeData = crimeData[crimeData.county != 185] # very high wser & prob of conviction
crimeData = crimeData[crimeData.county != 115] # prob of arrest > 1

# Removing rows with probability of arrest and conviction > 1
crimeData = crimeData[crimeData['prbarr'] < 1]
crimeData = crimeData[crimeData['prbconv'] < 1]

# The location cannot be both west and central together.
crimeData = crimeData[crimeData['west']+crimeData['central'] <= 1]

# dropping the Year column as it doesnt help in prediction
crimeData = crimeData.drop('year', axis=1)

# (Q) how many after deletion?
print (crimeData.shape)
```

```
(80, 24)
```

4 Evaluate Observations using Linear Regression Model

Lets evaluate the above observations by building Linear Regression Models, as it helps to understand the relation between variables better.

4.1 Creating Model with Most Correlated Feature

In [63]:
```
import statsmodels.api as sm

y = crimeData['crmrte']
# X = crimeData.drop('crmrte', axis=1)
X = crimeData['density']

# without a constant we are forcing our model to go through the origin
X = sm.add_constant(X) # To add an intercept to our model

# Note the difference in argument order
model = sm.OLS(y, X).fit()
# predictions = model.predict(X) # make the predictions by the model

density_pvalue = model.pvalues['density']
```

```
# Print out the statistics
model.summary()
```

Out[63]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.522
Model:                            OLS   Adj. R-squared:                  0.516
Method:                 Least Squares   F-statistic:                     85.18
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           3.88e-14
Time:                        13:47:00   Log-Likelihood:                 234.23
No. Observations:                  80   AIC:                            -464.5
Df Residuals:                      78   BIC:                            -459.7
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0222      0.002     10.949      0.000       0.018       0.026
density        0.0088      0.001      9.229      0.000       0.007       0.011
==============================================================================
Omnibus:                       31.606   Durbin-Watson:                   2.191
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               57.597
Skew:                           1.517   Prob(JB):                     3.11e-13
Kurtosis:                       5.841   Cond. No.                         3.28
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

Interim Observations:

a) As the p-value of density is 0 (small), the changes in crime rate has got close relation with changes in density.

b) R-squared value is found to be 0.525 with only density as predictor variable. This means that 52.5% variability of crime rate is explained by density feature.

c) Co-effient estimate of 0.0086 indicates one value increase of density would cause 0.0086 value increase in crime rate.

4.2 Creating Model with Top 2 Correlated Features

In [64]:
```
y = crimeData['crmrte']
# X = crimeData.drop('crmrte', axis=1)
# X = crimeData[('density', 'urban')]
X = crimeData[['density', 'urban']]
```

```
# without a constant we are forcing our model to go through the origin
X = sm.add_constant(X) # To add an intercept to our model

# Note the difference in argument order
model = sm.OLS(y, X).fit()

density_pvalue_upd = model.pvalues['density']
print('Difference in P-Value = ' + str(density_pvalue_upd - density_pvalue))

# Print out the statistics
model.summary()
```

```
Difference in P-Value = 2.2791391426354033e-05
```

```
Out[64]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.522
Model:                            OLS   Adj. R-squared:                  0.510
Method:                 Least Squares   F-statistic:                     42.12
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           4.38e-13
Time:                        13:47:00   Log-Likelihood:                 234.27
No. Observations:                  80   AIC:                            -462.5
Df Residuals:                      77   BIC:                            -455.4
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0226      0.002      9.170      0.000       0.018       0.027
density        0.0084      0.002      4.511      0.000       0.005       0.012
urban          0.0026      0.010      0.277      0.783      -0.016       0.022
==============================================================================
Omnibus:                       31.413   Durbin-Watson:                   2.193
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               56.769
Skew:                           1.514   Prob(JB):                     4.71e-13
Kurtosis:                       5.804   Cond. No.                         14.9
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

