# Deep Learning (2)

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### 목 차

- History of AI
- Linear/Logistic Regression
- Neural Network
- **Convolutional Neural Network**
- Recurrent Neural Network

# **Linear Regression**

## **Linear Regression**

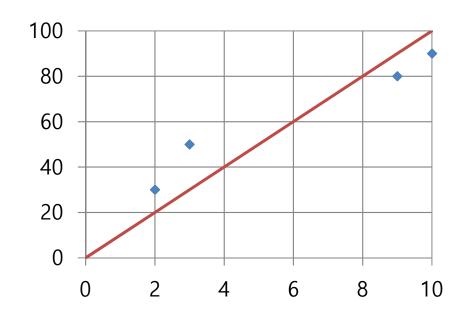
Predicting exam score

x(hour)	y(score)		
10	90		
9	80		
3	50		
2	30		

Hypothesis

$$H(x) = wx + b$$

weight bias



• Error/cost/loss/objective function

$$C(w,b) = \frac{1}{N} \sum_{i=1}^{N} \{H(x_i) - y_i\}^2$$

## **Building & Launching Graph**

```
x_train = [2, 3, 9, 10]
y_train = [30, 50, 80, 90]

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

```
hypothesis = x_train * w + b
cost = tf.reduce_mean(tf.square(hypothesis - y_train))
```

\* Gradient descent

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

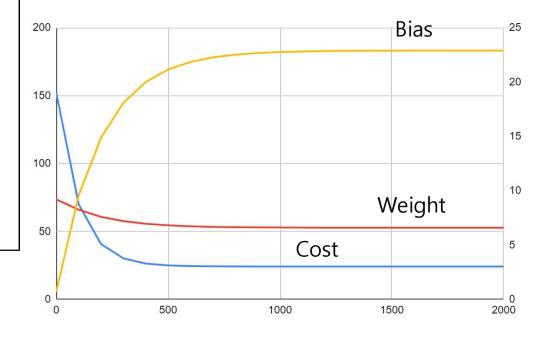
```
sess = tf.Session()
sess.run(tf.global_variables_initializer())

for step in range(2001):
    sess.run(train)
    if step % 100 == 0:
        print(step, sess.run(cost), sess.run(w), sess.run(b))
```

### **Training Output**

#### Cost Weight Bias

```
0 152.24857 [9.202369] [0.702132]
100 70.06434 [8.258013] [9.567877]
200 40.80526 [7.5966783] [14.88568]
300 30.232336 [7.1991315] [18.082363]
400 26.411758 [6.960155] [20.003979]
500 25.031162 [6.8164997] [21.159119]
600 24.532278 [6.730144] [21.85351]
700 24.351997 [6.678232] [22.270931]
800 24.286858 [6.647028] [22.521847]
900 24.263315 [6.62827] [22.672676]
1000 24.25481 [6.6169934] [22.763357]
1100 24.251734 [6.6102147] [22.817865]
1200 24.250633 [6.6061397] [22.85063]
1300 24.250229 [6.603691] [22.87032]
1400 24.250078 [6.602219] [22.882156]
1500 24.250027 [6.601334] [22.889273]
1600 24.25001 [6.600802] [22.893549]
1700 24.250008 [6.600482] [22.896122]
1800 24.25 [6.60029] [22.897667]
1900 24.249996 [6.6001744] [22.898596]
2000 24.249994 [6.600106] [22.89915]
```



#### **Placeholder**

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

x = tf.placeholder(tf.float32, shape=[None])
y = tf.placeholder(tf.float32, shape=[None])
```

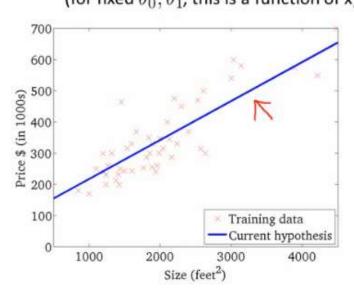
```
hypothesis = x * w + b
cost = tf.reduce_mean(tf.square(hypothesis - y))
```

