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-squa	red:	0.089	
Method:	Least	Squares	F-statistic	:	6.142	
Date:	Wed, 08	Oct 2014	Prob (F-stat	tistic):	0.000567	
Time:		18:24:05	Log-Likelih	ood:	-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-Watso	on:	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.

-2.586435e-12 Parameters: gdp

policy_index 5.257530e+00 life_expectancy -1.838591e+00 females_education 2.201553e+00

dtype: float64

OLS Regression Results _____

Dep. Variable:	persons_pr	osecuted	R-squared:		0.0	34
Model:		OLS	Adj. R-squared:		0.015	
Method:	Least	Squares	F-statistic:	:	1.8	28
Date:	Wed, 08	Oct 2014	Prob (F-stat	tistic):	0.1	44
Time:		18:24:05	Log-Likeliho	ood:	-1510	.8
No. Observations:		158	AIC:		302	8.
Df Residuals:		155	BIC:		303	7.
Df Model:		3				
	coef	std err	t	P> t	[95.0% Co	nf. 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-Watso	on:	0.5	38
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	10002.1	80
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.

5.425977e-12 Parameters: gdp

policy_index 1.017509e+02 life_expectancy -3.299698e+01 females_education 3.620564e+01

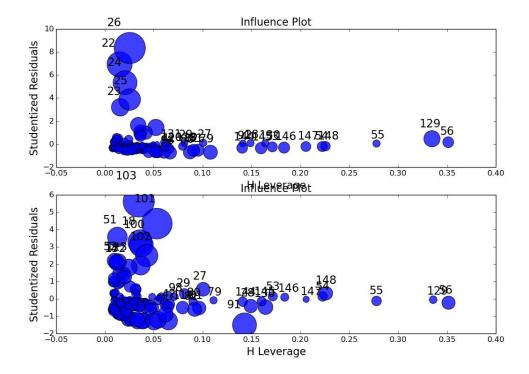
```
dtype: float64
```

```
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:

Method:	Least	Squares	F-statistic:	1	0.925	8
Date:	Wed, 08 (Oct 2014	Prob (F-statistic):		0.45	1
Time:	=	18:24:12	Log-Likeliho	ood:	-1278.	7
No. Observations:		158	AIC:		2567	
Df Residuals:		153	BIC:		2583	
Df Model:		4				
	coef	std er	r t	P> t	[95.0% Co	nf. Int.]
const					-1933.778	
gdp	4.989e-12	3.12e-1	1 0.160	0.873	-5.66e-11	6.65e-11
policy_index	16.6306	31.60	6 0.526	0.600	-45.810	79.071
females_education	-130.7897	84.94	0 -1.540	0.126	-298.596	37.017
life_expectancy	1.3003	9.13	9 0.142	0.887	-16.755	19.356
persons_prosecuted	-0.0182	0.01	9 -0.948	0.344	-0.056	0.020
child_victims	-0.6412	0.76	8 -0.835	0.405	-2.159	0.876
Omnibus:			Durbin-Watso		0.79	
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	5184.28	9
Skew:		4.886	Prob(JB):		0.0	0
Kurtosis:		29.306	Cond. No.		1.61e+1	4
==========			========			=

[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]

0	untry	year	persons_prosecuted	Adult_victims	child_victims	\
В	razil	2003	52	5223	0	
В	razil	2004	130	2887	0	
В	razil	2005	128	4348	0	
В	razil	2006	117	3417	0	
В	razil	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	
	OL	S Regress:	ion Results			
=======================================					:=======	==
Dep. Variable:	Adult_	victims	R-squared:		0.15	53
Model:		OLS	Adj. R-squar	red:	0.13	30
Method:	Least	Squares	F-statistic:		6.68	33
Date:	Wed, 08 0	ct 2014	Prob (F-stat	tistic):	5.68e-0)5
Time:	1	8:24:13	Log-Likeliho	ood:	-1037.	. 2
No. Observations:		153	AIC:		2084	1.
