Carolina_Crime_Exploratory_Analysis

September 18, 2018

1 Perform EDA on North Carolina Crime Rate Dataset (Part I)

1.1 Data Description:

The dataset contains the data for **crime rate in the state of North Carolina** aggregated by county.

1.2 Data Attributes:

1. county - county identifier
2. year - 1987
3. crmrte - crimes committed per person
4. prbarr - 'probability' of arrest
5. prbconv - 'probability' of conviction
6. prbpris - 'probability' of prison sentence
7. avgsen - avg. sentence, days
8. polpc - police per capita
9. density - people per sq. mile
10. taxpc - tax revenue per capita
11. west - =1 if in western N.C.
12. central - =1 if in central N.C.
13. urban - =1 if in SMSA
14. pctmin80 - perc. minority, 1980
15. wcon - weekly wage, construction
16. wtuc - wkly wge, trns, util, commun
17. wtrd - wkly wge, whlesle, retail trade
18. wfir - wkly wge, fin, ins, real est
19. wser - wkly wge, service industry
20. wmfg - wkly wge, manufacturing
21. wfed - wkly wge, fed employees
22. wsta - wkly wge, state employees
23. wloc - wkly wge, local gov emps
24. mix - offense mix: face-to-face/other
25. pctymle - percent young male

1.3 Objective:

1. To do a **univariate** and **bivariate exploratory analysis** of data and report the findings.

2. To develop a suitable **linear model with crmrte as the dependent variable** and explain the various aspects of the model.

1.4 1. Load Data

```
In [2]: import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        import numpy as np


        # Load haberman.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 doesnt have header information.
```

```
(91, 25)
```

```
Out[2]:    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]
```

2 2. Data Analysis & Data Cleaning

```
In [3]: # Check characteristics of data.
        crimeData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 91 entries, 0 to 90
Data columns (total 25 columns):
county      91 non-null int64
year        91 non-null int64
crmrte      91 non-null float64
prbarr      91 non-null float64
prbconv     91 non-null float64
prbpris     91 non-null float64
avgsen      91 non-null float64
polpc       91 non-null float64
density     91 non-null float64
taxpc       91 non-null float64
west        91 non-null int64
central     91 non-null int64
urban       91 non-null int64
pctmin80    91 non-null float64
wcon        91 non-null float64
wtuc        91 non-null float64
wtrd        91 non-null float64
wfir        91 non-null float64
wser        91 non-null float64
wmfg        91 non-null float64
wfed        91 non-null float64
wsta        91 non-null float64
wloc        91 non-null float64
mix         91 non-null float64
pctymle     91 non-null float64
dtypes: float64(20), int64(5)
memory usage: 17.9 KB
```

The last column was getting read as 'object' data. It was found to be due to the special symbol at the last row, last column 0.074198931'. Removed the special symbol from input csv file, to fix it.

```
In [4]: # To find stats of each feature.
        crimeData.describe()
```

```
Out[4]:            county  year    crmrte     prbarr    prbconv    prbpris  \
        count   91.000000  91.0  91.000000  91.000000  91.000000  91.000000
        mean   101.615385  87.0   0.033400   0.294917   0.551279   0.410766
        std     58.793569   0.0   0.018811   0.136940   0.352243   0.080236
        min      1.000000  87.0   0.005533   0.092770   0.068376   0.150000
        25%     52.000000  87.0   0.020927   0.205679   0.345411   0.364796
        50%    105.000000  87.0   0.029986   0.270950   0.452830   0.423423
        75%    152.000000  87.0   0.039642   0.344378   0.588859   0.456778
        max    197.000000  87.0   0.098966   1.090910   2.121210   0.600000

                  avgsen      polpc    density       taxpc     ...           wtuc  \
        count  91.000000  91.000000  91.000000   91.000000     ...      91.000000
        mean    9.646813   0.001702   1.428837   38.055066     ...     411.667954
        std     2.846913   0.000987   1.514481   13.077918     ...      77.266434
        min     5.380000   0.000746   0.000020   25.692865     ...     187.617264
        25%     7.340000   0.001231   0.547405   30.662366     ...     374.632080
        50%     9.100000   0.001485   0.962264   34.870213     ...     406.504059
        75%    11.420000   0.001877   1.568242   40.948238     ...     443.435822
        max    20.700001   0.009054   8.827652  119.761452     ...     613.226074

                    wtrd        wfir         wser        wmfg        wfed  \
        count   91.000000   91.000000    91.000000   91.000000   91.000000
        mean   211.552901  322.098207   275.564211  335.588683  442.900659
        std     34.216065   53.890163   206.251415   87.841262   59.677816
        min    154.209000  170.940170   133.043060  157.410004  326.100006
        25%    190.863731  286.527420   229.661842  288.875000  400.239990
        50%    203.016235  317.307678   253.228058  320.200012  449.839996
        75%    225.125992  345.353668   280.541275  359.580002  478.029999
        max    354.676117  509.465515  2177.068115  646.849976  597.950012

                    wsta        wloc        mix    pctymle
        count   91.000000   91.000000  91.000000  91.000000
        mean   357.521976  312.680769   0.128842   0.083962
        std     43.103312   28.235279   0.081331   0.023327
        min    258.329987  239.169998   0.019608   0.062158
        25%    329.324997  297.264999   0.080735   0.074430
        50%    357.690002  308.049988   0.101861   0.077713
        75%    382.589996  329.250000   0.151749   0.083498
        max    499.589996  388.089996   0.465116   0.248712

        [8 rows x 25 columns]
```

It is to be noted that the **maximum value of probability features, prbarr & prbconv, are found to be > 1** which is a data anomaly. The maximum values of prbpris & pctymle are found to be < 1, hence data may be correct.

```
In [5]: # To check how many zeros in each column - to find out missing data
        print('\n\nNumber of zeroes for each Feature:')
        (crimeData==0).sum()
```

```
Number of zeroes for each Feature:
```

```
Out[5]: county       0
        year         0
        crmrte       0
        prbarr       0
        prbconv      0
        prbpris      0
        avgsen       0
        polpc        0
        density      0
        taxpc        0
        west        68
        central     57
        urban       83
        pctmin80     0
        wcon         0
        wtuc         0
        wtrd         0
        wfir         0
        wser         0
        wmfg         0
        wfed         0
        wsta         0
        wloc         0
        mix          0
        pctymle      0
        dtype: int64
```

There are 91 entries for all the 25 columns. Hence, there is **no missing value in the input dataset. Thus, no need to do data imputation** or to drop any feature.

The zero values for features, west, central and urban are expected, as the data is inherently boolean.

```
In [6]: # This row has to be dropped because of data anomaly.
        crimeData[crimeData['prbarr'] > 1]
```

```
Out[6]:     county  year    crmrte   prbarr  prbconv  prbpris     avgsen     polpc  \
        50     115    87  0.005533  1.09091      1.5      0.5  20.700001  0.009054

             density      taxpc    ...          wtuc        wtrd        wfir  \
        50  0.385809  28.193104    ...    503.235077  217.490845  342.465759

                  wser        wmfg        wfed        wsta        wloc  mix   pctymle
        50  245.206085  448.420013  442.200012  340.390015  386.119995  0.1  0.072535
```

```
[1 rows x 25 columns]
```

In [7]:
```
# These rows has to be dropped because of data anomaly.
crimeData[crimeData['prbconv'] > 1]
```

