

Assignment 3: Multiple Regression for HIV rate vs. urbanization rate.

Hypothesis:

There is a strong correlation between the HIV rate and urban rate for 203 countries considered in my sample. I considered additional explanatory variables (one at a time), such as life expectancy and alcohol consumption, to identify potential confounders for this correlation.

Data preparation:

HIV rate is a quantitative response variable. Urbanization rate is a quantitative explanatory variable, I centered to its mean. Potential confounding variables (life expectancy and alcohol consumption) are quantitative; I centered them to their mean. During the data preparation NAN values were removed from the sample, resulting in the size of the sample of 146 countries.

Results:

1) Multiple Regression:

a) Case 1: no confounder included:

results for urban rate: $b_1 = -0.05$, $p = 0.001$, $R^2 = 7.4\%$.

The p value < 0.05 and $b_1 = -0.05$ show that the urban rate is significantly and negatively associated with the HIV rate. It means that with an increase of the urban rate, the HIV rate decreases. It supports my original hypothesis. R^2 of 7.4% show that there is a poor correlation between the HIV rate and the urban rate, and an addition of other explanatory variables may improve the fit.

b) Case 2: adding the second explanatory variable life expectancy:

results for urban rate: $b_1 = 0.032$, $p = 0.072$;

results for life expectancy: $b_1 = -0.29$, $p = 0.000$, $R^2 = 33.5\%$.

The p value > 0.05 for the urban rate shows that the urban rate is not significantly associated with the HIV rate after the addition the second explanatory variable life expectancy. However, the p value < 0.05 and negative b_1 for life expectancy show that there is a significant negative correlation between the HIV rate and the life expectancy. This means that with an increase of life expectancy, the HIV rate decreases. Also, adding the second explanatory variable improves the fit as R^2 increases from 7.4% to 33.5 %.

c) Case 3: adding the third explanatory variable alcohol consumption:

results for urban rate: $b_1 = 0.027$, $p = 0.129$;

results for life expectancy: $b_1 = -0.3$, $p = 0.000$;

results for alcohol consumption: $b_1 = 0.116$, $p = 0.069$, $R^2 = 35.0\%$.

The p value > 0.05 for the urban rate and for the alcohol consumption shows that the urban rate and alcohol consumption are not significantly associated with the HIV rate after the addition the third explanatory variable alcohol consumption. However, the p value < 0.05 and negative b_1 for life expectancy show that there is a significant negative correlation between the HIV rate and the life expectancy. This means that with an increase of life expectancy, the HIV rate decreases. Also, adding the third explanatory variable improves the fit as R^2 increases from 33.5% to 35.0 %.

2) Polynomial Regression:

a) Case 1: linear fit: results for urban rate: $b_1 = -0.05$, $p = 0.001$, $R^2 = 7.4\%$.

The p value < 0.05 and $b_1 = -0.05$ show that the urban rate is significantly and negatively associated with the HIV rate. R^2 of 7.4% show that there is a poor correlation between the HIV rate and the urban rate, and an addition of higher order polynomial may improve the fit.

b) Case 2: quadratic fit:

results for urban rate: $b_1 = -0.05$, $p = 0.001$;

results for the second order of the urban rate: $b_1 = 0.0$, $p = 0.804$, $R^2 = 7.4\%$.

The p value < 0.05 and $b_1 = -0.05$ for the first order term show that the urban rate is significantly and negatively associated with the HIV rate. The p value > 0.05 for the second order term is not significant. R^2 doesn't change after the addition of the higher order terms. Thus, including additional explanatory variables may improve the fit.

c) Case 3: quadratic fit with additional explanatory variable life expectancy:

results for urban rate: $b_1 = 0.033$, $p = 0.067$;

