

Lab 1: Applied data science

1) Which variables have the most explanatory power? Which have the least?

The next method is to use pearson test to compare both variables:

```
df = pd.read_csv("trafficking_data.csv")
print pearsonr(df["persons prosecuted"],df["Adult victims"])
.....and so on

person prosecuted VS adult victim:
(-0.048430976740660318, 0.54565160155960302)

child victim VS adult victim:
(-0.035024116929785513, 0.66219496601816152)

gdp VS adult victim:
(0.028646394597412601, 0.72087188051004913)

life expectancy VS adult victim:
(0.049826116824534659, 0.53412741414372966)

Female primary education VS adult victim:
(-0.10034340943285375, 0.20967825172658733)

policy index VS adult victim:
(0.063669987031620329, 0.42674651732545388)
```

where the return value is (Pearson's correlation coefficient, 2-tailed p-value). Here we understand that almost no correlation between two of them (pearson coefficient varies from -1 to 1, close to zero implies no correlation). P-value roughly indicates the probability of an uncorrelated system producing datasets that have a Pearson correlation at least as extreme as the one computed from these datasets. In addition, policy index seems to be dominant factor in predicting Adult victims.

Then we start implementing linear prediction model to try predicting each expected Y values by fixed x variables and compare the R squared value.

OLS Regression Results

```
=====
Dep. Variable:      Adult_victims    R-squared:              0.106
Model:              OLS              Adj. R-squared:         0.089
Method:             Least Squares    F-statistic:            6.142
Date:               Wed, 08 Oct 2014  Prob (F-statistic):       0.000567
Time:               18:24:05          Log-Likelihood:         -1280.2
No. Observations:   158              AIC:                    2566.
Df Residuals:       155              BIC:                    2576.
Df Model:           3
```

```
=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
gdp            -3.425e-12   3.06e-11   -0.112     0.911    -6.38e-11   5.7e-11
policy_index    19.3717      31.154     0.622     0.535    -42.169    80.913
life_expectancy  4.5127       8.912     0.506     0.613    -13.092    22.117
females_education -4.4773     11.804    -0.379     0.705    -27.795    18.840
=====
```

```
Omnibus:           198.128    Durbin-Watson:           0.777
Prob(Omnibus):      0.000     Jarque-Bera (JB):        5932.011
Skew:               5.132     Prob(JB):                0.00
Kurtosis:           31.208    Cond. No.                1.20e+12
=====
```

Warnings:

[1] The condition number is large, 1.2e+12. This might indicate that there are strong multicollinearity or other numerical problems.

```
Parameters: gdp            -3.425145e-12
policy_index    1.937171e+01
life_expectancy  4.512711e+00
females_education -4.477272e+00
dtype: float64
```

Warnings:

[1] The condition number is large, 1.2e+12. This might indicate that there are strong multicollinearity or other numerical problems.

```
Parameters: gdp                -2.586435e-12
policy_index      5.257530e+00
life_expectancy   -1.838591e+00
females_education  2.201553e+00
dtype: float64
```

OLS Regression Results

```
=====
Dep. Variable:    persons_prosecuted    R-squared:                0.034
Model:                OLS    Adj. R-squared:            0.015
Method:            Least Squares    F-statistic:            1.828
Date:                Wed, 08 Oct 2014    Prob (F-statistic):        0.144
Time:                18:24:05    Log-Likelihood:            -1510.8
No. Observations:    158    AIC:                    3028.
Df Residuals:        155    BIC:                    3037.
Df Model:                3
=====
```

```
=====
              coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----
gdp          5.426e-12  1.32e-10     0.041     0.967    -2.55e-10  2.65e-10
policy_index  101.7509   134.108     0.759     0.449    -163.163  366.665
life_expectancy -32.9970   38.363    -0.860     0.391    -108.779   42.785
females_education 36.2056   50.813     0.713     0.477    -64.169  136.581
=====
```

```
=====
Omnibus:                224.600    Durbin-Watson:            0.538
Prob(Omnibus):           0.000    Jarque-Bera (JB):         10002.180
Skew:                    6.162    Prob(JB):                  0.00
Kurtosis:                39.979    Cond. No.                  1.20e+12
=====
```

Warnings:

```
[1] The condition number is large, 1.2e+12. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
Parameters: gdp                5.425977e-12
policy_index      1.017509e+02
life_expectancy   -3.299698e+01
females_education  3.620564e+01
```

```
dtype: float64
```

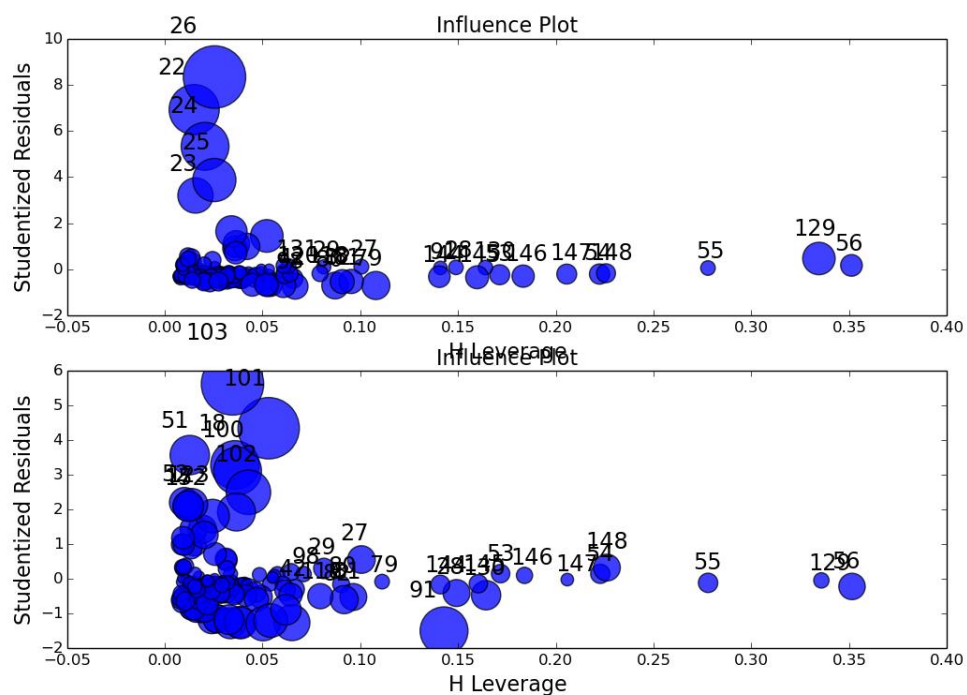
```
R^2 of results_victims 0.106242258731
```

```
R^2 of results_prosecuted 0.0341707197668
```

From the result above we could see that R squared for adult victim is larger than results prosecuted. Therefore, we will use Adult victims as the value to predict in this assignment.

