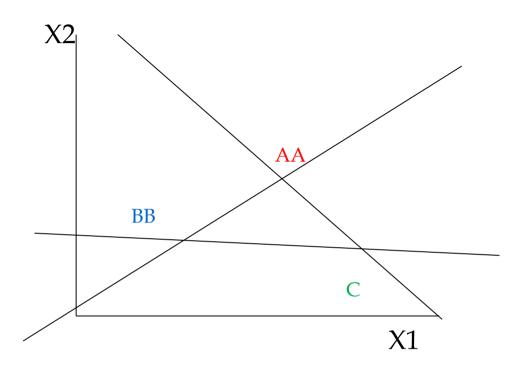
메디치소프트 기술연구소

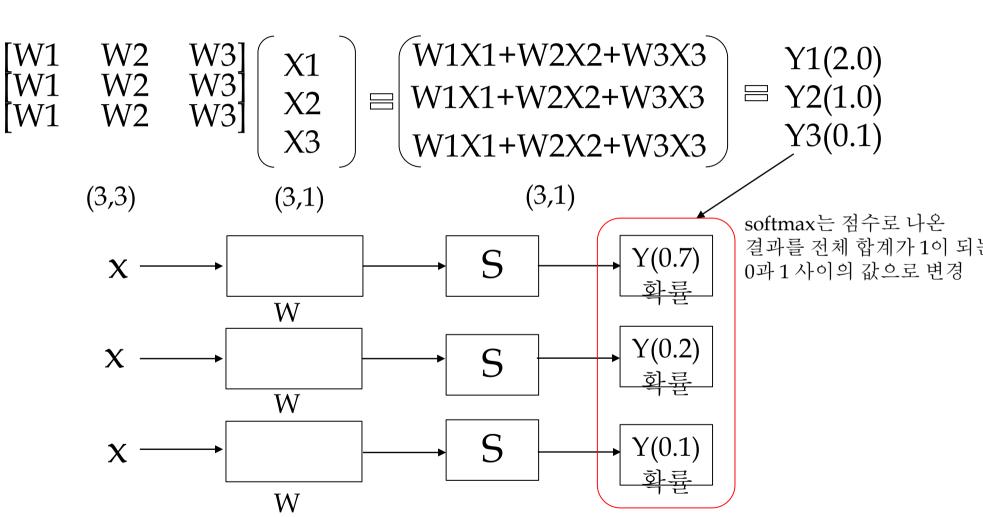


Multinomial regression

x1 (hours)	x2 (attendance)	y (grade)
10	5	Α
9	5	А
3	2	В
2	4	В
11	1	С



Multinomial regression



Softmax Classification& Cross entropy

$$y = softmax(Wx + b)$$

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

. Softmax regression 모델 학습 평가 Evaluation function은 cross-entropy

$$H_{y'}(y) = -\sum_{i} y'_{i} log(y_{i})$$

- . Cross-entropy: 모델의 예측값(prediction)이 실제 참값(truth)설명하는데 얼마나 비효율적(inefficient)를 나타낸다.
- . Coss-entropy가 최소화 => 경사하강법(gradient descent)방법 이용

Softmax Classification& Cross entropy

- . Softmax
- Binary Classification 보다는 n개의 예측 사용

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

Logistic Classifier
$$XW = y$$

$$\begin{array}{c}
2.0 \\
1.0 \\
0.1
\end{array}$$

$$\begin{array}{c}
f(\vec{x})_i = \frac{e^{x_i}}{\sum_{k=1}^{K} e^{x_k}} & \text{for } i = 1, ..., K \\
0.2 \\
0.1
\end{array}$$
Score(logits)
$$\begin{array}{c}
0.7 \\
0.2 \\
0.1
\end{array}$$
Probabilities

- . Cross Entropy
- 신경망 출력 확률 간주할 수 있는 경우 사용(손실함수)

```
# 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)
```

Softmax Classification& Cross entropy(예시)

```
x_{data} = [[1, 2, 1, 1], [2, 1, 3, 2], [3, 1, 3, 4], [4, 1, 5, 5], [1, 7, 5, 5],
                                                         [1, 2, 5, 6], [1, 6, 6, 6], [1, 7, 7, 7]]
y_{data} = [[0, 0, 1], [0, 0, 1], [0, 0, 1], [0, 1, 0], [0, 1, 0], [0, 1, 0], [1, 0, 0], [1, 0, 0]]
X = tf.placeholder("float", [None, 4])
Y = tf.placeholder("float", [None, 3])
nb classes = 3
W = tf.Variable(tf.random normal([4, 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)
hypothesis = tf.nn.softmax(tf.matmul(X, W) + b)
# 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)
# Launch 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}))
```

