05_3_TwoLayer_NN

2020년 12월 8일

```
In [1]: import numpy as np
        import matplotlib.pylab as plt

In [2]: np.set_printoptions(precision=4, suppress=True)

In [3]: def sigmoid(x):
            return 1 / (1 + np.exp(-x))

In [4]: def sigmoid_grad(x):
            return (1.0 - sigmoid(x)) * sigmoid(x)

In [5]: def softmax(x):
            if x.ndim == 2:
                x = x.T
                x = x - np.max(x, axis=0)
                y = np.exp(x) / np.sum(np.exp(x), axis=0)
                return y.T

            x = x - np.max(x) # 오버플로 대책
            return np.exp(x) / np.sum(np.exp(x))

In [6]: def cross_entropy_error(y, t):
            if y.ndim == 1:
                t = t.reshape(1, t.size)
                y = y.reshape(1, y.size)

            # 훈련 데이터가 One-hot 벡터라면 정답 레이블의 인덱스로 반환
            if t.size == y.size:
```

```
        t = t.argmax(axis=1)

    batch_size = y.shape[0]
    return -np.sum(np.log(y[np.arange(batch_size), t] + 1e-7)) / batch_size
```

```
In [7]: class TwoLayerNet:
    """
      A two-layer fully-connected neural network. The net has an input dimension of
      N, a hidden layer dimension of H, and performs classification over C classes.
    """

    def __init__(self, input_size, hidden_size, output_size, weight_init_std=0.01):
        """
        가중치 초기화
        Initialize the model. Weights are initialized to small random values and
        biases are initialized to zero. Weights and biases are stored in the
        variable self.params, which is a dictionary with the following keys:
        W1: First layer weights; has shape (D, H)
        b1: First layer biases; has shape (H,)
        W2: Second layer weights; has shape (H, C)
        b2: Second layer biases; has shape (C,)
        Inputs:
        - input_size: The dimension D of the input data.
        - hidden_size: The number of neurons H in the hidden layer.
        - output_size: The number of classes C.
        """

        self.params = {}
        self.params['W1'] = weight_init_std * np.random.randn(input_size, hidden_size)
        self.params['b1'] = np.zeros(hidden_size)
        self.params['W2'] = weight_init_std * np.random.randn(hidden_size, output_size)
        self.params['b2'] = np.zeros(output_size)

    def predict(self, x):
        '''
        Forward Pass: Loss computation
```

```
        '''
        W1, W2 = self.params['W1'], self.params['W2']
        b1, b2 = self.params['b1'], self.params['b2']

        a1 = np.dot(x, W1) + b1 # First layer pre-activation
        z1 = sigmoid(a1)  # # First layer activation
        a2 = np.dot(z1, W2) + b2
        y = softmax(a2)

        return y

    # x : 입력 데이터, t : 정답 레이블
    def loss(self, x, t):
        y = self.predict(x)

        return cross_entropy_error(y, t)

    def accuracy(self, x, t):
        y = self.predict(x)
        y = np.argmax(y, axis=1)
        t = np.argmax(t, axis=1)

        accuracy = np.sum(y == t) / float(x.shape[0])
        return accuracy

    # x : 입력 데이터, t : 정답 레이블
    def numerical_gradient(self, x, t):
        loss_W = lambda W: self.loss(x, t)

        grads = {}
        grads['W1'] = numerical_gradient(loss_W, self.params['W1'])
        grads['b1'] = numerical_gradient(loss_W, self.params['b1'])
        grads['W2'] = numerical_gradient(loss_W, self.params['W2'])
        grads['b2'] = numerical_gradient(loss_W, self.params['b2'])

        return grads
```

```
        def gradient(self, x, t):
            W1, W2 = self.params['W1'], self.params['W2']
            b1, b2 = self.params['b1'], self.params['b2']
            grads = {}

            batch_num = x.shape[0]

            # forward
            a1 = np.dot(x, W1) + b1
            z1 = sigmoid(a1)
            a2 = np.dot(z1, W2) + b2
            y = softmax(a2)

            # backward
            dy = (y - t) / batch_num # error or loss
            grads['W2'] = np.dot(z1.T, dy)
            grads['b2'] = np.sum(dy, axis=0)

            da1 = np.dot(dy, W2.T)
            dz1 = sigmoid_grad(a1) * da1
            grads['W1'] = np.dot(x.T, dz1)
            grads['b1'] = np.sum(dz1, axis=0)

            return grads
```

```
In [8]: network = TwoLayerNet(input_size=784, hidden_size=50, output_size=10)
```

```
In [9]: from dataset.mnist import load_mnist
        (x_train, t_train), (x_test, t_test) = load_mnist(normalize=True, one_hot_label=True)
```