Out[7]:
```
    county  year    crmrte    prbarr  prbconv   prbpris     avgsen     polpc  \
1        3    87  0.015253  0.132029  1.48148  0.450000   6.350000  0.000746
9       19    87  0.022157  0.162860  1.22561  0.333333  10.340000  0.002024
43      99    87  0.017187  0.153846  1.23438  0.556962  14.750000  0.001859
50     115    87  0.005533  1.090910  1.50000  0.500000  20.700001  0.009054
55     127    87  0.029150  0.179616  1.35814  0.335616  15.990000  0.001583
60     137    87  0.012666  0.207143  1.06897  0.322581   6.180000  0.000814
66     149    87  0.016499  0.271967  1.01538  0.227273  14.620000  0.001519
83     185    87  0.010870  0.195266  2.12121  0.442857   5.380000  0.001222
89     195    87  0.031397  0.201397  1.67052  0.470588  13.020000  0.004459
90     197    87  0.014193  0.207595  1.18293  0.360825  12.230000  0.001186

     density      taxpc    ...           wtuc        wtrd        wfir  \
1   1.046332  26.892078    ...     376.254181  196.010101  258.564972
9   0.576744  61.152512    ...     613.226074  191.245224  290.514099
43  0.547862  39.573483    ...     417.209900  168.269226  301.573425
50  0.385809  28.193104    ...     503.235077  217.490845  342.465759
55  1.338889  32.023758    ...     426.390076  257.600769  441.141296
60  0.316716  44.293674    ...     356.125366  170.871139  170.940170
66  0.609244  29.034021    ...     437.062927  188.768280  353.218201
83  0.388759  40.824535    ...     331.564972  167.372589  264.423065
89  1.745989  53.666927    ...     377.935608  246.061371  411.433014
90  0.889881  25.952581    ...     341.880341  182.801987  348.143250

           wser        wmfg        wfed        wsta        wloc       mix  \
1    192.307693  300.380005  409.829987  362.959992  301.470001  0.030227
9    266.093414  567.059998  403.149994  258.329987  299.440002  0.053347
43   247.629089  258.989990  442.760010  387.019989  291.440002  0.019608
50   245.206085  448.420013  442.200012  340.390015  386.119995  0.100000
55   305.761169  329.869995  508.609985  380.299988  329.709992  0.063055
60   250.836121  192.960007  360.839996  283.899994  321.730011  0.068702
66   210.441483  289.429993  421.339996  342.920013  301.230011  0.116822
83  2177.068115  247.720001  381.329987  367.250000  300.130005  0.049689
89   296.868439  392.269989  480.790008  303.109985  337.279999  0.156124
90   212.820511  322.920013  391.720001  385.649994  306.850006  0.067568

     pctymle
1   0.082607
9   0.077132
43  0.128947
50  0.072535
55  0.074003
```

```
60   0.070984
66   0.062158
83   0.070082
89   0.079451
90   0.074199

[10 rows x 25 columns]
```

```
In [8]: # The location cannot be both west and central together.
        crimeData[crimeData['west']+crimeData['central'] > 1]
```

```
Out[8]:     county  year    crmrte    prbarr  prbconv   prbpris  avgsen    polpc  \
        32      71    87  0.054406  0.243119  0.22959  0.379175   11.29  0.00207

             density      taxpc   ...           wtuc        wtrd        wfir  \
        32  4.834734  31.536579   ...     595.371948  240.367325  348.025391

                  wser        wmfg        wfed        wsta        wloc       mix  \
        32  295.230072  358.950012  509.429993  359.109985  339.579987  0.101861

            pctymle
        32  0.07939

        [1 rows x 25 columns]
```

Observations:

From above analysis, it is found, that **some rows have to be dropped** before doing regression analysis. The probability values of some rows are found to be > 1 and location of one row was found to be both 'west' and 'central' at the same time. We will drop these rows before building the model. The **special character error in the input dataset is also fixed.**

3 Univariate Analysis

Univariate visualization provides summary statistics for each field in the raw data set. It is conducted **to find out how much a single feature in the dataset** would be helpful to determine the target feature, here in this case, crime rate.

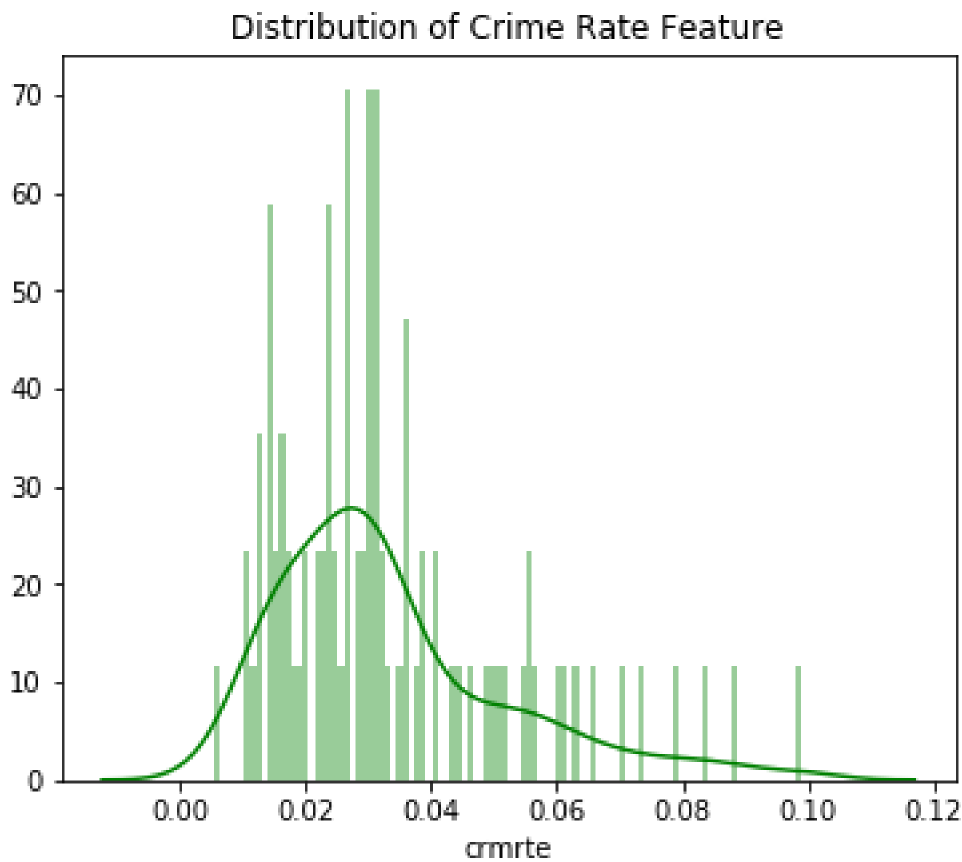
3.1 Distribution of Target Variable

```
In [44]: # Numerical data distribution of dependant variable: Crime Rate

         print('Statistics of Crime Rate: \n')
         print(crimeData['crmrte'].describe())
         plt.figure(figsize=(6, 5))
         plt.title('Distribution of Crime Rate Feature')
         sns.distplot(crimeData['crmrte'], color='g', bins=100, hist_kws={'alpha': 0.4})
```

```
Statistics of Crime Rate:
```