MEDICISOFT

1.0

0.0

0.0

One-hot

encoding

Test& one-hot encoding

```
hypothesis = tf.nn.softmax(tf.matmul(X,W)+b)
# Testing & One-hot encoding
a = sess.run(hypothesis, feed dict=\{X: [[1, 11, 7, 9]]\})
print(a, sess.run(tf.arg max(a, 1))) Argmax 가장 높은 값(첫번째 acces기준)
[[ 1.38904958e-03  9.98601854e-01  9.06129117e-06]] [1]
coftmax를 통과한 확률값(전체 합은 1)
all = sess.run(hypothesis, feed dict={X: [[1, 11, 7, 9],
                                         [1, 3, 4, 3],
                                         [1, 1, 0, 1]]
print(all, sess.run(tf.arg max(all, 1)))
  [[ 1.38904958e-03  9.98601854e-01  9.06129117e-06] [1]
  [ 9.31192040e-01 6.29020557e-02 5.90589503e-03] [0]
```

softmax_cross_entropy with_logits

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

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

Cross entropy cost/loss

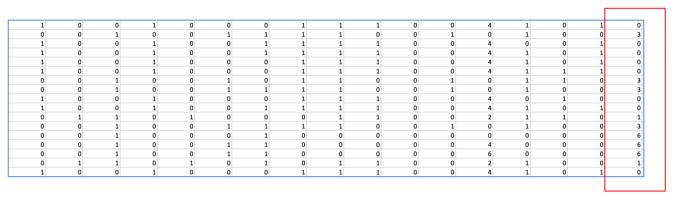
cost_i = tf.nn.softmax_cross_entropy_with_logits(logits=logits,

labels=Y_one_hot)

cost = tf.reduce_mean(cost_i)

Animal classification(다리=> 동물예측)

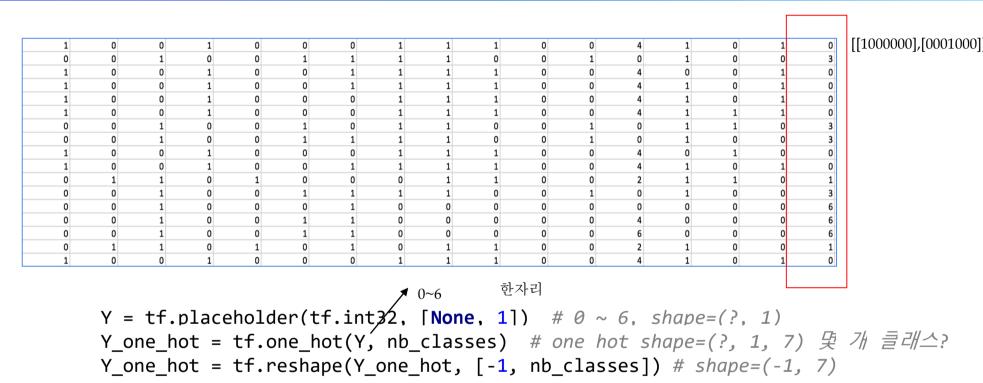
Birds	Insect	Fishes	Amphibians	Reptiles	Mammals
A B	Ø	D		***	
×.	1			3	
«	%				T H
	**	g g		Š	A SO
3				30	N.S.
Ø.	6			Kayla	



0~6 7가지

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

Tf.on_hot and reshape



If the input indices is rank N, the output will have rank N+1. The new axis is created at dimension axis (default: the new axis is appended at the end. (예 1차원=>2차원 변경)https://www.tensorflow.org/api_docs/python/tf/one_hot

