Information about data:

-> The MNIST dataset is in built in Tensor Flow Tutorials or we can get from Kaggle

-> The dataset contains of Hand written digits and their corresponding class lables

Objective:

-> To perform Multi Layer Perceptron on the MNIST dataset

-> To introduce different optimization algorithms like Gradient Descent, Stochastic Gradient Descent, Adadelta, Adam

-> To introduce different initializations of weights like Xavier, He

-> To try different activation functions like RELU, Sigmoid, Tanh

-> To introduce Batch Normalization

-> To introduce Drop out

-> To analyze the weights for each model

```
-> Importing the required libraries

-> Importing the in built dataset from Tensor Flow
```

In [3]:

```
import tensorflow as tf
import matplotlib.pyplot as mp
import numpy as np
from tensorflow.examples.tutorials.mnist import input_data
data = input_data.read_data_sets("MNIST_data/", one_hot = True)
```

```
WARNING:tensorflow:From <ipython-input-3-6c9780a2e235>:5: read_data_sets (f
rom 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 dep
recated 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/base.py:252: _inter
nal_retry.<locals>.wrap.<locals>.wrapped_fn (from
tensorflow.contrib.learn.python.learn.datasets.base) is deprecated and will
be removed in a future version.
Instructions for updating:
```

```
Please use urllib or similar directly.
Successfully downloaded train-images-idx3-ubyte.gz 9912422 bytes.
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
Successfully downloaded train-labels-idx1-ubyte.gz 28881 bytes.
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.
Successfully downloaded t10k-images-idx3-ubyte.gz 1648877 bytes.
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Successfully downloaded t10k-labels-idx1-ubyte.gz 4542 bytes.
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.
```

-> Dynamic plot function

In [0]:

```
def dynamic_plot(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)==1:
        mp.legend()
        mp.title(title)
    mp.yticks(ticks)
    fig.canvas.draw()
```

Train and Test data

In [5]:

```
print(data.train.images.shape)
print(data.test.images.shape)
print(data.train.labels.shape)
print(data.test.labels.shape)
```

```
print(data.test.labels.shape)
```

```
(55000, 784)
(10000, 784)
(55000, 10)
(10000, 10)
```

In [6]:

```
print('The number of data point in training are:',data.train.images.shape[0
],"and number of features for each data point are",data.train.images.shape[
1])
print('The number of data point to test  are:',data.test.images.shape[0],"a
nd number of features for each data point are",data.test.images.shape[1])
print("The shape of the class labels in the train and test dataset after ap
pling One Hot Encoding on the class labels")
print("The number of class labels in training are:",data.train.labels.shape
[0],"and each class label is of:",data.train.labels.shape[1],"dimensions")
print("The number of class labels in training are:",data.test.labels.shape[
0],"and each class label is of:",data.test.labels.shape[1],"dimensions")
```

```
The number of data point in training are: 55000 and number of features for
each data point are 784
The number of data point to test  are: 10000 and number of features for eac
h data point are 784
The shape of the class labels in the train and test dataset after appling O
ne Hot Encoding on the class labels
The number of class labels in training are: 55000 and each class label is o
f: 10 dimensions
The number of class labels in training are: 10000 and each class label is o
f: 10 dimensions
```

```
               NETWORK PARAMETERS:

                                   -> Number of hidden layers

                                   -> Number of Neurons in each Layer

                                   -> The input is of 784 Dimension

                                   -> The output is a SOFTMAX classifier
   with 10 class labels
```

In [0]:

```
n_hidden_1 = 512
n_hidden_2 = 128
n_input = 784
n_output = 10
```

```
             Variables and Place holders
```

In [0]:

```
x = tf.placeholder(tf.float32, [None,784])
```

```
y_ = tf.placeholder(tf.float32, [None,10])
prob = tf.placeholder(tf.float32) ##### place holder for drop out of input
prob_input = tf.placeholder(tf.float32) ##### place holder for drop out of output
keep_prob = tf.placeholder(tf.float32)
keep_prob_input = tf.placeholder(tf.float32)
```

Initializing Weights and Bias using different initialization algorithms like Xavier/Glorot, He

-> Xavier/Glorot weight initialization for SGD

-> He weight initialization for ReLU

In [0]:

```
sgd_weights = {
    'h1' : tf.Variable(tf.random_normal([n_input,n_hidden_1],stddev=0.039,mean=0)),  # 784*512 # sqrt(2/(784+512)) = 0.039
    'h2' : tf.Variable(tf.random_normal([n_hidden_1,n_hidden_2],stddev=0.055,mean=0)), # 512*128 # sqrt(2/(512+128)) = 0.055
    'out': tf.Variable(tf.random_normal([n_hidden_2,n_output],stddev=0.120,mean = 0))   # 128*10 #sqrt(2/(128+10)) = 0.120
}

relu_weights = {
    'h1' : tf.Variable(tf.random_normal([n_input,n_hidden_1],stddev=0.062,mean=0)),  # 784*512 # sqrt(2/(784+1)) = 0.062
    'h2' : tf.Variable(tf.random_normal([n_hidden_1,n_hidden_2],stddev=0.125,mean=0)), # 512*128 # sqrt(2/(512+1)) = 0.125
    'out': tf.Variable(tf.random_normal([n_hidden_2,n_output],stddev=0.120,mean = 0))   # 128*10 #sqrt(2/(128+1)) = 0.120
}
biases = {
    'b1': tf.Variable(tf.random_normal([n_hidden_1])),
    'b2': tf.Variable(tf.random_normal([n_hidden_2])),
    'out': tf.Variable(tf.random_normal([n_output]))
}
```

PARAMETERS

In [0]:

```
training_epochs = 25
learning_rate = 0.05
batch_size = 1000
display_step = 1
```

Model 1: INPUT (784) - SIGMOID(512) - SIGMOID(128) - SIGMOID(output 10)

-> Sigmoid Activation for hidden layers

In [0]:

```
def mulit_layer_perceptron(x,weights,biases):
  print('Input layer')
  print("X:", x.get_shape(), "W[h1]:", weights['h1'].get_shape(), 'b[h1]:', 
biases['b1'].get_shape())

  print('Hidden layer 1 with Sigmoid Activation')
  layer_1 = tf.add(tf.matmul(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[b1]:', biases['b2'].get_shape())

  print("Hidden layer 2 with Sigmoid Activation")
  layer_2 = tf.add(tf.matmul(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_shap
e, 'b3:', biases['out'].get_shape())

  print("Output layer")
  output_layer = tf.matmul(layer_2,weights['out']) + biases['out']
  output_layer = tf.nn.sigmoid(output_layer)
  print('Output Layer:', output_layer.get_shape())

  return output_layer
```

