

```

1  %% Machine Learning Online Class - Exercise 3 | Part 1: One-vs-all
2
3  % Instructions
4  % -----
5  %
6  % This file contains code that helps you get started on the
7  % linear exercise. You will need to complete the following functions
8  % in this exercise:
9  %
10 %     lrCostFunction.m (logistic regression cost function)
11 %     oneVsAll.m
12 %     predictOneVsAll.m
13 %     predict.m
14 %
15 % For this exercise, you will not need to change any code in this file,
16 % or any other files other than those mentioned above.
17 %
18
19 %% Initialization
20 clear ; close all; clc
21
22 %% Setup the parameters you will use for this part of the exercise
23 input_layer_size = 400; % 20x20 Input Images of Digits
24 num_labels = 10;      % 10 labels, from 1 to 10
25                       % (note that we have mapped "0" to label 10)
26
27 %% ===== Part 1: Loading and Visualizing Data =====
28 % We start the exercise by first loading and visualizing the dataset.
29 % You will be working with a dataset that contains handwritten digits.
30 %
31
32 % Load Training Data
33 fprintf('Loading and Visualizing Data ...\n')
34
35 load('ex3data1.mat'); % training data stored in arrays X, y
36 m = size(X, 1);
37
38 % Randomly select 100 data points to display
39 rand_indices = randperm(m);
40 sel = X(rand_indices(1:100), :);
41
42 displayData(sel);
43
44 fprintf('Program paused. Press enter to continue.\n');
45 pause;
46
47 %% ===== Part 2a: Vectorize Logistic Regression =====
48 % In this part of the exercise, you will reuse your logistic regression
49 % code from the last exercise. Your task here is to make sure that your
50 % regularized logistic regression implementation is vectorized. After
51 % that, you will implement one-vs-all classification for the handwritten
52 % digit dataset

```

```

52 % digit dataset.
53 %
54
55 % Test case for lrCostFunction
56 fprintf('\nTesting lrCostFunction() with regularization');
57
58 theta_t = [-2; -1; 1; 2];
59 X_t = [ones(5,1) reshape(1:15,5,3)/10];
60 y_t = ([1;0;1;0;1] >= 0.5);
61 lambda_t = 3;
62 [J grad] = lrCostFunction(theta_t, X_t, y_t, lambda_t);
63
64 fprintf('\nCost: %f\n', J);
65 fprintf('Expected cost: 2.534819\n');
66 fprintf('Gradients:\n');
67 fprintf(' %f \n', grad);
68 fprintf('Expected gradients:\n');
69 fprintf(' 0.146561\n -0.548558\n 0.724722\n 1.398003\n');
70
71 fprintf('Program paused. Press enter to continue.\n');
72 pause;
73 %% ===== Part 2b: One-vs-All Training =====
74 fprintf('\nTraining One-vs-All Logistic Regression...\n')
75
76 lambda = 0.1;
77 [all_theta] = oneVsAll(X, y, num_labels, lambda);
78
79 fprintf('Program paused. Press enter to continue.\n');
80 pause;
81
82
83 %% ===== Part 3: Predict for One-Vs-All =====
84
85 pred = predictOneVsAll(all_theta, X);
86
87 fprintf('\nTraining Set Accuracy: %f\n', mean(double(pred == y)) * 100);
88

```

```

1  function [h, display_array] = displayData(X, example_width)
2  %DISPLAYDATA Display 2D data in a nice grid
3  %   [h, display_array] = DISPLAYDATA(X, example_width) displays 2D data
4  %   stored in X in a nice grid. It returns the figure handle h and the
5  %   displayed array if requested.
6
7  % Set example_width automatically if not passed in
8  if ~exist('example_width', 'var') || isempty(example_width)
9      example_width = round(sqrt(size(X, 2)));
10 end
11
12 % Gray Image
13 colormap(gray);
14
15 % Compute rows, cols
16 [m n] = size(X);
17 example_height = (n / example_width);
18
19 % Compute number of items to display
20 display_rows = floor(sqrt(m));
21 display_cols = ceil(m / display_rows);
22
23 % Between images padding
24 pad = 1;
25
26 % Setup blank display
27 display_array = - ones(pad + display_rows * (example_height + pad), ...
28                       pad + display_cols * (example_width + pad));
29
30 % Copy each example into a patch on the display array
31 curr_ex = 1;
32 for j = 1:display_rows
33     for i = 1:display_cols
34         if curr_ex > m,
35             break;
36         end
37         % Copy the patch
38
39         % Get the max value of the patch
40         max_val = max(abs(X(curr_ex, :)));
41         display_array(pad + (j - 1) * (example_height + pad) +
42             • (1:example_height), ...
43             • pad + (i - 1) * (example_width + pad) +
44             • (1:example_width)) = ...
45             reshape(X(curr_ex, :), example_height, example_width) /
46             • max_val;
47         curr_ex = curr_ex + 1;
48     end
49 end
50 end