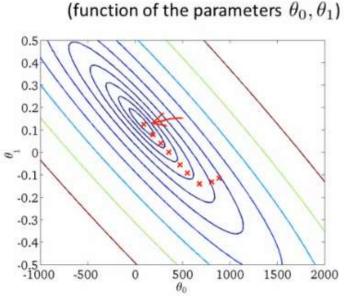
```
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.01)
train = optimizer.minimize(cost)
```

#### **Parameter Optimization**

Gradient (steepest) descent

$$\theta^* = \arg\min_{\theta} J(\theta)$$
  $\longrightarrow$   $\nabla J(\theta) = 0$  
$$\theta^{(\tau+1)} = \theta^{(\tau)} - \alpha \nabla J(\theta^{(\tau)})$$
 learning rate 
$$h_{\theta}(x)$$
 (for fixed  $\theta_0, \theta_1$ , this is a function of x)

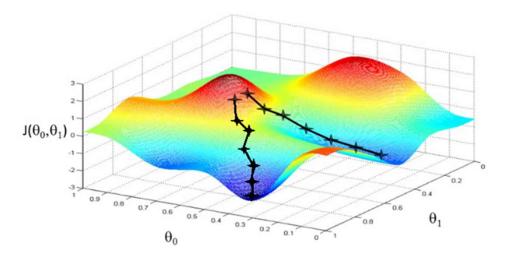




 $J(\theta_0, \theta_1)$ 

### **Gradient Descent Algorithm**

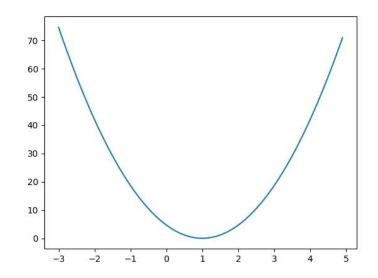
- Start with initial guesses
- Keep changing w and b a bit to try and reduce cost(w,b)
- Each time you change the parameters, you select the gradient which reduces cost(w,b) the most possible
- Repeat
- Do so until you converge to a local minimum
- Has an interesting property
  - Where you start can determine which minimum you end up



#### **Gradient Descent**

$$C(w,b) = \frac{1}{N} \sum_{i=1}^{N} \{H(x_i) - y_i\}^2$$

$$w = w - \alpha \frac{1}{N} \sum_{i=1}^{N} (wx_i - y_i)x_i$$



learning\_rate = 0.1
gradient = tf.reduce\_mean((w\*x-y)\*x)
descent = w-learning\_rate\*gradient
update = w.assign(descent)



optimizer = tf.train.GradientDescentOptimizer(learning\_rate=0.01)
train = optimizer.minimize(cost)

### compute\_gradient, apply\_gradient

Gradient에 변화를 주고자 할 때

```
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.01)

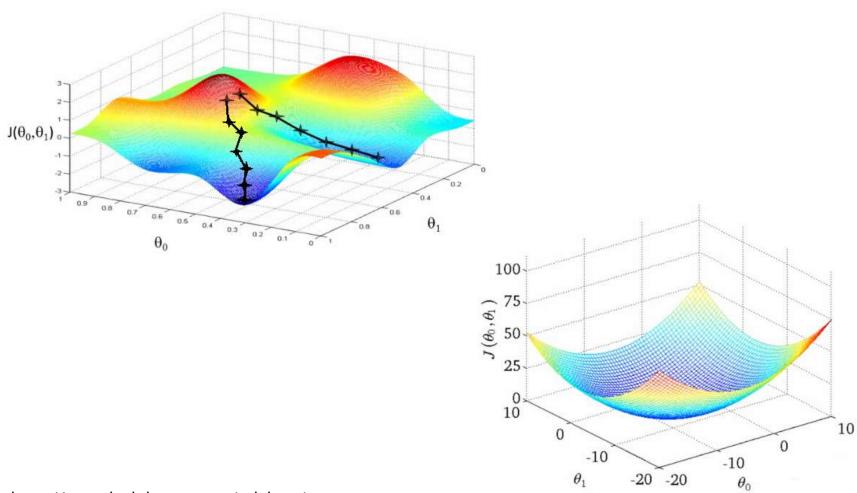
gvs = optimizer.compute_gradients(cost)
apply_gradients = optimizer.apply_gradients(gvs)

sess = tf.Session()
sess.run(tf.global_variables_initializer())

for step in range(100):
   print(step, sess.run([gradient, W, gvs]))
   sess.run(apply_gradients)
```