Df Residuals:		148	BIC:		2100).
Df Model:		4				
===========						
					[95.0% Cd	
const					-5687.410	
gdp	8.754e-12	8.38e-12	2 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	2.46	6 -2.899	0.004	-12.021	-2.275
persons_prosecuted	-0.0029	0.005	5 -0.555	0.580	-0.013	0.007
child_victims	0.3980	0.208	3 1.913	0.058	-0.013	0.809
===========						==
Omnibus:		91.217	Durbin-Watso	on:	0.73	38
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	417.75	53
Skew:		2.289	Prob(JB):		1.93e-9	91
Kurtosis:		9.676	Cond. No.		1.64e+1	L 4
=======================================						=

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

From the summary above we could see that R squared increased from 0.024 to 0.153, showing that the model works better without outliers.

3) Log-scale each of the variables, how does this change your model? Does it improve the models predictive power? How can you tell?

After scales were changed to logarithmic, we could observer that R squared increased significantly:

		_	sion Results			_
Dep. Variable:					0.15	
Model:		OLS	Adj. R-squar	red:	0.13	0
Method:	Least	Squares	F-statistic	:	6.68	3
Date:	Wed, 08 C	oct 2014	Prob (F-stat	tistic):	5.68e-0	5
Time:	1	9:50:51	Log-Likeliho	ood:	-1037.	2
No. Observations:		153	AIC:		2084	
Df Residuals:		148	BIC:		2100	
Df Model:		4				
					========	
	coef	std er	er t	P> t	[95.0% Co	nf. Int.]
Intercept	-3407.2866	1153.83	-2.953	0.004	-5687.410	-1127.163
persons_prosecuted	-0.0029	0.00	05 -0.555	0.580	-0.013	0.007
child_victims	0.3980	0.20	1.913	0.058	-0.013	0.809
gdp	8.754e-12	8.38e-1	.2 1.044	0.298	-7.81e-12	2.53e-11
policy_index	-0.3600	8.52	-0.042	0.966	-17.203	16.483
females_education	82.6792	23.40	3.533	0.001	36.438	128.920
life_expectancy	-7.1481	2.46	-2.899	0.004	-12.021	-2.275
=======================================						=
Omnibus:		91.217	Durbin-Watso	on:	0.73	8
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	417.75	3
Skew:		2.289	Prob(JB):		1.93e-9	1
Kurtosis:		9.676	Cond. No.		na	n
						_

[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:	Adul	t_victims	R-squared:		0.	454
Model:		OLS	Adj. R-squar	red:	0.	432
Method:	Leas	t Squares	F-statistic:		20	.27
Date:	Wed, 08	Oct 2014	Prob (F-stat	istic):	3.63e	-17
Time:		19:50:51	Log-Likeliho	ood:	-100	3.6
No. Observations:		153	AIC:		20	21.
Df Residuals:		146	BIC:		20	42.
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_pros	ecuted)	29.3962	7.357	3.995	0.000	14.855
43.937						
np.log1p(child_victim	s)	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_educ	ation)	2615.0982	911.383	2.869	0.005	813.891
4416.306						
<pre>np.log1p(life_expecta</pre>	ncy)	97.1963	137.693	0.706	0.481	-174.932
369.325						
Omnibus:	======	68.088	 Durbin-Watso	·	1	049
Prob(Omnibus):		0.000	Jarque-Bera	(UB):	198.	104

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

[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 0	ct 2014	Prob (F-stat	tistic):	3.63e-1	7
Time:	2	2:03:28	Log-Likeliho	ood:	-1003.	6
No. Observations:		153	AIC:		2021	
Df Residuals:		146	BIC:		2042	
Df Model:		6				
	coef	std er	r t	P> t	[95.0% Co	nf. Int.]