```

```
49     end
50
51     % Display Image
52     h = imagesc(display_array, [-1 1]);
53
54     % Do not show axis
55     axis image off
56
57     drawnow;
58
```

```
1  function g = sigmoid(z)
2  %SIGMOID Compute sigmoid function
3  %    J = SIGMOID(z) computes the sigmoid of z.
4
5  g = 1.0 ./ (1.0 + exp(-z));
6  end
7
```

```

1 function [J, grad] = lrCostFunction(theta, X, y, lambda)
2 %LRCOSTFUNCTION Compute cost and gradient for logistic regression with
3 %regularization
4 % J = LRCOSTFUNCTION(theta, X, y, lambda) computes the cost of using
5 % theta as the parameter for regularized logistic regression and the
6 % gradient of the cost w.r.t. to the parameters.
7 % Initialize some useful values
8 m = length(y); % number of training examples
9 % You need to return the following variables correctly
10 J = 0;
11 grad = zeros(size(theta));
12 % ===== YOUR CODE HERE =====
13 % Instructions: Compute the cost of a particular choice of theta.
14 %               You should set J to the cost.
15 %               Compute the partial derivatives and set grad to the
16 %               • partial
17 %               derivatives of the cost w.r.t. each parameter in theta
18 % Hint: The computation of the cost function and gradients can be
19 % efficiently vectorized. For example, consider the computation
20 %
21 %         sigmoid(X * theta)
22 %
23 %         Each row of the resulting matrix will contain the value of the
24 %         prediction for that example. You can make use of this to
25 %         • vectorize
26 %         the cost function and gradient computations.
27 % Hint: When computing the gradient of the regularized cost function,
28 % there're many possible vectorized solutions, but one solution
29 % looks like:
30 %         grad = (unregularized gradient for logistic regression)
31 %         temp = theta;
32 %         temp(1) = 0; % because we don't add anything for j = 0
33 %         grad = grad + YOUR_CODE_HERE (using the temp variable)
34 %
35
36 h=sigmoid(X*theta); % h predicciones
37
38 Jsin=(-1/m)*sum(y.*log(h)+(1-y).*log(1-h)); %sin regularizar
39 JregTerm=lambda/(2*m)*sum(theta(2:end).^2); %término para regularizar.
40 % Dejamos fuera theta zero
41 J=Jsin+JregTerm;
42
43 gradsin=X'*(h-y); %sin regularizar. nx1 = nxm * mx1
44 gradregTerm=lambda/m*[0;theta(2:end)]; %añado un 0 al ppio por theta
45 % zero y proceso el resto
46 grad=1/m*gradsin+gradregTerm;
47 % =====

