4. theano neural networks

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0.1 4. Neural Networks Learning 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/).

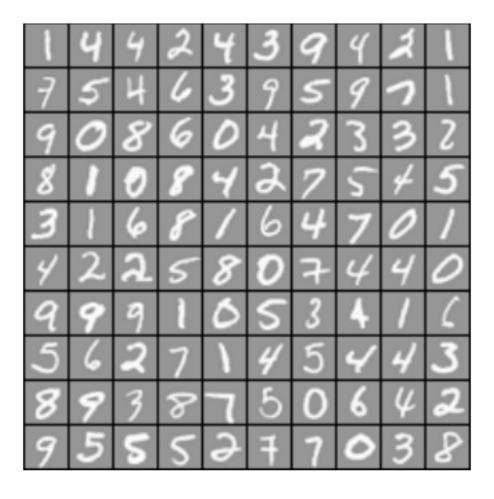
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0.1.1 4.1 Neural Networks

4.1.1 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/ex4data1.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 1 4 4 2 4 3 9 4
                         2 1
     5 4 6 3 9 5 9 7
2 9 0 8 6 0 4 2 3 3
3 8 1 0 8 4 2 7 5 4
4 3 1 6 8 1 6 4 7 0 1
 4 2 2 5 8 0 7 4 4
5
6 9 9 9 1 0 5 3 4 1 6
7 5 6 2 7 1 4 5 4 4 3
8 8 9 3 8 7 5 0 6 4 2
9 9 5 5 5 2 7 7 0 3 8
```



4.1.2 Feedforward and cost function

```
In [4]: def T_add_ones(x, a, b):
    var = T.concatenate([T.ones(a), x.flatten().T])
    return var.reshape((b, a))

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

# load precomputed network parameters
weights = sio.loadmat('data/ex4weights.mat')
t1 = weights['Theta1']
t2 = weights['Theta2']

print("X1:", X1.shape)
print("theta1:", t1.shape)
print("theta2:", t2.shape)

# layer sizes
input_layer_size = X.shape[1]
```

```
hidden_layer_size = t1.shape[0]
       num_labels = t2.shape[0]
       print('\ninput_layer_size: %i' % input_layer_size)
        print('hidden_layer_size: %i' % hidden_layer_size)
        print('num_labels: %i' % num_labels)
       x = T.matrix('x')
        y = T.vector('y')
        theta1 = theano.shared(t1, 'theta1')
        theta2 = theano.shared(t2, 'theta2')
        # first layer
        y1 = sigmoid(T.dot(theta1, x))
        # second layer
        y2 = T_add_ones(y1, m, hidden_layer_size+1)
       y3 = sigmoid(T.dot(theta2, y2))
        J = 0
        for i in range(num_labels):
            yy = T.eq(y,i+1)
            J += -T.sum(yy * T.log(y3[i,:]) + (1 - yy) * T.log(1 - y3[i,:])) / m
        cost = theano.function([x, y], J)
       print('\ncost: %f' % cost(X1, Y))
X1: (401, 5000)
theta1: (25, 401)
theta2: (10, 26)
input_layer_size: 400
hidden_layer_size: 25
num_labels: 10
cost: 0.287629
4.1.3 Regularized cost function
In [5]: # Weight regularization parameter (we set this to 0 here).
       lambda_ = 1
        x = T.matrix('x')
        y = T.vector('y')
        theta1 = theano.shared(t1, 'theta1')
        theta2 = theano.shared(t2, 'theta2')
        # first layer
        y1 = sigmoid(T.dot(theta1, x))
        # second layer
        y2 = T_add_ones(y1, m, hidden_layer_size+1)
        y3 = sigmoid(T.dot(theta2, y2))
```