const	-1.001e+04	3555.32	5 -2.815	0.006	-1.7e+04	-2981.212
gdp	-32.4480	3.50	9 -9.246	0.000	-39.384	-25.512
policy_index	82.4559	53.63	8 1.537	0.126	-23.552	188.464
females_education	2615.0982	911.38	3 2.869	0.005	813.891	4416.306
life_expectancy	97.1963	137.69	0.706	0.481	-174.932	369.325
persons_prosecuted	29.3962	7.35	7 3.995	0.000	14.855	43.937
child_victims	24.5572	7.60	2 3.231	0.002	9.534	39.581
						=
Omnibus:		68.088	Durbin-Watso	on:	1.04	9
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	198.13	4
Skew:		1.820	Prob(JB):		9.46e-4	4
Kurtosis:		7.222	Cond. No.		6.52e+0	3
						=

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

OLS Regression Results

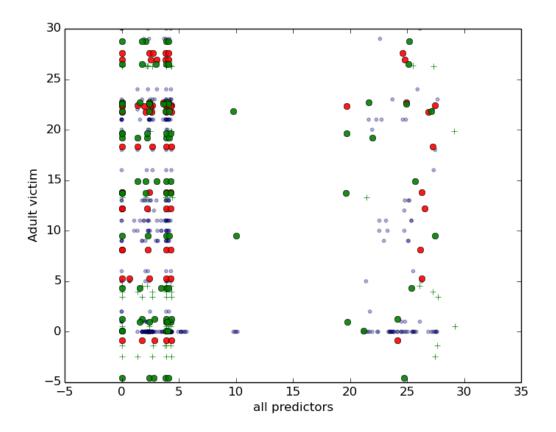
=======================================			
Dep. Variable:	Adult_victims	R-squared:	0.673
Model:	OLS	Adj. R-squared:	0.629
Method:	Least Squares	F-statistic:	15.29
Date:	Wed, 08 Oct 2014	Prob (F-statistic):	2.45e-24
Time:	22:03:28	Log-Likelihood:	-964.53
No. Observations:	153	AIC:	1967.
Df Residuals: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

======= coef std err t P>|t| [95.0% Conf. Int.] ______ -5.723e+07 1.04e+08 -0.551 0.582 -2.62e+08 Intercept 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 -107.1898 47.483 -2.257 0.026 -201.103 gdp -13.276 -637.5839 504.583 -1.264 0.209 -1635.560 policy index 360.393 females_education 4.34e+07 8e+07 0.542 0.588 -1.15e+08 2.02e+08 0.284 -3.52e+05 1.075 4.193e+05 3.9e+05 life_expectancy 1.19e+06 I(persons_prosecuted ** 2.0) 50.3547 10.252 0.000 30.079 4.912 70.631 I(child_victims ** 2.0) 8.6766 27.626 0.314 0.754 -45.962 63.315 3.8014 3.751 1.013 0.313 -3.618 I(gdp ** 2.0) 11.221 0.141 -202.792 I(policy index ** 2.0) 601.7357 406.774 1.479 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 0.289 -2.86e+05 -1.064 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					
<pre>I(policy_index ** 3.0)</pre>	-131.4920	86.698	-1.517	0.132	-302.965
39.981					
<pre>I(females_education ** 3.0)</pre>	9.435e+05	1.77e+06	0.534	0.594	-2.55e+06
4.44e+06					
<pre>I(life_expectancy ** 3.0)</pre>	7933.6415	7540.870	1.052	0.295	-6980.886
2.28e+04					
					====
Omnibus:	69.548	Durbin-Watso	n:	1.	.413
Prob(Omnibus):	0.000	Jarque-Bera	(JB):	283.	.826
Skew:	1.678	Prob(JB):		2.336	e-62
Kurtosis:	8.766	Cond. No.		8.61	e+10
				========	====

[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 0.673 R-squared: Model: Adj. R-squared: 0.629 Method: 15.29 Least Squares F-statistic:

Date:	Wed, 0	8 Oct 2014	Prob (F-sta	atistic):	2.45	5e-24
Time:		22:31:41	Log-Likelih	nood:	-96	64.53
No. Observations:		153	AIC:		-	1967.