Interim Observations:

a) **R-squared value is found to be slightly higher (0.527)** when the variable, 'urban' is coupled with density as predictor variables. But, R Squared always goes up when you add more variables regardless of whether the added variable help in prediction or not.

b) Adjusted R Squared, penalizes for adding more variables. Thus, it can go down when you add variables that don't contribute. Here note that, **Adjusted R-squared value has gone down from 0.519 to 0.514. Also, the AIC value is increased from -470 to -469** (the smaller the AIC value, the better the model is).

c) It has been noticed that the **p-value of 'density' feature has been increased slightly.**

Thus, **the model has become more less reliable to explain crime rate**, because the feature 'urban' doesnt contribute to prediction. The confusion about the correlation between 'urban' and 'density' variable during EDA step, has been sorted out.

Note: If we add variables that are not meaningful as predictor, then it **would cause 'Overfitting'.** Then, prediction model would perform great with the training data but not with the real world data.

5 Multiple Linear Regression

5.1 Model with all Features

In [65]:
```
y = crimeData['crmrte']
X = crimeData.drop('crmrte', axis=1)

# without a constant we are forcing our model to go through the origin
X = sm.add_constant(X) # To add an intercept to our model

# Note the difference in argument order
model = sm.OLS(y, X).fit()

# Print out the statistics
model.summary()
# density_pvalue = model.pvalues
```

Out[65]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.896
Model:                            OLS   Adj. R-squared:                  0.853
Method:                 Least Squares   F-statistic:                     20.94
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           9.21e-20
Time:                        13:47:00   Log-Likelihood:                 295.18
No. Observations:                  80   AIC:                            -542.4
Df Residuals:                      56   BIC:                            -485.2
Df Model:                          23
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
```

```
==============================================================================
const          0.0120      0.018      0.660      0.512      -0.024       0.048
county      2.584e-06   1.54e-05      0.168      0.867   -2.82e-05    3.33e-05
prbarr        -0.0522      0.010     -5.093      0.000      -0.073      -0.032
prbconv       -0.0073      0.006     -1.179      0.243      -0.020       0.005
prbpris        0.0110      0.012      0.890      0.377      -0.014       0.036
avgsen        -0.0008      0.000     -2.005      0.050      -0.002   -6.38e-07
polpc         10.7921      2.617      4.123      0.000       5.549      16.036
density        0.0049      0.001      3.523      0.001       0.002       0.008
taxpc          0.0002      0.000      1.918      0.060   -8.89e-06       0.000
west          -0.0051      0.004     -1.205      0.233      -0.014       0.003
central       -0.0063      0.003     -2.320      0.024      -0.012      -0.001
urban          0.0035      0.006      0.558      0.579      -0.009       0.016
pctmin80       0.0003   9.37e-05      2.877      0.006    8.19e-05       0.000
wcon        3.108e-05   2.67e-05      1.164      0.249   -2.24e-05    8.46e-05
wtuc        1.281e-05   1.52e-05      0.842      0.403   -1.77e-05    4.33e-05
wtrd        5.237e-05    4.2e-05      1.248      0.217   -3.17e-05       0.000
wfir       -4.966e-05    2.8e-05     -1.774      0.081      -0.000    6.41e-06
wser       -8.336e-05   3.05e-05     -2.729      0.008      -0.000   -2.22e-05
wmfg       -2.522e-06   1.35e-05     -0.186      0.853   -2.96e-05    2.46e-05
wfed        3.817e-05    2.5e-05      1.527      0.132   -1.19e-05    8.82e-05
wsta       -5.022e-05   2.42e-05     -2.074      0.043   -9.87e-05   -1.71e-06
wloc        4.453e-05   4.51e-05      0.987      0.328   -4.58e-05       0.000
mix           -0.0228      0.014     -1.632      0.108      -0.051       0.005
pctymle        0.1447      0.044      3.261      0.002       0.056       0.234
==============================================================================
Omnibus:                        6.753   Durbin-Watson:                   2.494
Prob(Omnibus):                  0.034   Jarque-Bera (JB):                6.098
Skew:                           0.639   Prob(JB):                       0.0474
Kurtosis:                       3.443   Cond. No.                     3.28e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
[2] The condition number is large, 3.28e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