#### **Convex Function**

Convex objective function



## Multi-variable Linear Regression

<b>X</b> <sub>1</sub>	<b>X</b> <sub>2</sub>	<b>X</b> <sub>3</sub>	Υ	
73	80	75	152	
93	88	93	185	
89	91	90	180	
96	98	100	196	
73	66	70	142	

Test score for general psychology

#### Hypothesis using matrix

$$H(x_1, x_2, x_3) = x_1 w_1 + x_2 w_2 + x_3 w_3$$

```
x1 data = [73., 93., 89., 96., 73.]
x2 data = [80., 88., 91., 98., 66.]
x3 data = [75., 93., 90., 100., 70.]
y data = [152., 185., 180., 196., 142.]
x1 = tf.placeholder(tf.float32)
x2 = tf.placeholder(tf.float32)
x3 = tf.placeholder(tf.float32)
y = tf.placeholder(tf.float32)
w1 = tf.Variable(tf.random normal([1]))
w2 = tf.Variable(tf.random_normal([1]))
w3 = tf.Variable(tf.random_normal([1]))
b = tf.Variable(tf.random_normal([1]))
hypothesis = x1*w1 + x2*w2 + x3*w3 + b
```

#### **Matrix Form**

$$\begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} x_1 w_1 + x_2 w_2 + x_3 w_3 \end{pmatrix}$$

### **Hypothesis Using Matrix**

$$\begin{vmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \\ x_{41} & x_{42} & x_{43} \\ x_{51} & x_{52} & x_{53} \end{vmatrix} \cdot \begin{vmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{vmatrix} = \begin{vmatrix} x_{11}w_{11} + x_{12}w_{21} + x_{13}w_{31} & x_{11}w_{12} + x_{12}w_{22} + x_{13}w_{32} \\ x_{21}w_{11} + x_{22}w_{21} + x_{23}w_{31} & x_{21}w_{12} + x_{22}w_{22} + x_{23}w_{32} \\ x_{31}w_{11} + x_{32}w_{21} + x_{33}w_{31} & x_{31}w_{12} + x_{32}w_{22} + x_{33}w_{32} \\ x_{41}w_{11} + x_{42}w_{21} + x_{43}w_{31} & x_{41}w_{12} + x_{42}w_{22} + x_{43}w_{32} \\ x_{51}w_{11} + x_{52}w_{21} + x_{53}w_{31} & x_{51}w_{12} + x_{52}w_{22} + x_{53}w_{32} \end{vmatrix}$$

$$H(X) = XW$$
  $H(X) = W^TX$ 

$$H(x) = Wx + b$$

## Indexing, Slicing, Iterating

- Arrays can be indexed, sliced, iterated much like lists and other sequence types in Python
- As with Python lists, slicing in NumPy can be accomplished with the colon(:)syntax
- Colon instances(:) can be replaced with dots(...)