Df Residuals:		134	BIC:		2	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		4 400	0.005	4 055		0.5005
life_expectancy		4.193e+05	3.9e+05	1.075	0.284	-3.52e+05
1.19e+06	ded 0 0		10.050	4 010	0.000	20.070
I (persons_prosecuted	** 2.0	50.3547	10.252	4.912	0.000	30.079
70.631	0.)	0 6766	27 (26	0 214	0.754	45.062
<pre>I(child_victims ** 2. 63.315</pre>	0)	8.6766	27.626	0.314	0.754	-45.962
I(gdp ** 2.0)		3.8014	3.751	1.013	0.313	-3.618
1(gap *** 2.0)		3.0014	3.731	1.013	0.313	-3.010
I(policy index ** 2.0	1	601.7357	406.774	1.479	0.141	-202.792
1406.263	,	001.7337	100.774	1.17	0.111	202.132
I(females education *	* 2.0)	-1.108e+07	2.06e+07	-0.538	0.591	-5.18e+07
2.97e+07	/		_,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	2.333	0.001	2.200,07
I(life expectancy **	2.0)	-9.996e+04	9.4e+04	-1.064	0.289	-2.86e+05
1(111e_expectancy **	∠.∪)	-9.996e+04	9.4e+04	-1.064	0.289	-∠.86e+U5

8.59e+04					
<pre>I(persons_prosecuted ** 3.0)</pre>	-3.8735	0.737	-5.257	0.000	-5.331
-2.416					
<pre>I(child_victims ** 3.0)</pre>	-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					
<pre>I(policy_index ** 3.0)</pre>	-131.4920	86.698	-1.517	0.132	-302.965
39.981					
<pre>I(females_education ** 3.0)</pre>	9.435e+05	1.77e+06	0.534	0.594	-2.55e+06
4.44e+06					
<pre>I(life_expectancy ** 3.0)</pre>	7933.6417	7540.870	1.052	0.295	-6980.886
2.28e+04					
=======================================		=======	========		===
Omnibus:	69.548	Durbin-Wats	on:	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
		=======			===

[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%

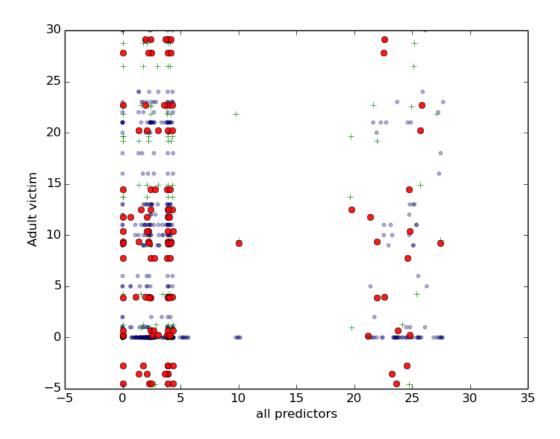
Conf. Int.]