In [66]:
```python
y = crimeData['crmrte']

# Feature 'urban' is found to be worsen the model as per above analysis.
# Intuitively county shouldnt contribute prediction and also p value is high.
X = crimeData.drop(['crmrte', 'urban', 'county'], axis=1)

# without a constant we are forcing our model to go through the origin
X = sm.add_constant(X) # To add an intercept to our model

# Note the difference in argument order
```

```
model = sm.OLS(y, X).fit()

# Print out the statistics
model.summary()
```

Out[66]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.895
Model:                            OLS   Adj. R-squared:                  0.857
Method:                 Least Squares   F-statistic:                     23.60
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           4.53e-21
Time:                        13:47:01   Log-Likelihood:                 294.95
No. Observations:                  80   AIC:                            -545.9
Df Residuals:                      58   BIC:                            -493.5
Df Model:                          21
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0099      0.017      0.568      0.572      -0.025       0.045
prbarr        -0.0524      0.010     -5.197      0.000      -0.073      -0.032
prbconv       -0.0076      0.006     -1.240      0.220      -0.020       0.005
prbpris        0.0104      0.012      0.862      0.392      -0.014       0.035
avgsen        -0.0008      0.000     -2.011      0.049      -0.002   -3.73e-06
polpc         10.6581      2.557      4.168      0.000       5.540      15.776
density        0.0055      0.001      6.517      0.000       0.004       0.007
taxpc          0.0002      0.000      2.012      0.049     1.1e-06       0.000
west          -0.0045      0.004     -1.108      0.272      -0.013       0.004
central       -0.0062      0.003     -2.343      0.023      -0.012      -0.001
pctmin80       0.0003   8.82e-05      3.231      0.002       0.000       0.000
wcon         3.12e-05   2.63e-05      1.186      0.240   -2.15e-05    8.39e-05
wtuc        1.339e-05   1.45e-05      0.924      0.359   -1.56e-05    4.24e-05
wtrd        5.361e-05    4.1e-05      1.308      0.196   -2.84e-05       0.000
wfir       -5.175e-05   2.73e-05     -1.899      0.063      -0.000    2.81e-06
wser       -8.318e-05   2.96e-05     -2.809      0.007      -0.000   -2.39e-05
wmfg       -1.573e-06   1.32e-05     -0.119      0.906    -2.8e-05    2.49e-05
wfed        3.676e-05   2.45e-05      1.500      0.139   -1.23e-05    8.58e-05
wsta       -4.646e-05   2.28e-05     -2.034      0.047   -9.22e-05   -7.44e-07
wloc        4.501e-05   4.44e-05      1.014      0.315   -4.39e-05       0.000
mix           -0.0223      0.014     -1.628      0.109      -0.050       0.005
pctymle        0.1439      0.043      3.330      0.002       0.057       0.230
==============================================================================
Omnibus:                        6.849   Durbin-Watson:                   2.503
Prob(Omnibus):                  0.033   Jarque-Bera (JB):                6.210
Skew:                           0.646   Prob(JB):                       0.0448
Kurtosis:                       3.438   Cond. No.                     3.24e+06
```

```
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly speci
[2] The condition number is large, 3.24e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

5.2 Removing features from all-feature Model

Interim Observations:

a) **Adj. R-squared improved** from 0.825 in all-feature model to 0.830, after removal of 2 features 'urban', 'county'.

b) **AIC value decreased** from -591.3 in all-feature model to -595.2, after removal of 2 features 'urban', 'county'.

Thus, **we have a better model than the all-feature model.** We will try to remove more features and analyze the model indicators.

