目录

1 Multi-class Classification

1.1 Dataset

data.X 是 5000 * 400, 400 是 20 * 20 的手写图像的灰度矩阵向量化的结果

每一行代表了一个手写数字。

data.y 则是对应的 label，表明对应的图像代表的数字是几。

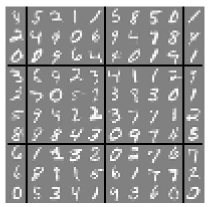
```
data = load('./ex3data1.mat');
data.X, data.y
```

```
ans = 5000×400
         0         0         0         0         0         0         0         0 ···
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
    ⋮
ans = 5000×1
    10
    10
    10
    10
```

```
10
10
10
10
10
10
⋮
```

1.2 Visualizing the data

```
[m, n] = size(data.X);
% Randomly select 100 data points to display
rand_indices = randperm(m);
sel = X(rand_indices(1:100), :);
displayData(sel);
```



1.3 Vectorizing Logistic Regression

以下三个小节全部归到一个函数中去。

1.3.1 Vectorizing the cost function

1.3.2 Vectorizing the gradient

1.3.3 Vectorizing regularized logistic regression

Testing lrCostFunction() with regularization

```
theta_t = [-2; -1; 1; 2];
X_t = [ones(5,1) reshape(1:15,5,3)/10];
y_t = ([1;0;1;0;1] >= 0.5);
lambda_t = 3;
[J grad] = lrCostFunction(theta_t, X_t, y_t, lambda_t);
```

Expected cost: 2.534819

```
fprintf('\nCost: %f\n', J);
```

```
Cost: 2.534819
```

Expected gradients:

0.146561

-0.548558

0.724722

1.398003

Gradients:

```
fprintf(' %f \n', grad);
```

```
0.146561
-0.548558
0.724722
1.398003
```

1.4 One-vs-all Classification

```
% figure, imshow(X(1, :))
```

Training One-vs-All Logistic Regression...

```
lambda = 0.1;
input_layer_size  = 400;  % 20x20 Input Images of Digits
num_labels = 10;          % 10 labels, from 1 to 10
                          % (note that we have mapped "0" to label 10)
% [all_theta] = oneVsAll(X, y, num_labels, lambda);
all_theta
```

```
all_theta = 10×401
   -2.0362         0         0    0.0000   -0.0002   -0.0002   -0.0000   -0.0024 ···
   -2.2285         0         0   -0.0000    0.0001   -0.0003   -0.0041   -0.0015
   -3.6456         0         0   -0.0000   -0.0000    0.0009    0.0036   -0.0058
   -1.3927         0         0   -0.0000    0.0000    0.0001   -0.0009   -0.0013
   -0.1185         0         0   -0.0000    0.0000   -0.0000   -0.0011   -0.0012
   -2.2970         0         0   -0.0000    0.0000   -0.0001   -0.0003   -0.0007
   -1.6068         0         0   -0.0000    0.0002    0.0003    0.0029    0.0103
   -6.8298         0         0   -0.0000    0.0000    0.0000   -0.0005   -0.0025
   -4.2045         0         0   -0.0000    0.0000    0.0002   -0.0053   -0.0055
   -3.1447         0         0   -0.0000   -0.0000    0.0002    0.0013    0.0001
```

1.4.1 One-vs-all Prediction

```
p = predictOneVsAll(all_theta, X)
```

```
p = 5000×1
    10
    10
    10
    10
    10
    10
    10
    10
    10
```

10
⋮

```
% sum(p == y) ./ length(y)
mean(double(p == y)) * 100
```

```
ans = 92.8000
```