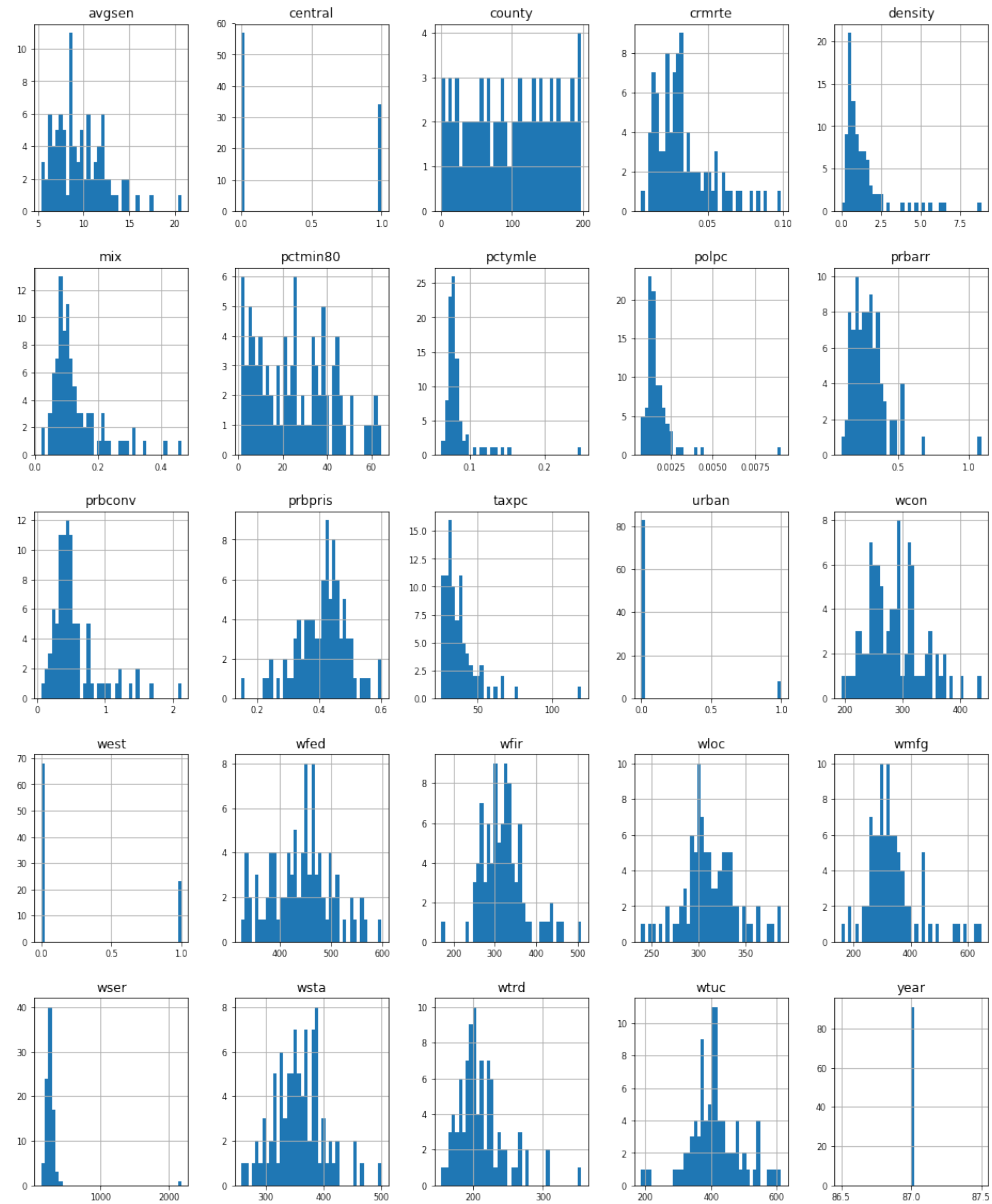
```
count    91.000000
mean      0.033400
std       0.018811
min       0.005533
25%       0.020927
50%       0.029986
75%       0.039642
max       0.098966
Name: crmrte, dtype: float64
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x10ddde80>



3.2 Distribution of All Features

```
In [45]: crimeData.hist(figsize=(16, 20), bins=40, xlabelsize=8, ylabelsize=8);
```

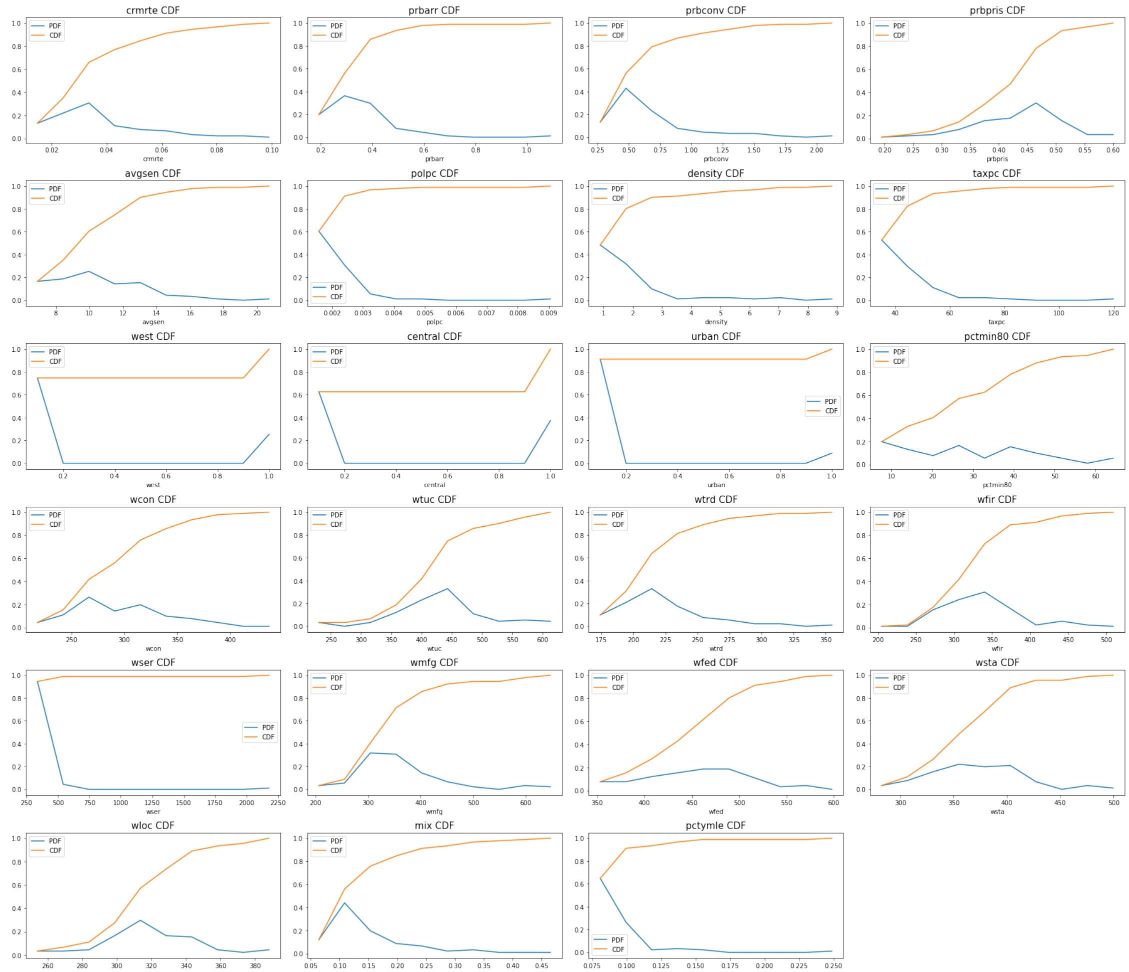


Observation:

The features **density, mix, police per capita, probability of conviction and tax revenue per capita seems to have similar distribution as crime rate.** But no definitive conclusion can be made from this observation. Lets examine further using bivariate analysis.

3.3 Probability/ Cumulative Distribution Function (CDF)

```
In [46]: # You can get the percentage directly from CDF given one x value.
         # Such information is not available from PDF directly

         plt.figure(figsize=(25,25))

         for idx, col in enumerate(crimeData.columns[2:]): #excluding county & year
             counts, bin_edges = np.histogram(crimeData[col], bins=10, density = True)
             pdf = counts/(sum(counts))
             cdf = np.cumsum(pdf)

             plt.subplot(7, 4, idx+1)
             plt.plot(bin_edges[1:],pdf, label='PDF')
             plt.plot(bin_edges[1:],cdf, label='CDF')
             plt.title(col + " CDF",fontsize=15)
             plt.xlabel(col)
         #     plt.ylabel('Probability')
             plt.tight_layout()