```

```

1  function [all_theta] = oneVsAll(X, y, num_labels, lambda)
2  %ONEVSALL trains multiple logistic regression classifiers and returns all
3  %the classifiers in a matrix all_theta, where the i-th row of all_theta
4  %corresponds to the classifier for label i
5  % [all_theta] = ONEVSALL(X, y, num_labels, lambda) trains num_labels
6  % logistic regression classifiers and returns each of these classifiers
7  % in a matrix all_theta, where the i-th row of all_theta corresponds
8  % to the classifier for label i
9
10 % Some useful variables
11 m = size(X, 1);
12 n = size(X, 2);
13
14 % You need to return the following variables correctly
15 all_theta = zeros(num_labels, n + 1);
16
17 % Add ones to the X data matrix
18 X = [ones(m, 1) X];
19
20 % ===== YOUR CODE HERE =====
21 % Instructions: You should complete the following code to train
22 % • num_labels
23 %           logistic regression classifiers with regularization
24 %           parameter lambda.
25 % Hint: theta(:) will return a column vector.
26 %
27 % Hint: You can use y == c to obtain a vector of 1's and 0's that tell
28 % • you
29 %       whether the ground truth is true/false for this class.
30 % Note: For this assignment, we recommend using fmincg to optimize the
31 % • cost
32 %       function. It is okay to use a for-loop (for c = 1:num_labels) to
33 %       loop over the different classes.
34 %
35 %       fmincg works similarly to fminunc, but is more efficient when we
36 %       are dealing with large number of parameters.
37 % Example Code for fmincg:
38 %
39 %     % Set Initial theta
40 %     initial_theta = zeros(n + 1, 1);
41 %
42 %     % Set options for fminunc
43 %     options = optimset('GradObj', 'on', 'MaxIter', 50);
44 %
45 %     % Run fmincg to obtain the optimal theta
46 %     % This function will return theta and the cost
47 %     [theta] = ...
48 %         fmincg (@(t)(lrCostFunction(t, X, (y == c), lambda)), ...
49 %             initial_theta, options);

```

```

49     initial_theta, options;;
50 %
51
52 theta_ini = zeros(n + 1, 1);
53
54 options = optimset('GradObj', 'on', 'MaxIter', 50); %options
55
56 % Run fmincg to obtain the optimal theta
57 for label_actual = 1:num_labels
58     all_theta(label_actual, :) = fmincg( @(t)(lrCostFunction(t, X, (y ==
    •   label_actual), lambda)), theta_ini, options);
59 end
60
61 %
    •   =====

```



```

1  function p = predictOneVsAll(all_theta, X)
2  %PREDICT Predict the label for a trained one-vs-all classifier. The
  • labels
3  %are in the range 1..K, where K = size(all_theta, 1).
4  % p = PREDICTONEVSALL(all_theta, X) will return a vector of predictions
5  % for each example in the matrix X. Note that X contains the examples in
6  % rows. all_theta is a matrix where the i-th row is a trained logistic
7  % regression theta vector for the i-th class. You should set p to a
  • vector
8  % of values from 1..K (e.g., p = [1; 3; 1; 2] predicts classes 1, 3, 1,
  • 2
9  % for 4 examples)
10
11  m = size(X, 1);
12  num_labels = size(all_theta, 1);
13
14  % You need to return the following variables correctly
15  p = zeros(size(X, 1), 1);
16
17  % Add ones to the X data matrix
18  X = [ones(m, 1) X];
19
20  % ===== YOUR CODE HERE =====
21  % Instructions: Complete the following code to make predictions using
22  %               your learned logistic regression parameters (one-vs-all).
23  %               You should set p to a vector of predictions (from 1 to
24  %               num_labels).
25  %
26  % Hint: This code can be done all vectorized using the max function.
27  %       In particular, the max function can also return the index of the
28  %       max element, for more information see 'help max'. If your
  • examples
29  %       are in rows, then, you can use max(A, [], 2) to obtain the max
30  %       for each row.
31  %
32
33  % X = m x 401
34  % all_theta = n x 401 (extra column of 1's)
35  % h = m x n where element ij = probabilidad de que la imagen input de la
36  % row i sea el digito de valor j (con j = 10 para el zero)
37  h = sigmoid(X * all_theta');
38
39  [M, p] = max(h, [], 2); % selecciona el valor maximo (mayor probabilidad
  • en todo vector fila de h
40