2) *Remove some the outlier countries, how does this effect your model? -----*

To get a better image on how removing outlier countries, we can observe the distribution of influential plot (H leverage VS studentized residuals). Here we remove Brazil who has unevenly distributed residual value, bigger than the standardized value of 3:



More detail summary of the coefficient can be seen here:

```

OLS Regression Results
=====
Dep. Variable:      Adult_victims      R-squared:                0.024
Model:              OLS                Adj. R-squared:          -0.002

```

```

Method:           Least Squares    F-statistic:           0.9258
Date:             Wed, 08 Oct 2014  Prob (F-statistic):        0.451
Time:             18:24:12         Log-Likelihood:          -1278.7
No. Observations: 158             AIC:                      2567.
Df Residuals:     153             BIC:                      2583.
Df Model:         4

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const          6367.3284    4201.836     1.515    0.132    -1933.778    1.47e+04
gdp             4.989e-12    3.12e-11     0.160    0.873    -5.66e-11    6.65e-11
policy_index     16.6306     31.606     0.526    0.600     -45.810     79.071
females_education -130.7897     84.940    -1.540    0.126    -298.596     37.017
life_expectancy   1.3003      9.139     0.142    0.887     -16.755     19.356
persons_prosecuted -0.0182     0.019    -0.948    0.344     -0.056     0.020
child_victims    -0.6412     0.768    -0.835    0.405     -2.159     0.876
=====

```

```

Omnibus:          191.304    Durbin-Watson:           0.794
Prob(Omnibus):    0.000    Jarque-Bera (JB):        5184.289
Skew:             4.886    Prob(JB):                0.00
Kurtosis:         29.306    Cond. No.                1.61e+14
=====

```

Warnings:

[1] The condition number is large, 1.61e+14. This might indicate that there are strong multicollinearity or other numerical problems.

Outlier: [22, 23, 24, 25, 26]

```

country year persons_prosecuted Adult_victims child_victims \
22 Brazil 2003          52          5223          0
23 Brazil 2004         130          2887          0
24 Brazil 2005         128          4348          0
25 Brazil 2006         117          3417          0
26 Brazil 2007         200          5975          0

gdp policy_index females_education life_expectancy
22 5.524693e+11          10          47.71990          71

```

23	6.637603e+11	11	47.70676	71
24	8.821857e+11	12	47.59256	71
25	1.088917e+12	11	47.20861	71
26	1.366824e+12	11	47.20861	71

OLS Regression Results

```

=====
Dep. Variable:      Adult_victims    R-squared:                0.153
Model:              OLS              Adj. R-squared:           0.130
Method:             Least Squares    F-statistic:              6.683
Date:               Wed, 08 Oct 2014  Prob (F-statistic):        5.68e-05
Time:               18:24:13         Log-Likelihood:          -1037.2
No. Observations:   153             AIC:                      2084.
Df Residuals:       148             BIC:                      2100.
Df Model:           4
=====

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const      -3407.2866    1153.837     -2.953     0.004    -5687.410  -1127.163
gdp         8.754e-12     8.38e-12      1.044     0.298    -7.81e-12  2.53e-11
policy_index -0.3600         8.523     -0.042     0.966    -17.203    16.483
females_education  82.6792        23.400      3.533     0.001      36.438   128.920
life_expectancy -7.1481         2.466     -2.899     0.004    -12.021    -2.275
persons_prosecuted -0.0029         0.005     -0.555     0.580     -0.013     0.007
child_victims  0.3980         0.208      1.913     0.058     -0.013     0.809
=====

```

```

=====
Omnibus:          91.217    Durbin-Watson:           0.738
Prob(Omnibus):    0.000    Jarque-Bera (JB):        417.753
Skew:             2.289    Prob(JB):               1.93e-91
Kurtosis:         9.676    Cond. No.                1.64e+14
=====

```

Warnings:

[1] The condition number is large, 1.64e+14. This might indicate that there are strong multicollinearity or other numerical problems.

Warnings:

[1] The smallest eigenvalue is -6.49e+08. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

OLS Regression Results

```

=====
Dep. Variable:          Adult_victims    R-squared:                0.454
Model:                  OLS              Adj. R-squared:         0.432
Method:                 Least Squares    F-statistic:             20.27
Date:                  Wed, 08 Oct 2014  Prob (F-statistic):       3.63e-17
Time:                  19:50:51          Log-Likelihood:          -1003.6
No. Observations:      153              AIC:                    2021.
Df Residuals:          146              BIC:                    2042.
Df Model:               6

=====
=====
                                coef      std err          t      P>|t|      [95.0%
Conf. Int.]
-----
-----
Intercept                -1.001e+04    3555.325     -2.815     0.006     -1.7e+04
-2981.212
np.log1p(persons_prosecuted)    29.3962      7.357      3.995     0.000      14.855
43.937
np.log1p(child_victims)        24.5572      7.602      3.231     0.002       9.534
39.581
np.log1p(gdp)                 -32.4480      3.509     -9.246     0.000     -39.384
-25.512
np.log1p(policy_index)         82.4559     53.638      1.537     0.126     -23.552
188.464
np.log1p(females_education)    2615.0982    911.383      2.869     0.005     813.891
4416.306
np.log1p(life_expectancy)      97.1963    137.693      0.706     0.481     -174.932
369.325

=====
Omnibus:                  68.088    Durbin-Watson:           1.049
Prob(Omnibus):            0.000    Jarque-Bera (JB):        198.134

```



```
Skew:                1.820    Prob(JB) :                9.46e-44
Kurtosis:            7.222    Cond. No.                6.52e+03
=====
```

Warnings:

```
[1] The condition number is large, 6.52e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Therefore, we may conclude logarithmic conversion did improve the predictive power of this particular regression model.

4) Can you think of any other modeling techniques (from class) that could be used instead of linear regression? Try using one of these and explain your results, with diagrams and if possible, a visualization as well as descriptive statistics.

One of the other model that was discussed in the class (not lab) were polinomial. In this assignment linear, 2nd order and 3rd order of polynomial regressions were tested. It can be done by implementing formula in statsmodels OLS feature:

```
# 3-rd order polynomial
poly_3 = smf.ols(formula='Adult_victims~ 1 + persons_prosecuted +
child_victims+      gdp+      policy_index+      females_education      +
life_expectancy+I(persons_prosecuted ** 2.0) + I(child_victims ** 2.0)+
I(gdp ** 2.0) + I(policy_index ** 2.0)+I(females_education ** 2.0) +
I(life_expectancy ** 2.0)+I(persons_prosecuted ** 3.0) + I(child_victims
** 3.0)+ I(gdp ** 3.0) + I(policy_index ** 3.0)+I(females_education ** 3.0)
+ I(life_expectancy ** 3.0)', data=df).fit()
print poly_3.summary()
plt.plot(x, poly_3.predict(X), 'go', label='Poly n=3 $R^2$=%.2f' %
poly_3.rsquared,
        alpha=0.9)
```

The statistic summary:

```
OLS Regression Results
=====
Dep. Variable:    Adult_victims    R-squared:        0.454
Model:            OLS             Adj. R-squared:    0.432
Method:           Least Squares    F-statistic:      20.27
```

```

Date:                Wed, 08 Oct 2014    Prob (F-statistic):        3.63e-17
Time:                22:03:28    Log-Likelihood:            -1003.6
No. Observations:    153    AIC:                2021.
Df Residuals:        146    BIC:                2042.
Df Model:            6

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const          -1.001e+04   3555.325     -2.815     0.006     -1.7e+04 -2981.212
gdp             -32.4480     3.509     -9.246     0.000     -39.384 -25.512
policy_index      82.4559     53.638      1.537     0.126     -23.552  188.464
females_education 2615.0982    911.383      2.869     0.005      813.891 4416.306
life_expectancy   97.1963    137.693      0.706     0.481     -174.932  369.325
persons_prosecuted 29.3962      7.357      3.995     0.000      14.855  43.937
child_victims     24.5572      7.602      3.231     0.002       9.534  39.581

=====

Omnibus:                68.088    Durbin-Watson:                1.049
Prob(Omnibus):          0.000    Jarque-Bera (JB):              198.134
Skew:                   1.820    Prob(JB):                      9.46e-44
Kurtosis:               7.222    Cond. No.                      6.52e+03

=====

```

Warnings:

[1] The condition number is large, 6.52e+03. This might indicate that there are strong multicollinearity or other numerical problems.

OLS Regression Results

```

=====
Dep. Variable:          Adult_victims    R-squared:                0.673
Model:                  OLS              Adj. R-squared:           0.629
Method:                 Least Squares    F-statistic:              15.29
Date:                   Wed, 08 Oct 2014    Prob (F-statistic):        2.45e-24
Time:                   22:03:28    Log-Likelihood:            -964.53
No. Observations:       153    AIC:                1967.
Df Residuals:           134    BIC:                2025.
Df Model:               18

=====

```

```

=====
                                coef      std err          t      P>|t|      [95.0%
Conf. Int.]
-----
-----
Intercept                    -5.723e+07    1.04e+08    -0.551    0.582    -2.62e+08
1.48e+08
persons_prosecuted           -133.4874     33.380    -3.999    0.000    -199.508
-67.467
child_victims                 -15.8600     59.138    -0.268    0.789    -132.825
101.105
gdp                          -107.1898     47.483    -2.257    0.026    -201.103
-13.276
policy_index                 -637.5839    504.583    -1.264    0.209    -1635.560
360.393
females_education             4.34e+07     8e+07     0.542    0.588    -1.15e+08
2.02e+08
life_expectancy              4.193e+05     3.9e+05     1.075    0.284    -3.52e+05
1.19e+06
I(persons_prosecuted ** 2.0)   50.3547     10.252     4.912    0.000     30.079
70.631
I(child_victims ** 2.0)        8.6766     27.626     0.314    0.754    -45.962
63.315
I(gdp ** 2.0)                 3.8014      3.751     1.013    0.313    -3.618
11.221
I(policy_index ** 2.0)        601.7357    406.774     1.479    0.141    -202.792
1406.263
I(females_education ** 2.0)   -1.108e+07    2.06e+07    -0.538    0.591    -5.18e+07
2.97e+07
I(life_expectancy ** 2.0)     -9.996e+04     9.4e+04    -1.064    0.289    -2.86e+05
8.59e+04
I(persons_prosecuted ** 3.0)  -3.8735      0.737    -5.257    0.000     -5.331
-2.416
I(child_victims ** 3.0)       -0.1597      3.171    -0.050    0.960    -6.431
6.112
I(gdp ** 3.0)                 -0.0361      0.075    -0.480    0.632    -0.185

```

```

0.113
I(policy_index ** 3.0)      -131.4920      86.698      -1.517      0.132      -302.965
39.981
I(females_education ** 3.0)  9.435e+05   1.77e+06      0.534      0.594      -2.55e+06
4.44e+06
I(life_expectancy ** 3.0)    7933.6415   7540.870      1.052      0.295      -6980.886
2.28e+04

```

```

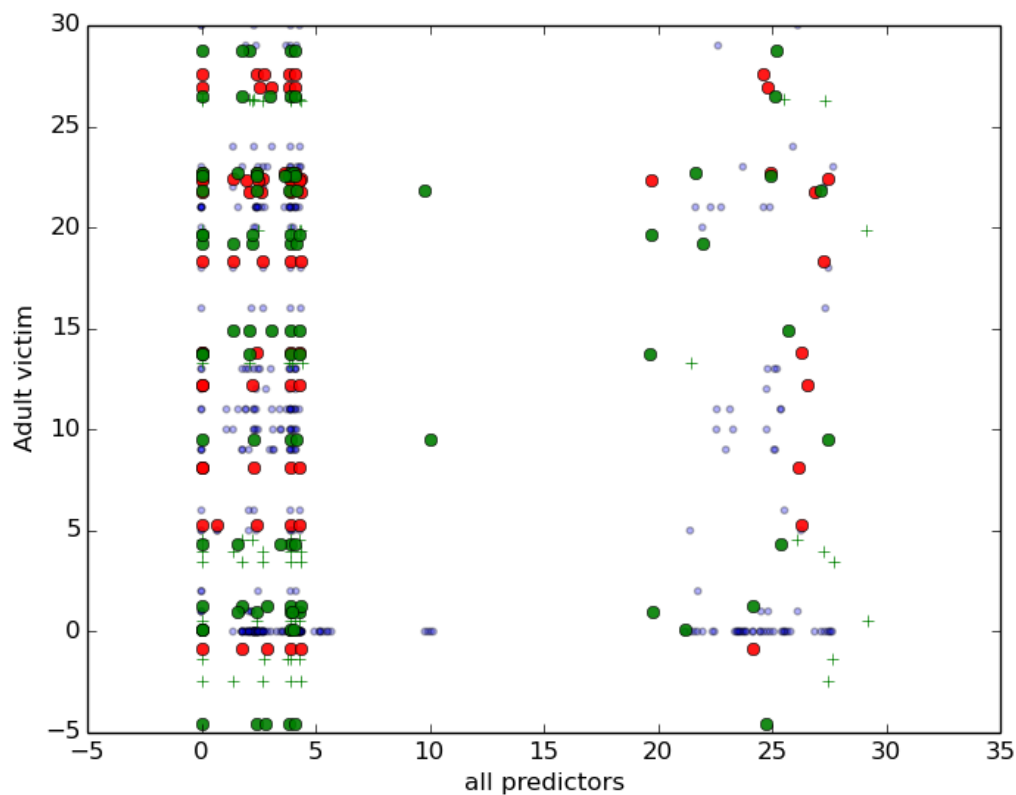
=====
Omnibus:                      69.548   Durbin-Watson:                1.413
Prob(Omnibus):                 0.000   Jarque-Bera (JB):             283.826
Skew:                          1.678   Prob(JB):                     2.33e-62
Kurtosis:                     8.766   Cond. No.                     8.61e+10
=====

```

Warnings:

```
[1] The smallest eigenvalue is 4.91e-12. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Therefore, we may conclude the best regression model is the one with highest R squared value, which is 3rd order of polynomial. In the following graphs, red is the 2nd order, green dots are the 3rd order polynomial, and plus sign shows regular linear regression.



5) *Think about how this model might be improved by adding more data. Then add this data to the model and test your hypothesis. What did you find. Provide descriptive statistics and visualizations as well as a few paragraphs explaining how you chose what data you did and why.*

Testing model achieved from the test training datasets and apply the same model to new unemployment rate data sets:

OLS Regression Results

```
=====
Dep. Variable:      Adult_victims    R-squared:          0.673
Model:              OLS              Adj. R-squared:     0.629
Method:             Least Squares    F-statistic:       15.29
```

```

Date:           Wed, 08 Oct 2014   Prob (F-statistic):       2.45e-24
Time:           22:31:41          Log-Likelihood:          -964.53
No. Observations:      153        AIC:                        1967.
Df Residuals:         134        BIC:                        2025.
Df Model:              18

```

```

=====
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	-5.723e+07	1.04e+08	-0.551	0.582	-2.62e+08 1.48e+08
persons_prosecuted	-133.4874	33.380	-3.999	0.000	-199.508 -67.467
child_victims	-15.8600	59.138	-0.268	0.789	-132.825 101.105
gdp	-107.1898	47.483	-2.257	0.026	-201.103 -13.276
policy_index	-637.5839	504.583	-1.264	0.209	-1635.560 360.393
females_education	4.34e+07	8e+07	0.542	0.588	-1.15e+08 2.02e+08
life_expectancy	4.193e+05	3.9e+05	1.075	0.284	-3.52e+05 1.19e+06
I(persons_prosecuted ** 2.0)	50.3547	10.252	4.912	0.000	30.079 70.631
I(child_victims ** 2.0)	8.6766	27.626	0.314	0.754	-45.962 63.315
I(gdp ** 2.0)	3.8014	3.751	1.013	0.313	-3.618 11.221
I(policy_index ** 2.0)	601.7357	406.774	1.479	0.141	-202.792 1406.263
I(females_education ** 2.0)	-1.108e+07	2.06e+07	-0.538	0.591	-5.18e+07 2.97e+07
I(life_expectancy ** 2.0)	-9.996e+04	9.4e+04	-1.064	0.289	-2.86e+05

```

8.59e+04
I(persons_prosecuted ** 3.0)      -3.8735      0.737      -5.257      0.000      -5.331
-2.416
I(child_victims ** 3.0)          -0.1597      3.171      -0.050      0.960      -6.431
6.112
I(gdp ** 3.0)                   -0.0361      0.075      -0.480      0.632      -0.185
0.113
I(policy_index ** 3.0)          -131.4920     86.698     -1.517      0.132     -302.965
39.981
I(females_education ** 3.0)      9.435e+05    1.77e+06     0.534      0.594     -2.55e+06
4.44e+06
I(life_expectancy ** 3.0)        7933.6417    7540.870     1.052      0.295     -6980.886
2.28e+04

```

```

=====
Omnibus:                        69.548      Durbin-Watson:                1.413
Prob(Omnibus):                  0.000      Jarque-Bera (JB):             283.826
Skew:                           1.678      Prob(JB):                     2.33e-62
Kurtosis:                       8.766      Cond. No.                     nan
=====

```

Warnings:

```
[1] The smallest eigenvalue is -5.15e-12. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

OLS Regression Results

```

=====
Dep. Variable:      Adult_victims      R-squared:                0.673
Model:              OLS                Adj. R-squared:           0.621
Method:             Least Squares      F-statistic:             12.85
Date:               Wed, 08 Oct 2014    Prob (F-statistic):       1.26e-22
Time:               22:31:42           Log-Likelihood:          -964.38
No. Observations:   153                AIC:                    1973.
Df Residuals:       131                BIC:                    2039.
Df Model:           21
=====
=====

```

```

coef      std err      t      P>|t|      [95.0%

```

Conf. Int.]

Intercept	-5.783e+07	1.05e+08	-0.550	0.583	-2.66e+08
1.5e+08					
persons_prosecuted	-132.5277	33.867	-3.913	0.000	-199.525
-65.530					
child_victims	-14.3127	59.915	-0.239	0.812	-132.839
104.214					
gdp	-108.7413	48.593	-2.238	0.027	-204.870
-12.612					
policy_index	-651.9263	511.092	-1.276	0.204	-1662.988
359.135					
females_education	4.389e+07	8.11e+07	0.541	0.589	-1.16e+08
2.04e+08					
life_expectancy	4.045e+05	3.95e+05	1.023	0.308	-3.78e+05
1.19e+06					
new_data	-0.1280	19.341	-0.007	0.995	-38.389
38.133					
I(persons_prosecuted ** 2.0)	50.3116	10.404	4.836	0.000	29.729
70.894					
I(child_victims ** 2.0)	7.8654	28.000	0.281	0.779	-47.524
63.255					
I(gdp ** 2.0)	3.9073	3.825	1.021	0.309	-3.660
11.474					
I(policy_index ** 2.0)	611.7667	411.725	1.486	0.140	-202.724
1426.257					
I(females_education ** 2.0)	-1.121e+07	2.09e+07	-0.537	0.592	-5.25e+07
3.01e+07					
I(life_expectancy ** 2.0)	-9.637e+04	9.52e+04	-1.012	0.313	-2.85e+05
9.2e+04					
I(new_data ** 2.0)	-5.8822	12.764	-0.461	0.646	-31.132
19.368					
I(persons_prosecuted ** 3.0)	-3.8810	0.748	-5.189	0.000	-5.361
-2.401					
I(child_victims ** 3.0)	-0.0741	3.213	-0.023	0.982	-6.430


```

6.282
I(gdp ** 3.0)          -0.0383      0.077      -0.500      0.618      -0.190
0.113
I(policy_index ** 3.0)  -133.3417     87.717     -1.520      0.131     -306.866
40.183
I(females_education ** 3.0)  9.544e+05  1.79e+06      0.533      0.595     -2.59e+06
4.5e+06
I(life_expectancy ** 3.0)  7644.0742  7642.478      1.000      0.319     -7474.570
2.28e+04
I(new_data ** 3.0)       1.0261      6.075      0.169      0.866     -10.991
13.044

