

hw6

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1 Homework 6

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- Repro: Open up hw6.ipynb in IPython Notebook.

1.1 1. Gradient Descent Updates

Square brackets denote element-wise operations.

1.1.1 Mean-squared Error

W1

$$J = 1/2 \sum (y_k - h_k(x))^2$$

$$dJ/dW_2 = - \sum (y_k - h_k(x)) * d/dW_2(h_k(x))$$

Note that $h(x) = g(\tanh(xW_1)W_2)$, where x is a row vector. Consider $d/dW_2(h(x))$:

$$\begin{aligned} d/dW_2(h(x)) &= d/dW_2(\tanh(xW_1)W_2) * g'(\tanh(xW_1)W_2) \\ &= \tanh(xW_1)^T * [g(\tanh(xW_1)W_2)(1 - g(\tanh(xW_1)W_2))] \\ &= \tanh(xW_1)^T * [h(x)(1 - h(x))] \end{aligned}$$

Thus:

$$dJ/dW_2 = -\tanh(xW_1)^T * [h(x)(1 - h(x))(y - h(x))]$$

W2

$$dJ/dW_1 = - \sum (y_k - h_k(x)) * d/dW_1(h_k(x))$$

Consider $d/dW_1(h(x))$:

$$\begin{aligned} d/dW_1(h(x)) &= d/dW_1(\tanh(xW_1)W_2) * g'(\tanh(xW_1)W_2) \\ d/dW_1(\tanh(xW_1)W_2) &= W_2^T \tanh'(xW_1)x^T \end{aligned}$$

Thus:

$$dJ/dW_1 = -x^T * [[h(x)(1 - h(x))(y - h(x))] * W_2^T \tanh'(xW_1)]$$

1.1.2 Cross-entropy Error

$$\begin{aligned}J &= \sum y_k \ln(h_k(x)) + (1 - y_k) \ln(1 - h_k(x)) \\dJ/dW &= \sum d/dW y_k \ln(h_k(x)) + d/dW (1 - y_k) \ln(1 - h_k(x)) \\dJ/dW &= \sum y_k d/dW \ln(h_k(x)) + (1 - y_k) d/dW \ln(1 - h_k(x)) \\dJ/dW &= \sum y_k / h_k(x) d/dW h_k(x) + (1 - y_k) / (1 - h_k(x)) d/dW (-h_k(x)) \\dJ/dW &= [y/h(x) - (1 - y)/(1 - h(x))] d/dW (h(x))\end{aligned}$$

Using the results from the previous part, we get:

$$\begin{aligned}dJ/dW_2 &= -\tanh(xW_1)^T * [y/h(x) - (1 - y)/(1 - h(x))] [h(x)(1 - h(x))] \\dJ/dW_1 &= -x^T * [[h(x)(1 - h(x))][y/h(x) - (1 - y)/(1 - h(x))] * W_2^T (\tanh'(xW_1))]\end{aligned}$$

1.2 2. Parameters

I used a learning rate of 0.01, with a pseudo-simulated annealing: every 5k iterations, if the validation accuracy hasn't increased, decrease the rate by a multiplicative factor of 0.8, resetting back to 0.01 every 100k iterations.

Weights were initialized to the normal distribution with mean 0 and variance 10^{-5} .

I got a training accuracy of 99.2%, and a Kaggle score of 96.4%.

The running time was about 10k iterations per minute, for a total of about 30-40 minutes for my final result.

