# Study Report

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#### Abstract

This report is mainly about the derivation process of the formulas backpropagation and calculation method of matrix form.

# **Derication pross**

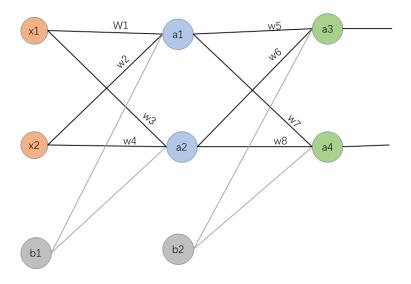


Figure 1: neural network

My derivation is about the picture above, and the following are the formulas I will use.

$$Z^{[l]} = W^{[l]}A^{[l-1]} + b^{[l]}$$
(1)

$$A^{[l]} = f(Z^{[l]}) = \frac{1}{1 + e^{-Z^{[l]}}}$$
 (2)

$$L = \frac{1}{2} \sum (Y - A)^2 \tag{3}$$

$$sigmoid: dZ^{[l]} = f'(Z^{[l]}) = f(Z^{[l]})(1 - f(Z^{[l]})) = A^{[l]}(1 - A^{[l]}).$$
 (4)

The upper case letters in the formula are all matrix forms, I will first complete the computation one by one, and then simplify the expression in matrix form.

#### Forward propagation

$$z_1 = w_1 x_1 + w_2 x_2 + b_1 z_2 = w_3 x_1 + w_4 x_2 + b_1 a_1 = \frac{1}{1 + e^{-z_1}} a_2 = \frac{1}{1 + e^{-z_2}}$$

$$z_3 = w_5 a_1 + w_6 a_2 + b_2 z_4 = w_7 a_1 + w_8 a_2 + b_2 a_3 = \frac{1}{1 + e^{-z_3}} a_4 = \frac{1}{1 + e^{-z_4}}$$

$$L = L_1 + L_2 = \frac{1}{2} (y_1 - a_3)^2 + \frac{1}{2} (y_2 - a_4)^2$$

If we use the matrix form to simplify the upper expression:

$$A_0 = X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad Z_1 = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \quad A_1 = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \quad Z_2 = \begin{bmatrix} z_3 \\ z_4 \end{bmatrix} \quad A_2 = \begin{bmatrix} a_3 \\ a_4 \end{bmatrix}$$

We have known the unmpy package in Python, according to its broadcast, b does not need to be processed. If we want to use matrix to simplify, the W we need are:

$$W_1 = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix} \quad W_2 = \begin{bmatrix} w_5 & w_6 \\ w_7 & w_8 \end{bmatrix}$$

In this case, we can use the formula 1 and 2, and if we use many examples to make the matrix X, these formulas are also effective. In order to facilitate my expression, I do not list this situation here.

### **Backward** propagation

Because the backward propagation is a little complicated, I will only talk about the top path. According to the chain rule we have:

$$da_3 = \frac{\partial L}{\partial a_3} = \frac{\partial L}{\partial a_3} = a_3 - y_1 \qquad dz_3 = \frac{\partial L}{\partial z_3} = da_3 \frac{\partial a_3}{\partial z_3} = da_3 \times a_3 (1 - a_3) \qquad dw_5 = \frac{\partial L}{\partial w_5} = dz_3 \frac{\partial z_3}{\partial w_5} = dz_3 \times a_1 (1 - a_3) = dz_3 \frac{\partial z_3}{\partial w_5} = dz_3 \frac{\partial z_3}{\partial$$

In the figure 1 we can see  $w_5$  and  $w_7$  are connected to  $a_1$ , if we want to calculate  $da_1$ , we need use two routes and that's the same to  $a_2$ ,  $b_2$  and  $b_1$ . Fortunately we don't need to calculate dx, and if we use the matrix, all the thing will be simple.