#### **Loading Data from File**

#### Data-01-test-score.csv

```
# EXAM1, EXAM2, EXAM3, FINAL 73,80,75,152 93,88,93,185 89,91,90,180 96,98,100,196 73,66,70,142 53,46,55,101
```

```
import numpy as np

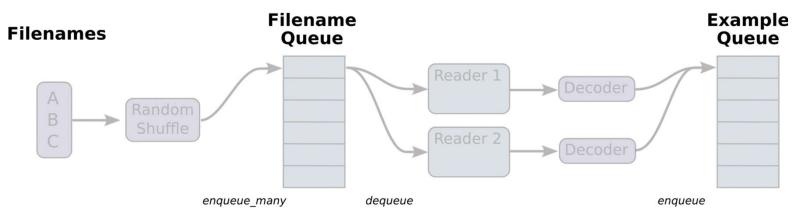
xy = np.loadtxt('data-01-test-score.csv',delimiter=',',dtype=np.floaf32)
x_data = xy[:, 0:-1]
y_data = xy[:, [-1]]

print(x_data.shape, x_data, len(x_data))
print(y_data,shape, y_data)
```

#### **Queue Runners**

```
filename_queue = tf.train.string_input_producer(
  ['data-01-test-score.csv', 'data-02-test-score.csv', ... ],
  shuffle=False, name='filename_queue')
```

record\_defaults = [[0.], [0.], [0.], [0.]]
xy = tf.decode\_csv(value, record\_defaults=record\_defaults)



2 reader = tf.TextLineReader()
key, value = reader.read(filename\_queue)

## **Batch Training**

```
train_x_batch, train_y_batch = \
    tf.train.batch([xy[0:-1], xy[-1:]], batch_size=10)

sess = tf.Session()

coord = tf.train.Coordinator()
threads = tf.train.start_queue_runners(sess=sess, coord=coord)

for step in range(2001):
    x_batch, y_batch = sess.run([train_x_batch, train_y_batch])
    ...

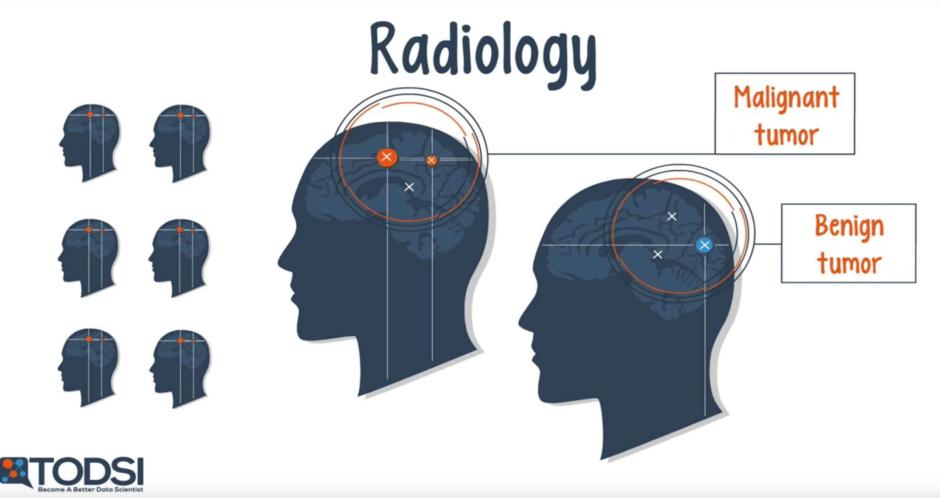
coord.request_stop()
coord.join(threads)
```

#### shuffle\_batch

```
min_after_dequeue = 10000
capacity = min_after_dequeue + 3 * batch_size
example_batch, label_batch = tf.train.shuffle_batch(
   [example, label], batch_size=batch_size, capacity=capacity,
   min_after_dequeue=min_after_dequeue)
```

