MLP_Tensorflow

September 16, 2020

0.1 MLP: Initializations

[0]:
```
## MLP: Initializations# https://leonardoaraujosantos.gitbooks.io/
↪artificial-inteligence/content/multi_layer_perceptron_mnist.html
# https://github.com/wagonhelm/NaNmnist/blob/master/NaNmnist.ipynb
# https://github.com/aymericdamien/TensorFlow-Examples/blob/master/notebooks/
↪3_NeuralNetworks/neural_network.ipynb

from tensorflow.examples.tutorials.mnist import input_data
import tensorflow as tf
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
WARNING:tensorflow:From <ipython-input-1-0db05428d778>:4: read_data_sets (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be
removed in a future version.
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from
tensorflow/models.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:260:
maybe_download (from tensorflow.contrib.learn.python.learn.datasets.base) is
deprecated and will be removed in a future version.
Instructions for updating:
Please write your own downloading logic.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:262:
extract_images (from tensorflow.contrib.learn.python.learn.datasets.mnist) is
deprecated and will be removed in a future version.
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting MNIST_data/train-images-idx3-ubyte.gz
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:267:
extract_labels (from tensorflow.contrib.learn.python.learn.datasets.mnist) is
deprecated and will be removed in a future version.
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting MNIST_data/train-labels-idx1-ubyte.gz
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:110:
dense_to_one_hot (from tensorflow.contrib.learn.python.learn.datasets.mnist) is
deprecated and will be removed in a future version.
Instructions for updating:
Please use tf.one_hot on tensors.
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:290:
DataSet.__init__ (from tensorflow.contrib.learn.python.learn.datasets.mnist) is
deprecated and will be removed in a future version.
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from
tensorflow/models.
```

[0]:

```python
# %matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, y, y_1, ax, ticks,title, colors=['b']):
    ax.plot(x, y, 'b', label="Train Loss")
    ax.plot(x, y_1, 'r', label="Test Loss")
    if len(x)=Fkee=1:
        plt.legend()
        plt.title(title)
    plt.yticks(ticks)
    fig.canvas.draw()
```

[0]:

```python
# Network Parameters
n_hidden_1 = 512 # 1st layer number of neurons
n_hidden_2 = 128 # 2nd layer number of neurons
n_input = 784 # MNIST data input (img shape: 28*28)
n_classes = 10 # MNIST total classes (0-9 digits)
```

[0]:

```python
# x isn't a specific value. It's a placeholder, a value that we'll input when we␣
↪ask TensorFlow to run a computation.
# We want to be able to input any number of MNIST images, each flattened into a␣
↪784-dimensional vector.
# We represent this as a 2-D tensor of floating-point numbers, with a shape X =␣
↪[None, 784].
# (Here None means that a dimension can be of any length.)
x = tf.placeholder(tf.float32, [None, 784])
y_ = tf.placeholder(tf.float32, [None, 10])
```

```
# keep_prob: we will be using these placeholders when we use dropouts, while testing model
keep_prob = tf.placeholder(tf.float32)
# keep_prob_input: we will be using these placeholders when we use dropouts, while training model
keep_prob_input = tf.placeholder(tf.float32)
```

[0]:
```
# Weight initialization

# https://arxiv.org/pdf/1707.09725.pdf#page=95
# https://www.tensorflow.org/api_docs/python/tf/random_normal
# Outputs random values from a normal distribution mean=0 std=1

# If we sample weights from a normal distribution N(0, ) we satisfy this condition with  =√(2/(ni+ni+1).
# h1 =>   =√(2/(fan_in+fan_out+1) = 0.039  => N(0, ) = N(0,0.039)
# h2 =>   =√(2/(fan_in+fan_out+1) = 0.055  => N(0, ) = N(0,0.055)
# out =>   =√(2/(fan_in+fan_out+1) = 0.120  => N(0, ) = N(0,0.120)
# SGD: Xavier/Glorot Normal initialization.
weights_sgd = {
    'h1': tf.Variable(tf.random_normal([n_input, n_hidden_1],stddev=0.039, mean=0)),    #784x512 # sqrt(2/(784+512)) = 0.039
    'h2': tf.Variable(tf.random_normal([n_hidden_1, n_hidden_2],stddev=0.055, mean=0)), #512x128 # sqrt(2/(512+128)) = 0.055
    'out': tf.Variable(tf.random_normal([n_hidden_2, n_classes],stddev=0.120, mean=0))  #128x10
}


# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu lates
# If we sample weights from a normal distribution N(0, ) we satisfy this condition with  =√(2/(ni).
# h1 =>   =√(2/(fan_in+1) = 0.062  => N(0, ) = N(0,0.062)
# h2 =>   =√(2/(fan_in+1) = 0.125  => N(0, ) = N(0,0.125)
# out =>   =√(2/(fan_in+1) = 0.120  => N(0, ) = N(0,0.120)
# He Normal initialization.
weights_relu = {
    'h1': tf.Variable(tf.random_normal([n_input, n_hidden_1],stddev=0.062, mean=0)),    #784x512
    'h2': tf.Variable(tf.random_normal([n_hidden_1, n_hidden_2],stddev=0.125, mean=0)), #512x128
    'out': tf.Variable(tf.random_normal([n_hidden_2, n_classes],stddev=0.120, mean=0))  #128x10
}
```

```
biases = {
    'b1': tf.Variable(tf.random_normal([n_hidden_1])),             #512x1
    'b2': tf.Variable(tf.random_normal([n_hidden_2])),             #128x1
    'out': tf.Variable(tf.random_normal([n_classes]))              #10x1
}
```

```
[0]: # Parameters
training_epochs = 15
learning_rate = 0.001
batch_size = 100
display_step = 1
```

Model 1: input (784) - sigmoid(512) - sigmoid(128) - softmax(output 10)

```
[0]: # https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/
 ↪multi_layer_perceptron_mnist.html
# Create model
def multilayer_perceptron(x, weights, biases):
    # Use tf.matmul instead of "*" because tf.matmul can change it's dimensions␣
 ↪on the fly (broadcast)
    print( 'x:', x.get_shape(), 'W[h1]:', weights['h1'].get_shape(), 'b[h1]:',␣
 ↪biases['b1'].get_shape())

    # Hidden layer with Sigmoid activation
    layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])␣
 ↪#(x*weights['h1']) + biases['b1']
    layer_1 = tf.nn.sigmoid(layer_1)
    print( 'layer_1:', layer_1.get_shape(), 'W[h2]:', weights['h2'].
 ↪get_shape(), 'b[h2]:', biases['b2'].get_shape())

    # Hidden layer with Sigmoid activation
    layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2']) #␣
 ↪(layer_1 * weights['h2']) + biases['b2']
    layer_2 = tf.nn.sigmoid(layer_2)
    print( 'layer_2:', layer_2.get_shape(), 'W[out]:', weights['out'].
 ↪get_shape(), 'b3:', biases['out'].get_shape())

    # Output layer with Sigmoid activation
    out_layer = tf.matmul(layer_2, weights['out']) + biases['out'] # (layer_2 *␣
 ↪weights['out']) + biases['out']
    out_layer = tf.nn.sigmoid(out_layer)
    print('out_layer:',out_layer.get_shape())

    return out_layer
```