```

```

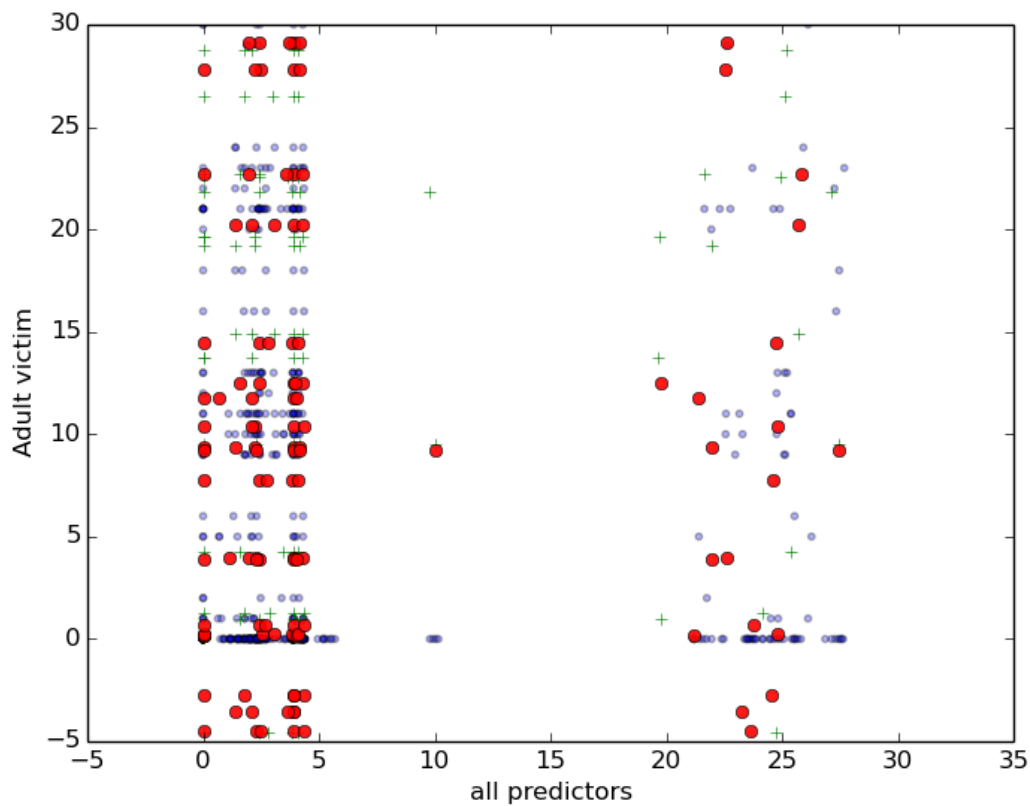
=====
Omnibus:                68.626   Durbin-Watson:                1.420
Prob(Omnibus):          0.000   Jarque-Bera (JB):          281.148
Skew:                   1.650   Prob(JB):                  8.90e-62
Kurtosis:               8.763   Cond. No.                  nan
=====

```

Warnings:

```
[1] The smallest eigenvalue is -1.37e-11. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

For initial testing random numbers was used to test whether the model consistently maintain the R squared given the polynomial effect. We could conclude that adding random variables to this model does not significantly change the R squared.



- 6) **Using the model and data discussed in class predict how many cases a set of "new countries" would have (data to be provided in a separate csv file) Provide visualizations and a few paragraphs explaining your results.**

Note that new.csv does not have Adult victim, child victim and people prosecution value, and to get the expected value, we recalculate the model using the same number of x variables (fields) as the new sets. Note that the model predictive power decreased dramatically because it is used against different set of x values (this time all other expected values such as persons prosecuted):

OLS Regression Results

```
=====
Dep. Variable:      Adult_victims    R-squared:      -0.315
Model:              OLS              Adj. R-squared: -0.315
```

```

Method:                Least Squares      F-statistic:                -inf
Date:                  Thu, 09 Oct 2014    Prob (F-statistic):         nan
Time:                  00:17:07           Log-Likelihood:             -1070.9
No. Observations:      153               AIC:                        2144.
Df Residuals:          152               BIC:                        2147.
Df Model:               0

=====
=====

                coef      std err          t      P>|t|      [95.0% Conf.
Int.]
-----
-----
Intercept                7.208e-48    1.28e-47      0.563      0.574      -1.81e-47
3.25e-47
gdp                    -3.066e-37    5.44e-37     -0.563      0.574      -1.38e-36
7.69e-37
policy_index           -2.808e-74    6.99e-74     -0.402      0.688      -1.66e-73
1.1e-73
females_education       3.482e-46    6.18e-46      0.563      0.574      -8.73e-46
1.57e-45
life_expectancy         4.694e-46    8.34e-46      0.563      0.574      -1.18e-45
2.12e-45
I (gdp ** 2.0)          3.778e-24    6.71e-24      0.563      0.574      -9.48e-24
1.7e-23
I (policy_index ** 2.0)  6.994e-46    1.24e-45      0.563      0.574      -1.75e-45
3.15e-45
I (females_education ** 2.0) 1.683e-44    2.99e-44      0.563      0.574      -4.22e-44
7.59e-44
I (life_expectancy ** 2.0)  3.1e-44     5.51e-44      0.563      0.574      -7.78e-44
1.4e-43
I (gdp ** 3.0)          -2.197e-37    5.47e-37     -0.402      0.688      -1.3e-36
8.61e-37
I (policy_index ** 3.0)   7.37e-45     1.31e-44      0.563      0.574      -1.85e-44
3.32e-44
I (females_education ** 3.0) 8.132e-43    1.44e-42      0.563      0.574      -2.04e-42
3.67e-42