# **Logistic Regression**

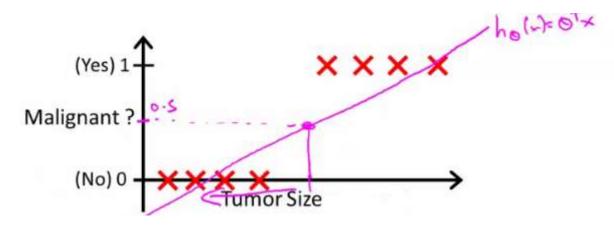
## **Tumor Malignancy**



<"Deep Learning Use Cases" (https://www.youtube.com/ watch?v=BmkA1ZsG2P4)>

## **Binary Classification (Logistic Regression)**

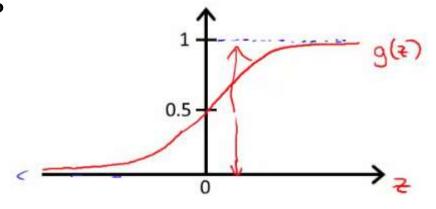
• Tumor size vs. malignancy (0, 1)



Linear regression work?

Logistic hypothesis

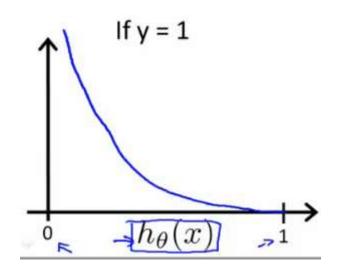
$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

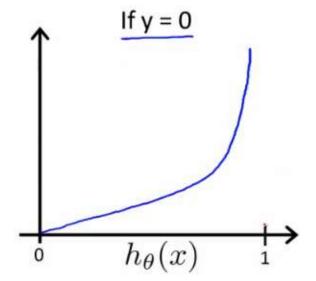


#### **Cost Function**

Convex logistic regression cost function

$$C(h_{\theta}(x), y) = \begin{cases} -\log(h_{\theta}(x)) & \text{if } y = 1\\ -\log(1 - h_{\theta}(x)) & \text{if } y = 0 \end{cases}$$





$$C(h_{\theta}(x), y) = -y \log(h_{\theta}(x)) - (1 - y) \log(1 - h_{\theta}(x))$$

### **Building Graph**

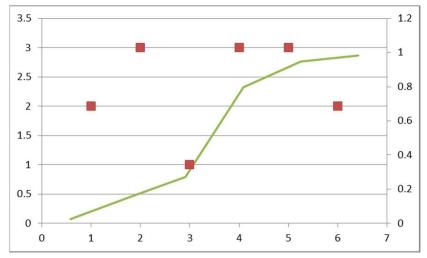
```
x_data = [[1, 2],[2, 3],[3, 1],[4, 3],[5, 3],[6, 2]]
y_data = [[0], [0], [0], [1], [1]]

x = tf.placeholder(tf.float32, shape=[None, 2])
y = tf.placeholder(tf.float32, shape=[None, 1])
w = tf.Variable(tf.random_normal([2, 1]), name="weight")
b = tf.Variable(tf.random_normal([1]), name="bias")
```

#### \* Cost function

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

### **Training Output**



```
0.02434957 -> 0
0.1491625 -> 0
0.27264518 -> 0
0.7965147 -> 1
0.94870824 -> 1
0.98327523 -> 1
```

