

# 11) Multiple Linear Regression

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**<https://www.quantopian.com/lectures>**

Lecture 15 Multiple Linear Regression

# Multiple Linear Regression

$$Y_i = \alpha + \beta_1 X_{1i} + \dots + \beta_k X_{ki} + \epsilon_i$$

```
import numpy as np
import pandas as pd
import statsmodels.api as sm

from statsmodels import regression
import matplotlib.pyplot as plt
```

$$\sum_{i=1}^n e_i^2$$

```
Y = np.array([1, 3.5, 4, 8, 12])
Y_hat = np.array([1, 3, 5, 7, 9])

print 'Error ' + str(Y_hat - Y)

# Compute squared error
SE = (Y_hat - Y) ** 2

print 'Squared Error ' + str(SE)
print 'Sum Squared Error ' + str(np.sum(SE))
```

Error [ 0. -0.5 1. -1. -3. ]

Squared Error [ 0. 0.25 1. 1. 9. ]

Sum Squared Error 11.25

# Toy Example

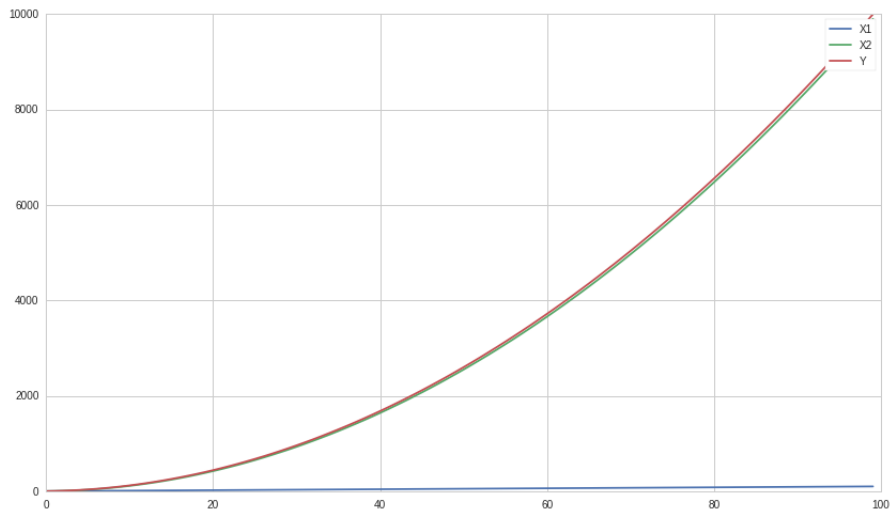
```
# Construct a simple linear curve of 1, 2, 3, ...
X1 = np.arange(100)

# Make a parabola and add X1 to it, this is X2
X2 = np.array([i ** 2 for i in range(100)]) + X1

# This is our real Y, constructed using a
# linear combination of X1 and X2
Y = X1 + X2

plt.plot(X1, label='X1')
plt.plot(X2, label='X2')
plt.plot(Y, label='Y')
plt.legend();
```

$$Y = X_1 + X_2$$



$$\hat{Y} = 0 + \hat{X}_1 + \hat{X}_2$$

```
X = sm.add_constant( np.column_stack( (X1, X2) ) )  
  
# Run the model  
results = regression.linear_model.OLS(Y, X).fit()  
  
print 'Beta_0:', results.params[0]  
print 'Beta_1:', results.params[1]  
print 'Beta_2:', results.params[2]
```

Beta\_0: 1.36424205266e-12

Beta\_1: 1.0

Beta\_2: 1.0

$$Y = X_1 + X_2$$

$$Y = X_1 + X^2 + X_1$$

$$Y = 2X_1 + X^2$$

$$MSFT = \alpha + \beta_1 INTC + \epsilon$$

```
start = '2014-01-01'
end = '2015-01-01'
asset1 = get_pricing('MSFT', fields='price',
                     start_date=start, end_date=end)
asset2 = get_pricing('INTC', fields='price',
                     start_date=start, end_date=end)
benchmark = get_pricing('SPY', fields='price',
                       start_date=start, end_date=end)

# First, run a linear regression on the two assets
slr = regression.linear_model.OLS(asset1,
                                  sm.add_constant(asset2)).fit()
print 'SLR beta of asset2:', slr.params[1]
```