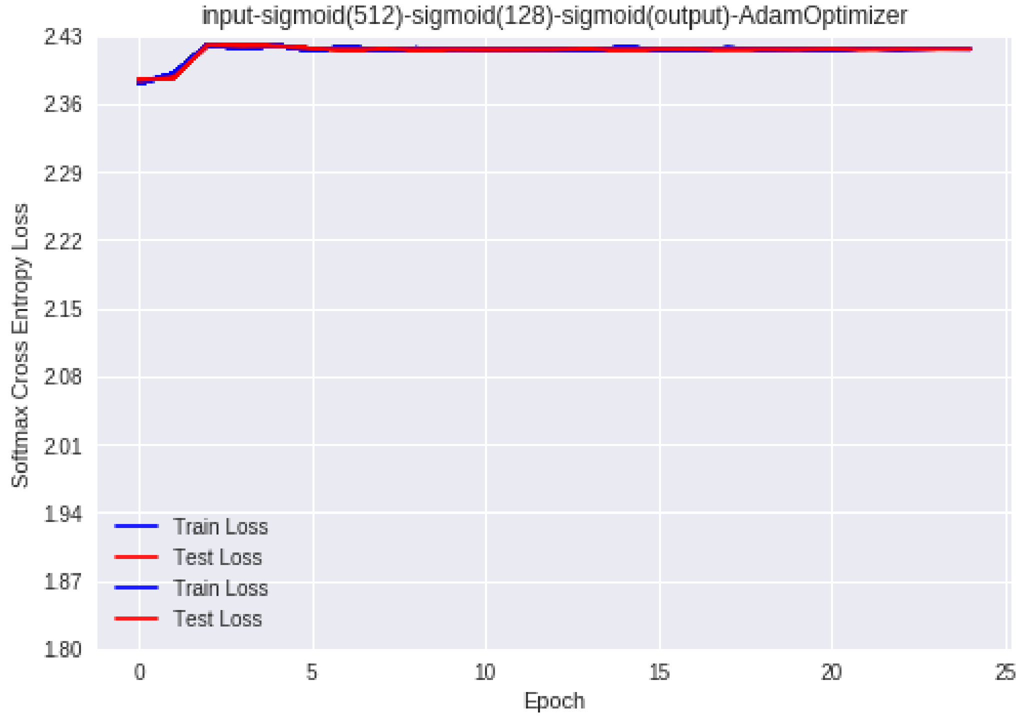
MODEL 1 + ADAM OPTIMIZER

In [33]:

```
y_sgd = mulit_layer_perceptron(x,sgd_weights,biases)
cost_sgd = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y_
sgd, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_sgd)
sgd_optimizer = 
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_sgd)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([adam_optimizer,cost_sgd,sgd_weights],feed_dict = {x:
xs_batch, y_:ys_batch})
```

```
        train_avg_cost += c/number_of_batches
        c = sess.run(cost_sgd, feed_dict = {x: data.test.images, y_: data.test
.labels})
        test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid(512)-sigmoid(128)-sigmoid(output)-AdamOptimizer")

    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid(512)-sigmoid(128)-sigmoid(output)-AdamOptimizer")
  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: data.test.images, y_: data.test.labe
ls}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with Sigmoid Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_9:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with Sigmoid Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_10:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=2.380851776 test cost=2.383974218
Epoch: 0002 train cost=2.390954169 test cost=2.386933439
Epoch: 0003 train cost=2.421044302 test cost=2.421044510
Epoch: 0004 train cost=2.416726303 test cost=2.419485166
Epoch: 0005 train cost=2.420288840 test cost=2.419811010
Epoch: 0006 train cost=2.414657515 test cost=2.416858786
Epoch: 0007 train cost=2.418963445 test cost=2.416482449
Epoch: 0008 train cost=2.414868160 test cost=2.416482449
Epoch: 0009 train cost=2.417286340 test cost=2.416482449
Epoch: 0010 train cost=2.416559072 test cost=2.416482449
Epoch: 0011 train cost=2.416633970 test cost=2.416482449
Epoch: 0012 train cost=2.416597613 test cost=2.416482449
Epoch: 0013 train cost=2.416495098 test cost=2.416482449
Epoch: 0014 train cost=2.414902340 test cost=2.416482449
Epoch: 0015 train cost=2.418383806 test cost=2.416482449
Epoch: 0016 train cost=2.415936505 test cost=2.416482449
Epoch: 0017 train cost=2.415633960 test cost=2.416482449
Epoch: 0018 train cost=2.417508897 test cost=2.416482449
Epoch: 0019 train cost=2.416322699 test cost=2.416482449
Epoch: 0020 train cost=2.416581622 test cost=2.416482449
Epoch: 0021 train cost=2.415613604 test cost=2.416482449
Epoch: 0022 train cost=2.417015800 test cost=2.416482449
Epoch: 0023 train cost=2.415947450 test cost=2.416482449
Epoch: 0024 train cost=2.416775062 test cost=2.416482449
Epoch: 0025 train cost=2.416436165 test cost=2.416482449
Accuracy: 0.1032
```

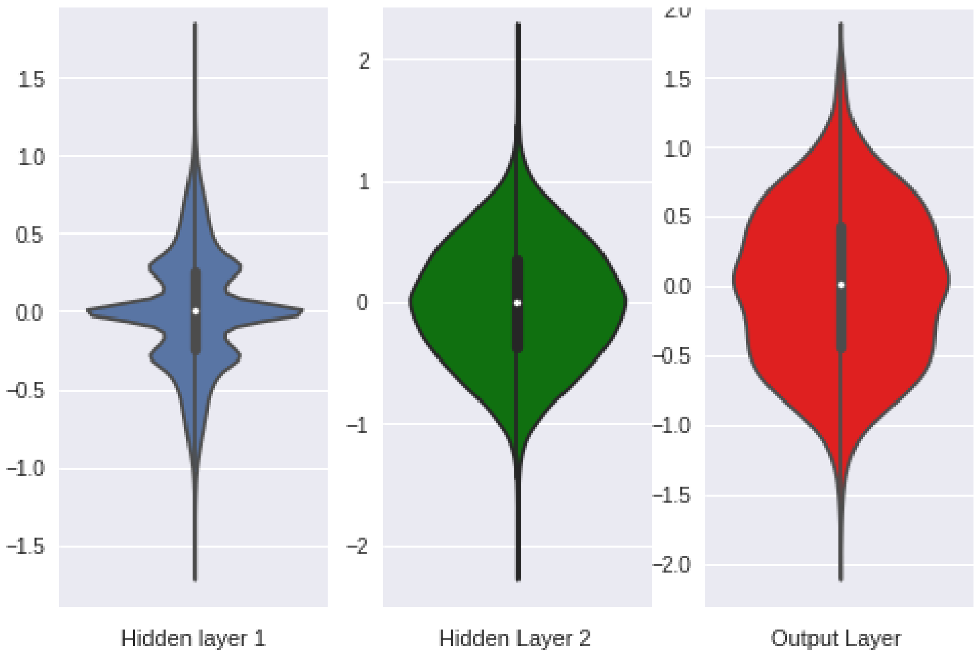


DISTRIBUTION OF WEIGHTS AT THE END OF TRAINING

In [36]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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



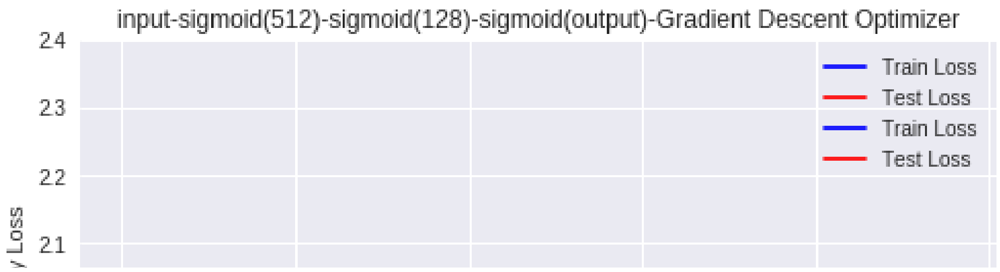
MODEL 1 + GRADIENT DESCENT OPTIMIZER

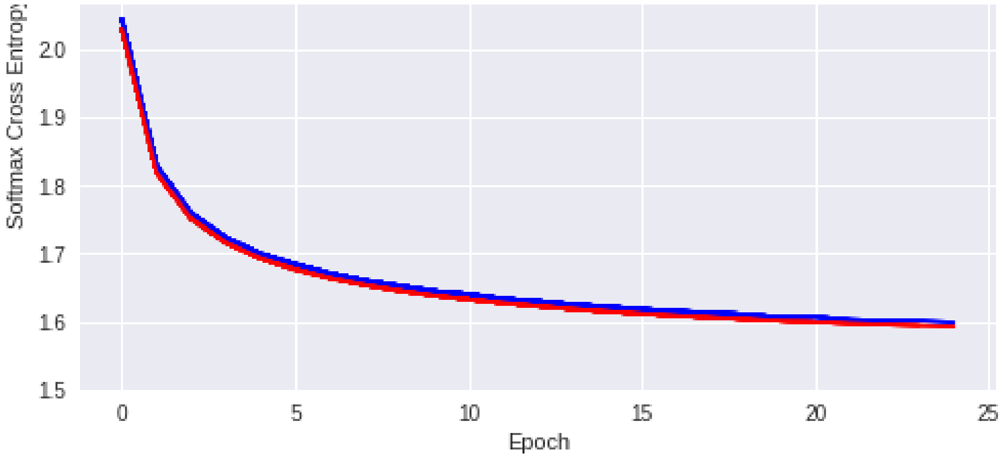
In [40]:

```
y_sgd = mulit_layer_perceptron(x,sgd_weights,biases)
cost_sgd = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y_
sgd, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_sgd)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_sgd)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([sgd_optimizer,cost_sgd,sgd_weights],feed_dict = {x:x
s_batch, y_:ys_batch})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_sgd, feed_dict = {x: data.test.images, y_: data.test
.labels})
      test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid(512)-sigmoid(128)-sigmoid(output)-Gradient Descent O
ptimizer")
```

```
    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.5, 2.5, step
=0.1), "input-sigmoid(512)-sigmoid(128)-sigmoid(output)-Gradient Descent Op
timizer")
  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: data.test.images, y_: data.test.labe
ls}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with Sigmoid Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_9:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with Sigmoid Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_10:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=2.043193551 test cost=2.029072599
Epoch: 0002 train cost=1.828018275 test cost=1.818836763
Epoch: 0003 train cost=1.758738297 test cost=1.750763631
Epoch: 0004 train cost=1.723038485 test cost=1.715592033
Epoch: 0005 train cost=1.699364166 test cost=1.692855772
Epoch: 0006 train cost=1.684273349 test cost=1.676451995
Epoch: 0007 train cost=1.670672937 test cost=1.663909405
Epoch: 0008 train cost=1.660386177 test cost=1.653847081
Epoch: 0009 train cost=1.652663500 test cost=1.645478160
Epoch: 0010 train cost=1.644776596 test cost=1.638397306
Epoch: 0011 train cost=1.640572270 test cost=1.632387510
Epoch: 0012 train cost=1.633569223 test cost=1.627141695
Epoch: 0013 train cost=1.629938219 test cost=1.622509373
Epoch: 0014 train cost=1.625114491 test cost=1.618449651
Epoch: 0015 train cost=1.621762742 test cost=1.614725340
Epoch: 0016 train cost=1.618119214 test cost=1.611504769
Epoch: 0017 train cost=1.615162013 test cost=1.608589630
Epoch: 0018 train cost=1.612940318 test cost=1.605904512
Epoch: 0019 train cost=1.610706869 test cost=1.603522582
Epoch: 0020 train cost=1.606590884 test cost=1.601215137
Epoch: 0021 train cost=1.607143675 test cost=1.599224574
Epoch: 0022 train cost=1.602653252 test cost=1.597340612
Epoch: 0023 train cost=1.601170429 test cost=1.595592232
Epoch: 0024 train cost=1.601869932 test cost=1.594005286
Epoch: 0025 train cost=1.598346431 test cost=1.592462624
Accuracy: 0.8936
```