## **Classifying Diabetes**



#### data-03-diabetes.csv

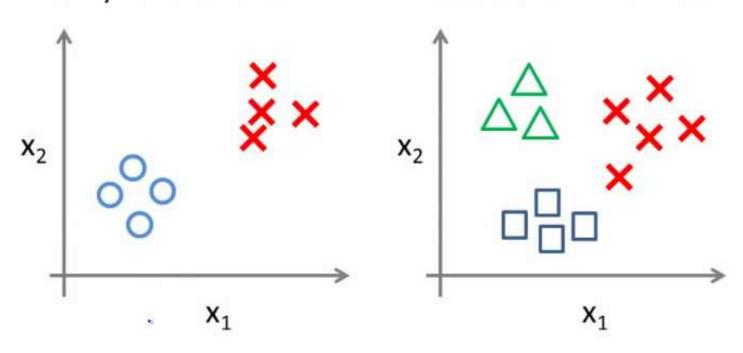
-0.411765	0.165829	0.213115	0	0	-0.23696	-0.894962	-0.7	1
-0.647059	-0.21608	-0.180328	-0.353535	-0.791962	-0.0760059	-0.854825	-0.833333	0
0.176471	0.155779	0	0	0	0.052161	-0.952178	-0.733333	1
-0.764706	0.979899	0.147541	-0.0909091	0.283688	-0.0909091	-0.931682	0.0666667	0
-0.0588235	0.256281	0.57377	0	0	0	-0.868488	0.1	0
-0.529412	0.105528	0.508197	0	0	0.120715	-0.903501	-0.7	1
0.176471	0.688442	0.213115	0	0	0.132638	-0.608027	-0.566667	0
0.176471	0.396985	0.311475	0	0	-0.19225	0.163962	0.2	1

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

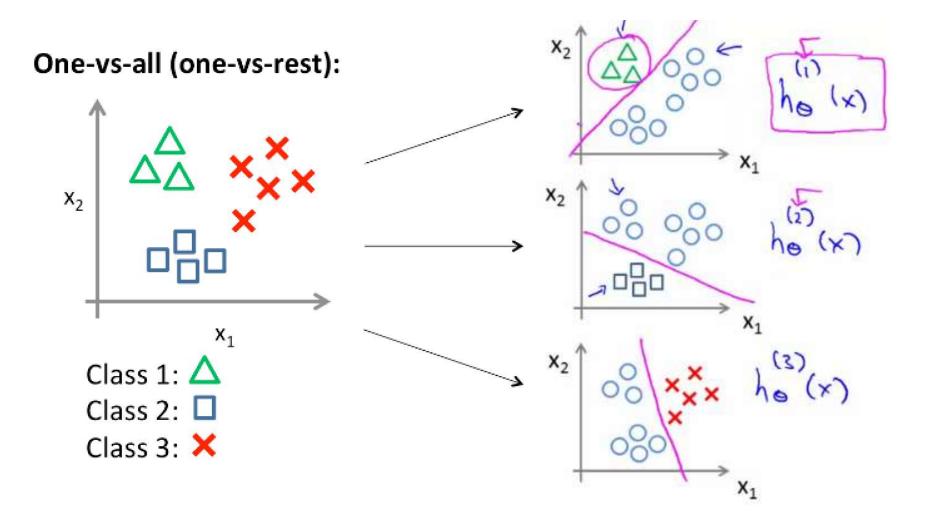
#### **Multi-class Classification**

Binary classification:

Multi-class classification:

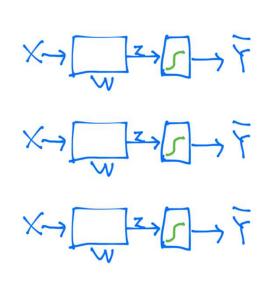


#### **One-vs-all Classification**

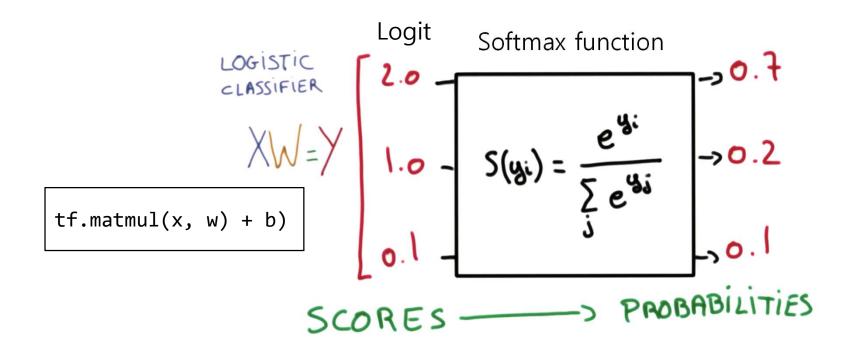


#### **Multidimensional Classification**

$$\begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_1 x_1 + w_2 x_1 + w_3 x_2 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_1 x_1 + w_2 x_1 + w_3 x_2 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_1 x_1 + w_2 x_1 + w_3 x_2 \\ x_3 \end{bmatrix}$$