             plt.legend()
```



Observations:

a) One **strange observation is in weekly wages of service industry (wser).** More than 95% of wages lies below 400, but the maximum wage is around 2250.

From the data, this is identified to be **county 185.** As the percentage of minorities in this county is high (nearly 65%) and wages in other sectors are comparatively less, the wages of service industry is mostly an error. **We will remove "county 185" from the input data.**

b) Though the maximum value of tax revenue per capita is 120, more than 50% of values lies below 40.

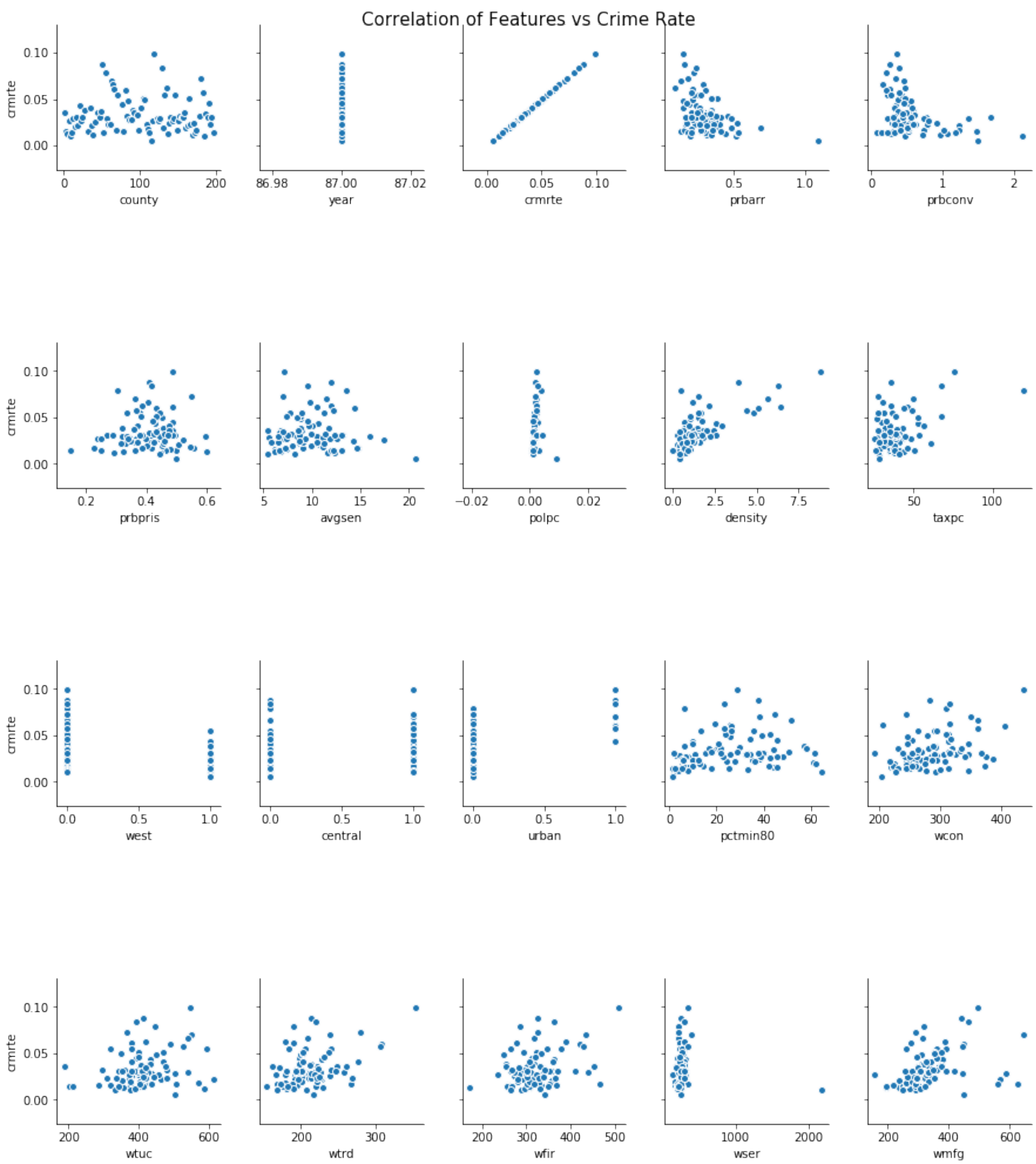
c) Though the maximum value of police per capita is 0.009, more than 60% of values lies below 0.001.

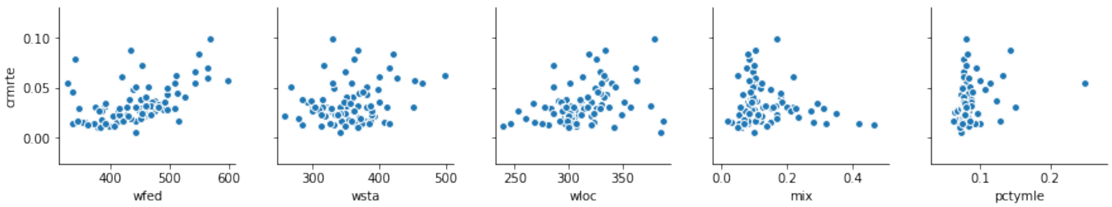
4 Bivariate Analysis

Bivariate visualization is performed to find the relationship between each variable in the dataset and the target variable of interest, i.e. crime rate.

The plot of all features against crime rate is done as below.

```
In [47]: # To plot the correlation of all features against crime rate

         for i in range(0, len(crimeData.columns), 5):
             sns.pairplot(data=crimeData,
                          x_vars=crimeData.columns[i:i+5],
                          y_vars=['crmrte'])
             if i == 0:
                 plt.suptitle('Correlation of Features vs Crime Rate', fontsize = 15)
```





Observations:

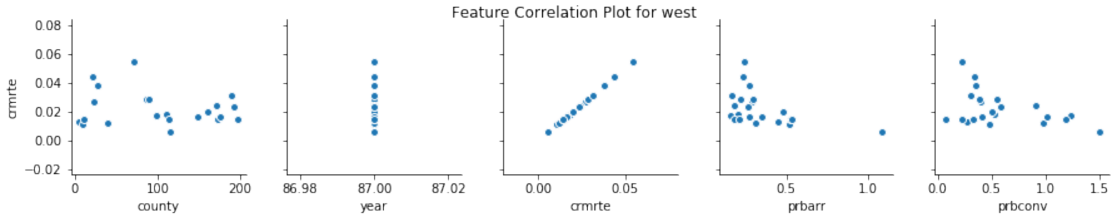
a) Based on the above pairplot, it can be noted that **density is most positively correlated with crime rate. There is also some correlation with weekly wages under different domains but it needs further investigation, as they are not so pronounced.**

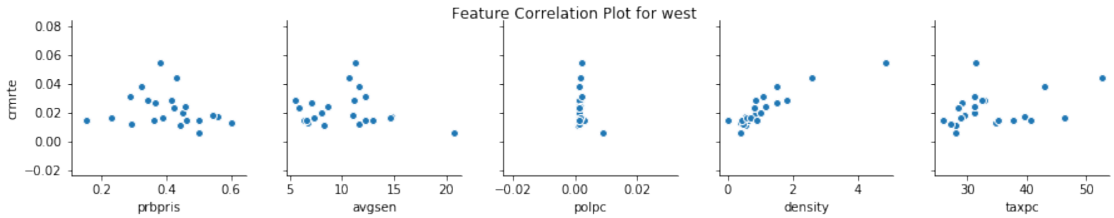
b) Strangely, the **weekly wage features and crime rate is found to be slightly positively correlated. This signifies unequal distribution of income** or probably high unemployment rate. One of the most important features that is not in the given data may be unemployment rate.

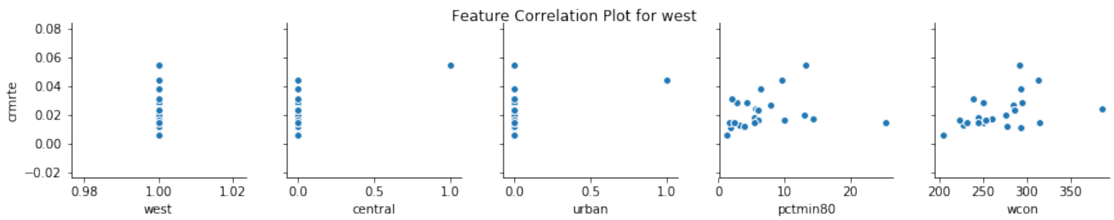
Lets try to find if there is any correlation among features for each location: 'west', 'central' & 'urban'.

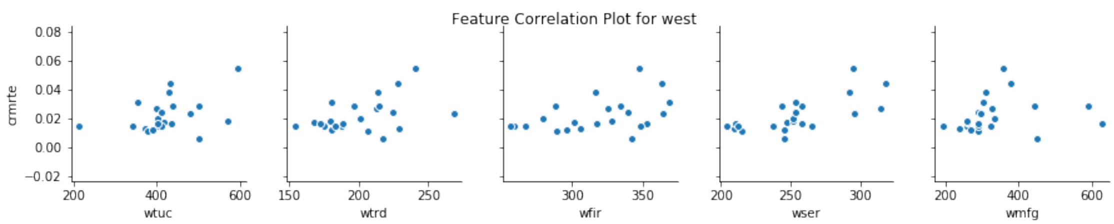
```
In [48]: # To plot the correlation of boolean features against crime rate

