
강화학습 스터디 2주차

Lec. 5-7

2020.1.20.

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◆ Lec1

- Machine Learning
- 지도/비지도/강화학습

◆ Lec2-4

- Linear Regression
- HCG (Hypothesis, Cost, Gradient Descent Algorithm -> minimize cost)

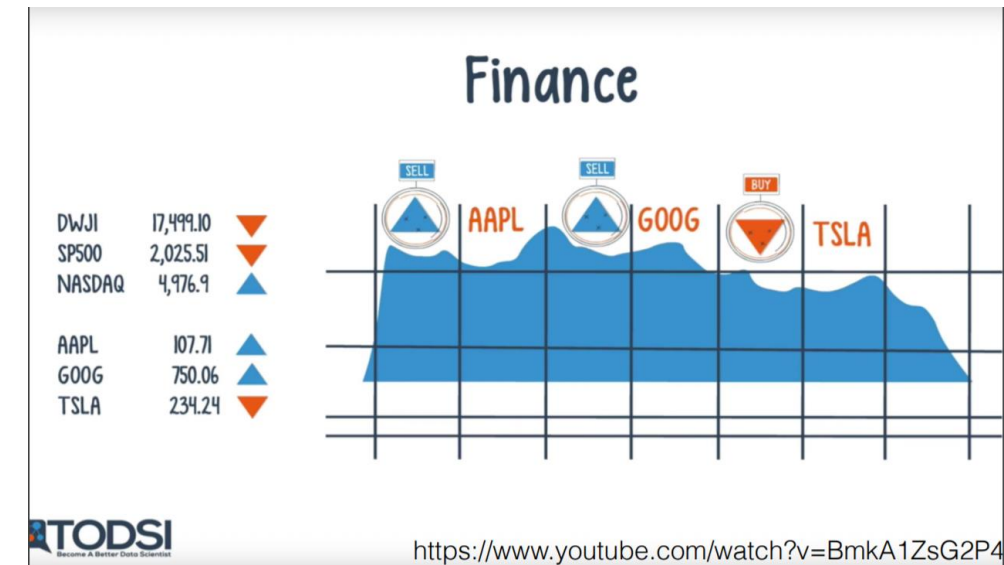
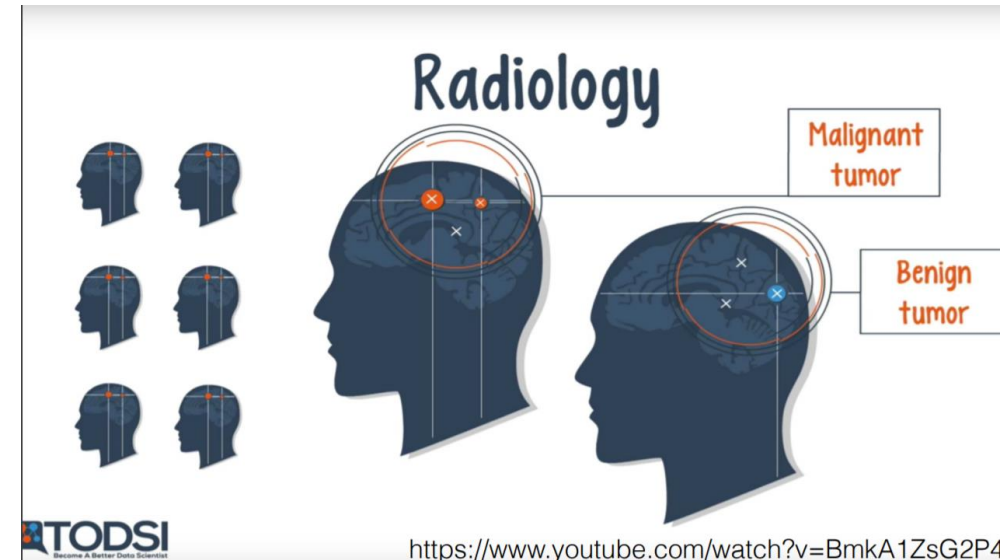
$$W := W - \alpha \frac{\partial}{\partial W} cost(W)$$