SLR beta of asset2: 0.856395904276



$$M\hat{S}FT = \hat{\alpha}_m + 0.48INTC + 0.21SPY$$

```
mlr = regression.linear_model.OLS(asset1,  
    sm.add_constant(np.column_stack((asset2,  
                                      benchmark))))).fit()  
  
prediction=mlr.params[0] + mlr.params[1]*asset2 \  
    + mlr.params[2]*benchmark  
prediction.name = 'Prediction'  
  
print 'MLR beta of asset2:', mlr.params[1], \  
    '\nMLR beta of S&P 500:', mlr.params[2]
```

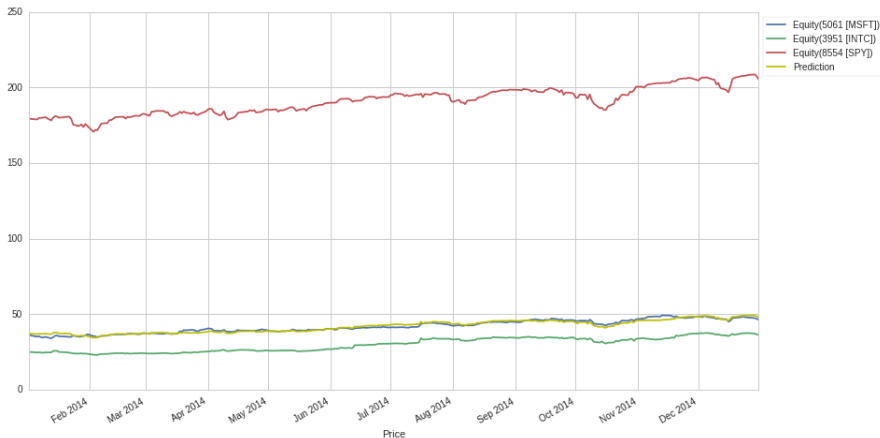
MLR beta of asset2: 0.480204841524

MLR beta of S&P 500: 0.210495422398

$$M\hat{S}FT = \hat{\alpha}_s + 0.85INTC$$

# 3 Variables and MLR Prediction

```
asset1.plot()  
asset2.plot()  
benchmark.plot()  
prediction.plot(color='y')  
plt.xlabel('Price')  
plt.legend(bbox_to_anchor=(1,1), loc=2);
```



# Dependent Variable and Prediction

```
asset1.plot()  
prediction.plot(color='y')  
plt.xlabel('Price')  
plt.legend();
```



# mlr.summary()

<b>Dep. Variable:</b>	Equity(5061 [MSFT])	<b>R-squared:</b>	0.923
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.922
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	1484.
<b>Date:</b>	Tue, 21 Aug 2018	<b>Prob (F-statistic):</b>	4.30e-139
<b>Time:</b>	17:15:21	<b>Log-Likelihood:</b>	-394.38
<b>No. Observations:</b>	252	<b>AIC:</b>	794.8
<b>Df Residuals:</b>	249	<b>BIC:</b>	805.4
<b>Df Model:</b>	2		
<b>Covariance Type:</b>	nonrobust		

	<b>coef</b>	<b>std err</b>	<b>t</b>	<b>P&gt; t </b>	<b>[95.0% Conf. Int.]</b>
<b>const</b>	-12.6540	3.140	-4.030	0.000	-18.838 -6.470
<b>x1</b>	0.4802	0.043	11.068	0.000	0.395 0.566
<b>x2</b>	0.2105	0.023	9.324	0.000	0.166 0.255

$$R^2 = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$

$$TSS = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$RSS = \sum_{i=1}^n e_i^2$$

$$\text{Adjusted } R^2 = 1 - (1 - R^2) \frac{n-1}{n-k-1}$$

# Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and *Adjusted* $R^2$

$$AIC = \frac{1}{n\hat{\sigma}^2}(RSS + 2k\hat{\sigma}^2)$$

$$BIC = \frac{1}{n\hat{\sigma}^2}(RSS + \log(n)k\hat{\sigma}^2)$$

$$\text{Adjusted } R^2 = 1 - \frac{RSS/(n-k-1)}{TSS/(n-1)}$$