         # Categories: west, central and urban
         categories = ['west', 'central', 'urban']

         for category in categories:

             categoricalCrime = crimeData[crimeData[category] == 1]
             print('Number of data points in category: ' +
                                        category + ' is '+ str(len(categoricalCrime)))

             for i in range(0, len(categoricalCrime.columns), 5):

                 sns.pairplot(data=categoricalCrime,
                              x_vars=categoricalCrime.columns[i:i+5],
                              y_vars=['crmrte'])
         #           plt.title('Feature Correlation Plot for ' + category, loc = 'left')
                 plt.suptitle('Feature Correlation Plot for ' + category)
```

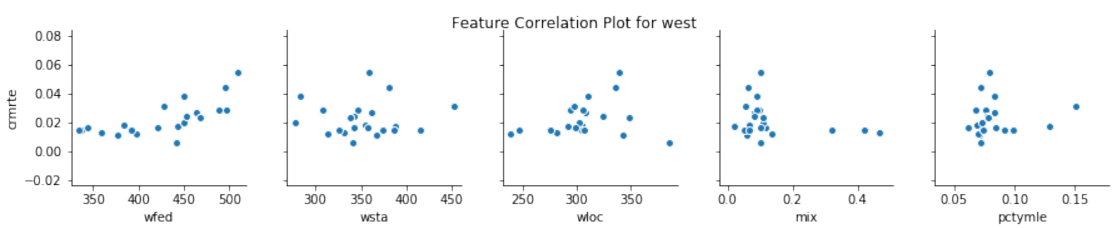
```
Number of data points in category: west is 23
Number of data points in category: central is 34
Number of data points in category: urban is 8
```

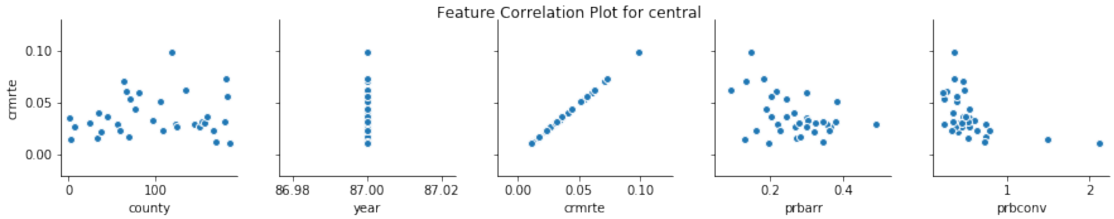

Feature Correlation Plot for west
crmrte
county
year
crmrte
prbarr
prbconv

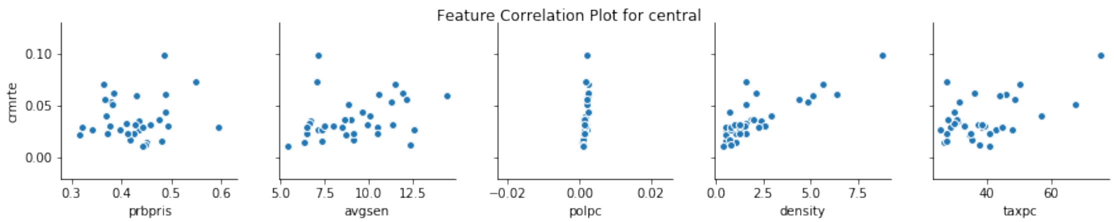

Feature Correlation Plot for west
crmrte
prbpris
avgsen
polpc
density
taxpc

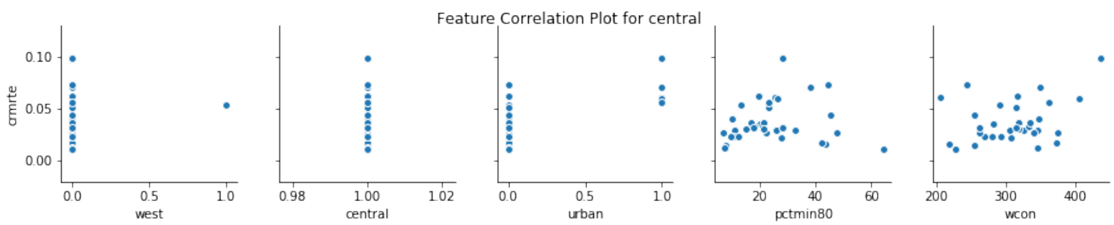

Feature Correlation Plot for west
crmrte
west
central
urban
pctmin80
wcon

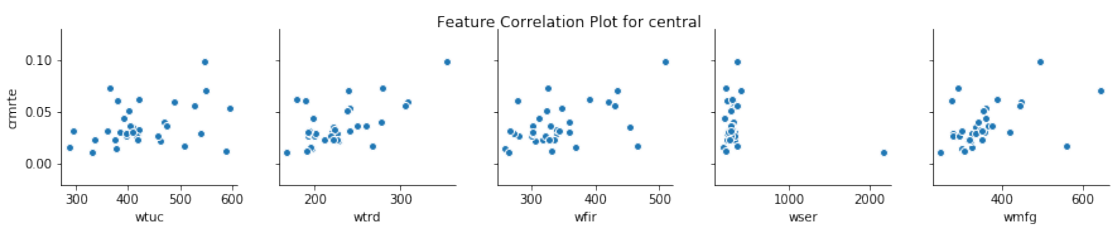

Feature Correlation Plot for west
crmrte
wtuc
wtrd
wfir
wser
wmfg

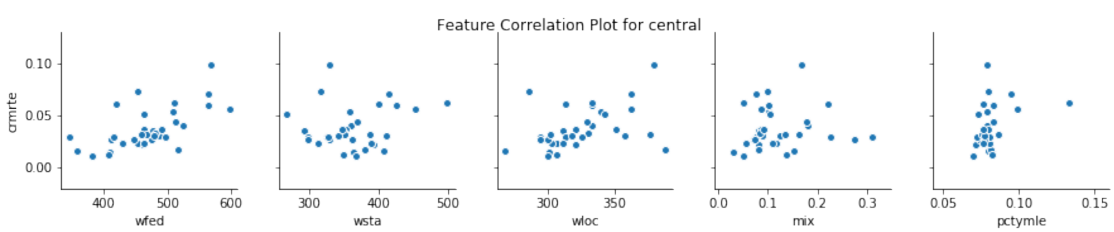

Feature Correlation Plot for west
crmrte
wfed
wsta
wloc
mix
pctymle

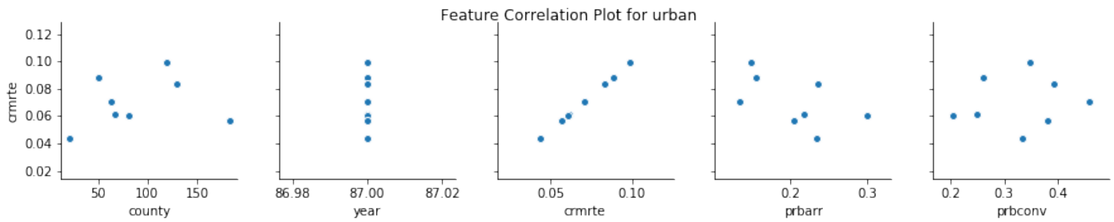

Feature Correlation Plot for central
crmrte
0.10
0.05
0.00
county
year
crmrte
prbarr
prbconv

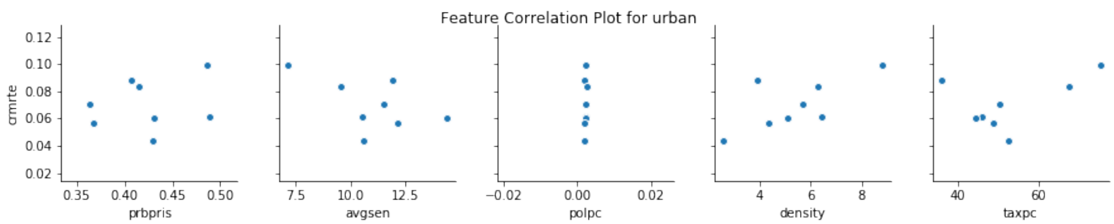

Feature Correlation Plot for central
crmrte