- Multivariable

◆ Logistic (Regression) Classification

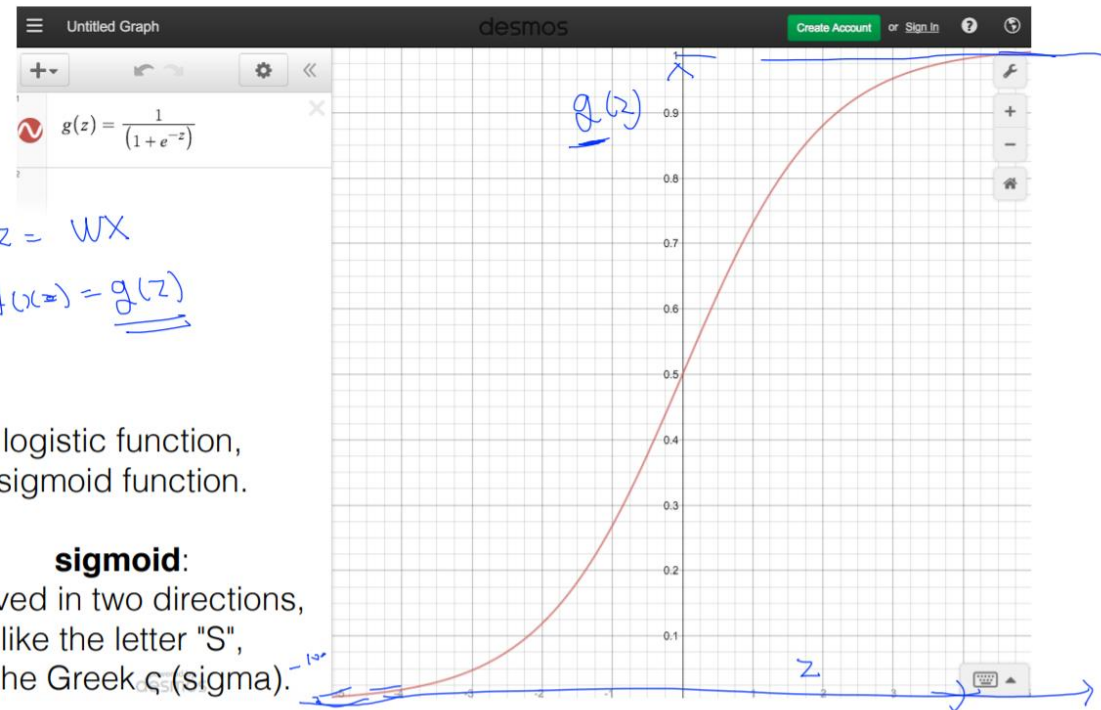
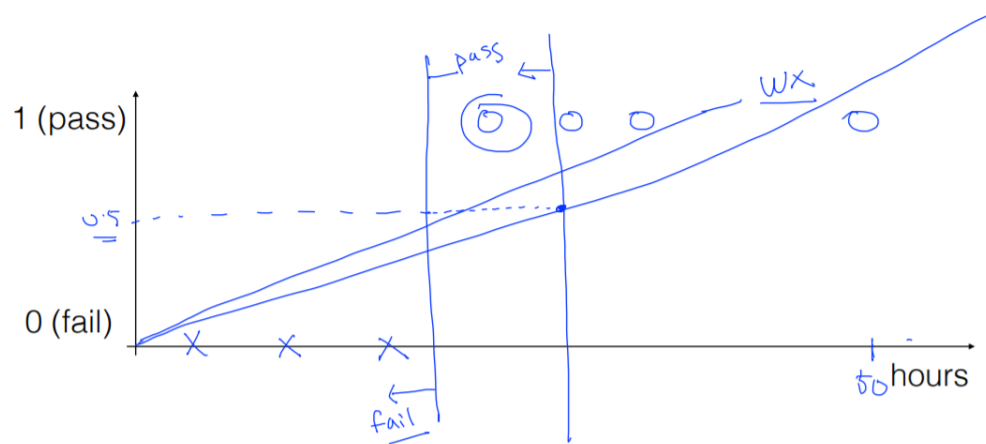
0, 1 encoding

- Spam Detection: Spam (1) or Ham (0)
- Facebook feed: show(1) or hide(0)
- Credit Card Fraudulent Transaction detection: legitimate(0) or fraud (1)

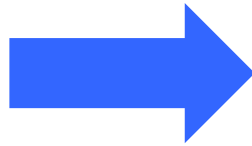
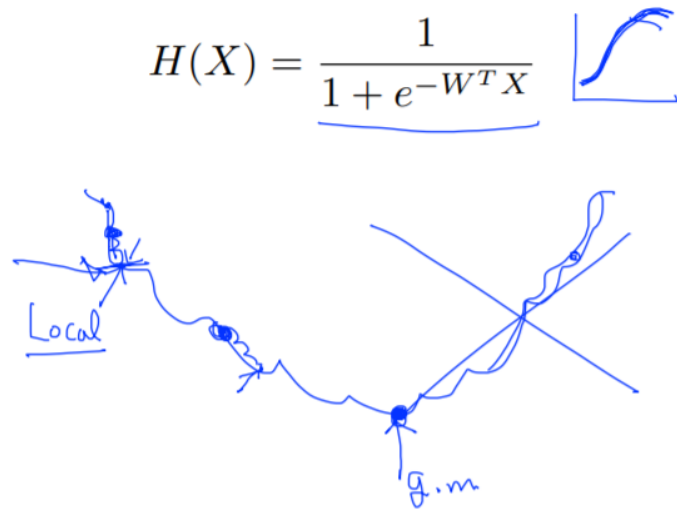


◆ Sigmoid

Linear Regression?



◆ Cost Function



understanding cost function

$$C(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$

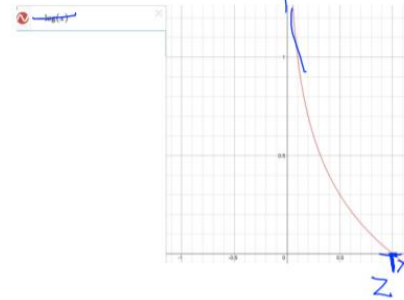
$$\frac{1}{1 + e^{-z}} \quad \frac{\log}{\log}$$

