# MATLAB Deep Learning Notes XI

Key Words: MNIST

## 1. MNIST Database

- 1. MNIST Database contains 70,000 images of handwritten numbers. In general, 60,000 images are used for training, and the remaining 10,000 images are used for the validation test. Each digit image is a 28-by-28 pixel black-and-white image.
- 2. In this note, we employ only 10,000 images with the training data and verification data in an 8:2 ratio. Therefore, we have 8,000 MNIST images for training and 2,000 images for validation of the performance of the neural network.

# 2. CNN Design and Implementation

3. The MNIST problem is caused by the multiclass classification of the 28-by-28 pixel image into one of the ten digit classes of 0 - 9. So the CNN can be designed as follows

Layer	Remark	Activation Function
Input	28×28 nodes	-
Convolution	20 convolution filters ( $9 \times 9$ )	ReLU
Pooling	1 mean pooling (2×2)	-
Hidden	100 nodes	ReLU
Output	10 nodes	Softmax

Figure 1: the CNN that we designed to process MNIST.

4. Although it has many layers, only three of them contain the weight matrices that require training; they are  $W_1$ ,  $W_5$ , and  $W_o$  in the square blocks.  $W_5$  and  $W_o$  contain the connection weights of the classification neural network, while  $W_1$  is the convolution layer's weight, which is used by the convolution filters for image processing.

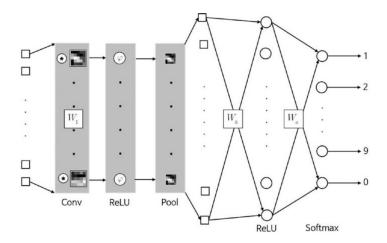


Figure 2: The architecture of this neural network.

5. In this CNN, we use mini-batch and momentum in order to get a better performance.

### Program 26: MnistConv

### Listing 1: MnistConv.m

```
function [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D)
2
3
   alpha = 0.01;
4
  beta = 0.95;
5
6
   momentum1 = zeros(size(W1));
   momentum5 = zeros(size(W5));
   momentumo = zeros(size(Wo));
9
10
   N = length(D);
11
12 |bsize = 100;
13 | blist = 1 : bsize : (N—bsize+1);
14
15 % one epoch loop
16 %
17
   for batch = 1 : length(blist)
        dW1 = zeros(size(W1));
18
19
        dW5 = zeros(size(W5));
20
        dWo = zeros(size(Wo));
21
        % mini—batch loop
22
23
        begin = blist(batch);
24
        for k = begin : begin + bsize - 1
25
            % forward pass = inference
26
27
            x = X(:, :, k); % Input, 28 x 28
28
            y1 = conv(x, W1); % Convolution, 20x20x20
29
            y2 = ReLU(y1); %
30
            y3 = pool(y2); % Pool, 10x10x20
31
            y4 = reshape(y3, [], 1); % 2000
32
            v5 = W5 * y4; % ReLU, 360
33
            y5 = ReLU(v5);
34
            v = Wo * y5; % softmax, 10
            y = softmax(v); %
36
37
            % One—hot encoding
38
39
            d = zeros(10, 1);
40
            d(sub2ind(size(d), D(k), 1)) = 1;
41
            % Backpropagation
42
```

March 2, 2020

```
43
            e = d - y; % Output layer
44
            delta = e;
45
46
            e5 = Wo' * delta; % Hidden(ReLU) layer
47
            delta5 = (y5 > 0) .* e5;
48
49
            e4 = W5' * delta5; % Pooling layer
50
51
            e3 = reshape(e4, size(y3));
52
53
            e2 = zeros(size(y2));
54
            W3 = ones(size(y2)) / (2 * 2);
55
            for c = 1 : 20
56
                e2(:, :, c) = kron(e3(:, :, c), ones([2 2])) .* W3(:, :, c);
57
            end
58
59
            delta2 = (y2 > 0) .* e2; % ReLU layer
60
61
            delta1_x = zeros(size(W1)); % Convolutional layer
62
            for c = 1 : 20
63
                delta1_x(:, :, c) = conv2(x(:, :), rot90(delta2(:, :, c), 2),...
64
                'valid');
65
            end
66
67
            dW1 = dW1 + delta1_x;
68
            dW5 = dW5 + delta5 * y4';
            dWo = dWo + delta * y5';
69
70
71
        end
72
        % Update weights
73
        dW1 = dW1 / bsize;
74
        dW5 = dW5 / bsize;
75
        dWo = dWo / bsize;
76
77
        momentum1 = alpha*dW1 + beta*momentum1;
78
        W1 = W1 + momentum1;
79
80
        momentum5 = alpha*dW5 + beta*momentum5;
81
        W5 = W5 + momentum5;
82
83
        momentumo = alpha*dWo + beta*momentumo;
84
        Wo = Wo + momentumo;
85
   end
86
   end
```

#### Program 27: testMnistConv

#### Listing 2: testMnistConv.m

```
1
  clear
2 | Images = loadMNISTImages('t10k-images-idx3-ubyte');
 3 | Images = reshape(Images, 28, 28, [ ]);
4 Labels = loadMNISTLabels('t10k-labels-idx1-ubyte');
5 | Labels(Labels == 0) = 10; % 0 --> 10
6 rng(1);
7
   % Learning
8
9
   W1 = 1e-2 * randn([9, 9, 20]);
10 \mid W5 = (2 * rand(100, 2000) - 1) * sqrt(6) / sqrt(360 + 2000);
11 | Wo = (2 * rand(10, 100) - 1) * sqrt(6) / sqrt(10 + 100);
12
13 X = Images(:, :, 1:8000);
14 \mid D = Labels(1 : 8000);
15
16 | for epoch = 1 : 3
17
        epoch
18
        [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D);
   end
19
20
21
   save('MnistConv.mat');
22
23 |% Test
24 %
25 \mid X = Images(:, :, 8001 : 10000);
26 \mid D = Labels(8001 : 10000);
27
28 | acc = 0;
29 \mid N = length(D);
30 | for k = 1:N
        x = X(:, :, k); % Input, 28x28
31
32
33
        y1 = conv(x, W1); % Convolution, 20x20x20
34
        y2 = ReLU(y1); %
        y3 = pool(y2); % Pool, 10x10x20
36
        y4 = reshape(y3, [], 1); % 2000
        v5 = W5 * y4; % ReLU, 360
38
        y5 = ReLU(v5); %
39
        v = Wo * y5; % Softmax, 10
40
        y = softmax(v); %
41
42
        [\sim, i] = max(y);
```

## Output 27:

```
Accuracy is 0.936000
```