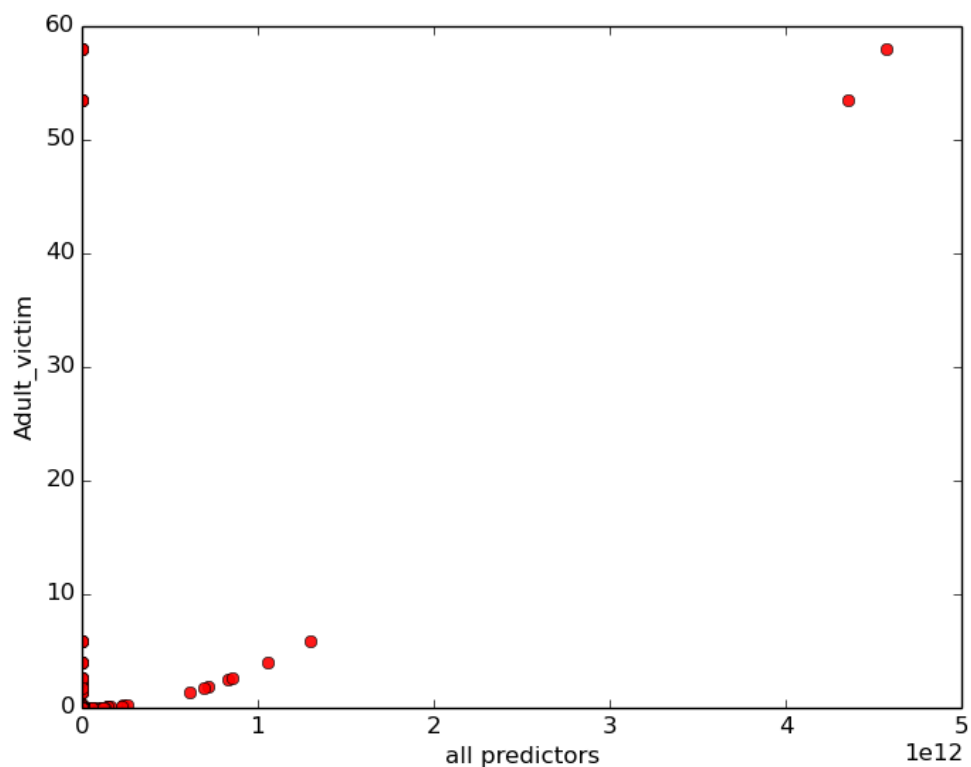
```

```
I(life_expectancy ** 3.0)    2.075e-42    3.69e-42    0.563    0.574    -5.21e-42
9.36e-42
```

```
=====
Omnibus:                    110.367    Durbin-Watson:                0.569
Prob(Omnibus):              0.000    Jarque-Bera (JB):            656.897
Skew:                      2.782    Prob(JB):                  2.27e-143
Kurtosis:                   11.490    Cond. No.                   nan
=====
```

Warnings:

```
[1] The smallest eigenvalue is -0.028. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```



7) **Try other models discussed from class. What do these models predict and how do they differ from the linear regression model?**

In this problem I used weighted least squares, to get the statistic summary as follows:

WLS Regression Results

```

=====
Dep. Variable:      Adult_victims      R-squared:      0.128
Model:              WLS      Adj. R-squared:      0.116
Method:             Least Squares      F-statistic:      11.02
Date:               Thu, 09 Oct 2014      Prob (F-statistic):      3.44e-05
Time:               01:13:24      Log-Likelihood:      -654.63
No. Observations:      153      AIC:      1315.
Df Residuals:         150      BIC:      1324.
Df Model:              2
=====

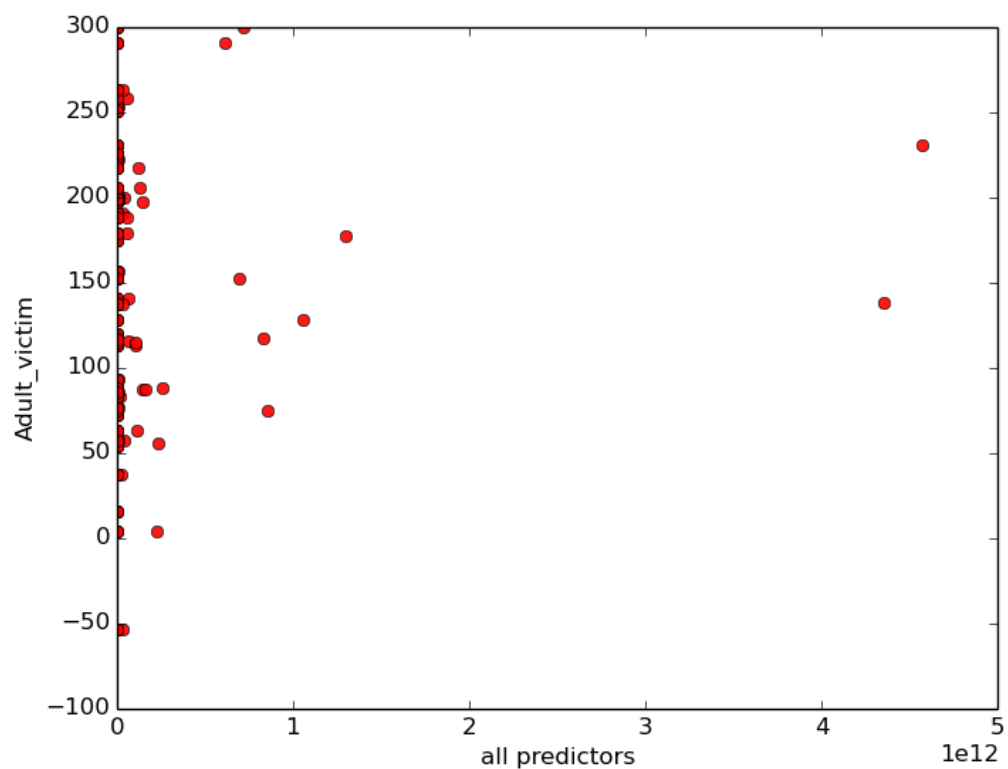
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const          -2951.2832    1089.960     -2.708     0.008     -5104.940    -797.626
gdp              8.351e-12    8.44e-12      0.989     0.324     -8.33e-12     2.5e-11
policy_index      0.9748         8.546      0.114     0.909     -15.912     17.861
females_education  74.1763         22.284      3.329     0.001      30.146     118.207
life_expectancy   -7.8345         2.436     -3.217     0.002     -12.647     -3.022
=====

Omnibus:           88.244      Durbin-Watson:      0.797
Prob(Omnibus):      0.000      Jarque-Bera (JB):      379.683
Skew:               2.229      Prob(JB):      3.57e-83
Kurtosis:           9.299      Cond. No.      1.54e+14
=====

```

Warnings:

[1] The condition number is large, 1.54e+14. This might indicate that there are strong multicollinearity or other numerical problems.



