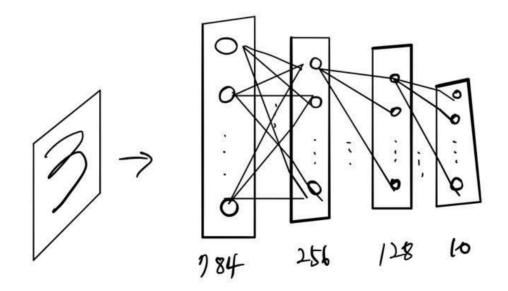
# 심층학습 [실습01] MLP-행렬곱 구현

SW융합학부 양희경

## MLP 를 행렬곱으로 구현하기

- 데이터셋: MNIST
- Multi-layered perceptron (MLP)
  - 2 hidden layers
- Forward propagation



### 1. 라이브러리 임포트

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import torch
import torchvision.datasets as dset
import torchvision.transforms as transforms
```

### 2. MNIST test dataset 가져오기

```
1 # "": 包재 番目에 MWIST 있음
2 mnist_test=dset.MNIST("", train=False,transform=transforms.ToTensor(), #test 용으로 쓰겠다.
3 target_transform=None, download=True)
```

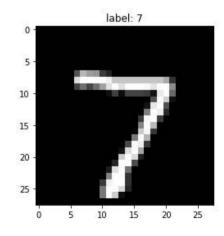
#### 3. 대략적인 데이터 형태

```
print "mnist_test 일이:", len(mnist_test)

# 데이터 하나 형태
image, label = mnist_test.__getitem__(0) # 0번째 데이터
print "image data 형태:", image.size()
print "label: ", label

# 그리기
img = image.numpy() # image 타일을 numpy 로 변환 (1,28,28)
plt.title("label: %d" %label )
plt.imshow(img[0], cmap='gray')
plt.show()
```

mnist\_test 길이: 10000 image data 형태: torch.Size([1, 28, 28]) label: 7



## 4. sigmoid, softmax 함수 구현

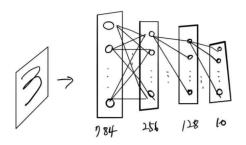
$$g(z) = \frac{1}{1 + e^{-z}}$$

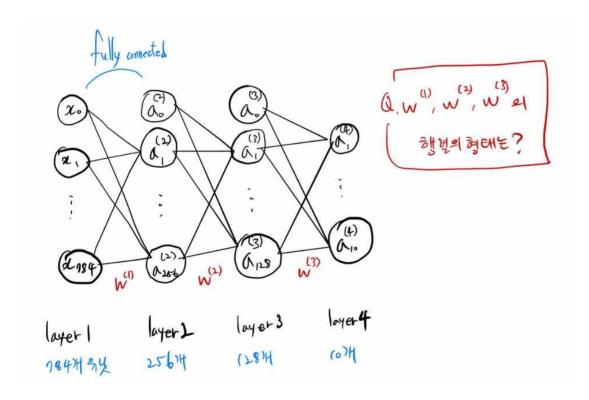
```
1 def sigmoid(x):
```

$$softmax(x)_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

```
1 def softmax(x):
2
3
```

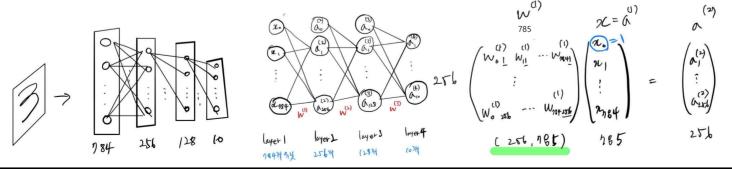
### 5. 모델 선언





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```
# Multi-lavered perceptron
  # # of units in each layer: 28+28 - 250 - 128 - 10
   class MyMLP:
        def init (self. n input. n hidden1. n hidden2. n output):
5
            # W^(1): layer1 -> layer2 에 메필되는 Weight
6
            self.W1 = np.zeros((n_hidden1, n_input), dtype=np.float32) # W1(258, 28+28)
            self.b1 = np.zeros((n hidden1.), dtype=np.float32)
8
9
            self.W2 = np.zeros((n_hidden2, n_hidden1), dtype=np.float32) # W2(128, 256)
10
            self.b2 = np.zeros((n_hidden2.), dtype=np.float32)
11
12
            self.W3 = np.zeros((n_output, n_hidden2), dtype=np.float32) # W3(10, 128)
13
            self.b3 = np.zeros((n_output), dtype=np.float32) # b3
14
15
        def __call__(self, x):
16
            # (1.28.28) -> (28*28)
           x = x.reshape(-1) # 일렬로 피기
17
18
           h1 = sigmoid(np.dot(self.\forall1, x) + self.b1) # \forall1(256, 28+28), x(28+28), b1(256) -> h1(256)
19
20
           h2 = np.dot(self.W2, h1) + self.b2 # W2(128, 250), h1(250), b2(128) -> h2(128)
21
            out = np.dot(self.\mathbb{W}3, h2) + self.b3 # \mathbb{W}3(10, 128), h2(128), h3(10) -> out(10)
22
23
            return softmax(out) # (10)
```



## 6. 모델 생성

```
1 model = MyMLP(28*28, 256, 128, 10)

1 print model.W1.shape, model.b1.shape
2 print model.W2.shape, model.b2.shape
3 print model.W3.shape, model.b3.shape

(256, 784) (256,)
(128, 256) (128,)
(10, 128) (10,)
```

8

## 7. 미리 학습된 weight 로드

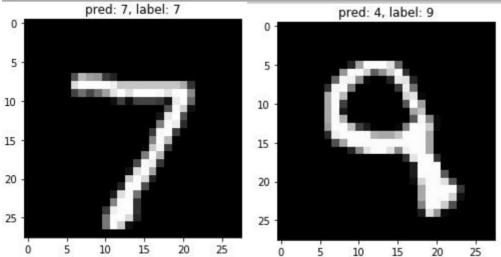
```
weights = np.load('./nets/mlp_weight.npz')
model.W1 = weights['W1']
model.b1 = weights['b1']
model.W2 = weights['W2']
model.b2 = weights['b2']
model.W3 = weights['W3']
model.W3 = weights['W3']
model.b3 = weights['b3']

print model.W1.shape, model.b1.shape
print model.W2.shape, model.b2.shape
print model.W3.shape, model.b3.shape
(256, 784) (256,)
(128, 256) (128,)
```

(10, 128)(10,)

### 8. 테스트

```
mysum = O
   m = len(mnist test)
4 \text{ cnt} = 0
   for i in range(m):
       image, label = mnist_test.__getitem__(i) # 0번째 데이터
       output = model(image)
8
       if (i%1000==0):
9
10
           img = image.numpy() # image 타입을 numpy 로 변환 (1,28,28)
11
           pred_label = np.argmax(output)
12
           plt.title("pred: %d, label: %d" %(pred_label, label) )
13
           plt.imshow(img[0], cmap='gray')
           plt.show()
14
15
16
       cnt += 1
       mysum += (np.argmax(output) == label)
18 print "정확도: %.2f" %( (float(mysum) / cnt) * 100.0 )
```



정확도: 91.91

## 오늘의 과제

- '[실습01] MLP-행렬곱 구현' 를 실습한다.
  - Sigmoid, softmax 함수 구현 포함
  - $P.3 \sim 9$
- HTML 파일을 다운받아 e-campus 에 제출한다.
- 마감: e캠퍼스 참조