- 형상 출력해보기

```
In [10]: x_train.shape, t_train.shape, x_test.shape, t_test.shape
```

```
Out[10]: ((60000, 784), (60000, 10), (10000, 784), (10000, 10))
```

학습하기

- Hyperparameters

```
In [11]: iters_num = 10000  # 반복 횟수를 적절히 설정한다.
         train_size = x_train.shape[0]
         batch_size = 100   # 미니배치 크기
         learning_rate = 0.1
```

```
In [12]: train_loss_list = []
         train_acc_list = []
         test_acc_list = []
```

- Train the network !

```
In [13]: # 1에폭당 반복 수
         iter_per_epoch = max(train_size // batch_size, 1)
         print('iter_per_epoch = {}//{}={}'.format(train_size, batch_size,iter_per_epoch))
```

```
iter_per_epoch = 60000//100=600
```

```
In [14]: for key in ('W1', 'b1', 'W2', 'b2'):
             print(key)
```

```
W1
b1
W2
b2
```

```
In [ ]:
```

```
In [15]: print('epoch\tloss\tacc_trn\tacc_test')
         print('---------------------------------')
         for i in range(iters_num):
             # 미니배치 획득
             batch_mask = np.random.choice(train_size, batch_size)
             x_batch = x_train[batch_mask]
             t_batch = t_train[batch_mask]
```

```
            # 기울기 계산
            #grad = network.numerical_gradient(x_batch, t_batch)
            grad = network.gradient(x_batch, t_batch)


            # 매개변수 갱신
            for key in ('W1', 'b1', 'W2', 'b2'):
                network.params[key] -= learning_rate * grad[key]

            # 학습 경과 기록
            loss = network.loss(x_batch, t_batch)
            train_loss_list.append(loss)

            # 1 에폭당 정확도 계산
            if i % iter_per_epoch == 0:
                train_acc = network.accuracy(x_train, t_train)
                test_acc = network.accuracy(x_test, t_test)
                train_acc_list.append(train_acc)
                test_acc_list.append(test_acc)

                print('{}\t{:.3f}\t{:.3f}\t{:.3f}'.format(i//iter_per_epoch, loss, train_acc,
```

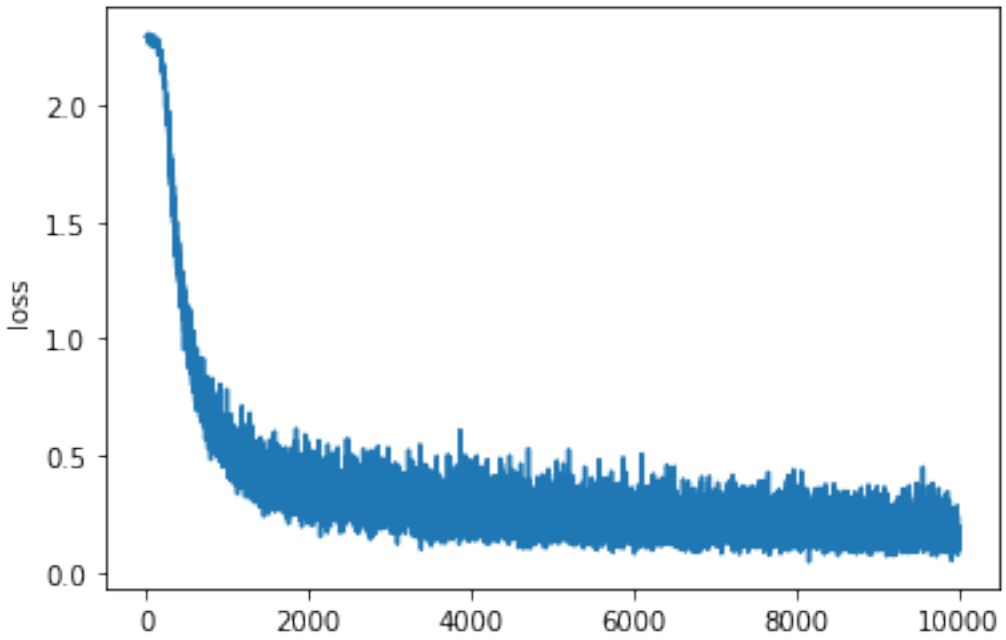
```
epoch        loss        acc_trn        acc_test
---------------------------------
0        2.292        0.109        0.106
1        0.762        0.776        0.786
2        0.512        0.878        0.881
3        0.270        0.898        0.900
4        0.271        0.907        0.910
5        0.463        0.914        0.915
6        0.325        0.920        0.921
7        0.213        0.924        0.924
8        0.157        0.927        0.928
9        0.330        0.931        0.931
```

10	0.274	0.934	0.932
11	0.175	0.935	0.935
12	0.325	0.939	0.937
13	0.212	0.940	0.938
14	0.203	0.942	0.941
15	0.204	0.944	0.942
16	0.235	0.946	0.944