This prediction

The WLS is capable of resulting higher R squared value compared to the previous 3rd order polynomial model, but not as good as the original linear model.

8) ***Now remove the variables with the least explanatory power. Does your linear regression improve compared to the other models? Does it do worse? Why? Please provide visuals and a few paragraphs of explanation***

From the summary we could see that gdb has the least explanatory power since it has smallest coefficient:

WLS Regression Results

```
=====
Dep. Variable:      Adult_victims      R-squared:                0.122
Model:              WLS                Adj. R-squared:          0.105
Method:             Least Squares      F-statistic:              6.925
Date:               Thu, 09 Oct 2014    Prob (F-statistic):       0.000214
```

```

Time:                01:22:09   Log-Likelihood:            -655.12
No. Observations:    153       AIC:                1318.
Df Residuals:        149       BIC:                1330.
Df Model:              3

=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const          -3161.9193   1076.032     -2.939     0.004    -5288.172 -1035.667
policy_index         4.1584     7.969      0.522     0.603     -11.589   19.906
females_education    77.4102    22.188     3.489     0.001      33.566  121.255
life_expectancy     -7.3936     2.410     -3.067     0.003     -12.157   -2.631
=====

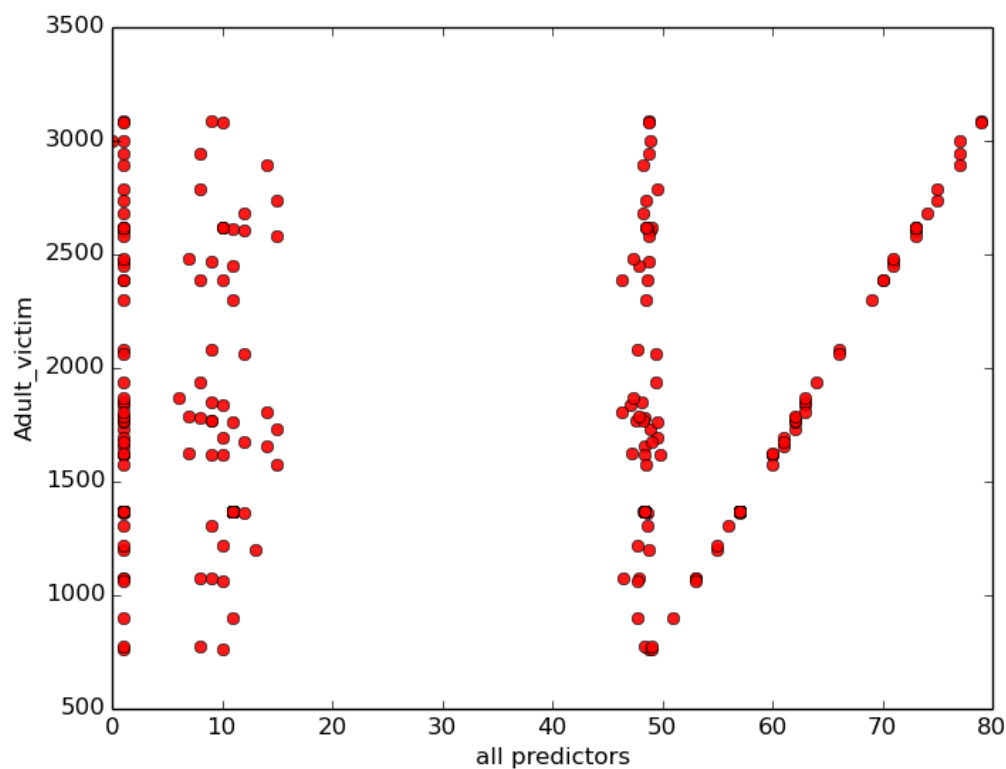
Omnibus:            87.565   Durbin-Watson:            0.798
Prob(Omnibus):      0.000   Jarque-Bera (JB):        373.048
Skew:                2.213   Prob(JB):                9.85e-82
Kurtosis:            9.239   Cond. No.                4.99e+03
=====

```

Warnings:

[1] The condition number is large, 4.99e+03. This might indicate that there are strong multicollinearity or other numerical problems.

From here we know that WLS gives relatively equal predictive power compared to last result since we only omitted the variable that does not have significant effect to the whole model.



9) **Now add in the extra data you found. Does your linear regression improved compared to the other models? Does it do worse? Why? Please provide visuals and a few paragraphs of explanation**

By adding unemployment variable it could be seen that the R squared and adjusted Rsquared does add up the value of R squared from 0.122 to 0.124.

WLS Regression Results

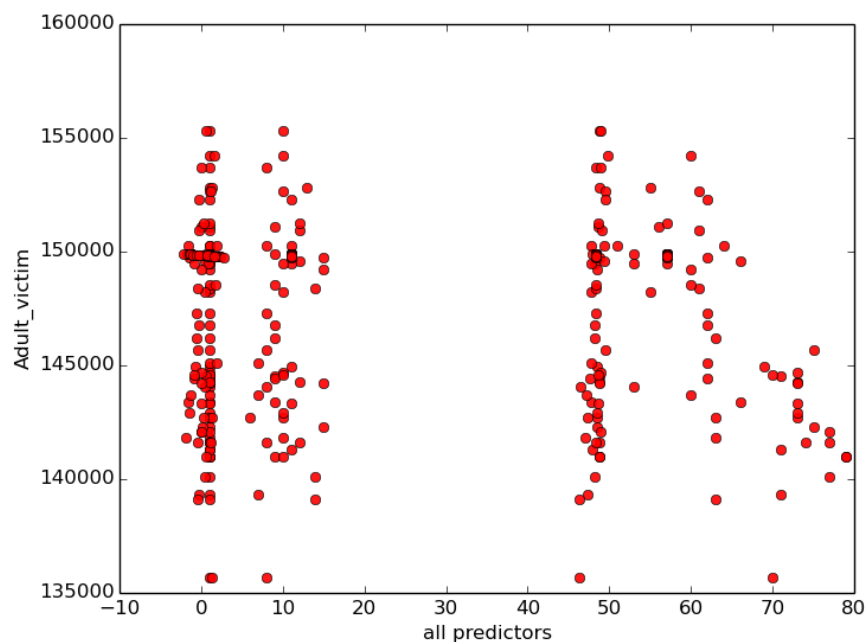
```
=====
Dep. Variable:      Adult_victims    R-squared:          0.124
Model:              WLS              Adj. R-squared:     0.101
Method:             Least Squares    F-statistic:        5.254
Date:               Thu, 09 Oct 2014  Prob (F-statistic):    0.000551
Time:               11:24:36          Log-Likelihood:     -654.95
No. Observations:   153              AIC:                1320.
Df Residuals:       148              BIC:                1335.
Df Model:           4
=====
```


