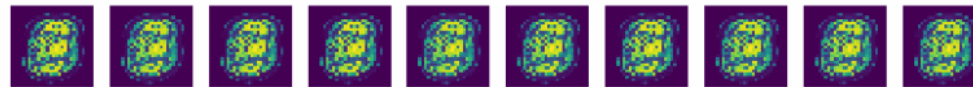




Image Classification

July 13, 2017

Seung-Chan Kim, Ph. D





- 1. 머신러닝 개론 및 주요 개념의 이해. Tensorflow 시스템 설치 및 환경설정 (7/4 화)
- 2. Tensorflow 에 익숙해지기 실습 및 Regression의 이해 (7/6 목)
- 3. Neural Network 이해 및 tensorflow 를 이용한 구현 (7/11 화)
- 4. **이미지 분류 이해 및 Tensorflow를 이용한 구현 (7/13 목)**

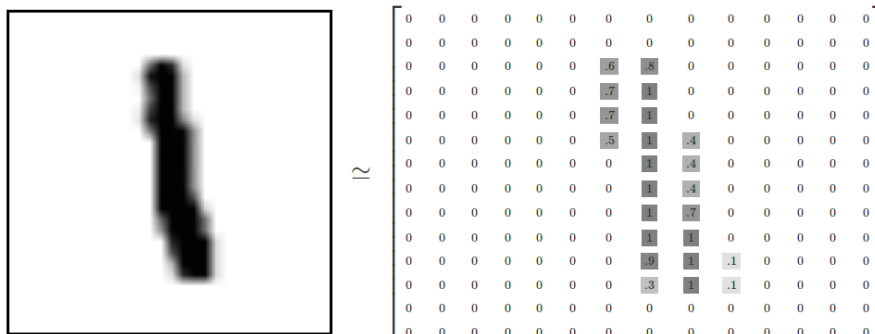


MNIST dataset



- MNIST Dataset

- Handwritten digits, which has a training set of 55,000 examples (학습용 이미지) and a test set of 5,000 examples (검증용 이미지).
- Includes 28 x 28 gray-scaled image and labels for each image.

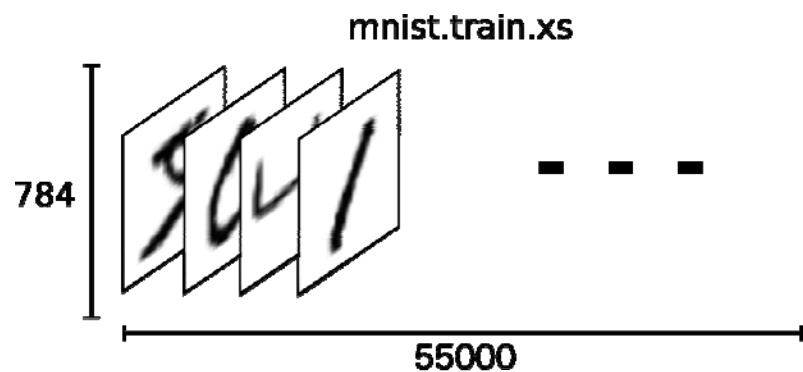




MNIST dataset

- MNIST Dataset

- 각 이미지는 28x28 크기를 가집니다. 이것을 일렬로 펼치면 784 (= 28x28) 차원의 벡터가 됨



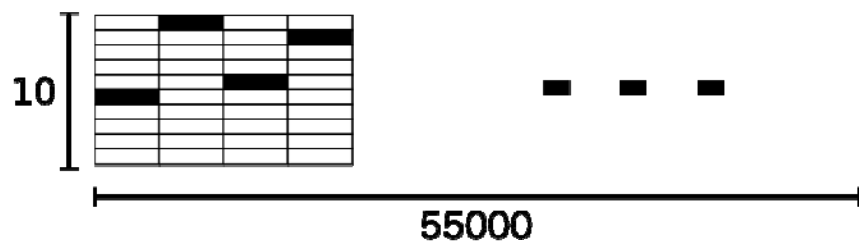
```
# input place holders  
X = tf.placeholder(tf.float32, [None, 784])  
Y = tf.placeholder(tf.float32, [None, 10])
```