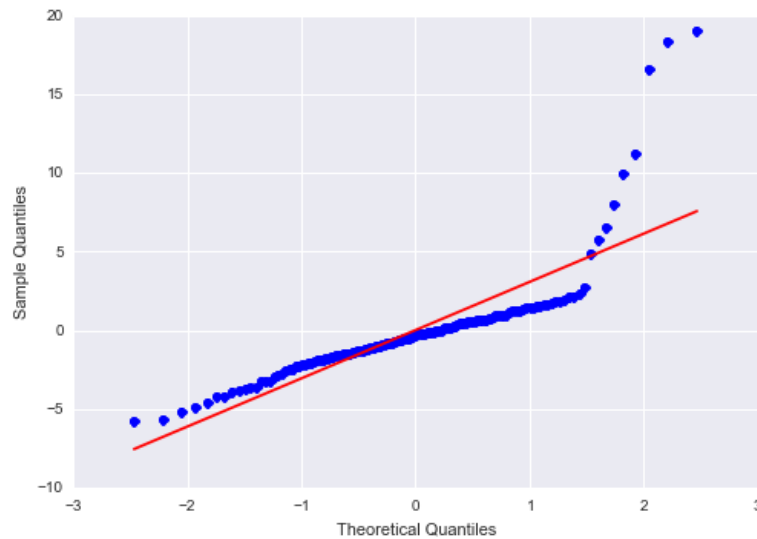
results for the second order of the urban rate: $b_1 = 0.0$, $p = 0.59$;

results for life expectancy: $b_1 = -0.29$, $p = 0.000$, $R^2 = 33.6\%$.

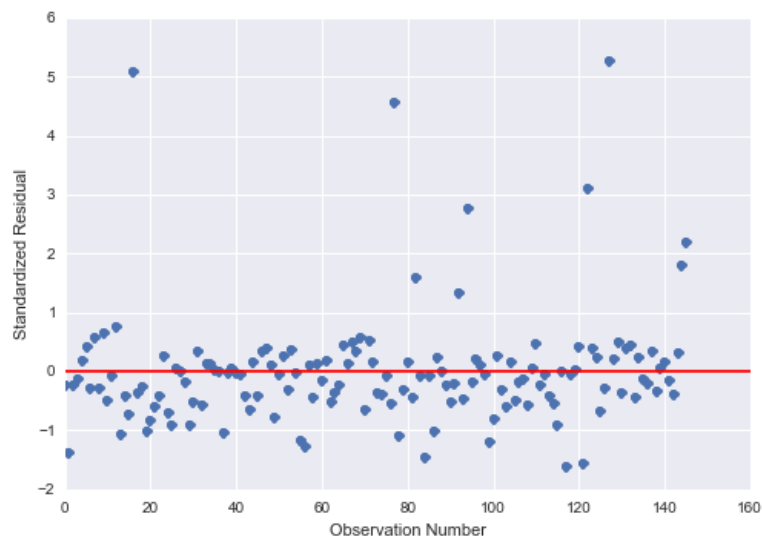
The p value > 0.05 for the first and the second order terms are not significant; therefore there is no association between the urban rate and the HIV rate after including another explanatory variable life expectancy. However, the p value < 0.05 and negative b_1 for life expectancy show that there is a significant negative correlation between the HIV rate and the life expectancy. This means that with an increase of life expectancy, the HIV rate decreases. Also, including another explanatory variable improves the fit as R^2 increases from 7.4% to 33.6%.

3) Regression Diagnostic Plots:

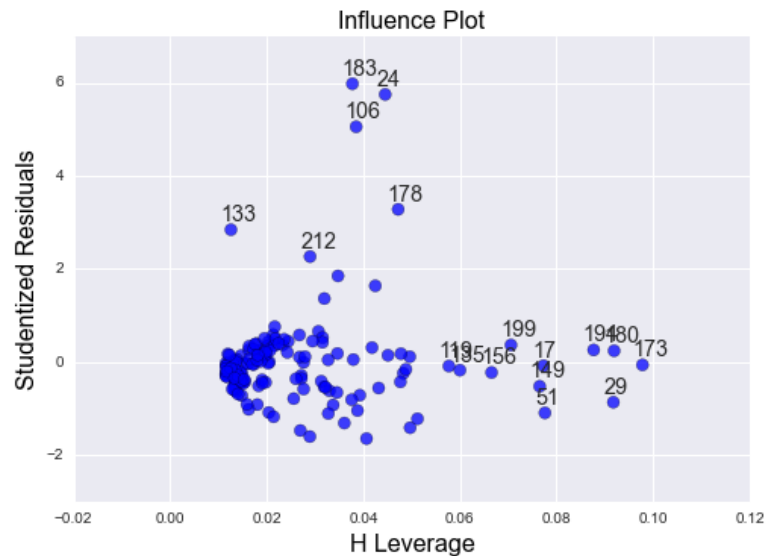
- a) Q-Q plot: The Q-Q plot doesn't follow the straight line. It shows that residuals do not follow the normal distribution. Addition of other explanatory variables in the model may provide a better correlation.