	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	-1.324e+04	4281.373	-3.092	0.002	-2.17e+04	-4777.917
policy_index	59.0554	64.946	0.909	0.365	-69.286	187.397
females_education	3918.4535	1097.999	3.569	0.000	1748.673	6088.234
life_expectancy	-473.9677	153.584	-3.086	0.002	-777.469	-170.466
unemployment	-27.6415	31.278	-0.884	0.378	-89.450	34.167

Omnibus:	87.335	Durbin-Watson:	0.798
Prob(Omnibus):	0.000	Jarque-Bera (JB):	370.310
Skew:	2.208	Prob(JB):	3.88e-81
Kurtosis:	9.212	Cond. No.	1.63e+03

Warnings:

[1] The condition number is large, 1.63e+03. This might indicate that there are strong multicollinearity or other numerical problems.



<http://www.internetworldstats.com/>

<http://data.worldbank.org/indicator/IT.NET.USER.P2/countries>

```
--number of connected devices
```

=====						
Dep. Variable:	Adult_victims	R-squared:	0.153			
Model:	OLS	Adj. R-squared:	0.130			
Method:	Least Squares	F-statistic:	6.683			
Date:	Thu, 09 Oct 2014	Prob (F-statistic):	5.68e-05			
Time:	09:51:59	Log-Likelihood:	-1037.2			
No. Observations:	153	AIC:	2084.			
Df Residuals:	148	BIC:	2100.			
Df Model:	4					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

const	-3407.2646	1153.837	-2.953	0.004	-5687.387	-1127.142
gdp	8.744e-12	8.37e-12	1.044	0.298	-7.8e-12	2.53e-11
policy_index	-0.3599	8.523	-0.042	0.966	-17.203	16.483
females_education	82.6786	23.400	3.533	0.001	36.437	128.920
life_expectancy	-7.1480	2.466	-2.899	0.004	-12.021	-2.275
persons_prosecuted	-0.0029	0.005	-0.555	0.580	-0.013	0.007
child_victims	0.3980	0.208	1.913	0.058	-0.013	0.809
=====						

```

Omnibus:                91.217    Durbin-Watson:                0.738
Prob(Omnibus):           0.000    Jarque-Bera (JB):         417.756
Skew:                    2.289    Prob(JB):                 1.93e-91
Kurtosis:                9.676    Cond. No.                 1.64e+14
=====

```

Warnings:

```
[1] The condition number is large, 1.64e+14. This might indicate that there are
strong multicollinearity or other numerical problems.
```

OLS Regression Results

```

=====
Dep. Variable:            Adult_victims    R-squared:                0.164
Model:                    OLS              Adj. R-squared:           0.135
Method:                   Least Squares    F-statistic:             5.760
Date:                     Thu, 09 Oct 2014  Prob (F-statistic):    6.94e-05
Time:                     09:51:59         Log-Likelihood:          -1036.3
No. Observations:         153              AIC:                    2085.
Df Residuals:             147              BIC:                    2103.
Df Model:                 5
=====

```

```

=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const          -3437.2616    1150.537      -2.988    0.003    -5710.992 -1163.532
gdp             1.536e-11     9.63e-12       1.595    0.113    -3.67e-12  3.44e-11
policy_index    -0.3827         8.497      -0.045    0.964    -17.175   16.410
females_education  80.6406        23.376       3.450    0.001     34.445  126.836
life_expectancy  -4.7612         3.006      -1.584    0.115    -10.702    1.180
persons_prosecuted -0.0039         0.005      -0.746    0.457     -0.014    0.006
child_victims     0.3724         0.208       1.788    0.076     -0.039    0.784
internet_penet    -1.8272         1.324      -1.380    0.170     -4.445    0.790
=====

```

```

Omnibus:                90.949    Durbin-Watson:                0.747
Prob(Omnibus):           0.000    Jarque-Bera (JB):         417.275
Skew:                    2.279    Prob(JB):                 2.45e-91
Kurtosis:                9.684    Cond. No.                 1.64e+14
=====

```

Warnings:

[1] The condition number is large, 1.64e+14. This might indicate that there are strong multicollinearity or other numerical problems.

OLS Regression Results

=====						
Dep. Variable:	Adult_victims	R-squared:	0.156			
Model:	OLS	Adj. R-squared:	0.127			
Method:	Least Squares	F-statistic:	5.435			
Date:	Thu, 09 Oct 2014	Prob (F-statistic):	0.000128			
Time:	09:51:59	Log-Likelihood:	-1037.0			
No. Observations:	153	AIC:	2086.			
Df Residuals:	147	BIC:	2104.			
Df Model:	5					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

const	-3556.1615	1173.716	-3.030	0.003	-5875.698	-1236.625
gdp	-9.496e-12	2.65e-11	-0.359	0.720	-6.18e-11	4.28e-11
policy_index	-1.1579	8.607	-0.135	0.893	-18.168	15.852
females_education	85.7290	23.811	3.600	0.000	38.674	132.784
life_expectancy	-7.1508	2.470	-2.895	0.004	-12.032	-2.269
persons_prosecuted	-0.0114	0.013	-0.888	0.376	-0.037	0.014
child_victims	0.4081	0.209	1.954	0.053	-0.005	0.821
connected_dev	8.891e-07	1.22e-06	0.726	0.469	-1.53e-06	3.31e-06
=====						
Omnibus:	92.312	Durbin-Watson:	0.741			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	433.177			
Skew:	2.310	Prob(JB):	8.65e-95			
Kurtosis:	9.826	Cond. No.	1.67e+14			
=====						

Warnings:

[1] The condition number is large, 1.67e+14. This might indicate that there are strong multicollinearity or other numerical problems.

Similarly, this shows that internet penetration was the only additional variable that has positive correlation to adult victim. We could observe that by adding internet penetration variable to the model from 0.153 to 0.164.

12) Can you give an explanation of why or why not this does not add to the model's explanatory power? Is there another variable you might take away that is related to these variables?

The pearson test was conducted and resulted in the following:

Internet penetration VS adult victim:

(-0.17378602791144523, 0.03168508364587453)

Connected device VS adult victim:

(-0.023572270737661622, 0.77241153794652262)

As Pearson correlation coefficient varies from -1 to 1, close to zero implies no correlation). This explained that the number of internet penetration have higher correlation to the object that we are interested in observing, Adult value.