3. theano multi-class classification

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0.1 3. Multi-Class Classification in 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 <u>University of Montreal</u> (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 <u>Machine Learning MOOC</u> provided by **Coursera** (see: https://www.coursera.org/learn/machine-learning) and performed in <u>Stanford University</u> 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 <u>Anaconda</u> Python 3.4 distribution provided by **Continuum Analytics** (see: https://www.continuum.io/). It requires the **Jupyter Notebook** (see: http://jupyter.org/).

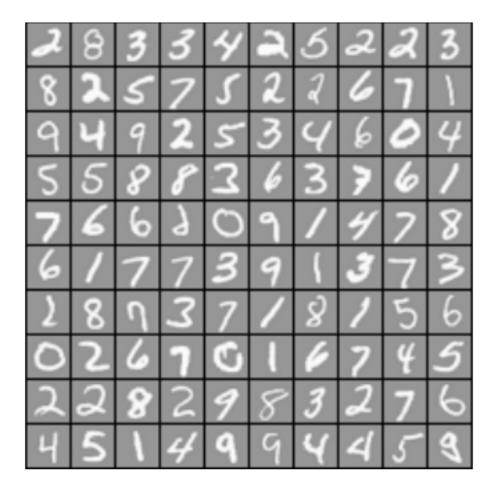
About the author: **Francis Wolinski** has an Engineering Degree From <u>Ecole des Ponts ParisTech</u> as well as a MSc. in Artificial Intelligence and a PhD. in Computer Science from <u>Université Pierre et Marie</u> Curie (UPMC).

0.1.1 3.1 Logistic Regression

3.1.1 Visualizing the data

```
In [1]: import theano
        import numpy as np
        import theano.tensor as T
        from theano.tensor.nnet import sigmoid
        import scipy.io as sio
        data = sio.loadmat('data/ex3data1.mat')
        X, Y = data['X'], data['y'].T[0]
        m = X.shape[0]
In [2]: %matplotlib inline
        import pandas as pnd
        import matplotlib.pyplot as plt
        def display_data(X, Y):
            example_width = int(np.sqrt(X.shape[1]))
            # Compute rows, cols
            m, n = X.shape
            example_height = int(n / example_width)
            # Compute number of items to display
```

```
display_rows = int(np.floor(np.sqrt(m)))
           display_cols = int(np.ceil(m / display_rows))
           # Between images padding
           pad = 1
           # Setup blank display
           display_array = - np.ones((pad + display_rows * (example_height + pad),\
                                 pad + display_cols * (example_width + pad)))
           # Copy each example into a patch on the display array
           # dataset contains 20 pixel by 20 pixel grayscale images of the digit
           curr_ex = 0
           for j in range(display_rows):
               for i in range(display_cols):
                  if curr_ex >= m:
                      break
                  # Get the max value of the patch
                  max_val = max(abs(X[curr_ex]))
                  display_array[(pad + j * (example_height + pad)):(pad + j * (example_height + pad))
                                (pad + i * (example_width + pad)):(pad + i * (example_width + pad))+e
                                 np.reshape(X[curr_ex], (example_height, example_width)) / max_val
                  curr_ex += 1
               if curr ex >= m:
                  break
           plt.figure(figsize=(8,6))
           plt.axis('off')
           plt.imshow(display_array.T, cmap="Greys_r")
           df = pnd.DataFrame(Y.reshape((display_rows, display_cols)).T)
           df = df.replace(10,0) # 0 is mapped to 10 in Y
           print(df)
In [3]: rnd = np.random.permutation(m)[0:100]
       sel = X[rnd,:] # 100 random digits
       res = Y[rnd]
       display_data(sel, res)
0 1 2 3 4 5 6 7 8 9
0 2 8 3 3 4 2 5 2 2 3
  8 2 5 7 5
                2 2 6 7
2 9 4 9 2 5 3 4 6 0
3 5 5 8 8 3 6 3 7 6 1
4 7 6 6 2 0 9 1 4 7 8
5 6 1
             3 9 1 3 7
6 2 8 7 3 7 1 8 1 5 6
7 0 2 6 7 0 1 6 7 4 5
8 2 2 8 2 9 8 3 2 7 6
9 4 5 1 4 9 9 4 4 5 9
```



3.1.2 Logistic Regression

```
In [4]: X1 = np.c_[np.ones(m), X] # Add intercept term to X
X1 = X1.T

# Choose some alpha and lambda values
alpha = 0.1
lambda_ = 0.1

num_labels = 10

all_theta = np.zeros((num_labels, X1.shape[0]))

for j in range(num_labels):
    print('Feature: %i' % (j+1))
    # Init Theta and Run Gradient Descent
    t = np.zeros(X1.shape[0])
    theta = theano.shared(t,name='theta')

x = T.matrix('x')
```

```
y = T.vector('y')
            h = sigmoid(T.dot(theta,x)) # 1.0 / (1.0 + T.exp(-T.dot(theta,x)))
            reg = lambda_ * T.sum(theta[1:]**2) / 2 / m # regularization on theta
            cost = -T.sum(y * T.log(h) + (1.0 - y) * T.log (1.0 - h))/m + reg
            grad = T.grad(cost,theta)
            train = theano.function([x,y],cost,updates = [(theta,theta-alpha*grad)])
            num_iters = 100
            for i in range(num_iters):
                costM = train(X1, Y==(j+1))
            all_theta[j] = theta.get_value()
        # number of positive predictions where best prediction == Y-1
        accuracy = np.sum(np.argmax(np.dot(all_theta,X1), axis=0) == (Y-1))/len(Y)
        print('\nTrain Accuracy: %f' % accuracy)
Feature: 1
Feature: 2
Feature: 3
Feature: 4
Feature: 5
Feature: 6
Feature: 7
Feature: 8
Feature: 9
Feature: 10
Train Accuracy: 0.841600
0.1.2 3.2 Neural Networks
3.2.1 Model representation
In [5]: # load precomputed network parameters
        weights = sio.loadmat('data/ex3weights.mat')
        theta1, theta2 = weights['Theta1'], weights['Theta2']
3.2.2 Feedforward Propagation and Prediction
In [6]: # layer sizes
        input_layer_size = X1.shape[0]
        hidden_layer_size = theta2.shape[1]
        output_layer_size = theta2.shape[0]
        print('input_layer_size: %i' % input_layer_size)
        print('hidden_layer_size: %i' % hidden_layer_size)
        print('output_layer_size: %i' % output_layer_size)
        x = T.matrix('x')
        # first layer
        y1 = 1 / (1 + np.exp(-np.dot(theta1,X1)))
```

```
# second layer
y2 = np.c_[np.ones(m), y1.T] # Add intercept term to y1
y2 = y2.T
y3 = 1 / (1 + np.exp(-np.dot(theta2, y2)))

input_layer_size: 401
hidden_layer_size: 26
output_layer_size: 10

In [7]: # number of positive predictions where best prediction == Y-1
accuracy = np.sum(np.argmax(y3, axis=0) == (Y-1))/len(Y)
print('Train Accuracy: %f' % accuracy)
```

Train Accuracy: 0.975200