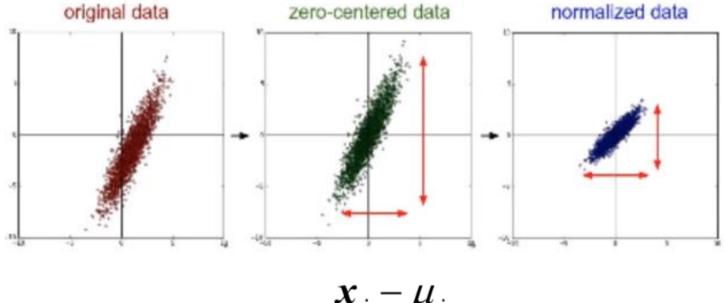
Tf.on_hot and reshape

```
# Predicting animal type based on various features
xy = np.loadtxt('zoo.csv', delimiter=',', dtype=np.float32)
x data = xv[:, 0:-1]
y_data = xy[:, [-1]]
nb classes = 7 \# 0 \sim 6
X = tf.placeholder(tf.float32, [None, 16])
Y = tf.placeholder(tf.int32, [None, 1]) # \theta \sim 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)
```

Tf.on_hot and reshape

```
cost = tf.reduce mean(cost i)
optimizer = tf.train.GradientDescentOptimizer(learning rate=0.1).minimize(cost)
                                                                                          1100 Loss: 0.097 Acc: 99.01%
prediction = tf.argmax(hypothesis, 1) # 0~6사이의 값(확률)
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())
                                                                                    Step: 1800 Loss: 0.059 Acc: 100.00%
   for step in range(2000):
       sess.run(optimizer, feed dict={X: x data, Y: y data})
                                                                                    [True] Prediction: 0 True Y: 0
       if step % 100 == 0:
                                                                                    [True] Prediction: 0 True Y: 0
           loss, acc = sess.run([cost, accuracy], feed dict={
                                                                                    [True] Prediction: 3 True Y: 3
                                  X: x data, Y: y data})
                                                                                    [True] Prediction: 0 True Y: 0
           print("Step: {:5}\tLoss: {:.3f}\tAcc: {:.2%}".format(
                step, loss, acc))
                                                                                    [True] Prediction: 0 True Y: 0
   # Let's see if we can predict
                                                                                    [True] Prediction: 0 True Y: 0
   pred = sess.run(prediction, feed dict={X: x data})
                                                                                    [True] Prediction: 3 True Y: 3
   # y data: (N,1) = flatten => (N, ) matches pred.shape
                                                                                    [True] Prediction: 3 True Y: 3
   for p, y in zip(pred, y data.flatten()): \#[[1],[\dashv]] \rightarrow [1, 0]
       print("[{}] Prediction: {} True Y: {}".format(p == int(y), p, int(y)))
```

Data(X)preprocessing for gradient descent



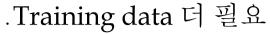
$$\mathbf{x}_j' = \frac{\mathbf{x}_j - \mu_j}{\sigma_j}$$

Standardization

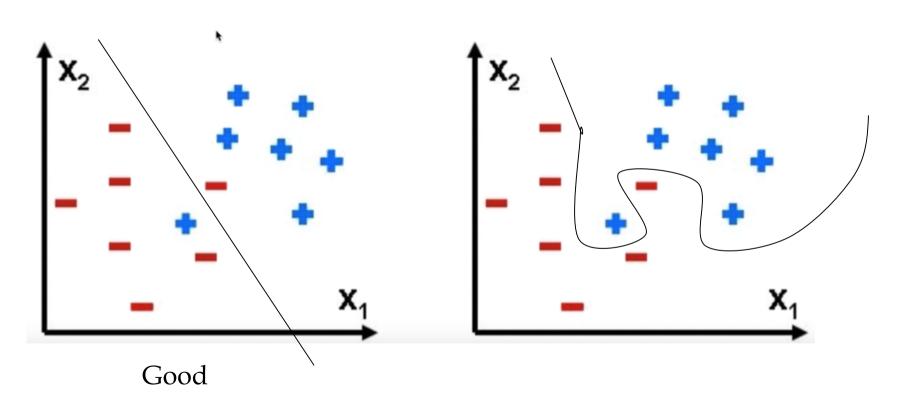
$$X_std[:,0] = (X[:,0] - X[:,0].mean()) / X[:,0].std()$$

