1. theano linear regression

April 4, 2016

0.1 1. Linear Regression with Theano

The aim of this IPython notebook is to show some features of the Python **Theano** library in the field of machine learning. It has been developed by the LISA group at the *University of Montreal* (see: http://deeplearning.net/software/theano/). The notebook also relies on other standard Python libraries such as *numpy*, *pandas* and *matplotlib*.

To exemplify the use of **Theano**, this notebook solves the assignments of the *Machine Learning* MOOC provided by **Coursera** (see: https://www.coursera.org/learn/machine-learning) and performed in *Stanford University* by **Andrew Ng** (see: http://www.andrewng.org/).

The original MOOC assignments should to be programmed with the **Octave** language (see: https://www.gnu.org/software/octave/). The idea with this notebook is to provide Python developpers with interesting examples programmed using **Theano**.

This notebook has been developed using the *Anaconda* Python 3.4 distribution provided by **Continuum Analytics** (see: https://www.continuum.io/). It requires the **Jupyter Notebook** (see: http://jupyter.org/).

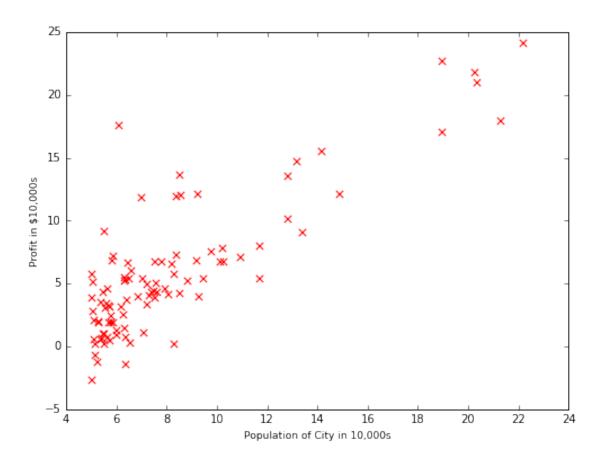
About the author: **Francis Wolinski** has an Engineering Degree From *Ecole des Ponts ParisTech* as well as a MSc. in Artificial Intelligence and a PhD. in Computer Science from *Université Pierre et Marie Curie* (UPMC).

0.2 1.1 Linear regression with one variable

1.1.1 Plotting the Data

```
In [1]: import pandas as pnd
    import matplotlib.pyplot as plt
    %matplotlib inline

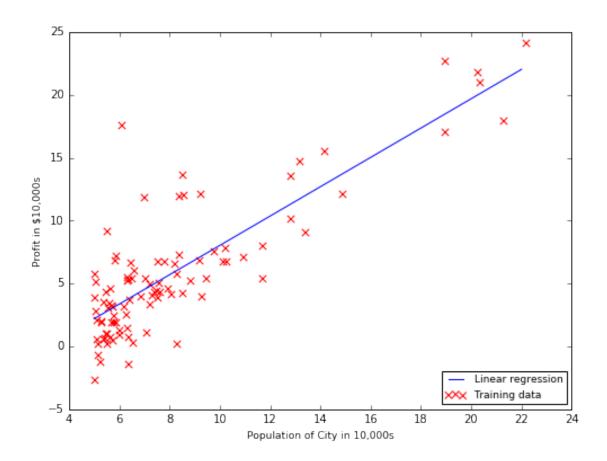
df = pnd.read_csv('data/ex1data1.txt', header=None)
    df.columns = ['X', 'Y']
    df.plot(kind='scatter', x='X', y='Y', marker='x', s=40, color='red', figsize=(8,6))
    plt.xlabel('Population of City in 10,000s', fontsize=9)
    plt.ylabel('Profit in $10,000s', fontsize=9)
    plt.axis((4, 24, -5, 25))
    plt.xticks(range(4,25,2));
```