Plots of accuracy over time can be found below; cross-entropy error performed much better than mean-squared error, as a loss function.

```
In [1]: import numpy as np
import scipy.io
import math
import random
from sklearn import preprocessing
from __future__ import division

# Load the data
mat = scipy.io.loadmat('digit-dataset/train.mat')
images = np.reshape(mat["train_images"], (1, -1, 60000))[0].T
labels = mat['train_labels']
labels = np.squeeze(np.asarray(labels))

# Preprocess X
X = preprocessing.scale(images.astype(float))
X = np.c_[X, np.ones(len(X))]

# Form y row vectors
Y = [[1 if label == i else 0 for i in range(10)] for label in labels]
Y = np.array(Y)

In [2]: class NeuralNet(object):
def __init__(self):
    e = 10**-5
    self.W1 = np.random.normal(0, e, (785, 200))
    self.W2 = np.random.normal(0, e, (201, 10))
```

```

def forward(self, x):
    a2 = np.tanh(x.dot(self.W1))
    a2 = np.c_[a2, np.ones(len(a2))]
    hx = sigmoid(a2.dot(self.W2))
    return hx

def train(self, X, Y, iterations, step, error):
    for i in range(iterations):
        i = random.randrange(0, len(X))
        x, y = X[i], Y[i] # x and y are both row vectors

        a2 = np.tanh(x.dot(self.W1))
        a2 = np.append(a2, 1)
        hx = sigmoid(a2.dot(self.W2))
        d3 = np.multiply(np.multiply(hx, 1 - hx), error(y, hx))

        dJdW2 = - np.outer(a2.T, d3)
        dJdW1 = - np.outer(x.T, d3.dot(self.W2.T) * (1 - a2**2))

        self.W2 -= step * dJdW2
        self.W1 -= step * dJdW1[:, :-1]

def predict(self, images):
    output = self.forward(images)
    return [max((v, i) for i, v in enumerate(o))[1] for o in output]

def score(self, data, labels):
    predictions = self.predict(data)
    return sum(d == l for d, l in zip(predictions, labels)) / len(labels)

def save(self, filename):
    np.savez(filename, self.W1, self.W2)

def load(self, filename):
    arrs = np.load(filename)
    self.W1, self.W2 = arrs['arr_0'], arrs['arr_1']

def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def mean_squared_error(y, hx):
    return y - hx

def cross_entropy_error(y, hx):
    return np.divide(y, hx) - np.divide(1 - y, 1 - hx)

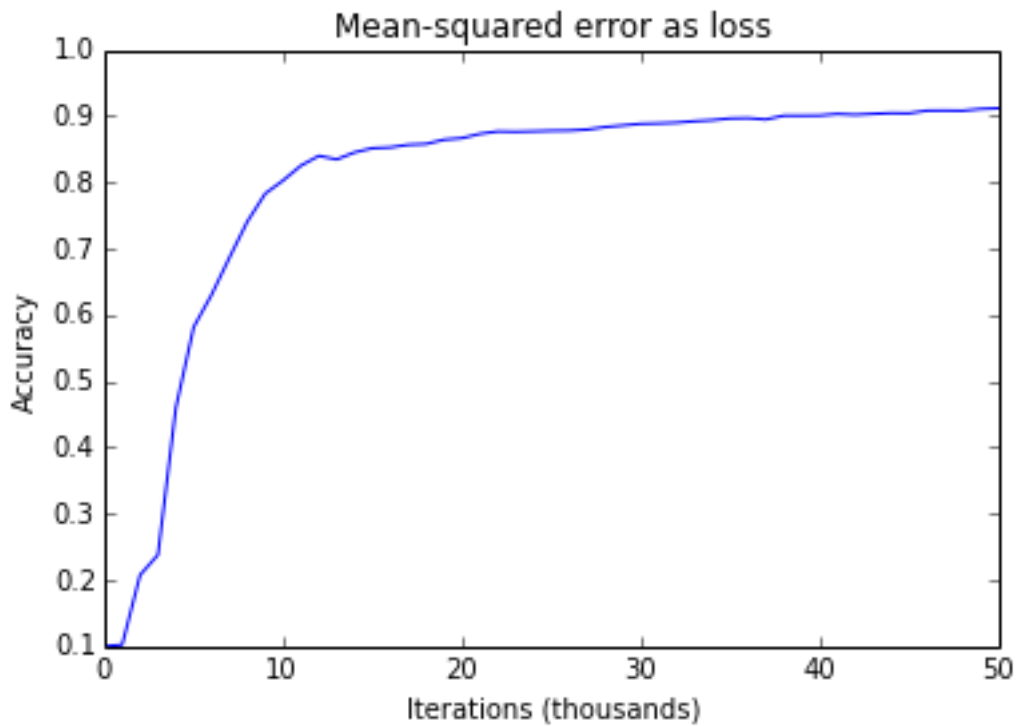
In [8]: import matplotlib.pyplot as plt
        %matplotlib inline

scores = [0.10]
nn = NeuralNet()
for _ in range(50):
    nn.train(X, Y, 1000, 0.01, mean_squared_error)
    scores.append(nn.score(X, labels))