Overfitting

- . Training data set에만 정확
- . Test dataset이나 real data 부정확



- . Features 개수 줄임
- . Regularization 필요



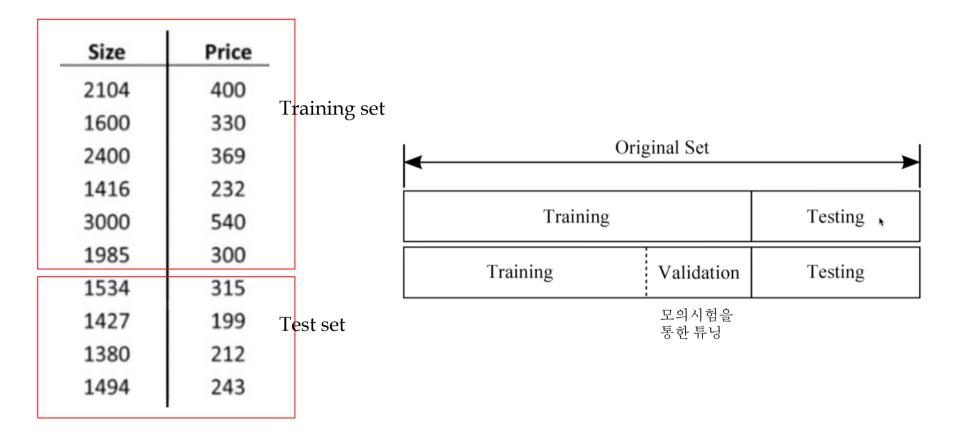
Regularization

- . 정규화는 데이터를 구분하는 선이 지나치게 구불구불해지지 않게 막아주는 역할
- . 최대한 직선에 가깝게 곡률을 줄여주는 역할을 하는 Factor를 Cost함수에 추가해서 그래프를 펴주는 역할

$$\mathcal{L} = \frac{1}{N} \sum_{i} D(S(wX_i + b), L_i) + \lambda \sum_{i} W^2$$
Regularization Strength

l2reg = 0.001 * tf.reduce_sum(tf.square(W))

Evaluation using training set



K-fold cross validation

.k개의 fold를 만들어서 진행하는 교차 검증이다

.데이터의 양이 충분치 않을 때, 분류기 성능 측정의 통계적 신뢰도를 높이기 위해서 쓰는 재 샘플링을 하는 기법 중 가장 대표적인 방법이다.

Machine learning을 할 때 사용자가 가지는 데이터는 오직 훈련집합과 테스트집합뿐이며, 집합 내에 샘플의 수가 무한정 제공 될 수 없기 때문에 사용하는 방법이다.

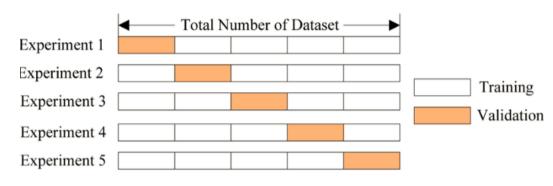


그림 5개의 fold로 나눴을 때의 검증

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^{k} MSE_i$$

크기로 나눈 다음에 하나의 부분씩을 test set으로 사용하여

나눈 다음에 하나의 부분씩을 test set으로 사용하여 k개의 test performance를 평균으로 내는 것을 의미한다 k개의 test performance를 평균으.

K-fold cross validation

모든 기계 학습 분류 모델을 평가하여 데이터 세트를 테스트 데이터와 학습 데이터로 분분리하는 것일반적이다. 100개의 데이터 세트가 있으면 20개의 행을 테스트 데이터로 사용하고 나머지 80개의 행은 학습 데이터로 사용한다. 다음 예제에서 사용하는 데이터 세트는 iris_data.csv파일을 사용한다. 꽃잎의 너비, 꽃잎이 길이, 꽃잎 길이와 꽃잎 너비를 사용하여 식물의 종류를 예측하려고 할 것이다. 일반적인 80:20 분할을 통해 데이터 집합을 분할하여 시작한다.