1.1.2 Gradient Descent

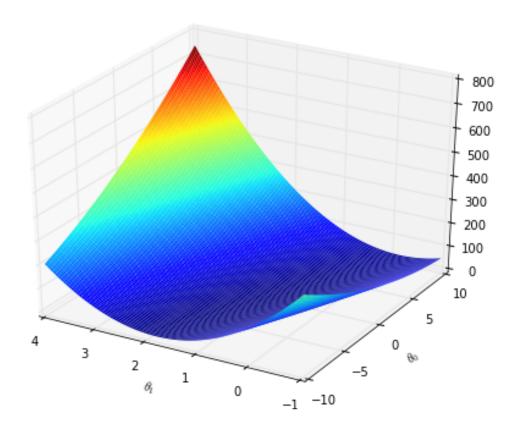
```
In [2]: import theano
        import numpy as np
        import theano.tensor as T
        import matplotlib.pyplot as plt
        #Training Data
        m = df.shape[0]
        X = \text{np.matrix}([\text{np.ones(m), df["X"}].values]) \# Add \ a \ column \ of \ ones \ to \ x
        Y = df["Y"].values
        t = np.array([0.0, 0.0]) # initialize fitting parameters
        theta = theano.shared(t,name='theta')
        x = T.matrix('x')
        y = T.vector('y')
        prediction = T.dot(theta,x)
        cost = T.sum(T.pow(prediction-y,2))/(2*m)
        grad = T.grad(cost,theta)
        # Some gradient descent settings
```

```
iterations = 1500
        alpha = 0.01
        train = theano.function([x,y],cost,updates = [(theta,theta-alpha*grad)])
        test = theano.function([x],prediction)
       for i in range(iterations):
            costM = train(X,Y)
            if i==0:
                print("Cost(%i):" % i)
                print(costM)
        print("\nCost(%i):" % i)
        print(costM)
        print("\nTheta found by gradient descent:")
       print(theta.get_value())
        # Plot the linear fit
        a = np.linspace(5,22,22)
       b = test(np.matrix([np.ones(a.shape), a]))
       plt.figure(figsize=(8,6))
       plt.plot(a,b, label='Linear regression')
       plt.scatter(df["X"].values,Y, s=40,marker='x', color='r', label='Training data')
       plt.xlabel('Population of City in 10,000s', fontsize=9)
       plt.ylabel('Profit in $10,000s', fontsize=9)
       plt.legend(loc=4, fontsize=9)
       plt.axis((4, 24, -5, 25))
       plt.xticks(range(4,25,2));
Cost(0):
32.072733877455654
Cost(1499):
4.483411453374869
Theta found by gradient descent:
[-3.63029144 1.16636235]
```

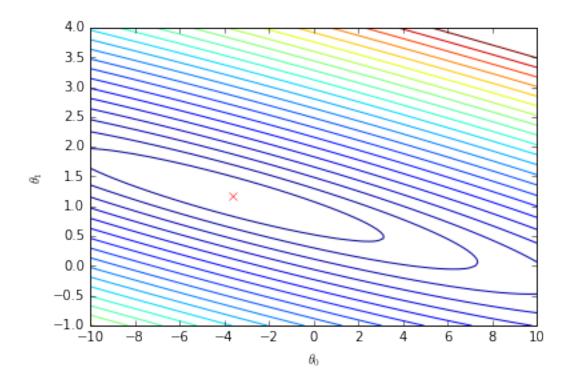


```
In [3]: # Predict values for population sizes of 35,000 and 70,000
        predict1 = np.dot(np.array([1, 3.5]), theta.get_value())
        print('For population = 35,000, we predict a profit of %f' % (predict1*10000))
        predict2 = np.dot(np.array([1, 7]), theta.get_value())
        print('For population = 70,000, we predict a profit of %f' % (predict2*10000))
For population = 35,000, we predict a profit of 4519.767868
For population = 70,000, we predict a profit of 45342.450129
1.1.3 Visualizing J(\theta)
In [4]: # Grid over which we will calculate J
        theta0_vals = np.linspace(-10, 10, 100)
        theta1_vals = np.linspace(-1, 4, 100)
        # initialize J_vals to a matrix of 0's
        J_vals = np.zeros((theta0_vals.shape[0], theta1_vals.shape[0]))
        # Fill out J_vals
        for i, theta0 in enumerate(theta0_vals):
            for j, theta1 in enumerate(theta1_vals):
                theta_ = np.array([theta0, theta1])
                J_vals[j,i] = np.sum(np.power(np.dot(theta_,X)-Y,2))/(2*m)
```

```
# Surface cost function
from mpl_toolkits.mplot3d import Axes3D
from matplotlib import cm
x_vals, y_vals = np.meshgrid(theta0_vals, theta1_vals)
fig = plt.figure(figsize=(8,6))
ax = fig.gca(projection='3d')
surf = ax.plot_surface(y_vals, x_vals, J_vals, rstride=1, cstride=1, linewidth=0, cmap=cm.jet);
# invert x axis to get the same 3D representation as in Octave
ax.invert_xaxis()
plt.xlabel(r'$\theta_{1}$')
plt.ylabel(r'$\theta_{0}$');
```



```
In [5]: # Contour cost function, showing minimum
    levels = [i*i for i in np.arange(25)]
    contour = plt.contour(theta0_vals, theta1_vals, J_vals, levels)
    plt.plot(theta.get_value()[0], theta.get_value()[1], 'rx')
    plt.xlabel(r'$\theta_{0}$')
    plt.ylabel(r'$\theta_{1}$')
    plt.xticks(np.arange(-10,11,2))
    plt.yticks(np.arange(-1,4.5,0.5));
```