Cost $y=1$

$$H(x) = 1 \rightarrow \text{cost} = 0$$

$$H(x) = 0 \rightarrow \text{cost} = \infty$$

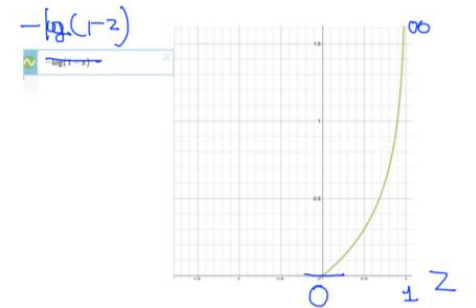
$$\text{cost} = -\log(2)$$



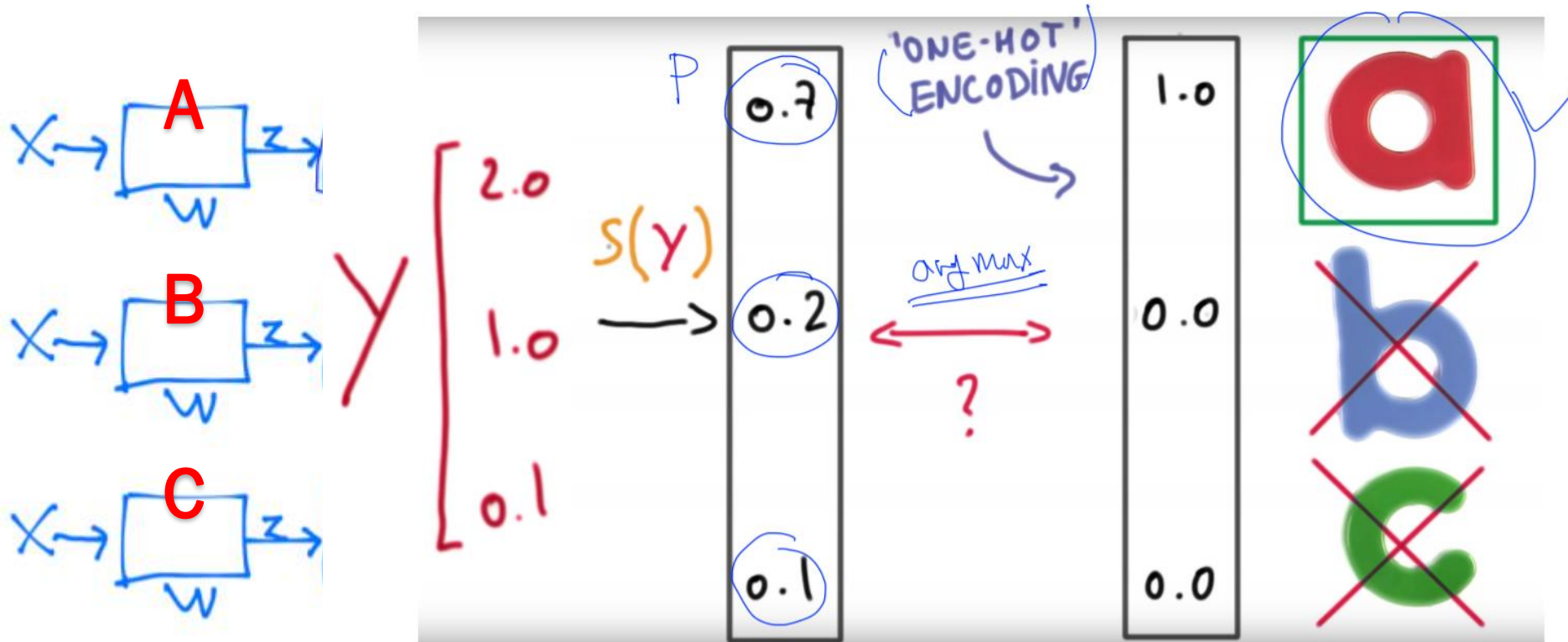
$$y=0$$

$$H(x) = 0, \text{ cost} = 0$$

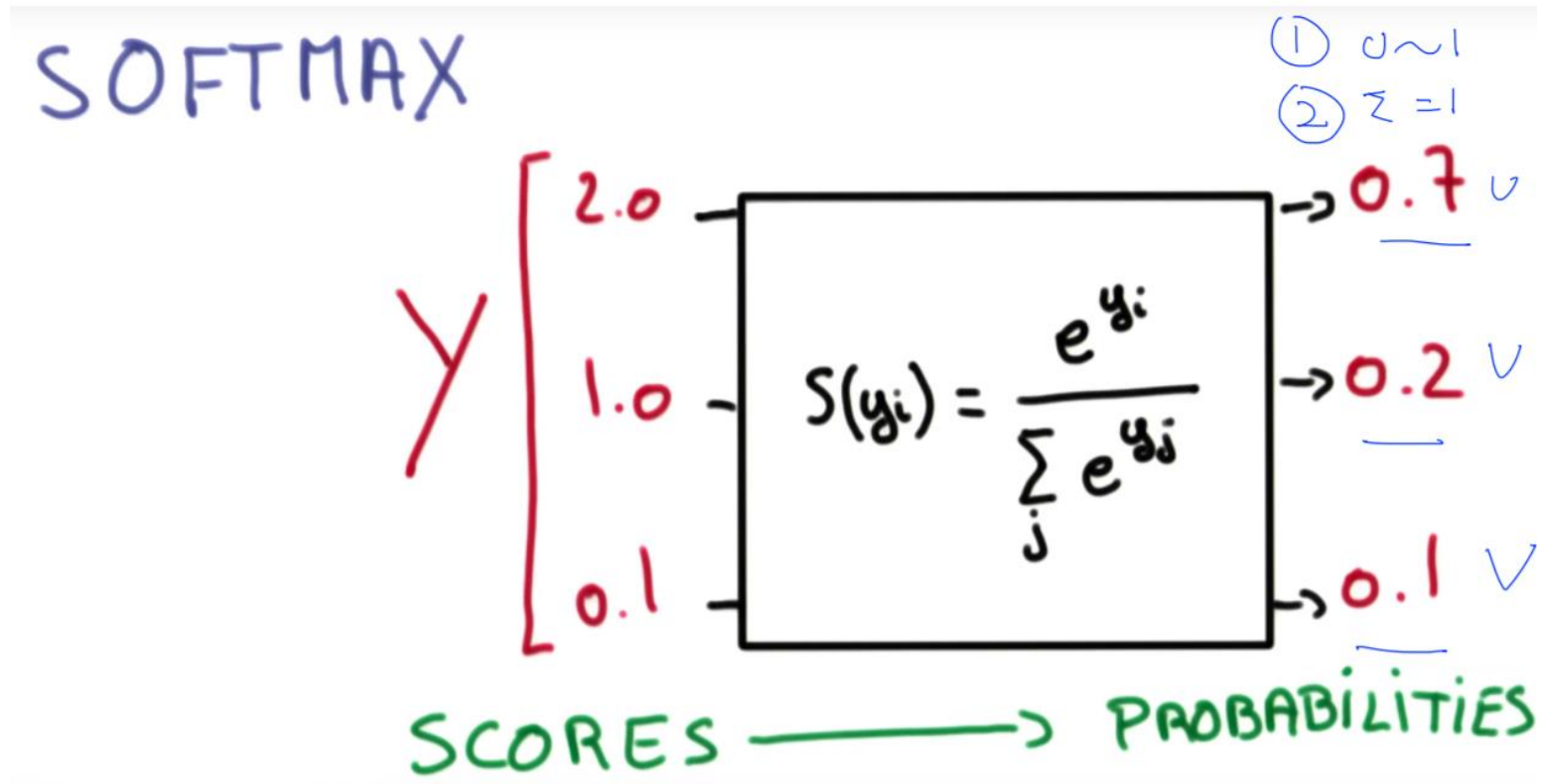
$$H(x) = 1, \text{ cost} = \infty$$



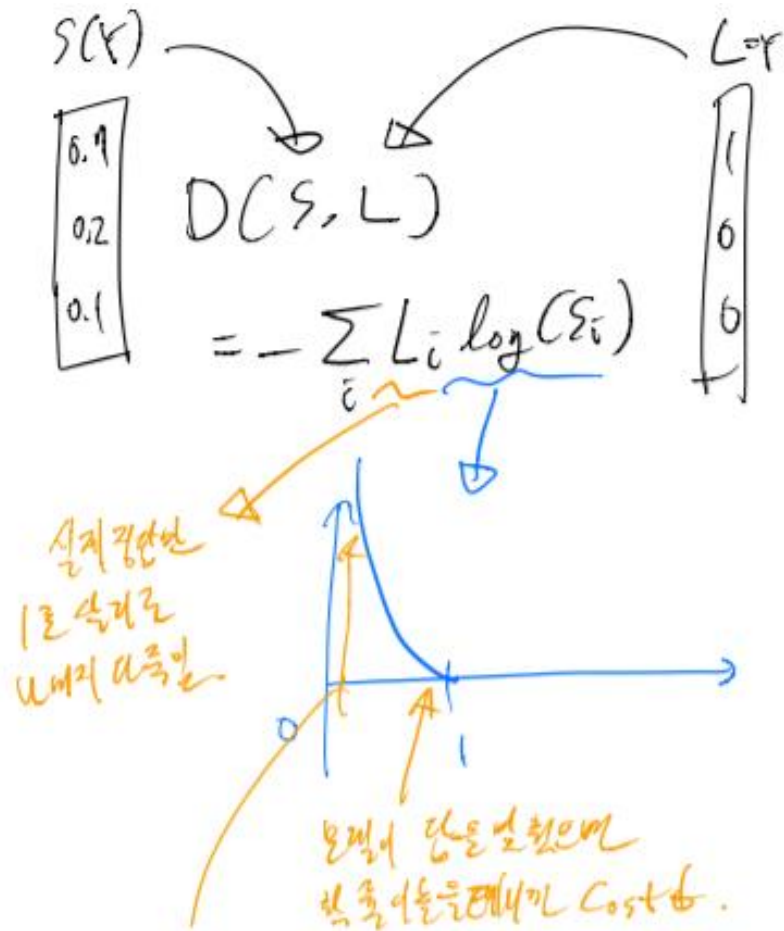
◆ Softmax Classification (Multinomial Classification)