```
# regularization on theta1 and theta2
       reg = lambda_ * (T.sum(theta1[:,1:]**2) + T.sum(theta2[:,1:]**2)) / 2 / m
        J = reg
       for i in range(num_labels):
            yy = T.eq(y,i+1)
            J += -T.sum(yy * T.log(y3[i,:]) + (1 - yy) * T.log(1 - y3[i,:])) / m
       cost = theano.function([x, y], J)
       print('cost: %f' % cost(X1, Y))
cost: 0.383770
     4.2 Backpropagation
0.2.1 4.2.1 Sigmoid gradient
In [6]: x = T.matrix('x')
       h = 1.0 / (1.0 + T.exp(-x))
       h_grad = h * (1-h)
       sigmoid2 = theano.function([x], h)
        sigmoid2\_grad = theano.function([x], h*(1-h))
       print(sigmoid2(np.array([[-1, -0.5, 0, 0.5, 1]])))
       print(sigmoid2_grad(np.array([[-1, -0.5, 0, 0.5, 1]])))
[[ 0.26894142  0.37754067  0.5
                                       0.62245933 0.73105858]]
                                       0.23500371 0.19661193]]
[[ 0.19661193  0.23500371  0.25
0.2.2 4.2.2 Random initialization
In [7]: def rand_initialize_weights(l_in, l_out, epsilon_init):
            return np.random.rand(l_out, l_in+1) * 2 * epsilon_init - epsilon_init
       epsilon_init = 0.12
       t1 = rand_initialize_weights(input_layer_size, hidden_layer_size, epsilon_init)
       t2 = rand_initialize_weights(hidden_layer_size, num_labels, epsilon_init)
       t = np.concatenate([t1.flatten(), t2.flatten()])
0.2.3 4.2.3 Backpropagation
In [8]: def T_add_ones(x, a, b):
            var = T.concatenate([T.ones(a), x.flatten().T])
            return var.reshape((b, a))
       theta = theano.shared(t, 'theta')
        # Choose some alpha value
       alpha = 1
       x = T.matrix('x')
       y = T.vector('y')
        # first layer
       theta1 = theta[:t1.shape[0]*t1.shape[1]]
       theta1 = theta1.reshape((t1.shape[0],t1.shape[1]))
```

```
y1 = sigmoid(T.dot(theta1, x))
        # second layer
        y2 = T_add_ones(y1, m, hidden_layer_size+1)
        theta2 = theta[t1.shape[0]*t1.shape[1]:]
        theta2 = theta2.reshape((t2.shape[0],t2.shape[1]))
        y3 = sigmoid(T.dot(theta2, y2))
        J = 0
        for i in range(num_labels):
            yy = T.eq(y,i+1)
            J += -T.sum(yy * T.log(y3[i,:]) + (1 - yy) * T.log(1 - y3[i,:])) / m
        grad = T.grad(J, theta)
        train = theano.function([x,y], [J, y3], updates = [(theta, theta-alpha*grad)])
       for i in range(2000):
            costM, y3 = train(X1,Y)
            if i\%500 == 0:
                print('[%i] %f' % (i, costM))
        print('cost: %f' % costM)
[0] 6.944886
[500] 0.474386
[1000] 0.332647
[1500] 0.259193
cost: 0.211194
In [9]: # 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: 0.978000
0.2.4 4.2.4 Regularized Neural Networks
In [12]: theta = theano.shared(t, 'theta')
         # Weight regularization parameter (we set this to 0 here).
         lambda_ = 3
         # Choose some alpha value
         alpha = 1
         # Weight regularization parameter (we set this to 0 here).
         lambda_{-} = 1
         x = T.matrix('x')
         y = T.vector('y')
         # first layer
         theta1 = theta[:t1.shape[0]*t1.shape[1]]
         theta1 = theta1.reshape((t1.shape[0],t1.shape[1]))
```

```
y1 = sigmoid(T.dot(theta1,x))
         # second layer
         y2 = T_add_ones(y1, m, hidden_layer_size+1)
         theta2 = theta[t1.shape[0]*t1.shape[1]:]
         theta2 = theta2.reshape((t2.shape[0],t2.shape[1]))
         y3 = sigmoid(T.dot(theta2, y2))
         # regularization on theta1 and theta2
         reg = lambda_ * (T.sum(theta1[:,1:]**2) + T.sum(theta2[:,1:]**2)) / 2 / m
         J = reg
         for i in range(num_labels):
             yy = T.eq(y,i+1)
             J \leftarrow T.sum(yy * T.log(y3[i,:]) + (1 - yy) * T.log(1 - y3[i,:])) / m
         grad = T.grad(J, theta)
         train = theano.function([x,y], [J, y3], updates = [(theta, theta-alpha*grad)])
         for i in range(2000):
             costM, y3 = train(X1,Y)
             if i\%500 == 0:
                 print('[%i] %f' % (i, costM))
         print('cost: %f' % costM)
[0] 6.949777
[500] 0.560771
[1000] 0.457988
[1500] 0.414050
cost: 0.390036
In [11]: # 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: 0.973200
In []:
```