One-hot encoding

MNIST의 레이블은 0~9의 값이지만, 이것은 연속된 숫자가 아닌 카테고리 값

`mnist.train.y`



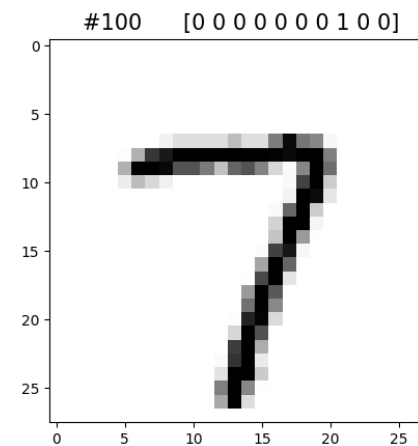
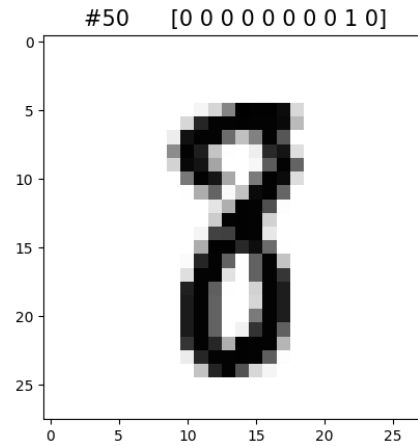
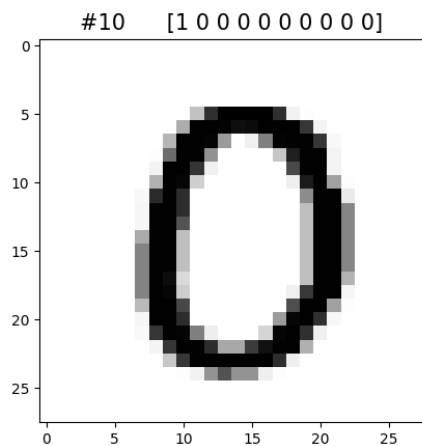
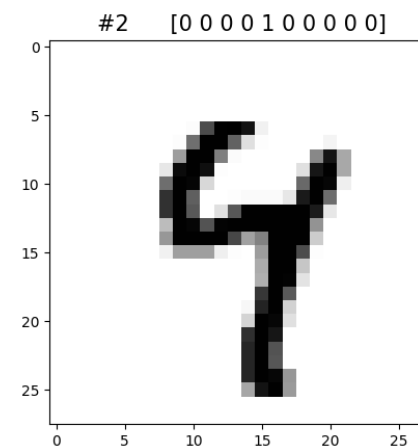
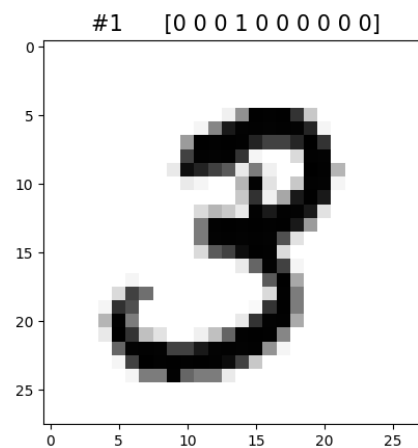
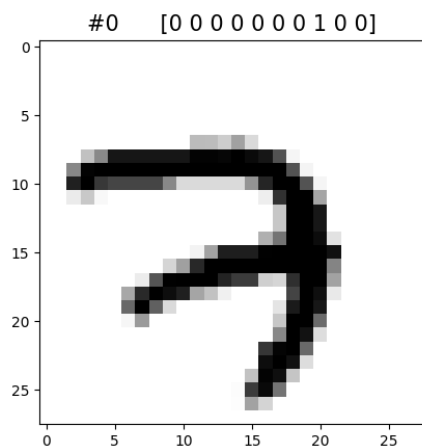
5는 $[0, 0, 0, 0, 0, 1, 0, 0, 0, 0]$,

0은 $[1, 0, 0, 0, 0, 0, 0, 0, 0, 0]$



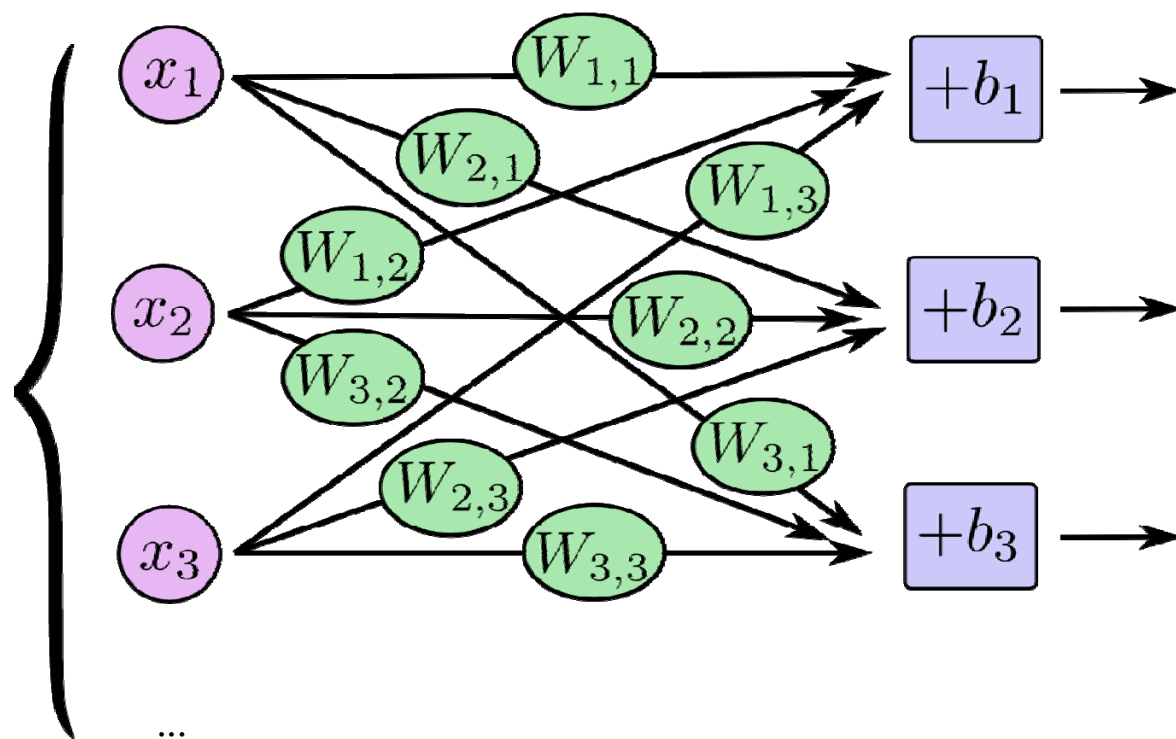
```
idx_to_test = 100  
img         = mnist.train.images[idx_to_test]  
label       = mnist.train.labels[idx_to_test]
```