## **Softmax Regression**

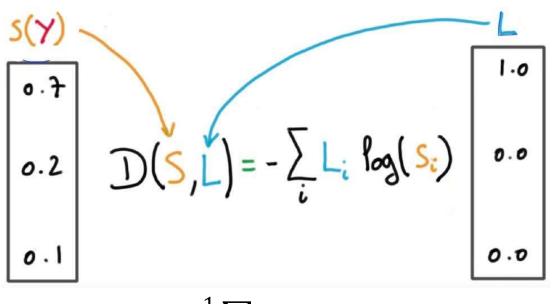


hypothesis = 
$$tf.nn.softmax(tf.matmul(x, w) + b)$$

#### **Cost Function**

Cross-entropy function

one-hot encoding



$$C(\theta) = \frac{1}{N} \sum_{i} D(S(\theta^{T} x_{i}), L_{i})$$

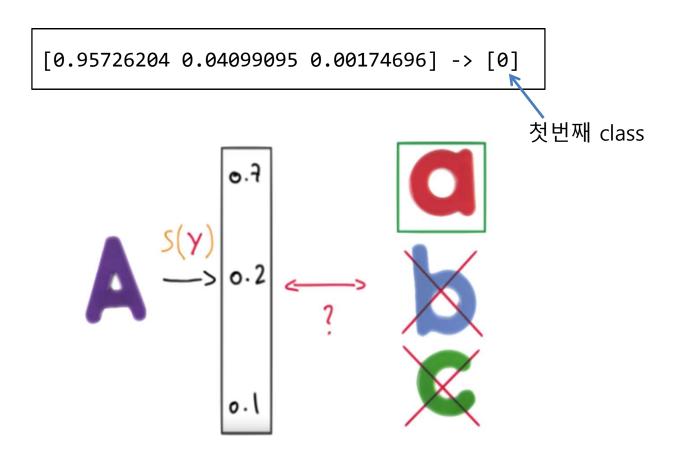
# Cross entropy cost function
cost = tf.reduce\_mean(-tf.reduce\_mean(y\*tf.log(hypothesis, axis=1))

### **Building Graph**

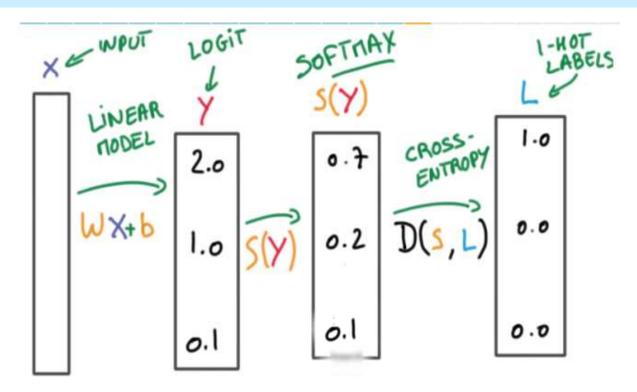
```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    for step in range(2001):
        sess.run(optimizer, feed_dict={x: x_data, y: y_data})
        if step % 200 == 0:
            print(step, sess.run(cost, feed_dict={x: x_data, y: y_data}))
```

## **Test Output**

```
a = sess.run(hypothesis, feed_dict={x: [[1,11,7,9]]})
print(a, sess.run(tfarg_max(a, 1)))
```



### softmax\_cross\_entropy\_with\_logits



logits = tf.matmul(x, w) + b

- cost = tf.reduce\_mean(-tf.reduce\_mean(y\*tf.log(hypothesis), axis=1)