◆ Softmax Function



◆ Cost Function – Cross Entropy



* Logistic Regression의 Cost는
Label이 2개인 Cross Entropy.

0 전체 Cost function.

$$L = \frac{1}{N} \sum_i D(S(x_i), L_i)$$

mean Cross Entropy Training Set Labels

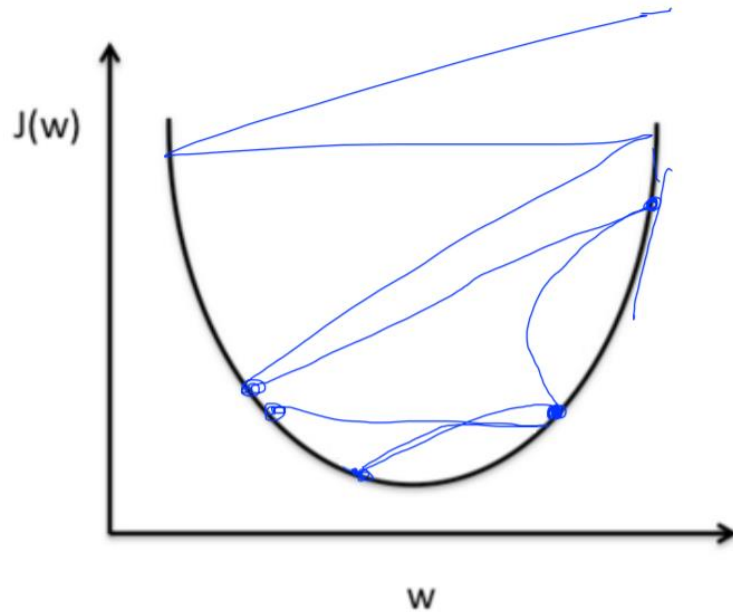
→ G.D.A.

◆ Application & Tips:

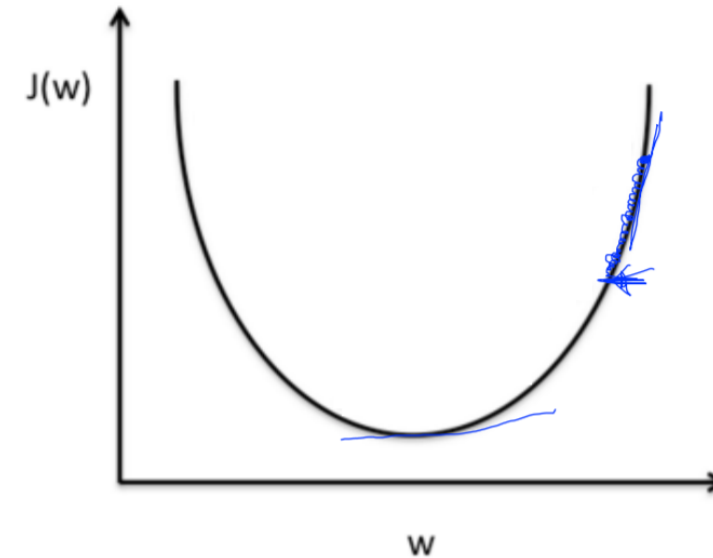
- Learning rate, data preprocessing, overfitting