03-3-mnist-show.py 를 열어주세요





784





Softmax ?!?



$$\text{evidence}_i = \sum_j W_{i,j} x_j + b_i$$

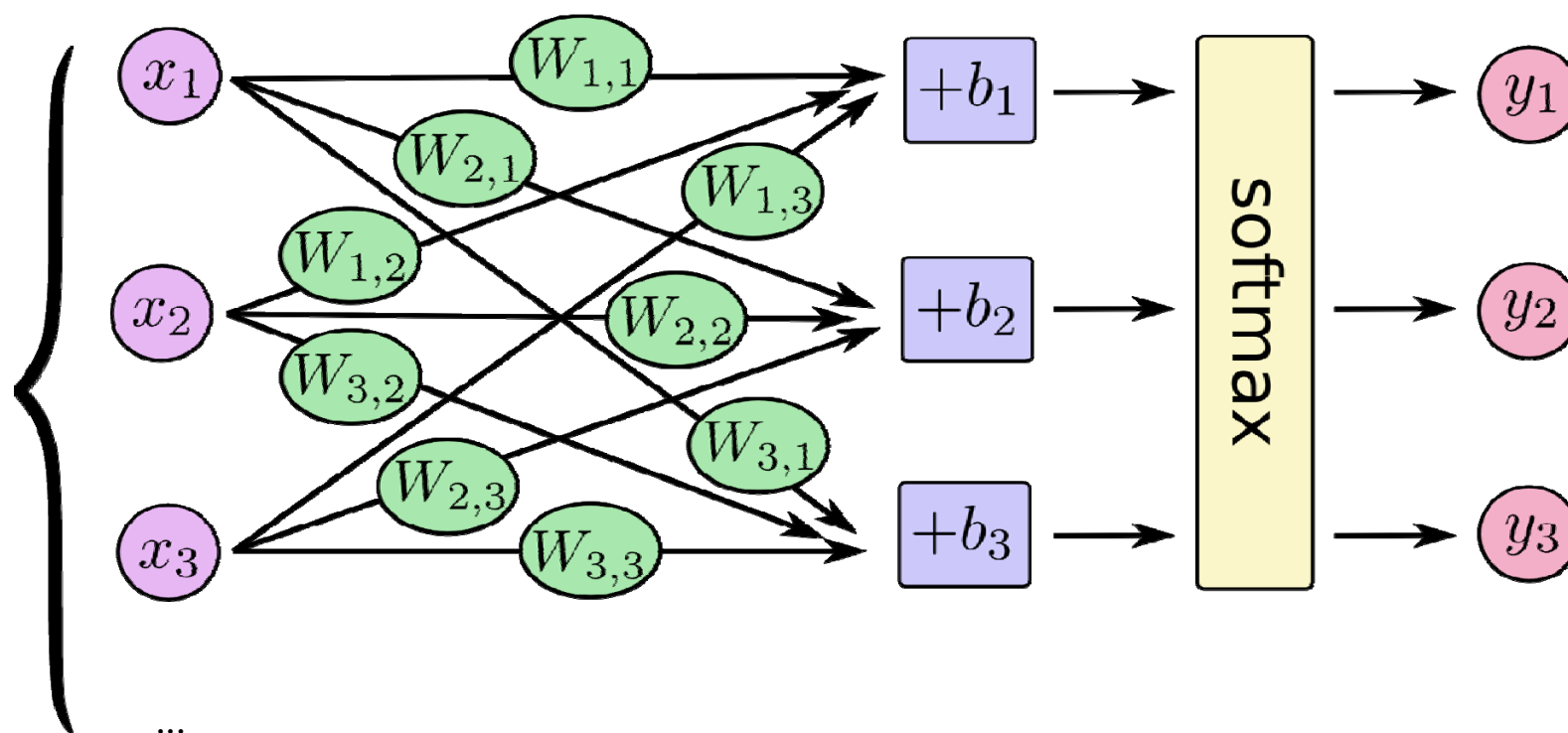
| | Scoring Function | Unnormalized Probabilities | Normalized Probabilities |
|----------|------------------|----------------------------|--------------------------|
| Dog | -3.44 | 0.0321 | 0.0006 |
| Cat | 1.16 | 3.1899 | 0.0596 |
| Boat | -0.81 | 0.4449 | 0.0083 |
| Airplane | 3.91 | 49.8990 | 0.9315 |