2 Neural Networks

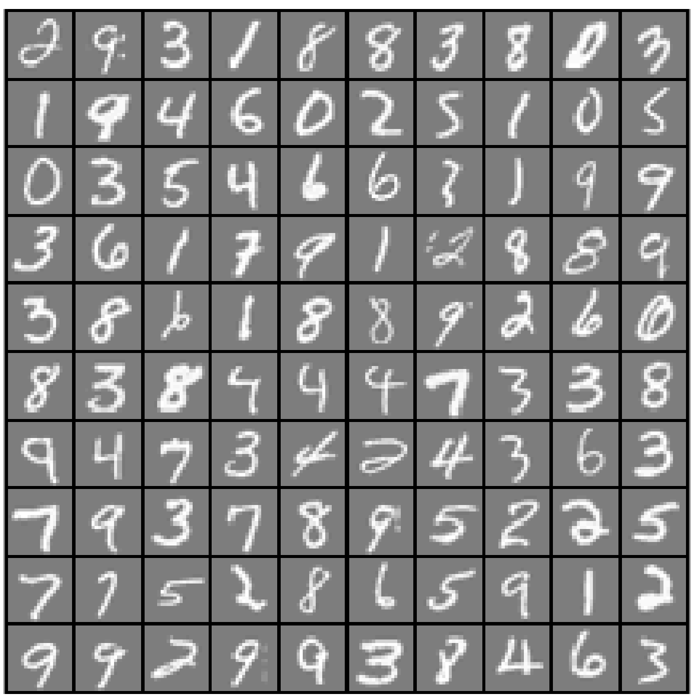
2.1 Model representation

```
fprintf('Loading and Visualizing Data ...\n')
```

```
Loading and Visualizing Data ...
```

```
load('ex3data1.mat');
m = size(X, 1);

% Randomly select 100 data points to display
sel = randperm(size(X, 1));
sel = sel(1:100);
displayData(X(sel, :));
```



```
X
```

```
X = 5000×400
         0         0         0         0         0         0         0         0 ···
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
         0         0         0         0         0         0         0         0
    ⋮
```

In this part of the exercise, we load some pre-initialized neural network parameters.

```
% Load the weights into variables Theta1 and Theta2
load('ex3weights.mat');
Theta1, Theta2
```

```
Theta1 = 25×401
   -0.0226   -0.0000    0.0000   -0.0000    0.0001   -0.0002   -0.0027    0.0015 ···
   -0.0984    0.0000   -0.0000    0.0000   -0.0000   -0.0000   -0.0005   -0.0010
    0.1162   -0.0000    0.0000   -0.0000    0.0000   -0.0001   -0.0008   -0.0010
   -0.2397   -0.0000    0.0000   -0.0000   -0.0001    0.0010    0.0091   -0.0015
   -0.7316    0.0000    0.0000   -0.0000    0.0000    0.0002    0.0005   -0.0031
   -0.5979   -0.0000    0.0000    0.0000   -0.0001    0.0006    0.0063   -0.0019
    0.1546   -0.0000   -0.0000    0.0000   -0.0000   -0.0002   -0.0020   -0.0032
   -0.0337    0.0000    0.0000    0.0000   -0.0001   -0.0001    0.0003   -0.0026
   -0.4107    0.0000    0.0000    0.0000   -0.0000   -0.0004   -0.0029   -0.0012
    0.0235   -0.0000   -0.0000   -0.0000    0.0000    0.0001   -0.0001    0.0046
    ⋮

Theta2 = 10×26
   -0.7610   -1.2124   -0.1019   -2.3685   -1.0578   -2.2082    0.5638    1.2111 ···
   -0.6179    0.6156   -1.2655    1.8575   -0.9185   -0.0550   -0.3859    1.2952
   -0.6893   -1.9454    2.0136   -3.1232   -0.2362    1.3868    0.9098   -1.5477
   -0.6783    0.4630    0.5849   -0.1650    1.9326   -0.2297   -1.8473    0.4901
   -0.5966   -2.0448    2.0570    1.9510    0.1764   -2.1614   -0.4039    1.8016
   -0.8779    0.4344   -0.9316    0.1839   -0.3608    0.6196    0.3862   -2.6515
   -0.5275    1.2156   -1.5010   -2.0320   -1.5237   -2.4373   -2.3757   -1.3999
   -0.7490   -0.7225   -3.1523    0.3658    0.1981   -0.7306    1.6526   -2.3004
   -0.6665    0.5360    1.3031   -1.0337   -4.0308    0.5817   -2.6572    0.8038
   -0.4609   -1.4394   -1.2181    0.7109    0.4522   -0.3595    0.6228   -0.6701
```