In [67]:
```python
y = crimeData['crmrte']
# Features are dropped based on p-value, R-Squared and AIC figures.
X = crimeData.drop(['crmrte', 'urban', 'county',
                    'wmfg', 'prbpris', 'wloc', 'west', 'wtuc'], axis=1)

# without a constant we are forcing our model to go through the origin
X = sm.add_constant(X) # To add an intercept to our model

# Note the difference in argument order
model = sm.OLS(y, X).fit()

# Print out the statistics
model.summary()
```

Out[67]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.887
Model:                            OLS   Adj. R-squared:                  0.859
Method:                 Least Squares   F-statistic:                     30.98
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           8.65e-24
Time:                        13:47:01   Log-Likelihood:                 292.00
No. Observations:                  80   AIC:                            -550.0
Df Residuals:                      63   BIC:                            -509.5
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0213      0.015      1.444      0.154      -0.008       0.051
prbarr        -0.0567      0.010     -5.893      0.000      -0.076      -0.037
prbconv       -0.0090      0.006     -1.501      0.138      -0.021       0.003
avgsen        -0.0007      0.000     -1.912      0.060      -0.001    3.15e-05
polpc          9.7105      2.378      4.083      0.000       4.958      14.463
density        0.0055      0.001      6.629      0.000       0.004       0.007
taxpc          0.0002   9.28e-05      2.657      0.010    6.11e-05       0.000
central       -0.0039      0.002     -2.058      0.044      -0.008      -0.000
pctmin80       0.0004   5.56e-05      6.573      0.000       0.000       0.000
wcon        4.224e-05   2.36e-05      1.786      0.079   -5.01e-06    8.95e-05
wtrd        6.553e-05   3.84e-05      1.705      0.093   -1.13e-05       0.000
wfir       -5.353e-05   2.64e-05     -2.028      0.047      -0.000   -7.86e-07
wser       -7.792e-05   2.82e-05     -2.768      0.007      -0.000   -2.17e-05
wfed        4.205e-05   2.35e-05      1.789      0.078   -4.91e-06     8.9e-05
wsta       -4.664e-05   2.18e-05     -2.136      0.037   -9.03e-05   -3.01e-06
mix           -0.0224      0.013     -1.697      0.095      -0.049       0.004
pctymle        0.1471      0.041      3.583      0.001       0.065       0.229
==============================================================================
Omnibus:                        3.198   Durbin-Watson:                   2.571
Prob(Omnibus):                  0.202   Jarque-Bera (JB):                2.731
Skew:                           0.450   Prob(JB):                        0.255
Kurtosis:                       3.089   Cond. No.                     2.39e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
[2] The condition number is large, 2.39e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Interim Observations:

a) **Adj. R-squared of the above model with 8 features dropped is better** than the all-feature model.

b) **AIC value of the above model is better** than the all-feature model.

Thus, we have a better model than the all-feature model by removing more features such as 'wmfg', 'prbpris', 'wloc', 'west', 'wtuc'. We will try to remove even more features with p > 0.05 and evaluate using RMSE.