Intercent	-5.783e+07	1.05e+08	-0.550	0.583	-2.66e+08
Intercept	-J./63e+0/	1.036+06	-0.550	0.363	-2.000+00
1.5e+08	-132.5277	33.867	-3.913	0.000	-199.525
persons_prosecuted -65.530	-132.3211	33.007	-3.913	0.000	-199.323
child_victims	-14.3127	59.915	-0.239	0.812	-132.839
104.214	-14.3127	39.913	-0.239	0.012	-132.039
gdp	-108.7413	48.593	-2.238	0.027	-204.870
-12.612	100.7413	40.333	2.250	0.027	204.070
policy index	-651.9263	511.092	-1.276	0.204	-1662.988
359.135	001.3200	011.032	1.270	0.201	1002.300
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					
<pre>I(child_victims ** 2.0)</pre>	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					
<pre>I(policy_index ** 2.0)</pre>	611.7667	411.725	1.486	0.140	-202.724
1426.257					
<pre>I(females_education ** 2.0)</pre>	-1.121e+07	2.09e+07	-0.537	0.592	-5.25e+07
3.01e+07					
<pre>I(life_expectancy ** 2.0)</pre>	-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					
<pre>I(persons_prosecuted ** 3.0)</pre>	-3.8810	0.748	-5.189	0.000	-5.361
-2.401					
<pre>I(child_victims ** 3.0)</pre>	-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					
<pre>I(policy_index ** 3.0)</pre>	-133.3417	87.717	-1.520	0.131	-306.866
40.183					
<pre>I(females_education ** 3.0)</pre>	9.544e+05	1.79e+06	0.533	0.595	-2.59e+06
4.5e+06					
<pre>I(life_expectancy ** 3.0)</pre>	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-Watso	on:	1.	.420
Prob(Omnibus):	0.000	Jarque-Bera	(JB):	281.	.148
Skew:	1.650	Prob(JB):		8.90	e-62
Kurtosis:	8.763	Cond. No.			nan
					====

[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.

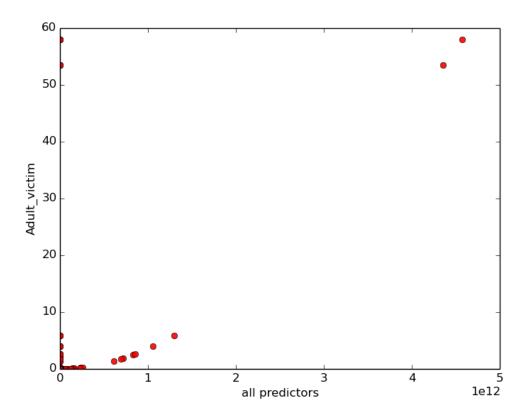
Note that new.csv does not have Adult victim, child victim and people prosecution value, and to get the expected value, we recalculate the model using the same number of x variables (fields) as the new sets. Note that the model predictive power decreased dramatically because it is used against different 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	Adi. R-squared:	-0.315				

Method:	Least Squares	F-statisti	c:		-inf
Date:	Thu, 09 Oct 2014	Prob (F-st	atistic):		nan
Time:	00:17:07	Log-Likeli	hood:	-10	070.9
No. Observations:	153	AIC:		2	2144.
Df Residuals:	152	BIC:		2	2147.
Df Model:	0				
			========		
=====					
	coef	std err	t	P> t	[95.0% Conf
<pre>Int.]</pre>					
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					
<pre>I(life_expectancy **</pre>	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					
<pre>I(policy_index ** 3.0</pre>	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					

<pre>I(life_expectancy ** 3.0)</pre>	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 (J	B):	656.	897
Skew:	2.782	Prob(JB):		2.27e-	143
Kurtosis:	11.490	Cond. No.			nan

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



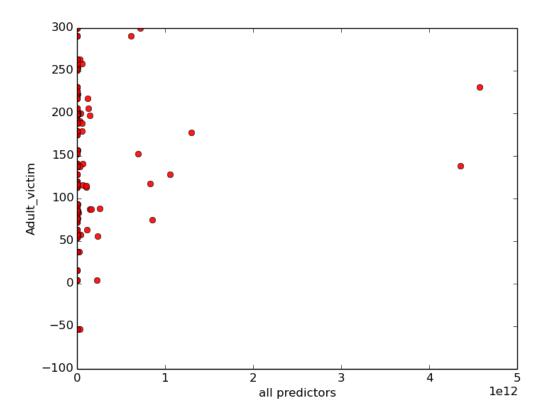
7) Try other models discussed from class. What do these models predict and how do they differ from the linear regression model?

