

Programming Exercise 4 - Neural Networks Learning

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0.1 Programming Exercise 4 - Neural Networks Learning

```
In [1]: # %load ../../../../standard_import.txt
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt

# load MATLAB files
from scipy.io import loadmat

pd.set_option('display.notebook_repr_html', False)
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 150)
pd.set_option('display.max_seq_items', None)

%%config InlineBackend.figure_formats = {'pdf',}
%matplotlib inline

import seaborn as sns
sns.set_context('notebook')
sns.set_style('darkgrid')
```

Load MATLAB datafiles

```
In [2]: data = loadmat('data/ex4data1.mat')
data.keys()

Out[2]: dict_keys(['__header__', '__version__', '__globals__', 'X', 'y'])

In [3]: y = data['y']
# Add intercept
X = np.c_[np.ones((data['X'].shape[0],1)), data['X']]

print('X:', X.shape, '(with intercept)')
print('y:', y.shape)
```

```
X: (5000, 401) (with intercept)
y: (5000, 1)
```

```
In [4]: weights = loadmat('data/ex3weights.mat')
        weights.keys()
```

```
Out[4]: dict_keys(['__header__', '__version__', '__globals__', 'Theta1', 'Theta2'])
```

```
In [5]: theta1, theta2 = weights['Theta1'], weights['Theta2']
        print('theta1 :', theta1.shape)
        print('theta2 :', theta2.shape)
        params = np.r_[theta1.ravel(), theta2.ravel()]
        print('params :', params.shape)
```

```
theta1 : (25, 401)
theta2 : (10, 26)
params : (10285,)
```

Neural Network Input layer size = 400 (20x20 pixels) Hidden layer size = 25 Number of labels = 10

0.1.1 Neural Networks - Feed Forward and Cost Function

```
In [6]: def sigmoid(z):
        return 1 / (1 + np.exp(-z))
```

Sigmoid gradient

$$g'(z) = g(z)(1 - g(z))$$

where

$$g(z) = \frac{1}{1 + e^{-z}}$$

```
In [7]: def sigmoidGradient(z):
        return (sigmoid(z) * (1 - sigmoid(z)))
```

Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \sum_{k=1}^K \left[-y_k^{(i)} \log((h_{\theta}(x^{(i)}))_k) - (1 - y_k^{(i)}) \log(1 - h_{\theta}(x^{(i)}))_k \right]$$

Regularized Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \sum_{k=1}^K \left[-y_k^{(i)} \log((h_{\theta}(x^{(i)}))_k) - (1-y_k^{(i)}) \log(1-h_{\theta}(x^{(i)}))_k \right] + \frac{\lambda}{2m} \left[\sum_{j=1}^{25} \sum_{k=1}^{400} (\Theta_{j,k}^{(1)})^2 + \sum_{j=1}^{10} \sum_{k=1}^{25} (\Theta_{j,k}^{(2)})^2 \right]$$

```
In [8]: def nnCostFunction(nn_params, input_layer_size, hidden_layer_size, num_labels, X, y, reg):
    # When comparing to Octave code note that Python uses zero-indexed arrays
    # But because Numpy indexing does not include the right side, the code is
    theta1 = nn_params[0:(hidden_layer_size*(input_layer_size+1))].reshape((hidden_layer_size, input_layer_size+1))
    theta2 = nn_params[(hidden_layer_size*(input_layer_size+1)):].reshape((num_labels, hidden_layer_size+1))

    m = features.shape[0]
    y_matrix = pd.get_dummies(classes.ravel()).as_matrix()

    # Cost
    a1 = features # 5000x401

    z2 = theta1.dot(a1.T) # 25x401 * 401x5000 = 25x5000
    a2 = np.c_[np.ones((features.shape[0],1)), sigmoid(z2.T)] # 5000x26

    z3 = theta2.dot(a2.T) # 10x26 * 26x5000 = 10x5000
    a3 = sigmoid(z3) # 10x5000

    J = -1*(1/m)*np.sum((np.log(a3.T)*(y_matrix)+np.log(1-a3).T*(1-y_matrix))) + (reg/(2*m))*np.sum(np.square(theta1[:,1:])) + np.sum(np.square(theta2[:,1:]))

    # Gradients
    d3 = a3.T - y_matrix # 5000x10
    d2 = theta2[:,1:].T.dot(d3.T)*sigmoidGradient(z2) # 25x10 * 10x5000 * 25x10 = 25x10
    delta1 = d2.dot(a1) # 25x5000 * 5000x401 = 25x401
    delta2 = d3.T.dot(a2) # 10x5000 * 5000x26 = 10x26

    theta1_ = np.c_[np.ones((theta1.shape[0],1)), theta1[:,1:]]
    theta2_ = np.c_[np.ones((theta2.shape[0],1)), theta2[:,1:]]

    theta1_grad = delta1/m + (theta1_*reg)/m
    theta2_grad = delta2/m + (theta2_*reg)/m

    return(J, theta1_grad, theta2_grad)

In [9]: # Regularization parameter = 0
nnCostFunction(params, 400, 25, 10, X, y, 0)[0]

Out[9]: 0.28762916516131892

In [10]: # Regularization parameter = 1
nnCostFunction(params, 400, 25, 10, X, y, 1)[0]
```

```
Out[10]: 0.38376985909092365
```

```
In [11]: [sigmoidGradient(z) for z in [-1, -0.5, 0, 0.5, 1]]
```

```
Out[11]: [0.19661193324148185,  
          0.23500371220159449,  
          0.25,  
          0.23500371220159449,  
          0.19661193324148185]
```