6 Model Evaluation Using Cross Validation & RMSE

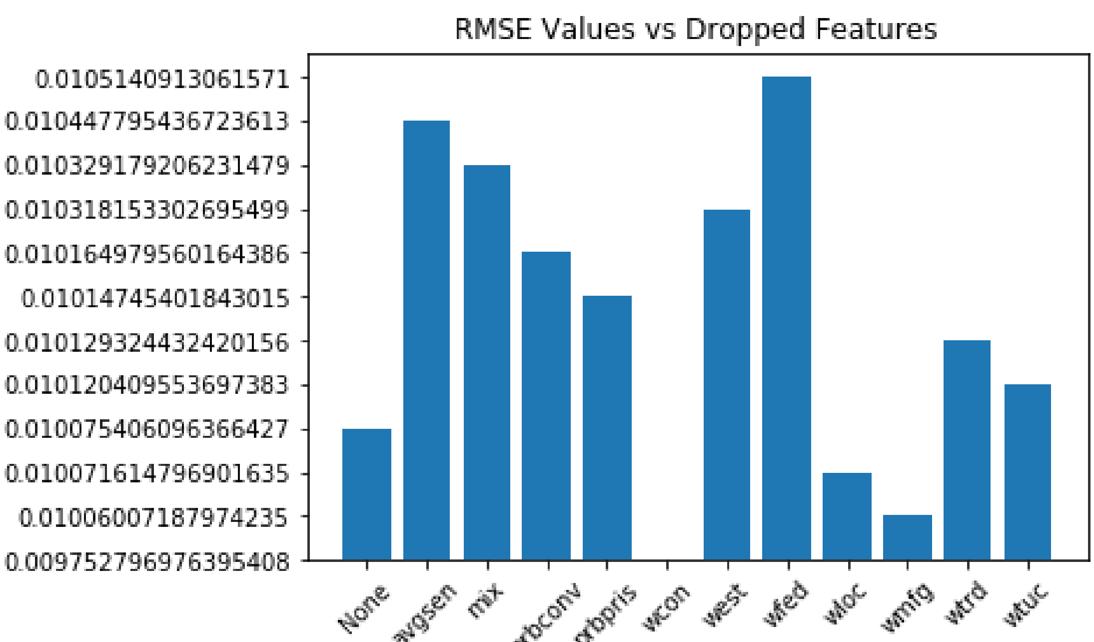
We will test the change in RMSE value when the features with p > 0.05 are removed. The features with p > 0.05 are prbconv, mix, wfed, wtrd, wcon & avgsen. We will also check the RMSE values for the features removed in the previous model.