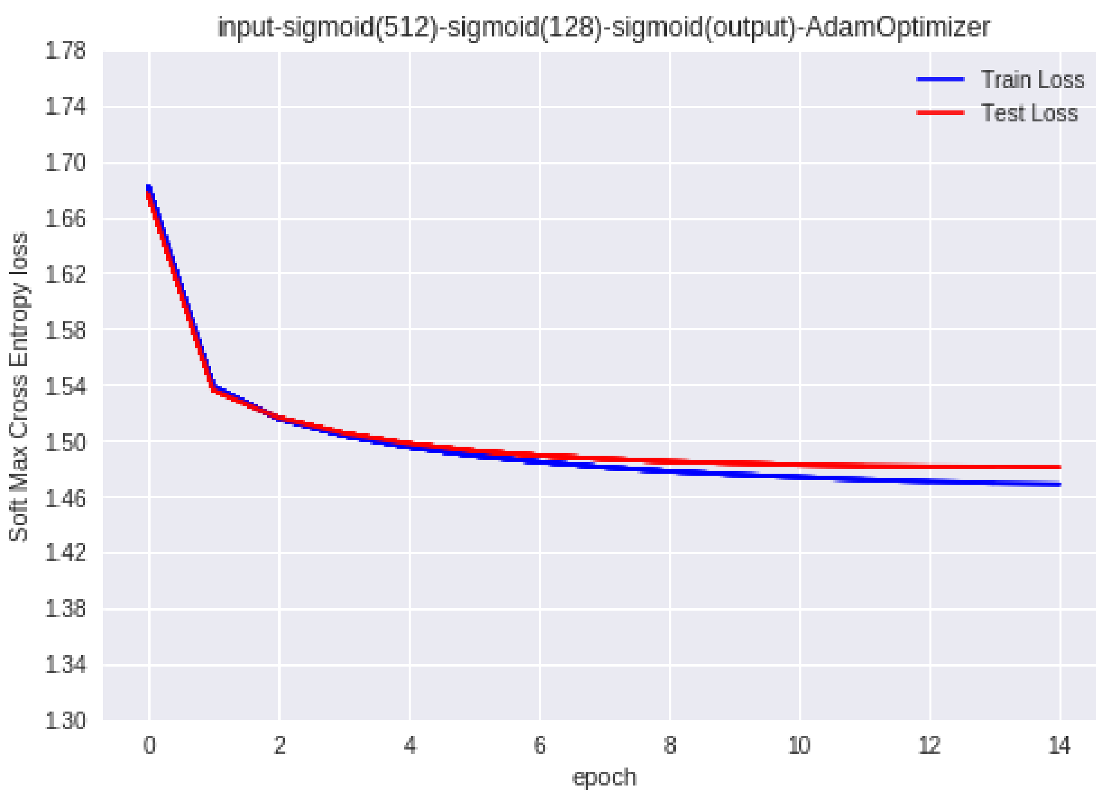
___ Model 1 + AdamOptimizer ___

[0]:
```
# Since we are using sigmoid activations in hiden layers we will be using␣
↪weights that are initalized as weights_sgd
y_sgd = multilayer_perceptron(x, weights_sgd, biases)

# https://www.tensorflow.org/api_docs/python/tf/nn/
↪softmax_cross_entropy_with_logits
cost_sgd = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits =␣
↪y_sgd, labels = y_))

# https://github.com/amitmac/Question-Answering/issues/2
# there are many optimizers available: https://www.tensorflow.org/versions/r1.2/
↪api_guides/python/train#Optimizers
optimizer_adam = tf.train.AdamOptimizer(learning_rate=learning_rate).
↪minimize(cost_sgd)
optimizer_sgdc = tf.train.GradientDescentOptimizer(learning_rate=learning_rate).
↪minimize(cost_sgd)

with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)

            # here c: corresponds to the parameter cost_sgd
            # w : correspondse to the parameter weights_sgd
            # c = sess.run() return the cost after every bath during train
            # w = sess.run() return the weights that are modified after every␣
↪batch through Back prop
            # w is dict w = {'h1': updated h1 weight vector after the current␣
↪batch,
            #                'h2': updated h2 weight vector after the current␣
↪batch,
            #                'out': updated output weight vector after the␣
↪current batch,
            #               }
            # you check these w matrix for every iteration, and check whats␣
↪happening during back prop
            #
```

```
            # note: sess.run() returns parameter values based on the input␣
↪parameters
            # _, c, w = sess.run([optimizer_adam, cost_sgd,weights_sgd]) it␣
↪returns three parameters
            # _, c = sess.run([optimizer_adam, cost_sgd ]) it returns two␣
↪parameters
            # _ = sess.run([optimizer_adam]) it returns one paramter (for the␣
↪input optimizer it return none)
            # c = sess.run([cost_sgd]) it returns one paramter (for the input␣
↪cost return error after the batch)

            # feed_dict={x: batch_xs, y_: batch_ys} here x, y_ should be␣
↪placeholders
            # x, y_ are the input parameters on which the models gets trained

            # here we use AdamOptimizer
            _, c, w = sess.run([optimizer_adam, cost_sgd,weights_sgd],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_sgd, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.3, 1.8, step=0.04),␣
↪"input-sigmoid(512)-sigmoid(128)-sigmoid(output)-AdamOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))
    plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.3, 1.8, step=0.04),␣
↪"input-sigmoid(512)-sigmoid(128)-sigmoid(output)-AdamOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(y_sgd,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

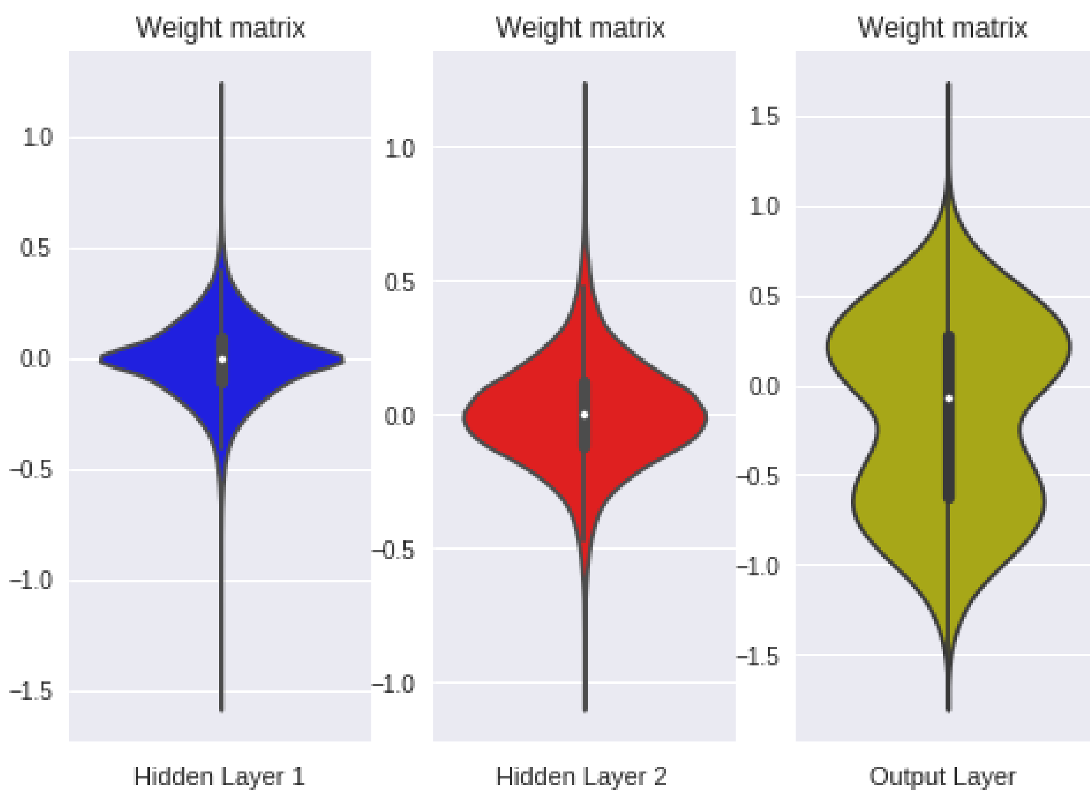
```
x: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
layer_1: (?, 512) W[h2]: (512, 128) b[h2]: (128,)
layer_2: (?, 128) W[out]: (128, 10) b3: (10,)
out_layer: (?, 10)
WARNING:tensorflow:From <ipython-input-8-743a1d69c459>:4:
softmax_cross_entropy_with_logits (from tensorflow.python.ops.nn_ops) is
```

```
deprecated and will be removed in a future version.
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See tf.nn.softmax_cross_entropy_with_logits_v2.

Epoch: 0001 train cost=1.681823547 test cost=1.676311211
Epoch: 0002 train cost=1.538490382 test cost=1.536218471
Epoch: 0003 train cost=1.515721546 test cost=1.516237581
Epoch: 0004 train cost=1.503663794 test cost=1.505241357
Epoch: 0005 train cost=1.495330883 test cost=1.497797373
Epoch: 0006 train cost=1.489064606 test cost=1.492622907
Epoch: 0007 train cost=1.484618232 test cost=1.489168651
Epoch: 0008 train cost=1.480839387 test cost=1.486846633
Epoch: 0009 train cost=1.477865693 test cost=1.484905369
Epoch: 0010 train cost=1.475599988 test cost=1.483736856
Epoch: 0011 train cost=1.473791684 test cost=1.482444747
Epoch: 0012 train cost=1.471931230 test cost=1.481658286
Epoch: 0013 train cost=1.470603549 test cost=1.481347544
Epoch: 0014 train cost=1.469495951 test cost=1.481273373
Epoch: 0015 train cost=1.468627278 test cost=1.480902303
Accuracy: 0.9792
```



[0]:
```python
# Plot weight distriubtion at the end of training.