- b) Standardized Residuals: Many observations fit between two standard deviations, however there are many observations that higher than 2.5-3 standard deviations. Current model has many outliers and thus poorly fit to the observed data. To improve the model fit, we need to add other explanatory variables.



- c) Leverage Plot: Many observations fit between two standard deviations, however there are many observations that higher than 2.5-3 standard deviations. Observations # 133 and 212 are outliers with low leverage; they don't influence the model fit. However, the observations # 24, 106, 178, 183 are outliers with higher leverage, and thus they influence the model fit.



Summary:

During my analysis, I found that the urban rate is significantly and negatively associated with the HIV rate. It means that with an increase of the urban rate, the HIV rate decreases. It supports my original hypothesis that the countries with low urban rate have a higher HIV rate. After adjusting for a potential confounder (urban rate) the life expectancy is significantly and negatively correlated with the HIV rate. This means that with an increase of life expectancy, the HIV rate decreases.

Python Output:

Multiple Regression Results:
HIV Rate vs. Urban Rate

OLS Regression Results

```
=====
Dep. Variable:          hivrate    R-squared:                0.074
Model:                  OLS        Adj. R-squared:           0.067
Method:                 Least Squares    F-statistic:            11.48
Date:                  Wed, 13 Jan 2016    Prob (F-statistic):      0.000909
Time:                  11:00:19          Log-Likelihood:         -417.01
No. Observations:      146             AIC:                   838.0
Df Residuals:          144             BIC:                   844.0
Df Model:               1
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]	
Intercept	1.9483	0.351	5.554	0.000	1.255	2.642
urbanrate_c	-0.0531	0.016	-3.388	0.001	-0.084	-0.022