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

WLS Regression Results

=======================================		-======				==
Dep. Variable:	Adult	_victims	R-squared:		0.12	28
Model:		WLS	Adj. R-squa	red:	0.13	16
Method:	Least	Squares	F-statistic	:	11.0	02
Date:	Thu, 09	Oct 2014	Prob (F-sta	tistic):	3.44e-0	05
Time:		01:13:24	Log-Likelih	ood:	-654.	63
No. Observations:		153	AIC:		131	5.
Df Residuals:		150	BIC:		132	4.
Df Model:		2				
					:=======	
	coef	std err	t	P> t	[95.0% Con	nf. 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-Wats	on:	0.79	97
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	379.68	33
Skew:		2.229	Prob(JB):		3.57e-8	33
Kurtosis:		9.299	Cond. No.		1.54e+	14
					.========	==

[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 linier 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:

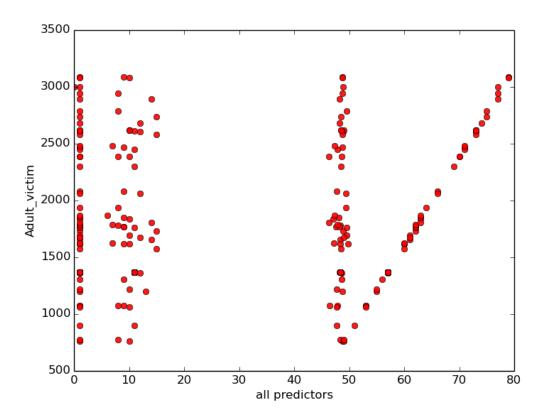
Dep. Variable:	Adult_victims	R-squared:	0.122
Model:	WLS	Adj. R-squared:	0.105
Method:	Least Squares	F-statistic:	6.925
Date:	Thu, 09 Oct 2014	Prob (F-statistic):	0.000214

WLS Regression Results

Time:		01:22:09	Log-Likeliho	ood:	-655.1	2
No. Observations:		153	AIC:		1318	•
Df Residuals:		149	BIC:		1330	
Df Model:		3				
	=======					======
	coef	std err	t	P> t	[95.0% Con	f. 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-Watso	on:	0.79	8
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	373.04	8
Skew:		2.213	Prob(JB):		9.85e-8	2
Kurtosis:		9.239	Cond. No.		4.99e+0	3
=========						=

[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

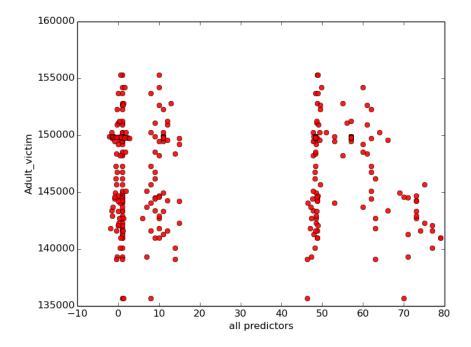
WLS Regression Results

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.

			=========
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% Cor	nf. 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-Wats	on:	0.79	98
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	370.33	10
Skew:		2.208	Prob(JB):		3.88e-8	31
Kurtosis:		9.212	Cond. No.		1.63e+0	03
=======================================						==

[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

--sources of internet usage

http://www.internetlivestats.com/internet-users/

--number of connected devices

10) download (or scrape) data from the above websites.

Downloaded from the website into CSV then run scripts to add to adding into main csv.

11) How much explanatory power does the model gain by adding the amount of internet penetration in a given country? How much does adding the total number of connected devices add?