◆ Learning Rate

Large learning rate: overshooting



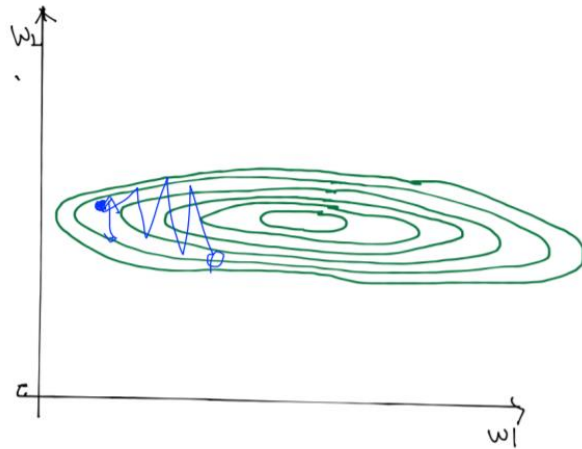
Small learning rate:
takes too long, stops at local minimum



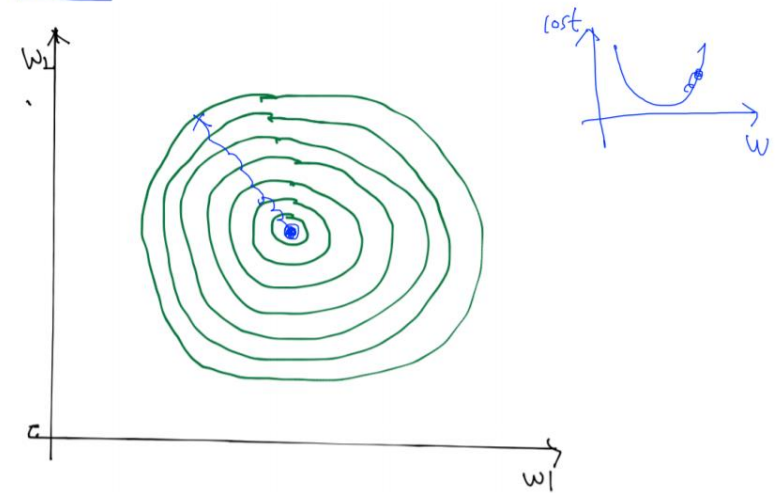
◆ data preprocessing

Data (X) preprocessing for gradient descent

| x1 | x2 | y |
|----|-------|---|
| 1 | 9000 | A |
| 2 | -5000 | A |
| 4 | -2000 | B |
| 6 | 8000 | B |
| 9 | 9000 | C |



Data (X) preprocessing for gradient descent



◆ Overfitting

Solutions for overfitting

- More training data!
- Reduce the number of features
- Regularization



◆ Overfitting

- Let's not have too big numbers in the weight

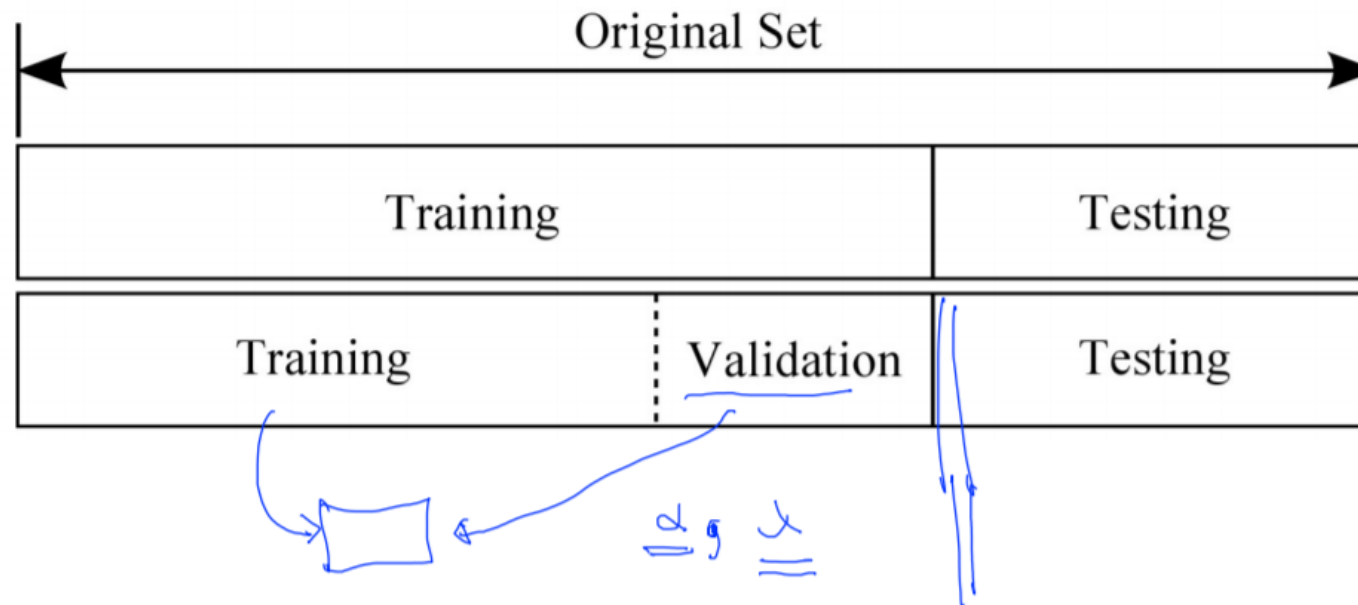
The diagram shows the loss function $\mathcal{L} = \frac{1}{N} \sum_i \mathcal{D}(s(w x_i + b), L_i)$ with several annotations:

- An arrow labeled "LOSS" points to the \mathcal{L} .
- An arrow labeled "TRAINING SET" points to the i in the summation.
- An arrow points from the $w x_i + b$ term to a red box containing the regularization term $+ \lambda \sum W^2$.
- An arrow labeled "regularization strength" points to the λ in the red box.
- Below the red box, there is a small table:

| | |
|-------|---|
| 0 | X |
| ↓ | ↑ |
| 0.001 | |

◆ Training / Test

Training, validation and test sets

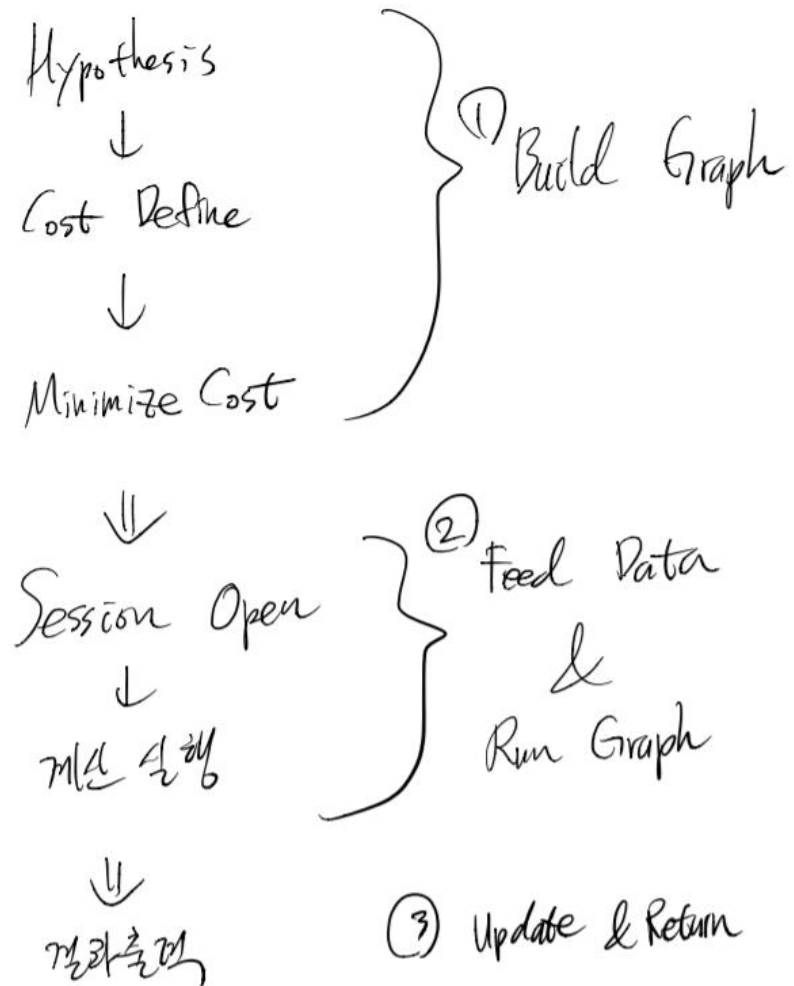


Lab



◆ 전체 프로세스

데이터 세팅




```
xy = np.loadtxt('data-03-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = xy[:, 0:-1]
y_data = xy[:, [-1]]
```

placeholders for a tensor that will be always fed.

```
X = tf.placeholder(tf.float32, shape=[None, 8])
```

```
Y = tf.placeholder(tf.float32, shape=[None, 1])
```

```
W = tf.Variable(tf.random_normal([8, 1]), name='weight')
```

```
b = tf.Variable(tf.random_normal([1]), name='bias')
```

Hypothesis using sigmoid: $\text{tf.div}(1., 1. + \text{tf.exp}(\text{tf.matmul}(X, W)))$

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

cost/loss function

```
cost = -tf.reduce_mean(Y * tf.log(hypothesis) + (1 - Y) * tf.log(1 - hypothesis))
```

```
train = tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(cost)
```

Accuracy computation

True if hypothesis > 0.5 else False

```
predicted = tf.cast(hypothesis > 0.5, dtype=tf.float32)
```

```
accuracy = tf.reduce_mean(tf.cast(tf.equal(predicted, Y), dtype=tf.float32))
```

Launch graph

```
with tf.Session() as sess:
```

```
    sess.run(tf.global_variables_initializer())
```

```
    feed = {X: x_data, Y: y_data}
```

```
    for step in range(10001):
```

```
        sess.run(train, feed_dict=feed)
```

```
        if step % 200 == 0:
```

```
            print(step, sess.run(cost, feed_dict=feed))
```

Accuracy report

```
h, c, a = sess.run([hypothesis, predicted, accuracy], feed_dict=feed)
```

```
print("\nHypothesis: ", h, "\nCorrect (Y): ", c, "\nAccuracy: ", a)
```

Data Load

Hypothesis

① Build Graph

Cost define
Min. Cost

결과 출력,
정확도 계산

② Feed Data
& Run Graph

③ 결과 출력.