	F	D E	C	В	A	
		1.3 Iris-versicolor	4.3	2.9	6.2	99
		1.1 Iris-versicolor	3	2.5	5.1	100
		1.3 Iris-versicolor	4.1	2.8	5.7	101
		2.5 Iris-virginica	6	3.3	6.3	102
		1.9 Iris-virginica	5.1	2.7	5.8	103
		2.1 Iris-virginica	5.9	3	7.1	104
		1.8 Iris-virginica	5.6	2.9	6.3	105
		2.2 Iris-virginica	5.8	3	6.5	106
		2.1 Iris-virginica	6.6	3	7.6	107
		1.7 Iris-virginica	4.5	2.5	4.9	108
	7	1.8 Iris-virginica	6.3	2.9	7.3	109
	Training	1.8 Iris-virginica	5.8	2.5	6.7	110
	3	2.5 Iris-virginica	6.1	3.6	7.2	111
	Set	2 Iris-virginica	5.1	3.2	6.5	112
	170	1.9 Iris-virginica	5.3	2.7	6.4	113
		2.1 Iris-virginica	5.5	3	6.8	114
		2 Iris-virginica	5	2.5	5.7	115
		2.4 Iris-virginica	5.1	2.8	5.8	116
		2.3 Iris-virginica	5.3	3.2	6.4	117
		1.8 Iris-virginica	5.5	3	6.5	118
		2.2 Iris-virginica	6.7	3.8	7.7	119
		2.3 Iris-virginica	6.9	2.6	7.7	120
Partition		1.5 Iris-virginica	5	2.2	6	121
		2.3 Iris-virginica	5.7	3.2	6.9	122
	ē	2 Iris-virginica	4.9	2.8	5.6	123
	Testing	2 Iris-virginica	6.7	2.8	7.7	124
	90	1.8 Iris-virginica	4.9	2.7	6.3	125
	Set	2.1 Iris-virginica	5.7	3.3	6.7	126
		1.8 Iris-virginica	6	3.2	7.2	127

K-fold cross validation

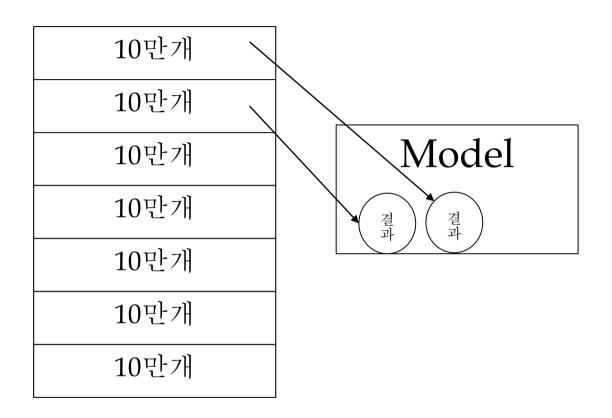
- . 장점:총 데이터의 개수가 적은 데이터 셋에 대하여 정확도를 향상시킬 수 있다. 이는 기존에 training/validation/test 세 개의 집단으로 분류하는 것보다, Training과 test로만 분류할 때 학습 데이터 셋이 더 많기 때문이다
- . 단점:일반적인 training set/test set을 통해 진행하는 학습법에 비해 시간 소요가 크다.
- 예제1(cross_validation_example.py) . 적절한 계층화 된 k-Folds cross validation

```
n cross_validation_example.py
Accuracy: 0.933333333333
Accuracy: 0.933333333333
Accuracy: 1.0
Accuracy: 0.933333333333
Accuracy: 0.933333333333
Accuracy: 0.933333333333
Accuracy: 0.86666666667
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
```

- 예제2(cross_validation_example2.py)
 - . 모든 폴드의 결과를 final_red_y 및 expected_y 목록으로 결합하여 비교할 수 있는 분류 기준 정확도의 척도를 얻는다.

n cross_validation_example2.py Accuracy: 0.953333333333

Online learning(대용량 데이터)



10만개

Training and Test datasets

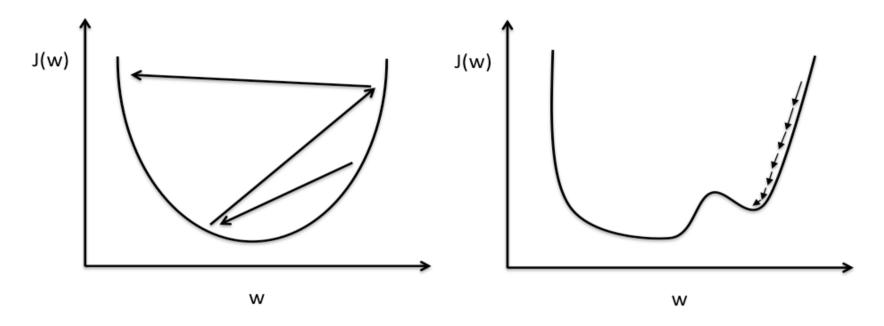
```
x_data = [[1, 2, 1], [1, 3, 2], [1, 3, 4], [1, 5, 5], [1, 7, 5], [1, 2, 5], [1, 6, 6], [1, 7, 7]]
y_data = [[0, 0, 1], [0, 0, 1], [0, 0, 1], [0, 1, 0], [0, 1, 0], [0, 1, 0], [1, 0, 0], [1, 0, 0]]

# Evaluation our model using this test dataset
x_test = [[2, 1, 1], [3, 1, 2], [3, 3, 4]]
y_test = [[0, 0, 1], [0, 0, 1], [0, 0, 1]]
```