import seaborn as sns
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```

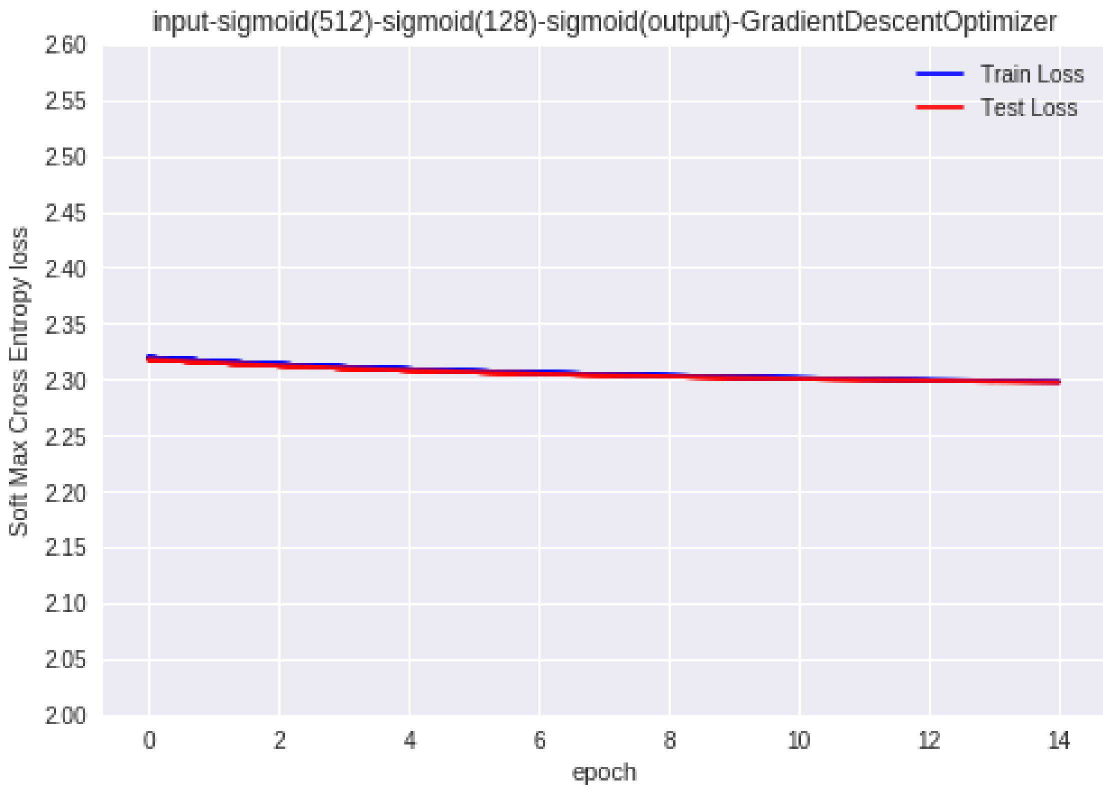


___ Model 1 + GradientDescentOptimizer ___

[0]:
```
# We can now launch the model in an InteractiveSession

# We first have to create an operation to initialize the variables we created:
# https://github.com/amitmac/Question-Answering/issues/2

# Note: make sure you initialize variables.

with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)
```

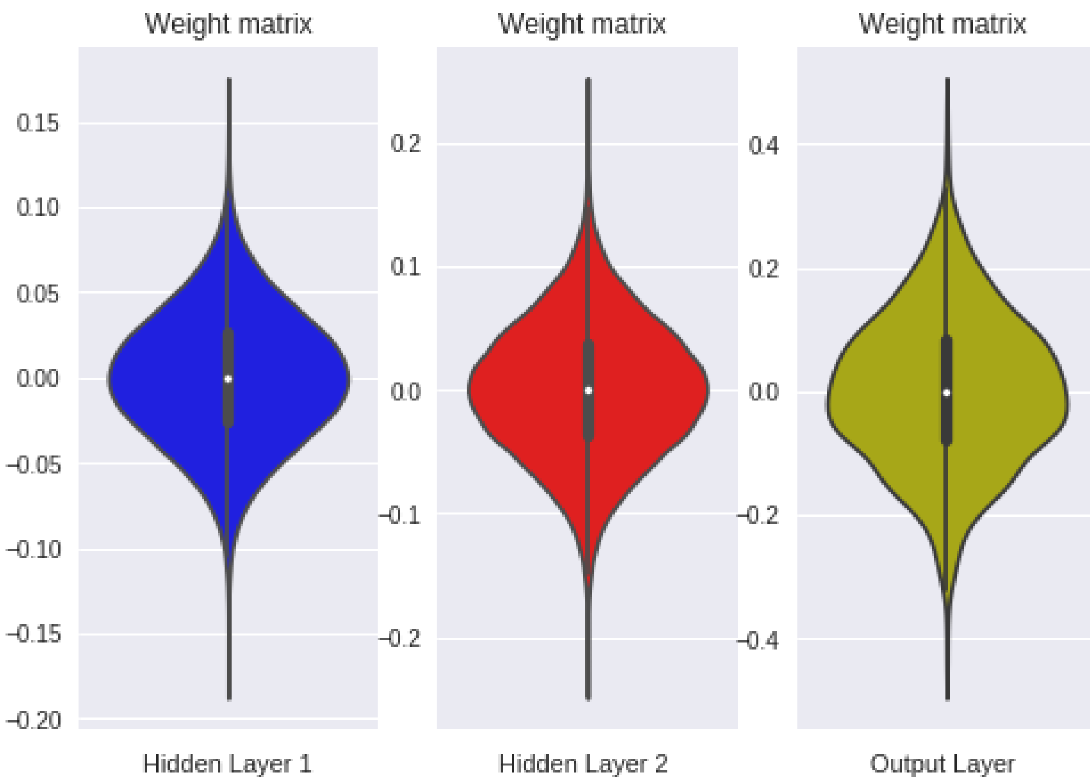
```
            # here we use GradientDescentOptimizer
            _, c, w = sess.run([optimizer_sgdc, cost_sgd, weights_sgd],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_sgd, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax, np.arange(2, 2.6, step=0.05),␣
↪"input-sigmoid(512)-sigmoid(128)-sigmoid(output)-GradientDescentOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))
    plt_dynamic(xs, ytrs, ytes, ax, np.arange(2, 2.6, step=0.05),␣
↪"input-sigmoid(512)-sigmoid(128)-sigmoid(output)-GradientDescentOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(y_sgd,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

```
Epoch: 0001 train cost=2.319404572 test cost=2.318047826
Epoch: 0002 train cost=2.316184991 test cost=2.314944556
Epoch: 0003 train cost=2.313415619 test cost=2.312310369
Epoch: 0004 train cost=2.311047141 test cost=2.310042647
Epoch: 0005 train cost=2.309026067 test cost=2.308095952
Epoch: 0006 train cost=2.307287374 test cost=2.306472156
Epoch: 0007 train cost=2.305776415 test cost=2.305014431
Epoch: 0008 train cost=2.304444027 test cost=2.303744715
Epoch: 0009 train cost=2.303249972 test cost=2.302621931
Epoch: 0010 train cost=2.302166392 test cost=2.301561712
Epoch: 0011 train cost=2.301172580 test cost=2.300602047
Epoch: 0012 train cost=2.300254010 test cost=2.299707088
Epoch: 0013 train cost=2.299401874 test cost=2.298892814
Epoch: 0014 train cost=2.298614489 test cost=2.298106769
Epoch: 0015 train cost=2.297889533 test cost=2.297402518
Accuracy: 0.0974
```



[0]:
```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```



Model 2: input (784) - ReLu(512) - ReLu(128) - sigmoid(output 10)

[0]:
```
# https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/
↪multi_layer_perceptron_mnist.html
# Create model
def multilayer_perceptron_relu(x, weights, biases):
    # Use tf.matmul instead of "*" because tf.matmul can change it's dimensions␣
↪on the fly (broadcast)
    print( 'x:', x.get_shape(), 'W[h1]:', weights['h1'].get_shape(), 'b[h1]:',␣
↪biases['b1'].get_shape())

    # Hidden layer with ReLu activation
    # https://en.wikipedia.org/wiki/Rectifier_(neural_networks)
    layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])␣
↪#(x*weights['h1']) + biases['b1']
```

```
    layer_1 = tf.nn.relu(layer_1)
    print( 'layer_1:', layer_1.get_shape(), 'W[h2]:', weights['h2'].
 ↪get_shape(), 'b[h2]:', biases['b2'].get_shape())

    # Hidden layer with ReLu activation
    layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2']) #␣
 ↪(layer_1 * weights['h2']) + biases['b2']
    layer_2 = tf.nn.relu(layer_2)
    print( 'layer_2:', layer_2.get_shape(), 'W[out]:', weights['out'].
 ↪get_shape(), 'b3:', biases['out'].get_shape())

    # Output layer with Sigmoid activation
    out_layer = tf.matmul(layer_2, weights['out']) + biases['out'] # (layer_2 *␣
 ↪weights['out']) + biases['out']
    out_layer = tf.nn.sigmoid(out_layer)
    print('out_layer:',out_layer.get_shape())

    return out_layer
```