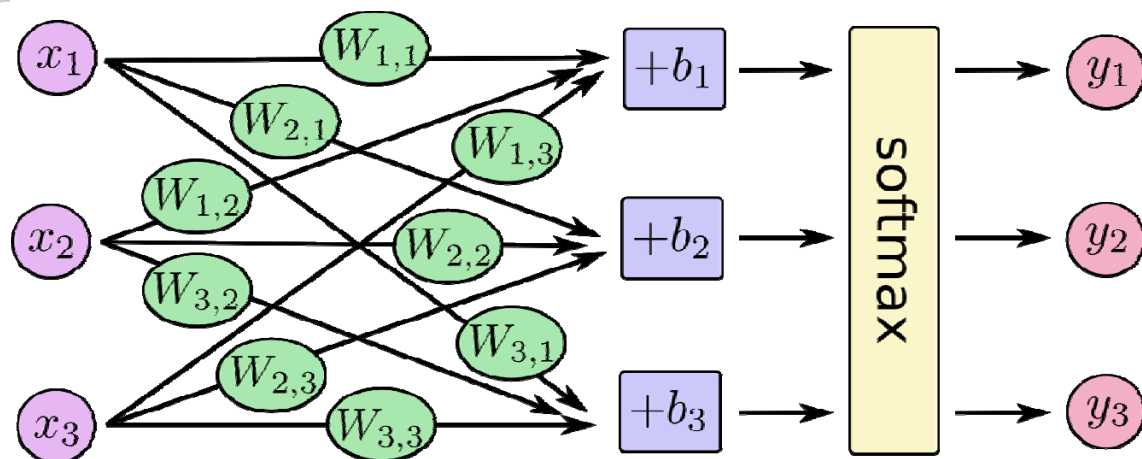
$$\text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

- Softmax 함수의 출력은 0~1 사이의 값이며, 출력들의 총 합은 1이 됨.
- 총합이 1이므로 출력을 '확률'로 해석할 수 있음
-> 문제를 확률/통계적으로 대응할 수 있게 됨!



784





$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \begin{bmatrix} W_{1,1}x_1 + W_{1,2}x_2 + W_{1,3}x_3 + b_1 \\ W_{2,1}x_1 + W_{2,2}x_2 + W_{2,3}x_3 + b_2 \\ W_{3,1}x_1 + W_{3,2}x_2 + W_{3,3}x_3 + b_3 \end{bmatrix}$$

$$y = \text{softmax}(Wx + b)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \left(\begin{bmatrix} W_{1,1} & W_{1,2} & W_{1,3} \\ W_{2,1} & W_{2,2} & W_{2,3} \\ W_{3,1} & W_{3,2} & W_{3,3} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right)$$

$$y = \text{tf.nn.softmax}(\text{tf.matmul}(x, W) + b)$$



신경망 구성 (hypothesis)



| X | W | Y |
|-----|--------|----|
| 784 | 784*10 | 10 |

```
# input place holders
```

```
X = tf.placeholder(tf.float32, [None, 784])
```

```
Y = tf.placeholder(tf.float32, [None, 10])
```

```
# weights & bias for nn layers
```

```
W = tf.Variable(tf.random_normal([784, 10]))
```

```
b = tf.Variable(tf.random_normal([10]))
```

```
hypothesis = tf.matmul(X, W) + b
```



Cross-Entropy



Cost 함수는 정보 이론의 크로스 엔트로피(Cross-Entropy) 방식으로 정의

$$H_{y'}(y) = - \sum_i y'_i \log(y_i)$$

y = our *predicted* probability distribution, (예측된 분포)

y' = the true distribution (the one-hot vector with the digit labels)., 라벨

In some rough sense, the cross-entropy is measuring how inefficient our predictions are for describing the truth.

```
# define cost/loss
y = tf.nn.softmax(tf.matmul(x, W) + b)
cost = -tf.reduce_sum(y_*tf.log(y))
train_step = tf.train.GradientDescentOptimizer(0.01).minimize(cost )
```

hypothesis
↑



Epoch & Batch

- `batch_size = 100`

```
for i in range(total_batch):  
    batch_xs, batch_ys = mnist.train.next_batch(batch_size)  
    feed_dict = {X: batch_xs, Y: batch_ys}  
    c, _ = sess.run([cost, optimizer], feed_dict=feed_dict)  
    avg_cost += c / total_batch
```

계속 100개씩 뽑아서 55000개 될 때까지 학습 !

Q: 왜 하나씩 하면 안되나요?



[참고] next_batch

```
def next_batch(self, batch_size, fake_data=False):
    """Return the next `batch_size` examples from this data set."""
    if fake_data:
        fake_image = [1] * 784
        if self.one_hot:
            fake_label = [1] + [0] * 9
        else:
            fake_label = 0
        return [fake_image for _ in xrange(batch_size)], [
            fake_label for _ in xrange(batch_size)
        ]
    start = self._index_in_epoch
    self._index_in_epoch += batch_size
    if self._index_in_epoch > self._num_examples:
        # Finished epoch
        self._epochs_completed += 1
        # Shuffle the data
        perm = numpy.arange(self._num_examples)
        numpy.random.shuffle(perm)
        self._images = self._images[perm]
        self._labels = self._labels[perm]
        # Start next epoch
        start = 0
        self._index_in_epoch = batch_size
        assert batch_size <= self._num_examples
    end = self._index_in_epoch
    return self._images[start:end], self._labels[start:end]
```

한 epoch가 끝나면 shuffle 하고 특정갯 수 뽑아줌

The images are returned as a 2-D NumPy array of size [batch_size, 784]

<https://stackoverflow.com/a/41454722>



03-4-mnist-softmax.py를 열어주세요



```
('mnist.train.num_examples = ', 55000)

('Epoch:', '0001', 'cost =', '5.745170846')
('Epoch:', '0002', 'cost =', '1.780056692')
('Epoch:', '0003', 'cost =', '1.122778638')
...
('Epoch:', '0049', 'cost =', '0.270640435')
('Epoch:', '0050', 'cost =', '0.269054373')
Learning Finished!

('Accuracy:', 0.91940016)
```