Training and Test datasets

```
X = tf.placeholder("float", [None, 3])
Y = tf.placeholder("float", [None, 3])
W = tf.Variable(tf.random normal([3, 3]))
b = tf.Variable(tf.random normal([3]))
hypothesis = tf.nn.softmax(tf.matmul(X, W)+b)
cost = tf.reduce mean(-tf.reduce sum(Y * tf.log(hypothesis), axis=1))
optimizer = tf.train.GradientDescentOptimizer(learning rate=0.1).minimize(cost)
# Correct prediction Test model
                                                                            199 0.672261 [[-1.15377033 0.28146935
prediction = tf.arg max(hypothesis, 1) #예측
                                                                            1.136326791
Is correct = tf.equal(prediction, tf.arg max(Y, 1))
                                                                            [ 0.37484586  0.18958236  0.33544877]
Accuracy = tf.reduce mean(tf.cast(is correct, tf.float32))
                                                                            [-0.35609841 -0.43973011 -1.25604188]]
                                                                            200 0.670909 [[-1.15885413 0.28058422
# Launch graph
                                                                            1.14229572]
With tf.Session() as sess:
                                                                            [ 0.37609792  0.19073224  0.33304682]
   # Initialize TensorFlow variables
                                                                            [-0.35536593 -0.44033223 -1.2561723 ]]
   sess.run(tf.global variables initializer())
                                                                            Prediction: [2 2 2]
   for step in range(201):
                                                                            Accuracy: 1.0
       cost val, W val, = sess.run([cost, W, optimizer],
                        feed dict={X: x data, Y: y data}) #train
       print(step, cost val, W val) #학습 끝
   # predict
   print("Prediction: ", sess.run(prediction, feed dict={X: x test}))
   # Calculate the accuracy
   print("Accuracy: ", sess.run(accuracy, feed_dict={X: x_test, Y: y_test}))
```

Learning rate (0.1/0.01)



Large learning rate: Overshooting.

Small learning rate: Many iterations until convergence and trapping in local minima.

Learning rate (0.1/0.01)

```
X = tf.placeholder("float", [None, 3])
Y = tf.placeholder("float", [None, 3])
W = tf.Variable(tf.random normal([3, 3]))
b = tf.Variable(tf.random normal([3]))
hypothesis = tf.nn.softmax(tf.matmul(X, W)+b)
cost = tf.reduce mean(-tf.reduce sum(Y * tf.log(hypothesis), axis=1))
optimizer = tf.train.GradientDescentOptimizer
              (learning rate=1.5).minimize(cost) Big learning rate(1.5): cost값이 변동 확인
# Correct prediction Test model
                                                        Small learning rate(1e-10): cost값 동일 확인
prediction = tf.arg max(hypothesis, 1)
is correct = tf.equal(prediction, tf.arg max(Y, 1))
accuracy = tf.reduce mean(tf.cast(is correct, tf.float32))
# Launch graph
with tf.Session() as sess:
   # Initialize TensorFlow variables
   sess.run(tf.global variables initializer())
  for step in range(201):
       cost val, W val, = sess.run([cost, W, optimizer],
                      feed dict={X: x data, Y: y data})
       print(step, cost val, W val)
  # predict
   print("Prediction:", sess.run(prediction, feed dict={X: x test}))
  # Calculate the accuracy
   print("Accuracy: ", sess.run(accuracy, feed dict={X: x test, Y: y test}))
```