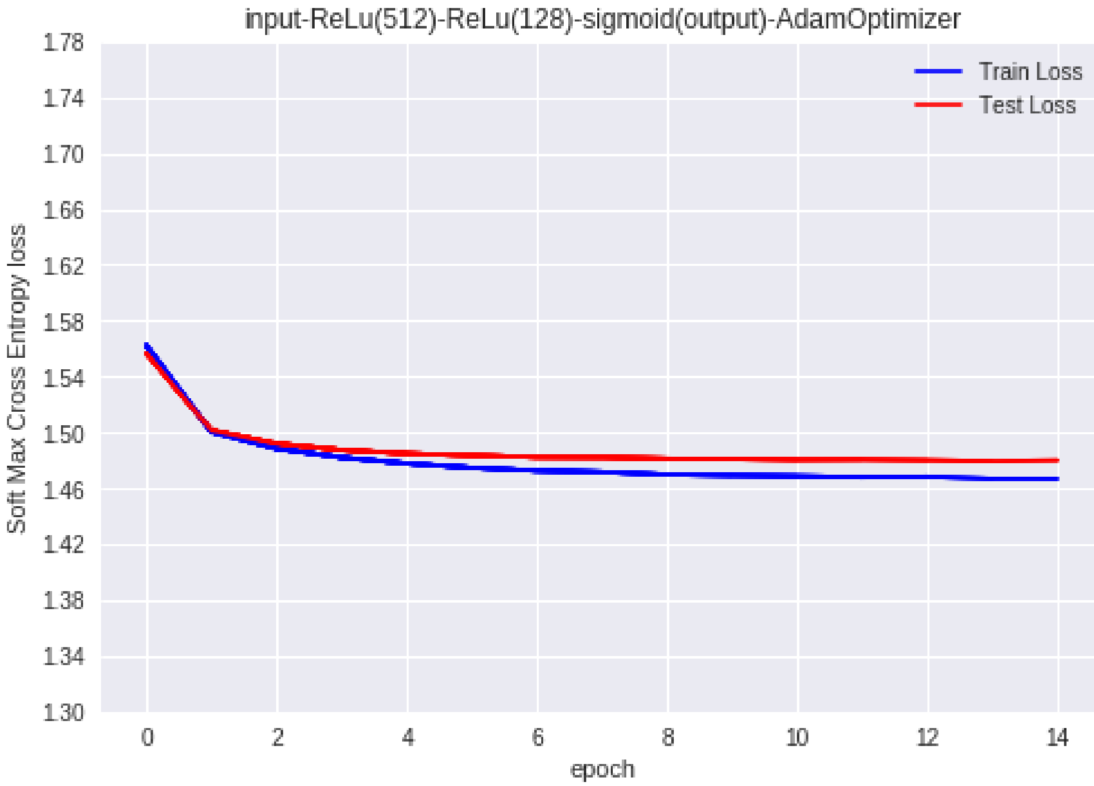
___ Input-ReLu(512)-ReLu(128)-sigmoid(output) - AdamOptimizer ___

[0]:
```
# Since we are using Relu activations in hiden layers we will be using weights␣
 ↪that are initalized as weights_relu
yrelu = multilayer_perceptron_relu(x, weights_relu, biases)

# https://www.tensorflow.org/api_docs/python/tf/nn/
 ↪softmax_cross_entropy_with_logits
cost_relu = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits =␣
 ↪yrelu, labels = y_))
# https://github.com/amitmac/Question-Answering/issues/2
# there are many optimizers available: https://www.tensorflow.org/versions/r1.2/
 ↪api_guides/python/train#Optimizers
optimizer_relu_adam = tf.train.AdamOptimizer(learning_rate=learning_rate).
 ↪minimize(cost_relu)
optimizer_relu_sgdc = tf.train.
 ↪GradientDescentOptimizer(learning_rate=learning_rate).minimize(cost_relu)
with tf.Session() as sess:
    tf.global_variables_initializer().run()

    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)
```

```
        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)

            # here we use AdamOptimizer
            _, c, w = sess.run([optimizer_relu_adam, cost_relu, weights_relu],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_relu, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.3, 1.8, step=0.04),␣
↪"input-ReLu(512)-ReLu(128)-sigmoid(output)-AdamOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))

    # plot final results
    plt_dynamic(xs, ytrs, ytes, ax,np.arange(1.3, 1.8, step=0.04),␣
↪"input-ReLu(512)-ReLu(128)-sigmoid(output)-AdamOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(yrelu,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

```
x: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
layer_1: (?, 512) W[h2]: (512, 128) b[h2]: (128,)
layer_2: (?, 128) W[out]: (128, 10) b3: (10,)
out_layer: (?, 10)
Epoch: 0001 train cost=1.562207396 test cost=1.556652784
Epoch: 0002 train cost=1.500463881 test cost=1.501601754
Epoch: 0003 train cost=1.488371294 test cost=1.492026712
Epoch: 0004 train cost=1.482039372 test cost=1.487420058
Epoch: 0005 train cost=1.477783545 test cost=1.484849013
Epoch: 0006 train cost=1.474736516 test cost=1.483547766
Epoch: 0007 train cost=1.472646466 test cost=1.482295828
Epoch: 0008 train cost=1.471696293 test cost=1.482177148
Epoch: 0009 train cost=1.469835149 test cost=1.481312513
Epoch: 0010 train cost=1.469276900 test cost=1.480974347
```

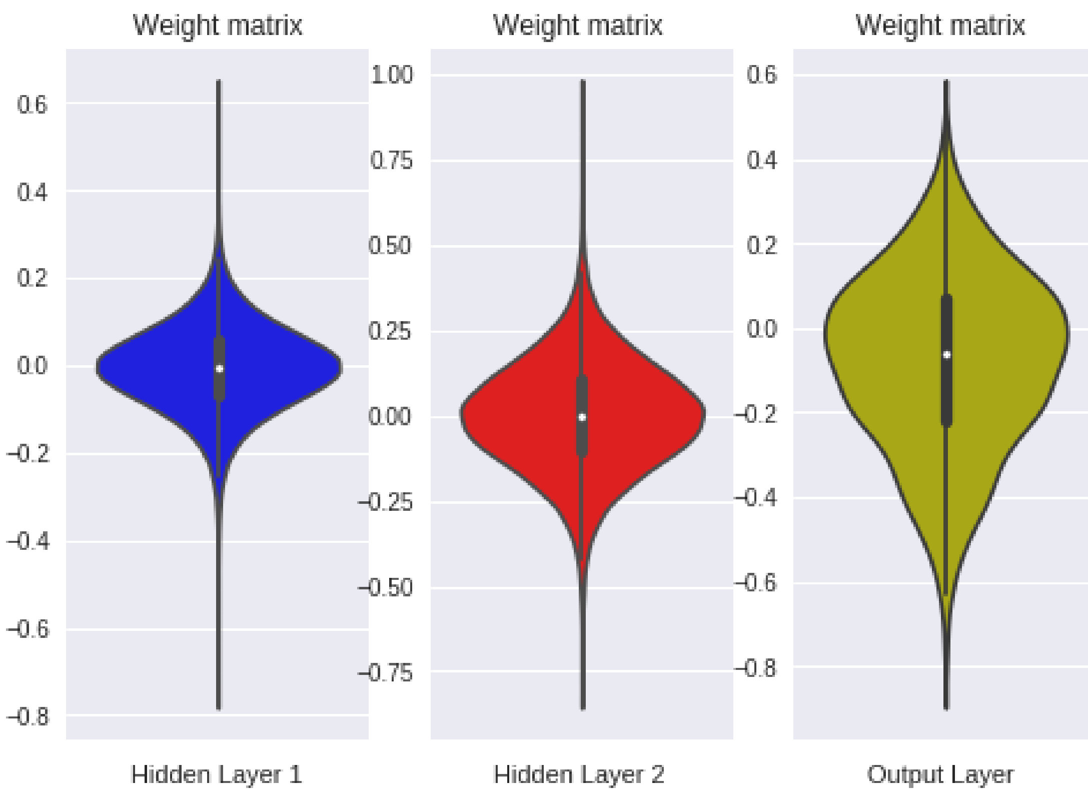
```
Epoch: 0011 train cost=1.468788507 test cost=1.480446307
Epoch: 0012 train cost=1.468029417 test cost=1.480591303
Epoch: 0013 train cost=1.468475725 test cost=1.480107398
Epoch: 0014 train cost=1.466739849 test cost=1.479299975
Epoch: 0015 train cost=1.466718120 test cost=1.480001667
Accuracy: 0.9785
```



[0]:
```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
```