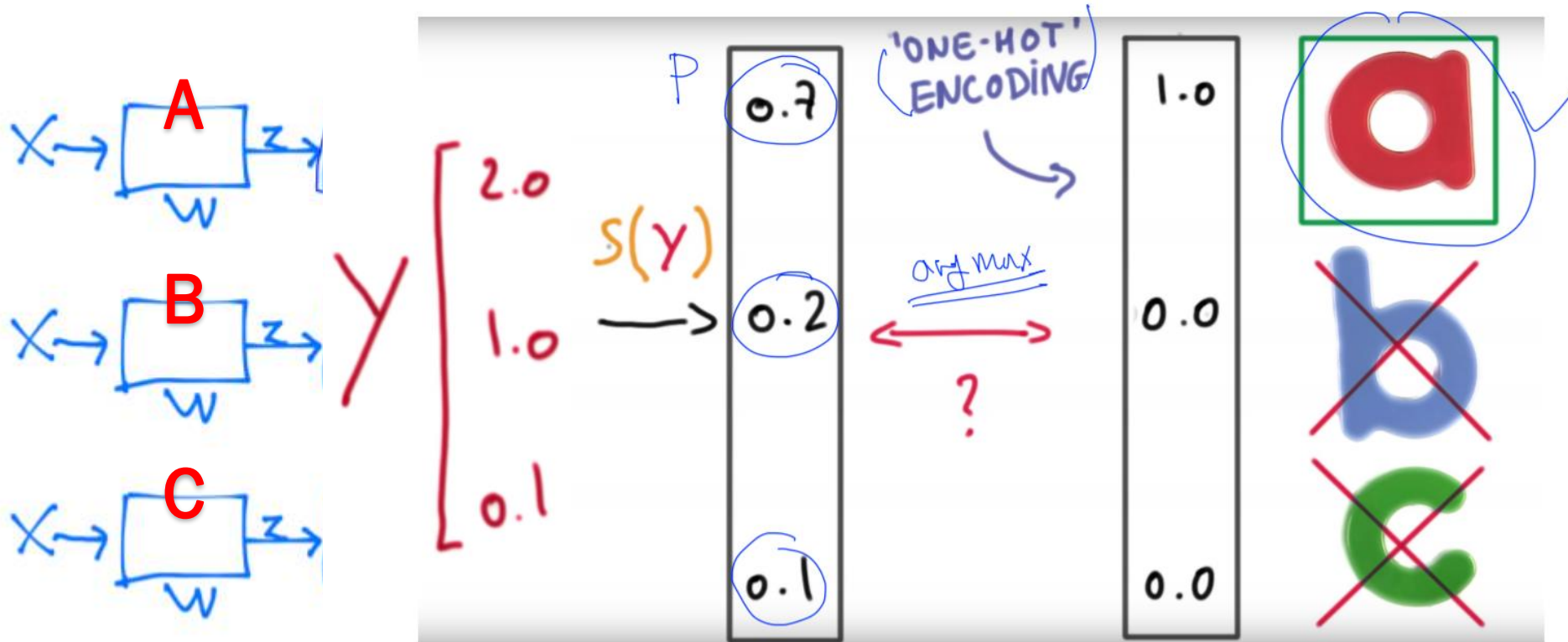
- ◆ 예측 값 계산, 정확도 계산할 때 tf.cast
- ◆ 한 data type에서 다른 data type으로 바꿔주는 함수

`# Accuracy computation`
`# True if hypothesis > 0.5 else False`
`predicted = tf.cast(hypothesis > 0.5, dtype=tf.float32)`
`accuracy = tf.reduce_mean(tf.cast(tf.equal(predicted, Y), dtype=tf.float32))`

dtype 변경
Boolean
0.0 or 1 in float32
mean

$$W' := W - \alpha \frac{\partial \sigma}{\partial W}$$

◆ Softmax Classification (Multinomial Classification)



◆ Softmax, Classification

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

Cost function: cross entropy

LOSS

$$\mathcal{L} = \frac{1}{N} \sum_i \mathcal{D}(S(WX_i + b), L_i)$$

TRAINING SET

STEP

$-\alpha \Delta \mathcal{L}(w_1, w_2)$
DERIVATIVE

`softmax_cross_entropy_with_logits`

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

1

```
# Cross entropy cost/loss
cost = tf.reduce_mean(-tf.reduce_sum(Y * tf.log(hypothesis), axis=1))
```

2

```
# Cross entropy cost/loss
cost_i = tf.nn.softmax_cross_entropy_with_logits(logits=logits,
                                                  labels=Y_one_hot)
cost = tf.reduce_mean(cost_i)
```

```
# Cross entropy cost/loss
cost = tf.reduce_mean(-tf.reduce_sum(Y * tf.log(hypothesis), axis=1))

optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)
```


Test & one-hot encoding

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

```
all = sess.run(hypothesis, feed_dict={X: [[1, 11, 7, 9],  
                                           [1, 3, 4, 3],  
                                           [1, 1, 0, 1]]})  
print(all, sess.run(tf.argmax(all, 1)))
```

최대값 찾기 *axis*

```
[[ 1.38904958e-03  9.98601854e-01  9.06129117e-06]  
 [ 9.31192040e-01  6.29020557e-02  5.90589503e-03]  
 [ 1.27327668e-08  3.34112905e-04  9.99665856e-01]]
```

```
[1 0 2]
```

tf.one_hot and reshape

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 3 |
| 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 4 | 0 | 0 | 1 | 0 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 0 | 1 | 0 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 0 | 1 | 0 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 3 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 3 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 0 | 1 | 0 | 0 |
| 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 0 | 1 | 0 |
| 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 1 | 1 | 0 | 1 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 3 |
| 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 6 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 6 |
| 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 2 | 1 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 4 | 1 | 0 | 1 | 0 |

```

Y = tf.placeholder(tf.int32, [None, 1]) # 0 ~ 6, shape=(?, 1)
Y_one_hot = tf.one_hot(Y, nb_classes) # one hot shape=(?, 1, 7) (0010000)
Y_one_hot = tf.reshape(Y_one_hot, [-1, nb_classes]) # shape=(?, 7)

```

```

# Predicting animal type based on various features
xy = np.loadtxt('data-04-zoo.csv', delimiter=',', dtype=np.float32)
x_data = xy[:, 0:-1]
y_data = xy[:, [-1]]

nb_classes = 7 # 0 ~ 6

X = tf.placeholder(tf.float32, [None, 16])
Y = tf.placeholder(tf.int32, [None, 1]) # 0 ~ 6

Y_one_hot = tf.one_hot(Y, nb_classes) # one hot
Y_one_hot = tf.reshape(Y_one_hot, [-1, nb_classes])

W = tf.Variable(tf.random_normal([16, nb_classes]), name='weight')
b = tf.Variable(tf.random_normal([nb_classes]), name='bias')

# tf.nn.softmax computes softmax activations
# softmax = exp(logits) / reduce_sum(exp(logits), dim)
logits = tf.matmul(X, W) + b
hypothesis = tf.nn.softmax(logits)

# Cross entropy cost/loss
cost_i = tf.nn.softmax_cross_entropy_with_logits(logits=logits,
                                                  labels=Y_one_hot)
cost = tf.reduce_mean(cost_i)
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)