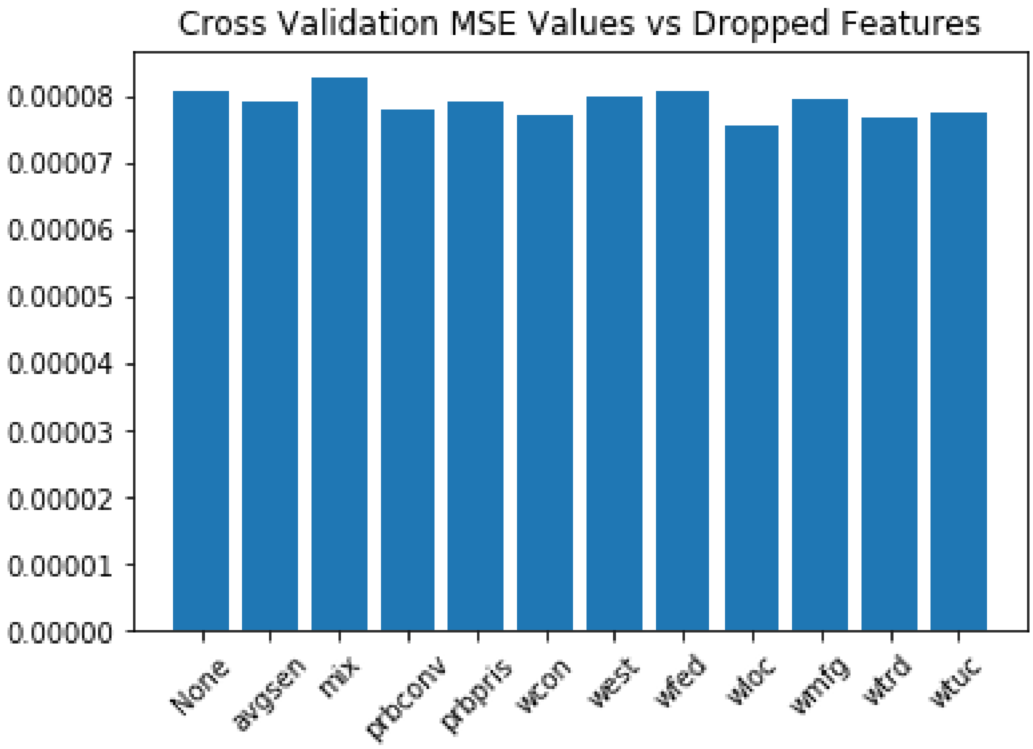
```
In [68]: from sklearn.cross_validation import train_test_split

         def calculateRMSE(X, y, feature='None'):
             # Split data
             X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)

             # Instantiate and fit the model
             lm = LinearRegression()
             lm.fit(X_train, y_train)
             y_pred = lm.predict(X_test)

             RMSE = str(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

             # RMSE
             print("RMSE with " + feature + " removed = " + RMSE)
             return RMSE
```

```
In [69]: from sklearn.cross_validation import cross_val_score

         rmseVals = []
         cv_scores = []
         droppedFeatures = []

         # Features are dropped based on p-value, R-Squared and AIC figures.
         features2Drop = ['crmrte', 'urban', 'county']

         y = crimeData['crmrte']
         X = crimeData.drop(features2Drop, axis=1)

         rmseVals.append(calculateRMSE(X, y))
         droppedFeatures.append('None')
         scores = cross_val_score(LinearRegression(),
                                  X, y, cv=10, scoring='neg_mean_squared_error')
         cv_scores.append(-1*scores.mean())

         # 'wmfg', 'prbpris', 'wloc', 'west', 'wtuc' are dropped in the previous model
         features2Test = ['wmfg', 'prbpris', 'wloc', 'west', 'wtuc',
                          'prbconv', 'mix', 'wfed', 'wtrd', 'wcon', 'avgsen']

         for feature in features2Test:
             features2Drop.append(feature)
             X = crimeData.drop(features2Drop, axis=1)
             features2Drop.remove(feature)
             rmseVals.append(calculateRMSE(X, y, feature))
             droppedFeatures.append(feature)

             scores = cross_val_score(LinearRegression(),
                                      X, y, cv=10, scoring='neg_mean_squared_error')
```

```
        cv_scores.append(-1*scores.mean())

    # print(droppedFeatures)
    # print(cv_scores)

    plt.bar(droppedFeatures, rmseVals)
    plt.title('RMSE Values vs Dropped Features')
    plt.xticks(rotation=45)
    plt.show()

    plt.bar(droppedFeatures, cv_scores)
    plt.title('Cross Validation MSE Values vs Dropped Features')
    plt.xticks(rotation=45)
    plt.show()
```

```
RMSE with None removed = 0.010075406096366427
RMSE with wmfg removed = 0.01006007187974235
RMSE with prbpris removed = 0.01014745401843015
RMSE with wloc removed = 0.010071614796901635
RMSE with west removed = 0.010318153302695499
RMSE with wtuc removed = 0.010120409553697383
RMSE with prbconv removed = 0.010164979560164386
RMSE with mix removed = 0.010329179206231479
RMSE with wfed removed = 0.0105140913061571
RMSE with wtrd removed = 0.010129324432420156
RMSE with wcon removed = 0.009752796976395408
RMSE with avgsen removed = 0.010447795436723613
```





From the bar chart, the RMSE values performs better than 'None' when wtuc, wtrd, wloc, west, wmfg and avgsen are removed. Thus, in addition to the previous model, **wtrd & avgsen features are removed.** But the R-squared and AIC figures degrade when both the features are removed. Since wtrd has a higher p value, **we will remove wtrd in our model.**

The lowest cross validation MSE is for wloc, wtrd, prbconv and wcon. Thus, in addition to the previous exclusions, prbconv & wcon also can be dropped. But removal of either feature would increase the RMSE value as per the above plot. Thus, we will remove only wtrd in our model.