```python
plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```



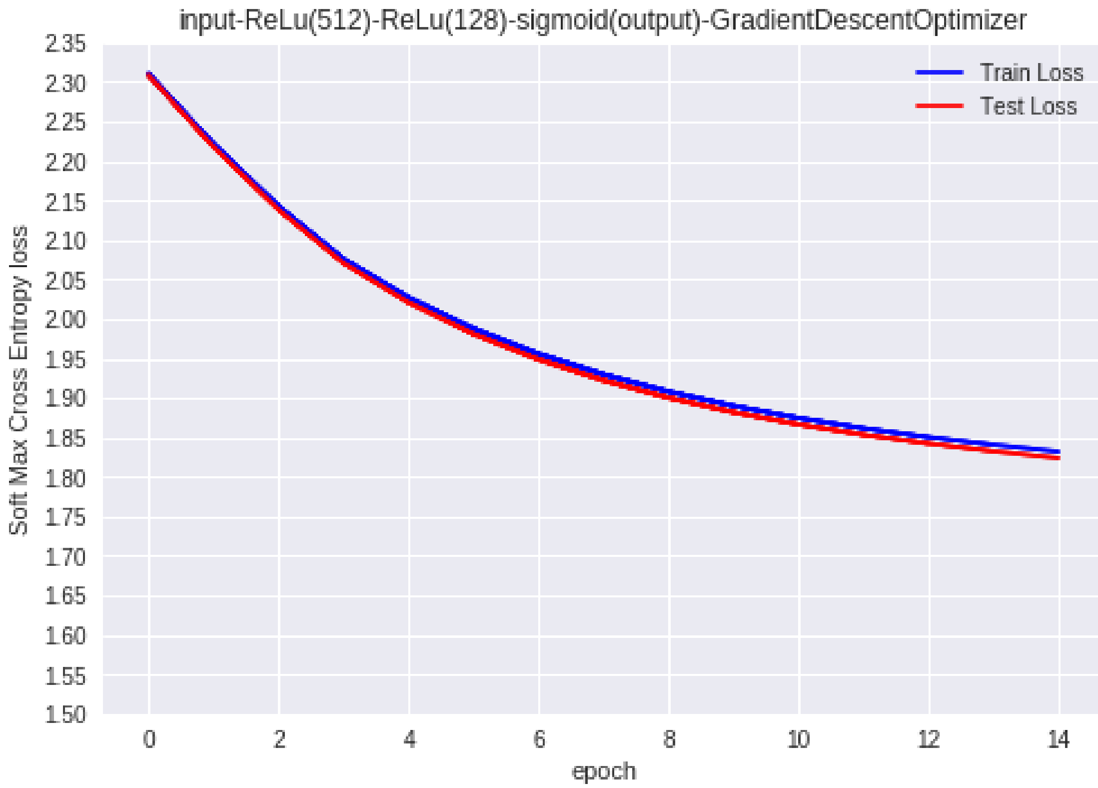
Input-ReLu(512)-ReLu(128)-sigmoid(output) - GradientDescentOptimizer

[0]:
```python
# We can now launch the model in an InteractiveSession

# We first have to create an operation to initialize the variables we created:
# https://github.com/amitmac/Question-Answering/issues/2

# Note: make sure you initialize variables after AdamOptimizer
```

```
with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)

            # here we use GradientDescentOptimizer
            _, c, w = sess.run([optimizer_relu_sgdc, cost_relu, weights_relu],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_relu, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.5, 2.4, step=0.05),␣
↪"input-ReLu(512)-ReLu(128)-sigmoid(output)-GradientDescentOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))

    # plot final results
    plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.5, 2.4, step=0.05),␣
↪"input-ReLu(512)-ReLu(128)-sigmoid(output)-GradientDescentOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(yrelu,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

```
Epoch: 0001 train cost=2.310429324 test cost=2.309331124
Epoch: 0002 train cost=2.221610156 test cost=2.218818418
Epoch: 0003 train cost=2.142771041 test cost=2.139230260
Epoch: 0004 train cost=2.075905863 test cost=2.071342851
```

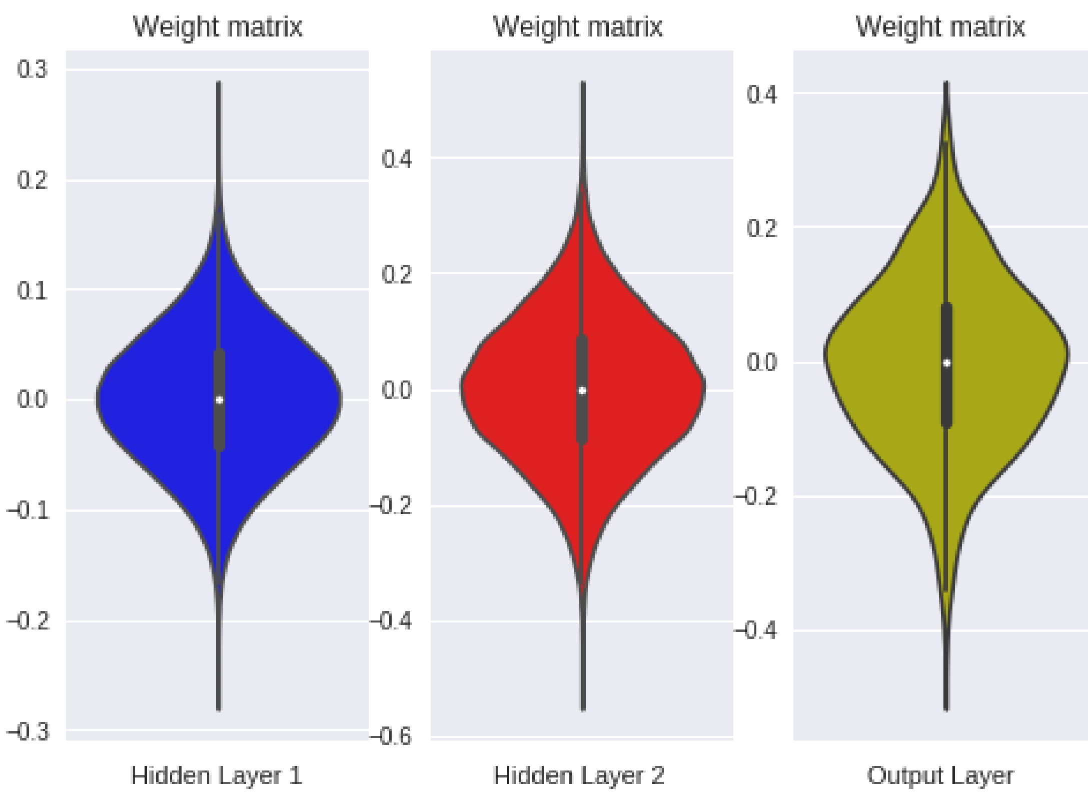
```
Epoch: 0005 train cost=2.027072112 test cost=2.021270330
Epoch: 0006 train cost=1.987932869 test cost=1.981295761
Epoch: 0007 train cost=1.956008127 test cost=1.948708092
Epoch: 0008 train cost=1.929796880 test cost=1.922126883
Epoch: 0009 train cost=1.908102709 test cost=1.900147488
Epoch: 0010 train cost=1.889981364 test cost=1.881854080
Epoch: 0011 train cost=1.874673119 test cost=1.866476579
Epoch: 0012 train cost=1.861609627 test cost=1.853379037
Epoch: 0013 train cost=1.850336982 test cost=1.842097878
Epoch: 0014 train cost=1.840515356 test cost=1.832302262
Epoch: 0015 train cost=1.831871038 test cost=1.823694615
Accuracy: 0.1066
```



[0]:
```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
```

```
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```



Model 3: Input - Sigmoid(BatchNormalization(512)) - Sigmoid(BatchNormalization(128))- Sigmoid(output)

[0]:
```
# https://www.tensorflow.org/api_docs/python/tf/nn/batch_normalization
# https://r2rt.com/implementing-batch-normalization-in-tensorflow.html
epsilon = 1e-3
def multilayer_perceptron_batch(x, weights, biases):
    # Use tf.matmul instead of "*" because tf.matmul can change it's dimensions␣
↪on the fly (broadcast)
    print( 'x:', x.get_shape(), 'W[h1]:', weights['h1'].get_shape(), 'b[h1]:',␣
↪biases['b1'].get_shape())

    ############################################################
    # Hidden layer with Sigmoid activation and batch normalization
    layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])␣
↪#(x*weights['h1']) + biases['b1']

    # https://www.tensorflow.org/api_docs/python/tf/nn/moments
    # Calculate the mean and variance of x.
    batch_mean_1, batch_var_1 = tf.nn.moments(layer_1,[0])

    scale_1 = tf.Variable(tf.ones([n_hidden_1]))
    beta_1 = tf.Variable(tf.zeros([n_hidden_1]))

    # https://www.tensorflow.org/api_docs/python/tf/nn/batch_normalization
    layer_1 = tf.nn.batch_normalization(layer_1, batch_mean_1, batch_var_1,␣
↪beta_1, scale_1, epsilon)
    layer_1 = tf.nn.sigmoid(layer_1)

    print( 'layer_1:', layer_1.get_shape(), 'W[h2]:', weights['h2'].
↪get_shape(), 'b[h2]:', biases['b2'].get_shape())

   ␣
↪#####################################################################################

    # Hidden layer with Sigmoid activation and batch normalization
    layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2']) #␣
↪(layer_1 * weights['h2']) + biases['b2']

    # https://www.tensorflow.org/api_docs/python/tf/nn/moments
    # Calculate the mean and variance of x.
    batch_mean_2, batch_var_2 = tf.nn.moments(layer_2, [0])

    scale_2 = tf.Variable(tf.ones([n_hidden_2]))
    beta_2 = tf.Variable(tf.zeros([n_hidden_2]))

    layer_2 = tf.nn.batch_normalization(layer_2, batch_mean_2, batch_var_2,␣
↪beta_2, scale_2, epsilon)
    layer_2 = tf.nn.sigmoid(layer_2)
```