91.94 %

tf.argmax함수는 텐서 내의 지정된 축에서 가장 높은 값의 인덱스를 반환.

```
correct_prediction =
tf.equal(tf.argmax(hypothesis, 1), tf.argmax(Y, 1))

accuracy = tf.reduce_mean(tf.cast(correct_prediction,
tf.float32))

sess.run(accuracy, feed_dict={
    X: mnist.test.images, Y: mnist.test.labels})
```



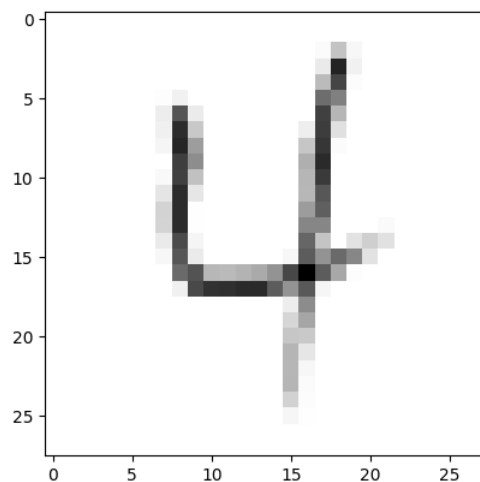

Mnist with a custom data

본인의 이미지를 만들어 넣어보세요

4

4

28x28



```
x = img.imread("data/4_28x.png")
x = x.astype(float)
x1 = np.array(x)
x1 = x1/255.0
x1 = 1.0 - x1
x1_flat = x1.reshape(1,784 )

print("Label: ", 4)
print("Prediction: ", sess.run(
    tf.argmax(hypothesis, 1), feed_dict={X:x1_flat}))
fig3 = plt.figure()
plt.imshow(x1_flat.
    reshape(28, 28), cmap='Greys',
    interpolation='nearest')

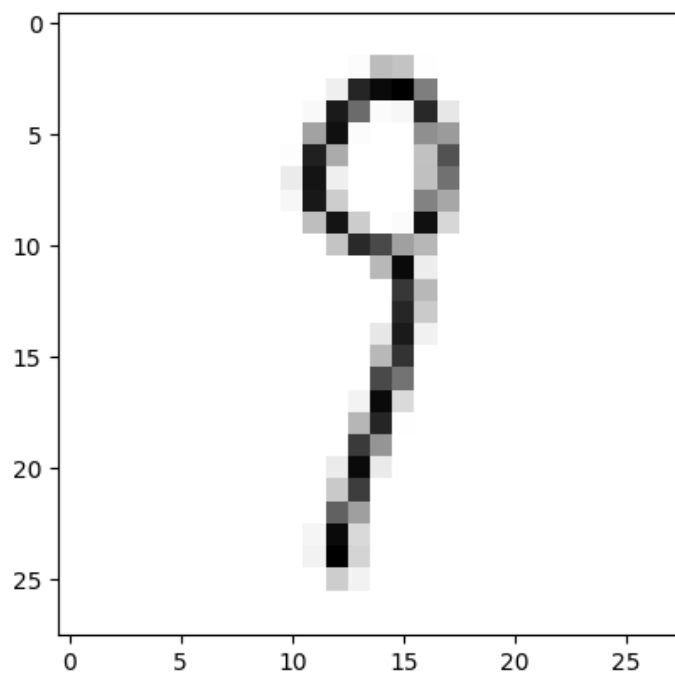
plt.show()
```

('Label: ', 4)
('Prediction: ', array([4]))



9

9
28x28



('Label: ', 9)
('Prediction: ', array([3]))





더 깊게.

- 92% 에서 더 올릴 수 있을까?

input place holders

```
X = tf.placeholder(tf.float32, [None, 784])
```

```
Y = tf.placeholder(tf.float32, [None, 10])
```

weights & bias for nn layers

```
W1 = tf.Variable(tf.random_normal([784, 256]))
```

```
b1 = tf.Variable(tf.random_normal([256]))
```

```
L1 = tf.nn.relu(tf.matmul(X, W1) + b1)
```

```
W2 = tf.Variable(tf.random_normal([256, 256]))
```

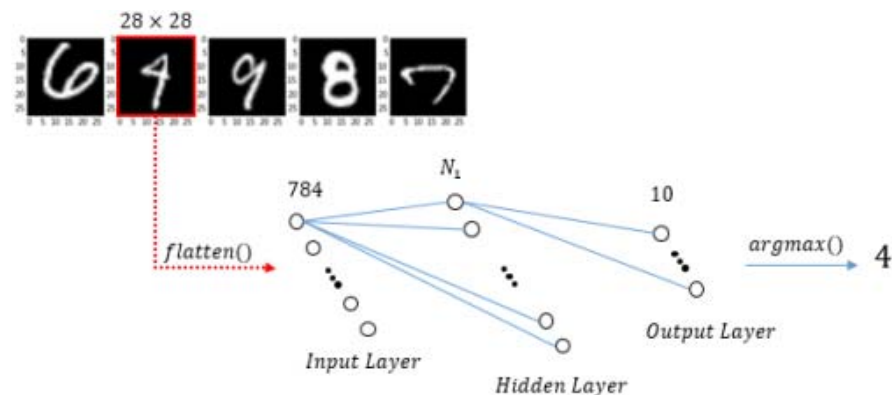
```
b2 = tf.Variable(tf.random_normal([256]))
```

```
L2 = tf.nn.relu(tf.matmul(L1, W2) + b2)
```

```
W3 = tf.Variable(tf.random_normal([256, 10]))
```

```
b3 = tf.Variable(tf.random_normal([10]))
```

```
hypothesis = tf.matmul(L2, W3) + b3
```