0.10
0.05
0.00
prbpris
avgsen
polpc
density
taxpc

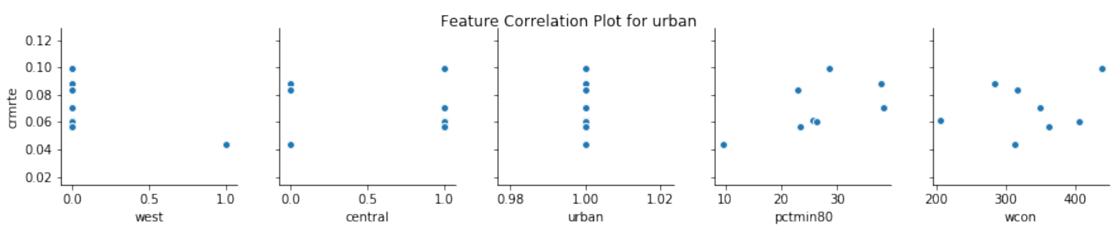

Feature Correlation Plot for central
crmrte
0.10
0.05
0.00
west
central
urban
pctmin80
wcon

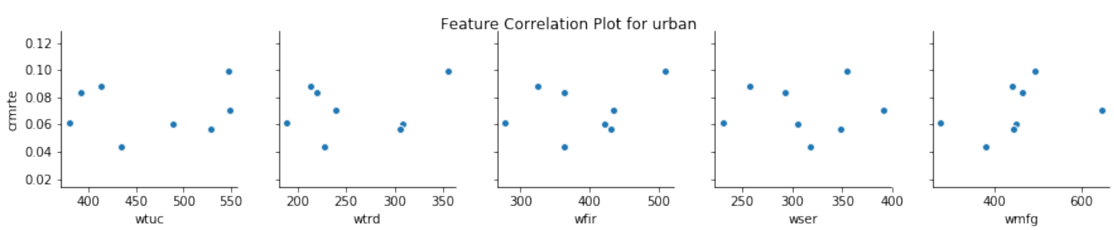

Feature Correlation Plot for central
crmrte
0.10
0.05
0.00
wtuc
wtrd
wfir
wser
wmfg

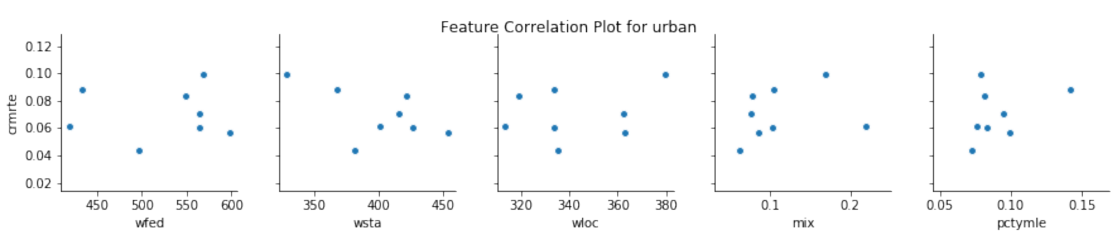

Feature Correlation Plot for central
crmrte
0.10
0.05
0.00
wfed
wsta
wloc
mix
pctymle


Feature Correlation Plot for urban
crmrte
county
year
crmrte
prbarr
prbconv


Feature Correlation Plot for urban
crmrte
prbpris
avgsen
polpc
density
taxpc


Feature Correlation Plot for urban
crmrte
west
central
urban
pctmin80
wcon


Feature Correlation Plot for urban
crmrte
wtuc
wtrd
wfir
wser
wmfg


Feature Correlation Plot for urban
crmrte
wfed
wsta
wloc
mix
pctymle

Observations:

1) Some of the correlation lines are showing upward or downward trends more than before.
2) **Probability of conviction is found to have negative correlation with crime rate in both west and central, but not in urban areas.**
3) **Tax Per capita is found to have positive correlation with crime rate in both central and urban areas.**
4) **Percentage of minority is positively correlated with crime rate, both in west and in urban areas.**
5) Thus, a combination of density and location (urban/ west/ central) might help aid crime rate prediction.
6) However, there seems to be **not much data for 'urban areas'** to arrive at a conclusion.

4.1 Linear Regression Fit of Strongly Correlated Features

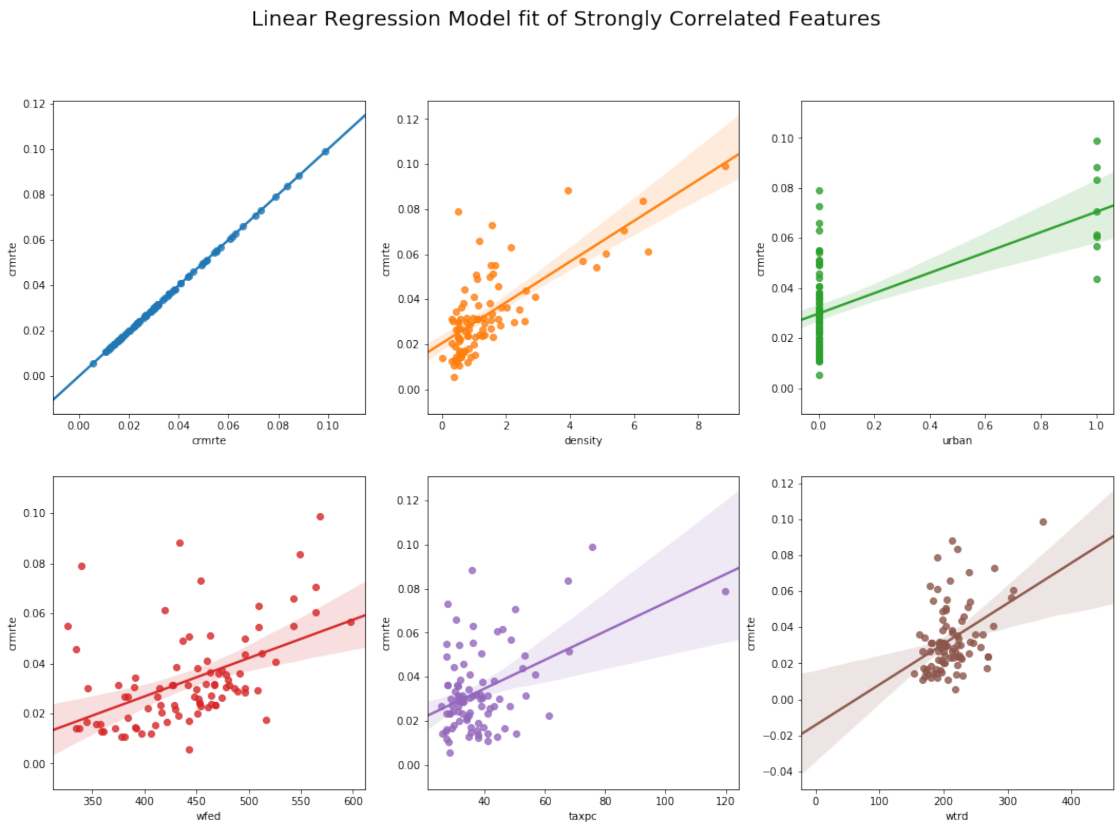
We have a lot of features to analyse in the input dataset. So let's take the strongly correlated quantitative features from this dataset and analyse them one by one.