```

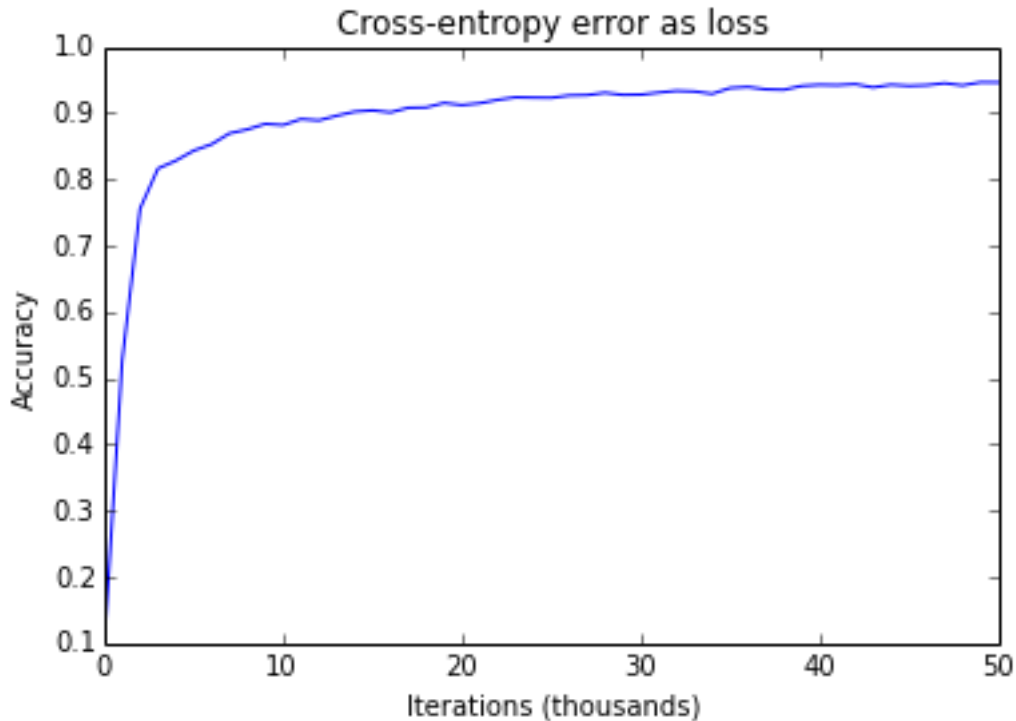
```
plt.plot(scores)
plt.title("Mean-squared error as loss")
plt.ylabel("Accuracy")
plt.xlabel("Iterations (thousands)")
```

Out[8]: <matplotlib.text.Text at 0x10eb18790>



```
In [10]: scores = [0.10]
nn = NeuralNet()
for _ in range(50):
    nn.train(X, Y, 1000, 0.01, cross_entropy_error)
    scores.append(nn.score(X, labels))
plt.plot(scores)
plt.title("Cross-entropy error as loss")
plt.ylabel("Accuracy")
plt.xlabel("Iterations (thousands)")
```

Out[10]: <matplotlib.text.Text at 0x10ec8e710>



```
In []: nn = NeuralNet()
nn.load('backup.npz')
step = 0.001
# prev_score = 0.98

for _ in range(40):
    nn.train(X, Y, 5000, step, cross_entropy_error)
    score = nn.score(X, labels)
    print(score)
nn.save('backup.npz')
#     if score < prev_score:
#         step *= 0.8
#         nn.load('backup.npz')
#     else:
#         prev_score = score
#         nn.save('backup.npz')
```

```
In [18]: # Load and preprocess test data
mat = scipy.io.loadmat('test.mat')
test_images = np.reshape(mat["test_images"], (1, -1, 10000))[0].T
test_X = preprocessing.scale(test_images.astype(float))
test_X = np.c_[test_X, np.ones(len(test_X))]
```

```
In [38]: # Load Neural Net weights from backup
nn = NeuralNet()
nn.load('backup.npz')
result = nn.predict(test_X)
```

```
# Write the results to a csv
f = open('digits6.csv', 'w')
f.write('Id,Category\n')
for i in range(len(result)):
    f.write("{0},{1}\n".format(i + 1, result[i]))
f.close()
```