$$\begin{split} da_1 &= \frac{\partial L}{\partial a_1} = \frac{\partial L1}{\partial a_1} + \frac{\partial L2}{\partial a_1} = dz_3 \frac{\partial z_3}{\partial a_1} + dz_4 \frac{\partial z_4}{\partial a_1} = dz_3 \times w_5 + dz_4 \times w_7 \\ dw_1 &= \frac{\partial L}{\partial w_1} = da_1 \frac{\partial a_1}{\partial w_1} = da_1 \times a_1 (1 - a_1) \\ db_2 &= \frac{\partial L}{\partial b_2} = \frac{1}{2} (dz_3 \frac{\partial z_3}{\partial b_2} + dz_4 \frac{\partial z_4}{\partial b_2}) = \frac{1}{2} (dz_3 + dz_4) \end{split} \qquad (b \text{ only have one example.})$$

Use matrix to simplify:

$$dZ_1 = \begin{bmatrix} db_1 \\ db_2 \end{bmatrix} \quad dA_1 = \begin{bmatrix} da_1 \\ da_2 \end{bmatrix} \quad dZ_2 = \begin{bmatrix} db_3 \\ db_4 \end{bmatrix} \quad dA_2 = \begin{bmatrix} da_3 \\ da_4 \end{bmatrix}$$

We can calculate the dZ and dA of the output layer according to different function. But the way to calculate dW, dB and another especial one,  $dA^{[l-1]}$ , is same in every neural network. According to the formula 1 we will have:

$$dW^{[l]} = \frac{1}{m} dZ^{[l]} A^{[l-1]T} \tag{5}$$

$$db^{[l]} = \frac{1}{m} \sum_{i=1}^{m} dZ^{[l](i)}$$
(6)

$$dA^{[l-1]} = W^{[l]T} dZ^{[l]} (7)$$

Here I will give some instructions. In the example that I give, we can easily find the way to calculate dW as formula 5, but if we want to calculate many datas at the same time, we shuld add the  $\frac{1}{m}$ .

# Update

We use  $\alpha$  as the learning rate, so now we can upadte the parameters, using gradient descent.

$$w_1 = w_1 - \alpha dw_1 \qquad b_1 = b_1 - \alpha db_1$$

Use matrix to simplify:

$$W^{[l]} = W^{[l]} - \alpha \ dW^{[l]}$$
$$b^{[l]} = b^{[l]} - \alpha \ db^{[l]}$$

# Leetcode

### Description

Given a string of numbers and operators, return all possible results from computing all the different possible ways to group numbers and operators. The valid operators are +, - and \*.

```
Example 1: Input: "2-1-1" Output: [0, 2] Explanation: ((2-1)-1) = 0 (2-(1-1)) = 2 Example 2: Input: "2*3-4*5" Output: [-34, -14, -10, -10, 10] Explanation: (2*(3-(4*5))) = -34 ((2*3)-(4*5)) = -14 ((2*(3-4))*5) = -10 (2*((3-4)*5)) = -10 (((2*3)-4)*5) = 10
```

#### Solution

This problem dosen't require us to make sure the return vector don't contain repeating elements, so it's easy to solve it. Traverse the string, if we find an operator, divide the string into two parts in this position and use the function itself to get two vectors. Then use the operator that we found to calculate all combinations of two vectors, and add every result to the final vector.

#### Code

```
class Solution {
1
   public:
2
        vector<int> diffWaysToCompute(string input) {
3
4
            vector<int> res;
            for (int i = 0; i < input.size(); i++){
5
                 if (input [i] < '0'){
6
                     vector<int> left = diffWaysToCompute(input.substr(0,i));
7
                     vector<int> right = diffWaysToCompute(input.substr(i + 1));
8
                     for (int j = 0; j < left.size(); j++)
9
10
                         for (int k = 0; k < right.size(); k++){
                             if (input [i] = '+')
11
                                  res.push_back(left[j] + right[k]);
12
                             else if (input [i] == '-')
13
                                  res.push_back(left[j] - right[k]);
14
15
                             else
                                  res.push_back(left[j] * right[k]);
16
                         }
17
                }
18
19
            if (res.empty())
20
21
                res.push_back(atoi(input.c_str()));
            return res;
22
23
   };
24
```

# Others

I want to know where we shuld use linux. And maybe the MLP still have something wrong. I was surprised by the curve drawn by the program. I don't understand why the part of the beginning of the curve is horizontal. 5000 epoches is enough for my program.