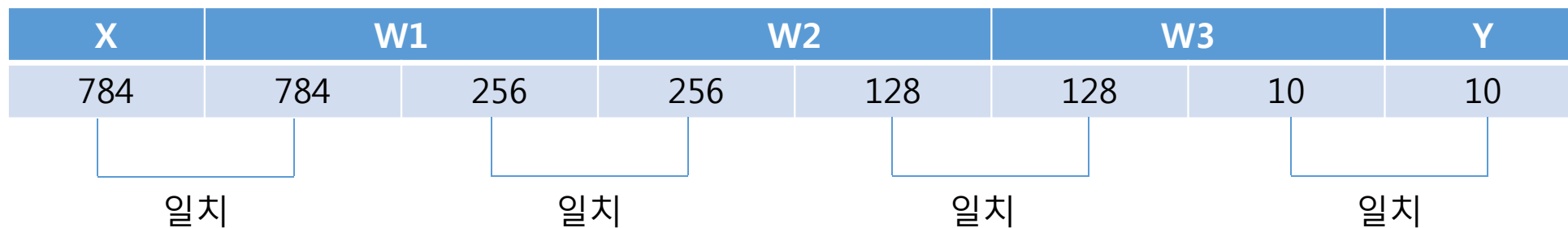
```
# input place holders
X = tf.placeholder(tf.float32, [None, 784])
Y = tf.placeholder(tf.float32, [None, 10])

# weights & bias for nn layers
W1 = tf.Variable(tf.random_normal([784, 256]))
b1 = tf.Variable(tf.random_normal([256]))
L1 = tf.nn.relu(tf.matmul(X, W1) + b1)

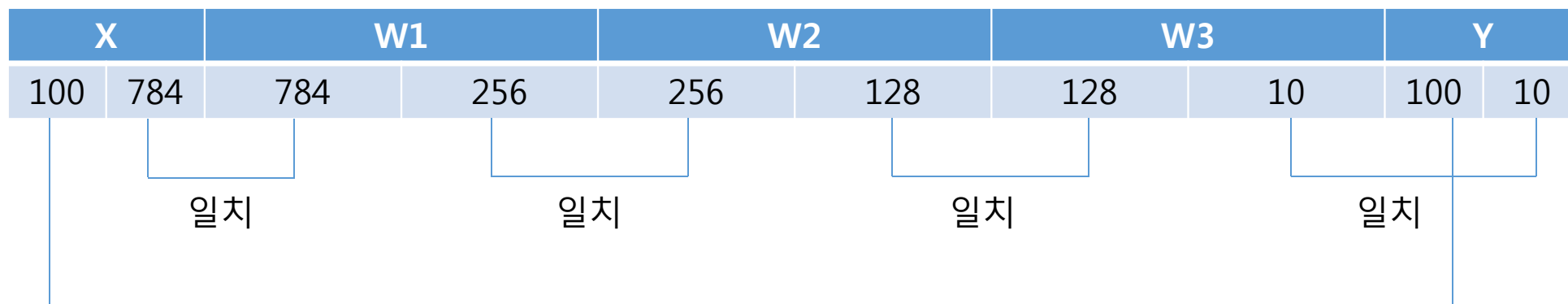
W2 = tf.Variable(tf.random_normal([256, 128]))
b2 = tf.Variable(tf.random_normal([128]))
L2 = tf.nn.relu(tf.matmul(L1, W2) + b2)

W3 = tf.Variable(tf.random_normal([128, 10]))
b3 = tf.Variable(tf.random_normal([10]))
hypothesis = tf.matmul(L2, W3) + b3
```

| X | W1 | | W2 | | W3 | | Y |
|-----|-----|-----|-----|-----|-----|----|----|
| 784 | 784 | 256 | 256 | 128 | 128 | 10 | 10 |
| 일치 | | 일치 | | 일치 | | 일치 | |