```
=====
Omnibus:                139.999    Durbin-Watson:           1.989
Prob(Omnibus):           0.000    Jarque-Bera (JB):        1643.875
Skew:                    3.648    Prob(JB):                0.00
Kurtosis:                17.730    Cond. No.:               22.4
=====
```

HIV Rate vs. Urban Rate and Life Expectancy
OLS Regression Results

Dep. Variable:	hivrate	R-squared:	0.335			
Model:	OLS	Adj. R-squared:	0.326			
Method:	Least Squares	F-statistic:	35.99			
Date:	Wed, 13 Jan 2016	Prob (F-statistic):	2.19e-13			
Time:	11:00:19	Log-Likelihood:	-392.85			
No. Observations:	146	AIC:	791.7			
Df Residuals:	143	BIC:	800.7			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

Intercept	1.9483	0.298	6.531	0.000	1.359	2.538
urbanrate_c	0.0317	0.017	1.813	0.072	-0.003	0.066
lifeexpectancy_c	-0.2881	0.038	-7.491	0.000	-0.364	-0.212
=====						
Omnibus:	118.714	Durbin-Watson:	2.131			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1116.653			
Skew:	2.953	Prob(JB):	3.33e-243			
Kurtosis:	15.193	Cond. No.	23.4			
=====						

HIV Rate vs. Urban Rate, Life Expectancy and Alcohol Consumption
OLS Regression Results

Dep. Variable:	hivrate	R-squared:	0.350			
Model:	OLS	Adj. R-squared:	0.336			
Method:	Least Squares	F-statistic:	25.51			
Date:	Wed, 13 Jan 2016	Prob (F-statistic):	2.92e-13			
Time:	11:00:19	Log-Likelihood:	-391.14			
No. Observations:	146	AIC:	790.3			
Df Residuals:	142	BIC:	802.2			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

Intercept	1.9483	0.296	6.585	0.000	1.363	2.533
urbanrate_c	0.0268	0.018	1.528	0.129	-0.008	0.062
lifeexpectancy_c	-0.3009	0.039	-7.759	0.000	-0.378	-0.224
alcoholconsumption_c	0.1159	0.063	1.833	0.069	-0.009	0.241
=====						
Omnibus:	118.009	Durbin-Watson:	2.079			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1107.734			
Skew:	2.928	Prob(JB):	2.87e-241			
Kurtosis:	15.157	Cond. No.	23.5			
=====						

Polynomial Regression Results:
Linear Fit: HIV Rate vs. Urban Rate

OLS Regression Results

Dep. Variable:	hivrate	R-squared:	0.074			
Model:	OLS	Adj. R-squared:	0.067			
Method:	Least Squares	F-statistic:	11.48			
Date:	Wed, 13 Jan 2016	Prob (F-statistic):	0.000909			
Time:	11:00:21	Log-Likelihood:	-417.01			
No. Observations:	146	AIC:	838.0			
Df Residuals:	144	BIC:	844.0			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

Intercept	1.9483	0.351	5.554	0.000	1.255	2.642
urbanrate_c	-0.0531	0.016	-3.388	0.001	-0.084	-0.022
=====						
Omnibus:	139.999	Durbin-Watson:	1.989			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1643.875			
Skew:	3.648	Prob(JB):	0.00			
Kurtosis:	17.730	Cond. No.	22.4			
=====						

Quadratic Fit: HIV Rate vs. Urban Rate

OLS Regression Results

Dep. Variable:	hivrate	R-squared:	0.074			
Model:	OLS	Adj. R-squared:	0.061			
Method:	Least Squares	F-statistic:	5.732			
Date:	Wed, 13 Jan 2016	Prob (F-statistic):	0.00403			
Time:	11:00:21	Log-Likelihood:	-416.98			
No. Observations:	146	AIC:	840.0			
Df Residuals:	143	BIC:	848.9			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	

Intercept	1.8633	0.490	3.801	0.000	0.894	2.832
urbanrate_c	-0.0528	0.016	-3.344	0.001	-0.084	-0.022
I(urbanrate_c ** 2)	0.0002	0.001	0.249	0.804	-0.001	0.002
=====						
Omnibus:	140.156	Durbin-Watson:	1.991			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1651.848			
Skew:	3.653	Prob(JB):	0.00			
Kurtosis:	17.771	Cond. No.	1.00e+03			
=====						

Quadratic Fit: HIV Rate vs. Urban Rate with Life Expectancy as a Confounder
OLS Regression Results

Dep. Variable:	hivrate	R-squared:	0.336
Model:	OLS	Adj. R-squared:	0.322
Method:	Least Squares	F-statistic:	23.97
Date:	Wed, 13 Jan 2016	Prob (F-statistic):	1.30e-12
Time:	11:00:21	Log-Likelihood:	-392.70
No. Observations:	146	AIC:	793.4
Df Residuals:	142	BIC:	805.3
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	1.7918	0.417	4.300	0.000	0.968 2.615
urbanrate_c	0.0325	0.018	1.848	0.067	-0.002 0.067
I(urbanrate_c ** 2)	0.0003	0.001	0.539	0.590	-0.001 0.001
lifeexpectancy_c	-0.2887	0.039	-7.486	0.000	-0.365 -0.212

Omnibus:	118.896	Durbin-Watson:	2.128
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1118.798
Skew:	2.960	Prob(JB):	1.14e-243
Kurtosis:	15.201	Cond. No.	1.00e+03

Python Code:

```
import numpy as np
import pandas as pd
import statsmodels.formula.api as smf
import statsmodels.api as sm
import statsmodels.stats.multicomp as multi
import scipy
import scipy.stats
import statsmodels.api
import seaborn as sb
import matplotlib.pyplot as plt
import matplotlib.figure as plt1

# load gapminder dataset
data = pd.read_csv('gapminder.csv',low_memory=False)
# lower-case all DataFrame column names
data.columns = map(str.lower, data.columns)

# bug fix for display formats to avoid run time errors
pd.set_option('display.float_format', lambda x:'%.2f'%x)

# remove missing values
data_copy=data.copy()
data_copy=data_copy.dropna()

# convert variables to numeric format using convert_objects function
```

```
# quantitative reponse variable - HIV rate; quantitative explanatory variable - urbanrate
data_copy['hivrate'] = data_copy['hivrate'].convert_objects(convert_numeric=True)
data_copy['urbanrate'] = data_copy['urbanrate'].convert_objects(convert_numeric=True)
# additional quantitative explanatory variables
data_copy['lifeexpectancy'] = data_copy['lifeexpectancy'].convert_objects(convert_numeric=True)
data_copy['alcoholconsumption'] = data_copy['alcoholconsumption'].convert_objects(convert_numeric=True)
```