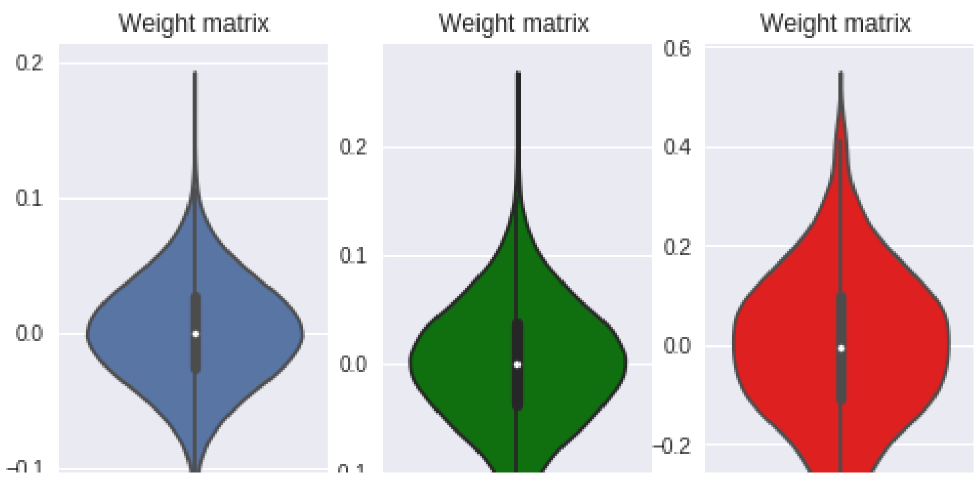


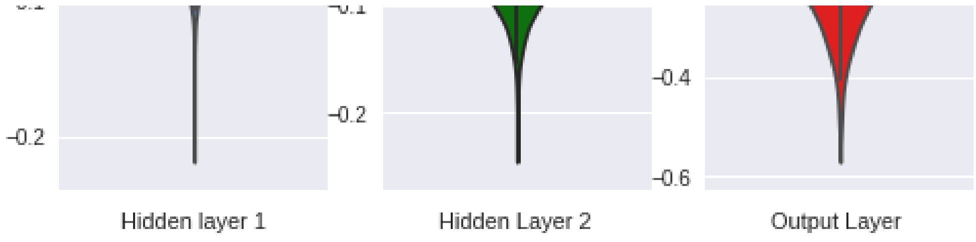


In [41]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:588: FutureWa
rning: 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: FutureWa
rning: 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) - ReLu(output 10)

-> The activation functions are ReLu

In [0]:

```
def mulit_layer_perceptron(x,weights,biases):
  print('Input layer')
  print("X:", x.get_shape(), "W[h1]:", weights['h1'].get_shape(), 'b[h1]:',
biases['b1'].get_shape())

  print('Hidden layer 1 with RELU Activation')
  layer_1 = tf.add(tf.matmul(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[b1]:', biases['b2'].get_shape())

  print("Hidden layer 2 with RELU Activation")
  layer_2 = tf.add(tf.matmul(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_shap
e, 'b3:', biases['out'].get_shape())

  print("Output layer")
  output_layer = tf.matmul(layer_2,weights['out']) + biases['out']
  output_layer = tf.nn.relu(output_layer)
  print('Output Layer:', output_layer.get_shape())

  return output_layer
```

MODEL 2 + ADAM Optimizer

Input-ReLu(512)-ReLu(128)-Relu(output) - AdamOptimizer

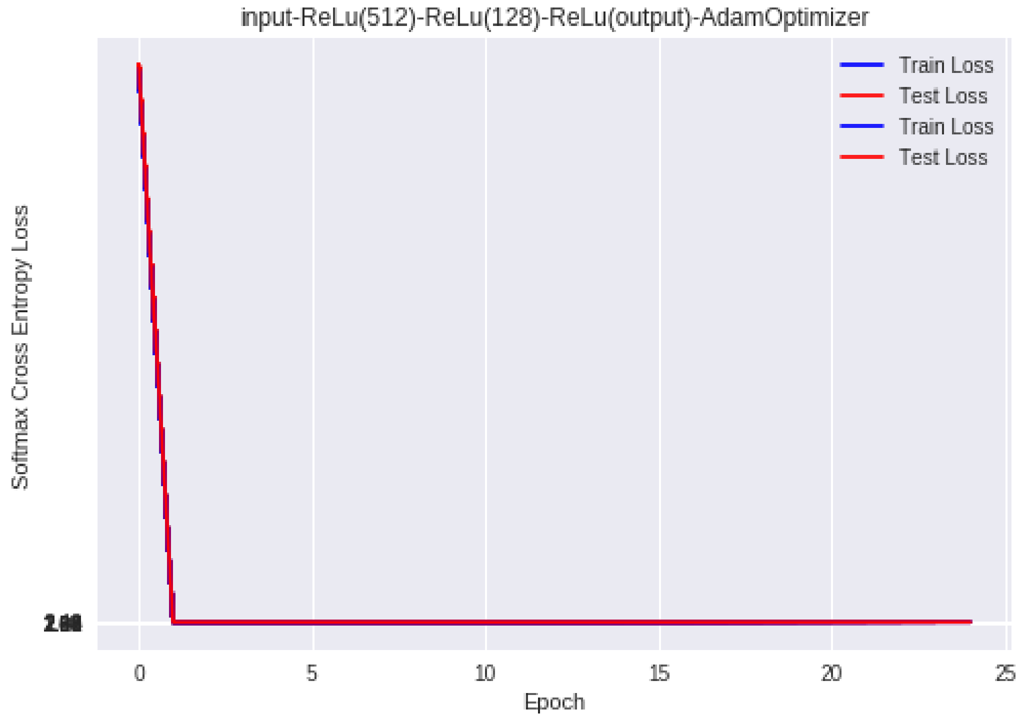
In [52]:

```
y_relu = mulit_layer_perceptron(x,relu_weights,biases)
cost_relu = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y
_relu, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_relu)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_relu)
```

```
t_relu)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([adam_optimizer,cost_relu,relu_weights],feed_dict =
{x:xs_batch, y_:ys_batch})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_relu, feed_dict = {x: data.test.images, y_: data.tes
t.labels})
      test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu(512)-ReLu(128)-ReLu(output)-AdamOptimizer")

    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu(512)-ReLu(128)-ReLu(output)-AdamOptimizer")
  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: data.test.images, y_: data.test.labe
ls}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with RELU Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_21:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with RELU Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_22:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=209.421812495 test cost=210.405454614
Epoch: 0002 train cost=2.302582741 test cost=2.302565488
Epoch: 0003 train cost=2.302582741 test cost=2.302571774
Epoch: 0004 train cost=2.302582741 test cost=2.302571774
Epoch: 0005 train cost=2.302582741 test cost=2.302571774
Epoch: 0006 train cost=2.302582741 test cost=2.302571774
Epoch: 0007 train cost=2.302582741 test cost=2.302571774
Epoch: 0008 train cost=2.302582741 test cost=2.302571774
Epoch: 0009 train cost=2.302582741 test cost=2.302571774
Epoch: 0010 train cost=2.302582741 test cost=2.302571774
```

```
Epoch: 0011 train cost=2.302582741 test cost=2.302571774
Epoch: 0012 train cost=2.302582741 test cost=2.302571774
Epoch: 0013 train cost=2.302582741 test cost=2.302571774
Epoch: 0014 train cost=2.302582741 test cost=2.302571774
Epoch: 0015 train cost=2.302582741 test cost=2.302571774
Epoch: 0016 train cost=2.302582741 test cost=2.302571774
Epoch: 0017 train cost=2.302582741 test cost=2.302571774
Epoch: 0018 train cost=2.302582741 test cost=2.302571774
Epoch: 0019 train cost=2.302582741 test cost=2.302571774
Epoch: 0020 train cost=2.302582741 test cost=2.302571774
Epoch: 0021 train cost=2.302582741 test cost=2.302571774
Epoch: 0022 train cost=2.302582741 test cost=2.302571774
Epoch: 0023 train cost=2.302582741 test cost=2.302571774
Epoch: 0024 train cost=2.302582741 test cost=2.302571774
Epoch: 0025 train cost=2.302582741 test cost=2.302571774
Accuracy: 0.0959
```