7 OLS Regression Characteristic of Final Model

```
In [70]: y = crimeData['crmrte']
         # Features are dropped based on p-value, R-Squared and AIC figures.
         X = crimeData.drop(['crmrte', 'urban', 'county',
                             'wmfg', 'prbpris', 'wloc',
                             'west', 'wtuc', 'wtrd'], axis=1)

         # without a constant we are forcing our model to go through the origin
         X = sm.add_constant(X) # To add an intercept to our model

         # Note the difference in argument order
```

```
model = sm.OLS(y, X).fit()

# Print out the statistics
model.summary()
```

Out[70]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 crmrte   R-squared:                       0.882
Model:                            OLS   Adj. R-squared:                  0.854
Method:                 Least Squares   F-statistic:                     31.90
Date:                Wed, 19 Sep 2018   Prob (F-statistic):           5.95e-24
Time:                        13:47:02   Log-Likelihood:                 290.20
No. Observations:                  80   AIC:                            -548.4
Df Residuals:                      64   BIC:                            -510.3
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0273      0.015      1.875      0.065      -0.002       0.056
prbarr        -0.0565      0.010     -5.786      0.000      -0.076      -0.037
prbconv       -0.0113      0.006     -1.909      0.061      -0.023       0.001
avgsen        -0.0007      0.000     -1.773      0.081      -0.001     8.3e-05
polpc          8.7668      2.347      3.735      0.000       4.078      13.455
density        0.0057      0.001      6.946      0.000       0.004       0.007
taxpc          0.0003   9.39e-05      2.735      0.008    6.93e-05       0.000
central       -0.0037      0.002     -1.896      0.062      -0.008       0.000
pctmin80       0.0004   5.63e-05      6.381      0.000       0.000       0.000
wcon        4.943e-05   2.36e-05      2.094      0.040    2.27e-06    9.66e-05
wfir       -3.692e-05   2.49e-05     -1.483      0.143   -8.67e-05    1.28e-05
wser       -7.727e-05   2.86e-05     -2.705      0.009      -0.000   -2.02e-05
wfed        5.208e-05   2.31e-05      2.256      0.028    5.96e-06    9.82e-05
wsta       -5.317e-05   2.18e-05     -2.438      0.018   -9.67e-05    -9.6e-06
mix           -0.0207      0.013     -1.550      0.126      -0.047       0.006
pctymle        0.1404      0.041      3.386      0.001       0.058       0.223
==============================================================================
Omnibus:                        7.285   Durbin-Watson:                   2.498
Prob(Omnibus):                  0.026   Jarque-Bera (JB):                6.695
Skew:                           0.608   Prob(JB):                       0.0352
Kurtosis:                       3.727   Cond. No.                     2.24e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
[2] The condition number is large, 2.24e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
"""
```

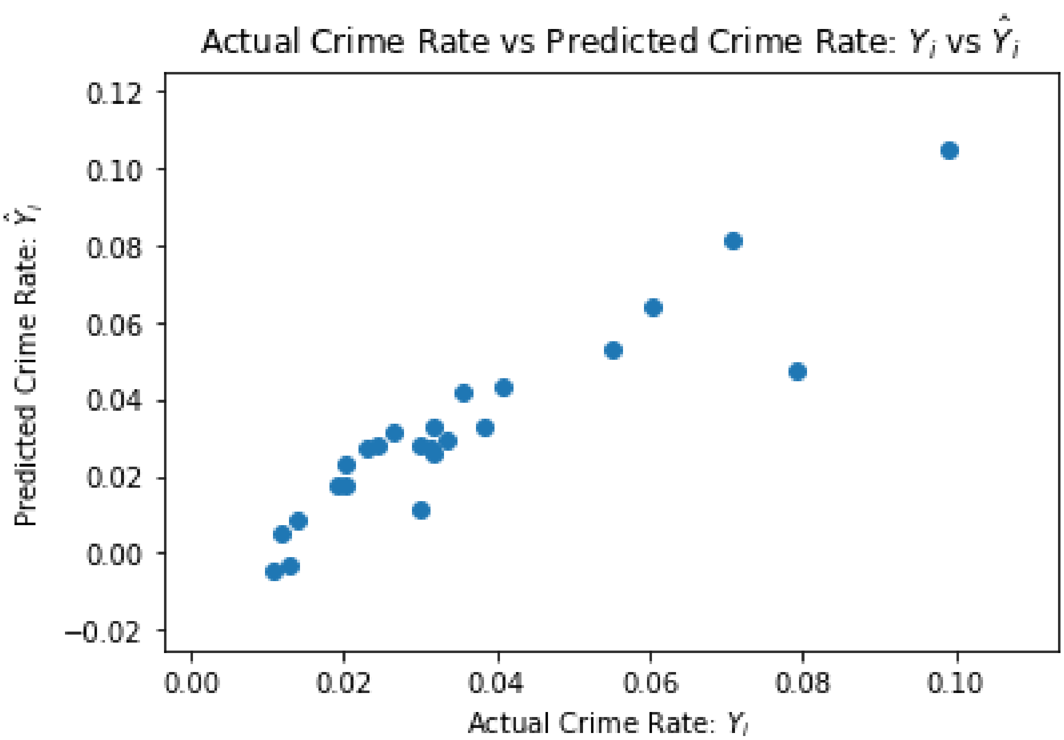
8 Testing the Model on Input Data