2.2 Feedforward Propagation and Prediction

```
pred = predict(Theta1, Theta2, X);
fprintf('\nTraining Set Accuracy: %f\n', mean(double(pred == y)) * 100);
```

```
Training Set Accuracy: 97.520000
```

掌握不好

1. 1.4 One-vs-all Classification 对应的函数理解的很垃圾，主要是其中 all_theta 的shape
2. lrCostFunction(theta, X, y, lambda)，注意 y 只有 0 和 1。代表是否属于此类，这个思想用于 onevsALL
3. predictOneVsAll(all_theta, X)，注意返回值的 shape
4. nn 的 predict 中的 θ 和 X 的 shape 分别代表什么意思。

函数定义区

```
function [h, display_array] = displayData(X, example_width)
%DISPLAYDATA Display 2D data in a nice grid
%   [h, display_array] = DISPLAYDATA(X, example_width) displays 2D data
%   stored in X in a nice grid. It returns the figure handle h and the
%   displayed array if requested.

% Set example_width automatically if not passed in
if ~exist('example_width', 'var') || isempty(example_width)
 example_width = round(sqrt(size(X, 2)));
end

% Gray Image
colormap(gray);

% Compute rows, cols
[m n] = size(X);
example_height = (n / example_width);

% Compute number of items to display
display_rows = floor(sqrt(m));
display_cols = ceil(m / display_rows);

% Between images padding
pad = 1;

% Setup blank display
display_array = - ones(pad + display_rows * (example_height + pad), ...
                       pad + display_cols * (example_width + pad));

% Copy each example into a patch on the display array
curr_ex = 1;
for j = 1:display_rows
 for i = 1:display_cols
  if curr_ex > m,
   break;
  end
  % Copy the patch

  % Get the max value of the patch
```

```
   max_val = max(abs(X(curr_ex, :)));
   display_array(pad + (j - 1) * (example_height + pad) + (1:example_height), ...
                 pad + (i - 1) * (example_width + pad) + (1:example_width)) = ...
       reshape(X(curr_ex, :), example_height, example_width) / max_val;
   curr_ex = curr_ex + 1;
  end
  if curr_ex > m,
   break;
  end
end

% Display Image
h = imagesc(display_array, [-1 1]);

% Do not show axis
axis image off

drawnow;

end
```

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}[-y^{(i)}\log\left(h_\theta(x^{(i)})\right) - (1-y^{(i)})\log\left(1-h_\theta(x^{(i)})\right)] + \frac{\lambda}{2m}\sum_{j=1}^{n}\theta_j^2$$

$$\theta_0 := \theta_0 - a\frac{1}{m}\sum_{i=1}^{m}((h_\theta(x^{(i)}) - y^{(i)})x_0^{(i)})$$

$$\theta_j := \theta_j - a[\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)} + \frac{\lambda}{m}\theta_j]$$

```
function g = sigmoid(z)
    g = 1 ./ (1 + exp(-z));
end

% y 只有 0 或者 1
function [J, grad] = lrCostFunction(theta, X, y, lambda)
    % theta = [0, 0, 0 ... ]^T
    m = size(X, 1);
    h_theta = sigmoid(X * theta);
    %J    = zeros(m, 1); % 这里理解错误，应该是一个值
    J = 0;
    grad = zeros(m, 1);
    temp = [0; theta(2:end)];
    %J = sum(-y .* log(h_theta) - (1 - y) .* log(1 - h_theta), 1); 这么写完全是没有算过 shape
    J = sum(-y .* log(h_theta) - (1 - y) .* log(1 - h_theta)) / m ...
            + lambda * temp' * temp / (2 * m);

%     theta_without_first = zeros(length(theta), 1);
%     theta_without_first = theta(2:end, :);
```

```
    grad = X' * (h_theta - y) / m + lambda .* temp / m;
end
```