```
In [49]: # To find out strongly correlated values with crime rate.
         # 40% is taken as the threshold beyond which we include the feature in model.

         crimeData_corr = crimeData.corr()['crmrte']
         selected_features_list = crimeData_corr[
                         abs(crimeData_corr) > 0.4].sort_values(ascending=False)
         print("There are {} strongly correlated values with Crime Rate:\n{}".format(
                         len(selected_features_list), selected_features_list))

         print(list(selected_features_list.index))
```

```
There are 6 strongly correlated values with Crime Rate:
crmrte      1.000000
density     0.728963
urban       0.615602
wfed        0.486156
taxpc       0.450980
wtrd        0.410106
Name: crmrte, dtype: float64
['crmrte', 'density', 'urban', 'wfed', 'taxpc', 'wtrd']
```

```
In [50]: # To plot data and a linear regression model fit.

         fig, ax = plt.subplots(round(len(selected_features_list) / 3), 3, figsize = (18, 12))
```

```
features = list(selected_features_list.index)
plt.suptitle('Linear Regression Model fit of Strongly Correlated Features',
                                                                    fontsize=20)

for i, ax in enumerate(fig.axes):
    if i < len(features):
        sns.regplot(x=features[i],y='crmrte',
                        data=crimeData[features], ax=ax)
```

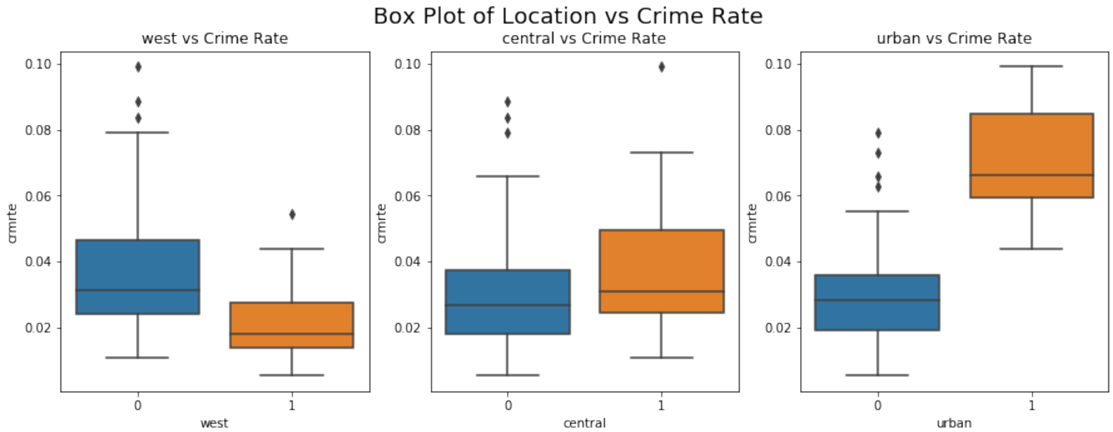


4.2 Box Plots

Let's do the box plot & violin plot for the boolean features 'west', 'central', 'urban' to find impact on crime rate, if any.

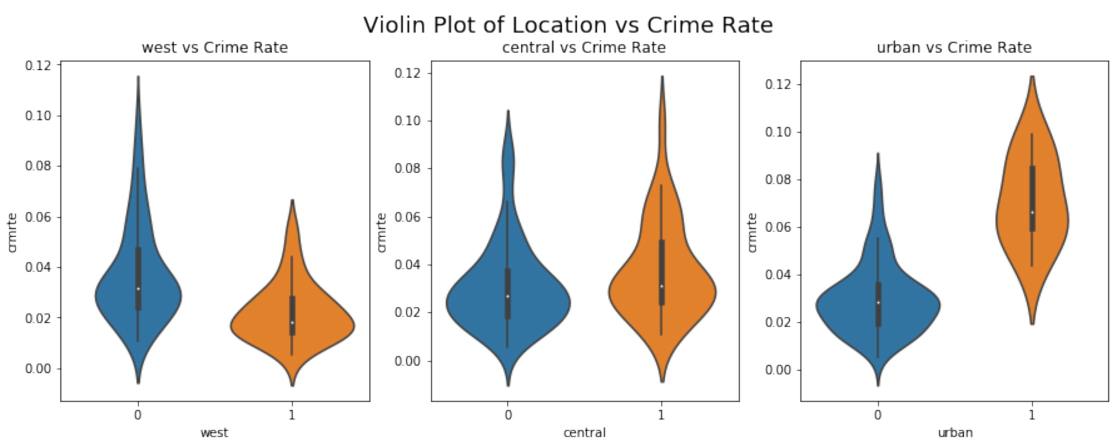
```
In [51]: #Box-plot: another method of visualizing the 1-D scatter plot more intuitively.

         # Categories: west, central and urban
         categories = ['west', 'central', 'urban']

         fig, axes = plt.subplots(1, 3, figsize=(15, 5))
```

```
plt.suptitle('Box Plot of Location vs Crime Rate', fontsize=18)

for idx, cat in enumerate(categories):
    sns.boxplot(x=cat,y='crmrte', data=crimeData,
                ax=axes[idx]).set_title(cat+' vs Crime Rate')
plt.show()
```



4.3 Violin Plots

In [52]:
```
# A violin plot combines the benefits of the previous two plots and simplifies them

# Denser regions of the data are fatter, and sparser ones thinner in a violin plot

fig, axes = plt.subplots(1, 3, figsize=(15, 5))
plt.suptitle('Violin Plot of Location vs Crime Rate', fontsize=18)

for idx, cat in enumerate(categories):
    sns.violinplot(x=cat,y='crmrte', data=crimeData, size=8, ax=axes[idx]) \
    .set_title(cat+' vs Crime Rate')
plt.show()
```



Observations:

a) The crime rate in urban areas is found to be significantly high. Thus, the feature 'urban' is an useful variable for prediction.

b) The crime rate in west is found to be less and central moderate. But as there is significant overlap, such variations may not be very helpful for prediction.

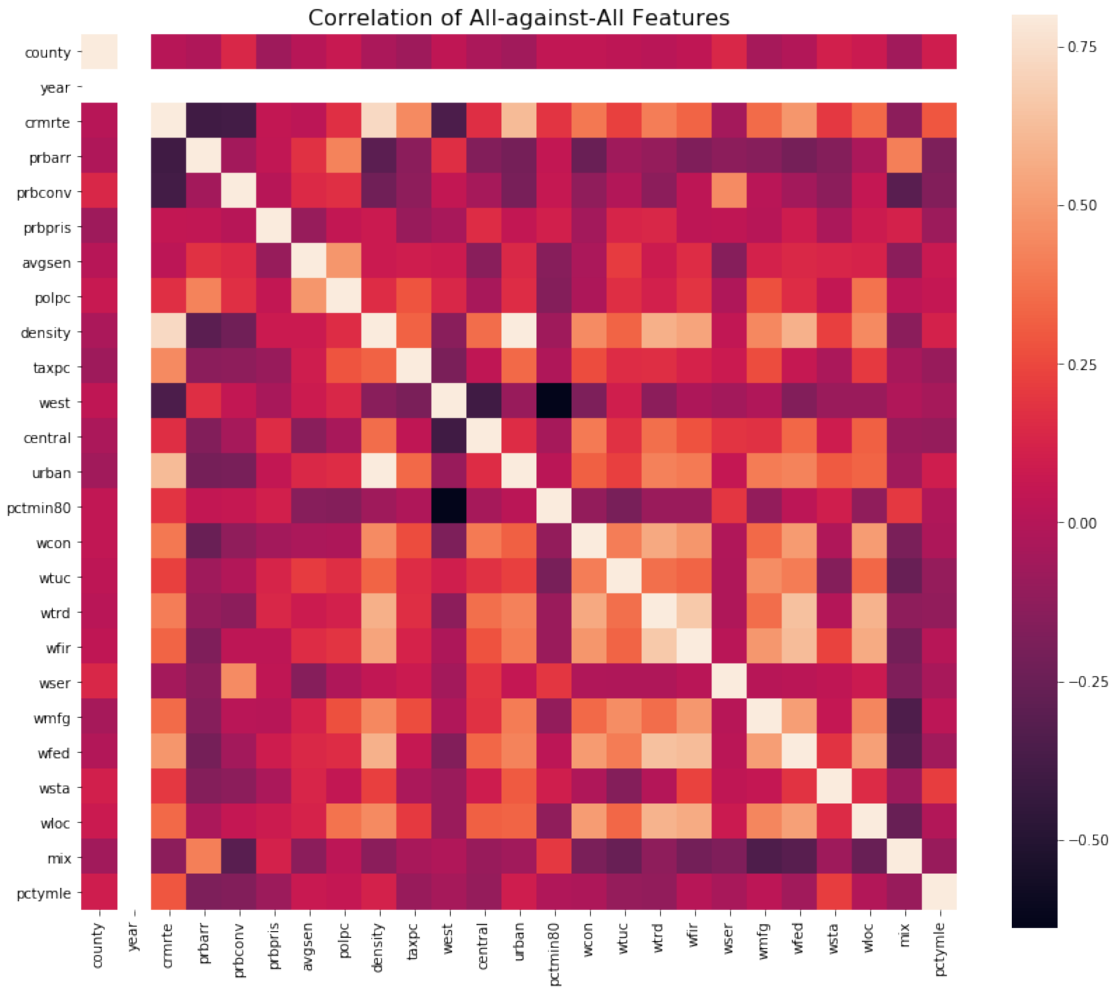
5 Feature-Feature Correlation Analysis

Many times, more than one input could be dependent on each other. In Linear Regression, the requirement is that all the input variables are independent of each other.

When a feature is dependent on one or more of the other input features, it leads to a phenomenon known as multi-collinearity. **Multi-collinearity among features can be identified by doing Feature-Feature correlation analysis.**

In [53]:
```
# Drawing a heatmap
crimeData_corr = crimeData.corr()

f , ax = plt.subplots(figsize = (14,12))
plt.title('Correlation of All-against-All Features',y=1,size=16)
sns.heatmap(crimeData_corr,square = True,  vmax=0.8)
```

Out[53]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xe501278>
```