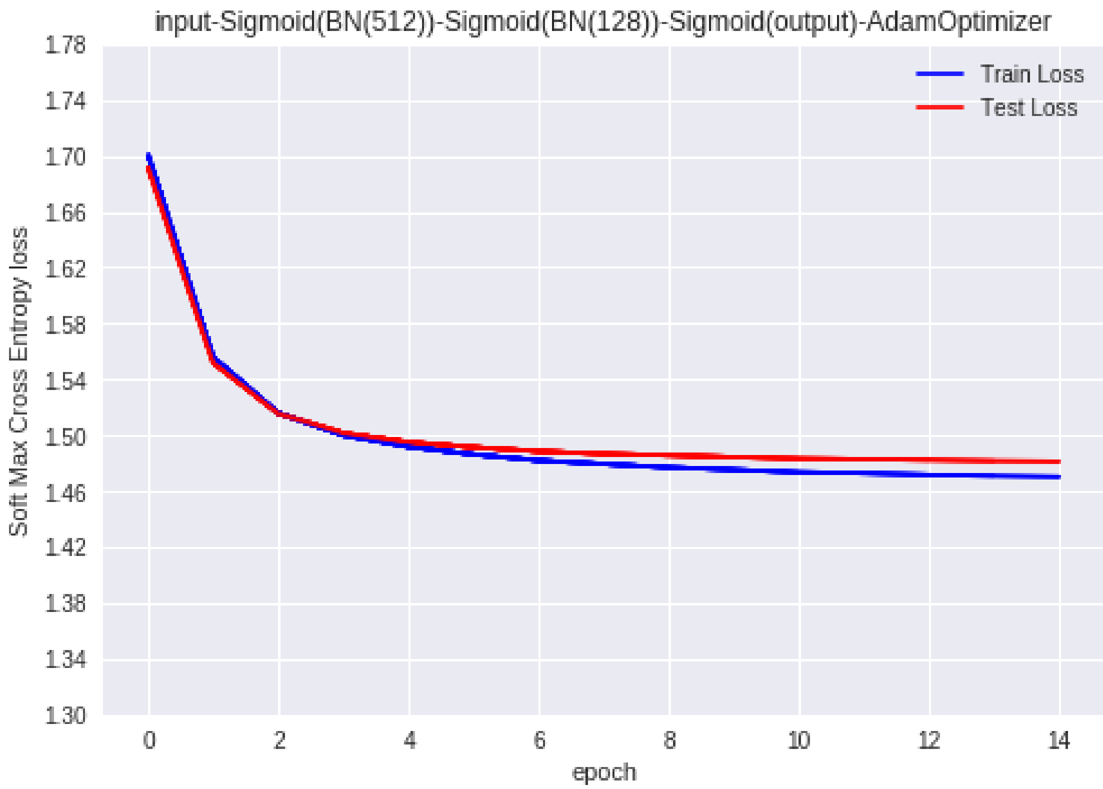
```
    print( 'layer_2:', layer_2.get_shape(), 'W[out]:', weights['out'].
→get_shape(), 'b3:', biases['out'].get_shape())

   ␣
→#####################################################################################

    # output layer with Sigmoid activation
    out_layer = tf.matmul(layer_2, weights['out']) + biases['out'] # (layer_2 *␣
→weights['out']) + biases['out']
    out_layer = tf.nn.sigmoid(out_layer)
    print('out_layer:',out_layer.get_shape())

    return out_layer
```

___ Model 3+ AdamOptimizer ___

[0]:
```
# Since we are using sigmoid activations in hiden layers we will be using␣
→weights that are initalized as weights_sgd
ybatch = multilayer_perceptron_batch(x, weights_sgd, biases)

# https://www.tensorflow.org/api_docs/python/tf/nn/
→softmax_cross_entropy_with_logits
cost_batch = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits =␣
→ybatch, labels = y_))
# https://github.com/amitmac/Question-Answering/issues/2
# there are many optimizers available: https://www.tensorflow.org/versions/r1.2/
→api_guides/python/train#Optimizers
optimizer_batch_adam = tf.train.AdamOptimizer(learning_rate=learning_rate).
→minimize(cost_batch)
optimizer_batch_sgdc = tf.train.
→GradientDescentOptimizer(learning_rate=learning_rate).minimize(cost_batch)
with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)

            # here we use AdamOptimizer
```

```
            _, c, w = sess.run([optimizer_batch_adam, cost_batch, weights_sgd],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_batch, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.3, 1.8, step=0.04),␣
↪"input-Sigmoid(BN(512))-Sigmoid(BN(128))-Sigmoid(output)-AdamOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))

    # plot final results
    plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.3, 1.8, step=0.04),␣
↪"input-Sigmoid(BN(512))-Sigmoid(BN(128))-Sigmoid(output)-AdamOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(ybatch,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

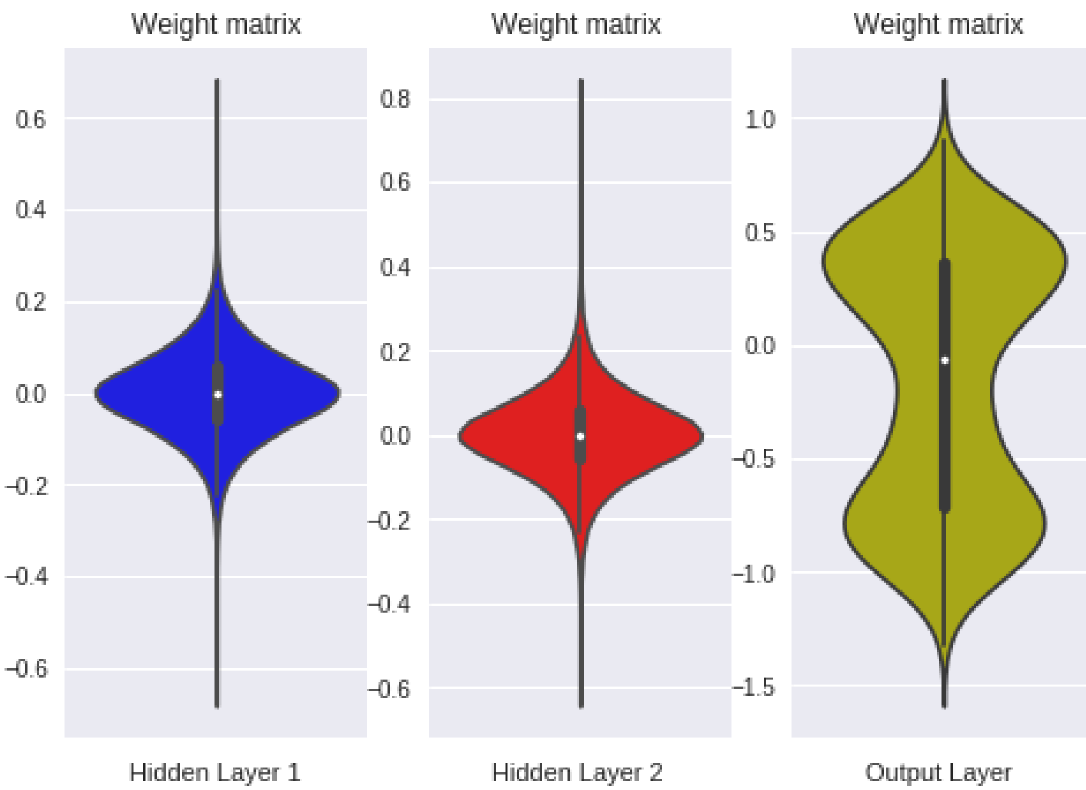
```
x: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
layer_1: (?, 512) W[h2]: (512, 128) b[h2]: (128,)
layer_2: (?, 128) W[out]: (128, 10) b3: (10,)
out_layer: (?, 10)
Epoch: 0001 train cost=1.700068553 test cost=1.691480070
Epoch: 0002 train cost=1.555593932 test cost=1.551793572
Epoch: 0003 train cost=1.515948518 test cost=1.515595129
Epoch: 0004 train cost=1.500090736 test cost=1.501608725
Epoch: 0005 train cost=1.491691740 test cost=1.495176234
Epoch: 0006 train cost=1.486215817 test cost=1.491377480
Epoch: 0007 train cost=1.481944979 test cost=1.488477005
Epoch: 0008 train cost=1.479413016 test cost=1.486683784
Epoch: 0009 train cost=1.476976019 test cost=1.485592169
Epoch: 0010 train cost=1.475328626 test cost=1.484361933
Epoch: 0011 train cost=1.473508603 test cost=1.483245888
Epoch: 0012 train cost=1.472790788 test cost=1.482792196
Epoch: 0013 train cost=1.471692099 test cost=1.482280265
Epoch: 0014 train cost=1.470980778 test cost=1.481615747
Epoch: 0015 train cost=1.470204555 test cost=1.481264244
Accuracy: 0.9811
```



[0]:

```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```

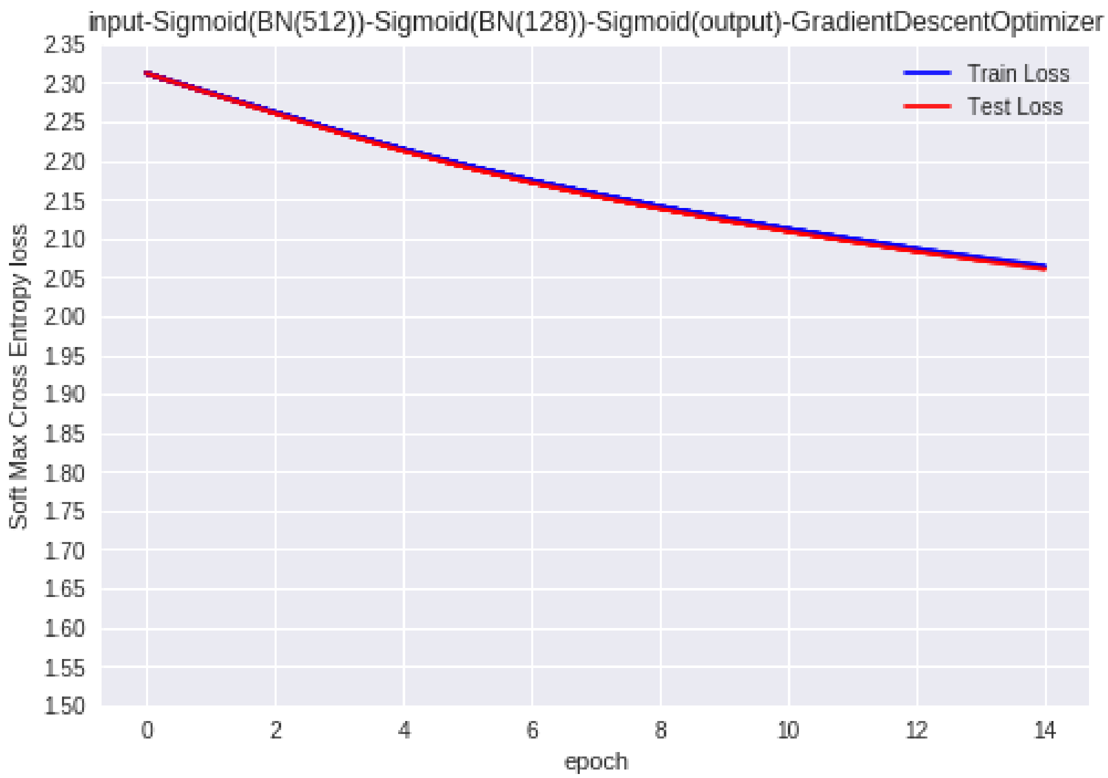


___ Model 3 + GradientDescentOptimizer ___

[0]:
```python
with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)
```

```
            # here we use GradientDescentOptimizer
            _, c, w = sess.run([optimizer_batch_sgdc, cost_batch, weights_sgd],␣
↪feed_dict={x: batch_xs, y_: batch_ys})
            train_avg_cost += c / total_batch
            c = sess.run(cost_batch, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax,np.arange(1.5, 2.4, step=0.05),␣
↪"input-Sigmoid(BN(512))-Sigmoid(BN(128))-Sigmoid(output)-GradientDescentOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))

    # plot final results
    plt_dynamic(xs, ytrs, ytes, ax, np.arange(1.5, 2.4, step=0.05),␣
↪"input-Sigmoid(BN(512))-Sigmoid(BN(128))-Sigmoid(output)-GradientDescentOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(ybatch,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels}))
```

```
Epoch: 0001 train cost=2.312056991 test cost=2.312045197
Epoch: 0002 train cost=2.286723345 test cost=2.286289722
Epoch: 0003 train cost=2.262095340 test cost=2.261143614
Epoch: 0004 train cost=2.237721429 test cost=2.236359837
Epoch: 0005 train cost=2.214522683 test cost=2.212769454
Epoch: 0006 train cost=2.193412623 test cost=2.191231863
Epoch: 0007 train cost=2.174389078 test cost=2.171921795
Epoch: 0008 train cost=2.157141389 test cost=2.154426692
Epoch: 0009 train cost=2.141131058 test cost=2.138286440
Epoch: 0010 train cost=2.126325870 test cost=2.123236751
Epoch: 0011 train cost=2.112224244 test cost=2.109058378
Epoch: 0012 train cost=2.099121217 test cost=2.095732109
Epoch: 0013 train cost=2.086694297 test cost=2.083267775
Epoch: 0014 train cost=2.075242446 test cost=2.071594143
Epoch: 0015 train cost=2.064474456 test cost=2.060690631
Accuracy: 0.125
```



[0]:

```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
FutureWarning: remove_na is deprecated and is a private function. Do not use.
  kde_data = remove_na(group_data)
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:816:
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  violin_data = remove_na(group_data)
```
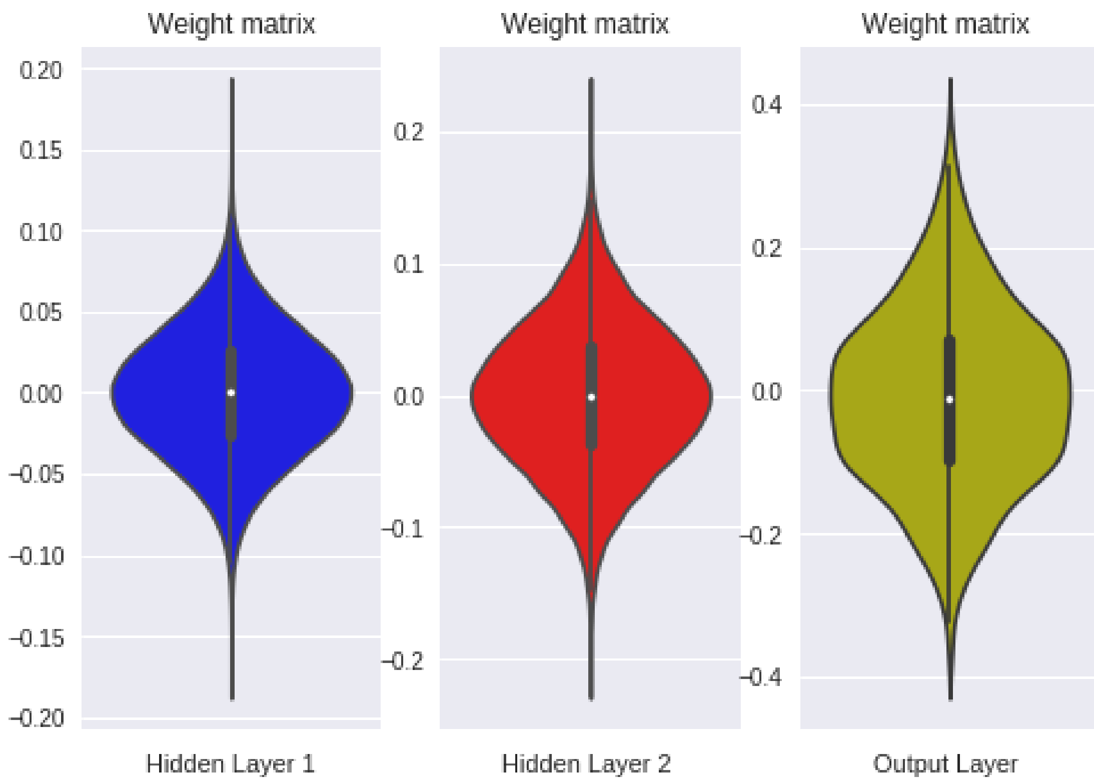



Model 4: Input - ReLu(512) - Dropout - ReLu(128)- Dropout -Sigmoid(output)