배치처리를 위한 형상

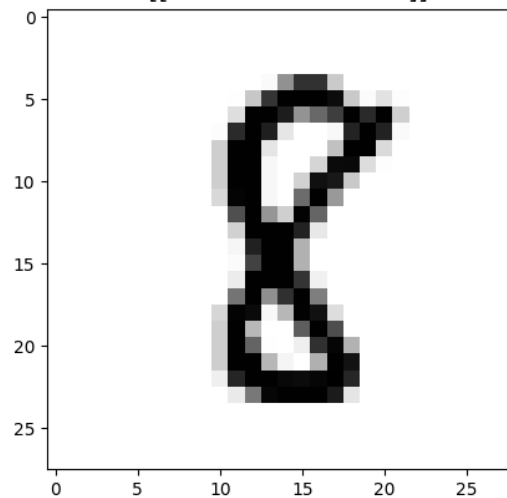


입력 형상 : 100×784

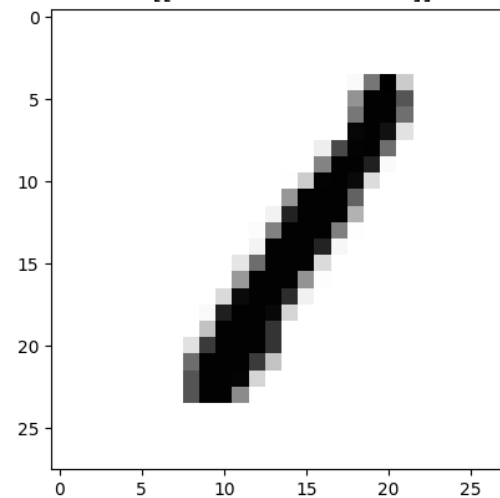
출력 형상 : 100×10



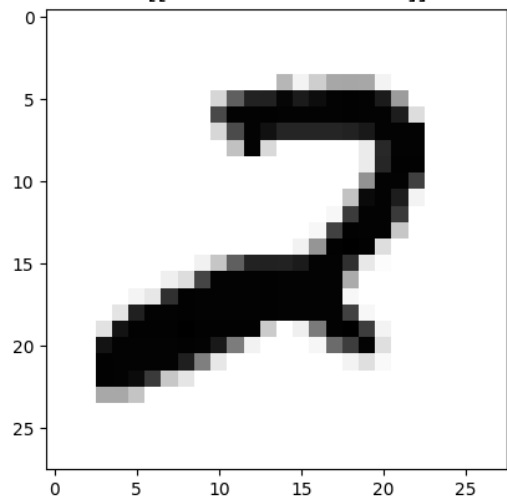
#7642 [[0 0 0 0 0 0 0 1 0]] 8 ==? 8



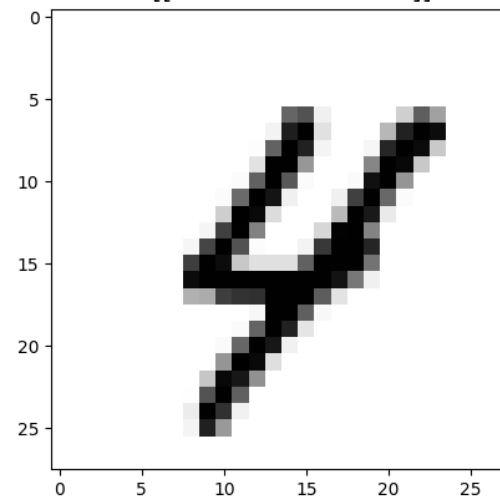
#7173 [[0 1 0 0 0 0 0 0 0]] 1 ==? 1



#9578 [[0 0 1 0 0 0 0 0 0]] 2 ==? 2

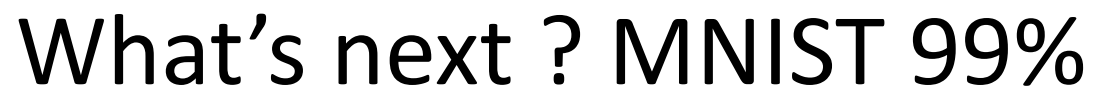


#8314 [[0 0 0 1 0 0 0 0 0]] 4 ==? 4



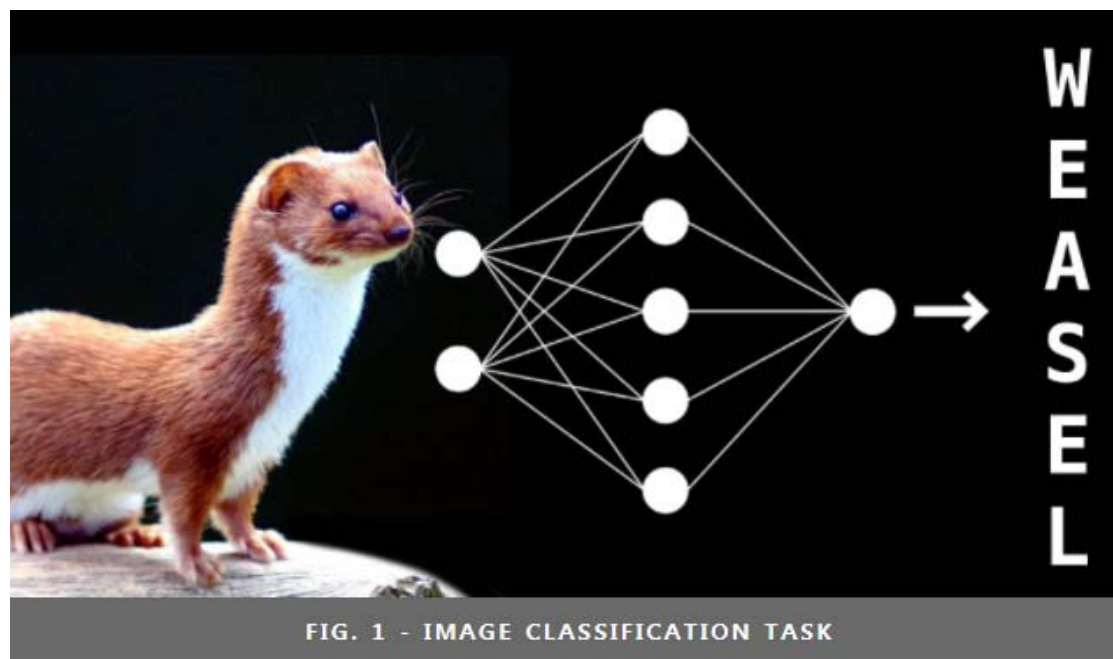
03-5-mnist-deeper.py 를 열어주세요

Random pick 결과들

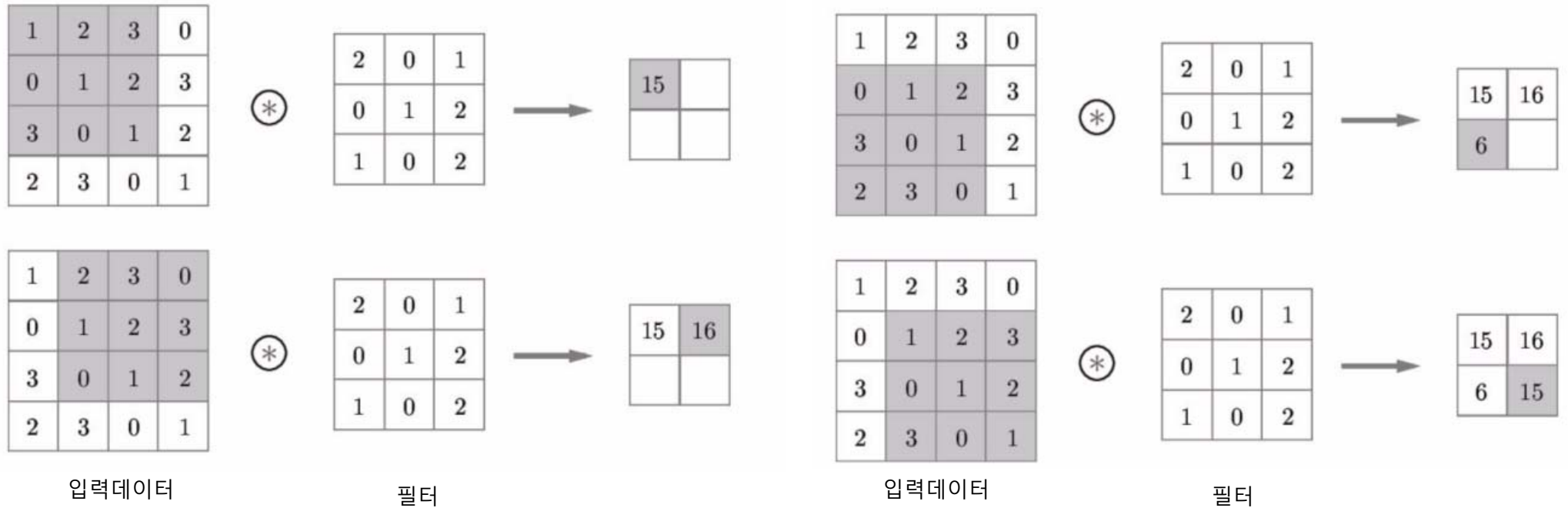


- # CNN
-
- The diagram illustrates a CNN architecture for handwritten digit recognition. It starts with an input image of a handwritten digit '3' (32 x 32). This input is processed through a series of layers:
- Input:** 32 x 32
 - Feature Maps:** The input is processed by a 5x5 convolution to produce feature maps C_1 (28 x 28). These are then processed by a 2x2 subsampling to produce feature maps S_1 (14 x 14).
 - Feature Maps:** The feature maps S_1 are processed by a 5x5 convolution to produce feature maps C_2 (10 x 10). These are then processed by a 2x2 subsampling to produce feature maps S_2 (5 x 5).
 - Feature Maps:** The feature maps S_2 are processed by a 5x5 convolution to produce feature maps n_1 (5 x 5).
 - Feature Maps:** The feature maps n_1 are processed by a 2x2 subsampling to produce feature maps n_2 (2 x 2).