```

```

1  %% Machine Learning Online Class - Exercise 3 | Part 2: Neural Networks
2
3  % Instructions
4  % -----
5  %
6  % This file contains code that helps you get started on the
7  % linear exercise. You will need to complete the following functions
8  % in this exercise:
9  %
10 %     lrCostFunction.m (logistic regression cost function)
11 %     oneVsAll.m
12 %     predictOneVsAll.m
13 %     predict.m
14 %
15 % For this exercise, you will not need to change any code in this file,
16 % or any other files other than those mentioned above.
17 %
18
19 %% Initialization
20 clear ; close all; clc
21
22 %% Setup the parameters you will use for this exercise
23 input_layer_size = 400; % 20x20 Input Images of Digits
24 hidden_layer_size = 25; % 25 hidden units
25 num_labels = 10; % 10 labels, from 1 to 10
26 % (note that we have mapped "0" to label 10)
27
28 %% ===== Part 1: Loading and Visualizing Data =====
29 % We start the exercise by first loading and visualizing the dataset.
30 % You will be working with a dataset that contains handwritten digits.
31 %
32
33 % Load Training Data
34 fprintf('Loading and Visualizing Data ...\n')
35
36 load('ex3data1.mat');
37 m = size(X, 1);
38
39 % Randomly select 100 data points to display
40 sel = randperm(size(X, 1));
41 sel = sel(1:100);
42
43 displayData(X(sel, :));
44
45 fprintf('Program paused. Press enter to continue.\n');
46 pause;
47
48 %% ===== Part 2: Loading Parameters =====
49 % In this part of the exercise, we load some pre-initialized
50 % neural network parameters.
51
52 fprintf('\nLoading Saved Neural Network Parameters    \n')

```

```

52     fprintf('Loading saved neural network parameters...\n');
53
54 % Load the weights into variables Theta1 and Theta2
55 load('ex3weights.mat');
56
57 %% ===== Part 3: Implement Predict =====
58 % After training the neural network, we would like to use it to predict
59 % the labels. You will now implement the "predict" function to use the
60 % neural network to predict the labels of the training set. This lets
61 % you compute the training set accuracy.
62
63 pred = predict(Theta1, Theta2, X);
64
65 fprintf('\nTraining Set Accuracy: %f\n', mean(double(pred == y)) * 100);
66
67 fprintf('Program paused. Press enter to continue.\n');
68 pause;
69
70 % To give you an idea of the network's output, you can also run
71 % through the examples one at a time to see what it is predicting.
72
73 % Randomly permute examples
74 rp = randperm(m);
75
76 for i = 1:m
77     % Display
78     fprintf('\nDisplaying Example Image\n');
79     displayData(X(rp(i), :));
80
81     pred = predict(Theta1, Theta2, X(rp(i),:));
82     fprintf('\nNeural Network Prediction: %d (digit %d)\n', pred,
83         • mod(pred, 10));
84
85     % Pause with quit option
86     s = input('Paused - press enter to continue, q to exit:', 's');
87     if s == 'q'
88         break
89     end
90 end
91

```

```

1  function p = predict(Theta1, Theta2, X)
2  %PREDICT Predict the label of an input given a trained neural network
3  %   p = PREDICT(Theta1, Theta2, X) outputs the predicted label of X given
4  %   the
5  %   trained weights of a neural network (Theta1, Theta2)
6
7  % Useful values
8  m = size(X, 1);
9  num_labels = size(Theta2, 1);
10
11 % You need to return the following variables correctly
12 p = zeros(size(X, 1), 1);
13
14 % ===== YOUR CODE HERE =====
15 % Instructions: Complete the following code to make predictions using
16 %               your learned neural network. You should set p to a
17 %               vector containing labels between 1 to num_labels.
18 % Hint: The max function might come in useful. In particular, the max
19 %       function can also return the index of the max element, for more
20 %       information see 'help max'. If your examples are in rows, then, you
21 %       can use max(A, [], 2) to obtain the max for each row.
22 %
23
24 X = [ones(m, 1) X]; % X = 5000 x 401
25
26 % a1 = 5000 x 401
27 a1 = X;
28
29 % a2 = 5000 x 25 --> 5000 x 26
30 % Theta1' = 401 x 25
31 a2 = sigmoid(a1 * Theta1');
32 a2 = [ones(m, 1) a2]; % a2 = 5000 x 26
33
34 % a3 = 5000 x 10 matrix
35 % Theta2' = 26 x 10 matrix
36 a3 = sigmoid(a2 * Theta2');
37 [M, p] = max(a3, [], 2);
38
39 % =====
40
41 end
42

```