[0]:
```
# https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/
↪multi_layer_perceptron_mnist.html
# Create model
def multilayer_perceptron_dropout(x, weights, biases):
    # Use tf.matmul instead of "*" because tf.matmul can change it's dimensions␣
↪on the fly (broadcast)
    print( 'x:', x.get_shape(), 'W[h1]:', weights['h1'].get_shape(), 'b[h1]:',␣
↪biases['b1'].get_shape())
    # we are adding a drop out layer after input layers with parameter␣
↪keep_prob_input

    # Hidden layer with ReLu activation
```

```
    layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])␣
↪#(x*weights['h1']) + biases['b1']
    layer_1 = tf.nn.relu(layer_1)
    # we are adding a drop out layer after the first hidden layer with parameter␣
↪keep_prob
    layer_1_drop = tf.nn.dropout(layer_1, keep_prob)

    print( 'layer_1:', layer_1.get_shape(), 'W[h2]:', weights['h2'].
↪get_shape(), 'b[h2]:', biases['b2'].get_shape())

    # Hidden layer with ReLu activation
    layer_2 = tf.add(tf.matmul(layer_1_drop, weights['h2']), biases['b2']) #␣
↪(layer_1 * weights['h2']) + biases['b2']
    layer_2 = tf.nn.relu(layer_2)
    # we are adding a drop out layer after the first hidden layer with parameter␣
↪keep_prob
    layer_2_drop = tf.nn.dropout(layer_2, keep_prob)
    print( 'layer_2:', layer_2.get_shape(), 'W[out]:', weights['out'].
↪get_shape(), 'b3:', biases['out'].get_shape())

    # Output layer with Sigmoid activation
    out_layer = tf.matmul(layer_2_drop, weights['out']) + biases['out'] #␣
↪(layer_2 * weights['out']) + biases['out']
    out_layer = tf.nn.sigmoid(out_layer)
    print('out_layer:',out_layer.get_shape())

    return out_layer
```

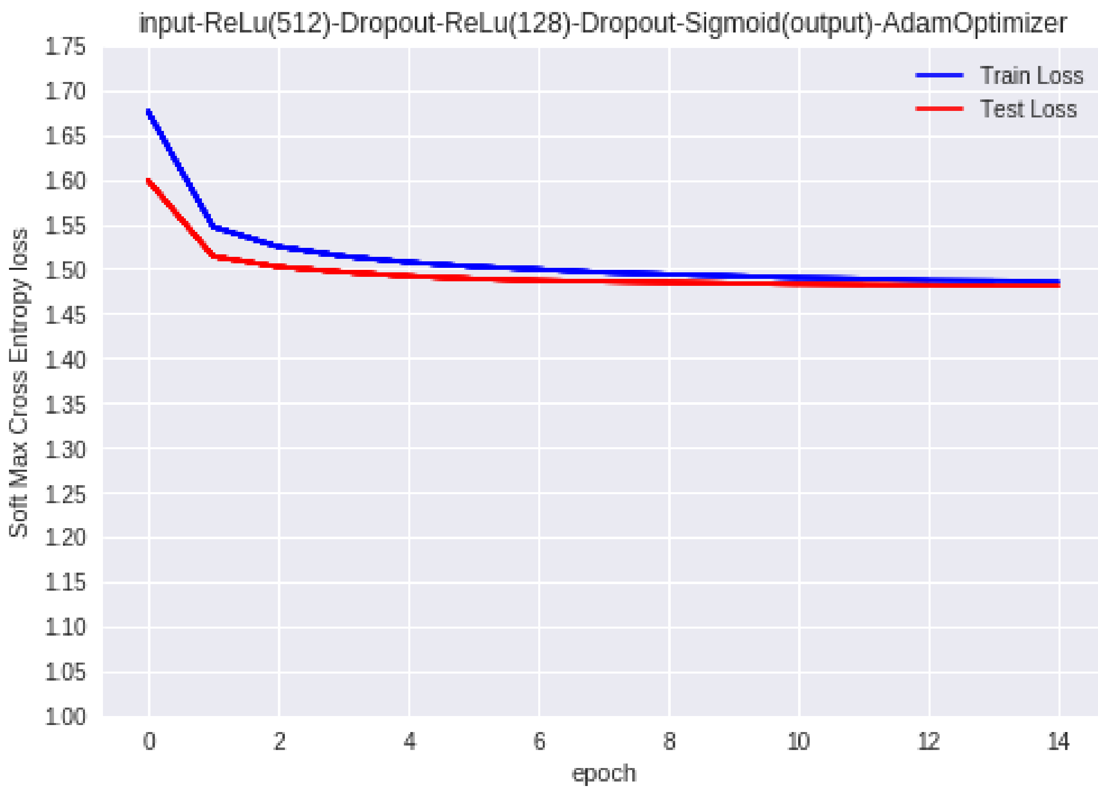
___ Model 4 + AdamOptimizer ___

[0]:
```
# Since we are using Relu activations in hiden layers we will be using weights␣
↪that are initalized as weights_relu
ydrop = multilayer_perceptron_dropout(x, weights_relu, biases)

# https://www.tensorflow.org/api_docs/python/tf/nn/
↪softmax_cross_entropy_with_logits
cost_drop = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits =␣
↪ydrop, labels = y_))
# https://github.com/amitmac/Question-Answering/issues/2
# there are many optimizers available: https://www.tensorflow.org/versions/r1.2/
↪api_guides/python/train#Optimizers
optimizer_drop_adam = tf.train.AdamOptimizer(learning_rate=learning_rate).
↪minimize(cost_drop)
optimizer_drop_sgdc = tf.train.
↪GradientDescentOptimizer(learning_rate=learning_rate).minimize(cost_drop)
```

```python
with tf.Session() as sess:
    tf.global_variables_initializer().run()
    fig,ax = plt.subplots(1,1)
    ax.set_xlabel('epoch') ; ax.set_ylabel('Soft Max Cross Entropy loss')
    xs, ytrs, ytes = [], [], []
    for epoch in range(training_epochs):
        train_avg_cost = 0.
        test_avg_cost = 0.
        total_batch = int(mnist.train.num_examples/batch_size)

        # Loop over all batches
        for i in range(total_batch):
            batch_xs, batch_ys = mnist.train.next_batch(batch_size)

            # here we use AdamOptimizer
            _, c, w = sess.run([optimizer_drop_adam, cost_drop, weights_relu],␣
↪feed_dict={x: batch_xs, y_: batch_ys, keep_prob: 0.5})
            train_avg_cost += c / total_batch
            c = sess.run(cost_drop, feed_dict={x: mnist.test.images, y_: mnist.
↪test.labels,  keep_prob: 1.0})
            test_avg_cost += c / total_batch

        xs.append(epoch)
        ytrs.append(train_avg_cost)
        ytes.append(test_avg_cost)
        plt_dynamic(xs, ytrs, ytes, ax,np.arange(1, 1.8, step=0.05),␣
↪"input-ReLu(512)-Dropout-ReLu(128)-Dropout-Sigmoid(output)-AdamOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".
↪format(train_avg_cost), "test cost={:.9f}".format(test_avg_cost))

    # plot final results
    plt_dynamic(xs, ytrs, ytes, ax,np.arange(1, 1.8, step=0.05),␣
↪"input-ReLu(512)-Dropout-ReLu(128)-Dropout-Sigmoid(output)-AdamOptimizer")

    # we are calculating the final accuracy on the test data
    correct_prediction = tf.equal(tf.argmax(ydrop,1), tf.argmax(y_,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
    print("Accuracy:", accuracy.eval({x: mnist.test.images, y_: mnist.test.
↪labels, keep_prob: 1.0 }))
```

```
x: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
layer_1: (?, 512) W[h2]: (512, 128) b[h2]: (128,)
layer_2: (?, 128) W[out]: (128, 10) b3: (10,)
out_layer: (?, 10)
Epoch: 0001 train cost=1.675481348 test cost=1.598583966
```

```
Epoch: 0002 train cost=1.546939785 test cost=1.514125155
Epoch: 0003 train cost=1.524996623 test cost=1.502378711
Epoch: 0004 train cost=1.514395935 test cost=1.496348261
Epoch: 0005 train cost=1.507464443 test cost=1.491901992
Epoch: 0006 train cost=1.502681051 test cost=1.488922666
Epoch: 0007 train cost=1.499395829 test cost=1.486873763
Epoch: 0008 train cost=1.495856912 test cost=1.485843970
Epoch: 0009 train cost=1.493913886 test cost=1.484971796
Epoch: 0010 train cost=1.491971510 test cost=1.483862281
Epoch: 0011 train cost=1.490074936 test cost=1.482910818
Epoch: 0012 train cost=1.488904240 test cost=1.482207586
Epoch: 0013 train cost=1.487357789 test cost=1.481696167
Epoch: 0014 train cost=1.486711373 test cost=1.480950590
Epoch: 0015 train cost=1.485781125 test cost=1.480801912
Accuracy: 0.9736
```



[0]:
```
h1_w = w['h1'].flatten().reshape(-1,1)
h2_w = w['h2'].flatten().reshape(-1,1)
out_w = w['out'].flatten().reshape(-1,1)


fig = plt.figure()
```

```python
plt.subplot(1, 3, 1)
plt.title("Weight matrix")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Weight matrix ")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Weight matrix ")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
# plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588:
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FutureWarning: remove_na is deprecated and is a private function. Do not use.
  violin_data = remove_na(group_data)
```

[0]: Text(0.5,0,'Output Layer ')