결과 그려보기 및 분석

```
In [16]: plt.plot(train_loss_list)
         plt.ylabel('loss')
```

```
Out[16]: Text(0, 0.5, 'loss')
```



- Train accuracy

```
In [17]: train_acc = network.accuracy(x_train, t_train)
         print(train_acc)
```

```
0.9467666666666666
```

- Test accuracy

```
In [18]: test_acc = network.accuracy(x_test, t_test)
         print(test_acc)
```

```
0.9447
```

- **하나만 테스트해보기** 그 림 그 리 는 과 정 은 03_NeuralNetwork/01_3_NN_MNIST_Exploration.ipynb 을 참고해보세요

```
In [43]: idx_to_test = 550-5 #0~9999 바꾸어서 해보세요
         x1 = x_test[idx_to_test]
         t1 = t_test[idx_to_test]
```

```
In [44]: x1.shape, t1.shape
```

```
Out[44]: ((784,), (10,))
```

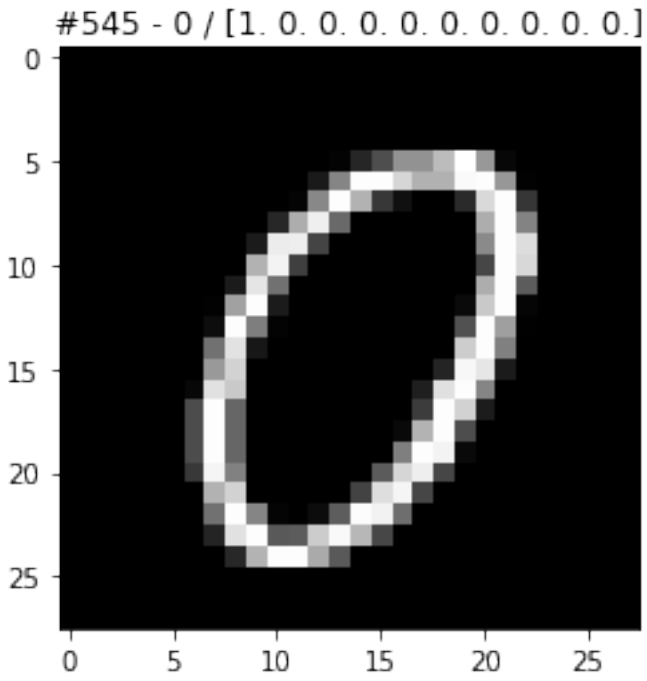
```
In [45]: title = '#{} - {} / {}'.format(idx_to_test, np.argmax(t1), t1)
         print(title)
```

```
#545 - 0 / [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

```
In [46]: img = x1.reshape((28,28))
```

```
In [47]: #plt.plot(img)


         plt.imshow(img, cmap='gray')
         plt.title(title)
         plt.show()
```




```
In [48]: y1 = network.predict(x1)

In [49]: print(y1)

[0.9299 0.     0.0018 0.0007 0.     0.0618 0.0001 0.0032 0.001  0.0014]


In [50]: print(t1) # 정답
         print(y1) # 학습된 neural network 가 구한 값.

[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
[0.9299 0.     0.0018 0.0007 0.     0.0618 0.0001 0.0032 0.001  0.0014]


In [51]: print('index\t정답\t예측값')
         for i in range(10):
             print('#{}\t{}\t{:.3f}'.format(i, t1[i], y1[i]))

index        정답     예측값
#0        1.0        0.930
```

```
#1        0.0        0.000
#2        0.0        0.002
#3        0.0        0.001
#4        0.0        0.000
#5        0.0        0.062
#6        0.0        0.000
#7        0.0        0.003
#8        0.0        0.001
#9        0.0        0.001
```

```
In [37]: np.argmax(t1) == np.argmax(y1)
```

```
Out[37]: False
```

TODO

- idx_to_test 를 바꾸어 가며 테스트해보고 결과값 논의해보기 (3개 이상)

  예를들면 네트워크가 약간이라도 확률을 만들어내는 숫자 분석을 해볼수 있음.
  : 7과 1이 비슷하기에 정답은 7이지만 1에도 약간의 확률값이 생겼다.

- Training 이 되기 전에는 어떻게 예측을 하는지 해보기

References

- Stanford CS231n, Two-layer network https://cs231n.github.io/ https://github.com/yunjey/cs231n/blob/master/assignment1/cs231n/classifiers/neural_net.py
- Implementing a two-layer neural network from scratch https://ljvmiranda921.github.io/notebook/2017/02/17/artificial-neural-networks/
- 주교재 https://github.com/WegraLee/deep-learning-from-scratch/blob/master/ch04/train_neuralnet.py