 - Output:** The feature maps n_2 are processed by a fully connected layer to produce the final output, which is a classification result (0, 1, 8, 9).
- The diagram is divided into two main sections by a dashed red line:
- Feature Extraction:** This section includes the input, the first two convolution and subsampling steps, and the resulting feature maps C_1 , S_1 , C_2 , and S_2 .
 - Classification:** This section includes the final convolution and subsampling steps, the resulting feature maps n_1 and n_2 , and the fully connected layer.

<http://parse.ele.tue.nl/cluster/2/CNNArchitecture.jpg>



약간의 산수 !!



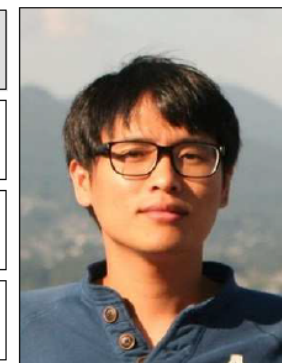
03-5-mnist-cnn.py 를 열어주세요



2017년도 2학기 수업계획서

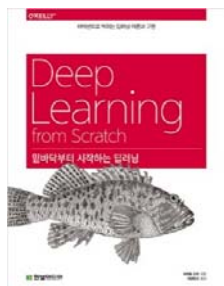
* 출력시간 : 2017-07-13 00:07:53

| 수강과목 | | | | 담당교수 | | | |
|------|--------|----------|-----------|------|--------------------------|--------|------------------------------|
| 과목명 | 인공지능개론 | 교과목번호/분반 | 717005/01 | 소속 | 융합전공 | 연구실 | |
| 이수구분 | 전선 | 시간 | 월7,8 수7 | 대표교수 | 김승찬 | 합동강좌 | |
| 강의실 | 10B111 | 학점-수업-실습 | 3-3-0 | 전자우편 | seungchankim12@gmail.com | | |
| | | | | 연락처 | | 면담가능시간 | 화,수 화 6교시, 수 5-6교시, 기타 사전 연락 |





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Seung-Chan

Jeung-Chan

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