Non-normalized inputs

Non-normalized inputs

```
xy=...
x data = xy[:, 0:-1]
v data = xv[:, [-1]]
# placeholders for a tensor that will be always fed.
X = tf.placeholder(tf.float32, shape=[None, 4])
                                                            xy = MinMaxScaler(xy)
Y = tf.placeholder(tf.float32, shape=[None, 1])
                                                            print(xy)
W = tf.Variable(tf.random normal([4, 1]), name='weight')
b = tf.Variable(tf.random normal([1]), name='bias')
hypothesis = tf.matmul(X, W) + b
cost = tf.reduce mean(tf.square(hypothesis - Y))
# Minimize
optimizer = tf.train.GradientDescentOptimizer(learning rate=1e-5)
train = optimizer.minimize(cost)
sess = tf.Session()
sess.run(tf.global variables initializer())
for step in range(2001):
   cost val, hy val, = sess.run(
       [cost, hypothesis, train], feed dict={X: x data, Y: y data})
   print(step, "Cost: ", cost val, "\nPrediction:\n", hy val)
```

Non-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]])
          [[0.99999999 0.99999999 0.
                                                1.
                                                       1.
           [ 0.70548491  0.70439552  1.
                                                 0.71881782
                                                             0.83755791]
           [ 0.54412549  0.50274824  0.57608696
                                                0.606468
                                                             0.6606331]
           [ 0.33890353  0.31368023  0.10869565
                                                 0.45989134
                                                             0.43800918]
           [ 0.51436
                                                 0.58504805
                        0.42582389 0.30434783
                                                              0.42624401]
           [ 0.49556179  0.42582389  0.31521739
                                                 0.48131134
                                                             0.49276137]
           [ 0.11436064 0.
                                    0.20652174
                                                 0.22007776
                                                             0.18597238]
           [ 0.
                       0.07747099 0.5326087
                                                              0.
                                                                   11
                                                 0.
```

xy = MinMaxScaler(xy)
print(xy)

Non-normalized inputs

```
xy=...
x data = xy[:, 0:-1]
v data = xv[:, [-1]]
# placeholders for a tensor that will be always fed.
X = tf.placeholder(tf.float32, shape=[None, 4])
                                                            xy = MinMaxScaler(xy)
Y = tf.placeholder(tf.float32, shape=[None, 1])
                                                            print(xy)
W = tf.Variable(tf.random normal([4, 1]), name='weight')
b = tf.Variable(tf.random normal([1]), name='bias')
hypothesis = tf.matmul(X, W) + b
cost = tf.reduce mean(tf.square(hypothesis - Y))
# Minimize
optimizer = tf.train.GradientDescentOptimizer(learning rate=1e-5)
train = optimizer.minimize(cost)
sess = tf.Session()
sess.run(tf.global variables initializer())
for step in range(2001):
   cost val, hy val, = sess.run(
       [cost, hypothesis, train], feed dict={X: x data, Y: y data})
   print(step, "Cost: ", cost val, "\nPrediction:\n", hy val)
```

Non-normalized inputs

```
def MinMaxScaler(data):
    numerator = data - np.min(data, 0)
    denominator = np.max(data, 0) - np.min(data, 0)
   # noise term prevents the zero division
    return numerator / (denominator + 1e-7)
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]])
 # very important. It does not work without it.
 xy = MinMaxScaler(xy)
 print(xy)
```

xy = MinMaxScaler(xy)
print(xy)

MNIST Dataset

. 손으로 필기한 숫자 각각의 이미지가 정수로 표시되는 데이터베이스 머신러닝 알고리즘의 성능을 벤치마킹하는 데 사용되며 99.7% 이상의 정확도 달성 55000개의 학습 데이터와 10000개의 테스트 데이터, 5000개의 검증 데이터 학습 데이터는 28 X 28 사이즈에 총 784개의 픽셀로 이루어진 흑백 이미지 컴퓨터는 흑색 이미지를 표현할 때 픽셀의 숫자가 0에 가까울수록 검정색으로 255에 가까울수록 하얀색으로 표현

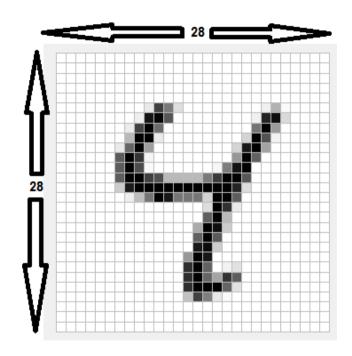
MNIST Dataset