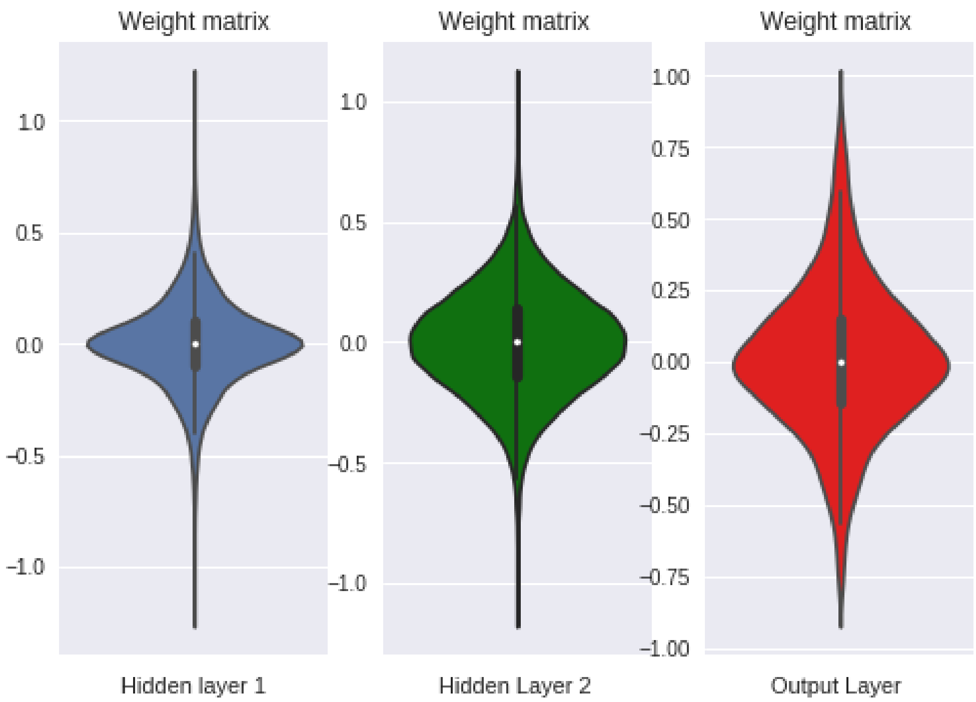


In [53]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

mp.subplot(1, 3, 3)
mp.title("Weight matrix ")
```

```
mp.title('Weight matrix')
ax = s.violinplot(y=out_w,color='r')
mp.xlabel('Output Layer ')
mp.show()
```

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




```
MODEL 2 + GRADIENT DESCENT OPTIMIZER
```

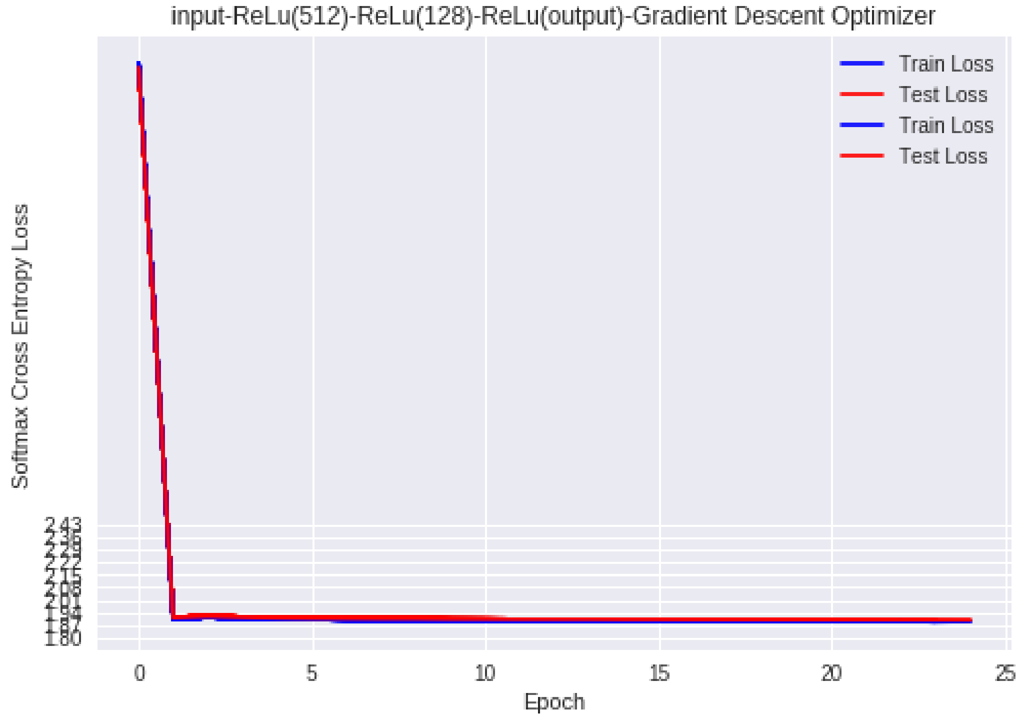
In [54]:

```
y_relu = mulit_layer_perceptron(x,relu_weights,biases)
cost_relu = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y
_relu, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_relu)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_relu)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
```

```
        xs_batch, ys_batch = data.train.next_batch(batch_size)
        _,c,w = sess.run([sgd_optimizer,cost_relu,relu_weights],feed_dict = {
x:xs_batch, y_:ys_batch})
        train_avg_cost += c/number_of_batches
        c = sess.run(cost_relu, feed_dict = {x: data.test.images, y_: data.tes
t.labels})
        test_avg_cost  += c/number_of_batches
      epchs.append(epoch)
      ytrainloss.append(train_avg_cost)
      ytestloss.append(test_avg_cost)
      dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu(512)-ReLu(128)-ReLu(output)-Gradient Descent Optimizer"
)

      if epoch%display_step == 0:
        print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
      dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu(512)-ReLu(128)-ReLu(output)-Gradient Descent Optimizer"
)
    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: data.test.images, y_: data.test.labe
ls}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with RELU Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_21:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with RELU Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_22:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=4.980333456 test cost=4.963308534
Epoch: 0002 train cost=1.904925619 test cost=1.912343695
Epoch: 0003 train cost=1.913920914 test cost=1.919963113
Epoch: 0004 train cost=1.906759251 test cost=1.914553289
Epoch: 0005 train cost=1.901835554 test cost=1.910970788
Epoch: 0006 train cost=1.902117114 test cost=1.909050426
Epoch: 0007 train cost=1.900284037 test cost=1.907728091
Epoch: 0008 train cost=1.898658954 test cost=1.906581226
Epoch: 0009 train cost=1.896835147 test cost=1.906401160
Epoch: 0010 train cost=1.896392504 test cost=1.904773519
Epoch: 0011 train cost=1.895304086 test cost=1.904421603
Epoch: 0012 train cost=1.894359940 test cost=1.903752665
Epoch: 0013 train cost=1.895284351 test cost=1.903683693
Epoch: 0014 train cost=1.895441476 test cost=1.903686699
Epoch: 0015 train cost=1.892990817 test cost=1.902676901
Epoch: 0016 train cost=1.893376431 test cost=1.902505441
Epoch: 0017 train cost=1.892992397 test cost=1.902061113
Epoch: 0018 train cost=1.891415631 test cost=1.901908773
Epoch: 0019 train cost=1.892247939 test cost=1.901883442
Epoch: 0020 train cost=1.891918295 test cost=1.901420602
Epoch: 0021 train cost=1.890442915 test cost=1.900770434
Epoch: 0022 train cost=1.891120323 test cost=1.900679348
```

```
Epoch: 0023 train cost=1.893256543 test cost=1.900676042
Epoch: 0024 train cost=1.888824339 test cost=1.900287646
Epoch: 0025 train cost=1.891013288 test cost=1.899846888
Accuracy: 0.0954
```

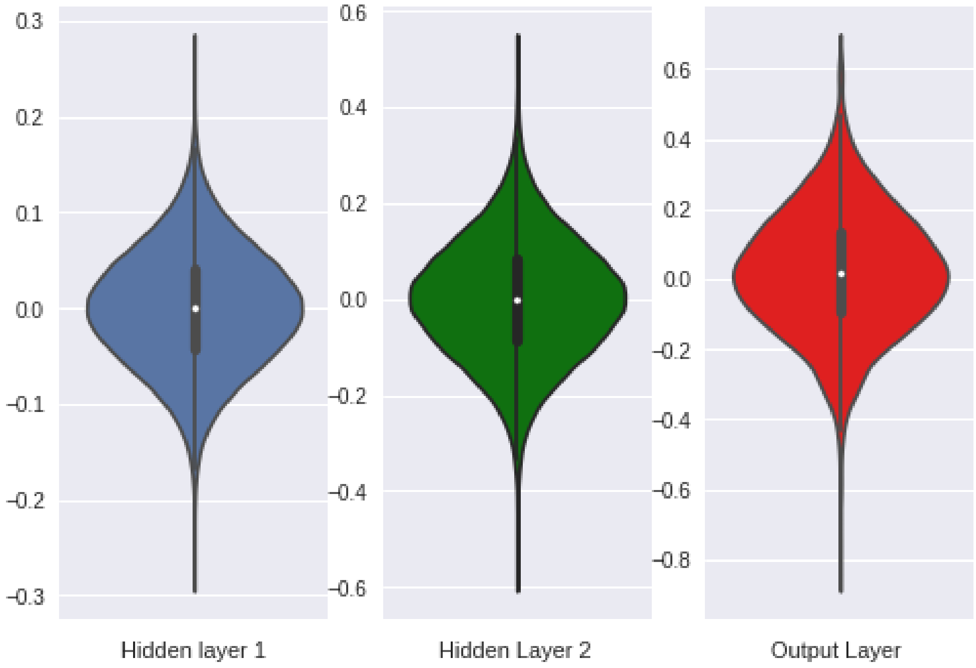


In [55]:

```python
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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

Weight matrix   Weight matrix   Weight matrix



MODEL 3: INPUT - SIGMOID(BatchNormalization(512)) - SIGMOID(BatchNormalization(128)) - SIGMOID(output)

-> The activation functions are SIGMOID

In [0]:

```
eplsilon = 0.01
def mulit_layer_perceptron(x,weights,biases):
  print('Input layer')
  print("X:", x.get_shape(), "W[h1]:", weights['h1'].get_shape(), 'b[h1]:',
biases['b1'].get_shape())

  print('Hidden layer 1 with Sigmoid Activation')
  layer_1 = tf.add(tf.matmul(x,weights['h1']),biases['b1'])
  mean_1, 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]))
  layer_1 = tf.nn.batch_normalization(layer_1,mean_1, var_1, scale_1,
beta_1,eplsilon)
  layer_1 - tf.nn.sigmoid(layer_1)
  print("Layer_1:", layer_1.get_shape(), 'W[h2]:', weights['h2'].get_shape,
'b[b1]:', biases['b2'].get_shape())

  print("Hidden layer 2 with Sigmoid Activation")
  layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2'])
  mean_2, 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,mean_2, var_2, scale_2,
beta_2,eplsilon)
  layer_2 - tf.nn.sigmoid(layer_2)
  print("Layer_2:", layer_2.get_shape(), 'W[out]:', weights['out'].get_shap
e, 'b3:', biases['out'].get_shape())

  print("Output layer")
  output layer = tf.matmul(layer 2,weights['out']) + biases['out']
```

```
  output_layer = tf.nn.sigmoid(output_layer)
  print('Output Layer:', output_layer.get_shape())

  return output_layer
```

In [0]:

```

```

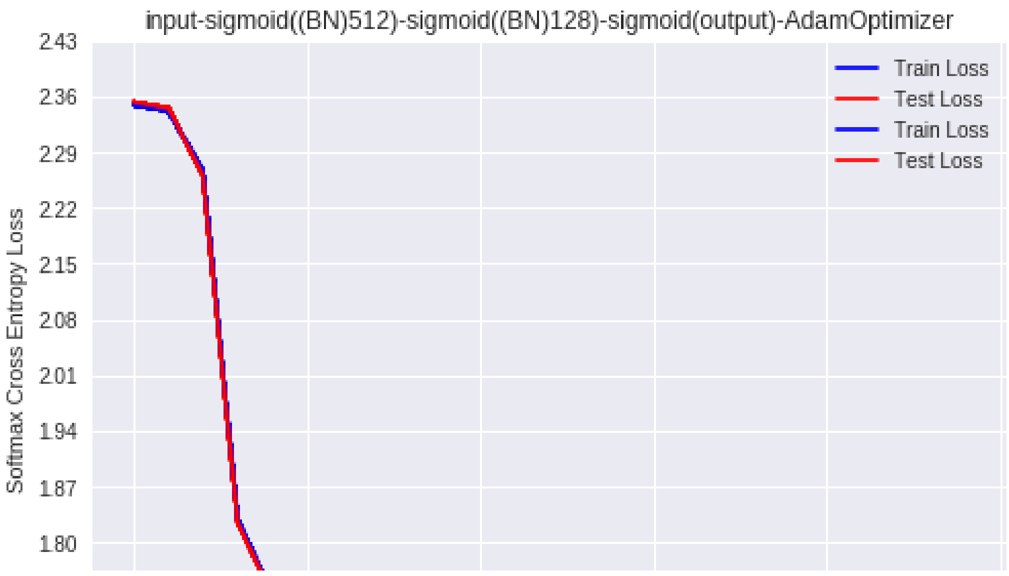
MODEL 3 + ADAM OPTIMIZER

In [69]:

```
y_sgd = mulit_layer_perceptron(x,sgd_weights,biases)
cost_sgd = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y_
sgd, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_sgd)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_sgd)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([adam_optimizer,cost_sgd,sgd_weights],feed_dict = {x:
xs_batch, y_:ys_batch})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_sgd, feed_dict = {x: data.test.images, y_: data.test
.labels})
      test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid((BN)512)-sigmoid((BN)128)-sigmoid(output)-AdamOptimi
zer")

    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid((BN)512)-sigmoid((BN)128)-sigmoid(output)-AdamOptimi
zer")
  correct_prediction = tf.equal(tf.argmax(y_sgd,1), tf.argmax(y_,1))
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

```
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
  print("Accuracy:", accuracy.eval({x: data.test.images, y_: data.test.labe
ls}))
```

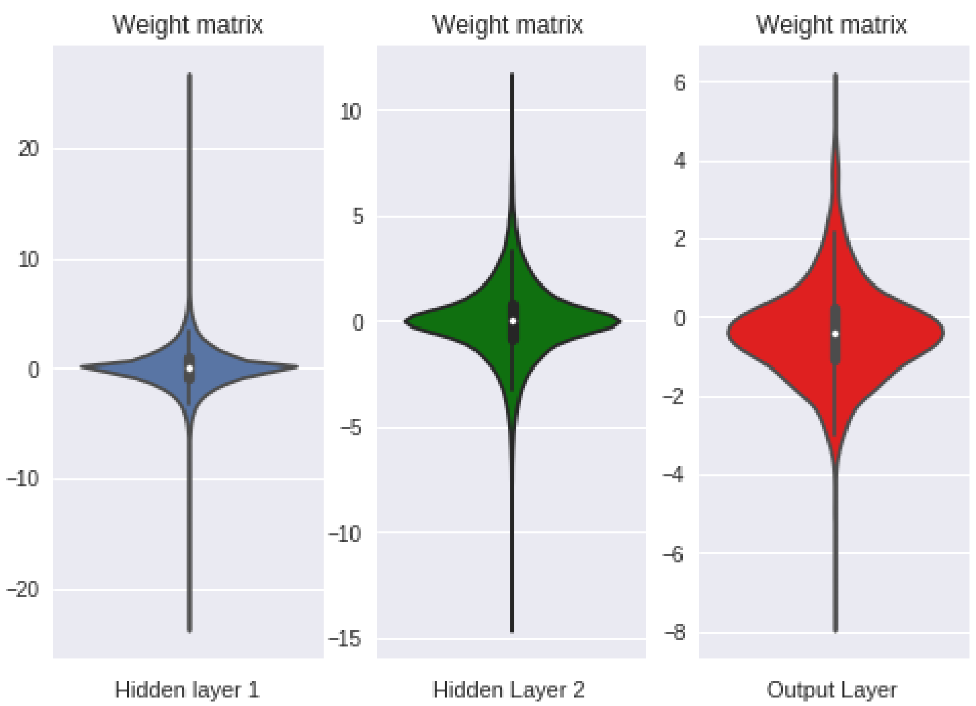
```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with Sigmoid Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_27:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with Sigmoid Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_28:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=2.349449171 test cost=2.352906570
Epoch: 0002 train cost=2.342291914 test cost=2.345360127
Epoch: 0003 train cost=2.266466056 test cost=2.261591890
Epoch: 0004 train cost=1.829162110 test cost=1.825918247
Epoch: 0005 train cost=1.734419727 test cost=1.733736868
Epoch: 0006 train cost=1.710431199 test cost=1.710253932
Epoch: 0007 train cost=1.706800042 test cost=1.706654499
Epoch: 0008 train cost=1.699189143 test cost=1.704543404
Epoch: 0009 train cost=1.700946758 test cost=1.704560947
Epoch: 0010 train cost=1.703178620 test cost=1.703930261
Epoch: 0011 train cost=1.696222058 test cost=1.702921508
Epoch: 0012 train cost=1.696756903 test cost=1.701534937
Epoch: 0013 train cost=1.699936199 test cost=1.701771749
Epoch: 0014 train cost=1.698799385 test cost=1.701496204
Epoch: 0015 train cost=1.695097373 test cost=1.700269287
Epoch: 0016 train cost=1.697288717 test cost=1.701145328
Epoch: 0017 train cost=1.698095374 test cost=1.701825302
Epoch: 0018 train cost=1.695608083 test cost=1.699904903
Epoch: 0019 train cost=1.695946338 test cost=1.700065361
Epoch: 0020 train cost=1.693136610 test cost=1.699424575
Epoch: 0021 train cost=1.701571848 test cost=1.703001423
Epoch: 0022 train cost=1.692584200 test cost=1.699309936
Epoch: 0023 train cost=1.696456705 test cost=1.700631369
Epoch: 0024 train cost=1.695445267 test cost=1.699066962
Epoch: 0025 train cost=1.693661974 test cost=1.700077118
Accuracy: 0.7294
```



In [70]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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



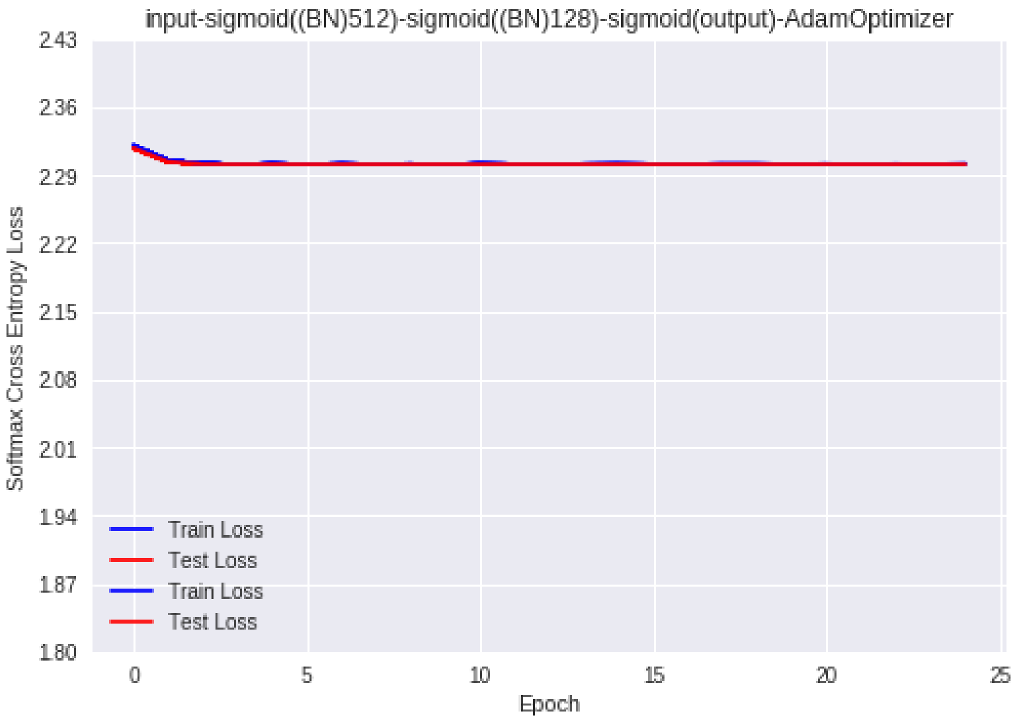
MODEL 3 + GRADIENT DESCENT OPTIMIZER

In [71]:

```
y_sgd = mulit_layer_perceptron(x,sgd_weights,biases)
cost_sgd = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y_
sgd, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_sgd)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_sgd)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([sgd_optimizer,cost_sgd,sgd_weights],feed_dict = {x:x
s_batch, y_:ys_batch})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_sgd, feed_dict = {x: data.test.images, y_: data.test
.labels})
      test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid((BN)512)-sigmoid((BN)128)-sigmoid(output)-AdamOptimi
zer")

    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-sigmoid((BN)512)-sigmoid((BN)128)-sigmoid(output)-AdamOptimi
zer")
  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: data.test.images, y_: data.test.labe
ls}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with Sigmoid Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable 27:0' shape=(512, 128) dtype=float32 ref>> b[b1]: (128,)
```

```
Hidden layer 2 with Sigmoid Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_28:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=2.320533943 test cost=2.318185780
Epoch: 0002 train cost=2.305083630 test cost=2.303832847
Epoch: 0003 train cost=2.301661552 test cost=2.301160088
Epoch: 0004 train cost=2.301111967 test cost=2.301026752
Epoch: 0005 train cost=2.301475495 test cost=2.301105400
Epoch: 0006 train cost=2.301193979 test cost=2.301031264
Epoch: 0007 train cost=2.301438288 test cost=2.301095143
Epoch: 0008 train cost=2.301250159 test cost=2.301060295
Epoch: 0009 train cost=2.301365215 test cost=2.301036874
Epoch: 0010 train cost=2.301085242 test cost=2.301097241
Epoch: 0011 train cost=2.301509380 test cost=2.301023938
Epoch: 0012 train cost=2.301304674 test cost=2.301086452
Epoch: 0013 train cost=2.301106496 test cost=2.301053021
Epoch: 0014 train cost=2.301367014 test cost=2.301043298
Epoch: 0015 train cost=2.301469621 test cost=2.301071037
Epoch: 0016 train cost=2.301324597 test cost=2.301045392
Epoch: 0017 train cost=2.301253176 test cost=2.301060603
Epoch: 0018 train cost=2.301400961 test cost=2.301052159
Epoch: 0019 train cost=2.301417836 test cost=2.301041339
Epoch: 0020 train cost=2.301236304 test cost=2.301039189
Epoch: 0021 train cost=2.301380183 test cost=2.301083261
Epoch: 0022 train cost=2.301128041 test cost=2.301049540
Epoch: 0023 train cost=2.301390479 test cost=2.301055999
Epoch: 0024 train cost=2.301089820 test cost=2.301090657
Epoch: 0025 train cost=2.301667773 test cost=2.301065579
Accuracy: 0.1135
```

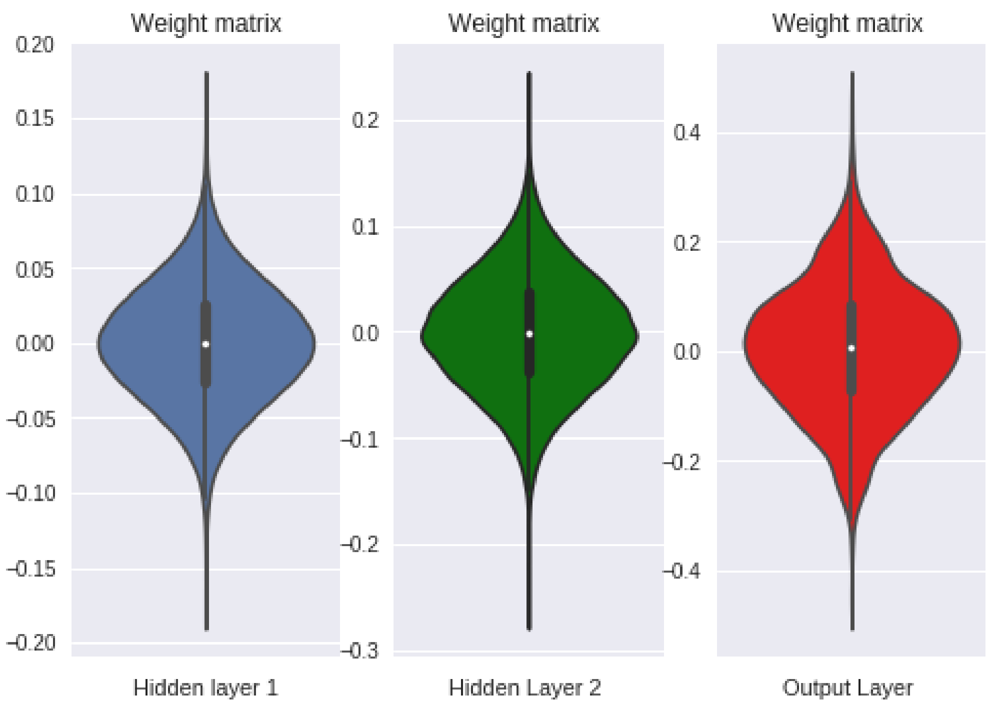


In [72]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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




```
                         MODEL 4: INPUT - ReLu(Drop out(512)) - ReLu(I
rop out(128)) - ReLu(output)

                                        -> The activation functions
are ReLU
```

In [0]:

```
def mulit_layer_perceptron(x,weights,biases):
```

```
def mulit_layer_perceptron(x,weights,biases):
  print('Input layer')
  print("X:", x.get_shape(), "W[h1]:", weights['h1'].get_shape(), 'b[h1]:', biases['b1'].get_shape())

  print('Hidden layer 1 with RELU Activation')
  layer_1 = tf.add(tf.matmul(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[b1]:', biases['b2'].get_shape())
  layer_1_drop = tf.nn.dropout(layer_1, keep_prob)

  print("Hidden layer 2 with RELU Activation")
  layer_2 = tf.add(tf.matmul(layer_1_drop,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())
  layer_2_drop = tf.nn.dropout(layer_2, keep_prob)

  print("Output layer")
  output_layer = tf.matmul(layer_2_drop,weights['out']) + biases['out']
  output_layer = tf.nn.relu(output_layer)
  print('Output Layer:', output_layer.get_shape())