```
# Data preparation
sub1 = data_copy[['hivrate', 'urbanrate', 'lifeexpectancy', 'alcoholconsumption']]
sub1 = sub1.dropna()
```

```
# center all quantitative explanatory variables
sub1['urbanrate_c'] = sub1['urbanrate'] - sub1['urbanrate'].mean()
sub1['lifeexpectancy_c'] = sub1['lifeexpectancy'] - sub1['lifeexpectancy'].mean()
sub1['alcoholconsumption_c'] = sub1['alcoholconsumption'] - sub1['alcoholconsumption'].mean()
```

```
#####
# MULTIPLE REGRESSION & CONFIDENCE INTERVALS
#####
```

```
print("Multiple Regression Results:")
# adding several explanatory variables
sub3 = sub1[['hivrate', 'urbanrate_c', 'lifeexpectancy_c', 'alcoholconsumption_c']].dropna()
print("HIV Rate vs. Urban Rate")
reg2 = smf.ols('hivrate ~ urbanrate_c', data=sub3).fit()
print(reg2.summary())
```

```
## multiple regression analysis: adding one variable at a time
print("HIV Rate vs. Urban Rate and Life Expectancy")
reg3 = smf.ols('hivrate ~ urbanrate_c + lifeexpectancy_c', data=sub3).fit()
print(reg3.summary())
print("HIV Rate vs. Urban Rate, Life Expectancy and Alcohol Consumption")
reg4 = smf.ols('hivrate ~ urbanrate_c + lifeexpectancy_c + alcoholconsumption_c', data=sub3).fit()
print(reg4.summary())
```

```
#####
# POLYNOMIAL REGRESSION
#####
```

```
print("Polynomial Regression Results:")
# first order (linear) scatterplot
scat1 = sb.regplot(x="urbanrate", y="hivrate", scatter=True, data=sub1)
plt.xlabel('Urbanization Rate')
plt.ylabel('HIV Rate')
```

```
# fit second order polynomial
# run the 2 scatterplots together to get both linear and second order fit lines
scat1 = sb.regplot(x="urbanrate", y="hivrate", scatter=True, order=2, data=sub1)
plt.xlabel('Urbanization Rate')
plt.ylabel('HIV Rate')
```

```
# linear regression analysis
```



```

print("Linear Fit: HIV Rate vs. Urban Rate")
reg1 = smf.ols('hivrate ~ urbanrate_c', data=sub1).fit()
print (reg1.summary())
print("Quadratic Fit: HIV Rate vs. Urban Rate")
# quadratic (polynomial) regression analysis
reg2 = smf.ols('hivrate ~ urbanrate_c + I(urbanrate_c**2)', data=sub1).fit()
print (reg2.summary())

#####
# EVALUATING MODEL FIT
#####

print("Quadratic Fit: HIV Rate vs. Urban Rate with Life Expectancy as a Confounder")
# adding lifeexpectancy variable
reg3 = smf.ols('hivrate ~ urbanrate_c + I(urbanrate_c**2) + lifeexpectancy_c', data=sub1).fit()
print (reg3.summary())

# Evaluate another confounder here

#Q-Q plot for normality
plt.figure(1)
fig1=sm.qqplot(reg3.resid, line='r')
#
## simple plot of residuals
plt.figure(3)
stdres=pd.DataFrame(reg3.resid_pearson)
plt.plot(stdres, 'o', ls='None')
l = plt.axhline(y=0, color='r')
plt.ylabel('Standardized Residual')
plt.xlabel('Observation Number')

# additional regression diagnostic plots
plt.figure(2)
fig2 = plt1.Figure(figsize=(12,8))
fig2 = sm.graphics.plot_regress_exog(reg3,"lifeexpectancy_c", fig=fig2)

# leverage plot
plt.figure(3)
fig3=sm.graphics.influence_plot(reg3, size=8)
print(fig3)

```