```
In [71]: # To calculate Linear Regression, do plotting and calculate error

         # Importing the statistics module
         from statistics import mean
         from statistics import median

         # used to format headings
         bold = '\033[1m'
         end = '\033[0m'

         def linearReg(x_train, y_train, x_test, y_test):

             lm = LinearRegression()
             lm.fit(x_train, y_train)

             y_pred = lm.predict(x_test)

             plt.scatter(y_test, y_pred)
             plt.xlabel("Actual Crime Rate: $Y_i$")
             plt.ylabel("Predicted Crime Rate: $\hat{Y}_i$")
             plt.title("Actual Crime Rate vs Predicted Crime Rate: $Y_i$ vs $\hat{Y}_i$")
             plt.show()

             # calculate MAE, MSE, RMSE
             print("Mean Absolute Error (MAE) = " + str(
                         metrics.mean_absolute_error(y_test, y_pred)))
             print("Median Squared Error (MSE) = " + str(
                         metrics.mean_squared_error(y_test, y_pred)))
             print("Root Mean Squared Error (RMSE) = " + str(
                         np.sqrt(metrics.mean_squared_error(y_test, y_pred))))

             print("Explained Variance = " + str(
                             metrics.explained_variance_score(y_test, y_pred)))

             # Calculating the error
             delta_y = y_test - y_pred;
             print("Median Absolute Error = " + str(median(abs(delta_y))))
```

```
In [79]: from sklearn.cross_validation import train_test_split

         y = crimeData['crmrte']
         X = crimeData.drop(['crmrte', 'urban', 'county',
                             'wmfg', 'prbpris', 'wloc',
```

```python
                                'west', 'wtuc', 'wtrd', 'wcon'], axis=1)

        # create training and testing data: 70/ 30 split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

        print('Train Data Shape:')
        print(X_train.shape, y_train.shape)
        print('Test Data Shape:')
        print(X_test.shape, y_test.shape)

        linearReg(X_train, y_train, X_test, y_test)
```

```
Train Data Shape:
(56, 14) (56,)
Test Data Shape:
(24, 14) (24,)
```




```
Mean Absolute Error (MAE) = 0.006986915112800922
Median Squared Error (MSE) = 9.631084350128324e-05
Root Mean Squared Error (RMSE) = 0.009813808817237233
Explained Variance = 0.8203755208633289
Median Absolute Error = 0.004534970460507454
```

9 Conclusion

a) **The Actual vs Predicted plot is linear. This signifies the prediction is working fine.** The input data set is limited. With more data, the plot could be more linear.

b) As an improvement, we can **combine the boolean features**: west, central and urban into a single feature with categorical values 1, 2 & 3. Such a single feature may be more helpful to aid prediction. **Functional-transforms** (like log) on features can also be helpful.

c) **Standardization** was not found to help model performance. Still it is advisable to standardisation in linear models.

d) If there is a chance to add features, then **it might be helpful to get 'unemployment rate'** as a predictor for crime rate.