Observations from the Feature HeatMap:

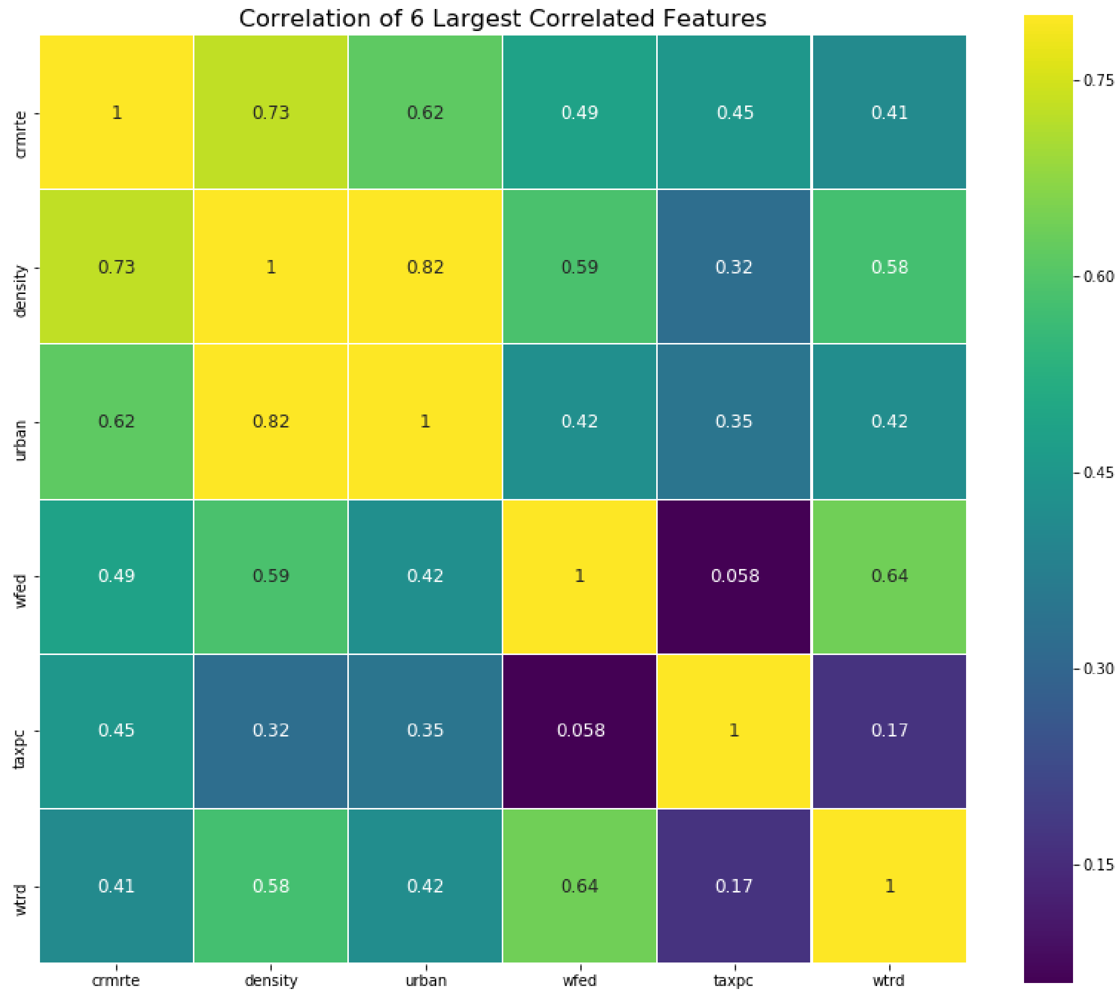
a) The **density and urban variable seems to be highly correlated**, which is obvious, because urban areas are densely populated.

b) **Some of the "wage features" are positively correlated**, as the wage increase/ decrease in one domain would certainly influence the other. For example, **wtrd & wfir are positively correlated to wfed & wloc. Also, wfir and wtrd have moderate correlation.**

In [54]:
```
# Zoomed HeatMap

k= 6
cols = crimeData_corr.nlargest(k,'crmrte')['crmrte'].index
# print(cols)

cm = np.corrcoef(crimeData[cols].values.T)
f , ax = plt.subplots(figsize = (14,12))
plt.title('Correlation of ' + str(k) + ' Largest Correlated Features',y=1,size=16)
```

```
sns.heatmap(cm, vmax=.8, linewidths=0.01,square=True,annot=True,cmap='viridis',
            linecolor="white",xticklabels = cols.values ,
            annot_kws = {'size':12},yticklabels = cols.values)
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x12e4e668>



Observations from Zoomed Feature HeatMap:

a) Density and crime rate have a correlation of 0.73. But **density has high correlation with 'urban' feature. Hence, whether both features, density and urban, are useful to predict crime rate needs further investigation. We wll use linear regression to sort out this question.**

b) 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.

c) 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 Conclusions

6.1 Data Analysis and Cleaning

Observations:

Some rows have to be dropped before doing regression analysis. The probability values of some rows are found to be > 1 and location of one row was found to be both 'west' and 'central', at the same time. We will drop these rows before building the model. The **special character error in the input dataset is also fixed.**

6.2 Univariate Analysis

a) The features **density, mix, police per capita, probability of conviction and tax revenue per capita seems to have similar distribution as crime rate**. But no definitive conclusion can be made from this observation.

b) One **strange observation is in weekly wages of service industry (wser).** More than 95% of wages lies below 400, but the maximum wage is around 2250.

From the data, this is identified to be **county 185**. As the percentage of minorities in this county is high (nearly 65%) and wages in other sectors are comparatively less, the wages of service industry is mostly an error. We will remove **"county 185"** from the input data.

c) Though the maximum value of tax revenue per capita is 120, more than 50% of values lies below 40.

d) Though the maximum value of police per capita is 0.009, more than 60% of values lies below 0.001.

6.3 Bivariate Analysis

a) Based on the pairplot, it can be noted that **density is most positively correlated with crime rate. There is also some correlation with weekly wages under different domains but it needs further investigation, as they are not so pronounced.**

b) Strangely, the **weekly wage features and crime rate is found to be slightly positively correlated. This signifies unequal distribution of income** or probability high unemployment rate. One of the most important features that is not in the given data is unemployment rate.

6.4 Correlation among features for each boolean feature

1) Some of the correlation lines are showing upward or downward trends more than before.

2) **Probability of conviction is found to have negative correlation with crime rate in both west and central, but not in urban areas**.

3) **Tax Per capita is found to have positive correlation with crime rate in both central and urban areas**.

4) **Percentage of minority is positively correlated with crime rate, both in west and in urban areas**.

5) Thus, a combination of density and location (urban/ west/ central) can help aid crime rate prediction.

6) However, there seems to be **not much data for 'urban areas'** to arrive at a conclusion.

6.5 Linear Fit of Top Correlated Features

a) The crime rate in urban areas is found to be significantly high. Thus, the feature 'urban' is an useful variable for prediction.

b) The crime rate in west is found to be less and central moderate. But as there is significant overlap, such variations may not to be very helpful for prediction.

6.6 Feature-Feature Correlation Analysis

a) Many times, more than one input could be dependent on each other. It leads to a phenomenon known as **multi-collinearity, which can be identified by doing Feature-Feature correlation analysis.** In Linear Regression, the requirement is that all the input variables are independent of each other.

b) The **density and urban variable seems to be highly correlated**, which is obvious, because urban areas are densely populated.

c) **Some of the "wage features" are positively correlated**, as the wage increase/ decrease in one domain would certainly influence the other. For example, **wtrd & wfir are positively correlated to wfed & wloc. Also, wfir and wtrd have moderate correlation**.

d) Density and crime rate have a correlation of 0.73. But **density has high correlation with 'urban' feature. Hence, whether both features, density and urban, are useful to predict crime rate needs further investigation. We wll use linear regression to sort out this question**.

e) 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.

f) 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.

The above observations from EDA are carried forward to help Linear Regression (Part II).