```

Load Data

ONE-HOT
ENCODING1.0
0.0
0.0① Build
Graph

Hypothesis

cost

Min

```

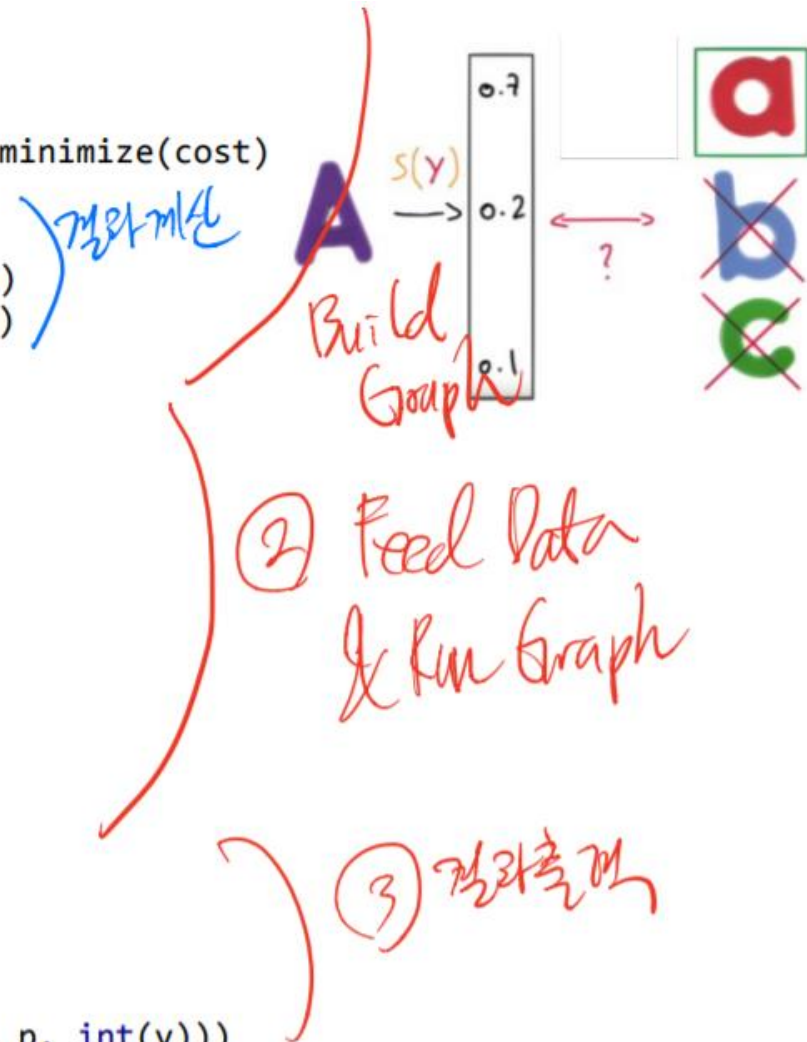
cost = tf.reduce_mean(cost_i)
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)

prediction = tf.argmax(hypothesis, 1)
correct_prediction = tf.equal(prediction, tf.argmax(Y_one_hot, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
# Launch graph
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())

    for step in range(2000):
        sess.run(optimizer, feed_dict={X: x_data, Y: y_data})
        if step % 100 == 0:
            loss, acc = sess.run([cost, accuracy], feed_dict={
                X: x_data, Y: y_data})
            print("Step: {:5}\tLoss: {:.3f}\tAcc: {:.2%}".format(
                step, loss, acc))

# Let's see if we can predict
pred = sess.run(prediction, feed_dict={X: x_data})
# y_data: (N,1) = flatten => (N, ) matches pred.shape
for p, y in zip(pred, y_data.flatten()):
    print("[{}] Prediction: {} True Y: {}".format(p == int(y), p, int(y)))

```



◆ Application & Tips:

- Learning rate, data preprocessing, overfitting

Normalized inputs (min-max scale)

```
xy = np.array([[828.659973, 833.450012, 908100, 828.349976, 831.659973],  
[823.02002, 828.070007, 1828100, 821.655029, 828.070007],  
[819.929993, 824.400024, 1438100, 818.97998, 824.159973],  
[816, 820.958984, 1008100, 815.48999, 819.23999],  
[819.359985, 823, 1188100, 818.469971, 818.97998],  
[819, 823, 1198100, 816, 820.450012],  
[811.700012, 815.25, 1098100, 809.780029, 813.669983],  
[809.51001, 816.659973, 1398100, 804.539978, 809.559998]])
```

```
xy = MinMaxScaler(xy)  
print(xy)
```

w_1 ↑

Training epoch/batch

In the neural network terminology:

- one **epoch** = one forward pass and one backward pass of *all* the training examples
- **batch size** = the number of training examples in one forward/backward pass. The higher the batch size, the more memory space you'll need.
- number of **iterations** = number of passes, each pass using [batch size] number of examples. To be clear, one pass = one forward pass + one backward pass (we do not count the forward pass and backward pass as two different passes).

Example: if you have *1000 training examples*, and your *batch size is 500*, then it will take 2 iterations to complete 1 epoch.

```
# parameters
training_epochs = 15
batch_size = 100

with tf.Session() as sess:
    # Initialize TensorFlow variables
    sess.run(tf.global_variables_initializer())
    # Training cycle
    for epoch in range(training_epochs):
        avg_cost = 0
        total_batch = int(mnist.train.num_examples / batch_size)

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

        print('Epoch:', '%04d' % (epoch + 1), 'cost =', '{:.9f}'.format(avg_cost))
```

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END OF PRESENTATION