We would like to know how much the know the explanatory power the model gain, so we run a multivariate linear regression:

		_	ion Results			:=	
Dep. Variable:	Adult_victims		R-squared:		0.15	i3	
Model:	OLS		Adj. R-squa	red:	0.13	0.130	
Method:	Least Squares		F-statistic	:	6.68	6.683	
Date:	Thu, 09 Oct 2014		Prob (F-sta	tistic):	5.68e-0	5.68e-05	
Time:	09:51:59		Log-Likelih	ood:	-1037.	-1037.2	
No. Observations:		153	AIC:		2084		
Df Residuals:		148	BIC:		2100		
Df Model:		4					
	coef	std er	r t	P> t	[95.0% Cc	onf. Int.]	
const	-3407.2646	1153.83	7 -2.953	0.004	-5687.387	-1127.142	
gdp	8.744e-12	8.37e-1	2 1.044	0.298	-7.8e-12	2.53e-11	
policy_index	-0.3599	8.52	3 -0.042	0.966	-17.203	16.483	
females_education	82.6786	23.40	0 3.533	0.001	36.437	128.920	
life_expectancy	-7.1480	2.46	6 -2.899	0.004	-12.021	-2.275	
persons_prosecuted	-0.0029	0.00	5 -0.555	0.580	-0.013	0.007	
child_victims	0.3980	0.20	8 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			

[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-sqi	uared:		0.16	4
Model:		OLS	Adj.	Adj. R-squared:		0.135	
Method:	Least	Squares	F-sta	atistic:		5.760	
Date:	Thu, 09 Oct 2014		Prob (F-statistic):			6.94e-05	
Time:	09:51:59		Log-1	Likelihood	:	-1036.3	
No. Observations:	153		AIC:			2085.	
Df Residuals:		147	BIC:			2103	
Df Model:		5					
=======================================							
	coef	std er	r	t	P> t	[95.0% Co	nf. Int.]
const	-3437.2616	1150.53	37	-2.988	0.003	-5710.992	-1163.532
gdp	1.536e-11	9.63e-1	L2	1.595	0.113	-3.67e-12	3.44e-11
policy_index	-0.3827	8.49	97	-0.045	0.964	-17.175	16.410
females_education	80.6406	23.37	76	3.450	0.001	34.445	126.836
life_expectancy	-4.7612	3.00	06	-1.584	0.115	-10.702	1.180
persons_prosecuted	-0.0039	0.00)5	-0.746	0.457	-0.014	0.006
child_victims	0.3724	0.20	08	1.788	0.076	-0.039	0.784
internet_penet	-1.8272	1.32	24	-1.380	0.170	-4.445	0.790
					=======		=
Omnibus:		90.949	Durb	in-Watson:		0.74	7
Prob(Omnibus):		0.000	Jarqı	Jarque-Bera (JB):		417.275	
Skew:		2.279	Prob	Prob(JB):		2.45e-91	
Kurtosis:		9.684	Cond	. No.		1.64e+1	4

[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-squar	red:	0.12	7	
Method:	Least Squares		F-statistic:		5.43	5.435	
Date:	Thu, 09 Oct 2014		Prob (F-stat	istic):	0.000128		
Time:	09:51:59		Log-Likeliho	ood:	-1037.0		
No. Observations:		153	AIC:		2086		
Df Residuals:		147	BIC:		2104		
Df Model:		5					
	coef	std er	r t	P> t	[95.0% Co	nf. Int.]	
const	-3556.1615	1173.71	-3.030	0.003	-5875.698	-1236.625	
gdp	-9.496e-12	2.65e-1	-0.359	0.720	-6.18e-11	4.28e-11	
policy_index	-1.1579	8.60	-0.135	0.893	-18.168	15.852	
females_education	85.7290	23.81	3.600	0.000	38.674	132.784	
life_expectancy	-7.1508	2.47	70 -2.895	0.004	-12.032	-2.269	
persons_prosecuted	-0.0114	0.01	-0.888	0.376	-0.037	0.014	
child_victims	0.4081	0.20	1.954	0.053	-0.005	0.821	
connected_dev	8.891e-07	1.22e-0	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-9	8.65e-95	
Kurtosis:		9.826	Cond. No.		1.67e+1	4	

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.

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)

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.