  return output_layer
```

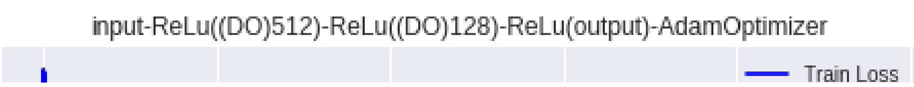
MODEL 4 + ADAM OPTIMIZER

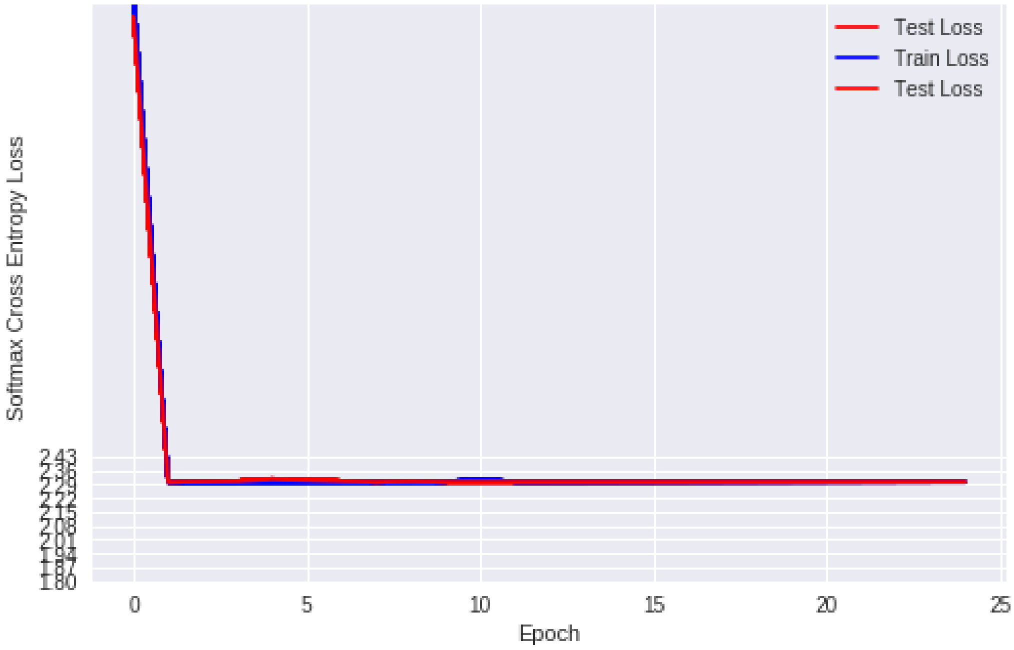
In [77]:

```
y_relu = mulit_layer_perceptron(x,relu_weights,biases)
cost_relu = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y_relu, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost_relu)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cost_relu)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([adam_optimizer,cost_relu,relu_weights],feed_dict = {x:xs_batch, y_:ys_batch, keep_prob:0.5})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_relu, feed_dict = {x: data.test.images, y_: data.test.labels, keep_prob:0.5})
```

```
t.labels, keep_prob:0.5})
            test_avg_cost  += c/number_of_batches
        epchs.append(epoch)
        ytrainloss.append(train_avg_cost)
        ytestloss.append(test_avg_cost)
        dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu(512)-ReLu(128)-ReLu(output)-AdamOptimizer")

        if epoch%display_step == 0:
            print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
        dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu((DO)512)-ReLu((DO)128)-ReLu(output)-AdamOptimizer")
    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: data.test.images, y_: data.test.labe
ls, keep_prob:0.5}))
```

```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with RELU Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_30:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with RELU Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_31:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=4.767311148 test cost=4.649149166
Epoch: 0002 train cost=2.302582741 test cost=2.302571774
Epoch: 0003 train cost=2.302582741 test cost=2.303704626
Epoch: 0004 train cost=2.302582741 test cost=2.305074540
Epoch: 0005 train cost=2.302582741 test cost=2.316208046
Epoch: 0006 train cost=2.302582741 test cost=2.310911512
Epoch: 0007 train cost=2.302582741 test cost=2.305555123
Epoch: 0008 train cost=2.302582741 test cost=2.302571774
Epoch: 0009 train cost=2.302582741 test cost=2.304625555
Epoch: 0010 train cost=2.302582741 test cost=2.302571774
Epoch: 0011 train cost=2.312040814 test cost=2.302571774
Epoch: 0012 train cost=2.302582741 test cost=2.302571774
Epoch: 0013 train cost=2.302582741 test cost=2.302571774
Epoch: 0014 train cost=2.302582741 test cost=2.302571774
Epoch: 0015 train cost=2.302582741 test cost=2.302571774
Epoch: 0016 train cost=2.302582741 test cost=2.302571774
Epoch: 0017 train cost=2.302582741 test cost=2.302571774
Epoch: 0018 train cost=2.302582741 test cost=2.302571774
Epoch: 0019 train cost=2.302582741 test cost=2.302571774
Epoch: 0020 train cost=2.302582741 test cost=2.302571774
Epoch: 0021 train cost=2.302582741 test cost=2.302571774
Epoch: 0022 train cost=2.302582741 test cost=2.302571774
Epoch: 0023 train cost=2.302582741 test cost=2.302571774
Epoch: 0024 train cost=2.302582741 test cost=2.302571774
Epoch: 0025 train cost=2.302582741 test cost=2.302571774
Accuracy: 0.0892
```

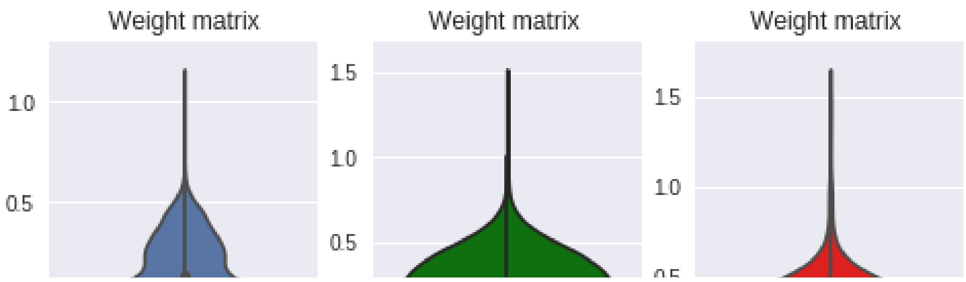


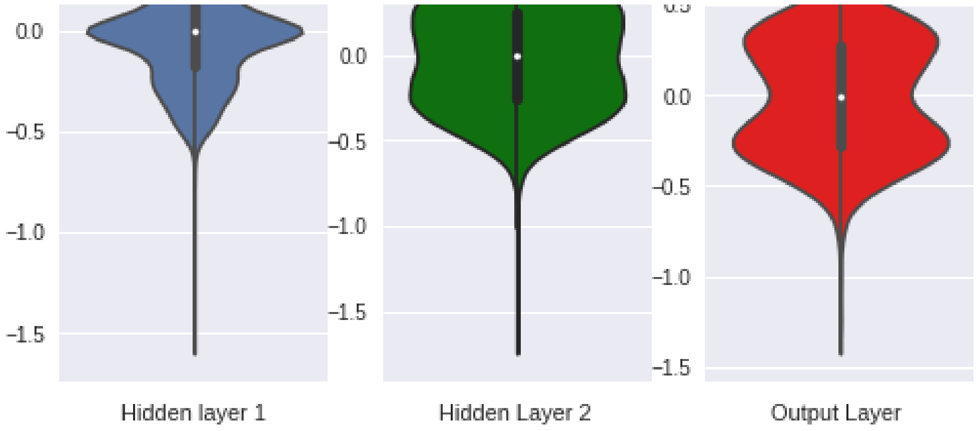


In [78]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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





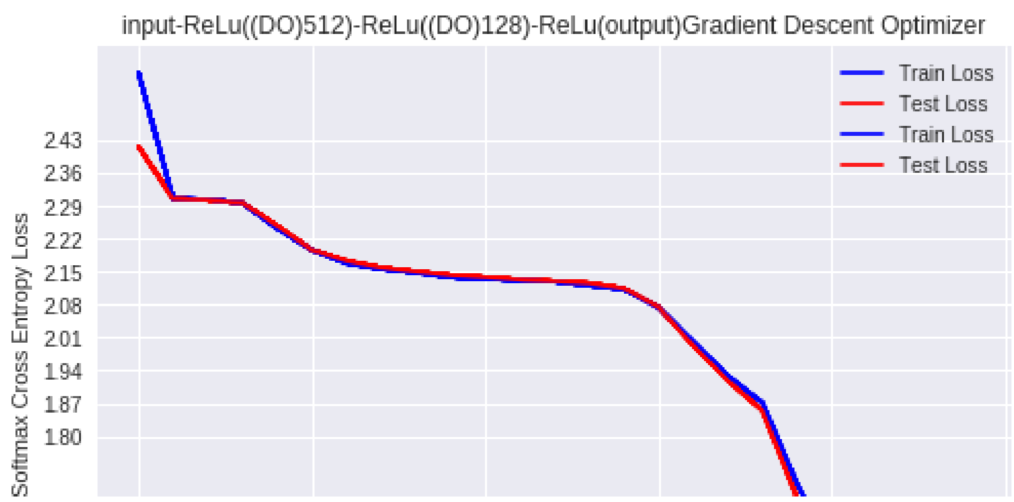
MODEL 4 + GRADIENT DESCENT OPTIMIZER

In [81]:

```
y_relu = mulit_layer_perceptron(x,relu_weights,biases)
cost_relu = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=y
_relu, labels = y_))
adam_optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimi
ze(cost_relu)
sgd_optimizer =
tf.train.GradientDescentOptimizer(learning_rate=learning_rate).minimize(cos
t_relu)

with tf.Session() as sess:
  tf.global_variables_initializer().run()
  fig,ax = mp.subplots(1,1)
  ax.set_xlabel('Epoch')
  ax.set_ylabel("Softmax Cross Entropy Loss")
  epchs, ytrainloss, ytestloss = [], [], []
  for epoch in range(training_epochs):
    train_avg_cost = 0
    test_avg_cost = 0
    number_of_batches = int(data.train.num_examples/batch_size)

    for i in range(number_of_batches):
      xs_batch, ys_batch = data.train.next_batch(batch_size)
      _,c,w = sess.run([sgd_optimizer,cost_relu,relu_weights],feed_dict = {
x:xs_batch, y_:ys_batch, keep_prob:0.5})
      train_avg_cost += c/number_of_batches
      c = sess.run(cost_relu, feed_dict = {x: data.test.images, y_: data.tes
t.labels, keep_prob:0.5})
      test_avg_cost  += c/number_of_batches
    epchs.append(epoch)
    ytrainloss.append(train_avg_cost)
    ytestloss.append(test_avg_cost)
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu((DO)512)-ReLu((DO)128)-ReLu(output)-Gradient Descent Op
timizer")

    if epoch%display_step == 0:
      print("Epoch:", '%04d' % (epoch+1), "train cost={:.9f}".format(train_a
vg_cost), "test cost={:.9f}".format(test_avg_cost))
    dynamic_plot(epchs, ytrainloss, ytestloss, ax, np.arange(1.8, 2.5, step
=0.07), "input-ReLu((DO)512)-ReLu((DO)128)-ReLu(output)Gradient Descent Opt
```

```
imizer")
  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: data.test.images, y_: data.test.labe
ls, keep_prob:0.5}))
```

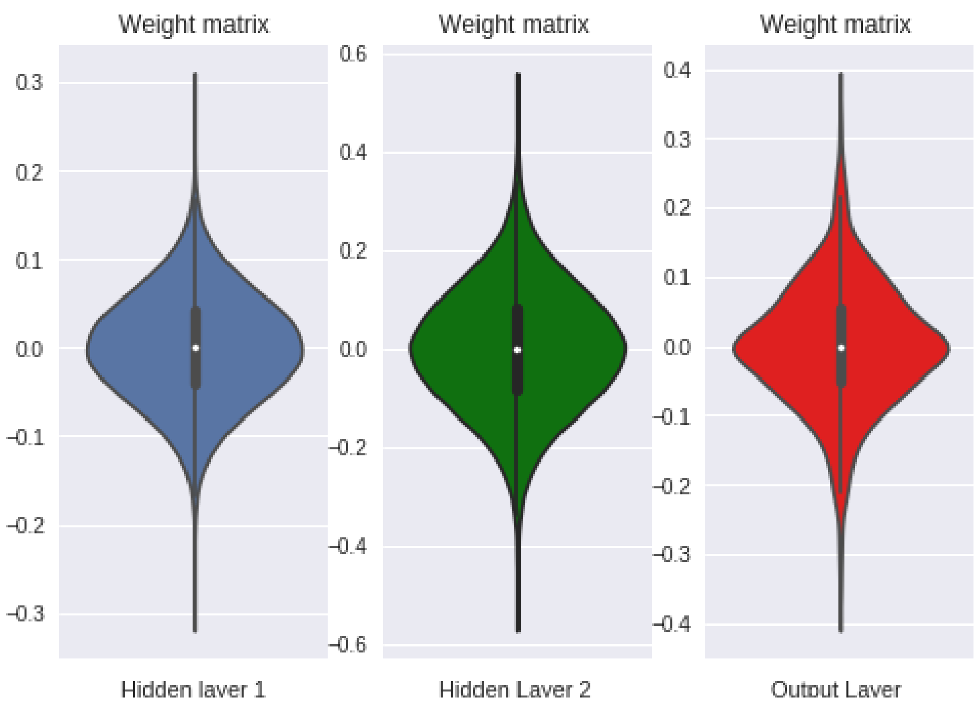
```
Input layer
X: (?, 784) W[h1]: (784, 512) b[h1]: (512,)
Hidden layer 1 with RELU Activation
Layer_1: (?, 512) W[h2]: <bound method Variable.get_shape of <tf.Variable '
Variable_30:0' shape=(512, 128) dtype=float32_ref>> b[b1]: (128,)
Hidden layer 2 with RELU Activation
Layer_2: (?, 128) W[out]: <bound method Variable.get_shape of <tf.Variable
'Variable_31:0' shape=(128, 10) dtype=float32_ref>> b3: (10,)
Output layer
Output Layer: (?, 10)
Epoch: 0001 train cost=2.572081514 test cost=2.416359403
Epoch: 0002 train cost=2.304764600 test cost=2.305176154
Epoch: 0003 train cost=2.303997738 test cost=2.303121476
Epoch: 0004 train cost=2.295936758 test cost=2.296186772
Epoch: 0005 train cost=2.242655997 test cost=2.247438860
Epoch: 0006 train cost=2.196123284 test cost=2.196128598
Epoch: 0007 train cost=2.168153858 test cost=2.172993187
Epoch: 0008 train cost=2.155915421 test cost=2.158906438
Epoch: 0009 train cost=2.148236782 test cost=2.150557015
Epoch: 0010 train cost=2.137970213 test cost=2.142845969
Epoch: 0011 train cost=2.134381212 test cost=2.138372343
Epoch: 0012 train cost=2.131681863 test cost=2.133029691
Epoch: 0013 train cost=2.129146788 test cost=2.129725161
Epoch: 0014 train cost=2.120631886 test cost=2.125522679
Epoch: 0015 train cost=2.112758988 test cost=2.114596488
Epoch: 0016 train cost=2.074142833 test cost=2.074843818
Epoch: 0017 train cost=2.000587242 test cost=1.993752909
Epoch: 0018 train cost=1.928366858 test cost=1.918500996
Epoch: 0019 train cost=1.871250831 test cost=1.853919181
Epoch: 0020 train cost=1.698395027 test cost=1.668408006
Epoch: 0021 train cost=1.550084251 test cost=1.521005119
Epoch: 0022 train cost=1.475075945 test cost=1.458681367
Epoch: 0023 train cost=1.454468053 test cost=1.427334798
Epoch: 0024 train cost=1.423312850 test cost=1.406613092
Epoch: 0025 train cost=1.407162792 test cost=1.387703720
Accuracy: 0.1028
```



In [82]:

```
import seaborn as s

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 = mp.figure()
mp.subplot(1,3,1)
mp.title("Weight matrix")
ax = s.violinplot(y = h1_w, clolr = 'b')
mp.xlabel("Hidden layer 1")


mp.subplot(1, 3, 2)
mp.title("Weight matrix ")
ax = s.violinplot(y=h2_w, color='g')
mp.xlabel('Hidden Layer 2 ')

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

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



```
CONCLUSION:

            -> MODEL 1

                     -> SIGMOID ACTIVATION FUNCTIONS

                             -> ADAM OPTIMIZER

                                     -> TRAIN LOSS  - 2.41(
                                     -> TEST LOSS   - 2.41·
                                     -> ACCURACY    - 10.3:

                             -> GRADIENT DESCENT OPTIMIZER

                                    -> TRAIN LOSS  - 1.598:
                                    -> TEST LOSS   - 1.592!
                                    -> ACCURACY    - 89.36

             -> MODEL 2

                      -> RELU ACTIVATION FUNCTIONS

                            -> ADAM OPTIMIZER

                                   -> TRAIN LOSS  - 2.3625
                                   -> TEST LOSS   - 2.3025
                                   -> ACCURACY    - 9.59

                             -> GRADIENT DESCENT OPTIMIZER

                                    -> TRAIN LOSS  - 1.891(
                                    -> TEST LOSS   - 1.899{
                                    -> ACCURACY    - 9.54

              -> MODEL 3

                        -> SIGMOID ACTIVATION FUNCTIONS WI'
BATCH NORMALIZATION

                               -> ADAM OPTIMIZER

                                       -> TRAIN LOSS  -
1.6936
                                       -> TEST LOSS   -
1.70007
                                       -> ACCURACY    - 72.!

                                -> GRADIENT DESCENT OPTIMI:
R
```

```
                                               -> TRAIN LOSS  -
2.3016
                                               -> TEST LOSS   -
2.3010
                                               -> ACCURACY    - 11.
                         -> MODEL 4

                                    -> RELU ACTIVATION FUNCTION WITH
ROP OUT

                                            -> ADAM OPTIMIZER

                                                   -> TRAIN LOSS  -
2.3025
                                                   -> TEST LOSS   -
2.3025
                                                   -> ACCURACY    -
8.92

                                             -> GRADIENT DESCENT OPT
IZER

                                                   -> TRAIN LOSS  -
1.4071
                                                   -> TEST LOSS   -
1.3877
                                                   -> ACCURACY    -
10.28
```