这个掌握的不是很好！注意如何设计 all_theta(num_labels * feature)，如何一次性训练每个分类的 theta

```
function [all_theta] = oneVsAll(X, y, num_labels, lambda)
%ONEVSALL trains multiple logistic regression classifiers and returns all
%the classifiers in a matrix all_theta, where the i-th row of all_theta
%corresponds to the classifier for label i
%   [all_theta] = ONEVSALL(X, y, num_labels, lambda) trains num_labels
%   logistic regression classifiers and returns each of these classifiers
%   in a matrix all_theta, where the i-th row of all_theta corresponds
%   to the classifier for label i
    % Some useful variables
    m = size(X, 1);
    n = size(X, 2);

    % You need to return the following variables correctly
    all_theta = zeros(num_labels, n + 1);

    % Add ones to the X data matrix
    X = [ones(m, 1) X];


    options = optimset('GradObj', 'on', 'MaxIter', 50);
    initial_theta = zeros(n + 1, 1);

    % 每个类训练一遍
    for i = 1:num_labels
%         [theta, cost] = fmincg(@(t)(lrCostFunction(t, X, y == i, lambda)), initial_theta, opt
%         all_theta(i, :) = theta;
        all_theta(i, :) = fminunc (@(t)(lrCostFunction(t, X, (y == i), lambda)), ...
                    initial_theta, options);
    end
end
```

```
function p = predictOneVsAll(all_theta, X)
    %PREDICT Predict the label for a trained one-vs-all classifier. The labels
    %are in the range 1..K, where K = size(all_theta, 1).
    %  p = PREDICTONEVSALL(all_theta, X) will return a vector of predictions
    %  for each example in the matrix X. Note that X contains the examples in
    %  rows. all_theta is a matrix where the i-th row is a trained logistic
    %  regression theta vector for the i-th class. You should set p to a vector
    %  of values from 1..K (e.g., p = [1; 3; 1; 2] predicts classes 1, 3, 1, 2
    %  for 4 examples)
```

```
    m           = size(X, 1);
%     num_labels = size(all_theta, 1);

    % You need to return the following variables correctly
    p = zeros(size(X, 1), 1);

    % Add ones to the X data matrix
    X = [ones(m, 1) X];


%     [M, p] = max(X * all_theta', [], 2); 忘记sigmoid! !
    [M, p] = max(sigmoid(X * all_theta'), [], 2);
end
```

`theta` 其尺寸为：以第 `j + 1` 层的激活单元数量为行数，以第 `j` 层的激活单元数加一为列数的矩阵

同时第二层的输入的形状是什么也要知道，我画了一个图，应该好理解。

sample * theta^T = 一个神经元(注意角度)

```
function p = predict(Theta1, Theta2, X)
    %PREDICT Predict the label of an input given a trained neural network
    %   p = PREDICT(Theta1, Theta2, X) outputs the predicted label of X given the
    %   trained weights of a neural network (Theta1, Theta2)

    % Useful values
    m = size(X, 1);
    num_labels = size(Theta2, 1);

    % You need to return the following variables correctly
    p = zeros(size(X, 1), 1);

    % ====================== YOUR CODE HERE ======================
    % Instructions: Complete the following code to make predictions using
    %               your learned neural network. You should set p to a
    %               vector containing labels between 1 to num_labels.
    %
    % Hint: The max function might come in useful. In particular, the max
    %       function can also return the index of the max element, for more
    %       information see 'help max'. If your examples are in rows, then, you
    %       can use max(A, [], 2) to obtain the max for each row.
    %

    % 1th
%     X        = [ones(m, 1) X];
%     a_sup_2 = sigmoid(Theta1 * X'); % 已经增加了一个 \theta 用于额外的 1。
%     a_sup_2 = [ones(1, size(a_sup_2, 2)); a_sup_2];
%     a_sup_3 = sigmoid(Theta2 * a_sup_2);
%     [M, p_t] = max(a_sup_3, [], 1);
%     p = p_t';
    % 2nd
    X       = [ones(m, 1) X];
```

```
    a_sup_2 = sigmoid(X * Theta1'); % a_sup_2 一行是 sample, sample * theta^T = 一个神经元
    a_sup_2 = [ones(size(a_sup_2, 1), 1) a_sup_2]; % 增加 one 列
    a_sup_3 = sigmoid(a_sup_2 * Theta2');
    [aa, p] = max(a_sup_3, [], 2);
end
```