```
import matplotlib.pyplot as plt
import numpy as np
# Training Data 로드
data_file = open('./MNIST_data/mnist_train.csv', 'r')
#Training Data 파일의 내용을 한줄씩 불러와서 문자열 리스트로 반환
training_data = data_file.readlines()
print(training_data[1])
#Training Data 의 두번째 데이터를 ','로 분리
training_data_array = np.asfarray(training_data[1].split(","))
 일렬로 늘어진 784 개의 픽셀 정보를 28X28 행렬로 변환
matrix = training_data_array[1:].reshape(28,28)
plt.imshow(matrix, cmap='gray')
plt.show()
```

MNIST Dataset

. 데이터 준비: 머신러닝의 고전적인 문제: 필기 숫자들의 그레이 스케일 28*28 픽셀 이미지를 보고, 0부터 9시까지의 모든 숫자들에 대해 이미지가 어떤 숫자를 나타내는지 판별

파일	목적
train-images-idx3-ubyte.gz	학습 셋 이미지 - 55000개의 트레이닝 이미지, 5000개의 검증 이미지
train-labels-idx1-ubyte.gz	이미지와 매칭되는 학습 셋 레이블
t10k-images-idx3-ubyte.gz	테스트 셋 이미지 - 10000개의 이미지
t10k-labels-idx1-ubyte.gz	이미지와 매칭되는 테스트 셋 레이블



28x**28**x**1** image

```
# MNIST data image of shape 28 * 28 = 784
X = tf.placeholder(tf.float32, [None, 784])
# 0 - 9 digits recognition = 10 classes
Y = tf.placeholder(tf.float32, [None, nb_classes])
```

MINIST Dataset

```
# Check out https://www.tensorflow.org/get_started/mnist/beginners for # more information about the mnist dataset
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
...
batch_xs, batch_ys = mnist.train.next_batch(100) #100개씩
...
print("Accuracy: ", accuracy.eval(session=sess, feed dict={X: mnist.test.images, Y: mnist.test.labels}))
```

Reading data and set variables

```
from tensorflow.examples.tutorials.mnist import input_data
# Check out https://www.tensorflow.org/get_started/mnist/beginners for
# more information about the mnist dataset
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)

nb_classes = 10

# MNIST data image of shape 28 * 28 = 784
X = tf.placeholder(tf.float32, [None, 784])
# 0 - 9 digits recognition = 10 classes
Y = tf.placeholder(tf.float32, [None, nb_classes])

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

Reading data and set variables

```
from tensorflow.examples.tutorials.mnist import input_data
# Check out https://www.tensorflow.org/get_started/mnist/beginners for
# more information about the mnist dataset
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# MNIST data image of shape 28 * 28 = 784
X = tf.placeholder(tf.float32, [None, 784])
# 0 - 9 digits recognition = 10 classes
Y = tf.placeholder(tf.float32, [None, nb_classes])

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

MINIST Dataset

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

cost = tf.reduce_mean(-tf.reduce_sum(Y * tf.log(hypothesis), axis=1))
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)

# Test model
is_correct = tf.equal(tf.arg_max(hypothesis, 1), tf.arg_max(Y, 1))
# Calculate accuracy
accuracy = tf.reduce mean(tf.cast(is correct, tf.float32))
```

Training epoch/batch

```
# 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) #전체사이즈(10000)/100 =100번 돌면 1번

for i in range(total batch):
    batch_xs, batch_ys = mnist.train.next_batch(batch_size)#100개씩 돌면서 학습
    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))
```

Training epoch/batch

In the neural network terminology:

- one **epoch** = one forward pass and one backward pass of *all* the training examples(전체)
- **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.

Report results on test dataset

```
# Test the model using test sets#sess.run()
print("Accuracy: ", accuracy.eval(session=sess,
  feed_dict={X: mnist.test.images, Y: mnist.test.labels}))
```

MINIST Dataset

```
hypothesis = tf.nn.softmax(tf.matmul(X, W) + b)
cost = tf.reduce mean(-tf.reduce sum(Y * tf.log(hypothesis), axis=1))
optimizer = tf.train.GradientDescentOptimizer(learning rate=0.1).minimize(cost)
is correct = tf.equal(tf.arg max(hypothesis, 1), tf.arg max(Y, 1))
accuracy = tf.reduce mean(tf.cast(is correct, tf.float32))
# 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))
```

MINIST Dataset