0.2.1 1.2 Linear regression with multiple variables

```
In [6]: df2 = pnd.read_csv('data/ex1data2.txt', header=None)
       df2.columns = ['X1', 'X2', 'Y']
       print('First 10 examples from the dataset:')
       for i in range(10):
            print(' x = [%i, %i], y = %i ' % (df2.loc[i, 'X1'], df2.loc[i, 'X2'], df2.loc[i, 'Y']))
First 10 examples from the dataset:
x = [2104, 3], y = 399900
x = [1600, 3], y = 329900
 x = [2400, 3], y = 369000
x = [1416, 2], y = 232000
x = [3000, 4], y = 539900
x = [1985, 4], y = 299900
x = [1534, 3], y = 314900
 x = [1427, 3], y = 198999
x = [1380, 3], y = 212000
x = [1494, 3], y = 242500
```

1.2.1 Feature Normalization

1.2.2 Gradient Descent

```
In [8]: #Training Data
       m = df3.shape[0]
       Xnorm = np.matrix([np.ones(m), df3["X1"].values, df3["X2"].values]) # Add intercept term to X
        Y = df2["Y"].values
        # Choose some alpha value
        alpha = 0.01
        num\_iters = 5000
        # Init Theta and Run Gradient Descent
        t = np.zeros(3)
        theta = theano.shared(t,name='theta')
        x = T.matrix('x')
        y = T.vector('y')
       prediction = T.dot(theta,x)
        cost = T.sum(T.pow(prediction-y,2))/(2*m)
        grad = T.grad(cost,theta)
        train = theano.function([x,y],cost,updates = [(theta,theta-alpha*grad)])
       for i in range(num_iters):
            costM = train(Xnorm,Y)
        print("Theta found by gradient descent:")
       print(theta.get_value())
Theta found by gradient descent:
[ 340412.65957447 110631.05025395
                                   -6649.47424592]
In [9]: # Predict values for 1650 sq-ft and 3 bedrooms
        # Need to normalize data
       X0 = np.array([1, (1650 - mu['X1'])/sigma['X1'], (3 - mu['X2'])/sigma['X2']])
        price = np.dot(theta.get_value(), X0)
        print('Predicted price of a 1650 sq-ft, 3 br house (using gradient descent):\n$%f' % price)
Predicted price of a 1650 sq-ft, 3 br house (using gradient descent):
$293081.464340
1.2.3 Selecting learning rates
In [10]: num_iters = 50
         x = T.matrix('x')
         y = T.vector('y')
         alphas = [0.01, 0.03, 0.10, 0.30]
         colors = ['k', 'r', 'g', 'b']
         1 = len(alphas)
         costM = np.zeros((1, 50))
         for j, alpha in enumerate(alphas):
             # Init Theta and Run Gradient Descent
             t = np.zeros(3)
             theta = theano.shared(t,name='theta')
             prediction = T.dot(theta,x)
```

```
cost = T.sum(T.pow(prediction-y,2))/(2*m)
        grad = T.grad(cost,theta)
        train = theano.function([x,y],cost,updates = [(theta,theta-alpha*grad)])
        for i in range(num_iters):
             costM[j, i] = train(Xnorm,Y)
   plt.figure(figsize=(8,6))
    for j, alpha in enumerate(alphas):
        plt.plot(costM[j], color=colors[j], label = r'$\alpha = %.2f$' % alpha)
    plt.xlabel('Number of iterations', fontsize=9)
   plt.ylabel('Cost J', fontsize=9)
    plt.legend(fontsize=10)
   plt.xticks(range(0,51,5));
                                                                             \alpha = 0.01
                                                                             \alpha = 0.03
   6
                                                                             \alpha = 0.10
                                                                             \alpha = 0.30
   5
   4
Cost J
   3
   2
   1
   0
            5
                    10
                            15
                                    20
                                            25
                                                     30
                                                             35
                                                                     40
                                                                             45
                                                                                     50
                                     Number of iterations
```

1.2.4 Normal Equations

```
In [11]: from numpy.linalg import pinv
    # Add intercept term to X

X = np.matrix([np.ones(m), df2["X1"].values, df2["X2"].values])
# Calculate the parameters from the normal equation
theta = np.dot(np.dot(pinv(np.dot(X.T, X)),X.T).T, Y)
```

```
print('Theta computed from the normal equations:')
    print(theta)
    X0 = np.array([1, 1650, 3])
    price = np.dot(theta, X0)
    print('\nPredicted price of a 1650 sq-ft, 3 br house (using normal equations):\n$%f' % price)

Theta computed from the normal equations:
[[ 89597.90955554    139.21067402 -8738.01911785]]

Predicted price of a 1650 sq-ft, 3 br house (using normal equations):
$293081.464335

In []:
```